Crude Oil Price Prediction

Category: Artificial Intelligence

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LITERATURE SURVEY :

The following literature surveys have been done by referring to papers related to "crude oil price prediction". The papers that implement or compare results from various models for price prediction are used for this literature survey.

1. **"A comparison between AdaBoost-LSTM and AdaBoost-GRU for improving forecast prediction". Ganiyu Adewale Busari, Dong Hoon Lim. (2021) [1]**

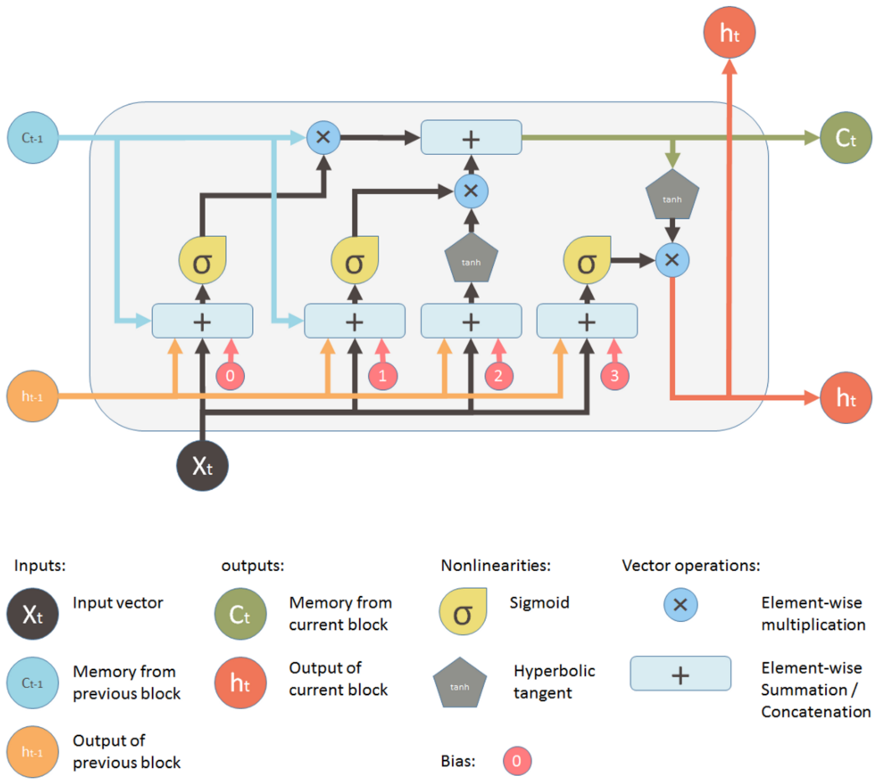
   Initially, many models such as Autoregressive Integrated Moving Average (ARIMA), Random Walk (RW), generalized autoregressive conditional heteroskedasticity (GARCH), Vector autoregressive (VAR) model, and Error Correction (ECM) model have been used to predict the crude oil prices. But some models like ARIMA assumed a linear relationship and failed to capture the complexity and non-linear nature of the crude oil price. Thus currently many non-linear relationships learning artificial neural networks (ANN) and deep learning networks are used for predictions.

   Even though neural networks can be used to learn the non-linear relationships between the input variables, they cannot remember the previous inputs. Thus they fail to predict a sequence of values. For such cases, Recurrent Neural Networks (RNN) can be used for the purpose of prediction. Either the input, output, or both in the RNN can be a sequence or a single value. But at least one of them has to be a sequence. But RNN has a vanishing gradient problem. In order to overcome this problem, two variants of RNN are used viz., Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU). This paper aims to compare the performance of both LSTM and GRU in predicting crude oil prices.

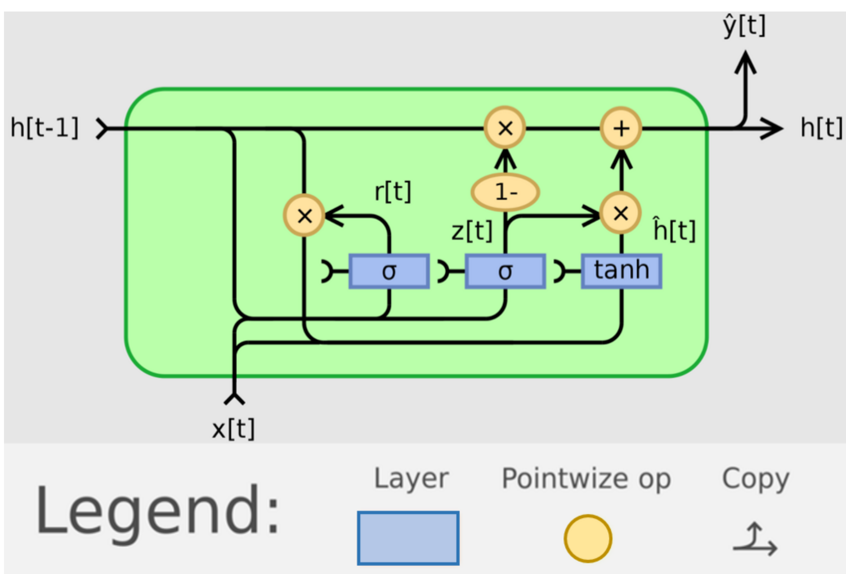
   LSTM is a variation of the vanilla RNN, where it uses three gates to control the flow of data, thereby preventing vanishing gradient problems and exploding gradient problems. The three gates are:

   1. Input gate
   2. Output gate
   3. Forget gate

The forget gate in LSTM decides the information to pass through or the information to throw away from the cell state, the input gate determines what new information should be stored in the cell state while the output gate regulates what each cell produces.[5]



GRU:



$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z)$$
$$r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r)$$
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \phi_h(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h)$$

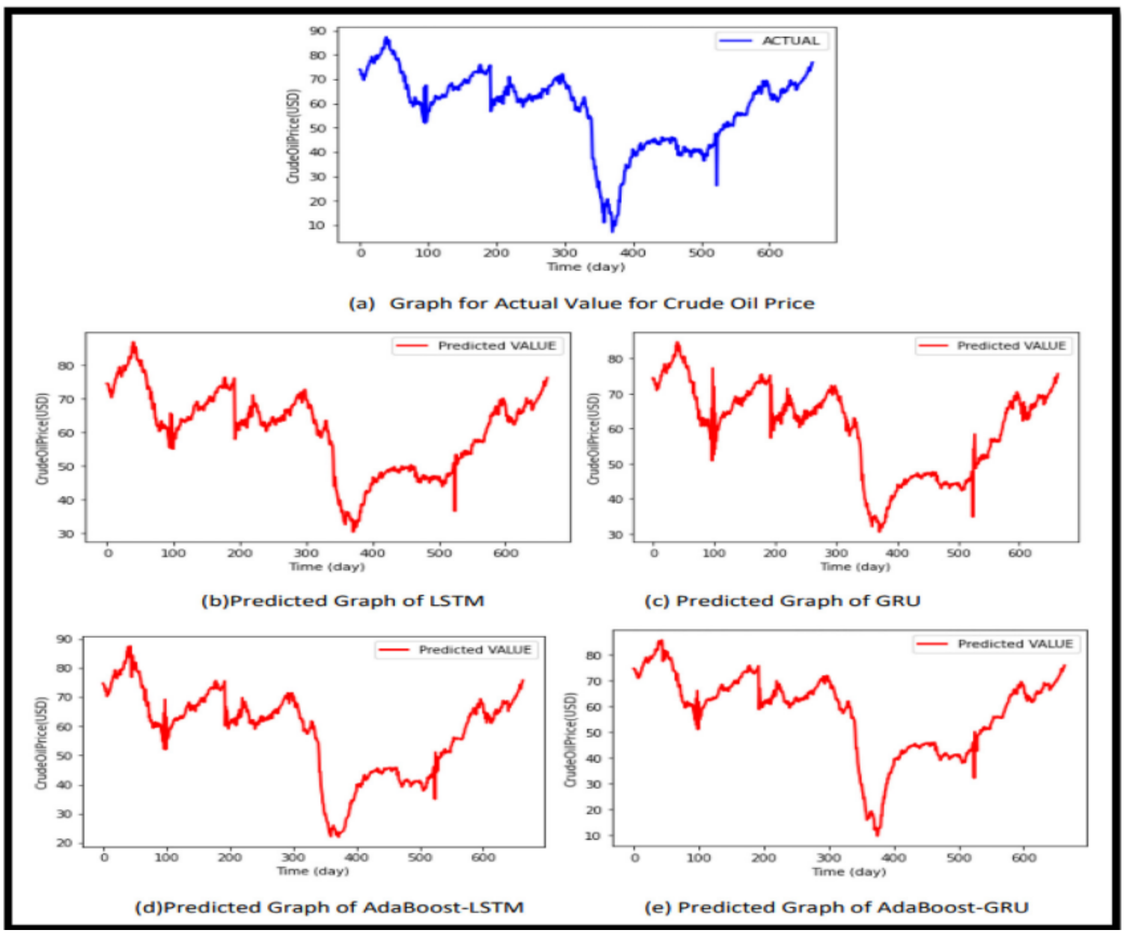
GRU layers work by using the same principle as LSTM, but it merges the input gate and the forget gate, also merges the cell state and the hidden state. Therefore, the GRU can be described as a simpler gating mechanism that requires fewer parameters than the LSTM.

The GRU consists of a reset gate and an update gate [6]. The reset gate mats the new input to the previous memory. That is, it decides how much previous information should be forgotten. The update gate, on the other hand, defines the amount of the previous memory to store.

Method

For better working of the ANN, the data needed to be preprocessed. For that purpose the data were normalized to the range [-1,1], using the min-max normalization method. During the prediction, a window size of 5 is used. Thus the sixth value is predicted using the first 5 values. Similarly, the seventh value is predicted from the second to sixth values. For this prediction process, they have used keras, sklearn and NumPy for implementing the required functions.

The resultant values from the models are depicted in graph form for easier understanding.



(a) Graph for Actual Value for Crude Oil Price

(b)Predicted Graph of LSTM

(c) Predicted Graph of GRU

(d)Predicted Graph of AdaBoost-LSTM

(e) Predicted Graph of AdaBoost-GRU

METRICS	LSTM	GRU	AdaBoost-LSTM	AdaBoost-GRU
MAE	3.2925	3.0372	1.6374	1.4164
RMSE	5.5120	5.2622	3.0161	2.4602
SI	0.722	0.0689	0.0395	0.0322
MAPE	0.1162	0.1071	0.0540	0.0354
WMAPE	0.0573	0.0529	0.0285	0.0247

These are the metrics used to measure the effectiveness of each model. And the values from the models have been tabulated above.

Conclusion

The results obtained indicate that the performances of the models are consistent with the single models having lower performances compared to the hybrid methods that show improved results. While a single GRU is better than a single LSTM, in this paper, the AdaBoost-GRU ensemble model that robustly delivers the smallest errors is superior to all of them including AdaBoost-LSTM. Consequently, the AdaBoost-GRU ensemble-learning model of all other models is a promising approach to forecasting crude oil prices.

2. **"Crude Oil Price Prediction Using LSTM Networks".Varun Gupta, Ankit Pandey. (2018) [2]**

Experiment with different types of models using different epochs, lookbacks, and other tuning methods

The proposed architecture :

- consists of four layers of LSTM layers followed by a dense layer with ten neurons and at the end dense layer with only one neuron.
- All the inputs to the proposed network were normalized to achieve the best results

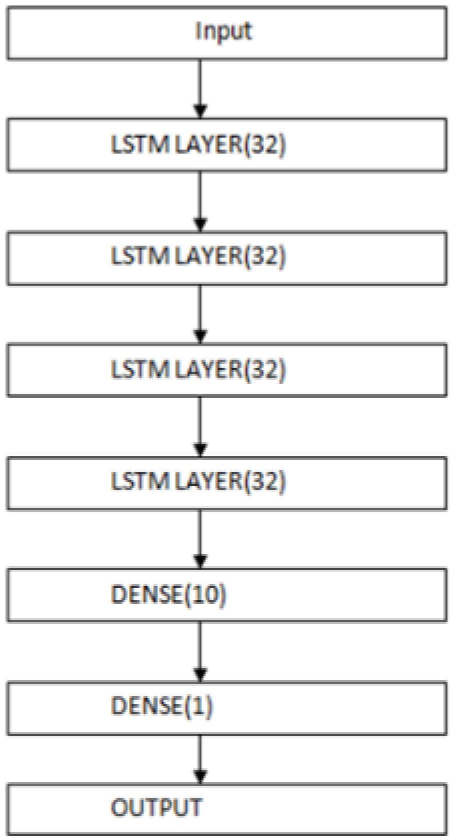


Fig. 5 Proposed Architecture

Dataset :

“Crude Oil Dataset” accessed online from https://www.kaggle.com/victor7246/weeklydatacommodity on 25-Dec2017

Different configurations of the network were tested

- Four LSTM layers were used with a lookback of 10 and 100 epochs. The training score obtained was 224.19 RMSE and the testing score was 550.50 RMSE
- 6 LSTM layers with 20 lookback and 100 epochs. The result of experimentation was that the training score obtained was 235.12RMSE and the testing score obtained was 793.24RMSE
- These results showed that with an increase in lookback, the accuracy of the network actually decreased
- Three LSTM layers with a lookback of 10 and 100 epochs were used and the training score obtained was 269.17 RMSE and the testing score obtained was 566.34 RMSE

RESULTS OBTAINED FOR VARIOUS CONFIGURATIONS OF THE PROPOSED NETWORK

LAYERS (LSTM)	LOOK BACK	EPOCH	TRAIN (RMSE)	TEST (RMSE)
4	1	100	240	608
4	20	200	226	727
4	20	100	247	824
4	10	100	224.19	550.5
6	20	100	235.12	793.2
3	10	100	269.1	566.3
4	10	100	283	532

conclusion :

- The results indicate that large lookups do not necessarily improve the accuracy of the predictions of crude oil prices.
- lookups up to the value of 10 are ideal for crude oil price prediction purposes.
- increasing the number of LSTM layers does not have much impact on the accuracy of the results

3. **"Crude Oil Price Prediction using Artificial Neural Network" - Nalini Gupta, Shobhit Nigam. [3]**

Crude oil is one of the most significant sources of energy available today. With over a third of all energy consumed worldwide, it continues to be the most popular fuel. In the current environment, when technology is taking over our lives and efforts are being made to reduce the need for human labor, the Artificial Neural Network Technique has emerged as one of the most valuable techniques for data prediction. This paper offers a method for predicting oil prices that uses an artificial neural network (Sigmoid Function with the Learning Algorithm). Complex and non-linear interactions between input and output can be modeled using ANNs. The ability of ANN to generalize allows it to infer relationships even in the absence of data or input after learning from the inputs. A trustworthy method for creating predictions, ANN also learns from hidden relationships in the data without imposing any fixed relationships on the data. Many economists and analysts forecast the price of crude oil using data transformation and regression techniques like autoregressive moving average (ARMA) models and vector autoregressive (VAR) models, each time using a different input value. They then plot the graph with their forecasted prices while considering the main economic factors.

Proposed Model:

An ANN performs its task by taking in examples and when given an input pattern, a neural network's goal is to create or build an output pattern. To optimize the

performance of the network, we employ the back-propagation learning technique, which propagates the error signal through the network in a backward direction. The process is repeated until the network can deliver the desired results. The four phases of the predictive model are a collection of data, normalizing the data, activating the function, and training the algorithm. Here, the suggested model is utilized to forecast the crude oil closing price. Using the Root Mean Square Error, the suggested model's performance has been assessed (RMSE).
Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{n}\ (y_i - \hat{y}_i)^2}$$

Result:

In this study, the objective of identifying the most advantageous lag in the data on crude oil prices is given to an artificial neural network model. This study shows that by selecting the best lags, the ANN model can be used well for short-term price forecasting and for predicting the price of crude oil. The results obtained utilizing the suggested model have greatly outperformed, and we have since validated our findings by measuring the root mean square error.

4. **"Crude Oil Price Forecasting based on Support Vector Machines". [4]**

The crude oil price is basically determined by its supply and demand. But more strongly influenced by many irregular past/present/future events like weather, stock levels, GDP growth, political aspects, and so on. At first, we proposed a new integrated methodology TEI@I methodology, and showed a good performance in crude oil price forecasting with a back-propagation neural network (BPNN) as the integrated technique. But BPNN is susceptible to over-fitting problems. So we proposed a support vector machine, a novel neural network algorithm.

Why SVM?

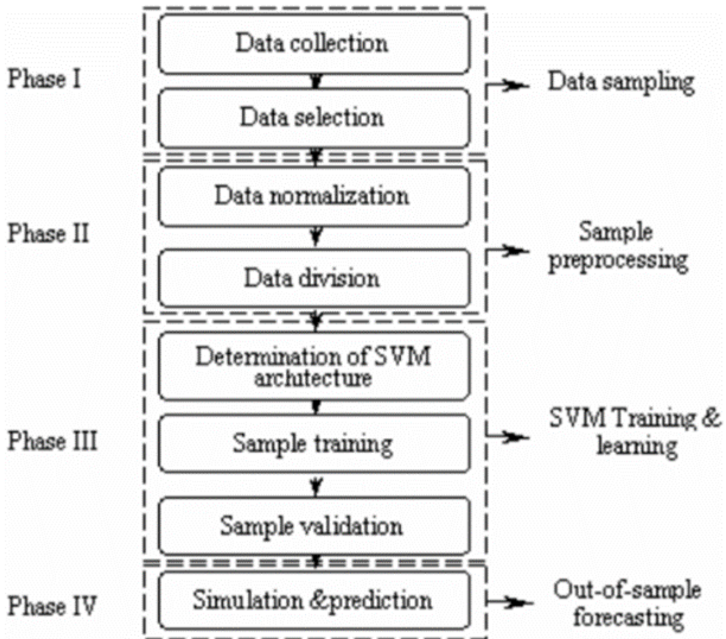
SVM is resistant to the over-fitting problem and can model nonlinear relations in an efficient and stable way. Furthermore, SVM is trained as a convex optimization problem resulting in a global solution that in many cases yields unique solutions. SVM has been extended to solve nonlinear regression and time series prediction problems, and they exhibit excellent performance. The goal of this paper is to propose a new method based on SVM for the task of crude oil price time series prediction. In addition, this paper examines the feasibility of applying SVM in crude oil price forecasting through the contrast with ARIMA and BPNN models.

Method:

SVM are linear learning machines which means that a linear function is always used to solve the regression problem. When dealing with nonlinear regression, SVM map the data x into a high-dimensional feature space via a nonlinear mapping ϕ and makes linear regression in this space.

$$f(x) = (\omega \cdot \varphi(x)) + b$$

It involves four steps:



(a) Data sampling. A variety of data can be collected for this research, such as WTI, NYMEX. Data collected can be categorized into different time scales: daily, weekly and monthly. For daily data, there are various inconsistencies and missing points for the market has been closed or halted due to weekends or unexpected events. As a result, weekly data and monthly data should be adopted as alternatives.

(b) Data pre-processing. The collected oil price data may need to be transformed into a certain appropriate range for the network learning by logarithm transformation, difference or other methods. Then the data should be divided into in-sample data and out-of-sample data.

(c) Training and learning. The SVM architecture and parameters are determined in this step by the training results. There are no criteria in deciding the parameters other than a trial-and-error basis. In this investigation, the RBF kernel is used because the RBF kernel tends to give good performance under general smoothness assumptions. Consequently, it is especially useful if no additional knowledge of the data is available. Finally, a satisfactory SVM-based model for oil price forecasting is reached.

(d) Future price forecasting.

Conclusions:

It has been shown in the literature that support vector machines can perform very well on time series forecasting. The largest benefit of SVM is the fact that a global solution can be attained. In addition, due to the specific optimization procedure it is assured that over-training is avoided and the SVM solution is general. In this paper, we propose a new method for predicting crude oil price time series based on support vector machines. There exist four phases when developing a SVM for time series forecasting: data sampling, sample preprocessing, training & learning and out-of-sample forecasting. The results show that SVM is superior to the other individual forecasting methods in monthly oil price prediction.

References:

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