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Prediction of Oil Price Using LSTM and Prophet

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ABSTRACT

With the fast development of the economy and industry, the demand for oil is increasing and the oil trade is becoming more and more frequent. And the oil price tends to be closely related to economic developments. So grasping the direction and trend of oil price is of great significance to the development of the world economy. In this paper, we selected the LSTM and Prophet algorithm to do the oil price's prediction, to reach good results. RMSE and MAE are selected to represent the prediction's precision. The RMSE and MAE values of LSTM are the smallest when setting the time_step as 10, which are 3.741 and 3.109 respectively. Values of Prophet are 3.212 and 2.471 respectively, which indicates that the prediction effect of Prophet is better.

Keywords: Oil price prediction, LSTM, Prophet

1. INTRODUCTION

As non-renewable energy, oil has been playing an important role in industrial production and development, and occupies a dominant position in the world energy system. Oil is also the lifeblood of economic development, the production and price of oil affect the stability and development of the economy at any time. In recent years, oil prices have maintained an upward trend while fluctuating greatly. And this provides an unstable factor for economic development, leading to global economic turmoil. Therefore, the prediction of oil price has become the focus of energy research, which can effectively ensure the stability of oil price and economic development.

In this paper, algorithms based on deep learning and machine learning are applied to the prediction of oil price, and it is found that the trend of oil price can be predicted with high precision. This will be of some help to both the country and enterprises. Therefore, the research significance of this paper is shown as follows:

(I) Predicting oil price trend can help countries formulate and adjust energy policies, which can effectively avoid political and economic risks associated with oil price fluctuations.

(II) Enterprises can adjust their development strategies according to the fluctuations of oil prices and make appropriate business plans to ensure profits.

2. RELATED WORK

The prediction of oil price has always been the hot spot and focus of researchers. With the development of artificial intelligence (AI) and computer technology, machine learning has been applied to the analysis and prediction of oil price. The commonly used algorithms include support vector machine (SVM), logistic regression (LR) and Long Short-Term Memory (LSTM). Moreover, it is found that machine learning algorithms have better effect and accuracy than other methods mentioned above.

Abdullah *et al.* have used artificial neural network (ANN) to analyze quantitative oil price data[1]. Kulkami and Haidar proposed the method of multilayer feedforward neural network (FNN) for oil price prediction [2]. Kaboudan uses genetic algorithm (GP) and ANN to predict oil prices [3]. Although machine learning can provide better models and more accurate results for non-linear prices data, it also has many disadvantages, such as overfit, a large number of parameters, parameter sensitivity. In order to overcome the above shortcomings, some hybrid models have been proposed and achieved good results. Amin-naseri and Gharacheh proposed a hybrid method based on FNN, genetic algorithm (GA) and K-means to predict the month data of international oil prices, which is superior

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to representative models [4]. Shabri and Samsudin constructed a PCA-PSO-MLR model based on wavelet decomposition for oil price prediction [5]. And being compared with MLR, ARIMA and GRRCH models, the experimental results show that this model is superior to single model in oil price prediction. Yu *et al*. constructed an AI model based on compressed sensing, which is an effective and robust oil price prediction method by eliminating noise from the original timing sequence through CSD [6].

3. MATERIALS AND METHODS

3.1 Materials

In order to obtain enough and accurate oil price data, we downloaded the oil price of 2003-01-02 to 2021-9-10 (Per Day) [7] from OPEC (Organization of the Petroleum Exporting Countries). Although data for some dates are not gotten, it does not affect the overall trend of oil price. The data downloaded from the website is XML format, and we converted it to CSV format for subsequent use.

There are 4,756 sets of oil price data, each representing the price of oil on a given day. We use 90% of them as training sets and 10% as test sets. Therefore, there are 4298 sets of data in the training set and 457 sets of data in the test set.

3.2 Methods

3.2.1 LSTM

LSTM neural network was proposed by Hochreiter and Schmidhuber (1997)[8]. It can find sequence’s long-term dependencies well and is often used to deal with sequence information, especially time series information. The structure of LSTM contains a memory storage cell and three gates. The cell records the state of the neuron. Input and output gates are used to receive, export, and modify parameters. And forget gates are used to control the forgotten degree of the state of the previous unit.

In this paper, we use a two-layer LSTM network, and the Dense layer is used for the output layer. In Tensorflow, the Dense layer is equivalent to the fully connected layer (FC). The purpose of dense layer is to do nonlinear changes on the features extracted previously and extract the correlation between these features, while finally mapping the correlation to the output space. Specific details about layers and data shape of each layer are shown in the Table. 1. We used the ADAM optimizer to optimize our algorithm, which combines the advantages of AdaGrad and RMSProp. Root Mean Squared Error (RMSE) and Mean Absolute Deviation(MAE) are selected as the loss function.

Table 1 Specific information about LSTM network

Layer(Type)	***Output Shape***	***Parameters***
Input Layer	(64, *time step*, 1)	0
LSTM_1	(64, *time step*, *time step*)	480
LSTM_2	(64, *time step*, *time step*)	840
Dense	(64, *time step*, 1)	11

3.2.2 Prophet

Prophet is an open source algorithm about time series prediction algorithm by Facebook [10]. Being compared with the traditional time series prediction algorithm, it has better adaptability on changepoint and mutation effect. In addition, the results with missing values and outliers are also robust. Time series forecasting is now widely used in various fields by using prophet, such as stocks, website traffic, oil and so on.

Prophet is a time series prediction model based on self-added model. The model is made up of three parts: Growth $g(t)$, seasonality $s(t)$ and holidays $h(t)$. The specific analytical formula is as follows:

$$P(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{1}$$

$g(t)$ is the core part of the model to realize the prediction, which mainly contains the parameters to make assumption of different degrees and adjust the smoothness of the curve. Growth obtains the variation trend from ChangePoint. *g(t)* can be expressed as follows:

$$g(t) = \frac{C}{1+e^{(-k(t-b))}} \tag{2}$$

Where C is the capacity of model and k is the increasing rate, while b being the bias. With time t increasing, the value of g(t) will get close to C.

Seasonality S(t) represents the periodic components of the data, which are represented by Fourier series:

$$S(t) = \sum_{n=1}^{N} (a_n cos(\frac{2\pi nt}{T}) + b_n sin(\frac{2\pi nt}{T})) \tag{3}$$

Holidays $h(t)$ represents contingencies in the data and has separate models, each of which sets a virtual variable.

$$h(t) = \sum_{i=1}^{L} k_i \cdot 1(t \in D_i) \tag{4}$$

$$Z(t) = [1(t \in D_1), \ldots, 1(t \in D_L)] \tag{5}$$

$$h(t) = Z(t)k \tag{6}$$

Where k_i *represent the impact of holidays in window period on prediction,* D_i *is the* i_{th} *virtual variable and Z(t) is the indicator function.*

3.2.3 RMSE and MAE

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}[(h(x_i) - y_i)]^2} \quad (7)$$

Where $h(x_i)$ *is the prediction value and* y_i *is the actual value, m is the total number of samples.*

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|h(x_i) - y_i| \quad (8)$$

Where $h(x_i)$ *is the prediction value and* y_i *is the actual value, m is the total number of samples.*

RMSE and MAE can both effectively reflect the difference between the actual value and the prediction value, which is the measure of the predicted result at the mean time.

4. RESULTS AND DISCUSSIONS

4.1 LSTM

As mentioned above, there are 4298 sets of data in the training set and 457 sets of data in the test set. And test data are belonging to 2019-09-02 to 2021-6-10. We use LSTM algorithm to train the training set and get the prediction model. Then the prediction effect of the model is verified by the test set.

In LSTM algorithm, the most important parameter is time_step, which is the key factor that affects the prediction effect. LSTM combines long-term and short-term memories, and time_step is the parameter that determines short-term memory. For example, if time_step=3, the prediction value for a given day (D_i) depends on the values of the previous three days ($D_{i-1}, D_{i-2}, D_{i-3}$). In order to study the influence of time_step on the results, we selected that time_step are equal to 10, 20 and 30 respectively. Table shows the prediction effect (RMSE and MAE) with different time_step values. According to Table 2, RMSE and MAE values are the smallest when time_step=10. Figure 1 shows the visual result when time_step=10.

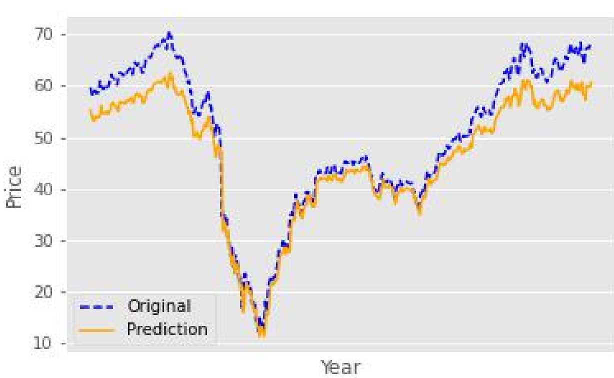

Figure 2 Prediction result of LSTM

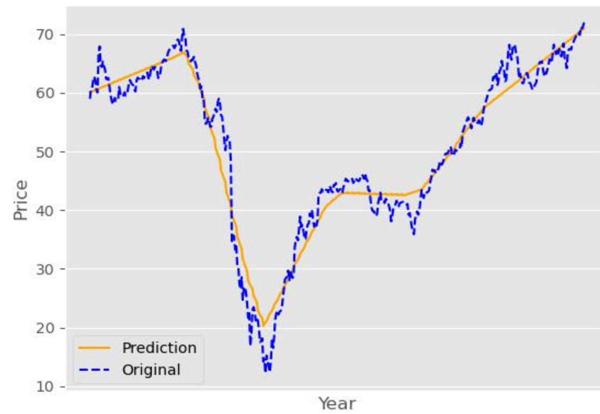

Figure 3 Prediction result of Prophet

Table 2 RMSE and MAE values of LSTM

Time_step	*RMSE*	*MAE*
10	3.741	3.109
20	4.419	3.493
30	3.928	3.207

4.2 *Prophet*

Prophet's development team (Facebook) takes a similar way to Scikit-Learn for users when providing open source projects. They integrate complex network structure settings and parameter settings. Users just need to call function *Prophet()* from python library fbprophet and use *.Fit()* command to run the prediction algorithm.

The Table 3 shows the result value of RMSE and MAE when using Prophet to make prediction. And Figure 1 also shows the visual results of it.

Table 3 RMSE and MAE values of Prophet

RMSE	*MAE*
3.212	2.417

4.3 Comparison between results of LSTM and Prophet.

According to the comparison between LSTM's and Prophet's results (RMSE and MAE), we found that Prophet had better prediction effect than LSTM. According to their results figure, the prediction result of LSTM at the initial time and the end time is very poor, which is far from the actual value.

5. CONCLUSIONS

In this paper, we selected LSTM and Prophet algorithms to predict the price of oil, both of which achieved good results. The RMSE and MAE values belonging to LSTM reach the best when the time_step is equal to 10, which are 3.741 and 3.109 respectively. The results of Prophet are 3.212 and 2.471 respectively, which shows that Prophet has a better effect in this work. The above results show that these two algorithms are of great help to the prediction of oil prices. Countries can make policies and plans according to the prediction of oil prices, which is conducive to keep world economic and political stable. In addition, these two algorithms can be used to make predictions in other fields when the data belongs to time series, such as stock and website traffic.

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