

论文摘要

This article attempts to establish a trading strategy framework based on deep neural networks for the futures market, which consists of two parts: time series forecasting and trading strategies based on trading signals. In the time series forecasting task, we experimented with three types of methods with different entry points, namely recurrent neural networks with gate structure, networks combining time and frequency domain information, and network structures using attention mechanism. In the trading strategy part, the buying and selling signals and the corresponding trading volume are established according to the prediction results, and trading is conducted with the frequency of hours. In the empirical exploration part, we tested the prediction effect and strategic rate of return of various models on the copper contract. The data shows that in general, the best strategy can obtain a relatively stable income growth that has nothing to do with market fluctuations, but lacks countermeasures for rare external events with greater impact.

系统模型

Time Series Prediction Methods:

1. Long- and Short-term Memory Networks
 1. LSTM
 2. BiLSTM
2. Methodology Incorporating Frequency Domain Characteristics
 1. Wavelet transform + LSTM
3. Methods of Introducing Attention Mechanisms
 1. Attention + LSTM
 2. Transformer

Trading Strategy Setting:

Based on the predicted closing price for the next hour and the current price, a buy signal is generated if the prediction is to rise and vice versa. The difference between the two prices is recorded as volume (rounded). A set of buy and sell logic can be set based on the buy and sell signals and spreads: if a buy signal is given and the current account is long or open, then the contract with the corresponding volume units is bought; if it is short, then a certain percentage of the holding contract is sold. For sell signals, a reverse treatment using the same rules is sufficient. In the event of a change in the main contract, the strategy empties the original contract holdings and buys the same number of new contracts. During the buying and selling process, trading-related fees and margin mechanisms are not taken into account due to the low trading frequency of the strategy. In addition, in order to better observe the accuracy of the buy and sell signals, no maximum position is set, taking into account the leverage effect of the margin system in the actual trading of futures.

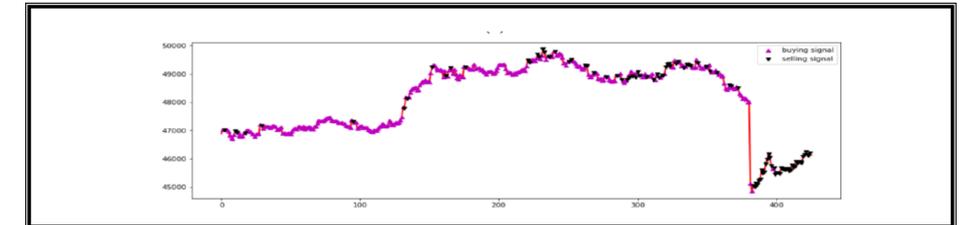
实验仿真

Table 12. Summary of strategy results

Evaluation indicators	Rate of return(%)	RMSE	F1 score
market	-1.62	-	-
LSTM	10.88	173.19	0.57
wLSTM	8.13	176.94	0.67
Attention+LSTM	8.19	177.50	0.60
Transformer	6.46	173.88	0.65

Table 13. Summary of pre-shock strategy results

Evaluation indicators	Rate of return(%)	RMSE	F1 score
market	2.43	-	-
LSTM	7.97	96.71	0.56
wLSTM	6.50	98.32	0.68
Attention+LSTM	9.64	97.28	0.62
Transformer	12.39	96.23	0.68



论文结论

This paper establishes a futures trading framework based on time-series forecasting that attempts statistical arbitrage by leveraging historical information about prices. For time series prediction, three different types of approaches are used, namely, LSTM with gate structures, wLSTM combining wavelet transformations with LSTM, and network structures that introduce attentional mechanisms (attention+LSTM, Transformer), all of which aim to obtain more information from long sequences. Experiments show that the performance gap between the root mean square error of each method is small in the final prediction result, but due to the different characteristics of the network, there is a certain gap between the actual strategy effect, which can be reflected in the F1 score to some extent. In general, the best-performing Transformer model can achieve stable excess gains independent of market ups and downs through both long and short mechanisms. However, neural network models based on internal market information can appear uncontrollable when relatively rare external shocks that cannot be reflected in prices occur, leading to a certain loss of yield. It can be found through experiments that the common root mean square error is not comprehensive for the measurement of prediction results, and the ability to distinguish between fitting and prediction is poor. More evaluation methods need to be combined, and the loss function and model evaluation function applicable to quantitative transactions can be further explored. In addition, unpredictable external information requires timely stop-loss and adjustment of the strategy, as well as the introduction of online information such as news to help the model make decisions.