MODULE 4 UNIT 1
Video set Video 1 Part 1 Transcript

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NIR VULKAN: Joining us again is Dr Ewan Kirk, the Chief Investment officer of Cantab. In this video, he will be imparting us with his insight on the key consideration of developing new algorithmic trading models. He is actively involved in research and development in the Cantab team, and is in an excellent position to share his insight. Thank you for joining us again, Ewan.

There is a big gap between finding a model that works with the data and creating something that works. Can you elaborate on that?

EWAN KIRK: About once a fortnight I get an email from some random person saying, “I've got a strategy and it's got a Sharpe ratio of three,” and I always write back and say, “You haven't”. Because there's a huge amount of work that goes from having a bit of code and it should be code, if it's in a spreadsheet then it doesn't count, which maybe picks up on some effect and produces a fantastic performance. Big, big amount of work that has to be done from going from that to something which is actually tradable and can be used in a real life situation. So typical things that people get wrong; I mean one of the favorite ones is future peaking, because they probably downloaded the data from, oh I don’t know, maybe somebody like Google Finance or Yahoo Finance, and it's not all contemporaneous.

Now, I know contemporaneous data is a little bit boring. It’s sort of the heavy lifting of quant work. But, unless your data lines up, everything that you're saying could be wrong. That's a big problem. Also, of course, there are all those pitfalls that quants can fall into, and they are legion. For example, you do an in-sample test, you come up with a model, it's a brilliant model in-sample. And then you “open the box”, as the phrase goes, to look at the out-of-sample data, and it's not so good. Now, the classic thing that people do is they say, “Oh well, maybe if I just tweaked my model a little bit, the out-of-sample test would look better”. I mean, I know it sounds stupid when you say it like that, but that's what happens, it's what people do.

You have to be brutally honest with yourself. And then, when you've actually come up with something, you then need to spend an enormous amount of time trying to work out why it's wrong, because the chances are, that it's wrong. I mean, we all dream, of course, of one day, you know, we're going to come up with this model and it's going to be scalable to 10 billion dollars and it's going to have a Sharpe ratio of three, both in-sample and out-of-sample, we all want that. But the reality is… probably that isn't the case. There are a limited number... this is possibly a little bit controversial. There's a limited number of effects which seem to be persistent in the world. So those effects are… trend is one that I'm sure you've talked about before. Possibly carry is another one, and then in cash equities, there's effects like value and momentum and the low-beta effect. And what's the other one, I've already forgotten… the quality effect.

So those things drive an enormous amount of the returns in world. Now, maybe, and this, as I say, is a little bit controversial… maybe there's nothing else other than that. Now, I don't think that's true. But, I think the effects beyond that are much harder to discover, need much better data, and are probably critically dependent on technology infrastructure to be able to do them, and they may not be persistent for a long period of time.

getsmarter.com | info@getsmarter.com
+44 203 457 5774 (UK) | +1 224 249 3522 (US) | +27 21 447 7565 (SA)

So, although when you're doing a course in algorithmic trading, when you're thinking about algorithmic trading, one of the things that you believe, or you hope, is that you will come up with something fabulous. And of course everyone should dream about that. I mean that's part of the job, is to dream about that and maybe it will be you that comes up with it.

But, most of the job of being a quant is about small, incremental improvements. It's the tiny things that make volatility forecasting a little bit better, that make your costs a little bit less. Those are the things that are actually the job. And those kind of changes… if you make enough of those little changes, they all add up into a big change.

How do you pick markets?

EWAN KIRK: How do we pick markets? That's a really interesting problem. There's clearly a known set of markets. There's probably 50 or 60 highly liquid futures contracts. The usual things, the 10-year-bond, the S&P, the FTSE, oil, those kinds of things.

There's also a reasonably liquid set of stocks. There's 15 thousand stocks that you can probably get data for. Might as well use that data set. However, there are increasingly new markets, or markets which become more liquid over time. Or ones that are just now tradable even though the data is quite… for example Iron Ore, or coal. Where those markets used to be OTC, they're now cleared OTC. There's a very long history of prices for coal, so we can use that market because we can do something with that market.

Now, on the other side, there are lots of new markets which are quite liquid. Obviously the poster child for that is bitcoin. Now, we don't really have much data for bitcoin. And also it's a little bit of a scary place to trade bitcoin, so maybe you wouldn't do that. So firstly looking for markets, we know the liquid ones, so there's the liquid ones and the well-known ones. So 15 thousand stocks, 100 liquid futures contracts.

Then there's some frontier markets. Choosing those is more of an art than a science really. Some of it is about data. If you've only got a very short history of data, you could still use the commodity or you could use the futures contract. Carbon emissions, for example. But your hypothesis there would be: this effect is universal and therefore, even though I don't have data on carbon emissions going back to 1980, I'm willing to make the intellectual leap that this effect is so universal I will use it on this. And I don't think that's a very big leap.

Much harder though, is the operational regulatory, liquidity side of things. There is an enormous number of commodities, which are exceptionally liquid, in commodity terms, in China. However, at the time of me speaking, they are very difficult to trade. For regulatory reasons, for actual just physically getting trades settled, working out how to do it. So, there's clearly an element of a quantitative decision here talking about liquidity, bid-offers spreads, the dynamics that you'd expect, times of day that you can trade, can you get real-time data if you're going to be trading multiple times during the day? How far back does that data go? That's just one part of it.

But there's a very big part of it, which is can we actually execute the trades? What's the method of executing the trade? Do you need a trader to phone up and have a chat with some freight broker so that you can buy four contracts of a Panamax ship? Those things are harder. And that is often the time frame from going from this is a new market, to this effect appears to work, or at least statistically we can't prove that it doesn't work, which is saying something slightly different and actually a very good way of thinking about things.

That bit is generally quite easy. The hard bit is actually being able to do all the rest of the things so that you can execute every day, when you wanted to execute, at the price that you expected to execute, with the costs that you expected to do that. Take that process all the way through to rolling contracts. What happens if the market goes down? What about holidays? All of that detail that really nobody wants to think about but it's actually really important. That's how you think about markets.

This is the end of Part 1. Move on to the next video for Part 2.