MODULE 6 UNIT 1
Video Set Video 2 Transcript

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STEFAN ZOHREN: In this last video, I wanted to look a bit more into what other areas are interesting right now, and what are potentially interesting areas to watch in the future. So, two areas I'm quite excited about beyond the topics I've already covered are techniques from networks as well as from natural language processing, and large language models in particular. So, let's just quickly cover those two and what are interesting areas to watch there.

Networks

ZOHREN: So, the first is network approaches. So, there have been quite some advances as well on utilising networks in the context of neural networks where similarly to when I have an image—and for example, I utilise techniques such as convolutional filters to utilise the geometry in images to find out about different properties of parts of the image—I can now use filters on networks where when I, for example, want to make a decision about a certain company, I'm taking the nearest neighbours into consideration.

This is quite similar to the image, but with a different type of metric space. When an image, neighbouring pixels by definition are close by, in a network, I have neighbouring companies, which could be companies of the same sector, which is similar, but they don't have to be kind of close by in a geographical sense or otherwise.

So, this is a quite interesting space. And, for example, it can be useful for risk modelling, to give one application. So, many of the traditional risk models are very static in nature. I have vector models or I have—which are often based also on industry sectors, and those industry sectors hardly change, but some of these network techniques help us to find also relationships which are outside of those traditional factors and also see how relationships might change over time.

So, we did some work some while back where we looked at company networks extracted from news status. So, if companies are mentioned together, they're most likely related, and we can kind of determine this relationship networks from the news. And as news change over time, we can see how this network changes. And we found some very interesting things. For example, when we ran it through the 2008 financial crisis, we could see how this network—which oftentimes in normal conditions has individual kind of clusters which more or less correspond to industry sectors like financial sector, banking sector. This network became very, very connected, and also at the centre was the financial sector, and in particular, Lehman Brothers. So, it became a very connected network. And then after the crisis, it somewhat moved apart again.

And, obviously, having such a kind of dynamic risk models is quite useful when looking at portfolio risk as, obviously, once the network is much more connected, risk can spread much quicker. And we also look at how certain things such as sentiment can spread over this network. So, this is just one example how one can utilise network techniques.

There are many other networks. For example, supplier networks are important. But I can also have networks between companies, not just companies and companies, but for example, companies and some form of topic – for example, climate disaster – and how closely related are certain companies with such topic, which can obviously be important when checking on things like ESG factors and other concepts.

Large language models

ZOHREN: Another area which obviously everyone knows because it has been everywhere in the news is large language models. You have all heard about generative AI and things like ChatGPT, which is obviously taking the world by storm. Here, I just wanted to focus a little bit on the specific use cases for crunch trading and crunch strategies.

And there, I see a big potential when combining the language information with time series information. We have seen in a couple of works—we did some work on volatility forecasting. We did a similar work in spirit also on COVID forecasting, where we saw if we, for example, used textual information on its own, we can forecast volatility from news, for example, or we can forecast COVID cases from social media comments on headaches and fevers, et cetera. But those forecasts aren't that much better than just using a time series model and effectively interpolating from previous observations. So this language models can give us predictions, but they aren't necessarily better than the time series prediction.

But what is better is when we combine the two. When we have a model which uses both time series information as well as kind of exogenous textual information to make predictions. And for the volatility forecasting, we have seen that on normal days following the time series is basically the best thing you can do is just follow the trend, most likely volatility tomorrow is somewhat similar to volatility today. But the news can help to deal with certain shocks to the market when now some news appears and volatility suddenly jumps. And when combining the two models the time series and the textual information, then we get the best overall predictions.

One important point to mention though is that one issue with all of these large language models which are currently available, especially the most complex ones, which are the most recent ones, is that we don't have any control about which data went into those models. And that's obviously a big problem because as you've learnt in this course, if I look at hedge fund strategies, I have to be able to back test those strategies. So, how would the strategy have performed over the last five years, the five years before then, the five years before then?

There's obviously an issue with this language models because they have effectively seen the future. If I ask them something—just to give some example, I could use it to have a stocks trading strategy, and it could easily figure out that, for example, Enron is associated with a negative sentiment because, obviously, had it seen all the news around Enron after it collapsed, and that would have made it perform very well in hindsight, were this information available.

But as you hopefully have seen in this example, if I apply those language models in the context of quant finance strategies, I really have to be very careful about the look ahead bias of maybe going backwards in time, testing a strategy, and finding this performance very well only because the language model effectively had information about the future.

I hope this gives you a good overview about what I think is exciting right now and what are exciting areas in the future. And hopefully, you'll be able to follow some of our future works from the Oxford-Man Institute. So, thank you very much.

SPEAKER: 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.