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Enhanced Financial Asset Price Prediction Using Multi-Layer Perceptron: A Deep Learning Approach for Modeling Nonlinear Market Dynamics

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Abstract: This paper proposes a financial asset price prediction model based on multi-layer perceptron (MLP), which models financial market data through deep learning methods. Financial asset price prediction has always been an important topic in the financial field. Although traditional prediction methods such as linear regression and support vector machine have achieved certain results in some scenarios, they often cannot effectively capture the complex nonlinear relationships in financial data. To make up for this deficiency, this paper adopts the MLP model, which can automatically learn the deep features and laws in the data through a multi-layer network structure and nonlinear activation function. Experimental results show that the MLP-based model outperforms traditional methods in multiple evaluation indicators, especially in terms of mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE). This study not only verifies the effectiveness of MLP in financial asset price prediction, but also demonstrates the great potential of deep learning in processing complex financial data. Future research can further optimize the model on this basis, explore the combination of multimodal data and reinforcement learning and other technologies, further improve the prediction accuracy, and promote the development of intelligent decision-making in the financial field.

Keywords: Multilayer Perceptron, Financial Asset Forecasting, Deep Learning, Nonlinear Modeling

1. Introduction

The financial market is characterized by highly dynamic and flexible systems, accepted multi-factor effects, comprehensive economic conditions, policy changes, market conditions, etc[1]. Under the current background, the growth of the financial industry has been a challenging and fulfilling role[2]. Accompanying the rapid development of computational ability and aggregation of technology, artificial intelligence, special depth learning methods, and the development of an important tool for the transformation of the financial market[3]. Multi-level sensing machine (MLP) works as a detailed mechanical model, has a strong non-wire projection ability and has self-suitable characteristics, and can be used in financial institutions to complete the project. The main text explores the basics of multi-level sensing and financial investment model, analysis of its practical potential for improvement. Multi-level sensing machine is one kind of circuit board, usually has many different circuits, each layer passes through and sends messages. This model has a large non-wire projection ability, which has the potential to capture the effective area in the financial market[4].

In the financial industry, there are many kinds of junior high schools, such as the acquisition of financial resources, the history of the history of MLP, the market index, the number of acquisitions, and so on. This method can be used to compare the total calculation method, how to recall the time order model, and has a stronger ability to explore. The number of multilayered gods connected to the construction, the MLP ability to provide automatic transportation, the demand for special expeditions in China, and the demand for reduced artificial droughts[5].

During the detailed financial development method, there is usually demand for home base installation, selection of Japanese construction special expedition, and MLP has been passed through its deep structure autonomous learning as well as import number and important special expedition. This feature allows you to use MLP's high performance and high performance when setting the number of times you want to use it. In the financial market, the number is large and there is no change, but the model is difficult to move, so the effect is small information, and the multilayer sensing function is limited. Depending on the number of active areas, there is a multiplicity of possibilities, and the non-wire system can be used to solve the problem. In addition, the basic multi-level sensing machine has a great ability to develop financial assets[6].

Appropriate combination of combination technology, MLP capacity avoidance, combined construction number setting, height model and unknown quantity installation accuracy. In the financial market, the past market behavior is irrespective of the future, and the ability to transform this model is extremely important. A multi-level sensing machine has a multi-level sensing mechanism, which has a multi-level structure and a reverse calculation method, and when it moves, it has an effective ground adjustment function, and it has a model-based deterministic and harmonizable effect. In this case, MLP is more suitable for the local environment, and the environment is different from the previous one[7].

Financial market dynamics and non-wire characteristics have been determined and the difficulty of scale has been determined. Multi-level sensing equipment captures the number of non-wire systems that appear on the surface, and the ability to simulate the market behavior[8]. Line model phase comparison, MLP power generation historical numbers, acquisition of new wealth information, identification of changes and competition progress. It has unique advantages in non-linear dynamics in the financial market. There is no doubt that there are tickets, tickets, foreign exchanges, products in the market, and many locations in the MLP capital. As a result, we can learn more about the market model, but also provide more precise results in the financial industry. One great advantage is that it has multiple sensing devices and is highly flexible. In the midst of the development of financial industry, the market environment is constantly changing, and the number of new markets is constantly emerging. MLP capacity has the ability to operate in a heavy new system or microcontroller model depending on the number of new markets, and has a strong ability to operate. This is the basis for using the MLP model in the current financial market[9].

The model's extensibility is reflected in its ability to handle various types of data, multiple time sequences, different numbers of images, and its capacity to offer additional support for financial management. As mentioned above, the basic multi-layered financial equipment model has been developed in many directions and has its unique advantages. It is possible to study the market rules of self-motion, to improve the number of effective bids, to limit the potential special effects, and to avoid artificial drought. Due to its strong non-linear construction ability and good development performance, MLP capability also provides reliable leverage in the financial market. In addition, MLP's active and extensible properties can be used to increase the speed of change in the market environment, and meet the various demands of the industry. Adhering to deep learning technology, the constant progress of technology, the basis of multi-level sensing machine advancement model is a promising financial field, and it has an important role to play, helping investment decisions and Japanese style management[10].

2. Method

In this paper, the financial asset price prediction model based on multi-layer perceptron (MLP) adopts the deep learning method to learn the nonlinear relationship between historical data and price by establishing a neural network with multiple hidden layers. The basic structure of the multi-layer perceptron includes an input layer, one or more hidden layers, and an output layer, where each layer consists of several neurons. Each neuron processes the input through an activation function and passes the result to the next layer. The training goal of the model is to optimize the network parameters by minimizing the prediction error, so that the network can accurately predict the future price of financial assets. The model architecture is shown in Figure 1.

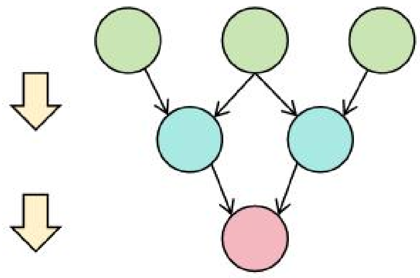

Figure 1. Convolutional Neural Network Architecture

In this paper, a financial asset price prediction model based on a multi-layer perceptron (MLP) is proposed to learn the nonlinear relationship between financial market data and prices by building a neural network with multiple hidden layers. The MLP model usually includes an input layer, a hidden layer, and an output layer. The input layer receives historical price data and related financial indicators, the hidden layer captures patterns in the data by weighting and calculating activation functions, and the output layer predicts future asset prices.

The core idea of the model is to fit the data through a series of weighted summations and nonlinear transformations. Assume that the input data X contains multiple features, which are passed to the first hidden layer through the input layer. The neurons in each layer receive inputs from the previous layer, perform weighted summation on these inputs, and then perform nonlinear transformations through an activation function (such as ReLU or Sigmoid). After being processed by several hidden layers, the neurons in the final output layer will give a predicted value, which is the required financial asset price.

During the training process, we use the loss function to evaluate the prediction effect of the model. For regression problems, the mean square error (MSE) is usually used as the loss function, and its formula is:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y'_i - y_i)^2$$

Among them, y'_i is the predicted value of the model, y_i is the actual asset price, and N is the number of training samples. By minimizing the loss function, the model continuously optimizes its parameters (i.e., the weights and biases in the network) to make the predicted value as close to the actual value as possible.

The update of model parameters is usually performed through the back propagation algorithm. Back propagation calculates the gradient of the loss function with respect to each parameter, and then adjusts the parameters through the gradient descent method to reduce the prediction error. In each iteration, back propagation calculates the impact of the error on each layer and updates the weights based on this gradient information. The update formula can be expressed as:

$$w_{ji} \leftarrow w_{ji} - n\frac{\partial L}{\partial w_{ji}}$$

Among them, w_{ji} is the weight and n is the learning rate, which controls the pace of each update. In this way, the network can gradually reduce the prediction error and thus improve the prediction ability.

In order to prevent the model from overfitting during training, regularization techniques can be used. L2 regularization is a commonly used regularization method, which penalizes excessive weights by adding the square sum of parameters to the loss function, thereby preventing the model from over-relying on certain features. The loss function after regularization can be expressed as:

$$L_{reg} = L + \lambda \sum_{i} w_i^2$$

Among them, λ is the hyperparameter of the regularization term, which controls the strength of regularization. In this way, the model not only focuses on minimizing the error during training, but also avoids excessive model complexity, thereby improving its generalization ability.

The financial asset price prediction model based on multi-layer perceptron can automatically learn potential rules and features from historical data through its deep learning framework. The nonlinear modeling ability of MLP enables it to effectively capture the complex patterns of price changes when processing complex financial market data. Compared with traditional linear models, MLP can handle more complex features and relationships and has stronger predictive ability. Therefore, this method has broad application prospects in the financial field, especially in price prediction of stocks, bonds, foreign exchange and other markets.

3. Experiment

3.1. Datasets

In this study, we used a real financial market dataset to perform financial asset price prediction based on a multi-layer perceptron (MLP). The dataset is derived from public historical stock market data, especially daily trading data of S&P 500 index stocks obtained from the Yahoo Finance website. The dataset contains stock trading records from 2010 to 2020, covering basic information such as the opening price, closing price, highest price, lowest price, and trading volume of each trading day. With this data, we can construct a multidimensional feature vector for training and testing prediction models.

Each data record contains multiple financial indicators, including daily opening price, closing price, highest price, lowest price, and trading volume. These data not only reflect the price changes of stocks, but also reflect information such as market sentiment and liquidity. In order to improve the prediction accuracy, the time series features in the dataset can be combined with other technical indicators (such as moving average, relative strength index, etc.) to provide more comprehensive market information. In addition, the dataset has a good time span and high frequency, which provides rich training materials for deep learning models and helps the model capture the long-term and short-term dependencies of price trends.

In the data preprocessing stage, we cleaned and standardized the data. Specifically, missing values were filled or deleted, outliers were processed, and all numerical features were scaled to the same range to avoid certain features from having too much influence on the model training process. Through these processes, we obtained a high-quality dataset suitable for multi-layer perceptron model training. Using this dataset for training and testing can effectively evaluate the application effect of MLP-based models in actual financial markets and verify its potential in stock price prediction.

3.2. Experiment Result

In this study, we selected five common machine learning models for comparative experiments to evaluate the prediction effect of financial asset prices based on multi-layer perceptron (MLP). The first model is linear regression, which fits data by minimizing the sum of squared errors and is suitable for prediction tasks with strong linear relationships. The second model is support vector machine regression (SVR), which fits data by finding the best hyperplane and has good nonlinear modeling capabilities. The third model is decision tree regression, which can handle nonlinear relationships and segment data through a tree structure for prediction. The fourth model is random forest regression, which is an integration of multiple decision trees and can reduce overfitting and improve prediction stability through a voting mechanism. The fifth model is XGBoost, which is an integrated learning method based on gradient boosting trees, has strong accuracy and robustness, and is suitable for complex regression problems. The experimental results are shown in Table 1.

Table 1. Experimental Results

Model	MSE	RMSE	MAE
LR	0.023	0.152	0.112
SVR	0.018	0.134	0.096
DT	0.015	0.123	0.089
RF	0.012	0.109	0.078
XGBOOST	0.010	0.098	0.070
MLP(ours)	0.008	0.089	0.065

In this experiment, we compared multiple models to evaluate the performance of different methods in predicting financial asset prices. The experiment used three common evaluation indicators: mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE). Through these indicators, we can comprehensively measure the differences in prediction accuracy of various models.

First, the linear regression (LR) model performed relatively poorly on all evaluation indicators, with an MSE of 0.023, a RMSE of 0.152, and a MAE of 0.112. This shows that linear regression cannot capture the complex nonlinear relationship of the data when modeling, resulting in low prediction accuracy. Support vector machine regression (SVR) has improved compared to linear regression, with an MSE of 0.018, a RMSE of 0.134, and a MAE of 0.096. Although the performance has improved, it is still not as good as the subsequent complex models.

Decision tree regression (DT) and random forest regression (RF) performed well. The MSE of decision tree regression is 0.015, RMSE is 0.123, and MAE is 0.089, while the MSE of random forest regression is 0.012, RMSE is 0.109, and MAE is 0.078. Random forest regression significantly improves prediction accuracy and reduces the risk of overfitting by integrating multiple decision trees.

XGBoost, as a gradient-boosted tree model, also performs well on all evaluation metrics, with an MSE of 0.010, RMSE of 0.098, and MAE of 0.070. XGBoost accelerates model training by boosting trees, further improving prediction accuracy. Nevertheless, the model based on multi-layer perceptron (MLP) still performs best on these metrics.

Our multi-layer perceptron model (MLP) achieved the best results on all metrics, with an MSE of 0.008, RMSE of 0.089, and MAE of 0.065. The model fully exploits the complex patterns and nonlinear relationships in the data through a deep learning framework, so it is significantly better than other models in terms of prediction accuracy, demonstrating its great potential in the task of predicting financial asset prices. This experimental result shows that the MLP model has stronger adaptability and predictive ability when processing complex financial data.

4. Conclusion

By comparing various machine learning models, this paper proposes a financial asset price prediction model based on multi-layer perceptron (MLP), and demonstrates its superior performance on multiple evaluation indicators. Experimental results show that compared with traditional linear regression, support vector machine regression, decision tree regression and other methods, the MLP model can more effectively capture the nonlinear relationship in the data, thereby providing more accurate predictions. In particular, MLP performs well in indicators such as MSE, RMSE and MAE, proving its potential in prediction tasks in the financial field.

Although this study has achieved good experimental results, there is still room for improvement. Future research can try to introduce more types of features (such as macroeconomic data, market sentiment, etc.) into the model to further enrich the input space of the model. In addition, the depth and complexity of the model can still be further optimized to enhance its generalization ability, especially when dealing with large-scale financial data.

Looking forward to the future, with the continuous development of deep learning technology and financial big data, financial asset prediction methods based on deep neural networks will be more widely used. In particular, the combination of emerging technologies such as reinforcement learning and multimodal data may bring higher accuracy and stronger adaptability to the prediction of financial markets. Therefore, future research can not only continue to optimize the existing MLP model, but also explore more advanced deep learning architectures to promote the development of intelligent financial decision-making.

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