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Predicting Option Prices and Volatility with High Frequency Data Using Neural Network

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Abstract. Neural network utilizes the huge amount of data for analysis and prediction. This paper predicts option prices and volatility using neutral network based on high frequency intraday data. We focus on short term prediction because option prices and volatility in fact are very volatile and almost impossible to predict. We find that neural network is able to predict option prices and volatility by using predictors constructed from the prices of option and its underlining index, especially in short term which is what practitioners care about more in practice.

Keywords: Option, Neural Network, Volatility, High Frequency Data, Price Prediction.

INTRODUCTION & LITERATURE REVIEW

Artificial neural network mimics the brain neural network and the artificial neural network contains input layer, output layer, and the inside layers. The network collects the information from input layer and output the processed information with output layer to provide useful outcomes.

The artificial neural network model provides a new tool to study the price movement of financial products and economic indices and numerous researches using artificial neural network model have been done on it [2, 3]. Some studies using artificial neural network model to focus on GDP growth rates predictions, CPI rates predictions and other major economic indices [4–8]. For economic activities, artificial neural network model has been used to predict of the default and bankruptcy for consumer borrowings, etc. [9, 10].

For financial instrument price prediction, a lot of studies utilize the huge amount of financial data and try to forecast the hidden relationships. For example, the price predication of financial derivative using artificial neural network model can provide suitable results comparing with close-formed option model [11]. There are various researchers using artificial neural network model for option pricing [12, 13]. By the degree of using the integration of the artificial neural network model. There are two major types of model: weak hybrid models and strong hybrid models [15, 16]. The prediction based on artificial neural network model for price movement is refined using traditional statistics models [16].

There are various research work on the prediction of major stock indices as well. For instance, Yao et al. [17] predict the price performance movements of Nikkei 225 index using artificial neural network model. Gradojevic et al. [19] using artificial neural network model based on the data of expire time and the moneyness of the underlying instruments to predict S&P-500 European options and empirical tests provided the proper results for the option pricing. Artificial neural network model with multiple levels of functions is used by Morelli et al. [18] to predict option price and forecast the hidden pricing movement relationship for financial derivatives and the option related variables. Shakya et al. [20] using artificial neural network models based on evolving algorithm to model demand scenarios and the results of the approach provide the proper price accuracy of the price predictions comparing with the traditional closed formed models.

There are numerous studies on option pricing based on the literature reviews, and our approach in the study applied artificial neural network model for the option pricing movements and compare with the short-term and long-term time periods. The paper focus on short term prediction because option prices and volatility in fact are very volatile and almost impossible to predict. The results show that neural network is able to predict option prices and volatility by using predictors constructed from the prices of option and its underlining index, especially in short term which is what financial practitioners care about more in the financial market trading.

DATA AND RESULTS

This paper studies the predictability of option close prices by using the "IO2003C4000" call option prices. That is said, the 2003 series of call option's underlined index is the CSI 300 Index and the strike price is 4000. The expiration date of the option is March 20th, 2020, the third Friday of the call option contract's expiration month. We also use the CSI 300 Index prices and other variables to construct several predictors which are used to predict the call option volatility by neural network. Our data set's frequency is by half hour (30 minutes), ranging from December 23th, 2019 to March 20th, 2020. In particular, we compute the following predictors: returns on the index, rolling volatility of index returns, implied volatility and implied prices of the option. Note that we set the risk-free rate to be 2% per year and assume no dividend when computing these predictors. The strike price is 4000. We compute rolling volatility of the index returns using prior 24 observations.

This paper uses the index price, index returns, rolling volatility of index returns, implied volatility and implied prices of the option to predict option prices by neural network. We use the first half of the data set to train the model and use the second half to test the model. We find that the neural network is expected to fit the data quite well in the train set as shown in Figure 1. Figure 2 shows that the model based on our predictors can predict the option prices in short term but cannot predict the prices well in long term. Figures 3 and 4 show the in-sample and out-of-sample prediction of neural networks on option volatility. We can see that the predicted volatility fits the true volatility quite well and the predicted one is able to predict the trend of the option volatility out of sample.

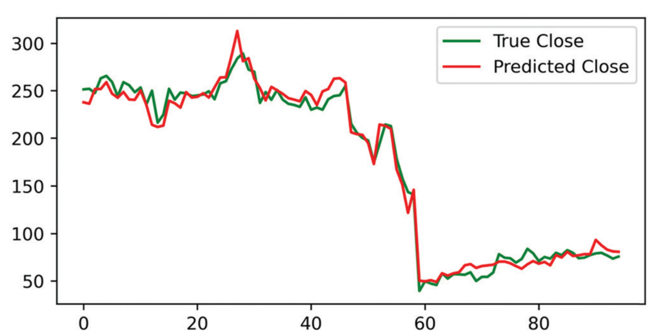

Figure 1. True and predicted close prices (in sample).

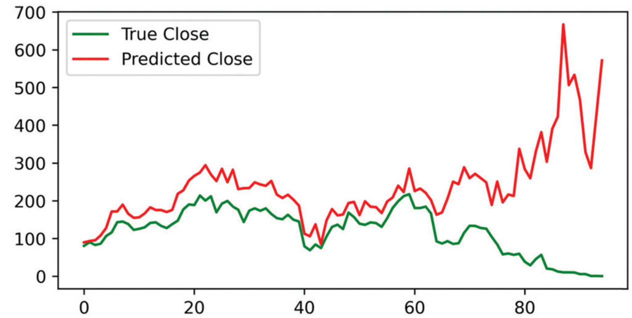

Figure 2. True and predicted close prices (out of sample).

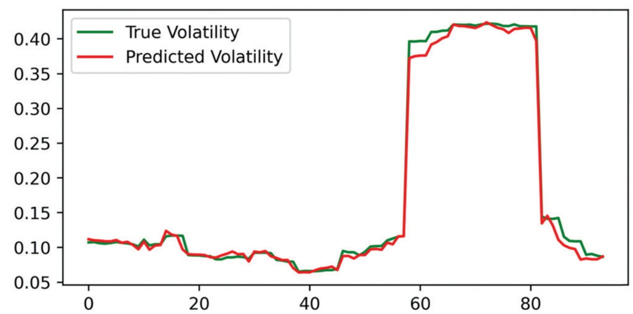

Figure 3. True and predicted volatility (in sample).

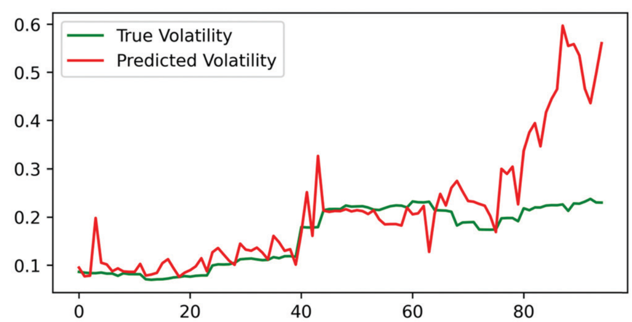

Figure 4. True and predicted volatility (out of sample).

We also conduct research on predicting option returns. At least for our data, we find that neural network with predictors constructed above is not able to predict the option returns. We conjecture that is because the option return is very volatile and computing return by inter differentiation makes the process lose a lot of memory which is very important for prediction. We are able to predict prices because the price process keep memory. One might suspect that the price process is unstable in the long run. We note that we focus on short run prediction in the option cases. Therefore, the unstable price process is not a big issue in this case. Also, the results on volatility prediction show that neural network is able to prediction the uncertainty on option markets.

CONCLUSION

The artificial neural network model provides a new tool to study the price movement of financial products. Our approach in the study applied artificial neural network model for the option pricing movements and compare with the short-term and long-term time periods. The paper focus on short term prediction because option prices and volatility in fact are very volatile and almost impossible to predict. The results show that neural network is able to predict option prices and volatility by using predictors constructed from the prices of option and its underlining index, especially in short term.

Since the Shanghai Shenzhen 300 stock index option started only from December 2019 and not much study has been done on the artificial neural network model on forecasting the stock index call option prices, our research approach develops an approach to examine the Chinese market which is an imperfect market. The test outcoming of our approach indicates that neural network with predictors constructed above is not able to predict the option returns in the stock index option and we conjecture that is because the option return is very volatile and computing return by inter differentiation makes the process lose a lot of memory which is very important for prediction. On the other hand, we are able to predict prices because the price process keep memory. One might suspect that the price process is unstable in the long run. We note that we focus on short run prediction in the option cases. Therefore, the unstable price process is not a big issue in this case. Also, our results show that neural network is able to predict option volatility.

For the future improvement of our artificial neural network model, we will combine the artificial neural network with the traditional statistical models such as GARCH for the optimization for the stock indices options, and we will examine the data in various financial markets and further study the long term trend in term of the price movements in the derivatives markets.

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