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Implications of Ai and Machine Learning Applications Towards Financial Markets

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ABSTRACT

With the development of economy, people are paying more attention to the financial investment. The prediction of the Stock/Future prices could have significant influence on the financial market. But it is hard to predict the prices for they are time series, dynamic and non-linear. To have valid data, machine learning methods are adopted, because they are good at dealing with those problems and have good performance on the financial market. The stock market is one of the most important and attractive markets in the financial industry. Though the stock market fluctuates randomnly from day to day,experienced traders know that much of the stock market fluctuations are not random.Ithas been demonstrated that onecan accurately predict daily stock market activity a lot of the time. This paper is mainly focused on the implications of AI and machine learning applications towards financial markets.
Index Terms: Machine Learning, Artificial Intelligence, Applications, Financial Markets

I. INTRODUCTION

Forecasting financial time series can be one of the main challenges in time series and machine learning scope. In past decades, several methods for forecasting financial markets and presenting decision-making back systems have been proposed. Soft calculation such as expert, phase, and neural systems has been used for financial series and modelling with relative success. Compared to traditional statistical forecasting methods; soft calculation techniques impose a non-linear relationship on input data distribution without having any prior knowledge. Artificial neural networks have recently become popular for forecasting financial markets. Artificial neural networks are data-based and self- compatible methods that are able to recognise time series' nonlinear behavior without any statistical hypothesis. For instance, [3] concluded that artificial neural networks work better statistical methods such as linear regression and Box Jenkins methods. A similar study was done by [4] show that artificial neural networks can be successfully used for modelling and forecasting nonlinear time series.

Some proposed neural networks that are widely used for forecasting financial markets are: the single-layer perceptron, multilayer perceptron. Although multilayer neural networks of more complex, they are used for modelling more than two other methods. In most researches, the MLP has been employed for learning relationship between some technical features and forecasting minimum and maximum of daily share prices. For example [5], MLP algorithm has been used to forecast Bangladesh share prices using a combination of the following: technical features of convergent-divergent mobile mean and relative power index. To categorize companies based on financial problems, the MLP algorithm has also been used for learning some financial amounts and company's balance sheet conformed with basic analysis. [2] suggest different learning algorithms in financial markets for the testing field. Each of those algorithms performs forecasting depending on the financial time series that input valuables receive. Suggestive approaches on amounts and types of variables used for modelling monetary markets are different in different papers [3]. For instance, [7] suggest ways to measure volume level and acceleration rates for forecasting testing learning algorithms to technical analysis of the body of technical features such as mobile mean, mobile illustration mean movement mean of convergence and divergence, volume ratio and relative power index. [8] suggest income price ratio and cash flow through fundamental technical analysis on some economic and key features of a company such as its size.

As the economy develops, it has witnessed a rapid increase of residents' wealth and distributable assets. A problem they are faced with is how to better allocate their assets. The forming of a large-scale and multi-level capital market pattern and the deepening of structural reform on the financial supply side in China bring vigor to the Chinese capital market, which is full of realistic driving forces now. Meanwhile, the real economic capacity of financial services has been correspondingly enhanced. Asset allocation, an important channel for financial services to the real economy, could inject new economic strength into the real economy.

In 2017, Artificial Intelligence (AI) was first written into the government report and the development of AI was raised to the national development strategy. Artificial Intelligence, Block Chain and 5G technology have led to the rapid development of financial technology. As an important means of financial technology, quantitative trading has greatly improved the income of asset allocation and reduced risks. It is gradually becoming an important part of the domestic financial market. Some financial institutions, such as Brokers, Banks, Trusts and Insurance are also paying more and more attention to quantitative trading. In the big data environment, artificial intelligence technology, represented by Machine Learning and Deep-learning, plays an increasingly important role in the financial market and has gradually attracted the interest and extensive attention of the financial industry and academia.

In recent decades, quantitative investment has become a hot spot in the development of capital markets in Europe and the United States. [3] proposed a mean variance model based on the mathematical statistics theory. In his model, the fluctuation of expected return rate of assets is adopted to represent financial market risks and this principle is applied to securities investment portfolio, opening a new way for quantitative trading. The market scale of quantitative investment has once reached 70% of the U.S. investment market. It has become a new method for investors. In recent years, the trading strategy of quantitative investment has performed in a stable way. With the market scale and share expanding, it has become one of the three mainstream methods together with Fundamental analysis and Technical index analysis. The concept of quantitative investment originated in the United States. Investors used computer technology, statistics and mathematical knowledge to build models to realize investment concepts and strategies. They trained and summarized market rules in a large number of historical transaction data to obtain excess market returns. The development of Chinese financial market is not very mature for the irrational pricing mechanism of stock price, the seriousness of the market speculation atmosphere and weak effectiveness of the market in China. Therefore, there is huge potential for finding excess returns and quantitative trading is feasible in Chinese market.

The main types of quantitative investment are trend trading, market neutral strategy and high frequency trading. Among them, market neutral investment measurement is currently the most mainstream and largest strategy in the market, including quantitative statistical arbitrage, quantitative hedging, quantitative Stock Selection and quantitative Timing strategy. Financial data, as a time series, are dynamic, non-stationary, non-linear and unpredictable. Machine learning enjoys great advantages in non-linear computation. It covers probability theory knowledge, statistics knowledge and mathematical algorithm knowledge. Computer is used as a tool to simulate human learning methods, and the existing content is divided into knowledge structures to effectively improve learning efficiency. Machine learning has experienced a tortuous development since the 1950s, the era of big data which makes it attracted much attention. It can be divided into supervised learning, unsupervised learning and semi-supervised learning. The main difference among the three learning methods lies in the difference of data sample labels. Supervised learning requires labels of samples, such as the rise and fall of stocks price, while unsupervised learning requires no label value and Semi-supervised learning some labels. The literature on the application of machine learning technology in financial markets is not very rich. Unlike some papers review the machine learning methods used in stock price predicting, the main methods of machine learning used in all financial market, classify the dozens of papers read according to the types of quantitative investments, briefly introduce and summarize them, and finally point out the shortcomings of current machine learning technology applied in financial market so as to give suggestions for future research directions.

II. MACHINE LEARNING TECHNOLOGY

Machine Learning is multi-disciplinary and cross-disciplinary. After learning a large amount of historical data, the model itself can have good self-learning ability, thus achieving Artificial Intelligence. Machine learning usually has two parts. In the first part, appropriate models and corresponding super variables are selected to learn the pre-segmented training set, and the models are verified and optimized. In the second part, the optimized model is applied to the untested data, and the prediction ability of the model is judged according to the corresponding indexes. The machine learning techniques used in the literature selected in this paper include Support Vector Machine (SVM), Decision Tree (Random Forest), Artificial Neural Network (ANN).

Random Forest (RF) enjoys a wide application prospect as an efficient and flexible machine learning algorithm, and financial markets have been frequently used in recent years. For example, [3], [4] both used RF to carry out multi-factors stock selection. [5] applied the RF to commodity futures to classify the market volatility and improve the profitability of investment strategies in different time periods. RF takes decision tree (DT) as the basic unit and integrates many decision trees to form a random forest. The basic working principle of random forest is to select m features from the data set, with a total of n features, and then build a decision tree according to the m features, and repeat it many times. After each random combination of the features, multiple decision trees are built, the results of each decision tree are stored, and finally the result with the largest number of votes is taken as the predicted result.

Artificial Neural Network (ANN) is currently the hottest foundation for deep learning. ANN is a machine learning technology that simulates the neural network of human brain. It is estimated that there are more than 100 billion neurons in the adult brain. [6] reviewed the development of neural network in recent 70 years. Therefore, ANN is more complex than SVM and RF. It consists of input layer, hidden layer and output layer. These layers are connected with each other. Each link is given weights at the beginning. These weights will be adjusted continuously during training and learning process to minimize errors. Finally, the output layer sums all signals of the previous layer into one output signal. [7] compared the performance of different Neural network methods include RNN, CNN, LSTM used in Stock index Futures. [8] use neural network to predict the trends of Shanghai-Shenzhen index, select the best time to buy or sell. ANN are generally asymptotical to common functions or algorithms, and do not obtain accurate values. At the same time, ANN may also be an expression of a logic structure strategy.

Scholars try to combined SVM, RF, ANN to achieve much better results, and it called ensemble Algorithm in the filed of machine learning. [9] used more than 300 factors to select stocks based on XGBoost, the quarterly return as the standard. [10] used an improved stacking framework to predict the trend of stock index by leveraging tree-based ensemble models and deep learning algorithms. All of ensemble methods listed above have good performance in the financial market.

III. CREDIT SCORING APPLICATIONS

Credit scoring tools that use machine learning are designed to speed up lending decisions, while potentially limiting incremental risk. Lenders have long relied on credit scores to make lending decisions for firms and retail clients. Data on transaction and payment history from financial institutions historically served as the foundation of most credit scoring models. These models use tools such as regression, decision trees, and statistical analysis to generate a credit score using limited amounts of structured data. However, banks and other lenders are increasingly turning to additional, unstructured and semi-structured data sources, including social media activity, mobile phone use and text message activity, to capture a more nuanced view of creditworthiness, and improve the rating accuracy of loans. Applying machine learning algorithms to this constellation of new data has enabled assessment of qualitative factors such as consumption behaviour and willingness to pay. The ability to leverage additional data on such measures allows for greater, faster, and cheaper segmentation of borrower quality and ultimately leads to a quicker credit decision. However, the use of personal data raises other policy issues, including those related to data privacy and data protections.

In addition to facilitating a potentially more precise, segmented assessment of creditworthiness, the use of machine learning algorithms in credit scoring may help enable greater access to credit. In traditional credit scoring models used in some markets, a potential borrower must have a sufficient amount of historical credit information available to be considered 'scorable.' In the absence of this information, a credit score cannot be generated, and a potentially creditworthy borrower is often unable to obtain credit and build a credit history. With the use of alternative data sources and the application of machine learning algorithms to help develop an assessment of ability and willingness to repay, lenders may be able to arrive at credit decisions that previously would have been impossible.[31] While this trend may benefit economies with shallow credit markets, it could lead to non-sustainable increases in credit outstanding in countries with deep credit markets. More generally, it has not yet been proved that machine learning-based credit scoring models outperform traditional ones for assessing creditworthiness.

Over the past several years, a host of FinTech start-up companies targeting customers not traditionally served by banks have emerged. In addition to more commonly known online lenders that lend in the United States, one firm is using an algorithmic approach to data analysis and has expanded to overseas markets, particularly China, where the majority of borrowers do not have credit scores. Another firm, based in London, is working to provide credit scores for individuals with 'thin' credit files, using its algorithms and alternative data sources to review loan applications rejected by lenders for potential errors. Additionally, some companies are drawing on the vast amounts of data housed at traditional banks to integrate mobile banking apps with bank data and AI to assist with financial management and make financial projections, which may be first steps to developing a credit history.

There are a number of advantages and disadvantages to using AI in credit scoring models. AI allows massive amounts of data to be analysed very quickly. As a result, it could yield credit scoring policies that can handle a broader range of credit inputs, lowering the cost of assessing credit risks for certain individuals, and increasing the number of individuals for whom firms can measure credit risk. An example of the application of big data to credit scoring could include the assessment of non-credit bill payments, such as the timely payment of cell phone and other utility bills, in combination with other data. Additionally, people without a credit history or credit score may be able to get a loan or a credit card due to AI, where a lack of credit history has traditionally been a constraining factor as alternative indicators of the likelihood to repay have been lacking in conventional credit scoring models.

However, the use of complex algorithms could result in a lack of transparency to consumers. This 'black box' aspect of machine learning algorithms may in turn raise concerns. When using machine learning to assign credit scores make credit decisions, it is generally more difficult to provide consumers, auditors, and supervisors with an explanation of a credit score and resulting credit decision if challenged. Additionally, some argue that the use of new alternative data sources, such as online behaviour or non-traditional financial information, could introduce bias into the credit decision.[33] Specifically, consumer advocacy groups point out that machine learning tools can yield combinations of borrower characteristics that simply predict race or gender, factors that fair lending laws prohibit considering in many jurisdictions. These algorithms might rate a borrower from an ethnic minority at higher risk of default because similar borrowers have traditionally been given less favourable loan conditions.

The availability of historical data across a range of borrowers and loan products is key to the performance of these tools. Likewise, the availability, quality, and reliability of data on borrower-product performance across a wide range of financial circumstances is also key to the performance of these risk models. Also, the lack of data on new AI and machine learning models, and the lack of information about the performance of these models in a variety of financial cycles, has been noted by some authorities.

IV. OTHER IMPLICATIONS OF AI AND MACHINE LEARNING APPLICATIONS

AI and machine learning applications in insurance markets could reduce the degree of moral hazard and adverse selection – but could also undermine the risk pooling function of insurance. Moral hazard and adverse selection are inherent problems in insurance. Nonetheless, if AI and machine learning are used to continuously adjust insurance fees in accordance with changing behaviour of the policyholders, this may reduce moral hazard. If AI and machine learning are utilised to offer customised insurance policies reflecting detailed characteristics of each person, it may also decrease adverse selection. On the other hand, these uses may pose various new challenges. For example, the more accurate pricing of risk may lead to higher premiums for riskier consumers (such as in health insurance for individuals with a genetic predisposition to certain diseases) and could even price some individuals out of the market. Even if innovative insurance pricing models are based on large data sets and numerous variables, algorithms can entail biases that can lead to non-desirable discrimination and even reinforce human prejudices. This warrants a societal discussion on the desired extent of risk sharing, how the algorithms are conceived, and which information is admissible.

Meanwhile, AI and machine learning can continue to be a useful tool both for financial institutions (RegTech) and supervisors (SupTech). Yet, if a similar type of AI and machine learning is used without appropriately 'training' it or introducing feedback, reliance on such systems may introduce new risks. For example, if AI and machine learning models are used in stress testing without sufficiently long and diverse time series or sufficient feedback from actual stress events, there is a risk that users may not spot institution-specific and systemic risks in time. These risks may be pronounced especially if AI and machine learning are used without a full understanding of the underlying methods and limitations.

Furthermore, as the current regulatory framework is not designed with the use of such tools in mind, some regulatory practices may need to be revised for the benefits of AI and machine learning techniques to be fully harnessed. For example, in MiFID II, where an obligation is placed on the firm to submit a report when a reportable event occurs, regulatory compliance is expected of the firm at all times. If AI and machine learning tools are used to deem if a particular activity is reportable or not, mistakes would still result in regulatory action, even if the tools can identify what information the regulators truly needs in order to reduce the risk of market disruption. In this regard, combining AI and machine learning with human judgment and other available analytical tools and methods may be more effective, particularly to facilitate causal analysis.[99] More generally, the greater adoption of AI, machine learning, and other technological advances in finance may benefit also from more of a 'systems' perspective in financial regulation to contribute to financial stability in an increasingly complex system.[100]

If optimisation solutions are adopted primarily by the private sector but not the public sector, there may be a risk that some individuals or firms may use them more successfully to 'game' regulatory rules or conduct regulatory arbitrage.

V. CONCLUSION

The use of AI and machine learning in financial services may bring key benefits for financial stability in the form of efficiencies in the provision of financial services and regulatory and systemic risk surveillance. The more efficient processing of information on credit risks and lower-cost customer interaction may contribute to a more efficient financial system. The internal (back-office) applications of AI and machine learning could improve risk management, fraud detection, and compliance with regulatory requirements, potentially at lower cost. In portfolio management, the more efficient processing of information from AI and machine learning applications could help to boost the efficiency and resilience of financial markets – reducing price misalignments earlier and (under benign assumptions) reducing crowded trades. This paper is mainly focused on the implications of AI and machine learning applications towards financial markets.

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