SuperDataScience

SDS PODCAST

EPISODE 1015:

MATHEMATICAL OPTIMIZATION IN THE AGENTIC AI ERA, WITH GUROBI'S JERRY YURCHISIN

Jon Krohn:	00:00:00	Large language models will confidently tell you they've optimized your entire business while quietly ignoring the one constraint that could cost you millions. Today's episode is about the AI technology that makes breaking a constraint mathematically impossible. Welcome to episode number 1015 of the SuperDataScience Podcast. I'm your host, Jon Krohn. Today, Jerry Yurchisin, manager of decision intelligence strategy at Gurobi Optimization, returns for our annual deep dive into mathematical optimization, the decision-making technology relied on by the vast majority of Fortune 100 companies. In this episode, Jerry Leza, where optimization fits in the agentic AI era, why LLMs formulating problems and solvers like Gurobi guaranteeing the answers. And he shares striking mathematical optimization applications, spanning energy grids, retirement planning, and the model that powered USA Cycling's women's team to a gold medal at the Paris Olympics. Enjoy. This episode of Super Data Science is made possible by Anthropic Notion and Excel data.
	00:01:04	Jerry, welcome back to the Super Data Science Podcast. How's it going? Oh,
Jerry Yurchisin:	00:01:09	It's going great. Jon, thanks for having me on again. I'm looking forward to diving into some more cool topics, optimization, and all around.
Jon Krohn:	00:01:18	For sure. For people who don't know Jerry, this is not his first time on the show. He's been here for a few years in a row. We do this kind of annual focus on mathematical optimization, which I hear from listeners is very important because we don't hear nearly enough kind of anywhere on any channel about mathematical optimization, which is a really important quiver to have in a data science role or in an AI engineering role. It can solve all kinds of problems that machine learning and statistics can't. And I know I relayed to you just before when we were doing a prep call for this, that we have a regular listener to this show. I won't name him, but he's

		probably listening. He's in Philadelphia. And he told me that his favorite episode every year is the one with you in it because they use mathematical optimization in their business and he always learns so much about it.
	00:02:16	So fantastic. I love it. I love
Jerry Yurchisin:	00:02:18	It.That's
Jon Krohn:	00:02:19	Great
Jerry Yurchisin:	00:02:19	To hear.
Jon Krohn:	00:02:19	You're probably calling in from Virginia again as usual.
Jerry Yurchisin:	00:02:22	I am. Yeah. I have yet to move. Don't plan on it anytime soon. So yeah, near DC, Northern Virginia, as always.
Jon Krohn:	00:02:30	Nice. And so for listeners who've never heard your previous episodes, quickly, what is mathematical optimization and how is it different from the machine learning or statistical approaches that usually get covered on a data science show?
Jerry Yurchisin:	00:02:42	All right. Ready? Set. When you think about solving a problem, there's a bunch of different angles or a bunch of different sort of sub-problems. There's a bunch of different ways to approach it. And a lot of the typical methods that people are getting sort of shown or you're used to using, be it machine learning or sort of pure statistics simulation, nowadays everything's agentic and stuff like that. They all solve a certain set of problems very well. Certain set of questions, give an input, you want a certain type of output, you get that. What mathematical optimization does differently is it focuses on decision making. It focuses on what to do with the forecast, what to do with perfect knowledge of the future that we always get from all of our machine learning models. We all know that accuracy 100% is there. But it focuses on, okay, what should I do next?

00:03:40 How should I plan my business decisions in the next year, the next quarter, the next week, the next few hours? What types of decisions am I able to make? How am I restricted in those decisions? And what's my overall goal? And those three parts right there sort of outline the basic building blocks of a mathematical optimization model where you have what we call decision variables. What are the things I actually have control over? What decisions am I making? How much of this certain type of product am I going to order versus this type, versus this type versus this type? What are my constraints? So how much money do I have available? How much budget do I have? How much maybe storage space do I have? Or things like that? How much of a diversity measures do I want? Do I want to make sure that I have at least 30% of my product is this type and 20% is this type or something like that?

00:04:35 And then there's some sort of objective. I want to get all of the things I need to get, order all my products at minimal cost or maybe maximize some sort of anticipated customer satisfaction or something along those lines. But if you have a problem that sort of checks those three boxes, I know the decisions that I can make. I have control. I know what I have control over. They may be influenced by outside things or something like that, but I know what I can control. I know how they're constrained from a sort of a business role perspective. Budgets, if I do this, then I must do that. Or if I do this, I cannot do that type of things. And then I have some sort of objective that I want to maximize or minimize. So be it profit, revenue, or you're minimizing cost, or you're sort of minimizing something like carbon footprints or something like that for sustainability efforts.

00:05:31 If you have any problem that has those three sort of characteristics, then you might be able to use mathematical optimization to solve it. And what that does is that essentially you as the modeler understand the business problem. You then translate it, translate that

		business problem into a series of inequalities or equations and things like that. And then that's when you code it up and that's when you're sort of done. And that's when you let a product like Gurobi take over. And what Gurobi does is it gives you the value of those decision variables that are guaranteed to meet your constraints, but then also push that objective function as high up as you can, if that's what you're looking for, or as low as you want if you're trying to minimize. So it's essentially just a different sort of problem solving framework. When you think about a machine learning model, it's built to do the prediction.
	00:06:28	It's not built to understand your whole business system or your whole decision making system. It can help, but it doesn't do that natively. And it's sort of all that logic just isn't necessarily built into that. So it just solves a very different problem. These things work hand in hand together as they should. And any sort of, you sort of mentioned as an arrow in your quiver type of thing, that's how we view optimization as something -
Jon Krohn:	00:06:56	Arrow in your quiver. I said that completely wrong. I was like, quiver in your. What's the thing you put in? Quiver in. Yeah. On
Jerry Yurchisin:	00:07:07	Your back. So
Jon Krohn:	00:07:08	To kind of recap, optimization allows you to solve problems that you wouldn't be able to solve with probabilistic approaches like statistics and machine learning. It allows you to, you talked about a scenario where you have lots of variables that you can model, and those are known variables. So you could have hundreds or thousands of variables. You code them all up, you identify them, and then you have constraints on those. So I have this many trucks, I have this many truck drivers. I have this many pallets that need to be delivered. And so you could have hundreds or thousands of those kinds of

		different variables that could have a specific range and that can actually, you can model in a mathematical optimization problem interplay between all of those different variables where like you were saying, okay, if this one is true, then this other one must be false.
	00:08:02	Those kinds of relationships. And ultimately all of those input variables are to, as we often see, in statistics and machine learning to optimize some objective function, which could be maximizing a value like maximizing profitability or minimizing a value like minimizing time to delivery, something like that.
Jerry Yurchisin:	00:08:25	Yeah, exactly.
Jon Krohn:	00:08:26	So yeah, so we definitely, we see mathematical optimizers based on episodes with you and some kind of light real life experience I have that we see this the most with things like logistics, supply chain. Those are fields that use mathematical optimization all the time. But there are also, we're going to go into examples today in energy, financial services. I think you have a USA cycling example. We'll get to those much later in the show. But there's a very, very wide range of industries that could be making use of this approach.
Jerry Yurchisin:	00:08:57	Yeah. And when I sort of went through my spiel about it, nothing about what the decision variables are and what the constraint. It's never industry specific, never a problem like, oh, I'm only doing this for supply chain. I'm only doing this for scheduling. No, if any problem that meets those characteristics that has those things, you can use. So yeah, it's all over the place. And your imagination sort of is the only limiter there. And
Jon Krohn:	00:09:26	We're also going to talk about as people think about, oh, wow, I imagine maybe this kind of problem that I have in my business or maybe even in your personal life that could use a solver like Eurobi, could use a mathematical

		optimization approach. At the end of the episode, we're going to get into brass hacks about how people can be learning specific resources that you and others have created. Jupyter Notebooks, Python code, video courses, all those kinds of things. So stay tuned. We'll dig into the latest and greatest stuff in mathematical optimization in this episode. And then we'll have practical ways at the end for you to be able to learn all this stuff. Let's talk about Gurobi a bit specifically, because it's a business that once you hear of Gurobi, you start to notice it everywhere, I find. It's a B2B business. So it's not like a consumer business that you see Pepsi ads all the time or Nike ads all the time because it's not typically considered to be a consumer product.
	00:10:28	But in the B2B world, pretty much everyone knows it, especially in big enterprises. We've talked about this stat before. It's something like 80% of Fortune 100 businesses use Gurobi optimization, right?
Jerry Yurchisin:	00:10:41	It's something up there. The statistic changes a lot or not a lot, but it changes enough to where I kind of like, okay, this is what it is now. But yeah, a ton of those businesses, big ones, middle one, mid-size. We're sort of all over the place in terms of size and scale and everything. Not just industry. You don't need to be a huge company. You don't need to be massive to use optimization. It definitely helps. But yeah, we have use cases where it's sort of like mom and pop shops, bakeries, and then mid-size marketing companies and then big, massive companies with where you see the logos and you're like, "Oh, okay. I could see why they would be using something like this for their logistic needs or something like that." But yeah, all over the place in terms of size and scope.
Jon Krohn:	00:11:32	To teach people about how optimization works, to sort of develop an intuition around it. In previous years, we've talked about a game that you had built at Gurobi called

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		the Burrito Game, which was free to use online. But Gurobi has just released a new one, right? Do you want to tell us about that?
Jerry Yurchisin:	00:11:50	This is about as hot off the press as you can get. We recently followed up the burrito optimization game, which has been sort of super widely used by us as a teaching tool, but as a way to communicate optimization, as a way to sort of get into educational programs as well. We have a game that's called Grow Bean. And the point of Gurow Bean is to, it sort of simulates a coffee shop where you're seeing customers come in and depending on what round you're in, they're going to come in. If you're familiar with queuing theory, it is built around that. So you have customers that arrive at a certain rate. And what your decision is, is how much of certain types of coffee to have sort of prepared for a certain amount of time. So you can just like, I have my coffee ready to go.
	00:12:46	Someone orders a hot cup of coffee, you pour it for them, boom, it's there. They move on their way. So how much do you want to brew at a certain time in order to make sure that your customers are satisfied? But then you could sort of think about, okay, well, if I brew one cup per person that comes in that says that's going to take forever, they're going to be dissatisfied, they may leave, stuff like that. But if I have too much, and I just have all of this ready, then you're going to probably might be wasting a lot of stuff. So a lot of your raw product as in your beans and things like that. So it's all about finding that middle ground. And that's what sort of optimization kind of is, is like, yes, I want to make sure that I'm making my decisions that really affect the objective that I want.
	00:13:32	So in this case, it could be you want to make sure that we're maximizing profit, or it could be a different objective. The game does talk about maximizing your profit and things like that. But again, you can also have

		different objectives in real world. I want to make sure that I'm maximizing my customer satisfaction or something like that. But the game focuses on the profit angle. And what it really brings to life that I like is I sort of talked about maybe the first episode, I think I did a verbal sort of drawing of what a feasible region looks like in linear programming. And this actually sort of puts some of those two-dimensional visualizations out there so you can see what's happening a little bit. So it just sort of peels back the onion a little bit there so you could see what's going on a little bit.
	00:14:24	And okay, this is why I can't use all of my beans to make this type of coffee now because it runs up against this particular constraint. And you sort of see it visually, which is really cool.
Jon Krohn:	00:14:33	Yeah, I've got it up in front of me here. It does look like fun. I haven't had a chance to play it yet, but I will be probably as soon as we finish recording this episode. I see that the burrito optimization game is still live, which is great. So I'll have a link to the burrito game in the show notes, as well as the new Gurobian coffee optimization game for sure. The game that lets you optimize your own coffee shop from the grounds up. Very clever.
Jerry Yurchisin:	00:14:57	There is no shortage of puns that come from compressed. It is impossible to stop and I don't want to anyways. Why would you?
Jon Krohn:	00:15:06	So in your discussion right there at the end about garobian, you mentioned linear optimization. And so that kind of begs the question about non-linear optimization. I know that we talked about that on one of your episodes at some point, but really quickly, I feel like that might be an important aspect to share with the audience that will broaden their mind further around what's possible with mathematical optimization. With

Jerry Yurchisin: 00:15:30 Gerobian, I mentioned a lot of the linear stuff is about kind of where the feasible region is. The actual objective. Oh, the feasible region is given all of your business rules, sort of think about, okay, my budget has this sort of equation to it or inequality in it. I must be below here. And then now I only have a certain number of coffee beans like this. I got you. So go like this. And then that's the area which this is, if you're in this area, you are guaranteed to meet your constraints. You're not going to be doing something that you physically cannot do with your products or something like that. I see.

Jon Krohn: 00:16:12 I see. So Jerry was making some gestures with his hands. He's kind of created some charts with his arms that won't be visible to podcasts, to audio only listeners. But basically the idea is the feasible region is kind of like the area in a graph. If you imagine you have two variables, an X and Y variable where it's like how many beans are reasonable to have and how many employees are reasonable to have, those could be like two different axes and you have kind of a reasonable range for each of those axes, then the feasible region is the part of that two-dimensional plane where reality can happen, where things are feasible.

Jerry Yurchisin: 00:16:48 So you're trying to find which point in there actually maximizes your objective, which is a different function altogether. But that objective function in the grobing game is actually non-linear. And you can kind of see some estimations of it. It gets pretty complicated pretty fast. The difference between the optimization game and this grobing game is pretty substantial, the complexity there. But that function is nonlinear. And the reason that we went that direction is because for Groby as a company, we have really gotten into the non-linear optimization space significantly. It's something that's just from a product perspective, it's something that our customers want, but it's something that we feel is much more attainable now because flashback to other episodes, I would talk about why optimization didn't take off as other technologies have. And part of it is because 20 years ago, you could only solve pretty small problems.

00:17:43 The computational effort was too much. But with advances in hardware and advances in the algorithmic side of things, you can now solve problems that are much larger than you could just a couple years ago, five years ago. And some of those problems are nonlinear. And we're sort of really seeing improvements from our side, from the algorithm side of solving problems like five times faster now because of algorithmic purely own improvements. So one of the drawbacks that someone would have about using mixed integer programming and that's sort of like Groby's bread and butter. But when you say mixed integer programming, that is where your decision variables can be continuous. They can be between A and B and anything in between. Or they could be integer zero, one or one, two, three, four, five, six, seven, something like that. That's what mixed integer programming is. But one of the downsides or people would say is the downside is, "Oh, well, I can't have an exponential function as part of one of my constraints because that's clearly nonlinear." And then the typical process that you would have is like, "Okay, well, let's what we call linearize that.

00:18:51 Let's build a piece-wise representation of it that is all lines itself." And people would be like, "Okay, well that's cool." But sometimes it would really make your problem really, really large because you're adding sort of dummy variables for each of those things. And so you'd make your problem a lot larger. And then you would also lose accuracy. It would not be a perfect representation of your exponential curve, let's say. So that would be a couple people who are like, "Oh, well, you can't use Gurobi, you can't use mixing your program because you would lose those things or you would have those issues." Now with just the improvement of the solver, now you can just directly model that and say, "Okay, I have a constraint that is purely an exponential function." And then that's it. You're not doing a linear representation of it or anything like that.

00:19:42 And so it provides the realism and it also provides that realism within a more attainable sort of timeframe to solve these problems. So it's not taking forever. Because sometimes some of these problems, even problems that don't seem all that complicated, just from a computational perspective, can take a really long time to solve. And it all depends on, again, the context that you're looking for. If a problem takes three hours to solve and it's for annual planning, then that's probably okay. So that makes sense. But if a problem takes three hours to solve and you want those decisions for minute by minute sort of shipping of products or something like that, then obviously that's not good. So all that is to say is from a nonlinear perspective, we have a lot of improvements and some of the drawbacks that people would say like, "Oh, you can't use Gurobi, you can't use mathematical optimization because of X, Y, and Z." Those have become a lot less of a reason to at least try.

00:20:41 So if you're someone who has five years ago like, "Oh, I couldn't solve my mixed injury linear program with commercial solvers. I couldn't do that. So I stopped. I'm not even going to worry about it." Revisit it. If you're like, "Oh, my problem's highly nonlinear and I can't do it," try it again. Can't guarantee everything. But then there's so much improvement that if you haven't tried within the last few years, you're behind the times on it. So it's evolving just as fast as other technologies in terms of how it's improving.

Jon Krohn: 00:21:11 Cool. I love that. Speaking of the times changing rapidly, since you were last on the show last October, we're now constantly talking about agentic AI, obviously on a data science podcast that focuses on AI, which is more and more what data science is all about, I think, certainly in

		the way that I've been curating content on the show and I've been experiencing the world. And so yeah, where does mathematical optimization fit into this new agentic world that we're in? From
Jerry Yurchisin:	00:21:43	Our perspective, that's the million dollar question, billion dollar question. Yeah,
Jon Krohn:	00:21:47	I bet it's more than a million.
Jerry Yurchisin:	00:21:49	Yeah. Million dollar question because that's the term that people used to use a lot. I don't know. But yeah, it's billion. It's massive now. But anyways, when you think about what, and I'm going to be a little bit sort of high level and not absolutely correct, but if you think about what an LLM does, LLM takes all the input tokens and then just produces more output tokens about text or something like that, let's say. If you're purely natural language type of stuff, like input tokens and your output tokens, that's it. That's all it really cares about is providing the tokens that sort of give you a really good response, highly likely response. So something that is all about just that sort of input output flow. That really doesn't jive with what I was talking about, the types of decisions that optimization can make and what it does and sort of the rigor that it provides.
	00:22:47	It provides these. The constraints are what we call hard constraints. These are things that cannot be violated. It's not like, "Oh, my context. I mentioned my constraints just outside of a context window type of thing. And now the LM's sort of forgetting this type of thing."
Jon Krohn:	00:23:04	Yeah. Or even if it's in the context window, it's still a very frequent occurrence that some piece of information that you say. There's an example. Sinan Osdimer, do you know that guy?
Jerry Yurchisin:	00:23:15	No, I don't think so. Sinaan

Jon Krohn:	00:23:17	Osdimer, I think he's been on this podcast more than anybody else. And he's a crazy prolific author of data science and AI books. I think he's younger than me. He might be in his mid - 30s and he's written at least 10 books. And he's created tons of online content. Recently he started working in fireworks AI. But the point that I'm getting to is that Snan Osdimer, I've seen him do a talk a couple of times where he shows surprising issues with even frontier LLMs where he would do something like have a tool available for an agent to call. And in his prompt, he would say, "You must use this tool." And it was like single digit percentages, but some single digit percentage of the time, that very simple, very specific instruction, the LLM controlling the agent just wouldn't do it. It wouldn't call the tool.
	00:24:15	It would find some other way of doing the approach. And so yeah, Sanan's done lots of. He did a whole book on agentic AI where these kinds of experiments that he was running, he published them in there. While you're talking, I'll look up the name of that book.
Jerry Yurchisin:	00:24:31	Yeah.
Jon Krohn:	00:24:33	Yeah,
Jerry Yurchisin:	00:24:33	Go
Jon Krohn:	00:24:33	Ahead.
Jerry Yurchisin:	00:24:34	Yeah. If you think about exactly what you said right there, when it comes to, again, the fate of my business, do I want to trust decision making to something where that can happen? Where it can forget a. Let's say you have some sort of environmental constraint where if you violate that, then you're going to be fined millions of dollars, something like that. And then you output a solution that is like. The one thing, all of these agentic tools and everything, the confidence is so high. It's like, "I

got you, boss. Just what you're looking for. We're 100% good to go, but it misses this environmental constraint. And then all of a sudden you put into production a solution that is not good and then the bad things happen and then all because of just forgetting, just doing something that happening. And the contrast to mathematical optimization is if that is a constraint in your model saying that here's my..." Again, I'm going to do the arm thing again for everyone listening just purely video.

00:25:44 "Here's my constraint and all my decisions are in here. I cannot go past this. I cannot break this environmental constraint. "You are guaranteed that. So that's what we think is a differentiator. First off, is that you have the trust of the model to actually do what it says. And what's really nice about it is what this line represents is something that you talked about. It is a constraint that the people who are designing the problem, who are talking about it, have hopefully agreed upon as an actual constraint. So it's not just some generated business rule type or something. It is something that as if you and I were working on a problem, I'd be like, "Hey, I think this is an environmental constraint." You're like, "Yes, it is, but it should look more like this." And then we agree what that is, and then it's represented in there mathematically.

00:26:36 So it's just a very different decision-making framework. But where I see this all fitting together is you mentioned that, okay, I have an agent that's going to call a tool. Okay. An agent should be able to. What an agent can do is help you develop the problem statement that you're really trying to solve. Help you understand all the other bits and pieces of all the other regulations. Say, "Hey, I have this environmental regulation." And an LM or an agent can do like, "Hey, these are other things that you may want to consider." And you might be like, "Holy crap. Yeah, I want to consider these. I forgot about them." So it

		can really help there. It can help you identify the problem, help you actually write the code, help you to come up with the mathematical formulation, do all of that kind of stuff, but it can't do the solving.
	00:27:25	It can't give you the optimal solution. It can't give you a solution that's close to optimal and have the defendability, the explainability, all that sort of stuff that comes with these high stakes decisions. So how we sort of see it as agents should be able to develop all those things and then call an optimization engine like Gurobi saying, "Here is the problem statement that we have. Here is the model they're trying to solve." And then Gurobi runs, gives you the output, sort of gives the solution. And then you can then dive deeper into why. Why is this happening? Why did I decide to build a new production facility in Atlanta as opposed to Baltimore or something like that? And those are actual questions that you can get answers to with mathematical optimization. Because essentially what can happen in that situation is it'll resolve with the Baltimore production facility there and say, "This is the difference.
	00:28:22	It is a difference because the cost is going to be this much higher or you're going to have this much less demand or whatever it may be. You can actually sort of figure those things out and get to be able to answer questions that people are going to have when it comes to business problems and decision making is why this? Why not that?" Those are all things that can happen with mathematical optimization because of the structure and the rigor that's there. And
Jon Krohn:	00:28:47	So that kind of best of both worlds that you were describing there where you can be having a conversation with a cutting edge LLM. You can be, at the time of us recording this, Fable five is probably the most advanced LLM that the general public has access to. And so you could be having a conversation with Fable five about

some business problem that you have, and it can be identifying potential gaps in your thinking. But then when it comes down to defining the mathematical optimization problem, it can also be helping you generate the code. And then you can review the code and could say, "Okay, great. Nothing is missing here. And it seems like soon you're going to be able to have Gurobi provided MCP servers, model context protocol servers that allow that quad agent or whatever agent." MCP is like a portable protocol that could be used by any LLM, any agent.

00:29:43 And so a Gurobi optimization solver could then be called by the agent so that you get this flawless, deterministic, guaranteed, optimal solution that the LLM on its own wouldn't be able to do. Yeah.

Jerry Yurchisin: 00:29:58 We're working on a lot of things in that space. And one is MCP servers. So how you can call our. We have a whole thing called the Gurobi Intelligence Hub now, and it has several agents within there that mostly right now we have a lot of interaction just with a chat interface and stuff like that, but it helps you really with that modeling part right there, there was just talking about how do I develop my problem statement? How do I write the code? How do I get the formulation and everything? We have a modeler agent that helps with that. So then you can then call that modeler agent within your ID or wherever you want to work to help you with all of that. Sort of say, "Okay, I have this formulation now. Can you check it?" And so it's really cool where this is going and what we're trying to take things next is we really want to streamline the modeling process.

00:30:53 We want to streamline the support process as in like, "Hey, I have an optimization model. It's not running fast enough or I get these issues or these errors, what can I do?" First line of support is also, we have an agent called GoRobot that does that as well. And we're working on an explainer as well. So if one of the big issues that you get in optimization modeling, and if you don't get this, you consider yourself very luckily is an infeasible model. Happens all the time. So if you're starting out and you get infeasible models, that's okay. It needs to happen. And what an infeasible model means is I've had all my arms so far, is essentially if that feasible region that I was describing has no points within it. So you have one constraint that points this way and another constraint that points that way, and there's nothing in between.

00:31:44 So there's nothing that actually satisfies all of your constraints. That's an infeasible model. Happens all the time. How do I understand what that. Why is it infeasible? It could just be because somebody fat fingered an extra digit somewhere and that's it. Or it could be because you literally have types of business rules that are legitimate that just can't work together.

00:32:09 So yeah, helping you sort of identify and explain those things as well. So being able to call all of that type of stuff where you work, what we think is pretty important. And again, lowering the barrier to entry, that's what we want. We want more people to be able to use optimization. And so yeah, that's what we're working for. And that's sort of like our vision is having all these other agents do all those other parts or help with all those other parts. But when it just comes to the actual churning of getting that optimal solution, the wrong tool for the wrong job.

Jon Krohn: 00:32:40 Yeah. Perfect. So agentic AI, LLMs, mathematical optimization, they can work perfectly together through these kinds of approaches that you're describing, MCP servers, chatbots, explainers that are helping you identify when you have created a model that is infeasible because you've added a bunch of constraints that you think maybe the business people in your organization, you talk to a bunch of different people in your business to identify where the constraints are on some problem. But when you put all those constraints together, you're like, wow, okay, there's no solution here because there's no point in the space where reality can exist. And yeah, I love that. I love that you guys are kind of taking the best of what's been happening on the AI side, the LLM side, the agentic side, and allowing that to make using mathematical optimization easier than ever and increasingly more automated than ever.

Jerry Yurchisin: 00:33:46 The explainer part of it is, and when you have people together and someone who says, "Oh, I'm on the planning side of things and this is going to be our budget for this or whatever." And then when you're able to clearly articulate, like say in this infeasible model, why it's infeasible and be like, "Oh, it's infeasible because these three constraints or these 20 constraints, one of which is a budget number, one of this is this and this," you're able to really sort of say, "If we had more budget by this percentage, you can get very, very precise in this. There's tools that Gurobi has that this explainer can help, one of which is called fees relax. If you have an infeasible model, you run this sort of helper command and it essentially expands the model and relaxes the model in a minimal way to sort of make it feasible.

00:34:39 And it's a really helpful thing to then be able to say, Oh, if you increased our budget by 10%, then this is what we'd be able to do. So you can actually very specifically not just say, oh, well, it's infeasible. We're done here for today. No, you could actually really say, oh, to this group or to that group, what would need to change? And it just really helps with that process and say, oh, if I were to do this, then this is what would be able to happen. So it's a really cool way of, again, the whole framework of optimization and everything, it really, really brings that stuff to light.

Jon Krohn: 00:35:14 Does any of the functionality that you've been describing relate to. I know that a couple of years ago we talked

		about on the podcast, Gurobi building custom GPTs in ChatGPT, which was a big trend for like a month, two years ago. And then I really haven't heard anybody talk about it since. And you've since brought that kind of custom GPT capability in-house as a standalone product. Is that product one of the things you were just discussing or something
Jerry Yurchisin:	00:35:39	Else?
Jon Krohn:	00:35:39	Yeah.
Jerry Yurchisin:	00:35:39	No, that's it. Yeah, that's our intelligence hub. If you need to work through ChatGPT or something like that, those custom GPTs still exist and they are helpful. But yeah, we decided to bring it in-house and really leverage the expertise of our technical teams to help guide these agents in their responses. We've found that there's either the best way to interact with an LLM or an agent about optimization is either using the best of the best models out there from an agent perspective or an LM perspective. Or if you can't do that, then what is also equally as good, sometimes a little bit better, sometimes a little bit worse, it all depends, is using information from our sources. So using our. We have a ton of what we call knowledge base articles. And these are articles that explain how to do things. I have this error, what do I do?
	00:36:38	I'm looking at my log file and this number that should be going down isn't going down fast enough, let's say. What should I do? All of that information, all of that knowledge is captured in what we call our. It's our robot is essentially our product support agent. And all that information is there. So you can get as technical as you want and it should be able to help you improve your formulation or improve your runtime if you already have a model. And as I was talking about the modeler agent before really helps you go from, I have a twinkle in my eye of an idea. You're like, "Ah, yes, this would be great." And

you could just sort of start with very basic stuff and again, asks you all those interesting questions to help you really define a good problem statement. One thing that we noticed is if you were to go to, let's say you're not an optimization expert and you were to go to any other, I'll call it vanilla agent or something like that, nothing that has the knowledge of, specifically is looking at the knowledge of Gurobi or something like that.

	00:37:40	It likely won't follow what we would call best practices of building an optimization model. And part of that is the iterative process of understanding the problem statement, but it's also building sort of test scenarios in which I know if I have a certain point that it should be a certain set of values for my decision variables, that it should be feasible at least. So you can then test that and it'll build tests that do that. I know this point should be infeasible. So it'll then test that. So it really helps you provide that, get that testing done that helps you get confidence in that the model that you're building is actually representative of the problem that you have. And which I
Jon Krohn:	00:38:23	Think
Jerry Yurchisin:	00:38:23	Is as people who are probably not, most of your audience is probably not optimization experts, that's an awesome thing to be able to do. It really just helps instill best practices.
Jon Krohn:	00:38:33	Gurobot is the name of that, right?
Jerry Yurchisin:	00:38:35	Gurobot is the support agent. We just call the modeler the modeler. I don't know. We didn't come up with a fancy name for that.
Jon Krohn:	00:38:42	Okay.
Jerry Yurchisin:	00:38:43	Yeah. But it's all under the Gurobi Intelligence Hub.

Jon Krohn: 00:38:46 Fantastic. All right. I'll have a link to the Gurobi Intelligence Hub for sure. And a specific link to the Grobot. I also just quickly, at some point while you were talking a while ago, I did look up the name of that Sinan Osdimer book where he has lots of experiments on LLMs not doing things that you specifically told him to do, which is a problem that you don't get with mathematical optimization. And that book is called Building Agentic AI. And I can't believe I didn't remember the name of it because that book is in the Jon Krohn signature series that Pearson publishes. But I wasn't 100%. He has so many books that I wasn't 100% sure that it was that book, which is the first and only book that he's published so far in my series that Pearson does. I promised our listeners at the beginning of the episode that we would have case studies beyond supply chain examples, which are kind of the bread and butter historically of optimization.

00:39:37 Do you want to hit us with some of those energy and financial services examples?

Jerry Yurchisin: 00:39:40 Yeah. Energy and financial services are two of the areas that we're seeing a lot more adoption of mathematical optimization. And part of that is some of the stuff that I was talking about before, particularly with, actually for both of these, but particularly in energy, the non-linear aspect of things was kind of like, oh yeah, this isn't representative of what we want, so we're not going to do it. Or if we do try and linearize things, it goes with the one of two ways where it blows up the problem or becomes not representative enough. So there's a bunch of problems that more people are using optimization for in terms of what we call a unit commitment problem. So essentially, what power supplies should I be using in order to meet demand? How should they be scheduled? What units should I commit at certain times and things like that?

	00:40:35	And there's other problem variants that really take into consideration the physics of energy, of energy supply and everything like that. And we're seeing a lot of renewable dispatch optimization problems as well. So okay, I'm able to have solar panels or wind energy or something like that. And those can fill out batteries. How can I then dispatch that in order to, when should I do it in order to make sure that you meet demand and minimize costs and things like that? So those are a few of the problems in energy that we're seeing more adoption of optimization for. And on the financial services part, there's a lot in sort of retirement planning is one where we have a pretty cool case study from a company called MyGoals, I believe they're called. So definitely sort of hop on and check out that case study as well. And what's really interesting about that case study is there's just a lot of regulations that need to be met when it comes to planning for your retirement.
	00:41:40	And I believe this is in. It's a Canadian company. So this is
Jon Krohn:	00:41:44	From the
Jerry Yurchisin:	00:41:44	Canadian.
Jon Krohn:	00:41:45	Yeah. I looked it up while you were speaking so that I could put a link in the show notes. MyGoals is a Toronto-based FinTech platform. And they use the Gurobi Optimizer to help individuals balance competing life and financial goals. So you talk about these constraints. And you could imagine people, this is a really good example of how you could as an individual kind of have an infeasible region in the way that you're thinking about your finances where you're like, "All right, I'm going to have this sweet car, send my kids to private school and have these kinds of savings on this salary." And yeah, the optimizer's like, "Sorry, that's infeasible."

Jerry Yurchisin:	00:42:24	That's rough. But then if you built this, if you have this model, you can then see like, okay, well, what changes should I make? Again, there's a lot of the explainability that I really want to sort of emphasize. It's like, okay, if it is infeasible, which. Kind of rough to say, okay, should I not send my kids to this school or should I not buy this card? I
Jon Krohn:	00:42:47	Mean, but that's life.
Jerry Yurchisin:	00:42:48	Yeah, that is. And those decisions can be sort of brought to light and what changes you would then need to make. For
Jon Krohn:	00:42:57	Sure. And so according to this case study, my goals using the Gurobi Optimizer improved after tax retirement income by 2% to 10% compared to conventional planning tools resulting in income outcomes 10 to 20% greater, which is a lot. If you think about how much more you'd have to work or the kinds of things you'd have to save on in order to save 10 or 20% more over your life. And then it also said that because of the kinds of things that you've been talking about throughout this episode where you can run the mathematical optimization in different scenarios, like you were talking about Baltimore versus Atlanta. And so that kind of thing applied to your own personal finances, your own life. It allows the MyGoals platform powered by Gurobi Optimizer to, instead of generic rules of thumb, evaluate multiple goals simultaneously and build actionable tailored strategies.
	00:43:51	So that's really cool example that I bet a lot of our listeners are going to want to check out.
Jerry Yurchisin:	00:43:56	Yeah. All of the other regulation stuff that happens is all stuff that. Yeah, those are all hard constraints. You don't want to want to follow that. You don't want to mess that stuff up. Yeah. It just makes sure that the things that

can't happen can't happen. The things that must happen will happen. Cool.

Jon Krohn:	00:44:11	And I believe you also have a fun USA Cycling example. Is that right?
Jerry Yurchisin:	00:44:14	Yeah, this one's one of my favorite over the last year. So when you think about riding a bike in a competitive situation, how that's not at all long-term supply chain network design planning. It's just so different. I'm like, okay, how should I physically be riding a bike? And they're just so different. That's why I sort of really like this problem. There's a paper, an academic paper that was written about this as well. So you can look into it. You can find a video on our website. I think you need to put in some information to get to it. Yeah. So essentially there was USA Cycling, I believe the women's team, they were doing one of the indoor events. And there's a lot of interesting sort of decisions that can be made when you think about, I have a four rider team and they're in certain positions.
	00:45:12	Each of those positions have different sort of drag amounts and things like that in terms of how much wind resistance there is. And you can think about how, okay, so I'm riding around in circles with my team. And then how can I conserve energy? How can I make sure that certain people are in certain positions at the right time? How can I make all these sort of types of decisions like rotation strategies and things like that while also making sure that you're adhering to the rules of the game? I think I used that as an analogy in the first or second time I was on. It's like optimizing rules to a game. This is actually rules of the sport that need to be adhered to. But essentially with optimization, they were able to develop a prescriptive plan about literally how much effort you're supposed to be putting forth at a certain time, what sort of order you're supposed to be in, a rotation strategy of between you and your teammates.

00:46:08 What's the best way for us to run a race given all of these physical, sort of the physics of air resistance plus energy levels, plus all this sort of stuff in order to minimize the race finishing time? How fast can we go? And it's just a really interesting and very different case study in which there's a lot of detail that happens in there, a lot of cool things. And it's just a very different perspective on optimization, which I think highlights the usefulness of it. Because if you think about going back to what I was talking about at the beginning and before, what are the building blocks of optimization models? I have decisions to make. Okay, who's going to be in the front at the beginning? When do they start swapping? How much effort should I be giving at certain times? Those are my decisions. How are they constrained?

00:46:54 Well, I need to have people on a line and then other things that need to happen. And then what's my objective? I want to minimize the time it takes to finish a race given all of these things. Yeah, that problem has those characteristics and therefore is able to be solved with mathematical optimization. So it's a really cool case study and really interesting application of optimization in a way that you just wouldn't normally think. And I find myself part of the problem sometimes with that because there's such big use cases, big case studies where tons of money's been saved and all of this sort of stuff with these big companies doing big problems. And it's like all supply chain and logistics. Yes, that's awesome. But then these things come around where something just very different is there and the benefits are awesome. And it led to a gold medal finish too.

00:47:43 So that's the thing I also want to mention too. It wasn't just like, oh, we got better. It was literally like part of the process was regression analysis to sort of figure out what times that they would need in order to fit it, in order to take the gold and that set their standard for the time. And then given this sort of like, we need to be in this ballpark.

		If our objective can get in this range, we have a shot. And it's just really interesting how they put everything together. And I highly recommend reading the paper on it, if you don't mind seeing a little bit of math in there. Even if you sort of gloss over those parts, it's still a really cool story. But then also heading over to our website to sort of check it out. And I know we'll probably hit on this a little bit, but the presentation that you would see there was given at our Decision Intelligence Summit.
	00:48:30	So that's the type of stories we like to tell when you go to our summit event to sort of learn more about optimization. So I think we'll hit on that a little bit. We
Jon Krohn:	00:48:43	Will. We'll hit on that for sure. Yeah. So I'll have a link to this paper in the Informs Journal on applied analytics. It's called Project 405: Optimizing USA Cycling's Women's Team Pursuit Gold. It's a mouthful of a title. But the key thing is that in this Project 405, the specific event that USA Women's Team won gold at was the Paris 2024 Olympics. Yeah. And yeah, so super cool. We got the paper and they used Python, mixed integer programming and the Guropi optimization solver to be able to optimize and contribute to that gold medal result. So super cool. It sounds like it even identified talent for the team, which is a wild kind of thing that I wouldn't have even though was a possibility, but basically talent that wouldn't have even been in a team were identified by identifying optimal physiological profiles and matching cross-training athletes to different cycling disciplines.
	00:49:49	That is wild. That
Jerry Yurchisin:	00:49:51	Right there sort of just shows the multidisciplinary sort of approach that I always preach with this kind of stuff is that a lot of that information, a lot of the data and a lot of that stuff is perfect for your traditional machine learning type of things. And that is so important. But then also it is also so important to come up with this optimal

strategy. So yeah, these types of analytics need to be working hand in hand pretty much for every problem, I think. So if you're not using both something that is prescriptive, it doesn't always have to be mathematical optimization. I'm not going to say it is like the holy grail of prescriptive techniques. It does a lot. But I just always encourage to make sure that you're using as many techniques to fill in the gaps as possible. Now you don't want to just throw everything at every problem.

	00:50:46	You want to make sure that it's actually applicable. But again, we just always sell ourselves short, I think. As
Jon Krohn:	00:50:52	Many quivers as you can fit on your back. Yes, precisely. That's the same.
	00:50:58	All right. So let's say we have a listener who's like, "Sweet, Gurobi optimization sounds perfect for this situation that I have in my business." And then they go check out some of your tutorials, chat with GoRobot or take advantage of Gurobi Intelligence Hub materials. And then they actually identify a problem that they're like, "Wow, look at this. Perfect situation. I'm pretty sure I identified an opportunity to save us money or increase profits or whatever." How do you get that change management to happen in your organization? How do you explain mathematical optimization to your boss, your boss's boss and so on to actually get your solution implemented?
Jerry Yurchisin:	00:51:43	Yeah, this has been a big effort on our part with the internal Tagurovy to help our customers do this because that exact problem is something that we hear a lot of. There'll be someone who is like what you just described, we would describe them as an internal champion of optimization. They're sold, they know the benefits, they know what they can do, they know the problem they can solve, but you can't just go run off and spend half of your time solving a problem that your boss doesn't think is useful. So up the chain, you're going to get some

resistance. And also in implementing things and sort of down onto the more planning level or something, the people actually doing the things that the model says, you might get some resistance there as well. So we've been putting together a lot of material, which is yet to be released, but we're working on it to really help with those questions to help people understand, okay, say I'm an optimization modeler now or your data scientist who's doing optimization and you've identified this.

00:52:48 If I'm talking to my CFO or CEO or maybe just a couple levels up, it's like a manager, director, somebody up there, how do I talk to them? What should I be bringing to their attention about the benefits of optimization? And a lot of that would be stuff like a big thing is the difference that I was talking about between sort of agentic sort of AI LLMs, generative AI, what that's good for and what that's used for versus optimization, what that's useful for versus again, traditional machine learning, what is that used for? So being able to clearly articulate the benefits of each of those things because if you bring this up and you say, "Oh, hey, I think I have a way to save us millions of dollars with using optimization. Here's all the things that we need to do." Probably a question is we have a cloud subscription.

00:53:42 We have a ChatGPT subscription. We have this, we have that. Why can't I just ask the LLM to do it? Because an LLM's going to be like, "Oh yeah, I got you." Again, that confidence that it has is so misleading at times that it'll be like, "Yep, I'm optimizing your supply chain right now." And then it forgets all the stuff that we talked about before. So being able to clearly articulate the differences there is super important. Understanding the right terminology to use, how you should frame the business problem. Because if you talk about to sort of management and you say, "Oh, well, I'm able to increase productivity by a small percentage or something like that," they'd be like, "Well, okay, that's great, but what does that really do for us? What benefits is that from our maybe possibly, probably likely the bottom line? How much monetary value is this producing?" So that's one way to think about it.

00:54:31 And then also, but then downstream of things, when you have the people who have 15 years of planning experience or something that they've been doing their job with their brains, their gut, and maybe an Excel spreadsheet or something like that. And they've been doing it that way for 10 years and they have all this experience. All of a sudden you're like, "Oh, well, I'm going to bring in this tool that is going to optimize things." And they're going to be like, "Well, what the heck's going on? How do I fit in? Am I being replaced?" Those are lots of questions that you need to be able to sort of answer. You're going to get pushback on that. And we've internally, when we talk to a big effort for us to understand this is talking to our sales representatives, our leadership on the sales team, our technical sales folks as well.

00:55:19 And that is a legitimate concern is if I implement an optimization model for some scheduling problem and you have someone whose job it is to do the scheduling, they're going to be like, "Well, where does this lead me? Are you forcing me out? Or what's happening there?" And essentially one of the big takeaways that I like to talk about from our NFL example where again, Gurobi's used as the engine to solve the NFL scheduling problem every year. It didn't replace the scheduling team. They're just able to be super more efficient. Instead of trying to come up with one schedule, now they're able to analyze thousands of them and they're all high quality schedules. So they're able to do their job differently. And I think that's what you want to articulate to the people whose sort of jobs this might replace or something that it's like, no, human in the loop is always going to need to be there.

00:56:22 There's the saying of all models are wrong, but some are helpful, that type of thing. There's always going to be some sort of human like, "Well, maybe this one's slightly better than this one, or this is the thing. I would rather go with this because of that." Something like that. There's going to need to be some sort of human in the loop. And optimization could still be teaming up with people in that respect. So when it comes to talking to one audience about optimization, you need to be highlighting, "Hey, this is the value that it brings. This is how it affects the bottom line. This is how it helps us become maybe more robust as an organization." And then down the line, when you get to the implementers of the decisions, this is how it's going to make your job easier. This is how it's going to incorporate your expertise.

00:57:12 Because one of the easiest things to start poking holes in the arguments that these tools bring is you'll run an optimization model and somebody with their 15, 20 years of experience be like, "I'd never do that. That's stupid to do that. I would never make this decision." Well, now you just learned a new constraint. That is something that shows that you need to have these people involved in the modeling process to be like, "What is a thing that you would never do? Or why would you never do this?" And be like, "Oh, well, because of X, Y, and Z, we would never do that." And now you just learn something about how your system needs to operate. So those types of people have the experience and the expertise to really bring the realism to your optimization model. So they should be just as involved as anybody else in terms of building the model, building the application and things like that.

00:58:07 So being able to talk to both sides, here's the value, here's where it affects our bottom line, but here's how it's going to make you more productive. Here's going to help your life. Here's how it's going to make your job easier or better are things that you need to be able to articulate as you're going down this optimization path. Yeah.

Jon Krohn:	00:58:24	So you can speak to management about the value, the bottom line, how they're going to save money, while simultaneously you can be speaking to the people who are going to be using these tools and make it clear that this is not going to replace them. It's going to make them better at their jobs. For people who now want to be able to get going and add optimization to their toolkit, where should they start?
Jerry Yurchisin:	00:58:46	The first website to go to is just grobi.com/learn. That will redirect you to another site where it has essentially all of the training that I've led over the past few years. We have a whole series of four trainings. It's optimization for data scientists, Opti 101, 201. We did a 202 and then a 301 where it takes you from the absolute beginning of optimization to some pretty techniques and things where we hit along things about the difference between machine learning and optimization. And again, from an AI perspective, how it fits into the AI landscape and how do you deal with uncertainty? Because that's a big thing. Your demand forecasts are not perfect all the time. So we really sort of tried to run the gamut there. So that's a great way to start. We worked with a professor, Dr. Joel Sokol at Georgia Tech. He helped us produce another more in-depth training.
	00:59:44	So the training that I was talking about, each of those are two four to five hour sessions and stuff like that, which all of those things are YouTube video, YouTube playlists now with Jupyter notebooks on our GitHub. The other thing is on a Udemy course that has four parts. So you can check. All that out to really get from I'm just starting out to, I kind of know what I'm doing now. I'm dangerous and a good kind of dangerous. I can actually solve some problems here. But again, I'll always say that there's always room to learn. So I think between that and then honestly hopping on at the intelligence hub using the modeler to help you understand your problem in the context that you want. So you can say, "I'm new at

		optimization. I want you to help me solve this problem. Limit the notation for now.
	01:00:32	I just want to see this." And really the modeler does an exceptional job of not showing you all of the, here's your formulation and it's all math right away. Just get rid of that for a while. You do need to understand it at some point, but you can really sort of give it a little bit of a profile on you and what you want, and that's super helpful as well. So I say that website, we have tons of Jupiter notebooks that you can use that are all over the place in terms of the industry and the application and the difficulty as well. So I'd say that's kind of like your one-stop shop. And if you do need to explain the optimization part, the burrito optimization game is good for you to learn, but then also that's a great tool to send to your management or to the planners, the end users and be like, "Oh, this is why optimization is helpful." Because within, again, two rounds of that, people are severely suboptimal.
	01:01:28	Same thing for the Gurobian game as well. There's a little bit more randomness there because there is some simulation involved and stuff, but you could really quickly see that gut intuition experience. I ended up just not. They're not great ways of making decisions. So all of those could be found at that one webpage. So I'd say that's the first place to start.
Jon Krohn:	01:01:53	Gurobian, the burrito optimization game, but above all, gurobi.com/learn for all the educational resources that you and your team have been putting together. If people want an intensive, more interactive session, I believe you also have an annual two-day training called Optimization for Data Scientists coming up. Do you want to talk about that?
Jerry Yurchisin:	01:02:11	So all of those, the Opti series that I was talking about, that is we have decided to rebrand that a little bit. So

we're done with the Optimization for Data Scientists, but it's going to be more GenAI focused. And not just talking about the tools that we have. It's not just going to be, oh, we're going to use the Gurobi Intelligence Hub for everything. We know that that's not how everyone's going to want to work. And we want to try and teach the lessons that we've learned of really how to put optimization together with generative AI and how these things should really work together in a more general context, general framework. So we're not going to be using all of our stuff, but we will be using cloud code and things like that. And how can you really get the most out of this? What are the things you really need to focus on in order to get the best output?

01:03:03 What are the best ways for me to prompt things? When should I be doing this versus that? So a bunch of techniques and a bunch of ways, a bunch of lessons learned that we have. So that will be, I believe, in mid-November. So we got some time, but it's going to be, I think we're calling it Opti GenAI something. I don't know. We haven't really finalized the name yet.

Jon Krohn: 01:03:23 Are there dates finalized or a URL people can go to or anything like that yet?

Jerry Yurchisin: 01:03:27 We don't have a URL or anything, but we do know that this training's going to happen either November 19th and 20th or one of those two days. We haven't finalized if it's going to be one day or two days, but the end of that week in November 19th or 20th, we're going to have that training that's again focused on GenAI and optimization. Working together as two best friends should.

Jon Krohn: 01:03:47 And that's online.

Jerry Yurchisin: 01:03:49 It'll all be all remote. If you can't make it, if you have other stuff happening, you can still register and do it all on demand afterwards. Everything's recorded. Notebooks

		are there, all that sort of stuff will be there. And we leave it open for, I think, a month or something like that. So you have plenty of time to dive into that content and work through it.
Jon Krohn:	01:04:12	Nice. We'll keep an ear out for that or reach out to Jerry as November approaches. I suspect we might have sponsored messages on the podcast for it, but something that we do already have sponsored messages running for is the Gurobi Summit, which is in person in Las Vegas. That is coming up as well. That's not necessarily as technical as what used to be called Optimization for Data Scientists thing. It's on September 22nd and 23rd at the Aria Hotel and Resort in Las Vegas. And that's more general, right?That isn't necessarily targeted at just technical people.
Jerry Yurchisin:	01:04:52	We know our audience, and if we didn't have some technical stuff there, they would be very upset with us. That's why we kind of have two days. The first day is sort of more focused on the usefulness of optimization, getting actual. We invite our customers, our people who use Gurobi to tell their story. So that's, again, where that USA Cycling example was discussed was at that event. So you'd be able to hear those cool stories, see how people are really using optimization, and not just see it. And then you can go talk to them.Be like, "Oh, that is something that's really close to what I'm doing. Can you tell me more about it?" And it's an event in which people really love to share what they're doing. So we have a lot of that. Let me share my story with how I'm using optimization and the benefits that it's giving.
	01:05:42	That's kind of the big day one focus. The second day is a little bit more technically focused. And we have two tracks, one of which is what we call an advanced track. So if you are someone who is really good at optimization, you can hear from our super genius experts on the cool stuff that they're working on and how to deal with these

problems at a very super advanced level. That's there. And then we also have what we call a beginner track. And again, we start from the basics and that is going to cover sort of, hey, what is optimization again in the context of the AI world that we're living in now? I want to get some basic examples out of the way, start with basic modeling. We use our Python API, so GurobiPi. And then we are going to go actually through a pretty longer session of using the intelligence hub and using the modeler and developing a model and then using Gerobot to help debug and make it run faster as a support tool.

01:06:47 And then also the explainer as well like, "Hey, things have gone wrong. Why? What can I do?" So we're going to try and have that whole story told there as well. So it's a great way to meet people who are doing the problems that you feel like you should be able to be doing in your company and sort of really see firsthand the benefits there. So I can't suggest the event enough. I will be there. So if you want to say to my face that you did not like my Opti 101 training, then you can do that as well. Or you can say, "Hey,

Jon Krohn: 01:07:18 It

Jerry Yurchisin: 01:07:18 Was pretty cool. I appreciate it." I don't know. I'm a little self-deprecating at times. So just in case if anyone does have some criticism, but you can then meet other people who are much smarter than me on this as well. We do bring a lot of growy folks there and you'll be able to talk with the best of the best to help you out.

Jon Krohn: 01:07:38 All right. So yeah, Jerry and some smart people at the Decision Intelligence Summit 2026 coming up in Las Vegas, September 22nd and 23rd. Jerry, we are out of time today. This has been another fantastic episode. So great to hear all of the updates happening in the mathematical optimization world this year, particularly as it pertains to say agentic AI and lots of other industry applications, including energy, finance, those USA cycling successes. Before I let you go, do you have another book recommendation for us?

Jerry Yurchisin: 01:08:10 Yes, I do. And this one's going to be a little on the oddball side of things. I did two stints of graduate school. One was general applied math, and then I got into operations research and statistics after that. But when I was doing the more general applied math, I had to take a graduate level geometry class. And part of the reading that we needed to take, we needed to do in there is we needed to read this book called Flatland. And it is a super unique way of exploring the relationship between geometrical objects like a point versus a line versus a polygon versus a three-dimensional shape. And if you were to take all of those sort of things and take those and make them sort of like living beings, then also put it in a medieval setting, that is what you would get in flatland.

01:09:08 And it's just a really interesting way of exploring the basic principles of geometry in a really weird way. That's the only way I could describe this book. It's really weird, but it's really interesting and it's really fun to read. It's got a little bit of. It has some issues in it, but overall it's still pretty cool. I would recommend reading it just for the comedy alone. But it is a really good way of, I guess one of the through lines that I've been talking about is you need to be able to talk to people the way that they are in their language. You need to be able to communicate complex ideas in different ways to reach different people. And that's kind of the takeaway of this book is you need to be able to talk about what you are as a geometrical figure and relate it to other ones that just kind of don't understand.

01:10:05 Imagine if you were a two-dimensional line and somebody said, "Oh, I have three dimensions. I have height, not just length and width or something like that. I have three dimensions instead of two." But it really has the interesting interplay of how do you talk about something that somebody has no idea what you really mean? So it's pretty cool from that perspective as well. So I highly recommend it.

Jon Krohn:	01:10:31	Nice. And you're not the first person who has recommended Flatland to me, so thank you for that recommendation. I think it's probably a good fit for this audience as opposed to an oddball suggestion. And yeah, final question, Jerry, as always on this show, we already know about things like gurobi.com/learn is a great resource for Gurobi. But for you personally, how should we follow you for your thoughts after this episode?
Jerry Yurchisin:	01:10:55	So I'm relatively active on LinkedIn, so follow me there. Follow Gurobi on there as well. I also have a Blue Sky handle, so you can check out what I have to say there so often. So that's @mathwithjerome on that platform because I do also go by Jerome just to throw that curve ball in there. Well, I think we probably explained that away a long time ago. So you can follow me there. Yeah. So that's the best
Jon Krohn:	01:11:25	Way. Nice.
Jerry Yurchisin:	01:11:29	So yeah, that's probably the best ways to keep up to date with what I'm thinking and what Gerobi's working on and what's happening in optimization.
Jon Krohn:	01:11:38	Well, thank you Jerome or Jerry or whatever you'd like me to call you. And I hope we'll have you on again next year to see whatever wild AI environment we're in in 2027 and how mathematical optimization is making all kinds of problems solved that otherwise would still not be solvable.
Jerry Yurchisin:	01:12:00	You'll probably talk to an AI agent named Jerome and I just won't be here.

Jon Krohn: 01:12:07 Sounds good. All right. Jerry, thanks so much again for coming on the show and catch you again soon. All

Jerry Yurchisin: 01:12:13 Right. Thanks Jon. I appreciate it.

Jon Krohn: 01:12:16 So great to have Jerry Yurchisin back on the show today. In this episode, he covered the three building blocks of any mathematical optimization problem. That's one, decisions you control. Two, constraints on those decisions, and three, an objective to maximize or minimize. He also talked about how any problem with those three characteristics can potentially be solved optimally regardless of industry. Separately, he talked about why LLMs shouldn't be trusted with high stakes decisions on their own since they'll confidently claim they've optimized your business while occasionally ignoring an instruction, whereas optimization treats constraints as hard guarantees that cannot be violated. He talked about the division of labor he sees for the agentic AI era. Agents help you define the problem statement, write the formulation and generate the code, then hand off to a solver like Gurobi, soon cullable via MCP servers for a defensible, explainable, guaranteed optimal solution.

01:13:13 And he provided some fun case studies at the end of the episode, including improvements in after-tax retirement income relative to conventional planning tools and USA Cycling, which used mixed integer programming to plan writer rotations and effort levels on route to gold at Paris 2024. As always, you can get all the show notes, including the transcript for this episode, the video recording, any materials mentioned on the show, the URLs for Jerry's social media profiles as well as my own at superdatascience.com/1015.

01:13:42 Yes, these numbers are getting big. Yeah, thanks of course to everyone on the Superdata Science podcast team, our podcast manager, Sonja Brajovic, media editor, Mario Pombo, our partnerships team Natalie Ziajski, our researcher, Serg Masís and our founder Kirill Eremenko. Thanks to all of them for producing another optimal episode for us today for enabling that optimal team to create this free podcast for you. We are so grateful to our sponsors. You can support this show by checking out our sponsor's links, which are in the show notes. Otherwise, help us out by sharing this episode with folks that would like to learn about mathematical optimization. Review the episode on your favorite podcasting platform or YouTube if you rate an Apple Podcast review that is particularly helpful for us for getting word out about the show. So bonus points if you do that. Subscribe if you're not already subscriber.

01:14:37 And most importantly, I just hope you'll keep on tuning in. I'm so grateful to have you listening, and I hope I can continue to make episodes you love for years and years to come. Until next time, keep on rocking it out there and I'm looking forward to enjoying another round of the SuperDataScience podcast with you very soon.