An Attempt to Predict Stock Market Prices

Data Description:

In this mission, we'll apply ARIMA on TCS stock market prices and LSTM on S&P500 time series da

a) TCS

The TCS dataset is taken from Official NSE website. Timeline of Data recording : 1-1-2015 to 31-12

Column Descriptors: Date: date on which data is recorded Symbol: NSE symbol of the stock Series

b) S&P 500

The S&P500 dataset is stored in sphist.csv. Each row in the file contains a **daily record of the price**

The columns of the dataset are:

```
Date -- The date of the record.
Open -- The opening price of the day (when trading starts).
High -- The highest trade price during the day.
Low -- The lowest trade price during the day.
Close -- The closing price for the day (when trading is finished).
Volume -- The number of shares traded.
Adj Close -- The daily closing price, adjusted for corporate actions.
```

We'll be using both datasets to develop a predictive model. For S&P 500, we'll train the model wit predictions from 2013-2015. For TCS, we will have a train and test data split.

```
import tensorflow as tf
tf.test.gpu_device_name()
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.
We recommend you upgrade now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: more info.

```
'/device:GPU:0'
```

Loading TCS Data

```
# Importing necessary modules
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt

# Importing the statistics module
from statistics import mean
from statistics import median

# To load the input data
```

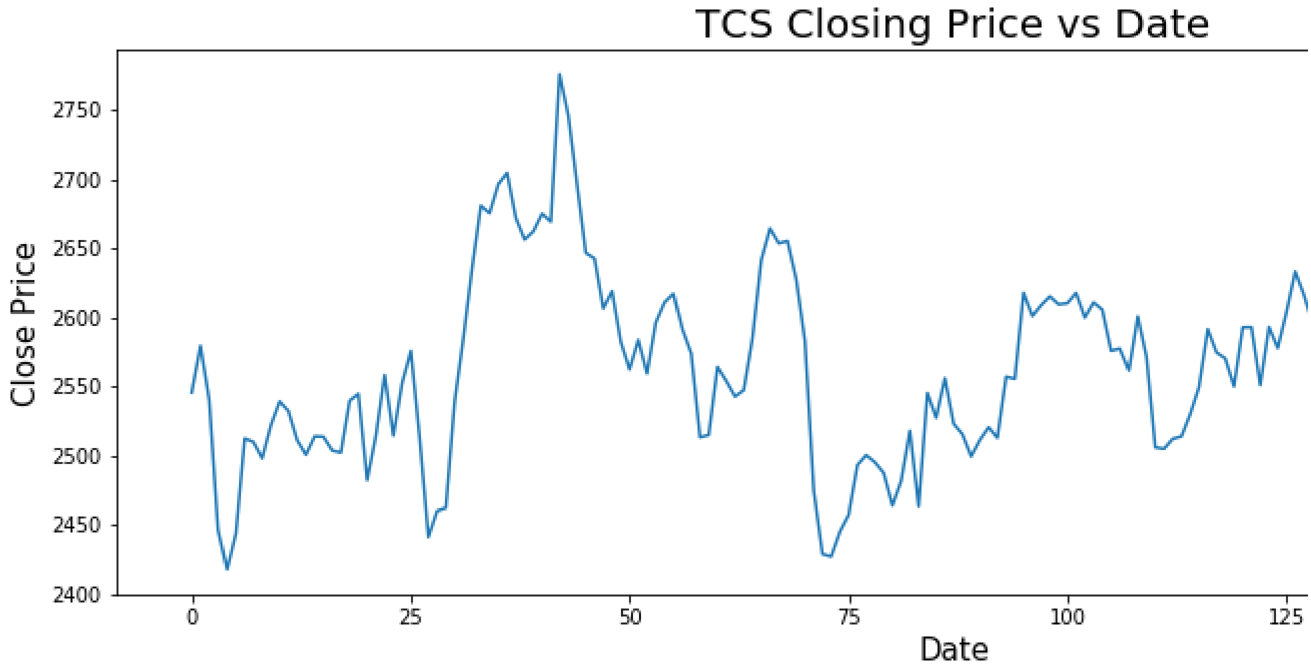
```
# To load the input data
import pandas as pd
import numpy as np
from datetime import datetime
from matplotlib import pyplot

# used to format headings
bold = '\033[1m'
end = '\033[0m'

from google.colab import drive
drive.mount('/content/gdrive')

# Read the s&p 500 input data set and sorting based on date.
sp500 = pd.read_csv("gdrive/My Drive/tseries/IT/tcs_stock.csv", index_col=False)

sp500["Date"] = pd.to_datetime(sp500["Date"])
sp_sorted = sp500.sort_values("Date")

print(sp_sorted.head(3))
# print(sp_sorted.tail(3))
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_

Enter your authorization code:
··········
Mounted at /content/gdrive
        Date Symbol Series  ...  Trades  Deliverable Volume  %Deliverble
0 2015-01-01    TCS     EQ  ...    8002               52870       0.2883
1 2015-01-02    TCS     EQ  ...   27585              309350       0.6683
2 2015-01-05    TCS     EQ  ...   43234              456728       0.5207

[3 rows x 15 columns]
```

From the sorted data, we can see that data since Jan 2015 is there in the input dataset.

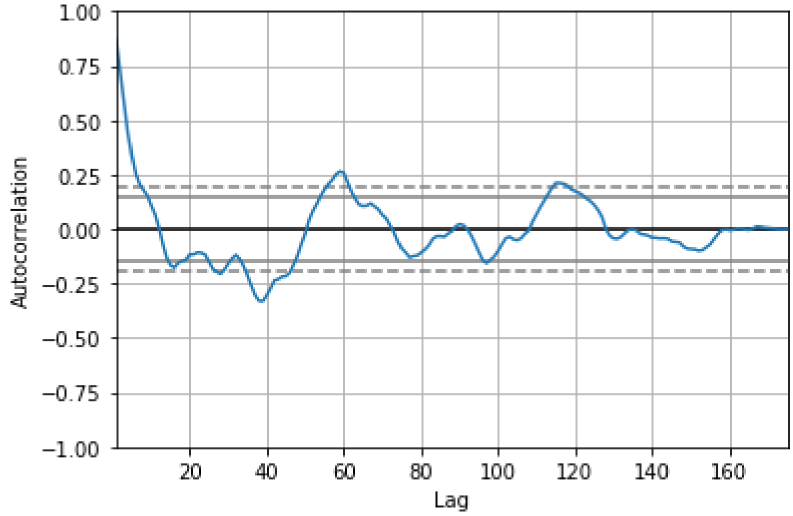
```
# Visualization Module

close = sp_sorted['Close'][:175]
x = np.arange(0, len(close))
print(len(close))

plt.figure(figsize=(15,5))
plt.plot(x, close, label="Close Price")

plt.legend()
plt.title("TCS Closing Price vs Date", fontsize=20)
plt.ylabel("Close Price", fontsize=15)
plt.xlabel("Date", fontsize=15)
plt.show()
```

175



To estimate the lag lets do a auto correlation plot.

```
from pandas.plotting import autocorrelation_plot
from matplotlib import pyplot

# close = np.real(filtered_sig)

autocorrelation_plot(close)
pyplot.show()
```

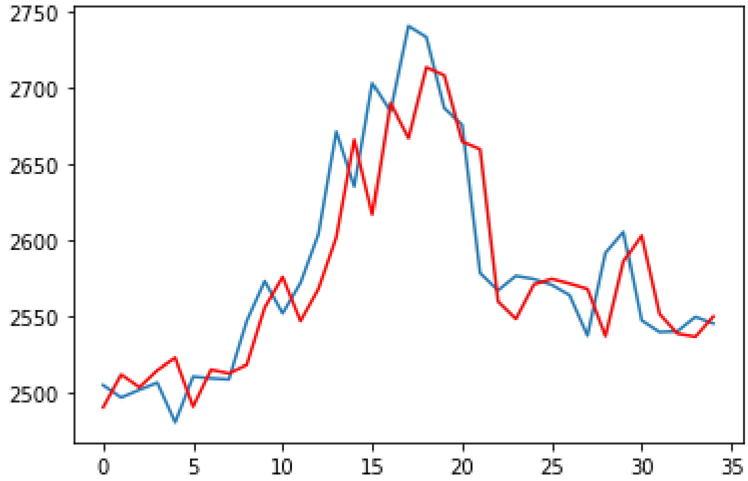


There is a positive correlation with the first 500 lags. Hence, a reasonable value for autocorrelatior

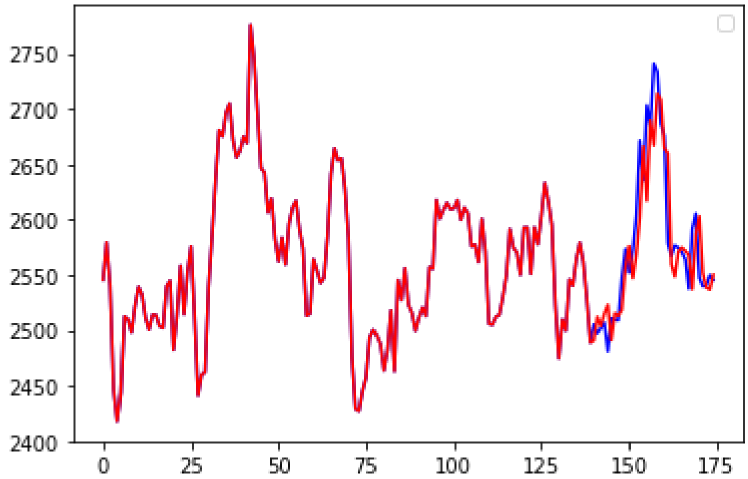
```
# https://machinelearningmastery.com/arima-for-time-series-forecasting-with-python/
import warnings
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_squared_error
```

```
X = close.values
size = int(len(X) * 0.8)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()
print(len(test))

warnings.filterwarnings("ignore")
for t in range(len(test)):
  model = ARIMA(history, order=(8,0,2))
  model_fit = model.fit(disp=0)
  output = model_fit.forecast()
  yhat = output[0]
  predictions.append(yhat)
  obs = test[t]
  history.append(obs)
  # print('predicted=%f, expected=%f' % (yhat, obs))
error = mean_squared_error(test, predictions)
print('Test MSE: %.3f' % error)
# plot
pyplot.plot(test)
pyplot.plot(predictions, color='red')
pyplot.show()

train_data = train.tolist()
for i in range(len(predictions)):
  train_data.append(predictions[i][0])
```

```
35
Test MSE: 1180.102
```

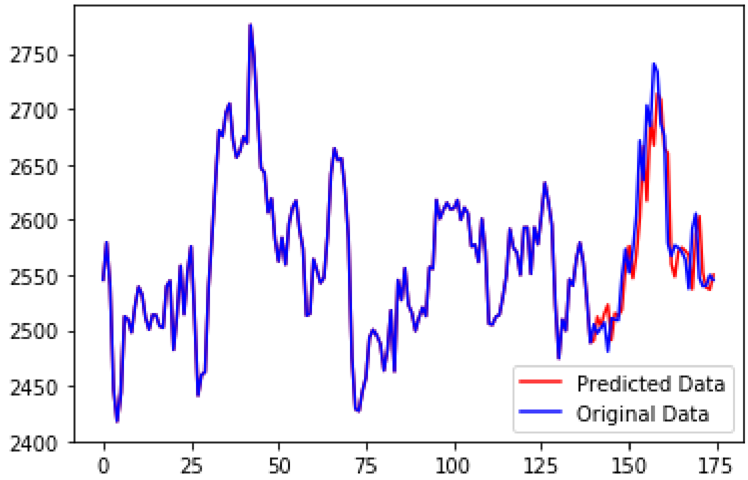



```
No handles with labels found to put in legend.
```




```
# Visualization with History + Prediction

print(predictions)
train_data = train.tolist()

for i in range(len(predictions)):
  train_data.append(predictions[i][0])
# print(train.tolist().append(predictions))
x_axis = np.arange(0, len(history))
pyplot.plot(train_data, color='red', label='Predicted Data')
pyplot.plot(close, color='blue', label='Original Data')
pyplot.legend()
pyplot.show()
```

```
[array([2490.52443477]), array([2512.00045077]), array([2503.73096076]), array
```



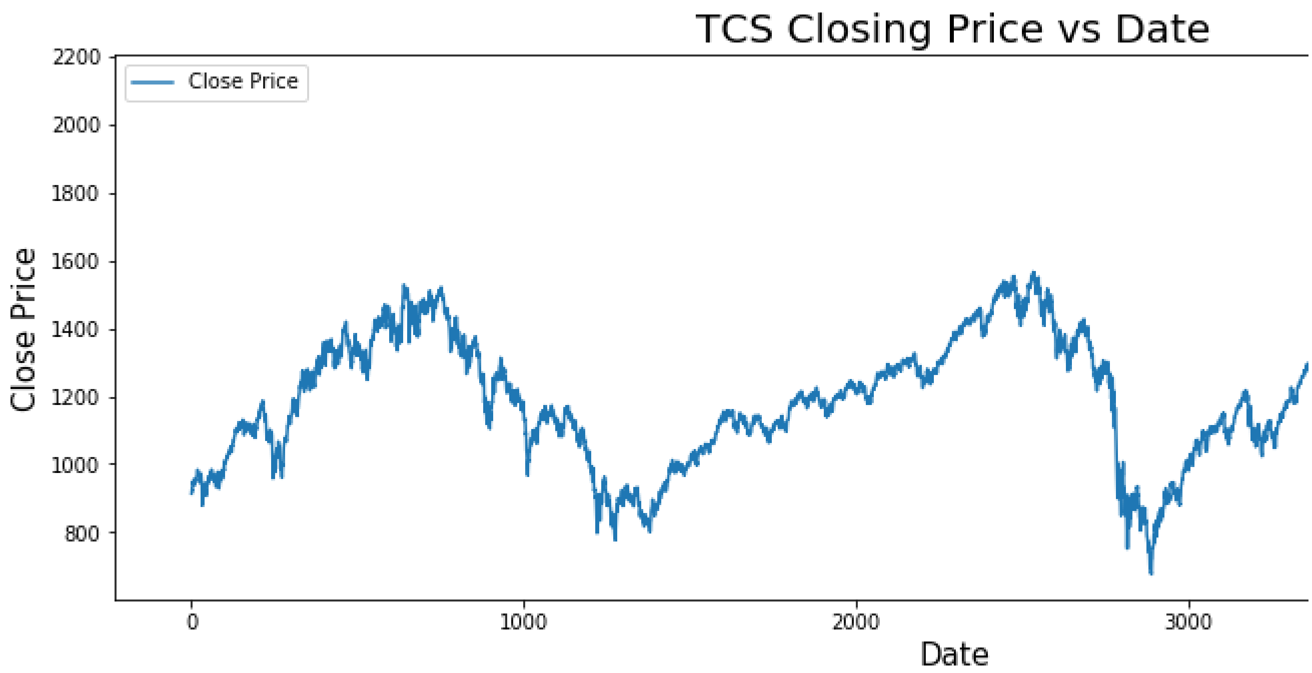
LSTM on S&P500 Time Series Data

```
# Read the s&p 500 input data set and sorting based on date.
sp500 = pd.read_csv("gdrive/My Drive/tseries/sphist.csv", index_col=False)

sp500["Date"] = pd.to_datetime(sp500["Date"])
sp_sorted = sp500.sort_values("Date")

print(sp_sorted.head(3))
```

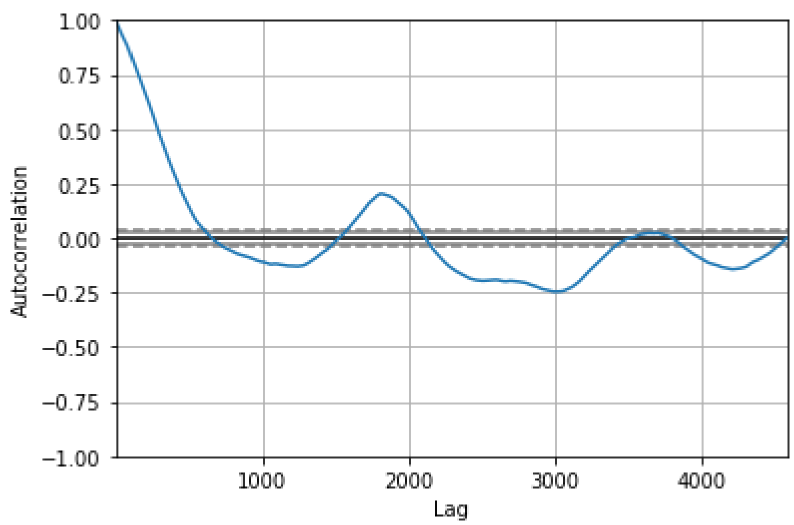
```
             Date   Open   High    Low  Close     Volume  Adj Close
16589 1950-01-03  16.66  16.66  16.66  16.66  1260000.0      16.66
16588 1950-01-04  16.85  16.85  16.85  16.85  1890000.0      16.85
16587 1950-01-05  16.93  16.93  16.93  16.93  2550000.0      16.93
```

```
# Visualization Module

close = sp_sorted['Close'][12000:]
x = np.arange(0, len(close))
print(len(close))

plt.figure(figsize=(15,5))
plt.plot(x, close, label="Close Price")

plt.legend()
plt.title("TCS Closing Price vs Date", fontsize=20)
plt.ylabel("Close Price", fontsize=15)
plt.xlabel("Date", fontsize=15)
plt.show()
```

```
4590
```




```
autocorrelation_plot(close)
pyplot.show()
```



From the above graph, we estimate the lag to be around 100.

```
# univariate LSTM example
from numpy import array
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dense
import warnings
from sklearn.metrics import mean_squared_error

# split a univariate sequence into samples
def split_sequence(sequence, n_steps):
  X, y = list(), list()
  for i in range(len(sequence)):
```

```
    # find the end of this pattern
    end_ix = i + n_steps
    # check if we are beyond the sequence
    if end_ix > len(sequence)-1:
      break
    # gather input and output parts of the pattern
    seq_x, seq_y = sequence[i:end_ix], sequence[end_ix]
    X.append(seq_x)
    y.append(seq_y)
  return array(X), array(y)

# define input sequence
raw_seq = list(close)
print(raw_seq)


size = int(len(raw_seq) * 0.9)
train, test = raw_seq[0:size], raw_seq[size:len(raw_seq)]
history = [x for x in train]
predictions = list()


# choose a number of time steps
n_steps = 100
print('before split sequence')
# split into samples
X, y = split_sequence(raw_seq, n_steps)

print('after split sequence')
# reshape from [samples, timesteps] into [samples, timesteps, features]
n_features = 1
X = X.reshape((X.shape[0], X.shape[1], n_features))
# define model
model = Sequential()
model.add(LSTM(50, activation='relu', input_shape=(n_steps, n_features)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
# fit model
model.fit(X, y, epochs=200, verbose=0)
print('model fitting over')

count = 0
warnings.filterwarnings("ignore")
# demonstrate prediction
for t in range(len(test)):
  x_input = array(raw_seq[-n_steps:])
  x_input = x_input.reshape((1, n_steps, n_features))
  yhat = model.predict(x_input, verbose=0)
  print(yhat[0][0])
  predictions.append(yhat[0][0])
  # as we predict the difference
  raw_seq.append(yhat[0][0])


error = mean_squared_error(test, predictions)
```

```
print('Test MSE: %.3f' % error)
pyplot.plot(test)
pyplot.plot(predictions, color='red')
pyplot.legend()
pyplot.show()

x_axis = np.arange(0, len(raw_seq))
pyplot.plot(x_axis, raw_seq, color='red')
pyplot.legend()
pyplot.show()
```

```
[912.590027, 923.909973, 919.7700199999999, 945.6400150000001, 943.0, 947.2899
before split sequence
after split sequence
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/t

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/t

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/t

Using TensorFlow backend.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizer

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow_core
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/t

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/t

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/t

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WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/t

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/t

model fitting over
2009.6586
1999.673
1996.5353
1995.6016
1995.3267
1995.2456
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1995.0874
1995.1855
1994.8098
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1985.3767
1985.3744
1985.3745
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1985.3969
1985.3641
1985.385
1985.2742
1985.2903
1984.8201
1981.6353
1983.1556
1972.917
1971.3711
1969.58
1961.4019
1961.8921
1951.626
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1913.4485
1898.5732
1894.972
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1889.4248
1889.4241
1889.4229
1889.4158
1889.4136
1889.3975
1889.384
1889.1948
1889.2465
1888.4417
1888.5308
```