Linear Regression on Algerian Forest Fire

Problem Statement

- To predict the temperature using Algerian Forest Fire Dataset

We have perform

- 1. Data Collection `Line_No:2`
- 2. Exploratory Data Analysis `Line_No:4`
- 3. Data Cleaning `Line_No:23`
- 4. Graphical Analysis `Line_No:35`
- 5. Outliers Handling `Line_No:36`
- 6. Removal of Outliers `Line_No:39`
- 7. Statistical Analysis `Line_No:48`
- 7. Model Building `Line_No:50`
- 8. Linear Regression Model `Line_No:62`
- 9. Ridge Regression Model `Line_No:74`
- 10. Lasso Regression Model `Line_No:84`
- 11. ElasticNet Regression Model `Line_No:94`
- 12. Comparision of all models `Line_No:104`

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- 8. Model Building `Line_No:50`
- 9. Linear Regression Model `Line_No:62`
- 10. Ridge Regression Model `Line_No:74`
- 11. Lasso Regression Model `Line_No:84`
- 12. ElasticNet Regression Model `Line_No:94`
- 13. Comparision of all models `Line_No:104`
- 14. Conclusion `Line_No:105`

Import Required Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.metrics import r2_score

warnings.filterwarnings('ignore')
%matplotlib inline
```

Data Collection

In [2]:
```
df = pd.read_csv(r"G:\Udemy\DATA SCIENCE ineuron\Resources\1_Oct_22\Algerian
```

Data Collection

In [2]:
```
df = pd.read_csv(r"G:\Udemy\DATA SCIENCE ineuron\Resources\1_Oct_22\Algerian
```

In [3]:
```
df.head()
```

Out[3]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not fire
1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not fire
2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire
3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not fire
4	05	06	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not fire

Exploratory Data Analysis

Checking Null Values

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
day            0
month          1
year           1
Temperature    1
 RH            1
 Ws            1
Rain           1
FFMC           1
DMC            1
DC             1
ISI            1
BUI            1
FWI            1
Classes        2
dtype: int64
```

In [5]:
```
df[df['Classes  '].isnull()]
```

Out[5]:

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

In [5]:
```
df[df['Classes  '].isnull()]
```

Out[5]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Cla
122	Sidi-Bel Abbes Region Dataset	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
167	14	07	2012	37	37	18	0.2	88.9	12.9	14.69	12.5	10.4	fire	

Drop rows which have null

In [6]:
```
# one way of doing this
df1 = df.dropna()
```

In [7]:
```
# Another way of removing null values
df.drop([122,123,167],axis = 0, inplace = True)
df = df.reset_index()
df.head()
```

Out[7]:

	index	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Class
0	0	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not f
1	1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not f
2	2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not f
3	3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not f
4	4	05	06	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not f

In [8]:
```
df.columns
```

Out[8]:
```
Index(['index', 'day', 'month', 'year', 'Temperature', ' RH', ' Ws', 'Rain ',
       'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes  '],
      dtype='object')
```

- Some columns have extra spaces, we have to remove them

Columns name having extra spaces

Columns name having extra spaces

In [9]:
```
[x for x in df.columns if " " in x]
```

Out[9]:
```
[' RH', ' Ws', 'Rain ', 'Classes  ']
```

Removed extra space in column names

In [10]:
```
df.columns = df.columns.str.strip()
df.columns
```

Out[10]:
```
Index(['index', 'day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain',
       'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes'],
      dtype='object')
```

Function to remove extra space in data

In [11]:
```
def Remove_Extra_Space2(x):
    return x.replace(" ","")
```

Remove extra space in the data

In [12]:
```
df['Classes'] = df['Classes'].apply(Remove_Extra_Space2)
```

In [13]:
```
df.head()
```

Out[13]:

	index	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Class
0	0	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	notf
1	1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	notf
2	2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	notf
3	3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	notf
4	4	05	06	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	notf

Drop extra index column, which was created for reset_index

In [14]:
```
df.drop(['index'],axis = 1, inplace = True)
```

In [14]:
```
df.drop(['index'],axis = 1, inplace = True)
```

In [15]:
```
df.head(2)
```

Out[15]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	notfire
1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	notfire

Create one region,just to identify the two region i.e.,Sidi-Bel Abbes Region and Bejaia Region

In [16]:
```
df.loc[:122, 'Region'] = 0
df.loc[122:, 'Region'] = 1
```

In [17]:
```
df[120:124]
```

Out[17]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Re
120	29	09	2012	26	80	16	1.8	47.4	2.9	7.7	0.3	3	0.1	notfire	
121	30	09	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1	notfire	
122	01	06	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	notfire	
123	02	06	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2	notfire	

Check null values in all the features

In [18]:
```
df.isna().sum()
```

Out[18]:
```
day            0
month          0
year           0
Temperature    0
RH             0
Ws             0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
```

Map `Classes` feature as 1 and 0 for fire and not fire respectively

In [19]:
```
df['Classes'] = df['Classes'].map({'notfire' : 0, 'fire' : 1})
```

In [20]:
```
df[235:240]
```

Out[20]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
235	23	09	2012	35	56	14	0	89	29.4	115.6	7.5	36	15.2	1
236	24	09	2012	26	49	6	2	61.3	11.9	28.1	0.6	11.9	0.4	0
237	25	09	2012	28	70	15	0	79.9	13.8	36.1	2.4	14.1	3	0
238	26	09	2012	30	65	14	0	85.4	16	44.5	4.5	16.9	6.5	1
239	27	09	2012	28	87	15	4.4	41.1	6.5	8	0.1	6.2	0	0

Check duplictes values in all the column

In [21]:
```
df.duplicated().sum()
```

Out[21]:
```
0
```

Check data types of all the features

In [22]:
```
df.dtypes
```

Out[22]:
```
day             object
month           object
year            object
Temperature     object
RH              object
Ws              object
Rain            object
FFMC            object
DMC             object
DC              object
ISI             object
BUI             object
FWI             object
Classes          int64
Region         float64
dtype: object
```

Convert features to its logical datatypes

In [23]:
```
convert_features = {
    'Temperature' : 'int64','RH':'int64', 'Ws' :'int64', 'DMC': 'float64', '
    'BUI': 'float64', 'FWI' : 'float64', 'Region' : 'object', 'Rain' : 'floa
    'day' : 'object', 'month' : 'object', 'year' : 'object'
}

df = df.astype(convert_features)
```

In [24]:
```
df.head()
```

Out[24]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Reg
0	01	06	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0	
1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0	
2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0	
3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0	
4	05	06	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0	

Converted Datatypes

In [25]:
```
df.dtypes
```

Out[25]:
```
day             object
month           object
year            object
Temperature      int64
RH               int64
Ws               int64
Rain           float64
FFMC           float64
DMC            float64
DC             float64
ISI            float64
BUI            float64
FWI            float64
Classes         object
Region          object
dtype: object
```

Check unique values in all features

In [26]:
```
1 df.nunique()
```

Out[26]:
```
day             31
month            4
year             1
Temperature     19
RH              62
Ws              18
Rain            39
FFMC           173
DMC            165
DC             197
ISI            106
BUI            173
FWI            125
Classes          2
Region           2
dtype: int64
```

Check Statistics of dataset

In [27]:
```
1 df.describe()
```

Out[27]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	
count	243.000000	243.000000	243.000000	243.000000	243.000000	243.000000	243.000000	243.0
mean	32.152263	62.041152	15.493827	0.762963	77.842387	14.680658	49.430864	4.7
std	3.628039	14.828160	2.811385	2.003207	14.349641	12.393040	47.665606	4.1
min	22.000000	21.000000	6.000000	0.000000	28.600000	0.700000	6.900000	0.0
25%	30.000000	52.500000	14.000000	0.000000	71.850000	5.800000	12.350000	1.4
50%	32.000000	63.000000	15.000000	0.000000	83.300000	11.300000	33.100000	3.5
75%	35.000000	73.500000	17.000000	0.500000	88.300000	20.800000	69.100000	7.2
max	42.000000	90.000000	29.000000	16.800000	96.000000	65.900000	220.400000	19.0

Segregate categorical feature from the dataset

In [28]:
```
1 categorical_feature = [x for x in df.columns if df[x].dtypes == 'O']
2 categorical_feature
```

Segregate categorical feature from the dataset

In [28]:
```
categorical_feature = [x for x in df.columns if df[x].dtypes == 'O']
categorical_feature
```

Out[28]:
```
['day', 'month', 'year', 'Classes', 'Region']
```

Check Value_counts() of Classes and Region feature

In [31]:
```
feature = ['Region','Classes']
for fea in categorical_feature:
    if fea in feature:
        print(df.groupby(fea)[fea].value_counts())
```

```
Classes  Classes
0        0          106
1        1          137
Name: Classes, dtype: int64
Region  Region
0.0     0.0       122
1.0     1.0       121
Name: Region, dtype: int64
```

Segregate numerical feature from the dataset

In [32]:
```
numerical_features = [x for x in df.columns if df[x].dtype != 'O']
numerical_features
```

Out[32]:
```
['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI']
```

Segregate discrete feature from the numerical feature

In [33]:
```
## Discrete features are those whose data is whole number means there is no
discrete_features = [x for x in numerical_features if df[x].dtypes == 'int64
discrete_features
```

Out[33]:
```
['Temperature', 'RH', 'Ws']
```

Segregate Continuous feature from the numerical feature

In [34]:
```
## Continuous features are those features where data has decimal value
continuous_feature = [fea for fea in numerical_features if fea not in discre
```

Segregate Continuous feature from the numerical feature

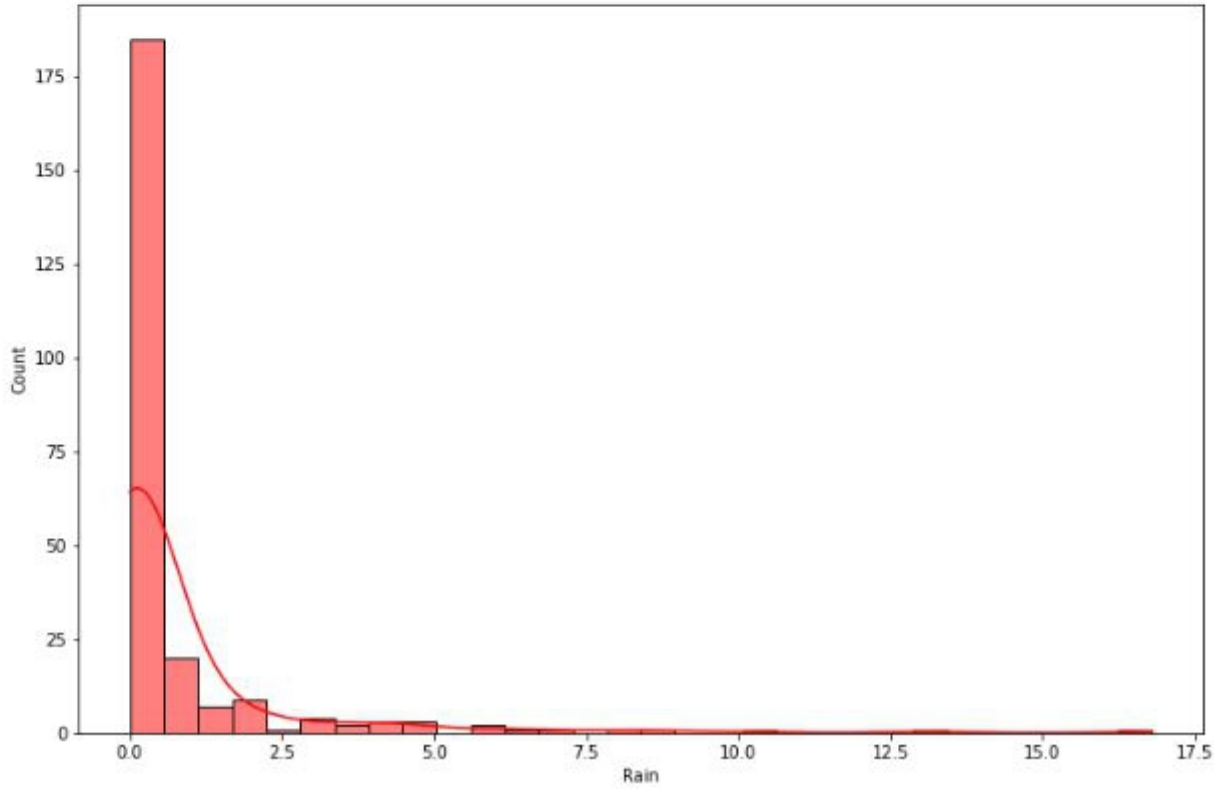
In [34]:
```
## Continuous features are those features where data has decimal value
continuous_feature = [fea for fea in numerical_features if fea not in discre
continuous_feature
```

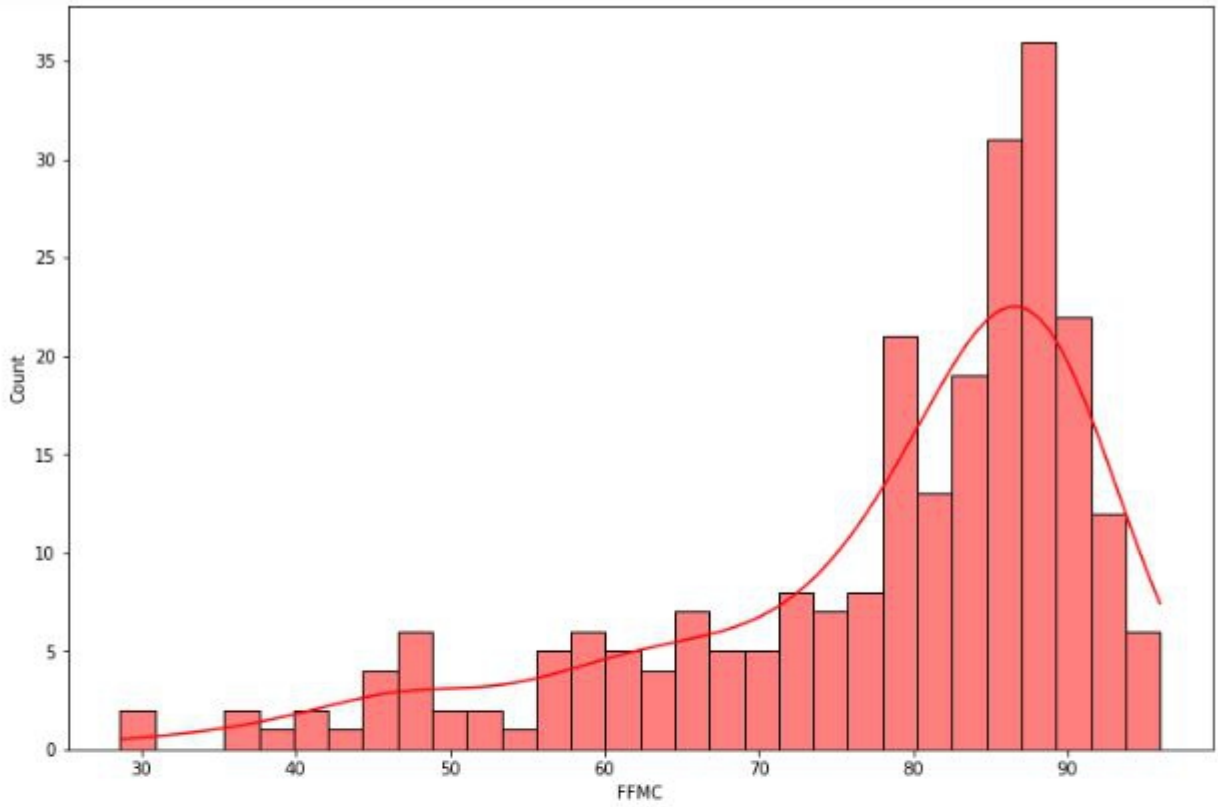
Out[34]: ['Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI']

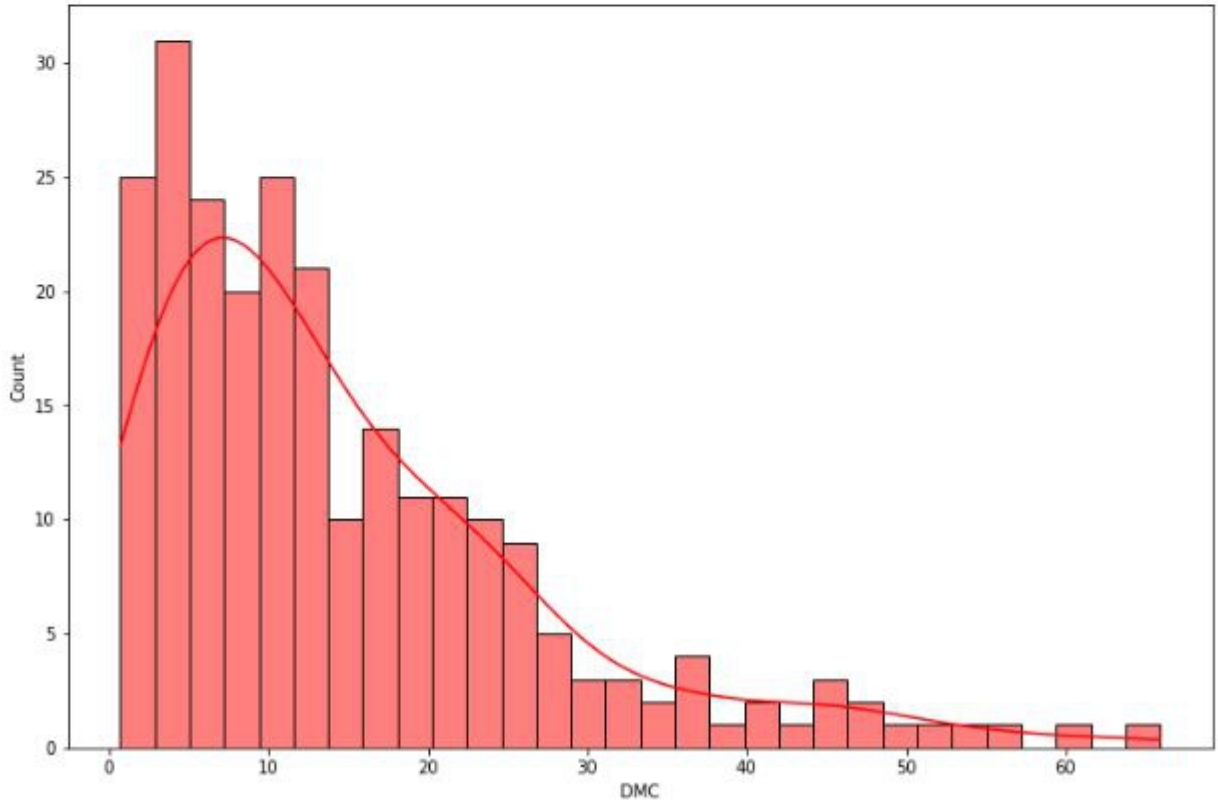
Graphical Analysis

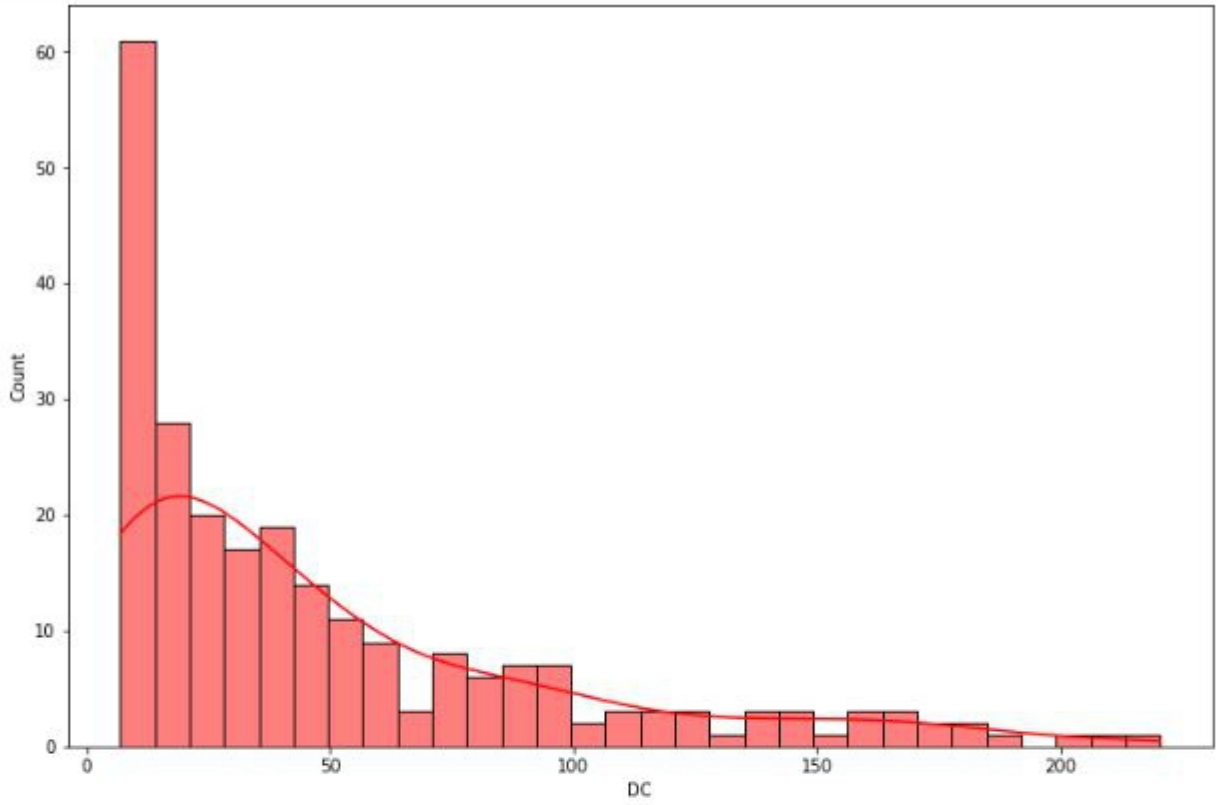
Checking distribution of Continuous numerical features

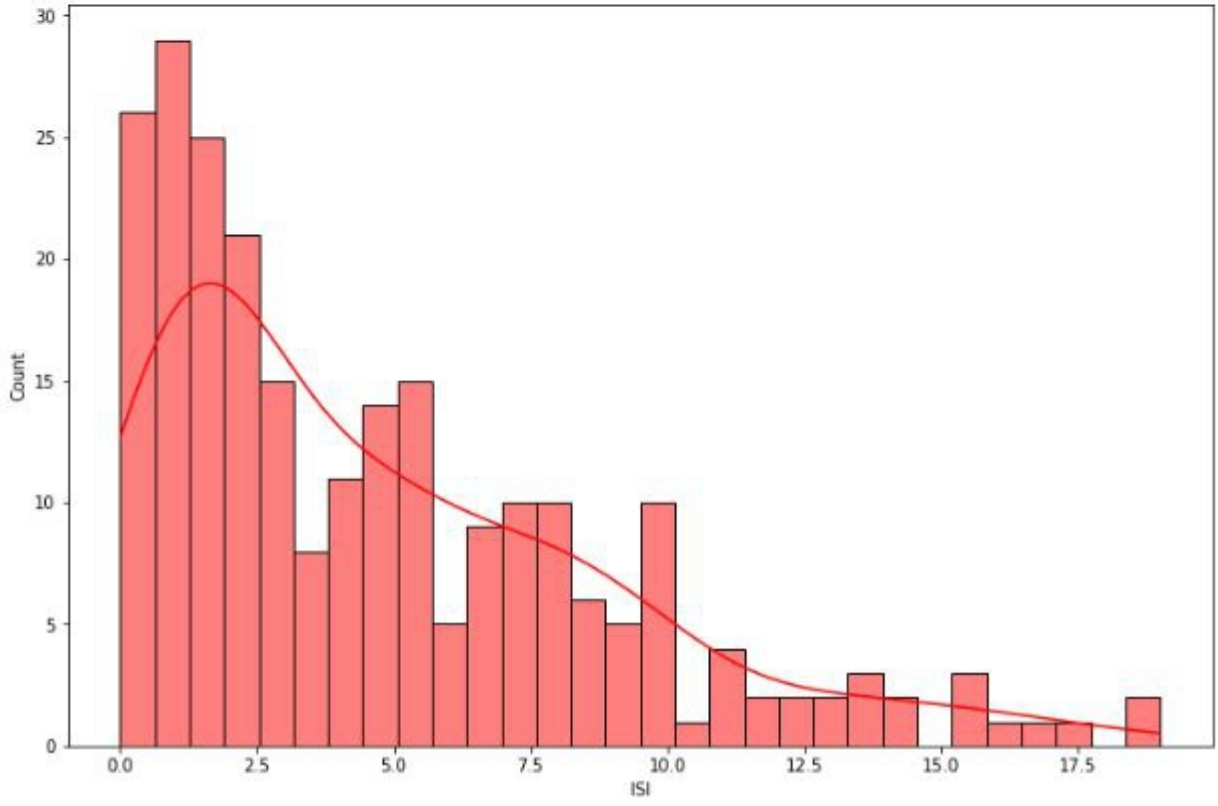
In [35]:
```
for feature in continuous_feature:
    plt.figure(figsize = (12,8))
    sns.histplot(data = df, x = feature,kde = True, bins = 30,color = "red")
    plt.show()
```

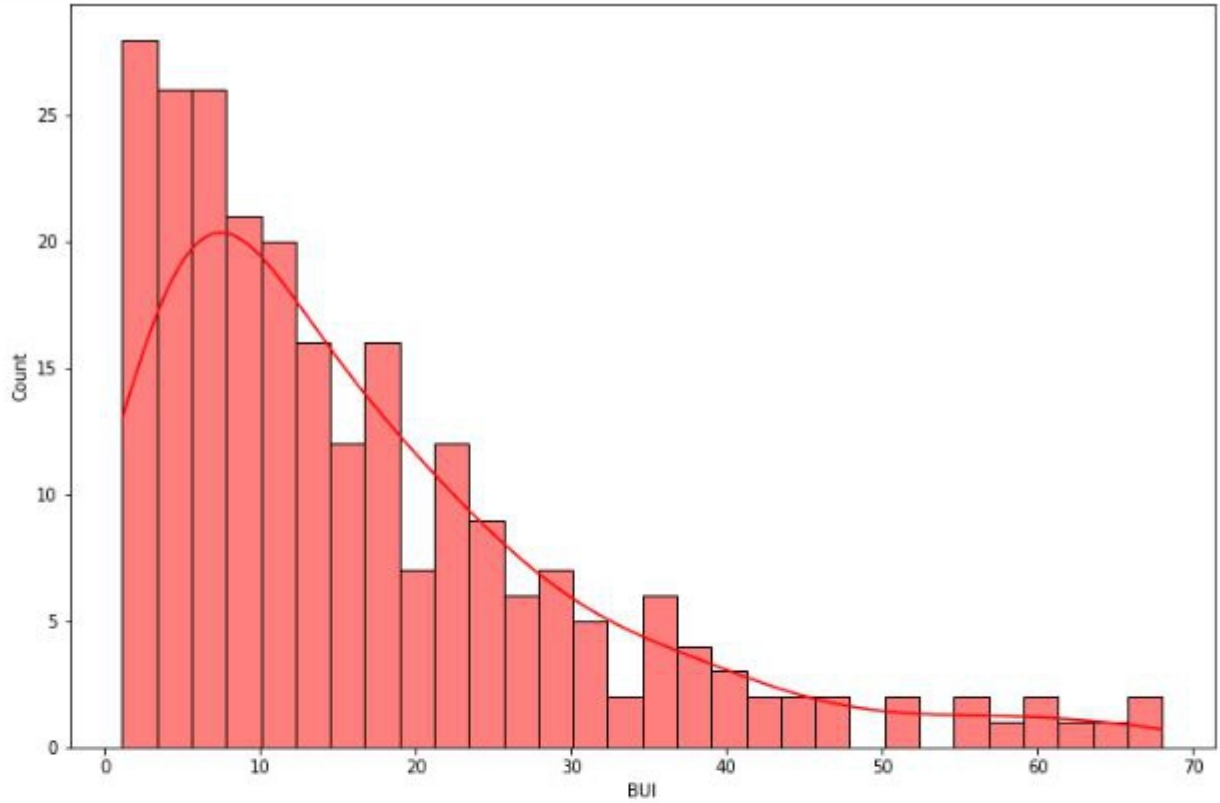


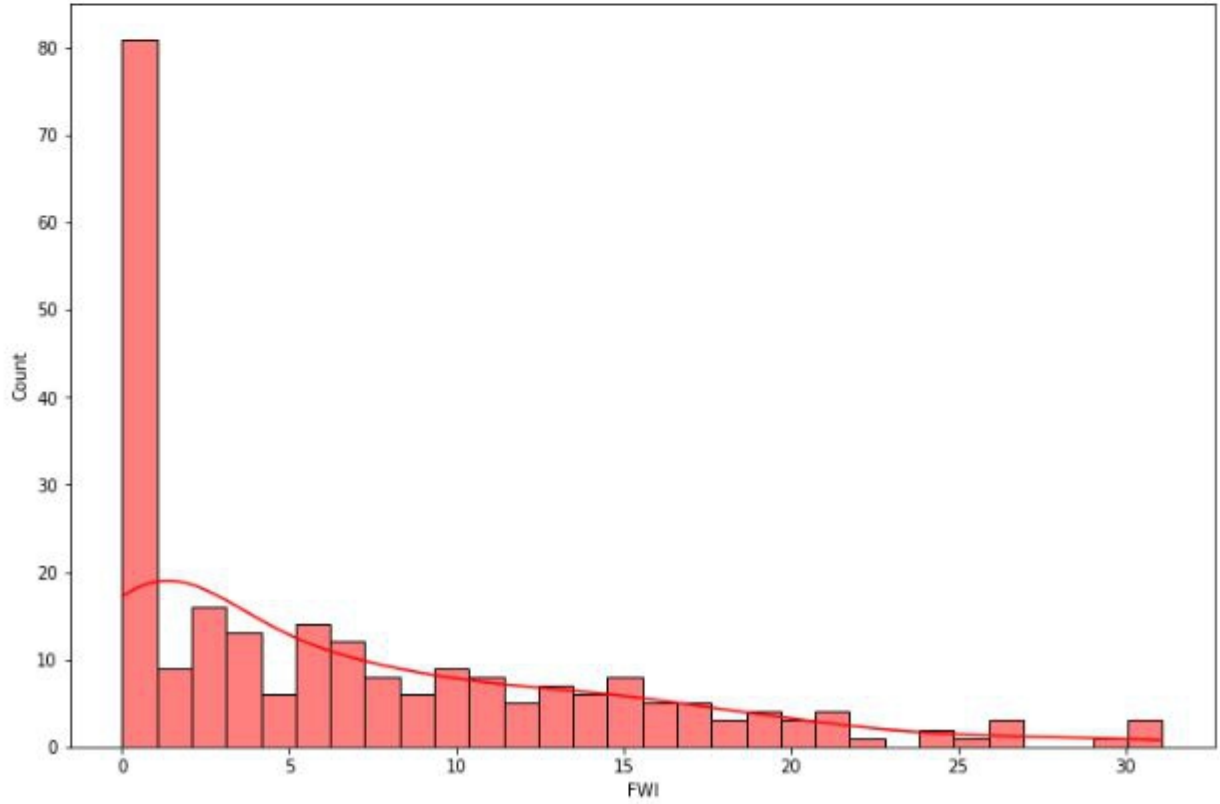

Count
FFMC
0
5
10
15
20
25
30
35
30
40
50
60
70
80
90


Count
DMC
0
5
10
15
20
25
30
0
10
20
30
40
50
60


Count
DC
0
10
20
30
40
50
60
0
50
100
150
200


Count
ISI
0
5
10
15
20
25
30
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


Count
BUI
0
5
10
15
20
25
0
10
20
30
40
50
60
70

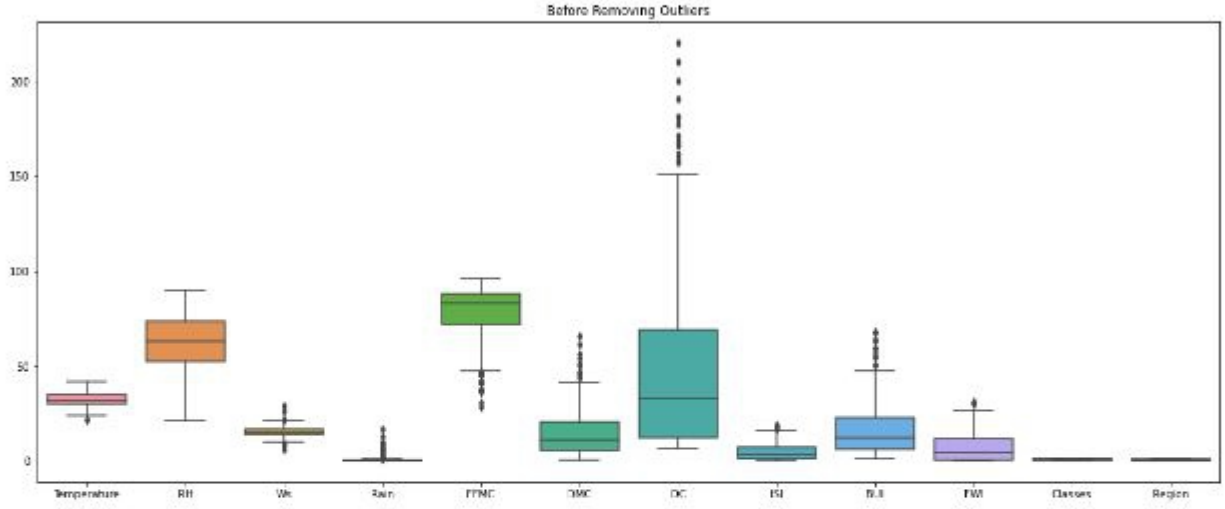

Count
FWI
0
10
20
30
40
50
60
70
80
0
5
10
15
20
25
30

Outliers Handing

Before Removing Outliers

In [36]:
```
plt.figure(figsize=(20,8))
sns.boxplot(data = df)
plt.title("Before Removing Outliers")
```

Out[36]:
```
Text(0.5, 1.0, 'Before Removing Outliers')
```



Function to find upper and lower boundaries

In [37]:
```
def find_boundaries(df, variable):
    IQR = df[variable].quantile(0.75) - df[variable].quantile(0.25)
    lower_boundary = df[variable].quantile(0.25) - (IQR*1.5)
    upper_boundary = df[variable].quantile(0.75) + (IQR*1.5)
    return upper_boundary,lower_boundary
```

In [38]:
```
## Upper and Lower boundaries of every feature
for fea in numerical_features:
    print(fea,"---->",find_boundaries(df,fea))
```

```
Temperature ----> (42.5, 22.5)
RH ----> (105.0, 21.0)
Ws ----> (21.5, 9.5)
Rain ----> (1.25, -0.75)
FFMC ----> (112.975, 47.17499999999999)
DMC ----> (43.29999999999999, -16.699999999999992)
DC ----> (154.22499999999997, -72.77499999999999)
ISI ----> (16.025, -7.374999999999998)
```

In [38]:
```
## Upper and Lower boundaries of every feature
for fea in numerical_features:
    print(fea,"---->",find_boundaries(df,fea))
```

```
Temperature ----> (42.5, 22.5)
RH ----> (105.0, 21.0)
Ws ----> (21.5, 9.5)
Rain ----> (1.25, -0.75)
FFMC ----> (112.975, 47.17499999999999)
DMC ----> (43.29999999999999, -16.699999999999992)
DC ----> (154.22499999999997, -72.77499999999999)
ISI ----> (16.025, -7.374999999999998)
BUI ----> (47.625, -18.974999999999998)
FWI ----> (27.575, -15.425)
```

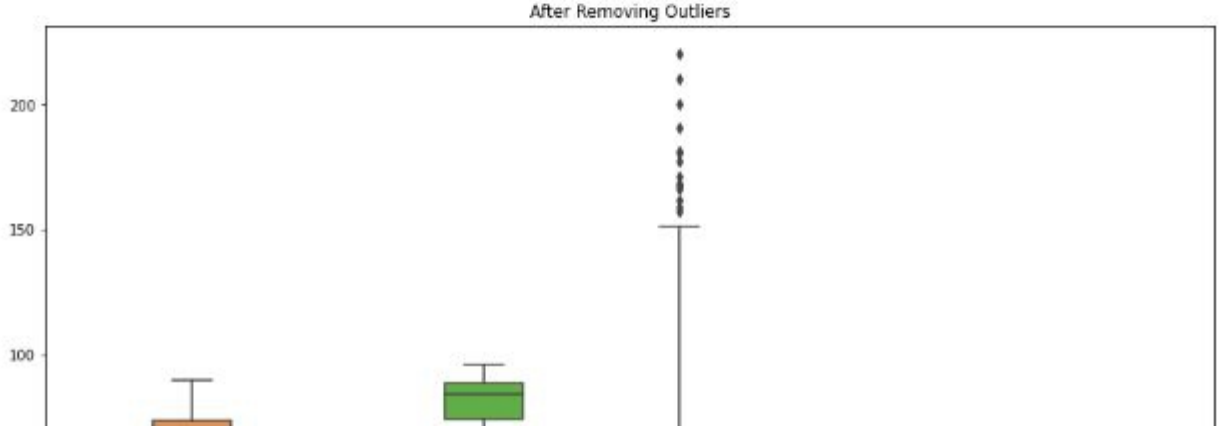
Deletion of outliers

In [39]:
```
outliers_columns = ['Temperature', 'Ws', 'Rain', 'FFMC','DMC','ISI','BUI','F
for i in outliers_columns:
    upper_boundary, lower_boundary = find_boundaries(df,i)
    outliers = np.where(df[i] > upper_boundary, True, np.where (df[i] < lowe
    outliers_df = df.loc[outliers, i]
    df_trimed = df.loc[~outliers,i]
    df[i] = df_trimed
```

After Removal of outliers

In [40]:
```
plt.figure(figsize=(15, 8))
sns.boxplot(data=df)
plt.title("After Removing Outliers")
```

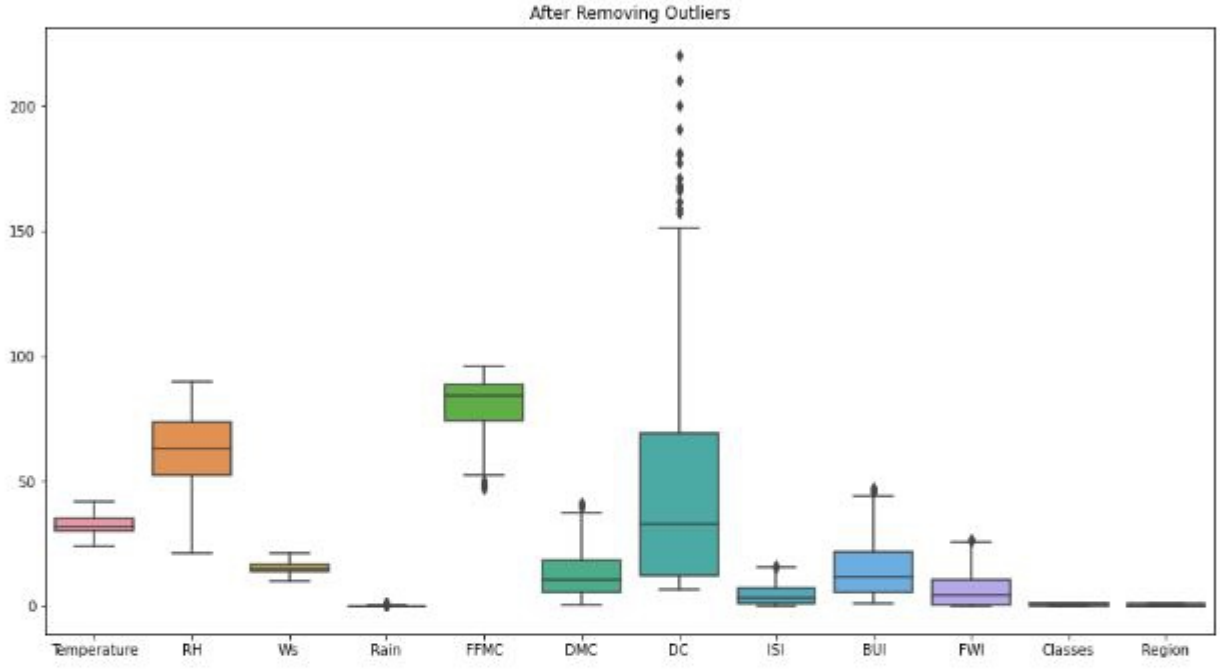
Out[40]: Text(0.5, 1.0, 'After Removing Outliers')



After Removal of outliers

In [40]:
```
plt.figure(figsize=(15, 8))
sns.boxplot(data=df)
plt.title("After Removing Outliers")
```

Out[40]:
```
Text(0.5, 1.0, 'After Removing Outliers')
```



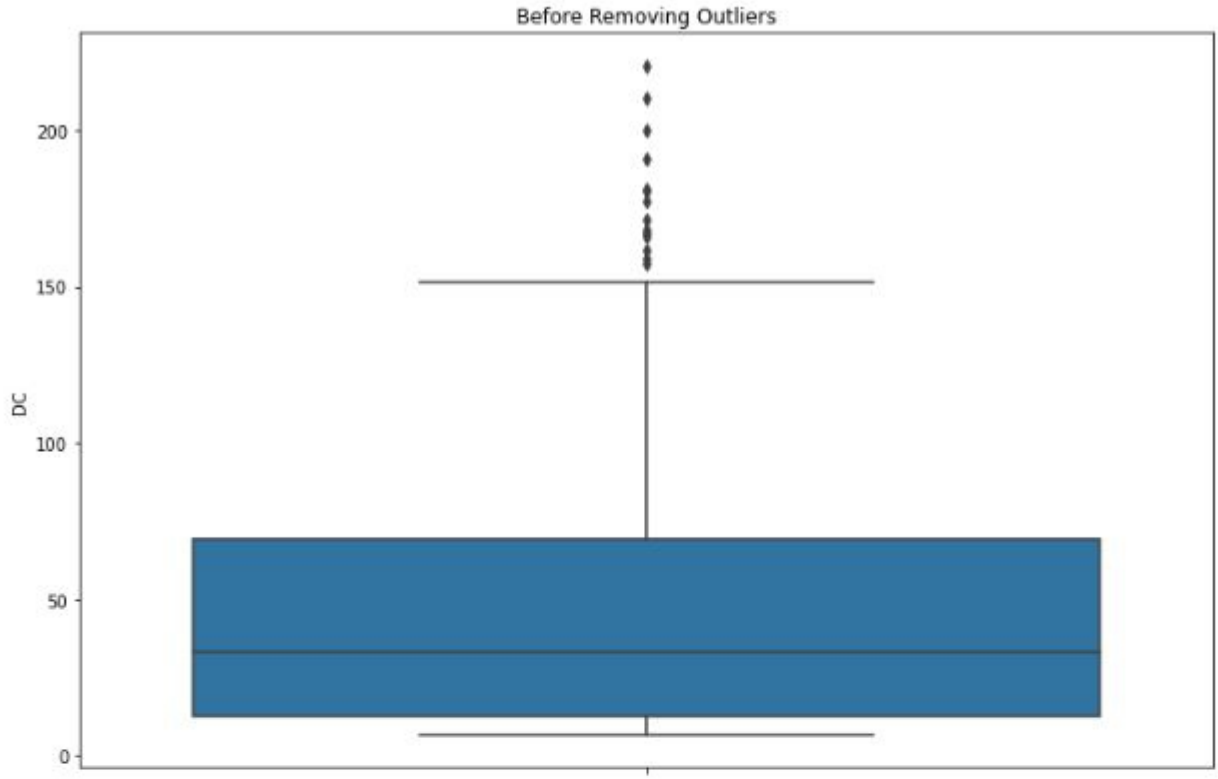
- Still there are many outliers in DC feature

Outliers handling in DC Feature

In [41]:
```
plt.figure(figsize = (12,8))
sns.boxplot(data = df, y = 'DC')
plt.title("Before Removing Outliers")
```

Out[41]:
```
Text(0.5, 1.0, 'Before Removing Outliers')
```

Out[41]: Text(0.5, 1.0, 'Before Removing Outliers')



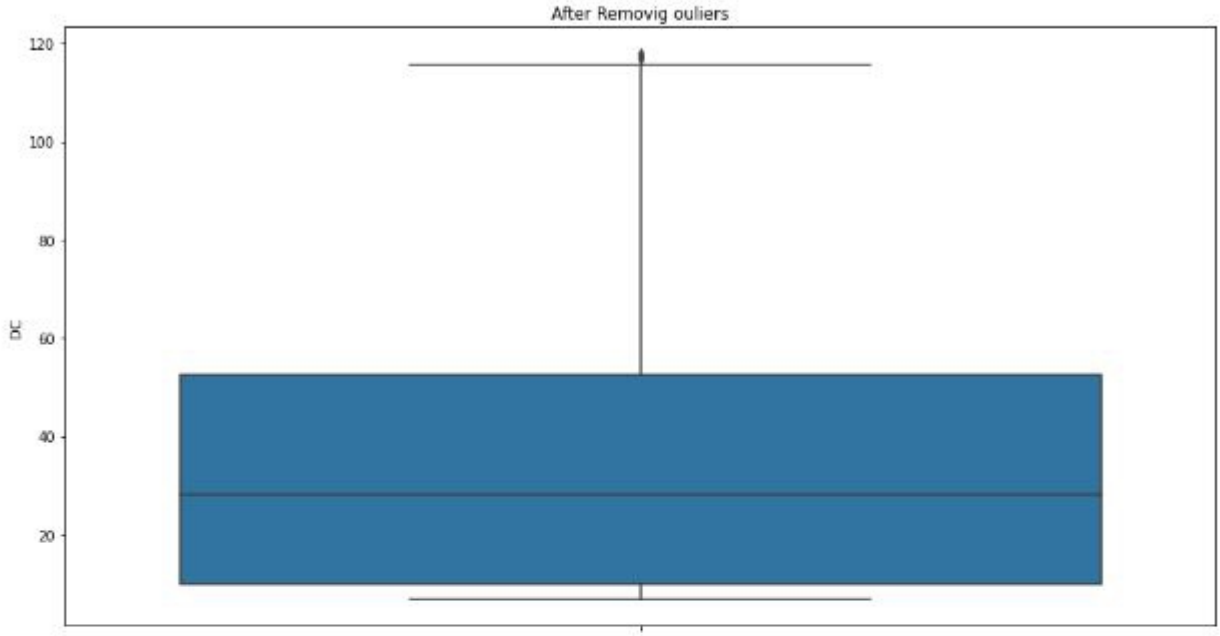
In [42]:
```
# These are the outliers of DC Feature
DC_outliers = df[df['DC'] >= 154]['DC']
DC_outliers
```

Out[42]:
```
83     161.5
84     171.3
85     181.3
86     190.6
87     200.2
88     210.4
89     220.4
90     180.4
206    157.5
207    167.2
208    177.3
209    166.0
211    159.1
212    168.2
Name: DC, dtype: float64
```

In [43]:
```
df["DC"] = df[df['DC'] < 118]['DC']
```

In [44]:
```
plt.figure(figsize = (15,8))
sns.boxplot(data = df, y ='DC')
plt.title("After Removig ouliers")
```

Out[44]: Text(0.5, 1.0, 'After Removig ouliers')



Check null value in each column after removing the outliers

In [45]:
```
df.isna().sum()
```

Out[45]:
```
day             0
month           0
year            0
Temperature     2
RH              0
Ws              8
Rain           35
FFMC           13
DMC            12
DC             25
ISI             4
BUI            11
FWI             4
Classes         0
Region          0
dtype: int64
```

Fill all the null values with mean

In [46]:
```
df.fillna(df.mean().round(1), inplace = True)
```

Check null value of each column

In [47]:
```
df.isnull().sum()
```

Out[47]:
```
day            0
month          0
year           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
```

Statistical Analysis

Correlation of numerical variable

In [48]:
```
data = round(df.corr(),2)
data
```

Out[48]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Regi
Temperature	1.00	-0.64	-0.22	-0.13	0.54	0.55	0.37	0.58	0.49	0.58	0.51	0.
RH	-0.64	1.00	0.16	0.14	-0.54	-0.45	-0.28	-0.64	-0.38	-0.54	-0.43	-0.
Ws	-0.22	0.16	1.00	0.06	-0.11	-0.01	0.00	0.05	0.06	0.05	-0.02	-0.
Rain	-0.13	0.14	0.06	1.00	-0.54	-0.31	-0.34	-0.46	-0.32	-0.44	-0.52	-0.
FFMC	0.54	-0.54	-0.11	-0.54	1.00	0.60	0.52	0.75	0.59	0.71	0.77	0.
DMC	0.55	-0.45	-0.01	-0.31	0.60	1.00	0.68	0.64	0.92	0.75	0.62	0.
DC	0.37	-0.28	0.00	-0.34	0.52	0.68	1.00	0.51	0.76	0.58	0.55	-0.

FWI	0.58	-0.54	0.05	-0.44	0.71	0.75	0.58	0.89	0.75	1.00	0.74	0.
Classes	0.51	-0.43	-0.02	-0.52	0.77	0.62	0.55	0.75	0.61	0.74	1.00	0.
Region	0.25	-0.40	-0.15	-0.05	0.18	0.21	-0.03	0.23	0.13	0.19	0.16	1.

In [49]:
```
sns.set(rc={'figure.figsize':(15,10)})
sns.heatmap(data = data, annot = True)
```

Out[49]: <AxesSubplot:>

Observations

- 1. BUI and DMC are 92% Positively correlated
- 2. FWI and ISI are 89% Positively Correlated
- 3. No features are more then 95% Postively correlated, therefore we cannot drop any feature

Model Building

Independent Variable vs target variable distribution

Convert `day` , `month` , `year` feature into one `Date` feature

In [50]:
```
df['Date'] = pd.to_datetime(df[['day','month','year']])
```

In [51]:
```
df.head()
```

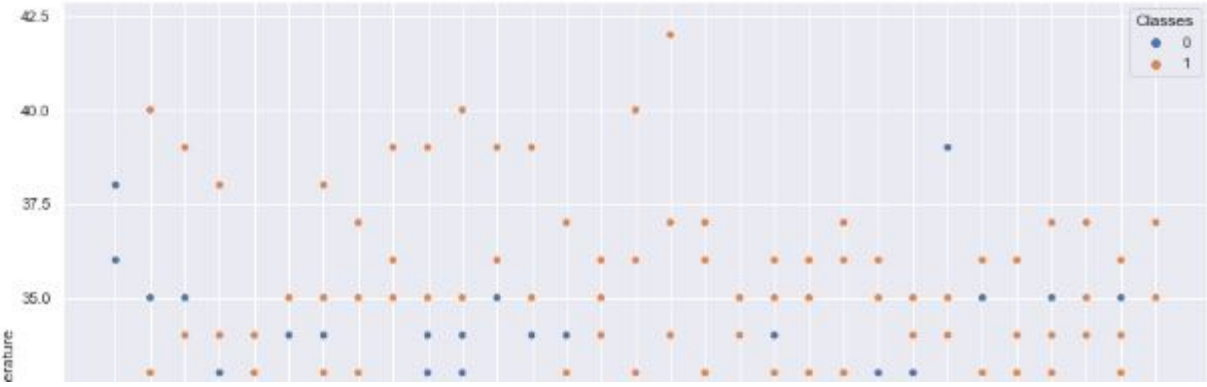
Out[51]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Re
0	01	06	2012	29.0	57	18.0	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0	
1	02	06	2012	29.0	61	13.0	0.2	64.4	4.1	7.6	1.0	3.9	0.4	0	
2	03	06	2012	26.0	82	15.5	0.2	80.0	2.5	7.1	0.3	2.7	0.1	0	
3	04	06	2012	25.0	89	13.0	0.2	80.0	1.3	6.9	0.0	1.7	0.0	0	
4	05	06	2012	27.0	77	16.0	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0	

Scatterplot day vs temperature

In [52]:
```
sns.scatterplot(data =df, x ='day', y='Temperature', hue = 'Classes')
```

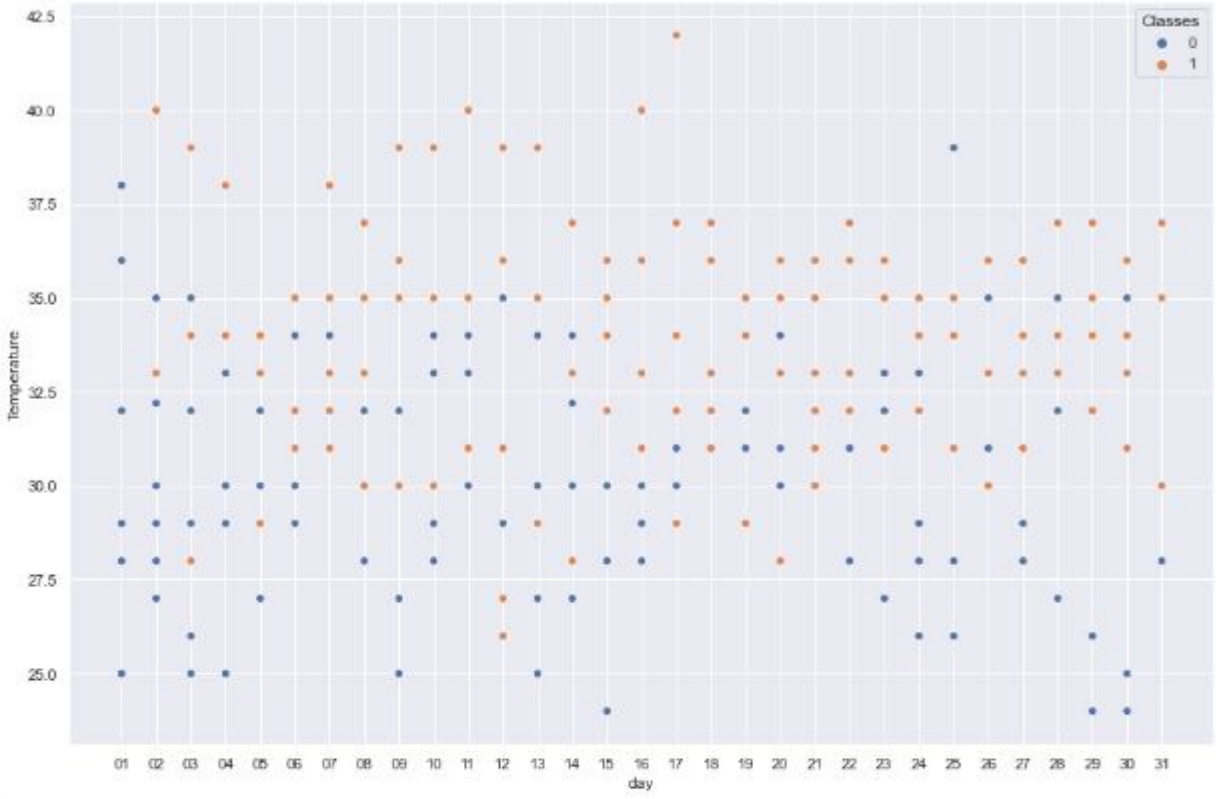
Out[52]: `<AxesSubplot:xlabel='day', ylabel='Temperature'>`



Scatterplot day vs temperature

In [52]:
```
1 sns.scatterplot(data =df, x ='day', y='Temperature', hue = 'Classes')
```

Out[52]:
```
<AxesSubplot:xlabel='day', ylabel='Temperature'>
```



Regression Plot

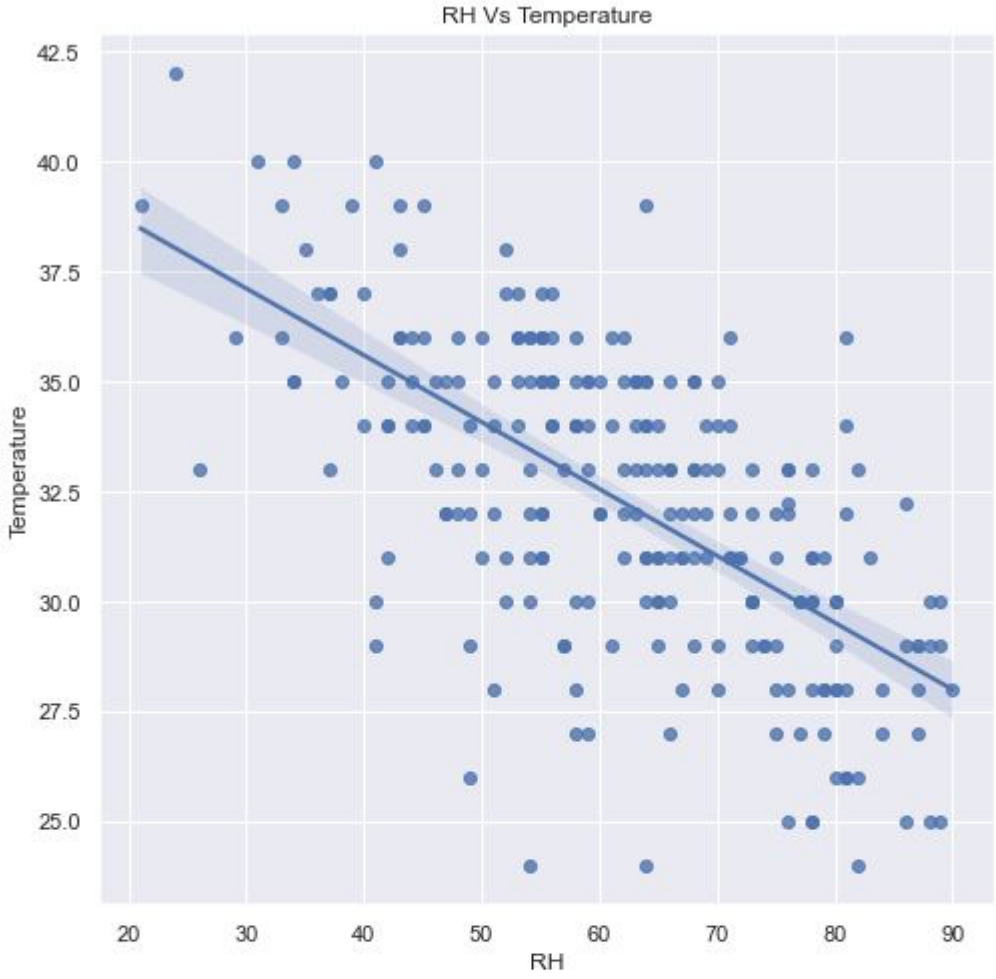
In [53]:
```
1 consider_feature = [fea for fea in df.columns if fea not in ['Temperature','
2 consider_feature
```

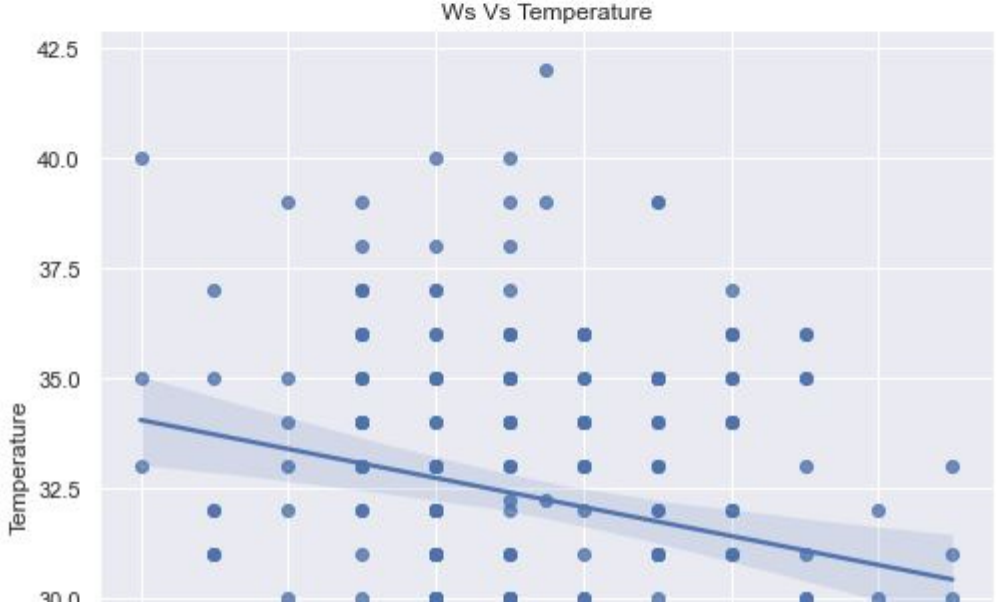
Out[53]:
```
['RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI']
```

In [54]:
```
1 for feature in consider_feature:
2     sns.set(rc={'figure.figsize':(8,8)})
3     sns.regplot(x = df[feature], y = df['Temperature'])
4     plt.xlabel(feature)
5     plt.ylabel("Temperature")
6     plt.title("{} Vs Temperature".format(feature))
7     plt.show()
```

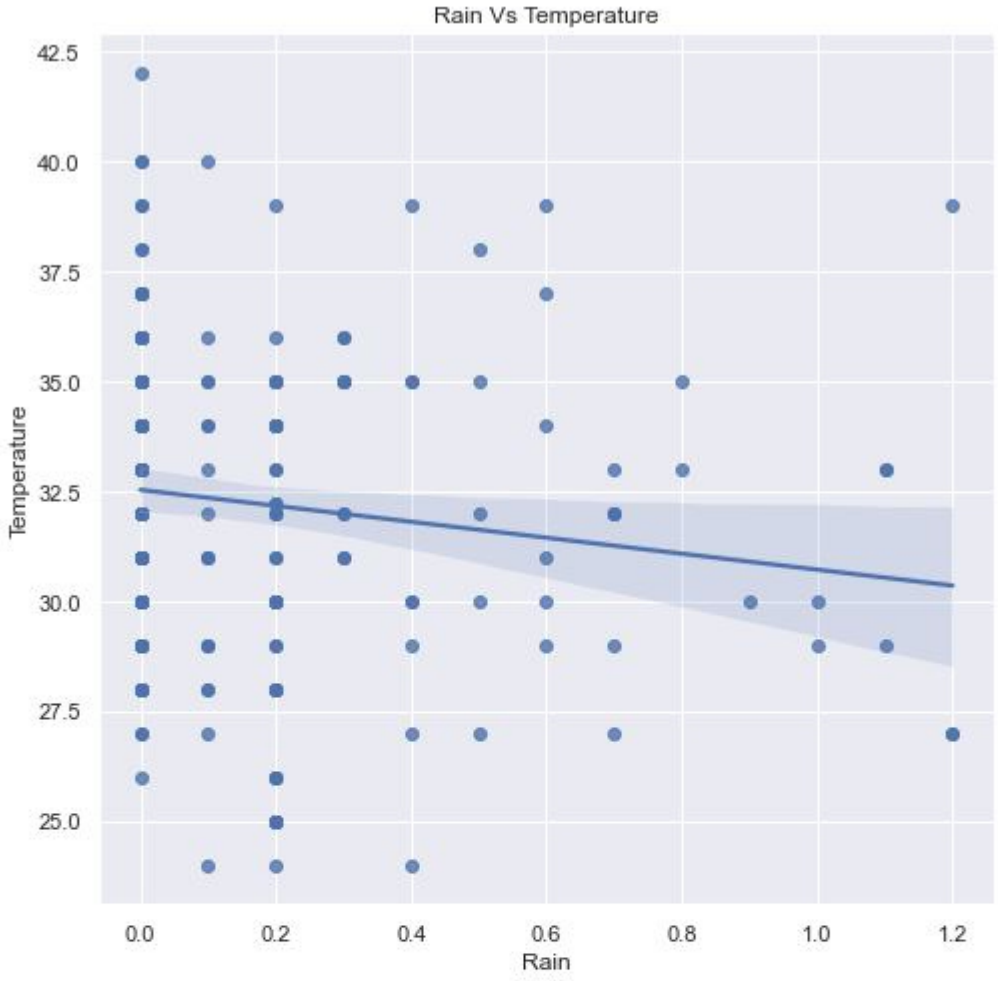
RH Vs Temperature

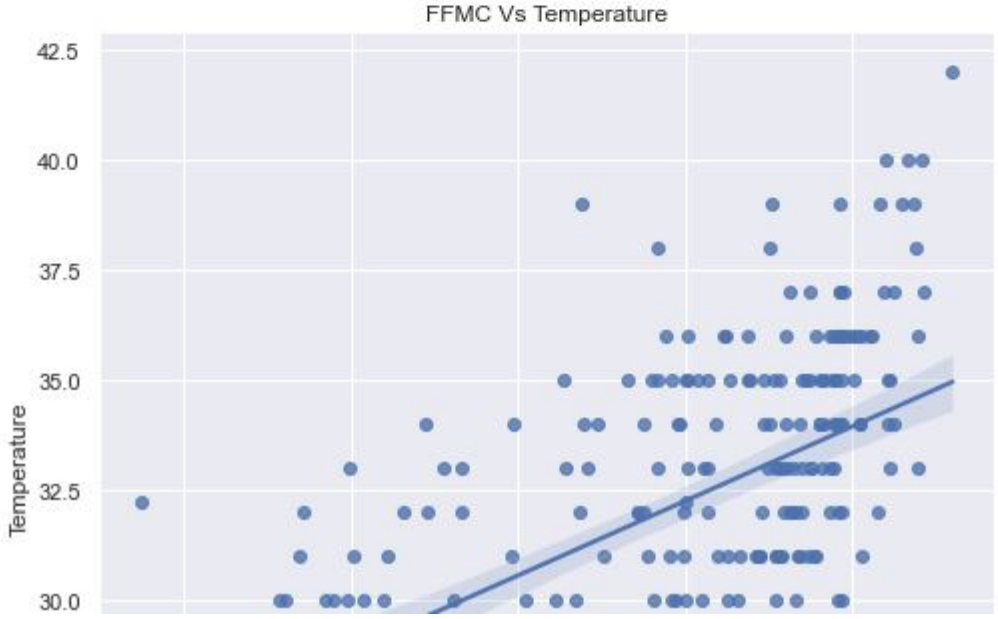
```
7    plt.show()
```

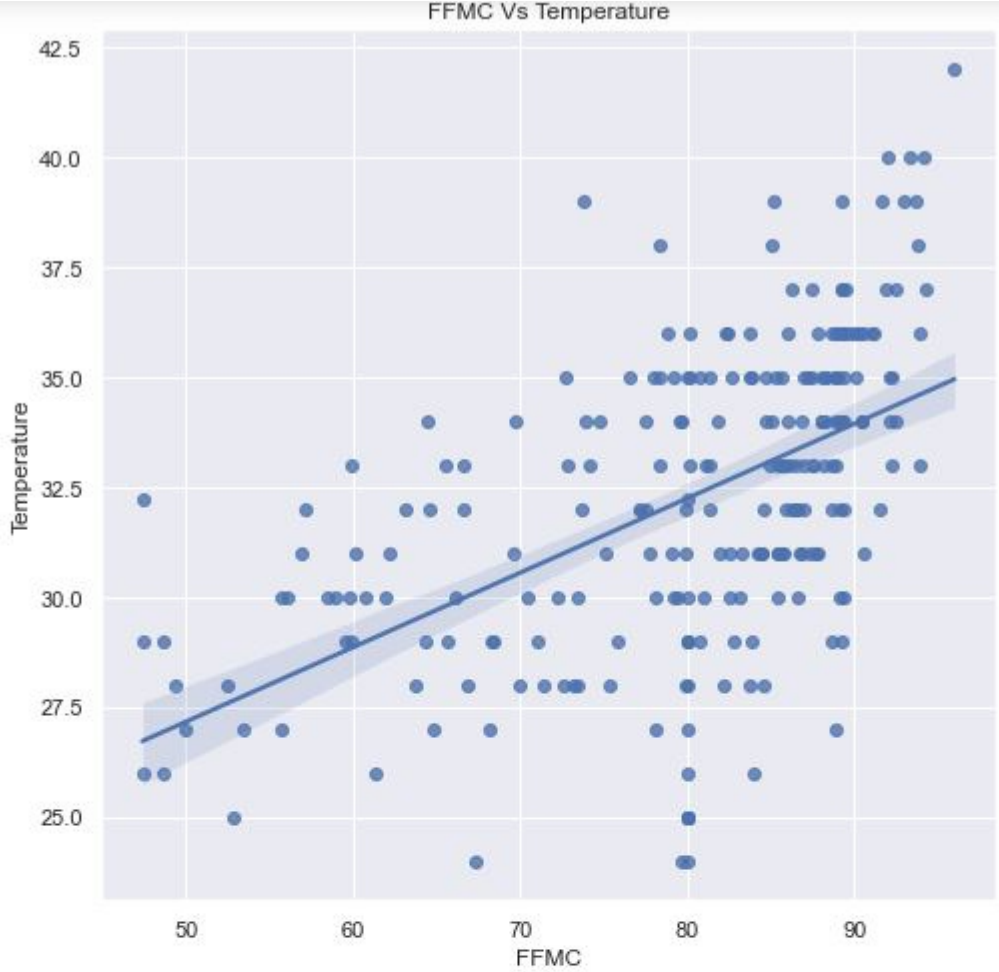

RH Vs Temperature
Temperature
RH
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
20
30
40
50
60
70
80
90

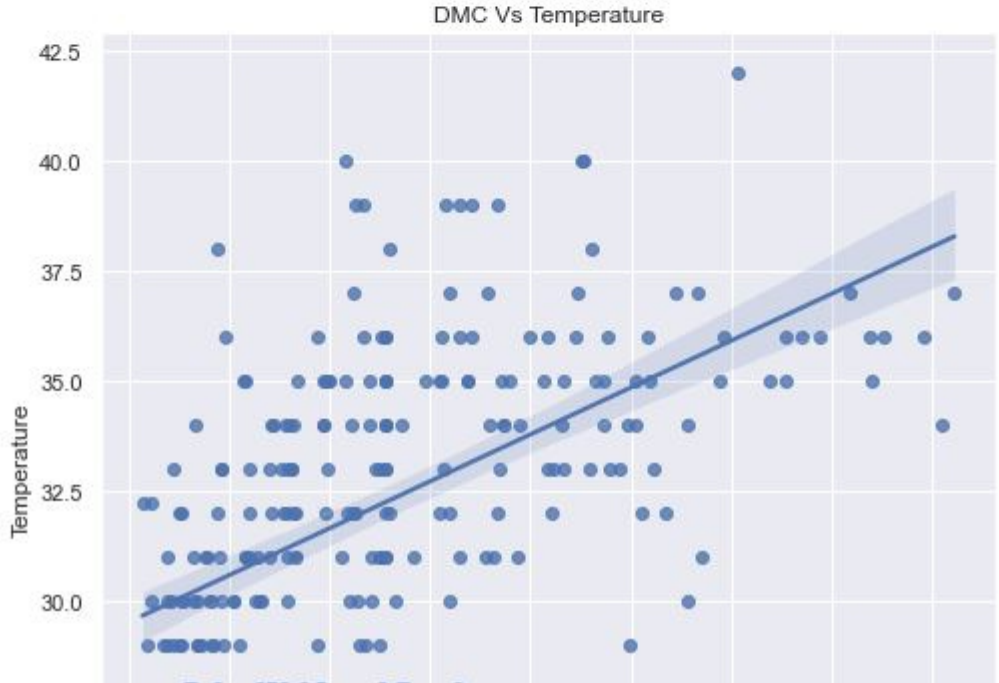

Ws Vs Temperature
Temperature
42.5
40.0
37.5
35.0
32.5
30.0

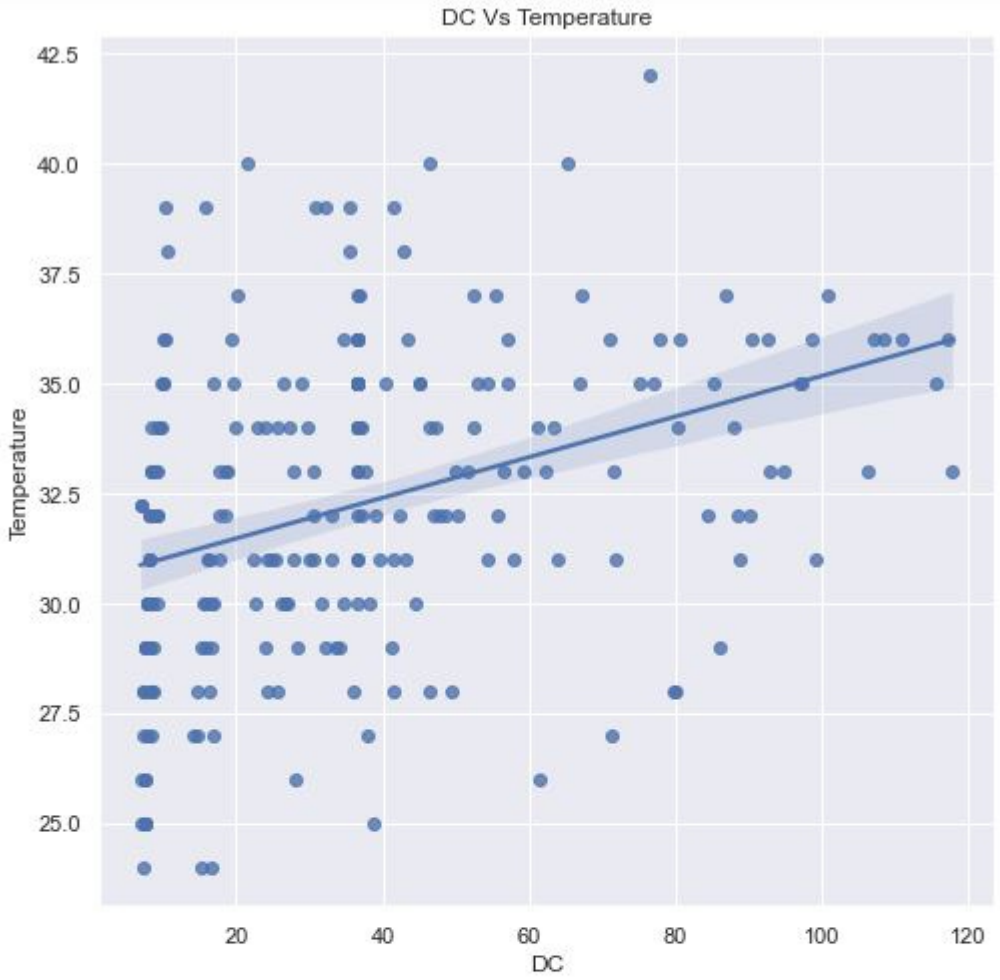
Vvs

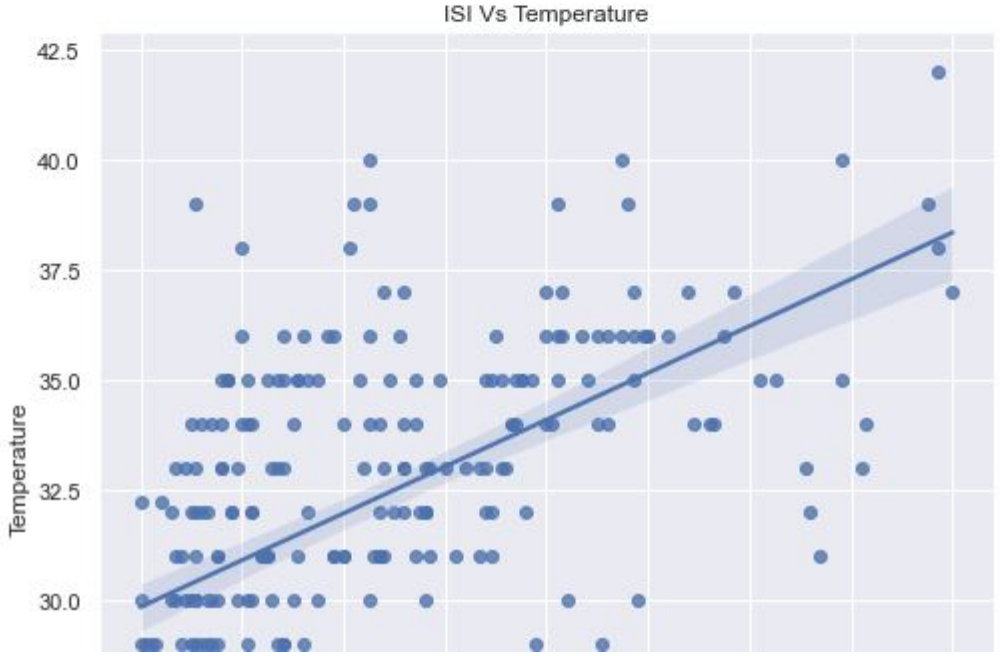

Rain Vs Temperature
Temperature
Rain
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
0.0
0.2
0.4
0.6
0.8
1.0
1.2

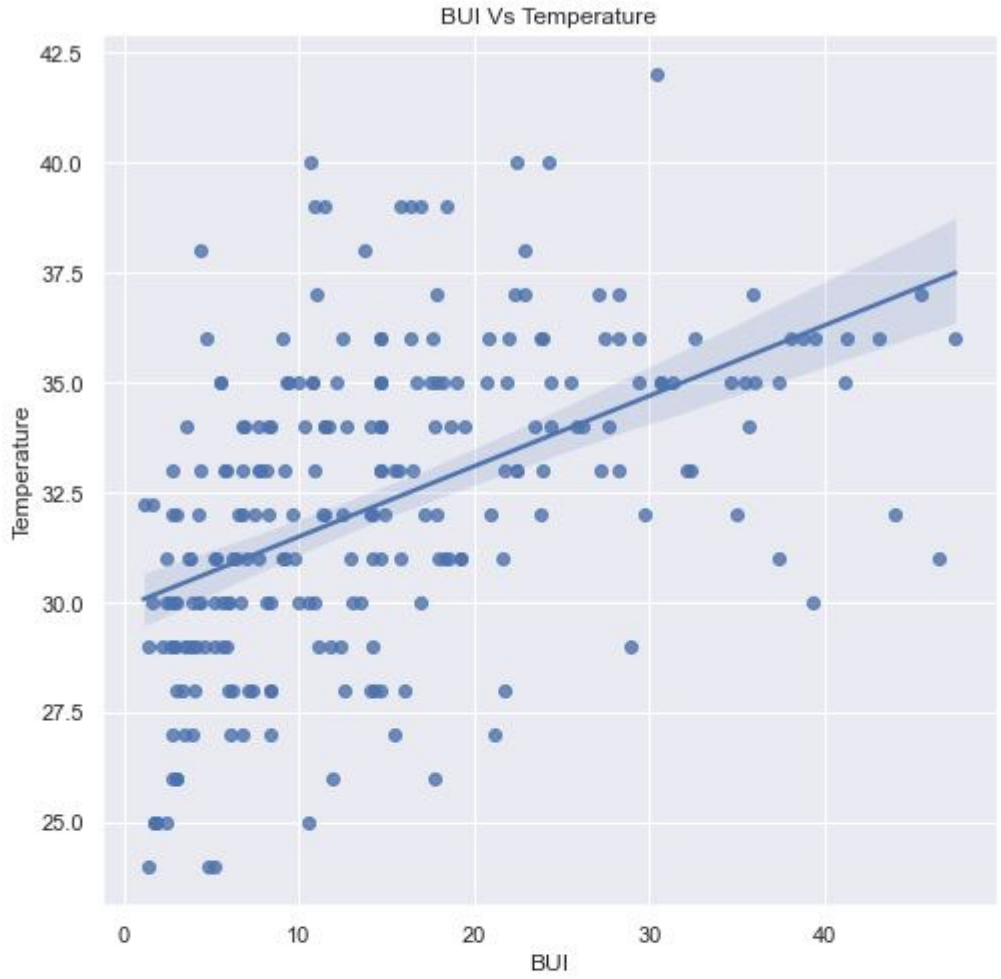

FFMC Vs Temperature
Temperature
42.5
40.0
37.5
35.0
32.5
30.0

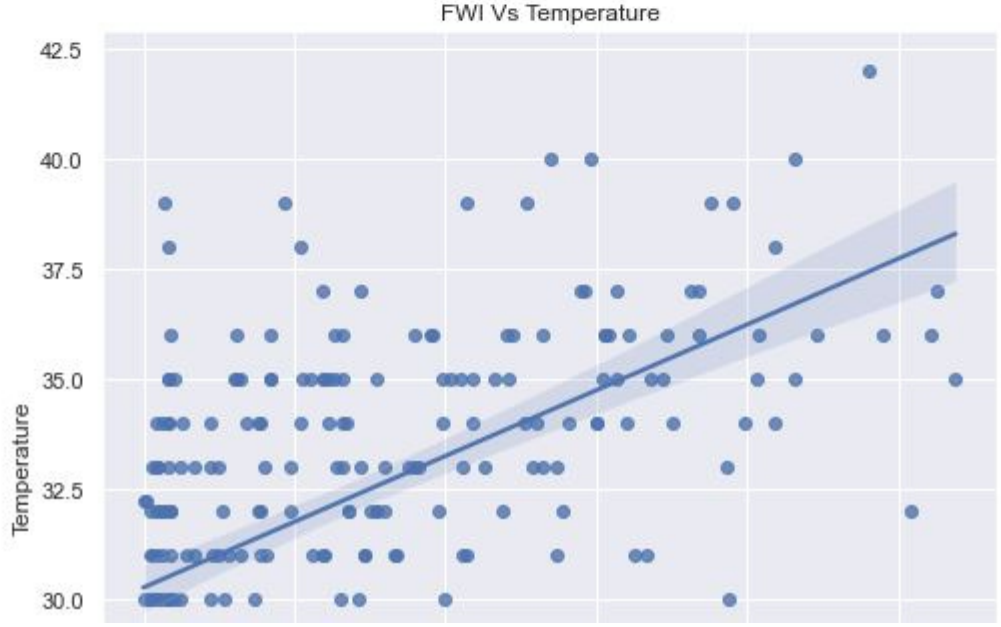

FFMC Vs Temperature
Temperature
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
50
60
70
80
90
FFMC

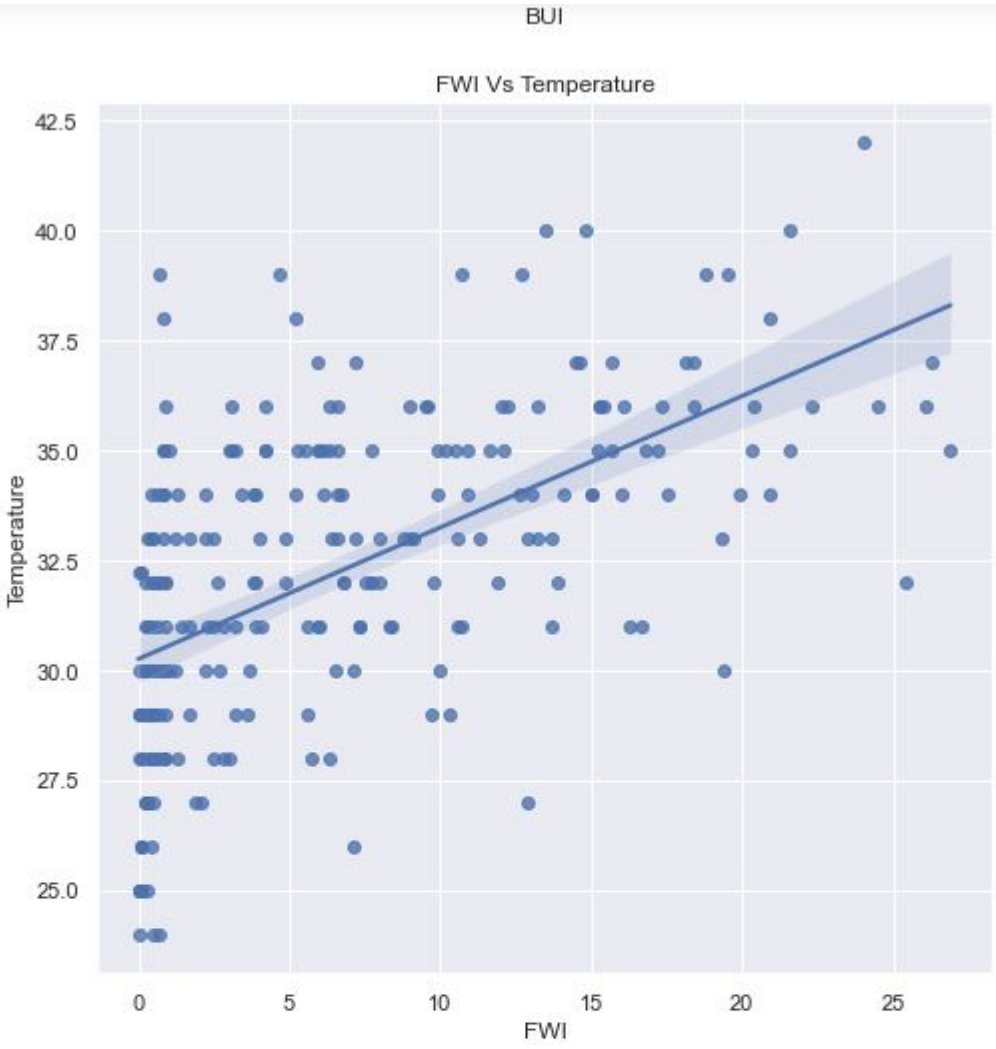

DMC Vs Temperature
Temperature
42.5
40.0
37.5
35.0
32.5
30.0


DC Vs Temperature
Temperature
DC
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
20
40
60
80
100
120


ISI Vs Temperature
Temperature
42.5
40.0
37.5
35.0
32.5
30.0


BUI Vs Temperature
Temperature
BUI
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
0
10
20
30
40


FWI Vs Temperature
Temperature
42.5
40.0
37.5
35.0
32.5
30.0



- Shaded region is basically with respect to Ridge and Lasso Regression

Segregate dependent and independent feature

In [55]:
```
### X : independent feature \\ y : dependent feature
X = df[['RH', 'Ws', 'Rain','FFMC', 'DMC', 'ISI','DC',
        'FWI', 'Classes', 'Region']]
y = df[['Temperature']]
```

In [56]:
```
X.head()    # Independent features
```

Out[56]:

	RH	Ws	Rain	FFMC	DMC	ISI	DC	FWI	Classes	Region
0	57	18.0	0.0	65.7	3.4	1.3	7.6	0.5	0	0.0

In [56]:
```
X.head()    # Independent features
```

Out[56]:

	RH	Ws	Rain	FFMC	DMC	ISI	DC	FWI	Classes	Region
0	57	18.0	0.0	65.7	3.4	1.3	7.6	0.5	0	0.0
1	61	13.0	0.2	64.4	4.1	1.0	7.6	0.4	0	0.0
2	82	15.5	0.2	80.0	2.5	0.3	7.1	0.1	0	0.0
3	89	13.0	0.2	80.0	1.3	0.0	6.9	0.0	0	0.0
4	77	16.0	0.0	64.8	3.0	1.2	14.2	0.5	0	0.0

In [57]:
```
y.head()    # Dependent features
```

Out[57]:

	Temperature
0	29.0
1	29.0
2	26.0
3	25.0
4	27.0

Splitt the data into training and test dataset

In [58]:
```
### random state train test split will be same with all people using random_
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, ra
```

StandardScalar

In [59]:
```
### creating a StandardScalar object
scaler = StandardScaler()
scaler
```

Out[59]:
```
StandardScaler()
```

In [60]:
```
### Using fit_transform to standardise Train data
X_train = scaler.fit_transform(X_train)
```

In [61]:
```
### Here using only transform to avoid data leakage
### (training mean and training standard deviation will be used for standard
```

In [61]:
```
### Here using only transform to avoid data leakage
### (training mean and training standard deviation will be used for standara
X_test = scaler.transform(X_test)
```

Linear Regression Model

In [62]:
```
## creating linear regression model
linear_reg = LinearRegression()
linear_reg
```

Out[62]:
```
LinearRegression()
```

Passing training data (X and y) to the model

In [63]:
```
linear_reg.fit(X_train, y_train)
```

Out[63]:
```
LinearRegression()
```

Printing co-efficients and intercept of best fit hyperplane

In [64]:
```
print("1. Co-efficients of independent features is {}".format(linear_reg.coe
print("2. Intercept of best fit hyper plane is {}".format(linear_reg.interce
```

```
1. Co-efficients of independent features is [[-1.62572989 -0.60047117  0.289211
92 -0.05938927  0.76367662  0.00760549
  -0.15916525  0.43191456  0.62332559 -0.26791113]]
2. Intercept of best fit hyper plane is [32.1617284]
```

Prediction of test data

In [65]:
```
linear_reg_pred = linear_reg.predict(X_test)
linear_reg_pred[:5]
```

Out[65]:
```
array([[32.87012119],
       [34.23661089],
       [30.17838715],
       [32.47680473],
       [32.63326791]])
```

In [66]:
```
# The difference between y_test and linear_reg_pred
```

In [66]:
```
# The difference between y_test and linear_reg_pred
residual_linear_reg = y_test - linear_reg_pred
residual_linear_reg[:5]
```

Out[66]:

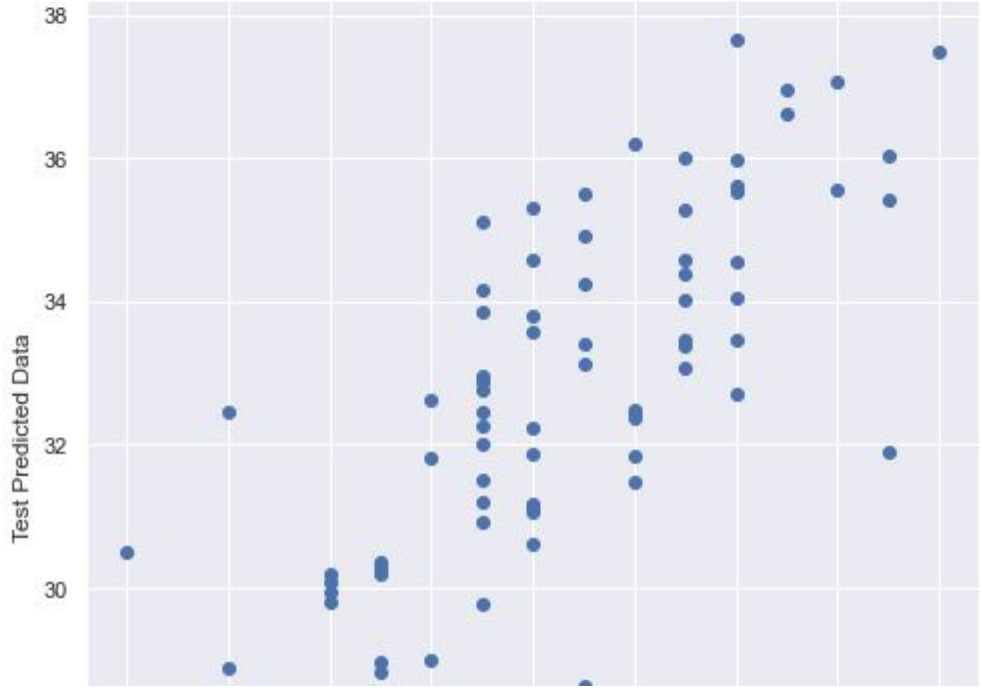
	Temperature
24	-1.870121
6	-1.236611
152	-2.178387
232	1.523195
238	-2.633268

Validation of Linear Regression assumptions

1. Linear Relationship

In [67]:
```
plt.scatter(y_test,linear_reg_pred)
plt.xlabel("Test Truth Data")
plt.ylabel("Test Predicted Data")
```

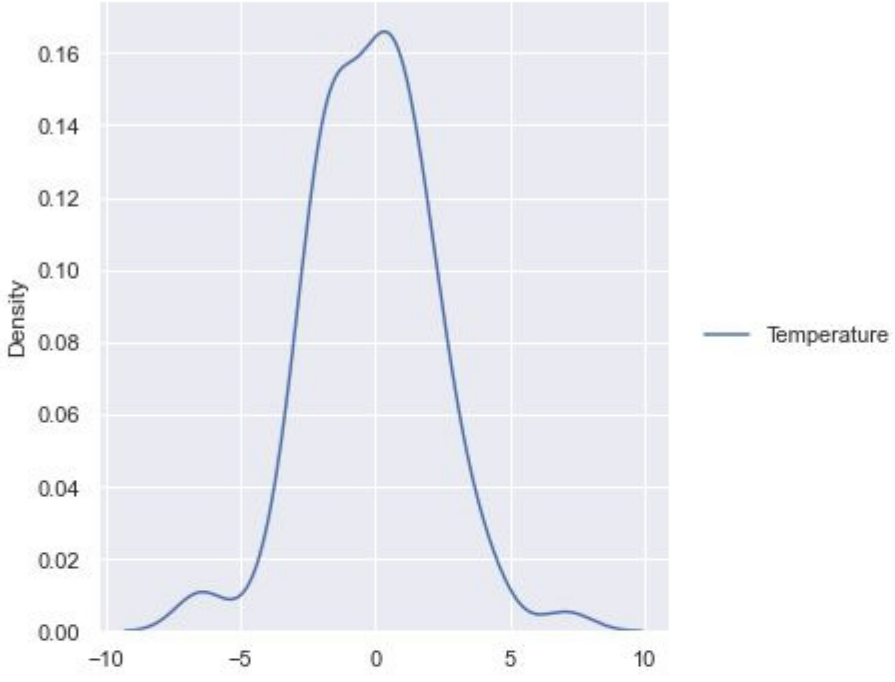
Out[67]: Text(0, 0.5, 'Test Predicted Data')



2. Residual should be normally distributed

In [68]:
```
1 sns.displot(data = residual_linear_reg, kind ="kde")
```

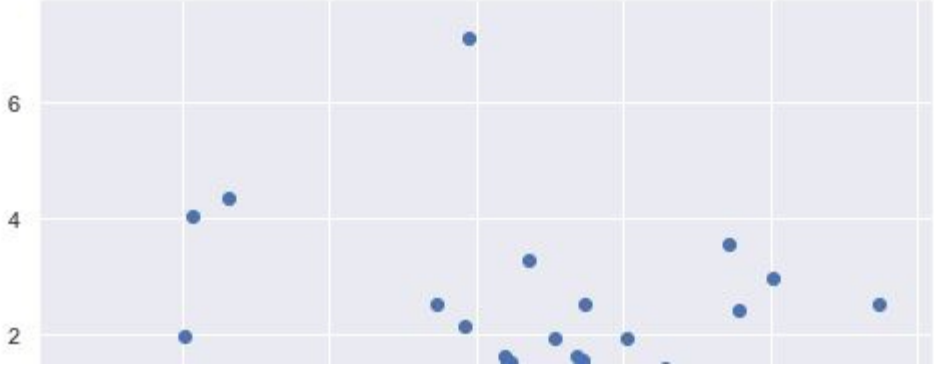
Out[68]:
```
<seaborn.axisgrid.FacetGrid at 0x1e4351bc6d0>
```



3. Residual and Predicted values should follow uniform distribution

In [69]:
```
1 plt.scatter(linear_reg_pred,residual_linear_reg)
2 plt.xlabel("Prediction")
3 plt.ylabel('Residuals')
```

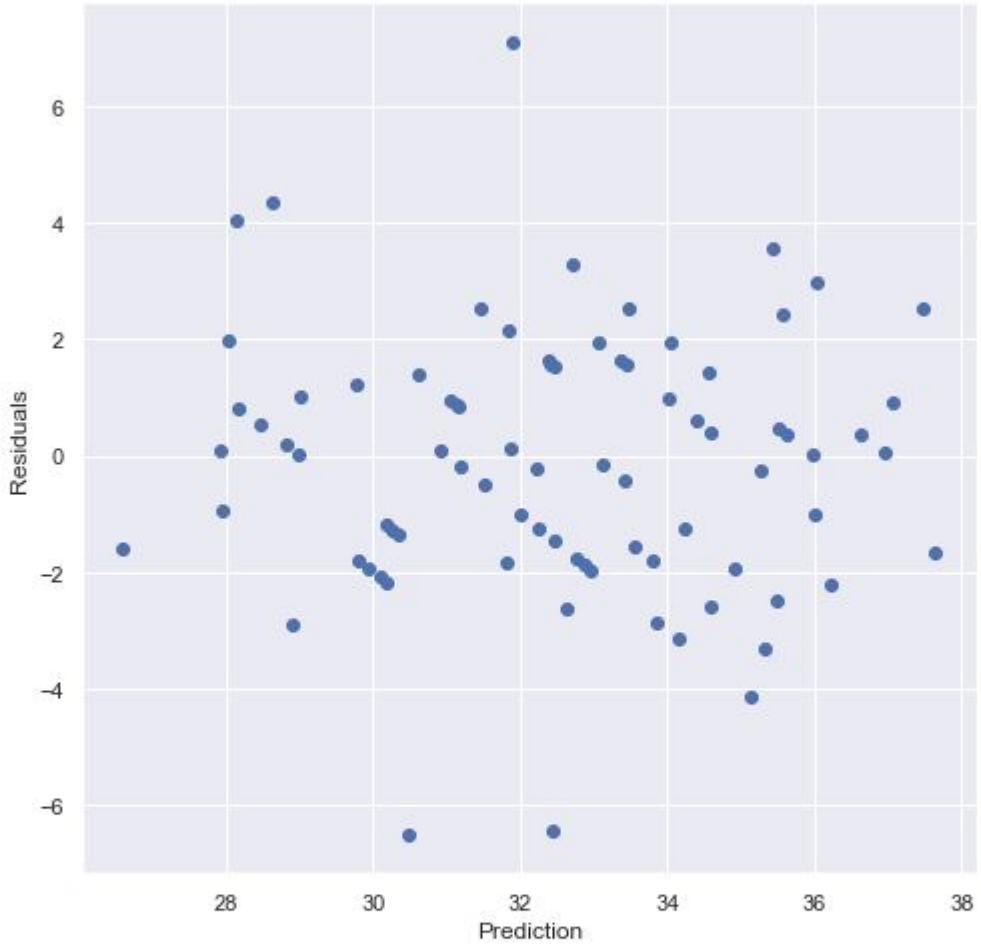
Out[69]:
```
Text(0, 0.5, 'Residuals')
```



3. Residual and Predicted values should follow uniform distribution

In [69]:
```
1 plt.scatter(linear_reg_pred,residual_linear_reg)
2 plt.xlabel("Prediction")
3 plt.ylabel('Residuals')
```

Out[69]: Text(0, 0.5, 'Residuals')



Cost Function Values

In [70]:
```
1 print(f"MSE : {round(mean_squared_error(y_test,linear_reg_pred),2)}")
2 print(f"MAE : {round(mean_absolute_error(y_test,linear_reg_pred),2)}")
3 print(f"RMSE : {round(np.sqrt(mean_squared_error(y_test,linear_reg_pred)),2)
```

```
MSE : 5.01
MAE : 1.74
RMSE : 2.24
```

Cost Function Values

In [70]:
```
print(f"MSE : {round(mean_squared_error(y_test,linear_reg_pred),2)}")
print(f"MAE : {round(mean_absolute_error(y_test,linear_reg_pred),2)}")
print(f"RMSE : {round(np.sqrt(mean_squared_error(y_test,linear_reg_pred)),2)
```

```
MSE : 5.01
MAE : 1.74
RMSE : 2.24
```

Performance Metrics

In [73]:
```
.inear_score = r2_score(y_test,linear_reg_pred)
)rint(f"R-Square Accuracy : {round(linear_score*100,2)}%")
)rint(f"Adjusted R-Square Accuracy : {round((1 - (1-linear_score)*(len(y_test
```

```
R-Square Accuracy : 56.52%
Adjusted R-Square Accuracy : 50.31%
```

Ridge Regresion Model

In [74]:
```
## creating Ridge regression model
ridge_reg=Ridge()
ridge_reg
```

Out[74]:
```
Ridge()
```

In [75]:
```
### Passing training data(X and y) to the model
ridge_reg.fit(X_train, y_train)
```

Out[75]:
```
Ridge()
```

In [76]:
```
### Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent features is {}".format(ridge_reg.coef
print("2. Intercept of best fit hyper plane is {}".format(ridge_reg.intercep
```

```
1. Co-efficients of independent features is [[-1.60178318 -0.59652426  0.291220
38 -0.04397446  0.75428229  0.0345659
  -0.15042974  0.41984204  0.606996   -0.25830502]]
2. Intercept of best fit hyper plane is [32.1617284]
```

Prediction of test data

In [77]:
```
1 ridge_reg_pred = ridge_reg.predict(X_test)
```

In [78]:
```
1 residual_ridge_reg = y_test - ridge_reg_pred
2 residual_ridge_reg[:5]
```

Out[78]:

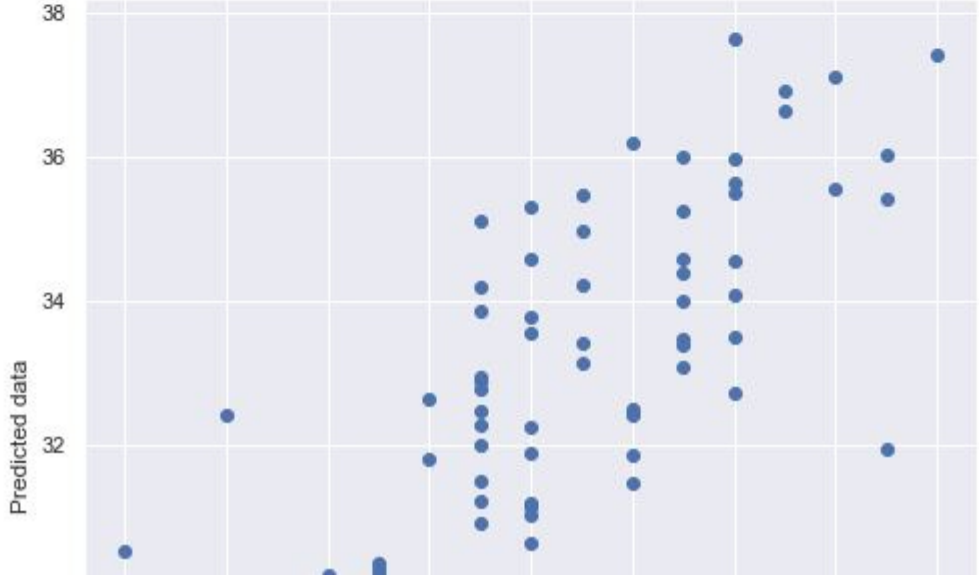
	Temperature
24	-1.866884
6	-1.217160
152	-2.170534
232	1.510022
238	-2.634740

Validation of Ridge Regression assumptions

1. Linear Relationship

In [79]:
```
1 plt.scatter(x=y_test,y=ridge_reg_pred)
2 plt.xlabel("Test truth data")
3 plt.ylabel("Predicted data")
```

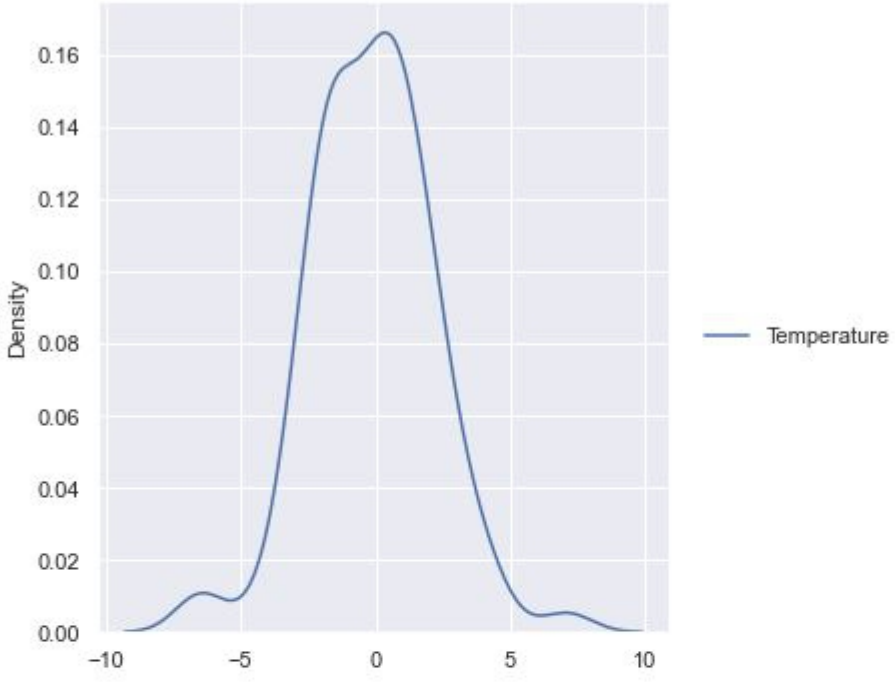
Out[79]: `Text(0, 0.5, 'Predicted data')`



2. Residual should be normally distributed

In [80]:
```
1 sns.displot(data = residual_ridge_reg, kind='kde')
```

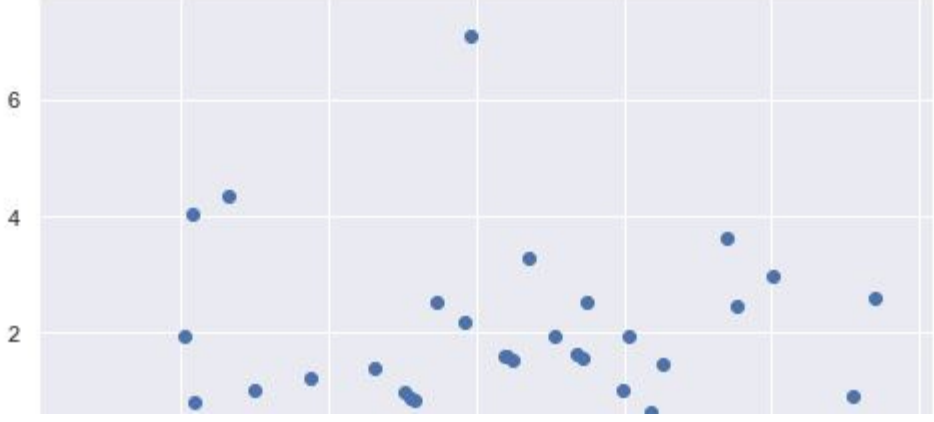
Out[80]:
```
<seaborn.axisgrid.FacetGrid at 0x1e4354a06d0>
```



3. Residual and Predicted values should follow uniform distribution

In [81]:
```
1 plt.scatter(x=ridge_reg_pred, y=residual_ridge_reg)
2 plt.xlabel('Predictions')
3 plt.ylabel('Residuals')
```

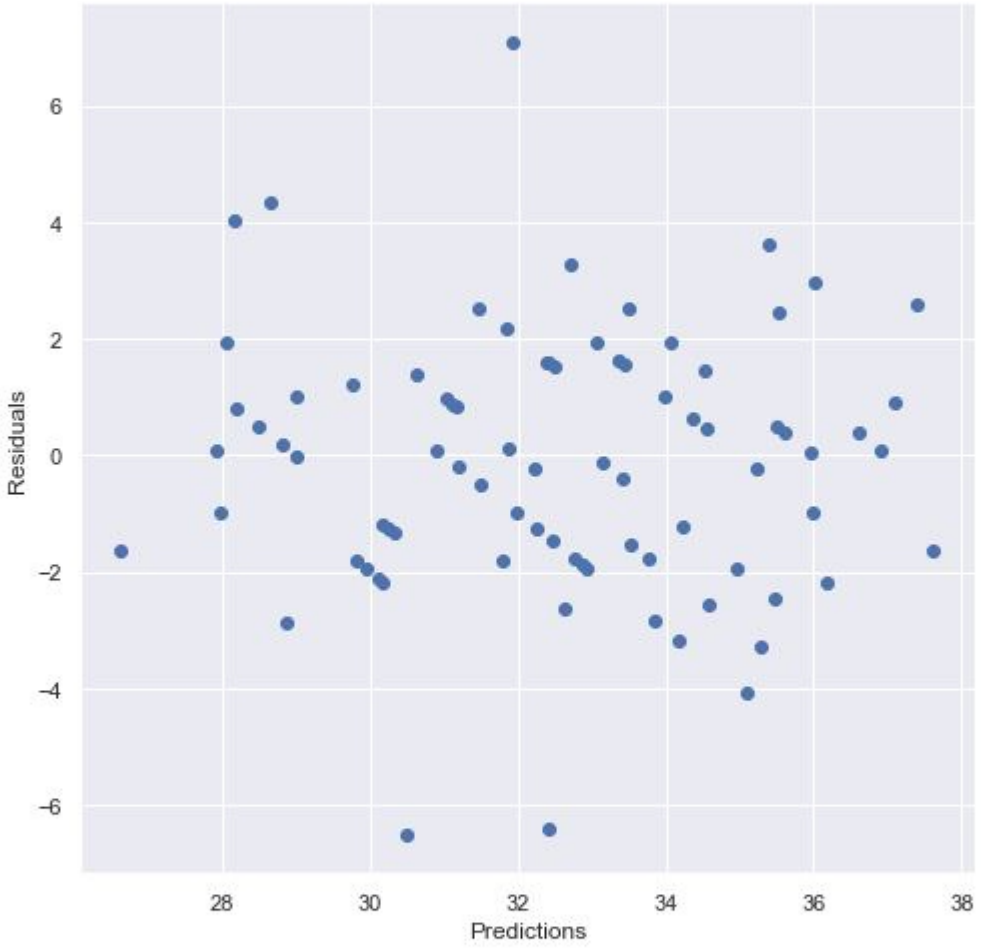
Out[81]:
```
Text(0, 0.5, 'Residuals')
```



3. Residual and Predicted values should follow uniform distribution

In [81]:
```
1 plt.scatter(x=ridge_reg_pred, y=residual_ridge_reg)
2 plt.xlabel('Predictions')
3 plt.ylabel('Residuals')
```

Out[81]: Text(0, 0.5, 'Residuals')



Cost Function Values

In [82]:
```
1 print(f"MSE : {round(mean_squared_error(y_test,ridge_reg_pred),2)}")
2 print(f"MAE : {round(mean_absolute_error(y_test,ridge_reg_pred),2)}")
3 print(f"RMSE : {round(np.sqrt(mean_squared_error(y_test,ridge_reg_pred)),2)}
```

```
MSE : 4.99
MAE : 1.74
```

Cost Function Values

In [82]:
```
print(f"MSE : {round(mean_squared_error(y_test,ridge_reg_pred),2)}")
print(f"MAE : {round(mean_absolute_error(y_test,ridge_reg_pred),2)}")
print(f"RMSE : {round(np.sqrt(mean_squared_error(y_test,ridge_reg_pred)),2)}
```

```
MSE : 4.99
MAE : 1.74
RMSE : 2.23
```

Performance Metrics

In [83]:
```
Ridge_score = r2_score(y_test,ridge_reg_pred)
print(f"R-Square Accuracy : {round(Ridge_score*100,2)}%")
print(f"Adjusted R-Square Accuracy : {round((1 - (1-Ridge_score)*(len(y_test
```

```
R-Square Accuracy : 56.67%
Adjusted R-Square Accuracy : 50.48%
```

Lasso Regression Model

In [84]:
```
## creating Lasso regression model
lasso_reg = Lasso()
lasso_reg
```

Out[84]:
```
Lasso()
```

In [85]:
```
### Passing training data(X and y) to the model
lasso_reg.fit(X_train, y_train)
```

Out[85]:
```
Lasso()
```

In [86]:
```
### Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent features is {}".format(lasso_reg.coef
print("2. Intercept of best fit hyper plane is {}".format(lasso_reg.intercep
```

```
1. Co-efficients of independent features is [-1.08278202 -0.         -0.
0.          0.23127133  0.
  0.          0.2378896   0.          0.        ]
2. Intercept of best fit hyper plane is [32.1617284]
```

Prediction of test data

In [87]:
```
lasso_reg_pred = lasso_reg.predict(X_test)
lasso_reg_pred[:5]
```

Out[87]:
```
array([32.16299347, 32.74098733, 32.05836623, 32.55720977, 32.07186032])
```

In [88]:
```
y_test = y_test.squeeze()
residual_lasso_reg = y_test - lasso_reg_pred
residual_lasso_reg[:5]
```

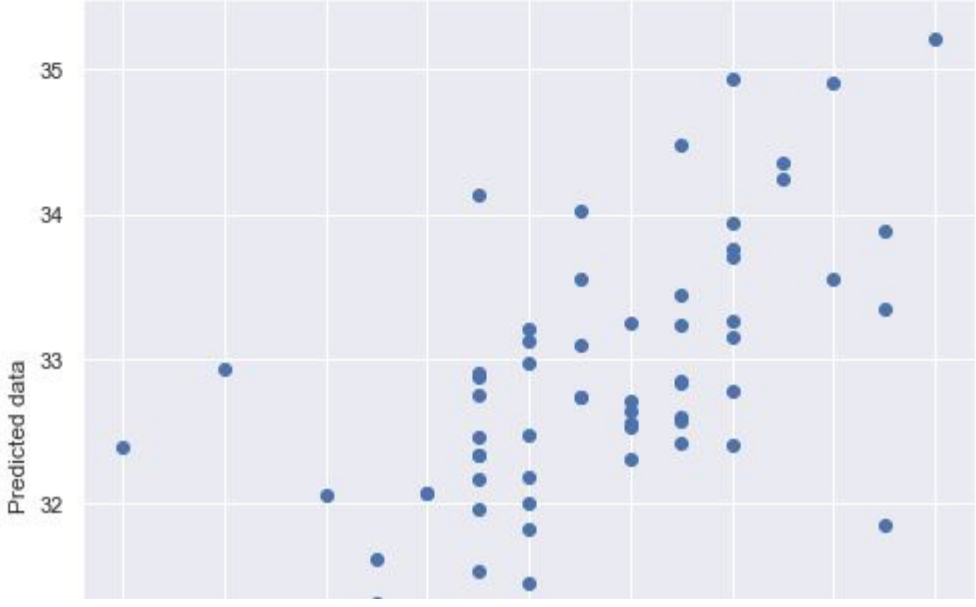
Out[88]:
```
24    -1.162993
6      0.259013
152   -4.058366
232    1.442790
238   -2.071860
Name: Temperature, dtype: float64
```

Validation of Lasso Regression assumptions

1. Linear Relationship

In [89]:
```
plt.scatter(y_test, lasso_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

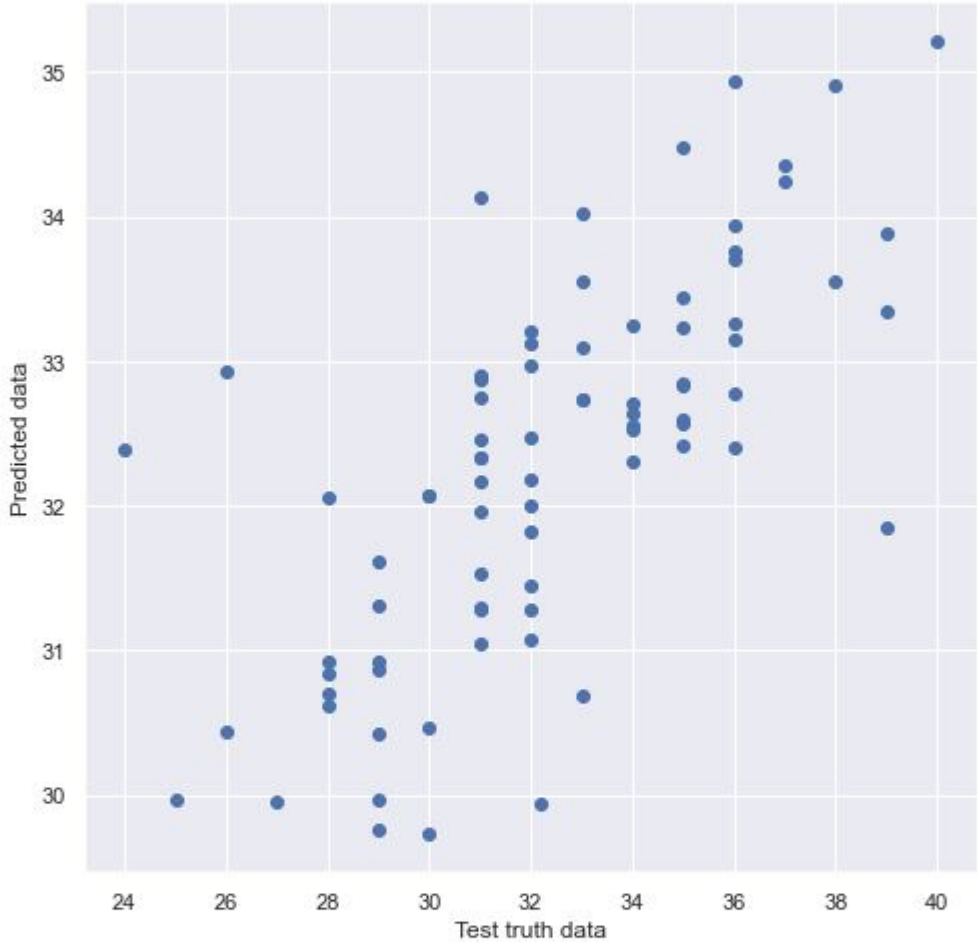
Out[89]:
```
Text(0, 0.5, 'Predicted data')
```



1. Linear Relationship

In [89]:
```
1 plt.scatter(y_test, lasso_reg_pred)
2 plt.xlabel("Test truth data")
3 plt.ylabel("Predicted data")
```

Out[89]:
```
Text(0, 0.5, 'Predicted data')
```



2. Residual should be normally distributed

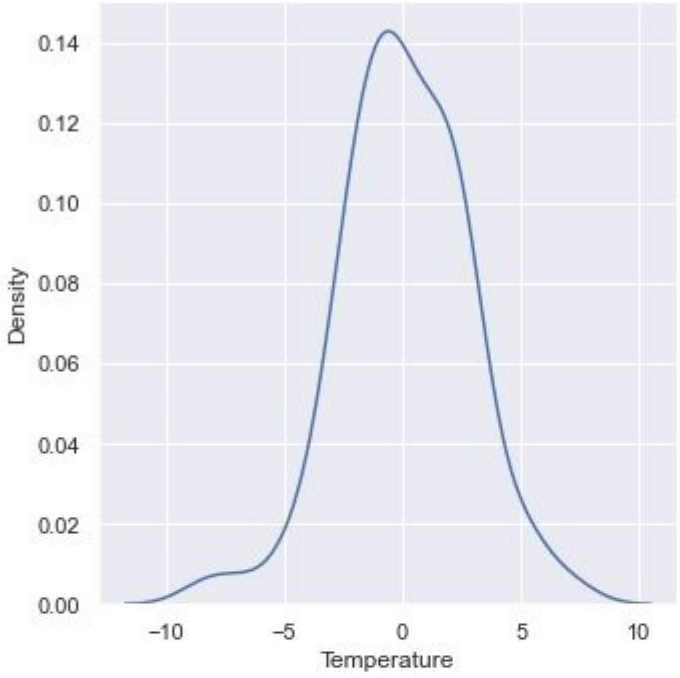
In [90]:
```
1 sns.displot( residual_lasso_reg, kind='kde')
```

Out[90]:
```
<seaborn.axisgrid.FacetGrid at 0x1e43550f3d0>
```

2. Residual should be normally distributed

In [90]:
```
1 sns.displot( residual_lasso_reg, kind='kde')
```

Out[90]: <seaborn.axisgrid.FacetGrid at 0x1e43550f3d0>



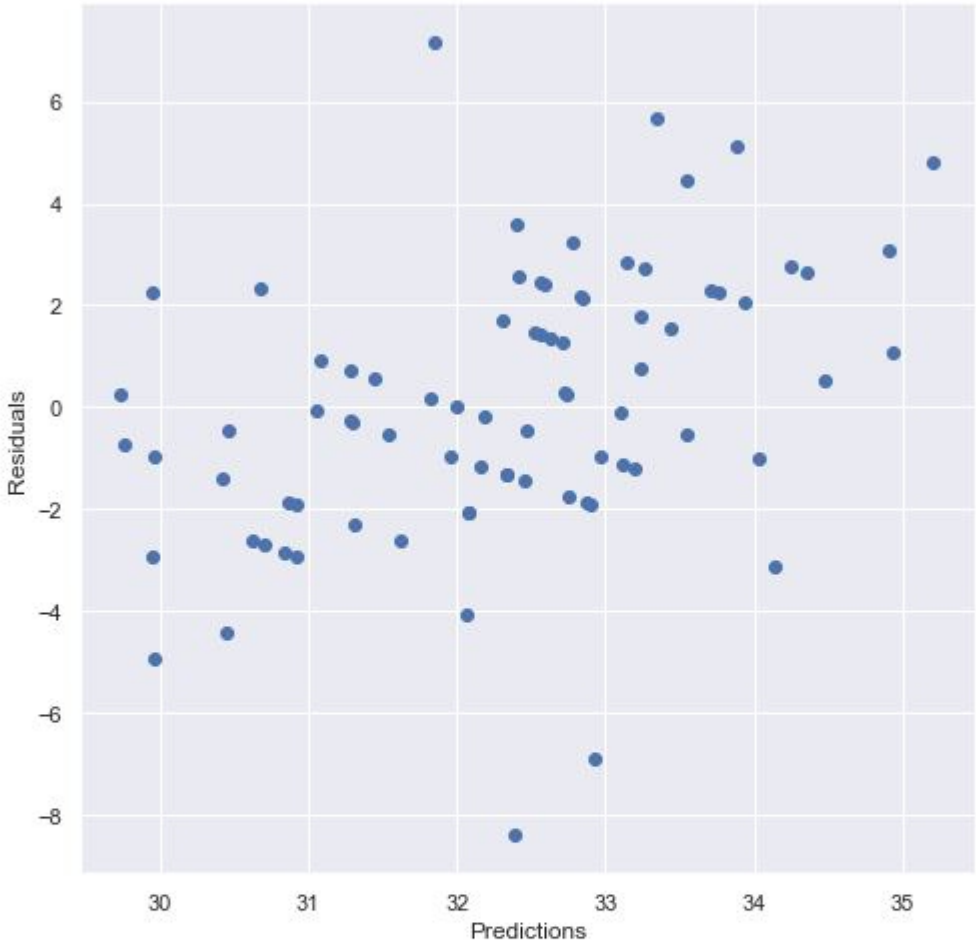
3. Residual and Predicted values should follow uniform distribution

In [91]:
```
1 plt.scatter(lasso_reg_pred, residual_lasso_reg)
2 plt.xlabel('Predictions')
3 plt.ylabel('Residuals')
```

Out[91]: Text(0, 0.5, 'Residuals')

In [91]:
```
plt.scatter(lasso_reg_pred, residual_lasso_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

Out[91]: Text(0, 0.5, 'Residuals')



Cost Function Values

In [92]:
```
print(f"MSE : {round(mean_squared_error(y_test,lasso_reg_pred),2)}")
print(f"MAE : {round(mean_absolute_error(y_test,lasso_reg_pred),2)}")
print(f"RMSE : {round(np.sqrt(mean_squared_error(y_test,lasso_reg_pred)),2)}")
```

```
MSE : 7.06
MAE : 2.07
RMSE : 2.66
```

Performance Metrics

In [93]:
```
lasso_score = r2_score(y_test,lasso_reg_pred)
print(f"R-Square Accuracy : {round(lasso_score*100,2)}%")
print(f"Adjusted R-Square Accuracy : {round((1 - (1-lasso_score)*(len(y_test
```

```
R-Square Accuracy : 38.7%
Adjusted R-Square Accuracy : 29.94%
```

Elastic Net Regression Model

In [94]:
```
## creating Elastic-Net regression model
elastic_reg = ElasticNet()
elastic_reg
```

Out[94]:
```
ElasticNet()
```

In [95]:
```
### Passing training data(X and y) to the model
elastic_reg.fit(X_train, y_train)
```

Out[95]:
```
ElasticNet()
```

In [96]:
```
### Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent features is {}".format(elastic_reg.co
print("2. Intercept of best fit hyper plane is {}".format(elastic_reg.interc
```

```
1. Co-efficients of independent features is [-0.79936853 -0.05286721 -0.
0.15025684  0.32720261  0.25459529
  0.          0.24934961  0.16518801  0.        ]
2. Intercept of best fit hyper plane is [32.1617284]
```

Prediction of test data

In [97]:
```
elastic_reg_pred = elastic_reg.predict(X_test)
```

In [98]:
```
residual_elastic_reg = y_test - elastic_reg_pred
residual_elastic_reg[:5]
```

Out[98]:
```
24    -1.534535
6      0.012176
152   -3.192632
```

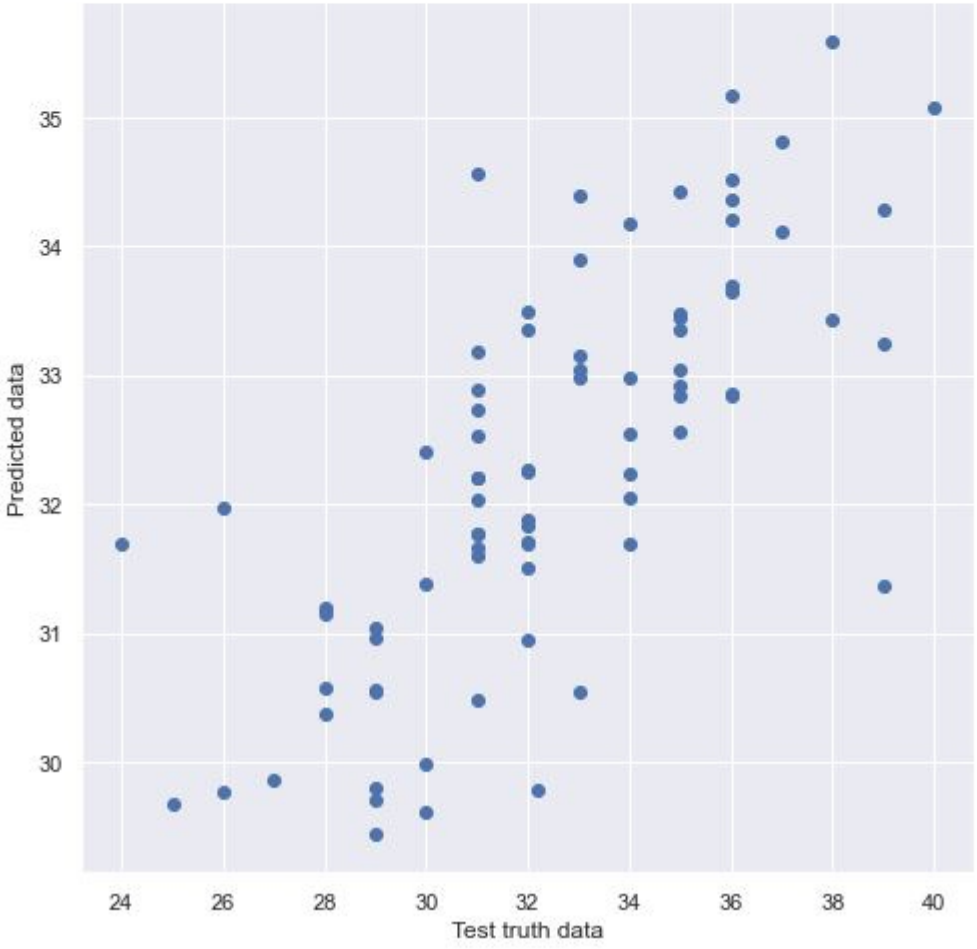
Out[98]:
```
24    -1.534535
6      0.012176
152   -3.192632
232    1.759639
238   -2.406341
Name: Temperature, dtype: float64
```

Validation of Elastic Regression assumptions

1. Linear Relationship

In [99]:
```
1 plt.scatter(y_test, elastic_reg_pred)
2 plt.xlabel("Test truth data")
3 plt.ylabel("Predicted data")
```

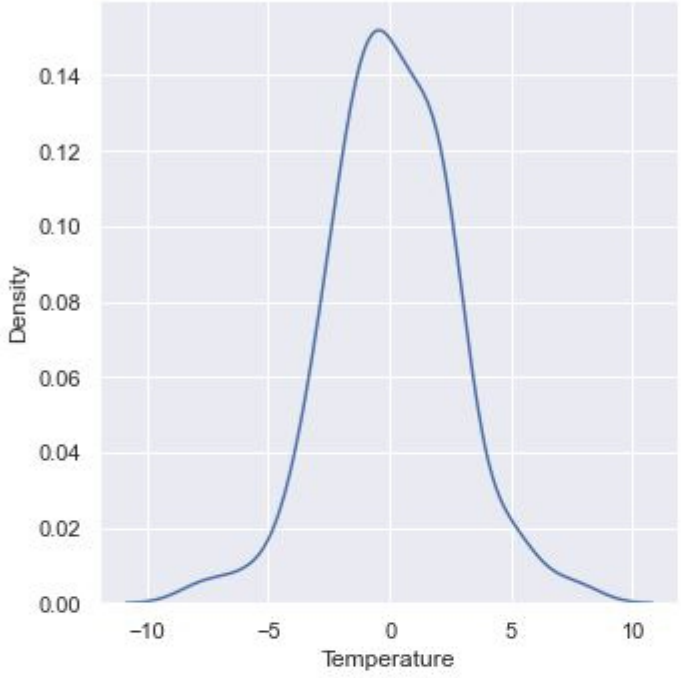
Out[99]:
```
Text(0, 0.5, 'Predicted data')
```



2. Residual should be normally distributed

In [100]:
```
1 sns.displot( residual_elastic_reg, kind='kde')
```

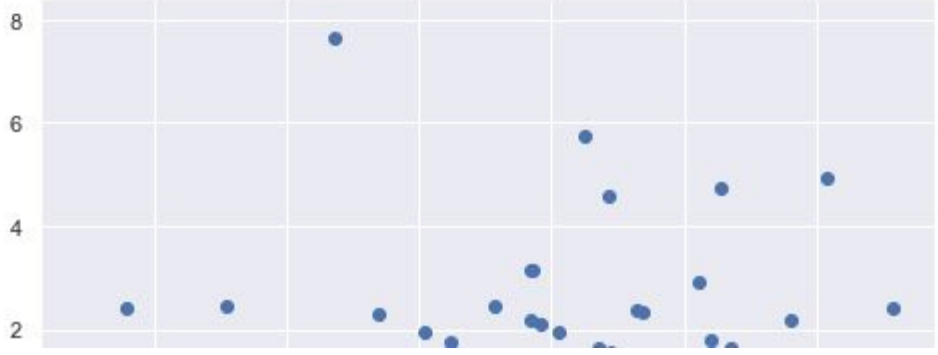
Out[100]: <seaborn.axisgrid.FacetGrid at 0x1e4365efe20>



3. Residual and Predicted values should follow uniform distribution

In [101]:
```
1 plt.scatter(elastic_reg_pred, residual_elastic_reg)
2 plt.xlabel('Predictions')
3 plt.ylabel('Residuals')
```

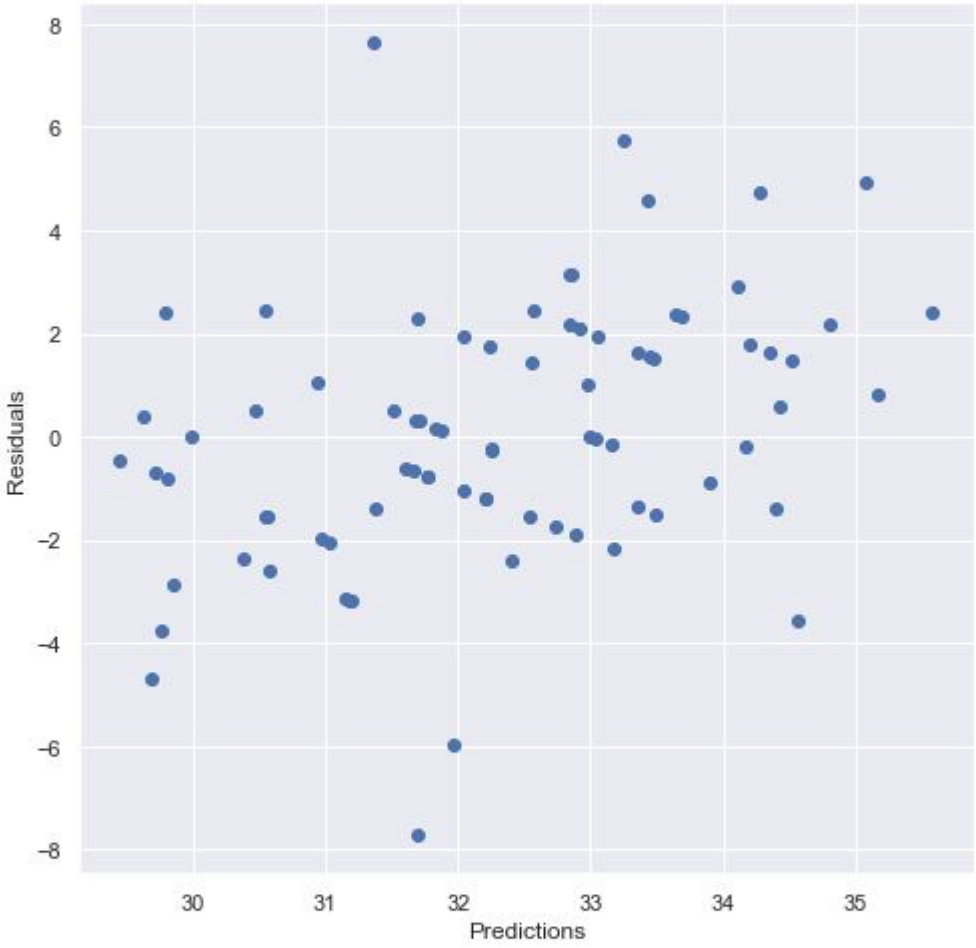
Out[101]: Text(0, 0.5, 'Residuals')



3. Residual and Predicted values should follow uniform distribution

In [101]:
```
1 plt.scatter(elastic_reg_pred, residual_elastic_reg)
2 plt.xlabel('Predictions')
3 plt.ylabel('Residuals')
```

Out[101]: Text(0, 0.5, 'Residuals')



Cost Function Values

In [102]:
```
1 print(f"MSE : {round(mean_squared_error(y_test,elastic_reg_pred),2)}")
2 print(f"MAE : {round(mean_absolute_error(y_test,elastic_reg_pred),2)}")
3 print(f"RMSE : {round(np.sqrt(mean_squared_error(y_test,elastic_reg_pred)),2
```

```
MSE : 6.37
MAE : 1.95
```

Cost Function Values

In [102]:
```
print(f"MSE : {round(mean_squared_error(y_test,elastic_reg_pred),2)}")
print(f"MAE : {round(mean_absolute_error(y_test,elastic_reg_pred),2)}")
print(f"RMSE : {round(np.sqrt(mean_squared_error(y_test,elastic_reg_pred)),2
```

```
MSE : 6.37
MAE : 1.95
RMSE : 2.52
```

Performance Metrics

In [103]:
```
astic_score = r2_score(y_test,elastic_reg_pred)
int(f"R-Square Accuracy : {round(Elastic_score*100,2)}%")
int(f"Adjusted R-Square Accuracy : {round((1 - (1-Elastic_score)*(len(y_test
```

```
R-Square Accuracy : 44.71%
Adjusted R-Square Accuracy : 36.81%
```

Comparisions of all Models

Cost Function Values

In [104]:
```
print("-----------------------------------------------------")
print(f"MSE:\n1. Linear Regression : {round(mean_squared_error(y_test,linear
print("-----------------------------------------------------")
print(f"MAE:\n1. Linear Regression : {round(mean_absolute_error(y_test,linea
print("-----------------------------------------------------")
print(f"RMSE:\n1. Linear Regression : {round(np.sqrt(mean_squared_error(y_te
print("-----------------------------------------------------")
```

```
-----------------------------------------------------
MSE:
1. Linear Regression : 5.01
2. Ridge Regression : 4.99
3. Lasso Regression : 7.06
4. ElasticNet Regression : 6.37
-----------------------------------------------------
MAE:
```

Comparisions of all Models

Cost Function Values

In [104]:

```
print("-----------------------------------------------------")
print(f"MSE:\n1. Linear Regression : {round(mean_squared_error(y_test,linear
print("-----------------------------------------------------")
print(f"MAE:\n1. Linear Regression : {round(mean_absolute_error(y_test,linea
print("-----------------------------------------------------")
print(f"RMSE:\n1. Linear Regression : {round(np.sqrt(mean_squared_error(y_te
print("-----------------------------------------------------")
```

```
-----------------------------------------------------
MSE:
1. Linear Regression : 5.01
2. Ridge Regression : 4.99
3. Lasso Regression : 7.06
4. ElasticNet Regression : 6.37
-----------------------------------------------------
MAE:
1. Linear Regression : 1.74
2. Ridge Regression : 1.74
3. Lasso Regression : 2.07
4. ElasticNet Regression : 1.95
-----------------------------------------------------
RMSE:
1. Linear Regression : 2.24
2. Ridge Regression : 2.23
3. Lasso Regression : 2.66
4. ElasticNet Regression : 2.52
-----------------------------------------------------
```

Performance Metrics

In [105]:

```
print("-----------------------------------------------------")
print(f"R-Square Accuracy:\n1. Linear Regression : {round(linear_score*100,2
print("-----------------------------------------------------")
print("Adjusted R-Square Accuracy:")
print(f"Linear Regression : {round((1 - (1-linear_score)*(len(y_test)-1)/(le
print(f"Ridge Regression : {round((1 - (1-Ridge_score)*(len(y_test)-1)/(len(
print(f"Lasso Regression : {round((1 - (1-lasso_score)*(len(y_test)-1)/(len(
print(f"ElasticNet Regression : {round((1 - (1-Elastic_score)*(len(y_test)-1
```

```
RMSE:
1. Linear Regression : 2.24
2. Ridge Regression : 2.23
3. Lasso Regression : 2.66
4. ElasticNet Regression : 2.52
-----------------------------------------------------
```

Performance Metrics

In [105]:

```
print("-----------------------------------------------------")
print(f"R-Square Accuracy:\n1. Linear Regression : {round(linear_score*100,2
print("-----------------------------------------------------")
print("Adjusted R-Square Accuracy:")
print(f"Linear Regression : {round((1 - (1-linear_score)*(len(y_test)-1)/(le
print(f"Ridge Regression : {round((1 - (1-Ridge_score)*(len(y_test)-1)/(len(
print(f"Lasso Regression : {round((1 - (1-lasso_score)*(len(y_test)-1)/(len(
print(f"ElasticNet Regression : {round((1 - (1-Elastic_score)*(len(y_test)-1
print("-----------------------------------------------------")
```

```
-----------------------------------------------------
R-Square Accuracy:
1. Linear Regression : 56.52%
2. Ridge Regression : 56.67%
3. Lasso Regression : 38.7%
4. ElasticNet Regression : 44.71%
-----------------------------------------------------
Adjusted R-Square Accuracy:
Linear Regression : 50.31%
Ridge Regression : 50.48%
Lasso Regression : 29.94%
ElasticNet Regression : 36.81%
-----------------------------------------------------
```

Conslusion

- If you use the date feature without categorizing then our accuracy will be around 50 % and after the inclusion of categorization it has increased to 66 %, though it is not so good.
- We can remove skewness from the data and also can use some method to handle imbalanced data in Rain feature. This is just a basic model. I will add all the possible techniques to improve accuracy in next session.