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## UNITED STATES COPYRIGHT OFFICE

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## COPYRIGHT IN THE AGE OF ARTIFICIAL INTELLIGENCE

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WEDNESDAY

FEBRUARY 5, 2020

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The meeting convened in the Montpelier Room, 101 Independence Avenue SE, Washington, D.C. 20540 at 9:00 a.m.

## PRESENT

MARIA STRONG, Acting Register of Copyrights and Director, U.S. Copyright Office

CATHERINE ZALLER ROWLAND, Associate Register of Copyrights and Director of Public Information and Education, U.S. Copyright Office

ROB KASUNIC, Associate Register of Copyrights and Director of Registration Policy and Practice, U.S. Copyright Office

JOHN ASHLEY, Chief, Visual Arts Division, U.S. Copyright Office

KATIE ALVAREZ, Counsel for Policy and International Affairs, U.S. Copyright Office

REGAN SMITH, General Counsel and Associate Register of Copyrights, U.S. Copyright Office

WHITNEY LEVANDUSKY, Attorney-Advisor, Office of Public Information and Education, U.S. Copyright Office

MARK GRAY, Attorney-Advisor, Office of the  
General Counsel, U.S. Copyright Office

ALSO PRESENT

FRANCIS GURRY, Director General, World  
Intellectual Property Organization (WIPO)

ANDREI IANCU, Under Secretary of Commerce for  
Intellectual Property, and Director, U.S  
Patent and Trademark Office

AHMED ELGAMMAL, Professor at the Department of  
Computer Science, Rutgers University, and  
Director of The Art & Artificial  
Intelligence Lab

ROS LYNCH, Director, Copyright & IP Enforcement,  
U.K. Intellectual Property Office (UKIPO)

ULRIKE TILL, Division of Artificial Intelligence  
Policy, WIPO

MICHELE WOODS, Director, Copyright Law Division,  
WIPO

SANDRA AISTARS, Clinical Professor and Senior  
Scholar and Director of Copyright Research  
and Policy of CPIP, Antonin Scalia Law  
School, George Mason University

ANDRES GUADAMUZ, Senior Lecturer in Intellectual  
Property Law, University of Sussex and  
Editor in Chief of the Journal of World  
Intellectual Property

JASON BOOG, West Coast correspondent for  
Publishers Weekly

KAYLA PAGE, Senior Counsel, Epic Games

MARY RASENBERGER, Executive Director, the  
Authors Guild and Authors Guild Foundation

MEREDITH ROSE, Policy Counsel, Public Knowledge

JOEL DOUEK, Cofounder of EccoVR, West Coast  
creative director and chief scientist for  
Man Made Music, and board member of the  
Society of Composers & Lyricists

E. MICHAEL HARRINGTON, Composer, Musician,  
Consultant, and Professor in Music  
Copyright and Intellectual Property Matters  
at Berklee Online

DAVID HUGHES, Chief Technology Officer,  
Recording Industry Association of America  
(RIAA)

ALEX MITCHELL, Founder and CEO, Boomy

AMANDA LEVENDOWSKI, Associate Professor of Law  
and founding Director of the Intellectual  
Property and Information Policy (iPIP)  
Clinic, Georgetown Law

MIRIAM VOGEL, Executive Director, EqualAI

JULIE BABAYAN, Senior Manager, Government  
Relations and Public Policy, Adobe

VANESSA BAILEY, Global Director of Intellectual  
Property Policy, Intel Corporation

MELODY DRUMMOND HANSEN, Partner and Chair,  
Automated & Connected Vehicles, O'Melveny &  
Myers LLP

SARAH HOWES, Director and Counsel, Government  
Affairs and Public Policy, SAG-AFTRA

IAN SLOTIN, SVP, Intellectual Property,  
NBCUniversal

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

2 9:09 a.m.

3 MS. ROWLAND: Thank you all for coming  
4 here today. We really appreciate it. We are  
5 really excited to be here with WIPO co-sponsoring  
6 this event on Copyright and the Age of Artificial  
7 Intelligence.

8 We did Part I in Geneva back in  
9 September, and here we have Part II where we are  
10 taking a deeper dive into all things copyright.  
11 We have a really exciting day planned and we have  
12 some incredible guests, like the Director General  
13 of WIPO, among many others.

14 Right now I'm going to invite Maria  
15 Strong, who is Acting Register of the Copyright  
16 Office, to introduce the Director General.

17 MS. STRONG: So, thank you, everybody,  
18 and welcome to the United States Copyright  
19 Office. It's our privilege to be hosting this  
20 continuing conversation on artificial  
21 intelligence.

22 I would like to thank all of our

1 colleagues at WIPO who are working on this, our  
2 colleagues in the Copyright Office, and our  
3 colleagues also in the Library of Congress who  
4 made this event possible.

5 I think there's going to be a lot of  
6 questions that are going to be raised during the  
7 day. I can't promise we'll have all the answers,  
8 but it's an important topic that crosses many in  
9 the copyright community.

10 With that, I would like to invite up  
11 to the stadium -- the podium -- it feels like a  
12 stadium in here -- Director General Francis  
13 Gurry. Thank you so much.

14 (Applause.)

15 MR. GURRY: Thank you very much,  
16 Maria.

17 Ladies and gentlemen, a very good  
18 morning to you all. It is a pleasure and a  
19 privilege to be here in Washington, the great  
20 city of Washington, for this event.

21 Let me start by thanking the United  
22 States Copyright Office, and the Library of

1 Congress also represented here. Thank you for  
2 all of your support, for reaching out to us, and  
3 for continuing this conversation here in  
4 Washington. We are very grateful for Ms. Maria  
5 Strong and all of her colleagues. Thank you very  
6 much indeed.

7 It's great to see -- I haven't seen  
8 him yet, but I know Andrei Iancu is going to be  
9 here this morning, the Under Secretary for  
10 Intellectual Property at the United States Patent  
11 and Trademark Office. And I'm pleased to see so  
12 many old friends as well.

13 Allow me to introduce two of my  
14 colleagues who you are going to see later in the  
15 morning. Michele Woods, known to many of you in  
16 the Copyright Office, of course, who is the  
17 Director of our Copyright Law Division. And  
18 Ulrike Till, who is newly Director of our  
19 Artificial Intelligence Policy Division.

20 So this is a very timely event, an  
21 extremely timely event, because, as we are all  
22 aware, we are increasingly seeing artificial



1 intelligence applications deployed across the  
2 economy and in the creative industries. It's a  
3 little difficult to keep track of it always, but  
4 we know that there are many instances of this.

5 Just in a different field, I saw that  
6 last week, in the United Kingdom -- and I use the  
7 words of the proprietors, with inverted commas,  
8 of the exercise -- the first entirely invented,  
9 machine invented, molecule has gone into human  
10 clinical trials. So it is quite clear that  
11 machine creation and machine invention is with  
12 us. So it's good that we can discuss these  
13 issues.

14 And I think the existence or the  
15 appearance of all of these applications that  
16 we're seeing across the economy is raising, of  
17 course, many policy questions. We've seen lots  
18 of papers. We've seen, in some cases, some  
19 executive decisions, and we are seeing judicial  
20 decisions emerge. And that creates a situation,  
21 I think, in which we are facing two risks in the  
22 area.

1           I think the first risk for us in our  
2 reasonably small world of intellectual property  
3 is that artificial intelligence is, of course, a  
4 general purpose technology and it is being  
5 deployed across every sector, and has  
6 applications in every sector of the economy, as  
7 well as social applications and military  
8 applications, of course.

9           And I think in those circumstances,  
10 from a policy point of view, we face some  
11 confronting questions, and there is a risk that  
12 the copyright questions, or the property  
13 questions in general, get drowned out by the  
14 urgency and the importance of some of the other  
15 questions that we're seeing in the area of, for  
16 example, privacy or security or data integrity.

17           And I think, for all of us who care  
18 about copyright, it's very important that we  
19 assert the role and importance of property, which  
20 has, after all, historically been such -- whether  
21 real property or intellectual property -- such an  
22 extremely important institution for the

1 organization of the market and the economy.

2           The second risk, I think, is a risk of  
3 incoherence. The policy responses we see  
4 emerging now, for those of us who are trained in  
5 and comfortable with the common law tradition,  
6 we're not so upset by the slow movement of the  
7 gradual evolution of a policy response, but that  
8 is not the whole world. And I think here in this  
9 instance we have two differences from other  
10 preceding situations. The first is, of course,  
11 the speed of technological development. I'm not  
12 sure we have the luxury for that slow evolution  
13 of a responsive policy response.

14           The second is interconnection and the  
15 likelihood that artificial intelligence will be  
16 all over production and distribution in the  
17 economy before we have a coherent international  
18 response which, as you all know, takes years and  
19 years and years.

20           At the same time we know that  
21 artificial intelligence capacity is at the  
22 center, or is perceived to be at the center, of

1 competitor capacity and competitiveness in the  
2 contemporary economy.

3 I think there's a danger here that we  
4 will see that competition that is there spill  
5 over into regulation and that we will see  
6 regulatory, and I think we are already seeing,  
7 regulatory competition.

8 Those who have scale, and those who  
9 are the first movers, have the great advantage in  
10 an interconnected world when dealing with an  
11 issue of connectivity of imposing the global  
12 rule.

13 This risk of incoherence is something  
14 that I think we all need to be aware of. We are  
15 especially grateful, therefore, to the Copyright  
16 Office and the United States Government for  
17 leading this conversation and leading us in the  
18 direction of finding some solutions.

19 Let me say a word about the WIPO  
20 process of which this is part. We have turned  
21 deliberately to conversation because we would  
22 like to allay any fears that there is going to be

1 any abrupt or sudden or precipitant move to  
2 establish international rulemaking in this area.

3 This is not the idea at all. We are  
4 simply wishing to share experience with the hope  
5 that dialogue on the basis of shared experience  
6 would inform national positions in a more  
7 harmonious way in this highly intense competitive  
8 environment where artificial intelligence is at  
9 the center.

10 It's very much a conversation, and I  
11 don't know about you, but I certainly don't have  
12 any answers in this area. I find it extremely  
13 difficult, extremely challenging and extremely  
14 complex. So let me go to those questions -- some  
15 of those questions.

16 I would like to make really just some  
17 comments, three sets of comments. Many of these  
18 issues are sub judice. They are the subject of  
19 litigation, so I will not be making terribly many  
20 suggestions but I think there are two general  
21 sets of questions that we need to address.

22 The first is the interaction, or the

1 impact of, artificial intelligence on our current  
2 copyright system and let's confine it to  
3 copyright here. The second, I think, is a much  
4 more challenging question which is whether we  
5 need to go further and the possibility of new  
6 approaches or new ways of dealing with this  
7 phenomenon of machine creation.

8 Dealing with the first, I think here  
9 I would just like to mention two -- I know there  
10 are many issues -- two issues that I think are at  
11 the center of the interaction of artificial  
12 intelligence and the deployment of artificial  
13 intelligence applications with the existing  
14 copyright system.

15 Here I think the first issue naturally  
16 is authorship. I was very interested to read  
17 coming over two decisions of the Chinese courts  
18 on this. One was the decision of the Beijing  
19 Internet Court, and the other is a decision of a  
20 provincial court in Guangzhou Province.

21 I'm not going to go through the exact  
22 details of the decisions but the decisions do, I

1 think, bear reading because they have taken an  
2 approach to the question of authorship where I  
3 think that they are looking at the creative  
4 process in a very comprehensive manner.

5           They come to their decisions  
6 ultimately that a machine creation, an artificial  
7 intelligence creation, which is original is  
8 eligible for copyright protection because when  
9 you look at the entire and the comprehensive  
10 creative process, then you have a human being  
11 that is involved in this process and it's a  
12 question of identifying the dominant human being.  
13 I think that's a very interesting approach.

14           I think we're going to see a cleavage  
15 between those countries and systems that are  
16 going to answer this on the basis of the  
17 proximate inventor, the immediate inventor,  
18 looking at it this way, as opposed to a more  
19 comprehensive view of the whole creative process  
20 which might give you a human being and might give  
21 you an author for the purposes of copyright  
22 protection.

1           The other, I think, huge question that  
2 we face in the area of copyright, of course, is  
3 the use of copyright works in data feeds to  
4 algorithms for artificial intelligence creations.  
5 Here this is obviously an issue that is raised,  
6 if not directly, then certainly obliquely, in the  
7 Amazon Audible case. We need to wait for the  
8 court's approach and decision in that litigation.  
9 There are lots of views about it.

10           This is a very fundamental question,  
11 I think, because you have many government  
12 policies at extremely high levels encouraging the  
13 free flow of data; the free flow of data in the  
14 interest of the development of artificial  
15 intelligence capacity and its spread across the  
16 economy.

17           You see in Japanese legislation an  
18 exception with respect to this which I think is  
19 something that we need to be very careful about.  
20 Can we take the whole repertoire of music of a  
21 music producer and feed it to an algorithm  
22 without that being a copyright infringement.



1           Of course, we will get some guidance  
2 on this from the Amazon Audible litigation. We  
3 won't necessarily get an answer to the broad  
4 policy question but we will certainly get, I  
5 think, some answer.

6           I think a somewhat similar question  
7 arises with respect to the use of deep fake  
8 technology in audiovisual performances. I am  
9 told -- I am not an expert but I am told that it  
10 is possible to construct an actor's role without  
11 the actor playing the role on the basis of the  
12 data that is gleaned from the preceding  
13 performances, or appearances, or photographs, or  
14 sounds, or images of the actor concerned.

15           Now, this is a very fundamental  
16 question also and I think it's very related to  
17 the first question of infringement of copyright  
18 by the use of copyrighted works in data feeds to  
19 algorithms. I don't know the answer and whether  
20 this is something that is going to require  
21 permission.

22           Of course there are other legal

1 remedies that will come into play. Privacy might  
2 come into play. Defamation might come into play.  
3 The whole deep fake question is a huge question  
4 for society in many, many ways.

5 This brings us back, I think, to the  
6 point that we really have to in the copyright  
7 community impose the importance of the property  
8 question in the policy considerations in relation  
9 to all of the questions that we are now seeing.

10 Those are just some fairly random  
11 comments on, I think, this first set of  
12 questions, I know there are many others, about  
13 the interaction of the copyright -- of artificial  
14 intelligence and the impact of artificial  
15 intelligence on the copyright system.

16 I would like to go to the second --  
17 say a few words on the second set of questions  
18 which is, and the way I would frame it is really  
19 as follows: When we look at the copyright  
20 system, as we all know, and there are many  
21 experts in the audience, it's a product really,  
22 or evolved out of, printing.

1                   Printing actually was really the first  
2 industrial process many centuries before the  
3 industrial revolution in Europe, and many, many  
4 centuries in China before the industrial  
5 revolution.

6                   It was the first industrial process  
7 because it was the first process of mass  
8 production that replaced human labor. The human  
9 labor of writing was replaced by an industrial  
10 process of mass production.

11                  Of course we know that this eventually  
12 led to the consideration of a copyright system  
13 but at the heart of that transition, that huge  
14 transition, of course, was always human creation.  
15 What changed was printing. It was really the  
16 expression and distribution capacity with respect  
17 to human creation. It didn't change human  
18 creation.

19                  I think here we are facing an entirely  
20 different situation. We're facing a situation in  
21 which machine learning has led to machine  
22 creation and machine invention. It's a very

1 different thing from changing the methods of  
2 production and distribution. I think it's a very  
3 radical change that we need to give serious  
4 consideration to.

5           If you look at our copyright system,  
6 all over it are provisions relating really to  
7 human creation; moral rights -- integrity,  
8 attribution -- the length of copyright, the life  
9 of the author plus 70 years. Are we going to do  
10 the life of the machine and its offspring? All  
11 over our system is human creation.

12           I think we do need to give very  
13 serious consideration from a policy point of view  
14 in a quiet manner to whether or not we don't need  
15 two different systems. One system, which is  
16 there to reward and incentivize human creation  
17 and another that is there to reward and  
18 incentivize machine creation.

19           It sounds very dramatic but I think  
20 this is something that we do need to consider  
21 very profoundly. Of course it's going to raise  
22 civilizational questions really of the extent to

1 which we want in our economy and society to favor  
2 machine creation or disfavor machine creation in  
3 relation to human -- in comparison to human  
4 creation.

5 I would say that is one of the new  
6 questions that is going to lie at the heart of  
7 our debate. You can imagine that you might have,  
8 for example, a system which is a property right  
9 in respective machine creations for 10 years or  
10 for 20 years -- I'm just drawing examples out of  
11 the hat -- which is modeled along the lines of  
12 the reality and use of machine creation in our  
13 economy as opposed to the reality and the use of  
14 human creation in our economy and in our society.

15 The biggest challenge as far as I can  
16 see -- besides the policy challenge of how we go  
17 about doing that -- the biggest challenge is  
18 going to be how will we ever know what is a  
19 machine creation and what is a human creation?

20 I don't have any answer to this but  
21 perhaps those of you who are experts in the area  
22 have thought about this and thought about the

1 ways in which you would be able to make that  
2 distinction. I'm not sure that people are going  
3 to necessarily tell you, or indeed are telling  
4 you that this is a machine creation as opposed to  
5 a human creation. This, I think, is a real  
6 challenge for us.

7 Two final words if I may. The first  
8 is another major question that I think underlies  
9 many of the other considerations that we have  
10 with respect to artificial intelligence and  
11 that's data and the status of data. Of course,  
12 it's a policy confusion and a policy mix.

13 We've got all sorts of issues, policy  
14 issues, that come into play with data and the  
15 data economy and the increasing use of data  
16 throughout the economy. We have privacy issues,  
17 we have integrity issues, we have security  
18 issues, we have competition issues, and the list  
19 goes on. Everything is coming out and converging  
20 on data.

21 You see that all come together, for  
22 example, with respect to medical data where you

1 have a market estimated at around about \$240  
2 billion United States dollars worldwide of  
3 medical data increasing rapidly. All of those  
4 questions come into play, whose data are they?

5 Property, I think, has an extremely  
6 important role here. Of course, the interaction  
7 of whatever you decide about policy in relation  
8 to data is going to have a major impact on the  
9 intellectual property system and on copyright.

10 If you start making policy  
11 pronouncements about the use of data and the  
12 flows of data then, of course, the intellectual  
13 property system is there saying that certain  
14 categories of data when they satisfy certain  
15 criteria are eligible for property rights.

16 I think data, besides machine  
17 creation, is another very profound question where  
18 we are a long way in the policy area from really  
19 knowing how we are going to be treating this.

20 My last remark would then be this. We  
21 have a lot of very profound questions here. We  
22 have at the same time a conjunction of awkward

1 circumstances, I think, in the law because these  
2 questions relate to -- these questions relate to  
3 technologies that are deployed on a global scale.  
4 And if you consider the creative industries, the  
5 platforms, operations are global.

6 At the same time these technologies  
7 lie at the heart of competitiveness and  
8 competitiveness lies at the heart of  
9 international economic relations. And, at the  
10 same time, we see a faltering multilateral system  
11 with respect to rulemaking. There are many  
12 things that are happening well in the  
13 multilateral system but rulemaking is not one of  
14 them.

15 So we have, I think, the conditions of  
16 a storm here. I think we all need to be aware of  
17 that in this area. It's for this reason that we  
18 are extremely grateful to the United States  
19 Copyright Office for engaging in this way.

20 The United States Patent and Trademark  
21 Office -- Andrei Iancu just walked in -- we are  
22 very grateful for your support for an



1 international conversation with respect to these  
2 extremely challenging questions. Thank you very  
3 much for this opportunity to say a few words this  
4 morning.

5 (Applause.)

6 MS. ROWLAND: Thank you so much,  
7 Director General.

8 Now we are going to hear from Maria  
9 Strong, Acting Register of the Copyright Office,  
10 to give a few remarks about the Copyright Office  
11 and artificial intelligence.

12 MS. STRONG: Thank you, everybody, for  
13 coming. Again, thank you Director General for  
14 your very insightful remarks to set up the stage  
15 for today's conversation and the continuing  
16 conversation that we'll have both here in the  
17 States and in other places around the world.

18 We are excited to begin and continue  
19 this conversation coming out of the Geneva event  
20 last September. The former Register of  
21 Copyrights Karyn Temple actually spoke and  
22 moderated the panel on copyright and today we

1 continue that conversation.

2 Here at the Copyright Office we are  
3 keenly aware and interested in the intersection  
4 of copyright and AI. As the primary agency  
5 charged with administering our nation's copyright  
6 system, the Copyright Office has long understood  
7 the importance of keeping up-to-date with  
8 changing technologies.

9 We look at these evolutions from both  
10 a practical and a policy standpoint.

11 Practically, we must adjust to the changing  
12 technology when we are examining works for  
13 registration because each application requires us  
14 to make a determination on whether a particular  
15 work is copyrightable.

16 In addition, we have long provided  
17 advice to Congress, the courts, and our  
18 intergovernmental colleagues on policy issues  
19 related to copyright and emerging technologies.  
20 This means that we must appreciate the  
21 complexities of how technology and copyright are  
22 developing both for individuals and companies,

1 both at the national and global levels.

2           Thankfully, we have experience in  
3 adapting to new technologies. Each wave of  
4 technological advancements has brought new  
5 challenges. The first federal copyright act in  
6 1790 protected only books, charts, and maps.

7           Over the years, and often after  
8 significant study, Congress has added a number of  
9 newly-developed types of works to the Copyright  
10 Act, all of which we have had to assess as part  
11 of our duties to administer the Act.

12           We at the office have handled a steady  
13 stream of evolving technologies since our  
14 founding in 1870. This is our 150th year  
15 anniversary. We'll be talking more about it then  
16 so it will be coming up to celebrate a little  
17 later. Some might criticize the speed, or lack  
18 thereof, of legislative change to reflect new  
19 technologies.

20  
21           Yet, at the same time, others recognize the  
22 importance of letting the marketplace have some

1 time to develop before attempting legislation. I  
2 think the Director General mentioned that sort of  
3 balance of time and thoughtfulness that needs to  
4 be taken into account for this complex system of  
5 change.

6 Now we are looking at a new  
7 technology, that of artificial intelligence. AI  
8 seems to mean different things to different  
9 people. Indeed, there remains a debate about its  
10 very definition. While many of the technologies  
11 that we're discussing today are new, the issues  
12 they raise are not. As the Director General  
13 said, we may not have answers for all these  
14 questions, and that actually could be a good  
15 thing.

16 The Copyright Office began thinking  
17 about some of these issues related to the  
18 intersection of AI and copyright back in the  
19 1960s. Yes, 1960s. The Office's 1965 annual  
20 report addressed the problem inherent in  
21 machine-generated works, noting that the  
22 determination of a line between human and machine

1 authorship would be a crucial question to  
2 establishing copyright authorship.

3 As we pointed out back then, finding  
4 the line between whether a computer is merely a  
5 tool or whether a computer has independently  
6 conceived and executed a work is very difficult.  
7 But, yet, this question is not so different from  
8 the question that we are already talking about  
9 here today.

10 Take, for example, photographs. When  
11 photography first appeared on the scene more than  
12 a century ago, there were debates about whether  
13 or not it would be protected at all. It was an  
14 issue eventually settled by the Supreme Court.  
15 Our office adjusted to that situation and today  
16 we register any photograph that displays a spark  
17 of creativity.

18 But there is a line as we saw in the  
19 famous monkey selfie. As our Compendium states,  
20 a photo taken by a monkey is generally not  
21 copyrightable regardless of how compelling that  
22 photo may be.

1 (Laughter.)

2 That is because the Supreme Court held  
3 in the 1879 Trade-Mark Cases decision the  
4 copyright law only protects "the fruits of  
5 intellectual labor" that "are founded on the  
6 creative powers of the mind." While the monkey  
7 selfie at first glance seems like an open and  
8 shut copyright matter, there are variables of  
9 complexity both in fact and in law that could  
10 mirror the copyright issues we see today in AI.

11 What could a photographer do to make  
12 a monkey's act of clicking the shutter something  
13 akin to a computer program, for example? That  
14 goes back to the 1884 Burrow-Giles v. Sarony  
15 decision where the court analyzed the  
16 copyrightability of photographs.

17 There is no question a copyright law  
18 allows for the use of tools in creation, but at  
19 what point does setting something into motion  
20 mean authorship? This is something photographs  
21 and AI have in common: where is the line of  
22 authorship? What about ownership issues?

1           So the past can help us to identify  
2           and sort the present and future questions about  
3           some of AI's complex issues. It may not give us  
4           all the answers but perhaps it provides us with a  
5           framework of a way to analyze things.

6           Today we are looking forward to  
7           hearing about how artificial intelligence is  
8           impacting different types of copyrighted works.  
9           Our first session will lay some groundwork on  
10          technological and legal copyright issues.

11          Our panels will delve into the details  
12          of specific kinds of works, such as music, visual  
13          art, literature, video games, digital avatars,  
14          and the impact of AI and copyright on consumer  
15          products like self-driving cars.

16          We will also hear about how important  
17          it is to identify an appropriate corpus of  
18          material for machine learning and the importance  
19          of being aware of bias that may arise in the use  
20          of algorithms.

21          So to wrap up, today is a  
22          conversation, and in conversations, sometimes

1 there are more questions asked than answers  
2 given. With that, I welcome everyone to today's  
3 conversation. Thank you so much.

4 (Applause.)

5 At this point I have the pleasure of  
6 introducing Andrei Iancu, Under Secretary of  
7 Commerce for Intellectual Property and Director  
8 of the United States Patent and Trademark Office.  
9 Director Iancu has held this position since 2017  
10 having left the private sector where his practice  
11 focused on IP litigation. He, too, was at the  
12 WIPO event last September in Geneva. We are very  
13 pleased he is able to join us today. Thank you  
14 so much.

15 (Applause.)

16 MR. IANCU: Thank you, Maria, for the  
17 opportunity to join you today. And Director  
18 General Gurry, so good to see you here in the  
19 United States. Obviously, we've seen each other  
20 in Geneva and elsewhere around the world.  
21 Actually, several times on AI issues. Here we  
22 are again.



1                   Very pleased to join the Copyright  
2 Office and WIPO with whom we work so closely on a  
3 daily basis as they open this conference on an  
4 important and fascinating topic, as we have  
5 heard, and will hear a lot more throughout the  
6 day.

7                   AI presents challenges for many forms  
8 of IP. Some of those challenges are similar from  
9 discipline to discipline. For instance, can an  
10 AI algorithm be an author? You've heard a little  
11 bit from Maria and I'm sure it will be a heavy  
12 subject today. Can an AI algorithm be an  
13 inventor when it comes to patents? For both, how  
14 much human contribution is needed before rights  
15 can be conferred? Any human contribution at all?

16                   Some of these questions are both  
17 ethical and legal. Though the answers may not  
18 always be easy, it's vitally important that at  
19 least we ask the questions and engage in the  
20 discussions like this one today and like the ones  
21 we've had in Geneva and elsewhere around the  
22 world.

1           We appear to be on the threshold of  
2           having to confront these issues at the USPTO and  
3           obviously the Copyright Office and in courts  
4           throughout the United States and throughout the  
5           world. AI, though, this is nothing new. It has  
6           been part of the national and international  
7           industry, academic, and even kitchen table  
8           discussions for a long time.

9           Although some of the innovations that  
10          AI embodies like speech recognition, image  
11          recognition, search optimization, and even early  
12          neural networks, were conceptualized as early as  
13          the 1950s. Significant breakthroughs are more  
14          contemporary.

15          Today AI is becoming ubiquitous in our  
16          society. I was at the CES show just a few weeks  
17          ago in Las Vegas. It seemed like almost every  
18          booth from computers to automobiles to biological  
19          companies all were discussing AI. Some now  
20          maintain that AI algorithms can create on their  
21          own with minimal, if any, human interaction.

22                 As the administration's lead agency on

1 intellectual property, the USPTO has been  
2 actively engaged on this topic of AI and IP  
3 policy. A year ago, for example, we gathered  
4 leading thinkers, policy makers, academics, and  
5 practitioners to discuss the growing capabilities  
6 and economic impacts of AI and implications for  
7 IP policy at the day-long conference similar to  
8 this at our headquarters in Alexandria.

9 Then last August we issued a request  
10 for comments on patenting artificial intelligence  
11 inventions. Two months later in October we  
12 followed up with a request for comments on  
13 intellectual property considerations for  
14 innovation more broadly including specific  
15 questions of the AI nexus with copyright law.

16 We've received many, many comments  
17 from the United States and internationally and we  
18 are now reviewing those comments that we have  
19 received and will be issuing the report hopefully  
20 in the coming months.

21 But as we go through these exercises,  
22 we should be careful. We should be careful not

1 to jump to conclusions. Instead, we obviously  
2 need to be deliberate and have a steady hand. As  
3 Maria mentioned, we have faced many technological  
4 advances over time; increasing automation. This  
5 new advance may be just another step along the  
6 spectrum.

7 Our current policies may work just  
8 fine. On the other hand, they may need to be  
9 updated as AI could also present brand new issues  
10 which we are exploring now throughout the U.S.  
11 Government and here at this conference today.

12 This is why I am so grateful to be  
13 working with all of you, with the Copyright  
14 Office, with WIPO on these very important issues.  
15 It's great that you all are having this deep  
16 discussion today. I wish you a great conference  
17 and hope to see you around the policy circles in  
18 Washington, D.C. again soon. Thank you very  
19 much.

20 (Applause.)

21 MS. ROWLAND: Thank you very much,  
22 Director Iancu.

1           Next we are going to turn to a  
2           foundational discussion of AI and copyright with  
3           the international discussion at play. We are  
4           going to be talking about -- I'm getting it all  
5           confused. I'm sorry. Excuse me.

6           We are doing the foundational  
7           discussion of AI and technology and the law. I  
8           would like to welcome to the stage Rob Kasunic  
9           who is head of our Registration Policy and  
10          Practice and the Associate Register here at the  
11          Copyright Office.

12          And Professor Elgammal at Rutgers  
13          University and is involved in both computer  
14          science and art and AI issues. He runs a very  
15          interesting lab over there in Rutgers. Thank you  
16          so much.

17          MR. ELGAMMAL: Hello everybody. Thank  
18          you for inviting me. I will try to give you an  
19          overview about how AI is used in making art, in  
20          particular visual arts.

21                 Let me start by this video.

22                 (Video played.)

1                   What you see is from HBO Silicon  
2 Valley show that was aired back in April 2018  
3 about AI art and the world. The two guys are  
4 talking and one of them is asking who is the  
5 builder and the other guy answering this is work  
6 done by AI. A third guy is coming in saying its  
7 actually the first art made by AI ever sold at an  
8 auction in Sotheby.

9                   That's fictional but AI work is real.  
10 That picture is now a reality six months later  
11 when Christie's actually auctioned a piece of AI  
12 art and it was sold for almost half a million  
13 dollars.

14                   I'll give you a brief historical view  
15 of where we are now in the context of history  
16 making art. Art has been evolved from cave  
17 paintings to painting on canvas like Caravaggio  
18 and the Renaissance. Then in the 19th century  
19 came photograph which changed the way of making  
20 images.

21                   Photography became an art form in the  
22 20th century. Then came digital photography in

1 the 20th century. There came digital  
2 manipulation of images like Photoshop and these  
3 software. In the '90s came graphic rendering  
4 with all its amazing abilities. Now we are  
5 entering a new age of the machine using AI can  
6 actually create an image, not just taking a photo  
7 like a camera.

8           However, the use of AI in making art  
9 is not new. It is as old as the AI itself, from  
10 the '50s. Here are two of the pioneers who have  
11 been experimenting with using AI in making  
12 artwork.

13           On the left is Harold Cohen, an artist  
14 who used AI in making works of art for a long  
15 time. On the right is Lillian Swartz, a graphics  
16 scientist who also experimented with AI. This is  
17 one example of Harold Cohen's work.

18           The difference here is this is what's  
19 called rule-based AI system where you actually  
20 have to write lots of rules about what to do,  
21 what AI is supposed to do. Here AI actually  
22 makes drawings with some flexibility or guidance.

1                   Okay. Move to the last five years.  
2           A lot of buzz has been around File Transfer where  
3           basically you start with a photo like I'm using a  
4           photo in the top left. Then you can stylize it  
5           by any style you like. There are many apps  
6           available that you can do that.

7                   Another version of that is Google  
8           Dream where basically you start with a photo and  
9           then put some objects on top of it. This comes  
10          from a machine for a different purpose of  
11          recognizing cats and dogs and other things so you  
12          end up with something that looks like Van Gogh  
13          but has lots of dogs over it.

14                   People liked that. If you search  
15          Google Dream you can find so many things you can  
16          do with it. However, these two examples of File  
17          Transfer and Google Dream are transformative AI  
18          where they transfer one image to another adding a  
19          style.

20                   It's not generative AI. Generative AI  
21          I'll talk about today which is really the  
22          important issue when it comes to today's topic.



1 So what is generative AI? This actually came  
2 about five years ago in a work by Goodfellow and  
3 others. It's called Generative Adversarial  
4 Network or GAN.

5 So what is GAN and how does it work?  
6 It's an AI algorithm that basically tries to  
7 generate images. We give it some data, for  
8 example, images of cats or images of flowers.  
9 You want to generate more of that. The way it  
10 works is you have two components, two players.

11 One is a generator, the one on the  
12 right there, who has no access to this data. It  
13 never sees the data in the whole process. The  
14 other player is actually a critic or a  
15 discriminator, a technical term, who actually has  
16 access to this data. In the case of flowers, it  
17 has access to images of flowers.

18 Basically the generator will start  
19 generating totally random images because it  
20 doesn't know anything about what a flower is. It  
21 passes the image to that critic and the critic  
22 will say, okay, this is not basically flowers and

1 send it back to the generator. The generator  
2 then has to improve, think about what to improve  
3 in that image to make something that will please  
4 the critic.

5 After so many tries hopefully that  
6 generator will be able to do something that looks  
7 like a flower that can fool that critic. The  
8 critic also tries to get better and better in  
9 telling whether that's a fake image coming from  
10 the generator or an actual flower image.

11 Here is an example after a few  
12 adaptations this will show up and the form is  
13 developed more and more until it's something that  
14 reasonably looks like a flower. That's a fake  
15 flower in that case.

16 All right. So this is the process of  
17 the kind of evolution on how art is made using  
18 AI. These are examples of actual artwork by  
19 different artists using AI art like Mario  
20 Klingemann, Tom White, Robbie Barrat, and others.

21 Actually, if you look at any of these  
22 examples, you can now think of what are the data

1 that came from behind them, like nude paintings,  
2 in one a fan in another. This has transformed  
3 the data into a new visual form.

4 What are the aesthetics exactly of  
5 this process? At the top here you see examples  
6 of what happens when we give it lots of images of  
7 classical portrait from Renaissance to 20th  
8 Century.

9 We give it lots of classical  
10 portraits. One generation you see is kind of a  
11 failed attempt to make a portrait. It tried to  
12 make a portrait but it failed. From that failure  
13 come the aesthetics. I call it the aesthetics of  
14 machine failure. The machine didn't give a  
15 perfect portrait but gave that failed portrait.

16 That exactly reminds us of Francis  
17 Bacon portrait on the bottom with a difference.  
18 At the bottom, for instance, they intended to  
19 make this deformed portrait, while on the top she  
20 failed to make a portrait. From that comes an  
21 interesting portrait that an artist would like to  
22 put in an exhibition. That is to keep in mind

1 of understanding the process here.

2           However, AI generation has evolved a  
3 lot in the last five years. At the right here  
4 you can see NVIDIA -- what is called fake faces  
5 where it generated lots of fake faces. By fake  
6 it means that it's not anybody the machine has  
7 seen in the training data.

8           It can actually look like somebody in  
9 reality because basically a human face is a  
10 combination of other faces anyway. This shows  
11 you how good is the rendering of these machines  
12 are now in creating realistic images.

13           On the left is an example of creating  
14 birds and flowers just from text. You give it a  
15 text of what you want to generate as a flower or  
16 a description of the bird you would like and the  
17 machine actually generates a good quality  
18 realistic bird which also can be a fake bird.

19           Where is artist in the process? So in  
20 this process of using GAN the artist would feed  
21 the machine some images like flowers and the  
22 machine would generate lots of other examples of

1 flowers, not necessarily copying the data because  
2 the generator doesn't see the data, it just  
3 generates things from the same distribution.

4 What is the role of the artist here?

5 The first thing is the artist actually  
6 pre-curates the inputs. The artists chooses what  
7 data to feed to the algorithm. You want to create  
8 something based on faces or flowers. What kinds  
9 of faces? What flowers? What paintings? What's  
10 the input? That's one of the roles.

11 Then the artist actually tweaks that.  
12 Most artists are not technical people so take an  
13 algorithm and change it a little bit or run it as  
14 it is or change some parameters. If the artists  
15 is technically savvy, he actually can change the  
16 code or write his own code. That's another role.

17 The third part is post-curation  
18 because - the machine would give thousands and  
19 thousands of possibilities and the artist chooses  
20 a few of them to show to the world exactly like a  
21 photographer would take one thousand photos and  
22 show ten or one in a show. The artist's role is

1 pre-curation, tweaking, and post-curation. It's  
2 totally a conceptual art process where artists  
3 are involved and AI is a tool that can actually  
4 create something with the artist.

5 In October of 2018 Christie's sold  
6 that artwork on the left here. Here is the  
7 problem because that artwork was the result of a  
8 GAN machine that was trained by another artist.  
9 The other artist was Robbie Barrat who trained  
10 that algorithm.

11 He tweaked it and trained it on  
12 classical portraits and other authors take that  
13 algorithm and basically generated from that  
14 algorithm after being trained. Basically you're  
15 coming to the diagram here. The algorithm was  
16 created. It was already pre-curated and trained.  
17 He pushed a button, selected an image, and sell  
18 it.

19 Who is the author of that? That was  
20 the debate at the time. I have a whole article  
21 on art and that if you want to know more.  
22 There's a lot of issues about authorship of these

1 kind of processes and the outcomes of these  
2 processes.

3 Another issue is that what you  
4 generate here is a very rich generation. You can  
5 - this video actually will, for example, show  
6 going through what the machine learned after  
7 trained on flowers. As you see it can really  
8 generate lots and lots of forms and flowers and  
9 intermediate forms and combination of forms. And  
10 that raise another issue. What if you train this  
11 kind of models and take away some of the results  
12 out with after being trained? Who owns that?

13 And for example, there are apps online  
14 like Artbreeder who actually do that. You can  
15 actually combine any images. This actually takes  
16 millions of images and train them and -- that  
17 include animals, objects, cars, many things. And  
18 train the machine to generate these kind of  
19 things. And once you do that you can actually  
20 navigate in that representation and generate lots  
21 of combination of things, amazing combination of  
22 things. For example, that video here will show

1 an example where I combined - I just do this to  
2 combine a cat, a panda, and a hamster. And what  
3 you generate here are all possible combination of  
4 these three animals -- this doesn't exist in  
5 reality.

6 So if you go to this amazing website  
7 and you create your own image out of that,  
8 another person can actually create the same image  
9 accidentally or eventually. Then that is the  
10 authorship and ownership issues.

11 So in that particular process the  
12 artist really here is just basically the  
13 post-curation because the algorithm is already  
14 trained and has ability to generate infinite  
15 amount of images. And as an artist or as a user  
16 your role is really searching for something  
17 interesting to you to - out of there to show to  
18 the world. So that's a very limited role.

19 So moving to autonomous generation,  
20 can AI generate art by itself and can the role of  
21 human become minimal to that? So what if you  
22 take these GANs and fit it for example all art



1 history, for example? What it will generate?

2 That's an experiment we did at Rutgers.

3 So basically we took 500 years of art  
4 history and - images of art history, about  
5 100,000 images and feed it through these GANs.

6 By definition, by construction GANs will not make  
7 anything creative, as I showed. It will just  
8 basically try to create something that looks like  
9 the data you give it. So the outcome will be  
10 more like what you see in the bottom here where  
11 basically emulation of what you have seen in art  
12 before, and mostly it's failed emulation.

13 So how can you move from being  
14 generative to being creative? And that's  
15 basically our contribution in that area, which  
16 was called Creative Adversarial Network or CAN,  
17 where basically you would try to - pushing a  
18 little bit further in the autonomy and becoming  
19 more creative.

20 So what is that? We call that artist  
21 AICAN. So basically we based our algorithm here  
22 on a theory from psychology by Professor

1 Martindale who was at the University of  
2 Massachusetts, and the theories basically can be  
3 summarized as this.

4 Imagine you're an artist living in the  
5 late 19th Century. So Impressionism has already  
6 happened, and you already have seen lots of  
7 Impressionist work by many artists and  
8 Impressionists have really painted every possible  
9 facade of a building or a street or an amazing  
10 landscape.

11 As an artist you're already bored of  
12 that, as a new artist. And so basically if you  
13 keep doing the same kind of art, it was called  
14 habituation, you kind of get bored of it as a  
15 viewer. And as an artist, avant-garde artist  
16 basically you got bored very early about - from  
17 that, not like the general public.

18 So as an artist your role really is to  
19 come, create something that's really innovative  
20 to push against habituation with the least  
21 effort, because if you push too much, that can be  
22 totally innovative and can be shocking. And that

1 was exactly what for example Picasso did in the  
2 Ladies of Avignon artwork that later sparks the  
3 cubism movement. So pushing innovation against  
4 habituation is right when you will drive the art  
5 forward.

6 So how can we implement a machine that  
7 do that? So what we did is we take these GANs  
8 and modify it in a way that we want to create  
9 something that's innovative. So if the machine  
10 creates something that's - repeats, for example,  
11 Renaissance or Baroque or Impressionism, it has  
12 to be (unintelligible), otherwise it's not going  
13 to be creative. That's how to push it forward.

14 In the same time if it generates  
15 something totally random that will not be copying  
16 any of these existing schools -- that's totally  
17 shocking. That's not really as interesting as  
18 art. So you have to put them here into a  
19 dilemma.

20 In one hand it has to follow the  
21 aesthetics, it has to follow the distribution of  
22 what art is. In the other hand it shouldn't

1 generate anything that's identified as an  
2 existing art movement. And by doing that the  
3 machine started generating these amazing forms  
4 for us that was very really interesting. And  
5 when we make surveys and show these mixed up with  
6 actual art by human artists from recent  
7 contemporary art fairs, we're surprised that  
8 people thought that this art was made by a human  
9 artist 75 percent of the time compared to 85  
10 percent of the time when they're shown art by  
11 abstract exhibitionist masters, and 48 percent of  
12 the time for actual art by artists from Art Basel  
13 2016.

14           So that really put the machine at the  
15 level of generating visual images. It has  
16 certain interesting forms that you cannot tell  
17 whether they're done by a machine or a human.  
18 And what's the role of the human here? For me  
19 nothing other than developing the algorithm, the  
20 process and feeding all art history. So I have  
21 no control of what will be generated next.

22           All right. So let me finish here.

1 And also we will associate words like intentional  
2 and inspirational, communicative, having human  
3 visual structure with these arts.

4 Let me finish by this, a social  
5 validation of AI art in society. So the first  
6 one in the top left is an LA gallery show back in  
7 2017 that show AI art. I think that was the  
8 first gallery show. Then the Christie's show in  
9 '18. Art - was shown in an art fair in Art  
10 Basel and SCOPE Art Fair. It was shown in  
11 galleries in New York and in Chelsea and another  
12 action by Sotheby later. The Barbican in London  
13 had made a show about the AI art. There was just  
14 an exhibition in China, in the National Museum of  
15 China in November -- expected one million people  
16 showing art and technology including AI art. And  
17 obviously many coverage in the media from top  
18 news coverage.

19 So I'll stop here for the time, and  
20 I'll start with the discussion.

21 (Applause.)

22 MR. KASUNIC: Good morning. That was

1 fascinating. Thank you.

2 Well, as the director general  
3 thoughtfully discussed earlier, we are at a time  
4 now where artificial intelligence is really  
5 forcing us to reconsider and question some of our  
6 foundational assumptions. And one of those would  
7 be just looking at the question of what is art?

8 I thought it would be helpful to look  
9 at some dictionary definitions of that just as  
10 context of where we now stand on that issue. The  
11 expression or application of human creative skill  
12 and imagination typically in visual form such as  
13 painting or sculpture producing works to be  
14 appreciated primarily for their beauty or  
15 emotional power. Works produced by human  
16 creative skill or imagination. And the conscious  
17 use of skill and creative imagination especially  
18 in the production of aesthetic objects.

19 So that is a - certainly art is not  
20 the question. There's a difference between what  
21 is art and what is copyrightable, but to get into  
22 the realm of what is copyrightable, we've had

1 several Supreme Court cases over many years that  
2 have looked at this question, looked at the  
3 constitutional provision of works, of what  
4 constitute works of authorship and what  
5 constitutes originality. And in the Bleistein  
6 decision Justice Holmes did look at that question  
7 of what is originality and stated that it was -  
8 wrote that it was the personal reaction of an  
9 individual upon nature or expression of the  
10 author's unique personality as the key to  
11 satisfying the constitutional requirement of  
12 originality.

13 Similarly, when we get to the case of  
14 Burrow-Giles versus Sarony dealing with the  
15 photograph of Oscar Wilde that you see there, the  
16 question of authorship was raised and in - and  
17 the question of whether photographs could be  
18 copyrightable. So it also was addressing what  
19 constitutes a writing under the copyright clause.

20 And the court said that an author is  
21 the person who effectively or as near as can be  
22 the cause of the picture which is produced; that

1 is, the person who has superintended the  
2 arrangement, who has actually formed the picture  
3 by putting the persons in position and arranging  
4 the place where the people are to be, the man who  
5 is the effective cause of that. The author is  
6 the man who really represents, creates, or gives  
7 effect to the idea, fancy, or imagination. And  
8 also said these views are of the nature of  
9 authorship and originality, intellectual creation  
10 and right to protection confirm what we have  
11 already said.

12 More recently the Supreme Court stated  
13 in the Feist decision versus Rural Telephone  
14 Service in an opinion written by Justice O'Connor  
15 that the sine qua non of copyright is  
16 originality, and to qualify for copyright  
17 protection a work must be original to the author.  
18 The court defined author in the constitutional  
19 sense to mean he to whom anything owes its  
20 origin, originator or maker.

21 While the word writings may be  
22 construed liberally - may be liberally construed



1 as it has been to include original designs for  
2 engraving, prints, et cetera, and photographs, it  
3 is only such as are original and are founded in  
4 the creative powers of the mind. The writings  
5 which are to be protected are the fruits of  
6 intellectual labor embodied in the form of books,  
7 prints, engravings, and the like, and that again  
8 reinforcing that originality is a constitutional  
9 requirement.

10 So some of the questions raised by  
11 works created by artificial intelligence are: can  
12 machine learning produce original works or is the  
13 product of such software inherently reproductive,  
14 derivative, and/or the result of a system or  
15 process devoid of that personal reaction of an  
16 individual upon nature or expression that is  
17 devoid of the author's unique personality? And  
18 also it can be asked can a computer program be  
19 the author in a constitutional sense?

20 And part of that question then answers  
21 does Congress have the constitutional authority  
22 to provide copyright incentives to computer

1 programs themselves as authors? Furthermore, if  
2 such authority does exist, should Congress  
3 exercise that? I think we heard earlier that  
4 this is a time to be deliberate and to not rush  
5 into answering some of these questions, but to  
6 see perhaps how the situation evolves.

7 Also, if authorship or ownership of AI  
8 output should be protected, is copyright the  
9 proper vehicle for such protection or perhaps is  
10 sui generis protection or some other form of  
11 intellectual property protection preferable to  
12 that?

13 Some of the types of uses. You've  
14 seen certainly a lot of examples, but just to  
15 more broadly look at how software may be used and  
16 a very high-level overview of software can be  
17 used in the creation of works is the computer  
18 program itself that is the tool to create other  
19 works. In that case the programmer of the  
20 computer program can unquestionably be the author  
21 of that computer program. So computer programs  
22 of artificial intelligence are protectable

1 themselves.

2           Furthermore, software as a tool, as we  
3 learned from the CONTU Commission many years ago  
4 when computer programs were incorporated into the  
5 Copyright Act that at the time viewing software  
6 primarily as a tool for others to use. So the  
7 programmer may own the software itself, but the  
8 user of the software owns the works created with  
9 the software as a tool much like a photographer  
10 would own the copyright to the photograph rather  
11 than having the camera manufacturer as the owner  
12 of that photograph.

13           Software can also be used as a  
14 template, a sort of Mad Libs-like use where the  
15 software can complete the template. And this  
16 seems to be the case for use in such types of  
17 works such as factual news articles. Sports  
18 articles, weather articles can use this form of  
19 template in which certain facts fill out the  
20 remainder of that. And this may entail some  
21 authorship by the author of the computer program  
22 in terms of creating that template that is going

1 to be used.

2 But the question is software as the  
3 creator of works based on machine learning or the  
4 output of random or process-driven expression is  
5 really I think the question that we're -  
6 questions that we're looking at today.

7 So where we currently stand in the  
8 United States Copyright Office is that the office  
9 will not register works produced by nature,  
10 animals, or plants. Examples that we've used in  
11 the Compendium of Copyright Office Practices  
12 include a mural painted by an elephant, a claim  
13 based on the appearance of an actual animal skin,  
14 a claim based on driftwood that has been shaped  
15 and smoothed by the ocean, or a claim based on  
16 cut marks, defects, or other qualities found in  
17 natural stone. Those are objects that cannot be  
18 copyrighted because the result is not the result  
19 of human authorship.

20 Similarly, as you heard, also another  
21 example is that a photograph taken by a monkey  
22 may not be protected by copyright. And we took

1 no actual position in the actual case involving  
2 the monkey at issue in Naruto here. Although the  
3 9th Circuit did decide that - although the court  
4 found that - the court's precedent required the  
5 court to conclude that the monkey's claim had  
6 standing under Article III of the United States  
7 Constitution, that the court did find that with  
8 respect to the copyright infringement claim that  
9 the monkey, as with all animals, since they are  
10 not human, lacked statutory standing under the  
11 Copyright Act and therefore could not - the  
12 court could not affirm the judgment of the  
13 district court, that there was no standing to  
14 bring a copyright infringement action.

15 It is a wonderful photograph though.  
16 Although there are some lingering questions about  
17 the degree of originality.

18 (Laughter.)

19 MR. KASUNIC: I think when you look at  
20 the comparison there and the pose by Naruto,  
21 there are some lingering questions.

22 Another example in the Compendium that

1 has been addressed is the Office will not  
2 register works produced by a machine or  
3 mechanical process that operates randomly or  
4 automatically without sufficient creative input  
5 or intervention from a human author in the  
6 resulting work.

7 And the example, the pictures that you  
8 see there were actually countertops that were  
9 produced by a mechanical process and for which  
10 there was no human that actually had sufficient  
11 input into what the resulting work was. So those  
12 were refused for registration, and generally  
13 those kind of processes will not be sufficient  
14 unless there can be some showing of sufficient  
15 human intervention or creative input into the  
16 actual result.

17 The question of process also raises  
18 questions with respect to the decision in Baker  
19 versus Selden, and ultimately what is now Section  
20 102(b) of the Copyright Act, which states that in  
21 no case does copyright protection for an original  
22 work of authorship extend to any idea, procedure,

1 process, system, method of operation, concept,  
2 principle, or discovery regardless of the form in  
3 which it's described, explained, illustrated, or  
4 embodied in such work.

5 So in many of these cases it does  
6 sound like the algorithms or the software that  
7 creates artificial intelligence could fall under  
8 the category of being a process itself that is  
9 creating these works -- in some cases.

10 There's also some question that I  
11 think needs to be considered at least in terms of  
12 - typically in the merger question. It would be  
13 not wanting to allow a - the way that an idea  
14 can be expressed in only a limited number of ways  
15 to allow that - those limited number of ways to  
16 basically protect the idea itself.

17 And I think that when we're looking at  
18 the question of the computational power of  
19 computers as opposed to the human mind and human  
20 ability that there are some concerns as well  
21 about whether computers could fix so many  
22 variations of expression in a very short amount

1 of time that there is basically no room left for  
2 human expression or original human expression  
3 from that. And at least one court had said that  
4 copyright should not be viewed as a game of chess  
5 in which the public can be checkmated. So it is  
6 a lingering question.

7           There -- as was discussed earlier, and  
8 I think is very obvious, is that the question of  
9 is a non-human work distinguishable from human  
10 authored works? And along with that, are  
11 machine-generated works creative? I think the  
12 answer to the first question: is a non-human work  
13 distinguishable? In many cases that answer is no.  
14 But I think that is not necessarily the relevant  
15 question.

16           Artificial intelligence can create  
17 creative works, but the question is whether the  
18 creativity is the output of artificial  
19 intelligence software; it may be considered  
20 authorship, without sufficient creative input or  
21 intervention from a human author in the resulting  
22 work.



1                   Another question is whether AI  
2                   creative output itself is derivative requiring  
3                   authorization of the works used in the course of  
4                   machine learning. And again, this was something  
5                   discussed by the director general in terms of the  
6                   data or the works that form the basis of machine  
7                   learning. And so there are significant questions  
8                   about access to those works and authorization for  
9                   those works.

10                   It's also important to consider that  
11                   not all creative works are copyrightable.  
12                   Certainly under the Copyright Act, under federal  
13                   law, a creative unfixed work is not protected by  
14                   federal copyright law, and a creative work that  
15                   is not within congressionally-designated  
16                   copyrightable subject matter is also not  
17                   protected by copyright.

18                   That picture there represents a claim  
19                   that we received for a genetically-altered fish  
20                   in which we did not find a Section 102(a)  
21                   category that was sufficiently - in which that  
22                   fell and so could not be registered.

1                   Should a creative fixed work created  
2 by a non-human be within the scope of federal  
3 copyright law? That's a question.

4                   Another consideration with that  
5 question, and it may seem unfair - I think there  
6 are similarities to this quote from Feist. It  
7 may seem unfair that with these works being  
8 created, why should not somebody be considered  
9 the author of that work, or also be considered -  
10 is it - should not somebody be considered the  
11 owner of that work and be able to reap the  
12 rewards from that work?

13                  Well, a similar question was raised  
14 with respect to the concept of sweat of the brow  
15 and industrious labor, that the money, expense  
16 and time and effort that went into creating  
17 certain factual works. And the court said it may  
18 seem unfair that much of the fruit of the  
19 compiler's labor may be used by others without  
20 compensation. As Justice Brennan has correctly  
21 observed however this is not some unforeseen  
22 byproduct of the statutory scheme. It is rather

1 the essence of copyright and a constitutional  
2 requirement. The primary objective of copyright  
3 is not to reward the labor of authors, but to  
4 promote the progress of science and the useful  
5 art.

6 So a significant question is does  
7 artificial intelligence require copyrights  
8 incentives? Do we need to or - and again, if it  
9 does require some kind of incentive, is copyright  
10 the proper vehicle? Thank you.

11 (Applause.)

12 MS. ROWLAND: Thank you so much Rob  
13 and Professor Elgammal.

14 Now we're going to turn to our  
15 international panel to talk about the  
16 developments in the international sphere, and we  
17 have some very interesting panelists here today.

18 It's going to be moderated by Maria  
19 Strong, and we are going to have Michele Woods  
20 who is at WIPO, but also an alum from here, and  
21 Dr. Till, who's going to also join us. We've  
22 heard earlier that she is the newly-appointed

1 Director of AI. And I believe we're also going  
2 to have Ros Lynch, who is the head of the U.K.  
3 IPO to talk about this.

4 So they're going to talk about all of  
5 the different issues that are arising in the  
6 world and in their countries. Thank you very  
7 much.

8 MS. STRONG: All right. Thank you,  
9 everybody, as we're getting settled here. Again  
10 we want to welcome everyone. As the Director  
11 General said, this is a question that is facing  
12 all national governments, but it's also a global  
13 issue. And so this is a panel where the  
14 international gets to meet the domestic.

15 And so the way we're going to do this  
16 is I'd first like to start off with the national  
17 experience from Dr. Ros Lynch, who is the  
18 Director of Copyright and IP Enforcement at the  
19 U.K. Intellectual Property Office. She will be  
20 discussing some of the challenges she has  
21 experienced in her country. And she had the  
22 benefit of working with WIPO last summer also

1 preparing a two-day presentation on AI.

2 Then we'll go to - after that we'll  
3 go to Dr. Ulrike Till, who's new to WIPO. I  
4 think this may be your first month maybe of work?  
5 So she'll be able to discuss some of the work of  
6 her new division.

7 And then we'll turn to Michele Woods  
8 who can also talk about additional WIPO  
9 initiatives at the international level.

10 And we hope to have time to have some  
11 Q&A between the panelists on some of the issues  
12 that are pressing.

13 So with that, Dr. Lynch?

14 DR. LYNCH: Good morning, ladies and  
15 gentlemen. And thank you, Maria, for correcting  
16 my job title. Whereas I would like to be the  
17 head of the U.K. Intellectual Property Office, I  
18 am not.

19 (Laughter.)

20 DR. LYNCH: I'm only responsible for  
21 copyright and IP enforcement, but I've also taken  
22 on the responsibility as the senior responsible

1 officer for everything we do on AI.

2 So I'm really very grateful for this  
3 opportunity to be here just to share with you  
4 some of the things that we've been thinking about  
5 and doing within the U.K.

6 For the U.K. the government has set AI  
7 as a priority, and it set an ambition to make the  
8 U.K. a global center for AI and data-driven  
9 innovation. And in the Intellectual Property  
10 Office we've been thinking for the past year  
11 about what our role is in relation to helping the  
12 government deliver on that ambition.

13 And we've been working on - basically  
14 on two streams. So we've been doing quite a bit  
15 of operational work, looking at the use of AI in  
16 terms of trademarks and patent registration, but  
17 that's not what I'm going to focus on because we  
18 think - we feel that the most challenging, the  
19 most interesting bits, of the AI field to fix on  
20 is the big questions around the policy around  
21 what happens in terms of trademarks, copyright,  
22 et cetera, policy and legislation. And that was

1 why in June last year we held an international  
2 conference to look - also in cooperation with  
3 WIPO to explore the economic, commercial, and  
4 legal implications of AI for IP.

5 We didn't focus exclusively on  
6 copyright, but covered all the rights, but it  
7 became very clear from the two days of discussion  
8 that some of the biggest challenges posed by AI  
9 lie with the copyright framework. And I think  
10 Director Gurry already posed some of those  
11 questions to you.

12 And he mentioned authorship, and I  
13 think it's come up in every conversation so far.  
14 And we do actually feel and agree that AI is  
15 actually challenging some of the very settled  
16 notions of what authorship is, and it's calling  
17 into question some - probably the very  
18 foundation on which copyright is based, which is  
19 human authorship.

20 We in the U.K. thought that we could  
21 answer some of these questions around who is the  
22 author if - well, whether or not there is an

1 author involved and who would that author be if  
2 an AI produced works in art, whether it's art,  
3 music, et cetera, and especially if there's very  
4 little human input into that work.

5 So we have in U.K. law a  
6 computer-generated works provision which is not  
7 something that you find in many other countries  
8 around the world. I think there are only about  
9 three other countries or so that have such a  
10 provision. And in our provision,  
11 computer-generated works are defined as works  
12 generated by a computer in circumstances where  
13 there is no human author.

14 This was proposed in 1987 and the  
15 provision, if - reading the - I certainly  
16 wasn't in the IP Office then, but reading the  
17 debates around it, it said that the provision was  
18 specifically included to deal with the advent of  
19 artificial intelligence.

20 I was quite shocked that they - the  
21 U.K. Parliament was actually thinking about AI,  
22 but - at that stage, but I - in my mind what we



1 know of AI now, I don't think that they could  
2 have conceived of where the technology would have  
3 gone and what it would be capable of doing now,  
4 let alone what it will be capable of doing in 20  
5 years' time.

6 For our provision, computer-generated  
7 works provision, the author is the person who  
8 made the necessary arrangements for the creation  
9 of the work. So this could be the operator of  
10 the AI. It could be the computer programmer who  
11 wrote the algorithm, whatever. It has never  
12 really been defined. It's just been left as the  
13 person who made the necessary arrangements.

14 Protection of these works lasts for 50  
15 years from the date the work was made, so it has  
16 quite a long period of protection within our law.  
17 However, there's a huge tension for us between  
18 the concept of computer-generated works as  
19 defined in law and the concept of originality.

20 To be protected, computer-generated  
21 works must be original. The law appears to  
22 assume that originality is a human quality only,

1 so in the U.K. and in Europe an original work is  
2 one which is the author's own intellectual  
3 creation. The concept has been further developed  
4 by the courts, and considerations include whether  
5 the author has made free and creative choices or  
6 reflected their own personal touch. So again,  
7 it's very, very human-defined.

8 And for us it's not immediately  
9 obvious how current AI-generated works could fit  
10 with this definition, and the tension makes it  
11 unclear to us how a work that is generated  
12 without a human author can actually be protected  
13 under the computer-generated provision within our  
14 law.

15 So we've got something in law, but  
16 actually we don't know what it means, and we  
17 don't know how we could use it in this context.  
18 So that's for us an added headache because we  
19 thought we were being very forward-thinking  
20 20-plus years ago, but actually it's just  
21 complicated the situation even more.

22 So looking beyond the specifics of

1 U.K. law, I just want to touch on a few other  
2 things, and this is something which has already  
3 been raised. There's an interesting global  
4 debate to be had around the role of copyright  
5 protection as an economic incentive when it comes  
6 to AI-generated works.

7 So copyright is generally considered  
8 somewhere between an economic tool that  
9 incentivizes and rewards creativity, but also a  
10 natural right of authors to protect their  
11 creative works as expressions of their own  
12 personalities.

13 There is a question then around  
14 whether AI development needs incentives, and I  
15 think that this was just raised. And if so, what  
16 is the best vehicle to achieve this? Is  
17 copyright protection a necessary incentive?  
18 Could there be another mechanism? And again, I  
19 know that Rob just raised that. Does AI actually  
20 need incentivizing?

21 We seem to be having - from what  
22 we've heard, AI is being used in so many

1 contexts. More and more works are being produced  
2 every day. It's being used across the economy.  
3 So is it doing okay, or do we actually need to do  
4 something to actually incentivize more creative  
5 works?

6 We've been asked do we need a new  
7 right, which is something we have to consider.  
8 We've also been asked to look at our exceptions  
9 to copyright, and should we have an exception for  
10 works created by AI? But also what is the role  
11 for licensing in this space? These are all  
12 questions which we are still trying to come up  
13 with answers to.

14 If it does make economic sense to  
15 protect AI-generated works, we need to ask when  
16 the copyright should subsist. So what type of  
17 works would qualify for the copyright protection,  
18 who should own the copyright, which we've had  
19 some of those conversations already this morning,  
20 and then how long, which again I think Director  
21 Gurry already alluded to.

22 The speed at which an AI can create

1 creative works, whatever they are, whether they  
2 be music or paintings, et cetera, just doesn't  
3 feel like 50 years is the right length of time to  
4 give it because these works are constantly coming  
5 out. They're being adapted. So we do need to  
6 have a conversation about if we're going to  
7 protect AI works, for how long do we need to  
8 protect them?

9           And I appreciate what Director Gurry  
10 said earlier about the length of time it takes to  
11 agree anything globally, but I do feel that we  
12 need to have a global conversation, and we do  
13 need to have some kind of global standards, or  
14 whatever, in this space. I'm not talking about a  
15 big treaty, but we do need to have some kind of  
16 agreement, some kind of shared understanding of  
17 not just what the problems are, certainly how to  
18 define it, and what we need to do in this space.

19           I also wanted to just briefly touch on  
20 infringement and liability. I know there are  
21 huge questions around whether or not the AI is  
22 making copies. Is it keeping copies? Where are

1 these copies stored? If it has permission for  
2 some of the data that's being fed in, who gave  
3 permission for that data to be used? If so, if  
4 there is infringement happening, who is liable?

5 Is there a case for also considering  
6 secondary infringement of copyright? Would that  
7 lie with the institution where the computer is  
8 based or with the individual who wrote the  
9 algorithm, et cetera? Those are all things which  
10 we need to consider.

11 And my final point is one which is not  
12 normally talked about in relation to copyright,  
13 but I think it's incredibly important that we do  
14 not lose this from the discussion on the  
15 relationship between AI and copyright, and that  
16 is the ethical use of AI in this space, in the  
17 creative process. I do really think that this is  
18 hugely important, and it shouldn't just be left  
19 to the medical field or to something else. We  
20 need to actually look at the ethics of doing this  
21 within the creative space.

22 So just to conclude, in the U.K. we

1 are still thinking about these questions, and  
2 we're still trying to work on answers to them.  
3 We are shortly going to launch our own call for  
4 views going into - we're going to do it across  
5 all the rights, not just copyrights, but we've  
6 asked - we will be asking quite detailed  
7 questions, some of which I've mentioned, some  
8 have been mentioned earlier around data and  
9 computation, et cetera. And following that we  
10 will be publishing a government response giving  
11 answers to these questions where we have them.

12 But we do recognize the importance, as  
13 I said earlier, of having a shared understanding  
14 of the issues, and I think also having  
15 consistency in some of our answers, even though  
16 we may have some kind of domestic flexibility.  
17 So we look forward to continued work with WIPO  
18 and also with the U.S. Copyright Office as we try  
19 to grapple with this. Thank you very much.

20 (Applause.)

21 MS. STRONG: Thank you. Thank you  
22 very much, Dr. Lynch. We too look forward to

1 working with you as you grapple with, as you  
2 said, your nagging headache. I think that might  
3 be coming across the pond to us as well.

4 And with that I turn to Dr. Till.

5 DR. TILL: Good morning. So I am the  
6 director of the brand new AI Policy Division at  
7 WIPO, and today marks three weeks in the role and  
8 three weeks for the new division. In some ways I  
9 feel like you should be standing up here and I  
10 should be sitting down there, because I certainly  
11 have more questions and no answers at all.

12 When I was preparing for this talk I  
13 was thinking I've only been in this job for three  
14 weeks. What can I do to add value to the  
15 discussion?

16 What I thought I would do is take you  
17 a little bit through the WIPO process, the  
18 conversation on AI and IP and where I came by my  
19 background. I come from private practice. I'm  
20 German-qualified and U.K.-qualified. I'll give  
21 you a little bit of an international perspective  
22 on why some of these questions might have



1 different answers or different perceptions in  
2 different countries and also why I think having  
3 an international discussion and a wider  
4 discussion of all the issues is so crucially  
5 important. And that feeds in why I think the  
6 WIPO conversation is so crucially important in  
7 raising awareness of different angles to the  
8 different questions.

9           The growth of AI. I'm not telling you  
10 anything new. It's everywhere, and it's  
11 expanding rapidly. I'm not sure how many of you  
12 have seen the WIPO Technology Trends report that  
13 came out at the end of last year. It's not  
14 copyright; it's patent, but it looks at more than  
15 130,000 patent applications.

16           It's one of the first studies to  
17 analyze the trends. It's a big volume, but some  
18 of the things are fascinating in it. All of them  
19 are, but what I took away is there's a real shift  
20 that you can see from theory to actual  
21 inventions. So there's patent application now,  
22 rather than just publications.

1           Machine learning is mentioned in more  
2 than a third of those applications, and really  
3 quite telling for me is that it is across a whole  
4 range of industries. It's from agriculture to  
5 education, from transport to IT technology. So  
6 it really hinges home that it concerns all  
7 industries. It's a rapidly evolving field.

8           With the field that is rapidly  
9 evolving, as we can tell even in the discussion  
10 today, is a multitude of discussions that are  
11 exploding. The -- discussions are national  
12 level, certainly of governments. A lot of  
13 governments have AI strategy papers or policy in  
14 place. Not very many of those mention IP at the  
15 moment, but that discussion is certainly  
16 starting.

17           There are four here nationally where  
18 issues are raised in the U.K. and the U.S. The  
19 patent offices around the world, the IP5, have  
20 got a cooperation to look at how they can use AI  
21 in the administration of IP, but also they've  
22 started amending the examining guidelines to deal

1 with issues of AI.

2 When you look into the academic papers  
3 and legal publications as I've done over the last  
4 three weeks, it is overwhelming. There are so  
5 many of them. There's so many views and so many  
6 discussions. And the discussions unsurprisingly  
7 go across all IPRs. It's from copyright to  
8 trademarks to patents to confidentiality to  
9 rights of data.

10 For me personally, where it comes down  
11 to policy question is really: is the current IPR  
12 system fit-for-purpose? Does it fit the new AI  
13 world or does it need adjustments in order to  
14 strike a fair balance between protecting the  
15 investment into AI and the fostering of  
16 technology going forward and innovation? And  
17 that really for me is at the heart of all of the  
18 discussions.

19 And really this is where the WIPO  
20 conversation on AI and IP comes in. Having all  
21 of those discussion points, having all of those  
22 opinions, having the question asked and having

1       them asked internationally in different forums is  
2       a fantastic way of helping us all understand the  
3       issues, not so much have the answers, but  
4       understand the issues that we ought to be looking  
5       at.

6                   WIPO is giving a forum to that. As  
7       you know, many of you were part of the discussion  
8       before I even started; the conversation started  
9       in September last year in Geneva. It is at the  
10      point at the moment where WIPO has published a  
11      draft issues paper. It's on our website. If you  
12      haven't seen it, have a look at the website.  
13      Should get a little bit more intuitive going  
14      forward; changing that at the moment.

15                   The call for comments is until  
16      February 14th. At the moment it simply is asking  
17      the question have we got the questions right?  
18      Are the things we're thinking about the things  
19      you are thinking about? Do we need to change  
20      that? Are they on the right emphasis?

21                   The idea is very much that we will,  
22      having received the comments on February 14th,

1 revise the draft issue paper, and that will guide  
2 the agenda for the next conversation that will  
3 happen in Geneva on May 11 to 12, and a second  
4 conversation planned for the end of this year Q3,  
5 Q4.

6 One of the things that is quite close  
7 to my heart is, as I said, we're at the stage of  
8 asking the questions. Are we getting the  
9 questions right? And getting the questions right  
10 for me is really important and comes a little bit  
11 from my background.

12 I spent very many years as a  
13 litigator, and I know what happens when systems  
14 get changed and they get changed in unforeseeable  
15 ways. That always happens when you tweak  
16 systems, but I think the more time we actually  
17 spend having the discussion to get the questions  
18 right, the more we can minimize unforeseen  
19 consequences when the systems get changed.

20 That is of course - as the Director  
21 General also said, it's a race for AI. The field  
22 is moving very fast, and there is a tension

1 between spending enough time on getting the  
2 questions right and seeking answers to those  
3 questions.

4 Without giving anything away, a lot of  
5 the comments on the draft issue paper are racing  
6 ahead to trying to answer the issues, but my call  
7 at the moment is: help us define the issues so we  
8 can better answer them, but we'll continue the  
9 conversation.

10 Coming to copyright. And really for  
11 me, when I was thinking about what I was going to  
12 say, copyright and AI falls into three buckets.  
13 There is of course the really important question  
14 on ownership and authorship. The works created  
15 with AI, does copyright apply? What are the  
16 implications of copyright?

17 But I think copyright for me  
18 implicates every part of the AI creation system.  
19 When you think of the algorithm that creates the  
20 works or does the invention, there are  
21 jurisdictions out there that will not patent  
22 protect software or mathematical method per se,

1 so is copyright the answer to actually protecting  
2 the AI underlying all of that?

3           And then there's the input. I mean  
4 the reason or one of the reasons AI is taking off  
5 is twofold. First of them is the increase in  
6 computation power, but also it's the increase of  
7 available data feeding into the AI systems. So  
8 what do we do with the new dawn of data? Does  
9 the data need protecting? Is copyright the right  
10 thing to do? Copyright impacts all parts of AI.  
11 For me, it's the input that goes into the AI.  
12 The AI does its thing. And the output. And  
13 really looking at all three areas is going to be  
14 absolutely crucial and has a lot of questions  
15 attached to it.

16           This is just whistle-stop tour for  
17 those that have not seen the draft issue paper.  
18 Here are the big headlines of the questions asked  
19 with regard to copyright in the issue paper.  
20 Unsurprisingly authorship and ownership is a big  
21 one. And really the question there is: can you  
22 think of it in legislation; and what does

1       legislation say; and do you need a human author  
2       in the legislation -- should be changed?

3               If you take a step back, really in two  
4       very broad-stroke buckets, there are two ways of  
5       thinking of copyright. One of them is an  
6       economic way of saying what's worth copying is  
7       worth protecting. The other one is seeing  
8       copyright very much as an extension of  
9       personality with moral rights. And then having  
10      that discussion, depending which view you take on  
11      copyright, might give you very different  
12      questions and very different answers to that, but  
13      a lot of the questions that we have at the moment  
14      center around that.

15             Infringement and exceptions. I think  
16      everyone's already mentioned it, but again  
17      infringement and exceptions are very different  
18      depending which countries you look at, from fair  
19      use to private copying exceptions, from data  
20      mining and really what does it mean for copyright  
21      and AI if you start tweaking those exceptions  
22      internationally?



1           Deep fakes are on everyone's mind.  
2           What should copyright do? Should they be  
3           excepted from copyright? Copyright or a right  
4           per se is another question. The big question of  
5           data. Should data be protected? And bias. I  
6           think we are going to have a session on bias  
7           later, so put that aside. But they're all  
8           buckets of questions currently raised in the  
9           draft issue paper.

10           And I will finish with a plea for your  
11           help. Help us get the questions right. The  
12           deadline is February 14th. It's not very long,  
13           but if you can help us define those questions,  
14           give your views on it, our commitment is to  
15           revise the draft paper and issue the revised  
16           paper at the end of March. And then I will look  
17           forward to seeing as many of you as possible for  
18           the second conversation in Geneva on May 11 and  
19           12. Thank you.

20           (Applause.)

21           MS. STRONG: Thank you, Dr. Till.

22           Michele has the final presentation

1 today on additional work of WIPO. And I'd like  
2 to leave time for one question to the panel.

3 Thank you.

4 MS. WOODS: So I'm happy to try to be  
5 very quick. And first though I just want to say  
6 how lovely it is to be invited back and to see so  
7 many friends here through different phases of my  
8 copyright career, including that continuing now,  
9 and also to be on this panel with distinguished  
10 women leaders in copyright.

11 I'm not sure if Francis is aware, but  
12 his office told me to make sure the Copyright  
13 Office complies with the requirements of his  
14 policy on gender equality, and particularly on  
15 the role of women. And I was able to say:  
16 Copyright Office, Copyright in D.C., no problem.

17 (Laughter.)

18 MS. WOODS: So it's great to be here  
19 with this distinguished panel.

20 So a lot has been said already. I'm  
21 going to be very quick here and just point out  
22 another side to the work at WIPO with respect to

1 artificial intelligence, and that is that while  
2 asking all these questions about policy and  
3 working with all of you and asking you for  
4 comments so that we define the important  
5 questions, we are also working with AI ourselves  
6 to come up with useful systems and tools that can  
7 be used both to enhance the functions and  
8 processes at WIPO, but also to be shared with  
9 international organizations, with IP offices,  
10 including copyright offices, and that work is  
11 very active.

12           There are a number of very interesting  
13 and useful tools now, and the development is  
14 really continuing at a fast pace. We have the  
15 Advanced Technology Applications Center taking  
16 the lead on this.

17           I'm just going to mention what some of  
18 the areas are. This isn't my area of specialty,  
19 and in any case we have other copyright-specific  
20 issues to talk about, but I did want  
21 to note that we have, for example, the WIPO  
22 Translate cutting edge translation tool for

1 documents. Right now it's mainly being used in  
2 patents, but it extends language coverage.

3 This is a very important area for  
4 patent examination as many of you I'm sure would  
5 be aware. And so this machine translation tool  
6 is really cutting edge and is being shared not  
7 only with other international organizations, but  
8 with IP offices around the world.

9 Then we have a Global Brands Database.  
10 This uses image search, or, is an image search  
11 service within the Global Brand Database. This  
12 allows trademark owners to identify visually  
13 similar trademarks and other brand information  
14 using AI tools.

15 Also another technology that's being  
16 shared, classification, automatic patent  
17 classification. This is a little different, but  
18 is also providing this information in order to  
19 help patent filers and examiners examine patent  
20 applications. And indexing tools for patent area  
21 once again. So as you can see, the area is  
22 really very active.

1                   There's a new tool that's been  
2                   announced, which is a new digital system for WIPO  
3                   meeting records. And this, instead of  
4                   text-to-speech is speech-to-text technology. And  
5                   our AI colleagues have been using our AI tools to  
6                   build this system.

7                   The hope is that instead of having  
8                   resource-intensive verbatim reports, and those of  
9                   you who have been to our meetings have seen those  
10                  reports; very thick, very labor-intensive to  
11                  prepare, we'll be able to have  
12                  automatically-generated and translated  
13                  speech-to-text transcripts of our meetings in all  
14                  six U.N. languages using these tools. That'll be  
15                  complemented by an audio-visual system to provide  
16                  digitally-indexed and searchable conference  
17                  records.

18                  This is a project very dear to my  
19                  heart as in my position I have to oversee the  
20                  preparation of these reports for the Copyright  
21                  Committee, the SCCR. And this takes a huge  
22                  amount of time. Big budget implication.

1                   And it would be great if we had this.  
2           I was very unhappy with the colleagues when they  
3           announced this on my birthday and my committee  
4           was not in the pilot. But I'm very hopeful that  
5           in another year or so we will also be taking  
6           advantage. And in fact we're allowed to use the  
7           tool in parallel with our current system, which  
8           is very, very interesting and useful in terms of  
9           seeing how it works and how we might use it in  
10          the future.

11                   Very quickly, we're working at WIPO  
12          with IP offices in a number of different areas.  
13          A lot of them have been mentioned. I'll just  
14          note that, for example, one way AI can be useful,  
15          and is being experimented with in a number of  
16          offices, is help desk services, automatic replies  
17          to clients. This can be very useful for  
18          copyright offices.

19                   Machine translation, linguistic tools  
20          and terminology, data analysis. There's a lot of  
21          potential here. I know we'll be hearing more  
22          from some of you about how some of these tools

1 are being used either in your offices or in your  
2 industries.

3 I wanted to just finish with a little  
4 bit of a snapshot and one that's dear to my heart  
5 and those of you who've worked on the Marrakesh  
6 Treaty, and that is in the area of accessibility  
7 and the potential for AI.

8 So I'm sure many of you know that at  
9 WIPO we have the Accessible Books Consortium, the  
10 ABC, and it operates the Global Book Service.  
11 There are almost 500,000 works in the catalog now  
12 that are available for sharing across borders  
13 through the Marrakesh Treaty. And another big  
14 function of the ABC is capacity building, helping  
15 countries, particularly developing countries, to  
16 prepare materials, usually educational materials,  
17 in local languages in accessible formats.

18 One of the big issues that has arisen  
19 in a lot of educational materials is using images  
20 or making images accessible. And up to now  
21 that's been a very labor-intensive and usually  
22 human-intensive work, but there's a lot of

1 research going on now on image captioning using  
2 computer vision. So this is a technology that  
3 the ABC is looking at very carefully and could be  
4 very useful in a broad sense for accessibility,  
5 something we're very excited about.

6 It's not entirely ready yet. When you  
7 have a possibility that the computer still says  
8 that people are various types of animals, you can  
9 imagine that that could lead to a lot of  
10 problematic situations, and we wouldn't want to  
11 put the persons using the tools into a situation  
12 where they're commenting as if the people in  
13 photos are animals and creating problems for  
14 them. So it's not ready yet, but there's a lot  
15 of really exciting work going on.

16 A lot of it's being driven by  
17 companies with social media platforms to increase  
18 inclusiveness of those platforms so users don't  
19 just skip over images and photographs, for  
20 example, but are able to engage with those  
21 materials. There are of course a lot of economic  
22 implications that are not related directly just



1 to accessibility, but the lens we're looking at  
2 this from right now accessibility is one where  
3 this is very important.

4 It also provides a case study of quite  
5 a few of the data and ethics issues that are  
6 being looked at in the WIPO AI conversation. So  
7 the machines need to be trained with large sets  
8 of images for machine learning. Are those  
9 copyrighted images? If we say, well, we should  
10 only use images that aren't in copyright, does  
11 that lead to questions of bias? Does that  
12 inadvertently lead to unrepresentative data?

13 There are privacy concerns with  
14 respect to the data sets and also the use of the  
15 tools. There are liability concerns if there is  
16 a mistake, a problem, and it leads to some kind  
17 of situation that generates liability. Who's  
18 responsible for that?

19 All of these are very important  
20 questions, but nevertheless the exciting thing  
21 here is that AI also offers tools that will help  
22 us to deliver on the promise of trying to in this

1 case provide accessible format works, published  
2 works, but that could also have much broader  
3 implications for accessibility, for  
4 inclusiveness. So this is another area where  
5 we're very excited about this work and happy to  
6 partner with all of you. Thank you.

7 (Applause.)

8 MS. STRONG: Thank you very much,  
9 Michele.

10 That leaves us time for a question I'd  
11 like to throw out to the panel and also for  
12 perhaps later discussion on other panels, and  
13 it's this: It seems like much of the discussion  
14 we have had is with respect to what is the  
15 policy, and we all agree I think on the  
16 importance of trying to get to the understanding  
17 level that Ros talked about. But it seems like  
18 it focuses on two aspects. One is the promise of  
19 the technology to address large societal  
20 problems, or it could be the threat that's going  
21 to be caused by unregulated or undefined  
22 problems.

1                   So how do we as policy makers and  
2 participants of the copyright community address  
3 this seeming polarization in both promise and  
4 threat?

5                   And then another question, should you  
6 choose to accept it, is - I'd like to follow on  
7 what the Director General mentioned, is the role  
8 of competition. How can licensing play here and  
9 in the copyright community, both for creation and  
10 for use?

11                   Take one, both, or anything you'd like  
12 to say. We'll just go down the line, maybe  
13 starting with Ros.

14                   DR. LYNCH: Oh, okay.

15                   (Laughter.)

16                   DR. LYNCH: I think every new  
17 technology brings promises and threats, and I  
18 think that where we need to get to is to have a  
19 very good understanding of what those are. And I  
20 think even from the conversation we've had this  
21 morning, we know that there's not even a clear  
22 definition of what artificial intelligence is.

1 So we need to get to a point where we understand  
2 both sides to find some kind of balance, and I  
3 think that's where we always try to end up, with  
4 a balance.

5 MS. WOODS: Well, tough to say  
6 anything after - yes, of course we always want a  
7 balance and obviously agree with that. And so I  
8 don't think that I want to talk in terms of  
9 threats, but in terms of making sure that we look  
10 at all the opportunities.

11 So I mentioned accessibility and  
12 inclusiveness. Let's not leave that behind in  
13 what I think are right now mainly commercial  
14 developments. And that's fine. That's a good  
15 thing. And usually throwing - thrown off from  
16 that can be some very good developments in other  
17 areas as well, but keeping in mind social  
18 inclusiveness, whether that's developing  
19 countries or individuals who have a need, there's  
20 a huge opportunity here for this technology.

21 And I'd also say let's be careful not  
22 to get so worried about the threats, the

1 liability, the definitional issues, the  
2 competition concerns, that we don't fully explore  
3 the opportunities that AI brings.

4 DR. TILL: From my view, a lot of the  
5 answers, what we're doing here is engaging with  
6 the topic. I think we all know that we don't  
7 have the answers. I think the only wrong thing  
8 to do would be not to ask the questions. So I  
9 think for me the balance is while the  
10 conversation might not be clear, while we wish  
11 we'd have the answers to it, actually feeling  
12 that uncertainty but having the discussion will  
13 go a long way there.

14 MS. STRONG: No, I agree. And I thank  
15 you all for your contributions today and for not  
16 only answering the question, but asking the many  
17 questions. We look forward to continuing this  
18 conversation as we welcome everyone to  
19 participate in the WIPO survey.

20 And I really appreciate, Dr. Till,  
21 your statement that the copyright seems to be not  
22 at this - at the center, but throughout the

1 entire discussion of AI, and I think that's  
2 really important for everyone in the intellectual  
3 property community to understand writ large.

4 Thank you, everybody. I think we're  
5 going to be taking a short break. Thank you so  
6 much.

7 (Applause.)

8 (Whereupon, the above-entitled matter  
9 went off the record at 11:00 a.m. and resumed at  
10 11:21 a.m.)

11 MR. ASHLEY: Ladies, gentlemen, I  
12 think we have successfully remedied some  
13 technology problems. So we are ready to resume.  
14 So if you would, please, join us. I'm glad to  
15 hear the buzz in the room and I know that it was  
16 all about this morning's brilliant and  
17 stimulating presentations you heard.

18 This panel we have this afternoon --  
19 or this morning -- is very appropriate. We have  
20 three presenters who combine lots of legal  
21 knowledge, lots of information about -- technical  
22 information about artificial intelligence, and at

1 the same time can contribute to today's  
2 discussion a general and very much needed  
3 information about how artists themselves are  
4 using artificial intelligence, and responding to  
5 the ethical, the commercial and the economic  
6 issues posed by artificial intelligence and other  
7 issues.

8           So you've met Ahmed. And Ahmed at the  
9 appropriate time will present some responses to  
10 some of the earlier issues you heard this  
11 morning. He has some new points that he wants to  
12 make about artificial intelligence, especially  
13 how he reacts to them and how he observes that  
14 authors and artists are reacting to them. Sandra  
15 Aistars is a principal at the Antonin Scalia  
16 School of Law. She runs a clinic there. That  
17 clinic is friend to -- supporters of assistance  
18 to individual artists, teaches them law, helps  
19 them preserve their rights, among other things.  
20 So she has much information about how the  
21 individual artists are using AI, reacting to it  
22 in much the way that Ahmed does.

1                   A third presenter is with us by  
2                   telephone. Thank goodness for technology, right?  
3                   He is a hostage of many of the passport issues  
4                   that are raging around the world these days and  
5                   so could not be with us. But Andres Guadamuz is  
6                   a professor at Sussex. In addition, he is an  
7                   artist in his own right who has both exhibited  
8                   and presented in exhibits that are artificial  
9                   intelligence related. And he's a researcher. So  
10                  a geek in several ways, as Ahmed is and to some  
11                  extent as Sandra and I are. And so we will  
12                  proceed with each of the three presenters taking  
13                  roughly, but hopefully not more than about 10  
14                  minutes to make their individual presentations.  
15                  We will begin first with Andres, then Ahmed and  
16                  then Sandra. We hope that we reserve a bit of  
17                  time at the end for some inter-panel, as well as  
18                  -- conversation as well as conversations and  
19                  responses to questions and comments that you  
20                  have. So with that, let's hope the technology  
21                  brings in Andres so that he can make his  
22                  presentation.



1 MR. GUADAMUZ: Okay, thanks. Can you  
2 hear me?

3 (Simultaneous speaking.)

4 MR. GUADAMUZ: Okay, excellent. So we  
5 should be on the first slide now. Thank you very  
6 much for the kind invitation. Apologies for not  
7 being there in person. I will try to be brief to  
8 let the other speakers have an interesting  
9 conversation and be able to foster some  
10 questions. First -- can we go to the second  
11 slide? Okay. It may be a little bit trite say  
12 that this subject has become extremely  
13 interesting -- you have already had a very  
14 fruitful morning, from what I hear -- and we may  
15 have caught a lot of people by surprise. We were  
16 just recovering from simian copyright and all  
17 sorts of questions about Naruto when the issue of  
18 artificial intelligence became even more trendy.

19 For those of us that are looking at  
20 this since almost the beginning, the options for  
21 protection have always been very clear. First  
22 there is the answer, none of these works should

1 be protected under copyright. They should all be  
2 in the public domain because there is no  
3 originality and there is no creativity. Only  
4 humans can create copyright, therefore all of  
5 these works should be in the public domain.

6 The other option for those countries  
7 with -- that have some form of registration is  
8 not to register the works. And I will let U.S.  
9 experts talk about these specifically. An  
10 interesting third option is on the table. This  
11 option is to recognize that these works deserve  
12 some form of protection and therefore either  
13 recognize that with copyright, or with some type  
14 of sui generis right. This is not, obviously, AI  
15 rights, or we are going to allocate rights to  
16 artificial intelligence. But this would be  
17 something akin to the EU database right.

18 All right, can we go to the third  
19 slide? The main proponents of the public domain  
20 option look at Europe as an example of where  
21 things are headed to think about this as not  
22 protection, or it being in the public domain.

1 The requirement for originality in European law  
2 is that a work can only be protected if it's the  
3 author's own intellectual creation reflecting his  
4 or her personality. This is well established in  
5 the directives and also in case law. We've had  
6 several cases that have elaborated this several  
7 -- this element.

8 So also, what conveys this idea of the  
9 author's own intellectual creation tends to be a  
10 combination of composition, it may be  
11 originality, et cetera. It is very unclear if  
12 some parameters and algorithms would be enough  
13 for -- for this. And so, for example, if you  
14 have -- if your parameter -- if you're an artist  
15 and you are selecting things that should go into  
16 your work, or you have lots of outputs and you  
17 select one or two that look very good. Is that  
18 enough to convey the author's own intellectual  
19 creation, or is it not?

20 So we have those questions. And can  
21 we go to the next one, slide 4? UK law has not  
22 been the same as the rest of Europe. And you can

1 insert your Brexit joke here.

2 (Laughter.)

3 MR. GUADAMUZ: Of course, there has  
4 been quite a -- quite a big change between -- or  
5 a divergence between UK law and European law.  
6 And this actually predates Brexit. What has  
7 happened with the UK is something very  
8 interesting. We have had in UK law, in Section  
9 93, paragraph 3 of the Copyright Designs Act, the  
10 CDPA, this very interesting formulation.

11 In the case of a literary, dramatic,  
12 musical or artistic work which is  
13 computer-generated, the author shall be taken to  
14 be the person by whom the arrangements necessary  
15 for the creation of the work are undertaken. So  
16 you can see first that we have this idea of  
17 computer-generated work. Now there may be a  
18 question of whether or not this is enough to  
19 cover things like artificial intelligence.  
20 People like me think that it is.

21 And the other question would be, who  
22 should this go to? Is that the programmer? Is

1 that the user? And these questions to open both  
2 Parliament discussion before the law was passed,  
3 and the only one case that we have leave me to  
4 believe that we think that this should cover the  
5 person that made it, also for the work to be  
6 created -- therefore the user, not the  
7 programmer.

8 And we go to the next one. That's  
9 slide five. Something really interesting has  
10 happened just this year. Earlier this year China  
11 surprised everyone by becoming the first  
12 jurisdiction to rule in this question. While it  
13 doesn't pertain to artistic works, I have  
14 included it here because it is still very  
15 relevant and very interesting. A court in the  
16 Chinese city of Shenzhen has decided that an  
17 article that was written by an artificial  
18 intelligence program has copyright protection.  
19 Now this is from Tencent, the big Chinese tech  
20 giant, they have something called Dreamwriter,  
21 and this is a machine learning program that  
22 writes about half a million articles per year in

1 subjects that range from sports to technology  
2 news to financial news to sports -- sorry, to  
3 some basic news. You can also insert the joke  
4 here about how sports is actually not very  
5 difficult to write about.

6 Now, the court agreed that the article  
7 has copyright. Sorry, the -- a competitor  
8 published an article from Tencent. So Tencent  
9 sued for copyright infringement. The defense was  
10 that this was in the public domain because it's  
11 not protected by copyright, this was created by a  
12 machine. And the court actually said that this  
13 article had copyright, and that it was original.  
14 Therefore Tencent is the owner and it is the  
15 first work that we know that has been allocated  
16 copyright. Okay, can we go to the next one?

17 Our -- the opinion of artists in my  
18 experience has been almost to ignore copyright.  
19 I've been talking about this subject for quite a  
20 while and I've met quite a lot of artists in  
21 Europe that are dealing with this subject, and  
22 that are creating things with artificial

1 intelligence. And they tend to be really not  
2 preoccupied whatsoever with the question of  
3 copyright, originality or copyright ownership.  
4 They're more concerned about whether or not they  
5 will be infringing works when they are feeding  
6 the artistic intentions of the machine learning  
7 algorithms, and whether or not doing this is  
8 actually going to be infringing copyright.

9           So the question is not so much the one  
10 of ownership and authorship, but one of  
11 infringement. And that's, I think, where  
12 probably we're going to be headed next. Can we  
13 go to the -- slide seven, concluding? I would  
14 like to leave you with a more philosophical  
15 question and that is, why do we protect artistic  
16 creations in the first place? From helmets to  
17 sofas to pictures to red buses, the courts in the  
18 UK have struggled with the definition of art. So  
19 we have very interesting case law, for example,  
20 dealing with whether or not the storm trooper  
21 helmet pictured here is a sculpture. Or whether  
22 a sofa is an artistic craft. So the courts have

1       been struggling with this.  But lately, what  
2       seems to be the question -- the answer, is that  
3       the author's own perception, or intention most  
4       importantly, is what is needed for something to  
5       be artistic.  A helmet cannot be artistic -- this  
6       cannot be a sculpture, because it is just a prop.  
7       It has a utility.  It's meant to do something.

8                   Now why do I bring this to this  
9       question?  Let's think for a second if we can  
10      have things that have a very low threshold of  
11      originality protected by copyright.  Then maybe  
12      we can stop thinking about the author and  
13      concentrating on the author so much and start  
14      thinking instead of originality.  Maybe it's a  
15      question of originality in the intellectual  
16      creation sense, in the European sense that  
17      something has to be an intellectual creation.  If  
18      the work would be original by means of at least a  
19      modicum of intellectual creation from the start,  
20      maybe in the shape, of choices of pictures,  
21      selection of outputs, and even some sort of  
22      programming that goes into -- into the program,



1 why shouldn't we give copyright to this work? As  
2 long as the process is not entirely random and  
3 mechanic, then there is a good reason to think  
4 that some sort of protection should be allocated.

5 Think of, for example, the Next  
6 Rembrandt. If you know the case, there was a --  
7 a team in Amsterdam that created this amazing  
8 painting that was a machine learning version of  
9 what a Rembrandt portrait should look like. The  
10 -- the programmers and the researchers and these  
11 put a lot of work -- a lot of work, a lot of  
12 thought into the creation of this painting. So  
13 that to me is enough to convey originality in the  
14 sense that this an intellectual creation that  
15 reflects personality of the author.

16 And maybe the -- the final execution  
17 is not -- wasn't created by -- by one artist.  
18 But I think that there is enough to give  
19 copyright to someone. And I think that that's  
20 where we should probably be heading. Thanks very  
21 much. Now you can go to the final slide. Thank  
22 you.

1 (Applause.)

2 MR. ELGAMMAL: Okay, hello again. I'm  
3 not going to, of course, repeat what I said  
4 earlier. I just want to follow up the discussion  
5 from where it was left now. I want to talk about  
6 what artists do with AI and amazing -- and a lot  
7 of things is being done using AI in the last  
8 three years. In particular we created a platform  
9 for artists to -- to allow them to experiment  
10 with AI. And the motivation is artists in  
11 general are usually not technology savvy. Most  
12 artists don't know how to write code or change  
13 code or even run code. If you go to one of the  
14 code sites that can find codes, for example  
15 GitHub, you can find 27,000 versions of GAN, that  
16 I talked about this morning. So an artist who is  
17 just starting there cannot even know the  
18 difference between them and what to write and  
19 what to use.

20 So we create a platform that allowed  
21 artists to create art will experiment with this  
22 kind of technology. And I want to show what

1 artists have been doing and different ways of  
2 interacting with this. Even some schools, like  
3 NYU Art School, have been using this now.

4 So this is an example of an artwork  
5 that the artist -- his name is Devin Gharakhanian  
6 -- used photos of Charlie Chaplin, fitted to AI  
7 algorithm, and generated this abstracted  
8 surrealist version, and painted it -- so just  
9 painted the outcome. So he and others are using  
10 the algorithm and finding, selecting an outcome  
11 and painting it. A very standard way. Another  
12 example of an artist, is Marco (phonetic) from  
13 New York, who had basically fed the -- the AI his  
14 own photos and fed it also his own style of  
15 artwork, how he makes art. Engineered this  
16 stylization of photos based on his own style, and  
17 then printed it and then painted over it. So you  
18 see -- so basically this work involves choosing  
19 the art, feeding through the machine, with the --  
20 manipulating the input and output and hand  
21 painting it.

22 Here's other example of an artist --

1 her name is Anne Spalter -- she actually was an  
2 artist on -- who for a long time, actually had  
3 been doing digital arts. And she used the  
4 platform and she was amazed by what it can  
5 generate. But she wasn't happy with that -- with  
6 the quality. There was a -- it was very small,  
7 actually, one inch by one inch basically. And  
8 she -- actually painted based on the idea that  
9 the AI give it to her. So this was all painted  
10 by -- by -- on canvas. And she was thinking that  
11 for the first time in 25 years I will go back and  
12 paint it using -- myself, using tools because I  
13 had been digital artist. So the AI inspired her  
14 and her ideas of what she wants to paint.

15 So the AI is an idea generation,  
16 totally different. This is again some of her  
17 work. And finally, an -- Carla Gannis who is a  
18 professor at NYU who is actually using also these  
19 kinds of tools for many amazing ideas, try to  
20 convey a concept.

21 For example, she made a competition  
22 between herself as a human artist and avatar

1 artist, it's called C.A.R.L.A G.A.N. Funny, her  
2 name starts with Gan. So in this competition,  
3 basically, she post -- posted works by herself  
4 and post works by -- AI-generated works based on  
5 her own inputs. And after a while you could not  
6 tell which one is the real person and which one  
7 is the avatar person of the artist.

8 And she did amazing, for example,  
9 virtual reality experiences that use AI in the  
10 making. So this is just an -- some examples of  
11 what artists would do. So, as you see, basically  
12 artists are using AI now as a tool. However,  
13 it's a very different kind of tool than --  
14 because, all this AI technology comes around,  
15 artists using it. From the invention of oil  
16 paints to print making to photography, always  
17 artists take notice and use this technology.

18 What's different here is the tool for  
19 the first time becoming -- has some element of  
20 creativity, it can surprise you even as an artist  
21 from -- and that can lead you to a new direction.  
22 And here is the -- the issues that we are

1 discussing today.

2           And in terms of authorship, there are  
3 different versions of using this process. Either  
4 you can -- you can be technology savvy and have  
5 control of the inward, the algorithm and the  
6 outcome, where you control the whole process and  
7 -- and this way -- that it deserves wider  
8 protection. Because if you develop an algorithm  
9 or a post that can generate your own art and it  
10 can generate an infinite amount of art, there's  
11 no sense of copyrighting or asking for  
12 copyrighting a single output of that. Because  
13 this machine, basically, you can generate an  
14 infinite amount forever.

15           And at the same time it is very hard,  
16 as we describe here also earlier, to patent this  
17 process because it's an algorithm and a software,  
18 which is very hard to patent. So we come into a  
19 point where it is very hard to protect the  
20 outcome and very hard to protect the process.  
21 And that means some -- some -- different ways of  
22 looking at -- at things.

1                   And the other way of doing things, if  
2                   you are not technology-savvy and just using  
3                   something that is already made, and you're just  
4                   pressing a button and generating more or  
5                   searching what can be generated and finding  
6                   something or combining things to generate in  
7                   something that you like. There is some creative  
8                   process here also, but here it's more into what a  
9                   photographer would use a camera and create  
10                  something of their -- of their own.

11                  Anyway, I -- this is just some of the  
12                  -- the feedback I was giving over the discussion  
13                  that has been in the morning. One last thing I  
14                  want to discuss also, open the question about the  
15                  use of data in the process. Suppose you use data  
16                  by a living artist, or somebody who is protected.  
17                  Take Warhol, for example, art and feed it to the  
18                  machine to create something. What is the  
19                  situation here? I basically see there is no  
20                  difference in that from a living artist who  
21                  actually go to a museum or take out a Warhol book  
22                  and look at all the photos and digest them and

1 make a creation at the end. Because the AI at  
2 the end, we are creating based on data, but in  
3 the same time, as long as that creation is not a  
4 direct derivative and it's transformative enough,  
5 it's -- for me I see it as no different than a  
6 human digesting that body of work and making a  
7 creation. So I don't see a reason why to treat  
8 the machine, or the AI generation -- authors  
9 using AI generation here differently. So this is  
10 just my comment about this. Thank you.

11 (Applause.)

12 MS. AISTARS: Should I just jump in?  
13 Okay. Well thank you again for inviting me to  
14 present here and for the stimulating conversation  
15 we've had so far. As was mentioned, I run a  
16 clinic at George Mason University Law School's --  
17 Scalia Law, and it is a program through which my  
18 students and I represent individual artists and  
19 small businesses in the arts, advise them on  
20 various copyright issues, help them protect their  
21 rights and so forth.

22 Through that work and through simply



1 the family I've grown up in and the community I  
2 have interacted in, I've had the opportunity to  
3 speak about AI issues and just arts issues in  
4 general with a variety of artists and a variety  
5 of fields and a variety of generations. And I  
6 have to say that, you know, there are many issues  
7 they are reacting to and considering, much like  
8 we have been raising today. But also much like  
9 today, they have more questions than answers. So  
10 I'm glad that I am not the only one starting my  
11 presentation with more questions than answers.

12 The Next Rembrandt Project was  
13 mentioned by Andres. And I thought it might be  
14 good to play the video so that everybody is  
15 starting from a common understanding of at least  
16 one of the ways that machine learning and AI is  
17 being used. So, if we could hit play on that.

18 (Video played.)

19 MS. AISTARS: Thank you. So let me  
20 ask folks in the audience, how many of you think  
21 that this is brilliant? How many of you think  
22 it's troubling?

1 (Laughter.)

2 MS. AISTARS: Seems like an even  
3 split. How many of you think it's brilliant and  
4 troubling?

5 (Laughter.)

6 MS. AISTARS: All right, well, let me  
7 tell you that you're not so different from the  
8 arts community on this. And to me, you know, as  
9 in many discussions of fair use, it's really how  
10 the work is being used that creates that feeling  
11 of, oh, this is brilliant or this is troubling,  
12 for the artist. So this particular example, I  
13 would say -- because it's based on Rembrandt  
14 works which are all in the public domain, and  
15 that's all that the AI was fed -- it may not  
16 raise many copyright issues at all. But think  
17 about if we were talking about the next Warhol.  
18 Or you know, identify any current living artist  
19 who's -- who's selling their work.

20 That seems to raise quite a few more  
21 issues. There are various ways that we can deal  
22 with the ingestion of works. And I think that

1 may be the place to start the discussion because  
2 that's certainly the place where an artist whose  
3 work may be being used to teach the AI starts.  
4 And so there are various possible policy answers.

5           You could consider it to be fair use  
6 because you're never actually reproducing the  
7 work that has been ingested publicly. And so  
8 maybe you would draw an analogy to the Google  
9 Books case. That may be troubling to some degree  
10 because the Google Books case, I would say,  
11 presents a completely different ultimate scenario  
12 which -- you know, arguably the court found  
13 benefitted the artist at the end by making the  
14 work, you know, find-able and purchase-able. And  
15 I view the Google Books decision as a narrow  
16 decision which, you know, requires a variety of  
17 factors to be in place before we would consider  
18 it fair use. But that's certainly one -- one  
19 option you could take.

20           Another possibility on the other end  
21 would be everything needs to be licensed that's  
22 fed into the work. You know, that's -- that's

1 also not an unreasonable position. And then I  
2 guess there's a position in the middle which is  
3 it's fair use, so long that the work that's  
4 produced in the end is automatically public  
5 domain -- which I think is what Andres was  
6 suggesting.

7 But clearly, if you are the artist and  
8 the next Warhol is what comes out at the end,  
9 isn't that actually the worst of all  
10 possibilities for you? Because the end result is  
11 competing with your -- your creative work. So  
12 even something that seems like a potentially  
13 reasonable policy analysis on a commercial level  
14 doesn't necessarily, you know, play out that way  
15 from the artist's perspective.

16 But let's look for a moment at the  
17 resulting artwork itself and how we feel about  
18 that artwork. And I just -- I have to read you  
19 this. And once I read it, you'll see why. So  
20 this is a UK art critic, Jonathan Jones, and he  
21 wrote about this project in The Guardian. These  
22 are his words, not mine.

1                   "What a horrible tasteless,  
2           insensitive and soulless travesty of all that is  
3           creative in human nature. What a vile product of  
4           our strange times when the best brains dedicate  
5           themselves to the stupidest challenges, when  
6           technology is used for things it should never be  
7           used for and everybody feels obliged to applaud  
8           the heartless results because we so revere  
9           everything digital."

10                   So my reaction to that was, tell us  
11           what you really think.

12                   (Laughter.)

13                   MS. AISTARS: He went on, and you  
14           might appreciate this, you know -- explaining why  
15           he feels this way. And he said, you know, art  
16           only has meaning if it comes as a historical  
17           record of the artist's encounter with people and  
18           with beliefs and with the anguishes of the time,  
19           and that great art is not just a set of  
20           mannerisms that should be digitized.

21                   He also then suggested that the AI  
22           should go to bed with Rembrandt's lover first

1 before trying to replicate Rembrandt's work. And  
2 that also the AI should experience plague,  
3 poverty and old age. So --

4 (Laughter.)

5 MS. AISTARS: So you can see that  
6 these issues are not going to be any less  
7 controversial than any copyright issue we have  
8 ever considered. So, but just to be serious for  
9 a moment -- not that that wasn't serious -- but I  
10 think what the critic here is raising is really  
11 the intense moral rights issues that artists feel  
12 around the works. And, you know, as -- as you  
13 from the EU and UK know more than I -- you know,  
14 there are more than 60 countries internationally  
15 that recognize moral rights of attribution, of  
16 disavowal, of publication, of withdrawal from  
17 market and of modification. And even here, in  
18 the United States, at least 9 states that have  
19 some form of protection for moral rights. And  
20 that comes most often in the realm of visual  
21 arts. So this is a great place to think about  
22 it, but also, I think, explains the outrage that

1 some in the community express.

2 I'd caution though, even where there  
3 are protections here in the states, those apply  
4 to works that are produced in a single copy, or  
5 in the case of photography in an exhibition  
6 print. And so, certainly the end results of this  
7 product likely would not qualify, if you're going  
8 to be able to run off however many next  
9 Rembrandts or next Warhols on your 3D printer as  
10 you'd like.

11 So the last thing I will say, so that  
12 we don't run totally out of time, is that there  
13 are other common law issues that we want to  
14 consider too, as we are considering these works.  
15 You know, any rights that might have been created  
16 by contract, rights that arise by tort or fraud,  
17 so-called passing-off concepts. And the one  
18 question after looking at this Next Rembrandt  
19 Project that I had myself was, is this just a,  
20 you know, brilliant forgery machine? Because if  
21 you listen to how the project was brought about  
22 and how the AI was instructed, that's actually

1 what art forgers in the analogue world do. And,  
2 you know, while we may recognize that the  
3 resulting work is a work of art, people have  
4 always had very complicated relations to forged  
5 works or works that are created in a style of an  
6 artist.

7 And so I would ask not just what's the  
8 impact on the artist, but what's the impact on  
9 the art-buying public? Are there trademark-like  
10 concerns? Are people being swindled? And I  
11 think we will have very many interesting  
12 discussions around that. And I'll stop there so  
13 that we have some time to actually talk.

14 MR. ASHLEY: At least eight or nine  
15 minutes for general conversation -- including  
16 with you, in our audience, if you have. But let  
17 me, as I usually do, play devil's advocate here.  
18 Because there should always be a devil in the  
19 room. Let's assume just for the sake of  
20 discussion that Rembrandt survived today and his  
21 works are protectable, all 10 zillion of them.  
22 And you raise an interesting moral rights slash



1 ethical issue, slash forgery issue. If my data  
2 mining is only to do the type of studying of all  
3 of his currently protect-able, in the  
4 hypothetical, works. I am not competing with  
5 those works. I am not copying and reproducing  
6 those works, at least, not reproducing and  
7 distributing them publicly. I'm merely for the  
8 process of research, doing what computer  
9 programmers do all the time with others' computer  
10 -- copyrighted programs, which is borrowing  
11 content, using it to advance the state of the  
12 art. In this case, I happen to be using it to  
13 produce -- advance the state of the art of visual  
14 artists. How is that scenario different from  
15 what the data miners do in the Rembrandt case?

16 MS. AISTARS: So you're not actually

17 --

18 MR. ASHLEY: I haven't gotten to the

19 --

20 MS. AISTARS: -- printing off a new --

21 MR. ASHLEY: No, I haven't gotten to

22 that point. It was just -- just --

1 MS. AISTARS: It is actually a good  
2 question, and one that I was going to mention but  
3 didn't have time to. Another application of AI  
4 has been to teach AI machines to distinguish  
5 forgeries. And so in those instances, at least  
6 the one example that I am aware of, they weren't  
7 feeding the entire work. But they were breaking  
8 -- ultimately, they fed the entire work, but  
9 they're breaking it up into tiles which are fed  
10 individually in to inform the AI machine. And  
11 that, for whatever reason, makes it more likely  
12 that the AI will be able to detect a forgery  
13 because they are looking at so much more, you  
14 know, data I suppose. You probably have a much  
15 better reason and explanation why it works.

16 But, I mean, there I think as a matter  
17 of copyright law you'd look to things like Google  
18 Books and say are you actually ever putting in  
19 output? Are you harming the market in any way?  
20 You know, how much of the work are you using? Is  
21 it just a -- you know -- but -- so I would feel  
22 more comfortable with that sort of a use than if

1 you're at the end of the day printing off, you  
2 know, the new Warhol, as I said -- or the new  
3 whatever, you know, today's, you know, most  
4 popular artist is. The new Banksy, perhaps.

5 MR. ASHLEY: This is really -- this is  
6 really -- this is really Ahmed's rhetorical at  
7 the end of his presentation just now where he  
8 really challenged us to think about how data  
9 mining in the hypothetical I just created --  
10 scanning, uploading, saving is how I'm defining  
11 it, data mining -- is any different than the  
12 artist actually data mining by living and  
13 interacting with encyclopedias, websites, the  
14 living world. Pulling from that his sense of  
15 Rembrandt's style and then mimicking it in the  
16 way that artists do -- or some photographer.

17 Okay, so you have some point that I am  
18 sure -- that Andreas wants a piece of this as  
19 well.

20 MR. ELGAMMAL: Yes, thank you for  
21 bringing this Rembrandt example. I think we have  
22 actually two different examples, the Rembrandt

1 case and the artwork I have shown using the  
2 artists. So the Rembrandt case is brilliant in  
3 making forged art, basically using tools  
4 available today to make some art in the style of  
5 another art. Basically, that's not known as --  
6 to be art, to start with, if you do that. If you  
7 do something in the style of Van Gogh, that's not  
8 art. That's basically maybe -- that might --  
9 think of it as decorative art for putting in your  
10 room, but not really art.

11 So an artist doesn't do that. A real  
12 artist tries to do something creative and new and  
13 - a new idea. And the example I have shown -- I  
14 have shown today was artists using AI. All of  
15 them are really brilliant in the way they're  
16 creating new things --

17 (Simultaneous speaking.)

18 MR. ASHLEY: But I am not -- I am more  
19 endangered by -- by that. That you would refer  
20 to creating something which is artistic as not  
21 art.

22 (Simultaneous speaking.)

1 MR. ELGAMMAL: -- as art, but as --

2 MR. ASHLEY: -- so that is a more --  
3 that is a more dangerous proposition to copyright  
4 than it seems to me AI is.

5 MR. ELGAMMAL: Yes. As I mentioned in  
6 my talk earlier today, what will drive  
7 progression of art is really innovation. So if  
8 you now or even hundred years ago try to copy Van  
9 Gogh, say, or Monet that already had been done  
10 before, you wouldn't be considered an artist.  
11 You wouldn't consider something -- whether to  
12 make some -- some beautiful images in the style  
13 of something in the past you can -- you can put  
14 in your room. But that wouldn't put you in a  
15 gallery or a museum anymore. That's not what the  
16 art world considers art.

17 (Simultaneous speaking.)

18 MR. ASHLEY: Okay, well would it be --

19 MR. ELGAMMAL: -- that's not what --  
20 I mean, you cannot copyright that in such ways  
21 because it's not -- with no innovation or  
22 creativity behind it.

1 MR. ASHLEY: But that's a high  
2 standard. We -- we -- copyright protects trash  
3 too.

4 (Laughter.)

5 MR. ASHLEY: Right? Very, very low  
6 standard. And the reason -- the reason for that  
7 low standard is a very good one. It is to avoid  
8 the aesthetical and, it seems to me, the  
9 moralistic judgments of deciding that's not good  
10 enough art, or innovative enough art, or  
11 whatever. So my point about trash is to preserve  
12 the principle that it seems to me are -- now,  
13 real quickly -- I am supposed to be wrapping up.

14 Real quickly, I wanted to -- and  
15 again, a friendly devil's advocate challenge  
16 here. And to you, as well Andres, if you want.  
17 The -- the sort of categorical treatment of the  
18 product of AI, at least in the Rembrandt, as  
19 really good forgery. They forged a style. Mr.  
20 Rembrandt did not own his style. He may have  
21 created one, but he alone did not own it. And  
22 that is true of all of the innovative people who

1 created categories. That is an essential  
2 proposition of copyright. That I can take your  
3 style -- I can research and reverse engineer to  
4 figure out your style -- even if by AI. And then  
5 I can use your style to produce things. That  
6 runs up against the moral rights issues that you  
7 were talking about.

8 MS. AISTARS: Right, so that's why I  
9 actually -- and I say this in a lot of instances  
10 -- I don't think copyright needs to address every  
11 single issue. And I don't really view this --  
12 this Rembrandt image as a copyright issue so much  
13 as a either, you know, consumer fraud or, you  
14 know, passing off or -- you know, contracts  
15 issue. And I -- I would urge copyright not to  
16 try to take on too much. Because we will get  
17 into these arguments, whether, a la Blurred  
18 Lines, or -- or, as you were pointing out, you  
19 know, is this art? Is this not art? I  
20 personally don't want judges making that  
21 decision, either for me or for my clients.

22 MR. ASHLEY: All right, we will let

1       Andres have the last word. And then that will be  
2       it.

3                   MR. GUADAMUZ: From a -- I guess from  
4       an international perspective, there is no  
5       question that this is -- for example, this would  
6       not be infringement if we were thinking about  
7       that. We would -- if Rembrandt was alive, even,  
8       I don't think that there is enough there to -- to  
9       say he has this. You were saying he has no  
10      ownership over his own -- his own style. There  
11      is no such thing as a Rembrandt-ness copyright.

12                   But from another perspective, perhaps  
13      that we -- we are not going to see this brought  
14      to court in things like art, I think. It is  
15      already -- it is happening and it is going to  
16      happen more and more with low-level music, a very  
17      large maker of artificial intelligence music, for  
18      example, Jukedek, just got purchased by TikTok.  
19      You can probably see where this is going. This  
20      is going to free music for people to -- to put in  
21      their videos instead of having some problems with  
22      copyright.



1           This is going to have -- to going to  
2           the fourth point with really low-level type of  
3           art. Maybe computer art, computer-generated art  
4           that is -- can be used as a background in a game,  
5           or even a movie or something. If we are not  
6           going to protect this, everything is going to go  
7           into public domain. Then the artists, musicians,  
8           journalists, are going to be competing with free  
9           works. And this is where I think we should think  
10          really hard about where we are going.

11           I'm not concerned that this is going  
12          to become an ownership issue. But definitely a  
13          -- or an infringement issue, but definitely it's  
14          going to be a -- litigated, and it's already  
15          being litigated.

16           MR. ASHLEY: Well thank you for that.  
17          And the Copyright Office and WIPO, like to thank  
18          Sandra, Ahmed and Andres for their very  
19          thoughtful participation. Thank you.

20           (Applause.)

21           MS. ROWLAND: Thank you so much.  
22          That's such a fascinating panel discussion.

1 We're saying goodbye to Andres, I believe. And  
2 we're here to take on the next panel, which is  
3 about the world of other works and AI. And we're  
4 going to be talking about interesting things,  
5 like literature and video games. And so I would  
6 like to welcome to the stage the panel for the  
7 world of other works.

8 MS. ALVAREZ: Hello everyone. So  
9 welcome to AI and creating a world of other  
10 works. Also the panel right before lunch, so it  
11 will be a good one. Obviously, AI is being used  
12 to create a wide variety of works. We just heard  
13 about visual art. After lunch we are going to  
14 hear more about music. So now we are going to  
15 hear from people who work in some other areas,  
16 specifically video games and literary works. I  
17 am going to have everyone give their own  
18 presentation and talk about AI and how their own  
19 works tie into all of this. And at the end, if  
20 we have some time, then we're going to have some  
21 Q&A. So I will just go through the lineup. Not  
22 everyone is quite in order, but Kayla is going to

1 be first to talk. Kayla Page, she is Senior  
2 Counsel for Epic Games. Then we're going to have  
3 Jason Boog, who is the West Coast Correspondent  
4 for Publisher's Weekly. Then Mary Rasenberger,  
5 who is Executive Director of the Author's Guild.  
6 And then Meredith Rose, who is Policy Counsel for  
7 Public Knowledge. And Kayla is up.

8 MS. PAGE: All right. Hello, so  
9 Kayla, Senior Counsel, Epic Games -- small video  
10 game company that no one has ever heard of and  
11 definitely isn't in the press all the time. So  
12 Epic is kind of at an interesting intersection of  
13 AI because it is both a game developer and  
14 publisher with that little-known title, Fortnite,  
15 that everyone knows. And also a game engine  
16 distributor. So in addition to actually creating  
17 immersive game play experiences and all of the AI  
18 that you may utilize to ensure you're enriching  
19 game play or matchmaking players effectively,  
20 they also support, via the architecture, the game  
21 engine, the actual build-out of this.

22 So we're in a kind of unique position

1 to watch how these items can play out from the  
2 programmer's standpoint of the AI, all the way  
3 into the final creative output that lands in the  
4 game. And just a little bit of background, I  
5 don't know how familiar everyone is with software  
6 engines, but -- so games run on a game engine.  
7 You need an architecture below you that allows  
8 for efficient game design. So you need a  
9 rendering engine, right, for your 2D and 3D  
10 graphics. You need audio. You need physics.  
11 And you need AI at this point.

12 I think that it's become a hot topic  
13 lately, but really video games and AI have been  
14 just inextricably -- that's a word -- linked  
15 since the 1950s when the first computer program  
16 was trained to play chess. And we have been  
17 pitting AI against human experts to try to, you  
18 know, learn from that for forever. You go back  
19 -- even Pac-Man has the fundamental essentials of  
20 what is now environment-based AI. It is going to  
21 detect where you are. It's going to predict  
22 where you're likely to go. And based on those

1 two inputs, decide on the creative-ish decision  
2 of whether it is going to chase you.

3 And it's simplistic, but it's actually  
4 a really, really effective model. And so I like  
5 the model because for me, AI is a tool. Like,  
6 video game companies are absolutely creators.  
7 They provide the creative direction. They  
8 provide the narrative structure. They provide  
9 all of the inputs that, like, eventually that AI  
10 is going to utilize as a tool to create these  
11 outputs.

12 But -- it's an increasingly  
13 sophisticated tool, but the bones are all the  
14 same. And so I kind of analogize it often to  
15 artists -- visual artists in a video game  
16 company. They're using -- they're probably using  
17 Photoshop, right? That's a tool. And if you  
18 give a creative direction to an artist and every  
19 -- to 10 artists, and 10 artists Photoshop it,  
20 you're going to get 10 different results. And so  
21 it's driven very much by the creative decisions  
22 that are being made inside of the company.

1           So what I've enjoyed watching is the  
2 evolution. And I think a lot of the discussion  
3 here is, like, okay, well at what -- what  
4 percentage -- at what point are we going to say  
5 that there's been so much machine intervention  
6 that we've lost that human authorship that --  
7 that has the -- typical, you know, copyright  
8 protections attached to it. And it's definitely  
9 evolving. You know, early on it was really  
10 static rules.

11           It was a deterministic environment.  
12 So you're playing chess, right? There are only  
13 so many moves in chess. The board state is  
14 known. And it's -- it's very meticulously  
15 written code at that point. And when I say code,  
16 it's really just if-then statements. So if the  
17 player moves the knight to B3, you are going to  
18 react in this way.

19           And now that -- that doesn't really  
20 work anymore, right? These predictable  
21 experiences are gone. We have massively -- you  
22 know, MMOs that have tons and tons of players all

1 around the world. The environment isn't static.  
2 It changes. And even if the environment has been  
3 coded at a base level to support certain physics,  
4 player interaction is going to change that in a  
5 second. I -- it never -- I have, you know,  
6 nieces and nephews that are like 14 and 15 years  
7 old. And I can't predict that they're going to  
8 kick the cat in that game.

9 And so when that cat hits the  
10 building, which it shouldn't -- this is not my  
11 game. I don't have anything to do with this  
12 hypothetical game -- nor am I in any way  
13 advocating -- sorry PETA.

14 (Laughter.)

15 MS. PAGE: You have to consider, like,  
16 the physics of that -- the physics of what we now  
17 support in games. Of smoke. Of light. Of  
18 ray-tracing that actually enables us to have  
19 these really realistic engines that are capable  
20 of doing things like we see in Pixar movies and  
21 giving real -- real-time, real kind of humanity  
22 to these virtual worlds.

1                   And so -- well, I look at it now and  
2                   we've moved from this sort of static model to  
3                   very much needing to utilize AI to ensure that  
4                   things are functioning in game as they should be.  
5                   And that's just from a game play perspective.  
6                   From an engine perspective, we support much, much  
7                   more. But you end up in a -- in a situation  
8                   where you simply could not efficiently,  
9                   effectively, cost-effectively code for every  
10                  possible contingency when you allow people to  
11                  interact in a virtual environment.

12                  And so, you know, some of the things  
13                  that we see significant development in are things  
14                  like adaptive game play. So you suck at video  
15                  games. You're like, I have never picked up a  
16                  controller. I don't have any idea what to do  
17                  with this. And if you enter a video game, and  
18                  you are playing with these -- with the AI, with  
19                  these bots that are non-player characters --  
20                  NPCs, if they just kick your ass every time, it's  
21                  not fun. It's not fun at all. And you have to  
22                  hit this sweet spot, right, between this is too



1 easy and I am bored and I don't want to play and  
2 this isn't enjoyable -- to I'm just being  
3 embarrassed.

4           And so you get adaptive game play that  
5 allows players to either match at commensurate  
6 skill levels, or an AI that's capable of kind of  
7 engaging with your game play style and giving you  
8 a personalized experience so that you're not  
9 miserable the whole time. I heard somebody on an  
10 earlier panel mention accessibility. That's huge  
11 too. Natural language processing in AI is  
12 amazing. And, you know, I don't know if anyone  
13 is familiar with the numbers, but there are a  
14 staggering number of people with disabilities  
15 that play games because it's a really easy place  
16 to connect socially. It's like, our online  
17 environments aren't fake online life anymore,  
18 right? They're part of our real life.

19           So that sort of natural dialogue that  
20 happens is really well supported by natural  
21 language processing. We're not seeing a ton of  
22 that yet. It's pretty sophisticated. But there

1 are many movers and shakers and -- in Microsoft  
2 and in Amazon that are also trying to figure out  
3 how we can harness some of that to remove, like,  
4 toxic players in chat. Get them out of there if  
5 they're harassing people, or if they're just  
6 being inappropriate.

7           Similarly with immersive game play,  
8 you want -- you want non-player characters that  
9 actually feel like they're not -- you know,  
10 they're not walking into a wall 16 times and  
11 you're just trying to interact with them. And it  
12 gives you this option to have, like, really  
13 believable and realistic body motion -- or  
14 dialogue options. Or they could react to you  
15 emotionally in a way that they just couldn't do  
16 that prior.

17           And in addition to procedural content,  
18 which is just anything in the environment that  
19 needs to render real-time as you walk around. So  
20 that's kind of a -- the high-level of those. I  
21 guess what I find interesting is the way that  
22 this is coded. Because I think that often AI is

1 either highly, highly simplified in a way that  
2 doesn't make it seem -- it doesn't really let us  
3 get into the meat of the copyright issue. Or  
4 it's just this black box of, like, it's a neural  
5 network and we have no idea how this works. But  
6 it's actually -- it's pretty interesting to watch  
7 it from the engine side when you go to code it.

8           So if you look at Epic's Unreal Engine  
9 4, it has a lot of AI that it supports. And one  
10 of the things that you can do is take -- let's  
11 take a very simple creature in a video game.  
12 We'll do an animal, right, because there's no  
13 dialogue or anything. So you have a cat in a  
14 video game. And you need this cat to behave in a  
15 certain way. You -- you have a creative  
16 expression. This is going to be a mean tom cat  
17 who -- devil may care -- whatever.

18           And you need to code certain things  
19 for his behavior. You have -- you have to have  
20 action tasks that exist. So here's your root AI,  
21 right? And then, you have a behavior that says  
22 the cat is going to groom itself. Okay. That's

1 a pretty easy path. But you need things to make  
2 it seem lifelike. It can't just -- it can't be a  
3 constant 20 seconds, and then it grooms itself  
4 again. It's not very engaging. So you put  
5 conditions on it. Cat grooms itself. Cat also  
6 has a startle response, right? And you have to  
7 marry those two concepts as related. You have to  
8 say, okay, cat would not be grooming itself.  
9 Like, it's not lifting its leg and playing the  
10 cello if it's startled, because someone has  
11 thrown a bottle at its head. I am really mean to  
12 cats in this. I didn't actually prepare this at  
13 all.

14 (Laughter.)

15 MS. PAGE: I love cats. I have a cat.  
16 And so you have all these interrelated tasks that  
17 without AI running real-time -- because you think  
18 about the -- the 3-dimensional space we occupy as  
19 human beings. The environment we have to  
20 interact with. Body placement, movement, the way  
21 we react to things, the way that that reaction  
22 changes when it's acted upon by another force.

1 And you have to assign these all priorities, or  
2 -- or exceptions, or they're conditional. And  
3 so, without AI to actually help facilitate those  
4 sorts of -- of real-time, like, machine-learning  
5 feedback of, okay, we need to make this more and  
6 more realistic -- you just don't get the same  
7 sort of immersive narrative experiences.

8 (Applause.)

9 MR. BOOG: So I am going to -- I am a  
10 journalist and an author. I am going to speak  
11 about how writers use artificial intelligence  
12 right now. But I wanted to start by reading just  
13 a really short excerpt from some -- it's a  
14 collection of essays.

15 "I had asked my parents for advice.  
16 They were at odds over whether or not I should go  
17 to the upcoming poetry competition. I grumbled  
18 at first, but I started to take action anyways.  
19 I asked my father for some of his old writing  
20 supplies, and he happily lent them to me. From  
21 that point forward, I took to spending my days in  
22 the studio perfecting my craft. However, as the

1 weeks passed by it became increasingly difficult  
2 to stay focused on my goal. I turned to alcohol  
3 and illegal drugs. And I found that instead of  
4 relaxing and reflecting, my thoughts grew more  
5 chaotic -- my actions, more destructive."

6 "But when the judges arrived to hear  
7 that poem, written by me, I was left with a  
8 bittersweet smile on my face. I was proud of  
9 myself for taking the challenge. And I wanted to  
10 continue this legacy and become a renowned poet."

11 I didn't write that. That was the  
12 absolute -- that was my moment of narrative  
13 singularity. Last year I worked for two months  
14 to create an AI that could actually tell a small  
15 little story. And that -- after reading hundreds  
16 and hundreds of pages of output, nonsense, all  
17 sorts of crazy stuff -- that was the first time  
18 that my little AI told me a story. So if you go  
19 to the first slide. I just put the text up  
20 there and you can see, I broke it into the  
21 three-act structure that you see in film. So you  
22 have act one when you introduce the conflict.

1 And act two, you have this young poet struggling  
2 with his craft. He even gets into drugs and  
3 alcohol, struggling to finish his -- to reach his  
4 goal of going to the poetry contest. And then  
5 you have act three when he or she actually goes  
6 to the poetry competition and delivers a poem.

7 And I cannot tell you how happy I was  
8 when I discovered that. And it was -- it was  
9 really magical. And I am not a coder. I worked  
10 with something called GPT-2, which is an open --  
11 a model released by OpenAI last year. It's -- it  
12 was scraped from 8 million different webpages.  
13 And this language model -- basically, when you  
14 feed it input, it will try to guess what the next  
15 part of that story is. So what I did is I fed  
16 this -- this really super-powerful AI a whole  
17 bunch of very short stories from this section of  
18 Reddit called writing prompts. And it's where  
19 people write very short stories -- much like this  
20 -- and I just gave it thousands and thousands of  
21 examples of those and then turned it on and set  
22 it loose. And then I had to read hundreds of

1 pages to find something like this. But when I  
2 found it, it was really magical.

3           So that's one example of how people  
4 can work with AI. Here is another -- this is  
5 Janelle Shane. She is an author who works a lot  
6 with different AIs and bots and things. And she  
7 took the names of spaceships from Iain Banks  
8 novels. I don't know if anyone reads Iain Banks  
9 novels, but they're amazing. And the -- one of  
10 the best things are these self-aware, AI-powered  
11 spaceships that fly around. And they all have  
12 really funny names like Prosthetic Conscience,  
13 and things like that.

14           And so she fed those names -- hundreds  
15 of those names to an AI, and it started to  
16 generate new fake names. And you can see some of  
17 them are up there. They're pretty hilarious:  
18 "Happy to Groom Any Animals You Want," -- which  
19 would probably be good in our video game --  
20 "Surprise Surprise," "And That's That!" And then  
21 she puts it up there. And thousands -- hundreds  
22 and thousands of people love to read these.



1 She's got a very popular blog, and she wrote a  
2 book recently as well. But her work is really  
3 wonderful. And that's one example of what  
4 writers are doing.

5 Here's another one. This is from  
6 Allison Parrish who teaches -- she's a poet. She  
7 teaches at NYU. So she took a whole 3 million  
8 lines of poetry scraped from Project Gutenberg.  
9 And she put those into a collection and gave it a  
10 -- turned it loose on -- with a natural language  
11 processing AI. And that started to sort these  
12 millions of poetry lines into what they meant.  
13 It tried to come up with the best interpretation  
14 of what they meant.

15 And then she took descriptions of  
16 movies from Wikipedia and fed those into it. And  
17 so, what the computer did is it substituted for a  
18 synopsis of Star Wars -- like the -- the crawl  
19 that you see at the beginning of Star Wars where  
20 they say "it's a period of civil war," she fed  
21 those sentences into it and it gave you a line of  
22 poetry -- the line of poetry that corresponded

1 most beautifully to that line. So you have this  
2 really excellent Star Sonnet: "What field of  
3 civil war whose lightnings make a terror of all  
4 Space. An army when its king has fled: for alms  
5 of memory with the after time, are slowly borne  
6 to earth, with a dirge of cries."

7           And so you come up with something  
8 really unique, special and -- I've never seen  
9 anything like it in my life. So -- let's go to  
10 the next one. And this is Robin Sloan who is a  
11 novelist who has two really super-powerful GPUs  
12 in his house. And he runs the same technology  
13 that I did for my thing, but he can do it with  
14 his own GPUs, which is pretty amazing. And he  
15 took 100 different fantasy novels; fed them into  
16 that same engine; and then gave the names of  
17 1,000 of his subscribers to that AI; and then  
18 generated a personalized, customized fantasy  
19 story for 1,000 of his readers. And here is just  
20 one example. And you can see, it's -- it's a  
21 really -- it's a little nonsensical, but it  
22 sounds like a quest. It sounds like this fantasy

1 story written about you. And he sent that to  
2 1,000 of his email subscribers. And people  
3 shared it all over the place. It was really  
4 special.

5 And then, I work with Film Threat  
6 magazine. And this is AI generated non-fiction.  
7 So using another engine, we fed hundreds of  
8 thousands of movie reviews into, kind of, the  
9 short, sort of user summaries and things that  
10 people leave on movies. Fed those to an AI, and  
11 then we came up with -- it's actually -- we  
12 invented kind of -- we call them artificial  
13 intelligence reviewer. And so we started sharing  
14 movie reviews from -- artificial intelligence  
15 reviewer. And they're really special. And here  
16 I am just going to read just a little bit of it.

17 This one is about -- I recommend this  
18 movie -- it's Pain and Glory, Pedro Almodóvar's  
19 new movie. And this is what he said -- this is  
20 what our AI reviewer said - "Pain and Glory, a  
21 movie by Spanish director Pedro Almodóvar that's  
22 filled with beautiful moments and some of the

1 most intense, beautiful scenes I've seen in a  
2 long time. The last act is nearly non-stop  
3 action and big explosions. It's epic, awesome  
4 and bloody awesome. Feels like a cross between  
5 the Matrix, Matrix Reloaded and Indiana Jones and  
6 the Temple of Doom." So -- I've seen it, but I  
7 don't want to spoil it for you. But --

8 (Laughter.)

9 MR. BOOG: And then finally, this is  
10 called AI Dungeon. And this is an interactive  
11 game that you can play. You can download it on  
12 your phone for free. This -- this college kid  
13 named Nick Walton built it using GPT-2. And it's  
14 basically -- it's loaded with hundreds and  
15 hundreds of -- it was trained on hundreds and  
16 hundreds of story games where you say, "I would  
17 like to go west," and see what happens. And you  
18 go -- it goes, you walk west. You find a  
19 treasure box. And you say, "open treasure box,"  
20 you open the treasure box and it says, "inside  
21 the treasure box is a trap." You just died.  
22 It's that sort of storytelling thing.

1                   But this is AI-generated. And it will  
2                   literally never end. This is just an example of  
3                   what it was. But this -- this app will literally  
4                   feed you story until your phone dies. And it's  
5                   really magical.

6                   (Laughter.)

7                   MR. BOOG: Or you die -- yes. And  
8                   then finally, I just -- about that Rembrandt  
9                   thing that we watched, the thing that makes me  
10                  the most upset about it is it's all smoke and  
11                  mirrors. Like, that was a highly produced video  
12                  by a bank. And it's like, they try to pretend  
13                  like they're doing something really  
14                  sophisticated, and they're not. Like, anyone in  
15                  this room could learn over the next month or two  
16                  how to do what those people are doing. And and  
17                  it's just out there. And I think it's important  
18                  for you to learn about it. I think it's  
19                  important for kids to learn about it. So I  
20                  introduced my kids to GPT-2. And we took one of  
21                  the stories that that the story engine had made.  
22                  And then we used the GAN, that same technology

1 that we saw in the art thing, to generate  
2 computer images and to illustrate the story. And  
3 we picked them ourselves. And I showed them how  
4 the GAN works, and I showed them how GPT-2 works.  
5 And we actually made these little zines. These  
6 little physical things that we can share with  
7 people in the world. And I think that's really  
8 important. Because I want my kids to be  
9 comfortable with that. And I want everybody to  
10 just know that you can handle this stuff  
11 yourself. And it's coming. And there's a world  
12 where this stuff is going to be in everyone's  
13 hands. And I think that's important.

14 So if you come up to me afterwards,  
15 I'll give you -- I brought a few copies of these,  
16 in lieu of cards. But thank you.

17 (Applause.)

18 MS. RASENBERGER: Okay, thanks. Well,  
19 I am going to be a little more boring. I am  
20 going to talk about copyright, actually. As you  
21 might guess. But you know, before I do, I just  
22 want to say, you know, artificial intelligence is

1 bringing a lot of really cool new tools to  
2 writing and to the writing profession. And we're  
3 all already using some of that. Spell check.  
4 Google completes your emails now for you if you  
5 want them to. I am looking forward to artificial  
6 intelligence that -- where I could just, like,  
7 dump all my ideas into it, and then it organizes  
8 it. So -- I am sure that's coming.

9 But I do -- because Jason spoke about  
10 GPT-2, I do want to mention another example of  
11 somebody using GPT-2. John Seabrook -- I don't  
12 know how many of you read his article in The New  
13 Yorker, The Next Word. He did an experiment  
14 where he took 20 years or so of New Yorker  
15 articles and fed them into GPT-2 and then gave it  
16 a prompt to see if it could -- the experiment was  
17 to see if it could write a New Yorker-style  
18 article. And the prompt was an article about  
19 Ernest Hemingway.

20 So I just want to read you what the AI  
21 writer did. As John said, the resulting language  
22 had imitated the cadence and narrative rhythms of

1 The New Yorker. You know, I said, when I read it  
2 I was like "God, this is a New Yorker piece.  
3 This is amazing." But let me read you the first  
4 couple sentences. It's -- it describes the --  
5 the AI writer describes "walking up to  
6 Hemingway's gate in Cuba and seeing a dog who had  
7 been a common visitor before the war gallop up a  
8 path to the main building with a tiny cow  
9 standing by her side. There is a puddle of red  
10 gravy in the front yard."

11 So -- you can see -- it's like --  
12 these are very good sentences, but there's a lot  
13 wrong here.

14 (Laughter.)

15 MS. PAGE: Where's the part about the  
16 cat?

17 MS. RASENBERGER: Yes -- I'm sure, if  
18 you go further, there's some cats because  
19 Hemingway did have about 30 cats when he lived in  
20 Cuba. But I want -- you know, it's like a dog  
21 has been a common visitor before the war? The  
22 dog is galloping? The tiny cow is standing next



1 to the dog that's galloping -- it's like hard to  
2 figure that out. The cow is tiny? Anyway. And  
3 then, of course, there's the puddle of red gravy  
4 in the front yard -- which, you can see how that  
5 might happen, but --

6 (Laughter.)

7 MS. RASENBERGER: So anyway. I do,  
8 though, want to focus on a couple of, what I see  
9 are, really leading issues in copyright regarding  
10 AI. The digital age, as most of you who are in  
11 the copyright industries are very aware, has  
12 already been really hard on creators. On, you  
13 know -- authors' incomes are down over 40  
14 percent. The mean income of writers today is --  
15 from their writing -- is around \$20,000. I know  
16 it's been hard on songwriters, photographers.  
17 But it's nothing like what AI is going to bring.  
18 And what I want to talk about today is the fact  
19 that there are some -- that our current law does  
20 not adequately address a couple issues. And that  
21 if we don't proactively address them, we are  
22 going to see the creative industries further

1 decimated.

2           After all this fun, I hate to be so  
3 negative. But there you go. So these are the  
4 two issues. One is the -- allowing the  
5 unlicensed use of copyright works to train AI  
6 under fair use, an issue that's been mentioned by  
7 a couple people already. And the second is the  
8 current volitional conduct in secondary liability  
9 cases where it's very possible that in the future  
10 we will have AI infringing, and there's no one to  
11 sue, there's no one to hold liable.

12           So first, when you talk about the --  
13 the ingestion issue. So you know, as we've  
14 already heard, for AI to generate -- an AI  
15 machine to generate new works -- and I will focus  
16 on literary works -- it has to train itself on  
17 large volumes of existing literary works. Right?  
18 So that's how -- that's how you -- and we saw  
19 this with -- with the new Rembrandt.

20           So it's copying those works. Now, the  
21 output, though, is not infringing. The New  
22 Rembrandt -- and you know, infringement is an

1 analysis of does this work -- is it substantially  
2 similar to this work? The outputs are really --  
3 they're -- in a sense, this is a very broad,  
4 sweeping way of describing them, but they're  
5 mash-ups of a lot of different works that they've  
6 been fed. And, you know, based on rules and  
7 parameters that they're given. But like the New  
8 Rembrandt, If Rembrandts were still in copyright,  
9 I don't think that you could say that the New  
10 Rembrandt necessarily infringed any true  
11 Rembrandt.

12 So -- now the -- we have to look at  
13 the actual -- the initial copying. What some --  
14 cases are called intermediate copying, and  
15 whether this is fair use. And I think there's  
16 some who argue that all of this should be fair  
17 use. This is -- you know, this is intermediate  
18 copying. Look at the existing case law, which  
19 Sandra spoke a little bit about.

20 I mean, this goes back to the older  
21 case in copying works in order to basically  
22 reverse engineer them was fair use. Google Books

1 we see -- the Court found that the end product  
2 was not infringing, it was just snippets. That  
3 was fair use in terms of what was human readable,  
4 but there were millions of copies made. Many  
5 copies of millions of different works made in  
6 order to get to that end product.

7 And in that case the -- the -- and as  
8 well as the HathiTrust case, the -- these -- they  
9 treat this mass reading as though it weren't real  
10 reading. That somehow because computers are  
11 doing it, it doesn't count. And companies, when  
12 they use computers to copy, you know, that's --  
13 it's -- they're given -- they're given a pass.

14 So -- and you know an issue is that  
15 there is -- there's value in those works, even if  
16 humans aren't reading them there's value in them.  
17 Obviously I don't agree that it should always be  
18 fair use, because what about when you're  
19 ingesting works to create competing works? And  
20 we can definitely see a future -- it's not that  
21 far off -- where a -- maybe it's a more advanced  
22 version of GPT-2, ingests a lot of romance books,

1       though in fact, the -- all the romance novels  
2       have already been ingested. And you can write  
3       new romance novels. Romance novels tend to  
4       follow a particular formula.

5                   And I'm actually not sure this isn't  
6       already happening. Kindle Unlimited has -- it's  
7       a -- basically a subscription service which has a  
8       lot of self-published books in it. And many of  
9       them are genre books, particularly a lot of  
10      romance books. You already find in there --  
11      there are all kinds of scammers. And the  
12      scammers are not authors, they're people who are  
13      just really good at scamming the system.

14                   So they take existing books, they put  
15      new covers on them. Amazon has pretty much put  
16      an end to that. They change the words around a  
17      little bit, maybe new characters. And in the  
18      last year or two, now, we see these called cut  
19      and paste books where they actually will take  
20      different passages from like 20 different books  
21      and put them together and create a new book. And  
22      using clip farms they manage to get these books

1 way up in the listings. And once you're high up  
2 in the listings on Amazon, then it's -- then  
3 you're being promoted to readers and you - you  
4 sell even more books.

5 So I think that there's a real  
6 potential here for using AI by copying existing  
7 works to create new works. And something that we  
8 need to protect against. So I read a lot of the  
9 submissions to the PTO's notice of inquiry. And  
10 I think a lot of people in the industry said,  
11 well, you know the fair use -- fair use will sort  
12 out the okay uses from the uses -- the competing  
13 uses. Because if you're -- if you actually scan  
14 -- not scan but copy works, ingest a lot of works  
15 in order to create competing works, that's not  
16 going to be fair use.

17 And the argument is that one, it's not  
18 transformative -- which I agree with. And two  
19 that under the fourth factor, the courts will  
20 find that it does negatively impact the market  
21 for the works. The problem is --

22 MS. ALVAREZ: I don't want to interrupt

1 too much. We have about ten minutes left.

2 MS. RASENBERGER: Oh, okay.

3 MS. ALVAREZ: I want to make sure that  
4 Meredith has a chance to go.

5 MS. RASENBERGER: Okay, okay. So let  
6 me -- so -- the problem there is that courts are  
7 not necessarily going to agree because the damage  
8 -- fair use cases are not set up to look at mass  
9 uses like this. The courts will say, this  
10 particular work isn't necessary -- the market for  
11 it isn't going to be damaged. Really the market  
12 that's damaged is the market for works like this  
13 in general. It's the overall ecosystem. And I  
14 don't think fair use is the right -- the right  
15 context to be making policy decisions about these  
16 things.

17 So I am going to jump ahead and say  
18 that what I would recommend is that there be some  
19 kind of licensing -- collective licensing. And  
20 -- because, you know, if we don't proactively  
21 address these issues I think we are making a  
22 decision to give preference to AI over human

1 writing. And I -- we need to be conscious about  
2 that. A collective licensing system is how  
3 copyright has approached situations in the past  
4 where the transaction costs of licensing them  
5 one-on-one are too high. I think an extended  
6 collective licensing will be most effective. And  
7 I am -- I am sure that blockchain could be used  
8 somehow to make it automated, but I have no idea  
9 how. So better minds need to figure that out.

10           Also, the -- just real, real quick --  
11 that AI could infringe without being liable,  
12 direct liability, the Cablevision case. You  
13 could find that there's no -- nobody in the  
14 company that owns the AI that has volitional  
15 conduct. So we need to think about the  
16 volitional conduct and secondary liability. You  
17 could easily find no secondary liability also,  
18 particularly when we get to the point where AI is  
19 creating new AI machines. So we need to come up  
20 with rules about who is going to be liable in  
21 those cases. And then I think licensing --  
22 collective licensing -- some kind of automated



1 collective licensing might be the answer there,  
2 too.

3 MS. ROSE: So luckily Jason actually  
4 covered a good swath of the uses. I was going to  
5 talk about Janelle Shane, but I am happy that she  
6 has a lot of love in this situation. She just  
7 recently wrote a book called, "You Look like a  
8 Thing and I Love You." And this was from when  
9 she tried generate pickup lines through neural  
10 net. And one of the results was "you look like a  
11 thing, and I love you." So now that's the title  
12 of her book. Highly recommend going out and  
13 picking up -- she's just wonderful.

14 So a couple things I want to talk  
15 about, and I will keep it brief. One, as Jason  
16 mentioned, we have to sort of deal with the  
17 reality of the situation, where it is right now.  
18 There are tools available. There are neural nets  
19 available for free or extremely low cost on the  
20 internet that you can play around with. You can  
21 go home today. You can probably pull some of  
22 them up on your phone right now and start feeding

1 it data. These are wildly democratized tools.

2 They are very popular, especially  
3 amongst the younger set. And you have situations  
4 where my nephew, for example -- 16 years old --  
5 he plays around with neural nets in his spare  
6 time because he actually saw Janelle's website  
7 and saw some of the stuff that she was doing,  
8 thought it was hilarious and began to start  
9 generating his own neural nets.

10 And so you have this sort of pocket of  
11 communities online who are exposed to these  
12 things largely through humor and start to play  
13 with them, sort of as-is. As Mary pointed out, a  
14 lot of the times, as you get further down, the  
15 longer the output, the less and less likely it is  
16 to be considered passable for something generated  
17 by a human. The one I would like to read,  
18 actually -- just because it is probably one of my  
19 favorite things -- is Janelle Shane, again, tried  
20 to generate recipes through a neural net. Some  
21 of the results, one of them was just iced fridge  
22 water was the name of the recipe. And then it

1 was -- but it involved shrimp. I mean, it was --  
2 it got pretty wild.

3 So she had one that was called  
4 chocolate baked and serves cookies desserts. And  
5 you can tell the exact moment where the AI got  
6 bored if you look through the ingredients list,  
7 which was one cup butter, two cups peanut butter,  
8 one cup sugar, one teaspoon vanilla extract,  
9 three eggs, one teaspoon baking powder, one cup  
10 white cocoa, one cup milk, one cup horseradish.

11 (Laughter.)

12 MS. ROSE: She baked these, God bless  
13 her. She said someone actually ate a quarter of  
14 one of them at the party she was at. So clearly  
15 there's a market there. And if you read through,  
16 at the very end, the last step in the actual  
17 process is, add chicken broth. So --

18 (Laughter.)

19 MS. ROSE: Nobody is going to be  
20 mistaking most of these things for Julia Child  
21 any time soon. But we sort of need to deal with  
22 the reality of the fact that these are out there.

1 Communities are using them organically. And  
2 these communities -- I deal a lot with fan  
3 communities online, which tend to be interesting  
4 as they're sort of representative of  
5 self-organized examples of these communities,  
6 which are largely in touch with each other and  
7 sort of have shared practices.

8 We hit a situation both -- to put this  
9 sort of -- get to the more important point -- I  
10 am trying to sort of pare down here. The most  
11 important point is that a lot of these  
12 communities online that engage in this kind of  
13 work, and this kind of sort of unpaid labor  
14 really do this -- they have a very different set  
15 of expectations about what is being done with the  
16 work than I think you're going to get from  
17 talking to folks who are primarily coming from an  
18 industrial perspective.

19 These are folks who generate these  
20 things without expectation of paying or being  
21 paid. These are things that are circulated onto  
22 the internet for laughs in many cases. They are

1 things that are circulated as kind of a here --  
2 here's an interesting concept work. And you have  
3 very different standards of what I sort of think  
4 of as folk copyright, that happens online and in  
5 these self-organized communities. It tends to  
6 place very different values than what we  
7 necessarily have enshrined in the statutory  
8 copyright scheme. They tend to value  
9 attribution. They tend to value acknowledgment.  
10 They tend to value non-monetization in many  
11 cases.

12           And some parts of this overlap with  
13 copyright law as written, and some of them do  
14 not. But we're sort of hitting a point where  
15 that delta between the sort of folk copyright  
16 that takes place on the internet -- which is,  
17 whether you agree with it or not, whether you  
18 think it's a net benefit or not, is very much the  
19 reality of how people think copyright works -- is  
20 running up against issues of how it actually  
21 works and how we have constructed it to deal with  
22 very specific priorities about monetization and,

1 you know, moral rights which sometimes map and  
2 sometimes don't.

3 But there's a very different set of  
4 priorities that have been ensconced in statutory  
5 law and how folks think copyright operates in  
6 sort of a common-sense way. And this is an  
7 interesting forum because text-based neural nets  
8 and AI generation are very low-processor power  
9 compared to a lot of other things. It's much  
10 easier to do than it is with video, for example,  
11 or sort of complex video game software where you  
12 have a lot of different sort of action  
13 conditions.

14 Feeding something Harry Potter  
15 chapters and generating a Harry Potter fan  
16 fiction through a neural net is a thing that has  
17 happened. And it happened several years ago.  
18 It's relatively easy to do because it is much  
19 easier to do. And if anyone is curious, the  
20 title of that fan fiction was "Harry Potter and  
21 the Portrait of a Thing That Looked Like a Pile  
22 of Ash." They actually printed it out in -- they

1 made -- the mocked up a cover with the title on  
2 it and printed it out. It's like a six-page  
3 thing. For some reason the AI thought Chapter 13  
4 was all that it needed to print, so it starts at  
5 Chapter 13.

6           You know -- and we laugh because these  
7 things are fundamentally very silly for now. I  
8 think there's certainly going to be a point where  
9 we might have a competition problem where people  
10 are generating things online that are in fact  
11 competitors for professionally-produced-by-humans  
12 products. But I think, you know, before we -- I  
13 urge caution in that as we start to make policy  
14 on this, we have to make it based on the reality  
15 of where people are because we are already, in  
16 many aspects of copyright policy broadly, facing  
17 real tensions between how people think copyright  
18 operates -- and it's not for lack of trying to  
19 educate, in many cases. It's just how people  
20 intuitively think what a common sense copyright  
21 system prioritizes and looks like -- and the  
22 complexities of a very, very intricate set of

1 laws that we have basically duct-taped one onto  
2 another since the 18th century.

3 And as we are moving into this age  
4 where we have potentially conflicts at scale, we  
5 need to be very careful about how we structure  
6 that. And whether we structure that grounded in  
7 people's understandings, or whether we structure  
8 it grounded onto this several-centuries-old  
9 system which, in many ways, in no way reflects  
10 people's understandings.

11 MS. ALVAREZ: All right. Thank you,  
12 that was perfectly timed.

13 (Applause.)

14 MS. ALVAREZ: That's the end of our  
15 session. So thank you everyone. Yes. We will  
16 be on a lunch break now. I'm not sure what time  
17 -- we're running a little late. So I'm not sure  
18 when we should be coming back. If we want to --  
19 what? 12:50 -- what is it? Okay, 2:50. Back  
20 here. 1:50? 1:50.

21 (Whereupon, the above-entitled matter  
22 went off the record at 12:50 p.m. and resumed at



1 1:54 p.m.)

2 MS. ROWLAND: Thank you guys. So  
3 thanks for coming back for our afternoon of  
4 copyright and AI. And we're going to kick off  
5 this afternoon with a panel on music, which is  
6 going to be led by our general counsel, Regan  
7 Smith. And so Regan, please take it away.

8 MS. SMITH: Thank you. Thanks for  
9 coming here. All right. So I'm really excited  
10 about this panel, which is about application of  
11 artificial intelligence for music creation.

12 And I'm going to start by introducing  
13 the panelists, and we're going to have this more  
14 as a discussion format I think than some of the  
15 other panels, which I think is going to be a lot  
16 of fun.

17 So starting on the end furthest from  
18 me is Alex Mitchell. He is the founder and CEO  
19 of Boomy, which is a company using AI to create  
20 instant music products.

21 And he previously founded Audiokite  
22 Research, a leading market research platform for

1 independent music and has served as a consultant  
2 and advisor for companies, including Shady  
3 Records and Current Media Groups.

4 Next to Alex is David Hughes, the  
5 Chief Technology Officer at the Recording  
6 Industry Association of America. His  
7 responsibilities at the RIAA include developing  
8 and promoting technical standards, outreach to  
9 the broader technical communities and  
10 representing the industry's interests on  
11 technology issues.

12 Before that, he was a Vice President  
13 of Technology Strategies and Digital Policy at  
14 Sony Music. Next to David is E. Michael  
15 Harrington.

16 He is a musician and musicologist, who  
17 has served as an expert witness in hundreds of  
18 music copyright cases, including those including  
19 music by Pharrell Williams, Led Zeppelin and  
20 Taylor Swift and the Civil Rights anthem, We  
21 Shall Overcome.

22 Dr. Harrington is also on the board of

1 the Future of Music Coalition and has taught as a  
2 professor for multiple institutions, including  
3 the Berklee College of Music.

4 And then next to me is Joel Douek.  
5 Joel is an award winning composer who has scored  
6 over 80 documentaries, including those by Sir  
7 David Attenborough, hundreds of TV episodes,  
8 blockbuster animes and feature films.

9 He is the cofounder of EccoVR, a  
10 company that creates music and sound design for  
11 virtual reality experiences and is also on the  
12 board of the Society of Composers and Lyricists.

13 So thank you all for coming here. And  
14 I'm really looking forward to this panel also  
15 because it is the only one where none of the  
16 panelists are attorneys.

17 Oh no. Joel said he got a law degree  
18 during lunchtime, but I don't think he passed the  
19 bar, so I'm looking forward to getting into some  
20 real takes. And no one here is giving anyone  
21 legal advice.

22 So before we dive in -- at least that

1 anyone should rely on. So for better or for  
2 worse, the music ecosystem has often been at the  
3 forefront of technological changes.

4 And depending upon your perspective,  
5 it either positions music creators and their  
6 business concerns at the vanguard of progress, as  
7 the canary in the digital coal mine, or as both,  
8 and the AI technologies are going to bring even  
9 more change to the process of music creation,  
10 discovery and consumption.

11 And I think to start, David, why don't  
12 you lay out kind of a landscape view of some of  
13 the roles that you see AI technologies might be  
14 expected to play in the music industry now and in  
15 the upcoming years.

16 MR. HUGHES: Okay. Thank you, Regan.  
17 It's a pleasure to be here today and to talk  
18 about something that's not blockchain. I am very  
19 excited. You have no idea.

20 So I guess I'd like to start by  
21 saying, and a lot of people said this, that this  
22 AI and computer generated music is nothing new.

1 I have recollections of an album made by David  
2 Cope, who is -- he's a professor at UC Santa  
3 Cruz.

4 And he had an album called Classical  
5 Music Composed by Computers. That was 1997, and  
6 that was a minor hit released by Centaur Records.  
7 But it was very interesting at the time.

8 And what he did was he was suffering  
9 from writer's block, and he was a computer guy  
10 and a composer. And so he said, well what if I  
11 just write an algorithm and just feed a whole  
12 bunch of stuff in here.

13 And one of the things he did was just  
14 took all of Beethoven's sonatas, fed them into a  
15 computer, pumped them out, listened to endless  
16 variations I'm assuming that the computer made,  
17 picked one, recorded it, put it on an album.

18 And just so you know, if you look at  
19 the credits under composer, it actually says  
20 computer generated composition. That's how he  
21 credited the composer, not himself, which I  
22 thought was kind of gimmicky at the time but may

1 have copyright implications in the future.

2 No, I didn't say that because I'm not  
3 a lawyer. But the reality is it goes way back.  
4 Computer generated music goes back to the '50s.

5 So 1951, Alan Turing, in an effort to  
6 try to have a computer do something that he  
7 thought only humans could do, turn his computers  
8 -- and you may remember Alan Turing from Breaking  
9 the Enigma Code or being in a movie with Keira  
10 Knightly. Yeah.

11 He's also going to be on the new 50  
12 pound note in the UK. Did you know that? That's  
13 big news. Anyway, in 1951, he created some music  
14 on his computer. So it goes way back.

15 But now what we're seeing is really AI  
16 and how we define AI as a different part of our  
17 conversation maybe, but computer generated  
18 machine learning AI, I'm going to bundle them  
19 all together, impacting every aspect of the music  
20 industry, pretty much every aspect.

21 So I'm just going to go through a list  
22 quickly to give people some ideas because

1 recently I was talking to an executive, not a  
2 major label executive but a music industry  
3 executive who said pretty soon, there's going to  
4 be music on Spotify composed by AI.

5 And I said, what year is it? There  
6 are tens and tens of thousands of production  
7 music, relaxation music, study music, yoga music  
8 already on all the streaming services, so this is  
9 a reality.

10 This isn't something that's going to  
11 happen, but let's take a step back. Some of the  
12 ways that AI can contribute to this whole process  
13 is we've seen AI.

14 I'm going to call them systems or  
15 tools, whatever you want to call them, that  
16 create ideas for lyrics. I call them lyric  
17 kernels, so it's gives you an idea to write your  
18 lyrics.

19 There's another one that does the same  
20 thing for melodies. It starts giving you some  
21 melodies to work on, so then if you had writers  
22 block, you have somewhere to start.

1                   And then we see another company  
2                   hypothetically creating -- generating beats. And  
3                   Alex will talk more about his company. And Sony  
4                   Computer Science Laboratories has a number of  
5                   initiatives.

6                   One was the composition of the song,  
7                   Daddy's Car, which as trained on all the Beatles'  
8                   catalogue and pumped out a song that sounds  
9                   pretty much like if my junior high school band  
10                  had tried to write a song that sounded like the  
11                  Beatles.

12                 It's pretty awful, but it's  
13                 identifiable as a Beatles song-ish. And then we  
14                 see more sophisticated companies, like Endo and  
15                 others doing personalized audio tracks to boost  
16                 mood or to be used for specific circumstances and  
17                 so on.

18                 But it keeps going. It's not just  
19                 this sort of idea of kernels and beats. We've  
20                 got companies and AI software out there that are  
21                 doing real compositions.

22                 So if you go on Spotify and you look



1 for AI playlists, one of the top songs is  
2 Lovesick by Taryn Southern.

3 And she trained her AI to write  
4 composition based on 19th century public domain  
5 pieces and then picked one, wrote the lyrics to  
6 it, went in the studio, recorded it and now  
7 hundreds of thousands of people, which sounds  
8 like a lot except on Spotify unless you're in the  
9 billions, it's really not -- but are streaming  
10 this track, okay.

11 And it goes even further though  
12 because now you can get an AI that starts writing  
13 lyrics. And then you do text to speech  
14 technology. Then you layer midi technology on  
15 top of the text to speech, so now it's singing  
16 according to the melody that the AI has written.

17 And it can create everything from  
18 scratch to finish for a sound recording. Might  
19 not be good, but the AI is there. And it's  
20 happening already.

21 And then I want to quickly talk about  
22 how it impacts everything else in the music

1 industry. So we talk about generating music to  
2 match a certain issue.

3 So you feed a video in there, and  
4 it'll match the mood and compose something in  
5 real time to create background music for your  
6 video. Or if you needed to engineer, there are  
7 AI that will help you mix.

8 There's AI that'll help you master.  
9 If you want to have your song remastered, you can  
10 go to a remaster engine room, pay thousands of  
11 dollars or you can use one of these AI tools to  
12 remaster for much less.

13 These are available now. And my  
14 present concern is that some of my close friends  
15 are audio engineers, and I'm not sure how this is  
16 going to impact their livelihoods. But hopefully  
17 they're old enough that they'll retire before  
18 they're all out of jobs.

19 Then we see other technologies doing  
20 some interesting things like recording  
21 decomposition. So this is where you take an old  
22 recording, maybe a stereo composition that was

1 just recorded in a couple tracks.

2 It goes in there, separates all the  
3 tracks out into what we would call recording  
4 stems and it pulls out the drums and the base and  
5 the vocals and everything.

6 You strip out the vocals. Now you  
7 have a cut okay track. And that's, you know, may  
8 or may not if it was licensed correctly, that's a  
9 great idea -- and could create all the stems from  
10 something that never even had stems.

11 It was recorded live with maybe just  
12 a stereo microphone. Then the next level is now  
13 we have a sound recording. We've got AI that are  
14 analyzing, predicting marketplaces for those  
15 human created songs.

16 There's a company working on AI that  
17 helps A&R people match songs to singers. There's  
18 everything. It's like blockchain four years ago  
19 for AI. If you can think of an idea, there's a  
20 company out there doing it.

21 There's AI that are generating these  
22 generic and thematic and personalized music

1 lists, so you, based on your interests and the  
2 only music that you like, it'll create a list  
3 that's personalized for you.

4 We see, for example, in the news just  
5 a week or two ago, iHeartRadio laid off 850  
6 people and when asked why, they basically said  
7 because now we have AI to create all our  
8 playlists. We don't need all those people.

9 And so it is impacting the music  
10 industry severely already. And it goes beyond  
11 making a sound recording or even marketing the  
12 sound recording in that sense.

13 Recommending concert locations,  
14 venues, days of week, who should open for the  
15 act, set lists in concerts, all of these things,  
16 people are starting to dabble with AI to do all  
17 of these things, anything to increase the ticket  
18 sales across the board.

19 There's another company called Muzio  
20 that listens to the sound recordings and  
21 automatically creates metadata. It pulls out all  
22 the, what we call objective metadata.

1                   That's beats per minute, key  
2                   signature, the language that it's being sung in,  
3                   the absolute pitch for classical music, if you  
4                   know. If it's an A, if it's 440 or not 440, it's  
5                   technical.

6                   Subjective measures, like the genre  
7                   and the tempo and the mood, is it happy? Is it  
8                   sad and all that stuff. And there's AI doing  
9                   that now. And then identifying the tracks of  
10                  artists and the metadata, putting it all  
11                  together, figuring out the metrics, trying to  
12                  figure out how to maximize royalties.

13                  You name it, AI is impacting the whole  
14                  chain from beginning to end. And I've said my  
15                  piece.

16                  MS. SMITH: All right. Well, let me  
17                  follow it up a little bit on your piece. So if  
18                  you're comparing AI to the blockchain of four  
19                  years ago, I'm not --

20                  MR. HUGHES: That's only because we  
21                  had a lot of panels about blockchain, which were  
22                  mostly not productive.

1 MS. SMITH: Well, we're going to have  
2 a productive panel.

3 MR. HUGHES: Oh, this is great. This  
4 is awesome. This is exciting.

5 MS. SMITH: Right. So an earlier  
6 panel mentioned that TikTok has acquired  
7 Jukedek. Large companies are acquiring AI  
8 technology companies.

9 And you just mentioned using machine  
10 learning for ID tracking at a time where we're  
11 seeing consolidation of collective management  
12 organizations globally.

13 We can see the U.S. effort with the  
14 Music Modernization Act to build this database.  
15 It's going to match sound recordings to their  
16 underlying musical works.

17 Are you seeing AI incorporated into  
18 viable businesses for royalty processing and  
19 creation issues?

20 MR. HUGHES: In the presence of the  
21 MLC I actually haven't seen anything, but that  
22 doesn't mean it's not there.

1 MS. SMITH: Right.

2 MR. HUGHES: Certainly a combination  
3 of fingerprinting technology plus the database  
4 plus training some systems on how to match, it'll  
5 happen if it's not happening already.

6 MS. SMITH: And then focusing on music  
7 creation, Alex, can you speak a little bit from  
8 the technical side --

9 MR. MITCHELL: Sure.

10 MS. SMITH: -- for what Boomy is  
11 doing?

12 MR. MITCHELL: Yeah, absolutely. I  
13 think, you know, I would start by just saying,  
14 you know, today there's been a lot of discussions  
15 of AI.

16 There's been discussions of GB2. And,  
17 you know, there's -- I want to stress that there  
18 isn't one, sort of one size fits all way to  
19 produce original works or recordings.

20 Certainly, our users are advanced as  
21 saying I want to make a hip hop beat that has  
22 cello at this BPM with these qualities. But it

1 can also be as simple as pressing a button.

2 And to, you know, sort of put some  
3 numbers on it, our users have created in the last  
4 six months about 350,000 original works and  
5 recordings because it takes five seconds to  
6 create something original.

7 If we're looking at AI through this  
8 lens where there's like -- the only way to do it  
9 is to train data, then I think that's very  
10 problematic. But that's not the way this stuff  
11 works.

12 I mean algorithms are the past,  
13 present and future of music. I really believe  
14 that. I think that's kind of what you're hinting  
15 at there. If everybody in this room isn't aware,  
16 I'm not a lawyer.

17 I do have friends who are lawyers.  
18 And I ask them, you know, can we pull, you know,  
19 a statutory definition of artificial intelligence  
20 from anywhere and they sent me the National  
21 Defense Authorization Act, which is probably the  
22 most recent definition.



1           Of course, it only applies to that  
2 bill. All right, fine. I'm not a lawyer. But  
3 that second definition in there was broad enough,  
4 and I can read it.

5           But it was broad enough where it isn't  
6 a stretch to say that the way it was defined in  
7 artificial intelligence would apply to Jimi  
8 Hendrix or Brian Eno or any one of the musicians  
9 we traditionally consider to be creating music  
10 using algorithms.

11           Guitar pedals are algorithms, right.  
12 So when we produce music, we're using a variety  
13 of different algorithms, not that different from  
14 sort of chaining together, you know, different  
15 types of methodologies.

16           And we are working on lyrics. We are  
17 working on vocals. We're using a variety of  
18 approaches to do that. So it's a fundamentally  
19 creative process to build what we refer to as  
20 music automation systems that can do a lot of  
21 different things.

22           MS. SMITH: So can you -- is there

1 more you can share about how Boomy does use  
2 artificial intelligence to create songs? It's  
3 not a guitar pedal company, right?

4 MR. MITCHELL: Right.

5 MS. SMITH: Your tag is save the songs  
6 you like, reject songs you don't, and teach Boomy  
7 to make songs you love.

8 MR. MITCHELL: Sure.

9 MS. SMITH: So if it's not doing this  
10 through just using algorithms with inputs, how is  
11 -- what makes Boomy stand out?

12 MR. MITCHELL: Sure, I mean without  
13 giving up some of the really interesting things  
14 we're doing kind of in the background there, I  
15 can give you one example.

16 So we have focused -- there's been a  
17 lot of research on how to generate compositions  
18 from feeding past compositions. And generally  
19 speaking, this produces many data, which on its  
20 own sounds pretty bad because you need  
21 instruments and you need, you know, software  
22 instruments or real instruments to actually play

1 those notes.

2           So we have taken an approach where  
3 we're looking as much at the production side of  
4 things, right. So we have systems, for example,  
5 that can create, you know, large volumes of  
6 sounds or different sounds for different purposes  
7 and then look at all those sounds and decide  
8 well, these are the sounds that are grouped  
9 together.

10           It's harder than you think because,  
11 you know, you could have a random, loud, silly  
12 guitar sound. You could also have, you know, a  
13 soft, interesting bass sound.

14           Those things might not go together,  
15 right. And so we're doing -- again, that's just  
16 one of many examples of an algorithm that we  
17 created that can create sounds, that can  
18 understand those sounds, how those sounds might  
19 work together.

20           Those use traditional training  
21 processes. Those are trained on samples that we  
22 purchased the rights to, also samples that we

1 created.

2 And by analyzing them, you know, part  
3 of our, you know, IP and part of why our music  
4 sounds so much better than some of the past, you  
5 know, attempts of this stuff is because we're  
6 looking at that production.

7 So that's one of example of something  
8 where a copyright and, you know, it isn't really  
9 about the composition. It isn't really about  
10 feeding it, data that's been copyrighted.

11 It's just an algorithmic approach to  
12 solving a specific problem, again, which I feel  
13 like even though we're taking it to this  
14 interesting, you know, extreme maybe  
15 historically, it isn't fundamentally different  
16 from the way musicians and artists have thought  
17 about creating music up until this point.

18 MS. SMITH: I think that's a good time  
19 to switch to the composer, right. Joel, how do  
20 you think about creating music, and how do you  
21 use algorithms or a set a rules apply into your  
22 practices? And how do you see AI being useful or

1 not to your craft?

2 MR. DOUEK: I mean I think the first  
3 important point I want to make is that it's not  
4 black and white.

5 Really, it's a spectrum from on the  
6 one hand, you know, the beginning of little tools  
7 that assist various parts of the process of the  
8 composition all the way to what we might imagine  
9 as, you know, full on composition without any  
10 involvement of, you know, the composer at all.

11 And I think right now we're kind of in  
12 this area here, and so it's -- there's technology  
13 that we're already bringing into, you know, our  
14 daily work habits as composers through a range of  
15 different things.

16 But fundamentally what we want as a  
17 composer or a songwriter is to try to deal with  
18 some of the more chore like tasks of composing.  
19 And AI's can actually help quite a lot with that  
20 kind of stuff.

21 We want to be able to liberate  
22 ourselves, accelerate those processes and

1 liberate ourselves to really focus on the  
2 creative side of things.

3 And that can, you know, involve both  
4 structural things, and I personally don't use AI  
5 in, you know, this rule based, algorithmic way to  
6 help me write music.

7 But I use other aspects of it, so for  
8 example, in mixing and mastering there's very  
9 clever AI machine learning tools that can help  
10 kind of analyze and mix and improve it for you  
11 almost immediately.

12 So I look at it as at this point we're  
13 helping us solve some of the chores. But that's  
14 going to change. It's going to change over time.  
15 And I think the line is going to get a little bit  
16 thinner.

17 And I think it's exciting. I'm  
18 definitely not one of those composers who feels  
19 that unlike the art critic comment that was  
20 written before, that this is a horrible travesty  
21 in the world of art.

22 On the contrary, I think it's very

1 interesting. We were talking about earlier. I  
2 think it's going to kind of generate its own  
3 influence on the future politics of music.

4 One aspect that I think in terms of  
5 music production that keeps coming up for me is  
6 that composing is really the same thing as  
7 improvising. That's really what we're doing.

8 You just sit there and you, at the  
9 piano or the guitar you noodle around. You just  
10 -- until you find something. And what's  
11 interesting about that process and where that  
12 might also feedback on the way artificial  
13 intelligence is done is that, if anything, it's  
14 not about a rule based algorithmic way that our  
15 brains are working.

16 Quite the contrary, it's about  
17 relinquishing a good deal of conscious control  
18 and letting these things happen without the  
19 self-criticism, the self-editing.

20 So there's some ethical implications  
21 there. I guess what I'm saying is that if you  
22 really want an AI to write good music, you've got

1 to free it completely of all boundaries.

2 So we'll see where that goes, but  
3 there is interesting work being done in that area  
4 of rethinking how AI is actually trying to write  
5 music and out trying to improvise.

6 By giving it a different kind of  
7 attitude, if you want, where it works in a much  
8 more probabilistic way, it might actually bear  
9 more fruit. Yeah, so the short answer is I think  
10 it's only days for us as composers.

11 It's working its way in, definitely  
12 it's a tool. It's super useful. It'll continue  
13 to be, and I think as long as keep that dialogue  
14 open between the developers of these tools and  
15 the composers so that we maximize how it can  
16 serve us, how it can help us to write music, this  
17 area here at the extreme is one I think we're  
18 going to get into in the rest of the discussion.  
19 So I'll kind of let anyone else chime in there.

20 MS. SMITH: Okay. So Dr. Harrington,  
21 maybe you can speak a little bit from your  
22 perspective as a musician, as a musicologist.



1 I think, you know, particularly for  
2 Western music and popular music, what many regard  
3 is pleasing is based on certain conventions of  
4 composition that's evolved over centuries that  
5 may be, you know, somewhat predictable  
6 algorithms.

7 Does that music especially favorable  
8 for machine learning? How does this change the  
9 type of music that we can expect to see created?

10 MR. HARRINGTON: I think that's a  
11 great question. I also think, going back to  
12 something Joel just said is one thing AI can do  
13 and computers in the old days, calculators, could  
14 do is even free up some of the chores.

15 Like if you read a book, if you read  
16 a 300-page book by Stephen King and say oh wow,  
17 how did you love page 87 or what are your  
18 favorite sentence or favorite clauses? You're  
19 not going to think that way.

20 So in a book, a lot of things have to  
21 move to get to the important points, the  
22 important characters. It's often the same with

1 music. Not every note in Taylor Swift's last  
2 song matter. These parts do.

3 And to go back also to what's  
4 pleasing, everything -- I can sound really cruel  
5 and objective and heartless on this and so on.  
6 Everything is math based.

7 If you write with three chords, your  
8 rules are don't use a whole lot of other chords.  
9 If you arrange an AI -- you mentioned about  
10 artist and repertoire.

11 If you want to find music that works  
12 for Hootie and Blowfish, he likes to sing in a  
13 certain range. And some other people want to  
14 sing in a different range.

15 So AI can be used in all this, but  
16 there's math underlying everything, whether it's  
17 the three chords, whether it's cerebral jazz.  
18 And a lot of times this is just helping us create  
19 it more easily seeing.

20 One thing that interested me a lot was  
21 when I was growing up and learning how to play  
22 classical music after I had my Beatles phase,

1 which never ended by the way, but of course.

2           Bach has this Prelude Number 1, C  
3 major. Every beginning pianist plays it, so  
4 these nice chords. They're three notes or four  
5 pitch classes, three or four.

6           And it occurred to me, this is  
7 perfect. And I thought well, how come Bach  
8 didn't use the others, you know, because he  
9 could. And then it occurred to me as a  
10 challenge.

11           Okay, use the others. So what I did,  
12 I found out later in terms of copyright, that's  
13 quite the derivative work. My work is completely  
14 derived from him.

15           It's the negative in terms of a  
16 photograph, and what could you do with that. And  
17 I want to apply -- well, I'm also interested in  
18 all the math of this, how we got to these points,  
19 what sounds good.

20           I used to study. I remember I found  
21 out Mozart was great one day. I always thought  
22 like you pulled one over on me. Mozart is awful.

1 I mean I love Bach and Beethoven and all that.

2 I thought Mozart was predictable. So  
3 I went to set up the theorem and all that. How  
4 could I prove my point? And well, I'd go to the  
5 library and open up Vivaldi and Beethoven,  
6 Scarlatti.

7 I'd look at the score I hadn't seen.  
8 I'd cover it and say, can I write what's coming.  
9 And I was really good at it. Telemi was simple.  
10 Scarlatti's easy.

11 I got to Mozart. I tried one. Ah,  
12 I'm wrong this time. So I kept doing this all

13 -- not all afternoon. After about 30  
14 minutes, I realized Mozart does the most clever,  
15 mathematically complex things in weird places.

16 This is simple. This is simple. This  
17 is simple. Holy God, what's that doing? It's  
18 like it makes no sense, and you can't predict it.

19 And that's what interests me a lot in  
20 melody, harmony, rhythm, lyrics, when you get to  
21 some strange, you know, why do these words go in.  
22 And what's the math behind it all?

1                   And to me, AI is, it's computer music.  
2           The stuff you mentioned, David Cope and Turing, I  
3           studied with Iannis Xenakis.

4                   And we would look at all the math  
5           involved in something and not only just melody  
6           but density class, timber class and all these  
7           other things.

8                   And I found all this does come  
9           together, and AI can just enhance it and make it  
10          easier for all of us to create. And if you want  
11          to do easy underscoring, you don't want to pay  
12          someone, yeah, it's going to take away jobs and  
13          playlists, which once playlists came about I  
14          thought like who's going to tell me what to  
15          listen to. I'm appalled at that, but.

16                   MR. DOUEK: Can I?

17                   MS. SMITH: Sure, yes.

18                   MR. DOUEK: Yeah, so stylistically, I  
19          mean we always love to beat up on yoga music, but  
20          I guess, you know, I think we -- on the panel, we  
21          could all agree that, you know, certain kinds of  
22          music and may be easier for an AI to attempt and

1 to succeed at.

2 And, you know, so music that doesn't  
3 get judged for being formulaic, but in fact it's  
4 one of its features. I think that can be a good  
5 thing.

6 I'm not sure whether jazz is then by  
7 definition the nirvana of, you know, what an AI  
8 could hope to achieve just in terms of its  
9 flexibility and inventiveness and improvisation  
10 quality. Just putting it out there.

11 MR. HUGHES: Yeah, so in terms of  
12 genre and how formulaic is it, I have to agree.  
13 So I think that country music is going to be  
14 biggest sort of paradox for AI because the  
15 underlying melodies and so on are very formulaic.

16 But the lyrics are based on human  
17 experience. I'd be very interested how long it  
18 would take an AI to come up with this song, Tammy  
19 Wynette song, D-I-V-O-R-C-E, unless that AI spent  
20 time in a kitchen fighting with their spouse in  
21 front of their 4-year-old AI, they probably  
22 wouldn't come up with it. I'm just going to

1 guess.

2 So, but going back to what Michael  
3 said about math, I think a lot of this  
4 composition is formulaic. And we think that  
5 that's so bad.

6 But I always remember this interview  
7 that I saw with Chuck Berry where they asked him  
8 how did you write all these hits. And he said  
9 well, of course he used the three chords.

10 He knew it had to be three minutes.  
11 He knew the hook had to come in 45 seconds in,  
12 all the standard stuff. But they said well, what  
13 about the topics.

14 He says, I used to sit in the soda  
15 jerk shop and listen to the kids talk. And he  
16 said kids only talk about four things, school,  
17 cars, music and falling in love.

18 That's it. He said, why waste time  
19 writing about anything else. The kids don't give  
20 a shit. So that's what he did. It is very  
21 formulaic. He used algorithms.

22 And then he layered on top of that the

1 unpredictability. So the songwriter, Desmond  
2 Child, I don't know if you know who he is, but  
3 he's a pretty famous guy and one of my friends,  
4 best friends.

5 He wrote songs like You Give Love a  
6 Bad Name. And he just did an interview not long  
7 ago for Bob Lefsetz. And he said when he was  
8 ready to write songs, the best lesson he ever  
9 learned was every line should have a  
10 contradiction.

11 You Give Love a Bad Name, he goes,  
12 that's a hit song. Now we have to write it. And  
13 I don't know if that can be trained. Maybe you  
14 can have an AI spit out hit song titles and then  
15 you have to actually do all the hard work.

16 MR. HARRINGTON: If I could say  
17 something about the unpredictability, too, in the  
18 -- what you said about Chuck Berry -- AI does  
19 miss the big picture.

20 And I'll give you an example. Why  
21 would Garth Brooks, him -- I'm living in  
22 Nashville. I have to -- I should mention Garth,



1 right. Why would he use an Egyptian drum in a  
2 hit song? And he did.

3 He used a doumbek. The AI couldn't  
4 have come up with that. Or how about Jimi  
5 Hendrix writing a lovely Viennese waltz? By that  
6 you're thinking, do I know a Viennese Waltz.  
7 Yeah, Manic Depression.

8 Yeah, it's beautiful. You dance a  
9 certain way to it. Why did he use -- why did his  
10 drummer use brushes on the opening song in the  
11 second album?

12 And you could go on and on with these  
13 moments that AI can't do that because it's  
14 against what it learned. Back to, I think it's  
15 learning from us and improving on us sometimes.

16 MS. SMITH: What do you think, Alex?

17 MR. MITCHELL: Sure. So what's not  
18 hard to do, what's not that hard to do anymore is  
19 create sort of a best guess copy of a style that  
20 came before.

21 I remember seeing some research some  
22 years ago before Boomy about an AI system that

1 was trained to create folk music. Do you  
2 remember this? I can't exactly remember what it  
3 was.

4 But it was trained on American folk  
5 songs, and it could faithfully reproduce American  
6 folk songs. And someone who studied fiddle and  
7 used to play American folk songs, in the back of  
8 my head I was like why, right?

9 No, seriously. It's a serious  
10 question. There's people that make American folk  
11 songs like all the time, and they're amazing at  
12 it.

13 So I think the utility question,  
14 right, of is there really so few people who can  
15 make American folk that we need to automate this?  
16 And what we're hitting now and what you're  
17 talking about is the real challenge, which is  
18 that it's very hard to do something new.

19 It's hard to allow an automated system  
20 to make those kinds of mistakes and to screw up  
21 in such a way that is still creative, right.

22 So this balance between creativity,

1 which necessarily means making mistakes and  
2 accuracy, which means I'm kind of just doing  
3 something that the people do -- people can do  
4 already, I think is crucial for the crop of music  
5 companies to think about because it comes down  
6 to, you know, this is a nascent market.

7           This is still -- there's a lot of  
8 different approaches being tried. And I question  
9 sort of some of the utility of just making a best  
10 guess copy of a jazz song or an American folk  
11 song because there's plenty of people who do that  
12 already, right. And you end up with the lowest  
13 common denominator.

14           MR. HUGHES: Sure.

15           MS. SMITH: Yeah, so I mean when we  
16 start to get copyright in this -- I think we  
17 heard earlier copyright protects, you know, the  
18 bad art along with the good, but the whole, you  
19 know, goal is to encourage the production of more  
20 of the good.

21           In the case of AI technology, does it  
22 matter? Is it likely that certain genres are

1 more right for wholesale substitution versus what  
2 you started saying of taking a kernel or building  
3 off a piece, a component of a song?

4           It might be in the case of country.  
5 Three chords can be predicted, but we're not  
6 quite sure if AI can find out the truth. But in  
7 the case of hip hop, is it -- that seems more  
8 layered and perhaps more difficult for an AI  
9 created song to be fully pleasing without human  
10 editing, interference and contributions.

11           MR. DOUEK: I mean, I personally think  
12 it is just a matter of time. Utility or not, I  
13 think it's going to get done. We're going to do  
14 it because that's what science does, if you like.

15           And this is really under the umbrella  
16 of science. Why do we do it? Because we can,  
17 and we need to find out. So it's going to  
18 happen, and then we'll have to kind of  
19 retroactively look back on it and say, you know,  
20 was this meaningful or was it not.

21           So I think all those stars of music  
22 are going to eventually going to come. I think,

1 you know, drilling a little bit more into the  
2 question of what makes music human, we've talked  
3 about this a little bit, is one of the ones I  
4 came up with is imperfection.

5 You know, a lot of time when we record  
6 a live instrument, it's not to introduce what  
7 you'd expect, which is the level of virtuosity.  
8 I mean that's a given.

9 Hopefully, they play in tune and  
10 everything. What it is, it's the nuance and it's  
11 the mistakes and it's that imperfection that  
12 comes into it.

13 And somehow for us, that translates  
14 into maybe a sense of heart and soul. I don't  
15 know. What makes music human, it's hard to, you  
16 know, get past that area without getting into the  
17 metaphysical.

18 But I can tell you that on a daily  
19 basis as composers when, for example, we're  
20 dealing with a small budget and you need to get a  
21 big orchestral sound, we will habitually just  
22 record a few instruments live and then layer it

1 on top of sampled instruments.

2 And with the sampled instruments,  
3 we'll use our AI effectively to humanize. I know  
4 the irony is not lost on me, that we use the  
5 computer to humanize the playing performance  
6 style so that it kind of matches and blends, you  
7 know, as something that is, you know, something  
8 that feels human.

9 So what makes music human? I don't  
10 know. It's an open question, and it's definitely  
11 going to end up as a metaphysical question  
12 because we'd like to believe that there is  
13 something kind of above and beyond, something  
14 intangible that we as composers bring to the  
15 table.

16 Is that true? Is that not? I think  
17 we're going to find out all of this. I'm not  
18 going to proclaim anything. I think we're going  
19 to find out all of this in some like giant  
20 singularity moment.

21 MS. SMITH: Can't wait.

22 MR. MITCHELL: He was staring at me

1 when you say what is -- I mean what music isn't  
2 human I think is another angle to look at that  
3 through, right.

4 MR. MITCHELL: According to Queen,  
5 synthesizers.

6 MR. HUGHES: Well, sure, right. I  
7 actually think that's a great point. I mean  
8 Queen used to tag all of their albums with no  
9 synths. And there was a conversation about  
10 synthesizers and how it was going to affect  
11 instrumentalists.

12 A more recent example would be auto  
13 tune. I think there's a lot of sort of protests  
14 against auto tune. And now find me something on  
15 Billboard that doesn't, you know, that doesn't  
16 use auto tune, Melodyne.

17 I think this is something that is, you  
18 know, when we look at these automation  
19 technologies, particularly as it pertains to the  
20 production side and the composition side where  
21 like now I have something, if I'm reacting to it,  
22 like I remember the first time I was moved,

1 right, by something that, an algorithm we  
2 created.

3 It was crazy. It was like this  
4 absolutely sounds -- it had sort of the  
5 imperfection you're talking about. We had  
6 modeled that as a piano in a room, sort of had a  
7 tape hiss.

8 And it was like this is -- I mean  
9 we're way past, you know, that's obviously  
10 robotic or that's obviously a computer. I think  
11 ultimately the arbiter is going to be the market.

12 Ultimately, it's going to come up to  
13 do people want to listen to it. Do they want to  
14 use it? Where are they using it? And I think  
15 that's what's interesting.

16 But I don't know that I've ever heard  
17 a piece of music that I would not consider human.  
18 I have a personal belief that there's no such  
19 thing as AI generated music.

20 There's people at every step of the  
21 way when you create these systems. Algorithms  
22 don't spontaneously just, you know, happen. I



1 believe there's intention and --

2 MS. SMITH: Well, certainly there's --

3 MR. MITCHELL: -- there's musicality  
4 still necessary to create an automated system  
5 that produces something that frankly is worth  
6 listening to at all.

7 MS. SMITH: But break that down a  
8 little bit because I think earlier we heard about  
9 some of the Copyright Office's practices in  
10 registering and requiring some human active  
11 creation.

12 And, you know, going back there is a  
13 certain case I know. I'm talking about layers,  
14 about taking a photograph. If you are a  
15 developer of a system of algorithms that doesn't  
16 know what the work is going to be, is that the  
17 same as creating the output of the work overall.  
18 I mean, is that what you're saying?

19 MR. MITCHELL: Again, it's --  
20 personally, that's what I believe. It's hard to  
21 draw a line, right. It's hard to draw a line  
22 between somebody who, I use the guitar as an

1 example because it's a common example like  
2 pre-computer use of algorithms in creating music.

3 It's strange to me to say well, this  
4 pedal, well that's okay. But this other pedal if  
5 you use some type of algorithm or training  
6 process, we're going to kind of treat that  
7 differently.

8 And certainly people who designed  
9 those systems, right, they're not going to do it  
10 in a vacuum. They're going to do it because they  
11 have something to express.

12 You know, we work not only with our,  
13 you know, internal resources, but we're also sort  
14 of looking out at the world and seeing, you know,  
15 researchers and composers, people who have unique  
16 ways of creating music with algorithms, many of  
17 which don't actually use any of the systems we've  
18 talked about today and which are creating things  
19 that are fundamentally new.

20 They sound different. I can't really  
21 put a genre on some of these algorithmic works.  
22 I don't understand why you wouldn't look at those

1 people as artists.

2 It's this kind of new type of artist  
3 that is maybe a little more common than we think  
4 it is of people who are adding their own  
5 theories, their technical backgrounds into  
6 creating these things.

7 And I would say if somebody never  
8 learns anything about music theory but uses code  
9 and creates a program that creates music, I don't  
10 understand why we would call that person anything  
11 other than a musician.

12 MR. DOUEK: I was just going to say --

13 MR. MITCHELL: You know, that's an  
14 opinion.

15 MR. DOUEK: Well, what keeps coming up  
16 for me is the idea of autonomy because the guitar  
17 pedal, it's still very much doing the bidding of  
18 the musician. And I think where we're getting to  
19 this part of the spectrum is where --

20 MR. MITCHELL: Yeah.

21 MR. DOUEK: -- things start to become  
22 autonomous. That's where the fears lie at many

1 different levels. And I think that's kind of a  
2 different question really at that point.

3 MR. HARRINGTON: I was just going to  
4 say about I agree that AI is human. I mean it  
5 came from a human. There's no such thing as  
6 non-human music. And I use the example of George  
7 Gershwin, who went through periods of study with  
8 Joseph Schillinger, who is doing math and music  
9 and plotting parametric equations to come up with  
10 melodies.

11 Summertime was supposedly involved in  
12 that way, and I can show you a lot of beautiful  
13 melodies that are oh, it's kind of like that  
14 curve, and it's this curve.

15 And so what. It's an image, just like  
16 if you saw mountains coming and going. You can  
17 plot the melody. That's been done for centuries.  
18 And what's different from a parametric equation  
19 doing that? That's human.

20 MS. SMITH: Well, I want to ask you a  
21 follow up question as to the role that AI is  
22 going to have and what we're seeing in music,

1 which has been, you know, whether actual or not I  
2 would say definitely perceived uptick in  
3 infringement cases in the last couple of years,  
4 which I know you have been involved in many of  
5 these cases.

6 So there's been recent headlines  
7 involving Katy Perry, Taylor Swift, Drake, Migos,  
8 Stairway to Heaven, and if you followed the 9th  
9 Circuit's Blurred Lines decisions where Judge  
10 Nguyen in the dissent criticized the decision as  
11 allowing the Gays to accomplish what no one has  
12 ever before with copyright and musical style.

13 So what is the increased use or  
14 discussion on AI to create wholesale or assist in  
15 the creation of music? What is that going to do  
16 to the landscape and these cases for infringement  
17 do you think?

18 MR. HARRINGTON: Well, I have a huge  
19 dark cloud over my head on this because I got  
20 dragged into the Blurred Lines appeal. 212  
21 musicians used my stuff in several places.

22 And suddenly I'm getting all these

1       congratulations for being involved and didn't  
2       know that I was, and then Ken Freilich said do  
3       you want to coauthor a brief and so got involved.

4               Got involved in the Led Zeppelin  
5       appeal, the Katy Perry appeal. What I hated  
6       about especially the Blurred Lines is the first  
7       time in history no one copied a melody.

8               No melody was copied. Sing it, right.  
9       No. No lyrics, no chord changes, no rhythmic  
10      features, no sampling. It's the -- it reminds me  
11      of standard, which is awful.

12              And this is the part that leads me to  
13      thinking about AI. If you say like Sony did when  
14      they had this Daddy's Car song you mentioned  
15      earlier, it's built on 45 songs fed into a  
16      computer.

17              And out came some stuff and I reverse  
18      engineered it as I think I can, you know, as best  
19      I could. And I found that a lot of it is not  
20      really, it's -- a lot of it's human.

21              But the fact that you said it was Sony  
22      doing Beatles and the reason was because they own

1 the catalogue. They're not going to sue  
2 themselves.

3           However, this a big problem if you say  
4 who your influences were because Pharrell and  
5 Robin said oh yeah, Marvin Gaye and especially  
6 that song. So you're influenced by that song,  
7 that now means you're ripe for lawsuits.

8           Publishers find this stuff out, who  
9 your influence is, especially if you say I want  
10 to get under the hood and see what was programmed  
11 or what did AI learn.

12           If it learned George Clinton, then  
13 Bridgeport is going to start suing, which they  
14 like to sue almost as much as the Gays like to  
15 sue. So I think there's some problems with that  
16 in that it shows influence, awareness, maybe the  
17 use of.

18           Well, it should be -- Paul McCartney  
19 said one time the Beatles are the biggest  
20 plagiarists there are. He said we copy from  
21 everyone. We're "Knickers Extraordinaire", that  
22 British saying, whatever that means.

1                   So to me, I'm worried about that. And  
2 I can already see where Daddy's Car could be  
3 sued. I do a lecture on this, so I've got all  
4 the examples. I could do the defense, too.

5                   And here's what I'm looking forward  
6 to. When does AI start to sue? And I'll give  
7 you one reason. Go check Daddy's Car, you know,  
8 on YouTube and then check the cover of it.

9                   There's a woman covering, and she's  
10 not doing it that well. Have you heard it? Oh  
11 my God. It's hysterical. And she's earnest.  
12 It's nice. She means it, you know, but that  
13 could -- there's a section of the copyright law  
14 that says you shall not change the basic melody  
15 or fundamental character.

16                   And that's sort of us like doing  
17 European moral rights, but if you don't like the  
18 version then uh oh, AI's going to sue for that or  
19 AI is going to create something, you guys. I  
20 don't know.

21                   MS. SMITH: I think to get to where  
22 you're trying to go, you need to I guess



1 recognize a copyright in AI. And I think that  
2 part of what we're circling around is whether a  
3 lot of these compositions or productions are  
4 created by an AI or whether they're created by a  
5 person using AI technology and whatever point in  
6 the process.

7 Or maybe it affects authorship, or if  
8 you do get to the point where it's an entirely  
9 work created without human involvement whether  
10 copyright should attach.

11 So I think that is a good time to  
12 discuss Boomy's approach to ownership of the  
13 music because Boomy asserts a copyright in each  
14 of the works, right. And then your model is you  
15 would sell it for \$5 to \$20 to --

16 MR. MITCHELL: Yeah, to the  
17 professionals --

18 MS. SMITH: -- the professional.

19 MR. MITCHELL: -- who need those  
20 rights or need that ownership, sure.

21 MS. SMITH: Okay. And then do you

22 -- who is listed as the author of the

1 works?

2 MR. MITCHELL: Yeah, so we're sort of  
3 maintaining just the best practices of now which  
4 is that it's basically the developers and sort of  
5 the team that is assigned the song writing, you  
6 know, credits so to speak.

7 But in the case of the professionals  
8 who want to integrate, for examples, works that  
9 they create with Boomy, you know, in their --  
10 they need specific licenses, they need synch  
11 licenses, we're happy to sell, you know, that  
12 composition and that recording to people.

13 We do it for \$20, actually as low as  
14 \$5. And we feel that's fair. And if they don't  
15 want to purchase it, there's still a lot they can  
16 do with it. But we just sort of continuing to  
17 again assert that ownership and assert that  
18 copyright.

19 And we're sort of covering that under  
20 the contract that our users agreed to when they  
21 use the free, you know, application that we  
22 produce.

1 MS. SMITH: So a user, you know,  
2 agrees to the terms which is that whatever they  
3 say, I want a song sort of like the Beatles but,  
4 you know, mixed up with something else.

5 MR. MITCHELL: You can't exactly do  
6 that.

7 MS. SMITH: Okay, can't exactly do  
8 that. That's not what Boomy does, guys.

9 MR. MITCHELL: That's a little --  
10 yeah.

11 MS. SMITH: Okay. Give me an example  
12 of what I could tell Boomy then. I don't want to  
13 get you in trouble.

14 MR. MITCHELL: You can say give me a  
15 rap beat at 90 bpm that's got cello and, you  
16 know, synth.

17 MS. SMITH: All right. And then can  
18 I say I don't like that, make it faster?

19 MR. MITCHELL: Sure. Yeah.

20 MS. SMITH: Okay.

21 MR. MITCHELL: You can go in. You can  
22 manipulate, and you can change it. You can also

1 edit it. You can delete sections. You can  
2 rearrange sections, you know.

3 So when it comes to some of this  
4 infringement, right, which is a really  
5 interesting question when it comes to the way the  
6 music is being produced.

7 You know, I'll give the lawyer answer  
8 which is it depends. It depends. If somebody  
9 takes something that Boomy creates, and they turn  
10 it into a song that they're heard and they  
11 download it and produce it, then there's probably  
12 situations under which you can consider it  
13 infringement.

14 But I think it really, again, it just  
15 depends on that person and their use of the  
16 technology. The notion that we would create  
17 something that's infringing sort of just the  
18 ether, it's unlikely.

19 It's mathematically very unlikely in  
20 which case we'll produce the DMCA and all the,  
21 you know, relevant requests. But what we're  
22 getting into is just to pertain to best practices

1 in some of this gray area.

2 MS. SMITH: Well, I want to drill down  
3 into that because I think what you've described  
4 and, you know, coupling that with what Dr.  
5 Harrington just described is a system where it  
6 seems like it's really charms you have with the  
7 user which are in part perhaps driving the  
8 authorship to vest in Boomy, right?

9 MR. MITCHELL: Yes.

10 MS. SMITH: We're not really probing  
11 whether it has to be. It is because there is an  
12 agreement that you're describing a situation  
13 where there does seem to be a human directing  
14 towards a predictable outcome, which may not be  
15 the whole universe of AI music.

16 But what you're saying, I think that  
17 when you're saying best practices, who is  
18 determining the best practices? Are you looking  
19 at other competitors in the marketplace, or yeah?

20 MR. MITCHELL: Remember, there're  
21 attorneys that we pay money to, to write these  
22 contracts for us.

1 MS. SMITH: Right.

2 MR. MITCHELL: And some of these  
3 attorneys, they represent multiple, you know, AI  
4 music clients. You might be friends with some of  
5 these people.

6 And there's starting to be kind of,  
7 again, in lieu of sort of guidance or, you know,  
8 exact law and where specific instances might lie  
9 within this gray, you know, contracts and sort of  
10 contract law is what we're going to rely on.

11 And we're going to do, you know,  
12 basically what the attorneys, you know, tell us  
13 is the best way to do it. We don't have a  
14 choice, right? That's pretty much all we can do.

15 But I will say that, you know, there  
16 are aspects of copyright law and there are  
17 aspects of this that make it kind of difficult to  
18 create systems that we might want to do.

19 For example, if we wanted to grant  
20 song writing ownership to every single user for  
21 every single song, if that was something we  
22 wanted to do, it would be -- I said that to our

1 attorney.

2 He just laughed. He's like, the  
3 amount of liability you'd be opening yourself up  
4 to, all the issues.

5 MS. SMITH: Because of infringement  
6 concerns or --

7 MR. MITCHELL: Infringement concerns  
8 or just the pure management of the data and  
9 managing all these different publishing  
10 contracts, it can get messy because nobody's ever  
11 really done it sort of this fast or this frequent  
12 before.

13 And so it's not as if I'm blaming, you  
14 know, the law, but we have to, you know, work  
15 within the framework that we, you know, that we  
16 have.

17 MS. SMITH: Yes. Okay. I want to  
18 switch to David for a second though. And can  
19 you, from the recorded music perspective, talk  
20 about how labels might be thinking about  
21 ownership in the AI context.

22 I know Warren Music just took a stake

1 or signed a deal in a company called Endel which  
2 -- and has a practice of listing software  
3 engineers as music authors.

4 How do you see sort of the -- do you  
5 agree with Alex's characterization of best  
6 practices or what other things we should be  
7 thinking about how the music community is looking  
8 at these issues of ownership?

9 MR. HUGHES: I think right now the  
10 major labels in particular are following it very  
11 closely and that's it. First, I'm not a lawyer.  
12 Second of all, I'm not going to speak for them.  
13 And third of all, I think there's a lot of balls  
14 in the air.

15 MS. SMITH: Joel?

16 MR. DOUEK: You know, again coming as  
17 a composer and also as a Board member of the  
18 Society of Composers and Lyricists, which is  
19 about as close as we've got to a union, I guess  
20 my salient hope is that, you know, we can find  
21 ways during all these changes that protects the  
22 ability of composers and songwriters to generate



1 revenue.

2 I think there's often the mistake  
3 because we make comparisons of like oh, let's  
4 suggest the Beatles and Beyoncé. And somewhere  
5 in that narrative we're looking at being  
6 incredibly powerfully wealthy.

7 And what gets discarded is that the  
8 vast majority of composers and songwriters are  
9 not in that bucket and just need to feed their  
10 families, pay their mortgages.

11 And that will go away. And so the  
12 question kind of makes me want to ask is does  
13 anyone care if real music written by real humans  
14 goes away or not.

15 Because if they don't really care and  
16 everyone is satisfied with whatever an AI might  
17 ultimately quite brilliantly create in the  
18 future, then it's a different discussion.

19 But I think where we are now is if  
20 we're talking about let's say the ethical use of  
21 AI, the idea of protecting artists, composers,  
22 songwriters as this moves forward and as we try

1 to shape these laws, it has to be mindful of  
2 that. It really does.

3 MS. SMITH: Well, you know what. I'll  
4 jump in there and I see maybe Alex wants to say  
5 something because you know what, like I care,  
6 right. I mean I bought a fair trade coffee this  
7 morning.

8 Are we going to enter a world where we  
9 see an attribution on a playlist whether music is  
10 human created, primarily human created. Is that  
11 going to be a trend that we're going to start to  
12 think about in our music consumption and how does  
13 that -- I know we've got no lawyers on the panel,  
14 but I think it does relate to some of the  
15 attribution and moral rights issues that were  
16 raised on earlier panels just in terms of giving  
17 credit where credit is due and recognizing what  
18 is underlying the creation of this song or a  
19 recording that we're listening to.

20 MR. DOUEK: Yeah, but at the same  
21 time, you know, I know firsthand that a large  
22 popular streaming platform is actively using AI

1 music because it owns it and therefore doesn't  
2 have to pay out any kinds of royalties in that it  
3 can therefore help its bottom line.

4 And so there is this, you know, it's  
5 a race to the bottom musically. And, you know,  
6 we've seen parallel type things happening in  
7 terms of how we accept the fidelity of music  
8 where the vast majority of younger generations  
9 are quite content with, you know, low bit depth  
10 mp3s and nobody really cares anymore about  
11 hi-fidelity and pristine sound and that kind of  
12 quality. So there are parallels in precedent.

13 MR. MITCHELL: For sure, and honestly  
14 I couldn't agree more. I mean I couldn't agree  
15 more. I think we also -- we didn't stop hiring  
16 wedding photographers because we all got iPhone  
17 cameras.

18 And maybe more pertinently, we didn't  
19 stop appreciating great singers or listening to  
20 great singers just because auto tune came out,  
21 right?

22 So I think this question on ethics is

1 crucial, and it's probably important to talk  
2 about, you know, why we're even doing what we're  
3 doing. What auto tune did was it allowed people  
4 to express themselves musically who could not  
5 sing.

6           And why couldn't those people sing?  
7 Well, maybe they couldn't afford lessons. Maybe  
8 they didn't have all the access to the time and  
9 resources necessary and the training, right, that  
10 we have been lucky enough to have received in our  
11 lifetimes to do.

12           The reality of music is that it leaves  
13 out the vast majority of people who don't have  
14 access to those resources or just simply don't  
15 have time to create music.

16           And I think that is related to the  
17 issue that you're talking about. If people don't  
18 understand music, if people aren't -- symphonies,  
19 right. I mean I have great friends who play in  
20 symphonies.

21           And every year there's less and less  
22 people going to a symphony simply because I think

1 there's less and less people who are just  
2 equipped to appreciate it or really even  
3 understand, you know, what's going on in the  
4 music that, you know, symphonies perform.

5 And so I think, you know, I'm not  
6 saying AI is going to like fix everything. What  
7 I am saying is there's a reason why we're  
8 releasing our technology for free.

9 And it's because we want to enable  
10 people to be able to create music. And when we  
11 build our technology, we test it on an iPhone,  
12 and we test it on a \$10 Tracfone that you can buy  
13 in different -- there are countries where, you  
14 know, the smartphones, they get the Internet and  
15 they get smartphones.

16 And these phones cost \$5, \$10. Our  
17 technology works on those phones because we are  
18 thinking very globally. We are thinking broadly  
19 about this. My hope is that people graduate  
20 honestly from what they're doing on Boomy and we  
21 get this -- we get it all the time.

22 We get can I do this? Can I do that?

1 Can I add this? And what we have to say is no,  
2 Boomy doesn't do that. Go download and learn how  
3 to, you know, make a DAW. There's free and cheap  
4 tools where you can go ahead and learn how to  
5 make music.

6 You can download what Boomy does and,  
7 you know, put it in these other systems. So our  
8 hope, and I think again when it comes to the  
9 ethics of it, is to just increase the overall  
10 opportunity for people to create music in the  
11 same way that auto tune did but maybe in a more  
12 advanced and maybe more extreme way. So that's  
13 the why, right. And I'm -- yeah, that's --

14 MS. SMITH: So I just want to say one  
15 thing because I know we don't have a platform  
16 representative on the panel. The idea that  
17 someone is using AI created music to save money  
18 on royalties may or may not be true.

19 But I don't know. From a copyright  
20 perspective, it may not be fundamentally  
21 different from, example, an ad agency that is  
22 using in house musicians instead of commissioning

1 something, right.

2 So I wanted to say that, and I also  
3 wanted to give this panel, which I think has been  
4 really interesting, opportunity to give some last  
5 thoughts.

6 I think the next panel is about AI  
7 ethics that we have sort of teed up very well,  
8 but this is, you know, anything else you'd like  
9 to share.

10 MR. HARRINGTON: I was going to say  
11 this is -- technology threatens business as usual  
12 until it becomes business as usual. And it  
13 threatens music until musicians start to  
14 incorporate it.

15 The drummers had a terrible thing  
16 happen to them in the early '80s, drum machines.  
17 Well, thank God, they had drums when they hadn't  
18 got the drum machine because at the gig you might  
19 want some of those sounds.

20 And I think we're always going to  
21 adjust to it. What you said about AI not being  
22 there for the turmoil in the kitchen, where you

1 can do the chords but you can't do the words, I  
2 think AI -- I looked at some AI recipes to see  
3 how language is used.

4 Let me just read a recipe. Use two  
5 large bones, sliced chicken or salmon. Think  
6 about that, two cups chicken stock or mayonnaise.  
7 1,100 versus 3200 calories. Cut the snow peas  
8 into quarter inch cubes. We're going to need  
9 humans for a long time.

10 MR. DOUEK: I get requests like that  
11 all the time.

12 MS. SMITH: All right, guys.

13 MR. DOUEK: Yeah, okay. I guess  
14 following on that thread of protecting, you know,  
15 composers' earning capacity I don't know that I  
16 have formed a really strong opinion about this,  
17 but I'd like to see -- we can never reverse  
18 engineer ultimately how the AI has created its  
19 music, what music it ingested and what choices  
20 it's made based on which of those, you know,  
21 large amounts of training paradigms that it's  
22 been exposed to.



1           So I'd like to see some kind of a  
2 blanket license type of model that is basically  
3 saying well, at some point in its history, the AI  
4 has gained the knowledge and the musical acumen  
5 from the body of music that is out there.

6           And therefore, we will then pass a  
7 fractional amount onto registered songwriters and  
8 composers. I would like to generate a pool  
9 effectively of money that can help during these  
10 transitional moments until we figure it out.

11           MS. SMITH: Anyone else?

12           MR. HUGHES: I guess going back to one  
13 idea we had before, in the same way that we have  
14 a hi-res music logo to promote high resolution  
15 music, maybe we need a free trade organic music  
16 logo if it's actually composed or played by human  
17 beings.

18           Then we at least know a real person is  
19 getting paid. I don't know. Then all of our  
20 music is gluten free.

21           MS. SMITH: All right.

22           MR. MITCHELL: All of our music gluten

1 free by the way. We built that in. I want to  
2 add two points. The first is that I feel like a  
3 crazy person sometimes that what's happening on  
4 Boomy is it's just people making music.

5 I actually don't think -- it's not as  
6 different as it is new both in terms of the  
7 -- maybe the user experience is new,  
8 but the underlying concepts, we only get to do it  
9 because of the digitization of music over the  
10 last 20, 30, 40 years that's been happening  
11 naturally.

12 So this was always kind of a natural  
13 endpoint of where creation was going to go. And  
14 I think we have an obligation to see where else  
15 it goes. You can't turn the clock, you know,  
16 back on some of this stuff.

17 And the second point would be that we  
18 don't have a technology environment today in  
19 which tech companies, right, Silicon Valley  
20 companies like us can get away with stuff, right.

21 There's so much scrutiny. People will  
22 read our EULA, and we're constantly in

1 communication with our users, with the industry,  
2 with all of the relevant stakeholders to make  
3 sure that this doesn't happen in an ethical way  
4 and that we are not just, you know, flooding the  
5 market with a bunch of crap.

6 That, in my view, is not the right way  
7 to build this business. Transparency and sort of  
8 being up front about these issues and being, you  
9 know, having a perspective of it isn't finished.

10 We're building this, and we're going  
11 to build this along with these perspectives. I  
12 think it's going to be frankly probably the  
13 difference between success and failure for us in  
14 the long run.

15 MS. SMITH: Okay. So I think that is  
16 a great point to wrap up on before we move to  
17 bias and ethics in AI. And on behalf of the  
18 Copyright Office and WIPO, thank you so much to  
19 the panelists for your participation.

20 MS. ALVAREZ: It's not a break just so  
21 you know. We're just switching panels here. I  
22 think that people are coming up here. So next,

1 we're going to be talking about bias in AI  
2 although apparently this music panel has really  
3 sparked some discussion.

4 MS. ROWLAND: Okay. Thank you so  
5 much. Now we're going to turn to our discussion  
6 about bias an AI. And Whitney Levandusky at our  
7 office is going to moderate this, so I'll let you  
8 take it over.

9 MS. LEVANDUSKY: All right. Thank  
10 you, Catie. Hi. Good afternoon. Thank you to  
11 the music panel for starting the conversation  
12 about bias and artificial intelligence and ethics  
13 and artificial intelligence.

14 This is a topic that touches on all  
15 matters involving AI. It is an issue if you are  
16 a consumer of AI, if you are a creator of AI, if  
17 you are a creator who has found their works  
18 incorporated into artificial intelligence.

19 So I'm really excited that we get to  
20 spend some time on this topic. And one of the  
21 things that's kind of repeated itself throughout  
22 the day is the tension between computer and

1 human.

2 So in copyright we think about it as  
3 the computer generated versus the human  
4 generated. And when it comes to bias and AI,  
5 when we find ourselves surprised that the outputs  
6 of an AI system don't reflect the best of us and  
7 sometimes reflects the worst of us.

8 We often talk about it in terms of  
9 objects. We talk about bad data. We talk about  
10 the algorithm. But within all of these  
11 situations are humans, humans making decisions.

12 They're selecting, coordinating,  
13 arranging the data that goes into the system.  
14 They're building the algorithm. They're making  
15 decisions based off of the raw output that the AI  
16 is making.

17 And so, for today what I'd like to  
18 discuss, we're going to be talking about those  
19 objects that are involved and that implicate --  
20 that kind of come into play when we talk about  
21 bias, but we're also looking to center humans.

22 If you are creating an AI system, what

1 might you be thinking of. If you are a consumer,  
2 what are your questions? And Dr. Ulrike Till in  
3 the international session said that the important  
4 thing with intellectual property and artificial  
5 intelligence is to ask the questions, that we may  
6 not have answers all the time, but it's important  
7 to keep asking the questions.

8 So that's my job as moderator. And as  
9 moderator, I get to ask questions of two great  
10 experts. And I'd like to spend just a moment  
11 introducing both of them.

12 So to my left, I have Amanda  
13 Levendowski. She is the Associate Professor of  
14 Law, and she's the founder of the Intellectual  
15 Property and Information Policy Clinic at  
16 Georgetown Law.

17 And then I also have Miriam Vogel, who  
18 is the Executive Director of EqualAI, which is an  
19 organization that is committed to addressing the  
20 question of bias in artificial intelligence.

21 So without further ado, I would like  
22 to turn to Miriam and ask her to set the scene

1 for us. What is bias in artificial intelligence?

2 MS. VOGEL: Well, thank you for that  
3 great question. Bias in artificial intelligence  
4 is inevitable from my perspective. I should take  
5 a step back and tell you what EqualAI is because  
6 most of you are probably not familiar with our  
7 new organization.

8 We were created a year and a half ago  
9 by Arianna Huffington, Rob LoCascio of Live  
10 Person, Jimmy Wales of Wikipedia and others who  
11 started seeing how AI is being used in ways big  
12 and small throughout our day and lives and that  
13 it's actually influenced by bias.

14 It turns out that is I would say  
15 inevitable because if you look at what machine  
16 learning is in particular but AI in general, it's  
17 pattern recognition.

18 It's getting to the answer quicker.  
19 It's solving for the answer by recognizing  
20 patterns. In the same way, if you look at what  
21 is implicit bias, it's recognizing patterns and  
22 making decisions accordingly.

1                   So there's no way you're going to,  
2                   from my perspective, remove bias from AI because  
3                   it is necessarily biased. What we can, should  
4                   and need to do is look at the ways that it is  
5                   unconsciously biased.

6                   We need to set the guard rails of what  
7                   are the biases that we will not accept, and how  
8                   do we solve for them.

9                   MS. LEVANDUSKY: Thank you. And so we  
10                  talk about unconscious bias, and maybe one of  
11                  things that we can think about is transparency,  
12                  right. So if bias is inevitable and we are  
13                  looking towards moving our unconscious bias to  
14                  conscious bias, how do we inform people about  
15                  that, like the bias that is reflected in an AI  
16                  system?

17                  MS. LEVENDOWSKI: Happy to take it.

18                  MS. VOGEL: I'd very much to hear what  
19                  the professor has to say. So I think that's  
20                  actually the most important piece of what we can  
21                  do here together.

22                  All of us have a responsibility once



1 we recognize this problem. We all have this  
2 responsibility I would argue, as a consumer, as a  
3 person, as a parent, as a classmate.

4           Whatever your role is, you have a  
5 responsibility to do something about it once you  
6 know that it exists. We have to hold companies  
7 accountable and we have to get our lawmakers to  
8 act on this because there's going to be this  
9 inevitability of companies answering to  
10 shareholders.

11           They have their bottom lines. They  
12 are set up for profits. They are not necessarily  
13 going to be looking for all the potential harms  
14 or downstream users of their products.

15           That's incumbent upon us to demand of  
16 them and to make that a part of the expectation  
17 for the products that they are creating.

18           MS. LEVANDUSKY: And so, are there  
19 best practices that companies and researchers can  
20 implement so maybe it does look less angry at the  
21 shareholder meeting?

22           MS. VOGEL: Absolutely. And for

1 anyone who wants more detail, I do a half day  
2 workshop. So I'll give you a brief snapshot  
3 today of what I share and what we talk about to  
4 that experience.

5 But basically, it's a two-part  
6 situation. First of all, it's recognizing all  
7 the different touch points where our bias can  
8 seep into AI. And that's essentially looking at  
9 all the human touch points.

10 It's looking at the design. It's  
11 looking at the data that's being used to feed the  
12 AI program. It's looking at who's testing this  
13 AI to make sure that it's not harming and  
14 hopefully is helping more people.

15 And so we have a variety of solutions  
16 that we ask companies to take on when creating  
17 AI, but we also have a five pillar framework that  
18 we recommend that all companies follow if they're  
19 serious about combating an AI.

20 We actually take a step back before  
21 the AI creation and before the hiring of  
22 employees who will be impacting this AI. And we

1 say that if you're going to be serious about  
2 combating bias in AI, you have to invest in the  
3 pipeline.

4 You have to make sure that we have  
5 more people of color, more women, more voices  
6 from more regions. It's not going to be solved  
7 for us by looking at one or two categories.

8 You need to be thinking about the  
9 universe of who would be impacted by the product  
10 and making sure that they are participating in  
11 the AI creation.

12 The second pillar is looking at your  
13 HR systems and calling it hiring, promoting with  
14 your values. So we know that there's implicit  
15 bias in hiring patterns and also in promoting.

16 For instance, if you look at women in  
17 the tech space, there're estimates that they are  
18 between 20 and 30 percent of the workforce. If  
19 you look at the executive level, it's half that.

20 And if you're talking about people of  
21 color, it's also half that. So we need to make  
22 sure that in addition to the implicit bias of the

1 humans who are in the hiring and promotion that  
2 we're not doubling down on discrimination through  
3 the AI products that are being used more and more  
4 with companies large and small across the world  
5 in hiring and promotion.

6 Third, we say that you have to  
7 evaluate the data set. You have to see, based on  
8 the data that you're using, where are the gaps.  
9 If you're talking about an AI for healthcare  
10 product, you're going to have limited data sets.

11 If it's insurance data, you're not  
12 going to have people of certain economic brackets  
13 who can't afford insurance. If it's genomic  
14 data, it's on average 80 person or more people  
15 from European descent.

16 So where are you going to find gaps  
17 that you need to change -- there are ways to  
18 change it. It's getting different data, or it's  
19 solving for over representing, under representing  
20 based on the population you want to be serving  
21 and that's not available to you in that data that  
22 you're using.

1           But you're not going to be able to see  
2 everything in the data because you're talking  
3 about terabytes. So then you have to dissect  
4 your data. That's the next pillar.

5           There are tools available, but there's  
6 also testing, just interrogating the data,  
7 solving for if it's a hiring program. Who are  
8 great candidates that are being left out if you  
9 test this system.

10           And we can use data, and I know  
11 Professor Levendowski will talk more about  
12 accessing different data sets. But it's  
13 imperative that you test out the AI products that  
14 are already in existence.

15           And this is true for both those who  
16 are developing the AI but also the majority of us  
17 who are the users. We are equally responsible  
18 for ensuring that the AI that we're using and  
19 consuming doesn't discriminate or produce  
20 outcomes that are different than what we want.

21           And then finally, we say the final  
22 problem is reevaluating who your team is because

1 a lot of people will tell you there's nothing we  
2 can do about the current biases if it's a  
3 reflection of us.

4 Our coding department is mostly white  
5 males. That's who's available to be coding these  
6 days, and our leadership team is what it is. But  
7 there's a really simple solution for that.

8 And one of the companies that sees  
9 things I mean Live Person has this really  
10 interesting work around where they create  
11 chatbots. So rather than just relying on the  
12 chatbot creator or coder or programmers, they  
13 actually went to the call centers and had their  
14 input in the chat box they are creating.

15 And it turns out not only was it  
16 skyrocketing in terms of the consumers  
17 satisfaction and the employee satisfaction, the  
18 products sold off the shelf because they had the  
19 input of the various perspectives, not just those  
20 who had been creating the AI initially so.

21 It's a much longer answer than you  
22 were probably looking for, but I'll stop myself

1 because I could go on.

2 MS. LEVANDUSKY: No, so it seems like  
3 we've got some good tenets to think about from a  
4 corporate standpoint.

5 So your human touchpoints, I really  
6 like that where you're taking a look at every  
7 time that human hands are involved in the AI  
8 system, and that's from hiring, that's building  
9 your team, looking at the skill set, making sure  
10 that there is sort of some effort put in on in  
11 terms of representation and making sure that  
12 there's a variety of perspectives and then taking  
13 a look at your data.

14 And it seems like it's both focusing  
15 on maybe the specific issues with your data but  
16 then also the general trends that come with  
17 certain sectors of data. And so I wonder, if  
18 Professor, you can drill down that data issue.

19 MS. LEVENDOWSKI: It would be my  
20 delight. Question. How many of the people in  
21 the room actually know how AI works, like they  
22 could explain it to a friend over dinner?

1           Oh, a pretty good number. So this is  
2 perfect. What I'm going to do is I'm going to  
3 use an easy example using my favorite topics of  
4 conversation, my cat.

5           And I'm going to explain to you how  
6 bias works its way into these AI systems. And  
7 I'm going to make it as simple as humanly  
8 possible though I'm sure a computer could do  
9 better.

10           So if I'm looking to build an AI  
11 system that recognizes cats because I want to  
12 walk into the world and whenever there's a cat  
13 nearby, I want to know about it. I think you all  
14 relate.

15           When you're walking around and you're  
16 thinking about that, I would first have to start  
17 with training data. I would need to train the  
18 artificial intelligence algorithm, the most  
19 common application currently that's commercially  
20 viable is called machine learning, something  
21 you've probably read about in the news.

22           So if I'm creating a machine learning



1 algorithm to recognize cats, I have to start with  
2 training data. And unfortunately, I've looked up  
3 how much it costs to license one image of a  
4 particular type of cat.

5 And it's \$175. And you need thousands  
6 and thousands of images to effectively train an  
7 AI system to be accurate. So I'm probably not  
8 going to want to license that.

9 Instead, I'm going to turn my  
10 attention to an easily available, legally low  
11 risk source of data. I want to know that I own  
12 the intellectual property rights so that I'm not  
13 dealing in licenses or even thinking about fair  
14 use, though I would love to think about it later.

15 And I want to make sure that it's  
16 easily available, not something that's going to  
17 take a lot of computing power for me to actually  
18 integrate into the algorithm.

19 And I have exactly the perfect source  
20 right in my pocket. It's my camera's photo roll.  
21 I have an incredible number of pictures of my cat  
22 just sitting and ready to become data for this

1 machine learning algorithm.

2           So I take the data that I selected.  
3 I feed it to the machine learning algorithm, and  
4 I realize that I have two different but equally  
5 important problems.

6           Miriam touched on the different  
7 potential human touch points at this stage in the  
8 process, and we've now touched on two. One of  
9 them is the selection of the data, and the second  
10 one is the creation of the algorithm.

11           And depending on how I create this  
12 algorithm, I'm going to get biased results based  
13 on the data I've input. But if I train the  
14 algorithm to focus on the colors of what a cat  
15 is, it's only going to pick up on the colors of  
16 my specific cat because that's 100 percent of the  
17 training data.

18           So the machine learning algorithm is  
19 going to think that a mélange of gray and orange  
20 and cream and black is what makes a cat. But if  
21 you looked around any urban environment, that  
22 actually describes an enormous number of

1 buildings, patches of dirt, brindle dogs, none of  
2 which are cats.

3 So I've essentially created a biased  
4 algorithm that specializes in false positives.  
5 Now we can go in the other direction and I say  
6 okay, pretend that the colors don't matter. And  
7 we're not looking for tortoise shell cats only.

8 We want to look for something  
9 different. It's going to look at a potential  
10 picture of a cat and say I want the features of a  
11 cat. I want big pointy ears. I want big fluffy  
12 fur. I want a long tail.

13 Well, now we're going to get some  
14 false negatives because if you know anything  
15 about cat taxonomy and based on some of your  
16 faces, you're like of course I don't. That's a  
17 very weird thing to know about.

18 If you do know anything about cat  
19 taxonomy, you have Scottish folds, which have  
20 folded down ears. You have Minx cats which have  
21 bobbed tails. You have cats like mine, a Devin  
22 Rex, that have short fur.

1           So you're going to get some false  
2 negatives, some things that are cats that the  
3 algorithm is not going to recognize as such. Now  
4 this might seem very like dumb and whimsical when  
5 we're talking about recognizing cats.

6           But if you're talking about facial  
7 recognition cats, but if you're talking about  
8 facial recognition algorithms that are used to  
9 make decisions about whether people are engaged  
10 with our criminal justice system, false negatives  
11 and false positives are not just engineering  
12 goofs but are life changing due process problems  
13 that we are still grappling with.

14           So that's the basics of how this final  
15 piece of how the human touchpoint gets  
16 integrated. It's the outputs in the data sets.  
17 So now we've got this full stack at how bias can  
18 get introduced at every step of the process.

19           And if we zoom out, there's even a  
20 bigger meta question about the human touchpoint  
21 and bias, which is should we building this system  
22 in the first place.

1 MS. LEVANDUSKY: And so there are some  
2 systems now, and you talk about facial  
3 recognition, that there are some companies who  
4 want to bring like facial recognition to the  
5 consumer sphere.

6 And so it's now governments and the  
7 private individual who have these tools at their  
8 use. How should an individual think about these  
9 things, and what makes a conscious consumer?

10 So this is both an ethical issue in  
11 terms of engaging with a product that will have a  
12 bias of some sort and then also an accountability  
13 issue.

14 Miriam, you talked about how we as  
15 individuals can hold businesses to account. So  
16 as an individual, how do we navigate this bias  
17 issue?

18 MS. LEVENDOWSKI: I think facial  
19 recognition is such a good example because it's  
20 something that people can experience in a way  
21 that commercially makes their lives easier.

22 If you're one of those folks who uses

1 facial recognition to log into your phone, you  
2 might find that to be a really easy, frictionless  
3 way to not have to remember yet another password.

4 But we can also think about it being  
5 used in its dual use, right, by governments. And  
6 I think this is one of those places we're saying  
7 decreasing the bias in the algorithm is maybe not  
8 always going to be the satisfying right answer  
9 because if you think about the way these systems  
10 are going to be deployed by government perhaps,  
11 they're going to be used for surveillance.

12 We statistically know that that  
13 surveillance is largely going to be targeted at  
14 communities of color, the way that it often is,  
15 and that's where a lot of the policing is going  
16 to occur.

17 And the problem with that is that  
18 having perfectly accurate facial recognition  
19 doesn't solve the underlying bias of how that  
20 technology is used.

21 And that's why I think it's so  
22 important for consumers who are engaged in this

1 question to think critically about whether these  
2 systems are something we even want to be  
3 introduced into our society.

4           So for example, facial recognition has  
5 been shown by research done by Georgetown's  
6 Privacy Center called perpetual lineup if you're  
7 curious in looking at the information,  
8 statistically shown to be biased amongst certain  
9 groups, against people of color, young people and  
10 women.

11           And so while you might be able to say  
12 introduce new data to compensate for those  
13 biases, even having perfect facial recognition  
14 doesn't solve the underlying problem about  
15 whether it's going to be used for  
16 over-surveillance against particular communities.

17           And you can think about this in other  
18 types of applications of machine learning as  
19 well. We still need to ask that interrogation  
20 ethical question as consumers of do we want this.

21           And the answer across multiple  
22 jurisdictions so far has been a resounding no.

1 Washington currently has a bill introduced.  
2 There's other bills that have been introduced in  
3 the suburbs of Boston to ban face recognition use  
4 by law enforcement in part because of these  
5 concerns that it's almost a sort of unsafe at any  
6 speed argument, right.

7 Bias is certainly a huge part of the  
8 problem, but it doesn't provide us all of the  
9 answers, as you were saying earlier.

10 MS. LEVANDUSKY: And Miriam, from a  
11 consumer's perspective, from an individual  
12 perspective, how should you think about or  
13 encounter these issues?

14 MS. VOGEL: I like the approach that  
15 some have taken when a consultant to engineer  
16 happened to be affiliated with the company tested  
17 the company and saw that it wasn't able to  
18 identify his face properly, he sounded loud on  
19 social media.

20 I think making sure that you're  
21 testing out. You should have access to any  
22 public product, and if it's not recognizing you



1 or serving your properly, then you know, we can't  
2 wait until the unmanned vehicle can't detect a  
3 female figure and has an accident before we  
4 correct for it.

5 So I think making sure that people are  
6 raising their hand and saying I want to make sure  
7 this is safe for me. I want proof this is  
8 accessible to me. Again, there's a variety of  
9 harms.

10 Nikon tried to make an AI program to  
11 enable people to be better photographers. And  
12 they apparently had no one Asian on their team  
13 because if you had Asian eyes, it would label  
14 them as closed.

15 So, you know, people should be  
16 demanding that this AI works for them and whether  
17 it's a fatal harm or a harm along that line, it's  
18 the company's responsibility.

19 And at the end of the day, the  
20 argument I make to companies and that I think  
21 consumers would certainly support and should is  
22 that it's their product's reputation on the line.

1           It is their trust and integrity. And  
2 Google is able to overcome that lapse in their AI  
3 identification, but could a smaller company that  
4 we're less reliant on?

5           And then you'd have to think -- I also  
6 talked to companies about the employee morale.  
7 Think about how at a company like that when they  
8 missed and when they've harmed a consumer whether  
9 it's by not being inclusive in their product or  
10 an actual physical harm, think about how that  
11 impacts employee morale where they're trying to  
12 create these AI products that are going to save  
13 the world, make it more efficient, make it more  
14 fun, make it safer.

15           There's a real impact. Right now we  
16 know there's a war to get the best employees  
17 possible. So if you're in the AI space, you  
18 can't afford to be harming employee morale in  
19 that way.

20           And then there's legal liability,  
21 which I found with most of the companies I talk  
22 to that's often a point where I get their

1 attention. So I think that we've seen a bit of  
2 case law so far trying to decipher where the  
3 liability resides, who's responsible in these  
4 oversights in the AI space. I think we can  
5 expect to see a lot more.

6 MS. LEVANDUSKY: So you talk about  
7 liability as sort of something that can hook  
8 people, can hook businesses. And so it seems  
9 like there's often a business decision and a  
10 legal analysis that happens.

11 And I wonder, Professor, if you could  
12 just speak very briefly about how individuals  
13 make choices to engage with or avoid trademark  
14 and IP issues in the selection of their data.

15 MS. LEVENDOWSKI: Sure. Well, because  
16 so much of the data that we were talking about  
17 earlier is protected by copyright law, there's a  
18 real question about how to pick data that's going  
19 to be legally low risk and easily accessible to  
20 use for machine learning.

21 And unfortunately, because of those  
22 hurdles related to potentially licensing all of

1 those images, it's not necessarily that people  
2 are just using them anyway, although that's often  
3 the case.

4 But one of the other things that  
5 happens is people turn to biased, low friction  
6 data, easy available, but definitely biased.  
7 Examples can include exclusively public domain  
8 data to train your natural language processing  
9 algorithm, which may seem like an incredible rich  
10 source of text.

11 But it's only going to be as --  
12 basically be as woke as the year 1925, which I  
13 think we all agree was not that woke. And that's  
14 a potential problem for the training data.

15 Another possibility would be turning  
16 to Creative Commons license data, which has an  
17 incredible number of benefits as well. It's a  
18 more contemporary corpus of work.

19 However, if you're look at who  
20 contributes to the largest resource of Creative  
21 Commons licensed data that's freely available to  
22 use, that's Wikipedia.

1                   And that's largely dominated by white  
2 male editors from Western countries, so the  
3 information is biased. The information I love,  
4 or the example I love to use about Creative  
5 Commons license data is Rob Gronkowski, tight end  
6 for the New England Patriots, not playing this  
7 year.

8                   But the article about Rob Gronkowski  
9 is about 3,000 words long. The article about the  
10 first woman admitted to the New York State Bar  
11 doesn't exist.

12                   So it's not even about what the  
13 articles say that you're feeding back into the  
14 algorithm. It's whether or not the articles are  
15 even available to train these systems.

16                   So in both of those cases, you can see  
17 how being concerned about intellectual property  
18 liability might channel creatives and AI to  
19 choose biased data because it seems easy.

20                   And in the paper that I wrote about  
21 this issue, the largest example is the Enron  
22 email data set, which if you don't know, most of

1 the machine learning that you've interacted with  
2 in the last five years has been trained on 1.6  
3 million real emails sent between the executives  
4 of a Houston oil and gas company that collapsed  
5 under investigation for fraud at a federal level.

6 And you can think about whether there  
7 might be some biases embedded in the Enron  
8 emails. And I think that there's actually some  
9 research that shows that the answer is yes.

10 It's not representative  
11 socioeconomically, geographically, not in terms  
12 of race and gender certainly. And all of those  
13 biases are then fed into a system that can  
14 potentially amplify them.

15 So all of those are in response to  
16 trying to avoid liability for intellectual  
17 property infringement. And instead, we get  
18 biased junky data that's informing the AI systems  
19 we interact with every day.

20 MS. LEVANDUSKY: So AI, we call it  
21 machine learning. We call it machine process,  
22 but there's actually -- all of this bias

1       implication is because of the human involvement,  
2       whether it's in the creation of the data, the  
3       selection of the data, the production of the AI  
4       or the deployment of the AI.

5                   MS. VOGEL: Even in the design.

6                   MS. LEVANDUSKY: Even in the design of  
7       the AI.

8                   MS. VOGEL: It's --

9                   MS. LEVANDUSKY: Yeah.

10                  MS. VOGEL: You know, if you're making  
11       a hiring -- sorry.

12                  MS. LEVANDUSKY: No, go.

13                  MS. VOGEL: If you're talking about a  
14       hiring algorithm -- most companies I work with  
15       now are using AI somewhere in their hiring  
16       process whether it's deciphering through resumes,  
17       video analysis, et cetera.

18                  The person who is designing that AI  
19       has a bias in mind of who the ideal candidate is.  
20       So aside from the fact that the data from the  
21       company or the data in the AI program their using  
22       is very likely to be biased, you can have it

1 starting out asking the question because an  
2 algorithm is often described as an opinion.

3 Who are you solving for? Who are you  
4 looking for? And I think we can only expect  
5 people to be creative, as creative as their  
6 mindset allows. And that's why this age old  
7 issue begs for an age old answer.

8 I wish I had something, a sexy AI  
9 answer I could give, but you have to have  
10 diversity of --

11 MS. LEVENDOWSKI: There's no sexy AI.

12 MS. VOGEL: Well, I'm going to leave  
13 that. You won't be limited by our bias. You  
14 have your own biases to whether or not that's the  
15 case.

16 MS. LEVENDOWSKI: That is my bias.

17 MS. VOGEL: There it is. And we can  
18 all share our biases as part of this. We can  
19 raise our hands and share. But at the end of the  
20 day, a diversity of thought and perspectives I  
21 think is the best tool.

22 And that's why the consumer awareness



1 is the best tool to make sure that we reduce this  
2 problem. But I'm sorry. You were

3 --

4 MS. LEVANDUSKY: No, it's great. I  
5 just want to spend just one moment to see if  
6 there are any questions in the audience, anyone  
7 that might -- yes. We've got a question in the  
8 back. Yeah.

9 MS. TANEN: Hi. I'm Becca Tanen. I'm  
10 a librarian here in the Copyright Office. I have  
11 a couple of questions about equal AI. So you  
12 talked about the five pillars of your  
13 recommendations for companies.

14 So how are those enforced? What are  
15 some of the, you know, follow up processes that  
16 you might have for companies that have committed  
17 to those recommendations and just in terms of  
18 incentive for signing on to those  
19 recommendations.

20 You mentioned legal liability, but I  
21 think we've seen and it's been discussed in the  
22 panels today that a lot of the legal regulations

1 haven't caught up to the technology that's being  
2 made.

3 And unfortunately, large tech  
4 companies are often the exception when it comes  
5 to those legal rulings, so would love to hear a  
6 little bit more about how that is being enforced  
7 and followed up on.

8 MS. VOGEL: Well, thank you, Becca for  
9 that great question. And I'd like to enlist your  
10 help going forward so we can put some of that to  
11 good use.

12 So enforcement of our pillars. I wish  
13 I could tell you that I am an enforcement agency  
14 or aligned with one that could enforce this in  
15 some way.

16 I do have the opportunity to brief  
17 lawmakers and regulators. Next week, I'll have  
18 another opportunity to do that at the FCC. And I  
19 briefed at the Fed last month.

20 But at this point, as a nonprofit  
21 organization, we offer best practices. We're  
22 working with companies to figure out what the

1 standards are that they could sign on for.

2 And an important part of upholding  
3 these standards is making sure that they are  
4 continually repeated. So it's not a one and done  
5 if you're looking to reduce bias in AI.

6 It is a rinse, wash, repeat, repeat,  
7 repeat, repeat because as we know, AI is  
8 iterative and these biases will continue to pop  
9 up in different or similar ways over time.

10 So at this point, it is absolutely  
11 voluntary, but would love your thoughts on how we  
12 can make that more mandatory.

13 MS. LEVANDUSKY: So we'll have to end  
14 it here. And so thank you so much. I want to  
15 thank Professor Levendowski and Miriam Vogel for  
16 their presence today on this panel. I think --

17 MS. LEVENDOWSKI: Well, thanks for  
18 having us, Whitney.

19 MS. LEVANDUSKY: Oh, anytime. You  
20 guys --

21 MS. LEVENDOWSKI: This has been fun.

22 MS. LEVANDUSKY: We'll put the stage

1 up for you anytime. So thank you. It seems like  
2 AI is much like Groundhog Day. It is something  
3 that we repeat and learn and learn and learn  
4 until we can improve and move on to February 3rd.  
5 Thank you.

6 Oh yes, and we'll have a 10-minute  
7 break here. Thank you.

8 (Whereupon, the above entitled matter  
9 went off the record at 3:25 p.m. and resumed at  
10 3:36 p.m.)

11 MS. ALVAREZ: Hello. We're going to  
12 start again after the break so we'll let people  
13 come and take their seats. This is going to be a  
14 panel that is different than the others because  
15 we're talking about the marketplace and things,  
16 the products and services that are out there that  
17 focus on AI.

18 Before we get started, though, I have  
19 a housekeeping note. There is, if there is a  
20 Kathleen Burke in the room, let us know. We may  
21 have some of your things, so please come and see  
22 us at the desk out front.

1                   But with that, I will turn it over to  
2 Mark Gray. Mark, take it away.

3                   MR. GRAY: Great. Thank you, Catie.  
4 Hi, everyone. Our next panel discussion is on  
5 consumer AI and AI in the consumer marketplace.  
6 Joining us today are three esteemed speakers. We  
7 have, starting with my left, Julie Babayan, from  
8 Adobe.

9                   Julie is a senior manager of public  
10 policy at Adobe, and she focuses on global  
11 technology policy and issues such as artificial  
12 intelligence and intellectual property. To her  
13 left is Vanessa Bailey. Vanessa is the global  
14 director of IP policy for Intel. She previously  
15 worked for the law firm, Jones Day and spent 12  
16 years at Nokia doing licensing, FRAND, patent  
17 litigation and a bunch of other cool stuff.

18                   And then, last but not least, is  
19 Melody Hansen. Melody is an IP partner at  
20 O'Melveny & Meyers, and she is the chair of the  
21 firm's Automated and Connected Vehicles Group.

22                   And so just -- I guess on a logistics

1 note, we're going to start kind of with a quick,  
2 about a five minute presentation with them  
3 talking about some interesting, AI consumer  
4 applications they're doing and then we're going  
5 to have a panel discussion afterwards.

6 So with that, Julie?

7 MS. BABAYAN: Great. Thank you. My  
8 name is Julie Babayan. Hi, there. I'm based in  
9 Washington, D.C. with the Global Government  
10 Relations and Public Policy Team at Adobe. You  
11 may know Adobe from some of our most well known  
12 products, such as Adobe Photoshop and Adobe  
13 Illustrator and Adobe Acrobat. But let me just  
14 give you a little bit more background on Adobe  
15 and how it fits into today's discussion.

16 Adobe's business is comprised of three  
17 cloud based solutions and all of them use  
18 artificial intelligence. We have the Adobe  
19 Creative Cloud, the Adobe Document Cloud and the  
20 Adobe Experience Cloud.

21 And what we're talking about here is  
22 really specialized AI that's designed for

1 specific purposes. So in the creative space, when  
2 at Adobe think about AI, we think about it in  
3 terms of how do we use AI to help creative  
4 professionals do their jobs.

5 And it's worth noting that we're  
6 unique in the copyright space because at Adobe we  
7 develop AI powered tools for creative  
8 professionals who then use those tools to create  
9 copyrightable works.

10 And we've really built an industry on  
11 helping creative professionals express  
12 themselves. And we vigorously support the ability  
13 of creative professionals to protect their work  
14 through copyright and to realize economic value  
15 from their creative works.

16 And AI is all part of this because it  
17 helps us deliver tools for creative  
18 professionals, and they appreciate the advantages  
19 that AI can bring to them. So, for instance,  
20 graphic designers can use AI assisted search to  
21 search for stock images on Adobe stock.

22 And film makers can review footage and

1 have it suggested to them and other creative  
2 professionals can have their tools, like  
3 Photoshop, customized to their interests and  
4 their areas of focus and their skill level.

5 So in all of these examples, we're  
6 talking about AI helping you do your job better.  
7 And I thought it would be helpful to take a  
8 closer look at a concrete example of how Adobe is  
9 using AI right now and the research that goes in  
10 to making these innovations possible.

11 So let me first just say that our  
12 research organization, Adobe Research, is really  
13 amazing and we ultimately incorporate many of the  
14 insights and discoveries from Adobe Research into  
15 our products.

16 So let me just walk you through some  
17 recent research. In this case, researchers wanted  
18 to colorize black and white photos, and there  
19 were all sorts of reasons why you might want to  
20 do this. You can gain new insights from historic  
21 photos and look at them in a new way.

22 And this is something where, you know,



1 colorizing black and white photos is very tedious  
2 and time consuming to do it, to do by hand. So  
3 actually, it's a problem that's very well suited  
4 to AI.

5           Researchers were able to start with  
6 colored photos and then convert them into black  
7 and white photos. And that is your training data.  
8 And then basically you were able to have the AI  
9 system predict the color version, given the black  
10 and white photos.

11           So just as you and I can look at a  
12 collection of photos and gain insights and  
13 knowledge from the content, here we have the AI  
14 system that is gleaning information about the  
15 objects that are depicted here, the various  
16 components, the variations in light and shading  
17 and shadows and how they behave.

18           Once researchers trained these AI  
19 systems, they noticed something that was  
20 interesting and that was that the AI on its own  
21 did a really bad job of colorizing black and  
22 white photos.

1                   And you can see from here the  
2                   automatic results are mostly gray and brown, so  
3                   not the greatest photos to look at. And there's  
4                   some reasons for this. Some of the colors in the  
5                   training data are really well defined, such as  
6                   skin tones, for instance. But other colors are  
7                   not well defined at all, like clothing.

8                   And ambiguity, as it turns out, is a  
9                   very, very hard problem for an AI system to  
10                  solve. So this gets us to Adobe's approach, which  
11                  is: let the artist decide. The AI gets you most  
12                  of the way there, but it's ultimately the artist  
13                  that's in control and the AI is merely a tool to  
14                  help the artist.

15                  So with this, you get much better  
16                  photos. And this is just one example. And maybe  
17                  you wanted slightly different color tones here in  
18                  the clothing or maybe here's another example as  
19                  well.

20                  And I bring this up just because I  
21                  think it illustrates Adobe's approach to AI in  
22                  general, which is it's ultimately about giving

1 people useful tools and letting them decide how  
2 they're going to use them. And this is a good  
3 segue into Adobe's approach to public policy on  
4 copyright and AI.

5 Recommendation number one is promote  
6 policies that expand access to data, avoid  
7 outcomes that limit access to data. AI opens up  
8 creative possibilities, but truly realizing these  
9 possibilities requires reasonably unrestrained  
10 access to data and often including copyrighted  
11 works to train AI systems.

12 So what would be a bad outcome is if  
13 copyright law were interpreted to limit access to  
14 data, because as we heard in our last panel,  
15 outdated and insufficient data also contributes  
16 to bias. And outdated and insufficient data also  
17 would put the U.S. at a disadvantage as compared  
18 to other countries that have clarified their law  
19 explicitly to permit such uses.

20 Which leads me to recommendation  
21 number two, which is harmonize international  
22 copyright laws to promote AI and, specifically,

1 continue the international trend of text and data  
2 mining exceptions.

3 So a number of countries have grasped  
4 the importance of AI and the role that data has  
5 to play here. And they've adopted copy rules to  
6 facilitate the development of AI. These are often  
7 referred to as text and data mining exceptions or  
8 TDM exceptions.

9 And Japan, for instance, recently  
10 amended the Copyright Act to add exemptions.  
11 Other countries such as Singapore, Australia,  
12 China, Thailand are also looking to update their  
13 copyright laws to further facilitate machine  
14 learning. And the EU recently adopted limited  
15 TDM exceptions as well and could be exploring  
16 further refinements in this area. So currently  
17 the U.S. is a world leader in AI, but the U.S.  
18 could quickly fall behind if our policy is to  
19 limit access to data.

20 And that finally leaves you -- I'll  
21 leave you with this last one, which is provide  
22 guidance in the United States to enable AI to

1 flourish. Here in the U.S., we do have the fair  
2 use doctrine and related case law that supports  
3 the legality of processing copyrighted material  
4 for the purposes of training AI models.

5 But we would still recommend specific  
6 guidance to promote certainty to enable AI to  
7 flourish. And providing guidance, establishing a  
8 clear right to use copyrighted materials to train  
9 AI systems is consistent with the goals of  
10 copyright law to promote the progress of science  
11 and useful arts and ultimately to help us  
12 encourage innovation. Thanks.

13 MR. GRAY: Thank you. Vanessa?

14 MS. BAILEY: Okay, I'm going to wait  
15 for my slides to come up there. But good  
16 afternoon. My name's Vanessa Bailey. I am the  
17 head of IP policy for Intel Corporation, based  
18 here in Washington, D.C.

19  
20 So basically we have a lot of really  
21 cool AI inventions that I will show you a couple  
22 of them just to let you guys know what's going on

1 in the tech sector in AI. But how did we get  
2 here? What do we really need for AI to flourish?

3 And one of the big things is data,  
4 right. So we're looking at a big data explosion.  
5 And we know that nowadays, especially among young  
6 people, there's like a lot of data going through  
7 on your phones, connected vehicles.

8 A lot of data, I have numbers up  
9 there. There's just a lot of data going through.  
10 With that, obviously you need compute to make the  
11 data make sense, to make -- be able to process  
12 the data. And of course, the goal here is  
13 connected devices.

14 Looking at the different solutions,  
15 you know, I speak on different AI panels and  
16 usually Microsoft's up there with me. And I give  
17 them so much kudos for having Common. I don't  
18 know if you guys know who Common is, the actor  
19 bringing AI to the masses, I say, with his, you  
20 know, agriculture commercial because it really  
21 does -- lets you know the usefulness of AI.

22 A lot of different areas that we see

1 AI, education, government, health. There's a lot  
2 of different health applications. You know,  
3 better research, quicker results.

4           People talk about this friendly robot  
5 that you actually know, like when they give you  
6 medicine, the robot has a special temperament  
7 because it's programed to have to deal with  
8 different personalities. You know, my mother  
9 would hate that, but, you know, different people  
10 have different things.

11           Looking at media, you know, the  
12 Olympics is coming up. We have things called  
13 3DAT, which is the 3 D athletic analysis, and  
14 it's like the overlay on the athletes. And it's  
15 actually quite amazing. I didn't actually realize  
16 what it was doing until somebody says, no, you  
17 know. You can't tell because it looks real time,  
18 but it's actually predictive and it's actually  
19 estimating what the athlete's going to do next.

20           And that's what it's -- the overlay is  
21 like a one millisecond behind them. But it knows  
22 where he's going, and I'm like, wow. Who knew? I

1 thought that was, you know, somebody sitting  
2 there trying to move, trying to figure out where  
3 they're going.

4 But with this AI, we actually have all  
5 this data in there and we're predicting where the  
6 athletes go and what's going to happen next? And  
7 we have the overlay on top of it. And apparently  
8 at the Tokyo Olympics is going to be some quite  
9 amazing things for the audience to see with that.

10 Looking at some of the practical  
11 applications of some of our AI, we have something  
12 called TrailGuard AI, which is a part of our AI  
13 For Good program. And in that we have partnered  
14 with, I think it's called the Leonardo DiCaprio  
15 Foundation and National Geographic to deal with  
16 the poaching problem in Africa of elephants.

17 And so the problem statement was that  
18 there's just too much land. There's not enough  
19 bandwidth for the rangers to deal with the  
20 poachers. And apparently there's some stat that  
21 every 15 minute an elephant was being poached.

22 And it seems quite amazing to me that



1 that was the stat, but, you know, that's what  
2 they said it was. And we looked at, well, how --  
3 what can we do, what's the problem here? And the  
4 problem was that you have to manually survey your  
5 thing to see if a sensor was tripped or a camera  
6 was tripped. And you had to manually go over  
7 there and then you make the judgment call of  
8 whether that's a person or not.

9 And then you had to, you know, tell  
10 the ranger to hurry up and get over there and  
11 deal with the problem. And they were missing a  
12 lot, obviously, as you can imagine.

13 So with that, we had this thing called  
14 TrailGuard AI, which deals with the on camera  
15 inferences. And it basically will detect whether  
16 it's -- you can't read that; the fonts are off  
17 there. But it basically detects, is it a human,  
18 an object or animal. And it makes a decision  
19 based on that and it will instantly send out a  
20 ranger; no manual checking needed. And it has a  
21 very, very, very high rate of accuracy. And so  
22 that's one of our AI for Good programs.

1                   Another program that we have which  
2 I've actually witnessed and it's quite amazing,  
3 quite frankly, it's called Wheelie. And what it  
4 is, it uses the Intel Core chip, the RealSense  
5 camera and the OpenVINO software, which is a  
6 Computer Vision, our Computer Vision AI product.  
7 And it helps people who are mobility impaired  
8 such that they don't have any functionality of  
9 their limbs, and they can use facial expressions  
10 to move the move their wheelchair.

11                   I think my next one, if we can do the  
12 video of it, just to give you a more of the sense  
13 of what it actually does. Yes.

14                   (Video played.)

15                   MS. BAILEY: And so that application  
16 is actually used, I think, at the University of  
17 Houston Hospital. And it's being used in a lot of  
18 the different Texas hospitals. One of the people  
19 helping with the training data for that is a  
20 Brazil -- sorry. That's not -- yeah, there we  
21 go. Other different aspects of some of the  
22 applications are the health applications. Now

1 people are called healthineers instead of  
2 engineers when they use AI, using it in a real  
3 time MRI analysis of a cardiovascular issues.

4 A lot of -- it's actually used quite  
5 uniquely. I was actually, you know, from the  
6 legal side, involved with the BrainIAK project,  
7 which is really cool. It's Intel's first venture  
8 into opensource for using AI in the neuroscience  
9 area. And it is quite an amazing project that  
10 we're still working on.

11 One of the applications, I guess, a  
12 lot of people can see is our autonomous driving  
13 department, which is a very big department for  
14 us. Obviously, we acquired Mobileye and we are  
15 heavily into autonomous driving. You know,  
16 there's a lot of different aspects there, but,  
17 you know, from our sense of what we're good at in  
18 that area and why we're excelling is that the  
19 fact that Mobileye can use all the sensor data  
20 and every day to create a very detailed map very  
21 quickly.

22 And we're using that for -- one of the

1 examples that shows up there, I don't know if you  
2 can read that, that we did in Las Vegas, we went  
3 through the roads in over 248 miles, 16,000  
4 drives, and we created a map in 24 hours, which,  
5 if you think about it, is quite amazing.

6 And of course, that's using a lot of  
7 the data that uploads -- here, let me -- I was  
8 going to -- oh. Yeah, if you want to run that,  
9 I'm just going to show you just generally why I  
10 talk, what -- no. There we go. Yeah -- what  
11 autonomous driving looked like because a lot of  
12 people have different thoughts about what it is.  
13 At CES actually, recently, Intel announced that  
14 we're actually at the Autonomous Driving Level 5,  
15 which is quite amazing, actually, because people  
16 are thinking that we're really not there.

17 Level 5 -- I don't know if you have a  
18 different the levels. So zero is where there is  
19 no autonomy, where you have full control over  
20 everything in the car. Level 5 is completely  
21 autonomous. There is no driver in the driver's  
22 seat.

1           At CES, now Intel announced we're  
2 actually at Level 4, which is a great advancement  
3 because it means that then, you know, there's a  
4 driver in the seat and he can take control over  
5 it, but all the functionality of it is there. So  
6 there's a lot of different things going on.  
7 Obviously, there's a lot of copyright things  
8 going on in that space. I tell people, you know,  
9 generally I'm like a patent person. I was a  
10 patent litigator for 24 years.

11           And I tell them now it's really cool  
12 to be a copyright person because it's so fun.  
13 It's all this technology. And there's really a  
14 lot of very hard and interesting questions being  
15 asked that need to be answered, especially in the  
16 different, various tech areas.

17           But so, you know, there's a lot going  
18 on in AI. And there's a lot further we can go in  
19 AI. But we are really getting to a good place, I  
20 think, rather quickly.

21           And but I think, though, that the --  
22 as far as copyright is concerned, I still think

1 that copyright laws are still adequate. I think  
2 we're doing fine with what we have and that smart  
3 lawyers are figuring things out.

4 And so maybe there's not the biggest  
5 conundrum in the world that maybe everyone  
6 thinks. But maybe I'm just not optimistic about  
7 everything in life, so.

8 MS. HANSEN: So, as Mark mentioned,  
9 I'm Melody Drummond Hansen and I have the  
10 perspective on this panel of being an outside  
11 counsel.

12 So rather than being responsible for  
13 advising primarily one company, although there  
14 are many hats for both of you within your  
15 companies and different types of products with  
16 different, potentially different, competing  
17 interests, you know, I have the pleasure of  
18 advising companies kind of across the ecosystem  
19 for AVs and connected vehicles and hearing from  
20 them, what keeps them up at night, what are their  
21 questions; what are the, you know, what are the  
22 different technology models they're using, what

1 are the different data models that they're using.

2           And one is one of the things that I  
3 like to remind folks of -- I mean, how many  
4 people who are very familiar with autonomous  
5 vehicles, follow it closely? We got some super  
6 fans. So maybe you'll tell you if I -- if you  
7 want to correct anything. But, you know, the  
8 DARPA challenges in the United States were back  
9 in the early 2000s. You know, in 2004, you have  
10 challenges for vehicles to drive -- I mean here,  
11 off road, in this picture, with being able to do  
12 their own navigation, their own detection of  
13 obstacles and navigation of obstacles for some of  
14 the challenges.

15           You know, some of them were in desert  
16 locations was, you know, where rock is one of the  
17 biggest obstacles to the technology. And then in  
18 urban environments, which we all know create  
19 different challenges for autonomous driving.

20           But you have back, you know, 15 years  
21 ago, cars perfectly capable of driving  
22 themselves, navigating novel environments,

1 sometimes without a lot of input or a lot of  
2 advanced knowledge. And that was part of the  
3 design challenge, is to create courses that would  
4 be unknown or have had details only known at the  
5 last minute.

6 And then, you know, today I live in --  
7 I work in Silicon Valley; I live in San  
8 Francisco. And I see a lot of AVs on the road  
9 every day from different companies. And on the  
10 roads -- I mean, to kind of echo Vanessa's point  
11 -- the technology really is capable here on the  
12 roads.

13 We may all have an experience with the  
14 lower levels of autonomy, with our assisted  
15 driving techniques. I mean, for me, when I drive  
16 with my cruise control on, just regular old  
17 cruise control, I see how stupid everyone's  
18 driving is because you start to notice when  
19 people are braking for no reason or braking  
20 because they're going under a tunnel or braking  
21 because they're going around a curve or just  
22 making a dumb decision that slows everyone down.



1           So I think there's a lot of promise  
2           and people acknowledge the promise. And echoing  
3           Julie's point, you know, the latest DOT guidance  
4           on AV, it's called a AV 4.0, they really put it  
5           in terms of we need to enable this technology so  
6           that we can remain competitive in the world and  
7           so that we can remain a world leader.

8           And so I think there's that  
9           recognition these days. There are a lot of  
10          diverse market players in this space. So in  
11          addition to, you know, the Waymos of the world or  
12          the Zoox of the world or the Cruise of the world,  
13          we're actually kind of designing around cars or  
14          designing their own cars.

15          There are other players who may  
16          supply, you know, only LiDAR or only software or  
17          only, for example, chips or data storage that are  
18          enabling the space. And all of them are  
19          potentially affected by the rules that we're  
20          making.

21          Like Vanessa, too, I come from the  
22          patent background, so it was more fun to be in

1 the copyright space a bit. But here is a picture  
2 of a device that's an aftermarket kit that you  
3 can add onto an existing car and make it self  
4 driving, and there are a number of players in  
5 this space who are doing that as well.

6 So I thought it would be helpful to  
7 have some examples of the types of data that are  
8 being collected by AVs. And this is from The New  
9 York Times and citing Google and depicting a  
10 modified Lexus. And you know, at number one, on  
11 the top of the vehicle, is the LiDAR, which is  
12 sort of like a point on, too, of light and radar.  
13 It can map, in the loose sense, an environment by  
14 shooting out light and receiving beams back.

15 Underneath that is a camera at number  
16 2. And then on, what's labeled as 4 on here is  
17 radar, to be able to detect information around  
18 you; 5 is another smaller LiDAR. And in the  
19 trunk, at 3, is a big fat computer to try to  
20 analyze and deal with all this data.

21 I mean, terabytes and terabytes of  
22 data being generated in a single day. So what

1 does this look like? You know, here's an example  
2 of LiDAR are from Luminar. This is the website  
3 that it came from. But this is driving down the  
4 Embarcadero in San Francisco. And you can see  
5 it's we're picking out different objects. And in  
6 the picture that Vanessa showed and we'll see  
7 another example of this, whether it's with  
8 cameras or with LiDAR, there is often metadata  
9 attached to that, often real time to kind of draw  
10 boxes around different types of objects.

11 So we need to be, as the other  
12 panelists were talking about, we need to be able  
13 to distinguish between a pedestrian and another  
14 vehicle in addition to being able to judge  
15 distance, stop signs and the like.

16 And so, you know, one of the things I  
17 joke about you know, folks want to ask about with  
18 AVs, how are we going to train the algorithm as  
19 to who it should kill when faced with two  
20 options?

21 And my first response to that is  
22 always, well, you've driven a lot. How many times

1 have you had to decide who you should kill during  
2 your daily commute?

3 But in reality, some of the more  
4 practical, immediate problems have to do with  
5 being able to accurately represent, you know,  
6 detect traffic cones in different positions and  
7 navigate these types of everyday obstacles, map  
8 those and make accurate depictions.

9 And so you can imagine that these have  
10 a lot of questions around them in terms of you've  
11 got a lot of video or photographs. You've got  
12 datasets that are potentially annotated with this  
13 type of metadata, either in real time or using  
14 its own AI.

15 And folks really don't know what to do  
16 about this. They really don't have a sense of how  
17 this will be treated. And I think different  
18 market players have different perspectives on it.

19 But to echo the point on the previous  
20 panel, the notion of having to get the rights to  
21 the hundreds of thousands of photographs of  
22 traffic cones or something like that is a kind of

1       daunting task. And yet everyone acknowledges  
2       that the industry benefits from sharing data and  
3       being able to share data about the routes that  
4       you're traveling, about the ways that you've  
5       identified obstacles about existing routes.

6               And there are a lot of efforts to do  
7       that these days. Waymo has released certain data  
8       sets, Lyft has released certain data sets with  
9       this type of thing. But there are a lot of  
10      questions around the rights on them. And to the  
11      extent folks are familiar with them, the data  
12      sets have different types of information on them.  
13      Some have video, some have 2D photographs. Often  
14      they have this attached metadata.

15             And they have terms. I mean, they're  
16      called open data sets, but they have terms  
17      attached that, you know, one of the data sets was  
18      sort of criticized for specifying that you can't  
19      use it to train an autonomous car.

20             So with that in mind, I'll finish up  
21      this part and another pick -- these are the  
22      practical realities of the car, not what -- who

1 they're going to kill. Can they drive in the  
2 snow? But that's the type of data we're talking  
3 about.

4 MR. GRAY: Great. Thank you, Melody.  
5 So I guess to start off and maybe to stay on the  
6 topic for a minute, you know, there's a lot of  
7 talk sort of in popular culture about, you know,  
8 self driving cars and what cities will look like  
9 in 10 or 20 years. How close practically are we  
10 based more where the technology is right now?

11 MS. HANSEN: I mean, I think we both  
12 have a lot of confidence and optimism.

13 MS. BAILEY: Right. That's right.  
14 Because I think, you know, as we've seen, that  
15 that was actually driving in Jerusalem when you  
16 saw it. But it was actually, you know, it wasn't  
17 staged. That's real driving.

18 So I think, you know, I think we're  
19 pretty close to being there. I mean, the whole  
20 issue, I find, is not where the technology is,  
21 but whether people will be accepting of the  
22 technology, right.

1           So when you drive in your Tesla, you  
2 know, it's doing pretty well until you know, you  
3 want to get all the way over an exit at the last  
4 minute, right, and that's when everything falls  
5 apart.

6           So, but I think that with the  
7 technology, we're getting better, but the whole  
8 key is data. And I would echo what Melody said.  
9 I think, you know, from an in house perspective,  
10 when you're looking at this and everybody's  
11 asking, you know, what are we going to do about  
12 this because, you know, I would even say more  
13 than that. But, you know, we need hundreds of  
14 thousands of data when, you know, say, for  
15 OpenVINO which is Computer Vision. You know,  
16 you've got to train dataset. And where are you  
17 going to do the data?

18           And when you get it, how can you not  
19 know if there's something in that's  
20 copyrightable? And I think that we just rely on  
21 the current case law and the current cases for  
22 fair use and just rely on the fact that, look,

1 we're not using this for an expressive value.

2 We've got to be able to turn over the  
3 data because safety is number one in autonomous  
4 driving and you only get safety by knowing all  
5 the variables, dealing with all the variables and  
6 having access to what every variable can look  
7 like in different countries, right? Because when  
8 you have autonomous driving, I mean, we do have  
9 the car, right? It has a sensor data. It's  
10 coming in. You might be in, say, I don't know,  
11 Jerusalem.

12 But then you're sending it to the  
13 cloud, and the cloud is in, you know, San Jose,  
14 California or something like that. So you have a  
15 lot of very, you know, things to consider,  
16 especially from a copyright perspective.

17 But it all comes down to the fact that  
18 you need the data, but that we are -- you know,  
19 we're closer than I think a lot of people realize  
20 on autonomous driving.

21 Go ahead.

22 MR. GRAY: Oh. And then I guess sort



1 of as a follow up question then, what are the  
2 specific, I guess, copyright law issues that come  
3 up that may be unique or particularly specialized  
4 to the autonomous driving space?

5 MS. BAILEY: So for me, I think that  
6 -- I don't know if it's unique, but there are  
7 different aspects as like ownership, right. I  
8 think, in autonomous driving, a lot of the  
9 contracts that you see are between the OEMs and  
10 the, you know, the person who owns the AI model,  
11 the trained data set.

12 From my perspective, like you have  
13 different contracts for different leads. So,  
14 well, for us, you know, we have the sensors on  
15 the car and we have the road work map and we have  
16 all of the -- we have the AI itself.

17 So for us, you know, when the -- the  
18 things, that sensor is sensing things in. You  
19 know, a lot of copyright issues comes with that,  
20 like what if it saw a billboard and there was  
21 copyright on the billboard. And now we took it in  
22 and we sent it to the cloud and now its fixed,

1 and what does that mean in the law in Africa  
2 because that's where it's sitting on the server.

3 So you've got a lot of different  
4 international aspects to consider that make it  
5 unique and fun. We also have that aspect of then,  
6 well, you know, when it comes back, you know,  
7 you've got the trained AI model. It's going to  
8 push information back to the car to give you the  
9 green boxes and tell you where things are.

10 But then, you know, in some countries  
11 where the driver's trying to say that, well,  
12 we're the driver and we tell the car where we  
13 want to go, from home to work. And so we want  
14 copyright or whatever it takes in from the  
15 cameras. And we're like, wow, really? Because,  
16 you know, there's a lot of different variables  
17 going on.

18 And, you know, and you read at least  
19 U.S. case law, it doesn't seem that that might be  
20 the right answer. And then there's just a lot of  
21 different unique variables, because you've got  
22 the information coming in. You've got the

1 information going out. You've got the  
2 information churning in the cloud and you've got  
3 the information coming back.

4 And there's a myriad of different  
5 copyright aspects involved in all of that, from  
6 video to imaging to everything.

7 MS. HANSEN: Yeah, I guess to echo  
8 that point, and I would say the questions are  
9 really -- I don't think they're unique to AVs. I  
10 think they have a lot to do with training AI  
11 machine learning.

12 But there are a lot of questions  
13 around data sets and there are myriad ways that  
14 these, that data sets are made. There are  
15 different players who are offering them. You may  
16 not have insight even to where the initial data  
17 came from if you're using other people's data.

18 And particularly with some of the data  
19 sets that are available, I think there are a lot  
20 of questions about how will those different types  
21 of data be treated, you know, whether it's visual  
22 data, location data or other information, are

1       there different ways it'll be treated?

2                   And I'll say, you know, there's a lot  
3       on these open data sets because they're being  
4       made available. They have terms. The terms are  
5       variable. And I should mention, we have in the  
6       room one of the foremost open source experts,  
7       Heather Meeker, who works at my firm. I have the  
8       pleasure of working with her on a lot of issues  
9       that involve the kind of convergence of questions  
10      and copyright with specific questions related to  
11      open source as well.

12                   And so I think there are a lot of  
13      questions around that. You can ask questions. We  
14      kind of talked about this in our prep. You can  
15      ask questions at every stage of it, right -  
16      author, infringement, and fair use.

17                   But I think a lot of the questions  
18      right now are around the default rules on fair  
19      use, because there are many in the industry, not  
20      everyone, but many in the industry who feel, just  
21      in their gut, you've got to be able to use this  
22      data.

1           But when you start to try to apply it,  
2           it's not -- it may be not so clear what the  
3           reason would be.

4           MR. GRAY: Right. And then I guess  
5           to sort of stay on the data set training side,  
6           Julie, what kind of data sets is Adobe using for  
7           their products? You know, are they looking at a  
8           lot of open data sets? Are they generating their  
9           own? What's the thought process there?

10          MS. BABAYAN: Yeah. So I guess some  
11          examples of some data sets that I know of that  
12          are -- and, you know, I won't speak for Adobe  
13          specifically because, you know, that are out  
14          there are, you know, the types of open data, the  
15          types of data sets that we see that are image  
16          collections that universities and other research  
17          institutions put out there for research purposes.

18          And, you know, for instance, some of  
19          these image collections provide thumbnails or  
20          URLs. And for many researchers, these can be  
21          just tremendous resources for doing the type of  
22          research that leads to new insights and

1 innovations.

2 MR. GRAY: Cool. And then another  
3 question I had is, you know, when we when we  
4 spoke before we, when we prepared for the panel,  
5 Vanessa, you had a really interesting point about  
6 the different ways different product groups look  
7 at their sharing or sort of maybe not wanting to  
8 share the training data that goes into a product  
9 where the product you're selling, maybe the fact  
10 that it is so accurate because of the data set.

11 MS. BAILEY: Right.

12 MR. GRAY: Could you talk a little bit  
13 about kind of different perspectives on either  
14 sharing or just maybe keeping a little bit more  
15 closed, the data set you use to train?

16 MS. BAILEY: Right. So one of the  
17 things we're looking at, because we have  
18 different -- different business units have  
19 different needs. You know, I would say one of  
20 our products might need to be trained. And so we  
21 need access to data. But then on the flip side,  
22 depending on the business model where you are in

1 the ecosystem and the value chain, you might be  
2 looking at the fact that, well, you've collected  
3 a lot of data that someone else needs.

4 So we need to protect it and so  
5 there's kind of this internal, I will call it,  
6 rivalry between, oh, well, we put all this effort  
7 into getting this data. We, you know, this is  
8 something we want to license out on very  
9 reasonable terms, but we still want to license it  
10 out versus the other core AI team.

11 It's like, no, everything's open  
12 source and so open data. You know, this is this  
13 is -- we're not using it for its expressive  
14 value. We're using it for, you know, to create  
15 metadata so that you know that that's a baby and  
16 not a dog. Surely, you know, everybody should  
17 have access to the data.

18 So there is this kind of you've got to  
19 figure out where you are in the business model on  
20 what you advise your clients, on what you base  
21 your business units on. You know, what they  
22 should be billing and looking out for on the

1 legal front.

2 MR. GRAY: Okay.

3 MS. HANSEN: I was just, on the way  
4 here, I was at the airport and I overheard a  
5 conversation. It's not uncommon in the Bay Area  
6 that it's about tech. And I overheard someone  
7 saying, oh, yeah, well, we had this data set and  
8 it's for facial recognition.

9 It's really great because copyright  
10 doesn't apply to it at all. I mean, it just is  
11 like completely not what you're doing. And I  
12 thought, well, that's interesting because I'm  
13 going into a conference where a whole lot of  
14 smart people are talking all day long to try to  
15 figure out that answer.

16 So I think, you know, that's another  
17 area like the, what you're doing with the data  
18 set. I mean, there are so many different uses of  
19 this.

20 MS. BAILEY: And also, I guess it  
21 depends on closed versus open, right. So I think  
22 Adobe -- and I could be completely wrong. I'm not



1 speaking for Adobe. But I would say that they  
2 have -- they use a lot of sometimes closed data  
3 sets. So it's their own and maybe it's more  
4 reliable.

5 And the data in AI is only good as --  
6 well, I guess the AI is only as good as the data,  
7 right. So a lot of times we, I guess, in tech,  
8 can't get our own closed data set.

9 So, but if you've a closed data set,  
10 you could be more reliant upon the fact that  
11 maybe you own the copyright, hopefully -- that's  
12 what they're talking about -- versus need to get  
13 a copyright.

14  
15 And, but then again, I find that, I guess,  
16 when you've got these big autonomous driving,  
17 you've got these kind of mobile applications,  
18 it's hard to have your own data. It's almost  
19 impossible to have your own data. It's also  
20 impossible to get it from just one source.

21 So, again, to have reliable, less  
22 biased data you have to look from different

1 sources. And so with that comes, you know the  
2 issue of what are you going to do if there's one  
3 in the data set that is copyrighted and you don't  
4 know anything about it.

5 You never know, when you think about  
6 it, quite honestly. I mean, how do you know?

7 MR. GRAY: Great. Well, I know we're  
8 already running a little late on time, and so  
9 I've been told to wrap up. So I'd really like to  
10 thank you very much, Julie, Vanessa and all of  
11 you. Thank you so much for this conversation.  
12 This was very interesting.

13 MS. ROWLAND: Thank you so much. We  
14 are actually going to do our final panel of the  
15 day now. It's about digital avatars and AI, and  
16 it is going to be quite interesting.

17 So I think we're going to be switching  
18 out the panel here. So we are, we saved the best  
19 for last, I think. This is going to be a great  
20 panel that talks about all the interesting  
21 information that you can learn about using a  
22 digital avatar. God forbid that you yourself

1 are, you know, in some other movie right now that  
2 you don't even know about, but we're going to  
3 learn about it now.

4 So we have two really great experts  
5 here to talk about it. We have Sarah Howes who is  
6 with SAG AFTRA, who's going to be talking about  
7 that perspective. And we have Ian Slotin from  
8 NBCUniversal, and he's is going to be talking  
9 about the movie studio side of this.

10 And I want to start with Ian, who's  
11 going to kind of set the stage for us today.

12 MR. SLOTIN: Great. Thanks, Catie.  
13 And so what we're going to talk about today is,  
14 as Catie mentioned, is not content in general,  
15 but professionally produced film and television  
16 content.

17 And what I'm going to go through is  
18 some copyright considerations. I'll go through  
19 that very quickly because it's a lot of repeating  
20 what's already been said today and then move on  
21 to sort of the right of publicity issues, which  
22 folks talk about a lot.

1                   So in thinking through copyright  
2 issues on this, I thought I would take an example  
3 of something that's not professionally produced  
4 and not something you would think of as a popular  
5 film or television show. But it's just kind of an  
6 interesting use of the Internet of deep -- oh.  
7 Okay, there it is. So this is a meme that's on  
8 the Internet where users are using -- oh, and now  
9 it's gone. There it is.

10                   MS. ROWLAND: Oh, no. There it is.

11                   MR. SLOTIN: Okay, so anyway -- no?  
12 Oh, well, I'll just say what it is. Essentially,  
13 it is users taking Nicolas Cage's face and  
14 putting them into various films where he didn't  
15 actually appear: Lord of the Rings, Superman,  
16 Titanic and other things like that.

17                   And so if you want to think about  
18 copyright issues related to that -- let's see if  
19 it moves to the next slide -- one before. There  
20 we go. So in thinking about the copyright  
21 considerations here, I've grouped them into two  
22 categories. So it's on standard clearance

1 issues, which is essentially the same issues that  
2 apply for content that doesn't include an avatar  
3 like, you know, what elements are eligible for  
4 copyright, what parts are new, what parts are  
5 not.

6 And secondly, what other elements are  
7 appearing in the footage and do those need to be  
8 cleared. And then the novel issues are the  
9 authorship issue that's been discussed a lot  
10 today. And secondly, the use of training data to  
11 create the Nicolas Cage avatar.

12 So speaking quickly about the standard  
13 clearance issues, very quickly, because this is  
14 obvious to everyone in the room, the question of  
15 eligibility. You know what, you know, the  
16 likeness itself is obviously not something that  
17 can be copyrighted, neither can contextual  
18 footage if you know, if it's from somewhere else.

19 But perhaps the avatar's performance  
20 and poses, movements and dialogue, and maybe if  
21 there's a new plot, you know, those could be  
22 eligible for copyright. One note is that, you

1 know, in the example of Nicolas Cage, you know,  
2 that's pretty much a derivative work. So that's  
3 not going to work.

4 Moving to the novel considerations on  
5 authorship, I think for -- while it is true, of  
6 course, that not -- that works created purely by  
7 machines are not eligible for copyright in the  
8 United States. I don't think we have to worry  
9 too much about that for professionally produced  
10 film and television content, because we're a long  
11 way off from a situation where a studio like mine  
12 will put out a film or a television show that's  
13 entirely created by a machine. There's just too  
14 much, too many variables.

15 We're just, as I think it's been shown  
16 here, that there's just too many moving parts  
17 there right now. So the question is more around,  
18 you know what we're worried about are disputes  
19 that may arise as to who the author is, who the  
20 human is, who did the lion's share of the  
21 creativity.

22 It could be the designer of the AI

1 algorithm, as has been discussed earlier today;  
2 who -- the person who selected the training data  
3 or the operator, the one who iterates on the  
4 results.

5 And from our perspective as a movie  
6 studio, our primary concern is to make sure that  
7 there's some clarity around that so that we know  
8 as a producer who's right, you know, who we need  
9 to clear the rights from -- you know, who we need  
10 to obtain those rights from.

11 Moving next to the training data  
12 issue, but in a situation where, like in the  
13 Nicolas Cage example, presumably a lot of footage  
14 of Nicolas Cage from various points would need to  
15 have been used to train the AI system to do what  
16 was just done.

17 And so the question would be, you  
18 know, using preexisting footage like that, you  
19 know, is it a fair use or not? And without  
20 judging that particular example, you know, our  
21 main points on this is that we don't need a  
22 special new fair use rule in United States to

1 deal with this question.

2 The existing fair use factors were  
3 supposed to be technology neutral when they were  
4 enacted. And indeed, when courts have applied  
5 them to mass digitization applications, they have  
6 come up with nuanced results.

7 So, for example, in the Google Books  
8 case, that was determined to be a fair use,  
9 whereas in the TVEyes case, which was a similar  
10 situation, except that the application was  
11 different, that was determined not to be a fair  
12 use.

13 So moving now to rights of publicity,  
14 just as a quick reminder, the rights of publicity  
15 are state rights. They're not federal. And it  
16 has to do with using a name, likeness or identity  
17 for a commercial purpose. There's a mix as to  
18 which states recognized postmortem rights. It's  
19 not across the board.

20 And finally, when we're talking about  
21 film and television and expressive works, you  
22 know, there needs to be a First Amendment



1 accommodation there because they are expressive  
2 works.

3 So what are the key tests that have  
4 come up in sort of accommodating the First  
5 Amendment? One is strict scrutiny, right, which  
6 will say that not really all users are exempt  
7 because a right of publicity statute is a content  
8 based regulation of speech.

9 And so under the Supreme Court's  
10 rubric, that requires a compelling government  
11 interest and a narrowly tailored solution to that  
12 interest. And in many respects, you know, simply,  
13 you know, wanting to have a say over what is said  
14 about you in an expressive work that is not  
15 defamatory, you know, probably generally would  
16 not rise to the level of being, you know, being a  
17 compelling interest.

18 Transformative use, this is a test  
19 that was developed in California, essentially  
20 saying how -- what was the transformative nature  
21 of the work and the use. And finally, the  
22 Supreme Court had one case that's a key note that

1 I'll mention a little bit later.

2 So strict scrutiny, this was a case --  
3 this is a case involving The Hurt Locker. The  
4 Hurt Locker is about, the main character is a  
5 bomb disposal technician in Iraq. It was based on  
6 an interview that was given to a reporter by  
7 Jeffrey Sarver.

8 And Sarver sued, saying you based the  
9 movie on me. That's not okay. The 9th Circuit  
10 held that, you know, applied strict scrutiny,  
11 applied the Supreme Court case Reed v. Town of  
12 Gilbert, which had come out the year before, to  
13 say that essentially the California right of  
14 publicity statute is content based and is subject  
15 to strict scrutiny.

16 And by the way, for that reason,  
17 Sarver lost his case. And by the way, one of the  
18 points that they made was that Sarver wasn't even  
19 in the business of monetizing his persona. So  
20 there wasn't even a loss of income or anything  
21 like that in that situation.

22 Transformative use, just very quickly,

1 established in two key cases in the California  
2 Supreme Court, one relating to lithographs of the  
3 Three Stooges, the other relating to a very  
4 fanciful comic book.

5 And essentially, you know, one thing  
6 to note about the transformative use test is it  
7 still needs to sit within the rubric of the First  
8 Amendment. So it may very well be that a test  
9 that can be applied and makes sense in certain  
10 cases, but it must -- that must be because it's  
11 consistent with the First Amendment.

12 One way of thinking about that is the  
13 transformative use tests might actually be a way  
14 of distinguishing between expressive uses and  
15 merchandising uses, right. So the example of the  
16 lithograph below was a picture, but it was on, I  
17 mean, it was on T shirts and other things.

18 So the question is, you know, we're at  
19 sort of a line between merchandising and an  
20 expressive and since merchandising has a lower  
21 level of scrutiny, commercial speech does, you  
22 know, perhaps, you know, that this is a way of

1 differentiating those things.

2           And finally, there is the only Supreme  
3 Court case about right of publicity and it's a  
4 human cannonball case. And, essentially, what  
5 happened is the local news showed a 10 minute --  
6 10 second story, which was essentially the entire  
7 act, right.

8           It showed him shooting out of the  
9 cannon. And Zacchini said, hold on a second. No  
10 one's going to the fair and see me perform my  
11 human cannonball act because they've already seen  
12 it on the news. And the Supreme Court said, yeah,  
13 you know, you got a good point there.

14           By casting the entire act, this is a  
15 substantial threat to the economic value of the  
16 performance. So a couple of caveats about this  
17 case, it's a very old case. It pre dates more  
18 recent Supreme Court pronouncements on strict  
19 scrutiny, and strict scrutiny wasn't applied in  
20 this case.

21           Another point, you know, well, one of  
22 the key interpretations of this case, possible

1       interpretations of this case, is that while, you  
2       know, is that taking a person's performance that  
3       they have worked to establish that, you know,  
4       their livelihood, you know, there can be a right  
5       to publicity claim for that.

6                 So now moving to, you know, avatars  
7       and depictions of performers, there's -- this  
8       leads to sort of a distinction between depictions  
9       of performers as themselves and depictions of  
10      performers performing overall.

11                So in the first example of showing up  
12      as themselves, I gave a couple of examples, you  
13      know, where avatars weren't used, but actors were  
14      used, right. So the top one is Once Upon a Time  
15      in Hollywood. The actor, Mike Moh, played Bruce  
16      Lee as himself. You know, Bruce Lee shows up on  
17      the film set and fights with Brad Pitt.

18                And then the second one is the FX  
19      series, Feud: Bette and Joan, in which Susan  
20      Sarandon and Jessica Lange, you know, played  
21      Bette Davis and Joan Crawford in a series about,  
22      you know, power dynamics in Hollywood and how

1 women were treated in Hollywood.

2 So, at least from our perspective, it  
3 seems that these portrayals are all perfectly  
4 okay and that I think most people would agree  
5 that, you know, that the subjects of these works  
6 should not have the right to approve or not  
7 approve their depiction in these sorts of works  
8 that are not defamatory.

9 And the corollary to that is should --  
10 does the technology make a difference? So it's  
11 Mike Moh, looks a lot like Bruce Lee. You know,  
12 he worked really, really hard to have the same  
13 mannerisms, the same voice, everything else.

14 And in fact, you know, if you look at  
15 some other portrayals, you know, people remark  
16 about how well an actor, you know, inhabited a  
17 role. You know, what's the difference between  
18 that and using a, you know, an avatar of the  
19 person?

20 From a First Amendment perspective, it  
21 seems that there probably isn't a difference. And  
22 that should probably be a guiding principle in

1 terms of thinking through, you know, the  
2 permissibility of these things.

3 The second category, right, is  
4 performing a role, right. So this is a scenario  
5 where essentially, say, Universal says we're  
6 going to make Jurassic World, the next movie. We  
7 don't want to hire Chris Pratt to play the lead  
8 role. So we're going to use the -- starring the  
9 avatar of Chris Pratt, and we're not going to get  
10 his permission to do that.

11 That seems to fall under this Zacchini  
12 precedent, potentially saying, well, you'd be  
13 sort of essentially taking away this actor's  
14 livelihood, you know, that is something, you  
15 know, to be considered. The examples in here are  
16 actually both of deceased celebrities.

17 The first one is Paul Walker from Fast  
18 and Furious when he passed away during filming.  
19 The second one is Carrie Fisher in the recent  
20 Star Wars film. Our view would be that there's a  
21 difference between living and deceased  
22 individuals in the sense that, you know, once

1 you're deceased, you no longer have the ability  
2 to earn a living.

3           You know, that is no longer taken, and  
4 under a strict scrutiny analysis, you know, the -  
5 - an interest of an heir to protect the  
6 reputation of their -- of the person when the  
7 actual defamation doesn't even apply after a  
8 person has passed away, you know, or the right to  
9 collect the money for it is not sufficient for  
10 that.

11           So a couple of other points on this.  
12 If there's going to be a consent required to use  
13 an avatar to perform a role, that doesn't sound  
14 like a right of publicity right. Because right  
15 of publicity relates to uses in commercial  
16 speech. And these are not commercial speech.

17           So if there's going to be a right like  
18 this, it's probably a, say, sui generis right.  
19 The second point is that any right like this  
20 needs to be appropriately tailored to exempt the  
21 kinds of performances that we think are okay when  
22 we use living actors.



1           So, for example, a biopic of an actor  
2           is probably going to have scenes in which that  
3           actor is performing a role as part of the biopic  
4           of the actor. Clearly, that's okay too. So. So  
5           just it's a very nuanced area.

6           And then the third point is that it  
7           probably makes sense to consider the concept of  
8           deception and fraud and passing off in this  
9           context, because thinking through the difference  
10          between having, hiring an actor to look exactly  
11          like someone and using an avatar, the difference  
12          may be that the second case is so realistic that  
13          people could actually think that someone  
14          performed when they didn't, that someone said  
15          something when they actually didn't say it, those  
16          sorts of things.

17          And if someone is taking active steps  
18          to profit from that, to deceive the public into  
19          thinking that someone, you know, endorsed  
20          something when they actually did not or were  
21          involved in the project when they were not, you  
22          know, that may be a framework to think through

1 some of these issues.

2 And finally, just a note, you know,  
3 the distinction I mentioned about performers as  
4 themselves versus performing a role, it doesn't  
5 really work for other kinds of public figures.  
6 So, you know, musicians, athletes, political  
7 figures, you know, it can't be the case that, you  
8 know, musicians are known for singing or playing  
9 instruments.

10 But in a biopic of Freddie Mercury,  
11 you can clearly show Freddie Mercury performing  
12 music. In, you know, or showing Jackie Robinson,  
13 you know, playing baseball or showing Dick  
14 Cheney, you know, doing his usual Dick Cheney  
15 stuff. So that's pretty much everything I have.

16 MS. ROWLAND: Great. Thank you, Ian.  
17 And now we're going to turn to Sarah, who has  
18 maybe a little bit of a different perspective on  
19 the issue, from SAG/AFTRA.

20 MS. HOWES: Yeah, definitely. I mean,  
21 I would say that, like, it's important to note  
22 that, you know, Ian and I have more in common

1 than we disagree. I do respect his work on the  
2 First Amendment, to a large degree. We do have  
3 some significant differences that always get nice  
4 headlines. But, anyway, so I'm going to start  
5 off.

6 And I'm going to talk a little bit  
7 more about this from a production standpoint, to  
8 be completely honest, just because part of this  
9 is, a lot of you are lawyers. And part of this is  
10 an opportunity to think about this from a  
11 perspective of sort of guidance on what the union  
12 kind of expects.

13 I'll spend a little bit of time kind  
14 of responding to some of the things Ian said  
15 about the law and things like First Amendment.  
16 But I really do want to focus on what is the  
17 technology, what are the advancements in the  
18 technology, you know, what are the union rules --  
19 a little bit about how we see the laws.

20 And then I'm going to go into a pretty  
21 serious topic, which is how I spend about a third  
22 of my time now, which is, you know, Me Too

1 related issues in the industry.

2           Okay, great. So this is taking about  
3 just generally some of the concerns we have about  
4 the uses of digital images and sort of how it  
5 runs into some of the things that Ian was talking  
6 about.

7           We have just the traditional, I'm sure  
8 everyone's familiar with the sports cases of  
9 using an athlete and a video game. I'll talk a  
10 little bit about using a musician in a video  
11 game.

12           We have the realistic -- what Ian was  
13 talking about in terms of, you know, bringing an  
14 actor to play a role with digital technology  
15 used. And you're talking about that in films.  
16 You're talking about that and TV shows, video  
17 games to give a realistic acting performance.

18           The next one is holographic live  
19 performances of musicians or actors. And this is  
20 happening right now. In fact, unfortunately, the  
21 leading hologram creator is also the person who  
22 created FilmOn. And also, he doesn't like

1 copyrights very much and then also just got the  
2 largest sexual harassment judgment against him.  
3 So I'm very happy that he is the leading person  
4 on holographic concert technologies.

5 The last piece is just voice cloning.  
6 That's something that has been interesting from  
7 the work that I've been doing for the last four  
8 years is just how advanced this technology is  
9 getting and all the different ways that you can  
10 use it and how that impacts people like voice  
11 performers.

12 Great. So we're going to talk a  
13 little bit about just -- I want to have a little  
14 bit about sort of the old school way of doing  
15 some type of false depiction. So there's --  
16 there was a film, Nymphomaniac. It was made  
17 overseas or it wasn't under one of our contracts.  
18 And the way that they revealed to depict Shia  
19 LeBeouf's character as engaging in simulated sex  
20 was they actually hired porn stars to come in and  
21 have real sex, right?

22 And then what they did was they didn't

1 actually use any type of CGI. They just actually  
2 edited it in such a creative way that it looked  
3 like it was him being depicted in these acts.

4 This is an important note. As I said  
5 right now, all of you are representing film  
6 companies, and just so you know, it doesn't  
7 matter if someone's a porn star or not. There is  
8 no actual sex in any union covered work, a body  
9 double as a principal performer.

10 And it is obviously for lots of  
11 reasons, very, very risky to have any performer  
12 performing actual sex. I'll talk a little bit  
13 about that later.

14 Okay, so then the next kind of, you  
15 know, more advanced form of doubling is where you  
16 want to actually see the person's face on to the  
17 body.

18 And so Natalie Portman -- this is a  
19 little bit scandalous because they didn't  
20 disclose that it was a body double at first and  
21 then it came out after she won an Oscar, but they  
22 hired -- so they hired a dancer to be the body

1 double in this film.

2 And she performed the scenes and then  
3 Natalie Portman performed the scenes. And, of  
4 course, the professional dancer did a little bit  
5 of a better job. So what they did was they put  
6 this mask on her and then they used CGI and, you  
7 know, some basic advanced tracking technologies.  
8 And this can be done with the software, After  
9 Effects, which is a pretty affordable consumer  
10 product. And then they just did CGI blending and  
11 adjustments.

12 Peter Cushing, this is where he gets  
13 a little bit interesting because this is really  
14 one of the biggest examples of what I call just  
15 like digital human technology, where you were  
16 able to create, even though you could, you know,  
17 if you looked close enough, you could tell that  
18 it was digitally done.

19 But I know people that literally were  
20 like, wow, he looks great for his age, right.  
21 They went to the film. They were duped. And this  
22 process was really using a lot of different types

1 of advanced motion picture sciences and special  
2 effects.

3 It was starting with, as you guys have  
4 seen through the last decade, right, performance  
5 capture Guy Henry, who was a very well respected  
6 British actor, decided to take on this role,  
7 which is good for him. Also, he got paid a lot  
8 because he wasn't really depicted as it. And he  
9 came in and they were able to do the basically  
10 mapping and sort of CGI with his face. They were  
11 able to capture all of his movements. And then  
12 the way that they made it look like Peter Cushing  
13 is that they couldn't just use it from images and  
14 old footage of Peter Cushing.

15 They were sort of lacking the ability  
16 to really get his bone structure and his actual  
17 face mapping. So they were able to track down,  
18 because Peter Cushing was known for being in a  
19 bunch of like British horror movies, and so they  
20 were able to track down this old face mold that  
21 they had.

22 And so they were taking -- because



1 when you're taking somebody from an older era  
2 before the digital era, you don't have things  
3 like which I'm about to show you, like on set  
4 scanning, right.

5           So, nowadays, particularly if you're  
6 doing any type of large budget or action  
7 adventure movie, part of a condition of your  
8 employment from being a background performer to  
9 being the leading star is to do various types of  
10 3 D, 360 degree scanning so that people have data  
11 basically of your entire body.

12           There are a number of my members who  
13 do not like this. They find it very intrusive.  
14 The public people who have talked to the press  
15 and media about it are Donald Glover was very  
16 upset about this. He did not like engaging in  
17 this. He had some concerns about the cultural  
18 and misappropriation, potential abuses of his  
19 body being scanned. And then also Jessica  
20 Chastain did not like being scanned in this way.  
21 They found it intrusive.

22           But this is becoming commonplace.

1 It's a condition of employment, including for  
2 background actors.

3 Okay, so then this is where we get to  
4 artificial intelligence, right. So all of those  
5 processes that I was talking to you about were  
6 very expensive and they were very time consuming.  
7 The Peter Cushing example took 18 months and  
8 millions of dollars, right.

9 And then in January 2017, an article  
10 dropped about artificial intelligence, deep  
11 fakes. Okay, so I'm going to show two examples.  
12 I'm not going to show the whole thing, just  
13 enough for you guys to see it.

14 So the first one is a fantastic  
15 professional impersonator. And then the ability  
16 to sort of take his impersonations -- yep, that's  
17 right, and then use deepfakes to have him  
18 depicted as the person.

19 (Video played.)

20 MS. HOWES: Okay.

21 (Video played.)

22 MS. HOWES: Okay, So for purposes of

1 time, we'll move on to the next one. It's great  
2 video, though. You can watch it. So the next  
3 one is -- was really scary, to be honest, for  
4 actors, when they saw this.

5 So this is putting Harrison Ford into  
6 the Solar movie.

7 (Video played.)

8 MS. HOWES: All right, so we can have  
9 that example. Oh, it's almost done anyway, just  
10 going to stop it.

11 So when that video came out, let's  
12 just say I got a lot of responses from the  
13 members and even directors started seeing it.  
14 And, you know, because to be honest, that was  
15 pretty much production ready, right. That's what  
16 was sort of scary about it.

17 And let's see here in the next slide.  
18 Okay, so then this is the part where I wanted to  
19 talk a little bit about voice cloning, because I  
20 actually think voice cloning has a lot more  
21 potential harms. And I honestly think it's going  
22 to impact your average middle class performer a

1 lot more, because if someone's going to take an  
2 image, right, there has to be a pretty valuable  
3 amount of money to that image for it to be worth  
4 taking.

5           Voices -- how many people in here, you  
6 know, can name the actor who played Little  
7 Mermaid or the actor that you hear at Walmart,  
8 right?

9           Those people make their living as  
10 voice performers, podcasters, videogame  
11 performers. And they're not the people you see on  
12 the red carpet. So Adobe Voco, this is one form  
13 of technology.

14           So what's interesting about the voice  
15 crowning and the new voice technologies is  
16 actually, you know, synthesizing and re editing  
17 that's been around for a long time. What they're  
18 saying is new is the ability to insert a new  
19 word. So have somebody say a word that they've  
20 never said and you think it's that person saying  
21 it.

22           So there's different ways to go about

1 doing this. So Adobe Voco, basically what it  
2 does is it takes a recording of someone's voice  
3 and it breaks it out into these tiny little bits  
4 of 80 different types of sounds that are common  
5 in the English language and it quickly rearranges  
6 them to have you say a word.

7           So Jordan Peele did a great  
8 presentation of this where he came in and he said  
9 something like, I love to kiss my wife when I  
10 come in the door and they he changed it to I love  
11 to kiss my dog when I come in the door, right, so  
12 they were able to insert the word dog.

13           So then the second one, with a link,  
14 this is a company that kind of started, which  
15 I'll have you click on, a couple years ago.  
16 They're using artificial intelligence to do voice  
17 cloning.

18           So I'll have you go to the bottom.  
19 And I'm going to explain a little bit about how  
20 this is done. So I did this, and I am not a  
21 professional actor, and it sounded a little bit  
22 robotic, right?

1                   And then we got, you know, people like  
2                   Richard Masser and Harry Shearer, people who are  
3                   top voice actors to do it and it sounded like it  
4                   was them. So what they do is it's literally a  
5                   minute of capture where they say a bunch of  
6                   random phrases. And then within a minute you have  
7                   a voice clone, and then you can just literally  
8                   type in sentences.

9                   So they're -- an example, if you click  
10                  on the little blue on the left, that's a person's  
11                  real voice.

12                  Oh, I'm sorry. Go to the Mozilla  
13                  Firefox at the bottom, like the other app. I have  
14                  it uploaded on there. There we go. Doesn't work  
15                  on --

16                  (Video played.)

17                  MS. HOWES: So then go to the next  
18                  one.

19                  (Video played.)

20                  MS. HOWES: So that was done with one  
21                  minute of audio. Yeah, okay, so then I want to go  
22                  back to the PowerPoint. Okay.

1           So there are union rules around some  
2 of this stuff. So I just want to spend a little  
3 bit of time talking about, because especially  
4 since a lot of people here have been talking  
5 about what your source material is, what your  
6 underlying licensing material is, is that if  
7 you're a production and you license out or you  
8 yourself use any type of existing footage that  
9 was made under our contracts, you actually have  
10 to go back.

11           And that new time of use that's  
12 important that you're going to use this footage  
13 again, you have to get permission. And if you  
14 don't get permission, there's going to be  
15 contractual damages from the performer.

16           It's really important to say that it's  
17 the time of use. You can't just have a contract  
18 that waives all re use for the future. You  
19 literally have to come back and say, oh, I want  
20 to use this scene from the latest Disney movie. I  
21 want to use it in the next sequel. You have to  
22 get re use permission.

1           And then there's the other aspect to  
2 this that has to do with copyright enforcement.  
3 So, for instance, if somebody uses your clip and  
4 they didn't get permission, the producer has to  
5 show us, they usually write me a letter that  
6 says, you know, here's the fair use reasons that  
7 the other side is going have.

8           This is really important under like  
9 the Lenz decision where you have to sort of show  
10 that you thought about fair use before you start  
11 enforcing things. And then if they don't have a  
12 good fair use argument for the person who did it  
13 without authorization, that the producer has to  
14 enforce their rights as a copyright owner.

15           In this last year, in 2019, we  
16 actually entered into our first ever Netflix  
17 agreement. So not only are they bound by our  
18 larger TV theatrical agreement, they also came to  
19 the table and we negotiated a special agreement.  
20 And inside of that -- people don't really know  
21 this, but background actors are covered by SAG  
22 AFTRA, but they're only covered a certain amount.



1 And they have to, like let's say you're in L.A.,  
2 you have to have, I think it's like 35 background  
3 performers who are covered union performers.

4 And the rule basically says that you  
5 can't use like digital doubling of background  
6 actors, which is pretty common in like fight  
7 scenes and stuff like that, as part of that  
8 count.

9 Oh, there's -- sorry, there's one more  
10 rule that is actually just the rights of the  
11 depicted person, which is, as you can imagine,  
12 where I see this voice cloning really being used  
13 in the future is going to be dubbing.

14 All over the world, movies are dubbed  
15 for those markets. As you could imagine, it's  
16 going to be a huge market incentive for like,  
17 let's say, you know, what's the last movie you  
18 think, one of the last movies you made?

19 MR. SLOTIN: Us?

20 MS. HOWES: Yes.

21 MR. SLOTIN: 1917.

22 MS. HOWES: 1917, right, so it's in

1 English, I would imagine. Yes. So you probably  
2 want to have it be in Chinese or whatever it is.  
3 And this technology is going to allow you to have  
4 -- what's one of the actors in 1917?

5 MR. SLOTIN: That I don't know.

6 MS. HOWES: Oh. To be fair, I should  
7 have known that. Okay, so you want to have him,  
8 with his voice and his resonance and his kind of  
9 performance, have him doing it in Chinese or  
10 Japanese because obviously foreign markets, I  
11 believe they're important to you, right? Yes.

12 Okay.

13 And so, you know, this is going to be  
14 really kind of harmful to the dubbing community,  
15 right, because they make a lot of money doing  
16 this. But then on top of that, we'd have in our  
17 contract, if somebody -- say that you're Antonio  
18 Banderas and you speak Spanish, you have a first  
19 right to do the dubbing yourself. And that's in  
20 the contract.

21 So the reason they -- you're thinking,  
22 oh, there are some union rules, you know. So

1 can't you handle all of these digital replica  
2 issues through union contracts, it's really  
3 important to talk about sort of why that's a  
4 problematic way of thinking about it.

5           Sometimes people are like, well, can't  
6 this just be handled by union contracts? So the  
7 way that -- and I'll try to be quick here -- I  
8 apologize -- the way that this works is that we  
9 are the exclusive bargaining partner for actors  
10 performing in audio visual works.

11           That does not mean that every audio  
12 visual work is union covered, right. The reason  
13 that we're able to hook NBC and all these other  
14 companies to doing union projects and coming to  
15 the table is I imagine you want to hire our stars  
16 and our members, right.

17           So in order to hire, they are bound,  
18 the stars and the actors are all bound to Global  
19 Rule One, which means they cannot do any type of  
20 cover jurisdiction or they're violating their  
21 role as a member.

22           And then on top of that, like I said,

1 we are exclusive bargaining agent for performing  
2 and labor. We're a labor union, right. So if  
3 someone is doing licensing of athletes and video  
4 games, that's an image licensing deal, right?  
5 That's not a labor issue.

6 And so that's the reason that it's  
7 really important to have external rules. Okay,  
8 great. So right of publicity here, we went into  
9 that and I'm running out of time. I didn't make a  
10 couple of notes just to respond to a couple of  
11 differences that we have.

12 You know, the way that read the Sarver  
13 decision about California is that I, a hundred  
14 percent, agree that biopics should be exempted in  
15 statute and I, a hundred percent, believe that if  
16 you were doing a biopic and having somebody  
17 depicted in their real life, that that should be  
18 bound by strict scrutiny.

19 I read the Sarver decision, and I'm  
20 not -- we're going to go back and forth on this.  
21 I just encourage you all to read it, which would  
22 be a great thing. I read it is that California

1 law still has the transformative test for that,  
2 for the right of publicity, generally.

3 And in the case itself, it actually  
4 goes through this long laundry list of like we're  
5 not talking about greeting cards or  
6 advertisements or merchandise or performance  
7 theft, is one of the examples that they use that  
8 in the traditional right of publicity framework.

9 And then it says we're talking about  
10 a biopic and right of publicity doesn't apply to  
11 biopics. And if it did apply to biopics, they  
12 would have to survive the strict scrutiny, which  
13 I think is a very big distinction. Yes. But  
14 there are states that have strict scrutiny as the  
15 standard, notably Florida and Nevada.

16 Okay, so, Gwen Stefani, this was a  
17 case out of California Court of Appeals. Oh,  
18 okay, and so this is a case that talked about  
19 basically like inside of the right of publicity,  
20 while citing Zacchini, said that basically a  
21 person, performance theft, if you are taking  
22 someone, a literal re creation of somebody doing

1 the activity for which they're known, that that  
2 is a right of publicity violation unless you have  
3 some sort of -- you've transformed it under the  
4 transformative test to the point that it's not  
5 just like stealing the economic value of that  
6 digital recreation.

7 Let's see here. So this is an example  
8 of something that was disputed but it never  
9 resulted in a lawsuit, and they ended up just  
10 changing it, but an example of how this can  
11 happen.

12 So, Ellen Page is one of our members  
13 and she was doing a video game and promoting it  
14 where she did her performance capture and all  
15 these different work. It was a covered contract  
16 for the video game called Beyond Two Souls. And  
17 right before Beyond Two Souls was supposed to  
18 release, The Last of Us came out. And a whole  
19 bunch of people were like, wow. Ellen Page is in  
20 The Last of Us. She was not. So the actor that  
21 was hired is Ashley Johnson, who I depict on the  
22 left. As you can tell, they look nothing alike,

1 as is being depicted in that little bucket that  
2 says The Last of Us original.

3 So Ellen Page, on a Reddit thread,  
4 someone said, oh, man, isn't it an honor to be  
5 depicted in this video game? And she did not  
6 think that was an honor. She thought she was  
7 being ripped off and she didn't appreciate it  
8 because she had another game coming out and she -  
9 - that was a lot of money to have -- she was  
10 basically competing with the digital version of  
11 herself.

12 Settlements were made or whatever.  
13 All of a sudden, it was adjusted a little bit.  
14 But if you were on the video game review, YouTube  
15 channels or whatever, people playing video games,  
16 the joke is that it's Juno.

17 Okay, so now I'm going to talk a  
18 little bit about a more, a very serious issue  
19 that's come up. And so everyone's probably heard  
20 of deepfake pornography. We were just talking  
21 about in the space of creating like, you know,  
22 Nicolas Cage memes and sort of putting, you know,

1 people into Hans Solo movies.

2 This is much more serious, right?

3 It's not a laughing matter. This is a form of  
4 image based sexual abuse. There's been multiple  
5 studies being done. It's actually almost  
6 impossible to find one of these deepfake porn  
7 videos, which is using still images to put people  
8 into very graphic pornography, as performing  
9 those pornographic works.

10 99 percent of this has been of women,  
11 so it's very gendered. And, you know, from our  
12 members' perspective, this is both a form of  
13 basically revenge porn and sexual abuse. It's  
14 very traumatizing. They are not happy about it.  
15 There are entire websites dedicated to fake porn  
16 that have a thousand profiles of our members of  
17 different members. It's being monetized on the  
18 Internet.

19 So my members view it as both a form  
20 of sexual abuse and a gigantic form of commercial  
21 exploitation. To give you an idea of how much  
22 money the porn industry makes, the worldwide



1 revenue of porn is \$96 billion dollars a year.  
2 To put that in perspective, and the people from  
3 ESA can correct me, but the worldwide video game  
4 market is \$81 billion dollars a year.

5 And as you could imagine, in the same  
6 way that people want to go out and see Scarlett  
7 Johansson's movies because they're a fan, people  
8 are going out to watch Scarlett Johansson porn  
9 because they're a fan. And so this is massive  
10 exploitation. It is very much predicted that  
11 these sections of these websites are going to be  
12 the most popular for these companies. And these  
13 are major websites that are hosting deepfake  
14 porn. And some of them are advertising it. But  
15 they're careful not to actually use the people's  
16 names or their images so that they don't have any  
17 liability under Section 230 of the Communications  
18 Decency Act.

19 Okay, finally, I'm going to end on an  
20 even less wonderful topic, which is the reason  
21 that SAG AFTA is also so committed to having laws  
22 about the digital manipulation for sexual content

1 is because we are in the process of really deep  
2 diving into what is a systemic, horrible practice  
3 in the industry of nudity violations in this  
4 industry.

5 So these are allegations. Like  
6 everything in Me Too, unfortunately, as everyone  
7 knows in this room, there aren't a lot of  
8 prosecutions and there aren't a lot of instances  
9 of liability or judgments or people bringing  
10 cases because of things like blacklisting and  
11 silencing and just fear of people coming forward  
12 with their stories.

13 So these two women came forward with  
14 their stories. These are allegations. We have --  
15 I cannot say it happened, but if it happened,  
16 it's pretty horrific. Emilia Clarke was on HBO,  
17 HBO's Game of Thrones, and she talked about how  
18 she was basically pressured her entire time to  
19 perform in the nude and to engage in sex acts.  
20 And Ruth Wilson recently came out that the reason  
21 she left The Affair was because of how much  
22 pressure she got to do those scenes and how some

1 of them would be like, oh, you're going to do  
2 like a basic sex scene and it would turn into  
3 like basically a form of rape.

4 So this is why, you know, doubling  
5 falls into this and why deepfakes is very scary  
6 to us. So just to give you an idea of how sort of  
7 doubling violations happen, you're sitting there  
8 and you're trying to pressure the actor to do  
9 this nude scene or the sex scene, and they just  
10 say no.

11 So we got this one call from this  
12 woman. It was actually a pretty large production.  
13 And she was like, can you guys just like, tell  
14 them to stop bugging me? I don't want to do a  
15 nude scene. And then a few months goes by and  
16 all of a sudden, oh, my God, they're using a body  
17 double. Please help me stop them, right?

18 The response is actually pretty  
19 similar to when you ask people who are making  
20 deepfake porn. Hey, why did you do this? Why did  
21 you use a body double to depict this person  
22 naked? And they say, well, it's not her real

1 body. I don't get what the big deal is.

2           These are very, very harmful. If you  
3 a performer who decides to do a nude scene or a  
4 sex scene, it's going to be harder for you to do  
5 commercials. It's going to be harder for you to  
6 get roles in kids' movies. It's going to live  
7 with you for the rest of the life, your life.  
8 It's going to show up on Mr. Skin, porn websites,  
9 things like that.

10           So when it comes to deepfakes, as you  
11 could imagine, we're not very happy about this  
12 technology, being able to give independent film  
13 producers work, which is a lot of where this  
14 abuse happens, a really cheap tool to just  
15 exploit a bunch of performers. And so that's why  
16 we worked very, very hard. California now has a  
17 new law, 1708.86, which gives victims of any type  
18 of either deepfake porn or manipulated content of  
19 manipulated performances, a civil cause of  
20 action.

21           When it comes to copyright, because  
22 we're here at a copyright forum, I do want to

1 point out that I consider this to be probably the  
2 best example of a moral rights violation of a  
3 performance. If you were to manipulate it into  
4 being sexual, the right of integrity under the  
5 Berne Convention is making something that causes  
6 massive reputational harm. And I feel that this  
7 law falls into that compliance with the U.S.

8 And then that's it.

9 MS. ROWLAND: Thank you, Sarah. We  
10 are running quite late. No, no, it was great.  
11 It was very interesting. I think that instead of  
12 me asking questions, because we are running late,  
13 I would like to give the opportunity for anyone  
14 out there to ask a question.

15 So before we wrap up, does -- oh,  
16 look, Ben. Hello, Ben.

17 PARTICIPANT: I just wanted to add,  
18 like movies, video games are expressive works and  
19 will be protected by the First Amendment. If you  
20 want to know more about our views on the right of  
21 publicity and digital avatars, feel free to come  
22 to my video game law class at Georgetown next

1 MS. ROWLAND: No, no. Anybody else?  
2 Okay, well, with that, thank you guys so much.  
3 That was really educational and great.

4 And I think we are supposed to -- we  
5 are just going to wrap this up, so we're not  
6 going to give any closing remarks except to say  
7 thank you all so much for being here.

8 Thank you to WIPO for partnering with  
9 us on this. And we will continue to work with  
10 them and keep you up to date about what's going  
11 on. If you don't subscribe to our NewsNet, you  
12 should because then you'll learn about all of  
13 these events in the future. And with that, I  
14 hope you have a great evening. Thank you for  
15 coming.

16 (Whereupon, the above entitled matter  
17 went off the record at 5:01 p.m.)  
18  
19  
20  
21  
22

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