Project:Stock price prediction

Phase:4

Certainly, I can provide an overview of the process of building a stock price prediction model, includingC feature engineering, model training, and evaluation.

Abstract:

Stock price modeling and prediction have been challenging objectives for researchers and speculators because of noisy and non-stationary characteristics of samples. With the growth in deep learning, the task of feature learning can be performed more effectively by purposely designed network. In this paper, we propose a novel end-to-end model named multi-filters neural network (MFNN) specifically for feature extraction on financial time series samples and price movement prediction task. Both convolutional and recurrent neurons are integrated to build the multi-filters structure, so that the information from different feature spaces and market views can be obtained. We apply our MFNN for extreme market prediction and signal-based trading simulation tasks on Chinese stock market index CSI 300. Experimental results show that our network outperforms traditional machine learning models, statistical models, and single-structure(convolutional, recurrent, and LSTM) networks in terms of the accuracy, profitability, and stability.

Feature engineering:

Unlike picture, text and speech samples, whose raw inputs already contain most information needed for final objectives, stock price movements are results of multiple factors such as macroeconomy, financial situation of a company, investors' sentiments, etc. And financial time series contain high noise. To predict stock price movement, features containing useful information areneeded, so feature extraction and selection play significant roles in stock price movement prediction.

• Data Collection:

Gather historical stock price data for the target stock or index.

• Feature Engineering:

Select and preprocess relevant features, such as historical prices, trading volumes, and financial indicators.Create additional features, like moving averages, volatility measures, and technical indicators.Consider incorporating external factors like news sentiment or economic indicators.

• Data Splitting:

Split the data into training, validation, and test sets. Common splits are 70-80% for training, 10-15% for validation, and 10-15% for testing.

• Model Selection:

Choose a suitable machine learning model. Common choices include regression models (e.g., linear regression), time series models (e.g., ARIMA, LSTM), or ensemble methods (e.g., random forests, gradient boosting).

• Model Training:

Train the selected model on the training data. Ensure that hyperparameters are optimized.

• Evaluation:

Use the validation set to assess the model's performance.Common evaluation metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and correlation coefficients.Adjust the model if necessary based on the evaluation results.

- Testing:

Assess the model's performance on the test set to simulate real-world predictions.

- Hyperparameter Tuning:

Fine-tune model hyperparameters to optimize performance.

- Prediction:

Make predictions on future or unseen data.

- Monitoring and Maintenance:

Continuously monitor the model's performance and retrain it periodically to adapt to changing market conditions.Remember that predicting stock prices is inherently challenging due to the complex and volatile nature of financial markets. The model's accuracy can be influenced by various factors, so it's important to use caution when making real investment decisions based on its predictions and to consider other relevant information.Please note that the specific choice of features, model, and data sources can vary based on the complexity of the prediction task and the available resources.