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Individual Stock Price Prediction Using Stacking Method

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Abstract: This paper explores the application of stacking in machine learning to predict the price of a single stock. The complexity of financial markets and the high noise in data make stock price prediction a challenging task. To improve prediction accuracy, this paper combines multiple machine learning models, including linear regression, decision trees, and random forests, using stacking to integrate the predictions of these base models. Experimental results indicate that the stacking model performs exceptionally well in predicting the stock price of Apple Inc. (AAPL), significantly outperforming individual models. This paper evaluates the model using mean squared error (MSE) and root mean squared error (RMSE) and demonstrated the model's prediction accuracy and robustness. The findings demonstrate that the stacking model not only reduces prediction errors but also enhances robustness against the volatile nature of stock prices. This study underscores the high potential of stacking in financial time series prediction, providing valuable insights and references for investment decisions. By integrating multiple predictive models, stacking offers a powerful tool for navigating the complexities of financial markets and making informed investment choices.

Keywords: Stock Price Prediction, Machine Learning, Stacking Method.

1. Introduction

The financial market is characterized by its dynamic and unpredictable nature. Among the various challenges faced by investors and analysts, one of the most prominent is the task of predicting stock prices accurately. Stock price prediction holds significant importance for investors, financial analysts, and policymakers alike, as it informs investment decisions, portfolio management strategies, and economic policies.

Traditionally, stock price prediction has relied on fundamental analysis, technical analysis, and market sentiment analysis. However, these approaches often struggle to capture the intricate patterns and non-linear relationships present in financial time series data. There are many factors affecting the company's stock price, such as trader expectations, the company's financial situation, dividend announcement, inflation, management changes, quarterly earnings reports, news reports, etc., which will have an important impact on the stock price. Moreover, the stock market has a large noise, which further increases the difficulty of constructing and predicting the index system of stock price crash risk [1]. In addition, the emergence of high-frequency trading and algorithmic trading has increased the demand for more sophisticated and data-driven prediction models.

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In recent years, machine learning techniques have gained prominence as powerful tools for stock price prediction. These techniques leverage historical market data, such as price movements, trading volumes, and macroeconomic indicators, to train predictive models capable of identifying patterns and making future price forecasts. However, the effectiveness of individual machine learning models can vary depending on the specific characteristics of the data and the underlying market dynamics. Many previous studies have shown that ensemble learning, which combines multiple individual learning algorithms, outperforms a single learning algorithm in both accuracy and robustness [2].

The motivation behind this research stems from the need to enhance the accuracy and reliability of stock price prediction models. By combining several machine learning models, including linear regression, decision trees, and random forests, and integrating their predictions using stacking, it aims to achieve more accurate stock price predictions. This study focuses on the stock of Apple Inc. (AAPL), and through experiments and evaluations, it intends to validate the effectiveness and superiority of the stacking model. Such a framework has the potential to provide valuable insights to investors, enabling them to make informed decisions in an increasingly complex and volatile financial landscape.

2. Data Preparation

2.1. Data Source

The study uses historical stock price data for Apple Inc. (AAPL) from 2020 to 2023, sourced from Yahoo Finance. The data includes daily open, close, high, low prices, and trading volume.

2.2. Data Preprocessing

To ensure that the data used for analysis is reliable and comprehensive, several preprocessing steps were meticulously carried out:

(1) Missing Value Handling: Any missing data points within the dataset were carefully addressed by imputing them with the average values derived from adjacent dates. This method ensures continuity and accuracy in the dataset, mitigating potential biases that could arise from incomplete information.

(2) Outlier Detection: The Interquartile Range (IQR) method, a robust statistical technique, was employed to systematically identify outliers within the dataset. Outliers, which can skew statistical analyses and modeling results, were subsequently removed to maintain the integrity and representativeness of the data.

(3) Feature Engineering: Beyond basic data preparation, additional features were engineered to enrich the dataset's predictive power. This included the calculation and integration of various technical indicators such as moving averages and relative strength index (RSI). These engineered features not only enhance the granularity of analysis but also provide deeper insights into the underlying patterns and trends in the financial data.

3. Models Selection

Three different types of base models were chosen, as follows.

3.1. Linear Regression

Linear regression is the most basic regression model that fits an optimal line by minimizing the squared error between the predicted value and the actual value. It is suitable for data with linear relationships, but has limited effectiveness when dealing with complex nonlinear relationships [3].

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3.2. Decision Tree

By constructing a tree-like structure, decision tree regression divides the data into different subsets according to the value of the feature, and each leaf node corresponds to a predicted value. The advantage is that the non-linear relationship of the data can be captured and is easy to interpret. However, the disadvantage is that it is easy to overfit, especially when the tree depth is large.

3.3. Random Forest

Random forest is an integrated model composed of multiple decision trees, which can improve the accuracy and robustness of prediction by averaging the prediction results of multiple decision trees. Each tree is trained on a random subset of the original data, and a random portion of the features is selected at each split.

The advantage is that the risk of overfitting a single decision tree is reduced and generally has high predictive performance. These models are based on five supervised learning techniques i.e., Support Vector Machine (SVM), Random Forest, K-Nearest Neighbor (KNN), Naive Bayes, and Softmax. The experimental results show that Random Forest algorithm performs the best for large datasets [4].

4. Stacking Method

4.1. First Layer: Base Model Predictions

In the first layer of the stacking method, several diverse base models are individually trained using the historical data from the training dataset. Each base model learns patterns and relationships within the AAPL stock price data, leveraging different algorithms and approaches Linear Regression, Decision Trees, and Random Forest. After training, these models generate predictions based on the features extracted from the training set. These predictions are then collected and treated as new features.

The Linear Regression model captures linear relationships between historical stock prices and various technical indicators, while Decision Trees and Random Forest models excel in capturing nonlinear relationships and complex interactions within the data, which can be applied to predict stock price movements based on historical patterns [5].

4.2. Second Layer: Meta-Model Training

In the second layer of the stacking approach, the predictions produced by the base models in the first layer serve as input features for a meta-model. This meta-model is trained using the predictions from the first layer as well as the actual AAPL stock prices, which serve as the target variable.

The goal of the meta-model is to effectively combine the predictions from multiple base models to further enhance predictive accuracy [6]. Typically, a simple and interpretable model. Linear Regression is chosen as the meta-model due to its ability to generalize well and handle the input features from the base models effectively [7].

The meta-model integrates the diverse predictions provided by the base models and learns to weigh their contributions appropriately to achieve a more accurate overall prediction of AAPL stock prices, as Figure 1 shown. This process allows the stacking method to capture complementary aspects of the data that individual models may overlook, thereby improving the robustness and reliability of the final prediction.

By sequentially integrating base models and a meta-model, the stacking method leverages the strengths of different algorithms and enhances the predictive power for AAPL stock prices, offering a comprehensive approach to forecasting in financial markets.

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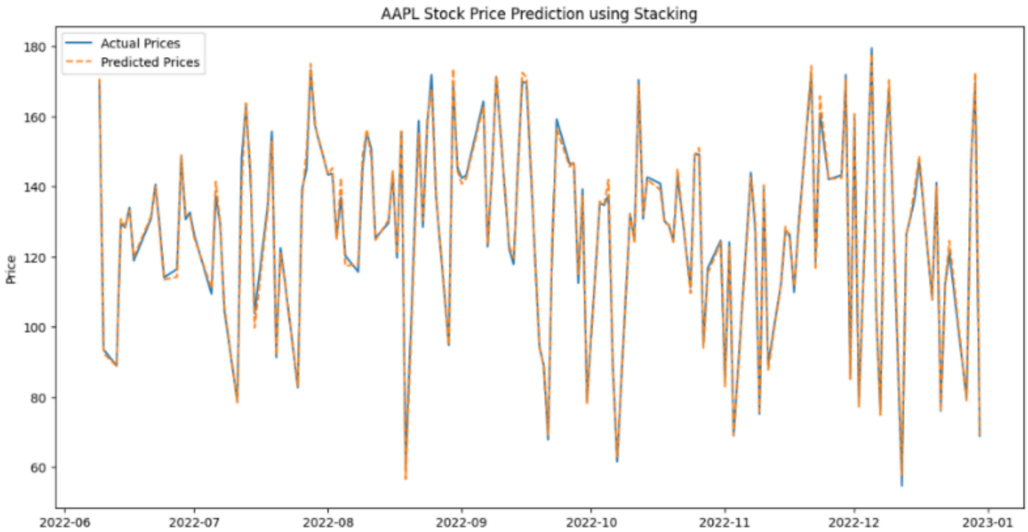

Figure 1: AAPL stock price prediction using stacking (Photo/Picture credit: Original).

5. Experimental Results and Discussion

5.1. Evaluation Metrics

In assessing the effectiveness of the predictive models, the evaluation relied on Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) as fundamental metrics (see Figure 2) [8]. MSE computes the average squared difference between predicted values and actual observed values, thereby quantifying the overall magnitude of prediction errors. RMSE, derived from MSE, represents the square root of MSE and offers a measure of the typical magnitude of these errors in the same units as the predicted values. These metrics are widely utilized in machine learning and statistical modeling to gauge the predictive accuracy and robustness of algorithms, ensuring rigorous analysis and comparison of model performances across various datasets and validation procedures [9]. Their application in this study provided a clear and quantitative assessment of the stacking method's capability to enhance the accuracy and reliability of AAPL stock price predictions compared to individual models [10]. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Determination Coefficient (R^2), and Cross Validation were used to evaluate the models, as Table 1 shown.

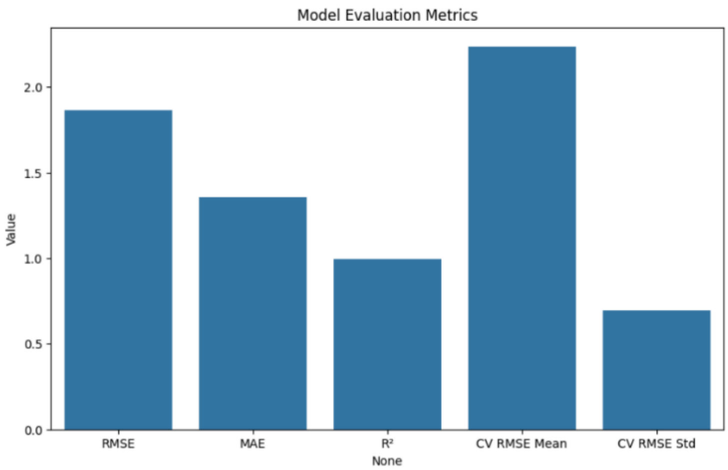

Figure 2: Model evaluation metrics (Photo/Picture credit: Original).

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Table 1: Results of Model evaluation metrics.

RMSE	1.87
MSE	1.39
R^2	1.00
CV RMSE Mean	2.08
CV RMSE Std	0.56

5.2. Experimental Results

As Figure 3 shown, the results of the study demonstrated that implementing the stacking method led to a significant reduction in both Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) when compared to the performance of any individual base model alone. Specifically, the stacking approach resulted in consistently lower MSE and RMSE values across all evaluated metrics (see Table 2), showcasing its robustness and superiority in predicting AAPL stock prices. This improvement underscores the effectiveness of combining diverse model outputs to achieve enhanced predictive accuracy in financial time series analysis.

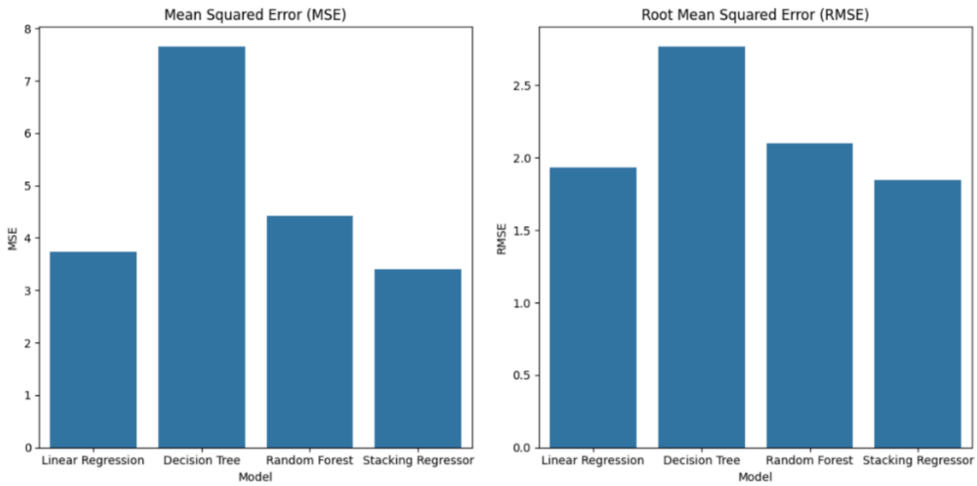

Figure 3: MSE and RMSE (Photo/Picture credit: Original).

Table 2: MSE and RMSE of different models.

Model	MSE	RMSE
Linear Regression	3.731411	1.931686
Decision Tree	7.648308	2.765557
Random Forest	4.419787	2.102329
Stacking Regressor	3.404015	1.844997

5.3. Discussion

The comparative analysis reveals that the stacking method synergistically harnesses the strengths of diverse models, resulting in a notable enhancement in overall predictive accuracy and reliability. Moreover, the incorporation of technical indicators and trading volume as supplementary features played a pivotal role in augmenting the predictive capability of the model. These additional inputs provided nuanced insights into market dynamics and trends, thereby enriching the model's predictive capacity beyond the capabilities of individual base models alone. This holistic approach not only

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mitigates the limitations of singular methodologies but also underscores the robustness and versatility of ensemble techniques in financial forecasting contexts.

6. Conclusion

This study implemented the stacking method to forecast AAPL stock prices, revealing superior performance compared to individual models in terms of both accuracy and robustness. By integrating predictions from diverse base models, the stacking approach effectively captures various dimensions of stock price dynamics. This comprehensive approach not only enhances predictive accuracy but also increases the model's reliability in capturing nuanced market behaviors, thereby providing significant practical utility for investors and analysts alike.

To enhance model accuracy and effectiveness, this approach involves integrating diverse datasets such as financial indicators, macroeconomic variables, and sentiment analysis data. Advanced models like neural networks and LSTM are explored alongside the development of new technical indicators and refined feature selection methods. Extensive hyperparameter tuning using automated frameworks, cross-validation techniques, and collaboration with academic and financial institutions ensure robust validation and optimization in real trading scenarios. Transparency in the prediction process and proactive bias management are integral to maintaining model integrity and reliability.

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