Google_predict_stock_market_indices_A_Time_Series_Analysis_Project

July 9, 2022

1 Summary

The dataset for this project originates from kaggle and contains Google daily stock prices between 2012 and 2016.

The art of forecasting stock prices has been a difficult task for many of the researchers and analysts. In fact, investors are highly interested in the research area of stock price prediction. For a good and successful investment, many investors are keen on knowing the future situation of the stock market. Good and effective prediction systems for the stock market help traders, investors, and analyst by providing supportive information like the future direction of the stock market. In this work, we present a recurrent neural network (RNN) and Long Short-Term Memory (LSTM) approach to predict stock market indices. We are interested in forecasting the 'Close' series.

2 Load and Exploratore the Data

[1]:
```
import sys
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter(action='ignore')
import pandas as pd
from datetime import datetime
import tensorflow as tf
import keras
from keras.models import Sequential
from keras.layers import Dense, SimpleRNN, LSTM, Activation, Dropout
import math
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

[2]:
```
data = pd.read_csv('./Google_Stock_Price_Data.csv',sep=",")
data.head()
```

[2]:

	Date	Open	High	Low	Close	Volume
0	1/3/2012	325.25	332.83	324.97	663.59	7,380,500
1	1/4/2012	331.27	333.87	329.08	666.45	5,749,400

```
2  1/5/2012  329.83  330.75  326.89  657.21   6,590,300
3  1/6/2012  328.34  328.77  323.68  648.24   5,405,900
4  1/9/2012  322.04  322.29  309.46  620.76  11,688,800
```

[3]:
```
data['Close'].isnull().sum()
```

[3]:
```
0
```

[4]:
```
data = data[['Date', 'Close']]
data.sample(5)
```

[4]:
```
           Date   Close
368   6/21/2013  878.52
105    6/4/2012  577.01
587    5/6/2014  513.73
52    3/19/2012  632.24
1115   6/9/2016  728.58
```

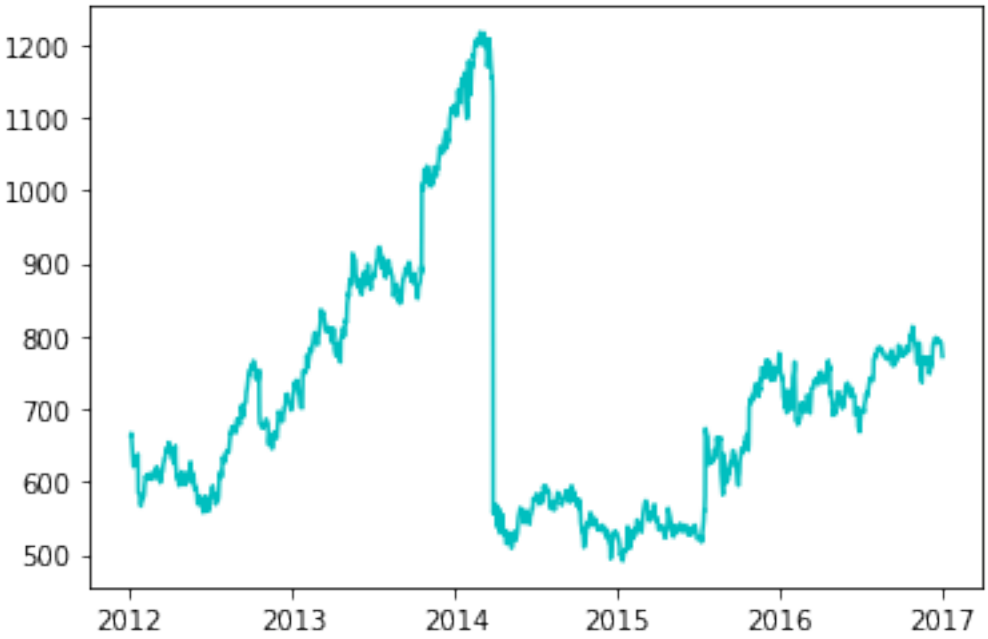
3 Feature Transformation

- Replace comma in **Close** column and convert values into float64
- Transform **Date** column into a datetime object

[5]:
```
data['Close'] = data['Close'].str.replace(',','')
data['Close'] = data['Close'].apply(lambda x : float(x))
```

[6]:
```
def make_date(row):
    return datetime(year = int(row.split('/')[2]),
                    month = int(row.split('/')[0]),
                    day = int(row.split('/')[1]))

data['Date'] = data['Date'].apply(make_date)
data.set_index(data.Date,inplace=True)
data.drop(columns=['Date'], inplace=True)

plt.plot(data, 'c')
```

[6]:
```
[<matplotlib.lines.Line2D at 0x1c9377b7220>]
```



4 Split the Data and Apply Feature Scaling

- Split the data into train and test data sets using **timestep = 50 days**
- use **MinMaxScaler** to scale the data

[7]:
```
timesteps = 50
```

[8]:
```
train = data[:len(data)-timesteps]['Close'].values
test = data[len(train):]['Close'].values
train=train.reshape(train.shape[0],1)
test=test.reshape(test.shape[0],1)
```

[9]:
```
sc = MinMaxScaler(feature_range= (0,1))
train = sc.fit_transform(train)
```

[10]:
```
train_X = []
train_y = []

for i in range(timesteps, train.shape[0]):
    train_X.append(train[i-timesteps:i,0])
    train_y.append(train[i,0])

train_X = np.array(train_X)
train_X = train_X.reshape(train_X.shape[0], train_X.shape[1], 1)
train_y = np.array(train_y)
```

[11]:
```
print('Training input shape: {}'.format(train_X.shape))
print('Training output shape: {}'.format(train_y.shape))
```

```
Training input shape: (1158, 50, 1)
Training output shape: (1158,)
```

[12]:
```
inputs = data[len(data) - len(test) - timesteps:]
inputs = sc.transform(inputs)

test_X = []

for i in range(timesteps, 100):
    test_X.append(inputs[i-timesteps:i,0])

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

[13]:
```
test_X.shape
```

[13]:
```
(50, 50, 1)
```

5 Train models

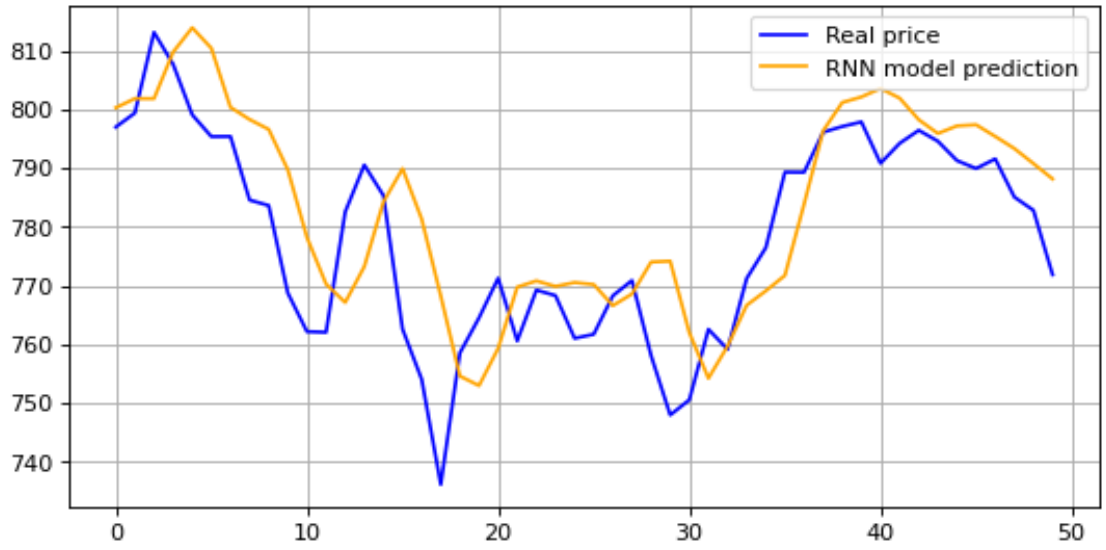
- Simple **RNN** layers each with 50 hidden units and tanh activation function per cell
- **LSTM** with 70 hidden units per cell
- Define the loss function and optimizer strategy
- Fit the model with 100 epochs
- Predict and plot the results

5.1 RNN

[14]:
```
model = Sequential()

model.add(SimpleRNN(50, activation='tanh',
                    input_shape=(train_X.shape[1],1), return_sequences = True))
model.add(Dropout(0.2))
model.add(SimpleRNN(50, activation='tanh', return_sequences = True,))
model.add(Dropout(0.2))
model.add(SimpleRNN(50, activation='tanh', return_sequences = True,))
model.add(Dropout(0.2))
model.add(SimpleRNN(50, activation='tanh'))
# output layer to make final predictions
model.add(Dense(1))

model.compile(loss='mean_squared_error', optimizer='adam')
model.fit(train_X, train_y, epochs=100, batch_size=32, verbose=0)
```

[14]: <keras.callbacks.History at 0x1c9463ecd00>

[15]:
```
predicted = model.predict(test_X)
predicted = sc.inverse_transform(predicted)

plt.figure(figsize=(8,4), dpi=80, facecolor='w', edgecolor='k')
plt.plot(test,color="blue",label="Real price")
plt.plot(predicted,color="orange",label="RNN model prediction")
plt.legend()
plt.grid(True)
plt.show()
```



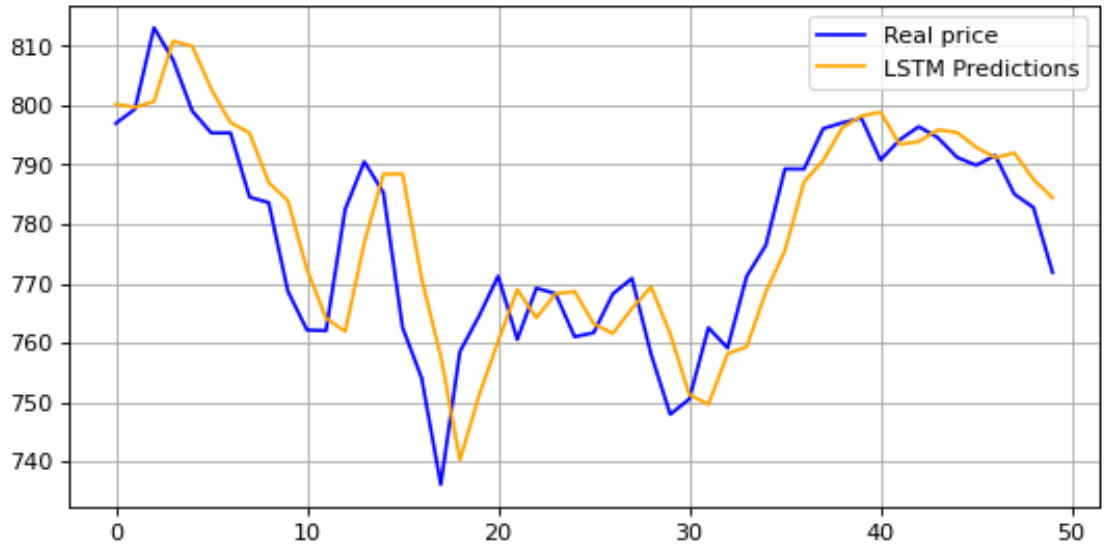
5.2 LSTM

[16]:
```
model2 = Sequential()
model2.add(LSTM(70, input_shape=(train_X.shape[1],1)))
model2.add(Dense(1))

model2.compile(loss='mean_squared_error', optimizer='adam')
model2.fit(train_X, train_y, epochs=100, batch_size=32, verbose=0)
```

[16]: <keras.callbacks.History at 0x1ca9f2fb9a0>

[17]:
```
predicted2 = model2.predict(test_X)
predicted2 = sc.inverse_transform(predicted2)

plt.figure(figsize=(8,4), dpi=80, facecolor='w', edgecolor='k')
plt.plot(test,color="blue",label="Real price")
```

```
plt.plot(predicted2,color="orange",label="LSTM Predictions")
plt.legend()
plt.grid(True)
plt.show()
```



[18]:
```
# RNN structure
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 simple_rnn (SimpleRNN)      (None, 50, 50)            2600

 dropout (Dropout)           (None, 50, 50)            0

 simple_rnn_1 (SimpleRNN)    (None, 50, 50)            5050

 dropout_1 (Dropout)         (None, 50, 50)            0

 simple_rnn_2 (SimpleRNN)    (None, 50, 50)            5050

 dropout_2 (Dropout)         (None, 50, 50)            0

 simple_rnn_3 (SimpleRNN)    (None, 50)                5050

 dense (Dense)               (None, 1)                 51
```

```
=================================================================
Total params: 17,801
Trainable params: 17,801
Non-trainable params: 0
_________________________________________________________________
```

[19]:
```
# LSTM structure
model2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 lstm (LSTM)                  (None, 70)                20160

 dense_1 (Dense)              (None, 1)                 71

=================================================================
Total params: 20,231
Trainable params: 20,231
Non-trainable params: 0
_________________________________________________________________
```

6 Results

If we compare the model summary for **Simple RNN** with the model summary for **LSTM**, we can see that there are more trainable parameters for the **LSTM**, which explains why it took a longer time to train this model.

Overall the plots show that our **LSTM** model with a less complex structure still performed better than our Simple RNN.

7 Next Steps

To improve the quality of forecasts over many time steps, we'd need to use more data and more sophisticated LSTM model structures. We could try training with more data or increasing cell_units and running more training epochs.