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The Impact of Prospect Theory on Asset Forecasting: A Comparative Study Based on Random Forest and Linear Regression

Jiayuan Zhang[1,a,*]

[1]*Department of Mathematical Finance, Tianjin University of Finance and Economics, Tianjin, China*
a. jiayuanzhang@stu.tjufe.edu.cn
**corresponding author*

Abstract: This study focuses on the application of predictive models and prospect theory in the field of machine learning to predict financial asset prices. Here, the linear regression and random forest algorithms were employed to forecast the price values and fluctuations of two different financial assets: the S&P 500 index and Bitcoin prices. Meanwhile, this study compared the performance of different financial asset datasets before and after the introduction of prospect theory models. Through calculation and comparative analysis, this article provides an in-depth discussion on the predictive performance of regression models and classification models. The research results indicate that in most cases, simple linear regression models have high prediction accuracy. Meanwhile, this paper also found that introducing prospect theory can effectively improve the accuracy of prediction models for specific financial assets. This result has a positive impact on the financial industry, helping to optimize risk management and investment decision-making, improving efficiency at the market level and promoting information transparency, while also promoting the development of emerging financial formats in financial innovation

Keywords: Asset Pricing Forecast, Linear Regression, Random Forest, Prospect Theory.

1. Introduction

In the financial market, asset price fluctuations are influenced by a combination of various factors, including asset value, total market funds, macroeconomic environment, industry development trends, and investor sentiment. Accurately predicting the trend and volatility of asset prices is crucial for investment banks, securities firms, and investors to avoid risks and achieve profitability [1-3]. However, financial markets are complex and constantly changing, with many intertwined factors affecting them, making predicting asset prices a highly challenging task.

To address this challenge, scholars around the world are constantly exploring and attempting to construct various prediction models to improve the accuracy of price forecasting. In this field of research, many models have been used, such as ARMA, ARIMA, LSTM and deep learning algorithms [4-6]. Among them, linear regression and random forest model, as two commonly used prediction methods, have been widely applied in the field of asset price prediction.

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This paper targets at further finding out the application effects of linear regression and random forest models in predicting the prices of S&P 500 index stocks and Bitcoin, and introduce prospect theory to measure the effect of investor sentiment on stock prices. The S&P500, as a representative of the US stock market, is composed of large listed companies that reflect the overall economic trends of the region and have a sound regulatory system; Bitcoin Price, with its extremely high price uncertainty and decentralized characteristics, attracts high-risk investors with the lowest level of regulation. Each of the two has its own characteristics, meeting the needs and risk preferences of different investors. Here, this article aims to improve the accuracy of asset price prediction and provide investors with more reliable decision-making basis by constructing a new prediction model and comparing its performance under two different asset categories.

2. Literature Review

Asset price prediction has been a topic of interest in various fields, including stock markets, real estate, and commodities. Accurately, in this field, many mathematical and computer techniques have been employed. Chen et al. proposed and validated a deep neural network-based asset pricing model that utilizes macroeconomic time series and no arbitrage conditions to construct test assets through adversarial methods, achieving high-precision prediction of stock returns, significantly outperforming existing benchmarks, and revealing key driving factors of asset prices [5]. Cakra et al. utilized sentiment analysis to predict stock prices in the Indonesian market, showing that social media sentiment can be indicative of market movements [7]. Similarly, Wagh et al. aimed to predict gold prices in India using LSTM, random forest regression, and linear regression algorithms, highlighting the importance of machine learning in forecasting asset prices [8]. Ceh et al. compared the computational performance of random forest and multiple linear regression models in the field of apartment housing prices [9]. The study noted challenges such as the non-linear nature of price prediction tasks and the impact of significant price changes in the market. Additionally, Liu et al. applied k-Nearest Neighbors regression to predict cloud spot instance prices, outperforming other models like linear regression and support vector machine regression [10]. In addition, Tang et al. proposed a non-iterative decomposition ensemble learning paradigm using RVFL network [11]. This emphasizes the efficiency of non-iterative algorithms in predicting crude oil prices. Chen et al. investigated sample dimension engineering in machine learning approaches for estimating Bitcoin prices at various frequencies [12]. Sharaf et al. proposed a comprehensive framework, Stock Predict, for stock price prediction using various learning models, including linear regression and random forest [13]. The framework aimed to address challenges in predicting stock prices efficiently and accurately.

Prospect theory is a famous business and psychological theory proposed by Amos Tversky and Daniel Kahneman in 1979, which explains how individuals evaluate risk and benefits in the decision-making process [14]. Subsequently, asset price prediction based on prospect theory has always been a research hotspot in the field of financial economics. Harbaugh et al. conducted a study on prospect theory in choice and pricing tasks, finding that results were robust even when subjects were allowed to review and change their decisions [15]. Li et al. analyzed the impact of prospect theory on asset prices and trading volumes by using a general equilibrium model [16]. Henderson explored prospect theory, liquidation, and the disposition effect in asset liquidation models, finding that investors may sell at a loss under certain conditions [17]. Selim et al. studied the price of assets trends with artificial marketplaces by utilizing agent-based modeling with prospect theory [18]. Ormos et al. introduced an equilibrium asset pricing model based on the relationship between Expected Downside Risk (EDR) and expected return, incorporating the risk-seeking behavior of loss-averse investors [19]. Barberis et al. conducted an empirical test on prospect theory and stock returns, finding that investors mentally represent stocks by the distribution of past returns and evaluate them according to prospect theory principles [20].

Overall, algorithms based on mathematics, statistics, and computer science have shown diverse applications in asset price prediction, providing powerful tools for financial market analysis by improving the accuracy and efficiency of predictions; At the same time, the importance of prospect theory is also emphasized, as it deepens our understanding of investor behavior and market dynamics, providing a more comprehensive perspective for financial market forecasting.

3. Methodology

Here, linear regression models that excel in handling linear data and random forests that excel in handling nonlinear data are selected, and these two supervised learning models complete the prediction task. The prediction task is mainly divided into two categories: numerical prediction and fluctuation classification. Numerical prediction focuses on predicting asset prices and providing feedback on predicted values; Volatility classification should predict the trend of assets, provide feedback on binary results, and indicate whether the asset value will rise or fall in the future.

3.1. Prediction Model

3.1.1. Linear Regression

Linear regression, a cornerstone of statistics and machine learning, is used to deeply explore and analyze relationships between variables. The core idea is to reveal how the dependent variable shows a corresponding change trend as one or more independent variables change. This model assumes that there is a linear correlation between variables and that the value of the dependent variable can be accurately or approximately predicted by a linear combination of the independent variables [21]. The general form of multiple linear regression model is as follows,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon \tag{1}$$

Where $y \in R$ is the observed variable; $x_i (i = 1,2, \dots, p)$ are the input variables; $\beta_0, \beta_1, \beta_2, \dots, \beta_p$ are the unknown parameters; ε is a residual term.

Researchers and practitioners favor linear regression models because of their many advantages. First, as one of the simplest regression models, it has intuitive and easy-to-understand mathematical formulas and powerful explanation capabilities, allowing researchers to easily understand the linear relationship between variables. Secondly, the training and prediction process of linear regression models are usually very efficient and can quickly process large-scale data sets to meet the timeliness requirements of modern data analysis. In addition, the linear regression model also has good interpretability and stability, providing a solid foundation for subsequent model optimization and expansion.

3.1.2. Random Forest

The random forest model is a powerful ensemble learning method based on the principle of decision trees, but does not rely solely on a single decision tree for prediction. In contrast, random forests improve the stability and accuracy of predictions by building and integrating a large amount of decision trees. The main idea of this algorithm is "ensemble intelligence", that is, the joint prediction of multiple models is usually more reliable than a single model. The schematic diagram of its work is as follows Figure 1.

Random forest models have many advantages and can often handle nonlinear relationships and high-dimensional data, achieving high prediction accuracy in a variety of scenarios. The random

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forest model is not prone to overfitting because it merges predictions from multiple decision trees, each constructed on a randomly chosen subset of data and features. Additionally, while Random Forest is a complex ensemble model that combines bagging and voting steps, feature importance scoring explains which features have the greatest impact on the prediction results. The random forest model can automatically handle missing values in the data without additional data preprocessing [22].

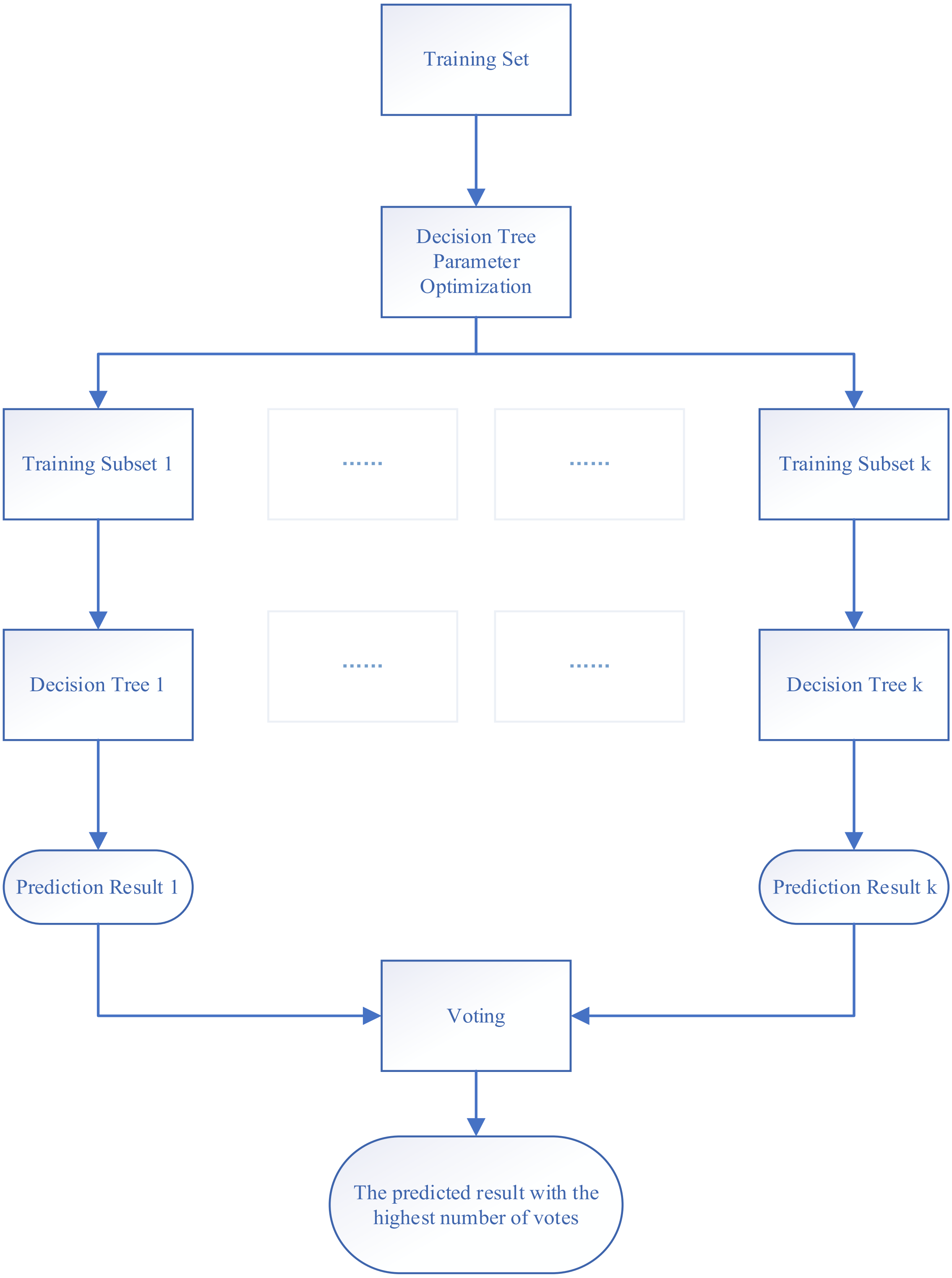

Figure 1: Random Forest Operation Method [22].

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3.1.3. Result Evaluation Criteria

After calculation, the utility of the prediction model is evaluated using three indicators which are Goodness of fit (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Use classification accuracy to evaluate the effectiveness of classification models.

3.2. Application for Prospect Theory

There is a close correlation between investor sentiment and asset prices. However, when constructing stock price prediction models, the academic community often overlooks the important factor of investor sentiment and only relies on stock price related data for prediction. To compensate for this deficiency, this study introduces prospect theory to quantify investors' emotional responses to different levels of stock rise and fall.

This article will use the utility function of prospect theory to construct an investor sentiment index to characterize the psychological response of investors to stock price trends. By using the utility function, a specific numerical value can be calculated to represent the emotional state of investors, reflecting their psychological expectations of stock prices rising or falling.

Using investor sentiment index as an input variable in the prediction model can theoretically enable the model to more comprehensively capture the influencing factors of stock price changes, which helps to make predictive algorithms more precise. On the basis of the previous text, this paper will explore the dynamic relationship between investor sentiment index and stock prices, providing new ideas for constructing more intelligent stock price prediction models.

The core of prospect theory function is cumulative prospect value, which consists of two parts: cumulative weight function and value function. The formula for calculating the prospect theory function (referred to as the prospect index in this article) is as follows:

$$U(x) = \begin{cases} w_1 v(x) & x \geq 0 \\ -w_2 v(-x) & else \end{cases} \tag{2}$$

here w_1 and w_2 are loss avoidance coefficients, and $v(x)$ is the value function. In different situations, there are different value functions that match it. This experiment selected three value functions: hyperbolic tangent value function, logistic value function, and commonly used exponential utility function in academia. The formula is as follows,

Hyperbolic Tangent Function (abbreviated as tanh function)

$$v(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

Logistic Function,

$$v(x) = \frac{1}{1+e^{-x}} \tag{4}$$

Exponent Utility Function,

$$U(x) = \begin{cases} x^{\beta} & x \geq 0 \\ -\lambda(-x)^{\beta} & else \end{cases} \tag{5}$$

Where, in the experiment, the parameter values are all classical values, which are $w_1 = w_2 = 10$, $\beta = 0.89$, $\lambda = 2.25$ [23].

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3.3. Experimental Setup

The purpose here is to compare and analyze which of the two machine learning algorithms is more suitable for financial asset data prediction tasks. Furthermore, prospect theory is introduced into the algorithm model. Discussing whether the introduction of prospect theory can effectively improve the accuracy of asset price prediction by analyzing the results.

3.3.1. Data Set

The option utilizes two datasets: S&P 500 Index stock data (1950-2015) and Bitcoin data (129,126units of time). The S&P 500 index dataset includes 16,590 rows and 7 columns. The Bitcoin dataset consists of 129,126 rows and 8 columns. Here, the closing price is the main data, which constitutes the majority of the input data and is also the designated prediction target. The above data was downloaded from Yahoo Finance website. Before making machine learning algorithm predictions, the data is preprocessed by searching for missing values and filling them in using mean interpolation.

3.3.2. Method and Procedures

The first step is data processing. Utilizing the open price, close price, adjusted close price, high price, low price of the past seven days and prospect index that computed by utility function on prospect theory as input variables to forecast the adjusted close price for the following day. Furthermore, leveraging the price movements from the preceding seven days to predict the price direction for the upcoming day.

Next are prediction methods and prospect theory processing. Developing and contrasting various data models, including linear and nonlinear models, to ascertain the superior performer in managing stock data. Introducing prospect theory to quantify the emotional utility of investors when monitoring stock price trends. Three commonly employed value functions—hyperbolic tangent function, logistic function, and exponential utility function—are chosen to compute the utility function. The variable x in the utility function signifies the difference between the previous day's closing price and the subsequent day's price, reflecting the stock price volatility.

Finally, here is the experimental dataset. Based on the combination of prospect theory and utilization value function, the input data is separated into four different datasets, one basic dataset, and three extended datasets. The basic dataset only contains basic trading information of the stock market, including open, close, adj-close, high, low. The first extended dataset is based on the basic trading data and incorporates the prospect index calculated using a hyperbolic tangent value function. The second extended dataset is based on the basic trading data and integrates the prospect index calculated through the index value function. The third extended dataset combines basic transaction data with prospect indices calculated using logical value functions

4. Results

4.1. Result Display

4.1.1. SP&500 Index

By calculation, the predicted S&P500 index results are shown in the Table 1.

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Table 1: Predict result for S&P500 index price.

Data Characteristics	Linear Regression	Random Forest Regression	Random Forest Classifier
Data Set without prospect theory	MAE: 11.259 MRSE: 15.576 R^2: 99.79%	MAE: 127.832 RMSE: 229.449 R^2: 61.89%	Accuracy: 47.96%
Data Set with prospect theory (value function: tanh)	MAE: 11.268 RMSE: 15.613 R^2: 99.79%	MAE: 127.495 RMSE: 229.170 R^2: 61.98%	Accuracy: 49.77%
Data Set with prospect theory (value function: exponent)	MAE: 11.284 RMSE: 15.600 R^2: 99.79%	MAE: 127.542 RMSE: 229.257 R^2: 61.95%	Accuracy: 50.32%
Data Set with prospect theory (value function: logistic)	MAE: 11.279 RMSE: 15.598 R^2: 99.79%	MAE: 127.480 RMSE: 229.018 R^2: 62.03%	Accuracy: 47.14%

Generally, the MAE and RMSE of linear regression are much lower than those of random forest regression. This indicates that linear regression has stronger predictive power than random forest regression on the stock index dataset. At the same time, there is a huge difference in the R^2 between the two models. The R^2 of linear regression is as high as 99.79%, while the R^2 of random forest regression is only 61.89%. This further confirms the advantage of linear regression in fitting data. Regardless of whether prospect theory is added or not, the performance indicators (MAE, RMSE, R^2) of the regression model remain almost unchanged. This indicates that the addition of prospect theory cannot improve predictive performance.

In classification tasks, the accuracy of the random forest classifier is relatively low, at 47.96% and 47.14%, with a slight increase after introducing prospect theory, reaching as high as 50%.

4.1.2. Bitcoin Price

By calculation, the predicted Bitcoin price results are shown in the Table 2.

Table 2: Predict result for bitcoin price

Data Characteristics	Linear Regression	Random Forest Regression	Random Forest Classifier
Data Set without prospect theory	MAE: 21.859 MRSE: 39.611 R^2: 100%	MAE: 624.699 RMSE: 42.609 R^2: 100%	Accuracy: 50.53%
Data Set with prospect theory (value function: tanh)	MAE: 15.655 RMSE: 32.123 R^2: 100%	MAE: 21.367 RMSE: 39.036 R^2: 100%	Accuracy: 50.27%
Data Set with prospect theory (value function: exponent)	MAE: 15.651 RMSE: 32.096 R^2: 100%	MAE: 21.353 RMSE: 39.003 R^2: 100%	Accuracy: 50.18%
Data Set with prospect theory (value function: logistic)	MAE: 15.651 RMSE: 32.098 R^2: 100%	MAE: 21.316 RMSE: 39.017 R^2: 100%	Accuracy: 50.13%

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Without incorporating prospect theory, the average absolute error of random forest regression is nearly 28 times higher than that of linear regression, with an MAE of 21.859. This indicates that the predictive ability of linear regression is much better than that of random forest regression on this dataset.

For RMSE, the value of linear regression is 39.611, while the value of random forest regression is 42.609. Although the RMSE of random forest regression is slightly higher, the difference between the two is small. For the goodness of fit, both models have a 100% indicator, indicating that both regression models can fully explain the data set. However, caution should be taken towards this statement.

After incorporating prospect theory, the MAE of linear regression obviously decreased from 21.859 to 15.655, indicating that prospect theory has a positive improvement effect on the linear regression model. For random forest regression, the addition of prospect theory also reduces the MAE, but the magnitude of the decrease is much smaller than that of linear regression. In addition, the value of RMSE has also decreased, but the remarkably decrease is also not observed. The performance difference of different value functions in regression models is very small, indicating that the selection of value functions has little impact on model performance on this data set.

The accuracy of the random forest classifier in predicting Bitcoin prices is approximately 50%, which is close to the natural classification probability. This indicates that random forest classifiers may not be the most effective classification method.

4.2. Result Analysis

4.2.1. Regression Model

Among all price prediction tasks, linear regression models have shown considerably advantages, with predictive performance far superior to random forest regression models. The prediction errors of linear regression models are much lower than those of random forest regression models, indicating that linear regression has higher accuracy and precision in predicting financial asset prices.

However, for the random forest regression model, although its R^2 is close to 1 for the two data sets of gold futures and Bitcoin, its performance in price prediction tasks is still not as good as the linear regression model. There are special cases of overfitting, or the random forest regression model is not suitable for financial asset price prediction.

Additionally, this research finds out the importance of variable. As shown in Figure 6, the four most important variables in the prediction task are the “adj close”, “close”, “high” and “low” on the first day. This indicates that the impact of the asset price data from the previous day on the price of the following day is much greater than others. This indicates that short-term price changes have a greater impact on the prediction model, and investors are more inclined to make trading decisions based on recent price changes, or short-term information flow and emotional changes have a more direct impact on market prices. In addition, the four variables are commonly used indicators in technical analysis. Historical price data contains all the information needed to predict future price trends. Therefore, these four variables were identified as important, further supporting the effectiveness of technical analysis in predicting market prices.

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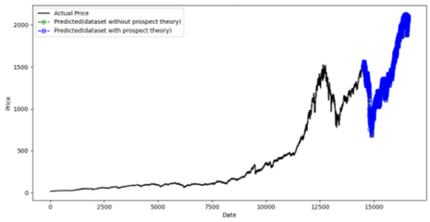

Figure 2: Visualization of S&P500 stock index data predicted by linear regression model.

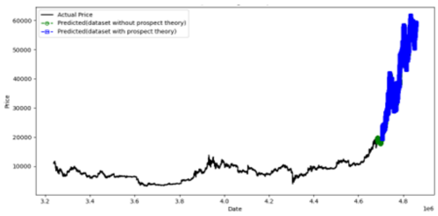

Figure 3: Visualization of Bitcoin price predicted by linear regression model.

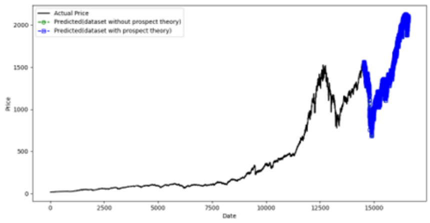

Figure 4: Visualization of S&P500 stock index data predicted by random forest model.

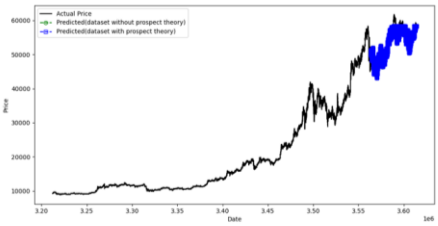

Figure 5: Visualization of Bitcoin price predicted by random forest model.

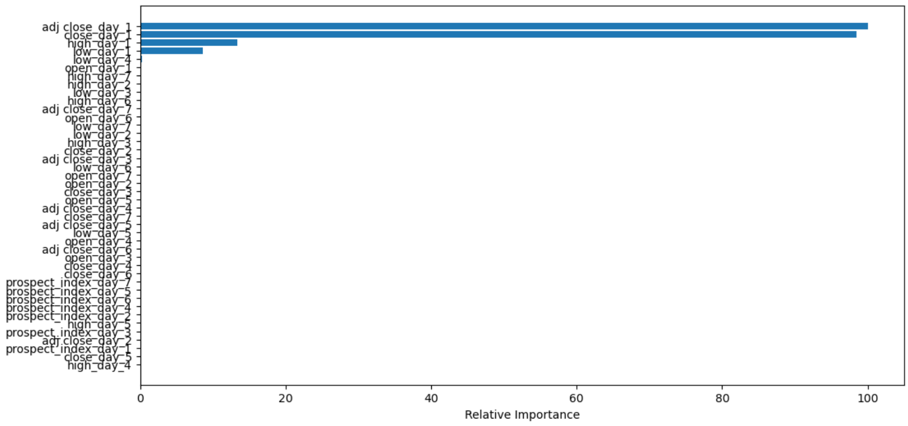

Figure 6: Visualization of Variable Importance.

4.2.2. Classification Model

Among all the price fluctuation prediction tasks, the random forest classifier did not demonstrate good performance in the Bitcoin price prediction task, with accuracy ranging from 47% to 51%. These results are not significantly different from a 50% natural classification probability. This indicates that the random forest classification model is not suitable for predicting the related tasks of financial asset fluctuations.

4.2.3. Introducing Prospect Theory

After incorporating prospect theory, the performance of the regression model in Bitcoin price prediction task has been further improved, proving the effectiveness of prospect theory in Bitcoin price prediction. In the task of predicting Bitcoin prices, the addition of prospect theory significantly improved the performance of the regression model, with a decrease in MAE and RMSE, indicating that prospect theory has played a positive role in Bitcoin price prediction.

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However, for the regression prediction models of another financial asset, the influence of prospect theory is relatively small. As shown in the Figure 2 and Figure 4, the two predicted curves almost completely overlap. In addition, the performance differences of different value functions in random forest regression are very small, indicating that the selection of value functions has little impact on the model performance for the dataset selected in this paper.

Therefore, by comparison, based on the research results, it can be inferred that prospect theory has strong applicability in emerging and poorly regulated financial asset markets. Due to the lack of rules in the above-mentioned market, investors trade almost freely in the market, and investment operations are not restricted, which has formed a herd effect and expanded the consequences. This is a useful portrayal of investor sentiment by prospect theory. By contrast, for more mature markets such as stock indices, market trading restrictions are far greater than the former, and there are also mandatory intervention measures to reduce investor herd behavior. Thus, the emotions of individual investors are difficult to greatly affect the prices of financial assets.

5. Conclusion

This study conducted experimental evaluations on linear regression models and random forest regression models in the field of financial asset prediction, and observed whether the addition of prospect theory would improve prediction performance. The results indicate that the linear regression model has significant advantages in predicting asset prices, with significantly lower prediction errors than the random forest regression model. This indicates that simple linear regression models are more effective in capturing price trends in financial data, especially when dealing with financial data that presents linear or near linear relationships.

Meanwhile, although prospect theory was introduced into the model and different value functions were attempted to improve model performance, experimental results showed that these attempts did not significantly improve the accuracy of all asset price predictions, only playing a significant role in the specific task of linear regression models predicting Bitcoin prices. This indicates the limitations of prospect theory in predicting financial asset prices.

In future research, in-depth research can be conducted in the following directions. Firstly, investor psychology can be effectively characterized by selecting more optimal prospect theory value functions. Secondly, alternative machine learning methods can be utilized to enhance the prediction of stock data, in order to better capture the complexity of the data and improve prediction accuracy.

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