Episode 14 Adventures of Analytics Models - 28.2.2023, 16.16
Length of recording: 32 minutes

Transcription notes

N:	Narrator
GB:	Gautam Basu
PM:	Pekka Malo
wo-	an unfinished word
(word)	an uncertain passage in speech or an unrecognised speaker
(-)	an unrecognisable word
(--)	unrecognisable words
[pause 10 s]	a pause in speech of at least 10 seconds
, . ? :	a grammatically correct punctuation mark or a pause in speech of less than 10 seconds

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[intro music]

N: The Operations Leadership podcast with Gautam Basu provides insights for today's business leaders on creating value through operations improvement, process excellence, digital innovation and organizational leadership.

GB: Our guest for this episode of the Operations Leadership podcast is Pekka Malo. Pekka is an Associate Professor in the Management Science department at Aalto University's School of Business and he has an extensive background and experience in quantitative analytical models including artificial intelligence, machine learning, natural language processing and multi-objective optimization to name a few. He has developed, built and implemented these models both in a research scientific as well as a business context. So, we hope you enjoy this conversation with Pekka, and if you like what you're hearing, then we kindly ask to you hit the subscribe button. Enjoy.

[intro music ends]

GB: Hello, Pekka and welcome to the Operations Leadership podcast.

PM: Yeah, hello. Thank you.

GB: Alright, great. Could you tell our audience a little bit about your background and experience and mainly what got you into or interested in management science, operations research and maybe (math) in general.

PM: I've got a background in quite a number of disciplines. So, mostly in mathematics and statistics, but then I also have done a business degree. The reasons why I mostly got interested in management science and operations research was that it offers a nice intersection between the practical side and the technical disciplines. So, it's not just doing theory, but also nice applications.

GB: Yeah. I can imagine that with the increased attention on business analytics and multi-national companies using analytics and AI and machine learning that that is also quite a hot skill.

PM: Yeah, there's a lot of demand, yes.

GB: Good.

PM: On that side.

GB: Very good. And you also have an extensive background with many of these quantitative models. We mentioned AI, machine learning, this multi-objective optimization. So, when you look at a certain application or a problem, could you describe your process for picking the appropriate mathematical model for the given, let's say problem or application?

PM: Yeah, well. I mean, clearly this depends a lot on the problem. So, there's not like a general pattern which works for all of them, but most of the time the problems we find interesting are the ones that cannot be directly solved with existing tools. So, that's the research side focus. So, as researches, we are essentially looking for problems which have something to them, why they are challenging and why there is some motivation which needs to be important enough to develop a new method that can address it. So, that's the kind of a side what we mostly take. But then, of course, when looking at consulting projects and so forth, so there the setup is quite different. So, one rarely develops new methods, but instead it's more like applying how they are relevant. When they're data-driven problems, a lot depends on what kind of data it is, what is the objective, what are they trying to achieve with it. And it's really conditioned on the data and the quality and also like, what sort of a background, skills, does the company itself have, and then so forth.

GB: Right. You mentioned something interesting, I mean, in that, for example in consulting versus the scientific research world, that in scientific research you have to maybe build the models from scratch. But in consulting you may just apply an already existing model. Could you talk a little bit more about that?

PM: Well, the reason why one typically tries to address the consulting problem is because of speed. So, if you cannot wait that you get the better solution, you have to get something that just works sufficiently. It might be that for instance you may need to then accept that the method and the problem are not completely matched even. So, you're accepting some degree of violation also of the conditions and so forth. But just to get results. Also many of those problems are such, that if you'd really want to genuinely provide a good solution, it would take a lot of time. Because then it's a research problem once again. And that's especially when it's about prescriptive modelling, so like when you deal with optimization and things like that, it tends to be difficult. Whereas when you're just solving a data-driven problem, predictive analytics for instance, then you know that you might get better results by applying some other approach, which would just take so much more time to implement, but you'd still know that well, yeah, you get something at least done.

GB: Right. And I mean in your kind of experience, if you had, let's say your time constrained. Let's say the deadlines are coming up et cetera, I mean. How much accuracy, maybe accuracy is not the right word, but how much better would a solution be, if you had more time? Let's say you had one month versus one year.

PM: That can affect really a lot. In many of the problems getting more time, if that strict time constraint is removed, the quality can improve a lot.

GB: Okay.

PM: Especially in prescriptive problems.

GB: So, prescriptive meaning more normative, technical (outputs)?

PM: Yeah, when you're really solving also mathematical optimization problems, so. There it's often the case that it helps.

GB: And in management science and quantitative methods and especially analytics, you have the segregation of diagnostic, descriptive, predictive and prescriptive. So, where do you see the analytics and kind of these models? Where is the majority? Is it going to predictive type of models, or?

PM: It's in descriptive and predictive. So, I mean. Because they are easy, and you can quickly get something done. And the thing is that they are also setups which are not so demanding regarding the background skills of people. So, like, if you know to a good extent programming and you know at least some of the underlying assumptions of the models, then you can sort of use them for that particular problem. So, then it's very easy. I mean, they are so nicely packaged, the tools exist, there are plenty of libraries, so. It's really not so much demanding on like research (grade) skills, but instead it's more like routine tasks. And also in the foreseeable future I would say that larger and larger amounts of these will be automated. The routine stuff gets automated whereas the ones where you have, for instance, something is wrong with the data, something is happening there, that though you know that you can kind of apply these, then you still need to do more to make it work. Then it's kind of creating still good slots for people to excel.

GB: Sure. And it’s interesting that you mention that some of these more predictive models, especially around (forecasting), I’m thinking specifically around sales and operations planning or integrated business planning, where you do statistical demand forecasting. Do you think that that will be automated also in the future?

PM: To some extent, but I mean there are also always dangers in the automation. So, unless you have a very nicely controlled setup and a predictive problem where you sort of know that the underlying process is at least stable, stationary in some sense, so then automation can work nicely. But if you have processes that tend to change and develop over time, there can be structural breaks and all that sort of stuff. So, then it’s increasingly more difficult to automate, because you need to make also judgements that, to what extent you can use the historical data, because it might get already outdated just because there’s, for instance, a law has changed or something in the economy has changed, there has been new, major technology that has caused dramatic change. Or, if you’re modelling like sensor data, if the machinery gets replaced, well, it’s a new process. I mean, what do you do with the historical data then? It’s not perhaps anymore relevant then.

GB: And so, there’s a bit of, let’s say, uncertainty there, whether it’s the actual machine or macroeconomic or some other stuff. Is that even possible to model that uncertainty, or would you have to? How would you build a model for something like that, with something like, as you said, a structural break?

PM: Well, some of structural breaks are that you know that okay, this is going to happen. If you’re purchasing new machinery, then you know that it is going to happen. Or if there’s a change in legislation forthcoming, then you know that in advance. And there you also know that okay, at that point there’s going to be something that most likely needs to be taken into account. But things like, this classical term, the black swan style (-) [11:17], things that change things a lot but are very unpredictable. They of course (-) [11:26] coming. You do what you can after that, but at that point usually the models tend to fail quite a bit.

GB: Yeah, that makes sense. And you in your career have worked in some interesting projects in the natural resources and forest management domain. Could you describe a little bit more about these projects? I know that you might be under some sort of NDA, but I mean, what you can describe in these type of models?

PM: Well, that’s a very long-term project and it’s ongoing, so. It’s a combination of research and the industry side work. In that we have been developing algorithms for solving optimal management problems. I mean, it’s always a difficult problem and there are a lot of components with uncertainty that need to be included in the models. But it’s kind of solving stochastic optimization problems. And we use machine learning as a part of that.

GB: Is that, like the application just forests in general and the planting and the harvesting?

PM: We have been now mostly focusing on the management of (Nordic) forests, because they are. I mean, of course there are all kinds of different forests in the Southern Europe and such. They are very different types. But now that there exist high-quality ecological models which, of course, we take those as given. So, based on them we then solve these problems and the quality of the ecological models then also affects what is the quality of the solutions that we produce. So, we can, of course, improve the methods, the algorithm side, but we cannot really decide ourselves how will the ecological model work. Because that's developed by other people.

GB: Right. Interesting. And you said this is a multi-year project, that you?

PM: A very long-term project, yeah.

GB: Okay. And have you worked on any of these type of models, maybe for supply chain management or logistics or even a service operations context?

PM: Not these type of models. On mathematical programming, yes, in logistics, but that was done as a kind of a confidential job for a company. But not so much.

GB: Okay. (Because) it has a deep history, of course, with the operations, like network optimization and things of that nature. So, going back a bit to what we were discussing regarding the rapid adoption of these advanced analytic models. What do you see as the, let's say barriers for successful adoption of these types of tools, within, let's say a business organization that's looking to gain or build core capabilities in these analytical models? What do you see as a barrier for adoption?

PM: Well, I mean a major barrier, of course, is like how the top level management takes it. Are they going for it or are they against it. Also, of course, like the people that are working there. Are they approving it or not? I mean, it's quite a lot about people, not that you could say that yeah, here we have a solution, use it. No. Then, if they have doubts for whatever reason, they will not want to use and also it's a complicated process to also like, even when the top management says that yeah, do this. But if they don't really understand, what is the current state of where they are now, what needs to be done, so it can get really messy and difficult to get.

GB: So, it's essentially the management buy-in from the top executive level?

PM: Yes, and the resourcing. It doesn't happen overnight. Like, of course, in smaller companies it's easier, because you don't have so much of legacy stuff going on there. But in general, it takes a lot of time and it takes investments into setting up the teams. You have to have also, the data side needs to work well. And also the processes where you plan to integrate these solutions, you need to kind of be able to prepare for it. So, how do you do it? How do you take advantage of it? And also, that of course affects also that what kind of a solution you need to get.

GB: Yeah.

PM: It's not like you can provide an off-the-shelf solution and say that well, here it is, just do whatever.

GB: There needs to be training.

PM: It won't go anywhere.

GB: Yeah. You mentioned the people part, so I can imagine that there is kind of a talent deficit for many organizations that want to embark on increasing these analytical capabilities. So, what is your advice for companies that may be managing this shortage of labour talent? Especially with these types of skills.

PM: That's of course putting kind of a price tag on how much they want to spend, but the most important thing I would say is to start from the management side. I mean, at least one of them needs to really understand what is going on and not just know that okay, we have this hype and we have all these kinds of things going on. But you really need to understand and also to a good extent know that how will it be done really on the kind of ground level, like in practice. So that the management can provide realistic expectations, realistic resourcing. And then they are better also able to match like, okay, we have this problem. And they understand the complexity level of the problem and they know what the current state is and what sort of resources they need to put in, if they want to pursue it. And if that kind of knowledge is missing from the management completely, then they are at the mercy of consultants or someone else and the process can get dangerous and it will be difficult to succeed.

GB: Sure. And I understand that, you know, obviously working in the university and being closely involved in the Business Analytics programme, you're involved with obviously the education. Is it possible to, let's say, upskill or retrain somebody that may have had a degree in statistics 10, 15 years ago to some of these newer models that you're talking about?

PM: Oh yeah, of course. I mean, what these newer models are, most of them have been invented a long time ago. But it's just that the computational side has picked up, so they can now be implemented on a scale that is hugely large, like neural networks. The components, what they're using, like many of them are kind of ancient. But they're able to stack them up and arrive at much bigger models. And I'm of course not saying that there haven't been any proper innovations. Of course there's been proper innovations as well, but the groundwork has existed there.

GB: So, in your view, if somebody is skilled in, let's say, mathematics or statistics, then it wouldn't be that much of a difficult jump to these newer models?

PM: No, it wouldn't. And also, if a business guy wants to get an understanding on the background, not wanting to aim for a technical position, but to become a person who understands sufficiently and is able to manage the stuff, I mean, that's also very much feasible. But starting with the business side and then aiming for purely technical side, that will require almost completing another degree in computer science in parallel, or stuff like that.

GB: That's interesting. And speaking of innovations, what is you view on these generative AI tools such as Chat GP which has garnered a lot of attention in recent weeks?

PM: Well, there's a lot of hype, nice thing. But if commenting as a researcher, very tricky to really see, what is the true value of that. There is an innovation, yes, but it's also quite difficult to evaluate from a research perspective. And most of these modern language models that are being used is that in order to replicate it you would need a budget of say, 10 million euros or so. Easily. Or even more. To just get the same thing retrained. It's ridiculously costly. So, I mean, that already setups like a major hurdle, like why as a researcher we may not have such a huge interest for a particular model that there is. So, rather it would be more like seeing that is there something on the technical side, the underlying elements of it that could be improved. But even there it would be then, like if you arrive at another solution, then you have the computation issue again and spending of money. So, it's a nice thing, but also these technologies, like. They're trained on huge data sets and it takes also a lot of critical attitude and a critical mindset from people. When they apply them, they need to also be aware of how it works, the main ideas at least, in order to be able to protect against the mistakes that these do. Because you can easily get misled by the results that look on the surface appealing and good, but are absolutely wrong.

GB: Yeah. I've heard that that is kind of a complaint, especially with this program, that it's giving out biased output. Was that actually programmed before to have that kind of a bias there?

PM: Usually in the machine learning things the bias is in the data and the setup. It's not that intelligent, at least the ones that are currently known. I mean, none of them are doing genuine inference, like humans do. But instead, I mean, it has the data, it has seen a lot of stuff and then based on that, it generates what, based on its history, seems reasonable. And there the machine, of course, itself does not have any ability to judge whether it's giving a biased output or not. Of course, one can intentionally create models that are biased, but that would be very rare and a very weird thing to do. Biased in a sense, like, that you would want to deliberately create a system that can mislead in terms of its answers. That doesn't sound like, yeah. No, no.

GB: Yeah, well. It’s, I guess.

PM: Possible for some evil things, but no. No, no.

GB: And I guess there’s a lot of new competitors now coming up with these generative AI as well from Chat GP. So, is that something that you see a lot of competition in the future with these kind of natural language processing (-) [24:23]?

PM: A lot of competition, but among those who have the budget. So, I mean. In order to compete in the field, you need to have this huge budget to invest. You need a lot of computational power to do it. That of course immediately puts a limit on whether you’re able to do it or not, or whether it even makes sense to participate in the competition.

GB: Got it, yeah.

PM: Just because, like, even if you want to evaluate one of the solutions and say that you want to still improve it, so you kind of have even higher demand for the computational power then.

GB: Understood.

PM: And so far it seems that the performance of these models has improved as their complexity has increased in terms of how much units are being stacked up, so.

GB: Interesting.

PM: They’ve just grown crazy big. The underlying mathematics is actually surprisingly simple, if people look at what it is, but the sheer size of those things, it’s so insanely big now. And it’s growing still.

GB: It’s growing still, I guess, with the number of training data with people inputting so much stuff, it just keeps going.

PM: And also, people are nowadays applying also other algorithms to generate these, for instance, neural architectures. So, you can have sort of automation or so in trying out what kind of stuff will work. So, they can generate these network structures which are then just tried out and you’re running like a competition between a huge number of architectures. It’s kind of automatically creating the best out of a larger pool of trials. So, there are clever algorithms built for that purpose and it seems that in some cases they are outperforming human engineering, even. Machines can create better architectures than people. Well, a part of that is that, I mean, they are already (-) [26:47] for people. People understand that when they add a certain component type into the, they understand, of course, like we have meaning why we do this. But when they kind of replicate it and just increase the size of the model, scaling it up, so then it gets very difficult to say at the end, that.

GB: It's fascinating. How do you see the next, let's say, five to ten years' evolution, let's say, in the field of these analytics? And that's kind of a broad term, but using, let's say, mathematical quantitative models to solve these various applications. How do you see the next five to ten years developing?

PM: The development, in some fields of course, it can be very rapid and so. But in general I would say that, of course, the standard tools are already available. Their reach is just growing. So, the basic things get available for most and they will be able to use them. So, the kind of basic building blocks of analytics will get very commonplace and also standard predictive analytics is likely to be increasingly common. But then, what is still going to be more challenging, is that if you try to move towards the prescriptive side like coming up with strategies or policies, like what to do. What should be done, given that you're taking all these things into account, so that's more difficult, because it also involves a lot more of the human side there to define what are the objectives, (under) what sort of constraints and that kind of stuff.

GB: Right. But do you see, let's say, in the next five years, maybe 10 years, that prescriptive models will be more commonplace?

PM: It's going to increase, but it's also limited a lot, that. Like, okay, there's the understanding side on the manager side, but also there isn't a huge supply of people, who can actually do it. So, there's a lot more people who can do predictive analytics. But that's more difficult.

GB: Right.

PM: And also because it sets up skill requirements more in mathematical programming direction.

GB: And I think you're playing, let's say, a part in this (role) for developing the young, eager minds here at Aalto University with the Business Analytics curriculum.

PM: Yeah, to some extent.

GB: Yeah. And do you keep in touch with some of the graduates from this Master's Programme? What are they doing these days?

PM: Well, some of them I know. People have established companies, even. They've had already some ideas while they've had their studies and picked up companies, but. Other, I mean. I haven't kept contact with many of them. Just a few.

GB: Alright. I can imagine that they're very much in demand.

PM: Oh yeah. But it's also like, often people struggle to define what is the kind of a title they have. What does it mean? Are they going to introduce themselves as business analytics or are going for data scientist type of things? And that can depend quite a lot on the particular blend of studies that they have acquired from Aalto, because you still have the same degrees and so, but what is under each particular degree can vary so much because we have now the opportunity that students can take courses all over the place. So, I mean, they can basically themselves decide what sort of profile they want to create. It's not us deciding that. That's what you get, but.

GB: That's the beauty.

PM: It's really good.

GB: Excellent. Well, this has been a fascinating conversation. I'd like to thank you, Pekka, for your time.

PM: Thank you.

[outro music]

GB: That's it for this episode of the Operations Leadership podcast. I'm your host Gautam Basu. If you like, what you're listening to, this podcast series, then please hit subscribe and until next time.

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