forest ffire prediction

November 2, 2022

1 data Details

- Machine Learning LifeCycle
    1. Data Ingestion
    2. EDA
    3. Preprocessing
    4. Model Building
    5. Performance Metrics
- Problem Statement

```
- The dataset includes 244 instances that regroup a data of two regions of Algeria,namely
  122 instances for each region.
  The period from June 2012 to September 2012.
  The dataset includes 11 attribues and 1 output attribue (class)
  The 244 instances have been classified into fire (138 classes) and not fire (106 classes
```

- Feature Description
    1. Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012) Weather data observations
    2. Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
    3. RH : Relative Humidity in %: 21 to 90
    4. Ws :Wind speed in km/h: 6 to 29
    5. Rain: total day in mm: 0 to 16.8 FWI Components
    6. Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
    7. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
    8. Drought Code (DC) index from the FWI system: 7 to 220.4
    9. Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
    10. Buildup Index (BUI) index from the FWI system: 1.1 to 68
    11. Fire Weather Index (FWI) Index: 0 to 31.1
    12. Classes: two classes, namely Fire and not Fire
- Machine Learning Models Used
    1. Linear Regression
    2. Ridge Regression
    3. Lasso Regression
    4. Elastic-Net Regression

- Assumtion of Linear Regession https://towardsdatascience.com/assumptions-of-linear-regression-fdb71ebeaa8b

[2]:
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

[3]:
```
df = pd.read_csv('Algerian_forest_fires_dataset_UPDATE.csv',header=1)
```

2 Data Cleaning

[4]:
```
df
```

[4]:
```
    day month  year Temperature  RH  Ws Rain   FFMC  DMC    DC  ISI   BUI  \
0    01    06  2012          29  57  18     0  65.7  3.4   7.6  1.3   3.4
1    02    06  2012          29  61  13   1.3  64.4  4.1   7.6    1   3.9
2    03    06  2012          26  82  22  13.1  47.1  2.5   7.1  0.3   2.7
3    04    06  2012          25  89  13   2.5  28.6  1.3   6.9    0   1.7
4    05    06  2012          27  77  16     0  64.8    3  14.2  1.2   3.9
..   ..   …     …           …  ..  ..    …     …    …     …    …     …
241  26    09  2012          30  65  14     0  85.4   16  44.5  4.5  16.9
242  27    09  2012          28  87  15   4.4  41.1  6.5     8  0.1   6.2
243  28    09  2012          27  87  29   0.5  45.9  3.5   7.9  0.4   3.4
244  29    09  2012          24  54  18   0.1  79.7  4.3  15.2  1.7   5.1
245  30    09  2012          24  64  15   0.2  67.3  3.8  16.5  1.2   4.8

     FWI      Classes
0    0.5  not fire
1    0.4  not fire
2    0.1  not fire
3      0  not fire
4    0.5  not fire
..     …          …
241  6.5      fire
242    0  not fire
243  0.2  not fire
244  0.7  not fire
245  0.5 not fire

[246 rows x 14 columns]
```

[5]:
```python
# how big the Data is
df.shape
```

[5]:
```
(246, 14)
```

[6]:
```python
# how the data is distributed
df.describe().T
```

[6]:
```
            count unique   top freq
day           246     33    01    8
month         245      5    07   62
year          245      2  2012  244
Temperature   245     20    35   29
 RH           245     63    64   10
 Ws           245     19    14   43
Rain          245     40     0  133
FFMC          245    174  88.9    8
DMC           245    167   7.9    5
DC            245    199     8    5
ISI           245    107   1.1    8
BUI           245    175     3    5
FWI           245    128   0.4   12
Classes       244      9  fire    131
```

[7]:
```python
df.columns = df.columns.str.strip()
```

[8]:
```python
df[df['day']=='Sidi-Bel Abbes Region Dataset']['day'] = np.nan
df[df['day']=='day']['day']= np.nan
df[df['year']=='year']['year']= np.nan
df[df['day']=='Sidi-Bel Abbes Region Dataset']
df.iloc[122,:][0] = np.nan
df1 = df.drop(123)
```

[9]:
```python
df1.dropna(inplace=True)
```

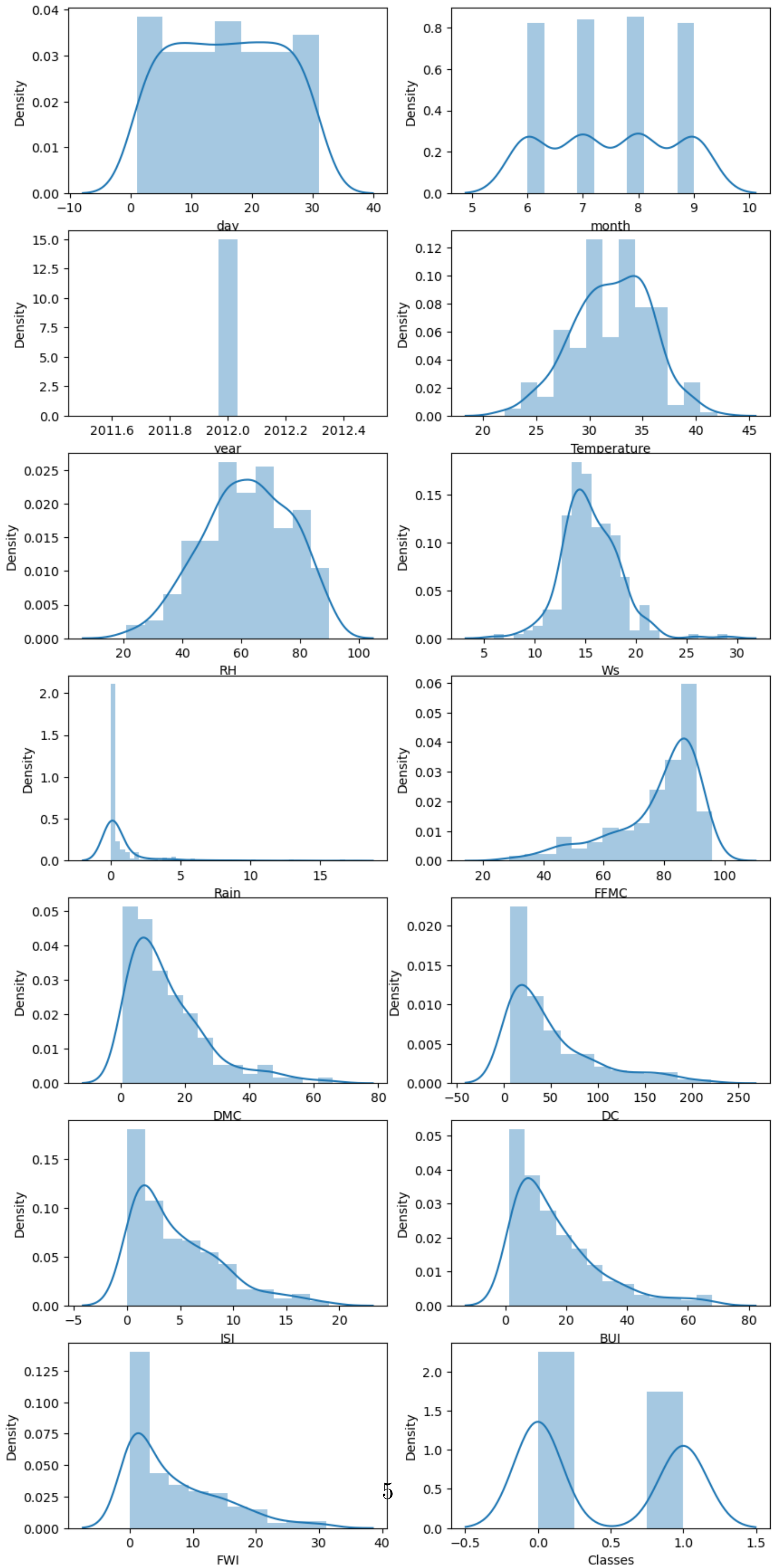
[10]:
```python
df1['Classes'] = df1['Classes'].str.strip()
```

[11]:
```python
cl = list(df1.columns)
for i in cl[:-1:]:
    df1[i] = pd.to_numeric(df1[i])
```

[12]:
```python
from sklearn.preprocessing import LabelEncoder
lb  = LabelEncoder()
df1['Classes'] = lb.fit_transform(df1['Classes'])
```

[13]:
```python
plt.figure(figsize=(10,25))
for i in zip(df1.columns,list(range(len(df1.columns)))):
```

```
    plt.subplot(8,2,i[1]+1)
    sns.distplot(df1[i[0]])
```


Density
day
month
year
Temperature
RH
Ws
Rain
FFMC
DMC
DC
ISI
BUI
FWI
Classes

3 Model Buliding

[14]:
```
from sklearn.linear_model import LinearRegression,Ridge,Lasso,ElasticNet
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
from sklearn.model_selection import cross_val_score
```

[15]:
```
x = df1.drop('Temperature',axis=1)
y = df1['Temperature']
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(x,y,test_size=0.
↪2,random_state=32)
```

4 Linear Regression:

[16]:
```
lr = LinearRegression()
lr.fit(X_train,y_train)
lr_predict = lr.predict(X_test)
print("Train Score:",lr.score(X_train,y_train))
print('Test Score: ',lr.score(X_test,y_test))
from sklearn.metrics import r2_score
score=r2_score(y_test,lr_predict)
print("The R2 Score for the model builded is",score)
Adjusted_r=1-(1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
print("The Adjusted R Square for the model is",Adjusted_r)
```

```
Train Score: 0.5796076040993602
Test Score:  0.5761842043675531
The R2 Score for the model builded is 0.5761842043675531
The Adjusted R Square for the model is 0.41876690884693
```

[17]:
```
from sklearn.preprocessing import StandardScaler
standard = StandardScaler()
X_train_s = standard.fit_transform(X_train)
X_test_s =standard.transform(X_test)
```

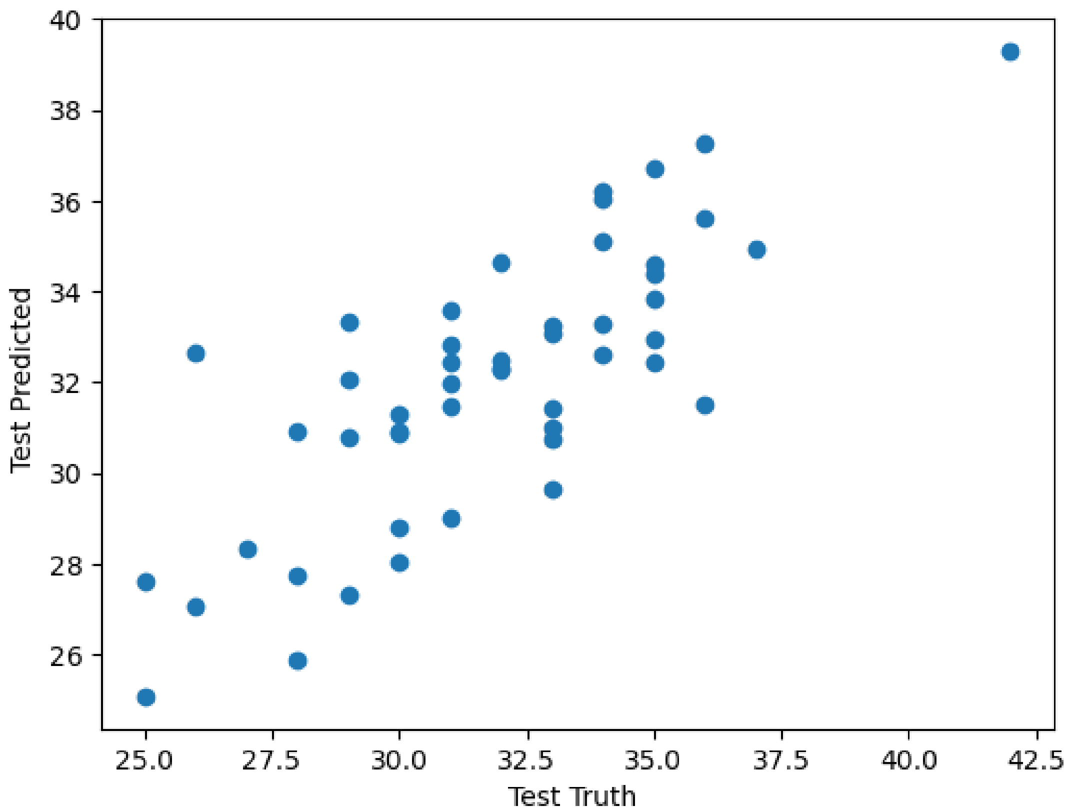
[18]:
```
# After Standartization
lr.fit(X_train_s,y_train)
lr_predict = lr.predict(X_test_s)
print("Train Score:",lr.score(X_train_s,y_train))
print('Test Score: ',lr.score(X_test_s,y_test))
from sklearn.metrics import r2_score
score=r2_score(y_test,lr_predict)
print("The R2 Score for the model builded is",score)
```

```
Adjusted_r=1-(1-score)*(len(y_test)-1)/(len(y_test)-X_test_s.shape[1]-1)
print("The Adjusted R Square for the model is",Adjusted_r)
```

```
Train Score: 0.5796076040993601
Test Score:  0.5761842043675535
The R2 Score for the model builded is 0.5761842043675535
The Adjusted R Square for the model is 0.41876690884693046
```

[51]:

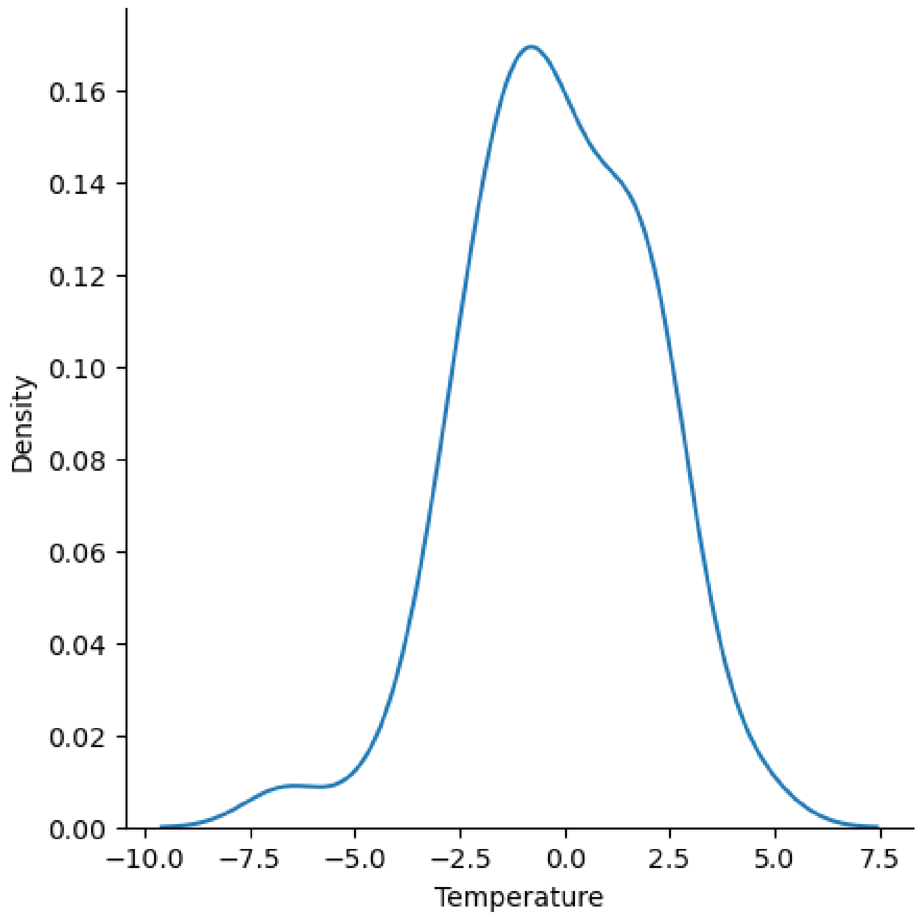
```
# ASSUMPTION
plt.scatter(y_test,lr_predict)
plt.xlabel("Test Truth ")
plt.ylabel("Test Predicted ")
plt.show()
```



[42]:

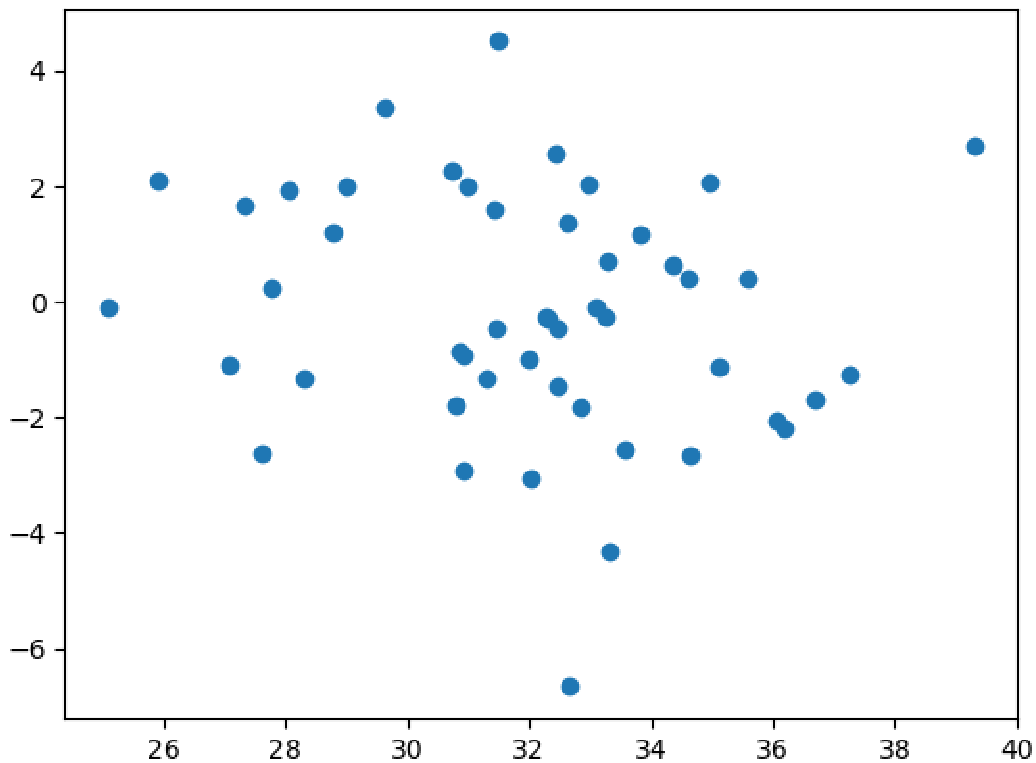
```
residuals=y_test-lr_predict
sns.displot(residuals,kind='kde')
```

[42]: <seaborn.axisgrid.FacetGrid at 0x7f2481cb6410>



[43]:
```
plt.scatter(lr_predict,residuals)
```

[43]: <matplotlib.collections.PathCollection at 0x7f2481afd0c0>

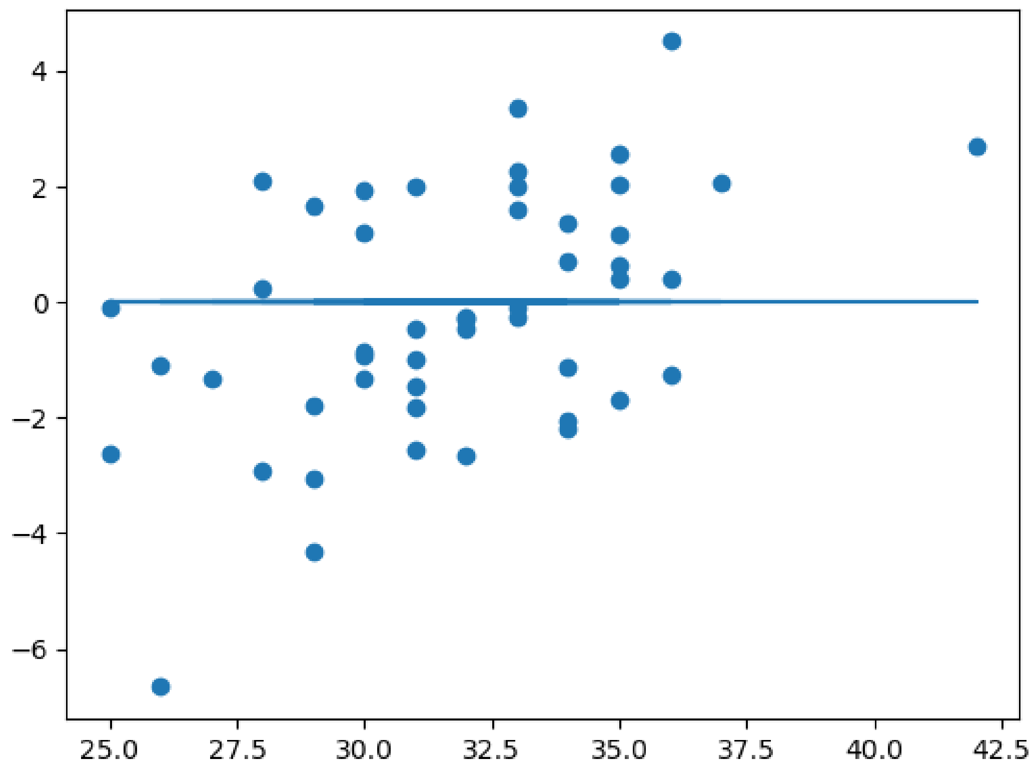


[46]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
{x.columns[i]: variance_inflation_factor(x.values, i) for i in range(1, x.
↪shape[1])}
```

[46]:
```
{'month': 1.0593677394567451,
 'year': 381.03887723157646,
 'RH': 2.860679742317785,
 'Ws': 1.2618825859478544,
 'Rain': 1.5751316142697394,
 'FFMC': 5.301788307992688,
 'DMC': 77.36193951221615,
 'DC': 25.199194461781985,
 'ISI': 23.250581619252316,
 'BUI': 172.04514981024676,
 'FWI': 41.1884258115508,
 'Classes': 3.474838521935455}
```

[50]:
```
plt.scatter(y_test, residuals)
plt.plot(y_test, [0]*len(y_test))
```

[50]:
```
[<matplotlib.lines.Line2D at 0x7f24742995a0>]
```



5 Ridge Regression

[ ]:

```
```

[19]:

```
rid = Ridge()
print(rid.fit(X_train_s,y_train))
lr_predict = rid.predict(X_test_s)
print("Train Score:",rid.score(X_train_s,y_train))
print('Test Score: ',rid.score(X_test_s,y_test))
from sklearn.metrics import r2_score
score=r2_score(y_test,lr_predict)
print("The R2 Score for the model builded is",score)
Adjusted_r=1-(1-score)*(len(y_test)-1)/(len(y_test)-X_test_s.shape[1]-1)
print("The Adjusted R Square for the model is",Adjusted_r)
```

```
Ridge()
Train Score: 0.5791326452390795
Test Score:  0.5916874165048187
The R2 Score for the model builded is 0.5916874165048187
The Adjusted R Square for the model is 0.4400284569208942
```

[21]:
```
# Lasso Regression
las =Lasso(alpha=0.04,max_iter=1000)
print(las.fit(X_train_s,y_train))
lr_predict = las.predict(X_test_s)
print("Train Score:",las.score(X_train_s,y_train))
print('Test Score: ',las.score(X_test_s,y_test))
from sklearn.metrics import r2_score
score=r2_score(y_test,lr_predict)
print("The R2 Score for the model builded is",score)
Adjusted_r=1-(1-score)*(len(y_test)-1)/(len(y_test)-X_test_s.shape[1]-1)
print("The Adjusted R Square for the model is",Adjusted_r)

a = np.mean(cross_val_score(estimator=las,X = x,y = y,cv=10,scoring='r2'))
print(a)
```

```
Lasso(alpha=0.04)
Train Score: 0.5758497343585591
Test Score:  0.6060660158722289
The R2 Score for the model builded is 0.6060660158722289
The Adjusted R Square for the model is 0.4597476789104853
0.036977819359694984
```

[22]:
```
# Hyper Parameter Tunning
from sklearn.model_selection import GridSearchCV
para = {}
para['alpha'] = list(np.linspace(0,0.2,40))
para['max_iter'] = [100,10000,10000]
grit = GridSearchCV(estimator=las,param_grid=para,verbose=1,cv = 10)
grit.fit(X_train_s,y_train)
grit.best_score_
```

```
Fitting 10 folds for each of 120 candidates, totalling 1200 fits
```

[22]: 0.5053909597293631

[39]:
```
# Ridge Hyperparameter tunning
from sklearn.model_selection import GridSearchCV
para = {}
para['solver'] =['auto', 'svd', 'cholesky', 'lsqr', 'sparse_cg', 'sag', 'saga',␣
 ↪'lbfgs']
para['alpha'] = list(np.linspace(0,300,100))
para['max_iter'] = [10000,100000]
grit = GridSearchCV(estimator=rid,param_grid=para,verbose=1,cv = 10,n_jobs=43)
grit.fit(X_train_s,y_train)
grit.best_score_
```

```
Fitting 10 folds for each of 1600 candidates, totalling 16000 fits
```

[39]: 0.5128037686657727

[40]:
```
grit.best_params_
```

[40]: {'alpha': 45.45454545454545, 'max_iter': 10000, 'solver': 'sparse_cg'}

[ ]:
```

```