Market Hunt S02 E08 Variational AI Transcript

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Thierry Harris: The power of artificial intelligence spreads through many different business sectors. Among them is drug discovery. Machine learning is used not only to discover new drugs but also to improve ones we already have in circulation. How is this happening? Who are some of the main players in this emerging field? What are the necessary elements needed to foster these new technologies and commercialize them? On this episode of Market Hunt, the worlds of pharma and artificial intelligence collide. Stay tuned.

[intro song music]

Nick Quain: Entrepreneurship is hard, you need to have support there.
Andrew Casey: We fundamentally have to learn how to live our lives differently. We can't keep going the way we have.
Handol Kim: It's not like Google can kind of come in and take the entire market. Not yet, right?
Thierry Harris: It's a real balancing act which requires a bit of insanity frankly. But I mean some people are into that stuff I guess.
Handol Kim: You know the size of the market, that's really all you've got.

Thierry Harris: True. We're coming up with some pretty interesting ideas here.
Andrew Casey: We've solved everything,
Thierry Harris: [chuckles] We've solved it all.
[End intro song]

[begin promo music]

Sébastien Blais-Ouellette: *You look at an object, with a camera, normally you only see the image, when you have the spectral image, you have this capability to look at the chemical composition of any object in front of you. When you start dreaming about what you can do with that, it's huge.*

Narration: *That's [Sébastien Blais-Ouellette](#) of Photon etc. Photon etc. manufactures analytical equipment. These include special cameras, filters and microscope platforms. Sebastien founded his company after a discovery he made while at the California institute of Technology. He needed to enter into a license deal with the institution where we developed the technology.*

Sébastien Blais-Ouellette: I you know had to license my invention from my institution. It took about 2 weeks. And I get, you know they say, 'oh you want to start a business? Here is the license deal.' I look at that and say, ok. It was very very fair. very very positive, very easy, and they just say, we are proud that you are starting a company, so go.

Narration: Sébastien came back to Montreal from California to found his company in his home town. He was able to take advantage of research and development credits offered in Canada.

Sébastien Blais-Ouellette: *I had no money of course, no place, and only an office at home, a small office, but it was also the laundry room. And when I did my first tax, I had a tax audit from the government. And they came and audit, so I kind of hid the appliance behind a curtain, and you know had these science posters and my computer. And they came, saw that and said 'ok, you are starting, that's alright.' And in the middle of the audit, you know the washer starts spinning, and I was like, 'an experiment. it's an experiment.' But that's how Photon started. in a laundry room, you know some are garage companies, mine is a laundry room company.*

Narration: *How was Sébastien able to take his invention and grow it into a company? Find out more at the end of the show. You can also checkout the Photon etc. case study by visiting ie hyphen knowledgehub.ca*

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[begin intro music]

Thierry Harris: Finding markets for new technologies is a challenging endeavour. You are facing an entrenched culture, weary of changing how problems get solved. The target client's pain points, i.e. the problems or potential problems they face, have to be strong enough to justify using your products or services. The current way of doing things needs to be enhanced or disrupted. You have to be cheaper. And if not, you need to prove that the value added by using your technology will justify the expense. For tech companies conquering new markets takes time, perseverance and money.

Building an AI company can add further complexity. For your machine learning algorithms to work, you need data. Often this data does not exist, or is difficult to access.

Handol Kim: You're working with the probability that you're going to fail and that probability is probably pretty high. You know what you're trying to do here, finding some sort of innovative way to dramatically change the needle in terms of the way this industry does this stuff. So there's that technical risk, which is if it doesn't work and you don't have a business.

Thierry Harris: On this episode of Market Hunt, we chat with Handol Kim, co-founder of Variational AI. His company uses generative AI to help develop new drugs. Variational wants to reduce the time it takes to produce drugs and increase the probability of their success.

In this episode, we're going to be covering a lot of concepts that a non-AI expert might not comprehend. You'll find links to definitions for some of these concepts on our episode show page and in the episode transcript. Have a look at these as you dive into this program. Let's listen in to our conversation:

[end intro music]

Thierry Harris: Handol welcome to Market Hunt.

Handol Kim: Thank you. Thanks very much for having me.

Thierry Harris: Please introduce yourself briefly and explain the difference between a core AI company and an application AI company and where does Variational fit into that paradigm?

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Handol Kim: We are a generative AI for drug Discovery startup based in Vancouver. And we were founded in October 2019. And we've been working really hard on trying to apply AI to discover new drugs faster that have a higher probability of getting approved. And we use this technology across multiple targets in many disease areas.

[music transition]

Handol Kim: So we're an applied AI company in the sense that we use AI to solve a problem. So it's AI for X. So if you're an AI for fintech, if you are an applied AI company if you're AI for you know digital marketing, you know, your applied AI company.

As opposed to maybe a core AI company where what you do is you develop algorithms and then you try and find a market and an application or product for that algorithm. So there are some multi-industry core AI companies, Element AI being kind of the most famous of them. They have their challenges to find commercial applications that can pay them enough money to grow and become an ongoing business. Whereas in an applied AI company we do fundamental research in AI but it's constrained to one specific domain or activity.

[music transition]

Thierry Harris: There's an important distinction between core and application AI companies. Core AI companies work more as consultants, adjusting their algorithms to suit whichever client solicits their services. Application AI companies work on one algorithm to solve one specific problem. So they need to be sure they are working on the right problems or else all of their work will be for nothing.

Variational AI is an applied AI company working on a product for a specific market, drug discovery. The startup applied for funding via Canada's Digital Supercluster, a government sponsored program to support the innovation economy. Bill Tam, the Supercluster's Co-Founder and COO describes the opportunity for application AI companies and their investment into VariationalAI's technology.

Bill Tam: I think the big thing in the Variational case and I think this is the case for AI investments in Canada broadly. Variational has taken a very deliberate attempt to actually make products and use cases in the life sciences, in the pharmaceutical space.
In that regard, my hope is that it will set them apart from many of the other AI initiatives in the country. Oftentimes, what we see is AI in itself has been an undertaking that is about applying know-how and more of a consultancy arrangement than it is about end product. With the likes of Variational, hopefully, we can establish a bit of a framework or at least a blueprint for how companies can take an AI notion that actually productize things as opposed to just being expertise provider in the equation.

[music transition]

Thierry Harris: The Digital Supercluster is funding Variational AI to work with other partners to further develop and perfect their algorithms allowing them to generate new molecules which could be attached to Drug Targets. For more on Drug Targets check out the episode show links.

I asked Handol to provide us with a bit more background on how drugs were traditionally developed, and what opportunity he saw for Variational AI to enter the drug development market.

Handol Kim: Yeah, so, you know in the area of therapeutics, I mean these are these are drugs that you would, you know be prescribed. Once you have a condition as opposed to vaccines and then within sort of the area of therapeutics, there's you know, what we might call biologics of these are larger molecules proteins for example. Companies like Abcellera, or Zymeworks in Canada do a great job, you know addressing that market. We are in the area of small molecules. And so we work in chemistry. So what we do is we find new chemicals in the in the vast, you know chemical space in order to drug certain targets that are related to certain diseases and these targets are usually proteins.

[music transition]

Thierry Harris: And what is different about what you're doing? Because I imagine that there are other companies that are doing this molecular work. What's the difference between what Variational is doing and what other more traditional drug development companies are doing?

Handol Kim: Yeah, so in general, you know, you have an idea you start with the target right at the target might be like I said a protein or enzyme or or something. And you have some kind of insight or there's research that states that this target is related to a disease. There's a mechanism of action that creates diabetes for example, or HIV. And so the idea is to take that target protein and then try and find a small molecule a chemical structure of molecular structure that will actually fit.

And it's like a three-dimensional sort of Tetris game where you're trying to put a little key inside this big amorphous floppy sort of structure. And so it's a very hard problem. And really what happens is that traditional drug discovery, you know, you start with what we might call experimental data. So you would actually you have a target and then you start with you actually screen and you can take some chemical compounds and you actually physically stick it inside a bunch of wells and then you see if those compounds have any activity if against the Target and if they do then you're like “yay,” this is what we call a lead.

And then you work on that lead and then you try and optimize try and make it bind better with that target and also you try to eliminate certain things that happen in drugs. For example, you don't want off-target effects. You'll want your drug binding to a different area and then causing a side effect that might be worse that the condition you're trying to address.

Or, you're also trying to ensure that it has the right pharmacokinetic properties that it is absorbed by the body, it’s distributed by the body is metabolized and then excreted. You don't want that drug building up in the liver and then causing damage down the line. And then obviously you also want, you want it not to be toxic and kill you. And most, you know, also finally you also want it to be a molecule that you can actually synthesize and manufacture.

So these are all various properties and then that you wanted to be potent so you don't want it to be to have a high too high of a dosage. You want it to be orally bioavailable. All of these properties that you're to trying to develop within a candidate molecule. It's a very very hard optimization problem. Imagine, you know, you've got a small blanket and you're trying to cover all of these points that you pull it over here and it exposes your foot and you pull it up and it exposes your arm.

So what you're trying to do is you're trying to ensure that the drug meets all of these properties. And then once it's done that you would go into clinical trials. It's a very hard problem.

And the fact is that within the field of drug discovery costs are increasing tremendously every year. On a cap on, on out-of-pocket cost you're talking hundreds of millions of dollars, you're talking, you know, 10 to 12 years and a lot of the drugs that go into clinical trials don't end up going out. Maybe only one out of eight and actually make it out. But some are higher some or lower depending. Cancer is very very hard. You know other drugs other areas are a lot easier.

In any case what happens is you're undertaking a massive risk, and a massive technical investment, in order to try and develop this one drug. And so it's very very hard. The failure rate is very high.

So what we're trying to do is we're trying to take that early stage drug development, early stage drug discovery. We start with the target. Once we know what the target is and we have data around the target then what we do is we use our generative AI to generate novel molecules that haven't been seen before and then we optimize them across multiple properties simultaneously. And that's where we get the time-saving.

So what we try and do is we're trying to reduce early stage drug discovery or maybe preclinical up the preclinical and turn it for a years and eventually if we do it, right we want to try and reduce that for months. And that in turn will help reduce the time required to develop drugs.

Now, obviously, this is a holy grail and you know, we're using an incremental approach to do this. But we've got some very promising results early on.

So we're able to do that, not only can we shorten the preclinical. But the idea and the hope is that we can also increase the probability of success such that by the time you know, you take a drug into clinical trials, which is where a lot of that expense goes, that you have higher confidence that the molecule will actually pass the trials and be approved.

So, the main problem that we address with our AI is that we are generative AI. So in that sense, if you look at the way drugs are discovered today, you know the the space we call it chemical space. And it's a concept of, out of all the molecules that exist in the universe. There are certain drugs that are drug like, right? And they follow certain heuristics such as the lipinsky's rule of five or various, you know, drug likeness types of heuristics.

And you know conservatively we're looking at his face of 10 to the 60 molecules. And that's just a mind-bogglingly large number. And drug discovery today uses sort of a brute force approach where I might screen a hundred thousand molecules or compounds against the target, experimentally. Or maybe up to million. But that's extraordinarily expensive and takes a really long time.

And then the other way of doing it is computationally using what we call virtual screening. So you can use high throughput virtual screening where you can take millions hundreds of millions, even over a billion molecules and screen those computationally or in-silico as we call it against the Target.

Now a billion molecules is the very large number. It's far far bigger than anything we can do in the lab. But at the same time, you know ten to the ninth is a very very it's effectively zero percent of the chemical space. So what we do is we use, instead of a brute force method, in trying to increase the number of molecules that we can screen virtually from a billion to a trillion to a quadrillion, you know, a million order speed up is still effectively zero chemical space.

What we do is we take a different approach. And our generative model essentially will take data that we have both experimental data as well as computational data and it will train the algorithm as inputs. The algorithm because it's generative will then learn sort of the distribution of the molecules. It will learn kind of what makes the molecule active against the target what doesn't make it active against the target and then we use some machine learning magic in our variational autoencoder ergo the name Variational.

And then what the algorithm then does is it generates molecules that were not in the training set, but should be from the same distribution, and these molecules that are optimized for the properties of interest. Such that when we come out we generate these molecules that are uniform within the space of properties that you're looking for, but are going to be diverse with respect to the structures.

So it's a very different way of looking at it and it's not a brute force method. It is a we generate these molecules that don't exist or we're not in the training set. And that's our difference.

And we're not the only ones doing it. But this is the province of you know, a handful of machine learning companies that are now that are working in the space of drug discovery.

[music transition]

Thierry Harris: How are you defining your market then if you are. You need data first of all to be able to do this business model. And so maybe you can describe a little bit of who are your stakeholders and how you are interfacing with each?

[music transition]

Handol Kim: Sure, and and right now we're in a stage because we're a young company where we're validating the algorithm. So what we need is then we need to identify targets of interest and so a target is something that for us we need data against that target.

So we work with biopharma partners pharma partners, that have concepts of that have targets. They have data and they screen against the target. And there's a relatively high confidence whether it's an established target or validated target that this target actually means something.

You don't want to go through all of this trouble and find a really awesome molecule that interacts with the Target. Only to find the Target didn't have any relation to the disease right?

So you want to try and de-risk, you know, these are not the droids you're looking for, right? So you spent all this time and like, “Oh, well that didn’t work out the way we wanted to.”

So we go to partners who know more than us because we are a small machine learning startup. And then secondly, but also importantly you want to make sure that you're targeting something that has commercial value, right? So that it is not something that you're not going to be able to make money out of. It's not a pressing disease area, right?

And you want to be able to make sure that you choose the right target along these axes as well as other considerations. So for us the we de-risk this by going to partners that have established programs or have more information or better knowledge than us. We also need to work with medicinal chemists. And these are chemists who are drug hunters who have this intuition. We work hand in glove with our partners and we know that our AI needs the human in the loop and the expert knowledge in order to make it better. You know, we're not we're not going to replace, you know jobs in medicinal chemistry any time soon. There's definitely an ongoing role for medicinal chemistry in tandem with machine learning.

So we de-risk our activities in order to validate. And where we are right now is we are in the stage of validation. We currently have three programs where we've got to find targets with great partners such as adMare BioInnovations as well as the University BC and others where we have a concept of a target. We have a target identified, we have data and we've got the expertise to help us ensure that we don't end up generating molecules of those AI that are obvious or don't work. So we need to be able to work with these partners.

Once we validate that the molecules that we generate that we're trained on the data against the target are then experimentally validated biochemically and in the cell lines then all of a sudden, you know, if we can say this molecule will have this kind of you know, you know efficacy and then we synthesize or order these molecules of test them and yes, in fact they do then I think we unlocked a very very big achievement.

And at that stage, you know, once we've done that enough times, then the idea is for us to do to raise a lot of money and then go and become a drug company that is powered by an AI platform. And that's no different than many drug companies today, but a lot of drug companies and biotech don't necessarily use AI but they'll use other sort of platforms. And the ability to use a platform in order to more rapidly generate, you know candidates and file your I and Ds and build your pipeline is really really what we're trying to do.

[music transition]

Thierry Harris: So drug companies once you have that let's say ceteris paribus, everything is going well. And you have your technology that is validated through the different tests that you're doing with AdMare, UBC excetera. Once you hit that stage you're saying that you want to develop the drugs then in house at Variational AI and then transform itself into a drug development company.

Why choose to do that over licensing your technology to bigger companies who are already in that stage with the clinical trials and everything that goes out.
Why make that choice and why make that choice right now. Why do you feel like you have to make no choice right now?

[music transition]

Handol Kim: Well, so, you know, this is a really good question and it's actually, you know, we spent a lot of time thinking about this. So just to be clear we're not saying that we're going to have we go and sponsor our own clinical trials and run these, you know, even if we're able to validate the technology. The idea would be for us to create an asset. In an asset is you know, an optimized lead that has gone through animal, you know models and and it is something that we can then license to larger companies who would then take that that compound and then take it through clinical trials.

Thierry Harris: Okay.

Handol Kim: In terms of why we want to focus on generating assets instead of being let's say a platform company and providing the service to others is the simple reason is because we talked to a lot of investors and people in the ecosystem and I come from the tech world. And I've had a fairly long career in the software, cloud, mobile and in tech, in digital technology or ICT, really what you're trying to do is you're trying to build a platform. And then the platform will have network effects that will generate tremendous value and naturally what you want.

But you know in the drug discovery world as we spoke to people and they said “let me get this straight you're saying that if you can do this that you will be able to generate, you know, drugs faster than the way it's they are developed today and you can do this on an economical basis, but why the heck won't you? Why the heck would you give that up? And not develop your own drugs?”

And after you know, the 10th person told us that we kind of thought like maybe we can be we should listen to what people say in the industry. So it was really, you know, the the challenge for us is that you know, we are all machine learning people. And there are certain benefits for that. I mean we can bring in the you know, the state-of-the-art machine learning and we have that. I mean, you know in terms of benchmark results in the machine learning community and then also other benchmarks results were state-of-the-art, we outperform, you know, every other lab that has publicly released their results. But at the same time, you know, we're new to this world where immigrants to you know, drug discovery. And as a result, we you know, a lot of this time is spent trying to understand how the industry works and align it properly. I mean, I don't want to spit the wind right? And the fact is that fundamentally if our value proposition is sound, And then then we can really, really make a meal of it. So, you know, we just we just talked to a lot of people and were told and we’re taking that advice.

[music transition]

Thierry Harris: Well and wisely, so because the so many ideas just get lost sort of diving board before you jump into the ocean. And once you are into the ocean, it's very hard to get out. You've burnt your runway so to speak for something that's not necessarily going to have legs. And so you've done two major decisions, number one, finding the right partners to work with to acquire the data and number two, conceptualizing your company so that you understand the value before you’ve made, even a commercial sale or maybe even had a letter of interest from one of these companies that eventually, you're going to be partnering with.

And your machine learning guys as you're saying but you instead of going to bed and saying: “Oh man and I wish I'd done chemistry when I was younger and I should have done that extra degree of why didn't I listen to my parents?” You just go ahead and find the medicinal chemists and you find the right people who can do that super specialized work of validating that yes your molecules are actually going in the right direction. And yes they have that credibility from also using those people to help enhance your product offering.

And you’ve listened to what folks have said that when you've gone and asked them money and you’ve applied that. So I think a lot of people personally humbly speaking here will be interested in that story because showing a pivot before you even take a product out into a commercial market as you say is nothing new in the fail fast world of tech, but in pharma, you're going into a different zoo over here and the animals are different than the expectations are different and the times the market are much more different.

So you're really embracing in a whole new culture from a different sector that you're going into. Can you give us an idea Handol, how long ago was it that sort of AI companies started working or started approaching or started thinking of approaching pharma companies?

[music transition]

Handol Kim: Yeah, I guess it depends on how you define AI but you know, I would say that you started from sort of Deep learning and you know, maybe about 2011, 2012 is when sort of seeing this deep learning explosion. And that was all brought about by rapid results in 2011, you know, ImageNet and Alexnet . And really the ability for research out Hinton's lab at the University of Toronto and Krizhevsky's work there. Showing that wow, you know this new deep learning thing actually is getting much better results against the standard benchmark and that was sort of the ImageNet moment. And all of a sudden you see like wow, there's this thing actually works and you see rapid rapid innovation.

And then pretty shortly after that. I you know, I'd say that Atomwise was probably one of the pioneers of applying a deep learning approach to this field. And I believe that would like 2012-2013.

And then you see sort of like at that stage the early sort of AI for drug discovery companies starting to get funded on the venture basis. Companies like Recursion, Atomwise, Benevolent AI etc. and over the course of a few years. These companies have been able to attract a lot of investment and strike deals with pharma.

And inside pharma itself. You see in certain companies investing quite heavily in machine learning and AI to see if the thing actually works. Of course, you know, it's impossible for them to fund all of this innovation. So they so they do it through the form of partnerships. But I'd say that you know, we start we hit sort of like a frenzy in about 2018-2019 where you see a lot of deals happening and you see a couple of these first generation AI drug discovery companies, you know, generate candidates that go into it to the clinic, and going to clinical trials.

We have not yet seen an approved drug that was you know discovered by AI. And you know just by dent of the way that drug development works that's going to take a little bit of time. But we see, you know, a growing pipeline. Then what I would say is that that was sort of the first AI for drug discovery.

So there's the other thing is there are a lot of AI companies that are solving different problems within sort of the discovery or drug development world. You have companies that are generating targets starting from that, you know companies like Deep Genomics based out Toronto. Who are doing great things. You know Benevolent AI is working in that area.

And then you have AI companies that are working on drug repurposing, right? Which is looking at approved drugs and seeing if they are efficacious against different indications are different different endpoints. And you have companies like Recursion you have companies that are doing that.

And then you have a you know other companies that are trying to basically use AI to vastly accelerate sort this fragment based method of structure based search. You know and generate novelty within these scaffolds. So you can either search the chemical space more efficiently. Still a brute force method, but they're they're generating a lot more. You know companies in that area are like, I would probably put Atomwise in that category, probably Cyclica.

And then over in the generative world, which is out of the new the new thing, you know, I would put us, companies like Insilico, inVivo, out of Montreal. So there's a very robust sort of ecosystem. We're all trying to solve. We're also trying to solve similar problems, but in different waves, right and and and that's good. You've got this great diversity and Canada does, you know quite well in that regard and we're just proud to be part of the ecosystem.

[music transition]

Thierry Harris: Well, I mean definitely you're really are solving a major pain point in the industry, which is the risk involved in putting assets towards drug discovery. Maybe Handol you can describe a little bit about the origination of Variational and what drove you to found this company.

[music transition]

Handol Kim: Well, so, you know, there are five co-founders and we all used to work together. And you know, and we developed an algorithm that was extraordinarily good at predicting molecular property and optimized molecular property. And it was based on that strength that we decided to start the company. So I'm the only non researching person. So that means I do everything that's not related to research.

And so and I think it's a good relationship in the sense that we are lean and we're very focused. And you know, we all decided when we started this company that, you know, to be honest, we actually were thinking of applying the AI to molecular discovery in fields outside of pharma. Because the idea was that, well pharma is so proud of their so many awesome companies who raise so much money and it's an ecosystem that is very different. And I had tremendous respect for biopharma and I knew that I didn't really know anything in biopharma. And you know, you kind of take a very sort of peaceful approach to go like oh, you know, there's a lot of competition they're well funded and here we are Johnny come lately. We don't have domain expertise. It's a sort of a Red Sea sort of Market. What do we go Blue Ocean? So we looked at, you know materials. We looked at you know, nanoparticles. We looked at electronics. Molecules using electronics. We looked at sents and flavorings. And these are all very large markets. We looked at polymers. We looked at materials.

And there is a tremendous amount of innovation happening there. We looked at enabling synthetic biology. All of these things are all based on molecules. And a molecule is a molecule, except they're very different. But we thought that we could apply this technology to areas outside of pharma.

And we actually spent you know, quite a quite a quite a bit of time, you know talking to large chemical companies, material companies and and investors, and one of the things that we found fairly quickly was that they didn't have enough data to train our models, right? To train our algorithm and it didn't look like they were going to have data for a while and that's because you know chemistry and materials are where maybe pharma was maybe 15-20 years ago in the sense that wasn't the digitalisation of the data. It's still very much bench driven, right?

Which is why you see some really exciting innovation happening and sort of [autonomist labs] and various other areas where you know, the first goal is to generate that data, then you can do something with it. And so we figured you know what? This will keep for a while. So let's go into pharma because let's wade into this crowded market and try to differentiate.

And we're glad that we did because even though there was a crowded market. I mean, it's a one point three trillion dollar market. It's a very very massive market you have hundreds of thousands of companies around the world all using you know, biology using various types of chemistry using different types of methods to try and solve the same problem, which is increase the probability probability of success, you know of a therapeutic. Right?

Thierry Harris: Yep

Handol Kim: And so so we thought well, you know, we can bring this to the party and we're really glad that we have and you know, the thing that that's been tremendously important to us is is not as machine learning researchers, you know, the community tends to focus on sort of projects and datasets trying to publish a paper. And you know in the research world, you know, your data sets are big and they're beautiful, they're balanced and you can do really really well. But in the real world, I mean data is not just definitely not of that nature.

And so you undertake you face challenges that you wouldn't in an academic setting this last year, we spent translating our research from machine learning into actual programs on actual target with actual data. And we learned so much. And doing so and in talking and working on and cooperating with people who know more than us in the world of chemistry. Organic chemistry, medicinal chemistry and biology. You know, we've made the algorithm that much better.

To the extent where you know, and this is where the Supercluster really comes in. Is you know when Covid came around, you know, obviously there was a tremendous sort of reckoning and a national team, and you know what are we going to do?

And you know, the Covid call from the Digital Technology Supercluster was tremendously opportune and ideal for us. In the sense that, because our you know, our approach is agnostic with respect to the target. We thought well, heck, you know, this is a virus right? This is an infectious disease. And there is data that we can use to train on it.

Because the sad fact about Covid-19 is, you know we faced SARS, you know some 15 years ago and it wasn't, you know, as serious of a pandemic as Covid-19 has been. But to a large extent when you look at the virus, I mean, it's SARS Co-V, right? Or SARS classic was what caused SARS 15 years ago. And then just up and disappeared, petered out. And then at that moment all the research stopped, right? People didn't want to fund it. Why would you fund research on it on the virus that doesn't exist anymore?

And it's unfortunate because had we continued and actually developed therapeutics and vaccines for SARS, there is a decent chance more than more than you know decent that these therapies and vaccines might have been efficacious against Covid. Because when you look at the virus and the SARS CO-V 2 to virus, which is what causes Covid, they're extraordinary similar.

But we were able to do is we were able to take that data because there's a lot of data with the public domain and supplemented with additional data and we were able to train on SARS Co-V, SARS classic and then do some you know transfer learning because of the fact is that the viruses are very very close to each other 96% I think similarly.

And then with the target we chose VCL Pro and that difference is even is even smaller. I think it's just one amino acid difference in the binding pocket.

And so we were able to avail ourselves of the data and efforts, you know that were done fifteen years ago to really kind of leap frog. And so is very ideal for us. And then to be able to have you know, the funding from the Digital Technology Supercluster to cover the costs of the research was was invaluable and certainly extremely material to our ability to continue to make progress on the research and development side. And so we're really really pleased that we were able to do that and generate some results against it.

And where we are right now is you know in partnership with Dr. Artem Cherkasov, from the Vancouver Prostate Center, which is part of VGH and UBC is you know, we're able to use resources from the ecosystem in order to generate some awesome compounds that so far look quite promising. We're in the stage where where we've actually ordered some samples and we're starting to test the biochemical assays and from that we are able to iterate and making good progress there, and we are really excited about the potential.

Then, you know, the question is obviously, the Digital technology Supercluster is extremely interested in commercialization then you know how do we commercialize it? Well, you know, that's where adMare comes in. AdMare is providing services as part of the consortium both on the Medicinal Chemistry, but also on the commercialization side.

So we feel that as a small company as an SME as the government likes to call it, you know, we were able to partner with large organizations that have both the network ability track record to go out and commercialize any kind of asset that we might be able to generate. And it's a win-win-win, so we're very happy about that.

[music transition]

Handol Kim: When you're in deep teck or in a very very difficult type of technology. You kind of go to where the deep expertise is and in general that's going to be a fairly rarefied pool of people. So you kind of need to know who you're going to be, you know, you're going to bring to the dance.

And with the Supercluster, you know, their whole thing is "Look we need to ensure that the Consortium that you put together for a project to get funded is capable of doing the work and then of commercializing it: and so we were able to bring in the partnerships. And really start making progress on it.

[music transition]

Thierry Harris: You know, what we're trying to study here with Market Hunt is how ideas get commercialized and it seems as you're saying with technologies that are developed for drugs that haven't even been conceptualized yet. You need to have some partnerships with different players who each have their own expertise. And some of them provide the data some of them the commercialization capabilities oftentimes startup a piece of the tech play, which is sort the inventor if you will, using that algorithm and how you're all playing together kind of in your sandbox being enhanced by the Supercluster really gives a lot of hope I think and optimism for the potential future collaborative entities to take a look at what you guys did and then try to apply that to their own paradigms and their own problems that they are working to solve. So very exciting stuff and very interesting for you to share that journey with us.

So what kind of challenges does Variational have? Are you feeling safe and secure and what you're doing right now? Because it's kind of impressive to really pivot there and take on that challenge.

[music transition]

Handol Kim: I mean, so there are certain nightmares that you have that are sort of intrinsic. To anyone trying to, to all entrepreneurs right? And you know, they're they're those, there is that bucket, and then there's the other bucket of working in sort of these moonshot deep technology words.

And so I'll talk about the latter first, which is you know, I don't think that if you're working in an area of deep technology, you know, you're working with a the probability that you're going to fail and that probability is probably pretty high. A lot higher than than you know, most companies are comfortable in taking.

Because it's kind of binary in one sense. It's like if it works or it doesn't. And there's a real risk of technical and scientific failure that you might come up with something that might work, that is no better than the status quo. In which case it's a failure.

You know what you're trying to do is you are trying to find some sort of innovative way to dramatically change the needle in terms of the way this industry does this stuff.

So right then and there, you know, it's really David and Goliath. And the fact of the matter is we go, who are we to go and talk to a pharma company that has 40 billion in sales and you know hundreds of thousands of people it's been around for a hundred years and say that “hey we think we can do what you do but better and a lot faster.” I mean you raise a lot of eyebrows.

The good thing about us is that we're in the space where this is, we're not the only ones. So, and I think there's a growing realization that there is some validity to machine learning being applied to this domain.

[music transition]

So at least we're not the first ones. You know, we're we basically are part of a wave which is tremendous and that completely de-risks us.

But again, you have to look at the technology you have to look at the teammates that you have. And I'm blessed by working, you know working with people who are you know, top-notch.

And you know at the end of the day it's about how good team is in executing. You know how rapidly we can make progress? How we can how we can adjust and and change your iterate and ensure that you know, we meet our goals. So there's that technical risk, which is if it doesn't work and you don't have a business.

Luckily we start from a position where academically and research wise, we knew what we were doing, we have great results. Then it's a translation issue. And that is a completely different set of challenges. We're at a stage now where we think we're getting close to a stage where we can validate and show data that shows that “hey we can actually do this.” And once we do this, we think that's a very large value generating milestone.

So there's that which is like, “is it going to work?” And you know, we work on that every day and I've got some of the best people, you know working on that within the company. So then there's the commercial list in terms of how do we interface with customers in the market right? And we don't even think about competitors that much at this stage, because it's such a large market, right?

There's going to be space for different AI for drug discovery companies to emerge, it’s not a winner-take-all situation. At least not yet. There's no, it’s not like Google can kind of move it and then take the entire market. Not yet. Right?

So you have these sort of fears and concerns of challenges. And then it's about, you know, then, you know, the rest of the stuff is being an entrepreneur and any I'm sure you know, you speak to a lot of entrepreneurs online on your podcast here. The fact is that you know, you look at someone starting a company and I read this article really good about sort of the psychological toll of starting companies and you look at wow, you look at this entrepreneur and it's like looking at someone riding a lion and you go like “wow that person’s really brave.” Meanwhile the person riding the line is like: “how the hell did I get on this lion?” And how do I get off without being eaten by the lion?” Right?

Thierry Harris: That’s brilliant, that’s great.

Handol Kim: Yeah, and and and really it's kind of like you just do it. You don't really think you know, you can't analyze it. You know, you just have to execute it. And that sort of reckless fearlessness and that audacity, you know tempered by you know, capability and IP and and your teammates, you know, the size of the market that's really all you've got.

You know, when you're when you're trying to enforce your reality on the market that is a massive market. So these are some pretty pretty fundamental sort of nightmares that you have.

[music transition]

Thierry Harris: I gave the analogy back in a previous podcast. I was comparing it to a downhill skier who you know knows what time they have to get at the finish line to become the winner of that race and they're just trying to visualize their run as they're at the top of the mountain right at the gates and they're getting ready to go. And they're seeing every single turn ahead of time and they're seeing how they're going to perform that turn. And it seems like entrepreneurs have to operate in this sort of spatial ether where they have to be present. They have to be, you know on top of every single day and kind of win the day so to speak. But they also have to look in their subconscious at the deeper kind of run that they're making and need to be able to ensure that they're at the right speed. They're at the right funding. They are at the right sort of market positioning to make that turn to be able to finish the race. So it's a real balancing act. I think which requires a bit of insanity frankly, but I mean some people are into that stuff.

[music transition]

We've interviewed quite a few of them. So there are people that are out there that are crazy enough to try this stuff.
And you seem to be one of them which is just a great trait to have so kudos on that.

[music transition]

Thierry Harris: How do you measure your success at this stage?

Handol Kim: I mean at this stage right now. I just want to make sure there's enough money in the bank to pay everyone in cover costs for long enough for the team to be able to execute on the technical goals. And that is simply put the most brutal metric that we have right now. If we're able to hit our technical goals, then we go out and raise another. You know we raise more money. We do more deals, and we further validate. And this is where we are right now. It's not like we flip a switch and suddenly we become all powerful molecular space researchers. It's a journey. And so, you know, we have this phase now where we are validating the algorithm and we're making excellent progress against then we hope to have some great results in the next, you know few months to validate this.

And then after that we raise more money so we can hire more people and get the resources we need. It would be you it's shocking to know how much GPU resources we use in machine learning. There's a reason why NVIDIA's stock is so high is because we basically take money and give it to them so that we can actually do the training of our algorithm and our model.

So again, to have enough runway, enough time and enough resources for the team, to hit their technical goals, after that, we raise more money, and then we rinse and repeat. Except this time our technical goals get more interlaced with business goals. Right now we have three shots on goal. And that's a really really awesome place to be. At this stage right now, where we are.

We’ve got you know state of the art results. And we just now need to hit that next value generating milestone. After that we move to the next phase of growth. Which is we start looking at different programs, we start looking at interfacing with larger partners. We already have some commercial deals. And so, you know, that's that's all very good at the validations there.

The goal itself is extraordinarily ambitious and difficult to achieve. And we have to take it in increments. And each increment that we hit, each milestone, unlocks more value that we can generate you know better results and get the capital and the resources and support that we need in order to make it to the next level.

The trajectory is very similar to other companies that you’ve seen. Like Abcellera is a great story here in Vancouver. They are worth a massive amount of money now, they are now one of the highest capitalized, by market cap life sciences company in Canada, Canadian life sciences company. Which is awesome. That took them awhile and you know, they made enormously rapid progress during COVID and but even before then the groundwork was laid. And they raised hundreds of millions of dollars from great investors. We're not there yet.

[music transition]

Thierry Harris: One recurring obstacle AI companies face is accessing reliable data to fuel their machines. I asked Handol about the importance of data for VariationalAI. What would data accessibility look like for Variational in an ideal world?

[music transition]

Handol Kim: So, data of course, it’s the fuel, without it, we really can’t do anything. Machine learning is inherently data driven, so, where we are, it's slightly different. So if I'm sort of a healthcare AI company, or I’m sort of trying to track the outburst of a pandemic. You know you want to rely on data in the health world. And you know life sciences, health, pharma generically they are all kind of lumped together but they are very different.

We don’t have to deal with things like privacy issues relating to patient data. The data that we use to train our AI is data about chemicals and molecules.

And so there is a tremendous amount of data that is out there in open sources repositories such as you know like Zinc, or Pubchem, or Chembl etc. And these are curated by some wonderful organizations that make this available to the research community.

And this is not data about people, therefore it’s not subject to the same ethics or privacy review that you would need right? As opposed to if I want to train a model on predicting breast cancer then I am going to need a lot of data about breast cancer. You know images.

And that comes with actual people and then you have to deal with that issue, so that is not an issue for us.

The issue though is that in many cases, the companies themselves, or the industry itself has not generated enough data for machine learning use. And that is a real limiting factor.

In an ideal world, we generate enough resources such that we can generate the data ourselves, and against target that we decide. It's an expensive proposition but it's something that you know makes our lives a lot easier. Or we find some method where we can access the data if it exists.

But in many cases if there is insufficient data against targets, and screen data that we would want to use, and so we want to supplement that.

But at the same time there is a lot of data that is already out there. So data for us is a function of resources. So we don't have the resources right now to go out and effectively pull out all the data that's available publicly. But also, we can't generate enough ourselves because we don't have the time or the resources to do that.

So that's why we look at partnerships at this stage. But in an ideal world, we choose a target, there's data there, and we generate against it, and we train our algorithm, we run our own experiment campaigns, or we hire a CRO or service provider to do that. And then we generate enough data such that we are able to apply our algorithm.

One thing I would say though is because we operate in a world of sparse data. Our algorithm is extraordinarily good at working with small amounts of data. And that's also another benefit of the generative approach, versus let's say a more discriminative approach that a lot of other AI drug discovery companies are using.

[music transition]

Thierry Harris: Tremendously interesting stuff. We do have an academic based audience. They love to look at companies such as yours and study them and study their evolution and study also you know sort of the ideation of what the entrepreneur is going through. You've given us some tremendous data to work with. What kind of questions would you like students to be working on if they are looking at VariationalAI. What kind of questions would you like to ask them and get these students working on?

[begin end music track]

Handol Kim: When start looking at various targets. There's a whole business element to biopharma industry that we haven't touched really that much. And it's you know how commercially valuable is a target? What is sort of the landscape, and sort of what is the portfolio of biopharmas working in this area?

And then really to a large extent is we want to be able to start programs that are targeted towards something of commercial value.

But also, you know, if we're up against this massive juggernaut of a drug that’s generating eight billion dollars a year for farming and you know, it's well serviced then maybe you know, we could pick a smaller Target first right?

But if something is maybe going off patent or that’s a good time to go for a best in class type of you know, approach.

But really at the end of the day are our business models is it’s malleable. I mean, you know within our company we've subscribe to people, you know, opinions strongly expressed we held, right? In the face of better data and better information. You know, you're the first ones to go. “Oh, okay. We're pretty stupid about that. What the heck were we thinking, let's change.” And you need that agility and that mental agility to be able to ensure that you don't.

You know, you're skiing analogy, like I would say that you are skiing blind. And you just got to use the force. And you want to make sure that you go left instead of right. But you might hit a tree. So you need to be able to, Oh, I think there's a tree in front of me, I better be able to switch left, right? Instead of like sticking true to your misguided principles, and then smacking into a tree and dying.

So where we would need to help with is to ensure that areas that we are going after, disease areas that are underserved. Because our approach is largely agnostic to the disease area, we want to find areas that we can actually bring an asset to market. Because that also increases the value of that asset.

If there's no drug for example, Alzheimer's there's no approved drug for that, you know, a lot of people lost tens of billions of dollars of market value trying to bring drugs to market. Biogen lost 16 billion dollars worth of market cap because they missed an endpoint on their phase three. That’s like a third of their market wiped out because this one drug didn’t make it. So we don’t want to be in that situation where we want to be savvy about it. And look at a disease area, where we don’t want to go on a kamikaze mission, as awesome as we think our AI is, we want to make sure that we go after viable targets that have good commercial payback, and a higher than random chance of success. So that's something you know, the analysis would be required again, you know sort of portfolios, and looking at where companies are active and not active and having that understanding to inform our decision. Because at some point, you know after we validate we are going to start looking at our own targets. So that’s where we need help.

Thierry Harris: In this episode we took a deep dive into the intricacies of drug development using artificial intelligence. We understood how market forces will continue to shape the development of drugs. These same forces will dictate how applied AI / pharma hybrids evolve. The Digital Supercluster's investment in Variational AI is the perfect example of this. For the technology to thrive, it will need to keep crossing that bridge between fundamental research and solving problems in the business world. Partnerships will be key to make this happen. More work needs to be done to keep fostering these networks. And we'll be here sharing this storyline with you as it continues to evolve.

[end music track]

[begin promo music]

Narration: *And now a final word from our sponsor, the IE-KnowledgeHub. IE-Knowledge Hub is a website dedicated to promoting learning and exchanges on international entrepreneurship.*

If you are an education professional looking for course content, an academic researcher seeking research material , or someone interested in business innovation check out IE-Knowledge Hub.

Let's pickup where we left off for Photon etc., a photonics company manufacturing measurement instruments for fundamental research and industrial applications.

Sébastien Blais-Ouellette: *Beginning of 2004, I borrowed a piece of lab in a university, and they allowed me to just have a small piece of the optical table. I made the first prototype. And then I was able to sell the first filter. And that gave me a bit of money to hire someone, and then rent a space at the university, and we were the first in the Joseph Armand Bombardier Incubator, from Polytechnique, University of Montreal.*

Narration: *That's Sébastien Blais founder of Photon etc. Photon was able to leverage support from incubators to help him get his business off the ground. Because his technology was born out of an academic lab, it was a natural fit to pursue scientists as early adopters of his technology.*

Sébastien Blais-Ouellette: *You know it's always the case with physicists and optical people, because we, and a lot of scientists, you know they develop a basic technology, and you ask yourself what you can do with that? Instead of starting from a problem, and saying, hey what solution can I find? You know it's very hard, to have a new technology, and analyze markets one after the other, and say, where can I fit? you don't know enough about these markets, and people in these markets cannot understand your technology. it's a very difficult position, so at some point you just say 'ok', and you go! and that's why we went to the people who are scientists*

Narration: *While allowing Photon etc. to survive and even grow for a long period of time, working with scientists also presented serious challenges.*

Sébastien Blais-Ouellette: *The academic community are early adopters, and they love new things, so they are great to develop a portfolio of products, to develop new products. It's painful at some point because they always want something different. because they want to go further than their last publication, they want to go further than their colleagues and so they ask things that are not there. It's very intellectually interesting, but business wise, you know you like to repeat things. but it was a good way to start.*

Narration: *You've been listening to segments of the Photon etc. video case study, available on ie knowledge hub. Learn more about how Photon etc. expanded their business into different markets, servicing multiple industries and even spinning off new companies from their foundational technology. Watch their full case available for free at ie hyphen knowledge hub dot ca.*

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Thierry Harris: Market Hunt is produced by Cartouche Media in collaboration with **Seratone Studios** in Montreal and **Pop Up Podcasting** in Ottawa. Market Hunt is part of the IE Knowledge Hub network. Funding for this program comes from the **Social Sciences and Humanities Resource Council of Canada.** Executive producers **Hamid Etemad**, McGill University, Desautels Faculty of Management and **Hamed Motaghi**, Université du Québec en Outaouais. Associate producer Jose Orlando Montes, Université du Québec à Montréal. Technical producers Simon Petraki, Seratone Studio and Lisa Querido, Pop up Podcasting. Show consultant JP Davidson. Artwork by Melissa Gendron. Voiceover: **Katie Harrington**. You can check out the IE-Knowledge Hub case studies at Ie hyphen knowledge Hub dot ca. For Market Hunt, I'm Thierry Harris, thanks for listening.

[end credits music]