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CRAIG: 00:08 Hi, this is Craig Smith with Eye on AI, a podcast about artificial intelligence. This is the second of a periodic series of sponsored episodes that looks at companies making a difference in the space.

 The dirty little secret in much of artificial intelligence today is that it depends on hordes of unskilled workers hunched in front of computer screens around the world, labelling the images that are used to train supervised learning models. Demand for labelling, as the process is called, is exploding as computer-vision systems and other forms of AI sweep through the global economy. However, in order to efficiently do that work, in order for data science teams to work with each other and with labelers around the world, they need a platform and tools. Without those things, managing large sets of data quickly becomes overwhelming.

 Most data science teams end up building their own infrastructure to handle the work. But my guests this week saw the opportunity to provide that platform to save data science teams and companies time and money in managing data and training machine-learning models. [Manu Sharma](https://www.linkedin.com/in/manuaero/) and [Brian Rieger](https://www.linkedin.com/in/riegerb/), together with [Dan Rasmuson](https://www.linkedin.com/in/danielrasmuson/), founded [Labelbox](https://labelbox.com/), which provides the software to manage this work. I hope you find Manu and Brian as inspiring as I did.

CRAIG: 01:31 Let's start with who you guys are. Manu or Brian? Whichever one wants to start.

BRIAN: Brian Rieger. I'm co-founder and COO of Labelbox.

MANU: Manu Sharma. And I'm founder and CEO of Labelbox.

CRAIG: And you guys met in college, is that right?

MANU: That's right. We met in our fourth year of college.

CRAIG: And that was at [Embry-Riddle](https://en.wikipedia.org/wiki/Embry%E2%80%93Riddle_Aeronautical_University)?

MANU: That's right. We both had a lot of interest to learn about airplanes and aviation and aerospace. I had arrived to Embry-Riddle from India and this was my first time in the West. So that's where I met Brian, in a class, which was aircraft design. And we were both extremely passionate students in the class competing with each other to design the best airplane.

CRAIG: Right. And you were designing a morphing wing structure. Did you work on that together?

BRIAN: We did. So, after this class that Manu is referring to, we had a summer off between our first semester and second semester of senior year and I grabbed Manu in the computer science lab and said, ‘Hey, we should work on a project together doing something interesting in aerodynamics,’ because I had recognized that he was passionate about aerospace and aircraft design.

CRAIG: Where did the neural nets come in? Because Embry-Riddle is not a machine learning focused university.

MANU: So, I think every engineering discipline today has some level of software engineering. We knew how to program before, but most of the things we did in our studies required us to program. We used [Matlab](https://en.wikipedia.org/wiki/MATLAB), a very popular software, and, you know, being just curious about AI and ML generally, we would tinker around [wondering] ‘what other modules does this software have?’ And we just stumbled across these neural net modules in the software. And, we had professors who had experience. So that's how we got into neural nets.

BRIAN: 03:36 We were using neural nets for the same reason people are beginning to use them for computer vision today, which is that modeling aerodynamics is nonlinear. And so, the classical statistical modeling techniques, we didn't think were a fit for modeling a non-gradient, nonlinear, non-analytical problem space in physics. And so we wanted to use neural nets because we thought that they were a more sophisticated pattern development system for creating the most optimal shape at thousands or millions of flight envelope points.

CRAIG: Hmm. And so then after school, you guys went your separate ways. Is that right? You went to Boeing and you went to [Drone Deploy](https://www.dronedeploy.com/).

MANU: But in between, we actually started two businesses together.

CRAIG: One of them was a wind turbine company...

MANU: That's right.

CRAIG: …in Chile was it?

MANU: That's right. So, we thought we could build a [small scale, efficient wind turbines for residential use cases](https://youtu.be/Yaik7N3re5M?t=612). And that led us to start this business. We got funded by the Chilean government and we moved there and built a bunch of prototypes. And then quickly realized solar was being adopted and especially after the Chinese started to manufacture solar panels, the cost dropped nearly by half within a year. And it just suddenly made so much more sense that this is actually a fundamentally better solution. And so, we moved back and went on to work on this.

CRAIG: 05:01 What happened to that company? The turbine company did it close?

MANU: We closed it.

BRIAN: There's a lot of problems with building residential wind turbines because the air stream that's flowing over the surface of the planet is what's called inside of a boundary layer. And so, the speed of the wind increases exponentially as you get higher and you don't really get the best winds until you're up, you know, 30, 50 feet above the ground. So even if the turbine is cheap, like you still have a $30,000 pole to put up.

CRAIG: What was the other business? The second one?

MANU: 05:34 So the second business we started was building and selling a small [CubeSat](https://en.wikipedia.org/wiki/CubeSat)[-like] research labs. Think about like small satellites, but they are always inside the international space station and an astronaut plugs [it] into the power outlet and a data outlet. And it is self-contained to do contained experiments. So, we would build up software and hardware and provide the launch services to kind of have this commercial path to do these science experiments. That was a lot of fun.

CRAIG: And what happened to that venture?

MANU: Well, a series of missteps, we had four or five of these payloads in a rocket launching from North Virginia, which had [a blast](https://www.baltimoresun.com/health/bs-md-nasa-antares-explosion-20141028-story.html) just after the launch actually. And then we also were on [the] SpaceX rocket and that [also blew up](https://www.wired.com/2015/06/spacexs-rocket-exploded-got-land-barge/).

CRAIG: Blew up. Yeah.

MANU: And so, it was, it was kind of harsh and we were, you know, we were very lean, so we didn't really have any insurance and things like that. But one made it up into the, into the space station.

CRAIG: Oh, really!

MANU: Yeah, and that was, that was great.

CRAIG: Wow, that's exciting. So, you went to Drone Deploy and then [Planet Labs](https://www.planet.com/), and that's where you found yourself spending a lot of time building infrastructure tooling for deep learning models or to handle the data labeling of deep learning models. Is that right? Can you talk a little bit about that?

MANU: 06:53 That's right. So, I spent about three and a half years at a company called Drone Deploy that builds software for mapping with commercial drones. And that was actually the first time when I started to see machine learning make a real-world impact to farmers and to construction companies. But it wasn't until I moved to planet labs, which at the time had about 300 satellites in low earth orbit, and the company was scanning the [entire globe every single day](https://www.planet.com/products/planet-imagery/). So, think of Google maps that updates every single day, and there is just [an] amazing amount of insight that you can capture when you can see the world with that much high fidelity in [the] time domain. Things like deforestation can be tracked. Corn plantation in the Midwest can be tracked from space.

MANU: 07:45 And what was fascinating was that the teams inside the company were using deep learning as a primary method to extract these insights, these patterns of life from this corpus of data. And it immediately became clear to me that every single team, in order to build these deep learning models, they had to take the data, get it labeled by an expert, whether it is a geospatial expert who understands certain geography or whether it is someone who understand what illegal plantations look like in Columbia. [For] Whatever patterns of life that we wanted the models to learn, we had to get [the data] labeled. Not only that, but we had to build an infrastructure to do that consistently over long periods of time and solve different problems. And all of this tooling was being built from scratch as if we were, you know, we were going to the moon, but we were building the whole rocket and the satellite, like nearly every single thing from, from scratch.

MANU: 08:38 And that was my first glimpse of the state of the art in the industry, but at the same time realizing that this industry is taking, just taking off and there's so much more potential. A lot of the deep learning [technology] started to work in 2012 to 2014. During those times there was monumental research papers that came out and certainly it brought the whole industry to follow. Since then, the rate of progress of algorithms and hardware has been doubling every three to five months, which is like three to four times faster than Moore's law. And if you look today, in order to build production, real-world artificial intelligence, you need three things. You need data, you need algorithms and hardware. Algorithms today in 2019 are nearly free. You can get it off the shelf from open source libraries. Lots of new models are being created [from] research papers. Hardware is getting better, cheaper and faster, at the rate of Moore's law. In fact, in some degrees faster, especially with specialized AI chips. And now, the focus for the entire world has come to data. How do these companies create the right training data to feed to these algorithms that can learn patterns of life and make decisions on behalf of the company? And that's the state of the art today.

MUSIC: INTERLUDE

CRAIG: 10:16 And then you guys, you, you had this light bulb go off that, ‘I'm spending all my time building this infrastructure. Somebody should build it commercially and offer it to industry.’ And how did you guys come back together then?

BRIAN: Manu and I talk about ideas a lot. This was one idea of many that we've talked about for the last 10 years. What we did was explore the industry after I encountered data labeling challenges, Manu encountered data labeling challenges in general, training, data development challenges and tooling challenges. We explored the industry. We tapped into a lot of Manu’s network and asked leaders of AI companies or data companies that were building machine learning technology, and we asked them about how they were doing data labeling, how they were building tooling. Were they building it internally, would they buy a commercial tool if it was available, what would that look like in their eyes? Things like that. And we talked to 10 or 20 different leaders and they really said the same thing. We're building an internally, it's causing us to delay our roadmap by a significant period of time. We would love to buy a commercial tool, let us know when you build one and, and I'm happy to pay for it.

CRAIG: 11:22 And there you go. Yeah. So, you started Labelbox and then Dan Rasmuson the CTO. He was also, I think at Drone Deploy. The three of you came together or how did then the, the company get started?

MANU: That's right. In fact, Dan also explored labeling problems at that time in his work, so we kind of all had this organic experience of seeing this problem in building our own companies that naturally kind of inclined all of us to kind of explore this together. And, yeah, we would do everyday meetups and, and, and sync and see what progress we made in research and prototyping and so forth. And then we started to build this on nights and weekends.

CRAIG: Oh, you did it before leaving your jobs, you built the initial prototype.

MANU: Yeah. On nights and weekends mostly. And we launched Labelbox on Reddit on the first of January of last year. And it was a very basic tool, very simple. And people had an amazing reaction to it. It sort of became an instant hit and more people started to sign up and ask for more things. And in a couple of weeks we started to ask for paying for the service and people started paying. And somewhere in between I think it just got immediately clear for us that we've got to do this, and, and make this a big business. And Brian just quit his job in a day and just moved to my living room. And that triggered Dan and us to give our notices.

CRAIG: Yeah. And somebody said, you guys all live in the same house. Do you still live in the same house?

MANU: That's right. We do.

CRAIG: Wow. That's all three of you and your partners?

BRIAN: 13:01 Manu is the only one with a spouse.

CRAIG: So, listeners to the podcast include people that are not deeply involved in deep learning and a lot of people don't realize that deep learning models or supervised learning models depend on labeled data and that there are tens of thousands of low skilled people that are labeling all this data. Do you have an idea of how large that community is?

BRIAN: We think it's somewhere between 40 and 70,000 people full time today. It's hard to calculate exactly because there's a lot of gig economy work in that sector and you do have to separate out supervised machine learning labeling from other types of traditional BPO work like data entry and receipt categorization and things of that nature. But when I pass these numbers through our data at Labelbox and other leaders at other data labeling companies, they seem to agree with something in the neighborhood of roughly 50,000.

CRAIG: As deep learning moves into industry, is that number going to grow, do you think? You have data augmentation or synthetic data, you have automated labeling and the body of labeled data is growing over time. So, is this labor force going to continue to grow or do you think that it’ll reach a point where there, on the one hand data sets that people can turn to that are already labeled, on the other hand, there’s automated labeling or augmented data that’ll take care of a lot of the need?

MANU: I think fundamentally, human supervision [work] will continue to grow, whether it is actually pure labeling work or whether it is just QA-ing—[and] there might be some nuances on where the industry shifts over time. But, we don't see any signs for this to slow down.

BRIAN: 15:03 The industry numbers, today, we're talking about something like $300 million per year in labeling spend that's projected to get over a billion by 2022 or 2023. That means we're looking at, you know, hundreds of thousands to potentially millions of people by the mid 2020s.

CRAIG: That's really remarkable.

BRIAN: You can also have the same thing being true, meaning you can also have synthetic data getting better. You can also have weak supervision or automated labeling getting better and you can have this growth because we're still in really the early adopter phase for supervised machine learning. And so, the rate at which companies are adopting the technology and spinning up this type of development is outpacing the rate at which we're developing automated labeling. Automated labeling and things like that itself come from a maturity of a particular domain in machine learning oftentimes.

CRAIG: 16:07 We're talking with regards to Labelbox about computer vision applications almost exclusively. Is that right?

MANU: That's right. We are extremely focused on computer vision for the short term. But we do have plans to expand that into all forms of data mid to long term.

CRAIG: Yeah. And computer vision, deep learning. Do you have any sense what the degree of penetration in the global economy is right now? I mean, is it …

BRIAN: I think we've only scratched the surface because a lot of what the economy is about is the human eye supporting human decision making as the main sensor system or organ. And the amount of power that the brain uses for the eyes is overwhelming compared to the other senses for a lot of reasons. And that's our main sense as a human species. And most of the decisions and work in the economy is based on the human eye. And so, it's only been in recent development of deep learning that the human eye is, is up for automation and augmentation. And so from that kind of first principle thinking, it's probably true that we're very early on in the penetration. What that number is, is hard to know because there isn't an analogy really. Maybe, maybe software, like the penetration of software early on was thought to be a lot, even in 2000 when there was a bubble. But even the value of Amazon at that time is infinitesimal compared to what it is today. And so, the penetration could be enormous as we have now the ability to understand with computers the complexity of what the human eye can understand.

MUSIC: INTERLUDE

CRAIG: 17:52 Well, maybe we should stop and describe exactly what Labelbox is. It's not something that's easy to visualize. It's a computer interface, right? A platform that a labeling operation or individual works on to label data, to look at images and identify features in the image and then label them in text, right? But there's a whole workflow - that's only one part of the workflow. Can you sort of walk from a to Z what Labelbox does?

MANU: For sure. So Labelbox solves the data problem in AI. And as I mentioned, there are three components needed to build real world applications. It's data, algorithms and hardware. And in order to build real world applications in AI, machine learning teams need a robust infrastructure that is able to get all the raw data from sensors and applications into an environment that can be streamed into labeling workflows. And Labelbox enables all of that from right when you have applications streaming the data into databases all the way to spitting out extremely high-quality labeled data into the algorithms. So, anything in between that happens, Labelbox provides tools and workflows to, to do that simply and reliably.

CRAIG: 19:19 And, and you have to have some sort of a platform or you're left emailing zip files of images and JSON files and things like that around to each other, and it gets very complicated if it's a project of any size, keeping track of all this stuff. Is that right? Or what, what other ways would people do this if they didn't have a platform like that?

MANU: Because all of this work came from academia, most tools are desktop tools. So, think about installing an old word processor on a local computer. And because labeling lots of training data requires working with lots of people, it is fundamentally really hard to go to everyone's computer, put some files and have them label certain things. And Labelbox, when it came out, it took all of that core concepts, the tooling, and brought it into the web and made it collaborative so that everyone could just simply upload the images to Labelbox, add N number of people and just label and export, create models.

CRAIG: And so, teams can be dispersed geographically.

MANU: Absolutely. And with, it can be a team of domain experts, like doctors working across different clinics or it could be uh, working with globally distributed uh, team members.

CRAIG: What are some of the other tools that are emerging and what direction do you see Labelbox going? We talked a little bit about weak supervision or automated labeling. What are some of the features you envision for the labeling workflow or what tools do you think will appear in Labelbox?

MANU: 21:05 So, Labelbox’s mission is to build the best products for humans to advance AI. And today we are very focused on the data problem and we also are extremely focused to build a software platform. And what that means is that right now strong supervision is predominant in the industry and that requires high quality training data consistently in any setting, whether it's internal teams or whether it's outsourcing it to offshore teams. But we are very focused in solving the problem of creating high quality training data as cheaply as possible. That means that we are building a lot of automation technologies that ultimately enables customers to create more data, faster, with less cost. And then I think over time we probably will explore weak supervision or whatever new technologies that might be emerging in the industry. Think of Labelbox as an institution that is bringing the best technologies to solve the data problem.

CRAIG: The training doesn't take place on Labelbox, does it.

MANU: That's right. Currently it doesn't take place on Labelbox. But I think we do have an ambition of making Labelbox the workspace to build and operate intelligence over the long term.

CRAIG: So, the full gamut, the, the entire workflow to deployment of models.

BRIAN: 22:24 Everywhere where the human is involved in making the model better and uh, directing it and supervising it. So, you know, one day we may be part of the compute piece, but the data problem itself spans a big piece of this process of developing the machine learning technology or the model itself. For example, developing high quality training data and then having the model be performant initially is great. But once that model goes out into the real world and starts to make some decisions for you, it may be degraded in some areas or not as performant as you want it to be in some areas or maybe it encounters a new environment that it wasn't trained on and therefore it's incapable of making good decisions in that environment.

BRIAN: You want to know about those things, you want to bring that information back into your data space, your training data development environment, your Labelbox hopefully, and at a human level, look at that visually because this is a visual problem, and understand where the model's deficient and then describe or administrate work and solutions that drive new training data into the model so that it can improve. And so there's a lot there. There's integrations with the deployment and compute environment. There’re integrations with how that model’s making decisions and how those decisions are coming back into the platform, your data platform. There are models inside of the data platform that are helping you work through millions or tens of millions or potentially hundreds of millions of images and understanding where it’s strong and weak and why and what those patterns are in the visual data that you can use to administrate solutions.

BRIAN: So, it's a very sophisticated problem space when you zoom out. That is truly the interface between the human and the machine, right? The data represents those decisions. And so, where the human and the machine interface and where the human is supervising the machine and assuring that it's aligned with whatever they want it to do, whether that's the business objectives or their own personal objectives, that's where Labelbox is.

MUSIC: INTERLUDE

CRAIG: 24:26 I mean, there's a lot of talk these days about bias and data and how that feeds bias in decision making, machine learning decision-making. This process of being able to look at where your data is weak or causing poor decisions, that relates directly to discovering bias in the data, wouldn't it?

BRIAN: Absolutely. The, the great news about bias is that bias presents similarly whether or not you have a degradation or a deficiency of model performance in a business context or whether it's an ethical context or a moral context. So the tools we build today for business problems perfectly translate to solving ethical or moral issues with bias in the model. So we will surface those biases in the same way and correct them in the same way. So the tools are available today in so far as there are good tools available to work bias out from a business moral, ethical, et cetera, context.

CRAIG: How then do you go back into the data and balance the data or remove that bias?

BRIAN: 25:31 That is one of the core theses of Labelbox, which is when you were up against that size of a data corpus and you have those kinds of understandings of the data, first of all, how do you figure that out and how do you figure out what images are subject to that, that, that issue or that bias? First of all, that's a difficult computer vision problem, all of its own, which no one really has a tools for. And then how do you go and correct that? And these are the big problems, that scope beyond just data labeling itself, these are the big problems and the big engineering challenges that stand in the way of mass AI adoption, right? Because looking through millions of images and finding like images that have this certain issue, that's a whole challenge in and of itself.

CRAIG: I mean, there was a famous example, you Google ‘CEO’ and you get almost exclusively white males. Right? And that's because out of the data there's a preponderance of white males. I mean, would you go back in and an augment that data to balance it and how, how do you balance the data so that it's not skewed for societal reasons or something like that?

BRIAN: I think it would depend on what the purpose of it was. If the purpose was to inspire a young generation of CEOs, you would want to present a diverse set of demographics in order to equally inspire and show the [potential] career paths of any individual that you're trying to inspire that's young. But the data is the data ultimately, and we do have this bias of white male CEOs and so from a purely heuristical sense, that's actually signal. What the application is, I think, is really important. Every application is unique in the way it's applied and therefore the data is often finely tuned to that application. Whether or not you're using a, an opensource data set or, or a community data set or data set you bought from another company, it has to be finely tuned exactly for how you're going to use it.

CRAIG: 27:26 Explainability is part of the problem in deploying deep learning models. I mean, certainly in Europe now with GDPR. Tools like Labelbox, they don't address the fundamental issue of how a neural net is surfacing features and making decisions based on those features. But presumably you can look back at the data and make some judgment about why certain decisions are being made based on the data. Does Labelbox help in, in that kind of judgment on how decisions are being made?

MANU: 27:57 I think so. I think more and more people and, and particularly businesses are thinking about model explainability and especially in the context of bringing these models in regulated industries like insurance or healthcare. And we are quite early, even in that world, where people haven't thought about how will they regulate this AI based decision making in these industries. I think one of the big ideas I heard in your podcast with [Yoshua Bengio](https://www.eye-on.ai/podcast-012) was that idea of certification of AI.

MANU: And I think if the world follows that path, which I actually am very supportive of, that basically means that there needs to be some mechanism to prove that this model is able to make good decisions over some constraints of the real world. And there are a lot of ideas around do you go inside the models and understand how each of these neural layers are making decisions or do you treat the network as a black box but you make more heuristic understanding of why a model is biased in making certain decisions. So, I think there is a lot of research happening in this space and Labelbox is particularly suited for providing it, model explainability, from a heuristic standpoint from the inputs and outputs and providing analytics based on that information. So, I think it's too early to tell honestly where the world will go in model explainability and to what level the world will require explainability of models.

MUSIC: INTERLUDE

CRAIG: 29:35 You talked about certification, which with this growing community of labelers out there who are largely are low skilled and someone's putting a margin on their labor …

BRIAN: Labor arbitrage.

CRAIG: Labor arbitrage, exactly. Is there some way of creating standards or principles so that labeling companies connected to Labelbox are doing things properly or according to a certain standard?

MANU: 30:03 I think the key, the thing is first of all, Labelbox is entirely a software platform. Our business is selling software infrastructure to, to the companies. Now when we think about building things like providing value to our customers, one of the most important things for us is to provide great quality. It is all about great quality of data versus quantity. And what we've seen is in order to create great quality of data consistently over long periods of time, you need to work with businesses or organizations that employ people on a fulltime basis and provide a great environment for them to be able to do this work. And that's something that we have embraced since day one. So nearly every company that we work with who provide labeling services to our customers via Labelbox, they are businesses providing employment to the low skilled workers and providing additional benefits and services to these people. And I think that's a big striking difference between Labelbox and nearly any other solution out there.

BRIAN: 31:01 While they may not have traditional academic training, they do get a significant amount of training and really do become experts on the application or the project that they're working on. So, if they are working with an agriculture tractor company and that company is doing precision spraying, for example, the people working on that project, let's say in India, they actually get very good at some parts of agronomy. They get good at identifying different types of plants, different stages of the plant life cycle. And that is interesting, but more to the point, their ability to come to work every day and work on that same problem and get better at that piece of agronomy for the tractor company is actually really important for the quality of the data. So their persistence and their ability to stay with that project is very important and it creates the best quality data, the best labeled data, and it also creates the best relationship between the data science team and the labeling or annotating team, meaning that as the annotation team or those labeling teams get better at understanding the domain, their sophistication of conversation increases with the data science team and therefore the harmony of these two teams is now more effective at solving new problems in agriculture.

BRIAN: 32:18 And so that's actually something that we focus on, we talk to our customers about. You can go to [Mechanical Turk](https://www.mturk.com/) and you can get really cheap labor, but you're not building a momentum for your business. You're not building an AI momentum. You're not building a cohort of people that work for you or work on your problem every day, even though they're not in your country. They are working on the problem you're working on every day and they're starting to get good at it. And that's value. That's very valuable.

CRAIG: 32:42 Will the world of annotators, or labelers, eventually separate into areas of domain expertise where you have people that label medical data who will be paid more than someone who's labeling clouds or snow, you know, something that's less specialized.

BRIAN: Certainly, I think one of the exciting things is that through machine learning and the opaqueness of the models you see, particularly in healthcare, a lot of the labeling work being done overseas for a healthcare model that will be used to diagnose people in Kansas with cancer for example. And so that model is built up of decisions that have been made by people that have been trained to find cancer in India who are not doctors and don't even really have a formal medical education. So, I absolutely think there's an opportunity for that type of skill to mature for those people in India for example, where they do start to get certified. What's exciting is that you're beginning to unlock this global workforce of experts. You're creating this organic way of, of them developing domain expertise. And then potentially we can have them be certified in some sense. And they unlock more value for their time and they, you know, are recognized in that way and, and the industry matures in that fashion, which is exciting.

CRAIG: 34:12 But in talking about the interface, so you guys spent a lot of time making it as easy as possible for the annotators even in terms of keyboard layout or eye tracking and that sort of thing so that it's not overly taxing. I was asking whether there's talk of gamifying the annotation exercise to make it more enjoyable or better incentivized or something like that.

MANU: Absolutely. So, the way we think about these things is from our core values. So Labelbox is primarily a product and design first company. And in addition to that, the tools that we are making are for a scientific purpose: to build great performing machine learning models. But at the same time have amazing human computer interaction because it requires a lot of interaction with humans. So, we absolutely are obsessed about thinking about these problems of how do we make our interfaces as best as possible for any person to efficiently tell the computer the intent, which, basically is the gap between human and computer. And so that remains our biggest emphasis and is such an important and exciting problem to solve.

CRAIG: 35:27 Yeah. And you see this only growing…

MANU: As you think about automation and as it permeates through the industry and we get better at automatically predicting these labels. I think the, the, the tools will continue to evolve to meet that balance. Right now, it is very heavily biased towards a human experience, but I think, with automation, it might be more with human QA or simple supervision. So, I think we also understand that and we are ready for that. It’s going to be an evolution. So as, as I mentioned, like our mission is to build the best products for humans to advance AI, and AI is a moving target. And at every point in that journey, we will need some evolution of these tools.

CRAIG: That’s it for this week’s podcast. If you’re working with big data sets to train a machine-learning model, I encourage you to look into Labelbox at labelbox.com. As always, I provide a link on our website, eye-on.ai. I spend a lot of time on the transcripts, including links that make it easier to follow things that might be unfamiliar to readers. I encourage anyone interested in learning more to download the transcript and read it. The eye captures much that the ear misses.

 We love to hear from listeners and your ratings and reviews on whatever service you use helps increase our visibility for others.

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