2020-11-18 Behind the Science of Optios

Hall T Martin: [00:06:29] Well, hello, this is Hall Martin with TEN Capital. We're here today with Optios Founder and President David Bach, and Paul Sajda, a Ph.D. professor at Columbia University. Paul, can you do a quick introduction to yourself and tell us more about your work?

Paul Sajda: [00:06:47] Yeah, sure. So, I'm a senior science advisor at Optios, as you mentioned. I'm also a professor at Columbia University specializing in neurotechnology.

Hall T Martin: [00:06:57] Great. And David, can you do a quick introduction about your role here as well?

David Bach: [00:07:03] Oh, sure. You know, as you said, I'm the founder and the CEO of the company. I'm originally trained as a physician and as a scientist at Harvard Medical School and this is my fourth healthcare technology company. And, all of them have been very successful but this is by far and away the one I am the most excited about.

Hall T Martin: [00:07:24] Well, thank you. So, the technology that Optios has is tremendous and to me, [00:07:29] one of the most important capabilities you have is the ability to use your technology with financial traders to accurately predict, in advance, whether any individual trade they make is going to be profitable or not. [00:07:41] Given the potential implications of this technology, a number of the people in our network have asked for a deeper dive into the science behind the technology. And so with that in mind, Dr. Bach and Dr. Sajda, can you walk us through this, how this technology evolved and how solid the science is here? And probably most importantly, what are the commercial implications of this technology, both near term and long term?

Paul Sajda: [00:08:06] Sure. So, I'll be happy to go with that. I'm going to actually show a few slides here, a picture is worth a thousand words, as they say. So, one of the key things that we do at Optios is we've developed these proprietary A.I. machine-learning systems that allow us to read activity from the brain and this is an example of our trader who is instrumented with what's called an EEG system, electroencephalography, that's measuring brain activity as he's doing his task, as he's trading. And from that, these

machine-learning algorithms allow us to really extract kind of an alphabet of the activity in the brain. We can use that alphabet to map the states of the brain to the decisions that the trader is making. And what's really exciting about this technology, this proprietary technology by Optios is that when we look to see how this alphabet, how these states are evolving over time as a function of lots of complicated interactions that are occurring either as the trader is assimilating information from different sources, as the markets are changing, that we're able to, with our model, predict probabilities of whether or not that decision the trader makes, in particular the trade that they make, is going to yield a positive or negative return. So, this was actually quite astounding at the beginning. We were, you know, being a scientist I was always at first, we hammered on this to make sure this was really solid and we can replicate it, and now we're at the point where we've done this several times and we think we really are on to being able to track this phenomenon with our proprietary intellectual property. And so, what's kind of key if you think about it for a moment, is that this is not information that is read out any other way, right? So the quality of the trade, [00:10:25]we're not predicting the stock market, what we're predicting is something about the state of the trader that's likely to indicate that they've integrated information in a way that is likely to yield a good outcome, a good trade. And [00:10:40] so, if you can actually predict that just a little bit above chance, you can potentially monetize it in ways that I'm not even completely clear of the implications. But, even just a couple of percent would be..

David Bach: [00:10:56] I can talk through how you can make money off of it.

Paul Sajda: [00:10:58] Yeah. David..

David Bach: [00:11:00] But I'll validate for Paul. If you can predict in advance whether a trade is going to be profitable, there is a way to make a lot of money off of it. And we'll get there...

Paul Sajda: [00:11:08] We'll get to that...

David Bach: [00:11:09] But for now, we're talking about the science.

Paul Sajda: [00:11:11] So, and what we've been really excited about is we're not just a couple percent above chance, but we're well above 10% above chance in terms of

predicting whether or not a trade is going to ultimately yield a profit or a loss. And there's a whole bunch of underlying neuroscience and the alphabet that we extract that is consistent with how we understand good decisions are made, how those decisions evolve over time. So, this is much more than just putting some data into some black box and cranking it out. It actually has quite a bit of underlying neuroscience principles involved, as well as very sophisticated machine learning that matches the underlying neural alphabet that we extract. So, how does the system work and how do we evaluate it? So we go through a rigorous process of using cross-validation techniques, multiple random starts, lots of things in the data science and machine-learning fields that are critical for really showing the robustness of the algorithm. And so what this plot shows is the x axis is the output of the model. So, this is the profit probability prediction that goes from zero to one. And the two distributions here, the green one and the red one and obviously brown is where they overlap, that's the actual _____, that's the reality. So after the fact, we can look at, alright, what were the actual profits or the losses for the trader on those trades, and the key thing is the model - our system - actually only sees the front end of a trade, it has no idea whether or not that trade is going to be profitable because it never sees the other side of the trade, the other side of the transaction. So, the nice thing here is what you're looking for in a system to do this type of prediction is something that essentially, when you take the model output and you relate it to the reality, the ground truths - which are these two curves - that when you're on this side, low probability, that the likelihood of the profit-to-loss ratio is low, and as you go up it gets higher and higher, right? Because what you would want to do is you'd want to say, "Alright, somewhere over here, I'm going to make a decision and say, all right, if I'm above, let's say 0.6, I'm going to do something with those particular trades because I think they're going to make money. Maybe I'm going to double them or triple them. And the trades over here, well, maybe I'm going to cancel those trades or I'm going to essentially hedge against those". So, that's like the simplest thing you could do with this type of system.

David Bach: [00:14:11] And so, Paul, could I just, if you could go back, I just want to make a couple points on this. The first thing I want to say is in the machine-learning world, having something that has 60% predictive power in a setting like this is mind-blowing, you don't see this very often in the finance world. And just kind of for those of you trying to make sense of the graphic, I just want to point out, if you look at the middle here where it says, you know, there's a 50-50 chance, it's behaving exactly

as you want because it's an equal number of profitable and unprofitable trades. And what's so cool is as you move to the right, what you see is there's more and more profitable versus unprofitable and vice versa. And so, the key thing is that blue line now, it's got some bumps out on the edges, but basically, it's a straight line going up, showing the ratio between the profit and the loss. And so, from a machine-learning-analytic perspective, you can't get more beautiful data. So, [00:15:07] it's a very powerful system all the way across the spectrum of the prediction. [00:15:12] So, you know, the problem in this podcast is Paul tends to be sort of too humble, given sort of the power of what he and his team have done here. But I hope that helps. Please take it away Paul.

Paul Sajda: [00:15:26] So, we can think about how you operationalize the output of this system. So, one thing you can do for instance is, you can imagine having these little cut offs, right? And you can say, "Alright, if the output of my Optios system says I'm in the mode of let's say I'm above, the model predicts above 60% chance that in fact the transaction I made that when I finally settled the trade, it's going to be profitable, I'll double down on that, right?" And so if you look at that and you operationalize it, you see that you can get like a 3 1/2% increase in your profit margin, right? And so, we actually did that, right? We actually looked with traders that were making real trades with real money, and we looked, for instance, so what was their final return after doing weeks and weeks of trading with our system? And so, this was actually in a time of the market was pretty volatile at that time, and if we look, you know, they actually lost about 2%, so a bit of money. But let's say at the same time, what we did was we use the Optios system and looking at the probabilities that it output and said, well, if it's above 60%, what we're going to do is we're going to double down on that transaction because we think that that's a good trade and ultimately that will get realized when the trade is closed. And if it's on the other side of the curve where it's like, you know, 30% or 40% or below, what we're going to do is hedge against it, so we're going to actually make a trade that essentially negates that transaction. And lo and behold if you do that, you go from losing 2% to gaining 3 1/2%. So, that's actually, not only is it a pretty sizable and financially-significant change, but it's actually one that's very consistent across the different traders that we looked at, because we've actually looked at traders with different levels of experience, very different portfolios, and so, we're pretty confident that this is kind of a system that can generalize to a lot of different financial platforms.

David Bach: [00:17:48] We'll talk in just a moment about how you can monetize this, but again, Hall, the purpose of this is speaking to the goals of your investors, just making sure that there was enough understanding about how the science was done. And so, I think before we go and talk about this next slide, you know, my question to you Hall is, does this make sense to you? Are there any clarifications you think you'd like to get? By the way, anyone who wants to talk to us, we're happy to walk through this. The statistical power of this model is, I think, unimpeachable, even at the level of the individual trader, right? This thing is statistically smaller and we've done it for several traders at this point.

Hall T Martin: [00:18:35] So, tell me more about the model. How many signals, how many factors are involved in the model itself?

Paul Sajda: [00:18:42] Right. So, the model has as its input, the EEG and we were looking across the scalp, so multiple sensors, and so there's kind of a bunch of secret sauce inside the model itself but I can't really get into. But the way to think about it is the fact that, so I've been studying decision making for about 20 years, and when we make good decisions, we believe that how the brain is connected together is kind of an important state. And it's not that just the brain is coupled together in one certain way, but it's the dynamics of that, right? So it's how that's changing on a moment-by-moment basis. And so, that becomes, we use machine learning and our understanding of neuroscience to build this alphabet that's actually individualized to each trader. So, that alphabet is individualized, but there's a lot of similarity between different traders. So I like to think, sometimes I say it's like, I learn an alphabet that's kind of the equivalent of the alphabet, the Greek alphabet for one person, and the Cyrillic alphabet for another person, and those alphabets then ultimately are used to decode these decision states that we relate to the quality of the decision, right? So, once again, the key thing is not that, we can't predict the market, right? We can just make a prediction on the quality of the decision that the trader is making, and presumably, if they're in a good state to make a quality decision by integrating information, that translates to a better decision and a higher probability of a profitable return.

Hall T Martin: [00:20:43] Well, a lot of bad trades come from human emotion and biases. Does this have in some way a measure of those or presence of those coming in

if you're becoming emotional? "I had a big loss and now I'm doing desperate trades to try to make up the difference." Is it measuring it in some direction in that way?

Paul Sajda: [00:21:06] I mean, it's likely that it includes that, but we take a very kind of different approach. There are groups that will try to measure these cognitive states that are linked to emotion or cognition. Instead of looking at it like that, we think of it very much like network states, right? And we know something about how the brain operates in terms of being able to be connected. You know, whenever we make decisions we have to integrate stuff then segregate stuff, and so, part of, I think, our unique approach for building this alphabet, is it's very much data-driven and we don't label things as being emotional, biased, flow, what have you, but after we learn this alphabet or vocabulary, we can go back and kind of look at what the states are. And clearly, there are some that are correlated or consistent with activity in the limbic system, but it's much more complicated than that. It's not just simply looking at emotion or....

David Bach: [00:22:16] Paul, I'd like to add to that. Actually, it's funny because yesterday I had discussions with two of the traders where we went over their data, and these guys they remember every one of these trades and so we were able to show them the data saying, "Here's where your brain was at the point when you made this decision". And I asked them that very question, I said, "You know, we've got something which is statistically viable, but do you have any idea what we're measuring? Like, if you had to put a word to it, what would you say?" And one unfortunate thing is they didn't both give exactly the same words, but they remembered it and they absolutely knew that we were measuring something which was real. And what they talked about was that it's some measure of being, you know, they talked about like the sense of like they were sort of in the zone, that they were in that moment confident, they were able to sort of see kind of the overall picture of what was happening. So, I think there probably is some kind of sense of ease and focus and, you know, just like that kind of you're in the zone thing. But it's a good question and we're going to keep learning about it. The cool thing about it is it works. We know we're measuring it, and by the way, Paul and his team developed this based on work that they did in the past with intelligence analysts in the military, so we're relying on stuff which has a multi-year track record of being associated with, when your brain looks like this, you make good decisions.

Hall T Martin: [00:23:51] And my final question is, what level of experience does the trader need to have for this system to work? Someone who has no idea what trading is, would it work on them, or someone with a little bit of experience or someone with extensive experience because you're measuring if they're making a good decision or not and someone with no experience, how do they know if they're making a good decision or not? What level of experience are you assuming for the use here?

Paul Sajda: [00:24:16] Yeah, no, excellent question. I think that we're not sure yet, we don't probably have enough data to be certain about this, but at least anecdotally it seems to even work better kind of the more sophisticated and the more experienced the individuals are, right? And so, you know, I think it's in some sense since it's tailored to the individual, I think that we expect these deltas to still be consistent across the different experience levels, but obviously, it's a delta relative to baseline, right? So, an inexperienced trader or a complete novice, their overall performance is probably going to be much lower than somebody who's a seasoned trader, and also obviously how much the size of their portfolio and things like that. But I think that the deltas will be nearly the same or maybe even get better as the experience level increases, but we don't have any evidence that there would be a dramatic change in the delta performance in terms of our ability to predict because it's so personalized to the individual.

Hall T Martin: [00:25:39]. And I did have one other question about signal-to-noise ratio. Different individuals, different signals, is there any chance of misfiring because a signal may be noisy or the sensor may not be picking up very well? What's been your experience there?

Paul Sajda: [00:25:57] Yeah, no, great, great question. And in fact, I've been working on this type of brain data for a long time and I think one of the beautiful aspects of the approach that Optios has taken, is that it is very data-driven. So, to start the process, we've collected lots of data from traders, right? And in fact, weeks, and it actually takes some time for some amount of data to learn that alphabet, right? So, you couldn't do this in a laboratory at Columbia so easily where you're doing an experiment one hour at a time or whatever. But, if you put this in the real world, you collect this data in the right way with the right set of machine-learning algorithms, this alphabet and vocabulary start to emerge and that actually helps quite a bit in terms of the signal-to-noise ratio,

because we end up integrating over a lot of the variability that occurs, not just in terms of a sensor not picking something up, but people moving around and all of these things that typically provide confounds and artifacts in the EEG, we're able to mitigate based on the way we designed the platform, the time over which we collect the data, and then once we collect that data, locking in onto this vocabulary that then is very robust and we can decode on the fly in real-time once it's all built.

David Bach: [00:27:32] I want to just kind of pile on to that and I'll say, you know, I think our ability to clean the data and to tell the difference between the signal and the noise, is probably one of the differentiating features that we're bringing to the table here. You know 95% of the work is not the machine learning. It's all the collecting the data, cleaning the data, making sure it's robust, and then really testing the algorithm. But I think at this point, I think we are sophisticated enough that that's not an issue for us here. And realize, we're collecting, this is being done over seconds not milliseconds, and the brain actually produces a whole lot of data in a few seconds. And so, you know, I think we've got a really, really clean signal at this point, which is exciting.

Hall T Martin: [00:28:24] Great.

David Bach: [00:28:26] Do you want me to just spend a couple of minutes kind of talking about it because I know if somebody is listening to this, they're not only interested in the science, but they want to kind of convince themselves that there's a way to make money and, you know, and so on and so forth.

Hall T Martin: [00:28:39] Yes. Tell us more how this can be applied into the financial trading world.

David Bach: [00:28:43] Yeah. So, the first thing I guess I want to share is I just want to give everybody listening assurance that [00:28:50] we have extremely strong intellectual property protection around this technology, and so it would be very hard for anyone to reproduce it, [00:29:01] A, without kind of trampling on our patent portfolio, but B, [00:29:06] it's very proprietary and we're certainly 18 months ahead of anybody else in terms of being able to do this. [00:29:13] We have a lot of interest from the finance market in this capability. Everyone we've talked to just sort of immediately sees how they can use it to make money and what this slide illustrates is the five most common

things we've heard from customers about, if you can predict whether a trade's profitable in advance, how do you make money on it? And the first thing which we're doing live with a group in New York called First New York - I can't remember what they're called First New York something, they're a trading platform - is what's called center book management and here we're doing precisely what Paul said. We're using the brainwave data to resize trades. And so you create a shadow account, you make the same trades that the trader does, but now if you think it's very likely for it to be profitable, you may double or triple or quadruple the bet, you know, and so on and so forth. And, the economic opportunity associated with that really is in the multi-billions of dollars. If you can outperform with more than 10% accuracy the market, it's worth a great deal of money. And so, that alone represents a very appealing opportunity to immediately make money and realize we have no more R&D to do, we can do that now, we will be doing that with them in a matter of weeks, we're just getting the baseline data today. The second thing we can do - this is a whole 'nother science discussion - is once you know what someone's brain looks like when they're at their best, you can then train them to have their brain in that state on a more consistently, you know, good basis. And that's what we're doing in golf, which is how we can take people and improve their putting accuracy by teaching them to be in the zone before they golf, so we can do that same thing with traders. And so you can imagine for some of the large platforms, the millenniums, the .72s, the Citadel's of the world, who have a lot of proprietary traders having a system that allows those traders to get themselves into the zone more consistently could be worth a lot. A number of people have talked to us about candidate screening here. When you hire a portfolio manager, you make a bad hire, it can cost $200, $300, $400 million, and to the extent that we use our system to help understand, you know, how to supplement all the other stuff that they analyze, we should be able to make those hires better. And again, that's worth a lot of money. And then you get into the really exciting stuff around using brain data to supplement algorithms. The ultimate expression of this, which Paul and his team have a lot of experience with, is actually creating teams between computers and humans where it's not the human making the decision, but it's also not the algo. It's actually now something where you form this partnership to create a better trading model than exists elsewhere. And this is something for the bigger shops, which is absolutely a high strategic priority. And so, just within the finance world, we are very confident that this technology, whether it's from us or whether it's from one of our inferior competitors, is going to become a necessity in the finance world within the next five years. Paul, if you could just go to the next couple of

slides. I just, I do want to say one thing for those people listening to understand is this isn't a finance product. We've tested and built it with financial traders, but foundationally we have a technology where if we put something on your head, you make 300 decisions, we can identify for you what is your optimal brain state look like and then develop a system to train you to get there. And so, there are dozens of verticals where that technology could be useful. So, this slide illustrates a number of them that we've been thinking about. But just as an example with software engineering, [00:33:04] the science suggests that this technology will be able to improve the productivity of software engineers by 25% and reduce error rates and [00:33:13] that's probably a bigger economic opportunity than the finance realm because we solve what is one of the largest problems in the software engineering world, which is the supply-demand imbalance. Because right now there is much more demand for software engineers than there is supply. Last I heard, there were 487,000 open positions worldwide for software engineers. And so, if you can improve productivity by 15%, 20%, 25%, it's worth literally trillions of dollars to the industry. So we are excited about this capability not just in finance, but as a generic tool that can be used. And Paul, just one more slide just to make the final point for people who have invested. My last company generated a 90X return cash-on-cash to people in two years, and we think there's a real possibility of doing that here again. And [00:34:07] the foundational thing which we see as our long-term source of value, is the data we're collecting. We [00:34:15] are collecting 10 million data points per person per hour. As Paul said, we've been collecting data from individuals for weeks and weeks at a time. I think, Paul, you've been telling us this is probably the largest real-world use case collection of EEG data that's ever been done in the world, right?

Paul Sajda: [00:34:34] Right.

David Bach: [00:34:35] And so we have a very large, rapidly-growing database and this can be used in a couple of ways. First, if you go to the center of this slide, we'll be able to leverage the so-called network effect that people like Google and Amazon use, where the more data you have, the more accurate we are in being able to understand things in the aggregate and at the individual level. What makes like YouTube so good is they figure out if you like this movie or this video, you're going to want this one. And here, too, we can wire up a trader and just get smarter and smarter about their brain, which creates stickiness and makes it very hard to switch. And the more data we get, the more

accurate this is. And so actually, you know, the data we showed is that our model is 61% accurate, but a month ago it was 59% accurate. So, it's just going to keep getting better and as we collect that data building on a really solid IP portfolio, the data itself adds to the power of our intellectual property ____and actually itself may have economic value. We don't even know what all of this brain data could yield. We're protecting it with HIPAA standard protections, and so you won't be able to figure out something individually, but in the aggregate, this certainly has economic value. And so, we are extremely excited about the opportunity of this technology, not only in its ability to actually make an impact in the world, but from a raw economic point of view, we are solving some huge, truly trillion-dollar problems out in the world.

Hall T Martin: [00:36:14] Great. Well, this is very compelling technology, appreciate you guys sharing that with us today. How best for listeners to get back in touch with you?

Paul Sajda: [00:36:23] You can send me an email at pauls@optios.com.

David Bach: [00:36:30] And you can actually, people can write to me directly, I'm david@optios.com.

Hall T Martin: [00:36:35] Well, we'll include those in the show notes so people can get back in touch with you. In the last few minutes that we have here, what else should we cover that we haven't?

David Bach: [00:36:49] Oh, I don't know.

Paul Sajda: [00:36:51] I don't know, we covered a lot. I mean, I think that the thing is, like David said, there's so much potential value here, we don't know what we don't know yet in terms of the value. But I also believe that if you look at the data set itself and how these systems improve by first building on themselves and then within the data, the cells there become really kind of compelling interactions and value that typically that's where you have this exponential effect in terms of technology development and progression is where you can start really leveraging the actual data you're collecting to build new and different algorithms. So, that's super exciting to me, both from a commercial side as well as from a scientific side.

Hall T Martin: [00:37:47] Great.

David Bach: [00:37:48] Hall, I actually would, I would like to if you want to give a little airtime, I'd love to close with a story...

Hall T Martin: [00:37:54] Sure.

David Bach: [00:37:55] ..that I think maybe valid. I will never forget this. 14 years ago, I had just started my first company and I had the opportunity to go to Silicon Valley to a conference - this was pre-COVID, so you could actually meet in person with people - and a very prominent Silicon Valley investor was up on the stage and he said, "I want you guys to know that 10 years from now, mobile technology, mobile phone technology is going to be pervasive. Everyone in this audience is going to be carrying around (what was called) a personal digital assistant, and you're not going to use that not only to make phone calls, but you're going to be searching the web and it's going to be a critical foundational part of your life." And Hall, I remember rolling my eyes when I heard that and I said, "No way is this going to be true for me." And sure enough, I am just you know, I'm completely locked into this because they were in the middle of it, they saw the power of the technology, they understood the consumer interest, and they recognized that a revolution was afoot. And I think it's accurate to say we are at that same point with neuroperformance technology. This sounds like really cool space-agey science, but the fact of the matter is [00:39:19] it is going to be pervasive in a decade because it's meeting a foundational human need and the technology is accelerating so quickly. [00:39:26] The ability to just put something in your ears or on your head which monitors your brain, so it allows you to know when you're at your best, trains you to get there, it is going to become foundationally integrated in everything we do. And so, for people who are interested, whether they want to be investors in us or just looking at the landscape here, we are in the midst of a very exciting, rapidly-emerging industry and it's going to be a very fun thing for all of us to be on this ride together. So that's how I would want to close.

Hall T Martin: [00:39:58] Great. Well, this is a compelling technology. I want to thank you for sharing that with us today and we look forward to the next steps soon.

Paul Sajda: [00:40:06] Thank you so much. Bye bye.