

# **Scope for the Usage of Ai and Machine Learning in Portfolio Management and Possible Effects on Consumers and Investors**

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**ABSTRACT:** AI and machine learning techniques are active areas of research and development for asset managers and trading firms. In addition to significant research and development (R&D), some firms now use machine learning to devise trading and investment strategies. The extent to which AI investment strategies are autonomous or incorporate human oversight varies on a case-by-case basis. In this section, we distinguish between trading execution (primarily sell-side) and portfolio management (buy-side). This paper explains the scope towards the usage of AI and machine learning in portfolio management and also provides the information about the possible effects on consumers and investors.

**KEYWORDS:** Artificial Intelligence(AI), Machine Learning(ML), consumers and investors.

## **I. AI AND ML IN TRADING EXECUTION**

Trading firms are looking to AI and machine learning to use data to improve their ability to sell to clients. For example, analysing past trading behaviour can help anticipate a client's next order. Trading generates large quantities of data, and this scale is typically required by machine learning tools to work effectively. If the current trend to increasing use of voice-to-text services continues, this will generate additional data from trades executed over the phone, which can be integrated with the pool of data from electronic platforms.

AI and machine learning can more pro-actively manage risk exposures. Machine learning can serve as a basis for risk modelling by exchanges to determine when members' trading account positions may have increased risk profiles that may warrant intervention. For large trading firms such as banks, the use of a central risk trading book, or risk management techniques based on big data analysis, have enabled these firms to manage risks and optimise their use of capital by centralising the risks that arise from various parts of their businesses.

AI and machine learning can help compliance with trading regulations. A RegTech application of AI to trading is voice-to-text technology powered by deep learning. This helps firms meet pre-trade and post-trade transparency requirements for non-equity markets.

### ***Scope for the use of AI and machine learning in portfolio management***

In portfolio management, AI and machine learning tools are being used to identify new signals on price movements and to make more effective use of the vast amount of available data and market research than with current models. Machine learning tools work on the same principles as existing analytical techniques used in systematic investing. The key task is to identify signals from data on which predictions relating to price level or volatility can be made, over various time horizons, to generate higher and uncorrelated returns.

Among asset managers, machine learning is used most extensively by systematic ('quant') funds, most of which are hedge funds. An AI unit tends to sit within a larger team at an asset manager to aid with portfolio construction. One view in the industry is that for AI and machine learning to be effective, both traders and quants need to have good oversight and understanding of the tools used. Many quant funds state that they are not comfortable fully automating and implementing a model if they cannot understand how a particular prediction is made. The concentration of machine learning tools among quant funds reflects how machine learning is fundamentally an approach to generating predictive power from data, which distinguishes it from investment approaches that use greater discretion and judgment.

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At the moment, machine learning likely only drives a minor subset of quant funds' trades. Quant funds manage on the order of \$1 trillion in assets, out of total assets under management (AUM) invested in mutual funds globally in excess of \$40 trillion. The market share of quant funds has not changed drastically in the years since the crisis, but between 2013 and 2016 the proportion of trades carried out by quant funds, on one measure, approximately doubled from 13% to 27%. In turn, some portion of the trading is based on machine learning. It is hard to quantify precisely what proportion use machine learning for several reasons:

- Firms are hesitant to share proprietary information.
- When firms share information on their use of machine learning, there is not always a standard definition or understanding of what is included within the concept.
- Some investments or trades may be made on a discretionary basis but informed (to varying extents) by the use of machine learning.

One contact in the industry estimates that 'pure' AI and machine learning players have about \$10 billion in assets under management, but that this figure is growing rapidly.

In addition to the use by fund managers, specialist firms are making available to asset managers machine learning tools to gain insight from the vast volume of news and market research available. In other cases, asset managers are themselves building indicators, using AI capability supplied by third parties. One general issue is that useful trading signals derived from AI and machine learning strategies may follow a decay function over time, as data are more widely used and hence become less valuable for gaining an edge over other investors.

## II. POSSIBLE EFFECTS OF AI AND MACHINE LEARNING ON CONSUMERS AND INVESTORS

If AI and machine learning reduce the costs and enhance the efficiency of financial services, consumers could obtain a number of benefits.

- a. Consumers and investors could enjoy lower fees and borrowing costs if AI and machine learning reduce the costs for various financial services.
- b. Consumers and investors could have wider access to financial services. For example, applications of AI for robo-advice might facilitate people's use of various asset markets for their investments. Moreover, AI and machine learning, through advanced credit scoring for FinTech lending, might make wider sources of funds available to consumers and small and medium enterprises (SMEs).
- c. AI and machine learning could facilitate more 'customised' and 'personalised' financial services through big data analytics. For example, AI and machine learning might facilitate the analysis of big data, thus clarifying the characteristics of each consumer and/or investor and allowing firms to design well-targeted services. Nonetheless, the use of consumers' data may entail issues of data privacy and information security. Moreover, since AI and machine learning analytics could analyse the characteristics of each customer through public data, it would be necessary to consider how the output of customer analysis should be protected, while protecting the anonymity of each consumer and facilitating the safe and efficient use of big data for better services. In addition, establishing well-designed governance structures for financial service providers using AI and machine learning would be important for consumer and investor protection purposes.

Avoiding discrimination in credit scoring, credit provision, and insurance is also an important topic. Even where data on sensitive characteristics such as race, religion, gender, etc. are not collected, AI and machine learning algorithms may create outcomes that implicitly correlate with those indicators, for example, based on geography or other characteristics of individuals. There is ongoing research on how to address and mitigate these biases. This is a key area in the broader discussion on AI ethics.

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## Analysis based on the publication years

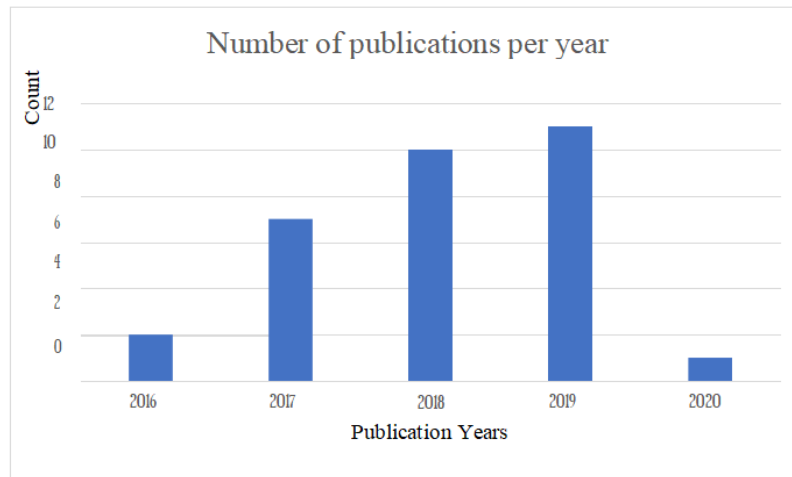


Figure 1: Numbers of publication of the articles considered in the survey

## Analysis based on used methods

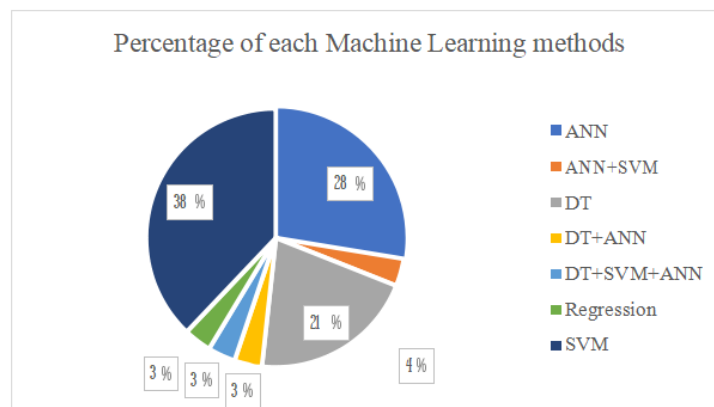


Figure 2: Frequency of machine learning methods employed in the research

According to the second section, the papers selected in this paper are all based on support vector machines, Decision Trees (Random Forests) and Neural Networks. Figure 2 describes the respective proportions of the three methods used in the paper. From Figure 2, it can be seen that 38% of the papers use SVM, 28% of the papers use Neural Networks, and 21% of the papers use Neural Networks, and SVM, Neural Networks and Decision Trees in combination account for 3% of the total. Using the traditional quantitative trading regression, [1] tested the classic five- factor asset pricing model in Chinese Stock market and proved that was effective. Therefore, SVM and Neural Network are the most commonly used methods.

## Analysis based on classification

According to the selected papers, the paper can be divided into two categories after read. One is Stock Selection strategy in stock market, which selects multiple factors according to the selected financial factors or technical factors, while another is Timing, predicting the trends. In the Stock and Futures markets, some financial data, index data and momentum data are used to predict the price of a stock. Some articles also predict stock indexes such as Shanghai and Shenzhen 300 Index. As can be seen from figure 3, there are 16 papers on quantitative Stock selection about 53%

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percent, 13 papers on quantitative Timing, 44% to the all papers. [2] pointed out that stock market trend prediction is very important. He selected 50 papers, introduced the machine learning method used in the article, and analyzed the methods used, model evaluation indexes and other aspects. Finally, he pointed out that the selection of characteristics in prediction is very important, and the accuracy and effectiveness need to be further improved.

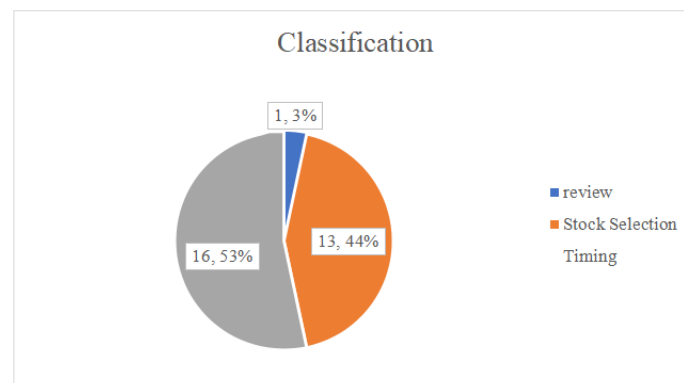


Figure 3: Classification to the papers.

Therefore, it can be concluded that the main direction of quantitative trading is quantitative stock selection and quantitative timing, and there are also some parts such as matching trading and arbitrage trading. Zhang Xun designed a statistical arbitrage strategy for commodity futures based on fundamental analysis, and applied it to copper futures arbitrage with good results.

## III. CURRENT REGULATORY CONSIDERATIONS REGARDING THE USE OF AI AND MACHINE LEARNING

Because AI and machine learning applications are relatively new, there are no known dedicated international standards in this area. Yet in light of some of the potential risks identified above, a few efforts by international standards-setters and similar international fora of regulators deserve note. For example, several international standards-setters have considered risks associated with algorithmic trading, as it has become a pervasive feature of markets that may, among other things, amplify systemic risk. Examples include the following:

- The International Organization of Securities Commissions (IOSCO) reported on the impact of new technologies including algorithmic trading on market surveillance, and made recommendations to consider, including for data collection and cross-border cooperation.
- The Senior Supervisors' Group (SSG), a forum for senior representatives of supervisory authorities from around the world, issued principles for supervisors to consider when assessing practices and key controls over algorithmic trading activities at banks.

Some national regulators note that, from a supervisory perspective, firms developing algorithmic models based on AI and machine learning should have a robust development process in place. They need to ensure that possible risks are considered at every stage of the development process. This is particularly important in order to avoid market abuse and prevent the strategy from contributing to, or causing, disorderly market behaviour. This requirement is part of MiFID II, which will come into force in the first quarter of 2018 in Europe. There are similar requirements for algorithms imposed on certain regulated entities by a US securities self-regulatory organisation.

Similarly, the Basel Committee on Banking Supervision (BCBS) notes that a sound development process should be consistent with the firm's internal policies and procedures and deliver a product that not only meets the goals of the users, but is also consistent with the risk appetite and behavioural expectations of the firm. In order to support new model choices, firms should be able to demonstrate developmental evidence of theoretical construction; behavioural characteristics and key assumptions; types and use of input data; numerical analysis routines and specified mathematical calculations; and code writing language and protocols (to replicate the model). Finally, it notes that firms should establish checks and balances at each stage of the development process. Assessing AI and machine learning

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applications for risks, including adherence to any relevant protocols regarding data privacy, conduct risks, and cybersecurity, is important at this stage. It is important that progress in AI and machine learning applications is accompanied with further progress in the interpretation of algorithms' outputs and decisions. Increased complexities of models may strain the abilities of developers and users to fully explain, and/or, in some instances, understand how they work.

## **IV. CONCLUSION**

There are few papers on quantitative transactions before 2016, and the number of papers grows rapidly in 2018 and 2019, presumably benefiting the development of big data and artificial intelligence technology. Machine learning methods commonly used in financial markets include ANN, SVM, SVR, DT (RF), LR, K-means, etc. However, ANN and SVM are applied more frequently in quantitative trading and have relatively better results. At present, the main problem of quantitative trading is that the accuracy of some models has reached a bottleneck, the winning rate is relatively low, and it is also affected by some other factors, including government policies and investment sentiment. This paper provided the scope towards the usage of AI and machine learning in portfolio management and also provided the information about the possible effects on consumers and investors.

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