1) Problem statement.

1.This dataset comprises 244 instances that regroup a data of two regions of Algeria, namely the Bejaia region located in the northeast of Algeria and the Sidi Bel-abbes region located in the northwest of Algeria. 2.Can get insights from the dataset to know which features have contributed more in predicting Forest fire

2) Data Collection.

1.Dataset used in this particular problem statements was a dataset on Algerian Forest Fires 2.The Dataset contain data from June 2012 to September 2012. 3.Each dataset contain 122 rows and 14 columns

#Importing Pandas, Numpy, Matplotlib, Seaborn and Warings Library.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings

warnings.filterwarnings("ignore")

%matplotlib inline
```

import dataset

```
df=pd.read_csv("C:\Algerian_forest_fires_dataset_UPDATE.csv")
```

Feature Information

Algerian Forest Fires:

1. Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012)
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:

1. Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
2. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
3. Drought Code (DC) index from the FWI system: 7 to 220.4
4. Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
5. Buildup Index (BUI) index from the FWI system: 1.1 to 68
6. Fire Weather Index (FWI) Index: 0 to 31.1
7. Classes: two classes, namely Fire and not Fire

Show Top 5 Records

```
df.head()
```

```
  day month  year Temperature  RH  Ws Rain   FFMC  DMC    DC  ISI  BUI
FWI  \
0   1     6  2012          29  57  18     0  65.7  3.4   7.6  1.3  3.4
0.5
1   2     6  2012          29  61  13   1.3  64.4  4.1   7.6    1  3.9
0.4
2   3     6  2012          26  82  22  13.1  47.1  2.5   7.1  0.3  2.7
0.1
3   4     6  2012          25  89  13   2.5  28.6  1.3   6.9    0  1.7
0
4   5     6  2012          27  77  16     0  64.8    3  14.2  1.2  3.9
0.5

     Classes
0  not fire
1  not fire
2  not fire
3  not fire
4  not fire
```

Shape of the dataset

```
df.shape
```

```
(247, 14)
```

Summary of the dataset

```
df.describe()
```

```
        day month  year Temperature   RH   Ws Rain   FFMC  DMC   DC
ISI  BUI  \
count   246   245   245         245  245  245   245   245  245  245
245  245
unique   33     5     2          20   63   19    40   174  167  199
```

```
107  175
top        1      7   2012           35    64    14      0   88.9   7.9     8
1.1     3
freq       8     62    244           29    10    43    133      8     5     5
8     5

        FWI Classes
count   245       244
unique  127         9
top     0.4    fire
freq     12       131
```

Check Datatypes in the dataset

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 247 entries, 0 to 246
Data columns (total 14 columns):
 #   Column       Non-Null  Count   Dtype
---  -------      --------------   ------
 0   day          246 non-null    object
 1   month        245 non-null    object
 2   year         245 non-null    object
 3   Temperature  245 non-null    object
 4    RH          245 non-null    object
 5    Ws          245 non-null    object
 6   Rain         245 non-null    object
 7   FFMC         245 non-null    object
 8   DMC          245 non-null    object
 9   DC           245 non-null    object
 10  ISI          245 non-null    object
 11  BUI          245 non-null    object
 12  FWI          245 non-null    object
 13  Classes      244 non-null    object
dtypes: object(14)
memory usage: 27.1+ KB
```

```python
#adding the region
df['Region']=[1 if i<121 else 0 for i in df.index]
```

```python
df.head()
```

```
  day month  year Temperature  RH  Ws Rain   FFMC  DMC    DC  ISI  BUI
FWI  \
0   1     6  2012          29  57  18     0  65.7  3.4   7.6  1.3  3.4
0.5
1   2     6  2012          29  61  13   1.3  64.4  4.1   7.6    1  3.9
0.4
2   3     6  2012          26  82  22  13.1  47.1  2.5   7.1  0.3  2.7
0.1
```

```
3   4      6  2012           25  89  13   2.5  28.6  1.3   6.9    0  1.7
0
4   5      6  2012           27  77  16     0  64.8    3  14.2  1.2  3.9
0.5

      Classes    Region
0  not fire          1
1  not fire          1
2  not fire          1
3  not fire          1
4  not fire          1
```

```
#droping the year column
df.drop(['year'],axis=1,inplace=True)

df
```

```
    day month Temperature  RH  Ws Rain   FFMC  DMC    DC  ISI   BUI
FWI  \
0     1     6          29  57  18     0  65.7  3.4   7.6  1.3   3.4
0.5
1     2     6          29  61  13   1.3  64.4  4.1   7.6    1   3.9
0.4
2     3     6          26  82  22  13.1  47.1  2.5   7.1  0.3   2.7
0.1
3     4     6          25  89  13   2.5  28.6  1.3   6.9    0   1.7
0
4     5     6          27  77  16     0  64.8    3  14.2  1.2   3.9
0.5
..   ..   ...         ...  ..  ..   ...   ...  ...   ...  ...   ...  .
..
242  26     9          30  65  14     0  85.4   16  44.5  4.5  16.9
6.5
243  27     9          28  87  15   4.4  41.1  6.5     8  0.1   6.2
0
244  28     9          27  87  29   0.5  45.9  3.5   7.9  0.4   3.4
0.2
245  29     9          24  54  18   0.1  79.7  4.3  15.2  1.7   5.1
0.7
246  30     9          24  64  15   0.2  67.3  3.8  16.5  1.2   4.8
0.5

         Classes    Region
0      not fire          1
1      not fire          1
2      not fire          1
3      not fire          1
4      not fire          1
..           ...       ...
242        fire          0
243    not fire          0
```

```
244    not fire          0
245    not fire          0
246   not fire           0

[247 rows x 14 columns]
```

Data cleaning

```python
df.isnull().sum()
```

```
day               1
month             2
Temperature       2
 RH               2
 Ws               2
Rain              2
FFMC              2
DMC               2
DC                2
ISI               2
BUI               2
FWI               2
Classes           3
Region            0
dtype: int64
```

```python
df[df.isnull().any(axis=1)]
```

```
                                day month Temperature   RH   Ws Rain  
FFMC   \
122                             NaN   NaN         NaN  NaN  NaN  NaN  
NaN
123  Sidi-Bel Abbes Region Dataset   NaN         NaN  NaN  NaN  NaN  
NaN
168                              14     7          37   37   18  0.2  
88.9

      DMC      DC   ISI   BUI      FWI Classes    Region
122   NaN     NaN   NaN   NaN      NaN       NaN       0
123   NaN     NaN   NaN   NaN      NaN       NaN       0
168  12.9  14.6 9  12.5  10.4  fire          NaN       0
```

```python
df.loc[:122,'Region']=1
df.loc[122:,'Region']=2
df[['Region']] = df[['Region']].astype(int)

# Remove null or na values rows
df =df.dropna().reset_index(drop=True)
df.shape
```

```
(244, 14)
```

```python
# Column which has string
df.iloc[[122]]
```

```
     day  month  Temperature   RH   Ws  Rain   FFMC  DMC  DC   ISI  BUI
FWI  \
122  day  month  Temperature   RH   Ws  Rain   FFMC  DMC  DC   ISI  BUI
FWI

      Classes    Region
122   Classes         2
```

```python
df[df.duplicated()]
```

```
Empty DataFrame
Columns: [day, month, Temperature,  RH,  Ws, Rain , FFMC, DMC, DC,
ISI, BUI, FWI, Classes  , Region]
Index: []
```

```python
#remove 122th column
df = df.drop(122).reset_index(drop=True)
```

```python
df.isnull().sum()
```

```
day            0
month          0
Temperature    0
 RH            0
 Ws            0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
Classes        0
Region         0
dtype: int64
```

checking data types of each column and change it correctly

```python
df.dtypes
```

```
day            object
month          object
Temperature    object
 RH            object
 Ws            object
Rain           object
FFMC           object
DMC            object
```

```
DC              object
ISI             object
BUI             object
FWI             object
Classes         object
Region           int32
dtype: object
```

```
df.columns
```

```
Index(['day', 'month', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC',
'DMC',
       'DC', 'ISI', 'BUI', 'FWI', 'Classes  ', 'Region'],
      dtype='object')
```

To fix Spaces in the column names

```
df.columns = df.columns.str.strip()
df.columns
```

```
Index(['day', 'month', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC',
'DMC', 'DC',
       'ISI', 'BUI', 'FWI', 'Classes', 'Region'],
      dtype='object')
```

To change and correct data types

```
df[['day','month','Temperature','RH','Ws']]=df[['day','month','Tempera
ture','RH','Ws']].astype('int')
```

```
objects = [features for features in df.columns if
df[features].dtypes=='O']
for i in objects:
    if i != 'Classes':
        df[i] = df[i].astype(float)
```

```
df.dtypes
```

```
day               int32
month             int32
Temperature       int32
RH                int32
Ws                int32
Rain            float64
FFMC            float64
DMC             float64
DC              float64
ISI             float64
BUI             float64
FWI             float64
Classes          object
```

```
Region             int32
dtype: object
```

```
df.astype(str)
```

```
    day month Temperature  RH  Ws  Rain  FFMC   DMC    DC  ISI   BUI  
FWI  \
0     1     6          29  57  18   0.0  65.7   3.4   7.6  1.3   3.4  
0.5   
1     2     6          29  61  13   1.3  64.4   4.1   7.6  1.0   3.9  
0.4   
2     3     6          26  82  22  13.1  47.1   2.5   7.1  0.3   2.7  
0.1   
3     4     6          25  89  13   2.5  28.6   1.3   6.9  0.0   1.7  
0.0   
4     5     6          27  77  16   0.0  64.8   3.0  14.2  1.2   3.9  
0.5   
..   ..   ...         ...  ..  ..   ...   ...   ...   ...  ...   ...  
...   
238  26     9          30  65  14   0.0  85.4  16.0  44.5  4.5  16.9  
6.5   
239  27     9          28  87  15   4.4  41.1   6.5   8.0  0.1   6.2  
0.0   
240  28     9          27  87  29   0.5  45.9   3.5   7.9  0.4   3.4  
0.2   
241  29     9          24  54  18   0.1  79.7   4.3  15.2  1.7   5.1  
0.7   
242  30     9          24  64  15   0.2  67.3   3.8  16.5  1.2   4.8  
0.5   

          Classes  Region  
0     not fire        1  
1     not fire        1  
2     not fire        1  
3     not fire        1  
4     not fire        1  
..          ...     ...  
238       fire        2  
239   not fire        2  
240   not fire        2  
241   not fire        2  
242  not fire         2  

[243 rows x 14 columns]
```

```
df["Classes"]=df["Classes"].str.replace("not fire","1")
df["Classes"]=df["Classes"].str.replace("fire","0")
df["Classes"]=df["Classes"].astype(int)
```

```
df
```

```
     day  month  Temperature   RH   Ws   Rain   FFMC    DMC     DC   ISI  
BUI   FWI  \
0      1      6           29   57   18    0.0   65.7    3.4    7.6   1.3  
3.4   0.5
1      2      6           29   61   13    1.3   64.4    4.1    7.6   1.0  
3.9   0.4
2      3      6           26   82   22   13.1   47.1    2.5    7.1   0.3  
2.7   0.1
3      4      6           25   89   13    2.5   28.6    1.3    6.9   0.0  
1.7   0.0
4      5      6           27   77   16    0.0   64.8    3.0   14.2   1.2  
3.9   0.5
..   ...    ...          ...  ..   ..    ...    ...    ...    ...   ...   ..
.  ...
238   26      9           30   65   14    0.0   85.4   16.0   44.5   4.5  
16.9   6.5
239   27      9           28   87   15    4.4   41.1    6.5    8.0   0.1  
6.2   0.0
240   28      9           27   87   29    0.5   45.9    3.5    7.9   0.4  
3.4   0.2
241   29      9           24   54   18    0.1   79.7    4.3   15.2   1.7  
5.1   0.7
242   30      9           24   64   15    0.2   67.3    3.8   16.5   1.2  
4.8   0.5

     Classes  Region
0          1       1
1          1       1
2          1       1
3          1       1
4          1       1
..       ...     ...
238        0       2
239        1       2
240        1       2
241        1       2
242        1       2

[243 rows x 14 columns]
```

3.Exploring data

```
# define numerical & categorical columns
categorical_features = [i for i in df.columns if df[i].dtypes == 
'object']
numeric_features = [i for i in df.columns if df[i].dtypes != 'object']
print(categorical_features)
print(numeric_features)
```

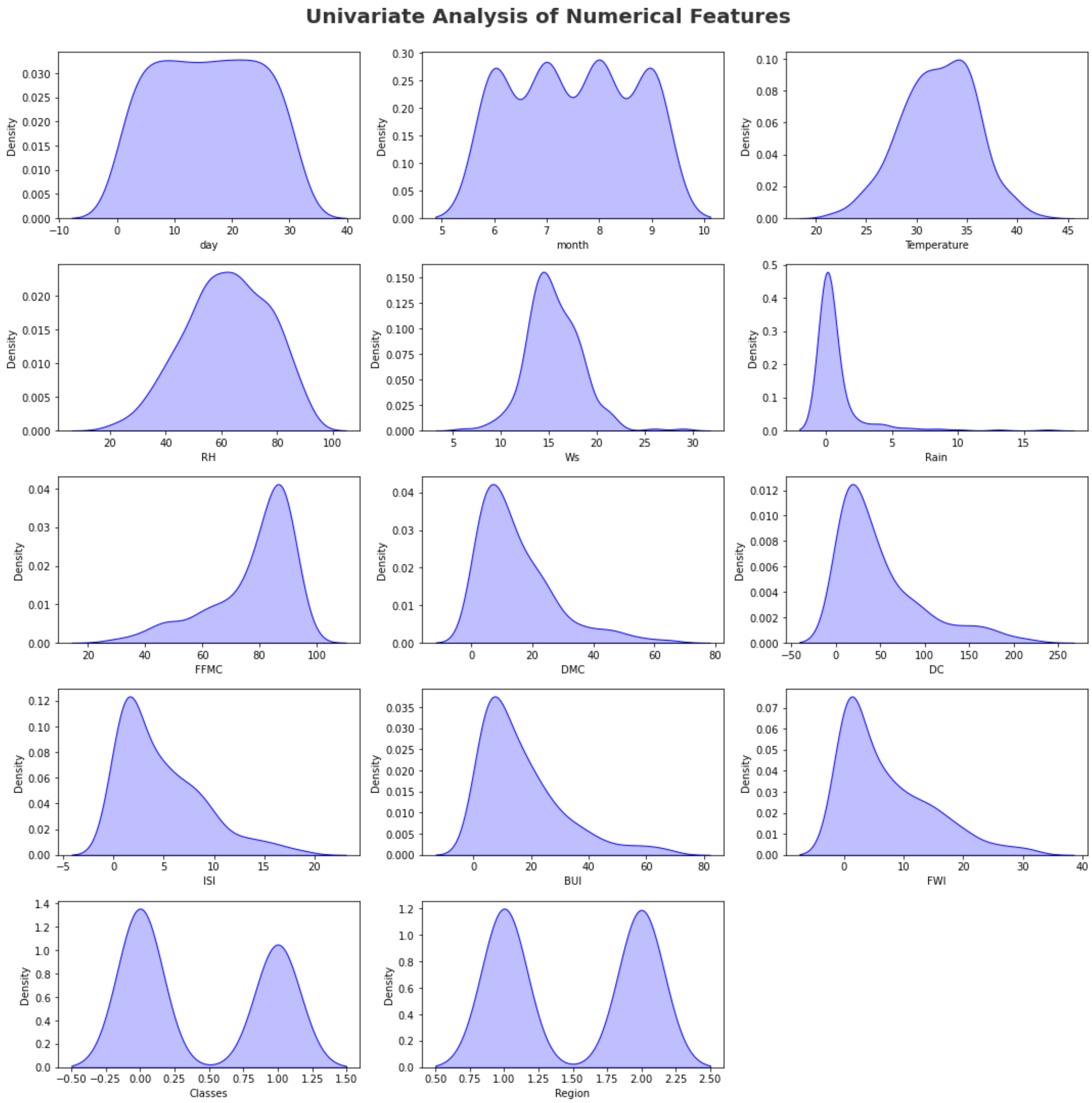
```
[]
['day', 'month', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC',
'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'Region']
```

Univariate Analysis

The term univariate analysis refers to the analysis of one variable prefix “uni” means “one.” The purpose of univariate analysisis to understand the distribution of values for a single variable.

numerical columns

```
plt.figure(figsize=(15, 15))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20,
fontweight='bold', alpha=0.8, y=1.)

for i in range(0, len(numeric_features)):
    plt.subplot(5, 3, i+1)
    sns.kdeplot(x=df[numeric_features[i]],shade=True, color='b')
    plt.xlabel(numeric_features[i])
    plt.tight_layout()
```



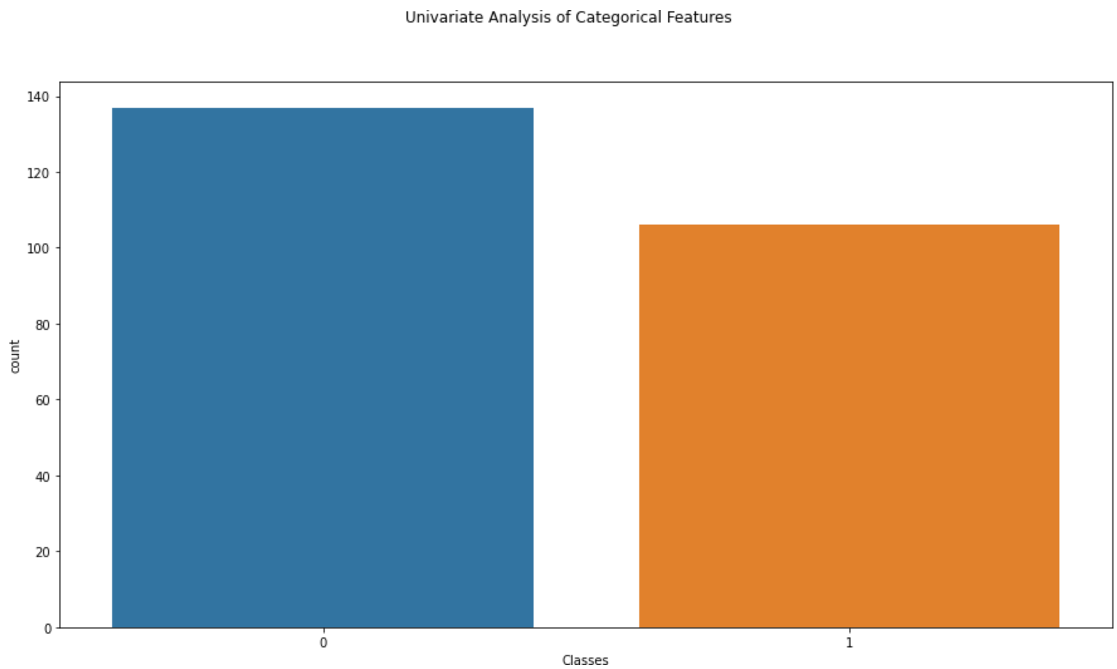
Report

- Temperature,RS,Ws are normally distributed.
- FFMC is right skewed.
- Rain,DMC,DC,ISI,BUI,FWI are left skewed or negatively skewed.

categorical analysis

```
plt.suptitle('Univariate Analysis of Categorical Features')
sns.countplot(x=df['Classes'])
```

```
<AxesSubplot:xlabel='Classes', ylabel='count'>
```



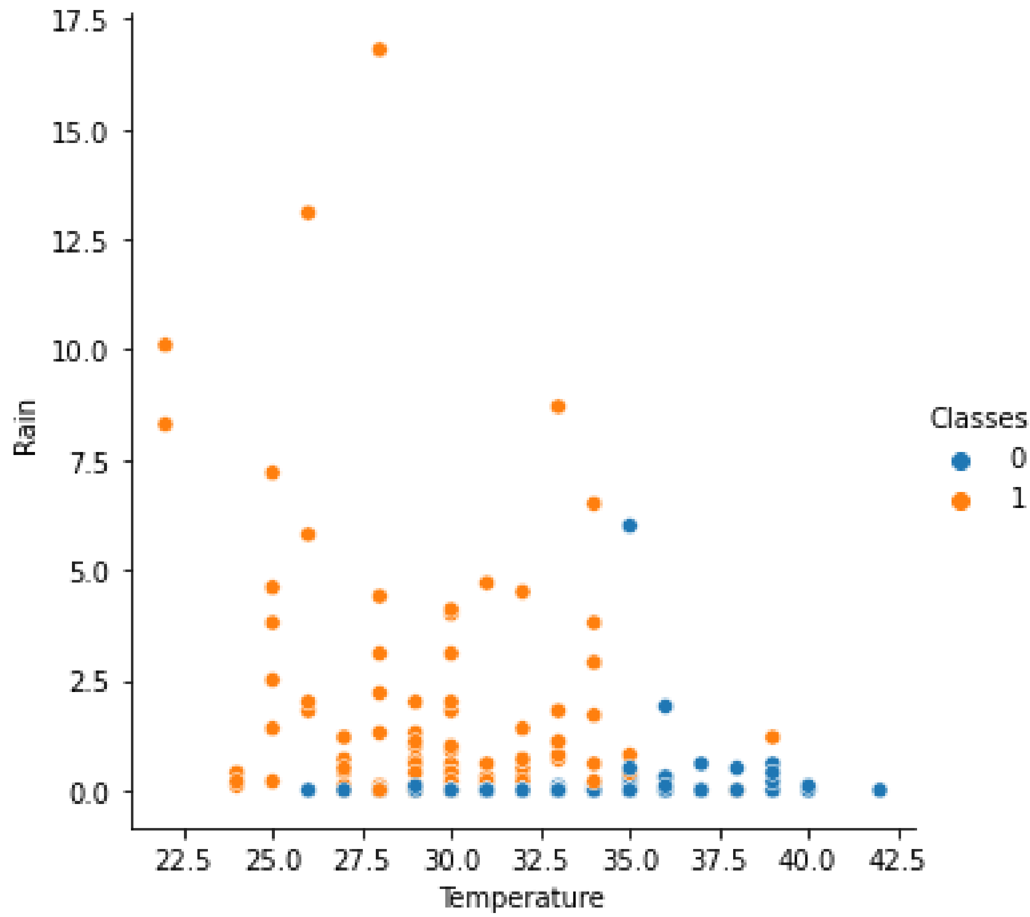
Report

from the plot we can observe that fire has occured many times

Bivariate analysis

```
sns.relplot(x='Temperature',y='Rain',data=df,hue='Classes')
```

```
<seaborn.axisgrid.FacetGrid at 0x1754b09fa30>
```



Multivariate analysis

```
#Multivariate analysis is the analysis of more than two variable.
```

Check Multicollinearity in Numerical features

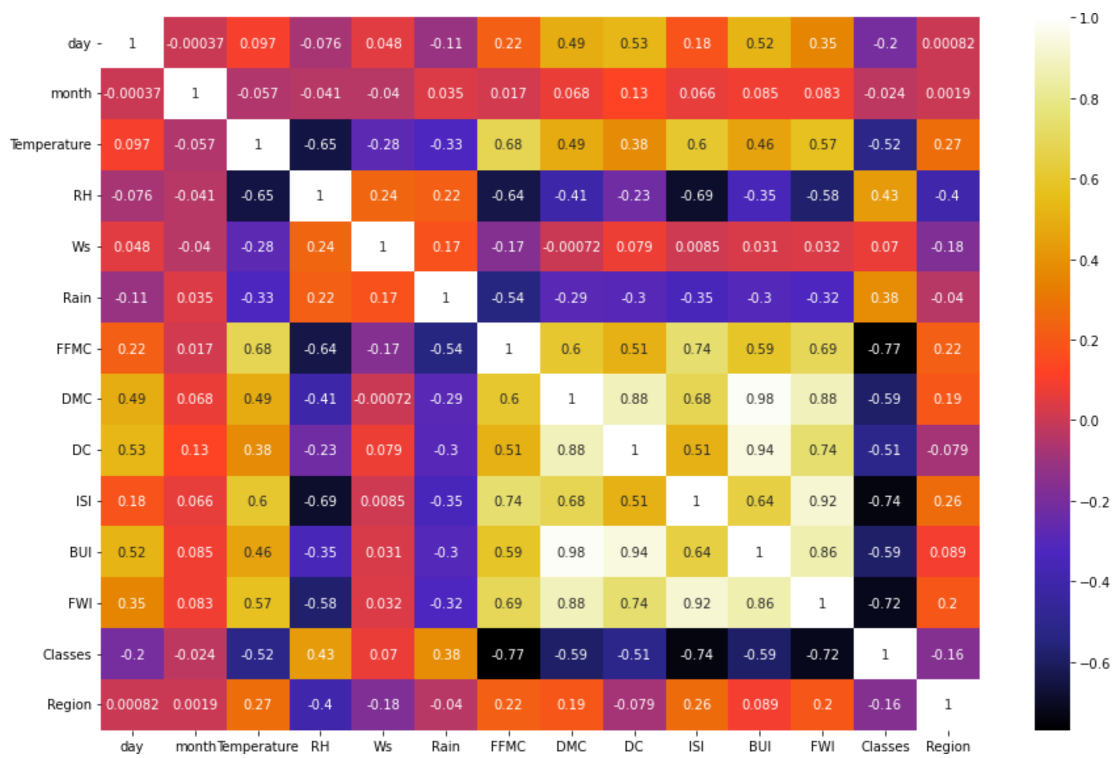
```
df.corr()
```

```
                  day     month  Temperature        RH        Ws    
Rain   \
day          1.000000 -0.000369     0.097227 -0.076034  0.047812 -
0.112523
month       -0.000369  1.000000    -0.056781 -0.041252 -0.039880  
0.034822
Temperature  0.097227 -0.056781     1.000000 -0.651400 -0.284510 -
0.326492
RH          -0.076034 -0.041252    -0.651400  1.000000  0.244048  
0.222356
Ws           0.047812 -0.039880    -0.284510  0.244048  1.000000  
0.171506
Rain        -0.112523  0.034822    -0.326492  0.222356  0.171506  
1.000000
```

```
FFMC          0.224956  0.017030     0.676568 -0.644873 -0.166548  -
0.543906
DMC           0.491514  0.067943     0.485687 -0.408519 -0.000721  -
0.288773
DC            0.527952  0.126511     0.376284 -0.226941  0.079135  -
0.298023
ISI           0.180543  0.065608     0.603871 -0.686667  0.008532  -
0.347484
BUI           0.517117  0.085073     0.459789 -0.353841  0.031438  -
0.299852
FWI           0.350781  0.082639     0.566670 -0.580957  0.032368  -
0.324422
Classes      -0.202840 -0.024004    -0.516015  0.432161  0.069964
0.379097
Region        0.000821  0.001857     0.269555 -0.402682 -0.181160  -
0.040013

                  FFMC       DMC        DC       ISI       BUI
FWI  \
day           0.224956  0.491514  0.527952  0.180543  0.517117
0.350781
month         0.017030  0.067943  0.126511  0.065608  0.085073
0.082639
Temperature   0.676568  0.485687  0.376284  0.603871  0.459789
0.566670
RH           -0.644873 -0.408519 -0.226941 -0.686667 -0.353841 -
0.580957
Ws           -0.166548 -0.000721  0.079135  0.008532  0.031438
0.032368
Rain         -0.543906 -0.288773 -0.298023 -0.347484 -0.299852 -
0.324422
FFMC          1.000000  0.603608  0.507397  0.740007  0.592011
0.691132
DMC           0.603608  1.000000  0.875925  0.680454  0.982248
0.875864
DC            0.507397  0.875925  1.000000  0.508643  0.941988
0.739521
ISI           0.740007  0.680454  0.508643  1.000000  0.644093
0.922895
BUI           0.592011  0.982248  0.941988  0.644093  1.000000
0.857973
FWI           0.691132  0.875864  0.739521  0.922895  0.857973
1.000000
Classes      -0.769492 -0.585658 -0.511123 -0.735197 -0.586639 -
0.719216
Region        0.222241  0.192089 -0.078734  0.263197  0.089408
0.197102

               Classes    Region
day          -0.202840  0.000821
```

```
month         -0.024004  0.001857
Temperature -0.516015  0.269555
RH             0.432161 -0.402682
Ws             0.069964 -0.181160
Rain           0.379097 -0.040013
FFMC          -0.769492  0.222241
DMC           -0.585658  0.192089
DC            -0.511123 -0.078734
ISI           -0.735197  0.263197
BUI           -0.586639  0.089408
FWI           -0.719216  0.197102
Classes        1.000000 -0.162347
Region        -0.162347  1.000000
```

```
plt.figure(figsize = (15,10))
sns.heatmap(df.corr(), cmap="CMRmap", annot=True)
plt.show()
```



Observation

1.DMC-BUI,DC-BUI,FWI-BUI are very high correlated.

2.FFMC-BUI,ISI-BUI,DC-ISI are high correlated

3.Range between 0.4 to 0.6 are moderate correlated

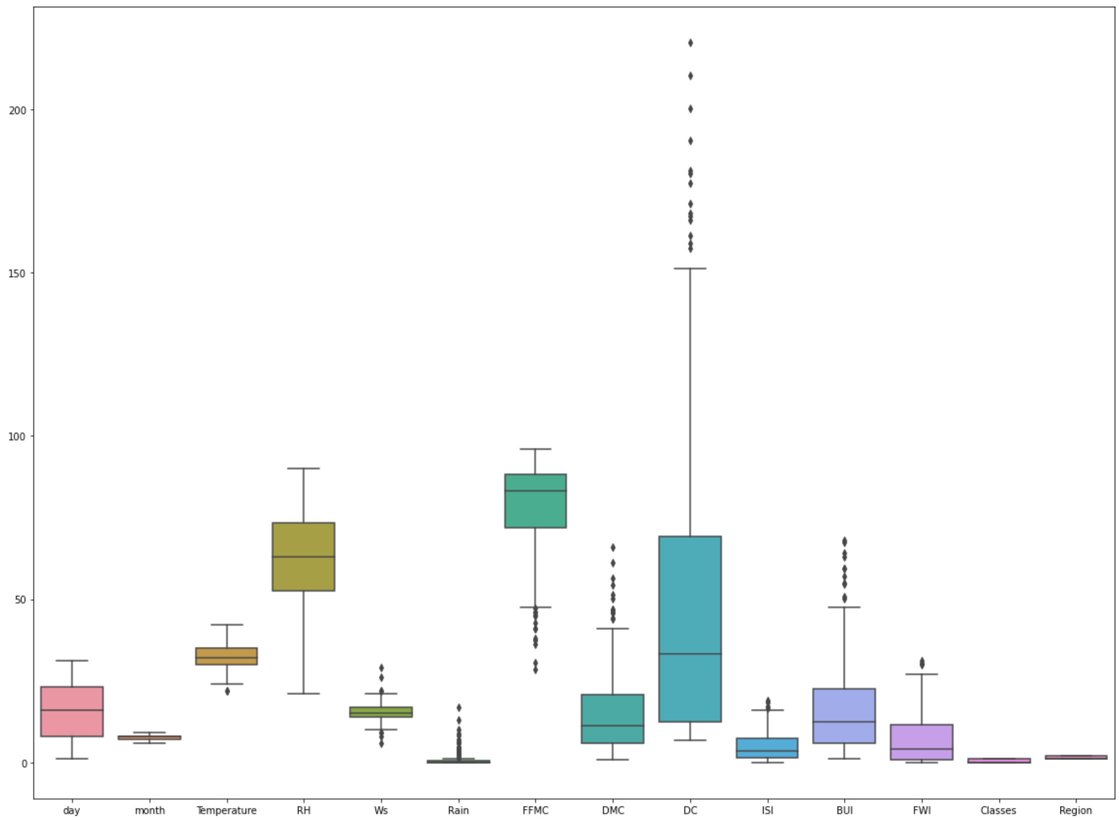
4. correlation coefficients between 0.2 to 0.4 are less correlated

5. correlation coefficients between 0 to .1 are negatively correlated

Boxplot to find outliers in the features

```
from matplotlib import rcParams
rcParams['figure.figsize']=20,15
sns.boxplot(data=df)
```

```
<AxesSubplot:>
```

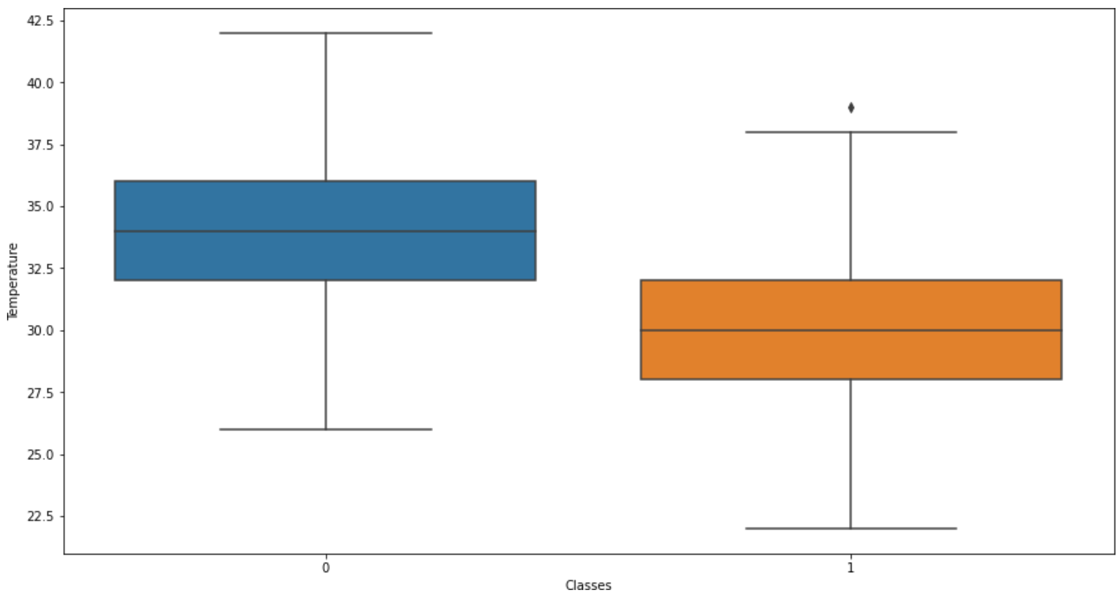


Observation

- With the help of boxplot figure we can see that some outliers are present in data

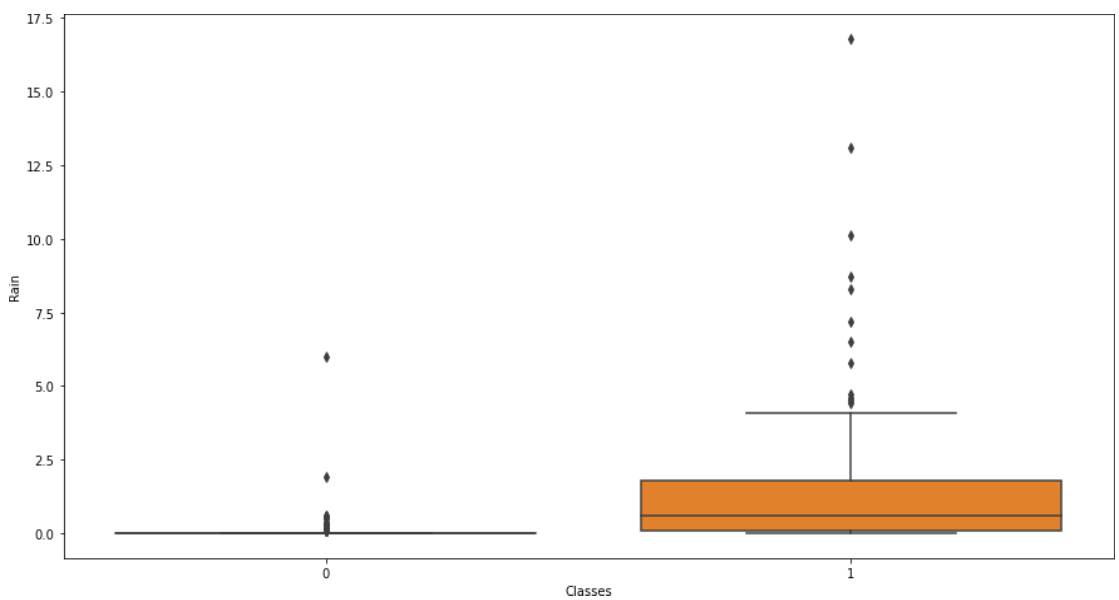
```
rcParams['figure.figsize']=15,8
sns.boxplot(x='Classes',y='Temperature',data=df)
```

```
<AxesSubplot:xlabel='Classes', ylabel='Temperature'>
```

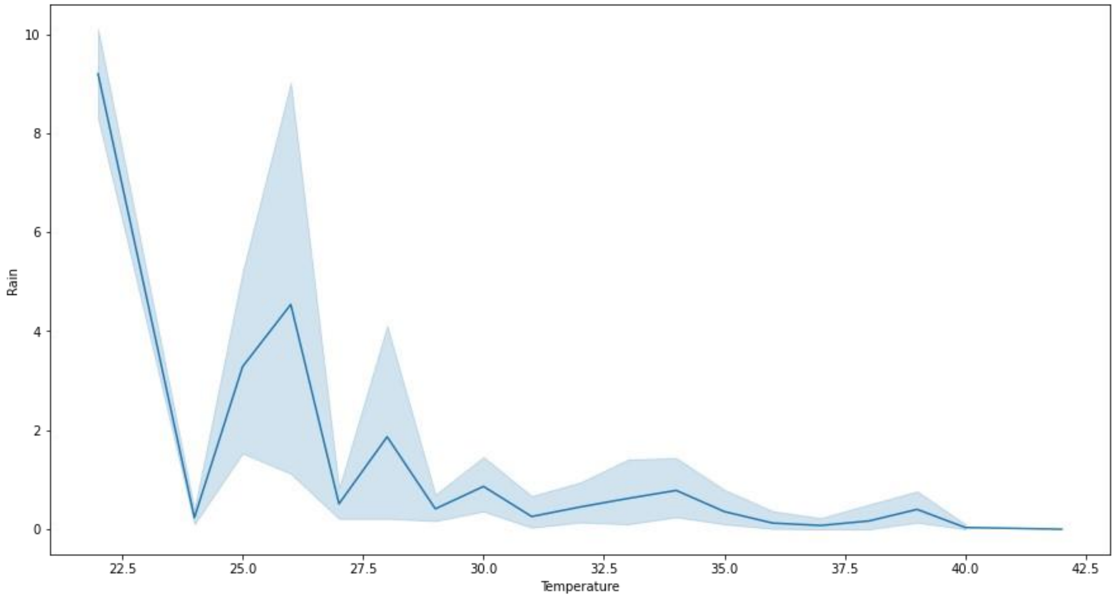



```
from matplotlib import rcParams
rcParams['figure.figsize']=15,8
sns.boxplot(x='Classes',y='Rain',data=df)
```

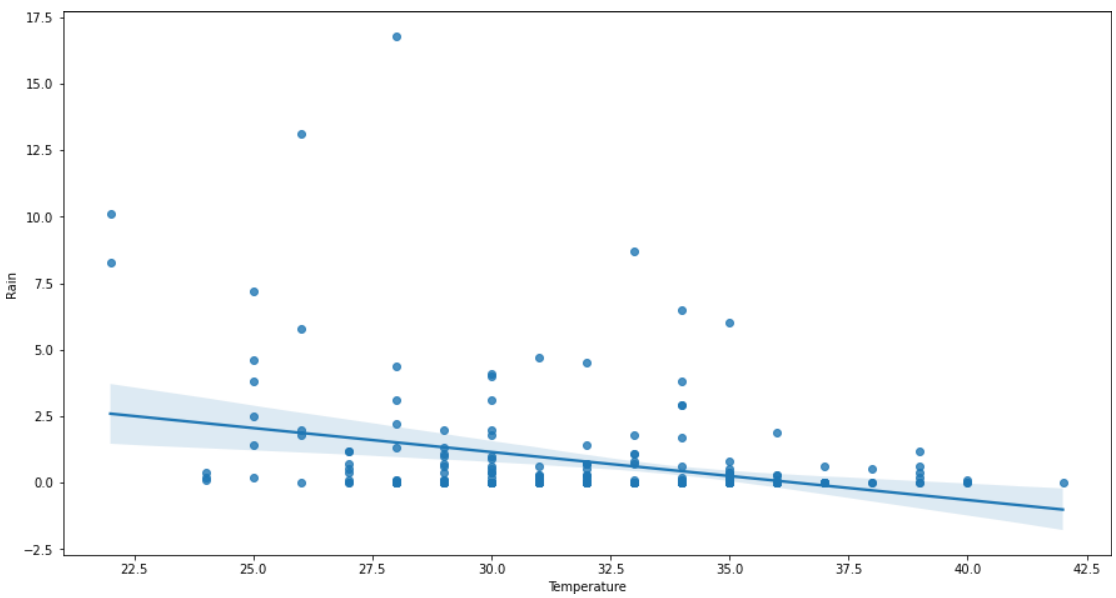
```
<AxesSubplot:xlabel='Classes', ylabel='Rain'>
```




```
from matplotlib import rcParams
rcParams['figure.figsize']=15,8
p=sns.lineplot(x='Temperature',y='Rain',data=df)
```




```
rcParams['figure.figsize']=15,8
p=sns.regplot(x='Temperature',y='Rain',data=df)
```



Splitting Training and Testing data

```
#independent and dependent features
X=df.iloc[:,df.columns!='Temperature']
y=df.iloc[:,2]
```

```
y
```

```
0        29
1        29
```

```
2      26
3      25
4      27
       ..
238    30
239    28
240    27
241    24
242    24
Name: Temperature, Length: 243, dtype: int32
```

X

```
     day  month  RH  Ws  Rain  FFMC   DMC    DC  ISI   BUI  FWI
Classes  \
0      1      6  57  18   0.0  65.7   3.4   7.6  1.3   3.4  0.5
1
1      2      6  61  13   1.3  64.4   4.1   7.6  1.0   3.9  0.4
1
2      3      6  82  22  13.1  47.1   2.5   7.1  0.3   2.7  0.1
1
3      4      6  89  13   2.5  28.6   1.3   6.9  0.0   1.7  0.0
1
4      5      6  77  16   0.0  64.8   3.0  14.2  1.2   3.9  0.5
1
..   ...    ...  ..  ..   ...   ...   ...   ...  ...   ...  ...      .
..
238   26      9  65  14   0.0  85.4  16.0  44.5  4.5  16.9  6.5
0
239   27      9  87  15   4.4  41.1   6.5   8.0  0.1   6.2  0.0
1
240   28      9  87  29   0.5  45.9   3.5   7.9  0.4   3.4  0.2
1
241   29      9  54  18   0.1  79.7   4.3  15.2  1.7   5.1  0.7
1
242   30      9  64  15   0.2  67.3   3.8  16.5  1.2   4.8  0.5
1

     Region
0         1
1         1
2         1
3         1
4         1
..      ...
238       2
239       2
240       2
241       2
242       2
```

```
[243 rows x 13 columns]
```

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.33,rand
om_state=10)
```

```
X_train.head()
```

```
     day  month  RH  Ws  Rain  FFMC   DMC    DC   ISI   BUI   FWI
Classes  \
25    26      6  64  18   0.0  86.8  17.8  71.8   6.7  21.6  10.6
0
121   30      9  78  14   1.4  45.0   1.9   7.5   0.2   2.4   0.1
1
173   23      7  71  17   0.0  87.3  46.6  99.0   6.9  46.5  16.3
0
72    12      8  51  13   0.3  81.3  15.6  75.1   2.5  20.7   4.2
1
185    4      8  35  15   0.0  93.8  23.0  42.7  15.7  22.9  20.9
0

     Region
25        1
121       1
173       2
72        1
185       2
```

```
y_train
```

```
25     31
121    25
173    31
72     35
185    38
       ..
64     34
15     29
228    33
125    30
9      28
Name: Temperature, Length: 162, dtype: int32
```

```
X_train.shape
```

```
(162, 13)
```

```
y_train.shape
```

```
(162,)
```

```
# Standardization or feature scaling the dataset
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()

X_train=scaler.fit_transform(X_train)

X_test=scaler.transform(X_test) #to avoid data leakage transformer

X_train

array([[ 1.30705791, -1.39305207,  0.06835876, ...,  0.52024214,
        -0.90566259, -1.01242284],
       [ 1.77217242,  1.29354835,  0.99672801, ..., -0.93452011,
         1.10416397, -1.01242284],
       [ 0.95822202, -0.4975186 ,  0.53254338, ...,  1.30997022,
        -0.90566259,  0.9877296 ],
       ...,
       [ 0.14427163,  1.29354835, -2.45150064, ...,  1.72561657,
        -0.90566259,  0.9877296 ],
       [-1.2510719 , -1.39305207,  0.06835876, ..., -0.8098262 ,
         1.10416397,  0.9877296 ],
       [-0.55340014, -1.39305207,  1.0630401 , ..., -0.82368108,
         1.10416397, -1.01242284]])

X_test

array([[ 0.26055026, -0.4975186 ,  0.46623129, ..., -0.44959936,
        -0.90566259, -1.01242284],
       [-0.20456425,  1.29354835, -0.92632258, ...,  0.4786775 ,
        -0.90566259,  0.9877296 ],
       [ 1.77217242, -0.4975186 , -0.46213796, ...,  0.88046898,
        -0.90566259,  0.9877296 ],
       ...,
       [ 1.30705791,  0.39801488, -1.72206765, ...,  3.24965322,
        -0.90566259,  0.9877296 ],
       [-0.43712151,  1.29354835,  0.93041592, ..., -0.90681035,
         1.10416397, -1.01242284],
       [ 0.37682889,  0.39801488, -0.59476213, ...,  1.28226046,
        -0.90566259, -1.01242284]])
```

Model selection

```
from sklearn.linear_model import LinearRegression

regression = LinearRegression()

regression

LinearRegression()

regression.fit(X_train,y_train)
```

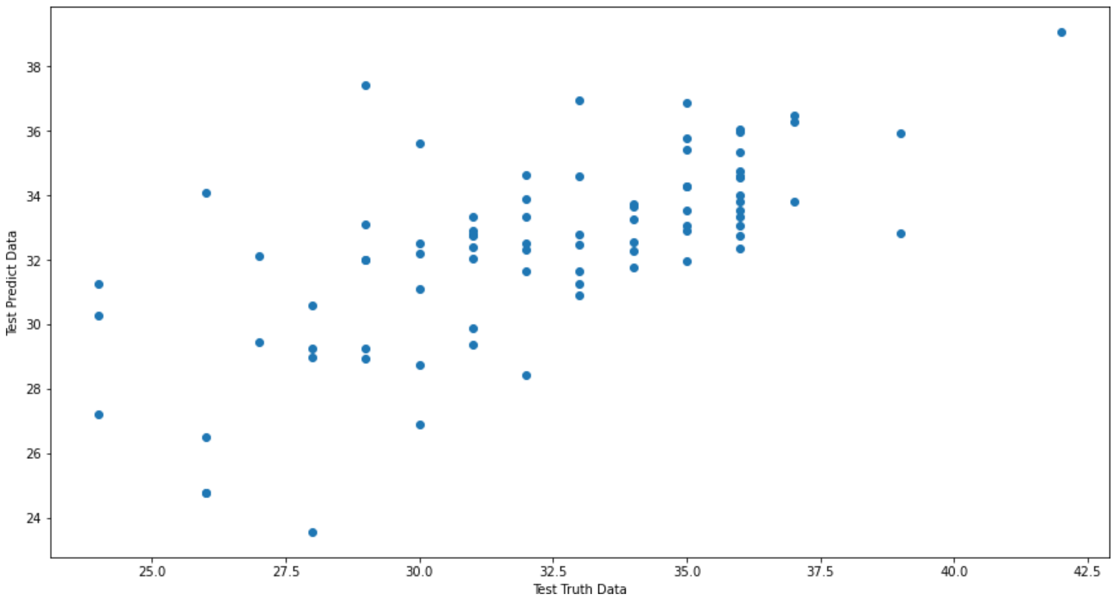
```
LinearRegression()

#print the coefficient and intercept
print(regression.coef_)

[-0.36077135 -0.2311454  -1.50045027 -0.70384333 -0.24625832
0.84766384
  0.09164637  0.68596622  0.10380813  0.16594124 -0.38469383 -
0.18553708
  0.22661524]

print(regression.intercept_)

32.074074074074076

#prediction for test data
reg_pred=regression.predict(X_test)

reg_pred

array([31.99493488, 33.12664016, 33.32629208, 24.7838569 ,
29.2460991 ,
       33.66799244, 31.64931814, 34.58818421, 31.79084174,
32.31038339,
       33.54818002, 33.34754307, 35.78255767, 32.03424221,
34.27923643,
       33.26037242, 26.52877687, 35.94057602, 33.33186761,
23.57110435,
       32.36221708, 32.52712236, 33.06301323, 32.81955926,
29.903744  ,
       32.73791527, 32.89973308, 32.14375238, 31.97567765,
34.09071758,
       34.61315534, 33.87565689, 34.55720694, 32.78051614,
31.25884225,
       28.73433642, 32.57424997, 31.67173881, 33.05658571,
34.00592683,
       33.83451992, 35.61866932, 34.26998499, 37.40865649,
32.90557183,
       36.49959526, 32.27373405, 35.35128002, 30.60009684,
31.10436839,
       32.39267139, 39.0865001 , 32.75773646, 34.64063089,
27.20344681,
       36.86613123, 33.83117207, 33.74796958, 28.98445209,
32.4738513 ,
       32.52599845, 31.99902312, 24.8016617 , 36.29777696,
36.03327802,
       28.94688288, 29.45302718, 29.37313652, 35.96924316,
28.45369633,
       29.27601583, 32.21720179, 30.29726821, 30.93046457,
34.76079441,
       32.8057019 , 35.40714492, 31.25361667, 36.9369251 ,
```

```
26.90785041,
       33.5503991 ])
```

Assumptions of linear regression

```
# relation between real and pred data
plt.scatter(y_test,reg_pred)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predict Data')
```

```
Text(0, 0.5, 'Test Predict Data')
```



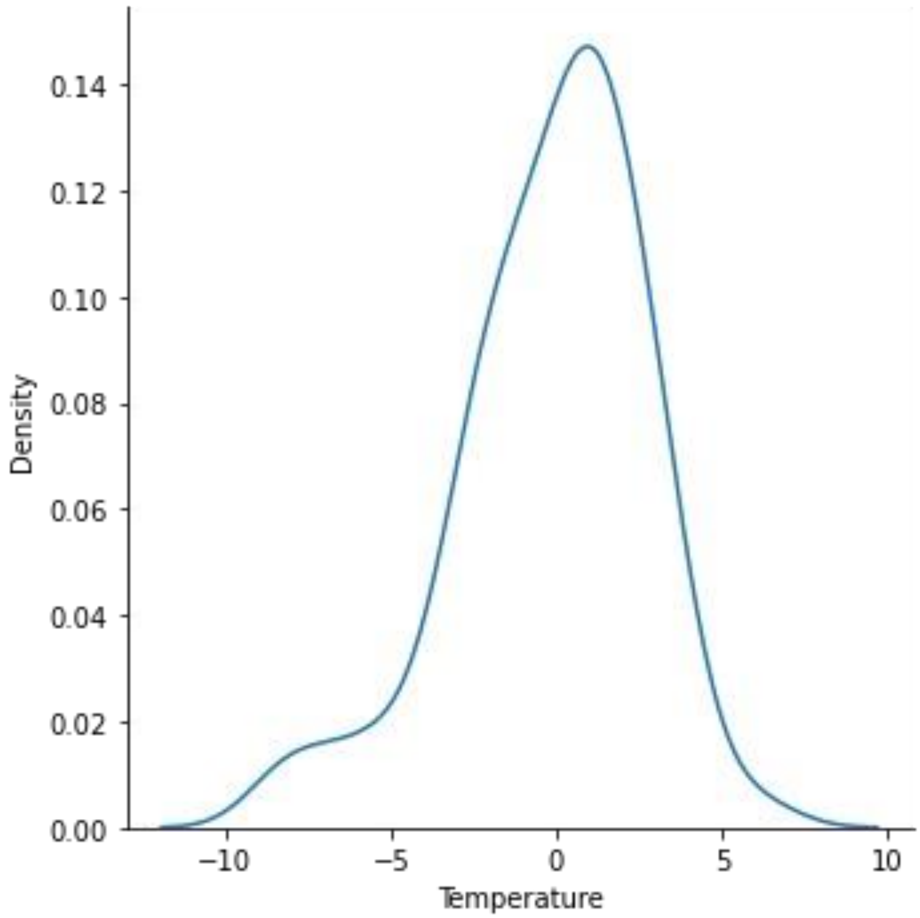

```
#calculate residuals
residual=y_test-reg_pred
```

```
residual
```

```
46    -2.994935
225   -4.126640
180    2.673708
116    1.216143
124   -0.246099
         ...
127   -0.407145
241   -7.253617
207   -3.936925
102    3.092150
78     2.449601
Name: Temperature, Length: 81, dtype: float64
```

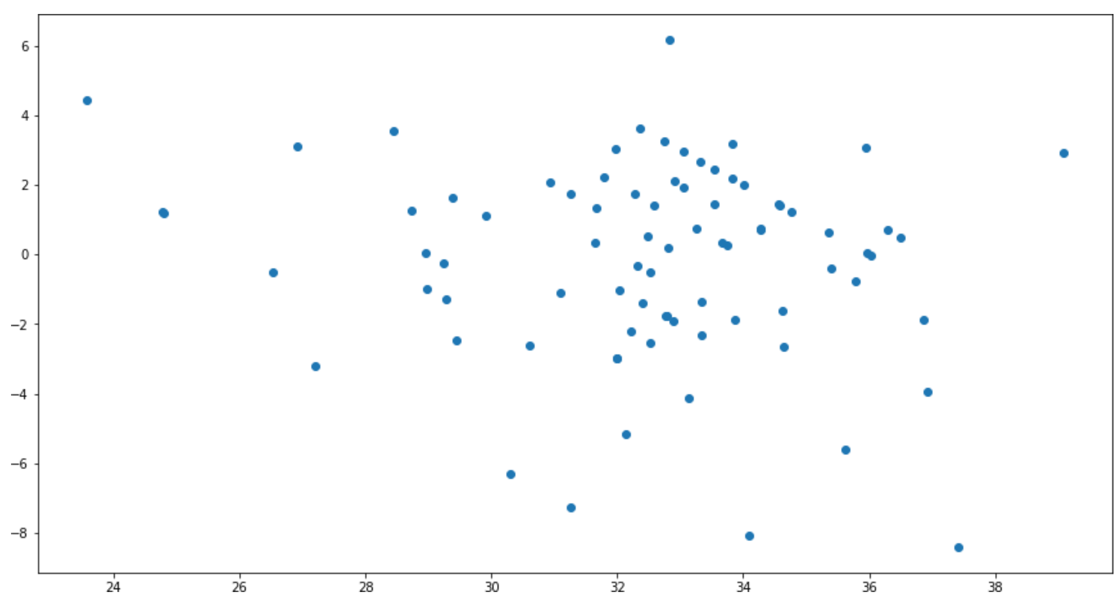
```
sns.displot(residual,kind='kde')
```

```
<seaborn.axisgrid.FacetGrid at 0x1754bca84c0>
```




```
plt.scatter(reg_pred,residual)
```

```
<matplotlib.collections.PathCollection at 0x1754c15d4f0>
```



Performance metrics

```
from sklearn.metrics import mean_squared_error,mean_absolute_error
print(mean_squared_error(y_test,reg_pred))
print(mean_absolute_error(y_test,reg_pred))
print(np.sqrt(mean_squared_error(y_test,reg_pred)))
```

```
7.7928584372969825
2.1532259595595913
2.7915691711467554
```

```
from sklearn.metrics import r2_score
score=r2_score(y_test,reg_pred)
print(score)
```

```
0.4370546969181548
```

```
## Adjusted R2 need to write
adjR=1-(1-score)*(len(y)-1)/(len(y)-X.shape[1]-1)
print(adjR)
```

```
0.4050971032934212
```

Ridge regression

```
from sklearn.linear_model import Ridge
```

```
ridge_reg=Ridge(alpha=1.0)
```

```
ridge_reg
```

```
Ridge()
```

```
ridge_reg.fit(X_train,y_train)
```

```
Ridge()
```

```
print(ridge_reg.coef_)
```

```
[-0.35498915 -0.22833494 -1.48029097 -0.70374866 -0.24661714
0.85405124
  0.08174868  0.64566072  0.07203342  0.17636996 -0.314502   -
0.17870778
  0.22535392]
```

```
print(ridge_reg.intercept_)
```

```
32.074074074074076
```

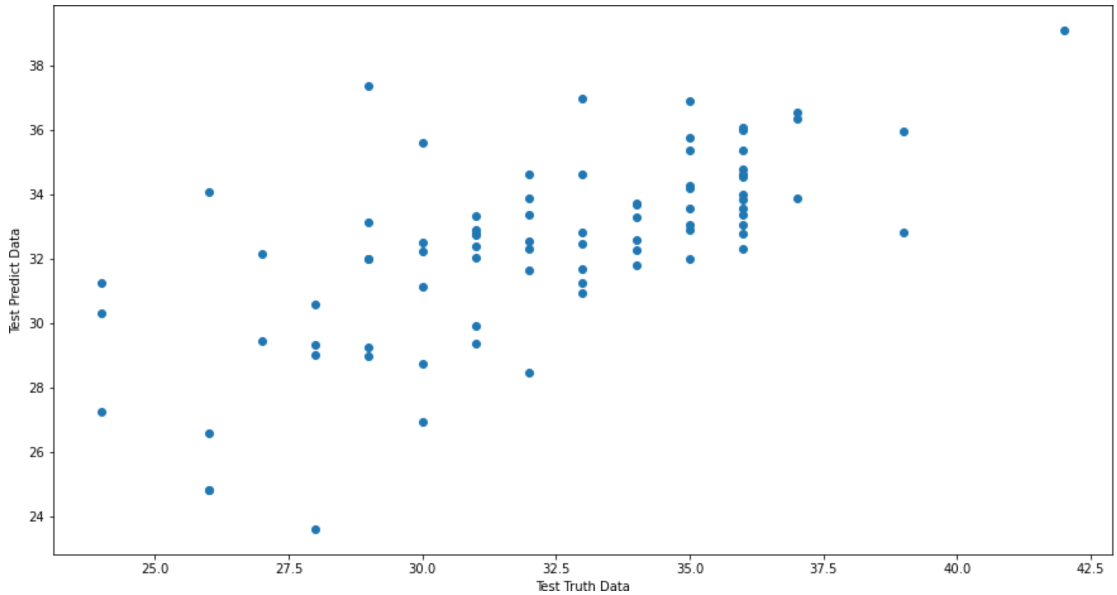
```
rid_pred=ridge_reg.predict(X_test)
rid_pred
```

```
array([31.99412337, 33.12040196, 33.34904202, 24.81531826,
29.25317586,
```

```
       33.68676155, 31.63059048, 34.61400469, 31.81080916,
32.30710445,
       33.54409223, 33.34199846, 35.75695644, 32.03039126,
34.196428  ,
       33.27080718, 26.56260115, 35.93359951, 33.31573076,
23.60085512,
       32.31428709, 32.51199227, 33.06509029, 32.82454574,
29.89856284,
       32.75584864, 32.90298721, 32.1343128 , 31.97312855,
34.06519694,
       34.59717106, 33.86491378, 34.5259007 , 32.78015204,
31.23264081,
       28.7431667 , 32.55777417, 31.67069931, 33.05264996,
33.9776409 ,
       33.85967669, 35.60302534, 34.26796346, 37.35281757,
32.90360982,
       36.53560291, 32.26187897, 35.34292679, 30.59554534,
31.10728523,
       32.39611356, 39.09427765, 32.7429986 , 34.63335351,
27.23033441,
       36.89104824, 33.84982341, 33.71470698, 29.01228005,
32.45261276,
       32.52613462, 31.98628733, 24.81143025, 36.32031857,
36.06254441,
       28.98050626, 29.42546164, 29.37614081, 35.99109657,
28.46194337,
       29.30529087, 32.22528184, 30.30676114, 30.93598706,
34.76967945,
       32.82275712, 35.37475572, 31.25349235, 36.97010006,
26.92609135,
       33.54489491])
```

```
#reation between real and predict data
plt.scatter(y_test,rid_pred)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predict Data')
```

```
Text(0, 0.5, 'Test Predict Data')
```



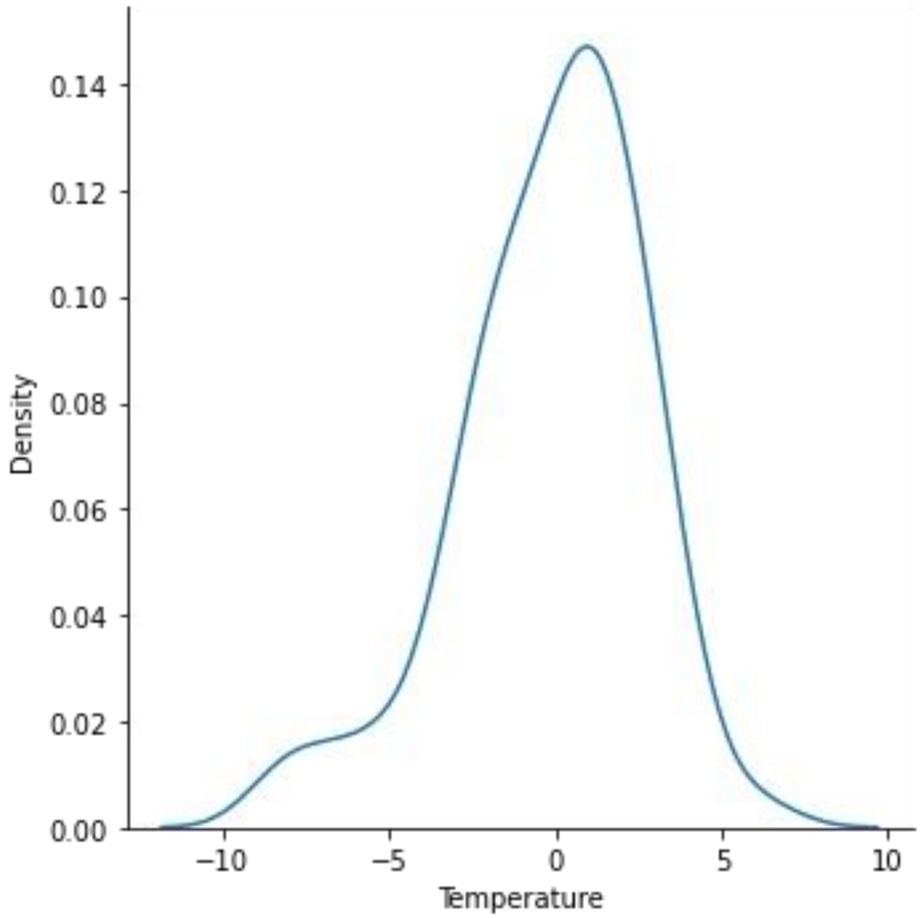

```
#calculate residuals
residual=y_test-rid_pred
```

```
residual
```

```
46    -2.994123
225   -4.120402
180    2.650958
116    1.184682
124   -0.253176
         ...
127   -0.374756
241   -7.253492
207   -3.970100
102    3.073909
78     2.455105
Name: Temperature, Length: 81, dtype: float64
```

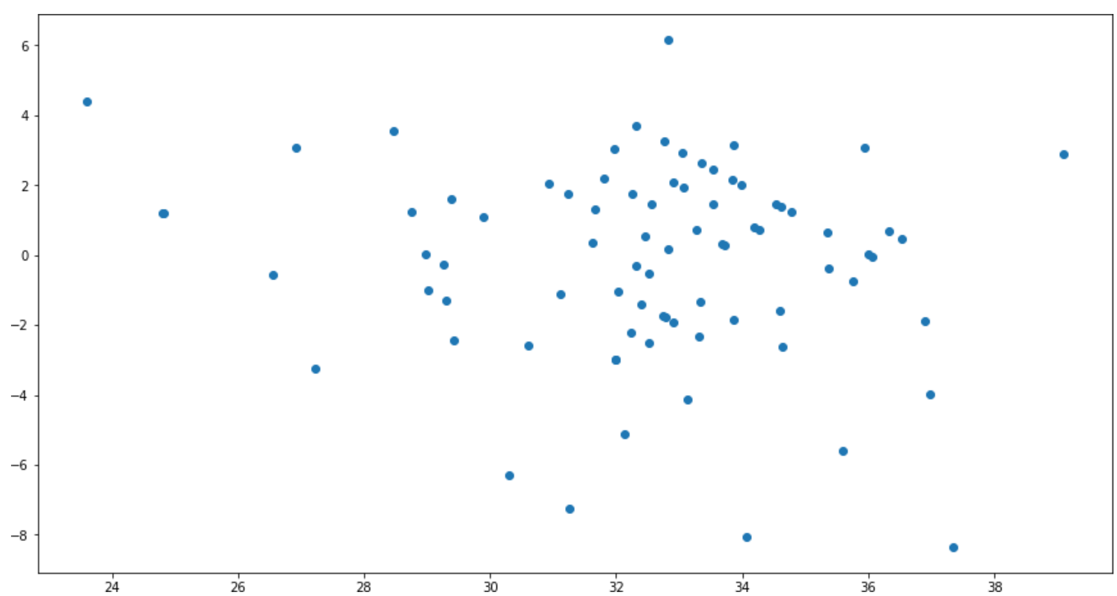
```
sns.displot(residual,kind='kde')
```

```
<seaborn.axisgrid.FacetGrid at 0x1754c1e44c0>
```




```
plt.scatter(rid_pred,residual)
```

```
<matplotlib.collections.PathCollection at 0x1754d808a60>
```



Performance metrics

```
from sklearn.metrics import mean_squared_error,mean_absolute_error
print(mean_squared_error(y_test,rid_pred))
print(mean_absolute_error(y_test,rid_pred))
print(np.sqrt(mean_squared_error(y_test,rid_pred)))
```

```
7.770134748047858
2.151505587243574
2.7874961431449297
```

```
from sklearn.metrics import r2_score
score=r2_score(y_test,rid_pred)
print(score)
```

```
0.438696224765018
```

```
## Adjusted R2 need to write
adjR=1-(1-score)*(len(y)-1)/(len(y)-X.shape[1]-1)
print(adjR)
```

```
0.4068318183106303
```

Lasso regression

```
from sklearn.linear_model import Lasso

lasso=Lasso(alpha=0.1)

lasso.fit(X_train,y_train)
```

```
Lasso(alpha=0.1)
```

```
print(lasso.coef_)
```

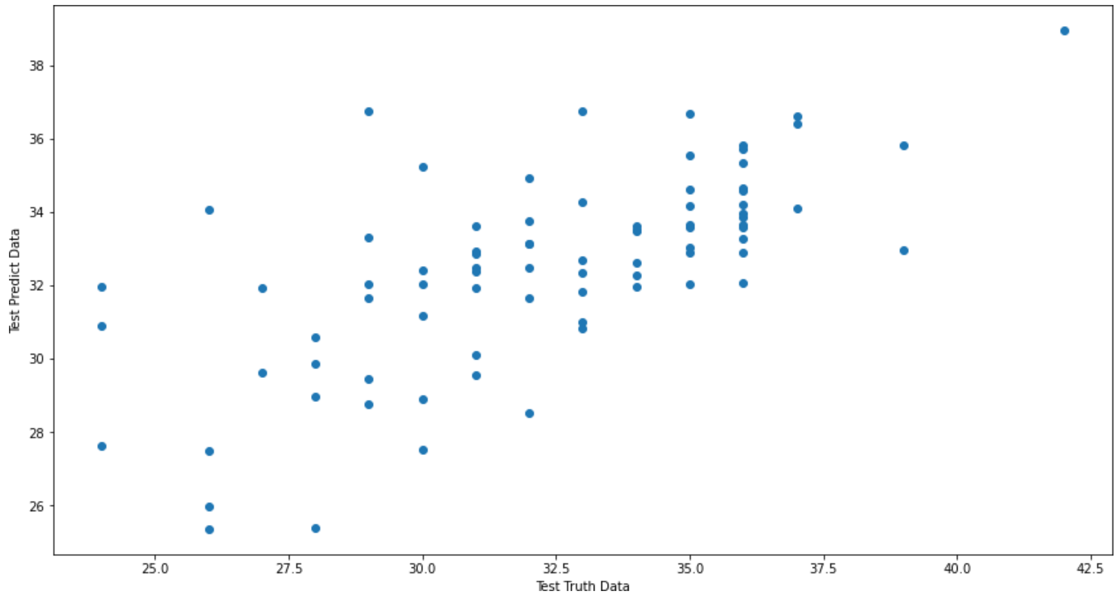
```
[-0.105944   -0.0832839  -1.37409593 -0.63447767 -0.1567129
1.00625551
  0.14183148  0.32399062  0.          0.          0.          -
0.05456468
  0.10290589]
```

```
print(lasso.intercept_)
```

```
32.074074074074076
```

```
Ls_pred=lasso.predict(X_test)

#reation between real and predict data
plt.scatter(y_test,Ls_pred)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predict Data')
```

```
Text(0, 0.5, 'Test Predict Data')
```



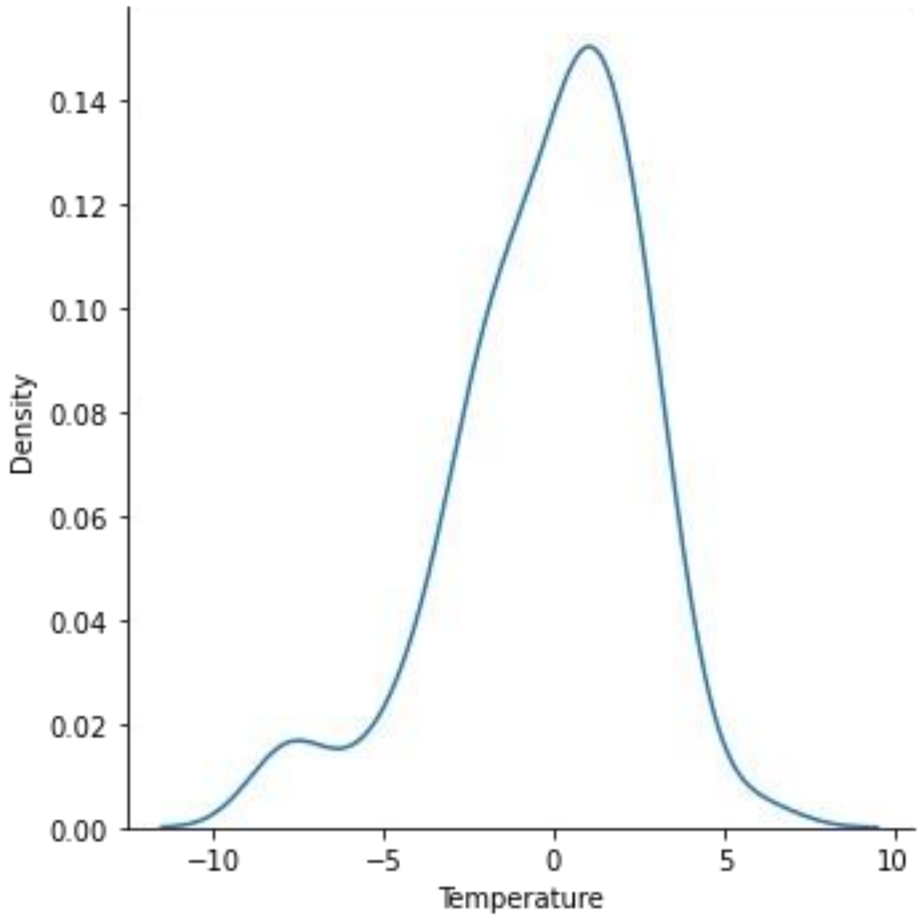

```
#calculate residuals
residual=y_test-Ls_pred
```

```
residual
```

```
46    -3.049143
225   -4.302261
180    2.362682
116    0.022311
124    0.240150
         ...
127    0.388053
241   -7.962346
207   -3.764752
102    2.464306
78     2.427680
Name: Temperature, Length: 81, dtype: float64
```

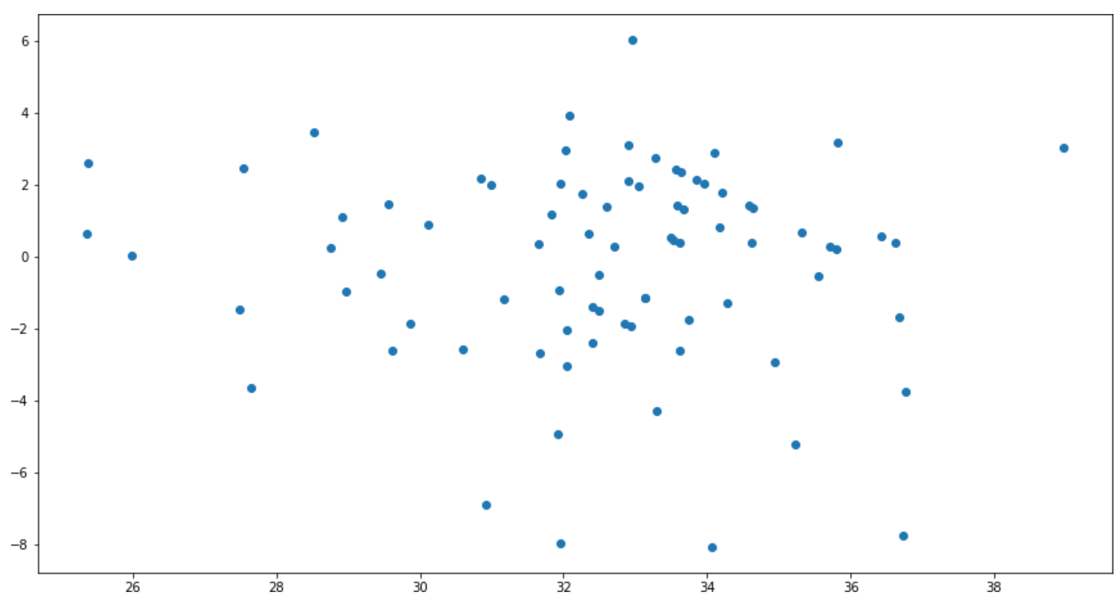
```
sns.displot(residual,kind='kde')
```

```
<seaborn.axisgrid.FacetGrid at 0x1754c193670>
```




```
plt.scatter(Ls_pred,residual)
```

```
<matplotlib.collections.PathCollection at 0x1754e194a90>
```



Performance metrics

```
from sklearn.metrics import mean_squared_error,mean_absolute_error
print(mean_squared_error(y_test,Ls_pred))
print(mean_absolute_error(y_test,Ls_pred))
print(np.sqrt(mean_squared_error(y_test,Ls_pred)))
```

```
7.615413002358264
2.1317374993041036
2.759603776334252
```

```
from sklearn.metrics import r2_score
score=r2_score(y_test,Ls_pred)
print(score)
```

```
0.4498731094372349
```

```
## Adjusted R2 need to write
adjR=1-(1-score)*(len(y)-1)/(len(y)-X.shape[1]-1)
print(adjR)
```

```
0.41864319861926136
```

Elastic net

```
from sklearn.linear_model import ElasticNet
```

```
el_reg=ElasticNet()
```

```
el_reg.fit(X_train,y_train)
```

```
ElasticNet()
```

```
print(el_reg.coef_)
```

```
[ 0.         -0.          -0.7730265   -0.26945253  -0.02396636
0.67644044
  0.10592038  0.           0.18367796   0.03890539   0.10736141 -
0.12263291
  0.        ]
```

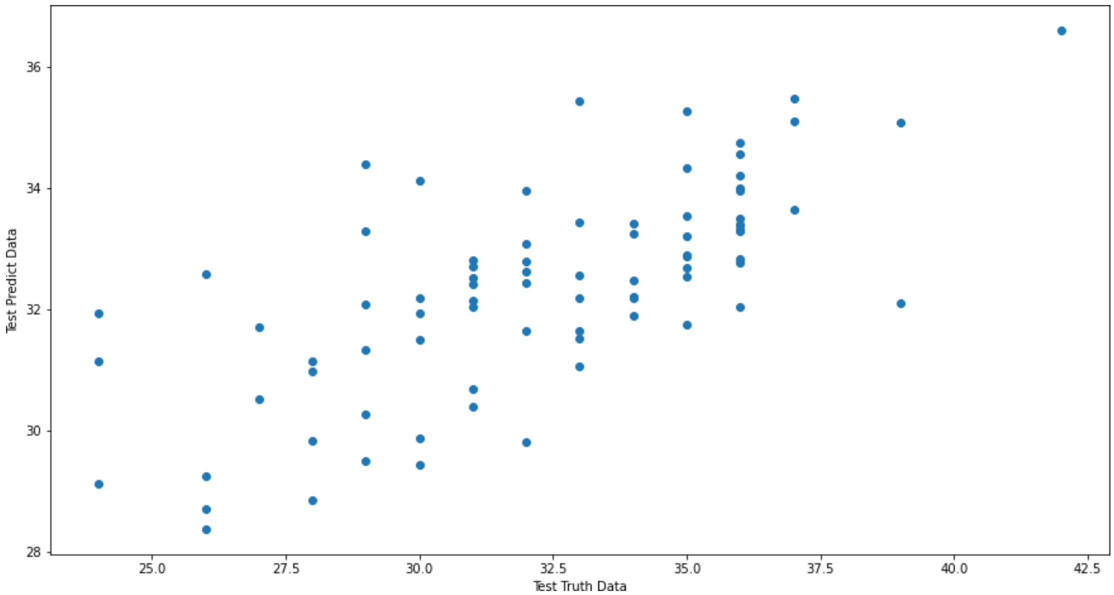
```
print(el_reg.intercept_)
```

```
32.074074074074076
```

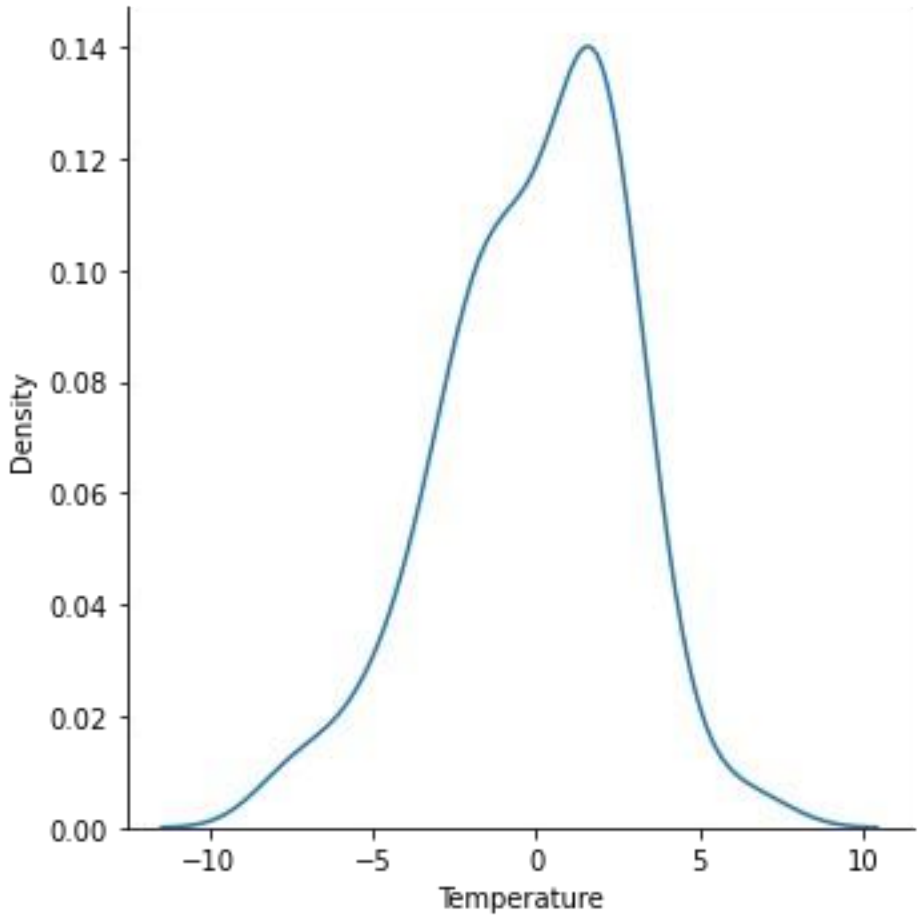
```
el_pred=el_reg.predict(X_test)
```

```
#reation between real and predict data
plt.scatter(y_test,el_pred)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predict Data')
```

```
Text(0, 0.5, 'Test Predict Data')
```

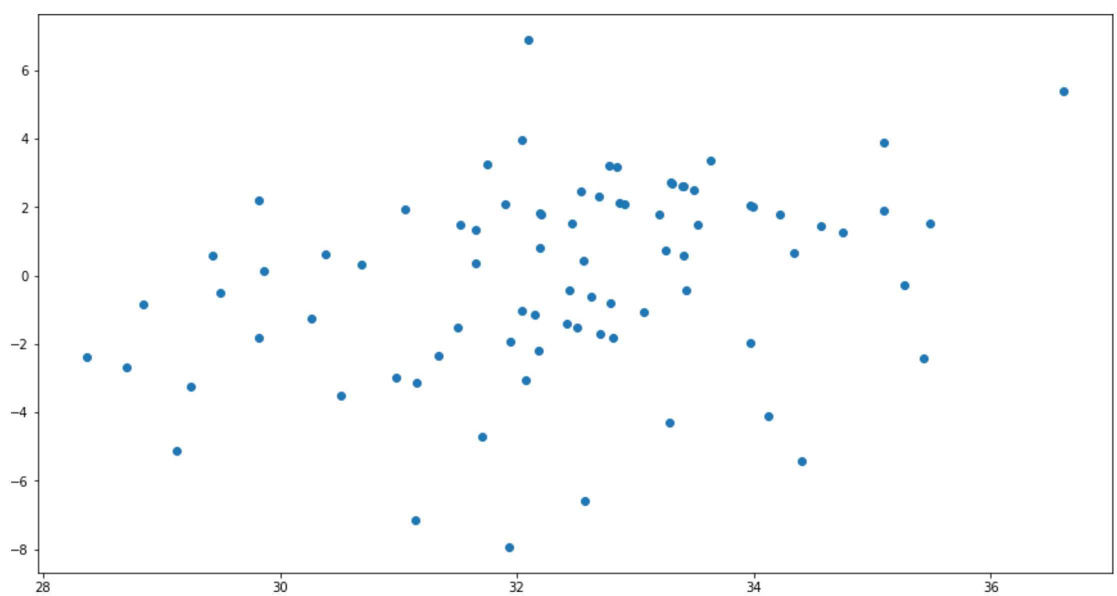



```
#calculate residuals
residual=y_test-el_pred

sns.displot(residual,kind='kde')

<seaborn.axisgrid.FacetGrid at 0x1754e21c6d0>
```




```
plt.scatter(el_pred,residual)
```

```
<matplotlib.collections.PathCollection at 0x1754e61b9a0>
```



Performance metrics

```
from sklearn.metrics import mean_squared_error,mean_absolute_error
print(mean_squared_error(y_test,el_pred))
print(mean_absolute_error(y_test,el_pred))
print(np.sqrt(mean_squared_error(y_test,el_pred)))
```

```
7.915513754032116
2.286670095063569
2.8134522839444274
```

```
from sklearn.metrics import r2_score
score=r2_score(y_test,el_pred)
print(score)
```

```
0.4281942466726337
```

```
## Adjusted R2 need to write
adjR=1-(1-score)*(len(y)-1)/(len(y)-X.shape[1]-1)
print(adjR)
```

```
0.3957336580557963
```