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<u>Via ECF</u> Hon. Lewis J. Liman United States District Court

December 23, 2025

Re: Lively v. Wayfarer Studios LLC et al., No. 1:24-cv-10049-LJL

Dear Judge Liman:

As counsel for Wayfarer Studios LLC, Justin Baldoni, Jamey Heath, Steve Sarowitz, It Ends With Us Movie LLC, Melissa Nathan, The Agency Group PR LLC, and Jennifer Abel (collectively, the "Wayfarer Parties"), we write in opposition to Blake Lively's motion for sanctions and other relief concerning the deposition of Nicole Alexander (the "Motion"). (Dkt. 1133).

Ms. Alexander is an expert in digital ecosystems, AI-mediated brand perception, and online reputation measurement. She was designated by the Wayfarer Parties to rebut certain expert reports concerning whether the social media activity regarding Ms. Lively from August 2024 through February 2025 was caused by a coordinated, negative manipulation campaign (as Ms. Lively alleges) or was the result of organic public engagement and entertainment industry media cycles. (Fritz Decl., ¶ 3). On December 15, 2025, Ms. Alexander was deposed, *for seven hours*, by Ms. Lively's counsel, Meryl Governski, about her expertise and her expert report. (Fritz Decl., Ex. 1).

Rule 30(c)(2) of the Federal Rules of Civil Procedures provides that "[a]n objection [during a deposition] must be stated concisely in a nonargumentative and nonsuggestive manner." Under Rule 30(d)(2), courts are authorized to impose sanctions for conduct that "impedes, delays, or frustrates the fair examination of the deponent." Ms. Lively submitted to the Court only 35 pages from Ms. Alexander's deposition transcript – a mere ten percent thereof – presumably to create a false narrative. We submit herewith the entire transcript so that the Court can see that *Ms. Alexander's deposition was not impeded, delayed, or frustrated*. Upon reviewing the transcript, the Court will see that the Wayfarer Parties' counsel concisely and appropriately objected to the form of certain questions, did not utilize speaking objections, and permitted Ms. Alexander to answer every question (except for one topic, which is addressed below). The Motion *does not*

¹ Ms. Alexander's deposition had nothing to do with Ms. Lively's sexual or romantic history. Nonetheless, the Motion attaches a self-serving letter, *from three months ago*, sent by Ms. Lively's counsel to the Wayfarer Parties' counsel, complaining (erroneously) about certain deposition questions purportedly concerning her "sexual or romantic history." (Dkt. 1133-3). The questions at issue therein pertained to Ms. Lively's reputation, which she put at issue. (Fritz Decl., Ex. 2). Given that Ms. Lively did not seek relief from the Court months ago *about any purportedly improper lines of questioning* and is not seeking such relief now, the Motion seemingly was filed solely to generate inflammatory headlines and falsely besmirch the character of the Wayfarer Parties' counsel. *See, e.g.*, William Earl, *Blake Lively's Lawyers Blast Justin Baldoni's Lawyers' Deposition Behavior, Say Questions About Her Sex History Should Be Off Limits*, Variety (Dec. 19, 2025), https://variety.com/2025/film/news/blake-lively-justin-baldoni-lawyers-sex-history-off-limits-1236613219/; BreAnna Bell, *Blake Lively's lawyers blast Justin Baldoni's team over probing her sex life in 'disruptive' depositions*, New York Post (Dec. 20, 2025), https://pagesix.com/2025/12/20/celebrity-news/blake-lively-lawyers-blast-justin-baldonis-team-over-disruptive-deposition-behavior/.

Hon. Lewis J. Liman Page 2

identify any material area of testimony Ms. Governski sought to explore that she was prevented from exploring by counsel's objections. *See Edwards v. Wilkie*, No. 16-cv-8031, WL 5957171, at *3 (S.D.N.Y. Nov. 13, 2019) (denying sanctions motion where objections to deposition questions "while numerous, were not inappropriate or unwarranted[,]" where the "vast majority of the objections were not speaking objections" and where "defense counsel only instructed [the witness] not to answer one time"); *IBM Corp. v. Micro Focus (US) Inc.*, No. 22-cv-9910, 2024 WL 535730 (S.D.N.Y. Jan. 3, 2024) (denying sanctions motion where deposition "transcript reveals that any speaking objections that occurred were not so pervasive or disruptive as to warrant sanctions").

A review of what Ms. Lively labels "frequent speaking objections" demonstrates the triviality of the Motion. Although Ms. Lively alleges that the Wayfarer Parties' counsel "interrupt[ed]" the deposition to ask whether Ms. Alexander should review an exhibit, the cited "examples" show that: (a) Ms. Lively's counsel Meryl Governski was unaware Ms. Alexander had amended her expert report, erroneously claimed that the amended report had not been served upon her (it had been, a month earlier) and the Wayfarer Parties' counsel professionally steered her in the right direction (Fritz Dec., Ex. 1, at 59:4 - 61:25); (b) Ms. Alexander (who had never previously been deposed, in any litigation, let alone remotely) was advised to download an exhibit (so she can review the entire document, as one would do in-person) rather than review only the portions viewable to her though Ms. Governski's "screen sharing" (id., at 93:5 - 94:2); and (c) Ms. Governski asked Ms. Alexander to "summarize" a lengthy article cited in the expert report, the witness was confused about whether she was being to summarize it "offhand" (from memory), and, when the Wayfarer Parties' counsel asked for clarity, Ms. Governski launched into a tirade instead of clarifying what she was asking Ms. Alexander to do. (Id., at 134:5 – 139:11). During one exchange cited by the Motion, Ms. Governski interrupted the witness, who was confused by the line of questioning, and the Wayfarer Parties' counsel suggested that Ms. Governski listen to the witness so that the questions could be clarified. (Id., at 182:5 – 185:5). See Kennedy v. City of New York, No. 12-cv-4166, 2016 WL 3460417, at *4 (S.D.N.Y. June 20, 2016) (denying sanctions motion because there was no indication that request for clarification of deposition question was made in bad faith or frustrated the deposing party's ability to conduct a fair examination). Even if such colloquy can be liberally construed to violate Rule 30(c)(2), which it should not, "violation of the rule is mitigated to some degree if the colloquy that occurred as a result of objections related to matters of clarification...." Wang v. New York-New Jersey Section of Ninety-Nines Inc., No. 18cv-1780, 2020 WL 13561262, at *4 (S.D.N.Y. Dec. 29, 2020) (internal quotation omitted) (denying sanctions motion even though "defense counsel spoke more than was necessary to state his objections" under Rule 30(c)(2)). Notably, at the start of the deposition, Ms. Governski failed to instruct the witness, as is standard in depositions, that if she did not understand a question, she should say so and Ms. Governski would rephrase it. (Fritz Decl., Ex. 1). As for Ms. Lively's criticism that Ms. Alexander was sometimes instructed to "answer again", such instruction is not improper. See Wang, 2020 WL 13561262, at *4 (instruction to answer "if you understood" or "if you can" were not improper and, to the contrary, "those phrases show defense counsel reminding the deponent to that she should answer the question notwithstanding the fact that he objected"). Examples of improper speaking objections are those made by Ms. Lively's counsel, Esra Hudson, at the deposition of non-party Jenny Slate. (Fritz Decl., Ex. 2).

Ms. Governski never instructed Ms. Alexander, at the outset of the deposition, that she could request a break (Fritz Decl., Ex. 1), which is a routine. Ms. Lively nevertheless inexplicably takes issue with a suggestion, *after two hours of questioning*, that Ms. Alexander (and the stenographer) be provided with a break during the deposition. After such break was requested by Ms. Alexander's

Hon. Lewis J. Liman Page 3

counsel, Ms. Governski proceeded to ask another question, then utilized the guise of a "pending question" as a basis to refuse a break and ultimately was proven wrong when the stenographer confirmed that no question had been pending. (Fritz Decl., Ex. 1, at 108:2-112:6). In sum, the questioning of Ms. Alexander went relatively smoothly, especially after the parties' counsel conferenced with the Court during a break, and Ms. Lively failed to show that the deposition was impeded, delayed or frustrated in any substantive manner. *See Severstal Wheeling Inc. v. WPN Corp.*, No. 10-cv-954, 2012 WL 1982132 (S.D.N.Y. May 30, 2012) (denying sanctions motion despite "a heated exchange at the end of the deposition" because any conduct that violated Rule 30 was not extreme and had no material effect on the testimony).

"A person may instruct a deponent not to answer only when necessary to preserve a privilege...." (Fed. R. Civ. P. 30(c)(2)). The only time Ms. Alexander was instructed not to answer was based on privilege/work product and in connection with questions concerning her conversations with "separate counsel" (the identity of whom she was unable to recall) about this case. (Fritz Decl., Ex. 1, at 19:2 – 21:12). Rule 26(b)(4)(C) protects, from disclosure, counsel's communications with testifying experts. See King v. Wang, No. 14-cv-7694, 2021 WL 5232454, at *17 (S.D.N.Y. Nov. 9, 2021) (Liman, J.) ("communications between a party's attorney and an expert witness 'retained or specially employed' are protected from disclosure except for communications that, among other things, 'identify facts or data that the party's attorney provided and that the expert considered in forming the opinions to be expressed.""). In response, Ms. Governski improperly attempted to debate counsel during the deposition about the instruction to Ms. Alexander not to answer. (Fritz Decl., Ex. 1, at 21:21 - 23:12). In violation of Rule 4.C of this Court's Individual Practices in Civil Cases, Ms. Lively's counsel failed to meet and confer, after the deposition (or even during a break therein), concerning the propriety of the objection. The Motion should be denied for that reason alone. See Jones et al. v. Abel, No. 25-cv-779 (S.D.N.Y. Sept. 26, 2025). Had Ms. Lively's counsel adhered to the Court's Individual Practices concerning the resolution of discovery disputes, we would have agreed to a short continuation of Ms. Alexander's deposition, via remote means and on a mutually convenient date, limited to questions concerning her communications with the "separate counsel" identifying facts or data that such counsel provided to her and that she considered in forming her opinions expressed in her report. We so stipulate now.

The Motion to sanction Bryan Freedman and the undersigned is frivolous because it is based upon an alleged "ongoing pattern of deposition misconduct" but cites no prior conduct by either attorney at any deposition. (Dkt. 1133-4; 1133-5). Furthermore, the Motion cites cases in which the attorney "deliberately violated repeated Orders of the Court" (Antolini v. McCloskey, No. 19-cv-09038, 2021 WL 5411176, at *12 (S.D.N.Y. Nov. 19, 2021), "engaged in prolonged and unnecessary argument regarding the relevancy of a simple question" and instructed the witness "not to answer on relevancy grounds" (Fashion Exch. LLC v. Hyrid Prom., LLC, 333 F.R.D. 302, 305 - 307 (S.D.N.Y. Sept. 26, 2019), or was held responsible for its client's violation of orders to produce documents (Syntel Sterling Best v. Trizetto Group, 328 F.R.D. 100, 124 (S.D.N.Y. 2018), none of which Ms. Lively even alleges (or demonstrates) that either Mr. Freedman or the undersigned did. The only "ongoing pattern" is Ms. Lively's use of the media to disparage others and distract the public from the legal issues at hand.

² Ironically, it was Ms. Governski's own improper attempt to debate counsel during the deposition that prompted Bryan Freedman's request to her that she cease such misconduct. (Fritz Decl., Ex. 1, at 21:9 – 23:12).

³ The citations to Jamey Heath's deposition transcript concern an entirely different situation where counsel was not responding to any pending question but raising concerns about lengthy breaks that Ms. Lively's counsel was taking.

Hon. Lewis J. Liman Page 4

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cc: all counsel of record (via ECF)

DECLARATION

UNITED STATES DISTRICT COURT SOUTHERN DISTRICT OF NEW YORK

BLAKE LIVELY,

Plaintiff,

-V-

WAYFARER STUDIOS LLC, JUSTIN BALDONI, JAMEY HEATH, STEVE SAROWITZ, IT ENDS WITH US MOVIE LLC, MELISSA NATHAN, THE AGENCY GROUP PR LLC, JENNIFER ABEL, JED WALLACE, and STREET RELATIONS INC.,

Defendants.

JENNIFER ABEL,

Third-Party Plaintiff,

-V-

JONESWORKS LLC,

Third-Party Defendant.

Case No. 1:24-cv-10049-LJL (consolidated with 1:25-cv-00449-LJL)

DECLARATION OF KEVIN FRITZ

- I, Kevin Fritz, pursuant to 28 U.S.C. § 1746, declare as follows:
- 1. I am an attorney admitted to practice before this Court, a partner in the law firm of Meister Seelig and Fein PLLC, 125 Park Avenue, 7th Floor, New York, NY 10017, and counsel of record for defendants Wayfarer Studios LLC, Justin Baldoni, Jamey Heath, Steve Sarowitz, It Ends With Us Movie LLC, Melissa Nathan, The Agency Group PR LLC, and Jennifer Abel (collectively, the "Wayfarer Parties") in the above-captioned action.
- 2. I respectfully submit this declaration in opposition to Blake Lively's motion for sanctions and related relief in connection with the deposition of Nicole M. Alexander.
- 3. Ms. Alexander is an expert in digital ecosystems, AI-mediated brand perception, and online reputation measurement. She was retained by the Wayfarer Parties to rebut certain expert reports concerning whether the social media activity regarding Ms. Lively during August 2024 through February 2025 was caused by a coordinated, negative manipulation campaign (as Ms. Lively alleges) or was the result of organic public engagement and entertainment industry media cycles.
- 4. A true copy of the transcript of the deposition of Ms. Alexander, taken on December 15, 2025, is attached as Exhibit 1.¹
- 5. True copies of excerpts from the deposition of Jenny Slate, taken on September 26, 2025, are attached as Exhibit 2.

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¹ The specifics of an illness suffered by Ms. Alexander have been redacted.

I declare under penalty of perjury under the laws of the United States that the foregoing is true and correct.

Dated: December 23, 2025

New York, NY

/s/ Kevin Fritz MEISTER SEELIG AND FEIN PLLC Kevin Fritz 125 Park Avenue, 7th Floor New York, NY 10017 (212) 655-3500 kaf@msf-law.com

Exhibit 1

	Page
	UNITED STATES DISTRICT COURT
	FOR THE SOUTHERN DISTRICT OF NEW YORK
	000
BL	AKE LIVELY,
	Plaintiff,
	vs. CASE NO. 24-CV-10049-LJL (LEAD CASE)
	25-CV-449 (LJL) (MEMBER CASE)
WA	YFARER STUDIOS LLC, ET AL.,
	Defendants.
	NATEED ADEL
υE	NNIFER ABEL, Third-party Plaintiff,
	vs.
	NESWORKS, LLC,
50	Third-party Defendant.
	inita party berendant.
WA	YFARER STUDIOS LLC, et al.,
	Consolidated Plaintiffs,
	vs.
ВL	AKE LIVELY, et al.,
	Consolidated Defendants.
	CONFIDENTIAL
	VIDEO-RECORDED DEPOSITION OF NICOLE ALEXANDER
	APPEARING REMOTELY FROM
	New York, New York
	Monday, December 15, 2025
St	enographically Reported by: Ashley Soevyn,
CA	LIFORNIA CSR No. 12019

CONTID	ENTIAL	
Page 2 1 UNITED STATES DISTRICT COURT 2 FOR THE SOUTHERN DISTRICT OF NEW YORK 3000 4 5 BLAKE LIVELY, 6 Plaintiff, 7 vs. CASE NO. 24-CV-10049-LJL (LEAD CASE) 25-CV-449 (LJL) (MEMBER CASE) WAYFARER STUDIOS LLC, ET AL., 9 Defendants. 10 JENNIFER ABEL, 11 Third-party Plaintiff, vs. 12 JONESWORKS, LLC, Third-party Defendant. 3 WAYFARER STUDIOS LLC, et al., 14 Consolidated Plaintiffs, vs. 15 BLAKE LIVELY, et al., Consolidated Defendants. 16 **CONFIDENTIAL** 18 Video-recorded Deposition of 19 NICOLE ALEXANDER, taken on behalf of the Plaintiff 20 Blake Lively, Pursuant to Notice, with all parties 21 appearing via video conferencing beginning at 22 8:04 a.m. PST; 11:04 a.m. EST and ending at 5:06 23 p.m. PST; 8:06 p.m. EST on Monday, December 15, 24 2025, before me, ASHLEY SOEVYN, California Certified 25 Shorthand Reporter No. 12019.	1 APPEARANCES: 2 3 For the Plaintiff Blake Lively: 4 MANATT PHELPS & PHILLIPS LLP 5 BY: ESRA HUDSON 6 BY: SARAH MOSES 7 Attorneys at Law 8 2049 Century Park East 9 Suite 1700 10 Los Angeles, California 90067 11 ehudson@manatt.com 12 smoses@manatt.com 13 (310) 312-4207 14 15 16 17 18 19 20 21 22 23 24 25	Page 4
Page 3 1 APPEARANCES: 2 3 For the Plaintiffs Stephanie Jones and Jonesworks 4 LLC: (NOT PRESENT FOR THIS DEPOSITION) 5 QUINN EMANUEL URQUHART & SULLIVAN 6 BY: KRISTIN TAHLER 7 BY: OLIVIA HOLMES 8 BY: LAURENNE M. BABAYAN 9 Attorneys at Law 10 865 S. Figueroa Street 11 8th Floor 12 Los Angeles, California 90017 13 kristintahler@quinnemanuel.com 14 oliviaholmes@quinnemanuel.com 15 laurennebabayan@quinnemanuel.com 16 (212) 849-7000 17 18 19 20 21 22 23 24 25	1 APPEARANCES: 2 3 For the Plaintiff Blake Lively: 4 WILLKIE FARR & GALLAGHER 5 BY: KRISTIN BENDER 6 BY: AUTUMN ADAMS-JACK 7 Attorneys at Law 8 1875 K Street 9 Northwest 10 Washington, D.C. 20006 11 kbender@willkie.com 12 aadams-jack@willkie.com 13 (202) 303-1245 14 15 16 17 18 19 20 21 22 23 24 25	Page 5

2 (Pages 2 - 5)

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1 APPEARANCES:	1 APPEARANCES:
2	2 For the Defendants Wayfarer Studios LLC, Jennifer
3 For the Plaintiff Blake Lively:	3 Abel, Melissa Nathan and Justin Baldoni, Jamey Heath
4 DUNN ISAACSON RHEE	4 and Steve Sarowitz:
5 BY: MERYL GOVERNSKI	5
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8 Washington, D.C. 20004	8 Attorney at Law
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12 -AND-	12 mitra@ahouraianlaw.com
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14 SLOANE OFFER WEBER AND DEF	N 14
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22	22
23	23
24	24
25	25
	Page 7 Page 9
1 APPEARANCES:	1 APPEARANCES:
2 For the Defendants Wayfarer Studios LLC, Jennife	2 For the Defendants Wayfarer Studios LLC, Jennifer
3 Abel, Melissa Nathan and Justin Baldoni, Jamey F	
4 and Steve Sarowitz:	4 and Steve Sarowitz:
5 LINER FREEDMAN TAITELMAN+COO	EY 5 MEISTER SEELIG & FEIN
6 BY: BRYAN FREEDMAN	6 BY: MITCHELL SCHUSTER
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13 (310) 201-0005	13
14	14
15	15
16	16
17	17
18	18
19	19
20	20
20 21	20 21
21 22	22 Also Present:
22 23	
L Z 3	23 Maggie Kane, Veritext Legal Solutions Concierge
	24 Ding Mayrlin Digitiff's Forest
24 25	24 Dina Mayzlin, Plaintiff's Expert25 John MacDonnell, Videographer

3 (Pages 6 - 9)

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Page 10 1	Page 12 1 INDEX TO EXHIBITS 2 NICOLE ALEXANDER 3 BLAKE LIVELY V. WAYFARER STUDIOS LLC, ET AL. 4 Monday, December 15, 2025 5 Ashley Soevyn, CSR No. 12019 6 EXHIBIT NO. DESCRIPTION PAGE 7 Exhibit 8 Social media post Do U on X 269 8 @Patrick webb 9 Exhibit 9 Social Media Post 12/22/24 272 Richard Sempertegui on X 10 Exhibit 10 3/23/24 Social Media Post 276 11 Sabrina Carpenter on Reddit 12 Exhibit 11 4/5/25 Social Media Post Francis 278 Bean Cobain on Reddit 13 Exhibit 12 10/18/25 Social Media Post Oh 279 14 and this show on Instagram 15 Exhibit 13 10/18/25 Social Media Post Oh 281 and this show on Instagram 16 Exhibit 14 10/25/25 Social Media Post Love 281 17 Island Finale on TikTok 18 Exhibit 15 10/27/25 Social Media Post Love 281 18 Exhibit 15 10/27/25 Social Media Post Love 281 19 Island Finale on TikTok 10 Exhibit 16 11/18/25 Reddit Analysis 285 Reproducible Code 21 Exhibit 17 12/4/25 Reddit Post Scraper 300
21 22 23 24 25	22 Exhibit 18 Reddit Scraper \$9 month 307 23 Exhibit 19 11/18/25 Excel Reddit INPUT.xlsx 308 24 Exhibit 20 11/18/25 TikTok README 315 25 Page 13
1 INDEX TO EXHIBITS 2 NICOLE ALEXANDER 3 BLAKE LIVELY V. WAYFARER STUDIOS LLC, ET AL. 4 Monday, December 15, 2025 5 Ashley Soevyn, CSR No. 12019 6 EXHIBIT NO. DESCRIPTION PAGE 7 Exhibit 1 Expert Report of Nicole M. 16	1 INDEX TO EXHIBITS 2 NICOLE ALEXANDER 3 BLAKE LIVELY V. WAYFARER STUDIOS LLC, ET AL. 4 Monday, December 15, 2025 5 Ashley Soevyn, CSR No. 12019 6 EXHIBIT NO. DESCRIPTION PAGE 7 Exhibit 21 12/4/25 TikTok Hashtag Scraper 321

4 (Pages 10 - 13)

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	Page 14		Page
1	000	1	you came down with . Has your resolved
2	CONFIDENTIAL DEPOSITION PROCEEDINGS	2	at this point?
3	MONDAY, DECEMBER 15, 2025	3	A It was , but yes, it has.
4	000	4	Q Is there any reason that the
5	THE VIDEOGRAPHER: We're on the record.	5	would prevent you from giving truthful and complete
6	It's 11:04 a.m. Eastern Time on December 15th, 2025.	6	testimony today?
7	This is the deposition of Nicole Alexander. We're	7	A None.
8	here in the matter of Blake Lively v. Wayfarer	8	MS. GOVERNSKI: I'm going to go ahead and
9	Studios LLC, et al.	9	we've marked as Exhibit 1, which is your report in
10	I'm John MacDonnell, the videographer	10	this matter.
11	with Veritext. Before the witness is sworn, would	11	(Exhibit 1 marked for identification.)
12	counsel please identify themselves beginning with	12	BY MS. GOVERNSKI:
13	noticing party, please.	13	Q The first page of your report says it was
14	MS. GOVERNSKI: Good morning. Meryl	14	prepared for Liner Freedman Taitelman & Cooley LLP.
15	Governski from Dunn Isaacson Rhee on behalf of	15	Did Liner Freedman retain you in this case?
16	Ms. Lively. Joining me today are Autumn Adams-Jack,	16	A Yes.
17	co-counsel at Willkie Farr & Gallagher, and Dr.	17	Q And when did Liner Freedman retain you?
18	Dina Mayzlin, Ms. Lively's one of Ms. Lively's	18	A September possibly. September, October.

- 18 Dina Mayzlin, Ms. Lively's -- one of Ms. Lively's 18
- 19 designated experts.
- MR. FRITZ: Good morning. Kevin Fritz
- 21 from Meister Seelig & Fein on behalf of the
- 22 defendants and the witness.
- 23 MR. SCHUSTER: And Mitch Schuster, also
- 24 from Meister Seelig & Fein, on behalf of the
- 25 defendants and witness.
 - Page 15 MS. GOVERNSKI: I'm sorry. One more

19

20

21

- 2 thing. Lindsey Strasberg, also co-counsel for
- 3 Ms. Lively is on as well.
- THE STENOGRAPHIC REPORTER: Good morning,
- 5 everyone, Ashley Soevyn, California. Steno
- 6 reporter, license 12019.
- 7 Ma'am, can I please have you raise your
- 8 right hand?
- Do you solemnly state that the testimony
- 10 you're about to give in this deposition will be the
- 11 truth, the whole truth, and nothing but the truth?
- THE WITNESS: Yes, I do.
- THE STENOGRAPHIC REPORTER: Great. Thank 13
- 14 you.
- **EXAMINATION**
- 16 BY MS. GOVERNSKI:
- Q Good morning, Ms. Alexander. Can you
- 18 please state your full name for the record?
- A Nicole Marie Alexander.
- Q Is there any reason today, Ms. Alexander,
- 21 that you won't be able to give truthful and complete
- 22 testimony?
- A None.
- Q You understand we originally were
- 25 supposed to meet last week, and I understand that

- 1 Q Kaltgrad?
 - 2 Yes, thank you.
 - 3 Q Did you interact with any other attorneys

Q In the course of putting together your 22 report, did you interact with any of the attorneys

A Yes, I interacted with Amir -- I'm sorry,

4 at Liner Freedman?

A '25, yes.

23 at Liner Freedman?

25 his last name is...

- 5 A Not while I was preparing my report, no.
- Q Well, when did you interact with any 6
- 7 other attorneys at Liner Freedman?

September of 2025?

- A I met Kevin Fritz, who is on currently,
- 9 afterwards. Probably three weeks ago.
- Q Okay. And how often, during the course
- 11 of putting together your report, did you speak with
- 12 Mr. Kaltgrad?
- A Maybe I touched base once a week via 13
- 14 email. Email or call.
- 15 Q Since you were retained in September or
- 16 October 2025?
- 17 A Correct.
- Q And what is your understanding of which 18
- 19 clients, on behalf of Liner Freedman, retained you?
- 20 A I believe it is Wayfarer and maybe
- 21 partially Baldoni as well. I'm not quite sure. I
- 22 know there are several different counsels. I'm not
- 23 sure the inter- -- the operations.
- 24 Q Okay. So the defendants in this case
- 25 include Mr. Baldoni, Wayfarer, Jamey Heath,

5 (Pages 14 - 17)

Page 16

Page 17

CONFIL	LITTAL
Page 18	Page 20
1 Steve Sarowitz, Melissa Nathan, Jennifer Abel,	1 BY MS. GOVERNSKI:
2 It Ends with Us and TAG PR?	2 Q Do you remember their names
3 A Uh-huh.	3 A I don't
4 Q Do you understand that you are testifying	4 Q their first names?
5 on behalf of all of those defendants today?	5 A I don't.
6 A I believe I am, because I thought it was	6 Q Kim?
7 part of the collective. So	7 A Honestly, it was about a 30-minute call
8 Q Okay. So if I refer to the Wayfarer	8 and I back in August maybe. I'm not sure of
9 defendants throughout the day, you will understand	9 their name.
10 that I'm referring to that big group of defendants?	10 Q Okay. What do you recall about that
11 A Yes.	11 call?
12 Q Prior to this litigation, have you had	12 A It was a
13 any interactions with any of the Wayfarer	13 MR. FRITZ: Hold on. I would just
14 defendants?	14 instruct you not to disclose the substance of the
15 A No.	15 conversation.
16 Q During the course of this litigation,	MS. GOVERNSKI: She wasn't engaged at
17 have you had any interaction with any of the	17 that time.
18 Wayfarer defendants?	18 MR. FRITZ: Attorney-client privilege. I
19 A No.	19 understand your position.
20 Q And you refer to "other counsel." You	20 BY MS. GOVERNSKI:
21 understand that the Wayfarer defendants have counse	
22 other than Liner Freedman, right?	22 not to answer questions?
23 A I believe so, yes.	23 MR. FRITZ: She is.
Q To what extent have you interacted with	24 THE WITNESS: Yes.
25 any attorneys other than those at Liner Freedman and	25
Page 19	Page 21
1 Mr. Fritz, as you just mentioned?	1 BY MS. GOVERNSKI:
2 A Prior to coming on board with the	2 Q Ms. Alexander, at the time you had this
3 engagement with Amir, I had a conversation with	3 conversation, had you ever spoken with any of these
4 separate counsel, which I believe is part of a	4 individuals before?
5 separate law firm.	5 A No.
6 Q And who is that?	6 Q Did you understand that they were
7 A I could not tell you. It was two two	7 speaking with a number of individuals; you called it
8 attorneys. It was part of a vetting process. They	8 part of a vetting process?
9 were looking to for someone with my background to	9 MR. FRITZ: Same instruction. To the
10 come on as an expert witness.	
	10 extent that your answer would require you to
11 Q And that was, you said, prior to you	11 disclose the substance of your conversation, I would
11 Q And that was, you said, prior to you 12 coming on with the engagement, right?	11 disclose the substance of your conversation, I would 12 instruct you not to answer that.
11 Q And that was, you said, prior to you 12 coming on with the engagement, right? 13 A With yes, correct.	11 disclose the substance of your conversation, I would 12 instruct you not to answer that. 13 BY MS. GOVERNSKI:
 11 Q And that was, you said, prior to you 12 coming on with the engagement, right? 13 A With yes, correct. 14 Q So that conversation preceded your 	11 disclose the substance of your conversation, I would 12 instruct you not to answer that. 13 BY MS. GOVERNSKI: 14 Q Are you following your counsel's
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11 Q And that was, you said, prior to you 12 coming on with the engagement, right? 13 A With yes, correct. 14 Q So that conversation preceded your 15 engagement? 16 A Correct. 17 Q Were those two attorneys with Shapiro 18 Arato Bach? 19 A Honestly, I'm not sure. 20 Q Were they female or male attorneys? 21 A Both female. 22 Q Is it possible that they were at 23 Liner Freedman?	11 disclose the substance of your conversation, I would 12 instruct you not to answer that. 13 BY MS. GOVERNSKI: 14 Q Are you following your counsel's 15 instruction not to answer? 16 A Yes. 17 Q Well, you mentioned 18 MR. FRITZ: Just going forward, she's 19 always going to follow my instruction not to answer, 20 so 21 MS. GOVERNSKI: Can you articulate your 22 basis for instructing her not to answer? 23 MR. FREEDMAN: Can we stop with the

6 (Pages 18 - 21)

Page 22 1 is. 2 MR. FREEDMAN: That's Bryan Freedman. 3 MS. GOVERNSKI: Mr. Freedman, you're not 4 entered in this -- in this, so you're --MR. FREEDMAN: You know what, you will 6 need to stop with the -- you'll need to stop with 7 the speaking objections. 8 MS. GOVERNSKI: It's my deposition. MR. FREEDMAN: Yeah, that's right, and 10 you're improperly handling it, and you don't know 11 what you're doing or how to practice law. So stop 12 with your speaking objections.

13 MS. GOVERNSKI: Counsel, please mute 14 Mr. Freedman who has not entered an appearance in 15 this deposition. And I am not giving speaking

16 objections. You're instructing your own counsel not 17 to give speaking objections. It's my deposition.

MR. FREEDMAN: No, you're the one giving 19 speaking objections, as your mouth is moving right 20 now.

21 MS. GOVERNSKI: Can we please --

- 22 Mr. Fritz, can you please control your co-counsel or
- 23 I'm going to have to seek relief from the Court.
- MR. FRITZ: I mean, he's not incorrect.
- 25 You're, like, trying to engage --

Page 23

- 1 (Cross talk.)
- MS. GOVERNSKI: I'm asking to understand
- 3 -- I'm asking, Mr. Fritz, you to explain the basis
- 4 for your objection so I can understand what your
- 5 perception is on the line on privilege.
- MR. FRITZ: You have it.
- 7 MS. GOVERNSKI: No, I would like you to
- 8 explain to me -- I am asking you to explain to me
- 9 your line on privilege when Ms. Alexander said she 10 was not engaged at that time.
- MR. FRITZ: I'm not going to engage in
- 12 the debate during the deposition.
- 13 BY MS. GOVERNSKI:
- Q Ms. Alexander, how did you come to be on 15 that phone call in August?
- A I was engaged via GLG, and GLG put me in
- 17 contact with the two women I referenced earlier.
- Q And what was your understanding of the
- 19 purpose of that call?
- 20 MR. FRITZ: Objection.
- 21 BY MS. GOVERNSKI:
- Q You can answer. 22
- A I was asked to come on to meet them to
- 24 talk about my background in social media and data
- 25 analysis.

Q And what about your background did you

Page 24

Page 25

- 2 understand prompted that call?
- MR. FRITZ: Instruct the witness not to
- 4 answer to the extent it would require the disclosure
- 5 of a privileged communication.
- 6 THE WITNESS: I will follow his
- 7 instructions.
- 8 BY MS. GOVERNSKI:
- Q Ms. Alexander, what is your understanding
- 10 of what in your background prompted GLG to reach out
- 11 to you?
 - MR. FRITZ: Same instruction not to
- 13 answer.

12

- 14 BY MS. GOVERNSKI:
- Q Ms. Alexander, did you have any 15
- 16 understanding before you got on that call of why you
- 17 were getting on it?
- 18 A Yes, I did.
- 19 Q And what was that understanding?
- 20 A As part of GLG, which is an expert
- 21 network of individuals with different backgrounds, I
- 22 had been asked to come on the call to discuss how I
- 23 would approach -- as an expert witness, how I would
- 24 approach the opportunity to do data science and
- 25 analytics as part of a case.

1

- Q Are you part of GLG?
- 2 A I am.
- 3 Q And when did you become part of GLG?
- 4 Twelve years ago.
- 5 Q And how did you describe your expertise
- 6 within the GLG Network?
- A So my background is -- my CV is published
- 8 as part of the network. And a basic summary is 25
- 9 years of experience across data analytics,
- 10 marketing, and some more of my credentials, just
- 11 being in academia, my book, et cetera.
- 12 Q And so you've been part of GLG Network
- 13 for 12 years. Have you ever been part of what you
- 14 described as the vetting process before?
- 15 A For litigation work, is that the
- 16 question?
- 17 O Yes. Yes.
- 18 A No, this is the first time.
- 19 Q So in 12 years as being part of GLG, this
- 20 was the first time you've received that call?
- 21 A For litigation work, yes.
- 22 Q And what did GLG say to you when they
- 23 called you?
- 24 A I'm sorry. It was not a call. I
- 25 shouldn't say that. It was outreach via electronic

7 (Pages 22 - 25)

Page 26

CONFIDENTIAL

1 correspondence. So it was a survey that I filled

- 2 out, and I answered the question.
- Q What were the questions in the survey?
- 4 A Honestly, I couldn't remember.
- 5 Q Do you have any recollection of the type
- 6 of questions the survey was asking you?
- 7 MR. FRITZ: Objection.
- 8 You can answer.
- 9 THE WITNESS: I don't. I fill out many,
- 10 many surveys.
- 11 BY MS. GOVERNSKI:
- 12 Q And this was the first survey you filled
- 13 out that you've received a callback in a litigation
- 14 matter; is that right?
- 15 A Correct.
- 16 Q How soon after that survey did you
- 17 receive a callback?
- 18 A I would say within three weeks.
- 19 Q And after you filled out that survey, did
- 20 you -- you receive a callback from GLG or was it
- 21 directly from the counsel that you spoke with?
- 22 A No, it was GLG.

1 call with the attorneys.

- 23 Q And what did GLG tell you when they
- 24 called you back?

11 that nature.

15

21

24 25

25 A They asked to set up a 30-minute Zoom

3 process." Why did you use that term?

Q Okay. And you used the term "vetting

A That would be what I call any -- any

5 conversation like that. I -- I made the assumption

7 to see if I was an appropriate fit. Specifically,

9 usually a part of any conversation that I've had

13 tell you that they were looking for you to testify

16 the witness not to answer. And similarly, for any

17 other question that seeks to obtain information that 18 is protected by the attorney-client privilege, I

14 that there was no smear campaign?

19 would give you the same instruction.

20 BY MS. GOVERNSKI:

23 attorney-client privilege?

10 with GLG, if I'm available for the work, things of

Q And did those individuals on the call

MR. FRITZ: I would -- let me instruct

Q Ms. Alexander, when you had that call,

MR. FRITZ: Instruction not to answer.

22 did you understand that it would be protected by

8 also around like things like availability, is

6 that they were looking to understand my background

- 1 BY MS. GOVERNSKI:
- 2 Q Did they tell you that anything you said

Page 28

Page 29

- 3 on that call would be protected by attorney-client
- 4 privilege?
- 5 MR. FRITZ: Same instruction.
- 6 BY MS. GOVERNSKI:
 - Q On that call, Ms. Alexander, did they
- 8 tell you that -- what they want your opinions on
- 9 this matter to be?
- 10 MR. FRITZ: Same instruction.
- 11 BY MS. GOVERNSKI:
- 12 Q Ms. Alexander, did they tell you how the
- 13 drafting of the report would be handled during that
- 14 call?

20

- MR. FRITZ: Same instruction.
- 16 BY MS. GOVERNSKI:
- 17 Q Did you discuss your report with anyone
- 18 other than Wayfarer defendants' counsel?
- 19 A No, no one else.
 - Q Your report refers to an assistant...
- 21 A I was going to say, I apologize. Let me
- 22 rephrase. No one outside of my team, which is the
- 23 assistant referenced, other than Wayfarer's counsel.
- Q Who is the assistant?
- 25 A Taylor Hunter, T-A-Y-L-O-R.

Page 27

- 1 Q Okay. Who is Taylor Hunter?
 - 2 A She's a data scientist.
 - 3 Q Does she work with you?
 - 4 A She worked with me on this particular
 - 5 piece of work.
 - Q Had you met Ms. Hunter before?
 - 7 A She was referred to me by someone else
 - 8 within my network. She's not the normal per- -- the
 - 9 normal data scientist I work with.
 - 10 Q Why didn't you use the normal data
 - 11 scientist that you work with?
 - 12 A She is -- she was unavailable and offline
 - 13 taking care of personal matters.
 - 14 Q And why were you looking for an
 - 15 assistant?
 - 16 A Because of the scope of the work that I
 - 17 do is just too much for one person.
 - 18 Q So tell me the process of you soliciting
 - 19 the assistance of Ms. Hunter.
 - 20 A I reached out to someone else in my
 - 21 network to see if they were available, someone who I
 - 22 had worked with previously. They were unavailable,
 - 23 and referred -- and gave a reference to Taylor
 - 24 Hunter. I contacted Taylor Hunter and asked some -
 - 25 again, I'm going to use the word "vetting" -- some

8 (Pages 26 - 29)

Page 30

CONFIDENTIAL

1	vetting	questions,	inst	around	her	hacl	koround	the
1	veumg	questions,	Just	around	псі	Daci	kgrouna,	uic

- 2 projects she had done previously, to see some of
- 3 those projects. And then I subsequently engaged
- 3 those projects. And then I subsequently engaged
- 4 her.
- 5 Q And who was the individual in your
- 6 network who was unavailable?
- A So I can't pronounce her full name. It's
- 8 Annu and Praavi. Her last name is Praavi (ph).
- 9 Q And when you say "in your network," what 10 do you mean?
- 11 A She's someone that I've known for I think
- 12 the last year. We've spoken at the same conference
- 13 together. I've seen the work that she does, and
- 14 yes, it's someone that I know, I guess, cordially.
- 15 Q And what were those vetting questions 16 that you asked Ms. Hunter?
- 17 A I don't know them offhand.
- 18 Q Well, what kind of questions would you
- 19 ask while you were vetting someone to assist you as 20 your assistant?
- 21 MR. FRITZ: Objection.
- 22 You can answer.
- 23 THE WITNESS: So I would ask what
- 24 projects specifically they've done around social
- 25 media, whether it was analytical, computational

- Page 32
- 1 myriad of different variables in order to -- sorry,
- 2 I've never had someone ask me that before. It's
- 3 someone that looks at data in order to interpret
- 4 that data into understanding outcomes, patterns --
- 5 yes
- 6 Q And what about Ms. Hunter's background
- 7 made you feel comfortable that she was experienced
- 8 sufficiently to handle that task?
- 9 A She currently works in data analysis
- 10 within the role that she currently has, and she's
- 11 done so for several years.
- 12 Q But for a company that you had never
- 13 heard of; is that right?
- 14 A Yes, there is a lot of companies that I'm
- 15 unaware of.
- 16 Q Understood. And did you retain
- 17 Ms. Hunter?
- 18 A Yes.
- 19 Q And so you pay Ms. Hunter?
- 20 A Correct.
- 21 Q And how much is Ms. Hunter paid?
- 22 A 280 an hour.
- 23 Q And when did you retain Ms. Hunter?
- A At the beginning of the project, so
- 25 sometime in September. I'm not sure.

Page 31

- 1 science or like forensics work. I would like to see
- 2 the project specifically if it's available and it's
- 3 not private. Asking them to also share the dataset
- 4 with me. Also, I would ask for data visualization
- 5 project, whether it was in conjunction with the
- 6 first project that they are sending me, or a
- 7 separate one, just to show their use of tools, how 8 they visualize data, how they story tell. And those
- o they visualize data, now they story ten. And the
- 9 are the core questions for this kind of work.
- 10 BY MS. GOVERNSKI:
- 11 Q And what is your understanding of
- 12 Ms. Hunter's academic background?
- 13 A Her academic background, I think she has
- 14 an advanced degree.
- 15 Q In what?
- 16 A It's not comp sci. I'm not sure.
- 17 Q Okay. And what is your understanding of
- 18 her current career?
- 19 A She handles -- she's a data scientist for
- 20 a company. I can't remember the company offhand.
- 21 Q Had you heard of that company before?
- A I'm assuming not if I can't remember it
- 23 easily, so I will say no.
- Q And what is a data scientist?
- 25 A It's someone that looks at data and a

- Page 33
- 1 Q September or October, after you had the 2 conversation -- or after you were retained by
- 3 Liner Freedman?
- 4 A Correct, after I was retained.
- 5 Q Okay. Where does Ms. Hunter live?
- 6 A She's in Texas.
- 7 Q Have you ever met Ms. Hunter in person?
- 8 A Not in person, no.
- 9 Q So how do you communicate?
- 10 A Via conference call, via telephone,
- 11 email.
- 12 Q And you mentioned in your answer that you
- 13 would have her share a dataset. What did you mean
- 14 when you said that?
- 15 A As part of the vetting process, I asked
- 16 her to share something that she was allowed to share
- 17 so that I could see exactly how she extrapolated,
- 18 you know, whatever insights she shared with me from
- 19 the project from the dataset itself.
- 20 Q Understood.
- Have you ever served as an expert witness
- 22 before?
- 23 A I have not.
- 24 Q So how did you go about putting together
- 25 a report having never done it before?

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	Page 34	Page 36					
1	A Putting together my expert report? I,	1 A I don't I don't break it out because I					
2	fortunately, was able to see other expert reports as	2 bill GLG altogether. So I would have to go in and					
3	part of this litigation, and I use similar	3 dissect the difference between the assistant and					
4	formatting.	4 myself.					
5	Q And what other expert reports did you	5 Q And could you do that?					
6	see?	6 A If I went into the Excel file, yes.					
7	A Aside from the ones shared with me from	7 Q How would you do that?					
8	the experts on the plaintiff's side, none.	8 A I have a column that says how much work					
9	Q So when you said you were able to put	9 I've done when it comes to total minutes versus how					
1	your report together based on looking at other	10 much work she's done in total minutes.					
	expert reports, you were referring to the expert	11 Q Do you have any recollection of how much					
	reports that you reviewed in this matter?	12 you've done?					
13	A Correct.	13 A I would say of that, I would guess it's					
14	Q Did you receive any samples of any other	14 probably about 75 percent or 80 percent.					
1	expert reports?	15 Q Is done by you?					
16	A No.	16 A Correct.					
17	Q How many hours did you spend on putting	17 Q And 20 to 25 by Ms. Hunter?					
	together the report?	18 A Correct.					
19	A The report itself?	19 Q Okay. How did you break down who did					
20	Q Yes.	20 what?					
21	A I don't have a breakout of just the	21 A So usually, if I have a research					
	report.	22 assistant, I would ask them to do a lot of the					
23		23 preparation. So things like the data scraping, the					
	Q As opposed to what? Preparing for the deposition too?	24 Python analysis, and then I would go and check their					
25	A Exactly, based on also doing the data	25 work and then take it from there for the so-what,					
23	A Exactly, based on also doing the data	25 Work and then take it from there for the so-what,					
	Page 35	Page 37					
	analysis, doing the report, like, the entire piece	1 now-what. So analyzing some of the analyzing					
2	analysis, doing the report, like, the entire piece of work, I don't have a breakout offhand of just the	1 now-what. So analyzing some of the analyzing2 what if it matters, where it's statistically					
3	analysis, doing the report, like, the entire piece of work, I don't have a breakout offhand of just the report.	 1 now-what. So analyzing some of the analyzing 2 what if it matters, where it's statistically 3 significant, what the implications are, things of 					
2 3 4	analysis, doing the report, like, the entire piece of work, I don't have a breakout offhand of just the report. Q Okay. So let's talk about all of those	 now-what. So analyzing some of the analyzing what if it matters, where it's statistically significant, what the implications are, things of that nature. 					
2 3 4 5	analysis, doing the report, like, the entire piece of work, I don't have a breakout offhand of just the report. Q Okay. So let's talk about all of those things. How much how many hours all in have you	 now-what. So analyzing some of the analyzing what if it matters, where it's statistically significant, what the implications are, things of that nature. Q Okay. So you said "usually," but what 					
2 3 4 5 6	analysis, doing the report, like, the entire piece of work, I don't have a breakout offhand of just the report. Q Okay. So let's talk about all of those things. How much how many hours all in have you spent doing all of everything for this matter?	 now-what. So analyzing some of the analyzing what if it matters, where it's statistically significant, what the implications are, things of that nature. Q Okay. So you said "usually," but what about in this case, what did Ms. Hunter do? 					
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10 (Pages 34 - 37)

25 they are similar to a Sprout Social or a myriad of

Q Oh, I'm just talking about for yourself.

25

CONFIL	ENTIAL
Page 38	Page 40
1 other tools or yeah, tools that you're able to go	1 instruction on how to approach it, how to run the
2 online and scrape from.	2 data, or how to scrape the data, anything to that
3 Q But there are different social media	3 effect.
4 tools for each I'm sorry, strike that.	4 Q So the clarifier, though, that came after
5 There are different actors for various	5 the data was scraped, right?
6 social media tools on Apify, aren't there?	6 A That's correct.
7 MR. FRITZ: Objection.	7 Q So I'm just talking specifically about
8 You can answer.	8 data scraping. How did Ms. Hunter know what data
9 THE WITNESS: Yes.	9 she should be looking for?
10 BY MS. GOVERNSKI:	10 A I gave her keywords.
11 Q So how did you pick what actors in Apify	11 Q What keywords did you give her?
12 to use for each of the social media?	12 A I believe I have them in the report.
A I selected the ones that I have used	13 Q Okay. And that's all that you gave her;
14 previously. And also, I think one was new and one	14 you said scrape these keywords?
15 was just relevant for this particular case.	15 A I said scrape those keywords. And then I
16 Q And who determined that it was relevant	16 asked her to let me know if any other keywords came
17 for this case?	17 up that had had that she saw significantly in
18 A I did.	18 the data outside of that.
19 Q Okay. And you said you checked work.	19 Q Did any other keywords come up?
20 Please explain how you checked Ms. Hunter's work.	A Nothing that she made note of for a high
A So once she was done doing the data	21 percentage, no.
22 scraping, we had a shared folder, so I would go into	Q Did you give her any other parameters
23 that shared folder. I would look at the data that	23 with respect to the data scraping?
24 she scraped for, let's say, that day or in total for	A Just the time frame.
25 that particular social media. I would go through,	25 Q What time frame did you give her?
Page 39	Page 41
1 look at the data, make sure that it was complete.	1 MR. FRITZ: Objection
2 When she ran Python code, I would go in and just	2 THE WITNESS: I asked her
3 drop it in to make sure that the Python code ran	3 MR. FRITZ: just let the witness
4 correctly. Then and that it was looking at the	4 finish, Meryl. Thanks.
5 correct components.	5 THE WITNESS: So for the last question, I
6 Q And did you ever go back to her and say,	6 asked her to look at a one-year time period,
7 I would like you to rerun this or run it a different	7 ideally, depending on the restrictions that some of
8 way?	8 the social media social media network set.
9 A If there was an error, then yes.	9 BY MS. GOVERNSKI:
10 Q What kind of an error?	Q What do you mean by the restrictions
11 A If if the if the code itself didn't	11 social media sets?
12 make sense, or if there was anything missing. So	12 A Sometimes there is date limitations for
13 maybe she hadn't selected the entire dataset or	13 how far they can go back.
14 something to that effect, I would ask her to go back	14 Q Which networks here had such date 15 limitations?
15 and do a rerun.	
16 Q So did you ever ask her to rerun based on	16 A All of the networks that we ended up
17 the content of the of the dataset? 18 A No, not on the content.	17 looking at were available from January 2024 through 18 October 2025.
19 Q And what were your instructions to 20 Ms. Hunter about what to scrape?	19 Q And so was that the time frame that you 20 provided her?
21 A I asked her to look across five different	20 provided her? 21 A Yes.
22 social media channels. I asked her to use both	21 A Tes. 22 Q So is it your understanding that
23 positive, as well as negative, and neutral	23 Ms. Hunter scraped for all content that hit on the
24 sentiment. So a three classifier. And that was	24 search terms between January 2022 and 2025?
25 predominantly it. I didn't give her any specific	25 A January 2024.
	145 A January 2024.

11 (Pages 38 - 41)

	CONFID	EN	NTIAL
	Page 42		Page 44
1	Q I'm sorry. January 2024. Let me ask	1	1 MR. FRITZ: Objection.
2	that question again.	2	2 You can answer.
3	So is it your understanding that	3	THE WITNESS: I'm sorry. Do they
4	Ms. Hunter scraped for all data that hit on any of	4	4 change does she have the same buckets as I do; is
5	the keywords between January 2024 through	5	5 that the question?
6	October 2025?	6	6 BY MS. GOVERNSKI:
7	A Everything that was available via Apify,	7	7 Q Let me ask it a better way.
8	yes.	8	8 So how would you divide up, from a
9	Q What does that mean, "available via	9	9 percentage perspective, the work done on just the
10	Apify"?	10	0 data analytics point?
11	A So all data is a little bit of a	11	1 A For Taylor, it's 100 percent data
12	misnomer. So because all data across the social	12	2 analysis.
13	media sites is different than what is available via	13	
14	Apify. So you can only scrape public accounts,	14	4 help you at all with the report itself?
15	so which is a well, which is a feature of any	15	, 1
	social media scraping tool. So yes, it should be	16	6 of the report.
1	the keywords based on public data from that time	17	7 Q Okay. Did anyone help you with the
18	frame.		8 writing of the report?
19	8	19	
1	dataset that Ms. Hunter provided you includes the	20	
1	universe of all data that was publicly available and	21	
1	hit on search terms between January 2024 and	22	
	October 2025?	23	,
24		24	,
25	THE WITNESS: Yes.	25	A Arguably, a different version every time
	Page 43		Page 45

1 BY MS. GOVERNSKI:

- Q Okay. So I know you said that you were
- 3 having difficulty remembering the exact breakdown in
- 4 terms of the hours that you spent on the research
- 5 versus the writing versus preparing for testimony.
- 6 Can you give any sort of a proportional breakdown,
- 7 like 50 percent of your time was doing the
- 8 analytics, 20 percent was writing? Like, can you do
- 9 any breakdown like that?
- A I would say the bulk of the work was the
- 11 data analysis.
- 12 Q Uh-huh.
- A Secondarily, was developing the report.
- 14 And tertiary, it's been preparing for the
- 15 deposition.
- Q And 169 hours, that included all of the
- 17 preparation to date for the depo, right?
- A Yes, that would be altogether.
- 19 Q Okay. And in terms of the breakdown
- 20 between you and Ms. Hunter, you said she did about
- 21 20 to 25; you did about 75 to 80. Are those
- 22 percentages the same when we look at different
- 23 categories; meaning, the analytics work, the report
- 24 writing, and then the preparing for deposition, or
- 25 did those proportions change?

1 I open and close the report. So...

- 2 Q When did you start drafting the report?
- 3 A I would say eight to ten days before
- 4 November 3rd.
- Q Eight to ten days before November 3rd. 5
- 6 Let's see, November 3rd is a Friday -- no, a
- 7 Monday --
- 8 A It's a Monday.
- 9 -- so like October 20th, something like
- 10 that?
- 11 A Around there. Yes.
- 12 Q And so was the data analytics completed
- 13 by October 20th then?
- A No, there was still some analytics going
- 15 on, but I began drafting the report.
- Q Okay. So do you stand by every word in
- 17 the report?
- 18 A Yes.
- 19 Q Did anyone edit your report?
- 20
- Q Did Wayfarer defendants' counsel edit 21
- 22 your report in any way?
- 23 A No.
- MR. FRITZ: Objection. 24
- 25

12 (Pages 42 - 45)

Page 46 Page 48 1 BY MS. GOVERNSKI: Q And what does a citation that is Q Did you use artificial intelligence to 2 hallucinated look like? 3 assist in the drafting of the report in any way? A I'm not sure exactly how to answer that. A So yes, because everything technically 4 What does it look like? 5 has AI in it. So I use Google Docs in order to Q Well, is it like the title might be 6 develop the report. So Gemini is attached to that, 6 wrong, or the authors might be wrong, or the page 7 and I have Gemini on for my Google Docs --7 numbers? Like what would it look like? Q Can you explain --8 MR. FRITZ: Objection. A -- but I did not use generative AI, if 9 You can answer. 10 that's the question. 10 THE WITNESS: So that could just be human Q Can you explain the difference? 11 11 error. So hallucinations are usually something that A So AI is the higher level. It is an 12 does not actually exist in real life. 12 13 algorithm. Most things that you use, including Zoom 13 BY MS. GOVERNSKI: 14 right now, has AI running in the background in some Q Okay. So if it, like, adds authors, for 15 way, shape or form. 15 example, that were not responsible for the 16 publication, that could be a hallucination? Generative AI is specifically developing 17 net new content in creative versus reshaping, copy 17 MR. FRITZ: Objection. 18 18 editing, copy writing, things of that nature. THE WITNESS: It could be, but that's Q So when you say you did not use 19 not -- it could be a hallucination. However, that 20 generative AI, did -- you mean that you did not use 20 doesn't mean that it is a hallucination. So I have 21 AI to write the report? 21 students get footnotes, citations, bibliographies A I did not use generative AI in any way, 22 incorrect all the time. There's a myriad of 22 23 so... 23 different reasons. One of those reasons could be a 24 24 hallucination. Q Even to edit the report? 25 MR. FRITZ: Objection. 25 Q And how do you check what the reason is, Page 47 Page 49 1 THE WITNESS: Correct. 1 as a professor? 2 BY MS. GOVERNSKI: A I mean, I don't normally grade on the 3 accuracy of the way that they use references and Q Your report refers to the concept of 4 hallucination and it defines it as "generating 4 bibliographies. I make sure that they exist, but 5 plausible but factually incorrect information"; is 5 aside from that, I don't necessarily debate if it's 6 that right? 6 APA, MLA, or if they've completely gotten it 7 A Correct. 7 accurate. 8 O What does that mean? 8 Q How do you make sure that they exist? 9 MR. FRITZ: Objection. 9 MR. FRITZ: Objection. 10 You can answer. 10 THE WITNESS: Normally, one of my CAs or 11 TAs will go in and check. It's just part of the 11 THE WITNESS: So it means to develop 12 something that would come next, based on a high 12 process I have with them. 13 propensity that that would be rational and make 13 BY MS. GOVERNSKI: 14 sense with the context that the rest of the sentence Q To run it through, like, Google Scholar 14 15 structure has developed. So it's a -- it's looking 15 or something like that? 16 at statistically does this make sense as the next 16 MR. FRITZ: Objection. 17 element within that -- within that string of words. THE WITNESS: There is different ways of 17 18 BY MS. GOVERNSKI: 18 checking, so... Q So what would that look like, you know, 19 BY MS. GOVERNSKI:

13 (Pages 46 - 49)

Q What are the different ways of checking?

A It depends on how they submitted it. It

22 could be a check system that the university uses.

23 It could be through asking for a link, specifically 24 if it's an online article or Googling or using

20

21

25 Google Scholar.

23 things.

24

25

20 if you're looking at a paper or something, what

A It can look like a myriad of different

Q Sometimes are citations hallucinated?

A Citations can be hallucinated. Yes.

21 would a hallucinated content look like?

	CONFID	ENTIAL
	Page 50	Page 52
1		1 AI checkers because AI checkers are not they are
2	institution uses, what do you mean? What kind of	2 not accurate at the end of the day. So I don't
3	check system?	3 allow them to use AI checker, just to be clear. I
4	A Most universities, when you submit	4 said Turnitin for things like citation that uses
5	something as a student, they have different software	5 probability or Google to actually look up. So they
6	solution packages that will check to see if there	6 are not AI they're not using a AI checker. They
7	are irregularities.	7 are looking up the citation itself.
8	Q Are you aware of any software packages	8 Q Okay. Well, what about the content of
9	that check for irregularities?	9 your students well, let me back up for a second.
10	A One is turn it Turnitin. That's the	Do you you're a professor at NYU and
11	only one I can think of offhand.	11 Columbia, right?
12	Q Have you heard of Grammarly?	12 A Correct.
13	A Yes, I don't know any universities that	13 Q Okay. Do you create your own syllabi for
14	use that, though, as a check. But yes, I know	14 those classes?
15	3	15 A For the classes that I've created, yes, I
16	Q What about GPTZero?	16 create my own syllabi.
17		17 Q Okay. And are those available online at
18	7 3	18 all?
19	any other system checks that universities use to	19 A The one for Columbia for this semester is
20	check student papers?	20 definitely.
21	A No.	21 Q Okay. And what is the class that you're
22		22 teaching at Columbia this semester?
23	, , , , , , , , , , , , , , , , , , ,	23 A It is AI and the knowledge organization.
- 1	with your TAs. What system do your TAs use?	24 Q So does your syllabi in that course
25	A Depending on how I've set up the the	25 discuss any academic policies for the class?
	Page 51	Page 53
1	submission, it would either be Turnitin or via	1 A Yes.
2	checking through Google	2 Q Like what?
3	•	3 MR. FRITZ: Objection.
4	A I don't specify.	4 Go ahead.

5 MR. FRITZ: Objection. 6 BY MS. GOVERNSKI: Q I'm sorry. I thought you finished. Go 7 8 on. 9 A I don't specify usually. Q So you let the TA choose whatever 10 11 checking system they would want to use?

THE WITNESS: The TA or the course 13 14 associate, ves. 15 BY MS. GOVERNSKI: Q Okay. And how do you know that you can

17 rely on the outcomes of whatever checking system 18 they've used? 19

A I -- I've hired them so I have faith in 20 their ability to -- to make the right checks. Q So if they run a student paper through an

MR. FRITZ: Objection.

22 AI checker and it says there is a high percentage

23 chance likelihood that this is AI, do you believe 24 the checker?

25 A No, I don't allow them to run it through THE WITNESS: The academic policies are,

6 quite frankly, a cut and paste, so all of the

7 syllabi have the exact same academic policy.

8 BY MS. GOVERNSKI:

Q When you say "all of the syllabi," it's 10 all of the Columbia syllabi or all of your syllabi?

A All of the syllabi within the college I

12 teach in has the exact same academic policy.

13 Q And how does that syllabi discuss the use

14 of AI, generative AI?

A So we are allowed to make distinctions on

16 AI specifically. That's the one you want because

17 it's not technically a -- it's not a Columbia-wide

18 policy. So that one, I wouldn't call a policy.

19 That's up to the discretion of each professor.

20

Q Okay. So what is your policy?

It has to be disclosed. 21

22 What has to be disclosed?

23 The use of AI and how the AI was used.

24 Okay. So how do you enforce that policy? Q

25 Well, the students usually -- well,

14 (Pages 50 - 53)

12

1	actually,	the	students	for	semester	have a	always
---	-----------	-----	----------	-----	----------	--------	--------

- 2 disclosed. I've asked -- I've given them examples
- 3 of how to disclose, and that is enforced based on
- 4 things like if they -- if it appears that someone
- 5 has used it and hasn't disclosed, I address it with
- 6 them. If they have submitted something, which
- 7 didn't happen -- if they have submitted something
- 8 that appears not to be their work in general -- and,
- 9 again, there's other reasons for that outside of
- 10 AI -- then I address that with them as well.
- Q So you said if it appears like it was
- 12 created by AI. What are some of the telltale signs
- 13 of AI usage?
- A If it appears that they have used -- used
- 15 frameworks incorrectly, for instance. If they
- 16 have -- especially ones that maybe show up in --
- 17 like an AI overview, if there is any -- if there is
- 18 any language that they use that just simply is not
- 19 normally used by them, again, after working with the
- 20 student for a semester, you know the way that they,
- 21 number one, communicate, and usually how they write.
- Q So how do you check whether their
- 23 material includes generative AI?
- 24 MR. FRITZ: Objection.
- 25 You can answer.

- Page 54 1 different signatures that are attributed to AI,

 - 2 which simply don't make sense in real life. So I'm
 - 3 sure you've heard things like using an ampersand.
 - 4 People use ampersands to write, particularly
 - 5 depending on the individual's age, how they were
 - 6 educated, things of that nature.
 - Q You talked about universities checking
 - 8 for AI. Do you know whether the universities for
 - which -- for which you work use AI checkers?
 - 10 A The colleges that I work for within the
 - 11 universities do not use AI checkers for any of the
 - 12 classes I'm aware of.
 - 13 Q So how do colleges discipline individuals
 - 14 if they suspect that a student is using generative
 - 15 AI?
 - 16 MR. FRITZ: Objection.
 - 17 You can answer.
 - 18 THE WITNESS: This is a conversation for
 - 19 the ages across education. So there is no answer to
 - 20 that currently.
 - 21 BY MS. GOVERNSKI:
 - 22 Q So it's your testimony that there are no
 - 23 AI checkers that provide any indicia of the use of
 - 24 generative AIs?
 - 25 MR. FRITZ: Objection.

Page 55

- THE WITNESS: Frankly, there is no way to 1
- 2 definitively check.
- 3 BY MS. GOVERNSKI:
- Q Okay. Not definitively, but do you just
- 5 take their word for it when they say, "no, I wrote
- 6 this?" And you don't do any sort of additional
- 7 checking?
- 8 MR. FRITZ: Objection.
- 9 You can answer.
- 10 THE WITNESS: As I mentioned, it would
- 11 depend on the case, so what specifically it looked
- 12 like they did. And then I would understand how to
- 13 address it appropriately.
- 14 BY MS. GOVERNSKI:
- Q So it's all subjective; is that your 15
- 16 testimony?
- 17 MR. FRITZ: Objection.
- THE WITNESS: Yes. 18
- 19 BY MS. GOVERNSKI:
- 20 Q Okay. So you mentioned that you find AI
- 21 checkers unreliable. What did you mean by that?
- A There's actually third-party research
- 23 that shows that they are not reliable. Depending
- 24 on -- they take into account things like
- 25 colloquialisms, the way that you write. There is

Page 57

Page 56

- THE WITNESS: I'm sorry. Could you
- 2 repeat that?
- 3 BY MS. GOVERNSKI:
- Q So it's your testimony that there is no
- 5 AI checker that can reliably predict the use of
- 6 generative AI?
- 7 A Yes, that's my opinion. Yes.
- Q And what if a student's paper is entered
- 9 into multiple AI checkers and they all come back
- 10 with a high percentage of likely to be AI; is that
- 11 also, in your opinion, not reliable?
- 12 MR. FRITZ: Objection.
- 13 THE WITNESS: So to my understanding and
- 14 the research that I've seen, most AI checkers are
- 15 all using the same -- the same way of codifying what
- 16 the assumption of AI is. And, again, this is simply
- 17 third-party research that I've read. So no, I don't
- 18 have a trust that AI checkers do an adequate job of
- 19 definitively, or even statistically significantly
- 20 proving, that something is AI versus not AI.
- 21 BY MS. GOVERNSKI:
- 22 Q Your report includes a number of charts.
- 23 Who made the charts?
- 24 The charts were made by Taylor.
- 25 So earlier when you testified that a

15 (Pages 54 - 57)

	CONFID	EN	ITIAL
	Page 58		Page 60
1	hundred percent of her time was dedicated to the	1	MR. FRITZ: Objection.
2	data analytics, would that include the work on the	2	THE WITNESS: I do not think this is
3	charts?	3	the sorry, I don't think this is the amended one.
4	A Yes. So the charts are data analysis.	4	BY MS. GOVERNSKI:
5	Q So how did you to what extent did you	5	Q When did you produce an amended report?
6	QC the charts?	6	A I sent the amended report November the
7	A So looking at the charts, I looked at the	7	week of November 3rd or the week after.
8	datasets and the code for which she provided that	8	MS. GOVERNSKI: Counsel, we have not
9	generated the visuals to make sure that they were	9	received an amended report. This is the only report
10	accurate.	10	we've received from Ms. Alexander.
11	Q And when you say "the datasets," those	11	MR. FRITZ: I will check with my team
12	are the datasets that Ms. Hunter created using the	12	whether that's accurate. You want to take a
13	scrapers we talked about?	13	MS. GOVERNSKI: Yeah, we're going to have
14	A Correct.	14	to, yeah, take a break, because if she's amended her
15	MS. GOVERNSKI: Okay. Let's look at your		report, then we're going to need to consider other
16	CV. If we pull up your report, we can go to page	16	options.
17	93. And I'm going to ask my colleague, Autumn, to	17	MR. FRITZ: Okay. Do you want to take a
18	share the report on the screen so we can all speak	18	break now?
19	the same language.	19	MS. GOVERNSKI: Yeah, we're going to go
20	Is it Autumn, are you able to share?	20	off record until you reach a resolution on this.
21	Autumn, are you able to share?	21	MR. FRITZ: Well, why don't we just take
22	THE A/V TECHNICIAN: It actually looks	22	five minutes?
23	like Autumn is not on the call. Oh, here she is.	23	MS. GOVERNSKI: We'll take as much time
24	She's rejoining right now.	24	until you figure out if there is an amended report
25	MS. GOVERNSKI: I think I can share.	25	because I'm not going to continue a deposition if
	Page 59		Page 61

1 BY MS. GOVERNSKI:

- Q Do you see my screen?
- 3 A Yes.
- Q And this is the expert report that you
- 5 submitted in this case, right?
- MR. FRITZ: Do you want the witness to
- 7 access the document herself so she can scroll
- 8 through it?
- 9 MS. GOVERNSKI: If she wants to.
- 10 MR. FRITZ: Okay.
- 11 Are you able to do that, Ms. Alexander?
- 12 THE WITNESS: I'm downloading it right
- 13 now, yes.
- 14 MS. GOVERNSKI: Do we need to go off
- 15 record for you to review it, or are you able to take
- 16 a look and let me know if this is your expert
- 17 report?
- MR. FRITZ: She'll -- we'll stay on 18
- 19 record and she will review it to ensure that it is
- 20 what you say that it is.
- 21 THE WITNESS: I just want to confirm that
- 22 this is the amended report.
- 23 BY MS. GOVERNSKI:
- Q Is it your testimony that you've provided
- 25 an amended report?

- 1 she -- if this report is not her current report, so
- 2 let's go off the record.
- MR. FRITZ: How would you like me to get
- 4 back to you, on the Zoom?
- MS. GOVERNSKI: Sure. 5
- 6 MR. FRITZ: All right.
- 7 THE VIDEOGRAPHER: We're off the record.
- 8 It's 12:00 p.m.
- 9 (Recess.)
- 10 THE VIDEOGRAPHER: We're back on the
- 11 record. It's 12:09 p.m.
- 12 BY MS. GOVERNSKI:
- Q Okay, Ms. Alexander, the report that I
- 14 previously entered as 001 was the original report
- 15 that you produced in this matter, right?
- A I can't confirm that. I -- I just looked
- 17 for the amended report. So...
- Q Okay. Can you please open the report
- 19 that I marked as 001 and confirm that was the
- 20 original report that you provided?
- 21 A Yes, it is.
- 22 MS. GOVERNSKI: And I've introduced
- 23 Exhibit 2, which you should see in the folder, which
- 24 is the amended report.
- (Exhibit 2 marked for identification.) 25

16 (Pages 58 - 61)

CONFIDENTIAL Page 62 1 BY MS. GOVERNSKI: 1 practitioner and an expert focus? A So I would say this would be more Q Do you see that? 3 A Can I -- I didn't receive the link 3 academic-focused, what you're seeing in Exhibit 2. 4 So it's giving additional information around my 4 originally, so someone shared it at the top of this 5 speaking engagements, my book. I think those are 5 hour. Can -- since he closed out the Zoom, I don't 6 have the link anymore. Q You don't have the link to the Exhibit 7 where you place -- where I placed information. 7 Q So what are some of the differences in 8 Share? this CV versus your regular one? 9 A No. When I exited Zoom, the chat A Let's see. It is -- sorry, I just have 10 functionality went away. 11 to get down to that page. It would be, as I 11 MS. GOVERNSKI: Okay. Let's go off the 12 mentioned, the detail of my speaking engagements. 12 record. 13 That's not in my practitioner CV. I don't have my 13 THE VIDEOGRAPHER: Off the record. It's 14 book in my practitioner CV. 14 12:11 p.m. 15 Q Why don't you have your book in your 15 (Recess.) THE VIDEOGRAPHER: We're back on the 16 practitioner CV? 16 17 record. It's 12:12 p.m. Thank you. 17 A Well, I haven't added it because I 18 BY MS. GOVERNSKI: 19 necessarily put that in a practitioner CV. Q Ms. Alexander, is the second item, what 20 I've marked as Exhibit 002, the amended report in Q Why not? 20 21 this matter? 21 MR. FRITZ: Objection. 22 You can answer. 22 A It is. 23 Q Why did you amend your report? 23 THE WITNESS: It's not the norm. 24 A I found two -- two elements in the 24 BY MS. GOVERNSKI: 25 original report that were a problem with the 25 Page 63 1 visualization and a reference to one of the standard Probably, yes. 1 A 2 deviations. 2 Q 3 CV? Q Okay. We will get to that in a moment, 4 but I would like to get -- direct your attention in 4 A My overall CV; is that the question, or 5 002 to your CV, which is Appendix A. Did you make 5 the short bio? 6 changes to Appendix A between the first and second Q Oh, sorry. The overall CV. 7 report? A I did it the way I would do it for A No, I don't believe so. 8 9 CV. Q Okay. And if I refer to the "first 10 report," you understand that's the Exhibit 001, and 10 Why didn't you use your academic CV? 11 if I refer to the "amended report," you will 11 12 understand that's 002? 12 it. 13 13 Q I see. You were just updating your A Yes. 14 Q Did you draft this CV? 14 academic CV? 15 A Yes. A Yes. So I would normally take this and I 15 16 Q When did you draft this? 16 would copy it to my academic CV moving forward.

18 adapted it for this report. Q Why did you adapt it? 19 A No.

20 A Just because my regular CV is -- is more

A It's an adaptation of my normal CV, so I

21 practitioner-focused --

Q Sorry, you were saying more

23 practitioner-focused?

A Yes. 24

17

19

25 Q What is the difference between a

6 the key differences. And then chronologically, just

18 haven't needed to. But usually, you wouldn't

Q Did you modify your short bio in any way?

Page 65

Page 64

Who -- how did you decide to modify your

8 academia. So this is more similar to my academic

Because it's outdated. I haven't updated

Q Did anyone at Liner Freedman assist you 17

18 in editing this CV in any way?

20 MR. FRITZ: Instruct the witness not to

21 answer questions designed to disclose

22 attorney-client privilege.

23 MS. GOVERNSKI: Is --

24 MR. FRITZ: Sorry. I wasn't finished 25 with my objection. Attorney-client privilege.

17 (Pages 62 - 65)

CONFIDENTIAL				
Page 66	Page 68			
1 MS. GOVERNSKI: It was a speaking	1 A Yeah. So it says "Current NYU			
2 objection.	2 Professor." That actually is probably the outdated.			
3 MR. FRITZ: Sorry. I wasn't finished. I	3 It should say "Current Columbia Professor," excuse			
4 would just caution the witness not to disclose any	4 me.			
5 information that would be protected from disclosure	5 Q You no longer teach at NYU?			
6 by the attorney-client privilege.	6 A I am not currently teaching there, no. I			
7 BY MS. GOVERNSKI:	7 finished teaching the semester at Columbia.			
8 Q Is all of the information in this CV	8 Q When did you stop teaching at NYU?			
9 accurate?	9 A My last the last time I taught was			
10 A So let me just go back to the CV. I	10 2022. I'm sorry. The last time I taught a full			
11 apologize. I had my local one open and not this	11 semester course was 2022.			
12 one.	12 Q Okay. Well, what have you taught since			
Yes. Everything is accurate.	13 then at NYU?			
14 Q I should have asked. Do you have	14 A I teach, like, seminars depending on if			
15 anything else open on your computer right now?	15 they need me.			
A No, no. Just my my original report,	16 Q Like one-off seminars or courses?			
17 the one I didn't download. So I closed that.	17 A No. One-off seminars.			
18 Q Okay. So when you were looking at your	18 Q And that's considered being a professor			
19 local CV, you were looking at a copy other than what	-			
20 is in either of the reports?	20 MR. FRITZ: Objection.			
21 A No. I had the amended report that was	21 THE WITNESS: Yes.			
22 not downloaded, that's sitting on my desktop. I had	22 BY MS. GOVERNSKI:			
23 that open in order to answer the earlier question of	Q Okay. How many seminars have you taught			
24 is this different, is this amended or not amended.	24 since 2022?			
25 So I've subsequently closed that. So I just want to	25 A For NYU, I don't know. I would say			
Page 67	Page 69			
1 make sure I was looking at the correct document.	1 three, both maybe three.			
2 I'm now looking at the document, Exhibit 2, that I	2 Q Okay. And how many courses how many			
3 downloaded.	3 times did you teach a full semester course at NYU?			
4 Q Okay. You've testified there is no	4 A How many times? Like over the years?			
5 difference between the CV in the original report and	5 Q Yeah. A full semester course.			
6 the CV in the amended report, right?	6 A I don't know. I would have to check.			
7 A I don't believe there is. I'm just	7 Q Okay. At least 15, you think?			
8 looking at Exhibit 2 right now.	8 A Not sure. I would rather just check to			
9 Q Okay. So what in the short bio, speaking	9 make sure I'm accurate.			
10 just about the short bio I'm going to go ahead	10 Q Why did you stop teaching full-semester			
11 and share my screen for 002 just to speed this up	11 courses at NYU?			
12 and make sure we're talking from the same document.	12 A No particular reason. Mostly because I			
Do you see what is on my screen?	13 was working full-time as well. So			
14 A Yes. Can you just zoom in a little bit?	14 Q Okay. So when you say when the short			
15 Yes.	15 bio says "Current NYU Professor", that is not			
16 Q So what in this short bio is different	16 accurate?			
17 here as compared to what you've called your regular	MR. FRITZ: Objection. You can answer.			
18 CV?	THE WITNESS: I'm not actively teaching,			
19 A All the content is identical. I may	19 correct.			
20 verbalize it slightly differently, but it's pretty	20 BY MS. GOVERNSKI:			
1.01 1.1				

18 (Pages 66 - 69)

Q Okay. And when your academic

"Adjunct Professor of Marketing

Technology, NYU, 2013 to present," is

22 appointments right below says:

(As read):

21

23

24

25

21 much the same.

25 accurate -- is accurate?

Q Okay. Your CV says that you -- oh,

Everything in this short bio is

22

24

23 sorry.

CONFID	ENTIAL
Page 70	Page 72
1 that accurate?	1 THE WITNESS: It is looking at leadership
2 A So as an adjunct, you can come in and	2 skills, understanding how to manage. I had a focus
3 teach one semester, skip three years, come back,	3 in marketing. So quite frankly, I remember more of
4 teach another semester. That's the whole point of	4 the marketing courses than the other courses for a
<u> </u>	5 Bachelor's degree.
5 being an adjunct.	6 BY MS. GOVERNSKI:
6 Q Got it. So when it says "2013 to	
7 present," it's just in case you come back to teach a	7 Q Okay. I'm going to share my screen
8 full-semester course in the future?	8 again, actually. So when you say here: "B.S.
9 MR. FRITZ: Objection.	9 Leadership in Management, NYU", it doesn't mention
10 THE WITNESS: Correct.	10 marketing, right?
11 BY MS. GOVERNSKI:	11 A I didn't list my concentration. No.
12 Q So you would consider yourself a current	12 Q Okay. What does a concentration mean at
13 Adjunct Professor of Marketing and Technology at	13 NYU?
14 NYU?	MR. FRITZ: Objection. You can answer.
15 A Yes.	THE WITNESS: I believe for any
16 Q Okay. And what about at Columbia	16 undergraduate degree, it's what your focus is that
17 University? Are you a current professor at Columbia	17 you decide to focus in.
18 University?	18 BY MS. GOVERNSKI:
19 A Yes.	19 Q Does your degree show a concentration in
Q How many courses do you currently teach	20 marketing?
21 at Columbia?	21 A On the paperwork, I'm not sure.
A The semester just ended. But one,	22 Q And is Leadership and Management the
23 normally.	23 major? Is that what it's called?
Q And how many credits is that course for?	24 A Leadership and Management is the degree.
A I'm not sure. I would guess three.	25 Q That's the degree. Okay. How is a
Page 71	Page 73
1 Q Okay. How many times a week does that	1 degree in Leadership and Management relevant to your
2 course meet?	2 assignment in this case?
3 A Once a week.	3 A I'm not sure.
4 Q Is this the right title of that course?	4 Q Is it relevant to your assignment in this
5 "Teaching AI for the Knowledge Driven Organization"?	5 case?
6 A Yes. Correct.	6 MR. FRITZ: Objection.
7 Q What does that course teach?	7 THE WITNESS: I look at it like my life
8 A It teaches practitioners or future	8 skills, my education, all culminates to who I am
9 practitioners about how to look at AI from a	9 now. So I would say yes.
10 strategic perspective, from an executionary	10 BY MS. GOVERNSKI:
11 perspective; how to think about the technology side	11 Q But your particular degree in Leadership
12 as well as the business implications.	12 and Management, how is that specific degree relevant
13 Q Okay. I'm going to go off of this for	13 to your assignment in this case?
14 I'm just going to stop the share for a second.	14 MR. FRITZ: Objection. You can answer
15 Your CV lists a Bachelor's of Science	15 again.
16 from NYU with a degree in Leadership Management; is	16 THE WITNESS: I think that the focus that
17 that right?	17 I had around marketing is relevant to the jobs that
18 A Correct.	
	18 I've taken, as well as my role as an expert in this
Q When did you graduate from NYU?A With my Bachelor's degree?	19 case. 20 BY MS. GOVERNSKI:
22 A 2012.	22 that it afforded you access to jobs in marketing,
23 Q What is a degree in Leadership and	23 which then informed your opinion in this case; is
24 Management? 25 MP EDITZ: Objection Voy can answer	24 that right? 25 MR. FRITZ: Objection. You can answer
MR. FRITZ: Objection. You can answer.	25 MR. FRITZ: Objection. You can answer

19 (Pages 70 - 73)

CONFIDENTIAL Page 74 Page 76 1 again. 1 degree. 2 THE WITNESS: Yes. 2 MR. FRITZ: Objection. You can answer. 3 BY MS. GOVERNSKI: 3 THE WITNESS: We looked at things such as Q Okay. And then your CV also lists an MST 4 4 how LLMs are created, some of the biases that go 5 in Artificial Intelligence Ethics and Society. 5 into LLM, based on the datasets; how LLMs are What kind of a degree is that? 6 developed and built. Everything from the natural 7 A It's a graduate degree at the University 7 language processing, through fine tuning the LLM. 8 of Cambridge. 8 We also look at things like small language models as Q Okay. MST, that's a Master of -- what 9 well. There is a lot. I'm not sure specifically 10 does ST stand for? 10 what to highlight. A Studies. 11 11 BY MS. GOVERNSKI: 12 Q And did you -- it doesn't list a date. Q How many courses did you take in those 12 13 When did you attend Cambridge? 13 aspects specifically, what you just described? 14 A 2023 to 2025. 14 A So they are not individual courses the 15 Q So you just received that degree? 15 same way you would think of in an undergraduate A I did. 16 16 degree. They are interwoven into each of the 17 Q When did you receive it? 17 different semesters. A We were -- my class was conferred over 18 18 Q So there are no courses. It's just a 19 the summer sometime. 19 general kind of programming; is that right? Q Okay. Did you move to Cambridge for this 20 A It's programming. Yes. 21 program? 21 Q So how many classes were specifically on 22 A I did not. 22 what we just discussed in terms of LLMs and how they 23 Q So how did you receive this degree from 23 are created, et cetera? 24 Cambridge? 24 A It came up in each program that we walk 25 MR. FRITZ: Objection. 25 through. Page 75 Page 77 1 THE WITNESS: How did I study? Is that Q What does the program look like? How 2 the question? 2 many times a week were you in school for this 3 BY MS. GOVERNSKI: 3 degree? Q Yeah. Was it a remote virtual program? 4 A In school? I'm sorry. 5 I'm just trying to understand how you took courses. 5 O In classes?

- A It was part-time. So it was hybrid.
- 7 That's why it's a Master's of Studies and not a
- 8 Master's of Philosophy. So M-Phil is for full-time
- 9 students. Master's of Studies is for part-time
- 10 hybrid students.
- Q Okay. So that's why you were -- it took
- 12 you from 2023 to 2025. That was the two years
- 13 because it was a part-time program?
- 14 A Correct.
- 15 Q Okay. And so what is a Master's in
- 16 Artificial Intelligence Ethics in Society?
- A So we study the roots of AI from a power
- 18 philosophy perspective. We also talk about -- we
- 19 look at insights around how AI has developed; the
- 20 uses of AI particularly across, you know, public
- 21 society, organizations, government.
- Q So do you as part of this program study
- 23 AI technology itself?
- 24 A Yes.
- 25 Q So tell me about those aspects of the

- MR. FRITZ: Objection. You can answer.
- 7 THE WITNESS: So there is a specific
- 8 amount of classroom hours that any degree granting
- 9 has to have. I don't know what that is offhand. I
- 10 was physically in Cambridge around two weeks. Every
- 11 quarter -- or every term, excuse me, they use a
- 12 different verbiage. Every term. And then there was
- 13 remote work where we had to log on. So long story
- 14 short, I'm not sure offhand.
- 15 BY MS. GOVERNSKI:
- Q So you're not sure how many total hours
- 17 you needed to participate in order to receive that
- 18 degree?
- 19 MR. FRITZ: Objection. You can answer
- 20 again.
- 21 MS. GOVERNSKI: Sorry. I didn't hear
- 22 your answer.
- 23 THE WITNESS: I'm not sure offhand.
- 24 BY MS. GOVERNSKI:
- 25 Q Any ballpark?

20 (Pages 74 - 77)

CONFIDENTIAL				
Page 78	Page 80			
1 A I wouldn't venture to guess. Over	1 A No.			
2 two years. I'm not sure.	2 MR. FRITZ: Objection.			
3 Q Was it sporadic or something you did	3 THE WITNESS: No, it's not a ten-week			
4 every week?	4 program.			
5 A No. It was done every week.	5 BY MS. GOVERNSKI:			
6 Q And to what extent is your Master's of	6 Q Okay. So online, when they describe it			
7 Studies degree in Artificial Intelligence Ethics and	7 as a ten-week program, that's not accurate?			
8 Society relevant to your assignment in this case?	8 MR. FRITZ: Objection.			
9 A It gives me a deeper understanding of	9 THE WITNESS: I don't believe they			
10 specifically how LLMs operate. Understanding how	10 describe it as a ten-week program. It may be stated			
11 looking at the the ethics or the elements around	11 as ten weeks in-person, but it's not a ten-week			
12 AI, particularly around things like manipulation	12 program.			
13 across social media, which was specifically one of	13 BY MS. GOVERNSKI:			
14 my areas of study. How that all culminates. How to	14 Q Understood. So how many weeks is the			
15 think about identifiers. And how AI is leveraged,	15 full program, do you think?			
16 pro or con, in marketing.	16 A I believe it's 18 months.			
17 Q And all of the other experience in your	17 Q A full-time program over 18 months?			
18 CV predated the receipt of this degree, right?	MR. FRITZ: Objection.			
19 A I'm sorry. Could you repeat that?	THE WITNESS: It's not full-time because			
20 MR. FRITZ: Objection.	20 it's targeted to executives. So it is literally			
21 MS. GOVERNSKI: I will withdraw the	21 formatted for individuals who are usually executives			
22 question.	22 within their organization. So it's 18 months, I			
23 BY MS. GOVERNSKI:	23 believe, start to finish.			
24 Q Your CV also lists an executive MBA.	24 BY MS. GOVERNSKI:			
25 What is an executive MBA?	25 Q And to what extent is your executive MBA			
Page 79	Page 81			
1 A It's a MD A but for avacutives. It	1 relevant to your assignment in this case?			

- A It's a MBA but for executives. It
- 2 doesn't really answer the question.
- It is a part-time MBA that is targeted
- 4 specifically to usually executives with a certain
- 5 amount of years of experience to help them get
- 6 additional knowledge for business.
- 7 Q When did you receive this degree?
- 8 A 2014.
- Q It talks about it being a joint degree.
- 10 Where were you physically located when you obtained
- 11 this degree?
- A During the 18 months of study, I was in
- 13 Paris, Chennai, India, Shanghai, China, New York,
- 14 and -- did I say London and Paris?
- Q Okay. And you said over 18 months.
- 16 About how many weeks would you say that you spent on
- 17 this program before you obtained the degree?
- A Weeks of working towards the degree or
- 19 weeks of travel?
- 20 Q Weeks of working towards the degree.
- A It was aggressive. I would say probably 21
- 22 20 hours a week.
- Q For how many weeks?
- 24 A Over the course of the degree.
- 25 Q But it's a ten-week program, isn't it?

1 relevant to your assignment in this case?

- A It has allowed me to understand -- again,
- 3 my focus was on data analytics as part of that
- 4 degree. So it gave me both a finance perspective,
- 5 it's given me depth in strategy in particular, as
- 6 well as marketing.
- 7 Q When you refer to data analytics, that's
- 8 not listed as part of this degree on your CV, right?
- A Data analytics is part of the executive
- 10 MBA. It's actually part of the NYU module.
- Q Okay. So how did -- how was it part of
- 12 your executive MBA?
- 13 A It's a class.
 - How long was the class?
- 15 It's for the term. So 14 weeks.
- 16 Q Okay. So a 14-week class in data
- 17 analytics. Was there anything else part of this
- 18 executive MBA during which you learned about data
- 19 analytics?

14

- 20 A Data analytics was integrated within
- 21 other parts as well that weren't actually called
- 22 data analytics as a class. So we had finance
- 23 analytics, which looks at a myriad of different
- 24 data. We also had strategy classes that also
- 25 incorporated data analysis.

21 (Pages 78 - 81)

Page 82 1 Q What is data analytics? 2 A Looking at data, and it depends on how 3 big you want to cleaning, sorting, aggregating 4 data in order to provide an informed decision on 5 what that data tells you. 6 Q Okay. None of these three degrees you 7 list here reflect that you have a degree in data 8 analytics, right? 9 MR. FRITZ: Objection. You can answer. 10 THE WITNESS: None of the degrees are 11 called data analytics. 12 BY MS. GOVERNSKI: 13 Q Are these three entries the extent of the 14 degrees that you possess? 15 A Degrees, yes. 16 Q Are you familiar with the term, 17 "computational social sciences"? 18 A Yes. 19 Q Computational social sciences also is not 20 mentioned here; is that right? 21 A Correct. I don't have a degree in it. 22 Q What are computational social sciences? 23 A I don't know how I would define that. Page 82 1 Q Do you have a degree in digital 2 marketing? 3 A The degree is not listed as digital 4 dmarketing. No. 5 Q Your CV talks about you being at Meta. 6 You were at Meta for two years? 7 A Two years, six months. 8 Q It talks about Global Head of Marketing, 9 Business and Product Marketing. Were you that's 10 of all of Meta? 11 A That's of the Business and Product 12 Marketing division. So I was on the side of what 13 most people would refer to as B2B. 14 Q Can you explain what B2B means, other 15 than the literal definition? What is that? 16 A Business to business. So Meta works 17 Meta has goods and services that they promote to 18 consumers, such as you, Kevin, et cetera. So people 19 that use Facebook, WhatsApp, a myriad of different 20 solutions. That's what we call the B2B side. 21 B2B is about working with the 22 advertisers, small to medium businesses. Things of 23 that nature.
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24 O Con you try?
24 Q Can you try? 25 A I'm not sure. 24 Q And what did you do from a day-to-day 25 perspective as a Global Head of Marketing Business
25 A I'm not sure. 25 perspective as a Global Head of Marketing Business
Page 83
1 Q Can you try? 1 and Product Marketing?
2 MR. FRITZ: Objection. 2 A I ran a couple of different teams that 3 BY MS. GOVERNSKI: 3 include data analytics, engineering, owned the
4 Q Do you know what computational social 5 science means? 4 owned services team. So that is all the things like 5 e-mail, social media, website. And my goal was to,
6 MR. FRITZ: Objection. You can answer. 6 number one, maintain our site on the business side;
7 THE WITNESS: It's an interdisciplinary 7 ensure that clients or potential customers were able
8 field. It looks at analyzing large scale datasets. 8 to find what they needed. I also had revenue stream
9 That's how I would describe it. 9 goals. So making sure that we were converting
10 BY MS. GOVERNSKI: 10 potential customers into active customers. And then
11 Q An interdisciplinary of what disciplines? 11 a myriad of promotional activities. Yeah. That's
12 A Computer science, data science, and I'm 12 the gist.
13 sure there is another science in there. Those are 13 MR. FRITZ: Objection.
14 the two I can think of. 14 the two I can think of. 15 Wilk, PKITZ. Objection. 14 BY MS. GOVERNSKI:
15 Q Do you have a degree in computer science? 15 Q Why did you
16 A I don't have a degree in comp-sci. 16 Why did you leave in 2023?
17 Q Do you have a degree in data science? 17 A There were changes in the organization so
18 A I don't have a degree in data science. 17 A There were changes in the organization so 18 I decided it was a good time for me to depart.
19 Q What about mathematics? Do you have a 19 Q So it was a voluntary departure?
20 degree in mathematics? 20 A Yes, correct.
20 degree in mathematics: 21 A I don't have a degree in mathematics. 21 Q Who did you report to while you were
22 Q What about statistics? 22 there?
23 A I do not. 22 there: 23 A I reported to the SV I'm sorry. I
24 Q What about economics? 24 reported to the VP, her role then was VP of I'm
25 A No. 25 going to say Skilled Solutions. But I'm not sure if
22 (Pages 82 - 85

22 (Pages 82 - 85)

Page 86

CONFIDENTIAL

7

1 that's the overarching name.

- Q You've referenced having direct reports.
- 3 How many direct reports did you have?
- A Direct reports, I had 15 at the highest.
- Q And you mentioned data analytics, but
- 6 this description doesn't mention data analytics.
- 7 Why doesn't it include that?
- A I didn't put it in there. But most of my
- 9 job was around data analysis, data analytics.
- Q Why have you mentioned that describing 11 this role when it wasn't in your CV?
- MR. FRITZ: Objection. 12
- 13 THE WITNESS: I'm sorry. Can you repeat
- 14 that?
- 15 BY MS. GOVERNSKI:
- Q Yeah, I'm just saying you've volunteered
- 17 data analytics as part of this position, but it's
- 18 not mentioned in your CV. I'm just wondering why
- 19 you mentioned it when it's not listed in your CV.
- A I volunteered it as one of the teams that
- 21 Loversaw.
- 22 Q How did you oversee that team?
- 23 MR. FRITZ: Objection.
- THE WITNESS: It was one of the teams 24
- 25 that sat under my purview. So it's actually one of

- Page 88
- A Yes.
- 2 Q What type of specific data was the data
- 3 analytics team that you supervised performing?
- A They would run -- we would look at things
- 5 like social graph, click stream data. We would look
- 6 at potential threats across our network.
 - Q What does potential threats mean?
- 8 A It could mean anything from bots to DDS.
- 9 Someone trying to access our network. To -- it was
- 10 predominantly around things like bots, click flow
- 11 traffic, reporting to see if these were -- if we
- 12 were on target to hit revenue goals, usage behavior.
- 13 Things of that nature.
- Q Describe your experience with bots while 15 you were at Meta.
- 16 A Part of the work that we did was to look
- 17 at bot activities specifically across when it came
- 18 to clients. So specifically if there were accounts
- 19 that were -- accounts that looked like there were --
- 20 that bots were used in order to spike traffic,
- 21 whereas clients had to then pay for said traffic, we
- 22 would do forensics work around if that traffic was
- 23 realized, if it was associated with users, or if it
- 24 was non-organic.
- 25 Q Okay. You use the term "non-organic."

Page 87

- 1 the teams I developed while I was there.
- 2 BY MS. GOVERNSKI:
- 3 Q Tell me about that.
- 4 MR. FRITZ: Objection.
- THE WITNESS: So in order to lead our
- 6 owned properties we specifically had to have
- 7 insights on how data was captured; how data was
- 8 cleaned; how we were aggregating data; how we were
- 9 using data. And then ensuring that it was not only
- 10 responsible, but also in line with Meta's overall
- 11 policies. So I had a team of data analysts that did
- 12 all of that work.
- 13 BY MS. GOVERNSKI:
- Q How much of that work did you perform 15 yourself?
- A On an ongoing basis for what they did to 17 what I performed, marginal.
- Q Okay. There is a data analytics team
- 19 separate from one under the marketing department at 20 Meta, isn't there?
- 21 A There are a lot of data analytics teams 22 at Meta.
- Q Got it. So when you talk about running a
- 24 data analytics team, that's a specific team that you
- 25 created in the marketing department?

1 What does non-organic mean?

- A Non-organic means that it doesn't have
- 3 qualifiers. That would mean that users actually
- 4 were the ones that generated the traffic.
- Q So when you use the term "non-organic",
- 6 you're referring to automated conduct like the use 7 of bots?
- 8 A It could be bots or it could be other 9 things as well.
- 10 Q What other things?
- A It could be users of -- coordinated 11
- 12 actual users attempting to spike traffic or to, in a
- 13 negative or positive way, manipulate the traffic
- 14 somehow.
- 15 Q So users coordinating to spike traffic
- 16 would be non-organic?
- A That would be non-organic. We wouldn't 17
- 18 classify it as that. Internally, we would classify
- 19 it as sort of -- we use words like maleficent, but
- 20 that makes no sense in the real world. So it would
- 21 be something that would be a coordinated
- 22 manipulation pretty much.
- 23 Q So you didn't use the term "organic"
- 24 while at Meta?
- A We used organic but not in the sense that

23 (Pages 86 - 89)

Page 89

1 we're discussing here.

- Q So how are we discussing organic in the 3 sense here?
- A So I believe that when you brought up how
- 5 we used it, it was in regards to data analytics
- 6 for -- around bot traffic. We used organic more
- 7 from where the origin of traffic came from. So for
- 8 instance, organic versus paid in an advertising
- 9 perspective.
- 10 Q I see. So you use the term non-organic
- 11 to describe the use of bots so how were you using
- 12 that term?
- 13 MR. FRITZ: Objection.
- THE WITNESS: Sorry. So non-organic, I'm
- 15 using it that it is a coordinated sort of
- 16 manipulation in some way, shape or form, whether
- 17 through technology or through humans.
- 18 BY MS. GOVERNSKI:
- Q But that is not how you would use the 19
- 20 term when you were at Meta?
- 21 A Every company has their own verbiage. I
- 22 would use Meta's verbiage internally.
- MS. GOVERNSKI: Okay. Let's look at 23
- 24 Meta's verbiage. I'm going to put into the Exhibit
- 25 Share what I will mark as Exhibit 3. Autumn, are

Page 91

25

- 1 you here?
- 2 (Exhibit 3 marked for identification.)
- 3 MS. ADAMS-JACK: I'm back. I can handle
- 4 it.
- MS. GOVERNSKI: Okay. You know the one 5
- 6 I'm asking for?
- 7 MS. ADAMS-JACK: Yes. Yes, got it.
- 8 BY MS. GOVERNSKI:
- Q As my colleague is putting up Meta's
- 10 policy, are you familiar with a term called
- 11 "inauthentic behavior"?
- 12 A Yes.
- 13 Q What does inauthentic behavior mean?
- A It is activity that is not based on the
- 15 usual way that users interact with content across
- 16 Meta's platforms.
- Q What are the usual ways that users 17
- 18 interact with content on Meta?
- 19 A The usual ways would be taking a baseline
- 20 based on data that we have internally.
- O What does that mean? 21
- MR. FRITZ: Objection. You can answer. 22
- 23 THE WITNESS: So within Meta, we have
- 24 baselines that we can see how users have
- 25 historically interacted with our content. Based on

Page 90 Page 92

- 1 that, we would form a baseline. So things outside
- 2 of that baseline would be things that were -- that
- 3 we would check to see why the traffic or whatever
- 4 the activity was, was skewed.
- 5 BY MS. GOVERNSKI:
- 6 Q Okay. So when you used the term earlier
- 7 "non-organic" how, if at all, does that relate to
- 8 inauthentic behavior?
- A From the way that we use that at Meta, it 10 could be a synonym.
- Q What about the way that you use the term 11
- 12 organic in your report, to what extent does the way
- 13 that you use the term organic in your report
- 14 coincide with inauthentic behavior?
- 15 A I didn't associate the use of inorganic
- 16 in my report with anything, any verbiage related to
- 17 Meta, for instance.
- 18 Q What did you associate the use of organic
- 19 in your report to?
- A In my report, I specifically look at
- 21 organic behavior, being things within the norm that
- 22 didn't have classifiers of inorganic manipulation.
- 23 Q What are classifiers of inorganic
- 24 manipulation?
 - A It could be anything like temporal

Page 93

- 1 oddities. It could be user activity that would be
- 2 outside of a normal timeframe. It would be things
- 3 like amplification ratios. Looking at those kind of
- 4 fingerprints.
- Q Let's go down in Exhibit 3 to the first
- 6 paragraph on the next page. Oh, sorry. Let me
- 7 share.
- MS. GOVERNSKI: Autumn, can you share
- 9 your screen on this so we're all looking at the same 10 thing?
- 11 MS. ADAMS-JACK: I think you have to stop 12 sharing and then I can switch.
- 13 MR. FRITZ: Nicole, I would just download
- 14 the document so you can look at it as you see fit.
- 15 MS. GOVERNSKI: Well, I won't share it if
- 16 that's not helpful. I was doing it more as a
- 17 helpful.
- 18 THE WITNESS: It's easier for me to look
- 19 at it on my screen.
- 20 MS. GOVERNSKI: Okay. So if you look at
- 21 the second page, it says --
- MR. FRITZ: Just take a -- excuse me. 22
- 23 sorry. Take a moment to look at the entire document
- 24 and then let Meryl know when you're ready.
- 25 MS. GOVERNSKI: I'm not going to ask

24 (Pages 90 - 93)

CONFID	ENTIAL
Page 94	Page 96
1 about the entire document, though.	1 Q And coordinated activities could be
2 MR. FRITZ: I understand.	2 manual, right, not automated?
3 THE WITNESS: Okay.	3 A They can be, yes. It would have to be
4 BY MS. GOVERNSKI:	4 very, very synchronized for it to work at scale, but
5 Q Okay. If you can look at the first	5 yes, it is possible.
6 paragraph, and it says:	6 Q When you say "to work at scale," what do
7 (As read):	7 you mean?
8 "In line with our commitment to	8 A To to make a difference. So you, as
9 authenticity, we don't allow people to	9 an individual, clicking on things across the site is
misrepresent themselves on our service,	10 not going to make an impact when it comes to
11 use fake accounts, artificially boost	11 traffic.
the popularity of content or engage in	12 Q But but it's possible that you could
behaviors designed to enable other	13 synchronate in order to artificially boost without
14 violations under our community	14 using automated tools, right?
15 standards."	MR. FRITZ: Objection.
Do you see that?	You can answer.
17 A Yes.	17 THE WITNESS: So as I stated before, it's
18 Q Did you engage in any of these type of	18 possible, but it's extremely difficult to do so.
19 behaviors while you were at Meta?	19 BY MS. GOVERNSKI:
20 MR. FRITZ: Objection.	Q Right. You would have to be an expert in
21 THE WITNESS: I'm sorry? Could you	21 order to do that?
22 repeat that?	22 MR. FRITZ: Objection.
23 BY MS. GOVERNSKI:	THE WITNESS: I wouldn't say that.
Q When you were	24 That's I'm not sure what that means particularly.
25 MR. FRITZ: Note my objection.	25 But you would need to have a vast network of human
Page 95	Page 97
1 BY MS. GOVERNSKI:	1 in order to pull that off.
2 Q When you were doing marketing at Meta,	2 BY MS. GOVERNSKI:
3 did you engage in any of these type of behaviors?	3 Q Okay. And would, under the way that you
4 A Let me just read this again. So I so	4 use the term "organic" in your report, would that
5 I want to clarify first. So you have me looking at	5 type of artificial boosting that uses a manual
6 a document from Meta that is about user standards.	6 network be considered organic or not organic?
7 So this is community-based standards on what	7 A That would be considered inorganic, the
8 consumers or users that sign up on Meta's platforms	8 way that I'm using it.
9 agree to.	9 Q Okay. And if we look at the next
So to answer your question, as a user at	
	10 sentence, it says:
11 Meta, someone with a Facebook account, someone with	11 (As read):
12 an Instagram account, I did not do any of these	11 (As read): 12 "Inauthentic behavior refers to a
12 an Instagram account, I did not do any of these13 activities while at Meta as a user.	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception
 12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic
 12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same
12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal
 12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer 17 that. 	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal 17 of deceiving Meta or a community."
 12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer 17 that. 18 BY MS. GOVERNSKI: 	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal 17 of deceiving Meta or a community." 18 Do you see that?
12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer 17 that. 18 BY MS. GOVERNSKI: 19 Q What is your understanding of	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal 17 of deceiving Meta or a community." 18 Do you see that? 19 A Sorry, what page are you on for that one?
12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer 17 that. 18 BY MS. GOVERNSKI: 19 Q What is your understanding of 20 "artificially boost"? What does that mean?	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal 17 of deceiving Meta or a community." 18 Do you see that? 19 A Sorry, what page are you on for that one? 20 Q The same paragraph.
12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer 17 that. 18 BY MS. GOVERNSKI: 19 Q What is your understanding of 20 "artificially boost"? What does that mean? 21 A So in this context for Meta, as part of	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal 17 of deceiving Meta or a community." 18 Do you see that? 19 A Sorry, what page are you on for that one? 20 Q The same paragraph. 21 A Oh.
12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer 17 that. 18 BY MS. GOVERNSKI: 19 Q What is your understanding of 20 "artificially boost"? What does that mean? 21 A So in this context for Meta, as part of 22 their user agreement, it would mean using things	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal 17 of deceiving Meta or a community." 18 Do you see that? 19 A Sorry, what page are you on for that one? 20 Q The same paragraph. 21 A Oh. 22 Q Just the next sentence.
12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer 17 that. 18 BY MS. GOVERNSKI: 19 Q What is your understanding of 20 "artificially boost"? What does that mean? 21 A So in this context for Meta, as part of 22 their user agreement, it would mean using things 23 like different programs or bots or coordinated	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal 17 of deceiving Meta or a community." 18 Do you see that? 19 A Sorry, what page are you on for that one? 20 Q The same paragraph. 21 A Oh. 22 Q Just the next sentence. 23 A Oh, yes, sorry.
12 an Instagram account, I did not do any of these 13 activities while at Meta as a user. 14 Q And why not? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know how to answer 17 that. 18 BY MS. GOVERNSKI: 19 Q What is your understanding of 20 "artificially boost"? What does that mean? 21 A So in this context for Meta, as part of 22 their user agreement, it would mean using things	11 (As read): 12 "Inauthentic behavior refers to a 13 variety of complex forms of deception 14 performed by a network of inauthentic 15 assets controlled by the same 16 individual or individuals with the goal 17 of deceiving Meta or a community." 18 Do you see that? 19 A Sorry, what page are you on for that one? 20 Q The same paragraph. 21 A Oh. 22 Q Just the next sentence.

25 (Pages 94 - 97)

Page 98

CONFIDENTIAL

1 Meta's terms. I'm not sure...

- Q But do you agree that inauthentic
- 3 behavior includes complex forms of deception
- 4 performed by a network of inauthentic assets
- 5 controlled by the same individuals -- individual or
- 6 individuals?
- 7 MR. FRITZ: Objection.
- 8 You can answer again.
- 9 THE WITNESS: I would say yes, that's
- 10 accurate.
- 11 BY MS. GOVERNSKI:
- Q What does that mean to you when it says
- 13 "a network of inauthentic assets controlled by the
- 14 same individual or individuals"?
- A The way that I would -- okay. Do you
- 16 want me to put my Meta hat on, or do you want me to 16 coordinated way with a network of humans.
- 17 speak from the perspective of an expert outside of
- 18 Meta? Because there's two different answers.
- Q Give me both. 19
- A So within Meta, that means if you own a 20
- 21 link farm, if you are coordinating with bots,
- 22 particularly around -- to deceive around advertising
- 23 or politics, those are usually the two forms.
- Outside of Meta, I would say it's more
- 25 about am I orchestrating something that I have

17

- 1 access to a myriad of different -- most likely,
- 2 computers and algorithmic programs. Because, again,
- 3 as I mentioned, human beings is extremely difficult
- 4 to coordinate that. And am I trying to do it in
- 5 order to impact something in either a negative or
- 6 positive way.
- Q And when it says "a network of
- 8 inauthentic assets," what is your understanding of
- 9 "inauthentic assets"?
- 10 So the way that Meta is looking at
- 11 this --
- 12 Q I'm asking how you are looking at it.
- 13 Sorry.
- 14 MR. FRITZ: Sorry.
- 15 Objection.
- MS. GOVERNSKI: I wanted to clarify my 16
- 17 question.
- MR. FRITZ: Why doesn't -- do you want to
- 19 withdraw it? Are you withdrawing the first one or
- 20 you're going to ask another one?
- 21 MS. GOVERNSKI: I specifically asked, how
- 22 do you define the term "inauthentic assets"?
- MR. FRITZ: Okay.
- 24 Go ahead, Nicole.
- 25 THE WITNESS: Outside of this context, I

Page 100

- 1 would say inauthentic assets would mean any asset
- 2 that is attempting to either negatively or
- 3 positively impact something, defraud or cause harm
- 4 or specific benefit.
- 5 BY MS. GOVERNSKI:
- O And that could be automated or it could
- 7 be manual, right?
- A As I said before, it's normally
- 9 automated. And in rare cases, with a lot of
- 10 coordination at scale, it could also be manual.
- Q What is your basis for saying that it's 11
- 12 ordinarily automated?
- A So, again, in the context of social
- 14 media, for it to be impactful, make a dent at scale,
- 15 it is extremely difficult to do that in a
- - Q How could you do it?
- 18 MR. FRITZ: Objection.
- 19 THE WITNESS: I mean, there is probably
- 20 several different ways. The one way I could think
- 21 of would be to rally a massive amount of, again,
- 22 individuals, human beings in a coordinated attempt
- 23 that would either cause benefit or cause harm. But
- 24 there would have to be -- it would have to have
- 25 signatures -- I'm trying to think how -- it would
- Page 99
- Page 101 1 have to have signatures of authenticity, though, for
 - 2 it not to be identifiable.
 - 3 Q What does that mean, "signatures of
 - 4 authenticity"?
 - 5 A I'm sorry. I should flip that. I should
 - 6 have said signatures of inauthenticity. Apologies.
 - Q Can you explain what you mean by
 - "signatures of inauthenticity"?
 - A Signatures of inauthenticity?
 - Q Uh-huh. 10
 - A So as I mentioned before, things like,
 - 12 you know, like temporal analysis, content,
 - 13 homogeneous content. It would be things like
 - 14 coordination clusters. But, again, that would all
 - 15 be based on actually doing the analysis to figure
 - 16 out if that -- if that was there.
 - Q So if someone was really good at doing 17
 - 18 this, couldn't it avoid those signs of
 - 19 inauthenticity?
 - 20 MR. FRITZ: Objection.
 - 21 You can answer.
 - 22 THE WITNESS: Sorry. There's -- I'm not
 - 23 going to say always, but there is usually
 - 24 identifiers, which is why you don't just look at one
 - 25 element of inauthenticity. You look at several

26 (Pages 98 - 101)

CONFIDENTIAL Page 102 Page 104 1 different ones. So, for instance, you know, posting 1 behavior. 2 times, that would just be one. So if someone got 2 A Oh --3 around posting times, there is still six or seven 3 MR. FRITZ: Objection. 4 other fingerprinting techniques that you can use. 4 Go ahead. 5 So you don't just check one factor; you check a 5 THE WITNESS: -- so that actually is one. 6 myriad of different factors. 6 That is one that we saw specifically in my work at 7 BY MS. GOVERNSKI: 7 Meta. So that's one that I'm -- one example. We've O But if someone understood what all those 8 also seen actual use case at Meta. We've seen 9 factors are, couldn't they devise a campaign at 9 issues where there were like temporal -- where 10 scale to avoid those signs of inauthenticity? 10 coordination across different regions. So they were MR. FRITZ: Objection. 11 11 outside of, like, normal posting times, based on the 12 baseline of when users authentically post, 12 THE WITNESS: I have not seen that to 13 actually be possible, where it's -- that it's not 13 re-tweet -- sorry, for -- repost in this case. I've also seen specifically in previous 14 identifiable in any of the different ways that you 15 would analyze it. 15 work with Ipsos, through Synthesio, which is a 16 BY MS. GOVERNSKI: 16 social media tool that we had. We've seen things Q Isn't it possible that you just wouldn't 17 like coordinated signatures around, like, age 18 be able to identify it because it was untraceable? 18 activity. So where accounts were, like, newly 19 MR. FRITZ: Objection. 19 created and they were all the ones -- they were the 20 THE WITNESS: So untraceable sounds good 20 ones that were posting problematic content. 21 from a marketing perspective. Untraceable is still 21 BY MS. GOVERNSKI: 22 traceable. So there are usually signatures that 22 Q But I'm trying to understand a specific 23 fall outside of what the norm would look like or 23 incident. Like not just talking generally, but what 24 was the specific content that you saw to be 24 outside of a baseline. And that would, then, get 25 you to dig deeper into understanding why that 25 inauthentic? You gave two examples at Meta. What Page 103 Page 105 1 happened, if it was authentically an anomaly or if 1 were the specific content that you determined that 2 it was a coordinated act. 2 was inauthentic? 3 3 BY MS. GOVERNSKI: MR. FRITZ: Objection. Q So you say "usually," but that doesn't 4 You can answer again. 5 mean that there is always signatures, right? 5 THE WITNESS: So at Meta, in one specific MR. FRITZ: Objection. 6 case, it was seeing duplicative identical content

- 7 You can answer again.
- THE WITNESS: In all of the ways that I
- 9 have seen and been privy to, there are usually --
- 10 there have been ways of determining inauthentic
- 11 behavior.
- 12 BY MS. GOVERNSKI:
- Q How have you seen that? Can you explain? 13
- 14 A Sure. So I've seen it based on -- again,
- 15 going back to, like, content, homogeneous content.
- 16 So things where you have -- this is just one
- 17 example -- things where you have identical verbiage,
- 18 like literally identical, or even things around
- 19 social media as consistent as the flow of hashtags.
- 20 So the -- you know, how hashtags actually show up.
- 21 And I'm seeing that from an original piece of
- 22 content dropping, not a re-tweet, not a repost.
- Q But I'm trying to ask, like, specific
- 24 case studies that you have performed or been
- 25 involved in where you have seen inauthentic

- 7 showing up at a higher propensity than normal.
- 8 BY MS. GOVERNSKI:
- 9 Q What was the specific content?
- A So I cannot tell you the specific content 10
- 11 for anything I did within Meta. Are you asking --
- 12 Q You can designate it as confidential, but
- 13 I'm entitled to understand the basis of your
- 14 knowledge.

17

- 15 What was the specific type of content
- 16 that, in that case, you determined was inauthentic?
 - MR. FRITZ: Well, if there is some
- 18 contract that she's bound by or regulations that
- 19 said this is proprietary information, then I'm not
- 20 sure the protective order would cover that.
- 21 THE WITNESS: I can tell you that it was 22 political.
- 23 BY MS. GOVERNSKI:
- 24 Q And what was your role in sussing out
- 25 that content?

27 (Pages 102 - 105)

CONFID	EN	TIAL
Page 106		Page 108
A So my role was to look at the vast amount	1	what they thought were inauthentic customers.
of data over a certain period of time in order to	2	Q And if someone wanted to appear to be an
look at anomalies that this content was being	3	authentic customer, that would be possible, wouldn't
that this content was inflated or the activity	4	it?
around the content was inflated.	5	MR. FRITZ: Objection.
Q How was it inflated?	6	THE WITNESS: In this case, it would not
A Trying to think of how I can how I can	7	have been.
share. There were actors that were pushing this	8	BY MS. GOVERNSKI:
content across Meta's platforms, and we saw bot	9	Q What about in any case?
behavior in that circumstance, or in that particular	10	MR. FRITZ: Objection.
use case.	11	THE WITNESS: That's a lot of different
Q And so that case included bot behavior.	12	assumptions I would have to make. I couldn't answer
Did the other specific Meta case that you were	13	that.
referring to include bot behavior?	14	BY MS. GOVERNSKI:
A The other one did. It was different bot	15	Q Well, what would it take for someone to
behavior. So I mean, because bot is a very	16	make a coordinated campaign look authentic?
general term, just to be specific, right?	17	MR. FRITZ: Objection.
Programmatic advertising is bots. So this was	18	THE WITNESS: I don't know all the
manipulative bot behavior in the political case that	19	factors to be able to answer that.
was foreign actors.	20	MR. FRITZ: We've been going for about
The second case was bot activity specific	21	two hours. Why don't we take a break now?
to inflating advertising numbers in order to harm a	22	MS. GOVERNSKI: When I'm done with this
business.	23	line of questioning.
Q And have you ever identified, in any of	24	MR. FRITZ: Well, no, actually, we're
your positions, any campaigns that did not include	25	going to
	Page 106 A So my role was to look at the vast amount of data over a certain period of time in order to look at anomalies that this content was being that this content was inflated or the activity around the content was inflated. Q How was it inflated? A Trying to think of how I can how I can share. There were actors that were pushing this content across Meta's platforms, and we saw bot behavior in that circumstance, or in that particular use case. Q And so that case included bot behavior. Did the other specific Meta case that you were referring to include bot behavior? A The other one did. It was different bot behavior. So I mean, because bot is a very general term, just to be specific, right? Programmatic advertising is bots. So this was manipulative bot behavior in the political case that was foreign actors. The second case was bot activity specific to inflating advertising numbers in order to harm a business. Q And have you ever identified, in any of	A So my role was to look at the vast amount of data over a certain period of time in order to look at anomalies that this content was being that this content was inflated or the activity around the content was inflated. Q How was it inflated? A Trying to think of how I can how I can share. There were actors that were pushing this content across Meta's platforms, and we saw bot behavior in that circumstance, or in that particular use case. Q And so that case included bot behavior. Did the other specific Meta case that you were referring to include bot behavior? A The other one did. It was different bot behavior. So I mean, because bot is a very general term, just to be specific, right? Programmatic advertising is bots. So this was manipulative bot behavior in the political case that was foreign actors. The second case was bot activity specific to inflating advertising numbers in order to harm a business. Q And have you ever identified, in any of

Page 107 Page 109 1 bot behavior? MS. GOVERNSKI: When I'm done with this A Yes. 2 question -- I was in the middle of a question. 3 3 MR. FRITZ: You weren't in the middle of Q Tell me about those. 4 MR. FRITZ: Objection. 4 a question. THE WITNESS: We've had -- so some were MS. GOVERNSKI: I was. 5 5 6 with Ipsos. We were looking through Synthesio, 6 MR. FRITZ: You weren't. 7 which was our social media solution, for when a CPG 7 MS. GOVERNSKI: The court reporter -- can 8 company felt that sales and the subsequent return 8 you read --9 9 of -- yeah, return -- return of goods was around bot (Cross talk.) MR. FRITZ: -- we've been going for two 10 activity. We saw that that was not the case. So we 10 11 were able to identify that it had the signatures of 11 hours and now you're trying to pose a question. 12 authentic activity where people were just 12 MS. GOVERNSKI: I will take a break after 13 purchasing, were unhappy, and were returning goods. 13 this. 14 BY MS. GOVERNSKI: 14 So the court reporter, can you read back Q And how did you rule out that it was this 15 the question? 16 type of manual network that did not rely on bots? 16 (Cross talk.) A So we looked at sort of -- in that case. 17 MR. FRITZ: We're going to --18 MS. GOVERNSKI: Kevin, there's a question 18 we looked at tracking. So we looked at where the 19 purchases were taking place, where the order was 19 pending. 20 taking place, where the purchases were sent to. And 20 (Cross talk.) 21 we looked to see if there were any signifiers that 21 MR. FRITZ: There wasn't. 22 22 skewed outside of what their normal base of (Cross talk.) 23 customers looked like. So we were able to see that 23 MS. GOVERNSKI: Let's ask the court 24 their authentic customers, which they agreed with 24 reporter.

28 (Pages 106 - 109)

MR. FRITZ: Frankly, with all due respect

25 were authentic customers, had the same signatures as

CONFID	DENTIAL
Page 110	Page 112
1 to the court reporter, I don't care what this court	1 MR. FRITZ: So the record should reflect
2 reporter said. I suggest that we take a break and	2 there was no question pending.
3 then you start to ask another question.	3 MS. GOVERNSKI: Well, I asked a question,
4 MS. GOVERNSKI: That's not true.	4 but the record was not
	,
6 that before.	6 MR. FRITZ: See you in ten minutes.
7 MS. GOVERNSKI: Ash there's a question	7 THE VIDEOGRAPHER: We are off the record.
8 pending. If she says no	8 It's 1:16 p.m.
9 (Cross talk.)	9 (Recess.)
MR. FRITZ: Nicole, we're going to come	10 THE VIDEOGRAPHER: We're back on the
11 back at 11:25. You can put yourself	11 record. It is 1:26 p.m.
12 (Cross talk.)	12 BY MS. GOVERNSKI:
MS. GOVERNSKI: Kevin, if the court	13 Q Ms. Alexander, we moved into Exhibit
14 reporter says there is a question pending, I will	14 Share actually, I should ask, Ms. Alexander, did
15 we should believe her. If not, then I'll step	15 you have any substantive conversations with your
16 Ash, please speak.	16 counsel during the break?
17 (Cross talk)	17 A No.
MS. GOVERNSKI: Please respect Ash.	MS. GOVERNSKI: We've moved into Exhibit
MR. FRITZ: I know the sequence. I know	19 Share what will be marked as Exhibit 4. Can you
20 the sequence.	20 look at that?
21 MS. GOVERNSKI: Ash, what was the	21 (Exhibit 4 marked for identification.)
22 sequence?	22 BY MS. GOVERNSKI:
23 MR. FRITZ: With all due respect to the	23 Q Can you look at that?
24 court reporter, it doesn't matter.	24 A Yes, I have it.
25 (Cross talk.)	25 Q What is it?
, ,	`
Page 111	Page 113
1 MS. GOVERNSKI: Ash	1 A My book cover.
2 (Cross talk.)	2 MS. GOVERNSKI: Okay. I'm going to admit
3 MR. FRITZ: You started asked the	3 as Exhibit 4 your book. We're going to send to
4 question, which you didn't finish, after I asked for	4 Veritext a copy of your actual physical book. And
5 a break. It's inappropriate. So we're going to	5 then for purposes of the exhibit of the
6 take a break now. We'll come back at 1:25.	6 discussion today, I have an excerpt from your book,
7 MS. GOVERNSKI: Kevin, I'm allowed to	7 which I will mark as Exhibit 4A, which should also
8 ask	8 be in your Exhibit Share.
9 (Cross talk.)	9 (Exhibit 4-A marked for identification.)
10 MR. FRITZ: Nicole	10 BY MS. GOVERNSKI:
11 MS. GOVERNSKI: Stop talking, Kevin.	11 Q If you can pull that up.
12 Ash, please, was a question pending?	12 A Just a sec. I'm downloading it.
THE STENOGRAPHIC REPORTER: I would have	13 Q Sure.
14 to check.	14 A 4A. Got it.
15 MS. GOVERNSKI: Please check.	15 MR. FRITZ: Are you going to send me a
16 THE STENOGRAPHIC REPORTER: Here it is.	16 copy of the book too, Meryl?
17 (The record read.)	17 MS. GOVERNSKI: Sure.
18 MS. GOVERNSKI: Okay. Let's go on break.	18 MR. FRITZ: Thanks.
19 Ten minutes?	19 BY MS. GOVERNSKI:
	20 Q Ms. Alexander, do you see the excerpt
1 2 ,	· · · · · · · · · · · · · · · · · · ·
21 THE STENOGRAPHIC REPORTER: I don't know.	21 that is marked as Exhibit 4A is page 15 of your
22 I'll have to look at the	22 book? 23 A Yes.
23 MR. FRITZ: What happened after that?	
24 What happened after that?	Q Okay. And you write:
25 (Cross talk.)	25 (As read):

29 (Pages 110 - 113)

	CONFID	EN	TIAL
12 13 14 15	Page 114 "AI-driven content curation on social media platforms influences not just purchasing decisions but also opinions and beliefs. Algorithms prioritize content that is likely to engage users, often amplifying sensational or polarizing material." When you use the terms "sensational or polarizing material," what did you mean? A I can't think in my mindset at that particular time, but I think I was probably referencing things like specifically, you know, coordinated attempts around politics, around I'm not sure. Just major major events where we've seen harm come to companies, governments, individuals, based on coordinated attacks. Q Okay. And when it says: (As read): "This can skew perceptions and contribute to the spread of misinformation, as seen in various	1 2 3 4 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21	Page 116 escalation of it to get to sensationalism is usually coordinated. Q I see. So something can be both inorganic and organic? MR. FRITZ: Objection. THE WITNESS: So I would tease those two out. Something can start off as organic and it can be manipulated into being inorganic. BY MS. GOVERNSKI: Q What about vice versa? Can start off inorganic and be manipulated to seem organic? A That's more difficult to do. It's not impossible, but it's extremely difficult to do. Q How would you do it? MR. FRITZ: Objection. THE WITNESS: I mean, that I'm not quite sure of the ways you would go about escalating it. I'm sure there's a myriad of different ways. BY MS. GOVERNSKI: Q But as you sit here today, you don't know any ways that would be used to do that, other than that that it's possible?
22 23 24	viral."	23	A To go from something that is inorganic to make it I'm sorry.
25	A Yes.	25	Q Appear organic.
5 6 7 8	A So misinformation, specifically I was talking about where information is presented as either slightly skewed versus what the original information actually is or completely false. Q Uh-huh. And how has	3 4 5 6 7 8	Page 117 A No. Because you would need you would need no. I can't think of anything. I can't think of how you would go about that. Q Let's just do in your hypothetical. You said that if something is sensational or polarizing, it can motivate people to on their own post, right? A Correct. Q What if the sensational or polarizing material is something that is planted and not
10 11 12 13 14 15 16	Q Okay. And how how is the spread of misinformation related to fake news going viral? A So a couple of different ways. So this information is usually meant to feed on emotions.	10 11 12 13 14 15 16	truthful? Couldn't that have the exact same effect you just described? A For it to be sensationalized, yes. Q For then users to pick it up and organically spread it? A Yes, that is possible.

30 (Pages 114 - 117)

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(As read):

can take years."

"Reputational harm can be even more

devastating than legal penalties. In

especially bad news, travels fast. A

single incident can tarnish a brand's

impact overnight and rebuilding trust

today's digital landscape, news,

18

25

From an algorithmic perspective, we've

19 seen studies that have shown that misinformation

22 depending on how users engage with that content.

Q So the engagement that you've just

24 described, that would be organic engagement, right?

A Misinformation is organic, yes. The

21 algorithms show more and more intense information

20 also has been able to radicalize individuals and

CONTID	
Page 118	Page 120
1 Do you see that?	1 also have to mitigate their own risk as well.
2 A I do.	2 Q Okay. So other than the book, your CV
3 Q Do you stand behind that sentence?	3 doesn't list any other publications that you've
4 MR. FRITZ: Sorry. You said page 22,	4 authored. Have you authored any other publications?
5 Meryl? I thought we were looking at page 15.	5 A Do you mean like academic papers, I'm
6 MS. GOVERNSKI: Oh, I'm sorry. Let's go	6 assuming you mean?
7 to page 22.	7 Q Anything.
8 MR. FRITZ: Is this a new exhibit?	8 MR. FRITZ: Objection.
9 MS. GOVERNSKI: Well, I did say 22.	9 THE WITNESS: I've authored other papers,
10 Amber, is this the same exhibit? Autumn. Sorry.	10 yes.
11 Oh, let's go to 4B.	11 BY MS. GOVERNSKI:
12 (Exhibit 4-B marked for identification.)	12 Q What papers?
13 THE STENOGRAPHIC REPORTER: Meryl, we're	13 A I've authored papers at all of my
14 going to 4B. We need to announce it. Thank you.	14 companies. So at Meta
15 MS. GOVERNSKI: Yup, 4B. While my	15 Q Okay
16 colleague is getting it pulled out.	16 MR. FRITZ: Objection.
17 BY MS. GOVERNSKI:	17 THE WITNESS: Ipsos, Nielsen
18 Q Do you recall writing that reputational	MR. FRITZ: Go ahead and finish your
19 harm can be even more devastating than legal	19 answer, Ms. Alexander.
20 penalties and that a single incident can tarnish a	20 THE WITNESS: That was it.
21 brand's impact overnight and rebuilding trust can	21 BY MS. GOVERNSKI:
22 take years?	22 Q Have you have any of your other
23 A Yes. I know that statement. I remember	23 publications that you've authored been published?
24 writing that.	24 A No.
25 Q Do you agree with that statement?	25 Q So the book is the only piece of
Page 119	· · · · · · · · · · · · · · · · · · ·
1 A Yes.	Page 121 1 literature that you've published?
2 Q Okay. And you continued:	2 A Correct.
' '	
3 (As read):	
3 (As read): "Recovering from reputational damage	3 Q What sort of journals exist in your
4 "Recovering from reputational damage	3 Q What sort of journals exist in your 4 discipline?
4 "Recovering from reputational damage 5 requires substantial investment in	 3 Q What sort of journals exist in your 4 discipline? 5 A Sorry, in marketing?
4 "Recovering from reputational damage 5 requires substantial investment in 6 public relations, marketing, and	 Q What sort of journals exist in your discipline? A Sorry, in marketing? Q How would you define your discipline?
4 "Recovering from reputational damage 5 requires substantial investment in 6 public relations, marketing, and 7 operational changes."	 Q What sort of journals exist in your discipline? A Sorry, in marketing? Q How would you define your discipline? MR. FRITZ: Objection.
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31 (Pages 118 - 121)

Page 122 Page 124 1 either of those, are there journals that exist in 1 obligation of having to publish. Whereas, academics 2 usually do. 2 any of those three disciplines? 3 Q You mentioned that you wrote a number of A There are several. You want me to just 4 papers for Meta in the course of your career. Have 4 name them? 5 any of the papers you've written been peer-reviewed? 5 Q That would be great. 6 A Journal of Marketing, God, they all have A None that -- well, actually, no, that's 7 not true. Yes. A paper that I wrote in conjunction 7 long names. Nature Human Behavior and something. I 8 with another author at Ipsos was peer-reviewed and 8 don't actually subscribe to the journals so... Q Any --9 we presented that at an academic -- jointly at an 10 academic forum. And that was peer-reviewed. I 10 A I don't have to. We get them free as 11 think that's it. A peer review process like in 11 faculty. 12 academia is a little bit different than 12 Q Which ones do you receive as a member of 13 peer-reviewed for a practitioner. 13 the faculty? A I read -- because receiving and reading Q When you were referring to peer-reviewed 15 in this context, was it for a practitioner or was it 15 are different. I read American Marketing 16 Association and their journal. I read ANA's 16 academic? 17 Journal. I'm sorry. Stands for American National 17 A That was academia. 18 Advertisers, I think the acronym is. 18 0 Okay. And what was the topic of that 19 paper? Q Okay. 19 20 Those are the ones I usually read. 20 A We looked at -- we looked at marketing Α So American Marketing Association and the 21 effectiveness and behavior across -- across a global 22 American National Association's Journal; is that 22 dataset. 23 Q And why did you not list that paper in 23 right? 24 24 your CV? A Of Advertisers. 25 A Because it wasn't published. 25 American National Association of Page 123 Page 125 1 Advertisers? 1 Q Do you have a copy of it? A Yes. 2 A Honestly, I don't know. I may have a Q Any other journals that you read on a 3 copy of it somewhere. 3 Q What was the methodology that was tested 4 regular basis? A Journals themselves, no. I usually read 5 in that paper? 5 6 individual articles when they interest me. A So we looked at marketing effectiveness. 7 Q How do you decide what articles to read? 7 So we looked at regression analysis of a myriad of A Depending on topic. It could be 8 different campaigns across different disciplines. 9 something that is shared with me, something that is 9 In order to talk about things like concepts, how 10 in my queue based on different tags or hashtags. 10 concepts actually worked well if they went live, if Q But it's just like an ad hoc basis what 11 they didn't go live. We appended sales data to 12 you decide to read? 12 that, for the ones that did go live, obviously. And 13 MR. FRITZ: Objection. 13 just looking at the overall trend of how to bring a 14 THE WITNESS: Yes. 14 product concept to fruition. Q Did you rely on that analysis for 15 BY MS. GOVERNSKI: Q Have you ever edited any of the journals 16 purposes of this report? 17 that you just discussed? 17 A No. A I'm not an editor for any journal. No. 18 Q Let's go -- if you can pull up your 18 19 Q But none of the work that you've done has 19 report, please. Let's do the latest one, 20 been published in any of the specific journals that 20 Exhibit 002. Let's go to Appendix C. What is your 21 understanding of what Appendix C is? 21 you've just discussed? A No. That's usually for more full-blown 22 A Those are materials I considered when

32 (Pages 122 - 125)

24

25

23 drafting my report.

A Yes.

Q Did you draft Appendix C?

23 academics.

Q Can you explain that distinction? A As a practitioner, I don't have the

24

25

CONFID	ENTIAL
Page 126	Page 128
1 Q Did you consider any materials that are	1 you used that you relied on for purposes of your
2 not listed in Appendix C?	2 report?
3 A For the end report, no.	3 A Yes, I believe so.
4 Q What does that mean, "for the end	4 Q Okay. And if you look at page 109, there
5 report"?	5 is a report by you cite an article by Bellutta,
6 A For the report that you're looking at,	6 right?
7 no.	7 A Yes.
8 Q But did you consider any other materials	8 Q Okay. You see there's an article by
9 for in the course of preparing your report?	9 Bellutta, right?
10 A In the course of preparing it, no.	MR. FRITZ: Are you looking at page 108,
11 Q So Appendix C lists everything you	11 Meryl?
12 considered in the course of preparing your report?	MS. GOVERNSKI: Nope. I'm looking at
MR. FRITZ: Objection. You can answer	13 oh, you know what, it might be the new report.
14 again.	14 Sorry. I'm working off the old report. Yup.
THE WITNESS: Just doing a read-through.	15 BY MS. GOVERNSKI:
16 Yes.	16 Q 108, you see Bellutta?
MS. GOVERNSKI: Okay. Autumn, go ahead	
18 and let's share this on the screen so at least I can	18 Q And it's called "Investigating
19 look at it on the screen, please.	19 coordinated account creation using burst detection
20 BY MS. GOVERNSKI:	20 and network analysis."
21 Q What quality control steps did you ensure	Do you see that?
22 that Appendix C contained all of your sources?	22 A Yes.
23 A I used Zotero, which is a software for	Q Okay. That's in the article it's in
24 citation and reference clipping and storing.	24 The Journal of Big Data. That wasn't one of the
25	25 journals that you read regularly?
Page 127	Page 129
1 Q Okay. Is Terow does it include an AI	1 A It's not one of the ones I listed
2 feature?	2 earlier, no.
3 A It's Zotero. And I do not believe it	3 Q Is it one of the ones you read regularly?
4 does. It's Z-O-T-E-R-O.	4 A No.
5 O Lappreciate that Thank you	5 O Let's go to your report paragraph 20

5 Q I appreciate that. Thank you.

6 And where you include citations in your

7 report -- strike that.

8 You include certain footnotes with

9 citations in your report, but a lot of paragraphs

10 have no citations. What is -- how are we supposed

11 to know the basis for the paragraphs where you don't

12 include a citation?

13 MR. FRITZ: Objection. You can answer.

14 THE WITNESS: If I'm not using a

15 citation, then it comes from personal knowledge.

16 BY MS. GOVERNSKI:

17 Q Rather than academia?

18 A Rather than having to reference -- me

19 going to reference something.

20 Q Understood. Let's look at 108.

21 A Okay.

Q Okay. You see it lists academic

23 materials?

24 A Yes.

25 Q Are these all the academic papers that

5 Q Let's go to your report, paragraph 20.

6 A Okay

7 Q Let me just make sure it's still 20. You

8 see that there is a footnote there at the end of

9 paragraph 20, to footnote 2?

10 A Yes.

11 Q You see that it's unlike the other title,

12 which was "Investigating coordinated account

13 creation using burst detection and network

14 analysis", this has a different title. Why is that?

5 A I do not know. I would have to check to

16 see the copy of the article that I provided, on what

17 the actual name is.

18 Q Well, it can't be both, right?

19 MR. FRITZ: Objection.

20 THE WITNESS: I would say not.

21 BY MS. GOVERNSKI:

2 Q Is this what a hallucinated cite looks

23 like? It has plausible but factually incorrect

24 information?

25 MR. FRITZ: Objection. You can answer.

33 (Pages 126 - 129)

CONFIL	JENTIAL
Page 130	Page 132
1 THE WITNESS: I'm sorry. Hallucinated	1 Q What do those numbers, 1139 to 1160,
2 cite or citation?	2 indicate?
3 BY MS. GOVERNSKI:	3 A It should be the journal, the page,
4 Q Hallucinated cite. Is there a	4 the I'm not sure.
5 difference?	5 Q The page number where the journal starts,
6 A I'm not sure what a hallucinated cite is.	6 where the article starts?
7 That's why I wanted to clarify.	7 MR. FRITZ: Objection.
8 Q Okay. Well, is this a hallucination?	8 THE WITNESS: Honestly, I can't remember
9 MR. FRITZ: Objection.	9 how that is usually signified. But something to
THE WITNESS: I wouldn't say that. No.	10 that effect. Yes.
11 I would say that it's probably wrong if the two	11 BY MS. GOVERNSKI:
12 don't match. But I wouldn't say it's a	Q Let's go to the next page and you will
13 hallucination.	13 see 1140. Does that help explain what those numbers
14 BY MS. GOVERNSKI:	14 indicated?
15 Q Well, what is the explanation for the two	15 A Yes. So I'm assuming it's the page, yes.
16 not matching?	16 Q So the pages of this particular article
17 MR. FRITZ: Objection. You can answer	17 is 1139 to 1160 in the Journal of Computational 18 Social Science?
18 again. 19 THE WITNESS: Possible error.	19 A Yes.
20 BY MS. GOVERNSKI:	20 Q Who are the authors of this paper?
21 Q Okay. Well, let's look at one of the	21 A Timothy Graham, Sam Hames, and Elizabeth
22 articles that your counsel provided us. I'm going	22 Alpert.
23 to move and mark as Exhibit where are we, 5?	23 Q Okay. And those are the only three
24 THE STENOGRAPHIC REPORTER: Yes. We're	24 authors listed here, right?
25 on Exhibit 5.	25 A Yes. On this publication, yes.
	1 ,,
Page 131 1 (Exhibit 5 marked for identification.)	Page 133 1 Q Are you familiar with who those
2 BY MS. GOVERNSKI:	2 individuals are?
3 Q Okay. I'm going to introduce Exhibit 5,	3 A No.
4 and it should be in marked exhibits, if you can open	4 Q Do you know anything about them?
5 that.	5 A No.
6 A Yes, I have it.	6 Q Do you know anything about the quality of
7 Q And what is this?	7 their research?
8 A It appears to be from the Journal of	8 A No.
9 Computational Science. It's an article, "The	9 Q How did you identify this article?
10 coordination network toolkit."	MR. FRITZ: Objection. You can answer.
11 Q "The coordination network toolkit: A	11 THE WITNESS: I don't know how I
12 framework for detecting and analyzing coordinated	12 identified it.
13 behavior", right?	13 BY MS. GOVERNSKI:
14 A On social media. Yes.	14 Q How did you know about it?
15 Q This is from this is from the Journal	15 A It could have been one of the ones that
16 of Computational Social Science. If you look at the	16 have it I have a myriad of references to
17 top. That's right, right?	17 different articles.
18 A That's what is listed. Yes.	18 Q I understand. But how did you decide to
19 Q This is also not one of the journals you	19 review this article for purposes of your report?
20 regularly read?	MR. FRITZ: Objection. You can answer
21 A No.	21 again.
22 Q And if you look at the top, it says	THE WITNESS: I'm not sure how I selected
23 7.1139 to 1160.	23 this particular article.
Do you see that?	24 BY MS. GOVERNSKI:
25 A Yes.	25 Q Well, who would have selected it for you?

34 (Pages 130 - 133)

Page 134	
1 MR. FRITZ: Objection.	1 BY MS. GOVERNSKI:
2 THE WITNESS: I would have selected it	2 Q Okay. And what are some of the specific
3 for myself.	3 tools that they identify?
4 BY MS. GOVERNSKI:	4 MR. FRITZ: Objection.
5 Q How would you have how did you find	5 THE WITNESS: I don't know this
6 it?	6 particular one just offhand.
7 A I have, as I mentioned, I have a lot of	7 BY MS. GOVERNSKI:
8 articles that I either have read, I've clipped. I	8 Q Okay. Can you name one of the tools that
9 have numerous articles that I've read previously and	9 this article identifies?
10 I store, and then I usually sort through them.	10 A One from the toolkit? No.
11 Q I understand. But you don't have a	11 Q Okay. Does this paper provide any formal
12 recollection of doing that with respect to this	12 definition of coordinated behavior in social media?
13 article?	13 A I would have to go through and read it
14 A I don't have a recollection of how I	14 again.
15 chose the specific article.	15 Q Okay. Well, as you reviewed it for
16 Q Okay. Did you read the entirety of this	16 purposes of your report, did you rely on any
17 paper?	17 definition in this article for coordinated behavior
A Probably not recently. But yes, at some	18 in social media?
19 point.	19 A For this one, I'm not sure.
Q Well, recently, like at some point, what	20 Q As you sit here today, can you explain
21 do you mean?	21 how this paper defines coordinated behavior in
A I didn't review this for the deposition.	22 social media?
23 I would have read this probably months ago. But	23 MR. FRITZ: You want her to review the
24 yes.	24 article?
25 Q You said you were retained in September,	25 MS. GOVERNSKI: Kevin, stop with the
Page 135	Page 137
1 October. Did you read it since then?	1 speaking objections.
2 A Yes.	2 MR. FRITZ: I just want to make sure the
3 Q So can you summarize the contents of this	3 question is clear
a de la compania de la contenta del la contenta de	
4 paper for me, please?	1
4 paper for me, please? 5 MR. FRITZ: Objection.	4 MS. GOVERNSKI: No, she's
5 MR. FRITZ: Objection.	4 MS. GOVERNSKI: No, she's 5 MR. FRITZ: Sorry
5 MR. FRITZ: Objection.6 THE WITNESS: I cannot. Offhand?	4 MS. GOVERNSKI: No, she's 5 MR. FRITZ: Sorry 6 MS. GOVERNSKI: She cited this. I'm
5 MR. FRITZ: Objection. 6 THE WITNESS: I cannot. Offhand? 7 MR. FRITZ: You want her to read the	4 MS. GOVERNSKI: No, she's 5 MR. FRITZ: Sorry 6 MS. GOVERNSKI: She cited this. I'm 7 entitled to her information that she has in her
5 MR. FRITZ: Objection. 6 THE WITNESS: I cannot. Offhand? 7 MR. FRITZ: You want her to read the 8 entire article now?	4 MS. GOVERNSKI: No, she's 5 MR. FRITZ: Sorry 6 MS. GOVERNSKI: She cited this. I'm 7 entitled to her information that she has in her 8 recollection today, about this article.
5 MR. FRITZ: Objection. 6 THE WITNESS: I cannot. Offhand? 7 MR. FRITZ: You want her to read the 8 entire article now? 9 BY MS. GOVERNSKI:	4 MS. GOVERNSKI: No, she's 5 MR. FRITZ: Sorry 6 MS. GOVERNSKI: She cited this. I'm 7 entitled to her information that she has in her 8 recollection today, about this article. 9 MR. FRITZ: Please try not to interrupt
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5 MR. FRITZ: Objection. 6 THE WITNESS: I cannot. Offhand? 7 MR. FRITZ: You want her to read the 8 entire article now? 9 BY MS. GOVERNSKI: 10 Q No. Ms. Alexander, you cite this article 11 multiple times in your report. I'm asking for you 12 to summarize it. 13 MR. FRITZ: Do you want her to read it 14 first? 15 MS. GOVERNSKI: No. She's supposedly 16 read it as she was preparing her report, Kevin. 17 Ms. Alexander, I'm asking you to please 18 summarize the article that you cited multiple times.	MS. GOVERNSKI: No, she's MR. FRITZ: Sorry MS. GOVERNSKI: She cited this. I'm rentitled to her information that she has in her recollection today, about this article. MR. FRITZ: Please try not to interrupt me. I just want to make sure that the witness and I both understood what you're asking her. If you're asking her from memory, then we understood MS. GOVERNSKI: Ash, please repeat back my question which said, "as you sit here today." MR. FRITZ: Sorry, I don't know why you interrupted me again. I excused it the first time kerning it might not be. So you should just make
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MR. FRITZ: Objection. THE WITNESS: I cannot. Offhand? MR. FRITZ: You want her to read the entire article now? BY MS. GOVERNSKI: Q No. Ms. Alexander, you cite this article multiple times in your report. I'm asking for you to summarize it. MR. FRITZ: Do you want her to read it first? MS. GOVERNSKI: No. She's supposedly read it as she was preparing her report, Kevin. Ms. Alexander, I'm asking you to please summarize the article that you cited multiple times. MR. FRITZ: Objection. THE WITNESS: I understand that. So the article in and of itself is about coordinated networks and the toolkit that the authors used to	MS. GOVERNSKI: No, she's MR. FRITZ: Sorry MS. GOVERNSKI: She cited this. I'm rentitled to her information that she has in her recollection today, about this article. MR. FRITZ: Please try not to interrupt me. I just want to make sure that the witness and I both understood what you're asking her. If you're asking her from memory, then we understood MS. GOVERNSKI: Ash, please repeat back my question which said, "as you sit here today." MR. FRITZ: Sorry, I don't know why you interrupted me again. I excused it the first time kecause I thought it was a mistake, and now I'm learning it might not be. So you should just make clear whether you want her to go from memory or you want her to read the article. That's all I'm MS. GOVERNSKI: Mr. Fritz, you should

35 (Pages 134 - 137)

	CONFID	EN	HAL
	Page 138		Page 140
1	(Record read as follows:	1	and control hubs."
2	"QUESTION: As you sit here today, can	2	Please identify what parts of this
3	you explain how this paper defines	3	article you used to support that statement.
4	coordinated behavior in social media?")	4	MR. FRITZ: Objection. You can answer.
5	MR. FRITZ: So sitting here today, do you	5	THE WITNESS: Specifically, I would have
1	want her to scroll through the entire thing?	6	to go through to reference the page and the location
7	<u> </u>		of I would have to look to see how I used it
8	speaking objections. No, I am going to have to call		within the report and then go through the paper to
	the Court. It's my deposition. Stop with the		see how I cited it.
1	speaking objections. Ms. Alexander, as you	10	
11	MR. FRITZ: We can call the Court if	11	Let's go to 109 in your report.
1	you'd like, because you keep interrupting me.	12	MR. FRITZ: Are you saying you want her
1	BY MS. GOVERNSKI:		to read the article now?
14			BY MS. GOVERNSKI:
15	MR. FRITZ: I just want to understand	15	Q No. Go to 109 of your report, is what I
1	your question.		said. Paragraph 109. I'm sorry. Let's go to
17	MS. GOVERNSKI: As she sits here today,	17	paragraph 87.
	I'm entitled to her recollection as she sits here	18	A Okay.
1	today.	19	Q Are you at paragraph 87 of your report?
20	•	20	
	you do not want her to read the article now?	21	Q You refer to Graham, et al.
22	•	22	Do you see that?
1	her report. As you sit here today can you please	23	A Yes.
1	repeat the question back, Ash, because Mr. Fritz's	24	Q You have a footnote, footnote 11.
	one minute long speaking objection has distracted me	l	Do you see that?
-			•
1	Page 139	1	Page 141
$\frac{1}{2}$	from what the actual question was. MR. FRITZ: I just wanted to make sure	$\begin{bmatrix} 1 \\ 2 \end{bmatrix}$	A Yes.
	we're all understanding what your question was.		Q If you can look at this footnote, it says
4	• • •	3	"Graham, et al." and you see the title here, right? "Detecting coordination networks in
1	speaking objections. Ash, please repeat back the	5	social media."
	question.	6	Do you see that?
7		7	A Yes.
8	· ·	8	Q So that's a different title than what we
9			
10	• • • • • • • • • • • • • • • • • • • •	1	just discussed which was "The coordination network toolkit: A framework for detecting and applyzing
11	· · · · · · · · · · · · · · · · · · ·	1	toolkit: A framework for detecting and analyzing
11	3	11	coordinated behavior on social media", right?
1		13	You can go back and look at Exhibit 5.
13	going through and referencing the paper. BY MS. GOVERNSKI:	13	A Okay.
15			Q And you can see the two titles don't
			match again, right?
	page 87 as the only source for your claim that,	16 17	MR. FRITZ: Objection.
/	quote:		THE WITNESS: To what I have listed in
		18	
18	` '	10	BV MC 1311/EDNCKI
18 19	"Coordinated influence operations		BY MS. GOVERNSKI:
18 19 20	"Coordinated influence operations exhibit distinctive network	20	Q No. The actual article.
18 19 20 21	"Coordinated influence operations exhibit distinctive network fingerprints, tight temporal	20 21	Q No. The actual article.A Okay.
18 19 20 21 22	"Coordinated influence operations exhibit distinctive network fingerprints, tight temporal synchronization, limited participant	20 21 22	Q No. The actual article.A Okay.Q The actual article, you've read the title
18 19 20 21 22 23	"Coordinated influence operations exhibit distinctive network fingerprints, tight temporal synchronization, limited participant dispersion, high clustering	20 21 22 23	 Q No. The actual article. A Okay. Q The actual article, you've read the title as being "The coordination network toolkit: A
18 19 20 21 22	"Coordinated influence operations exhibit distinctive network fingerprints, tight temporal synchronization, limited participant dispersion, high clustering coefficients, and centralized network	20 21 22 23 24	Q No. The actual article.A Okay.Q The actual article, you've read the title

36 (Pages 138 - 141)

CONFIL	DENTIAL
Page 142	Page 144
1 That's not the same title as "Detecting	1 MR. FRITZ: Objection.
2 coordination networks in social media", right?	2 THE WITNESS: By definition, no.
3 MR. FRITZ: Objection. You can answer.	3 BY MS. GOVERNSKI:
4 THE WITNESS: That is not.	4 Q If it made up authors who were not the
5 BY MS. GOVERNSKI:	5 authors, that would not be a hallucination?
6 Q So why is there different titles here?	6 MR. FRITZ: Objection.
7 A I am not sure.	7 THE WITNESS: If a generative AI solution
8 Q Okay. And then we talked about the page	8 made up authors, then yes, that would be a
9 numbers and we talked about the page numbers 1139 to	9 hallucination.
10 1160 represent the number of pages that reflect this	10 BY MS. GOVERNSKI:
11 article, right?	11 Q Okay. So let's look at Exhibit 55, which
12 A Yes.	12 we already talked about. And we talked about the
13 Q Okay. Let's look at this footnote. You	13 three authors. You recall that, Graham, Hames and
14 cite pages 23 to 47.	14 Alpert. Do you recall that those were the only
15 Do you see that?	15 three authors identified in this article?
16 A I do.	16 A In one that we're looking at, yes.
17 Q And this is the those are the page	17 Q Okay. So let's go back to your report,
18 numbers that you say supports this statement:	18 which is Exhibit 002, and let's go to page 108. I'm
19 (As read):	19 going to share my screen so it's a little easier.
20 "These findings align closely with	20 Oh, I am showing my screen, I guess.
21 recent computational social science	21 And you see right here, Graham this is
22 research."	22 the article we're talking about, right?
23 Which is the sentence I just read. So	23 "Detecting coordination networks in
24 please direct me to pages 23 to 47 in Exhibit 5.	24 social media. 'Journal of Computational Social
25 A So I'm assuming this is an error. But I	25 Science."
25 II BOTH assuming this is an error. But I	25 Science.
Page 143	Page 145
Page 143 1 don't that's not part of your exhibit.	
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the	Page 145 1 Do you see that? 2 A Yes.
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right?	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right?	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell.
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No.	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation?	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes.
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation?	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes.
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation? 7 MR. FRITZ: Objection.	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes. 7 Q Those authors were not in the article,
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation? 7 MR. FRITZ: Objection. 8 THE WITNESS: No, I wouldn't call it	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes. 7 Q Those authors were not in the article, 8 right?
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Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation? 7 MR. FRITZ: Objection. 8 THE WITNESS: No, I wouldn't call it 9 hallucinated because it's an actual paper. It's 10 incorrect on the way that it was picked up for the 11 title and the year. 12 BY MS. GOVERNSKI: 13 Q So it says Graham, et al., but if you	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes. 7 Q Those authors were not in the article, 8 right? 9 A On the article we looked at, no, they 10 were not. 11 Q Well, do you have any reason to believe 12 that the other article that your counsel provided to 13 us as this article is not the article that you
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Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation? 7 MR. FRITZ: Objection. 8 THE WITNESS: No, I wouldn't call it 9 hallucinated because it's an actual paper. It's 10 incorrect on the way that it was picked up for the 11 title and the year. 12 BY MS. GOVERNSKI: 13 Q So it says Graham, et al., but if you 14 listed authors who were not the authors who 15 appeared, would that be an indication of a 16 hallucination? 17 A I'm sorry. If I listed authors that did 18 not appear? 19 Q On the publication.	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes. 7 Q Those authors were not in the article, 8 right? 9 A On the article we looked at, no, they 10 were not. 11 Q Well, do you have any reason to believe 12 that the other article that your counsel provided to 13 us as this article is not the article that you 14 intended to reference here? 15 A No, I believe it is the article I 16 intended to reference. 17 Q So how can you explain a citation that 18 makes up authors who are not the authors identified 19 in the article?
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation? 7 MR. FRITZ: Objection. 8 THE WITNESS: No, I wouldn't call it 9 hallucinated because it's an actual paper. It's 10 incorrect on the way that it was picked up for the 11 title and the year. 12 BY MS. GOVERNSKI: 13 Q So it says Graham, et al., but if you 14 listed authors who were not the authors who 15 appeared, would that be an indication of a 16 hallucination? 17 A I'm sorry. If I listed authors that did 18 not appear? 19 Q On the publication. 20 A So I think that you're using the word	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes. 7 Q Those authors were not in the article, 8 right? 9 A On the article we looked at, no, they 10 were not. 11 Q Well, do you have any reason to believe 12 that the other article that your counsel provided to 13 us as this article is not the article that you 14 intended to reference here? 15 A No, I believe it is the article I 16 intended to reference. 17 Q So how can you explain a citation that 18 makes up authors who are not the authors identified
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation? 7 MR. FRITZ: Objection. 8 THE WITNESS: No, I wouldn't call it 9 hallucinated because it's an actual paper. It's 10 incorrect on the way that it was picked up for the 11 title and the year. 12 BY MS. GOVERNSKI: 13 Q So it says Graham, et al., but if you 14 listed authors who were not the authors who 15 appeared, would that be an indication of a 16 hallucination? 17 A I'm sorry. If I listed authors that did 18 not appear? 19 Q On the publication. 20 A So I think that you're using the word 21 "hallucination." That is not hallucination to me.	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes. 7 Q Those authors were not in the article, 8 right? 9 A On the article we looked at, no, they 10 were not. 11 Q Well, do you have any reason to believe 12 that the other article that your counsel provided to 13 us as this article is not the article that you 14 intended to reference here? 15 A No, I believe it is the article I 16 intended to reference. 17 Q So how can you explain a citation that 18 makes up authors who are not the authors identified 19 in the article? 20 MR. FRITZ: Objection. 21 You can answer again.
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation? 7 MR. FRITZ: Objection. 8 THE WITNESS: No, I wouldn't call it 9 hallucinated because it's an actual paper. It's 10 incorrect on the way that it was picked up for the 11 title and the year. 12 BY MS. GOVERNSKI: 13 Q So it says Graham, et al., but if you 14 listed authors who were not the authors who 15 appeared, would that be an indication of a 16 hallucination? 17 A I'm sorry. If I listed authors that did 18 not appear? 19 Q On the publication. 20 A So I think that you're using the word 21 "hallucination." That is not hallucination to me. 22 That is incorrect. But hallucination is different.	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes. 7 Q Those authors were not in the article, 8 right? 9 A On the article we looked at, no, they 10 were not. 11 Q Well, do you have any reason to believe 12 that the other article that your counsel provided to 13 us as this article is not the article that you 14 intended to reference here? 15 A No, I believe it is the article I 16 intended to reference. 17 Q So how can you explain a citation that 18 makes up authors who are not the authors identified 19 in the article? 20 MR. FRITZ: Objection. 21 You can answer again. 22 THE WITNESS: I'm sorry, Kevin?
Page 143 1 don't that's not part of your exhibit. 2 Q Those page numbers don't match the 3 exhibit that your counsel provided to us, right? 4 A It doesn't match the paper that I 5 submitted. No. 6 Q Is this a hallucinated cite citation? 7 MR. FRITZ: Objection. 8 THE WITNESS: No, I wouldn't call it 9 hallucinated because it's an actual paper. It's 10 incorrect on the way that it was picked up for the 11 title and the year. 12 BY MS. GOVERNSKI: 13 Q So it says Graham, et al., but if you 14 listed authors who were not the authors who 15 appeared, would that be an indication of a 16 hallucination? 17 A I'm sorry. If I listed authors that did 18 not appear? 19 Q On the publication. 20 A So I think that you're using the word 21 "hallucination." That is not hallucination to me.	Page 145 1 Do you see that? 2 A Yes. 3 Q Okay. And you see that it lists 4 additional authors here: Bruns, Zhu, and Campbell. 5 Do you see that? 6 A Yes. 7 Q Those authors were not in the article, 8 right? 9 A On the article we looked at, no, they 10 were not. 11 Q Well, do you have any reason to believe 12 that the other article that your counsel provided to 13 us as this article is not the article that you 14 intended to reference here? 15 A No, I believe it is the article I 16 intended to reference. 17 Q So how can you explain a citation that 18 makes up authors who are not the authors identified 19 in the article? 20 MR. FRITZ: Objection. 21 You can answer again.

37 (Pages 142 - 145)

25 of things wrong. So it's -- in general, it's just

25 a hallucination?

	Page 146		Page 148
1	incorrect. I mean, outside of the author, the date		me know when you have it.
2	is also incorrect, so	2	A I can look at your screen. It's
3	BY MS. GOVERNSKI:	3	taking it's taking a while to download.
4	Q Right. So how did you just said	4	Q Okay. This is a GPTZero report. And you
5	earlier that if a cite citation were to include	5	will see it has the exact verbatim of paragraph 87.
6	authors who did not appear on the article, it would	6	Do you see that?
7	be a sign of a hallucination.	7	A Can you zoom in?
8	MR. FRITZ: Objection.	8	Q Uh-huh. Right here.
9	BY MS. GOVERNSKI:	9	(As read):
10	Q How is that not the case here?	10	"These findings align closely with
11	A So I believe I said if something was	11	recent computational social science
12	developed through a generative AI solution that	12	research."
13	added authors, it would be an example of	13	And you will see it's that same citation
14	hallucination.	14	to Graham that we just looked at in paragraph 87?
15	Q And how do you know that's not the case	15	A Okay.
16	here?	16	Q Okay. And at the top, it states that:
17	A Because I know this wasn't generated by	17	(As read):
18	generative AI.	18	"We are highly confident this text is
19	Q Okay. Well, let's look at that. Let's	19	AI generated."
20	look at the paragraph that you cite this for,	20	And lists AI probability at 100 percent.
	paragraph 86.	21	Do you see that?
22	MR. FRITZ: Objection.	22	A I see that.
23	BY MS. GOVERNSKI:	23	Q Do you have any explanation for GPTZero's
24	Q Sorry. 87. This is the same paragraph	24	finding that it's 100 percent probability that
25	we've been looking at, right, where you cite Graham?	25	paragraph 87 is AI generated?
	Page 147		Page 149
1		1	
2	concepts that you cite Graham for in your	2	
	professional life?	3	BY MS. GOVERNSKI:
4	1	4	Q You have no explanation for that?
5	specifically talking about?	5	
6		6	again.
7	this paragraph 87.	7	THE WITNESS: I do not. As I mentioned
8	A So temporal synchronization, yes.	8	earlier, I don't believe in AI analysis for the use
9	Participant dispersion, yes. And command and	9	of identifying if something is generative AI. I
10	control hubs, yes.	10	think we talked about that earlier.
11	Q Okay. But when you applied those	11	BY MS. GOVERNSKI:
12	concepts, were you relying on Graham?	12	Q So if another if Grammarly found the
13	A As a practitioner, no.	13	same paragraph had a 70 percent chance of being
14	MS. GOVERNSKI: So my colleague is going		generated by AI, would that change your perception
15	to be moving into a document, which I will mark as		at all?
16	Exhibit 6. Let me know when you have it.	16	A So Grammarly has a feature that is also
17		17	an AI checker
18		18	Q Uh-huh.
19	entered it in. It says it's being introduced.	19	~
20		20	I mentioned earlier with the accuracy of overall AI
21	BY MS. GOVERNSKI:		checkers.
22	Q Okay. Do you have that document,	22	Q Okay. So what about the fact that
23	Exhibit 6, up?	23	GPTZero predicted this paragraph was 100 percent
24	A It's downloading right now.		likely to be AI, and Grammarly predicted this
25			paragraph to be 70 percent, your response is that

38 (Pages 146 - 149)

	DENTIAL
Page 150	Page 152
1 both GPTZero and Grammarly must be inaccurate?	1 BY MS. GOVERNSKI:
2 MR. FRITZ: Objection.	2 Q So do you have any explanation for why
3 You can answer again.	3 164 paragraphs out of 200 in your report had an
4 THE WITNESS: So I don't think it's about	4 80 percent likelihood of being AI?
5 the inaccuracy. I think it's about AI generator	5 MR. FRITZ: Objection.
6 checks not simply being accurate. And research,	6 THE WITNESS: I don't know.
7 outside of my statement, has also seen this to be	7 BY MS. GOVERNSKI:
8 true.	8 Q Okay. Let's go back to your report where
9 BY MS. GOVERNSKI:	9 you cite Graham again. And I'm sharing it on my
10 Q Okay. And then a third AI checker,	10 screen for ease of use.
11 TextGuard, found this one paragraph to be 86 percent	11 Do you see paragraph 97?
12 likely to be AI. So I'm just trying to understand,	12 MR. FRITZ: I would use the Exhibit
13 is it your testimony that that is just a	13 Share, Ms. Alexander.
14 coincidence?	14 THE WITNESS: I'm there.
15 MR. FRITZ: Objection.	15 BY MS. GOVERNSKI:
16 You can answer again.	16 Q Okay. And you see that in the first
17 THE WITNESS: My testimony is that AI	17 paragraph, you you cite Graham, Howard and
18 generator checkers are are inadequate and not	18 Woolley and Ferrara.
19 accurate.	19 Do you see that?
20 BY MS. GOVERNSKI:	20 A I do.
21 Q How come the paragraphs in your report	21 Q Okay. What is the Howard and Woolley
22 that describe your background all came back as human	22 article?
23 generated?	23 A I would have to go back to reference the
	24 documents or the articles that I submitted.
24 MR. FRITZ: Objection. 25 THE WITNESS: I do not know why.	25 Q As you sit here today, based on your
25 THE WITNESS. I do not know why.	23 Q As you sit here today, based on your
Page 151	Page 153
1 BY MS. GOVERNSKI:	1 recollection, what is this article about?
2 Q And why did the paragraphs in	2 A I can't tell you offhand. I would
3 Dr. Mayzlin's report come back as zero percent AI	3 have I'd have to reference the article itself.
4 generated?	4 Q Okay. As you sit here today, can you
5 MR. FRITZ: Objection.	5 explain why the Howard and Woolley article support
6 THE WITNESS: I couldn't answer that.	6 the statements in this paragraph?
7 BY MS. GOVERNSKI:	7 MR. FRITZ: Objection.
	l
8 Q Do you have any explanation for why	8 THE WITNESS: I cannot.
9 GPTZero would predict that 101 paragraphs of your	9 BY MS. GOVERNSKI:
9 GPTZero would predict that 101 paragraphs of your 10 report have a 100 percent probability of being AI?	9 BY MS. GOVERNSKI: 10 Q What about Ferrara, et al., what do you
9 GPTZero would predict that 101 paragraphs of your 10 report have a 100 percent probability of being AI? 11 MR. FRITZ: Objection.	9 BY MS. GOVERNSKI: 10 Q What about Ferrara, et al., what do you 11 recall about that article?
9 GPTZero would predict that 101 paragraphs of your 10 report have a 100 percent probability of being AI? 11 MR. FRITZ: Objection. 12 THE WITNESS: I couldn't answer that.	9 BY MS. GOVERNSKI: 10 Q What about Ferrara, et al., what do you 11 recall about that article? 12 A I'd have to look at the article.
9 GPTZero would predict that 101 paragraphs of your 10 report have a 100 percent probability of being AI? 11 MR. FRITZ: Objection. 12 THE WITNESS: I couldn't answer that. 13 BY MS. GOVERNSKI:	9 BY MS. GOVERNSKI: 10 Q What about Ferrara, et al., what do you 11 recall about that article? 12 A I'd have to look at the article. 13 Q As you sit here today, do you have any
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9 GPTZero would predict that 101 paragraphs of your 10 report have a 100 percent probability of being AI? 11 MR. FRITZ: Objection. 12 THE WITNESS: I couldn't answer that. 13 BY MS. GOVERNSKI: 14 Q Do you have any explanation for why 15 GPTZero predicted that an additional 28 paragraphs 16 of your report had a 90 percent probability of being	9 BY MS. GOVERNSKI: 10 Q What about Ferrara, et al., what do you 11 recall about that article? 12 A I'd have to look at the article. 13 Q As you sit here today, do you have any 14 recollection about what that article was about? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know offhand.
9 GPTZero would predict that 101 paragraphs of your 10 report have a 100 percent probability of being AI? 11 MR. FRITZ: Objection. 12 THE WITNESS: I couldn't answer that. 13 BY MS. GOVERNSKI: 14 Q Do you have any explanation for why 15 GPTZero predicted that an additional 28 paragraphs 16 of your report had a 90 percent probability of being 17 AI?	9 BY MS. GOVERNSKI: 10 Q What about Ferrara, et al., what do you 11 recall about that article? 12 A I'd have to look at the article. 13 Q As you sit here today, do you have any 14 recollection about what that article was about? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know offhand. 17 BY MS. GOVERNSKI:
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9 GPTZero would predict that 101 paragraphs of your 10 report have a 100 percent probability of being AI? 11 MR. FRITZ: Objection. 12 THE WITNESS: I couldn't answer that. 13 BY MS. GOVERNSKI: 14 Q Do you have any explanation for why 15 GPTZero predicted that an additional 28 paragraphs 16 of your report had a 90 percent probability of being 17 AI? 18 MR. FRITZ: Objection. 19 THE WITNESS: I still can't answer that. 20 BY MS. GOVERNSKI:	9 BY MS. GOVERNSKI: 10 Q What about Ferrara, et al., what do you 11 recall about that article? 12 A I'd have to look at the article. 13 Q As you sit here today, do you have any 14 recollection about what that article was about? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know offhand. 17 BY MS. GOVERNSKI: 18 Q And as you sit today, do you have any 19 recollection for how the article by Ferrara supports 20 any of the statements in paragraph 97?
9 GPTZero would predict that 101 paragraphs of your 10 report have a 100 percent probability of being AI? 11 MR. FRITZ: Objection. 12 THE WITNESS: I couldn't answer that. 13 BY MS. GOVERNSKI: 14 Q Do you have any explanation for why 15 GPTZero predicted that an additional 28 paragraphs 16 of your report had a 90 percent probability of being 17 AI? 18 MR. FRITZ: Objection. 19 THE WITNESS: I still can't answer that. 20 BY MS. GOVERNSKI: 21 Q And do you have any explanation for why	9 BY MS. GOVERNSKI: 10 Q What about Ferrara, et al., what do you 11 recall about that article? 12 A I'd have to look at the article. 13 Q As you sit here today, do you have any 14 recollection about what that article was about? 15 MR. FRITZ: Objection. 16 THE WITNESS: I don't know offhand. 17 BY MS. GOVERNSKI: 18 Q And as you sit today, do you have any 19 recollection for how the article by Ferrara supports 20 any of the statements in paragraph 97? 21 MR. FRITZ: Objection.
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39 (Pages 150 - 153)

		LIV	
	Page 154		Page 156
1	A Yes.	1	, , ,
2	Q Every word?	2	
3	A So the citations themselves, I get from		academia, yes, correct.
4	, , , , , , , ,	4	
5	Q Any idea how GPTZero would predict the	5	A I'm sorry, what do you mean by "what
6	likelihood of this paragraph?		academia"?
7	MR. FRITZ: Objection.	7	Q What academia supports these specific
8	THE WITNESS: I don't know.		bullets that we've been discussing?
9		9	A There is research around account
10	Q Would you be surprised to learn that		clustering, sentiment homogeneity, across data
	GPTZero projected that this paragraph was		analysis and computational science.
	100 percent likely to be AI generated?	12	
13	MR. FRITZ: Objection.	13	A I believe you're asking if I can cite the
14	You can answer.		authors and/or a paper. I can't do that offhand.
15	THE WITNESS: I'm sorry. What was the	15	Q I'm asking for the basis of the bullets
	question there? I apologize.		that don't include a citation.
	BY MS. GOVERNSKI:	17	3
18	Q Would you be surprised to learn that	18	E
	GPTZero predicted that there was 100 percent	19	, , , , , , , , , , , , , , , , , , ,
	likelihood that this paragraph was AI generated?		experience, as well as, I believe, norms across
21	MR. FRITZ: Objection.		social analysis of social media in academia as well.
22	THE WITNESS: It wouldn't surprise or not		BY MS. GOVERNSKI:
	surprise me.	23	Q Okay. But you can't, as you sit here
	BY MS. GOVERNSKI:		today, cite any academia that supports these
25	Q Okay. And then TextGuard also found that	25	specific bullets?
			1
	Page 155		Page 157
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2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24	this paragraph was 92 percent most likely to be AI generated. Would that surprise you? MR. FRITZ: Objection. THE WITNESS: Same answer. I wouldn't be surprised or not surprised. BY MS. GOVERNSKI: Q Okay. And so these bullets here: (As read): "Centralized amplification hubs, Temporal synchronization, Sentiment homogeneity." You wrote it's your testimony that you wrote these bullets? A Yes. Q Okay. And there's no citation for these bullets. So is this one of those examples where the basis for these are just your own experience? A Yes. Those are also some of the same verbiage I used earlier when we talked about the work that I did at Meta as well as at Ipsos. Q Right. So that verbiage, and when you talked about it earlier, that's not based on academia; that's just based on your own experience?	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24	Page 157 MR. FRITZ: Objection. THE WITNESS: I can't provide an author and a paper offhand. BY MS. GOVERNSKI: Q I'm not asking for the paper and the author, but just what academia supports these specific bullets? MR. FRITZ: Same objection. THE WITNESS: Maybe I don't understand the question when you say which academia. So looking at marketing and social analysis in academia, right, which is a discipline, so there's been research done to show coordinated fingerprinting in academia, as well as on the practitioner side. BY MS. GOVERNSKI: Q I'm trying to identify and understand what academia you relied on when you came up with this bulleted list. A The bulleted list is based on my lived experience, as I mentioned. But it's also supported, in addition, in academic research. Q And I'm entitled to know what academic

40 (Pages 154 - 157)

Page 158 1 MR. FRITZ: Objection. 1 BY MS. GOVERNSKI: THE WITNESS: So I think we're saying --2 3 I'm saying the same thing over and over again. So 3 out? 4 it's based on the research that I've done, myself, 4 5 as a practitioner. And in addition to that, I also 5 keywords. 6 believe that there is research on these particular 6 7 elements across marketing science and social 7 8 analysis. I do not have -- before you ask -- I do 8 putting together Appendix C? 9 not have a citation to offer you offhand. 10 BY MS. GOVERNSKI: 10 11 content, again, it's based on practitioner work, Q So your report does not disclose the 12 academia on which you relied for these paragraphs in 12 which would not be needed for an academic citation. 13 paragraph 97? 13 14 MR. FRITZ: Objection. 14 you, again, are expected to list all of the THE WITNESS: That's incorrect --15 materials that form the basis of your opinion. And 15 16 on page 108, you cite a legal case called Daubert. 16 BY MS. GOVERNSKI: 17 Q So --17 18 A -- as I stated. 18 19 Q -- what is the academia? Yeah, go on. 19 20 Sorry. 20 21 A It's based on my experience as a 21 I -- when I was -- when this -- when the litigation 22 practitioner, period. I'm saying I also believe, in 22 first was presented to me. 23 addition to that being the basis of the bullets, I 23 24 also believe that there is academic research that 24 25 supports it as well. 25

Q But that's a belief based on your

THE WITNESS: It's based on my

5 understanding of articles I've read across academia

6 of different conferences, a myriad of other things.

Q And do you understand that you're

THE WITNESS: I understand that if I'm

14 using academic sources. As I mentioned in my last

15 answer, these bullets, first and foremost, are based

Q And you cannot, as you sit here today,

THE WITNESS: Of the citations, no, I

9 required to identify all of the academia that 10 supports the opinions that you're offering in this

MR. FRITZ: Objection.

19 think of any of the articles that inform these

MR. FRITZ: Objection.

23 cannot. Of referencing a title of a paper and the

16 on my practitioner experience.

17 BY MS. GOVERNSKI:

24 authors, no, I cannot.

2 intuition and not what is cited in your report?

MR. FRITZ: Objection.

7 BY MS. GOVERNSKI:

14

15

Page 159

Page 161 1 Daubert? MR. FRITZ: I would instruct the witness 3 to the extent your answer requires you to disclose 4 substantive communications with counsel, you not 5 reveal that. But independent of that, go ahead. THE WITNESS: So it was nothing to do 7 with any conversation with counsel. It was 8 something that I did just proactively. 9 BY MS. GOVERNSKI: 10 Q Okay. How did you learn about Daubert? Honestly, I think I Googled it. 11 12 Q Okay. What prompted you to Google 13 Daubert?

Q And how would you go about finding that

Q So why didn't you do that when you were

Q Okay. Let's go to your Appendix C, where

A Daubert is something I read early on when

Did you just decide on your own to read

For just research and knowledge.

A So as I mentioned, for this particular

A I would do a scholar search based on

Q And you can do that?

Do you see that?

Q Why did you list Daubert?

Q Why did you read Daubert?

A Yes.

A Yes.

A When GLG reached out to me regarding a 17 18 potential litigation case, I Googled it. 19 Q Okay. And what is your understanding of 20 Daubert? A So this was -- I read it a while ago. I 21 22 can't quote the case but it talks about

16 years ago or in this case?

A The engagement with GLG.

Q The engagement with GLG or -- like 12

23 methodology -- methodology rigor and being able 24 to -- sorry, I'm paraphrasing -- source and have a

25 chain of custody, I believe. Something to that

25

21

1

3

11 case?

20 bullets?

12

13

41 (Pages 158 - 161)

Page 160

	CONFIDENTIAL				
	Page 162		Page 164		
1	effect on how you represent information.	1	progeny, Courts evaluate expert		
2	Q And is your entire understanding of what	2	methodology based on several key		
3	Daubert stands for based on your own Google search?	3	criteria."		
4	A Yes, based on my own reading, correct.	4	A I mean, it's		
5	Q Okay. You're not a lawyer?	5	MR. FRITZ: Objection.		
6	A No, I'm not.	6	THE WITNESS: Again, I probably read it		
7	Q Do you hold yourself out as an expert on	7	on the Justice's website.		
8	the Daubert standards?	8	BY MS. GOVERNSKI:		
9	A Not at all.	9	Q Okay. And I don't understand why you		
10	Q So when your ninth opinion states that	10	were offering an opinion on whether your methodology		
11	the methodologies employed in this analysis meet	11	meets Daubert's standard if you're not an expert in		
12	established standards, you have no expertise in	12	Daubert. Can you please explain?		
13	determining what meets Daubert standards, right?	13	MR. FRITZ: Objection.		
14	A Outside of what I read, no.	14	THE WITNESS: So I added that in		
15	Q Outside of what you read on Google?	15	specifically to ensure that I, my work, would meet		
16	A Well, actually, outside of what I read on	16	the criteria that would be relevant for the report		
17	the U.S. Justice website.	17	itself.		
18	Q Okay. You have no independent experience	18	BY MS. GOVERNSKI:		
19	other than having read the case?	19	Q Even though you have no expertise in the		
20	A Correct.	20	Daubert standards?		
21	Q And you talk about Daubert in paragraphs	21	A Outside of what I read, no.		
22	100 to 106 of your report. And you write:	22	Q Okay. What is your understanding of what		
23	(As read):	23	your assignment was in this case?		
24	"Under the Daubert standard and its	24	MR. FRITZ: Objection.		
25	progeny, Courts evaluate expert	25	You can answer again.		
	Page 163		Page 165		
1	methodology based on several criteria."	1	THE WITNESS: So excuse me. So my		
2	What is your understanding of Daubert	2	assignment was to as a rebuttal expert, was to		
3	progeny?	3	review the plaintiff's experts well, select		
4	A So it is the case the components,	4	expert reports and offer my perspective on if the		
5	based on what I downloaded and read from the U.S	- 5	inferences made on the reports were accurate. If		
6	U.S. Justice's website.	6	there were areas that I would say made sense, didn't		
7	Q Okay. And you wrote that sentence,	7	make sense, answering questions around specifically		
8	"under the Daubert standard and its progeny"?	8	is a campaign inorganic or organic, and offering any		
9	MR. FRITZ: Objection.	9	additional context in regards to Dr. Mayzlin's		
10	THE WITNESS: Yes.	10	report or Dr. Humphrey's report.		
11	BY MS. GOVERNSKI:	11	BY MS. GOVERNSKI:		
12	Q Okay. And would it surprise you that	12	Q Were those terms, "organic" and		
13	GPTZero predicted this paragraph also to be	13	"inorganic" specifically used when discussing your		
14	100 percent likely to be AI?	14	assignment with you?		
15	MR. FRITZ: Objection.	15	A That term		
16	THE WITNESS: Okay. Is it the word	16	MR. FRITZ: Hold on. Hold on.		
	"progeny" that's I'm sorry. I'm confused about	17	To the extent your extent the question		
	that. It's a case and then it's the word "progeny"		and your response is calling for the disclosure of		
	added onto it. So I'm not sure what would be		information that would be protected by the		
	generative AI about that.	20	attorney-client privilege, I would instruct you not		
21	BY MS. GOVERNSKI:	21	to answer. And that is how I understood the		
22	Q I'm just trying to understand how you		question.		
23	came up with the sentence:	23	BY MS. GOVERNSKI:		
24	(As read):	24	Q What is your you used the terms		
l .					
25	"Under the Daubert standard and its	25	"organic" and "inorganic" to describe your		

42 (Pages 162 - 165)

CONFIDENTIAL				
Page 166	Page 168			
1 assignment, right?	1 MR. FRITZ: Objection.			
2 A I did, yes.	2 THE WITNESS: I can't recall the name of			
3 Q Okay. And you understood that your	3 the article. It's in my report as a footnote. I			
4 assignment was to make the determination between	4 originally read through the article and was going to			
5 organic and inorganic, those specific words?	5 use it within the context of my report. I decided			
6 A So that was not the charge. I used that	6 not to, and I removed the the commentary but left			
7 based on the way that I looked at the analysis.	7 the footnote.			
8 Q Okay. What was the charge?	8 BY MS. GOVERNSKI:			
9 A Excuse me. The charge was to	9 Q And you didn't list that, actually, in			
10 MR. FRITZ: Objection.	10 your Appendix C C. Why is that?			
11 You can answer again.	11 A Because I didn't end up using the her			
12 THE WITNESS: The charge was to read	12 article.			
13 through Dr. Mayzlin's and Dr. Humphrey's reports and	13 Q But you read her article			
14 offer any perspective as a rebuttal witness to see	14 A I did.			
15 if the outcomes, the inferences that they made or	15 Q in THE context of preparing your			
16 the way that they analyzed the data was accurate or	16 report?			
17 inaccurate.	17 A Yes, I read the article.			
18 BY MS. GOVERNSKI:	18 Q And who told sorry. Strike that.			
19 Q And that was the entire scope of your	19 How did you decide that you didn't need			
20 assignment?	20 to list it in Appendix C C?			
21 A Yes, that was the charge I was given.	21 A To my understanding, the materials relied			
	22 upon was the materials that I relied upon for the			
	1 -			
23 reports that you were assigned to rebut?	23 final report. So based on the content that was in 24 that report.			
24 A I'm not sure of the exact date. I know	<u> </u>			
25 there was only about two-and-a-half-weeks turnaround	25 Q So it's your testimony that your			
Page 167	Page 169			
1 time for November 3rd. So I would say	1 Appendix C C does not include everything that you've			
2 November 3rd, backing that out by two and a half	2 reviewed in the course of preparing your report but			
3 weeks.	3 only the things that you determined you would rely			
4 Q Yeah, like October 17th is, I believe,	4 upon?			
5 the date that the experts were served, so that	5 MR. FRITZ: Objection.			
6 sounds about right.	6 THE WITNESS: Correct. I believe, yes.			
7 So did you start so did you and	7 BY MS. GOVERNSKI:			
8 Ms. Hunter start your data analysis before that time	8 Q So why did you cite the Mayzlin study and			
9 or only after you received the reports?	9 then keep the citation in your report, but then not			
10 A After we received the reports.	10 list it in your materials considered?			
11 Q What is your experience with Dr. Mayzlin?	11 MR. FRITZ: Objection.			
12 A I don't know Dr. Mayzlin.	12 You can answer again.			
13 Q Have you ever met Dr. Mayzlin?	13 THE WITNESS: I'm sorry. Could you just			
14 A No.	14 repeat the question?			
15 Q You cite in your report an article by	15 BY MS. GOVERNSKI:			
16 Dr. Mayzlin. Do you recall reading an article that	16 Q Yeah. It's your testimony that you			
17 she wrote?	17 didn't list it in Appendix C Appendix C because you			
18 A I do.	18 didn't rely on it, but you still cite it as support			
19 Q Okay. Tell me about it.	19 in your report. So I'm trying to understand why you			
20	20 included it as a citation.			
21	21 MR. FRITZ: Objection.			
22	22 THE WITNESS: Because I don't cite it in			
23	23 my report, I should have removed the footnote when I			
24	24 removed the copy from the report.			
25	25			
1 T				

43 (Pages 166 - 169)

	CONTIDENTIAL				
	Page 170		Page 172		
	BY MS. GOVERNSKI:		versions.		
2		2	Q Okay. And when you cite the four expert		
	relied on Mayzlin is inaccurate?		reports, Dr. Mayzlin, Dr. Humphreys, Mr. Culotta,		
4	3		and Mr. Kinrich, did you review only the expert		
5			reports or did you also review their underlying		
6	BY MS. GOVERNSKI:		data?		
/	Q How many footnotes in your report did you	7	A I reviewed I reviewed some of the data		
	not actually rely on?	l .	packages, yes.		
9	A So having gone through it, Dr. Mayzlin's specific paper was the only footnote that was left	10	Q Okay. So what data packages did you review?		
	that was inaccurate.	11	A I'm sorry so the ones that were given		
12			to me as part of their expert submission, I		
	were not included in Appendix C C but are still		reviewed.		
	included as footnotes. Why is that?	14	Q Okay. So you reviewed all of the backup?		
15	· · · · · · · · · · · · · · · · · · ·	15	A That was provided to me, yes.		
16	•	16	Q Okay. And did you review all of the		
	what you're asking.	1	backup data?		
	BY MS. GOVERNSKI:	18	A I personally read through it, yes.		
19	12.1 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	19	Q All of well, read through it, but I'm		
	that reflect publications that are not otherwise		talking about the actual data. Did you did you		
	listed in Appendix C C. Why is that?	l .	personally review all of the data in their backup		
22	•		materials?		
23	=	23	A Dr. Mayzlin's, yes. Dr. Humphreys', yes.		
24	BY MS. GOVERNSKI:	24	For Culotta and Kinrich, I don't remember the data		
25	Q So how are we supposed to know what you	25	packages.		
2 3 4 5 6 7 8 9	THE WITNESS: Should be from my Appendix C and from my footnotes. BY MS. GOVERNSKI:	3 4 5 6 7 8 9	Q Okay. And did you review all of the materials that any of these experts cited in their reports? A Did I review each of the articles that were cited, no. Q Did you review any of the articles that they cited? A Yes, some. Q So if there were articles that they cited that you reviewed, did you list them in Appendix C?		
11		11	A No, because they were part of the		
	report article.		experts' submissions. So for instance, with		
13	-		Dr. Mayzlin, she provided a myriad of different		
14	- •		academic articles. I may have reviewed some of		
15	=	l .	them, for instance, as as part of my job of		
16		16	reviewing the experts' submissions.		
17	bit of an echo from versioning, so it should have	17	Q How are we supposed to understand which		
18			ones you reviewed and which ones you didn't?		
	BY MS. GOVERNSKI:	19	MR. FRITZ: Objection.		
20		20	THE WITNESS: So to my knowledge, it was		
21		l .	my job to review all of the experts' submissions,		
22			but relying on them for my report is different.		
172	Q What content did you remove?	23	BY MS. GOVERNSKI:		
23					
24		24	Q So if you didn't list it in Appendix C, then it's your testimony that they are irrelevant to		

44 (Pages 170 - 173)

Page 174 Page 176 1 your report? 1 actually argue that neither my dataset nor 2 MR. FRITZ: Objection. 2 Dr. Mayzlin's set is representative of the overall THE WITNESS: It means I did not rely on 3 universe that encompasses Blake Lively during the 4 given periods of time that we looked at because it's 4 them for my report. 5 BY MS. GOVERNSKI: 5 physically impossible, based on the data that is Q What does that mean to you, "not rely on 6 available to either of us. 7 them"? 7 BY MS. GOVERNSKI: A I did not take the content or context 8 Q Understood. So you cannot, as you sit 9 into regard into my report. 9 here today, represent that your dataset is Q Okay. So you said that you reviewed 10 representative of the full dataset that would be 11 Dr. Mayzlin's dataset. How many pieces of social 11 reflective of the Blake Lively-related content 12 media items do you understand that Dr. Mayzlin 12 during this time period? 13 reviewed for purposes of her report? 13 MR. FRITZ: Objection. A She listed 1.1 million, approximately. 14 You can answer again. THE WITNESS: So "representative" would Q Okay. And you testified that you've 15 15 16 first have to be defined. Representative of the 16 reviewed all of them? MR. FRITZ: Objection. 17 entire mass of data for any given time period, no THE WITNESS: I'm not sure what you mean 18 one's dataset is representative unless you're 18 19 by that, so could you clarify? 19 looking at a social media platform looking at their 20 BY MS. GOVERNSKI: 20 own data. So anybody with access to second-party or Q Well, you testified that you reviewed all 21 third-party data, which would be any of the experts 22 of the data that Dr. Mayzlin provided. 22 involved in this trial, would not have access to 23 A Yes, I looked through the dataset. 23 representative data based on the entire universe. 24 BY MS. GOVERNSKI: Q Okay. So did the dataset include all of 25 the social media items that comprised her report? 25 Q I'm asking you specifically about your Page 175 Page 177 1 A I did not go into each individual line of 1 report, so if you can stay focused on yourself and 2 data -- like, row of data and read them verbatim. 2 your own dataset. MR. FRITZ: Objection. Q Okay. Your dataset is 96 percent smaller 3 4 than Dr. Mayzlin's, right? 4 BY MS. GOVERNSKI: 5 MR. FRITZ: Objection. Q How would you define "representative" in 5 THE WITNESS: My dataset is 44,000. 6 the context of your report? 6 7 BY MS. GOVERNSKI: A So I wouldn't define representative in my 8 report because "representative" isn't necessary for 8 Q And that's 96 percent smaller than 1.1 9 million, right? 9 the data analysis. 10 MR. FRITZ: Objection. Q Okay. So what does your dataset -- what THE WITNESS: 44,000, is my dataset. 11 is your dataset comprised of? What does it show? 11 12 Yeah. 12 MR. FRITZ: Objection. THE WITNESS: It shows five different 13 BY MS. GOVERNSKI: 13 Q Okay. Well, can you explain how you can 14 social media networks. So I was representative from 15 be confident that your dataset is representative 15 the diversity of the social media platforms that I 16 when Dr. Mayzlin's is 96 percent larger? 16 looked at, which was higher than Dr. Mayzlin's, for A Size is not a signifier of accuracy or --17 instance. I looked at X, Reddit, Instagram, 17 18 of accuracy, I would say. 18 YouTube, and -- sorry. I'm missing one. Sorry, I'm Q Right. So I'm asking how could you 19 blanking on the fifth one. 20 ensure that your 43,992 posts were a representative 20 BY MS. GOVERNSKI: 21 sample? 21 Q But what is -- it's just representative 22 MR. FRITZ: Objection. 22 of what posts hit on the search terms; is that what 23 You can answer again. 23 it's representative of? THE WITNESS: Yeah, so I would say 24 A So I'm going to not use the word

45 (Pages 174 - 177)

25 "representative" because I think we need to define

25 representative is extremely difficult. I would

CONFIDENTIAL Page 178 Page 180 1 what representative means. 1 it that you're trying to conclude? My data is based on the keywords that 2 MR. FRITZ: Objection. 3 were accessible for public -- public posts, similar 3 THE WITNESS: So when looking at social 4 to, again, anybody not using first-party data. 4 media data, it's not about a representative sample; Q Okay. Well, how would you use the term 5 it's about a statistically significant sample. "representative" generally in your everyday life? 6 Because keywords, in and of themselves, means that 7 MR. FRITZ: Objection. 7 you're not looking at a representative sample 8 THE WITNESS: Representative in my 8 because you are only using a specific amount of 9 keywords. There are a myriad of different 9 everyday life? MR. FRITZ: Hold on. Do you mean as a 10 combinations that represent Blake Lively globally 11 across social media. There's also accounts that are 11 verb or a noun? 12 BY MS. GOVERNSKI: 12 inaccessible by any second-party individual trying 13 Q Answer the question as you understand it. 13 to look and analyze data. MR. FRITZ: Go ahead. 14 14 BY MS. GOVERNSKI: 15 THE WITNESS: So having a research 15 Q So if you were to identify an entirely 16 separate set of 43,992 social media items, like 16 background, I would use representative in the 17 context of does this represent the majority of 17 entirely separate, there's no overlap between the 18 individuals within a class, a segment, a majority, a 18 two, how do you know the results would be the same? 19 minority, or the majority of information available. A Again, the question would be what is the 19 20 BY MS. GOVERNSKI: 20 second set of data about. 21 O Okay. Is it your testimony that your 21 Q Well, you said that you can't possibly 22 dataset meets your definition of "representative"? 22 identify everything, even if it hits on search 23 MR. FRITZ: Objection. 23 terms, right? 24 24 You can answer again. MR. FRITZ: Objection. 25 THE WITNESS: My dataset and no one 25 THE WITNESS: No one -- no one can, Page 179 Page 181 1 else's dataset, unless it's a first-party, would be 1 that's not first-party. 2 representative of the keywords around Blake Lively. 2 BY MS. GOVERNSKI: 3 BY MS. GOVERNSKI: Q Right. So what if someone else searches Q Okay. So just speaking about your 4 for 43,992 using search terms and that came up with 5 dataset, I just want to make sure I understand. 5 a different dataset than the 43,992 that were part 6 Adopting your definition of "representative," it's 6 of your dataset, how could you guarantee that the 7 your testimony that your dataset is not 7 results would be the same? 8 representative of the majority of the individual MR. FRITZ: Objection. 9 statements about Blake Lively during this time 9 THE WITNESS: So by replicating the 10 period? 10 subscription that I referenced, so Apify in this MR. FRITZ: Objection. 11 case, by representing the prompts that I -- or the 12 BY MS. GOVERNSKI: 12 keywords that I used when inputting them into Apify Q Is that right? I just want to understand 13 for the same time period, they are replicatable 14 what your testimony is.

11

13

15 MR. FRITZ: Same objection.

16 THE WITNESS: It's not possible for a

17 dataset to be, quote, unquote, representative of all

18 of the social media discussion around Blake Lively,

19 unless you are a first-party that is -- has access 20 to that data, such as Twitter, Instagram, Facebook,

21 et cetera.

22 BY MS. GOVERNSKI:

Q Okay. So if you are a scientist and

24 you're conducting an experiment, don't you need to

25 create a representative sample? Otherwise, what is

14 based on, again, that criteria.

15 BY MS. GOVERNSKI:

Q Okay. So but -- so it's your testimony

17 that the 43,992 represents the entire universe of

18 all social media items that hit on your keywords?

19 MR. FRITZ: Objection.

20 BY MS. GOVERNSKI:

21 Q Is that -- is that your testimony?

22 A I'm sorry. Can you repeat that?

23 Q Yeah. Is it your testimony that the

24 43,992 items represents the universe of all social

25 media items that hit on your search terms?

46 (Pages 178 - 181)

CONFIDENTIAL				
Page 182	Page 184			
1 A The dataset that I reference, as part of	1 hypotheticals that I am not able to answer.			
2 my expert report, is the complete dataset that I was	2 BY MS. GOVERNSKI:			
3 able to receive from Apify, based on doing the	3 Q Okay. Let's make it not a hypothetical.			
4 analysis.	4 You know Dr. Mayzlin's set includes more			
5 Q Okay. So what if someone else was able	5 than a million social media items, right?			
6 to use a different Apify tool and come up with	6 MR. FRITZ: Objection.			
7 43,992 items that are not duplicative of your	7 THE WITNESS: Her dataset includes 1.1			
8 dataset?	8 million, yes.			
9 MR. FRITZ: Objection.	9 BY MS. GOVERNSKI:			
10 You can answer again.	10 Q How do you know that applying your			
11 MS. GOVERNSKI: I didn't finish the	11 methodology to her dataset would result in the same			
12 question.	12 outcome?			
13 MR. FRITZ: Okay.	13 A I'm sorry. Could you repeat the second			
14 BY MS. GOVERNSKI:	14 part of that question?			
15 Q How do you know that the outcome would b				
	EE			
MR. FRITZ: Same objection. And also,	17 MS. GOVERNSKI: No, you can't. I'm in			
18 compound.	18 the middle of a question.			
Go ahead. You can answer again.	MR. FRITZ: I'm sorry. If she's telling			
THE WITNESS: So couple of things. The	20 you she doesn't understand the question			
21 first part of the question is, in order to use the	MS. GOVERNSKI: I'm rephrasing it.			
22 same tool, they would have to use the same inputs,	MR. FRITZ: Excuse me. And she's			
23 and they would have access to the same underlying	23 explaining to you why she doesn't understand it, I'd			
24 dataset through Apify. So if that is done then	24 suggest you wait until she's finished so you			
25 MS. GOVERNSKI: That's not what my	25 completely and fully understand why she's confused.			
Page 183	Page 185			
1 question is. I'm sorry to interrupt, but I just	1 MS. GOVERNSKI: We're going to go off the			
2 want to make sure you're answering what my question	on 2 record. Off the record. I'm going to call the			
3 is	3 Court about speaking objections. So let's go off			
4 (Cross talk.)	4 the record, please.			
5 MR. FRITZ: Excuse me. Then don't	5 MR. FRITZ: Go ahead.			
6 interrupt her. Let her finish, and if you have a	6 THE VIDEOGRAPHER: We're off the record.			
7 follow-up, then ask.	7 It's 2:53 p.m.			
8 Finish your answer, Ms. Alexander.	8 (Recess.)			
9 THE WITNESS: If someone were to	9 (Whereupon, a conference call was had with the Court			
10 replicate the process that I went through, through	10 which has been transcribed and bounded in a separate			
11 the tool that I went through, using the exact same	11 transcript.)			
12 methods that I did, they should receive during	12000			
13 the same time period, they should receive the same	13 THE VIDEOGRAPHER: We are back on the			
14 outputs from Apify that I received.	14 record. It's 3:58 p.m.			
15 BY MS. GOVERNSKI:	15 MS. GOVERNSKI: Ms Ashley, do you			
16 Q That's not my question, though.	16 mind repeating back the last question I asked?			
17 If someone used a different tool on Apify	17 THE STENOGRAPHIC REPORTER: Okay. If you			
18 that identified an entirely different dataset than	18 give me a few minutes, I have to go all the way			
19 the one that you identified, but also which hit on	19 back			
20 your search terms, how can you guarantee that the	20 MS. GOVERNSKI: Oh, no. That's okay.			
21 results of your study would be the same as the study	21 That's okay. I'm good.			
22 of that other dataset?	22 BY MS. GOVERNSKI:			
23 MR. FRITZ: Objection.	23 Q Ms. Alexander, I was asking you if			
24 You can answer again.	24 applying the methodology from your report to the			
25 THE WITNESS: That's a lot of	25 dataset in Dr. Mayzlin's analysis would lead to the			
LO TILL WITTENDS. THAT'S & TOUGH	25 Gataset III D1. May Ziiii 8 anaiysis would fead to the			

47 (Pages 182 - 185)

Page 186 1 same conclusions? A That is -- that is not something that I 3 would be able to say. Q Why is that? 4 A So Dr. Mayzlin used an LLM in order to 5 6 get to her outputs. I cannot replicate, based on 7 what she's given me, the outcome -- of how she's 8 been able to get to those outcomes because it's an 9 LLM. If I were to use my dataset -- I'm sorry. If 10 I were to use my prompts or queries in an LLM, 11 specifically the one that she used, I'm not sure how 12 it would come out. 13 Q Okay. But I'm asking if you were to 14 apply whatever methodology you applied to draw 15 conclusions about your dataset, if you applied your 16 methodology to her dataset, would the outcome be the 16 17 same? 18 MR. FRITZ: Objection.

19 THE WITNESS: I would assume not because 20 they are different raw datasets.

21 BY MS. GOVERNSKI:

Q Right. So the outcome of your

23 methodology depends upon what your dataset was

24 comprised off?

25 A Outcomes of any analysis comes from the

Page 187

1 underlying raw data.

Q And if we were to take 43,000 of the 3 social media items from Dr. Mayzlin's dataset that 4 was not part of the 43,000 data items in her -- in

5 your dataset, you would not be able to determine,

6 with any certainty, what the outcome would be; is 7 that right?

A So because Dr. Mayzlin used an LLM, even

9 if she were to use the same prompts, again, for

10 instance, the outputs would be different because it 11 is an LLM that she used. So it's hard for me to say

12 if my data was applied within that LLM, what the

13 output would be.

14 Q But I'm asking about your methodology

15 that you applied. If you were to apply your

16 methodology to another 43,000 media items that were

17 not part of your dataset, would your opinions be the

18 same?

19 MR. FRITZ: Objection.

THE WITNESS: I wouldn't be able to say 20

21 that until I do the actual analysis.

22 BY MS. GOVERNSKI:

Q Okay. So your opinions are solely based

24 on these 43,000 social media items?

MR. FRITZ: Objection. 25

Page 188 THE WITNESS: So my outputs are based on

2 the analysis that I did, based on the APIs that

3 pulled raw data from each of those five platforms.

4 So I'm taking the data, based on the time frame, the

5 queries I provided, and I'm doing analysis of that

6 raw dataset.

7 BY MS. GOVERNSKI:

Q Right. Analysis of the 43,992 items that

9 comprised your dataset?

10 A Correct.

Q In your report, you list -- you list 11

12 eleven opinions. Are those all the opinions you

13 intend to offer in this matter?

A Yes, that's everything I included in the 15 report.

Q You don't intend to offer any other 17 opinions that are not listed in your report at

18 page -- at the section on your opinions, right?

A Not based on any of the data that I've

20 already looked at. If new information comes into

21 play, then I can assert additional opinions. But

22 based on everything, all the research I've done, the

23 analysis, those are my opinions.

24 Q So today as you sit here, the opinion

25 section in your report reflects all of your opinions

Page 189

1 that you are offering in this case?

A Yes, based on everything that is in the

3 report, those are my opinions.

Q Okay. Are there any opinions that are 5 not offered in your report that you are offering in

6 this case?

7 MR. FRITZ: Objection.

THE WITNESS: If new information were to

9 come to light or additional information were to come

10 to light after the report, then I may have

11 additional opinions. But everything that I've

12 offered is based on the research that I've done.

13 BY MS. GOVERNSKI:

14 Q I understand, in the future, you may 15 supplement. But I'm trying to just get at a very 16 basic question.

17 Are there any opinions, as you sit here 18 today, that you are offering that you did not

19 articulate in your current amended report?

20 A No, there are not.

21 Q Okay. Thank you. You use the term

22 "organic" nearly 90 times in your report. Does it

23 mean the same thing every time you use the term?

24 A I try to stay consistent with my use of

25 "organic," so I would have to confirm each of the

48 (Pages 186 - 189)

Page 190

CONFIDENTIAL

1 times I've used it. But in general, yes, there

- 2 should be consistency with the underlying definition 3 of the term.
- 4 Q Okay. What is the underlying definition 5 of the term "organic"?
- 6 A So I look at organic as being a --
- 7 signatures of non-manipulative traffic usage,
- 8 et cetera.
- 9 Q And what does "non-manipulative" mean?
- 10 A Basic users talking, commenting, liking,
- 11 upping content across social media platforms.
- 12 Q Okay. And you use the term -- actually,
- 13 does the term "organic," is that definition rooted
- 14 in any academia?
- 15 A I don't know how it's rooted in academia.
- 16 It's rooted in practice as a term that is used 17 daily.
- 18 Q Okay. So as you just defined, organic is
- 19 based on your own definition of the term?
- 20 MR. FRITZ: Objection.
- 21 THE WITNESS: The way that I defined it
- 22 was based on industry definition of the term.
- 23 BY MS. GOVERNSKI:
- 24 Q What industry?
- 25 A Social media technology.

Page 191

- 1 Q Okay. So what is your basis for stating 2 that social media technology as an industry uses the
- 3 term "organic" the way that you just described it?
 4 A Having worked in technology and social
- 6 Q Okay. So it's based on --
- 7 A -- going to conferences -- sorry.
- 8 Q No, no. You go. I'm sorry.
- 9 A Having spoken at industry conferences on
- 10 the topic, having written a book using that
- 11 verbiage, yes.

5 media --

- 12 Q And your report uses the term "legitimate
- $13\,$ news cycles." What did -- what did you mean when
- 14 you use the term "legitimate"?
- 15 A When I say "legitimate news cycles," I
- 16 meant news that does not contain misinformation. So 16
- 17 there are legitimate news cycles on the -- not the
- 18 book, excuse me -- the movie launching, that is a
- 19 legitimate news cycle. The movie exists, the movie
- 20 launched, and there was news around that movie
- 21 launch.
- Q So what about news about how the film was
- 23 marketed; would that be considered legitimate?
- 24 MR. FRITZ: Objection.
- 25 THE WITNESS: So marketing activity would 25

Page 192

- 1 be considered legitimate when it comes to PR, press
- 2 coverage, because, again, it's things that are taken
- 3 from interviews with actors, actresses, producers,
- 4 whomever is involved in the film. There is news
- 5 coverage by a slew of different media sources,
- 6 things of that nature.
- 7 BY MS. GOVERNSKI:
- Q Okay. And so does it matter what the
- 9 content of the communication is? If it's solely
- 10 about marketing, it's legitimate irrespective of
- 11 what the contents is?
- 12 A I'm not sure I understand. Are you
- 13 saying if the content is paid marketing or organic
- 14 marketing?
- 15 Q No, let's say -- let's do a hypothetical.
- 16 Someone says something about the marketing of the
- 17 film that turned out not to be true. Would that, in
- 18 your opinion, be considered legitimate because it
- 19 had to do with marketing even though it was not a
- 20 truthful statement?
- A So based on what I understood the
- 22 question, I wouldn't call that marketing, number
- 23 one, because that's not the marketing of the film.
- 24 That would be commentary around it. So it could
- 25 be -- I don't know -- something happened in the news
 - Page 193
- 1 that had nothing to do with the film or the actors,
- 2 actresses, et cetera. So that, in and of itself,
- 3 could have legitimate properties or it could have
- 4 illegitimate properties, depending on where it came 5 from.
- 6 Q What if an actor was talking about the
- 7 marketing of the film; would that be legitimate or
- 8 not legitimate?
- 9 A If they were talking about the marketing
- 10 of the film and they were being honest, then I would
- 11 say yes, that would be legitimate. Alternatively,
- 12 if they were saying something that was untrue
- 13 knowingly, it could be misinformation.
- Q So how do you tell what is legitimate or
- 15 illegitimate? It sounds a little bit subjective.
 - MR. FRITZ: Objection.
 - THE WITNESS: Well, one way is by simply
- 18 looking at is this true or is this not true.
- 19 BY MS. GOVERNSKI:
- Q And so you would have to do that at a
- 21 post-by-post analysis?
- A To look at if something was legitimate as
- 23 part of a news cycle?
- Q Uh-huh.
 - 5 A So there would be additional patterns.

49 (Pages 190 - 193)

17

1 Because, again, just because you say something, 2 doesn't mean that it's going to get scale. So if it 3 got scale and it was true, right, there would be 4 other ways to identify, number one, if it's true, 4 5 and if the origins was an individual saying it, a 5 6 press release, whatever the case may be, and vice 7 versa. 8 Q Okay. So is there like a scientific way 9 to determine if something is part of a legitimate 10 news cycle or an illegitimate news cycle? A So there is a way to identify 12 misinformation. If you want to identify if 12

- 13 something is true regarding a news cycle, usually
- 14 you look at things of credibility of who
- 15 disseminated it, you look at confirmation of that
- 16 dissemination or the story. So in other words, did
- 17 the New York Times publish it, and then,
- 18 subsequently, did AP News publish it. So there is a
- 19 collective mentality of, the assumption is that not
- 20 every major news outlet would knowingly publish
- 21 incorrect information.
- 22 Q Well, what you just described seems like
- 23 a pretty subjective process.
- 24 MR. FRITZ: Objection.
- 25 THE WITNESS: I'm sorry.
 - Page 195 (Audio interruption.)
- 2 THE WITNESS: Sorry. Was that a
- 3 question?

1

- 4 BY MS. GOVERNSKI:
- O What was that?
- A You just -- you just -- for some reason
- 7 you knocked my Google Home. Sorry.
- Q Okay. Is your Google Home turned on?
- A My Google Home is always turned on.
- 10 Everything -- yes, it's turned on.
- Q Is it providing you feedback on the
- 12 deposition?
- A No, it's -- no, it's not. Like, usually,
- 14 you should have to say -- I won't say it, but
- 15 usually you have to say the prompt.
- 16 Q Say the prompt?
- 17 A Yes.
- Q Okay. So I'm specifically focused on the 18
- 19 words "legitimate" versus "not legitimate." Is
- 20 there a scientific definition of legitimacy?
- 21 MR. FRITZ: Objection.
- THE WITNESS: There may be. I don't know
- 23 what the scientific definition would be.
- 24 BY MS. GOVERNSKI:
- Q Okay. And you don't know -- I'm sorry.

1 Strike that.

Are you an expert on what is legitimate

Page 196

- 3 or not legitimate in terms of news cycles?
- MR. FRITZ: Objection.
 - THE WITNESS: So I have done work
- 6 on legitimate and illegitimate around social media
- 7 in conjunction with news cycles and politics.
- 8 BY MS. GOVERNSKI:
- Q Okay. So can you explain how you are an
- 10 expert in determining whether a news cycle is
- 11 legitimate or illegitimate?
- A So I have looked at Discourse across
- 13 different news cycles. Specifically the one I'm
- 14 referencing right now is in conjunction with
- 15 politics. And looking at stories -- or coverage
- 16 stories that were seeded versus not seeded for
- 17 different political gains and dissecting if those
- 18 news stories were true or false and if they were --
- 19 how do you say -- if they were manipulative within
- 20 the context of how they were planted across Meta's 21 network.
- 22 Q It sounds like a lot of the determination
- 23 between whether something is legitimate or
- 24 illegitimate depends on whether the content is true
- 25 or false; is that right?

Page 197

- MR. FRITZ: Objection. 2 THE WITNESS: It's one factor, but it
- 3 wouldn't be the only factor.
- 4 BY MS. GOVERNSKI:
- Q Well, what are some other factors? 5
- A If something is true or false. If
- 7 something -- sorry. If something had been boosted,
- 8 for instance. Sorry, I can't think of how else to
- 9 say that. Increased in its popularity based on
- 10 manipulation. Also if something is true, but it's
- 11 contextually positioned. So it's not wrong, but
- 12 it's contextually positioned as inaccurately.
- Q And those are all examples of things that 14 are -- news cycles that would be illegitimate,
- 15 right?

1

- 16 A Correct.
- 17 Q Your first opinion in this case refers to
- 18 a time frame of August 2024 through February 2025.
- 19 And that's a six-month period. Is your first
- 20 opinion limited to that specific time frame? I'm
- 21 happy to share.
- 22 A Can you just --
- 23 Q Of course. Let me go up to the top so
- 24 you can see what I'm in. I'm in -- wait, what did
- 25 we look at? B1? I just want to make sure that

50 (Pages 194 - 197)

Page 198

CONFIDENTIAL

1	we're oriented	that	this	is	your	latest report.
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- 2 Here, right? B2, this is your latest report, right?
- A Yes, number 2, Exhibit 2.
- Q Yup. Exhibit 2, exactly. So if we can 4 5 go to paragraph 22. Oh, actually, I want to go to 6 the opinions.
- 7 Opinion 1 is right here:
- 8 (As read):
- 9 "The social media activity surrounding 10 Ms. Lively during August 2024 through
- February 2025 exhibited patterns 11
- consistent with organic public discord 12
- 13 driven by legitimate news cycles, film
- 14 publicity, and entertainment media 15 coverage."
- 16 Do you see that?
- 17 A Yes.
- 18 Q Oh, and you use the term "coordinated 19 manipulation" and "astroturfing." So I would like
- 20 you to explain those one by one.
- 21 A So coordinated manipulation is similar to
- 22 what we talked about before. It can either be
- 23 through technology or, less frequently, through
- 24 coordinated human ways of manipulating data. So

- 25 from a bot perspective, specifically manipulative

Page 199

- 1 bots, because there are bots that are not
- 2 manipulative that are used every single day, to
- 3 also, you know, having a coordinated group of
- 4 individuals or humans, you know, make something
- 5 either more positive or more negative based on --
- 6 based on coordinated activity.
- Q Okay. It sounds like that is similar to
- 8 how you define illegitimate news cycles, film
- 9 publicity, and entertainment; is that right? That's
- 10 kind of the opposite of legitimate news cycles, film
- 11 publicity, and entertainment media coverage?
- 12 A I believe so.
- 13 Q Okay. What is "astroturfing"?
- A Astroturfing, to my understanding, is 14
- 15 similar to manipulative behavior. Astroturfing
- 16 isn't a term that I use normally.
- Q So why did you use it in your report? 17
- A So specifically, I used it because it was 18
- 19 used in Dr. Mayzlin's report, so I wanted to use
- 20 similar terminology.
- Q Okay. But do you have any independent 21
- 22 expertise in astroturfing?
- A Yes. Astroturfing is a different word,
- 24 but it's the same underlying behavior of
- 25 manipulative, legitimate or illegitimate work that

- Page 200 1 is done in a coordinated effort either through bots
- 2 or through human activity. It's a different coined
- 3 term.
- Q Okay. And how do you know that the way 5 you define astroturfing is the way that Dr. Mayzlin 6 defines astroturfing?
- A I believe it's an inference from reading
- 8 through her report and the contextualization in that
- 9 report. Also, I understand the general term of
- 10 astroturfing outside of both of our reports.
- Q Okay. So opinion 1 says that you looked 11
- 12 at social media activity between August 2024 through
- 13 February 2025. So is this opinion limited to that 14 time period?
- 15 A This opinion, yes. I looked at larger
- 16 datasets, but this particular opinion is based on
- 17 that time frame.
- 18 Q So that was my next question. Why did
- 19 you collect from a broader time period but limit
- 20 this opinion solely to the more narrow time period?
- 21 A Because I didn't have enough volume of
- 22 data in order to offer that opinion through the
- 23 larger frame of time that I was hoping to look at.
- 24 Q So why didn't you just use Dr. Mayzlin's
- 25 data?

Page 201

- A So I couldn't replicate Dr. Mayzlin's
- 2 data, first of all.
- And secondly, using someone else's data
- 4 just point blank without ensuring that, number one,
- 5 I could reproduce it. Number two, that the data is,
- 6 you know, accurate of that time period, doesn't
- 7 really make sense. So I specifically wanted to pull
- 8 raw data from the social media platforms themselves
- 9 to analyze.
- 10 Q So you have no idea -- well, you use the
- 11 term -- what did you just say? Accurate -- you just
- 12 used the term "accurate of the time period," is that
- 13 the term you used?
- 14 MR. FRITZ: Objection.
- 15 THE WITNESS: I'm not sure what I just
- 16 said. I'm not sure if it was accurate or -- number
- 17 one, her data, it wasn't reproducible based on what
- 18 I was given. Secondly, it was -- to ensure that the
- 19 data was -- I'm going to use it in a different way
- 20 than we used it earlier -- representative of the
- 21 actual raw data during the time frame.
- 22 BY MS. GOVERNSKI:
- 23 Q Okay. So how -- based on the way you
- 24 just used it, how did you ensure that your data was
- 25 representative of the actual raw data from the time

51 (Pages 198 - 201)

CONFIDENTIAL Page 202 Page 204 1 period? 1 replicate the dataset, based on the prompts that she A It was pulled directly from the social 2 gave. I was not able to do that. 3 media platforms, from their raw datasets. 3 BY MS. GOVERNSKI: Q Okay. So you don't know one way or the Q But my question is: Why didn't you just 5 other whether Dr. Mayzlin's data was representative 5 run your methodology, your sentiment analysis on her 6 of the actual raw data from the time period? 6 dataset to see if you had a valid methodology? A There is no way to tell because she used 7 MR. FRITZ: Objection. 8 an LLM. 8 THE WITNESS: Well, the methodology Q Right. So you can't tell one way or the 9 itself is valid, it's peer-reviewed, it's all 10 other whether her data was representative of the 10 methodology that you would run in academia, as well 11 time period? 11 as in practitioner spheres of doing regression 12 MR. FRITZ: Objection. 12 analysis, doing sentiment analysis, so my 13 THE WITNESS: I cannot tell if her raw 13 methodology is not something that is new form by any 14 data is accurate of the time period that she has, 14 means. 15 BY MS. GOVERNSKI: 16 BY MS. GOVERNSKI: Q But my question is -- if you could please 17 Q Okay. So when you said there was not 17 just answer my question -- why didn't you run that 18 enough, not sufficient social media activity after 18 methodology on Dr. Mayzlin's dataset? 19 February 2025, what was that based on? 19 MR. FRITZ: Objection. 20 A So what I said was, for this particular THE WITNESS: Because I did not -- in 21 opinion, there wasn't enough volume of data in order 21 order to run the methodology on anyone's dataset, 22 to derive an insight outside of this time period. 22 you'd first have to ensure that the dataset itself 23 Q What volume of data would you have 23 was, I'm going to say, accurate, or -- or 24 needed? 24 representative based on the time frame, which is why 25 A It would have to be consistent across all 25 you try and repeat to make sure that you're able to Page 203 1 pull the same data. And then if I was able to pull 1 five of the networks. So there should be an even 2 the same data, I would have then run the methodology 2 sample across all networks in order to make an

Page 205

- 3 opinion after this time frame.
- Q Why do you need an even sample across all
- 5 the networks?
- A So it doesn't have to be exactly the
- 7 same, but there has -- it has to be proportional.
- 8 So ideally, I would have had more of two of the
- 9 networks, which I did not just based on
- 10 availability, I guess, through Apify. So I used the
- 11 data that I felt was the most -- the most
- 12 substantive and without making any assumptions on
- 13 smaller datasets.
- Q Okay. But you said there wasn't enough
- 15 volume, so do you have a ballpark of how much volume
- 16 you would need for the period after February 2025?
- A I don't know offhand. It would -- I
- 18 would have to go back and crunch the numbers.
- Q So what I'm confused about is why didn't
- 20 you just accept Dr. Mayzlin's dataset for whatever
- 21 value it has and run your analysis on that?
- 22. MR. FRITZ: Objection.
- THE WITNESS: So I didn't accept it at
- 24 face value, and nor should anyone just accept data
- 25 at face value. What I did was, I first tried to

- 3 on that dataset.
- 4 BY MS. GOVERNSKI:
- Q Okay. So how did you ensure that your
- 6 dataset was representative based on the time frame,
- 7 as you just used those words?
- A I pulled it through Apify, and I made
- 9 sure it was -- all of the keywords that were
- 10 available -- that I plugged in that were available
- 11 during the time frame that I stated in the report,
- 12 and that there was enough data, based on total
- 13 volume, in order to analyze it.
- 14 Q What was the total volume?
- A I would have to -- I would have to look 15
- 16 at the report, but it was 44,000 unique records.
- 17 Q So how did you know that 44,000
- 18 represented the universe of what you've called
- 19 accurate information from the time period?
- 20 MR. FRITZ: Objection.
- 21 THE WITNESS: Because it's pulled from
- 22 the raw data across all five of those platforms.
- 23 BY MS. GOVERNSKI:
- 24 Q So it's your testimony that there were
- 25 only 44,000 social media items between January 2024

52 (Pages 202 - 205)

Page 206 Page 208 1 and October 2025? 1 only, say, Instagram scraper that Apify provides? A It's the only one that was available to 2 MR. FRITZ: Objection. 3 THE WITNESS: The dataset that I provided 3 select, yes. 4 is what came back from the data scrapes, and there Q Did you personally go to Apify to see if 4 5 this was the only Instagram scraper? 5 is a myriad of different reasons for why the 6 datasets could be different if you pulled it with A I logged into Apify, yes. So I didn't 7 additional keywords. For the keywords I used, so 7 validate Instagram specifically, but I logged in in 8 order to see the options. 8 for the parameters, the query I put in and the time Q Well, I'm asking specifically with 9 frame I put in, those were the ones that were 10 available through Apify across the time frame. 10 Instagram. Did you personally verify that this is 11 the only scraper for Instagram? 11 BY MS. GOVERNSKI: MR. FRITZ: Objection. Q Okay. Let's talk about what you did with 12 13 Apify. Give me one second. Let me stop sharing my 13 THE WITNESS: I verified the interface of 14 screen. 14 Apify, and that, for Instagram, this is the scraper 15 15 that was available to use. However, the scraper How did you come up with the search terms 16 that you used? 16 itself is scraping the API, which is the raw dataset 17 A I used terms that were relevant for Blake 17 on Instagram. So even if there are two scrapers, 18 which there wasn't available, you're still scraping 18 Lively and It Ends with Us and the movie title. 19 Q How did you determine what terms were 19 the raw dataset. 20 BY MS. GOVERNSKI: 20 relevant? A I used terms that were general enough, 21 Q Okay. You separated your -- your opinion 22 but that I saw had a good amount of volume across 22 into different time periods. I want to focus on 23 your baseline time period. Your baseline time 23 Apify. 24 period was May to July 2024, right? 24 Q Have you -- so okay. So for Reddit --25 actually, one second. So tell me how you selected 25 A Yes. Page 207 Page 209 1 which specific scrapers to use. If we go --Q And so if I refer to "baseline," you'll 2 actually, let's do it this way. 2 understand I'm talking about that baseline? If you go to page 110 of your report, you 3 A Yes. 4 list five specific data sources and tools. My 4 Q Okay. And then when I refer to --5 question is whether what you list here reflects the 5 actually, let's go -- let's look at your report, 6 universe of the scrapers that you used? 6 Exhibit 2, and let's go to paragraph 32, which is on 7 A So sorry. Let me go to page 110, you 7 page 17, I think. A I'm sorry, could you repeat the number? 8 said? 8 9 9 Q Yeah, 42. I'm looking at 42 right O Uh-huh. 10 here -- oh, no, I want to go to 32. 10 A There is -- Exhibit 2, there's only 109 11 You see paragraph 32 --11 pages. 12 Q Oh, 109. Sorry. That changed. See 12 A Yes. 13 where it says "Data Sources and Tools"? 13 Q -- that says: A Yes. 14 14 (As read): 15 Q Okay. So is this the universe of the 15 "The meta-analysis combined data from 16 scrapers that you used? 16 all 43,992 social media items." You use the term "August 2024 spike." 17 A Yes. 17 18 What did you mean by that? 18 Q And how did you decide which scrapers to 19 use? 19 A That's the spike that you see in one of 20 20 the charts, for instance. It means that we saw A So those were the scrapers for the

53 (Pages 206 - 209)

21 total volume of sentiment for that particular month

Q Okay. So you mentioned statistical

22 increase with a statistical significance.

25 deviation. What does that mean?

24 significance, and there is a 1,096 standard

23

25

21 particular social media platforms. So first, I

23 scrape. And after that, I selected the scrapers

24 that were available through the API on Apify.

22 decided which social media platforms I wanted to

Q So is it your testimony that this is the

CONFIDENTIAL Page 210 1 A So it is outside of the -- outside of the 2 normal baseline amount. Q What does specifically the 1,096 standard 4 deviation mean? 4 A So I'm looking at the 1,191 items per 5 6 month, and that means it's extraordinary --7 extraordinarily statistically significant. 7 Q So what specific data points did you use 8 9 to determine that? 10 A I'm sorry? Q What specific data points did you use to 11 12 determine the standard deviation? A So I looked at the baseline period, which 14 we already talked about, and the overall activity 15 across all of the platforms combined. Q Okay. And did you use monthly or daily

17 data for those three months?

18 A That's monthly data.

19 Q So why did you use monthly data?

A Monthly data looks at things like the

21 de-dupes. It looks at smoothing out. It removes

22 usually oddities that come in on a daily basis.

23 It's -- it normally is smoother and cleaner data

24 than looking at a daily.

25 Q What if, though, you -- the daily Page 212

1 close to the number indicative that the underlying

2 data is variable?

A I'm sorry. Can you repeat that?

Q Isn't a standard deviation this high and

5 this close to the total number of items indicative

6 of variable data?

MR. FRITZ: Objection.

THE WITNESS: No would be my answer.

9 It's indicative that there is a very high -- a very

10 high -- I'm trying not to use word "deviation."

11 There's a very high variance between the baseline

12 and the output of the data.

13 BY MS. GOVERNSKI:

Q So what does that mean because we're

15 trying to look at the baseline?

A Right. In this case, it's showing that

17 the baseline is -- it's showing that the baseline is

18 higher for these particular terms than, for

19 instance, some other celebrity terms that you may

20 identify. So in general, Lively starts at a higher

21 baseline when compared to, arguably, other

22 celebrities, actors, actresses.

23 Q But you didn't disclose baselines for

24 other actors or actresses?

25 A No. I didn't --

Page 211

1 aberrations were important? A So daily wouldn't make a statistical

3 significance looking at it daily or monthly because

4 the monthly is still just looking at an average of

5 the dailies. So you're not going to get massive

6 skews one way or the other going from daily or 7 monthly.

8 O Did you try it?

A I didn't need to because I -- I know that

10 looking at daily and looking at monthly, the same

11 argument could be made why didn't I look at it

12 yearly or quarterly. There is smoothing of the

13 overall data by looking at it on a monthly -- a

14 monthly basis versus the daily.

Q So if you were only looking at three

16 months, May, June and July, you had three data

17 points that went into this analysis?

A I had three months that went into it.

Q Right. So that's three data points that

20 you entered in order to reach your conclusion,

21 right? A data point from each month, an average

22 from each month?

A It's an aggregate that rolls up into a

24 monthly data point.

Q And so isn't a standard deviation so 25

MR. FRITZ: Objection.

THE WITNESS: -- because I didn't need to

3 -- oh, sorry. Oh, I thought Kevin said something.

MR. FRITZ: I did. I just noted my

5 objection.

1

2

You can answer. 6

7 THE WITNESS: Because I didn't need to.

8 That's, again, based on my knowledge of actually

9 working with celebrities across social media and

10 tracking individuals, whether they are brands or

11 people.

12 BY MS. GOVERNSKI:

13 Q How many times have you run a standard

14 deviation before?

15 A How many times have I done the

16 calculation? Numerous.

17 Q In the course of your career, how many

18 times?

19 A Over 25 years, I can't give you a number.

20 Is it part of your day-to-day work?

It was part of my prior day-to-day work, 21

22 yes.

23 Q Prior, meaning at Meta?

24 At Meta, Ipsos, at Nielsen, which are all

25 market research companies. And, again, market

Page 213

Page 214

CONFIDENTIAL

1 research, standard deviation is a key element of

2 doing massive research initiatives.

- 3 Q And when you analyzed August 2024, you 4 described that as "a spike." Why did you use those
- 5 words -- or that word, sorry, "spike"?
- 6 A I used that word because you have to look 7 at a larger set of data across multiples months.
- 8 And if something goes up dramatically, I would call 9 that a spike.
- 10 Q In fact, you've used the word
- 11 "extraordinary" to describe the August 2024 spike,
- 12 right?
- 13 A I'm not sure if that's the actual word I
- 14 used, but I will say yes, this was a significant
- 16 Q Okay. Well, let's go to opinion 2 of
- 17 your report, which is in paragraph 169.
- 18 A Yes.
- 19 Q Okay. And if you can look at opinion 2, 20 you say:
- 21 (As read):
- 22 "The 4.9 statistical deviation, while
- 23 extraordinarily, reflects organic
- 24 news-driven interest rather than
- 25 manipulated [sic] manipulation."
- Page 215
- 1 Do you see that?
- 2 A I do see that.
- 3 Q Okay. So what were you describing as 4 extraordinary there?
- 5 A The fact that it is an extreme spike.
- 6 Q Okay. So you would describe the spike as 7 extraordinary?
- 8 MR. FRITZ: Objection.
- 9 THE WITNESS: Yes, that's how I used the 10 term there.
- 11 BY MS. GOVERNSKI:
- 12 Q Okay. And what are "temporal patterns"?
- 13 A So temporal patterns could be a myriad of
- 14 different things. But basically, it's looking at
- 15 the overall volume of something in order to
- 16 understand if there is an observable irregularity.
- 17 Q Okay. Are timing signatures the same 18 thing as temporal patterns?
- 19 A Timing signatures offer inputs into
- 20 temporal -- sorry, that offers inputs into temporal
- 21 patterns. If something occurs, like, over time as
- 22 part of a norm, then something that would be an
- 23 irregularity around timing would be everyone else,
- 24 let's say, in a city posts around this time. So we
- 25 see spikes outside of this time frame, which is an

- 1 irregularity.
- Q Okay. And we talked about the five
- 3 platforms that you looked at: Twitter, YouTube,
- 4 Instagram, Reddit, and TikTok. How did you pick

Page 216

- 5 those five platforms?
- 6 A They are the five major social media
- 7 platforms across the U.S.
- 8 Q Did you do any research to determine
- 9 whether there are any allegations that the
- 10 defendants specifically used those five platforms?
- 11 A No.
- 12 Q So if it turns out that the defendants
- 13 only used, say, one of these platforms, how would
- 14 your analysis change?
- 15 A I'm sorry. Just repeat that once more.
- 16 Q If it turns out that the defendants only
- 17 used one of these platforms, how would your analysis 18 change?
- 19 A My analysis wouldn't change based on that 20 assumption.
- 21 Q Why not?
- A So what I did was analyze real-life data.
- 23 So I looked at five different sites specifically to
- 24 detect any patterns because in order to have
- 25 something be manipulative, there needs to be scale
 - Page 217
- 1 as one form factor, especially for social media. So
 - 2 looking at five different platforms instead of two
 - 3 or three, gives additional contextualization to
 - 4 understand if there is any oddities that we see in
 - 5 one network, two networks, three networks. Looking
 - 6 across five allows us just better analysis.
 - 7 Q Okay. You reviewed 2,039 items on
 - 8 Twitter, 16,000 items on YouTube, 6,000 on
 - 9 Instagram, 879 on Reddit, and 688 on TikTok; is that 10 right?
 - 11 A I believe those numbers are correct, yes.
 - 12 Q Okay. So what if the only smear campaign
 - 13 were on Reddit and TikTok?
 - 14 MR. FRITZ: Objection.
 - 15 BY MS. GOVERNSKI:
 - 16 Q How would your analysis be the same when 17 you are including so many more items from the other
 - 18 platforms?
 - 19 A So sorry. I had to think about what you
 - 20 were asking. So if I'm looking at several different
 - 21 platforms, I analyze those platforms first
 - 22 individually and then part of the collective. So
 - 23 that's why I provide a meta-analysis as well as an
 - 24 individual analysis across each of the platforms.
 - 25 So if something was an oddity across one or two

55 (Pages 214 - 217)

5

12

Page 218 1 platforms, then that would come up in the data 2 itself that was analyzed. Q Okay. So you use the term 4 "meta-analysis." What does that term mean?

A It's an aggregate across all the platforms.

Q Okay. And who -- is that a term of art 8 in your industry?

A Is it a term of -- I'm sorry?

10 Q A term of art. Does it mean something 11 specific in your industry?

A Meta-analysis usually just means it's a 13 high-level analysis across whatever you're looking 14 at, examining.

Q So across what in particular?

A In this case, it's across five platforms. 16

17 Q Okay. And when you described earlier

18 that your methodology was sound and rooted in

19 academia, is that a meta-analysis that you were 20 talking about?

A So yes, looking at an aggregate is done

22 in academia as well as in practitioner -- in

23 practice. So you look at different social media

24 networks individually. And then in order to do a

25 larger analysis at the aggregate scale, you would

Page 219

- 1 then -- and maybe folks would call it different 2 things, but it's called meta-analysis most of the
- 3 time that I've interacted with it, whether, again,
- 4 in academia or as a practitioner.
- Q Are you -- do you know who Professor Gene 6 Glass is?
- 7 A I don't think so.
- 8 Q Have you ever heard of Professor Gene

9 Glass?

10 MR. FRITZ: Objection.

11 THE WITNESS: The name sounds familiar,

12 but I don't know. It's not something that comes to 13 mind, no.

14 MS. GOVERNSKI: Okay. My colleague will

15 mark what will be Exhibit 7? Am I up to 7?

THE STENOGRAPHIC REPORTER: Yes, you are.

17 Exhibit 7.

18 (Exhibit 7 marked for identification.)

19 MS. GOVERNSKI: Let me know when it's in

20 there, and then we'll share it on the screen.

21 THE WITNESS: I downloaded it.

22 BY MS. GOVERNSKI:

Q Okay. Great. Oh, my gosh, my computer

24 just turned off. Okay. If you can look at -- I'm

25 sorry. I'm having some technical issues. I'm

1 sorry. I'm back.

If you look at the screen, in the -- it

Page 220

3 discusses the definition of "meta-analysis."

Do you see that? 4

A I do. From Karl Pearson, yes.

6 Q Yup, and it says Gene Glass coined the

7 term in 1976.

8 Do you see that?

9 A Yes.

10 Q So when you use the term "meta-analysis,"

11 is this the meta-analysis that you're talking about?

MR. FRITZ: Objection.

13 THE WITNESS: So let me see how they're

14 describing it here, but several independent studies

15 considered to be combinable -- yes. At a high

16 level, this would be the definition. So looking at

17 doing different analysis and having them be able to

18 be aggregated.

19 BY MS. GOVERNSKI:

20 Q Okay. But what you just read said, "a

21 meta-analysis is a statistical method that

22 integrates the results of several independent

23 studies considered to be combinable."

24 So what independent studies analyzing

25 whether there was a coordinated campaign did you

Page 221

1 integrate?

A So that specific definition I'm assuming

3 in 1976 when it was coined probably meant a very

4 specific thing. The way that Meta analysis are used

5 currently, literally from I would say 2022 up until

6 the present, is looking at individual analysis of

7 social media sites such as Instagram as a silo;

8 Facebook as a silo; Reddit as a silo.

And then using the same time period, the

10 exact same parameters or queries that you use would

11 be classified as the individual studies. And being

12 able to roll that up would be the meta-analysis in

13 aggregate.

14 Q Okay. Well, but this is from the

15 Encyclopedia of Research Design, and you can see I

16 pulled it on December 9th. It's not purporting to

17 define the term then.

18 Are you saying that this is not the way

19 that meta-analysis is defined in the research world?

20 MR. FRITZ: Objection.

21 THE WITNESS: In the research world, we

22 use it in the way that I just defined it. Or the

23 way that --

24 BY MS. GOVERNSKI:

Q Okay.

56 (Pages 218 - 221)

	CONTIDENTIAL				
	Page 222		Page 224		
1	A Yeah.	1	72 hours), proportional distribution		
2	Q What authorities do you have for the way	2	stability, and identical decay		
3	that you define meta-analysis?	3	patterns."		
4	A We've used it at Ipsos. We've used it at	4	This is paragraph 169.		
5	Nielson. And this is not just in the U.S. but	5	When opinion 5 refers to a meta-analysis,		
6	global studies in the U.S., China, parts of Asia for	6	that's describing the analysis you just described		
7	doing individual analysis across social media sites.	7	which looks at your dataset, right?		
8	And then looking at making sure that certain	8	A I'm sorry. I found it. Can you just		
9	variables hold true. Which are things like the	9	repeat the question again?		
10	keywords or the parameters or the queries. Looking	10	Q Sure. When opinion number 5 refers to a		
11	at the exact same time frame, and aggregating and	11	meta-analysis, you're describing the analysis we		
12	doing an overall a roll-up analysis.	12	just discussed which was your analysis of your		
13	Q I see. So as you used the term	13	dataset, right?		
14	"meta-analysis,' it's based on what you've done in	14	A That is correct.		
	your career?	15	Q Okay. And when I refer to your dataset,		
16		16	that's the 42,992 items, right?		
17	THE WITNESS: Yes.	17	A Yes. The complete dataset that I		
18	BY MS. GOVERNSKI:	18	submitted. Yes.		
19	Q But it's a different definition than in	19	Q When I refer to your dataset, you'll		
20	this encyclopedia that I showed you?	20	understand that I'm referring to that universe, that		
21	A I would argue that it's not different.		42,995 so I don't have to keep repeating that?		
22	Some of the individual verbiage may be different,	22	A Yes.		
23	because it says "study."	23	Q Okay. So you opined that your dataset		
24	So I would argue that a study of	24	showed:		
25	Instagram, a study of Facebook, a study of Reddit	25	(As read):		
	Page 223		Page 225		
1	would be exactly similar to what they're talking	1	"Synchronous timing across all five		
	about here.	2	platforms based on peak activity within		
3	Q But the study was just data from each of	3	48 to 72 hours."		
1	those, right?	4	What does "synchronous timing" means?		
5	A That is a quantitative study.	5	A So it was timing that was that was on		
6		_	par sorry. If you look at like a bell curve,		
	meta-analysis also strike that.		right, thinking of synchronous of the center of the		
8		l .	bell curve. So it was where most of the activity		
	definition of meta-analysis here refers to studies,	l .	took place. Which was in the normal sorry, I		
1	it also means the combination of different datasets?		shouldn't say normal. In the on-average hours of		
11	A I agree with the fact that it says		when posting takes place for that particular time		
1	individual studies and those could be qualitative or		zone.		
13		13	Q So the synchronous timing didn't refer to		
1	combining, or being combinable.		the time period of 48 to 72 hours?		
15	<u> </u>	15	MR. FRITZ: Objection.		
1	definition of meta-analysis, can you provide me with	16	THE WITNESS: So for UTC, which is how I		
17			do the data stamp, it looks at a specific period of		
18	*		time, when the posts were posted. And there is		
19	•	l .	usually a 48 to 72 hour time frame for any oddities		
	report. My colleague will share that again. Where		for when the reporting sorry when the data in		
	you have opinion 5. And you say:	l .	the dataset ensures that it's available.		
22		22	So usually when I do the analysis, I		
23			would look at a 48 to 72 hour time frame to make		
24	1		sure that there is no outliers.		
25	•	25			
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57 (Pages 222 - 225)

	CONFIDENTIAL				
	Page 226		Page 228		
1	BY MS. GOVERNSKI:	1	first person I would ask. Yes.		
2	Q Okay. And so you consider anything	2	BY MS. GOVERNSKI:		
3	posted within 48 to 72 hours to be synchronous?	3	Q So if I wanted to find literature to		
4	A As part of this analysis, yes.	4	support that 48 to 72 hours was synchronous, where		
5			could I look?		
6		6	MR. FRITZ: Objection.		
7	social media, then yes.	7	THE WITNESS: I don't know.		
8		8	BY MS. GOVERNSKI:		
	72 hours is considered synchronous?	9	Q I just have to ask you?		
10	-	10	A In this context?		
	analysis within these confines. There is a myriad	11	MR. FRITZ: Objection.		
	of different social media analysis and different	12	THE WITNESS: If I'm the expert, then		
	ways of looking at things. But in this context,		yes.		
	yes.		BY MS. GOVERNSKI:		
15		15	Q Let's go to paragraph 97. Where the		
1	synchronous in different ways depending on what	_	report explains that the three-day period was		
	you're looking at?		between August 6th and 9th.		
1	•		<u> </u>		
18	· ·	18	How did you pick those dates?		
19	1 2	19	A What paragraph?		
	what you're trying to analyze. Yes.	20	Q Paragraph 97. You can go to keep		
	BY MS. GOVERNSKI:		going down, Autumn.		
22		22	A My paragraph 97?		
1	definition of what it means to be synchronous?	23	Q Sorry. Let's go to paragraph 36. It's		
24	3	1	miscited in my outline. Paragraph 36 says:		
25	THE WITNESS: I believe there's in	25	(As read):		
	Page 227		Page 229		
1	context, it is standard. So within this context, I	1	"All five platforms exhibit virtually		
2	do believe there is a standard definition.	2	simultaneous activity surges between		
3	BY MS. GOVERNSKI:	3	August 6th and 9th."		
4	Q I don't understand how there is a	4	Is that right?		
5	standard definition, but only in this context.	5	A Yes.		
6	Can you explain that?	6	Q You described this two to three-day		
7	MR. FRITZ: Objection.	7	period as "tight temporal synchronization", right?		
8		8	A I did.		
9	social media data in the medical field or in	9	Q That's based on the definition that you		
1	finance, there is arguably and that's outside of	10	just provided from your experience?		
	my purview. There's arguably different ways of	11	A Yes.		
1	looking at synchronization, the same way as I know	12	Q Okay. And if we look at go up to		
	there is different ways of looking at forensics and	13	•		
	tracking in those domains.		where you state that:		
	BY MS. GOVERNSKI:	15	(As read):		
16		16	"Analysis of posting activity in August		
	different domains define synchronous, where would I	17	of 2024"		
	look?	18	And you explain some of the data. And		
19			you say:		
1	subject matter expert, assumingly, in that domain.	20	(As read):		
21		21	"This increase was so unusual that,		
1		21 22	statistically speaking, it would occur		
	determine what synchronous means in any given	23			
23	context?		by chance less than once if you observed 100,000 random pieces of		
	MR. FRITZ: Objection.	24	observed 100,000 random pieces of		
25		25	data."		

58 (Pages 226 - 229)

CONFID	DENTIAL
Page 230	Page 232
1 Is that accurate?	1 simultaneously, coinciding with the
2 A Yes.	2 film's release date, suggests a
3 Q Okay. And then the next paragraph says	3 connection between these events.
4 that:	4 However, while the statistics confirm
5 (As read):	5 something significant happened in
6 "The August 2024 posting represents an	6 August 2024, additional analysis would
7 exceptional departure from typical	7 be needed to definitively establish
8 patterns."	8 that the film caused this increase
9 Is that your testimony?	9 rather than simply occurring at the
10 A Yes. I should probably have caveated it	10 same time."
11 for social media. But yes.	So does that paragraph that I just read
12 Q Okay. And it's your opinion that the	12 outloud accurately summarize your opinion?
	, , ,
13 August 2024 spike was, quote:	13 MR. FRITZ: Objection. 14 THE WITNESS: I'm sorry. Can you just
14 (As read):	1
"Not a random fluctuation, but rather	15 tell me what paragraph you're on?
an extraordinary event requiring	16 BY MS. GOVERNSKI:
17 explanation."	Q Yup. Paragraph 34. It's right on the
Right? That's your opinion?	18 screen, "the fact that this spike occurred across
19 MR. FRITZ: Objection.	19 multiple platforms". Right there.
20 THE WITNESS: Yes, it is.	20 A Yes.
21 BY MS. GOVERNSKI:	21 Q So that those sentences, "the fact
Q So why does the August 2024 spike require	22 that" ending in "at the same time," accurately
23 explanation?	23 summarizes your opinion?
24 A I would say it requires explanation	24 A Yes.
25 because one would wonder what caused the spike. So	25 MR. FRITZ: Objection.
Page 231	Page 233
1 you look at data points around that time period	1 THE WITNESS: What I put in the report
2 specifically in order to ideally explain what caused	2 does.
3 it.	3 BY MS. GOVERNSKI:
4 Q Okay. Let's look at the next paragraph.	4 Q Okay. So you have not definitively
5 You say:	5 established whether the film's release is what
6 (As read):	6 caused the August 2024 spike, right?
7 "The August 2024 posting activity	7 A Definitively, no.
8 represents an exceptional departure	-
1 1	1
9 from typical patterns."	9 right?
And then could you please go down,	10 A Right. So I just wanted to answer it in
11 Autumn. And you say:	11 that same context. So definitively, no.
"The fact that this spike occurred	12 Q You would need additional analysis in
across multiple platforms	13 order to make a definitive conclusion, right?
simultaneously."	14 A Having a definitive conclusion would be,
So when you use the term "simultaneously"	15 number one, very difficult. Even if I had a
16 does that mean the same thing as that 48 to 72 hour	16 forensics background. So that's why I say
17 window that we talked about earlier?	17 definitive is usually not something that you would
18 A Yes. From sorry 48 to 72 hours	18 get even from a sophisticated data analysis or
19 from sorry, August. I don't have the date in	19 computational science analysis. Because there are
20 front of me. But yes.	20 so many additional events that are unknown-unknowns
21 Q Okay. So you use the term "simultaneous"	21 that you would have to take into account.
22 which also could just mean synchronous. Okay.	So based on what is what is
23 (As read):	23 accessible, which is news cycles, which is public
24 "The fact that this spike occurred	24 commentary, public information, I was able to
1	1 2/1
25 across multiple platforms	25 associate the spike with the news cycle excuse

59 (Pages 230 - 233)

CONFIDENTIAL Page 234 Page 236 1 me -- the launch of the film itself. 1 BY MS. GOVERNSKI: Q But you chose to use these words, that an Q What if you determined that you were 3 additional analysis would be needed to definitively 3 missing a set of data from May, June, and July, how 4 establish that the film release caused this increase 4 would that change your proportional analysis? 5 rather than simply occurring at the same time. A So the reason I chose to analyze data 6 MR. FRITZ: Objection. 6 across five platforms was to mitigate any issues 7 BY MS. GOVERNSKI: 7 with not having sampling from the key social media 8 sites that are used globally but specifically in the 8 O Right? 9 A Definitively, yes, that is correct. 9 U.S. 10 Q And you did not perform that additional 10 Q Okay. But my question is, if it turns 11 analysis that would be needed to definitively 11 out that the few hundred posts that you had from 12 establish that the film release caused this increase 12 TikTok, the 688 posts from TikTok were just the ones 13 rather than simply occurring at the same time, 13 you happened to capture, but really there were 14 right? 14 20,000 items on TikTok, wouldn't that end up 15 A I did not do an analysis of correlation 15 changing your proportion for your subsequent 16 to definitively prove it was in -- the spike was the 16 analysis? 17 outcome of the film launch. 17 A So I would have to look at the data in O What does "correlation" mean? 18 18 order to know that. Because, again, I'm scraping 19 A Correlation means that there is a 19 the public posts that are available. Because 20 connection between what happened and the outcome. 20 private posts, obviously, are not available as part 21 Q Okay. And is that different from 21 of the API. 22 22 causation? So I would have to look to see if 23 MR. FRITZ: Objection. 23 additional data, again with the same parameters, THE WITNESS: So correlation and 24 24 with the same time frame, if there would be any 25 causation are different. 25 difference. But on average, because I'm looking at Page 235 1 BY MS. GOVERNSKI: 1 not just one site but five different sites, this

Page 237

- Q So you don't perform a causation 3 analysis, right?
- A I did not. Not in this instance, no.
- 5 Q Okay. Let's turn to paragraph 37. Which
- 6 I think should be the next paragraph. You see
- 7 paragraph 37 where it talks about Proportional
- 8 Platform Distribution?
- 9 Do you see that?
- 10 A I do.
- 11 Q It says:
- 12 (As read):
- 13 "The distribution of activity across
- 14 the platforms during August 2024
- 15 closely matched baseline proportions."
- 16 What do you mean when you say "baseline
- 17 proportions"?
- 18 A So the baseline that we established and
- 19 discussed earlier. Which was May, June, July.
- 20 Q What if your May, June, July dataset was
- 21 incomplete? How would the proportional analysis 22 change?
- 23 MR. FRITZ: Objection.
- THE WITNESS: I'm not sure what you mean 24
- 25 by "incomplete."

- 2 should mitigate any issues or I should be able to
- 3 capture if there is any issue in a particular social
- 4 media site having odd spikes or things of that
- 5 nature.
- Q But you're analyzing a proportion based 7 on the proportion that existed during the baseline
- 8 period, right? 9 A Based on a dataset during that time
- 10 period, yes.
- Q My question is, if your dataset was not
- 12 complete, if it missed certain posts from certain
- 13 activities, wouldn't your proportion change?
- A So the net new dataset that you're 14
- 15 hypothetically talking about would have to
- 16 completely skew completely differently than the
- 17 dataset that I was able to pull based on the raw
- 18 data on that platform. So the chances of that is
- 19 relatively small.
- Q But I'm not asking you the chances of it. 20
- 21 I'm asking you, if it turns out that say the scraper
- 22 you used for TikTok turned out not to scrape
- 23 everything, and that really there was a different
- 24 universe of TikTok posts that you did not capture,
- 25 wouldn't that alter the proportion that you were

60 (Pages 234 - 237)

Page 238 1 using for your future analyses? MR. FRITZ: Objection. 3 BY MS. GOVERNSKI: Q I don't think this should be all that 5 complicated. Like if a dataset for TikTok 6 increases, wouldn't that change your 7 proportionality? 8 MR. FRITZ: Objection. THE WITNESS: To answer your question, 10 the dataset would have to be completely different 11 than the dataset that I pulled. And directionally, 12 that wouldn't make sense. Because, again, it's a 13 randomized pull based on those keywords. So you're getting a sampling of the 15 parameters that I've selected, the keywords, and 16 it's a random sample of the raw data that's 17 reflective of that. So you shouldn't get -- with 18 the same time frame, with the same keywords, you 19 shouldn't have completely different raw data that 20 wasn't represented in the initial pull. 21 BY MS. GOVERNSKI: 22 Q So I'm asking in the hypothetical. If 23 what you've called a random sample turned out to be 24 under inclusive, wouldn't that alter your 25 proportionality analysis?

Page 239

23

25

24 scrapers?

1 MR. FRITZ: Objection. THE WITNESS: I don't see how that's 3 possible with the way that a scraper pulls from the 4 raw data API. So I can't -- I can't give you -- I'm 5 sorry, I can't give you a yes or no based on a 6 hypothetical. 7 BY MS. GOVERNSKI: Q So if -- let's just take this out of this 9 report. If you were to determine proportionality 10 based on ten to two, okay, like ten posts on X and 11 two posts on Reddit, but it turned out there weren't 12 really two posts on Reddit; there were 100. 13 Wouldn't your proportionality analysis change as 14 between ten and two and ten and 100? 15 A Technically, that is always true because 16 there are many other posts that we do not see 17 because they are private. So, for instance, all of 18 this is dependent on, number one, you're scraping a 19 smaller amount of data than actually exists because 20 you're scraping public posts. So you've already 21 shrunk the universe down to what is public versus 22 private. So if it is based on the same keywords,

23 then there should be the same direction

Q Okay. So how do you reconcile saying

1 that you've shrunk this down to publicly available 2 posts with your testimony that it's a random sample? I'm just trying to understand. Does your 4 dataset reflect a random sample or does it reflect 5 the universe of all public items that hit on your 6 search terms? 7 MR. FRITZ: Objection. 8 THE WITNESS: It is a random sample of 9 all public posts across each of the social media 10 sites. You can only scrape and only have access to 11 data that is public and not private. 12 BY MS. GOVERNSKI: 13 Q Okay. So but it's a sample; it's not 14 everything that was publicly available? A It is everything that Apify -- let me 16 rephrase that, actually, because Apify has access to 17 the API. It's everything that the API across each 18 of the social media networks allowed Apify to have 19 access to. 20 Q Okay. How do you know that? 21 A I know how APIs work for -- APIs in 22 general.

Q But you didn't use APIs; you used

MR. FRITZ: Objection.

Page 241

Page 240

THE WITNESS: So the scraper is Apify's 2 terminology. They scrape through an API. So in one 3 instance, Instagram has an API. They allow access 4 to their API which connects to a raw dataset for 5 companies such as Apify, Sprout Social, a myriad of 6 different organizations or content creators to 7 scrape from. Meaning, that they say Instagram, for 9 instance, says this is all the public posts based on 10 the keywords that you have chosen. We are going to 11 allow you access to be able to pull that data. 12 So when I say that it's everything that 13 Instagram, Reddit, YouTube, et cetera, gave access 14 to, it simply means of the public data they say this 15 is -- whatever the confines that they decide as a 16 social media site -- this is the API's that they 17 have available for you to pull from. 18 BY MS. GOVERNSKI: 19 Q Okay. So it's your testimony that every 20 actor on Apify acts the way you just described? MR. FRITZ: Objection. 21 THE WITNESS: I don't know how every 22 23 actor on Apify operates. 24 BY MS. GOVERNSKI:

Q Did you look at how the specific Apify

61 (Pages 238 - 241)

24 proportionally.

25

CONFIDENTIAL				
Page 242				
1 actors that you used operate?	1 the API first. Just because I think in general,			
2 A The ones that I used, yes. There are	2 it's ideal. If I'm not if for whatever reason it			
3 ones that I did not use that they have.	3 wasn't available, I used Apify.			
4 Q So you understand how each of these four	4 Q If the APIs were not available, you used			
5 specific scrapers work?	5 Apify?			
6 A Yes.	6 A Yes. So sometimes APIs can simply be			
7 Q Okay. And it's your testimony that these	7 down. They can be sensitive. They cannot run for a			
8 four specific scrapers captured all of the publicly	8 myriad of different reasons. You might just be			
9 available data that hit on your search terms during	9 500th in the queue versus in Apify or Sprout Social,			
10 the January 2024 to October 2025 time period?	10 that could be number one in the queue.			
11 A No. That's not what I said.	11 Q Okay. You just used what happened			
12 Q Okay. Say it again, please.	12 what was available to you at the time when you were			
13 MR. FRITZ: Objection.	13 ready to scrape, right?			
14 THE WITNESS: Social media platforms give	14 A Yes. I used the best source available to			
15 access to third-parties such as Apify through their	15 what I had access to.			
16 API. Based on the keywords, I'm able to ask Apify	16 Q Okay. Let's go to report, paragraph 22,			
17 to go in and quote/unquote scrape the API based on	17 where you say that:			
18 the time period and the keywords. Therefore, Apify	18 (As read):			
19 and I have access to whatever the social media	19 "Data was collected through publicly			
20 platforms have allowed them to have access to.	20 available application programming			
21 BY MS. GOVERNSKI:	21 interfaces or authorized data-scraping			
22 Q So you don't know what the social media	22 tools between January 2024 and			
23 platforms have allowed the Apify actors to have	23 October 2025."			
24 access to?	24 So did you I'm trying to understand.			
25 A I don't know what constraints, if any,	25 Did you run the tools during that entire time			
Page 243	Page 245			
1 social media sites put on their APIs.	1 period, or you ran the tools to capture information			
2 Q Okay. So it's possible that they only	2 from that time period?			
3 allow Apify to access a small amount of the data	3 A I ran the tools to capture information			
4 that would have hit on your search terms, right?	4 from that time period.			
5 MR. FRITZ: Objection.	5 Q Okay. So when and you didn't run the			
6 THE WITNESS: So, no. That's not what I	6 tools, right; your assistant ran the tools?			
7 would say. Apify would have the same access as	7 A My assistant, Taylor Hunter, ran the			
8 Sprouts Social or any other assuming third-party.	8 tools. I double checked the tools. I also am the			
9 What I mean is that I don't of the	9 one who ran the API scrape sorry, the YouTube,			
10 universe that Instagram, as an example, has access	10 YouTube API scrape.			
11 to give of public posts. I'm simply saying they can	11 Q When did those tools run?			
12 put constraints, the same way as YouTube can, the	12 A October 2025.			
13 same way as X can, on what is available to be	13 Q On a single day or?			
14 harvested from the API.	14 A No. Over the course of so each of the			
15 BY MS. GOVERNSKI:	15 platforms ran on a single day. But each platform			
16 Q Right. And so you don't know what those	16 ran on a subsequent day. So I'm just giving this as			
17 constraints are?	17 an example. This is not the specifics. YouTube ran			
18 MR. FRITZ: Objection.	18 on Monday, Twitter ran on Tuesday, so on and so			
19 THE WITNESS: I do not.	19 forth.			

62 (Pages 242 - 245)

Q Got it. So you ran each network on a

And you produced to us your backup data,

21 single day, but not all on the same day?

A Correct.

A Yes.

Q

20

24 right?

22

23

25

23

24

25

20 BY MS. GOVERNSKI:

22 the YouTube data API; is that right?

Q And your Appendix C says that you used

Q So you didn't use Apify for YouTube?

A So I used -- I used all of the -- I used

Page 246

CONFIDENTIAL

7

1	Q You produced a number of actually
2 le	s, you know, we have we're going to mark as
3 ex	nibit am Lat 8?

- 4 THE REPORTER: Yeah. And I would like a 5 break as soon as we can. We've been going a long
- 6 time. Thank you.
- 7 MS. GOVERNSKI: Yeah, sure. Let's take a
- 8 break. Ms. Alexander, I realize we worked right
- 9 through lunch and it's almost dinner. Do you want
- 10 to take a longer break and get something to eat or
- 11 do you want to just take a quick break and get back
- 12 into it?
- 13 THE WITNESS: I prefer to take a quick
- 14 break and get back into it.
- MS. GOVERNSKI: Okay. Let's go off the
- 16 record.
- 17 THE VIDEOGRAPHER: We're off the record, 17
- 18 It's 5:20 p.m.
- 19 (Recess.)
- THE VIDEOGRAPHER: We are back on the
- 21 record. It is 5:31 p.m.
- 22 BY MS. GOVERNSKI:
- 23 Q Ms. Alexander, you describe a sentiment
- 24 classification analysis and in paragraph 52 of your
- 25 report, you state that:

Page 247

- 1 (As read):
- 2 "Statistical volume analysis alone
- 3 provides an incomplete picture of
- 4 online reputation dynamics."
- 5 And that:
- 6 "A systematic sentiment classification
- 7 analysis was essential."
- 8 That is your opinion, right?
- 9 MR. FRITZ: Objection.
- 10 THE WITNESS: Yes.
- 11 BY MS. GOVERNSKI:
- 12 Q Okay. And what is a systematic sentiment
- 13 classification analysis?
- 14 A Going through and having it look at -- I
- 15 use the three score, which is positive, negative,
- 16 and neutral, on a classifier like BERT. Which is a
- 17 natural language processing solution that is used
- 18 academically, practitionerly. It shows up in
- 19 research, to systematically associate each of the
- 20 data or verbatims qualitative post with a sentiment
- 21 score.
- 22 Q And what is -- you used the terms
- 23 "positive and negative", and what was the third you
- 24 used?
- 25 A The third is neutral.

Page 248
1 Q Neutral. How do you define each of those

- 2 three terms?
- 3 A So positive in the classifier looks at
- 4 things that positive -- I'm trying to figure out how
- 5 to define something without using the word. Looks
- 6 at things that are --
 - THE REPORTER: Sorry, can you guys hold
- 8 on for a second? I can't hear anything.
- 9 MS. GOVERNSKI: Yeah, let's go off the 10 record.
- 11 THE VIDEOGRAPHER: Sure. We're off the 12 record. It's 5:33 p.m.
- 13 (Off the record due to audio issues on Zoom.)
- 14 THE VIDEOGRAPHER: We are back on the
- 15 record. 5:44 p.m.
- 16 BY MS. GOVERNSKI:
- 17 Q Ms. Alexander, can you please explain how
- 18 your sentiment analysis defined positive, negative
- 19 and neutral?
- A So the way that the classifier looks at
- 21 it versus how I would define it, in general, is
- 22 slightly different. The classifier I used for -- it
- 23 looks at it from a score system. So if something is
- 24 based on natural language processing, based on
- 25 fine-tuning, if something is more positive, it has a
- Page 249
- 1 higher positive score. If something is more
- 2 negative, based on its training model, it classifies 3 it as negative. And if it's more neutral, is --
- 4 neutral is normally something that is -- I don't
- 5 know want to say factual -- it's something that is
- 6 usually more just straightforward without -- without
- o usually more just straightforward without -- without
- 7 additional nuance of being positive or negative.
- 8 But they're score systems, in BERT.
- 9 Q So the way -- when you were describing
- 10 the classifier, which is positive, negative, or
- 11 neutral, that's the classifiers that BERT itself
- 12 assigns; is that right?
- 13 A Yes. Based on the model, based on
- 14 fine-tuning, the BERT model looks at natural
- 15 language processing to derive if it's positive,
- 16 negative or neutral.
- 17 Q What is "fine-tuning"?
- 18 A Fine-tuning means the sensitivity, the --
- 19 a myriad of different factors. It could be to
- 20 reduce bias, to reduce how the model takes into
- 21 account different parameters.
- Q Did you fine tune your BERT model?
- A No, I did not.
- Q Why not?
- 25 A One, I didn't have access to fine tune.

63 (Pages 246 - 249)

Page 250

CONFIDENTIAL

1 It is -- the BERT model is for social media 2 analysis. Well, I'm sorry -- it's for natural

3 language processing, so I would argue that it

4 doesn't need to be fine tuned. And I wouldn't -- I

5 wouldn't make any adjustments to the --

6 Q So what would be -- strike that.

What did the -- what types of contents

8 did the BERT model designate as negative in this

10 A What types of content -- content that

11 was -- had different degrees. Because again, it's

12 not just negative, it labels it as a score, first,

13 that's on a negative side. It would be things that

14 are derogatory -- derogatory, mean, rude, things of

15 that nature.

16 Q Okay. Derogatory as to whom?

17 A Well, in this case, Blake Lively.

18 Q Okay. So how would it classify content

19 that was derogatory of Mr. Baldoni?

20 A So it would -- if it looked at

21 Mr. Baldoni, based on keywords, it would look at

22 things like the association of the name, the context

23 that his name appeared in, and if the -- if the

24 negative sentiment or -- sorry. If the negative

25 words were applied to Baldoni versus anyone in the

Page 252

1 THE WITNESS: So if there was negative

2 content in the post that had Blake Lively, because

3 again, there had -- Blake Lively had to show up

4 based on the keyword or parameters I put in. If

5 there was also -- if there was negative content

6 about Baldoni in the same post, then it would,

7 again, associate what the -- what the sentiment was

8 for Lively and not Baldoni.

9 BY MS. GOVERNSKI:

10 Q And how did you teach BERT to look for 11 the sentiment as to Ms. Lively and not look for the

12 sentiment as to Mr. Baldoni?

13 A So it's part of the parameters that I put 14 in around the keywords that you saw in my report.

15 Q What parameters did you put in? How 16 would I know that?

17 MR. FRITZ: Objection.

18 THE WITNESS: Those are the keywords that

19 you see in my report that I've included.

20 BY MS. GOVERNSKI:

Q So your keywords were Ms. -- Blake Lively

22 and we can go through some of the specifics, but how

23 did BERT -- how was BERT able to derive from

24 Blake Lively that you're only looking for content

25 that is negative as to Ms. Lively as opposed to

1 negative as to any other of the content in the

Page 251

1 post -- in the post.

2 Q So what if a post was about both

3 Ms. Lively and Mr. Baldoni and included positive and

4 negative language, how would BERT know how to

5 classify such a piece of content?

6 A So BERT is trained on natural language

7 processing. It has context, so it looks at the

8 sentence structure and it looks at -- similar to, I

9 guess, deconstructing the English language about who 9

10 the negative or the positive personifier is

11 associated with, and then it would classify it as

12 positive, negative, or neutral, depending on the

13 keywords ---

14 Q So were you able to tell BERT --

15 A -- that you're looking for.

16 Q -- that negative content about Ms. Lively

17 should be classified as negative, but negative

18 content about Mr. Baldoni should not?

19 A So I was not -- I didn't include negative

20 content about Baldoni because it was out of scope

21 for the analysis.

Q Well, what if your search terms hit on a

23 post that included negative language about

24 Mr. Baldoni?

25 MR. FRITZ: Objection.

Page 253

2 report?

A So you're able to isolate who the subject

4 of the sentiment is for. So in this case, it was

5 for Blake Lively. It could mention six other people

6 in the content, but I was only concerned with the

7 sentiment as associated with Blake Lively.

8 BY MS. GOVERNSKI:

9 Q Okay. How are you able to give BERT that 10 direction?

11 MR. FRITZ: Objection.

12 THE WITNESS: So it's part of the

13 parameters when you're setting up the classifier

14 run.

15 BY MS. GOVERNSKI:

16 Q Okay. So did you produce your parameters

7 when you set up the classifier run?

18 A I'm sorry? Did I produce?

19 Q Did you provide to us the parameters for

20 your classifier run?

A No, because it specifically negates

22 any -- so the way that you put it into the system,

23 you specify who the subject matter is. And in this

24 case, it's the keywords around Lively. So it's not

25 fine-tuning or anything like that. I'm simply

64 (Pages 250 - 253)

Page 254

CONFIDENTIAL

- 1 saying negate anyone other than Lively when applying
- 2 sentiment scores.
- Q And where have you explained that in your 4 report?
- 5 A I don't believe I did.
- Q So if I wanted to understand all the
- 7 different parameters that you instructed BERT to
- 8 follow, how would I do that?
- A You would still be able to take my
- 10 dataset, put it into BERT, based on python code that
- 11 I provided you and keywords and the time frame.
- 12 There is an element that says do you -- I'm not sure
- 13 exactly what it says -- but should I focus on the
- 14 core keywords only or should I analyze additional
- 15 keywords. Using the keywords I provided, that's the
- 16 focus of the analysis.
- Q So the only way that you educate BERT was
- 18 by putting in the keywords --
- MR. FRITZ: Objection.
- 20 BY MS. GOVERNSKI:
- Q -- in the instructions?
- A In the dataset, yes. 22
- Q Okay. And you refer to BERT as "the BERT
- 24 family." You understand that there are multiple
- 25 types of BERT models, right?
- Page 255

- 1 A Yes.
 - Q So what BERT model did you use?
- A I used the most recent BERT model, and I
- 4 believe I specify it in my report.
- 5 Q Where did you specify that in your
- 6 report?

2

- 7 A Let's see. I don't put it in there.
- 8 It's currently the only BERT model that is available
- 9 through Google. I don't think I specify the date --
- 10 the launch date of the BERT model.
- Q Okay. Well, can you identify the BERT
- 12 model that you used?
- 13 MR. FRITZ: Objection.
- 14 THE WITNESS: I would have to go and
- 15 reference it. I would have to look it up.
- 16 BY MS. GOVERNSKI:
- Q Okay. Is there a reason you didn't 17
- 18 disclose the specific BERT model you used?
- A There's no reason. It's part of the BERT
- 20 family so it's the one that's is currently
- 21 accessible.
- Q But BERT models -- in order to replicate
- 23 it, there is a lot BERT models, right?
- 24 MR. FRITZ: Objection.
- 25 THE WITNESS: There's different versions

- 1 of the BERT models.
- 2 BY MS. GOVERNSKI:
 - Q Too many to even enumerate, right?

Page 256

Page 257

- 4 MR. FRITZ: Objection.
- 5 THE WITNESS: I don't know if that's
- 6 true. It's the current version of BERT.
- 7 BY MS. GOVERNSKI:
- Q Okay. But if we wanted to replicate your
- 9 sentiment analysis based on what you disclose in
- 10 your report, we would have to guess what BERT model
- 11 you used?
- 12 MR. FRITZ: Objection.
- 13 THE WITNESS: I would say you could do
- 14 that by going to the current BERT model, the latest
- 15 version.
- 16 BY MS. GOVERNSKI:
- 17 Q And just guessing that that's the one you
- 18 used.
- MR. FRITZ: Objection. 19
- 20 BY MS. GOVERNSKI:
- 21 Q Is that right? We'd have to just
- 22 guess --
- 23 A Was that statement or a question?
- 24 Q A question. We would have to just guess
- 25 that you used the most recent BERT model?
- - 1 MR. FRITZ: Objection.
 - 2 THE WITNESS: You -- you -- there would
 - 3 be an inference that the latest one would be the one
 - 4 that you could default to.
 - 5 BY MS. GOVERNSKI:
 - Q Okay. Is BERT or LLM a newer model?
 - A LLM stands for Large Language Model. So
 - 8 you'd have to be specific on what LLM you're
 - 9 referring to.
 - 10 Q Okay. Well, did BERT models precede
 - 11 large language models?
 - 12 A They did.
 - Q Okay. So it doesn't depend on what type 13
 - 14 of LLM, right, it just -- BERT preceded LLMs?
 - 15 MR. FRITZ: Objection.
 - 16 THE WITNESS: So BERT is natural language
 - 17 processing. And BERT is -- I believe BERT models
 - 18 came out, I'm guessing, but maybe 20 -- 15 to 20
 - 19 years ago.
 - 20 BY MS. GOVERNSKI:
 - Q Okay. And where did you obtain your BERT 21
 - 22 model from, you said Google?
 - 23 A Yes, correct.
 - 24 Q Did you run the BERT model using a
 - 25 computer program?

65 (Pages 254 - 257)

Page 258 Page 260 1 A Using Python, yes. Q But I'm not asking for an aggregate, I'm 2 Q And how did you write the code to call 2 asking for the score for each individual post. 3 the specific model and version that you mentioned? MR. FRITZ: Objection. A So my assistant wrote the code, and I 4 THE WITNESS: So the output from BERT is 5 shared the code for each of the -- for each of the 5 it clusters together. So it provided the score 6 scrapes and for the sentiment. 6 of -- the score of positive, negative and neutral. 7 BY MS. GOVERNSKI: 7 Q Do you know how to write code? 8 A I know how to write code, enough. I Q So there is no way to see how it 9 wouldn't say I am the person to write code for classified any individual social media item? 10 complex matters by any means. 10 MR. FRITZ: Objection. Q Okay. So in the code that you produced, THE WITNESS: Is there a way to classify, 11 12 what version of the BERT model does it reflect? 12 no. 13 MR. FRITZ: Objection. 13 BY MS. GOVERNSKI: Q So you have no way of knowing if it THE WITNESS: It should reflect the most 15 accurately classified any of the 43,992 pieces of 15 recent version. 16 BY MS. GOVERNSKI: 16 social media items? 17 Q The most recent as of what date? 17 MR. FRITZ: Objection. MR. FRITZ: Objection. THE WITNESS: I'm sorry. You mean 18 18 THE WITNESS: As of October 2025. 19 44,000? 19 20 BY MS. GOVERNSKI: 20 BY MS. GOVERNSKI: Q Okay. Did you apply the BERT model on 21 O 43,992. 22 all of your dataset? 22 A So I was able to go in the system and we 23 A Yes. 23 hand verified a certain portion, which I reference Q Okay. If I want to understand how your 24 in my report. So we went through and looked at 300 24 25 BERT model classified all of the information in your 25 different posts. I believe it was 300, I'd have to Page 259 Page 261 1 dataset, how would I do that? 1 just double check. MR. FRITZ: Objection. 2 Q Okay. THE WITNESS: How it classified? You A To -- hand eye verify the sentiment 4 would have to go into BERT to understand its general 4 scores that they were correct in conjunction with 5 classifier system. 5 the individual posts. 6 BY MS. GOVERNSKI: Q Well, how did you know sentiment scores Q But if I wanted to understand any one 7 of those 300 posts? 8 post to understand how your BERT model classified A Because it provides it in a -- you can 9 that one post, how would I do that? 9 open the tabs to see how their -- how the system is 10 MR. FRITZ: Objection. 10 identifying the individual pieces of content. THE WITNESS: So you can see the score 11 11 Q So you -- there is a way in the system to 12 based on the dataset I provide. You can see the 12 know how it's identifying each individual post? 13 score that BERT gave each piece of -- each piece 13 A Yes. To verify it, correct. 14 of -- of -- excuse me -- each post. But if your 14 Q And why haven't you provided us with that 15 question is how it classified, there is -- you would 15 underlying classification data? 16 have to go into the BERT model itself when 16 MR. FRITZ: Objection. 17 replicating the run. Actually, I'm sorry. I'm 17 THE WITNESS: Because it wasn't necessary 18 going to -- that wouldn't be. You would have to go 18 in order to replicate my work. 19 into BERT itself to understand, into the developer 19 BY MS. GOVERNSKI: 20 tools. Q Well, if we want to be able to check how 20 21 your BERT analyzer classified each one of the 43,992 21 BY MS. GOVERNSKI: 22 social media items, how could we do that? Q So where did you disclose the score for 23 each post? 23 MR. FRITZ: Objection. 24 THE WITNESS: You could -- you could 24 A So I provided an aggregate, and it's in

66 (Pages 258 - 261)

25 replicate the run itself, based on the data that I

25 the zip file that was submitted.

CONFIDENTIAL Page 262 Page 264 1 provided. 1 is -- because it's just the subset, it's a 2 BY MS. GOVERNSKI: 2 randomized subset. So that was, again, randomized, Q But if we wanted to understand how your 3 so we went through and hand confirmed that the score 4 BERT model, the way you ran it, classified each one 4 made sense to the physical post. And we did that in 5 of those posts, how could we do that? 5 the environment itself. 6 MR. FRITZ: Objection. 6 BY MS. GOVERNSKI: 7 THE WITNESS: The only way would be to Q I understand. But how long did it take 7 8 rerun it based on the code and dataset that I 8 you to pull the specific sentiment classify --9 provided. 9 strike that. 10 BY MS. GOVERNSKI: 10 How long did it take you -- I'm not 11 talking about performing the analysis -- just to Q Well, if you were able to go in and see 11 12 how all of the 43,000 social media items were 12 pull the information about how the 300 posts were 13 classified, couldn't you just produce the outcome of 13 classified? 14 that for us? 14 MR. FRITZ: Objection. 15 THE WITNESS: So I'm not sure how much 15 MR. FRITZ: Objection. THE WITNESS: So the extract was an 16 time it took because we looked at 300 randomized 16 17 aggregate, was -- the downloadable version is an 17 rows in the environment to confirm or disconfirm 18 aggregate. 18 that the score itself was accurate. 19 BY MS. GOVERNSKI: 19 BY MS. GOVERNSKI: Q But for the 300 posts, couldn't you just, Q So if you don't know how long that took, 20 21 like, take a screenshot of it? 21 how do you know how long it would take you to run MR. FRITZ: Objection. 22 the same instruction on all of the social media 22 23 THE WITNESS: I'm sure, yes, that's one 23 items in your dataset? 24 feasible way of capturing something that is on the 24 A So doing a -- performing by eye or hand 25 screen. You wouldn't get all 300 in said 25 to confirm if the score is accurate or not is done Page 263 Page 265 1 screenshot, but yes. 1 in real time in the environment. I simply can't 2 BY MS. GOVERNSKI: 2 tell you how long that took. I'm not sure what your 3 question... Q Yeah, but there is a feasible way that 4 you could give us the classifications of your 4 Q Yeah, what I'm asking you is --5 sentiment analysis, right? 5 MR. FRITZ: Objection. MR. FRITZ: Objection. 6 BY MS. GOVERNSKI: Q -- you were able to identify 300 posts, 7 THE WITNESS: So I did in aggregate. I 8 right? You were able to do a query and say pull 300 8 didn't on each individual post. 9 BY MS. GOVERNSKI: 9 posts and tell me how you classified these 300, Q But there is a way, a feasible way that 10 right? 11 you could do it for each individual post, right? 11 A We looked at 300 posts that were MR. FRITZ: Objection. 12 12 classified. THE WITNESS: It would have -- it would 13 13 Q Okay. So how were you able to understand 14 the classifications of those 300 specific items? 14 have been more work to extract it, and I didn't 15 believe it was necessary. 15 A We looked at the content. So the post 16 BY MS. GOVERNSKI: 16 itself, the verbiage, and we looked at the score 17 that was given by BERT, the classifier to understand 17 Q How much more work? A I'd have to go through in the system to 18 if that score was accurate, based on general 18 19 see, but it's not just a download of the CSV. 19 knowledge of reading the posts and interpreting,

67 (Pages 262 - 265)

20 based on just general knowledge of what would be

23 how your sentiment analysis classified each of the

24 42,000, how would you do that? 43,000. Sorry.

MR. FRITZ: Objection.

Q Okay. And if you wanted to understand

21 positive, negative or neutral.

25

21 300 posts?

20

22 23

24 25 Q So how long did it take you to do those

A To do the verification of the 300 posts?

THE WITNESS: So the verification which

Q No, to pull that data of 300 posts.

MR. FRITZ: Objection.

CONFIDENTIAL Page 266 THE WITNESS: So one way is to go through 2 2 and eyeball every single one, to go through and look 3 3 at the score and to look at the copy that is from 4 the post. 5 BY MS. GOVERNSKI: Q I'm trying to understand where you would 7 look to see the score for each individual post. MR. FRITZ: Objection. THE WITNESS: You would look in the BERT 10 model itself, after it's classified, each piece of 11 content. 11 12 BY MS. GOVERNSKI: Q Okay. So there exists, in the BERT 14 model, a way to see how it classified each 15 individual post? 16 A In the environment, yes. 16

Q And you did not produce to us any

18 individual scores for any individual posts, right?

19 MR. FRITZ: Objection.

20 THE WITNESS: I did not produce scores

21 for each individual piece of content.

22 BY MS. GOVERNSKI:

23 Q And you didn't produce even -- sorry.

24 Scratch that.

17

25 You didn't identify the specific 300

1 posts that you checked, right?

A No, it was a randomized post -- it was

3 randomized 300 in order to confirm that the

4 classifier was accurate. Again, to reproduce it,

5 you wouldn't need that. You're able to reproduce it

6 based on what we provided.

Q Are we? Are we able to reproduce a

8 randomized -- how do you know that my randomized

9 sample would be the same as your randomized sample?

10 MR. FRITZ: Objection.

11 THE WITNESS: You're able to produce

12 the -- in aggregate, the classifier, based on the

13 model that I gave you -- or based on the BERT family

14 using the latest model and the dataset.

15 BY MS. GOVERNSKI:

Q But that's not my question. My question

17 is: How could I receive the exact same 300 posts

18 that you conducted your manual review on?

19 MR. FRITZ: Objection.

20 THE WITNESS: If it's randomized, you

21 cannot.

22 BY MS. GOVERNSKI:

Q So I cannot identify what 300 posts you

24 manually reviewed based on the information that

25 you've disclosed, right?

MR. FRITZ: Objection.

THE WITNESS: That is correct.

MS. GOVERNSKI: My colleague is going to

Page 268

4 move nine documents into being Exhibit Share. I'm

5 going to mark them as exhibits -- starting with

6 Exhibit 8. So it will be 8, 9, 10, 11, 12, 13, 14,

7 15, 16. So she's going to move them all in there.

8 BY MS. GOVERNSKI:

Q And while she does, can you tell me what

10 BERT stands for?

A Bidirectional -- bidirectional is the

12 most important part. I'm not sure what the rest of

13 it stands for.

Q And how often have you used BERT other

15 than in this case?

A Probably once a week, this particular --

17 from September to present. I use it for class. I

18 use it for work previously. Yeah, often.

19 Frequently.

20 Q So you personally run BERT weekly?

21 A I personally use BERT for a myriad of

22 different things in relation to my class. So my

23 students are asked to run simulations, things of

24 that nature. I use it for nonwork-related elements,

25 as well as previously for work-related.

Page 267 Page 269

Q Okay. Do you see Exhibits 8 through 16

2 in your Exhibit Share? Or it's 8 to 11 right now.

3 But there are more coming in. Why don't you go

4 ahead and open Exhibit 8. And my colleague, Autumn,

5 will also put it on the screen.

A One second. Eleven is the last one?

Q I'm looking at Exhibit 8 right now.

8 A I'm downloading, is 11 the last one?

MS. GOVERNSKI: Oh, there is 13. Well,

10 it should be 8 through 16. There's going to be nine

11 altogether.

7

12 (Exhibit 8 marked for identification.)

13 THE WITNESS: Okay. Go right ahead.

14 BY MS. GOVERNSKI:

15 Q Okay. So you see the post on your

16 screen, it's looks like a Twitter post.

17 A Exhibit 6?

18 Q Exhibit 8.

19 Sorry. 8.

20 Q It's also on your screen, you can see it

21 marked.

22

23 Q Okay. And you see the second tweet that

24 says:

25 (As read):

68 (Pages 266 - 269)

CONFIDENTIAL		
Page 270	Page 272	
1 "Paying their effing salaries and	1 as neutral.	
pensions. WTF is wrong with us?	2 Q And if we wanted to figure that out, we	
That's \$5 billion we sent to Ukraine	3 would have to go into your BERT system?	
4 this week. Eff @ZelenskyyUA. It will	4 MR. FRITZ: Objection.	
5 be great when this grift ends."	5 THE WITNESS: The BERT system?	
6 Do you see that?	6 BY MS. GOVERNSKI:	
7 A Yes. I have it, yes.	7 Q Yes.	
8 Q Do you have any opinions as to this	8 A Yes.	
9 tweet?	9 MS. GOVERNSKI: Okay. Let's go to	
10 A I don't have any opinions, no.	10 Exhibit 9. Hopefully, we can get through these	
11 Q Does it have anything to do with	11 pretty quick.	
12 Ms. Lively?	12 (Exhibit 9 marked for identification.)	
MR. FRITZ: Objection.	13 BY MS. GOVERNSKI:	
14 THE WITNESS: Sorry. Not based on what	14 Q This is a tweet let's zoom in a little	
15 I'm looking at right now, no.	15 bit that says:	
16 BY MS. GOVERNSKI:	16 (As read)	
17 Q Okay. Based on what you're looking at	"@DrainBamager, MJF is better than us	
18 right now, would you include this tweet in your	and we all know it. Pretty sad Adam	
19 dataset?	Cole with his henchman and the devil	
A Would I include it or would it come up in	garbage. Can't wait till MJF kicks his	
21 my dataset? I'm sorry. I just need to specify.	21 chulo and ends this story."	
22 Q Both.	Do you have any opinions on this tweet?	
MR. FRITZ: Objection.	23 A No, I don't have any opinions.	
24 BY MS. GOVERNSKI:	24 Q Would you expect to see this tweet in	
25 Q Both.	25 your dataset?	
Page 271	Page 273	
1 MR. FRITZ: Objection.	1 A So if it showed up in the dataset, it	
THE WITNESS: So I don't include any of	2 should be either negated or marked as neutral.	
3 the data in my dataset, just to be clear. The data	3 Q So when you say "negated," what does that	
4 that I pull, for instance, comes from the keywords	4 mean?	
5 through Apify from the API.	5 A Negated meaning that it it wouldn't	
6 BY MS. GOVERNSKI:	6 actually be a part of the extraction of the data	
7 Q Okay. Would you expect to see this tweet	7 that was pulled.	
8 in your dataset?	8 Q So how do we know if posts have been	
9 MR. FRITZ: Objection.	9 negated?	
THE WITNESS: I wouldn't expect it. I	MR. FRITZ: Objection.	
11 would have to see why it would have come up, maybe	<u>*</u>	
12 because of a hashtag or something. But no.	12 that I sent you, it wouldn't be in that dataset.	
13 BY MS. GOVERNSKI:	13 BY MS. GOVERNSKI:	
Q Okay. But based on the content on your	14 Q Oh, okay. So it would if it was	
15 screen, you wouldn't expect this to be in your	15 negated, it wouldn't be in the dataset you sent us?	
16 dataset?	A So there's two ways of negating. There's	
17 A No.	17 negating at the extraction through Apify. So	
18 Q And how would your BERT sentiment	18 confirming that the content is is based on the	
19 analysis categorize this tweet?	19 parameters that we plugged into Apify. The second	
20 A I can't say definitively how BERT would	20 area of negation when it comes to when it comes	
21 classify it because that's just outside of my	21 to sentiment scoring. So on the sentiment scoring	
22 knowledge set. You would have to go in and run it	22 side, it would either be marked as neutral or it	
23 through BERT. But if it was asked to classify it	23 wouldn't say N/A., but it would have, like, a score	
24 for Blake Lively ground the keywords that Luce in	24 of zoro	

69 (Pages 270 - 273)

Q So it would be included in the dataset

24 of zero.

25

24 for Blake Lively around the keywords that I use in

25 my report, it would either negate it or classify it

Page 274 1 you provided us? 2 A If it wasn't negated at the Apify pull 3 and it was one of the posts in the dataset, then it 4 wouldn't have been reflective in the sentiment 5 analysis as a positive or negative. 5		CONTIDENTIAL		
2 Å If it wasn't negated at the Apify pull 3 and it was one of the posts in the dataset, then it 4 wouldn't have been reflective in the sentiment 5 analysis as a positive or negative. 6 Q And how could we check to understand if 7 your sentiment analysis negated a post like this? 8 A So the classifier would negate it because 9 it's not talking about Blake Lively. The terms that 10 C But my question is: How would we know if 12 your sentiment analyzer negated this post or 13 classified it? 14 MR. FRITZ: Objection. 15 THE WITNESS: So it's not my sentiment 16 classifier. The BERT classifier would usually look 17 at something like this, and based on it not having 18 Blake Lively or the terms that 1 referenced in my 19 report, then there is no negative or positive 20 scoring to put in conjunction with that name. 21 BY MS. GOVERNSKI: 22 Q So we should just assume that sentiment 23 analysis that you did, did something with this post? 24 MR. FRITZ: Objection. 25 THE WITNESS: So this post, number one, I 26 Q So we should just assume that sentiment 27 analysis that you did, did something with this post? 28 Q So we should just assume that sentiment 29 analysis that you did, did something with this post? 20 Lord the three is no negative or positive 21 analysis that you did, did something with this post? 22 Q So we should just assume that sentiment 23 analysis that you did, did something with this post? 24 MR. FRITZ: Objection. 25 THE WITNESS: So this post, number one, I 26 Well, show do you define subReddits in very different ways. So 27 So that's a subreddit? 28 Q So that's a subreddit? 29 Q So well, low do you define "subReddits"? 30 Q So that's a subreddit? 31 A T-rather, instead using the word, I 4 would rather just be specific in distinguishing what it it is a section on Reddit or a group on Reddit. 31 I it is a section on Reddit or a group on Reddit. 32 Q Well, how do you define "subReddits"? 33 Q So that's a subreddit? 34 A T-rather, instead using the word, I 4 would rather just be specific in distinguishing what it i		-		
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25 DOOKISTNAPSOCIC? 25 Q And it says "finale" followed by a series	15 16 17 18 19 20 21 22 23	A The one on the screen, "me, my books"? Q No, on the right side, you see the first comment: (As read): "Okay. And this show of course! What's your comfort read, song, show?" Do you see that? A Yes.	16 17 18 19 20 21 22 23	A If it was, again, it would be negated from a sentiment perspective. But yeah, no. MS. GOVERNSKI: Okay. And let's go to Exhibit 14, which is a post on TikTok. It's really hard to see, Autumn, can you Zoom in as much as you can to the bottom where you see "moon struck fate." (Exhibit 14 marked for identification.)	
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71 (Pages 278 - 281)

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Page 2	Page 284
1 of hashtags.	1 looking at it, it would classify this either as
2 "IP, only pen voiceover on hyphen be	2 again going to null or as neutral.
3 lift on hyphen island hyphen is	3 Q Okay. So you produced your underlying
4 island.	4 data to us, right?
5 Do you see that?	5 A Yes.
6 A Yeah. I can't make it out but I see the	6 Q And you produced a series of README
7 post itself.	7 files, actually five of them. One for each
8 Q Would you expect that this post to be	8 platform; is that correct?
9 included in your dataset?	9 A That's correct.
10 A Not sure. I would say no.	10 Q Okay. Who what are the README files?
11 MS. GOVERNSKI: Okay. Let's look at the	11 MR. FRITZ: Objection.
12 next one. Exhibit 15, which is another TikTok and	12 THE WITNESS: The README files are
13 let's zoom way in again, Autumn.	13 instructions.
14 (Exhibit 15 marked for identification.)	14 BY MS. GOVERNSKI:
15 BY MS. GOVERNSKI:	15 Q Instructions to what?
16 Q The message on the bottom says:	16 A Instructions to the recipient to give
17 (As read):	17 context, to give additional information, to
18 "Massage is a path to a happier life.	18 contextualize.
Book a massage appointment and let's be	19 Q Who wrote the content of the README
20 happy."	20 files?
21 And then it has a series of hashtags.	A My assistant wrote the content for the
Do you see that?	22 README files.
23 A I do.	23 Q Your assistant we talked about?
24 Q Would you expect this to be in your	24 A Taylor Hunter.
25 dataset?	25 Q Okay. Ms. Hunter. Did you review the

Page 283

Page 285

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A Again, just because this is obviously a
2 video still, I don't know what the rest of the video
3 content is. So based on just the content that I can
4 see at the bottom, then I would say no.
      Q So when your BERT sentiment analyzer was
6 looking at content, would it look at the actual
7 video?
8
         MR. FRITZ: Objection.
         THE WITNESS: It would look at the -- it
10 would look at the data around the post. So when
11 it's video for instance, it looks at things like the
12 metadata. It looks at context around what the --
13 what the hashtags are, what the posts are, written
14 content is underneath. And any other data points
15 that are able to be extracted.
16 BY MS. GOVERNSKI:
       Q Okay. So that way you just described
```

18 what's underneath, it would look at included in what

A Correct. That would be one of the pieces

Q How would your BERT analyzer classify

A In the context of the keywords that I was

19 it would look at would be this text: "Massage is a

20 path to a healthier life", et cetera?

Q Did you -- is all of the README files you 3 4 produced to us accurate? A I would have flagged anything that I saw 6 as an issue. So accuracy on a README file is -- I'm 7 not sure how to say if something is right or 8 wrong --Q But you would have reviewed all of the 10 README files before you produced them to us? 11 A Before I submitted them. Yes. 12 MS. GOVERNSKI: I'm going to mark as 13 Exhibit 16 the README file that you produced to us 14 in connection with your Reddit analysis. Just give 15 Autumn a second. Okay. It should be in there and

1 content of the README files?

16 Autumn will put it on the screen.

18 BY MS. GOVERNSKI:

(As read):

A Yes.

19 Q Okay. Ms. Alexander, is this the Reddit 20 README file that you produced to us? 21 A I'm sorry. Which -- is this Exhibit 16? Q Yes. 22 23 A Yes. It looks like. 24 Q It says here.

(Exhibit 16 marked for identification.)

72 (Pages 282 - 285)

17

25

24 this post?

22 it would look at.

21

23

CONFIDENTIAL		
Page 286	Page 288	
1 "Quick Analysis of Blake Lively Reddit	1 Q The comments would be contained within	
posts, (January 2024 to October 2025)	2 the spreadsheet?	
3 879 posts total from the dataset."	3 A Within the row, yes.	
4 Do you see that?	4 Q Okay. And the date here is January 2024	
5 A I'm sorry. What are you?	5 to October 2025. Why for purposes of Reddit did you	
6 Q Just reading the first two lines. 879	6 include posts that went back to January 2024?	
7 posts total from the dataset.	7 A So the target that I was looking at was	
8 Do you see that?	8 January 2024 to the present, which for this report,	
9 A I do.	9 was October 2025.	
10 Q Okay. So this references posts, not	10 Q But if your baseline was May to June of	
11 comments, right?	11 2024, why did you include in your Reddit analysis	
12 A This is referring to posts. Correct.	12 posts between January and May 2024?	
13 Q So you didn't collect comments. Only	13 A So that helps when doing the forecast	
14 posts on Reddit?	14 that is in my report to have a larger period of data	
15 A So with the posts, there are comments	15 in order to look at a regression and to forecast	
16 associated with them as well.	16 with and without the spike.	
17 Q But this doesn't say that. This says 879	17 Q Okay. So the specific if we were	
18 posts.	18 to wanted to understand what of the 18,879 posts	
19 MR. FRITZ: Objection.	19 were from the baseline period, we would look in your	
20 THE WITNESS: So with the posts, comments	20 backup data and look at the dates of the posts	
21 are usually associated. So you just showed me	21 themselves?	
22 TikTok. That was a post. And then you README the	22 A I'm sorry. Say that once more?	
23 comments that were associated with that post.	23 Q Let's look. It says baseline period is	
24 BY MS. GOVERNSKI:	24 May to July 2024. Mean is about 20 posts a month.	
25 Q So is the database that you produced of	Do you see that?	
Page 287		
1 Reddit, does it include all of the posts and the	1 A Yes.	
2 comments that were that comprised your dataset?	2 Q So 20 posts a month for three months	
3 A So the I have to go back and look.	3 would be 60 posts?	
4 But the posts should include the comments that were	4 A Baseline period May through July.	
5 on that post.	5 August 2024. Mean is approximately 20 posts per	
6 MS. GOVERNSKI: Okay. So it's your	6 month. Yes. The average is approximately 20 posts	
7 position when it says 879 posts, that each	7 per month.	
8 individual one would include however many comments	8 Q Your dataset of May to July 2024, the	
9 were part of that post?	9 baseline period is around 60 posts?	
10 A If they were associated with the post.	10 A Sixty posts via 11 Q Reddit.	
11 Q Associated with the post means under the 12 post? Responding to the post?	12 A This particular. Yes.	
13 A So if the data extract allowed for the	13 Q Okay. And in your opinion is 60 posts	
14 comments to be pulled with the post, then yes, the	14 sufficient to draw any conclusions about that	
15 comments would be associated with the post.	15 baseline period?	
16 Q Well, this isn't hypothetical. Did your	16 A So in itself, no. In aggregate, yes.	
17 Reddit scraper that you used allowed you to pull the	17 Q In aggregate with the other baseline	
18 comments?	18 numbers in your other dataset?	
19 MR. FRITZ: Objection.	19 A Right. Which is why I looked at five	
20 THE WITNESS: I would need to go in and	20 different	
21 actually look at the data.	21 Q Okay.	
22 BY MS. GOVERNSKI:	22 A social media platforms.	
23 Q How would it look like in the data? What	23 Q Okay. And this is accurate that August	
24 would it look like?	24 of 2024 had 105 posts?	
25 A It would be a row of data.	25 A I would have to go back and just double	
	J	

73 (Pages 286 - 289)

CONFIDENTIAL Page 290 Page 292 1 check. 1 BY MS. GOVERNSKI: Q Okay. But 250,000 comments and posts is Q But you have no reason to think that your 3 README files are not accurate, right? 3 250,000 plus more than your entire dataset. MR. FRITZ: Objection. A No. There's no reason to assume that. 4 5 THE WITNESS: So again, quantity is not Q Actually do you know how many comments 6 and posts on Reddit were included in Dr. Mayzlin's 6 always a factor in accuracy or representation. 7 dataset? 7 BY MS. GOVERNSKI: A How many comments and posts from Reddit 8 Q Right. But you did not do any analysis 9 were included in Mayzlin's? I don't have offhand. 9 of Dr. Mayzlin's actual data to understand if it's 10 I have to refer to the report. 10 representative, right? Q If I were to represent to you that there 11 MR. FRITZ: Objection. 12 were 250,000 comments and posts on Reddit just 12 THE WITNESS: I couldn't replicate what 13 between May 2024 and February 2025, would that 13 she developed in order to analyze it. 14 BY MS. GOVERNSKI: 14 number surprise you? MR. FRITZ: Objection. 15 Q But you didn't just look at the comments 15 16 and do any of your own spot checking on the 250 THE WITNESS: It wouldn't surprise me. I 16 17 believe Reddit was the one that she scraped the most 17 posts in her Reddit data? 18 18 data from. MR. FRITZ: Objection. 19 BY MS. GOVERNSKI: 19 THE WITNESS: No. Because that wasn't to Q Okay. So how do you reconcile that you 20 my understanding my assignment. 21 pulled 879 posts from a longer time period than 21 BY MS. GOVERNSKI: 22 Dr. Mayzlin's from a shorter time period? 22 Q But it didn't strike you as a proffered A Again she -- based on my recollection of 23 expert in this case that, I don't know, 870 versus 24 her approach, she used an LLM to produce this 24 250, that seems a little off, maybe we should check? 25 information. So again, I tried to replicate it in 25 MR. FRITZ: Objection. Page 291 Page 293 THE WITNESS: No, it did not. 1 order to understand the post, the sentiment, 2 BY MS. GOVERNSKI: 2 et cetera. And I wasn't able to do that. Q Sorry. Go on. 3 Q Okay. It says: 4 4 A Period. I will end there. (As read): 5 "September dropped back down to 25, Q But what I don't understand is why didn't 6 (76 percent decline.)" 6 you just look at the 250,000 posts and comments on 7 Dropped down to 25 what? 7 Reddit and look at them and compare them with just 8 A Baseline period. 9 (Witness reading.) MR. FRITZ: Objection. THE WITNESS: Because I needed to 10 So that's looking at volume. 11 Q So in September, the posts dropped down

Q But what I don't understand is why didn't
6 you just look at the 250,000 posts and comments o
7 Reddit and look at them and compare them with ju
8 the 879 in your dataset?
9 MR. FRITZ: Objection.
10 THE WITNESS: Because I needed to
11 understand the origins and verify the origins in
12 order to do any subsequent analysis.
13 I'm not able to verify where the data
14 came from, from her dataset, based on the
15 information I was given in her expert report. So
16 alternatively, I went to pull a more diverse set of
17 data across more networks in order to analyze it.
18 BY MS. GOVERNSKI:
19 Q I'm having trouble understanding how 879
20 posts from Reddit is a greater set of data points

21 than the 250,000 comments and posts in Dr. Mayzlin's

THE WITNESS: I refer to a larger number

MR. FRITZ: Objection.

25 of social media sites for diversity.

12 to 25 posts? A Yes, based on this. So August was 175 13 14 posts and we saw -- sorry -- a 76 percent decline in 15 September down to 25 posts is what --Q Okay. So your conclusions about what the 17 Reddit data showed after the August spike was based 18 on 25 posts? 19 MR. FRITZ: Objection. 20 THE WITNESS: I'm sorry. Can you just 21 repeat the last question? 22 BY MS. GOVERNSKI: Q Sure. Your opinion based on the Reddit 24 dataset of what occurred after the August spike was 25 based on 25 posts.

74 (Pages 290 - 293)

22 Reddit dataset.

CONTIDENTIAL			
	Page 294 Page 296		
1 A A piece of the analysis was based on 2:			
2 posts that month during that on Reddit.	2 Q Okay. Do you have any personal knowledge		
3 Q Well, I'm talking about just Reddit.	3 about whether or when sorry strike that.		
4 So were there other posts other than the			
5 25 mentioned here that you considered with res			
6 to Reddit?	6 August 2nd?		
7 A No. I would have to go into the datase			
8 But it would be the amount in the file.	8 Q Yeah.		
9 Q Okay. So under Results, it says:	9 A No.		
10 (As read):	10 Q Do you have any knowledge generally based		
11 "Spike is real and statistically 12 significant."	11 on what you reviewed in this case? 12 A Maybe I don't understand what you're		
significant." Which refers to the August spike. "But"			
14 in capital letters.	13 asking. 14 Q Let me ask the question in a better way.		
15 (As read):	15 MR. FRITZ: Objection.		
16 "BUT the timing is right when the mo			
came out (August 9th) and when the	17 Q Do you have any reason to believe that		
18 alleged campaign started (August 2nd			
So can't really say which caused it	19 MR. FRITZ: Objection.		
from temporal data alone."	20 THE WITNESS: Based on the discovery		
That's an accurate statement, right?	21 material I was given, the alleged campaign had a		
22 A All right. Just one second. Yes. But	22 date associated with it. And I believe that's where		
23 you would have to go on and read the results in			
24 entirety.	24 BY MS. GOVERNSKI:		
25 Q Okay. Well, it says:	Q Okay. And what if it turned out that the		
	Page 295 Page 297		
1 (As read):	1 digital part of the campaign started after		
1 (As read): 2 "The fact it immediately crashed	1 digital part of the campaign started after 2 August 2nd?		
2 "The fact it immediately crashed	2 August 2nd?		
2 "The fact it immediately crashed 76 percent in September suggests mo	2 August 2nd? vie 3 MR. FRITZ: Objection.		
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75 (Pages 294 - 297)

CONFIDENTIAL		
Page 298	Page 300	
1 an actual launch of a movie. Whatever could	1 increased. I believe I gave a date in the report.	
2 aggressively increase sentiment one way or the	2 BY MS. GOVERNSKI:	
3 other. Which is why I chose that for the baseline.	3 Q Okay. And you said that in your report	
4 Q Right. So I mean your August spike is	4 that you used the Reddit scraper actor, right?	
5 only one month. So August 1st through ninth or	5 A Yes. The API.	
6 August 2nd through ninth is a whole week, right,	6 Q Okay. The Reddit scraper actor does not	
7 that's seven days?	7 allow users to perform searches.	
8 A Yes.	8 Are you aware of that?	
9 MR. FRITZ: We'll stipulate to that.	9 MR. FRITZ: Objection.	
10 BY MS. GOVERNSKI:	10 THE WITNESS: So in Apify, you are able	
11 Q So your data about the August spike would	11 to pull Reddit based on keywords.	
12 go from three weeks of data or from four weeks of	-	
13 data to three weeks of data, right?	13 be Exhibit 17.	
14 A No.		
	14 (Exhibit 17 marked for identification.)	
,	MS. ADAMS-JACK: Which document, Meryl?	
16 THE WITNESS: The spike itself is based	MS. GOVERNSKI: The Reddit scraper actor.	
17 on just data. Based on what happened in real life.	17 While we're here, let's go into the README where it	
18 So there was a spike in sentiment, in overall	18 says sorry, Autumn, while you're pulling that up,	
19 volume. Just overall. So the spike happened	19 can you scroll down to the bottom of this?	
20 irrespective of if it was a marketing campaign,	20 BY MS. GOVERNSKI:	
21 despite whatever caused it. The spike still	21 Q Okay. It says:	
22 occurred.	22 (As read):	
23 BY MS. GOVERNSKI:	23 "Reddit API pulls for Blake Lively, It	
Q So why would the period from August 2nd	Ends With Us, Justin Baldoni, top subs,	
25 to August 9th not be included in the baseline?	pop-culture chat, 265 posts, Fauxmoi,	
-		
Page 299	Page 301	
1 MR. FRITZ: Objection.	Page 301 1 189 posts, Romance books, 154."	
1 MR. FRITZ: Objection. 2 THE WITNESS: I wouldn't include it in	_	
1 MR. FRITZ: Objection.	1 189 posts, Romance books, 154."	
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1 MR. FRITZ: Objection. 2 THE WITNESS: I wouldn't include it in 3 the baseline because I would end the baseline at a 4 month a month outside of where we see an 5 effective month. So you would want ideally several	1 189 posts, Romance books, 154." 2 Do you see that? 3 A Yes.	
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76 (Pages 298 - 301)

CONTIL	
Page 302	Page 304
1 MR. FRITZ: Objection.	1 Q Well, what are you double checking?
2 THE WITNESS: So subsections, I believe,	2 A I am looking at the exhibit that you
3 is a more general use of looking at groups or	3 provided in the README files.
4 sections across websites. SubReddits is very	4 Q In the README file where it says "top
5 specific in someone understanding and knowing the	5 subs, pop culture, chat fauxmoi, and romance books"
6 architecture of Reddit.	6 A No. To see if we stated in the README
7 BY MS. GOVERNSKI:	7 file that there was any so that should have been
8 Q When you recall that we actually looked	8 left blank.
9 at posts from pop sub Reddit called pop culture	9 Q Well, then how would you search?
10 chat and from FauxMoi, right?	Because as we just looked at, this
A From pop culture chat, yes. I don't	11 scraper requires you to either enter the subreddit
12 remember the FauxMoi.	12 or the username or the specific link or the
13 Q Do you remember the Kurt Cobain one?	13 homepage.
14 A Yes.	14 MR. FRITZ: Objection.
15 Q So 608 of the Reddit posts in your	THE WITNESS: Here, we would have entere
16 dataset were from these three subReddits, right?	16 the homepage and the
17 A Top subs, yes. So 265 posts, 189, and	17 BY MS. GOVERNSKI:
18 154.	18 Q I'm not asking what you would have done.
19 Q Okay. And then it says Reddit API pulls.	19 What did you do?
20 You didn't list Reddit API in your data sources.	20 MR. FRITZ: Objection.
21 Why not?	21 THE WITNESS: So for this run, we would
A So we didn't use the Reddit API pulls.	22 not have filled out any of the optional.
23 We used the Apify excuse me Apify Reddit pull.	23 BY MS. GOVERNSKI:
24 Q Let's now the exhibit should be in	24 Q What would you have filled out?
25 there. Exhibit 17. The Reddit post scraper. You	Let's go back, Autumn, please to the
Page 303	Page 305
1 see it's Reddit scraper. Is this the API that you	1 scraper that Ms. Alexander said she used, 17. Which
2 used?	2 says that it can provide these things based on a
3 You can see in the bottom, it's	3 provided subreddit, username, specific link or the
4 Apify.com.	4 homepage. So you have to give one of them.
5 A Yes. That should be the scraper.	5 A No. So one of the options when you go
6 Q That you used?	6 in, again, they are all optional. So we would have
7 A Yes, I believe so.	7 provided the keywords
8 Q Okay. And you can see it says:	
	8 Q Where on?
9 (As read):	8 Q Where on? 9 MR. FRITZ: Objection.
9 (As read): 10 "Fastest, the most affordable, and	
	9 MR. FRITZ: Objection.
10 "Fastest, the most affordable, and 11 stable, doesn't need any login or 12 authentication, scrapes data (detailed	9 MR. FRITZ: Objection. 10 BY MS. GOVERNSKI:
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10 "Fastest, the most affordable, and 11 stable, doesn't need any login or 12 authentication, scrapes data (detailed 13 posts, comment with votes, media,	9 MR. FRITZ: Objection. 10 BY MS. GOVERNSKI: 11 Q Sorry. Go on. 12 A We would have provided the keywords 13 under, I believe it's under information.
10 "Fastest, the most affordable, and 11 stable, doesn't need any login or 12 authentication, scrapes data (detailed 13 posts, comment with votes, media, 14 links, and replies) from Reddit based	9 MR. FRITZ: Objection. 10 BY MS. GOVERNSKI: 11 Q Sorry. Go on. 12 A We would have provided the keywords 13 under, I believe it's under information. 14 MS. GOVERNSKI: Okay. I actually have
10 "Fastest, the most affordable, and 11 stable, doesn't need any login or 12 authentication, scrapes data (detailed 13 posts, comment with votes, media, 14 links, and replies) from Reddit based 15 on a provided subReddits, username,	9 MR. FRITZ: Objection. 10 BY MS. GOVERNSKI: 11 Q Sorry. Go on. 12 A We would have provided the keywords 13 under, I believe it's under information. 14 MS. GOVERNSKI: Okay. I actually have 15 that. So let's go to the next Reddit scraper,
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10 "Fastest, the most affordable, and 11 stable, doesn't need any login or 12 authentication, scrapes data (detailed 13 posts, comment with votes, media, 14 links, and replies) from Reddit based 15 on a provided subReddits, username, 16 specific link, or the homepage, with an 17 optional limit on the number of posts 18 retrieved." 19 Do you see that? 20 A I do. 21 Q So what subReddits did you enter here?	9 MR. FRITZ: Objection. 10 BY MS. GOVERNSKI: 11 Q Sorry. Go on. 12 A We would have provided the keywords 13 under, I believe it's under information. 14 MS. GOVERNSKI: Okay. I actually have 15 that. So let's go to the next Reddit scraper, 16 Autumn. 17 THE WITNESS: Sorry. This is on manual 18 so I would just look at the Json. So if you would 19 like, I can refer to the Json file. 20 BY MS. GOVERNSKI: 21 Q Did you produce the Json file?
"Fastest, the most affordable, and stable, doesn't need any login or authentication, scrapes data (detailed posts, comment with votes, media, links, and replies) from Reddit based on a provided subReddits, username, specific link, or the homepage, with an optional limit on the number of posts retrieved." Do you see that? A I do. So what subReddits did you enter here? A So the excuse me. So the subreddit is	9 MR. FRITZ: Objection. 10 BY MS. GOVERNSKI: 11 Q Sorry. Go on. 12 A We would have provided the keywords 13 under, I believe it's under information. 14 MS. GOVERNSKI: Okay. I actually have 15 that. So let's go to the next Reddit scraper, 16 Autumn. 17 THE WITNESS: Sorry. This is on manual 18 so I would just look at the Json. So if you would 19 like, I can refer to the Json file. 20 BY MS. GOVERNSKI: 21 Q Did you produce the Json file? 22 A So that would have been part of
10 "Fastest, the most affordable, and 11 stable, doesn't need any login or 12 authentication, scrapes data (detailed 13 posts, comment with votes, media, 14 links, and replies) from Reddit based 15 on a provided subReddits, username, 16 specific link, or the homepage, with an 17 optional limit on the number of posts 18 retrieved." 19 Do you see that? 20 A I do. 21 Q So what subReddits did you enter here? 22 A So the excuse me. So the subreddit is 23 optional.	9 MR. FRITZ: Objection. 10 BY MS. GOVERNSKI: 11 Q Sorry. Go on. 12 A We would have provided the keywords 13 under, I believe it's under information. 14 MS. GOVERNSKI: Okay. I actually have 15 that. So let's go to the next Reddit scraper, 16 Autumn. 17 THE WITNESS: Sorry. This is on manual 18 so I would just look at the Json. So if you would 19 like, I can refer to the Json file. 20 BY MS. GOVERNSKI: 21 Q Did you produce the Json file? 22 A So that would have been part of 23 assumingly the raw data or the script that Taylor

77 (Pages 302 - 305)

CONFIDENTIAL Page 306 1 review the script that Taylor used? MR. FRITZ: Objection. THE WITNESS: So in the README file, it's A The Json, no. I reviewed the python and 2 3 the extracts. 3 looking at showing where the greatest amount of Q Okay. So you don't actually know what 4 volume came from and again, if those are the major 5 Taylor filled out to scrape Reddit? 5 subReddits, then that would take up a large amount MR. FRITZ: Objection. 6 of volume. Irrespective of the rest of Reddit.com. THE WITNESS: I don't have the data 7 BY MS. GOVERNSKI: 8 readily available in front of me to reference. Q Okay. Well, let's look at your input. 9 Let's mark as Exhibit 18 your Reddit input. Sorry. 9 BY MS. GOVERNSKI: 10 Q As you sit here today, you don't know 10 It was Exhibit 19, which is an Excel spreadsheet. 11 what Ms. Hunter did to scrape Reddit? By the way, who created the input 11 MR. FRITZ: Objection. 12 12 spreadsheets? THE WITNESS: I'm happy to reference it 13 13 (Exhibit 19 marked for identification.) 14 to provide an answer. A Those were done by Taylor. 14 15 BY MS. GOVERNSKI: 15 Q Did you review them? Q Well, you don't provide an answer in your A I looked through each of the Excels 16 17 report, right? 17 before submitting them. A The question isn't posed in my report. Q Okay. And so these input spreadsheets 18 18 Q But describing how you identified the 19 accurately reflect all of the data on which your 20 content on Reddit is not described in your report, 20 opinions are based? MR. FRITZ: Objection. 21 other than saying that you used an Apify scraper? 21 MR. FRITZ: Objection. 22 22 THE WITNESS: As a whole, it's based on 23 THE WITNESS: That's what I provided in 23 all of the data that we collected and analyzed. 24 BY MS. GOVERNSKI: 24 my report. Yes. 25 Q Yeah, so all of the five input files that Page 307 1 BY MS. GOVERNSKI: 1 comprise your entire dataset is what your opinions Q So Exhibit 18 is the information tab for 2 are based on, correct? 3 the same Reddit scraper you can say it says based on 3 A That is correct. 4 a provided subreddit username specific link or the 5 homepage and you see the specific input fields. 5 I'm told that all this weird stuff on top is from The actor accepts the following input 6 the CSV file conversion to Excel. 7 fields. If none are provided, it defaults to just 7 So if we go to 161, you see that this is 8 a post from January 5th 2024, which is consistent 8 scraping Reddit.com.

Page 309

Page 308

Q Okay. So let's scroll down to row 161.

9 with the README file explaining that the Reddit

10 dataset started back in January, right?

A So this is a time stamp of January 2024, 11

12 yes, via Reddit.

13 Q Okay. So that is consistent with the

14 README file which said that the Reddit dataset

15 collected content dating back to January 2024,

16 right?

17 A Yes. So the input date for Reddit should

18 have started in January 2024. That was input.

19 Q Okay. And if we go to column F, you see

20 it says "pop culture chat", right?

A I see that. 21

22 Q Okay. And that's one of those subReddits

23 that we talked about?

24 A Yes. That's one of them.

Q Okay. Can you look at the content and

9 (Exhibit 18 marked for identification.)

10 A Yes. I see that. So you don't have to

11 define an optional -- like I said, on the first

12 page, they were all optional. So if you do not put

13 a definition in, it scrapes Reddit as a whole.

Q Okay. So your dataset scraped Reddit as 14 15 a whole?

A I can answer that definitively if I

17 reference the Json file that she used.

O But the Json file --

19 A Because we didn't specify any optional

20 input in the README file, then I would say there

21 were no optional inputs that were added.

Q So was it just a coincidence that 608 of

23 the items in your Reddit dataset are from those

24 three specific subReddits identified in the README

25 file?

78 (Pages 306 - 309)

Page 310 Page 312 1 tell me how your BERT sentiment analyzer 1 BY MS. GOVERNSKI: 2 characterized this post? Q And isn't the most logical conclusion A I would have to -- I don't want to make 3 that you typed in -- or that Ms. Hunter typed in 4 an assumption. I would have to go back and look at 4 these three subReddits into the scraper? MR. FRITZ: Objection. 5 the score that was given. Q Okay. So we couldn't, based on this 6 THE WITNESS: No, because I believe there 7 data, know how your sentiment analyzer categorized 7 is data outside of the subReddits. 8 this post? 8 BY MS. GOVERNSKI: 9 MR. FRITZ: Objection. Q Right, but I'm talking about just the 608 10 THE WITNESS: Unless you reproduced it in 10 within the subreddit. 11 the BERT classifier. A I'm not sure I understand. You're asking 11 12 did she input into the optional field to identify 12 BY MS. GOVERNSKI: Q Okay. And if you scroll down. Let's 13 those specific subReddits? 14 just, Autumn, scroll down to column F a little bit. Q The specific subReddits that she noted in We see movies, movies, romance books, 15 her file that add up to 608 of the posts, isn't it 16 possible that she just searched those Reddits using 16 fauxmoi, movies, pop culture chat, pop culture chat, 17 romance books. 17 the data scraper we talked about? So does this column, row F, adequately A If she only searched those, then you 18 18 19 capture the subReddits that are comprised in your 19 wouldn't have data from any other section. 20 Reddit dataset? Q Unless she did an additional search, A This would pull from the subReddits, yes. 21 right, for that remaining 100 plus? 22 This would attach where the post pulled from across A I don't believe that's what she did. 22 23 Reddit. 23 Q But you don't know? 24 24 Q Okay. And we've already established that MR. FRITZ: Objection. 25 608 of these posts in this column were from those 25 THE WITNESS: I would say with confidence Page 311 Page 313 1 three subReddits that we identified in the README 1 that that is not -- not how she utilized the 2 file, right? 2 scraper. 3 A Yes. From a volume perspective. Yes. 3 BY MS. GOVERNSKI: Q And you don't really know why the scraper Q But as you sit here today, you can't tell 5 pulled 608 items specifically from those three 5 us what she did to utilize the scraper. 6 subReddits, right? MR. FRITZ: Objection. 6 7 THE WITNESS: I did not give her any A I would guess that it was because the 8 keywords were relevant or the content somehow was 8 direction to add in optional fields, so I do not 9 relevant based on, again, Blake Lively, 9 believe that she took it on her own onus to add in 10 It Ends with Us, and the other keywords that I 10 subreddit classifiers into fields that were 11 specify in the report. 11 optional. Q Well, why do you have to guess? 12 12 BY MS. GOVERNSKI: A Because I didn't write the code for the 13 Q But how do you explain that the API 14 scraper that you used specifically does not 14 scraper. Q So we would have to ask Ms. Hunter to 15 contemplate entering search terms? 16 really understand how you identified your dataset? 16 MR. FRITZ: Objection. MR. FRITZ: Objection. THE WITNESS: So the subReddits, or the 17 17 THE WITNESS: No, I'm not the one who 18 categories that are the largest across any social 18 19 wrote the API, for instance, for Reddit because the 19 media platform, will be ones that come back most 20 question, I believe, was why did it pull this 20 often with data, especially if the information is 21 particular data. So that wouldn't be necessarily on 21 relevant to that particular genre, classification, 22 the README file. That would also be on how the 22 subreddit. 23 scraper itself is -- or how API is used across 23 BY MS. GOVERNSKI: 24 Reddit. 24 Q Okay. Let's go to row 225. And sorry --

79 (Pages 310 - 313)

25 oh, no. Sorry. 227. You see the post "Frances

Page 314 Page 316 1 Bean Cobain Pays Tribute to Her father, Kurt Cobain, 1 that's global or U.S. 2 30 years After His Death," and in column Fit's 2 BY MS. GOVERNSKI: 3 FauxMoi. Q But it doesn't sound crazy to you that 4 there would be tens of millions of TikTok videos Do you see that? 4 5 A Yes, I'm on that row. 5 every day posted? 6 Q Okay. And that's the post we looked at 6 A No, that sounds rational. 7 earlier, right? Q Okay. Exhibit 20 is your -- the TikTok 7 8 README file. Do you see that on your screen? A It has the same title, yes. 8 Q Okay. And the same subreddit, FauxMoi? 9 9 10 10 Q Okay. And you see it says "Analysis of Q Okay. So how did your BERT sentiment 11 Blake Lively TikTok videos, 688 videos total from 11 12 analyzer characterize this post? 12 the dataset." 13 MR. FRITZ: Objection. 13 Is that right -- is that right? THE WITNESS: So I think -- you asked me A Sorry, just give me a second. 14 15 that question when we were looking at the actual 15 August 27th, I believe that's correct. 16 image. So again, I would say it should have Q Okay. So when you look at what it 16 17 classified it as null or neutral. 17 calculates, you see the baseline period mean about 18 eleven videos per month; is that right? Is that 18 BY MS. GOVERNSKI: 19 accurate? Q Okay. So how many of the posts in this 20 dataset should have been qualified as null or 20 MR. FRITZ: Objection. 21 neutral? 21 THE WITNESS: I'd want to go into the 22 dataset to just confirm, but that's what this reads, 22 A I would have to go through and look at 23 them individually to see which ones would be 23 yes. 24 classified as positive sentiment, negative 24 BY MS. GOVERNSKI: 25 sentiment, null, or neutral. 25 Q Okay. But we talked about earlier that Page 315 Page 317 1 Q Okay. From this, we wouldn't be able to 1 you would have confirmed the accuracy of the README 2 determine these things? 2 files before you produced them to us, right? A On how the classifier would classify it, A I would have gone through and README each 4 no, we're not able to tell based on this. 4 of the README me files. MS. GOVERNSKI: Let's -- Autumn, if you Q So this README file says that there were 6 can move the TikTok README and we will mark that as 6 eleven videos per month, which is about 33 videos 7 Exhibit 20. 7 from May to July 2024; is that right? (Exhibit 20 marked for identification.) 8 A That's what this says, yes. Q Okay. And it says the August spike is 9 9 BY MS. GOVERNSKI: 10 187 videos, right? Q Do you know, Ms. Alexander, how many 11 videos are on TikTok every month? 11 A It does. A In TikTok? Q Okay. So your analysis of the August 12 12 13 spike, with respect to TikTok, was based on 187 13 O Uh-huh. 14 A I don't know offhand, no. 14 videos? 15 Q What about every day? 15 A That's what this says. Again, I would A I don't know offhand. 16 16 want to check the data. 17 Q Ballpark? Q Okay. We'll do that. And then September 17 18 MR. FRITZ: Objection. 18 dropped to 31, right? 19 THE WITNESS: I couldn't even venture to 19 A Based on this read my file, yes. 20 guess. 20 Q Okay. And then the -- in the results, 21 BY MS. GOVERNSKI: 21 the results in the README file would be based on the Q Does 34 million sound like maybe around 22 other data described in the README file, right? 23 what you would expect? 23 A I'm not sure I understand the question. MR. FRITZ: Objection. 24 Q I mean, the results here are based on the 24

80 (Pages 314 - 317)

25 number of posts it describes that we just discussed,

THE WITNESS: I guess it would depend if

CONFIDENTIAL		
Page 318	Page 320	
1 right?	1 refresh your recollection. If you can put it on the	
2 A So	2 screen on page 109. Okay. You see it says "Apify	
3 MR. FRITZ: Objection.	3 TikTok hashtag crawler actor."	
4 THE WITNESS: again, I would want to	4 Do you see that?	
5 go in and just double check that the that the	5 A Oh, so if that's the way I identified it	
6 total numbers are, indeed, accurate. But the	6 there, then I'm assuming that is the way it is it	
7 results should be consistent with what I have in my	7 has named itself, yes.	
8 report.	8 Q Well, why are you assuming if you put it	
9 BY MS. GOVERNSKI:	9 in your appendix?	
10 Q And the comment that:	10 A So if that's the way that it is	
11 (As read):	· ·	
, ,	11 described, then when I use it in sourcing, I use the	
5	12 verbiage of what it is called.	
platforms: Movie came out August 9th,	13 Q Okay. And do you understand that TikTok	
alleged campaign, August 2nd, can't say	14 hashtag scraper allows you to extract data from	
what caused it from timing alone"	15 TikTok videos that used a particular hashtag?	
16 Is still your opinion, right?	16 A Yes.	
17 A Yes, again, going back to use of the word	17 Q So what specific hashtags did you use?	
18 "definitive" that we talked about earlier.	18 A So you don't have to specify a hashtag,	
19 Q Okay. So you but they don't use the	19 just to be clear. You can use keywords in that	
20 word she doesn't use the word "definitive" here,	20 scraper as well.	
21 right?	21 MS. GOVERNSKI: Okay. Well, let's take a	
22 A I believe I use it in my report.	22 look at that scraper. Actually, before we do, the	
23 Q Right. But not it's not in the README	23 TikTok hashtag scraper is called TikTok hashtag	
24 file, right?	24 crawler actor. Okay. Let's look at Exhibit 21.	
25 MR. FRITZ: Objection.	25 And Autumn, go ahead and do Exhibit 22 as the TikTok	
Page 319	Page 321	
1 THE WITNESS: The README file was written	1 input.	
2 by Taylor Hunter, the report was written by myself.	2 (Exhibit 21 marked for identification.)	
3 BY MS. GOVERNSKI:	3 BY MS. GOVERNSKI:	
4 Q Oh, so do you not stand behind	4 Q You should have Exhibit 21 in your	
5 Ms. Hunter's work as described in the README files?	5 Exhibit Share. We will put it in up on screen.	
6 MR. FRITZ: Objection.	6 You see this is Apify TikTok hashtag	
7 THE WITNESS: I use different verbiage,	7 scraper, right?	
8 based on, again, analyzing and doing the	8 A Yes.	
9 interpretation of the data. That's why I am the end	9 Q It says:	
10 publisher of the report. This is information that	10 (As read):	
11 Taylor is feeding in based on her analysis,	11 "What is TikTok Hashtag Scraper. It's	
12 aggregation, and pulling of the datasets.	12 a powerful tool that allows you to	
13 BY MS. GOVERNSKI:	extract data from TikTok videos that	
14 Q But you didn't make any edits to her	14 use a particular hashtag."	
15 comments in the README file, right?	Do you see that?	
16 A No, I did not.	16 A Yes, I'm reading it.	
17 Q And you used a TikTok hashtag crawler	17 Q Okay. And then if you look, it provides	
18 actor, right?		
18 actor, right? 19 A I'm sorry. A hashtag crawler actor?	18 how to scrape TikTok with the TikTok hashtag	
19 A I'm sorry. A hashtag crawler actor?	18 how to scrape TikTok with the TikTok hashtag 19 scraper. And it has five specific points. The	
19 A I'm sorry. A hashtag crawler actor? 20 Q Uh-huh.	18 how to scrape TikTok with the TikTok hashtag 19 scraper. And it has five specific points. The 20 third of one, says "Add one or more TikTok	
 19 A I'm sorry. A hashtag crawler actor? 20 Q Uh-huh. 21 A So it was the actor for the API for 	18 how to scrape TikTok with the TikTok hashtag 19 scraper. And it has five specific points. The 20 third of one, says "Add one or more TikTok 21 hashtags."	
 19 A I'm sorry. A hashtag crawler actor? 20 Q Uh-huh. 21 A So it was the actor for the API for 22 TikTok, I don't believe it actually calls itself a 	18 how to scrape TikTok with the TikTok hashtag 19 scraper. And it has five specific points. The 20 third of one, says "Add one or more TikTok 21 hashtags." 22 Do you see that?	
 19 A I'm sorry. A hashtag crawler actor? 20 Q Uh-huh. 21 A So it was the actor for the API for 22 TikTok, I don't believe it actually calls itself a 23 crawler. I don't remember that verbiage in the way 	18 how to scrape TikTok with the TikTok hashtag 19 scraper. And it has five specific points. The 20 third of one, says "Add one or more TikTok 21 hashtags." 22 Do you see that? 23 A Yes, I do.	
 19 A I'm sorry. A hashtag crawler actor? 20 Q Uh-huh. 21 A So it was the actor for the API for 22 TikTok, I don't believe it actually calls itself a 	18 how to scrape TikTok with the TikTok hashtag 19 scraper. And it has five specific points. The 20 third of one, says "Add one or more TikTok 21 hashtags." 22 Do you see that?	

81 (Pages 318 - 321)

CONFIDENTIAL		
Page 322	Page 324	
1 A So we would not have used hashtags. So I	1 Q Okay. Let's go to 31 and 32. These are	
2 would have to go back into the dataset to see if	2 the same two, right, as each other?	
3 this is the appropriate scraper or if it's a	3 A Yes.	
4 different one.	4 Q Do you have any idea of how many of the	
5 Q So when you listed a TikTok hashtag	5 entries in your TikTok data are actually duplicates?	
6 crawler, it's your testimony that you did not	6 A I don't know.	
7 actually ask it to crawl certain hashtags?	7 Q Isn't it important for you to know that?	
8 MR. FRITZ: Objection.	8 MR. FRITZ: Objection.	
9 THE WITNESS: No. So hashtags some	9 THE WITNESS: It's not necessarily	
10 hashtags came with the data, but the point of the	10 important. Because again, as I'm pulling them from	
11 data analysis was not to specify a hashtag, so it	11 the scraper or from the API, TikTok is looking at	
12 shouldn't have been this particular scraper.	12 these as individual entries, which is why they are	
13 BY MS. GOVERNSKI:	13 on individual rows, assuming on the conversion	
14 Q How would I determine what scraper you	14 process from the file that I submitted. So they may	
15 used if it's not the scraper that you listed in your	15 be duplicative, but if you were to back out why they	
16 materials?	16 show up twice, the assumption is they would show up	
17 A So I would have to check the output data,	17 twice on two different accounts.	
18 but we did not use a hash we did not use	18 BY MS. GOVERNSKI:	
19 hashtags. We identified the keywords that I	19 Q Okay. So let's assume, hypothetically,	
20 mentioned in my report. So it would have to be a	20 that every single one of your TikTok videos is in	
21 scraper that was not hashtag only.	21 here twice, that would mean that your dataset of	
22 MS. GOVERNSKI: Okay. So let's go to	22 TikTok videos is not actually 688, it's 688 divided	
23 Exhibit 22, which is your TikTok input data. And	23 by two, right?	
24 we'll mark this as Exhibit 22.	•	
25 (Exhibit 22 marked for identification.)	24 A Based on the assumption that you just 25 outlined?	
23 (Exhibit 22 marked for identification.)	23 Outilieu?	
Page 323	Page 325	
1 BY MS. GOVERNSKI:	1 Q Yup.	
2 Q Okay. Let's well, I don't know, let's	2 A Based on your assumption, that's one way	
3 look at rows 3 and 4. That looks like the exact	3 of calculating, yes.	
4 same post, right?	4 MS. GOVERNSKI: Okay. Let's go to what	
5 A Rows 3 and 4?	5 we will mark as Exhibit 23, which will be the	
6 Q Uh-huh.	6 YouTube README.	
7 A Yes.	7 (Exhibit 23 marked for identification.)	
8 Q Why does your data include two of the	8 BY MS. GOVERNSKI:	
9 same posts?	9 Q You should have Exhibit 23 now.	
10 A Let's look at the time stamp.	10 A Yes.	
Q Let's scroll over. We can look at all	Q And you see that this says "16,337	
12 the columns to see that they are all the same.	12 comments."	
A I'm not sure why there's duplicate, but	Do you see that?	
14 it could be from translation, it could be from	14 A 1,789 comments?	
15 I'm not sure	Q 16,337 comments, right?	
16 Q Okay.	16 A This is YouTube analysis?	
17 A each post should be a unique post.	Q YouTube analysis, on the screen.	
18 Q It should be. Why is that?	18 A Oh, at the top, it says 16,337. Yes.	
A So again, it may be a unique post. It	19 Q Okay. That says "comments," not videos,	
20 may be an identical post so it could have been from	20 right?	
21 two different	21 A This says "comments," yes.	
22 (Witness reading.)	22 Q So your YouTube analysis looked only at	
I don't see any differentiation across	23 comments?	
24 any of the columns, so I'm not sure why it shows up	24 A I would have to go back into the data,	
25 twice.	25 but to see how how it was collapsed. So if it	

82 (Pages 322 - 325)

Page 326	Page 328
1 looked at comments only, or if each line had a	1 explanation."
2 comment, along with any additional metadata or data	2 Do you see that?
3 from the videos.	3 A I do.
4 Q But that would be in your input files,	4 Q Is that your opinion or is that
5 right?	5 Ms. Hunter's opinion?
6 A No, not necessarily.	6 MR. FRITZ: Objection.
7 Q What do you mean?	7 THE WITNESS: So that is an inference
8 A So if I classify something as a post on	8 that Ms. Hunter made. It is an inference that I've
9 Instagram, you can interpret that as one post, or as	9 also made in addition to that.
10 some of the images that you showed me, there was one	10 BY MS. GOVERNSKI:
11 post but there were multiple frames that you have to	11 Q Okay. So what is your basis for
12 analyze. So depending how the data what is able	12 understanding that spikes in January and February
13 to be extracted with the data, it could show	13 and October were related to newsworthy events?
14 information for that one Instagram post that you	14 A So based on the data, we saw that there
15 show. But as I mentioned, there were like five	15 was the spike initially in August. And then in
16 different tabs. So it could also give information	16 December, around the time of filing the lawsuit,
17 for those different tabs.	17 there was additional spike.
18 Q So that wouldn't be in the Excels that	18 Q So you didn't consider any other events
19 you produced to us?	19 that occurred in December that could have caused
20 A No, it should. If it was available, it	20 that spike?
21 should.	21 A I didn't see I didn't find any other
22 Q So that was my question. If you pulled	22 data that highlighted other key news cycles that
23 more than the comments, that would be reflected in	23 would be able to be considered.
24 the input Excel that you provided us.	Q In the dataset, in your dataset, right?
25 A In the dataset, yes.	25 A Correct.
Page 327	Page 329
1 Q Okay. And if let's go down to	1 Q You didn't go out and look for other
2 magnitus Wall actually vya com atom vyith vyhat it	2 avalenations?

2 results. Well, actually, we can start with what it 3 calculates. It shows 85 comments per month for the 4 May to July. 1789 comments for August. And 445 for 5 September. Do you have any reason to think that 6 those numbers are inaccurate? A No, I don't believe they are. I believe 8 they are accurate. Q Okay. And then in results, it again says 10 "spike is absolutely massive." And in the second 11 paragraph, it says: 12 (As read): 13 "Same timing issue as all other 14 platforms - movie came out August 9, 15 alleged campaign August 2. Can't definitively say which caused it." 16

17 Right? 18 A Yes, I'm reading that. 19 Q Then is says: 20 (As read): 21 "Then there were additional spikes in

22 January/February (when lawsuit was 23 filed) and October 2025 - which shows

24 that volume correlates with newsworthy

25 events, supporting organic 2 explanations?

A No, I didn't actively look at

4 macroeconomic factors.

MS. GOVERNSKI: Okay. Let's' look at the 5 6 input for your YouTube, which should be Exhibit 24.

(Exhibit 24 marked for identification.)

8 BY MS. GOVERNSKI:

This is your underlying YouTube data,

10 right?

11 Yes, this looks like the CSV.

12 Okay. And so column B shows the time

13 stamp, you see it starts with May 16, right?

14 A Yup.

Q Okay. And let's go over to column I, you 15

16 see "search term," so that reflects the search terms

17 that you used in YouTube, right?

A That is the search term that is used with 18

19 the scraper, yes.

20 Q Yeah, so why -- well, a scraper, you

21 didn't use a scraper, you used the YouTube data API,

22 right?

23 A With the API.

24 Okay. So why does this spreadsheet have

25 a search term and your other spreadsheets don't?

CONFIDENTIAL Page 330 Page 332 1 A It would be the way we were able to MR. FRITZ: Objection. 2 extract the file itself. THE WITNESS: So we collected what was Q So if you didn't actually use search 3 available via the keywords that we entered and the 4 terms with the other scrapers, could that also be an 4 time frame. This is the dataset that was given back 5 explanation of why there is not a column that says 5 from the API. 6 "search terms"? 6 MS. GOVERNSKI: Okay. Autumn, let's get A No, the output of the files is dependent 7 Exhibit 25, which is the post that matches what we 8 on the parameters that either a scraper or an API 8 just looked at, the It Ends with Us trailer. 9 gives you back. So you wouldn't add or remove (Exhibit 25 marked for identification.) 10 anything. 10 BY MS. GOVERNSKI: 11 Q So if we go to -- there is video ID 11 Q And how many comments do you see in this 12 column, column F and a title of the video in J. 12 document? 13 Do you see that? 13 A In total -- let's see, 8,582 comments. A Column F, yes --14 14 Q Okay. So why does your dataset only 15 Q And J. 15 include 200 of them? Do you see that? 16 16 A There's -- one of the possible reasons is 17 A Yes. 17 because there is a maximum amount of comments that Q Okay. And you see the video title for --18 18 are available via the API. I'd have to go back to 19 gosh, everything on screen right now is 19 YouTube's API to just double check that. But 20 It Ends with Us official trailer, right? 20 there's usually a maximum. It could also mean that, 21 A For video title, yes. 21 at the time, that was all that was available. I 22 Q Yeah. So who picked this video? 22 mean, I'm not sure of the specific reason why. 23 A I'm not sure what you mean "who picked 23 Q That's a pretty big difference between 24 the video." 24 208,000. Wouldn't that be important for you to 25 Q Well, who picked to analyze this video? 25 understand? Page 331 Page 333 1 A So all of this data came back based on 1 MR. FRITZ: Objection. 2 the keywords and the time that we provided to 2 THE WITNESS: So it wouldn't if the 200 3 YouTube's API. 3 is a randomized sample of the 8,352. 4 BY MS. GOVERNSKI: MS. GOVERNSKI: So Autumn, can you copy 5 the video ID here? The Dlet_U31, can you copy that? Q Well, how do you know whether the 200 is 5 6 And then can you do a filter for that? If you go to 6 an accurate sample of the 8,000 posts? 7 the -- yeah, perfect. Oh, no. You just took it A All I can say is that based on the API, 8 away. Thank you. And go to video ID, and let's 8 that is the data that we would have received from --9 look for that one. Autumn, if you just go -- wait, 9 from scraping or from providing those keywords. So 10 Autumn. Can you just -- go to -- go out of this. 10 I would assume that there is a maximum. I would

11 Just go to the top -- the arrow, the arrow on F, on

12 F, the arrow on F. Right there and paste it right

13 here under "search." Okay? And then do "okay."

14 BY MS. GOVERNSKI:

Q So do you see on the bottom left,

16 Ms. Alexander, it's 200 of 16,337 records?

17 A 200 -- yes, I see that.

Q So why are there exactly 200 comments to 18

19 this trailer?

20 MR. FRITZ: Objection.

21 THE WITNESS: I wouldn't know why there

22 is 200 comments on a trailer.

23 BY MS. GOVERNSKI:

Q Do you know whether you could have 24

25 collected all of the comments to this trailer?

11 have to go into -- I'm not as familiar with

12 YouTube's API, I would have to confirm and why it

13 would cut off. But the likely assumption is that

14 there are sometimes maximum amounts of downloads

15 that you could get. And I'm assuming it was cut off

16 at 200, which is why it's a specific number.

17 Q Well, I don't understand why you have to

18 assume that if this is your report and your search.

19 MR. FRITZ: Objection.

20 BY MS. GOVERNSKI:

Q Why don't you know whether the API that 21

22 you used was capped at 200 comments?

23 A That's not readily -- that's not

24 knowledge I readily have available.

Who would have that my knowledge readily

84 (Pages 330 - 333)

Page 336		CONFIDENTIAL				
2 MR. FRITZ: Okay. You can answer that. 3 BY MS. GOVERNSKI: 4 Q Ms. Hunter? 5 A Google – no, Google. 6 Q Okay. 7 A YouTube. 8 Q And you didn't think it was important for you to understand that. 10 MR. FRITZ: Objection. 11 THE WITNESS: I don't think that it would 2 change the analysis. 13 BY MS. GOVERNSKI: 14 Q Okay. Are you aware of how many people 15 viewed this trailer? Are you aware when the trailer 6 came out? 17 A No, no. 18 Q Are you aware that the trailer came out 19 during the baseline period? 19 A I wasn't until you just mentioned it. 20 Q Wouldn't that feter your analysis of 22 what the appropriate baseline period is? 21 Q Wouldn't that dieter your analysis of 22 what the appropriate baseline need to come from a 3 THE WITNESS: Not necessarily. So 4 ideally, a baseline should be of a non-statistically 5 significant news cycle or period of time without any 6 large media cycles. So if, as you said, this came 7 out during that period of the baseline, that would a actually increase, assumingly, my overall baseline and not lower it. Which would then mean the spike, 10 subsequently — again, assumptions — that the spike 11 subsequently wasn't as high from the baseline as I 2 originally thought. 14 Q Okay. Let's goto for ow 53. And it says: 11 lime? 15 Tows 2 through 7, you see rows 2 and 3, 4 and 5, 6 and 7, 8 and 9, 10 and 11, 12 and 13, I mean, all 17 the way down, they're exact duplicates. Fight, they 18 are counted twice. 24 THE WITNESS: So duplicate — so I just 19 was 10 and 11, 12 and 13, I mean, all 19 the way down, they're exact duplicates. Fight, they 18 are counted twice. 25 THE WITNESS: So duplicate — so I just 19 was 10 and 11, 12 and 13, I mean, all 19 the way down, they're exact duplicates. Fight, they 18 are counted twice. 3 THE WITNESS: So duplicate — so I just 19 was 10 and 10 to know the was a the exact duplicates. Fight, they 18 are counted twice. 3 THE WITNESS: So duplicate — so I just 19 was 10 and 10 to know 10 the mean the spike. 10 Q Okay. Let's go to row 53. And it says: 11 was 10 and		Page 334		Page 336		
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MS. GOVERNSKI: There was. My question 25 A Or this data specifically, and go through	l .			=		
	24	So just note my objection.	24	Q The data that you didn't provide us?		

85 (Pages 334 - 337)

Page 338 Page 340 1 each one. A I would have to check the data file -- I Q Okay. Well, let's do that. How do you 2 mean, sorry. The data folder itself. If they are 3 know how this one was categorized? 3 not in there, to caveat, that's not necessary to A So I could replicate that, as you could, 4 reproduce it. 5 by putting the data into the classifier that's Q So how would we know what nodes you used? 6 accessible and seeing the output on what the score 6 A So unless I'm fine-tuning the nodes 7 is. 7 themselves, you can use any nodes outside of Google 8 or any other third party in order to look at a 8 Q Was this one of the posts that you 9 manually checked? 9 similar analysis. A I do not know. 10 Q And what are your edges? MS. GOVERNSKI: Okay. I think we can 11 A I don't know without looking. 11 12 pause right now. I'd like to go off the record. 12 Q Okay. So you wouldn't know unless you 13 THE VIDEOGRAPHER: We're off the record. 13 looked at the data? 14 MS. GOVERNSKI: John, can you tell me how 14 A Correct. 15 15 much time we've been on the record? Q Okay. And you conducted a time series 16 THE VIDEOGRAPHER: Sure. Off the record. 16 forecasting, right? A That's in the report, yes. 17 It's 7:42 p.m. 17 18 (Recess). 18 Q But you didn't use your BERT sentiment 19 THE VIDEOGRAPHER: We're back on the 19 analysis for purposes of the time series 20 record. It's 7:49 p.m. 20 forecasting, right? 21 BY MS. GOVERNSKI: 21 A No, I did not. 22 Q Ms. Alexander, you create -- your report Q Why didn't you? 23 says you performed a network structure analysis; is 23 A Because BERT is -- is -- does its best 24 that right? 24 job on looking at natural language processing versus 25 25 forecasting. I used it for the sentiment analysis A Yes. Page 339 Page 341 1 Q Have you -- well, what are your notes? 1 specifically. 2 A I'm sorry. What are my notes? 2 Q What is your basis for that statement 3 Q Nodes. N-O-D-E-S. 3 about BERT being best used for the way you used it A Oh, I'm sorry. So the nodes that I used 4 but not for time series forecasting? 5 for the analysis are from Google -- sorry, there's a A BERT was built to be a natural language 6 word associated with it. 6 processor. It has a myriad of data that backs it up 7 Q What are you looking at right now, 7 for contextualization, tonality. It's -- it's an 8 Ms. Alexander? 8 industry standard for use. A I'm looking at my report. Q But why wouldn't you -- well, what did 10 Q Okay. Where in your report does it 10 you use for your sentiment -- time series 11 describe your nodes? 11 forecasting sentiments? 12 A On page -- actually, so it doesn't 12 A I used the -- I used the -- I used just 13 describe it on the report itself. 13 the forecasting. I used a regression model and a 14 Q Okay. So how would I know what your 14 forecasting technique. 15 nodes were? Q How did you identify the sentiment of the A I would have to go back into the dataset 16 posts for purposes of your time series forecasting? 17 that I provided you in the -- in the 17 A I took it from the sentiment, the 18 README file. I'm not sure where I included it. 18 aggregate sentiment of the -- of the output of BERT. 19 Q You didn't produce any work product 19 Q Oh, so you did use the BERT outcome for 20 relating to your network structure analysis? 20 purposes of the time series forecasting? 21 A So that's not necessary to replicate the 21 A As the baseline for sentiment, but the 22 data. 22 forecast itself was done with a regression model. 23 Q Well, you just described that the nodes 23 Q Okay. So you did not use a keyword-based 24 would be located in a README file, but you didn't 24 classification for your time series forecasting? 25 produce to us with the README file, right?

86 (Pages 338 - 341)

A For my time series, with the spike and

Page 342

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1 without the spike, that's a specific chart in my

- 2 report, the baseline is the outputs of BERT, which
- 3 is a classifier. And I used a regression model
- 4 forecasted with the spike and without the spike.
- 5 Q And so when, in your report, you describe
- 6 using 20 positive keywords and 20 negative keywords,
- 7 how did you use those keywords?
- 8 A So those keywords are still the keywords
- 9 based on the inputs that I provide in my report.
- 10 Those keywords were the ones that I used
- 11 consistently for the scraper across the APIs and
- 12 were part of the aggregate of the data that came out
- 13 of the classifier. And I used that into the
- 14 regression model.
- 15 Q Well, you have 20 -- you have specific
- 16 keywords here. You say positive keywords like love,
- 17 amazing, talented, support, and then negative
- 18 keywords like hate, terrible, toxic, boycott. So
- 19 it's your testimony that you used those terms in
- 20 your BERT analysis?
- 21 A So I pulled out the major cluster of --
- 22 based on volume. I pulled those out, and I asked
- 23 it -- sorry. I instructed the system to give me a
- 24 sentiment score based on those keywords. Based on
- 25 the output from the BERT model, or BERT classifier,

Page 344

- A So in order to recreate the forecast with
- 2 spike and without spike, you are able to go into the
- 3 dataset I provided and Python code, and you should
- 4 be able to replicate it, based on everything I
- 5 provided.
- 6 Q Well, you didn't provide us with all of 7 your positive and negative keywords.
- 8 A But it's not based on all of the positive
- 9 and negative keywords. So if you look -- so if you
- 10 take the output from BERT, which is the classifier,
- 11 it provided aggregate sentiment scores. I used that
- 12 as a base. Outside of that, I also looked at
- 13 keywords that were associated with the sentiment,
- 14 and I provided a forecast and a counterfactual.
- 15 Q So if we wanted to recreate, how would we 16 find the complete list of the keywords that you
- 17 used?
- 18 A You don't need the complete list of the
- 19 keywords in order to recreate it. So if you go into
- 20 the files that I provided, you should be able to see
- 21 the details in the dataset and the README file.
- Q Who came up with the list of keywords?
- 23 A For that specific -- for the forecast and
- 24 the counterfactual?
- 25 Q Uh-huh.

Page 343

1

- Page 34
- 1 I then conducted a regression analysis.
 2 O So why didn't you just use the sentiment
- 3 scores from the BERT model that we discussed 4 earlier?
- 5 A Because the total sentiment was an
- 6 aggregate. So I needed more granular information
- 7 than the aggregate scores.
- 8 Q But you testified earlier that you could
- 9 look at the specific scores for each post.
- 10 A And in a subsequent question that you
- 11 asked me was why I did not give that as an output.
- 12 One of the reasons is because it was difficult to
- 13 get the data on a subaggregate level out of BERT in
- 14 order to do the analysis. So --
- 15 Q I understand -- sorry. Go on.
- 16 A So I used specific keywords.
- 17 Q Okay. So your time series forecasting
- 18 depends on both, as an initial level, the BERT
- 19 sentiment classifier and then -- and keywords from
- 20 the BERT sentiment analysis?
- A So it's the sentiment scores, the
- 22 keywords that I provided, and then outside of that,
- 23 the final step is to do a forecast.
- 24 Q Okay. So if I wanted to recreate what
- 25 you just described, how would I do that?

- Page 345
- 2 Q Okay. So do you have that list?

A I believe that was me.

- 3 A I would have to look at the -- I would
- 4 have to look at my data folder.
- 5 Q Do you have a data folder of --
- 6 A The zip file that I provided to -- to
- 7 counsel.
- 8 Q Okay. So you're saying that the data
- 9 file you provided us should include the list of
- 10 keywords that you used?
- 11 A It should provide you with everything you
- 12 need to replicate --
- 13 Q That wasn't my question.
 - MR. FRITZ: Objection.
- 15 BY MS. GOVERNSKI:
- 16 Q Does the data you provided us include the
- 17 list of all the keywords you used?
- 18 A I would have to look to see if that is
- 19 included.

14

- 20 Q Okay. So how often have you created a
- 21 regression model?
- A How often?
- 23 O Yeah.
- 24 A I -- so a regression analysis, I've done
- 25 it at Ipsos, as well as Nielsen, as part of leading

87 (Pages 342 - 345)

Page 346

CONFIDENTIAL

1 the Bases team, which is a product that we use on a

- 2 daily basis for clients.
- 3 Q How often did you create a regression?
- 4 A I probably did regressions or checked
- 5 regressions that my team did on a weekly basis.
- 6 Q Okay. Your report lists certain
- 7 documents including Ms. Lively's discovery
- 8 responses. Did you personally review all of her
- 9 responses to the interrogatories?
- 10 A The last word was "interrogatories"?
- 11 Q Yup.
- 12 A I'm not sure what -- what you mean.
- 13 Q In your Exhibit Appendix C, it states
- 14 that you reviewed Ms. Lively's third amended
- 15 responses and objections to a set of
- 16 interrogatories. It lists four documents. I'm
- 17 wondering if you reviewed personally all of those
- 18 interrogatory responses.
- 19 A I would have, yes. I went through the
- 20 files meticulously, so --
- 21 Q Okay.
- 22 A -- I went through everything that was
- 23 provided.
- 24 Q Okay. And did you review the underlying
- 25 materials that are referenced in the

- Page 348
- 1 I'm not sure if it's from the amended or from
- 2 Dr. Mayzlin and Dr. Humphreys.
- 3 Q Okay. So in one of the communications,
- 4 they talked about successfully shifting the
- 5 narrative online. Did you consider that
- 6 communication?
- 7 A The communication, no, that was not part
- 8 of my consideration. So the goal that I went into
- 9 with analyzing was to look at it without assumptions
- 10 or applied assumptions to look at the dataset from a 11 clean perspective.
- MR. FRITZ: John, how long have we been
- 13 on the record?
- MS. GOVERNSKI: Well, we can go off the
- 15 record, if you want to get a check of the time.
- 16 THE VIDEOGRAPHER: Seven hours exactly.
- MS. GOVERNSKI: Was his question included
- 18 in that?
- 19 Okay. I have one final question. Are we
- 20 still on the record, John?
- 21 THE VIDEOGRAPHER: Yes.
- 22 BY MS. GOVERNSKI:
- 23 Q One final question. So when you said you
- 24 wanted to look at the data without considering the
- 25 external materials, you then did not consider any of
- Page 347

- 1 interrogatories?
- 2 A I'm not sure I reviewed the underlying
- 3 materials, no.
- 4 Q Okay. What was your response to parts of
- 5 the interrogatory that discussed how the defendants
- 6 boosted contents on social media?
- 7 A I can't -- I don't recall the data
- 8 that -- or the context that you're referring to.
- 9 Q Okay. Well, what is your reaction to
- 10 understanding that the defendants communicated about
- 11 boosting social media?
- 12 MR. FRITZ: Objection.
- 13 THE WITNESS: So I read through -- I
- 14 recall some of the claims, but I can't remember if
- 15 it was in that report or if it was part of
- 16 Dr. Mayzlin's and Dr. Humphreys' report and them
- 17 referencing it. I can't tease out the difference
- 18 between where the information came from in my mind.
- 19 BY MS. GOVERNSKI:
- 20 Q Okay. Well, Ms. Lively's interrogatory
- 21 included multiple pages of quotes from direct emails
- 22 and communications amongst the defendants.
- 23 Do you remember reviewing those?
- 24 A Not offhand. I remember some of it, but
- 25 again, I'm not sure if it's from the report or --

- Page 349
- 1 the communications amongst the defendants when you 2 were reaching your conclusions?
- 3 A I'm not sure I understand the question.
- 4 Are you talking about the underlying data that
- 5 was -- or the material that is referenced outside of
- 6 the actual amended itself?
- 7 Q I'm talking about in the interrogatory,
- 8 the specific quotes over multiple pages from email
- 9 communications and text communications amongst the 10 defendants.
- 11 A So, I'm sorry. So you keep using the
- 12 word "interrogatories," and that's not something I'm
- 13 familiar with. So I read through the amended -- the
- 14 amendment from Ms. Lively. If you're referring to
- 15 references of emails or, I don't know, any content
- 16 that was not in that amended document, then no, I
- 17 probably did not review and/or consider it.
- 18 MS. GOVERNSKI: Okay. I'm going to keep
- 19 this deposition open and seek relief from the Court
- 20 to have an additional 30 minutes of time, given how
- 21 the deposition started.
- MS. ADAMS-JACK: Can we claw back
- 23 Exhibit 26? We didn't get to it, and I think it
- 24 expired my ability to pull it back.
- THE STENOGRAPHIC REPORTER: That's a

88 (Pages 346 - 349)

Page 350	Page 352	
1 Maggie question.	1 REPORTER'S CERTIFICATE	
2 THE A/V TECHNICIAN: I think that should	2 I, ASHLEY SOEVYN, a Certified Shorthand	
3 be that can be done. I won't be able to do that	3 Reporter of the State of California, do hereby	
4 right now. I also don't have access to that because	4 certify:	
5 of the time that's elapsed. But we can we can	5 That the foregoing proceedings were taken	
6 figure that out.	6 before me at the time and place herein set forth;	
7 MS. GOVERNSKI: Okay. I will send an	7 at which time the witness was put under oath by me;	
8 email.	8 That the testimony of the witness, the	
9 THE STENOGRAPHIC REPORTER: Thank you.	9 questions propounded, and all objections and 10 statements made at the time of the examination were	
10 MS. GOVERNSKI: Okay. Well,		
11 Ms. Alexander, we may be back here, at least for	11 recorded stenographically by me and were thereafter 12 transcribed;	
12 some time, so we will work to schedule that	13 That a review of the transcript by the	
13 promptly.	14 deponent was/ was not requested;	
14 MR. FRITZ: And the record should reflect	15 That the foregoing is a true and correct	
	16 transcript of my shorthand notes so taken.	
15 we proposed an additional five minutes to avoid	17 I further certify that I am not a relative	
16 judicial intervention and that was rejected by	18 or employee of any attorney of the parties, nor	
17 Ms. Lively's counsel.	19 financially interested in the action.	
18 THE STENOGRAPHIC REPORTER: And Counsel,	20 I declare under penalty of perjury under	
19 do we need that part with the judge earlier on that	21 the laws of California that the foregoing is true	
20 court call, do we need that transcribed with the	22 and correct. Dated this 16th day of December, 2025.	
21 same transcript?	23 / ray ()	
22 MS. GOVERNSKI: It should be transcribed,	(- free Die Die	
23 but it can be its own separate transcript. We	24	
24 probably need to then provide that to the Court.	ASHLEY SOEVYN	
25 THE STENOGRAPHIC REPORTER: Okay.	25 CSR No. 12019	
Page 351	Page 353	
1 MS. GOVERNSKI: Thank you.	1 BLAKE LIVELY vs. WAYFARER STUDIOS LLC, ET AL.	
2 THE VIDEOGRAPHER: Okay to go off the	2 12/15/2025 - NICOLE ALEXANDER	
3 record, everybody?	3 ERRATA SHEET	
	4 PAGELINECHANGE	
5 THE VIDEOGRAPHER: Okay. We're off the	5	
	5	
6 record. It's 8:06 p.m.	6 REASON	
6 record. It's 8:06 p.m. 7 (WHEREUPON THE DEPOSITION CONCLUDED AT 5:06 p.m.	6 REASON 7 PAGELINECHANGE	
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6 record. It's 8:06 p.m. 7 (WHEREUPON THE DEPOSITION CONCLUDED AT 5:06 p.m. 8 PST, 8:06 p.m. EST)	6 REASON	
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89 (Pages 350 - 353)

Page 354	
1 BLAKE LIVELY vs. WAYFARER STUDIOS LLC, ET AL.	
2 12/15/2025 - NICOLE ALEXANDER	
3 ACKNOWLEDGEMENT OF DEPONENT	
4 I, NICOLE ALEXANDER, do hereby declare that I	
5 have read the foregoing transcript, I have made	
6 any corrections, additions, or changes I deemed	
7 necessary as noted on the Errata to be appended	
8 hereto, and that the same is a true, correct and	
9 complete transcript of the testimony given by me.	
10	
11	
12 NICOLE ALEXANDER Date	
13 *If notary is required	
14 SUBSCRIBED AND SWORN TO BEFORE ME THIS	
15 DAY OF, 20	
16	
17	
18	
19 NOTARY PUBLIC	
20	
21	
22	
23	
24	
25	

90 (Page 354)

[**& - 18**] Page 1

	1711010	4460 404 00	4
&	154:12,19	1160 131:23	15 1:22 2:23
& 3:5 4:4 5:4	162:22 163:14	132:1,17	10:6 11:4,14
9:5 14:17,21	239:12,14	142:10	12:4,18 13:4
14:24 16:14	295:16 312:21	118 11:15	14:3 69:7 86:4
0	100,000 229:24	11:04 2:22 14:6	113:21 118:5
-	10017 9:9	11:25 110:11	257:18 268:7
001 61:14,19	10049 1:7 2:7	12 10:16,20	282:12,14
63:10	101 151:9	12:13 25:13,19	154 301:1,4
002 62:20 63:5	10100 6:17	161:15 268:6	302:18
63:12 67:11	105 289:24	279:8,9,10	15th 14:6
125:20 144:18	106 162:22	335:16	16 11:7 12:20
000 1:3 2:3	108 127:20	12/15/2025	268:7 269:1,10
14:1,4 185:12	128:10,16	353:2 354:2	285:13,17,21
1	144:18 160:16	12/22/24 12:9	329:13
1 10:14 11:7	109 128:4	12/4/25 12:21	16,000 217:8
16:9,11 198:7	140:11,15,16	13:7	16,337 325:11
200:11 297:21	207:10,12	12019 1:24	325:15,18
1,096 209:24	320:2	2:25 11:5 12:5	331:16
210:3	11 12:12	13:5 15:6	161 309:4,7
1,191 210:5	140:24 268:6	352:25	164 152:3
1,789 325:14	269:2,8 278:8	125 9:8	169 35:22
1.1 174:14	278:10 335:16	12:00 61:8	43:16 214:17
175:8 184:7	11/18/25 12:20	12:09 61:11	224:4
10 10:12 12:10	12:23,24 13:8	12:11 62:14	16th 352:22
268:6 276:6,8	13:9,10	12:12 62:17	17 12:21 209:7
335:16	110 207:3,7	13 12:15 268:6	300:13,14
10/18/25 12:13	110,000 35:12	269:9 280:22	302:25 305:1
12:15	35:13,19	281:1 335:16	1700 4:9
10/25/25 12:16	112 11:11	131 11:17	175 293:13
10/23/25 12:10 10/27/25 12:18	113 11:14	14 12:16 81:15	1789 327:4
10/2//25 12:18 100 44:11	1139 132:1,17	81:16 268:6	17th 167:4
	142:9	281:20,23	18 12:22 79:12
148:20,24	1140 132:13	147 11:21	79:15 80:16,17
149:23 151:10	152.15		80:22 307:2,9
		ral Calutions	00.22 301.2,7

[18 - 282] Page 2

308:9	354:15	309:11,15,18	325:9
18,879 288:18	20,000 236:14	317:7	24 1:7 2:7
1801 7:9	200 152:3	2025 1:22 2:24	10:14,15 13:10
187 317:10,13	331:16,17,18	11:4,7,9 12:4	329:6,7
1875 5:8	331:22 332:15	13:4 14:3,6	240-2927 6:10
189 301:1,4	333:2,5,16,22	16:19 17:16	248-5100 6:19
302:17	20004 6:8	41:18,24 42:6	25 1:7 2:7
19 12:23	20006 5:10	42:23 74:14	13:11 16:20
308:10,13	201-0005 7:13	75:12 197:18	25:8 36:17
1976 220:7	2012 71:22	198:11 200:13	43:21 213:19
221:3	2013 69:25	202:19 203:16	293:5,7,12,15
1:16 112:8	70:6	206:1 242:10	293:18,25
1:25 111:6	2014 79:8	244:23 245:12	294:1,5 295:16
1:26 112:11	202 5:13 6:10	258:19 286:2	332:7,9
1st 298:5	2022 41:24	288:5,9 290:13	250 292:16,24
2	68:10,11,24	327:23 352:22	250,000 290:12
2 10:18 11:8	221:5	2029 8:9	291:6,21 292:2
61:23,25 64:3	2023 74:14	2049 4:8	292:3
67:2,8 129:9	75:12 85:16	208,000 332:24	26 349:23
198:3,3,4	2024 41:17,25	20th 45:9,13	265 300:25
207:10 209:6	42:1,5,22	21 10:13,17	301:4 302:17
214:16,19	197:18 198:10	13:7 320:24	269 12:7
327:15 335:15	200:12 205:25	321:2,4	27 10:16,17
335:15	208:24 209:17	212 3:16 9:11	272 12:9
2,039 217:7	214:3,11	219 11:23	276 12:10
20 10:12 12:24	229:17 230:6	22 11:16 13:8	278 12:12
36:17 43:8,21	230:13,22	117:16 118:4,7	279 12:13
79:22 129:5,7	231:7 232:6	118:9 198:5	27th 316:15
129:9 257:18	233:6 235:14	244:16 320:25	28 10:18,19,20
257:18 288:24	242:10 244:22	322:23,24,25	151:15
289:2,5,6	286:2 288:4,6	225 313:24	280 32:22
315:7,8 316:7	288:8,11,12,24	227 313:25	281 12:15,16
342:6,6,15	289:5,8,24	23 13:9 142:14	282 12:18
2 .2.0,0,10	290:13 309:8	142:24 325:5,7	
		ral Calutions	

[285 - 6th] Page 3

305 12.20	210 4.12 6.10	401 (.7	225.15
285 12:20	310 4:13 6:19	401 6:7	335:15
28th 299:10	7:13 8:13	42 209:9,9	5/16/2024
2:53 185:7	312-4207 4:13	42,000 265:24	13:11
2nd 294:18	315 12:24	42,992 224:16	50 43:7
295:22 296:6	32 209:6,10,11	42,995 224:21	500th 244:9
296:18,23	324:1	43,000 187:2,4	52 246:24
297:2,8,9,14,18	321 13:7	187:16,24	55 144:11
298:6,24	323 13:8	262:12 265:24	5:20 246:18
318:14	325 13:9	43,992 175:20	5:31 246:21
3	329 13:10	180:16 181:4,5	5:33 248:12
3 11:7,9,10	33 229:13	181:17,24	5:44 248:15
90:25 91:2	317:6	182:7 188:8	5th 7:9 309:8
93:5 323:3,5	332 13:11	209:16 260:15	6
335:15	34 232:17	260:21 261:21	6 10:13 11:21
3/23/24 12:10	315:22	44,000 175:6,11	147:16,20,23
30 20:7 26:25	344 336:16	205:16,17,25	269:17 335:15
278:21 314:2	35 151:22	260:19	6,000 217:8
349:20	353 337:9	445 327:4	60 289:3,9,13
300 12:21	36 228:23,24	449 1:7 2:7	295:15
	37 235:5,7	47 142:14,24	
260:24,25 261:7 262:20	376-7878 8:13	48 223:25	608 301:5,11,11 302:15 307:22
	3:58 185:14	225:3,14,19,23	310:25 311:5
262:25 263:21	3rd 45:4,5,6	226:3,8 228:4	
263:22,23	60:7 167:1,2	231:16,18	312:9,15
264:12,16	4	4a 113:7,14,21	62 11:8
265:7,8,9,11,14	-	4b 118:11,14	650 35:19
266:25 267:3	4 11:11,14,15	118:15	655-3549 9:11
267:17,23	112:19,21	5	6669 352:23
303-1245 5:13	113:3,9 118:12		688 217:9
307 12:22	323:3,5 335:15	5 11:17 130:23	236:12 316:11
308 12:23	4.9 214:22	130:25 131:1,3	324:22,22
31 317:18	4/5/25 12:12	141:12 142:24	6th 228:17
324:1	400 8:10	223:19,21	229:3
		224:5,10 270:3	

[7 - academic] Page 4

7 7 10:19 11:23 219:15,15,17 219:18 335:15	86 146:21 150:11 865 3:10 87 139:16 140:17,19	228:15,20,22 9th 6:7 221:16 228:17 229:3 294:17 297:8,9 297:15,17,19	252:23 253:3,9 254:9 260:22 261:20 262:11 265:7,8,13 267:5,7,11
335:16 7.1139 131:23 70 149:13,25 72 224:1 225:3 225:14,19,23 226:3,9 228:4 231:16,18 75 36:14 43:21 750 6:17 76 293:6,14 295:3 79.5 295:10 7:42 338:17	146:24 147:7 148:5,14,25 870 292:23 879 217:9 286:3,6,17 287:7 290:21 291:8,19 89,101 35:16 8:04 2:22 8:06 2:23 351:6 351:8 8th 3:11 297:22	298:25 318:13 336:17 a a.m. 2:22,22 14:6 aadams 5:12 abel 1:10 2:10 7:3 8:3 9:3 18:1 aberrations 211:1 ability 51:20	283:15 291:2 291:13 300:10 315:1,4 326:12 328:23 330:1 344:2,4,20 350:3 above 229:13 absolutely 327:10 academia 25:11 65:8 124:12,17
7:49 338:20 7th 9:8 8 12:7 246:3 268:6,6 269:1 269:2,4,7,10,12 269:18,19 335:16 8,000 333:6 8,352 333:3 8,582 332:13 80 36:14 43:21 151:23 152:4 849-7000 3:16 85 327:3	9 9 10:15 12:9,22 268:6 272:10 272:12 327:14 335:16 90 151:16 189:22 90017 3:12 90067 4:10 6:18 7:10 8:11 91 11:10 92 155:1 93 58:17 96 175:3,8,16 97 152:11 153:20 158:13	349:24 able 15:21 34:2 34:9 38:1 58:20,21 59:11 59:15 85:7 102:18 107:11 107:23 108:19 115:20 161:23 182:3,5 184:1 186:3,8 187:5 187:20 204:2 204:25 205:1 220:17 221:12 233:24 237:2 237:17 241:11 242:16 251:14	127:17 155:23 156:1,3,4,6,7 156:12,21,24 157:6,10,12,14 157:18 158:12 158:19 159:5,9 190:14,15 204:10 218:19 218:22 219:4 academic 31:12 31:13 52:25 53:5,7,12 64:3 65:8,10,14,16 69:21 120:5 124:9,10,16 127:22,25 157:22,23

[academic - actually]

Page 5

158:24 159:14	accuracy 49:3	activities 85:11	143:9 172:20
160:12 173:14	149:20 175:17	88:17 95:13,24	187:21 201:21
223:17	175:18 285:6	96:1 237:13	201:25 202:6
academically	292:6 317:1	activity 91:14	214:13 283:6
247:18	accurate 49:7	92:4 93:1	292:9 298:1
academics	52:2 58:10	104:18 106:4	314:15 349:6
123:23 124:1	60:12 66:9,13	106:21 107:10	actually 48:12
accept 203:20	67:25,25 69:9	107:12 191:25	52:5 54:1
203:23,24	69:16 70:1	198:9 199:6	55:22 58:22
accepts 307:6	80:7 98:10	200:2,12	68:2 72:8
access 59:7	150:6,19 165:5	202:18 210:14	81:10,21 86:25
73:22 88:9	166:16 201:6	223:25 225:2,8	89:3 101:15
99:1 176:20,22	201:11,12,16	229:2,16 231:7	102:13 103:20
179:19 182:23	202:14 204:23	235:13 295:9	104:5 108:24
240:10,16,19	205:19 230:1	295:13	112:14 115:6
241:3,11,13	264:18,25	actor 193:6	122:8 124:6
242:15,19,20	265:18 267:4	241:20,23	125:10 162:16
242:24 243:3,7	285:4 289:23	300:4,6,16	168:9 170:8
243:10 244:15	290:3 294:21	307:6 319:18	171:9 176:1
249:25 350:4	316:19 318:6	319:19,21	190:12 198:5
accessible	327:8 333:6	320:3,24	206:25 207:2
178:3 233:23	accurately	actors 38:5,11	209:5 213:8
255:21 338:6	232:12,22	106:8,20 192:3	239:19 240:16
account 55:24	260:15 308:19	193:1 212:22	246:1 259:17
95:11,12	acknowledge	212:24 242:1	273:6 284:7
128:19 129:12	354:3	242:23	287:21 290:5
156:9 233:21	acronym	actresses 192:3	302:8 305:14
249:21 275:19	122:18	193:2 212:22	306:4 319:22
275:19	act 103:2	212:24	320:22 322:7
accounts 42:14	action 352:19	acts 241:20	324:5,22 327:2
88:18,19 94:11	active 85:10	actual 89:12	330:3 334:24
104:18 180:11	actively 69:18	104:8 113:4	335:8 337:2
324:17	329:3	129:17 139:1	339:12
		141:20,22	

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[ad - al] Page 6

ad 123:11	350:15	260:1 262:17	320:25
adam 272:18	additions 354:6	262:18 263:7	ahouraian 8:6
adams 5:6	address 54:5,10	267:12 289:16	8:7
14:16 91:3,7	55:13	289:17 341:18	ahouraianlaw
93:11 147:18	adds 48:14	342:12 343:6,7	8:12
300:15 349:22	301:5	344:11	ai 11:11,16,21
adapt 63:19	adequate 57:18	aggregated	46:5,9,12,14,16
adaptation	adequately	220:18	46:20,21,22
63:17	310:18	aggregating	51:22,23 52:1
adapted 63:18	adjunct 69:24	82:3 87:8	52:1,3,6,6,23
add 301:10	70:2,5,13	222:11	53:14,14,16,23
312:15 313:8,9	adjustments	aggregation	53:23 54:10,12
321:20 330:9	250:5	319:12	54:13,17,23
added 64:17	admit 113:2	aggressive	55:20 56:1,8,9
115:9 146:13	adopting 179:6	79:21	56:11,15,23
163:19 164:14	advanced	aggressively	57:5,6,9,10,14
307:21	31:14	298:2	57:16,18,20,20
addition	advertisers	ago 17:9 25:4	71:5,9 75:17
157:22 158:5	84:22 122:18	134:23 161:16	75:19,20,23
158:23 328:9	122:24 123:1	161:21 257:19	78:12,15 114:1
additional 55:6	advertising	agree 95:9	127:1 144:7
64:4 79:6	90:8 98:22	97:24 98:2	146:12,18
145:4 151:15	106:18,22	118:25 119:10	148:19,20,25
165:9 188:21	advise 20:21	223:11	149:8,9,14,17
189:9,11	affect 334:21	agreed 107:24	149:20,24
193:25 206:7	affordable	agreement	150:5,10,12,17
217:3 232:6	303:10	95:22	151:3,10,17,23
233:12,20	afforded 73:22	ahead 16:8	152:4 154:12
234:3,10	age 56:5 104:17	53:4 67:10	154:20 155:1
236:23 249:7	ages 56:19	99:24 104:4	163:14,20
254:14 280:18	aggregate	120:18 126:17	ais 56:24
284:17 312:20	211:23 218:5	161:5 178:14	akaltgrad 7:12
326:2 327:21	218:21,25	182:19 185:5	al 1:8,13,15 2:8
328:17 349:20	221:13 259:24	269:4,13	2:13,15 11:3

[al - analysis] Page 7

		1	1
12:3 13:3 14:9	align 142:20	amended 11:8	ana's 122:16
140:21 141:3	148:10	59:22,25 60:3	analyses 226:5
143:13 153:10	aligning 11:12	60:5,6,9,14,24	238:1
353:1 354:1	allegations	61:17,24 62:20	analysing
alexander 1:19	216:9	63:11 66:21,24	11:19
2:19 10:2 11:2	alleged 294:18	66:24 67:6	analysis 11:24
11:7,9,13 12:2	295:22 296:5	189:19 346:14	12:20 23:25
13:2 14:7	296:21 297:25	348:1 349:6,13	32:9 35:1
15:17,19,20	299:12 318:14	349:16	36:24 43:11
21:2 23:9,14	327:15	amendment	44:12 58:4
24:9,15 27:21	allow 51:25	349:14	81:25 86:9
28:7,12 59:11	52:3 94:9	american	101:12,15
60:10 61:13	241:3,11 243:3	122:15,17,21	121:15,20,22
62:19 112:13	300:7	122:22,25	125:7,15
112:14 113:20	allowed 33:16	amir 7:7 16:24	128:20 129:14
120:19 135:10	53:15 81:2	19:3	149:8 156:11
135:17 138:10	111:7 240:18	amount 77:8	156:21 157:11
138:14 152:13	242:20,23	79:5 100:21	158:8 162:11
183:8 185:23	287:13,17	106:1 119:18	166:7 167:8
246:8,23	allows 217:6	180:8 206:22	177:9 182:4
248:17 285:19	320:14 321:12	210:2 239:19	185:25 186:25
305:1 315:10	alpert 11:18	243:3 294:8	187:21 188:2,5
331:16 338:22	132:22 144:14	308:3,5 332:17	188:8,23
339:8 350:11	alter 237:25	amounts	193:21 203:21
353:2,24 354:2	238:24	333:14	204:5,12,12
354:4,12	alternatively	ampersand	209:15 211:17
alexander's	193:11 291:16	56:3	216:14,17,19
11:14,15	altogether 36:2	ampersands	217:6,16,23,24
algorithm	43:18 269:11	56:4	218:4,12,13,19
46:13	amazing	amplification	218:25 219:2
algorithmic	342:17	93:3 155:9	220:3,10,11,17
99:2 115:18	amber 118:10	amplifying	220:21 221:4,6
algorithms	amend 62:23	114:6	221:12,19
114:4 115:21			222:3,7,12,14

[analysis - api] Page 8

	I	I	
223:7,9,16,23	analytics 24:25	8:11	149:5 150:3,16
224:5,6,11,11	25:9 43:8,23	announce	151:6,12,19,25
224:12 225:22	44:10 45:12,14	118:14	154:14 155:4
226:4,6,8,11,12	58:2 81:3,7,9	annu 30:8	156:18 159:15
229:16 232:6	81:17,19,20,22	anomalies	161:3 164:25
233:12,18,19	81:23 82:1,8	106:3	165:21 166:11
234:3,11,15	82:11 85:3	anomaly 103:1	169:12 171:15
235:3,21 236:4	86:5,6,9,17	answer 10:10	175:23 176:14
236:16 238:25	87:18,21,24	20:22 21:10,12	178:13,24
239:13 246:24	88:3 90:5	21:15,19,22	182:10,19
247:2,7,13	analyze 102:15	23:22 24:4,13	183:8,24 184:1
248:18 250:2	180:13 201:9	26:8 27:16,24	204:17 212:8
251:21 254:16	205:13 216:22	30:22 33:12	213:6 233:10
256:9 263:5	217:21 226:20	38:8 44:2	238:9 297:12
264:11 265:23	236:5 254:14	47:10 48:3,9	306:14,16
271:19 274:5,7	291:17 292:13	54:25 55:9	307:16 336:2
274:23 277:19	326:12 330:25	56:17,19 64:22	337:22
279:2 285:14	analyzed	65:21 66:23	answered 26:2
286:1 288:11	166:16 214:3	69:17 71:25	111:20
291:12 292:8	218:2 308:23	72:14 73:14,25	answering
294:1 297:5	analyzer	76:2 77:6,19	165:7 183:2
316:10 317:12	261:21 274:12	77:22 79:2	answers 98:18
319:11 322:11	275:17 283:5	82:9 83:6	anybody
325:16,17,22	283:23 310:1,7	91:22 95:10,16	176:20 178:4
334:12,21	314:12 337:5	96:16 98:8	anymore 62:6
337:1 338:23	337:13	101:21 103:7	anyone's
339:5,20 340:9	analyzing 37:1	105:4 108:12	204:21
340:19,25	37:1 83:8	108:19 120:19	ap 194:18
342:20 343:1	131:12 141:10	121:9 126:13	apa 49:6
343:14,20	141:24 220:24	127:13 129:25	api 207:24
345:24	237:6 319:8	130:17 133:10	208:16 236:21
analysts 87:11	348:9	133:20 139:11	239:4 240:17
analytical	angeles 3:12	140:4 142:3	240:17 241:2,3
30:25	4:10 6:18 7:10	145:21,23	241:4 242:16

[api - article] Page 9

242:17 243:14	321:6	173:24 243:21	area 273:20
243:22 244:1	apify's 241:1	320:9 346:13	277:7
245:9,10 271:5	apify.com.	application	areas 78:14
300:5,23	303:4	244:20	165:6
302:19,20,22	apis 188:2	applied 147:1	arguably 44:25
303:1 311:19	240:21,21,23	147:11 186:14	212:21 227:10
311:23 313:13	243:1 244:4,6	186:15 187:12	227:11
319:21 324:11	342:11	187:15 250:25	argue 176:1
329:21,23	apologies 101:6	348:10	222:21,24
330:8 331:3	apologize 28:21	apply 186:14	250:3
332:5,18,19	66:11 154:16	187:15 258:21	argument
333:7,12,21	appear 108:2	applying	211:11
api's 241:16	116:25 143:18	184:10 185:24	arrow 280:6
apify 13:7	146:6 337:2	254:1	331:11,11,12
37:21,22 38:6	appearance	appointment	art 218:7,10
38:11 42:7,10	22:14	282:19	article 11:17
42:14 181:10	appeared	appointments	49:24 128:5,8
181:12 182:3,6	143:15 250:23	69:22	128:23 129:16
182:24 183:14	appearing 1:20	appreciate	131:9 132:6,16
183:17 203:10	2:21	127:5	133:9,19,23
205:8 206:10	appears 54:4,8	approach	134:13,15
206:13,23	54:11,14 131:8	24:23,24 40:1	135:8,10,18,21
207:24 208:1,4	280:4 336:4	290:24	136:9,17,24
208:6,14	appended	appropriate	137:8,20
240:15,16,18	125:11 354:7	27:7 322:3	138:21 139:15
241:5,20,23,25	appendix 63:5	334:22	140:3,13
242:15,16,18	63:6 125:20,21	appropriately	141:20,22
242:23 243:3,7	125:24 126:2	55:13	142:11 144:15
243:24 244:3,5	126:11,22	approximately	144:22 145:7,9
244:9 271:5	160:9,13	174:14 289:5,6	145:12,13,13
273:17,19	168:10,20	arato 19:18	145:15,19
274:2 300:10	169:1,17,17	architecture	146:6 152:22
302:23,23	170:13,21	302:6	153:1,3,5,11,12
306:21 320:2	171:3,6 173:10		153:14,19,23

[article - attend] Page 10

167:15,16	99:21 111:3,4	81:1 164:23	assuming 31:22
168:3,4,12,13	112:3 137:24	165:2,14 166:1	120:6 132:15
168:17 171:12	185:16 268:23	166:4,20	142:25 221:2
articles 123:6,7	271:23 275:21	292:20	243:8 320:6,8
130:22 133:17	314:14 342:22	assigns 249:12	324:13 333:15
134:8,9 152:24	343:11	assist 30:19	assumingly
159:5,19 173:4	asking 23:2,3,8	46:3 65:17	227:20 305:23
173:6,9,14	26:6 31:3	assistance	335:8
articulate	49:23 91:6	29:19	assumption
21:21 189:19	99:12 105:11	assistant 28:20	27:5 57:16
artificial 46:2	121:13 135:11	28:23,24 29:15	194:19 216:20
74:5 75:16	135:17 137:11	30:20 36:3,22	275:25 297:22
78:7 97:5	137:12,21	245:6,7 258:4	310:4 324:16
artificially	156:13,15	284:21,23	324:24 325:2
94:11 95:20	157:5 170:17	associate 51:14	333:13
96:13	175:19 176:25	92:15,18	assumptions
ash 110:7,16,18	185:23 186:13	233:25 247:19	108:12 203:12
110:21 111:1	187:14 208:9	252:7	335:10 348:9
111:12,20	217:20 237:20	associated	348:10
137:13,23	237:21 238:22	88:23 156:2	astroturfing
138:24 139:5	260:1,2 265:4	251:11 253:7	198:19 199:13
ashley 1:24	296:13 304:18	286:16,21,23	199:14,15,22
2:24 11:5 12:5	312:11	287:10,11,15	199:23 200:5,6
13:5 15:5	aspects 75:25	296:22 339:6	200:10
185:15 352:2	76:13	344:13	attach 310:22
352:24	assert 188:21	association	attached 46:6
asia 222:6	asset 100:1	122:16,21,25	attacks 114:16
aside 34:7 49:5	assets 97:15	250:22	attempt 100:22
asked 23:23	98:4,13 99:8,9	association's	attempting
24:22 26:25	99:22 100:1	122:22	89:12 100:2
29:24 30:16	assigned	assume 186:19	attempts
33:15 39:21,22	166:23	274:22 290:4	114:13
40:16 41:2,6	assignment	324:19 333:10	attend 74:13
54:2 66:14	73:2,4,13 78:8	333:18	

[attention - back]

Page 11

44 49 60 4	200 10 10 22	100 60 10	222 24 224 1
attention 63:4	299:19,19,23	100:6,9,12	333:24 334:1
attorney 6:6,16	316:15 317:9	autumn 5:6	avenue 9:8
8:8 9:7 20:18	317:12 318:13	14:16 58:17,20	average 211:4
27:18,23 28:3	318:14 327:4	58:21,23 90:25	211:21 225:10
65:22,25 66:6	327:14,15	93:8 118:10	236:25 289:6
165:20 352:18	328:15 336:17	126:17 147:17	avoid 101:18
attorneys 3:9	authentic	228:21 231:11	102:10 350:15
4:7 5:7 7:8	107:12,24,25	269:4 278:9	aware 50:8
16:22 17:3,7	108:3,16	281:21 282:13	56:12 300:8
18:25 19:8,17	authentically	285:15,16	301:4 334:14
19:20 27:1	103:1 104:12	300:18 304:25	334:15,18
attributed 56:1	authentication	305:16 310:14	b
audio 195:1	303:12	315:5 320:25	b 11:15 118:12
248:13	authenticity	331:4,9,10	329:12
august 20:8	94:9 101:1,4	332:6	b.s. 72:8
23:15 197:18	author 124:8	availability	b1 197:25
198:10 200:12	146:1 157:2,6	27:8 203:10	b2 198:2
209:17 214:3	authored 120:4	available 27:10	b2b 84:13,14
214:11 228:17	120:4,9,13,23	29:21 31:2	84:20,21
229:3,16 230:6	authorities	41:17 42:7,9	babayan 3:8
230:13,22	222:2	42:13,21 52:17	bach 19:18
231:7,19 232:6	authorized	176:6 178:19	bachelor's
233:6 235:14	244:21	205:10,10	71:15,20 72:5
289:5,23	authors 48:6	206:10 207:24	back 20:8
293:13,17,24	48:14 132:20	208:2,15,18	26:24 35:10
294:13,17,18	132:24 135:22	223:18 225:21	39:6,14 41:13
295:16,22	143:14,14,17	236:19,20	52:9 57:9 61:4
296:6,18,23	143:23,24	240:1,14	
297:2,8,8,9,9	144:4,5,8,13,15	241:17 242:9	61:10 62:16
297:14,15,17	145:4,7,18,18	243:13 244:3,4	66:10 70:3,7
297:18,19,21	146:6,13	244:12,14,20	91:3 103:15
297:22 298:4,5	156:14 159:24	255:8 306:8	109:14 110:11
298:6,11,24,25	automated	326:20 332:3	111:6 112:10
299:10,11,13	89:6 96:2,14	332:18,21	117:16 137:13
		<u>'</u>	

[back - baseline] Page 12

137:24 138:24	backup 172:14	188:4,19,22	298:16,17
139:5 141:12	172:17,21	189:2,12	300:11 303:14
144:17 150:22	245:23 288:20	190:19,22	305:2 307:3
151:3 152:8,23	bad 117:22	191:6 192:21	308:20,22
185:13,16,19	baldoni 7:3 8:3	197:9 199:5,6	309:2 310:6
203:18 206:4	9:3 17:21,25	200:16 201:17	311:9 315:4
220:1 246:11	250:19,21,25	201:23 202:19	317:13,19,21
246:14,20	251:3,18,20,24	203:9 204:1,24	317:24 319:8
248:14 278:2,3	252:6,8,12	205:6,12 213:8	319:11 324:24
279:6 287:3	300:24 301:15	216:19 222:14	325:2 328:14
288:6 289:25	336:19	225:2 229:9	331:1 333:7
293:5 304:25	ballpark 77:25	233:22 237:6,9	341:23 342:9
309:10,15	203:15 315:17	237:17 238:13	342:22,24,24
310:4 313:19	base 17:13	239:5,10,22	344:4,8
318:17 322:2	107:22 344:12	241:9 242:16	baseline 91:19
324:15 325:24	based 34:10,25	242:17 248:24	92:1,2 102:24
330:9 331:1	39:16 42:17	248:24 249:2	104:12 208:23
332:4,18	47:12 54:3	249:13,13	208:23 209:1,2
335:14 337:7	76:5 91:14,20	250:21 252:4	210:2,13
338:19 339:16	91:25 95:7	254:10 256:9	212:11,15,17
349:22,24	101:15 103:14	259:12 261:25	212:17,21
350:11	104:11 114:16	262:8 265:18	235:15,16,18
background	123:10 152:25	265:20 267:6	237:7 288:10
19:9 23:24	155:22,23,24	267:12,13,24	288:19,23
24:1,10 25:7	157:20 158:4	270:14,17	289:4,9,15,17
27:6 30:1	158:21 159:1,4	271:14 273:18	293:8 295:15
31:12,13 32:6	159:15 160:4	274:17 275:8	297:19,24
46:14 150:22	160:11 162:3,4	276:3 277:22	298:3,25 299:3
178:16 233:16	163:1,5 164:2	281:9 283:3	299:3,14,16
backgrounds	166:7 168:23	290:23 291:14	316:17 334:19
24:21	171:1 176:5,23	293:13,17,23	334:22,24,25
backing 167:2	178:2 181:14	293:25 294:1	335:4,7,8,11
backs 341:6	182:3 186:6	295:15,18,23	341:21 342:2
	187:23 188:1,2	296:10,20	

[baselines - bio] Page 13

baselines 91:24	136:12,17,21	305:13 311:20	271:20,23
212:23	138:4 139:10	312:6,22 313:9	272:3,5 274:16
bases 346:1	141:11,25	316:15 318:22	275:12,25
basic 25:8	199:15,24	319:22 327:7,7	276:4 277:18
189:16 190:10	behaviors	345:1	277:21 279:2
basically	94:13,19 95:3	bell 225:6,8	283:5,23 310:1
215:14	behaviour	bellutta 128:5	310:11 314:11
basis 21:22	11:20	128:9,16	340:18,23
23:3 87:16	beings 99:3	bender 5:5	341:3,5,18,19
100:11 105:13	100:22 115:16	benefit 100:4	342:2,20,25,25
123:4,11	belief 159:1	100:23	343:3,13,18,20
127:11 155:17	beliefs 114:4	bert 247:16	344:10
156:15 158:23	believe 17:20	249:8,11,14,22	best 244:14
160:15 191:1	18:6,23 19:4	250:1,8 251:4	340:23 341:3
210:22 211:14	40:12 51:23	251:6,14	better 44:7
328:11 341:2	63:8 67:7	252:10,23,23	217:6 272:17
346:2,5	72:15 80:9,16	253:9 254:7,10	296:14
bean 12:12	80:23 90:4	254:17,23,23	bfreedman
278:20 314:1	110:15 127:3	254:25 255:2,3	7:11
began 45:15	128:3 135:23	255:8,10,11,18	bias 249:20
beginning 2:21	145:11,15	255:19,22,23	biases 76:4
14:12 32:24	146:11 149:8	256:1,6,10,14	bibliographies
behalf 2:19	156:2,13,20	256:25 257:6	48:21 49:4
14:15,21,24	158:6,22,24	257:10,14,16	bidirectional
17:19 18:5	161:25 167:4	257:17,17,21	268:11,11
behavior 11:10	169:6 199:12	257:24 258:12	big 18:10 82:3
88:12 91:11,13	200:7 217:11	258:21,25	128:24 332:23
92:8,14,21	226:25 227:2	259:4,8,13,16	bill 36:2
97:12 98:3	254:5 255:4	259:19 260:4	billed 35:8,11
103:11 104:1	257:17 260:25	261:21 262:4	35:12,19
106:10,12,14	263:15 290:17	265:17 266:9	billion 270:3
106:16,19	295:24 296:17	266:13 267:13	bio 64:25 65:5
107:1 122:7	296:22 300:1	268:10,14,20	67:9,10,16,24
124:21 131:13	302:2 303:7	268:21 271:18	69:15

[bit - calculating]

Page 14

bit 42:11 67:14	113:22 119:13	boycott 342:18	bullets 155:7
124:12 171:17	120:2,25	brand 119:19	155:13,16
193:15 272:15	191:10,18	119:20 275:20	156:8,15,25
278:9 310:14	279:24 282:19	brand's 117:23	157:7,25
blake 1:5,15	bookishrhaps	118:21	158:23 159:15
2:5,15,20 4:3	279:13	branding	159:20
5:3 6:3 11:3	bookisrhapso	121:16	burst 128:19
12:3 13:3 14:8	279:25	brands 119:12	129:13
176:3,11 179:2	books 279:16	119:13,14,15	business 71:12
179:9,18	301:1 304:5	119:23,25	79:6 84:9,11
180:10 206:17	310:15,17	213:10	84:16,16,25
250:17 252:2,3	boost 94:11	break 36:1,19	85:6 106:23
252:21,24	95:20 96:13	60:14,18	119:16,20
253:5,7 271:24	boosted 197:7	108:21 109:12	businesses
274:9,18 275:5	347:6	110:2 111:5,6	84:22
275:21,22	boosting 97:5	111:18 112:16	c
278:6 286:1	347:11	246:5,8,10,11	c 3:1 4:1 5:1 6:1
300:23 301:15	bot 88:17 90:6	246:14	7:1 8:1 9:1
311:9 316:11	106:9,12,14,15	breakdown	125:20,21,24
336:21 337:4	106:16,19,21	43:3,6,9,19	126:2,11,22
353:1 354:1	107:1,9 198:25	breakout 34:21	160:9,13
blank 201:4	bots 88:8,10,14	35:2	168:10,10,20
304:8	88:20 89:7,8	bring 125:13	168:20 169:1,1
blanking	90:11 95:23	broader 200:19	169:17,17
177:19	98:21 106:18	brought 90:4	170:13,13,21
bloom 280:25	107:16 199:1,1	bruns 145:4	170:21 171:3,6
281:14	200:1 295:5	bryan 7:6 22:2	173:10,24
blown 123:22	bottom 281:10	buckets 44:4	243:21 346:13
blvd 6:17	281:22 282:16	bug 16:3,4	calculate 35:7
board 19:2	283:4 300:19	built 76:6	calculates
book 11:11,14	303:3 331:15	341:5	316:17 327:3
11:16 25:11	bound 105:18	bulk 43:10	calculating
64:5,14,15	bounded	bulleted 157:19	325:3
113:1,3,4,6,16	185:10	157:20	

[calculation - certainty]

Page 15

calculation	cambridge 74:8	case 1:7,7,7 2:7	categorized
213:16	74:13,20,24	2:7,7 16:15	310:7 338:3
calculator	77:10	17:24 24:25	causation
35:18 301:8	campaign	37:6,8 38:15	234:22,25
california 1:24	27:14 102:9	38:17 55:11	235:2 299:14
2:24 3:12 4:10	108:16 165:8	59:5 70:7 73:2	cause 100:3,23
6:18 7:10 8:11	217:12 220:25	73:5,13,19,23	100:23
15:5 352:3,21	294:18 295:4	78:8 81:1	caused 230:25
call 17:14 20:7	295:22 296:18	103:24 104:8	231:2 232:8
20:11 23:15,19	296:21 297:1,7	104:13 105:6	233:6 234:4,12
24:2,16,22	297:17 298:20	105:16 106:11	294:19 298:21
25:20,24 27:1	299:10,12	106:12,13,19	318:15 327:16
27:4,12,21	318:14 327:15	106:21 107:10	328:19 336:12
28:3,7,14	campaigns	107:17 108:6,9	caution 66:4
33:10 53:18	106:25 125:8	121:18,19	caveat 340:3
58:23 84:20	campbell 145:4	146:10,15	caveated
138:8,11 143:8	capital 294:14	159:11 160:16	230:10
185:2,9 192:22	capped 333:22	161:16,18,22	celebrities
214:8 219:1	capture 236:13	162:19 163:4	212:22 213:9
258:2 350:20	237:3,24 245:1	163:18 164:23	celebrity
callback 26:13	245:3 310:19	181:11 189:1,6	212:19
26:17,20	captured 87:7	194:6 197:17	center 225:7
called 21:7	242:8	212:16 218:16	centralized
25:23 26:24	capturing	250:9,17 253:4	139:24 155:9
67:17 72:23	262:24	253:24 268:15	century 4:8 7:9
81:21 82:11	care 29:13	292:23 296:11	8:9
91:10 128:18	110:1	cases 100:9	certain 79:4
160:16 205:18	career 31:18	171:8	106:2 127:8
219:2 238:23	124:4 213:17	categories	171:1,2 222:8
277:8,8 302:9	222:15	43:23 313:18	237:12,12
320:12,23	carpenter	categorize	260:23 322:7
calling 165:18	12:11 276:7	271:19 274:10	346:6
calls 319:22	cas 49:10	277:19 279:3	certainty 187:6
		337:5,13	
L	Varitart Lac	1	

[certificate - clarify]

Page 16

4 • 6 •	1 4 •	246.4	120 2 142 6 22
certificate	characterize	346:4	130:2 143:6,23
352:1	314:12	checker 51:22	145:17 146:5
certified 2:24	characterized	51:24 52:3,6	148:13 155:15
352:2	310:2	57:5 149:17	156:16 158:9
certify 352:4,17	charge 166:6,8	150:10	160:12 169:9
cetera 25:11	166:9,12,21	checkers 52:1,1	169:20 223:17
76:23 84:18	chart 342:1	55:21 56:9,11	citations 47:24
121:16 179:21	charts 57:22,23	56:23 57:9,14	47:25 48:21
190:8 193:2	57:24 58:3,4,6	57:18 149:21	127:6,9,10
241:13 283:20	58:7 209:20	150:18	154:3 159:22
291:2	chat 62:9	checking 49:18	170:19
chain 161:25	276:20 277:9	49:20 51:2,11	cite 128:5
chance 51:23	300:25 302:10	51:17 55:7	129:22 130:2,4
149:13 229:23	302:11 304:5	56:7 292:16	130:6 135:10
chances 237:18	309:20 310:16	304:1	139:15 142:14
237:20	310:16	checks 50:19	143:6 146:5,20
change 43:25	check 36:24	51:20 150:6	146:25 147:2
44:4 149:14	48:25 49:11,22	chennai 79:13	152:9,17
216:14,18,19	50:1,3,6,9,14	china 79:13	156:13,24
235:22 236:4	50:20 54:22	222:6	160:16 167:15
237:13 238:6	55:2 60:11	choose 51:10	169:8,18,22
239:13 297:4	69:6,8 92:3	280:25 281:14	172:2
334:12 353:4,7	102:5,5 111:14	chose 134:15	cited 135:18
353:10,13,16	111:15 129:15	234:2 236:5	137:6 140:9
353:19	261:1,20 274:6	298:3	159:2 171:1
changed	290:1 292:24	chosen 241:10	173:2,5,7,9
207:12	295:19,24	chronologica	city 215:24
changes 63:6	303:25 317:16	64:6	claim 139:16
85:17 119:7	318:5 322:17	chulo 272:21	claims 347:14
354:6	332:19 340:1	circumstance	clarifier 40:4
changing	348:15	106:10	clarify 95:5
236:15	checked 38:19	citation 48:1	99:16 130:7
channels 39:22	38:20 245:8	52:4,7 126:24	174:19 335:21
	267:1 338:9	127:12,15	

[class - column] Page 17

	1	1	
class 52:21,25	275:3,3,5,9,18	165:20	coined 200:2
74:18 81:13,14	276:4 310:11	clients 17:19	220:6 221:3
81:16,22	315:3 337:16	85:7 88:18,21	cole 272:19
178:18 268:17	338:5 342:3,13	346:2	collapsed
268:22	342:25 343:19	clipped 134:8	325:25
classes 52:14	344:10	clipping 126:24	colleague 58:17
52:15 56:12	classifiers	close 45:1	91:9 118:16
76:21 77:5	92:22,23	212:1,5	147:14 219:14
81:24	249:11 313:10	closed 62:5	223:20 268:3
classification	classifies 249:2	66:17,25	269:4
246:24 247:6	classify 89:18	closely 142:20	collect 200:19
247:13 261:15	89:18 250:18	148:10 235:15	286:13
313:21 341:24	251:5,11	cluster 342:21	collected
classifications	260:11 264:8	clustering	244:19 308:23
263:4 265:14	271:21,23,25	139:23 156:10	309:15 331:25
classified	277:23 279:7	clusters 101:14	332:2
221:11 251:17	283:23 284:1	260:5	collective 18:7
258:25 259:3,8	315:3 326:8	cobain 12:12	194:19 217:22
259:15 260:9	classroom 77:8	278:20,20	college 53:11
260:15 261:21	claw 349:22	302:13 314:1,1	colleges 56:10
262:4,13	clean 299:6	code 12:20 39:2	56:13
264:13 265:9	348:11	39:3,11 58:8	colloquialisms
265:12,23	cleaned 87:8	254:10 258:2,4	55:25
266:10,14	cleaner 210:23	258:5,7,8,9,11	columbia 52:11
274:13 314:17	cleaning 82:3	262:8 278:4	52:19,22 53:10
314:24 337:21	clear 52:3	311:13 344:3	53:17 68:3,7
classifier 39:24	137:3,19	codifying 57:15	70:16,17,21
247:16 248:3	138:20 271:3	coefficients	column 36:8
248:20,22	320:19	139:24	309:19 310:14
249:10 253:13	click 88:5,10	coincide 92:14	310:18,25
253:17,20	clicking 96:9	coincidence	314:2 329:12
259:5 265:17	client 20:18	150:14 307:22	329:15 330:5
267:4,12 274:8	27:18,23 28:3	coinciding	330:12,12,14
274:16,16	65:22,25 66:6	232:1	

[columns - concept]

Page 18

columns	comfortable	communicate	completely
323:12,24	32:7	33:9 54:21	49:6 115:6
combinable	coming 19:2,12	communicated	184:25 237:16
220:15,23	157:24 269:3	347:10	237:16 238:10
223:14	command	communication	238:19
combination	139:25 147:9	24:5 192:9	complex 97:13
223:10	comment	348:6,7	98:3 258:10
combinations	279:12,18	communicati	complicated
180:10	280:9,13,15,17	161:4 347:22	238:5
combined	281:16 303:13	348:3 349:1,9	components
209:15 210:15	318:10 326:2	349:9	39:5 163:4
combining	commentary	community	compound
223:14	168:6 192:24	94:14 95:7	182:18
come 19:10	233:24	97:17	comprise 309:1
23:14,23 24:22	commenting	comp 31:16	comprised
40:19 47:12	190:10	83:16	174:25 177:11
57:9 70:2,3,7	comments	companies	186:24 188:9
110:10 111:6	286:11,13,15	32:14 114:15	287:2 310:19
114:15 150:21	286:20,23	120:14 213:25	computational
151:3 182:6	287:2,4,8,14,15	241:5	30:25 82:17,19
186:12 189:9,9	287:18 288:1	company 31:20	82:22 83:4
206:15 210:22	290:5,8,12	31:20,21 32:12	131:9,16
218:1 270:20	291:6,21 292:2	90:21 107:8	132:17 142:21
271:11 278:2,3	292:15 319:15	compare 291:7	144:24 148:11
279:6 313:19	325:12,14,15	compared	156:11 233:19
334:25	325:19,21,23	67:17 212:21	computer
comes 36:9	326:1,23 327:3	complete 15:21	66:15 83:12,15
96:10 127:15	327:4 331:18	16:5 39:1	219:23 257:25
186:25 188:20	331:22,25	182:2 224:17	computers 99:2
192:1 219:12	332:11,13,17	237:12 344:16	con 78:16
271:4 273:20	333:22 336:17	344:18 354:9	concentration
273:20	commitment	completed	72:11,12,19
comfort 279:21	94:8	45:12	concept 47:3
280:12			125:14

[concepts - content]

Page 19

concepts 125:9	confident	348:5,25	contact 23:17
125:10 147:2,4	148:18 175:15	349:17	contacted
147:6,12	confidential	consideration	29:24
concerned	1:17 2:17 14:2	348:8	contain 191:16
253:6	105:12	considered	contained
concierge 9:23	confines 226:11	68:18 97:6,7	126:22 288:1
conclude 180:1	241:15	125:22 126:12	contemplate
concluded	confirm 59:21	169:10 191:23	313:15
351:7	61:16,19	192:1,18	content 39:17
conclusion	189:25 232:4	220:15,23	39:18 41:23
211:20 233:13	264:17,25	226:9 294:5	46:17 47:21
233:14 312:2	267:3 275:17	328:23	52:8 67:19
conclusions	316:22 333:12	considering	91:15,18,25
186:1,15	confirmation	348:24	94:12 101:12
289:14 293:16	194:15	consistency	101:13 103:15
349:2	confirmed	190:2	103:15,22
conduct 89:6	223:23 264:3	consistent	104:20,24
conducted	317:1	103:19 189:24	105:1,6,9,10,15
267:18 340:15	confirming	198:12 202:25	105:25 106:3,4
343:1	273:18	295:5 309:8,13	106:5,9 114:1
conducting	confused	318:7	114:5 115:17
179:24	163:17 184:25	consistently	115:22 160:11
conference	203:19	342:11	168:23 171:22
30:12 33:10	conjunction	consolidated	171:23 174:8
185:9	31:5 124:7	1:14,15 2:14	176:11 190:11
conferences	196:7,14 261:4	2:15	192:9,13
159:6 191:7,9	274:20	constraints	196:24 241:6
conferencing	connection	242:25 243:12	250:10,10,18
2:21	232:3 234:20	243:17	251:5,16,18,20
conferred	285:14	construed	252:2,5,24
74:18	connects 241:4	276:21	253:1,6 261:10
confidence	consider 60:15	consumers	265:15 266:11
312:25	70:12 126:1,8	84:18 95:8	266:21 271:14
	226:2 328:18		273:18 278:8

[content - counsel]

Page 20

283:3,3,6,14	contract	138:4 139:10	71:6,18 75:14
284:19,21	105:18	139:19 141:11	82:21 85:20
285:1 306:20	contribute	141:24 157:13	117:7 121:2
309:15,25	114:20	198:18,21,24	156:3 162:4,20
311:8 336:4	control 22:22	199:3,6 200:1	169:6 188:10
349:15	126:21 140:1	220:25 295:12	197:16 217:11
contents 135:3	147:10	coordinating	224:14 234:9
192:11 250:7	controlled	89:15 98:21	245:22 257:23
347:6	97:15 98:5,13	coordination	261:4,13 268:2
context 47:14	conversation	11:18 100:10	283:21 284:8,9
95:21 99:25	19:3,14 20:15	101:14 104:10	286:12 309:2,3
100:13 124:15	21:3,11 27:5,9	131:10,11	316:15 328:25
165:9 168:5,15	33:2 56:18	141:4,9,23	340:14 352:15
174:8 177:6	161:7	142:2 144:23	352:22 354:8
178:17 196:20	conversations	copy 46:17,18	corrections
226:6,13 227:1	112:15	65:16 66:19	354:6
227:1,5,23	conversion	113:4,16 125:1	correctly 39:4
228:10 233:11	309:6 324:13	125:3 129:16	correlates
250:22 251:7	converting	154:4 169:24	327:24
275:5,19	85:9	266:3 331:4,5	correlation
280:19 281:10	cooley 7:5	cordially 30:14	234:15,18,19
283:12,25	16:14	core 31:9	234:24
284:17 347:8	coordinate	254:14	corresponden
contextualiza	99:4	corporate	26:1
200:8 217:3	coordinated	119:14	counsel 14:12
341:7	11:20 89:11,21	correct 17:17	14:17 15:2
contextualize	90:15 95:23	19:13,16 26:15	18:20,21 19:4
284:18	96:1 100:16,22	32:20 33:4	22:13,16,22
contextually	103:2 104:17	34:13 35:21	26:21 28:18,23
197:11,12	108:16 114:13	36:16,18 37:11	45:21 60:8
continue 60:25	114:16 116:2	39:5 40:6 47:1	112:16 130:22
continued	128:19 129:12	47:7 52:12	143:3 145:12
119:2	131:12 135:21	58:14 67:1	161:4,7 345:7
	136:12,17,21	69:19 70:10	350:17,18

[counsel's - cycles]

Page 21

		I	
counsel's 20:21	cover 105:20	110:9,12,17,25	customers 85:7
21:14	113:1	111:2,9,25	85:10,10
counsels 17:22	coverage 192:2	112:5 183:4	107:23,24,25
count 276:1	192:5 196:15	223:23	108:1
counted 335:18	198:15 199:11	crunch 203:18	cut 53:6 115:8
counterfactual	cpg 107:7	csr 1:24 11:5	333:13,15
344:14,24	crashed 295:2	12:5 13:5	cv 1:7,7 2:7,7
couple 85:2	crawl 322:7	352:25	25:7 58:16
115:12 145:24	crawler 319:17	csv 263:19	63:5,14,17,20
182:20 229:13	319:19,23	309:6 329:11	64:9,13,14,16
course 16:21	320:3,24 322:6	culminates	64:19 65:3,4,6
17:10 18:16	crazy 316:3	73:8 78:14	65:9,10,14,16
51:13 52:24	create 52:13,16	culotta 172:3	65:18 66:8,10
68:11 69:3,5	179:25 338:22	172:24	66:19 67:5,6
70:8,24 71:2,4	346:3	culture 276:19	67:18,22 71:15
71:7 79:24	created 52:15	277:8 300:25	74:4 78:18,24
124:4 126:9,10	54:12 58:12	302:9,11 304:5	81:8 84:5
126:12 169:2	76:4,23 87:25	309:20 310:16	86:11,18,19
197:23 213:17	104:19 308:11	310:16	120:2 124:24
245:14 279:20	345:20	curation 114:1	cycle 191:19
280:11	creation 128:19	current 31:18	193:23 194:10
courses 68:16	129:13	61:1 68:1,3	194:10,13
69:2,11 70:20	creative 46:17	69:15 70:12,17	196:10 233:25
72:4,4 75:5	creators 241:6	189:19 256:6	335:5
76:12,14,18	credentials	256:14	cycles 191:13
court 1:1 2:1	25:10	currently 17:8	191:15,17
22:23 109:7,14	credibility	32:9,10 56:20	196:3,7,13
109:23 110:1,1	194:14	68:6 70:20	197:14 198:13
110:13,24	credits 70:24	221:5 255:8,20	199:8,10
138:9,11 185:3	criteria 163:1	curve 225:6,8	233:23 328:22
185:9 349:19	164:3,16	295:11	335:6
350:20,24	181:14	custody 161:25	
courts 162:25	cross 23:1	customer 11:12	
164:1	109:9,16,20,22	108:3	

[d - dataset] Page 22

_	121,20,22	226.17.22	224.5.225.24
d	121:20,22	236:17,23	324:5 325:24
d 339:3	125:11 128:24	237:18 238:16	326:2,12,13
d.c. 5:10 6:8	156:10 166:16	238:19 239:4	328:14,22
dailies 211:5	167:8 172:6,7	239:19 240:11	329:9,21 331:1
daily 190:17	172:9,17,20,21	241:11,14	333:8 336:13
210:16,22,24	172:24 174:22	242:9 243:3,22	337:20,23,24
210:25 211:2,3	175:2,2 176:5	244:19,21	337:25 338:5
211:6,10,14	176:17,20,21	245:23 247:20	339:22 340:1,2
299:22 346:2	176:23 177:9	261:15,25	340:13 341:6
damage 119:4	178:2,4 179:20	263:23 271:3,3	342:12 343:13
data 23:24	180:4,13,20	273:6 278:5	345:4,5,8,16
24:24 25:9	187:1,4,12	280:7 283:10	347:7 348:24
29:2,9,10 31:4	188:3,4,19	283:14 284:4	349:4
31:8,19,24,25	198:24 200:22	287:13,21,23	database
32:3,4,9 34:25	200:25 201:2,3	287:25 288:14	286:25
36:23 37:9,12	201:5,8,17,19	288:20 290:18	dataset 31:3
37:13,14 38:21	201:21,24,25	291:13,17,20	33:13,19 39:13
38:23 39:1	202:5,6,10,14	292:9,17	39:17 42:20
40:2,2,5,8,8,18	202:21,23	293:17 294:20	124:22 174:11
40:23 42:4,11	203:11,24	297:9,14	174:23,24
42:12,17,21	205:1,2,12,22	298:11,12,13	175:3,6,11,15
43:11 44:10,11	206:4 207:4,13	298:13,17	176:1,9,10,18
45:12 58:2,4	209:15 210:8	299:7,22,25	177:2,10,11
81:3,7,9,16,18	210:11,17,18	301:12 302:20	178:22,25
81:20,22,24,25	210:19,20,23	303:12 305:23	179:1,5,7,17
82:1,2,4,5,7,11	211:13,16,19	306:7 308:19	181:5,6 182:1
83:12,17,18	211:21,24	308:23 310:7	182:2,8,24
85:3 86:5,6,9,9	212:2,6,12	311:21 312:7	183:18,22
86:17 87:7,7,8	214:7 216:22	312:17,19	184:7,11
, ,	218:1 223:3	313:20 317:16	185:25 186:9
87:9,11,18,21	225:17,20	317:22 319:9	186:15,16,23
87:24 88:2,2,5	227:9 229:18	320:14 321:13	187:3,5,17
90:5 91:20	229:25 231:1	322:10,11,17	188:6,9 203:20
106:2 121:15	233:18 236:3,5	322:23 323:8	204:1,6,18,21

[dataset - define]

Page 23

324:21 326:25	daubert's	241:15
328:24,24	164:11	decided 37:14
332:4,14	day 18:9 38:24	85:18 168:5
336:14 339:16	52:2 84:24,24	207:22
344:3,21	199:2 213:20	deciding 37:17
348:10	213:20,21,21	decision 82:4
datasets 58:8	228:16 229:6	decisions 114:3
58:11,12 76:5	245:13,15,16	declare 352:20
83:8 186:20	245:21,21	354:4
200:16 202:3	315:15 316:5	decline 293:6
203:13 206:6	352:22 354:15	293:14
223:10 319:12	days 45:3,5	deconstructing
date 35:12	298:7	251:9
41:12,14 43:17	dds 88:8	dedicated 58:1
74:12 146:1	de 210:21	deemed 354:6
166:24 167:5	death 278:21	deeper 78:9
231:19 232:2	314:2	102:25
255:9,10	debate 23:12	default 257:4
258:17 288:4	49:5	defaults 307:7
296:22,23	decay 224:2	defendant 1:12
300:1 309:17	deceive 98:22	2:12
353:24 354:12	deceiving 97:17	defendants 1:9
dated 352:22	december 1:22	1:15 2:9,15 7:2
dates 228:18	2:23 11:4 12:4	8:2 9:2 14:22
288:20	13:4 14:3,6	14:25 17:24
dating 309:15	221:16 328:16	18:5,9,10,14,18
daubert 160:16	328:19 352:22	18:21 28:18
160:19,20,23	deception	45:21 216:10
161:1,10,13,20	97:13 98:3	216:12,16
162:3,8,13,21	deceptive 115:9	347:5,10,22
162:24 163:2,8	decide 65:2	349:1,10
163:25 164:12	72:17 123:7,12	define 82:23
164:20	133:18 160:25	99:22 121:6,11
	168:19 207:18	177:5,7,25
	328:24,24 332:4,14 336:14 339:16 344:3,21 348:10 datasets 58:8 58:11,12 76:5 83:8 186:20 200:16 202:3 203:13 206:6 223:10 319:12 date 35:12 41:12,14 43:17 74:12 146:1 166:24 167:5 231:19 232:2 255:9,10 258:17 288:4 296:22,23 300:1 309:17 353:24 354:12 dated 352:22 dates 228:18 288:20 dating 309:15 daubert 160:16 160:19,20,23 161:1,10,13,20 162:3,8,13,21 162:24 163:2,8 163:25 164:12	328:24,24 332:4,14 336:14 339:16 344:3,21 348:10 213:20,21,21 228:16 229:6 58:11,12 76:5 83:8 186:20 200:16 202:3 203:13 206:6 223:10 319:12 date 35:12 41:12,14 43:17 74:12 146:1 166:24 167:5 231:19 232:2 255:9,10 258:17 288:4 296:22,23 300:1 309:17 353:24 354:12 dated 352:22 dates 228:18 288:20 dating 309:15 daubert 160:16 160:19,20,23 161:1,10,13,20 162:3,8,13,21 162:24 163:2,8 163:25 164:12 164:20 164:11 day 18:9 38:24 52:2 84:24,24 199:2 213:20 245:13,15,16 245:21,21 245:13,15,16 245:13,15,16 245:21,21 245:13,15,16 245:13,15 245:13,15 245:13,15 245:13,15 245:13,15 245:13,15 245:14 245:14 245:14 245:14 24:12,4 13:12,4 14:12,4 14:12,4 14:12,4 14:12,4 14:12,4 14:12,4 14:12,4 14:12,4 14:12,4 14:12,4 14:12,4 1

[define - destructive]

Page 24

199:8 200:5	271:20 307:16	115:22 123:8	described
221:17 222:3	327:16	193:4 226:16	25:14 76:13
226:15 227:17	defraud 100:3	226:19 251:12	115:24 117:11
248:1,5,21	degree 31:14	278:4 326:12	191:3 194:22
276:25 277:2	71:16,20,23	depends 49:21	214:4 218:17
307:11	72:5,16,19,24	82:2 186:23	224:6 229:6
defined 176:16	72:25 73:1,11	196:24 343:18	241:20 283:17
190:18,21	73:12 74:6,7	depo 43:17	306:20 317:22
221:19,22	74:15,23 76:1	deponent	319:5 320:11
248:18	76:16 77:3,8	352:14 354:3	339:23 343:25
defines 47:4	77:18 78:7,18	deposition 1:19	describes
136:21 138:3	79:7,9,11,17,18	2:18 3:4 14:2,7	317:25
139:9 200:6	79:20,24 81:4	15:10 22:8,15	describing
definitely 52:20	81:8 82:7,21	22:17 23:12	86:10 215:3
definition	83:15,16,17,18	34:24 43:15,24	220:14 224:6
84:15 136:12	83:20,21 84:1	60:25 134:22	224:11 249:9
136:17 144:2	84:3	138:9 195:12	306:19
178:22 179:6	degrees 82:6,10	349:19,21	description
190:2,4,13,19	82:14,15	351:7	11:6 12:6 13:6
190:22 195:20	250:11	depth 81:5	86:6
195:23 220:3	dent 100:14	derive 202:22	deserves
220:16 221:2	depart 85:18	249:15 252:23	336:20 337:11
222:19 223:9	department	dern 6:14	design 11:24
223:16,17	87:19,25	derogatory	221:15
226:23 227:2,5	departure	250:14,14,16	designate
229:9 307:13	85:19 230:7	250:19	105:12 250:8
definitive	231:8	describe 25:5	designated
233:13,14,17	depend 55:11	80:6,10 83:9	14:19
318:18,20	257:13 315:25	88:14 90:11	designed 65:21
definitively	dependent	150:22 165:25	94:13
55:2,4 57:19	239:18 330:7	214:11 215:6	desktop 66:22
232:7 233:4,7	depending 41:7	246:23 278:15	despite 298:21
233:8,11 234:3	50:25 55:23	339:11,13	destructive
234:9,11,16	56:5 68:14	342:5	299:7

[detail - disagree]

Page 25

detail 64:12	developing	108:11 115:12	323:21 324:17
detailed 303:12	43:13 46:16	116:18 119:19	326:16,17
details 344:21	deviation	122:15 123:10	336:5
detect 216:24	209:25 210:4	124:12 125:8,8	differentiation
detecting 11:19	210:12 211:25	129:14 133:17	323:23
131:12 141:4	212:4,10	141:8 142:6	differently
141:10 142:1	213:14 214:1	143:22 159:6	67:20 237:16
144:23	214:22	173:13,22	difficult 96:18
detection	deviations 63:2	177:13 180:9	99:3 100:15
128:19 129:13	devil 272:19	181:5 182:6	116:12,13
determination	devise 102:9	183:17,18	175:25 233:15
166:4 196:22	difference 36:3	186:20 187:10	343:12
determine	46:11 63:25	192:5 196:13	difficulty 43:3
187:5 194:9	67:5 96:8	196:17 199:23	dig 102:25
206:19 210:9	130:5 236:25	200:2 201:19	digital 84:1,3
210:12 216:8	276:14 277:25	206:5,6 208:22	117:21 296:5
227:22 239:9	332:23 347:17	215:14 216:23	296:18 297:1
315:2 322:14	differences	217:2,20	dina 9:24 14:18
determined	64:6,8	218:23 219:1	dinner 246:9
38:16 105:1,16	different 17:22	220:17 222:19	direct 63:4 86:2
169:3 236:2	24:21 32:1	222:21,22	86:3,4 142:24
determining	38:3,5 39:7,21	223:10 226:12	347:21
103:10 162:13	42:13 43:22	226:12,16	directing
196:10	44:23,24,25	227:11,13,17	141:24
devastating	47:22 48:23	234:21,25	direction
117:20 118:19	49:17,20 50:5	237:1,23	239:23 253:10
develop 46:6	56:1 66:24	238:10,19	313:8
47:11 299:15	67:16 76:17	241:6 244:8	directionally
developed	77:12 81:23	248:22 249:19	238:11
47:15 75:19	84:19 85:2	249:21 250:11	directly 26:21
76:6 87:1	95:23 98:18	254:7 255:25	202:2
146:12 292:13	99:1 100:20	260:25 268:22	dirllp.com 6:9
developer	102:1,6,14	276:25 289:20	disagree 97:25
259:19	104:10 106:15	319:7 322:4	

[discipline - dr] Page 26

70 0 10	242 2 247 5	10 0 1 44 0	1 11 2450
discipline	343:3 347:5	divide 44:8	double 245:8
56:13 121:4,6	discusses 220:3	divided 324:22	261:1 289:25
121:13 157:12	discussing 90:1	division 84:12	295:19 303:25
disciplines	90:2 156:8	dlet 331:5	304:1 318:5
83:11 122:2	165:13	docs 46:5,7	332:19
125:8	discussion	document	download
disclose 20:14	113:6 179:18	11:10,21,23	66:17 93:13
21:11 54:3	dispersion	59:7 67:1,2,12	148:3 263:19
65:21 66:4	139:23 147:9	93:14,23 94:1	downloadable
158:11 161:3	dissect 36:3	95:6 147:15,22	262:17
212:23 255:18	dissecting	300:15 332:12	downloaded
256:9 259:22	196:17	349:16	66:22 67:3
disclosed 53:21	disseminated	documents	163:5 219:21
53:22 54:2,5	194:15	152:24 268:4	downloading
267:25	dissemination	346:7,16	59:12 113:12
disclosure 24:4	194:16	doing 22:11	147:24 269:8
66:5 165:18	distinction	34:25 35:1,6	downloads
disconfirm	123:24	38:21 43:7	333:14
264:17	distinctions	93:16 95:2	dr 14:17 151:3
discord 198:12	53:15	101:15,17	165:9,10
discourse	distinctive	126:15 134:12	166:13,13
196:12	139:20	182:3 188:5	167:11,12,13
discovery	distinguishing	204:11,12	167:16 170:9
295:25 296:20	277:4	214:2 220:17	171:11 172:3,3
346:7	distracted	222:7,12	172:23,23
discretion	138:25	264:24 288:13	173:13 174:11
53:19	distribution	319:8	174:12,22
discuss 24:22	224:1 235:8,13	domain 226:19	175:4,16 176:2
28:17 52:25	district 1:1,2	227:16,20	177:16 184:4
53:13	2:1,2	276:15	184:15 185:25
discussed 76:22	diverse 291:16	domains	186:5 187:3,8
123:17,21	diversity	227:14,17	199:19 200:5
141:9 224:12	177:15 291:25	dots 281:9	200:24 201:1
235:19 317:25			202:5 203:20

[dr - employee] Page 27

201102005	226444	1.50.5	100 7 200 1
204:18 290:6	336:1,4,14	echo 170:5	199:5 200:1
290:22 291:21	duplicative	171:17,20	271:25 273:2
292:9 347:16	105:6 182:7	economics	273:22 279:6
347:16 348:2,2	324:15	83:24	284:1 304:11
draft 63:14,16	dynamics	edges 340:10	330:8 337:17
125:24 171:25	247:4	edit 45:19,21	elapsed 350:5
drafted 44:20	e	46:24	electronic
drafting 28:13	e 3:1,1 4:1,1 5:1	edited 123:16	25:25
45:2,15 46:3	5:1 6:1,1 7:1,1	editing 46:18	element 47:17
125:23		65:18	101:25 214:1
drafts 44:22	8:1,1 9:1,1 85:5 127:4	editor 123:18	254:12
drainbamager	339:3 353:3,3	edits 319:14	elements 62:24
272:17	353:3	educate 254:17	78:11 119:22
dramatically	earlier 23:17	educated 56:6	158:7 268:24
214:8	57:25 66:23	education	eleven 188:12
draw 186:14	92:6 129:2	56:19 73:8	269:6 316:18
289:14	146:5 149:8,10	eff 270:4	317:6
driven 71:5	149:20 155:19	effect 39:14	elizabeth 11:18
114:1 198:13	155:22 201:20	40:3 117:10	132:21
214:24	218:17 231:17	132:10 162:1	else's 179:1
drop 39:3	235:19 301:24	334:23	201:3
dropped 293:5	314:7 316:25	effective 299:5	email 17:14,14
293:7,11	318:18 343:4,8	effectiveness	33:11 349:8
317:18	350:19	124:21 125:6	350:8
dropping	early 160:20	effing 270:1	emails 347:21
103:22	ease 152:10	effort 200:1	349:15
due 109:25	easier 93:18	ehudson 4:11	emanuel 3:5
110:23 248:13		eight 45:3,5	emotions
dunn 6:4 14:15	144:19	either 51:1	115:13,14
dupes 210:21	easily 31:23	66:20 99:5	employed
duplicate	east 4:8 8:9	100:2,23 115:5	162:11
323:13 335:20	eastern 14:6	115:14 119:24	employee
duplicates	eat 246:10	122:1 134:8	352:18
324:5 335:17		176:6 198:22	
	1		L

[enable - examination]

Page 28

enable 94:13	204:22 205:5	enumerate	193:2 241:13
	ensures 225:21	256:3	283:20 291:2
encompasses 176:3		environment	353:1 354:1
	ensuring 87:9 201:4		ethical 11:11
encyclopedia 11:23 221:15		264:5,17 265:1	ethics 11:16
	enter 303:21	266:16 eras 276:11	
222:20	304:11		74:5 75:16
ended 41:16	entered 22:4,14	errata 354:7	78:7,11
70:22	57:8 61:14	error 39:9,10	evaluate
ends 13:11 18:2	147:19 211:20	48:11 130:19	162:25 164:1
206:18 270:5	304:15 332:3	142:25 278:2,3	event 230:16
272:21 300:24	entering	escalating	335:1
301:15 311:10	313:15	116:17	events 114:14
330:20 332:8	enterprise	escalation	232:3 233:20
enforce 53:24	119:16,19	116:1	327:25 328:13
enforced 54:3	entertainment	especially	328:18
engage 22:25	198:14 199:9	54:16 117:22	everybody
23:11 94:12,18	199:11	217:1 313:20	351:3
95:3 114:5	entire 35:1	esra 4:5	everyday 178:6
115:22	39:13 93:23	essential 247:7	178:9
engaged 20:16	94:1 135:8	est 2:22,23	exact 43:3 53:7
23:10,16 30:3	138:6 162:2	351:8	53:12 117:10
engagement	166:19 176:17	establish 232:7	148:5 166:24
19:3,12,15	176:23 181:17	234:4,12	183:11 221:10
115:23,24	244:25 280:19	established	222:11 267:17
161:14,15	292:3 309:1	162:12 233:5	323:3 335:17
engagements	entirely 180:15	235:18 310:24	336:1,4,10
64:5,12	180:17 183:18	et 1:8,13,15 2:8	exactly 33:17
engineering	entirety 134:16	2:13,15 11:3	34:25 48:3
85:3 121:15	294:24	12:3 13:3 14:9	170:5 198:4
english 251:9	entitled 105:13	25:11 76:23	203:6 223:1
ensure 59:19	137:7 138:18	84:18 121:16	254:13 331:18
85:7 126:21	157:23	140:21 141:3	348:16
164:15 175:20	entries 82:13	143:13 153:10	examination
201:18,24	324:5,12	179:21 190:8	10:1,5 15:15

[examination - expert]

Page 29

252.10	organitivas 70.1	279.9 10 270.0	200.2 12 201.5
352:10	executives 79:1	278:8,10 279:9	280:2,13 281:5
examining	79:4 80:20,21	279:10 280:22	281:15 282:8
218:14	exhibit 11:6,7,8	281:1,20,23	282:24 315:23
example 48:15	11:10,11,14,15	282:12,14	expected
103:17 104:7	11:17,21,23	285:13,17,21	160:14
146:13 171:11	12:6,7,9,10,12	300:13,14	experience 25:9
243:10 245:17	12:13,15,16,18	302:24,25	78:17 79:5
examples 54:2	12:20,21,22,23	304:2 307:2,9	88:14 121:20
104:25 155:16	12:24 13:6,7,8	308:9,10,13	121:25 155:17
197:13	13:9,10,11	315:7,8 316:7	155:23,24
excel 12:23	16:9,11 61:23	320:24,25	156:20 157:21
13:8,10 36:6	61:25 62:7,20	321:2,4,5	158:21 159:16
308:10 309:6	63:10 64:3	322:23,24,25	162:18 167:11
326:24	67:2,8 90:24	325:5,7,9	229:10
excels 308:16	90:25 91:2	329:6,7 332:7	experienced
326:18	93:5 112:13,18	332:9 346:13	32:7
exceptional	112:19,21	349:23	experiment
230:7 231:8	113:3,5,7,8,9	exhibited	179:24
excerpt 11:14	113:21 118:8	198:11	expert 9:24
11:15 113:6,20	118:10,12	exhibits 11:1	11:7,8 19:10
117:16	125:20 130:23	12:1 13:1	24:20,23 33:21
excuse 68:3	130:25 131:1,3	131:4 268:5	34:1,2,5,11,11
77:11 93:22	139:20 141:12	269:1	34:15 59:4,16
165:1 166:9	142:24 143:1,3	exist 48:12 49:4	64:1 73:18
183:5 184:22	144:11,18	49:8 121:3	96:20 98:17
191:18 233:25	147:16,20,23	122:1 275:24	121:18,19
259:14 295:11	152:12 198:3,4	existed 237:7	155:24 162:7
302:23 303:22	207:10 209:6	exists 191:19	162:25 164:1
excused 137:16	219:15,17,18	239:19 266:13	164:11 165:2,4
executionary	229:1 246:3	exited 62:9	166:22 172:2,4
71:10	268:4,6 269:2	expand 336:22	172:12 182:2
executive 78:24	269:4,7,12,17	expect 271:7,10	196:2,10
78:25 80:25	269:18 272:10	271:15 272:24	227:20,21,25
81:9,12,18	272:12 276:6,8	277:13 278:22	228:12 291:15

[expert - feeding]

Page 30

292:23	explanations	eyeball 266:2	197:6
expertise 25:5	329:2	f	familiar 82:16
121:11 162:12	extent 18:24	f 309:19 310:14	91:10 133:1
164:19 199:22	21:10 24:4	310:18 314:2	219:11 333:11
experts 14:19	58:5 73:21	330:12,14	349:13
34:8 165:3	78:6 80:25	331:11,12,12	family 254:24
167:5 173:2,12	82:13 92:12	face 203:24,25	255:20 267:13
173:16,21	161:3 165:17	facebook 84:19	275:12
176:21	165:17	95:11 179:20	far 41:13
expired 349:24	external 348:25	221:8 222:25	farm 98:21
explain 23:3,8	extract 262:16	fact 149:22	farr 5:4 14:17
23:8 38:20	263:14 287:13	214:10 215:5	fast 117:22
46:8,11 84:14	320:14 321:13	223:11 231:12	fastest 303:10
101:7 103:13	330:2	231:24 232:18	fate 281:22
123:24 132:13	extracted	232:21 295:2	father 278:20
136:20 138:3	283:15 326:13	factor 102:5	314:1
139:9 145:17	extraction	197:2,3 217:1	fauxmoi 278:14
153:5 164:12	273:6,17	292:6	300:25 302:10
175:14 196:9	extracts 306:3	factors 102:6,9	302:12 304:5
198:20 227:6	extraordinarily	108:19 197:5	310:16 314:3,9
229:18 231:2	210:7 214:23	249:19 299:8	feasible 262:24
248:17 276:14	extraordinary	329:4	263:3,10
313:13	210:6 214:11	factual 249:5	feature 42:15
explained	215:4,7 230:16	factually 47:5	127:2 149:16
254:3	extrapolated	129:23	february
explaining	33:17	faculty 122:11	197:18 198:11
184:23 309:9	extreme 215:5	122:13	200:13 202:19
explains 228:16	extremely	faith 51:19	203:16 290:13
explanation	96:18 99:3	fake 94:11	327:22 328:12
130:15 148:23	100:15 115:15	114:22 115:11	feed 115:13
149:4 151:8,14	115:15 116:13	fall 102:23	feedback
151:21 152:2	175:25	false 115:6	195:11
230:17,23,24	eye 261:3	196:18,25	feeding 319:11
328:1 330:5	264:24	, -	

[feel - focused] Page 31

6 1 22 7	245.60	6. 1 55 20 05 0	107 10 201 2
feel 32:7	345:6,9	find 55:20 85:8	197:19 201:2
fein 9:5 14:21	filed 327:23	134:5 228:3	203:25 204:22
14:24	files 284:7,10	328:21 344:16	207:21 217:21
felt 107:8	284:12,20,22	finding 148:24	228:1 244:1
203:11	285:1,3,10	160:2	250:12 279:12
female 19:20	290:3 304:3	findings 142:20	279:17 286:6
19:21	308:25 317:2,4	148:10	299:18 307:11
ferrara 152:18	319:5 326:4	fine 76:7	fit 27:7 93:14
153:10,19	330:7 344:20	248:25 249:14	five 39:21
fever 16:1,1	346:20	249:17,18,22	60:22 177:13
field 83:8 227:9	filing 328:16	249:25 250:4	188:3 203:1
312:12	fill 26:9 305:24	253:25 340:6	205:22 207:4
fields 307:5,7	filled 26:1,12	fingerprinting	216:2,5,6,10,23
313:8,10	26:19 304:22	102:4 157:14	217:2,6 218:16
fifth 177:19	304:24 306:5	fingerprints	223:24 225:1
figueroa 3:10	film 191:22	93:4 139:21	229:1 236:6
figure 60:24	192:4,17,23	finish 41:4	237:1 284:7
101:15 248:4	193:1,7,10	80:23 111:4	289:19 308:25
272:2 350:6	198:13 199:8	120:18 182:11	321:19 326:15
file 36:6 259:25	199:10 232:8	183:6,8	350:15
285:6,13,20	234:1,4,12,17	finished 51:7	flagged 285:5
294:8 304:4,7	335:1	65:24 66:3	flip 101:5
305:19,21	film's 232:2	68:7 184:24	floor 3:11 7:9
307:17,18,20	233:5	firm 19:5	9:8
307:25 308:2	filter 331:6	first 16:13 20:4	flow 88:10
309:6,9,14	final 168:23	25:18,20 26:12	103:19
311:2,22	343:23 348:19	31:6 63:6,9	fluctuation
312:15 316:8	348:23	93:5 94:5 95:5	230:15
317:5,19,21,22	finale 12:17	99:19 135:14	focus 64:1 72:2
318:24 319:1	281:25	137:16 152:16	72:16,17 73:16
319:15 324:14	finance 81:4,22	159:15 160:22	81:3 208:22
330:2 339:18	227:10	176:16 178:4	254:13,16
339:24,25	financially	179:1,19 181:1	focused 63:21
340:1 344:21	352:19	182:21 197:17	63:23 64:3

[focused - fritz] Page 32

177:1 195:18	341:16,20,24	346:16	frequently
folder 38:22,23	343:17	frame 40:24,25	198:23 268:19
61:23 340:2	foregoing	41:19 42:18	friday 45:6
345:4,5	352:5,15,21	188:4 197:18	fritz 14:20,20
folks 219:1	354:5	197:20 200:17	17:8 19:1,24
follow 21:19	foreign 106:20	200:23 201:21	20:13,18,23
24:6 183:7	foremost	203:3 204:24	21:9,18,25
254:8	159:15	205:6,11 206:9	22:22,24 23:3
followed	forensics 31:1	206:10 215:25	23:6,11,20
281:15,25	88:22 227:13	222:11 225:19	24:3,12 26:7
following 20:21	233:16	225:23 236:24	27:15,24 28:5
21:14 119:25	form 46:15	238:18 254:11	28:10,15 30:21
307:6	90:16 92:1	332:4	38:7 41:1,3
follows 138:1	95:25 160:15	frames 326:11	42:24 44:1
139:7	204:13 217:1	framework	45:24 46:25
footnote 129:8	formal 136:11	11:19 131:12	47:9 48:8,17
129:9 140:24	formatted	141:10,24	49:9,16 51:5
140:24 141:2	80:21	frameworks	51:12 53:3
142:13 168:3,7	formatting	54:15	54:24 55:8,17
169:23 170:2	34:4	frances 278:19	56:16,25 57:12
170:10,19	forms 97:13	313:25	59:6,10,18
171:13	98:3,23	francis 12:12	60:1,11,17,21
footnotes 48:21	forth 245:19	frankly 53:6	61:3,6 64:21
127:8 170:7,12	352:6	55:1 72:3	65:20,24 66:3
170:14 171:6,9	fortunately	109:25	68:20 69:17
forecast 288:13	34:2	free 122:10	70:9 71:25
288:15 341:22	forum 124:10	freedman 7:5,6	72:14 73:6,14
343:23 344:1	forward 21:18	16:14,15,17,23	73:25 74:25
344:14,23	65:16	17:4,7,19	76:2 77:6,19
forecasted	found 62:24	18:22,25 19:23	78:20 80:2,8
342:4	149:12 150:11	21:23 22:2,2,3	80:18 82:9
forecasting	154:25 224:8	22:5,9,14,18	83:2,6 85:13
340:16,20,25	four 172:2	33:3 65:17	86:12,23 87:4
341:4,11,13,14	242:4,8 298:12		90:13 91:22

[fritz - fritz] Page 33

93:13,22 94:2	145:23 146:8	194:24 195:21	267:19 268:1
94:20,25 95:15	146:22 149:1,5	196:4 197:1	270:13,23
96:15,22 98:7	150:2,15,24	201:14 202:12	271:1,9 272:4
99:14,18,23	151:5,11,18,24	203:22 204:7	273:10 274:14
100:18 101:20	152:5,12 153:7	204:19 205:20	274:24 275:11
102:11,19	153:15,21	206:2 208:12	276:2,17
103:6 104:3	154:7,13,21	212:7 213:1,4	277:15,20
105:3,17 107:4	155:3 156:17	215:8 217:14	278:24 279:4
108:5,10,17,20	157:1,8 158:1	219:10 220:12	281:7 283:8
108:24 109:3,6	158:14 159:3	221:20 222:16	284:11 286:19
109:10,17,21	159:12,21	225:15 226:18	287:19 290:15
109:25 110:5	161:2 163:9,15	226:24 227:7	291:9,23 292:4
110:10,19,23	164:5,13,24	227:24 228:6	292:11,18,25
111:3,10,23	165:16 166:10	228:11 230:19	293:19 296:15
112:1,6 113:15	168:1 169:5,11	232:13,25	296:19 297:3
113:18 116:5	169:21 170:4	234:6,23	297:11 298:9
116:15 118:4,8	170:15,22	235:23 238:2,8	298:15 299:1
120:8,16,18	171:4,14	239:1 240:7,25	299:21 300:9
121:7 123:13	173:19 174:2	241:21 242:13	301:8 302:1
126:13 127:13	174:17 175:5	243:5,18 247:9	304:14,20
128:10 129:19	175:10,22	251:25 252:17	305:9 306:6,12
129:25 130:9	176:13 177:3	253:11 254:19	306:22 308:1
130:17 132:7	177:12 178:7	255:13,24	308:21 310:9
133:10,20	178:10,14,23	256:4,12,19	311:17 312:5
134:1 135:5,7	179:11,15	257:1,15	312:24 313:6
135:13,19	180:2,24 181:8	258:13,18	313:16 314:13
136:4,23 137:2	181:19 182:9	259:2,10 260:3	315:18,24
137:5,9,15,22	182:13,17	260:10,17	316:20 318:3
138:5,7,11,15	183:5,23 184:6	261:16,23	318:25 319:6
138:20 139:2,4	184:16,19,22	262:6,15,22	322:8 324:8
139:11 140:4	185:5 186:18	263:6,12,24	328:6 331:20
140:12 141:16	187:19,25	264:14 265:5	332:1 333:1,19
142:3 143:7	189:7 190:20	265:25 266:8	334:2,10 335:2
144:1,6 145:20	191:24 193:16	266:19 267:10	335:19,22

[fritz - go] Page 34

336:2 337:15	212:20 240:22	98:19 185:18	globally 180:10
345:14 347:12	244:1 248:21	206:13 213:19	236:8
348:12 350:14	259:4 265:18	239:4,5 242:14	go 16:8 33:24
fritz's 138:24	265:20 299:23	243:11 253:9	36:2,24 37:17
front 231:20	302:3	263:4 275:6	38:1,22,25
306:8	generally	284:16,17	39:2,6,14
fruition 125:14	104:23 178:6	285:14 305:4	41:13 49:11
full 15:18 30:7	296:10	313:7 316:14	51:7 53:4
68:10 69:3,5	generated	326:16 342:23	58:16 59:14
69:10,13 70:8	11:22 58:9	343:11	60:19 61:2
75:8 80:15,17	89:4 146:17	given 54:2 81:5	62:11 66:10
80:19 121:14	148:19,25	166:21 172:11	67:10 71:13
123:22 176:10	149:14 150:23	176:4,17 186:7	76:4 93:5
281:10	151:4 154:12	201:18 227:22	99:24 104:4
fully 184:25	154:20 155:2	265:17 291:15	111:18 116:17
functionality	generating	296:21 310:5	116:23 117:3
62:10	47:4	332:4 349:20	117:16 118:6
further 352:17	generative 46:9	354:9	118:11 120:18
future 11:16	46:16,20,22	gives 78:9	125:11,12,18
70:8 71:8	53:14 54:23	217:3 330:9	125:20 126:17
189:14 238:1	56:14,24 57:6	giving 16:5	129:5 132:12
g	144:7 146:12	22:15,18 64:4	136:13 137:19
gains 196:17	146:18 149:9	245:16	140:6,8,11,15
gallagher 5:4	163:20	glass 219:6,9	140:16 141:12
14:17	generator	220:6	144:17,18
garbage 272:20	150:5,18	glg 23:16,16	152:8,23
gemini 46:6,7	genre 313:21	24:10,20 25:1	158:19 160:2
gene 219:5,8	getting 24:17	25:3,6,12,19,22	160:13 161:5
220:6	118:16 238:14	26:20,22,23	175:1 178:14
general 54:8	gist 85:12	27:10 36:2	182:19 185:1,3
76:19 106:17	give 15:10,21	161:14,15,17	185:5,18 191:8
145:25 190:1	22:17 27:19	global 84:8,25	197:23 198:5,5
	39:25 40:11,22	124:21 222:6	203:18 207:1,3
200:9 206:21	40:25 43:6	316:1	207:7 208:4

[go - governski] Page 35

209:5,6,10	343:15 344:2	247:14 256:14	22:13,21 23:2
214:16 223:19	344:19 348:14	259:18 268:3,5	23:7,13,21
228:15,20,23	351:2	268:7 269:10	24:8,14 26:11
229:12 231:10	goal 85:5 97:16	284:2 285:12	27:20 28:1,6
242:17 244:16	348:8	318:17 349:18	28:11,16 31:10
246:15 248:9	goals 85:9	good 14:14,20	38:10 41:9
252:22 255:14	88:12	15:4,17 85:18	43:1 44:6 46:1
259:4,16,18	god 122:6	101:17 102:20	47:2,18 48:13
260:22 262:11	goes 214:8	185:21 206:22	49:13,19 51:6
263:18 266:1,2	going 16:8	goods 84:17	51:15 53:8
269:3,13	21:18,19 22:23	107:9,13	55:3,14,19
271:22 272:3,9	23:11 28:21	google 46:5,7	56:21 57:3,21
276:5 277:6	29:25 35:17	49:14,25 51:2	58:15,25 59:1
278:7 279:8	45:14 58:17	52:5 161:12	59:9,14,23
280:21 281:19	60:13,15,19,25	162:3,15 195:7	60:4,8,13,19,23
287:3,20	67:10 71:13,14	195:8,9 255:9	61:5,12,22
289:25 291:3	72:7 85:25	257:22 334:5,5	62:1,11,18
294:7,23	90:24 93:25	339:5 340:7	64:24 65:23
295:19 298:12	96:10 99:20	googled 161:11	66:1,7 68:22
300:17 304:25	101:23 103:15	161:18	69:20 70:11
305:5,11,15	108:20,25	googling 49:24	72:6,18 73:10
309:7,19 310:4	109:10,17	gosh 219:23	73:20 74:3
313:24 314:22	110:10 111:5	330:19	75:3 76:11
316:21 318:5	113:2,3,15	gotten 49:6	77:15,21,24
320:25 322:2	115:11 118:14	government	78:21,23 80:5
322:22 324:1	127:19 130:22	75:21	80:13,24 82:12
325:4,24 327:1	131:3 138:8	governments	83:3,10 85:14
329:1,15	139:13 144:19	114:15	86:15 87:2,13
330:11 331:6,8	147:14 168:4	governski 6:5	90:18,23 91:5
331:9,10,10,11	177:24 185:1,2	10:6 14:14,15	91:8 92:5 93:8
332:18 333:11	191:7 194:2	15:1,16 16:8	93:15,20,25
336:16 337:7,9	201:19 204:23	16:12 20:1,16	94:4,23 95:1
337:23,25	211:5,6 228:21	20:20 21:1,13	95:18 96:19
338:12 339:16	241:10 246:2,5	21:21 22:3,8	97:2 98:11
	l .	1	

[governski - governski]

Page 36

99:16,21 100:5	149:11 150:9	195:24 196:8	263:2,9,16
102:7,16 103:3	150:20 151:1,7	197:4 201:22	264:6,19 265:6
103:12 104:21	151:13,20	202:16 204:3	266:5,12,22
105:8,23	152:1,7,15	204:15 205:4	267:15,22
107:14 108:8	153:9,17,24	205:23 206:11	268:3,8 269:9
108:14,22	154:9,17,24	208:20 212:13	269:14 270:16
109:1,5,7,12,18	155:6 156:22	213:12 215:11	270:24 271:6
109:23 110:4,7	157:4,16	217:15 219:14	271:13 272:6,9
110:13,18,21	158:10,16	219:19,22	272:13 273:13
111:1,7,11,15	159:7,17 160:1	220:19 221:24	274:21 275:7
111:18 112:3	161:9 163:11	222:18 226:1	275:14 276:5,9
112:12,18,22	163:21 164:8	226:21 227:3	276:18 277:17
113:2,10,17,19	164:18 165:11	227:15 228:2,8	277:24 278:7
116:9,19 118:6	165:23 166:18	228:14 230:21	278:11 279:1,8
118:9,15,17	168:8 169:7,15	232:16 233:3	279:11 280:21
120:11,21	170:1,6,18,24	234:7 235:1	281:2,11,19,24
121:10 123:15	171:7,19	236:1 238:3,21	282:11,15
126:17,20	173:23 174:5	239:7 240:12	283:16 284:14
127:16 128:12	174:20 175:7	241:18,24	285:12,18
128:15 129:21	175:13 176:7	242:21 243:15	286:24 287:6
130:3,14,20	176:24 177:4	243:20 246:7	287:22 290:19
131:2 132:11	177:20 178:12	246:15,22	291:18 292:1,7
133:13,24	178:20 179:3	247:11 248:9	292:14,21
134:4 135:9,15	179:12,22	248:16 252:9	293:2,22
136:1,7,25	180:14 181:2	252:20 253:8	296:16,24
137:4,6,13,22	181:15,20	253:15 254:20	297:6,16
138:7,13,17,22	182:11,14,25	255:16 256:2,7	298:10,23
139:4,14	183:15 184:2,9	256:16,20	299:9 300:2,12
140:10,14	184:17,21	257:5,20	300:16,20
141:19 142:5	185:1,15,20,22	258:16,20	301:6,9 302:7
143:12 144:3	186:21 187:22	259:6,21 260:7	304:17,23
144:10 146:3,9	188:7 189:13	260:13,20	305:10,14,20
146:23 147:14	190:23 192:7	261:19 262:2	306:9,15 307:1
147:21 149:3	193:19 195:4	262:10,19	308:7,24

[governski - hashtags]

Page 37

310:12 312:1,8	graham 11:17	311:12 315:20	handled 28:13
313:3,12,23	132:21 140:21	315:25	275:17
314:18 315:5,9	141:3 143:13	guessing	handles 31:19
315:21 316:2	144:13,21	256:17 257:18	handling 22:10
316:24 318:9	146:25 147:2	guys 248:7	happen 54:7
319:3,13	147:12 148:14	h	happened
320:21 321:3	152:9,17	h 353:3	103:1 111:23
322:13,22	grammarly	half 166:25	111:24 192:25
323:1 324:18	50:12,15	167:2	232:5 234:20
325:4,8 328:10	149:12,16,24	hallmark	236:13 244:11
329:5,8 331:4	150:1	295:12	298:17,19
331:14,23	granting 77:8	hallucinated	happier 282:18
332:6,10 333:4	granular 343:6	47:21,24,25	happy 115:15
333:20 334:3	graph 88:5	48:2 129:22	197:21 282:20
334:13 335:13	great 15:13	130:1,4,6	306:13
335:25 336:9	122:5 219:23	143:6,9	hard 187:11
337:18 338:11	270:5	hallucination	281:21
338:14,21	greater 291:20	47:4 48:16,19	harm 100:3,23
345:15 347:19	greatest 308:3	48:20,24 130:8	106:22 114:15
348:14,17,22	grift 270:5	130:13 143:16	117:19 118:19
349:18 350:7	group 18:10	143:21,21,22	harvested
350:10,22	199:3 277:1,7	143:25 144:5,9	243:14
351:1,4	278:17	146:7,14	hash 322:18
gptzero 11:21	groups 302:3	hallucinations	hashtag 13:7
50:16 148:4	growth 11:12	48:11	271:12 319:17
149:23 150:1	guarantee	hames 11:18	319:19 320:3
151:9,15,22	181:6 183:20	132:21 144:13	320:14,15,18
154:5,11,19	guess 19:25	hand 15:8	320:23,23
163:13	30:14 36:13	260:23 261:3	321:6,11,14,18
gptzero's	70:25 78:1	264:3,24 280:6	322:5,11,21
148:23	144:20 203:10	handle 32:8	hashtags
grade 49:2	251:9 256:10	91:3	103:19,20
graduate 71:19	256:22,24	71.5	123:10 280:23
74:7	297:13 311:7		281:15 282:1

[hashtags - hunter's]

Page 38

		T	
282:21 283:13	higher 46:12	homogeneous	323:6 344:25
320:17 321:21	105:7 177:16	101:13 103:15	human 48:10
321:24 322:1,7	212:18,20	honest 193:10	99:3 100:22
322:9,10,19	249:1 301:19	honestly 19:19	115:16,17
hat 98:16	334:24	20:7 26:4	122:7 150:22
hate 297:12	highest 86:4	125:2 132:8	198:24 200:2
342:18	highlight 76:10	161:11	humans 90:17
head 84:8,25	highlighted	hopefully	96:25 100:16
healthier 12:18	328:22	272:10	199:4
283:20	highly 148:18	hoping 200:23	humphrey's
hear 77:21	hired 51:19	hour 32:22	165:10 166:13
248:8	historically	35:19 62:5	humphreys
heard 31:21	91:25	225:19,23	172:3,23
32:13 50:12	hit 41:23 42:4	231:16	347:16 348:2
56:3 219:8	42:22 88:12	hourly 295:11	hunch 275:8
heart 280:25	177:22 181:18	hours 34:17	hundred 58:1
281:14	181:25 183:19	35:5,8,22 43:4	236:11
heath 7:3 8:3	240:5 242:9	43:16 77:8,16	hunter 28:25
9:3 17:25	243:4 251:22	79:22 108:21	29:1,6,19,24,24
help 44:14,15	hits 180:22	109:11 224:1	30:16 32:17,19
44:17 79:5	hoc 123:11	225:3,10,14	32:21,23 33:5
132:13	hold 20:13	226:3,9 228:4	33:7 36:17
helpful 93:16	162:7 165:16	231:18 348:16	37:6,9,14
93:17	165:16 178:10	howard 152:17	39:20 40:8
helps 288:13	222:9 248:7	152:21 153:5	41:23 42:4,20
henchman	holmes 3:7	hubs 140:1	43:20 44:13
272:19	home 195:7,8,9	147:10 155:9	58:12 167:8
hereto 354:8	homepage	hudson 4:5	245:7 284:24
high 40:20	303:16 304:13	huge 336:19	284:25 306:11
47:12 51:22	304:16 305:4	huh 18:3 43:12	311:15 312:3
57:10 139:23	307:5	101:10 115:7	319:2 328:8
212:4,9,10,11	homogeneity	148:8 149:18	334:4
218:13 220:15	155:11 156:10	193:24 207:9	hunter's 31:12
335:11		315:13 319:20	32:6 38:20

[hunter's - include]

Page 39

	1		
319:5 328:5	272:12 276:8	ignore 277:23	inaccurate
hybrid 75:6,10	278:10 279:10	278:1	150:1 166:17
hype 295:4	281:1,23	illegitimate	170:3,11 327:6
hyphen 282:2,3	282:14 285:17	193:4,15	inaccurately
282:3	300:14 307:9	194:10 196:6	197:12
hypothetical	308:13 315:8	196:11,24	inadequate
117:4 184:3	321:2 322:25	197:14 199:8	150:18
192:15 238:22	325:7 329:7	199:25	inappropriate
239:6 287:16	332:9	image 314:16	111:5
hypothetically	identified	images 280:5	inauthentic
237:15 324:19	106:24 133:12	281:9 326:10	11:10 91:11,13
hypotheticals	144:15 145:18	immediately	92:8,14 97:12
184:1	183:18,19	295:2	97:14 98:2,4
i	306:19 307:24	impact 96:10	98:13 99:8,9
idea 154:5	311:1,16 320:5	99:5 100:3	99:22 100:1
201:10 324:4	322:19	117:24 118:21	103:10,25
ideal 244:2	identifiers	297:10	104:25 105:2
ideally 41:7	78:15 101:24	impactful	105:16 108:1
203:8 231:2	identifies 136:9	100:14	inauthenticity
299:5 335:4	identify 14:12	implications	101:6,8,9,19,25
identical 67:19	102:18 107:11	37:3 71:12	102:10
103:17,18	133:9 135:23	important	incident 104:23
105:6 224:2	136:3 140:2	211:1 268:12	117:23 118:20
323:20	157:17 159:9	324:7,10	include 17:25
identifiable	180:15,22	332:24 334:8	58:2 85:3 86:7
101:2 102:14	194:4,11,12	impossible	106:14,25
139:25	212:20 255:11	116:13 176:5	127:1,6,8,12
identification	265:7 266:25	improperly	146:5 156:16
16:11 61:25	267:23 312:12	22:10	169:1 174:24
91:2 112:21	341:15	inaccessible	251:19 270:18
113:9 118:12	identifying	180:12	270:20 271:2
131:1 147:20	149:9 261:10	inaccuracy	287:1,4,8
219:18 269:12	261:12	150:5	288:6,11
217.10 207.12			297:20 299:2
L	1	1	

[include - input]

Page 40

	I	
		information
209:22 229:21	324:12,13	27:17 47:5
232:8 234:4,12	individual's	64:4,7 66:5,8
298:2 335:8	56:5	105:19 115:4,6
increased	individually	115:13,21
197:9 300:1	217:22 218:24	129:24 137:7
increases 238:6	314:23	162:1 165:19
independent	individuals	178:19 188:20
161:5 162:18	21:4,7 24:21	189:8,9 194:21
199:21 220:14	27:12 56:13	205:19 233:24
220:22,24	80:21 97:16	245:1,3 258:25
index 10:1 11:1	98:5,6,14	264:12 267:24
12:1 13:1	100:22 114:16	284:17 290:25
india 79:13	115:20 133:2	291:15 305:13
indicate 132:2	178:18 199:4	307:2 313:20
indicated	213:10	319:10 326:14
132:14	industry	326:16 343:6
indication	190:22,24	347:18
143:15	191:2,9 218:8	informed 73:23
indicative	218:11 341:8	82:4
212:1,5,9	inference 200:7	initial 238:20
indicia 56:23	257:3 328:7,8	343:18
individual 30:5	inferences	initially 328:15
76:14 96:9	165:5 166:15	initiatives
97:16 98:5,14	inflated 106:4	214:2
123:6 175:1	106:5,6	inorganic
179:8 180:12	inflating	92:15,22,23
194:5 217:24	106:22	97:7 116:4,8
221:6,11 222:7	influence	116:11,23
222:22 223:12	139:19	165:8,13,25
260:2,9 261:5	influences	166:5
261:10,12	114:2	input 307:5,6
263:8,11 266:7	inform 159:19	307:20 308:8,9
266:15,18,18		308:11,18,25
	298:2 335:8 increased 197:9 300:1 increases 238:6 independent 161:5 162:18 199:21 220:14 220:22,24 index 10:1 11:1 12:1 13:1 india 79:13 indicate 132:2 indicated 132:14 indication 143:15 indicative 212:1,5,9 indicia 56:23 individual 30:5 76:14 96:9 97:16 98:5,14 123:6 175:1 179:8 180:12 194:5 217:24 221:6,11 222:7 222:22 223:12 260:2,9 261:5 261:10,12 263:8,11 266:7	209:22 229:21 232:8 234:4,12 298:2 335:8 increased 197:9 300:1 increases 238:6 independent 161:5 162:18 199:21 220:14 220:22,24 index 10:1 11:1 12:1 13:1 india 79:13 indicate 132:2 indicated 132:14 indication 143:15 indicative 212:1,5,9 indicia 56:23 individual 30:5 76:14 96:9 97:16 98:5,14 123:6 175:1 179:8 180:12 194:5 217:24 221:6,11 222:7 222:22 223:12 260:2,9 261:5 261:10,12 263:8,11 266:7 324:12,13 individual's 56:5 individually 217:22 218:24 314:23 individuals 21:4,7 24:21 27:12 56:13 80:21 97:16 98:5,6,14 100:22 114:16 115:20 133:2 178:18 199:4 213:10 industry 190:22,24 191:2,9 218:8 218:11 341:8 inference 200:7 257:3 328:7,8 inferences 165:5 166:15 inflated 106:4 106:5,6 inflating 106:22 influence 139:19 influences 114:2 inform 159:19

[input - ip] Page 41

309:17,18	241:3,9 271:4	intended	interrogatories
312:12 321:1	283:11 297:21	145:14,16	346:9,10,16
322:23 326:4	311:19	intense 115:21	347:1 349:12
326:24 329:6	instances	inter 17:23	interrogatory
input.csv 13:10	114:22	interact 16:22	346:18 347:5
input.xlsx	institution 50:2	17:3,6 91:15	347:20 349:7
12:23	instruct 20:14	91:18	interrupt 137:9
inputs 182:22	21:12 24:3	interacted	183:1,6
215:19,20	27:15 65:20	16:24 18:24	interrupted
307:21 342:9	161:2 165:20	91:25 219:3	137:16
inputting	instructed	interaction	interrupting
181:12	254:7 342:23	18:17	138:12
inputxlsx 13:8	instructing	interactions	interruption
insight 202:22	21:22 22:16	18:13	195:1
insights 33:18	instruction	interdisciplin	intervention
75:19 87:7	10:10 21:9,15	83:7,11	350:16
instagram	21:19 24:12	interest 123:6	interviews
12:14,15 95:12	27:19,24 28:5	214:24	192:3
177:17 179:20	28:10,15 40:1	interested	interwoven
208:1,5,7,10,11	264:22	352:19	76:16
208:14,17	instructions	interface	introduce
216:4 217:9	24:7 39:19	208:13	131:3
221:7 222:25	254:21 284:13	interfaces	introduced
241:3,8,13	284:15,16	244:21	61:22 147:19
243:10 279:9	integrate 221:1	internally	intuition 159:2
280:2,19,22	integrated	89:18 90:22	investigating
326:9,14	81:20	91:20	128:18 129:12
instance 54:15	integrates	interpret 32:3	investment
90:8 92:17	220:22	326:9	119:5,18
102:1 173:12	intelligence	interpretation	involved
173:15 177:17	46:2 74:5	319:9	103:25 176:22
187:10 197:8	75:16 78:7	interpreting	192:4
209:20 212:19	intend 188:13	265:19	ip 282:2
235:4 239:17	188:16		

[ipsos - keywords]

Page 42

ipsos 104:15 107:6 120:17 124:8 155:20 213:24 222:4 345:25 irregularities 50:7,9 irregularity 215:16,23 216:1 irrelevant 173:25	187:3,4,16,24	jobs 73:17,22	justice 162:17
	188:8 205:25	john 9:25 14:10	justice's 163:6
	209:16 210:5	338:14 348:12	164:7
	212:5 217:7,8	348:20	justin 7:3 8:3
	217:17 224:16	joining 14:16	9:3 300:24
	236:14 240:5	joint 79:9	301:15 336:19
	260:16 261:22	jointly 124:9	337:11
	262:12 264:23	jones 3:3	k
	265:14 307:23	jonesworks	k 5:8
	311:5	1:12 2:12 3:3	kaltgrad 7:7
	j	journal 122:6	17:1,12
	330:12,15	122:16,17,22	kane 9:23
irrespective 192:10 298:20 299:12,13 308:6 isaacson 6:4 14:15 island 12:17 282:3,4 isolate 253:3 299:8 issue 237:3 285:6 318:12 327:13 issues 104:9 219:25 236:6 237:2 248:13 item 62:19 260:9 items 174:12,25 180:16 181:18 181:24,25 182:7 184:5	jack 5:6,12 14:16 91:3,7 93:11 147:18 300:15 349:22 jamey 7:3 8:3 9:3 17:25 january 41:17 41:24,25 42:1 42:5,22 205:25 242:10 244:22 286:2 288:4,6 288:8,12 309:8 309:10,11,15 309:18 327:22 328:12 jennifer 1:10 2:10 7:2 8:2 9:2 18:1 job 57:18 86:9 173:15,21 340:24	123:18 128:24 131:8,15 132:3 132:5,17 144:24 journals 121:3 122:1,8 123:3 123:5,16,20 128:25 131:19 json 305:18,19 305:21 306:2 307:17,18 judge 350:19 judicial 350:16 july 208:24 211:16 235:19 235:20 236:3 288:24 289:4,8 317:7 327:4 june 211:16 235:19,20 236:3 288:10	karl 220:5 kbender 5:11 keep 138:12 169:9 224:21 228:20 349:11 349:18 kevin 14:20 17:8 84:18 109:18 110:13 111:7,11 135:16 136:25 145:22 213:3 301:6 key 64:6 164:2 214:1 236:7 328:22 keyword 252:4 341:23 keywords 40:10,11,14,15 40:16,19 42:5

[keywords - large]

Page 43

42:17 160:5	kinrich 172:4	192:25 195:22	knowingly
178:2 179:2	172:24	195:25 199:3,4	193:13 194:20
180:6,9 181:12	knocked 195:7	200:4 201:6	knowledge
181:18 205:9	know 17:22	202:4 203:17	52:23 71:5
206:7,7 222:10	21:25 22:5,10	205:17 211:9	79:6 105:14
238:13,15,18	30:14,17 33:18	219:5,12,19	127:15 160:24
239:22 241:10	35:7 40:8,16	227:12,16,19	173:20 213:8
242:16,18	43:2 47:19	228:7 236:18	265:19,20
250:21 251:13	50:13,14,17,18	240:20,21	271:22 276:3
252:14,18,21	51:16 54:20	241:22 242:22	296:2,4,7,10
253:24 254:11	56:8 59:16	242:25 243:16	333:24,25
254:14,15,15	68:25 69:6	246:2 249:5	known 30:11
254:18 271:4	75:20 77:9	251:4 252:16	kristin 3:6 5:5
271:24 275:22	82:23 83:4	256:5 258:7,8	kristintahler
277:22 278:6	91:5 93:24	261:6,12	3:13
283:25 300:11	95:16 101:12	264:20,21	kurt 278:20
305:7,12 311:8	102:1 103:20	267:8 272:18	302:13 314:1
311:10 320:19	108:18 110:19	273:8 274:11	1
322:19 331:2	110:19 111:21	276:10 283:2	1 28:25
332:3 333:9	114:12 116:20	290:5 292:23	labels 250:12
342:6,6,7,8,8	118:23 125:2	299:17 306:4	landscape
342:10,16,16	127:11 128:13	306:10 310:7	117:21
342:18,24	129:15 133:4,6	311:4 312:23	language 54:18
343:16,19,22	133:11,14	315:10,14,16	58:19 76:7,8
344:7,9,13,16	136:5 137:15	323:2 324:6,7	247:17 248:24
344:19,22	146:15,17	331:21,24	249:15 250:3
345:10,17	147:16 148:1	333:5,21 336:3	251:4,6,9,23
kicks 272:20	150:25 152:6	336:7,13 338:3	257:7,11,16
kim 20:6	153:16 154:8	338:10 339:14	340:24 341:5
kind 30:18 31:9	157:23 166:24	340:5,11,12	large 83:8
39:10 50:2	167:12 170:23	349:15	257:7,11 308:5
74:6 76:19	170:25 180:18	knowing	335:6
93:3 199:10	182:15 184:4	260:14 302:5	
	184:10 190:15		

[larger - lists] Page 44

larger 175:16	leading 345:25	license 15:6	18:22,25 19:23
200:15,23	learn 154:10,18	life 12:19 48:12	33:3 65:17
214:7 218:25	161:10	56:2 73:7	lines 286:6
288:14 291:24	learned 81:18	147:3 178:6,9	link 49:23 62:3
largest 313:18	learning	216:22 282:18	62:6,7 98:21
latest 125:19	137:18	283:20 298:17	303:16 304:12
198:1,2 256:14	leave 85:16	lift 282:3	305:3 307:4
257:3 267:14	left 115:14	light 189:9,10	links 303:14
launch 191:21	168:6 170:10	likelihood	list 72:11 74:12
234:1,17	304:8 331:15	51:23 152:4	82:7 120:3
255:10 298:1	legal 9:23	154:6,20	124:23 157:19
launched	117:20 118:19	likely 57:10	157:20 160:14
191:20	160:16	99:1 114:5	160:19 168:9
launching	legitimacy	149:24 150:12	168:20 169:10
191:18	195:20	154:12 155:1	169:17 173:10
laurenne 3:8	legitimate	163:14 333:13	173:24 188:11
laurennebaba	191:12,14,15	liking 190:10	188:11 207:4,5
3:15	191:17,19,23	limit 200:19	302:20 344:16
law 3:9 4:7 5:7	192:1,10,18	303:17	344:18,22
6:6,16 7:8 8:6	193:3,7,8,11,14	limitations	345:2,9,17
8:8 9:7 19:5	193:22 194:9	41:12,15	listed 81:8 84:3
22:11	195:19,19	limited 139:22	86:19 126:2
law.com 9:10	196:2,3,6,11,23	197:20 200:13	129:1 131:18
laws 352:21	198:13 199:10	lindsey 6:15	132:24 141:17
lawsuit 327:22	199:25	15:2	143:14,17
328:16	letters 294:14	line 10:11 23:5	170:21 174:14
lawyer 162:5	level 46:12	23:9 87:10	188:17 322:5
lead 1:7 2:7	218:13 220:16	94:8 108:23	322:15
87:5 185:25	343:13,18	175:1 326:1	lists 71:15 74:4
leaders 37:24	leveraged	353:4,7,10,13	78:24 126:11
leadership	78:15	353:16,19	127:22 145:3
71:16,23 72:1	lftcllp.com 7:11	liner 7:5 16:14	148:20 346:6
72:9,22,24	7:12	16:15,17,23	346:16
73:1,11		17:4,7,19	

[literal - look] Page 45

1;tamal 94.15	275.21.22	login 202.11	194:15 197:25
literal 84:15	275:21,23 278:6 286:1	login 303:11 london 79:14	200:23 205:15
literally 80:20			
103:18 221:5	300:23 301:15	long 77:13	209:5 211:11
literature	311:9 316:11	81:14 122:7	212:15 214:6
121:1 228:3	336:21 337:4	138:25 246:5	214:19 218:23
litigation 18:12	337:12 349:14	263:20 264:7	219:24 220:2
18:16 25:15,21	353:1 354:1	264:10,20,21	225:6,23
26:13 34:3	lively's 14:18	265:2 348:12	227:18 228:5
160:21 161:18	14:18 337:2	longer 68:5	229:12 231:1,4
little 42:11	346:7,14	246:10 290:21	236:17,22
67:14 124:12	347:20 350:17	look 38:23 39:1	241:25 247:14
144:19 193:15	ljl 1:7,7 2:7,7	39:21 41:6	250:21 252:10
272:14 278:9	llc 1:8,12,13 2:8	43:22 47:19,21	252:11 255:15
292:24 310:14	2:12,13 3:4 7:2	47:22 48:2,4,7	266:2,3,7,9
live 33:5	8:2 9:2 11:3	52:5 58:15	274:16 280:18
125:10,11,12	12:3 13:3 14:9	59:16 71:9	282:11 283:6,9
lived 156:19	353:1 354:1	73:7 75:19	283:10,18,19
157:20	llm 76:5,7	76:8 77:1 88:4	283:22 287:3
lively 1:5,15	186:5,9,10	88:5,16 90:23	287:21,23,24
2:5,15,20 4:3	187:8,11,12	92:20 93:14,18	288:15,19,20
5:3 6:3 11:3	202:8 257:6,7	93:20,23 94:5	288:23 291:6,7
12:3 13:3 14:8	257:8,14	97:9 101:24,25	292:15 295:9
14:16 15:3	290:24	102:23 106:1,3	299:20 305:18
176:3,11 179:2	llms 76:4,5,22	108:16 111:22	308:8 309:25
179:9,18	78:10 257:14	112:20,23	310:4 314:22
180:10 198:10	llp 4:4 16:14	126:19 127:20	316:16 319:25
206:18 212:20	local 66:11,19	128:4 130:21	320:22,24
250:17 251:3	located 79:10	131:16,22	321:17 323:3
251:16 252:2,3	339:24	140:7 141:2,12	323:10,11
252:8,11,21,24	location 140:6	142:13 144:11	329:1,3,5
252:25 253:5,7	log 77:13	146:19,20	331:9 335:14
253:24 254:1	logged 208:6,7	148:2 153:12	337:23 340:8
270:12 271:24	logical 312:2	180:13 190:6	343:9 344:9
274:9,18 275:5		193:22 194:14	345:3,4,18

[look - making]

348:9,10,24	128:12 144:16	283:12 285:23	maintain 85:6
looked 55:11	146:25 157:11	323:3 329:11	major 72:23
58:7 61:16	176:19,19	los 3:12 4:10	114:14,14
76:3 88:19	180:3,7 193:18	6:18 7:10 8:11	194:20 216:6
107:17,18,18	196:15 209:9	lot 32:14 36:22	308:4 342:21
107:21,23	210:5,24 211:3	76:9 87:21	majority
124:20,20	211:4,10,10,13	100:9 108:11	178:17,18,19
125:6,7 145:9	211:15 215:14	127:9 134:7	179:8
148:14 166:7	217:2,5,20	183:25 196:22	make 35:19
174:23 176:4	217.2,3,20	255:23 280:23	39:1,3,12
177:16,17	220:16 221:6	love 12:16	47:13,16 49:4
188:20 196:12	222:8,10	342:16	49:8 51:20
200:11,15	226:13,17	lower 335:9	53:15 56:2
210:13 216:3	227:12,13	lunch 246:9	58:9 63:5 67:1
216:23 250:20	236:25 251:15		67:12 69:9
260:24 264:16	252:24 269:7	m	96:8,10 100:14
265:11,15,16	270:15,17	m 3:8 11:7,9	108:12,16
289:19 302:8	274:10 283:6	75:8	116:24 129:7
304:10 308:16	284:1 288:7	ma'am 15:7	137:2,10,18
314:6 325:22	293:10 302:3	macdonnell	139:2 165:7
326:1 332:8	304:2 308:3	9:25 14:10	166:4 179:5
340:13 344:12	314:15 324:11	macroecono	183:2 184:3,16
looking 19:9	337:20 339:7,9	329:4	197:25 199:4
27:6,13 29:14	340:11,24	made 27:5 32:7	201:7 203:2
34:10 39:4	looks 31:25	40:20 57:23,24	204:25 211:2
40:9 41:17	32:3 58:22	144:4,8 165:5	225:23 233:13
47:15,20 52:7	81:23 83:8	165:6 166:15	238:12 250:5
58:7 66:18,19	129:22 210:20	205:8 211:11	282:6 310:3
67:1,2,8 72:1	210:21 224:7	264:4 328:8,9	319:14 334:24
78:11 82:2	225:17 248:3,5	352:10 354:5	makes 89:20
93:3,9 95:5	248:20,23	maggie 9:23	145:18 280:25
99:10,12 107:6	249:14 251:7,8	350:1	281:14
118:5 125:13	269:16 277:6	mail 85:5	making 85:9
126:6 128:10	278:17 283:11		203:12 222:8
120.0 120.10	270.17 203.11		203.12 222.0

Page 46

[male - mayzlin]

Page 47

male 19:20	manually	monkatina	matahina
	manually	marketing	matching 130:16
maleficent	267:24 338:9	11:12 25:10	
89:19	marginal 87:17	69:24 70:13	material 54:23
manage 72:2	marie 15:19	72:3,4,10,20	114:7,9 117:9
management	mark 90:25	73:17,22 78:16	296:21 349:5
71:16,24 72:9	113:7 130:23	81:6 84:2,4,8,9	materials
72:22,24 73:1	147:15 219:15	84:12,25 85:1	125:22 126:1,8
73:12	246:2 268:5	87:19,25 95:2	127:23 160:15
manatt 4:4	285:12 308:9	102:21 119:6	168:21,22
manatt.com	315:6 322:24	121:5,14,14,20	169:10 171:1,2
4:11,12	325:5	121:22 122:6	172:22 173:2
manipulate	marked 16:9	122:15,21	295:25 296:1,1
89:13	16:11 61:19,25	124:20 125:6	322:16 346:25
manipulated	62:20 91:2	157:11 158:7	347:3 348:25
116:8,11	112:19,21	191:25 192:10	mathematician
214:25	113:9,21	192:13,14,16	35:18
manipulating	118:12 131:1,4	192:19,22,23	mathematics
198:24	147:20 219:18	193:7,9 298:20	83:19,20,21
manipulation	269:12,21	mass 176:17	matter 14:8
78:12 89:22	272:12 273:2	massage 12:18	16:10 26:14
90:16 92:22,24	273:22 276:8	282:18,19	28:9 34:12
197:10 198:19	278:10 279:10	283:19	35:6 61:15
198:21 214:25	281:1,23	massive 100:21	62:21 110:24
296:5 297:25	282:14 285:17	211:5 214:2	188:13 192:8
manipulative	300:14 307:9	327:10	227:20 253:23
106:19 190:7,9	308:13 315:8	master 74:9	matters 29:13
196:19 198:25	321:2 322:25	master's 75:7,8	37:2 258:10
199:2,15,25	325:7 329:7	75:9,15 78:6	maximum
216:25	332:9	match 130:12	332:17,20
manual 96:2	market 213:25	141:15 143:2,4	333:10,14
97:5 100:7,10	213:25	matched	mayzlin 9:24
107:16 267:18	marketed	235:15	14:18 167:11
305:17	191:23	matches 332:7	167:12,13,16
			169:8 170:3

[mayzlin - melissa]

Page 48

172:3 173:13	115:1 116:16	218:12 223:10	198:9,14
174:12,22	120:5,6 121:16	225:4 226:23	199:11 200:12
186:5 187:8	126:4 134:21	227:22 234:19	201:8 202:3,18
200:5 348:2	146:1 156:5	241:14 249:18	205:25 207:21
mayzlin's	164:4 171:20	258:10 276:15	207:22 209:16
151:3 165:9	174:6,18	287:11	213:9 216:6
166:13 170:9	178:10 189:23	meant 115:13	217:1 218:23
171:11 172:23	190:9 191:13	191:16 221:3	221:7 222:7
174:11 175:4	194:2 209:18	media 11:20	226:7,8,12
175:16 176:2	209:25 210:4	12:7,9,10,12,13	227:9 230:11
177:16 184:4	212:14 218:4	12:15,16,18	236:7 237:4
184:15 185:25	218:10 231:16	23:24 30:25	240:9,18
187:3 199:19	231:22 234:18	37:24 38:3,6	241:16 242:14
200:24 201:1	235:16,24	38:12,25 39:22	242:19,22
202:5 203:20	243:9 250:14	41:8,8,11	243:1 250:1
204:18 290:6,9	260:18 273:4	42:13,16 78:13	260:9,16
290:22 291:21	288:24 289:5	85:5 100:14	261:22 262:12
292:9 347:16	298:4 301:25	103:19 104:16	264:22 289:22
mba 78:24,25	316:17 317:24	107:7 114:2	291:25 303:13
79:1,3 80:25	324:21 326:7	131:14 136:12	313:19 335:6
81:10,12,18	330:23 332:20	136:18,22	347:6,11
mean 22:24	332:22 335:9	138:4 139:10	medical 227:9
30:10 33:13	335:16 337:6	141:5,11,25	medium 84:22
41:10 42:9	340:2 346:12	142:2 144:24	119:16,20
46:20 47:8	meaning 43:23	156:21 174:12	meet 15:25
48:20 49:2	213:23 241:8	174:25 176:19	23:23 71:2
50:2 55:21	273:5	177:14,15	162:11 164:15
72:12 88:7,8	means 47:11	179:18 180:4	meets 162:13
89:1,3 91:13	83:5 84:14	180:11,16	164:11 178:22
91:21 95:20,22	89:2 96:24	181:18,25	meister 9:5
96:7 98:12	98:20 171:21	184:5 187:3,16	14:21,24
100:1,19 101:3	174:3 178:1	187:24 190:11	melissa 7:3 8:3
101:7 103:5	180:6 204:14	190:25 191:2,5	9:3 18:1
106:16 114:9	209:20 210:6	192:5 196:6	

[member - models]

Page 49

member 1:7 2:7	91:18,23 92:9	186:14,16,23	194:12
122:12	92:17 94:19	187:14,16	misnomer
memory 137:12	95:2,6,11,13,21	204:5,6,8,10,13	42:12
137:19	97:17 98:16,18	204:18,21	misrepresent
mentality	98:20,24 99:10	205:2 218:18	94:10
194:19	104:7,8,25	methods 11:23	missed 237:12
mention 72:9	105:5,11	183:12	missing 39:12
86:6 253:5	106:13 120:14	meticulously	177:18 236:3
mentioned 19:1	121:12,13	346:20	mistake 137:17
21:17 33:12	124:4 155:20	mgovernski 6:9	mitch 14:23
50:23 55:10,20	209:15 213:23	middle 109:2,3	mitchell 9:6
64:12 82:20	213:24 217:23	184:18	mitigate 120:1
86:5,10,18,19	218:4,12,19	million 174:14	236:6 237:2
99:3 101:11	219:2 220:3,10	175:9 184:5,8	mitra 8:7,12
119:17 124:3	220:11,21	315:22	mjf 272:17,20
134:7 149:7,20	221:4,12,19	millions 316:4	mla 49:6
157:21 159:14	222:3,14 223:7	mind 185:16	model 249:2,13
160:10 209:23	223:9,16,23	219:13 347:18	249:14,20,22
258:3 279:6	224:5,11	mindset 114:10	250:1,8 255:2
294:5 322:20	meta's 87:10	minority	255:3,8,10,12
326:15 334:20	90:22,24 91:9	178:19	255:18 256:10
337:12	91:16 95:8	minute 20:7	256:14,25
meryl 6:5 14:14	98:1 106:9	26:25 138:25	257:6,7,22,24
41:4 93:24	196:20	minutes 36:9	258:3,12,21,25
113:16 118:5	metadata	36:10 60:22	259:8,16 262:4
118:13 128:11	283:12 326:2	111:19 112:6	266:10,14
300:15	method 220:21	185:18 349:20	267:13,14
message 282:16	methodologies	350:15	341:13,22
met 17:8 29:6	162:11	miscited	342:3,14,25
33:7 167:13	methodology	228:24	343:3 345:21
meta 11:24	125:4 161:23	misinformation	models 76:8
84:5,6,10,16,17	161:23 163:1	114:21 115:2,3	254:25 255:22
87:20,22 88:15	164:2,10	115:11,19,25	255:23 256:1
89:24 90:20	184:11 185:24	191:16 193:13	257:10,11,17

[modify - needed]

Page 50

modify 64:25	moses 4:6	116:18 125:7	341:5
65:2	motivate 117:6	133:16 159:6	nature 27:11
module 81:10	mouth 22:19	173:13 180:9	37:4 46:18
moment 63:3	move 74:20	206:5 215:13	56:6 84:23
93:23	130:23 268:4,7	226:11 241:5	88:13 122:7
monday 1:22	315:6	244:8 249:19	192:6 237:5
2:23 11:4 12:4	moved 112:13	268:21 341:6	250:15 268:24
13:4 14:3 45:7	112:18	n	nearly 189:22
45:8 245:18	movie 191:18	n 3:1 4:1 5:1	necessarily
monica 6:17	191:19,19,20	6:1 7:1 8:1 9:1	49:5 64:19
month 12:22	206:18 294:16	273:23 339:3	311:21 324:9
197:19 209:21	295:3 298:1	name 15:18	326:6 335:3
210:6 211:21	318:13 327:14	16:25 20:9	necessary
211:22 288:24	336:20	30:7,8 86:1	177:8 261:17
289:2,6,7	movies 310:15	122:4 129:17	263:15 339:21
294:2 298:5	310:15,16	136:8 168:2	340:3 354:7
299:4,4,5	moving 22:19	219:11 250:22	need 22:6,6
315:11 316:18	65:16 147:15	250:23 274:20	59:14 60:15
317:6 327:3	msf 9:10	337:2	68:15 96:25
monthly	mst 74:4,9	named 320:7	117:1,2 118:14
210:16,18,19	multiple 44:22	names 20:2,4	168:19 177:25
210:20 211:3,4	57:9 135:11,18	122:7	179:24 203:4
211:7,10,13,14	231:13,25	narrative 348:5	203:16 211:9
211:24	232:19 254:24	narrow 200:20	213:2,7 233:12
months 79:12	278:5 280:4	nathan 7:3 8:3	250:4 267:5
79:15 80:16,17	326:11 347:21	9:3 18:1	270:21 287:20
80:22 84:7	349:8	national 122:17	303:11 334:25
134:23 210:17	multiples 214:7	122:22,25	344:18 345:12
211:16,18	mute 22:13	natural 76:6	350:19,20,24
214:7 289:2	myriad 32:1	247:17 248:24	needed 64:18
299:6,7,15	37:25 47:22	249:14 250:2	77:17 85:8
moon 281:22	48:22 81:23	251:6 257:16	160:12 202:24
morning 14:14	84:19 85:11	295:10 340:24	232:7 234:3,11
14:20 15:4,17	99:1 102:6	273.10 340.24	291:10 343:6

[needs - normally]

Page 51

needs 216:25	network 11:18	337:17,21	99:24 110:10
negate 254:1	24:21 25:6,8	never 32:2,12	111:10 353:2
271:25 274:8	25:12 29:8,21	33:25 110:5	353:24 354:2,4
negated 273:2	30:6,9 37:22	new 1:2,21,21	354:12
273:3,5,9,15	41:8 88:6,9	2:2 9:9,9 38:14	nielsen 120:17
274:2,7,12	96:25 97:6,14	46:17 79:13	213:24 345:25
281:17	98:4,13 99:7	118:8 128:13	nielson 222:5
negates 253:21	100:16 107:16	188:20 189:8	nine 268:4
negating	128:20 129:13	194:17 204:13	269:10
273:16,17	131:10,11	237:14	ninth 162:10
negation	139:20,24	newer 257:6	297:23 298:5,6
273:20	141:9,23	newly 104:18	nodes 339:3,4
negative 39:23	196:21 217:5	news 114:22	339:11,15,23
89:13 99:5	245:20 338:23	115:11 117:21	340:5,6,7
115:15 199:5	339:20	117:22 191:13	non 88:24,25
247:15,23	networks 41:14	191:15,16,17	89:1,2,5,16,17
248:18 249:2,3	41:16 121:21	191:19,20,22	90:10,14 92:7
249:7,10,16	121:24,25	192:4,25	190:7,9 335:4
250:8,12,13,24	135:22 141:4	193:23 194:10	nonwork
250:24 251:4	142:2 144:23	194:10,13,18	268:24
251:10,12,16	177:14 203:1,2	194:20 196:3,7	nope 128:12
251:17,17,19	203:5,9 217:5	196:10,13,18	norm 64:23
251:23 252:1,5	217:5 218:24	197:14 198:13	92:21 102:23
252:25 253:1	240:18 291:17	199:8,10	215:22
260:6 265:21	neutral 39:23	214:24 233:23	normal 29:8,9
274:5,19 275:6	247:16,25	233:25 328:22	29:10 63:17
314:24 342:6	248:1,19 249:3	335:5	93:2 104:11
342:17 344:7,9	249:4,11,16	newsworthy	105:7 107:22
negatively	251:12 260:6	327:24 328:13	210:2 225:9,10
100:2	265:21 272:1	nicole 1:19 2:19	295:9
neither 176:1	273:2,22	10:2 11:2,7,8	normally 49:2
net 46:17	277:23,25	11:13 12:2	49:10 54:19
237:14	279:7 284:2	13:2 14:7	65:15 70:23
	314:17,21,25	15:19 93:13	100:8 199:16

[normally - objection]

Page 52

210:23 249:4	303:17 317:25	65:25 66:2	151:5,11,18,24
norms 156:20	333:16 337:8	68:20 69:17	152:5 153:7,15
northwest 5:9	numbers 48:7	70:9 71:25	153:21 154:7
notary 354:13	106:22 132:1	72:14 73:6,14	154:13,21
354:19	132:13 142:9,9	73:25 74:25	155:3 156:17
note 40:20	142:18 143:2	76:2 77:6,19	157:1,8 158:1
94:25 335:24	203:18 217:11	78:20 80:2,8	158:14 159:3
noted 213:4	289:18 318:6	80:18 82:9	159:12,21
312:14 354:7	327:6	83:2,6 85:13	163:9,15 164:5
notes 339:1,2	numerous	86:12,23 87:4	164:13,24
352:16	134:9 213:16	90:13 91:22	166:10 168:1
notice 2:20	nw 6:7	94:20,25 95:15	169:5,11,21
noticing 14:13	nyu 52:10 68:1	96:15,22 98:7	170:4,15,22
noun 178:11	68:5,8,13,25	99:15 100:18	171:4,14
november 11:7	69:3,11,15,25	101:20 102:11	173:19 174:2
11:9 45:4,5,6	70:14 71:16,19	102:19 103:6	174:17 175:5
60:6,7 167:1,2	72:9,13 81:10	104:3 105:3	175:10,22
nuance 249:7	0	107:4 108:5,10	176:13 177:3
null 279:7		108:17 116:5	177:12 178:7
	$\begin{bmatrix} \mathbf{a} & 28.25 & 127.4 & 4 \end{bmatrix}$	100.17 110.5	177.12 170.7
284:2 314:17	o 28:25 127:4,4	116:15 120:8	178:23 179:11
	339:3		
284:2 314:17	339:3 oath 352:7	116:15 120:8	178:23 179:11
284:2 314:17 314:20,25	339:3 oath 352:7 objection 19:24	116:15 120:8 120:16 121:7	178:23 179:11 179:15 180:2
284:2 314:17 314:20,25 337:17,21	339:3 oath 352:7 objection 19:24 23:4,20 26:7	116:15 120:8 120:16 121:7 123:13 126:13	178:23 179:11 179:15 180:2 180:24 181:8
284:2 314:17 314:20,25 337:17,21 number 21:7	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9
284:2 314:17 314:20,25 337:17,21 number 21:7 54:21 57:22	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7 41:1 42:24	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19 129:25 130:9	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9 182:17 183:23
284:2 314:17 314:20,25 337:17,21 number 21:7 54:21 57:22 85:6 124:3	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7 41:1 42:24 44:1 45:24	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19 129:25 130:9 130:17 132:7	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9 182:17 183:23 184:6 186:18
284:2 314:17 314:20,25 337:17,21 number 21:7 54:21 57:22 85:6 124:3 132:5 142:10	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7 41:1 42:24 44:1 45:24 46:25 47:9	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19 129:25 130:9 130:17 132:7 133:10,20	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9 182:17 183:23 184:6 186:18 187:19,25
284:2 314:17 314:20,25 337:17,21 number 21:7 54:21 57:22 85:6 124:3 132:5 142:10 192:22 194:4	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7 41:1 42:24 44:1 45:24 46:25 47:9 48:8,17 49:9	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19 129:25 130:9 130:17 132:7 133:10,20 134:1 135:5,19	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9 182:17 183:23 184:6 186:18 187:19,25 189:7 190:20
284:2 314:17 314:20,25 337:17,21 number 21:7 54:21 57:22 85:6 124:3 132:5 142:10 192:22 194:4 198:3 201:4,5	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7 41:1 42:24 44:1 45:24 46:25 47:9 48:8,17 49:9 49:16 51:5,12	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19 129:25 130:9 130:17 132:7 133:10,20 134:1 135:5,19 136:4 138:25	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9 182:17 183:23 184:6 186:18 187:19,25 189:7 190:20 191:24 193:16
284:2 314:17 314:20,25 337:17,21 number 21:7 54:21 57:22 85:6 124:3 132:5 142:10 192:22 194:4 198:3 201:4,5 201:16 209:8	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7 41:1 42:24 44:1 45:24 46:25 47:9 48:8,17 49:9 49:16 51:5,12 53:3 54:24	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19 129:25 130:9 130:17 132:7 133:10,20 134:1 135:5,19 136:4 138:25 139:11 140:4	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9 182:17 183:23 184:6 186:18 187:19,25 189:7 190:20 191:24 193:16 194:24 195:21
284:2 314:17 314:20,25 337:17,21 number 21:7 54:21 57:22 85:6 124:3 132:5 142:10 192:22 194:4 198:3 201:4,5 201:16 209:8 212:1,5 213:19	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7 41:1 42:24 44:1 45:24 46:25 47:9 48:8,17 49:9 49:16 51:5,12 53:3 54:24 55:8,17 56:16	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19 129:25 130:9 130:17 132:7 133:10,20 134:1 135:5,19 136:4 138:25 139:11 140:4 141:16 142:3	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9 182:17 183:23 184:6 186:18 187:19,25 189:7 190:20 191:24 193:16 194:24 195:21 196:4 197:1
284:2 314:17 314:20,25 337:17,21 number 21:7 54:21 57:22 85:6 124:3 132:5 142:10 192:22 194:4 198:3 201:4,5 201:16 209:8 212:1,5 213:19 224:10 233:15	339:3 oath 352:7 objection 19:24 23:4,20 26:7 30:21 38:7 41:1 42:24 44:1 45:24 46:25 47:9 48:8,17 49:9 49:16 51:5,12 53:3 54:24	116:15 120:8 120:16 121:7 123:13 126:13 127:13 129:19 129:25 130:9 130:17 132:7 133:10,20 134:1 135:5,19 136:4 138:25 139:11 140:4 141:16 142:3 143:7 144:1,6	178:23 179:11 179:15 180:2 180:24 181:8 181:19 182:9 182:17 183:23 184:6 186:18 187:19,25 189:7 190:20 191:24 193:16 194:24 195:21 196:4 197:1 201:14 202:12

[objection - oh]

Page 53

212:7 213:1,5	277:15,20	352:9	odd 237:4
215:8 217:14	278:24 279:4	obligation	oddities 93:1
219:10 220:12	281:7 283:8	124:1	210:22 217:4
221:20 222:16	284:11 286:19	observable	225:19
225:15 226:18	287:19 290:15	215:16	oddity 217:25
226:24 227:7	291:9,23 292:4	observed	offer 6:14
227:24 228:6	292:11,18,25	229:24	158:9 165:4
228:11 230:19	293:19 296:15	obtain 27:17	166:14 188:13
232:13,25	296:19 297:3	257:21	188:16 200:22
234:6,23	297:11 298:15	obtained 79:10	215:19
235:23 238:2,8	299:1,21 300:9	79:17	offered 121:18
239:1 240:7,25	302:1 304:14	obviously	189:5,12
241:21 242:13	304:20 305:9	119:16,18	offering 159:10
243:5,18 247:9	306:6,12,22	125:12 236:20	164:10 165:8
251:25 252:17	308:1,21 310:9	283:1	189:1,5,18
253:11 254:19	311:17 312:5	occur 229:22	offers 215:20
255:13,24	312:24 313:6	occurred	offhand 30:17
256:4,12,19	313:16 314:13	231:12,24	31:20 35:2
257:1,15	315:18,24	232:18 293:24	50:11 77:9,14
258:13,18	316:20 318:3	298:22 299:13	77:23 135:6
259:2,10 260:3	318:25 319:6	299:25 328:19	136:6 139:12
260:10,17	322:8 324:8	occurring	153:2,16
261:16,23	328:6 331:20	232:9 234:5,13	156:14 157:3
262:6,15,22	332:1 333:1,19	occurs 215:21	158:9 203:17
263:6,12,24	334:2,10 335:2	october 16:18	223:18 290:9
264:14 265:5	335:19,24	17:16 33:1	315:14,16
265:25 266:8	337:15 345:14	41:18 42:6,23	337:22 347:24
266:19 267:10	347:12	45:9,13 135:1	official 13:12
267:19 268:1	objections	167:4 206:1	330:20
270:13,23	21:24 22:7,12	242:10 244:23	offline 29:12
271:1,9 272:4	22:16,17,19	245:12 258:19	oh 12:13,15
273:10 274:14	137:1,23 138:8	286:2 288:5,9	35:25 58:23
274:24 275:11	138:10 139:5	327:23 328:13	65:6 67:22
276:2,17	185:3 346:15		93:6 97:21,23

[oh - okay] Page 54

104:2 118:6,11	79:15 80:6	162:5,18 163:7	220:20 221:14
128:13 144:20	81:11,16 82:6	163:12,16	221:25 223:6
145:24 147:1	87:18 88:25	164:9,22 166:3	223:15,19
185:20 198:5	90:23 91:5	166:8,22	224:15,23
198:18 207:12	92:6 93:20	167:19 170:2	226:2,15
209:10 213:3,3	94:3,5 97:3,9	170:12 171:8	229:12 230:3
219:23 269:9	98:15 99:23	172:2,9,14,16	230:12 231:4
273:14 313:25	111:18 113:2	173:1 174:10	231:21,22
319:4 320:5	113:24 114:17	174:15,24	233:4 234:21
325:18 331:7	115:10 119:2	175:3,14	235:5 236:10
337:3 339:4	120:2,15	177:10 178:5	239:10,25
341:19	122:19 124:18	178:21 179:4	240:13,20
okay 17:10,24	126:17 127:1	179:23 181:16	241:19 242:7
18:8 20:10	127:21,22	182:5,13 184:3	242:12 243:2
27:2 29:1	128:4,8,23	185:17,20,21	244:11,16
31:17 33:5	129:6 130:8,21	186:13 187:23	245:5 246:15
35:4,9,17,22	131:3 132:23	189:4,21 190:4	247:12 250:16
36:19 37:5	134:16 136:2,8	190:12,18	250:18 253:9
38:19 40:13	136:11,15	191:1,6 192:8	253:16 254:23
43:2,19 44:17	139:15 140:10	194:8 195:8,18	255:11,17
45:16 48:14	140:18 141:13	195:25 196:9	256:8 257:6,10
51:16 52:8,13	141:21 142:8	199:7,13,21	257:13,21
52:17,21 53:20	142:13 144:11	200:4,11	258:11,21,24
53:24 55:4,20	144:17 145:3	201:23 202:4	261:2 265:13
58:15 59:10	146:19 147:11	202:17 203:14	265:22 266:13
60:17 61:13,18	147:22,25	205:5 206:12	269:1,13,15,23
62:11 63:3,9	148:4,15,16	206:24 207:15	270:17 271:7
66:18 67:4,9	149:22 150:10	208:21 209:4	271:14 272:9
67:22 68:12,23	152:8,16,21	209:23 210:16	273:14 276:5
69:2,7,14,21	153:4 154:25	214:16,19	276:19 278:7
70:16 71:1,13	155:7,15	215:3,6,12,17	278:19 279:8
72:7,12,25	156:12,23	216:2 217:7,12	279:20 280:2
73:21 74:4,9	160:13 161:10	218:3,7,17	280:11,21
74:20 75:11,15	161:12,19	219:14,23,24	281:19 282:11

[okay - order] Page 55

283:17 284:3	332:14 334:6	313:19 314:23	224:10 230:12
284:10,25	334:14 335:14	342:10	230:18 232:12
285:15,19	336:2,10,16	ongoing 87:16	232:23 247:8
286:10 287:6	337:4,9,19	online 38:2	289:13 293:23
288:4,17	338:2,11	49:24 52:17	318:16 328:4,5
289:13,21,23	339:10,14	80:6 247:4	opinions 28:8
290:20 292:2	340:12,15	348:5	114:3 159:10
293:3,16 294:9	341:23 343:17	onus 313:9	187:17,23
294:25 295:14	343:24 345:2,8	open 45:1	188:12,12,17
295:21 296:2	345:20 346:6	61:18 66:11,15	188:18,21,23
296:25 300:3,6	346:21,24	66:23 131:4	188:25 189:3,4
300:21 301:23	347:4,9,20	261:9 269:4	189:11,17
302:19 303:8	348:3,19	349:19	198:6 270:8,10
305:14 306:4	349:18 350:7	operate 78:10	272:22,23
307:14 308:8	350:10,25	242:1 275:4	277:10 308:20
308:18 309:4	351:2,5	operates	309:1
309:13,19,22	old 128:14	241:23 275:18	opportunity
309:25 310:6	olivia 3:7	operational	24:24
310:13,24	oliviaholmes	119:7	opposed 34:23
310:13,24 313:24 314:6,9	oliviaholmes 3:14	119:7 operations	opposed 34:23 252:25 297:8
, and the second		operations 17:23 139:19	
313:24 314:6,9 314:11,19 315:1 316:7,10	3:14 once 17:13 38:21 71:3	operations 17:23 139:19 opined 224:23	252:25 297:8
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25	3:14 once 17:13 38:21 71:3 216:15 229:23	operations	252:25 297:8 opposite 199:10 optional 303:17
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22	operations	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25 320:2,13,21,24	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18 ones 34:7 38:13	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10 188:24 192:18	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11 307:12,19,21
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25 320:2,13,21,24 321:17 322:22	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18 ones 34:7 38:13 54:16 89:4	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10 188:24 192:18 197:17,20	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11 307:12,19,21 312:12 313:8
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25 320:2,13,21,24 321:17 322:22 323:2,16 324:1	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18 ones 34:7 38:13 54:16 89:4 102:1 104:19	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10 188:24 192:18 197:17,20 198:7 200:11	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11 307:12,19,21 312:12 313:8 313:11
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25 320:2,13,21,24 321:17 322:22 323:2,16 324:1 324:19 325:4	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18 ones 34:7 38:13 54:16 89:4 102:1 104:19 104:20 122:12	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10 188:24 192:18 197:17,20 198:7 200:11 200:13,15,16	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11 307:12,19,21 312:12 313:8 313:11 options 60:16
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25 320:2,13,21,24 321:17 322:22 323:2,16 324:1 324:19 325:4 325:19 327:1,9	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18 ones 34:7 38:13 54:16 89:4 102:1 104:19 104:20 122:12 122:20 125:12	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10 188:24 192:18 197:17,20 198:7 200:11 200:13,15,16 200:20,22	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11 307:12,19,21 312:12 313:8 313:11 options 60:16 208:8 305:5
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25 320:2,13,21,24 321:17 322:22 323:2,16 324:1 324:19 325:4 325:19 327:1,9 328:11 329:5	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18 ones 34:7 38:13 54:16 89:4 102:1 104:19 104:20 122:12 122:20 125:12 129:1,3 133:15	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10 188:24 192:18 197:17,20 198:7 200:11 200:13,15,16 200:20,22 202:21 203:3	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11 307:12,19,21 312:12 313:8 313:11 options 60:16 208:8 305:5 orchestrating
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25 320:2,13,21,24 321:17 322:22 323:2,16 324:1 324:19 325:4 325:19 327:1,9 328:11 329:5 329:12,15,24	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18 ones 34:7 38:13 54:16 89:4 102:1 104:19 104:20 122:12 122:20 125:12 129:1,3 133:15 172:11 173:18	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10 188:24 192:18 197:17,20 198:7 200:11 200:13,15,16 200:20,22 202:21 203:3 208:21 214:16	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11 307:12,19,21 312:12 313:8 313:11 options 60:16 208:8 305:5 orchestrating 98:25
313:24 314:6,9 314:11,19 315:1 316:7,10 316:16,25 317:9,12,17,20 318:19 319:25 320:2,13,21,24 321:17 322:22 323:2,16 324:1 324:19 325:4 325:19 327:1,9 328:11 329:5	3:14 once 17:13 38:21 71:3 216:15 229:23 268:16 288:22 one's 176:18 ones 34:7 38:13 54:16 89:4 102:1 104:19 104:20 122:12 122:20 125:12 129:1,3 133:15	operations 17:23 139:19 opined 224:23 opinion 57:7,11 73:23 160:15 162:10 164:10 188:24 192:18 197:17,20 198:7 200:11 200:13,15,16 200:20,22 202:21 203:3	252:25 297:8 opposite 199:10 optional 303:17 303:23 304:22 305:6 307:11 307:12,19,21 312:12 313:8 313:11 options 60:16 208:8 305:5 orchestrating

[order - p.m.] Page 56

55.45.00.4	101 0 100 10		200 10 10
77:17 82:4	191:3 192:13	outliers 225:24	298:18,19
87:5 88:20	198:12 214:23	outline 228:24	335:8
96:13,21 97:1	327:25	outlined 324:25	overarching
99:5 105:20	organically	outloud 232:12	86:1
106:2,22	117:14	output 187:13	overlap 180:17
107:19 125:9	organization	212:12 260:4	overnight
182:21 186:5	52:23 71:5	322:17 330:7	117:24 118:21
200:22 202:21	80:22 85:17	338:6 341:18	oversaw 86:21
203:2 204:21	organizations	342:25 343:11	oversee 86:22
205:13 208:8	75:21 241:6	344:10	overview 54:17
211:20 215:15	oriented 198:1	outputs 183:14	own 22:16
216:24 218:24	origin 90:7	186:6 187:10	52:13,16 90:21
231:2 233:13	original 61:14	188:1 342:2	98:20 117:6
236:18 255:22	61:20 62:25	outreach 25:25	120:1 155:17
261:18 267:3	66:16 67:5	outside 28:22	155:23 160:25
288:15 291:1	103:21 115:5	40:18 54:9	162:3,4 176:20
291:12,17	originally	92:1 93:2	177:2 190:19
292:13 299:15	15:24 62:4	98:17,24 99:25	275:8 292:16
340:8 343:14	168:4 335:12	102:23,24	313:9 350:23
344:1,19	origins 194:5	104:11 107:22	owned 85:3,4
ordinarily	291:11,11	146:1 150:7	87:6
100:12	outcome	162:14,15,16	р
organic 88:24	182:15 184:12	164:21 200:10	p 3:1,1 4:1,1
88:25 89:1,2,5	186:7,16,22	202:22 210:1,1	5:1,1 6:1,1 7:1
89:16,17,23,25	187:6 234:17	215:25 227:10	7:1 8:1,1 9:1,1
90:2,6,8,10,14	234:20 262:13	271:21 299:4	p.m. 2:23,23
92:7,12,13,18	297:10 341:19	299:14 312:7	61:8,11 62:14
92:21 97:4,6,6	outcomes 32:4	340:7 343:22	62:17 112:8,11
115:24,25	51:17 166:15	344:12 349:5	185:7,14
116:4,7,11,25	186:8,25	overall 65:4,6	246:18,21
165:8,12,25	outdated 65:11	87:10 125:13	248:12,15
166:5 189:22	68:2	149:20 176:2	338:17,20
189:25 190:5,6	outlet 194:20	210:14 211:13	351:6,7,8
190:13,18		215:15 222:12	331.0,7,0
	I .	I .	1

[packages - particular]

Page 57

	T		
packages 50:6	134:17 135:4	235:5,6,7	172:12 173:11
50:8 172:8,9	136:11,21	244:16 246:24	173:15 181:5
172:25	138:3 139:9,13	327:11	182:1,21
page 10:5,11	140:8 143:4,9	paragraphs	184:14 187:4
11:6,14,16	143:24 156:14	127:9,11	187:17 193:23
12:6 13:6	157:3,5 159:23	150:21 151:2,9	194:9 213:20
16:13 48:6	170:10	151:15,22	213:21 215:22
58:16 64:11	papers 50:20	152:3 158:12	217:22 226:4
93:6,21 97:19	120:5,9,12,13	162:21 229:13	236:20 252:13
113:21 117:16	124:4,5 127:25	parameters	253:12 255:19
118:4,5,7	paperwork	40:22 206:8	268:12 273:6
119:25 128:4	72:21	221:10 222:10	273:11 276:13
128:10 132:3,5	par 225:6	236:23 238:15	278:23 287:9
132:12,15	paragraph	249:21 252:4	297:1,19
139:16 140:6	93:6 94:6	252:13,15	305:22 336:19
142:8,9,17	97:20 129:5,9	253:13,16,19	342:12 345:25
143:2 144:18	140:16,17,19	254:7 273:19	347:15 348:7
160:16 188:18	146:20,21,24	277:22 330:8	350:19
207:3,7 209:7	147:7 148:5,14	paraphrasing	partially 17:21
307:12 320:2	148:25 149:13	161:24	participant
339:12 353:4,7	149:23,25	paris 79:13,14	139:22 147:9
353:10,13,16	150:11 152:11	park 4:8 7:9	participate
353:19	152:17 153:6	8:9 9:8	77:17
pages 132:16	153:20,25	part 18:7 19:4	particular 29:4
142:10,14,24	154:6,11,20	19:8 21:8	38:15,25 69:12
207:11 280:8	155:1 158:13	24:20,25 25:1	73:11 81:5
347:21 349:8	163:13 198:5	25:3,8,12,13,19	106:10 114:11
paid 32:21	209:6,11	27:9 33:15	132:16 133:23
35:13,15 90:8	214:17 224:4	34:3 49:11	136:6 158:6
192:13	228:15,19,20	75:6,9,13,22	160:10 200:16
paper 47:20	228:22,23,24	79:3 81:3,8,9	202:20 207:21
51:21 57:8	229:13 230:3	81:10,11,17	209:21 212:18
124:7,19,23	231:4 232:11	86:17 88:16	218:15 225:11
125:5 132:20	232:15,17	95:21 143:1	226:10 237:3

[particular - perspective]

Page 58

268:16 289:12	paying 270:1	293:14 295:3	231:1 237:8,10
311:21 313:21	pays 278:20	295:10	242:10,18
320:15 321:14	314:1	percentage	245:1,2,4
322:12	peak 223:25	40:21 44:9	288:14,19,23
particularly	225:2	51:22 57:10	289:4,9,15
56:4 75:20	pearson 220:5	percentages	290:21,22
78:12 96:24	peer 124:5,8,10	43:22	291:4 293:8
98:22	124:11,13,14	perception	295:15 297:18
parties 2:20	204:9	23:5 149:14	297:24 298:24
242:15 352:18	pen 282:2	perceptions	316:17 334:19
parts 81:21	penalties	114:19	334:22 335:1,5
140:2 222:6	117:20 118:20	perfect 331:7	335:7
347:4	penalty 352:20	perform 37:12	periods 176:4
party 1:11,12	pending 109:19	87:14 234:10	208:22
2:11,12 14:13	110:8,14	235:2 300:7	perjury 352:20
55:22 57:17	111:12 112:2	performed 37:9	person 29:17
176:20,21	335:23	87:17 97:14	33:7,8 80:11
178:4 179:1,19	pensions 270:2	98:4 103:24	228:1 258:9
180:12 181:1	people 56:4	338:23	275:21
243:8 340:8	84:13,18 94:9	performing	personal 29:13
paste 53:6	107:12 117:6	88:3 264:11,24	127:15 296:2,4
331:12	213:11 253:5	period 41:6	296:7
path 12:18	276:25 334:14	106:2 158:22	personally
282:18 283:20	percent 36:14	176:12,17	172:18,21
patrick 12:8	36:14 43:7,8	179:10 181:13	208:4,10
patterns 32:4	44:11 58:1	183:13 197:19	268:20,21
193:25 198:11	148:20,24	200:14,19,20	346:8,17
215:12,13,18	149:13,23,25	201:6,12 202:1	personifier
215:21 216:24	150:11 151:3	202:6,11,14,22	251:10
224:3 230:8	151:10,16,23	203:16 205:19	perspective
231:9 295:9	152:4 154:12	208:23,24	44:9 71:10,11
pause 338:12	154:19 155:1	210:13 221:9	75:18 81:4
pay 32:19	163:14 175:3,8	225:14,17	84:25 90:9
88:21	175:16 293:6	228:16 229:7	98:17 102:21

[perspective - positive]

Page 59

	1	1	
115:17,18	225:9,11 352:6	318:13 327:14	117:8
165:4 166:14	placed 64:7	plausible 47:5	policies 52:25
198:25 281:18	plaintiff 1:6,11	129:23	53:5 87:11
311:3 348:11	2:6,11,19 4:3	play 188:21	policy 53:7,12
ph 30:8	5:3 6:3	please 14:12,13	53:18,18,20,24
phelps 4:4	plaintiff's 9:24	15:7,18 22:13	91:10
phil 75:8	34:8 165:3	22:21,22 38:20	political 105:22
phillips 4:4	plaintiffs 1:14	61:18 110:16	106:19 196:17
philosophy	2:14 3:3	110:18 111:12	politics 98:23
75:8,18	planted 117:9	111:15 125:19	114:13 196:7
phone 23:15	196:20	126:19 135:4	196:15
physical 113:4	platform	135:17 137:9	pop 276:19
264:4	176:19 223:23	137:13,23	277:8 300:25
physically	235:8 237:18	138:23 139:5	302:9,9,11
77:10 79:10	245:15 284:8	140:2 142:24	304:5 309:20
176:5	313:19	164:12 185:4	310:16,16
pick 38:11	platforms	204:16 231:10	popularity
117:13 216:4	91:16 95:8	242:12 248:17	94:12 197:9
228:18	106:9 114:2	304:25	portion 260:23
picked 143:10	177:15 188:3	plugged 205:10	pose 109:11
330:22,23,25	190:11 201:8	273:19	posed 306:18
picture 247:3	202:3 205:22	plus 292:3	position 20:19
piece 29:5 35:1	207:21,22	301:4,4 312:21	86:17 287:7
103:21 120:25	210:15 216:3,5	point 16:2	positioned
251:5 259:13	216:7,10,13,17	44:10 70:4	171:25 197:11
259:13 266:10	217:2,18,21,21	134:19,20	197:12
266:21 278:8	217:24 218:1,6	201:4 211:21	positions
294:1	218:16 223:25	211:24 322:10	106:25
pieces 174:11	225:2 229:1	points 210:8,11	positive 39:23
229:24 260:15	231:13,25	211:17,19	89:13 99:6
261:10 283:21	232:19 235:14	231:1 283:14	199:5 247:15
336:13	236:6 242:14	291:20 321:19	247:23 248:3,4
place 64:7	242:20,23	polarizing	248:18,25
107:19,20	245:15 289:22	114:7,9 117:5	249:1,7,10,15

[positive - predicted]

Page 60

251:3,10,12	276:6,10	239:11,12,16	potential 85:7
260:6 265:21	277:11,13,19	239:20 240:2,9	85:10 88:6,7
274:5,19 275:6	278:22 279:3,9	241:9 243:11	161:18
314:24 342:6	279:14 280:3	260:25 261:5,7	power 75:17
342:16 344:7,8	280:19,22	262:5,20	powerful
positively	281:20 282:7,8	263:21,22,23	321:12
100:3	283:10,24	264:12 265:7,9	pr 18:2 121:16
possess 82:14	286:22,23	265:11,19	192:1
possible 19:22	287:5,9,10,11	266:18 267:1	praavi 30:8,8
96:5,12,18	287:12,12,14	267:17,23	practice 22:11
102:13,17	287:15 291:1	273:8 274:3	190:16 218:23
108:3 116:22	302:25 309:8	275:2 283:13	practitioner
117:15 130:19	310:2,8,22	286:2,3,7,10,12	63:21,23 64:1
179:16 239:3	313:25 314:6	286:14,15,18	64:13,14,16,19
243:2 312:16	314:12 323:4	286:20 287:1,4	123:25 124:13
332:16	323:17,17,19	287:7 288:6,12	124:15 147:13
possibly 16:18	323:20 326:8,9	288:18,20,24	157:15 158:5
180:21 336:7	326:11,14	289:2,3,5,6,9	158:22 159:16
post 12:7,9,10	332:7 337:6,8	289:10,13,24	160:11 204:11
12:12,13,15,16	337:13 343:9	290:6,8,12,21	218:22 219:4
12:18,21	posted 225:18	291:6,20,21	practitionerly
104:12 117:6	226:3 316:5	292:2,17	247:18
193:21,21	336:6,10	293:11,12,14	practitioners
247:20 251:1,1	posting 102:1,3	293:15,18,25	71:8,9
251:2,23 252:2	104:11,20	294:2,4 295:15	precede 257:10
252:6 259:8,9	225:11 229:16	295:16,16	preceded 19:14
259:14,23	230:6 231:7	300:25 301:1	257:14
260:2 261:12	295:10	302:9,15,17	predated 78:18
263:8,11 264:4	posts 175:20	303:13,17	predict 57:5
265:15 266:4,7	177:22 178:3	310:25 312:15	151:9 154:5
266:15 267:2	215:24 225:18	314:19 317:25	predicted
269:15,16	236:11,12,19	323:9 333:6	149:23,24
274:7,12,23,25	236:20 237:12	337:19 338:8	151:15,22
275:1,10,15,16	237:24 239:10	341:16	154:19 163:13

[predominantly - projected]

Page 61

predominantly	principle	problematic	product 84:9
39:25 88:10	119:21	104:20	84:11 85:1
prefer 246:13	prior 18:12	proceedings	125:14 339:19
preparation	19:2,11 213:21	14:2 352:5	346:1
36:23 43:17	213:23	process 19:8	professional
prepared 16:14	prioritize 114:4	21:8 25:14	147:3
preparing 17:5	private 31:3	27:3 29:18	professor 49:1
34:23 43:5,14	236:20 239:17	33:15 49:12	52:10 53:19
43:24 126:9,10	239:22 240:11	124:11 183:10	68:2,3,18
126:12 135:16	privilege 20:18	194:23 324:14	69:15,24 70:13
168:15 169:2	23:5,9 27:18	processing 76:7	70:17 219:5,8
present 3:4	27:23 28:4	247:17 248:24	proffered
9:22 69:25	65:22,25 66:6	249:15 250:3	292:22
70:7 221:6	165:20	251:7 257:17	progeny 162:25
268:17 288:8	privileged 24:5	340:24	163:3,8,17,18
presented	privy 103:9	processor	164:1
115:4 124:9	pro 78:16	341:6	program 74:21
160:22	proactively	produce 60:5	75:4,13,22
press 192:1	161:8	253:16,18	76:24 77:1
194:6	probability	262:13 266:17	79:17,25 80:4
pretty 67:20	52:5 148:20,24	266:20,23	80:7,10,12,15
89:22 194:23	151:10,16,23	267:11 290:24	80:17 257:25
272:11,18	probably 17:9	305:21 339:19	programmatic
332:23	36:14 65:1	339:25	106:18
prevent 16:5	68:2 79:21	produced	programming
previous	100:19 114:11	61:15 245:23	76:19,20
104:14 119:24	130:11 134:18	246:1 258:11	244:20
299:15	134:23 164:6	284:3,6 285:4	programs
previously	221:3 230:10	285:10,13,20	95:23 99:2
29:22 30:2	268:16 295:19	286:25 317:2	project 31:2,5
37:19 38:14	346:4 349:17	326:19	31:6 32:24
61:14 134:9	350:24	producers	33:19
268:18,25	problem 62:25	192:3	projected
279:6			154:11

[projects - pulled]

Page 62

	I		1
projects 30:2,3	proportions	261:14 262:1,9	publicity
30:24	43:25 235:15	267:6 274:1	198:14 199:9
promote 84:17	235:17	303:15 304:3	199:11
115:16 336:20	proposed	305:3,7,12	publicly 42:21
promotional	350:15	306:23 307:4,7	240:1,14 242:8
85:11	propounded	326:24 331:2	244:19
prompt 195:15	352:9	339:17 343:22	publish 124:1
195:16	proprietary	344:3,5,11,14	194:17,18,20
prompted 24:2	105:19	344:20 345:6,9	published 25:7
24:10 161:12	protected	345:16 346:23	120:23 121:1
promptly	27:18,22 28:3	provides 208:1	123:20 124:25
350:13	66:5 165:19	247:3 261:8	publisher
prompts	protective	321:17	319:10
181:11 186:10	105:20	providing	pull 35:17
187:9 204:1	prove 234:16	195:11 333:9	58:16 97:1
pronounce	provide 56:23	proving 57:20	113:11 125:18
30:7	82:4 136:11	pst 2:22,23	201:7 205:1,1
propensity	157:2 217:23	351:8	237:17 238:13
47:13 105:7	223:16 253:19	public 42:14,17	238:20 241:11
properties 87:6	259:12 303:24	75:20 119:6	241:17 263:23
193:3,4	305:2 306:14	178:3,3 198:12	264:8,12 265:8
proportion	306:16 337:24	233:23,24	271:4 274:2
236:15 237:6,7	342:9 344:6	236:19 239:20	287:17 291:16
237:13,25	345:11 350:24	239:21 240:5,9	300:11,12
proportional	provided 41:20	240:11 241:9	302:23 310:21
43:6 203:7	42:20 58:8	241:14 243:11	311:20 349:24
224:1 235:7,21	59:24 61:20	354:19	pulled 118:16
236:4	129:16 130:22	publication	188:3 202:2
proportionality	143:3 145:12	48:16 132:25	205:8,21 206:6
238:7,25 239:9	172:15 173:13	143:19	221:16 238:11
239:13	174:22 188:5	publications	273:7 277:7
proportionally	206:3 229:10	120:3,4,23	287:14 290:21
239:24	254:11,15	170:20	296:23 310:22
	259:24 260:5		311:5 326:22

[pulled - r] Page 63

242.21.22	227.16 252.7	16.10 65.1	225,22 25
342:21,22	337:16 352:7	46:10 65:4	335:23,25
pulling 300:18	putting 16:21	66:23 75:2	343:10 345:13
319:12 324:10	17:11 33:24	78:22 79:2	348:17,19,23
pulls 239:3	34:1,17 91:9	95:10 99:17	349:3 350:1
300:23 302:19	160:9 254:18	109:2,2,4,11,15	questioning
302:22	338:5	109:18 110:3,7	108:23
purchases	python 36:24	110:14 111:4	questions 20:22
107:19,20	39:2,3 254:10	111:12,20	26:3,6 30:1,15
purchasing	258:1 306:2	112:2,3 137:3	30:18 31:9
107:13 114:3	344:3	137:14,24,25	65:21 165:7
purporting	q	138:2,16,24	352:9
221:16		139:1,3,6,8	queue 123:10
purpose 23:19	qc 58:6	154:16 157:10	244:9,10
purposes 113:5	qualified 314:20	165:17,22	quick 246:11
115:9 125:16		169:14 178:13	246:13 272:11
128:1 133:19	qualifiers 89:3	180:19 182:12	286:1
136:16 174:13	qualitative	182:21 183:1,2	quinn 3:5
288:5 340:19	223:12 247:20	183:16 184:14	quinnemanue
341:16,20	quality 126:21	184:18,20	3:13,14,15
pursuant 2:20	133:6	185:16 189:16	quite 17:21
purview 86:25	quantitative	192:22 195:3	53:6 72:3
227:11	223:5,13	200:18 204:4	116:17
pushing 106:8	quantity 292:5	204:16,17	quote 139:17
put 23:16 34:9	quarter 77:11	207:5 224:9	161:22 179:17
64:19 86:8	quarterly	236:10 237:11	230:13 242:17
90:24 98:16	211:12	238:9 256:23	281:12
110:11 206:8,9	queries 186:10	256:24 259:15	quotes 347:21
233:1 243:1,12	188:5 221:10	265:3 267:16	349:8
252:4,13,15	222:10	267:16 274:11	
253:22 254:10	query 206:8	293:21 296:14	r
255:7 269:5	265:8		r 3:1 4:1 5:1 6:1
	question 25:16	297:12,13,13	7:1 8:1 9:1
274:20 277:21	26:2 27:17	301:14 306:18	28:25 127:4
285:16 307:12	41:5 42:2 44:5	311:20 314:15	276:19 278:14
320:1,8 321:5		317:23 326:22	

[r - really] Page 64

0.70.00		1.0011.1	227.10
353:3,3	238:16,19	163:24 164:6	327:18
radicalize	239:4 241:4	164:21 166:12	readme 12:24
115:20	305:23	168:4,13,17	13:9 284:6,10
raise 15:7	reach 24:10	172:18,19	284:12,19,22
rally 100:21	60:20 211:20	175:2 198:8	285:1,3,6,10,13
ran 39:2,3 85:2	reached 29:20	209:14 214:21	285:20 286:22
245:1,3,6,7,9	161:17	220:20 223:22	290:3 295:18
245:15,16,17	reaching 349:2	224:25 228:25	295:21 300:17
245:18,20	reaction 347:9	229:15,20	304:3,4,6
262:4	read 57:17	230:5,14 231:6	307:20,24
random 229:24	69:23 94:7	231:23 232:11	308:2 309:9,14
230:15 238:16	95:4 97:11	235:12 244:18	311:1,22 315:6
238:23 240:2,4	109:8,14	247:1 269:25	316:8 317:1,3
240:8	111:17 113:25	272:16 278:13	317:4,5,21,22
randomized	114:18 117:18	279:19,21	318:23 319:1,5
238:13 264:2,2	119:3 122:14	280:10,12,24	319:15 325:6
264:16 267:2,3	122:15,16,20	281:13 282:17	339:18,24,25
267:8,8,9,20	123:3,5,7,12	285:25 293:4	344:21
333:3	126:15 128:25	294:10,15,23	reads 316:22
rare 100:9	129:3 131:20	295:1,8 300:22	ready 93:24
rather 69:8	134:8,9,16,23	303:9 317:19	244:13
127:17,18	135:1,7,13,16	318:11 321:10	real 48:12 56:2
214:24 230:15	136:13 137:20	327:12,20	89:20 216:22
232:9 234:5,13	137:24 138:1	336:18 337:10	265:1 294:11
277:3,4	138:21 139:7	347:13 349:13	298:17
rational 47:13	139:18 140:13	354:5	realize 246:8
316:6	141:22 142:19	readily 223:18	realized 88:23
ratios 93:3	142:23 148:9	306:8 333:23	really 79:2
raw 186:20	148:17 155:8	333:24,25	101:17 201:7
187:1 188:3,6	159:5 160:20	reading 122:14	236:13 237:23
201:8,21,25	160:23,25	162:4 167:16	239:12 281:20
202:3,6,13	161:21 162:14	200:7 265:19	294:19 311:4
205:22 208:16	162:15,16,19	286:6 293:9	311:16
208:19 237:17	162:23 163:5	321:16 323:22	

[reason - reference]

Page 65

reason 15:20	received 25:20	138:1,20 139:7	290:6,8,12,17
16:4 48:25	26:13 60:9,10	185:2,2,4,6,14	291:7,20,22
69:12 145:11	74:15 167:9,10	246:16,17,21	292:17 293:17
195:6 236:5	183:14 333:8	248:10,12,13	293:23 294:2,3
244:2 255:17	receiving	248:15 338:12	294:6 295:14
255:19 290:2,4	122:14	338:13,15,16	300:4,6,11,16
296:17 297:20	recent 142:21	338:20 348:13	300:23 301:12
327:5 332:22	148:11 255:3	348:15,20	301:12,20,22
353:6,9,12,15	256:25 258:15	350:14 351:3,6	302:6,9,15,19
353:18,21	258:17	recorded 1:19	302:20,22,23
reasons 48:23	recently 134:18	2:18 352:11	302:25 303:1
48:23 54:9	134:20	records 205:16	303:14 305:15
206:5 244:8	recess 61:9	331:16	306:5,11,20
332:16 336:5,8	62:15 112:9	recovering	307:3,13,14,23
343:12	185:8 246:19	119:4	308:9 309:9,12
rebuilding	338:18	recovery	309:14,17
117:24 118:21	recipient	119:23	310:20,23
rebut 166:23	284:16	recreate 343:24	311:19,24
rebuttal 165:2	recognize	344:1,15,19	reddit.com.
166:14	275:1	reddit 12:11,12	307:8 308:6
recall 20:10	recollection	12:20,21,22,23	reddits 312:16
118:18 119:8	26:5 36:11	177:17 206:24	reduce 249:20
144:13,14	134:12,14	216:4 217:9,13	249:20
153:11 167:16	137:8 138:18	221:8 222:25	refer 18:8,20
168:2 302:8	153:1,14,19	239:11,12	63:9,11 81:7
347:7,14	290:23 320:1	241:13 276:6,6	84:13 140:21
receipt 78:18	reconcile	276:12,13,16	209:1,4 224:15
receive 26:17	239:25 290:20	276:22 277:1,1	224:19 225:13
26:20 34:14	record 14:5	277:6,7 278:9	254:23 290:10
62:3 74:17,23	15:18 59:15,19	278:16,17,22	291:24 305:19
77:17 79:7	60:20 61:2,7	285:14,19	337:7
122:12 166:22	61:11 62:12,13	286:1,14 287:1	reference 29:23
182:3 183:12	62:17 111:17	287:17 288:5	37:21 63:1
183:13 267:17	112:1,4,7,11	288:11 289:11	126:24 127:18

[reference - removing]

Page 66

127:19 140:6	reflect 82:7	regularly	168:21,22
145:14,16	112:1 142:10	128:25 129:3	170:3 171:1,9
147:6 152:23	170:20 240:4,4	131:20	relief 22:23
153:3 182:1	258:12,14	regulations	349:19
255:15 260:23	308:19 336:14	11:16 105:18	rely 51:17
306:8,13	350:14	rejected 350:16	107:16 125:15
307:17	reflected	rejoining 58:24	136:16 169:3
referenced	326:23	relate 92:7	169:18 170:8
23:17 28:23	reflective	related 92:16	174:3,6
86:2 181:10	176:11 238:17	115:11 176:11	relying 147:12
274:18 275:22	274:4	268:24,25	173:22
295:25 296:1	reflects 188:25	328:13 335:1	remaining
346:25 349:5	207:5 214:23	relating 339:20	312:21
references 49:3	329:16	relation 268:22	remember 20:2
133:16 141:18	refresh 320:1	relations 119:6	26:4 31:20,22
286:10 349:15	regard 174:9	relative 352:17	72:3 118:23
referencing	regarding	relatively	132:8 171:24
114:12 139:13	161:17 194:13	237:19	172:24 302:12
153:22 159:23	regards 90:5	release 194:6	302:13 319:23
196:14 347:17	119:17 165:9	232:2 233:5	347:14,23,24
referred 29:7	regions 104:10	234:4,12	remembering
29:23	regression	relevant 38:15	43:3
referring 18:10	125:7 204:11	38:16 73:1,4	remote 75:4
34:11 89:6	288:15 341:13	73:12,17,21	77:13
106:14 124:14	341:22 342:3	78:8 81:1	remotely 1:20
224:20 257:9	342:14 343:1	164:16 206:17	remove 171:13
279:14 286:12	345:21,24	206:20 311:8,9	171:23 297:14
295:6 347:8	346:3	313:21	330:9
349:14	regressions	reliable 55:23	removed 168:6
refers 28:20	346:4,5	57:11	169:23,24
47:3 97:12	regular 63:20	reliably 57:5	171:18,22
197:17 223:9	64:9 67:17	relied 128:1	removes 210:21
224:5,10	123:4	138:22 157:18	removing
294:13 301:22		157:24 158:12	297:9

[repeat - represent]

Page 67

repeat 57:2	37:21 40:12	168:24 169:2,9	342:9 346:6
78:19 86:13	43:13,23 44:14	169:19,23,24	347:15,16,25
94:22 137:13	44:16,18,20,22	170:7 171:12	reported 1:24
138:24 139:5	45:1,2,15,17,19	173:22 174:1,4	85:23,24
169:14 181:22	45:22 46:3,6	174:9,13,25	reporter 2:25
184:13 204:25	46:21,24 47:3	177:1,6,8	15:4,6,13
209:8 212:3	57:22 58:16,18	182:2 185:24	109:7,14,24
216:15 224:9	59:4,17,22,25	188:11,15,17	110:1,2,14,24
293:21	60:5,6,9,9,15	188:25 189:3,5	111:13,16,21
repeating	60:24 61:1,1	189:10,19,22	118:13 130:24
185:16 224:21	61:13,14,17,18	191:12 198:1,2	137:25 139:7
rephrase 28:22	61:20,24 62:20	199:17,19	185:17 219:16
240:16	62:23,25 63:7	200:8,9 205:11	246:4 248:7
rephrasing	63:10,11,18	205:16 207:3	349:25 350:9
184:21	66:16,21 67:5	209:5 214:17	350:18,25
replicatable	67:6 85:21	223:20 228:16	352:3
181:13	92:12,13,16,19	233:1 239:9	reporter's
replicate	92:20 97:4	244:16 246:25	352:1
183:10 186:6	125:16,19,23	252:14,19	reporting
201:1 204:1	126:3,5,6,9,12	253:2 254:4	88:11 225:20
255:22 256:8	127:7,9 128:2	255:4,6 256:10	reports 34:2,5
261:18,25	128:5,13,14	260:24 271:25	34:11,12,15
290:25 292:12	129:5 133:19	274:19 288:8	66:20 86:2,3,4
338:4 339:21	135:11,16	288:14 290:10	165:4,5 166:13
344:4 345:12	136:16 138:23	291:15 299:24	166:23 167:9
replicating	140:8,11,15,19	300:1,3 306:17	167:10 172:3,5
181:9 259:17	144:17 148:4	306:18,20,24	173:3 200:10
replies 303:14	150:21 151:3	311:11 318:8	repost 103:22
report 11:7,8	151:10,16,23	318:22 319:2	104:13
16:9,13,22	152:3,8 158:11	319:10,25	represent
17:5,11 28:13	159:2 162:22	322:20 333:18	142:10 162:1
28:17,20 33:25	164:16 165:10	338:22 339:9	176:9 178:17
34:1,10,18,19	165:10 167:15	339:10,13	180:10 290:11
34:22 35:1,3	168:3,5,16,23	340:17 342:2,5	301:10

[representation - rhee]

Page 68

4 7	4 40 22	107.00
_	_	return 107:8,9
		107:9
_		returning
		107:13
_		reveal 161:5
	287:12	revenue 85:8
requires 119:5	response	88:12
161:3 230:24	149:25 165:18	review 59:15
304:11	347:4	59:19 124:11
requiring	responses	133:19 134:22
230:16	346:8,9,15,18	136:23 165:3
rerun 39:7,15	responsibility	172:4,5,10,16
39:16 262:8	11:12	172:21 173:1,4
research 11:23	responsible	173:6,21
11:23 36:21	48:15 87:10	267:18 284:25
43:4 55:22	rest 47:14	306:1 308:15
57:14,17 133:7	268:12 283:2	346:8,24
142:22 148:12	308:6	349:17 352:13
150:6 156:9	restrictions	reviewed 34:12
157:13,22,24	41:7,10	124:5,8,10,13
158:4,6,24	result 184:11	124:14 136:15
160:24 178:15	results 180:18	169:2 172:7,7
188:22 189:12	181:7 183:21	172:13,14
213:25 214:1,2	220:22 294:9	173:10,14,18
216:8 221:15	294:23 295:14	174:10,13,16
221:19,21	317:20,21,24	174:21 204:9
247:19	318:7 327:2,9	217:7 267:24
reshaping	retain 16:15,17	285:9 296:11
46:17	32:16,23	306:2 346:14
resisted 301:23	retained 17:15	346:17 347:2
resolution	17:19 33:2,4	reviewing
60:20	134:25	173:16 347:23
resolved 16:1	retrieved	rhee 6:4 14:15
	303:18	
	304:11 requiring 230:16 rerun 39:7,15 39:16 262:8 research 11:23 11:23 36:21 43:4 55:22 57:14,17 133:7 142:22 148:12 150:6 156:9 157:13,22,24 158:4,6,24 160:24 178:15 188:22 189:12 213:25 214:1,2 216:8 221:15 221:19,21 247:19 reshaping 46:17 resisted 301:23 resolution 60:20	352:14 109:25 110:18 require 21:10 24:4 230:22 294:5 317:13 required 159:9 354:13 responding requires 119:5 161:3 230:24 349:25 165:18 304:11 response 149:25 165:18 347:4 requiring 346:8,9,15,18 responses 346:8,9,15,18 responsibility 11:12 responsible 48:15 87:10 research 11:23 responsible 48:15 87:10 rest 47:14 268:12 283:2 308:6 restrictions 41:7,10 result 184:11 result 1

[richard - running]

Page 69

• 1 1 10 0	10600 1055	200 4 201 1 5	201.1
richard 12:9	186:22 187:7	300:4 301:16	romance 301:1
right 15:8	188:8,18 194:3	302:10,16	304:5 310:15
18:22 19:12	196:14,25	306:17 309:10	310:17
22:9,19 26:14	197:15 198:2,2	309:16,20	rooted 190:13
32:13 35:20,23	198:7 199:9	311:2,6 312:9	190:15,16
40:5 43:17	202:9 208:24	312:21 314:7	218:18
46:14 47:6	209:9 211:19	316:13,13,18	roots 75:17
51:20 52:11	211:21 212:16	317:2,7,10,18	row 175:2
58:24 59:5,12	214:12 217:10	317:22 318:1	287:25 288:3
61:6,15 66:15	223:4 224:7,13	318:16,21,23	309:4 310:18
67:6,8 69:22	224:16 225:7	318:24 319:15	313:24 314:5
71:4,17 72:10	229:4,7 230:18	319:18 321:7	336:16 337:9
73:24 76:19	232:17,19	323:4 324:2,23	rows 264:17
78:18 81:8	233:6,9,10,13	325:15,20	278:5 323:3,5
82:8,20 96:2	234:8,14 235:3	326:5 327:17	324:13 335:15
96:14,20 100:7	237:8 243:4,16	328:24 329:10	335:15
103:5 106:17	243:22 244:13	329:13,17,22	rude 250:14
111:20 115:15	245:6,24 246:8	330:19,20	rule 107:15
115:24 117:6	247:8 249:12	331:12,12	run 39:7 40:1
119:21 122:23	254:25 255:23	335:17 336:1	49:14 51:21,25
128:6,9 129:18	256:3,21	338:12,24	88:4 184:15
131:13,17,17	257:14 263:5	339:7,25	203:21 204:5
132:24 137:25	263:11 265:8	340:16,20	204:10,17,21
141:3,11,15	265:10 266:18	350:4	205:2 213:13
142:2,11 143:3	267:1,25 269:2	rigor 161:23	244:7,25 245:5
144:21,22	269:7,13	risk 120:1	245:11 253:14
145:8 146:4,25	270:15,18	role 32:10	253:17,20
147:24 148:8	279:17 280:6	73:18 85:24	257:24 259:17
155:21 156:1	284:4 285:7	86:11 105:24	261:25 264:21
157:12 162:13	286:11 289:19	106:1	268:20,23
166:1 167:6	290:3 292:8,10	roll 221:12	271:22 304:21
175:4,9,19	294:16,21,22	222:12	running 46:14
179:13 180:23	295:17 298:4,6	rolls 211:23	87:23
181:3 184:5	298:13 299:20		

[s - scrape] Page 70

S	299:25 328:14	295:21 300:18	sciences 82:17
s 3:1,10 4:1 5:1	saying 63:22	300:21 301:16	82:19,22
6:1 7:1 8:1 9:1	86:16 100:11	302:19 303:8	scientific 194:8
339:3 353:3	140:12 158:2,3	304:4 305:2	195:20,23
sabrina 12:11	158:22 192:13	307:3 309:20	scientist 29:2,9
276:7	193:12 194:5	316:10 317:5,8	29:11 31:19,24
	221:18 239:25	317:9,15 320:2	179:23
sad 272:18	243:11 254:1	321:9,20	scope 29:16
sage 11:23 salaries 270:1	306:21 336:17	325:11,18,19	166:19 251:20
salaries 270.1 sales 107:8	345:8	325:21 327:9	score 247:15,21
125:11	says 16:13 36:8	327:11,19	248:23 249:1,8
sam 11:17	51:22 67:22	330:5 337:9	250:12 259:11
132:21	68:1 69:15,22	338:23	259:13,22
sample 175:21	70:6 93:21	scale 83:8 96:4	260:2,5,6
179:25 180:4,5	94:6 97:10	96:6 100:10,14	264:3,18,25
180:7 203:2,4	98:12 99:7	102:10 194:2,3	265:16,18
238:16,23	110:8,14	216:25 218:25	266:3,7 273:23
240:2,4,8,13	114:17 117:17	schedule	275:23 310:5
267:9,9 333:3	131:22 141:2	350:12	338:6 342:24
333:6	143:13 147:19	scholar 49:14	scores 254:2
samples 34:14	170:2 192:16	49:25 160:4	261:4,6 266:18
sampling 236:7	200:11 207:13	school 77:2,4	266:20 343:3,7
238:14	209:13 220:6	schuster 9:6	343:9,21
santa 6:17	222:23 223:11	14:23,23	344:11
sarah 4:6	228:24 230:3	sci 31:16 83:16	scoring 273:21
sarowitz 7:4	235:11 241:9	science 24:24	273:21 274:20
8:4 9:4 18:1	243:21 254:12	31:1 71:15	275:6
sat 86:25	254:13 269:24	83:5,12,12,13	scrape 38:2
saw 40:17	272:15 278:12	83:15,17,18	39:20 40:2,14
104:6,24 106:9	280:22,23	131:9,16	40:15 42:14
107:10 206:22	281:25 282:16	132:18 142:21	207:23 237:22
209:20 252:14	285:24 286:17	144:25 148:11	240:10 241:2,7
285:5 293:14	287:7 288:23	156:11 158:7	242:17 244:13
	293:3 294:9,25	233:19	245:9,10 306:5

[scrape - see] Page 71

206.11 221.10	gamaning 26.22	160.2 177.00	sections 302:4
306:11 321:18	scraping 36:23	162:3 177:22	
321:24	37:10,12,13,15	180:22 181:4	see 27:7 29:21
scraped 38:24	38:22 40:8,23	181:25 183:20	30:2 31:1
40:5 41:23	42:16 208:16	206:15 240:6	33:17 34:2,6
42:4 280:7	208:18 236:18	242:9 243:4	45:6 50:6 59:2
290:17 307:14	239:18,20	251:22 304:9	61:23 62:2
scraper 12:21	244:21 307:8	312:20 313:15	64:10 65:13
12:22 13:7	333:9	329:16,16,18	67:13 88:11
208:1,5,11,14	scratch 266:24	329:25 330:3,6	90:10 91:24
208:15 237:21	screen 58:18	331:13 333:18	92:3 93:14
239:3 241:1	59:2 67:11,13	searched	94:16 97:18
287:17 300:4,6	72:7 93:9,19	312:16,18	107:21,23
300:16 302:25	126:18,19	searches 181:3	112:6 113:20
303:1,5 304:11	144:19,20	300:7	114:24 116:3
305:1,15	147:25 148:2	sec 113:12	118:1 127:22
306:21 307:3	152:10 206:14	second 52:9	128:8,16,21
311:4,14,23	219:20 220:2	62:19 63:6	129:8,11,16
312:4,17 313:2	232:18 262:25	71:14 93:21	131:24 132:13
313:5,14	269:5,16,20	106:21 176:20	140:7,9,22,25
320:14,20,22	271:15 279:16	180:12,20	141:3,6,14
320:23 321:7	285:16 316:8	184:13 206:13	142:15 144:21
321:11,19	320:2 321:5	206:25 248:8	145:1,3,5
322:3,12,14,15	325:17 330:19	269:6,23	148:5,6,13,21
322:21 324:11	screenshot	273:19 285:15	148:22 152:11
329:19,20,21	262:21 263:1	294:22 299:19	152:16,19
330:8 342:11	script 305:23	316:14 327:10	160:17 166:14
scrapers 58:13	305:25 306:1	secondarily	197:24 198:16
207:1,6,16,18	scroll 59:7	43:13	204:6 207:12
207:20,23	138:6 278:9	secondly 201:3	208:4,8 209:11
208:17 240:24	300:19 309:4	201:18	209:19 215:1,2
242:5,8 330:4	310:13,14	section 188:18	215:25 217:4
scrapes 206:4	323:11	188:25 276:22	220:4,8,13
258:6 303:12	search 41:24	277:1 312:19	221:15 222:13
307:13	42:22 160:4		235:6,9 236:22

[see - separate] Page 72

239:2,16	336:23,24	70:22	sentiment
252:19 255:7	344:20 345:18	semesters	39:24 155:10
259:11,12	seeded 196:16	76:17	156:10 204:5
260:8 261:9	196:16	seminars 68:14	204:12 209:21
262:11 263:19	seeing 64:3	68:16,17,23	246:23 247:6
266:7,14 269:1	103:21 105:6	sempertegui	247:12,20
269:15,20,23	336:17 338:6	12:9	248:18 250:24
270:6 271:7,11	seek 22:23	send 113:3,15	252:7,11,12
272:24 275:4	349:19	350:7	253:4,7 254:2
277:13 279:12	seeks 27:17	sending 31:6	256:9 258:6
279:14,17,22	seelig 9:5 14:21	sensational	261:3,6 263:5
280:1,5,6	14:24	114:6,8 117:5	264:8 265:23
281:3,8,10,21	seem 116:11	117:8	271:18 273:21
281:22 282:5,6	seems 194:22	sensationalism	273:21 274:4,7
282:22 283:4	292:24	116:1	274:10,12,15
286:4,8 288:25	seen 30:13	sensationalized	274:22 275:16
299:4 301:2,16	57:14 102:12	117:12	275:23 277:18
303:1,3,8,19	103:9,13,14,25	sense 39:12	279:2 281:18
304:6 307:5,10	104:8,8,14,16	47:14,16 56:2	283:5 291:1
309:7,19,21	110:5 114:15	89:20,25 90:3	298:2,18 310:1
310:15 313:25	114:21 115:19	165:6,7 201:7	310:7 314:11
314:4,23 316:8	150:7	238:12 264:4	314:24,25
316:10,17	segment 178:18	sensitive 244:7	337:1,5 340:18
320:2,4 321:6	select 165:3	sensitivity	340:25 341:10
321:15,22	208:3	249:18	341:15,17,18
322:2 323:12	selected 38:13	sent 60:6	341:21 342:24
323:23 325:11	39:13 133:22	107:20 270:3	343:2,5,19,20
325:13,25	133:25 134:2	273:12,15	343:21 344:11
328:2,21	206:25 207:23	sentence 47:14	344:13
329:13,16	238:15	97:10,22,24	sentiments
330:13,16,18	semester 52:19	118:3 142:23	341:11
331:15,17	52:22 54:1,20	163:7,23 251:8	separate 19:4,5
332:11,13	68:7,11 69:3,5	sentences	31:7 87:19
335:15 336:22	69:10 70:3,4,8	232:21	180:16,17

[separate - similar]

Page 73

185:10 350:23	sets 41:11	she'll 59:18	sic 214:25
separated	setting 253:13	shifting 348:4	side 34:8 71:11
208:21	seven 102:3	short 64:25	84:12,20 85:6
september	298:7 348:16	65:5 67:9,10	157:15 250:13
16:18,18,19	several 17:22	67:16,24 69:14	273:22 279:17
17:15 32:25	32:11 100:20	77:14	280:6
33:1 134:25	101:25 122:3	shorter 290:22	sign 95:8 146:7
268:17 293:5	163:1 164:2	shorter 250:22 shorthand 2:25	signature
293:11,15	217:20 220:14	352:2,16	352:23
295:3,16	220:22 299:5,6	show 12:14,15	signatures 56:1
317:17 327:5	shanghai 79:13	31:7 54:16	100:25 101:1,3
sequence	shape 46:15	72:19 103:20	101:6,8,9
110:19,20,22	90:16 95:24	115:21 157:13	102:22 103:5
series 281:25	shapiro 19:17	177:11 252:3	104:17 107:11
282:21 284:6	share 31:3	275:23 279:20	107:25 190:7
340:15,19	33:13,16,16	279:21 280:11	215:17,19
341:4,10,16,20	58:18,20,21,25	280:12 324:16	significance
341:24,25	62:8 67:11	324:16 326:13	209:22,24
343:17	71:14 72:7	326:15	211:3
served 33:21	90:25 93:7,8	showed 222:20	significant 37:3
167:5	93:15 106:8	224:24 273:1	180:5 210:7
service 37:23	112:14,19	286:21 293:17	214:14 232:5
94:10	113:8 126:18	326:10	294:12 335:5
services 84:17	144:19 152:13	showing 105:7	significantly
85:4	197:21 219:20	144:20 212:16	40:17 57:19
set 26:25 41:8	223:20 268:4	212:17 308:3	signified 132:9
50:25 176:2	269:2 321:5	shown 115:19	signifier 175:17
180:16,20	shared 33:18	shows 55:23	signifiers
184:4 214:7	34:7 38:22,23	177:13 247:18	107:21
236:3 253:17	62:4 123:9	323:24 327:3	signs 54:12
271:22 291:16	258:5	327:23 329:12	101:18 102:10
291:20 346:15	sharing 93:12	shrunk 239:21	silo 221:7,8,8
352:6	147:25 152:9	240:1	similar 34:3
	206:13		37:25 65:8

[similar - software]

Page 74

	1		
149:19 178:3	site 85:6 96:9	smear 27:14	179:18 180:3
198:21 199:7	237:1,4 241:16	217:12	180:11,16
199:15,20	sites 42:13	smoother	181:18,24
223:1 251:8	216:23 221:7	210:23	184:5 187:3,24
340:9	222:7 236:8	smoothing	190:11,25
similarly 27:16	237:1 240:10	210:21 211:12	191:2,4 196:6
279:5	243:1 291:25	smoses 4:12	198:9 200:12
simply 54:18	sits 138:17,18	social 11:20	201:8 202:2,18
56:2 57:16	sitting 66:22	12:7,9,10,12,13	205:25 207:21
150:6 193:17	138:5	12:15,16,18	207:22 209:16
232:9 234:5,13	six 84:7 102:3	23:24 30:24	213:9 216:6
241:14 243:11	170:19 197:19	37:24,25 38:3	217:1 218:23
244:6 253:25	253:5	38:6,12,25	221:7 222:7
265:1	sixty 289:10	39:22 41:8,8	226:7,8,12
simulations	size 175:17	41:11 42:12,16	227:9 230:11
268:23	skew 114:19	78:13 82:17,19	236:7 237:3
simultaneous	237:16	82:22 83:4	240:9,18 241:5
229:2 231:21	skewed 92:4	85:5 88:5	241:16 242:14
simultaneously	107:22 115:5	100:13 103:19	242:19,22
231:14,15	skews 211:6	104:16 107:7	243:1,8 244:9
232:1	skilled 85:25	114:1 121:21	250:1 260:9,16
single 117:23	skills 72:2 73:8	121:23,24,25	261:22 262:12
118:20 199:2	skip 70:3	131:14,16	264:22 289:22
245:13,15,21	slew 192:5	132:18 136:12	291:25 313:18
266:2 324:20	slightly 67:20	136:18,22	347:6,11
sit 116:20	115:5 248:22	138:4 139:10	society 74:5
136:20 137:14	sloane 6:14	141:5,11,25	75:16,21 78:8
138:2,14,23	small 76:8	142:2,21	soevyn 1:24
139:8 152:25	84:22 119:15	144:24,24	2:24 11:5 12:5
153:4,13,18	119:19 237:19	148:11 156:21	13:5 15:5
156:23 159:18	243:3	156:21 157:11	352:2,24
176:8 188:24	smaller 175:3,8	158:7 174:11	software 37:23
189:17 306:10	203:13 239:19	174:25 176:19	50:5,8 126:23
313:4		177:14,15	

[solely - specific]

Page 75

solely 187:23	140:16 143:17	305:11,17	22:15,17,19
192:9 200:20	145:22 146:24	308:9 313:24	64:5,12 66:1
solemnly 15:9	147:4 154:15	313:25 316:14	67:9 137:1,23
soliciting 29:18	156:5 158:20	319:19 339:2,4	138:8,10,25
solution 50:6	161:24 163:17	339:5 340:2	139:5 179:4
107:7 144:7	168:18 169:13	342:23 343:15	185:3 229:22
146:12 247:17	172:11 177:18	349:11	specific 39:25
solutions 9:23	177:18 181:22	sort 43:6 55:6	73:12 77:7
84:20 85:25	183:1 184:13	89:19 90:15	87:24 88:2
song 279:21	184:19 186:9	107:17 121:3	100:4 103:23
280:12	191:7,8 194:25	134:10	104:22,24
soon 26:16	195:2,7,25	sorting 82:3	105:1,5,9,10,15
246:5	197:7,8 207:7	sound 35:23	106:13,17,21
sophisticated	207:12 209:8	218:18 315:22	123:20 134:15
233:18	210:10 212:3	316:3	136:2 156:7,25
sorry 15:1	213:3 214:5	sounds 102:20	157:7 166:5
16:24 21:25	215:20 216:15	167:6 193:15	170:10 171:24
25:24 32:1	217:19 218:9	196:22 199:7	180:8 197:20
37:7 38:4 42:1	219:25 220:1	219:11 316:6	207:1,4 210:8
44:3 51:7 57:1	224:8 225:6,9	source 139:16	210:11 218:11
60:3 63:22	225:20 228:23	161:24 244:14	221:2,4 225:17
64:10 65:6,24	231:18,19	sources 126:22	241:25 242:5,8
66:3 67:23	232:14 239:5	159:14 192:5	255:18 257:8
68:10 77:4,21	245:9 248:7	207:4,13	258:3 264:8
78:19 85:23	250:2,24	302:20	265:14 266:25
86:13 90:14	253:18 259:17	sourcing	275:15,16
93:6,23 94:21	260:18 265:24	320:11	276:24 277:4
97:19,23 99:13	266:23 269:19	southern 1:2	280:9,13,17
99:14 101:5,22	270:14,21	2:2	288:17 302:5
104:13 115:8	277:8 278:3	speak 17:11	303:16 304:12
116:24 118:4,6	285:21 286:5	58:18 98:17	305:3 307:4,5
118:10 121:5,8	288:22 291:3	110:16	307:24 312:13
122:17 128:14	293:14,20	speaking 21:7	312:14 320:17
130:1 137:5,15	296:3,7 300:18	21:24 22:7,12	321:19 332:22

[specific - statement]

Page 76

	1		
333:16 342:1	311:11 320:18	spoken 21:3	214:1 226:22
342:15 343:9	322:11	30:12 191:9	227:1,2,5
343:16 344:23	speed 67:11	275:20	341:8
349:8	spend 34:17	sporadic 78:3	standards
specifically	spent 35:6 43:4	spot 292:16	94:15 95:6,7
27:7 30:24	79:16	spotlight	162:8,12,13
31:2 40:7	spheres 204:11	337:11	164:20
46:16 49:23	spike 88:20	spread 114:20	stands 122:17
53:16 55:11	89:12,15	115:10 117:14	162:3 257:7
76:9,13,21	209:17,19	spreadsheet	268:10,13
78:10,13 79:4	214:4,5,9,11,15	288:2 308:10	start 45:2
87:6 88:17,18	215:5,6 230:13	329:24	80:23 110:3
92:20 99:21	230:22,25	spreadsheets	116:7,10 167:7
104:6,14	231:12,24	308:12,18	167:8 327:2
114:12 115:3	232:18 233:6	329:25	336:17
121:21 140:5	233:25 234:16	sprout 37:25	started 111:3
147:5 164:15	288:16 293:17	241:5 244:9	294:18 295:22
165:7,13	293:24 294:11	sprouts 243:8	296:5,18 297:1
176:25 186:11	294:13 298:4	st 74:10	297:7,17,23
195:18 196:13	298:11,16,18	stability 224:2	299:10,18
198:25 199:18	298:19,21	stable 303:11	309:10,18
201:7 208:7,9	299:11,13,15	staff 121:14	349:21
210:3 216:10	299:18,23,24	stamp 225:17	starting 268:5
216:23 231:2	299:24 317:9	309:11 323:10	starts 132:5,6
236:8 253:21	317:13 327:10	329:13	212:20 329:13
296:23 311:5	328:15,17,20	stand 45:16	state 15:9,18
313:14 337:25	335:9,10	74:10 118:3	229:14 246:25
341:1	341:25 342:1,4	319:4	352:3
specifics	342:4 344:2,2	standard 63:1	stated 80:10
245:17 252:22	spikes 215:25	162:24 163:8	96:17 158:18
specify 51:4,9	237:4 327:21	163:25 164:11	205:11 304:6
253:23 255:4,5	328:12	209:24 210:3	statement
255:9 270:21	spoke 26:21	210:12 211:25	118:23,25
299:24 307:19		212:4 213:13	119:10,17,24

[statement - subreddit]

Page 77

140:3 142:18	stenographic	street 3:10 5:8	study 75:1,17
150:7 192:20	1:24 352:11	6:7	75:22 78:14
256:23 294:21	step 110:15	strike 38:4	79:12 169:8
337:14 341:2	343:23	50:22 127:7	183:21,21
statements	stephanie 3:3	168:18 196:1	222:23,24,25
153:6,20 179:9	steps 126:21	223:7 250:6	222:25 223:3,5
352:10	steve 7:4 8:4	264:9 292:22	stuff 309:5
states 1:1 2:1	9:4 18:1	296:3	sub 276:15,21
148:16 162:10	stipulate 298:9	string 47:17	302:9
346:13	301:6	struck 281:22	subaggregate
stating 191:1	stomach 16:3,4	structure 47:15	343:13
statistical	stop 21:23 22:6	251:8 338:23	subcategories
209:22,23	22:6,11 68:8	339:20	301:24
211:2 214:22	69:10 71:14	structures	subject 227:20
220:21 247:2	93:11 111:11	139:25	253:3,23
statistically	136:25 137:23	student 50:5,20	subjective
37:2 47:16	138:7,9 139:4	51:21 54:20	55:15 193:15
57:19 180:5	206:13	56:14	194:23
210:7 229:22	store 134:10	student's 57:8	submission
294:11 335:4	stories 196:15	students 48:21	51:1 172:12
statistics 83:22	196:16,18	52:9 53:25	submissions
232:4	storing 126:24	54:1 75:9,10	173:12,16,21
stay 59:18	story 31:8	268:23	submit 50:4
177:1 189:24	77:13 194:16	studies 74:11	submitted
ste 6:17	272:21	75:7,9 78:7	49:21 54:6,7
steno 15:5	straightforward	103:24 115:19	59:5 143:5
stenographic	249:6	220:14,23,24	152:24 224:18
15:4,13 111:13	strasberg 6:15	221:11 222:6	259:25 285:11
111:16,21	15:2	223:9,12	324:14
118:13 130:24	strategic 71:10	studios 1:8,13	submitting
185:17 219:16	strategy 81:5	2:8,13 7:2 8:2	308:17
349:25 350:9	81:24	9:2 11:3 12:3	subreddit
350:18,25	stream 85:8	13:3 14:9	276:12,13,20
	88:5	353:1 354:1	276:23 303:22

[subreddit - surprise]

Page 78

304:11 305:3	194:18 335:10	supervised	103:14 105:20
307:4 312:10	335:11	88:3	113:13,17
313:10,22	subset 264:1,2	supplement	114:14 116:17
314:9	substance	189:15	116:18 121:8
subreddits	20:14 21:11	support 140:3	129:7 130:6
276:25 277:2	substantial	153:5 169:18	132:4 133:22
301:21 302:4	119:5	228:4 342:17	136:19 137:2
302:16 303:15	substantive	supported	137:10 139:2
303:21 307:24	112:15 161:4	157:22	142:7 163:19
308:5 309:22	203:12	supporting	166:24 170:16
310:19,21	successfully	327:25	174:18 179:5
311:1,6 312:4	348:4	supports	183:2 186:11
312:7,13,14	succinct 135:23	142:18 153:19	192:12 197:25
313:17	sufficient	156:7,24 157:6	201:15,16
subs 300:24	202:18 289:14	158:25 159:10	204:25 205:9
301:13,16,18	sufficiently	223:17	214:13 222:8
301:19,19,21	32:8	supposed 15:25	224:10 225:24
302:17 304:5	suggest 110:2	127:10 170:25	235:24 246:7
subscribe	184:24	173:17	248:11 254:12
122:8	suggestion	supposedly	262:23 264:15
subscribed	184:16	135:15	265:2 268:12
354:14	suggests 232:2	sure 17:21,23	280:20 282:10
subscription	295:3	19:19 20:8	285:7 293:23
181:10	suite 4:9 8:10	31:16 32:25	301:14 312:11
subsection	sullivan 3:5	39:1,3 48:3	317:23 323:13
278:16	summarize	49:4,8 56:3	323:15,24
subsections	135:3,12,18	58:9 61:5 67:1	330:23 332:22
302:2	232:12	67:12 69:8,9	336:12 338:16
subsequent	summarizes	70:25 72:21	339:18 346:12
107:8 119:24	232:23	73:3 76:9	347:2,25 348:1
236:15 245:16	summary 25:8	77:14,16,23	349:3
291:12 343:10	135:24	78:2 82:25	surges 229:2
subsequently	summer 74:19	83:13 85:9,25	surprise 154:22
30:3 66:25		96:24 98:1	154:23 155:2

[surprise - taught]

Page 79

	I		
163:12 290:14	228:4 231:22	76:12 93:22,23	149:10 155:19
290:16	synonym 92:10	108:15,21	155:22 198:22
surprised	synthesio	109:12 110:2	210:14 216:2
154:10,18	104:15 107:6	111:6 117:25	231:17 284:23
155:5,5	system 49:22	118:22 174:8	309:23 312:17
surrounding	50:1,3,19,23,24	187:2 233:21	316:25 318:18
198:9	51:11,17	239:8 246:7,10	348:4
survey 26:1,3,6	248:23 253:22	246:11,13	talking 35:25
26:12,16,19	259:5 260:22	254:9 262:21	40:7 67:12
surveys 26:10	261:9,11	263:20 264:7	104:23 111:11
suspect 56:14	263:18 272:3,5	264:10,21	115:4 121:12
sussing 105:24	342:23	308:5 320:21	144:22 147:5
sustained 295:4	systematic	344:10	172:20 190:10
sv 85:23	247:6,12	taken 2:19	193:6,9 209:2
switch 93:12	systematically	73:18 171:21	218:20 220:11
sworn 14:11	247:19	192:2 352:5,16	223:1 227:8
354:14	systems 249:8	takes 225:11	237:15 264:11
syllabi 52:13	t	249:20 275:18	274:9 275:15
52:16,24 53:7	t 28:25 127:4	275:19	294:3 312:9
53:9,10,10,11	353:3,3	talented 342:17	349:4,7
53:13	ta 51:10,13	talk 23:1,24	talks 79:9 84:5
synchronate	tab 307:2	35:4 75:18	84:8 161:22
96:13	tabs 261:9	87:23 109:9,16	223:13 235:7
synchronizati	326:16,17	109:20,22	target 88:12
139:22 147:8	tag 18:2	110:9,12,17,25	288:7
155:10 227:12	tags 123:10	111:2,9,25	targeted 79:3
229:7	tahler 3:6	112:5 119:12	80:20
synchronized	taitelman 7:5	119:13,25	tarnish 117:23
96:4	16:14	125:9 162:21	118:20
synchronous	take 36:25 55:5	183:4 206:12	tas 49:11 50:24
223:24 225:1,4	55:24 59:15	223:15 226:10	50:24
225:7,13 226:3	60:12,14,17,21	talked 56:7	task 32:8
226:9,16,23	60:23 65:15	58:13 142:8,9	taught 68:9,10
227 17 22	00.23 03.13	1 4 4 4 9 4 9	60 10 00
227:17,22		144:12,12	68:12,23

[taylor - testimony]

Page 80

taylor 28:25	technique	294:20	terms 41:24
29:1,23,24	341:14	ten 45:3,5	42:22 43:4,19
35:24 44:11	techniques	79:25 80:3,7	76:22 98:1
57:24 245:7	102:4	80:10,11,11	114:8 165:12
284:24 305:23	technology	111:19 112:6	165:24 177:22
305:25 306:1,5	69:25 70:13	239:10,10,14	180:23 181:4
308:14 319:2	71:11 75:23	239:14	181:25 183:20
319:11	90:17 190:25	tens 316:4	196:3 206:15
teach 53:12	191:2,4 198:23	term 27:2,3	206:17,19,21
68:5,14 69:3	telephone	77:11,12 81:15	212:18,19
70:3,4,7,20	33:10	82:16 88:25	240:6 242:9
71:7 252:10	tell 19:7 26:23	89:5,23 90:10	243:4 247:22
teaches 71:8	27:13 28:2,8	90:12,20 91:10	248:2 251:22
teaching 52:22	28:12 29:18	92:6,11,13	274:9,18
68:6,7,8 69:10	31:8 35:8	97:4 99:22	313:15 329:16
69:18 71:5	75:25 87:3	106:17 115:1	330:4,6 342:19
team 28:22	105:10,21	165:15 178:5	terow 127:1
60:11 85:4	107:3 153:2	189:21,23	terrible 342:18
86:22 87:11,18	167:19 193:14	190:3,5,12,13	tertiary 43:14
87:24,24 88:3	202:7,9,13	190:16,19,22	tested 125:4
346:1,5	206:25 232:15	191:3,12,14	testified 57:25
teams 85:2	251:14 265:2,9	198:18 199:16	67:4 174:15,21
86:20,24 87:1	268:9 310:1	200:3,9 201:11	343:8
87:21	313:4 315:4	201:12,13	testify 27:13
tease 116:6	338:14	209:17 215:10	testifying 18:4
347:17	telling 184:19	218:3,4,7,9,10	testimony 15:9
technical	tells 82:5	220:7,10	15:22 16:6
219:25	telltale 54:12	221:17 222:13	43:5 55:16
technically	temporal 92:25	231:15,21	56:22 57:4
46:4 53:17	101:12 104:9	301:24 329:16	59:24 150:13
239:15	139:21 147:8	329:18,25	150:17 155:12
technician	155:10 215:12	terminology	168:25 169:16
58:22 350:2	215:13,18,20	199:20 241:2	173:25 178:21
	215:20 229:7		179:7,14

[testimony - time]

Page 81

181:16,21,23	85:4 88:4,10	161:11 177:25	298:13 301:13
205:24 207:25	88:13 89:9,10	197:8 209:7	302:16 307:24
223:6,8 230:9	92:1,2,21 93:2	217:19 219:7	311:1,5 312:4
240:2 241:19	95:22 96:9	235:6 238:4	tight 139:21
242:7 322:6	101:11,13	244:1 255:9	229:7
342:19 352:8	103:16,17,18	290:2 299:23	tiktok 12:17,19
354:9	104:16 114:12	314:14 327:5	12:24 13:7,8
texas 33:6	125:9 145:25	334:8,11	216:4 217:9,13
text 148:18	159:6 169:3	335:22 338:11	236:12,12,14
283:19 337:6	182:20 192:2,6	349:23 350:2	237:22,24
349:9	194:14 197:13	thinking 225:7	238:5 281:20
textguard	210:20 215:14	third 1:11,12	282:12 286:22
150:11 154:25	219:2 222:9	2:11,12 55:22	315:6,11,12
thank 15:13	226:13 237:4	57:17 150:10	316:4,7,11
17:2 62:17	248:4,6 250:13	176:21 242:15	317:13 319:17
118:14 127:5	250:14,22	243:8 247:23	319:22 320:3
189:21 246:6	268:22,23	247:25 321:20	320:13,15,23
331:8 350:9	283:11 305:2	340:8 346:14	320:23,25
351:1,4	315:2	thought 18:6	321:6,11,13,18
thanks 41:4	think 30:11	51:7 108:1	321:18,20,25
113:18	31:13 38:14	118:5 137:17	322:5,23 324:5
thing 15:2	50:11 58:25	213:3 335:12	324:11,20,22
93:10 121:23	60:2,3 64:5	threats 88:6,7	till 272:20
138:6 158:3	69:7 71:11	three 17:9	time 14:6 20:17
189:23 215:18	73:16 76:15	26:18 39:24	21:2 23:10
221:4 231:16	78:15 80:15	69:1,1 70:3,25	25:18,20 40:24
301:25	83:14 93:11	82:6,13 122:2	40:25 41:6,19
things 27:8,10	100:20,25	132:23 144:13	42:17 43:7
35:5 36:23	106:7 114:10	144:15 210:17	44:25 48:22
37:3 46:13,18	114:11 117:2,3	211:15,16,18	58:1 60:23
47:23 52:4	119:23 122:18	211:19 217:3,5	68:9,10 69:13
54:4 55:24	124:11 143:20	228:16 229:6	75:6,8,9,13
56:3,6 76:3,8	149:10 150:4,5	247:15 248:2	79:3 80:17,19
78:12 84:22	158:2 159:19	289:2 298:12	85:18 106:2

[time - traceable]

Page 82

340:15,19	today 14:16	135:22 136:10
341:4,10,16,20	15:20 16:6	141:10,23
341:24,25	18:5 113:6	tools 31:7
343:17 348:15	116:20 136:20	37:15,17,22
349:20 350:5	137:8,14 138:2	38:1,1,4,6
350:12 352:6,7	138:5,14,17,19	96:14 136:3,8
352:10	138:23 139:8	207:4,13
timeframe 93:2	152:25 153:4	244:22,25
times 69:3,4	153:13,18	245:1,3,6,6,8,8
71:1 77:2	156:24 159:18	245:11 259:20
102:2,3 104:11	176:9 188:24	top 62:4 131:17
115:16 135:11	189:18 306:10	131:22 148:16
135:18 189:22	313:4	197:23 300:24
190:1 194:17	today's 117:21	301:13,16,18
213:13,15,18	together 16:21	301:19 302:17
timing 215:17	17:11 30:13	304:4 309:5
215:19,23	33:24 34:1,10	325:18 331:11
223:24 225:1,4	34:18 160:9	topic 123:8
225:5,13	260:5	124:18 191:10
294:16 318:12	told 168:18	total 36:9,10
318:15 327:13	309:5	38:24 77:16
timothy 11:17	tonality 341:7	205:12,14
132:21	took 75:5,11	209:21 212:5
title 48:5 71:4	225:9 264:16	286:3,7 316:11
129:11,14	264:20 265:2	318:6 332:13
141:3,8,22	299:14 313:9	343:5
142:1 143:11	331:7 341:17	touched 17:13
159:23 206:18	tool 37:19,22	tour 276:11
278:19 314:8	42:16 104:16	towards 79:18
330:12,18,21	182:6,22	79:20
titled 11:10,11	183:11,17	toxic 342:18
11:18,21,23	321:12	traceable
titles 141:14	toolkit 11:19	102:22
142:6	131:10,11	
	341:4,10,16,20 341:24,25 343:17 348:15 349:20 350:5 350:12 352:6,7 352:10 timeframe 93:2 times 69:3,4 71:1 77:2 102:2,3 104:11 115:16 135:11 135:18 189:22 190:1 194:17 213:13,15,18 timing 215:17 215:19,23 223:24 225:1,4 225:5,13 294:16 318:12 318:15 327:13 timothy 11:17 132:21 title 48:5 71:4 129:11,14 141:3,8,22 142:1 143:11 159:23 206:18 278:19 314:8 330:12,18,21 titled 11:10,11 11:18,21,23 titles 141:14	341:4,10,16,20 341:24,25 343:17 348:15 349:20 350:5 350:12 352:6,7 352:10 138:23 139:8 152:25 153:4 153:13,18 71:1 77:2 102:2,3 104:11 135:18 189:22 190:1 194:17 213:13,15,18 109:1 194:17 213:13,15,18 109:1 194:17 215:19,23 223:24 225:1,4 225:5,13 294:16 318:12 318:15 327:13 100:1 194:17 132:21 1111

[tracking - u.s.]

Page 83

tracking 37:24	trouble 291:19	tuesday 245:18	245:18 269:16
107:18 213:10	true 110:4	tune 249:22,25	two 19:7,7,17
227:14	124:7 150:8	tuned 250:4	23:17 62:24,24
traffic 88:11,20	192:17 193:18	tuning 76:7	75:12 77:10
88:21,22 89:4	193:18 194:3,4	248:25 249:14	78:2 83:14
89:12,13,15	194:13 196:18	249:17,18	84:6,7 98:18
90:6,7 92:3	196:24 197:6	253:25 340:6	98:23 104:25
95:24 96:11	197:10 222:9	turn 50:10	108:21 109:10
190:7	239:15 256:6	235:5	116:6 130:11
trailer 13:12	352:15,21	turnaround	130:15 141:14
330:20 331:19	354:8	166:25	166:25 167:2
331:22,25	trust 11:13	turned 192:17	180:18 201:5
332:8 334:15	57:18 117:24	195:8,9,10	203:8 208:17
334:15,18	118:21	219:24 237:22	217:2,5,25
trained 251:6	truth 15:11,11	238:23 239:11	229:6 239:10
training 249:2	15:11	296:25	239:11,12,14
transcribed	truthful 15:21	turnitin 50:10	273:16 281:9
185:10 350:20	16:5 117:10	50:18 51:1	286:6 323:8,21
350:22 352:12	192:20	52:4	324:2,17,23
transcript	try 82:24 83:1	turns 216:12	type 26:5 88:2
185:11 350:21	137:9 189:24	216:16 236:10	94:18 95:3
350:23 352:13	204:25 211:8	237:21	97:5 105:15
352:16 354:5,9	trying 22:25	tweet 103:22	107:16 257:13
translation	75:5 88:9 99:4	104:13 269:23	typed 312:3,3
323:14	100:25 103:23	270:9,18 271:7	types 250:7,10
travel 79:19	104:22 106:7	271:19 272:14	254:25
travels 117:22	109:11 150:12	272:22,24	typical 230:7
treat 275:9	157:17 163:22	twelve 25:4	231:9
trend 125:13	169:19 180:1	twice 323:25	u
trial 176:22	180:12 189:15	324:16,17,21	u 12:7
tribute 278:20	212:10,15	335:18 336:6	u.s. 162:17
314:1	226:20 240:3	336:10	
tried 203:25	244:24 248:4	twitter 179:20	163:5,6 216:7
290:25	266:6 301:11	216:3 217:8	222:5,6 236:9

[u.s. - use] Page 84

216.1	10.0 21 20.10	242.15 240.2	227.24 220.21
316:1 u31 331:5	18:9,21 20:19	343:15 349:3	237:24 239:21
	21:6 23:2,4	understanding	240:5 243:10
uh 18:3 43:12	24:2 27:6,22	17:18 23:18	universities
101:10 115:7	55:12 63:10,12	24:9,16,19	50:4,13,19
148:8 149:18	75:5 81:2 94:2	31:11,17 32:4	56:7,8,11
193:24 207:9	104:22 105:13	41:22 42:3,19	university
315:13 319:20	133:18 134:11	57:13 72:2	49:22 70:17,18
323:6 344:25	135:20 138:15	78:9,10 95:19	74:7
ukraine 270:3	150:12 157:9	99:8 102:25	unknown
un 299:7	157:17 159:8	121:17 125:21	233:20
unavailable	159:13 163:22	139:3 159:5	unknowns
29:12,22 30:6	164:9 169:19	161:19 162:2	233:20
unaware 32:15	170:16 173:17	163:2 164:22	unquote 179:17
under 86:25	174:12 178:13	168:21 199:14	242:17
87:19 94:14	179:5,13	291:19 292:20	unreliable
97:3 162:24	184:20,23,25	302:5 328:12	55:21
163:8,25	189:14 192:12	347:10	untraceable
238:24 287:11	200:9 209:2	understood	102:18,20,21
294:9 305:13	215:16 217:4	32:16 33:20	untrue 193:12
305:13 331:13	224:20 227:4	80:14 102:8	unusual 229:21
352:7,20,20	240:3 242:4	127:20 137:11	updated 65:11
undergraduate	244:24 254:6	137:12 165:21	updating 65:13
72:16 76:15	254:24 258:24	166:3 176:8	upping 190:11
underlying	259:4,7,8,19	192:21 276:19	urquhart 3:5
172:5 182:23	262:3 264:7	unhappy	usage 54:13
187:1 190:2,4	265:13,17,22	107:13	88:12 190:7
199:24 212:1	266:6 274:6	unique 205:16	use 27:3 29:10
261:15 284:3	280:7 288:18	323:17,19	29:25 31:7
329:9 346:24	291:1,5,11	united 1:1 2:1	34:3 37:15,18
347:2 349:4	292:9 296:12	universe 42:21	38:12 39:22
underneath	301:11 311:16	176:3,23	46:2,5,9,13,19
283:14,18	312:11 317:23	181:17,24	46:20,22 49:3
understand	320:13 332:25	205:18 207:6	50:14,19,24
15:24,25 18:4	333:17 334:9	207:15 224:20	51:11 52:3

[use - usual] Page 85

53:13,23 54:18	268:24 271:24	216:13,17	username
56:4,9,11,23	302:3,22	221:4 222:4,4	303:15 304:12
57:5 65:10	318:17,19,20	222:13 233:8	305:3 307:4
77:11 84:19	318:22 319:7	236:8 237:22	users 88:23
88:25 89:5,6	320:11,11,17	240:23 242:1,2	89:3,11,12,15
89:19,23 90:10	320:19 321:14	243:21,25,25	91:15,17,24
90:11,19,22	321:24 322:18	243:25 244:3,4	95:8 104:12
92:9,11,13,15	322:18 329:21	244:11,14	114:5 115:22
92:18 94:11	330:3 340:7,18	247:17,22,24	117:13 190:10
97:4 102:4	341:8,10,19,23	248:22 255:3	300:7
104:8 106:11	342:7 343:2	255:12,18	uses 49:22 50:2
114:8 149:8	346:1	256:11,18,25	52:4 75:20
152:10,12	used 27:2 37:19	268:14 277:22	97:5 191:2,12
168:5 177:24	38:13 51:18	287:17 290:24	using 49:24
178:5,16 182:6	53:23 54:5,14	300:4 302:23	52:6 56:3,14
182:21,22	54:14,19 88:20	303:2,6 305:1	57:15 58:12
186:9,10 187:9	89:25 90:5,6	305:24,25	87:9 90:11,15
189:21,23,24	92:6 116:21	306:1,21	95:22 96:14
190:12 191:14	126:23 128:1	307:17 311:23	97:8 127:14
198:18 199:16	135:22 140:3,7	313:14 319:17	128:19 129:13
199:17,19	155:19 165:13	320:15 322:1	143:20 159:14
200:24 201:10	165:24 166:6	322:15 329:17	168:11 178:4
201:19 207:1	181:12 183:17	329:18,21	180:8 181:4
207:19 208:15	186:5,11 187:8	333:22 339:4	183:11 191:10
209:17 210:8	187:11 190:1	340:5,25 341:3	201:3 221:9
210:11,16,19	190:16 199:2	341:3,12,12,12	238:1 248:5
212:10 214:4	199:18,19	341:13 342:3	254:15 257:24
218:3 220:10	201:12,13,20	342:10,13,19	258:1 267:14
221:10,22	201:24 202:7	343:16 344:11	277:3 301:23
231:15,21	203:10 205:7	344:17 345:10	312:16 342:6
234:2 240:23	206:7,16,17,21	345:17	349:11
242:3 243:24	207:6,16 214:6	user 93:1 95:6	usual 91:15,17
247:15 255:2	214:10,14	95:10,13,22	91:19
268:17,18,21	215:9 216:10	336:6	

[usually - volume]

Page 86

		1	
usually 27:9	variance	version 44:25	62:16 112:7,10
36:21 37:5,8	212:11	256:6,15 258:3	185:6,13
48:11 51:9	variety 97:13	258:12,15	246:17,20
53:25 54:21	various 38:5	262:17	248:11,14
64:18 79:4	114:21	versioning	338:13,16,19
80:21 98:23	vast 96:25	171:17	348:16,21
101:23 102:22	106:1	versions 44:23	351:2,5
103:4,9 115:13	vastly 119:18	44:24 172:1	videos 315:11
115:16 116:1	venture 78:1	255:25	316:4,11,11,18
122:20 123:5	315:19	versus 36:9	317:6,6,10,14
123:22 124:2	verb 178:11	43:5,5 46:17	320:15 321:13
132:9 134:10	verbalize 67:20	57:20 64:9	324:20,22
194:13 195:13	verbatim 148:5	90:8 115:5	325:19 326:3
195:15 210:22	175:2	119:19 195:19	viewed 334:15
218:12 225:19	verbatims	196:16 211:14	violations
225:22 233:17	247:20	239:21 244:9	94:14
249:6 274:16	verbiage 77:12	248:21 250:25	viral 114:23
286:21 332:20	90:21,22,24	292:23 340:24	115:11
utc 225:16	92:16 103:17	vetting 19:8	virtual 75:4
utilize 313:5	155:19,21	21:8 25:14	virtually 229:1
utilized 313:1	191:11 222:22	27:2 29:25	visualization
v	265:16 319:7	30:1,15,19	31:4 63:1
v 11:3 12:3	319:23 320:12	33:15	visualize 31:8
13:3 14:8	verification	vice 116:10	visuals 58:9
58:22 350:2	263:22,25	194:6	voiceover
valid 204:6,9	verified 208:13	video 1:19 2:18	282:2
validate 208:7	260:23	2:21 283:2,2,7	volume 200:21
value 203:21	verify 208:10	283:11 330:11	202:21,23
203:24,25	261:3,13	330:12,18,21	203:15,15
variable 212:2	291:11,13	330:22,24,25	205:13,14
212:6	veritext 9:23	331:5,8	206:22 209:21
variables 32:1	14:11 113:4	videographer	215:15 247:2
222:9	versa 116:10	9:25 14:5,10	293:10 298:19
	194:7	61:7,10 62:13	299:25 301:19

Veritext Legal Solutions www.veritext.com

[volume - week] Page 87

308:4,6 311:3 276:24 299:5,6 193:17 194:8 ways 49:17,20 327:24 342:22 310:3 316:21 194:11 200:4,5 91:17,19 voluntary 317:16 318:4 201:19,23 100:20 102:14 85:19 335:21 348:15 202:4,7,9 103:8,10 votes 303:13 139:2 199:19 222:2 227:12 194:4 198:24 vp 85:24,24 201:7 207:22 239:3 241:20 226:13,16 vs 1:7,11,14 2:7 227:16 228:3 243:12,13 227:11,13 256:8 259:7 253:22 254:17 262:3 265:22 260:8,11,14 30:12 60:10 331:9 262:3 265:22 260:8,11,14 30:12 60:10 104:7,8,16 want 19:25 348:24 263:10,10 109:10 112:18 4 want 19:25 38:51:11 282:13 283:17 109:10 112:18 5:10 6:8 299:17 308:11 245:22 46:3,15 122:3 135:7,13 136:23 137:2 57:15 64:25 320:10 325:2 20:11:3 98:13 90:16 91:15 92:9,11 82:2 9:2 11:3 164:7 140:12 179:5 79:3,8 98:15 17:20,25 18:8<				
voluntary 317:16 318:4 201:19,23 100:20 102:14 85:19 335:21 348:15 202:47,9 103:8,10 volunteered wanted 99:16 207:2 211:6 115:12 116:17 86:16,20 108:2 130:7 221:4,18,22,23 116:18,21 votes 303:13 139:2 199:19 222:2 227:12 194:4 198:24 vp 85:24,24 201:7 207:22 239:3 241:20 226:13,16 vs 1:7,11,14 2:7 227:16 228:3 243:12,13 227:11,13 2:11,14 353:1 233:10 254:6 248:20 249:9 273:16 276:25 wait 184:24 272:2 288:18 261:11 262:4,7 30:12 60:10 wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 107:5 108:20 331:9 want 76:24 wants 59:9 266:1,14 282:13 283:17 109:10 112:18 53:16 59:6,21 60:12,17 66:25 823 95:5 98:16,16 99:18 39:13 90:16 319:23 320:5,6 338:15 299:14 298:2 30:13 33:15 246:5 310:24 246:5 310:24	308:4,6 311:3	276:24 299:5,6	193:17 194:8	ways 49:17,20
85:19 335:21 348:15 202:4,7,9 103:8,10 volunteered wanted 99:16 207:2 211:6 115:12 116:17 86:16,20 108:2 130:7 221:4,18,22,23 116:18,21 votes 303:13 139:2 199:19 222:2 227:12 194:4 198:24 vp 85:24,24 201:7 207:22 239:3 241:20 226:13,16 vs 1:7,11,14 2:7 227:16 228:3 243:12,13 227:11,13 2:11,14 353:1 233:10 254:6 248:20 249:9 273:16 276:25 wait 184:24 256:8 259:7 253:22 254:17 we've 16:9 wait 184:24 272:2 288:18 261:11 262:4,7 30:12 60:10 107:5 108:20 331:9 want 19:25 348:24 263:10,10 109:10 112:18 112:18 want 19:25 washington 282:13 283:17 296:14 298:2 156:8 222:4,4 82:3 95:5 98:16,16 99:18 57:15 64:25 320:10 325:2 38:15 webr 12:8 98:16,19,20 338:6,15,21 45:22 46:3,	327:24 342:22	310:3 316:21	194:11 200:4,5	91:17,19
volunteered wanted 99:16 207:2 211:6 115:12 116:17 86:16,20 108:2 130:7 221:4,18,22,23 116:18,21 votes 303:13 139:2 199:19 222:2 227:12 194:4 198:24 vp 85:24,24 201:7 207:22 239:3 241:20 226:13,16 vs 1:7,11,14 2:7 227:16 228:3 243:12,13 227:11,13 2:11,14 353:1 233:10 254:6 248:20 249:9 273:16 276:25 354:1 256:8 259:7 253:22 254:17 we've 16:9 wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 197:24 272:20 348:24 263:10,10 109:10 112:18 want 19:25 28:8 51:11 348:24 263:10,10 109:10 112:18 want 59:9 266:1,14 114:14 115:18 114:14 115:18 53:16 59:6,21 5:10 6:8 29:17 308:11 246:5 310:24 60:12,17 66:25 46:22 49:3 320:10 325:2 338:15 98:16,16 99:18 55:15 64:25 330:1 335:17 365:7,18 76:1	voluntary	317:16 318:4	201:19,23	100:20 102:14
86:16,20 108:2 130:7 221:4,18,22,23 116:18,21 votes 303:13 139:2 199:19 222:2 227:12 194:4 198:24 vp 85:24,24 201:7 207:22 239:3 241:20 226:13,16 vs 1:7,11,14 2:7 227:16 228:3 243:12,13 227:11,13 2:11,14 353:1 233:10 254:6 248:20 249:9 273:16 276:25 354:1 256:8 259:7 253:22 254:17 we've 16:9 wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 197:24 272:20 331:9 wants 59:9 266:1,14 109:10 112:18 want 19:25 28:8 51:11 29:10 6:8 296:14 298:2 156:8 222:4,4 way 39:8 44:7 299:17 308:11 246:5 310:24 338:15 82:3 95:5 46:22 49:3 320:10 325:2 330:1 335:17 338:15 98:16,16 99:18 57:15 64:25 341:3 wayfarer 18 12:21 16:26 338:15 98:13 90:16 91:15 92:9,11 82:2 9:2 11:3 32:2 11:3	85:19	335:21 348:15	202:4,7,9	103:8,10
votes 303:13 139:2 199:19 222:2 227:12 194:4 198:24 vp 85:24,24 201:7 207:22 239:3 241:20 226:13,16 vs 1:7,11,14 2:7 227:16 228:3 243:12,13 227:11,13 2:11,14 353:1 233:10 254:6 248:20 249:9 273:16 276:25 354:1 256:8 259:7 253:22 254:17 we've 16:9 wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 197:24 272:20 348:24 263:10,10 109:10 112:18 want 19:25 28:8 51:11 266:1,14 114:14 115:18 salis 45:22 46:3,15 296:14 298:2 156:8 222:4,4 45:22 46:3,15 46:22 49:3 30:1 335:17 319:23 320:5,6 338:15 98:16,16 99:18 57:15 64:25 341:3 246:5 310:24 133:6;23 137:2 89:13 90:16 89:13 90:16 82:2 9:2 11:3 29:12 95:24 29:12 95:24 29:21 1:3 20:12 31:3:3 14:8 20:17 163:6 16:77 163:6 179:13 183:2 99:6,10 100:16 18:13,18,21 <t< td=""><td>volunteered</td><td>wanted 99:16</td><td>207:2 211:6</td><td>115:12 116:17</td></t<>	volunteered	wanted 99:16	207:2 211:6	115:12 116:17
vp 85:24,24 201:7 207:22 239:3 241:20 226:13,16 vs 1:7,11,14 2:7 227:16 228:3 243:12,13 227:11,13 2:11,14 353:1 233:10 254:6 248:20 249:9 273:16 276:25 w 262:3 265:22 260:8,11,14 30:12 60:10 wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 197:24 272:20 343:24 344:15 262:24 263:3 107:5 108:20 331:9 wank 76:24 wants 59:9 washington 266:1,14 114:14 115:18 53:16 59:6,21 way 39:8 44:7 299:17 308:11 21:12 146:25 582:3 95:5 98:16,16 99:18 45:22 46:3,15 319:23 320:5,6 320:10 325:2 338:15 98:13 90:16 89:13 90:16 1:13 2:8,13 7:2 website 85:5 179:13 183:2 99:6,10 100:16 18:13,18,21 71:13 60:7,7 198:5 208:22 209:10 246:9 166:7 16 28:18 45:21 78:4,5 79:22 209:10 246:9 166:7 16 289:10 10:14:1 289:10 11:1 289:	86:16,20	108:2 130:7	221:4,18,22,23	116:18,21
vs 1:7,11,14 2:7 227:16 228:3 243:12,13 227:11,13 2:11,14 353:1 233:10 254:6 248:20 249:9 273:16 276:25 354:1 256:8 259:7 253:22 254:17 we've 16:9 wait 184:24 272:2 288:18 261:11 262:4,7 30:12 60:10 197:24 272:20 343:24 344:15 262:24 263:3 107:5 108:20 331:9 wank 76:24 wants 59:9 266:1,14 104:7,8,16 want 19:25 28:8 51:11 282:13 283:17 121:12 146:25 5:10 6:8 296:14 298:2 156:8 222:4,4 way 39:8 44:7 299:17 308:11 246:5 310:24 52:3 95:5 46:22 49:3 320:10 325:2 388:15 98:16,16 99:18 57:15 64:25 320:10 325:2 338:15 98:13 90:16 91:15 92:9,11 8:2 9:2 11:3 26:17 163:6 122:3 135:7,13 65:7,18 76:15 89:13 90:16 1:13 2:8,13 7:2 46:217 163:6 138:6,15,21 92:12 95:24 12:3 13:3 14:8 164:7 194:	votes 303:13	139:2 199:19	222:2 227:12	194:4 198:24
2:11,14 353:1 233:10 254:6 248:20 249:9 273:16 276:25 354:1 256:8 259:7 253:22 254:17 we've 16:9 wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 197:24 272:20 348:24 262:24 263:3 107:5 108:20 331:9 walk 76:24 wants 59:9 washington 282:13 283:17 109:10 112:18 28:8 51:11 washington 282:13 283:17 121:12 146:25 5:10 6:8 296:14 298:2 156:8 222:4,4 45:22 46:3,15 296:14 298:2 156:8 222:4,4 46:22 49:3 30:1 335:17 38:15 98:16,16 99:18 57:15 64:25 320:10 325:2 38:15 98:16,16 99:18 57:15 64:25 330:1 335:17 36:23 137:2 137:10,19,20 57:15 64:25 341:3 36:3 137:2 140:12 179:5 99:6,10 100:16 1:13 2:8,13 7:2 36:17 164:7 179:13 183:2 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 100:20 119:12 28:18 45:21 78:4,5 79:22 209:10 246:9	vp 85:24,24	201:7 207:22	239:3 241:20	226:13,16
w 256:8 259:7 253:22 254:17 we've 16:9 wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 197:24 272:20 343:24 344:15 262:24 263:3 107:5 108:20 331:9 348:24 263:10,10 109:10 112:18 wank 76:24 wants 59:9 266:1,14 114:14 115:18 want 19:25 washington 282:13 283:17 121:12 146:25 28:8 51:11 53:16 59:6,21 way 39:8 44:7 299:17 308:11 246:5 310:24 53:16 59:6,21 45:22 46:3,15 319:23 320:5,6 338:15 82:3 95:5 46:22 49:3 30:1 335:17 webb 12:8 98:16,16 99:18 57:15 64:25 30:1 335:17 webb 12:8 136:23 137:2 89:13 90:16 1:13 2:8,13 7:2 164:7 138:6,15,21 91:15 92:9,11 8:2 9:2 11:3 websites 302:4 140:12 179:5 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 198:5 208:22 143:10 147:1 28:18 45:21 78:4,5 79:22 199:10 246:9 143:10 147:1 353:1 35	vs 1:7,11,14 2:7	227:16 228:3	243:12,13	227:11,13
wait 184:24 262:3 265:22 260:8,11,14 30:12 60:10 197:24 272:20 343:24 344:15 262:24 263:3 107:5 108:20 331:9 walk 76:24 wants 59:9 266:1,14 114:14 115:18 want 19:25 washington 282:13 283:17 121:12 146:25 28:8 51:11 way 39:8 44:7 299:17 308:11 126:8 222:4,4 53:16 59:6,21 way 39:8 44:7 299:17 308:11 246:5 310:24 60:12,17 66:25 46:22 49:3 30:1 32:2 38:15 98:16,16 99:18 57:15 64:25 320:10 325:2 web 12:8 136:23 137:2 45:22 46:3,15 341:3 website 85:5 137:10,19,20 89:13 90:16 1:13 2:8,13 7:2 162:17 163:6 138:6,15,21 92:12 95:24 12:3 13:3 14:8 162:17 163:6 179:13 183:2 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 198:5 208:22 143:10 147:1 353:1 354:1 29:25 80:3,7 166:7 16 166:7 16 160:7 16 <td>2:11,14 353:1</td> <td>233:10 254:6</td> <td>248:20 249:9</td> <td>273:16 276:25</td>	2:11,14 353:1	233:10 254:6	248:20 249:9	273:16 276:25
wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 197:24 272:20 343:24 344:15 262:24 263:3 107:5 108:20 331:9 walk 76:24 wants 59:9 266:1,14 114:14 115:18 want 19:25 washington 282:13 283:17 121:12 146:25 28:8 51:11 53:16 59:6,21 way 39:8 44:7 299:17 308:11 246:5 310:24 60:12,17 66:25 46:22 49:3 320:10 325:2 webs 12:8 98:16,16 99:18 57:15 64:25 320:10 325:2 web 12:8 122:3 135:7,13 57:15 64:25 341:3 website 85:5 138:6,15,21 91:15 92:9,11 8:2 9:2 11:3 164:7 websites 302:4 194:12 179:5 97:3,8 98:15 99:6,10 100:16 18:13,18,21 71:1,3 77:2 78:4,5 79:22 198:5 208:22 199:0,10 246:9 166:7 16 166:7 16 166:7 16 160:7,16	354:1	256:8 259:7	253:22 254:17	we've 16:9
wait 184:24 272:2 288:18 261:11 262:4,7 104:7,8,16 107:5 108:20 331:9 walk 76:24 wants 59:9 wants 59:9 washington 266:1,14 114:14 115:18 114:14 115:18 121:12 146:25 28:8 51:11 way 39:8 44:7 299:17 308:11 246:5 310:24 246:5 310:24 82:3 95:5 way 39:8 44:7 299:17 308:11 246:5 310:24 338:15 98:16,16 99:18 46:22 49:3 320:10 325:2 webb 12:8 98:16,16 99:18 57:15 64:25 330:1 335:17 341:3 weber 6:14 136:23 137:2 89:13 90:16 1:13 2:8,13 7:2 162:17 163:6 164:7 138:6,15,21 92:12 95:24 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 100:20 119:12 28:18 45:21 78:4,5 79:22 209:10 246:9 166:7 16 waysfarer's 80:10 11 81:16	W	262:3 265:22	260:8,11,14	30:12 60:10
197:24 272:20 343:24 344:15 262:24 263:3 107:5 108:20 331:9 walk 76:24 wants 59:9 266:1,14 114:14 115:18 want 19:25 28:8 51:11 296:14 298:2 156:8 222:4,4 53:16 59:6,21 5:10 6:8 299:17 308:11 246:5 310:24 60:12,17 66:25 46:22 49:3 320:10 325:2 338:15 98:16,16 99:18 54:20 55:1,25 320:10 325:2 338:15 136:23 137:2 57:15 64:25 341:3 weber 6:14 137:10,19,20 91:15 92:9,11 92:12 95:24 12:3 13:3 14:8 140:12 179:5 92:12 95:24 12:3 13:3 14:8 164:7 194:12 197:25 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 143:10 147:1 353:1 354:1 79:25 80:3,7 209:10 246:9 166:7 16 166:7 16 166:7 16	woit 184.24	272:2 288:18	261:11 262:4,7	104:7,8,16
331:9 348:24 263:10,10 109:10 112:18 walk 76:24 want 19:25 266:1,14 114:14 115:18 28:8 51:11 5:10 6:8 296:14 298:2 156:8 222:4,4 53:16 59:6,21 5:10 6:8 299:17 308:11 246:5 310:24 60:12,17 66:25 46:22 49:3 319:23 320:5,6 338:15 98:16,16 99:18 57:15 64:25 320:10 325:2 338:15 122:3 135:7,13 57:15 64:25 341:3 341:3 341:3 136:23 137:2 89:13 90:16 1:13 2:8,13 7:2 162:17 163:6 137:10,19,20 91:15 92:9,11 92:12 95:24 8:2 9:2 11:3 164:7 140:12 179:5 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 143:10 147:1 353:1 354:1 79:25 80:3,7 209:10 246:9 166:7 16 166:7 16 166:7 16		343:24 344:15	262:24 263:3	107:5 108:20
walk 76:24 want 19:25 28:8 51:11 282:13 283:17 114:14 115:18 53:16 59:6,21 5:10 6:8 296:14 298:2 156:8 222:4,4 60:12,17 66:25 45:22 46:3,15 319:23 320:5,6 338:15 98:16,16 99:18 57:15 64:25 320:10 325:2 338:15 122:3 135:7,13 57:15 64:25 330:1 335:17 341:3 341:3 136:23 137:2 89:13 90:16 1:13 2:8,13 7:2 162:17 163:6 138:6,15,21 91:15 92:9,11 8:2 9:2 11:3 164:7 140:12 179:5 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 198:5 208:22 143:10 147:1 28:18 45:21 78:4,5 79:22 209:10 246:9 166:7 16 353:1 354:1 90:10 11 81:16		348:24	263:10,10	109:10 112:18
want 19:25 washington 282:13 283:17 121:12 146:25 28:8 51:11 53:16 59:6,21 5:10 6:8 296:14 298:2 156:8 222:4,4 60:12,17 66:25 45:22 46:3,15 45:22 46:3,15 319:23 320:5,6 338:15 98:16,16 99:18 54:20 55:1,25 320:10 325:2 webb 12:8 122:3 135:7,13 57:15 64:25 341:3 weber 6:14 136:23 137:2 89:13 90:16 91:15 92:9,11 92:12 95:24 123 13:3 14:8 164:7 140:12 179:5 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 143:10 147:1 28:18 45:21 79:25 80:3,7 209:10 246:9 166:7 16 166:7 16 166:7 16 18:13,18,21 79:25 80:3,7		wants 59:9	266:1,14	114:14 115:18
28:8 51:11 53:16 59:6,21 60:12,17 66:25 82:3 95:5 98:16,16 99:18 122:3 135:7,13 136:23 137:2 137:10,19,20 138:6,15,21 140:12 179:5 179:13 183:2 194:12 197:25 198:5 208:22 209:10 246:9 5:10 6:8 way 39:8 44:7 45:22 46:3,15 46:22 49:3 54:20 55:1,25 57:15 64:25 65:7,18 76:15 89:13 90:16 91:15 92:9,11 92:12 95:24 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 71:1,3 77:2 78:4,5 79:22 79:25 80:3,7 80:10 11 81:16		washington	282:13 283:17	121:12 146:25
53:16 59:6,21 way 39:8 44:7 299:17 308:11 246:5 310:24 60:12,17 66:25 45:22 46:3,15 319:23 320:5,6 338:15 82:3 95:5 46:22 49:3 320:10 325:2 338:15 98:16,16 99:18 54:20 55:1,25 320:10 325:2 338:15 122:3 135:7,13 57:15 64:25 320:10 325:2 330:1 335:17 136:23 137:2 65:7,18 76:15 341:3 website 85:5 137:10,19,20 91:15 92:9,11 91:15 92:9,11 92:12 95:24 92:12 95:24 12:3 13:3 14:8 164:7 164:7 179:13 183:2 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 71:1,3 77:2 71:1,3 77:2 78:4,5 79:22 78:4,5 79:22 79:25 80:3,7 198:5 208:22 143:10 147:1 353:1 354:1 79:25 80:3,7 80:10 11 81:16		5:10 6:8	296:14 298:2	156:8 222:4,4
60:12,17 66:25 45:22 46:3,15 319:23 320:5,6 338:15 82:3 95:5 46:22 49:3 320:10 325:2 webb 12:8 98:16,16 99:18 54:20 55:1,25 330:1 335:17 weber 6:14 122:3 135:7,13 65:7,18 76:15 wayfarer 1:8 162:17 163:6 136:23 137:2 89:13 90:16 1:13 2:8,13 7:2 164:7 138:6,15,21 91:15 92:9,11 8:2 9:2 11:3 websites 302:4 140:12 179:5 92:12 95:24 12:3 13:3 14:8 week 15:25 17:13 60:7,7 71:1,3 77:2 78:4,5 79:22 198:5 208:22 143:10 147:1 353:1 354:1 79:25 80:3,7 209:10 246:9 166:7 16 166:7 16 160:20 11 81:16		way 39:8 44:7	299:17 308:11	246:5 310:24
82:3 95:5 46:22 49:3 320:10 325:2 webb 12:8 98:16,16 99:18 54:20 55:1,25 330:1 335:17 weber 6:14 122:3 135:7,13 57:15 64:25 341:3 website 85:5 136:23 137:2 89:13 90:16 1:13 2:8,13 7:2 162:17 163:6 137:10,19,20 91:15 92:9,11 8:2 9:2 11:3 websites 302:4 140:12 179:5 92:12 95:24 12:3 13:3 14:8 websites 302:4 179:13 183:2 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 198:5 208:22 143:10 147:1 28:18 45:21 78:4,5 79:22 143:10 147:1 353:1 354:1 79:25 80:3,7 166:7 16 166:7 16 166:7 16	,	45:22 46:3,15	319:23 320:5,6	338:15
98:16,16 99:18 54:20 55:1,25 330:1 335:17 weber 6:14 122:3 135:7,13 136:23 137:2 65:7,18 76:15 wayfarer 1:8 162:17 163:6 137:10,19,20 91:15 92:9,11 8:2 9:2 11:3 website 85:5 138:6,15,21 91:15 92:9,11 8:2 9:2 11:3 websites 302:4 140:12 179:5 92:12 95:24 12:3 13:3 14:8 week 15:25 179:13 183:2 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 143:10 147:1 353:1 354:1 79:25 80:3,7 166:7 16 166:7 16 166:7 16 166:7 16	′	46:22 49:3	320:10 325:2	webb 12:8
122:3 135:7,13 57:15 64:25 341:3 website 85:5 136:23 137:2 89:13 90:16 1:13 2:8,13 7:2 162:17 163:6 138:6,15,21 91:15 92:9,11 8:2 9:2 11:3 website 85:5 140:12 179:5 92:12 95:24 12:3 13:3 14:8 week 15:25 179:13 183:2 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 143:10 147:1 28:18 45:21 78:4,5 79:22 209:10 246:9 166:7 16 wevfarer's 80:10 11 81:16		54:20 55:1,25	330:1 335:17	weber 6:14
136:23 137:2 137:10,19,20 138:6,15,21 140:12 179:5 179:13 183:2 194:12 197:25 198:5 208:22 209:10 246:9 65:7,18 76:15 89:13 90:16 91:15 92:9,11 92:12 95:24 97:3,8 98:15 100:20 119:12 143:10 147:1 65:7,18 76:15 89:13 90:16 91:15 92:9,11 92:12 95:24 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 71:1,3 77:2 78:4,5 79:22 79:25 80:3,7 80:10 11 81:16	,	57:15 64:25	341:3	website 85:5
137:10,19,20 89:13 90:16 1:13 2:8,13 7:2 164:7 138:6,15,21 91:15 92:9,11 8:2 9:2 11:3 164:7 140:12 179:5 92:12 95:24 12:3 13:3 14:8 17:13 60:7,7 179:13 183:2 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 198:5 208:22 100:20 119:12 28:18 45:21 78:4,5 79:22 198:5 208:22 143:10 147:1 353:1 354:1 79:25 80:3,7 166:7 16 166:7 16 166:7 16 166:7 16	,	65:7,18 76:15	wayfarer 1:8	162:17 163:6
138:6,15,21 91:15 92:9,11 8:2 9:2 11:3 websites 302:4 140:12 179:5 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 100:20 119:12 28:18 45:21 78:4,5 79:22 209:10 246:9 166:7 16 wevferer's 80:10 11 81:16		89:13 90:16	1:13 2:8,13 7:2	164:7
140:12 179:5 92:12 95:24 12:3 13:3 14:8 week 15:25 179:13 183:2 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 198:5 208:22 100:20 119:12 28:18 45:21 78:4,5 79:22 209:10 246:9 166:7 16 166:7 16 166:7 16 166:7 16		91:15 92:9,11	8:2 9:2 11:3	websites 302:4
179:13 183:2 97:3,8 98:15 17:20,25 18:8 17:13 60:7,7 194:12 197:25 99:6,10 100:16 18:13,18,21 71:1,3 77:2 198:5 208:22 100:20 119:12 28:18 45:21 78:4,5 79:22 209:10 246:9 166:7 16 166:7 16 166:7 16	' '	92:12 95:24	12:3 13:3 14:8	week 15:25
194:12 197:25 198:5 208:22 209:10 246:9 199:6,10 100:16 100:20 119:12 143:10 147:1 166:7 16 18:13,18,21 28:18 45:21 353:1 354:1 79:25 80:3,7 80:10 11 81:16		97:3,8 98:15	17:20,25 18:8	17:13 60:7,7
198:5 208:22 209:10 246:9 100:20 119:12 143:10 147:1 166:7 16 28:18 45:21 353:1 354:1 79:25 80:3,7 80:10 11 81:16		99:6,10 100:16	18:13,18,21	71:1,3 77:2
209:10 246:9 143:10 147:1 353:1 354:1 79:25 80:3,7 wayfarer's 80:10 11 81:16		100:20 119:12	28:18 45:21	78:4,5 79:22
166:7 16 wayfarer's 80:10 11 81:16		143:10 147:1	353:1 354:1	79:25 80:3,7
//10:11 //19:3	246:11 249:5	166:7,16	wayfarer's	80:10,11 81:16
258:24 261:20		171:24 185:18	28:23	268:16 270:4
190:21 191:3 298:6 299:18	230.27 201.20	190:21 191:3		298:6 299:18

[week - witness] Page 88

299:19	witness 10:2,10	116:16 120:9	176:15 177:13
weekday	14:11,22,25	120:17,20	178:8,15,25
295:10	15:12 19:10,25	121:8 123:14	179:16 180:3
weekly 268:20	20:24 24:3,6	126:15 127:14	180:25 181:9
346:5	24:23 26:9	129:20 130:1	182:20 183:9
weeks 17:9	27:16 30:23	130:10,19	183:25 184:7
26:18 77:10	33:21 38:9	132:8 133:11	186:19 187:20
79:16,18,19,20	41:2,3,5 42:25	133:22 134:2	188:1 189:8
79:23 80:11,14	44:3 47:1,11	135:6,20 136:5	190:21 191:25
81:15 166:25	48:10,18 49:10	137:10 139:12	193:17 194:25
167:3 298:12	49:17 51:13	140:5 141:17	195:2,22 196:5
298:12,13	53:5 55:1,10	142:4 143:8	197:2 201:15
weird 309:5	55:18 56:18	144:2,7 145:22	202:13 203:23
went 36:6	57:1,13 59:6	145:24 149:2,7	204:8,20
62:10 125:10	59:12,21 60:2	150:4,17,25	205:21 206:3
183:10,11	64:23 65:20	151:6,12,19,25	208:13 212:8
211:17,18	66:4 68:21	152:6,14 153:8	213:2,7 215:9
260:24 264:3	69:18 70:10	153:16,22	219:11,21
275:3 288:6	72:1,15 73:7	154:8,15,22	220:13 221:21
291:16 346:19	73:16 74:2	155:4 156:19	222:17 225:16
346:22 348:8	75:1 76:3 77:7	157:2,9 158:2	226:19,25
west 7:9	77:23 80:3,9	158:15 159:4	227:8,25 228:7
whatsapp	80:19 82:10	159:13,22	228:12 230:20
84:19	83:7 86:13,24	161:2,6 163:10	232:14 233:1
wide 53:17	87:5 90:14	163:16 164:6	234:24 235:24
willkie 5:4	91:23 93:18	164:14 165:1	238:9 239:2
14:17	94:3,21 95:16	166:12,14	240:8 241:1,22
willkie.com	96:17,23 98:9	168:2 169:6,13	242:14 243:6
5:11,12	99:25 100:19	169:22 170:5	243:19 246:13
window 231:17	101:22 102:12	170:16,23	247:10 252:1
withdraw	102:20 103:8	171:5,16	252:18 253:12
78:21 99:19	104:5 105:5,21	173:20 174:3	255:14,25
withdrawing	107:5 108:6,11	174:18 175:6	256:5,13 257:2
99:19	108:18 116:6	175:11,24	257:16 258:14

[witness - yeah]

Page 89

258:19 259:3	316:21 318:4	29:11,16 30:13	153:25 162:22
259:11 260:4	319:1,7 322:9	31:1,9 35:2	258:2,7,8,9
260:11,18	323:22 324:9	36:8,10,25	311:13
261:17,24	328:7 331:21	38:19,20 43:10	writing 43:5,8
262:7,16,23	332:2 333:2	43:23 44:9	43:24 44:15,18
263:7,13,25	334:11 335:3	54:8 56:9,10	46:18 118:18
264:15 266:1,9	335:20 336:3	58:2 77:13	118:24 119:8
266:20 267:11	337:16 347:13	87:12,14 88:16	written 124:5
267:20 268:2	352:7,8	88:22 96:4,6	191:10 283:13
269:13 270:14	women 23:17	104:6,15	319:1,2
271:2,10 272:5	wonder 230:25	123:19 155:20	wrong 48:6,6
273:11 274:15	wondering	160:11 164:15	130:11 145:25
274:25 275:12	86:18 346:17	196:5 199:25	197:11 270:2
276:3 277:16	woolley 152:18	213:20,21	285:8
277:21 278:25	152:21 153:5	240:21 242:5	wrote 55:5
279:5 281:8	word 29:25	261:18 263:14	124:3,7 155:12
283:9 284:12	44:20 45:16	263:17 268:18	155:13 163:7
286:20 287:20	55:5 143:20	268:25 319:5	167:17 258:4
290:16 291:10	154:2 163:16	339:19 350:12	284:19,21
291:24 292:5	163:18 177:24	worked 29:4,22	311:19
292:12,19	199:23 212:10	125:10 191:4	wtf 270:2
293:1,9,20	214:5,6,10,13	246:8	X
296:20 297:4	233:8 248:5	working 54:19	x 12:7,9 177:17
297:12 298:16	277:3 318:17	69:13 79:18,20	239:10 243:13
299:2,22	318:20,20	84:21 128:14	
300:10 302:2	339:6 346:10	213:9	y
304:15,21	349:12	works 32:9	y 28:25
305:17 306:7	words 47:17	84:16 275:13	yeah 22:9 38:1
306:13,23	89:19 166:5	276:4	60:13,14,19
308:2,22	194:16 195:19	world 89:20	68:1 69:5 75:4
310:10 311:18	205:7 214:5	221:19,21	85:11 86:16
312:6,25 313:7	234:2 250:25	write 46:21	107:9 158:19
313:17 314:14	work 25:15,21	54:21 55:25	167:4 169:16
315:19,25	27:10 29:3,5,9	56:4 113:24	175:12,24

[yeah - zotero] Page 90

181:23 209:9 222:1 246:4,7 248:9 263:3 265:4 268:18 281:18 282:6 296:8 308:25 329:20 330:22 331:7 345:23 year 30:12 41:6 143:11 yearly 211:12 years 25:4,9,13 25:19 32:11 69:4 70:3 75:12 78:2 79:5 84:6,7 117:25 118:22 161:16 213:19 257:19 278:21 314:2 york 1:2,21,21 2:2 9:9,9 79:13 194:17 youtube 13:9 13:10,12 177:18 216:3 217:8 241:13 243:12,22,24 245:9,10,17 325:6,16,17,22 329:6,9,17,21 334:7 335:14 336:14 337:20	youtube's 331:3 332:19 333:12 yup 118:15 128:14 198:4 220:6 232:17 280:16 325:1 329:14 346:11 z z 127:4 zelenskyyua 270:4 zero 151:3 273:24 zhu 145:4 zip 259:25 345:6 zone 225:12 zoom 26:25 46:13 61:4 62:5,9 67:14 148:7 248:13 272:14 281:21 282:13 zotero 126:23 127:3 154:4
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Federal Rules of Civil Procedure Rule 30

- (e) Review By the Witness; Changes.
- (1) Review; Statement of Changes. On request by the deponent or a party before the deposition is completed, the deponent must be allowed 30 days after being notified by the officer that the transcript or recording is available in which:
- (A) to review the transcript or recording; and
- (B) if there are changes in form or substance, to sign a statement listing the changes and the reasons for making them.
- (2) Changes Indicated in the Officer's Certificate. The officer must note in the certificate prescribed by Rule 30(f)(1) whether a review was requested and, if so, must attach any changes the deponent makes during the 30-day period.

DISCLAIMER: THE FOREGOING FEDERAL PROCEDURE RULES

ARE PROVIDED FOR INFORMATIONAL PURPOSES ONLY.

THE ABOVE RULES ARE CURRENT AS OF APRIL 1,

2019. PLEASE REFER TO THE APPLICABLE FEDERAL RULES

OF CIVIL PROCEDURE FOR UP-TO-DATE INFORMATION.

VERITEXT LEGAL SOLUTIONS

Veritext Legal Solutions represents that the foregoing transcript is a true, correct and complete transcript of the colloquies, questions and answers as submitted by the court reporter. Veritext Legal Solutions further represents that the attached exhibits, if any, are true, correct and complete documents as submitted by the court reporter and/or attorneys in relation to this deposition and that the documents were processed in accordance with our litigation support and production standards.

Veritext Legal Solutions is committed to maintaining the confidentiality of client and witness information, in accordance with the regulations promulgated under the Health Insurance Portability and Accountability Act (HIPAA), as amended with respect to protected health information and the Gramm-Leach-Bliley Act, as amended, with respect to Personally Identifiable Information (PII). Physical transcripts and exhibits are managed under strict facility and personnel access controls. Electronic files of documents are stored in encrypted form and are transmitted in an encrypted

fashion to authenticated parties who are permitted to access the material. Our data is hosted in a Tier 4 SSAE 16 certified facility.

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MOTION TO SEAL



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December 23, 2025

VIA ECF

Hon. Lewis J. Liman United States District Court Southern District of New York 500 Pearl Street, Room 1620 New York, NY 10007

Re: Lively v. Wayfarer Studios LLC et al., No. 1:24-cv-10049-LJL

Dear Judge Liman:

On behalf of Wayfarer Studios LLC, Justin Baldoni, Jamey Heath, Steve Sarowitz, It Ends With Us Movie LLC, Melissa Nathan, The Agency Group PR LLC, and Jennifer Abel (collectively, the "Wayfarer Parties"), we write pursuant to Rule 4.b of Attachment A to Your Honor's Individual Rules to respectfully request that the Court preliminarily seal Exhibit 2 to the Declaration of Kevin Fritz, which is submitted by the Wayfarer Parties in opposition to Blake Lively's motion for sanctions and other relief. (Dkt. 1133). Exhibit 2 contains excerpts from the transcript of the deposition of non-party Jenny Slate, which has been designated as confidential by her counsel.

By this letter, the Wayfarer Parties also respectfully request that the Court permanently seal the excerpts of the transcript of the deposition of one of their experts, which contains specifics of an illness from which she recently suffered. (Dkt. 1133-1). The Wayfarer Parties have filed contemporaneously herewith the full transcript of that deposition, which redacts the aforementioned information. (See Dkt. 1134) (approving the redaction of medical information).

Respectfully submitted,

/s/ Kevin Fritz
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Hon. Lewis J. Liman Page 2

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cc: all counsel of record (via ECF)