

Foreign Exchange Prediction

1st Akanksha Dewangan
Computer Science Engineering
Indraprastha Institute of Information Technology
Delhi, India
akanksha19049@iiitd.ac.in

2nd Priyanka Boral
Computer Science Engineering
Indraprastha Institute of Information Technology
Delhi, India
priyanka19127@iiitd.ac.in

I. PROBLEM STATEMENT AND MOTIVATION

Forecasting the foreign exchange rate prediction is a major problem to find out in microeconomics of country. And structured the data in time series will be helpful in solving the problem. In foreign exchange market is it the fantasy of many investors to have any forecasting method to predict rates so they can reduce the risk investment and easy in profiting. In past years several models were proposed in time series data such as ARIMA (Autoregressive Integrated Moving Average), LSTM (Long short-term memory), regression, bagging, boosting. Our motivation to research and develop the a model which predict accurately the currency rate of the dataset. In this project we tried gaussian process regression which by statistical modeling to see how will it work in forex rate prediction with inherited properties of normal distribution and another one Prophet based on additive model.

II. INTRODUCTION

An exchange rate is the cost to exchange the currency of one country with another. As currency is actively traded in globalisation that's the reason why it will fluctuate constantly within week or days. It can relate to assets like stock market rates and varying rates with time. In globalisation currencies sell and buy twenty four hours throughout the week. As a trade to occur a currency gets exchanged. Whatever currency is used there will be currency pair form which quotes two currencies of different country first one called base currency and second one is quote currency, it indicates the cost to buy a unit of base currency by quote currency. Currency rates depend on the major factors like inflation rates as a country with low inflation rate will see rise up in the value of currency, interest rates, Forex rate are correlated and should be high, Government debt owned by central govt., trades in terms of export and import prices, political stability performance, Recession will reduce country interest rates downfall in foreign capital etc. And after considering mentioned factors a currency rate gets calculated. There is a procedure to calculate exchange rate like US/INDIA currency pair is 1.7345 which means 1.7345 cost of INDIAN rupees for US dollars, in that way we were like to calculate one unit of currency and show that how much will it cost to purchase 1 unit of first (US) currency when purchased by second (INDIA)

currency. And in case if we want to know the reverse cost then we have to $1/1.7345 = 0.5765$, which means 0.5765 cost US dollar pay to buy 1 rupees of INDIA. We are going to predict the same currency data explained above of US/INDIA which throughout a week, month, quarterly and yearly then analyse them

III. LITERATURE REVIEW

Since past many years machine learning are used forecasting on time series dataset like in stocks. Generally foreign exchange rate prediction try to predict trends direction by analysing whether will it go upward, downward or stationary. Box and Jenkins' Autoregressive Integrated Moving Average (ARIMA) technique has been widely used for time series forecasting and consider this model as benchmark in rate predictions [5]. Also several other techniques like Prophet Model created by Facebook to analyse the exchange rate throughout week, months and yearly. Ramakrishnan, Butt, Chohan, and Ahmad (2017) find that, when trained with commodities prices, Random Forests outperform Support Vector Machines and Neural Networks in forecasting the Malaysian FX. Furthermore, Amat, Michalski, and Stoltz (2018) conclude that economic fundamentals gain power to forecast exchange rate even at short horizons if ML methods are applied. Also in stock price prediction principle component analysis is done to identify hidden risk factors in dynamically changing rates by applying unsupervised models applied by, an unsupervised learning technique, have been applied by Connor and Korajczyk (1988), Fan, Liao, and Wang (2016), Kelly, Pruitt, and Su (2018) and Lettau and Pelger (2018). [4] Bagging (Bootstrap Aggregation) is used to decrease the variance for increasing accuracy in prediction (Han et al., 2012) [6]. Regressions like gaussian process regression were generally applied in stock price predictions Gaussian Process Regression Models for Predicting Stock Trends M. Todd Farrell Andrew Correa † December 5, 2007 [7] but never tried in foreign exchange prediction dataset.

IV. DATASET

A. details

The data set used in this project having multiple columns of currency pairs of foreign exchange of 1 unit of US dollars with 22 different countries and one date column. Date column names as Time-Series which is having dates of all varying

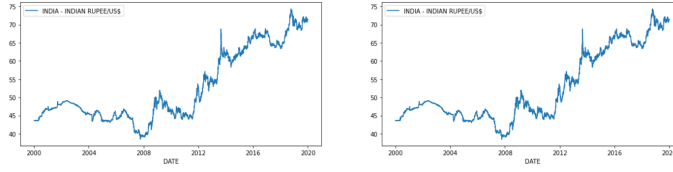


Fig. 1. original data(left),After increasing dataset they are not effecting on trends(right)

currencies from 3Jan2000 to 31Dec2019 which is 20 years of dataset. There are 5217 rows and 23 columns in this dataset.

B. source

Data taken from kaggle which is generated on Federal Reserve's Download Data Program where they perform some changes in name of columns for simplification and inverse the base currency with quote currency. So we used the dataset as it is present.

C. preprocessing of dataset

Little variation did by removing rows having ND(Not in dollars). Also fill up all the gaped dates between the given duration so new dataset having total 7303 rows and 23 columns. We are working on predicting and analysing the INDIA-USD column with corresponding date. (refer fig1)

V. PROPOSED ARCHITECTURE

In preprocessed dataset various Models of Regression, Bagging, Boosting, LSTM which is RNN neural network, ARIMA, Prophet, Gaussian process regression (new technique for analysis) where being applied with metric of mse (mean square error) and rmse (for ARIMA evaluation) to evaluate all the models. For predictions dataset were split in 80:20 train test split, and apply cross-validation of 10 folds in most of the models, after tuning it with some standard parameters analysis. As it is stated that prediction is done at INDIA-USD currency exchange so we vary the windows of that single column from 2 to 365 which indicate the number of shifts we do to analyse the predictions like value 2 shift indication rate analysis within 2 days, 7 indicate for a week, 15 for half month, 30 for a month, 60 for two months, 180 for quarterly analysis till 365 for yearly analysis and then predict them one by one in all the models. And lag dependent variable (LDA) are made according to the windows which are made by shifting them days to year as describes above row-wise. All models used LDA variables except prophet in our project. As in out window approach we are increasing attributes by keeping last column as a target. When target values were known then regression comes in role. Regression will look for two or more dependent variables and then estimate a dependent variable. We analyse and predict following variations.

A. Linear Regression

It is popularly used for predicting TRENDS in time series dataset. It is used to estimate lagged dependent variable by analysing the effect of independent variable but due

to using lagged dependent variables (LDV) in regression but having negatively biased coefficient estimates even though it is part of data-generating process.

B. Gaussian process Regression

As Gaussian processes are generally applied in time series dataset like stock prices prediction. Generally we apply GP in the stationary dataset which repeats its value within a fixed time interval. Our dataset has trends (in upward direction) that's why our data set is not stationary. So we have to remove that non-stationarity from the dataset before applying of Gaussian process. We are also applying various kernels like-

1. $\text{kernel} = \text{WhiteKernel}() + \text{DotProduct}()$

2. $C(1.0) * \text{Matern}(\text{length_scale} = 1.0, \nu = 2.5) * \text{RBF}() + \text{WhiteKernel}() + \text{DotProduct}()$

3. $\text{kernel} = C(1.0, (1e-3, 1e3)) * \text{Matern}(\text{length_scale} = 1.0, \nu = 2.5) + \text{WhiteKernel}(\text{noise_level} = 1e-5, \text{noise_level_bounds} = (1e-10, 1e-4)) + \text{DotProduct}()$

4. $\text{kernel} = \text{Matern}(\text{length_scale} = 1.0, \nu = 2.5) + \text{WhiteKernel}() + \text{DotProduct}()$

5. $\text{kernel} = 34.4 * *2 * \text{RBF}(\text{length_scale} = 41.8) + 3.27 * *2 * \text{RBF}(\text{length_scale} = 180) * \text{ExpSineSquared}(\text{length_scale} = 1.44, \text{periodicity} = 1) + 0.446 * *2 * \text{RationalQuadratic}(\alpha = 17.7, \text{length_scale} = 0.957) + 0.197 * *2 * \text{RBF}(\text{length_scale} = 0.138) + \text{WhiteKernel}(\text{noise_level} = 0.0336)$

In above applied kernel number 2 it will give maximum mean square error because of having convergence problem in lags by predicting variance smaller than 0. So for that we have to increase number of iteration to converge it. Except this kernel other were giving better mse.

C. Ridge Regression

It is one of the regularisation technique which are proposed to reducing size of coefficient. It penalizes sum of squared coefficient which is commonly known for L2 penalty which is L2 norm. It will underfit in the dataset.

D. Lasso Regression

Another popular regularization which penalise the L1 penalty which minimises the sum of absolute values of the coefficient commonly known for L1 norms. It will do overfit in the dataset which is bad.

1) *Elastic Net* : It uses both L1 and L2 norms as a regularizer which is convex combination of ridge and Lasso. It will give a balance model.

E. Bagging

Bagging taking random samples of data from the dataset and train model over that. We have used here SVM model to bagged the result.

F. Boosting

Here gradient boosting regression is used. As we know boosting takes the features randomly, and we have time series data which should consider the features in order of corresponding date. Like suppose if it leave features of 2 or 3 days while feature selection then definitely that's the reason it will give bad predictions.

G. LSTM

Long short term is a type of Recurrent Neural Network. It works best in sequence dataset and time series dataset is a kind of sequence dataset in which currency rates are made sequence with time which gives best prediction with less loss.

H. ARIMA

ARIMA is made up of 2 models Autoregressive Model and Moving average Model with integration. As it is first checking for type of data by looking at whether it is seasonality or trends. As our dataset is having trends and to predict any time series dataset it should be stationary which is checked by rolling mean average which is visualisation test and also by Perform Dickey-Fuller test if the values of test data which are either taken as log or can take something (here log of data is done to give equally importance to all as here values are floating points) if pvalue is less than critical point which is 0.05 then it rejects the null hypothesis and data is stationary else we have to make it stationary by differencing it with exponential values of log dataset and then subtracting that log value with shift value of log and again check for stationarity once it will accept it then ready to predict the rates. Here is model parameters value $p(25), q(1)$ and $d(1)$ are selecting on basis of first drop of value $pacf$ (partial correlation function), acf (autocorrelation function) graph and d is difference done to make the data stationary. ARIMA is good because it checks for stationarity and then starts predicting values.

I. Prophet

It is created by facebook for predicting time series dataset. Its inputs are date and another is currency value to predict trends changing yearly or weekly. In our dataset trends are vary yearly that the reason why we are consider seasonality as 365. And here we are predicting the yearly prediction so we will keep period as 365. Here it will predict $yhat$ (predicting value), $yhat_{lower}$ (lower bound of prediction), $yhat_{upper}$ (upper bound of prediction).

VI. RESULTS

1. Linear regression gives least rmse 0.031, ridge gives 0.029, lasso gives 0.037 and elastic net gives 0.031 among these regressions ridge regression is best because of giving least mse values and lasso is worst performer among all by giving more mse.

2. In gaussian process regression it giving bad some time in kernel 2 (as mention above) by giving mse 700 but good in rest of the kernels by having values between 0.03 to 0.41.

3. In Bagging gives least mse 0.045 with SVC model and Boosting with gradient boosting regression gives mse 0.4 so

boosting is best among above 2.

4. As time series models like ARIMA and prophet are giving RMSE values 5.45 and 5.05 correspondingly so they seem best and equally in comparison.

Now following are the details of figures.

Figure 1, 2, 3, 4, 5, 6, 7 shows mse vs windows (time interval) of all regression model.

Fig. 8 shows the variation of MSE in different kernels in GPR among which 3 and 4 is best.

Fig. 9 loss vs epoch in LSTM.

Fig. 10 show ARIMA stationary data.

Fig. 11 dicky fuller test and rolling visualization.

Fig. 12 acf arima.

Fig. 13 pcf Arima model.

Fig. 14 RSS arima.

Fig. 15 rmse arima model.

Fig. 16 arima predict 2040.

Fig. 17 prophet variation interval.

Fig. 18 MSE of prophet model.

Fig. 19 prediction 2020 prophet.

VII. ANALYSIS OF RESULTS

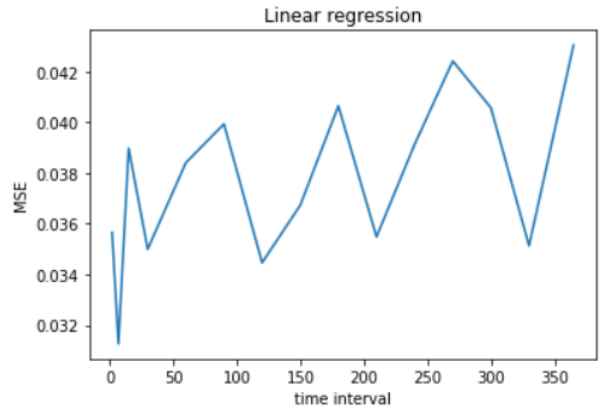


Fig. 2. Linear regression

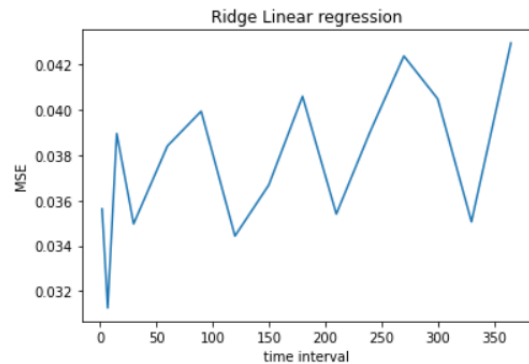


Fig. 3. Ridge regression

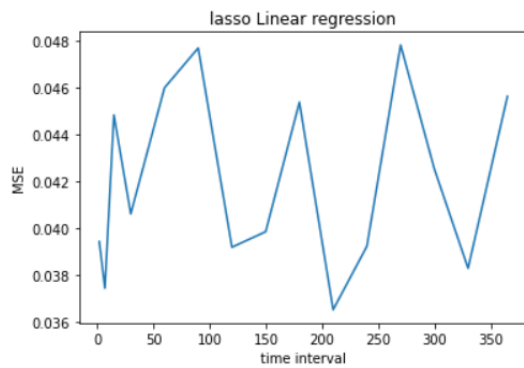


Fig. 4. Lasso regression

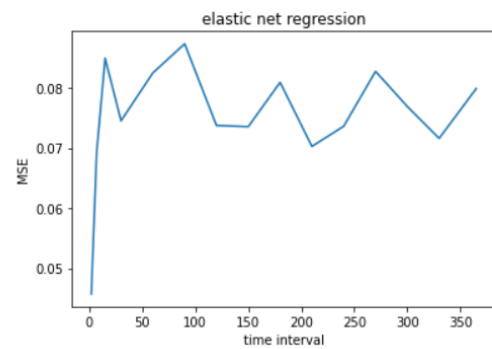


Fig. 7. elastic net

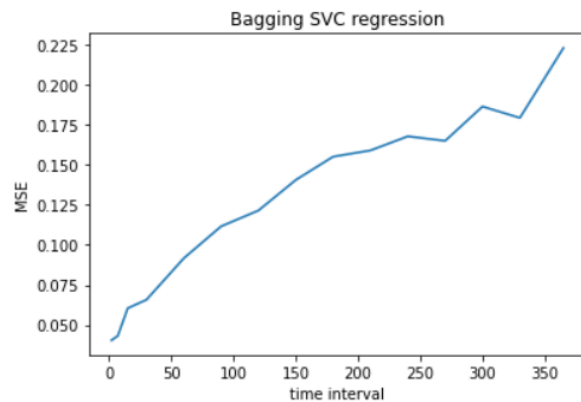


Fig. 5. Bagging SVC

mse values at window 2 with different kernels:

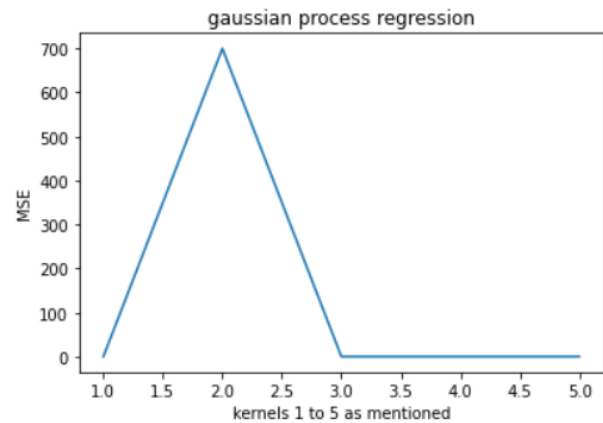


Fig. 8. Gaussian process regression

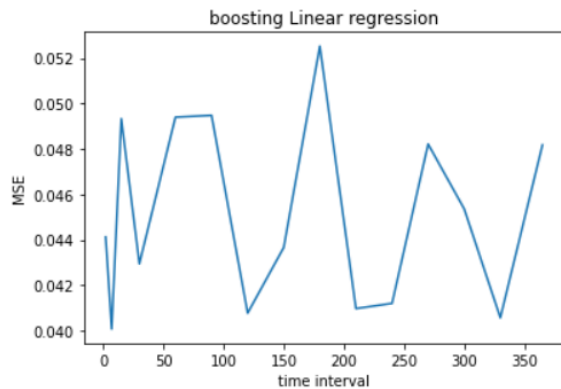


Fig. 6. Boosting

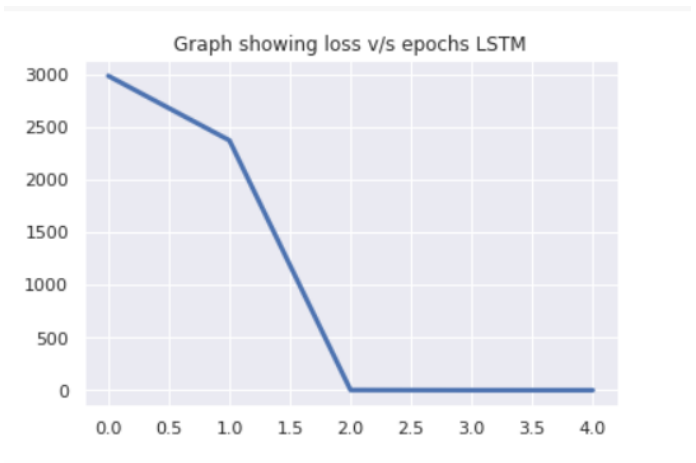


Fig. 9. LSTM

VIII. CONCLUSION

GPR didn't give better result in regression in this dataset, instead of that all other regression model used above give better result. Among all variation of regression Ridge will give best mse. Also bagging and boosting didn't give less mse. As it is observed that LSTM gives less loss in 5 epochs which means it is better to apply neural networks like RNN models and their variation in currency prediction instead of all

other models.

IX. REFERENCES

1. <https://www.investopedia.com/articles/forex/090314/how-calculate-exchange-rate.asp>.

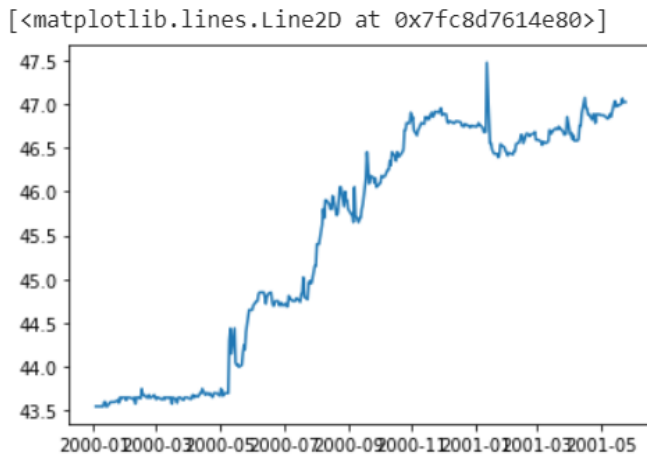
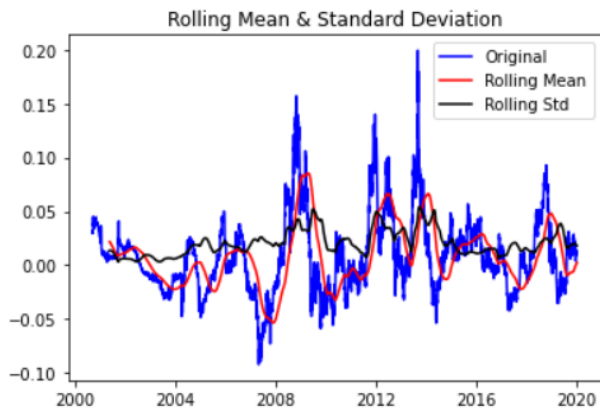


Fig. 10. data is of upward trend after checking in ARIMA with date



Results of Dickey-Fuller Test:

Test Statistic	-4.746337
p-value	0.000069
#Lags Used	26.000000
Number of Observations Used	5011.000000
Critical Value (1%)	-3.431656
Critical Value (5%)	-2.862117
Critical Value (10%)	-2.567077
dtype:	float64

Fig. 11. making data stationary

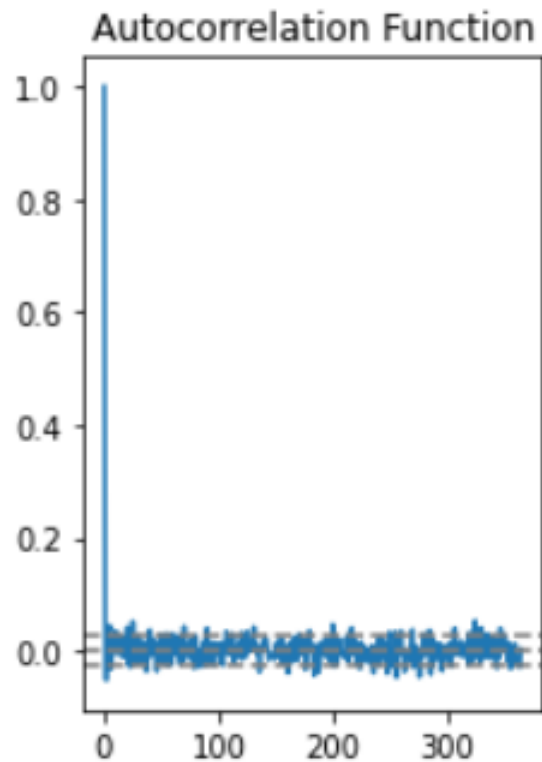


Fig. 12. ARIMA ACF

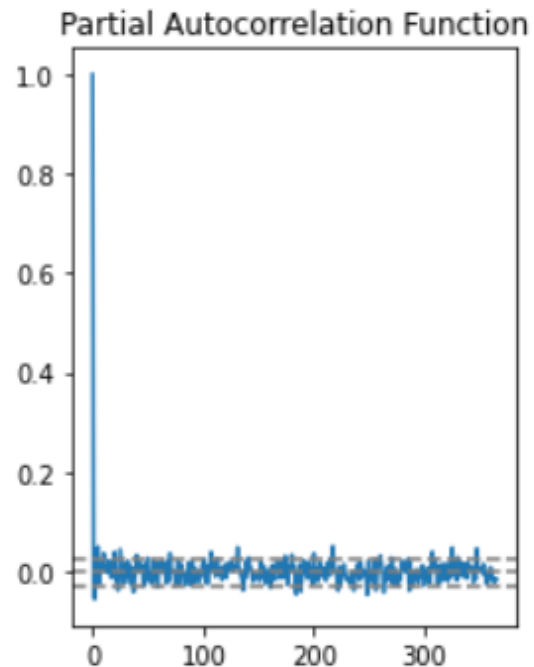


Fig. 13. ARIMA PACF

2. <https://www.comparereemit.com/money-transfer-guide/key-factors-affecting-currency-exchange-rates/>
3. <https://www.kaggle.com/brunotly/foreign-exchange-rates-per-dollar-20002019ForeignExchangeRates.csv>
4. <http://cs229.stanford.edu/proj2018/report/76.pdf>
5. <https://www.researchgate.net/publication/236896558FOREXDailyTrendPredictionUsingMachineLearning>
6. <http://mtmi.us/rbtr/sept2017/06-Sharma-Hota-Handa-pp29-33.pdf>
7. <https://www.researchgate.net/publication/249769503GaussianprocessRegressionModelsforpredictingstockTrends>
8. <https://www.kaggle.com/voltvipin/indian-foreign-exchange-prediction-using-lstm>

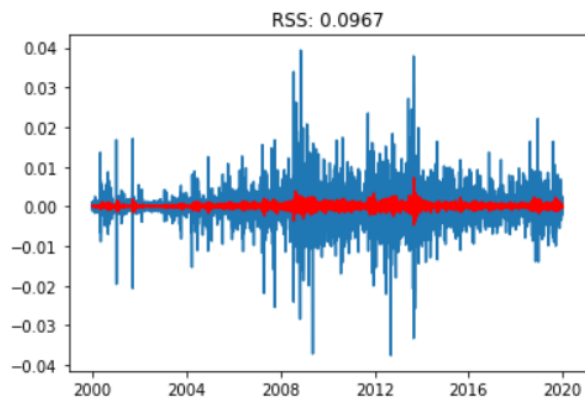


Fig. 14. ARIMA RSS value

Fig. 15. ARIMA RSS value

Text(0.5, 1.0, 'RMSE: 5.5468')

RMSE: 5.5468



```
results_ARIMA.plot_predict(1,11000)
x=results_ARIMA.forecast(steps=120)
# plt.title('RMSE: %.4f' % np.sqrt(sum((predictions_ARIMA-xdf['INDIA'])**2)/1
```

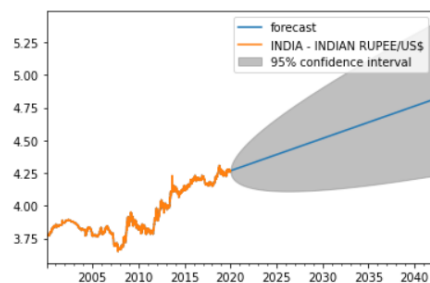


Fig. 16. ARIMA prediction till 2040

9. <https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/>

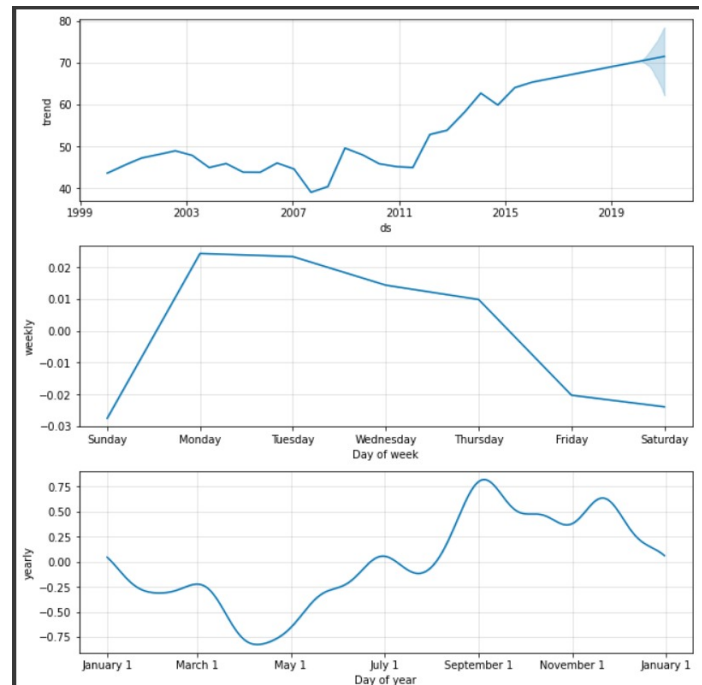


Fig. 17. Prophet visualization of day, week and month

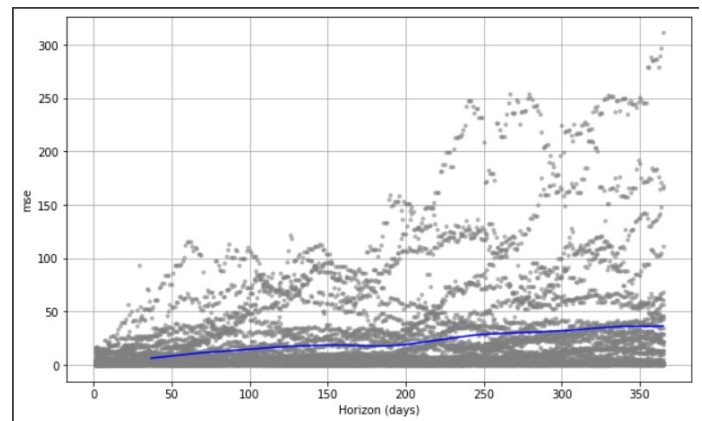


Fig. 18. Prophet MSE

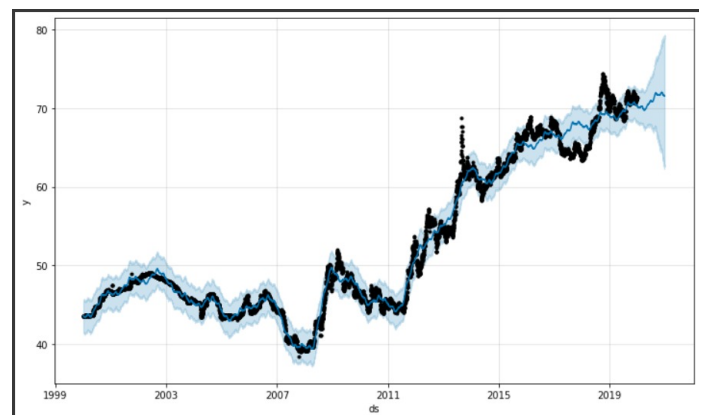


Fig. 19. prophet prediction