

```

In [21]: # Question 1:

def split(endYear,startYear=2012):

    import pandas as pd
    import numpy as np
    from datetime import datetime

    #Importing dataset
    df_energy = pd.read_excel(r"D:\Ruchi Folder\Python\Assignment5\Energy.xlsx")

    # Column columns "Accumulated Other Comprehensive Income (Loss)" to "Selling, Gene
    df_selected=df_energy.loc[:, "Accumulated Other Comprehensive Income (Loss)": "Selli

    date_dataf=df_energy.loc[:, "Data Date": "Fiscal Year"]

    # Joining df_Selected with df_Dates
    new_dataf=date_dataf.join(df_selected)

    if endYear==None:

        Test=new_dataf[new_dataf["Fiscal Year"]==startYear]

        Train=new_dataf[new_dataf["Fiscal Year"]!=startYear]

    elif endYear!=None:

        Test= new_dataf[(new_dataf["Fiscal Year"] >= startYear) & (new_dataf["Fiscal

        Train=new_dataf[~((new_dataf["Fiscal Year"] >= startYear) & (new_dataf["Fisc

    return(Test, Train)

split(2013)

```

C:\Users\Bipin\anaconda3\lib\site-packages\openpyxl\styles\stylesheet.py:221: UserWarning: Workbook contains no default style, apply openpyxl's default
 warn("Workbook contains no default style, apply openpyxl's default")

```

Out[21]: (
  8    Data Date  Fiscal Year  Accumulated Other Comprehensive Income (Loss) \
  9    20120331      2012      -1057.0
  10   20120630      2012      -779.0
  11   20120930      2012      -675.0
  12   20121231      2012      -493.0
  13   20130331      2013      -452.0
  ..          ...          ...          ...
  827  20121231      2012      -464.0
  828  20130331      2013      -382.0

```

829	20130630	2013	-254.0
830	20130930	2013	-205.0
831	20131231	2013	-204.0

	Current Assets - Other	- Total	Current Assets - Total	\
8		1421.0	8212.0	
9		1699.0	7925.0	
10		2167.0	8157.0	
11		2148.0	8387.0	
12		8448.0	11418.0	
..		
827		110.0	13029.0	
828		172.0	15297.0	
829		190.0	14252.0	
830		206.0	13531.0	
831		197.0	12737.0	

	Other Long-term Assets	Non-Current Assets - Total	\
8	3675.0	32435.0	
9	3417.0	32689.0	
10	3302.0	34055.0	
11	3596.0	35054.0	
12	3104.0	30961.0	
..	
827	254.0	14194.0	
828	320.0	15476.0	
829	328.0	15443.0	
830	320.0	15472.0	
831	324.0	15648.0	

	Assets Netting & Other Adjustments	\
8	-350.0	
9	-305.0	
10	-186.0	
11	-227.0	
12	-205.0	
..	...	
827	84.0	
828	138.0	
829	-30.0	
830	-62.0	
831	-21.0	

	Accum Other Comp Inc - Derivatives Unrealized Gain/Loss	\
8	-547.0	
9	78.0	
10	-152.0	
11	-24.0	
12	-11.0	
..	...	
827	0.0	
828	4.0	
829	4.0	
830	4.0	
831	4.0	

	Accum Other Comp Inc - Other Adjustments	...	\
8	107.0	...	
9	-270.0	...	
10	67.0	...	
11	170.0	...	
12	28.0	...	
..	
827	0.0	...	
828	0.0	...	

829	0.0	...
830	0.0	...
831	0.0	...

	Implied Option EPS Diluted	Implied Option EPS Diluted Preliminary \
8	0.0	0.0
9	0.0	0.0
10	0.0	0.0
11	0.0	0.0
12	0.0	0.0
..
827	0.0	NaN
828	0.0	NaN
829	0.0	NaN
830	0.0	NaN
831	0.0	NaN

	Implied Option EPS Basic 12MM	Implied Option 12MM EPS Basic Preliminary \
8	0.0	0.0
9	0.0	0.0
10	0.0	0.0
11	0.0	0.0
12	0.0	0.0
..
827	NaN	NaN
828	NaN	NaN
829	NaN	NaN
830	NaN	NaN
831	NaN	NaN

	Implied Option EPS Basic	Implied Option EPS Basic Preliminary \
8	0.0	0.0
9	0.0	0.0
10	0.0	0.0
11	0.0	0.0
12	0.0	0.0
..
827	0.0	NaN
828	0.0	NaN
829	0.0	NaN
830	0.0	NaN
831	0.0	NaN

	Implied Option Expense	Implied Option Expense Preliminary \
8	0.0	0.0
9	0.0	0.0
10	0.0	0.0
11	0.0	0.0
12	0.0	0.0
..
827	0.0	NaN
828	0.0	NaN
829	0.0	NaN
830	0.0	NaN
831	0.0	NaN

	Research and Development Expense \
8	NaN
9	NaN
10	NaN
11	NaN
12	NaN
..	...
827	NaN
828	NaN

829	NaN
830	NaN
831	NaN

	Selling, General and Administrative Expenses
8	385.0
9	340.0
10	1011.0
11	749.0
12	400.0
..	...
827	314.0
828	243.0
829	358.0
830	304.0
831	336.0

[240 rows x 362 columns],			
	Data Date	Fiscal Year	Accumulated Other Comprehensive Income (Loss) \
0	20100331	2010	-1749.0
1	20100630	2010	-1603.0
2	20100930	2010	-1377.0
3	20101231	2010	-1159.0
4	20110331	2011	-873.0
..
839	20151231	2015	-318.0
840	20160331	2016	-318.0
841	20160630	2016	-321.0
842	20160930	2016	-327.0
843	20161231	2016	-234.0

	Current Assets - Other - Total	Current Assets - Total \
0	1502.0	8780.0
1	1434.0	8296.0
2	865.0	8839.0
3	1002.0	8780.0
4	759.0	9436.0
..
839	183.0	9471.0
840	204.0	8097.0
841	142.0	10304.0
842	176.0	9545.0
843	236.0	10401.0

	Other Long-term Assets	Non-Current Assets - Total \
0	2568.0	21169.0
1	2587.0	21204.0
2	2742.0	24646.0
3	2638.0	26616.0
4	2602.0	27201.0
..
839	119.0	33644.0
840	886.0	33661.0
841	875.0	33829.0
842	848.0	33748.0
843	107.0	34012.0

	Assets Netting & Other Adjustments \
0	-299.0
1	-254.0
2	-228.0
3	-517.0
4	-789.0
..	...
839	-62.0

840	-67.0
841	-146.0
842	-278.0
843	-688.0

Accum Other Comp Inc - Derivatives Unrealized Gain/Loss \	
0	-1312.0
1	-1058.0
2	-962.0
3	-786.0
4	-688.0
..	...
839	4.0
840	4.0
841	4.0
842	4.0
843	4.0

Accum Other Comp Inc - Other Adjustments ... \	
0	-33.0 ...
1	-148.0 ...
2	-27.0 ...
3	11.0 ...
4	192.0 ...
..
839	0.0 ...
840	0.0 ...
841	0.0 ...
842	0.0 ...
843	0.0 ...

Implied Option EPS Diluted		Implied Option EPS Diluted Preliminary \	
0	0.0		0.0
1	0.0		0.0
2	0.0		0.0
3	0.0		0.0
4	0.0		0.0
..
839	NaN		NaN
840	NaN		NaN
841	NaN		NaN
842	NaN		NaN
843	NaN		NaN

Implied Option EPS Basic 12MM		Implied Option 12MM EPS Basic Preliminary \	
0	0.0		0.0
1	0.0		0.0
2	0.0		0.0
3	0.0		0.0
4	0.0		0.0
..
839	NaN		NaN
840	NaN		NaN
841	NaN		NaN
842	NaN		NaN
843	NaN		NaN

Implied Option EPS Basic		Implied Option EPS Basic Preliminary \	
0	0.0		0.0
1	0.0		0.0
2	0.0		0.0
3	0.0		0.0
4	0.0		0.0
..
839	NaN		NaN

840	NaN	NaN
841	NaN	NaN
842	NaN	NaN
843	NaN	NaN

	Implied Option Expense	Implied Option Expense Preliminary \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
..
839	NaN	NaN
840	NaN	NaN
841	NaN	NaN
842	NaN	NaN
843	NaN	NaN

	Research and Development Expense \
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
..	...
839	NaN
840	NaN
841	NaN
842	NaN
843	NaN

	Selling, General and Administrative Expenses
0	559.0
1	576.0
2	608.0
3	805.0
4	760.0
..	...
839	403.0
840	378.0
841	401.0
842	420.0
843	406.0

[604 rows x 362 columns])

In [37]:

Question 3:

```

import sklearn
from sklearn import linear_model
from sklearn import preprocessing
from sklearn import datasets
from sklearn import svm
import numpy as np

from sklearn import linear_model
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import mean_squared_error, r2_score

```

In [38]:

#Question 3 - 1

```
#Load the dataset
diabets_df=datasets.load_diabetes()
```

```
In [39]: #Display the data
diabets_df
```

```
Out[39]: {'data': array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
    0.01990842, -0.01764613],
 [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
   -0.06832974, -0.09220405],
 [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
    0.00286377, -0.02593034],
 ...,
 [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
   -0.04687948,  0.01549073],
 [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
    0.04452837, -0.02593034],
 [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
   -0.00421986,  0.00306441]]),
 'target': array([151.,  75., 141., 206., 135.,  97., 138.,  63., 110., 310., 101.,
   69., 179., 185., 118., 171., 166., 144.,  97., 168.,  68.,  49.,
   68., 245., 184., 202., 137.,  85., 131., 283., 129.,  59., 341.,
   87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
  259.,  53., 190., 142.,  75., 142., 155., 225.,  59., 104., 182.,
  128.,  52.,  37., 170., 170.,  61., 144.,  52., 128.,  71., 163.,
  150.,  97., 160., 178.,  48., 270., 202., 111.,  85.,  42., 170.,
  200., 252., 113., 143.,  51.,  52., 210.,  65., 141.,  55., 134.,
   42., 111.,  98., 164.,  48.,  96.,  90., 162., 150., 279.,  92.,
   83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
  104.,  59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,
  173., 180.,  84., 121., 161.,  99., 109., 115., 268., 274., 158.,
  107.,  83., 103., 272.,  85., 280., 336., 281., 118., 317., 235.,
   60., 174., 259., 178., 128.,  96., 126., 288.,  88., 292.,  71.,
  197., 186.,  25.,  84.,  96., 195.,  53., 217., 172., 131., 214.,
   59.,  70., 220., 268., 152.,  47.,  74., 295., 101., 151., 127.,
  237., 225.,  81., 151., 107.,  64., 138., 185., 265., 101., 137.,
  143., 141.,  79., 292., 178.,  91., 116.,  86., 122.,  72., 129.,
  142.,  90., 158.,  39., 196., 222., 277.,  99., 196., 202., 155.,
   77., 191.,  70.,  73.,  49.,  65., 263., 248., 296., 214., 185.,
   78.,  93., 252., 150.,  77., 208.,  77., 108., 160.,  53., 220.,
  154., 259.,  90., 246., 124.,  67.,  72., 257., 262., 275., 177.,
   71.,  47., 187., 125.,  78.,  51., 258., 215., 303., 243.,  91.,
  150., 310., 153., 346.,  63.,  89.,  50.,  39., 103., 308., 116.,
  145.,  74.,  45., 115., 264.,  87., 202., 127., 182., 241.,  66.,
   94., 283.,  64., 102., 200., 265.,  94., 230., 181., 156., 233.,
   60., 219.,  80.,  68., 332., 248.,  84., 200.,  55.,  85.,  89.,
   31., 129.,  83., 275.,  65., 198., 236., 253., 124.,  44., 172.,
  114., 142., 109., 180., 144., 163., 147.,  97., 220., 190., 109.,
  191., 122., 230., 242., 248., 249., 192., 131., 237.,  78., 135.,
  244., 199., 270., 164.,  72.,  96., 306.,  91., 214.,  95., 216.,
  263., 178., 113., 200., 139., 139.,  88., 148.,  88., 243.,  71.,
   77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
   58., 262., 206., 233., 242., 123., 167.,  63., 197.,  71., 168.,
  140., 217., 121., 235., 245.,  40.,  52., 104., 132.,  88.,  69.,
  219.,  72., 201., 110.,  51., 277.,  63., 118.,  69., 273., 258.,
   43., 198., 242., 232., 175.,  93., 168., 275., 293., 281.,  72.,
  140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
   84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
   94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
  220.,  57.]])
```

```

'frame': None,
'DESCR': '.. _diabetes_dataset:\n\nDiabetes dataset\n-----\n\nTen baseline v
ariables, age, sex, body mass index, average blood\npressure, and six blood serum measur
ements were obtained for each of n =\n442 diabetes patients, as well as the response of
interest, a\nquantitative measure of disease progression one year after baseline.\n\n**D
ata Set Characteristics:**\n\n :Number of Instances: 442\n\n :Number of Attributes: Fi
rst 10 columns are numeric predictive values\n\n :Target: Column 11 is a quantitative m
easure of disease progression one year after baseline\n\n :Attribute Information:\n
- age      age in years\n      - sex\n      - bmi      body mass index\n      - bp      av
erage blood pressure\n      - s1      tc, T-Cells (a type of white blood cells)\n      -
s2      ldl, low-density lipoproteins\n      - s3      hdl, high-density lipoproteins\n
- s4      tch, thyroid stimulating hormone\n      - s5      ltg, lamotrigine\n      - s6
glu, blood sugar level\n\nNote: Each of these 10 feature variables have been mean center
ed and scaled by the standard deviation times `n_samples` (i.e. the sum of squares of ea
ch column totals 1).\n\nSource URL:\nhttps://www4.stat.ncsu.edu/~boos/var.select/diabete
s.html\n\nFor more information see:\nBradley Efron, Trevor Hastie, Iain Johnstone and Ro
bert Tibshirani (2004) "Least Angle Regression," Annals of Statistics (with discussion),
407-499.\n(https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)',
'feature_names': ['age',
'sex',
'bmi',
'bp',
's1',
's2',
's3',
's4',
's5',
's6'],
'data_filename': 'C:\\Users\\Bipin\\anaconda3\\lib\\site-packages\\sklearn\\datasets\\d
ata\\diabetes_data.csv.gz',
'target_filename': 'C:\\Users\\Bipin\\anaconda3\\lib\\site-packages\\sklearn\\datasets
\\data\\diabetes_target.csv.gz'}

```

In [40]:

#Question3 - 2:

```

new_df= diabets_df.data[:,np.newaxis,2]

atest=new_df[-20:]
atrain=new_df[:-20]

btest=diabets_df.target[-20:]
btrain=diabets_df.target[:-20]

```

In [41]:

#Question3 - 3:

```

var_lm=linear_model.LinearRegression()

var_lm.fit(atrain,btrain)
model_y= var_lm.predict(atest)
model_y
coef=var_lm.coef_
ms_error=mean_squared_error(btest,model_y)
r_square=r2_score(btest,model_y)
print(coef)
print(ms_error)
print(r_square)

```

```

[938.23786125]
2548.0723987259703
0.47257544798227136

```


In [46]:

#Question3 - 4:

```

var_fold=10

new_var_lm=var_lm.fit(atrain,btrain)

rang=list(range(1,11))

#use For Loop
for res_data in rang:

    res_data=cross_val_score(new_var_lm,atrain, btrain,cv=10)
    #print the result
    print(res_data)

```

```

[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]
[0.28527158 0.05133253 0.24112318 0.44536036 0.23478297 0.38300126
 0.43946172 0.25480749 0.32934734 0.31765983]

```

In [48]:

#Question3 - 5

```

from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import accuracy_score

regressor = RandomForestRegressor(max_depth = 7,random_state = 0)

```

In [49]:

```

regressor.fit(atrain,btrain)
pred = regressor.predict(atest)
print(pred)

```

```

[296.05572177  95.45286735 203.13858856  86.22366823 134.69925732
 172.44011759 266.00002655 113.6590721  102.92884903  97.98467848
 181.16902649  84.89712172 178.36582945 110.96031125  89.13732091
 234.07248578 111.99641223 111.99641223 187.42421128  98.03151117]

```

In [50]:

```

regressor.score(atrain,btrain)

```

Out[50]: 0.5264240887187687

In [51]:

#Question3 - 6

```
from sklearn.model_selection import GridSearchCV
```

```
In [52]: hy_parameters = {'max_depth': [None,7,4], 'min_samples_split': [2,10,20]}
```

```
In [53]: grid_GBR = GridSearchCV(estimator = regressor, param_grid = hy_parameters, cv = 2, n_jobs
```

```
In [54]: grid_GBR.fit(atrain, btrain)
```

```
Out[54]: GridSearchCV(cv=2, estimator=RandomForestRegressor(max_depth=7, random_state=0),
                    n_jobs=1,
                    param_grid={'max_depth': [None, 7, 4],
                                'min_samples_split': [2, 10, 20]})
```

```
In [56]: print('Results')
          print('\nThe best estimator:', grid_GBR.best_estimator_)
          print('\nThe best score :', grid_GBR.best_score_)
          print('\nThe best parameter:', grid_GBR.best_params_)
```

Results

The best estimator: RandomForestRegressor(max_depth=4, min_samples_split=20, random_state=0)

The best score : 0.2854161850966666

The best parameter: {'max_depth': 4, 'min_samples_split': 20}

```
In [57]: # Question 2
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import datetime as dt
```

```
In [59]: data = pd.read_excel('D:\Ruchi Folder\Python\Assignment5\ResearchDatasetV2.0.xlsx', pars
```

```
In [63]: data['Date'] = pd.to_datetime(data['Date'], format='%Y%m%d')
          data.describe()
```

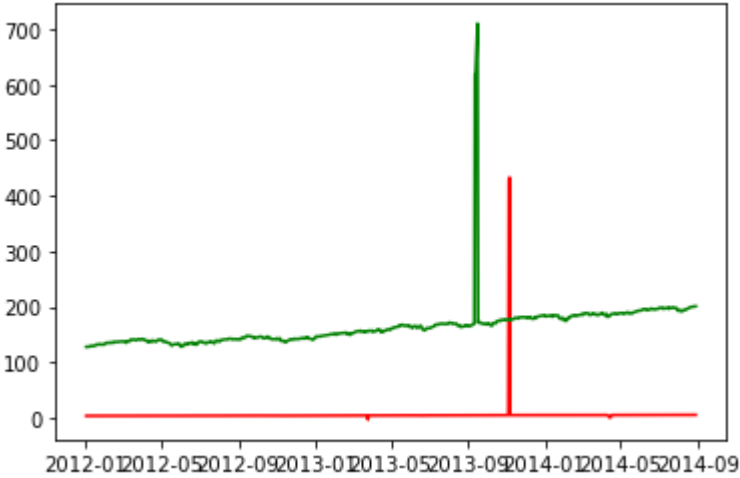
```
Out[63]:
```

	Signal	ClosePrice
count	667.000000	667.000000
mean	5.166802	163.169369
std	23.392809	39.210384
min	-3.802670	127.495000
25%	3.418083	140.880000

	Signal	ClosePrice
50%	3.893689	159.750000
75%	4.408313	181.500000
max	432.961165	710.310000

```
In [62]: y = data['Signal'].tolist()
x = data['ClosePrice'].tolist()
```

```
In [64]: plt.plot(data['Date'].tolist(), y, color='r', label='signal')
plt.plot(data['Date'].tolist(), x, color='g', label='closeprice')
plt.show()
```



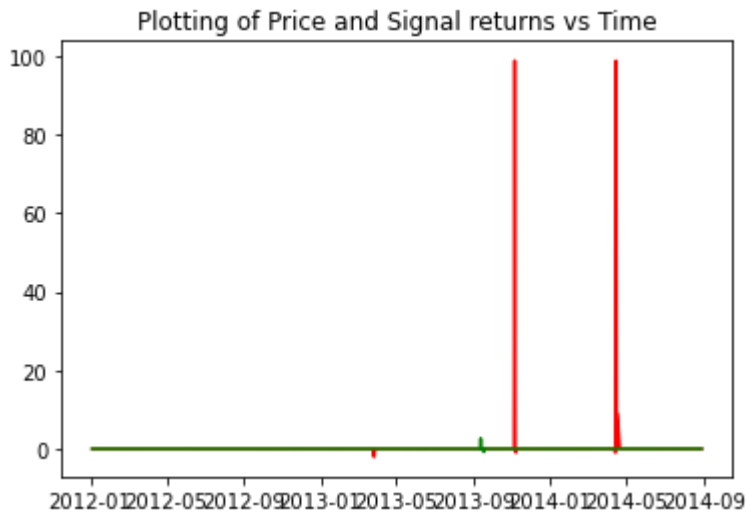
```
In [65]: data['signal_return'] = data['Signal'].pct_change()
data['price_return'] = data['ClosePrice'].pct_change()
data.describe()
```

Out[65]:

	Signal	ClosePrice	signal_return	price_return
count	667.000000	667.000000	666.000000	666.000000
mean	5.166802	163.169369	0.301753	0.003760
std	23.392809	39.210384	5.421266	0.107373
min	-3.802670	127.495000	-2.003073	-0.759161
25%	3.418083	140.880000	-0.003357	-0.003199
50%	3.893689	159.750000	0.000111	0.000727
75%	4.408313	181.500000	0.005180	0.005070
max	432.961165	710.310000	98.796977	2.653778

```
In [67]: plt.plot(data['Date'].tolist(), data['signal_return'], color='r', label='signalreturn')
plt.plot(data['Date'].tolist(), data['price_return'], color='g', label='closepriceretur')
```

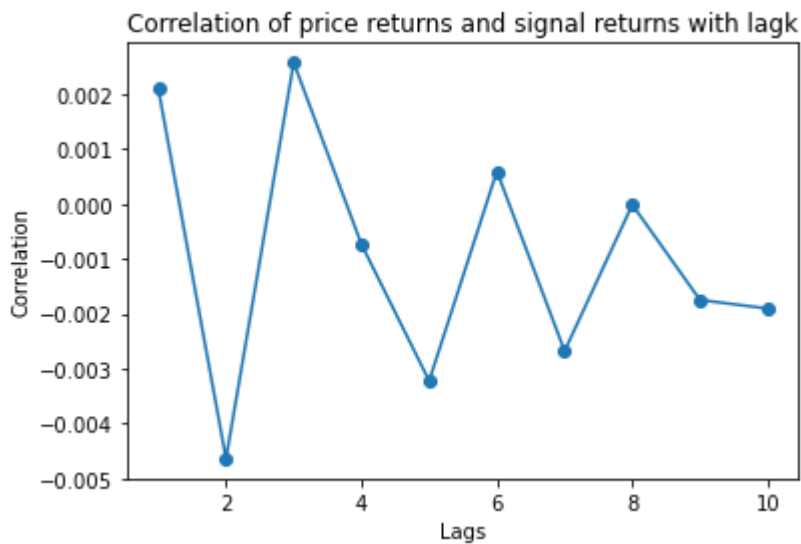
```
plt.title('Plotting of Price and Signal returns vs Time')
plt.show()
```



```
In [68]: def cross_correlate(x, y, lag):
         return x.corr(y.shift(lag))
```

```
In [70]: cross_corrs = []
         for lag in range(1, 11):
             cross_corrs.append(cross_correlate(data['price_return'],
                                                data['signal_return'], lag))

         plt.plot(range(1,11), cross_corrs, marker='o')
         plt.xlabel('Lags')
         plt.ylabel('Correlation')
         plt.title('Correlation of price returns and signal returns with lagk')
         plt.show()
```



```
In [72]: grp_1 = []
         grp_1_idx = []
         grp_2 = []
         grp_2_idx = []
         grp_3 = []
```

```

grp_3_idx = []
grp_4 = []
grp_4_idx = []
for index in range(len(data['signal_return'])):
    if data['signal_return'][index] < -0.01:
        grp_1.append(data['signal_return'][index])
        grp_1_idx.append(index)
    elif data['signal_return'][index] >= -0.01 and data['signal_return'][index] < 0:
        grp_2.append(data['signal_return'][index])
        grp_2_idx.append(index)
    elif data['signal_return'][index] >= 0 and data['signal_return'][index] < 0.01:
        grp_3.append(data['signal_return'][index])
        grp_3_idx.append(index)
    elif data['signal_return'][index] >= 0.01:
        grp_4.append(data['signal_return'][index])
        grp_4_idx.append(index)
grp_1_idx = [x+3 for x in grp1_idx if x+3 < len(data.index)]
grp_2_idx = [x+3 for x in grp2_idx if x+3 < len(data.index)]
grp_3_idx = [x+3 for x in grp3_idx if x+3 < len(data.index)]
grp_4_idx = [x+3 for x in grp4_idx if x+3 < len(data.index)]

#calculate the average return
average_returns = [np.mean(data['price_return'][grp_1_idx]),
                    np.mean(data['price_return'][grp_2_idx]),
                    np.mean(data['price_return'][grp_3_idx]),
                    np.mean(data['price_return'][grp_4_idx])]
grps = ['<-0.01', '-0.01:0', '0:0.01', '>0.01']

```

In [73]: average_returns

Out[73]: [0.0005273010550047138,
0.0017594901175337868,
0.009988932451912276,
-0.010687383162841551]

In [78]: plt.bar(grps, average_returns)
plt.title('Plot of average return')
plt.xlabel('Groups of singal return')
plt.ylabel('Average returns across group')
plt.show()



```
In [ ]: value = [100]
investment_available = 100
data['buy_signal'] = pd.Series(np.zeros(len(data.index)))
data['sell_signal'] = pd.Series(np.zeros(len(data.index)))
invested = False
for i in range(len(data.index)):

    if data['buy_signal'][i] == 1:
        shares = investment_available/data['ClosePrice'][i]
        invested = True

    if data['sell_signal'][i] == 1:
        investment_available = shares * data['ClosePrice'][i]

    if data['signal_return'][i] < 0 and invested == False:
        data['buy_signal'][i+3] = 1

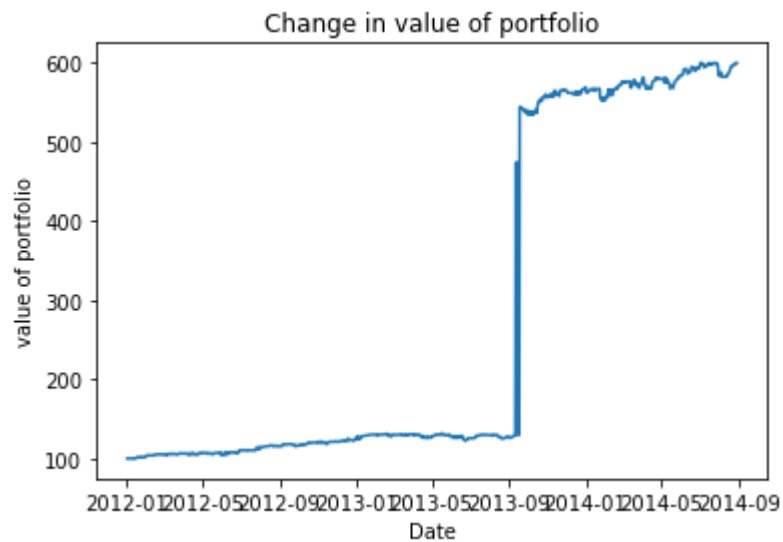
    if invested == False:
        value.append(value[i-1])

    if invested == True:
        value.append(shares*data['ClosePrice'][i])

    if data['sell_signal'][i] == 1:
        invested = False

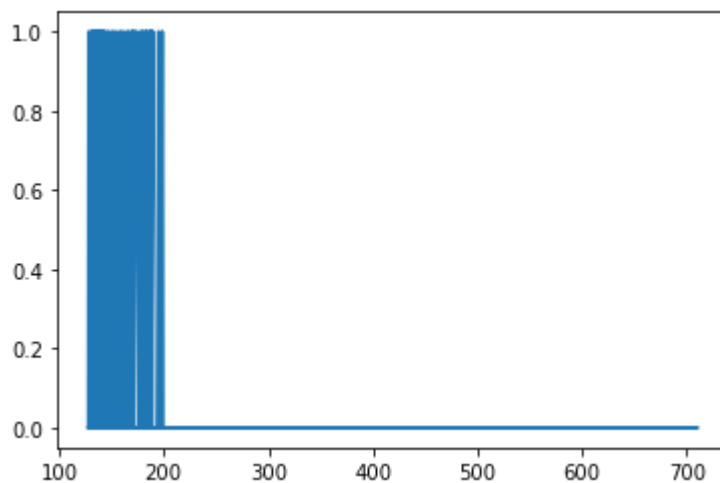
    if data['signal_return'][i] > 0.01 and invested == True:
        data['sell_signal'][i+3] = 1
```

```
In [79]: plt.plot(data['Date'], value[1:])
plt.xlabel('Date')
plt.ylabel('value of portfolio')
plt.title('Change in value of portfolio')
plt.show()
```



```
In [80]: total_return = value[-1]/value[0] - 1
total_return
plt.plot(data['ClosePrice'], data['buy_signal'])
risk_free = 0.01 #1% rate of return on risk free asset
portfolio_return = total_return # Calculated above
std = np.std(pd.Series(value).pct_change())
sharpe = (total_return - risk_free) / std
sharpe
```

Out[80]: 25.612455172694524



In []: