**Fabio Ramos – Me, my robot and I**

>> Welcome to the podcast series of Raising the Bar, Sydney. Raising the Bar in 2017 saw 20 University of Sydney academics take their research out of the lecture theatre and into bars across Sydney, all on one night. In this podcast you'll hear Fabio Ramos' talk, "Me, My Robot and I." Enjoy the talk.

[ Applause ]

>> Okay. Thanks very much. Thanks for the introduction, Louie, wherever you are. Ah, there you go. Thanks for coming. So it's a great event. Great to be here. That's actually the second time I gave a talk in a pub. It's quite challenging. Usually I start my lectures with students, and I say, "Look, I'll give you a little prize if you don't sleep, and here maybe if you don't drink too much during this talk, and concentrate on what I'm saying, I might give you another drink at the end of this." Okay? That's the idea. And I'll try to actually look at you, rather than those nice bottles over there. There's some of my favourites there. This will be quite interesting. Right? When I received this invitation here, I said, "Great. Finally I have the chance, an opportunity, to talk to, you know, a general audience on robotics. And I can pick the questions, and the way I'm going to drive this conversation here, at least at the beginning." Right? You're going to have a section, 15 minutes, to ask me questions later on. Because what has been happening to me, you know, someone that actually works in machine learning, artificial intelligence, we're going to call it AI for short, and robotics. So when I go to the media, radio, TV stations, and they say, "Oh, Fab, you're great. I would like to interview, and ask you about the kind of things you do." When I turn up to these talks, to these events, and they start asking me, "Okay. So you work in AI. That's great. How many jobs are you going to, you know, destroy? And, you know, is your work going to, you know, completely destroy humanity? And can your robots kill?" And things go on and on for several minutes. You know, I remember giving a radio interview for 20 minutes, and all I got was questions like that. And I was supposed to talk about nice things. You know? Nice things about AI. [inaudible] said, "Great. So maybe I'll take this chance, this opportunity, to actually talk to you about the good things about AI, the good things that we can do with machine learning today." There's also some little things that we need to be careful. But, hopefully, we'll be able to balance both of these, and actually working something better. I just want to keep track of my time here, otherwise I spend, you know, we usually give lectures, two-hour lectures, and 30 minutes will be a bit tricky for me. But let me start to tell you a little bit about the history of AI. Right? So just a few weeks ago there are a number of TV shows on artificial intelligence. Right? And some people looking at artificial intelligence with the eyes of, "Oh, maybe AI will change the way people do their jobs." And it's becoming very popular now. But let me tell you AI is quite old. Okay? So it's probably as old as, you know, it started even before digital computers. And it started in the School of Physics, you might, you know, believe it or not. And, you know, it was the late '50s, around late '50s there was some researchers in Cornell University. And they had this computer, analogue computer, just imagine a big room, this big analogue computer which has these nice valves, so little, you know, big circuits like this big, which are essentially doing switches. And they had potentiometers, these kind of resistors. They're all there spread around the room. And I had one camera at that time. It was a 20 by 20 pixel camera. Okay? Every pixel was a little diode. Okay? So it's essentially responds to light. And what they were trying to do at that time was, well, can I recognise a digit? I present an image, or I write a digit, number seven, for example, on the wall. And I put my camera, my 20 by 20 super resolution camera, facing that digit. And this computer needs to recognise what was in there, okay, automatically. That was 1957. Well, let me then tell you how Frank Rosenblatt, who was probably the person who has started with this idea, solved the problem. Well, how do I transfer these pixels to something that is meaningful, which is the digit that's right there? He said, "Okay. Let me organise my circuits in the following way." And he was inspired, very loosely, by how the brain would work, right, or how people believed the brain would work at that time. And the idea was, "Look, I'm going to take each of these pixels, and I'm going to multiply that signal by, you know, a little bit. There is a fraction in there. It's just a constant. And then I'm going to pass that through a little circuit that will just say yes or no. And I'm going to do that 20 times 20, so 400 times. And at the end I will somehow balance all the answers, every little switch. I will combine them to then tell me which digit was there." Okay? So you think about this computer, okay, 400 pixels. Each pixel has one parameter, one potentiometer to adjust. Plus the, you know, the thing at the top that would put all of them together. So it's more than 400 parameters. Just that. And he said, "Okay. How am I going to, how on earth am I going to actually regulate all these potentiometers? How am I going to adjust these things?" So he had the brilliant idea, we keep on having these ideas even today, he hired lots of Ph.D. students. Okay? And he said, "Okay, Ph.D. students, I will lock in you in this room for, I know, two weeks. And you are only allowed to leave after this machine recognises the digits. So that was the students there inside this room changing the potentiometers. And he would say, "Okay. I got the number eight right. Oh, but now number four is totally wrong. So let me adjust that thing." And it was on and on. They actually couldn't finish the process to recognise all of this. So, you know, to recognise just digits zero to nine. It was impossible. So then he had another idea, "Hmm. Let me make this system a little bit more complicated. Instead of hiring all of these Ph.D. students, I am going to hire maybe two or three very good ones." That also works today. Right? So quality is better than quantity. "And I am going to connect each of these potentiometers with an electric motor." Okay? So he put motors for each of these little potentiometers, electric motors. Okay? And he had a very interesting idea. He said, "Can I make this process automatic? So I will essentially adjust these potentiometers by presenting my computer with some, you know, the labels, the correct labels." So here's the idea. He has the camera right there, filming. Right? The 20 by 20 pixel. And then you have the correct label for this. And if the label is correct, don't do anything. Just leave the parameters, the potentiometers, as they were. If the labels are incorrect, then I kind of start to adjust. I use the motors to automatically adjust these things. Okay? And, so, the process is an iterative process. And he figured out that if you present this huge computer with enough training data, they call this training, so you input an image, and you get the right label. And you do that multiple, multiple times adjusting these parameters. He could then have a machine that could automatically learn the weights, the position of these potentiometers to recognise the digit. That was 1957. And this was the very first development that we now call machine learning. There was actually a machine with electric motors that self-adjusted to recognise digits. That was the task. And this set of, you know, these instances, these observations, were called training sets. Right? So you present that with the digit. You know the label. And you adjust. And if you provide many of these things to the machine, it will automatically learn that thing. So that's machine learning. And that was the perceptron algorithm that some people started in 1957. Interesting enough he wrote a paper, and I have to read the title of that paper, so you see what happened. Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms. It was a beautiful paper published in '62. Unfortunately, as happens many, many times in science, he was heavily criticised, because these things, these big computers, which was implementing something that we now know as neural networks, a lot of the mathematicians said, "Oh, this is never going to work for real. It doesn't, it won't work." And essentially his work was destroyed. For the next 20 years nobody talked about machine learning at all, or neuro networks. Until the 80s when you kind of saw oh, maybe there is [inaudible], maybe this thing can actually work. There was digital computers were there, the PCs were there. Madonna was there. Rick Ashley was there. All good stuff. And neural networks had this resurgence. We became big again. Now why am I telling you this story about machine learning and neural nets is because, have you heard about this term called deep learning at all? I mean have you seen this before? Deep learning in industry, or big data? People are talking about big data. You know? There's big data everywhere. [inaudible] a bank, let's do big data. And, so, deep learning is one model that can do big data. Okay? And deep learning started, you know, maybe ten years ago. But the ideas were laid down by Frank in 1957. And this is the point where we are at in AI at the moment. Right? This is before I moved to my robots. If you now have a computer, and you have lots and lots of data. Just imagine you are Google, and you have one billion images, each one with a label associated with that image. And you say, "Look, I built this neural network here. And I'm going to build another neural network on top of another one. And I grow this in a hierarchical way where the outputs of one model are the inputs of the next one, and so on. Kind of loosely inspired by how the brain works in the sense that you, you know, you process the information in a hierarchical way. Although we know that the brain has way more connexions than just that. But that's the idea of this deep learning. And what turns out is that deep learning today, if you have enough data, if you have these new algorithms, new optimization algorithms, and gamers. Actually one of the main reasons why you hear about AI today is because of gamers. People gaming. I'll tell you why. Without the graphics cards that we now can buy for a thousand bucks, in Harvey Norman and other places, we wouldn't be able to do AI as well as we do that today. And because people keep on buying faster graphics cards, so they can have 150 hertz on the refreshing of their gaming instead of 110, the prices of these graphics cards are going down. And because the prices are going down, we at the university can buy them. You can buy lots of them. Then we can do the computation, and actually train models that are incredibly complicated, okay, to the point that deep learning today can recognise digits, characters, on a piece of paper better than any human. They can recognise speech better than any human. They are approaching to the object recognition level of a person. So if you just take a picture, and what is that object? Is that, you know, a [inaudible], is that [inaudible] deep learning can do, and achieve very, very high accuracy in these kind of tasks when you have a lot of data. Right? And it can also do other things that I'm going to be describing today. But now this was a brief history of AI and where we are now. We have these GPUs. We have a lot of computers. Let's bring on the robots. Right? It's time. Bring on the robots. Ten minutes [inaudible].

>> You're listening to Raising the Bar, Sydney 2017.

>> I'll tell you a little, you know, another story. I was finishing my Ph.D. It was back in 2007. And a big mining company came to us and said, "Look, Fabio, you are here at university. And I'm there in the Pilbara. And I need to dig a lot of iron ore off the ground. Do some, you know, crushing, put that on a truck, and then send it to China. Can you help me with that process? Can you make it any better? Can you speed up, improve performance, whatever, do something? Because I can get very good prices on this iron ore." And I said, "Okay. But how do I start?" That's actually a very complicated thing. Right? If you look at all the processes involved in mining it's tricky. And I said, "Okay. Maybe I would start by automating some of the machines you have in a mine." And the first machine we decided to automate was a drill, a drill rig. So if you have never been to a mine, is the sound okay? Yeah? It's good? Yeah. So in a mine, you know, an iron ore mine, this is what happens. Right? So you have these big drill rigs. They drill holes, maybe 50-metres deep. And you drill 200 of them in a square or a rectangular area. And you fill them with explosives, maybe 100 kilogrammes of TNT in each of these holes. And then you blast it. It's actually quite fun to be there and doing the blasting. So I had this opportunity. The ground would shake. The rocks were fragmented. And then you can have machines to remove that stuff and crush it, and send it to China. Right? So that's in a nutshell the process of mining. So we decided to instrument this big machine, this machine called a drill. And while you are drilling, it's actually the very first time you have physical contact with the rocks. You're kind of, you know, this stuff, the material you want to send to China. And one of the main problems they have in mining is that, well, as opposed to warehouses where you know how much stuff you have, you know, in your stock. In mining you never know, because it's all dig there. It's under. You don't observe that. So the main thing for mining was trying to estimate the quality of these stockpiles they had, what they had the resources down there. So we automated this machine. And while we were automating, you know, the machine with them, it's a 80-tonne drill, so not a, you know, a little toy. While it was moving around and drilling these holes, we then learnt, using machine learning, some of these things that I described, a mapping function from all the vibration and things you would get from the drilling processing to the quality of the rock. Quality in terms of, you know, some chemistry that could be related to that. And once we automated this, we transformed the process of assessing what's going on in that mine into an information system, where you'd get the quality of the rock being inputted into the system, which will be improved the next time you visit that area, and so on. So the mine would become a continuous improvement in terms of your knowledge of what's going on. So then they came back to us and said, "Okay. That sounds good. So now can you automate everything?" Okay? So obviously we went and talked to a few OEMs, you know, producers of trucks. And now what we have is maybe the first, well, it is the first fully autonomous mine, maybe one or two pieces of equipment are not autonomous, operating in a Pilbara. Right? Operating there where you have 42 trucks drive themselves, being loaded by excavators. The drills are autonomous. We have sensing vehicles moving around collecting data. And now the mining process became essentially an information system where you get more data, and you improve as you go along. You might ask, "What happened to the jobs of the drivers?" Yeah? "What happened? Did you fire all of them?" It was actually interesting because we did a study of what happened to the employees at that company. And the number of people employed by the company is almost the same, maybe a little bit more actually now than what it was before. But now a lot of them are leaving Perth, rather than the Pilbara. They are not doing the flying, fly out kind of stuff that, you know, is quite annoying if you want to have a family. But we hired people to do maintenance of this equipment, to essentially analyse the process, how we improve the process. So essentially we have many more mathematicians working with the process. Instead of doing the job, we are now improving the job done by other things. And that's my take on this automation process, right, and how we are shifting things, particularly in industries like that. Instead of doing the job, maybe we can now work on always improving what's currently ongoing, and becoming more competitive. But that was the autonomous mine. Now I want to talk to you something, actually even more challenging than making an autonomous mine autonomous. And that has to do with robots that operate among us. You know, home robots. And really the main motivation for that was when I, you know, I have a few collaborators in hospitals, particularly Saint Vincent's Hospital. And Stephen Faux is the doctor there. And he runs the Rehabilitation Clinic. And he said, "Look, Fabio, I have a terrible problem here, because as the population ages, we just don't have enough health professionals to do treatment with them, to take care of them, and, you know, the part of the hospital I was responsible for, you know, just ten years ago I would have 15 beds. Now I have more than 60. And as people age, there's more chance they will have strokes. And when you have a stroke, you know, that will damage part of your emotion, and so on. Can you do something for me?" I said, "Okay. That sounds interesting, challenging. But I think we can have a good impact in that. And that's when we decided to move our focus to robots that could operate among us, with the idea that if someone had a stroke or suffered from any kind of mental illness, they probably lose independence. They need to have someone else living with them. And the crucial thing for these people is to realise that maybe we can give that independence back if we are smart about technology, so they become part of the society back again. We developed this robot, which has, you know, it's relatively small, maybe 50 centimetres by 50, and has a robotic arm on top. And what we would like to do with that arm was maybe, you know, you drop something, the patient drops something on the floor. And you could essentially ask, "Robot, can you just grab that for me, and bring that back to me?" That was the idea. Or maybe the robot could, "Can you please feed me? Can you, you know, get a fork out there, and give me food, because I just can't. Or can you hold a glass, and bring it to me, so I can drink?" We started on this idea. But it turns out that mobile manipulation in home robotics is so complicated. You have no idea. Right? Because, you know, you probably heard from the media that now, you know, Google can, you know, solve the AlphaGo game better than any human will possibly do. But we can still, there is no robot that will be able to just open a door. You know? Just going there with the hand, robotic hand, and opening a door. We can't do it. It's way too complicated. There are way too many types of doors. And some open this way, some others only that way, and so on, and so on. It's so complicated. And the reason we do a good job in games is because the environment is well defined. You know the rules. When you are out, you know, in the world you have to understand the rules, and learn these rules. So I was super concerned with that, because, okay, what are we going to? How are we going to solve this problem, and help these people? There is a little bit of hope though, because, you know, have you ever been asked in your company to do a strategic plan? Yeah? Yeah? Strategic plans? Yeah? And then they say, "Oh, what's your strategy for, you know, next year, and so on?" Well, they asked for us to do these things at university, too. But there is actually a very good thing about the strategic plan. It connects to an area in machine learning that is now being very well developed. And it's the idea of learning how to act to improve a particular goal. And here's the intuition behind that. Suppose I have my robot there. And I tell the robot, "Here's your goal. You have to grasp that little cup." I can't programme the robot to do exactly that, because there are so many variables. The cup could be small. It could be big, and so on. Can I actually make a robot learn that on its own? And, so, it's basically inspired by how babies would learn things. You know, when they are young, they start, you know, playing with things, trying to manipulate things. So we developed some of these methods. It's called reinforcement learning. The idea is you leave the robot there. There is an object there. We give them a mission. And the robot starts to accomplish that mission missing many, many, many times. But it slowly starts to learn how to act in that complicated environment. And the advantage is I can be upstairs in my office, not down on the floor with, you know, some of my students like Harrison right here, [inaudible]. So that's automated. The learning process is automated. And we are now able to learn some of these actions, and how robots can, you know, just imagine grasping that glass. You've got to navigate, close. You need to know how far your grasp can extend, check the weight, see if that's good or not, and so on. But robots can now start to learn by themselves how to perform these actions. And I think that's a great thing that is happening in robotics. We will see more of this coming. And, hopefully, we'll be able to solve the manipulation problem that I just mentioned. But, yeah, I still have time? Yeah? Good. Moving on from this robotic arm on a platform, which is still 40 to 50 thousand bucks, which not everybody can afford. Can we actually do something cheaper? Can we use robots that we already have? Actually there's plenty of robots here. Right? Louie has one [inaudible]. Can we actually make these things help us? But for that we need to extend a little bit the definition of what a robot is. So you might imagine a robot is something, you know, that moves like that, and has a motion associated with that. So let's relax that assumption, as we say in mathematics. Let's call a robot something that can sense the environment. So it has cameras or GPS or accelerometers, something that can perform a few actions. For example, displaying things on the screen. And something that can reason from sensors to actions. So essentially map sensor inputs to some actions. And we have devices that can do that for us. Yeah? So we have mobile phones. So I'm calling a mobile phone now a robot. And I'm calling these little wearable things a robot, too. How do I make them useful? I mean assuming that they are already useful. Can I make them more useful, and try to solve some problems related to health? And, so, we had this idea. This is a little robot. It's on me. And it's collecting a lot of physiological data of me. So, for example, my heartrate, how much I sleep, motions, and so on. And I give this robot one mission. And the mission of this robot here is to make my sleep better. So we went and talked to some doctors on sleep medicine. And they said, "Oh, that sounds good, because, look, based on how much you move, your heartrate, how well you slept last night this watch, or this device, can give you recommendations on how to improve your sleep." So, for example, it can tell you don't have coffee from that time to that time. Go to bed at that particular time. Wake up at that particular time, and so on. And depending on how you react to these suggestions, you will improve the suggestions to make you sleep better as you go on, you know. So it essentially learns on how you react. And its mission now is to improve your sleep. Okay? So that actually works quite well for people, except those with babies. Yeah? So if you don't have a baby, this will work. If you have a baby, that doesn't really tell you what to do with a baby. That's one of my challenges, you know, lately. Well, we can move on from just helping people with sleep to something even more interesting. When I went there and talked to Stephen, you know, to the hospital and talked to Stephen Faux, he said, "Look, another thing we'd like to do is identify how our patients spend their days. And if they forget things maybe you can remind them that, you know, don't forget to do this, or don't forget to do that, and so on." So we came up with this idea. If we could embed a little intelligence in a robot that captures, for example, a first-person view of what the person is doing, and then do what is called activity recognition, we can then have someone with, let's say Alzheimer's disease or something like that, give them feedback, and reminding them of things that they should be doing. For example, don't forget to turn off the stove. This person in front of you is your cousin. And things like that. Right? So, you know, using some of this stuff here. This is a kind of little Google glass type of thing, which is good because elderly people usually would need glasses. And all the intelligence is right there. And that's tricky, because I've never seen so many wires in my hand. But there you go. This thing has a little camera in it. It has accelerometers. It can talk to you. It can tell you that you forgot to do something. Don't forget to take your medication. Don't forget to do x, y and z. And the doctors also will now have an understanding how patients actually spend most of their day in there. And maybe this thing will help improve, you know, their quality of life while they are at home trying to live independently, okay, which is a major problem for them. Okay? So that's another robot right here. Okay? It can tell you what to do based on what you are doing, and the activity recognition. Now I actually need to kind of wrap up very quickly, because I want to give you time to ask me questions. Yeah? I'm sure you have lots of questions. Okay. So I've told you that AI is actually not a new thing. It has been around since the '50s. Thanks to gamers, and to a company that's collecting huge amounts of data, we can now do, we have the power to do much more interesting things. We can connect this with machines to solve very large problems, automating industries like mining, for example. Port Botany, you know, I didn't mention that to you. But Port Botany is another project where we automated the entire port, and the movement of these containers. But more than that, we can use these strategies to improve the quality of life for everybody, you know, those with diseases, and those just with sleep problems, like I had last night when my baby decided to wake up at 3:00 a.m. And this thing actually did not help me much. But maybe one day it will help the babies, you know, help to take care of babies as well. So just a bit of a conclusion. And I want to just finish with this message here. Right? In the same way we can use a knife to kill, we can also use a knife to prepare our food in a much more efficient way. So AI is not different than that. I mean in the same way you can use that for good, you can use that for bad. And there are ethical issues. But at the moment, as we are, with the development of AI, machine learning, and so on, we still have the control. We can embed ethics inside of what this robot should be doing. And we can guide to what we want to see in the future. And you don't need to understand AI to appreciate the ethics behind that. And everybody can contribute to that. So since we have the control, you can all help me to steer AI to the right direction. Thank you very much.

[ Applause ]

>> Thanks for listening to the podcast series Raising the Bar, Sydney. If you want to hear more search for Raising the Bar, Sydney on your podcast app. For more free talks and forums from the University of Sydney, as well as even more great ideas, visit www.sydney.edu.au/sydneyideas. Sydney Ideas brings leading thinkers from Australia and the world to the Sydney community. Thanks for listening. And look out for Raising the Bar in 2018.