



Planet Depos®
We Make It *Happen™*

Transcript of Wenke Lee, Ph.D.

Date: September 28, 2023

Case: Crowdstrike, Inc. -v- Open Text Inc. (PTAB)

Planet Depos

Phone: 888.433.3767

Email: transcripts@planetdepos.com

www.planetdepos.com

IPR2023-00289
Open Text Inc. EX-2018

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

4 CROWDSTRIKE, INC.,
5 Petitioner,
6

7 vs.
8

9 OPEN TEXT INC.,
10 Patent Owner.
11

12 Case IPR2023-00289
13 Patent No. 8,418,250
14

15 Videotaped Virtual Deposition of WENKE LEE, Ph.D.
16 Thursday, September 28, 2023
17 9:06 a.m. CST
18

19 Job No.: 508065

20 Pages: 1 - 65

21 Reported Stenographically by:

22 Tiffany M. Pietrzyk, CSR RPR CRR

1 Videotaped virtual deposition of WENKE LEE,
2 Ph.D., pursuant to notice, before Tiffany M.
3 Pietrzyk, a Certified Shorthand Reporter in the
4 States of Illinois, Texas, and California,
5 Registered Professional Reporter, Certified Realtime
6 Reporter, and a Notary Public in and for the State
7 of Illinois.

8
9
10
11
12
13
14
15
16
17
18
19
20
21
22

1 A P P E A R A N C E S

2 ON BEHALF OF THE PETITIONER:

3 PAUL R. HART, ESQUIRE

4 ERISE IP

5 5299 DTC Boulevard

6 Suite 1340

7 Greenwood Village, Colorado 80111

8 913.777.5600

9

10 ON BEHALF OF THE PATENT OWNER:

11 BRIAN EUTERMOSER, ESQUIRE

12 MIKAELA STONE, ESQUIRE

13 KING & SPALDING LLP

14 1401 Lawrence Street

15 Unite 1900

16 Denver, Colorado 80202

17 720.535.2300

18

19 ALSO PRESENT:

20 Sue Pybas, Planet Depos Remote Technician

21

22

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22

C O N T E N T S

EXAMINATION OF WENKE LEE, Ph.D.	PAGE
By Mr. Eutermoser	5

E X H I B I T S

(Attached to transcript.)

DEPOSITION EXHIBITS	PAGE
Exhibit 1003 Declaration of Dr. Wenke Lee	9
Exhibit 1004 U.S. Patent Application Publication 2005/0210035	5
Exhibit 1005 U.S. Patent Number 7,225,343	28

1 P R O C E E D I N G S

2 (Witness sworn.)

3 WHEREUPON:

4 WENKE LEE, Ph.D.,

5 called as a witness herein, having been first duly
6 sworn, was examined and testified as follows:

7 EXAMINATION

8 BY MR. EUTERMOSER:

9 Q. Good morning, Dr. Lee.

10 A. Morning.

11 Q. Nice to see you again.

12 A. Yep. Thank you. Same here.

13 Q. You've been deposed many times before;
14 right?

15 A. Ten times.

16 Q. Is there any reason you can't give truthful
17 and accurate testimony today?

18 A. No.

19 Q. I want to start by talking about the Kester
20 reference, which is Exhibit 1004.

21 (Exhibit 1004 was marked for
22 identification and is attached to the

1 transcript.)

2 A. Okay.

3 Q. You have a copy of that; right, sir?

4 A. Yes.

5 Q. Let me ask you to turn to paragraph 89,
6 please. It's on page 30.

7 A. Okay.

8 Q. In the middle of that paragraph Kester says
9 that, [As read] A human reviewer interacts with the
10 application analyst's classification module 302 to
11 perform the categorization or recategorization;
12 right?

13 A. Yes, I see that.

14 Q. Do you agree that Kester teaches that it's a
15 human analyst who performs Kester's categorization
16 steps?

17 MR. HART: Object to form.

18 A. So if you read -- I mean, so to answer your
19 question, I would say that human reviewer is
20 involved in the categorization and recategorization.
21 If you read further down, for example, paragraph 90,
22 it talks about, let's say, [As read] For a human

1 reviewer, a set of PC-based software tools can
2 enable the human reviewer to manipulate, scrutinize,
3 and otherwise manage the applications from the
4 master application database.

5 And continues to say that, [As read] The
6 human reviewer can interact with the application
7 analyst classification module via a graphical user
8 interface.

9 So obviously, you know, there are tools and
10 even a classification module that has the human
11 analyst. So to summarize, the human analyst is
12 involved, but there are tools that the human analyst
13 is using.

14 Q. You're saying that Kester discloses software
15 tools that a human analyst can use to do the
16 categorization step; is that fair?

17 A. That's fair in a sense that the human
18 analyst can use some of these tools to help
19 classify -- to help classification and
20 reclassification, right, because, like I say, in
21 paragraph 90, in the middle, it talks about, [As
22 read] The human reviewer can interact with the

1 application analyst classification module via a
2 graphical use interface.

3 Q. Kester does not disclose a categorization
4 process that is fully automated.

5 Do you agree with that?

6 A. So if you use the interpretation of the term
7 "fully automated," fully automated means, if fully
8 automated, means that human is completely not
9 involved. Then Kester is not teaching that. Kester
10 teaching humans involved using the tools.

11 Q. And one thing the human reviewer does is
12 perform certain steps in generating a hash/policy
13 table; right?

14 MR. HART: Object to form.

15 A. Where do you -- are you referring which
16 paragraph in Kester? Can you point me to that?

17 Q. I don't have a specific paragraph in mind.
18 I'm just talking generally about what Kester
19 discloses and what the human's role is.

20 MR. HART: Same objection.

21 A. That's how I recall that the human has to
22 manually generate a hash. That's -- yeah, I -- I

1 don't recall seeing that.

2 Q. I'm gonna have you turn to Exhibit 1003.

3 (Exhibit 1003 was marked for
4 identification and is attached to the
5 transcript.)

6 A. 03.

7 Q. And that's your declaration in this case;
8 right?

9 A. Yeah, sorry. Okay. 1003. Yep. Okay, I
10 have it.

11 Q. If you turn to page 76 and paragraph 122,
12 please?

13 A. Okay.

14 Q. And you note in that paragraph that Kester
15 explains that the process for classifying or
16 categorizing applications can be based upon adaptive
17 learning systems.

18 Do you see that?

19 A. Yes, I see that.

20 Q. And the phrase "adaptive learning systems"
21 appears in paragraph 92 of Kester; is that correct?

22 A. Double-check. I believe that's the case but

1 just let me double-check. Yep.

2 Q. And specifically in the last sentence of
3 that paragraph, which reads, [As read]
4 Categorization can be based upon word analysis,
5 adaptive learning systems, and image analysis;
6 right?

7 A. Yes.

8 Q. And Kester does not suggest the use of an
9 adaptive learning system for the purpose of
10 determining expected network activity; correct?

11 A. Let me look at this. Can you rephrase your
12 question again?

13 Q. Paragraph 92 refers to categorization;
14 right?

15 A. Yes.

16 Q. And Kester's reference to adaptive learning
17 systems is in the context of the categorization
18 step, not the step of determining expected network
19 activity.

20 Do you agree with that?

21 A. I would say that paragraph 92 specifically
22 talks about adaptive learning system can be used for

1 categorization. Paragraph 92 did not specifically
2 talking about the determination step. But, I
3 mean -- sorry -- so here in paragraph 122 of my
4 declaration, I basically say, you know, I mean,
5 first of all, because Kester suggested -- suggested
6 that adaptive learning system can be used for the
7 step of classifying or categorizing applications,
8 one of skill in the art would have found it obvious
9 to use, you know, such system, right, to perform
10 categorization or classification. And Honig teaches
11 that.

12 I think some other -- I think later on,
13 maybe not for this claim, we talk about the fact
14 that, you know, the motivation of using adaptive
15 learning, obviously, is to make your classification
16 model work better and faster. And when a POSITA is
17 motivated to do that step, it's also natural to say,
18 Oh, if I apply machine learning for categorization,
19 meaning that I use a machine learning base model to
20 automate the step to run it automatically, how do I
21 generate this model.

22 So Honig actually teaches the step of

1 automatically generating that model that you use for
2 classifying and categorization. And that's
3 essentially automating the determination step.
4 Right? So the point is that a POSITA, you know, is
5 motivated to speed up the process and will not stop
6 only at the categorization step. It would naturally
7 say, Oh, I also look at whole work flow, I also
8 speed up the determination step. And also, in fact,
9 in machine learning, we talk about using machine
10 learning to automate certain task, and people
11 sometimes only look at, you know, the automation
12 done by applying the machine learning model, let's
13 say, for classification. Sometimes people forget
14 that you have to train the model, and that's also
15 part of the automation and, in the context of this
16 case, generating the model is actually the step of
17 determining, you know, what's the, let's say,
18 appropriate behaviors. Yeah.

19 Q. I understand that that's your opinion and
20 we'll get to that. Right now I just want to focus
21 on what's in Kester. And in Kester, you agree that
22 Kester teaches using adaptive learning systems only

1 for the categorization step and not for the
2 determining step; is that fair?

3 A. I would say that Kester suggested using
4 machine learning for categorization or classifying
5 application. One thing that a POSITA reading this
6 say, Oh, that's obviously interesting idea and it is
7 actually even an obvious idea for POSITA in the time
8 around 2005. Then a POSITA say, Okay, I understand
9 you want to speed up and automate. Why stop there?

10 What I'm trying to say is that, yes, that's
11 what Kester saying, but Kester did not exclude to
12 say, Oh, you should only use machine learning for
13 classification. You shall not use that for
14 determination. Right? And so that's one aspect of
15 how I interpret Kester teaching.

16 Another aspect is that a POSITA reading this
17 would say, Oh, okay, I got that. Great idea. I
18 will not stop at classification. I will also
19 automate determination. And, again, like I said,
20 that's part of the machine learning process anyway.

21 Q. Kester refers to adaptive learning systems,
22 and in your answer, you refer to machine learning.

1 Is it your opinion that those two terms are
2 interchangeable?

3 A. Not exactly. I mean, so adaptive learning
4 obviously is part of -- I mean how to put it --
5 machine learning is, you would say, in general, you
6 know, can be referred to very broad scope of
7 techniques that include adaptive learning. So in
8 particular, adaptive learning here means that you
9 can learn new things. You can basically update a
10 model based on new things that you see. And that's
11 also very obvious to a POSITA that sometimes they
12 use these two terms interchangeably, but sometimes
13 they will use adaptive learning system to emphasize
14 that you can actually learn new things based on new
15 data, just kind of they call it either train it or
16 incrementally learn it. Yeah.

17 Q. Your opinion is that adaptive learning, as
18 used here in Kester, means that you can learn new
19 things or update a model based on new things you
20 see; is that correct?

21 A. Yes. And also that's what Honig teaches as
22 well.

1 Q. Does the use of an adaptive learning system
2 imply that a process will be fully automated?

3 MR. HART: Object to form.

4 A. So, again, you have to look at this in the
5 context. Right? You cannot say, Well, I use
6 machine learning. Okay? Then people ask exactly
7 how you gonna use it. Then we can tell you, Okay,
8 is this fully automated? And so yeah, so that's how
9 I would answer the question is say give me the
10 context.

11 Now, I also add that a POSITA would agree
12 that, when you apply a model that has been already
13 learned by machine learning algorithm to, let's say,
14 you are codify or put the machine learning model in
15 the software so that, you know, when object comes in
16 or activity comes in, you want to use the model to
17 categorize or classify, yeah, that process fully
18 automated. That's basically running the software.

19 And in this case, the software actually runs
20 the machine learning model. And this whole thing,
21 this particular step, a POSITA would agree that this
22 is fully automated.

1 Q. When you say "in this case, the software
2 actually runs the machine learning model," what is
3 the case you're referring to there?

4 A. The case is, in the context of this IPR
5 case, when you try to classify object as malware or
6 not, yeah, so you basically learning the software to
7 look at, you know, some of the behaviors or
8 activities of the file or the object running or the
9 process running on a remote computer. For
10 example -- yeah, and then you essentially apply
11 machine learning to -- a machine learning base model
12 to classify is this behavior acceptable or not or is
13 this behavior indicates this is malware or not. So
14 that's what I mean. Yeah.

15 Q. What about in the case of Kester's system
16 and model?

17 Does the use of adaptive learning systems
18 imply a fully automated categorization process in
19 that context?

20 A. So I think that the -- let me see here.
21 Well, I'll refer to my declaration where I talk
22 about -- talk about combining Kester and Honig.

1 So ...

2 Q. Well, right now, I'm just asking about
3 Kester. I understand you have opinions about the
4 combination. But for purposes of my questions right
5 now, I just want to talk about what's in Kester.

6 A. Okay. So let's say if you focus on
7 paragraph 122 in my declaration. Right? And I
8 would say that, you know, if you read paragraph, you
9 know, 122 again, it says, [As read] However, Kester
10 explains that the process for classifying or
11 categorizing applications, such as to obtain the
12 'expected or allowed network activity' (i.e., mask)
13 as set forth in Kester ... can be based upon
14 adaptive learning -- learning systems.

15 And then I say [As read] One of skill in the
16 art, therefore, would have found it obvious to look
17 to known adaptive learning systems to perform
18 Kester's classification and/or categorization
19 process.

20 So then, you know, I said, you know, Honig
21 teaches that. So really -- so my point here is that
22 a POSITA, reading this, will understand that Kester

1 is suggesting that we can use adaptive learning
2 system for classifying or categorizing application.
3 And a POSITA will understand that, hey, when you
4 apply machine learning base model to this process,
5 essentially, you are fully automated, this
6 particular process, which is you see object, you see
7 activity, then you classify, malicious or not,
8 that's fully automated.

9 Q. Well, Kester itself doesn't suggest fully
10 automating the categorization process, using
11 adaptive learning systems, does it?

12 A. So my point is that Kester suggests that
13 this can be -- can be done based upon adaptive
14 learning system. My point is a POSITA will
15 understand if you apply machine learning here, that
16 means that you have -- we call it the classifier.
17 Right? A POSITA will tell you that -- you work in
18 securities, hey, what will you use to categorize or
19 classify a object or activity is malicious or not?
20 I say, well, I use a classifier.

21 And people also understand that a POSITA
22 will understand that the -- sometimes we call it,

1 the machine learning model itself, the classifier,
2 except that the classifier is produced by machine
3 learning algorithm, not machine manually codified.

4 So really, the point is that a POSITA reads
5 this, he or she will understand, okay. Yeah, you
6 just, essentially, try to fully automate the
7 classification step, using a software, and the
8 software in this case is -- you know, is basically
9 the machine learning base model, adaptive learning
10 model. I mean, that's -- to me, a POSITA would read
11 this and say, okay. Yep, I know what you are
12 referring to.

13 Q. Well, isn't this paragraph 92 in Kester
14 teaching that adaptive learning systems are one of
15 multiple tools that a human analyst could use to
16 perform the classification step?

17 A. Yeah, so the last sentence talks about, you
18 know, [As read] Categorization can be based upon
19 word analysis, adaptive learning systems, and image
20 analysis.

21 So a POSITA reading this would say, yeah,
22 you are referring to -- you know, can be multiple

1 things, can be actually, basically, same things
2 repeated. In a sense that when it say,
3 "Categorization can be based upon word analysis" --
4 let's say word analysis and image analysis, that is
5 suggesting that those are the things that you are
6 looking for when you classify.

7 And you say, how is that going to be
8 automated? That's why I talked about the
9 determination step, meaning that if you apply
10 machine learning -- well, a POSITA would be
11 motivated to apply machine learning, not just on the
12 classification step, also in the determination step,
13 meaning generating or producing the classifier
14 automatically. And what Kester is suggesting here
15 that we should, for example, look at, you know, some
16 aspects of the behavior, such as word and image,
17 that's essentially suggesting, hey, these are the
18 things that you should consider when you use machine
19 learning to build a model or build a distribution or
20 build a automation model so that in classifying, you
21 also look at those things because your model has
22 been instructed to look at the word, the images. So

1 that's one aspect.

2 Another aspect is that really, by 2005, some
3 of these word analysis or image analysis
4 applications, they were already using machine
5 learning in those tasks. So to me, it's like Kester
6 is basically repeating same thing. All right. You
7 can use machine learning, you know, and you can use
8 adaptive learning system to make the system, kind
9 of, incrementally learn and learn new things, and
10 you can also look at some of the features that you
11 may not have thought about, for example, word and
12 image, yeah, that's how I read it.

13 Q. Right.

14 Kester is telling the human analyst to use
15 word analysis, adaptive learning systems, and image
16 analysis as tools in performing the classification
17 step; right?

18 MR. HART: Object to form.

19 A. So like I said, I think Kester using those
20 as examples of things that you could look for, you
21 could use to analyze, to categorize an application.
22 There are many things that Kester, kind of, talks

1 about, right, some of the network behavior, some of
2 the system behavior, some of the, you know, file
3 attributes. I mean, here, it is suggesting, hey,
4 there are also other things you could look for.
5 Yeah.

6 And then also, just so you know that a
7 POSITA would, when they look at these kind of
8 things, okay, use machine learning. Then people
9 say, okay. First of all, what algorithm? Okay.
10 You want adaptive. Okay. That means you want it to
11 be doing something, like learning new things.

12 And then also say, what's your machine
13 learning -- what's your machine learning task? Not
14 just okay, your goal is to classify applications.
15 But people -- a POSITA would say, okay. Do you
16 suggest where to look? Right?

17 So that's, to me, is like Kester is
18 suggesting some additional attributes and that
19 may -- a POSITA may find it useful. That's what it
20 is.

21 Q. Kester isn't suggesting that you can replace
22 the human analyst with any of these machine learning

1 tools. Is that fair?

2 A. So like I said, that when Kester suggesting
3 that this can be based upon this word analysis,
4 image analysis, and adaptive learning system. Like
5 I said, POSITA would say, oh, you want to use
6 machine learning. And like I said, by 2005, you
7 know, that's already a lot of work, including my own
8 thesis which was done in 1999. We basically trying
9 to automate the whole step of classification, using
10 machine learning-based model.

11 So my point is that by then, people look at
12 this and say, okay. I know you basically say --
13 suggesting that we can use machine learning system
14 to fully automate a particular step of
15 classification and categorization. That's an --
16 essentially, a well-known, well-accepted solution, I
17 would say.

18 Q. Is it your opinion that Kester teaches that
19 you can completely eliminate the human analyst from
20 the classification step, using machine learning
21 tools?

22 MR. HART: Object to form.

1 A. So, again, I think Kester did not explicitly
2 say, oh, our goal is to throw away human being. It
3 does not say that. It just say, you know,
4 categorization can be based on these automatic
5 analysis, in particular, machine learning. So a
6 POSITA would understand and agree, okay. Yes, we
7 can use machine learning to build a model and use it
8 for classification.

9 Now, Kester did not exclude the possibility
10 that, hey, some humans just want to every now and
11 then, check in, and take a look. Yeah, what
12 prevents it? Nothing. I mean, what's the point of
13 preventing human if the human wants to get involved?

14 But the whole point is that -- the whole
15 point that I think Kester is trying to make and that
16 a POSITA reading this would agree is that Kester
17 suggests that this step can be automated if you use
18 machine learning.

19 Q. I'm gonna have you take a look at
20 paragraph 94 of your declaration.

21 A. Okay. 94. Okay.

22 Q. You say in that paragraph that, [As read]

1 Honig's unsupervised SVM algorithm is an adaptive
2 learning system.

3 Correct?

4 A. Yep.

5 Q. Just so the record is clear, can you remind
6 me what SVM stands for?

7 A. Support vector machine.

8 Q. And you don't cite anything in your
9 declaration in support of your opinion that a
10 support vector machine is an adaptive learning
11 system; right?

12 A. I think it's well known that unsupervised
13 SVM algorithm is an adaptive learning system, in
14 that it would be able to, you know, learn new things
15 as new data comes in, yeah.

16 Q. Is a supervised SVM algorithm an adaptive
17 learning system, in your opinion?

18 A. You can still make adaptive, just -- you
19 know, I mean it can be engineered to be adaptive,
20 yeah, sure.

21 Q. How would you do that?

22 A. So, again, some of these terms are very

1 broad. So adaptive really means that, you know, can
2 your new model -- can your model learn new things?
3 And really, the principle is, basically, you supply
4 it with new data and say, hey, retrain it, you know,
5 or just revise the model. So supervise means that
6 you give it new data. Say, hey, I know this data.
7 I tell you this data is malicious or is not
8 malicious, and here are things you should look for.
9 So that's where supervise is coming from.

10 Unsupervised just means that hey, here's new
11 data. You figure it out, which cluster it belongs
12 to. Does it belong to the, you know, cluster of
13 legitimate software or cluster of malware? So is
14 this a less -- so that's why it's called
15 unsupervised, meaning that you don't have to really
16 label each data item if you don't want to, yeah.

17 But the gist is that adaptive means that you
18 can supply data and it will learn, it will
19 incrementally learn and update a model.

20 Q. So only an unsupervised algorithm is an
21 adaptive learning system, in your opinion?

22 MR. HART: Object to form.

1 A. No. Yeah. So like I said, you can still
2 engineer a supervised learning system to be
3 adaptive.

4 Q. But you'd have to engineer the supervised
5 learning system to transform it into an adaptive
6 learning system. Is that your testimony?

7 A. What I'm trying to say is that -- I would
8 just say the POSITA would agree that in machine
9 learning -- actually, the bulk of the work has set
10 up the machine learning task, meaning hey, what data
11 you can supply, you know, to the -- and then how
12 often you train the model and then how do you
13 validate the model and then, you know, how do you
14 put the model into the software that you're learning
15 it and automate things.

16 So, basically, these are the -- that's why I
17 call engineer in a sense that you set it up so that
18 you want to be adaptive? Okay. Then set up a
19 mechanism when there's a new thing that you supply
20 to the -- to the system that, you know, kick off the
21 relearning or incremental or adaptive learning
22 process. That's what I meant.

1 And that actually applies to supervised or
2 unsupervised. It doesn't really matter. You have
3 to, basically, say, okay. Here's a new piece of
4 data. Please, adapt yourself. High level, that's
5 what it is.

6 Q. Let me ask you to take a look at Honig,
7 which is Exhibit 1005.

8 A. Okay.

9 (Exhibit 1005 was marked for
10 identification and is attached to the
11 transcript.)

12 Q. If you turn to column 7, starting around
13 line 17, Honig says, [As read] Automated model
14 generation trains detection models from data stored
15 in a data warehouse. The process for converting the
16 data into the appropriate form for training is fully
17 automated.

18 Do you see that?

19 A. Yes. Yeah, I see that.

20 Q. Honig does not explain how the process for
21 converting data into the appropriate form is fully
22 automated, does it?

1 A. I don't recall seeing it in the rest of the
2 patent so I don't want to say that it did not
3 explain, it did not give example explicitly to this
4 point -- to this point of automatic transforming
5 data in the patent. I don't recall seeing that
6 detail. But I would say the POSITA reading this
7 would say, yeah, they know exactly how to do it.

8 In fact, I will say that part of my thesis
9 was about doing that, how do you automatically,
10 let's say, transform, let's say, network data which
11 is completely binary. Tcpdump data into ASCII data
12 format that you can apply machine learning algorithm
13 to learn stuff. I mean, that's like, by 1999, my
14 thesis was already published. So that's already, I
15 would say, well-known art that people looked at,
16 Yep, I know what you're talking about. Yes, we can
17 do this. Yeah.

18 Q. The thing that Honig says is fully automated
19 is the process for converting data into an
20 appropriate form for training; right?

21 A. So what he meant is that you run fully
22 automatic. Fully automatic means that you don't

1 need to have a human to, okay, look at this traffic,
2 okay, now I need to look at this thing and then type
3 something else for machine learning. No, that's
4 not -- so that's not automated. Of course not.

5 But what Honig talking about here that every
6 POSITA would agree and understand is that you run a
7 tool that takes, let's say, data, you know, whatever
8 data you get from the network or the systems or
9 file, then you -- this tool will process it and
10 convert it into a format that your machine learning
11 algorithm is expecting. That's all.

12 I mean, that's a well-known step in machine
13 learning process that people actually build tools to
14 do this. I mean, like I said, the algorithms or the
15 heuristics, all those things have been talked about
16 and searched about. In fact, that's part of my
17 thesis.

18 Q. Right. But what Honig is describing here as
19 fully automated is a data conversion process;
20 correct?

21 A. Yes, like I said, the data conversion
22 process is one of the step in machine learning.

1 Machine learning, you cannot say, hey, you want to
2 learn something, I say I want to learn how to, let's
3 say, classify apple versus orange. You can say,
4 okay, I just told machine algorithm to data. What
5 data? You basically have to process data in some
6 way that the machine learning algorithm will
7 learn -- would know how to process. And that's a
8 step that every machine learning application or
9 process would have to do and -- I haven't seen an
10 exception yet. Most, if not all, such steps are
11 fully automated. Otherwise, how do you prepare a
12 ton of data that's required by the machine learning
13 algorithm. Of course it's fully automated. Like I
14 said, a POSITA reading this would say, Yeah, I know
15 exactly what we're talking about. Either I've known
16 tools that do this or I can develop a tool to do
17 this. Yeah. So very obvious.

18 Q. Would you agree that Honig doesn't describe
19 its model generation algorithms as fully automated?

20 MR. HART: Object to form.

21 A. So where does it talk about model
22 generation? Which paragraph are you referring to?

1 Q. Well, right now, I'm just referring to the
2 same disclosure in column 7, starting at line 17,
3 where it refers to a fully automated data conversion
4 process. And my question is, that doesn't say that
5 Honig's entire model generation algorithms are fully
6 automated.

7 Do you agree with that?

8 A. Well, okay. If you read 17, right, so
9 automatic model generation trains detection models
10 from data stored in a data warehouse. Right? And
11 then we were discussing the next sentence, [As read]
12 The process of converting data into the appropriate
13 form for training is fully automated.

14 Like I said, that particular transformation,
15 like transferring -- sorry -- converting data, that
16 step is fully automatic. That's completely
17 well-known, accepted, and understood by a POSITA.

18 But even this sentence 17 says, which says
19 automatic model generation trains detection model
20 from data stored in the warehouse, if that's what
21 you talk about automating -- automatic model
22 generation, I would say that any POSITA would

1 understand and agree that, yeah, the model
2 generation itself, when you apply machine learning,
3 of course it's fully automatic. You apply a machine
4 learning algorithm to data to produce the model. So
5 that's automatic process.

6 Or you say, hey, basically you run the
7 machine learning algorithm, let's say in this case,
8 can be support vector machine but not based on a
9 machine. Actually, it's the algorithm, the software
10 that runs the support vector machine algorithm, you
11 give the algorithm, in this case, that's the SVM,
12 the data which has been automatic, you know,
13 transferred or converted. You apply the data to --
14 you say, hey, SVM run on this data, and, boom, after
15 a while, the SVM produce the model. And that's a
16 fully automatic process of model generation. That's
17 the -- essentially the essence of machine learning.
18 That's why people think of it is so magical, Oh, the
19 machine learned new thing, wow, it does this
20 automatically.

21 Think about it, if it's not automated who
22 cares if you call it machine learning or not? Why

1 don't you just call it human learning? There's a
2 reason we call it machine learning. Why? Because
3 automated. Fully automated.

4 Q. Well, some steps in Honig's model generation
5 process require manual intervention; right?

6 A. Which step are you talking about?

7 Q. Just some steps. It's not the case that
8 every step is fully automated.

9 Do you agree with that?

10 MR. HART: Object to form.

11 A. So, again, depending on context, you need to
12 point me to the patent that it talks about, Oh, this
13 step we can automate. Then I can opine on that.

14 Q. Take a look at column 3, lines 28 to 30.

15 A. Okay. Column 3, which line again?

16 Q. 28 to 30.

17 A. Okay. Column 3, 28 to 30. Okay. Yeah,
18 talks about labeling, yeah, I mean, that's a
19 well-known, understood step that may require some
20 human intervention but, again, it says about
21 semiautomated. I hope that he's actually referring
22 to my thesis, to be honest. My thesis say, hey, I'm

1 tired of having to generate, what we call it,
2 feature construction meaning constructing what the
3 machine learning algorithms should be looking for.
4 I was thinking it can be somehow automating this
5 step. I would just be honest, at the end of my
6 thesis, I claim semiautomatic. I would not say
7 fully automatic.

8 But, again, might talk about labeling,
9 right, creating label. That's part of the
10 supervised machine learning process. If it's
11 unsupervised, you don't get label data. Just like
12 here's data, figure it out. And I think Honig talks
13 about unsupervised machine learning. I think I talk
14 about in my declaration when we give the background
15 overview of Honig, it specifically talks about why
16 such a big deal of using unsupervised machine
17 learning. In fact, we use unsupervised machine
18 learning, that means you don't have to label the
19 data, which means you may not even need any human
20 intervention.

21 Again, it really depends on the context that
22 I want to be careful, say, hey, some specific

1 application in this particular situation, whatever.
2 But in general, like I said, the reason we call it
3 unsupervised is that you don't need human
4 supervision, that means you don't need human
5 intervention.

6 Q. Let me see if I can unpack some of that. So
7 in Honig at column 3, lines 28 through 30, where it
8 says, [As read] Some of the processes still require
9 some manual intervention, such as labeling data, but
10 even these can be semiautomated.

11 It's your opinion that that text refers to
12 supervised machine learning as opposed to
13 unsupervised machine learning; is that correct?

14 A. Yeah.

15 MR. HART: Object to form.

16 A. In general, yeah. In general, that's the
17 case. Now, whether somebody come up with some --
18 you know, I don't know, some specific situation, Oh,
19 this is unsupervised but has label data, I was,
20 like, that's strange, that's not how we understand
21 general unsupervised means. Like I said,
22 unsupervised typically means that you don't need to

1 supply label data.

2 Supervised machine learning means that you
3 need to supply label data. And the reason that
4 Honig says "may require some manual intervention,
5 but even these can be semiautomated," I mean, a
6 company understand, right, for example, if you say
7 the data that you supply to the machine learning
8 algorithm, you know, the labels so obvious, meaning
9 that some of the attributes or behavior patterns so
10 obvious that you can use a tool, let's say, a
11 traditional signature base or pattern matching
12 software tools, you know, from the antivirus or
13 anti-malware companies or products that already tell
14 you, Hey, this object is malware. Well, in that
15 case, those tools already did the label for you.
16 You don't need human intervention there.

17 So, again, it really depends on the context
18 of how much manual intervention is required. But
19 definitely I would say that any POSITA will agree
20 that yes, some of these tasks can already be
21 automated. May not be fully but definitely some.
22 Yeah. Again, that's in the context of supervised

1 machine learning. But as Honig, you know, kind of
2 promotes unsupervised SVM so, which does not require
3 labeling.

4 Q. Well, supervised SVM is one of three
5 different types of model generation algorithms that
6 Honig discloses; right?

7 A. Yes. But my point is that a POSITA would,
8 you know, understand the requirements and can
9 decide, you know, what's the best model approach
10 that they find useful and productive. You know, a
11 POSITA can, you know, definitely, if the -- if the
12 situation allows, would offer unsupervised SVM.
13 Why? Because it doesn't require human intervention.
14 It's completely fully automated. You know, you
15 don't need any label data. So everything -- you
16 know, because, you know, because -- because all
17 these automation is just easier. So if I'm a
18 POSITA, I would do that, definitely.

19 Q. You said if the situation allows. What is
20 an example of a situation that would allow
21 unsupervised SVM?

22 A. Unsupervised SVM? Yeah, I mean, I think

1 most -- in particular, if you say -- if your main
2 task is to -- I mean, just this is really my opinion
3 is that if your main task is to say malware or not,
4 that I think unsupervised SVM can do -- can do, you
5 know, can do a great job already. Yeah. So really,
6 to me, in other words, for this IPR case, I would
7 say, yeah, unsupervised SVM, if I'm a POSITA, that's
8 how I would use it, you know, use it until -- I
9 mean, unless I'm proven to be, Oh, you need
10 something in addition. Okay. But right now I don't
11 perceive. Like I say, if the main goal is to
12 classify malware or not, unsupervised SVM is plenty.

13 Q. Can you give me an example of a situation
14 that wouldn't allow for unsupervised SVM?

15 A. I cannot think of anything right off the top
16 of my head, like I say, in the context of malware
17 classification. Malware or not classification.

18 Q. What about in some other context?

19 A. Well, I would say, completely off the topic,
20 you know, completely out of scope of this case,
21 yeah, there could be, you know, cases, let's say,
22 you know, the most famous example would be face

1 detection. All kind of biases. All kind of biases
2 because the data that people use to train those
3 models are predominantly white males, and you create
4 problems. So there, I could imagine, you know,
5 there's some human intervention in terms of
6 procuring what data should be supplied. But that
7 still is a very sort of, you know, very specific
8 case.

9 Q. Do you agree that unsupervised SVM requires
10 lots of normal data as input in order to operate
11 effectively?

12 MR. HART: Object to form.

13 A. I say, you know, at this point, I would
14 rather go to my declaration where I talk about
15 overview of Honig. Let me see. I think he
16 explicitly talks about -- yeah, let me see that.

17 Yeah, so if you go to paragraph 64 of my
18 declaration, right, I talk about Honig. And then I
19 think in, sort of, one, two, three, four, the fifth
20 line on page 43, I quoted Honig saying that,
21 [As read] Unsupervised anomaly detection algorithms
22 examine unlabeled data and attempt to detect

1 intrusions buried within the unlabeled data.
2 Unsupervised anomaly detection algorithms operates
3 under the principle that intrusions are very rare
4 compared to the normal data, and they are also
5 quantitatively different. Because of this,
6 intrusions are outliers in the data and can be
7 detected.

8 Yeah. So a POSITA reading this would say,
9 yes, you need a lot of normal data. You also --
10 hopefully, the data set that you have also have the
11 not normal data so the SVM will figure, oh, here's
12 what -- here's how we should classify as normal,
13 what is not normal. Or here's how we should
14 classify what's malicious, what is not.

15 So you need data in multiple classes that
16 you want to learn to classify. But I want to
17 caution that the beauty of unsupervised anomaly
18 detection is that you don't need labeled data
19 because it talks about you -- examines unlabeled
20 data, as long as, you know, the different classes,
21 the object that you are hoping to learn, they are
22 quantitatively different.

1 MR. HART: Brian, can we take a quick break?

2 MR. EUTERMOSER: Sure.

3 (A short break was had.)

4 BY MR. EUTERMOSER:

5 Q. Dr. Lee, I just want to follow up on the
6 answer that you gave before the break.

7 Is it your opinion that unsupervised anomaly
8 detection algorithms are useful primarily for
9 finding outliers?

10 A. So outlier, in the contexts of one class of
11 data, is different from the other class. I will say
12 it that way. Meaning, that as long as let's say
13 you -- your goal is to be able to use unsupervised
14 SVM to come up with a classifier so that it will
15 know how to distinguish, let's say, malware and
16 normal program, normal application, as long as these
17 two classes objects, they look different. You know,
18 however -- whatever the feature you decide to look
19 at, they look different, then it's good. It doesn't
20 have to be -- you don't have to say one is the
21 outlier. Oh, that's really relative, meaning that
22 one is the outlier with respect to whatever the base

1 class you want to call a base class.

2 So, really, my point is that the principle
3 classification is that you can find things that
4 separate classes. Right? So meaning that these
5 classes, you know, when you look at certain
6 attributes, they look different. Yeah.

7 Q. Don't unsupervised anomaly detection models
8 need to identify outliers among a large data set of
9 regular or nonoutliers?

10 A. So, again, like I said, you know, outlier is
11 really in the context of the classes of the object
12 that you hope to put them into the appropriate
13 classes. Right? So which means that, you know, one
14 class may look -- you know, you can define one class
15 as the outlier of the rest. So, really, the machine
16 learning algorithm, supervised or not supervised,
17 their job to -- you know, to find which class this
18 object belongs to. And, in particular, for
19 unsupervised anomaly detection algorithm, because
20 you don't pre-label the data, you don't -- you know,
21 oftentimes, you don't even tell the machine learning
22 algorithm, you know, how many classes, but sometimes

1 people do. Sometimes people do say, hey, I expect
2 you to produce two classes for me. But I cannot
3 give you label data because I don't have the time or
4 I don't have the energy. I don't want to figure
5 this out. Whatever -- whatever reason you don't
6 give the unlabeled data.

7 Then, the machine learning algorithm -- in
8 this case, can be unsupervised machine learning
9 algorithm -- you try to find how to separate, let's
10 say, you know, this set of data into two classes.
11 And you can say one class is the outlier with
12 respect to the others. It really doesn't matter
13 what you want to say.

14 Q. Can an unsupervised SVM classify a single
15 unclassified object as malware?

16 MR. HART: Object to form.

17 A. So, I mean, really, I want to answer in the
18 context. Can you rephrase the question?

19 Q. Well, I'm just trying to understand your
20 testimony or your opinions about how these
21 unsupervised anomaly detection models work. So I'm
22 wondering what would happen if you applied that

1 model in the case of a single unclassified object.

2 A. Uh-huh.

3 Q. Would the unsupervised model be able to
4 detect or identify that single object as malware?

5 MR. HART: Object to form.

6 A. Okay. So now I think I understand the
7 question. So after you have trained or produced the
8 model, meaning that you have automated the
9 determination step using, let's say, unsupervised
10 SVM, so SVM produce now a classifier, then you give
11 a single malware to the model, say, categorize for
12 me. Yes, that's what you expect it to be produced.
13 Yep, that's malware. And if it correctly -- if it
14 classifies correctly, yeah.

15 So to rephrase, when you apply the machine
16 learning-based model in the categorization step,
17 it's actually should be able to classify an object
18 per-object basis.

19 Q. Is that true even if there is no previously
20 known data for the object?

21 A. So what do you mean by "no previously known
22 data for the object"? What does that mean?

1 Q. That you don't know anything about the
2 object before you apply the model.

3 A. So I can tell you, for example, right, if
4 let's say -- let's say you supply the SVM only the
5 normal data, only normal data, suppose. And then
6 you say, okay. Now, I give you a piece of malware,
7 tell me, classify for me. The SVM can say, well, it
8 doesn't look like any of the thing that I know about
9 normal, so it's not normal.

10 Yeah, that's what anomaly detection means,
11 actually. Anomaly detection means it doesn't fit in
12 the models that we have trained. So even though you
13 have previously not supply a malware object to the
14 SVM, the SVM can still say, yep, it doesn't look
15 like anything that I've seen before. So that's why
16 it can say -- it can classify as not normal, if it
17 has been trained using normal data.

18 Q. You agree that a support vector machine is a
19 binary classifier; right?

20 A. Yes, that's what it does, yes.

21 Q. And a binary classifier makes a binary
22 determination like whether something does or does

1 not satisfy a specified condition.

2 Do you agree with that?

3 A. Binary classifier, I would try to rephrase
4 what you said is that it tells you in a binary it's,
5 you know, one or zero or two classes. It tell you
6 whether it's this class or that class or you can say
7 also, there's one class support automation, meaning
8 that it's about to learn, you know, what's that one
9 class and tell you, hey, it either belongs to this
10 class or not.

11 So yeah, I mean, in principle, that's what
12 binary classification means. Yeah, you belong to
13 this class or not.

14 Q. And in Honig, for example, Honig determines
15 whether activity is anomalous or not; right?

16 A. Can you refer to where you are pointing? I
17 mean, in the -- I want to make sure that we know the
18 context, so that it doesn't -- so we don't miss some
19 of the other examples that Honig may have, in terms
20 of, you know, what he meant by anomaly and so on.

21 Q. I'm just talking about Honig as a general
22 matter and the purpose of the SVM it discloses.

1 MR. HART: Object to form.

2 A. I mean, can you repeat the question again?

3 Q. The binary classification that's happening
4 in Honig is determining whether activity is
5 anomalous or not; right?

6 MR. HART: Same objection.

7 A. I mean, like I say, I'd rather have context.
8 Point to some specific language that Honig was
9 saying in his patent to comment on that because your
10 question is very -- I don't want to give you a
11 general -- how to put it -- a generalized answer
12 that covers all cases because -- that's why I'm
13 trying to ask, hey, if there's any, you know, place
14 in the patent that talks about other specific cases,
15 what he meant by anomaly.

16 But, you know -- but in principle, like I
17 said, anomaly detection, in particular, use SVM as
18 binary classifier would be, hey, is this thing
19 belong to this class or not? So you can say, is
20 this anomalous or not? Yeah, in principle, that's
21 what SVM, unsupervised SVM anomaly detector would
22 do.

1 But, like I said, I want to say maybe there
2 are places in Honig -- I mean, I can spend time
3 looking for them, or you can point me to it, to talk
4 about specifically when Honig's unsupervised SVM
5 used in the context of malware or intrusion
6 detection, you know.

7 Yeah, so for example, I mean, the one --
8 like I said, I want to cover -- I don't want to omit
9 some of the specific examples or languages from
10 Honig. So, for example, if you read my declaration,
11 paragraph 65, actually, on page 44, right, at the
12 top, I say, you know, [As read] Honig teaches a
13 method and system for classifying applications as
14 normal or anomalous.

15 Essentially, [As read] Honig (describing an
16 automated process to classify suspicious activity as
17 'either anomalous' (anomalous malware) or normal).

18 Meaning, there is anomalous versus normal,
19 so that's why it's malware. Yeah. So, essentially,
20 it fulfills the job of automatically classifying
21 activity as either malicious or normal.

22 Q. Right.

1 And my question is just whether that's the
2 binary classification that Honig is directed to.

3 MR. HART: Object to form.

4 A. So like I said, if you strictly using the
5 interpretation of SVM being a binary classifier,
6 that's the -- that's the expectation of what a SVM
7 classifier can do. You do in this context to say,
8 hey, is this malicious or normal? Which is what --
9 you know, what '250 patent is all about.

10 Q. Let's go back to Kester, which, for the
11 record, is Exhibit 1004.

12 A. Okay.

13 Q. Kester's stated goal is to "control network
14 access by programs on a workstation; right?

15 MR. HART: Object to form.

16 A. Where do you cite that from?

17 Q. For example, at paragraph 11.

18 A. Okay.

19 Q. Page 23 of the exhibit.

20 A. 11. Okay. Okay. You mean, are you reading
21 the first sentence?

22 Q. Correct.

1 A. Okay. Yeah, so it says that's [As read]
2 Still, another aspect is a method of updating a
3 system which controls network access by programs on
4 a workstation.

5 Q. Kester discloses a hash/policy table for
6 controlling those programs; right?

7 A. Well, it says the following. Right? So the
8 method -- so the second sentence in paragraph 11,
9 [As read] The method comprises detecting a network
10 access request of an application, generating a hash
11 value for the application, wherein the hash values
12 includes network access data, comparing the
13 generated hash value to one or more hash values in a
14 hash/policy table that includes one or more policies
15 associated with the one or more hash values ...

16 And so on.

17 Okay. Yeah. So, basically, that's one
18 component of the method is, essentially, using a
19 hash for you to look up is there any sort of policy
20 that's applicable to this network access request.

21 Q. Right.

22 And Kester's method consults the hash/policy

1 table any time an application is launched or a
2 network access request is made; right?

3 MR. HART: Object to form.

4 A. Yeah. So as the sentence says, that's one
5 of the component, and that's the first thing that it
6 would do. Right? Meaning, that when a request
7 comes in, when there's a network access request
8 being made by an application, you try to first, you
9 know, find out whether the policy allows it by using
10 the hash of -- you know, hash of that access data to
11 look up the policy table. That's the first step.
12 But the other step, if there's -- you know, if it
13 match versus not match and so on, so forth. Yeah.

14 So that's a -- like I said, that's one of
15 the steps, so one of the first steps in this
16 process.

17 Q. The entries in Kester's hash/policy table
18 associate hashes with policies to allow or not allow
19 an access request; correct?

20 A. Let me see here. Well, I mean, if I recall,
21 right, so obviously there are cases where they say
22 allow or not allow, but also there are cases where

1 it does not match. So in this case you don't know,
2 and you basically can decide to let the request, you
3 know, go forward and then see what it does. And
4 then further, you know, update your policy. I mean,
5 I think that's how I understand Kester would do.
6 So ...

7 Q. What do you mean when you say "cases where
8 it does not match"?

9 A. Let me see. Let's see here. So at the end
10 of the paragraph 11 in -- of Kester, it talks about
11 the method further comprises -- hold on. Let me
12 see. Back up. So basically said that, [As read] If
13 the generated hash value does not match one or more
14 hash values in the hash/policy table, then posting
15 the application to a logging database. The method
16 further comprises uploading the logging database to
17 an application server module, determining whether
18 the application from the logging database is in an
19 application inventory database, and if the
20 application is not in the application inventory
21 database, then posting the application to a network
22 access database.

1 Yeah, so my point is that it's not a simple
2 allow/not allow. When it does not match, there is
3 further action to be taking by posing this query
4 into the database of the application server module,
5 for example, and then also application inventory
6 database to essentially do some further analysis
7 down the road.

8 Q. I'm gonna have you take a look at
9 paragraph 6 in Kester.

10 A. Paragraph 6. Okay. All right.

11 Q. And that's the end of the background section
12 of the application.

13 A. Uh-huh.

14 Q. Right?

15 A. Yep.

16 Q. The last sentence in paragraph 6 says that,
17 [As read] With the growth of the new threats
18 described above, employers need new solutions to
19 manage the broader intersection of employees with
20 their computing environments.

21 Do you see that?

22 A. Yes.

1 Q. Would a person of ordinary skill in the art
2 find Kester relevant to classifying different
3 communication applications like instant messaging or
4 email?

5 A. Let me see here. Yeah. So within the
6 context, again, you know, the sentence starts by
7 saying "However, with the growth of the new
8 threats." So to me, the keyword is "threats" here.
9 Right? Then you basically, in the context of try to
10 mitigate potential threats, you want to manage the
11 interaction, you know, between user and their
12 computing systems or networks. That's -- any POSITA
13 would say, yeah, that's the goal of, the nature of
14 security. Why do you do security? Data threats.
15 Why? Fear of data threats. There are bad guys out
16 there. Then each organization say, Well, what are
17 the threats that are important to your organization?
18 And what are things you can do with respect to your
19 employees and how they use their computers?

20 I mean, that's like -- to me, this last
21 sentence is essentially bread and butter of
22 cybersecurity in the sense that it's always in the

1 context of something. You don't talk about
2 cybersecurity out of context. You talk about
3 cybersecurity in this case with the enterprise
4 environment. There are growing threats, but user
5 also are going to go ahead and keep want to using
6 their computer and networks so you want to better
7 manage so that you provide security but also still
8 maintain the productivity. That's, yeah.

9 That's how I teach, to be honest. I don't
10 teach cybersecurity as something that you go there
11 and annoy people and stop them being productive.
12 No, if that's your mindset, you can never be
13 successful.

14 Q. I'm going to have you take a look at
15 figure 4A in Kester. That's on page 5 of
16 Exhibit 1004.

17 A. Okay. Figure 4? Okay. All right.
18 Figure 4A. Yes.

19 Q. Figure 4A shows a number of different
20 classification categories; right?

21 A. Yeah. Uh-huh.

22 Q. And the first two categories in the list are

1 operating systems and device drivers.

2 Do you see that?

3 A. Yeah.

4 Q. So would a person of ordinary skill in the
5 art find Kester relevant to classifying different
6 system applications like operating systems and
7 device drivers?

8 MR. HART: Object to form.

9 A. I mean, if you allow me, I can go back to
10 some of the language in Kester that talks about, for
11 example, of course classifying the object as malware
12 or not, and if it's not malware, sometimes, okay,
13 here is allowed, allow normal applications, and you
14 can put them in some categories, for example, OS
15 operating systems or device driver. But also
16 sometimes you're not sure. Right? You say, I've
17 not seen this before, I don't know whether it's
18 normal, but I don't know if it's malware or not.

19 Still, even in that case, you may still put
20 them into some system category and say, Well, but
21 this looks like an application that, you know,
22 touched my file so I put it in file management.

1 So those things are useful, even from a
2 security point of view, to say, if you want to
3 further analyze it or further things to look for,
4 right, to say, Hey, what's the behavior, what's the
5 mask that I should look for? You know, based on the
6 application, which category you put them in, there
7 are specifically things you look for that are more
8 likely indicative of malicious activity.

9 For example, let's say file management.
10 Well, if this application comes in and starts
11 messing with your Windows registry, which is the
12 most infamous action that malware do, then you say,
13 Oh, something really crazy going on here. Right?
14 Or device drivers are a well-known crazy thing that
15 Microsoft would blame everything on device driver
16 because they don't write it. They incorporate
17 device driver into the operating system. And you
18 definitely want to watch those things even though
19 you don't know what's normal, what's malicious.

20 So my point is that, if you look at this
21 table, right, figure 4A, it does talk about
22 malicious applets and scripts and put them into

1 parent category malware. But what I'm trying to say
2 is that all these other categories that it put the
3 objects to it useful. It's useful from both
4 security and productivity point of view.

5 And, yeah, to me, as a cybersecurity person,
6 when you apply some classification process, you may
7 as well classify, you know, hey, malicious versus
8 not, right, when it's not malicious you say, by the
9 way, also know this belongs to a system or this
10 belongs to whatever. I mean, why not? Yeah.

11 But really the point is that don't forget
12 the goal of this whole Kester patent is driven by,
13 you know, the growth of threats. Right? And then
14 the fact that user interacting with systems in a
15 variety of ways, and that's why you want to make
16 sure you account for things that they're doing but,
17 more importantly, whether you see malware, meaning
18 the malicious applets or scripts, and try to stop
19 them. Yeah.

20 Q. Well, you'd agree that not every category
21 listed on figure 4A relates to malware or security;
22 right?

1 A. So like I said earlier -- well, maybe I will
2 just say that -- like I said earlier, the example
3 for device driver, you know, application to touch
4 your file system, installers, all those things
5 actually, they are not by accident, to be honest.
6 If I am the person -- for example, I access in
7 piracy for antivirus software, authentication
8 encryption, firewalls, spyware, system audit, my
9 God, all these are security things. And a POSITA
10 would say, wow, that's exactly what a lot of
11 security systems would do, would watch that kind of
12 behavior. So my point is that the thing you put in
13 here is not by accident.

14 And, in fact, another point I want to make
15 is that modern-day malware, in particular, after
16 2000, they do all sorts of crazy things on the
17 system. So, in fact, you know, to better protect
18 your system, you want to actually look at many, many
19 things. So knowing the applications in different
20 categories and watch their behaviors when you don't
21 know for sure they're malware or not actually is a
22 great idea. I mean, I really, you know, think that

1 every product should do the same.

2 Q. Is it your opinion that the categories
3 within the productivity and entertainment parent
4 groups relate to security?

5 MR. HART: Object to form.

6 A. Yeah, so, again, these examples, definitely
7 useful. I mean, how many times -- well, maybe you
8 don't know, but how many times people got into
9 trouble by downloading some videos and the video
10 file, oh, you need to download a new video player.
11 The video knows that, yeah, the video player can
12 play the video, but also it's malware. That happens
13 a lot. In particular, with teen-age kids.

14 Okay. You can strike that from the record.

15 My point is all these things are useful from
16 a security modeling point of view, so let's not
17 forget the ultimate goal is to stop bad things. And
18 that's why they put malware as a category and
19 specifically mention about malicious applets and
20 scripts.

21 But you look at all these categories.

22 Right? Entertainment, adult, gambling, games. Wow.

1 Are those good things? I don't know. I mean, from
2 a security point of view, those things, I definitely
3 watch. So my point is all these categories, from
4 security point of view, from POSITA point of view,
5 they all agree that these are things that are now
6 being monitored, really by modern-day products. But
7 definitely, even go back to 2005, we have already
8 seen malware doing all these -- you know, touching
9 many aspects of the system. So that's why, you
10 know, putting all these categories out there and
11 being able to put application into the appropriate
12 categories would help you categorize -- or even
13 before that, determining what mask or expected
14 behaviors you want from the application, those are
15 very, very useful things that a product should be
16 doing.

17 Q. And Kester teaches applying policy specific
18 to each type of application or each category of
19 application; right?

20 A. Like I say, I can go back to the -- maybe my
21 declaration. We talk about that. I -- just -- you
22 know, it talks about having to categorize and

1 recategorize applications. It talks about, you
2 know, looking at, you know, the kind of data or the
3 behaviors, and so that's very divided behavior model
4 from is what you expect the behaviors of this
5 application. And then say, how do you know? Well,
6 the -- you have to know the context of the
7 application. Right? So knowing which category this
8 application is doing, then you -- that helps you
9 define what are the expected behaviors. Pretty
10 obvious to a POSITA to think that way.

11 MR. EUTERMOSER: I don't have a whole lot
12 left. Why don't we take a quick five-minute break
13 and then we can wrap up.

14 THE WITNESS: Okay. All right. Thank you.

15 (A short break was had.)

16 MR. EUTERMOSER: Dr. Lee, I don't have any
17 more questions for you, so I can pass the witness or
18 we can go off the record.

19 THE WITNESS: Okay. Thank you.

20 MR. HART: Nothing from me.

21 THE WITNESS: Okay.

22 (Off the record at 10:39 a.m.)

1 CERTIFICATE OF COURT REPORTER - NOTARY PUBLIC

2
3 I, TIFFANY M. PIETRZYK, Certified Shorthand
4 Reporter No. 084-004371, CSR, RPR, CRR, and a Notary
5 Public within and for the State of Illinois, do
6 hereby certify:

7 That WENKE LEE, Ph.D., the witness whose
8 deposition is hereinbefore set forth, was duly sworn
9 by me before the commencement of such deposition and
10 that such deposition was taken before me and is a
11 true record of the testimony given by such witness.

12 I further certify that the adverse party,
13 CROWDSTRIKE, INC., was represented by counsel at the
14 deposition.

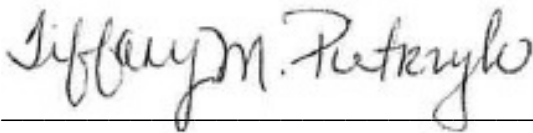
15 I further certify that the deposition of
16 WENKE LEE, Ph.D. occurred virtually, via Zoom
17 videoconference, on Thursday September 28, 2023,
18 commencing at 9:06 a.m. CST to 10:39 a.m. CST.

19 I further certify that I am not related to
20 any of the parties to this action by blood or
21 marriage, I am not employed by or an attorney to any
22 of the parties to this action, and that I am in no

1 way interested, financially or otherwise, in the
2 outcome of this matter.

3 IN WITNESS WHEREOF, I have hereunto set my
4 hand and affixed my notarial seal this 3rd day of
5 October, 2023.

6
7 My commission expires: February 28th, 2024

8
9 
10 _____

11 NOTARY PUBLIC IN AND FOR THE
12 STATE OF ILLINOIS

13
14
15
16
17
18
19
20
21
22

A			
able	accident	25:19, 26:1,	31:6, 31:13,
25:14, 42:13,	60:5, 60:13	26:17, 26:21,	33:4, 33:7,
45:3, 45:17,	account	27:3, 27:5,	33:9, 33:10,
62:11	59:16	27:18, 27:21	33:11, 37:8,
about	accurate	add	43:16, 43:19,
5:19, 6:22,	5:17	15:11	43:22, 44:7,
7:21, 8:18,	action	addition	44:9
10:22, 11:2,	54:3, 58:12,	39:10	algorithms
11:13, 12:9,	64:20, 64:22	additional	30:14, 31:19,
16:15, 16:22,	activities	22:18	32:5, 35:3,
17:2, 17:3,	16:8	adult	38:5, 40:21,
17:5, 19:17,	activity	61:22	41:2, 42:8
20:8, 21:11,	10:10, 10:19,	adverse	all
22:1, 29:9,	15:16, 17:12,	64:12	11:5, 21:6,
29:16, 30:5,	18:7, 18:19,	affixed	22:9, 30:11,
30:15, 30:16,	47:15, 48:4,	65:4	30:15, 31:10,
31:15, 31:21,	49:16, 49:21,	after	38:16, 40:1,
32:21, 33:21,	58:8	33:14, 45:7,	48:12, 50:9,
34:6, 34:12,	actually	60:15	54:10, 56:17,
34:18, 34:20,	11:22, 12:16,	again	59:2, 60:4,
35:8, 35:13,	13:7, 14:14,	5:11, 10:12,	60:9, 60:16,
35:14, 35:15,	15:19, 16:2,	13:19, 15:4,	61:15, 61:21,
39:18, 40:14,	20:1, 27:9,	17:9, 24:1,	62:3, 62:5,
40:16, 40:18,	28:1, 30:13,	25:22, 34:11,	62:8, 62:10,
41:19, 44:20,	33:9, 34:21,	34:15, 34:20,	63:14
46:1, 46:8,	45:17, 46:11,	35:8, 35:21,	allow
47:8, 47:21,	49:11, 60:5,	37:17, 37:22,	38:20, 39:14,
48:14, 49:4,	60:18, 60:21	43:10, 48:2,	52:18, 52:22,
50:9, 53:10,	adapt	55:6, 61:6	54:2, 57:9,
56:1, 56:2,	28:4	agree	57:13
57:10, 58:21,	adaptive	6:14, 8:5,	allowed
61:19, 62:21,	9:16, 9:20,	10:20, 12:21,	17:12, 57:13
62:22, 63:1	10:5, 10:9,	15:11, 15:21,	allows
above	10:16, 10:22,	24:6, 24:16,	38:12, 38:19,
54:18	11:6, 11:14,	27:8, 30:6,	52:9
acceptable	12:22, 13:21,	31:18, 32:7,	already
16:12	14:3, 14:7,	33:1, 34:9,	15:12, 21:4,
accepted	14:8, 14:13,	37:19, 40:9,	23:7, 29:14,
32:17	14:17, 15:1,	46:18, 47:2,	37:13, 37:15,
access	16:17, 17:14,	59:20, 62:5	37:20, 39:5,
50:14, 51:3,	17:17, 18:1,	ahead	62:7
51:10, 51:12,	18:11, 18:13,	56:5	also
51:20, 52:2,	19:9, 19:14,	algorithm	3:19, 11:17,
52:7, 52:10,	19:19, 21:8,	15:13, 19:3,	12:7, 12:8,
52:19, 53:22,	21:15, 22:10,	22:9, 25:1,	12:14, 13:18,
60:6	23:4, 25:1,	25:13, 25:16,	14:11, 14:21,
	25:10, 25:13,	26:20, 29:12,	15:11, 18:21,
	25:16, 25:18,	30:11, 31:4,	20:12, 20:21,

21:10, 22:4, 22:6, 22:12, 41:4, 41:9, 41:10, 47:7, 52:22, 54:5, 56:5, 56:7, 57:15, 59:9, 61:12 always 55:22 among 43:8 analysis 10:4, 10:5, 19:19, 19:20, 20:3, 20:4, 21:3, 21:15, 21:16, 23:3, 23:4, 24:5, 54:6 analyst 6:15, 7:7, 7:11, 7:12, 7:15, 7:18, 8:1, 19:15, 21:14, 22:22, 23:19 analyst's 6:10 analyze 21:21, 58:3 annoy 56:11 anomalous 47:15, 48:5, 48:20, 49:14, 49:17, 49:18 anomaly 40:21, 41:2, 41:17, 42:7, 43:7, 43:19, 44:21, 46:10, 46:11, 47:20, 48:15, 48:17, 48:21 another 13:16, 21:2, 51:2, 60:14 answer 6:18, 13:22,	15:9, 42:6, 44:17, 48:11 anti-malware 37:13 antivirus 37:12, 60:7 any 5:16, 22:22, 32:22, 35:19, 37:19, 38:15, 46:8, 48:13, 51:19, 52:1, 55:12, 63:16, 64:20, 64:21 anything 25:8, 39:15, 46:1, 46:15 anyway 13:20 appeal 1:2 appears 9:21 apple 31:3 applets 58:22, 59:18, 61:19 applicable 51:20 application 4:11, 6:10, 7:4, 7:6, 8:1, 13:5, 18:2, 21:21, 31:8, 36:1, 42:16, 51:10, 51:11, 52:1, 52:8, 53:15, 53:17, 53:18, 53:19, 53:20, 53:21, 54:4, 54:5, 54:12, 57:21, 58:6, 58:10, 60:3, 62:11, 62:14, 62:18, 62:19, 63:5, 63:7, 63:8	applications 7:3, 9:16, 11:7, 17:11, 21:4, 22:14, 49:13, 55:3, 57:6, 57:13, 60:19, 63:1 applied 44:22 applies 28:1 apply 11:18, 15:12, 16:10, 18:4, 18:15, 20:9, 20:11, 29:12, 33:2, 33:3, 33:13, 45:15, 46:2, 59:6 applying 12:12, 62:17 approach 38:9 appropriate 12:18, 28:16, 28:21, 29:20, 32:12, 43:12, 62:11 around 13:8, 28:12 art 11:8, 17:16, 29:15, 55:1, 57:5 ascii 29:11 asking 17:2 aspect 13:14, 13:16, 21:1, 21:2, 51:2 aspects 20:16, 62:9 associate 52:18 associated 51:15 attached 4:7, 5:22, 9:4,	28:10 attempt 40:22 attorney 64:21 attributes 22:3, 22:18, 37:9, 43:6 audit 60:8 authentication 60:7 automate 11:20, 12:10, 13:9, 13:19, 19:6, 23:9, 23:14, 27:15, 34:13 automated 8:4, 8:7, 8:8, 15:2, 15:8, 15:18, 15:22, 16:18, 18:5, 18:8, 20:8, 24:17, 28:13, 28:17, 28:22, 29:18, 30:4, 30:19, 31:11, 31:13, 31:19, 32:3, 32:6, 32:13, 33:21, 34:3, 34:8, 37:21, 38:14, 45:8, 49:16 automatic 24:4, 29:4, 29:22, 32:9, 32:16, 32:19, 32:21, 33:3, 33:5, 33:12, 33:16, 35:7 automatically 11:20, 12:1, 20:14, 29:9, 33:20, 49:20 automating 12:3, 18:10, 32:21, 35:4
--	---	---	--

automation 12:11, 12:15, 20:20, 38:17, 47:7 away 24:2 B back 50:10, 53:12, 57:9, 62:7, 62:20 background 35:14, 54:11 bad 55:15, 61:17 base 11:19, 16:11, 18:4, 19:9, 37:11, 42:22, 43:1 based 9:16, 10:4, 14:10, 14:14, 14:19, 17:13, 18:13, 19:18, 20:3, 23:3, 24:4, 33:8, 58:5 basically 11:4, 14:9, 15:18, 16:6, 19:8, 20:1, 21:6, 23:8, 23:12, 26:3, 27:16, 28:3, 31:5, 33:6, 51:17, 53:2, 53:12, 55:9 basis 45:18 beauty 41:17 because 7:20, 11:5, 20:21, 34:2, 38:13, 38:16, 40:2, 41:5, 41:19, 43:19,	44:3, 48:9, 48:12, 58:16 been 5:5, 5:13, 15:12, 20:22, 30:15, 33:12, 46:17 before 1:2, 2:2, 5:13, 42:6, 46:2, 46:15, 57:17, 62:13, 64:9, 64:10 behalf 3:2, 3:10 behavior 16:12, 16:13, 20:16, 22:1, 22:2, 37:9, 58:4, 60:12, 63:3 behaviors 12:18, 16:7, 60:20, 62:14, 63:3, 63:4, 63:9 being 24:2, 50:5, 52:8, 56:11, 62:6, 62:11 believe 9:22 belong 26:12, 47:12, 48:19 belongs 26:11, 43:18, 47:9, 59:9, 59:10 best 38:9 better 11:16, 56:6, 60:17 between 55:11 biases 40:1 big 35:16	binary 29:11, 46:19, 46:21, 47:3, 47:4, 47:12, 48:3, 48:18, 50:2, 50:5 blame 58:15 blood 64:20 board 1:2 boom 33:14 both 59:3 boulevard 3:5 bread 55:21 break 42:1, 42:3, 42:6, 63:12, 63:15 brian 3:11, 42:1 broad 14:6, 26:1 broader 54:19 build 20:19, 20:20, 24:7, 30:13 bulk 27:9 buried 41:1 butter 55:21 C california 2:4 call 14:15, 18:16, 18:22, 27:17, 33:22, 34:1, 34:2, 35:1,	36:2, 43:1 called 5:5, 26:14 can't 5:16 cannot 15:5, 31:1, 39:15, 44:2 careful 35:22 cares 33:22 case 1:12, 9:7, 9:22, 12:16, 15:19, 16:1, 16:3, 16:4, 16:5, 16:15, 19:8, 33:7, 33:11, 34:7, 36:17, 37:15, 39:6, 39:20, 40:8, 44:8, 45:1, 53:1, 56:3, 57:19 cases 39:21, 48:12, 48:14, 52:21, 52:22, 53:7 categories 56:20, 56:22, 57:14, 59:2, 60:20, 61:2, 61:21, 62:3, 62:10, 62:12 categorization 6:11, 6:15, 6:20, 7:16, 8:3, 10:4, 10:13, 10:17, 11:1, 11:10, 11:18, 12:2, 12:6, 13:1, 13:4, 16:18, 17:18, 18:10, 19:18, 20:3, 23:15, 24:4, 45:16 categorize 15:17, 18:18,
---	---	--	---

21:21, 45:11, 62:12, 62:22 categorizing 9:16, 11:7, 17:11, 18:2 category 57:20, 58:6, 59:1, 59:20, 61:18, 62:18, 63:7 caution 41:17 certain 8:12, 12:10, 43:5 certificate 64:1 certified 2:3, 2:5, 64:3 certify 64:6, 64:12, 64:15, 64:19 check 24:11 cite 25:8, 50:16 claim 11:13, 35:6 class 42:10, 42:11, 43:1, 43:14, 43:17, 44:11, 47:6, 47:7, 47:9, 47:10, 47:13, 48:19 classes 41:15, 41:20, 42:17, 43:4, 43:5, 43:11, 43:13, 43:22, 44:2, 44:10, 47:5 classification 6:10, 7:7, 7:10, 7:19, 8:1, 11:10, 11:15, 12:13, 13:13, 13:18, 17:18,	19:7, 19:16, 20:12, 21:16, 23:9, 23:15, 23:20, 24:8, 39:17, 43:3, 47:12, 48:3, 50:2, 56:20, 59:6 classifier 18:16, 18:20, 19:1, 19:2, 20:13, 42:14, 45:10, 46:19, 46:21, 47:3, 48:18, 50:5, 50:7 classifies 45:14 classify 7:19, 15:17, 16:5, 16:12, 18:7, 18:19, 20:6, 22:14, 31:3, 39:12, 41:12, 41:14, 41:16, 44:14, 45:17, 46:7, 46:16, 49:16, 59:7 classifying 9:15, 11:7, 12:2, 13:4, 17:10, 18:2, 20:20, 49:13, 49:20, 55:2, 57:5, 57:11 clear 25:5 cluster 26:11, 26:12, 26:13 codified 19:3 codify 15:14 colorado 3:7, 3:16 column 28:12, 32:2,	34:14, 34:15, 34:17, 36:7 combination 17:4 combining 16:22 come 36:17, 42:14 comes 15:15, 15:16, 25:15, 52:7, 58:10 coming 26:9 commencement 64:9 commencing 64:18 comment 48:9 commission 65:7 communication 55:3 companies 37:13 company 37:6 compared 41:4 comparing 51:12 completely 8:8, 23:19, 29:11, 32:16, 38:14, 39:19, 39:20 component 51:18, 52:5 comprises 51:9, 53:11, 53:16 computer 16:9, 56:6 computers 55:19 computing 54:20, 55:12	condition 47:1 consider 20:18 constructing 35:2 construction 35:2 consults 51:22 context 10:17, 12:15, 15:5, 15:10, 16:4, 16:19, 34:11, 35:21, 37:17, 37:22, 39:16, 39:18, 43:11, 44:18, 47:18, 48:7, 49:5, 50:7, 55:6, 55:9, 56:1, 56:2, 63:6 contexts 42:10 continues 7:5 control 50:13 controlling 51:6 controls 51:3 conversion 30:19, 30:21, 32:3 convert 30:10 converted 33:13 converting 28:15, 28:21, 29:19, 32:12, 32:15 copy 6:3 correct 9:21, 10:10, 14:20, 25:3,
--	---	---	--

30:20, 36:13, 50:22, 52:19 correctly 45:13, 45:14 could 19:15, 21:20, 21:21, 22:4, 39:21, 40:4 counsel 64:13 course 30:4, 31:13, 33:3, 57:11 court 64:1 cover 49:8 covers 48:12 crazy 58:13, 58:14, 60:16 create 40:3 creating 35:9 crowdstrike 1:4, 64:13 crr 1:22, 64:4 csr 1:22, 64:4 cst 1:17, 64:18 cybersecurity 55:22, 56:2, 56:3, 56:10, 59:5	29:5, 29:10, 29:11, 29:19, 30:7, 30:8, 30:19, 30:21, 31:4, 31:5, 31:12, 32:3, 32:10, 32:12, 32:15, 32:20, 33:4, 33:12, 33:13, 33:14, 35:11, 35:12, 35:19, 36:9, 36:19, 37:1, 37:3, 37:7, 38:15, 40:2, 40:6, 40:10, 40:22, 41:1, 41:4, 41:6, 41:9, 41:10, 41:11, 41:15, 41:18, 41:20, 42:11, 43:8, 43:20, 44:3, 44:6, 44:10, 45:20, 45:22, 46:5, 46:17, 51:12, 52:10, 55:14, 55:15, 63:2 database 7:4, 53:15, 53:16, 53:18, 53:19, 53:21, 53:22, 54:4, 54:6 day 65:4 deal 35:16 decide 38:9, 42:18, 53:2 declaration 4:9, 9:7, 11:4, 16:21, 17:7, 24:20, 25:9, 35:14, 40:14, 40:18, 49:10,	62:21 define 43:14, 63:9 definitely 37:19, 37:21, 38:11, 38:18, 58:18, 61:6, 62:2, 62:7 denver 3:16 depending 34:11 depends 35:21, 37:17 depos 3:20 deposed 5:13 deposition 1:15, 2:1, 4:8, 64:8, 64:9, 64:10, 64:14, 64:15 describe 31:18 described 54:18 describing 30:18, 49:15 detail 29:6 detect 40:22, 45:4 detected 41:7 detecting 51:9 detection 28:14, 32:9, 32:19, 40:1, 40:21, 41:2, 41:18, 42:8, 43:7, 43:19, 44:21, 46:10, 46:11, 48:17, 49:6 detector 48:21	determination 11:2, 12:3, 12:8, 13:14, 13:19, 20:9, 20:12, 45:9, 46:22 determines 47:14 determining 10:10, 10:18, 12:17, 13:2, 48:4, 53:17, 62:13 develop 31:16 device 57:1, 57:7, 57:15, 58:14, 58:15, 58:17, 60:3 different 38:5, 41:5, 41:20, 41:22, 42:11, 42:17, 42:19, 43:6, 55:2, 56:19, 57:5, 60:19 directed 50:2 disclose 8:3 discloses 7:14, 8:19, 38:6, 47:22, 51:5 disclosure 32:2 discussing 32:11 distinguish 42:15 distribution 20:19 divided 63:3 doing 22:11, 29:9, 59:16, 62:8,
D data 14:15, 25:15, 26:4, 26:6, 26:7, 26:11, 26:16, 26:18, 27:10, 28:4, 28:14, 28:15, 28:16, 28:21,			

62:16, 63:8 done 12:12, 18:13, 23:8 double-check 9:22, 10:1 down 6:21, 54:7 download 61:10 downloading 61:9 dr 4:9, 5:9, 42:5, 63:16 driven 59:12 driver 57:15, 58:15, 58:17, 60:3 drivers 57:1, 57:7, 58:14 dtc 3:5 duly 5:5, 64:8	emphasize 14:13 employed 64:21 employees 54:19, 55:19 employers 54:18 enable 7:2 encryption 60:8 end 35:5, 53:9, 54:11 energy 44:4 engineer 27:2, 27:4, 27:17 engineered 25:19 enterprise 56:3 entertainment 61:3, 61:22 entire 32:5 entries 52:17 environment 56:4 environments 54:20 erise 3:4 esquire 3:3, 3:11, 3:12 essence 33:17 essentially 12:3, 16:10, 18:5, 19:6, 20:17, 23:16, 33:17, 49:15, 49:19, 51:18, 54:6, 55:21 eutermoser 3:11, 4:3, 5:8,	42:2, 42:4, 63:11, 63:16 even 7:10, 13:7, 32:18, 35:19, 36:10, 37:5, 43:21, 45:19, 46:12, 57:19, 58:1, 58:18, 62:7, 62:12 every 24:10, 30:5, 31:8, 34:8, 59:20, 61:1 everything 38:15, 58:15 exactly 14:3, 15:6, 29:7, 31:15, 60:10 examination 4:2, 5:7 examine 40:22 examined 5:6 examines 41:19 example 6:21, 16:10, 20:15, 21:11, 29:3, 37:6, 38:20, 39:13, 39:22, 46:3, 47:14, 49:7, 49:10, 50:17, 54:5, 57:11, 57:14, 58:9, 60:2, 60:6 examples 21:20, 47:19, 49:9, 61:6 except 19:2 exception 31:10 exclude 13:11, 24:9	exhibit 4:9, 4:11, 4:13, 5:20, 5:21, 9:2, 9:3, 28:7, 28:9, 50:11, 50:19, 56:16 exhibits 4:8 expect 44:1, 45:12, 63:4 expectation 50:6 expected 10:10, 10:18, 17:12, 62:13, 63:9 expecting 30:11 expires 65:7 explain 28:20, 29:3 explains 9:15, 17:10 explicitly 24:1, 29:3, 40:16
E			F
each 26:16, 55:16, 62:18 earlier 60:1, 60:2 easier 38:17 effectively 40:11 either 14:15, 31:15, 47:9, 49:17, 49:21 eliminate 23:19 else 30:3 email 55:4			face 39:22 fact 11:13, 12:8, 29:8, 30:16, 35:17, 59:14, 60:14, 60:17 fair 7:16, 7:17, 13:2, 23:1 famous 39:22 faster 11:16 fear 55:15 feature 35:2, 42:18

features 21:10	forget 12:13, 59:11, 61:17	54:3, 54:6, 58:3, 64:12, 64:15, 64:19	50:10, 53:3, 56:5, 56:10, 57:9, 62:7, 62:20, 63:18
february 65:7	form 6:17, 8:14, 15:3, 21:18, 23:22, 26:22, 28:16, 28:21, 29:20, 31:20, 32:13, 34:10, 36:15, 40:12, 44:16, 45:5, 48:1, 50:3, 50:15, 52:3, 57:8, 61:5	G	goal 22:14, 24:2, 39:11, 42:13, 50:13, 55:13, 59:12, 61:17
fifth 40:19	format 29:12, 30:10	gambling 61:22	going 20:7, 56:5, 56:14, 58:13
figure 26:11, 35:12, 41:11, 44:4, 56:15, 56:17, 56:18, 56:19, 58:21, 59:21	forth 17:13, 52:13, 64:8	games 61:22	gonna 9:2, 15:7, 24:19, 54:8
file 16:8, 22:2, 30:9, 57:22, 58:9, 60:4, 61:10	forward 53:3	gave 42:6	good 5:9, 42:19, 62:1
financially 65:1	found 11:8, 17:16	general 14:5, 36:2, 36:16, 36:21, 47:21, 48:11	graphical 7:7, 8:2
find 22:19, 38:10, 43:3, 43:17, 44:9, 52:9, 55:2, 57:5	four 40:19	generalized 48:11	great 13:17, 39:5, 60:22
finding 42:9	fulfills 49:20	generally 8:18	greenwood 3:7
firewalls 60:8	fully 8:4, 8:7, 15:2, 15:8, 15:17, 15:22, 16:18, 18:5, 18:8, 18:9, 19:6, 23:14, 28:16, 28:21, 29:18, 29:21, 29:22, 30:19, 31:11, 31:13, 31:19, 32:3, 32:5, 32:13, 32:16, 33:3, 33:16, 34:3, 34:8, 35:7, 37:21, 38:14	generate 8:22, 11:21, 35:1	groups 61:4
first 5:5, 11:5, 22:9, 50:21, 52:5, 52:8, 52:11, 52:15, 56:22	fulfills 49:20	generated 51:13, 53:13	growing 56:4
fit 46:11	four 40:19	generating 8:12, 12:1, 12:16, 20:13, 51:10	growth 54:17, 55:7, 59:13
five-minute 63:12	fulfills 49:20	generation 28:14, 31:19, 31:22, 32:5, 32:9, 32:19, 32:22, 33:2, 33:16, 34:4, 38:5	guys 55:15
flow 12:7	fully 8:4, 8:7, 15:2, 15:8, 15:17, 15:22, 16:18, 18:5, 18:8, 18:9, 19:6, 23:14, 28:16, 28:21, 29:18, 29:21, 29:22, 30:19, 31:11, 31:13, 31:19, 32:3, 32:5, 32:13, 32:16, 33:3, 33:16, 34:3, 34:8, 35:7, 37:21, 38:14	gist 26:17	H
focus 12:20, 17:6	further 6:21, 53:4, 53:11, 53:16,	give 5:16, 15:9, 26:6, 29:3, 33:11, 35:14, 39:13, 44:3, 44:6, 45:10, 46:6, 48:10	hand 65:4
follow 42:5		given 64:11	happen 44:22
following 51:7		go 40:14, 40:17,	happening 48:3
follows 5:6			happens 61:12
			hart 3:3, 6:17,

8:14, 8:20, 15:3, 21:18, 23:22, 26:22, 31:20, 34:10, 36:15, 40:12, 42:1, 44:16, 45:5, 48:1, 48:6, 50:3, 50:15, 52:3, 57:8, 61:5, 63:20 hash 8:12, 8:22, 51:5, 51:10, 51:11, 51:13, 51:14, 51:15, 51:19, 51:22, 52:10, 52:17, 53:13, 53:14 hashes 52:18 head 39:16 help 7:18, 7:19, 62:12 helps 63:8 here 5:12, 11:3, 14:8, 14:18, 16:20, 17:21, 18:15, 20:14, 22:3, 26:8, 30:5, 30:18, 52:20, 53:9, 55:5, 55:8, 57:13, 58:13, 60:13 here's 26:10, 28:3, 35:12, 41:11, 41:12, 41:13 hereby 64:6 herein 5:5 hereinbefore 64:8	hereunto 65:3 heuristics 30:15 hey 18:3, 18:18, 20:17, 22:3, 24:10, 26:4, 26:6, 26:10, 27:10, 31:1, 33:6, 33:14, 34:22, 35:22, 37:14, 44:1, 47:9, 48:13, 48:18, 50:8, 58:4, 59:7 high 28:4 hold 53:11 honest 34:22, 35:5, 56:9, 60:5 honig 11:10, 11:22, 14:21, 16:22, 17:20, 28:6, 28:13, 28:20, 29:18, 30:5, 30:18, 31:18, 35:12, 35:15, 36:7, 37:4, 38:1, 38:6, 40:15, 40:18, 40:20, 47:14, 47:19, 47:21, 48:4, 48:8, 49:2, 49:10, 49:12, 49:15, 50:2 honig's 25:1, 32:5, 34:4, 49:4 hope 34:21, 43:12 hopefully 41:10 hoping 41:21	however 17:9, 42:18, 55:7 human 6:9, 6:15, 6:19, 6:22, 7:2, 7:6, 7:10, 7:11, 7:12, 7:15, 7:17, 7:22, 8:8, 8:11, 8:21, 19:15, 21:14, 22:22, 23:19, 24:2, 24:13, 30:1, 34:1, 34:20, 35:19, 36:3, 36:4, 37:16, 38:13, 40:5 human's 8:19 humans 8:10, 24:10 I idea 13:6, 13:7, 13:17, 60:22 identification 5:22, 9:4, 28:10 identify 43:8, 45:4 illinois 2:4, 2:7, 64:5, 65:12 image 10:5, 19:19, 20:4, 20:16, 21:3, 21:12, 21:15, 23:4 images 20:22 imagine 40:4 imply 15:2, 16:18 important 55:17	importantly 59:17 inc 1:4, 1:9, 64:13 include 14:7 includes 51:12, 51:14 including 23:7 incorporate 58:16 incremental 27:21 incrementally 14:16, 21:9, 26:19 indicates 16:13 indicative 58:8 infamous 58:12 input 40:10 installers 60:4 instant 55:3 instructed 20:22 interact 7:6, 7:22 interacting 59:14 interaction 55:11 interacts 6:9 interchangeable 14:2 interchangeably 14:12 interested 65:1 interesting 13:6 interface 7:8, 8:2
--	--	--	--

interpret 13:15 interpretation 8:6, 50:5 intersection 54:19 intervention 34:5, 34:20, 35:20, 36:5, 36:9, 37:4, 37:16, 37:18, 38:13, 40:5 intrusion 49:5 intrusions 41:1, 41:3, 41:6 inventory 53:19, 53:20, 54:5 involved 6:20, 7:12, 8:9, 8:10, 24:13 ip 3:4 ipr 1:12, 16:4, 39:6 item 26:16 itself 18:9, 19:1, 33:2 J job 1:19, 39:5, 43:17, 49:20 K keep 56:5 kester 5:19, 6:8, 6:14, 7:14, 8:3, 8:9, 8:16, 8:18, 9:14, 9:21, 10:8, 11:5,	12:21, 12:22, 13:3, 13:11, 13:15, 13:21, 14:18, 16:22, 17:3, 17:5, 17:9, 17:13, 17:22, 18:9, 18:12, 19:13, 20:14, 21:5, 21:14, 21:19, 21:22, 22:17, 22:21, 23:2, 23:18, 24:1, 24:9, 24:15, 24:16, 50:10, 51:5, 53:5, 53:10, 54:9, 55:2, 56:15, 57:5, 57:10, 59:12, 62:17 kester's 6:15, 10:16, 16:15, 17:18, 50:13, 51:22, 52:17 keyword 55:8 kick 27:20 kids 61:13 kind 14:15, 21:8, 21:22, 22:7, 38:1, 40:1, 60:11, 63:2 king 3:13 knowing 60:19, 63:7 known 17:17, 25:12, 31:15, 45:20, 45:21 knows 61:11 L label 26:16, 35:9,	35:11, 35:18, 36:19, 37:1, 37:3, 37:15, 38:15, 44:3 labeled 41:18 labeling 34:18, 35:8, 36:9, 38:3 labels 37:8 language 48:8, 57:10 languages 49:9 large 43:8 last 10:2, 19:17, 54:16, 55:20 later 11:12 launched 52:1 lawrence 3:14 learn 14:9, 14:14, 14:16, 14:18, 21:9, 25:14, 26:2, 26:18, 26:19, 29:13, 31:2, 31:7, 41:16, 41:21, 47:8 learned 15:13, 33:19 learning-based 23:10, 45:16 lee 1:15, 2:1, 4:2, 4:10, 5:4, 5:9, 42:5, 63:16, 64:7, 64:16 left 63:12 legitimate 26:13	less 26:14 let's 6:22, 12:12, 12:17, 15:13, 17:6, 20:4, 29:10, 30:7, 31:2, 33:7, 37:10, 39:21, 42:12, 42:15, 44:9, 45:9, 46:4, 50:10, 53:9, 58:9, 61:16 level 28:4 likely 58:8 line 28:13, 32:2, 34:15, 40:20 lines 34:14, 36:7 list 56:22 listed 59:21 llp 3:13 logging 53:15, 53:16, 53:18 long 41:20, 42:12, 42:16 look 10:11, 12:7, 12:11, 15:4, 16:7, 17:16, 20:15, 20:21, 20:22, 21:10, 21:20, 22:4, 22:7, 22:16, 23:11, 24:11, 24:19, 26:8, 28:6, 30:1, 30:2, 34:14, 42:17, 42:18,
--	---	---	--

Transcript of Wenke Lee, Ph.D.
Conducted on September 28, 2023

75

42:19, 43:5, 43:6, 43:14, 46:8, 46:14, 51:19, 52:11, 54:8, 56:14, 58:3, 58:5, 58:7, 58:20, 60:18, 61:21 looked 29:15 looking 20:6, 35:3, 49:3, 63:2 looks 57:21 lot 23:7, 41:9, 60:10, 61:13, 63:11 lots 40:10	31:6, 31:8, 31:12, 33:2, 33:3, 33:7, 33:8, 33:9, 33:10, 33:17, 33:19, 33:22, 34:2, 35:3, 35:10, 35:13, 35:16, 35:17, 36:12, 36:13, 37:2, 37:7, 38:1, 43:15, 43:21, 44:7, 44:8, 45:15, 46:18 made 52:2, 52:8 magical 33:18 main 39:1, 39:3, 39:11 maintain 56:8 make 11:15, 21:8, 24:15, 25:18, 47:17, 59:15, 60:14 makes 46:21 males 40:3 malicious 18:7, 18:19, 26:7, 26:8, 41:14, 49:21, 50:8, 58:8, 58:19, 58:22, 59:7, 59:8, 59:18, 61:19 malware 16:5, 16:13, 26:13, 37:14, 39:3, 39:12, 39:16, 39:17, 42:15, 44:15, 45:4, 45:11,	45:13, 46:6, 46:13, 49:5, 49:17, 49:19, 57:11, 57:12, 57:18, 58:12, 59:1, 59:17, 59:21, 60:15, 60:21, 61:12, 61:18, 62:8 manage 7:3, 54:19, 55:10, 56:7 management 57:22, 58:9 manipulate 7:2 manual 34:5, 36:9, 37:4, 37:18 manually 8:22, 19:3 many 5:13, 21:22, 43:22, 60:18, 61:7, 61:8, 62:9 marked 5:21, 9:3, 28:9 marriage 64:21 mask 17:12, 58:5, 62:13 master 7:4 match 52:13, 53:1, 53:8, 53:13, 54:2 matching 37:11 matter 28:2, 44:12, 47:22, 65:2 maybe 11:13, 49:1, 60:1, 61:7, 62:20 mean 6:18, 11:3,	11:4, 14:3, 14:4, 16:14, 19:10, 22:3, 24:12, 25:19, 29:13, 30:12, 30:14, 34:18, 37:5, 38:22, 39:2, 39:9, 44:17, 45:21, 45:22, 47:11, 47:17, 48:2, 48:7, 49:2, 49:7, 50:20, 52:20, 53:4, 53:7, 55:20, 57:9, 59:10, 60:22, 61:7, 62:1 meaning 11:19, 20:9, 20:13, 26:15, 27:10, 35:2, 37:8, 42:12, 42:21, 43:4, 45:8, 47:7, 49:18, 52:6, 59:17 means 8:7, 8:8, 14:8, 14:18, 18:16, 22:10, 26:1, 26:5, 26:10, 26:17, 29:22, 35:18, 35:19, 36:4, 36:21, 36:22, 37:2, 43:13, 46:10, 46:11, 47:12 meant 27:22, 29:21, 47:20, 48:15 mechanism 27:19 mention 61:19 messaging 55:3 messing 58:11
M			
machine 11:18, 11:19, 12:9, 12:12, 13:4, 13:12, 13:20, 13:22, 14:5, 15:6, 15:13, 15:14, 15:20, 16:2, 16:11, 18:4, 18:15, 19:1, 19:2, 19:3, 19:9, 20:10, 20:11, 20:18, 21:4, 21:7, 22:8, 22:12, 22:13, 22:22, 23:6, 23:10, 23:13, 23:20, 24:5, 24:7, 24:18, 25:7, 25:10, 27:8, 27:10, 29:12, 30:3, 30:10, 30:12, 30:22, 31:1, 31:4,			

method 49:13, 51:2, 51:8, 51:9, 51:18, 51:22, 53:11, 53:15 microsoft 58:15 middle 6:8, 7:21 might 35:8 mikaela 3:12 mind 8:17 mindset 56:12 miss 47:18 mitigate 55:10 model 11:16, 11:19, 11:21, 12:1, 12:12, 12:14, 12:16, 14:10, 14:19, 15:12, 15:14, 15:16, 15:20, 16:2, 16:11, 16:16, 18:4, 19:1, 19:9, 19:10, 20:19, 20:20, 20:21, 23:10, 24:7, 26:2, 26:5, 26:19, 27:12, 27:13, 27:14, 28:13, 31:19, 31:21, 32:5, 32:9, 32:19, 32:21, 33:1, 33:4, 33:15, 33:16, 34:4, 38:5, 38:9, 45:1, 45:3, 45:8, 45:11, 45:16, 46:2, 63:3	modeling 61:16 models 28:14, 32:9, 40:3, 43:7, 44:21, 46:12 modern-day 60:15, 62:6 module 6:10, 7:7, 7:10, 8:1, 53:17, 54:4 monitored 62:6 more 51:13, 51:14, 51:15, 53:13, 58:7, 59:17, 63:17 morning 5:9, 5:10 most 31:10, 39:1, 39:22, 58:12 motivated 11:17, 12:5, 20:11 motivation 11:14 much 37:18 multiple 19:15, 19:22, 41:15 N natural 11:17 naturally 12:6 nature 55:13 need 30:1, 30:2, 34:11, 35:19, 36:3, 36:4, 36:22, 37:3, 37:16, 38:15, 39:9, 41:9, 41:15, 41:18, 43:8, 54:18, 61:10 network 10:10, 10:18, 17:12, 22:1, 29:10, 30:8, 50:13, 51:3, 51:9, 51:12, 51:20, 52:2, 52:7, 53:21 networks 55:12, 56:6 never 56:12 new 14:9, 14:10, 14:14, 14:18, 14:19, 21:9, 22:11, 25:14, 25:15, 26:2, 26:4, 26:6, 26:10, 27:19, 28:3, 33:19, 54:17, 54:18, 55:7, 61:10 next 32:11 nice 5:11 nonoutliers 43:9 normal 40:10, 41:4, 41:9, 41:11, 41:12, 41:13, 42:16, 46:5, 46:9, 46:16, 46:17, 49:14, 49:17, 49:18, 49:21, 50:8, 57:13, 57:18, 58:19 notarial 65:4 notary 2:6, 64:1, 64:4, 65:11 note 9:14 nothing 24:12, 63:20 notice 2:2 number 4:13, 56:19 O object 6:17, 8:14, 15:3, 15:15, 16:5, 16:8, 18:6, 18:19, 21:18, 23:22, 26:22, 31:20, 34:10, 36:15, 37:14, 40:12, 41:21, 43:11, 43:18, 44:15, 44:16, 45:1, 45:4, 45:5, 45:17, 45:20, 45:22, 46:2, 46:13, 48:1, 50:3, 50:15, 52:3, 57:8, 57:11, 61:5 objection 8:20, 48:6 objects 42:17, 59:3 obtain 17:11 obvious 11:8, 13:7, 14:11, 17:16, 31:17, 37:8, 37:10, 63:10 obviously 7:9, 11:15, 13:6, 14:4, 52:21 occurred 64:16 october 65:5
---	--

offer 38:12 office 1:1 often 27:12 oftentimes 43:21 oh 11:18, 12:7, 13:6, 13:12, 13:17, 23:5, 24:2, 33:18, 34:12, 36:18, 39:9, 41:11, 42:21, 58:13, 61:10 okay 6:2, 6:7, 9:9, 9:13, 13:8, 13:17, 15:6, 15:7, 17:6, 19:5, 19:11, 22:8, 22:9, 22:10, 22:14, 22:15, 23:12, 24:6, 24:21, 27:18, 28:3, 28:8, 30:1, 30:2, 31:4, 32:8, 34:15, 34:17, 39:10, 45:6, 46:6, 50:12, 50:18, 50:20, 51:1, 51:17, 54:10, 56:17, 57:12, 61:14, 63:14, 63:19, 63:21 omit 49:8 one 8:11, 11:8, 13:5, 13:14, 17:15, 19:14, 21:1, 30:22, 38:4, 40:19, 42:10, 42:20,	42:22, 43:13, 43:14, 44:11, 47:5, 47:7, 47:8, 49:7, 51:13, 51:14, 51:15, 51:17, 52:4, 52:14, 52:15, 53:13 only 12:6, 12:11, 12:22, 13:12, 26:20, 46:4, 46:5 open 1:9 operate 40:10 operates 41:2 operating 57:1, 57:6, 57:15, 58:17 opine 34:13 opinion 12:19, 14:1, 14:17, 23:18, 25:9, 25:17, 26:21, 36:11, 39:2, 42:7, 61:2 opinions 17:3, 44:20 opposed 36:12 orange 31:3 order 40:10 ordinary 55:1, 57:4 organization 55:16, 55:17 os 57:14 other 11:12, 22:4, 39:6, 39:18, 42:11, 47:19,	48:14, 52:12, 59:2 others 44:12 otherwise 7:3, 31:11, 65:1 out 26:11, 35:12, 39:20, 44:5, 52:9, 55:15, 56:2, 62:10 outcome 65:2 outlier 42:10, 42:21, 42:22, 43:10, 43:15, 44:11 outliers 41:6, 42:9, 43:8 overview 35:15, 40:15 own 23:7 owner 1:10, 3:10 P page 4:2, 4:8, 6:6, 9:11, 40:20, 49:11, 50:19, 56:15 pages 1:20 paragraph 6:5, 6:8, 6:21, 7:21, 8:16, 8:17, 9:11, 9:14, 9:21, 10:3, 10:13, 10:21, 11:1, 11:3, 17:7, 17:8, 19:13, 24:20, 24:22, 31:22, 40:17, 49:11, 50:17,	51:8, 53:10, 54:9, 54:10, 54:16 parent 59:1, 61:3 part 12:15, 13:20, 14:4, 29:8, 30:16, 35:9 particular 14:8, 15:21, 18:6, 23:14, 24:5, 32:14, 36:1, 39:1, 43:18, 48:17, 60:15, 61:13 parties 64:20, 64:22 party 64:12 pass 63:17 patent 1:1, 1:2, 1:10, 1:13, 3:10, 4:11, 4:13, 29:2, 29:5, 34:12, 48:9, 48:14, 50:9, 59:12 pattern 37:11 patterns 37:9 paul 3:3 pc-based 7:1 people 12:10, 12:13, 15:6, 18:21, 22:8, 22:15, 23:11, 29:15, 30:13, 33:18, 40:2, 44:1, 56:11, 61:8 per-object 45:18
--	--	--	--

perceive 39:11 perform 6:11, 8:12, 11:9, 17:17, 19:16 performing 21:16 performs 6:15 person 55:1, 57:4, 59:5, 60:6 petitioner 1:5, 3:2 ph 1:15, 2:2, 4:2, 5:4, 64:7, 64:16 phrase 9:20 piece 28:3, 46:6 pietrzyk 1:22, 2:3, 64:3 piracy 60:7 place 48:13 places 49:2 planet 3:20 play 61:12 player 61:10, 61:11 please 6:6, 9:12, 28:4 plenty 39:12 point 8:16, 12:4, 17:21, 18:12, 18:14, 19:4, 23:11, 24:12, 24:14, 24:15, 29:4, 34:12, 38:7, 40:13,	43:2, 48:8, 49:3, 54:1, 58:2, 58:20, 59:4, 59:11, 60:12, 60:14, 61:15, 61:16, 62:2, 62:3, 62:4 pointing 47:16 policies 51:14, 52:18 policy 8:12, 51:5, 51:14, 51:19, 51:22, 52:9, 52:11, 52:17, 53:4, 53:14, 62:17 posing 54:3 posita 11:16, 12:4, 13:5, 13:7, 13:8, 13:16, 14:11, 15:11, 15:21, 17:22, 18:3, 18:14, 18:17, 18:21, 19:4, 19:10, 19:21, 20:10, 22:7, 22:15, 22:19, 23:5, 24:6, 24:16, 27:8, 29:6, 30:6, 31:14, 32:17, 32:22, 37:19, 38:7, 38:11, 38:18, 39:7, 41:8, 55:12, 60:9, 62:4, 63:10 possibility 24:9 posting 53:14, 53:21 potential 55:10 pre-label 43:20	predominantly 40:3 prepare 31:11 present 3:19 pretty 63:9 preventing 24:13 prevents 24:12 previously 45:19, 45:21, 46:13 primarily 42:8 principle 26:3, 41:3, 43:2, 47:11, 48:16, 48:20 problems 40:4 process 8:4, 9:15, 12:5, 13:20, 15:2, 15:17, 16:9, 16:18, 17:10, 17:19, 18:4, 18:6, 18:10, 27:22, 28:15, 28:20, 29:19, 30:9, 30:13, 30:19, 30:22, 31:5, 31:7, 31:9, 32:4, 32:12, 33:5, 33:16, 34:5, 35:10, 49:16, 52:16, 59:6 processes 36:8 procuring 40:6 produce 33:4, 33:15, 44:2, 45:10	produced 19:2, 45:7, 45:12 producing 20:13 product 61:1, 62:15 productive 38:10, 56:11 productivity 56:8, 59:4, 61:3 products 37:13, 62:6 professional 2:5 program 42:16 programs 50:14, 51:3, 51:6 promotes 38:2 protect 60:17 proven 39:9 provide 56:7 public 2:6, 64:1, 64:5, 65:11 publication 4:12 published 29:14 purpose 10:9, 47:22 purposes 17:4 pursuant 2:2 put 14:4, 15:14, 27:14, 43:12, 48:11, 57:14, 57:19, 57:22, 58:6, 58:22,
--	--	--	--

59:2, 60:12, 61:18, 62:11 putting 62:10 pybas 3:20	31:14, 41:8, 50:20 reads 10:3, 19:4 really 17:21, 19:4, 21:2, 26:1, 26:3, 26:15, 28:2, 35:21, 37:17, 39:2, 39:5, 42:21, 43:2, 43:11, 43:15, 44:12, 44:17, 58:13, 59:11, 60:22, 62:6 realtime 2:5 reason 5:16, 34:2, 36:2, 37:3, 44:5 recall 8:21, 9:1, 29:1, 29:5, 52:20 recategorization 6:11, 6:20 recategorize 63:1 reclassification 7:20 record 25:5, 50:11, 61:14, 63:18, 63:22, 64:11 refer 13:22, 16:21, 47:16 reference 5:20, 10:16 referred 14:6 referring 8:15, 16:3, 19:12, 19:22, 31:22, 32:1, 34:21 refers 10:13, 13:21,	32:3, 36:11 registered 2:5 registry 58:11 regular 43:9 relate 61:4 related 64:19 relates 59:21 relative 42:21 relearning 27:21 relevant 55:2, 57:5 remind 25:5 remote 3:20, 16:9 repeat 48:2 repeated 20:2 repeating 21:6 rephrase 10:11, 44:18, 45:15, 47:3 replace 22:21 reported 1:21 reporter 2:3, 2:5, 2:6, 64:1, 64:4 represented 64:13 request 51:10, 51:20, 52:2, 52:6, 52:7, 52:19, 53:2 require 34:5, 34:19,	36:8, 37:4, 38:2, 38:13 required 31:12, 37:18 requirements 38:8 requires 40:9 respect 42:22, 44:12, 55:18 rest 29:1, 43:15 retrain 26:4 reviewer 6:9, 6:19, 7:1, 7:2, 7:6, 7:22, 8:11 revise 26:5 right 5:14, 6:3, 6:12, 7:20, 8:13, 9:8, 10:6, 10:14, 11:9, 12:4, 12:20, 13:14, 15:5, 17:2, 17:4, 17:7, 18:17, 21:6, 21:13, 21:17, 22:1, 22:16, 25:11, 29:20, 30:18, 32:1, 32:8, 32:10, 34:5, 35:9, 37:6, 38:6, 39:10, 39:15, 40:18, 43:4, 43:13, 46:3, 46:19, 47:15, 48:5, 49:11, 49:22, 50:14, 51:6, 51:7, 51:21, 52:2, 52:6, 52:21, 54:10, 54:14, 55:9,
Q			
quantitatively 41:5, 41:22 query 54:3 question 6:19, 10:12, 15:9, 32:4, 44:18, 45:7, 48:2, 48:10, 50:1 questions 17:4, 63:17 quick 42:1, 63:12 quoted 40:20			
R			
rare 41:3 rather 40:14, 48:7 read 6:9, 6:18, 6:21, 6:22, 7:5, 7:22, 10:3, 17:8, 17:9, 17:15, 19:10, 19:18, 21:12, 24:22, 28:13, 32:8, 32:11, 36:8, 40:21, 49:10, 49:12, 49:15, 51:1, 51:9, 53:12, 54:17 reading 13:5, 13:16, 17:22, 19:21, 24:16, 29:6,			

56:17, 56:20, 57:16, 58:4, 58:13, 58:21, 59:8, 59:13, 59:22, 61:22, 62:19, 63:7, 63:14 road 54:7 role 8:19 rpr 1:22, 64:4 run 11:20, 29:21, 30:6, 33:6, 33:14 running 15:18, 16:8, 16:9 runs 15:19, 16:2, 33:10 S said 13:19, 17:20, 21:19, 23:2, 23:5, 23:6, 27:1, 30:14, 30:21, 31:14, 32:14, 36:2, 36:21, 38:19, 43:10, 47:4, 48:17, 49:1, 49:8, 50:4, 52:14, 53:12, 60:1, 60:2 same 5:12, 8:20, 20:1, 21:6, 32:2, 48:6, 61:1 satisfy 47:1 saying 7:14, 13:11, 40:20, 48:9, 55:7	says 6:8, 17:9, 28:13, 29:18, 32:18, 34:20, 36:8, 37:4, 51:1, 51:7, 52:4, 54:16 scope 14:6, 39:20 scripts 58:22, 59:18, 61:20 scrutinize 7:2 seal 65:4 searched 30:16 second 51:8 section 54:11 securities 18:18 security 55:14, 56:7, 58:2, 59:4, 59:21, 60:9, 60:11, 61:4, 61:16, 62:2, 62:4 see 5:11, 6:13, 9:18, 9:19, 14:10, 14:20, 16:20, 18:6, 28:18, 28:19, 36:6, 40:15, 40:16, 52:20, 53:3, 53:9, 53:12, 54:21, 55:5, 57:2, 59:17 seeing 9:1, 29:1, 29:5 seen 31:9, 46:15, 57:17, 62:8	semiautomated 34:21, 36:10, 37:5 semiautomatic 35:6 sense 7:17, 20:2, 27:17, 55:22 sentence 10:2, 19:17, 32:11, 32:18, 50:21, 51:8, 52:4, 54:16, 55:6, 55:21 separate 43:4, 44:9 september 1:16, 64:17 server 53:17, 54:4 set 7:1, 17:13, 27:9, 27:17, 27:18, 41:10, 43:8, 44:10, 64:8, 65:3 shall 13:13 short 42:3, 63:15 shorthand 2:3, 64:3 should 13:12, 20:15, 20:18, 26:8, 35:3, 40:6, 41:12, 41:13, 45:17, 58:5, 61:1, 62:15 shows 56:19 signature 37:11 signature-plkal 65:8 simple 54:1 single 44:14, 45:1,	45:4, 45:11 sir 6:3 situation 36:1, 36:18, 38:12, 38:19, 38:20, 39:13 skill 11:8, 17:15, 55:1, 57:4 software 7:1, 7:14, 15:15, 15:18, 15:19, 16:1, 16:6, 19:7, 19:8, 26:13, 27:14, 33:9, 37:12, 60:7 solution 23:16 solutions 54:18 some 7:18, 11:12, 16:7, 20:15, 21:2, 21:10, 22:1, 22:2, 22:18, 24:10, 25:22, 31:5, 34:4, 34:7, 34:19, 35:22, 36:6, 36:8, 36:9, 36:17, 36:18, 37:4, 37:9, 37:20, 37:21, 39:18, 40:5, 47:18, 48:8, 49:9, 54:6, 57:10, 57:14, 57:20, 59:6, 61:9 somebody 36:17 somehow 35:4 something 22:11, 30:3, 31:2, 39:10,
---	---	--	---

46:22, 56:1, 56:10, 58:13 sometimes 12:11, 12:13, 14:11, 14:12, 18:22, 43:22, 44:1, 57:12, 57:16 sorry 9:9, 11:3, 32:15 sort 40:7, 40:19, 51:19 sorts 60:16 spalding 3:13 specific 8:17, 35:22, 36:18, 40:7, 48:8, 48:14, 49:9, 62:17 specifically 10:2, 10:21, 11:1, 35:15, 49:4, 58:7, 61:19 specified 47:1 speed 12:5, 12:8, 13:9 spend 49:2 spyware 60:8 stands 25:6 start 5:19 starting 28:12, 32:2 starts 55:6, 58:10 state 2:6, 64:5, 65:12	stated 50:13 states 1:1, 2:4 stenographically 1:21 step 7:16, 10:18, 11:2, 11:7, 11:17, 11:20, 11:22, 12:3, 12:6, 12:8, 12:16, 13:1, 13:2, 15:21, 19:7, 19:16, 20:9, 20:12, 21:17, 23:9, 23:14, 23:20, 24:17, 30:12, 30:22, 31:8, 32:16, 34:6, 34:8, 34:13, 34:19, 35:5, 45:9, 45:16, 52:11, 52:12 steps 6:16, 8:12, 31:10, 34:4, 34:7, 52:15 still 25:18, 27:1, 36:8, 40:7, 46:14, 51:2, 56:7, 57:19 stone 3:12 stop 12:5, 13:9, 13:18, 56:11, 59:18, 61:17 stored 28:14, 32:10, 32:20 strange 36:20 street 3:14 strictly 50:4	strike 61:14 stuff 29:13 successful 56:13 sue 3:20 suggest 10:8, 18:9, 22:16 suggested 11:5, 13:3 suggesting 18:1, 20:5, 20:14, 20:17, 22:3, 22:18, 22:21, 23:2, 23:13 suggests 18:12, 24:17 suite 3:6 summarize 7:11 supervise 26:5, 26:9 supervised 25:16, 27:2, 27:4, 28:1, 35:10, 36:12, 37:2, 37:22, 38:4, 43:16 supervision 36:4 supplied 40:6 supply 26:3, 26:18, 27:11, 27:19, 37:1, 37:3, 37:7, 46:4, 46:13 support 25:7, 25:9, 25:10, 33:8, 33:10, 46:18, 47:7	suppose 46:5 sure 25:20, 42:2, 47:17, 57:16, 59:16, 60:21 suspicious 49:16 svm 25:1, 25:6, 25:13, 25:16, 33:11, 33:14, 33:15, 38:2, 38:4, 38:12, 38:21, 38:22, 39:4, 39:7, 39:12, 39:14, 40:9, 41:11, 42:14, 44:14, 45:10, 46:4, 46:7, 46:14, 47:22, 48:17, 48:21, 49:4, 50:5, 50:6 sworn 5:2, 5:6, 64:8 system 10:9, 10:22, 11:6, 11:9, 14:13, 15:1, 16:15, 18:2, 18:14, 21:8, 22:2, 23:4, 23:13, 25:2, 25:11, 25:13, 25:17, 26:21, 27:2, 27:5, 27:6, 27:20, 49:13, 51:3, 57:6, 57:20, 58:17, 59:9, 60:4, 60:8, 60:17, 60:18, 62:9 systems 9:17, 9:20, 10:5, 10:17, 12:22, 13:21,
---	---	---	--

16:17, 17:14, 17:17, 18:11, 19:14, 19:19, 21:15, 30:8, 55:12, 57:1, 57:6, 57:15, 59:14, 60:11	53:10, 57:10, 62:22, 63:1 task 12:10, 22:13, 27:10, 39:2, 39:3 tasks 21:5, 37:20 tcpdump 29:11 teach 56:9, 56:10 teaches 6:14, 11:10, 11:22, 12:22, 14:21, 17:21, 23:18, 49:12, 62:17 teaching 8:9, 8:10, 13:15, 19:14 technician 3:20 techniques 14:7 teen-age 61:13 tell 15:7, 18:17, 26:7, 37:13, 43:21, 46:3, 46:7, 47:5, 47:9 telling 21:14 tells 47:4 ten 5:15 term 8:6 terms 14:1, 14:12, 25:22, 40:5, 47:19 testified 5:6 testimony 5:17, 27:6,	44:20, 64:11 texas 2:4 text 1:9, 36:11 th 65:7 thank 5:12, 63:14, 63:19 therefore 17:16 thesis 23:8, 29:8, 29:14, 30:17, 34:22, 35:6 thing 8:11, 13:5, 15:20, 21:6, 27:19, 29:18, 30:2, 33:19, 46:8, 48:18, 52:5, 58:14, 60:12 things 14:9, 14:10, 14:14, 14:19, 20:1, 20:5, 20:18, 20:21, 21:9, 21:20, 21:22, 22:4, 22:8, 22:11, 25:14, 26:2, 26:8, 27:15, 30:15, 43:3, 55:18, 58:1, 58:3, 58:7, 58:18, 59:16, 60:4, 60:9, 60:16, 60:19, 61:15, 61:17, 62:1, 62:2, 62:5, 62:15 think 11:12, 16:20, 21:19, 24:1, 24:15, 25:12, 33:18, 33:21,	35:12, 35:13, 38:22, 39:4, 39:15, 40:15, 40:19, 45:6, 53:5, 60:22, 63:10 thinking 35:4 thought 21:11 threats 54:17, 55:8, 55:10, 55:14, 55:15, 55:17, 56:4, 59:13 three 38:4, 40:19 through 36:7 throw 24:2 thursday 1:16, 64:17 tiffany 1:22, 2:2, 64:3 time 13:7, 44:3, 49:2, 52:1 times 5:13, 5:15, 61:7, 61:8 tired 35:1 today 5:17 told 31:4 ton 31:12 tool 30:7, 30:9, 31:16, 37:10 tools 7:1, 7:9, 7:12, 7:15, 7:18, 8:10, 19:15, 21:16, 23:1, 23:21, 30:13,
T			
table 8:13, 51:5, 51:14, 52:1, 52:11, 52:17, 53:14, 58:21 take 24:11, 24:19, 28:6, 34:14, 42:1, 54:8, 56:14, 63:12 taken 64:10 takes 30:7 taking 54:3 talk 11:13, 12:9, 16:21, 16:22, 17:5, 31:21, 32:21, 35:8, 35:13, 40:14, 40:18, 49:3, 56:1, 56:2, 58:21, 62:21 talked 20:8, 30:15 talking 5:19, 8:18, 11:2, 29:16, 30:5, 31:15, 34:6, 47:21 talks 6:22, 7:21, 10:22, 19:17, 21:22, 34:12, 34:18, 35:12, 35:15, 40:16, 41:19, 48:14,			

31:16, 37:12, 37:15 top 39:15, 49:12 topic 39:19 touch 60:3 touched 57:22 touching 62:8 trademark 1:1 traditional 37:11 traffic 30:1 train 12:14, 14:15, 27:12, 40:2 trained 45:7, 46:12, 46:17 training 28:16, 29:20, 32:13 trains 28:14, 32:9, 32:19 transcript 4:7, 6:1, 9:5, 28:11 transferred 33:13 transferring 32:15 transform 27:5, 29:10 transformation 32:14 transforming 29:4 trial 1:2 trouble 61:9 true 45:19, 64:11	truthful 5:16 try 16:5, 19:6, 44:9, 47:3, 52:8, 55:9, 59:18 trying 13:10, 23:8, 24:15, 27:7, 44:19, 48:13, 59:1 turn 6:5, 9:2, 9:11, 28:12 two 14:1, 14:12, 40:19, 42:17, 44:2, 44:10, 47:5, 56:22 type 30:2, 62:18 types 38:5 typically 36:22 U uh-huh 45:2, 54:13, 56:21 ultimate 61:17 unclassified 44:15, 45:1 under 41:3 understand 12:19, 13:8, 17:3, 17:22, 18:3, 18:15, 18:21, 18:22, 19:5, 24:6, 30:6, 33:1, 36:20, 37:6, 38:8, 44:19, 45:6, 53:5 understood 32:17, 34:19	unite 3:15 united 1:1 unlabeled 40:22, 41:1, 41:19, 44:6 unless 39:9 unpack 36:6 unsupervised 25:1, 25:12, 26:10, 26:15, 26:20, 28:2, 35:11, 35:13, 35:16, 35:17, 36:3, 36:13, 36:19, 36:21, 36:22, 38:2, 38:12, 38:21, 38:22, 39:4, 39:7, 39:12, 39:14, 40:9, 40:21, 41:2, 41:17, 42:7, 42:13, 43:7, 43:19, 44:8, 44:14, 44:21, 45:3, 45:9, 48:21, 49:4 until 39:8 update 14:9, 14:19, 26:19, 53:4 updating 51:2 uploading 53:16 use 7:15, 7:18, 8:2, 8:6, 10:8, 11:9, 11:19, 12:1, 13:12, 13:13, 14:12, 14:13, 15:1, 15:5, 15:7,	15:16, 16:17, 18:1, 18:18, 18:20, 19:15, 20:18, 21:7, 21:14, 21:21, 22:8, 23:5, 23:13, 24:7, 24:17, 35:17, 37:10, 39:8, 40:2, 42:13, 48:17, 55:19 useful 22:19, 38:10, 42:8, 58:1, 59:3, 61:7, 61:15, 62:15 user 7:7, 55:11, 56:4, 59:14 using 7:13, 8:10, 11:14, 12:9, 12:22, 13:3, 18:10, 19:7, 21:4, 21:19, 23:9, 23:20, 35:16, 45:9, 46:17, 50:4, 51:18, 52:9, 56:5 V validate 27:13 value 51:11, 51:13, 53:13 values 51:11, 51:13, 51:15, 53:14 variety 59:15 vector 25:7, 25:10, 33:8, 33:10, 46:18 versus 31:3, 49:18,
--	---	--	--

52:13, 59:7 via 7:7, 8:1, 64:16 video 61:9, 61:10, 61:11, 61:12 videoconference 64:17 videos 61:9 videotaped 1:15, 2:1 view 58:2, 59:4, 61:16, 62:2, 62:4 village 3:7 virtual 1:15, 2:1 virtually 64:16 vs 1:7	32:20 watch 58:18, 60:11, 60:20, 62:3 way 31:6, 42:12, 59:9, 63:10, 65:1 ways 59:15 we'll 12:20 we're 31:15 well-accepted 23:16 well-known 23:16, 29:15, 30:12, 32:17, 34:19, 58:14 wenke 1:15, 2:1, 4:2, 4:9, 5:4, 64:7, 64:16 whatever 30:7, 36:1, 42:18, 42:22, 44:5, 59:10 wherein 51:11 whereof 65:3 whereupon 5:3 whether 36:17, 46:22, 47:6, 47:15, 48:4, 50:1, 52:9, 53:17, 57:17, 59:17 white 40:3 whole 12:7, 15:20, 23:9, 24:14, 59:12, 63:11 windows 58:11	within 41:1, 55:5, 61:3, 64:5 witness 5:2, 5:5, 63:14, 63:17, 63:19, 63:21, 64:7, 64:11, 65:3 wondering 44:22 word 10:4, 19:19, 20:3, 20:4, 20:16, 20:22, 21:3, 21:11, 21:15, 23:3 words 39:6 work 11:16, 12:7, 18:17, 23:7, 27:9, 44:21 workstation 50:14, 51:4 wouldn't 39:14 wow 33:19, 60:10, 61:22 wrap 63:13 write 58:16	31:14, 31:17, 33:1, 34:17, 34:18, 36:14, 36:16, 37:22, 38:22, 39:5, 39:7, 39:21, 40:16, 40:17, 41:8, 43:6, 45:14, 46:10, 47:11, 47:12, 48:20, 49:7, 49:19, 51:1, 51:17, 52:4, 52:13, 54:1, 55:5, 55:13, 56:8, 56:21, 57:3, 59:5, 59:10, 59:19, 61:6, 61:11 yep 5:12, 9:9, 10:1, 19:11, 25:4, 29:16, 45:13, 46:14, 54:15 yourself 28:4
W			Z
want 5:19, 12:20, 13:9, 15:16, 17:5, 22:10, 23:5, 24:10, 26:16, 27:18, 29:2, 31:1, 31:2, 35:22, 41:16, 42:5, 43:1, 44:4, 44:13, 44:17, 47:17, 48:10, 49:1, 49:8, 55:10, 56:5, 56:6, 58:2, 58:18, 59:15, 60:14, 60:18, 62:14 wants 24:13 warehouse 28:15, 32:10,			zero 47:5 zoom 64:16
			.
			.2300 3:17 .5600 3:8
			0
			00289 1:12 004371 64:4 0210035 4:12 03 9:6
		Y	
		yeah 8:22, 9:9, 12:18, 14:16, 15:8, 15:17, 16:6, 16:10, 16:14, 19:5, 19:17, 19:21, 21:12, 22:5, 24:11, 25:15, 25:20, 26:16, 27:1, 28:19, 29:7, 29:17,	

06 1:17, 64:18 084 64:4 1 10 63:22, 64:18 1003 4:9, 9:2, 9:3, 9:9 1004 4:11, 5:20, 5:21, 50:11, 56:16 1005 4:13, 28:7, 28:9 11 50:17, 50:20, 51:8, 53:10 122 9:11, 11:3, 17:7, 17:9 1340 3:6 1401 3:14 17 28:13, 32:2, 32:8, 32:18 1900 3:15 1999 23:8, 29:13 2 2000 60:16 2005 4:12, 13:8, 21:2, 23:6, 62:7 2023 1:12, 1:16, 64:17, 65:5 2024 65:7 23 50:19	250 50:9 28 1:16, 4:13, 34:14, 34:16, 34:17, 36:7, 64:17, 65:7 3 30 6:6, 34:14, 34:16, 34:17, 36:7 302 6:10 39 63:22, 64:18 3rd 65:4 4 43 40:20 44 49:11 4a 56:15, 56:18, 56:19, 58:21, 59:21 5 508065 1:19 5299 3:5 6 64 40:17 65 1:20, 49:11 7 7,225,343 4:14 720.535 3:17 76 9:11	8 8,418,250 1:13 80111 3:7 80202 3:16 89 6:5 9 9 1:17, 64:18 90 6:21, 7:21 913.777 3:8 92 9:21, 10:13, 10:21, 11:1, 19:13 94 24:20, 24:21	
---	--	--	--