**Craig:** Hi, I'm Craig Smith, and this is Eye on AI. This week, I talked to Andrew Ng, who hardly needs an introduction. His resume includes starting Google Brain, Google AI's elite research team, co-founding Coursera, the online education company, and most recently Landing AI through which he is pushing a data-centric approach to deep learning, focusing on the quality of data fed to AI models. Andrew talked about his data centric view about Landing AI and about his vision of the future.

Before we begin, let me give a shout out to ClearML. a collaborative open source MLOps solution. They're sponsoring the podcast. You can set up your own server, log your entire process, version data, build model repositories, provision machines, schedule containers, and deploy pipelines directly from code. Check out ClearML at clear.ml. Tell them Eye on AI sent you.

**Craig:** Meanwhile, I hope you find the conversation with Andrew as exciting as I did.

**Craig:** So, Andrew, I'm delighted to have you on the podcast. I look forward to the stay for a long time. Can you start by introducing yourself? You're obviously well-known to the machine learning community, but can you start by introducing yourself and giving us a little bit of your background?

**Andrew:** I was born in the UK where my father was practicing medicine. That's why my family was there. Moved to Hong Kong when I was just an infant and then spend about seven years in Hong Kong before we moved to Singapore where I grew up, went to school until I came to the United States for college.

**Craig:** And you went to CMU, Carnegie Mellon?

**Andrew:** So, I was at CME undergrad, and then went to MIT to start my PhD there, but my advisor moved from MIT to Berkeley. So, I moved with him, and I wound up finishing a master's degree from MIT, then a PhD from Berkeley.

**Andrew:** And then I became a professor at Stanford.

**Craig:** Who was the advisor? And what was the PhD

**Andrew:** Mike Jordan was my advisor. So, my dissertation turned out to be on using reinforcement learning to fly autonomous helicopters. So, I actually did reinforcement learning way back and actually used a neural network.

**Andrew:** It was a very small neural network that I trained to fly a helicopter back then.

**Craig:** Yeah. Peter Abbeel also did a lot of work with autonomous helicopter flight.

**Andrew:** Yes. So, Peter was my PhD students at Stanford. So, after I finished my work at Berkeley my first project at Stanford was autonomous helicopters and Peter was my first PhD student at Stanford and winded up working with me on that.

**Andrew:** After, teaching at Stanford for many years. I ran the Stanford AI lab. I was the director of Stanford AI lab I wound up starting and leading the Google Brain team. So, in fact Geoff Hinton was my intern for a period of time. For a very strange reason. clearly, he is overqualified to be an intern, but from getting the paperwork done, they Google point of view, it turned out it was simpler to bring him in as an intern via some of their mechanism.

**Andrew:** So that was fun to have Geoff on my team for a while. And he left and his company got acquired and that became the second time he joined Google. But the first time he joined my team, and then along the way, I also co-founded Coursera, which grew out of some of the machine learning teaching work that I was doing.

**Andrew:** And I remained chairman of Coursera to this day. And then had a stint at Baidu and after I left that, started Landing AI.

**Craig:** You've launched this campaign on data-centric AI, to get people to stop thinking about building better models or tweaking models. There are a lot of models already out there. There's a lot of compute out there and the challenge, now, this is the way I understand it, in penetrating the economy is to figure out ways for companies to be able to use limited data sets to build AI models.

**Craig:** Is that a fair description of what you're interested in now?

**Andrew:** Yeah. So, data centric AI is the discipline of systematically engineering the data needed to build an AI system. And I think that part of my motivation for starting Landing AI, and then also working on data-centric AI technology was the realization that AI has transformed consumer software internet companies and it's supposed to transform all industries, but if you look in other industries, anything from manufacturing to healthcare, to logistics and so on and so forth, its impact is very early. And I think that's because the recipe that some of my friends and I and others have developed for AI adoption in consumer software internet, that recipe does not work for many of these other industries.

**Andrew:** I think the two major differences between consumer software internet and many of these other industries are first, instead of having massive datasets of hundreds of millions or billions of users, the data size is much smaller. When I work in computer vision problems in manufacturing, they may have only 50 images and you've have to get an AI to work with that size of data.

**Andrew:** And then the second problem is, in consumer internet, you have these very large user bases say a billion users. That makes it possible to build one AI system, better web search, more relevant ads, something that generates massive economics. And so, we figured out how to hire dozens or hundreds of machine learning engineers to build a system like that.

**Andrew:** But when you look at other industries, the industries are much more heterogeneous. So, for example, in manufacturing, every single manufacturing plant makes something different. And so, a company that makes pharmaceutical pills will need his own AI system to inspect pills. And they'll be different than a semiconductor wafer where the pictures of semi-conductor wafers look totally different than the pictures of pharmaceutical pills.

**Andrew:** So, they need a different custom AI, and then someone else making sheets of steel, it needs a third different custom AI. This is true for other sectors too. I've deployed a few systems that read electronic health records, in Stanford Hospital and other hospitals, but it turns out that every hospital codes its electronic health records a little bit differently, right?

**Andrew:** There's similar conditions just slightly different medical codes. So, I don't think it's possible to build one monolithic AI system to read all electronic health records in the world to make recommendations to patients and doctors. And the challenges if every hospital has his own conventions and if thus every hospital needs a customer system, how can you get these tens of thousands of AI systems built without, someone like me trying to hire a tens of thousands of machine learning engineers to do all this work.

**Andrew:** So, this heterogeneity, small data sets, and the fact that instead of one $1 billion application, you may have 10,000, $1-to-$5 million applications. These are hurdles we need to overcome. And I think data-centric AI would be key piece of that.

**Craig:** So, you built a platform that enables companies with limited data sets to prepare data or augment data sets in order to be suitable for machine learning models. Can you talk about some of the tools that you use and then, what I really want to talk about, this is all supervised learning, deep learning primarily, and even if it's just 50 images, it relies on hand labeling those images. With the larger language models and what's happening in unsupervised learning, it looks to me as a layman, that the future, as Yann LeCun likes to say will be unsupervised - or I guess he says the revolution will be unsupervised - that eventually you'll not need to label data in order to feed deep learning models. So, can you talk about the platform and the different strategies that you use to deal with small data sets and then what is the future of supervised versus unsupervised learning?

**Andrew:** Yeah. So, I think lots of things go on different timescales. In the near term for the next few years, supervised learning will continue to create the bulk of economic value of deep learning. So LandingLens is a platform, is a tool that helps companies large or small build custom computer vision systems.

**Andrew:** And the approach is rather than asking a company, say the IT staff of a manufacturing plant, rather than asking them to invent the next generation of a neural network, we provide cutting edge neural network architectures and provide tools to engineer the data fed to the neural network.

**Andrew:** In many manufacturing plants there'll be two inspectors inspecting parts. And for the last decade, these two inspectors have actually not agreed with each other about what is a defect and what is not a defect.

**Andrew:** And it turns out that if you were to ask these labelers to train an AI system it would get confused because it was just inconsistent. One person says it's okay, one person says it is a defect, who do I believe? So, one of the tools that Landing AI has developed are things to help figure out when the data is inconsistent or try to figure out when the data is just flat out incorrectly labelled, which happens, or when the images are too blurry, and we need to design a new lighting system.

**Andrew:** But it is this iterative process of not just labeling the data but creating a dataset that clearly shows an AI system, what you want it to do. And we've found that because this work can be done by subject matter experts, not just a machine learning engineer, but really the inspectors that know what is quality in their factory.

**Andrew:** This opens up the number of people significantly that can build a successful AI system. So, this recipe that Landing AI has been executing to invite subject matter experts to engineer data, to express knowledge by data, I think it would be a key recipe, not just for computer vision, which we're focused on, but for many other applications.

**Craig:** Correcting bad data is one thing, but if you only have 50 images, that's not enough to train a neural network to convergence, to some acceptable level of accuracy.

**Andrew:** That turns out not to be true. There's a lot of hype about training a network on like a gazillion images.

**Andrew:** And I once built a face recognition system using 350 million images. And when you have that much data it's great. But, even today, I'm sometimes surprised by how well a neural network trained on 50 examples of a defect you want to detect can do. But, the key part of that, when your data set is small is if I show you 50 inconsistent, blurry images, you as a person, can't really figure out what's going on and neither can the neural network, but I've show you 50 images that clearly illustrates the difference between a scratch versus a chip, and when is the scratch so small, you can safely ignore it. If those 50 examples clearly illustrate it, then you as a person may be able to figure out. And in many cases, despite the big data hype, so can the neural network. So, it's systematic tools to engineer that dataset that then sets up the learning algorithm for success.

**Craig:** I remember you were big on augmenting data, on adjusting the color cast of images or flipping images and things like that to multiply the number of images in the data set. Is that also part of the Landing AI platform?

**Andrew:** Yes. It is this one of the tools in the toolbox to take an image and tell the algorithm that the mirror image, or if it's a little bit rotated, they are still the same thing. One of the things that Landing AI's tool called LandingLens does is it makes it fast and easy for user to toss in those tools, if they wish to without, and then you can do it by writing code.

**Andrew:** But if you don't want to write code, you can also do it without writing code. So, this opens this up to a lot more people to use.

**Craig:** Yeah, I just did a piece for the times on no code platforms. Is your platform a low code platform or a no code platform?

**Andrew:** LandingLens is a data centric, no code, low code platform for building cutting-edge deep learning systems for computer vision.

**Craig:** MLOps is an increasingly crowded field. Actually, the podcast is sponsored by a company called clear ML, which is an MLOps platform. Why did you choose MLOps? You're somebody who has the entire gamut of AI possibilities available to you. Why did you choose MLOps and how do you survive in that crowded market?

**Andrew:** The term MLOps today is still used differently by different organizations. What we've been focused on is helping with the entire life cycle of a machine learning project, including, the initial scoping of the project to collecting the initial data sets to training the model and then deploying and maintenance.

**Andrew:** So, the deployment and maintenance is a key part of MLOps. And I find it for a lot of applications, a platform that integrates the data collection and the training, as well as the deployment, the maintenance, that enables customers to work even more effectively than just narrowly focusing on deployment and maintenance, which is which is an important problem as well.

**Andrew:** So, the way that we approach MLOps has tended to be a more integrated approach. It turns out in traditional software engineering before machine learning, there was an important field of DevOps. And there was often a separation between the developers and DevOps people. The software engineers write the code.

**Andrew:** Then they throw over the wall to the DevOps teams that then puts it up in the cloud, does server maintenance and scalability. And so on. I find that this separation between development and deployment, we could debate how well it worked in software engineering, does not work for machine learning.

**Andrew:** And the reason is when you deploy a machine learning system, the world will often change, and so it's important to take data from post deployment and feed it back to the development process. Because machine learning is a much more iterative process, you can't build a machine learning system and train it all day and throw it over the wall for someone to operationalize. It needs much tighter integrations than software engineering which is why we tend to take a view of MLOps that goes back much earlier in their process as well.

**Craig:** There are big platforms for data prep out there. And there are integrated MLOps platforms, but there are some that really focus on the front end on labeling. Is there a role for those companies as these integrated MLOps platforms come online? Are you looking at a different segment of the market? is there room for all of these.

**Andrew:** Landing AI serves enterprises of all sizes, including large ones.

**Andrew:** Because I find, for example, even a large semiconductor manufacturer, a large automaker or a large company doing drug discovery. They also have problems where they don't have a billion data points. And so being able to help even very large companies address a problem where they have only 50 or a thousand images, that's been core part of what Landing AI does.

**Andrew:** I think AI is still early and there's lots of room for lots of people. Among the companies, I'm actually very happy to see the number of startups that are appreciating the importance of data centric AI. There's actually lots of room for everyone, I think.

**Craig:** On deep learning versus forms of supervised learning, I had a conversation with a guy named Tom Siebel who has a company called C3.AI. And he was saying that in most of the applications, industrial applications that C3.AI gets involved with, people don't want a deep learning system because they need a clearly explainable system.

**Craig:** He mentioned particularly healthcare, but also other industrial applications where intervention is going to cost a lot of money and the clients need to explain that to their superiors or board or whatever, they need to be able to provide an explainability document that lays out why the AI is making a particular suggestion.

**Craig:** What do you think about that? And he was saying that as AI goes into the economy, the vast majority of it is still not deep learning.

**Andrew:** I've not seen this pushback myself certainly in the computer vision applications that we work on.

**Andrew:** The world is large and there are a lot of use cases. I have seen more demands for auditability and explainability in some of the financial services businesses, for example. I feel in the case of computer vision, deep learning seems to work much better than other technologies like decision trees.

**Andrew:** There are structured data problems where decision tree algorithms seem to work really well. And then I think both for deep learning, and for other approaches, explainability is key for some applications. My experience has typically been that if I work on application and if you need an explanation, we could often through some hardware, figure out a way to generate an explanation - not easily and not dismissing the importance.

**Andrew:** Actually, I have this one story, we were working on a system to look at electronic health records at Stanford Hospital to recommend patients for consideration for palliative care. And so, you would think, if we're going to a doctor to say, hey, this patient is at risk of mortality that really demands an explanation. And so initially when we showed the system to doctors, they very understandably said, why are you telling me that this patient is at high risk of mortality? So, my PhD student, Anand Avati, spend a lot of effort to build out an explainability system so that when we surface one medical record to a doctor, we'll say, it's because of these traits of this patient that we think you should take a look.

**Andrew:** The thing I did not expect was the doctors took one look at those explanations and they go, oh, OK, got it. And then they never looked at the explanations again because in hindsight, what they needed was not a patient-by-patient explanation.

**Andrew:** What they needed was really, can I trust your system to be reasonable? And is it worth my while?

**Andrew:** So, the system every night looks at health records and then recommends for consideration a list of patients.

**Andrew:** So, the process that we established was one or a few doctors will look at the output of the algorithm to help them prioritize, but then the doctor ultimately, makes the final recommendation, not the AI system.

**Andrew:** I find that explainability is one of those complicated issues where I often step back and ask myself who do I need to give an explanation to and what is the task that they need to do, or the purpose needs to do with that explanation?

**Andrew:** And I find that asking that question of who needs, what information to do with. Often clarifies the type of explanation that needs to be generated. And then that sometimes you can work backwards to coming up with a suitable explanation, to help someone decide that they should trust the system or not or decide if it is fair or not fair and reasonable and biased or not or decide if they need to jump in to intervene.

**Andrew:** Or to explain to an engineer how they need to improve the system. So, I think figuring out the purpose, it has been a key lesson that I learned in terms of when I'm designing systems. But when I find that when the purpose is clear, not always, but lot of the time we could go back to engineer some explanation.

**Craig:** Where do you see AI going? Do you think these large language models and the unsupervised systems are the future, and I'm not talking about applications, I'm talking about research?

**Andrew:** AI is a very broad field. So, I think we need lots of people working on lots of different things. Even though supervised learning is creating the vast majority of the economic value of AI today, I feel like there are many other tools like generative synthesis algorithms like GANs even reinforcement learning algorithms and then also the various forms of unsupervised or self-supervised learning algorithms. When I started Google Brain, many years ago, I actually initially started off betting on unsupervised learning.

**Andrew:** And I was motivated at the time by, actually by some conversations with Geoff Hinton that, made me realize that a lot of human learning is much closer to the unsupervised end of the spectrum.

**Andrew:** There's a case to be made that a lot of human learning is not supervised learning, with parents pointing out every single little thing to you. Back then, and even to this day, I still have that AGI dream of building machines that maybe a few decades or few centuries from now, we’ll finally get them to be as intelligent as a human.

**Andrew:** I don't know how long it'll take, but I actually do believe that unsupervised learning will play a big role in that. So, I think it's a great research topic. I started Google Brain thinking that if we scale up unsupervised learning algorithms, but then what happened was as we built really big neural networks at Google, we found it was so useful for supervised learning that then distracted us all right to just focus on supervised learning. But I think unsupervised learning will be, it is a key tool already with web embeddings and that large language models and nascent things in computer vision, but I hope that there'll be more research on that.

**Craig:** I'm interested in no code because I can't code. Along with everybody else. I'm amazed at what these large language models can do. DeepMind just came out with AlphaCode, which is mind blowing to me, in that you can describe something with natural language and the AI will code it pretty well. I'm looking at the day where I can talk to a computer and code an application.

**Craig:** Do you think that's something that's going to happen in the say next 20 years?

**Andrew:** There's actually one other paradigm of developing machine learning systems that I'm even more excited about which is helping subject matter experts engineer data. And this is data-centric AI development.

**Andrew:** So, I think, large language models, attempts to generate code automatically for the simpler problems. All of these are exciting research areas and will be useful for some applications in the near term.

**Andrew:** I think large language models will be very important and will lead to some new applications. I feel that automated code generation, I think it works for some classes of problems. And I think that it will certainly help make developers more efficient.

**Andrew:** But having a person tell a computer about the requirements for a complex computer program, rather than a simple one and have that all that get coded, that still seems quite some distance away. In the near term, meaning the next few years, one thing that I think is realistic is no code, low code machine learning development platforms that makes it easy for subject matter experts to upload data, label data, and get out of that a cutting-edge AI system.

**Andrew:** That path to democratizing access to AI technology seems clearer to me right now than automatic code generation.

**Craig:** I thought you would be more excited about large language models because that in effect is a data centric approach. You're just scaling up the amount of data and training that the model can handle. And as a result of that, it's able to do things that no one expected it would be able to.

**Andrew:** It's true that for many years, going back to, when I started pushing for using GPUs with deep learning when I started Google brain. I have for a long time, been excited about compute and scaling data set sizes. And I think it's been interesting that recipe that I was pushing for almost 15 years ago still continues to work today.

**Andrew:** I don't think of the large language model work as a data centric approach for the most part, because I think one recipe for improving the AI has been scaling compute and dataset size, and people should keep on doing that. This is a great recipe it works, and we have a lot of data. I feel like the data centric approach is a shift to also pushing a different direction than just scaling.

**Andrew:** And that is that, rather than taking tons of data that may be imperfect, messy, garbled, if you can provide tools to create really great data, even very small, even small data sets like 50 images, that can also give good performance for the AI system. AI has been in the era of big data for the last decade.

**Andrew:** Nothing wrong with that. If you have a lot of data, let's keep doing that. But because not everyone has giant data sets. I think AI needs a new direction in addition to big data, which is a movement to good data where we can figure out how they get, 50 or a hundred or 500 examples that have that really show an AI system, what you want to learn, and then getting an AI system to do things from there.

**Craig:** Would it be possible to create a system like that, that crawls through the internet and curates or cleans and builds big data sets that are much more precise.

**Andrew:** Yeah, that would be interesting. Actually.

**Andrew:** In fact, part of the data centric AI movement there are definitely teams working on engineering very large data sets as well. So just because you have a large data set doesn't mean you don't want to improve it. In fact, for the large language models, one dimension of this would be attempts to remove from the training sets examples of toxic speech or highly biased speech. Because taking that data out, it reduces the amounts of bias. Certain types of bias that the language model therefore demonstrates. And I feel like for the most part, there have been really clever researchers spotting a problem and then engineering the data to take out certain types of toxic speech from the data set and that worked and should be celebrated. And there's lots of good work there. The data-centric AI movement is working to make this type of work possible, not just by the brilliant researchers that spot the problem and use skill or luck to fix it, but to build tools and principles that makes it possible for a much larger group of people to do these things to the data.

**Craig:** You mentioned your interest in AGI as kind of the ultimate goal, as you said, AI is extremely broad and there are many different areas of research and kinds of applications. But if we just focus on human level intelligence, it appeared to a lot of people that the large language models and particularly WuDao 2.0 out of Beijing, which was multimodal, that these models are approaching the kind of general multimodal model that we'll at some point, approximate human intelligence. Is that wrong? That thesis? And if so, if we're assuming that AGI or human level intelligence is the ultimate goal of a lot of this research, what directions currently in the research are you most interested in?

**Andrew:** AGI is a grand challenge that I hope we'll bring to fruition, maybe within our lifetimes, hopefully no more than a few centuries from now. While I'm excited by the great research in large language models, I don't think there's a clear shot from large language models to AGI. I feel like while building skyscrapers is very impressive and being at the top of a skyscraper gets you closer to the moon. And the ability to build really tall structures was a key part of how we eventually got to the moon. I think building tall structures was also not the only thing that was needed to get to the moon. I feel like today's large language models have consumed way more text than any human will ever consume in a lifetime.

**Andrew:** And they are still far less capable than a typical human. Maybe if there was a way to generate even vastly more texts than all of humanity has ever generated. And a lot of other things that have not yet been discovered, frankly, and that none of us really know what they are then, in a few decades with new technology that doesn't exist today yet, we'll get to AGI.

**Andrew:** But that's how I feel about the challenge of the difficulty ahead of us. Once we thought chess was the ultimate problem. And surely once we beat the human world chess champion, isn't that the highest expression of intelligence. Well, that didn't work out. I think that maybe large language models, we're many hundreds of meters closer to the moon now, which has fantastic progress, but the remaining path is still very long.

**Craig:** Is there an area in AI research that you're particularly excited about?

**Andrew:** Gosh. Yeah, so many areas to be excited about. In the near term, I'm very excited about all the work that many teams are doing on data centric, AI.

**Andrew:** Colleagues and I organized a NeurIPS workshop on data centric AI, and even I was surprised by the volume of research papers, I think with 170 research papers submitted for the first NeurIPS workshop on data centric AI. And I think that's because articulating the data centric movement, it coalesced a lot of feelings and worries and direction that people were heading in and also brought together a community that had been intuitively feeling and trying to work on these problems of the data. So, I think that's exciting. But beyond data centric, AI, I think, continue to scale models is exciting. There's nascent work on foundation computer vision models that I think it would be great to work on. There are advances in generative synthesis that I think are exciting and much more efficient than the algorithms previously. A lot of innovation in small data algorithms, including other things, few-shot learning, one-shot learning. Oh, and of course I think, unsupervised learning remains exciting to me. Sometimes on weekends, I think about some of the research I've done on unsupervised learning and wonder if scaling up those we'll learn very interesting things as well.

**Andrew:** So, AI is a big place. I actually think there's a lot to do.

**Craig:** Do you think China is advancing on the basic research ahead of the US? There was a lot of dismissive talk about WuDao 2.0.

**Andrew:** I see a lot of countries the U S China. Canada the UK even others like a growing presence in LatAm, other European countries increasingly, able to make significant contributions to basic research in AI. There are some algorithms that we use today that really were from Singapore, which is a smaller population than the United States.

**Andrew:** We live in an era where AI research is still wide open, and all nations still have to stay on their toes. I certainly hope that the U S will keep on increasing the investments in basic research in AI. For myself, I can tell you that if I had not received NSF and DARPA funding years ago, I wouldn't have done the basic research that allowed me to start and lead the Google Brain project.

**Andrew:** So, with research funding in the US some years feeling like just a lot of work to write an NSF grant proposal, I worry about that younger researcher and how to set them up for success so that they can spend their time doing great research to start the next thing.

**Craig:** That's it for this week's episode. I want to thank Andrew for his time. I also want to thank ClearML for their support. Take a look at what they have to offer at clear.ml.

**Craig:** And remember, the singularity may not be near, but AI is about to change your world. So, pay attention.