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Gold Commodity Price Prediction Using Tree-based Prediction Models

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Abstract: Commodity price forecasting is always a matter of research for practitioners and academia as a non-linear price structure of commodity with large volatility is associated with it. The efficiency of price prediction systems has been proven with the recent expansion of Artificial Intelligence and enhanced capabilities of computational equipment. Machine Learning (ML) is widely used in predicting the prices across the markets. Though a variety of ML methods are in use to predict commodity prices in recent times, this paper attempts to predict gold commodity closing prices specifically using tree-based models including Decision Tree, Adaptive Boosting (AdaBoost), Random Forest, Gradient Boosting, and eXtreme Gradient Boosting (XGBoost). The inputs to each of the prediction models were chosen from a total of nine technical indicators such as Simple 10-day moving average, Weighted 14-day moving average, Momentum, Stochastics K%, Stochastic D%, Relative Strength Index (RSI), William's R%, Moving Average Convergence Divergence (MACD) and Commodity Channel Index (CCI) and four metrics namely RMSE, MAE, MSE and R^2 were analysed for each technique of all the tree-based models considered and which were internally competing to explain superior forecast. All four metrics were calculated to check the effectiveness of different prediction models.

Keywords: *Commodity Price, Gold, Machine Learning, Price Prediction, Tree-based Model*

1. Introduction

The commodity market is a very unpredictable and complex investment choice as it can offer both high risks and huge returns, drawing the attention of large number of investors, speculators, hedgers and arbitragers. Because of the commodity market's imprecise, complex, unpredictable, and vague characteristics, predicting its future is a difficult task. National and International commodity exchanges play major role in the price discovery of various commodities. Commodity price prediction is similar to stock price prediction in terms of the application of various technical analysis indicators usages. Many researchers in past have narrated various tools to predict uncertain prices of stocks and commodities. Logistic regression is even used for trading in stocks to optimise the risk-return framework [1]. However, it is a very challenging task to analyse any price movement behaviour in a highly volatile market. Therefore, there is a need for robust predictive modelling that can assist investors to identify and segment high-performing securities thereby making good investment decisions [2]. With general economic conditions and commodity price indices in changing expectations of traders, it is extremely difficult to understand the traders' psychology that affects the price movements [3]. There are two main approaches for predicting market movements i.e. Fundamental and Technical Analysis. Fundamental Analysis helps investors to project long-term movement by examining basic demand and supply forces of commodities in broader economic and industry set-up. Technical Analysis involves analysis of historical prices such as open, close, volume, and adjusted close price for predicting the prices.

With the advent of technology, the forecasting has now gone beyond the simple computing and now algorithms are in popularity that uses various fundamental and technical indicators for predicting the markets. Machine learning (ML) is a complex technology that allows a range of algorithms to improve a model's performance in a given case study. Machine learning is thought to have a great ability to recognize reliable data and find patterns in a dataset [4]. Gold is the oldest form of currency used in international trade settlements and domestic savings purposes. A country like India has the dual purpose of investment and consumption in holding the gold by households. Gold is still used as the safest investment by Indian investors and has given sustainable returns over a period of time. Even, the central banks are also holding gold as reserves for foreign transactions like debt repayments or import bills. It is also used to control the inflation and money supply in the economy to stabilise confidence and improve the economic indicators. Gold price movements are crucial for investors as their trading strategies are based on price trend predictions. It is extremely important for investors to identify the correct time to enter and exit from gold investment to make maximum profit with minimum risk. Investors are always trying to understand the factors that influence gold prices. The major factor is the high demand for gold due to consumption and investment where the production of gold via mining is very limited. Inflation

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also influences the gold price as gold is used as hedging against inflation by large number of investors. Similarly, interest rate structure in the economy also affects the gold price in inverse proportion. The exchange rate of INR against USD also influences the gold prices. Finally, the domestic demand due to festivals and marriage ceremony also affect gold prices. Government policy about gold import and duty structure also affect the gold demand in domestic market.

According to ANZ analysts, Daniel Hynes and Soni Kumari, “Aggressive monetary tightening, rising yields and a stronger dollar are key drags for the gold prices. Rising inflation failed to impress the market, instead raising fears of a more hawkish stance by the central banks. That said, the spread between the Fed funds rate and CPI is at its widest, suggesting the Fed is struggling to contain inflation.” The same is the case with India, where the Reserve Bank of India (RBI) is planning to increase repo rate in response to curb the inflation. This will finally lead to changes in gold prices.

We have tried to forecast the gold prices with various indicators suggested by the technical analysts using different tree-based machine learning algorithms. The various algorithm results are then compared to find the optimum solutions. This paper tries to predict gold prices using such tree-based models. The review of the literature is discussed in section 2. The section 3 explores the tree-based models and the methodologies employed in each. The section 4 explores the details of the result acquired by employing various plots for tree-based models. The conclusion is found in section 5, while the references are included in the last section.

2. Literature Review

The majority of the researchers in this domain are using the stock market to predict the prices using Artificial Intelligence (AI) and Machine Learning (ML) approaches. Only few studies like Livieris [5] have used gold prices for the prediction. Table I summarizes the various ML techniques used for the prediction purposes. Stock market forecasting employing AI and ML approaches like Random Forest (RF), Support Vector Machine (SVM) [6] have shown encouraging results. Long Short Term Memory (LSTM) and Artificial Neural Network (ANN) too have showed promising results [7][8]. The k-NN algorithm uses this output, combined with past stock prices, to forecast future stock prices. Table I shows the results of our comprehensive study on stock market prediction using machine learning, including technical indicators, multiple prediction methodologies, and performance criteria.

Using a variety of tools and techniques, many researchers have attempted to build a prediction model based on machine learning algorithms to accurately estimate prices, but still the best and optimum forecast is not made. Table I describes the machine learning methodologies that the researchers have used to estimate market trends and prices using ML and AI algorithms, taking into account the comprehensive details, features, and factors involved. Even after examining the primary influencing factors, a reliable price forecast is impossible. Support Vector Machine (SVM), Random Forest (RF), Boosted Decision Tree (Boosted DT), and other significant techniques are discussed in the literature. Though, according to their assessing variables and the datasets utilized for their research, each model has its own merits and demerits over the others. Some models are more effective when using historical data, while others are more effective when using technical indicators. We incorporate the essential technical analysis indicators for the prediction of gold commodity prices. As presented in Table I, most of the technical analysis indicators are used in stock market prices data and few are using commodity prices data for prediction of price trends. Basic price data like open, low, high and close is also used by many researchers. This gives enough rational for using technical analysis indicators presented in Table II for prediction model. Technical indicators are always giving superior information compare to basic price data in estimation modelling.

3. Methodology

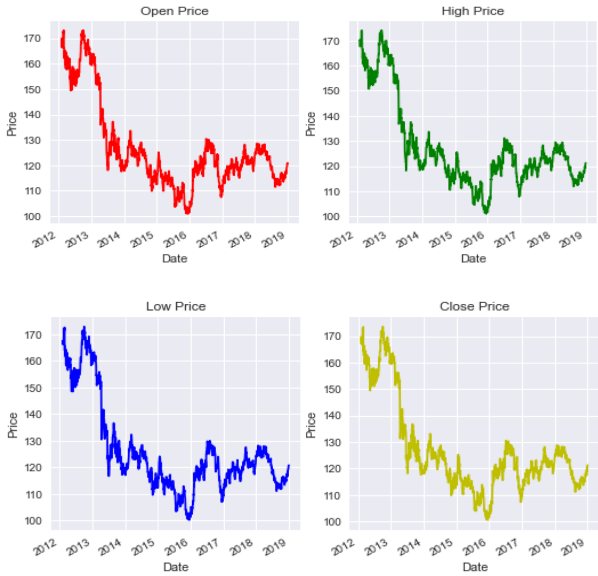

Fig. 1 Historical Prices of Gold commodity during year 2012 to 2019

3.1. Data Description

Between 18th November, 2011 to 1st January, 2019, the data for this study was gathered. The total data comprised of 1685 records. This data included volume, high, low, open, close of gold commodity. Fig. 1 represents the trends of historical prices of gold commodity prices during the period from 2012 to 2019.

3.2. Technical Indicators

Following new technical indicators are calculated from historical data. Because of their summative depiction of patterns in time series data, technical indicators have been widely employed for price prediction in stock and commodity markets. In some studies, many types of technical indicators, including trend, momentum, volatility, and volume indicators, were investigated [28]. Additionally, a variety of technical indicators have been combined in numerous studies to forecast market trends. Nine technical indicators were used in the study, and the results, which represented the closing prices for the following day, were derived from historical price data. Using historical gold price data, the various technical analysis indicators are calculated as shown in Table II and the descriptive statistical summary of nine technical indicators are given in Table III. Fig. 2 displays the trends of all technical indicators such as RSI, CCI, 10-day Simple Moving Average (SMA), 3-day Weighted Moving Average (WMA) during the year 2011-2019.

3.3. Tree-based Models

Decision Tree (Benchmark Model): A common supervised learning method for classification and regression task is use of decision trees. The objective is to create prediction model that can forecast a gold price using fundamental decision-making guidelines derived from data attributes. On the one hand, there are some advantages to using this method, such as its ease of understanding and interpretation or the ability to solve problems involving several outputs [29].

Random Forest Regression: For most regression issues, the random forest regression approach is appropriate. In comparison to a single decision tree, an ensemble model of several decision trees is more reliable and effective. Each tree in this method is trained on the subset of the dataset. In order to reduce overfitting, the random forest algorithm combines many decision trees with randomness.

AdaBoost Regression: AdaBoost is an effective prediction model that improves learning problem accuracy by overcoming the limitations of weak regressors such as ridge, linear, lasso and SVR regressors. The output of the weak regressor is combined with the output of the boosted strong regressor using AdaBoost to create a weighted sum that reflects both [30].

Table 1. Review of machine learning forecasting models, technical indicators and performance criteria

Authors	***Data used Companies /Index***	***Prediction Methods***	***Technical Indicators***	***Performance Criteria***
Vijh, M., et. al., [9]	Nike, Goldman Sach, JP Morgan Chase and Co., Johnson and Johnson, Pfizer	ANN, Random Forest	High-Low, Open-Close, 7 - days MA (Moving Average), 14 - days MA, 21 - days MA 7 – days SD (Standard Deviation)	RMSE, MAPE
Parmar. I. et.al., [10]	NA	Regression, LSTM	Open, Close, High, Low, Volume	RMSE, MSE
Reddy V.K.S. [11]	IBM	SVM	Sector and Price volatility and momentum	log2c, log2g
Usmani. M. et.al., [12]	KSE-100	SVM (Support Vector Machine), SLP (Single Layer Perceptron), MLP (Multi-Layer Perceptron), RBF (Radial Basis Function),	Oil Prices, Gold Prices, Silver Prices, Rate of Interest, FOREX Rate, SMA, ARIMA, KIBOR, Text feeds from News and Media	Accuracy
M. Umer Ghani et.al., [13]	AMAZON, FB, APPLE, GOOGLE	Linear Regression, 3 month moving average, Exponential smoothing	Open, Close, High, Low, Volume	RMSE, MAE
Moghar A. et. al., [14]	Google, NIKE	LSTM, RNN	Open, Close, High, Low, Volume	Loss
Pahwa, K., & Agarwal, N. [15]	Google	SVM	High-Low Adj_close, Open-close, Adj_Volume	R^2, Adjusted R2, RMSE
Ravikumar, S., & Saraf, P. [16]	S&P500	Linear Regression, Polynomial Regression, SVR, DTR, RF	Open, Close, High, Low, Volume	Accuracy
Mokhtari, S. et.al., [17]	NASDAQ	LSTM	SMA (Simple Moving Average), EMA (Exponential Moving Average), RSI (Relative Strength Index, MACD (Moving Average Convergence and Divergence), OBV (on-balance-volume)	RMSE, MAE, R^2, MAPE
Naik, N., & Mohan, B. R. [18]	NSE	ANN	SMA, WMA, MOM, RSI, MACD, CCI	MAE, RMSE
Nikou, M., et. al., [19]	iShares MSCI United Kingdom	ANN, SVM, RF, LSTM	NA	RMSE, MSE
Livieris, I. E. [20]	Gold Prices	CNN-LSTM	Open, Close, High, Low, Volume	MAE, RMSE, ACCURACY, PRECISION, RECALL
Hiransha, M. [21]	NSE	MLP, RNN, CNN, LSTM	Open, Close, High, Low, Volume	MAPE
Nandakumar, R. [22]	Dixon Hughes,Cooper Tire & Rubber, PNC Financial,CitiGroup, Alcoa Corp	ANN, LSTM	Open, Close, High, Low, Volume	RMSE
Roondiwala, M., et.al., [23]	NSE	LSTM, RNN	Open, Close, High, Low, Volume	RMSE

Nabipour, M., et. Al., [24]	Tehran Stock Exchange	DT, bagging, RF (Adaboost), GBM, XGBoost , ANN, RNN, LSTM	WMA, ADO, LWR, SIG, STCK, RSI, SMA, MOM, SIG, STCD	MAE, RMSE, MSE, MAPE
Sadorsky, P. [25]	Solar stock prices	RF, Bagging, SVM, Extremely randomized tree	MA200, MA20, WAD, silver price volatility, oil price volatility	NA
Kilimci, Z. H [26]	Gold prices	Linear Regression, polynomial regression, RF, DTR, SVR, Voting Regression, Stacking Regression	Open, Close, High, Low	MAPE
Stokanovic Sevic, J [27]	Gold Prices	DTR, SVR, k-NN, Linear regression	Open, Close, High, Low, Covid-19	MSE, MAE, RMSE, R2

Table 2 Technical Analysis indicators and their description

Sr. No	Technical analysis Indicator	Description
1	Simple 10-day moving average	This indicator can be used to predict whether a price will continue on its current path. SMA = $\frac{A_1 + A_1 + A_1 + \cdots + A_n}{n}$, where A_n is closing price at period *n* and *n* is number of periods.
2	Weighted 14-day moving average	WMA determines a "weighted average" of the previous *n* prices, with the weights getting smaller with each price before it.
3	Momentum	Since MOM tracks the rate at which prices rise or fall, it is a very useful tool for assessing price strength or weakness. $Momentum = C_t - C_{t-n+1}$ where C_t is the closing price at time *t*.
4	Stochastics K%	Closing price is compared to its price range using a momentum indicator over a predetermined time frame. It is possible to reduce the oscillator's sensitivity to changes in the market by altering the time period or utilizing a "moving average" of the data.
5	*Stochastic D%:*	It evaluates the relationship between the closing price and the size of price fluctuations over time. This indication is based on the upper half of the price movement area from the previous period, and that when prices decrease, the opposite will be true. An indicator of momentum called LWR evaluates oversold and overbought levels. On occasion, market exit and entrance times are calculated using LWR.
6	*Relative Strength index (RSI):*	Another popular momentum indicator that is frequently employed in technical analysis is the relative strength index. The indicator, which has a range from 0(oversold) to (overbought), is frequently used to pinpoint overbought and oversold conditions in an investment (overbought). $RSI = 100 - \left[\frac{100}{1+RS}\right]$ (1) where $RS = Average\ \left[\frac{x\ day's\ UP\ Closing\ price}{x\ day's\ Down\ Closing\ price}\right]$ (2)
7	*William's R%:*	The market entry and exit points can be determined using this indicator. A momentum indicator, the William R% traves overbought and oversold levels and has a range of 0 to -100. Similar to the stochastic oscillator, the indicator compares the closing price to the high-low range over a predetermined time period, typically 14 days or intervals.
8	*Moving Average Convergence Divergence (MACD)*	The indicator establishes the distinction between a short-and long-term moving average. The formula is calculated using (3) and (4). $MACD = [0.075 * E] - [0.15 * E]$ (3) $where\ E\ is\ EMA(Closing\ Price)$ $Signal\ Line = 0.2 * EMA\ of\ MACD$ (4)
9	Commodity Channel Index (CCI)	The Commodity Channel Index is created by dividing the mean price by the average of the means over a certain period of time. The average difference over time is contrasted with this difference. Calculating commodity volatility involves evaluating the variances between the averages. The output is multiplied by a constant to make sure that most numbers fall within the standard range of +/-100. $CCI = \frac{(M_t - SM_t)}{0.015 * D_t}$ (5) $M_t = \frac{H_t + L_t + C_t}{3}$ (6) $SM_t = \sum_{i=0}^{n} M_{t-1}$ (7) $D_t = \sum_{i=0}^{n-1} \lvert M_{t-1} - SM_t \rvert$ (8) The 0.015 constant ensures 70 to 80 percent of CCI values fall within the +100 to -100 range.

Table 3 Descriptive statistics of nine financial indicators

	Min	Max	Mean	STD
SMA-10	102.101000	171.875000	126.842141	17.180170
WMA-14	101.420000	172.990001	126.732125	17.120149
MOM	-22.029998	10.839996	-0.115739	2.322667
STCK	-72.245048	78.714247	9.995169	33.104487
STCD	-57.673180	74.558773	9.981896	30.230201
WillR	-100.00000	0.000	-51.72961	31.337595
RSI	0.991253	100.00000	48.720846	20.71417
MACD	-4.323152	3.314851	-0.179859	1.217394
CCI	-245.81057	194.808057	-6.110688	87.036989

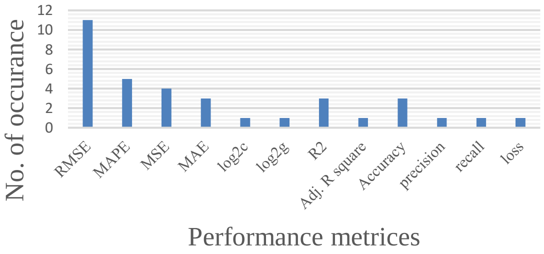

Fig. 2 Trends of technical indicators RSI, CCI, 10 days (SMA), 3-Day Weighted Moving Average (WMA)

XGBoost Regression: XGBoost provides good extension and flexibility of the boosting tree models by combining various tree models to create a more powerful model [31]. It was introduced by Chen and Guestrin [32] as a technique for forecasting output variables. It builds decision trees one by one, utilizing the residuals from the preceding tree to train each subsequent model (tree). To put it another way, before making a prediction, the new model fixes mistakes made by the previously trained tree [31].

4. Performance Metrics

To evaluate how well the models are performing, the comparative analysis is done between Random Forest Regression, AdaBoost and XGBoost on gold commodities using all three models. Mean Absolute Error(MAE), Root Mean Square Error (RMSE), and Mean Squared Error (MSE) are used to determine how effective a model is. A more effective model is indicated by smaller values for these metrics.

In comparison to other measures, MSE is the one most frequently used to assess regression models. It represents the square root of the actual value minus the projected value. It is punished when minor inaccuracy happens.

$$\text{MSE} = \boldsymbol{\frac{1}{n}\sum_{i=1}^{n}(y-yi)^2} \quad (8)$$

The "Root Mean Square Error" (RMSE) is very popular statistics for assessing regression models. It is the squared root of the sum of the squares of the difference between the predicted value by the model and the actual value. It is preferable in situations where significant errors are undesirable. It comes with a substantial cost because the errors are squared prior to averaging.

$$\text{RMSE} = \sqrt{\boldsymbol{\sum_{i=1}^{n}\frac{(y-yi)^2}{n}}} \quad (9)$$

The MAE refers to the difference between the actual and expected values. It is less susceptible to "outliers" and does not penalise "errors" as severely as "MSE". It isn't appropriate for applications that require you to pay careful attention to outliers. Because MAE is a linear measure with equally weighted individual differences.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y-yi| \quad (10)$$

R^2 is the proportion of MSE of the current model and baseline model. R^2 is scale-free score and it doesn't matter whether the values are too large or too small. R^2 will always be less than or equal to 1. It is also very popular measures for research community.

$$R^2 = \frac{MSE(model)}{MSE(baseline)} \quad (11)$$

It is evident from Fig. 3 that RMSE is the most popular metric. Most researchers also utilise other metrics, including as MSE, MAE, MAPE, and R^2 to gauge the effectiveness of price

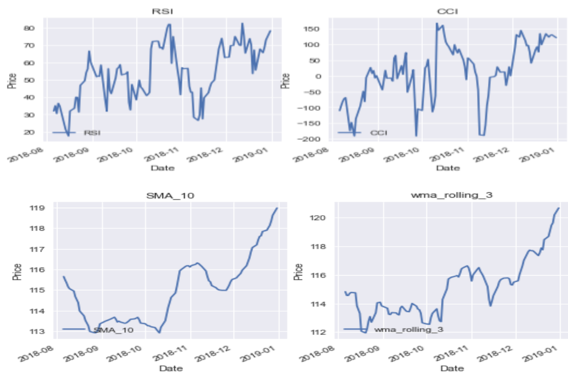

Fig. 3 Count of Performance Measures in the Literature Studies

prediction.

5. Results and Discussion

The model was trained for gold commodity prices which were available in a Comma Separate Values (CSV) file and then it was converted into pandas' data-frame using *pandas* library in python. After that, we have normalized data in 0 to 1 through usage of the *sklearn* library in python. We calculated nine indicators and removed all missing data. For training and testing, the data set was divided accordingly. The training set was 80% and testing set was 20% of the normalized datasets. The developed model was developed on Anaconda 3 Jupyter environment.

We used all 9 technical indicators as input features in this study, with a total of 1685 data points. Our main dataset was split into train and test data in order to prevent overfitting. We then fitted our models using the train data. Train data accounts for 80% of the primary dataset (1348 data points). With test data (337 data points), the models are then utilized to forecast future values and produce metrics. In addition, throughout training, we fine-tune our hyper-parameters (the training process for tree-based models).

Decision Tree is not an ensemble approach; hence it always has the lowest rank for prediction (MAE: 0.6572). Based on performance measures of all prediction model, GradientBoost performs better than Random Forest, Decision Tree, AdaBoost, XGBoost. Even after parameter tuning GradientBoost algorithm performs better than all predictive models as shown in Table V.

Fig. 4 Trends of Gold commodity predicted prices vs actual prices using Gradient Boosting Model

As shown in Fig. 4 the prediction is shown by red line and the actual trend is shown by blue using Gradient Boosting model. The proximity of these two lines tells how efficient the gradient boosting model is. The prediction approximates real trends when a considerable amount of time has passed.

Table 4 Performance Analysis of machine learning algorithm for gold commodity

	Performance Measures			
Prediction Model	**MAE**	**MSE**	**RMSE**	**R^2 Score**
Decision Tree Regression(base line Model)	0.65724	0.85527	0.92480	0.99724
Random Forest Regression	0.48068	0.50108	0.70787	0.99838
AdaBoost Regression	1.20650	2.30787	1.51917	0.99255
XGBoost Regression	0.47447	0.47521	0.68936	0.99846
Gradient Boost Regression	**0.47404**	**0.41996**	**0.64804**	**0.99864**

The Table IV shows comparative performance analysis of all five-machine learning algorithms for the gold commodity prices. It can be observed from the Table IV that gradient boost regression outperforms other tree-based models.

Table 5 Performance of Prediction model after parameter tuning

Prediction Model	**MAE**	**MSE**	**RMSE**	**R^2 Score**
Random Forest Regression	0.49868	0.51933	0.72064	0.99832
AdaBoost Regression	1.20935	2.33905	1.52939	0.99245
XGBoost Regression	0.49479	0.46366	0.68092	0.99850
Gradient Boost Regression	**0.36725**	**0.60601**	**0.42696**	**0.99881**

The Table V shows comparative performance analysis of all four machine learning algorithms for the gold commodity prices with hyper-parameter tuning. It can be observed from the Table V that gradient boost regression outperforms other tree-based models.

6. Conclusion and Future Research Directions

Forecasting market prices is crucial for traders and investors in order to identify profitable trades and minimise market risks. Tree-based models, viz. Decision Tree, Random Forest, AdaBoost, Gradient Boosting, and XGBoost were used for the present research work. The inputs for the prediction of gold commodity prices were technical indicators that had been exponentially smoothed. The strategies employed in this article for forecasting gold prices were able to dramatically increase performance levels. Gradient Boost Regression outperformed all others in the majority of the parameters. Overall, as a natural conclusion, tree-based algorithms demonstrated astounding potential in regression problems to forecast the future prices of gold. After considering the effects of the hyper-parameters on the findings, the Gradient Boost regression model outperformed all other models in terms of accurately forecasting gold prices with the 'lowest error' and 'best capacity to fit', by the average values of MAPE (0.49, 1.20,0.49,0.36). In the future, artificial neural network-based models will be developed with the same financial indicators for achieving better prediction results. Other deep learning based models such as LSTM, RNN can also be used for the prediction of gold commodity prices. We will also analyze how news affects the gold commodity prices using sentiment analysis through machine learning.

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