Deep Learning for Stock Price Prediction

Jayachandra Reddy Kamineni, Surya Pavan Malireddy, Karthikeya Vayuputra Chittuluri

Department of Computer Science

Under the Guidance of Dr. Minwoo Jake Lee

Introduction

- Build a Deep Learning system to predict stock prices of next day(one step time series forecast) and also for a specific period of time(multi step time series forecast). Using this system, stock traders can automate the process of decision making.
- Predicting Stock prices is best achieved using deep learning models like LSTM (Long Short Term Memory Networks), GRU (Gated Recurrent Unit) CNN (Convolutional Neural Network)over LSTM, models because of their ability to remember past information.

Approach

- **One step prediction** takes the test set till the previous day and predicts the next price.
- **Multistep prediction** starts with first window in test set, predicts next price, then pops out oldest price in window, appends the predicted price and predicts the next price on this new window for specified period.

Data Preparation

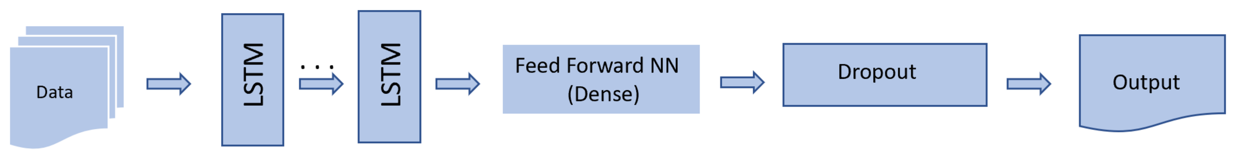
- Daily Price data over 3000 stocks (from 2004 – 2018) of Google's Stock prices from Alpha vintage.
- Each record consists of 5 features : (open, high , low, close , volume).
- Out of these five features, we have used open price feature to predict the future prices.
- Normalized our data using min-max normalization so that the mean of the data is 0 and variance is 1.
- Finally, the company's stock prices are split into 60-day windows for training and testing.

Hyperparameter Tuning

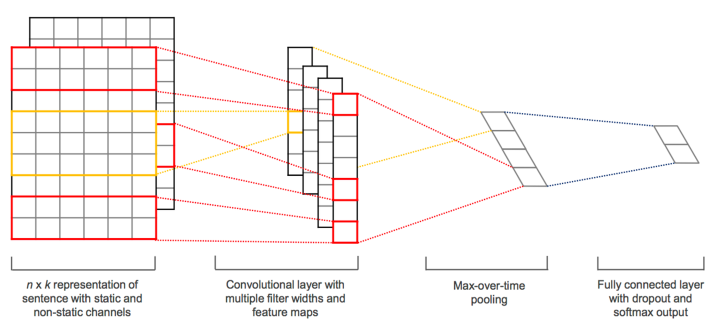
- We performed Hyperparameter tuning by changing the number of layers, dense layers, epochs, batch size, units in each cell(LSTM/GRU), optimizer, activation functions in each model.
- Change in number of layers effected the model to a large extent compared to other parameters
- We used RMSE, Accuracy(change in trend), F1score to evaluate the model.

Models

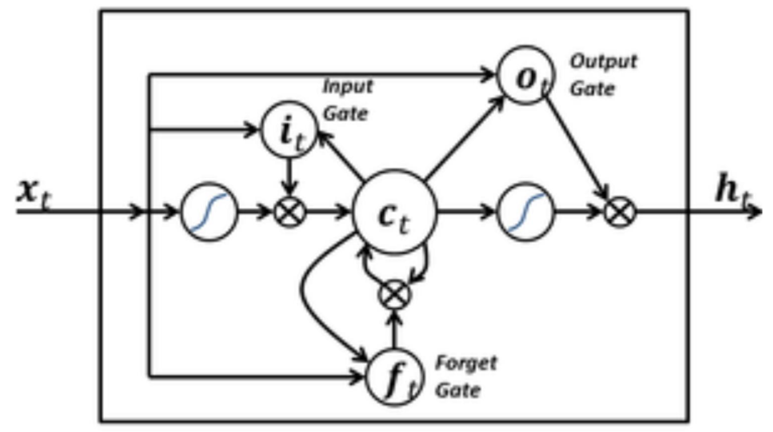
- LSTM : We used 3 fully connected bi directional LSTMs with 50 hidden units, 2 dense layers and dropout.
- GRU : We used 2 fully connected bi directional GRUs with 50 hidden units, 2 dense layers and dropout.
- CNN - LSTM : We used 3 conv1d layers, 2 LSTM layers with hidden units of 150.



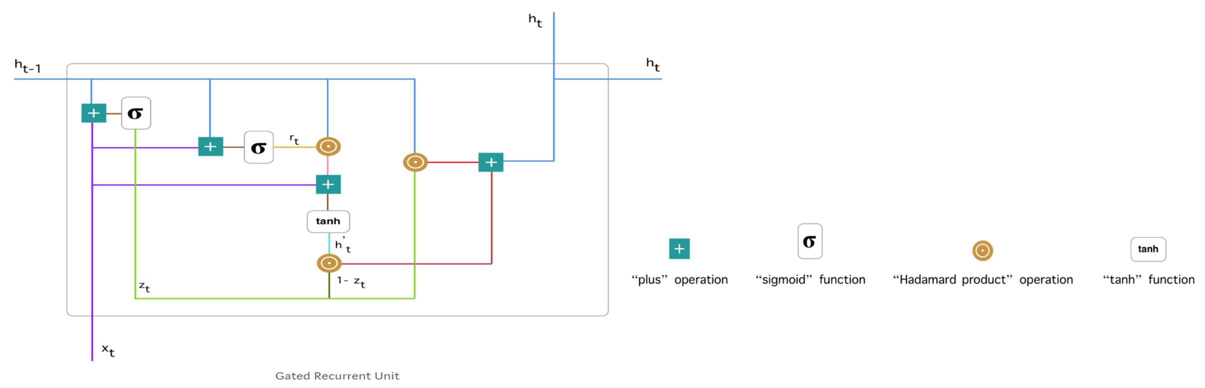
LSTM Architecture

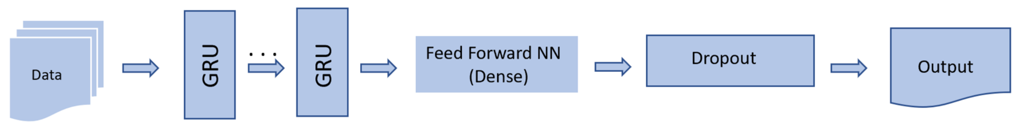


CNN Architecture



LSTM Unit





GRU Architecture

Hyperparameter Results

LSTM,GRU - Epochs:40, Batch size:256, Optimizer: Adam, Loss: MSE, Units:50
CNN LSTM - Epochs: 100, Batch size:50, Optimizer: Adam, Loss: MSE, Units:50,150,250.

LSTM

Layers	1	2	3	4	5
RMSE	29.56	30.806	28.38	32.38	35.068
F1 Score	0.407	0.333	0.415	0.392	0.392
Accuracy	0.515	0.515	0.53	0.53	0.53

GRU

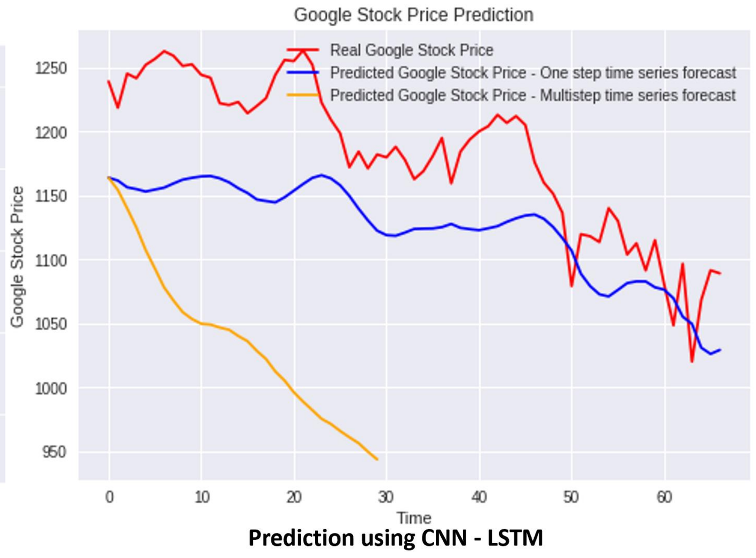
Layers	1	2	3	4	5
RMSE	123.82	27.38	30.459	27.84	34.25
F1 Score	0.516	0.413	0.436	0.436	0.436
Accuracy	0.545	0.484	0.530	0.530	0.530

CNN-LSTM

Layers	3-Conv 1D,1-LSTM	4-Conv 1D,3- LSTM	3-Conv 1D,2- LSTM	4-Conv 1D,2-LSTM	3-Conv 1D, 3-LSTM
RMSE	89.33	131.41	65.56	116.4	102
F1 Score	0.515	0.514	0.483	0.532	0.516
Accuracy	0.447	0.386	0.418	0.459	0.463

Model Evaluation

Prediction using LSTM



Prediction using CNN - LSTM

Prediction using GRU

Analysis

- Overall, analyzing the performance of above three models Day by Day prediction seems to work better.
- Sequence predictions did not work well in predicting pattern. It showed downward movement even there is an upward trend.
- Increasing number of layers by a large value did not improve the model performance.
- Batch size did not have much effect on RMSE so we choose 256 to reduce training time.
- Similarly we choose number of epochs as 40 to balance RMSE and training time.

Conclusion and Future work

- We worked on predicting stock price patterns using 3 different approaches. GRU worked better in predicting day by day stock prices and LSTM worked better in sequence stock price movements.
- Price change depends on several other factors such as events taking place in company, data from social media. For future work, we can include this information as extra features in our model.