Quants turn to AI for market insights

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A new breed of hedge funds are applying artificial intelligence techniques to trade the markets, with some success

The dawn of man. Our ancestors discover tools and conquer their surroundings. Flash forward a few million years and humans have mastered space travel. A sentient computer called HAL 9000 leads an expedition to Jupiter to discover the secrets of the universe.

The future envisioned by Arthur C Clarke and Stanley Kubrick in the science fiction classic 2001: A Space Odyssey isn’t quite here, but it’s close.

Artificial intelligence (AI) – computing that mimics human behaviour – is already part of our daily lives. It powers Google’s search algorithms, Facebook’s friend recommendations and Apple’s Siri application. It’s found in medical diagnosis programs, aircraft landing systems and self-driving cars.

Some hedge funds are even using AI systems to manage investment portfolios.

New York-based Rebellion Research launched one of the first pure AI-based investment funds in 2007. The firm’s trading system is based on Bayesian machine learning, a form of AI associated with predictive algorithms that evolve in response to new information and past experience.

Rebellion’s system – created seven years ago by a group of engineering, mathematics and computer science graduates in their 20s – effectively taught itself to trade stocks, bonds, commodities and currencies across 44 countries.

“We gave the system 20 years of global economic and market data – a history of modern finance – and left it to figure out how different factors impact prices across asset classes, sectors and geographies,” says Alexander Fleiss, chief investment and risk officer at Rebellion. “It wasn’t programmed to follow any specific trading strategies or rules. We didn’t tell it to look for momentum or relative value. The system recognised those concepts autonomously and associated them with performance in certain market conditions.”

Rebellion is one of a handful of start-up hedge funds that are touting their use of AI techniques to trade the markets. San Francisco-based Cerebellum Capital and Edinburgh’s Level E Capital have been running trading programs based principally on machine learning since 2009, while London-based Castilium Capital launched an AI hedge fund earlier this year.
Some well-established hedge funds have also adopted this technology to varying degrees. DE Shaw and Renaissance Technologies have been using AI techniques to enhance their investment and risk models for some time, according to people familiar with those firms.

Bridgewater Associates, the world’s largest hedge fund, also jumped on the AI bandwagon in 2013 when it hired David Ferrucci, the lead engineer on the IBM research team that developed the AI engine Watson. Ferrucci became something of a celebrity in 2011 after his creation beat a pair of former human champions on the US game show Jeopardy!.

Despite some early scepticism, hedge fund investors also seem to be coming around the idea of AI-based quantitative investment strategies.

Fund of hedge funds (FoHF) manager Paamco has reviewed a number of emerging managers that utilise various forms of AI as part of their investment process.

James Jarvis, a London-based associate director at the firm focusing on quantitative strategies, believes this technology could have useful applications in finance.

“A common problem all quants face is figuring out how to build models that can navigate different market regimes – how do you deal with changes in volatility, correlation and dispersion? AI techniques could be part of the answer, possibly in the form of ‘smart’ portfolio allocation systems that shift capital around in different environments or trading models that are themselves adaptive,” he says.

He declines to say if Paamco has invested in any AI-based funds, but some other investors have already taken the plunge.

In February 2012, Colin McLean’s Edinburgh-based SVM Asset Management made a “significant investment” in Level E Capital’s Maya Market Neutral fund, which uses machine-learning techniques to model price behaviour in equity markets. Although that fund was liquidated in August, Level E’s flagship $15m equity long/short Maya fund continues to be seeded by three Baillie Gifford investment trusts. Launched in April 2010, in April 2013 it became investor ready. Level E is in the process of launching a Maya Ucits fund to supersede its current vehicle which is structured as a professional investor fund.

FRM, the FoHF division of Man Group, also pitched in with a seed investment – believed to be around $25 million – in CommEq, an AI-based hedge fund start-up in London, in June.

CommEq’s investment approach combines quantitative models with natural language processing (NLP) – a form of AI that enables computers to make sense of incomplete and unstructured information by making inferences and logical deductions, as humans do.

NLP is found in speech recognition programs such as Apple’s Siri and can be used to extract data out of everything from news reports, blog posts, Twitter feeds and Ben Bernanke’s speeches – any information source intended for consumption by humans as opposed to machines.

The AI crowd believes NLP and machine-learning techniques are an essential element of quantitative finance in the era of ‘big data’, where information is measured in petabytes and computing power is almost infinite.
Patric de Gentile-Williams, the London-based head of FRM’s hedge fund seeding business, sees some truth in that argument. “AI and advanced machine-learning techniques have some very interesting applications in the investment space. In this internet age, we have access to far more data than human beings can possibly process. The only way to analyse and spot patterns in this vast sea of information is with the use of machine-learning tools and techniques. It’s a path to developing better investment strategies,” he says.

The term machine learning is used to describe computer programs that ‘learn’ from data and adjust their behaviour as the information changes. NLP systems use machine learning to recognise and adapt to changes in the way people use language. The same techniques are being used to create algorithms that learn and adapt to information on the markets and the broader economy.

“Bayesian machine learning is about adaptation,” says Rebellion’s Fleiss. “Our algorithm recalibrates seamlessly as it receives more information. The forecasting techniques and trading strategies are constantly evolving in response to changes in the data and the results of past actions.”

For instance, he says, Rebellion’s system has learned that market cycles in commodities and currencies have become shorter in the past 18 months. “The average holding period for currency trades has gone from six to nine months in 2007 to less than three months.”

This ability to respond to shifting market dynamics on the fly makes AI systems superior to conventional quantitative approaches, which rigidly implement a predefined strategy irrespective of the circumstances.

“Traditional quant systems are based on the assumption that existing correlations will persist indefinitely. That’s what has caused problems in the past. The strength of an AI system is that it does not imply a correlation and instead constantly evolves as old relationships decay and new ones emerge,” says Guy Mitchinson, co-founder and managing partner of Castilium Capital, a London-based hedge fund that uses AI to manage investments.

But some old finance hands aren’t buying the AI hype.

Emanuel Derman, the New York-based co-head of risk management for FoHF manager Prisma Capital Partners, says applying machine learning and NLP in their current form to markets is essentially a “glorified data-mining” exercise.

“[AI] is great for medical epidemiology and selling things to people on the internet, but I’m less impressed with it as a way of discovering the nature of things, especially the financial markets. If you look at the way NLP is used for translation services, it ‘works’ but the results bear no resemblance to human speech. It still takes a human mind to really comprehend what an article means and translate that into another language. I think the same is true of market information,” he says.

Ben Appen, chief executive of FoHF manager Magnitude Capital, is also sceptical of machine-learning systems. “It’s very difficult to discern sensible rules – the building blocks of quantitative models – from raw financial data,” he says.
Appen has a unique perspective on the intersection of quantitative finance and technology. He worked at the quantitative hedge fund manager DE Shaw for seven years before starting Magnitude. In between, he formed a technology company called Alkindi that developed a collaborative filtering application based on ‘n-dimensional clustering algorithms’ to make movie recommendations.

The system Alkindi created made predictions based on people’s shared interests – similar to Netflix’s algorithms. This sounds simple, but doing this rigorously is beyond the capabilities of the human brain. We can map simple relationships between a pair of variables in two-dimensional space – for instance, a quadrant chart with people who like or dislike both science fiction and romantic comedies and those that like one but not the other different sections. Introduce a third element – dramas – and each sector becomes a cloud or cluster in a three-dimensional space. But add a fourth dimension, and we can no longer visualise the relationships because we cannot see in four-dimensional space.

“If you add more relationships, it becomes imponderable [for humans], but the clustering is computationally possible,” says Appen.

This is similar to the way machine learning works: searching for patterns and changing the outputs as more information becomes available.

But this form of data mining “isn’t really artificial intelligence as I would use the term”, says Appen. “The system isn’t building the rules independently by looking at the data. The rules are pre-specified.”

Data-mining tools can help quants find more subtle patterns in financial markets, but Appen doesn’t believe it should fundamentally change the way people go about building models.

“The reason AI hasn’t been more widely applied is because the rules we have in finance are quite weak. That’s why economists and finance professors couldn’t predict the last crisis. There are instances when the market does things that are not in the data,” he says. “If you have a system where the rules are driven by the raw data, it will waste its time chasing some things that don’t really exist and it won’t warn you about some problems that do. The more fruitful way to use maths and computers to make money in the markets is generally to identify laws that are likely to be true on a first principles basis and then use machines to exploit that behaviour.”

The most famous examples of AI – IBM’s Deep Blue and Watson computers – illustrate the capabilities of this technology, and also its limitations. Computers have beaten humans at chess and Jeopardy!, but no one has built a machine that is even competent at poker – a game that many believe more closely resembles the art of trading.

The main concern is that AI systems are prone to what’s known in quant circles as the ‘over-fitting’ problem – the tendency for models to latch on to coincidental or spurious correlations.

Data mining can produce all sorts of nonsensical – albeit statistically sound – market indicators. The best example is the so-called ‘Butter in Bangladesh’ theory. Back in the 1990s, finance and computing expert David Leinweber, then a managing director at hedge fund First Quadrant, discovered that butter production in Bangladesh taken together with cheese production in the US and the sheep population of Bangladesh had a 99% statistical

The question is whether autonomous machines can learn to distinguish significant correlations from this type of noise?

David Andre, a machine-learning expert and co-founder of Cerebellum Capital, which manages close to $90 million in AI-based hedge fund strategies, admits this is one of the main challenges for AI systems.

“Computers are very good at performing defined, repeatable tasks very quickly, but they’re fairly bad at recognising the relevance and significance of things outside the data on which they’ve been trained,” he says.

Andre founded Cerebellum in 2008 with another AI expert, Astro Teller, currently the director of new projects at Google, and entrepreneur George Mueller and his brother Gary, the former chief executive officer of Institutional Investor, a US media firm.

Cerebellum’s AI system is able gauge the over-fitness level of potential strategies it finds, but it’s not infallible. So the firm employs what Andre calls “a hybrid process of man and machine”. The machine learning system “stumbled across an arbitrage possibility” in 2009 that formed the basis of the firm’s main hedge fund, he says. “The machine found something, but it was really the people watching the system that saw the significance of it and figured out how to take advantage of that anomaly.”

Cerebellum initially gave its system lots of leeway to define its own rules and definitions, but Andre has since decided to reduce the level of autonomy. “We define a lot of the factors and risk exposures – especially the ones we don’t want to have exposure to. The machine then searches for the best strategies within those parameters,” he says.

There are some within the AI community itself who believe machine learning is ill-suited to finance. Technology that was developed for web searches or medical diagnosis isn’t likely to work as well in the markets, says Alicia Vidler, co-founder and senior portfolio manager at Castilium in London.

“In medicine, the symptoms are a function of the disease. In the financial markets, the same cause can have multiple different effects. You can’t take a generic machine learning system and apply it to asset management. The markets are far too complex for that,” she says.

Castilium was founded in 2012 by Vidler, an ex-Bank of America Merrill Lynch proprietary trader, along with former Deutsche Bank derivatives expert Guy Mitchinson and Arnold Amstutz, a former chairman and chief executive of Citicorp Investment Services and Insurance Group and a professor at the Massachusetts Institute of Technology. The firm uses a different type of AI called an ‘expert system’. Its algorithms are based on research conducted by Amstutz when he was working at RiskMetrics and Citigroup in the 1990s and early 2000s. The aim, according to Vidler, is to replicate the reasoning and decision-making process of human analysts, traders and risk managers with a computerised system, rather than simply using computers to search for patterns.
Expert systems like Castilium’s are closer to what people generally think of as artificial intelligence – machines that think like humans. The programs essentially consist of a series of ‘what if’ rules and decision trees extracted from human experts. Amstutz spent years interviewing traders and fund managers about their decisions and incorporated them into his algorithms.

“Expert systems are constructed for their specific environments and purposes. Essentially, you’re taking an expert [or group of experts] in their field, replicating their decision-making process and embedding them in a robust and repeatable computational framework,” says Mitchinson.

This approach is laborious and time consuming, but it has some advantages over machine learning, according to Vidler. “Machine learning systems can find all manner of patterns. Expert systems can give you a coherent decision,” she says. “[It’s] also very transparent and tractable. The portfolio manager should be able to intuitively understand and explain every decision.”

AI is still an emerging technology and it comes with obvious health warnings. But that’s not to say it doesn’t have useful applications in quantitative finance, says Andre. For one, it makes the process of creating models faster and cheaper. “Typically, you build a model and then spend a lot of time testing and tweaking it. Now all that tweaking can be done at computer speed,” he says. This might make it more viable to run certain strategies that were previously considered too expensive.

He draws a parallel with Amazon’s approach to selling books. Bricks-and-mortar bookstores have to focus on selling a small number of higher-margin titles due to limited shelf space. Amazon, with its infinite shelf space, low costs and predictive analytics, makes a big chunk of its profits selling obscure books that high street stores cannot afford to carry. Similarly, quant funds often ignore low-capacity strategies with a ‘long tail’ because the returns may not cover the cost of paying an expensive quant to build and maintain the necessary models. “If we can use AI to find and implement those strategies more cheaply, we can go after the long tail,” says Andre.

Even AI sceptics see some potentially promising uses for this technology in the long run. Prisma’s Derman says one possible application is in modelling collective behaviour and contagion risks in financial markets. “Big data techniques could make it possible to model the interactions between market participants – the feedback loops between banks, hedge funds and central banks,” he says. “The big dangers in the markets come from collective behaviour – when one group influences another and everyone rushes off to do the same thing – but those dynamics are not well understood.” He gives the example of portfolio insurance in the 1980s, which made sense to people in isolation but was destructive when everyone jumped in.

Funds that apply AI to investing say they are seeing promising results. Rebellion’s AI program predicted the stockmarket crash in 2008 and slapped an ‘F’ rating on Greek bonds in September 2009, when they still carried an A rating from Fitch and a month before the first official downgrades.
The firm’s equity strategy has beaten the S&P 500 by 7% a year since 2007. An absolute return fund opened to investors in January 2012 has returned 6% annually with a Sharpe ratio of nearly three.

Cerebellum has been trading its market neutral equity fund since 2009 with no down months.

At press time, Level E’s founder and chief executive Sonia Schulenburg said the firm’s flagship fund had returned 5.57% net of all fees since April 1 to November 30 versus the FTSE 100’s 3.9%. Volatility was 7.09 versus 12.70 for the FTSE 100, and its Sharpe ratio was 1.07 versus the FTSE 100’s 0.45.

For now, AI firms say they are keeping their technology on a pretty tight leash, at least until they figure out how to deal with problems like over-fitting and conflicting or contradictory signals.

At Rebellion, every trade signal generated by the AI system is reviewed and approved by the firm’s employees. “The system doesn’t get to place its own trades. It could, but we choose to have human oversight of everything,” says Fleiss.

Cerebellum’s Andre says it’s important to recognise there are situations that machines simply cannot handle. “The question we’re always asking is, does the model have sufficient training data to figure out what might happen given the situation at hand,” he says. He cites the examples of a major terrorist attack or significant regulatory change, such as a ban on short-selling. “In those types of situations we would go to cash and let humans take care of the risk management rather than have the machine navigate untested waters.”

Castilium’s Vidler agrees. “A human risk manager has to be able to step in and remove the risk from the portfolio if there’s an exogenous event like an act of terrorism.”

Anyone who’s seen 2001: A Space Odyssey will agree it is probably best to proceed with caution. In the movie, the computer HAL tries to kill the ship’s crew when he’s faced with conflicting orders to complete the mission while keeping its true nature hidden. Computer scientists will have to make sure their systems can exercise better judgment than HAL before unleashing their full capabilities on the markets.