**Scott Downes:** 0:00

AGI is kind of a big concept to take it down to a smaller level and just say like is this generally useful across problem domains? And it turns out that large language models are phenomenally useful across problem domains in ways that we wouldn't have anticipated. I certainly didn't anticipate this a few years ago. We have an internal terminology for this. We call it giving our agents iron man suits. What we want to do is maximise the impact that a single trainer can provide. We want to find ways that we can take advantage of high judgement, really intelligent, sophisticated individuals. There's a confidence that there's the problems related to hallucination or are more focused on expressing things than whether there's an internal model that actually matches something that we would describe as real.

**Craig Smith:** 0:45

Hi, I'm Craig Smith and this is my AI. There's been a lot of talk about the human trainers behind large language models, how, despite oceans of data and rocks of GPUs, generative AI still depends on people in much the way that supervised learning depends on people to label data. This week, I talked to Scott Downs, chief Technology Officer at Invisible Technologies, whose platform is used for reinforcement learning with human feedback, otherwise known as RLHF, the Dirty Little Secret Behind Generative AI. I hope you enjoy the conversation and I think you'll find it enlightening.

**Scott Downes:** 1:33

I'm Scott Downs. I'm the CTO at Invisible Technologies. Where to start? I'll talk a little bit about myself. I'll say that I'm sort of a. I think you might hear a lot of people say this. I'm a different kind of CTO. I'm someone with a lot of interests and one of the reasons why I love start-ups so much is I've loved being in the space where you wear lots of hats. So I'm a CTO whose first paid job when I was 14 was writing code. But then I went off to college and studied literature and in my 20s I worked in radio, I worked as a musician, I worked in design and I think I did pretty much everything I could to stay out of sort of what I perceived at the time as sort of an uncool nerd factory type of jobs where I would just sling code. But with the dot-com era, all of a sudden it actually became really valuable to have a breadth of interests and the impact of computing and the scope of what you might do in a software development job just spread, spread open in a way that created lots of opportunities for folks like me. I remember, like at a college reunion, I looked around the room and this is a very 90s thing to say, but like all of my classmates, we all had goatees, we all had degrees in like English and theatre, and we were all working for dot-coms all working in tech jobs and I think that that energy has sustained for me this idea that it used to be that working in technology might mean producing a piece of software that you put on a shiny disk and put in a cardboard box and sell at CompUSA. I've done that, and then it evolved more and more to where the practices, the ceremonies and process of software development became so pervasive that it's actually what everybody does in every company. So there was a time when normal business teams didn't have stand-ups, that the idea of a sprint or an epic was unique to maybe a software development team in a company that's building software. And I think that one of the things that's been interesting and exciting for me really is that over my career, seeing that change has meant that those of us who work in that space find more and more opportunities for broader impact. And the way that I say broader impact, what I really mean is like does my mother understand what I do? That's the final metric. Can I explain this to my mom? So I said a lot of things.

**Craig Smith:** 4:32

And then invisible. How did you get to be invisible? And what does invisible do? Sure.

**Scott Downes:** 4:39

And I think that tells you a little bit about who I am. But in terms of my adult journey, once I found technology as my calling, I've worked to build out a SaaS platform for what was originally an SMS aggregator but eventually became a mobile marketing software company, and so I experienced the sort of traditional enterprise SaaS world where we built solutions for large companies whose names you would know the American Express, comcast, at&t type of customers. And I found that maybe it was sort of a last gasp at that moment of expecting your clients, your customers, to learn complex technology systems and take that on board. They might need to learn 20 different software packages. Of course that's a source of a lot of pain. And after that, after that experience, I was helped to build a company that was a marketplace for residential moving, so sort of an Uber of residential moving and as the CTO in that company, what I found was that I was selling a product to consumers where the technology powered things behind the scenes and managed a workforce, but it wasn't presenting a lot of sort of digital surfaces for people to interact with. So our workforce used iPhone apps and Android apps, but our clients would just order a service and somehow the technology behind the scenes was supposed to sort of deliver the optimal moving experience, and we did pretty well at that. There are a lot of things that you can do by making sure that you have high quality workers showing up on time and following a great plan on how to execute. So that's what brought me to. Invisible was sort of. I was at a moment where I found both of those adventures of building a workforce management platform for a marketplace. How interesting is that? It's really cool. That's a complex problem space that has real impact on the world, and then, meanwhile, I also am somebody who enjoys building complex, sophisticated software platforms that solve really, really complex problems, and Invisible to me immediately appeared to be like, from a product perspective, the perfect intersection of those. So that's a long way to go to tell you what Invisible does, but what Invisible does is a blend of a workforce management platform and an automation SaaS platform, and the form that that takes is that we see everything starts and ends with a process, and when we say a process, the kind of process that we work on for our clients one that we'll probably talk about a lot today is data training. So that's a service that we provide for clients of ours that we define in terms of a process that's mapped onto a visual canvas and then executed in the form of steps, some by people, some by automations or scripts or integrations with third party platforms. So I know that that is very horizontal and generic as a description. We're stubbornly horizontal as a company. So what what we think of ourselves as being really good at is taking on problems largely related to scaling up areas of a business that are particularly in need of of well, a combination of consultative engagement Maybe, maybe a significant amount of labour and a significant amount of automation to optimise the solution that we're providing. So some examples of that kind of space where we've thrived. We really grew up as a business during the early pandemic era by working really closely with on demand delivery companies. So it's a great example for us where you look at a business that's under a unique moment of pressure and prevailing alternatives for how to solve that problem never quite fit. So if you're DoorDash and you're looking at figuring out how to encode restaurant menus into your platform, one approach might be to go with a traditional outsourcing firm. So this is the sort of problem space where we think of deploying the kind of proverbial army of people. What if we had a thousand people around the globe, or maybe in emerging markets where labour costs are lower, grinding away on a problem and the solution that we'd be providing in that case is human scale? There are limitations to that approach. That approach tends to be sometimes their challenges related to quality and there's really very few incentives in that kind of a structure. If what you're selling is bodies and what your business model is based on is kind of labour arbitrage, let's sell hours and add a few dollars on top for us to run our business. That doesn't really create aligned incentives. So our incentive as a vendor in that model would just be to drive up the number of people and drive up the number of hours, which is not really super positive for those companies. Thank you. On the other hand, you might build a fully automated solution. So you might look at the moment of like how do I get a million restaurant menus into a proprietary platform as a task that is driven by OCR tools, web scrapers, custom scripting, custom code, rpa tools, maybe tools like UiPath, like there are lots of ways to solve that problem with a pure tech approach. Those tend to be really effective once they're in place, but they also tend to have kind of a long runway to build and they also tend to be sort of fragile. So it's not typically easy to build a fully automated solution and then maintain it over time without having a standing team. So we sort of live in that sweet spot between those two by saying, okay, you know what, we're gonna take your problem, we're gonna start working on it. Today we can apply some amount of labour to solving the problem. Once we've mapped it, once we put it in a clear form that we can execute and we can imagine you can imagine a workflow on a canvas and, having a Sharpie, you might kind of draw a circle around a specific area and say, hmm, this area is requiring a lot of labour, it's costing us a lot of money, this is an area that's ripe for optimization. So what if we applied technology solutions in that space? And I think that what we really do is sort of the common sense of running a scaling part of a business, but we make it explicit. So there are plenty of cases where our clients might see their problem and not have the same kind of precise instruments to address it that we do. So I'll give you a concrete example. Say that you've implemented a new policy or the way that you execute a certain process Got new business rules. Okay, now when insurance claims are based in Florida, we have to do the following three things. You can imagine that a lot of businesses are in a world where they might send out an email, they might contact managers, they might write up new SOPs, but enforcement becomes a very big problem. So how do we know that people follow new rules as they are established? So for us, being able to build all that into a platform that manages the interfaces through which people engage means that a change in policy can be implemented perfectly, 100% in a day. So that's kind of the background of our business that kind of brought us into this moment where we have a very flexible platform, we're very responsive to client needs and we've seen opportunities in the last few years that have just kind of gone crazy in terms of applying that sort of approach of blending people and automations in an explicit but very configurable process. While it turns out, that's really useful when you think about data training for AI.

**Craig Smith:** 13:42

Yeah, and this is something that's fascinated me for a while, the idea that, first of all, we supervised learning. Unseen to most of the people who were using it is this army of labourers, human labourers spread out across the world that are segmenting and clicking on computer images or on text and labelling them very tediously. Even as they process their automation tools to speed that process it still comes down to a human. Now we're in the age of unsupervised learning with these big transformer based models. Yet again, there's this army of humans in the background who are helping train this model to these models to behave in particular ways, and so this is one of the things and I understand you're horizontal and do a lot of different things, but that's what I wanted to talk about this human element and, in particular, with regard to large language models. Can you talk about how many people are employed, in your case, are using the invisible platform to do this, how many are employed, how specific the tasks are and how rapid is the progress in the underlying models when you're doing that? Or maybe just start with what we're talking about really is reinforcement learning with human feedback? Maybe start with talking about how you actually do reinforcement learning with human feedback and then the numbers of people involved in the progress.

**Scott Downes:** 15:57

It's a big part of our business especially we've seen a really huge increase over the last year and we employ we have a little bit of a different model in some ways, but I think that the simple translation is to say that our human operators who work on our platform we call them agents our human operators who are working on both reinforcement learning with human feedback and other sorts of processes there are thousands, and I think the thing that I would say about the nature of the work that we're doing in RLHF is that it's actually not sort of that bulk giant army of folks anymore. That's as relevant to the problems that we deal with with our specific clients, and I can't go into any huge amount of detail with our clients that we're working on, we're working with, but we do work with WAI and several other household names to do this sort of work. And I think that what I've seen and what I've been maybe even I mean definitely surprised by, is how quickly we've moved from a model that is more like deploying thousands of humans against generic problems to small targeted groups of people working on very specific problems, and I think that's kind of the nature of RLHF, right, like what we found is this kind of. I feel like there's always a pendulum right. A few years ago people were saying, well, machine learning is great for specialised models, but I mean, god knows when we'll ever have anything that reproaches, like AGI or something that's even even to not take. Agi is kind of a big concept. But to take it down to a smaller level and just say like, is this generally useful across problem domains? And it turns out that large language models are phenomenally useful across problem domains in ways that we wouldn't have anticipated. I certainly didn't anticipate this a few years ago. And what we're finding is that as the pendulum has swung back to a place where LLMs are, like, massively useful for all sorts of business problems, that we're thinking about refinements to create more accuracy in specific problem domains. So we're kind of like now the pendulum swings back to specialised cases. How do we execute those? Super well, and there are a number of approaches in that space. But I think that the reason why RLHF is relevant to us is the same reason it's relevant to everybody in the world right now, which is that we've got these like almost incomprehensible alien intelligence, intelligences that have landed on our planet, landed in our business reality, and now we're trying to figure out ways to make them useful for very narrow problem domains. But I'll say I mean, if our work is any example, a good example, and I think it is we work both sides of the street. So while we're helping to build large language models and working on our LLHF task, we also sell solutions using those platforms to our clients, other clients so we see new opportunities. For I'll take as an example we're using large language models to solve problems like text cleanup and classification of products and in large product catalogues, things that we used to just think, well, you're gonna have to have a person to do that. So I think that we have a unique perspective on it, having worked with the companies that are producing the tech and enabling that, but also then being sort of a Johnny Appleseed of technology to bring the benefits of LLMs to the non-AI companies who are saying what do I do with this stuff?

**Craig Smith:** 20:02

Yeah, two questions. One of you is using LLMs to address company specific problems. Is part of that to automate labelling, so you don't need human labellers? I just saw something from Andrew O'Oone's landing AI about using LLMs or not, or large models. I should say I guess they're not languages any longer to automate segmentation and labelling. The demo is pretty impressive. Are you using it in that direction to label datasets for supervised learning models?

**Scott Downes:** 20:51

Yeah, I think we are in some cases. That's not specifically what I was talking about, but that is a really interesting space because I think again, I think there tend to be some misconceptions about the way that RLHF can work and supervised learning can work, in that there's sort of a there can be a misconception that we're just throwing a lot of human bodies at a problem and that they might not have a high degree of expertise and that we might be sort of solving a problem in bulk rather than solving narrower, more specific problems. And I think that one aspect of that is that people may underestimate the sophistication of the way that RLHF processes can be run and the variety of ways that they can be run. So the reason why I would say probably our biggest competitive advantage in that space is having a platform that enables us to configure new interfaces, new digital surfaces for trainers to interact with, based on ongoing feedback with researchers. And I think that if you talk to folks in that space, as we do, we hear a lot of likes. They think that a lot of the benefit they're gonna get and they're continuing to get over time is through. We have an internal terminology for this. We call it giving our agents iron man suits. So what we want to do is maximise the impact that a single trainer can provide and we want to find ways that we can take advantage of high judgement, really intelligent, sophisticated individuals. We're not at a place like let's have a hundred people look at a picture and decide whether it's a hot dog or not. We're at a place where we're solving really complex and interesting problems and you want a high level of human expertise and, as they go through that process, having a tightly designed process that's flexible and has a feedback loop with researchers to change the way that we're collecting that data. That's really critical and I think it's really exciting to me and a validation for us kind of as being a very horizontal, flexible platform. I think I'll just say I would not want to try to put a stake in the ground by saying these are the five ways that I want to approach data training for the next two years. It's going to change in a few months. It's changing for us every day.

**Craig Smith:** 23:24

Yeah, on training large language models themselves. You're saying that you have a highly educated and finite workforce working on these problems. Is this? I mean, there are all kinds of LLMs that are being developed for very specific use cases. Is it those problems that you're working on or are you working on more general behaviours of LLMs? And of course I'm talking about the hallucination problem which you and I have had this conversation before OpenAI is using RLHF to address. But the extent of the problem is so large that I can't imagine LIFE having to make a dent. I can imagine it in very specific use cases, coding for example. I mean these models have tremendous promise for automating code generation, but if it's just an autocomplete or it gives you, you know, half a dozen options and the programmer has to choose between them, it's useful. But it would certainly be much more useful if the language model knew exactly what was the correct or the optimal code sequence. And you know, I can see RLHF maybe being able to refine the large language model in that particular case. But more generally, if I ask GPT-4 to tell me about myself, it composes this beautiful paragraph or two that gets my name right and a few of the places I worked for the rest of it. You know I wish it were true. You know it was all about wonderful things that I've never done. So yeah, can you talk about the effectiveness of ELF on the behaviour of large language models more generally, and then about working on very narrow, specific problems, and maybe give us some examples?

**Scott Downes:** 26:18

Sure, I mean, I think you know, because we work in this space, I kind of hear a lot of people's opinions and I kind of marinate in it and I think that I'm hearing in your question kind of a scepticism about whether large language models are accessing truth. Yeah, it's not just. I mean, isn't it a funny little euphemism to call it hallucinations? You might call them lies. Yeah, I think that you know my personal opinion, just based on a lot of what I hear and what I see with experts in the field, is I'm actually incredibly optimistic about how far RLHF can go to solve those problems, incredibly optimistic. And I think that one of the things you'll hear in talking to folks in that space. It's sort of like the positive side of the whole Dunning-Kruger thing. I love working with these folks because they have a very kind of open-minded, playful attitude about like, well, let's see, let's try this and see what happens. Because I think that any conversation about what's happening with large language models needs to acknowledge that there have been emergent properties that even the people building the dang things had no idea we're coming. And I think that one of the analogies that I use when I think about it is that, like, what really has happened is that we're we talk about RLHF and I like to demystify it by taking, removing the terminology and just say like well, so we've got teachers and it's like raising a child, right. So the first thing that you know is that, like, languages learn through imitation and that there's a lot of interesting philosophical debates that we could have about how much knowledge is actually just actually fully existing, coded in a linguistic form, like is there some kind of sense of, I don't know, say like a Platonist kind of idea of that there is a real world and real things and words, or a description of those, or is it just that reality is constructed of linguistic constructs? So I think I personally kind of lean more towards the idea that there's a lot embedded in language and symbolic structures that actually does encode meaning, does create world models maybe not the literal world model, it does have a sense of truth but that as you're growing up this child, this new intelligence that's come into the world, it's just natural to want to have them go to school and that what's happening with our alums now and what we're expecting out of RLHF is for our kids to go to school. And I don't just, like I would say with my own children, who are both in school right, that I have high hopes for what they can get out of engaging with teachers and I have high hopes that a lot of things that they might say that are demonstrably wrong will be corrected through formal instruction in specific areas of like academic interest. So if someone's saying two plus two is five, I think maybe I'm anthropomorphizing LLMS a bit, but I think that the approach is to send them to maths class and say no, no, no, two plus two is four and they'll learn, rather than trying to implant a calculator in their skull.

**Craig Smith:** 29:53

That's interesting. Yeah, one very specific problem. Maybe maths is one. I can see how that would work. But on the general problem of hallucination, how do you teach a language model through RLHF, which is basically on specific examples, telling the language model that no, you're wrong, try again, and then, when they get it right, saying yes, you're right. Analysing specific domains like mathematics, I can see that, but just generally, how does the language model know what is reality and what is not, or what reflects reality and what does not, without going through each of those examples? I just don't see how you generalise without and you and I have talked about world models without a world model that it can refer to, that is not language-based.

**Scott Downes:** 31:14

Yeah, I think that what we're circling around is that there's some amount of objective truth and that, again, if I'm sorry if there's a controversial direction to go, but when I hear about world models, I often think as well of what we're looking for are value systems almost like we're asking for our LLM to join a church that we have some faith that there are facts that are objectively real and true and verifiable or maybe not verifiable, but we still accept that they're true and that that forms sort of a lattice, a framework around sensible ideas being formed, and that I'm not totally opposed to that idea. I think that the angle that I take on that and I know that there's some research in this space as well is just thinking about something else that people aren't necessarily awesome at is understanding the dimension of time, and I think that if you think about and this comes out when you think about a few shot, learning opportunities and gathering context and conversations, I think that the meaningful things that will happen in this broader space is that we'll have interactions with models whether the next generation version of an LLM, or maybe even we'll just call them LLMs that will have access to real-time data and they'll have trusted systems and in that kind of a world, some of these things where we're seeing hallucinations or lies, or cases where we do have generally agreed upon objective truth, that's not being matched, that there are different solutions to that problem, and I get the sense that you're the kind of anxiety that you're describing of, like how on earth did we cover every potential case with human trainers saying what did Craig do in 11th grade and did we report that he won this competition? That he didn't win, or he finished in second place and not first? There's no way that humans could ever exhaustively track all that stuff down. I get that. I get that, but I also have been amazed at how far we've gone with LLMs. When I had the same scepticism about specific cases that are no longer true, like a year ago, so yeah, and can you talk about that?

**Craig Smith:** 33:51

Because that's right. That's one of the things that intrigued me the first time we spoke. You said that you've seen such tremendous progress, and is it in general behaviour? That way I mean, because what OpenAI is trying to do with early chef, as I understand it, is not cover this exhaustive or possibly infinite list of examples, but to teach the LLM just through example, that they have to find as objective a truth as they can find in the data that they've absorbed so that it becomes a habit or a behaviour that then applies to every situation. And that, yeah, I'm sceptical, but maybe you can talk about the progress that you've seen in some examples that would show that progress?

**Scott Downes:** 35:09

Sure, I mean. I think there are some easy examples where I can say that there are specific tasks Like I was alluding to some before that we do for certain types of clients like e-commerce companies or delivery companies that are maintaining these giant catalogues, and a lot of the value of their brand is driven by accuracy and the user experience and customer experience of interacting with those. And one of my classic examples is if a restaurant has the wrong options on a menu item at my favourite restaurant through DoorDash, then it's not my favourite restaurant anymore. I can't go there because I can't have this particular dish with ground beef. I want it with chop steak and if it's not an option, it's just right for me. So, familiar problem space for us and again, partly because we're the kind of company that metaphorically draws sharpie markers, circles around problems and replaces human pieces with automated pieces, we found that things like language, cleanup, style guide, compliance, classification of menu items knowing that, for example, you probably don't want to order chicken medium rare those sorts of things we thought of in the past as being optimally solved by people, and if there was enough scale then we might look at specialised models. And what we found, even in the last. When was this? Okay, there was a project we were working on in December, so four months ago where we were thinking, when we initially engaged we wouldn't have considered a large language model addressing this problem space. But, as it turns out, we could use like, really off the shelf GPT with smart, prompt engineering to get results that are better than what we get from people, and that was pretty mind blowing. Pretty mind blowing for me to think that. Another example that I think of in classification, we were looking at a catalogue of items and I'm going to keep. I'm going to keep struggling with this. I don't know the difference between eyeliner and mascara. Maybe my wife should tell me, but I don't know. But GPT knows quite well and was able to look at something and see that it was miscategorized and I just never would have guessed with the information provided, and so that that's an example of feeling like there's like shifting goalposts on what AGI is. That's a classic example for me of a tool that's actually able to provide a general and useful intelligence that used to require a specialised solution if a tech solution worked at all. So that was like a boom, light bulb moment for me, like wait a second. Like large language models can solve problems that we used to think would require a person or a specialised model. So that's a movement, a change, that's happened Right.

**Craig Smith:** 38:13

And in that case it was the large language model out of the box, or you.

**Scott Downes:** 38:20

It was as a result, amazingly, so, and I think so, I guess part of the reason that I have a little bit more okay, here's a better example Part of the reason why I have a little bit more optimism about, or maybe just belief in, the power of existing large language models is that is the story of prompt engineering as it's been playing out. I think that and I hear this from experts in the field that we talked to, or even that I just hear presentations by that there's a confidence that there's the problems related to hallucination, or are more focused on expressing things than whether there's an internal model that actually matches something that we would describe as real. So two angles on that. One super practical thing when you think about how to solve the problem that I just described is being able to clean up text or do classification problems or just clean up a catalogue so that the user experience of a restaurant menu is better. What we used to do in that space was specialise models and humans. We moved to LLMs and since moving to LLMs, we found that we get the best juice for our squeeze by using LLMs with custom tailored prompts. I'm sorry, custom one, custom tailored prompts. It's asking the question the right way In a concrete sense of how we implement it, that we look at specific use cases and iterate over not whether we're going to build our own model, but asking the question in a way that will lead to a more useful outcome. This has happened for everybody, but I think that what you see is that there's just as much progression of quality of outcome in experimenting with the way that you form the question to an LLM in the form of what we can euphemistically call prompt engineering, which feels like asking the Oracle at Delphi the question in the right way. That's where we get a lot of benefits. I think that what that tells me is that there's more latent possibility and intelligence and world models of some flavour that exist inside of an LLM than we might think, and that the problem may be more superficial and has to do more with interaction. Imagine that the monolith comes down to Earth or there's some alien intelligence that we're engaging with. I would probably be less critical of its syntax and speaking English and more curious about how I can ask questions in the right way. It feels like that's what it experienced to me. I think that there are enough legs with existing LLMs that we could be finding new business uses that create better lives and more wealth and more opportunity for a decade, even if we froze development right now because it just takes a while for the possibilities of technology to filter through. That was one of my examples of why I think that there's more there when it comes to LLMs today than we might think if we're focused on hallucinations and accuracy and alignment.

**Craig Smith:** 42:11

Right, maybe you have to come at it from two different directions. You work on LHF to get the model to ground itself. However, it's doing that in some more objective reality. Then I'm from the other direction. You're refining the way that you talk to a model through a problem engineering. I understand how improving your prompts improves the output. Do you have an example of how RLHF, specifically, has improved models, or is that just too fuzzy a world to know what's happening?

**Scott Downes:** 43:07

We're just one company out here doing this work. We're close to some pretty cool stuff that's happening with some pretty well-known companies. I think that, while I can't talk about specific projects that we've worked on, I've seen literal work that we've done lead to specific, provable, testable outcomes in updated versions of large language models. I've seen a situation where we say, oh, with this newer version of a large language model, this question can be answered. That couldn't be answered before. I saw an inside baseball perspective of the work that led to that, which, by the way, is super cool to be able to see that. But also, what's even cooler is the speed at which it happened. You might find that a piece of work that you worked on a few months ago has now influenced the way that the world can perceive their interactions with an LLM. I know that might be maddeningly vague, but I can't go into huge particulars. But I can say that the space that I'm thinking of and the example that I'm thinking of fits in that category of. We used to say 2 plus 2 equals 5, and now we say, of course it's 4. I've seen, experienced firsthand places where RLHF has led to observable improvements in existing models.

**Craig Smith:** 44:40

On specific questions or more generally.

**Scott Downes:** 44:44

Slightly more general than that. It's hard to say. I don't have visibility into every project that's going on for a particular LLM, but I think it's pretty clear that some of the areas of focus that we've had have been directly impactful in the way that people can experience these technologies. I guess what you're asking is, did we teach it that 2 plus 2 is equal to 4 and not 5, and then go check that specific example versus checking 3 plus 4 is equal to 7 and not 6? Yeah, my experience of that firsthand is that it's more like the latter, in that we've corrected 2 plus 2 and seen improvements on 3 plus 4.

**Craig Smith:** 45:38

And that's purely through RLHF. It's not by some fine tuning in the training of the model, because that's happening too. You take a foundational model and then you refine it with supervised training to have an expertise in a particular domain.

**Scott Downes:** 46:09

The example that I'm thinking of relates to seeing improvements in LLMs, not with the mechanism of fine tuning, but I'll say, even though we do a bit of fine tuning work, I thought that was going to be a bigger opportunity for us in our Johnny Appleseed type of role. I thought that we would be helping a lot of our clients to do some fine tuning, particularly with GPT, which I just love the way OpenAI has documented their fine tuning approach and I thought, wow, this is going to be wonderful to work with dozens of companies in tailoring this super powerful general purpose LLM to their specific needs. And then, time and time again, we find that it turns out that stock GPT solves a lot more problems than we thought and that fine tuning has not been as big of a need for us with our clients. There's just so much you can do with some of these stock LLMs.

**Craig Smith:** 47:16

Yeah, yeah, that's amazing actually. I mean it's exciting. And I tell people who complain about chat, gpt which is what most people experience that hey, man, this thing was released to the public six months ago or maybe less. Wait five years and see if you have something to complain about. Then it reminds me of people when the various GPS systems came out and people took great pride and said I never use them, they're always wrong. And they did. They had problems, but I think everyone relies on GPS.

**Scott Downes:** 48:16

Yeah, I mean, I feel like this is one of those disruptive moments, and the concept of disruption has been cheapened by having. I don't know how long it has been since we've had a good, real new disruption. Is it the iPhone? I think that sometimes it's really hard. These kinds of moments serve as more of a Rorschach test for what people are really concerned about or their own attachment to an existing way of things working. I think that this one is, especially if we're talking about chat, gpt. I think that space and generative AI in general is pushing into spaces where humans have thought that it was purely their domain, like writing copy, doing visual design, and I think that I get it. I am a songwriter. The idea of GPT writing songs for me creeps me out and it's not good enough yet. But I also have observed that the younger folks on our team, like our person who works in PR, one of our young designers they were all over the generative AI stuff from the start and I think that if you have an open mind to it, it's a way to accelerate and to, like we say, it's an Iron man suit. So why not take advantage of that? And people who are open-minded to it will really fly.

**Craig Smith:** 49:52

Yeah, on the numbers of people in RLHF that you have working on these problems, again you said you had thousands of human agents around the world, but on RLHF, specifically for these general use cases, for like teaching an LLM, not to hallucinate how many people would be doing that and you also talked the first time we spoke about the qualifications that these are not, you know, low paid wage workers in third world countries necessarily.

**Scott Downes:** 50:35

Yeah, I mean we, yeah, to kind of address the scale thing, I have to be a little bit vague about it, for because of the confidentiality with the clients that we work with, but we've worked on projects that are larger, involving hundreds of agents on a specific project, and even projects where it's dozens. And I think that we're just to be clear, we're not working on one project for one client. So we work on lots of projects and some of them go away and we work on new ones and some get more people. The needs change, but I've seen enough to have to be able to sort of characterise a change in the general requirements for advanced data trainers, and I've also, you know, just seen what our needs are in our business overall and I think that our particular problem space of working on problems with where we want to layer in automation inherently biases us towards hiring high judgement individuals all around the world and, as our founder likes to say, we're more selective than Harvard. We expect people to be, you know, college educated, great English speakers or, in some cases where we need them to speak another language, great as speaking those other languages. We have a high bar for what our agent workforce looks like. And then, as I would say, like just to generally characterise, without talking about any specific projects, I think that we've seen a trend in our data training needs towards more for the work that we do, towards more folks who are based in the US and who have more and more advanced degrees, and that could just be a reflection of some of the work that we've taken on. But I hear this from other folks as well that, like, the expertise required in this space obviously is going to increase year over year and there are real opportunities for folks to. These aren't like digital drudgery jobs, they're interesting, creative jobs that we don't have. I mean, part of the whole point of this technology is to have humans doing things that uniquely require humans.

**Craig Smith:** 53:00

Yeah, and do you think that the human element in AI will, that the supervised learning labellers, that workforce will eventually shrink and a smaller but more effective RLHS workforce will grow? I mean, will there be a shift?

**Scott Downes:** 53:31

I mean I do. I do think that we're going to move more and more towards higher expectations for what humans do as they engage with these sort of training processes, but I don't think that necessarily means that it's a smaller number of people working. It may be that we have, you know, you're talking to someone who's in a business that's growing really rapidly, so it's very. I can't even imagine shrinking at all. So for me, I think it's more about raising the bar on requirements for folks who are working in that kind of space than it is about a shrinking number of people, and I can't really make a broader social characterization about it. Maybe there are fewer, maybe there are more.

**Craig Smith:** 54:14

Yeah, but the human workforce, that is, it will shift from labellers to RLHF workers. That's what I'm asking.

**Scott Downes:** 54:33

Yeah, I mean, I may have opinions about that. I do have opinions about that but I also am just kind of observing and seeing what happens and trying to build around a responsive, flexible approach, like I would say. I think that there's going to be, and there continues to be, a lot of economic pressure on like and other business considerations that drive people to not want to be dependent on one big, big winner in the LLM space. There are people who don't want their data going to open AI, for example, and there we talked about this a few months ago, about how there's this sense of like. Well, it looks like everybody's going to have their own LLM in about five minutes and it's true, it's happening in real time. If I haven't checked the news today, I bet there's another announcement this morning. So I think that, and if you look into what goes into creating those, to some extent, I read a CEO of a major company recently said that it takes billions of dollars to train an LLM combination of compute and labour, and then, at the same time, you hear these stories about like oh, here's this new open source LLM that I trained in 30 minutes for a nickel and it runs on an iPhone 4 and it's smarter than a seven year old. So there's just like there will continue to be so much interest in this space and so much variety and so many different perspectives on it that if people were thinking about this as like, is this an interesting career opportunity? I'd say yeah, I think it is. I think it's an interesting space to be in and I don't think that we're even with models, training models, reflection techniques, all the stuff that will inevitably happen Human in the loop is going to be here for a while for lots of reasons, as it always has been, and I think that one of the things that we are excited about invisible is like being in a position to move work problems, big chunks of work, more from kind of dehumanising people acting like machines and doing menial labour to people doing high judgement work and having the machines do the work that elevates them and allows them to work on these highly complicated, sophisticated things where they get to use their minds and their human judgement.

**Craig Smith:** 57:03

Yeah, okay. Well, I'm about up to an hour. Why don't I work with this? I may move stuff around, but this LLM discussion is fascinating. Is there anything that you wanted to talk about that I didn't ask about?

**Scott Downes:** 57:27

There are definitely things that I thought we might talk about, but I'm not too stressed about it. I do feel like the intro and talk about my background and I felt like that was a little too much. I'm sure that's worth editing, but yeah, I feel generally comfortable about it.

**Craig Smith:** 57:47

Okay, if there's. When you say something you thought we'd talk about, that we didn't. What are you referring to?

**Scott Downes:** 57:53

I think, just sort of. We hit it a few times, but I think that there's some sort of implicit question about social impact and we kind of skimmed off of it when we talk about, like young people are now using generative AIs, but I generally that's when I have these conversations this ends up being a big part of it, because they're like you're a writer, Like how do you feel about it? It tends to circle around that, but maybe that's not your question.

**Craig Smith:** 58:32

No, no, no, it's interesting. I think that it'll increase productivity For writing. You know, surprisingly to people that are accustomed to writing, a lot of the world can't write. I mean, they can read but they're not very good at writing. That's why this company, grammarly, which I remember, when it came out I kind of thought there's no way this is going to fly. My, you know, spell check on Word does that. But it's been a pretty big success because there's, you know, there's just a lot of people that struggle with writing. So I think, yeah, I think it'll increase productivity for a lot of people that don't have the language skills that their jobs require. But I think there'll, and I think it'll get to the point where it can produce stuff that's considered creative or high quality by discerning users. Or, you know, I'm not. You know you mentioned songwriting. I expect very shortly that I will be writing songs. Personally, I think that's great, you know, but I'm not a songwriter. I do think that as AI becomes increasingly created that way, that the value of true human creativity will go up. I have a son who's an actor and I tell him yeah, you know that's, people will crave genuine human creativity because it's like, oh, I use the first of those style transfer apps Prism it was called, I think, and I know there've been iterations since and you know you take a photograph, you turn it into a van Gogh style painting or into a watercolour. And when it first came out, you know I'm sort of on the front edge of seeing that stuff and I use that and send it around to friends and everyone was amazed and how did you do this? And it's beautiful. And now you see him and you don't think twice about him and you they kind of irritate you. You know like, yeah, big deal, the guy put it in an app, so. But that doesn't mean that people who can paint will not be appreciated. I think. On the contrary, somebody who produces something that's very human is going to only be valued more. But how?

**Scott Downes:** 1:01:48

Do you do the same way? I definitely feel that way. So there's many examples of this, but one that's making the rounds on Twitter lately is AI Drake. And there are these new songs, new Drake songs that are entirely AI generated, and you know, no shade on Drake. I like, like, like a lot of Drake songs, but it's kind of disturbing how easy it is to encapsulate Drake songs in a formula and how real they sound. And I do think I mean again, this is something that's kind of implicit in invisible's business. We are big believers in human potential and that's where our name comes from. The idea of invisible technologies is that technologies are best when they're invisible, like what our goal is to elevate humans. So I think about maybe AI Drake makes people a little bit bored with lowest common denominator music and what it means is that, whether it's somebody else or maybe Drake produces better tracks. But I just have high confidence, just like you, that if you've seen enough like low quality generative AI writing or art, it just gives you a finer appreciation and taste for the real thing and there will always be opportunities for greatness and human expression.

**Craig Smith:** 1:03:10

That's it for this episode. I want to thank Scott for his time, as always. You can find the transcript of our conversation today on our website. I am AI, that's EYE-ONAI. I encourage you to download it and read, because the eye catches a lot that the ear misses. Please like or review the podcast on YouTube, apple Podcasts, spotify or whatever platform you use to listen. It really helps us a lot. And in the meantime, remember the singularity may not be near, but AI is about to change your world, so pay attention.