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Stock Prediction Using Recurrent Neural Networks LSTM & Bi-LSTM

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Introduction



Stock Prediction Using Neural Network

Machine Learning became very useful to the **Stock Market Forecasting** over the last years, and today, many investment companies are using Machine Learning to make decisions in the Stock Market.

The successful prediction of a stock's future cost could return noteworthy benefit.

Stock Prediction Using Neural Network



Different types of RNNs are taken in forecasting stock trend in the previous years.

In this approach, a stock price prediction method is proposed with Recurrent Neural Networks (RNN) models.

Datasets

The datasets used to fit to models:



Apple dataset

This dataset contains Apple's (AAPL) stock data for the last 10 years (from 2010 to date) reached from Nasdaq

There are 2515 rows and 5 columns in apple Historical Quotes dataset

Datasets

The datasets used to fit to models:



Google dataset

This dataset contains Google's stock data for the last years (to 2017)

There are 1258 rows and 5 columns in Google_Stock_Price_Train dataset & 20 rows and 5 columns in Google_Stock_Price_Test dataset

Datasets



Since the data is sent as a list of candlesticks, it has 6 values:

Date

- The date represents the transactions date

Open

- The stock price at the time of opening sales

Close/Last

- The stock price at the time of Closing sales

High

- The highest price of stock during sale

Low

- The lowest price during sale

Volume

- the Volume indicates total volume of stock being traded each day

Datasets



The Apple dataset head lines:

Date	Close/Last	Volume	Open	High	Low
2022-06-22	\$135.35	73409230	\$134.79	\$137.76	\$133.91
2022-06-21	\$135.87	81000490	\$133.42	\$137.06	\$133.32
2022-06-17	\$131.56	134520300	\$130.065	\$133.079	\$129.81
2022-06-16	\$130.06	107961500	\$132.08	\$132.39	\$129.04
2022-06-15	\$135.43	91532970	\$134.29	\$137.34	\$132.16

Datasets



The google dataset head lines:

	Open	High	Low	Close	Volume
Date					
2012-01-03	325.25	332.83	324.97	663.59	7,380,500
2012-01-04	331.27	333.87	329.08	666.45	5,749,400
2012-01-05	329.83	330.75	326.89	657.21	6,590,300
2012-01-06	328.34	328.77	323.68	648.24	5,405,900
2012-01-09	322.04	322.29	309.46	620.76	11,688,800



Problem statement



Understanding the Problem

forecast stock price
is about use
Sequential data,
where the past data
matters and
influence directly in
our predictions.

We are going to
give to our model a
Stock Price history
of datasets, it will
work on this data to
identify patterns
and make a lot of
calculus to, and give
us the predictions.

Here we will predict
Closing price (Y)
using past closing
prices (as input
vector X)

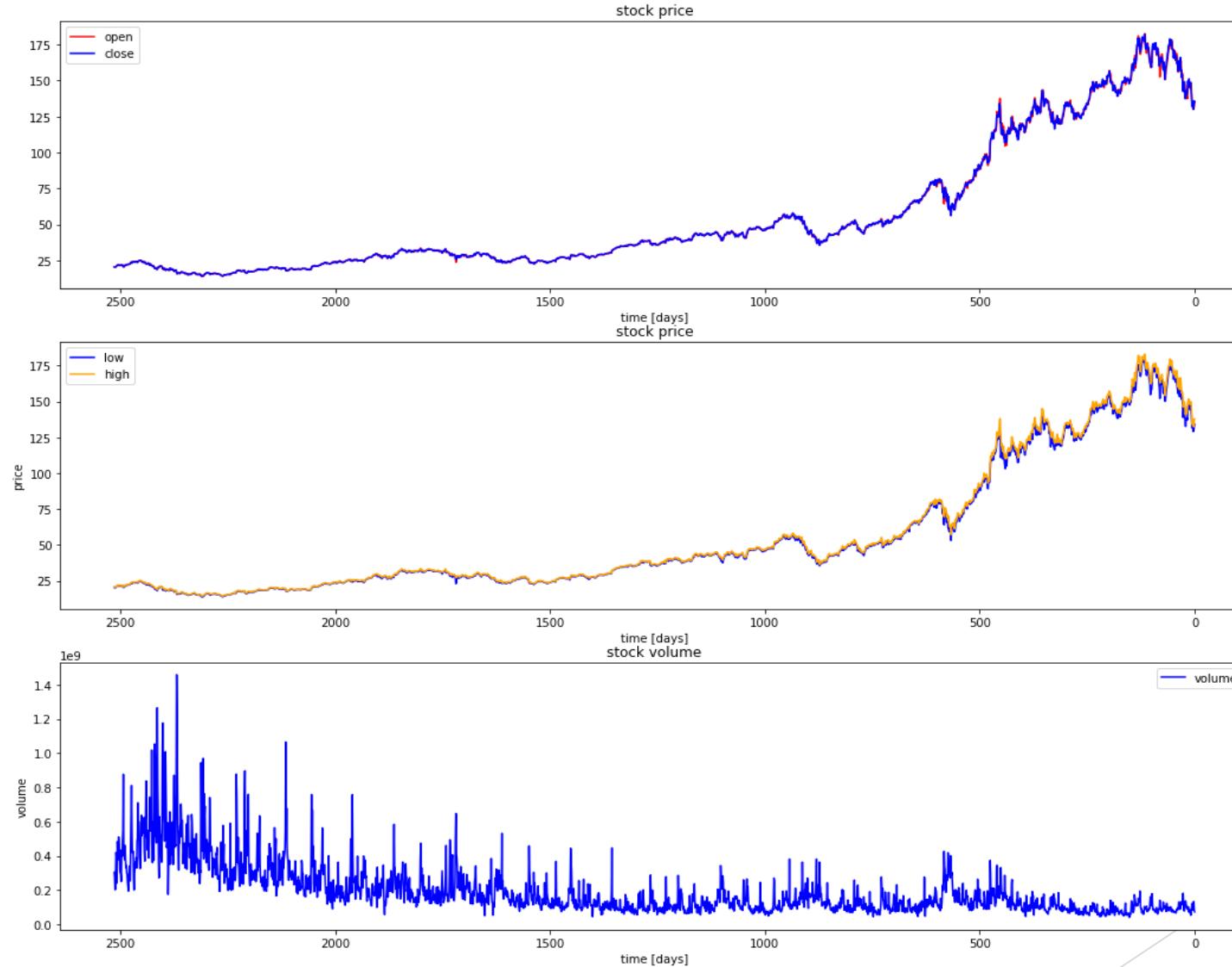
Understanding the Problem



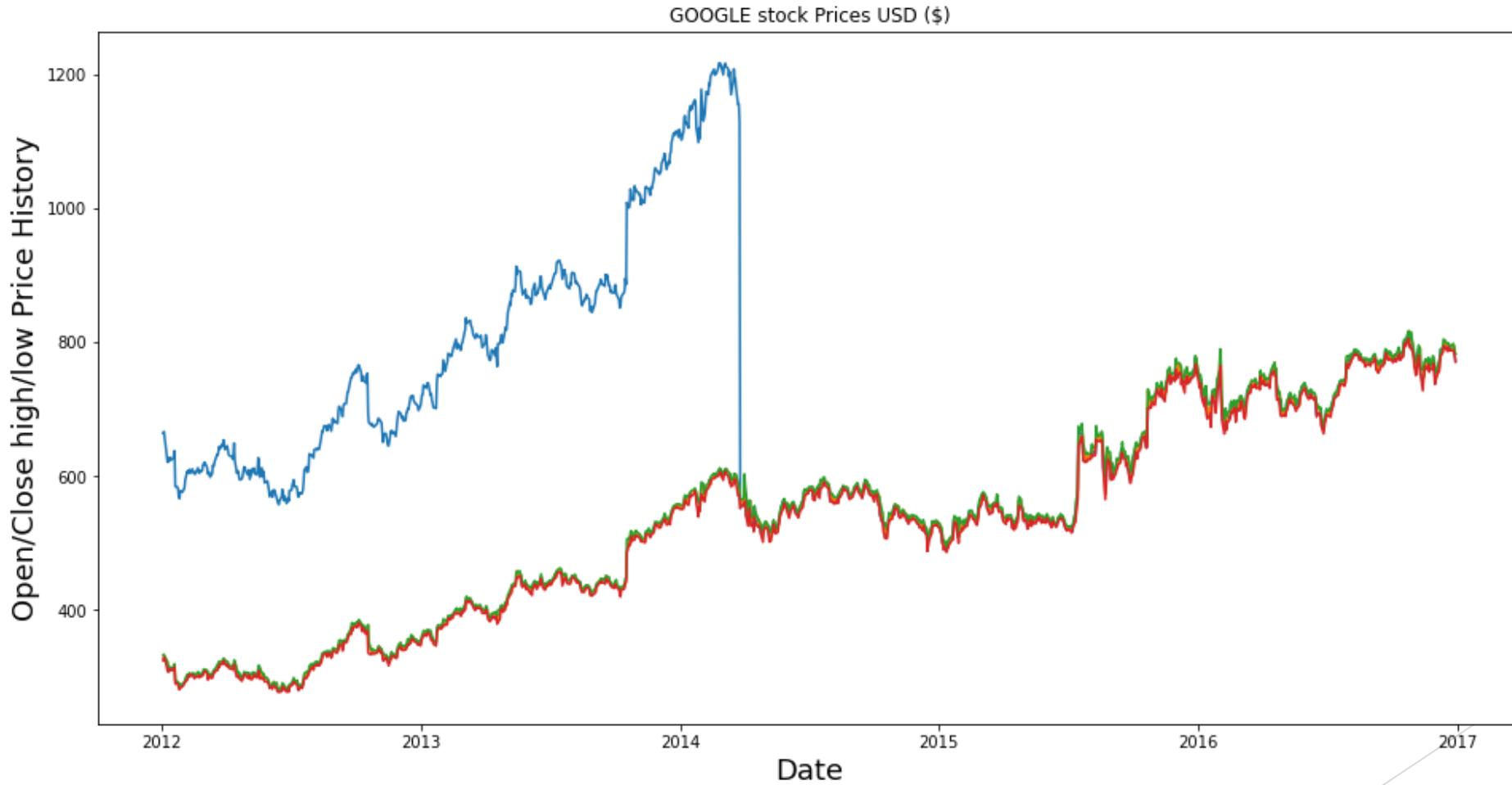
- ▶ In addition to the start and end values given by the start and end dates, values such as interval and period can be given.

Understanding the Problem

Apple open/close and high/low graph



Understanding the Problem



Understanding the Problem



The time interval inside each candle, that is from open to close, is a few minutes, called the **interval**.

With the help of the **period** value, it is possible not to give the start, end dates, and for example request the data of the last 24 hours.



The risk of the stock

We are going to analyze the risk of the stock.

Then find the daily Closing value of the stock by model prediction

In order to predict the risk, we need to inspect the **daily changes of the stock**, and not just its absolute value

Moving Average (MA) Lines



Moving averages are one of the most commonly used technical indicators in stock, futures and forex trading.

Market analysts and traders use moving averages to help identify trends in price fluctuations, smoothing out the noise and short-lived spikes (from news and earnings announcements, for example) for individual securities or indexes.



Most Commonly-Used Moving Averages

The 5 -, 10 -, 20 - and 50 - day moving averages are often used to spot near-term trend changes.

Changes in direction by these shorter-term moving averages are watched as possible early clues to longer-term trend changes.

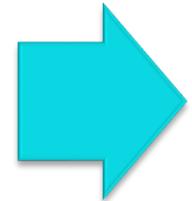
Crossovers of the 50-day moving average by either the 10-day or 20-day moving average are regarded as significant.

The 10-day moving average plotted on an hourly chart is frequently used to guide traders in intraday trading.

Types of Moving Averages

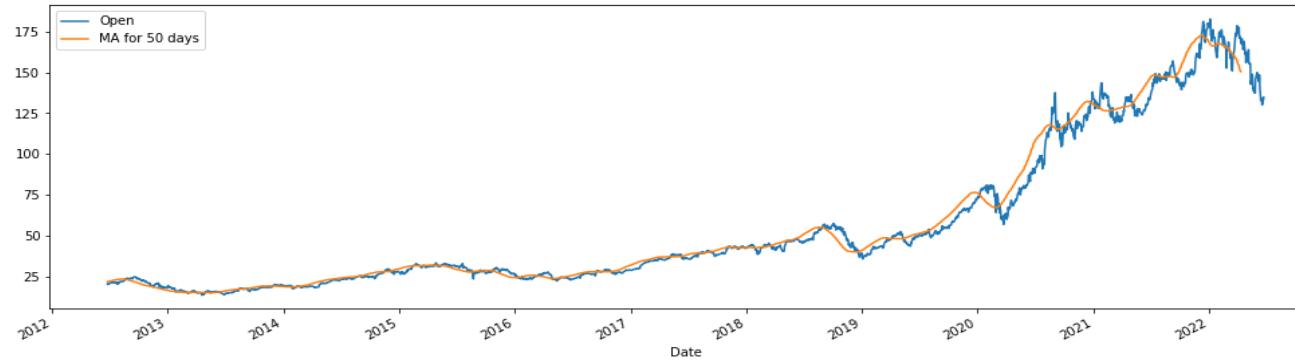
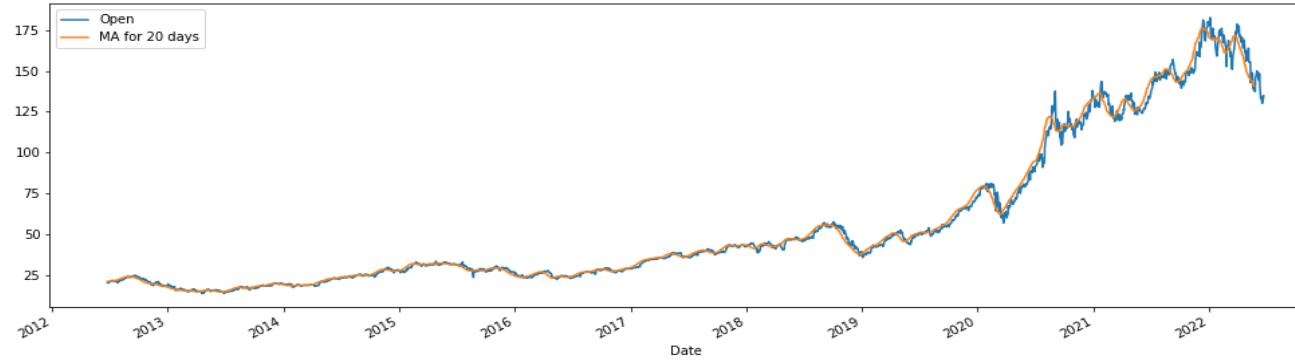
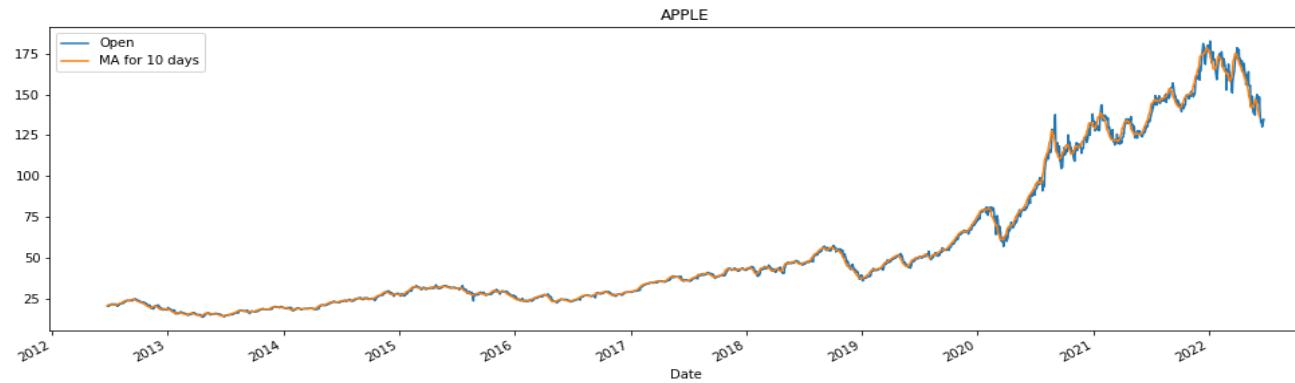


Most moving averages are some form of the simple moving average (SMA), which is the average price over a given time period

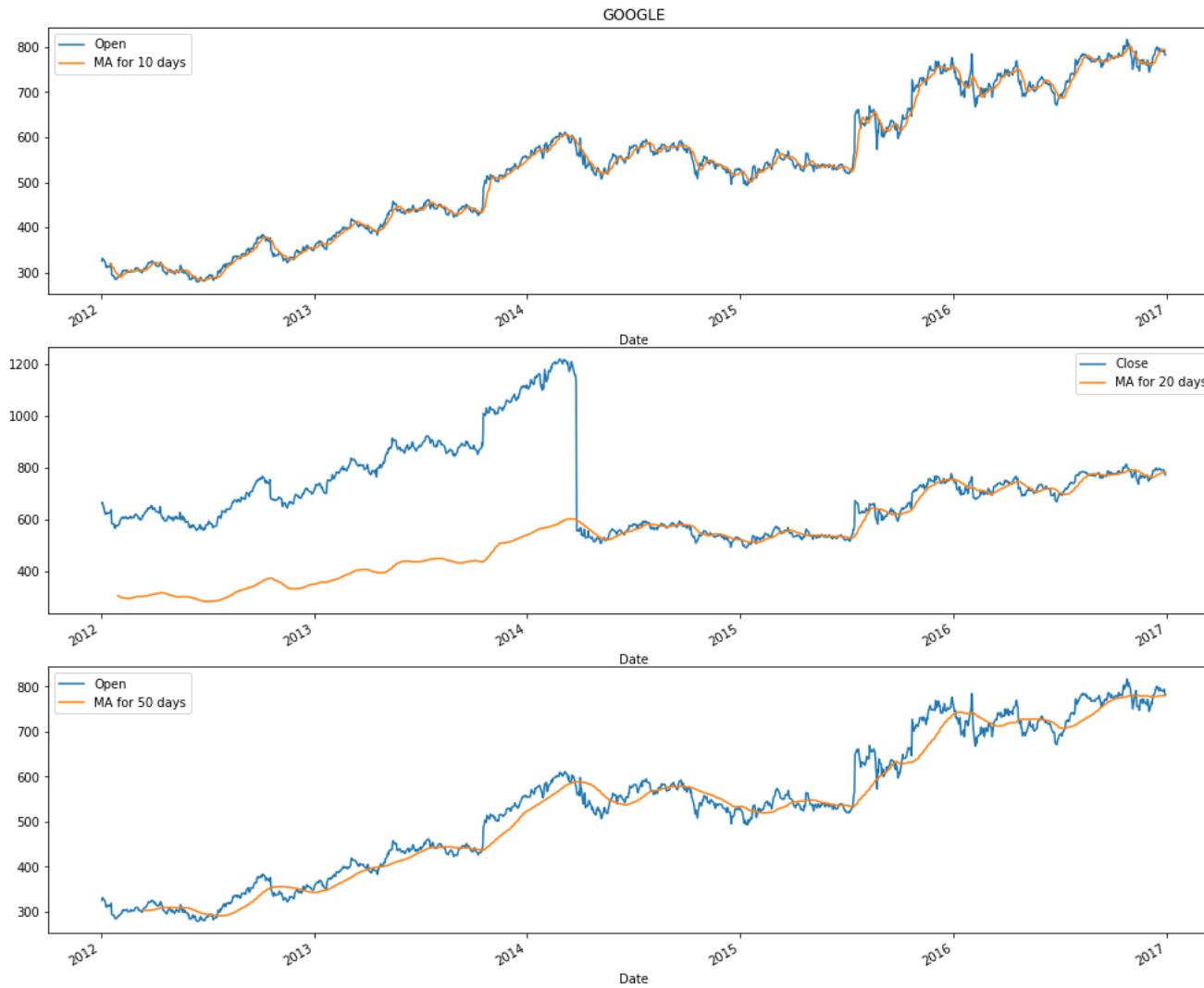


As a general guideline, if the price is above a moving average, the trend is up. If the price is below a moving average, the trend is down.

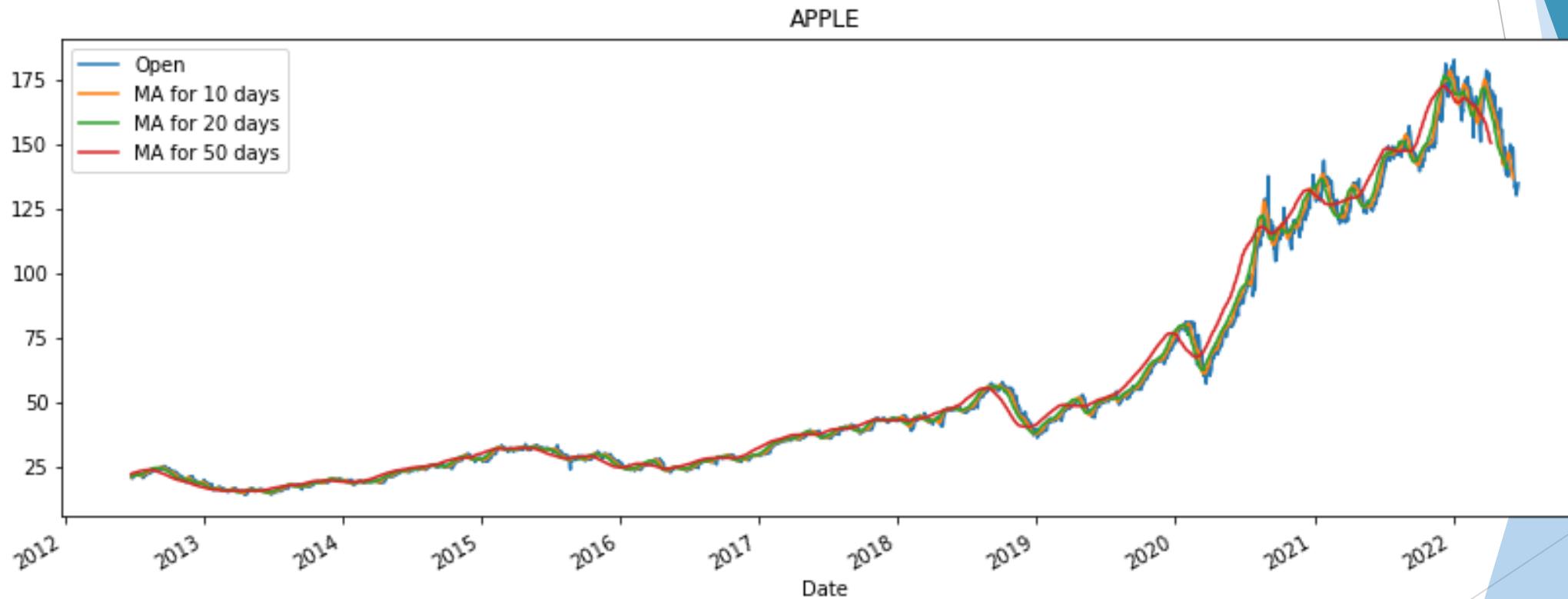
Moving Averages for Apple dataset



Moving Averages for Google dataset

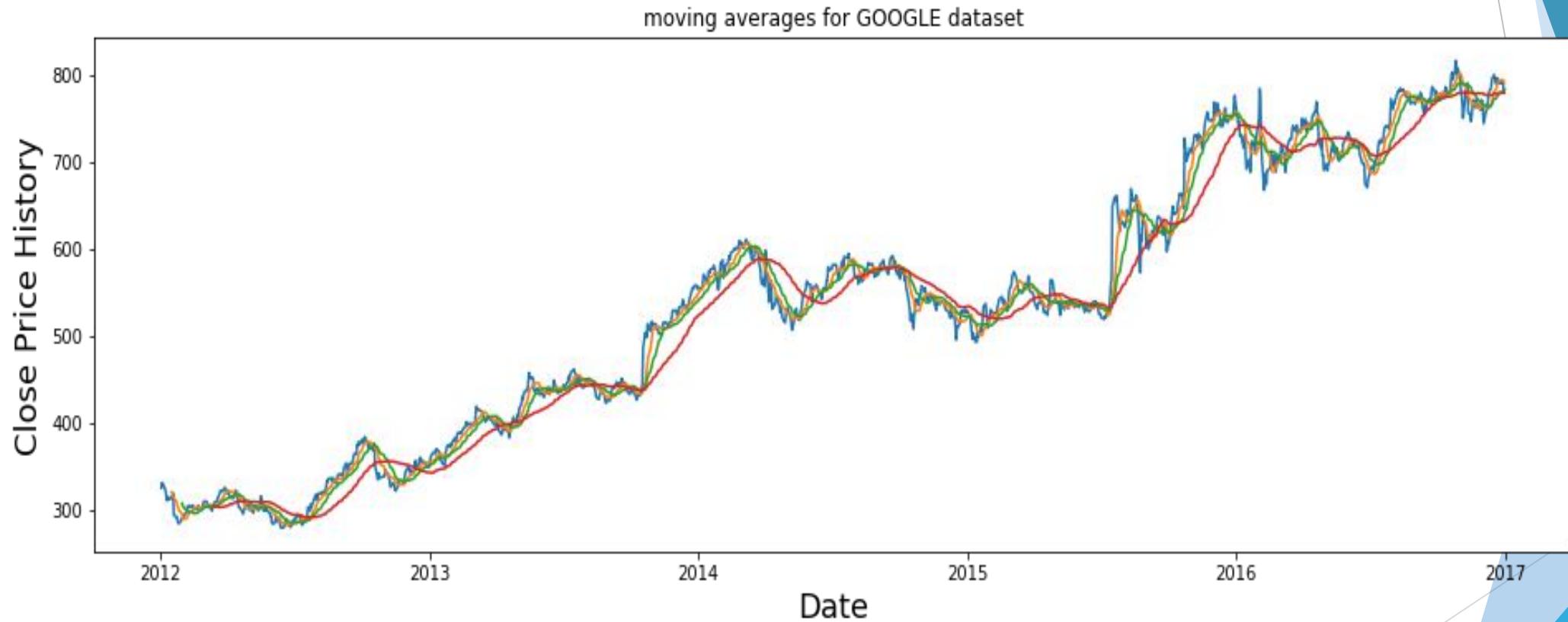


Moving Averages for Apple dataset





Moving Averages for Google dataset





Models

RNN models



RNN Is a type of artificial neural network where connections between nodes form a sequence. This allows temporal dynamic behavior for time sequence.

Long Short Term Memory models



From the simulation results, it can be noted that using RNN models i.e. LSTM, and BI-LSTM with proper hyper-parameter tuning, can forecast future stock trend with high accuracy.

Recurrent Neural Network (RNN) models



we have tested 2 kind of models for each dataset:

1. Long Short Term Memory
(LSTM) model

2. Bidirectional long short term
memory, Bi-LSTM model



LSTM model

LSTM Models



There are 3 types of vanilla recurrent neural network:

the simple
(RNN)

gated
recurrent unit
(GRU)

long short
term memory
unit (LSTM).

LSTM Models



In regular RNN,
the problem
frequently
occurs when
connecting
previous
information to
new information

Long short term
memory
networks,
usually called
LSTM
are a special
kind of RNN.

They were
introduced to
avoid the
long-term
dependency
problem.

LSTM Models



Recurrent networks have an **internal state** that can represent context information. In this model we call it **history**.

The history **keeps information about past inputs** for an amount of time.

LSTM Models



Only the hidden state is passed into the output layer. The memory cell is internal.

LSTMs have three types of gates that control the flow of information.

input gates

forget gates

output gates

LSTM Models



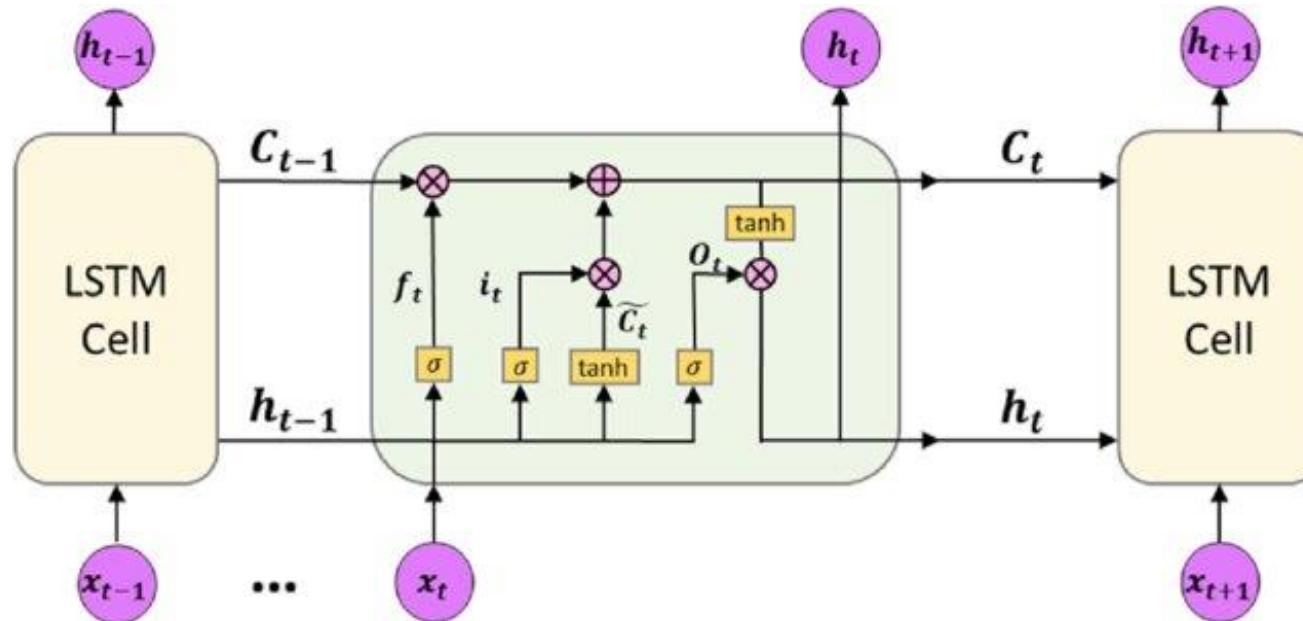
The hidden layer output of LSTM includes the hidden state and the memory cell

LSTMs can alleviate **vanishing** and **exploding** gradients.

LSTM Model formulation



A LSTM layer structure for a time step, with a detailed calculation illustration shown in the LSTM cell at time step t.



$$\begin{aligned} f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\ i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\ o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\ \tilde{c}_t &= \sigma_h(W_c x_t + U_c h_{t-1} + b_c) \\ c_t &= f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \\ h_t &= o_t \circ \sigma_h(c_t) \end{aligned}$$

Layer Copy Pointwise operator

LSTM Model formulation



The parameters in a LSTM unit is associated with the functions involved in calculation



A LSTM Cell has four functional units:

3 Sigmoids (f, i, o functions below)

1 Tanh (c function below)



We can generalize all these 4 functions :

$\text{Sig} / \tanh (W.x + U.h + b)$



Where, W, U, b are the parameters and x is the input and h is the hidden layer values calculated using above parameters.

LSTM Model formulation



Sig / tanh ($W \cdot x + U \cdot h + b$)

W is the weight parameter of input vector. So, it would be of size n, where n is the dimension of input vector.

U is the weight parameter of hidden state vector. So, it should be equal to the number of units in layer - m.

bias is a constant with dimension 1.

Total number of parameters for a function within LSTM unit would be $n+m+1$

where m is dimension of input vector, m is number of LSTM units in a layer and 1 is bias parameter

LSTM unit has 4 functions (3 sigmoid + 1 tanh).
So, total number of params will be $4 * (n+m+1)$

If LSTM has m units, total number of params will be $4 * (n+m+1) * m$

LSTM Model formulation



Formula for calculating current state:

$$h_t = f(h_{t-1}, x_t)$$

h_t -> current state
 h_{t-1} -> previous state
 x_t -> input state

Formula for applying Activation function(tanh):

$$h_t = \tanh (W_{hh}h_{t-1} + W_{xh}x_t)$$

W_{hh} -> weight at recurrent neuron
 W_{xh} -> weight at input neuron

Formula for calculating output:

$$y_t = W_{hy}h_t$$

y_t -> output
 W_{hy} -> weight at output layer

LSTM Model No.1



```
# Build the LSTM model
model = Sequential()
model.add(LSTM(100, return_sequences=True, input_shape = (x_train.shape[1],1)))
model.add(Dropout(0.2))
model.add(LSTM(64 , return_sequences=True,activation='tanh'))
model.add(Dropout(0.2))
model.add(LSTM(32, return_sequences=False))
model.add(Dense(1,activation='linear'))
model.summary()

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error',metrics=['accuracy'])
```

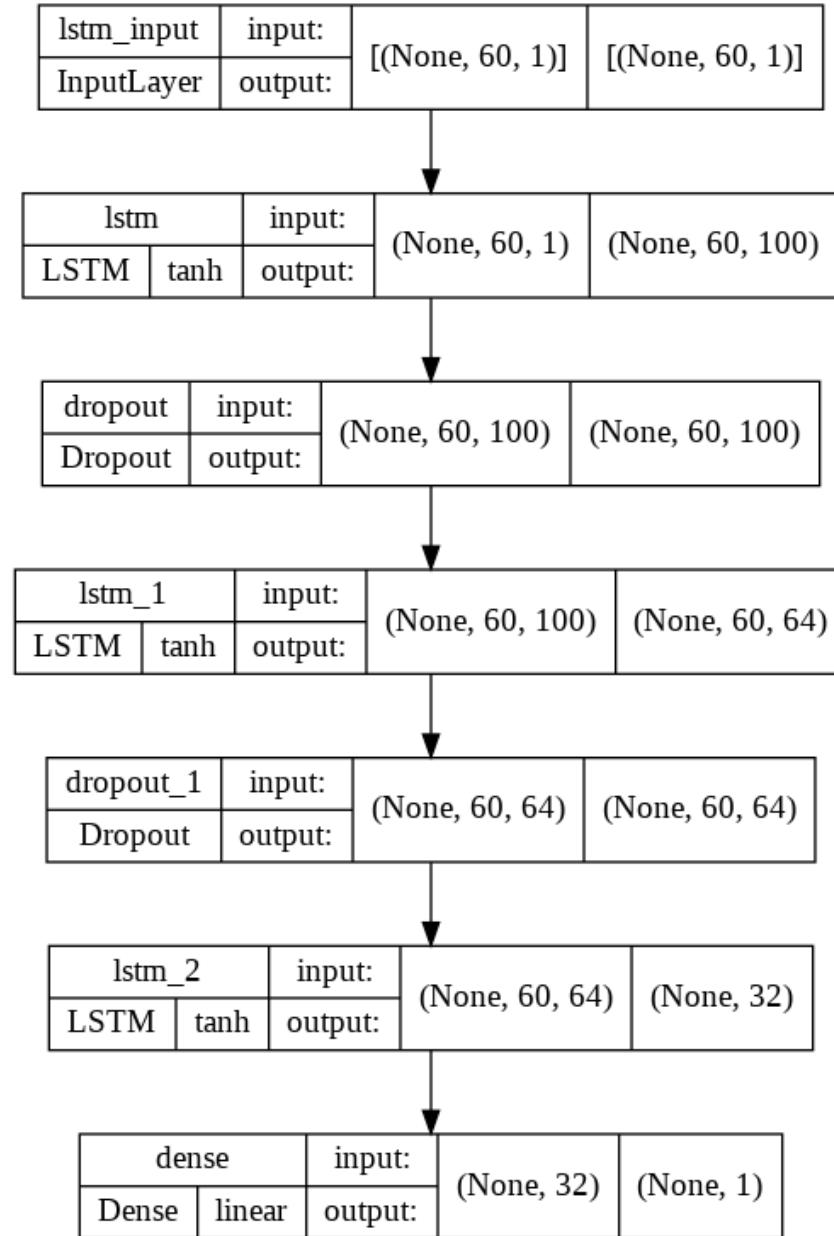
LSTM Model No.1



1. We defined a sequential model which consists of a linear stack of layers.
2. Add a LSTM layer by 100 network units. setting `return_sequence = true` means the output of the layer will be another sequence of the same length.
3. Adding each dropout layer to prevent overfitting. when defining drop out layers we specify 0.2,meaning that 20% of the layers will be dropped.
4. `Return-sequences` is True as we need to add another LSTM layer after the current one.
5. add another LSTM layer with 100 units and `return_sequence = false` means that this time just the last output returns in the output unit.so, the last LSTM layer, `Return-sequences` is False as we will not add more LSTM layers.
6. adding a densely connected layer that specifies the output of 1 network unit. The output dimension is 1 since we are predicting 1 price each time.

LSTM Model No.1

Total params: 95,489
Trainable params: 95,489
Non-trainable params: 0



LSTM Model NO.2



We changed model layer architecture and parameters to compare the results and fitted it over same condition on both datasets. Thus, the second model is as below:

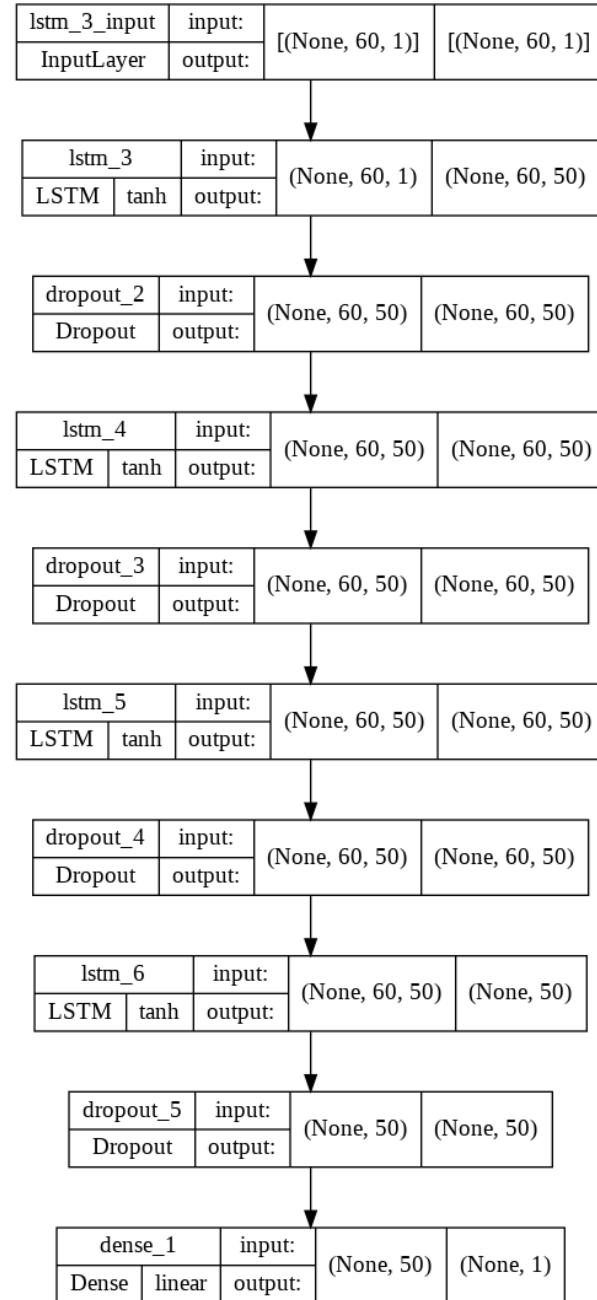
```
# Building Model:  
model = tf.keras.models.Sequential()  
model.add(tf.keras.layers.LSTM(units=50, return_sequences=True, input_shape=(x_train.shape[1], 1)))  
model.add(tf.keras.layers.Dropout(0.5))  
model.add(tf.keras.layers.LSTM(units=50, return_sequences=True))  
model.add(tf.keras.layers.Dropout(0.5))  
model.add(tf.keras.layers.LSTM(units=50, return_sequences=True))  
model.add(tf.keras.layers.Dropout(0.5))  
model.add(tf.keras.layers.LSTM(units=50))  
model.add(tf.keras.layers.Dropout(0.5))  
model.add(tf.keras.layers.Dense(units=1))  
model.summary()
```

LSTM Model NO.2

Total params: 71,051

Trainable params: 71,051

Non-trainable params: 0





Bi-LSTM model

BI-LSTM Model



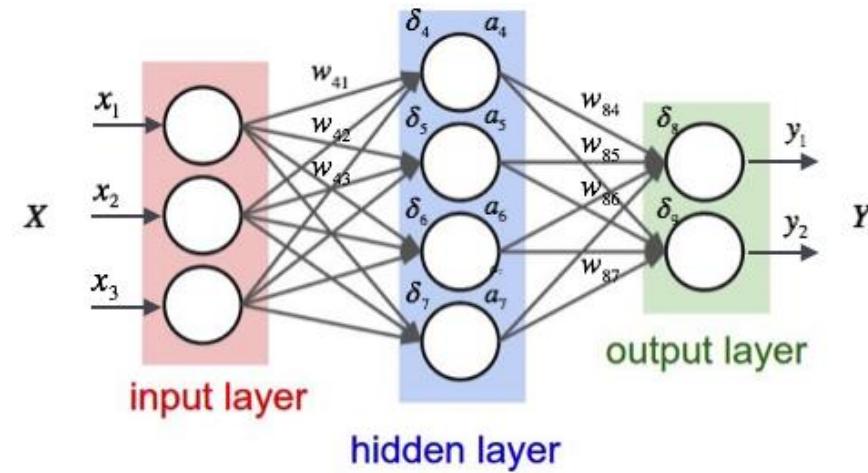
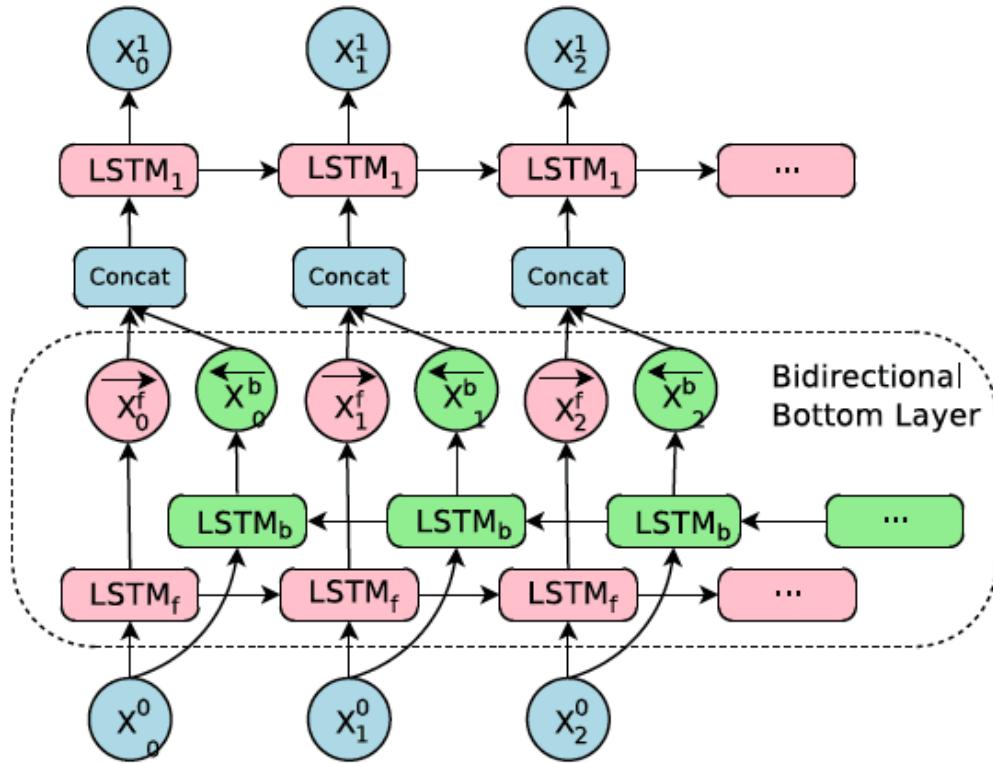
Bidirectional long-short term memory (bi-lstm)

the process of making any neural network to have the sequence information in both directions

backwards
(future to past)

Or forward
(past to future)

BI-LSTM Model



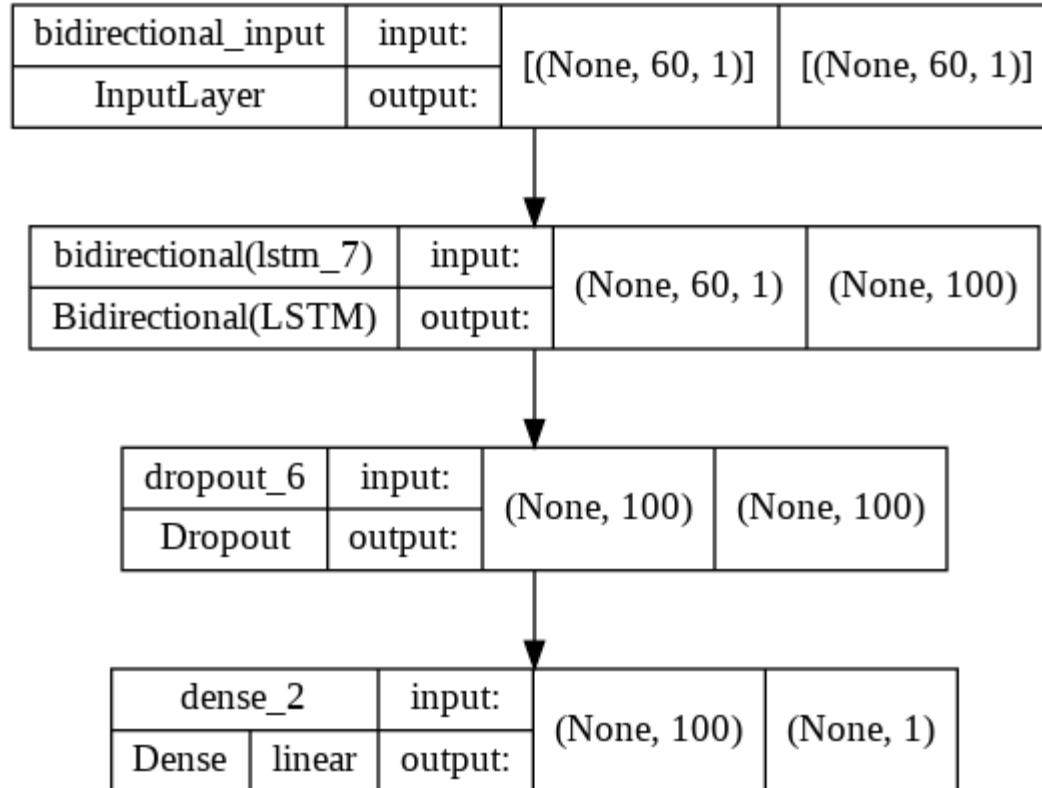
BI-LSTM Model



- The bidirectional model used for both datasets:

```
# define model
model = Sequential()
model.add(Bidirectional(LSTM(50, activation='tanh'), input_shape=(x_train.shape[1], 1)))
model.add(Dropout(0.2))
model.build((x_train.shape[1],1))
model.add(Dense(1))
```

BI-LSTM Model



Model Evaluation



we evaluate our model with test set and then apply following metrics to examine the performance of the model:

- mean squared error (MSE)
- Root mean squared error(RMSE)
- R_squared



$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2}$$

$$\begin{aligned} R^2 &= 1 - \frac{\text{sum squared regression (SSR)}}{\text{total sum of squares (SST)}}, \\ &= 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}. \end{aligned}$$

Model Evaluation



MSE is beneficial when the spread of prediction values is significant and larger values must be punished.

When the spread is important and bigger values need to be penalized, RMSE (NRMSE) is also useful. When compared to MSE, RMSE is easier to interpret because the RMSE number is on the same scale as the projected values.

When the relation between the forecasted and actual value is to be known then R^2 is used.



The procedure

The procedure



- ▶ now we choose a specific stock feature
- ▶ drop feature: volume
- ▶ normalize stock data
- ▶ Normalization is a very important part for any Recurrent Neural Network. For our LSTM model, normalization will play an important role. Normalization using MinMaxScaler will bring our entire datapoints between a minimum and a maximum value. For this purpose, we will use the values (0,1).
- ▶ then create train, validation and test data sets

The procedure



At First call the libraries and read the dataset

then normalize the data

get the moving averages of the stocks

get their weight, which changes by a few percent.

We use this model to make predictions and store the predictions.

In the model, we use the normalization batch, train it, and then validate it.

In the next step, using the min max scaler, we cut the data in the range of zero and one.

Find the changes and match the data to the model.

Finally, we use the inverse scaler to inverse the scales as before,

obtain the values of the loss and the accuracy of the model.

evaluate model with MSE , RMSE and R2 metrics to examine performance of the model.

The model setups



define the shape of the input dataset:

- Number of time steps, the number of lags in the data frames we set in Step #2.

define the number of units, and the number of hyper parameters of the LSTM.

- The higher number, more parameters in the model.

The model setups



Define the dropout rate, which is used to prevent overfitting.

Specify the output layer to have a linear activation function.

Then we also define the optimization function and the loss function.

- Tuning these hyper parameters to find the best option would be a better practice.



Apple Dataset Results

LSTM Model NO.1 for Apple dataset



We trained our model with the training data over bellow parameters :

epochs = 50

with a batch size = 32

optimizer= Adam

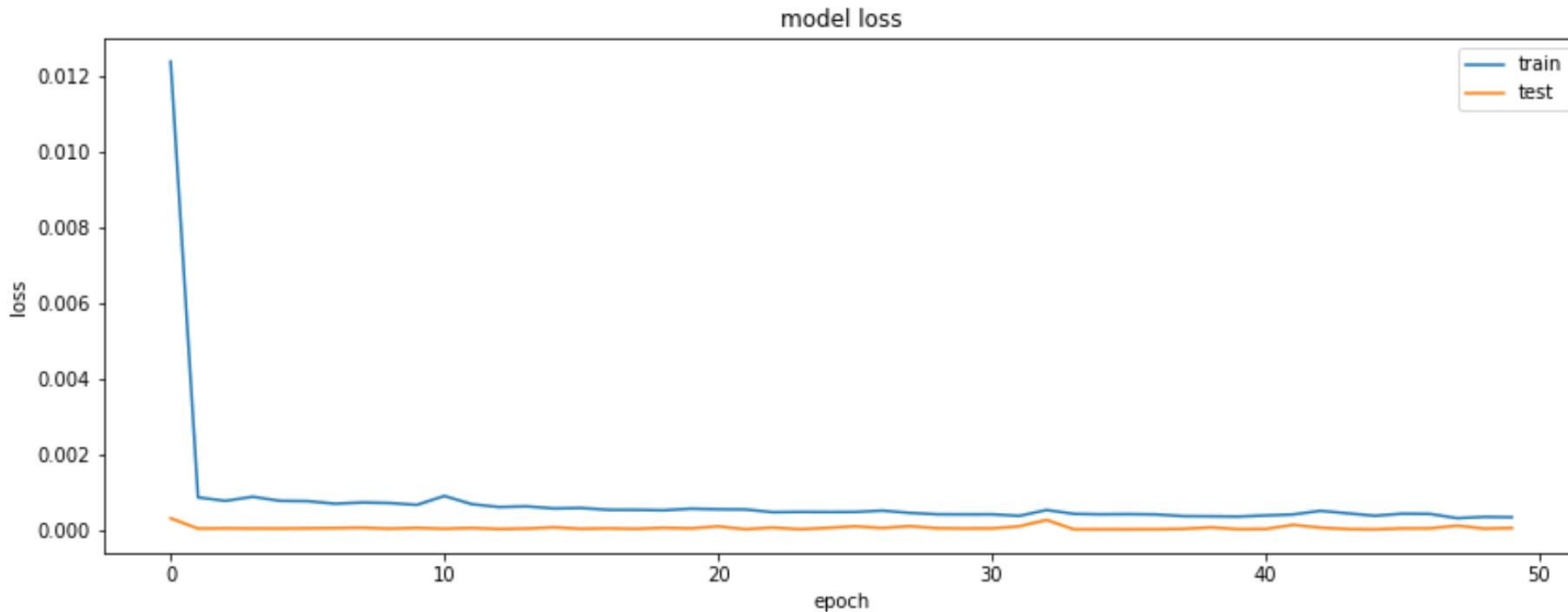
loss= mean squared error (MSE)

Validation split=0.25

Drop out = 0.6

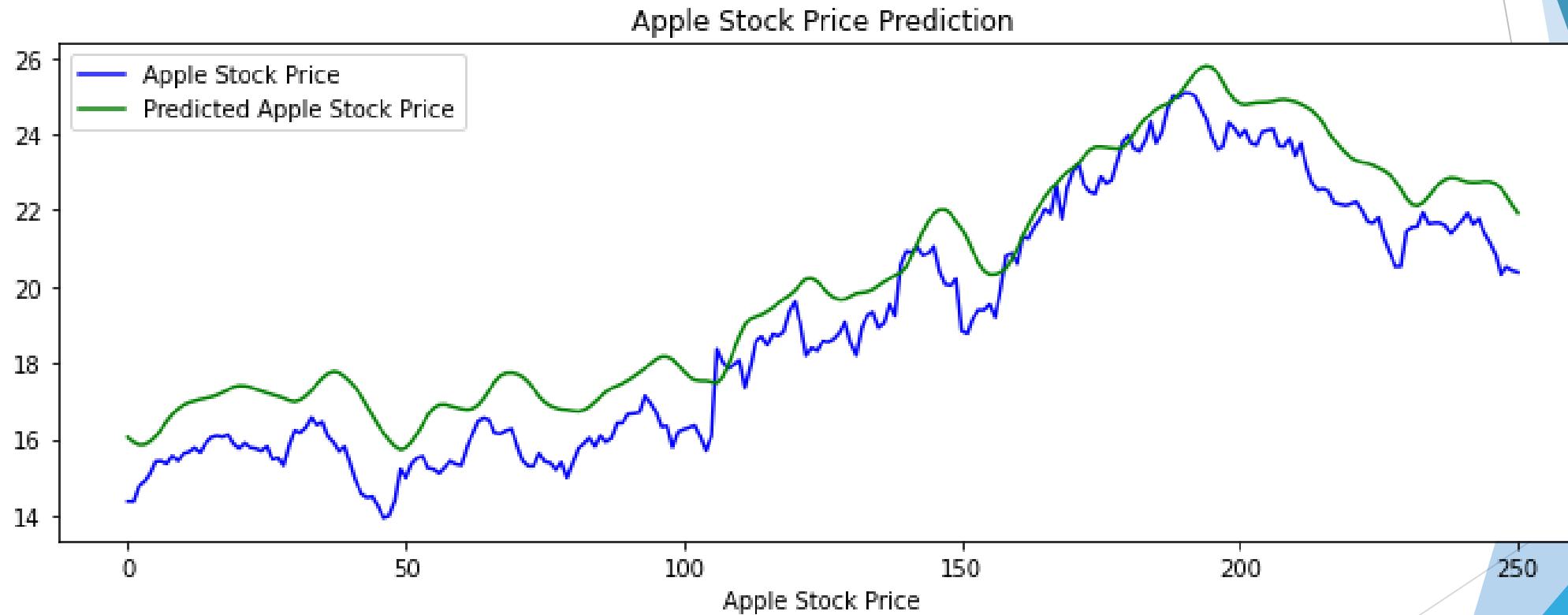
LSTM Model NO.1 for Apple dataset

- The Loss graph for LSTM model no.1



LSTM Model No.1 for Apple dataset

- The prediction



LSTM Model No.1 for Apple dataset



RMSE

- 1.1292269819160854

MSE

- 1.275153576687311

R2

- 0.8409089295587304

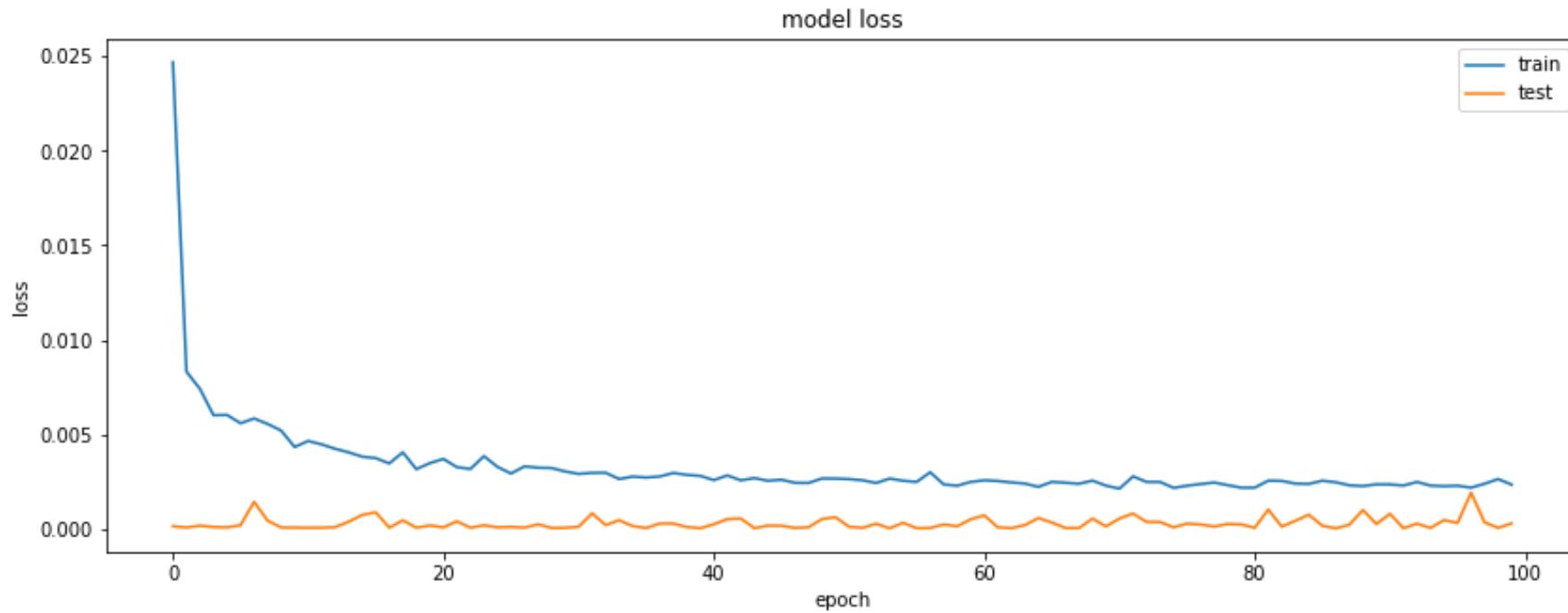
Accuracy

- 0.0008841733215376735

LSTM Model No.2 for Apple dataset

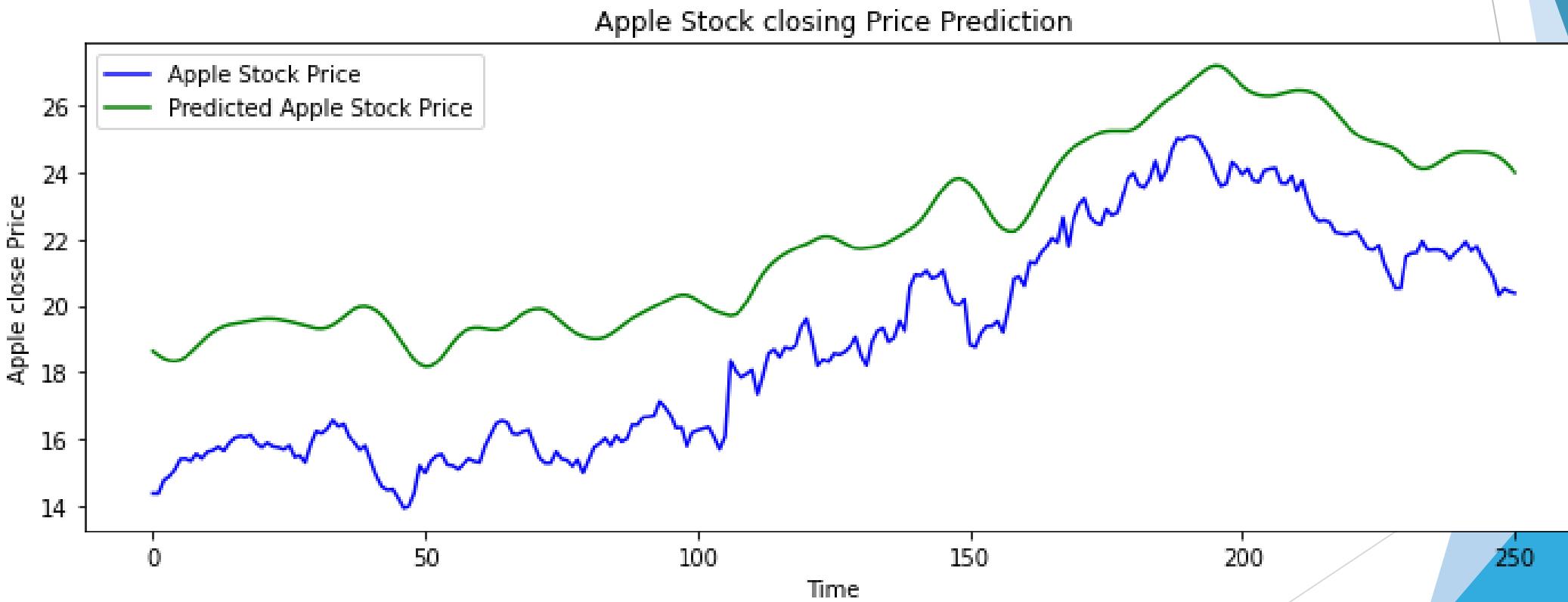


- ▶ The Loss graph for LSTM model no.2 over 100 epochs and batch size 32:



LSTM Model No.2 for Apple dataset

- The prediction



LSTM Model No.2 for Apple dataset



RMSE

- 3.120903760823406

MSE

- 9.740040284321678

R2

- 0.0006180498835880455

Accuracy

- 0.0006049606599844992

Bi-LSTM Model for Apple dataset



We trained our model with the training data over bellow parameters :

epochs = 50

with a batch size = 32

optimizer= Adam

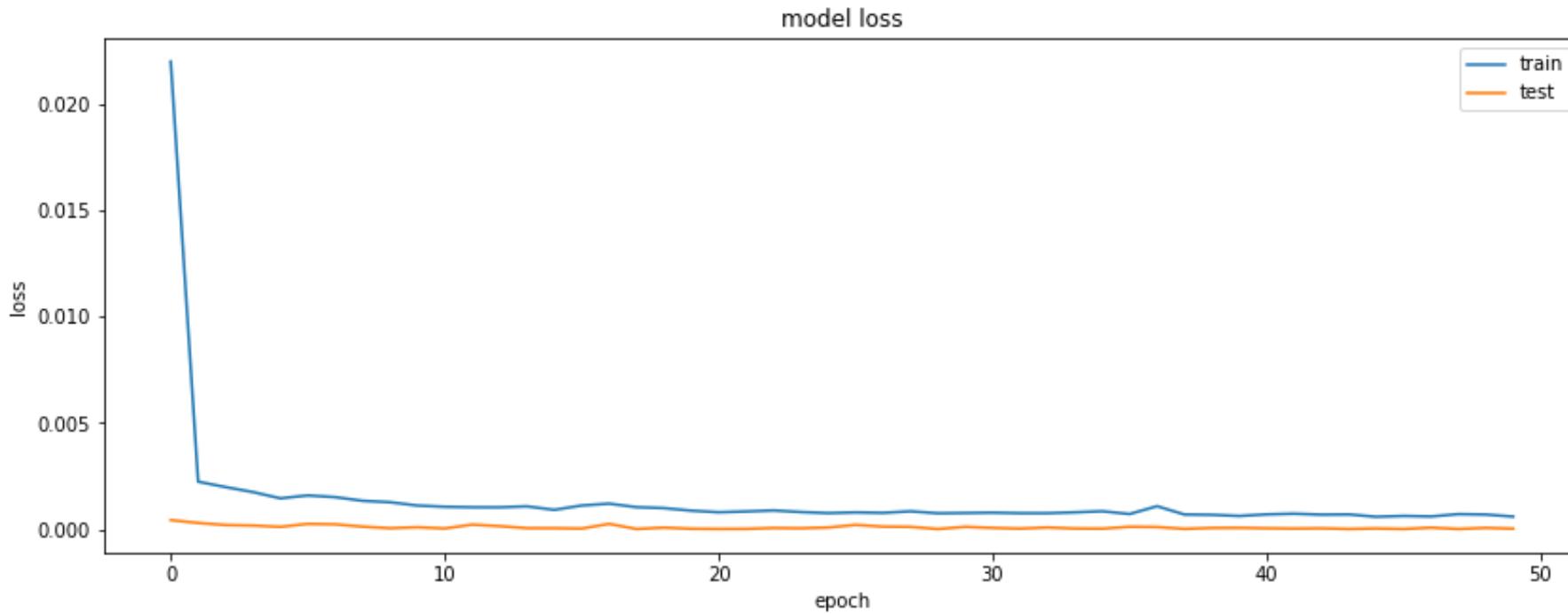
loss= mean squared error (MSE)

Validation split=0.2

Drop out = 0.2

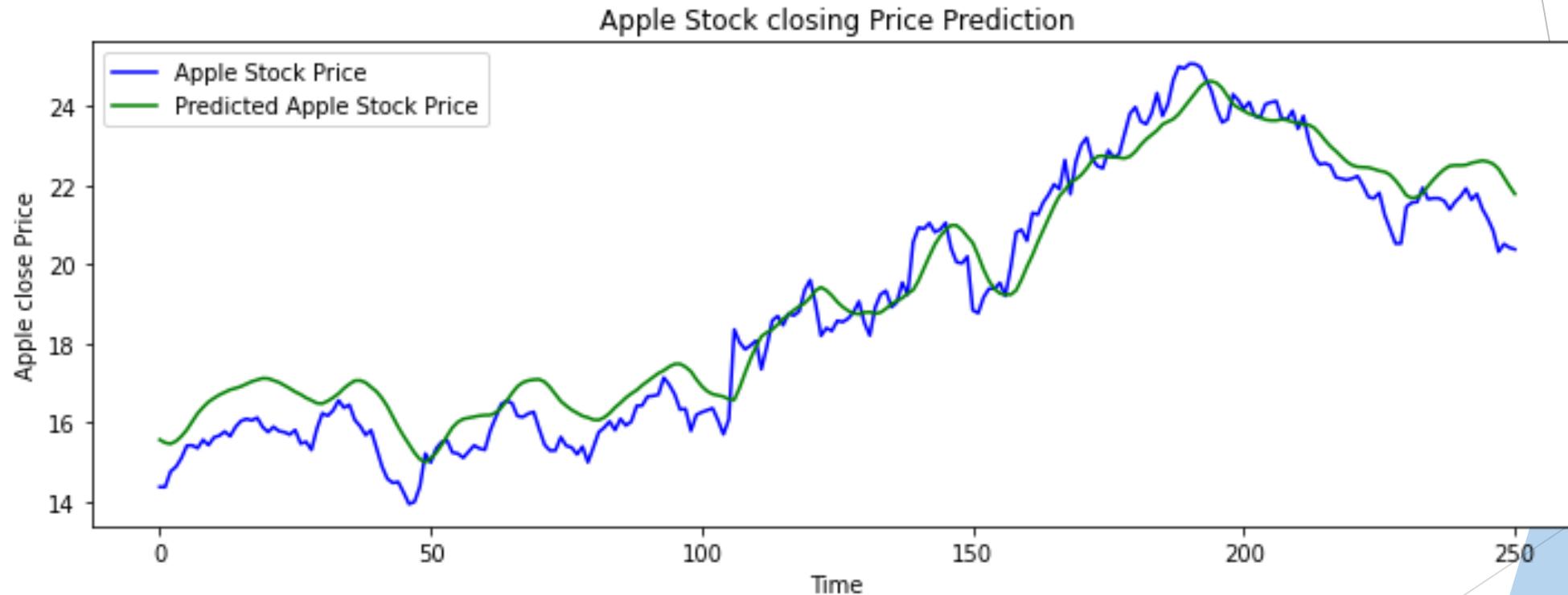
Bi-LSTM Model for Apple dataset

- The Loss graph



Bi-LSTM Model for Apple dataset

- The prediction



Bi-LSTM Model for Apple dataset



RMSE

• 0.39104942785012287

MSE

• 0.15291965502190846

R2

• 0.9340726278285816

Accuracy

• 0.0005672149709425867



Google Dataset Results

LSTM Model No.1 for Google dataset



We trained model no.1 with the training data over bellow parameters :

epochs = 100

with a batch size = 64

optimizer= Adam

loss= mean squared error (MSE)

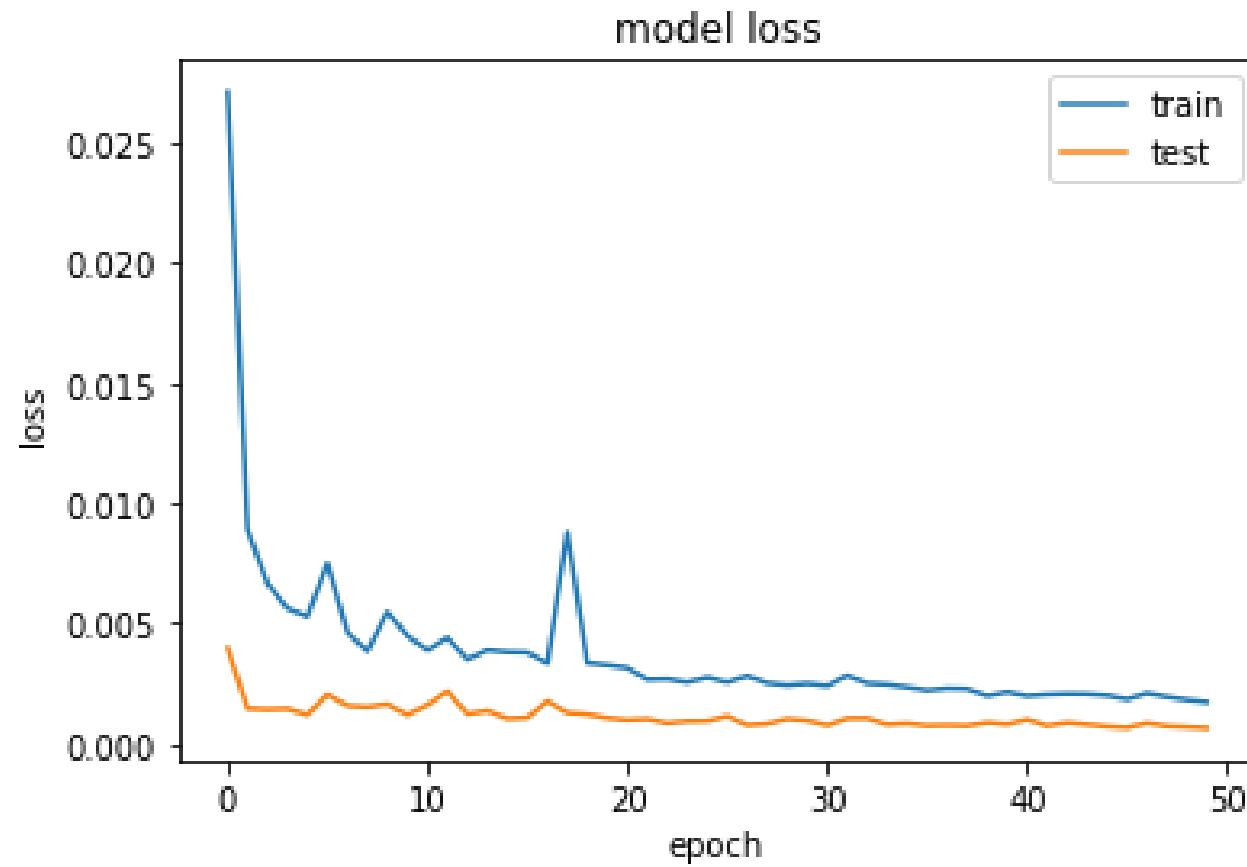
Validation split=0.10

Drop out = 0.6

LSTM Model No.1 for Google dataset

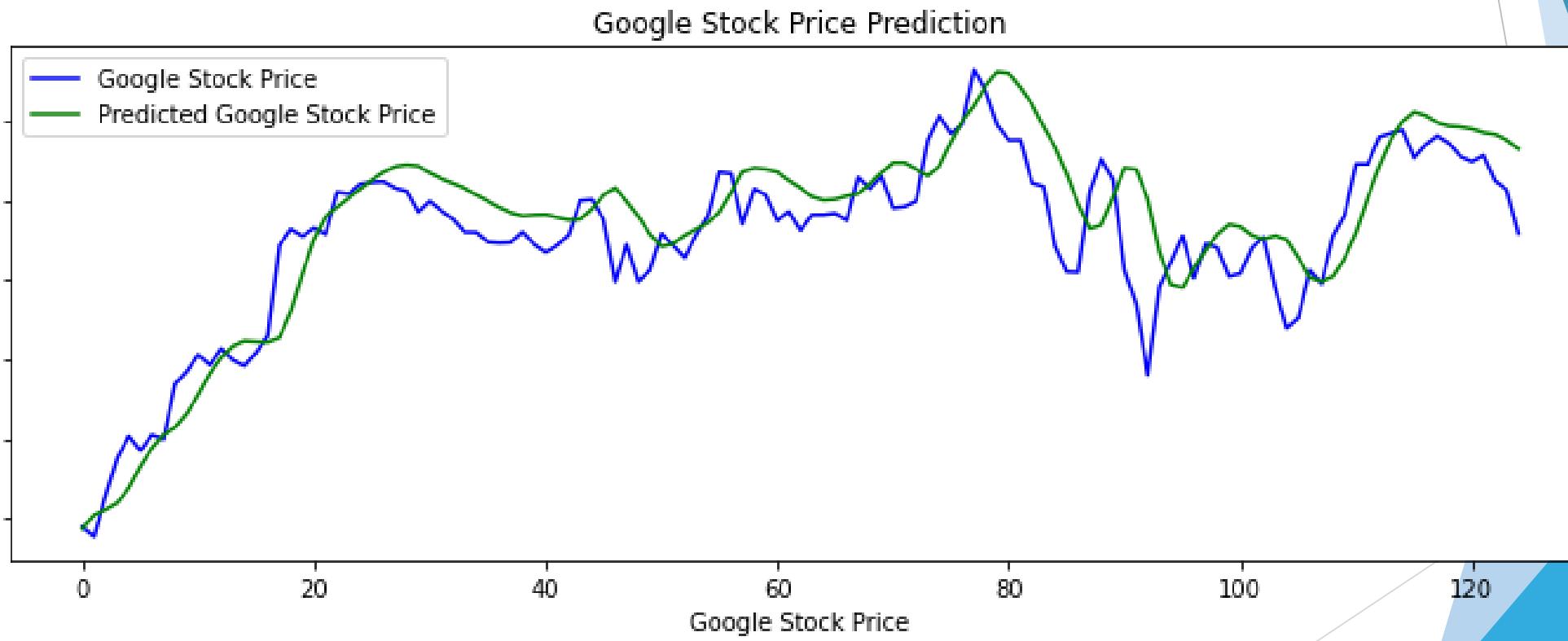


- The Loss graph for LSTM model no.1



LSTM Model No.1 for Google dataset

- The prediction



LSTM Model No.1 for Google dataset



RMSE

- 3.729775312500001

MSE

- 13.91122388173448

R2

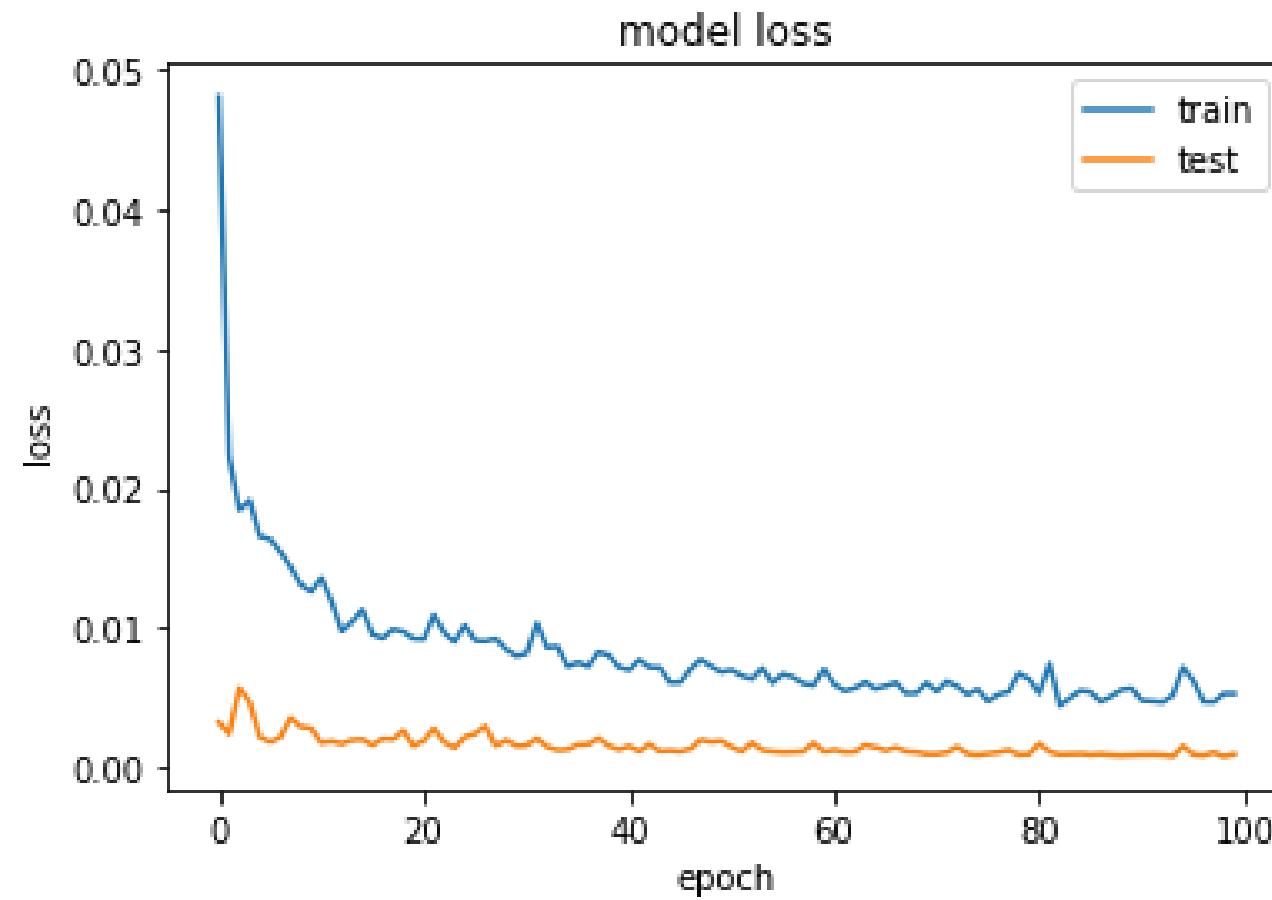
- 0.7389681205217664

Accuracy

- 0.002487562131136656

LSTM Model No.2 for Google dataset

- The Loss graph for LSTM model no.2



LSTM Model No.2 for Google dataset

- The prediction



LSTM Model No.2 for Google dataset



RMSE

- 6.235203535156251

MSE

- 38.87776312482501

R2

- 0.6655010188246948

Accuracy

- 0.002487562131136656

Bi-LSTM Model for Google dataset



We trained our model with the training data over bellow parameters :

epochs = 50

with a batch size = 32

optimizer= Adam

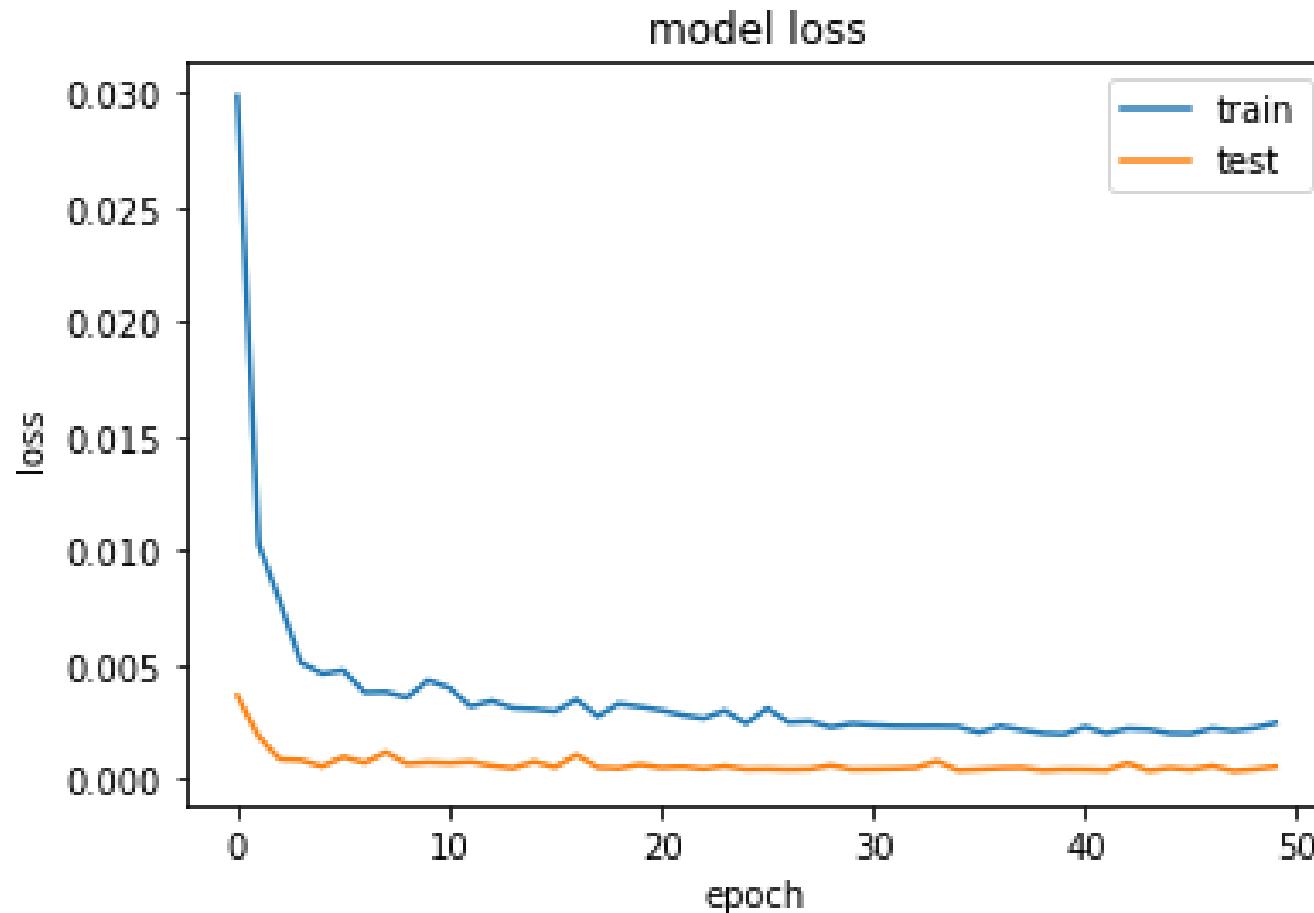
loss= mean squared error (MSE)

Validation split=0.2

Drop out = 0.6

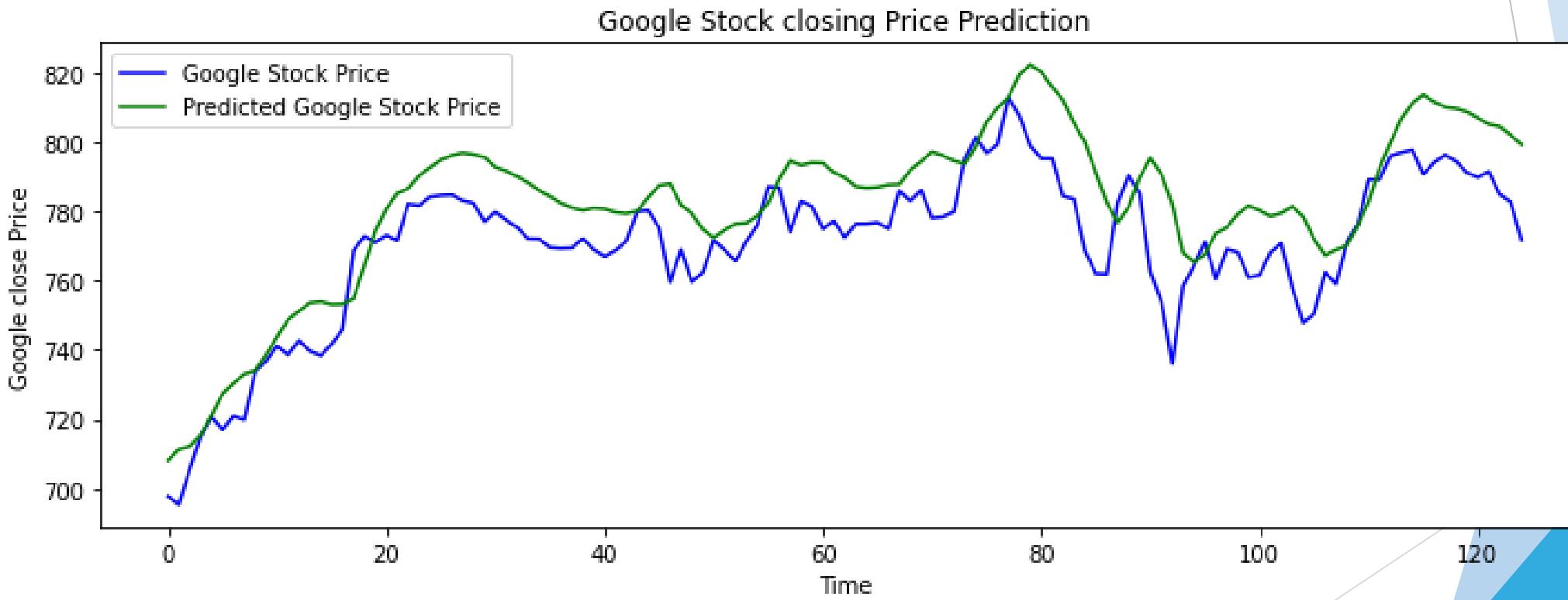
Bi-LSTM Model for Google dataset

- The Loss graph



Bi-LSTM Model for Google dataset

- The prediction



Bi-LSTM Model for Google dataset



RMSE

- 11.538846113281252

MSE

- 133.14496962598585

R2

- 0.5392159314681311

Accuracy

- 0.0023310023825615644

Conclusion



In this approach, the goal was to predict stock prices using a recurrent neural network.



For this purpose, several model architectures for stock price forecasting were presented. Also, tried to test different model parameters such as number of layers, nodes and drop outs and fitting over several batch size, epoch size, optimizer and different activation functions to determine the effect of different parameters in accuracy of the model prediction.



With proper layers and hyper parameters, the LSTM and the Bi-LSTM models give good results for stock prediction.

References



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- ▶ [Bi-LSTM. What is a neural network? Just like our... | by Raghav Aggarwal | Medium](#)
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- ▶ [9.4. Bidirectional Recurrent Neural Networks — Dive into Deep Learning 0.17.5 documentation \(d2l.ai\)](#)
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Thank you

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