Group ID: 13

Topic: Stock Market Trading using Machine Learning and Deep Learning

Members:

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Github Link: https://github.com/vrutik2906/Stock-Market-Trading-using-Machine-Learning.git (https://github.com/vrutik2906/Stock-Market-Trading-using-Machine-Learning.git)

Implementation:

Importing the required Libraries

In [ ]:

```
import pandas as pd #For data related tasks
import numpy as np
import matplotlib.pyplot as plt #For data visualization
from sklearn.tree import DecisionTreeRegressor # Decision Tree classifier
from sklearn.linear_model import LinearRegression #Linear Regression
from sklearn.ensemble import RandomForestRegressor #Random Forest Regression
from sklearn.metrics import mean_absolute_error #Mean Absolute Error
from sklearn.metrics import mean_squared_error #Mean Squared Error
import math
from sklearn.preprocessing import MinMaxScaler #Min Max Scaler Normalization
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM
```

Importing the CSV named 'Amazon'

We chose a dataset from Amazon dated 04-01-2010 to 31-12-2020. \ This dataset attribute is open, high, low, close and volume but we selected close as a label data and the rest of to extract the features that will help to predict the result.

Source: https://finance.yahoo.com/quote/AMZN/history?p=AMZN (https://finance.yahoo.com/quote/AMZN/history?p=AMZN)

In [ ]:

```
from google.colab import files
uploaded = files.upload()
```

Choose files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving Amazon.csv to Amazon.csv
```

Converting the values into a dataframe

In [ ]:

```
import io
df = pd.read_csv(io.BytesIO(uploaded['Amazon.csv']))
```

In [ ]:

```
df.head()
```

Out[ ]:

	Date	Open	High	Low	Volume	Close
0	04-01-2010	136.250000	136.610001	133.139999	7599900	133.899994
1	05-01-2010	133.429993	135.479996	131.809998	8851900	134.690002
2	06-01-2010	134.600006	134.729996	131.649994	7178800	132.250000
3	07-01-2010	132.009995	132.320007	128.800003	11030200	130.000000
4	08-01-2010	130.559998	133.679993	129.029999	9830500	133.520004

In [ ]:

```
df.tail()
```

Out[ ]:

	Date	Open	High	Low	Volume	Close
2764	24-12-2020	3193.899902	3202.000000	3169.000000	1451900	3172.689941
2765	28-12-2020	3194.000000	3304.000000	3172.689941	5686800	3283.959961
2766	29-12-2020	3309.939941	3350.649902	3281.219971	4872900	3322.000000
2767	30-12-2020	3341.000000	3342.100098	3282.469971	3209300	3285.850098
2768	31-12-2020	3275.000000	3282.919922	3241.199951	2957200	3256.929932

In [ ]:

```
df.shape
```

Out[ ]:

```
(2769, 6)
```

Data Pre-Processing

1. We will check for null values in the entire dataset

2. Round all the values upto 2 decimal places

In [ ]:

```
df.isnull().sum()
```

Out[ ]:

```
Date      0
Open      0
High      0
Low       0
Volume    0
Close     0
dtype: int64
```

In [ ]:

```
df.round({'Open': 2, 'High': 2, 'Low': 2, 'Volume': 2, 'Close': 2})
```

Out[ ]:

	Date	Open	High	Low	Volume	Close
0	04-01-2010	136.25	136.61	133.14	7599900	133.90
1	05-01-2010	133.43	135.48	131.81	8851900	134.69
2	06-01-2010	134.60	134.73	131.65	7178800	132.25
3	07-01-2010	132.01	132.32	128.80	11030200	130.00
4	08-01-2010	130.56	133.68	129.03	9830500	133.52
...	...	...	...	...	...	...
2764	24-12-2020	3193.90	3202.00	3169.00	1451900	3172.69
2765	28-12-2020	3194.00	3304.00	3172.69	5686800	3283.96
2766	29-12-2020	3309.94	3350.65	3281.22	4872900	3322.00
2767	30-12-2020	3341.00	3342.10	3282.47	3209300	3285.85
2768	31-12-2020	3275.00	3282.92	3241.20	2957200	3256.93

2769 rows × 6 columns

Converting the dataframe into array.values for easy access to features and target variable and also for training the model.

In [ ]:

```
array = df.values
```

Features X: Attributes: {'Open', 'High', 'Low', 'Volume'}

Target Y: Attribute: {'Close'}

In [ ]:

```
X = array[:,1:5]
Y = array[:,5]
```

In [ ]:

```
print('Features X: \n\n{} '.format(X))
```

```
Features X:

[[136.25 136.610001 133.139999 7599900]
 [133.429993 135.479996 131.809998 8851900]
 [134.600006 134.729996 131.649994 7178800]
 ...
 [3309.939941 3350.649902 3281.219971 4872900]
 [3341.0 3342.100098 3282.469971 3209300]
 [3275.0 3282.919922 3241.199951 2957200]]
```

In [ ]:

```
print('Target Variable Y: \n\n{} '.format(Y))
```

```
Target Variable Y:

[133.899994 134.690002 132.25 ... 3322.0 3285.850098 3256.929932]
```

Train-Test Split into 80-20 ratio

The percentage of trains and tests would impact the accuracy of predicting the result. \ At this stage what ratio you want to choose for the train and test dataset it's up to you but if you take more train dataset compare to test then accuracy would be better. The general ratio for train and test dataset is 80% and 20% respectively

In [ ]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,Y,test_size = 0.2,random_state = 0)
```

To compare, we'll use three algorithms. The algorithms are picked based on the findings of our survey paper.

Result from Survey Paper:

Algorithms/Paper	Paper 1	Paper II	Paper III	Paper V	Average Accuracy
Simple Linear Regression	97.6	81.52	-	98.76	92.63
Polynomial Regression	-	91.45	-	-	91.45
Support Vector Regression (SVR)	-	87.41	-	-	87.41
Decision Tree Regression	-	98.09	-	-	98.09
Random Forest Regression	-	99.57	-	-	99.57
Support Vector Machine (linear)	-	68.41	68.2	94.32	76.97
Support Vector Machine (poly)	-	64.8	-	-	64.8
Support Vector Machine (rbf)	-	67.86	-	-	67.86
Support Vector Machine (sigmoid)	-	58.65	-	-	58.65
K – Nearest Neighbors	-	61.5	65.2	-	63.35
Logistic Regression	-	68.27	78.6	-	73.435
Naïve Bayes	-	67.1	-	-	67.1
Decision Tree Classification	-	57.99	-	-	57.99
Random Forest Classification	-	63.33	80.7	-	72.015

On the basis of highest accuracy, the three algorithms are:

**1. Simple Linear Regression \ 2. Decision Tree Regression \ 3. Random Forest Regression **

In [ ]:

```
LR = LinearRegression()
Classifier = DecisionTreeRegressor()
clf=RandomForestRegressor()
```

We will fit all these three algorithms with X_train and y_train.

In [ ]:

```
LR.fit(X_train,y_train)
Classifier.fit(X_train,y_train)
clf.fit(X_train,y_train)
```

Out[ ]:

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=
None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

Prediction of X_test i.e. Testing data using all three algorithms

In [ ]:

```
y_pred_LR = LR.predict(X_test)
y_pred_DT = Classifier.predict(X_test)
y_pred_RFR = clf.predict(X_test)
```

Since these are regression algorithms, we'll utilise the following metrics:

- Mean Absolute Error
- Mean Squared Error
- Root Mean Squared Error

In [ ]:

```
mae_lr =  mean_absolute_error(y_test,y_pred_LR)
mae_dt =  mean_absolute_error(y_test,y_pred_DT)
mae_rfr = mean_absolute_error(y_test,y_pred_RFR)

mse_lr =  mean_squared_error(y_test,y_pred_LR)
mse_dt =  mean_squared_error(y_test,y_pred_DT)
mse_rfr = mean_squared_error(y_test,y_pred_RFR)

rmse_lr = np.sqrt(mse_lr)
rmse_dt = np.sqrt(mse_dt)
rmse_rfr = np.sqrt(mse_rfr)

print('\033[1m' + "Simple Linear Regression \t       Decision Tree Regression \t
 Random Forest Regression")
print("MAE: {0:.4f} \t\t              MAE: {1:.4f} \t                       MAE: {2:.4
f}".format(mae_lr,mae_dt,mae_rfr))
print("MSE: {0:.4f} \t\t              MSE: {1:.4f} \t                       MSE: {2:.4
f}".format(mse_lr,mse_dt,mse_rfr))
print("RMSE: {0:.4f} \t\t              RMSE: {1:.4f} \t                       RMSE:
 {2:.4f}".format(rmse_lr,rmse_dt,rmse_rfr))
```

```
Simple Linear Regression                Decision Tree Regression
Random Forest Regression
MAE: 5.0599                             MAE: 8.8233
MAE: 6.9075
MSE: 104.9888                           MSE: 327.9825
MSE: 188.3498
RMSE: 10.2464                           RMSE: 18.1103
RMSE: 13.7241
```

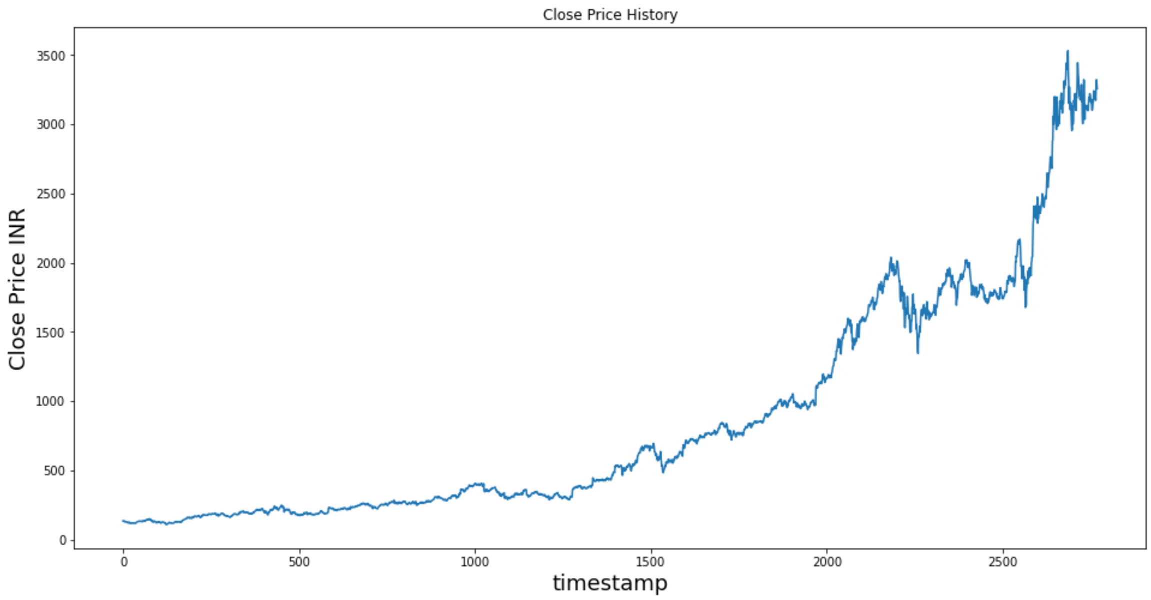
According to the above MAE and RMSE Score, the Simple Linear Regression Algorithm is the most accurate with least Mean Absolute Error and Root Mean Squared Error.

Long Short-Term Memory

Plotting Close Price History using matplotlib

In [ ]:

```
import seaborn as sns
plt.figure(figsize=(16,8))
plt.title('Close Price History')
plt.plot(df['Close'])
#ax=sns.lineplot(data=df, x='timestamp',y='close', color="blue");
plt.xlabel('timestamp',fontsize=18)
plt.ylabel('Close Price INR',fontsize=18)
plt.show()
```



Converting data to a numpy array

In [ ]:

```
data = df.filter(['Close'])
dataset = data.values
training_data_len = math.ceil( len(dataset) *.8)
```

In [ ]:

```
dataset
```

Out[ ]:

```
array([[ 133.899994],
       [ 134.690002],
       [ 132.25    ],
       ...,
       [3322.      ],
       [3285.850098],
       [3256.929932]])
```

Transforming the dataset array to range between 0 and 1

In [ ]:

```
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(dataset)
```

In [ ]:

```
train_data = scaled_data[0:training_data_len  , : ]
x_train=[]
y_train = []
for i in range(60,len(train_data)):
    x_train.append(train_data[i-60:i,0])
    y_train.append(train_data[i,0])
```

Spliting data for training and testing

In [ ]:

```
x_train, y_train = np.array(x_train), np.array(y_train)
```

In [ ]:

```
x_train = np.reshape(x_train, (x_train.shape[0],x_train.shape[1],1))
```

Building a LSTM Model for Stock Market Prediction

In [ ]:

```
model = Sequential()
model.add(LSTM(units=50, return_sequences=True,input_shape=(x_train.shape[1],1)))
model.add(LSTM(units=50, return_sequences=False))
model.add(Dense(units=25))
model.add(Dense(units=1))
```

Using adam optimizer and mean_squared_error as the loss function

In [ ]:

```
model.compile(optimizer='adam', loss='mean_squared_error')
```

Epochs = 5 as per trial and error method and batch size = 64

In [ ]:

```
model.fit(x_train, y_train, batch_size=64, epochs=5)
```

```
Epoch 1/5
34/34 [==============================] - 7s 81ms/step - loss: 0.0023
Epoch 2/5
34/34 [==============================] - 3s 84ms/step - loss: 1.4746e-04
Epoch 3/5
34/34 [==============================] - 3s 83ms/step - loss: 7.1117e-05
Epoch 4/5
34/34 [==============================] - 3s 84ms/step - loss: 6.3308e-05
Epoch 5/5
34/34 [==============================] - 3s 85ms/step - loss: 6.5671e-05
```

Out[ ]:

```
<keras.callbacks.History at 0x7fe1632dc490>
```

Creating the x_test and y_test datasets

In [ ]:

```
test_data = scaled_data[training_data_len - 60: , : ]
x_test = []
y_test =  dataset[training_data_len : , : ]
for i in range(60,len(test_data)):
    x_test.append(test_data[i-60:i,0])
```

In [ ]:

```
x_test = np.array(x_test)
```

In [ ]:

```
x_test = np.reshape(x_test, (x_test.shape[0],x_test.shape[1],1))
```

Prediction on test dataset

In [ ]:

```
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)
```

Finding the root mean squared error, mean absolue error and mean squared error

In [ ]:

```
mae_lstm =  mean_absolute_error(y_test,predictions)

mse_lstm =  mean_squared_error(y_test,predictions)

rmse_lstm = np.sqrt(mse_lstm)

print('\033[1m' + "Long Short-Term Memory")
print("MAE: {0:.4f}".format(mae_lstm))
print("MSE: {0:.4f}".format(mse_lstm))
print("RMSE: {0:.4f}".format(rmse_lstm))
```

```
Long Short-Term Memory
MAE: 94.8269
MSE: 16582.2000
RMSE: 128.7719
```

Plotting the predicted values

Blue color - Plot of Training Data

Orange color - Plot of Validation Data

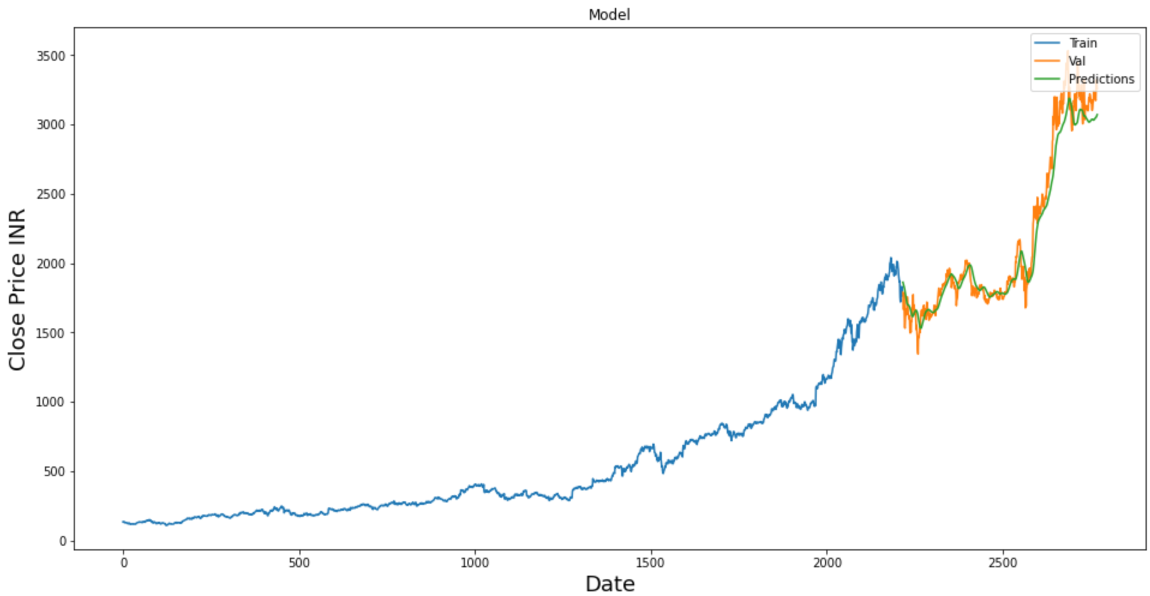
Green color - Prediction of Validation Data

In [ ]:

```
train = data[:training_data_len]
display = data[training_data_len:]
display['Predictions'] = predictions#Visualize the data
plt.figure(figsize=(16,8))
plt.title('Model')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price INR', fontsize=18)
plt.plot(train['Close'])
plt.plot(display['Close'])
plt.plot(display['Predictions'])
plt.legend(['Train', 'Val', 'Predictions'], loc='upper right')
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing import
s until
```



Final Result

In [ ]:

```
print('\033[1m' + "Simple Linear Regression \t        Decision Tree Regression \t
 Random Forest Regression \t             Long Short-Term Memory")
print("MAE: {0:.4f} \t\t                MAE: {1:.4f} \t                     MAE: {2:.4
f}\t                           MAE: {3:.4f}".format(mae_lr,mae_dt,mae_rfr,mae_lstm))
print("MSE: {0:.4f} \t\t                MSE: {1:.4f} \t                     MSE: {2:.4
f}\t                           MSE: {3:.4f}".format(mse_lr,mse_dt,mse_rfr,mse_lstm))
print("RMSE: {0:.4f} \t\t                RMSE: {1:.4f} \t                     RMSE:
 {2:.4f}\t                           RMSE: {3:.4f}".format(rmse_lr,rmse_dt,rmse_rfr,rm
se_lstm))
```

```
Simple Linear Regression                Decision Tree Regression
Random Forest Regression                     Long Short-Term Memory
MAE: 5.0599                             MAE: 8.8233
MAE: 6.9075                                  MAE: 94.8269
MSE: 104.9888                           MSE: 327.9825
MSE: 188.3498                                MSE: 16582.2000
RMSE: 10.2464                           RMSE: 18.1103
RMSE: 13.7241                                RMSE: 128.7719
```

Conclusion

We implemented the Simple Linear Regression algorithm, Decision Tree Regression algorithm, Random Forest Regression algorithm and Long Short-Term Memory algorithm on the Stock market data from 4 January 2010 to 31 December 2020 to predict its stock price.

As the results show, the lowest RMSE was found for Simple Linear Regression algorithm. This was the best from all the four algorithms. The next was Random Forest followed by Decision tree algorithm to predict the nearest close value of the stock price. The most RMSE was found for LSTM.

Ranking all the four algorithms from best to least to predict the close value of stock price are:

I - Simple Linear Regression

II - Random Forest Regression

III - Decision Tree Regression

IV - Long Short-Term Memory