

1 UNITED STATES PATENT AND TRADEMARK OFFICE
2 BEFORE THE PATENT TRIAL AND APPEAL BOARD
3

4 MICROSOFT CORPORATION,)
5)
6 Petitioner,)
7)
8 vs.) Case IPR2023-01046
9) U.S. Patent No. 10,740,985B2
10 REALD SPARK, LLC,)
11)
12 Patent Owner.)
13)
14)

15 REMOTE DEPOSITION OF LINA J. KARAM, Ph.D.
16 Tuesday, February 27, 2024
17 Volume I
18
19
20

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22 NADIA NEWHART, CSR No. 8714
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14 Remote deposition of LINA J. KARAM, Ph.D.,
15 Volume I, taken on behalf of Patent Owner, with all
16 participants appearing remotely via videoconference and
17 the witness testifying from Scottsdale, Arizona,
18 beginning at 9:08 a.m. and ending at 2:38 p.m. on
19 Tuesday, February 27, 2024, before NADIA NEWHART,
20 Certified Shorthand Reporter No. 8714.
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INDEX

WITNESS

EXAMINATION

LINA J. KARAM, Ph.D.

volume I

BY MS. MOORE

6

EXHIBITS

(None)

1 Tuesday, February 27, 2024

2 9:08 a.m.

3
4 LINA J. KARAM, Ph.D.,
5 having been first duly sworn, was examined and
6 testified as follows:

7
8 EXAMINATION

9 BY MS. MOORE:

10 Q Is it "Care-am"? Is that how you say it?

11 A That's good enough, yeah.

12 Q Dr. Karam, if you could please introduce
13 yourself on the record so we get your full name.

14 A Yeah. My name is Lina Karam. And is this --
15 yeah. Okay.

16 Q "Ka-rom," then, right? Is that better?

17 A That's kind of -- to tell you the truth, I
18 pronounce it different ways, also. It depends, like --
19 yeah, Lina Karam. That's right.

20 Q Since we're going by Zoom, I just want to do a
21 little checklist of things first, and then we'll get
22 into the content of the IPR.

23 Is that okay?

24 A Yes.

25 Q Is anyone in the room with you today?

1 A No.

2 Q Do you have any notes with you apart from the
3 binders of the exhibits to the petition?

4 A No. I just have my declaration and the
5 exhibits.

6 Q Do you have any --

7 A Can I explain something? My declaration,
8 like, when it was printed, some figures were -- like,
9 were truncated, so I just printed these pages again.
10 Like, it's my declaration still, just...

11 Q Okay. And if there's something in your
12 declaration that we need to make sure is correct with
13 the filed copy version, then we can do that at some
14 point later today.

15 Do you have any devices other than your
16 computer in front of you today?

17 A I do have my cell phone.

18 Q Okay. If you could put that, maybe, on the
19 bookshelf behind you or something, just to ensure --
20 and I'm not suggesting this would happen, but make sure
21 no messages about the content of your testimony are
22 happening.

23 A How about I put it on the floor, like, face
24 down?

25 Q Sure. That's fine. Do you have any other

1 windows or programs open on your computer apart from
2 what we're using to do this deposition?

3 A Let me close the Chrome browser, because I
4 logged in through it. Okay. So I can close it now.

5 Q Okay. So no email application is open on your
6 computer?

7 A No.

8 Q No chat applications?

9 A No.

10 Q No electronic documents?

11 A No.

12 Q You understand you're not to communicate with
13 your counsel while I'm questioning you, right?

14 A Yes.

15 Q No text messages or DMs on your phone or your
16 computer?

17 A Huh-uh.

18 Q Okay. And if that happens, you understand you
19 need to notify me immediately, right?

20 A Sure.

21 Q Okay. You understand you're supposed to give
22 truthful answers today in your testimony?

23 A Yes, to the best of my knowledge.

24 Q Is there any reason that you can't do that,
25 like medications or anything?

1 A Not to my knowledge, no.

2 Q And if you don't understand my question, will
3 you ask me to clarify it?

4 A Yes.

5 Q Otherwise, is it fair for me to assume you
6 understood my question?

7 A Yeah.

8 Q So when were you hired by Microsoft in this
9 case?

10 A I don't really recall the exact date. I don't
11 recall the exact date. I didn't look it up.

12 Q Was it last year, sometime in 2023?

13 A It was -- yeah, it was in 2023 for sure.

14 Q Do you remember the month?

15 A No.

16 Q Do you remember if it was in the first half of
17 2023 or the second half?

18 A I don't really remember. I don't want to
19 answer from memory. I don't really quite remember.

20 Q Do you remember when you began working on this
21 IPR?

22 A Before its filing date for sure.

23 Q Do you remember what the filing date was?

24 A June, in June 2023. That's what I remember.

25 Q Do you remember how many months prior to

1 filing your declaration that you began working on this
2 IPR?

3 A A few months before.

4 Q So since it was filed in June, probably around
5 March 2023?

6 A I cannot really confirm. You know, a few
7 months before. Not sure. February, March or before.
8 Not sure, really. I mean, several months before, but
9 I'm not sure, really, when.

10 Q Do you recall if you were hired in 2022 versus
11 2023?

12 A I believe I was hired in 2023, but, again,
13 this is, like, from memory.

14 Q How much time have you spent on this IPR so
15 far?

16 A I know I spent a lot of hours. I don't
17 remember the exact number of hours.

18 Q Can you give me a range?

19 A Can you clarify the question? This is
20 including reviewing prior art and...

21 Q Yes, everything you've done to prepare for the
22 IPR, whether it was --

23 A Oh, to prepare -- oh, to prepare now or
24 before?

25 Q No, no, no. So let me start over.

1 What have you done, including reviewing prior
2 art and drafting your declaration? How much time have
3 you spent in that process?

4 A A lot of times. I can't really give you
5 hours. A lot of hours.

6 Q More than ten?

7 A For sure.

8 Q More than a hundred?

9 A Here, I cannot tell you.

10 Q Did you work on the invalidity contentions
11 that are part of the District Court litigation between
12 Microsoft and RealD?

13 MR. STEIN: Objection; form.

14 THE WITNESS: I'm not sure, really.

15 BY MS. MOORE:

16 Q You don't know whether you participated in
17 drafting invalidity contentions?

18 MR. STEIN: Same objection.

19 THE WITNESS: I do not believe I did.

20 BY MS. MOORE:

21 Q But you don't know one way or the other?

22 A Yeah, I don't want to, like, answer things,
23 like, I'm not sure about, yeah, but I do not believe I
24 participated in -- yeah, in that. No, I didn't
25 draft -- I know I worked on the IPR drafting, but --

1 and other thing. I didn't draft anything for the --
2 yeah.

3 Q You have not drafted anything associated with
4 the District Court litigation?

5 MR. STEIN: Objection; form.

6 THE WITNESS: I did not draft -- I do not
7 recall drafting anything, yeah.

8 BY MS. MOORE:

9 Q Did you review the invalidity contentions in
10 the District Court litigation?

11 MR. STEIN: Objection; form.

12 THE WITNESS: I'm not sure. Really, to tell
13 you the truth, I'm not sure.

14 BY MS. MOORE:

15 Q So what's causing the confusion about whether
16 you know if you've reviewed something or not?

17 A You know, we have the exhibits. They are
18 there in my IPR. Whatever exhibits are there, I did
19 also look at them, and these include -- and these were
20 filed with the IPR, I believe. But for my declaration,
21 I didn't rely on those, but because they were part of
22 the exhibit, I looked at some of those. I don't recall
23 all the documents I looked at, you know.

24 Q So you reviewed documents in addition to the
25 exhibits that are cited in your declaration?

1 A No. They are exhibits in my declaration, and
2 some of them relate to the District Court, you know, in
3 the exhibit. For example, you could see there is
4 complaint 1031 -- Exhibit 1031. And there were other
5 exhibits, I guess I saw. Yes, there is Exhibit 1055,
6 "Joint Claim Construction and Prehearing Statement."

7 Q Did you --

8 A I believe it was for the District Court.

9 Q Right. Did you review any documents that are
10 not cited as exhibits to your declaration?

11 A I didn't get documents to review that are
12 related to -- I didn't get documents. These are the
13 ones, basically, the exhibits.

14 Q When you say "basically," does that mean you
15 reviewed additional documents that are not cited in
16 your declaration?

17 MR. STEIN: Objection; mischaracterizes.

18 THE WITNESS: No. I didn't get documents that
19 are -- other than exhibits here that I reviewed.
20 Definitely, I reviewed some prior art. Like, to cancel
21 out some prior art, maybe I did some search myself, you
22 know, to see which are the best or something, but I
23 don't recall all these documents.

24 BY MS. MOORE:

25 Q Did you review prior art apart from the prior

1 art that you rely on in your declaration?

2 A I looked for but not reviewed. Maybe I
3 looked -- usually, when I'm -- I'm also -- I'm not
4 sure, really, for this IPR, but, typically, when I work
5 on an IPR declaration, I like to check, I mean, is this
6 the best prior art, but for me. But for this
7 declaration, I don't recall, really, whether I did
8 that.

9 Q So how did you decide what prior art to use
10 for this IPR?

11 A I looked at -- you know, now, I mean, if you
12 could let me look at the exhibit to refresh my
13 memory --

14 Q Sure.

15 A -- so I can tell you, basically, things,
16 wherever I -- like, things I found or not, whether it
17 refreshes my memory, whether also...

18 Q And while you're reviewing, can you tell me
19 what exhibit you're looking at?

20 A I'm looking at all -- like, mostly, the
21 exhibits. Yeah, a lot of the exhibits were kind of
22 provided by myself. I can see at least a few that were
23 provided by myself, and others that I -- were provided,
24 and I reviewed, and I basically said these are good or
25 not good, and then we kept -- so it's like a

1 collaborative effort where I was provided some prior
2 art that I kind of reviewed and removed some and said
3 these are pretty good.

4 Some of the things that were missing, I did
5 look for prior art -- yeah, now I'm looking here. I
6 don't remember exactly which one except some of them, I
7 know that, also, I found myself, but I don't
8 remember -- there are some exhibits I found, also, but
9 I don't recall each one of them.

10 Does this make sense?

11 Q So I'm looking at the exhibit list present in
12 Petitioner Exhibit 1003, which is your declaration. Is
13 that where you're looking, as well?

14 A Yes, yes.

15 Q Exhibit 1005, Chalom, or that's how I say it,
16 C-h-a-l-o-m, did you find that piece of prior art, or
17 was it provided to you by Microsoft?

18 A You know, I don't remember, really. I mean,
19 like, I don't want to, like, from memory answer the
20 question, like, to go through -- you know, I don't
21 really quite remember in here, like, each -- like,
22 which one was provided by whom. I don't want to answer
23 from memory.

24 Q Okay. So is that an "I don't know"?

25 A Yeah. I mean --

1 MR. STEIN: Objection --

2 THE WITNESS: I don't know.

3 MR. STEIN: Objection.

4 (Simultaneous speaking - unreportable.)

5 THE WITNESS: I'm not -- you know, some of
6 them -- because a lot of -- I went through a lot of
7 prior art. These is 200-plus documents. Some of them
8 were provided by counsel that I reviewed and said, yes,
9 these are good or these are not good.

10 And some of them I found, also, and also,
11 definitely, I mean, I got -- you know, yeah, and also
12 looked at them, yeah.

13 BY MS. MOORE:

14 Q So I'm just going to ask you the same set of
15 questions for a few more of these. Exhibit 1006, do
16 you see that in your list there, Ganin, G-a-n-i-n?

17 A Yes, I see that.

18 Q Did you find Ganin, or was it provided to you
19 by Microsoft?

20 A Again, I don't want to answer from memory.
21 Some of these were provided by Microsoft that I
22 reviewed, and some of them -- I found some of them, and
23 I provided those to counsel. So I don't want to answer
24 from memory, like, going back seven months ago. I
25 prefer not to do that.

1 Q So the answer is you don't remember?

2 MR. STEIN: Objection; mischaracterizes.

3 THE WITNESS: I don't want -- I don't feel
4 comfortable answering whether I remember or not,
5 meaning I don't want to go from memory, as I said, so
6 that's what I said. I don't want to base my answer on
7 memory. I want to base it on facts.

8 BY MS. MOORE:

9 Q Well, you do have to answer my questions to
10 the best of your ability. You understand that, right?

11 A Yes.

12 Q And so I'm just trying to know, do you
13 remember whether Ganin is something that you found or
14 whether Microsoft provided it to you.

15 A No, Ganin, I believe, you know, because --
16 like, Ganin is part of the file history. One version
17 of Ganin is part of the file history of the '101. And
18 so, definitely, I got to see it there first.

19 I mean -- and then -- you know, yeah, and then
20 this is one place Ganin is, and it was a collaborative
21 effort where kind of Ganin, they are looking at it.
22 Can we use that? And counsel provide some prior art.
23 I provide them others and so forth.

24 Q And then Aslan, which is Exhibit 1007, did you
25 find that piece of prior art or did Microsoft?

1 A To the best of my recollection, Aslan was
2 provided by counsel. Then I reviewed and said -- found
3 it a pretty good reference of prior art to use.

4 Q So how did you decide which of the prior art
5 that was provided to you would be the basis of your
6 declaration?

7 A Based on my expertise in the field, okay? So
8 we have to limit the number of grounds on everything,
9 so these are the references that I found to be good for
10 the grounds in my declaration.

11 Q And who drafted your declaration?

12 MR. STEIN: Objection; form, privileged.

13 THE WITNESS: Typically, when I work on my
14 declarations as expert -- and this is consistent
15 throughout my depositions -- usually, it's a
16 collaborative effort, and, however, the declaration, it
17 reflects my opinion. I revise it. I rewrite it. So
18 it's a collaborative effort.

19 And for this one, because I kind of worked a
20 lot on writing myself from scratch a lot of my
21 declaration, other sections were collaborative effort.
22 And some things, you know, I asked the counsel, also,
23 to help with from figures, et cetera. But it reflects
24 all of my opinion and -- my expert opinion, and I
25 really carefully work on my declarations.

1 And, again, anything that does not reflect my
2 opinion -- because we have discussions, active
3 discussions where I tell my opinion and so forth, if
4 the collaborative part that we work on -- they have to
5 reflect my opinions. I go through those carefully,
6 revise them, rewrite them as needed to reflect my
7 opinion.

8 BY MS. MOORE:

9 Q And you stand by the content of your
10 declaration today?

11 A Yes, I stand by the content of my declaration
12 today. Yes, I mean, I stand by the content of my
13 declaration.

14 Q Are there any changes you think you need to
15 make to your declaration as you sit here today?

16 A As I was reviewing my declaration, you know --
17 you know, and I think -- I believe, like -- like, you
18 were sent a message, also, about that. I see that one
19 exhibit, Exhibit 1006. The one that was sent to me in
20 the binder is not the Exhibit 1006 I based my
21 declaration upon. Actually, the exhibit is the pages
22 starting from 7, I think, to 23 or 24.

23 And Exhibit 1048, that was the exhibit I
24 based -- was my Exhibits 1006 I based my declaration
25 on. So this is one thing in here, yeah.

1 Q So when you cited to Exhibit 1006 in your
2 declaration, what you meant to cite was Exhibit 1048.
3 Is that a fair statement?

4 (Simultaneous speaking - unreportable.)

5 THE WITNESS: It should have -- yeah, I'm
6 sorry. It should have been filed as also Exhibit 1006.
7 The 1006 currently has the same substance, but there is
8 one page I didn't print, which is the same as the other
9 one, but -- so Exhibit 1048, pages 7 to -- let me check
10 in here what -- starting at page 7, that paper until
11 the end, let me check one moment. I don't want to go
12 from memory.

13 Yes, 7 to page 24 in Exhibit 1048, this should
14 be also Exhibit 1006, also. Like, it should stay there
15 and also be Exhibit 1006.

16 THE REPORTER: Counsel, I didn't get your
17 objection. There was talking over. What was your
18 objection?

19 MR. STEIN: Form.

20 BY MS. MOORE:

21 Q So, for example, if you'll turn to your
22 declaration, which is Petitioner Exhibit 1003, if
23 you'll go to page 44 of that declaration for me.

24 A Yes.

25 Q And if you'll look at paragraph 75.

1 Do you see that?

2 A I'm going there. One -- yes.

3 Q At the very end of paragraph 75, it says
4 Exhibit 1006, page 4, and so if we're going to be
5 talking about Exhibit 1048, I want to understand, are
6 these pages number correct --

7 A Yes.

8 Q -- for Exhibit 1048, or are they the original
9 1006?

10 A This is the -- page 4 of the PDF here, not
11 page 4 of what the counsel put as pages on the bottom.

12 Q So I just want to understand and make sure
13 that what I understand what you're citing to is page 4.
14 So should I be going to Exhibit 1048 for that?

15 A Yes, please. This was the -- this should --
16 yeah. So page 4 is the PDF page. You could see the --
17 on the top right corner, these are the pages.

18 Q So if we're looking at Exhibit 1048 now --

19 A Yes.

20 Q -- when you're citing to page 4 in
21 paragraph 75, will you direct me to the page as it
22 exists at the bottom of that. So where it says,
23 "Microsoft Exhibit 1048 - Page 1," for example, what
24 page should I be looking at of Exhibit 1048 to match it
25 up with this page 4 that you're referencing in

1 paragraph 75?

2 A It's just the pages of the file as they --
3 page 1 would be the cover page. Page 2 would be the
4 second page in that file. Page 3 would be the third.
5 Page 4 would be the fourth, page 5, the fifth, page 6,
6 the sixth page in that paper, 7, the seventh, 8, et
7 cetera, 9 and 10.

8 Q Okay. So paragraph 75 where it says page 4 is
9 the citation for that proposition, I should be looking
10 at page 4 of Exhibit 1048 that has a paragraph stating,
11 "User assessment interface"; is that right?

12 A I'm -- "User assessment" -- I don't -- this is
13 like -- that's not the exhibit I have. I'm looking at
14 1048, but you can point me where you're looking.

15 Q So I'm looking at Exhibit 1048 as it was filed
16 with the USPTO. That's why I'm trying to figure out
17 where the disconnect is here.

18 A Okay.

19 Q So tell me what the, I guess, title or --

20 A Yeah, I guess the disconnect --

21 Q -- what you have on page 4 that you're looking
22 at.

23 A Yes. So it's like -- it's like Exhibit B in
24 1048, that paper there, "DeepWarp" -- the title is
25 "DeepWarp: Photorealistic Image Resynthesis for Gaze

1 Manipulation." And --

2 Q Ah, okay. I see. Are you looking at the page
3 numbers that exist at the top of the "DeepWarp:
4 Photorealistic Image Resynthesis for Gaze
5 Manipulation," that page number that's --

6 A Yes.

7 Q -- at the top there?

8 A This is what I relied on in my declaration
9 and --

10 Q Okay. So when you say "page 4" -- and I just
11 want to make sure I got it right so we're all aligned
12 on what these citations refer to. So on page 75 of
13 your declaration, you cite to page 4.

14 That means the page 4 as it exists at the top
15 of the article, and it has Figure 2 at the top, and the
16 next subsection underneath that is "3, The model"; is
17 that right?

18 A Yes.

19 Q Understood. And that would be the way that
20 these pages are reflected throughout your declaration?

21 A Yes.

22 Q Thank you. How many IPRs -- apologies.

23 Is there anything else we need to correct in
24 your declaration apart from understanding this
25 Exhibit 1006 to Exhibit 1048 issue?

1 A I guess for now. I mean, if there is anything
2 later, I mean, I think counsel can file -- I don't know
3 what's the legal procedure. I don't know if sometimes
4 you can have some errata or anything, you know.

5 Q But nothing comes to your mind right now that
6 you need to change?

7 A Not at this time.

8 Q How many IPRs have you submitted declarations
9 for?

10 A I work -- I don't want to do it, like, out of
11 memory, you know, here, like, also, but you could look
12 up the public record and see my declarations there, I
13 guess.

14 Q Actually, I can't, which is why I'm asking
15 you.

16 Do you have any idea whether it's more or less
17 than ten, for example?

18 A More than ten.

19 Q More than ten. Is that what you said?

20 A Yes.

21 Q More than 50?

22 A No, I don't believe.

23 Q How many of those IPR declarations would be on
24 behalf of patent owners?

25 A Could you repeat your question, please.

1 Q How many of your IPR declarations have been on
2 behalf of a patent owner?

3 A I don't want to do it from memory. You know,
4 patent owner, I don't -- like, to my recollection,
5 again, based on memory and to the best of my knowledge,
6 I didn't really work for a patent owner on an IPR.
7 That's what I remember.

8 Q So to your recollection, you've never
9 submitted an IPR declaration that defended the
10 patentability of a patent?

11 MR. STEIN: Objection; form.

12 THE WITNESS: No, I misunderstood your
13 question. I'm sorry. I thought, like, I'm working on
14 invalidity for a patent owner, which doesn't make
15 sense, you know, so that's why in my -- yeah, so that's
16 why I said to the best of my knowledge, I wouldn't do
17 that.

18 So what was the question again? Could you --
19 so -- defending, you mean?

20 BY MS. MOORE:

21 Q Defending the patentability of a patent that
22 is being the issue of an IPR?

23 A I don't want to do it from recollection. I do
24 have some confidential engagement I don't -- I cannot
25 talk about, but, you know, as far as filing, I mean, I

1 don't recall, really. But as far as helping as part of
2 that engagement, I don't want to really answer from
3 memory, you know.

4 But as far as filing an IPR, I guess we can
5 check the public record. I don't want to answer from
6 memory, no, because I worked on a lot of IPRs, so I
7 don't want to...

8 Q Have you ever submitted a declaration where
9 you defended the patentability of the patent at issue
10 in the IPR?

11 A Again, I don't want to answer from memory.

12 Q You don't know if you've ever done it?

13 A I don't want to answer from memory, again.

14 Q You have to give me your best recollection.
15 That is how this process work. So do you remember if
16 you have ever submitted a declaration on behalf of a
17 patent owner defending the patentability of the patent
18 in the IPR?

19 MR. STEIN: Objection; form.

20 THE WITNESS: What I can say is mostly the
21 IPRs I worked on mostly -- like, the majority -- let's
22 put it this way, I mean. So, mostly, I recall my IPRs
23 are -- you know, were done for -- like, I don't know
24 how to phrase this. Do you see what I mean?

25 So most -- mostly, my IPRs were done in

1 validating patents to protect the rights of people who
2 had -- like -- because, like, they were invalid and to
3 protect the rights of people who are getting sued or --
4 for that. So, mostly, I would have touched IPRs. Now,
5 whether, like, I have or other -- I don't want to do it
6 from memory. I hope this answered your question.

7 BY MS. MOORE:

8 Q How many IPRs have you worked on for
9 Microsoft?

10 A This is like -- for Microsoft, to my
11 recollection, I believe that's the first one in here.
12 That's what I recall, again.

13 Q So this IPR that we're talking about today is
14 the first one you've done for Microsoft?

15 A That's what I recall, uh-huh.

16 Q Have you ever worked for Microsoft in a
17 district court patent litigation?

18 A No.

19 Q Did you know that the inventors of the '985
20 patent at issue in this IPR now work at Microsoft?

21 MR. STEIN: Objection; form, scope.

22 THE WITNESS: Yes, I know.

23 BY MS. MOORE:

24 Q Have you talked to them?

25 A No.

1 MR. STEIN: Objection; form.

2 BY MS. MOORE:

3 Q Have you reviewed Microsoft's gaze correction
4 software as part of your work on this IPR?

5 MR. STEIN: Objection; form, scope.

6 THE WITNESS: I did not. You know, like --
7 excuse me. Like, I don't want to do from recollection.
8 You know, I don't -- to my recollection -- I don't
9 know. I take this back. Can we, like, please cross
10 this out of the record, please, because I don't want to
11 do it out of memory.

12 I don't recall. I'm -- I -- I don't know. I
13 might or not, so I don't really quite recall.

14 BY MS. MOORE:

15 Q So you don't know whether you have looked at
16 Microsoft's gaze correction software as part of your
17 work on this case?

18 MR. STEIN: Same objections; form and scope.

19 THE WITNESS: Like I -- you know -- yeah, so I
20 would say, like, I don't want to do it from memory.

21 BY MS. MOORE:

22 Q And, ma'am, again, that's not how this process
23 works. You have to give me your best recollection.
24 And if you don't know, you can tell me you don't know,
25 but you have to answer the question.

1 A I worked on a lot of projects and things, so
2 sometimes things get mixed up, and I don't want to be
3 answering something -- yeah, I don't recall, and I
4 don't know for now because of -- like, my schedule is
5 busy. So I don't want to be mixing up things. I do
6 work with code and software, so I don't want to mix up
7 things that I don't recall at this point, yes.

8 Q So I'll ask it again just so we can have a
9 clean Q and A, okay?

10 A Yeah.

11 Q Have you ever reviewed Microsoft's gaze
12 correction software as part of your work on this case?

13 MR. STEIN: Same objections; form and scope.

14 THE WITNESS: So I don't recall for now
15 whether I reviewed, like, a gaze correction software.

16 BY MS. MOORE:

17 Q Have you reviewed RealD's gaze correction
18 software as part of your work on this case?

19 MR. STEIN: Objection; form, scope.

20 THE WITNESS: I do not believe so.

21 BY MS. MOORE:

22 Q Does either party's gaze correction software
23 code impact your opinions in this IPR?

24 MR. STEIN: Objection; scope.

25 THE WITNESS: Could you rephrase the question,

1 please.

2 BY MS. MOORE:

3 Q So does Microsoft's code have any impact --
4 strike that.

5 So Microsoft's gaze correction software, does
6 that have any impact on your opinions in this IPR?

7 A No, not at all, for sure. My declaration was
8 not based on any software or anything.

9 MR. STEIN: Same objections to form and scope
10 to the prior question.

11 BY MS. MOORE:

12 Q And RealD's gaze correction software, does
13 that have any impact on your opinion in this IPR?

14 MR. STEIN: Same objection.

15 THE WITNESS: For sure not. It wasn't even
16 considered as part of -- when I was doing my
17 declaration, neither of these were considered at all.

18 BY MS. MOORE:

19 Q How long were you a tenured professor at
20 Arizona State?

21 A It is in my CV, but, like -- so let me -- I
22 don't want to do it from memory. One moment.

23 If you go to the employment section -- okay.
24 One moment.

25 Q And for the record, you are looking at

1 Exhibit 1004, which is your CV in the IPR; is that
2 right?

3 A Yes.

4 Okay. So as a tenured professor? Can you --
5 the question was...

6 Q How long were you a tenured professor at
7 Arizona State?

8 A Okay. So here, at least 19 years. In here,
9 19 years, almost.

10 Q And what page were you looking at --

11 A I have to recall -- I'm taking full professor,
12 but I wasn't tenured from the associate professor. So
13 from 2001, you know, I was tenured associate professor,
14 so going back 2001 to 2019. So -- yeah, so I guess,
15 like, it is -- yeah, 2001 to 2019. August 2001, I
16 was -- received my tenure.

17 Before that, I was a professor, but, you know,
18 assistant professor. So I started at ASU in
19 August 1995. In 2001, I received my tenure, okay? And
20 then -- yeah.

21 Q In December of 2019, did you retire?

22 A What I did, I wanted -- yes, I did do early
23 retirement myself, and I am affiliated now as emerita
24 professor with ASU, so I'm still having this
25 affiliation, yeah.

1 Q And what do you do for Arizona State as an
2 emerita professor?

3 A I still direct my R&D lab and still have Ph.D.
4 students I'm supervising there.

5 Q How many students are you supervising?

6 A Currently, I have one Ph.D. student I'm
7 supervising, currently.

8 Q What subject matter are you supervising that
9 Ph.D. student for?

10 A Machine learning.

11 Q Let's look at your declaration again, which is
12 Petitioner Exhibit 1003. I'd like to go to
13 paragraph 11, which is on page 4. Let me know when you
14 get there.

15 A One moment. Page 11?

16 Q Page 4, paragraph 11.

17 A Oh, page 4, paragraph 11. Yes.

18 Q That first sentence says:

19 "As a part of my various roles at ASU,
20 PICARIS, ISO and IEEE, I am actively
21 involved in industry."

22 Do you see that sentence?

23 A Yes.

24 Q Are you currently involved with PICARIS?

25 A Yeah, I mean, it's my -- yes, I'm the

1 president. It's my company, PICARIS LLC.

2 Q What do you do at PICARIS?

3 A It's my consulting company.

4 Q Are you currently active in ISO?

5 A Yes. I am an expert delegate to the ISO.

6 Q And what does that mean?

7 A This is the international standard --
8 standardization organization. They work on standards,
9 okay? Like, a lot of standards, including, for
10 example, maybe something you might all be familiar with
11 is like JPEG, like a JPEG image, you know, or MPEG
12 video like the ones we're doing now here.

13 These are all standards. ISO works on those,
14 so JPEG, and recently, there's a JPEG AI. I was
15 involved in that. So they're now more and more also
16 standardizing things related to artificial intelligence
17 within different aspects. So the ISO is the, you know,
18 International Standardization Organization.

19 In order to allow devices to interoperate, you
20 need to have standards. So we work with industry --
21 mainly people from industry or other experts. It can
22 be academia, also, but mainly industry people work with
23 the ISO on standards.

24 Q What is your current involvement with IEEE?

25 A IEEE -- I'm an IEEE fellow. I serve on

1 various boards within the IEEE. I'm currently serving
2 on the IEEE Educational Activities Board and also on
3 the TechRxiv board. And, also, I was an
4 editor-in-chief of the -- one of the journals. Also, I
5 have organized various conferences as chair and
6 technical program chair. So I'm, like, heavily
7 involved with the IEEE.

8 Q What journal are you working on?

9 A Could you repeat -- like, ask more
10 specifically your question?

11 Q Sure. So I asked what your current
12 involvement with the IEEE was, and you listed being
13 editor-in-chief of one of the journals. Which journal?

14 A Yes. I served my term, I mean, up to 2019
15 or -- I have it there, also, in my -- so I was -- it is
16 the IEEE special topics -- actually, "Journal or
17 Selected Topics in Signal Processing."

18 Q So you are not currently the editor-in-chief
19 of that journal?

20 A It's a rotation. I mean, but -- you know, so
21 being editor-in-chief is really highly prestigious.
22 They don't -- to be nominated and to be accepted to be
23 editor-in-chief is by itself an honor, and having
24 served that is just like -- you know, this gives you,
25 like -- you know, so not everybody is picked to be

1 editor-in-chief. This by itself speaks highly of the
2 person.

3 Q I'm trying to get what your current role today
4 in 2024 is at the IEEE. Can you tell me --

5 A Yeah, I'm serving on various boards, and I --
6 you know, it is in here. It's in my -- actually,
7 currently, because it's since changed, also, from my
8 bio now, so I'm serving on various boards of the IEEE,
9 okay?

10 Like, I was serving recently on the product
11 board of the IEEE, the PSPB, product services --
12 Products and Services Committee where we are discussing
13 different products for the IEEE. That was one of them
14 that I just, like, finished my term. I'm currently
15 serving on the IEEE Educational Activities Board, and
16 also, I am serving on the TechRxiv board.

17 These are a few of the boards. And I'm
18 serving on the -- helping on organizing committee of
19 some conferences, also, and as an area chair, technical
20 area chair of an upcoming conference and so forth,
21 yeah.

22 Q So in paragraph 11, that first sentence that I
23 read to you earlier that ends in "actively involved in
24 industry," how are you defining industry there?

25 A Industry are the -- industry like

1 productization, working on product for an industry and
2 with various industries, yes.

3 Q So I want to understand what you mean by
4 industry. What do you mean in paragraph 11?

5 A I mean, you could define -- look definition
6 for industry. Industry are companies. It's like
7 versus, also, product like -- yeah, so companies, and
8 they work on R&D and products and so forth.

9 Q I see. So industry, you simply mean companies
10 that make products?

11 A Yeah. And they do R&D to make products also.
12 I mean, you have to push the frontier of products. You
13 can't just make products. You have to push, innovate
14 and work on products of the future, so you have the R&D
15 components also there.

16 Q Have you taught courses on neural networks?

17 A For sure. I developed the first course at ASU
18 on neural networks, deep learning. I developed it back
19 in 2016, 2017. I taught it. It was a graduate-level
20 course, and we developed, also, a hands-on -- hands-on,
21 actually -- not only the fundamentals but also the
22 hands-on.

23 So, yeah, that's the course I developed at ASU
24 and taught for several years after that, but -- yeah,
25 that's one of them.

1 Q How many neural networks have you implemented?

2 MR. STEIN: Objection; form.

3 THE WITNESS: Yeah. I mean, we can look at
4 the publications that we have. We worked on various
5 neural networks, so -- yeah.

6 BY MS. MOORE:

7 Q More than one?

8 A Yes, for sure. You could go to our hands-on
9 lab book. All these projects I worked on, we have a
10 hands-on lab book, and if you go to
11 deeplearningtextbook.org, if I remember correctly,
12 that's our hands-on book on neural networks.

13 And I advise this project and work on refining
14 them and work with student on them in addition to
15 working with my student on reviewing their codes and
16 also helping with the implementation of the neural
17 network. So, yeah, I mean, this will give you an idea,
18 also. So our publications are all in that book.

19 BY MS. MOORE:

20 Q So setting aside what your students may have
21 been working on, how many neural networks have you
22 personally implemented?

23 A At least -- at least the one -- you could look
24 at the handbook you have, and at least, you could see
25 there, I mean, these projects, so I worked actively on

1 those. And I'm not going to answer from memory, also,
2 how many.

3 Q Is it at least one?

4 A For sure.

5 Q Is it more than 50?

6 A I'm not going to answer from memory, so...

7 Q Do you know?

8 A At this point, basically, I'm not -- again,
9 I'm not going to answer from memory, so you want -- you
10 want me to say I do not know? Okay. I can tell you I
11 do not know.

12 Q What kind of neural networks have you
13 personally implemented?

14 A Convolutional neural networks, fully connected
15 neural networks.

16 THE REPORTER: I'm sorry, Doctor. Can you
17 start over.

18 THE WITNESS: Okay. Sure. So types of neural
19 networks I implemented include convolutional neural
20 networks and fully connected, also, neural networks.
21 And also, you have variations of those that include
22 convolutional layers and so forth.

23 BY MS. MOORE:

24 Q The neural networks that you've implemented,
25 are they deep or shallow, or does it depend?

1 A Both deep and shallow.

2 Q How many layers would a deep network have?

3 A That's a very good question. If you look in
4 the -- so this is a very good question, and it depends
5 on who's answering it. Like, there is no specific
6 agreement on this. Let me put it this way, okay?

7 Yes, I mean, so, you know, for me, definitely,
8 it should have more than one layer, but there is no
9 specific agreement on this, more than -- more than one
10 hidden layer. Other than the input/output layer, it
11 should be more than one. That's what I mean, yeah.

12 Q More than one hidden layer?

13 A In my opinion, again, I'm saying this is not
14 something, you know, very well agreed upon.

15 Q What is the largest number of layers you've
16 personally implemented in a neural network?

17 A Like, definitely more than one hidden layer
18 for sure and several. I wouldn't really -- I wouldn't
19 really answer this from memory, so it was -- we have
20 deep neural networks with millions of parameters and --
21 and, especially, you could also use networks and build
22 on them, okay? So definitely, like, several layers.

23 Q What kind of loss functions have you used --

24 MR. STEIN: Objection.

25 BY MS. MOORE:

1 Q -- in implementing neural networks?

2 MR. STEIN: Form objection.

3 THE WITNESS: Several loss functions. We have
4 different kinds of loss function for different tasks,
5 okay? So several of them, and I refer you to our
6 papers because we use different loss functions, not
7 only one.

8 BY MS. MOORE:

9 Q Which different ones have you used?

10 A I cannot tell them. Like, I cannot say all
11 the functions we used because some of them, they target
12 different things, you see, so they don't have quite,
13 like, a name I can give. Like, for object detection,
14 you have to take the regression of the bounding box.

15 And this goes to the loss function, also, and
16 so -- but, definitely, we use the cross-entropy, we use
17 l1, we use l2 as part of the loss function because,
18 typically, a loss function is more than one term that
19 you use to regularize or to take constraint into
20 account and take other information into account. You
21 could have a simple one with a single term, but,
22 typically, it's more than that for various
23 applications.

24 Q Have you ever worked with random forest
25 classifiers?

1 A Yeah. I guess implementing things in terms of
2 projects and so forth, but, you know, for our R&D,
3 however, I mean, these are -- because prior art now,
4 and I mean very well known -- I mean, we're working on
5 the next level of things, so we -- we use them, like,
6 for projects, mainly.

7 Q When was the last time you used a random
8 forest classifier?

9 A I do not recall, really.

10 Q Was it within the last five years?

11 A Perhaps. I do not recall.

12 Q How would you apply a random forest classifier
13 in a teacher-student module?

14 A I explain, also this very clearly in my
15 declaration, how we apply, especially in the ground --
16 the Chalom/Aslan combination. So I explain that there.
17 I don't like to answer out of context.

18 So if you want to ask me a specific question,
19 I could, like, show -- I mean, I could go and -- and
20 tell you one example we use, which is clearly described
21 in my declaration in here. It's one way you could use
22 a random forest model. Just one moment.

23 So, like, in paragraph 219 of my
24 declaration -- like, I don't know if you want --

25 Q Paragraph 219 of Exhibit 1003 is what you're

1 referring to?

2 A Yes.

3 Q The single sentence:

4 "One way is using Chalom's RFC as a
5 teacher model to train an even more
6 compact MLA, e.g., a smaller random
7 forest"?

8 A Yeah. And you can continue, also, like, in
9 220, so, yeah. So that's how you can use a random
10 forest classifier in a teacher-student framework. And
11 we do have also -- I have in my declaration. I'm
12 referring -- if you look at page 121, there is a figure
13 there, Exhibit 1003, page 121.

14 And paragraph 227 describes, also, more how
15 this can be used as a teacher-student -- I mean
16 teacher-student framework, and so you could use, like,
17 a random forest like Chalom's random forest classifier
18 in this case to train a more compact student in a more
19 compact network and, yeah, so one would be the teacher,
20 and one would be student.

21 They use the same training data as shown in
22 Figure 8. You have the same training data being used
23 by both. And the teacher can pass information to the
24 student so the student can learn from the teacher and
25 use the past information in addition to using the

1 training data.

2 Q Would both the teacher and the student be a
3 random forest?

4 A They can be, but it's not necessary.

5 Q Is a neural network a type of machine learning
6 model?

7 A Yes.

8 Q Does one neural network represent one machine
9 learning model?

10 MR. STEIN: Objection; form.

11 THE WITNESS: Could you be more specific?

12 BY MS. MOORE:

13 Q Yes. If I use the term "neural network," am I
14 talking about one machine learning model?

15 A Not necessarily.

16 Q So singular can mean plural and vice versa in
17 that context?

18 MR. STEIN: Objection; form.

19 THE WITNESS: Yeah. One shouldn't take things
20 out of context, because one single architecture can
21 contain several machine learning models or algorithms
22 that are there, so it depends what's being referred to
23 and what the context is.

24 BY MS. MOORE:

25 Q Can a deep neural network have multiple

1 layers?

2 A Multiple hidden layers, you mean, or anything?
3 What's the question here? Layers of what?

4 Q Any layers, whether it's the input, the output
5 or a hidden layer?

6 A Neural network have -- has -- yeah, it has
7 layers.

8 Q One type of deep neural network is a
9 feedforward neural network; is that fair?

10 A Yes.

11 Q And in a feedforward neural network, each
12 previous layer feeds into the next layer?

13 A You could build the network like that, yeah.

14 Q Is it possible for each layer to perform a
15 different function?

16 A Like -- it's like the question is not very
17 clear. What do you mean by that?

18 Q What is the purpose of a layer in a deep
19 neural network?

20 A Again, like, I mean, this is very kind of
21 general and ambiguous, to tell you the truth. I do not
22 understand the question. You should be more specific.
23 I describe, actually, the layers of a deep neural
24 network in my declaration in the "Background" section,
25 and I illustrate those, that the layers consist of

1 neurons, no? If you go to Figure 2. Like, this is
2 Exhibit 1003, page 21. You see this is with one hidden
3 layer in here showing a fully connected layer in here.

4 And you could see, basically, in this
5 particular architecture of the neural network, that
6 each node is computing, like, a weighted sum with some
7 nonlinear function applied. And you learn -- I mean,
8 it's -- so you -- so these are -- the weights there are
9 being learned, and these are learned from the training
10 data, okay?

11 So, basically, it's a parametric model that --
12 so each node is a parametric function, okay? And from
13 the training data, these weights or parameters are
14 learned. And this is like -- basically, the networks,
15 they learn tasks.

16 Definitely the optimization requires that you
17 use an objective function; otherwise, you can't
18 optimize the weights. But at the end of the day, once
19 you learn -- I mean, the weights are learned; then you
20 can deploy it as shown, okay?

21 Q So you said each node in a layer is a
22 function; is that right?

23 MR. STEIN: Objection; form.

24 THE WITNESS: Each node in the layer in this
25 particular -- I'm showing you one architecture is

1 implementing this parameterized function as shown here
2 in Figure 2, and it's implementing -- it is a node
3 called a neuron, and the cascade of neurons is called a
4 layer.

5 This is this particular architecture. You can
6 have different architectures, but this particular one
7 -- that's why it should be very specific. In Figure 2,
8 this architecture, I'm showing you what it's doing.

9 BY MS. MOORE:

10 Q Is each layer doing something different?

11 A Again, the question is not -- is very
12 ambiguous, and it depends on the network architecture.

13 Q So there are some architectures where each
14 layer is doing the identical functions?

15 A It depends --

16 MR. STEIN: Objection to form.

17 THE WITNESS: -- what you mean by identical
18 and different. So, really, it's ambiguous, and I
19 cannot answer the question. What is identical? Do
20 they have the same form or not? What is basically
21 being asked here?

22 BY MS. MOORE:

23 Q What do you understand the word "identical" to
24 mean?

25 A That's the thing. It's not understood out of

1 context. I'll give you an example. For example, these
2 neurons may be -- the parameterized function might take
3 a distinct format, I think, if -- depending on the
4 design, okay?

5 But at the end of the day when you learn the
6 weights, the weights are different for each or can
7 be -- you can constrain them to be the same so -- so it
8 depends. What's identical? The form is identical?
9 The weights are identical? Or, like, the form and the
10 weights together are identical?

11 So identical by itself is very ambiguous, just
12 to ask this out of context. I don't want to answer
13 just general, out-of-context questions, because I don't
14 know how to answer those. I mean, there should be
15 context; otherwise, the answer would not be correct.
16 BY MS. MOORE:

17 Q And that's what I'm asking you to do is tell
18 me what your understanding of identical is so that we
19 can proceed with the questions.

20 So what is your understanding of identical?

21 A It depends. If you're in math, like, you're
22 doing equation, 1 plus 1 equal 2 versus, you know, 0.5
23 plus 1.5 equals 2. I mean, are the answers identical?
24 Here, I can answer, yes, it's 2. You see?

25 But when you say it's a network identical

1 function, no, and that is very ambiguous, and you
2 cannot define what identical is because I can't
3 understand the question. You could say, Oh, does the
4 node has, like, a similar function parameterized or
5 something? Is it, like, identical -- this row here is
6 a nonlinear operator. Is it the -- identical --
7 identical operator? I could tell you yes or no. These
8 things like that. It should be more specific.

9 Q So do the nodes in each layer of a
10 convolutional neural network have a similar function?

11 MR. STEIN: Objection; form.

12 THE WITNESS: Similar in what way?

13 BY MS. MOORE:

14 Q I'm simply repeating what you said in your
15 previous answer. What did you mean by similar?

16 A No. I'm saying similar by itself, one has to
17 specify. For example, you could say it has the same
18 form. You know, you could see here in this particular
19 architecture, they have similar form of weights being
20 multiplied the output. This doesn't mean, necessarily,
21 there are -- I mean, this is like same form in here.
22 So this is basically -- you could say, Oh, yeah, the --
23 this weighting and bias, so in this way, it's the same.
24 So it's very specific. You see what I mean?

25 Q Are the weights the same across layers?

1 A The weights typically -- because it's
2 learning-based, they're not going to be the same across
3 layers.

4 Q What are the components of a neuron besides
5 the weight?

6 A You could design neuron different way, but in
7 this particular context like as shown here and -- the
8 neuron is taking input and creating one output, so it's
9 taking several input and creating one output.

10 In this particular situation, the output is
11 created by taking a weighted combination of the input
12 so W1 times x1, W2 times x2, W3 times x3, et cetera, and
13 then you have a nonlinear function like a -- can be
14 something that threshold that -- for example, if it's
15 negative, you put it to 0, or you want to -- if not,
16 you keep it. For example, I'm giving one particular
17 role, for example, or it can be other nonlinear
18 functions. So this is what these neurons are doing
19 here.

20 Q Is the output from the input layer the same as
21 the output from the hidden layer?

22 MR. STEIN: Objection; form.

23 THE WITNESS: Like, could you, like, repeat
24 the question, please.

25 BY MS. MOORE:

1 Q Sure. Is the output from the input layer the
2 same as the output from the hidden layer?

3 A Output from the input layer, you said?

4 Q Correct.

5 A But the input doesn't have an output. This is
6 input. These are the input getting into that function.
7 So it is, by definition, an input layer.

8 Q What does the arrow from x1 in the input layer
9 to the circle identified as fw1,1 in the hidden layer
10 reflect?

11 A It reflects that this is getting input into
12 that, okay? So this is -- that's -- you know, this
13 isn't fully connected here, but sometimes you could
14 have something that's not fully connected. For
15 example, you could have a neuron that would have only
16 x1, x2, x3 as input, so then you wouldn't have an arrow
17 from xn to that.

18 So here, it's showing that all of these are
19 being used by that neuron to compute -- to compute --
20 here, in this case, we're showing how the output is
21 computed of that -- the output of that neuron is
22 computed.

23 Q So the neuron x1, what information is passed in
24 the arrow going into the hidden layer?

25 A The value x1, and also -- the value in x1, but,

1 also, later, you'll apply the weights, okay? Yeah.

2 Q Do you apply the weights when going from the
3 input layer to the hidden layer?

4 A The hidden layer is really applying the
5 weights, but, graphically, different people can
6 represent things differently. Some people can put --
7 like, for illustration, some people can put the weights
8 on the arrows. Like, they would put W_1 . But you could
9 also say -- I mean, the f is implementing those, so you
10 don't have to do that. So it depends on how you
11 graphically illustrate that.

12 Q The arrow going from the hidden layer to the
13 output layer, what information does that reflect?

14 A The output of that -- which -- can you kind of
15 point me out to which arrow you're --

16 Q Sure. The topmost one that goes from $fw_{1,1}$ to
17 $fw_{2,1}$.

18 A Okay. Yeah, this is the output of that node
19 or, like, neuron. Like, the fw on one neuron, the
20 output, is going as input to the next one.

21 Q What is the value of that output?

22 A It's given as -- you could see the top --
23 like, if you -- do you see the equation on the bottom,
24 the $fw_1(x)$? And you could see one of the elements on
25 the top is $fw_{1,1}(x)$, and it's given by this equation.

1 The weighted sum of the input plus a bias rho.
2 Like, you see rho times -- rho, like where there is
3 parentheses?

4 Q Yes.

5 A Dot $w_{1,1}$, transpose, plus $b_{1,1}$, yeah.

6 Q So that equation that you just read off is the
7 value that's being passed from $fw_{1,1}$ into the output
8 layer?

9 A This is the value of that, because once you
10 have a specific x, then you pass -- then you put it
11 there, and you pass the value, okay?

12 Q Does a neural network learn with one set of
13 inputs and one set of outputs?

14 MR. STEIN: Objection; form.

15 THE WITNESS: Again, like, these -- like, if
16 you can repeat the question.

17 BY MS. MOORE:

18 Q Does a neural network learn with one set of
19 inputs and one set of outputs?

20 A It's out of context. I don't know. I mean, I
21 cannot answer this general question because you
22 might -- I'm not sure, like, what the question is
23 asking, really. One set of inputs and one set of
24 outputs, what does that mean? Do you mean the training
25 data?

1 Q Yes.

2 A Okay. Thank you. So it depends. You have
3 different kinds of neural networks. Supervised neural
4 networks require training data as pairs, or, like, you
5 would have to have ground truth like you -- typically,
6 you have, like, input and desired output, like, not the
7 output, actually, of the network, desired -- like, you
8 say, oh, ground truth.

9 So this is supervised, but you have also
10 unsupervised training. You have weekly supervised
11 required. Unsupervised requires just inputs, okay?
12 You don't give another pair. So there are different
13 types of networks.

14 Q So in a supervised neural network, does it
15 learn with one set of inputs and one set of outputs?

16 A Again, like, I don't like the term "one set,
17 one set," you know. I'm not sure that means, what you
18 mean by one set of input, one set of outputs.
19 Typically, you have the data -- you know, training data
20 given in input sample. If it's supervised, you like,
21 also, to give the desired ground truth that's paired
22 with that input sample. So instead of saying one set,
23 one set like that...

24 Q Then would it be fair to say that it's one
25 pair, so one input and one desired output, then?

1 A Yeah, for each input sample in the training
2 data, you like to give the target or ground truth --
3 what you call ground truth of desired outputs that
4 you'd like to reach.

5 Q In a feedforward neural network, does the
6 input go into the top input layer, and then,
7 ultimately, the output comes out from the last layer?

8 MR. STEIN: Objection; form.

9 THE WITNESS: Could you repeat that question.
10 Feedforward, you're saying?

11 BY MS. MOORE:

12 Q Yes. In a feedforward neural network, does
13 input go into the top layer, and the output comes out
14 of the last layer?

15 MR. STEIN: Same objection.

16 THE WITNESS: Outputs are coming -- as we saw
17 here, you have outputs of the hidden layer, outputs of
18 the last layer. It depends on -- you could define your
19 output, okay? Sometimes we use these networks as
20 feature extractors, so some people would take the
21 output to be the output of the first hidden layer, and
22 they use it. They say, I want this.

23 So, really, I mean, it depends on how you've
24 designing the network that -- what you're trying to
25 optimize, and you could use several outputs, if you

1 want, from different layers, even, in addition to the
2 last layer.

3 So it depends on the context. I cannot really
4 answer that question without context. And different
5 people use different outputs from different layers, or
6 can be just one single output from a layer, but to do
7 something, to do -- so you could kind of make use of
8 those four different things, and it depends on your
9 task, okay?

10 (Mr. Devkar joined the proceedings.)

11 BY MS. MOORE:

12 Q So let's say we have a feedforward neural
13 network that is for gaze correction.

14 A Yes.

15 Q The input would be the uncorrected gaze,
16 right?

17 A For gaze correction, yeah, I mean, you
18 could -- you could say so. That's one example.

19 Q And the output would be the corrected gaze,
20 right?

21 A And the output of what? Could you be more
22 specific? Would be the corrected gaze? The output of
23 what?

24 Q The feedforward neural network.

25 A Not necessarily.

1 Q Why not?

2 A Because -- for example, let's go -- and I can
3 show you the figure. I mean, let's go to -- let's go
4 to page 115 of Exhibit 1003.

5 Q Okay.

6 A Let me know when you're there.

7 Q I'm there.

8 A So you could see this Figure 3, okay? You
9 could see -- I mean, random forest classifier here, but
10 it could have been a neural network.

11 You could see that the correction is done by
12 the warp and integrate module. Do you see that? Here,
13 this random forest classifier is given a pixel flow
14 feed or motion vector field, which gives you the
15 correction to be done, the -- what you need to make the
16 correction. So this will give you how to correct, and
17 then this is applied by another module called warp and
18 integrate to correct.

19 So in this case, the output of the machine
20 learning of neural network or whatever you want to use
21 here is, like, the corrections -- like how to -- the
22 displacement feed, how you want to warp your image.
23 But then you take that and apply another editing
24 algorithm or -- that applies it like the warp and
25 integrate here. So you see, it should be, like, within

1 a context because different -- different systems would
2 kind of implement different things.

3 Q So would you agree that in a feedforward
4 network, the information flows from the input layer to
5 the output layer?

6 MR. STEIN: Objection; form.

7 THE WITNESS: I mean, information is flowing,
8 but, again, output -- I mean, the last layer in here,
9 because it can be the output layer -- again, you could
10 take output from any layers, also, if you need to.
11 That's what I'm saying. So it flows -- it flows
12 forward, yes. It flows forward.

13 BY MS. MOORE:

14 Q So then you agree that in a feedforward
15 network, information flows from the input layer to the
16 output layer?

17 MR. STEIN: Objection; mischaracterizes.

18 THE WITNESS: I agree it -- basically, it goes
19 forward through the layers, like, characterizing what's
20 output and so forth, the last layer if you want to say
21 it, okay, and -- which can be your output or not, or
22 you want other layers to be output, so...

23 BY MS. MOORE:

24 Q And in that feedforward network, the
25 information would flow from an input layer through

1 hidden layers to the output layer, right?

2 MR. STEIN: Objection; form.

3 THE WITNESS: You have, as we saw in Figure 2,
4 a network -- the last layer typically is called the
5 output layer. The input -- the first layer is -- you
6 know, which is input, the input data, and you have
7 hidden layers. That's a neural network, one of -- one
8 example of neural network.

9 BY MS. MOORE:

10 Q So do you agree or disagree that in the
11 feedforward network, information would flow from an
12 input layer through hidden layers to the output layer?

13 MR. STEIN: Objection; form.

14 THE WITNESS: It can flow that way.

15 BY MS. MOORE:

16 Q What is an objective function?

17 A You know, I discussed this, also, maybe for
18 the sake of it and to make it, also, easier when -- I
19 discussed the objective function, also, in my
20 declaration as part of the background, you know, in
21 here. So let me just see.

22 So 14, like, if you go to page 14. Okay. So
23 when you want to train a neural -- if you go to 14 of
24 Exhibit 1003, like, paragraph 28, I guess we start
25 there, but as written here, like, when you want to

1 train a neural network, you know, in addition to the
2 training dataset, how are you going to train?

3 You require -- it's an optimization, okay?
4 You want to determine these weights we talked about or
5 other parameters, so how do you determine these
6 weights? You have to have a function that you
7 optimize.

8 An optimization, we call these objective
9 functions, okay? These objective functions can be cost
10 or gain. This cost usually -- or loss, also another
11 word -- you try to minimize it. If it's gained, you
12 try to maximize it. Typically, if it's a gain, we can
13 flip it, also, do a negative term, minus gain becomes a
14 loss.

15 And what, typically, we use -- especially in
16 machine learning, we use gradient descent techniques,
17 stochastic gradient, to minimize that function. But
18 that said, if we take this objective function and we
19 say we have the training data, you know, you want to
20 learn using the training data or some other factors
21 because a lot of time, we have regularization, because
22 machine learning in a very -- for very general -- if
23 you want to solve a very general problem like
24 everything in the world, machine learning doesn't work.

25 A lot of time, we use prior knowledge about

1 our machine learning, what task we're doing, for
2 example, gaze correction or something. So we have some
3 prior knowledge. Oh, I want this placement feed. I
4 want that. And we can put constraint. So a lot of
5 time in optimization, we have a loss function subject
6 to constraints, okay?

7 These constraints get incorporated as terms in
8 the objective functions through Lagrange multipliers,
9 for example. You can add other terms. So now your
10 objective function not only have the input -- the
11 pairs, the data training pairs, but, also, it has,
12 also, other constraints to make sure you make use of
13 the prior knowledge you have or other things you want
14 to achieve a better fit.

15 That said -- so when you're saying I want to
16 learn from the training dataset, what does it mean?
17 You pass this training dataset to the network, so you
18 have to take into account -- take it into account in
19 the objective function. So every term in your
20 objective function has to use what you're passing.
21 It's not -- otherwise, you're not using it, so you
22 would not pass it. The way you learn is through this
23 objective function and taking what got passed and
24 putting that there. If you don't you do that, this
25 means you are not making use of this information you're

1 taking, okay?

2 So I guess that's the gist of it. If you
3 want, we can read, also, through more because it's
4 written much better in my declaration. So if you want,
5 we can go through it unless I answered your question.

6 Q Is an objective function an equation?

7 A The objective function, we want to optimize
8 with -- like, we express it as an expression. I
9 wouldn't -- I don't know equation -- like, equation,
10 something equals something -- it's a function, function
11 equals -- yes, I mean, this is like -- so we express it
12 in terms of the function that we want to optimize, but
13 that function takes whatever you're passing and you
14 want to use to learn.

15 It should be inside of it. If it's not inside
16 it, this means you're not learning from it, and you're
17 not using it. To learn you need to take into account
18 within the objective function of what you're passing to
19 learn from.

20 Q One type of an l2 -- strike that.

21 One type of an objective function is an l2
22 distance, right?

23 MR. STEIN: Objection; form.

24 THE WITNESS: You could use the l2 distance,
25 yes. Typically, this is used with other terms for

1 regularization. By itself, it's not very -- I mean,
2 you could use an l2 distance or several l2 distances
3 within an objective function, not only one. I mean,
4 you could make your own objective function.

5 What objective function you use definitely
6 would affect the learning of your network, so not only
7 the training data but what objective function you're
8 using and how you're making use of the training data
9 and other data to learn, yes.

10 BY MS. MOORE:

11 Q Is l2 distance an error term?

12 A L2 distance? In -- it depends on the context,
13 again. If I'm doing -- it's a distance, okay? You
14 could use it to quantify the loss, yes, you can.

15 Q Does l2 distance reflect the difference
16 between a synthesized output and a ground truth?

17 MR. STEIN: Objection; form.

18 THE WITNESS: I wouldn't, like, answer --
19 like, the question -- I mean, reflect in what way? You
20 decided to use it -- it doesn't -- depending -- I mean,
21 it depends what you're trying to reflect.

22 For example, let me give you an -- like, a --
23 for example, suppose you want to -- you synthesize
24 something, and it's noisy, okay? The l2 distance might
25 give you something, but it won't tell you where the

1 noise is. Maybe the noise is in the background rather
2 on the eyes you're trying to synthesize. You don't
3 care about the background. You care about the eyes.

4 The l2 distance doesn't give you this
5 information. If the nose is on eye, you care about it,
6 and you need to know it. So the l2 distance, if you
7 take just the l2 distance, it just tell you that it's
8 some noise, maybe, but you don't know where it is. So
9 it doesn't really reflect the real equality of this
10 entire picture. People use it sometimes for
11 mathematical convenience to reflect something.

12 BY MS. MOORE:

13 Q So do you agree or disagree that the l2
14 distance can correspond to the difference -- a
15 difference term between the output generated by a
16 machine learning model and the corresponding ground
17 truth?

18 MR. STEIN: Objection; form.

19 THE WITNESS: You could use l2 -- l2 as a
20 distance, so you do distance, and you decide, I want to
21 use this as an error term. Is it good or bad? It
22 depends on the application, what you're trying to do.
23 It might not be a good error term. It can -- it
24 depends on the context, or it might be a good error
25 term. It depends on the context and the objective you

1 want to achieve.

2 BY MS. MOORE:

3 Q So I just want to ask it again to make sure I
4 understand. Do you agree or disagree that the l2
5 distance can correspond to a difference term between
6 the output generated by a machine learning model and
7 the corresponding ground truth?

8 MR. STEIN: Objection; asked and answered.

9 THE WITNESS: So the output, it can be between
10 any two things. It doesn't have to be necessarily --
11 you could take -- I want to use that to compute a
12 difference, and I want to use it as my performance
13 measure. You could. I mean, any two things, you could
14 decide to use it as you're saying if you want.

15 BY MS. MOORE:

16 Q When do you assess the objective function? Is
17 it during training or runtime?

18 MR. STEIN: Objection; form.

19 THE WITNESS: Okay. Definitely during the
20 training, you need the objective function. This is
21 definite. You need to -- the objective function to
22 train your network. Typically, we need something to
23 optimize our networks, you know, and, typically, we use
24 these objective functions or cost functions or gain
25 functions, whatever you want to call them.

1 Now, during deployment, a lot of time, you
2 want to assess the performance of your network, also,
3 to assess how well it is doing. So sometimes you could
4 be -- for known data, you could be testing it and
5 trying to assess its performance. And maybe if you see
6 that it's deviating from the performance you want, you
7 might want to retrain it or fine tune it or so forth.

8 So it depends, again, on the objective and
9 context of the question. Typically, if you just want
10 to run the network without assessing it at all, you
11 could be just running it and not using any term,
12 because you don't care about assessing your performance
13 and improving the network or getting feedback. So it
14 depends, again, on the application.

15 BY MS. MOORE:

16 Q Let's look at paragraphs 56 and 57 of your
17 declaration, which is Petitioner Exhibit 1003, and that
18 would be pages --

19 A Okay. Excuse me.

20 Q -- 33. Let me know when you get there.

21 A Okay. So paragraph 56 and 57?

22 Q And 57, yes. Are you there?

23 A Yes, yes, I am there.

24 Q Okay. You say here that Microsoft has long
25 been a pioneer in gaze correction research, and then

1 you cite to a 1999 article from Microsoft, a 2000, a
2 2002 and a 2017.

3 Do you see that?

4 A Yes. So 1999. I have 2000 in here. And in
5 57, there is a 2002, and then 2017, yes, that's right.

6 Q You have not opined that any of these
7 Microsoft publications listed in 56 and 57 invalidate
8 the '985 patent, right?

9 MR. STEIN: Objection --

10 THE WITNESS: My grounds, you know, that I
11 relied upon. You have my grounds, and these, like, are
12 not the main references used in the grounds. I believe
13 some are supportive references. We have to -- I don't
14 want to answer from memory.

15 In addition to my main references, I used some
16 secondary references but just, like, to support an
17 application or something, so these were not the main
18 references in my grounds. I agree with that.

19 BY MS. MOORE:

20 Q Were they any of the references in any of your
21 grounds?

22 MR. STEIN: Objection; form.

23 THE WITNESS: Excuse me. I'm not sure. I
24 can't answer from memory. I have to look because,
25 like, it's a big -- in here, we had grounds, and we

1 have a lot of references and exhibits. So we used some
2 secondary references.

3 You know, I don't have the electronic version
4 to do the search to see if these were, like, mentioned
5 even in any of these grounds later. So we could -- I
6 could, like, if you want, go and look in my declaration
7 if you want to give me the time.

8 BY MS. MOORE:

9 Q Well, did you list the grounds anywhere in
10 your declaration?

11 A Excuse me?

12 Q Did you list the grounds anywhere in your
13 declaration?

14 A What does that mean?

15 Q You said you wanted to look through the
16 grounds to see if they were in there. Did you list
17 them anywhere?

18 A I have in my table of content the grounds
19 listed with which pages they start. So is this the
20 question?

21 Q Yes.

22 A Yeah. I have the grounds, like, in the TOC.
23 For example, you have like -- yeah, so, basically,
24 starting from page 53, you know, and then going further
25 on until, basically, the concluding -- through 208. So

1 these are where I discuss the grounds in my
2 declaration.

3 Q So the prior art that forms your grounds is
4 Chalom, Ganin, Aslan, Grau, Pace and Liu.

5 Do you see that in your TOC?

6 A Yes, I see those in my TOC.

7 Q And those prior art references are not any of
8 the ones cited in paragraph 56 or 57, right?

9 A In the TOC. But, for example, if we go -- let
10 me -- I'll show you an example what I mean, okay, so
11 that we are...

12 I recall we cite other references while
13 discussing the ground. They're not like the one -- but
14 we cite them as examples. So let me just, like, try to
15 look to give you an example of what I mean.

16 Yeah, for example, just to give you an example
17 what I mean, like, on page 203 of my declaration,
18 paragraph 383, but page 203.

19 Q Okay.

20 A Are you there? Yeah. So if you look at
21 page 203, for example, the second sentence there, like,
22 I write (as read):

23 "It was when known that high-quality
24 gaze correction often involves texture
25 blending, which often involves

1 filtering and brightness adjustment."

2 And with respect to blending, of course, I
3 give other exhibits. Do you see Exhibit 1037, 1038,
4 1039, 1058?

5 Do you see that?

6 Q I do.

7 A Yeah. So these are not like the one you
8 mentioned based on ground, but like we do -- like, I do
9 here mention other exhibits just, like, supportive,
10 saying this was well known or something, you know, so
11 that's what I meant, yeah.

12 Q But none of the references that you list in
13 paragraphs 56 or 57 are mentioned anywhere else in your
14 declaration --

15 MR. STEIN: Objection.

16 THE WITNESS: You can do a search if you want.
17 I don't recall from memory. I know they're listed
18 there since we looked at them, though, but I cannot
19 tell you -- I don't remember from memory this.

20 But maybe for you, it would search -- you'll
21 be able to see. I don't have now the electronic
22 version. I could look in my grounds and -- but this
23 will take some time, I guess.

24 BY MS. MOORE:

25 Q Sure. Let's look at your table of contents.

1 A Okay.

2 Q Your first opinion is that the asserted claims
3 are anticipated by Ganin. Ganin is not any of the
4 references listed in paragraph 56 or 57, is it?

5 A Yeah. So to answer your question a different
6 way, I mean, if this will satisfy, if we look in the
7 TOC as part of the grounds here, in the TOC, they are
8 not mentioned.

9 Q And none of the references in paragraph 56 or
10 57 form any of your grounds for invalidity, right?

11 MR. STEIN: Object; form, asked and answered.

12 THE WITNESS: I mean, based on my TOC, my main
13 reference are Ganin, Ganin in view of Liu. Let me see
14 here. Yeah. And then I have Aslan, Chalom and Grau,
15 Pace from the TOC. These are the main and secondary
16 references in here. Some other things are listed as
17 supporting some other statements like as we saw.

18 BY MS. MOORE:

19 Q So I think my question is much simpler here.
20 None of the references in paragraph 56 or 57 of your
21 declaration form any of the grounds of invalidity in
22 your declaration, right?

23 MR. STEIN: Objection; form, asked and
24 answered a couple times.

25 THE WITNESS: Per the TOC, I guess, looking at

1 the TOC, these are not there, but, you know, I mean,
2 they're not the main for the invalidity of the ground,
3 yes. I mean, if you want that, whether I referenced
4 them somewhere there, I'm not sure. I have to look.
5 Like, I showed you the example why I was saying that,
6 like, to just -- yeah.

7 BY MS. MOORE:

8 Q Well, the example you showed me wasn't a
9 reference to any of the references in 56 or 57 either.

10 A Yes. I'm showing you that we do -- I do cite
11 some other references other than the ones in the TOC
12 that I base my ground on that we have supporting
13 reference for some statement. And that's why I can't
14 tell out of memory whether I -- I cite those anywhere
15 other than here, you know, so I'm not sure.

16 Q So you think the USPTO got it wrong when
17 issuing the '985 patent over Ganin, right?

18 A You know, based on -- like, my opinion are in
19 my declaration, and, yeah, in view of -- this is
20 anticipated in view of Ganin as explained in my
21 declaration here, and I have other grounds, also, like
22 obviousness.

23 Q But you think the examiner was wrong when he
24 issued the '985 patent over Ganin?

25 A The examiner overlooked some things, yeah. I

1 disagree with the examiner.

2 Q It's your opinion that each of the claim
3 elements in the '985 are expressly disclosed in Ganin?

4 MR. STEIN: Objection; form.

5 THE WITNESS: In Ganin, they are disclosed,
6 anticipated by Ganin, disclosed in Ganin, expressly or
7 inherently. Like whatever -- like, I discussed this,
8 like, for each element in my declaration.

9 BY MS. MOORE:

10 Q Well, is it your opinion that they are
11 expressly disclosed or inherently disclosed by Ganin?

12 MR. STEIN: Objection; form.

13 THE WITNESS: For each claim -- I don't want
14 to do it out of memory, because like I -- in detail,
15 I -- for every element, I go through it. So if you
16 want to point me out to an element, because I don't
17 want to answer from memory in general sense and out of
18 context. So if you can point me to the specific
19 element, I could reorient myself, look in my
20 declaration and answer a question.

21 BY MS. MOORE:

22 Q Would you have said in your declaration
23 whether you were opining that the anticipation was
24 inherent or express for each claim element?

25 A I said it's anticipated by Ganin in here like

1 in paragraph 96. Each element is anticipated. And
2 then I go into each one of them, and, like, for
3 example, 1[P], Ganin discloses -- expressly discloses
4 that and so forth.

5 I mean, we can go through it and just see in
6 here. But here, it is expressly disclosed -- like, I'm
7 looking at some elements here so far. It says
8 expressly disclosed, so -- and we can go -- like, so
9 far, it's expressly disclosed. Yeah, so here, also
10 expressly.

11 Q So it's your opinion that Ganin expressly
12 discloses each of the claim elements of the --

13 MR. STEIN: Objection.

14 BY MS. MOORE:

15 Q -- '985 patent; is that fair?

16 MR. STEIN: Same objection for the question
17 asked previously.

18 THE WITNESS: Again, for each element, I'd
19 like to be more specific and not -- but for -- you
20 know, like, the elements -- from what I've seen so far,
21 but I didn't go through all of them, whatever I saw is
22 expressly disclosed. That said, I mean, if you can be
23 more specific, then we can go -- I'll orient myself
24 with my declaration and answer better your question.

25 BY MS. MOORE:

1 Q What's the difference between an express
2 disclosure versus an inherent disclosure of a claim
3 element?

4 A Okay. This is a legal question. I mean, I
5 know it myself, but using my own terms and to keep it
6 with the legal, I have -- I guess I put some legal
7 here. I'll see if it's there. If it's not, I'll try
8 to the best of my knowledge -- of my ability to express
9 it, basically, but I prefer, if I already wrote it
10 down, to go there. Let's see.

11 Okay.

12 THE REPORTER: Doctor, could I ask you to look
13 forward when you speak, please.

14 THE WITNESS: Oh, look forward? Okay.

15 THE REPORTER: Yes, so I can see you. Yes.

16 THE WITNESS: Yeah, like, it's hard with the
17 computer because -- okay. I'll try. Like, this is
18 fine?

19 THE REPORTER: Yes.

20 THE WITNESS: Yeah? Okay.

21 So if you go to -- like, this is Exhibit 1003,
22 paragraph 88. You see? So I wrote that (as read):

23 "I understand that anticipation of a
24 claim requires that every element of
25 the claim be disclosed expressly or

1 inherently in a single prior art
2 reference, in combination, as claimed.
3 I understand that a single prior art
4 reference may anticipate claims
5 without expressly disclosing a feature
6 of the claimed invention if that
7 feature is necessarily present, or
8 inherent, in that reference. I
9 understand that a reference is read
10 from the perspective of one of
11 ordinary" -- like a POSA, you know --
12 "at the time of the invention."

13 BY MS. MOORE:

14 Q What does it mean for a feature to be
15 inherently within a reference?

16 A For example, I'm drinking water here. I mean,
17 we know H2O -- water is H2O inherently present in here.

18 Q Can you give me another example? I'm not
19 understanding what you're meaning by that.

20 A For example, if somebody said, like, the claim
21 limitation requires hydrogen to be present, and
22 somebody mentions water, so the hydrogen limitation is,
23 like, inherently present in the water. Like, when I
24 say "water," hydrogen is there. You don't have to say,
25 Oh, they have to expressly say hydrogen. This is an

1 example.

2 Q What test did you apply for determining
3 whether a prior art reference inherently discloses a
4 claim element?

5 A You know, we have to be specific here,
6 because, again, I discuss each element of the claim and
7 how I did things and why I think this is the case. And
8 I wouldn't want to answer out of generality, because
9 each claim element is different.

10 And, again, as I told you, I don't want to
11 answer out of memory. Whether I had disclosed any
12 inherent feature here, I don't remember. It's
13 very -- it's already discussed in my declaration. So
14 if you point me out where I'm discussing this inherent
15 thing, I will be, then, happy to answer your question.

16 Q And I'm just asking what test you would
17 apply --

18 A You would?

19 Q -- to whether a prior art reference would
20 inherently disclose versus expressly disclose a claim
21 element.

22 A I mean, based on a POSA and based on the
23 understanding of the field and based on that like the
24 water, for example, in here. I mean, it's something
25 that -- inherent, I mean, as -- a POSA would know it's

1 inherent there. so this is the answer -- my answer to
2 this question.

3 Q So the test you applied for inherency was
4 whether a POSA would know it's inherent?

5 MR. STEIN: Objection; form, mischaracterizes.

6 THE WITNESS: I didn't say that, but this is
7 something that's, like, known, and definitely, a POSA
8 would know -- should know it's inherent, too, I mean,
9 yes. If it's inherent, the POSA should know that's
10 inherent. It is like a necessary but not sufficiently
11 necessary condition. I don't want to answer out of
12 context, so if it's something specific, I will be happy
13 to answer.

14 BY MS. MOORE:

15 Q Well, the tests that you apply would be
16 something you do for every claim element, whether it's
17 express or inherent, so I'm trying to just understand,
18 when you decided something one way or the other, what
19 framework you were applying.

20 A Again, like, I don't really quite understand
21 the question, to tell you the truth. And -- and if you
22 give me more specific, maybe this would orient me to
23 answer your question, but like that, I don't really
24 quite understand the question.

25 Q Well, did you just assume that every single

1 claim element was expressly present in each reference?

2 A No. You look for it. I mean, as a POSA,
3 like, you look at -- you know, especially from the lens
4 of the POSA, also, then you would need to -- it should
5 be expressly -- you would know that this is expressly
6 disclosed. I mean, if something is expressly
7 disclosed, you would know, okay, this corresponds to
8 that, and it's expressly disclosed, yeah, so...

9 Q And if you didn't find an element expressly
10 disclosed, what would you do next to decide if it was
11 inherently disclosed?

12 A It should be something that would necessarily
13 contain that feature.

14 Q Let's talk about Ganin. That's one of your
15 references that you rely on for a ground of invalidity
16 in your declaration, right?

17 A Yes, I did.

18 Q Ganin discloses a neural network, correct?

19 A Ganin discloses -- yeah, I mean, one or more
20 neural networks, a neural network, one or more neural
21 networks there. I mean, we -- I mean, in my
22 declaration, I point out at least -- he has two neural
23 networks there, at least.

24 Q So when I asked you if Ganin discloses a
25 neural network, you said Ganin discloses one or more

1 neural networks.

2 Do you recall that in your previous answer?

3 A Yeah. I'm going to point you out, also, to --
4 also, like, my declaration, I show this, and like in --
5 like, I show those in my declaration, also.

6 Q Right. Well, I mean, my question is that
7 Ganin never says it's one or more neural networks, does
8 it?

9 A According to my declaration, he does disclose
10 it's one or more neural networks. There's, like, at
11 least two neural networks there. I mean --

12 Q I mean, that's what you're saying, but Ganin
13 does not say that?

14 MR. STEIN: Objection; form. Objection.

15 BY MS. MOORE:

16 Q Ganin has not used the term "one or more
17 neural networks," does it?

18 MR. STEIN: Objection; form, asked and
19 answered.

20 THE WITNESS: Actually, I could point you out
21 in Ganin where. If you go to -- I mean, it is in my
22 declaration, and let me see if I can -- but if we go to
23 that Exhibit 1006, but the 1048, the one I -- this is
24 my -- the one I relied on, 1006.

25 One moment. If we go to page 18, again, this

1 is -- I'm not sure what I should say. Exhibit 1006 or
2 what here?

3 BY MS. MOORE:

4 Q Let's say 1048 since that's what we have in
5 the record right now and --

6 A Yeah. Again, I will say 1048, which was what
7 I relied on as Exhibit 1006.

8 So if we go to what's put in Exhibit B
9 under 1048, and we go to page 18 -- okay.

10 In the Figure 10 caption -- one moment in
11 here. So you could see, actually, (b) and (c), the
12 modules here, the .5 scale processing module, and,
13 also, you have the (c), 1 time scale processing module.
14 These are the two different neural networks, one
15 producing motion vector field at a more -- less dense
16 motion vector field and one more dense with a 1 time
17 scale.

18 But not only that, if you go to (d) in Ganin,
19 Ganin says both models have the -- this structure, the
20 neural networks, the two neural networks, the one in
21 the .5 scale and the one in the 1 time scale have the
22 same form, these convolution layers. And I have this
23 in my declaration, and it is in Ganin, also. So let go
24 me go to my declaration to point you out to where,
25 also, Ganin says that, basically.

1 Q Yeah, that's my point. I mean, I realize
2 that's what you wanted to say, but Ganin never calls
3 those "neural networks," does it? It says "processing
4 module."

5 MR. STEIN: Objection; form.

6 THE WITNESS: These convolution layers, you
7 know, I mean, these are neural networks, convolution
8 layers. You know, I don't want to answer from memory.
9 I discuss this in my declaration, so I want to -- just
10 give me a moment to orient myself and find that -- what
11 Ganin is saying, and I'm referring to Ganin and what --
12 where he's saying so, et cetera. One moment. I want
13 to find the right portion.

14 Okay. I refer you to page 64. This is
15 paragraph 112 of Exhibit 1003, but page 64. And so I'm
16 like -- you could see -- like, you see that in here --
17 okay. So I'm -- like, maybe let's start with the third
18 sentence (as read):

19 "According to Ganin, each of the two
20 processing modules is a machine
21 learning algorithm, comprising a
22 neural network having convolution
23 layers."

24 When you see convolution layers, and these are
25 two separate -- these are two separate neural networks,

1 but in addition, if we continue, you see page 17, and
2 there is a parentheses open? The architecture --
3 architectures, with an s, the architectures of the two
4 working modules, but the neural network here are same.

5 Why I'm putting of the convolution neural
6 network, because are same and are shown in Figure
7 10(d). This is a convolution neural network, and the
8 architectures are same, so each one, the architectures
9 -- the convolution layers are the same, and these are
10 two architectures here, and each one has a convolution
11 layer, convolution neural network.

12 And this is referenced in Figure 10(d)
13 clearly, these architectures being neural networks
14 that's in the .5 scale module and in the 1 time scale
15 module. And, you know, you could see that S is used
16 here, a plural.

17 So, yeah, indeed -- as a POSA, I mean, and
18 having also technical expert, indeed, Ganin is
19 disclosing at least two neural networks here.

20 BY MS. MOORE:

21 Q Okay. So when Ganin says it's a single
22 architecture, it's lying?

23 MR. STEIN: Objection; form.

24 THE WITNESS: I'm saying here that you cannot
25 take things out of context. So you can see now Ganin

1 himself is saying "architectures" here with an s, but
2 you're mentioning that Ganin, also, is saying "single"
3 also before.

4 I mean, an architecture can contain several
5 architectures within it, and you could say this is my
6 architecture that consists of ten neural networks
7 inside. Still, it's a -- it's like more complex
8 architecture.

9 It's like a set you put in another set, and
10 you have a bigger set, and you can have several sets
11 within a set. You could call them subsets. You could
12 still call them models. You could call them, still,
13 architectures there, and these, all together, they
14 comprise a bigger architecture and --

15 (Simultaneous speaking - unreportable.)

16 THE WITNESS: -- the context. Like, here, you
17 have s, architectures, so are -- you know, so -- and
18 before -- that's why we shouldn't take things out of
19 context.

20 BY MS. MOORE:

21 Q Single means one, right?

22 MR. STEIN: Objection; form.

23 THE WITNESS: One of what? You know --

24 BY MS. MOORE:

25 Q I'm asking you, what does single mean? It

1 means one, right?

2 MR. STEIN: Objection; form.

3 THE WITNESS: Single means -- okay. Single,
4 it depends on the context. Single can mean divorced or
5 married, and so it depends on the context and how it's
6 written and how a POSA would understand what is being
7 meant within the context that is being discussed.

8 And as a POSA, when you see here -- I just
9 showed you saying the architectures with an s here. So
10 you have two architecture within a system, and also, we
11 can call that system the architecture, whether -- you
12 know, and...

13 THE REPORTER: Counsel, when it's convenient,
14 may we take a break?

15 MS. MOORE: Sure. Let's just finish this last
16 couple of questions, and we can take a break.

17 BY MS. MOORE:

18 Q So your opinion, as a person of ordinary skill
19 in the art, is that single means more than one?

20 MR. STEIN: Objection; form, asked and
21 answered.

22 THE WITNESS: I already said that I don't like
23 to take something out of context. You know, I like to
24 be -- I also expressed my opinion that you could say an
25 architecture having architectures inside of it, and I'm

1 saying this is -- I put it in a single figure so I
2 could put things -- two architecture in a single place.
3 I can say "single figure." Yeah, it's one figure.

4 So saying single architecture does not -- does
5 not rule out many architectures within that bigger
6 single architecture. And I'm showing you here that
7 Ganin himself, if he mentioned single architecture
8 before, mentioning architectures with an s, later,
9 specifically, he's now discussing the neural networks
10 within that more complex architecture. And the neural
11 networks are architectures, because we have more than
12 one in there.

13 BY MS. MOORE:

14 Q And I think my question was a lot simpler than
15 the very long answer you gave.

16 As a person of ordinary skill in the art,
17 which you are, your opinion is that single means more
18 than one?

19 A I didn't --

20 MR. STEIN: Objection to the form, asked and
21 answered multiple times.

22 THE WITNESS: I didn't say that. No, I
23 disagree. I said "single." It should be within the
24 context. If one says "single figure," yes, it's one
25 figure. If one said "single system," it's one single

1 system, but the system itself can contain other
2 modules.

3 It doesn't mean -- it does not mean single
4 neural network if that is what you're -- like it does
5 not mean -- yes, as a POSA, single does not mean single
6 neural network, because it's not saying single neural
7 network. Ganin never said single neural network.

8 BY MS. MOORE:

9 Q Ganin also never says multiple neural
10 networks --

11 A He does. I just --

12 Q -- or the module is a network or that the fine
13 module is a network?

14 A I disagree. I showed you Figure 10. I
15 referred to Figure 10, and my discussion in the
16 declaration, it clearly shows that you have at least
17 two neural networks there, two convolution neural
18 networks, one belonging -- and they're separated even
19 there, even in Ganin.

20 And (b) is the first one with the convolution
21 network inside, and 10(c) is the second one, and
22 furthermore, Ganin uses the plural the architectures
23 are the same as shown in Figure 10(d), because we have
24 two of them, one in each module.

25 Q Yes. They're called modules, not neural

1 networks in Ganin, right?

2 (Simultaneous speaking - unreportable.)

3 MR. STEIN: Objection to form.

4 THE WITNESS: You see, these are not -- you
5 know, as a technical expert and a POSA, Ganin, also,
6 clearly shows that these modules have each one
7 convolution neural network architecture that -- he
8 shows it very clearly in 10(b), 10(c), and further
9 saying these share similar form.

10 BY MS. MOORE:

11 Q Ganin never calls the fine or coarse warping
12 module a neural network, does it?

13 MR. STEIN: Objection; form, asked and
14 answered at least ten different times.

15 THE WITNESS: I disagree. I don't want to
16 answer from memory. As a POSA, if I look at 10(c) and
17 I have a convolution layer, this is a neural network,
18 convolution layers. Any POSA you ask, any -- and I
19 challenge any POSA is not going to tell me convolution
20 layers is not a neural network.

21 I mean, this is written for somebody -- it's
22 not written for a layman, Ganin, okay? Convolution
23 layers, what is that? We just talked about it.
24 Layers, convolution, there is no other than a neural
25 network. Convolution layers means convolution neural

1 networks, period. This is 10(c). 10(b), you have
2 another convolution layers. That's another neural
3 network.

4 BY MS. MOORE:

5 Q And the words "neural network" do not appear
6 in any of those figures, right?

7 MR. STEIN: Objection to form.

8 THE WITNESS: Convolution layers is a neural
9 network. You don't have to necessarily put "neural."
10 Convolution -- I mean, it's more specific, because if
11 you put "neural network," neural network can be
12 anything.

13 It can be tutorial. It can be a recurrent.
14 It can be anything. Convolution layers is saying it's
15 the convolution neural networks. That's what it means.

16 BY MS. MOORE:

17 Q It doesn't appear anywhere in that figure,
18 does it?

19 MR. STEIN: Objection; form, asked and
20 answered now 11 --

21 THE WITNESS: Convolution layers means neural
22 network, okay? It's a special type of neural network.

23 BY MS. MOORE:

24 Q Do you see the words "neural network" in that
25 figure you're looking at?

1 MR. STEIN: Objection; form.

2 THE WITNESS: I see convolution layers, which
3 is a neural network, okay? And, also, I see the
4 diagram (d), which shows all the aspects of a neural
5 network including a conv 5 by 5 -- here, I need to use
6 my -- you see the conv 5 by 5, 16 maps, that's a known
7 neural network kernel.

8 Batch normalization, a known neural network
9 layer. ReLU, a known -- this is the nonlinear, also
10 known. Conv 3 by 3, 32 maps, known neural network
11 conversion, neural network layer. Batch normalization
12 again. ReLU again.

13 THE REPORTER: You're going too fast, Doctor.
14 Please slow down.

15 THE WITNESS: Sorry, sorry. So if you look at
16 (d), which is what conv layers are, you could see the
17 neural network structure, conv 5 by 5, conv 3 by 3 with
18 the batch normalization of each one of them, conv 3 by
19 3, all these layers, conv 1 by 1, et cetera, conv 1 by
20 1 --

21 THE REPORTER: You're reading too fast,
22 Doctor.

23 THE WITNESS: Okay. So you could see the -- I
24 apologize for reading fast.

25 So Figure 10(d), you could see the

1 structure -- the convolution that's known. It's a
2 known -- very much known by all POA of the structure
3 of a convolution neural network consisting of a conv 5
4 by 5 layer, the 16 maps, then followed by conv 3 by
5 3 -- conv is c-o-n-v -- followed by ReLU, which is the
6 nonlinear function, followed by another conv 3 by 3
7 layer, followed by, also, the conv 1 by 1 layer and,
8 also, conv -- another conv 1 by 1.

9 So several convolution layers, and this is
10 specific, and the neural network -- that's the neural
11 network convolution -- known convolution neural
12 network. I mean, I -- no POA would tell you this is
13 not a neural network.

14 BY MS. MOORE:

15 Q And my question is very, very simple. Figure
16 10, the words "neural network" do not appear anywhere
17 in it, do they?

18 MR. STEIN: Objection; form, asked and
19 answered 15 times.

20 THE WITNESS: Whether they appear or not,
21 that's the convolution -- convolution layers is a
22 neural network. It is known, and if I was Ganin
23 writing this paper -- this is like -- I would put conv,
24 also, like that because this is for the technical
25 people.

1 When you are writing a technical document, you
2 don't want to put things that are -- you're writing a
3 figure. You want to put something that's more
4 illustrative. You want to put that's the convolutional
5 layer here rather than saying NN. And it's known.
6 Conv layer is like -- conv layer is a neural network.
7 That's what I'm saying.

8 It's like -- like, to give an -- I don't
9 know -- an example, I mean, if this is a technical
10 document, writing NN doesn't fit the purpose of -- we
11 need to know what this neural network is, so we use the
12 conv layers to explicitly disclose the convolution
13 neural network, okay? I will stop here, I guess.

14 MS. MOORE: I think, Nadia, did you need a
15 break?

16 THE REPORTER: Yes, please.

17 (Recess.)

18 BY MS. MOORE:

19 Q Dr. Karam, you understand you're still under
20 oath?

21 A Yes.

22 Q Let's look at Figure 4 of Ganin, if you would,
23 and let me know when you get there.

24 A Okay. Do you want me to -- okay. Figure 4,
25 Ganin. This would be Exhibit 1048. The Exhibit 1048,

1 like, which is Exhibit 1006 that I -- just to -- and
2 then I'm going to page 8 that is Figure 4?

3 Q Yes. Are you there?

4 A Yes.

5 Q On the right-hand side of Figure 4, do you see
6 that it contains an example of two training pairs?

7 A Yes.

8 Q The upper images are the input images, and the
9 lower images are the output images, right?

10 A Yes.

11 Q What is meant here by input image?

12 A This is within the context of the training
13 dataset, okay? So that's the input image that's going
14 to be input, and then you have the desired ground truth
15 if I take it in the context of training dataset, which
16 is the bottom.

17 Q And there's only one ground truth per input,
18 right?

19 MR. STEIN: Objection; form.

20 THE WITNESS: It depends on the context.

21 Actually, even Ganin and others -- typically, for the
22 same subject, you can take several images, and you
23 could assign the same ground truth to it. So,
24 basically, the same subject can be looking left, right,
25 top, bottom, and the same ground truth -- like, each

1 one of these would have the same ground truth.

2 BY MS. MOORE:

3 Q In Figure 4, there is one input and one
4 associated ground truth, right?

5 A That's an example.

6 MR. STEIN: Objection to form.

7 THE WITNESS: That's an example, yeah. That's
8 an example.

9 BY MS. MOORE:

10 Q Do you see any other ground truths here
11 besides the two on the bottom of Figure 4?

12 MR. STEIN: Objection; form.

13 THE WITNESS: I mean, in Figure 4, they show
14 two sample pairs of training data. One, they call an
15 input and one corresponding ground truth, you know.

16 BY MS. MOORE:

17 Q And what is a ground truth?

18 A I mean, here, it's not output image on the
19 bottom but two training pairs. And, again, in Ganin,
20 if you look at Section 4.2 on the same page, "Training
21 Procedure," okay, and the ground truth or GT.

22 And you see they use an objective function,
23 also, to assess the performance after -- this is gaze,
24 like, correction, so to assess the performance of
25 obtaining the ground truth, whatever it is, so how far

1 you are from the ground truth.

2 Q Is the ground truth the desired output?

3 A Desired output, yes, that's right.

4 Q How does having bad training data impact the
5 function of a machine learning algorithm?

6 A Bad training data?

7 Q Correct.

8 A Define bad. Just one moment.

9 Q It doesn't do a good job of training the
10 machine learning algorithm.

11 A So I believe you're answering the question,
12 then.

13 Q What would be the output of a poorly-trained
14 machine learning algorithm?

15 MR. STEIN: Objection; form.

16 THE WITNESS: Okay. I mean, there are
17 different -- poorly is relative, you see? It's
18 relative to what your objective is, okay? So there are
19 different performance metrics in machine learning. One
20 of them is to know whether the net -- what the machine
21 learning generalizes to unseen samples, and if you
22 train on a training dataset, it does really well on the
23 dataset.

24 But then you like it to -- usually, in
25 deployment, you like it to operate on samples that are

1 unseen that were not part of your dataset. And if it
2 doesn't perform well on these unseen samples, that can
3 be taken as poor performance, you see, so there are
4 different metrics. So this records generalization
5 performance. We want to -- typically, we'd like our
6 machine learning to generalize to unseen samples.
7 That's one of them.

8 So doing well on the training dataset doesn't
9 mean it's going to do well for the task. And this
10 depends on the -- your objective function that you use,
11 on the network structure that you use, on the active
12 parameters that you use. The training dataset is not
13 everything, many things.

14 So you could be doing real well on the
15 training dataset, but you don't generalize not only
16 because of your training dataset, because of many other
17 factors, not using the right objective function, not
18 using the right structure that can perform your task,
19 so the structure of the network itself and the training
20 dataset, whatever you want to train, on should be
21 representative of the task that you want to operate.
22 So there are a lot of factors, so it's not a single
23 answer to your question.

24 BY MS. MOORE:

25 Q So what would be the first step to improve the

1 performance of a machine learning algorithm that is
2 performing poorly on unseen data?

3 MR. STEIN: Objection; form.

4 THE WITNESS: There are different -- it
5 depends on the architecture. And there are different
6 ways to, basically, improve on the network performance.
7 I do talk about the generalization here, and the
8 underfitting in my declaration, by the way. And I
9 guess under the -- like, maybe page 14. Let's see.

10 THE REPORTER: What did you say? "Maybe"
11 what?

12 THE WITNESS: Page 14, I believe, like, maybe
13 that's the section that I -- this is where I discuss,
14 like, this aspect, underperformance and so forth.

15 Yes. So if you go to, for example,
16 paragraph 30, 30 of my declaration on page 15. So
17 paragraph 30 (as read):

18 "When training a machine learning
19 model, it is important not only to
20 achieve a small error on the training
21 dataset set but also to ensure that
22 the trained model can generalize to
23 unseen data samples."

24 This means data samples not included in this
25 part of the training.

1 So the generalization of the model is tested
2 by deploying the trained model on unseen samples like a
3 testing dataset or validation dataset that you use that
4 you didn't -- that you did not choose for the training
5 and checking that the testing error is small enough,
6 and you check that -- you want to ensure the gap
7 between the training error. So you have a training
8 error, maybe, that small, but important -- the gap, how
9 far is the testing error from it?

10 To have a small gap in addition to a small
11 training error is very important. And otherwise, if
12 you have a very small training error but the testing
13 error is wide, this is called overfitting. You're
14 doing really well on your training set and overfit it
15 because you have -- versus, like, the testing set,
16 you're not.

17 So it does not generalize. However, you can
18 have a large training error also on the training set.
19 This means underfitting. The model is not able to fit
20 well the training dataset.

21 And these -- both of these should be avoided,
22 okay? And I'm saying, how can this -- like, examples
23 of these, how can -- that if we continue on the next
24 page, same paragraph (as read):

25 "This can be done by running the

1 training process through more
2 iterations or restarting" --

3 You can restart the training with different
4 initialization of the weight or some hyperparameters
5 change by tuning the model hyperparameters, and you
6 restart, and -- the training process or even adding
7 more layers to the network.

8 So, typically, you have some training data
9 that represent your task. And sometimes you have very
10 good training data, but the network structure cannot
11 sometimes fit because maybe the network structure can
12 underfit, because it cannot learn that training
13 dataset, because the structure of the network is not
14 really compatible.

15 Maybe it's too small to learn it. You need a
16 bigger network because you have a pretty good training
17 dataset. So it's not -- so many factors there. So you
18 don't really just, like, no, increase my training
19 dataset. No, it doesn't work this way. Suppose you
20 have a good training dataset. Still your machine
21 learning might not perform well.

22 BY MS. MOORE:

23 Q So the ways to improve a poorly-performing
24 machine learning algorithm are described by you in
25 paragraph 30, starting on page 16 at the "This can be

1 done" sentence; is that correct?

2 A Well, some examples, I'm saying. I'm not
3 like -- it's not exhaustive. It's like example of how
4 you could improve, okay?

5 Q But these are the ones that came to your mind,
6 right?

7 MR. STEIN: Objection --

8 THE WITNESS: These are perfectly -- these are
9 the minimum things you need to do.

10 BY MS. MOORE:

11 Q That's where you would start?

12 MR. STEIN: Objection; form.

13 THE WITNESS: No. I'm saying, at least, like,
14 do these things. Definitely, it's no-brainer that you
15 need a good training set to start that's representative
16 of your task because -- in addition to all of this
17 stuff in here, so this is no-brainer.

18 We're assuming we have a good training
19 dataset. And even so, your network -- your machine
20 learning might not be doing well because you're not
21 using the right objective function, you're not using
22 the right hyperparameters, you're not using the right
23 initialization. Maybe you're not using the right
24 structure.

25 For example, in Figure 10(d) of Ganin, Figure

1 10(d) of Ganin, you could see several convolutional
2 layers there, conv 5, 5; conv 3, 3; conv 1, 1, and you
3 have two conv 1, 1. How many layers you need to put,
4 you know? How many? So maybe one layer versus two
5 versus three versus ten, this can affect the
6 performance in terms of underfitting and overfitting.

7 MR. STEIN: And just one reminder,
8 Dr. Karam -- sorry, Ashley -- but just give me a couple
9 seconds to object just to make it easy for the court
10 reporter.

11 THE WITNESS: Yes. Thank you.

12 BY MS. MOORE:

13 Q I know it's hard, and it feels like a
14 conversation, and pausing is unnatural.

15 Let's look at Figure 7 for a minute, and let
16 me know when you get there. Figure 7 of Ganin, which
17 is -- I guess we'll call Exhibit 1048 for now.

18 A Okay. Figure 7 of Ganin. And let's see.
19 Okay. So Figure 7, this is on page 12?

20 Q Yes. Are you there?

21 A Yes. Kind of I have a challenge here because,
22 like, when I'm holding the binder like that, it hides
23 my microphone, so it's hard. Like, I want to tilt like
24 that, and -- so it's, like, a little bit challenging.
25 Okay.

1 Q If you'll look at the -- I guess I'll call it
2 the headings that are right above the figure that forms
3 Figure 7. Do you see those?

4 A Yeah. I see those, but -- yeah, I have to
5 remind myself what the short names -- you know, they
6 are defined in here, so I have to see where Figure 7 is
7 discussed, you know, and -- one moment. And these
8 short notations -- yeah. For example, if you look, can
9 we -- can I say something?

10 Q Sure.

11 A If you look at Section 4.3, there, the models
12 are listed, so I'm defining these shorthand notations.
13 I didn't memorize them. That's why, yeah. Okay. So
14 yeah, now, I mean, with this in reference, Section 4.3
15 and Figure 7, okay?

16 Q So tell me what is meant by "Input" in
17 Figure 7.

18 A Okay. Yes. So input is the input image we
19 want to process by the system.

20 Q And then the next column over, it says "RF."
21 What does that mean?

22 A RF. One moment. Oh, yeah, I mean, this is
23 like random forest. So it's compared with an existing
24 technique based on random forest.

25 Q So RF reflects the output of a random forest

1 based model to correct the gaze; is that fair?

2 MR. STEIN: Objection; form.

3 THE WITNESS: Yes, so RF is a system -- you
4 know, a prior art system. It's Reference 16, so let's
5 see 16 here. One moment. In that -- yeah, learning to
6 look up, you know, so this is -- we have this as one of
7 the exhibits, also, this Kononenko.

8 So it's comparing with the system that's
9 incorporate, integrate a random forest structure
10 classifier, so it's a component in that whole system,
11 yeah.

12 BY MS. MOORE:

13 Q But the picture there under "RF," that
14 represents the output from the random forest system,
15 right?

16 MR. STEIN: Objection; form.

17 THE WITNESS: Random forest based system.
18 Just like if you recall, remember when I pointed you
19 out to -- just like for the record, I pointed you
20 out -- and we can look at page 175 in my declaration,
21 Exhibit 1003. This is like Figure 3 in Chalom. See
22 that? So page 175, Exhibit 1003, paragraph 328.

23 BY MS. MOORE:

24 Q Right. My question is simply that that's the
25 output, the picture there of the eye. It's the output?

1 A Yeah, but what I want to say, the random
2 forest doesn't output the corrected one. If you look
3 at Figure 3 of Chalom, for example, it's outputting the
4 displacement field, the flow. Then you have another
5 module or an integrated with output, the ECCI, which is
6 the corrected eye.

7 So, yeah, I mean, that's the output, not
8 necessarily, however, of the random forest classifier.
9 I just want to make sure we are -- so it's an output of
10 the system that incorporates a random forest, just
11 to -- yeah, okay.

12 Q What does "CFW" mean in Figure 7?

13 A So this is the coarse-to-fine warping. Like,
14 the system incorporated the coarse warping module and
15 the fine warping module of Ganin in cascade.

16 Q And it's the output of the Ganin system,
17 right?

18 A It is the output --

19 MR. STEIN: Objection to form.

20 THE WITNESS: Here, it's showing, yeah, the
21 cascade.

22 MR. STEIN: Objection; form on the last
23 question.

24 BY MS. MOORE:

25 Q And "+LCM," what is that one in Figure 7?

1 A Yeah, I know what that is, but I don't want to
2 do it from memory. This is the light correction
3 module. So you could -- that's again -- I mean, you
4 could also cascade a light correction module that would
5 improve the performance of the system or -- you know,
6 yeah.

7 And this actually -- the light correction
8 module can be implemented using a nonneural network.
9 And this is disclosed -- I discussed this in my
10 declaration, that this module, LCM, can be done using a
11 neural network off the top.

12 So now we have three neural networks: The
13 coarse neural network, the fine neural network and the
14 light correction module, which can also be done using a
15 neural network, as discussed in my declaration.

16 BY MS. MOORE:

17 Q And "GT" in Figure 7, what does that stand
18 for?

19 A The desired output that you like to achieve.

20 Q The objective function would then be measuring
21 the difference between the GT and whichever of these
22 outputs we were interested in; is that fair?

23 MR. STEIN: Objection; form.

24 THE WITNESS: Not really. I mean, it depends.
25 Not only this. This can be a term, but, also, usually,

1 we add other factors in the objective function,
2 regularization factors, not only the ground truth.

3 And this -- plus you might want to also -- for
4 example, in a student-teacher architecture, you might
5 want to add a term that makes sure that the student
6 output matches. The output can be, again, the vector
7 displacement field, the pixel flow, not the actual
8 image. So you want not only the ground truth, but you
9 want the flow that's predicted by the network to match
10 the teacher network, for example, as I discuss in my
11 declaration.

12 So you can have a term there that you want to
13 minimize the distance between those if you pass this
14 information. If you're passing information from the
15 teacher and you wanted to -- and you want to use this
16 information to teach the student, you have to then
17 include it somehow in your optimization. And,
18 typically, this is a term in your objective function,
19 so you take it, and you try to minimize the distance.
20 That's how you learn.

21 Otherwise, if you don't take it into
22 account -- so here in Ganin, I mean, he discusses,
23 typically, the objective function can be done to
24 train -- you incorporate in the objective function the
25 terms that you want to optimize, basically. You see?

1 And if you want to optimize the flow of the
2 first model, the coarse module, you want to
3 incorporate, also, that you are within the limitation
4 of the structure. That's saying, I want -- I don't
5 want to have a dense pixel flow. I want to have
6 coarse, but still, do your best to approximate my
7 ground truths. You have to give the ground truths
8 there, too.

9 So that first network, you have to give -- I
10 want to get these ground truths within my constraint of
11 having a coarser flow. Same thing for the fine. You
12 say, I want to know -- also, estimate the ground truth
13 given now that I can have it finer.

14 In both of them, you have to incorporate your
15 task so that you optimize your network, and you pass
16 this in the objective -- in the training -- you have to
17 account for both in the training because you would like
18 them to estimate the network that would best match the
19 ground truths, but given the constraints that here I
20 want to have less dense, here I want -- flow, here, I
21 want to have higher dense flow. I'm not sure if I'm --
22 can you hear me well, by the way? I noticed my binder
23 was on top of the mic. Maybe is this --

24 MS. MOORE: Yeah. We -- we can hear you.

25 THE WITNESS: Okay. Thank you. So -- so that

1 objective function can take different forms, you know,
2 where -- but when you are training your network to do a
3 task, you have to optimize it based on the desired task
4 plus the constraint to make sure you incorporate prior
5 knowledge that can help your task. Because
6 optimization has various solutions.

7 And a lot of times these do not convert to
8 global minimum, for sure. It's always finding a -- a
9 local minimum. You want to direct it to your problem,
10 to your task. So a lot -- so you have to incorporate
11 other constraint to make sure it directs to the right
12 minimum that's more -- can achieve the more desired
13 solution.

14 And this is what we discussed. For example,
15 teacher-student helps to have a teacher pass
16 information, because you can incorporate this also in
17 the training. And this would be one term of your
18 objective function, saying, okay, use this information
19 to more direct the learning, for example. I don't know
20 if this answers your question.

21 BY MS. MOORE:

22 Q I mean, it was, like, a four-minute answer, so
23 who knows.

24 My question next is, the objective defined
25 function in Ganin, that is shown as equation 7 on --

1 let's see -- in section 4.5, page 13 of Exhibit 1048,
2 right?

3 A Okay. I'm going there. Just one moment. One
4 moment.

5 This is an improvement, he said, by
6 incorporating more to adjust alignment. It's not part
7 of the original system. That's what actually is being
8 said here. We found that result can be further
9 perceptually improved. See 4 also. Yeah, if the
10 objective is slightly modified to take into account.

11 So -- so here, he's showing something that --
12 not part of maybe -- what I understood here -- because
13 it's calculated later. Figure 7 was produced not using
14 this function. Does this make sense? Because this was
15 later discovered. And we found further improvement and
16 see the results there. That's how I take it. So it's
17 not, per se, the -- the objective function being used
18 to produce the result in Figure 7 based on the
19 discussion here.

20 And based on the fact that Figure 7 -- based
21 on the fact that Figure 7, where the -- like, if Figure
22 7 was discussed before, which it was, I guess, no?
23 Yeah, so 4.4, Figure 7 was discussed.

24 And then 4.5, say, oh, we can do this also to
25 further improve. So this is not the function that was

1 used -- the function that was used to generate the
2 Figure 7.

3 Q Does Ganin give the objective function that
4 was used to generate Figure 7?

5 MR. STEIN: Objection -- (Simultaneous
6 speaking - unreportable.)

7 THE WITNESS: Okay. I'm sorry.

8 MR. STEIN: Yeah, objection; form.

9 Thank you.

10 THE WITNESS: Okay. So under the training
11 procedure, you see if you look at section 4.2, second
12 sentence (as read):

13 "We used a regular l2 distance between
14 synthesized output and the ground
15 truth as the objective function. We
16 tried to improve over this simple
17 baseline in several ways."

18 So they tried different variations, according
19 to here, to put emphasis on the actual eye region. So
20 it's more weighted towards the eye region versus -- so
21 it's a weighted approach to adjust the distance. But
22 they said this weighting did not get any significant
23 improvements.

24 Also, they tried adversarial loss. That's
25 what I'm talking about. You can have these terms,

1 "adversarial loss" added, et cetera. It was also
2 inconclusive, as the residual flow predicted by the 1
3 x-scale module tends to be quite noisy. (as read):

4 "We attempted to smoothen the
5 flow-field by imposing a total
6 variation penalty."

7 You know, so you see, so you try to regularize
8 by putting these regularization terms. It happens when
9 they got these results, whatever regularization terms
10 they used here, like total variation for them -- I
11 mean, I have the stamp of the Microsoft on this, so I
12 cannot read this.

13 But anyhow, this total variation penalty was
14 not maybe the best they used. So they said, okay, the
15 l2 loss was worse; however, this doesn't imply the
16 perceptual quality was worse. So that's what I was
17 trying to say. l2 is the distance. It doesn't
18 necessarily reflect the perceptual quality of the
19 synthesized image.

20 So the total variation resulted in a higher --
21 higher, basically, l2, but I don't know if it was
22 better perceptually. I -- they don't talk about that.
23 But this is what I'm talking -- I mean, in my
24 declaration, by the way, I talk about this noisy field
25 and ways to approve it using also prior art that it

1 would be -- that would be by incorporating other
2 things, because here they're trying to improve it by
3 doing these regularization term.

4 The total variation did not work for them.
5 Other things would work. So if we want to take to the
6 minimum at least, they have a term that's based on l2
7 and the l2 based on this distance between the synthesis
8 output and the ground truth, okay?

9 BY MS. MOORE:

10 Q Do you agree that the '985 patent claims
11 require that both MLAs use the same training data?

12 MR. STEIN: Objection; form.

13 THE WITNESS: Yeah, based on the claim, to my
14 recollection, it requires using the same training data
15 based on my recollection, okay? And we can see -- I
16 mean, let me check, because I do have the claim
17 elements, no, in here.

18 And we can look at either one or my
19 declaration, I understand. So I'll go to my
20 declaration, because it's handy. One moment.

21 I'm going to go to page 53 of my declaration,
22 Exhibit 1003. There, we have -- on page 54, we have
23 the claim elements listed, okay? Okay. So if we go to
24 claim element 1[D] on page 54, and this is claim 1 --
25 one element of the '985 patent, okay? (As read):

1 "Using a first machine learning
2 algorithm to generate first reference
3 data using the training data."
4 Then if you go to 1[E], claim element 1[E] (as
5 read):
6 "...using a second machine learning
7 algorithm to generate second reference
8 data using the same training data as
9 the first machine learning."

10 BY MS. MOORE:

11 Q So was that a yes, both MLAs of the '985
12 patent claims used the same training data?

13 A Based on here, yeah, the claim elements.

14 Q You applied the plain and ordinary meaning to
15 the '985 patent claims in your analysis, right?

16 A Yes.

17 Q I'm sorry. You broke up. What did you say?

18 A Yes, yes. Maybe it is my mic again. I don't
19 know.

20 Yes. Yes, I did.

21 Q What is the plain and ordinary meaning you
22 applied to the '985 patent term "training data"?

23 A Training data is data that's used for
24 training. And in the context of machine learning,
25 for -- for training the machine learning algorithm so

1 that it learns how to perform a task.

2 Q What is the plain and ordinary meaning you
3 applied to the '985 claim term "input patches"?

4 A And within the context by the way, I would
5 like just to put this in context. The claim element
6 1[A] starts "receiving data comprising," you see,
7 "input patches."

8 So the set of input patches according to the
9 '985 claim elements are part of the training data,
10 okay? And these patches, input patches -- and I talk
11 about this, by the way, in my declaration so -- because
12 there it's very well -- because I discuss it, so that's
13 what I applied. So -- but you want like in the context
14 of just the claim elements or what?

15 Q Yes. I'm just trying to understand the plain
16 and ordinary meaning you applied to the term "input
17 patches."

18 A Okay. Okay. I mean, taking the specification
19 into account and everything, you know -- I mean, we
20 have to take this, too -- because if you look, "input
21 patch," is it a Band-Aid patch here? It's not. I
22 mean, because there is no image being -- you see if you
23 look at the claim element, you don't see the word
24 "image" there, no?

25 But per the specification, this guide doesn't

1 orient us to input patch being here, input patch a -- a
2 visual representation from the spec. It's not like a
3 Band-Aid patch, okay? So taking the specification as a
4 context, okay, the input patch would be an image
5 region, okay, that's being input. That's to be input
6 into a system.

7 Q What is the plain and ordinary meaning you
8 applied to the '985 claim term "target feature"?

9 A Again, taking the specification into account,
10 the specification of the '985 defined "target feature"
11 to be a specific -- and I talk about this in my
12 declaration.

13 But it is like a portion of this had
14 representation. Some example is given, and I will tell
15 you where because -- to be more -- to validate.

16 If you go to -- one moment. Yeah. For
17 example, claim 18, for example -- and there is another
18 one, but this is -- claim 18. If you go to page 98 of
19 my declaration, so Exhibit 1003, page 98, you could see
20 there claim -- element 18[F] (as read):

21 "Wherein the target feature comprises
22 an eye region comprising at least part
23 of an eye of the adjustment of the
24 digital representation of the head."

25 And then continues can be a nose region, et

1 cetera.

2 So target feature by itself if it wasn't
3 defined in the specification, it would be like
4 indefinite, you see. It would be ambiguous by itself.
5 But because in light of the specification, in light of
6 disclosed also, it's understood to be what is being
7 disclosed here like an eye region. So a portion of the
8 head, nose region, chin, so forth, okay? Neck region,
9 head region.

10 Q What's the plain and ordinary meaning you
11 applied to the '985 claim term "output patches"?

12 A Okay. So given that this is the training
13 data, okay, and, you know, and it said "input patches,"
14 "output patches," so the output are the ground truth
15 desired patch, how you want the -- you would like the
16 overall task, okay, by your system.

17 You would like the input patch -- whatever
18 your system, you'd like the -- the output of a system
19 or a subsystem that you're applying this to, you would
20 like it to estimate as closely as possible that output
21 patch.

22 Q What is the plain and ordinary meaning you
23 applied to the '985 claim term "first machine learning
24 algorithm"?

25 A I mean, when I see "first machine learning"

1 and "second," this means there are two machine learning
2 algorithms.

3 Q And what's the plain and ordinary meaning you
4 applied to the '985 claim term "machine learning
5 algorithm"?

6 A Machine learning algorithm, basically, I
7 define what a machine learning algorithm is in my
8 declaration, and it's the plain and ordinary meaning to
9 be here. So I'll refer you to machine learning,
10 page 11. It says (as read):

11 "Used a machine learning algorithm
12 also referred as machine learning
13 model is an algorithm that learns from
14 data to perform a task or a class of
15 tasks."

16 And I'm referring to -- here I reference the
17 Exhibit 1043, so what's -- one moment, so, yeah. I
18 mean, the reference is (indiscernible) book, textbook.

19 THE REPORTER: "The reference is" what?

20 THE WITNESS: I'm referring to a reference,
21 Exhibit 1046 [sic]. Yeah. Sorry, Exhibit -- I take it
22 out. Exhibit 1043. 1-0-4-3. I'm sorry.

23 BY MS. MOORE:

24 Q What's the plain and ordinary meaning of the
25 '985 claim term "first reference data"?

1 A Again, I mean, we have to go by what the
2 specification -- because if you just take "first
3 reference data" by itself, it will be indefinitely.
4 But in light of the specification and in light also
5 later, I mean, the limitation in the claim. If you go
6 to claim 1, I mean, again -- just one moment here.

7 If we go to page 53 of that Exhibit 1003, 53,
8 page 53. And 54, page 54. So you can see claim
9 element 1[F] (as read):

10 "Wherein the first reference data
11 comprised first editing instructions
12 for a range of possible configurations
13 of the target feature and first
14 selection instructions for selecting
15 editing instructions for a particular
16 input patch from the first editing
17 instructions based on the
18 configuration of the target feature of
19 the input patch."

20 In the specification, it gives examples of the
21 first editing instruction and first selection, et
22 cetera. So in preparing my declaration, I took all of
23 these into consideration, the specification, the claim,
24 also the -- yeah, the claim limitations, claim elements
25 and the limitation and also file history, relevant

1 portions there to see if anything was defined,
2 construed, et cetera.

3 Q So are you saying that the plain and ordinary
4 meaning of the term "first reference data" is editing
5 instructions for adjusting the digital representation
6 of the head region for a range of possible digital
7 representations of the head region?

8 MR. STEIN: Objection; form.

9 THE WITNESS: I mean, it comprised first
10 editing for the range of the target feature. Okay.
11 One moment. It -- no, I didn't say this. And I'm
12 reading here and it doesn't, like, say -- I mean,
13 reference data comprised editing and selecting
14 instructions.

15 And it's limited here, the editing
16 instructions for a range of -- representation of the
17 input patch. That's what's written, you know, and
18 that's what I took. So you have a range of input patch
19 having different orientation, different -- so this
20 first reference data represents all of these editing
21 instructions. And this is further in 1[D], by the way.
22 This is how it explains, like, generating and first
23 reference data comprising editing instructions.

24 I mean, here -- and, you know, for adjusting
25 the digital representation of the head. Yeah, for that

1 task, it is adjusting the digital representation of the
2 head region, you know, within the '985 task being done.
3 The task that's being done in '985 is teaching
4 adjusting the digital representation of the head
5 region.

6 BY MS. MOORE:

7 Q What is the plain and ordinary meaning you
8 applied to the '985 claim term "first editing
9 instructions"?

10 A You know, I discussed this throughout my
11 declaration, the editing instructions. There are
12 different types of editing instructions. Some examples
13 are given in the specifications, one of them, like a
14 pixel flow field and motion vector displacement fields.

15 These -- this editing instruction is disclosed
16 by the '985 patent also. So this -- this further -- I
17 mean, so we know that this is one example of editing
18 instructions that's being taught by the '985 patent.

19 Q What is the plain and ordinary meaning you
20 applied to the '985 claim term "second reference data"?

21 MR. STEIN: Objection; form.

22 THE WITNESS: Okay. "Reference data" by
23 itself, first or second, they can -- they are -- if you
24 remove "first" and "second" from the claim elements,
25 it's like the same definition for reference data, okay?

1 And here, the second reference data is in
2 relation of being produced by the second machine
3 learning algorithm. The first reference data is with
4 respect to being produced by the first machine learning
5 algorithm.

6 BY MS. MOORE:

7 Q Are the first reference data and the second
8 reference data the same?

9 MR. STEIN: Objection; form.

10 THE WITNESS: There is no limitation saying
11 they cannot be. It's this -- in here, to my
12 recollection. There is no limitation saying that these
13 are not the same. I mean, in terms of the claim
14 limitations, I'm saying.

15 BY MS. MOORE:

16 Q What is the plain and ordinary meaning you
17 applied to the '985 claim term "first selection
18 instructions"?

19 MR. STEIN: Objection; form.

20 THE WITNESS: I mean, I discuss also -- I
21 don't want to do out-of-content answer here, but I
22 discussed -- and based on what's disclosed in the
23 specification, we could go to the '985 patent to see
24 how selection instructions are being disclosed.

25 But for a given -- as stated in the claim

1 element 1[F], the selected instructions that are -- the
2 first reference data includes editing instructions and
3 also selection instructions. The selection
4 instructions -- given a particular input patch, the
5 selection instruction would select the editing
6 instruction for that patch, okay, based on the
7 computation of that target patch.

8 So it's like the mechanism to select, to allow
9 you to select out of the editing instructions that are
10 there in the reference data for all combination or
11 ranges of possible configuration of the patch. When
12 you have an input patch with a specific configuration,
13 the selection instructions are the means to select the
14 editing instruction for that patch out of the editing
15 instructions.

16 BY MS. MOORE:

17 Q Are the first selection instructions and
18 second selection instructions the same --

19 MR. STEIN: Objection; form.

20 BY MS. MOORE:

21 Q -- in the '985 patent? Sorry.

22 MR. STEIN: Sorry, Ashley.

23 Objection; form.

24 THE WITNESS: Again, I mean, there are no
25 limitations in the claims saying they should be

1 different. They can be different for sure but also no
2 limitation that they -- saying they cannot -- they
3 don't -- they have to be different.

4 BY MS. MOORE:

5 Q Are the first editing instructions and the
6 second editing instructions the same in the --

7 MR. STEIN: Objection.

8 BY MS. MOORE:

9 Q -- the '985 patent?

10 A I believe I answered this question also before
11 saying the claims do not limit -- providing limitations
12 saying these should be different.

13 Q Let's look at paragraph 115 of your
14 declaration. It's on page -- it starts on page 66 of
15 Exhibit 1003. And let me know when you get there.

16 A I am there, but like -- yeah. I am there.

17 Q In your declaration, you say that the
18 synthesized output 0output could refer to both a coarse
19 output 0coarse and a final output 0.

20 Do you see that part of your declaration?

21 A Where is it, please? Which line? Which --
22 no, I don't see it. Sorry.

23 Q So let's see. Probably the easiest way to
24 find it is to go to page 67, and it's the -- like, the
25 first, second and third lines.

1 Do you see it?

2 A One moment.

3 Okay. So I'm on page 67, just like (as read):

4 "In my opinion" --

5 (Reading to self).

6 So which line? "Accordingly" or --

7 Q The -- it was that first sentence that you
8 just started to read (as read):

9 "A PHOSITA would have understood that
10 the synthesized output Ooutput could
11 refer to both coarse estimate Ocoarse
12 and final output O."

13 Do you see that?

14 A Yeah. I mean, there is Ooutput. And we're
15 referring this to not be out of the context. There is
16 (as read):

17 "Id. p. 8."

18 Let's see that. Like, so let's go to
19 page 8 to see what --

20 Q Well, hold on. I want to ask you questions
21 about that sentence, so that's why I'm bringing you
22 there first.

23 So I just want to understand. "Ocoarse," what
24 does that mean in that sentence?

25 A Actually, Ocoarse is just like a notation to say

1 it's the output. It's the output of the coarse module.
2 That's what it means.

3 Q And --

4 A (Indiscernible) any module -- any one, you
5 know, to say, okay, Ocoarse is the output of the first
6 module.

7 Q And "Ooutput," what does that refer to?

8 A Ooutput is the output of anything, of any
9 module. It can be the coarse module output. It can be
10 the fine module output. And if you want to -- I mean,
11 you can include the output of each. I mean, these are
12 two different outputs, but they are outputs -- out.

13 When I'm training a network, this is an Oout.
14 The other is an Oout. However, when I'm writing a paper,
15 I want to differentiate. So I give Ocoarse to the first
16 one to say, okay, that's the output of the first
17 module. And I can still give Oout as long as I have
18 something to distinguish the notation. But Ocoarse is an
19 Ooutput for the coarse module.

20 Q And what is "Ooutput"?

21 A Could you refer me to where you're seeing the
22 Ooutput and -- where?

23 Q In the sentence on page 67.

24 A I'm saying that the synthesized output could
25 refer to both, like -- like, Ocoarse is an Ooutput and

1 when -- when also the 0 is an 0output, too. I mean, the
2 output of the final module of the fine warping, fine
3 warping module, is an output. At the same time, the
4 output of the first module is also an output.

5 In some certain applications, you might want
6 to use only that. For example, low bandwidth or low
7 resources applications, you might be satisfied at least
8 with some corrections because you don't have a lot of
9 resources. And it's a nice scalable system here.

10 Then if you have more resources, you could
11 define it further. But still both should approximate
12 the target within your constraint, because one is
13 operating on a -- like, on some constraint, saying, I
14 want a coarse field. One is saying, I can have more
15 dense field.

16 So it depends on your application, but both
17 can produce an output that's adjusted that's doing the
18 task. The first one is adjusting based on a, like,
19 coarser, less dense motion vector displacement field
20 that's being made dense through interpolation rather
21 than estimation at every point from the network.

22 So you estimate at some point, and then you
23 interpolate to estimate using interpolation so it
24 becomes dense. But network is the estimation first.

25 The second one is using the network to more

1 refined estimation and produce a denser field, a more
2 refined field. But both of them can produce the output
3 for the task. Both of them can produce an eye gaze
4 corrected image and that can approximate. And you
5 would like -- you want to train both networks to
6 approximate that ground truth and to do their best
7 based on the constraint. One is based on constraint
8 just approximate a less dense. Less dense field one,
9 more dense field.

10 Q So the Ooutput reflects the eye gaze corrected
11 image; is that fair?

12 MR. STEIN: Objection; form.

13 THE WITNESS: Not -- I mean, one moment,
14 because I don't want to -- I want to -- that's why I
15 don't want to answer it out of context. That's why I
16 want to refer -- I'm referring to page 8 and what
17 output refers to. Ganin teaches using, on page 8 -- so
18 if we go to page 8, basically, yes, I mean the
19 synthesized output and the ground truths.

20 Synthesized Ooutput in here -- I mean, if I just
21 take that sentence -- I'm not sure it's -- Ooutput was
22 used before in Ganin somewhere to refer to something
23 else, but -- one moment.

24 For example, I want to -- I want to refer you
25 to equation 6, for example, now in Ganin. This is

1 Exhibit 10- -- 1048. And this is page 7 of the paper,
2 section 3.4. You could see here the output of the
3 model is used to modify using a single element that is
4 Ofinal. That's an output. That's an 0 output, too, you
5 see, but it's called Ofinal to distinguish it. Ocoarse is
6 an 0output. Ofinal is a normal output. Ofine is an 0output.

7 So, you see -- so that's still an output, an
8 0output. If you want to -- you would want to minimize
9 the distance, the l2 distance between this Ofinal and the
10 ground truth if it's the image. And how you do it, you
11 know, you put it in the objective function, but then
12 you express it in terms of the parameters you want to
13 learn.

14 The network might not be learning 0output or
15 Ofinal but might be learning the editing instructions to
16 get you to the 0output. So you express 0output in terms of
17 that, and the network would learn it, although your
18 objective function is 0 out minus the ground truth, but
19 you express 0 out in terms of what you want to learn,
20 the editing, the vector placement field are the
21 parameters now, for example.

22 I'm giving you an example. So what you're
23 learning, the output of your network would be the
24 vector displacement field, but you're using those to
25 make sure you learn them so that you get the 0 outputs

1 you want that's as you close to -- to -- as you can to
2 the ground truth.

3 So even though your objective function, it
4 shows you a distance with the 0 out and the ground
5 truth, what you're learning is how 0 out was obtained.
6 It was obtained by learning a pixel flow. These are
7 your parameters. So you learn those, and you have to
8 express it in your objective function.

9 When you program the thing, you express 0 out
10 in terms of the parameters you're learning and in terms
11 of these pixel displacement fields. And then you learn
12 those to get you that 0 output. I'm hopefully -- I don't
13 know if I answered more than your question, but...

14 BY MS. MOORE:

15 Q Is 0coarse used to calculate 0final?

16 MR. STEIN: Objection; form.

17 THE WITNESS: So excuse me. I didn't get the
18 question.

19 BY MS. MOORE:

20 Q Is 0coarse used to calculate 0final?

21 A 0coarse used to calculate 0final? Is 0coarse used
22 to calculate 0 final? Meaning 0final in the sixth
23 equation here? I have like -- this is after the
24 lighting correction module. You -- the thing is that
25 there are -- you can use the coarse vector field, and

1 you can either directly apply -- it depends how many
2 modules.

3 For example, I could take the coarse working
4 module and add a light correcting feature to it. If I
5 did that, then -- so can you rephrase your question?
6 Is it like to -- is it like used to produce the final
7 output or to learn, you said? So I didn't really get
8 your question. To produce or to learn?

9 Q To produce.

10 A You could use the coarse -- the vector field
11 and then the lighting correction. Yeah, if I use the
12 coarse module, for example, the model for light
13 correction, then I learn the coarse field. Then I
14 apply to produce Ocoarse, but what I'm learning -- I'm
15 learning the coarse field.

16 And this produced the output of that stage by
17 applying the learned editing instructions based on the
18 target input patch I put. So I get some output. If
19 it's the coarse module, I'm calling it Ocoarse to
20 differentiate from the lighting correction model, which
21 is called Ofinal here if you use the lighting correction
22 module.

23 I now have a lighting correction module. Then
24 I apply that, and I get Ofinal. The lighting correction
25 module can be also learned -- part of it -- like, it

1 can incorporate neural networks model that would learn
2 the transformation and the mapping.

3 In that case, the input to that next module,
4 which is doing another task, lighting correction, would
5 be 0coarse as input, okay, but the target is still the
6 ground truth because at the end of the day, you learn
7 your network, the course network, you learn it to match
8 the ground truth.

9 So all coarse should match as much as possible
10 the ground truth given the constraint of the coarse
11 field. But now when you're designing and learning the
12 lighting network, you should also -- definitely you
13 want to learn it to approximate the ground truth, too,
14 to improve the output of the first network as much as
15 possible if there is an improvement and learn to
16 produce still all ground truths.

17 So always you have the all ground truth being
18 a target at the end. And then it's going to learn now
19 what? The transformation, the mapping, to map the
20 lighting better so that it matches ground truth.

21 But at every level, I'm matching the ground
22 truth. And if I want to learn these together, I would
23 have an objective function with two terms, one for the
24 first one saying ground truths with the 0output of the
25 coarse network which we call 0coarse here plus another

1 term, which is the lighting, O_{final} , minus the ground
2 truth. Plus I express O_{final} with respect to the
3 transformation parameters that I'm learning.

4 How O_{final} is produced? I express it. Maybe
5 it's a weighted combination of pixels, so I just do W_1
6 times whatever and I learn these parameters. I learn
7 the mapping. And then the network applies this to
8 produce it.

9 So I'm -- so that's how -- and you can apply
10 some weighting to these terms. But anything you want
11 to use to learn, you have to incorporate in your
12 objective function. And you want to put what you're
13 learning -- I mean, so it's the ground truth -- that's
14 the ground truth you want, you have to incorporate it
15 in your objective function.

16 (Ms. Fortier left the proceedings.)

17 BY MS. MOORE:

18 Q Do you remember what my question was?

19 A I --

20 MR. STEIN: Objection --

21 THE WITNESS: Yes.

22 MR. STEIN: I mean --

23 THE WITNESS: I believe your question was
24 whether O_{coarse} is producing the O_{final} . Now I explained
25 to you how it can be used to produce that, whether

1 during training or whether during running, because you
2 have two stages to produce this.

3 BY MS. MOORE:

4 Q Is your answer different if there is no
5 lighting correction model -- module?

6 A If there is no lighting correction module, I
7 would stop at the output of the coarse module, because
8 I don't want to correct it further. And my objective
9 function would have one term without the second one,
10 without the light correction module, or I could -- for
11 example, or I could just -- also you could train them
12 independently where you train the first one and train
13 the second one independently. But anyhow -- so both
14 are fine. So I answered your question during training
15 and during testing because didn't specify whether we're
16 talking about training or testing.

17 Q Do you agree that the l2 distance described in
18 Ganin is a regular l2 distance between the single
19 synthesized output -- Ooutput and the single ground truth
20 Ogt as the objective function?

21 MR. STEIN: Objection; form.

22 THE WITNESS: I mean, he states it's irregular
23 as to distance.

24 BY MS. MOORE:

25 Q He states what? I'm sorry.

1 A Section 4.2, second sentence in Ganin (as
2 read):

3 "We used irregular l2 distance."

4 Is that your question?

5 Q Yes. What is the l2 distance described by
6 Ganin?

7 A Basically, it's like a -- usually, you take --
8 here, if you have two matrices or vectors, you could
9 unroll the metric, scan it into a vector, or you take
10 point by point difference and you square them and you
11 sum them, okay? But you can also normalize them by
12 dividing by the number. Sometimes you leave it
13 unnormalized. So regular here doesn't mean exactly --
14 he tells us whether he's normalizing by dividing or
15 not. So like -- but that's the gist of it.

16 Q And you're referring to that second sentence
17 underneath section 4.2, "Training Procedure," right?

18 A Yes. Yes.

19 Q Let's look at section 4.5 of Ganin, which
20 is -- Exhibit 1048 is the one that we're using.

21 A Yes.

22 Q Are you there?

23 A Yes, I am there. I guess I just flipped to
24 it, although it's, like, very hard to manipulate this
25 big binder.

1 Q It's entitled, "Incorporating Registration."

2 A Yes, yes.

3 Q Do you see equation 7 there?

4 A Yes, I see it.

5 Q That equation, is that an objective function?

6 A You could take it to be an objective function,
7 yes.

8 Q And it compares the output 0output to the ground
9 truth?

10 A Yeah, I see that.

11 Q Is 0gt or 0 ground truth the training data
12 output used to train the Ganin MLA?

13 MR. STEIN: Objection; form.

14 THE WITNESS: So are you -- can you clarify?
15 Are you saying is 0gt part of the training data?

16 BY MS. MOORE:

17 Q Correct. Is 0gt part of the training data?

18 A Yeah. I mean, like if we go to the training
19 procedure, basically, to my recollection, 0gt is
20 ground -- it should be part of the training data.
21 Ground truth, like it's not used except you could --
22 you could ignore it, too, even if you have it in the
23 training data and you're unsupervised during your --
24 you could use a modification of that because you could
25 see here the distance changed in equation 7, for

1 example. It's no longer a point by point. Do you see
2 that? It's changing. It's not using O_{gt} minus 0
3 anymore. It's just used for turning it around for
4 alignment in here.

5 So you can see here -- so they're taking O_{gt}
6 and enlarging it by adding to the border of it. You
7 see $H + 2k$, $W + 2k$ and using it in the objective. So
8 they're not using O_{gt} anymore as is but an enlarged one.
9 And the distance can be l_2 or l_1 , he's saying, so it's
10 no longer necessarily l_2 . You know, and he says l_1
11 gives sharper results than l_2 .

12 And he's saying that -- he's taking a cropped
13 version of O_{gt} with top left corner as position ING . So
14 he's taking basically a pixel in the O_{gt} and cropping
15 it -- cropping -- taking a box around that. So he's
16 not taking O_{gt} anymore but taking different portions of
17 O_{gt} and trying to compute a distance to incorporate
18 further alignment. So does this make sense?

19 Q Do you know Dr. Saber?

20 A Yeah, I know Dr. Saber.

21 Q How long have you known him?

22 A You know, I don't want to answer this from
23 memory. You know -- and plus, like, we met at
24 conferences. That's how we -- I got like -- I got to
25 know him, at conferences, these IEEE conferences and so

1 forth.

2 Q Have you ever worked with Dr. Saber?

3 A No, we didn't collaborate.

4 Q Are you familiar with Dr. Saber's work?

5 A To some aspects, some aspects of it.

6 Q What aspects?

7 A I mean, he did work on -- on things related to
8 document processing and text processing and some image
9 processing. So work definitely, but it's more -- I was
10 more familiar when he was like at the start of his
11 career also in academia.

12 Plus, he was working at Xerox. So he was
13 focusing on text analysis, document analysis and things
14 like that back then and some image processing work,
15 yeah.

16 Q Are you familiar with his qualifications?

17 A I mean, he's a -- he's like a, you know, I
18 would say like -- he's a full professor, tenured full
19 professor, so this has its own merit.

20 Q Do you have any reason to doubt that he's
21 qualified on the subject matter of the '985 patent?

22 A To tell you the truth, no comment over here.
23 I don't know his qualifications. I cannot assess his
24 qualifications with respect to the '985 patent and his
25 knowledge about the subject. So this I cannot comment

1 on.

2 Q Do you believe him to be a person of ordinary
3 skill in the art?

4 A In light of the '985 patent, I cannot comment,
5 again. I cannot say he is or he's not. I -- yeah.

6 Q You don't know?

7 A I --

8 MR. STEIN: Objection.

9 THE WITNESS: -- wouldn't know because, like,
10 I'm not familiar with him doing machine learning work
11 until very recently. So that's why -- his work I'm
12 familiar with did not involve machine learning before,
13 so that's why I kind of -- I don't want to comment on
14 that.

15 I haven't reviewed his machine learning or
16 recent work in that area to comment. Based on my
17 knowledge and knowledge of his work before, it doesn't
18 apply to the '985 patent.

19 BY MS. MOORE:

20 Q You don't know if he's done machine learning
21 work?

22 A I haven't reviewed his recent machine learning
23 work and what he has done. That's what I'm saying,
24 like, no comment on that, like, you know. So I haven't
25 been referencing his work in any of my papers or

1 looking at it recently. And the -- you asked me
2 whether I knew him, and I told you I'm familiar with
3 his earlier work more than his later work.

4 So I cannot comment about his qualifications
5 in relation of the '985 patent. So I'm not saying
6 anything, neither positive nor negative, but I cannot
7 comment, because I'm not familiar with his machine
8 learning work.

9 Q Your other -- let's see. I think it's
10 ground 3 is a combination of Chalom and Aslan; is that
11 right?

12 A Yes, that's right.

13 Q Chalom and Aslan is an obviousness
14 combination?

15 A Yes.

16 Q Chalom only discloses one machine learning
17 algorithm, right?

18 MR. STEIN: Objection; form.

19 THE WITNESS: Just one moment. I'm just
20 reorienting myself also to this section on my
21 declaration with -- so we have there the figures of
22 Chalom and everything.

23 So, yeah, I mean, if you could look at
24 Figure 3, okay, what I want to say -- I mean, you
25 could -- let me -- could you look at page 115 in my

1 declaration, paragraph 214.

2 BY MS. MOORE:

3 Q I see it.

4 A Yes. So you can see that first sentence (as
5 read):

6 "First, Chalom contemplates that its
7 RFC 306 'may apply different random
8 forest models--" with an s.

9 And also, you have other disclosures in Chalom
10 saying he can have -- so here, by itself, like he does
11 teach more than one machine learning model because you
12 could have different machine learning models and sample
13 together each one corresponding to different ranges or
14 subranges.

15 So based on that and other disclosure by
16 Chalom in his specification, he does teach more than
17 one machine learning model.

18 Q So if you look at paragraph 209 of your
19 declaration, you say it's your opinion that Chalom
20 discloses all the features in claim 1 except for the
21 training of two MLAs.

22 What did you mean by that?

23 A Okay. So 209; is that right?

24 Q Yes.

25 A Okay. Okay. (Reading to self). Yeah, yeah,

1 yeah. Within the claim limitations of the '985 patent
2 requiring that you have, like, a first machine learning
3 algorithm passing information to the second machine
4 learning algorithm is not expressly disclosed in
5 Chalom. It's not expressly disclosed. That's what is
6 meant here.

7 So if you take the claim limitations -- I
8 mean, Chalom does indeed -- through his specifications,
9 does -- he does teach an expressly disclosed training
10 more than one machine learning, but he doesn't, like,
11 expressly disclose the elements and limitations of
12 claim 1 of the -- as taught in the patent. I mean, he
13 doesn't disclose training two MLAs as taught by the
14 '985 patent. That's what's meant here.

15 Q What is hindsight?

16 A Again, this is a legal question. So I'd like
17 first to refer to my declaration to see if I wrote
18 anything about it, because this is -- I make sure I'm
19 not expressing things -- not in a -- I mean, it's
20 expressed much better than it would be if it's written.
21 Let's see if I have anything about it in here. If not,
22 I'll tell you what --

23 THE REPORTER: Can you please move the binder
24 off your mic, Doctor.

25 THE WITNESS: Oh, thank you. I'm sorry.

1 Okay.

2 (Ms. Fortier rejoined the proceedings.)

3 THE WITNESS: Okay. So I think in
4 paragraph 91 of Exhibit 1003, this is where I refer to
5 hindsight there, and I say (as read):

6 "I also understand that when
7 considering the obviousness of a
8 patent claim, one should consider
9 whether a teaching, suggestion, or
10 motivation to combine the references
11 exists to avoid impermissibly applying
12 hindsight when considering the prior
13 art.

14 "I understand this test should not be
15 applied rigidly, but that the test can
16 be important to avoid such hindsight,"
17 okay?

18 BY MS. MOORE:

19 Q So what is hindsight?

20 A So hindsight is, basically, after you read
21 something, you know, you get ideas from it and now you
22 apply them. You use that lens to apply it to the prior
23 art. But as I testified in my declaration, I'm using
24 the lens of a POSA, which is prior to the filing date
25 of the '985 patent.

1 And so this is to avoid any impermissible
2 hindsight, so I'm -- from the lens of the POSA prior to
3 the filing date of the '985, I'm avoiding this
4 hindsight here.

5 Q Well, let's be clear. You did read the '985
6 patent before you wrote the declaration, right?

7 MR. STEIN: Objection; form.

8 THE WITNESS: Definitely. I mean, if I'm
9 going to see and opine on something, whether it's
10 like -- whether prior art teaches and discloses it, I
11 have to read it. But still, as a POSA with a lens
12 prior to the filing date, I'm depending only on prior
13 art and their teaching and their disclosure. But I
14 have to show how this discloses what '985 is teaching
15 so -- and in my declaration, I discuss that.

16 BY MS. MOORE:

17 Q Do you agree that all of the challenged
18 independent claims of the '985 require a second MLA
19 that uses the first MLA's editing instructions?

20 A One moment. Let me go to the claim elements
21 also, because I don't want -- to answer your question
22 and look at them, this would help more and also seeing
23 in the claim what you're asking.

24 So you're asking about the second machine
25 learning algorithm; is that right?

1 Q I'm asking whether the second machine learning
2 algorithm uses the first machine learning algorithm's
3 editing instructions.

4 A Okay. So 19[E] on page 110 of my declaration,
5 you can see the claim element related to that and the
6 limitations there. And -- to better answer your
7 question, you can see that claim element 19[E] (as
8 read):

9 "Using a second machine learning
10 algorithm to generate second reference
11 data using the same training data of
12 the first" -- so first, we have the
13 same training data there -- "and the
14 first reference data generated by the
15 first machine learning algorithm."

16 And then it continues to clarify what part of
17 the first reference -- one moment. Oh, yeah, later in
18 the claim element -- I'm using -- actually, I'm looking
19 at claim 19. I want to look at claim 1, I'm sorry,
20 because claim 1 is more relevant, I guess, to your
21 question. One moment. I'm sorry.

22 So it's page, I guess, 125. Like because
23 we're looking -- that's where is -- like the claim
24 elements are. Okay. Here we go. So it's page 125 and
25 126. The claim element that straddles it is on

1 page 126 of Exhibit 1003. So 1[E], claim 1[E] (as
2 read):

3 "Using a second machine learning
4 algorithm to generate second reference
5 data using the same training data as
6 the first machine learning."

7 That's one (as read):

8 "And the first reference data
9 generated by the first machine
10 learning."

11 So we have the first, okay? But then claim
12 1[F] continues saying (as read):

13 "Wherein the first reference data
14 comprised first editing instructions
15 for a range of possible configurations
16 of the target."

17 And first -- but that said, I guess, like, we
18 have to make use of more claim limitations, because
19 1[D] should be also taken into account before 1[E]. If
20 we use -- because 1[D] says (as read):

21 "Using a first machine learning
22 algorithm to generate first reference
23 data using the training data, the
24 first reference data comprising
25 editing instructions for adjusting the

1 digital representation."

2 So at 1[D] level, we have the reference data
3 comprising editing instructions now. And now the
4 second machine learning algorithm is using this first
5 reference data generated. So far, in step 1[E], it's
6 -- you know, it's using the first reference data.

7 One part is the editing instruction, but here
8 is not like the -- you know, so I don't know. It's
9 using the first reference data. That's what it's
10 saying. But in my declaration, I applied this using
11 the first editing instruction of the reference data,
12 because based on the specifications also, it also
13 discloses using first editing instruction part of the
14 first reference data.

15 The claims, they just say first reference
16 data. The claim element before that said first
17 reference comprising editing instruction, and then the
18 second is using it. The specifications show that it's
19 using the editing instruction of the reference data.
20 Many figures in '985 show that, okay?

21 Q So is that a yes, the '985 claims require a
22 second machine learning algorithm that uses the first
23 machine learning algorithm's editing instructions?

24 A Yes.

25 MR. STEIN: Objection --

1 THE WITNESS: I'm sorry.

2 MR. STEIN: -- form.

3 THE WITNESS: So, basically, the -- like just
4 to, like, clarify, so the '985 patent based on the
5 claim and the specification discloses -- I mean, the
6 claim, they said the second machine learning algorithm
7 should use the same training data and also the first
8 reference data that's generated by the first machine
9 learning algorithm, okay?

10 Now, the specification shall, using the first
11 editing instruction. That's what I can say. The claim
12 elements kind of -- I mean, the claim -- the 1[E]
13 doesn't say using the first editing instruction. It
14 just says, using the first reference data. The spec --
15 one part of using it, the spec discloses using the
16 first editing instruction. Does this make sense? But
17 in the claim element 1[E], it says just "and the first
18 reference data."

19 BY MS. MOORE:

20 Q So I'm going to have to ask it again, because
21 I don't think you've answered. Is it a yes, a no or an
22 I don't know? The '985 claims require a second machine
23 learning algorithm that uses the first machine learning
24 algorithm's editing instructions?

25 A The first machine learning algorithm reference

1 data which comprises editing instructions. So you
2 could use them for sure, but to say reference data,
3 okay?

4 Q Well, what is the reference data if it does
5 not include the editing instructions?

6 A It does include the editing instructions, but
7 later on in the claim elements, it includes also
8 selecting instructions, okay? So if you go at 1[G]
9 or -- you know, or 1[F], "first reference data." So
10 1[F] claim element says (as read):

11 "Wherein the first reference data
12 comprise first editing instructions
13 for a range and for selection
14 instructions for selecting editing."

15 That said, I mean, you could use any part of
16 your first reference data, but in the specification,
17 Ganin teaches more -- I mean discloses using the
18 editing. This is not explicitly expressed in the
19 claims.

20 So you're telling me "claim element." I want
21 to be more specific. Claim element -- I mean, show me,
22 please -- point me out to your question. Where does
23 the claim element say -- expressly say that you're
24 using the editing instructions of the reference data?
25 Where does it say?

1 Q That's what I'm asking you, is, what's your
2 interpretation? Does the second machine learning
3 algorithm use the first editing instructions?

4 MR. STEIN: Objection; asked and answered
5 three times.

6 THE WITNESS: If it uses the -- the -- if the
7 second uses the first editing instruction, it does
8 satisfy the claim that it's using the first reference
9 data. That's how I can answer. It does satisfy and
10 disclose that claim.

11 So if -- since the reference data has the
12 editing, if you have something using the first editing
13 instruction, this means it's using the first reference
14 data, because it's part of the first reference data. I
15 could -- this is my answer.

16 BY MS. MOORE:

17 Q So you think that when the second machine
18 learning algorithm uses the first reference data, it
19 means any part, meaning some or all of the reference
20 data?

21 A It could be. There is nothing limiting saying
22 you have to use all of it.

23 Q Okay.

24 A And even the specification shows not using all
25 of it, of the '985.

1 Q Chalom says that its machine learning
2 algorithm is fast enough for real-time implementation.

3 Do you agree with that?

4 A Excuse me --

5 MR. STEIN: Objection --

6 THE WITNESS: Can you repeat the question.

7 MR. STEIN: -- foundation.

8 BY MS. MOORE:

9 Q Chalom says its machine learning algorithm is
10 fast enough for real-time implementation.

11 Do you agree with that?

12 MR. STEIN: Objection; foundation.

13 THE WITNESS: I'm discussing this in my
14 declaration, actually, and I'm -- I quote this thing.
15 So let's go there and -- one moment. I will go to
16 Chalom. But I remember discussing that and actually
17 talking about that, so I prefer to point you out to my
18 declaration about this. One moment.

19 Could you point me out in Chalom where,
20 basically, this is like stated so -- or I have -- like
21 I could look in my declaration, but we can look in
22 Chalom also.

23 BY MS. MOORE:

24 Q So Chalom is Exhibit 1005.

25 A Uh-huh.

1 Q Do you have that handy?

2 A Yes, I do. Exhibit 1005 is here. Uh-huh,
3 yeah, I do have it. Hopefully, I could -- yeah, it's
4 fine. It's like the fine print here. I have to get
5 closer to it.

6 MR. STEIN: It's your first chance to use that
7 magnifying glass.

8 THE WITNESS: Yeah. I mean, luckily, there
9 are no equations here that are small, but just in case,
10 I have my magnifying glass here.

11 Yeah. Could you please point me out to the
12 relevant -- meanwhile, I'll look into my declaration
13 while you're doing that.

14 BY MS. MOORE:

15 Q So maybe it will be easier if we go to
16 page 114 of your declaration, paragraph 212.

17 A Okay. Let's see.

18 Q That is where Chalom teaches a machine
19 learning system that is not only fast enough to support
20 real-time implementation --

21 A Paragraph 212 on my declaration?

22 Q Yes.

23 A Yeah, I was looking for that thing. I
24 remember discussing it. So thank you. Yeah, and
25 I'm -- we're quoting here where in Chalom it is. So

1 what I'm saying here, like this is part of the
2 motivation to combine section. And it's stated here
3 (as read):

4 "Chalom and Aslan are at least
5 reasonably pertinent to this
6 efficiency versus accuracy problem."

7 Chalom teaches a machine learning system that
8 is not only fast enough to support real-time
9 implementation but also robust enough in terms of
10 quality. This is -- so (as read):

11 "e.g., by 'reducing the histogram of
12 oriented gradient features' provided
13 to the Random Forest Classifier...
14 and predicting 'motion vectors...to
15 warp the eye.'"

16 And here we have where this is in Chalom,
17 column 1, 16 to 25. So -- okay. So that's the
18 problem. For example, if we look at column 1, 16 to
19 25, he says (as read):

20 "Current techniques may not be fast
21 enough to support real-time
22 implantation, may require special
23 additional camera hardware... may not
24 be robust enough."

25 So this is where I quote that from, like fast

1 and robust. And plus I quote it from 9, 48-65. So
2 let's go, because I don't want to be talking about
3 things -- I don't want to be talking about things out
4 of context.

5 So here also, 48 to 65, Chalom states (as
6 read):

7 "Returning to Figure 3, any number of
8 eye contact corrected images may be
9 generated such as a video sequence of
10 eye contact corrected images. The
11 techniques discussed herein may
12 provide for high quality -- may
13 provide for high quality eye contact
14 correction in real time. For example,
15 the discussed processing as performed
16 by system 200 may be performed at a
17 rate such that videotelephony,
18 videoconferencing or the like... in
19 real-time between users."

20 Okay. Yeah. So he's talking about there is
21 an -- there is an important -- there is an important
22 issue in existing techniques being not fast enough,
23 okay? And -- and not getting the quality needed and
24 he's trying -- his invention is to improve on this by
25 making a faster and real-time -- and more -- for

1 real-time applications.

2 BY MS. MOORE:

3 Q So do you agree that Chalom discloses a
4 machine learning system that is fast enough to support
5 real-time implementation?

6 A What is -- let me tell you about real-time,
7 because, like, I cannot answer your question for one
8 thing, because I don't want to answer it out of
9 context. Real-time -- I developed a real-time DSP
10 course that I taught and developed also using embedded
11 system. Real-time is relative.

12 For example, if you're driving your car and
13 you want to brake not to hit a pedestrian, you want the
14 real-time or the brake to -- real-time there is like
15 0 milliseconds or, like, very, very fast.

16 In a video, I mean, real-time -- or in a slide
17 show, real-time is one second. And a video, depending
18 on your video, is it 30 frames a second? 60 frames a
19 second? It can be. So real-time is relative to the
20 application you're considering. That one's first.

21 So whatever is real-time for Chalom might not
22 be sufficient real-time for other applications that
23 want more high quality, for example, HD video.
24 Videotelephony might be at lower resolution. It is
25 using a lower resolution thing versus HD. And you want

1 to, like, basically have HD quality in a more
2 professional setting.

3 Another important thing, you could actually
4 real-time if you use a super computer. For example, to
5 achieve real-time using a system, maybe I need a
6 hundred GPUs, whereas in other systems you can actually
7 real-time with 5 GPUs or 1. So you can always improve
8 on real-time. I mean, real-time, he doesn't say here
9 how many GPUs he's using or whatever. He's saying, oh,
10 he wants real-time and faster than the other
11 techniques.

12 That said, when you look at Aslan, Aslan is --
13 they're considering limited resources and low power.
14 And you can see that there, also to low power, so for
15 devices with limited resources like mobile telephone,
16 wearable, laptops. So this is what they're
17 considering, the low-power constraints.

18 Within that constraint, with low power, so
19 less resources, how can you achieve real-time? And
20 that's the improvement over Chalom, because Chalom is
21 not considering limited resources and low power. So a
22 POSITA looking at two devices with limited resources
23 would look at Aslan to improve that.

24 And by the way, also, this is in line with the
25 problem of the '985 patent. In the beginning they're

1 saying limited resources, low power. This is known in
2 the prior art by Aslan. That's the same problem Aslan
3 is talking about. Aslan is saying limited resources,
4 low power.

5 If you go to the '985 patent, go to the first
6 column there -- actually, I want to show you -- I mean,
7 otherwise, Chalom would be good enough. But the '985
8 people didn't think so either. Aslan did not think so.

9 So if you go to column 1 in Exhibit 1001,
10 column 1 in Exhibit 1001. And this is, basically, the
11 '985 patent. If we go to column 1 and 47 -- line 46
12 until maybe 55. Let's see if this is the one I want
13 to -- (as read):

14 "The present disclosure is concerned
15 with process techniques (e.g., image
16 processing techniques) for adjusting
17 digital representations (e.g., images)
18 of a head region to correct the
19 perceived gaze and/or to improve other
20 aspects of a computer-
21 generated display of the head region.
22 The present disclosure is particularly
23 concerned with implementing such
24 processing techniques with minimal
25 demands on computer hardware and/or

1 power" --

2 Do you see that?

3 -- "such that they provide results at
4 or near input data frame rate or user
5 feedback requirements."

6 So not only the real-time performance here but
7 low power constraints, limited resources. That's what
8 Aslan teach. That's the problem. It's not to the
9 '985. Chalom just cares about real-time. Did not
10 mention about low power; did not mention limited
11 resources.

12 You could have real-time with more resources,
13 with a bigger computer desktop that you can move
14 around. But if you want limited resources and low
15 power, it requires different techniques which Aslan
16 solves using the teacher-student model. It's -- Aslan
17 exactly his -- like he talks about the low power and
18 limited resources before -- and this was before the
19 '985 patent.

20 MS. MOORE: Move to strike as --

21 THE REPORTER: Counsel -- Counsel, when
22 it's --

23 MS. MOORE: Yes?

24 THE REPORTER: When it's convenient, I'm going
25 to need a break, please.

1 MS. MOORE: Sure.

2 So move to strike as nonresponsive.

3 Why don't we take a break, and then we'll try
4 it again.

5 MR. STEIN: I would object to that motion.
6 That was a perfectly responsive answer, before we go
7 off the record.

8 MS. MOORE: It was a six-minute non-answer.

9 MR. STEIN: She's entitled to respond as she
10 sees fit, and that's what she's doing. Her answer was
11 fully responsive.

12 MS. MOORE: And contrary to her declaration.

13 MR. STEIN: No, it wasn't, but okay.

14 THE REPORTER: Shall we break, Counsel?

15 MS. MOORE: Yes. We're off -- we're off the
16 record, yeah.

17 (Recess.)

18 BY MS. MOORE:

19 Q Dr. Karam, you understand you're still under
20 oath?

21 A Yes, I do.

22 Q Do you agree or disagree that Chalom teaches a
23 machine learning system that is fast enough to support
24 real-time implementation?

25 A I cannot answer this out of context. I

1 mentioned what real-time means. It depends on the
2 context. He mentions he wants to improve on things to
3 be faster and to support real-time. That said, one can
4 always improve on real-time.

5 And you -- I'm not sure how much real-time is.
6 I mean, you can always with more resources achieve
7 real-time. Even these techniques he's talking about,
8 existing techniques, they could also achieve real-time
9 with bigger resources.

10 So he's saying that's what his invention aims
11 to achieve. He's improving on the real-time
12 performance of previous techniques to make them faster
13 for his invention. But how fast he is, I know he's
14 like a -- this is like a -- so real-time is relative,
15 so I cannot agree really.

16 Q Okay. So do we need to change paragraph 212
17 of your declaration where you say (as read):

18 "Chalom teaches a machine learning
19 system that's fast enough to support
20 real-time implementation"?

21 A So let's go --

22 MR. STEIN: Objection.

23 THE WITNESS: -- back to 212 of -- oh, sorry.

24 MR. STEIN: Yeah, just form objection.

25 THE WITNESS: Let's go back to 212 of my

1 declaration, okay?

2 Basically, let's go to where -- so we're
3 saying "teaches a machine learning." That's what he's
4 stating and teaching. "Fast enough to support
5 real-time implementation."

6 I'm saying, yeah, it can support but here
7 there is no limit on the resources, okay? So it can
8 support real-time implementation given the right
9 resources. There's no limit on resources. But if you
10 want to limit to low power and have limited resources
11 for mobile, then you have to seek to improve on Chalom
12 in order to have that.

13 BY MS. MOORE:

14 Q Chalom creates high quality images, correct?

15 A Could you point me out to where high quality
16 is mentioned.

17 Q Do you have Chalom, which is Exhibit 1005,
18 handy?

19 A Yeah. I can go to that. So 1005. Yeah, I'm
20 there.

21 Q And column 9, line 50 says (as read):
22 "The techniques discussed herein,"
23 meaning inside Chalom, "may provide
24 for high quality eye contact
25 correction in real time."

1 Do you see that?

2 A Column -- which one? 9?

3 Q Column 9, line 50.

4 A One moment. I'm going there. I'm still not
5 there.

6 So column 9, line 50 is referring to the --
7 (reading to self).

8 (As read):

9 "... may provide."

10 "May." There is "may," okay? It's not
11 guaranteed. (As read):

12 "... may provide for high quality eye
13 contact correction in real time."

14 "May," it depends on the situation and whether
15 he has the perfect, like, input for his method. So
16 "may provide."

17 Q Yes. So there are instances where Chalom
18 provides high quality images, right?

19 A I would like to say because one of my areas of
20 expertise is image quality, what does "high quality"
21 mean? What does it -- I mean, when you say "high
22 quality" or optimum, if you don't define optimum with
23 respect to what, it doesn't have any meaning. So high
24 quality with respect to what?

25 I mean, quality is relative, also. If I

1 can -- so it depends on your application. If you can
2 improve the quality, high quality in what respect? HD
3 quality? SD quality? You know, videotelephony
4 quality? So quality is relative again. So, yeah, I
5 mean, he may provide high quality -- whatever high
6 quality means for Chalom -- for his particular setup,
7 resources, et cetera.

8 This doesn't mean we can't improve on the
9 quality further in terms of this -- his setup or
10 another setup with more limited resources that you
11 could achieve similar or high -- similar quality or
12 higher quality with limited resources. So -- yeah, so
13 that's my answer.

14 Q So you are unable to understand what Chalom
15 means when it says that they -- the techniques in
16 Chalom can provide for high quality eye contact
17 correction?

18 MR. STEIN: Objection; mischaracterizing.

19 THE WITNESS: I'm not saying this. I mean,
20 what's mainly here is, like, Chalom disclosing that his
21 invention is trying to solve this problem of speeding
22 up existing techniques while keeping a good quality,
23 what -- that he calls high quality. We are maintaining
24 the quality too, okay?

25 But exactly what his quality is, he doesn't

1 disclose how he measured quality, how -- whatever. But
2 the important thing this teaches us is that that's the
3 problem he's trying to solve, which is in line with
4 every -- with like being discussed, which is in line
5 with Aslan.

6 That's why the motivation to combine, which is
7 also within the field of the -- also -- the problem
8 also is trying -- is -- also this issue was brought up
9 in '985. But the prior art -- Aslan brought it up,
10 too, and Chalom is bringing it up -- you can find other
11 also patents, prior art bringing. It's all relative.

12 Like, you're trying to improve. You improve
13 up to a certain degree. Does this mean that you
14 reached the perfect quality? Not necessarily. We keep
15 improving our quality because you can reach a very good
16 quality if you have a lot of resources. But now if I
17 put a constrain on you, I want low power and give me --
18 give me a good quality -- or whatever, high quality is.

19 So kind of that's what here is saying.
20 Definitely, I mean, Chalom is saying that his technique
21 improves on the real-time performance, improves on --
22 like generates high quality -- relative high quality
23 compared to the other techniques.

24 This doesn't mean that you achieve -- you
25 cannot improve on quality further and you cannot

1 improve on the real-time performance especially when --
2 with limited resources. Then it becomes -- yeah, if
3 you have the -- you don't limit your power or
4 resources, it's easier to achieve the quality you need
5 with -- yeah.

6 BY MS. MOORE:

7 Q So you don't know what Chalom means when it
8 says "high quality"?

9 MR. STEIN: Objection; form, asked and
10 answered at least three times.

11 THE WITNESS: I'm not saying that, but Chalom
12 doesn't quantify how he measures quality. He likes to
13 achieve quality that's as good as the other technique.
14 That's how, as a POSITA, I would understand that. So a
15 quality that's as good as the other technique or
16 better, that's how I understand.

17 BY MS. MOORE:

18 Q Other techniques that existed in October 2017?

19 A Whatever technique he compared to and he
20 references in his -- he has referenced in his, like,
21 patent application. So he considers these techniques,
22 and he's improving on whatever he's -- I can say
23 whatever he's meaning at least and referencing, he's
24 trying to improve on those. Whether he achieves that
25 or not, I don't know. I mean, he's stating "may

1 provide." In certain instances, this is what he's
2 stating.

3 Q And what are the other techniques that he
4 provides high quality images compared to?

5 A I didn't look into like a -- I don't recall
6 out of memory now what -- what he's comparing to. But
7 he's making the statement that this is his objective,
8 is to keep the quality, preserve the quality, whatever
9 high is. "High" means different things to different
10 people.

11 So -- and then while -- so he wants to
12 preserve certain quality while being able to be
13 real-time. That's what he's saying.

14 Q What quality is he preserving?

15 A He said "high quality." You know, it could be
16 based on an l2 distance, like we discussed before,
17 because you can measure quality. It can -- it could be
18 measured based on the perception metric. It could be
19 very subjective quality at the end of the day. So his
20 high quality is relative to what he wants. I mean,
21 what quality preserve? We have to test the systems and
22 see, and you have to conduct subjective testing and so
23 forth. But that's his intent. That's the main thing.

24 I mean, the spirit of that is Chalom wants
25 indeed to achieve to keep the quality that's acceptable

1 to the users of the task while making it faster, okay?

2 Q What is Chalom's parameterized surface
3 fitting?

4 A Okay. I mean, it's a technique to compress --
5 you know, you can parameterize, like, for example --
6 I'll give you an example. A line, okay? This is not a
7 surface but, like, for a -- a plane also is a surface.
8 You can parameterize a plane now using just how many
9 parameters, like four parameters to a plane.

10 For a line, you have three: A, B, C; $Ax +$
11 $By + C$. So you have parameters instead of like --
12 instead of sending every point on the line, you can
13 just give an equation with three parameters.

14 So the plane also -- instead of sending every
15 point in the plane, so now you could represent surfaces
16 by some basic surfaces, like spline. And you give only
17 the weights for those. And this way, you can generate
18 different surfaces. So you could express a surface
19 instead of sending every point using few parameters.
20 That's what it is.

21 MR. STEIN: There was a little bit of a
22 technical glitch there. Did everyone else see that, or
23 was that just me?

24 MS. MOORE: It was fine for me. I don't know
25 for the court reporter. Nadia, was everything okay for

1 you, or do we need to go back?

2 THE REPORTER: I didn't get a glitch.

3 MR. STEIN: Oh, okay. Sorry to interrupt,
4 Ashley.

5 MS. MOORE: Oh, no, that's okay.

6 BY MS. MOORE:

7 Q What is Chalom's "pre-trained classifier"?

8 A Could you point me out to the section you're
9 asking about and where it occurs in Chalom or in my
10 declaration that's referring to Chalom.

11 Q I'll try and find it in your declaration just
12 so we can use that.

13 Let's go to paragraph 244, which is on
14 page 134. And let me know when you get there.

15 A Okay. I'm there, but I'm -- yeah.

16 Q So in paragraph 244, the second line of that
17 paragraph talks about Chalom's pre-trained classifier.
18 Do you see that?

19 A Yeah, but I want to, like, put myself --
20 myself into the context of that, so one moment.

21 Okay. So the question is -- and I can go to
22 4, 19-22 just a moment, also, in Chalom. One moment.
23 Because I want to --

24 Q Sure.

25 A -- make sure I know the context of that.

1 Q And my question is, what is Chalom's
2 pre-trained classifier?

3 A I mean, here, I mean, I -- I mean, pre-trained
4 classifier can be -- in Chalom, I mean, we can look at
5 the different -- where it occurs, but typically,
6 pre-trained classifier, like, you could have a
7 classifier -- I mean, sometimes you could -- Chalom
8 based on some embodiment uses pre-trained as the one to
9 be trained, like in some embodiments to my recollection
10 and to the training of the classifier that you're going
11 to use during deployment as the pre-trained classifier.
12 So that -- in some embodiments, he said, yeah,
13 deploying the pre-trained classifier, you see? So he
14 never -- like, he didn't use "trained classifier." He
15 used "pre-trained." So training of the pre-trained,
16 he's reserving -- he's referring to the classifier.
17 That's -- that's -- you know, to -- like when he
18 deploys it, he called it pre-trained, too.

19 I don't -- I didn't -- to my recollection, I
20 didn't see in Chalom saying trained classifier. He
21 calls the trained classifier "pre-trained classifier."
22 That's according to my recollection.

23 Q Is a parameterized surface fitting a way to
24 compress the pre-trained classifier?

25 A If we go to Chalom Figure -- if you go to

1 Figure 14. Okay. The last stage here, you have 1406,
2 the block diagram. This is in Chalom, Exhibit 1005.
3 The last thing here, he says (as read):

4 "Compressed Random Forest
5 Classification based on parameterized
6 surface fitting."

7 I mean, he -- this is one where he doesn't
8 however talk at all how to do that, meaning, he just
9 say "compressed," and he just mentioned you can use
10 surface fitting or any other suitable technique, by the
11 way. He said "or any other suitable technique."

12 I discuss this in my declaration. One moment,
13 because -- let's see. One moment. Yeah, so you can
14 see on paragraph 216 of my declaration, page 116. So,
15 like, I write (as read):

16 "Alternatively, or in addition, Chalom
17 expressly motivates looking for ways
18 to further compress its random forest
19 by indicating that 'it may be
20 compressed using any suitable
21 technique or techniques.'

22 Here he's giving one example, but -- yeah, so
23 this is in Chalom, line -- column 15, line 4 to 7, if
24 you go there to give it context. So if we go to 15
25 where the -- (reading to self.)

1 The pre- -- okay. So the pre- -- like, 6 --
2 column 15, line 6, the pre-trained classifier may be
3 compressed using any suitable technique or techniques.
4 In an embodiment, the pre-trained classifier may be
5 compressed based on parameterized surface fitting. And
6 you're using the processor.

7 Anyhow, okay. So generates. So this shows
8 that random forest for implementation --

9 THE REPORTER: I'm sorry, I -- so that shows
10 what?

11 THE WITNESS: Excuse me? So I'm saying that,
12 like, line 6 and 7, Chalom discloses the pre-trained
13 classifier may be compressed using any suitable
14 technique or techniques and continues to say in an
15 embodiment the pre-trained classifier may be compressed
16 based on parameterized surface fitting. Yeah, so here.
17 I'll stop here.

18 BY MS. MOORE:

19 Q So that's a yes that parameterized surface
20 fitting is a way to compress the pre-trained
21 classifier?

22 MR. STEIN: Objection; form, mischaracterizes.

23 THE WITNESS: This is one way that -- in an
24 embodiment channel -- will refer to using parameterized
25 surface fitting to compress the classifier.

1 BY MS. MOORE:

2 Q Is having two machine learning algorithms more
3 complex than having one?

4 MR. STEIN: Objection; form.

5 THE WITNESS: Are you talking about during
6 deployment or during training?

7 BY MS. MOORE:

8 Q We'll take them one at a time. Let's start
9 with during training.

10 A Okay. I mean, it -- it depends how you want
11 to do it. I mean, and so it depends on whether -- so
12 more complex, the complexity in terms of -- it can go
13 both ways. If you have the right combination and you
14 are doing the training, because they could help each
15 other, like the teacher-student combination, and if
16 you're passing information from one to the other, it
17 can speed up the training.

18 For example, if I take a network and I want to
19 train it from scratch, actually, it's going to take a
20 long time to train. However, if I can have a teacher
21 already trained and then I make use of that teacher
22 to -- to, basically, train that, my other network is
23 going to be faster.

24 So the training of that network will be faster
25 and it will learn to be more accurate because it's

1 trying to match the output of the teacher. So it helps
2 in that regard. At the same time, I could save on
3 resources. So that's the advantage of doing that.

4 That's -- you know, so given if you have
5 like -- and also sometimes you could have also two way
6 passing where the student learns, then passes back.
7 And the situation may help also give you a better
8 solution.

9 Yes. And so it depends on your goals and
10 objectives and what you're trying to achieve.

11 Q What are the factors that impact the
12 complexity of a machine learning algorithm?

13 A The factors that impact the complexity of a
14 machine learning algorithm? The number of parameters
15 you need to train is one of them. I mean, I'm saying
16 some factors that can impact, okay? Definitely having
17 a big training data. If you have a large training data
18 set, you have to go through them.

19 So this -- I mean, can you define
20 "complexity"? I mean, complexity can be -- go in
21 different direction. I mean, what -- what do you mean
22 by "complexity" when you're asking?

23 Q Well, the previous question was having two
24 MLAs is more complex than having one. And you
25 understood and answered that question, so whatever

1 definition of complexity you're using.

2 A Yeah. Okay. So based on that, what I'm
3 saying like in terms maybe that -- I'm saying if you
4 have more data, bigger dataset, a more complex model
5 with a lot of parameters, big structure, this can
6 affect the complexity of your machine learning training
7 and deployment -- deployment later if it's, like, a big
8 structure. The training data is for the training
9 phase.

10 Q So I heard the number of parameters, the
11 amount of training data and the size of the structure.
12 Is there anything else that you can think of that
13 affects the complexity of a machine learning algorithm?

14 A There are some factors. I can't think now,
15 like, out of my memory of many things. You know, these
16 are some factors as an example. I don't want to be
17 up -- going, like, generally -- general -- out of
18 context stuff.

19 If you can point me to my declaration where I
20 discuss that, I will be happy to maybe more answer
21 within this context. But other than that, I'll just
22 give you examples.

23 But again, it depends on your application,
24 your task, what you care about, because complexity can
25 be relative to the context again. Like in our case,

1 low power. That's the context. You want to minimize
2 power. So complexity will get measured in low power,
3 or limited resources, you want to -- so it depends on
4 what the task is.

5 But if you can point me to my declaration, if
6 I -- if I discuss that somewhere in my -- or somewhere
7 you need clarifications on, I'll be happy to answer.

8 Q When you say it depends on your application,
9 what did you mean by that?

10 A Like when I discussed with you real-time.
11 It's, like, relative. I mean, whether you're on a --
12 when you're driving a car and want to brake, I mean,
13 the real-time there is like really -- it should be
14 quick. Otherwise, it's not real-time, versus you're
15 watching a video. So same thing. It depends on your
16 application, what complexity factors you care about.

17 Q And when you said it depends on your task,
18 what did you mean by that?

19 A Again, driving versus watching a video.

20 Q So application and task are the same thing?

21 A I don't want to use this out of context. You
22 know, task can be used like -- I like to look at the
23 context. Now I'm talking -- I don't want to do
24 general. I mean, task can be application. It depends
25 on the context.

1 Now I'm using it when talking now in terms of
2 this application, yes, but it could be in a different
3 context meaning something else. So this is why I would
4 like to be more specific, if you -- you know, point you
5 out to my declaration to the same context. There I
6 would have to look and...

7 Q Yeah. I'm looking at the answer you gave me a
8 moment ago. It says, "It depends on your application,
9 your task, what you care about because complexity can
10 be relative."

11 So "application" and "task," are those the
12 same things or different things in your answer?

13 A So let's remove task. So like it depends on
14 your application. Let's put that. In that context, I
15 mean -- I was referring to the same thing, yeah.

16 Q Okay. I appreciate that. I was just trying
17 to understand your answer.

18 A No problem. Thanks.

19 Q Is it more efficient to augment a training
20 dataset or to augment the number of parameters in order
21 to make an MLA less complex?

22 MR. STEIN: Objection; form.

23 THE WITNESS: Remember, you have something you
24 want to achieve, okay? And already like in my
25 declaration, I discuss overfitting, underfitting, et

1 cetera, no? If you go augment your dataset and the
2 network cannot handle this, you might really cause
3 underfitting.

4 So these do not go -- we can't just say, oh, I
5 want to augment my dataset, and this is where I want
6 the efficiency. It doesn't work this way. And I mean,
7 these patents are not discussing training dataset in
8 terms of the quality. They're assuming -- I mean, like
9 a POSITA would assume the training dataset is adequate
10 for whatever it's doing to -- to learn. So they're
11 not -- you have to have a training dataset. This is
12 not being discussed, like the adequacy.

13 So given that you have a reasonable dataset
14 that you can learn from, augmenting the dataset by
15 itself is not going maybe to solve your problem if your
16 network is limited or the network is too complex
17 already. And I mean, it -- like, we're assuming here
18 we have the adequate dataset, okay? Now what can you
19 do with this adequate dataset? Your network might be
20 consuming a lot of resources. It cannot run real-time.

21 Having a small network that can run -- well,
22 it cannot run on low power. Real-time on low power,
23 limited resources -- unlimited resources in real time.
24 So having a smaller network, augmenting the dataset
25 more and more, the smaller network would not be able to

1 learn that. Usually, very, very -- like a very complex
2 dataset might require a bigger network. That's the
3 problem.

4 That's why this teacher-student combination is
5 advantageous, because you would have a bigger network
6 learning and then passing the knowledge. So this would
7 avoid some of the problems related to the overfitting,
8 underfitting, you know, that we discussed before.

9 A smaller network might not be able to learn
10 from a complex dataset, because it doesn't have the
11 capabilities by itself. And that's why if you want to
12 do low power and -- while maintaining the quality, we
13 need this student -- this teacher-
14 student combination is advantageous, because it helps
15 us achieve that.

16 BY MS. MOORE:

17 Q So is it easier to reduce the complexity of an
18 MLA by decreasing the number of parameters or
19 decreasing the amount of training data?

20 A I would say that the training data -- you use
21 the training data that is representative of your task.
22 This should be independent of really -- you need the
23 good training data. You need to sample enough to
24 represent your task. If you don't have enough samples,
25 you cannot generalize, you see? So some structures can

1 learn differently from training data.

2 So we have to assume we have the good training
3 data to start with. And now what can we do? So the
4 problem here at issue is not the training data, I'm
5 saying. Suppose you have a good training data and a
6 complex network for your task, okay?

7 How can you have a smaller network learn from
8 that? Having a smaller network, especially, you know,
9 a -- learn from that training data you have, the
10 smaller network would not have good quality because
11 it's small and it cannot -- it cannot learn everything
12 it needs to do.

13 So you need -- that's why the teacher-student
14 model would make sure that the student would learn from
15 the teacher, so it maintains the accuracy while
16 reducing the complexity.

17 And if you remove that in between, it might be
18 problematic. You won't achieve the accuracy you need.
19 And you have -- and you're going to have lower accuracy
20 and -- yeah.

21 Q When you mentioned the size of the MLA
22 structure as affecting complexity, were you referring
23 to the parameters or something else?

24 A I mean number of layers, parameters in there.
25 And usually, these can go together because the more

1 layers, the more parameters you have. So -- and plus
2 the structure can affect, like some structures are more
3 efficient than others but the learning -- some others
4 are more complex, can learn more, but some are more
5 efficient.

6 That said, for low power, you want to -- I
7 mean, you always want to improve, you know, so given a
8 certain task, it requires some -- a certain complexity
9 to learn it. And sometimes going beyond that will
10 affect your accuracy. You know, like, so given that,
11 if you want to reduce your power and make it faster at
12 the reduced power, you would need to reduce the
13 complexity.

14 And that's why the teacher-student model would
15 give you that advantage, because it takes the knowledge
16 of the teacher now, learn, and passes it to the
17 student. In addition, the student is taking the
18 training data but also is taking that knowledge -- the
19 knowledge would bring the student to a level so that it
20 can deal better with that training data. We have a
21 different minimum.

22 So if I can put you next to the minimum you
23 need to be close to, you will converge faster to that.
24 And that's what the teacher does. It guides to the
25 minimum that is -- gives the better accuracy. And now

1 the student would need to learn around that instead of,
2 like, starting from scratch and the student is a
3 student and wouldn't know where to go. So that's the
4 whole thing. And the student is the smaller network.

5 Q So you said some structures are more efficient
6 than others.

7 Can you tell me what is a more complex example
8 of a structure versus a less complex example of a
9 structure?

10 A At the level --

11 MR. STEIN: Objection.

12 THE WITNESS: -- of the POSA? -- I'm sorry.

13 MR. STEIN: Objection; foundation, form.

14 THE WITNESS: I mean, through -- I mean, we --
15 I discuss in my declaration, by the way, in here.
16 Remember, I have to look in the -- in the lens of a
17 POSA, okay? So looking at the prior art here, at least
18 what I'm considering now for my declaration. Also,
19 here where I say -- one moment. I have like a -- I
20 talk about some examples of this.

21 I have, like, a place where I talk about Aslan
22 mentioning a deep neural network. I don't know if you
23 can point me out to this because you have the outline,
24 like a deep neural network being more accurate, but
25 something -- then so that paragraph is what I'm looking

1 for here. Oh, yeah. I found it, I guess.

2 BY MS. MOORE:

3 Q Well, you mention three different
4 architectures in your declaration: Random forest,
5 neural networks and teacher-student architectures.

6 Can you tell me between a random forest and a
7 neural network which one is more efficient.

8 A Excuse me. So I mentioned in my -- in random
9 forest, neural network and -- could you point me out
10 where in my declaration?

11 Q The background.

12 A Background? Oh, I see. Okay. Thank you.
13 Let's go there. 16:24- -- again, if we want to go to
14 the background without going further -- and I'm just
15 looking at the TOC here. It depends how big the neural
16 network is, how big the random forest is, et cetera.

17 If I take a one-layer neural network but the
18 random forest with a hundred thousand trees and a lot
19 of layers in the tree like levels and nodes, I mean,
20 depends what we're talking about.

21 So you have to look at -- you know, it can't
22 be -- it depends what I'm looking at. So I cannot
23 compare apples to oranges. I would have to look at the
24 specific network and tell you, yeah, this network which
25 is this, like -- like Aslan showing this or Chalom or

1 '985 or whatever. This particular network, because
2 they've given us the parameters, they've given us --
3 it's billion versus this is -- then you can do the
4 analysis.

5 Again, however, in terms of the learning, you
6 know, based on the prior art -- and also, even the
7 '985, like in my -- let's go back to that. I just
8 found it and now I missed it, the 400-something-12.
9 224.

10 So Exhibit 1003, paragraph 224 -- so as
11 recognized by the '985 patent, I'm saying (as read):

12 "It was well known at the time of the
13 '985 patent" -- this is like the '985
14 disclosing it as prior art -- "that
15 using random forest resulted in less
16 optimal prediction accuracy as
17 compared to deep convolutional neural
18 networks for image
19 processing/classification tasks."

20 So this is, like, based on some prior art,
21 '985 even saying that random forest has often less
22 optimal prediction accuracy as compared to deep
23 convolutional neural networks for image
24 processing/classification tasks.

25 This is for tasks of interest --

1 Q Ma'am, I'm sorry. You've been talking for
2 like five minutes, but I'm -- I'm not talking about
3 accuracy. I'm talking about efficiency. So can -- can
4 you answer my question?

5 A Efficiency. Okay. Okay. So in terms of
6 efficiency, I go back and tell you in terms of, but
7 these -- you want to maintain the accuracy and the
8 efficiency, okay?

9 So, again, it depends on the network, but I
10 can tell you that with the same complexity, random
11 forest versus deep convolutional network, with the same
12 complexity -- I mean, I don't want to answer based on
13 generality. But in general, like -- but I don't want
14 to answer in generality. I mean, deep neural network
15 has shown like outstanding -- like -- has shown
16 significant improvement in performance relative to
17 other, you know, machine-learning algorithms, including
18 random forest, but this depends on the task again. It
19 depends on what you're looking at.

20 But in terms of, you know, the performance on
21 image classification or a prediction and things, the
22 deep convolutional neural network has shown over a lot
23 of tasks that they can perform better. That's what I'm
24 saying. And they can generalize better, generalize the
25 unseen data sample which we want, okay? Remember the

1 generalization.

2 Training could give you a small error, but
3 when you generalize, it doesn't work anymore. So deep
4 convolutional neural network, they generalize better.
5 They perform better on a lot of tasks as compared to
6 the random forests, as recognized also by the prior
7 art.

8 (Mr. Devkar left the proceedings.)

9 BY MS. MOORE:

10 Q What do you mean by "performance"?

11 A Could you -- could you rephrase what the
12 sentence and -- I said and within that context? So
13 what -- could you say, you said this and what do you
14 mean by that?

15 Q You said, "but in terms of, you know, the
16 performance on image classification." So what did you
17 mean by "performance"?

18 A Performance is like a -- like a -- again, I'm
19 telling you, given the same complexity -- we started
20 with that. Performance is accuracy. This is one
21 performance, how accurate it is.

22 Q Okay. And this is the third time I'll ask.
23 I'm not talking about accuracy. I'm accurate -- asking
24 about efficiency.

25 A But it should be related to accuracy, because

1 I can give you a highly efficient network that's not
2 accurate. I could just give you -- take one node in a
3 neural network. Yes, I select very efficient, but it
4 doesn't perform the task.

5 You cannot -- you cannot have this disjoint.
6 Given a certain complexity, which one is more accurate
7 or given a certain accuracy, which one. You cannot --
8 if you want just to talk about complexity without
9 accuracy, I could tell you, yeah, take a single node in
10 both and we're done. I mean, you don't care about the
11 performance. I added zero classification accuracy. It
12 doesn't -- it doesn't make sense for me to answer such
13 a question, because it doesn't work.

14 Q I'm asking you about them separately, because
15 you addressed them separately.

16 So what is efficiency separate from accuracy
17 when you're comparing a random forest and a neural
18 network?

19 A I didn't address them separately. Actually,
20 if you look at my -- when I discuss that, I said
21 efficiency versus accuracy, for example --

22 Q No. Page 170, you say (as read):

23 "This is consistent with Aslan's
24 objective of efficiency."

25 And that's what I'm asking you about. So what

1 does --

2 (Simultaneous speaking - unreportable.)

3 THE WITNESS: Could you point me out, please.

4 BY MS. MOORE:

5 Q 170.

6 A 1-7-0?

7 Q Yes.

8 A Page or paragraph?

9 Q Page.

10 A But this is within the context I discussed
11 before, so I have to go back. You know, we cannot --
12 the context -- you can see it in the motivation to
13 combine. And this is what I want to bring you. Like,
14 but let me go to what you're asking and then -- this is
15 after I discussed for so many pages efficiency versus
16 accuracy that I'm using it here based on what I
17 discussed before. So I've said the context. But
18 anyhow, let's look at that page and see.

19 So which paragraph on that page?

20 Q First paragraph -- one, two three, four --
21 fifth line says (as read):

22 "Objective of efficiency."

23 A 311? Oh, I'm sorry. 170. 308? 307?

24 Q I said the fifth line down.

25 A In 307? The paragraph number is 307?

1 Q I'm on page 170, the fifth line down.

2 A I don't see the word "efficiency" there. I'm
3 on page 1-7-0, fifth line down.

4 Q Yes. The first word is "objective," then
5 "of," then "efficiency."

6 A You know, does the -- does this page start
7 with (as read):

8 "Chalom's Figure 3"?

9 Q Yeah.

10 A Okay. One, two, three, four, five. I have --
11 okay. So this is also -- so I have to go back to see
12 what context we're saying. Because I'm discussing this
13 within a context, so I have to go to the beginning of
14 this paragraph. Try -- let -- give me like just a few
15 minutes to -- for me just to review, one minute or
16 something.

17 Okay. But this is in context definitely to
18 maintain -- also, it's a certain level of accuracy.
19 You cannot take them, because that's what we discussed
20 in all the pages before motivation to combine the
21 efficiency versus accuracy.

22 So what this is saying is if you compress,
23 then you have to operate on less input because it's
24 compressed, fewer parameters. You could then have a
25 more lighter model, lighter, meaning less parameters to

1 operate on the input because you have less input but
2 more compressed. You could design something to operate
3 on that.

4 You could design a lighter model, more
5 efficient in here in terms of power consumption, in
6 terms of flaps. You know, efficiency can go different
7 ways here. So that's what it means.

8 But definitely we care about maintaining the
9 accuracy, because definitely, I could -- I could
10 decrease my model and make it one node and so
11 efficient. If I don't care about maintaining a certain
12 level of accuracy, it wouldn't really -- it is -- it
13 wouldn't make sense, you know.

14 Q If a random forest and a neural network had
15 the same level of complexity, which one would be more
16 accurate?

17 A Again, out of context, I cannot answer,
18 because it depends how you trained your neural network,
19 whether you trained it well, you didn't -- you
20 initialized it well. It -- I have to have all of this.
21 This is how it was trained. These are the two systems,
22 you know, and then test it. And you do retesting to
23 that. So the training aspect is very important.

24 Now, if it's -- now, as I said before, also,
25 the deep neural network had more ability to generalize,

1 but this assumes you trained it well. You trained --
2 you had -- so I cannot answer out of context.

3 Q If a random forest and a neural network both
4 were trained well and had the same level of complexity,
5 which one would be more accurate?

6 A It depends on the number of layers used. Same
7 complexity, you mentioned. Okay.

8 So same complexity and a deep neural network,
9 if it was trained well, the deep neural network would
10 have better ability to generalize. This means -- and
11 this, again, given some benchmarks, you see that were
12 there -- I mean, you could give me a task specific to
13 something.

14 So given -- this is based on benchmarks of
15 there. I mean, testing, like prior -- you know, prior
16 art, prior art results, okay? Then the deep neural
17 network can generalize better based on this prior art
18 for a lot of the tasks, okay?

19 Q Can you deploy a neural network on a cell
20 phone?

21 A Neural -- the deep neural network on a cell
22 phone? I mean, look, we're talking about this as the
23 POSITA from the -- I have to -- so are you asking me
24 now or before?

25 Q Can -- I'll just ask the question again so it

1 has all the right context in it, okay?

2 Can you deploy a neural network on a cell
3 phone as a POSITA in 2017?

4 A I cannot answer this. I have to have the
5 specific reference, what was published then, what
6 was -- and plus, remember, I could deploy a neural
7 network that doesn't perform the task accurately, yes.
8 I could have a one-layer neural network. But again,
9 accuracy is important. I mean, whether -- like how
10 accurate you want your task to be.

11 The idea of the teacher-student model is to
12 maintain a certain level of accuracy matching that of
13 the teacher while minimizing the complexity and making
14 the model more efficient to be deployed on low power.
15 So we have to keep in mind the accuracy level. Yes, I
16 could take a neural network that is very small and
17 doesn't perform much and put it on my -- on a cell
18 phone.

19 But to do the task at hand here, you would
20 need something like the disclosed teacher-student
21 model, for example, to have it low power.

22 Q So you could deploy a neural network on a cell
23 phone in 2017?

24 A I'm telling you if you take, like -- like
25 seven nodes, few layers, but it's not going to perform

1 the task at hand. And the accuracy is not going --
2 it's not going to be accurate at all. I could -- I
3 could deploy in one node, like -- like a neural layer,
4 one network, edge, basically, neural network.

5 But it's not going -- plus in terms of the
6 cell phone, the battery is very important, okay? You
7 could deploy it, but it depends -- the neural network
8 might consume a lot of power then, even. It depends on
9 your neural network.

10 If you want to have higher accuracy, it's
11 going to consume low power. Guess what, your phone
12 will last you one hour. When you watch video on your
13 phone now, the -- your (indiscernible). Battery is
14 dead.

15 So always we need improvement on getting lower
16 and lower power. Whether we can deploy or not is not
17 like the question. The question is to have low power
18 that's more suitable so that I can use my mobile
19 devices and wearable like for a longer range plus
20 deploying a neural network that will give you the
21 accuracy needed for this application, you know, and --
22 you know, and be efficient on whatever it was -- was
23 not -- what was not something then that is -- what was
24 not -- was not then the prior art -- except the prior
25 art was not then basically for the neural network, the

1 complex was not. So you needed to have -- to teach
2 a -- the complex -- so you needed to have -- so I'll
3 take it -- I'll phrase it back.

4 There was a problem then to deploy low-power
5 devices. You could deploy in your network, for sure.
6 If it wanted to be high accuracy, it will be complex.
7 It will drain your power. You would improve it by,
8 yeah, designing a smaller neural network. But to train
9 the smaller neural network from scratch -- I am just
10 going to, like, clarify what I'm saying because,
11 like -- to have a smaller neural network perform at the
12 accuracy of more complex neural network, you need a
13 teacher-student. Yes, you could then teach that
14 smaller neural network, and it will help deploy it
15 then.

16 But to start from scratch, training from
17 scratch in your network to achieve the accuracy was
18 problematic, wouldn't give you the accuracy needed.
19 You could improve the power and maintain the accuracy
20 through the teacher-student. And so then the batteries
21 can last longer or it can maintain the accuracy also
22 more. We're using a smaller network, so that's the
23 problem we're looking at.

24 So, basically, I answered the question
25 assuming we're training from scratch a complex network.

1 But with a teacher-student combination, you could,
2 yeah, deploy a neural network after being taught with
3 this respect and to maintain the accuracy.

4 I don't know if this answered your question.

5 Q What's a motion vector field?

6 A I describe this also in the -- in my -- also
7 "Background" section, "Optical Flow and Warping," so
8 page 34.

9 So you're asking motion vector field? Like I
10 prefer, basically, if I have it written because it
11 would be nicer, like, to -- and it saves time.

12 So under optical flow and warping, it -- I
13 start talking about warping in there, and -- and I
14 said, like, one of them, warping includes coordinate
15 transformation, which is pixel displacement accounting
16 for translation, scale, et cetera.

17 The motion vector field -- so paragraph 61 in
18 my declaration on page 35, I say (as read):

19 "In particular, translational
20 coordinate transformation models
21 ('translational models') are included
22 as part of the affine transformation
23 and 'have been used successfully for
24 estimating and representing the
25 optical flow field [e.g., pixel

1 displacement" -- also called -- or
2 "vector field, warping field]', and
3 they offer a computational advantage
4 by only 'requir[ing] two basis flow
5 fields, horizontal and vertical
6 translation, while [more general]
7 affine models require six basis flow
8 fields.'"

9 So these models have been applied locally
10 within small image regions. And then I go and I
11 explain (as read):

12 "Let I be an input image and O be the
13 output image obtained by warping I,
14 where the warping is performing
15 through local translational
16 transformations according to an
17 optical flow field (also called
18 pixel-flow field, displacement vector
19 field, motion vector field, warping
20 field.) The optical flow field
21 consists of two dimensions also known
22 as two channels, (u, v), with the
23 first dimension u corresponding to the
24 horizontal displacement and v
25 corresponding to the vertical

1 displacement. Such an optical field
2 provides an optical flow vector."

3 So for each pixel or for each position (x, y),
4 you could have u and v. u for the horizontal
5 displacement. v for the vertical. It could be at each
6 pixel location, or it could be at, like, varied pixel
7 locations in a select set of pixel locations in a
8 regional interest.

9 The output image O can then be obtained by
10 sampling the image I according to the optical flow
11 vector. And given the equation showing how the output
12 can be obtained from an input image by applying the
13 motion vector field. So you can see the equation here.

14 So I'm saying in English, in other words, the
15 pixel value at (x, y) in the output image is
16 copy-pasted from another location in the input image
17 determined by the flow vector (u, v), which corresponds
18 to the motion vector displacement.

19 And yeah, and I'm saying (as read):
20 "Alternatively, the 'copy-paste'
21 operation can be used in combination
22 with other mapping and/or image
23 processing (e.g. bilinear
24 interpolation, low-pass filtering,
25 texture mapping, landing)."

1 And so forth. And I'm saying later on the
2 next paragraph 63 --

3 Q Are you just going to read multiple paragraphs
4 out of your declaration?

5 A No. I mean, are you satisfied?

6 MR. STEIN: Ashley, I think we've got to make
7 sure we don't interrupt, though, because -- it'd be
8 good to wrap up if we can, but she -- she's answering
9 the question.

10 THE WITNESS: Yeah, because it's --

11 MS. MOORE: Well, she's reading from her --

12 THE WITNESS: It's in my declaration. It is
13 very well in my declaration. And this describes very
14 well the -- your question.

15 BY MS. MOORE:

16 Q What was my question?

17 A Can you describe what is the vector
18 displacement field? And that's what it is.

19 Q No. I asked, what's a motion vector field?

20 A And this is the motion vector field. It's the
21 same.

22 Q Do you have any idea what it is apart from
23 simply reading three paragraphs out of your
24 declaration?

25 A I wrote it. So that's what it is. And

1 because I wrote and put time into writing it, instead
2 of just, like, answering in English like this, I prefer
3 to be reading it because I don't want to be answering
4 out of memory. And I believe it is well written here,
5 and that satisfies an answer to your question.

6 Q So if a student were to ask you what a motion
7 vector field is, you would read these three paragraphs
8 out of your declaration?

9 A No. I -- oh, sorry to interrupt. You would
10 what?

11 Q So if a student asked you what a motion vector
12 field is, you would just be reading these three
13 paragraphs out of your declaration?

14 MR. STEIN: Objection --

15 THE WITNESS: Well, it's a -- look, it's an
16 informal setting more. Here, I'm under oath, okay?
17 That's different. That's one thing. Another thing is,
18 there, I would be using the board, and I would
19 illustrate to them, Look here, this, that, this. Here,
20 I can't do that.

21 And I prefer for accuracy to go to my
22 declaration, because this is accurate. I'm -- you
23 know, I'm more comfortable. I spent time on it to go
24 through it. You're welcome to visit me, and I can
25 explain to you on a board. Then it's different.

1 BY MS. MOORE:

2 Q You don't have any pictures here in your --
3 this part of your declaration, do you?

4 A No, I didn't think it's needed.

5 Q No. Not if you wanted to actually explain it,
6 right?

7 A No. I thought I explained it well enough. If
8 a student reads that, they are going to understand.
9 And if they have a question, they would ask me, What
10 did you mean by this? Then I could explain it further.
11 But I think --

12 Q So what did you mean by this?

13 A Excuse me?

14 Q So then what did you mean by this?

15 A By "this," specifically what? I would ask
16 them, What? I mean by what? Can you point me out to
17 what you didn't understand, what section, what part,
18 what word.

19 Q What's a motion vector field?

20 A Okay. The motion vector field gives
21 displacement -- like it's written here, it's a -- it
22 gives you -- I mean, you can generate using the motion
23 vector field. It gives you a way -- it's a
24 transform -- it gives you a way to transform one image
25 into another.

1 But it has other uses, to tell you the truth.
2 Within our context, it's used for warping the image,
3 the input image. You apply the motion vector field.
4 It's like editing instruction to produce an output
5 image that is transformed version, a warped version.
6 The warping using the motion vector field is using
7 displacement in the vertical and horizontal direction,
8 okay?

9 So you just, like, take your value, displace
10 it horizontally and vertically. So you -- so for a
11 given pixel position, you go to the original image, you
12 go u along the horizontal direction, v along the
13 vertical -- because you have a motion vector that's (u,
14 v) -- you find the value, you copy it into that. And
15 so that's kind of one way.

16 But you can use it a lot for many things.
17 Motion vector field can tell you the motion, and you
18 could use it in other applications for recognizing
19 gestures or action recognition or video compression.
20 For example, now we wouldn't be able to talk real-time
21 if it wasn't for motion vector fields and estimation.

22 Because when I move my head, they send motion
23 vectors, they copy from the previous frame, and they
24 just send the difference. So we wouldn't have this
25 real-time Zoom even weren't it for motion vector

1 estimation and prediction, the motion vector fields.
2 So they have a lot of applications.

3 But they give you displacement at -- at
4 different pixels, in different regions and you can make
5 the motion vector field dense or coarse, and you can
6 interpolate in between. So there are different ways to
7 generate these motion vector fields.

8 Q Is the motion vector field a two-dimensional
9 displacement vector in the x and y directions?

10 A Yeah. I mean, you could -- for images, it's
11 typically two dimensions. If you have, like, a
12 three-dimension data and things, you could have also
13 three-dimensional. But here in our -- this context,
14 this is two dimensions. We're taking it to be a
15 two-dimensional field for now, but it doesn't have to
16 be just two dimensions.

17 Q What is a class?

18 MR. STEIN: Objection; form, foundation.

19 THE WITNESS: A class? I mean, it can be --
20 out of context, it can be every -- anything. Could you
21 point me out in my declaration to a specific context so
22 that I could --

23 BY MS. MOORE:

24 Q Do you know what a class is in the context of
25 machine learning?

1 MR. STEIN: Objection; form, same foundation.

2 THE WITNESS: In the context of
3 classification, I mean, you could have different
4 categories also called classes, okay?

5 BY MS. MOORE:

6 Q Are classes and labels the different --
7 different things or the same thing?

8 A Again, it depends on the context, okay? A lot
9 of time we use labels for classes because the class
10 label. You can have an index, even class 1. One would
11 be the label, or you can give it a number or you can
12 quantify it or you can give it an index. That's the
13 class label. You can decide a representative label for
14 your class. It can be an index: class 1, class 1,
15 class 2, class 3.

16 Q So the class would be an integer?

17 A It could --

18 MR. STEIN: Objection.

19 THE WITNESS: I'm -- it could be, I'm saying.

20 BY MS. MOORE:

21 Q Would you -- strike that.

22 MS. MOORE: Why don't we take a break for
23 about five minutes. I'm going to go through my notes
24 and see if I have anything else, but we might be done.

25 THE WITNESS: Okay.

1 (Recess.)

2 MS. MOORE: All right. Well, if we're back on
3 the record I'm happy to announce I'm done. So no
4 further questions.

5 THE WITNESS: Okay.

6 MR. STEIN: Okay. So it's our turn now. So
7 just give me -- I won't need much time but give me the
8 same sort of five, maybe ten minutes just to review
9 notes and see, but I don't really expect any -- any
10 redirect. But just give me sort of five minutes.

11 (Recess.)

12 MR. STEIN: Okay. Well, thank you,
13 Dr. Karam, for your testimony today. I have -- I have
14 no questions.

15 THE WITNESS: Okay. Thank you.

16 (TIME NOTED: 2:38 p.m.)

17

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25

1 I, LINA J. KARAM, Ph.D., do hereby declare
2 under penalty of perjury that I have read the foregoing
3 transcript; that I have made any corrections as appear
4 noted, in ink, initialed by me, or attached hereto;
5 that my testimony as contained herein, as corrected, is
6 true and correct.

7 EXECUTED this ____ day of _____,
8 20____, at _____, _____.
9 (City) (State)

10
11
12
13 _____
14 LINA J. KARAM, Ph.D.

15 Volume I
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25

1 I, the undersigned, a Certified Shorthand
2 Reporter of the State of California, do hereby certify:

3 That the foregoing proceedings were taken before me
4 at the time and place herein set forth; that any
5 witnesses in the foregoing proceedings, prior to
6 testifying, were administered an oath; that a record of
7 the proceedings was made by me using machine shorthand
8 which was thereafter transcribed under my direction;
9 that the foregoing transcript is a true record of the
10 testimony given.

11 Further, that if the foregoing pertains to the
12 original transcript of a deposition in a Federal Case,
13 before completion of the proceedings, review of the
14 transcript [] was [] was not requested.

15 I further certify that I am neither financially
16 interested in the action nor a relative or employee of
17 any attorney or any party to this action.

18 IN WITNESS WHEREOF, I have this date subscribed my
19 name.

20 Dated: February 29, 2024

21
22 
23

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