00:04
Speaker 1
Hello and welcome to the Human and Machine podcast. This is Jaco from element eight and.

00:10
Speaker 2
Always me, Lenny, joining Jaco this morning.

00:13
Speaker 1
So another week, another podcast. Thank you for joining us. Thank you for listening. If you missed, last week we spoke with Albertas from Stratus technologies about not the edge specifically, but although we did have a lot of say about the edge, but more specifically high availability and the edge. There was a really cool chat with Alberta then.

00:31
Speaker 2
Yes, it's incredible to understand the technology depending on how many nines of availability you want to actually deploy to your manufacturing environment. And a really good discussion just to guide people in the manufacturing world how to deliver a high availability or a disaster coverage solutions to their manufacturing plants.

00:49
Speaker 1
Yeah, definitely good chat with Albatus. Very knowledgeable guy. He's also been in the automation and software industry for more than 20 plus years. So yeah, that was an insightful chat. So right from that end of the spectrum, we are now this week or this specific episode, I mean, we're in for a treat. We're going way on the other side, as far away from the edge as possible, but really where it begins at the edge. And today we are. I don't even know what to title it. We are talking what all the buzwords, data science, artificial intelligence, machine learning, deep learning. It's very common these days to come across all of these terms.

01:24
Speaker 2
Yeah, it's with the rapid rise of artificial intelligence, it's almost impossible to miss. You hear all of these words, terms like AI, machine learning, digitization, automation, industry.

01:37
Speaker 1
4.0, what does all mean?

01:39
Speaker 2
Industrial artificial intelligence, they use it almost as a form of punctuation. And every vendor is obviously flying for attention on these topics and terms because that is the next step in our manufacturing journey.

01:52
Speaker 1
So very importantly is what do these buzwords actually mean and why should you care about one or all of them? And hopefully we're going to get some answers today. So today we're in for a treat. We are chatting with Dr. McCallary Hoffman and Johan van Marva. These folks are from pre Lexus head office down based down in the Western Cape, and they describe themselves as not only data scientists, but crafters of machine learning. So that already tells me it's going to be a fascinating chat. Welcome McCallary and Johan. Thanks for joining us.

02:24
Speaker 3
Many thanks for the invitation. Thanks for having us podcast, great to meet you all.

02:29
Speaker 1

Yeah, we did say we typically aim for about 45 minutes or so. I'm not sure. It feels like we can probably talk about these things for a couple of hours, but let's get into it. And maybe as a departure point, if you can sort of tee it off with how you guys came together. I know, McCallary, you were a computer science lecturer at the University of Stellenbosch. That's where a lot of these sort of journey and these things started for you.

02:56
Speaker 3
Yes, indeed, it started there. I also studied machine learning and artificial intelligence as part of my postgraduate studies. And actually about 910 years ago, I spent a year in Belgium and I was doing a postdoc there at the university and I gave a lecture there on my research vision for the future. I mean, at that point I thought, I will become a professor and spend my time in academia. And the feedback that I got was predominantly that, well, it's interesting, but why don't you actually go and do this in practice and do it industry? And after I came back, I worked for a bit longer at the university, but that comment stayed with me. And then eventually I joined with the other co founder of the business, Georgie, and we essentially then started the company with the aim of doing machine learning.

03:56
Speaker 3
And we can discuss maybe later the distinction between machine learning and artificial intelligence, but essentially doing machine learning and AI for businesses. And it was an interesting journey at that point, since eight years ago, when you googled machine learning, you mostly got academic material. And I can distinctly remember some people told me, don't call it machine learning, call it something else, since no one will talk about this thing now. It's funny, it's eight years and to be honest, I think we should have called it something else. Since then, we would have been able to differentiate ourselves maybe a bit better, it would have been a different word. But the long disorders.

04:36
Speaker 3
It was interesting to see how machine learning over the past eight years and even longer, I mean, I've seen my first machine learning algorithm in 2002 as part of my undergraduate studies, and to see how a simple thing like that it was in the context of facial recognition, has progressed now to a point where it's really changing the world.

05:05
Speaker 1
Yeah, for sure. That's a very good practical example, and there's many like them. So before we get into that, I think the last time we spoke, there was something about, I think I probably read it on your website, and it's something that we speak about often is the notion of conscious capitalism. And if you are not familiar with that, there's a book by Ivan Shernard, who's the founder of Patagonia. He obviously started Patagonia, the clothing and outdoor brand. In 1973, he wrote a book, the book is incredible. It's entitled let my people surf or let my people go surfing. Sorry. It's a really great book. And in there he alludes to conscious capitalism. And conscious capitalism obviously is characterized by four guiding principles, which is about higher purpose, stakeholder orientation, conscious leadership, and conscious culture.

06:05
Speaker 1
And one of the things about your website, McCallary, that stood out for me is I think it was the first time that I visited your website, I read that, I can't remember the exact words that you use, but I think you call it purpose before profit. Tell us a little bit more about that and why that is specifically such an accentuated piece of your communication.

06:29
Speaker 3
The purpose before profit, I guess also I started maybe in the world of academia. So when we started, I said that we don't want to become this hierarchical organization where so we have a very flat structure actually. And part of that is, and actually when we start reading on this, we actually discovered something called teal organizations, which is similar to what we structure. Now, we've seen many times organizations where there's just this chase for profit. But in the end, we are a bunch of people who wants to solve interesting problems that can have value to our clients, but also it's interesting for us to solve. Therefore, we see it as more, we have a

bigger purpose, a purpose to take machine learning to the market to help our clients to solve, as I said, interesting problems with value.

07:30
Speaker 3
And of course, once you have a purpose, the value or the profit will naturally come. I mean, in a big sense, our purpose is to solve data driven problems or interesting problems with data. And that kind of drives this thing. There's actually even a bigger thing behind this, and that we align ourselves to the sustainable development goals. So when we pick clients, we make sure that they align to those principles so that we do things also good. I mean, the reality is that many of these people in AI and machine learning can find positions anywhere in the world. I mean, from the Googles and the Facebook to the smaller companies elsewhere in the world. So by being a group of people around here, we certainly want to make a difference. And that is then part of our motto. You want to add something?

08:29
Speaker 4
No, definitely. Because I like all those. The book that you mentioned just now, one I like is capitalism, as if the world matters, and some other books that also focus on this whole idea of doing well while doing good, being a good corporate citizen, and following the triple bottom line of people, planet and profit. And I think what McGowary mentioned now with the sustainable development goals is that's sort of the filter that defines our why. And it's not only about the what and the how, it's about the why. Why do we get up in the morning and when we are involved in different industries. Of course, if there's no profit, there's no company, there's nothing to make a difference with.

09:13
Speaker 4
But once we are in an industry, the question is, how do we focus that on something that will make the world a better place? For example, if we are in FSI, in financial services, then it's all about economic empowerment, it's about alleviating poverty when we are in medical insurance or something else. It's about health and wellness when we are in agriculture, it's about food security or whatever the case may be. And defining our why is very important to us.

09:40
Speaker 1
I love that. I think it's such an important part of, obviously, Simon Sinek talks about the why. And I think that's so often a very important, overlooked part of why do we actually do what we do and how does it fit in the bigger world of things. I love that. I really like that, and well done for that. And especially in the world of machine learning, I suppose you hear all of these, the scary bits about machines taking over nuclear bombs and autonomous tanks and navies. That's the very sort of far extent of what's possible with machine learning and very often the bits that people hear about. So I like that. And I also like that you've built your company around that doing good, because doing good is good business and absolutely the profits will follow.

10:29
Speaker 4
It's very interesting, Jaco, that I, interestingly enough, originally comes from the social sciences side, and my studies was actually initially in ethics and philosophy and so on. And the whole thing of AI ethics and preventing bias and algorithms and all of that is a very fascinating topic. That is opposite topic for a different day. But that also is very important for us to make sure that what we do it well, we do it without bias and discrimination, and that our algorithms is actually responsible in a certain sense.

11:08
Speaker 1
Yeah, no, absolutely is. I can imagine that's a topic for another day, probably a couple of extra hours, so maybe to kick it off in terms of our world. So, lady, we spoke about data earlier and the proliferation of just devices and collectors all over a couple of years ago. A challenge that we had is to get data now today, with the advent of cheap sensors and cheap networks and affordability and scalability, there's too much data almost in certain cases. And you've spoken about being a data driven business or decision making, and a lot of that has changed.

11:49
Speaker 2

Yeah, and maybe to this whole point as well. I think sometimes we as software know, we use these terms a lot loosely coupled as well, and we spoke about this a lot. Jaco, is that the expectation for some businesses now is that AI and machine learning is going to be this all encompassing solution. It's going to solve all my business problems that I have. But it's not true.

12:15
Speaker 3
Right.

12:16
Speaker 2
The reality is a little bit somewhere in between. It can be very effective, but you have to have the right context, you have to understand those contexts and you need to understand what type of AI technology will then apply to your context. It all works best when it applies to solving a specific problem or a very closely related set of problems. And I think that falls into the whole thing. Don't go into this journey just because think about consciously what is the problem that you want to solve before going on this AI journey. And yes, you need to have the data for that, but it works the best when you have a related set of problems that you need to address.

12:58
Speaker 1
Yeah. So when we talk about being a data driven enterprise or business, how important is this, and do you see a lot of that? I'm sure you have a model for how you build this data driven enterprise, but how important is that? Why and what are we trying to achieve?

13:13
Speaker 3
Yes, I just want to also mention now to the previous comments you make. Certainly AI and machine learning, we should not just do it for the sake of it. And it is so important to think about the problems that you want to solve in your business. At the same time, I want to say that one should not ignore this. I mean, there's consensus that if you look at the so called waves of computation. And I'll get back to the other question now that it started off basically with the mainframe and then later the pc, and then later comes the Internet, mobile phones, and it's now considered that machine learning and AI is this fifth wave of mean.

13:58
Speaker 3
If we look at the effect of the Internet, for example, on our lives, I mean, this talk, we're sitting in Stalin, we're sitting up in the north, and that is only possible because we use the Internet as the bad bone. So certainly machine learning can do those things. But back to the data driven enterprise. I almost see data as the fingerprint of your business operations. So you're doing some stuff, and wherever you touch something as a business, you're leaving data behind. And in the same way that you do forensics, to eventually find out if a person was there or should not have been there. I mean, we have now biometrics to allow people in or out. You can use this data to get value out of it, but ultimately that value is still tied to your business.

14:54
Speaker 3
The other analogy that people sometimes use is this ore. So if you think of data as the ore, the gold, or something that you take out of the ground. Now, in itself, if you just take out ground from the earth, that doesn't have value per se, but then there's a process that you have to go through to actually refine this and to get to the pure gold that has now some value. That part is what I believe, that machine learning, AI and also other data processing techniques enables you to take the raw material, your data, and transform it into something that's of value. But that value is only determined by what is important for you. I mean, if you don't wear rings or earrings or whatever the gold is used for, then the gold might not have any value to you.

15:50
Speaker 3
Of course we can sell it, but just to get that value is dependent on what is relevant in your business.

15:58
Speaker 4
So if I can add to that, I'm so glad you asked the question, because you have to know what you are looking for.

In your analogy, if you get the soil from the earth and now you have to distill or get some gold from it, you have to know that you're looking for gold. And that also is driven from what do you want to do with the gold, as you say, the earrings or whatever. I once heard a story of a guy that he wanted to get directions to get to the post office or whatever the case may be. And the person started to describe to him exactly how we should go. And it was a very complex route. Over this robot left at that stop, go over that, et cetera. And then eventually the guy just gave up.

16:44
Speaker 4
And he just said, sir, sorry, if you want to get to the post office, you cannot start the. That's the thing. Sometimes people bring us data, and McGallary always talk about the crystal ball approach. They bring us data and they say, we have data. What can you do? I mean, the question is, what do you want to do? And that's where the business case discovery becomes so important. You have to start there. You can even start further back. We can talk about that as well with your data culture and the people and so on. But the business case discovery is incredibly important. The most simple way of doing that is we use the user story format sometimes with customers and say, well, as a. What you don't want to do what? To do what? I mean, who's the user?

17:31
Speaker 4
What's the purpose that you want to use this for? And then eventually, also definitely look at the value, because that's why the uptake is sometimes so slow of technology in several industries, is because the business value are not properly calculated. But the business case discovery, just to stress the point, is incredibly important. If we don't start there, we cannot get where we want to go.

17:58
Speaker 1
Yeah, I really like that analogy about the soil. And bring me more dirt. Bring me more soil, and let's see what we can get from it. I like that. What are we looking for in this heap of soil that we've just unearthed? So when you talk about the business case discovery, is that the first step to how you build out this, I'm just going to call it data driven business or enterprise, is that the first step? Was there something before that almost establishes a little bit of readiness or maturity or appetite? Or is there something before kicking off straight into the business case discovery?

18:39
Speaker 3
Johannes, the one that can talk detail about this, but I think there's one thing that almost comes before this, and that is a mindset, or maybe even in a belief that data is important to you and you want to make a difference with data. It sounds like it's a trivial thing, but we've been in an institution where that belief does not exist, or maybe the execs or the team doesn't buy into that vision. And if there's not this thing that we believe that data is important and there's a buy in from everyone, then you're not going anywhere. But once that is in place, then certainly once we start looking and start understanding, then what can be done. Do you want to add?

19:25
Speaker 4
You've said it. Well, I mean, the data strategy is actually all about change management. It's about how do you define your business and your strategy in terms of your data assets. So instead of just having it somewhere and having only the it guys looking at the data or having somewhere in.

19:49
Speaker 1
A basement, certain silos.

19:51
Speaker 4
Yeah, certain silos working on it, or bi or wherever, making sure that there's a general data culture in the organization, if you ask me, where does it start? Of course, the business case discovery is a very good starting point, but from there, you should work backwards and forwards. We always use an iceberg analogy and say, well, the machine learning models, the sexy stuff, the cool stuff. I mean, that's the tip of the iceberg, and even that is much more a process of data cleaning and ETL extract transfer and load the data and EDA, exploratory

data analysis and so on, and only then applying the craft, which we mentioned, namely the modeling of the data. But that is the machine learning model. That's the tip of the iceberg. It starts with a culture.

20:48
Speaker 4
It starts with the buy in of executives and of the whole company. As McGallary mentioned, it goes towards business case discovery. But then there's also the thing of data people, who are the people that will be the users and that will be working with this, and how would the data and the results be presented to them? And then very importantly, the data systems. I mean, what does your architecture look like? So therefore, if you would ask me, where do we start? We need to assess the AI maturity levels, whether it's still nascent or more mature.

21:26
Speaker 4
And we do that in terms of assessing the current infrastructure and the current condition of the data sources, et cetera, and then define the ideal and doing a gap analysis and saying, well, if this is the gap, this is the business value that can be gained from that, and that we need to do collaboratively with customers. I mean, we absolutely believe that this is not something that we do on our own. Typical consultants who comes in with a heat and run approach. You are the experts on your business. We also always tell customers, and that is where we need to look at the gaps and then define the features, define the architecture. Is it going to be cloud on prem hybrid, et cetera?

22:12
Speaker 4
And what are the specific tech stack that you will be using, and what's the costing of it, and what's the roadmap of implementing that? So that's the whole process that leads up to the modeling that goes with specific business cases.

22:27
Speaker 1
Yeah, you spoke about the people. And do you find that I must be careful which generation brackets and labels I refer to. I think Nene is a lot younger than me, baby boomer aside. But when we talk specifically around the people in these businesses and leading these drives and these initiatives, do you find that with an introduction of a younger workforce, do you find that there's a lot more of a willingness and an understanding? And to give you an example, years ago went to a mine and it was all about vibration analysis and all of these sort of AI type. I understand machine learning is only a subset, but all these AI type systems and the specific gentleman on the site, I mean, he's been with the mind probably at that stage for 40 years. He sort of listened to this conversation.

23:21
Speaker 1
He said, no, he doesn't need any of that. He just walks and hears something and he'll know immediately if there's something wrong with this mole or whatever this piece of machinery was. He doesn't need a clever system to tell him that. And obviously, those individuals are now, in many cases, no longer with those companies. And all of that tacit knowledge, potentially, that they had is also gone, or tribal, and tacit knowledge has also gone. And I have these younger people stepping into those roles without that sort of experience. Do you find that also playing a role in many cases, just before McGallery.

23:56
Speaker 4
Continues, the know the machines are better at and people are better at.

24:05
Speaker 1
I've never heard that.

24:07
Speaker 4
Yeah, machines are better at and people are better at. You need to define which vibrations is important to be sensed by machine learning models, et cetera. But you won't ignore the vibration if you walk past the machine and you hear the rattle. That's where machines and people. There should be people in the loop and human in the

loop. So just to answer that, it's not one or the other, but maybe McGillery has some ideas on generational approaches.

24:40
Speaker 3
So I don't think we can really generalize. We've seen, actually, in companies where there's, let's say, the older generation, and they're very much interested and keen to explore these things. And then, similarly, when there's younger people, where there's an unwillingness to do that. What I do believe now, and what we're seeing is not believe, what we're seeing is that there's definitely a trend, that more and more people are adopting data driven solutions as part of their operations. So to segment that now into age group, I cannot say. But the trend is definitely growing. And even your smaller companies start looking at what can data do for me, and how can I actually make value.

25:34
Speaker 4
Out of this asset that I have with younger people? They are fluent in data, and tech, on the one hand. On the other hand, I think what older people sometimes bring is the basic knowledge of statistics and mathematics and so on. Not that younger people are not schooled in that, but I think it's important also to realize that we shouldn't generalize, as McAdri said, and think that younger people are just about absent, sexy, cool stuff, and older people are just about doing things without machines. It's really the intergenerational conversations. I think, even within our organization, the older and younger people engaging from different perspectives on mathematics, on statistics, on machine learning, on predictive maintenance, et cetera, the way in which we bring different perspectives.

26:37
Speaker 4
I mean, that's where the magic really lies, in that collaboration and not having to sit at one pole or the other in terms of generations.

26:47
Speaker 1
Yeah. People, process and technology. The technology exists to improve processes that will enable people. I mean, it's a notion or something that's been around for very long. And I'm so happy that you mentioned a value driven approach as well. I think the last research that I saw in this, Lenny always jokes, according to research or recent studies show, but I think it was a Gartner piece that mentioned that more than half of all AI projects actually make it from prototype to full production. And I think the number one or the primary reason was, is because they failed to generate any of the expected return or understanding of what they could get as a return. So I'm so happy that you speak about a value driven approach.

27:41
Speaker 3
Yes, indeed. It's interesting that you mentioned now about this project that's failing, and we've certainly also seen that many times, as you said, now, if the value is not defined, then that's typically a problem to get it. But we also take an end to end view, which is very important for us. In other words, we've been around the block and seen a couple of projects going from the start towards the end. And I mean, you certainly, if you start down this journey, you have to think about all the little things in between. I always make the example when I was in academia and you developed a machine learning algorithm, the end result was an academic paper and you're done. Nowadays, if you're in academia again, you might still, it's now open research, you will publish the code on the Internet.

28:37
Speaker 3
Someone else can go and re implement that. But that's not enough. If you have an algorithm that can be perfect on your data, that doesn't mean it will solve your problem. Then you still have to go through a process of putting this into production, operationalize this thing, and actually make sure that it can run at scale, serve the business the way it was intended to do, make sure you test it and make sure that it behaves the way that you intended it to do behave. And that's why it is important to have this, that book of seven habits of highly effective people begin with the end in mind. I think I read it there. So if you begin with the end in mind, then certainly the chances of success are much higher. Otherwise you end up with that.

29:30
Speaker 3
Many institutions fail or companies failures is that they employ a data scientist and not one. They employ an army of them. And I mean, the skills come at quite a cost. And now the people start developing algorithms left, right and center yet no one has think of value of those things and what do they want to do with it? They don't think about the whole process. And then the problem is once people start burning and they don't get value out of it, then they think, okay, but there's no value in machine learning to start with. And meanwhile, it was not the machine learning that was the problem. It was all the other things around it that caused that. We don't get to your value.

30:13
Speaker 1
We need a data lake. We need to collect data and we need a lake. And we need some scientists to work with this data lake and give us some answers. Answers on what exactly? So you Guys are obviously the experts, I would imagine folks on your team that are engineers and mathematicians and scientists. So you've got theory, you've got the integration or integrating theory with some of the practical lessons that you've learned as well. So give us a couple of examples of some of the sort of industries or verticals or businesses that you've done or deployed, some specific solutions, and some of the learnings and amazing things that these businesses were able to learn from their data.

31:00
Speaker 3
Yes, please fill in. As I talk, one area where we do a lot of work is within financial services, and within that we have a couple of specializations. That one is to understand the client better, in other words, building a so called client smart client profile or a client story, and really to understand the kind of actions that you should take on a client in order to make, first of all, the life of the client easier and make the client happier. But then at the same time, I mean, it will also then give benefits to the financial institution. Part of the things that we've done, for example, there is to look at, for example, bank statements, understanding the transactions. There you can calculate affordability of a client directly from a bank statement. You can understand when a client is about to leave your institution.

32:02
Speaker 3
So that would be churn. You can understand some of the work we've done in forensics, in fraud detection. So there it would be things like, is this transaction a valid one? Or at the same time, should I allow this? Now, interesting enough, I want to draw a quick parallel there of how these things are the same. Let's take for example, customer churn. So that would be when is a client about to leave a company to move to another company? Think for example, insurer or a bank. I'm going from insurer a to insurer b.

32:40
Speaker 3
What I want to know essentially is I want to know how long will this client still be a client of mine, given its history and the history almost regards as its sensor readings, I mean, you can think of my bank account and my transaction interactions as the sensor readings you have. This is the exact same problem, for example, that you will see in predictive maintenance. Now, all of a sudden, the question is just how long will this machine last and when will it fail? And it's amazing that the same kind of techniques that you will use in the one, you can use in the other, since ultimately it's the same kind of underlying question that you want to answer. How long will this thing still last? I mean, it's maybe not nice to talk about a client like this. How long will you last?

33:30
Speaker 3
But if we ignore that part now, for the moment, the principle behind that is the same.

33:37
Speaker 4
How about credit?

33:39
Speaker 3

Yes, in credit, I mean, we've done there also some work, and there it is. Of course, should I give you this loan, grant this loan, and at what price? We've also developed, of course, tools around that to assist them. Maybe it is relevant at this point also to explain what kind of problems can machine learning solve. I think it is relevant to discussion. Now, let's do think of the non machine learning solutions that where you use data, that's typically where you can use a rule. In other words, you can go in your data and you can write down a perfect rule to calculate what you need to know. I mean, if I want to know what is the average salary of a company, you don't need machine learning to do that. In fact, the last time I checked, calculate that directly.

34:35
Speaker 3
But then there are other problems. Let's take a different one, which we mentioned at the beginning of this podcast, a facial recognition. Now, I mean, we all know how a picture looked like on a computer. It's a bunch of zeros, ones, where each pixel is basically the color of color value of that pixel. Now, I don't know. And I don't know anyone in this world will be able to write down a set of rules to classify a face there. I mean, would you say if the color is between, I don't know, these values and it's at this position, and it's maybe combined with this color, then that's a face. I mean, you cannot even comprehend writing rules down. And this is where machine learning is very useful. So now I can give it examples of faces and non faces.

35:23
Speaker 3
So I tell the computer, I don't know how to define a face or not face, but I can give you examples of what I know is phases and non phase. And then the algorithms, the machine learning algorithm, that's where the learning part is. It will look at this data and it will learn. And I'm using inverted commas, the rules, since it's not necessarily explicit rules, but for the purpose of discussion, think of it that way. It will then learn and discover these rules to make this computation. Then we say, okay, but there's a face or there's not a face. So in business problems, it is especially then useful for those cases where it's not possible to write down the exact business rule, especially if there's some noise, we don't know the thing, the answer correctly, then machine learning plays a role there.

36:14
Speaker 3
You can think of it's almost like intuition modeling, especially if there's humans in the loop, they can classify it. So you know it's a face, or you know it's not a face, but you don't know how to get to it. Then machine learning is able to discover those kind of groups. And in fact, the thing that I've just explained to you, nice, is what people would call supervised learning, since I supervise it with examples of phases and non phases. And then the machine will learn this from the example. The other one, while I distinguish between these types of machine learning, is unsupervised learning. And an example here would be, for example, fraud detection. If you look at fraud, you don't necessarily always have all the cases of this is fraud and non fraud, especially at the beginning.

37:09
Speaker 3
You can also think maybe of a machine that's running. If it starts to running just now, you don't have any failures. So how can I give you these two examples?

37:17
Speaker 1
You can't exactly do the duct test when it comes to fraud.

37:21
Speaker 3
Exactly. Then the machine is given all this data and it says, okay, can I identify, let's call it strange patterns or how things are, it's out of the norm. And then these things are then highlighted and presented to a human to make a decision on. And that would be called unsupervised, since I don't give it examples of what's right and wrong. As I said, typical cases would there before detection. Now, I know I took a segue now to explain a bit of these methods, and the question was actually to see what kind of other areas we work you on. Do you maybe want to add more?

38:02
Speaker 4
I like the one that you've mentioned now about unsupervised learning. The other example that I can mention is

when we worked in the retail industry, for example, is customer segmentation. That's also an unsupervised problem where you just look at the data, you look at spending patterns and what the market basket analysis, what do people buy? And then you are able to segment them in different archetypes, if you wish. And that was a very interesting case because we could also see in the COVID time how the patterns then changed and the customer archetypes also changed and new archetypes emerged and so on. So that's just besides the point when you mentioned now, unsupervised learning. Yes, I think, indeed, in manufacturing, of course, you have your predictive maintenance and your remaining useful life cases.

39:00
Speaker 4
We have an interesting one on switch gear, high voltage switch gear with partial discharges. And it's very interesting to then detect, as you say, those anomalies and the business value that create. Now, you don't have to send inspectors every time. You only send inspectors. You bring in the human on the loop. When you see those specific anomalies arising, saving lots of costs to the companies.

39:29
Speaker 1
Yes.

39:30
Speaker 4
In retail price optimization, for example, at which price will a product solve, create the best profit margins, et cetera. So, yeah, many different kinds of examples. In agriculture, of course, you have lots of computer vision going on there currently to see how crops are doing. And then also other machine learning would be to see how your crop, what do you call it, the spray.

40:07
Speaker 1
The.

40:07
Speaker 4
Nutrition and the pesticides and so on, what gives you the best yield and so on. You can predict that because it's all about not only about prediction, it's actually about intervention. It's about having the opportunity to intervene and say, well, if I do this, then this will most likely happen. So it's not only about describing descriptive analytics, seeing what statistics tells us about the past. It's not only even about predicting what will happen in the future. So it's about getting actionable results and insights so that you can then decide on what can you do which will most likely give a certain effect. So that is prescriptive analytics, where you prescribe something and then, okay, we can have a whole debate on correlation and causation, but where you can most likely then give the probabilities for something having a positive response.

41:06
Speaker 1
Yeah, you're very quiet. I think you want to jump in here.

41:11
Speaker 2
I love the concept where only bring the human when he's needed to. I think one of the earliest stories for that was Henry Ford. When he started to automate production lines, he actually paid his people to sit in the break room. That sounds like a very weird concept, but it's exactly that. The more time you spend in the break room, that means the plant is running. You don't have to do maintenance. If they had machine learning, I think Henry Ford would have been bankrupt. Because if you can predict your maintenance, then, yeah, everybody would sit in the break room. Maybe just to bring this a little bit back to manufacturing. I know we spoke a little bit about supervised learning and unsupervised learning.

41:50
Speaker 2
And in manufacturing is actually quite easy, or we try to make it as easy as possible to understand what type of learning do you need to apply on your particular question or problem that.

42:03
Speaker 3
You'Re trying to track?

42:04
Speaker 2
So let's take two examples. A big thing, obviously, as we mentioned on this podcast already, is predictive maintenance. So I want to know, predictively, from an assets perspective, when a mechanical failure is going to cause downtime on a piece of assets. Now, very important to understand that is to understand is the losses that piece of equipment is going to have. Is it frequent problems or infrequent problems? Because for frequent problems, you've got a lot of data. You know exactly what causes the downtime for that piece of asteroid assessment. And then you can actually train your machine learning algorithm, right? You train them on these past patterns of anomalies because you have a lot of them. The model can then understand what is a good outcome from a machine operating versus the bad outcome, right?

43:00
Speaker 2
So it knows exactly what it looks like when it's operating normally versus it's operating in an incident kind of condition. So that's just a little bit. Bringing it back is to understand also, how frequent is it when it's an infrequent problem. Those are the ones that's a little bit more tricky. When this thing only breaks down one or twice a year, you don't have a lot of anomaly detection. It's only a few batches from a process perspective that fails the test or the Qi or the quality test. And for that type of data, unsupervised learning is probably the better option to go. So we like to divide these things into quadrants. Is it high frequency failures? Is it process driven versus asset driven?

43:45
Speaker 2
And that kind of gives you a little bit of just a guiding step into what type of machine learning algorithm being unsupervised or supervised do you need to go? But there's so many terms. I mean, there's AI, machine learning, deep learning, regression analysis. I mean, we spoke about just normal moving averages and averages. It doesn't have to go this deep, I suppose, or it can go as deep as what the problem is to solve.

44:13
Speaker 1
It's all about your capability to make the best informed decision that you can. So how far do you want to take the rule even go beyond that? And I love the example that you guys have spoken us through in terms of the financial world and credit. And I can absolutely understand from a retail consumer. I mean, I was fascinated last year. I think a lot of people still trying to get the hedged around IoT and now there's something called IOB out the Internet of behavior. I was like, okay, what is IOB all about? And I can understand a lot of the sort of consumer financial world is driving a lot of that.

44:49
Speaker 1
But when I again bring it back to manufacturing outside of just asset lifecycle and getting the most out of a piece of equipment, I mean, there's got to be incredible value in deploying some of these sort of methods and learnings in our manufacturing world. And I'm fascinated that it hasn't evolved a little bit faster than what it has in manufacturing world. And there's so much benefit to be obtained from unlocking all of this value sitting in the data. I'm amazed that it's taken the manufacturing world so long to get there.

45:28
Speaker 3
Yes, of course, one can ask now, why is it the case? Certainly I don't have the correct answer. There can be many reasons, but it could probably start with maybe there is not a mindset or a belief that it can make a difference. I mean, the reality is the manufacturing world is already highly optimized and there's a lot of things going on there. You can't almost believe that there can be more value from the data. It could be at that point, it could also be related to manufacturing systems. Setups are typically quite advanced. I mean, if you think of all those sensor data and things that flows in can go at quite a speed. And if your data systems can't handle that, then there's no chance you can unlock the value later.

46:23
Speaker 3
I can remember, for example, a mind contacted us once to do an exercise on predictive maintenance and actually on understanding when the plant will go down. We did a nice tour. I've had my heart rate on understand the system, and at some point I walked to them and said, okay, but where is this data now, since we must work with it? And they had a small server there. And I said, oh, that's interesting. We're able to store all the data here since it's basically like a pc under the desk in the office of the operation. And then they know, but we actually delete the data every month since there's no space. My conclusion was then to them, okay, but it will not help us to do, we can't do anything for you.

47:09
Speaker 3
Get a new server, store the data for longer, and then we can have another discussion. So it might be those things then. At the same time, I should add, there is also a lot going on in the field. I mean, Johanne did a bit of a survey quickly this morning, I guess a desktop research, and there's certainly lots of cases of where predictive, not predictive, where machine learning can be used within the manufacturing world. I mean, maybe, Jan, you can highlight those things that you find.

47:41
Speaker 4
Yes, I think mostly things that we mentioned already and that you guys know very well. It was just interesting to me when I did my bit of, how did you say? Research suggests, studies show that 30% of the AI in manufacturing is maintaining machinery and production assets. That is indeed money. Yeah, absolutely. But it's important what McAdry said, that the proof of value is probably preventing the takeup of machine learning in the manufacturing industry, because like you said, it's so incremental, the improvements that you now get with the data. And it is actually, if you make the calculation, then over longer periods of time, you will show the value and the profit. But it seems like you said, it's almost like this mindset that's holding one back. Yeah.

48:43
Speaker 4
So, predictive maintenance, like we said, cameras on robots, and then of course, the other thing is demand forecasting and inventory management and selecting raw materials, et cetera. Those are, in my mind, the two main areas of application at the moment is, like I say, the predictive maintenance or the real time monitoring of machinery, and then demand forecasting and inventory management. And there are other things, of course, the robots, price optimization, looking at the cost of goods, et cetera. But it was just interesting to see that those are the two main areas. The demand forecasting and inventory management is an interesting one because you don't want cash tied up inventory, but you also don't want to lose stock or lose sales with out of stock occurrences.

49:39
Speaker 2
Do you think maybe there's also a perception of the complexity of this?

49:45
Speaker 4
Yeah, I think so. And what of course adds to that is the fact that infrastructure is so important, so people feel a bit, I almost want to say, overwhelmed by the complexity of the tech stack. It's difficult to make the decision, should we move to cloud, should we be on prem, et cetera? And because of the hype around AI and machine learning, it sounds so complicated. Now, don't make the mistake. I mean, it is complicated but there are ways to simplify the process, at least so that users are able to fairly easily utilize the technology that we have. But it's definitely about the complexity not only of the modeling, but of the whole process, the end to end process, like you mentioned earlier, the scaling of the process, the monitoring of models, the productionization, all of that.

50:44
Speaker 4
It is scary if you want to start out as a company that wants to deploy machine learning in your environment and you don't know where to start. So that's where the maturity process comes in. But it definitely is scary if you're not used to it already.

51:04

Speaker 1
Yeah, I'm really excited. If we spoke about consumer behavior a little bit earlier, I'm really excited. And you already hear whispers of a lot of these sort of manufacturing companies that are looking to marry a lot of the consumer behavior data and predictive models that they have around launching of new products and the ability for their production or manufacturing to deliver that new category or that new product within a certain amount of time. And there's a lot of that happening or starting to happen where they're marrying that behavior or expected product success or failure or whatever the correct term is.

51:46
Speaker 1
I'm not an expert in the consumer space, but marrying that demand and that need and that viability with what production can actually do based on, for example, past experience or current capacity, I'm really excited to see those two worlds come together in this space. And I think that's potentially where a lot of these manufacturing and production companies are going to see incredible value if they have the ability to marry those two walls of behavior.

52:16
Speaker 4
That's also typically where your recommender systems comes in. And it's interesting how that can be done right or wrong. I mean, we all know this obnoxious way of and how annoyed we get when the recommender systems get it wrong, when they keep spamming you with things that you don't really don't want, or you have bought it already or you googled this and now you get these recommendations all along. But we also know how incredible it is. If you get a movie recommendation or a book recommendation or a product recommendation, that's absolutely spot on, as if they read your mind. That is how important it is. If we get it right, we will have better uptake. If we get it wrong, it will change the perception for the worse. In terms of the uptake of machine learning and AI.

53:08
Speaker 1
Yeah, definitely. Sure. We're running what are we on time then? All right. In terms of where to begin, how to start, you have a toolkit or you've constructed or devised your own toolkit to help individuals and businesses on how to get learning on this. You want to maybe give us a quick recap of that or what it consists of, or how to get started?

53:35
Speaker 3
Yes. When we actually started many years ago, we realized that there is a lot of repetition when you do these kind of things. And so what we've done is we've packaged these things as a toolkit together, so that on the one end, it gives you kind of a roadmap for change. And you can also think of it as almost as the business aspects of it. So what do I need to do in order to get machine learning ready and also get these things going? And then at the same time, you also then have things automated around the technical parts and the things needed set up to do that, since, I mean, if we look back.