MODULE 3 UNIT 2
Video set Video 1 Transcript

Module 3 Unit 2 Video set Video 1 Transcript

NIR VULKAN: We are now going to see four PhD students and postdocs from the OMI, talking about the kind of research they do, and the application for algorithmic trading. You can see the pictures of the students and postdoc. Click on either of these if you want to hear more about what they do.

Siddartha Ghoshal – Finding patterns and optimisation

SIDDARTHA GHOSHAL: My name is Sid Ghoshal, and I'm a PhD student here at the Oxford-Man Institute of Quantitative Finance. Most of my buy-side research boils down really to two questions. Firstly, given the huge amount of data available out there that could potentially influence financial markets, how do you go about determining where to look? How do you identify what features you want to include? And supposing you're able to do that, how do you go about combining them in some optimal manner?

So the problem there is really twofold. It's both one of automating your feature selection, but also of identifying how you might go about creating an optimal functional mapping between your inputs and some target of interest – say, what will happen in the S&P next day.

My second question really follows on from the first. Supposing you are able to identify that one domain has interesting information, what are the best tools available to you to extract patterns from it? Quite a different challenge there, since you're really looking at automating feature extraction from data that is often raw or even unstructured.

My research has aimed to tackle both of these problems. My early work looked at trying to forecast S&P 500 returns using a variety of data sets. We drew on data from technical analysis, sentiment data, options market metrics, and broker recommendations. Model-wise, we opted for automatic relevance determination Gaussian process regression models, due to desirable properties of that set-up. Automatic relevance determination kernels automatically scale their parameters in function of the relevance of their features. So they provide a built-in method, really, for pruning what's irrelevant and only keeping what you're really interested in.

And the output of such a model is a mean surface telling you how returns vary as a function of those features you're really interested in. The results were quite remarkable. It emerged that price base is actually a curved surface and that options market data provided a way of inferring regions where returns might be directionally biased or compressed.

Technical indicators were also valuable in reminder to look at financial markets as they truly are, rather than how we might wish that an idealised or rational market behaved.

Sentiment data was typically inversely correlated with future returns, a stark reminder to beware of the exuberance of crowds. Finance is emphatically not a domain where you want to be crowdsourcing your wisdom. And as for the buy, hold, and sell recommendations of Wall Street analysts, they didn't have, in aggregate, a whole lot of predictive prowess.

The task of data fusion for a stock market prediction is a particularly thorny one, and part of the challenge lies in how you engineer your features. We borrowed from modern practice in computer vision, where convolutional neural nets are able to identify patches within an image that are informative of a broader object being present. The analogue for us in finance is to use convolution to find fragments of a time series that are indicative of a broader motion.

Convolence applied to financial time series data yielded best-in-class classifiers, vastly outperforming both what could be achieved through Chartis pattern-seeking, and a wide range of standard off-the-shelf, ML alternatives. For the benefit of the convolutional approaches that there's an inherently visual interpretation to it. We can actually look inside the weight matrix of a neural of the conv layer, and back-translate it into a picture, effectively a chart or a fragment of chart.

So you retain some degree of interpretability, along with the performance edge. Finance is very much a needle in a haystack kind of business. Huge amounts of data and a terrifyingly low signal-to-noise ratio mean it is far too easy for sometimes dubious practices to endure, and one of the promises of algorithmic finance is to try and cut through that and inject a little bit more rigor and understanding into the field.

Favour Mandanji Nyikosa – Machine learning and algo

FAVOUR MANDANJI NYIKOSA: My name is Favour Mandanji Nyikosa, I'm a DPhil or a PhD student here at the Oxford-Man Institute of Quantitative Finance and Engineering. My main research area is in machine learning. I mainly work on techniques that can be used to adaptively configure trading algorithms. Because when you think of a trading algorithm or trading strategy, it’s often constructed using assumptions about the market or any sort of empirical observation about the market which someone wants to exploit. But these algorithms often have parameters that are often estimated from past data.

So usually you have practitioners configuring these algorithms, and then using those parameters to trade live on the financial market. But as many people know about financial markets, the data is non-stationary, so there is no guarantee that the parameters that I estimated from past data will work the same way in the future.

So I develop machine learning techniques that can take over this configuration task and change the parameters as the algorithm is running live in the market. Basically, this algorithm learns the patterns of the parameter space and then determines what the best parameters are to configure the algorithm.

The benefit of doing this is that you learn a relationship between the data that's being fed to the algorithm in sequence – you also learn a relationship between the algorithm and the parameters. And because I work on methods that make use of probability theory, you can actually characterise how uncertain you are about how useful these parameters are. In essence, you have a measure of how risky these parameters are, and you can exploit this risk to basically select parameters that are pessimistic and manage your downside risk of trading using those parameters.

The other benefit is that because of the types of methods we use for this type of configuration, you often learn patterns that are often useful to the practitioners of these methods. So basically, they will tell the practitioner that a certain trend or a certain behaviour happens at different points in time. Their ability to interpret these sort of patterns that – or insights that are generated by the algorithm are often a good indicator or they basically reinforce some beliefs that practitioners may have.

The other benefit is that because you learn the relationship of these parameters over time, any experience in the past can be used or exploited in the future. So if your algorithm in the past didn't do so well, the value of not doing so well is the information you learn from trading as you did previously. So this algorithm essentially is very data-efficient in that it exploits all the information that's available from past data and exploits the uncertainty to give you the best possible outcome for the future.

And because you're using probability theory to basically create these algorithms, it gives you a characterisation of how uncertain you are. So at the end of the day, the use of this algorithm is… it can be can be interpreted by practitioners and can be interpreted to the clients as a way of determining how risky or how, you know, what to expect in terms of future performance.

Babak Mahdavi-Damghani – Model interaction

BABAK MAHDAVI-DAMGHANI: My name is Babak Mahdavi-Damghani. I'm a PhD student here at the Oxford-Man Institute of Quantitative Finance. So, in terms of my research, it would be perhaps useful to take a step back and maybe a provide a little bit of context. In 2008, we had this big financial crisis. A lot of people were very unhappy. We had the social uproar and this sort of malaise sort of got into the scientific community as well.

This pushed some of the, I would say regulators, to review some of their risk systems and try to anticipate what the next financial crisis could be. And sort of quite quickly after the crisis, around 2010, the consensus started getting towards electronic trading being that specific area of, you know, potential crash.

And I would illustrate my, you know, my thought with perhaps the flash crash of 2010, where the Dow Jones dropped by 10% in a matter of few minutes or, you know, the flash crash of 2011, in which we saw the [Nasdaq] crash as well. What was peculiar with these crashes was a very bizarre sequence of oscillations that preceded these crashes, which, if you work in quantitative finance, you realise very quickly that it's only the interaction of perhaps systematic strategies or robots that could yield such a bizarre sequence of oscillation.

And, so these kind of events led some of the highest authorities in quantitative finance to call for some sort of modelling revolution. The modelling revolution came from going from a top-down approach to a bottom-up approach. So, what's a top-down approach? Which is currently, sort of the status quo in the world of quantitative finance is the following.

Imagine you have – you're trying to predict the fluctuation of the S&P 500, you have some data, you have some leading indicators, and you try to build functions which predict that… these fluctuations. However, this approach assumes all sorts of things. For example, that the ecosystem of strategies is consistent through time and that past data is a reliable source for predicting the future.

What is the bottom-up approach? Which is my area of expertise, or at least the area in which I'm doing my research at the moment, is to instead take a look at the strategy level.

So try to see how the interaction of two different strategies would yield fluctuations, instead of going from the top down, go from the bottom up.

If you – to try to take a look at some of the revolutions in the past in the world of quantitative finance, they always came from, you know, closely related fields. So if you take a look at Bachelier, for example, or if you take a look at the Black-Scholes models, some of these models were taken from other fields, like probability theory, you know Brownian motion, or from physics, the heat equation and stuff like that.

And what I'm trying to currently do is to try to bring some of the material in mathematical biology and in evolutionary dynamics. So in order to perhaps keep you, you know, interested, and maybe keep this a little bit intuitive, in a mathematical biology, you have this branch in which you try to model predator-preys.

So, for example, let's say you try to model the frequency of gazelles and cheetahs through time, then you have some equations that try to model the fluctuations or the frequency of these two species through time. So, you know, with the same idea, I'm trying to see whether similarly in the financial system, you could have predator sort of strategies, and prey strategies, and, depending on the ecosystem, you could have some strategies that could do really well, but that, you know, that requires the presence of other kinds of strategies and this is also where evolutionary dynamics come into play.

Again, trying to understand and bring the concept of mathematical invasion or strategy invasion is my – currently the area in which I'm trying to find interesting information.

Jaleh Zand – Time series prediction

JALEH ZAND: My name is Jaleh Zand. I'm a PhD student at Oxford-Man Institute of Quantitative Finance. My research area is time series prediction. Within the first stage of my research, I looked at making a prediction time series not as a point estimation, but as a probability distribution, and my distribution, I sort of relaxed the assumption of normal distribution, trying to have a multimodal distribution. This allows flexibility, so we can think of you're predicting distribution which can basically take any shape.

Now how this is relevant to finance? Financial data is non-stationary. It's also multimodal. We also have fat tails. So, multimodal distributions are usually good candidates within financial time series.

As a next stage of my research currently, I'm looking at reinforcement learning and using multimodality within reinforcement learning. The idea of reinforcement learning in machine learning generally is if you think of it in a simple world, you're trying to learn from your past experiences. So if you think of a child trying to, you know, learn to walk, and then walking, they will fall but they will learn, you know, they kind of keep repeating their mistakes until they learn how to walk. And it's a very powerful concept and I'm trying to sort of use a combination of reinforcement learning but also a bit multimodality, which I think is something new in a sense that most of the current research is either point estimation within reinforcement learning, or they use very simple probability distributions.

This is going to be the next phase. Now in terms of the actual estimating of my distribution, I used two main techniques. One is I use neural networks and the other one is I use Gaussian processes. Now both have their sort of advantages and disadvantages, but both are quite interesting techniques, and this is sort of the next step that I'm going to be looking at, going forward.

Conclusion

NIR VULKAN: I hope you've enjoyed these short videos and it gave you an insight on the current research that is happening, at least here in Oxford, into the future of algorithmic trading.

Did you understand all of the concepts in this video? If you would like to review any of the questions, click on the corresponding button.