CASE STUDIES

1. ENHANCING TRADING STRATEGY AND EXECUTION WITH MACHINE LEARNING: MAN AHL

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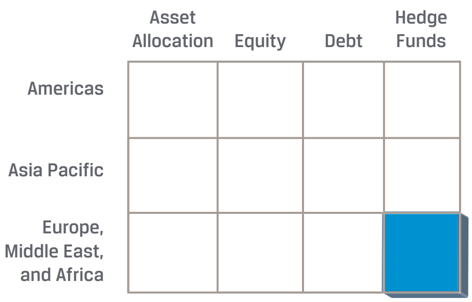

Background

Man Group is an active investment management firm that provides long-only and alternative investment products with USD114.4 billion assets under management as of 30 June 2019. Man AHL is a quantitative investment manager that is part of Man Group; it is headquartered in London with USD29.9 billion assets under management as of 30 June 2019.

Man AHL trades a wide range of hedge fund and long-only investment strategies that typically span asset classes and geographies. All of these feature some degree of machine learning. For example, the execution process—common to all of Man AHL's strategies—uses an adaptive intelligent routing algorithm to pick the optimum route to market for a given trade. Machine learning is most widely used within our multi-strategy programs, where it is used in various guises, such as pattern recognition, trend following, and natural language processing.

Man AHL first started researching ML and its application in investments in 2009, but that effort did not lead to implementation in the program portfolio. In 2012, we approached it again, but this time, we used a different ML approach. The team was very skeptical, but after an extended period of research testing, paper trading, and live trading using Man AHL's own capital,[19] the first ML strategy eventually entered Man AHL's program portfolio in 2014.

Investment Process

So far, machine learning has had the most impact in two areas of Man AHL's investment management activity: first, in the development of trading strategies (these are the algorithms that generate trades—i.e., what to buy or sell and when to do so), and second, in improving the efficiency of execution of such trades (i.e., their delivery to and completion within financial markets). When we apply ML techniques while developing trading strategies, we put a lot of effort into ensuring that the resulting strategies diversify our existing portfolios. In other words, the ML algorithm does not perform an undirected search but instead is modified to seek features that provide both alpha and diversification and to discount or ignore existing portfolio features or nuisance effects we don't want to capture. Building up this research experience was hard, especially in the beginning, but we believe it is now a well-trodden path within the team.

Once the trading strategies have determined the current optimal positions (e.g., long 700 shares in ABC, short 250 shares in XYZ), any trades needed to obtain these positions are passed to the execution system. The job of the execution system is to trade to each desired position within a specified time horizon while minimizing the total transaction cost (market impact) incurred in doing so. Man AHL has been using its own electronic trade execution algorithms for over a decade, and they are complemented by third-party algorithms developed by broker or bank counterparties. The key question that needs to be answered—potentially thousands of times a day—is, What is the most efficient (cheapest) way to get each trade completed? That is, which algorithm should we use, or should a human deal with it instead?

This question is answered online, in real time, using ML techniques to automatically allocate trades to one of the available execution channels (e.g., Algo A, Algo B, …, human). In our experience, human decision makers find this optimal routing problem notoriously difficult because of the nonstationarity and high degree of noise in transaction cost data. We started looking at this problem with tools from reinforcement learning at the end of 2016 and found benefits in both money and time saved. From modest beginnings trading a handful of futures contracts in Man AHL, the approach has been scaled up and is now used to help optimize the futures and cash equities order flow from across Man Group.

18 Chief Scientist, Man AHL. This case is prepared based on our interview with him and materials submitted by Man AHL.
19 Monitoring a new strategy in live trading using Man AHL's own capital is one of the final validation steps required before the strategy can enter the program portfolio.

AI/Big Data Technology

We are open-minded about the full spectrum of ML techniques; for example, we are agnostic as to whether we solve a problem with deep learning or Bayesian machine learning. Our job, I believe, is to explore the space, find out what works and what doesn't, and integrate the things that add value into client trading. In terms of strategies that have made it through the R&D phase and into the client portfolio, we have live trading with Bayesian ML, DL, and pattern recognition algorithms. More recently, strategies based on NLP, where the underlying data are text articles, are also now live in client trading. Researching such strategies requires specialist hardware—that is, a processor called a graphical processing unit (GPU) can complete the calculations required for DL research in 1/30th of the time taken by the CPU in a standard computer.

For researching trade execution strategies, the use of simple time-series data, even if sampled at high frequency, are inadequate because the relevant data object is more complicated—namely, the dynamically changing limit order book (LOB). Such market microstructure research can require orders-of-magnitude more data throughput and computing power than simple time-series data, especially when combined with ML models, which themselves can be computationally expensive, even for modestly sized data sets.

The choice of programming language is especially important. Man AHL has used Python for researching both trading and execution algorithms since 2011, and the live implementation of these algorithms for trading the client portfolio is also undertaken in Python. Previously, researchers used a combination of S-Plus, Matlab, and R, while live implementation was in C++ and Java. Using one language for both research and implementation has improved throughput—for example, by removing the need for double-coding—but has also assisted in less expected ways (e.g., enabling researchers and technologists to work closer together, on a single codebase).

Team Structure and Development Process

The great majority of the researchers at Man AHL have scientific backgrounds (e.g., in mathematics, statistics, computing, physics, engineering, or seismology, to name but a few). Members of our ML team have very diverse non-financial backgrounds (e.g., computational neuroscience, online news) and bring post-doctoral research experience to the application of ML techniques in different areas. Initially, we applied machine learning in futures markets because this area was where we had the highest familiarity. Later, once we'd learned some lessons about what worked and what did not, we broadened our research to cover cash equities. The chief investment officer and other senior members of Man AHL identify the main directions; the ML team and the rest of research then seek to capture trading signals within those areas, which are additive to our existing strategies. All staff are encouraged to complement this top-down perspective by suggesting research projects where they suspect a gap in our current systems or some feature that can be improved.

The teams are highly integrated. There is no clear distinction between researchers, technologists, and portfolio managers; they are all on a continuum. Successful researchers whose strategies have made it through to the client portfolio maintain oversight of the live trading and performance of their strategies.

Key Takeaways

This stuff is hard. Nothing works off the shelf. It is a common misperception that by putting a lot of data, fancy computers, and smart people together, you'll be able to extract useful signals. Experience matters. Only a fleetingly small percentage of data is "useful." Alternative data provides new opportunities but often does not have enough history.

What you can extract using non-ML tools should be the benchmark for deciding whether to use machine learning. Is what extra you capture with machine learning worth the extra complexity? Our maxim is, therefore, "Use the simplest tool that does the job."

Embrace open source. Stay involved over the long term by contributing back. Form a virtuous circle.

Be bold in the process. Have resolve to decide what is worth pursuing, and kill off projects that don't look promising.