Studying Stock Prediction in the Context of Machine Learning Exemplified by Analyzing SVM and LSTM Models

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Abstract. The impact of stocks on economic development is significant, with most companies employing quantitative finance methods to analyze and trade stocks. In the present day, there is a growing plethora of stock prediction methods, requiring individuals to carefully select the appropriate means of prediction. This study aims to present the highly regarded machine learning algorithms of recent years. Machine learning enables the extraction of trading strategies by learning patterns from historical stock data. Deep learning, a subset of machine learning, eliminates the need for researchers to manually extract features, instead utilizing neural network models that have proven effective for stock analysis. This paper also provides an extensive analysis of Support Vector Machine (SVM) and Long Short-Term Memory (LSTM), elucidating their algorithmic principles and assessing their strengths and weaknesses based on the findings of other researchers. It is observed that SVM is effective for predicting small quantities, but lacks suitability for non-stationary data prediction due to the non-informative nature of financial time series data, which significantly diminishes the accuracy of SVM predictions. In contrast, LSTM emerges as the most comprehensive single algorithm, exhibiting high accuracy and efficiency across all aspects. The paper also explores advanced hybrid models, which demonstrate that combining the advantages of multiple models can lead to higher accuracy and efficiency. The future of stock prediction algorithms holds promise for development, with the potential to construct an intelligent system that automatically selects data for analysis.

Keywords: Machine Learning, Stock prediction, SVM, LSTM.

1. Introduction

Since its inception, the stock market has been recognized for its attributes of high risk and high return. Simultaneously, it serves as a crucial determinant of the global economy's vitality. The fluctuations in stock prices significantly impact business operations, market dynamics, and even worldwide development. For investors and creditors to attain substantial returns in the stock market, they must possess a formidable capacity to forecast stock movements.

In the past, a plethora of traditional methods was employed to predict stock behavior, including moving average analysis, trend line analysis, and fundamental analysis. However, these approaches were laborious in computation and failed to ensure forecast accuracy. Stocks are influenced by multiple factors and their conditions change incessantly, rendering accurate and swift predictions a daunting task. The advent of econometric methods in the 1980s facilitated some advancements in stock forecasting. Researchers utilized Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), and Autoregressive Conditional Heteroskedasticity (GRACH) to predict stock prices. However, these methods fell short of achieving the desired forecast outcomes. In contrast, the latest Machine Learning techniques offer an improved prediction methodology. Machine Learning leverages the computational power of computers to process and analyze stock data in real time. Furthermore, Deep Learning within the realm of Machine Learning enhances prediction accuracy through learning and computation.

In recent years, interdisciplinary research on stock prediction has delved into greater depths, resulting in the proposal of numerous novel algorithmic models. Nevertheless, these models possess certain imperfections and lack systematicity. This paper focuses on recent literature concerning the utilization of Machine Learning methods in stock prediction. From the perspectives of Machine Learning and Deep Learning, the SVM and LSTM models are introduced, and various hybrid prediction models are analyzed. The objective is to provide readers with a comprehensive understanding of the current state of research in this field and to present potential avenues for future investigation.

2. The Advantages of Machine Learning in Predicting Stock Prices

The concept of artificial intelligence pertains to the utilization of advanced computer technology to simulate and comprehend the cognitive faculties and actions of human beings. This technology enables the automation of tasks that previously required human intervention. Machine Learning constitutes a crucial element of artificial intelligence and assumes a significant role within this domain. By employing data and past experiences, Machine Learning can enhance the performance of computer programs. In instances where certain data remains hidden, it can assimilate knowledge from a selected sampling of stock prices to derive a decision function for determining a purchasing strategy. Next, this paper will analyze and discuss the topic from the perspective of two large models.

2.1. Machine Learning Models

Machine Learning, a subset of Artificial Intelligence, has been extensively explored for its potential in predicting stock prices. Fig.1 summarizes the machine learning models commonly used to predict stock prices. Machine Learning involves tasks categorized as supervised or unsupervised learning. In supervised learning, training data with labeled instances are used to forecast stock market prices and patterns based on historical data. This approach provides valuable insights by analyzing past price trends. The study of Machine Learning in stock price prediction has gained significant attention due to its ability to assist investors and traders in making informed decisions. This intersection of Machine Learning and stock market analysis presents opportunities for further research as prediction models are refined for accuracy and reliability. The use of supervised learning techniques in this context enables the development of robust models capable of capturing the intricate dynamics and volatility of the stock market. Integrating historical price analysis with Machine Learning algorithms enhances our understanding of market trends and facilitates more accurate predictions. This integration empowers investors to navigate the complex stock trading landscape with confidence and success.

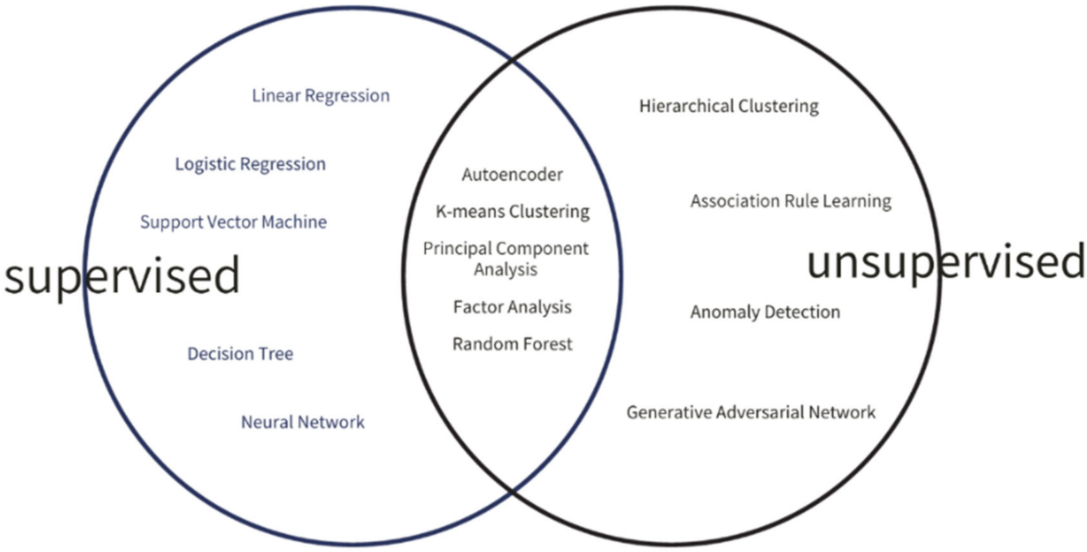

Figure 1. Machine Learning models for stock prediction

2.2. Deep Learning Models

Deep Learning, a novel domain of Machine Learning, emerged in 2006 and is referred to as deep structured learning or Deep Learning. Unlike traditional Machine Learning approaches, Deep Learning eliminates the need for manual feature selection by enabling the automatic generation of features. This innovative approach involves acquiring knowledge at various levels of description and interpretation, providing a more comprehensive understanding of data such as images, sound, and text. Fig.2 classifies the deep learning algorithm models used to predict stocks. While classification techniques like the k-nearest neighbor and Naïve Bayes algorithms are commonly employed to forecast stock price trends, the application of Deep Neural Networks in prediction tasks offers significant advantages. Deep neural networks, characterized as non-linear algorithms, excel at mapping complex, non-linear functions. Diverse types of Deep Learning models are employed based on the specific application, including Recurrent Neural Networks (RNN), Long Short -Term Memory (LSTM), and Convolutional Neural Network (CNN).

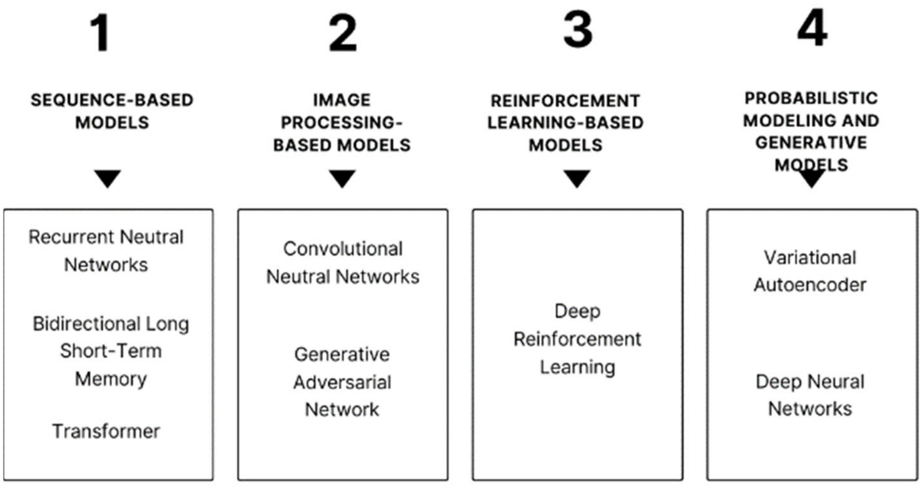

Figure 2. Deep Learning models for prediction

3. The Application of Machine Learning in Predicting Stock Prices

3.1. The Challenge of Predicting Stock Movements

There exist numerous intricate elements that impact stocks. The performance of a company, the trends within the industry, the economic climate, political aspects, market demand, investor sentiment, and various other factors all affect stock investments. The fluctuations in stock prices are largely uncertain. Consequently, the research on methods for predicting stock market trends and the minimization of errors in stock forecasting have become areas of great interest for scholars globally. Currently, most methods used for stock speculation are rooted in quantitative finance, wherein both companies and individuals analyze the financial market using mathematical models and algorithms to develop trading strategies. These strategies aim to leverage small price differences to maximize returns by capitalizing on the rapid processing capabilities of computers. Due to the instantaneous nature of stock trading, investment firms may execute thousands of trades within a matter of minutes, with a significant portion of these trades relying on automated forecasting and trading. If an algorithmic model fails to accurately predict future trends within a short time frame, it will forfeit its most critical competitive advantage. The crucial aspect of upholding a competitive advantage in the rapidly evolving field of stock trading is the effective application of these algorithms in forecasting future trends within a brief timeframe. Due to the abundance of machine learning algorithms available for predictive purposes, enumerating them individually becomes a challenging task. For this study, a more proficient SVM is chosen as a representative model for analysis.

3.2. SVM

3.2.1. Principle introduction

SVM is a classification algorithm that offers numerous distinct advantages in addressing challenges such as limited sample sizes, nonlinear patterns, and high-dimensional recognition. As shown in Fig.3, in a two-dimensional scenario, points such as R, S, G, and other points in proximity to the intermediate G-line are considered support vectors. These support vectors play a crucial role in determining the parameters of the classifier, namely the G-line. SVM functions as a binary classification model to identify a hyperplane to separate the sample. The underlying principle for segmentation is to maximize the boundary, ultimately transforming it into a convex quadratic programming problem that can be solved.

Moreover, SVM can be expanded to various Machine Learning problems. In nonlinear classification, it can be employed in conjunction with the Lagrange multiplier method, KKT condition, and kernel function to produce a nonlinear classifier, thereby facilitating the classification of nonlinear data. Hence, it is highly suitable for nonlinear stock forecasting as it can effectively undertake both classification and regression tasks, enabling the prediction of stock fluctuations.

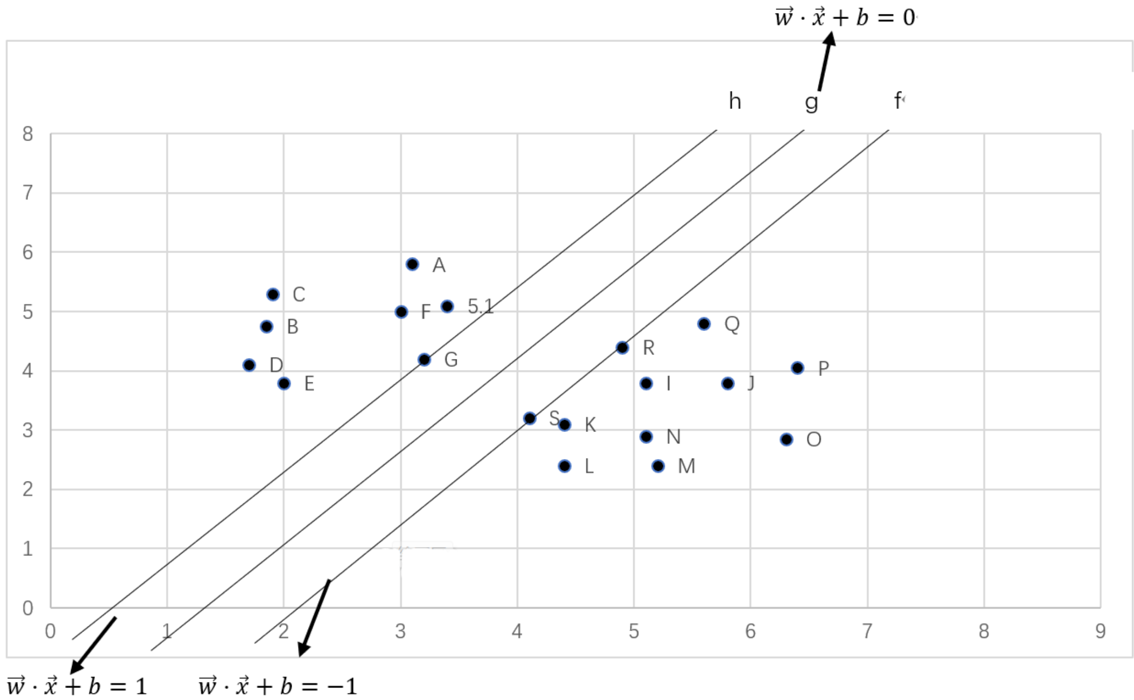

Figure 3. SVM algorithm schematic

3.2.2. Specific application

Takahide etal.[1] employed SVM as a data mining technique to forecast the fluctuations in the Nikkei index, which is recognized as the most renowned stock index in Japan. The study reveals that by utilizing historical data on US stock prices and past data on the Nikkei index, one can enhance the precision of daily stock predictions consistently.

The SVM model is employed as the foundation, whereby the parameters are altered for investigating the investment approach of retail investors, and subsequently, a technique for forecasting changes in stock prices is proposed [2]. Based on the Support Vector Machine (SVM) approach, the grid search algorithm, particle swarm optimization algorithm, and genetic algorithm are employed to enhance and rectify the model. It has been ascertained that the predictive model based on support vectors can accurately depict the dynamic behavior of stocks [3]. Previous research findings explore hybrid models like artificial neural networks (ANN-map) and GARCH-map, coupled with anti-propagation algorithms and multi-layer feedforward networks, leading to commendable outcomes [4]. Zhang Heli introduced the Grey Wolf Optimizer as a means to explore optimal parameters and presented the GMO-SVM model, which was subsequently integrated into the stock market forecasting framework. This integration effectively mitigated the risk associated with stock purchases [5]. Regarding SVR, He Yiyue employed empirical mode decomposition (EMD) in conjunction with SVR to construct a model for stock data prediction. The resulting EMD-SVRF method, based on occupation-insensitive SVR under EMD decomposition, offers a novel approach to addressing the fundamental issue of stock forecasting [6]. Concerning deep neural networks, Zhang Xiaoxu trained a 24-dimensional feature deep neural network to achieve binary prediction of daily stock price fluctuations [7].

Nonetheless, SVM possesses three inherent drawbacks in the context of stock forecasting. Firstly, SVM is ill-suited for predicting non-stationary data, which is the case for stock price data. Secondly, financial time series data encompasses numerous non-informative attributes, which significantly diminishes the accuracy of SVM prediction. Thirdly, SVM outcomes based on corporate financial statements may not be effectively utilized due to their lack of timeliness. Hence, these limitations should be duly acknowledged when employing SVM for stock price prediction.

3.3. LSTM

3.3.1. Theory

In the extensive model of Deep Learning, the LSTM, which demonstrates exceptional performance in all aspects, is examined as a case study. Originally introduced by Sepp Hochreiter and Jurgen Schmid Huber in 1997, LSTM was developed to address the limitations of insufficient backflow and attenuation in backpropagation. By employing a gradient-based approach, LSTM ensures a continuous flow of errors through specialized units, known as error roasts, thereby facilitating the retention of information over extended data intervals.

When confronted with long-term dependencies, traditional RNNs encounter significant challenges. Consequently, researchers have proposed various methods to tackle this issue in the future. Among these methods, the threshold RNN has proven to be the most successful, with LSTM standing out as the most renowned example within this category.

LSTM effectively manages the cell state by selectively removing or incorporating information through a meticulously designed gate structure. These gates act as a mechanism for selectively allowing information to pass through. The gate structure comprises a sigmoid neural network layer and a point-by-point multiplication operation. In LSTM, there are three gates: the Forget gate, the input gate, and the output gate, all of which serve to safeguard and regulate the cell state (Fig.4).

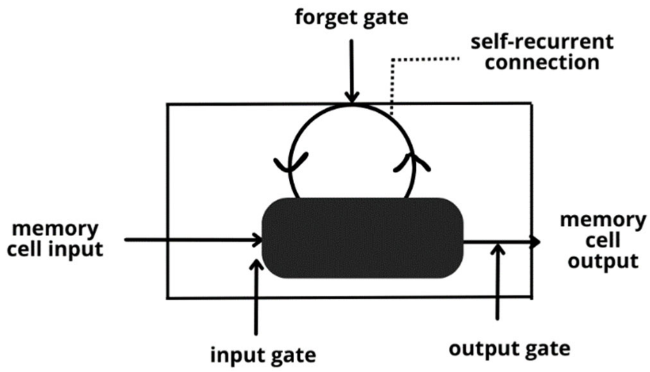

Figure 4. Structure of LSTM

3.3.2. Specific application

Using real-world stock market data, they assess the performance of LSTM, RNN, CNN, and MLP models through the application of linear and nonlinear regression techniques [8]. Their findings indicate that LSTM exhibits superior performance, thus providing empirical evidence of the efficacy of RNN and LSTM models in enhancing investment decision-making. The utilization of stacked LSTM and historical stock price data enables accurate long-term forecasting, particularly when independent data is employed. Upon model training, the accuracy of the LSTM model can be verified using test data, thereby facilitating predictions regarding the future fluctuations of the stock market over the next 30 days [9]. By considering the Shanghai and Shenzhen stock markets from 2019 to 2021 as the contextual backdrop, the authors employ the LSTM neural network to extract features from the original data. Subsequently, the rolling window method is employed to predict future stock market behavior and conduct analysis [10].

3.4. Hybrid Model

3.4.1. Brief introduction

Since each model possesses its unique characteristics and advantages, it inevitably gives rise to numerous shortcomings. For instance, when dealing with extensive datasets, SVM necessitates the verification and adjustment of hyperparameter combinations, resulting in a significant reduction in SVM's timeliness. Furthermore, SVM is susceptible to overfitting when confronted with small samples. Accurate predictions in the context of SVM require intricate feature engineering, rendering the determination of key features a highly complex task. On the other hand, LSTM exhibits a robust fitting ability but also presents a propensity for overfitting. Moreover, LSTM solely relies on historical stock price data, neglecting the influence of external factors such as policy. Consequently, in practical applications, there exists a multitude of hybrid algorithm models that align better with actual circumstances and requirements.

3.4.2. Specific application

By combining the Naive Bayes sentiment analyzer with the LSTM neural network model and focusing on sentiment analysis of news reports to predict stock price trends, it was discovered that the LSTM model outperforms the ARIMA model in stock price prediction. Furthermore, the inclusion of sentiment indicators enhances the accuracy of prediction[11]. Utilizing multi-layer perceptron, long short-term memory, and convolution neural network models to assess emotions on social media, and employing financial and sentiment-related data from Twitter between 2015 and 2019 to make stock predictions for AAPL, CSCO, IBM, and MSFT, the results indicate that the amalgamation of financial and sentiment information enhances the performance of stock market prediction, yielding a next-hour prediction performance of 74.3% [12]. Despite incorporating K nearest neighbors, Linear Regression, Deep Belief Network, and Decision models to forecast stocks, it was discovered that such an approach proved inadequate in addressing the intricate dynamics of the stock market, as it is characterized by perpetual fluctuations [13].To address this limitation, a stock prediction model named PSO-LSTM is proposed, which leverages the particle swarm optimization algorithm to enhance the LSTM model. This approach not only improves the accuracy of prediction but also demonstrates universal applicability [14]. In the present study, their aim is not only to classify literature based on various graph neural network models but also to provide an objective description of the models and ideas proposed in each paper [15].

4. Development Trend

The algorithms and models explicated in this article are founded on precise individual models or precise combined models. Nonetheless, in actual implementation, precise predicaments must be meticulously scrutinized and the most suitable algorithmic model ascertained based on the obtainable data sets and information. If researchers possess historical information about the ascent and descent of all stocks, then stock prognostications would be the most scientifically substantiated and realistic. If only some or even a few stocks are corroborated by their rise and fall data, the stock projection will be unilaterally inclined. However, in the current state of affairs, the latter is pervasive. As a result, the algorithm model itemized in this article is not adequate. Concurrently, political factors, public opinion, and investor sentiment will also exert a substantial influence on the volatility of stocks. This necessitates investors to possess an in-depth comprehension and assessment of the current milieu; investors also need to reference a voluminous number of textual materials. Naturally, these are arduous and protracted undertakings. This approach is presently embraced by numerous businesses and individuals, albeit not without imperfections and oversights that warrant further scrutiny and analysis by researchers.

5. Conclusion

This paper introduces machine learning and deep learning algorithms for stock prediction. SVM and LSTM are discussed extensively, their principles explained, and their strengths and weaknesses analyzed by other researchers' papers. SVM is effective for small quantity prediction, but not suitable for non-stationary data. The non-informative nature of financial time series data greatly reduces SVM's prediction accuracy. Relatively speaking, LSTM is the most comprehensive algorithm, with high accuracy and efficiency. Hybrid models combine the advantages of multiple models, resulting in higher accuracy and efficiency. The paper proposes the future development of an intelligent system for stock prediction, saving time for investors and improving trading returns.

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