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A Review of Gold Price Prediction Models Based on the Least Square Method

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Abstract: ***With the increasing complexity of the global financial market, gold, as a traditional safe-haven asset, has received widespread attention for its price fluctuations. Accurately predicting the gold price is not only crucial for investors to formulate strategies, but also an important part of the risk management of financial institutions. The least square method, as a classic regression analysis technique, has been widely applied in financial time series prediction due to its simplicity and effectiveness. This paper reviews the research progress of gold price prediction models based on the least square method, covering the evolution from traditional linear regression to advanced nonlinear models. It analyzes the characteristics, application scenarios and prediction performance of different models, and discusses the model optimization strategies and future research directions.***

Keywords: Least Square method; Gold price prediction; Linear regression; Nonlinear model; Model optimization.

1. INTRODUCTION

Gold, as a special commodity, possesses both commodity and financial attributes. Its price is influenced by various factors such as the global economic situation, monetary policy, geopolitical risks, and inflation expectations [1]. In recent years, with the increase in global economic uncertainty, the demand for gold as a safe-haven asset has risen, and the fluctuation of gold prices has intensified, bringing new challenges and opportunities to investors and financial institutions [2]. Against this background, how to effectively predict the gold price has become a topic of common concern in both the academic and practical fields.

Accurately predicting the gold price is of great significance for investors to formulate investment strategies and optimize asset allocation [3]. Investors can hedge more effectively and reduce the risk of their investment portfolios by accurately predicting the fluctuations in gold prices [4]. Meanwhile, financial institutions also need to rely on accurate gold price predictions in aspects such as risk management and product design [5]. Therefore, studying the gold price prediction model not only helps enhance the decision-making ability of market participants, but also promotes the stability and development of the financial market.

The least square method, as one of the most fundamental parameter estimation methods in statistics, seeks the best functional match of data by minimizing the sum of the squares of the errors between the observed values and the predicted values. Since Gauss proposed it, the least square method has been widely applied in various fields, especially in the analysis of financial time series, providing a theoretical basis for the construction of prediction models [6]. With the development of computer technology and the improvement of data processing capabilities, the gold price prediction model based on the least square method has developed rapidly [7]. From simple linear regression models to complex nonlinear models, and then to hybrid models combined with other technologies, it has continuously promoted the in-depth research on gold price prediction.

This paper aims to review the current research status of gold price prediction models based on the least square method, analyze the advantages and disadvantages of various models, and provide references for future research.

2. THE BASIC THEORY OF THE LEAST SQUARE METHOD

Chapter 2: Fundamental Theory of the Least Squares Method

The Least Squares Method is a highly critical mathematical optimization technique in data analysis and scientific computing. Its core objective is to find the best functional fit for data by minimizing the sum of the squares of errors. This method originated in the field of astronomy and was proposed by Carl Friedrich Gauss in the late 18th to early 19th century to address the fitting problem of astronomical observational data.

The basic idea of the Least Squares Method is both intuitive and powerful. Given a set of observational data points (xi,yi), i=1,2,...,n, it attempts to find a function f(x) such that the sum of the squares of the vertical distances (i.e., errors) from all observational points to this function is minimized. This objective function can be expressed as S=∑i=1n(yi−f(xi))2. By adjusting the parameters of the function f(x) to minimize S, the best-fitting model for the data is obtained.

Depending on the form of the function, the Least Squares Method can be divided into linear least squares and nonlinear least squares. Linear least squares assumes that f(x) is a linear function of x, i.e., f(x)=β0+β1x, where β0 and β1 are parameters to be estimated. Solving linear least squares typically involves solving the normal equation system $X_T X\beta = X_T y$ to obtain the optimal solution for the parameters β, where X is the design matrix and y is the vector of observed values. Nonlinear least squares, on the other hand, deals with cases where f(x) is not a linear function of x, such as exponential or logarithmic functions. Solving nonlinear least squares usually employs iterative algorithms, such as the Gauss-Newton method or the Levenberg-Marquardt algorithm, to approximate the optimal solution by continually updating the parameter estimates.

The Least Squares Method has a wide range of applications. In regression analysis, it serves as the foundation for establishing mathematical relationship models between independent and dependent variables, enabling the prediction and interpretation of trends and patterns in data. In the field of signal processing, the Least Squares Method can be used for tasks such as filtering, denoising, and parameter estimation, thereby improving the quality and accuracy of signals. In machine learning, many algorithms, such as linear regression, logistic regression, and support vector machines, are based on the Least Squares Method or its variants and are used for tasks such as classification, clustering, and prediction.

However, the Least Squares Method also has certain limitations. It is sensitive to outliers because minimizing the sum of the squares of errors means that outliers can have a significant impact on the results. Additionally, the Least Squares Method assumes that errors follow a normal distribution and are independently and identically distributed, which may not hold true in practical applications. To overcome these limitations, researchers have proposed many improvement methods, such as robust regression and weighted least squares, to enhance the robustness and accuracy of models.

To gain a deeper understanding and application of the Least Squares Method, many scholars have conducted extensive research. For example, Golub and Van Loan [8] provide a detailed introduction to the basic theories and methods of matrix computation in their work, offering a solid mathematical foundation for the practical application of the Least Squares Method. The classic textbook by Hastie et al. [9] comprehensively introduces the Least Squares Method and its applications in statistical learning, helping readers to gain a deep understanding of its principles and practices. These studies have made significant contributions to the development and application of the Least Squares Method.

3. CLASSIFICATION OF GOLD PRICE PREDICTION MODELS BASED ON THE LEAST SQUARE METHOD

Gold price prediction models based on the least square method can be roughly divided into three categories: linear regression models, nonlinear regression models, and hybrid models combined with other techniques.

3.1 Linear Regression Model

The linear regression model is the simplest model that applies the least square method. It assumes that there is a linear relationship between the gold price and the factors influencing its changes. These factors may include the US dollar index, real interest rates, inflation rates, crude oil prices, etc. The linear regression model is easy to understand and implement, has high computational efficiency, and is suitable for scenarios where the data relationship is relatively simple and the linear characteristics are obvious. However, financial data in the real world often has nonlinear characteristics, and linear models may not be able to capture all the important dynamic relationships, resulting in limited prediction accuracy.

3.2 Nonlinear Regression Model

To overcome the limitations of linear models, researchers have proposed various nonlinear regression models, such as polynomial regression, exponential regression, logarithmic regression, etc. These models, by introducing nonlinear terms, can better fit the nonlinear relationships in the data and improve the prediction accuracy. For instance, polynomial regression captures nonlinear trends by adding higher-order terms to the independent variable, while exponential regression and logarithmic regression are applicable in scenarios where there is an exponential or logarithmic relationship between the dependent variable and the independent variable.

3.3 Hybrid Model

The hybrid model combines the least square method with other statistical or machine learning techniques, aiming to further enhance the predictive performance.

The combination of Autoregressive Moving Average Model (ARIMA) and the least square method. The ARIMA model is a classic model in time series analysis and is applicable to the prediction of stationary time series. By combining the ARIMA model with the least square method, the least square method can be used to optimize parameters in the model estimation stage and improve the prediction accuracy.

The fusion of neural networks and the least square method. Neural networks have a powerful nonlinear mapping ability and can handle complex high-dimensional data. Combining neural networks with the least square method can utilize the least square method to optimize the network weights during the training process, accelerate convergence, and improve the stability of prediction.

The combination of Support Vector Regression (SVR) and the least square method. SVR is a support vector machine regression method based on statistical learning theory, which is suitable for data prediction in small samples, nonlinearity and high-dimensional Spaces. By introducing the least squares loss function, SVR can be transformed into a quadratic programming problem and solved by using the least squares method, thereby improving the computational efficiency while maintaining the advantages of SVR.

4. MODEL OPTIMIZATION STRATEGY

In the process of constructing and training models, model optimization is a key step to improve model performance, enhance its generalization ability, and meet specific application requirements. The model optimization strategy aims to achieve the best performance of the model on the given data set by adjusting aspects such as the model structure, parameter Settings, and training methods, and also demonstrate good prediction or classification capabilities on unseen data.

4.1 Parameter Adjustment

Parameter adjustment is the basis of model optimization. In machine learning models, there are two types of parameters: model parameters (such as weights and biases in linear regression) and hyperparameters (such as learning rate, regularization coefficient, the number of layers of the neural network, and the number of neurons in each layer). The model parameters are automatically adjusted through the optimization algorithm during the training process, while the hyperparameters need to be manually set before training. Reasonable hyperparameter selection has a significant impact on the model performance. For example, a learning rate that is too high may lead to unstable model training, while a learning rate that is too low will make the training process slow. Hyperparameter adjustment usually adopts methods such as grid search, random search or Bayesian optimization. By trying different combinations of hyperparameters, the hyperparameter Settings that make the model perform best on the validation set are found.

4.2 Regularization Technology

Regularization technique is an important means to prevent model overfitting. Overfitting refers to the phenomenon where a model performs well on the training set but its performance declines on the test set. Regularization reduces the complexity of the model by adding additional penalty terms to the loss function to limit the size of the model parameters. Common regularization methods include L1 regularization (Lasso regression) and L2 regularization (Ridge regression). L1 regularization tends to produce sparse solutions, that is, many parameters are zero, which is helpful for feature selection; L2 regularization makes the parameter values smaller and uniformly distributed, improving the stability of the model.

4.3 Integrated Learning

Ensemble learning improves overall performance by combining the prediction results of multiple models. Individual models in ensemble learning can be homogeneous (such as a random forest composed of multiple decision trees) or heterogeneous (such as a combination of decision trees and neural networks). Ensemble learning can reduce the variance of a single model and improve the generalization ability of the model. Common integration methods include Bagging, Boosting and Stacking. Bagging generates multiple training sets through the self-sampling method, trains individual models respectively, and finally obtains the final prediction result through voting or averaging. Boosting gradually improves the model performance by iteratively adjusting the weights of the training samples, enabling subsequent models to focus on the samples that were wrongly classified by the previous models. Stacking takes the outputs of multiple different types of base learners as new features and inputs them into the meta-learner for the final prediction.

4.4 Characteristic Engineering

Feature engineering is an important link in model optimization. It involves extracting, selecting and transforming features from the original data to better represent the data and improve the predictive ability of the model. Effective feature engineering can significantly improve model performance and reduce training time and computing resource consumption. The methods of feature engineering include feature selection (such as filtering method, packaging method and embedding method), feature extraction (such as principal component analysis, linear discriminant analysis) and feature construction (such as creating new features based on domain knowledge).

4.5 Model Architecture Optimization

For deep learning models, the optimization of the model architecture is equally crucial. The model architecture determines the way data flows and is processed in the model, directly affecting the performance of the model. Model architecture optimization includes selecting appropriate network layers (such as convolutional layers, loop layers, and attention layers), adjusting the parameters of network layers (such as convolution kernel size, step size, and filling), introducing skip connections or residual blocks, etc. Furthermore, with the development of technology, some new model architectures such as Transformer and graph neural networks have also demonstrated outstanding performance in specific fields.

In conclusion, the model optimization strategy is a comprehensive process, involving multiple aspects such as parameter adjustment, regularization techniques, ensemble learning, feature engineering, and model architecture optimization. By comprehensively applying these strategies, the performance of the model can be significantly improved, enabling it to better meet the requirements of practical applications.

5. APPLICATION CASES AND EMPIRICAL ANALYSIS

In recent years, the gold price prediction model based on the least square method has achieved remarkable results in empirical research. For instance, a certain study adopted a polynomial regression model and combined independent variables such as the US dollar index, real interest rates and crude oil prices to predict the gold price. The empirical results show that the polynomial regression model has higher prediction accuracy compared with the linear regression model and can better capture the nonlinear fluctuation characteristics of gold prices.

Another study combined neural networks with the least square method to construct a hybrid model for gold price prediction. By introducing the least square method to optimize the weights of the neural network, this model is superior to the traditional neural network models in both training speed and prediction stability. Empirical analysis shows that the hybrid model performs well in the short-term prediction of gold prices, providing valuable decision-making basis for investors.

6. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Although the gold price prediction model based on the least square method has made remarkable progress in theory and practice, it still faces some challenges. The quality of financial data directly affects the performance of the prediction model. However, actual data often have problems such as noise and missing values. How to effectively handle these problems and improve data quality is an important research topic at present. As the complexity of the model increases, although the prediction accuracy may improve, the interpretability of the model often decreases. How to improve the interpretability of the model while ensuring the prediction performance is a problem that needs to be focused on in future research. The financial market changes rapidly, requiring the prediction model to have real-time performance and dynamic adaptability. How to design a prediction model that can respond quickly to market changes is one of the current research difficulties.

In terms of future research directions, deep learning should be integrated with the least square method: deep learning technology has unique advantages in dealing with complex nonlinear data. Combining deep learning with the least square method is expected to further improve the accuracy and stability of gold price prediction. In addition to traditional economic and financial data, unstructured data such as social media and news reports also contain rich market information. How to effectively integrate multi-source data and construct a more comprehensive gold price prediction model is an important direction for future research. With the rapid development of artificial intelligence technology, model interpretability has become a research hotspot. The development of an interpretable gold price prediction model helps investors better understand the model's decision-making process and enhance their decision-making confidence.

7. CONCLUSION

This paper reviews the research progress of gold price prediction models based on the least square method, covering the evolution from traditional linear regression to advanced nonlinear models. It analyzes the characteristics, application scenarios and prediction performance of different models, and discusses the model optimization strategies and future research directions. The least square method, as a classic regression analysis technique, plays an important role in gold price prediction. However, with the increasing complexity of the financial market, the single least square method model has been difficult to meet the practical application requirements. Future research should focus on integrating multiple technologies to build more efficient, stable and interpretable gold price prediction models, providing more accurate decision support for investors and financial institutions.

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