Deloitte.

AI Ignition

Ignite your AI curiosity with Manuela Veloso

Beena Ammanath: Hi everyone. My name is Beena Ammanath, and I lead our Global Deloitte AI Institute. And today on AI Ignition we have Dr. Manuela Veloso. She is the head of JPMorgan Chase AI Research and a Herbert A. Simon University Professor Emerita at Carnegie Mellon University, where she was previously head of the machine learning department and faculty in the computer science department. Manuela is an accomplished researcher with interests that are in AI, symbiotic human robot autonomy, continuous learning systems, and AI in finance.

Her accolades include the National Science Foundation Career Award, Alan Newell Medal for Excellence in Research, and the Einstein Chair Professor of the Chinese Academy of Sciences. Manuela, welcome to the show. I am so excited for our conversation because you have such a unique journey and a unique role that you are straddling between academia and industry. So, let's start with, you know, tell us a little bit about your story, your career so far, and how did you get to where you are today?

Manuela Veloso: OK, thank you for having me. So, I basically started my AI journey with my PhD in computer science, and AI particularly in the early nineties. And then I became a faculty in the computer science department at Carnegie Mellon University. And then I was the head of the machine learning department later on, also at CMU, and in 2018, I joined JPMorgan Chase as the head of AI Research. In terms of education also, I am, by education, an electrical engineer, and then I did electrical and computer engineering for my master's and then computer science for my master's. So, I've kind of been in these (now) computing disciplines for a while.

Beena Ammanath: And what got you interested in finance specifically and that intersection of AI and finance?

Manuela Veloso: Oh, that's a good question. I mean, I have to confess that I did not specifically have the—did not search specifically for this intersection of interest. It was more of an opportunity that came up. And basically, I was approached to start this group at JPMorgan Chase—AI Research. And in my career, I decided that this was the time if I wanted to try something different to do that. I've been since—for the last 40+ years—in a very large and very complex and very fascinating industry and the national services. And I've been enjoying a lot what I do. Before that, I spent 30 years, or close to 30 years, doing robotics.

Beena Ammanath: What does the head of AI Research at JPMorgan do? What does your day look like? What are some of your focus areas?

Manuela Veloso: It's a good question. Right. So, there aren't many applied AI groups that work on a lot of problems that are more like dealing needed for the business, as we speak. Somehow at AI Research, we have the opportunity to think about the transformation, to think about somehow innovate processes, and try to open these lines that can lead into some more deeper transformation.

But, in some sense, also one of our roles here is a lot related with education too. So we are culture change of front of the staff. There is this famous question that I think everybody has. It's about, like, what can I do after all? You know, there's this, but wow, what is this thing about AI? And there is a lot of AI and machine learning, and the two terms seem to be used interchangeably.

And, of course, I don't think that AI is machine learning only. And so a lot of what we do here also is try to look at the problems with these. I mean, I believe, a long experience of teaching AI, research in AI, that I bring to the picture. So it's a combination of my experience. These amazing problems that make it fascinating, and AI Research is a group I built. We all have PhDs, most of us—60% of us—have PhDs in computer science in AI and machine learning, in math and statistics, and electrical engineering.

Then we have a lot of people with master's degrees in these same areas, so people obsessed, in some sense, with solving problems in computation, intelligent computation, and trying to bring such solutions to financial problems.

Beena Ammanath: Yeah, so true. And I believe the original quants, right, before they were called data scientists actually came from the financial services and is what I've seen. And, you know, it's just that, you know, what used to be done privately with statistics and we always had quant groups became this new discipline around data scientists. It's fascinating and, you know, financial services specifically can do so much more with AI because it's a data-rich industry.

There's always been data due to regulation and compliance. So, you know, there is so much, you know, that you can advance in the AI journey. How do you instruct—yeah…

Manuela Veloso: —Let me just explain one thing about this that I want to clarify here. That is great, but there is more to life then data, and I really want to—[in having] this opportunity—to explain this a little bit. I mean, in a sense, let me just give an analogy with soccer. The rules of the game exist before the actual day.

So there is knowledge or chess. The rules of chess exist as something that's principles, that are rules. And then the data provides, in some sense, illustrations of how a game is conducted, executed—be it like soccer, be it like chess. So what I believe is that we cannot just think that data has all the information because, in some sense, people and the regulators and every single process has their own rules …

Beena Ammanath: Yes.

Manuela Veloso: …their own principles. So when people think, oh my gosh, the rules are not all they are, or I don't know, now it's just data, it's not that we need to give up on all that knowledge that we have…

Beena Ammanath: Yeah—especially in the financial industry. People have so much experience, they have so much knowledge, they have so much kind of like also principles that they are supposed to follow.

Manuela Veloso: So I bring this view also that, yeah, is about how do we represent those principles? How do we find—how do we assist humans in providing information about the processes? Which are not exactly just the real data use of like extracting from data, like patterns of how the customers behave; there is like all these scenarios of representing—and you know, I just want to add one more thing.

You know, it's—so why is this so challenging, and why do we need the effort? It's because it's hard to represent principles, especially when they are changing. Even the regulators' rules are changing. They give us again next time, another big document, 400 pages. And you have to now find how these 400 pages are different than 400 pages of last year or last month.

So there is this problem that AI can enable the processing of all these information, correlating, finding differences. And that's not necessarily just data that you feed into some machine that classifies. So AI is a much bigger part than just classification and the actual prediction based on data. It's very large, yeah.

Beena Ammanath: Manuela, I completely agree with you, that domain knowledge, the subject-matter expertise is crucial, right?

Manuela Veloso: Crucial, crucial.

Beena Ammanath: It is absolutely important. I will clarify more in terms of, you know, what I was sharing was in some industries, like say, for example, manufacturing, right. Or, well I've had experiences also in the industrial cases, right? Predicting jet engine failure: There was not enough data.

We had the subject-matter expertise, we had the compute bar, but not enough data because those machines were not set up in a way to capture data, right. And then you cannot do effective IoT [Internet of Things]. So at least there is one leg of the stool, right? The data compute and subject-matter expertise. When you try to think of it that way, there is—at least one step of it is taken care of.

But you're absolutely right, you cannot make progress without the subject-matter expertise, the principles that you mentioned. And, you know, I think people also moved beyond that phase of where you expect your data scientist or AI researcher to be an expert at the subject, right? To be expert, right? Those are unique roles and need to be filled by experts in each of these areas to produce the most effective AI solutions.

How is your team structured? And, you know, do you have the subject-matter experts embedded within the research team, or how do you do that kind of cross-pollination across the teams?

Manuela Veloso: Actually, that's a wonderful question, and that's probably the biggest challenge because the subject experts, one way or another, have their processes, and there is not a clear need for AI. I mean, in the sense that everything works perfectly. I mean, believe it or not, nothing—nothing failed. Everything was perfect. And AI's more of an opportunity for improvement or for more effectiveness or for assisting them, really, and need.

So, the way we function—and this is important for us to understand—is like this we interact a lot with the business, and especially, you know, me—also coming from a world that had no finance background. We are always in these learning modes, except that the difference is that when we hear problems, you know, we think our background makes us think about the problems in a different way.

So we kind of like look at the here about the problems and then we first of all think, "oh, this is the same thing as this other problem," or "this is all about making sure we are able to do some kind of optimization here." So then these building blocks in our mind optimization, search, representation, classification, learning, and basically we are trying to match what the business tells us about these solutions, one way or another.

And for example, I'll give you an example, which is an interesting example from my point of view. When I joined JPMorgan, at the beginning, I was brought to the traders' floor. And we were like—I was visiting the traders' floor, which is fascinating what's happening, but I could not see more than basically people standing, surrounded by screens full of lots of assets.

I mean, so basically, it was like a bunch of like time series data plotted on screens around these people that were making decisions. So when I looked at this, I mean, we were trying to bring AI to this decision-making. Of course, we explored reinforcement learning solutions. But I look at that and I can only see images.

Beena Ammanath: Yeah, yeah. (laughs)

Manuela Veloso: You know, it's only—I can only see pictures. They are pictures of—I've seen this data for sure. But they're pictures and images. And so, based on a lot of the work that has been done in AI and deep learning using images where so many others compelling problems that have been solved by face recognition all the way to object recognition, I actually developed the solution or the approach in which we use actual images, so pixels, to actually also make decisions regarding trying it.

It's not the solution that is fully being deployed yet, but it's a very different way of looking at the problem, and we can show that it does really well to sell, too, and that's an example. But you know, other examples that I would like also to emphasize is the following: In computer science, we have many data, a lot of data, and we try to—we aim at standardizing the data. We kind of want to represent all the objects the same way. We put as many properties as these. Currently in our firm that's large, covers many countries, many regulations, many sources of the data coming, the data is very, you know, it's not very uniform, just to say.

I think that one of the contributions of AI also is to bring that standardization as the representation of the concept and then enable the translation from different types of representation to the standardized one. And if we solve this problem, you know, if we solve the problem of when we are working on these representing companies—standardized representation of companies—whether the information comes from websites, from annual reports, from documents from all sorts of communication, then you bring all of that information through basically natural language processing into the standardized representation and then use the representation to do the matching with companies to investors, to the matching of companies, to all sorts of like that.

I mean, so all sorts of needs that you have across the company—now it's standardized. So these principles that, you know, images—the value of images is one example. The value of standardized representations is also something that AI brings to the industry. Yeah, so I could give many examples. We have a lot of these. I can give another example which is …

Beena Ammanath: Yes.

Manuela Veloso: The concept that we use now of actually searching. So, think about problems that require of looking at many alternatives, need reconciling, like different ledgers and statements, and all sorts of other matches that you have to go through all possible alternatives. The combinatoric nature of many of the problems that are in the financial industry, and now AI is one of the best to really do this search.

So basically, we now look at problems from an optimization point of view, not only as mixed integer programming, which we can do, but the AI magic is the formalization of complex problems into a way that then mathematical techniques can actually be applied to solve it. So, there is this representation issue—how to represent ledgers and statements and all sorts of issues and payments in a way that then you can do this mixed integer programming to solve.

So that's the beauty. And, of course, there are many techniques. AI is always using many techniques in math, in statistics, in all sorts of engineering. But the secret is the representation thing. How do you formalize if you are mixing profit, if you are mixing all sorts of information into a single framework, and that's basically the power of AI.

These knowledge representations and the combination with all that—ways of searching the information. So, search is a very beautiful tool that we also brought to many of the business problems to analyze in a very elegant way. It could be AI solutions and eventually determine what are the best solutions and which conditions.

Beena Ammanath: Yeah, so Manuela, you know, all these amazing solutions, the tools that you build, you know, it's all—I feel success is fully dependent on the adoption, on how many users actually take it, use it. And what are some of your best practices on driving adoption? Thinking about the user upfront and making sure that you really get the level of adoption you need to make it into a successful project.

Manuela Veloso: This is a very good question about adoption, and as I do, as I try to understand it like this: We've developed many projects that are basically, especially in AI Research, proof of cost, and they are sometimes wiped away from the way people solve them. And therefore, it becomes more difficult to engage on that chance. However, the magic is the following.

There needs to be someone in the business side who really believes and is not skeptical, and if they, in fact, embrace these changes and they embrace the great potential that eventually these techniques have, then something happens. So, it's kind of like I now, I mean, kind of in the search, people who actually believe that there could be a change, that there could be a different way of doing things.

If you don't find these people, it's very hard to really impose. You can't because people are doing the wrong business. And so we are, no matter what, still outside it. I mean, the business goes on. You have to balance accounts. You have to make loans; you have to invest. So, there is a whole business. It's like entering a hospital and telling like the surgeon, "yeah, you know, do it like this" when they have their own functions.

So now the question becomes when we find these people—actually, there are many here where I work—whether they are believers that this can make a difference, then it's good. It's beautiful because they engage explaining the business rules. They engage explaining like what is the potential impact of the techniques.

And then basically there is a moment, which is the thing that I also want to emphasize, you know, this magic of AI transitions to the business, and then [inaudible], they take over, and they do it. So, for example, I'll tell you, we have done some work a couple of years ago on trying to automate the generation of some of the reports because the data is all in some files and then basically you need to convert that data to some language, and you need to convert that language into insights, into tables, into numbers to go inside to the table, to do numbers. So, we did this AI to generate these documents automatically. We call it "docubot" and basically now some of the business uses it—we just know they use it—and sometimes it's not really—did they adjust it to what they actually need? They do all this kind of like different aspects, different variables for different use cases. It's beautiful when we see they're eventually contributing that way, so we don't follow all the way to seeing the actual outcome coming out.

But I think that true business is like the same thing with these reconciliations of applying search to math. I mean, it's beautiful that eventually the business takes over, understands the value, and then it makes it happen. Because the important thing about business versus AI, or versus the research, is the scale. I mean, this business, it's to address all countries, all views, all thousands, and millions of transactions. It's the scale, while we in AI, we know that the scale exists, but we think about it like this: OK, let's reduce the scale to this type of typical example. Can we process them? Fine. And then they—the business—has to handle the actual…

Beena Ammanath: Mm-hmm.

Manuela Veloso: —Running this.

Beena Ammanath: Yes.

Manuela Veloso: But one final thought about this business and AI. And I hear many discussions about this. Oh, you have to learn tons about finance. Oh, they have to know tons about AI. I think that this is not the way to collaborate.

Beena Ammanath: Yeah.

Manuela Veloso: I mean I understand enough eventually, and I will hopefully improve over time to be able to have a conversation. But do I really need to know the basics of derivatives, the basics of customer service, the basics of ATM machines and all? And how do you …? No. Do they need to know how the algorithms for a search or for representation, or for heuristics, and for a source of deep learning and adjustment of parameters, and …? No.

So, it's like the beautiful thing is to keep that knowledge in the right place and to still be able to collaborate. So, when people say, "oh, we don't know anything about AI," you need to know enough when we talk about search or when we talk about eristics or when we talk about [inaudible], you understand some. We have actually developed AI academy that includes these little lectures on "AI can…" AI can search, AI can do reinforcement learning. AI can learn from example. AI can process natural language, AI can do machine vision, and they are like a portfolio of 15-minute lectures, very short, on really like the capabilities of AI. And that's enough, and sometimes—even the other day, someone told me, "I mean your 'AI can search' is difficult." Even if I made it like the simplest possible way, I still have to redo it slightly so that it's more understandable by people that don't know what necessarily a graph is or nodes or search. But that's, I think, the beautiful thing about AI Research also here because, as I have this teaching background all my life, I thought.

Beena Ammanath: Yeah, I know!

Manuela Veloso: I mean, I've been teaching all my life. So, for me, it's natural to try to explain things in a way that eventually the audience can understand. And that makes it slightly easier for me to be in this position of bringing AI education.

Beena Ammanath: But we're definitely seeing—and I've seen it as well—more and more companies having this basic AI literacy training, right, just so that you can all speak to the same language. It's like the alphabets of AI and, you know, I would say 10 years ago there was an expectation the data scientist was a unicorn that knew all these skill sets. But we've certainly now realized you need that deep expertise, and you need to be able to collaborate to drive the most outcome. And, you know, AI literacy is becoming more and more crucial as AI itself advances. So that's one of the challenges—that culture change that you need to drive, along with, you know, bringing AI into the organization.

The other one that we hear a lot about in our field is around the topic of ethical AI. What are some of your thoughts on this, and how do you think about it? How are you addressing it?

Manuela Veloso: So, we actually have research pillars in our—we organize along seven research pillars. One of them is exactly about values of society, not only ethics but the fairness, ESG, all sorts of values. Values that are a bit orthogonal to the techniques and a bit orthogonal also to the financial actual service, its patterns as of society.

And the important thing for us here to understand is the following. AI does not have intentions. [laughing] Right? The problems always are with people, not with really AI. AI only enables eventually people to manipulate, do, or to do unethical things. But it's not because AI itself has anything inside.

However, we have a center of excellence in my team, at JPMorgan, on explainable AI. So, one of the first things that we delved into is the problem of actually understanding why. Why is the machine saying no loan, loan? Why is the machine saying this price versus that price? And of all this infrastructure, you learn some decision tree, and you used 400 features and then magically the thing says, "Well, $112! That's like what the price should be."

Or "No, you don't get loan to this particular person." There is this, kind of like, why in the world does this thing come up with this? So explainable AI is something that we have been working a lot to try to break this gap between the machine, the AI, the code, the algorithm running, and the actual user understands. Notice the difference between these type of like explanations or versus the matching.

The matching problem: If you say that "10 is the same as five plus five," but he has a problem with that. You know, he doesn't really need to explain. You might have to explain what the match—why didn't you match 10 to eight plus two? But not really like the essence of explanation. So, we are working on these explanations, looking at eventually trying to bring out the features that were relevant for the decision, trying to organize features along time and along visual type of classes.

And all sorts of trying to bring explanation. At the same time, you know, in coordination with people, regulators, with people in compliance, we try to, you know—it's very beautiful. We try to use AI to search different subsets to prove that this is right by contrast with others. So, we basically go and say, what if we had used all this counterfactual thinking, what if we had used all these other features?

And then everybody's happy to see that the result if we had used these other features would not have—would have been worse in the metrics we are trying to use than these words that the machine AI came up with. So, we do a lot of like, I'll just say again, like analysis of like what-if scenarios, counterfactuals—and counterfactuals can also be used as explanations.

The ethical problem is complicated, and recently we have several people that joined the team for responsible AI. So, it's, and they are trying to find principles. Also, there is a lot of work being done in the community. The AI community on ethical AI and balance of AI and principles of trying to bring all of these types of like training with the right data, having the right tests, being able to put the right principles, even having diversity working on the development.

If you have teams that embrace the diversity of our society, we may bring more ethical decisions on the code itself. And so, I just want to tell that the contrast between these days of AI in industry and early on when I was in university or when I leave Earth and to go up to Mars, when I optimize or robots that played soccer, the big difference is the following: Here, the concern with these problems—which is very well concerned—brings multidisciplinary teams together.

You bring the people who know about the social impact of things with the people that actually now are making sure they are represented, and all the code should be written, which in the past, when we are putting robot soccer, you don't have—it doesn't matter. What does it matter scoring one goal more or one goal less?

It doesn't have a human as a target as a target and here the fact that the social scientists play a role in these conversations, that the lawyers play a role, that people that understand philosophy play a role, and ethical people play a role. So, it's, for me, it has been also transformation coming from academia to open my mind also and my techniques to these ethical values and the societal realm.

So, I honestly say that I was not thinking that much about these issues when I had robots move around Carnegie Mellon, bringing me coffee or taking this package. I just wanted to make sure that the robots would not hit anyone, nor bump into chairs, and they would come back, and they would know where to go.

So the data, for me, was more on functionality than on values. Now, we cannot afford to do that "only functionality" thinking in a lot of your problems that we cover in financial services even if they are humans. I mean, OK, I care about the robots not going over

Beena Ammanath: I totally understand. I'm a computer scientist by training as well. And it's, you know, our focus is all on the things that you can do, right—the functionality—and not necessarily the negative impacts. So I totally can relate to, you know, what you're describing. So Manuela, recently you were elected to the National Academy of Engineering for your contributions to AI and its applications in robotics and the financial service industry.

Can you tell our audience a little bit about your research in AI and robotics, and what have you learned?

Manuela Veloso: I'm very humbled by this honor, and I really believe that it has been a lifetime of experience. But let me explain to you. So, I—always in robotics—worked on the problem of connecting perception, cognition, and action. And I looked at AI as basically using the data to be input to the decision-making and then eventually to execute the decision.

So, robotics gives us this heart on all areas of this intelligence—not just doing natural language, not just doing machine vision, not just doing planning, but robotics is about—well, this robot needs to move! This robot needs to do a task from beginning to end. So, there is

That's what I always knew as my AI experience, and so here it's the same thing. At JPMorgan because I've had this experience, and there's AI in the financial industry, I look at the end-to-end problems. I mean, I like to say, "What is the data? So, why do we do that?" So, I don't see myself as a data scientist.

I see myself always as an AI person because I don't just analyze the data. I want the data to be then given what we do with it. What is the action you need to take, and eventually actually do the action. So, I bring this connection between data, reasoning, and action and more and get feedback and be improving over time and being a learner with some experience. Not just learning from that, but learning from doing, learning from instruction, learning from observation. So, all these other techniques that we use in robotics that are very helpful to have this more, how do you say, complete view of learning, not just the data. Then you have to actually talk with the person, they are a chatbot, you have to talk! You better become better over time.

You better learn. That's the challenge—is to think about AI not as a one-shot kind of system, but as a road—a journey. Journey. AI is a journey. It becomes, over time, better and better the humans say things. And eventually this is like an experience process. So, I bring that from my robotics experience because they kept like not spotting goals at the beginning and then over time, you know, with more inputs from humans they ended up knowing more what to do and the robots moving around too. So, my robotics world has always been about mobile robots; not only manipulate. There are areas in robotics for manipulation, all sorts of planetary experience, autonomous driving. My robotics was always mobile inside of the buildings. I was [inaudible]. But another thing that it brought—that my choosing robotics brought—which I think is extremely relevant, and I'll share this final thought with you about this is the following: Back in mid-2010, 2015, when we were moving our robots at Carnegie Mellon, these famous CoBot robots…

Beena Ammanath: Yeah.

Manuela Veloso: … you know, what happened was that we realized that they couldn't do everything. You know? There was this issue about they could not open all the doors of the building, no matter what actuators we would have. They could not press the elevator buttons of the elevators, and they could not pick up things in the kitchen. I mean, they could not pick up a packet. Even if we would give them arms, it would have been hard to pick up anything.

So, there was that moment in which I realized that, unfortunately, these robots would always have limitations. Limitations. The problem of accepting that AI and the robots exactly that I was developing had limitations. And so, we introduced this concept of symbiotic autonomy in which these robots ask for help from the humans a lot..

So, the beautiful thing is that the humans didn't have to follow that; they will just stand there in front of the elevator and say, "Can you please press the elevator button for me?" or "Can you put something in my basket?" or "Can you take these out of the basket?" Things that they cannot do. And so, it changed my way of thinking about AI, in which I was thinking, Oh, I could do it all. They will play soccer as well as humans. They will do all this stuff. But then, no! I realized in the mid-2000s that it was not the case that they were going to be able to do everything. And that has changed the way I perceive problems even here, because they say, oh, this is so hard. I mean, this is really a very difficult decision.

That's fine. Then the machine needs to say, "I cannot do this one, but I can do that one." So, it became an architecture of thinking in which you now test if the thing is AI solvable. And if it's not, hopefully the human will solve it. So, I believe that the future, these ethics, all these questions. The future is about understanding how AI and humans can work together. We'll never only be humans, and we'll never only be AI

We'll always be here. We know much more than this AI does, in many things. But this AI can do repetitive tasks much better than we can. Much more accurately than we can. It can do searches. It can search information like no human can. I mean, I cannot go through all the webpages of the whole world, and AI can!

Beena Ammanath: Yeah,.

Manuela Veloso: But this is the magic of the discovery of AI—is to try to make these humans and this AI build better on their own capabilities. And it's not about denying that AI exists now. And it's not about denying that humans have knowledge. They do. So, that's the magic. And I learned this in my robotics because, in some sense, there was that 3 a.m. kind of acknowledgment that, oh my gosh, And I realized at that moment that this is it, and you need to embrace that they [robots/AI] should be asking for help. They are surrounded by humans. We don't have any problem pressing an elevator button—we don't! We don't have any problem putting something in a basket—we don't. But we may not want to go all around the building, delivering all these packages to the whole building.

OK. OK, so then what? We combine the things. So that's what I believe is the secret here, this amazing combination of AI and humans. I learned this from my robotics, and I'm bringing it to the financial services too.

Beena Ammanath: That's so true. So, the magic is [that] humans with machines is the most powerful use. I love it. So, Manuela, you know, what are some of the advances you're seeing in AI, whether it's generative AI or image recognition? What are some of the advances in AI that you are most excited about?.

Manuela Veloso: I have put first that the advances of AI to process language are amazing. Amazing. And being having worked so much with robots, I did not have my heart on the language for many years. Because I was, I cared about the images, I cared about lasers, I cared about sensors. But language—we need to just—we have it in robot but just minimal interaction with humans.

"Get me coffee. Go to Manuela's office." It's not Shakespeare, and not any type of document, it was just very plainlike. So, coming to JPMorgan, coming to the financial industry world, you have to realize that the humans—humans—communicate with other humans through language. This language thing is ridiculously pervasive everywhere. You know, documents, phone calls, conversations—everything is about humans talking or writing, and therefore all the advances that AI has done on these large language models, on this extremely convincing language processing, are amazing.

So, I have a big admiration for all the results that have been shared with everyone in language. In language—unbelievable! I do think that the images will also play an equal role—going back to my first example—because we make so many decisions based on what we see. So, I think that images are a little bit underrated now because it's all only images for object detection. But we humans, we look at the sky, oh wow, it's dark. We take an umbrella. We make so many decisions. We look at how the face of that person—oh, they are sad. So, you talk in a different way. Everything is—so many things are driven by what people see. Not just what people hear. But just, to answer your question, language is what I think is the best. And of course, all the learning, all the learning, all these amazing algorithms to be able to process enormous amounts of data.

But when we combine the missing data with the human knowledge, that's also a big secret for the future. I think we have to do more on that. But the language. Language, I tell you. Maybe other people say, oh, she's so naive. She thought… But I believe it's a major, major accomplishment. Now, I do want to add one more major accomplishment, just to cover everything that we have been working on also, which are the ability to really create synthetic data.

So, the "fake data" problem, which can be that—if we call it "fake," it seems that it's bad. If we call it synthetic, it probably has the rightful use. When you don't have enough real data, even fraud examples, or you know, all other examples—when the data is very limited, by creating this synthetic data, you can really do really much better in terms of using AI, use the data—the real and the synthetic. We have results that show great improvements on AI systems by using also synthetic data, which we can generate either by expanding the real data or by using models. We can use simulations that create the same type of data through principles. And so, I think synthetic—that is very important. And finally, one thing that is the most kind of like not used yet, but I find it fascinating, which I experience with robots often, is that simulations of multiple agents, interactions between multiple agents. Because these multi-agents—the game theoretical aspects, the security aspects, the crypto aspects—if one talks with the other but doesn't want to give the right information that they need to for the night. They need to juggle giant computations. This amazing world of multiple agents, not just one—it's like all of them. We have a very big area of multi-agent simulation and multi-agent privacy, that these distributed kind of like systems—we cannot imagine that we have a single AI system. I mean, it's going to be this AI system is going to talk with some other AI system somewhere else, and, you know, these humans need to talk with other humans.

So, this is, all the world is all about multiple parties, multiple negotiations, multiple understanding of like interest, and all sorts of dialoging. And unfortunately, I believe that these algorithms for languages and deep learning did not yet embrace the commercial aspect on these multi-agents, on this ability to [inaudible] about multiple aspects and multiple leads. So multi-agents, synthetic data, standardized data, all sorts of language vision, and all sorts of search and optimization and representation, while we are covering the whole world of AI.

Beena Ammanath: Yeah,.

Beena Ammanath: So true, Manuela. You're doing some cool work. How can people stay connected with you and follow your work?

Manuela Veloso: It's a good question. I'm not very good at all social media, but I do have one webpage which I keep updated with our publications, which is the most exciting things happen there. It's at Carnegie Mellon. If you Google it, you're going to see my best webpage, which has several research projects, and then a pointer to our JPMorgan.com/AI website, which is an external website, in which we represent all our problems, our projects, the collaborations with universities.

We have a very big mission of staying connected with universities in the community. Everything is there: JPMorgan.com/AI. And my email address is also there.

Beena Ammanath: Manuela, that was great. Thank you so much for being with us on the show.

Manuela Veloso: Thank you very much also for having me.

Beena Ammanath: Thanks to our audience for tuning in to AI Ignition. Be sure to stay connected with the Deloitte AI Institute for more AI research and insights. Take care.

Visit the AI Ignition Podcast Episode Library
Deloitte.com/us/ai-ignition