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1 Algerian Forest Fire Dataset linear regression modelling

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pylab as plt
%matplotlib inline
```

[2]:
```
data = pd.read_csv("Algerian_forest_fires_dataset_UPDATE.csv",header=1)
data
```

[2]:
```
    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]
```

[ ]:
```
data[data.isna().any(axis=1)]
data.iloc[121:125,:]
data.drop([122,123],inplace=True)
data.reset_index(inplace=True)
data.drop(['index',"day","month","year"],axis=1,inplace=True)
data["region"] = None
data.iloc[:122,-1] = "Bejaia"
data.iloc[122:,-1] = "Abbes"
data
```

2 Data cleaning operations

[ ]:
```
data.info()
```

Getting unique values from y data column:
Getting unique values from a column involves identifying and selecting only the distinct or unique values in that column.

[ ]:
```
data["Classes  "].unique()
```

Apply `str.strip()` to clean the data:
As we can see y data has some blank spaces so we need to remove then before use.
I have used the `.strip()` method in Python to remove the leading and trailing spaces from the data in a column.

[6]:
```
data["Classes  "] = data["Classes  "].str.strip()
```

[ ]:
```
data
```

[8]:
```
data["Classes  "].unique()
```

[8]:
```
array(['not fire', 'fire'], dtype=object)
```

Convert data type of all data column:
In below code I am selecting all data which are intiger and making the column data type as float64

[ ]:
```
columns = data.columns[:-2]
for i in columns:
    data[i] = data[i].astype("float64")
data.info()
```

I am converting Rain from numerical to categorical data.
Reason is While analysing the data I found that rain has 52-56% zero values.

And from EDA for rain, we can see where is rain change for fire is very less,

So I am changing this dataset from numerical to categorical data.

I will put `rain` if rain > 0 else `not rain`

```
[46]: data["Rain "] = data["Rain "].apply(lambda x: 'not rain' if x == 0 else 'rain')
```

3 Outlier handaling

```
[53]: # mean is affected by outlier so i am using median for replasing outliers
      floate_col = data.select_dtypes([np.number]).columns
```

```
[55]: for i in floate_col:
          q3 = data[i].quantile(0.75)
          q1 = data[i].quantile(0.25)
          iqr = q3 - q1
          upper = q3 + (1.5 * iqr)
          lower = q1 - (1.5 * iqr)
          median = data[i].median()
          # data[i] = np.where(data[i]>upper,median,data[i])
          # data[i] = np.where(data[i]<lower,median,data[i])
          data[i] = data[i].apply(lambda x: median if (x < lower) | (x > upper) else␣
       ↪x)
```

4 Data standardization and data imputetion for zero values

4.1 data imputetion for zero values

```
[ ]: for i in floate_col:
         count = (data[i] == 0).sum()
         print('Count of zeros in column ', i, ' is : ', count)
```

```
[59]: for i in floate_col:
          mean = data[i].mean()
          data[i] = data[i].apply(lambda x: mean if (x == 0) else x)
```

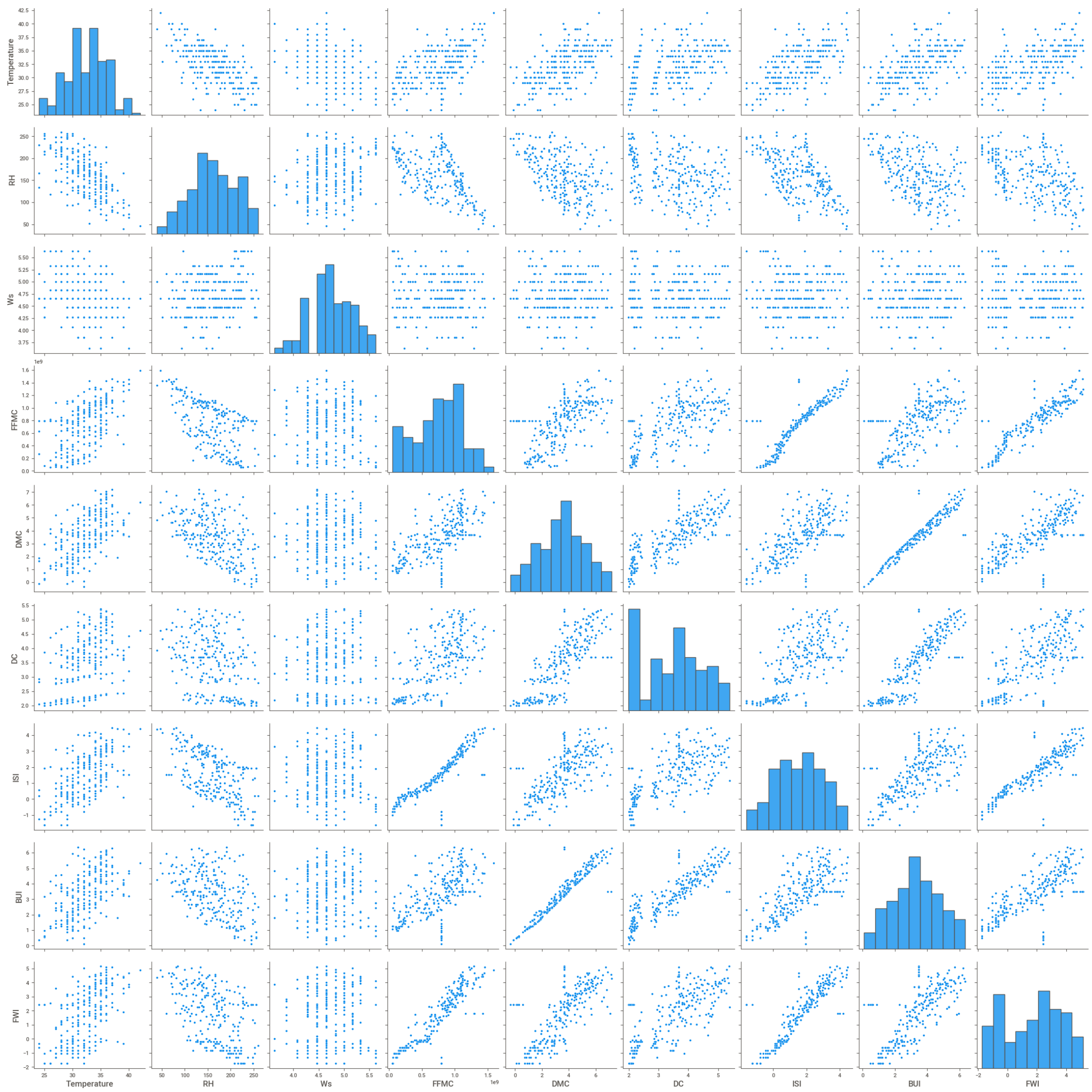
```
[ ]: for i in floate_col:
         count = (data[i] == 0).sum()
         print('Count of zeros in column ', i, ' is : ', count)
```

4.2 Appling Box-Cox on dataset to make is notmalize

```
[61]: from scipy.stats import boxcox
      for i in floate_col[1:]:
          data[i],_ = boxcox(data[i])
```

```
[62]: sns.pairplot(data)
```

[62]: <seaborn.axisgrid.PairGrid at 0x7ff570d62d00>



5 Starting ML modeling with all transformetions

5.1 Creating dummy for categorical data

[63]:
```
data_dummy = pd.get_dummies(data,drop_first=True)
data_dummy.head()
```

[63]:

	Temperature	RH	Ws	FFMC	DMC	DC	\
0	29.0	143.372066	5.165577	2.397096e+08	1.500687	2.088219	
1	29.0	156.584073	4.274100	2.169371e+08	1.787143	2.088219	

```
2          26.0  229.913004  4.652957  7.938513e+08  1.066187  2.016165
3          25.0  255.688760  4.274100  7.938513e+08  0.273793  1.985954
4          27.0  211.889717  4.830483  2.237512e+08  1.318603  2.756670

        ISI       BUI       FWI  Rain _rain  Classes  _not fire  region_Bejaia
0  0.273654  1.425881 -0.635298           0                    1              1
1  0.000000  1.613893 -0.817037           1                    1              1
2 -0.999762  1.123805 -1.741158           1                    1              1
3  1.939132  0.566472  2.429965           1                    1              1
4  0.187727  1.613893 -0.635298           0                    1              1
```

[64]:
```python
y = data_dummy["Classes  _not fire"]
y.head()
```

[64]:
```
0    1
1    1
2    1
3    1
4    1
Name: Classes  _not fire, dtype: uint8
```

[65]:
```python
X = data_dummy.drop(["Classes  _not fire"],axis=1)
X.head()
```

[65]:
```
   Temperature          RH        Ws          FFMC       DMC        DC  \
0          29.0  143.372066  5.165577  2.397096e+08  1.500687  2.088219
1          29.0  156.584073  4.274100  2.169371e+08  1.787143  2.088219
2          26.0  229.913004  4.652957  7.938513e+08  1.066187  2.016165
3          25.0  255.688760  4.274100  7.938513e+08  0.273793  1.985954
4          27.0  211.889717  4.830483  2.237512e+08  1.318603  2.756670

        ISI       BUI       FWI  Rain _rain  region_Bejaia
0  0.273654  1.425881 -0.635298           0              1
1  0.000000  1.613893 -0.817037           1              1
2 -0.999762  1.123805 -1.741158           1              1
3  1.939132  0.566472  2.429965           1              1
4  0.187727  1.613893 -0.635298           0              1
```

5.2 Spliting all data in training and testing data

[66]:
```python
from sklearn.model_selection import train_test_split
```

[82]:
```python
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.
↪33,random_state=42,stratify=y)
```

[83]:
```python
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(163, 11)
(81, 11)
(163,)
(81,)
```

5.3 Standardize the scalling of all data

[84]:
```python
data.describe()
```

[84]:
```
       Temperature          RH          Ws          FFMC         DMC  \
count   244.000000  244.000000  244.000000  2.440000e+02  244.000000
mean     32.254098  161.523372    4.715794  7.657288e+08    3.520849
std       3.513786   49.228206    0.413556  3.613599e+08    1.691828
min      24.000000   38.860636    3.629415  5.317822e+07   -0.336911
25%      30.000000  127.237112    4.467800  5.287821e+08    2.365885
50%      32.000000  163.286993    4.652957  7.986227e+08    3.678303
75%      35.000000  198.595767    5.001140  1.049498e+09    4.784115
max      42.000000  259.420891    5.626742  1.593463e+09    7.181914

               DC         ISI         BUI         FWI
count  244.000000  244.000000  244.000000  244.000000
mean     3.511171    1.545551    3.351128    1.714493
std      0.977107    1.430895    1.461055    1.916790
min      1.985954   -1.631019    0.096426   -1.741158
25%      2.675595    0.432850    2.246782   -0.216908
50%      3.680945    1.539991    3.479520    2.064279
75%      4.238154    2.703364    4.486560    3.256517
max      5.381883    4.456251    6.356533    5.159718
```

[85]:
```python
from sklearn.preprocessing import StandardScaler
std = StandardScaler()
X_train_std = std.fit_transform(X_train)
X_test_std = std.transform(X_test)
```

[86]:
```python
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression()
```

[87]:
```python
log_reg.fit(X_train_std,y_train)
```

[87]: LogisticRegression()

[88]:
```
y_predict = log_reg.predict(X_test_std)
y_predict
```

[88]:
```
array([0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1,
       0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1,
       0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0], dtype=uint8)
```

[89]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
accuracy = accuracy_score(y_test,y_predict)
accuracy
```

[89]:
```
0.9753086419753086
```

[90]:
```
conf_mat = confusion_matrix(y_test,y_predict)
conf_mat
```

[90]:
```
array([[45,  1],
       [ 1, 34]])
```

[91]:
```
true_positive = conf_mat[0][0]
false_positive = conf_mat[0][1]
false_negative = conf_mat[1][0]
true_negative = conf_mat[1][1]
```

[92]:
```
Accuracy = (true_positive + true_negative) / (true_positive +false_positive +␣
 ↪false_negative + true_negative)
Accuracy
```

[92]:
```
0.9753086419753086
```

[93]:
```
Precision = true_positive/(true_positive+false_positive)
Precision
```

[93]:
```
0.9782608695652174
```

[94]:
```
Recall = true_positive/(true_positive+false_negative)
Recall
```

[94]:
```
0.9782608695652174
```

[95]:
```
F1_Score = 2*(Recall * Precision) / (Recall + Precision)
F1_Score
```

[95]:
```
0.9782608695652174
```

[96]:
```
auc = roc_auc_score(y_test, y_predict)
auc
```

[96]: 0.9748447204968944