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Application of artificial intelligence and machine learning in financial forecasting and trading

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Abstract. Artificial Intelligence (AI) and Machine Learning (ML) have been employed in the field of financial forecasting for many years. Existing scientific research has substantiated the effectiveness of AI/ML in the financial market. Currently, approximately 35% of the total capitalization of the US stock market is influenced by quantitative analysis, primarily consisting of AI/ML methodologies and their variants. This paper reviews classical advanced methodologies of AI/ML in financial forecasting and automated trading. Specifically, it focuses on discussing representative methods from three categories: statistical approach (including ARIMA-GARCH), machine learning approach (including SVM and LSTM), and the logistic approach (including the Fuzzy System). In detail, this paper delves into the fundamental aspects of each method and illustrates their effectiveness through existing results from relevant papers. The structure of this paper begins with the introduction of each method, followed by their applications, and a discussion of their pros and cons. Furthermore, this paper offers an outlook on the hotspots and prospects for the development of this research topic.

Keywords: Artificial Intelligence, Machine Learning, Financial Forecasting.

1. Introduction

Given the complex and chaotic nature of the financial market, predicting prices or trends is often considered challenging. Alongside this market's inherent complexity, psychological and political factors influence financial market decisions, introducing further uncertainties into the prediction task. With such an abundance of information and factors circulating in the market, human beings are unable to capture all the correlations within the financial market. Therefore, AI and ML models can assist both individual and institutional traders in making better and faster decisions. The primary goal of this paper is to introduce advanced models in financial forecasting.

The application of AI/ML models in financial trading takes the form of automated trading. Traders build AI/ML models based on their needs, with the ultimate goal of creating an automated trading system. In recent years, high-frequency trading has become ubiquitous. In reference [1], the author notes that traders often earn profits by holding positions briefly and accumulating small gains through numerous transactions, highlighting the need for a high-frequency automated trading mechanism. Nowadays, the effectiveness of high-frequency trading has been well-established. This perspective is reinforced in reference [2], which states that combination of HFT and ML in financial forecasting has improved the efficiency of modern automated trading system tremendously. The same paper suggests an automated HFT grid trading system. The performance of suggested system, including reduced drawdown, validates the effectiveness of this approach. Along with advanced technologies, integration of AI/ML models in trading strategies has become ubiquitous in financial market. The motivation behind this paper arises from the limited availability of relevant literature in the field. Despite the fact that AI/ML algorithms in financial forecasting constitute a sophisticated area of research, the process of gathering relevant literature yielded scant results. Consequently, this paper is dedicated to assisting new scholars in swiftly gaining insights into classical and vital AI/ML algorithms within the realm of financial forecasting.

This paper aims to provide an overview of some advanced methodologies in algorithmic trading. Specifically, it discusses four major models: Hybrid ARIMA-GARCH, SVM, LSTM, and the Fuzzy System. Alongside the introduction of these models, the paper mentions some applications and potential areas for further research based on these models. With this general overview, readers can gain a comprehensive understanding of the four methodologies mentioned. Hopefully, this paper will provide readers with introductory knowledge in the area of algorithmic trading with AI/ML models.

2. The application of machine learning algorithm in financial trading

Machine learning algorithm is now used in financial trading comprehensively, especially in high-frequency trading. In the following of this section, we will be discussing four models: Hybrid ARIMA-GARCH Model, SVM, LSTM, and Fuzzy System.

2.1. Introduction and Application of Hybrid ARIMA-GARCH Model

The Autoregressive Integrated Moving Average (ARIMA) is a statistical tool used for predicting future trends based on historical data, often applied in market price predictions. ARIMA's benefits include making non-stationary data stationary by eliminating seasonality and trends, simplifying data analysis. While ARIMA works well for one-step ahead forecasting, its accuracy declines for multi-step ahead predictions, and its predicted trend doesn't hold over extended time periods, limiting its predictive validity.

In reference to [3], the author proposed an integrated ARIMA-GARCH method that dramatically enhances performance in multi-step ahead predictions. The proposed hybrid model follows the structure that displays in Figure 1

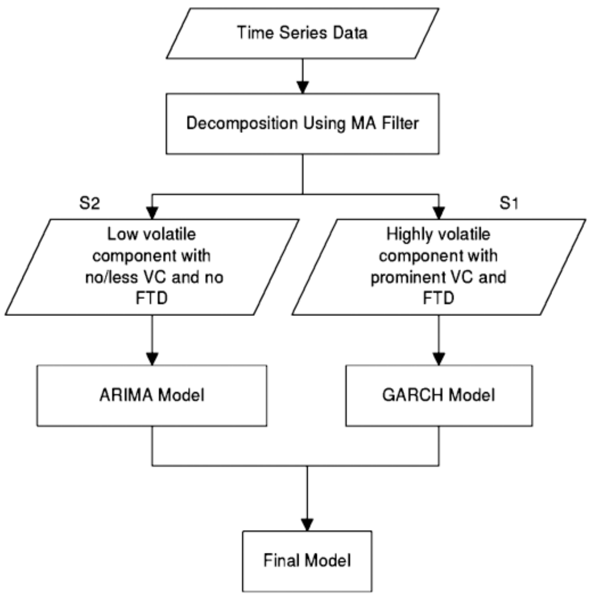

Figure 1. Structure of the proposed ARIMA-GARCH model [3].

In their experiment involving Tata Steel's data, the integrated ARIMA-GARCH method exhibited significant improvements in trend prediction. When compared to the traditional ARIMA method, the

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accuracy increased dramatically. The results also indicated that the validity of this method in multi-step ahead predictions is reliable for high-volatile time-series.

In reference to [4], the authors utilized the hybrid ARIMA-GARCH model to forecast the trend of S&P 500 stock prices. They present a estimation process to develop a best-fitted ARIMA-GARCH model, the general steps can be summarized by Figure 2.

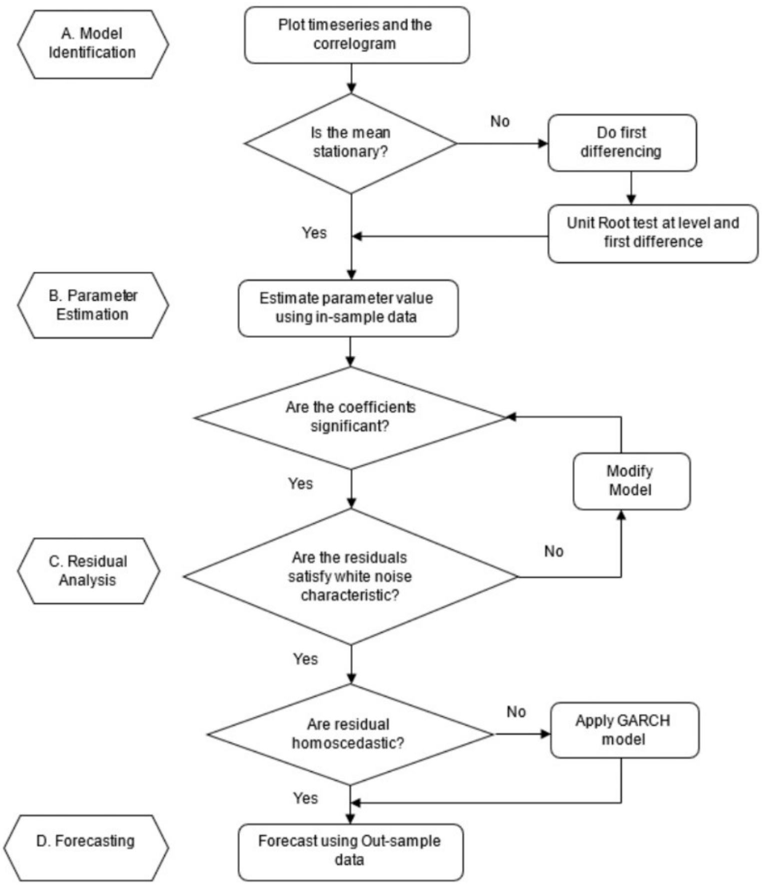

Figure 2. Research Methodology of reference [4].

Through their methodology, they proposed ARIMA (2, 1, 2)-GARCH (1, 1) as the best model for their forecasting of S&P 500 stock prices based on the observations on January 2001 – December 2017. Their work provides a systematic instruction on how to properly implement Hybrid ARIMA-GARCH model and how to find the best model based on particular dataset.

2.2. Financial Forecasting based on Support Vector Machine (SVM)

Introduced by Vapnik, SVM is a machine learning model rooted in kernels, serving classification and regression tasks. SVM's exceptional ability to generalize remarkably well, along with its optimal solutions and strong discriminatory prowess, has garnered significant interest from the fields of data mining, pattern recognition, and machine learning. SVM stands as a potent instrument for tackling real-world binary classification issues, demonstrating superiority over alternative supervised learning techniques. Given its sound theoretical underpinnings and robust generalization prowess, SVMs have emerged as one of the most widely adopted classification methods [5]. SVM can be visualized by Figure 3

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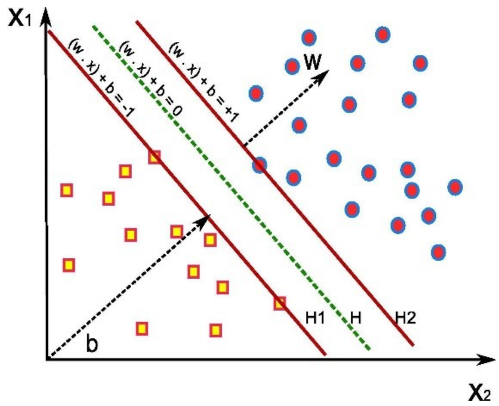

Figure 3. Support Vector Machine Example.

In the context of financial trading, SVM is commonly applied to predict whether the future price of a stock will be higher or lower than its value on a given day [6].

A significant practical application of SVM is in stock selection. In reference to [7], the authors use SVM to identify stocks that perform better than the average of the market. The return of selected portofolio is 208% for five-years period of time, while the benchmark return of the stock market was approximately 71%. Additionally, in reference [8], the authors compared SVM with multilayer back-propagation (BP) neural networks and regularized radial basis function (RBF) neural networks. According to the results, compared with BP neural betworks, SVM exhibited better performance and able to generalize better. Moreover, SVM with adaptive parameters demonstrated superior ability of generalization, and less support vectors are used compared with traditional SVM.

2.3. Implementation of LSTM in financial forecasting

RNNs struggle to grasp relevant information from input data when faced with significant input gaps. The incorporation of gate functions into cell structures brought about the Long Short-Term Memory (LSTM), effectively addressing issues tied to long-term dependencies. The fundamental advantages of LSTM are its ability to preserve information of past data. Additionally, LSTM can effectively resolve the problem of vanishing gradient, which RNN suffered the most. In the application perspective, LSTM are used to predict the prices of a stock. Figure 4 demonstrate the general structure of LSTM

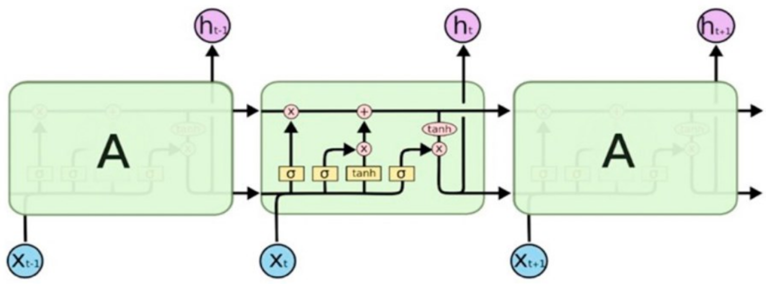

Figure 4. Structure of LSTM [9].

In [9], author aims to build a LSTM model to predict trend of stock. It examines the precision of model in details and the epochs needed to improve the prediction. The paper proposed that with more epochs, the accuracy increases dramatically.

In reference [10], the authors adopt encoder-decoder attention mechanism, adding such mechanism from two aspects of feature and time. Such method resolves two problems, one is different weight of multiple input features and the second is the time-correlated property of before and after data. Their results shows that the solution, introducing attention-mechanism, can obtain a lower forecasting error.

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2.4. Fussy Systems in Financial Forecasting

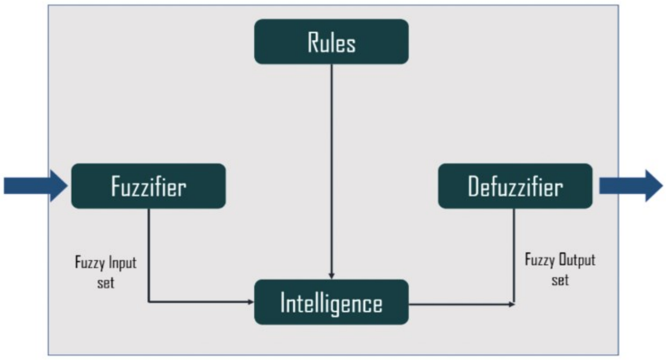

Figure 5. Idea of Fuzzy System [11].

A fuzzy system stands out as a particular arrangement recognized by its assembly of interconnected elements structured in a clear manner (Figure 5). What sets fuzzy techniques apart is their ability to handle information, a task that classical theory or binary logic cannot achieve. Fuzzy systems excel in representing intricate and frequently ambiguous real-world issues. The inputs for these systems consist of datasets characterized by membership degrees ranging from 0 to 1, which indicate the extent of affiliation with a particular fuzzy set. Fuzzy logic mirrors the way human decision-making occurs and serves as a method of reasoning. The general

A subtractive clustering-based adaptive neuro fuzzy approach was proposed for predicting the prices of Apple stock data [12]. Four technical indicators were utilized as inputs: the 1-week simple moving average, the 2-week simple moving average, 14-day Disparity, and Larry Williams R%. The results demonstrated that this approach's performance surpassed that of other models such as ANFIS training and subtractive clustering methods.

3. Advantages and Problems with current Algorithmic Models

Several financial forecasting models have been introduced, with some being suitable for smaller datasets and others performing well under specific settings. In the following sections, we will provide a detailed introduction to the advantages and drawbacks of each of these models.

3.1. ARIMA-GARCH Model*s*

Utilizing ARIMA for time series forecasting is particularly valuable when dealing with uncertainty, given its ability to function without requiring an awareness of underlying models or relationships, unlike certain alternative approaches. ARIMA primarily relies on historical series values and preceding error terms to make predictions. In short-term forecasting, ARIMA models are more efficient and robust compared to other intricate structural models.

However, the problem with traditional time-series models such as ARIMA is that they assume the data is generated linearly and sequentially. Unfortunately, real-world problems often involve non-linear patterns. Employing ARIMA-based models in such scenarios can introduce irreducible biases in long-term predictions [13].

3.2. SVM

SVM was originally proposed to improve consistency and predictability over noisy data. When noise in a given dataset is controllable, SVM can significantly enhance performance compared to traditional methods. Additionally, compared with other traditional ML models, SVM demonstrates higher generalization ability. Along with these mentioned benefits, SVM operates with a finite set of control parameters, which helps mitigate overfitting issues and leads to quicker convergence.

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However, it's important to note that SVM's effectiveness heavily depends on the quality of the data. Given the complexity of financial markets, SVM might struggle to capture intrinsic relationships among data due to excessive noise in the dataset. Furthermore, aside from dealing with noisy datasets, SVM can encounter challenges with large datasets, as training time is negatively correlated with the size of the data.

3.3. LSTM

In financial price forecasting, an LSTM's strength lies in its ability to disregard information deemed irrelevant by the system designer, which is crucial for accurate predictions. This process is delicate since it could significantly impact a model's ability to accurately predict prices due to the potential loss of information during the discarding process and the dynamic nature of financial markets.

In contrast to the unique ability that LSTM possesses, it is prone to overfitting when the dataset is small. LSTM requires a large dataset to perform well effectively. Additionally, LSTM is computationally expensive due to the numerous hyperparameters the model incorporates.

3.4. Fuzzy Systems

Fuzzy systems offer an advantage in forecasting trends of financial asset prices due to their inherent simplicity and capacity to incorporate diverse information sources. However, a drawback of these systems is their limited adaptability to evolving financial conditions and their rigidity in adjusting predetermined rules that might require modification (table 1) [11].

Table 1. Summary of Pros and Cons of Above Methods.

Name	Pros	Cons
ARIMA-GARCH	Good with uncertainties, Robust and Efficient in Short-Term Forecastings	Bad at Non-linear problem
SVM	High generality, Good for dataset with controllable noise	Need high quality data, poor with large dataset
LSTM	Able to discard useless information	Computational expensive, require large dataset
Fuzzy System	Able to incorporate diverse information	Limited Adaptability

4. Conclusion

This paper presents a review of some advanced methodologies in the field of financial forecasting, stressing on a couple methods: ARIMA-GARCH, SVM, LSTM, and the Fuzzy System. Furthermore, this paper offers a detailed analysis of the advantages and disadvantages associated with each of these models. Given the inherent complexity and dynamism of financial markets, price forecasting remains a formidable challenge. However, the four models discussed in this paper offer a powerful toolkit for generating reliable predictions of financial activity.

The ARIMA-GARCH Hybrid model excels in addressing linear problems and doesn't rely heavily on underlying correlations. However, its effectiveness in solving real-world, non-linear problems is questionable. On the other hand, SVM demonstrates its prowess in classification problems, especially with high-quality data, showcasing strong generality. In contrast, the Fuzzy System can effectively incorporate diverse information, making it particularly suitable for complex systems. Nevertheless, its adaptability remains a significant challenge. Finally, LSTM stands out as one of the most prominent models in financial forecasting, thanks to its exceptional memory capacity and flexibility in handling the information it retains. However, it comes at the cost of high computational expenses and a substantial amount of data.

In the future, the development of AI and ML models in financial trading should prioritize optimizing the cost-effectiveness of these methods. Moreover, the emergence of quantum computing in the foreseeable future could lead to revolutionary advancements in the field. Consequently, the integration of AI/ML in financial trading with quantum computers is poised to become a prominent research area.

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