Podcast: Watching shoes untie, Cassini’s last dive through the breath of a cryovolcano, and how human bias influences machine learning

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[music]
00:06 Sarah Crespi: Welcome to the Science podcast for April 14, 2017. I'm Sarah Crespi. In this week's show Aylin Caliskan joins us to talk about implicit bias in artificial intelligence. Does machine learning teach human prejudice to computers? And David Grimm is here to give us this week's hits from our online news site.

00:30 SC: Now we have David Grimm, editor for our daily news site. He's here to talk about some recent online stories. First stop, we have a story about record-setting seed dispersal. Plant seeds are known to go along for the ride, on air, water, on or inside of animals. Dave, why do seeds do this? What's the point in getting far away from their point of origin?

00:55 David Grimm: For one reason, they don't wanna have to compete with their parents. If you go sort of far afield you might have the land all to yourself. But also it's really beneficial for seeds to get eaten by animals, somewhat counter-intuitively, because when they get excreted they get deposited with a lot of nutrients. And actually, some of the dung that they end up in can actually be protective; elephant dung, for example, somehow protects seeds from predation by beetles.

01:21 SC: Okay, this is a little bit of a hint about the record I mentioned up top. This is for furthest seed dispersal on the African savanna. What animal won the prize and how far do they go?

01:33 DG: Well, it's furthest seed dispersal on the African savanna by a land mammal.

01:37 SC: Oh, boy.

01:38 DG: It's actually just furthest seed dispersal by a land animal and the winner is the African elephant, more specifically the Savanna elephant, not the Forest elephant, who according to the study, can transport seeds up to 65 kilometers. That's 30 times farther than savanna birds, and birds can fly, [chuckle] take seeds.

02:00 SC: Okay, I am really surprised about the bird thing. But let's talk about how they track seeds traveling inside of an elephant. Go.

02:08 DG: Okay. [chuckle] Well, it wasn't pleasant, as you might imagine. Researchers actually fed elephants at a sanctuary fruit and fruit from the honey dew melons, actually they fed them honey dew melons, because their seeds are smaller and softer than other types of seeds, so they're easier to track, but that didn't mean the researchers didn't have to go through a whole lot of elephant dung to find those seeds. And really what they were after was to figure out how long it took for the elephants to poop out the seeds.

02:40 SC: What were the short and the long runs through the elephant?

02:45 DG: Well, most of the seeds made it through the elephants in about 33 hours, but some of them stayed in the animals for as long as 96 hours.

02:53 SC: Is that how they got the distance calculation?

02:55 DG: Right, well, when you combine this timeframe with the average distance that these elephants roam, you can come up with... Well, some seeds might travel 2.5 kilometers, some might travel 20 kilometers. In extreme cases, a seed could travel up to 65 kilometers, such as when a male elephant takes long treks searching for a mate.

03:19 SC: Okay, is it the important thing that elephants are doing this or how far seeds can go? What's the big picture story here?

03:27 DG: Well, one thing it reveals is that elephants are really contributing a lot more to the savanna ecosystem than we thought, because if all these seeds were being deposited locally, you'd have local diversity, but by transferring these seeds such long distances, they're actually contributing to biodiversity along a much larger range than scientists initially thought. And that's sort of good news, but it also adds an extra note of caution when we're thinking about conserving elephants, because elephants aren't just important because we like elephants, but elephants are also very important to their ecosystem and this study just shows how important they are.
04:02 SC: Yeah, and that they need to range in order to perform their ecosystem functions.

04:06 DG: That's right.

04:07 SC: Now we have story on the last hurrah of the Cassini mission, or should I say hurrahs. Cassini was sent off to investigate Saturn a long time ago, and this September its time is up. The craft will plunge into Saturn, throwing a few more data points back our way before it vaporizes in the atmosphere. But a few exciting things are gonna happen before then. Let's talk about Enceladus first. This is a watery moon that is circling Saturn pretty far out and it has thick icy crust, a salty ocean and we think a hot core. What did Cassini find out about this moon?

04:48 DG: So, 12 years ago Cassini discovered this jet of water erupting into space from these tiger stripes that are along Enceladus' south pole, and that was some of the first evidence of the salty ocean. Now, when Cassini flew through these plumes, it found a host of life-associated molecules, including water, of course, but also carbon dioxide, methane and nitrogen. And in this latest mission, the team wanted to see whether there was any hydrogen gas. And the reason they were interested in hydrogen is because if there is hydrogen it must have been produced by hydrothermal activity, much like the hydrothermal activity that occurs in deep vents in Earth's ocean that have long been tied to microbial life.

05:32 SC: Just to give away the ending here, it did find molecular hydrogen. It was kind of a challenge because it's pretty easy to get contaminated with hydrogen and this is the last pass through the plumes. So what does it mean that Enceladus has molecular hydrogen when it comes to the chances for life there, underneath the ocean?

05:52 DG: Well, it could be a good thing, because if there's a lot of hydrogen and there are microbes around that are eating it, then they've got a lot of stuff to eat. But if there is a lot of hydrogen, it also could mean there's nothing eating it. [laughter]

06:06 DG: [06:06]_. You wouldn't have as much hydrogen, so it's not clear cut at this point.

06:11 SC: Okay, so now Cassini is moving on from Enceladus. What is its final mission?

06:17 DG: Well, its final mission is a bit of a sad one. First, what it's gonna do is, which is kinda cool, is it's gonna dive in and out of Saturn's rings, and try to give us a bit more info on how old the material in those rings are, which has been a long unsettled question in astronomy. After that, it's going to basically crash into Saturn. It's going to burn up in Saturn's atmosphere, along the way giving us maybe some more information about Saturn, but also preventing it from contaminating some of these moons, not just Enceladus, but also Europa, both of whom are really big targets for finding life elsewhere in the solar system.

06:55 SC: Next up, we have a story on why our shoes come untied. You're walking along, minding your own business, laces comfortably knotted and lightly flapping against the top of your shoes. Things are feeling different. Little looser, and bang. Next thing you know, your shoe is untied. What happened, Dave? Is it just like, I'm not doing this right?

07:18 DG: [chuckle] Could be. There's a couple of knots, ones called the granny knot, which is the knot that most of us are familiar with. There's also something called the square knot, which is kinda like the granny knot, but its loops tend to be parallel to the shoe, rather than perpendicular to the shoe.

07:34 SC: So it doesn't look good?

07:35 DG: It doesn't look good, but apparently, it's a much stronger knot. Anyway, so it could be that you tied the granny knot, but the bigger question of why these knots come untied in the first place has actually flummoxed scientists for as long as we've had knots. Either that, or nobody's just bothered to try to answer the question before.

07:51 SC: And finally, someone took a look by capturing high speed video of a person walking with shoes on.

07:57 DG: Right.
07:57 SC: What did they see when they played back the footage?

08:00 DG: Well, they discovered that shoe laces come undone in about two stages, not about two stages, actually two stages. One is a gradual loosening with each step, and then there's a sudden, wait for it, catastrophic failure of the shoe laces.

08:16 SC: I don't think this is answered in the story, but how many hours of walking did the person have to do in order to get their shoe to come untied?

08:23 DG: I'm going to guess many, many hours.

08:25 SC: It's hard to tell from the footage.

08:26 DG: That's right.

08:27 SC: One of the other things they looked into was this difference between the granny knot and the square knot. Was one notably different than the other?

08:36 DG: Yeah, actually, the granny knot, the knot that most of us tie, failed almost all the time, whereas the square knot only failed about half of the time, and the other interesting thing the team found was that walking was really key, so if the volunteers just sorta stomped up and down with their feet, the knots didn't really come undone. It was the walking motion itself that seemed to have undone... Seemed to have undid... Undone. That seemed to have made the knots fail.

09:03 SC: So it's swinging and stomping on the ground that unties your shoes? Is this one of those findings where it seems really simple, but of course, there's big complicated outcomes to understanding this?

09:16 DG: Well, there's some interesting physics involved. In another experiment, the researchers actually took the human out of the equation, and they designed a mechanical pendulum, it smacked a plate, it was supposed to replicate the human foot hitting the ground, and they added these sort of accelerometers, and they could try to figure out how much force was being acted on. They actually found that the G force the knot experienced as it bobbed up and down was more than any rollercoaster can generate, so actually there's a lot of interesting physics going on here, but more importantly, this isn't just about shoelaces. This is, we tie knots for things like boats, for mountaineering, even DNA ties itself in knots, which is actually kind of important for testing new drugs, and so this work has implications beyond your tennis shoes.

10:03 SC: Okay. What else is on the site this week, Dave?

10:06 DG: Well, Sarah, we've got a story about whether there are differences in the male and female brain, significant differences, and it turns out there may be. Also a story about glowing bacteria that might help us detect land mines. For our ScienceInsider, our policy blog, we are ramping up our coverage of the March for Science, which is occurring not just in Washington DC, but around the US, and around the world on April 22nd. We've got some stories up about the organizers of the march, what they hope to accomplish, and also some stories coming up in the lead-up to the march, including stories about the number of people that might show up at these marches, and also stories about scientists just becoming more involved in the political process. So be sure to check out all of these stories on the site.

10:50 SC: Thanks, Dave.

10:51 DG: Thanks, Sarah.

10:52 SC: David Grimm is the editor for Online Daily news site. You can check out the latest news and the policy blog, ScienceInsider, at news.sciencemag.org.

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11:06 SC: And just a reminder that we are getting free transcripts from scribie.com this week, so be sure to check out the Science site, check out the transcripts, let us know what you think, or we will find you through analytics. That's
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Podcast: Watching shoes untie, Cassini’s last dive through the breath of a cryovolcano, and how human bias influences machine learning

11:40 SC: Machines learn from us and sometimes surpass us. For example, last year an artificial intelligence defeated a top player of the game of Go, but is making machines like us, even if they are better, always a good idea? Aylin Caliskan and colleagues investigated if machines are learning human prejudices when they are trained using large corpuses of human language. Hi, Aylin.

12:07 Aylin Caliskan: Hi, Sarah. Thanks for having me on the podcast.

12:11 SC: Sure, no problem. Can we start with what is machine learning used for? Can you describe the basics of the process?

12:19 AC: First of all, as you introduced, yes, artificial intelligence has greatly advanced in the last decades to a degree that it's at times used to make decisions about people without any human's help during the process. And machine learning basically performs automated tasks to save human effort and also aid humans in decision-making. Machine learning is a type of artificial intelligence that learns from large amounts of data and it's able to uncover statistical patterns in large-scale data which would take a very long time for humans to manually analyze. And once machine learning uncovers statistical patterns, it can provide insights about the data and can make decisions or future predictions based on the statistical models it learns. For instance, it can be used to automatically translate from one language to another or summarize articles or predict future criminals, make loan application decisions and many other mundane or interesting tasks. Nowadays, it's being incorporated to a vast array of potential decision-making processes and future prediction tasks.

13:39 SC: So you wanted to know if this kind of training, where you feed it a large mass of human language, might replicate the biases that are seen in people and our writings. And by bias here we actually mean stereotypes and prejudice about race or gender. How did you look for this bias in the machine learning?

14:00 AC: So basically we look for bias by adapting a widely-used societal psychology test to machines. This test is called the implicit association test, which was developed by Greenwald and his colleagues in 1998, and this test has been taken by millions of people around the world, so its findings provide truth about the world and different cultures. For example, it's able to measure how humans associate two concepts. Given African American names and European American names, along with pleasant and unpleasant terms, does one classify African American names as being pleasant or unpleasant faster? Based on the latencies in classifying certain groups of people with certain stereotypical terms, the test uncovers the implicit bias that European American names are easily associated with pleasant terms, whereas African American names are linked to unpleasant terms faster. So we adapted this method to semantic space models, which are numeric representations of words in a language generated by machine learning that analyzed billions of sentences from the web to come up with a model of language. So once we have the numeric representations of words, we can use sets of words that represent certain groups of people and also stereotype terms to measure the mathematical businesses between stereotypical associations.

15:36 SC: So here what you're saying is that in the implicit association test, basically how quickly you respond shows how much more associated two terms are. And in this mathematical model that you use with the machines, it's this distance between different terms like in the machine's model of language?

15:54 AC: Yes, that's correct. For example, if a person is able to associate a musical instrument, let's say piano, with being pleasant quickly, then we look at the mathematical distance between piano and a pleasant term. And if it's close enough, that means that it's quickly associated with that word. And based on this, the results that we found were astonishingly replicating the findings of implicit association tests that have been taken by millions of people over two decades.

16:28 SC: Were you surprised when you fed a machine a bunch of human language that does probably contain our biases that the machine then has these biases?

16:37 AC: Yes. I was quite surprised when our method, we'd replicated tens of implicit association tests that were taken
by millions of people. And all of our results were showing the same biases, namely neutral biases for flowers and insects or weapons and instruments, our stereotypes for gender and race, attitude towards the elderly or even mental health stigma. And we preferred the neutral bias test as a sanity check, because the attitude towards flowers being pleasant and insects being unpleasant is regarded as a universally accepted stereotype. These biases are regarded as neutral, because they are not harmful to society or groups of people the way stereotypes are. For the future, I'm predicting that the real unexpected results will show up when we discover unknown biases automatically with our method, instead of experts first testing hundreds of human subjects. That will save so much time for sociologists and psychologists before they start testing for certain stereotypes. Our method can be a first step for uncovering bias from language, and then experts can use this as evidence to start investigating potential stereotypes in society in detail.

18:02 SC: What are the implications for applications of machine learning? Where we use this already or where we're gonna use it in the future? Where might the fact that the machines have this bias in them have a big impact?

18:16 AC: One straightforward example would be machine translation, which incorporates meanings of words from different languages in order to improve translation quality. Accordingly, for example, when we translate from a language that has genderless pronouns, such as Turkish, there is no he, she or it, it's all represented with one word. So when I try to translate from the Turkish sentence 'he, she or it is a nurse,' the English translation results in 'she's a nurse.' And when I translate from 'he, she or it is a doctor,' the English translation results in 'he's a doctor.' Basically, the translation system is assigning a gender to the occupation name based on historical biases and statistics.

19:03 AC: Another example would be resume screening. Many companies first screen job applications by artificial intelligence. Would artificial intelligence find a male applicant less fit for a nursing position? Or would this lead to women having lower chances to be called for a programming position? Or black Americans getting fewer interview offers? So if artificial intelligence is making such biased decisions based on historical data, it would result in perpetuating the bias in society, and this directly leads to unfairness. Being able to uncover and quantify bias that's embedded in machine learning models is a first step and a warning to take action against unfairness.

19:53 SC: How can this be undone? Is there a way of untraining the machines on this particular bias, this certain part of the corpus that it's ingested in the first place?

20:05 AC: I will have a slightly longer answer for this. This is a tricky question. It's also tricky for humans. So I'll first start answering this by talking about humans. For example, humans by nature are biased beings. Humans adopted certain biases during the evolutionary process in order to speed decision-making in the brain. Nevertheless, even if humans have implicit biases, they know how to not act on stereotypes and they can avoid prejudiced behavior. The learning part is similar for machines. Artificial intelligence also learns biases, but it needs the awareness not to make prejudiced decisions. Since machines do not possess self-awareness the way humans do, a human in the loop can help machines make ethical decisions.

20:55 AC: So in this case, I cannot exactly recommend undoing or untraining the machine, because doing that would cause it to lose information about the facts in the world. For example, we have a second method, it investigates the correlation between facts about the world and our findings. And by facts, I mean statistical facts about the world. So for example, we took occupation names and percentage of women in each occupation from the United States Bureau of Labor Statistics. When we measured the association between women and occupation names, we saw 90% correlation with labor statistics.

21:36 AC: We also applied this to androgynous names from 1990 United States census data, and then we measured the association of names with genders, and we had 84% correlation with the 1990 statistics. This shows that these semantic models of language imibe facts about the world, and culture is a part of these facts. The cultural part of language contributes the biases to the machine learning model, but on the other hand, statistics about the world are also reflected in these models, which make them powerful tools for machine learning.

22:14 AC: So if we start removing certain components from these models, we will break the accurate representation of the world, which can cause unexpected negative side effects in different aspects. And accordingly, we suggest that while using such artificial intelligence tools, we have expert humans in the loop that make sure that whatever the machine learning task is, the outputs will be unbiased and fair decisions will be made.

22:43 SC: So do you think that this finding in the output of machine learning says something broader about language or
bias?

22:54 AC: This is a great question. It opens up so many discussion points and it opens up many questions about language, culture, and how we make bias associations. So maybe the way we learn language is causing us to make bias associations. Based on the frequencies of words that we heard during the language learning process, maybe bias is embedded in language and evolves as culture and language evolves and has an impact on stereotypical associations at a large scale in society. And these are great future research questions that we are planning to investigate.

23:36 SC: Okay. Well, Aylin, thank you so much for talking with me.

23:40 AC: Thank you so much, Sarah, and thanks for your insightful questions and your time.

23:45 SC: Aylin Caliskan and colleagues write about biases in machine learning in this week's issue of Science.

[music]

23:56 SC: And that concludes this edition of the Science podcast. If you have any comments or suggestions for the show, write us at sciencepodcast@aaas.org, or tweet to us @sciencemagazine. You can subscribe to the show on iTunes, Stitcher and many other apps, or listen to us on the Science site. This show is a production of Science Magazine. Jeffery Cook composed the music. I'm Sarah Crespi. On behalf of Science Magazine and its publisher, AAAS, thanks for joining us.
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