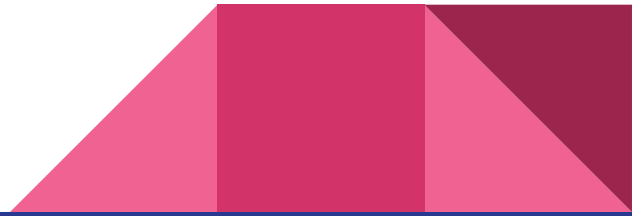
ReCurrency Network Interim Report

Abhishek Maiti, Deepak Srivatsav

Introduction

Through this project, we wish to be able to predict currency futures, specifically targeting the USD/INR exchange rate.

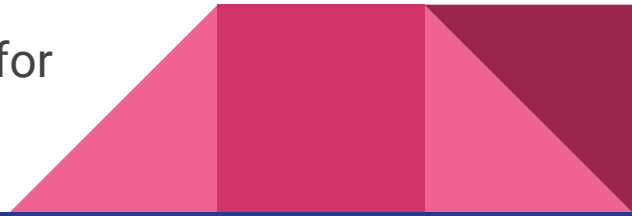
At the end of this project, we will strive to have a monthly forecast.



Dataset

We scraped and created the dataset on our own on reading several papers in this domain. We came up with the following parameters -

Open, High and Low price for a day
Gold price - India
Inflation Rate - USA
Inflation Rate - India
Foreign Direct Investment - India
Foreign Direct Investment - USA
Using the above features, we try to predict the price for the next day.



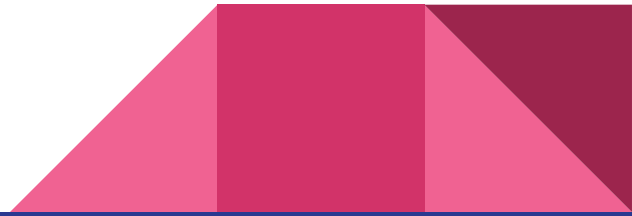
Approaches Used

Baseline - Simple linear and polynomial regressors with no temporal factor

We introduced a temporal aspect to the dataset by making a sliding window of the data. To predict the price on day x, we would use the data from days x-n to n.

Advanced models aimed at introducing a temporal factor and showing its advantage over traditional stats based prediction -

1) Multivariate ARIMA - statistical model
2) Univariate ARIMA - statistical model
3) Stacked LSTM Recurrent Neural Network
4) Stacked GRU Recurrent Neural Network



Hyperparameter Tuning

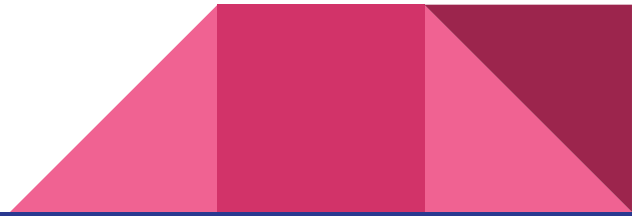
Grid Search on Baseline models for the Hyperparameters - learning rate.

For the RNNs, one training batch took around 30 mins to train, so a comprehensive grid search was not feasible with the available computing power. Instead, we observed the running mse at each epoch to determine whether the model was under/over fitting.

For ARIMA, we performed a grid search.

Architecture

Both Neural Networks were stacked with LSTM and GRU cells. They had 4 hidden layers with 50 and 100 units per cell respectively. The output was a dense layer with 1 neuron.

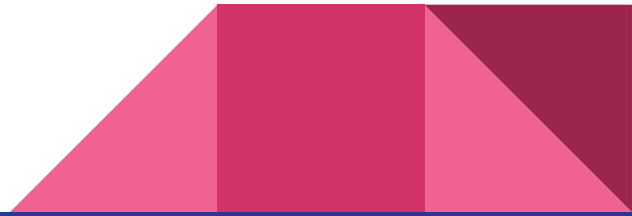


Results

After performing some analysis on the data, we ran some basic regression models.

A basic Linear Regression model gave us an RMSE of 0.2823.

We also ran a Polynomial Regression Model which gave us an RMSE of 0.2884.



Results

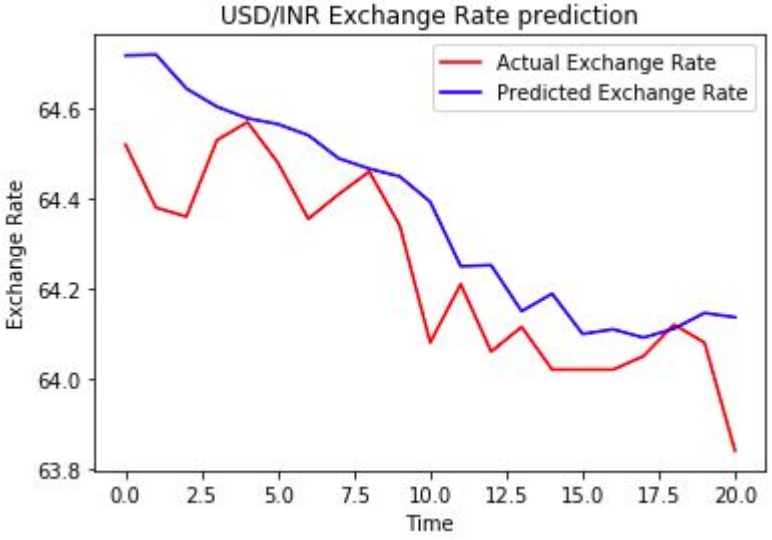
RNN - LSTM - rmse of 0.164 over a prediction period of 1 month

RNN - GRU - rmse of 0.258 over a prediction period of 1 month

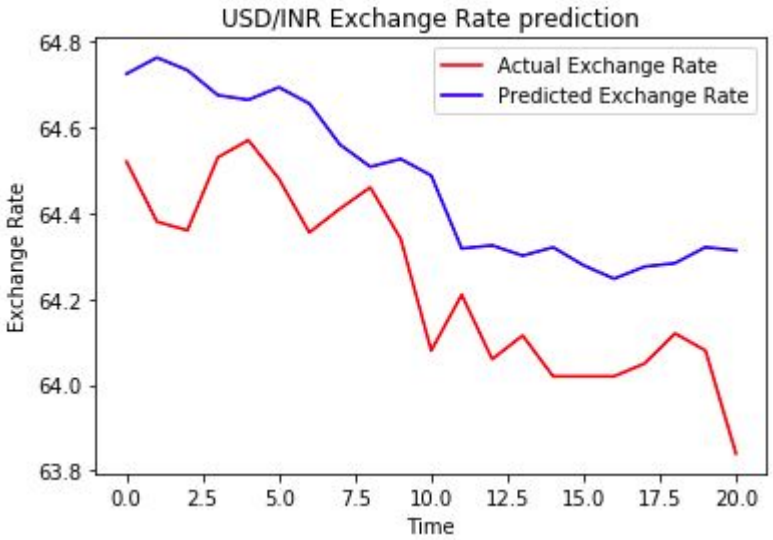
Multivariate ARIMA - rmse of 0.2890 over a prediction period of 1 month -> This is a state of the art statistical model.

We observed that GRUs trained a lot faster than the LSTMs. However due to the large size of the dataset, as expected, LSTMs performed slightly better in terms of error.

Analysis

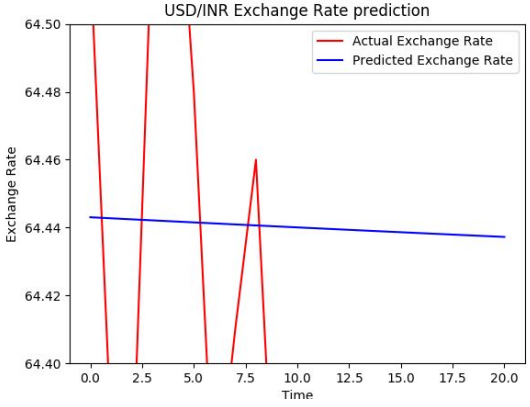


RNN - LSTM

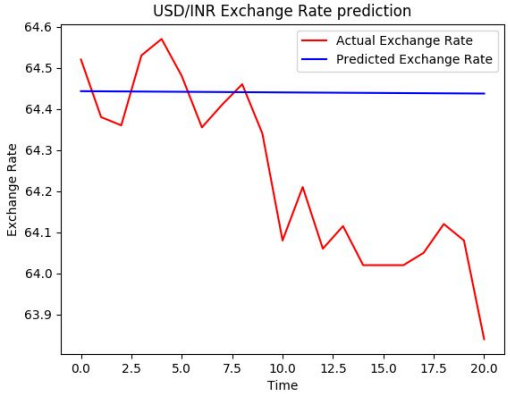


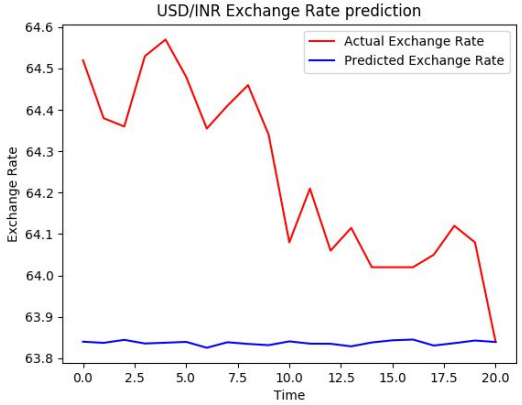
RNN - GRU

Analysis



Multivariate ARIMA



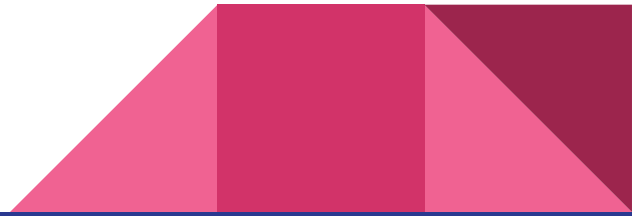


Univariate ARIMA

Contributions

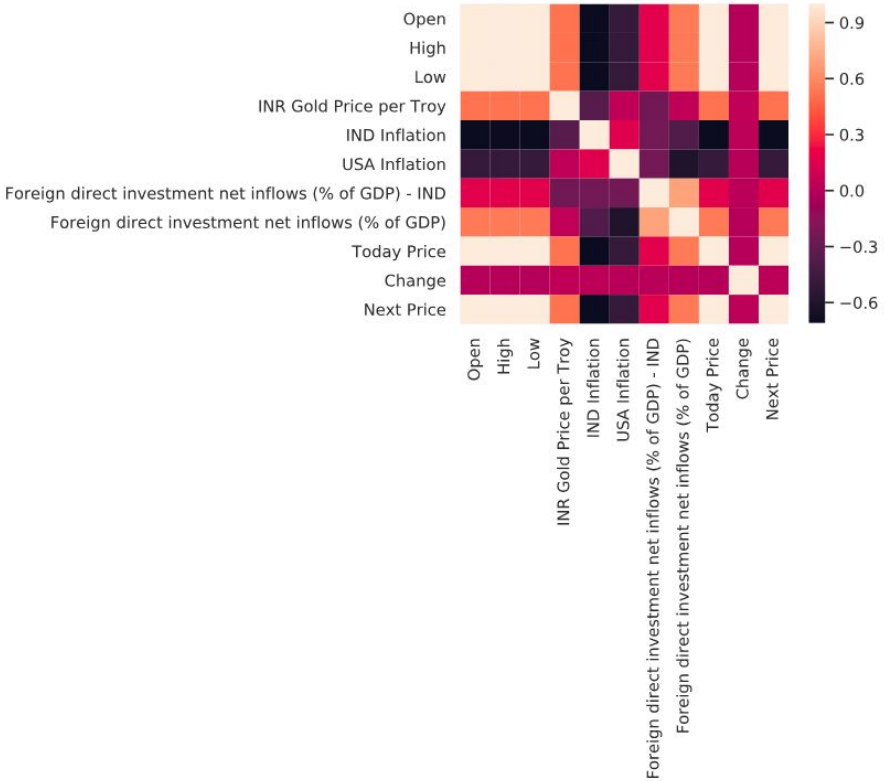
Abhishek Maiti - Dataset creation, Baseline SVM, Arima, Marima

Deepak Srivatsav - Dataset Analysis, RNNs with LSTMs and GRUs, Baseline regression



Appendix

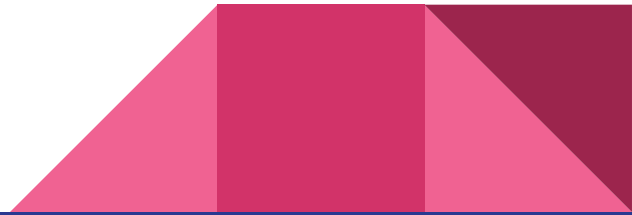
Dataset Analysis



We saw linear correlation between our output, high and low price. We decided to remove these features from our final training set for this reason.

Results

We ran an SVM classifier to try and determine the direction of movement of the price.
We only achieved an accuracy of 56.7% on the classification accuracy front, and this was done with an RBF kernel. We obtained the hyperparameters required for this accuracy with an extensive grid search.



Future Work

Incorporating Sentiment Analysis into the prediction mechanism.