SDS PODCAST EPISODE 907: NEUROSCIENCE, AI AND THE LIMITATIONS OF LLMS, WITH DR. ZOHAR BRONFMAN

Jon Krohn:	00:00:00	This is episode number 907 with Dr. Zohar Bronfman, co-founder and CEO of Pecan AI.
	00:00:13	Welcome to the SuperDataScience Podcast, the most listened-to podcast in the data science industry. Each week, we bring you fun and inspiring people and ideas, exploring the cutting edge of machine learning, AI, and related technologies that are transforming our world for the better. I'm your host, Jon Krohn. Thanks for joining me today. And now, let's make the complex simple.
	00:00:46	Welcome back to the SuperDataScience Podcast. Today, we've got a mind-blowing, perhaps even frighteningly so, episode with the brilliant, forward-thinking AI entrepreneur, Dr. Zohar Bronfman. Zohar is the co-founder and CEO of Pecan AI, a predictive analytics platform that has raised over $100 million in venture capital. He holds two PhDs, one in computational neuroscience and another in philosophy. Bringing a deep, multidisciplinary lens to the design and impact of AI systems. He focuses on the evolution of machine learning from statistical models to agentic systems that influence real world outcomes.
	00:01:22	Today's episode will be fascinating for every listener. In it, Zohar details the trippy implications of the reality that your brain makes decisions hundreds of milliseconds before you're consciously aware of them. He talks about the intelligence feat that bumblebees can do, that current AI cannot with implications for the realization of human-like intelligence in machines. He talks about why predictive models are more important than generative models for businesses, but how generative LLMs can nevertheless make building and deploying predictive models much easier and accessible. And he fills us in on the roller coaster journey that led him to create a

sensationally successful AI startup immediately upon finishing his academic degrees. All right. You ready for this extraordinary episode? Let's go.

00:02:12 Zohar, welcome to the SuperDataScience Podcast. I'm really excited to have you on the show because our research, that our researcher, Serg Masis, did on you was mind-blowing. I can't wait to hear the answers and learn from you in this episode. Anyway, I should be letting you talk right off the bat and already I'm just gushing about you. So Zohar, how's it going? Where are you calling in from?

Zohar Bronfman: 00:02:35 Hi, Jon. It's all good. I'm calling from Tel Aviv in Israel and it's great to be here today.

Jon Krohn: 00:02:38 Yeah. For people watching the video version or I guess for people not watching the video version, it's even more critical that I narrate this. There's a beautiful skyline in behind Zohar and I thought he was in Manhattan. So yeah, it's kind of a perspective on Tel Aviv that I haven't seen. Very cool and nice. So you are the CEO and co-founder of Pecan AI, a no-code predictive analytics platform. But before we get into Pecan too much, I also want to talk about your philosophical perspectives. Because if I'm understanding this correctly, you have two PhDs, is that right?

Zohar Bronfman: 00:03:14 Yep.

Jon Krohn: 00:03:15 You have two PhDs. So one is in computational neuroscience and the other is in philosophy.

Zohar Bronfman: 00:03:20 Yeah.

Jon Krohn: 00:03:22 Yeah. So that's a pretty rare combination of both technical depth and philosophical interests. And so, I thought it would make sense to talk about how we can distinguish practical AI progress from philosophical illusions. So leaderboards and research papers claim better than human performance for large language models LLMs. But like Yann LeCun, you are LLM skeptics. So in an interview from last year you said, "I don't think LLMs are taking us anywhere closer to AGI." So tell us about what it means to be intelligent and why you think LLMs will fall short on getting us to human level intelligence.

Zohar Bronfman: 00:04:03 I think LLMs are amazing. I don't want to sound like I'm downplaying large language models and GPTs and all of that. I think it's a remarkable advancement of technology. Having said that, I'm not sure that all the conversations about we are getting very close to artificial general intelligence are necessarily right or warranted. So at least from my perspective, when you think about intelligence, there are many ways to define intelligence. It's, in some respects, ill-defined. The reason people allow themselves to speculate about intelligence is because we don't really have a definition we all agree about.

00:04:46 But I would say from my, at least perspective, intelligence pertains mostly to, let's call it, the ability to solve problems in your life, in your environment. And the more complex the problems you are able to solve, the more unique and the better you can solve them and better being what creates more value for you by solving them the better or the higher the intelligence is.

00:05:21 And artificial general intelligence means you'll have an entity or being or whatever you want to call it, that can solve a similar level of complexity, different problems from different domains, and creating similar value to itself. So I don't think many of us would say, "Hey, the Deep Blue of the nineties that was able to beat Garry Kasparov is intelligent in any general way," and I don't see any conceptual reason to claim that today's remarkable,

remarkable AI capabilities have any general human-like problem solving capabilities.

Jon Krohn: 00:06:14 Right, right. And so, a fascinating paper of yours from four years ago called, When Will Robots be Sentient, and we'll be sure to include that in the show notes. It proposes that a machine that would be capable of domain general learning, so unlike Deep Blue which is very specialized to chess only and can't drive your car or write an essay for you, to get to domain general learning that it would require the dynamics of an Unlimited Associative Learning architecture, UAL, Unlimited Associative Learning. What is UAL? And yeah, why is it relevant in this context?

Zohar Bronfman: 00:06:58 Yeah. So I think at least... This is all controversial. I just want to put it right in front of all of our listeners. There's no one single theory everyone agrees on. It is my and some of my colleague's theory and thoughts. We think consciousness or sentience, let's say it's the same thing for the simplicity of the discussion, are tied in the hip to intelligence or the ability to, like I said, learn and solve problems. Now, as you mentioned, different AI systems or different models we have today are very good in mimicking solutions for specific domains. Be that writing code, writing essays, summarizing a website, or maybe optimizing a price, or maybe driving a car and so on and so forth.

00:07:57 But there are no signs so far for general ability to solve problems. Especially problems you haven't encountered before and especially problems that you solve by relying on learning that happened at another domain. This is key, okay? The last sentence I said is crucial. If you learn something, say, at the domain of chess. Okay. You learn something. Maybe you learn the principle of making sacrifice. And then five years later, you encounter a situation of negotiation in your business and you, even unconsciously, implicitly, pull up that learning you had back in the day when you specialize or learned chess and you negotiate by making a sacrifice, I would say it's some form of two-transfer learning. Not to be mistakenly understood as the transfer learning we are all seeing today, which is a hallmark, in my mind at least, of both intelligence and consciousness.

00:09:17 Now, this will require... The reason we believe this type of a learning requires or entails consciousness is because it... By definition, because it's unified and it serves all of those different domains via one centrical core of intelligence, it requires a unified value system. And value system is of utmost importance to the question of sentience, consciousness, and in my mind also, intelligence. And we know large language models have zero value. They don't care about anything. They don't have the concept of good or bad, of survival promoting or survival diminishing. They don't have any evolutionary or any vectors that lead them towards a certain direction.

00:10:13 They basically just optimize the cost function that we, engineers, decided they should optimize. That relates only to the error they are marking on a dataset. So to distill all of it to a take-home message when it comes to something like Unlimited Associative Learning, you want to be able to learn at a certain domain with a certain value something that promotes you as an organism or as an entity. And then, you want to be able to assign that learning or harness that learning in a completely different setting that has almost no conceptual overlap with your "training protocol". That would be, to me, general intelligence.

Jon Krohn: 00:11:10 That is a fascinating perspective and all of it makes a lot of sense to me, Zohar. Particularly what you're saying there about lessons from one domain not transferring well to others. I think there is a little bit in LLMs where I think there's examples of things like multimodal models getting a better understanding of universal principles or physics through the combination of natural language and visual learning. So this is... I'm stretching back a little bit here. It might be like a year-old in research or something like that. But video generation multimodal would tend to have better physics, like a soccer ball being kicked, a football being kicked consistently moving across the frame if it was also trained on natural language about that kind of behavior. So there's a little bit there and I wonder... Well, I guess LLMs probably aren't the answer. Or maybe that's a better question for you is if a kind of LLM structure isn't going to give the kind of Unlimited Associative Learning that would allow for general intelligence capabilities, do you have some sense of what the right structure would be?

Zohar Bronfman: 00:12:27

I would say that it's probably... Again, my guess is good as anyone's but I would probably say I don't think just bigger or better context models are going to be the next qualitative leap. I think the architecture... We call it neural networks and we say that it's mimicking some of the brain processes. In reality, it mimics only a very small fraction of the brain dynamics we are aware of and there are probably more brain dynamics we are not aware of that contributes to intelligence. The solution, in my mind, for adding more domain general or general intelligence capabilities would come from different architectures. Architectures that are far better in providing layers of meta-learning and providing layers of learning about the networks themselves.

00:13:34

I think, first of all, neural networks is not the only way of the brain to learn. And also, obviously, shouldn't be the only way for machines to learn. And there are many different architectures people are talking about super interesting that can contribute to modulating the dynamics of the network in kind of a meta-architecture way. I think it would be more of a direction in that area. I also think to supplement to your question, embodiment is going to be a huge component. So kind of fusing the existing type of neural networks with the robotics or some form of embodiment will really help both in expanding the landscape of what could be learned and what should be learned. And also, obviously, providing the substrate for the transfer as well as potentially providing initial vectors for real value. Real world value rather than just a loss function.

Jon Krohn: 00:14:39 Yeah. The embodiment thing is something that I've said a number of times. So real world embodiment where you're exploring the world, it seems like this is pretty critical. I know that there's some efforts like Fei-Fei Li has now raised hundreds of millions of dollars to create datasets that involve kind of more immersive 3D environments. And so, I think she's kind of thinking in that direction.

00:15:03 But then, yeah, your point about having some kind of modulation of the network. It reminds me of maybe how our prefrontal cortex in apes, but the prefrontal cortex in homo sapiens, in humans, is particularly large and it allows us to have executive control over the rest of our brain. It allows us to maintain a thought kind of consistently. We can loop between our prefrontal cortex and some other sensory cortex, our visual cortex or our auditory cortex, which allows us to keep some kind of concept in our mind over a longer period of time.

00:15:41 And I think that might be kind of the thing that you're describing there, that we definitely don't... Like you said, we call a transformer a kind of deep learning architecture which is a kind of artificial neural network but it's such a simple mathematical representation of what artificial neurons do. You don't have that kind of macro level executive control over the system happening like we do with our prefrontal cortex. So that's probably the kind of

		thing you're describing. And maybe, there's all kinds of other things like modeling the hippocampus and memory formation. And there's all kinds of other brain structures that we could be bringing into the picture in order to get closer to this kind of general intelligence that humans have.
Zohar Bronfman:	00:16:21	Yeah. Agreed, Jon. I think there are many architectures by which we can draw inspiration when we develop further and more advanced models. I do want to say though, we don't have to possess an ideal of intelligence that is based on our intelligence or animal intelligence or we don't have to necessarily draw inspiration just from the brain itself. It's just the best example we have. Intelligence can have many forms and, obviously, it will materialize differently with machines. But I definitely think that from everything we know about artificial general intelligence, because we are probably the best species we know at it, we're still quite far from it with the existing technologies.
Jon Krohn:	00:17:07	Yeah. I hope we're some ways off. I recently saw a chart. Actually, Yann LeCun posted it on his social media which is interesting. He's posting on LinkedIn a lot more, so I see it a lot more because people have moved away a lot from Twitter and Yann LeCun had he showed this chart. He was reposting a chart that someone had made of luminaries in AI and the range of their predictions of the earliest to the latest that AGI could happen.
	00:17:38	And so, there's some people in the chart like Ilya Sutskever, the top end of their range has already been passed. So he predicted maybe 10 years ago that it would happen in the next five to eight years and now we're two years beyond that. There's other... It's interesting but perhaps not surprising to me that people who are trying to raise huge sums of money, tens of billions, hundreds of billions maybe of dollars in order to create huge data

		centers to train next generation LLMs. People like Sam Altman, their prediction of when AGI is going to come is pretty soon. It's in the next couple of years.
	00:18:23	But of course, they're incentivized to have that kind of opinion because it allows them to create this kind of race mentality. That if we don't do this now, someone else is going to get there first. That will change everything. Google will have all the power instead of us. But yeah, it's kind of even people like Yann LeCun, Geoff Hinton, Yoshua Bengio, the so-called godfathers of AI, their predictions are a little bit less aggressive. There's some like Geoff Hinton, he's the top end of his range, was decades from now. But there was still... Like Geoff Hinton had a very broad range and so there's also the possibility that it happens in his view in the next 5, 10 years.
Zohar Bronfman:	00:19:05	It is very interesting and making predictions about technological leaps is almost impossible. In all honesty, I don't think anyone really knows. It's just throwing out numbers. I don't think we are able to predict the leap that happened with the LLMs and GPTs. I think we were all surprised by how amazing they performed, how there's this uncanny valley of you get closer to something that resembles human fluency and it actually creates some eerie feeling. We completely, completely went over that uncanny valley which was a huge surprise. You would expect something a bit more linear, a bit more continuous. So I don't have a prediction. I can't tell you what's my point of view. I think I leave predictions to machine learning algorithms. But I will say, that it's quite clear to me at least that there's still a road ahead of us. There's still a road ahead of us.
Jon Krohn:	00:20:18	Yeah. And I guess what I was working towards with all those ranges is that I hope that there's still some road ahead of us because it'll give me a bunch to talk about on the podcast for years to come.

Zohar Bronfman: 00:20:30 And jokes aside, I mean, people are scared from artificial general intelligence and they should. We don't know how it will behave. And I'm just saying, it's good that we have the road ahead of us because I've been talking a lot about the need in real regulation. I don't think we are... There's also a road ahead of us when it comes to regulation so it's good that we have a little bit of time to prepare ourselves.

Jon Krohn: 00:20:57 100% and I think the silver lining around this preparedness thing is that it does get a lot of attention. There's a lot of people talking about AI safety and there is a non-trivial amount of funding going into it. There's research sections at major conferences that focus on it. So it's nice to see that people aren't just racing on capabilities. There are some people concerned out there. One thing that came out of your... I don't really have a question here necessarily because I think you answered the question that we had prepared around this.

00:21:26 But something fascinating that I wanted to call out from your When Will Robots be Sentient paper that I thought was really cool, something I didn't know, is you talk about how bumblebees can transfer knowledge between senses. And so, bumblebees can apparently... And maybe you can go into a bit more detail on this, maybe that's the question, is that apparently bumblebees can learn object shapes via touch. And then, later recognize them by sight which you could imagine doing that as a human. You could imagine having some objects on a desk in front of you and you feel them. And then, when you see them later, you build up a representation, a visual representation in your mind just through touch. I don't know. I thought it was interesting that bumblebees could do that too. You think about their neural network is a lot smaller than ours but they're still capable of doing some pretty impressive things.

Zohar Bronfman:	00:22:19	Yeah. When I just started my PhD, so my professor kind of exposed me to the world of animal learning and I can tell you I was like... I didn't sleep at night just from the awe and from the kind of wonder of what animals we thought are almost as simple as miniature robot are doing amazing things. Amazing things. I know some animals that are smarter than some humans I know.
	00:22:49	True. I can tell you, like just as an example, so yeah, bumblebees can transfer across modalities. Spiders, there are spiders who can be conniving by intention when they wait for prey and it can't be explained just by instinctual behavior. It's a learned behavior that is very context specific. There are rats and mice that show causal understanding of the world. Real causal understanding in terms of when there's correlation, what causes what and when it's spurious correlation. By the way, in many cases, LLMs still fail in that relatively simple causal task. And understanding mechanistic structure of events is also one of the hallmarks of, obviously, intelligence and abstraction. So animals are amazing. They have their own limitations, sensory limitations, and so on and so forth. But for the things they have developed over millions of years, they have remarkable learnings, sometimes domain general.
Jon Krohn:	00:24:11	It is fascinating. It's the kind of thing... You probably wouldn't know this about me, Zohar. I have a PhD in neuroscience-
Zohar Bronfman:	00:24:17	Something told me you might.
Jon Krohn:	00:24:19	And so, I spent some time on animal models. I ended up getting... Something that I realized basically a few months into my PhD is I was like, "You know what? I like the idea of working at machines, computational statistics, machine learning." That seemed like a really easy win for me because some other people in my PhD program would

do things like become specialists in putting recording electrodes into the brain of a ferret or growing some kind of tissue culture. And I was like, "Those aren't super transferable skills. But if I learn computer stuff, there's a lot of industries that would probably like that skillset." So that's kind of how I got into the machine learning side of things but...

00:25:10 Oh, where the heck was I going with that? I don't know. I don't know. I was going somewhere with that but I completely lost my train of thought. It was going to bring me to another fascinating question anyway which is that in a recent blog post, you cited Margaret Bowden's framework to distinguish generative AIs combinatorial creativity from human transformational creativity. And so, what risks do you see in businesses conflating these two kinds of ideas: combinatorial versus transformational? I think it relates to some things that you've already said in this episode around how machines making these leaps from chess to negotiation, to go into an example you gave earlier.

00:25:53 And this also now reminded me of what I was going to say and why I started talking about my neuroscience background, which is that there's so many fascinating things within animal models that I feel like I've only, in the stuff that I've read, really scratched the surface. And so, hopefully, I can get to a point where I can't sleep at night, just like you couldn't, over the things that they're doing. Anyway, the question I was asking was this idea of generative AI's combinatorial creativity relative to transformational.

Zohar Bronfman: 00:26:19 Yeah. So in philosophy, there's a nice distinction. Again, these concepts are tough, intelligence, creativity, the things that make us human. Obviously, anyone can define it in any way they want. But in the philosophical studies, smart people have been doing very, very deep

		work around those concepts for quite some time. One example would be the distinction between combinatorial and generative creativity, was it?
Jon Krohn:	00:26:51	Yeah. Exactly. So combinatorial where it's-
Zohar Bronfman:	00:26:55	Combination of a couple of different... I will give you an example in a second. I just forgot the term. Sorry. Combinatorial-
Jon Krohn:	00:27:03	Yeah. That's-
Zohar Bronfman:	00:27:03	... and what was the other by Bowden?
Jon Krohn:	00:27:05	Transformational.
Zohar Bronfman:	00:27:06	Transformational was the term. Yeah. It's jargon. So I'll explain quickly combinatorial and transformational creativity, because I think the distinction is interesting and it indeed relates to what we just discussed in terms of a specific versus general domain intelligence. Combinatorial creativity would be creating something new and unique, hence creativity. That is some kind of an assembly of existing things, right? So you take a few interesting pieces across domains and you put it together. You create something new. And it's unique and it's creative and it checks the box of being creative.
	00:27:54	However, it's a relatively "simple form" of being creative. LLMs can do it. They can take a couple of jokes that one stand-up comedian said, a couple of jokes that another one said, maybe something from a movie, and create a new joke that draws on those three. Now, obviously, it's a continuum and it's not like a completely two separate categories because in some sense everything is being composed of other elements.

	00:28:28	But transformational creativity, again, has this concept of meta approach to a problem where it's not like you just compose different aspects that exist. You take a completely new perspective to the problem or to the issue and you get a completely new approach. And yes, the approach is inspired by something and, yes, it has elements of existing things for sure always. But it is very different, it's order of magnitudes different than how people thought about the specific problem previously. Obviously, the great examples would be when Albert Einstein came up with a relativity and said, "No, we are looking at it completely differently. It's a matter of geometry rather than mechanistics and..." That's an example of transformational creativity. And one of the arguments is that if you have domain specific intelligence, it would be extremely hard for you to build transformational creativity and synthesize, basically, knowledge. This is something... This is key, in my mind at least, for where we want to get one day without artificial general intelligence.
Jon Krohn:	00:29:47	I love that. That was such a fascinating section. It's like when we think about generative AI capabilities in these terms, combinatorial versus transformational. I mean, probably most listeners use LLMs, have conversations with them on a regular basis. And it's certainly amazing to see that combinatorial thing work, where you ask for some science concept to be explained in the style of Snoop Dogg and it works unbelievably well. It does it at a level that would be superhuman for most humans to be able to reel off science in the style of whoever. But it's not transformational as you described there. We've talked about generative AI a fair bit here. But you, actually, in a keynote two years ago, you declared that prediction is all you need. That generative AI isn't necessarily... That shouldn't necessarily be prioritized by the AI community as much as it has been. So tell us about that perspective. Do you still feel that way two years later?

Zohar Bronfman: 00:31:03 I think to a large degree, yes. I think if you ask yourself... And again, I'm talking specifically about businesses, not about consumers and prosumers who obviously have a lot of value just even from the existing capabilities LLMs possess. I do think that specifically for businesses, if you are thinking about a business that is trying to transform how things operate within the business in a way that is going to be a real needle mover, then today, the vectors of value that come out of LLMs are quite limited. I don't think LLMs changed entirely a trajectory of a business in a way that is even close to how machine learning and predictive capabilities did or are doing. If you think about the biggest companies, the most successful companies out there, from Google and Facebook to Amazon, Uber, Spotify, I think it's a fair argument to say it was machine learning and predictive modeling that got them to the place they are. So there's this joke that the ones that made the most money of the gold rush were the ones that were selling the... How do you say? The smaller-

Jon Krohn: 00:32:35 The picks-

Zohar Bronfman: 00:32:35 Yeah.

Jon Krohn: 00:32:37 It's like picks and axes and maps-

Zohar Bronfman: 00:32:38 Exactly. The picks and the axes and all of that. Now, again, I'm not being cynical in any way. But today, the big money still goes for companies that enable LLM computationally, infrastructurally and that's amazing. I'm all for it. We use LLMs throughout our stack in many different ways. But ultimately, the real business value of taking a certain process and optimizing it with your data still, I think, relies 99% of cases on one or another form of making predictions or advanced analysis of the data. I don't think this will change. And therefore, I think we should, for sure, continue investing in large language models. We for sure need to find ways of tying them closer

		and closer to business value because we know ultimately this is where value lies. And I still think machine learning has maybe only 5% of its potential uncovered in the sphere of companies.
Jon Krohn:	00:33:44	Yeah. There is whether we are close to AGI or not. One thing that's for sure is that there's a lot of opportunity still in enterprises to be taking advantage of data that they have or that they can collect and automate things. And absolutely, a huge amount of that will happen in the predictive realm. I mean, there are particular places, and we're going to talk about this more later in the episode, particularly with respect to your startup, to Pecan. Oh, do you pronounce it Pecan or Pecan?
Zohar Bronfman:	00:34:15	It actually depends where you're from in the US or in North America for that matter. So usually in the East Coast, they say Pecan. I also say Pecan for some reason. But West Coast and Midwest would usually go with Pecan or something like that.
Jon Krohn:	00:34:35	Yeah. So you're okay with either? It's okay.
Zohar Bronfman:	00:34:37	I'm okay with either. I'm like a pluralist.
Jon Krohn:	00:34:40	Nice. Yeah. I'm an East Coaster, born in Toronto and now 13 years in New York. And so-
Zohar Bronfman:	00:34:45	So you say Pecan-
Jon Krohn:	00:34:46	Yeah. It's Pecan for sure. Yeah. It sounds funny to me when I hear Pecan. But yeah, so we'll talk about how LLMs are useful in your platform. And a lot of that is around having an interface, a natural language interface with some underlying backend, some code being generated in the backend, some data being pulled automatically using natural language. That's really useful and there's a huge amount of places in the enterprise

where that kind of capability can still be added or having something convert from a tabular structure or some unstructured data, converting that into some natural language that can be output to a customer support person or maybe to a user directly.

00:35:37 There's lots of places where generative AI can be useful for an enterprise. But there's still, I think as you say, there's vastly more opportunity for predictive. I agree with you 100%. And so, there's an interesting... So something interesting that blends together predictive machine learning and the neuroscience that we've been talking about already in this episode is we tend to... So different ways of doing recordings from the human brain.

00:36:09 For me, something that has stood out for me as one of the craziest things that I've learned in neuroscience are these experiments by a guy named Benjamin Libet, L-I-B-E-T. Yeah. And so, you're familiar with these. And so, I'll explain briefly my memory of this to the audience. But basically, I think he was using EEG. So relatively simple approach where you have recording electrodes on someone's scalp and it gets kind of this coarse reading, coarse spatially because the skull kind of interferes with the electrical activity of the brain. So spatially, you get a bit of a coarse response. But in terms of time, you get very precise millisecond time-scale precision on recording events of the brain.

00:36:55 And something very interesting that Benjamin Libet and countless others have shown is that you can have a neurological... The neural basis of some conscious idea that you have happens hundreds of milliseconds before you have the conscious thought. And this is a very disturbing thing to think about because most of us go around through the day with this illusion that you have some kind of control over what thoughts come into your head or what action you take next. But in fact what these experiments show is that you become aware of a decision after that decision has already been made subconsciously in your brain. And so, yeah, I don't know. There's plenty to dig into there. But maybe talk to us about this a bit more and then maybe tie it into your belief in AI's ability to anticipate user behavior.

Zohar Bronfman: 00:37:56 So I think we were talking about once you get exposed to something in the realm of neuroscience and AI, you lose sleep. This was probably the biggest sleep deprivation I had because it's mind-blowing, right? If we think about it deep, we might end up in a rabbit hole of, "Am I just an agent carrying my neurons?", or something like that, which I don't think is very easy to disprove, by the way, in all honesty. So it's mind-blowing. It's obviously a lot to digest but yes. By the way, those experiments happened first sometimes during the '80s. Since then, it's been replicated and reproduced in different settings and in different environments, in different technologies, in different animals. So many times that I don't think it's anymore even just an open question. It's a truism. It's given.

00:38:52 Now, obviously, there's room for interpretation. But the fact that there are brain processes that are directly causally related to decisions we make and that we don't have access, we don't have conscious access to those processes, I think is already completely agreed upon. Obviously, you can ask the questions of how elaborate these processes are, whether as something reaches consciousness it can override or change some of these or veto some of these processes, and so on and so forth. But the fact that this happen is hard fact.

00:39:27 Now, it means that much of what we are doing as humans is predetermined by things that have nothing to do with our immediate desires. So you can put someone in FMRI, like a functional MRI that basically shows the blood in your brain and you know which areas are active, and they drive in a car simulator, you can know 10 or 15 minutes in advance before they reach the junction, whether they're going to turn left or right.

00:40:00 And it has many contributors to it. Maybe it's a question of your stronger side. Maybe it's something that happened in the morning. Maybe your neck was sore and it's harder for you to look to the right. By the way, it's my case at the moment. So there are many different ways that can contribute to these unconscious processes that end up affecting your decision or your action.

00:40:27 But what it also means... And this is something again that is quite known for many years, it means that as a consumer, your behavior is also affected by many things that you are not aware of. And it means that as a business that sells to consumers, you can probably know much in advance of your specific customer's behaviors before the event takes place. So you can predict the purchases that customer is going to make, the conversions or lack of those, lifetime value, best products, churn, and so on and so forth.

00:41:11 And that ability to make those predictions based on their historical behavior is, like I said earlier, the biggest level we know in the industry for transforming businesses. So I'm basically saying, "If you collect data about your consumers as a business, there's a good chance you can start making predictions about their behavior in the future. And you can optimize their experience, you can optimize your processes. You can basically just make the most out of those precious interactions the consumers have with your business." My personal, and this is what Pecan is all about, my personal mission, I want to bring these capabilities to as many small and mid-sized businesses as possible, because they also deserve "that remarkable technology" that basically tells you what people are going to do even before they know what they're going to do. And that's why we've invested so much in connecting LLMs, data, and machine learning together in one nice package.

Jon Krohn: 00:42:28 Nice. That was... Yeah. So fascinating to hear. You definitely know a lot more about the kind of Benjamin Libet stuff that I was talking about. And subconscious neural correlates of decisions before we become consciously aware of those decisions. And it reminds me of how... So that also is a reason that I ended up doing machine learning is because I got a full scholarship to go to University College London to study the neural correlates of consciousness. And I had a nervous breakdown writing that PhD proposal because like you said, when you think deeply about these things, it kind of becomes... And I just try to live the rest of my life forgetting basically that I know this, but that it becomes very hard to see yourself as outside of a machine or having any real free will.

Zohar Bronfman: 00:43:25 I hear you. I think we went through a very similar thing. I just decided, "I'm going to jump to these waters nonetheless. Let's see what comes up on the other side." But these are remarkable disciplines, so interesting. And by the way, it's not an incident that so many of the AI researchers and leaders, and by the way you mentioned earlier, the forefathers of AI and so on and so forth, most of them are cognitive and neuroscientists. And it's quite remarkable and it's very interesting. It doesn't mean that you can't come from other disciplines. Obviously, computer science and other statistics and so on. But there's definitely something about brain dynamics and those functional organizations there that really contribute to our network thinking.

Jon Krohn: 00:44:14 For sure and a large amount of neuroscience inspiration that goes into AI systems for sure. Even if it ends up being a gross oversimplification, it can end up being powerful scaled up. One last question for you before we get into some really Pecan-specific questions, one kind of big philosophical questions. You ended a blog post which I will put in the show notes. You ended one blog post with a challenge, what question would a machine never ask? And I've been dying to find out what you mean by that and if you have examples of the kinds of questions that machines would never ask.

Zohar Bronfman: 00:44:55 Yeah. I mean, I think it relates mostly to the discussion we had earlier about value systems. So I think I'm expecting machines not to ask questions around why, why questions. Not why mechanistically. I mean, like, "Write me a letter." "Why are you trying to write to a CEO or to a board of directors?" No, but like, "Why? Why do you ask me to do that? Why should I do it?" These types of why questions, they are the latest ones that children develop. But then, when they do... I don't know if you have children, Jon, or not. But I can tell you for my children, they don't stop asking, understanding why. Not the mechanistic why, the real why, the value why. This is where when we assign them, the children, their understanding of the value system that surrounds us in society, in the family, as humans. And I don't think machines... For sure, they're not asking it today and it's completely irrelevant for them but I don't think they will ask themselves until we'll get very, very far in the AGI role.

Jon Krohn: 00:46:15 Mm-hmm. Yeah. This is something fascinating that fiction writers, movie creators have dug into for a long time. This threshold over which machines start to kind of ask that question like your children and I don't have children just to... But I've seen... It's kind of this trope of the kid asking, "Why? Why?" Going down the rabbit hole further and further until you get to a point where you're like, "I don't know."

Zohar Bronfman: 00:46:40 Exactly. Because so many times, the answer you provide them is a mechanistic answer and they're not trying to get the mechanistic answer. It's not a question of what happens if this ball hits that one? It's the causal, it's the value question that lies underneath. Why do we want to be kind? Why do we want to be supportive? Why should I love my relative? These are a core value. And then, in many cases, what we provide are actually axioms, right? And they have to just accept those axioms or not accept them. And these are the types of conversations that machines are very far from being able to conduct.

Jon Krohn: 00:47:20 We eventually run into fences that we can't climb over and see what's on the other side. It doesn't take too many why's to get to a fence that is unclimbable with things like, "Why is there anything? Why is there matter? And how did it come to be that there's a few billion conscious monkeys talking to each other over podcasting platforms on a one rock that's floating to space-"

Zohar Bronfman: 00:47:50 There you go. Here's another [inaudible]. Thank you.

Jon Krohn: 00:47:58 But I have a... Just really quickly. There's a film I watched a couple of years ago. I guess when it came out because it's only a film from 2021. It stars Colin Farrell and it's called After Yang and it is an exceptionally, fascinating... I absolutely love it. I think about it all the time and it's a great... It deals with this kind of idea of machines getting to a threshold where there's something... Yeah. This depth of question or of emotion, of wondering why, of trying to get down deeper into things. And After Yang, I'll have that in the show notes. I really loved it.

00:48:43 Anyway, let's get to Pecan. So at Pecan, you've taken on the biggest challenge. Yeah. You've said that the biggest challenge of making a model is not the training but the data. And actually, this is something that's come up in a number of recent episodes on the show, this kind of this idea of how critical... And it's kind of obvious when you say it. We spend so much time worried about model capabilities and performance on benchmarks. But in practice, none of that matters or it matters very little typically, relative to the underlying data that you're training the model on or that you're trying to use that inference time in some consumer or enterprise AI use case.

00:49:28 And so, just as some other examples of episodes recently where we've talked about that, we've got Episode 906 with Professor Jason Corso from the University of Michigan. We've got Episode 901 with Lilith Bat-Leah who leads a section at some of the big conferences like Neurips on data-centric machine learning. She calls it Data-centric Machine Learning Research, DMLR. And so, I think this is something that... It's interesting because we haven't talked about that a lot.

00:50:00 We've done over 900 episodes of this show. And in most episodes, we are talking about model capabilities. But for some reason, recently in episodes on this show, so maybe that's some kind of indicator of where consciousness is more generally around this, this realization that data are often the key limiting factor in having an AI model today that works effectively in your organization. A reason why that should be obvious to a lot of our listeners is if you're a hands-on practitioner, the hard part usually in a data science and an AI project is getting the data into a place where it can be fed into a model, where it can do something useful. And the model itself is often... You could be using open source model weights for a lot of it, maybe some fine-tuning. And so, yeah, you have a quote here that if you analyze the work of a team of data scientists 90% of their time is going to be modeling the data as opposed to passing it through some existing models. So why is data modeling so challenging and how can we overcome the bottleneck it creates?

Zohar Bronfman: 00:51:07 Yeah. Jon, let's break it up to a couple of components. First of all, we are very much obsessed with performance and accuracy for several reasons. First of all, it's very easy to measure. It's a classic bias, right? It's very easy to say, "My model does this and that on this and that dataset and reached this and that benchmark." I don't say it's not important and, obviously, especially for pure research purposes, you have to have benchmarks and you have to measure accuracy for sure. However, in the business context, the difference between a 91% area under the curve or 91.5 is usually, not always but usually meaningless. Absolutely meaningless.

00:51:57 There's so many other considerations that are 95 times more important than the statistical accuracy of the final model. For example, what are you even trying to model? Are you trying to, for example... Let me just give you a very simple example. Let's say you want to predict churn, okay? Let's say that you predict churn a week in advance, so you're saying this customer is going to churn and it's seven days before they notify about canceling the subscription.

00:52:27 In that case, you reach 95% accuracy. But let's say that from a business perspective, those seven days leave you no time whatsoever to change their mind. And let's say that 14 days in advance, you only reach 70% accuracy but you can actually have time to give them a call, suggest a promotion, or send some nice customer experience gift or whatever. It's the actual business framing that is crucial rather than the accuracy of the model. In many cases, the accuracy would be just vanity metrics.

00:53:08 The other thing which relates to the data is also a hint into why the realm of generative AI and LLMs and all of that are still struggling when it comes to predictive modeling. The reason is every company, every company, has its own data fingerprint. No two companies have the exact same data structure and data context and semantics and quality and so on and so forth. And every company has to go through a data transformation from how the data resides in the warehouse and the data stores and whatnot, into the data that is actually being fed to the predictive model.

00:54:07 That transformation, that one sentence, you just need to go through transformation. Transform your data and make it ready for machine learning or for predictive modeling. That is, by far, the most challenging aspect because it unfolds the whole discipline of data science into it. How do you define the entity you are going to predict for? How do you define the label? How do you define the stride and the frequency of the dataset? How do you consolidate the different features and different attributes?

00:54:44 How do you prevent leakage? How do you prevent drift? How do you make sure you don't have crucial anomalies? How do you make sure you have enough samples of positive and negatives and you don't have any skews that are going to completely mess up your model? How do you make sure it corresponds to the framework that you are going to use the model within? All of these questions make the work of the data scientists long and hard as all data scientists will attest. And if you ask yourself, what is the real barrier for non-data scientists, for people who are just data savvy builders and they want to become data scientists in practice? It is that data transformation and structuring. It's not the modeling itself.

Jon Krohn:	00:55:38	Right, right, right. So let's get into some mechanics, why kind of questions or how, actually, I suppose is more what I'm getting into here. But so you went through an impressive list there of the kinds of issues that data scientists run into when they are preparing data for a model or trying to get a model to work like the business would like it to in production. That was impressive in itself. So things like you said, data leakage, concept drift, real-time model validation, how does Pecan AI... Mechanistically, how does that work? Walk me through a user journey. Like I go to your website, I download a tool, and then how do I use it? Or maybe there's a couple different kinds of user stories you can go through to kind of practically give us a sense of how Pecan is solving these kinds of problems for people.
Zohar Bronfman:	00:56:42	Yeah. So like I mentioned, our mission is to help everyone in small, mid, and large businesses to benefit from the remarkable capability of harnessing machine learning and building predictive models. What we've done over the course of the last seven years is develop very big and very deep and wide technology that automates all of those data structuring and transformations that are so crucial for building a real business valuable model. It includes a lot of LLMs. LLMs that go over your data, understand the semantic relationship, do a lot of the transformation and the engineering. It also includes data engineering, proprietary, actually, patented data engineering processes we've developed.
	00:57:36	And we've actually built... Think of it as if it's a vibe data science notebook. So it's kind of a Copilot that has a conversational interface and it walks you, the data savvy yet not data scientist user, in the various, I should say, processes that are involved in building a predictive model. It understands the data. It understands the business goal. It helps you define your entities and your label. It creates queries. It shows it to you. It asks you whether it

		makes sense, whether the output makes sense. It creates metrics for you. Basically, just think of it as a little agent that works with you in all of those different steps and it does it all superfast so that you end up with a model very quickly. Now, you can evaluate that model. You can try and understand that model to a greater extent with our agent. And then, this becomes a quick iterative process until you reach a model you feel comfortable with.
Jon Krohn:	00:58:50	This is really cool. And so, the website is at pecan.ai and... Actually, really quickly, what is behind that name?
Zohar Bronfman:	00:58:59	The reason we are calling ourselves Pecan is because we believe AI is a hard nut to crack. But when you do, it's very good for you like pecans.
Jon Krohn:	00:59:11	Right.
Zohar Bronfman:	00:59:11	So we just want everyone to crack the nut with us and just get all the value they can from AI.
Jon Krohn:	00:59:16	I love that. I'm so glad I asked. I was worried you were just going to say, "Well, it was a five character .ai domain we could get."
Zohar Bronfman:	00:59:25	No. We started before AI was so hyped so we were lucky.
Jon Krohn:	00:59:29	Nice. And yeah, so basically it ties together a lot of things we've been describing in this episode already. So it seems like it's tailored towards people who want to be building predictive models where, as we've discussed earlier in the episode, that's where there's the most juice to squeeze in enterprises overall. But you've figured out clever ways of including LLMs in a lot of places so that it allows people to, with even just natural language alone, be able to describe some problem that they're trying to solve and have the data be cleaned up. So that it can go into a

		predictive model and you can get that predictive model in production much faster and with much less effort.
Zohar Bronfman:	01:00:20	Exactly. You can think of it as your predictive agent, like an agent that really helps you become a predictive builder.
Jon Krohn:	01:00:29	Really cool. I like that a lot. And yeah, is there kind of... So in terms of an organization, I guess any kind of organization could make use of this tool. It's enterprises, government organizations. I guess anybody who's trying to automate aspects of their business with AI, right?
Zohar Bronfman:	01:00:48	Yeah. I'd say if you could potentially benefit from machine learning, which is probably the case for most organizations out there, you could use Pecan and depending on the use case and the business process, see the benefit. Obviously, there are simpler use cases, there are more complex ones, but the platform is ML Cloud and there are so many different ways you can do it.
Jon Krohn:	01:01:20	Really cool. And so, something that is an important part of the platform to you, you talked about Pecan having kind of like a Copilot and natural language interface. And this enables organizations to harness predictive analytics without reliance on data scientists. So you've said if only data scientists can use it, Pecan has failed. So tell us a bit more about this. Especially our primary audience is hands-on data scientists-
Zohar Bronfman:	01:01:48	I know.
Jon Krohn:	01:01:49	And so, how do you see tools like yours evolving so that people like analysts... And I don't mean data analysts necessarily, I mean like financial analysts-
Zohar Bronfman:	01:02:00	Business analysts-

Jon Krohn:	01:02:02	... business analysts, marketers, operations teams, those are the kinds of people that you want to be using your tool. Not just data scientists. And so, yeah. How does that work? How is that going? Are you getting that that's working? And how does this impact us... As hands-on practitioners, as many of our listeners are, how are data scientists, data engineers, ML engineers, ML ops people... Do you see them being less critical in the future with more tools like Pecan coming along?
Zohar Bronfman:	01:02:38	So I want to say right off the bat to all of our data science listeners, guys, I love you. I love data scientists. I consider myself a data scientist. I have nothing against data scientists. However, we all know as data scientists that there are probably 100 times more use cases and potential for data science and machine learning out there and so many organizations that just don't have data scientists and could benefit from data science. So what we are basically saying, yes, we obviously have a lot of customers who are data scientists. And they love the platform and they use the platform and it's a terrific match.
	01:03:22	And what we do for data scientists is usually helping them to accelerate because data scientists, and we all know it, have limited capacity. They can deal X amount of use cases a year. With our platform, they can just take a little bit more and accelerate some of the processes, prototype real quick. So there's a lot of benefits for data scientists for sure. However, when you think about the company's core mission, I sleep well at night whenever I see another customer who's all of the sudden running four different models in production and have no data scientist in their org chart because they are too small, because they didn't prioritize, because they couldn't hire, whatever might be the reason. So we serve data scientists, we are proud of our data scientist users. And we still also love getting other companies that don't have

enough data science resources just across that threshold of predictive modeling.

Jon Krohn: 01:04:26 Nice. I like that. And-

Zohar Bronfman: 01:04:27 And Jon... Sorry. With regards to your question about what is the future work of data scientists and ML ops and ML engineers, I would say it's a bright future. I'm not from the camp that holds some kind of a catastrophic perception that we won't need data scientists in the future. I think it's very far before we won't need data scientists, even with a platform like Pecan. Because data science, and again, data scientists know that very well, has levels of complexity and has levels of nuances. The idea here is that you take the less complex use cases, the ones that are already very well-defined and well-understood, you automate those. And then, you free up data scientists to deal with the more complex and nuanced things, right? It's like think about lawyers or accountants. GPT can probably do 95% of what a lawyer or a counsel intern can do. But you'd still want to have lawyers because you want to deal with the very nuanced and complex and human-related aspects that LLMs can't really address. Same goals for data science in my mind.

Jon Krohn: 01:05:47 They need more embodiment. They need to-

Zohar Bronfman: 01:05:51 Exactly. They need just body time.

Jon Krohn: 01:05:52 Yeah. Robots in the courtroom before they can really replace lawyers. Nice. So one final question for you around Pecan is you've described its origin as a roller coaster so I've got a why for you. So why Pecan? I understand there's something to do with missing a deadline in a data science competition that the company came about.

Zohar Bronfman: 01:06:15 Yeah. So I would say the... First of all, Noah, my co-founder and our CTO and myself, we started Pecan back-to-back from graduating our PhD studies. So first of all, we never worked in a company before that. I didn't even know what a payslip looks like. So it was a roller coaster even from Day 1 when you were overwhelmed with everything. We raised $4 million seven years ago and it was just for us like, "Oh my god. What just happened? What are we doing now?"

01:06:51 So from that moment on, everything just became increasingly more insane. It is a roller coaster. I'm experiencing, almost at a daily level, huge wins and success stories and, obviously, huge challenges. It's non-linear in the most non-linear way you can imagine. Specifically, the deadline was that we decided we want to test our system and we want to participate at a competition and we... Speaking of accuracy, in benchmarks, we wanted to see what happens when we let Pecan solve some of the hardest data science problems. Specifically, it was around the customer next best offer use case without us intervening.

01:07:42 So basically, here's the data, do all of the structuring we talked about, do all of the cleansing, do all of the feature engineering. Build a model, do the predictions, send them to the competition, let's see how well you are able to perform. And we got to the first place and we were psyched. We were absolutely psyched. And then, we realized a little bit later that we submitted after the deadline. It is just an example of how things constantly change, you get... Within the day, You get good and bad news every moment basically. But I guess over time, you get used to it and you just try to focus on the goal and constantly push forward.

Jon Krohn:	01:08:32	Well, congratulations on your success, Zohar, and to your continued success. May those daily successes marginally outnumber the daily challenges and you continue-
Zohar Bronfman:	01:08:46	Exactly.
Jon Krohn:	01:08:47	... to see some great-
Zohar Bronfman:	01:08:47	We just need them to marginally outnumber and we're good-
Jon Krohn:	01:08:48	Exactly. So before I let you go, this is actually... I have a note that I'm supposed to warn people before we actually start recording, that at the end of every episode, I ask for a book recommendation. But I forgot to give you that warning so you're getting this cold. Do you happen to have a book recommendation for us? It doesn't need to be related to our field, though it can be.
Zohar Bronfman:	01:09:09	Wow. So here's the story. I used to read. Every week, I had to finish at least one book. Otherwise, I was upset with myself. Obviously, it was during the philosophical and neuroscience studies and I have a ton of recommendations. So I will give you one mainstream recommendation but then I will give you one fringe recommendation which is very recent. So the number one book, my most favorite book on the planet is Samuel's Beckett Trilogy. I mean, the way I define books, there are a couple handful of transformative books. Books you read and then you become a different person. To me, that was a transformative book. I carry it in too many places and try to revisit it. It's a very weird book, right? If that's my mainstream, what would be my fringe recommendation? But it's still a piece of art that I don't think any AI will ever be able to create. It's just amazing. Okay? So that's the mainstream recommendation.

01:10:27 I will send you the name in English because I'm reading it in Hebrew at the moment, but there's a book that I'm reading now. I don't read a lot of books unfortunately now. But now, I'm reading one book and it's very fringe. It's very freaky but it's extremely interesting and it's about aliens. And it's about a person writing on his own encounters with aliens during the '90s and early 2000s. I have an alien thing, not sure yet exactly what thing I have. But for those of us who question the day-to-day assumptions, I recommend reading that book. It's definitely eye-opening and it's definitely... It gives you an angle that, I mean, we don't come across everyday. You just need to keep an open mind and don't be judgmental. I'm not saying it's true or false. I'm just saying it's a very interesting narrative and story.

Jon Krohn: 01:11:32 Yeah. There are interesting things going on there. So yes, you're going to have to send me, I guess, the name of this book for me to put in the show notes. Because it occurred to me, I was like, "Maybe you can just tell it to me in Hebrew and I can google it," but I can't even do that. I can't Google things in Hebrew because I can't possibly... I don't have an internal LLM that can convert phonetic spellings into-

Zohar Bronfman: 01:11:55 Yeah. I can show... I can put the... I have it on my desk now. In Hebrew, that's the book.

Jon Krohn: 01:12:02 Yeah. See, I can't type that.

Zohar Bronfman: 01:12:04 You can't type. I'll send you all the information. I mean, if someone is into aliens, it's an interesting story.

Jon Krohn: 01:12:14 Yeah. I've been trying for the past year and we'll see how it goes. I've been developing a TV series idea related to AI. And so, I've been talking to a lot of production companies and someone who's been involved with this over the whole year. She's an Emmy award-winning documentarian and

		a project that she did relatively recently was a series called Encounters for Netflix. And yeah, it's kind of... I think there's four episodes and the first episode, I thought, was really interesting. They dig into radar data that are quite anomalous around UFO sightings and some of the other episodes I didn't find had as much kind of substantial, underlying hard data. But yeah, there's certainly... When you watch something like that or I guess read something like the book that you're reading, there's some unexplained things going around.
Zohar Bronfman:	01:13:21	And hey, we are all here data scientists. We can assess that the likelihood there are no aliens is probably as close to zero as the likelihood can be. Now, the only question is, what to do with that?
Jon Krohn:	01:13:36	Yeah, yeah, yeah. Nice. All right. Thank you so much, Zohar. Before I let you go, what are the best ways to be following you? I mean, this has been a fascinating episode. People want to get more of your thoughts. Yeah. Where should they follow you on social media or Pecan on social media?
Zohar Bronfman:	01:13:53	Yeah. I'd say probably my LinkedIn account. I'm usually active on LinkedIn more than any other social media. So everyone are more than welcome and sometimes I share my thoughts and other interesting pieces, so by all means.
Jon Krohn:	01:14:08	Nice. Fantastic. We'll have that in the show notes as well. Zohar, this has been a fascinating conversation. I could go on for hours and hours and maybe we will have that chance. Hopefully, we can have another episode again in the not too distant future with you to check in on how Pecan is coming along. And yeah, get more of your insights at the intersection of neuroscience and AI. It has been a fascinating episode. Thank you.

Zohar Bronfman: 01:14:32 Thank you so much, Jon. Happy to be here.

Jon Krohn: 01:14:40 Wow, wow, wow. Thanks to Dr. Zohar Bronfman for such a mind-blowing episode. In it, he covered how LLMs lack the unified value systems and domain general learning capabilities needed for AGI. LLMs can't, for example, transfer learn from chess to business negotiation like humans can. We talked about how bumblebees demonstrate Unlimited Associative Learning by recognizing objects by sight that they've only touched before. Illustrating that even simple brains can do cross-domain transfer that AI cannot. We talked about Benjamin Libet's experiments demonstrating that our brains make decisions hundreds of milliseconds before we're consciously aware of them. With existential implications as well as implications for businesses, they could theoretically predict customer behavior before customers know what they'll do themselves. And we talked about how while LLMs show impressive combinatorial creativity mixing existing ideas, they lack the transformational creativity needed for paradigm shifts like Einstein's Relativity. And we talked about how Pecan AI uses LLMs to democratize predictive analytics, automating the 90% of data science work that involves data preparation rather than modeling.

01:15:51 As always, you can get all the show notes including the transcript for this episode, the video recording, any materials mentioned on the show, the URLs for Zohar's social media profiles, as well as my own at superdatascience.com/907. And yeah, thanks to everyone on the Super Data Science Podcast team. Our podcast manager, Sonja Brajovic, media editor, Mario Pombo, our partnerships team which is Nathan Daly and Natalie Ziajski, our researcher, Serg Masis, writer, Dr. Zara Karschay, and our founder, Kirill Eremenko. Thanks to all of them for producing another extraordinary episode for us today. For enabling that super team to create this free podcast for you, we're deeply grateful to our sponsors. You can support the show by checking out the sponsor's links which are in the show notes. And if you ever want to sponsor an episode yourself, you can get the details on how to do that by making your way to jonkrohn.com/podcast.

01:16:44 Otherwise, support us by sharing the show with people that would like to have their minds blown by Zohar. Review the show on your favorite podcasting app or on YouTube. Subscribe obviously. But most importantly, we just hope you'll keep on tuning in. I'm so grateful to have you listening and hope I can continue to make episodes you love for years and years to come. Until next time, keep on rocking it out there and I'm looking forward to enjoying another round of the SuperDataScience Podcast with you very soon.