The Machines Are Coming

Executive Summary

» The potential of Artificial Intelligence (AI) in asset management is considerable, with applications that may touch all aspects of the investment management process.

» Global Manager Research is seeing a broad range of AI implementation in its coverage of traditional and hedged strategies. Asset managers are incorporating AI-based techniques in their investment practices from idea generation to execution.

» While advances in AI implementation are accelerating, there are inherent limitations associated with AI that likely will mean that its greatest impacts will be in areas of finance that are the least efficient or where it increases human capacity (at least in the near term).

Overview

AI is moving out of the laboratory and into our daily financial lives, from digital assistants in banking apps to fraud detection algorithms used by credit card companies. Worldwide spending on AI systems is expected to double to $79.2 billion in 2022, with the banking sector expected to be second only to the retail industry in total dollar amount. Macro trends are driving the adoption of AI systems across the financial services industry—trends such as mounting regulatory reporting, cheaper processing power, the exponential increase in data production, and consumer preferences. We are seeing the world’s large asset managers and niche hedge funds spend heavily on developing or acquiring AI-enabled systems to automate some front and back office functions. While these firms have had some success in using AI to inform investment decisions, we believe there is a long way to go before asset managers and hedge funds will be able to deploy AI at scale to develop a competitive advantage through unique investment strategies. When it comes to investment portfolios, it is a subdiscipline of AI called machine learning (ML) that is already making an impact.

The machines in question are computers, or technically, graphic processing units (GPU) that process data in parallel at unimaginable speed, mimicking the processes of the human mind. ML as a discipline combines knowledge based in statistics, computer science, engineering, and mathematics. At the most basic level, an algorithm that performs linear regression while automatically incorporating new data could be considered ML. For investment managers, ML’s potential is twofold:

- ML techniques can free up the modeling process behind quantitative investment strategies by allowing researchers to leave behind the assumption that there is a linear relationship between data and variables.
- Second, ML has the potential to find actionable information from large unstructured data sets—including data that is not categorized into rows and columns (as in a spreadsheet).

ML—putting vast amounts of data to work

The explosive growth of available data and processing power available in the public cloud is behind the race to adopt ML techniques. Predictions about the growth of data keep escalating, with a current prediction that there will be 40 times more data bytes than there are stars in the observable universe by 2020. ML models are adept in situations in which there may be little intuition about why data might be related. That is its Achilles heel as well, but we will come back to that point. First, we will review a few points on how ML models work and where they are being used today.

Advanced ML techniques depend heavily on having access to vast amounts of data to identify patterns or signals that lead to a desired outcome. The observed outcomes from that process inform or train the system in how to adapt its parameters. ML is already being successfully deployed within investment management in areas where data is plentiful. This includes quantitative data like the millions of tick data points generated on stock exchanges, or qualitative data like news feeds on social media that may indicate something about the likelihood of a stock’s price rising or falling.

In our coverage of traditional and alternative investments, Global Manager Research is already seeing a broad range of ML deployment. That coverage includes niche hedge funds that are deploying autonomous ML-based investment strategies. Yet, the overwhelming majority of asset managers are using ML techniques to enhance an investment management process that depends on human intervention and decision making.

Irrespective of whether a manager employs a fundamental or systematic process, asset managers already are using ML across the four traditional steps in the investment process: idea generation (data intake), security selection (modeling), portfolio construction, and execution.

- Starting with the first step, ML enables asset managers to harness the vast potential of alternative data sets to generate ideas and to inform the investment decision making. For example, asset managers may incorporate satellite image processing of car parking lots to better estimate consumer visits for a retailer, or consumer credit card data for insights into consumer purchases or debt levels. However, the informative power of alternative data sets often poses its own challenges, when it becomes widely available (thus losing its predictive power), or due to a lack of precision (cars in parking lots may not translate to sales). Still, ML techniques are adept at parsing large data sets; for example, one systematic fund manager uses ML techniques to process a data set that has the equivalent of one trillion rows of data.

- In security selection and modeling, asset managers employ ML techniques to model alpha signals. Alpha is excess return over the market-based return. These are signals with predictive power potential about the likelihood that the price of a security may rise or fall. Systematic, ML-based investment strategies generally act on the basis of hundreds or thousands of signals with varying degrees of capacity over shorter time frames. The problem is that these signals often become crowded, with too many other market participants chasing too few alpha signals and the signal loses its predictive power or staying power. As such, the signals are said to “decay,” and ML techniques assist in adapting the investment strategy to account for that eventuality. A fundamental security selection process may benefit from ML-based natural language processing that screens transcripts of management guidance for key words that indicate a change in tone about upcoming prospects. The lesser frequency of these quarterly data points, however, constrains their applicability to some extent. In the third instance, ML

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2 Domo, “Data Never Sleeps 7.0.”
4 Two Sigma hedge fund.
plays a role in helping asset managers optimize portfolios to account for changing conditions or market regimes in which certain models or signals may prove less effective.

- Finally, execution is one of the areas in which ML is frequently conflated with more straightforward program trading in which rules and heuristics are specified in a program in an attempt to achieve improved trade execution. These programs help to account for impact costs and control for risk. Indeed, bank platforms are seeking to deploy ML-based trading platforms. Yet, in the heavily regulated financial services domain, the deployment of true ML-based trading is still in its early days. In this instance as well, it is the exponential increase in data availability that is driving advancement—as exchanges (such as NASDAQ) have enhanced transparency by releasing all outstanding buy and sell limit order process and volumes in real time. This, sometimes is referred to as market microstructure data.5

The reality of ML—its application for asset managers has a long way to go

Certainly, the number of fund managers deploying ML-based investment strategies is growing rapidly, but the degree to which ML is incorporated in the investment process still varies widely. In response to a BarclaysHedge poll of hedge funds last year, 56% of respondents reported using AI or ML in their investment process, with 33% reporting its usage in risk management, and 27% in trade execution.6 Still, with all the progress that has been made, ML's potential in modeling financial assets still appears to be in its infancy.

A vexing problem for ML is that the problems it aims to solve range from random to deterministic. Financial data tends to have a high degree of noise, and it is prone to exogenous shocks. On the other side is the predictability of the physics that govern the development of a driverless car. If the training data used to inform the model changes, it could result in a very different model—this is the variance problem. For example, the autonomous vehicle learning algorithm that trains in the deserts of Arizona may come to a different model specification than a model trained in the mountains of Colorado. Similarly, ML systems have resoundingly beat human world champions at the games of chess and Go (a strategy board game), but games have states and actions (i.e., queen to rook five) that allow a ML algorithm to learn what actions to deploy in different states. In financial markets, the state is not always obvious. Are we just in a late cycle economic expansion, or headed for more serious economic headwinds?

As market makers look to deploy ML-driven trading platforms, or as asset managers seek unique ML-based investment strategies, they must contend with regulatory and transparency requirements, along with the fact that it is the tails of the portfolio return distribution that often matter most to investors—and not simply the average. The consequences of an unintended “computer glitch,” which resulted from faulty testing of new program trading software, led to a $460 million loss for one financial services firm in less than 30 minutes.7 It took the firm’s programmers that amount of time to identify the root cause and shut down eight servers. It is possible to imagine that a properly trained ML-based execution platform that is penalized for unexplained losses would have responded in a fraction of that time, thus curtailing the losses. On the other hand, we believe the need to explain why a model chose an action are reasons enough to keep human overseers in charge.

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ML—challenges and opportunities

Let’s return to discussion of that Achilles heel for ML. Probably the greatest challenge for wider ML application in the investment arena is that investors want to understand why they are making money or losing it. ML algorithms that are fed large amounts of data will eventually find a pattern, even if the pattern (correlation) is of a spurious nature such as stock prices rise when rain falls in New Mexico. ML in finance is subject to interpretability. That means that it is difficult to deploy a ML model if there is no rational – easily understandable explanation behind its success.

As we have noted, ML is already playing a role in investment portfolios, and that role is expected to grow. Wells Fargo Asset Management is in the process of deploying a stock research tool that employs ML techniques to leverage the capabilities of its portfolio management teams by broadening the scope of the idea generation process, or to help corroborate the human intuition of its team. WFAM is also developing a virtual analyst tool that has the potential to make security recommendations across bonds and stocks for portfolio managers’ consideration.

In the nearer term, ML’s greatest impacts likely will be in areas of finance such as real estate, regulatory supervision, and standardized asset allocation models (i.e., robo-advisors). While asset management firms are developing (and deploying) potentially profitable ML strategies, autonomous ML hedge funds are still few and far between. In this area, the limits include the difficulties of implementing ML, along with the competition. The most profitable ML strategies often do not scale (meaning only a limited amount of capital may be deployed into the strategy), and the anomalies they exploit are transitory. Essentially, they are at risk of being “competed away” by another machine.
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