[DAISY THE GREAT](https://daisythegreatband.bandcamp.com/): 00:00 [Built my House on Hollow Ground](https://youtu.be/z-1sC1lkmKw)

CRAIG: 00:07 Hi, this is [Craig Smith](https://www.nytimes.com/by/craig-s-smith) with a new podcast about artificial intelligence. This week we returned to the world of thinking robots, one of my favorite subjects, with [Chelsea Finn](http://people.eecs.berkeley.edu/~cbfinn/), one of the youngest experts in the field. Chelsea did her PhD at the University of California Berkeley, where she's been working as a postdoc on robotics at the [Berkeley Artificial Intelligence Research Lab](https://bair.berkeley.edu/). She's also a research scientist at [Google Brain](https://ai.google/research/teams/brain/) and this fall will join the faculty of [Stanford University's Computer Science Department](https://cs.stanford.edu/). Chelsea recently received the 2018 ACM Doctoral Dissertation Award for her dissertation, ['Learning to Learn with Gradients,](https://www2.eecs.berkeley.edu/Pubs/TechRpts/2018/EECS-2018-105.html)' in which she introduced algorithms for meta-learning that enable deep networks to solve new tasks from small datasets. We talked about her journey, about her work in meta-learning and about lifelong learning for robots. I learned a lot from Chelsea and I hope that you do, too.

DAISY THE GREAT: 01:10 Built my House on Hollow Ground

CRAIG: 01:16 I'm always interested in how people got into machine learning, where you were born and brought up what your parents did and when that spark first ignited the interest. So if you could tell me that, then I'll start asking my other questions.

CHELSEA: 01:32 Yeah, absolutely. So I grew up in California, it actually in the Bay Area not too far from Silicon Valley and both of my parents were engineers, not software engineers, chemical engineering and civil engineering. And so it was pretty clear to me that I really enjoyed solving problems and engineering was a field in which you could learn how to solve problems. So that was something that really appealed to me. In high school, I was excited about computer science, about actually biology as well in genetics, how cells actually work together to create everything that we are, which is pretty fascinating and also maybe connects a little bit to building intelligence, artificial systems. And after that experience, I went to MIT for Undergrad and I was kind of deciding between bio and computer science - ended up going with computer science because it seemed like there's so many different things you can do from it afterwards, including like a [computational biology](https://en.wikipedia.org/wiki/Computational_biology) type thing potentially.

CHELSEA: 02:23 Then I guess at MIT I was naturally drawn more to the things that use things like probability theory and robotics and computer vision. I was fascinated by how you can have something that could understand what's in an image and also act in the world in a way that was intelligent. I like actually front loaded with the more advanced courses and saved some of the easier courses that were requirements for a bit later just so I could really dig into some of the depth right from the beginning and try to understand some of those concepts. I did an internship at Google in like my second year of Undergrad, and nothing against Google, but I didn't really find software engineering to be that interesting personally and I found it much more interesting to be trying to solve problems that people hadn't solved before or didn't really know how to solve and it seemed like research was the way to do that and doing things like robotics and having them learn was one way to do that.

CHELSEA: 03:18 It took me a while to decide that I wanted to go to Grad school to do a PhD. It was not something that my parents were actually initially supportive of because they didn't feel like PhD's were that useful at least in in things like civil engineering or chemical engineering where you're, you're kind of applying the knowledge that you learned in practice in industry. But it was clear to me that [people] in industry that were doing exciting work in machine learning and in robotics all had PhDs. And so if I wanted to do those things and things that I found exciting, then then I should also do a PhD. And so, I ended up deciding to go to UC Berkeley for, for Grad school because there were people there that were doing robotics and machine learning, which I found quite exciting. There are a lot of people doing robotics at other places, but not using ideas from learning, instead using ideas from [classical control](https://en.wikipedia.org/wiki/Classical_control_theory).

CRAIG: 04:02 Right.

CHELSEA: 04:02 That was kind of where things all started for me with regard to actually like using machine learning to build robots to do interesting things. And since then, a lot of my research has focused on how can we build a robot in the real world that can do intelligent things. And in particular, not just doing one individual narrow skill but being more general purpose and, and being able to act intelligently in a variety of real-world environments, which requires some notion of, and I think this is a long-term goal, but it requires some notion of common sense, some understanding of the world and, and how the world operates in order to accomplish a variety of things.

CRAIG: 04:38 Yeah. So, I spoke with [Aude](http://lasa.epfl.ch/people/member.php?SCIPER=115671) [Billard] yesterday. Have you used any of her research? She uses a combination of classical control and machine learning. Are you purely machine learning or are you blending the two like she is?

CHELSEA: 04:53 So at the beginning of my PhD we started with blending the two because that was actually a bit easier to get some traction on. And then more recently I've been focusing on more pure learning approaches that move a bit away from classical control. Sometimes like the low-level controller of the robot uses ideas from classical control. But ultimately I think that some of the tools there are useful, but they don't extend very naturally to perception to, to how to actually incorporate a system that needs to see from image pixels and handle things like deformable objects like, like a napkin or paper or a towel and just modeling those things is incredibly challenging. Even modeling just how a cap will screw onto a bottle. Trying to model the friction between the grooves and the cap and the grooves in the bottle is an extremely challenging physical simulation problem and a lot of the classical control techniques assume that you can do that modeling. In some ways I find the learning approach more appealing there because you don't want to - to screw a cap on a bottle, you don't need to be simulating the physics in order to accomplish that. And so having a very rough notion of physics I think is potentially useful. But I also think that you can learn that very rough notion from experience and from data.

MUSIC: 06:08

CRAIG: 06:09 That's interesting. Yeah. So tell me a little bit about meta-learning first.

CHELSEA: 06:14 Yeah. So the motivation for meta-learning came from the fact that at the beginning of my PhD we were able to get robots to learn how to do things like screwing caps onto bottles and using like a spatula to lift up an object. But every single time we had to learn a skill, we started from scratch, we kind of wiped any previous experience the robot had, had learned through trial and error to accomplish that task. And then once it accomplished the task, we then like wiped the memory and tried it for a new task. While we got really impressive results and it was quite exciting that we were able to get the robot to actually and in this case learn directly from raw camera pixels, it's so unnatural to start from nothing for each and everything. And if you want a robot to have a greater understanding of the world or to do many different tasks, it's going to be impractical to learn everything from scratch.

CHELSEA: 06:57 So, we actually started from the realm of lifelong learning. We were thinking about how we could have an agent kind of continuously build upon its previous experience and use its previous experience when learning a new skill such that they could learn the skill more quickly. And so one way you can do this is to say that it will kind of accumulate knowledge and be able to learn more and more things with a single model, like be able to predict the actions given one task versus given another task versus given another task. But if you do that, it may figure out how to reuse things but it may not actually learn new things faster by building upon what it has done before. And the idea behind meta-learning is we want to explicitly figure out how to accelerate learning for future tasks based off our previous experience.

CHELSEA: 07:40 And so, the reason why this is important is that if you want to learn a lot of different things, you can't just be like, have continuously learning and kind of accumulating knowledge in a way that isn't organized and structured. Once you kind of recognize the structure among tasks and like recognize objects, recognize what makes up a task, like, maybe you need to perform a screwing motion or maybe and you need to do the same thing for screwing a lid onto a jar or rotating a dial or something. Those sorts of things all share a lot of common structure and so once you've learned one of them, figuring out how to do the next one should be a lot faster. So what meta-learning algorithms do, or, or learning to learn algorithms. Is they try to figure out the common structure and they're trained to be flexible, they're trained to be able to learn new things much more quickly with less data than if you were to just kind of continuously train it or certainly a lot less data than training from scratch.

CRAIG: 08:28 Yeah, and learning that structure on which then to do various things. Is that supervised? Is that imitation learning or how do you get that structure?

CHELSEA: 08:39 Yeah, that's a good question. Actually. The idea of meta-learning is, is general to things like imitation learning or to reinforcement learning and can also be applied to things like supervised learning. I guess maybe just for the sake of a concrete example, we could say that we're kind of in an imitation learning setting and we want to learn, we're given a demonstration and we want to be able to imitate that demonstration. Typically imitation learning will require a very large data set of demonstrations for training, if you want to train like a deep neural network for example, to, to learn just an individual skill. And so what meta-learning does is it says, okay, maybe we learned like a hundred skills so far and we had fairly large data sets for each of those skills and demonstrations. What meta-learning does with that data is it actually automatically figures out the structure from those demonstrations across those tasks such that when it sees a few demonstrations for a new task, it can figure out how to learn it just from a few demonstrations rather than from a large data set.

CRAIG: 09:30 And the data from the past tasks is stored in videos or how is that stored?

CHELSEA: 09:36 Typically it's stored with videos as well as the sequence of actions that was taken in the demonstration. So with the video for each frame in the video, what action should the robot take from that frame? Um, like how should it move its arm? Should it move his arm to the left, move its arm to the right, should it rotate its arm, et cetera.

CRAIG: 09:54 So, and I'm sure I'm using the wrong term, but it's not implicit knowledge, or memory. It's not the weights that have been tuned for a particular task. It's indexing into a video or something like that.

CHELSEA: 10:07 I guess there are a couple of different approaches for meta-learning and once they're more explicit in terms of trying to recall past experiences, but in general, many of the meta-learning algorithms actually do learn some set of weights or some features from the data such that when you see a new, like a few demonstrations for a new task, you can quickly learn that. And the reason why it's kind of compiled down into a set of weights or a set of parameters for a neural network is that then you don't have to worry about kind of traversing all of the data that you saw previously. And instead you have things down and into like a, a very concise representation that can be used very quickly for a new setting. Just like you don't want to have to kind of recall all of your past experiences to figure out how that relates to your new experience.

CRAIG: 10:50 Right. And so the purpose is, I was talking to [Yann Lecun](https://www.eye-on.ai/podcast-017) not too long ago, last week, uh, and he was talking about representation, learning. And, and the problem with a lot of these learning systems is they take a very long time, as you said, and he was saying that a human can learn to ride a bike or drive a car in a matter of a few hours with very little supervision. So is that what meta-learning does? It just shortens that time and presumably allows the agents to learn at a speed comparable to a human or at least more comparable to a human?

CHELSEA: 11:31 That's basically right and humans are able to learn new concepts just from a few examples. Like if you see an image of a Segway, and you've never seen a Segway before, you can figure out just from a single image how to recognize other Segways, for example. And these systems are capable of the same sort of thing. If you give them an image of a new concept, they can figure out just from like a single example, what encapsulates that concept. And the way that they do that is based on previous experience of seeing other types of objects and by training them across a diverse range of concepts.

CRAIG: 11:59 And then that relates to lifelong learning because you want to learn a lot in life or in as long as an AI agent is powered. Can you describe then how that relates to lifelong learning?

CHELSEA: 12:13 Yeah, so it's essentially one slice of the lifelong learning problem. So it's given all of your past experience at a current point in time. You want to quickly learn a new task or a new skill or a new concept. And so ultimately this should feed back into lifelong learning problems. Once you start actually saying, okay, I have a bunch of experience, I want to learn a new task quickly, now let's integrate that, that new task that I've just learned very quickly back into my experience and continue to close the loop and continue to learn and continue to, to meta-learn across, across experiences.

MUSIC: 12:48

CRAIG: 12:50 So your work on lifelong learning. Do you have an agent that is learning continuously now and will accumulate knowledge from now until, I don't know who's life lifelong refers to, yours or the agents, but that will accumulate knowledge for years, presumably decades going forward.

CHELSEA: 13:09 So we have some initial work on studying how meta-learning can be used in these lifelong learning situations. We have promising results there that it can actually learn better than some of the existing methods for trying to handle these lifelong learning problem situations. Basically I have another line of work where we've also been studying lifelong learning and separately from meta-learning ideas and that kind of the two lines of work are complimentary and I can also talk about that.

CRAIG: Sure. Yeah. No, I'd love to hear.

CHELSEA: Yeah, so I guess transitioning from, from some of the meta-learning conversations is that one of the challenges that does come up in meta-learning is that while you're, you can train these networks to be very flexible and be able to adapt to new tasks and new skills very quickly. The meta-learning process itself, all of its past experience in most of our work, is still fairly heavily supervised.

CHELSEA: 13:55 It still requires either human labels for labeling images or requires demonstrations that are provided by a human or like what's known as reward functions in reinforcement learning to help supervise the agent and tell it how well it's doing. And ultimately what we'd like is for a system and for an agent that can actually, like, learn continuously without a lot of supervision on its own, autonomously by it, through his own experience with the world. And so one of the things that we've been studying is how we can have an agent interact with the world, learn from that experience without any supervision only given basically the images that it sees from its camera. And of course it also has [proprioception](https://en.wikipedia.org/wiki/Proprioception). It knows where its arms are. And that's basically it. This is an incredibly hard problem because it breaks a lot of existing, like, like there's no labels, there's no notion of progress or success if you're interacting with the world.

CHELSEA: 14:46 But it's also incredibly scalable. You can collect data with hundreds of different objects because the robot can collect its own data. The robot can kind of continue to collect data and, and interact with the world and experience different objects overnight without a human there.

CRAIG: Right.

CHELSEA: And so I think that these methods will be able agents to learn. Like if you're able to learn from that data, then they'll learn general things about the world because there's nothing else that's in that data. It’s just information about the world, about physics, about objects. And so what we've been doing with that data and the way that we've been learning from it is building a predictive model, being able to predict what will the future look like if I move my arm in a certain way and what will it look like if I move my arm in a different way.

CHELSEA: 15:28 It's kind of a way, like, for the agent, this is maybe not the best word to use, but kind of imagining what the future will look like if it took a sequence of actions.

CRAIG: Building a model of the world, is that?

CHELSEA: Yeah, exactly. And one of the things that make this different from kind of existing works for modeling the world is that we're actually outputting image pixels. We're outputting videos of what it thinks the world would look like, based off of how it moves its arm. And of course the images aren’t pixel perfect. They're a bit blurry. I, if I was probably predicting the future roughly, they would probably also be a bit blurry. But one of the remarkable things to me is that we can actually use these predictive models of video to figure out how to accomplish goals. So, we can say that, okay now here's an image of, of putting an apple on top of a plate.

CHELSEA: 16:09 Can you figure out like how to move your arm to, to accomplish that goal and it can figure out that it should move its arm towards the apple, close its gripper and then move its arm towards the plate and open. It can do that for it for the apple on the plate. It can also do this for like folding a towel for example and you can show it an image of a full towel or tell it that I want you to move this pixel over here and it can figure out that it should grasp on one point of the towel and move that to, to another position.

CRAIG: This process of building this model of the world, is that what [Pieter](https://people.eecs.berkeley.edu/~pabbeel/) refers to as self-play?

CHELSEA: In some ways they are complimentary. So self-play is means to collect experience that is rich. So, it's often actually been used in games, incidentally, where you want to learn how to solve the game.

CHELSEA: 16:53 And what you do is if you don't have a human there to play with you, you just play yourself. And you can do this for, for games. You can also do it for situations where you want to figure out how to grasp an object very robustly. You could have one part of yourself try to figure out how to like make it difficult to grasp things. And the other part of yourself try to figure out how to robustly grasp things. And so it's a way to collect data in a way that you don't get any supervision from a human. And the approaches for that typically haven't involved learning a model of the world, but they are somewhat complimentary. So, the self-play, it allows you to get a fairly rich experiences because you're putting the environment in more complex states by playing yourself. Whereas learning a model of the world is one way to figure out how to learn from that data.

CRAIG: Right. Is [self-supervised learning](https://project.inria.fr/paiss/files/2018/07/zisserman-self-supervised.pdf) this learning a model just by exploring the world?

CHELSEA: Yeah, exactly. And I, I actually if you talked to Yann Lecun, he probably talked about this sort of stuff as well. It's very aligned with the, some of the things that he's been thinking about.

CRAIG: Yeah. And the model that you're building, I've also heard

CRAIG: 17:50 The term forward model. Is that what this is? So, that you have an approximation of how things will be if you do take certain actions.

CHELSEA: Facing forward into the future.

CRAIG: Yeah. And some of the knowledge then that's accumulated is an understanding of the laws of physics for example, rght? That you know, if you push something off the edge of a table, it'll fall, right?

CHELSEA: 18:11 And if you push an object into another object, then both objects will move. Things like that. We also found that it can actually figure out in some ways how to use objects as tools using these kinds of models. So, if you're studying both to use with conventional tools and if you have like, it can figure out how to use a sponge to wipe something off of a plate, even if it's never seen a sponge before because it understands how objects will push other objects and roughly how kind of friction works in that regard. Also, maybe it's not given a conventional tool, but maybe it needs to sweep some trash off of a table and there's a water bottle there, it can figure out that it can use the water bottle to push two objects at a time rather than trying to kind of move them one at a time.

CRAIG: 18:47 Wow. So when you put it into a lifelong learning situation or if you create an agent for lifelong learning, have you done that yet? I mean that's what [Tom Mitchell](https://en.wikipedia.org/wiki/Tom_M._Mitchell) is doing, right? He has [multiple agents](http://rtw.ml.cmu.edu/rtw/) that are networked and that are accumulating knowledge that's stored and it gets smarter and smarter presumably and will continue to do so for as long as the power is plugged in, I guess.

CHELSEA: 19:11 Yeah. So we've been continuing to collect data on these robots interacting with the world. And as, as we collect more data, we should be able to get better models of the world and better models of a more diverse range of objects such that it’s able to continuously bootstrap off of its experience and achieve more and more complex skills.

CRAIG: 19:28 Yeah, but is there one agent that you have doing this?

CHELSEA: 19:32 We actually have multiple, we have multiple robots that are, that have been collecting data

CRAIG: 19:37 And that data is being stored in one massive block of code somewhere, is that right? Or …

CHELSEA: 19:43 It's stored in a dataset, not necessarily code, similar to how you might be like storing your videos, videos of your friends or something like that.

CRAIG: 19:49 But for the meta-learning, there is a model that it's creating that it can refer to without having to search or is it still basically a search function.

CHELSEA: 20:00 So, for, for the meta-learning work, we do still store. The data is compiled down into a smaller set of weights, a smaller model such that if it wants to learn a new thing, it can simply just use those, those weights. With the current algorithms that we have, if it wants to continue to learn it, it does need to kind of look back at some of the data that it stored previously so that it doesn't forget some of those things. Although ultimately there, there are a lot of ideas for how to continuously learn models in ways that don't forget old data and don't forget old experiences without even storing those experiences on disc.

CRAIG: 20:33 How long have you been doing this and are your agents indeed getting smarter and learning faster,

CHELSEA: 20:39 So, they’re certainly getting smarter. That might be because we're developing better algorithms and developing better methods. I guess smarter is a, is kind of a weird term to use. Maybe that's not the best term, but they're getting more capable in terms of tasks and, and flexibility. The work on learning predictive models, we actually started that work in 2015 so it's been about four years since then. We do have actually all the data from, from all of those models stored and we don't always use all of it, but we are hoping to train models on all of the data actually across robots at some point in the future.

CRAIG: 21:12 One question I have about this is both power consumption and storage because we use very little power in our brains and we store a tremendous amount of data in a very small space. What sort of power is being consumed to do this? Is it reasonable or is it very power intensive? And what sort of storage is required because of it's lifelong, is it growing exponentially and at some point the limit will be a hardware limit?

CHELSEA: 21:43 Yeah. So, I'll start with power. I mean the brain is incredibly power efficient. In comparison, like, things like GPUs are somewhat crazy. The most power consuming thing that we do use is GPUs to process images and that's kind of the heart of the neural network. And so that's, I mean that's on the hardware side. I don't know too much about the hardware side and I'm leaving that up to other folks who are looking into that

CRAIG: 22:08 in terms of gigabytes and terabytes.

CHELSEA: 22:10 Yeah. Yeah, so with regard to storage, that's certainly not the bottleneck at this point. I think that we're certainly in in the gigabytes range still, actually. Assuming that we compress our images and videos appropriately when we store them, like, like jpeg compression for example. Yeah, we're still in the gigabytes range. The bottleneck for us actually is the time to run things on the robot. Things can't move faster than real time when you're collecting data in the real world. Although when you do have more robots, you can collect data in parallel. Right. And that can accelerate the data collection. So we're actually still bottlenecks by data collection speed. Another thing I'll mention is that, I guess the memory storage, you can think of as two ways. One is actually storing the data and one is storing the actual model. The models are much smaller in general than the the data that we're storing.

CHELSEA: 22:55 People have done calculations for like how big the human brain would be. I think that's, it's like many orders of magnitude larger than the models, than the size of the neural networks that we use. I don't know how it would compare to the neural networks plus the data, but I expect that it would still be orders of magnitude more. The brain is small, but it stores data extremely efficiently. And also, I mean in terms of physical space, the actual size of the hard drive that you need to store the data is probably extremely small. The reason why it's larger is, is everything else that that goes in. Yeah.

MUSIC: 23:30

CRAIG: 23:32 that's right. So you're moving to Stanford, is that right?

CHELSEA: Yeah, that's right.

CRAIG: What's your work in Stanford going to be? Do you port all this over? Do you continue to collaborate? Do you start fresh?

CHELSEA: 23:42 Yeah, so I'm starting a lab at Stanford in the computer science department and we'll be studying both fundamental machine learning algorithms as well as robotics applications in robotics. In the real world, we will both be starting new initiatives and efforts as well as continuing existing ones in collaborating. And we actually already have a robot that's collecting data at Stanford to contribute to that effort as well. And I think that actually that's the right way to go in terms of these lifelong learning systems is if you're able to have robots at different institutions that are collecting data and sharing experiences because then we'll be much closer to being able to collect the level of, of experience and data that humans have or maybe come comes like a tiny bit closer to that.

CRAIG: 24:24 How many institutions at this point or networked in that way, and these are networks, is it just over the internet or do you use something more sophisticated?

CHELSEA: 24:34 Mostly just over the Internet? Yeah, we've started actually a collaboration across roughly four to five institutions, three universities and two industry labs.

CRAIG: 24:44 Is this relevant to what Tom Mitchell is doing at all?

CHELSEA: 24:47 It's certainly relevant. We're not directly connected, but it's certainly related.

CRAIG: 24:51 Yeah, I mean could you be directly connected? I don't know how these systems connect. It's essentially through an API or do they have to be built on the same architecture?

CHELSEA: 25:01 I think that it would be difficult to connect the two based off of the kind of knowledge that Tom Mitchell is collecting versus the kind of knowledge that we're looking at. But ultimately I do think that it would be interesting to kind of combine multiple modalities and figure out how they can compliment each other to build up more knowledge and more information.

CRAIG: 25:17 Do you have a vision or a hope of where you'll be - I don't mean physically or in your career - I mean, with this research where it will be in five or 10 years?

CHELSEA: 25:28 Yeah, that's a good question. So a lot of the work during my PhD, I was focusing on enabling robots to generalize to new objects that they hadn't seen before. And this may sound trivial because humans are, or this is so just like innate to humans in some regard. But for robots, it's actually quite challenging and a lot of people when focused on robot learning, are focusing in one very narrow setting. Now that we've been able to have robots generalized to new objects. The next step is to generalize to new tasks and new environments. And what I'd love to see is first having robots that are learning continuously, not just in a single environment but across many environments and actually exploring. So a lot of the work that we've done is with arms that are stationary and if we put an arm on a mobile base and have it actually explore different environments, then you can get much more rich experiences and, and maybe also be in dynamic environments that are changing as, as humans are in the environment and other things. So that's one thing.

CHELSEA: 26:18 And the other thing is generalization to different tasks. Being able to do things like setting a table or packing a suitcase, things like that are beyond the capabilities of robots right now. But I think exhibit some interesting properties in terms of reasoning on slightly longer horizons cause you need to manipulate lots of different objects and being able to generalize new objects that you haven't seen before. And also being able to compose skills that you may have learned like, like picking up a glass and then pouring water and then putting that glass on the table and using that to, to perform other parts of the kind of the whole task of setting a table.

CRAIG: 26:54 Five years, 10 years. It's a relatively short period of time, but is the field moving quick enough that just the things that you talked about just now should be accomplished by then or do you think you'll have robots doing things beyond that by then? I have to say the reason I'm asking the question is because of course I'm a layman and the lay public is wondering when are there going to be robots that can actually do things independently. And I was speaking to Aude yesterday and she made an offhand comment as we were leaving that it won't be in her lifetime. And that surprised me. Somehow, I thought it was closer than that.

CHELSEA: 27:33 It's a good question. I think that the field of machine learning is moving quickly. The field of robotics and machine learning for robotics I think is moving more slowly because there's less people working on it. It's also a really hard problem. I think that things like setting a table, packing a suitcase, my guess is that in five to 10 years we will be able to do tasks like that in fairly narrow settings such as like in a lab environment. Being able to go into someone's home and doing it in their home, I think that that is probably beyond five to 10 years because each home, each environment has so many different variations and it's just an environment that is so dynamic. It's, it's, there's nothing structured about it. You don't, you can't directly observe where objects are, you just get kind of your sensor observations.

CHELSEA: 28:13 So I think we will be able to do these things in like a lab environment where maybe the kind of the position of the table is always in the same place or all the suitcases in the same location or the suitcases are like roughly the same size or something. Once you have this more like combinatorial explosion of all the things that might be varied across all these environments, it becomes a challenge of building algorithms that can learn from data that is unstructured, that doesn't have a lot of supervision from it. So you can scale data collection. And so far we have been able to scale data collection in, in like lab environments for example. But as you move towards mobile robots for example, that gets a lot harder because you need to worry a little bit more about safety so that you're not running into things and everything. It's a hard problem. So I think that the general problem of having robots in homes is, it's certainly not within five to 10 years, but I think that we can push things more in like lab environments in an academic environment.

CRAIG: 29:06 Not to corner you into a prediction, but do you think it's within your lifetime?

CHELSEA: 29:10 I think that's hard to say. I think that like given the pace of things like predicting beyond five to 10 years is, is, is quite challenging. I would love for it to be my lifetime, but at the same time, it's a really hard problem.

CRAIG: 29:25 That's it for this week's podcast. I want to thank Chelsea for her time. For those of you who want to go into greater depth about the things we talked about today, you can find a transcript of this show in the program notes. If you don't see it, visit eye-on.ai and you'll find a link for it there. Let us know whether you find the podcast interesting or useful and whether you have any suggestions about how we can improve. You can help a lot by rating or reviewing the podcasts on whatever platform you use to listen. The ratings and reviews increase our visibility and help other listeners find us.

CRAIG: 30:08 The singularity may not be near, but AI is about to change your world, so pay attention.