1. Problem statement

- We are given Google stock price from 01/2012 to 12/2017.
- The task is to predict the trend of the stock price for 01-06 2018.

2. Import library

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
```

3. Data processing

3.0 import the data

```
dataset_train = pd.read_csv('Google_Stock_Price_Train.csv')
```

```
dataset_train.head()
```

	Date	Open	High	Low	Close	Volume
0	01/03/2012	325.25	332.83	324.97	663.59	7,380,500
1	01/04/2012	331.27	333.87	329.08	666.45	5,749,400
2	01/05/2012	329.83	330.75	326.89	657.21	6,590,300
3	01/06/2012	328.34	328.77	323.68	648.24	5,405,900
4	01/09/2012	322.04	322.29	309.46	620.76	11,688,800

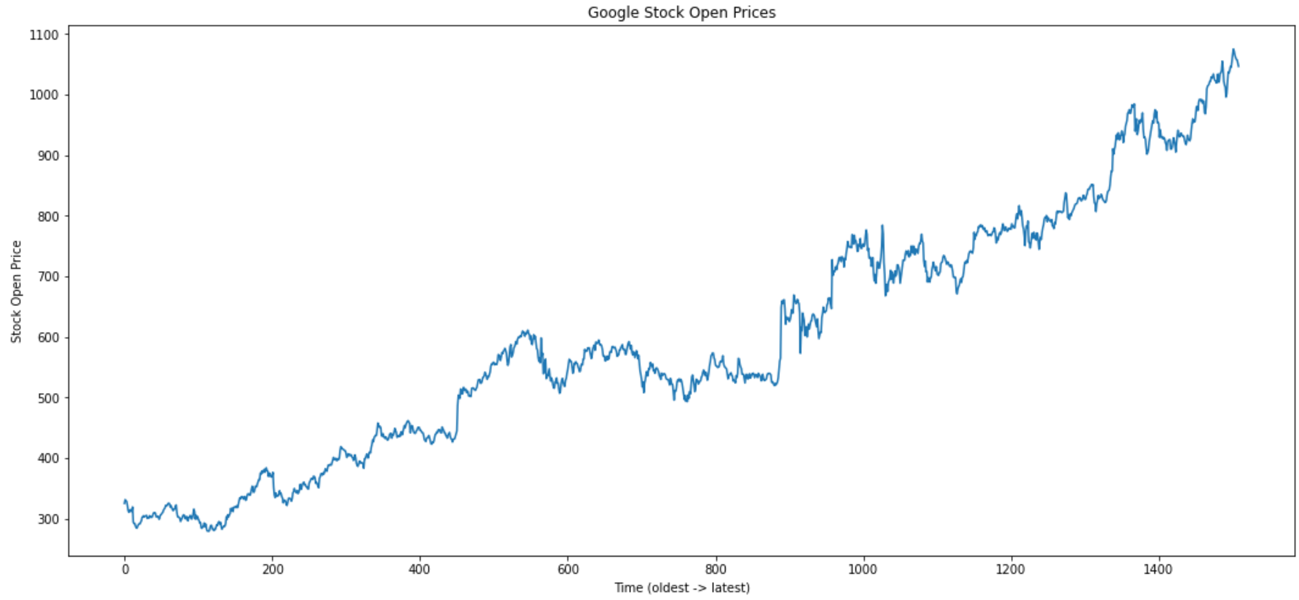
```
#keras only takes numpy array
training_set = dataset_train.iloc[:, 1: 2].values
```

```
training_set.shape
```

```
(1509, 1)
```

```
plt.figure(figsize=(18, 8))
plt.plot(dataset_train['Open'])
```

```
plt.title("Google Stock Open Prices")
plt.xlabel("Time (oldest -> latest)")
plt.ylabel("Stock Open Price")
plt.show()
```



3.1 Feature scaling

```
import os
if os.path.exists('config.py'):
    print(1)
else:
    print(0)
```

```
0
```

```
sc = MinMaxScaler(feature_range = (0, 1))
#fit: get min/max of train data
training_set_scaled = sc.fit_transform(training_set)
```

3.2 Data structure creation

- taking the reference of past 60 days of data to predict the future stock price.

- It is observed that taking 60 days of past data gives us best results.
- In this data set 60 days of data means 3 months of data.
- Every month as 20 days of Stock price.
- X train will have data of 60 days prior to our date and y train will have data of one day after our date

```
## 60 timesteps and 1 output
X_train = []
y_train = []
for i in range(60, len(training_set_scaled)):
    X_train.append(training_set_scaled[i-60: i, 0])
    y_train.append(training_set_scaled[i, 0])

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

```
X_train.shape
```

```
(1449, 60)
```

```
y_train.shape
```

```
(1449,)
```

3.3 Data reshaping

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

1. Number of stock prices - 1449
2. Number of time steps - 60
3. Number of Indicator - 1

```
X_train.shape
```

```
(1449, 60, 1)
```

4. Create & Fit Model

4.1 Create model

```
regressor = Sequential()
#add 1st lstm layer
regressor.add(LSTM(units = 50, return_sequences = True, input_shape = (X_train.shape[1], 1
```

```
regressor.add(Dropout(rate = 0.2))

##add 2nd lstm layer: 50 neurons
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(rate = 0.2))

##add 3rd lstm layer
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(rate = 0.2))

##add 4th lstm layer
regressor.add(LSTM(units = 50, return_sequences = False))
regressor.add(Dropout(rate = 0.2))

##add output layer
regressor.add(Dense(units = 1))

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

4.2 Model fit

```
regressor.fit(x = X_train, y = y_train, batch_size = 32, epochs = 100)
```

```
Epoch 1/100
46/46 [==============================] - 12s 107ms/step - loss: 0.0197
Epoch 2/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0043
Epoch 3/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0048
Epoch 4/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0038
Epoch 5/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0031
Epoch 6/100
46/46 [==============================] - 5s 102ms/step - loss: 0.0029
Epoch 7/100
46/46 [==============================] - 5s 102ms/step - loss: 0.0031
Epoch 8/100
46/46 [==============================] - 5s 102ms/step - loss: 0.0029
Epoch 9/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0031
Epoch 10/100
46/46 [==============================] - 5s 119ms/step - loss: 0.0028
Epoch 11/100
46/46 [==============================] - 5s 112ms/step - loss: 0.0031
Epoch 12/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0023
Epoch 13/100
46/46 [==============================] - 5s 102ms/step - loss: 0.0025
Epoch 14/100
46/46 [==============================] - 5s 106ms/step - loss: 0.0027
Epoch 15/100
46/46 [==============================] - 5s 105ms/step - loss: 0.0024
Epoch 16/100
46/46 [==============================] - 5s 106ms/step - loss: 0.0021
```

```
Epoch 17/100
46/46 [==============================] - 5s 105ms/step - loss: 0.0023
Epoch 18/100
46/46 [==============================] - 5s 104ms/step - loss: 0.0024
Epoch 19/100
46/46 [==============================] - 5s 104ms/step - loss: 0.0020
Epoch 20/100
46/46 [==============================] - 5s 104ms/step - loss: 0.0021
Epoch 21/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0019
Epoch 22/100
46/46 [==============================] - 5s 102ms/step - loss: 0.0022
Epoch 23/100
46/46 [==============================] - 5s 104ms/step - loss: 0.0023
Epoch 24/100
46/46 [==============================] - 5s 102ms/step - loss: 0.0018
Epoch 25/100
46/46 [==============================] - 5s 104ms/step - loss: 0.0022
Epoch 26/100
46/46 [==============================] - 5s 102ms/step - loss: 0.0020
Epoch 27/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0019
Epoch 28/100
46/46 [==============================] - 5s 103ms/step - loss: 0.0021
Epoch 29/100
```

4.3 Model evaluation

4.3.1 Read and convert

```
dataset_test = pd.read_csv('Google_Stock_Price_Test.csv')
```

```
dataset_test.head()
```

	Date	Open	High	Low	Close	Volume
0	02/01/2018	1048.339966	1066.939941	1045.229980	1065.000000	1237600
1	03/01/2018	1064.310059	1086.290039	1063.209961	1082.479980	1430200
2	04/01/2018	1088.000000	1093.569946	1084.001953	1086.400024	1004600
3	05/01/2018	1094.000000	1104.250000	1092.000000	1102.229980	1279100
4	08/01/2018	1102.229980	1111.270020	1101.619995	1106.939941	1047600

```
#keras only takes numpy array
real_stock_price = dataset_test.iloc[:, 1: 2].values
real_stock_price.shape
```

```
(125, 1)
```

4.3.2 Concat and convert

```
#vertical concat use 0, horizontal uses 1
dataset_total = pd.concat((dataset_train['Open'], dataset_test['Open']),
                          axis = 0)
##use .values to make numpy array
inputs = dataset_total[len(dataset_total) - len(dataset_test) - 60:].values
```

4.3.3 Reshape and scale

```
#reshape data to only have 1 col
inputs = inputs.reshape(-1, 1)

#scale input
inputs = sc.transform(inputs)
```

```
len(inputs)
```

```
185
```

4.3.4 Create test data strucutre

```
X_test = []
for i in range(60, len(inputs)):
    X_test.append(inputs[i-60:i, 0])
X_test = np.array(X_test)
#add dimension of indicator
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

```
X_test.shape
```

```
(125, 60, 1)
```

4.3.5 Model prediction

```
predicted_stock_price = regressor.predict(X_test)
```

```
#inverse the scaled value
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
```

4.3.6 Result visualization

```
##visualize the prediction and real price
plt.plot(real_stock_price, color = 'red', label = 'Real price')
plt.plot(predicted_stock_price, color = 'blue', label = 'Predicted price')
```

```
plt.title('Google price prediction')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.show()
```