In [674]:

```
import warnings
warnings.filterwarnings('ignore')
```

1. Introduction

1.1 Understanding Stock Market

1. Stock Market :
A Stock market or Share Market is the aggregation of buyers and sellers of stocks which represent ownership claims on business. Investment in the stock market is most often done via stockbrokerages (https://en.wikipedia.org/wiki/Stockbroker) and [electronic trading platforms] (https://en.wikipedia.org/wiki/Electronic_trading_platform (https://en.wikipedia.org/wiki/Electronic_trading_platform)). Investments is usually made with an investment strategy in mind.

Every investor looks for a profit by buying stocks with low price and selling those stocks with high price. The price of stock usually depends on supply demand gap. Following points illustarate how the price of stocks changes.

1. If more number of buyers want to buy a share than the more number of sellers selling, then sellers are in control then can fix the price of the stock.
2. If number of buyers are less than the number of sellers, then buyers are in control and the can fix the price.

2. Stock Index :
A Stock index or stock market index, is an index that measures a stock market or a subset of the stock market, that helps investors compare curretn price levels with past prices to calculate market performance.

The major stock indices in usa are:
a) Nasdaq composite (https://en.wikipedia.org/wiki/NASDAQ_Composite)
b) S&p 500 (https://en.wikipedia.org/wiki/S%26P_500_Index)
c) DJIA (https://en.wikipedia.org/wiki/Dow_Jones_Industrial_Average)

The major stock market indices in india are:
a) BSE Sensex (https://en.wikipedia.org/wiki/BSE_SENSEX)
b) NSE Nifty (https://en.wikipedia.org/wiki/NIFTY_50)

You can understand more about stock market here (https://www.youtube.com/watch?v=ZCFkWDdmXG8).

1.2 Problem Description

Every stock market index contains low, high, open, closing prices of every day stock prices.
LOW: low indicates the lowest price of the stock on that day.
HIGH: High indicates the highest price of the stock on that day.
Open: Open indicates the opening price of the stock on that day.
Close: Close indicates the closing price of the stock on that day.

If closig price is greater than selling price then it means sellers are in control. Otherwise, buyers are in control.

The main objective in my problem is to predict the closing price of a stock market index.

In [675]:

```
#imports

import tensorflow as tf

import matplotlib as mpl
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
from tensorflow.keras.layers import Input
# gloabl params for all matplotlib plots
mpl.rcParams['figure.figsize'] = (8, 6)
mpl.rcParams['axes.grid'] = False
os.listdir('../DataSet/S&P_500/raw_data/')

from tensorflow.keras.layers import Layer, LSTM, Dense, Bidirectional, Flatten
from tensorflow.keras.models import Sequential
import tensorflow.keras.backend as K
import datetime

tf.random.set_seed(1)
```

1. Understanding Dataset

In [676]:

```
data_path = '../DataSet/'
raw_data = pd.read_csv(data_path + 'nasdaq/raw_data/finance.txt')
raw_data["Date"] = pd.to_datetime(raw_data["Date"])
print("Top 5 rows of the dataset:")
raw_data.head()
```

```
Top 5 rows of the dataset:
```

Out[676]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	1991-01-02	373.000000	373.500000	371.799988	372.200012	372.200012	92020000
1	1991-01-03	371.200012	371.799988	367.399994	367.500000	367.500000	108390000
2	1991-01-04	366.500000	367.899994	365.899994	367.200012	367.200012	103830000
3	1991-01-07	363.500000	365.799988	360.100006	360.200012	360.200012	109460000
4	1991-01-08	359.100006	360.500000	358.200012	359.000000	359.000000	111730000

In [677]:

```
raw_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7424 entries, 0 to 7423
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype         
---  ------     --------------  -----         
 0   Date       7424 non-null   datetime64[ns]
 1   Open       7424 non-null   float64       
 2   High       7424 non-null   float64       
 3   Low        7424 non-null   float64       
 4   Close      7424 non-null   float64       
 5   Adj Close  7424 non-null   float64       
 6   Volume     7424 non-null   int64         
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 406.1 KB
```

In [678]:

```
print("number of data points:", raw_data.shape[0])
```

```
number of data points: 7424
```

2 Descriptive Analysis

In [679]:

```
for column in raw_data.columns:
    print("Descriptive statistics of " + column + ":")
    print(raw_data[column].describe())
    print('\n')
```

```
Descriptive statistics of Date:
count                    7424
unique                   7424
top       2017-08-21 00:00:00
freq                        1
first     1991-01-02 00:00:00
last      2020-06-19 00:00:00
Name: Date, dtype: object


Descriptive statistics of Open:
count     7424.000000
mean      2854.273284
std       2071.833698
min        354.899994
25%       1440.725036
50%       2238.505005
75%       3756.090027
max      10042.129883
Name: Open, dtype: float64


Descriptive statistics of High:
count     7424.000000
mean      2873.521296
std       2083.938531
min        357.399994
25%       1454.302521
50%       2256.135009
75%       3791.617493
max      10086.889648
Name: High, dtype: float64


Descriptive statistics of Low:
count    7424.000000
mean     2832.226635
std      2058.699329
min       353.000000
25%      1419.029999
50%      2218.710083
75%      3711.435059
max      9962.580078
Name: Low, dtype: float64


Descriptive statistics of Close:
count     7424.000000
mean      2854.097181
std       2072.373566
min        355.799988
25%       1441.679962
50%       2239.590088
75%       3760.837524
```

```
max      10020.349609
Name: Close, dtype: float64


Descriptive statistics of Adj Close:
count     7424.000000
mean      2854.097181
std       2072.373566
min        355.799988
25%       1441.679962
50%       2239.590088
75%       3760.837524
max      10020.349609
Name: Adj Close, dtype: float64


Descriptive statistics of Volume:
count    7.424000e+03
mean     1.511702e+09
std      8.191678e+08
min      5.626000e+07
25%      7.473525e+08
50%      1.718650e+09
75%      2.021585e+09
max      6.572850e+09
Name: Volume, dtype: float64
```

In [680]:

```
#https://seaborn.pydata.org/examples/distplot_options.html
sns.set(style="white", color_codes=True)
# Set up the matplotlib figure
f, axes = plt.subplots(2, 2, figsize=(15, 7), sharex=True)

sns.despine(left=True)

sns.distplot(raw_data['Close'], hist=False, color="r",\
             kde_kws={"shade": True}, ax=axes[0, 0]).set_title("Distribution plot of closin

sns.distplot(raw_data['Open'], hist=False, color = "g", \
             kde_kws={"shade": True}, ax=axes[0, 1]).set_title("Distribution plot of Openin

sns.distplot(raw_data['Low'], hist=False, color="b", \
             kde_kws={"shade": True}, ax=axes[1, 0]).set_title("Distribution plot of Low pr

sns.distplot(raw_data['High'], hist=False, color="y", \
             kde_kws={"shade": True}, ax=axes[1, 1]).set_title("Distribution plot of High p
plt.tight_layout()
```

Observations

1. After Observing the distribution plots and descriptive statistics of stock prices, It seems they are highly correlated and most of the stock prices are around 2000 dollars.
2. Maximum stock price is 10000 dollars.

3. Feature Engineering

3.1 Date related Features

In [681]:

```
processed_data = raw_data.copy()
processed_data['year'] = processed_data["Date"].dt.year                    #generating yea
processed_data['month'] = processed_data['Date'].dt.month                  #generating mon
processed_data['day'] = processed_data['Date'].dt.day                      #genearating da
processed_data['dayofweek_num'] = processed_data['Date'].dt.dayofweek      #generating wee
processed_data['dayofweek_name'] = processed_data['Date'].dt.day_name()    #generating wee

processed_data.head()
```

Out[681]:

	Date	Open	High	Low	Close	Adj Close	Volume	year	month
0	1991-01-02	373.000000	373.500000	371.799988	372.200012	372.200012	92020000	1991	1
1	1991-01-03	371.200012	371.799988	367.399994	367.500000	367.500000	108390000	1991	1
2	1991-01-04	366.500000	367.899994	365.899994	367.200012	367.200012	103830000	1991	1
3	1991-01-07	363.500000	365.799988	360.100006	360.200012	360.200012	109460000	1991	1
4	1991-01-08	359.100006	360.500000	358.200012	359.000000	359.000000	111730000	1991	1

3.2 Buyers are sellers are control features

In stock market if closig price is greater than opening price it means sellers are in control. Otherwise, buyers are in control. let's add this feature to the dataset.

In [682]:

```
processed_data['control_stock'] = processed_data.apply(
    lambda x: 'sellersControl' if (x['Close'] > x['Open'])  else 'buyersControl' , axis = 1
    )      #generating control_stock column whcih gives whether buyers are in control or se
```

In [683]:

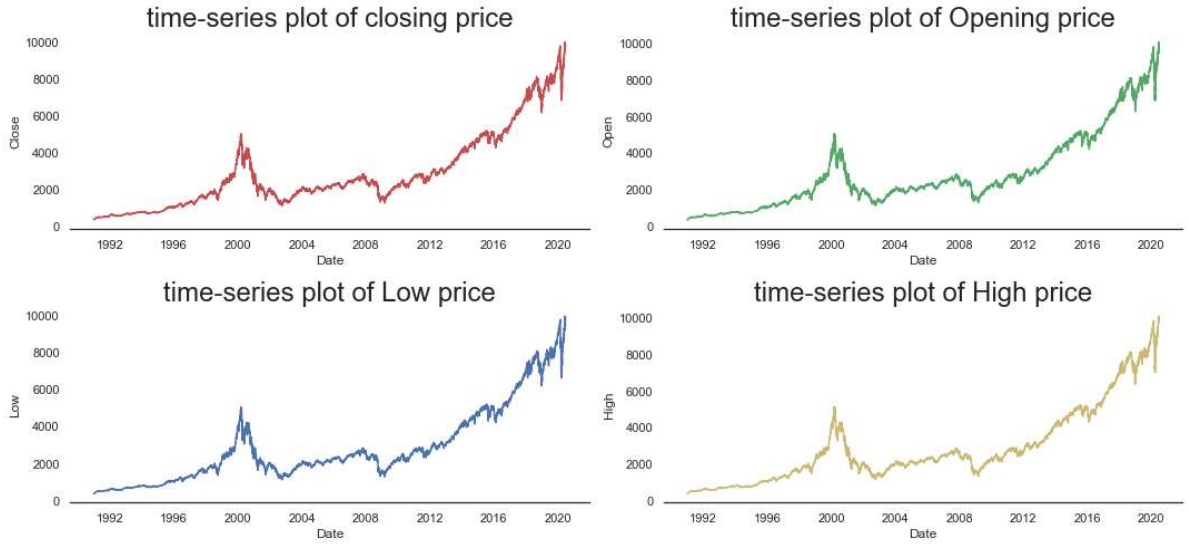
```
#storing the processed data in the local directory
outdir = data_path + 'nasdaq/processed_data'
outname = 'processed_finance.csv'
if not os.path.exists(outdir):
    os.mkdir(outdir)
fullname = os.path.join(outdir, outname)
processed_data.to_csv(fullname)
```

4. Exploratory Analysis

4.1 Exploratory Analysis on raw data

In [684]:

```
# Set up the matplotlib figure
f, axes = plt.subplots(2, 2, figsize=(15, 7))
sns.despine(left=True)

sns.lineplot(raw_data['Date'], raw_data['Close'], color="r", \
             ax=axes[0, 0]).set_title("time-series plot of closing price", size = 24)

sns.lineplot(raw_data['Date'], raw_data['Open'], color = "g", \
             ax=axes[0, 1]).set_title("time-series plot of Opening price", size = 24)

sns.lineplot(raw_data['Date'], raw_data['Low'], color="b", \
             ax=axes[1, 0]).set_title("time-series plot of Low price", size = 24)

sns.lineplot(raw_data['Date'], raw_data['High'], color="y", \
             ax=axes[1, 1]).set_title("time-series plot of High price", size = 24)


plt.tight_layout()
```



4.2 Exploratory Analysis on processed data

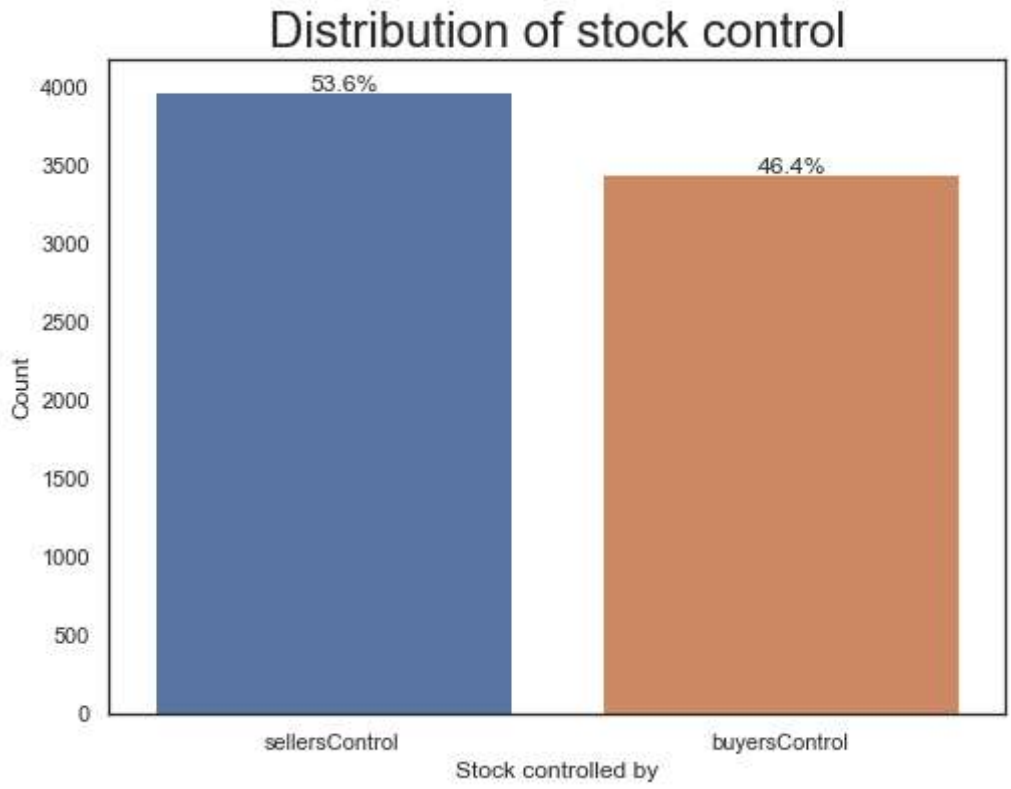
4.2.1 Distribution of sellers control vs buyers control

In [685]:

```
#https://stackoverflow.com/questions/35692781/python-plotting-percentage-in-seaborn-bar-plo
def without_hue(plot, feature1):
    """
    This function labels the percentage on count plots

    parameters:
        plot(plot object): matplotlib plot object
        feature1(array): array of counts

    returns:
        doesn't return anything but annotates the percentage on count plot

    """
    total = feature1.sum()
    for p in plot.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() / 2 - 0.05
        y = p.get_y() + p.get_height()
        plot.annotate(percentage, (x, y), size = 12)
```

In [686]:

```
counts = processed_data.control_stock.value_counts()
df_counts = pd.DataFrame(counts).reset_index()
df_counts.columns = ['control_stock', 'count']
ax = sns.barplot(x = 'control_stock', y='count', data = df_counts)
plt.xlabel('Stock controlled by', size = 12)
plt.ylabel('Count', size = 12)
plt.title('Distribution of stock control', size = 24)
without_hue(ax, df_counts[['count']].values)
```



Observations

1. By observing the count plot we can see that most of the times sellers are in control compared to buyers.

Finding years where distribution of stock control differs from the original distribution

In [687]:

```
#group by year of stock control
year_control = processed_data[['year', 'control_stock']].groupby('year').control_stock.valu
df_year_control = pd.DataFrame(year_control)
df_year_control.columns = ['count']
df_year_control.reset_index(inplace = True)
```

In [688]:

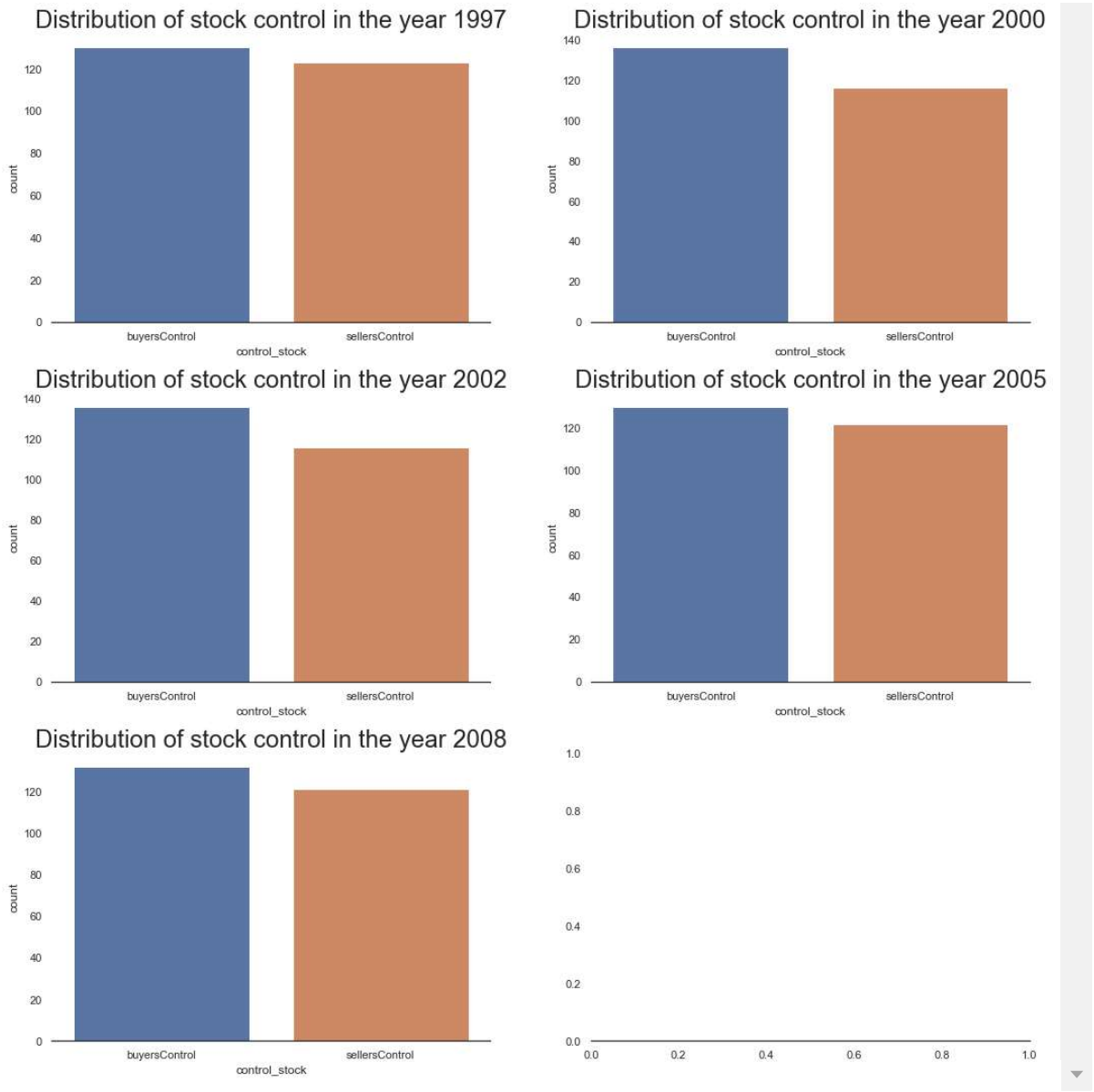
```
def return_years(df):
    """
    This function purpose is to find the years where the distribution of stock control diff

    parameters:
        df(dataframe): This dataframe contains the stock control grouped by year

    returns:
        array: returns the array of years

    """
    year_values = []
    for year in df['year'].unique():
        temp_df = df[df['year'] == year]
        if temp_df[temp_df['control_stock'] == 'sellersControl']['count'].values[0] < \
            temp_df[temp_df['control_stock'] == 'buyersControl']['count'].values[0]:
            year_values.append(year)
    return year_values
```

In [689]:

```
years = return_years(df_year_control)
```

In [690]:

```
# Set up the matplotlib figure
f, axes = plt.subplots(3, 2, figsize=(15, 15))
sns.despine(left=True)

sns.barplot(x = 'control_stock', y='count', \
            data = df_year_control[df_year_control['year'] == years[0]], \
            ax = axes[0,0]).set_title("Distribution of stock control in the year {}".format

without_hue(ax, df_counts[['count']].values)

sns.barplot(x = 'control_stock', y='count',\
            data = df_year_control[df_year_control['year'] == years[1]],\
            ax = axes[0,1]).set_title("Distribution of stock control in the year {}".format


sns.barplot(x = 'control_stock', y='count', \
            data = df_year_control[df_year_control['year'] == years[2]],\
            ax = axes[1,0]).set_title("Distribution of stock control in the year {}".format


sns.barplot(x = 'control_stock', y='count', \
            data = df_year_control[df_year_control['year'] == years[3]], \
            ax = axes[1,1]).set_title("Distribution of stock control in the year {}".format


sns.barplot(x = 'control_stock', y='count', \
            data = df_year_control[df_year_control['year'] == years[4]], \
            ax = axes[2,0]).set_title("Distribution of stock control in the year {}".format

plt.tight_layout()
```



Observations

1. After exploring the year-wise stock-control, it seems that the years **1997, 2000, 2002, 2005, 2008** are in favour of buyers comapred to sellers.

Finding months where distribution of stock control differs from the original distribution

In [691]:

```
# group stock control by month-wise
month_control = processed_data[['month', 'control_stock']].groupby('month').control_stock.v
df_month_control = pd.DataFrame(month_control)
df_month_control.columns = ['count']
df_month_control.reset_index(inplace = True)
```

In [692]:

```
def return_months(df):
    """
    This function purpose is to find the months where the distribution of stock control dif

    parameters:
        df(dataframe): This dataframe contains the stock control grouped by months

    returns:
        array: returns the array of months

    """
    month_values = []
    for month in df['month'].unique():
        temp_df = df[df['month'] == month]
        if temp_df[temp_df['control_stock'] == 'sellersControl']['count'].values[0] < \
            temp_df[temp_df['control_stock'] == 'buyersControl']['count'].values[0]:
            month_values.append(month)
    return month_values
```

In [693]:

```
months = return_months(df_month_control)
```

In [694]:

```
print(months)
```

```
[]
```

Observations

1. After exploring month-wise it seems that the month wise there are no months where the distribution of stock control differs from the orignal distribution.

Finding days where distribution of stock control differs from the original distribution

In [695]:

```
# group stock control by month-wise
day_control = processed_data[['dayofweek_name', 'control_stock']].groupby('dayofweek_name')
df_day_control = pd.DataFrame(day_control)
df_day_control.columns = ['count']
df_day_control.reset_index(inplace = True)
```

In [696]:

```
def return_days(df):
    """
    This function purpose is to find the days where the distribution of stock control diffe

    parameters:
        df(dataframe): This dataframe contains the stock control grouped by days

    returns:
        array: returns the array of days

    """
    day_values = []
    for day in df['dayofweek_name'].unique():
        temp_df = df[df['dayofweek_name'] == day]
        if temp_df[temp_df['control_stock'] == 'sellersControl']['count'].values[0] < \
            temp_df[temp_df['control_stock'] == 'buyersControl']['count'].values[0]:
            day_values.append(day)
    return day_values
```

In [697]:

```
days = return_days(df_day_control)
```

In [698]:

```
print(days)
```

```
[]
```

Observations

1. After exploring day-wise it seems that the day-wise there are no days where the distribution of stock control differs from the orignal distribution

5. Predictive Analytics

5.1 Data Pre-processing

In [699]:

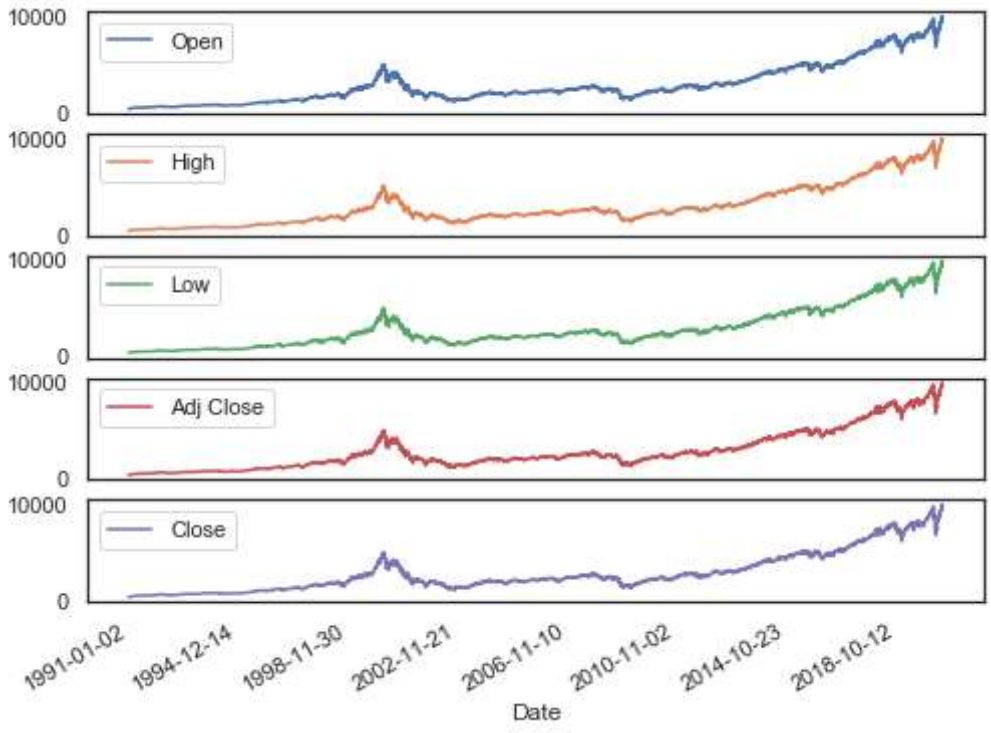
```
# Features
features_considered = ['Open', 'High', 'Low', 'Adj Close', 'Close']

features = df[features_considered]
features.index = df['Date']
features.head()
```

Out[699]:

Date	Open	High	Low	Adj Close	Close
1991-01-02	373.000000	373.500000	371.799988	372.200012	372.200012
1991-01-03	371.200012	371.799988	367.399994	367.500000	367.500000
1991-01-04	366.500000	367.899994	365.899994	367.200012	367.200012
1991-01-07	363.500000	365.799988	360.100006	360.200012	360.200012
1991-01-08	359.100006	360.500000	358.200012	359.000000	359.000000

In [700]:

```
_ = features.plot(subplots = True)
```



In [701]:

```
dataset = features.values
```

In [702]:

```
TRAIN_SPLIT = int(features.shape[0] * 0.65) #getting index for traind dataset
VAL_SPLIT = int(features.shape[0] * 0.85)  #getting index for validation dataset
```

In [703]:

```
# Standardize data

dataset = features.values
data_mean = dataset[:TRAIN_SPLIT].mean(axis=0)
data_std = dataset[:TRAIN_SPLIT].std(axis=0)

dataset = (dataset-data_mean)/data_std
```

In [704]:

```
def multivariate_data(dataset, target, start_index, end_index, history_size, train_flag = F

    """
    This function purpose is to returing the dataset and the labels

    parameters:
        dataset(nd-array): It contains the daily stock data
        target(1d-array): It contains the daily closing prices
        start_index(int): It contain the starting point of the dataset to starrt splitting
        end_index(int or None): It contains the ending point os the dataset to end splittin
        history_size(int): It contains the time-steps (window-size)
        train_flag(boolean): It contains boolean value which represents whether the data is

    returns:
        data(array): final dataset read for training or validating
        labels(array): array contains the labels for trianing dataset

    """
    data = []
    labels = []

    if train_flag is True:
        start_index = start_index + history_size

    if end_index is None:
        end_index = len(dataset)

    for i in range(start_index, end_index):
        indices = range(i-history_size, i)
        data.append(dataset[indices])

        labels.append(target[i])

    return np.array(data), np.array(labels)
```

In [705]:

```
# Generate data
past_history = 10

x_train_single, y_train_single = multivariate_data(dataset, dataset[:, -1], 0,
                                                   TRAIN_SPLIT, past_history, train_flag =
x_val_single, y_val_single = multivariate_data(dataset, dataset[:, -1],
                                               TRAIN_SPLIT, VAL_SPLIT, past_history, train_
x_test_single, y_test_single = multivariate_data(dataset, dataset[:, -1], VAL_SPLIT,
                                                 None, past_history, train_flag = False)

print("train data shape:", x_train_single.shape)
print("train label shape:", y_train_single.shape)
print("validation data shape:", x_val_single.shape)
print("validation label shape:", y_val_single.shape)
print("test data shape:", x_test_single.shape)
print("test label shape:", y_test_single.shape)
```

```
train data shape: (4815, 10, 5)
train label shape: (4815,)
validation data shape: (1485, 10, 5)
validation label shape: (1485,)
test data shape: (1114, 10, 5)
test label shape: (1114,)
```

In [706]:

```
#storing the final datasets in .npy files so that can reuse in another notebooks

outdir = data_path + 'nasdaq/final_data/'
x_train_outname = 'train/x_train_normalised.npy'
y_train_outname = 'train/y_train_normalised.npy'

x_val_outname = 'validation/x_val_normalised.npy'
y_val_outname = 'validation/y_val_normalised.npy'

x_test_outname = 'test/x_test_normalised.npy'
y_test_outname = 'test/y_test_normalised.npy'

data_mean_outname = 'standardization/data_mean.npy'
data_std_outname = 'standardization/data_std.npy'

if not os.path.exists(outdir):
    os.mkdir(outdir)
full_x_train = os.path.join(outdir, x_train_outname)
full_y_train = os.path.join(outdir, y_train_outname)

full_x_val = os.path.join(outdir, x_val_outname)
full_y_val = os.path.join(outdir, y_val_outname)

full_x_test = os.path.join(outdir, x_test_outname)
full_y_test = os.path.join(outdir, y_test_outname)

full_data_mean = os.path.join(outdir, data_mean_outname)
full_data_std = os.path.join(outdir, data_std_outname)

#https://thispointer.com/how-to-save-numpy-array-to-a-csv-file-using-numpy-savetxt-in-pytho
np.save(full_x_train, [x_train_single])
np.save(full_y_train, [y_train_single])

np.save(full_x_val, [x_val_single])
np.save(full_y_val, [y_val_single])

np.save(full_x_test, [x_test_single])
np.save(full_y_test, [y_test_single])

np.save(full_data_mean, [data_mean])
np.save(full_data_std, [data_std])
```

5.2 AT-LSTM model

In [707]:

```
#https://www.tensorflow.org/tensorboard/get_started

# defining log_dir and tensorboard_call back for storing log files
log_dir = "logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = keras.callbacks.TensorBoard(log_dir=log_dir, histogram_freq=1)
```

In [708]:

```
#Attention model

class attention(Layer):
    """
    This is an extended attention layer for our custom implemention

    """
    def __init__(self,**kwargs):
        super(attention,self).__init__(**kwargs)

    def build(self,input_shape):
        """
        The function to define weights and bias.

        parameters:
            inpu_shape(dimenstion of the array): It's the shape of previous LSTM output

        returns:
            doesn't return anything

        """
        self.W=self.add_weight(name="att_weight",shape=(input_shape[-1],1),initializer="nor
        self.b=self.add_weight(name="att_bias",shape=(input_shape[1],1),initializer="zeros"
        super(attention, self).build(input_shape)

    def call(self,x):
        """
        This function calculates the attention weights of the input and gives the output af

        parameters:
            x(LSTM output): It's the previous LSTM output

        returns:
            returns the attention weighted LSTM output

        """
        #print("X_shape", x.shape)
        et=K.squeeze(K.tanh(K.dot(x,self.W)+self.b),axis=-1)
        #print("et_shape", et.shape)
        at=K.softmax(et)
        #print("at_shape_1", at.shape)
        at=K.expand_dims(at,axis=-1)
        #print("at_shape_2", at.shape)
        output=x*at
        #print("output_shape", output.shape)
        #return(output)
        return K.sum(output,axis=1)

    def compute_output_shape(self,input_shape):
        return (input_shape[0],input_shape[-1])

    def get_config(self):
        return super(attention,self).get_config()
```

In [709]:

```
def create_model(time_steps, num_features, num_neurons_lstm):

    """
    This function creates the AT-LSTM model

    parameters:
        time_steps(int): window-size for model creation.
        num_features(int): number of features contains in the dataset.
        num_neurons_lstm(int): number of neurons contains for LSTM model.

    returns:
        returns the deep_learning model created using tensorflow.
    """

    opt = tf.keras.optimizers.Adam(learning_rate=0.01)
    # define model
    model = Sequential()
    model.add(LSTM(num_neurons_lstm, activation='relu', return_sequences = True, input_shap
    model.add(attention())
    model.add(Dense(1))
    model.compile(optimizer=opt, loss='mae', metrics = ['mape'])

    return model
```

In [710]:

```
model = create_model(time_steps = 10, num_features = 5, num_neurons_lstm = 8)
```

In [711]:

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_2 (LSTM)                (None, 10, 8)             448
_________________________________________________________________
attention_2 (attention)      (None, 8)                 18
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 9
=================================================================
Total params: 475
Trainable params: 475
Non-trainable params: 0
_________________________________________________________________
```

In [712]:

```
# Train and evaluate
EPOCHS = 600
batch_size = 50
# https://www.tensorflow.org/api_docs/python/tf/keras/Model#fit
model.fit(x_train_single, y_train_single, validation_data = (x_val_single, y_val_single ),
          epochs=EPOCHS, batch_size = batch_size, callbacks=[tensorboard_callback])
```

```
Epoch 579/600
97/97 [==============================] - 1s 6ms/step - loss: 0.0275 - map
e: 18.6496 - val_loss: 0.0920 - val_mape: 4.2474
Epoch 580/600
97/97 [==============================] - 1s 6ms/step - loss: 0.0276 - map
e: 18.7688 - val_loss: 0.0555 - val_mape: 3.1962
Epoch 581/600
97/97 [==============================] - 1s 6ms/step - loss: 0.0275 - map
e: 18.5471 - val_loss: 0.0813 - val_mape: 4.0610
Epoch 582/600
97/97 [==============================] - 1s 6ms/step - loss: 0.0269 - map
e: 17.7228 - val_loss: 0.0687 - val_mape: 3.4899
Epoch 583/600
97/97 [==============================] - 1s 7ms/step - loss: 0.0273 - map
e: 18.6838 - val_loss: 0.0673 - val_mape: 3.3487
Epoch 584/600
97/97 [==============================] - 1s 8ms/step - loss: 0.0272 - map
e: 18.4396 - val_loss: 0.0371 - val_mape: 2.1590
Epoch 585/600
97/97 [==============================] - 1s 8ms/step - loss: 0.0267 - map
```

In [713]:

```
#https://www.tensorflow.org/tutorials/keras/save_and_load
model.save('saved_model/my_model')
```

```
INFO:tensorflow:Assets written to: saved_model/my_model\assets
```

In [714]:

```
y_test_predict = model.predict(x_test_single)
```

In [715]:

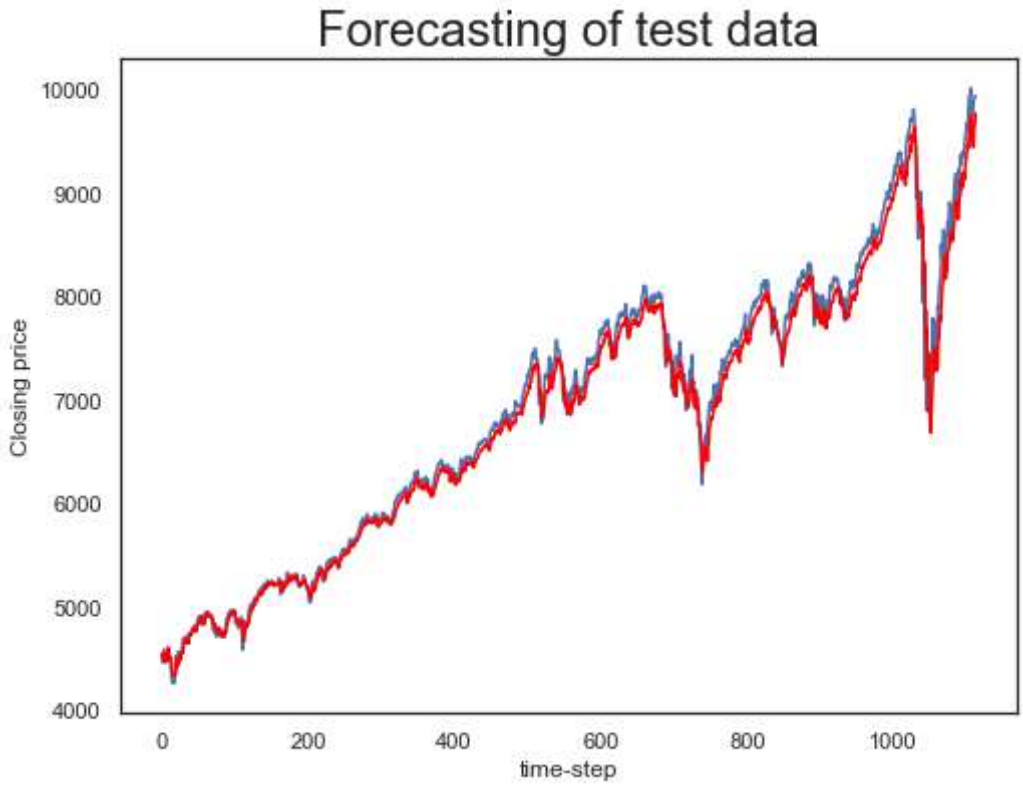
```
y_test_predict_new = (y_test_predict * data_std[-1] ) + data_mean[-1]
```

In [716]:

```
y_test_single_new = (y_test_single * data_std[-1]) + data_mean[-1]
```

In [717]:

```
plt.plot(y_test_single_new)
plt.plot(y_test_predict_new, color = 'red')
plt.title("Forecasting of test data", size = 24)
plt.xlabel("time-step")
plt.ylabel("Closing price")
plt.show()
```



In [718]:

```
#https://stackoverflow.com/questions/47648133/mape-calculation-in-python
def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true))
```

In [719]:

```
mape = mean_absolute_percentage_error(y_test_single_new, y_test_predict_new)
print(mape)
```

```
0.23028757122005095
```