​​**Michael Jordan [Guest]** 00:00

But what's new and exciting is the economists really never talked about adaptivity into data that much econometrics, which measures the economy and tries to say what is the GDP going up or down or whatever. But what's really exciting is mechanism design and contracts and auctions and interactions between people, recommendation systems brought into economic decisions, where what I do depends on what you've done and the data is being shared and decisions are being made based on updated data. How do you imagine that Amazon can sell a billion products to hundreds of millions of people? There's no human being that could ever work out the logistics that are needed to do that. That's all been done by machine learning. So Amazon, in fact, the advent of cloud computing didn't just arise because Amazon thought we should put lots of computers out there and let people use them. It instead arose because Amazon had lots of computers, because it was all doing machine learning on logistics data, supply chain data and then eventually on kind of commerce data.

## **Craig Smith [Host]** 01:00

Hi, I'm Craig Smith and this is my AI. This week I speak to Michael Jordan, not the basketball legend, but Michael I Jordan, a towering figure in the world of AI. Michael is co-author of the book Machine Learning a probabilistic perspective, which is a standard textbook in the field. We spoke about his perspective on deep learning, deep learning, statistical foundation and his interest in networks. I hope you enjoy the conversation as much as I did. Hi, I wanted to jump in and give a shout out to our sponsor, netsuite by Oracle.

## 01:42

I'm a journalist and getting a single source of truth is nearly impossible. If you're a business owner, having a single source of truth is critical to running your operations. If this is you, you should know these three numbers 36,000, 25, 1. 36,000 because that's the number of businesses that have upgraded to NetSuite by Oracle. Netsuite is the number one cloud financial system accounting, financial management, inventory, hr and more. 25 because NetSuite turns 25 this year. That's 25 years of helping businesses do more with less, close their books in days, not weeks, and drive down costs. One because your business is one of a kind, so you get a customized solution for all of your KPIs in one efficient system with one source of truth, manage risk, get reliable forecasts and improve margins. Everything you need all in one place. As I said, I'm not the most organized person in the world and there's real power to having all of the information in one place to make better decisions. This is an unprecedented offer by NetSuite to make that possible Right now.

## 03:12

Download NetSuite's popular KPI checklist, designed to give you consistently excellent performance, absolutely free at netsuite.com. Slash I on AI. That's I on AI, e-y-e-o-n-a-i all run together. Go to netsuite.com slash I on AI to get your own KPI checklist. Again. That's netsuitecom. Slash I on AI, e-y-e-o-n-a-i. They support us, so let's support them.

## **Michael Jordan [Guest]** 03:53

It's my pleasure to be joining you. I'm Mike Jordan from the University of California, Berkeley. I've been working in machine learning for roughly 30 years and continue to be very engaged and active.

## **Craig Smith [Host]** 04:08

You started in deep learning, or at least you were involved in deep learning some years ago. Then, from what I've read, and heard you've become a critic of deep learning and have spent your time more in statistics and other forms of machine learning that don't rely on neural nets. Is that right?

## **Michael Jordan [Guest]** 04:39

No, I'm definitely not a critic of deep learning. It's gradient descent and it fits data and generalizes in high dimensional spaces. That's all for the good. I would also debate. It is a statistical technique. You analyze it with statistics. You say how well will it generalize? That's a question of statistics. There's an unknown distribution out in the world which is generating future data. You'd like to estimate how well you'll do relative to that. You'd also like to put uncertainty quantification around your deep neural net, which is an active area I'm engaged in. That it's all for the good. It's just that deep learning itself doesn't solve all problems. In fact, it's one tool in the toolbox. It's as if you were a civil engineer and you said I've got a hammer that solves all problems. It's a very good hammer. My critique is more about the casting of the overall bigger problem. It's definitely not a critique about deep learning. I definitely don't see it. It is statistical. It should be analyzed with statistics. It has a statistical foundation. There's no conflict whatsoever between deep learning and statistical thinking.

## **Craig Smith [Host]** 05:54

How do you see the current trend in deep learning fitting into the larger progress of machine learning or AI? As I mentioned, I'm particularly interested, as everyone is right now, in the development of large language models and the multimodality of large models and the increasing generalization of these models. Is that a direction that we'll begin to draw on these other kinds of AI?

## **Michael Jordan [Guest]** 06:30

There's not another way to do language. Right now, language is about understanding and semantics and meaning. We're conversing. That's what really matters. But, just like vision, there's also lots of lower correlations, small changes in inputs that are interesting but are not the major communicative issue.

## 06:57

Naive methods focus too much on all the little stuff. Again, for visual scenes it's kind of obvious. If I could have visually seen, there's all kinds of stuff in it, all the pixels and most of those pixels don't matter. Naive methods pick up on most of the stuff that doesn't matter and get lost. The deep learning technology has been able to focus down on some of the stuff that matters in the scene. Think of it as kind of poor man semantics. It captures all kinds of little correlations that most of us are not aware of or don't even really care about. Some of them are interesting, but it's still poor man semantics. It's not doing human level, abstraction, human level, reasoning, human level. What if experiments in our head are planning over long stretches of time, pulling together diverse kinds of knowledge? It's not doing that stuff. Does that mean it will never do that stuff? No, I wouldn't say that. It's a platform. It's a tool that allows you to get started. Instead of having to focus on all the little details, classical AI would have started with all the little details and tried to build an edifice on top of that. It just says learning will kind of handle a lot of those things and you don't have to worry about them. You can now start to build abstractions of various kinds on top of this, and so I think that's the way to think about it. If your focus is language and you should be impressed or wowed by accomplishments, surprising things that come out that seem a little bit like a hint of semantics or a hint of reasoning, well that suggests that it may not be as terribly hard as we all thought it was, because human knowledge is so rich and every little thing seems to matter the little subtleties and what words we choose and how we place them and how we string together arguments and all that. So some of that can just be picked up in the statistics of billions of words. It's not how humans learn with gradient descent on billions of words. It gives a platform for building more things that are more human-like on top of that and starting to lead to things that are even more surprising and look more and more like understanding of semantics.

## 09:20

When I say semantics, it's not even a technical term, it's just as you and I are conversing. We both started to build up a model in our head of what we're talking about, and it may be things in the world, it might be events, it might be social relationships, it might be philosophical issues, it might be emotional things, but we start to build up a model of things that we're talking about and we communicate around that model, and so if I'll say something in 20 minutes, it'll be in the context of not just the string of words I've uttered, but the model that you and I have built up based on our commonalities. And so we're very far away from doing that kind of thing with computers. Just to say it doesn't mean that it's impossible that we won't start to get there, but we're very far away from that. So you know, deep learning should be thought of in context of one step towards a much, much more complex problem that wasn't being solved before at all, and maybe this is a glimmer of a path forward. But just gradient descent on large amounts of data to me is not the answer. It's an engineering discipline also and it's thinking about what are the structures and what are the things that we need, and it's not classical AI and it's not just gradient descent, it's more. And so there's open research questions there. But the other part is that large language models and large visual models and all that generate interesting looking things. So it's a palette. You can now do it, to use it to do creative things, just like artists had new kinds of technology available to them in the past, and they use them creatively. Modest amounts of businesses, business plans, can be built on some aspects of this. So it's you know it's all to the good.

## 11:07

But again, it's a small part of a bigger, much bigger kind of set of issues. It's pattern recognition. There's many correlations and high order correlations and large amounts of data and, hopefully, generalizing from one day to the next. I should say I don't think that's really being done particularly well. There's lots and lots of distribution shift issues, which are very much the real problem in real life, because things change all the time that these methods are still quite poor at. They're also quite poor at uncertainty, quantification and reasoning. They're poor at causal reasoning and what if experiments. And when we start thinking about hard decisions, we start doing what if experiments on our head and they don't do that particularly well and so on and so forth. So this isn't a critique fundamentally, it's just that these are the open research questions. These aren't the ones that are solved by just running gradient descent on vast amounts of data. And so there's a little naïve thing. I think that you see people that are wowed by billion parameter models and billion parameters and just so you can do it is pretty interesting and that surprising stuff comes out is pretty interesting. But that's that we should tamp down a little bit of that wow experience and realize that this is a hard field to make progress in and most of the challenges are still ahead.

## 12:24

Yeah, the other part is kind of what field is this? Does this imitate humans? Because if you think about natural language, the obvious goal is that I could do the Turing test. I could talk with a human and I'm a computer and it would be just as good as a human talking and it would understand a lot of the richness and subtleties of language and so on and so forth. And yes, that's a great question or a great aspiration or goal.

## 12:56

In the 1940s and 50s it was very natural to ask this question: Can you do this? Because there weren't really computers before that. The whole notion that we have hardware and software looks a little bit like mind and brain and that maybe just algorithmic rules can do things like language was for grabs, and it was exciting to be able to take a philosophical question and turn it into a almost an algorithmic or mathematical question, and so a lot of people, including in my generation, were raised on that. If you can imitate humans and natural language is probably the key venue in which you should be exploring that then that's a fantastic intellectual achievement by humans. True, and we still haven't really achieved that. We don't have machines that understand and reason remotely close to what humans do, but on the other hand, it's not necessarily the real problem to imitate a human you can ask about well, if I could imitate a human, what would I do with that? You see a lot of AI people scrambling around and saying, well, it'll do this and that, but most of the things it'll do are low-level, replacing lots of jobs like call centers or robotics, things.

## 14:17

In the meantime, computers are being used for all kinds of things: financial markets, transportation systems, commerce, education. All kinds of network phenomena are rising in Healthcare that are being labeled as technology, ai technology, but that were very far away from the original vision of replacing a human or substituting a computer. The skills of a computer are those of a human. We have billions of humans. Having a few more is not going to necessarily change things. Then the goal becomes well, it's going to be better than humans.

## 14:58

Now you're off into science fiction. I'd like to think about what are the current problems? To me, they're more in the network. They're more in the economy. When I say economy, I mean the network. If you and I are interacting on a computer or maybe you're a computer or maybe I'm not, and maybe there's thousands of us or millions of us we're all interacting. There's got to be principles that govern those interactions. A lot of them are not going to be just logic and language. A lot of them are economic. What's your value on this? What can you tell me? What do you want to tell me? What are our incentives to interact? How's that all conditioned? My data? How does that flow forward over time? How does the change in conditions reflect in that overall system? Ai? People just for the most part not everybody just don't think this way. They don't think about the overall, bigger network and system. Think of that. The goal is to study that and study the principles of that. It's not just the AI goal of putting intelligence in a computer.

## **Craig Smith [Host]** 16:03

Yeah, to me AI is there. One of the goals is to create systems or computer systems that optimize existing systems beyond what humans are capable of doing. And then part of that is making, or maybe an offshoot of that is making a decision based on that optimization, or getting to that optimization that maybe the variables or the data is too great for a human to be able to manage. Intellectually, an AI system could make a decision based on a much broader field of data than a human could and make a decision that is quite unquote correct. And then there's building a cognitive model, and I think you did some work on that when you were at MIT at the Brain and Cognitive Sciences Department and from there. Then there's a question of whether you can build a system that does reason, and I know that there's a lot more going on than those three buckets, but that's the way I think about it.

## 17:37

Like optimization on a very grand scale. You have Russia and Ukraine, for example. There are competing goals and desires. Presumably, if you took all of the variables and threw them into a system that could optimize perfectly, it would come up with a solution between those two states that would satisfy everybody, or at least come close to satisfying everybody and then, if you have a system that is allowed to have a certain amount of autonomy, it could make a decision based on that optimization. Can we talk about that first? And then I wanted to talk about cognitive models and reasoning. There was a fascinating talk at NURUP's by a guy named David Chalmers you probably know him about the possibility that large language models could develop some form of reasoning and low level consciousness. But on optimization and decision making, do you have any thoughts on that?

## **Michael Jordan [Guest]** 19:04

Yeah, probably more than you want to hear, I don't. Yeah, I have a very different perspective than the one you're alluding to. Really, economics people have talked about these kinds of things a lot. When you say the word system, I think you keep referring to the system as a computer, as the operating system that does something, or the system that we, the cognitive model, that we put in a box and it does something as it makes a decision. And really the system should be thought of as like a whole network in an economy, the system that brings food into New York every day.

## 19:39

If you didn't know any better, if you're sitting on Mars looking out the earth, you'd say, wow, there's something really intelligent going on there, and it's composed of many parts which apparently are these little individuals deciding whether to bring carrots from one side of a city or to the other or not, or whether to supply wheat or bake things. It's all these kinds of things happening and what happens at the end of it? The output of all that is that people eat, that several millions of people every day have the food they need, and it happens day in and day out for a long time. That's amazingly intelligent, that system, All right.

## **Craig Smith [Host]** 20:12

Yeah.

## **Michael Jordan [Guest]** 20:13

And that is a system and it has its principles, and a lot of them are not optimization principles. In fact, most of them are not optimization really. They're like equilibria finding and Pareto equilibrium, that we can't exactly have what we want, but we'll trade off this and that We'll price it. They're also looking, I'd like to, I'm your boss and I'd like to get you to do something, but I don't know how much, how sick you are or not. You're not going to tell me. Or I want to get people to pay for something like health insurance, right? I don't know how sick they are, how willing they are, and so I don't know how to price that and they're not going to tell me. So I've got to develop a system of incentives that is responsive to that situation of asymmetric information, missing information. Interimation is not just available, and so when you talk about Ukraine and Russia, a lot of information is not available. It can't be, it's impossible to consider an optimization. That's science fiction, signing science fiction. It's unrealistic. And so what do we do as human beings that we can't even conceive of optimizing? We find equilibria, we set up incentives so that even I don't know what you're, I know that I've incentivized you to behave in a certain way and that'll hopefully lead to more of a satisfying equilibrium that we arrive at All right now.

## 21:38

The economists didn't necessarily solve all these problems but they talked about it and, with all due respect to computer science and philosophers, they missed some of this economics discussion and they bring in the fairness issues that are being treated fairly and really it's about this overall system. But what's new and exciting is the economists really never talked about adaptivity in the data that much econometrics, which measures the economy and tries to say, well, is the GDP going up or down or whatever. But what's really exciting is mechanism design and contracts and auctions and interactions between people. Recommendation systems brought it into economic decisions where what I do depends on what you've done and your data is being shared and decisions are being made based on updated data. It's not even a decision you can localize in a single quote, unquote system. It's the overall system. The air traffic control system is making decisions all the time that are reasonably intelligent and the economy is making decisions all the time at all kinds of levels.

## 22:48

And so just this way of talking and thinking, it just wasn't present what you were saying and this notion that there's the technology of optimization on the one hand and then there's the human cognitive thing on the other hand, to me just missing the entire picture of what real computer science is being used for. Our cell phones give us compute power. They network with each other. We create value where producers and consumers are various things. We do that over time. We interact, we learn about outcomes. If you had a nice experience in a restaurant, I learned about that and so on. That changes the economy. It's a whole big closed loop system and this is going to take a long time to work out.

## 23:26

But to me this is the problem of the era. And with all due respect to cognitive modeling and thinking about the philosophy of consciousness and all those wonderful things to work on too in parallel, it'll take a couple of hundred years and for each of these things but one does not depend on the other at all what I'm talking about is just. I think the problem is if you go to Europe, she'll hardly hear anything about it. Do we have intelligence and consciousness in the classical AI sense? And so that's what exercises me. It's the kind of lack of understanding of the real world implications of throwing computers and AI out there in the world and hoping our systems perform well and do the right things and they're not, and there's going to be a lot of problems. This happens in any engineering discipline.

## 24:15

Now, if you're into the deep neural nets thoroughly this is the you're excited about the potentials here, that it maybe starts to do some reasoning or something like that. Again, that feels a little science fiction to me, frankly, but I do believe new things will happen. It's not just that we're going to take our current economic systems or current transportation systems or current systems and just add some data and it'll be a little bit better. No, it's going to be new things will happen. That's what really any sufficiently powerful technology does is that creates new possibilities, new ways to interact. Like I say, the economics models didn't have a lot of learning or data in them. You throw that in there. It's going to be a brand new kind of market that will arise and brand new ways to interact.

## 25:01

And, like I said, the deep neural nets. One of the things is that they look like a bit of a toy sometimes. That's good, because humans like toys. We can create new kinds of entertainment, new kinds of art can arise, but it's going to often involve humans directly the idea that an autonomous entity there, sitting there in a box with wires, is going to do things that are artistic all by itself, maybe not, I don't really care. Frankly, what I care about is that the next Mozart can come along and make use of all this technology and do something amazing, because Mozart's got emotions and Mozart can speak to me, and so on. So, anyway, I hope that what I really wanted to convey here is that there is an economics perspective on the system, which includes all the interactions of huge numbers of individuals, be they computers or humans. That is really the focus of what I think we're most responsible for doing right now, in this era.

## **Craig Smith [Host]** 25:58

Yeah, looking at systems from that much, much broader, heterogeneous perspective, how does machine learning play a role in that? Take logistics right Now there's a supply change, disruptions all over. My sort of science fiction vision is there's this AI that can pick up all of the different data points in the supply chain and see where the problems are and how to resolve them, or how to reach that equilibrium that you're talking about.

## **Michael Jordan [Guest]** 26:48

Ok, that's not an equilibrium. Now we're talking about a limited problem, which is more about how do you get goods from one place to another, and you can start talking about optimization, because you can measure everything and there's no adversary, there's no strategic aspects of it. But you just got to understand that that's what you just said already was happening in the 1990s and certainly into the 2000s. How do you imagine that Amazon can sell a billion products to hundreds of millions of people? There's no human being that could ever work out the logistics that are needed to do that. That's all been done by machine learning. So Amazon, in fact, the advent of cloud computing didn't just arise because Amazon thought we should put lots of computers out there and let people use them. It instead arose because Amazon had lots of computers, because it was all doing machine learning on logistics data, supply chain data and then eventually on commerce data the human facing side and then recommendation systems, which had to do with human choices. Their computer systems were built circa 2000, let's say, to do these large scale supply chains and indeed they would measure. There's now a strike in China, or there's a weather event in the South Indian Sea that's going to affect these ships and so on. That was all done with machine learning and so we would have never had Amazon or Alibaba or whatever without that. And so it's already happened and the question is going to be better. And that answers definitely yes.

## 28:18

But first of all, the supply chains we have now are amazing, rich and complex. It's a huge accomplishment that people don't really talk about so much, but 50 years ago people were super jealous that such things were possible. But they could be more abstraction oriented. They could take into account strategic aspects of it. They could do some of the bargaining that humans do between themselves. They could have auctions like you have in search engines. They could do much more, and they will. That's an ongoing thing, but that is what a company that takes products all the way out to people does in the modern world. And again, it's not so sexy that you'll see lots of articles about it in the New York Times, but it's been missed that it really already happened.

## 29:07

So the cloud, just to finish that thought. In circa 2000, amazon built all these computers to do all their internal data processing of logistics chains and then commerce, and at some point they realized, hey, this is really working well for us. We can run our data analysis on 10,000 computers and do a really good prediction of the logistics chain. Why don't we let other people start to use our computers too? Because we're able to scale it arbitrarily. And that thought was that it was the cloud. And so the cloud emerged from machine learning. I thought it's the other way around, but no, the history is that it emerged from the machine learning workloads.

## **Craig Smith [Host]** 29:48

And how do you apply something like the Amazon system to a non-proprietary supply chain where you have actors all over and there's no central authority that's going to be managing it?

## **Michael Jordan [Guest]** 30:14

So now those are starting to be really interesting questions. I think we're now on the material I'm most interested in. So first of all, forget the specifics of the Amazon supply chain. That's going to be internal to a company, but think about health care. Health care is a big supply chain, if you will. There's all kinds of obviously, the drugs or the needs for surgery, the supplies that you need to run a hospital and all that. But there's also the supply of knowledge about genomes and tumors and treatments and all that, and those could be thought of as internal and proprietary, and in some ways they have been for much of history. But that's changing.

## 30:56

The pandemic really helped a lot that people are revealing. Hospitals are passing lots of data among themselves, doctors have up-to-date predictions of treatments, clinical trials are being more adaptive and that overall system is now responding to the availability of machine learning and it's led now to this emergence of what's called personalized medicine, where go in and they analyze your body in that moment in the context of all the other human bodies that have been measured in the last few years, in the context of all the treatments that have been tried, and that overall system starts to make better predictions and then hopefully help you with better decisions. I don't think it'll autonomously make the decisions, but that overall system will feed that information through a doctor to you and it's a big supply chain of information as well as all the products that are needed. That allows us all, collectively on the planet, to be more healthy. And even though we're pretty healthy now, way more than past history, the pandemic shows us how unhealthy we really are in some sense. Millions of us died and, looking back, one could have done it much better, and a lot of the solutions there are like machine learning systems thinking and hidden information thinking and incentives kind of thinking, and some of it is just old fashioned politics or legal barriers that prevent people from sharing, but some of those are also based on lack of information. I don't know what the consequences will be If I give out some data. Maybe I'll get thrown in jail or something. So working out the overall system, which now will start to include legal people and medical people and advocates of all stakeholders of all kinds, that's the modern technology.

## 32:46

Those are the issues to focus on, and it's not just one company that will do that. It won't be locked up inside a part of your company. It'll be an overall societal effort, and so the supply chain knowledge we have from a company like Amazon, it's already clear. A lot of that is actually fairly open, and in fact, a lot of their methodology has been brought to the fore, like in SageMaker and the other platforms that these companies have built, because if they keep it bottled up, they don't have a very good business model. They need to make it open source so people will actually buy it and use it, and so there's not that many huge secrets stuck inside the detailed data maybe, but it really is not just locked up in the company, and people who work in these fields are pretty much aware of this People in health care, people in commerce, people in finance that oh, I got all this data and oh, I've got the platforms and the algorithms and if I get good engineers and I work hard on this, I can start to do things.

## **Craig Smith [Host]** 33:50

You on healthcare and the example of my going into a doctor and having them take a scan or collect data from my current state and then relating that to all of the other people that have provided data and the various outcomes for various treatments and that sort of thing. That's one kind of network, right that you're talking about, where every node is informing every other node, so my state of health, my history and treatment, then an outcome would go into the pot and inform everyone else. How do you see that being managed? Because for that to happen, don't you need a central authority to manage that, or does it become? Is there a network of fact that you have all these different systems that are tied together, that are learning from each other and collectively get better?

## **Michael Jordan [Guest]** 35:15

I don't think anything I said required any kind of central authority. There's lots of federated learning methods. There's lots of concern about long tails. There's lots of peer-to-peer kind of methods that allow systems of all kinds to be built that mostly don't require central authorities. Again, just think about economies, the system, the technology that brings food into any city in the world, not just New York. There's no central authority that runs it, certainly, and there's certainly no central authority that designed it. But there were principles that were put in place and there were incentives created and there were roads created because they knew that would help this overall process and so on. So it's more than that level of thinking. Central authorities are. There's roles for them.

## 36:08

Again, economists have talked a lot about this, the tragedy of the commons kind of issues, free writing kinds of issues. How do you structure systems? There's not the negative externalities. When you think about those issues in the new context, all this data flow and all these nodes, sharing data and all these competitive issues, all that, it just becomes exciting as an academic and as a person thinking about public policy, because now over the next few decades it's all going to change.

## 36:37

The previous systems we had for medicine, the previous markets we have for the economy, for entertainment at all, are going to have to completely evolve in this new world. If we're smart as human beings, we'll do things like previous engineering disciplines Civil engineering or chemical engineering. We'll organize it as a big set of principles that allow us to think about these overall systems and allow them not just to be a big black box but allow them to be a working, breathing system that has pieces that will have all this machine learning. Part of it is technology. But it's not just the big black box that solved our problems, or that we created an artificial entity that solved our problems for us.

## 37:20

It's us, as kind of creators of principles, that figured out how to design systems that we want, and then the future engineers of this field whatever you want to call it will learn all these tools and these principles, and then they'll go into particular domains. I need to design a education system in Southeast Asia, or I need to design a climate mitigation policy using adaptive measurements, whatever, not too soon. This will be exactly the same. It'll be just like no two chemical factors are exactly the same. There will be an engineering process that brings all these things together.

## **Craig Smith [Host]** 37:59

Yeah, that's interesting. And maybe when I said central authority, I didn't mean a government or a company.

## **Michael Jordan [Guest]** 38:05

No, I didn't take you to mean that, but I see you seem to imply that there had to be a computer or an entity that would collect all this stuff and organize it and, like I say, that's just not. Most economies don't have that kind of thing happening and you don't have to think of systems that way. And, like I say, we are all over that in our research field, things like peer-to-peer or federated or all that already are very much focused on issues like that.

## **Craig Smith [Host]** 38:33

Yeah, can you talk a little bit about your work in multi-agent learning and how that might relate to this?

## **Michael Jordan [Guest]** 38:42

Sure, maybe. Just let me give an example of. I mean, maybe to give a couple of examples. But one of the topics I'm really interested in right now is asymmetry of information, like I was alluded to earlier.

## 38:59

In economics it's something called contract theory or that's the solution methodology, and in our federated learning situations we often have this model, this idea that data resides at the edge of a huge network. People have their cell phones or their cars, and it would be nice if you'd collect all that data centrally so you could build a huge mega model and then everyone would profit from that. That's the original vision and for some cases that's appropriate. For other cases, you really have to worry about the incentives. Why would anyone willingly allow their data to be sent in? And if they wouldn't allow their data to be sent in, could at least some of it be sent in? And now you start to talk about trade-offs. You say I'm going to lose a little privacy, but maybe it all gets a benefit from that.

## 39:57

So I like to think about things like recommendation systems for real-world goods, like I go into a brand new city Singapore. I've never been there. It's 6 PM, I finish my meetings and I'd like to get dinner. I'd like to be now in a system which knows something about me. I like Sichuan cuisine, I have a certain price point, I'm located in a certain location. Here's the kind of things I've tried before when I'm in Southeast Asia. Whatever, it knows some things about me, but it doesn't know everything about me. It doesn't know lots of stuff, so it knows some limited things about me.

## 40:32

The overall system. It takes that information then and it broadcasts it in a market that there's also on the other side of the market. There's restaurants or whatever that see me as a possible client and they see other possible clients. Maybe there's 10,000 people at that moment with their cell phones out looking for dinner. And that overall two-way market does a kind of a matching, but again based on all the data that's been provided by some history. And so now I am glad I gave up a little privacy because suddenly on my cell phone there's a sign for a nice restaurant that is perfect for me and it was a match for me. And it's not just that I got a search engine that gave me a long list of things or some advertisements or whatever. I got something that actually was matched to me for good reasons, and the matching means that they're not going to send 10,000 people to the same restaurant because different people are going to have different preferences and they can get placed at other places. So I like that kind of way of thinking. It shows that privacy is just part of the trade-off, that sharing data is part of the overall system that I want to get some value out of, and so people now work on that.

## 41:41

How do you value data? What do you think about building systems that value data? And now, in situations where two people have the same data, how should I value them equally? If 5.1, is that enough? How do I pay people for supply data? These are issues that really touch on lots of fields, not obviously computer science, but statistics, sociology, and law and this is what excites me to think about how to build such systems.

## **Craig Smith [Host]** 42:19

The multi-agent learning. What role does that play in this?

## **Michael Jordan [Guest]** 42:24

So multi-agent learning is a buzzword. It just means any learning where there's multiple entities. I like to think of these entities as strategic. You're not just collecting passively from agents and they're just not willing to share. And so let me give you this concrete example that helped us think about contract theory a little bit.

## 42:47

So the FDA, the Federal Drug Administration, every year has got, or ongoing, has, this problem of trying to figure out what drugs should go to market. But they don't develop the drugs themselves, they test the drugs, and a test costs tens of millions of dollars. It's a clinical trial. So we've seen that with the vaccines, all right. So the FDA is running a statistical test. So it's collecting data from the clinical trial and trying to decide whether a drug is actually good or it's actually not good or not effective. A big, important decision. It's a statistical decision, though, because there could be false positives. There's data being collected, all right. So now the agents are the pharmaceutical companies, and there's a large number of them, and they're all sitting out there and they are trying to build and construct new molecules or new proteins or whatever, and they're trying to, and they test them internally and start to learn a little bit about what's promising and what's not. But at the end of the day they're gonna send some drug candidates to the FDA and the FDA is gonna test those drug candidates and if it passes the test they're allowed to go to market and they can make billions of dollars. So clearly they're highly motivated to send lots of candidates into the FDA.

## 44:05

All right, now the FDA is sitting there saying I'm getting all these candidates and for people hoping to get false positives or maybe true positives, it wouldn't be nice if I could ask those drug companies hey, that candidate you just sent me, that's a really good candidate or not? Internally, maybe you don't know if it's really good. You've done some internal tests, if you put your best engineers on it or not. So if you ask the drug company that, hey, is that a good candidate or not, they're not gonna tell you or they're gonna lie. And that's what humans do A lot of times when we ask humans for data. If you ask me if you're an insurance company, you ask me how much I exercise, I'm gonna lie, and so lots of data has that strategic flavor to it in the multi-agent setting. So now the FDA is sitting there and saying, okay, I can't just ask them and that's called. Well, that's a problem of moral hazard, or adverse selection in economics language. There's people that possess information. They're not just willing to provide it and they won't provide it, and if you ask them, you push them. They'll provide you false information.

## 45:11

Okay, so contract theory is a way to set up what are called contracts, and these are menus of options. If you pay this amount, you'll get this, if you pay this amount, you'll get this, and so on. Just like when you go on the airplane, you've got business class fare and you've got economy class fare, and so on, and you've got different services. That allows you to effectively charge people different amounts based on their self-selection, and so contract theory is a mathematical theory of how to do that and some generality, all right. But again, it wasn't ever statistical. It was not a statistical contract theory. You didn't collect data as part of the process and do a hypothesis test, all right. So that's what we've done.

## 45:47

We've created this statistical version of contract theory where the FDA now offers the drug companies a menu of options. If you pay this amount, I'm gonna do this kind of test and you'll get this kind of outcome. You pay this amount, you'll get a different outcome, and so on, and the drug company will look at that. And now you set it up so they are incentivized to mostly sit in their effective drugs, the ones they think are most effective. And now see, the FDA is collecting things and they have to pay out a little bit of money and they're making bets really, but they've set it up so that most of those bets are likely to be good ones, just like the airplane has set things up so they fill their airplane and most people are happy and that's not being done because this problem hadn't been thought about before. But now I hope you can see that this is a very common situation.

## 46:35

I've got lots of agents who possess private data and there's no way you're gonna get that data because they're not incentivized to get it to you. But you'd like an overall system to run effectively by supplying some aspects of that data, and so you gotta set up these options, and now you're using data to inform the menu of options, so it becomes this fiscal thing. Okay, that's probably a little bit of a technical description, but when you really say the word multi-agent, this is what you gotta start thinking about: Strategic agents who possess things that others don't possess. It's decentralized, and it has to be because people hold on to the value they have internally. They don't want their competitors to know, but they also don't want decision makers to know, and so this is leaked into the machine learning world.

## 47:24

We do things like ask people for loans. When you ask a bank for loans and you're trying to use machine learning internally to assess whether to give someone a loan, when you collect data from people, if they know a little bit about the algorithm being used at some neural net or some logistic regression, they're going to fake their data a little bit so they seem more likely to be loan worthy. The system should know that a priori. Machine learning is now starting to work on this a little bit and treat these as fairness issues or adversarial issues and all, but really a lot of these frameworks already exist. If we take the more broad perspective, we're designing economic systems that have got contractual and strategic issues and valuations being made and so on, and how does data inform all those kinds of issues? So I have a lot of work on that, and this to be is the field of multi-agent. It's critical that the agents be strategic for me, because that makes it really interesting. That makes it. There's opportunities for cooperation. There's opportunities for competition.

## **Craig Smith [Host]** 48:32

And in that view agents are human agents or organizations.

## **Michael Jordan [Guest]** 48:38

No, they don't want to be any. They could be all the above and so, for example, think about a system that we're already close to traffic control. If I want to get to the airport, I plug in from here to the airport and I get the fastest route right. It's the fastest route based on historical data and at the moment it's not clear that it's the fastest route and the calculations are getting better and better. But the point, the problem, is that as soon as you start making this into a decision-making system, not just pattern recognition from past data, you can send lots of people down the same route and you will create congestion and that'll show up pretty quickly. Other people coming will see the congestion. They may avoid it, but you've created congestion and these kinds of smart pricing systems, like you have now in some cities, start to feel like a solution.

## 49:42

I might want to really get to the airport quickly, because I've got a flight that's leaving and I've got someone sick I've got to go see, and so I'm willing to spend a little money or some currency, whatever, whereas you are. Hey, I can go slowly. Or hey, I wouldn't mind taking a longer trip and seeing the mountains. I've never been here before, or I got to stop off at the pharmacy or whatever. And so there's all these human little decisions that kind of decide who gets to go on a certain route and who would go maybe, on other routes. It shouldn't be an arbitrary, top-down, centralized decision. It should be more like an economy and a market. And now who's going to sit in your car and actually run an auction for people to see who values a certain route the most? No way.

## 50:26

What'll happen instead is there'll be like avatars and those will be like computing systems who are like acting on your behalf, and so think of these like brokers. And so they will look at the situation, gather all these bids and they will run a little auction on your behalf, just like we have with search engines and ads. And then people will get routed and it has to be verifiable and all that. But this kind of system we're not that far away from that. But with the last step that I mentioned, creating an economic version of the current data gathering systems and prediction systems is still not. We don't have it yet, but I bet in 10 years we will, and the overall effect of this will be social value. You will have much better flow where this economic part gives it to you. So yeah, lots of great problems of that kind are multiple strategic agents interacting via data-informed markets.

## **Craig Smith [Host]** 51:30

Yeah, although the agent isn't learning through that interaction. It's just drawing data from the agents, right? When you think of autonomous cars? In a community where all of the autonomous vehicles are communicating with each other and learning from maybe one, that's what I think of as multi-agent learning, where one car encounters some side case in the long tail and then informs all the others about what to do in that case. That could also apply to the traffic problem when you get in an autonomous car.

## **Michael Jordan [Guest]** 52:12

I don't see the distinction. We're talking about the overall transportation problem, getting huge numbers of people from one point to another, and some of that is to recognize what's happening on the street currently, and that should feed into this system. But I'm just saying, on top of that should be also who gets to go where? Kind of a decision. If everything was literally autonomous and it was just sharing data, then you would still have the problem if you sent too many people down the same street and you'd still have the problem of. Moreover, you just learned the street is blocked or that some kid had just run into the street so people shouldn't go there. That's great. But then how do you then percolate the decision making to who goes where from that? You can't again just send everybody one place and all. So the overall system is, and so the one I'm referring to as this little economic layer, but that's a learning system too.

## 53:03

When you run auctions, those are learning systems, those are. When you run contracts, those are learning systems. They base how they make their decisions on past decisions and on past interactions. And if I go into a new city, people drive differently. I should have my avatar know that or learn that quickly, and people have certain valuations. From that should be learned and should come into the way my avatar interacts. I was just trying to emphasize that it's not just humans doing all the decision making, it's also avatars. But that's why we need the theory of decision making that includes valuations, and then eventually the valuations have to be okayed by the human. I want my avatar acting on my behalf, not wildly or weirdly.

## **Craig Smith [Host]** 53:58

Yeah, that's fascinating. You work with Amazon, it is. How do these ideas find their way into the real world?

## **Michael Jordan [Guest]** 54:12

Very directly, but I do a day a week. I'm an Amazon scholar and so partly I just go in and it's for my own benefit. I see emerging problems and a lot of the things I'm talking about here were informed by experiences. Also, I spent time at Alibaba in China watching real merchant producer interactions. I've also spent time in a company that's changing the music business by creating a direct consumer or a listener to a producer, to brand relationships and all that.

## 54:49

I go into companies. I think like any classical engineer or scientist saying what are the new problems that are emerging? And you see the kind of things I'm talking about Logistics, you see uncertainty, quantification, you plan it. You see what if experiments, causal inference, you see all kinds of data flows, of race kinds. You see the attempts to create market-based mechanisms, and not just Amazon but just most companies have a lot of this going on and I just wish our academic world would be a little more tied in, responsive to that and a little more aware of the problems that are emerging there. But yeah, there's no secrets that all of these companies have got, especially Amazon.

## 55:43

What I chose Amazon was because they literally do the Indian problem. They're taking products made by anybody anywhere roughly and they're sending it all the way to the doorstep of other people. And there's human preferences all along. There's scale issues, there's uncertainties. It's not just. They're creating a website or a platform or a service on the web, which is fine, but then it's a little artificial. You have to monetize it with advertising and all that, and I'm more enamored of situations where you monetize via. People actually pay for things because they're getting value out of the overall process. And how do you make that fair? How do you make that efficient? What are the new issues that arise when you look at that?

## **Craig Smith [Host]** 56:24

Yeah, I'm up against an error, but I just want to ask about the music. My son is in the music business and is looking at applying AI to surfacing catalogs that have future life. Can you talk about the company that you're referring to and what it is that they're doing, or that?

## **Michael Jordan [Guest]** 56:46

you're doing. No, the company is amazing. It's called United Masters and I'd highly recommend having a look at it on the web. It has over 2 million musicians, mostly young people, who are really good at making music but who are never getting paid directly, and when they were never really in a market for their music, they were up-gloating songs that were getting streamed by other people who were selling subscriptions. So now, for example, the National Basketball Association is one of the brands that United Masters has signed a contract with, and so music being streamed on the NBA website is actually coming from these United Masters musicians, who are often 16 or 18-year-olds and they get paid when their music is streamed, and so it's a three-way market. You've got the musicians and they create music, and also you have listeners, and so now the data starts to inform you about who's listening to what. It's a recommendation system and a two-way market, but then you also have brands who want to be associated with certain kinds of music, and so it becomes a three-way kind of entity here, all informed by data analysis, all informed by adaptively connecting people, and it's actually a thriving economic entity.

## 58:08

It's not the old record company business, it's different. It's, I think, revolutionizing the industry. The record companies were not acting in the favor of musicians, or young musicians especially, and so a new market needed to be created, and I think United Masters is the best example of this. I'm on the board and I've been involved in this for about four or five years, and the CEO is Steve Stout, who's a legendary figure in the music world, the hip-hop world especially, and he's had the vision to create a company.

## 58:40

That really turned out to be a multi-setted market, and I've been delighted to be involved in that, and I think it's a healthy thing. So it's AI in the sense that it's networks and it's data and it's preferences and it's all the stuff we've been talking about, but it's also AI that has created new jobs. Roughly speaking, you have 2 million people who've got some form of a job, and some of these jobs are not a billion dollar salary to make your music, but it's maybe $100,000. And if you do that over 2 million people, you've added a lot to social value. So I think that's a vision of AI or whatever you call it that I really want to push.

## **Craig Smith [Host]** 59:21

Wow, that's fascinating and, yeah, I will look into that. The incentive on the end users is that it's cheaper than the streaming, than the traditional streaming services, or what's the incentive?

## **Michael Jordan [Guest]** 59:41

An end user can choose any number of places to listen to music. The advantage here is that the music that United Masters produces and streams, you have a real connection between the musician that made it and the people that are listening to it, and the musician can actually know how many people listen to my music in each city in the United States. That becomes data for them and they could now discover, for example, that they're popular in Dayton Ohio 10,000 people listed in their music last week and they can then offer the venue owners in Dayton Ohio to come give a show there. The venue owners say, yeah, you're popular. Moreover, we know who's listening to you. Or we can ping them, say, hey, so-and-so is coming to town and they'll show up at the venue. So everybody's happy, the venue owner, the people get to see their favorite young musician, they know whenever they know about it, but they like this person, and the musician's happy because they get to go and maybe make $20,000. So that triad of kind of data flow allows a market to emerge. And then you can have things like I give a go to this show and I say look, I can broadcast to the people listening to me. If you want me to come to your daughter's wedding, I'll do it. That's $10,000, whatever that's. What markets do? They create new possibilities when you start to actually link the people who are making the music to the people that are listening to music. So the listeners are. That's probably the third leg in this in a certain sense, but they get more direct access.

## 01:01:17

You can also imagine a version of this. I think, as it goes forward, you'll imagine a version where there's a web presence of the artists where they go and they can buy merchandise. They could wear a cap with their favorite musicians, not just Beyonce or the Beatles. It's musician X, who lives in inner city Baltimore, who's really good and I love that musician. I want to wear a cap.

## 01:01:42

Right now I can't do that, but if I could do that, that would be an economic value to me as a cap wearer and certainly to the musician who would get the money for it. And if you do that at scale, this starts to feel like a really powerful use of new data and technology and networking. And this is not. You know, this is no wildly new vision. Sometimes this is called the creator economy and you don't see that terminology used much in academic circles, but you do see it, even you do see it nowadays in Silicon Valley, and I think it's real. I think people do create, they want to create and they want to be connected to get value out of the things they create via all of our technology and not just hand it over to the big companies to be sold on their behalf.

## **Craig Smith [Host]** 01:02:23

Yeah, except what I don't understand and what you just described is how that's different from Spotify, or somebody likes Spotify.

## **Michael Jordan [Guest]** 01:02:31

I'm not saying there can be an intermediate system that collects things and sends them on, but and I don't know that much about the Spotify business model, exactly how it's done and all that but if I'm a musician, I just blindly put my songs up there on the web and Spotify streams them and I don't have any clue who's listening to them. I can't monetize that, okay. And I'm not in a market where my songs could be played by Pepsi Cola because I'm connected directly to them and there's a bidding process where the artists are made available. That level of economic integration is not present in the Spotify model. If I understand correctly, Spotify is really more of a subscription model, so they're making a fair amount of money by just throwing people away, giving them money to listen to songs, and then Spotify, I think, sends some money back to musicians.

## 01:03:29

But that's not really the business model. They're not incentivized to do that, and maybe they do it out of their goodness or their heart or maybe they feel they have to do some work. Companies give money back to the influencers partly because they just feel they have to, partly because they have to create a community of influencers. But it's not a very strong business model where the influence to themselves should have economic agency, economic visibility, should be directly connected to listeners, be directly connected to brands, and so that's not the Spotify model. Again, from a pure computer science point of view, bits are bits being streamed from one place or another, but that's not the right perspective. It should be from an economics perspective. Who knows what and when, and how can they monetize that individually, not via the company?

## **Craig Smith [Host]** 01:04:12

Yeah, wow, fascinating. Okay, I've taken up too much of your time already. I hope I can have another conversation with you in a year or so.

## **Michael Jordan [Guest]** 01:04:23

I enjoy talking to you as well, so hopefully we'll talk again.

## **Craig Smith [Host]** 01:04:27

Okay, thanks, michael. Hi, I wanted to jump in and give a shout out to our sponsor, netsuite by Oracle. I'm a journalist and getting a single source of truth is nearly impossible. If you're a business owner, having a single source of truth is critical to running your operations. If this is you, you should know these three numbers 36,000, 25, 1. 36,000 because that's the number of businesses that have upgraded to NetSuite by Oracle.

## 01:05:03

Netsuite is the number one cloud financial system, streamlining accounting, financial management, inventory, hr and more. 25 because NetSuite turns 25 this year. That's 25 years of helping businesses do more with less, close their books in days, not weeks, and drive down costs. One because your business is one of a kind, so you get a customized solution for all of your KPIs in one efficient system with one source of truth. Reach risk, get reliable forecasts and improve margins Everything you need all in one place. As I said, I'm not the most organized person in the world and there's real power to having all of the information in one place to make better decisions. This is an unprecedented offer by NetSuite to make that possible Right now, download NetSuite's popular KPI checklist, designed to give you consistently excellent performance, absolutely free at netsuite.com. That's I on AI E-Y-E-O-N-A-I all run together. Go to netsuitecom I on AI to get your own KPI checklist. Again, that's netsuite.com slash I on AI E-Y-E-O-N-A-I. They support us, so let's support them.