Predicting Exchange Rate

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Time Series Analysis

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About Project

Goal :-

Develop a model which will help investors and business owners to decide about their investment opportunities across globe.

Benefits:-

- Maximize their profit
- Manage the cash flow and take business expansion decisions
- Helps to evaluate foreign borrowing decisions , investment opportunities
- Minimize the risk

About the Data

The data set represents

- Exchange Rate Analysis from INR to USD
- Daily exchange rate information from the year 1973 till date
- The data source is https://fred.stlouisfed.org

Data Cleaning

Missing values

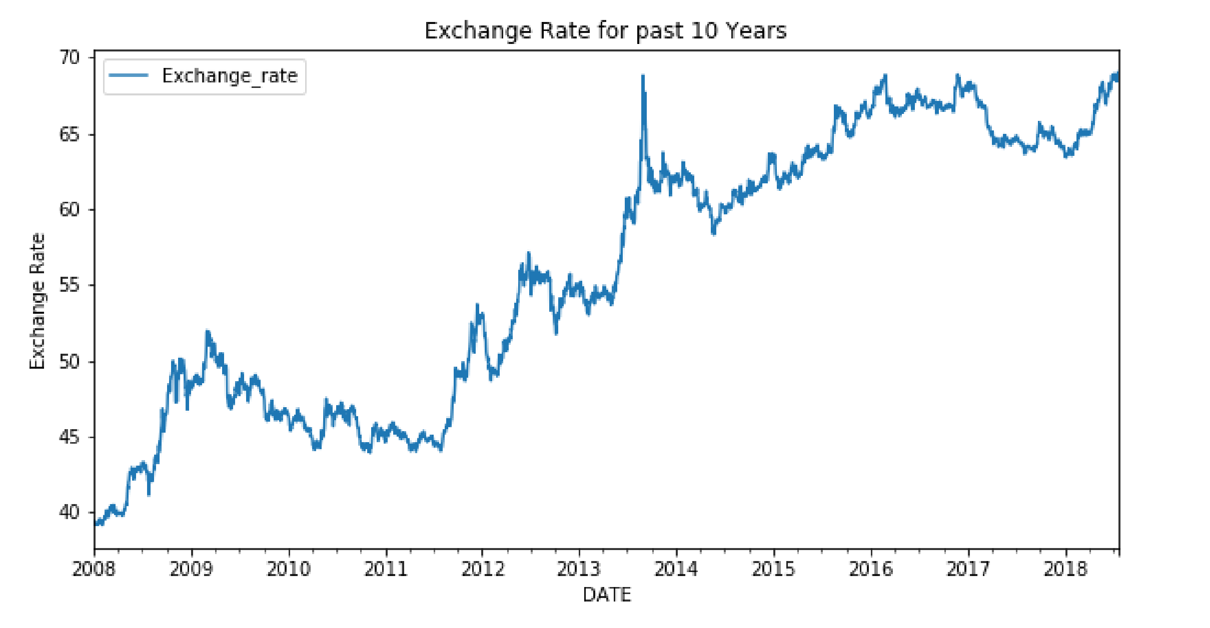
- 458 missing values in this dataset
- Used a forward-fill to propagate the previous value to next observation.

Other:

- Given appropriate column name
- Changed the datatype of Date column from object to datetime
- Set the Date column as Index
- Changed the datatype of Exchange Rate column from object to numeric.

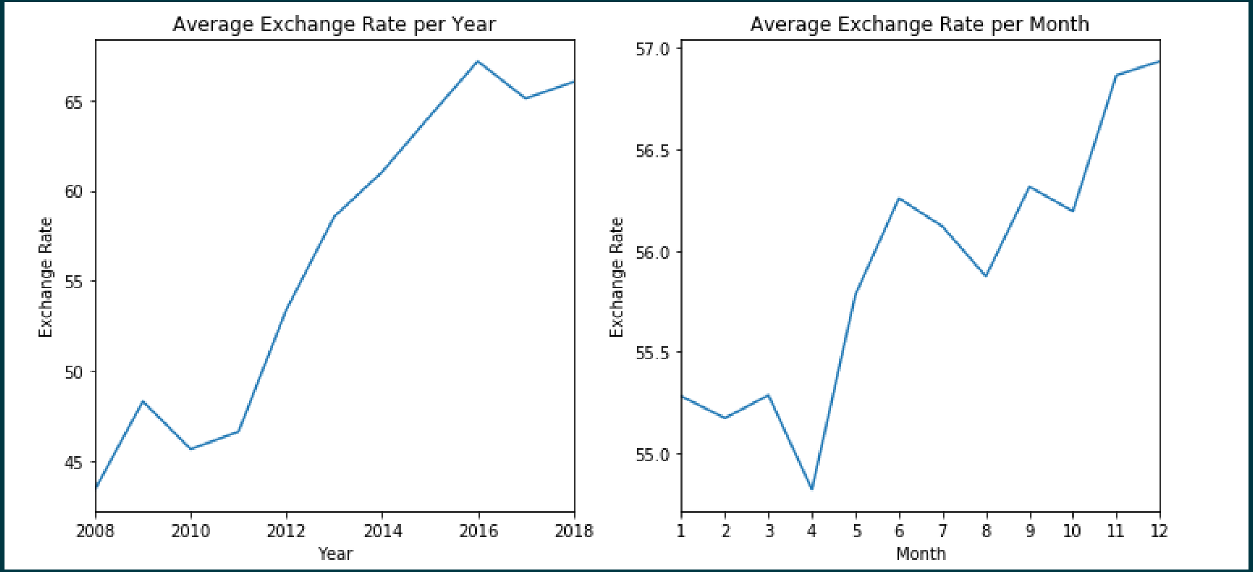
Exploratory Data Analysis

Exchange Rate for past 10 years



The exchange rates shows volatility, but illustrates an overall increasing trend.

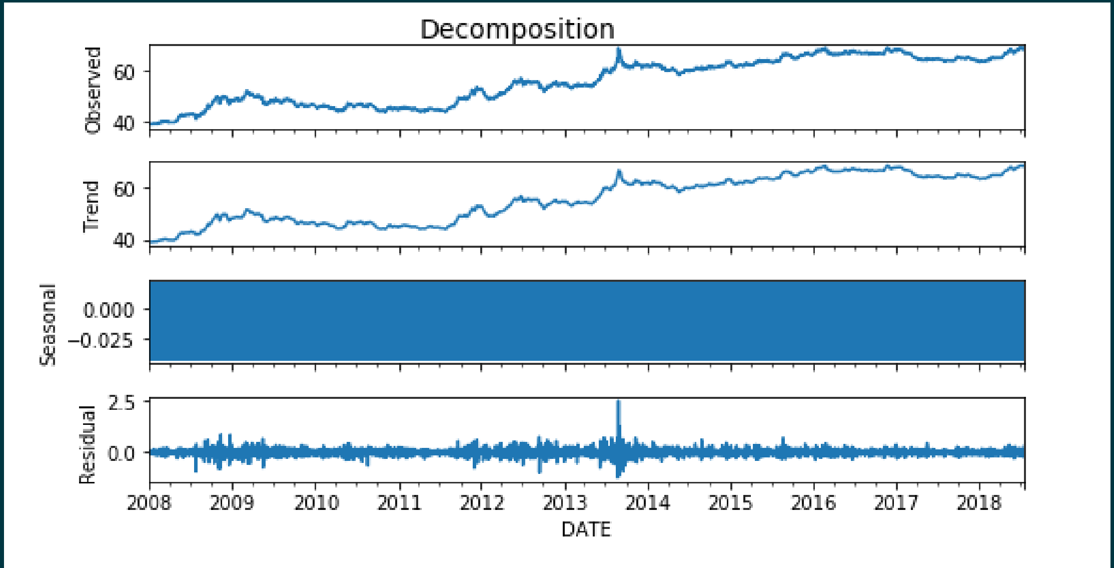
Average Exchange Rate per year and Month



There is no seasonality, but we see an upward trend.

Decomposition

Decomposition



Decomposed the time series data to find patterns of Seasonality, Trend.

Modelling

Model Assumption and preprocessing:

Important Assumption :

Time Series Data is Stationary

Stationary:

Mean, variance and autocorrelation does not depend on time.

How to check stationarity ?

- Plotting Rolling Statistics
- Augmented Dickey-Fuller Test

How to achieve stationarity?

- First or second order difference
- Different transformation

Augmented Dickey-Fuller (ADF) test

Used to test for a unit root in a time series sample.

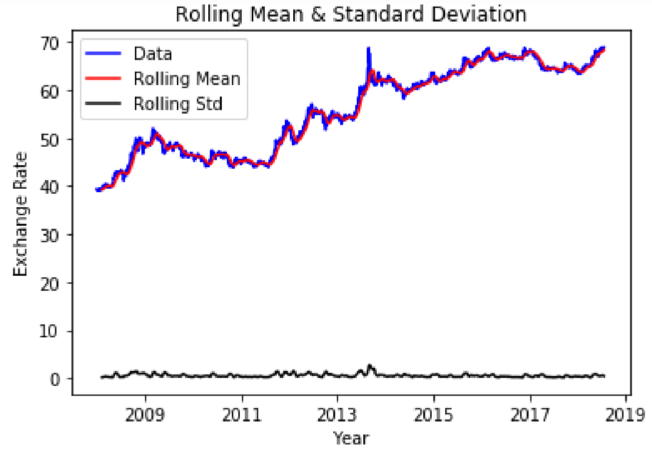
Null hypothesis : there is a unit root,
alternative hypothesis : there is no unit root.

Interpretation of ADF Test result:

- p-value > 0.05:
  Accept the null hypothesis (H0),
  the data has a unit root and is non-stationary.

- p-value < 0.05:
  Reject the null hypothesis (H0),
  the data does not have a unit root and is stationary.

ADF test – Actual Data

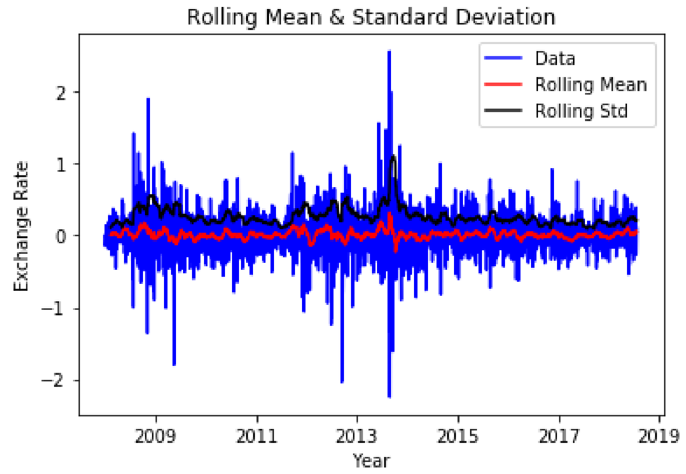



```
Results of Dickey-Fuller Test:
------------------------------
Test Statistic                  -1.281828
p-value                          0.637444
#Lags Used                       5.000000
Number of Observations Used   2749.000000
Critical Value (1%)             -3.432731
Critical Value (5%)             -2.862592
Critical Value (10%)            -2.567330
dtype: float64
```

P value is more than 0.05

TS is not Stationary

ADF test – Differenced Data




```
Results of Dickey-Fuller Test:
--------------------------------
Test Statistic                 -22.092389
p-value                          0.000000
#Lags Used                       4.000000
Number of Observations Used   2749.000000
Critical Value (1%)             -3.432731
Critical Value (5%)             -2.862592
Critical Value (10%)            -2.567330
```

P value is less than 0.05
TS is Stationary

ACF and PACF

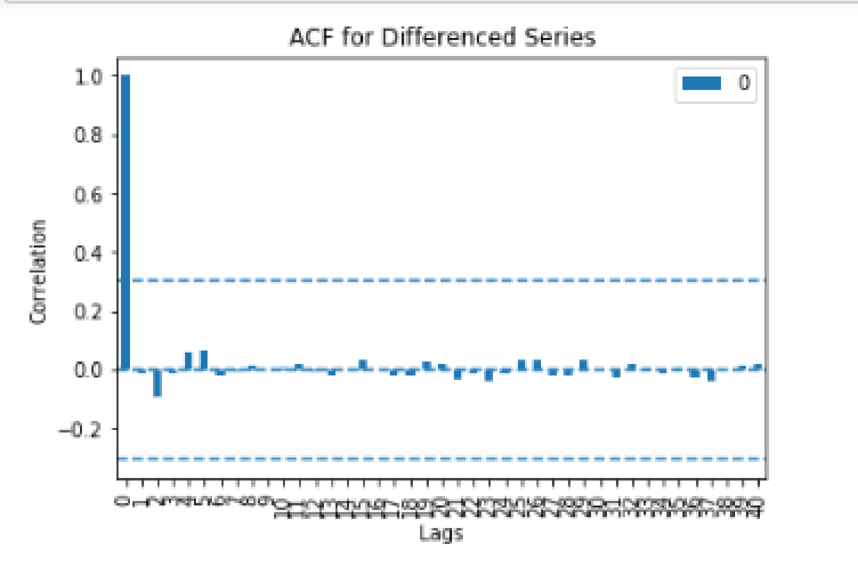
ACF

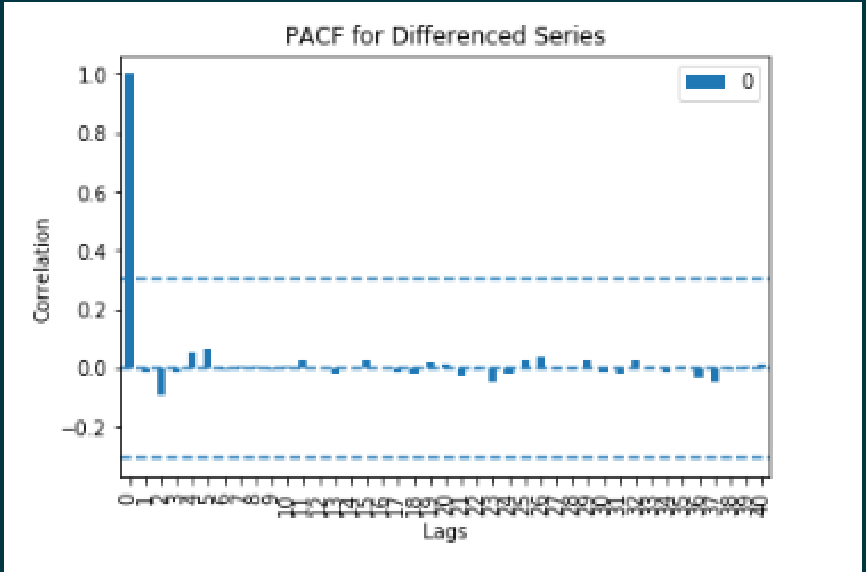
Autocorrelation Function:
Measure of the correlation between the Time series with a lagged version of itself.

PACF

Partial Autocorrelation Function:
Measures the correlation between the Time series with a lagged version of itself, but after eliminating the variations already explained by the shorter lags.

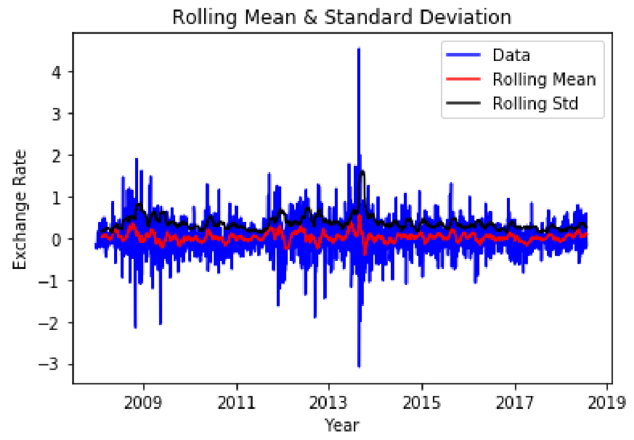
ACF and PACF plot





No significant lags.

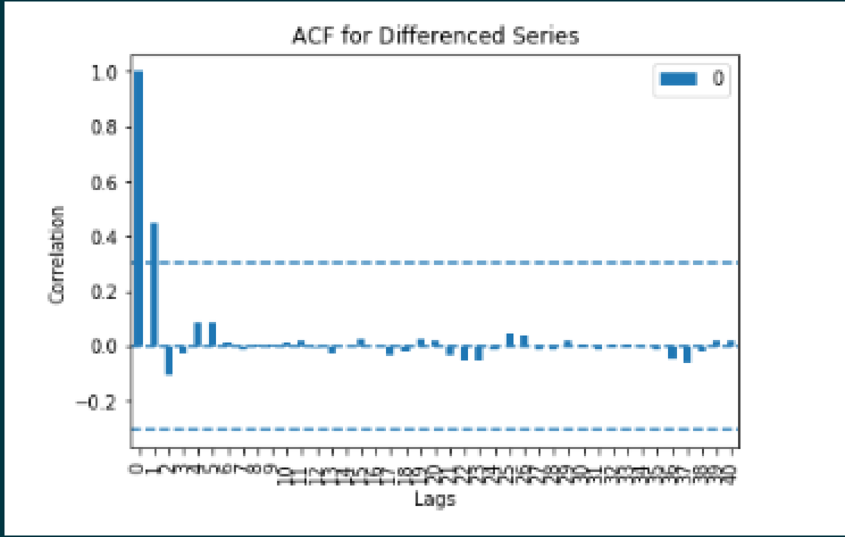
ADF test – Differenced Data

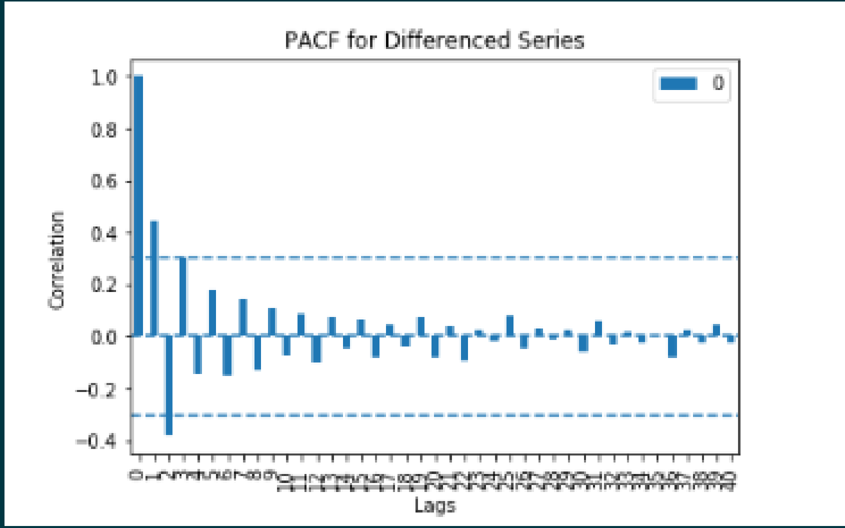



```
Results of Dickey-Fuller Test:
------------------------------
Test Statistic                -1.031000e+01
p-value                        3.203941e-18
#Lags Used                     2.500000e+01
Number of Observations Used    2.727000e+03
Critical Value (1%)           -3.432750e+00
Critical Value (5%)           -2.862600e+00
Critical Value (10%)          -2.567335e+00
dtype: float64
```

Stationary
P value is less than 0.05

ACF and PACF plot





ACF plot suggests MA of order 1
PACF plot suggests AR of order 2 or 3

ARIMA Modelling

Enables to use linear regression models on non-stationary data.

AR (Autoregression):

Uses the relationship between an observation and it's lagged observations.

I (Integrated):

Order of differencing of observations to make the time series stationary.

MA (MovingAverage):

Uses the dependency between an observation and past error.

ARIMA Modelling

Denoted with the notation ARIMA(p, d, q)

p : Number of AR terms
d : the degree of differencing.
q : Number of MA terms

Tried Grid search on

p – 0,1,2,3
d – 0,1,2
q - 0,1,2,3

Train Test Split and Evaluation

Split:

The last 90 observations as the test data and remaining as training data

AIC:

Akaike information criteria : provides a way of model selection.

MSE:

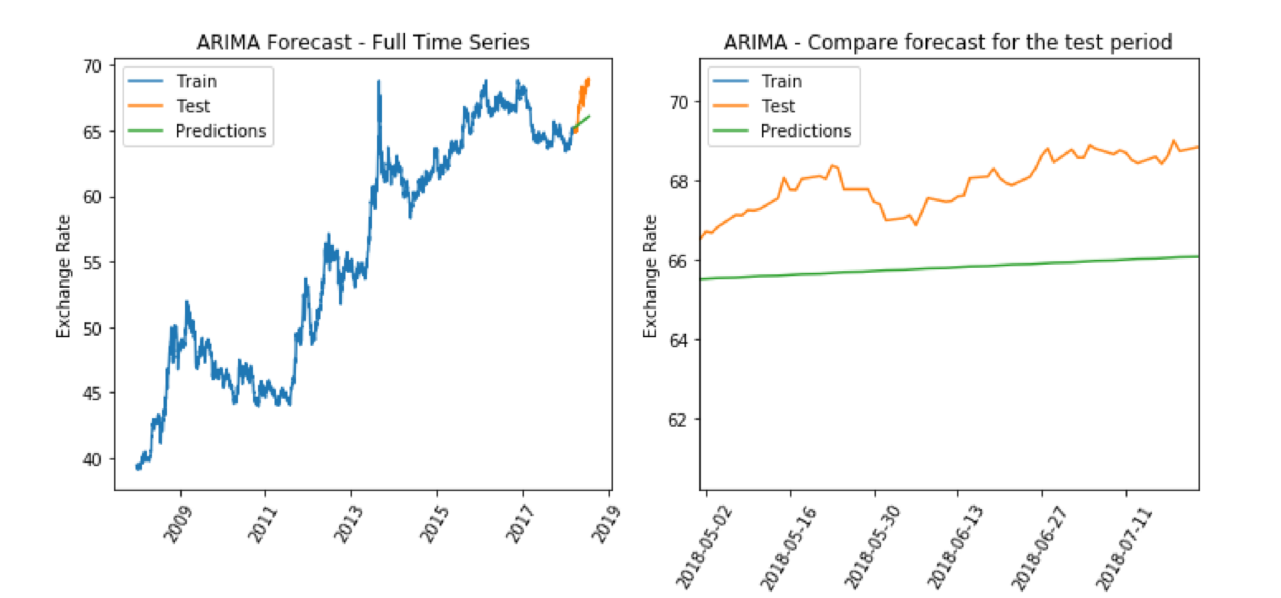
Mean squared error

Validation:

walk-forward model validation

ARIMA Best Model - Prediction

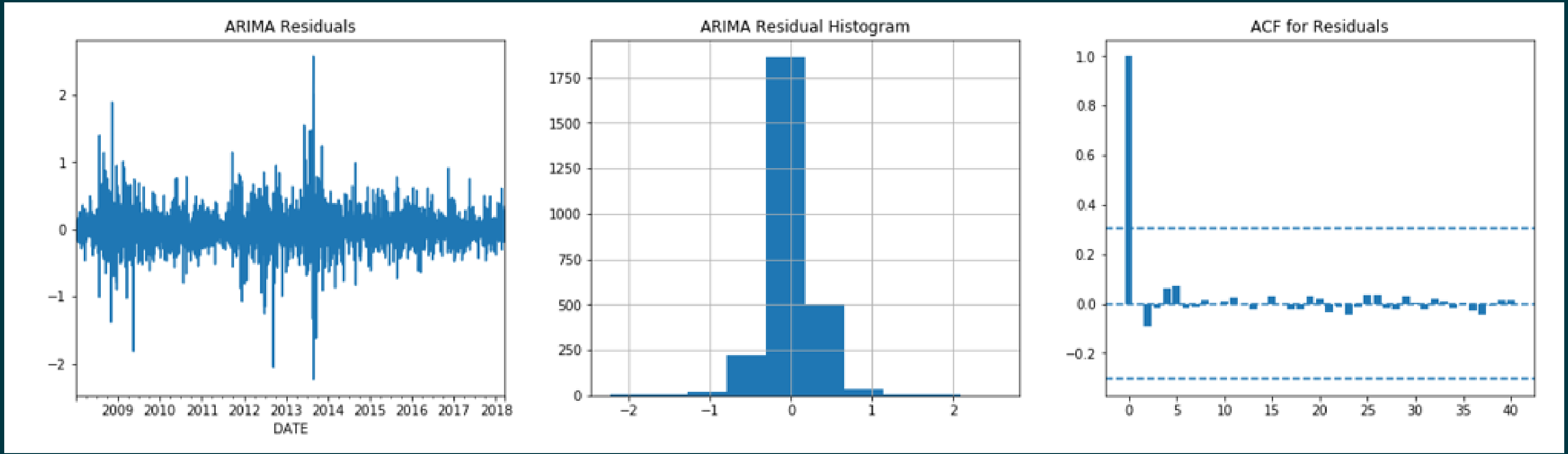
Lowest MSE



Best Model Chosen by ARIMA- 1,1,0

AIC: 940.7
MSE: 3.33

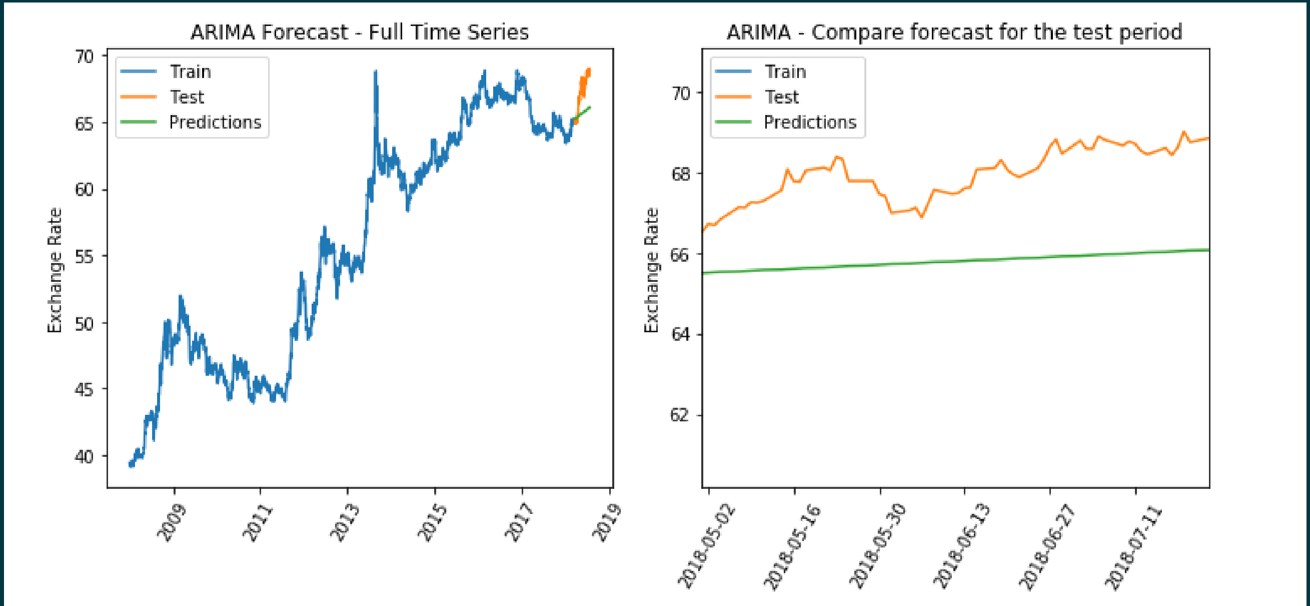
ARIMA Best Model - Residual



The residuals appear to be normally distributed and the ACF plot for residuals also don't show any significant lag values.

ARIMA Best Model - Prediction

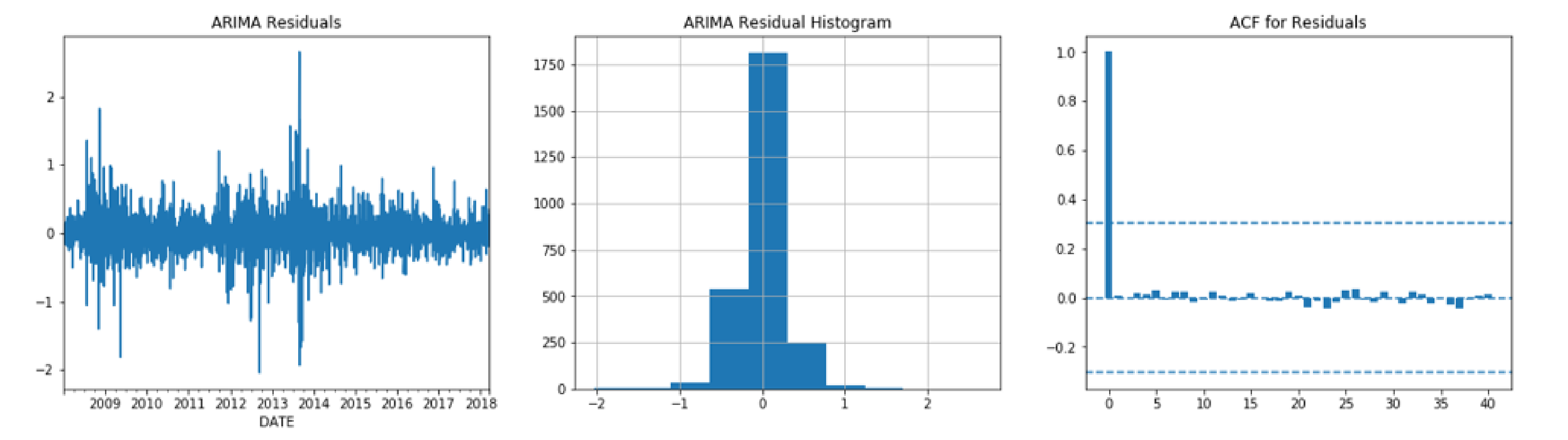
Lowest AIC



Best Model Chosen by ARIMA- 2,1,2

AIC: 907.2
MSE: 3.37

ARIMA Best Model - Residual



The residuals appear to be normally distributed and the ACF plot for residuals also don't show any significant lag values.

AUTO ARIMA Modelling

- Wraps statsmodels' well-tested ARIMA and SARIMAX estimators in a single, easy-to-use package
- Uses pyramid-arima library for Python
- allows to quickly perform grid search

Installation Requirement :

pyramid-arima should be installed

Other Parameters:

m : The period for seasonal differencing.
seasonal : Whether to fit a seasonal ARIMA. Default is True.
stepwise : less likely to over-fit the model.

Auto ARIMA Modelling - Result

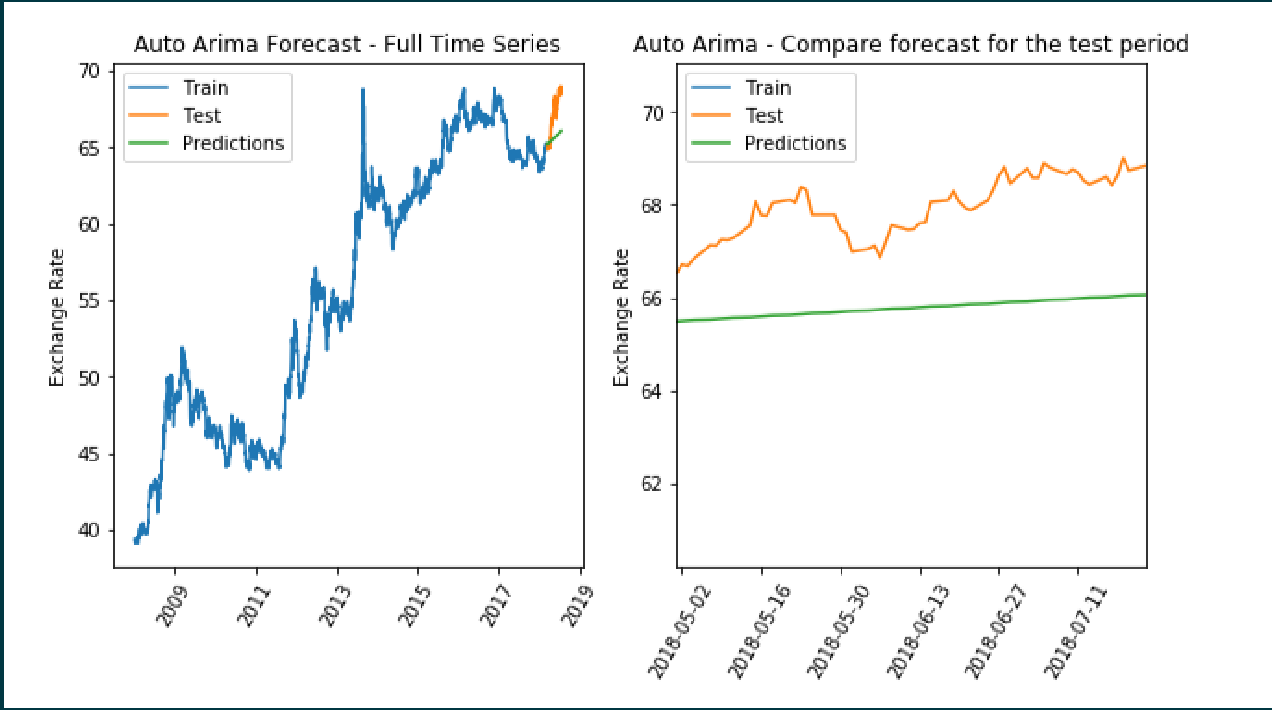
Grid Search Parameters
P = 0,1,2
D = 0,1
Q = 0,1,2
m = 1,7,30
p = 0,1,2,3
d = 0,1,2
q = 0, 1,2,3

Best Configuration: (2, 1, 0)

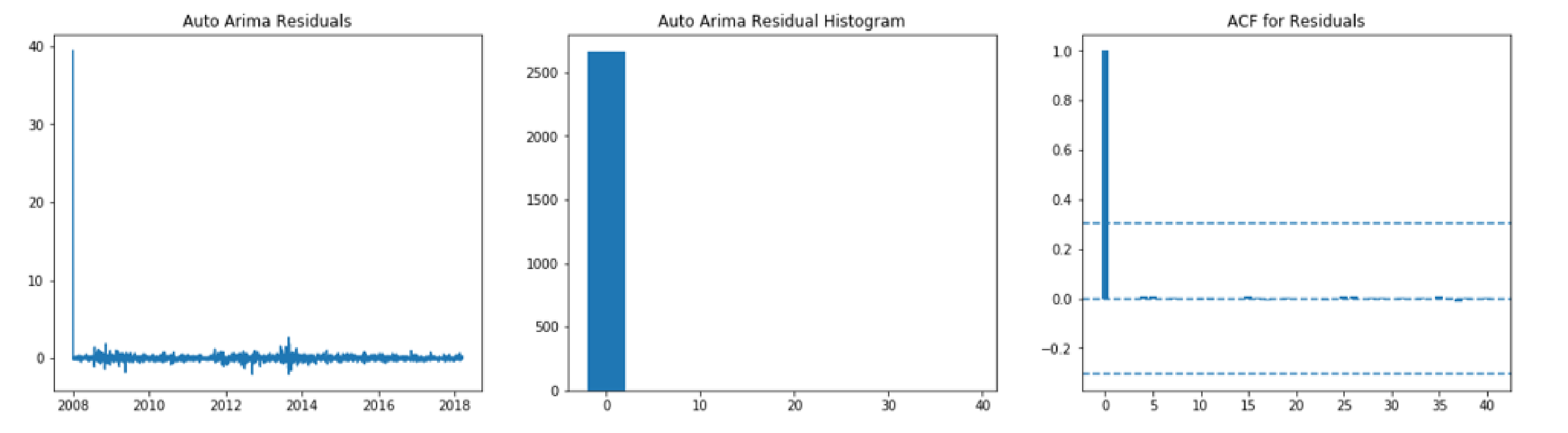
AIC : 976.28

MSE : 3.39

Auto ARIMA Best Model - Prediction



Auto ARIMA Best Model - residual



The residuals appear to be normally distributed and the ACF plot for residuals also don’t show any significant lag values.

Prophet Model

- Developed by Facebook for forecasting time series data.
- Based on an additive model
- Non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
- Works best with time series that have strong seasonal effects and several seasons of historical data.
- Robust to missing data and shifts in the trend, and typically handles outliers well.

Prophet Model

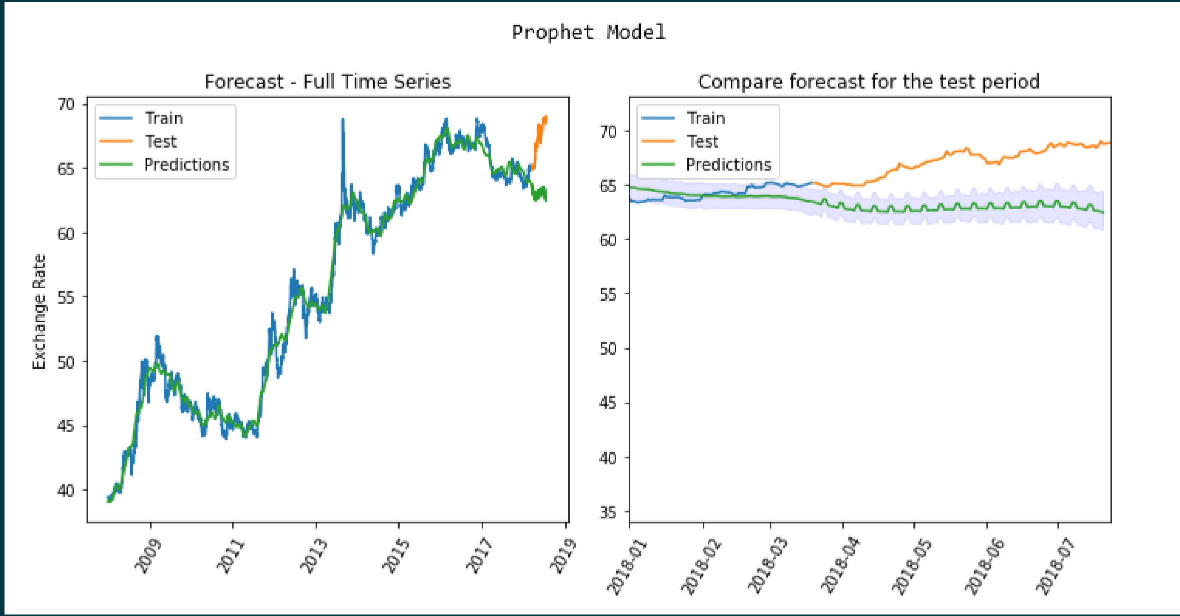
Installation Requirements:

Need pystan, cython and fbprophet modules installed .

Input Requirements:

- Requires specific input format.
- Columns names must be lowercase,
- date column should be named as 'ds', data as 'y'

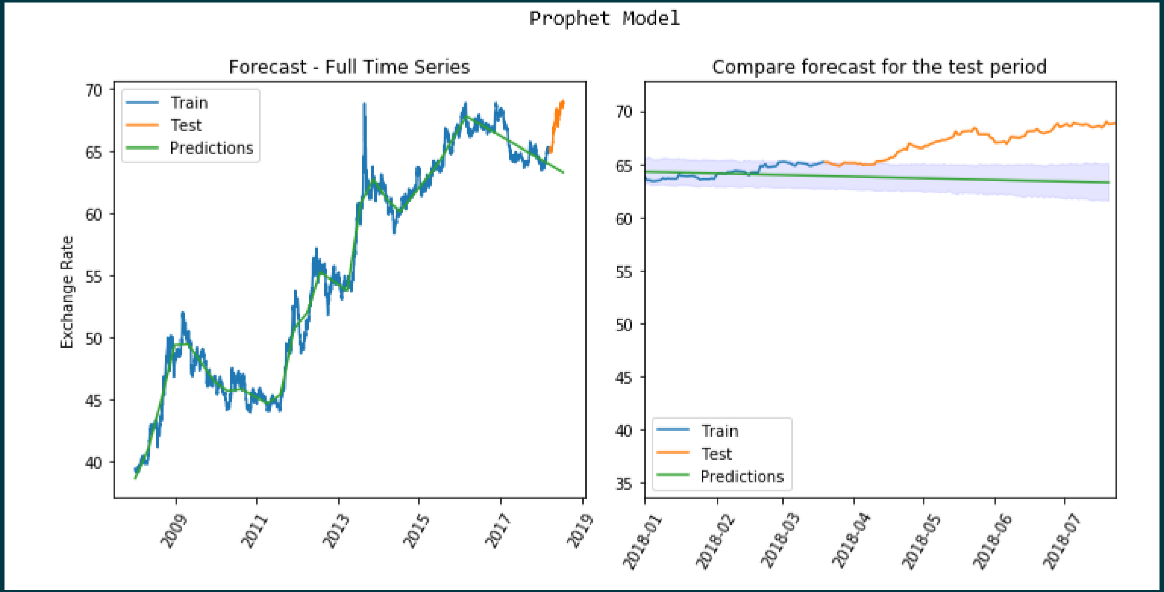
Prophet Model - prediction



Prophet Model
(Default parameters)

MSE : 1.43

Prophet Model - prediction

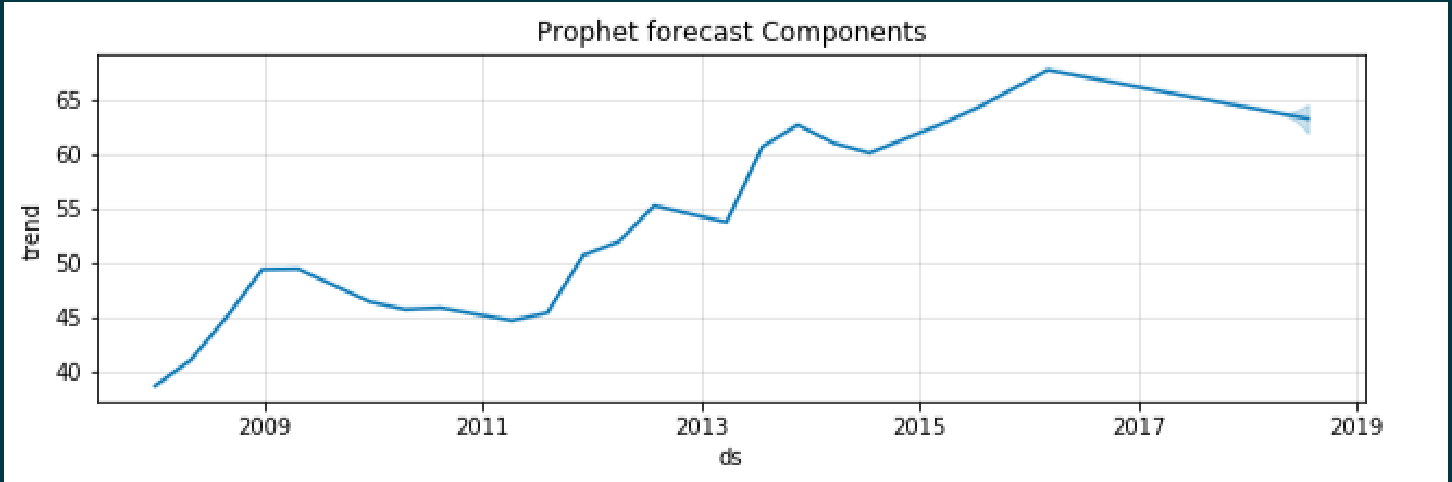


Prophet Model (parameter tuning)

Daily, weekly and yearly seasonality=False

MSE : 1.39

Prophet Model – forecast components



Prophet forecast a decreasing Trend

LSTM network

- Stands for Long Short-Term Memory Network
- A recurrent neural network
- Trained using Backpropagation Through Time
- Overcomes the vanishing gradient problem

Preprocessing - LSTM

- Sensitive to the scale of the input data
- Took last 90 observations as test data and rest as training data
- Needs input in the form of: [samples, time steps, features]
- Wrote a simple function to convert our single column of data into a multi-column dataset and consider the last column as dependent variable.

LSTM Model

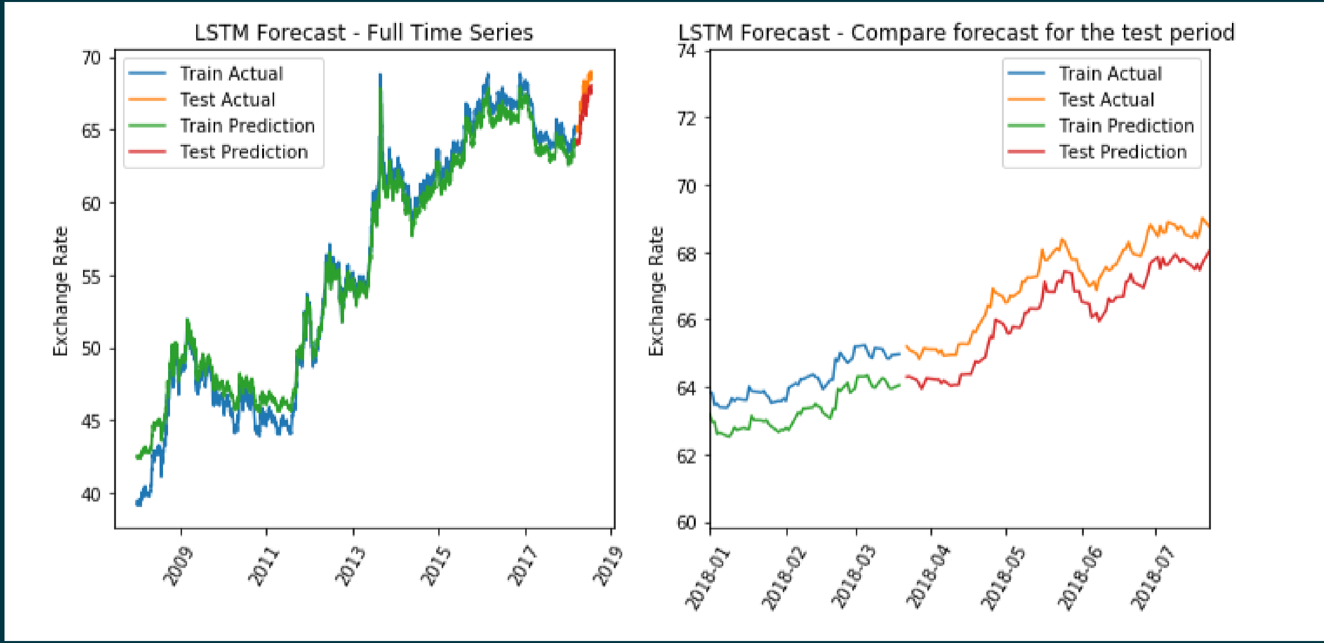
- Fitted a Model with 1 input layer, 1 hidden layer with 4 LSTM blocks, and 1 output layer

- default sigmoid activation function is used for the LSTM blocks.

- Dropout – for addressing overfitting problem

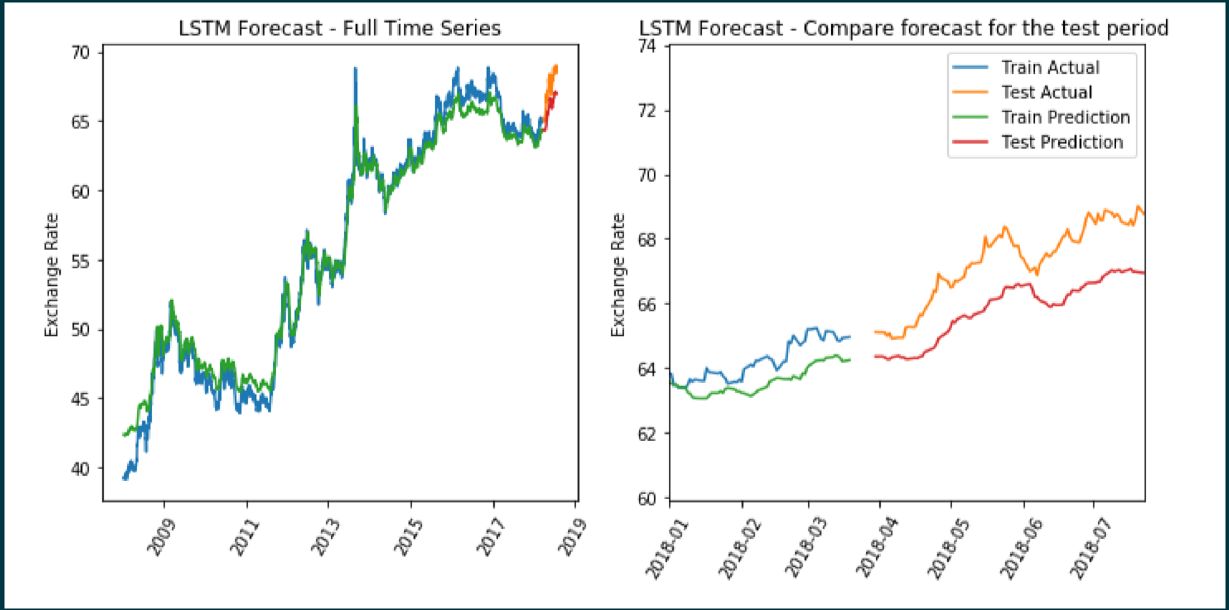
- The network is trained for 100 epochs and a batch size of 64.

LSTM network – Prediction – 1 day Look Back



- Look back of 1 day data- MSE = 0.98

LSTM network – Prediction – 7 days Look Back



- Look back of 7 days data- MSE = 2.3

Model Comparison – Using MSE

```
model_comp_df.sort_values(by= 'Mean_Squared_error')
```

	Model	AIC_Value	Mean_Squared_error
3	LSTM_1_look_back	NaN	0.980652
2	PROPHET	NaN	1.389718
4	LSTM_7_look_back	NaN	2.300942
0	ARIMA	940.706970	3.335052
1	AUTO_ARIMA	976.279331	3.399531

The LSTM model with 1 day look back, provided the lowest mean squared error

Conclusion

We looked at a large range of ARIMA configurations as well as a more powerful forecasting tool developed by the Facebook. We also looked at the LSTM Neural Network model. All of the models did fairly well.

Model improvements:

- For prophet – adding Holiday calendar
- For LSTM models - try parameter tuning and adding More layers

THANK YOU

Questions