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AI LEADERS PODCAST – AI+X

VIDEO TRANSCRIPT

Kian Katanforoosh [00:00:00] I think the best companies to date in AI and Data Science are the ones with the highest learning velocity.

Fernando Lucini [00:00:14] So hello, everybody. I'm Fernando Lucini, I'm the Chief Data Scientist of Accenture. And today I am very lucky to have my friend Kian with me. Kian, do you want to do introductions to yourself? I think it would be much better if I do it. Yeah, you can try. You can try.

Kian Katanforoosh [00:00:28] Hi, everyone. I'm Kian. I'm the CEO and co-founder of Workera and the lecturer of Computer Science at Stanford University, where I focus on deep learning or neural networks.

Fernando Lucini [00:00:40] So, the sexy stuff.

Kian Katanforoosh [00:00:42] The sexy stuff, exactly.

Fernando Lucini [00:00:44] And for all the listeners, I think if we can introduce maybe the way to do this is tell the story a little bit of how we came together, of how we met. Because I think it'll become clear how we complement this, this, this problem that we find out in the world that we will define as AI+X. So, at one point maybe. Kian, was it a year and a half ago? It's going to be more than that. Anyway, a bit of a while ago I had the vision that one of the things I wanted to do with my global team of data scientists at Accenture, just as one can imagine, sizable and highly distributed is to really turn it from what it is today, which is a highly efficient, you know, highly specialized team to a very highly specialized team, but driven by data of what our skills are. So we can actually even better predict how we can be relevant in the future. So how do we do that? And I was looking for ways to assess my folks in an intelligent way because everybody's very busy. And, of course, data scientists in many cases, right, come from a very academic background. So how do I assess these folks in an intelligent way so that I can really feedback to them, you know, where they sit in the expertise, in different topics. So then they can actually be smart about how they get trained and then we can be smart about how we react to the market. Right. And, I met Kian. Right Kian, that's how we, that's when we started working together and we adopted Workera globally for all data science and machine learning teams in Accenture. And, and our relationship kind of grew from there. I wanted to have you in the call today with our listeners for a bunch of good reasons. Now, number one, you obviously see a lot of the expertise out in the industry, what is actually needed, but more importantly, I think you have quite a definitive and interesting view about the progress. So how are these skills progressing? And then we'll talk about AI+ in a second and it's progressing at a very fast speed. So, how can our listeners, the companies that listen to us, our CEOs, etc., etc., how can these folks really, with some of the advice we're given today, set themselves better for success as they're trying to create their own data science, AI, in their organizations, right. Should we define AI+X? Should we have a go at that?

Kian Katanforoosh [00:03:13] Yes, we can try. I you want me to kick things off with AI+X?

Fernando Lucini [00:03:17] Actually, go for it.

Kian Katanforoosh [00:03:18] So, a little bit of the history behind AI+X and how we started identifying this trend. I think if you go back 30 years ago and you look at the software job category, you realize that software was a highly specialized skill that only a few people had. So you were a coder and you were coding as a software engineer. And if you look 30 years later, almost any engineer today has some sort of a coding capability, whether you are in mechanical engineering or an electrical engineer or whether you are in chemistry or even aerospace and aeronautics, a lot of them are coding MATLAB, as you know, you have now coding skills and this has shifted from 30 years ago. So coding has almost become this horizontal skill that applies to many engineering disciplines. And today I think AI skills and I use AI as a very broad term to describe anything from machine learning to data analytics, even business intelligence and so are whole the set of skills that are applicable to any job category. So when I started teaching at Stanford, I think it was in 2017, we slowly realized that despite being despite teaching in the computer science department, a graduate class, two-thirds of our students were not from the computer science major. They were from other majors. They were sent by their advisor across. The campus in order to come and acquire, if you will, an c And that's what we call AI+X. At the same time, we saw that in the industry with a lot of large enterprises who are leaders of their subject matter, experts at telecom, at banking, at finance, you know, health care or mechanics. We see that there is a willingness to blend subject matter expertize with AI, and those folks do very well in AI projects. And I can give a few example, but I see how you react to that share first.

Fernando Lucini [00:05:43] It's super interesting, incidentally, I don't know if you this, but I teach AI at an MBA school, so I teach the subject in and it's exactly the same. These are people that are coming up with a, trying to look f or a business degree. Right. Majoring in finance or whatever. Right. And 12-hourwe force upon them a 12 hour course on AI, which I teach, for which I enjoy a lot. But and it's the same kind of principle and they find it entirely normal. It's totally normal for them. But literally, it's not a, you know, not surprised by this. And to some degree, maybe they even come to the course because of it. So my other reaction is that if you look at us at Accenture, which I think reflects a lot of others. Right. We have a lot of data scientists. But, but they are the ultimate reflection of AI+X, because they're all in a field. They don't live uniquely in a bubble called I'm a data scientist, right? I'm a mathematician. And just give me a mathematics problem and I'll go and crack it. They sit there and they look at problems with turning machinery or pharmaceuticals or finance or whatever the case may be. Right. And their job is to really look at the business problem and apply the engineering or the AI to try to solve it in an interesting and unique, unique way, not for the sake of uniqueness, but for the sake of modernity and doing it faster, better, cheaper, etc., etc., etc.. Right. So I think, I think we're totally aligned. And I do see more and more of all, more and more people out there. Let me express in a slightly different way. What job can you find out there where data is not part of that job in some way. Right. It just doesn't exist anymore. Right. So, I'm totally and I'm totally aligned with the AI+X, as you know. Let's align with a citizen data scientist, which we should touch on, because I think that is one of the places where you and I disagree somewhat. Right. And we should touch on that. I'll decrypt that. So if we think about my position is that if you think about the AI+X is totally, totally acceptable, that we have a lot of professions out there where data and AI knowledge of this in a reasonably advanced fashion. Right. Is critical. I mean, these days, if you're trying to design a boat or an aircraft and you're not using some kind of advanced mathematics, you're obviously, you're in the wrong place, or architecture or even medicine or, you know, you're using EMR.

Everything is there to have some of this integrated into it. Where I make the distinction is the joke that poor Kian has to live with is the difference between a citizen data scientist and an enthusiastic amateur. Right. So, so and I think to some degree, in the next five years these things may become even more difficult to distinguish. But there's an element of the professional data scientist who's it's a profession they've trained up to be a data scientist. They've gone to school and studied the maths and all that kind of stuff and all the techniques and all the appropriate history of all these things and all the engineering. And they land at a company to learn the X, right, the industry side of of the problem but they hold up versus maybe, maybe other people that come at it from a totally different place and, and they want to catch up on that, some of that learning to become more close to the mathematics and the algorithms and stuff. And I do think and I do think there's this place for all of these folks and our job in the industry. I'd love your take on this to some degree is how do we, number one, create the right education packages and paths right, to make sure that these folks are all working in a safe way, and two, we create the environments in companies and in the government and other places where these folks can do the data science again safely, given that they may not know everything there is to know about the mathematics underlying and deep learning, which is your topic, right? So they're sitting there trying to, you know, build some crazy variation on to encoder or whatever or some reinforcement learning thing, and they might be able to use all the tooling that does it but truly understand how this thing actually works inside.

Kian Katanforoosh [00:09:54] Yeah, if we're thinking about the dangers because you're saying, you know, I heard you say, you know, dangerous amateurs sometimes.

Fernando Lucini [00:10:03] Yes. Which is my joke. And everybody's, I think, amateur as opposed to, I mean, dangerously enthusiastic amateurs.

Kian Katanforoosh [00:10:10] But in my view, there's two to different dangers, and they're different nature. One is more around data science or analytics for decision making, and the other one is around machine learning or data science, but in production. And I think that's, if you consider an enthusiast data scientist. Well, today they're taking a dataset, running some analysis, writing and insights, creating a slide deck with visualization and presenting it to management or to a client is easy nature. Even for someone who has not been professionally trained as a data scientist, will the insights be wrong? Possibly. And is it easy for the audience to see that the insight is wrong? Probably not in a fast moving environment. So at the end of the day, the data scientist needs to hold himself or herself accountable for making sure that their insights are correct. And this comes with a cultural value and a set of a strong sense of ethics, but it also comes with tangible skills to build their search and must have skills. For example, in this scenario hypothesis testing or certain statistical rigor that doesn't come overnight, but comes through a lot of work and a lot of experience in war stories of having done something that you thought worked but actually did not work. And so that's one thing that I think is important in the years ahead, to look for a strong sense of ethics and accountability in our data scientists around the world. And the second part is around production, because often time we are underestimating the complexity of deploying AI systems. And it can be both, you know, software engineers that are enthusiastic about machine learning, putting an immense system into production and realizing later that it is slightly different than creating a software system because you need to be able to identify the cause of machine learning system failures that are different in nature than what you would expect from a traditional API. Or it can come from a data scientist that has been trained in prototyping but less so in production and is realizing all the challenges that come with using an AI system. And I think those are topics that we could spend an hour on, but it's another danger to look for.

Fernando Lucini [00:13:01] Absolutely. I tend to simplify and think, well, if you think about simple problems like overfitting or, you know, understanding the separation of data sets. Right, which happens a lot and is connected to overfitting, obviously. So there's a lot to be said, I guess, about most of our enthusiastic amateurs being well-educated on statistics more broadly. Right. Because if they've kind of well, well educated in statistics more broadly, do they really have to understand the governance of a neural net, but at least they understand how to represent the results and some of the issues associated with all of these things. But you're quite right. What's your take on the low-code no-code. You know, I know there's a lot of software companies that will tell you there are no code AI. And I roll my eyes a little bit because it's, not quite sure I go with that. What what's your, given where you sit, what's your sense about what's going on with low-code, no-code and how it relates to AI?

Kian Katanforoosh [00:13:58] I think it's an important trend and I always try to map it as a proxy to what happened in software engineering. What are the tools that we had in software 30 years ago versus what we have now? And my take here is that we often say that machine learning systems fail silently and they fail silently because you don't realize and they completely fail. And so can we have this set of tools that can bring that up to us, whether it's monitoring, alerting notifications, whether it is deployments on the sort of black-box manner so that you don't need to do much and you deploy. I definitely think we will get there. But today, if I look at the spectrum of email tooling, I still see that it's limited and it is not standardized. So different tools will take different approaches. And so there is no real agreement on what is the lifecycle of an AI project and what are the, you know, outstanding tools for each of the blocks of the lifecycle of an AI project? The other risk is, is to go too hard on low-code no-code and think that in the next ten years you will not need to be able to code or you will not be able you will not need to understand how code works. And I think this is a trap somehow. If we look at the software world where it, despite the software world be much more mature today, you still expect the software engineer to be outstanding at coding. It's one of the first thing you would screen for. And I think for data science, it would be the same thing even in ten years from now. Despite all the tooling and frameworks and APIs, you would still screen for a deep understanding of statistics, a deep understanding of coding and algorithms and other topics that allow these data scientists to prototype rapidly.

Fernando Lucini [00:15:54] Yeah, that's a really good way of putting it, because that's the way I tend to see it. So and as I said, I've spent lots of years in software engineering, as you know. So for me, it's exactly that. If you look at the software engineering world, gosh, the amount of tools that come out and then we as software engineers love to reuse new tools and this is the new gizmo that connects to a database better by 2%. We still go and chase it. Right. But that doesn't change at all our skills in the fundamentals of the coding in our particular language. And that doesn't change them at all. And I think you're right. And today this is where I get the low-code stuff gets me. On one hand, there's never been a better time in terms of you being able to download a piece of kit, you know, the chorus of the world or whatever it may be that allows you to effectively get an algorithm and just turn it on and tweak it a bit. It's never been better, it's fantastic. Anybody doing computer vision these days, I mean, come on, you know, you know, you know the staff, you know the three places where you can go for this? Um, so that's, so that's actually already a reality to some degree. I think where the low-code no-code where I struggle a bit more is in a lot of the stuff I've seen is either a bit of all HTML, which is great stuff, but I love it. Nothing wrong with that.

Some magnificent stuff we created there, but also a lot of a lot of stuff that helps you drive the beginning of the problem, right? The data collection, feature selection. It's almost like giving you the guardrails to do that in a way that if you take the data and you actually shape it in the way the vendor needs it, all the other things fit into play quite easily and it feels like it's a plug of play and it feels like it is a low-code, no-code. But what it is, is you've done a lot of the hard work of getting the data to the point where if you need to do a pricing optimization, what you kind of already fit the data, the algorithm is going to work no matter what, right? Um, to some degree, that doesn't feel much different than, than the normal realm, which is, hey, you know, fit the data to this, to this, to this formula the thing will figure out if this is a feature or not. And if it is a feature and it matches with what the algorithm needs, the algorithm will go and do what you need it to do. Right. And I do think that and I do agree with you, all these things are fabulous because they add to the richness of, how can I do this better, quicker, safer? Better, quicker, safer. That's all it is. Right. Let me challenge you with another topic that I think is fascinating.

Kian Katanforoosh [00:18:18] I was also going to follow up on what you just said, because I think this is very interesting. And another consideration is that the field is moving so fast. And we say that the half life of skills in data science is low. If you look at the last ten years, you had this set of frameworks, lasagna, cafe, all of all of these, and you then had a TensorFlow, you had Python. Today you have new framework coming out. There is an interesting fact that about these frameworks that are all by the way, let's call them all points open source frameworks is that they're built by engineers and scientists and they are deployed very rapidly on GitHub. So you can access them even in the early days of the tool. It turns out that in the early days of all of these tools, you will have a hard time understanding the tool in the framework if you are not savvy enough at coding. And so in a discipline where the half life of skill is low and when there is no really a practitioner that has ten years of experience in TensorFlow because TensorFlow has not been long enough to be able to call yourself a tenured expert practitioner in TensorFlow. The people who are going to benefit the most from the low-code no-code are the ones that are going to be the savviest, the most savvy, in acquiring those skills and being able to deploy stuff with the with the low code, no code or all these APIs. And so I think in our discipline, it is extremely important to have this culture of lifelong learning and to be able to learn as fast as possible. Because no-code low-code, API, framework platforms are going to come through every single year. There's going to be new stuff coming out. And if you're not savvy, you cannot keep up with the progress.

Fernando Lucini [00:20:16] That's a super interesting. I was going to say I saw some some requirements from one of our customers for data scientist. And one of the requirements was a bunch of programing languages, including C++. And I thought, okay, that's an interesting thing to ask that the data science community. You might not get a lot of takers, but but it kind of validates what you're saying, which is, you know, the programing part of what we do. I mean you and I have had this discussion before, which is that there's a it's a spectrum, right? You've got the data science on one side of software engineers on the other. And the truth is, the spectrum is becoming grayer and grayer. We've got amazing data scientists that are great software engineers and amazing software engineers that, you know, that, you know, live in the in the light in the world of data science, quite comfortably and in between. And you're right in the middle of that, there's a parallel with the software world and how it evolved in. And even to this day. Right. You still have packages, the software packages. You go online and you go and look at these packages. You go to your StackOverflow, you've got a kid, you go to these things, you see these things.

And if you're really sharp and you know your stuff and it's from a source that we all trust, right? We kind of go in there and you start picking and you start seeing how source problems, you add them to your stack and you know they're going to be changed by something else in a year's time. And that's okay. You're absolutely right. It is. It is. It is fascinating. And it goes back to the AI+X. And is X only industry though, or is X all of the all of these other things that we're talking about to surround the world and make the world evolve as a discipline. Next. Which actually brings me to the next topic, which I think it will be another have some follow-up, which is the AI democracy topic. I'll say off for you the way I set up with CEO's and then you're going to tell them be told wrong and we'll have some fun with that. But I always, as I could talk to CEOs, I say, look, if you look at the world of AI these days and you and I are using AI quite broadly and being quite generous with it, which I think is right. Um, I see it as a three stages and we got the, the AI desert as in the, you know, like the desert of Kobe, right? We've got the forest and the jungle. And and what I try to tell them is that, look, you know, it counterintuitively, in big companies, you're probably more likely to be in the AI desert, which is where you have these, you know, pockets of greatness, right? Where you have the oasis, which is where the water is, the water being the data. Right. All this data sitting in the oasis and is green and plush, and AI experiments are happening is a wonderful, but it is sitting in a desert quietly. That means the oasis are far away from each other. You're probably sitting there. Now, the next evolution for you is the forest. And in the forest you have rivers and the rivers is the data that flows, which allows all the things to build and the more interconnected. And you start to have higher-level problems, a higher order problems, which is to your point before how you organizing yoursel using data science methods and frameworks to make sure it's been done safely. You have more and more participants now. How do you organize them? You know, there's a question of safety and responsibility and ethics. Are you managing that? And there's partners, etc.. And then the highest order is the the what I call the AI jungle, which is, okay. There's a danger that we think of jungle as chaotic things. Let's just say these things that they're sprawling with life. Water is everywhere, green is everywhere, wonderful things are happening everywhere. And everybody's ready to just exploit data at the touch of a button, which is this concept of AI democracy. And my argument always is there's nobody in the jungle stage. That's nonsense. But there's nobody in the jungle stage in software engineering either. It just comes to a point where we have to be organized and sensible or just things just fall out of control. How do you think about the democracy? And I use that simple way to think about it, because I want to I mean, as a good consultant, I want to organize my mind in a way that I can shape the story and have a conversation with somebody who maybe knows less than than me or knows more than me, but disagrees with me. Well, how do you sit in this idea of where AI democracy is going and when?

Kian Katanforoosh [00:24:08] I love the analogy, by the way, I think it's a really powerful way to communicate it.

Fernando Lucini [00:24:15] I'll send you the slides.

Kian Katanforoosh [00:24:16] Okay. Perfect. I'm glad I had not heard before. So I'm wondering, why didn't you talk about it earlier? It's amazing. The democracy topic is is an interesting one as well. I think if you go back to the roots, well, democracy means making it accessible to everyone. So, yeah, AI democracy's is AI accessible to everyone. I don't think it is. I think for several reasons very, very few people have AI skills. There's a global shortage, whether you think about it at the world level or in every company. And there are fewer people that have the skills needed compared to the demand. And if you look at LinkedIn's, I think jobs emerging jobs report, AI specialist was the highest growth in terms of demand job category in the case.

The second thing is very few countries or companies have these people globally. So the large majority of the top experts are located in a few places around the world and it hasn't really been democratized as much. And where I think we could say that AI has been democratized is in the sense that AI is impacting everyone's life today. And most of us are impacted through advertisements or content recommendations. I think there's maybe 4.5 billion active social media users. So everybody's somehow touched with aid, not necessarily in a good way, but if you look at actual complex problems in the industry, I don't think AI is democratized yet. I think there's a lot of work to be done to get there.

Fernando Lucini [00:26:01] Yeah, it's interesting because I have this debate every now and then in some forums and I sometimes feel like I'm going crazy when somebody is facing off against me, make me feel like a dinosaur. Because I'm not so enthusiastic about the idea that democracy of AI is going to come in three years. And I look and think, well, no, as a matter of fact, if you if you look around us, there's a as you say, you and I and I don't know if I've told you about this challenge that I give myself every month. Every month, I sit down and I take and I start my day, I wake up and I calculate and I write down every AI that's touched my life. I know is super pedantic. It's an excel sheet and everything is going funny. But what I'm trying to what I'm trying to do there is try to figure out what are those contact points in a way that is sensible. And I just try to keep it real, right? So rather than just being a bobbing head that says AI is wonderful, I actually sit down and actually think to know the basics. And I think, okay, well, has it really impacted my life? And it hasn't changed very much in the last two years. So as I do this analysis, it's as you say it, it hits me and social media hits you in. And the other thing I notice is that when I share it with others, many of the ones I find, I find and I can identify it because I'm an expert. I know where to look. Which if I asked somebody else that they'd just it just wouldn't even occur to them that it's some kind of AI in your phone is telling you when you when I go and take the kids to something separate to me every day when I take the kids to school, when I turn the call back on to come back a little a little thing comes up and the phone company will remain unnamed. The says it's 5 minutes if you go back home. Fabulous. Love it. No problem. There, I'll take it. But people don't react to that and say, well, that's an AI. Well it is, it is what it is, but that's what it is. So I'm a 100% with you. Let me ask you the question in a slightly different way because I'm super interested, um, with regards to education. Right. So have you seen a big change with how many universities are actually driving AI. I within, just within the curriculums and other departments we've talked up bit about how you've got 90% of the people that you teach are not necessarily computer science people. Right. But have you seen a big difference in the last two or three years or even things that are going to come up in change? Because I'll tell you why. It's a loaded question in the sense that one of my pieces of logic is that we're going to raise the level of the water because universities, which are the first to, you know, to react to these things and they're the thinkers of our world. Right. Are going to give us give us more of what we need. So the question you see, why don't you see where I'm coming from?

Kian Katanforoosh [00:28:38] Yeah, I think education is changing very rapidly right now and universities are trying to reinvent themselves. Where I see things going is with the notion of content available online today, If you take machine learning on Google machine learning course you get ten thousand of them. And you can be anywhere in the world and take classes from the top professors at the top universities. And so, what is the point of each university around the world having their own teacher teaching machine learning or AI topics? It doesn't make sense anymore. Instead, the university can become the primary location where mentorship happens, where feedback loops happen, where a group learning happens, and people can be motivated to learn. And so there is a shift from traditional learning to flip classroom model that is happening in many universities around the world where you actually study online or the theory, and you know all the definitions, you need to know and content, and then you show up to class in order to work on practical application, do exercises and projects and codes and so on. I think by leveraging this model, universities can produce students that are very qualified at building systems rather than just knowing the theory because they become the central place where the building happens. The second thing is that that is not really positive is a challenge, but is the shortage of mentors. If you are beginning your data science journey today where you have a ton of content to get started, but what happens when you get to a certain level and you start getting bored by classes or it starts becoming repetitive and you're feeling that you're not making progress anymore, where the next stage of your journey is probably hands on and hopefully monitored by your mentor. Now, when we were looking at it in our university, we were trying to figure out what is the right mentorship framework to put together so that every student has a qualified mentor to help them improve and gain these more advanced practical skills. Right. When you think about the ratio of PhD students to undergraduate students is very low, meaning for every maybe 100 undergrad students, you have one PhD student that is probably more and more proficient at the learning we're talking about. And so how do you do to map these? And we we run into challenges back to the days when we were trying to build that kind of mentorship, mentorship relationship between students because of this ratio. But the measurements helped us a lot in the sense that when you start measuring people and allowing them to test themselves, you can now project their capability along one dimension along the line and understand how far they are in their data science journey. Ideally, you don't get the top practitioner to mentor the beginner, you get the top practitioner to mentor the person who's right behind them in the journey. And you get that person to mentor the person who right behind them in the journey. And you get the person who started data science three months ago to mentor to one that is starting to date. And by building this sort of a pyramid of mentorship, you can start scaling what happens in the university. And and building this ecosystem of mentors and students and producing students that are more qualified than they are today at the end of their degree.

Fernando Lucini [00:32:27] Yeah. And let me ask you a question, because this is a it kind of feels like there's a burden on the companies as well to continue that legacy after the university. Right. So, you're creating better, more rounded, almost professionals. It feels like you're thinking about like the teaching hospital kind of concept, right? They're sitting there. They're not only learning the theory, like a good teaching hospital, you're learning doing the job as well. But then question for you, is there an onus on the companies to change the way they're set up so that they can help and almost like continue that journey? So you land in your company, and actually your learning experience actually continues to where you left it in the university. It's the same kind of method. Do you think that that's also part of this journey?

Kian Katanforoosh [00:33:18] Yeah, I think companies have to become like universities to a certain extent, on top of all the other things they need to be doing. So the first day of employment is the beginning of a new journey for an AI or data science practitioner. I think companies today are just at the beginning of measuring and improving capabilities in a data-driven manner. We often talk at work, and I know we've had several conversations together about it, about skills based talent management. It's once you have access to the skills of your practitioners, it opens the door to so many talent applications on top of it.

If you know that Alice and Bob have certain skills that are complementary to each other, you can help Alice and Bob spend more time together so that they can teach each other those things. If you noticed that Joe and Jennifer have supplementary skills and they may actually not be fit to be on the same project, but they would benefit from being on separate projects. You can figure it out if you have access to that signal. If you notice that someone has a certain skills gap, you can recommend content that is highly connected to their skills gap in order then to fill the gap that you need in another project. And so, companies need to have a skill signal that is continuous on which they have a pulse in order to be able to run their organizations effectively. And I wouldn't be surprised if ten years from now these measurements are the de facto way to run an organization effectively and educate their people.

Fernando Lucini [00:35:10] Yeah, because it feels like there's a bit of a revolution around skills, right? Which has changed dramatically how we think of how our people skills funding. I know you and I have discussed because we've recognized that in Accenture that we do it all the time. And by the way, let's work the challenge. I think the challenge as you come out of university with a great set of with a great set of fundings. Right. I'll tell you. You're in a company or a government or wherever it is that you've decided to work and there's so many pieces to data science AI we're missing, it's incredibly broad. Incredibly broad. It's like, it's like talking about physics. I mean, which part of physics come on, let's be specific. And so our job in this field is to not judge everybody as, hey, this person knows everything from econometrics to neural nets to reinforcement learning. I mean, but to have the fortitude to say that clearly have the the greatest center of backing or background. And our job is to give them access to an ability to pick up that skill and reinforcement learning and apply it safely and quickly and maybe be able to deepen their skill in that as opposed to write a CV that says you must be proficient in supervise and supervise reinforcement, neural networks. I mean, the list would be enormous, right. But I do see these CV's that have these enormous lists. And I do think that's the revolution. The revolution is in great founding. And I think you've said it now in a very in a much nicer way than I have. But then also that training from university to be adaptive to gain the next skill, right, to have that hunger. And I do feel some of our, some of the people around the field feel that they need to know everything. And I think that's a mistake. Do you get a similar feeling? You see what I mean? They need to know everything. They need to be broad. They they need to, they need to be building neural nets all day. Otherwise, they're not great at a scientist. And all of that, of course, is not true.

Kian Katanforoosh [00:37:15] I completely agree, I tell my my students that if you want to be a T-shaped professional or a high-tech professional in the sense that you have the student that takes a hundred different classes and keeps taking classes, classes, classes, and then they have an incredible resumé with A-plus is everywhere. But when you think about who you want to have on a project, you would rather have the students who may have taken less classes and has enough breadth, but maybe less, and has spent a significant time on a project and has gone super deep in that project. Going deep in a project is something that I find to be a great indicator of their ability to build something later on. And so one question that I ask them is think about what is your most significant achievement? And in data science? And try to make sure that it's an outstanding achievement that you can talk about that is deep enough for you too show that you also can be a specialist. You're just not the generalist that can do different things, but you can go deep in what you do.

Fernando Lucini [00:38:28] And that's it. And it's funny because when I do interviews for that with people, I try to stay away from trying to force them to demonstrate this very broad, kind of amazing plateau skill. Right. I love the fact that in America, you guys sometimes call it like peanut butter, know it's spread everywhere. Right? Um, and I ask similar question. I ask, you know, how do you learn? I simply ask, how do you learn, you know, what makes you happy? How do you learn? How do you evolve? What drives your choices of learning? Right. And I think that that's a much more fun way to look at it solely for the student. Um, and by the way, we're all students for life these days, right? In data science and AI. And it is what it is. If you're not a student for life, I think you'll be stuck very quickly. By the way I, the one I use all the time is, is medicine; is you just become more or less like not like doctors in the same of how you save lives. And obviously we take our hat to that wonderful profession. But you've just effectively put yourself in the same box, which is like doctors, like architects, like engineers, this is the same. Learning for life is part of the journey. It shouldn't be a drag. It shouldn't be felt like it's something that, gosh thats difficult, I've got to keep up. It has to be understood. And I do think companies have to understand that as well. You have to, you make it part of your remit, right? Which is, hey, if your data scientist in the same way if you were an engineer, we understand that part of your life is going to be keeping up with that skill. And that's wonderful. That's part of the journey, right?

Kian Katanforoosh [00:40:11] Yeah, I completely, completely agree. I think that what it reminds me of when we engage with executives at companies, typically they would ask us what is the state of the nation? How, you know, what is our current state of capabilities in-house? What is the supply of skills we have? And then you provide them an answer, but you also tell them that it is, you know, we benchmarks of how you compare to other enterprises. But really, this is not the only thing that matters because it's, I know we discussed it together, it is not fair to compare a company that has a maturity in AI of level four let's say, so it's been trying to transform for many years to a company that is at the beginning of their workforce transformation. And so when you look at the benchmarks, it just doesn't match. And it's perfectly fine. What matters is in that scenario is the learning velocity is you want to know, okay, here is where we are and versus here is where the market is, but how fast are we growing? How fast or we growing the skills are we growing at a pace that is reasonable enough? And and I think the best companies to date, in AI and data science, are the ones with the highest learning velocity. They're the ones that are able to acquire the top innovative skills faster than the competition.

Fernando Lucini [00:41:37] And I think that's going to be the bombshell we're going to leave it on. I mean, what a bombshell. So, the best AI companies have to have the greatest learning velocity. I mean, that's I don't know. I agree entirely. It's not a matter of having a 4,000, 10,000 data scientist, but if you have the velocity means you've cracked the ability to bring people in and get them to where you need them to be. And you don't know where that's going to be because the world is changing so fast, the skills change so fast, but you have the ability to get there quicker. So, I think that's a ths a wonderful place to leave it. So you heard it here, folks, learning velocity is the key. With that, I am going to say thank you very much to Kian for being a wonderful guest and friend, as always. Thank you, Kian. And to all of you guys, I'm going to thank you for listening to us. Please, please subscribe. Please come back and listen to our other AI Leaders podcast. And we will be with you in the next episode. Thank you very much.