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FORECASTING GOLD FUTURES PRICES CONSIDERING THE BENCHMARK INTEREST RATES

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Abstract. This study uses the benchmark interest rate of the Federal Open Market Committee (FOMC) to predict gold futures prices. For the predictions, we used the support vector machine (SVM) (a machine-learning model) and the long short-term memory (LSTM) deep-learning model. We found that the LSTM method is more accurate than the SVM method. Moreover, we applied the Boruta algorithm to demonstrate that the FOMC benchmark interest rates correlate with gold futures.

1. Introduction

Gold is one of the popular safe assets in terms of economic instability, and it is the preferred option for investors seeking wealth accumulation and an alternative to the uncertainty of money. Furthermore, investors often use gold as a hedge against inflation and predict crude-oil prices using gold prices [4]. In this context, the development of methods to predict the price of gold futures is one of the important research themes in financial engineering.

However, because of the volatility of gold futures data and the complexity of the market, it is very difficult to predict gold futures prices. Therefore, researchers have recently applied various machine-learning methods to generate these predictions. In this regard, Grudnitski and Osburn [1] used an artificial neural network to predict the monthly prices of Standard and Poor's 500 index and gold futures . Nikou et al. [6] evaluated the prediction power of machine-learning models in the stock market. The data used in their study included the daily close price data of

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the iShares MSCI United Kingdom exchange-traded fund from January 2015 to June 2018. Their findings demonstrated that the long short-term memory (LSTM) model afforded better predictions than other methods, with the support vector machine (SVM) ranked second in the list of neural networks and random forest methods that afforded small errors. Das et al. [7] found that the SVM technique outperformed the backpropagation (BP) method in predicting the futures prices traded in the Indian stock market. Karmiani et al. [8] studied the use of the BP, SVM, LSTM, and Kalman filter approaches to predict the stock market. The LSTM afforded the highest accuracy and low dispersion, although it was slower than the BP approach. In addition, a t-test analysis of the prediction results confirmed that LSTM and BP are more reliable than SVM. In this context, here, we consider the U.S. benchmark interest rates in predicting the price of gold futures by further developing on previous approaches.

The U.S. benchmark interest rate, which significantly impacts global economic conditions, is determined at regular meetings of the Federal Open Market Committee (FOMC). In this regard, Jang et al. [5] studied the relationship between energy prices and anticipated changes in monetary policy during the times of FOMC announcements. They found that the energy market experienced abnormal price movements before scheduled FOMC announcements; these movements were correlated with the FOMCs monetary-policy decisions on the following day. Against this backdrop, in this study, we predict the price of US gold futures using the SVM and LSTM models and compare their prediction performances. In addition, we use the Federal Reserve Bank rate as an index to improve the overall prediction accuracy of the model.

The remainder of this manuscript is organized as follows. Chapter 2 briefly examines the correlation between gold and oil through correlation analysis. Chapter 3 introduces the SVM and LSTM approaches for forecasting gold futures prices. Chapter 4 introduces the preprocessing method and the Boruta algorithm. The results of the feature selection with the use of the Boruta algorithm are discussed. Chapter 5 examines the prediction results obtained with the SVM and LSTM models, and Chapter 6 presents our conclusions.

2. Preliminaries on Machine Learning and Deep Learning

In this chapter, we briefly review the machine-learning and deep-learning techniques used to predict gold futures prices.

SVM is a machine-learning algorithm used alongside random forest methods for many classification and regression problems. The commonly used SVM was proposed by Cortes et al. [9], and it has been successfully applied to a number of real-world problems such as the recognition of handwritten characters and digits. The SVM algorithm creates a non-probabilistic binary linear classification model that determines the classification category of the new data based on a given dataset. The basic concept underlying SVM is the measurement of the distance between each data point in the two categories of interest to estimate the center between the two data points. The two categories are subsequently divided by the optimal hyperplane from the center, where the hyperplane forms the criterion for classifying the data. Among the various hyperplanes, the hyperplane with the closest vector and the longest vertical distance is called the maximum-margin hyperplane. The vector closest to the maximum-margin hyperplane is called the support vector. The SVM can also be used for nonlinear classification. In such cases, it is necessary to map the data for a given nonlinear classification into a high-dimensional space, and this mapping is performed using the kernel method. The most commonly used kernel methods are linear, polynomial, and radial basis functions. These functions determine the learning of the hyperplane [14].

The LSTM model was proposed by Hochreither and Schmidhuder [11] to address the vanishing gradient problem in recurrent neural networks. The LSTM comprises the cell and hidden states. The cell state remembers certain values, whereas the hidden state sends information to the next processing unit.

The LSTM can be expressed as the following set of functions

$$\begin{aligned}
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f)\\
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i)\\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o)\\
g_t &= \tanh(W_{xg}x_t + W_{hg}h_{t-1} + b_g)\\
C_t &= f_t \circ C_{t-1} + i_t \circ g_t\\
h_t &= o_t \circ \tanh(c_t).
\end{aligned}$$

The first LSTM unit is the forget gate that determines whether the cell state is remembered. In this unit, f_t is calculated and applied to the weighted sum of the bias to determine the amount of information to forget. The second unit is the input gate, wherein g_t and i_t are calculated; the functions g_t and i_t decide the amount of new information

Table 1. Elementary Statistics of Gold Futures (1Toz=31.1034768g and *=$/1Toz)

	Price*	**Open***	**High***	**Low***	**Volatility (%)**
mean	1333.43	1281.57	1285.82	1277.35	0.85
std	93.82	109.06	108.92	109.22	6.28
min	1070.80	1053.70	1062.00	1046.2	0.00
25%	1280.20	1209.70	1214.80	1205.13	0.01
50%	1329.95	1275.25	1279.80	1270.53	0.05
75%	1384.40	1334.30	1338.18	1330.88	0.22
max	1587.40	1584.50	1590.70	1572.00	129.00

to be accessed. The next unit is the output gate, which determines the value that utilizes the information in the cell state. In this unit, the o_t form is calculated, wherein o_t decides the amount of information of the output. The final unit is the hidden state, wherein h_t is calculated. Thereafter, the tanh activation is applied to the cell state, and the result is sent to the output gate.

3. Materials and Methods

3.1. Data Sets

The historical data of gold futures and FOMC interest-rate data were downloaded from the website named investing.com. The historical data of gold futures include parameters such as the Price, Open, High, Low, Vol, and Change, whereas the FOMC interest-rate parameters include Actual, Forecast, and Previous. Here, the units of Price, Open, High, Low, and Vol are troy ounces, which is the unit of gold futures price, and the Change, Actual, Forecast, and Previous values are expressed in units of %. These data were collected from January 2015 to December 2019 and classified into training data from January 2015 to December 2018 and test data from January 2019 to December 2019. Table 1 lists the elementary statistics related to gold futures.

3.2. Preprocessing Method

Neural networks learn from input variables to generate output variables. However, the use of unscaled variables may lead to unstable, slow, or failed learning. In addition, unscaled variables can lead to gradient vanishing and gradient expansion. To solve this problem, all the inputs are required to be in a comparable range. The preparation of the data before using them to train a model is called data preprocessing. In this study, we used the data preprocessing method called standardization.

Standardization transforms the input data such that the resulting distribution has a mean of 0 and a standard deviation of 1. The data center is transformed by deleting the mean of each feature and adjusting each feature by applying a standard deviation. Standardization can be expressed as follows:

$$X' \triangleq \frac{X - \mu}{\sigma} \tag{3.1}$$

where X denotes the original feature vector, μ is the expectation of the feature vector, and σ is its standard deviation.

3.3. Boruta Algorithm

The Boruta algorithm proposed by Kursa et al. [12] is a random-forest-based variable selection technique. The Boruta algorithm is based on the idea of the "restoration extraction of existing variables to generate shadow characteristics, and variables with less influence than shadow characteristics do not have a significant effect".

The Boruta algorithm consists of the following steps:

1. Certain variables that were previously and automatically created using the Boruta feature selection are deleted.
2. The shadow features for the input variables are created through restoration extraction and added to the input variables.
3. Iterations are continued until all variables are classified based on their significance level (0.01) by hypothesis testing via the binomial distribution. The algorithm stops when the maximum number of iterations is reached.
4. Hypothesis testing is performed through corrections based on the Bonferroni correction or Benjamini–Hochberg false discovery rate (FDR).

The Bonferroni correction and the Benjamini–Hochberg FDR are statistical inference methods that correct errors that may occur in multiple comparison problems. These are statistical reasoning methods that are widely used for controlling Type 1 errors. The Bonferroni correction addresses Fasten Type 1 errors in the whole test. Meanwhile, the Benjamini–Hochberg method is used to estimate the FDR as follows:

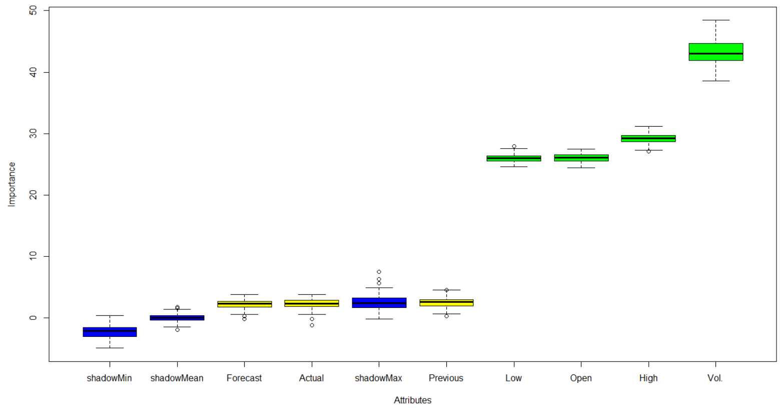

FIGURE 1. Feature importance of Boruta (Original Data)

DEFINITION 3.1. *The FDR can be defined as*

$$\mathrm{FDR} \triangleq \frac{\text{False Positive}}{\text{Total Positive}}$$

where (Total Positive) $\triangleq$ (False Positive) + (True Positive).

The Benjamini–Hochberg procedure [13] consists of the following steps:

1. Determine the α value, where α is FDR.
2. Test H_i based on the corresponding p-values, namely, P_i, and sort the p-values in ascending order for each $i \in \{1, 2, \cdots, k\}$.
3. Set $j \triangleq \max\{i : P_i \leq \frac{i}{k}\alpha,\ i = 1, 2, \cdots, k\}$.
4. Then, reject all H_i for $i \in \{1, 2, \cdots, j\}$.

4. Results

4.1. Results of Boruta Algorithm

This section discusses the feature-selection results of gold futures prices obtained with the use of the Boruta algorithm. In this study, we used the Boruta open-source library for our feature-selection experiments.

Figures 1 and 2 show the experimental results obtained using the Boruta algorithm. Figure 1 shows the original data, that is, the unprocessed data applied to the Boruta algorithm, whereas Figure 2 shows

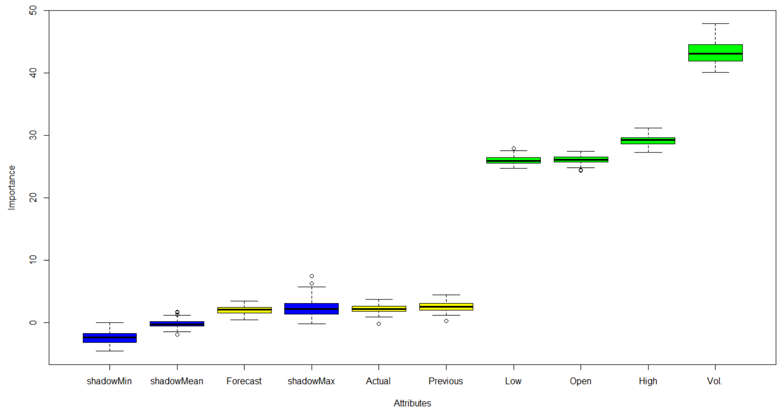

FIGURE 2. Feature importance of Boruta (Standardization Data)

the results obtained with the standardization data set. In both these figures, Previous, Low, Open, High and Vol are commonly selected as meaningful variables. However, in Figure 2, we note that Actual is additionally selected. Because the units are different, the results of scaling through standardization in Figure 2 and Figure 1 exhibit a difference. Considering these two sets of results, we can conclude that the variables of Previous, Low, Open, High, and Vol are strongly correlated with the price of gold futures.

4.2. Evaluation Index

In this study, we used the root-mean-square error (RMSE) as an index to evaluate the model performance. In the case of RMSE, the error is weighted when compared with the mean absolute error (MAE) via the squaring of the error. In other words, when compared with MAE, RMSE is more sensitive to errors.

DEFINITION 4.1. RMSE *can be defined as follows:*

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

where n *represents the # of observations,* $\hat{y}_i$ *the predicted value, and* y_i *the observed value for* $i = 1, 2, \cdots, n$.

4.3. Forecasting Results Obtained with SVM

Here, we discuss the SVM prediction results and our analysis of the SVM predictions of the gold futures prices. In this study, we used the open-source machine learning analysis library (Sklearn 0.20.3) for our SVM experiments. SVM was implemented via the support vector regression (SVR) of the Sklearn library. The SVM parameter was selected as the poly kernel with degree 3. The free parameters in the model are C and epsilon. Table 2 lists the RMSE obtained for various SVM-parameter settings. The smallest RMSE obtained with the SVM is 124.83. Figure 3 shows the best prediction results for gold futures prices with the use of the SVM.

Table 2. RMSE According to Parameter of SVM

RMSE	$\epsilon = 0.1$	$\epsilon = 0.3$	$\epsilon = 0.5$	$\epsilon = 0.8$	$\epsilon = 1.0$
C = 0.1	139.98	135.34	131.47	125.64	126.80
C = 0.3	139.43	135.26	131.39	125.13	126.63
C = 0.5	139.36	135.21	131.43	125.04	126.43
C = 0.8	139.29	135.16	131.74	**124.83**	126.42
C = 1.0	139.17	135.35	131.91	125.08	126.24

4.4. Forecasting Results Obtained with LSTM method

In this section, we discuss the gold-futures-price prediction results obtained using the LSTM method. For the LSTM experiments, we used the open-source deep-learning analysis library (Keras 2.1.2, Tensorflow 1.4.0), and LSTM was implemented via the Keras library of Python.

Figure 4 shows the loss and validation data loss obtained for the LSTM learning process. We note that the loss is sufficiently reduced for epochs ¿25. Therefore, we estimated the optimal epoch number via the confirmation of the prediction performance. Thus, the number of epochs was varied as 200, 500, 1000, 2000, 5000, and 10000. The best prediction performance was obtained with 200 epochs. Moreover, the batch size was set between 300 and 400. In general, larger batch sizes afford increased learning stability.

Figure 5 shows the gold-futures-price forecasting results obtained with LSTM. The orange curve represents the actual price of gold futures, whereas the blue curve represents the LSTM-predicted values. Upon comparing Figures 3 and 5, we note that the LSTM prediction results are significantly more accurate.

FIGURE 3. Gold-futures-price predictions obtained with SVM. The horizontal axis indicates days (from January 2015 to December 2019), and the vertical axis represents \$/1 Toz (1 Toz = 31.1034768 g).

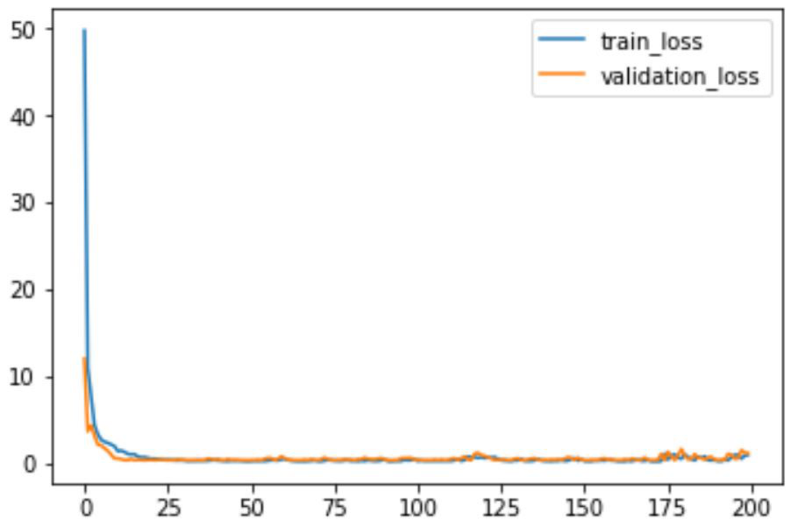

FIGURE 4. Training and validation losses obtained for LSTM

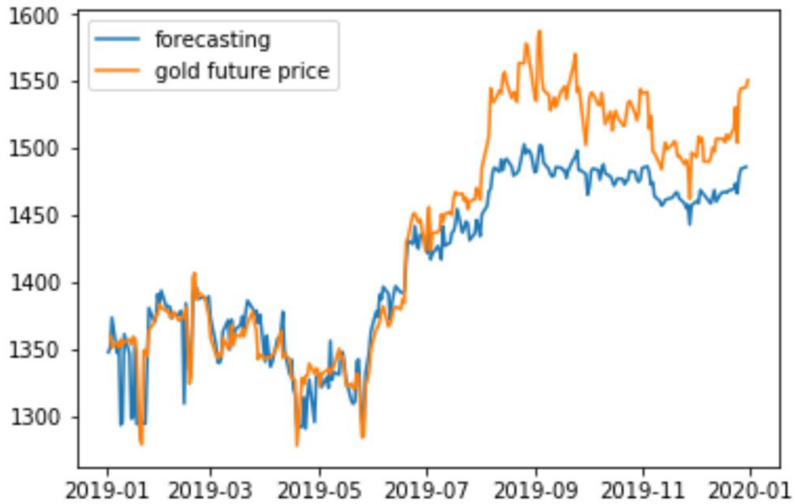

FIGURE 5. Gold-futures-price forecasting results obtained with LSTM. The horizontal axis indicates days (from January 2015 to December 2019), and the vertical axis represents \$/1Toz (1 Toz = 31.1034768 g).

5. Conclusion and Future work

The main findings of this study are as follows: (i) Using the Boruta algorithm, we confirmed that the interest rates are strongly correlated with gold futures prices. (ii) When we applied the benchmark interest rate variable to LSTM and SVM, the LSTM outperformed the SVM in forecasting.

Our approach can further be developed to predict not only the price of gold futures, but also the prices of important traded items such as crude oil, silver, and copper on exchanges. In future, we also plan to specifically examine the impact of the benchmark interest rate on the futures market.

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