

Cowen 43rd Annual Health Care Conference

Company Participants

- Brad Gray, President and Chief Executive Officer
- Kimberly Powell, Vice President of Healthcare
- Molly Gibson, Co-Founder & Chief Strategy and Innovation Officer

Other Participants

- Daniel Brennan, TD Cowen
- Matthew Ramsay, TD Cowen
- Steven Mah, TD Cowen

Presentation

Matthew Ramsay {BIO 17978411 <GO>}

Thank you for coming and welcome to what I think should be a really exciting and maybe different type of session than you guys are used to. And my name is Matt Ramsay. I lead the semiconductor research practice at Cowen, and I guess we'll start by addressing the elephant in the room, why the hell are you listening to a semiconductor analyst at a healthcare conference. But I'm really excited to talk about the topic of AI in healthcare with the leading AI company in the industry, NVIDIA.

I started working with the NVIDIA folks about 10 years ago, and they were a gaming company. About \$15 billion market cap and have, in the last 10 years, basically invented the science of artificial intelligence and accelerated computing and are now the sixth or seventh largest company in the stock market. And one of the biggest areas of focus, not just in Big Data, not just in automotive is healthcare. And really excited to have Kimberly Powell come and spend some time with us. She leads to healthcare AI business at NVIDIA across all of these segments among with us. The guys that you probably know, Steve, Dan, thank you for co-hosting with us -- with me, and we'll have hopefully a good discussion.

I'm going to spend a little bit of time with NVIDIA to start with and have Kimberly introduce what NVIDIA is doing in healthcare. What the business looks like. How across different healthcare verticals they're using AI computing for -- to help companies speed innovation and do things that are disruptive and exciting.

So, anyway, and then, Dan and Steve will introduce the other panelists and kind of go from there. So, if there's -- if you guys have any questions that are about healthcare, I'm not your guy, but if it's anything about AI computing, then we'll go from there. But Kimberly, thank you. Thank you all so much for being on the panel.

And if you want to spend a couple of minutes, just introducing to this audience what NVIDIA is doing in healthcare, and then we can go from there.

Kimberly Powell {BIO 22145194 <GO>}

Absolutely. So, if you don't mind, I will kick it off with -- as a reminder, this presentation contains forward-looking statements and investors are advised to read our reports filed with the SEC for information related to risks and uncertainties facing our business. Now we got that over with, thank you for joining us. I'm glad we have a packed house.

I've been at NVIDIA for 15 years, and as Matt said, we are known as a gaming company. We aren't known as being in healthcare sector. But I started the practice 15 years ago, because there was this revelation that said in order for us to do efficient computing, computing that is going to take us through the next 10, 20, 30 years, and beyond, Moore's law is ending and we need this idea of accelerated computing. The problems and challenges that were coming to the industry needed a paradigm shift. So, we took that gaming and that graphics technology and we invented a new paradigm called Accelerated Computing. We've since gone through our next transition, which is into an AI computing company.

So, if you think about the three most advanced computing approaches in the world today, computer graphics, accelerator computing, and artificial intelligence, our job in the healthcare business unit is to essentially make that accessible to healthcare and healthcare broadly. So, some of the first things that we ever worked on was actually here in Boston. Radiologists, who are inventing new mathematical approaches to things like CT reconstruction.

In order to reduce the radiation, in order to have it clinically viable, where you could turn around these images in a time, where a patient is still with a doctor in critical care, you needed accelerated computing. And so it absolutely triggered us to say what we are building is going to be applicable broadly.

So, we made our first journey in medical devices. It is the core of our business today. Brad and his team are inventing some of the most important new tools and platforms, helping us understand biology. It's such an exciting time, because it takes something I'm deeply passionate about, which is imaging, and it marries it to something that the world has conquered and really used as a new tool, which is genomics and the insights we can really pull out of biology and it marries us to in. And I think the next 10 years that this technology is going to enable us, it's going to take us to places we've never seen before.

In this journey of an Accelerated Computing company, we were discovered by the computer scientists, who are looking at deep neural networks that this was the right platform, this was the right architecture in order to do this new thing called Deep Learning. This reinvented for the second time thing called Deep learning. So, we had the opportunity to now look at how Deep Learning was transforming and how it could be applied into Healthcare. We build right now the industry standard tools for

developing AI for all imaging types, whether that be radiology, pathology, surgical video. And it's taken us along on this journey to say, the world -- the number of applications -- maybe think about driving a car, for example, maybe you're looking at about 12, maybe 24, algorithms to drive the car, that's usually why you can get your license at 16.

Well, the number of algorithms that a clinician potentially needs to use in order to do his or her job is on the order of hundreds thousands if not hundreds of thousands. So, we need to create the capabilities of giving the scientists the subject matter experts, the clinicians the ability to develop AI applications. And so, we build those tools of software and the services now to put it in the power of the hands of the healthcare industry.

And then in this new realm, the ChatGPT realm, if you will, it has been discovered and highly leveraged Generate being a company whose put it to fantastic use, where we have the ability, the invented many, many years ago, decades ago to represent chemicals and proteins in a sequence that looks just like characters that are the same thing you feed into a ChatGPT model and it can reason about it, it can generate new ideas and it can bring us into yet the next, I think, paradigm shift in healthcare.

And so, these are the -- some of the areas that NVIDIA focuses on. This is how we sort of understand the market by listening to the innovators in the market, the academic communities, building the hardware. But more importantly, the software platforms and services to put it into the hands of all of the passionate and innovative thinkers in the industry, so that we can really see a future we haven't seen before, where we can start to take medicine as a science and more and more push it into the realm of an engineering practice.

So, if -- that is a bit of a summary of where we are and what we're doing, and happy to have --

Questions And Answers

Q - Matthew Ramsay {BIO 17978411 <GO>}

(Question And Answer)

Q - Daniel Brennan {BIO 15426025 <GO>}

Great. My name is Dan Brennan, I cover life science tools and diagnostics with Steve Mah and a third colleague, and I follow NanoString, who's up here on the podium. And for those of you, who aren't in the healthcare field, so NanoString is amongst a handful of companies tackling new field, single-cell spatial biology. Ten years ago single-cell sequencing analysis became a new technology and it's really proliferated, but the spatial context of looking at single cells is brand-new. NanoString was one of the leaders rolling out their first platform a few years ago, and now they're just embarking upon their newest platform, which is truly single cell in situ in this -- kind of in the native tissue and it's themselves and a handful of companies going after it.

So, there's a tremendous amount of excitement, but there's also uncertainty from investors about really where does this go? And is it a cool discovery tool? It doesn't really lead to some new insights that you can find, new drug signatures and really bend the curve if you will. So, it's interesting. I just hosted Brad on the prior panel and they have their comics platform and they've made a big, big deal out of their informatics approach to their single-cell technologies, it's atomics and it's a cloud-based approach, whereas the other players really haven't gone that route.

So, it's very interesting to ask Brad now with that long introduction about, and atomics I believe is obviously incorporating NVIDIA. So, Brad, maybe walk us through a little bit about when NanoString kind of how you came in to start to work with NVIDIA? When you made the decision? How you decided that you needed to harness their technology? And what it's going to hopefully allow you to do with atomics.

A - Brad Gray {BIO 16814265 <GO>}

Yes. Thanks, Dan. Well, there's a lot of faces in here. I don't know how familiar you're with NanoString, so let me back up and explain a little bit about what spatial biology is.

Spatial biology, as Kimberly said, well, it's kind of the marriage of traditional imaging technologies, look at tissue, like anybody would through microscope when you're in high school and genomic technologies that look molecule by molecule at every RNA or protein in a cell. And spatial biology allows us to see how cells are talking to each other, all the different unique cell types, what the physical architecture of a tissue is at a molecular and cellular level. So, think of it as, tissue is almost like it's made of legos and every cell is the -- might look the same, but they're actually unique lego blocks and they serve different functions.

And in the past, biology is basically, ground up that tissue and built a big pile of legos and said, is it mostly orange or green or red, it's not even really looking at the shapes. And then single-cell biology came along and allowed us to capture cells and droplets and look at each lego piece individually and say, there's cubes here and there's long skinny ones and there are some circular ones, and these are differently -- serve different functions. Well now, spatial biology allows us to look at the tissue on an intact basis, see all those legos, how they fit together, and what they're doing.

The -- with spatial biology, the first application is spatial biology on research. So, we're -- it's a new tool discovery researchers are figuring out basic questions about how tissue works. And then later translational researchers will help take those insights and make them into new diagnostics and new drugs. But it's -- we're at the very beginning of what will, without a doubt, be a 10-year revolution in the field of biology. The customers, who're applying it today are academic medical centers like Harvard and the (inaudible) biotech companies, and the like, that's who our customers are.

So, what are some of the opportunities and challenges unique to spatial biology that got us into informatics? Our cosmic system is capable of taking a tissue of a million

cells and visualizing a thousand different RNAs in each of those cells with its X, Y, and Z coordinate. So, it can generate a data set from a single one centimeter by one centimeter piece of tissue box, like a mold that you might have removed or a tumor that was biopsied. That's about half a gigabyte in raw data. And that's at 1,000 plex. We announced just last month that we'll be going to 6,000 plex so 6,000 unique molecules times a million cells, which could be 3 terabytes to 6 terabytes of data for a single sample. So, that's an unprecedented amount of data.

And the nature of the data is such that the human mind can't really make sense of all the different relationships and signals that are happening. So, we began to realize as a company several years ago, that suddenly we were in -- a bunch of engineers and chemists were embarking on one of the biggest informatics challenges in healthcare. So, we added two amazing women to our Board of Directors to help us with that, the Chief Data Officer of Moffitt Cancer Center, named Dana Rollison and a woman named Janet George, who now runs the cloud computing portion of Intel that was at the time, the AI/ML leader of Oracle, to help us think about how are we going to help our scientific customers, actually, get insights out of all this data, and how are we going to prepare for them.

Around the same time, we embarked on two aspects of spatial biology. One is, building compute, an unprecedented amount of compute power into our actual systems to do raw image analysis on the system. And then secondarily, stream into the cloud to store and analyze, and work together on the data sets using the elastic compute power and storage capabilities of the cloud.

So, NVIDIA was the company, whose GPUs we selected to build into our CosMx Spatial Molecular Imager. The GPU architecture they offered was 5x faster at doing a very important function, which was identifying the cell boundaries so that every RNA and molecule can be assigned to the right cell called cell segmentation. It's an AI/ML-based algorithm that runs on an NVIDIA card inside our latest product CosMx Spatial Molecular Imager. It is fundamental. If we assign the molecules to the wrong cell, we'll absolutely get misleading results. So, that's critical.

And now, once we get those terabytes and terabytes of data into the cloud, there's a whole another set of opportunities to apply informatics and AI/ML to look at those datasets to learn from them, to see patterns that will be hard to see without those tools. And we have an opportunity to work with NVIDIA on how we optimize those algorithms for NVIDIA processors in the cloud, taking full advantage of their roadmap of ever-increasing power of the GPUs.

Q - Daniel Brennan {BIO 15426025 <GO>}

So, now Brad, maybe as a question, you're only as good as what you've done today. And you're talking about increasing the number of things you can look at by six fold over the next year, and you're probably talking about tripling that again at some point through the whole transcriptome to 20,000 genes. So, not only doing more, but then you're also going to develop more insights and you probably want to speed it up, which is one of the factors we hear a lot and it's probably not the informatics side. So, long way of saying and may Kimberly, like what is the roadmap

between what you're doing today, and how important is, I mean, further progress using the existing chips or future chips that will allow you to scale and do kind of bigger, faster, better.

A - Brad Gray {BIO 16814265 <GO>}

Yes, I'll start and Kimberly can build on if she likes.

So, for us to -- the number one thing we can do for scientists is give them tools that extract the maximum amount of insights from the precious tissue samples they have. And so, driving up the plex from one marker that you might look at or staying to your microscope through conventional means, to the 1,000 we offer today, to the 6,000 we offer next year, to the 20,000 that we cover the entirety of the human genome. That is our mission. And we're going to push it as far and as fast as we possibly can.

Each time we're successful, we make the informatics challenge harder, though, on a kind of geometric way. So, we're pushing the chemical and engineering and optical ability to extract data from the tissue, but we're going to need Kimberly's help to -- in taking advantage of NVIDIA and others kind of compute resources and to make sense of all of that over time. So, we're experts on the first piece, but we rely on partnership and outside help on the informatics piece.

A - Kimberly Powell {BIO 22145194 <GO>}

Yes. And I think the way we think about the problem is, we think about it, in what we call a full stack. You can think about NVIDIA as a layered cake. Again, a lot of people know us for the chip and the chip architecture itself, and that is absolutely fundamental. For example, in our latest architecture, we have hardware silicon that does -- it's called the transformer core that is vital to being able to do these large language models like ChatGPT.

However, you need to be able to expose that technology not only all the way out to the application developer, but across GPUs in a single node, across nodes inside of a data center and do it at 1,000x scale. So, these models take many, many thousands, 5,000 to 10,000 GPUs working in unison across an entire data center networked with NVIDIA's networking and doing that level of processing for weeks and months at a time.

And so, in order for us to give Brad and his team, who are not computer architects and we don't want them to have to be, the ability to access this, we have to look at these application challenges at every single level. At the individual chip level, the system level, the data center level, and the ability for these applications that they're trying to do, like cell segmentation at scale, as he's going to 60x his data set and being able to do that at scale. So, we take a full stack approach. And it's quite a unique position for our company to not only be designing and architecting the silicon itself, but also have all the components to go at a data center scale, and then the software investments that NVIDIA has made over the last two decades allows for these application development to happen at a very rapid pace.

So, for example, I think we all have heard of Moore's Law and the end of Moore's Law. With full stack optimization, we can see speedups of a million times over a 10-year period, where Moore's Law would be many orders of magnitude lower than that. And you can't just do that on chip architecture alone. It's just not possible anymore. So, this full stack optimization is super important.

And then the other aspect of what Brad said is, machine learning and artificial intelligence is part of those X factors. If you had to compute everything in its full physics-based computation, it would be too computational intense and too expensive. But artificial intelligence can help us augment that, can help us essentially be a functional approximator of some of these more difficult calculations that is also part of that X factor.

And so, we work with the leaders in the field, working and pioneering approaches that are never done before because they exercise our full stack more so than we could ever do just sitting in our own back office. And that is largely the chart of our team is to partner up with innovators and to make sure that we apply that whole stack for them to achieve their life's goal, which is spatial genomics and eliciting all the amazing parts of biology we don't even understand yet.

Q - Matthew Ramsay {BIO 17978411 <GO>}

Steve, you want to go ahead and introduce yourself and Molly and the Generate team?

Q - Steven Mah {BIO 21796111 <GO>}

Sure. Yes. So, Steven Mah, one of the analysts at TD Cowen, covering life science tools and diagnostics, specifically covering data-driven drug discovery and also synthetic biology. So, yes, it's my pleasure to introduce Molly Gibson, CIO of Generate Biomedicines. So, our thesis and this is derived from a recent multi-analyst piece we did, which is the primer on AI and data-driven drug discovery.

So, basically, just settling on the thesis side -- of the -- side, the return on investment dollars and the -- using the traditional drug discovery model hasn't been realized, right? So, even though there's been multiple advances in R&D technologies, multiple advances in terms of understanding human biology has not been reflected in increased clinical successes. So, our thesis is that, by applying artificial intelligence to these vast amounts of data that NanoString is generating and others, we'll be able to increase the probability of clinical success and deliver better drugs and at a lower cost. So, maybe with that kind of introduction, Molly, maybe can you spend a few minutes on Generate, and how you're using AI?

A - Molly Gibson {BIO 20208012 <GO>}

Absolutely.

So, Generate -- at Generate, we focus on using ML and AI to generate novel proteins. And so, proteins, we're really interested in them, because almost everything in biology happens because of proteins. So, if you think about DNA, it's really kind of

the software, proteins are how that software is executed. And so, to us, historically, proteins have been discovered for medical purposes through this process of drug discovery. And it's really the discovery word that is so interesting to us from the perspective that, it's really empirical process, it's very bespoke. And like was mentioned, it's -- it really leads to challenges in economies of scale. It's not a scalable approach.

And so, if you think about what could actually give us the returns on investment that we want and we actually lead to successful molecules having an understanding of how protein leads to a particular function and to particular clinical outcome is really essential. And that's something that's just not seen today. And a lot of that become -- comes down to the fact that we're discovering these through these really empirical processes, trial and error essentially, these medicines. And at the end of the day, you get out whatever comes out at the end of the funnel, not what you want, not what you've specified. And so, to us, the question is, can you actually flip that on its head? Can you actually say, this is the molecule I want, now what is the sequence, the protein sequence, the amino acid sequence that would fold into the right protein and gives us the right function?

And if you think about the combinatoric of this, it's really -- it blows up insane to a place, where really AI and ML are the only way we can imagine being able to do that. So, the standard protein is about 100 different amino acids, each amino acid can be 20 different letters. And so, if you think about any different combination of that, that combination is more than the atoms per meter squared. So, the combinatorics isn't same. And so, we're asking that question of, can you actually start to use ML to understand the rules by which these proteins function, be able to specify a particular problem, and then you able to not just learn those rules, but then generate novel proteins.

And so, we're applying those two problems, where we can actually say, I want an antibody, for example, so like anything like the antibodies that protect us against COVID or HUMIRA, for example. We want antibody that does that. And because of that, we're going to be able to dose this drug at a reasonable interval, maybe six months to a year. We're going to be able to give it to these patient populations that are in high need, high risk very safely. So, more effective, more safe molecules for people faster.

And to me, the thing that gets really exciting about this is, one of the challenges in drug discovery is that we haven't been able to see the same types of economies of scale that you see in the tech industry. And so, you've not seen those kinds of returns that you have on your technology. And so, really about putting the technology first in the biology, we're able to flip that on its head and think about these economies of scale that we want to see in drug discovery, and more importantly, the successes that we want to see. A lot of the challenges, which I've discovered today is, is not just discovering the molecules, but making sure that they're successful. So, being able to do this more drugs faster and more successfully.

Q - Steven Mah {BIO 21796111 <GO>}

Thanks for that. And maybe this is a question for the whole panel here. We've heard people say that they have the best algorithms. My personal opinion is that it is table stakes. And where the rubber hits the road is, how you're actually taking your functional data or your mass data and then using that to train your machine learning algorithms. So, I'm curious to get your guys' perspective on that. And especially with you, Molly, how are you -- how you are generating data to train your machine learning algorithms?

A - Molly Gibson {BIO 20208012 <GO>}

Yes. So, to me, this is kind of a conversation we have all the time, which is like out of all the components of compute algorithms and data, what's the most important? At the end of the day, it's all of them. It's important that you're thinking about all components of that. And so, when we've thought about, for example, for data, it's not just any data that's important, it's the data that's going to be able to give you the most information, the most high-quality information at scale.

And so, to us, what I -- when we think about the question of, can you get to what - how protein functions in the body, we know that sequence dictates structure of a protein, the three-dimensional structure of the protein, and then dictates function. And so, the most important things, pieces of data for us are two things. One is structure, which is incredibly generalizable across any type of data that you -- any type of protein that you want. And so, we've built out a cryo-EM core, four different microscopes, it's one of the largest in the country, have been able to produce structural data in mass to test things that we actually generate with our algorithms.

So, instead of protein prediction -- structure prediction, where you already have the answer of the structure that you want to test. For us, when you generate something new, there's no answer, you don't have the answer. So, you have to actually test it. And so, we're doing that with our cryo-EM core. And then there's also function. So, high-throughput functional data is also the second thing that we want to be able to do. So, we're constantly generating a fully automated lab, where we can generate the function of the molecule itself. And so, it's not just that we have more data, it's that we have the right type of data for the questions that we're answering, which is really important to us and how we're investing on data.

A - Kimberly Powell {BIO 22145194 <GO>}

Yes. I think, Steve, to comment on this is, there's a few fundamental things to think about, what Molly described and so many of the tech bios, we call them, who have realized that it's not just a single algorithm. And what I -- my version of what Molly said is two things. One, it's about the method. And two, it's about turning it into an engineering process. It's repeatable, it's auditable, it's studiable. And that is a really a fundamental difference. And so, all three are absolutely important. No person with the most chips wins, no person with only the data wins, and actually, no person with just an algorithm wins. Because that algorithm and the data is ever-changing. I mean, as we know healthcare, the platform technologies are not standing anywhere near still. And so, the methods development is super, super critical across the gamut here.

And the other thing to realize what's different now is not just that we have the ability to build something like ChatGPT, which honestly was able to be born because of the Internet, let's say. But now through lab automation and through platforms and digital biology, we now have the necessary data feeders. And so, it's -- we -- this is new. This isn't within the last five years that terabytes of cryo-EM data is coming out. These things are winning the Nobel Prize, new microscopes, new platforms are entering the market and getting more accessible all the time, and then we're able to automate them. And so, the scales of the data are completely unprecedented.

And then this meeting of the capability of generative models in AI is going to be able to help us make sense of it, reason through this data, discover things nature has never seen before, right, which is what the Chroma algorithm has done is, nature would go through 4 billion years of evolution and say, okay, that worked, and on to the next job. It didn't sit there and say, what other proteins might work. No, it just had to move on, right? It had to be very efficient. Well, here, because we can generate data, we can encode this data into these models, we can explore like we could never explore before. And not in a 4 billion evolutionary time scale, we're talking now within a week or two weeks or a month. So, this is what's super transformational is this new method and the ability to generate data at the scale and at this resolution and fidelity.

A - Brad Gray {BIO 16814265 <GO>}

Yeah. Just build on, I think both made great points. Our -- I want to go back to the question of kind of the relative value and importance of data algorithm and compute, we -- our tools are the data-generating tools. So, obviously, if you haven't tested in biology, if you haven't tested the right sample with the right tool, the data doesn't exist. There's no way you can get any insights no matter how much your computer or your algorithms.

But our goal is to help people generate the most interesting data to put it into the cloud, whereas algorithms evolve and as compute power evolves, it can be queried over and over and over again and have a long life of generating insight by insight. So, this is why the -- having a data-intensive production, extracting the maximum amount of data out of tissue, getting that to the place, where it can be shared amongst collaborators all around the world -- actually, we haven't met -- that place in the cloud is called our atomic spatial informatics platform.

And the critical aspect of it is -- because algorithm innovation is such a huge part of what's happening in science on these new datasets. We have a total -- totally open-source approach. The algorithms that we provide on Day 1 are open source, you're going to be able to look at the code and R or Python to figure out exactly what we're doing. There's no black box. And as you are an academic, who invents a new method, you're going to be able to upload it straight to our cloud and take advantage of the compute power and architecture and visualization tools and the residency of the data to innovate on algorithms.

We're not going to be -- NanoString Technologies is not going to be the algorithm inventor of the world, the huge academic environment is. And then the beauty of

having it all in the cloud is, as successive generations of technology and GPUs and CPUs come out, we can forever take advantage of those improvements in speed and processing power, et cetera, without a scientist ever having to throw out their old server and buy a new one. We're totally taking that out of their hands. They had access to NVIDIA's entire roadmap of technology by virtue of putting it in the cloud and letting the data centers deal with the upgrade cycles.

Q - Matthew Ramsay {BIO 17978411 <GO>}

I think that's a really sort of interesting segue to something that I wanted to ask. And I talked to NVIDIA's founder, Jensen Huang, he's sort of the founder of AI, so to speak, along with their Chief Scientist, Bill Dally. And we talk a lot about pushing -- what you guys have been talking about here, pushing the boundaries of more data, more compute intensity, higher up the AI stack. And then there's a separate vector, which is democratizing AI. And actually getting these sort of compute intensive, cost intensive models to be accessible by the masses. And Brat you touched on it briefly by putting things in the cloud. I remember going to demonstrations three or four years ago, where taking ultrasounds and enhancing them through AI and piping it back down into the doctor's office and having things where you can infer 50-100x resolution. And all of those things are really cool, but they're deployed in how many hospitals in the world? Just because most folks can't afford \$300,000 supercomputer let alone know what the heck to do with it if they had it, right?

So, I guess what I want to talk a little bit about Kimberly is just, NVIDIA announced a couple weeks ago, and this has been coming for a while, so the DGX in the cloud, right? So, imagine that example of -- instead of doing ultrasound piping into the cloud, piping it back at real time, taking the ultrasound, saving it as a video file, uploading it with a few doctor's notes, and then getting something back from the AI that you can use, and that can be done on a subscription basis or a per-query basis. Anyway, if you could spend a little bit of time about that other vector of democratizing AI of things, maybe we've solved, but are deployed in a fraction of where they should be deployed globally in the healthcare space?

A - Kimberly Powell {BIO 22145194 <GO>}

Yes. It's a super important point, which why our move to the cloud is so important. And if you go back just 5-10 years ago, supercomputing centers are largely funded by large government entities and there's 10 of them in the United States, programmable by another 10 people in the United States. And so, that's really been one of our core missions is how do we make that more and more accessible. One way you make that more and more accessible is through software and applications.

So, I've spent the last 15 years of my life with my entire team partnering with application developers, codifying what we can into to libraries that are reusable by everybody, right? Working with the open source community such that these frameworks that helped develop all the algorithms are accelerated and are available everywhere. So, the software part piece of it has been ongoing for a long, long time. We decided to put this CUDA, which is our -- essentially our way to program a GPU on every GPU that NVIDIA ever made all the way into our gaming GPUs that back when we did it didn't know you were going to run generative AI algorithms on your

gaming rig, but now you do because you can create gaming animation characters with it. And so, that was just an amazingly wise decision, but part of the democratization, and the ability for this large software ecosystem to abound and really democratize it from that regard.

Now the second thing that Matt described is, we invented the DGX, which is essentially our AI supercomputer. One for our own AI scientists, but also for a lot of the academic Godfathers in the world who said in order to further this research, we need to have very dense, very high-performance computing.

And so, AI has triggered not only does the astronomy team at Oak Ridge National Labs need a high-performance computer, but now with ChatGPT like generative AI, every enterprise needs access to this level of supercomputing. So, the only way you can do that is not by building more data centers. Actually, in some countries, there were some moratoriums on building more data centers, because we're going to hit a power limit very, very quickly here.

And so, no, it's how do we make this supercomputing superpower technology for doing very now common generative AI tech in the cloud. So that, once again, it's completely democratized to every enterprise. You don't want just one company, who can afford the computer to win. We need all companies to be able to exercise this technology and push our industries forward. So, that was a big conscious move is to make the computers, because it is one of the three ingredients tremendously accessible in this architecture that we've built in DGX and our data center scale computing architecture needs to be readily available in the public clouds than it is now.

Q - Matthew Ramsay {BIO 17978411 <GO>}

Totally makes sense. I don't know, Molly or Brad, do you guys want to spend a little bit of time on how you've felt the process has been onboarding with NVIDIA? I mean, is the stuff accessible? How's the experience been? Your competitors that maybe are doing things in traditional methods rather than in AI compute method? Like why are they doing that? I mean, it seems as computer architect in a semiconductor person, it seems very, very obvious to me. I mean, we used to talk about the companies that had data or the ones that had the advantage. Now it's the ones that can actually manage the data and get conclusions out of it that have an advantage rather than just collecting data for data sake. I'm just wondering what your experience has been onboarding with NVIDIA and competitors of yours that might not be -- why not -- Molly, do you want to kick off? Go for it.

A - Molly Gibson {BIO 20208012 <GO>}

Sure. Yes. So, I mean this is something that we've been talking about a lot is, one of the things that what Generate is very good at is and we're experts at is building the algorithms that allow us to generate novel proteins. And we can do that well with access to the types of computers we have today, but when we think about being able to do that at scale to democratize type of capability beyond our pipeline to others in the field academics that have hypotheses maybe that they want to test and

do this at scale and really allow the world have access to these types of technologies.

Being able to do that in a scalable way becomes -- becomes a bigger engineering problem, where the types of experts that NVIDIA has, the type of hardware that NVIDIA has will enable us to do that type of scaling capability to not only just generate 100 molecules that we could potentially test in the lab, but hundreds of millions of molecules that we can go into the lab and test across many different types of targets, many different types of diseases and really start to tackle the drug discovery problem with engineering fashion, which is one of the places that is kind of the next frontier of what we're working on.

A - Brad Gray {BIO 16814265 <GO>}

Yes. My -- relays great things about working with NVIDIA. I mean, I think the first way we began working with NVIDIA was the selection of one of their cards, I think it's the 4K as the GPU processor on our new instrument, which was selected, because the CUDA instruction set was super easy to work with for the image analysis since algorithms we need right on the box. It was 5x times faster to 20x faster, depending on the situation of anything else we tested. And interchangeability and knowing that that kind of CUDA library set was going to be on every NVIDIA chip.

It gave us the idea that hey, over time, we can actually slot out this version and into new versions and upgrade the computer in a really seamless way on future generations of the cosmic system. So, that's been positive. I think the next step, which we haven't fully realized will be to take our cloud-based computing, work together to optimize the code for NVIDIA GPUs and direct the computer resources towards taking advantage of those. And I think we're just at the outset of atomics. I'm sure opportunities like that will present themselves over time. And I think NVIDIA has made it really easy for companies to engage that way.

Q - Matthew Ramsay {BIO 17978411 <GO>}

I think one of the things that we've been focusing on genomics and drug discovery here, but just to level the conversation and give Kimberly an opportunity to do that and talk about the other verticals of healthcare that NVIDIA is attacking, I think you guys have identified sort of 20 independent verticals and have teams that are working across all of those. Some of the things are similar in terms of onboarding, offloading things to the cloud, getting AI compute in the hands of all of these researchers, but I think each vertical market also brings its own unique little industry challenges.

And so, I mean there's investors here that our shareholders across companies and lots of verticals in healthcare. So, maybe some of the investments that your team is making. What's the scale of the team now? If folks aren't using AI-based computing and/or maybe on the fence about it, just kind of give the picture of what NVIDIA is doing to set them up on board?

A - Kimberly Powell {BIO 22145194 <GO>}

Yes, sure. Yes. And I'll give the team of experts that we've been so lucky to hire. I think it's the fundamental difference is, we have lots of Ph.D.s in genomics in computational chemistry. We have cardiothoracic surgeons on staff and it's really so that we can have a really deep application level. There's no way you can go the full stack. If one, you don't have somebody translating the biology application or the clinical application to all the way down to that chip level to really have these many orders of magnitude X factors.

So, it's one of the things we're really-really proud of is attracting this amazing talent that you might have studied to be a surgeon her whole life, but now can imagine how instead of touching maybe 1,000 patients' lives, how can I touch 100,000 or 1 million patient lives through by way of technology? Some of the other areas, if I could draw some analogies, what Brad is describing to you in Bionano is exactly what any medical device company can and should be doing, and are at different paces, I would say. And the idea is this, any -- imaging is core to the entire healthcare delivery process from screening all the way through to robotic surgery and image-guided therapy. And so, there's so much AI enhancement that can be made and/or optimization on the sensor technology itself.

If we want to make an ultrasound machine that is super cheap or an MRI on wheels, like Hyperfine has done, you reduce the cost of the technology of the sensor, you reduce its footprint, you make it more accessible, but you have to apply a lot more computation on the back end to recover the lack of sensor abilities, and then also to guide, the user who is not maybe a trained sonographer or a trained technician.

And to me, that two thirds of the world that doesn't have access to proper surgery or diagnostic and medical imaging could now potentially have it. And it's this mix of the ability to now put this computational ability in the instrument itself, do things in real-time, but always be connected to a cloud resource to enhance on an even more cost-effective analysis manner, and pipe that back down to the user. This is no different than the car industry. You do some decision-making on the car, you do some up in the cloud.

And so, medical devices and this idea of creating that capability as one, it's essentially how can as a medical device can I become software-defined? How can I as a medical device become much more cheaper and accessible by way of using this technology? And then thirdly, as a medical device makers, which many of these are large companies, who've acquired lots of different companies. They now have an opportunity to optimize a lot of engineering.

We have a general-purpose computer platform that can plug into any sensor on the planet. We have a general-purpose software platform that can run any AI developed on the planet. And so, they can now realize an AI platform, their own API AI platform, run it on instrument or on cloud wherever they see fit for the application that it's useful for. And so, I see that as becoming the real transition in healthcare is a lot of AI platforms, GE HealthCare, for example, their Edison platform is an initial realization of this, Siemens and their Rad Companion.

These are realizations of software-defined AI platforms-as-a-service that can be connected to all of their devices and rapidly -- much more rapidly bring innovation to market. So, that's what I'm super excited about, and it's a known architecture. It's a known need of this hybrid compute in sensor, in cloud and being able to draw real-time insights.

So, another area that is very, very exciting would be exactly what we're experiencing in our own consumer life with ChatGPT. I mean, natural language processing and truly pushing the next paradigm of being able to sift through, whether it be payer-provider or clinical trial information and draw new insights to be able to design and predict clinical trials on a much more effective basis, being able to predict readmission rates in your patient population and developed new operational efficiencies in the healthcare practice being able to reimagine call centers and processing of new payer systems.

This natural language and this capability is going to be completely transformational. But we all know, it speaks a slightly different language than ChatGPT that's today. And so that's the whole idea to be able to customize these models so that they're fit for function for either the operational purpose or for the clinical or biomedical purpose is another super exciting area that really cuts across all of healthcare in earnest, and really can I think make these electronic health records in the operations of what's happening in the health -- in the hospitals themselves, truly transformational.

Q - Matthew Ramsay {BIO 1797841} <GO>}

I guess one thing I wanted to ask about and this comes up in the AI work that NVIDIA is doing in the automotive industry towards autonomous driving, right? And that technology moves at one speed and the regulators move at a different speed, let's just say, to be kind. And as I started off this conversation, I probably know less about healthcare than most of the people in this room. But I've seen the way that regulation pushes back against innovation in the auto space, even as simple things of taking away a visual rearview mirror and replacing it with a camera-based one, which doesn't seem like that big of a deal, but got massive regulatory push back in the auto industry and took a long time to happen.

There's a lot of things that the three of you have been talking about, and the pace of computing innovation is going to accelerate massively. That's my own view in a lot of different verticals, healthcare in particular. How did the regulate -- I mean, this is a big broad conversation. But Kimberly, your teams like and how do you interact with the regulators? Like what is their thought or simulated protein versus traditional methods and that can matter across a whole bunch of areas, right, imaging of like we have the AI machine that's going to diagnose brain cancer rather than radiologist actually doing it.

How does that pass the FDA? How does it pass and liability lawsuits? I don't know. Maybe I'm opening up a big can of worms here, but I think that's a super interesting topic that I get asked about in the automotive space a lot and I'm quite certain it applies to healthcare. So, if anybody wants to take a crack at that one.

A - Kimberly Powell {BIO 22145194 <GO>}

Yes. I'll take it. It is a huge can of worms without a doubt. But I think it behooves and is upon all of us to have a relationship with the regulatory bodies. Just as we need to educate ourselves about different fields so that we can make a difference, we need to help educate the FDA and also be educated on the FDA. And so, we've gone off and built processes into our own platforms to adhere to medical-grade hardware and software platforms.

A lot of that has to do with things like documentation, sounds simple, but it is absolutely imperative to have traceability back to all of the software, which, by the way, now is a lot to run a single algorithm. There's a lot of software that is running that and finally documenting that and passing that on in a way that can be audited is something that we're doing now. So, we're taking the onus upon ourselves, because we feel like otherwise, we could be in the critical path.

We can't just have all these layered cake that I just described and say good luck GE or good luck brand new startup that has an amazing idea. I mean, it's more about making pace with the innovation. So, a couple of things: one is, learn it and if you can from a product perspective, apply yourself, you should. And I think the other thing that's also I think the world is learning in real-time and the automotive industry learned is, what are other methods that might be able to be used to help?

One of the methods that had to be discovered in self-driving cars was simulation. Because NVIDIA creates games that simulate the natural world, you can apply that same technology to driving your car in a simulated digital twin, physically accurate world. So, you can predict -- you can not only create the training data, synthetic data generation to find that corner case of an unfortunate child, who might run in front of the car, but be able to generate enough of those scenarios that now you have a lot more confidence that your AI is going to catch it, so synthetic data generation.

And then to replay that in the hardware in the loop world. If my car actually saw this, how would it react? And so, these systems are plate -- ways that we can get an auditable trail, enhance our data that the corner cases that the world doesn't see very often and build more robust development systems. It comes back to that notion of the method. And so, our methods are going to have to evolve.

You don't just make an AI algorithm that can circle a lung nodule, because guess what, when people had COVID and they might have had lung cancer, it's a completely -- it up the skates the problem to some degree. So, you have to retrain the algorithms for COVID-presenting patients. And so, it has to be this ever-evolving loop and we have to figure out processes and tools in order to facilitate it. But so one, I think it's just be active and learn both directions; and two, think about how technology can actually be applied to make it easier.

A - Molly Gibson {BIO 20208012 <GO>}

Yes. I think I'd expand on that and just kind of emphasize the education component of it to us as we've been thinking about developing and actually taking AI-generated

molecules into the clinic and into people. A lot of what we're realizing is that for the FDA, they're just behind what the technology actually is. And so, it's not that they're worried about anything in particular of AI-generated molecules. In a lot of ways, we have lots of reasons to do that. They're going to be safer for people.

It's just a fear of the unknown. And so there's a lot of education. Like can we decide both ways of us educating the FDA and other regulatory bodies as well as learning from them. What areas that they need more confidence in. And so, from the beginning, we've been working on those types of questions since the day we were founded. As you can imagine, our -- if you're creating new molecules, new proteins that have never been seen by nature before, our own immune systems have never seen those proteins before.

So, you could imagine a scenario in which those you have a large immune reaction to these molecules. But if we understand that process, we can actually reduce that immunogenicity to a place well below what molecules that nature discovered has. So, we've actually been able to show that we can learn how the immune system responds to proteins and be able to reduce that to safer levels than what our traditional discovery methods have been able to do. And so, as long as we can both show that in every possible preclinical model that we can demonstrate and share that and continue to educate the regulatory bodies on with where we actually believe that we should be safer in almost every way than a molecule, it was discovered through nutritional random mechanisms will be good.

I can imagine a world in which -- in the future today we're using the -- all of the same safety and regulatory processes and preclinical models and animal models that traditionally you're seeing before drugs go into people. I imagine a world in which we'll change that completely, where you could actually get rid of animals and start to do things like either simulation or you could do things, where you can actually have human organoid models, where you don't need animals anymore, but through a combination of data AI and new experimental methods, you can start to more easily represent what the human body is. Like, a mouse is not a human, but we use it all the time to simulate what a human looks like and we can do better.

And so, being able to have that conversation back and forth as to what we should be believing and what we believe that these methods can do for us. And then also learn where the potential pitfalls are or the potential concerns are, and we can address those rapidly through this iterative process, the better it will be.

A - Brad Gray {BIO 16814265 <GO>}

I'll just say, the life science tools industry, we're lucky enough not to be regulated. And now our scientists -- our scientific customers are incredibly fast-moving and embrace innovation and change faster than the other markets. I think we have a possibility to be one of the fastest areas of application within healthcare for these new computed AI approaches.

Q - Matthew Ramsay {BIO 17978411 <GO>}

Yes. So, Brad, actually talking about that, and spatial being essentially used for go commanding diagnostics given maybe use AI to discover patterns or whatnot. There should be any issues with that as long as you both go through the regulatory process of validating the marker recently in -- programs.

A - Brad Gray {BIO 16814265 <GO>}

Yes. I think the next several years of spatial biology are largely focused on discovery. Discovering patterns in tissue that might predict, who responds to a drug or who doesn't and AI will help us make those discoveries. AI may or may not be required to steal them into diagnostics, I think we just don't know that yet. But I think without a doubt, it can be a helpful tool in the discovery endeavor. And that, of course, has no regulatory issue whatsoever.

Q - Matthew Ramsay {BIO 17978411 <GO>}

Okay. And then maybe a question for you, Kimberly: in healthcare you have a unique perspective, because you can actually see your customers and I know there's some sensitivities potentially. But are you saying most of the interest from the discovery aspect or the -- in the translational, where you're taking discoveries and trying to move them into clinic or is it in clinical trials or --

A - Kimberly Powell {BIO 22145194 <GO>}

Yes. I will say that early discovery and discovery has been very active part. But as of late, there's a couple of other areas that are picking up. So, early discovery, which Molly and her platform are really all about is you can apply these generative AI methods to target discovery to identification of a lead to now the optimization of these interactions and understanding how they're going to interact in the body.

And so, literally, every stage of drug discovery has now fully been affected by the generative AI era. There are models that are being applied to each and the combination of these models can potentially replace what's known today as what we're doing in virtual screening. And so, the early discovery is, I think, it's a well-known future that it will be heavily in silicon, informed by, of course, wet lab. But you might go from a lot of the early discovery being -- I don't know what the ratio is, but 80% wet lab, 20% compute to 80% compute, 20% wet lab.

Now that some of the other tools that I was describing later on are becoming super useful in clinical trials. I mean, you have pharma companies, who are sitting on decades' worth of images. You can use these same approaches, where unlabeled data can now be shoved into these algorithms and they can be trained to do pretty phenomenal things and things that are a lot cheaper than hiring a radiologist to annotate clinical trial data, and frankly, probably more precise, because when you're looking at whether patients are responding in their tumor response, the accuracy of that measurement can be a responder or non-responder. So, there's a lot of potential, I think, opportunity in the imaging space.

And then just as DALL-E and some of these other algorithms have showed us, being able to build multimodal algorithms from patient outcomes and their phenotypic

image data is going to produce a lot more translational applications as well as clinical trial opportunities and efficiencies and improving that. We know that's the most expensive part of developing drugs. And we know that we're not very good with this 10% -- success rate -- excuse me, after we get into patient. So, that's a function of garbage in from the early discovery and garbage out, but it's also obviously a huge function of how we're choosing and monitoring the patients in trials.

And then I'll go further to say, on the commercialization side, of course, the natural language processing is a huge tool there. To be able to constantly be able to analyze what's going on in the real-world data and be able to discover the goods and the bads of your medicines and be able to feed that back into the whole loop. So, while today I think there's a lot of pent-up focus on early, the other two are really coming in earnest, especially after ChatGPT moment has happened and now the ubiquitousness of being able to apply AI to images. And partially, I feel like we've made a great contribution and some of the open source tools we've made in the imaging space that the field has really said, we've got a lot more we can do with the image data that we have, so --

Q - Matthew Ramsay {BIO 1797841} <GO>}

I think we have just a couple of minutes left. And again, this has been super interesting and I very much appreciate you guys all being part of this. And so, I have to sort of ask the devil's advocate question at the end just to make this fun. One of the things that we spent my team and Sammy has spent a lot of time in the autonomous car arena, different levels of automated driving and all of the different things that have gone into that as a science and as a technology application into a very slow-moving industry in the automotive space.

And if you were to had a conversation with NVIDIA's founder Jensen 10 years ago, I think he -- his timeline for when we were all going to be sitting around and not having steering wheels in cars would have been a little bit off. He's admitted that. And the realities of moving and transforming a huge and incumbent industry take time, right? So, my gut tells me there's going to be some of that in the healthcare world. There's huge, huge potential here.

I think Jensen's described AI and healthcare as the next billion-dollar business for NVIDIA. Just for all three of you, what's like hindering the pace of adoption and innovation? Is it -- do we have too much data and not know what to do with it? Do we not have enough data scientists? Is it the cost of the hardware? Is it regulation? Just I don't know how you're thinking about, but if we could get rid of these two or three factors, things could move a heck of a lot faster, because the two of your companies are making things move quickly, but you're the outlier rather than maybe everyone doing it at the pace you are. So, let's just use that analogy comparing to the auto industry that just took longer. What do you think of the impediments to this AI innovation in healthcare?

A - Brad Gray {BIO 16814265 <GO>}

I mean, I think one of the things in -- our customers are scientists and they are -- every scientist's individual scale of data generation is pretty small. And machine learning algorithms need massive training sets, more than honestly can be generated by any one individual scientist. So, I think what's required to truly unlock machine learning's potential on scientific data sets is a paradigm of sharing and pooling data that honestly is new to that community.

Most scientists have viewed their data as precious to themselves, it's proprietary. They want to go back and look at it over and over again. It's very hard to generate. They don't have a single repository for all that data (inaudible). So, I think that's one of the rate limiting steps in the scientific field. Now, certain areas that we're working hard by creating a single repository in a data lake for all the spatial biology data ever generated on our platforms to go to help create a situation, where the data is all in one place and allow us to get to that scale. But I do think in the scientific world finding data sets still the clean algorithms is part of what is rate limiting.

A - Molly Gibson {BIO 20208012 <GO>}

Yes, I'd agree with that. I think it's -- it comes down to a cultural component in the scientific community, and this is something that surprisingly that doesn't just persist between companies, it's even within scientists individually in their own companies, which I think is probably quite surprising to people, who aren't familiar with the field that there is this kind of ownership over data in scientific arena. It's one of the things that at Generate, we spend a lot of time. Building from the very beginning, the data is a collective asset.

And by having that mantra over and over and over again, that you can't even really see your data until it goes into a central repository at Generate was something that was -- it doesn't sound like a big step, but in many companies, many biotech companies that you would see, that's not happening. In many companies, you'll have data on individual computer. It might be an Excel spreadsheet. And if someone leaves a company, it's -- who knows where that data goes.

And so, there's a lot of cultural components to it. And I think that extends beyond the biotechs to the pharmas that are then eventually the real kind of commercializer and developers of the drugs, like we spent a lot of time talk into pharma companies about their view on the type of technology that we're developing at Generate and how they would use it. One of the challenges is that each of those were generating novel proteins.

Protein engineering has been a field for decades. There are people, who have trained to engineer proteins for drug discovery. And so one of the cultural changes is getting those people on board with the fact that there's a new way to do things, because they've been trained for last 20 years in their way of doing something.

So, there's multiple cultural elements to this that I think will be the bigger barriers than all of the other things that are still challenges, like generating lots of data, getting the right -- the regulatory agencies to be educated. But I think those things will move faster than getting the full community to kind of change into this way of

data is a collective asset, integration between computation and experimentation and the view that there is a new way to do things in a field that has been around for decades.

A - Kimberly Powell {BIO 22145194 <GO>}

Yes. And I guess I'll kind of clean it up to some extent. In the healthcare delivery side of things, I mean, I think we can all recognize we have a bit of a systemic problem in the healthcare system itself, whereas I'm talking to a friend on the soccer field and last year, we helped achieved the Guinness World Record for the fastest time to sequencing diagnosis with Stanford on Oxford Nanopore's genomics platform. And this helped a child know that his -- he was going to be on death's doorstep soon because of a heart failure. He was put on a transplant and he is alive and well today; or a seizing child, who was able to be sequenced within hours of its like knowing it just needs sort of that vitamin D supplement; and this dear friend on the soccer field talking about how his mom going through this diagnostic odyssey and she actually has a mutation that is 80% treatable, but hasn't known that for the last six months.

So, part of it to me is, we're making this technology more readily accessible. The genome is going down to \$100. Can we -- how, why, and can't we make it more a standard of care? And so, that's why we continuously partner with these clinicians, who have a dream of changing that standard of care and showing that it's actually plausible and being able to kind of create that inside the healthcare system. That's truly a challenge.

I think other ideas are, one I think unique vantage point NVIDIA does have is because we work across so many different industries, you can see how a car and a spatial genomics platform are not that dissimilar in what they need and how they can become more software-defined. As Brad was telling you, informatics is going to be his innovation engine in the not too distant future. So, you have these 40-year-old or more medical sensing device companies that have built the platform, but now how can they innovate on a -- in a software-defined way and realize huge economies. Some of that is a problem of reimbursement. If the reimbursement isn't there what, would drive them to sort of disrupt their own innovation, innovators dilemma kind of a thing.

So, that's -- so, on healthcare, those are not that solvable, but the more we can make these world records known and advertise to really see the possibilities, you hope that it can start to have some formidable change in healthcare delivery. And then I have to agree with Molly just us being a tech company, I went to J.P. Morgan several years ago where I had a conversation, I won't say with who, a large pharma and their CIO was saying, we're never going to do AI in house, we're going to farm it all out. And Jensen, of course, respectfully disagreed and said, why would you ever say that? This is the biggest technology breakthrough of our time. How silly would it be for you not to become well-versed in how to use this technology and apply it everywhere?

You can, of course, drug discovery -- I mean, pharmaceuticals is one of the most challenging industries on the planet Earth. But get educated on how to use AI, invest

in it to some degree, and partner on another degree. If you're not doing some of it internally, how would you even pick a good partner?

So that was just a little bit of humorosity that I think is starting to change pretty rapidly here. But it's that notion of change management and culture tech-first biology seconds in some ways. I know that's a little hard for people to hear maybe, but and a little self-serving perhaps. But it's -- we believe in it and we hope to contribute to it. And I think that the end of last year and generative AI in biology was absolutely a milestone. It was an eye-opener milestone and I'm excited to see what this year brings.

Q - Matthew Ramsay {BIO 17978411 <GO>}

Well, thank you, everybody, for -- hopefully, you guys found this conversation unique and interesting. And thank you to the three panelists, Steve, your partnership in pulling this together, and thank you all so much.

A - Kimberly Powell {BIO 22145194 <GO>}

Thank you.

A - Brad Gray {BIO 16814265 <GO>}

Thank you.

A - Molly Gibson {BIO 20208012 <GO>}

Thank you.

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