Experiment No. 4

Aim - To implement multivariate linear regression.

Theory:

Step 1: Import libraries and load the data into the environment.

Step 2: Generate the features of the model that are related with some measure of volatility, price and volume.

Step 3: Visualize the correlation between the features and target variable with scatterplots.

Step 4: Create the train and test dataset and fit the model using the linear regression algorithm.

Step 5: Make predictions, obtain the performance of the model, and plot the results.

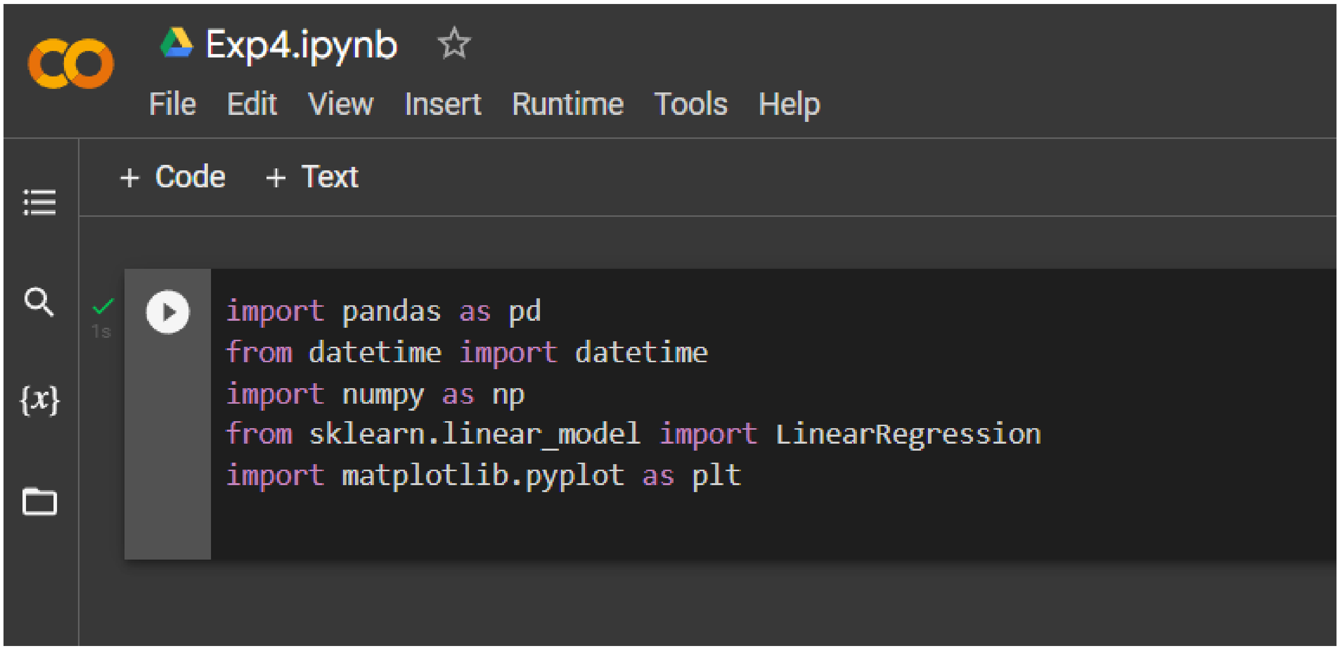
Step 1: Import libraries and load the data into the environment.

We will first import the required libraries in our Python environment.

Code:

```
import pandas as pd

from datetime import datetime

import numpy as np

from sklearn.linear_model import LinearRegression

import matplotlib.pyplot as plt
```

We will work with SPY data between dates 2010-01-04 to 2015-12-07.



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SPY Regression Data – CSV

Let's now set the Date as index and reverse the order of the dataframe in order to have oldest values at top.

Code –

```
SPY_data = pd.read_csv("SPY_regression.csv")
# Change the Date column from object to datetime object
SPY_data["Date"] = pd.to_datetime(SPY_data["Date"])
# Preview the data
SPY_data.head(10)
```

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SPY_data = pd.read_csv("SPY_regression.csv")

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# Preview the data
SPY_data.head(10)
```

	Date	Open	High	Low	Close	Volume	Adj Close	Unnamed: 7
0	1970-01-01 00:00:00.000000000	2015-12-07	2090.419922	2090.419922	2066.780029	2077.070068	4043820000	2077.070068
1	1970-01-01 00:00:00.000000001	2015-12-04	2051.239990	2093.840088	2051.239990	2091.689941	4214910000	2091.689941
2	1970-01-01 00:00:00.000000002	2015-12-03	2080.709961	2085.000000	2042.349976	2049.620117	4306490000	2049.620117
3	1970-01-01 00:00:00.000000003	2015-12-02	2101.709961	2104.270020	2077.110107	2079.510010	3950640000	2079.510010
4	1970-01-01 00:00:00.000000004	2015-12-01	2082.929932	2103.370117	2082.929932	2102.629883	3712120000	2102.629883
5	1970-01-01 00:00:00.000000005	2015-11-30	2090.949951	2093.810059	2080.409912	2080.409912	4245030000	2080.409912
6	1970-01-01 00:00:00.000000006	2015-11-27	2088.820068	2093.290039	2084.129883	2090.110107	1466840000	2090.110107
7	1970-01-01 00:00:00.000000007	2015-11-25	2089.300049	2093.000000	2086.300049	2088.870117	2852940000	2088.870117
8	1970-01-01 00:00:00.000000008	2015-11-24	2084.419922	2094.120117	2070.290039	2089.139893	3884930000	2089.139893
9	1970-01-01 00:00:00.000000009	2015-11-23	2089.409912	2095.610107	2081.389893	2086.590088	3587980000	2086.590088

Set Date as index

SPY_data.set_index('Date',inplace=True)

Reverse the order of the dataframe in order to have oldest values at top

SPY_data.sort_values('Date',ascending=True)

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1970-01-01 00:00:00.000000000	2015-12-07	2090.419922	2090.419922	2066.780029	2077.070068	4043820000	2077.070068
1970-01-01 00:00:00.000000001	2015-12-04	2051.239990	2093.840088	2051.239990	2091.689941	4214910000	2091.689941
1970-01-01 00:00:00.000000002	2015-12-03	2080.709961	2085.000000	2042.349976	2049.620117	4306490000	2049.620117
1970-01-01 00:00:00.000000003	2015-12-02	2101.709961	2104.270020	2077.110107	2079.510010	3950640000	2079.510010
1970-01-01 00:00:00.000000004	2015-12-01	2082.929932	2103.370117	2082.929932	2102.629883	3712120000	2102.629883
...	...	...	...	...	...	...	...
1970-01-01 00:00:00.000001488	2010-01-08	1140.520020	1145.390015	1136.219971	1144.979980	4389590000	1144.979980
1970-01-01 00:00:00.000001489	2010-01-07	1136.270020	1142.459961	1131.319946	1141.689941	5270680000	1141.689941
1970-01-01 00:00:00.000001490	2010-01-06	1135.709961	1139.189941	1133.949951	1137.140015	4972660000	1137.140015
1970-01-01 00:00:00.000001491	2010-01-05	1132.660034	1136.630005	1129.660034	1136.520020	2491020000	1136.520020
1970-01-01 00:00:00.000001492	2010-01-04	1116.560059	1133.869995	1116.560059	1132.989990	3991400000	1132.989990

1493 rows × 7 columns

Step 2: Generate features of the model

We will generate the following features of the model:

High - Low percent change

5 periods Exponential Moving Average

Standard deviation of the price over the past 5 days

Daily volume percent change

Average volume for the past 5 days

Volume over close price ratio.

Code:

SPY_data['High-Low_pct'] = (SPY_data['High'] - SPY_data['Low']).pct_change()

SPY_data['ewm_5'] = SPY_data["Close"].ewm(span=5).mean().shift(periods=1)

SPY_data['price_std_5'] = SPY_data["Close"].rolling(center=False,window= 30).std().shift(periods=1)

SPY_data['volume Change'] = SPY_data['Volume'].pct_change()

SPY_data['volume_avg_5'] = SPY_data["Volume"].rolling(center=False,window=5).mean().shift(periods=1)

SPY_data['volume Close'] = SPY_data["Volume"].rolling(center=False,window=5).std().shift(periods=1)

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SPY_data['volume Close'] = SPY_data["Volume"].rolling(center=False,window=5).std().shift(periods=1)
```

Step 3: Visualize the correlation between the features and target variable

Before training the dataset, we will make some plots to observe the correlations between the features and the target variable.

Code:

jet= plt.get_cmap('jet')

colors = iter(jet(np.linspace(0,1,10)))

```
def correlation(df,variables, n_rows, n_cols):
   fig = plt.figure(figsize=(8,6))
   #fig = plt.figure(figsize=(14,9))
   for i, var in enumerate(variables):
      ax = fig.add_subplot(n_rows,n_cols,i+1)
      asset = df.loc[:,var]
      ax.scatter(df["Adj Close"], asset, c = next(colors))
      ax.set_xlabel("Adj Close")
      ax.set_ylabel("{}".format(var))
      ax.set_title(var +" vs price")
   fig.tight_layout()
   plt.show()
```

```
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    fig.tight_layout()
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```
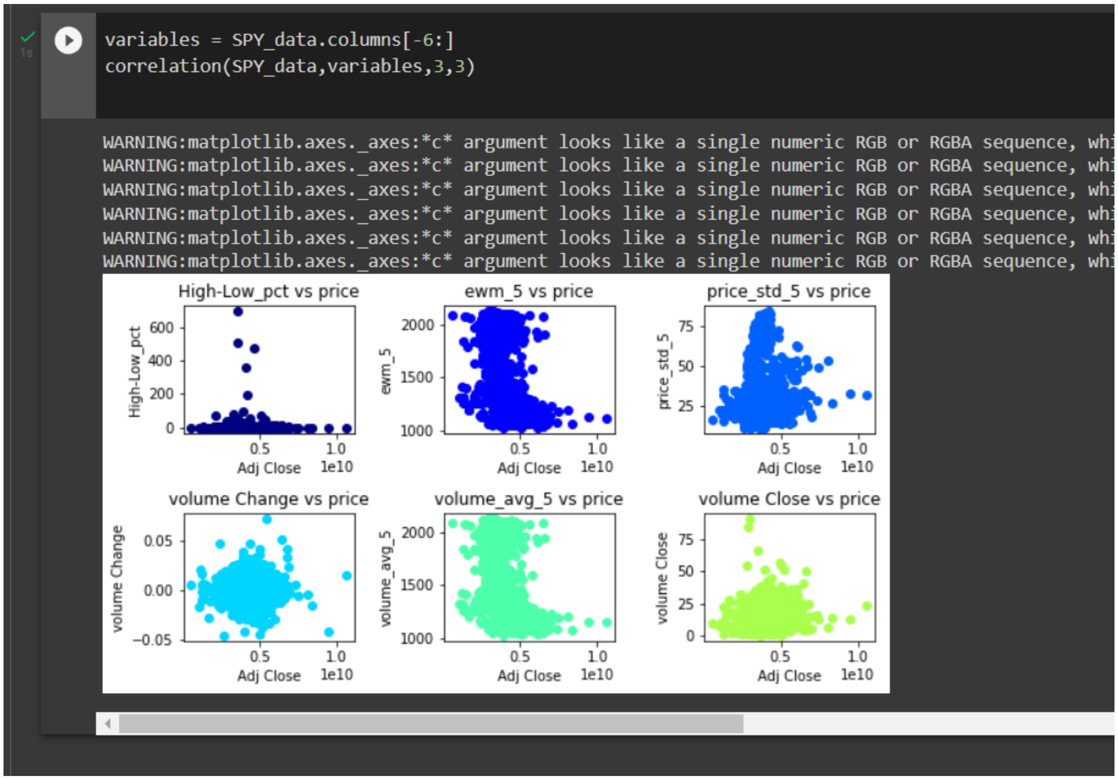

```
# Take the name of the last 6 columns of the SPY_data which are the model features
variables = SPY_data.columns[-6:]
correlation(SPY_data,variables,3,3)
```



Correlations between Features and Target Variable (Adj Close)

The correlation matrix between the features and the target variable has the following values:

SPY_data.corr()['Adj Close'].loc[variables]

```
SPY_data.corr()['Adj Close'].loc[variables]

High-Low_pct      0.010117
ewm_5            -0.412932
price_std_5       0.148941
volume Change     0.012828
volume_avg_5     -0.411242
volume Close      0.167878
Name: Adj Close, dtype: float64
```

Either the scatterplot or the correlation matrix reflects that the Exponential Moving Average for 5 periods is very highly correlated with the Adj Close variable. Secondly is possible to observe a negative correlation between Adj Close and the volume average for 5 days and with the volume to Close ratio.

Step 4: Train the Dataset and Fit the model

Due to the feature calculation, the SPY_data contains some NaN values that correspond to the first's rows of the exponential and moving average columns. We will see how many Nan values there are in each column and then remove these rows.

SPY_data.isnull().sum().loc[variables]

High-Low_pct 1

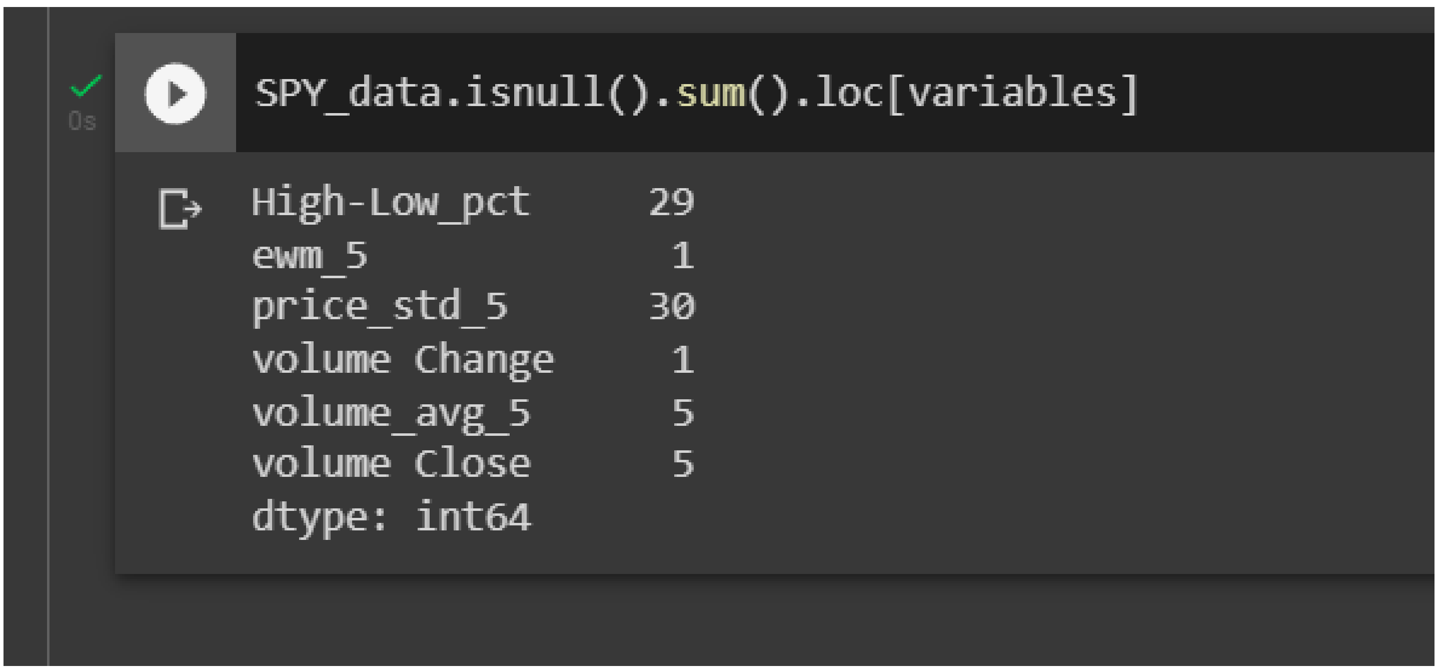
ewm_5 1

price_std_5 30

volume Change 1

volume_avg_5 5

volume Close 5



```
SPY_data.isnull().sum().loc[variables]

High-Low_pct     29
ewm_5             1
price_std_5      30
volume Change     1
volume_avg_5      5
volume Close      5
dtype: int64
```

To train the model is necessary to drop any missing value in the dataset.

SPY_data = SPY_data.dropna(axis=0)

Generate the train and test sets

train = SPY_data[SPY_data.index < datetime(year=2015, month=1, day=1)]

test = SPY_data[SPY_data.index >= datetime(year=2015, month=1, day=1)]

dates = test.index

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```

Step 5: Make predictions, obtain the performance of the model, and plot the results

In this step, we will fit the model with the LinearRegression classifier. We are trying to predict the Adj Close value of the Standard and Poor's index. # So the target of the model is the "Adj Close" Column.

lr = LinearRegression()

X_train = train[["High-Low_pct","ewm_5","price_std_5","volume_avg_5","volume Change","volume Close"]]

Y_train = train["Adj Close"]

lr.fit(X_train,Y_train)

```
[ ] lr = LinearRegression()

    X_test = test[["High-Low_pct","ewm_5","price_std_5","volume_avg_5","volume Change","volume Close"]]

    Y_test = test["Adj Close"]

    lr.fit(X_test,Y_test)
```

Create the test features dataset (X_test) which will be used to make the predictions.

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X_test = test[["High-Low_pct","ewm_5","price_std_5","volume_avg_5","volume Change","volume Close"]].values

The labels of the model

Y_test = test["Adj Close"].values

```
[ ] X_test = test[["High-Low_pct","ewm_5","price_std_5","volume_avg_5","volume Change","volume Close"]].values

[ ] Y_test = test["Adj Close"].values
```

Predict the Adj Close values using the X_test dataframe and Compute the Mean Squared Error between the predictions and the real observations.

close_predictions = lr.predict(X_test)

mae = sum(abs(close_predictions - test["Adj Close"].values)) / test.shape[0]

print(mae)

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    print(mae)

    13.401156619923697
    /usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
      "X does not have valid feature names, but"
```

We have that the Mean Absolute Error of the model is 18.0904. This metric is more intuitive than others such as the Mean Squared Error, in terms of how close the predictions were to the real price.

Finally we will plot the error term for the last 25 days of the test dataset. This allows observing how long is the error term in each of the days, and asses the performance of the model by date.

Create a dataframe that output the Date, the Actual and the predicted values

df = pd.DataFrame({'Date':dates,'Actual': Y_test, 'Predicted': close_predictions})

df1 = df.tail(25)

set the date with string format for plotting

df1['Date'] = df1['Date'].dt.strftime('%Y-%m-%d')

df1.set_index('Date',inplace=True)

error = df1['Actual'] - df1['Predicted']

```python
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df1.set_index('Date',inplace=True)
error = df1['Actual'] - df1['Predicted']
```

Plot the error term between the actual and predicted values for the last 25 days

error.plot(kind='bar',figsize=(8,6))

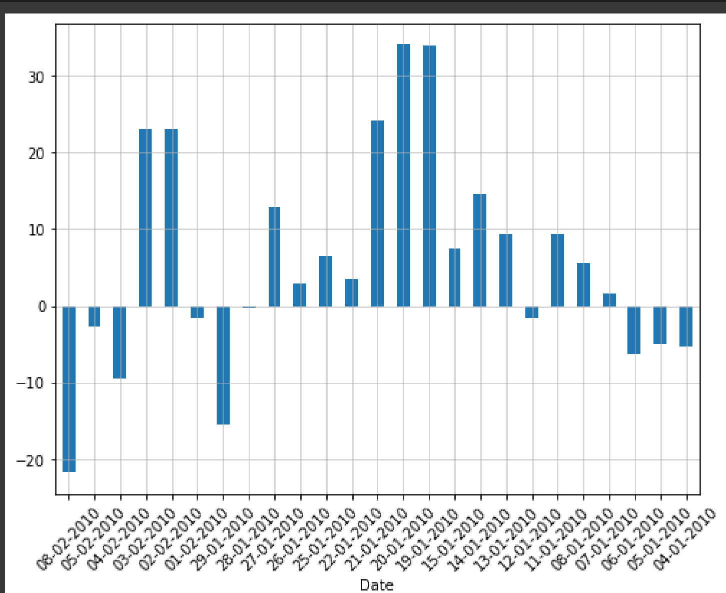
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')

plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')

plt.xticks(rotation=45)

plt.show()

```
[ ]  error.plot(kind='bar',figsize=(8,6))
     plt.grid( which='major', linestyle='-', linewidth='0.5')
     plt.grid(which='minor', linestyle=':', linewidth='0.5')
     plt.xticks(rotation=45)
     plt.show()
```



Conclusion – This concludes our example of Multivariate Linear Regression in Python.