QUANTUM-INSPIRED FOR PREDICTIVE ANALYTICS IN MARKET VALUATION

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ABSTRACT

Because of the multifactorial and non-linear nature inside the gold market, it is difficult to predict the gold price. The gold price is affected by many external elements, including market environment, economic crises, oil price increases, tax advantages and interest rates. Therefore, multivariate models can better predict the gold price than univariate models. This study investigated the effects of gold price, crude oil price, consumer price index, exchange rate index, stock market index, and interest indicators between 2001 and 2021. Models created using LSTM, Bi-LSTM and GRU methods were evaluated using lowest Root Mean Square Error (RMSE), The metrics Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE). LSTM model performed best, with

3.48 MAPE, 61,728 RMSE and 48.85 MAE values.

Keywords: Gold Price, LSTM, Bi-LSTM, GRU.

1. Introduction

A chronological compilation of information about any given event based on time is called a time series. By examining past occurrences and transactions throughout time, time series analysis is a valuable method for drawing conclusions (Parmezan et al., 2019).

Future predictions can be made using relationships that are based on past events that have been observed consecutively.

When more than one time-dependent variable predicts the output, the time series is said to be multivariate (Nguyen et al., 2021). In other words, the calculation is based on correlations between variables—which are typically present—as well as past data. Including all important factors in the model rather than just one will yield better prediction results (Du et al., 2020). But in order to make an accurate prediction, it's crucial to choose the right set of factors (Munkhdalai et al., 2019).

Different time series analysis methods are used in the literature. The most commonly used methods for univariate analyses include linear regression, exponential smoothing and autoaggressive integrated moving average methods, such as ARIMA. ARIMA models, developed by Box and Jenkins, are the most commonly used method. However, these models are not sufficient for nonlinear time series (Zhang, 2003; Shen et al., 2020). Instead, machine learning and neural networks are used in a wide variety of applications due to their superior ability to understand nonlinear relationships between complex inputs and outputs. The prominence of deep learning

(LeCun et al., 2015; Schmidhuber, 2015), with its strong representation, has brought different

applications in many fields.Temporal dependencies in time series are modeled by the Recurrent Neural Networks (RNN) Model. There is a gradient issue, though (Karim et al., 2019). Thus, the Long Short-Term Memory (LSTM) model was created by Hochreiter and

Schmidhuber which they presented as a new method. This adds a gate mechanism into the RNN layers to control information flow. By retaining knowledge of many previous timesteps, this method derives relationships from the information in older timesteps more effectively than traditional RNN. LSTM is also designed to store information better, thereby eliminating the short-term memory problem of standard RNN. (Gunduz, 2021). LSTM is utilized in numerous fields, but particularly finance (Alpay, 2020; Güleryüz and Özden, 2020; Aygun and Kabakcu Gunay, 2021; Yıldırım et al., 2021). In time series, the Gated Recurrent Units (GRU) approach is also often utilized. issues since its structure resembles that of LSTM (Shen et al., 2018; Dutta et al., 2020).

Gold is used in various industries, including electronics, aerospace, medicine and jewelry. It is also used as an investment tool. Gold is considered a precious metal for both its commodity and monetary qualities. It is simultaneously a commodity, a precious metal and a currency. Within the financial market, the gold market attracts great attention from individuals, institutional investors and governments. Gold is and has always been valued as a precious metal. It has also proven to have an exceptional capacity to hold onto its value through political, financial, and economic downturns. Global central banks have gold reserves to protect depositors' funds as well as that of external loan holders and holders of

foreign currencies. Gold reserves are another tool used by central banks to manage

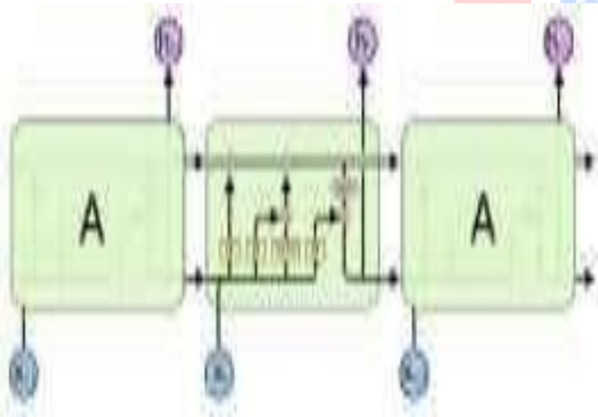
inflation.Although gold is notin existence anymore used as money, it is one of the most important commodities traded worldwide. For example, the best hedging tool is this one, especially for governments and central banks.

According to Dar and Maitra (2017), gold retains its value in times of economic crisis when the significance of other assets drops significantly. Because of its popularity and importance, forecasting gold prices is very important, not only for economists, but also for government treasury units, central banks, financial institutions and individuals.

Because of the global nature of the gold market, it is a fluctuating nonlinear system influenced by many factors As of 2019, Almameer et al. Consequently, the causes of gold price fluctuations are very complex (Livieris et al., 2020). Therefore, it is an opportunity to create models that can predict the future gold price.

Different models have been created by researchers to forecast the price of gold. While Yazdani-Chamzini et al. (2012) employed the Adaptive Neuro-fuzzy Inference System and Artificial Neural Network (ANN) model, which they compared to the ARIMA model, Parisi et al. (2008) used iterative and rolling neural network models. Li (2014) used a novel artificial bee colony algorithm with the wavelet neural network approach. Xian et al. (2016) created a gold price model using ensemble empirical model decomposition and independent component analysis while Gangopadhyay et al. (2016) used the vector error correction model. Sivalingam et al. (2016) developed extreme learning machines, which made used of the past prices of gold, silver and oil, the S&P 500 index and the exchange rate. Jianwei et al. (2019) presented a new combination based on independent component analysis and neural network techniques using gated recurrent units. Alameer et al. (2019) used an advanced multilayer neural network with perceptrons and whale optimization method.

Risse (2019) combined discrete wavelet decomposition and support vector regression methods. Hassani et al. (2015) used multivariate Bayesian autoregression (BAR) models and five variations of Bayesian VAR. Zhang and Ci (2020) used the deep belief network method while Weng et al. (2020) aimed to reduce the effect of randomness on prediction results by the use of a genetic algorithm and improved extreme machine learning.



Many empirical studies identified elements influencing the price of gold in order to estimate it. Statistical and econometric analyses suggest various explanatory variables. The link between gold and oil prices is typically positive in that crises tend to raise both (Shafiee and Topal, 2010; Yazdani-Chamzini et al., 2012; Chen and Xu, 2019). Similarly, Wang and Chueh (2013) concluded that gold and oil prices increase each other whereas interest rates and the US dollar reduces the gold price. Currency depreciations also make investors to turn to gold, which explains the negative relationship between the gold price and the exchange rate (Giannellis and Koukouritakis, 2019). Investors include gold in their portfolios to protect against inflation (Gokmenoglu and Fazlollahi, 2015).

Material and Method

2.1. LSTM, Bi-LSTM

The LSTM deep learning Hochreiter and Schmidhuber created the algorithm, a recurrent neural network, in 1997 to eliminate the disadvantages of RNN architecture. In the RNN approach, each item in the source data is iteratively examined by considering the value of the earlier output. In general, RNN is disadvantaged because gradients are lost when learning long data sequences. LSTM solves this issue by determining when certain information is used or not. An LSTM model consists of the input layer, hidden layers and output layer. Each block has several memory cells attached to it and three multiplier units, input, output, and forget gates. Depending on these components, the LSTM cell block contains a memory cell and three gates unit capable of forgetting or memorizing information to decide how much data should be moved to the following cell. The LSTM architecture is depicted in Figure 1.

Figure 1. LSTM Architecture (Olah, 2015).

The equations that perform these operations are as follows.

$$ft = \sigma(Wf * [ht{-}1, xt] + bf) \tag{1}$$

$$it = \sigma(Wi * [ht{-}1, xt] + bi) \tag{2}$$

$$\acute{C}t = tanh(WC * [ht{-}1, xt] + bC) \tag{3}$$

$$Ct = ft * Ct{-}1 + it * \acute{C}t \tag{4}$$

$$ot = \sigma(Wo * [ht{-}1, xt] + bo) \quad (5)$$

$$ht = ot * \tanh(Ct) \quad (6)$$

In order to get around the LSTM cell's inability to use the future while working with past content, Schuster and Paliwal (1997) introduced bidirectional recurrent neural networks, which are made up of two distinct LSTM hidden layers that have similar outputs but are oriented in opposite directions. In this architecture, the output layer makes use of both past and future data. In specifically, Bi- LSTM integrates the idea of time order by conducting learning in two directions: from the future to the past and from the past to the future.

2.1. GRU

A gate mechanism in the GRU model controls information flow, allowing context to be remembered across numerous time steps (Cho et al., 2014). It determines what historical data can be retained or deleted using an update gate and reset gate. Although GRU and LSTM are similar, GRU combines the input and forget gates of LSTM into a single update gateway. The reset gate determines how much information from the past is erased, while the update gate determines how much is passed on. A GRU unit's organization is depicted in Figure 2. Because of its extremely straightforward structure, GRU performs better than LSTM in terms of training time and prediction accuracy (Jianwei et al., 2019).

Figure 2. GRU Architecture

$$rt = \sigma(Wrht{-}1 + Urxt) \quad (7)$$

$$\hat{h}t = tanh(\mathrm{W}\,(rt * ht{-}1\,) + \mathrm{U}xt) \quad (8)$$

$$zt = \sigma(Wzht{-}1 + Uzxt) \quad (9)$$

$$ht = (1 - zt) * ht{-}1 + zt * \hat{h}t) \quad (10)$$

ht and $ht{-}1$ represent the output of the current and previous states, respectively while rt and zt indicate the reset and update gates, respectively. σ is the logistic sigmoid function while Wr and Ur are the weight matrices.

3.DATA

Five explanatory factors and 20 years of gold ounce price data (2001–2021) made up the study's data set. The price of crude oil, the consumer price index, the effective exchange rate, the effective federal funds rate, and the S&P 500 stock market index were the economic indicators that were employed. The price of an ounce of gold is said to be influenced by each of these factors. The price of one ounce of gold (Index Mundi, 2021) during a 20-year period is depicted Each and every model was trained using Python 3.6 on Microsoft Windows 10 operating system.

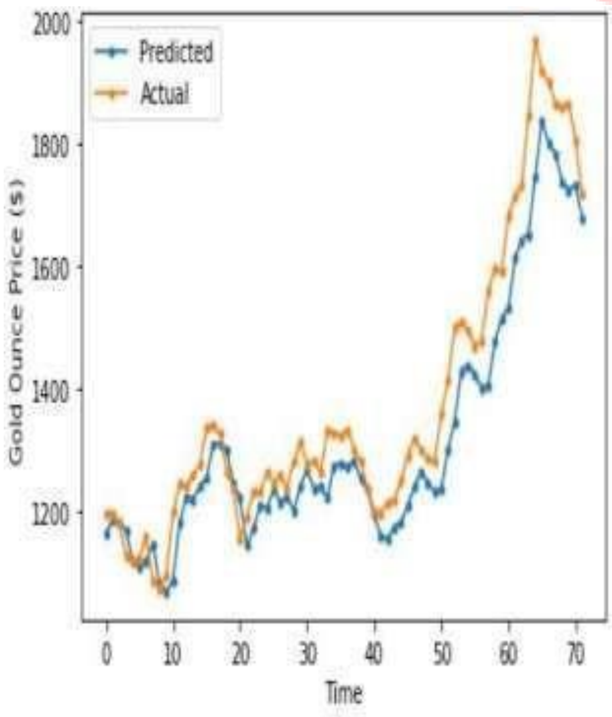
Data were rescaled between 0 and 1 by normalization. After normalizing the dataset before training and testing, the first 170 observations (70%), from January 2001 to January 2015, were allocated for training. Then, the last 72 observations (30%), from February 2015 to February 2021, provided the test data to validate the accuracy of the proposed model.

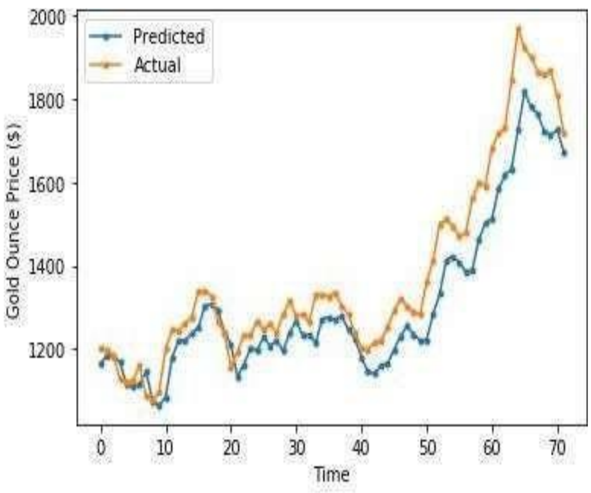
Variable	Frequency	Source
Consumer Price Index	Monthly	Organization for Economic Co-operation and Development (2021)
Effective Federal Funds Rate	Monthly	Board of Governors of the Federal Reserve System (2021)
Crude Oil Price	Monthly	U.S. Energy Information Administration (2021)
Real Broad Effective Exchange Rate	Monthly	Bank for International Settlements (2021)
S&P 500	Monthly	Yahoo Finance (2021)
Gold Price	Monthly	Index Mundi (2021)

RESULTS

A 6×244 data set covering January 2001 to March 2021was created with the five economic indicators and the gold ounce cost. In this investigation, the price of gold, which is important for decision makers, was estimated using deep learning methods. The values of the independent variables from one month ago were utilized to project the value of the dependent variable in the future. The input indicators served as the basis for the gold ounce price prediction. Across different experiments, the batch size and epochs directly affected the prediction accuracy. Some of the models that were tried while creating the model within the study are displayed in Table 3. LSTM produced the best RMSE, MAPE and MAE values, followed in ascending order by Bi-LSTM and GRU.

The performances of the models listed in Table 3 were calculated by contrasting the estimation outcome using the actual values. The model featuring the highest performance ratio is the 6th LSTM model.





Discussion and Conclusion

This compared the three performers' performances multivariate models (LSTM, Bi-LSTM and GRU) for predicting the gold price using monthly time series data. To evaluate their accuracy, MAE, RMSE and MAPE values were checked. Five economic indicators were used: interest rates, the price of crude oil, the consumer price index, the stock market index, and the effective exchange rate.Comparison of the actual gold price with each model's predicted values showed that LSTM performed best. The models also showed that economic indicators affect the gold ounce price, which is consistent with previous findings (Gokmenoglu & Fazlollahi, 2015; Sivalingam et al., 2016; Chen & Xu, 2019). Deep learning applications have been widely used in various fields of science in recent years. In this context, the field of finance has also started to use deep learning applications effectively. The main reason for this is the highly volatile nature of financial markets and their capacity to be affected by many variables. The results suggest that LSTM, Bi-LSTM and GRU are all satisfactory estimators for the ordinal data used in this study.

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