Algerian_Forest_FIre_Linear_Regression

October 28, 2022

1 Regression Model

Types: 1. Linear Regression 2. Ridge Regression 3. Lasso Regression 4. Elastic-Net Regression

2 Problem Statement

- To predict the temperature using Algerian forest fire dataset

Import Required Libraries

[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

pd.set_option('display.max_columns', 500)
```

Read data from github

[2]:
```
url = "https://raw.githubusercontent.com/subhashdixit/Linear_Regression/main/
 ↪Algerian_Forest_Dataset/Algerian_forest_fires_dataset.csv"
df=pd.read_csv(url,header=1 )
```

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

[3]:
```
  day month  year Temperature  RH  Ws Rain   FFMC  DMC    DC  ISI  BUI  FWI  \
0  01    06  2012          29  57  18     0  65.7  3.4   7.6  1.3  3.4  0.5
1  02    06  2012          29  61  13   1.3  64.4  4.1   7.6    1  3.9  0.4
2  03    06  2012          26  82  22  13.1  47.1  2.5   7.1  0.3  2.7  0.1
3  04    06  2012          25  89  13   2.5  28.6  1.3   6.9    0  1.7    0
4  05    06  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
```

3 Data Checks and cleaning

Checking Null Values

[4]:
```python
df[df.isnull().any(axis=1)]
```

[4]:
```
                                 day month  year Temperature   RH   Ws Rain   \
122  Sidi-Bel Abbes Region Dataset   NaN   NaN         NaN  NaN  NaN   NaN
167                                   14    07  2012          37   37   18   0.2

     FFMC   DMC      DC   ISI   BUI      FWI Classes
122   NaN   NaN     NaN   NaN   NaN      NaN       NaN
167  88.9  12.9  14.6 9  12.5  10.4  fire           NaN
```

Drop rows which have null

[5]:
```python
df.drop([122,123, 167],axis=0, inplace=True)
df = df.reset_index()
df.head()
```

[5]:
```
   index day month  year Temperature  RH  Ws Rain   FFMC  DMC    DC  ISI  BUI  \
0      0  01    06  2012          29  57  18     0  65.7  3.4   7.6  1.3  3.4
1      1  02    06  2012          29  61  13   1.3  64.4  4.1   7.6    1  3.9
2      2  03    06  2012          26  82  22  13.1  47.1  2.5   7.1  0.3  2.7
3      3  04    06  2012          25  89  13   2.5  28.6  1.3   6.9    0  1.7
4      4  05    06  2012          27  77  16     0  64.8    3  14.2  1.2  3.9

   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
```

Show all the columns

```
[6]: df.columns
```

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

Column name having extra space

```
[7]: [x for x in df.columns if ' ' in x]
```

```
[7]: [' RH', ' Ws', 'Rain ', 'Classes  ']
```

Remove extra space in column names

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

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

Function to remove extra space in the data

```
[9]: import re
     def Remove_Extra_Space(x):
       return (re.sub(' +', ' ', x).strip())
```

Remove extra space in the data

```
[10]: df['Classes'] = df['Classes'].apply(Remove_Extra_Space)
```

Drop extra index column, which was created for reset_index

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

Create data feature with the help of day, month and year feature and converted to datetime

```
[12]: df['date'] = pd.to_datetime(df[['day', 'month', 'year']])
```

Drop day, month and year feature

```
[13]: df.drop(['day', 'month', 'year'], axis = 1, inplace = True)
```

Imputation of date based on temperature. Usually in summer temperature is more and in winter it is less. So, we have categorized it based on month

[14]:
```python
def date_imputation(x):
  if (x >= pd.to_datetime('2012-07-01')) and (x <= pd.
↪to_datetime('2012-09-01')):
    return 1
  else:
    return 0
df['date'] = df['date'].apply(date_imputation)
```

[15]:
```python
df['date'].value_counts()
```

[15]:
```
1    125
0    118
Name: date, dtype: int64
```

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

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

check null values in all the features

[17]:
```python
df.isnull().sum()
```

[17]:
```
Temperature    0
RH             0
Ws             0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
Classes        0
date           0
Region         0
dtype: int64
```

Map classes feature as 1 and 0 for fire and not fire respectively

[18]:
```python
df['Classes'] = df['Classes'].map({'not fire' : 0, 'fire': 1})
```

Check duplictes values in all the column

[19]:
```python
df.duplicated().sum()
```

[19]:
```
0
```

Check data types of all the features

[20]:
```
df.dtypes
```

[20]:
```
Temperature     object
RH              object
Ws              object
Rain            object
FFMC            object
DMC             object
DC              object
ISI             object
BUI             object
FWI             object
Classes          int64
date             int64
Region         float64
dtype: object
```

Convert features to its logical datatypes

[21]:
```
convert_data = {'Temperature' : 'float64', 'RH': 'float64', 'Ws': 'float64',
 'DMC' : 'float64', 'DC' : 'float64', 'ISI': 'float64', 'BUI': 'float64', 'FWI'␣
↪: 'float64',
 'Region' : 'object', 'Rain' : 'float64', 'FFMC' : 'float64' , 'Classes':
↪'object','date':'object'}
df = df.astype(convert_data)
```

Converted datatpyes

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

[22]:
```
Temperature    float64
RH             float64
Ws             float64
Rain           float64
FFMC           float64
DMC            float64
DC             float64
ISI            float64
BUI            float64
FWI            float64
Classes         object
date            object
Region          object
dtype: object
```

Check unique values in all the features

[23]:
```
df.nunique()
```

[23]:
```
Temperature     19
RH              62
Ws              18
Rain            39
FFMC           173
DMC            165
DC             197
ISI            106
BUI            173
FWI            125
Classes          2
date             2
Region           2
dtype: int64
```

Check statistics of dataset

[24]:
```
df.describe()
```

[24]:
```
       Temperature          RH          Ws        Rain        FFMC  \
count   243.000000  243.000000  243.000000  243.000000  243.000000
mean     32.152263   62.041152   15.493827    0.762963   77.842387
std       3.628039   14.828160    2.811385    2.003207   14.349641
min      22.000000   21.000000    6.000000    0.000000   28.600000
25%      30.000000   52.500000   14.000000    0.000000   71.850000
50%      32.000000   63.000000   15.000000    0.000000   83.300000
75%      35.000000   73.500000   17.000000    0.500000   88.300000
max      42.000000   90.000000   29.000000   16.800000   96.000000

              DMC          DC         ISI         BUI         FWI
count  243.000000  243.000000  243.000000  243.000000  243.000000
mean    14.680658   49.430864    4.742387   16.690535    7.035391
std     12.393040   47.665606    4.154234   14.228421    7.440568
min      0.700000    6.900000    0.000000    1.100000    0.000000
25%      5.800000   12.350000    1.400000    6.000000    0.700000
50%     11.300000   33.100000    3.500000   12.400000    4.200000
75%     20.800000   69.100000    7.250000   22.650000   11.450000
max     65.900000  220.400000   19.000000   68.000000   31.100000
```

Segregate categorical feature from the dataset

[25]:
```
categorical_feature=[feature for feature in df.columns if df[feature].
 ↪dtypes=='O']
categorical_feature
```

[25]:
```
['Classes', 'date', 'Region']
```

[26]:
```
for feature in categorical_feature:
 print(df.groupby(feature)[feature].value_counts())
```

```
Classes  Classes
0        0          106
1        1          137
Name: Classes, dtype: int64
date  date
0     0       118
1     1       125
Name: date, dtype: int64
Region  Region
0.0     0.0       122
1.0     1.0       121
Name: Region, dtype: int64
```

Segregate numerical feature from the dataset

[27]:
```
numerical_features=[feature for feature in df.columns if df[feature].dtypes!
 ↪='O']
print(numerical_features)
```

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

Segregate discrete feature from the numerical feature

[28]:
```
#here the assumption to consider a feature discrete is that it should have less␣
 ↪than 35 unique values otherwise it will be
# considered continuous feature
discrete_features=[feature for feature in numerical_features if len(df[feature].
 ↪unique())<18]
discrete_features
```

[28]:
```
[]
```

Segregate continuous feature from the numerical feature

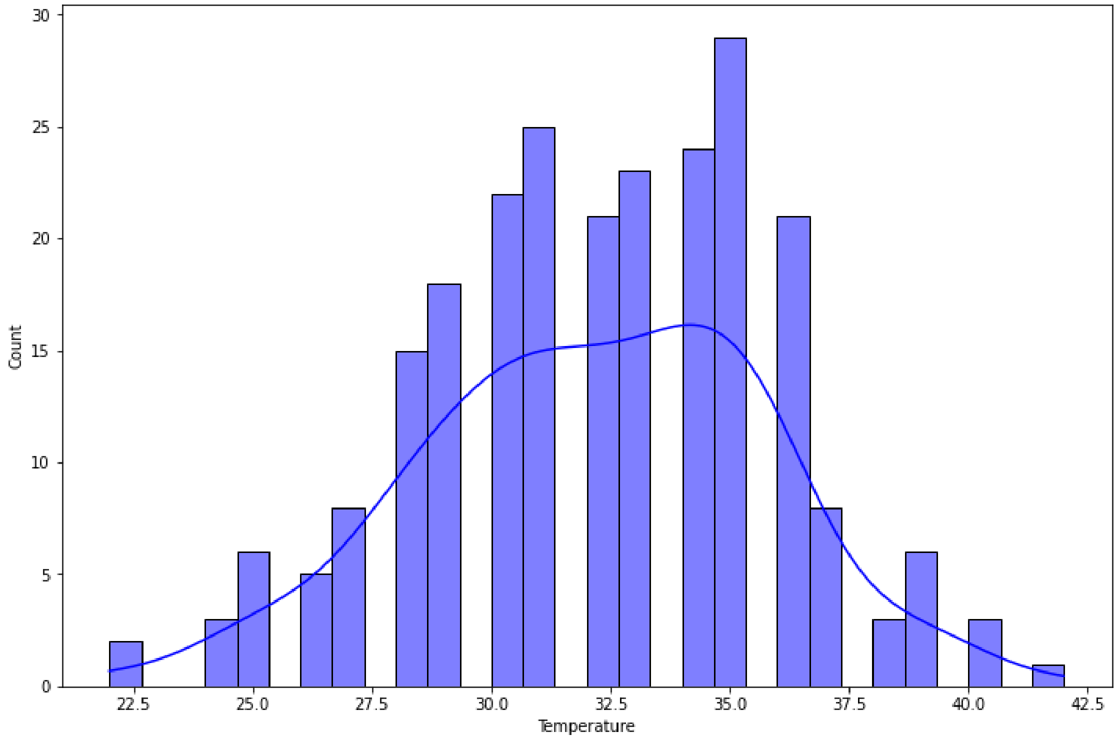
[29]:
```
continuous_features=[feature for feature in numerical_features if feature not␣
 ↪in discrete_features]
print(continuous_features)
```

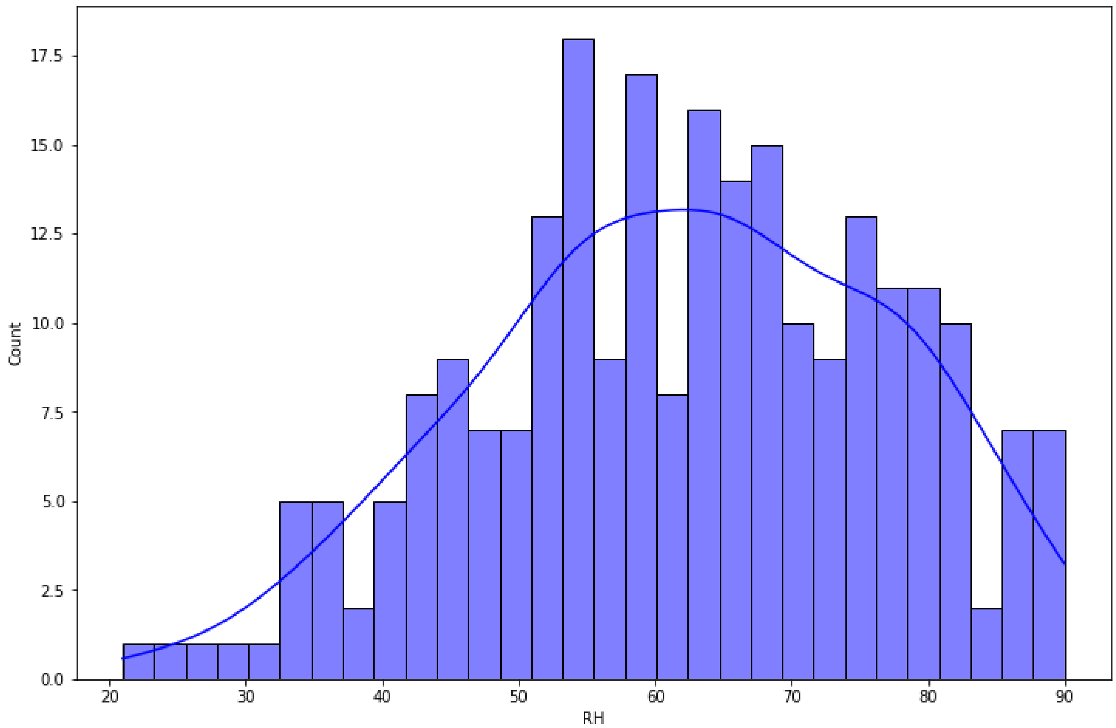
```
['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI']
```

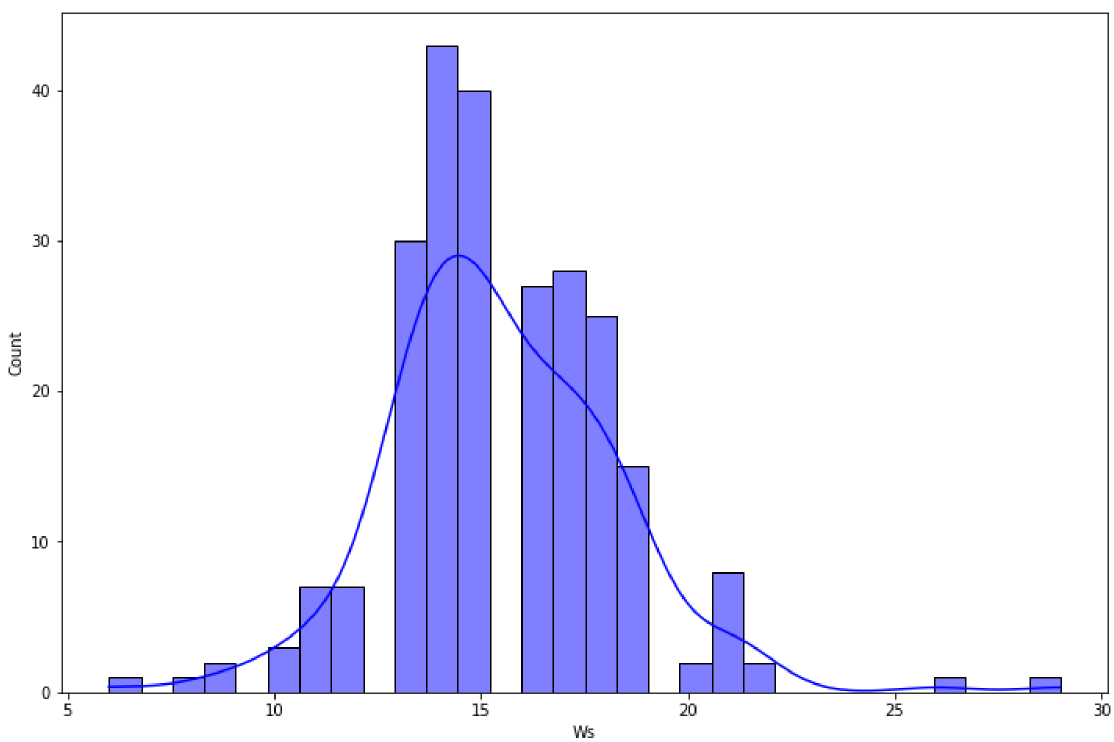
4 Graphical Analysis

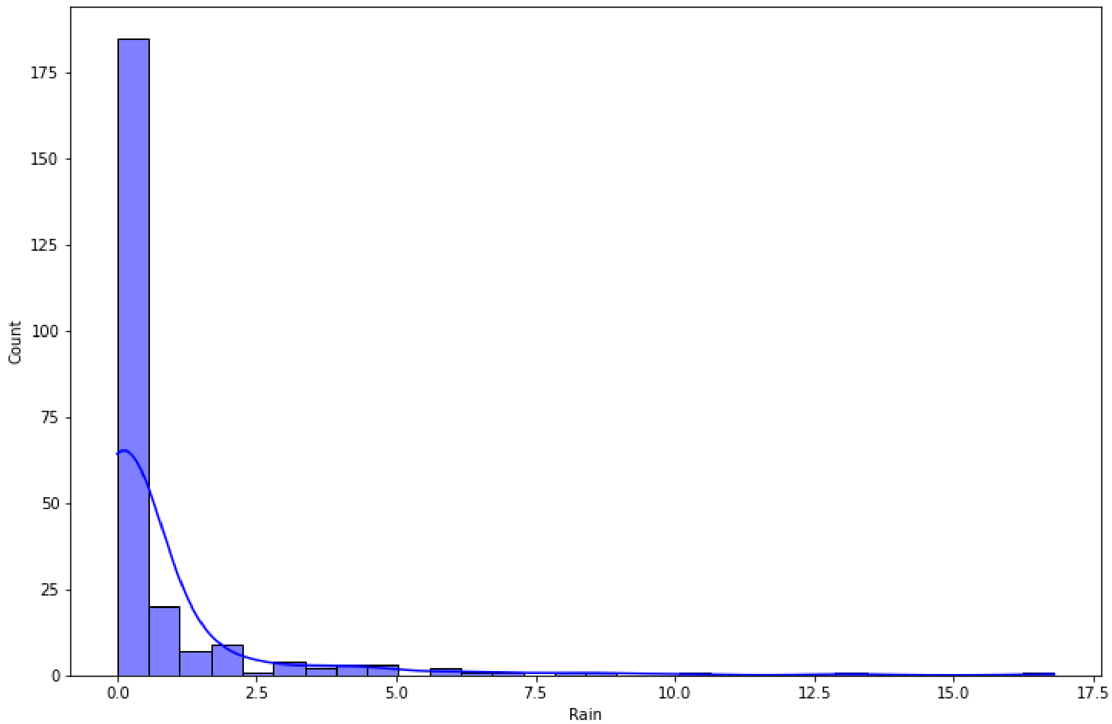
Checking distribution of Continuous numerical features

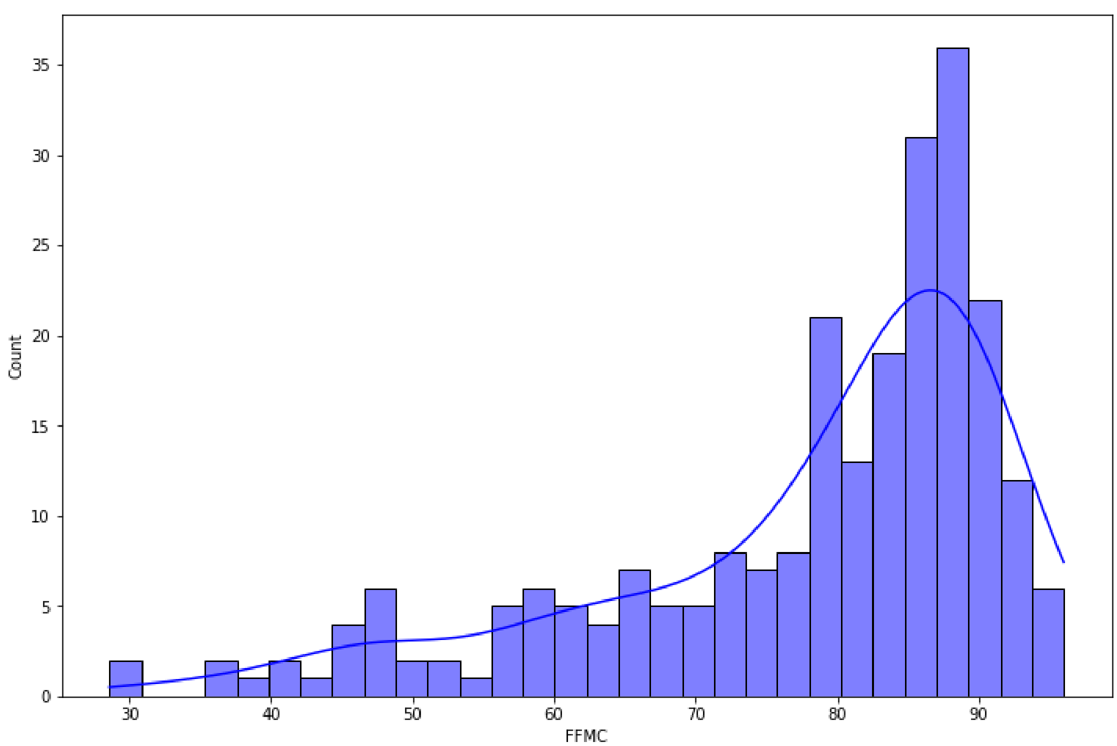
[30]:
```python
for feature in continuous_features:
    plt.figure(figsize=(12,8))
    sns.histplot(data=df, x=feature,kde=True, bins=30, color='blue')
    plt.show();
```

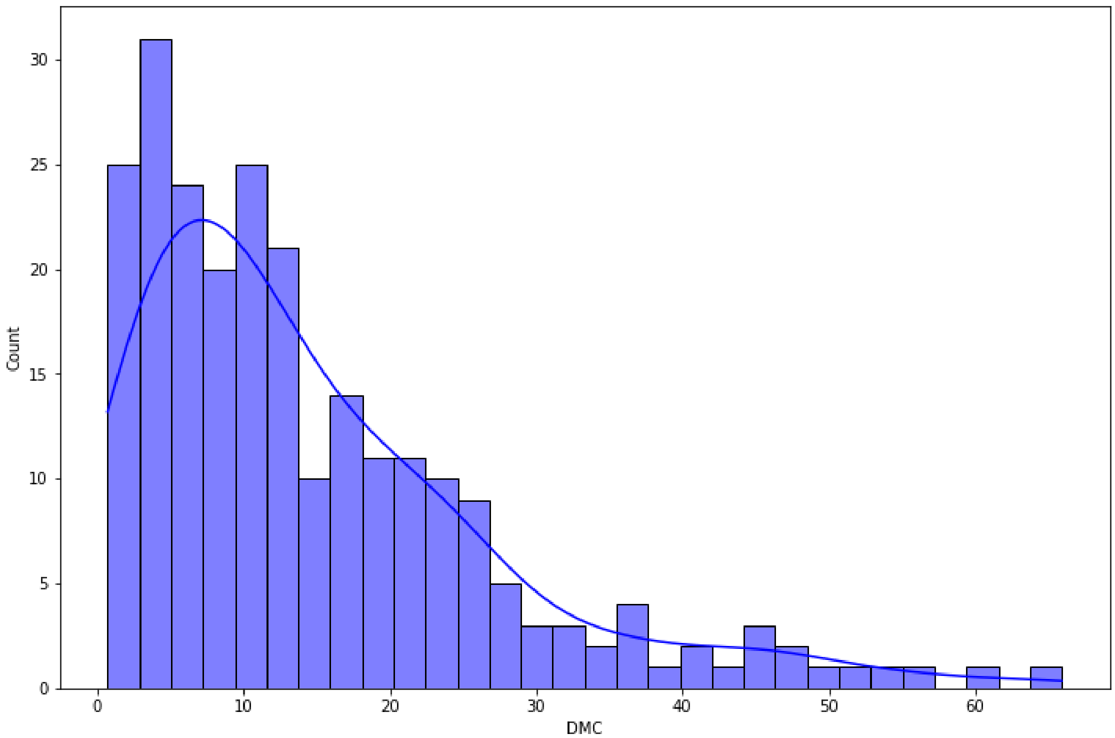


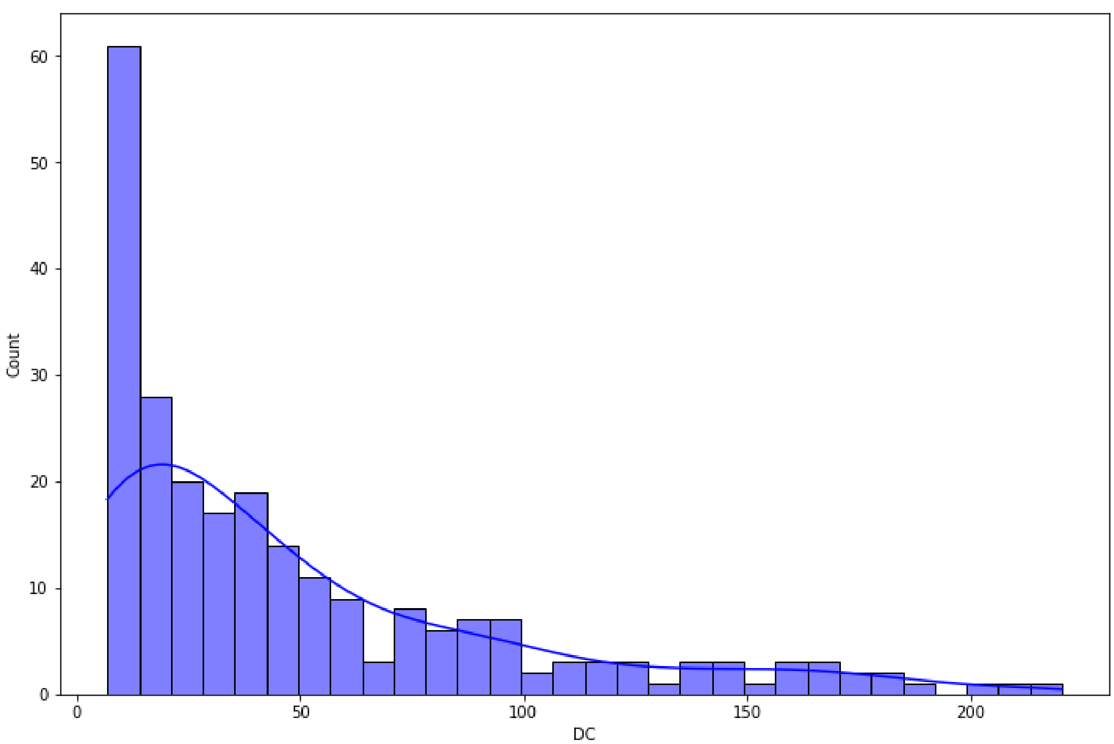

Count
RH
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20
30
40
50
60
70
80
90

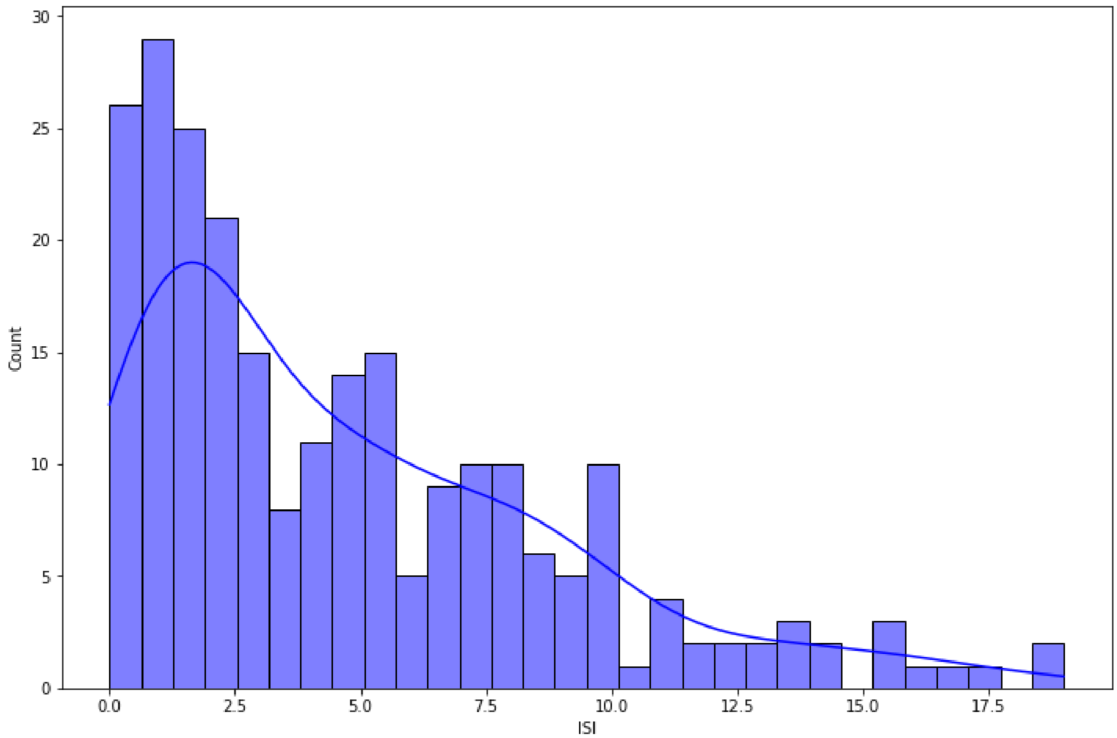

Count
Ws
0
10
20
30
40
5
10
15
20
25
30

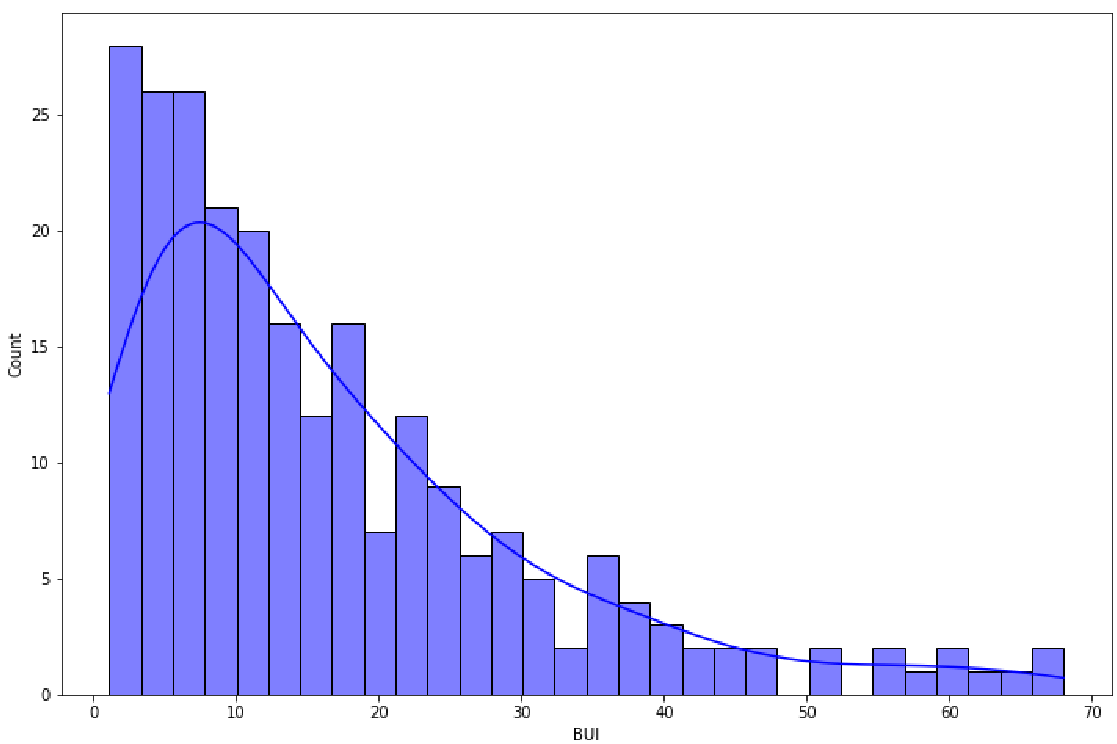

Count
Rain
0
25
50
75
100
125
150
175
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

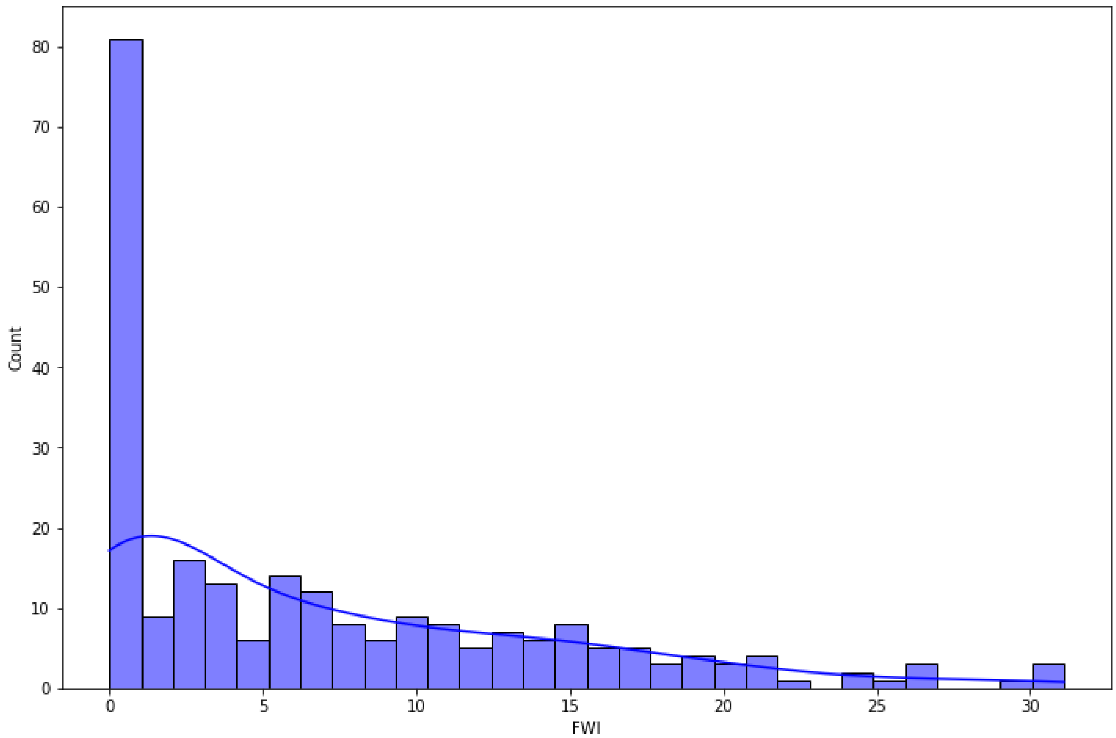

Count
FFMC
0
5
10
15
20
25
30
35
30
40
50
60
70
80
90


Count
DMC


Count
DC


Count
ISI


Count
BUI

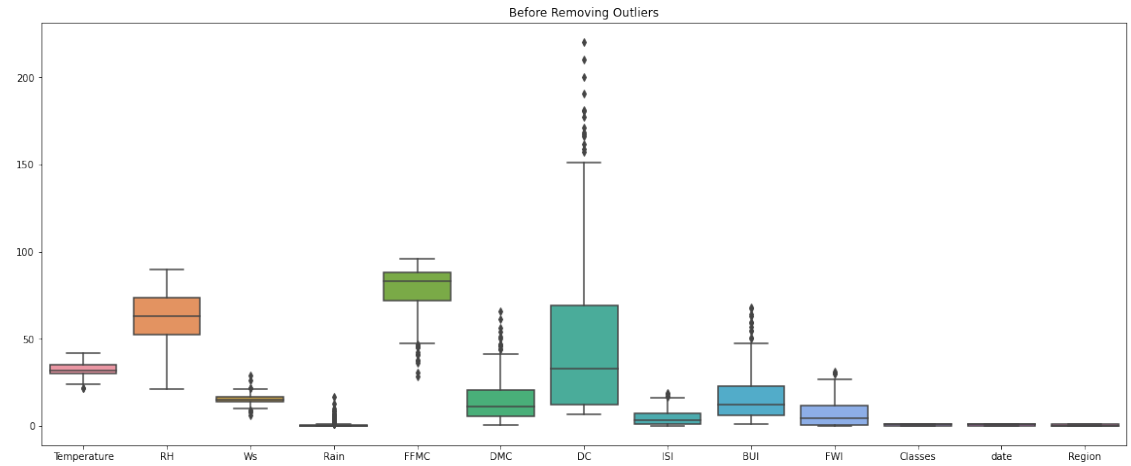


5 Outliers Handling

Before removing Outliers

[31]:
```
plt.figure(figsize=(20, 8))
sns.boxplot(data=df)
plt.title("Before Removing Outliers")
```

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



Function to find upper and lower boundaries

[32]:
```
def find_boundaries(df, variable, distance):
 IQR = df[variable].quantile(0.75) - df[variable].quantile(0.25)
 lower_boundary = df[variable].quantile(0.25) - (IQR*distance)
 upper_boundary = df[variable].quantile(0.75) + (IQR*distance)
 return upper_boundary, lower_boundary
```

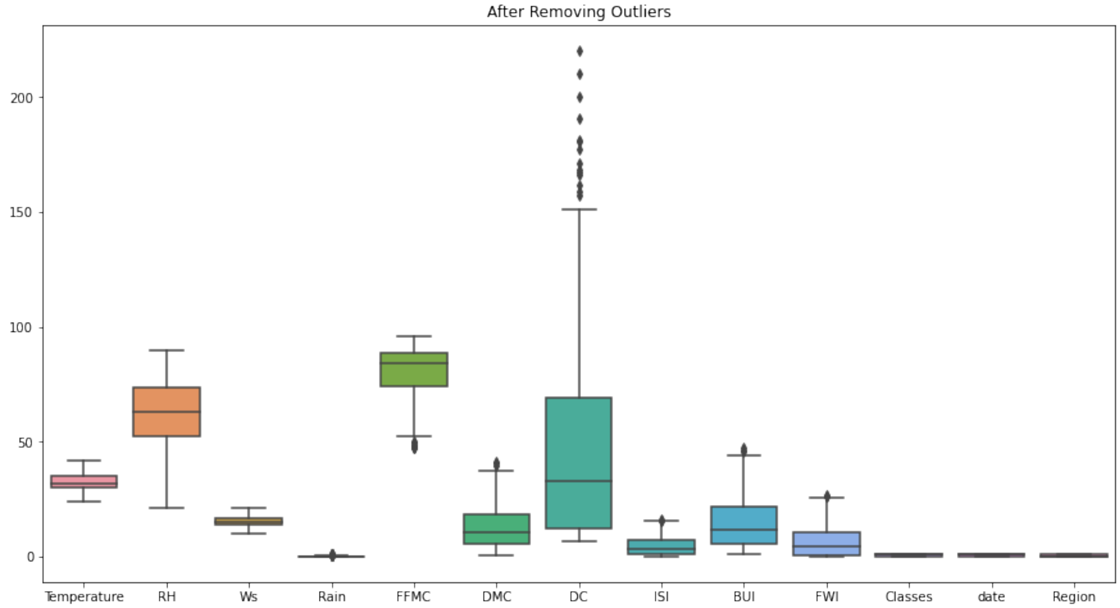
Deletion of outliers

[33]:
```
outliers_columns = ['Temperature', 'Ws','Rain','FFMC','DMC','ISI','BUI', 'FWI']
for i in outliers_columns:
  upper_boundary, lower_boundary = find_boundaries(df,i, 1.5)
  outliers = np.where(df[i] > upper_boundary, True, np.where(df[i] <␣
↪lower_boundary, True, False))
  outliers_df = df.loc[outliers, i]
  df_trimed= df.loc[~outliers, i]
  df[i] = df_trimed
```

After removal of outliers

[34]:
```
plt.figure(figsize=(15, 8))
sns.boxplot(data=df)
plt.title("After Removing Outliers")
```

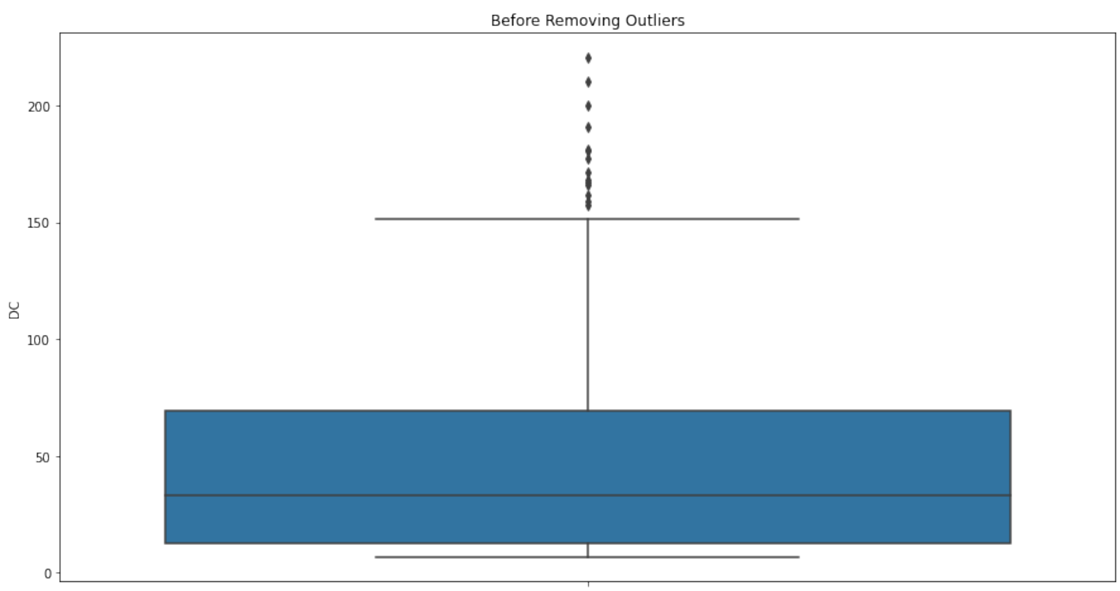
[34]: Text(0.5, 1.0, 'After Removing Outliers')



Outliers Handling For DC feature

[35]:
```
plt.figure(figsize=(15, 8))
sns.boxplot(data=df, y= 'DC')
plt.title("Before Removing Outliers")
```

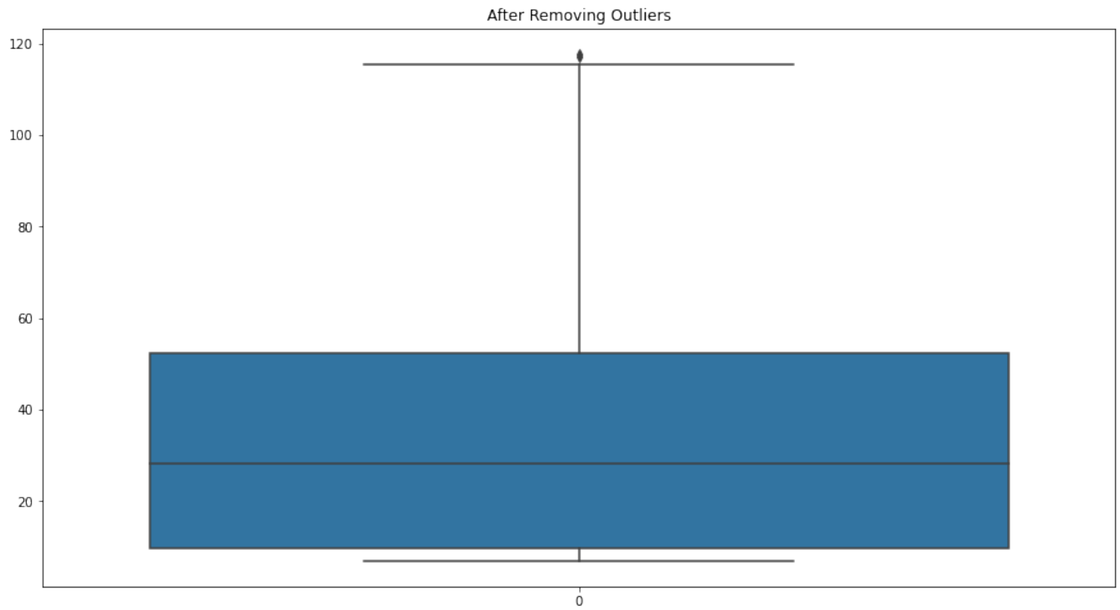
[35]: Text(0.5, 1.0, 'Before Removing Outliers')



[36]:
```
outliers = df[df['DC'] >=118]['DC']
df['DC'] = df[df['DC'] < 118]['DC']
```

[37]:
```
plt.figure(figsize=(15, 8))
sns.boxplot(data=df['DC'])
plt.title("After Removing Outliers")
```

[37]:
```
Text(0.5, 1.0, 'After Removing Outliers')
```



Check null value in eaxh column

[38]:
```
df.isnull().sum()
```

[38]:
```
Temperature     2
RH              0
Ws              8
Rain           35
FFMC           13
DMC            12
DC             25
ISI             4
BUI            11
FWI             4
Classes         0
date            0
Region          0
dtype: int64
```

Imputation of null value with the mean

[39]:
```
df.fillna(df.median().round(1), inplace=True)
```

Check null value of each column

[40]:
```
df.isnull().sum()
```

[40]:
```
Temperature    0
RH             0
Ws             0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
Classes        0
date           0
Region         0
dtype: int64
```

6 Statistical Analysis

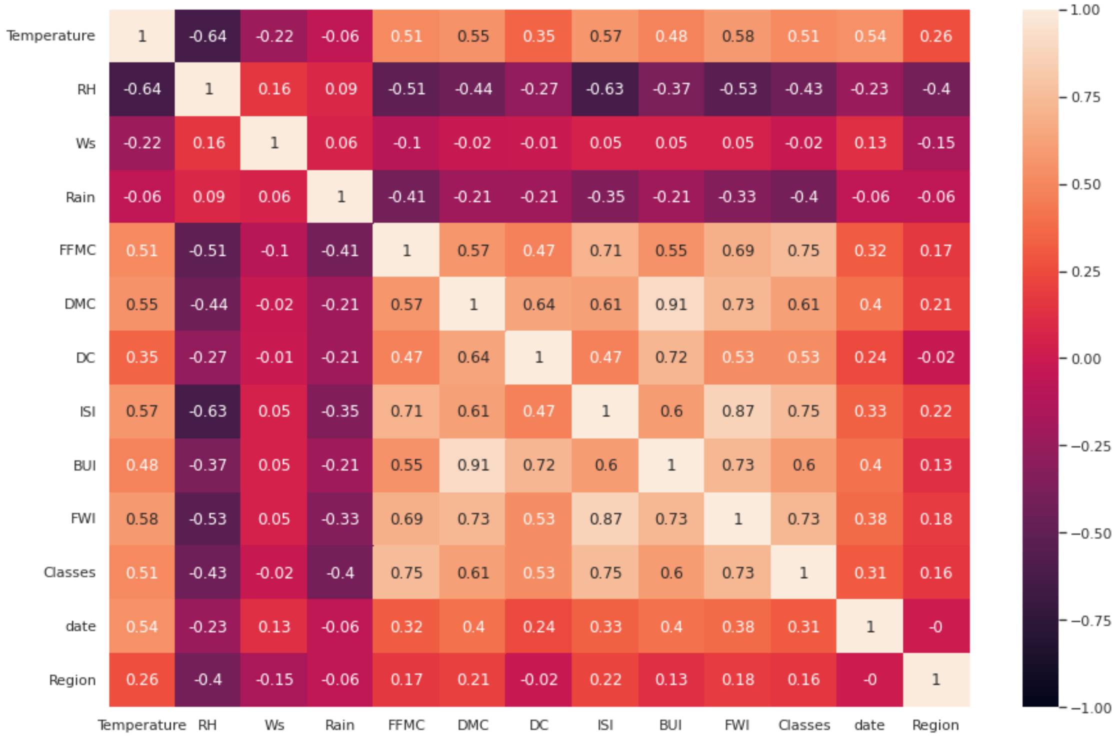
Correlation of numerical variable

[41]:
```
data = round(df.corr(),2)
```

Heatmap to check correlation between different variable

[42]:
```
sns.set(rc={'figure.figsize':(15,10)})
sns.heatmap(data=data, annot=True,  vmin=-1, vmax=1)
```

[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5c4c28ab50>
```



Observations 1. BUI and DMC are highly positvely correlated, so we will delete one feature i.e., BUI

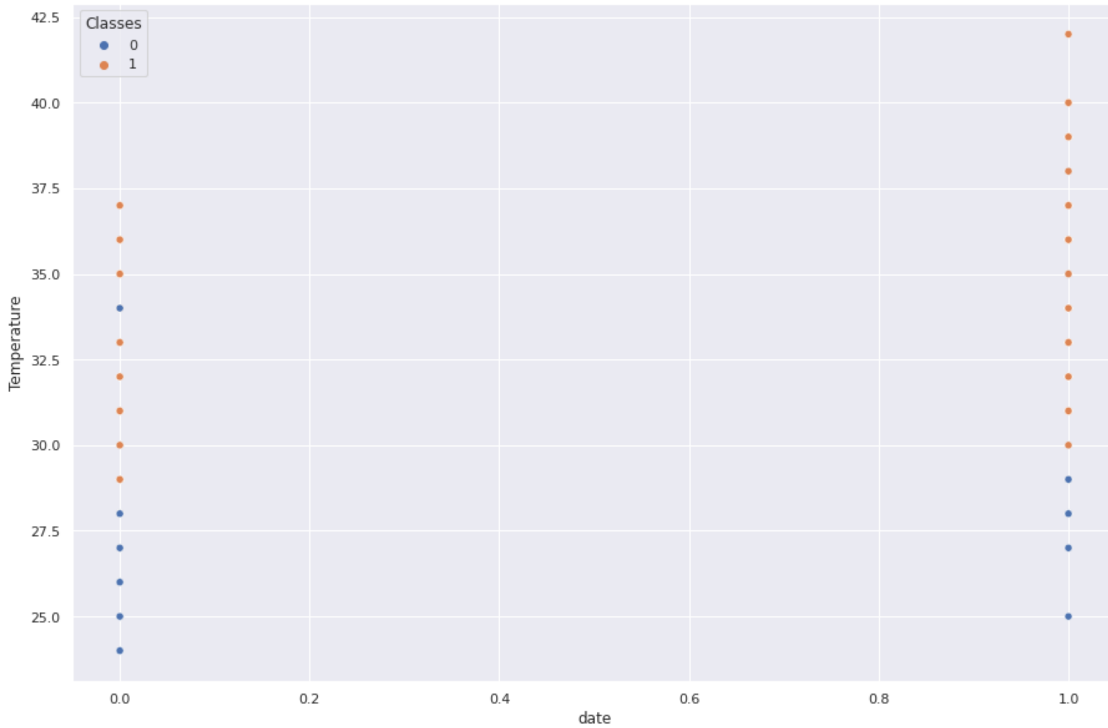
[43]:
```
df.drop('BUI', axis=1, inplace=True)
```

7 Model Building

Independent variable vs target variable distribution

[44]:
```
sns.scatterplot(data=df, x='date', y='Temperature', hue='Classes' )
```

[44]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5c4940a790>



[45]:
```
df.columns
```

[45]:
```
Index(['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'FWI',
       'Classes', 'date', 'Region'],
      dtype='object')
```

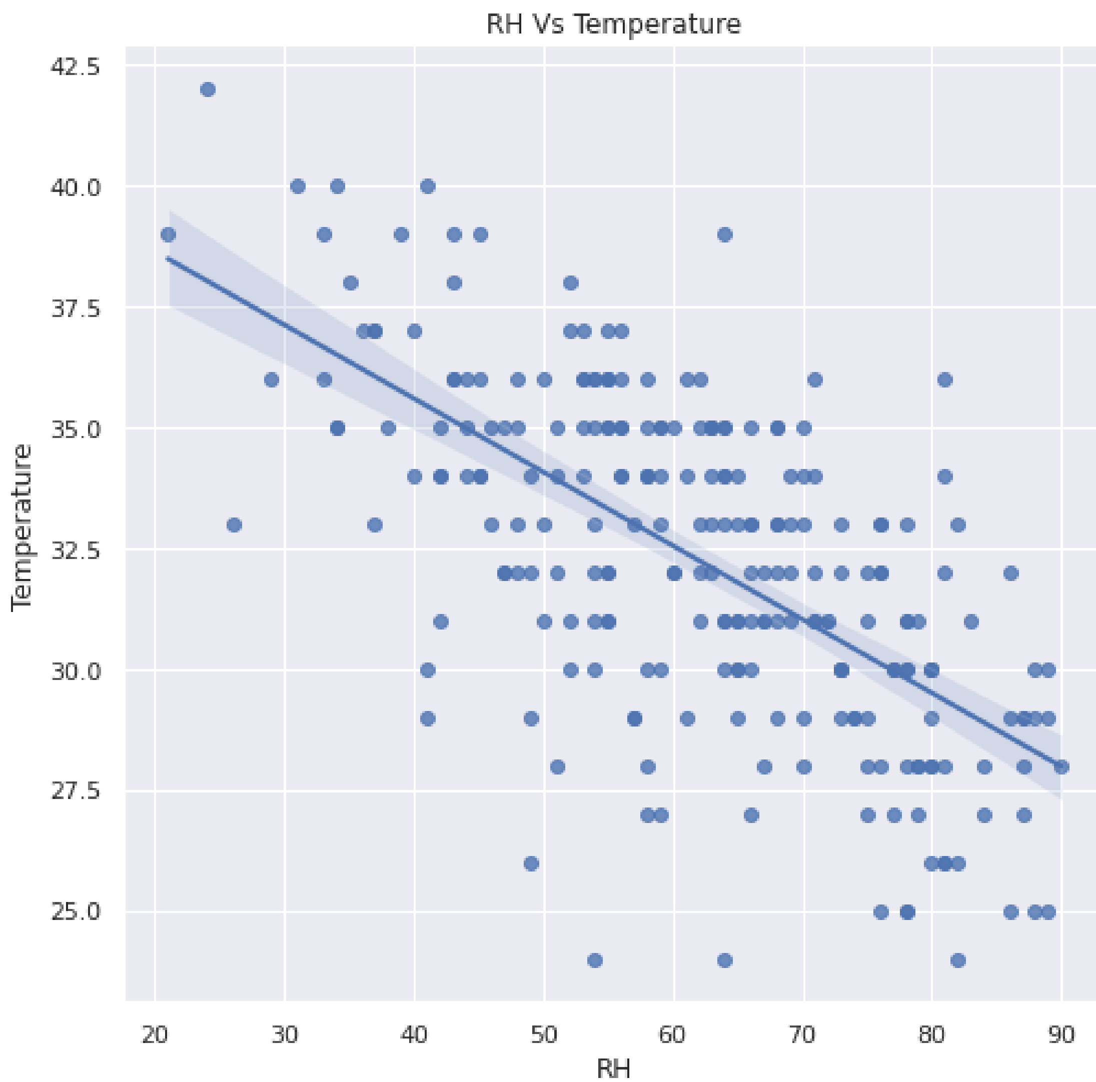
[46]:
```
df.info()
```

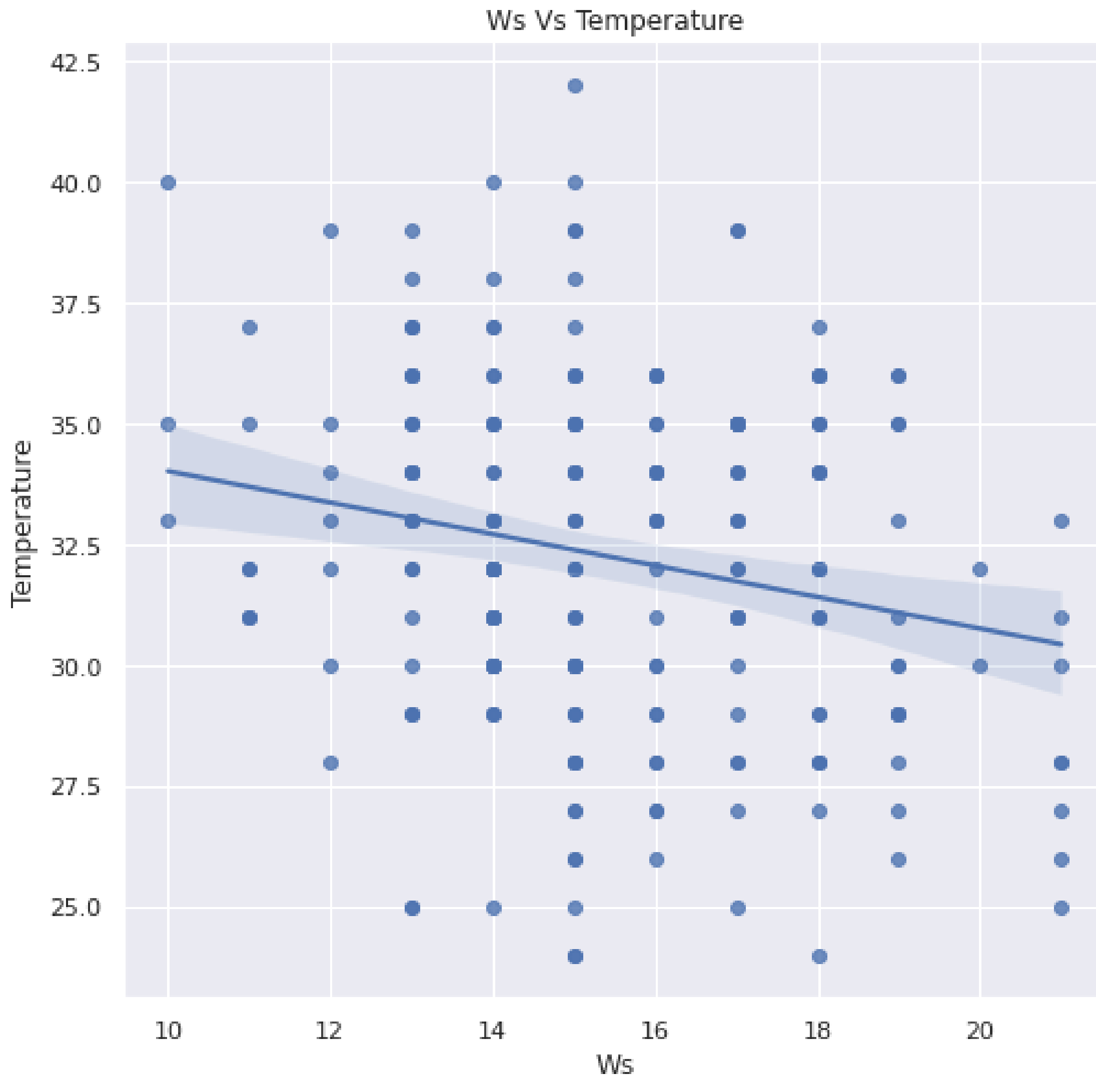
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243 entries, 0 to 242
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Temperature  243 non-null    float64
 1   RH           243 non-null    float64
 2   Ws           243 non-null    float64
 3   Rain         243 non-null    float64
 4   FFMC         243 non-null    float64
 5   DMC          243 non-null    float64
 6   DC           243 non-null    float64
 7   ISI          243 non-null    float64
 8   FWI          243 non-null    float64
 9   Classes      243 non-null    int64
 10  date         243 non-null    int64
```

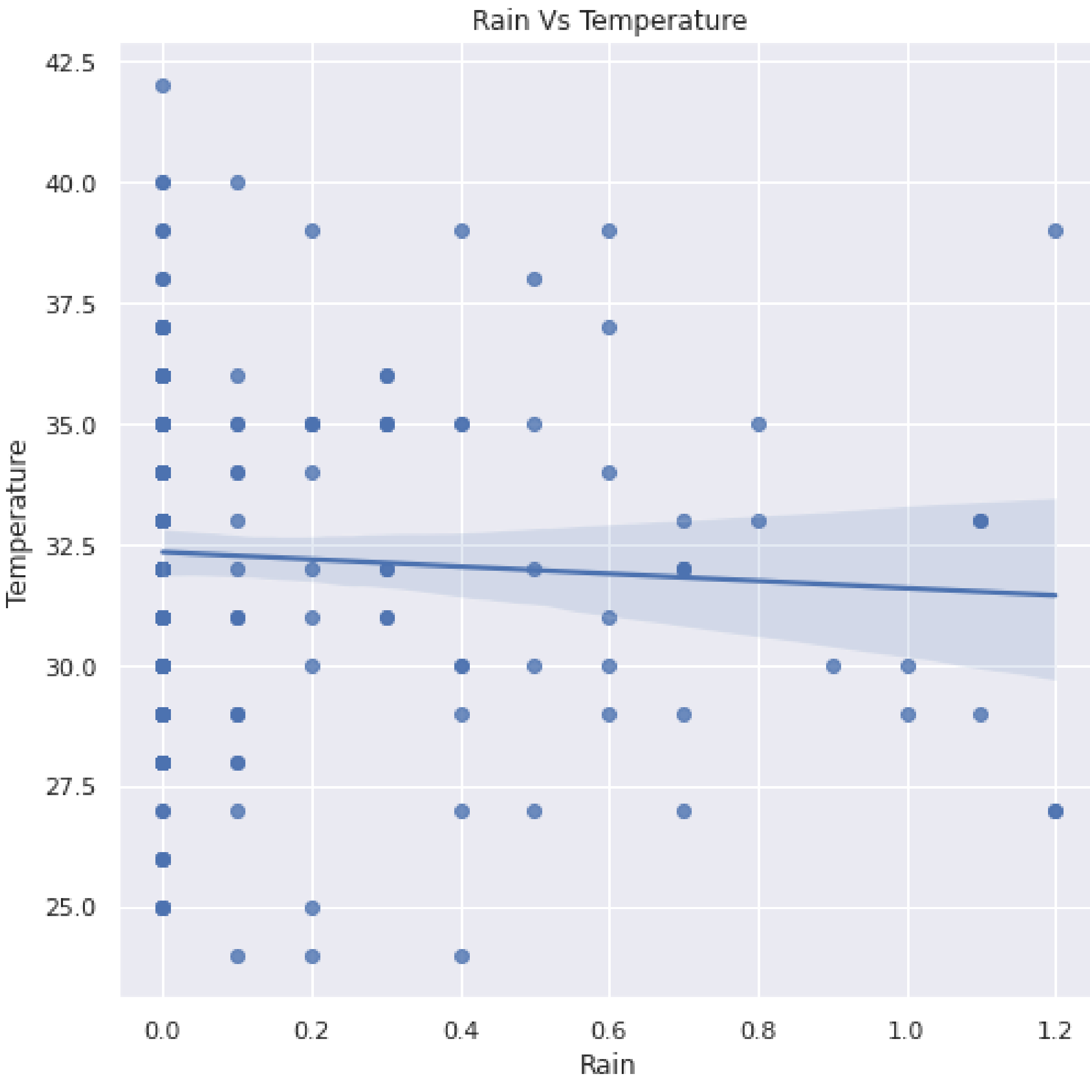
 11   Region   243 non-null   float64
dtypes: float64(10), int64(2)
memory usage: 22.9 KB

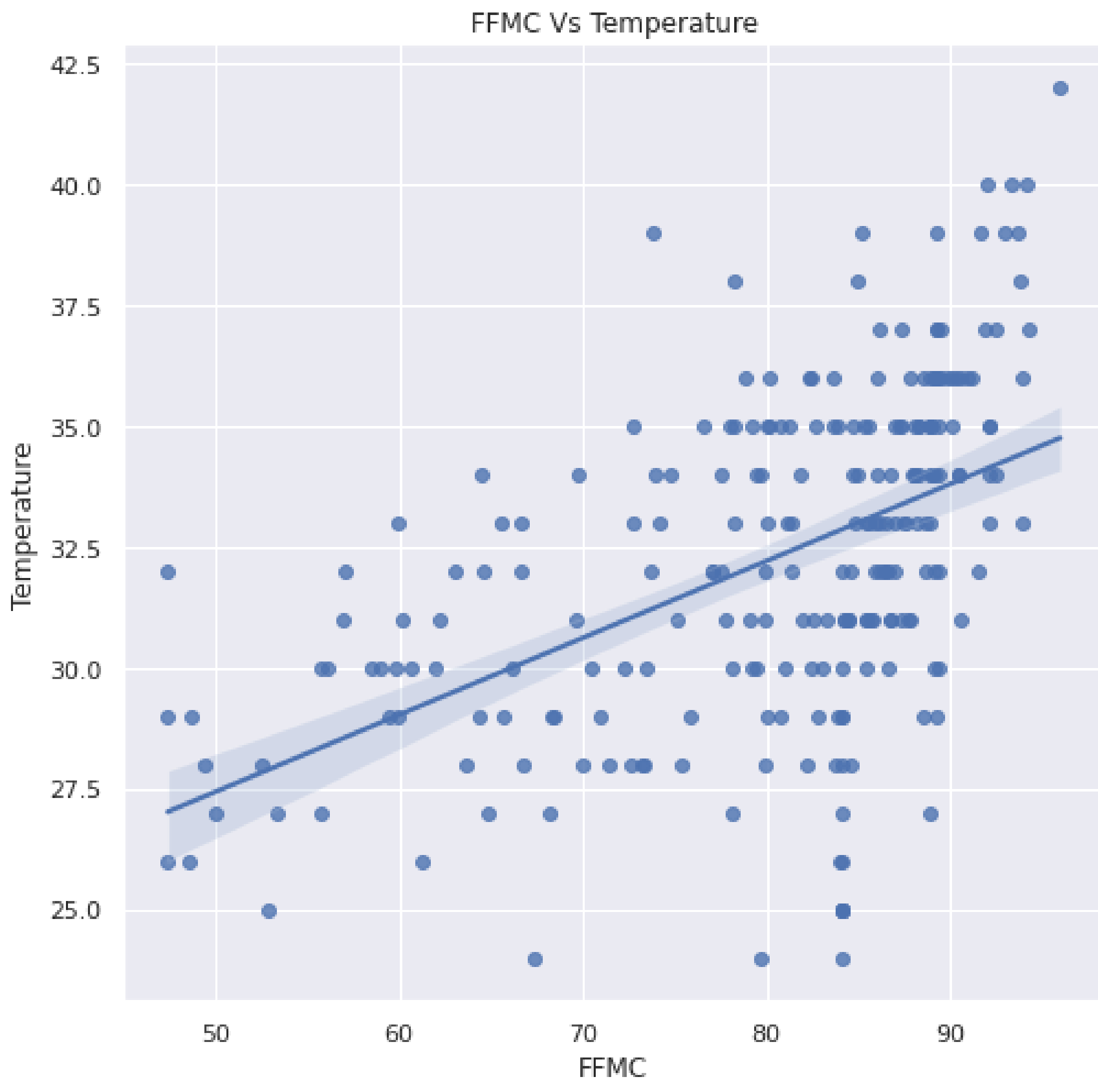
Regression PLot

[47]:
```
#### shaded region is basically with respect to ridge and lasso (lambda)
for feature in [feature for feature in df.columns if feature not in␣
↪['Temperature', 'date', 'Region', 'Classes']]:
    sns.set(rc={'figure.figsize':(8,8)})
    sns.regplot(x=df[feature], y=df['Temperature'])
    plt.xlabel(feature)
    plt.ylabel("Temperature")
    plt.title("{} Vs Temperature".format(feature))
    plt.show();
```

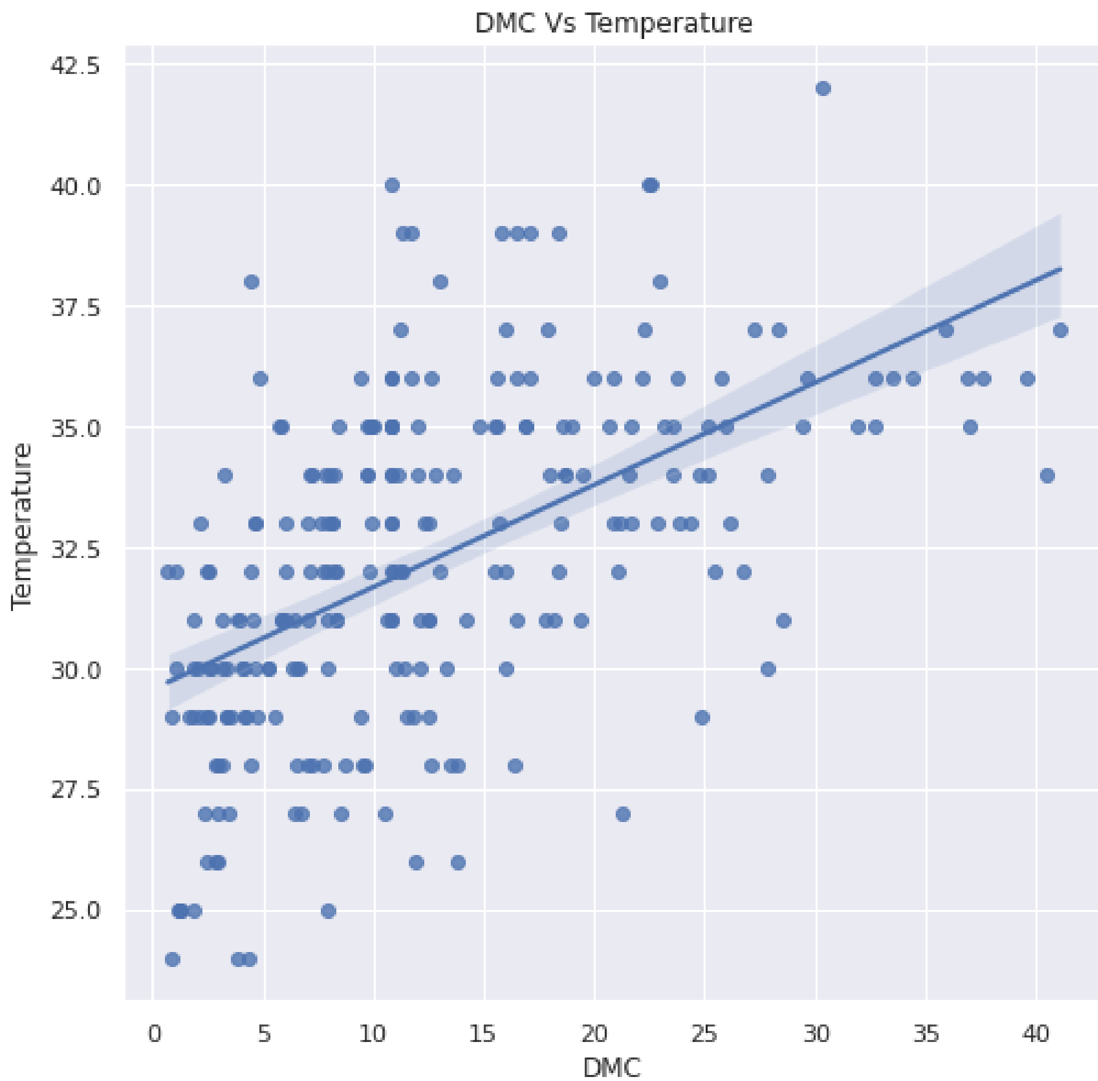



Ws Vs Temperature
Temperature
Ws
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
10
12
14
16
18
20

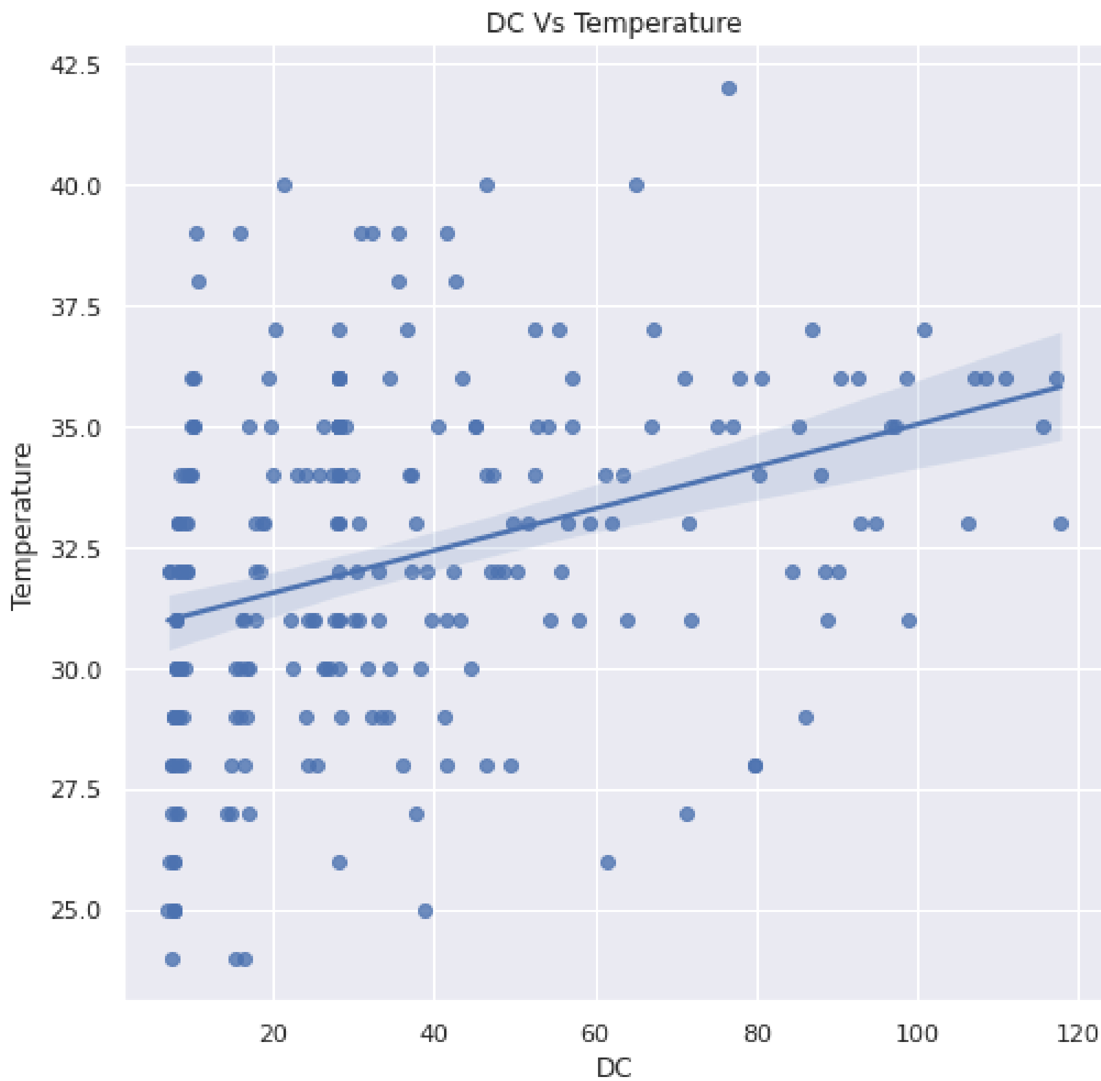

Rain Vs Temperature
Temperature
Rain
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
0.0
0.2
0.4
0.6
0.8
1.0
1.2

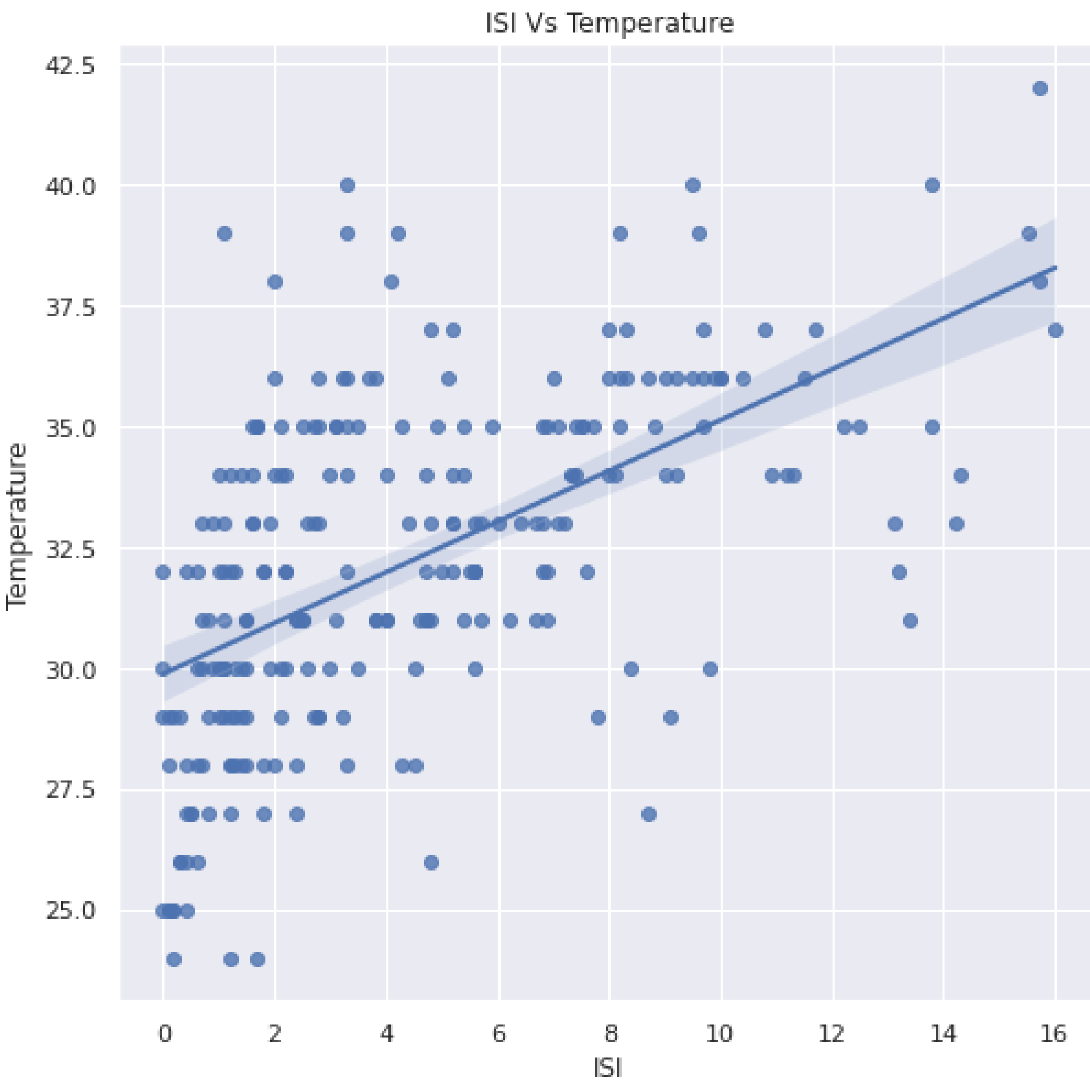


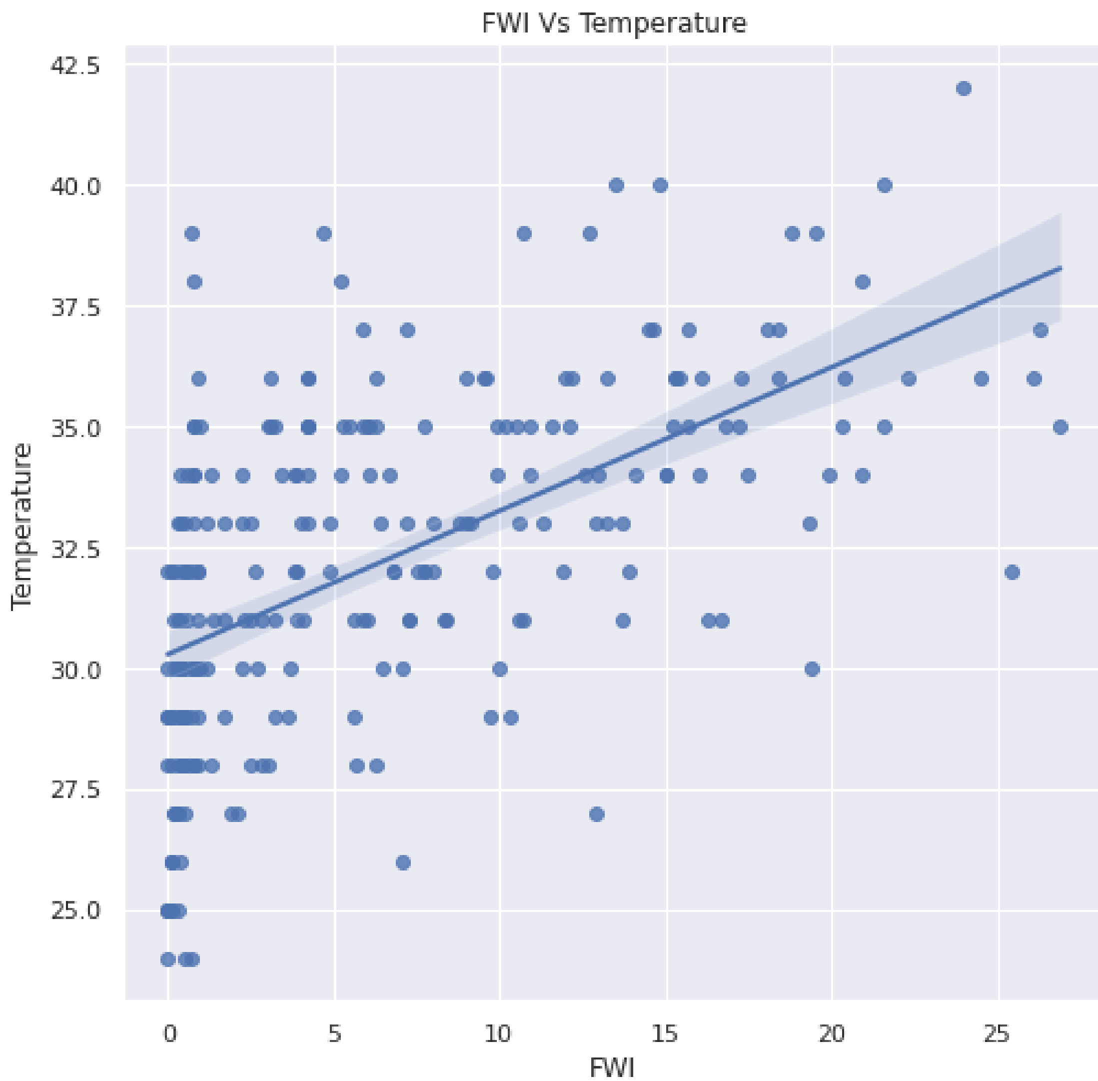
FFMC Vs Temperature
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
Temperature
50
60
70
80
90
FFMC



DMC Vs Temperature
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
Temperature
0
5
10
15
20
25
30
35
40
DMC


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
42.5
40.0
37.5
35.0
32.5
30.0
27.5
25.0
Temperature
0
2
4
6
8
10
12
14
16
ISI



Segregate dependent and independent feature

[48]:
```
### X independent features and y dependent feature
X= df[['RH', 'Ws', 'Rain','FFMC', 'DMC', 'ISI','DC',
         'FWI', 'Classes', 'Region', 'date']]
y=df[['Temperature']]
```

[49]:
```
X
```

[49]:

	RH	Ws	Rain	FFMC	DMC	ISI	DC	FWI	Classes	Region	date
0	57.0	18.0	0.0	65.7	3.4	1.3	7.6	0.5	0	0.0	0
1	61.0	13.0	0.0	64.4	4.1	1.0	7.6	0.4	0	0.0	0
2	82.0	15.0	0.0	84.1	2.5	0.3	7.1	0.1	0	0.0	0
3	89.0	13.0	0.0	84.1	1.3	0.0	6.9	0.0	0	0.0	0

```
4    77.0  16.0   0.0  64.8   3.0  1.2  14.2  0.5         0     0.0     0
..    ...   ...   ...   ...   ...  ...   ...  ...        ...     ...   ...
238  65.0  14.0   0.0  85.4  16.0  4.5  44.5  6.5         1     1.0     0
239  87.0  15.0   0.0  84.1   6.5  0.1   8.0  0.0         0     1.0     0
240  87.0  15.0   0.5  84.1   3.5  0.4   7.9  0.2         0     1.0     0
241  54.0  18.0   0.1  79.7   4.3  1.7  15.2  0.7         0     1.0     0
242  64.0  15.0   0.2  67.3   3.8  1.2  16.5  0.5         0     1.0     0

[243 rows x 11 columns]
```

splitting the data into training and test dataset

[50]:
```
### random state train test split will be same with all people using␣
↪random_state=42
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
↪random_state=42)
```

Scaling the feature

[51]:
```
### creating a StandardScalar object
scaler=StandardScaler()
scaler
```

[51]:
```
StandardScaler()
```

[52]:
```
### Using fit_transform to standardise Train data
X_train=scaler.fit_transform(X_train)
```

[53]:
```
### here using only transform to avoid data leakage
### (training mean and training std will be used for standardisation of test␣
↪when we use transform on test data)
X_test=scaler.transform(X_test)
```

8 Linear Regression Model

[54]:
```
## creating linear regression model
linear_reg=LinearRegression()
linear_reg
```

[54]:
```
LinearRegression()
```

[55]:
```
pd.DataFrame(X_train).isnull().sum()
```

[55]:
```
0      0
1      0
```

```
2     0
3     0
4     0
5     0
6     0
7     0
8     0
9     0
10    0
dtype: int64
```

[56]:
```
### Passing training data(X and y) to the model
linear_reg.fit(X_train, y_train)
```

[56]:
```
LinearRegression()
```

[57]:
```
### Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent features is {}".format(linear_reg.coef_))
print("2. Intercept of best fit hyper plane is {}".format(linear_reg.
 ↪intercept_))
```

```
1. Co-efficients of independent features is [[-1.54124901 -0.70322143
0.13806361 -0.56701813  0.39154581  0.22987985
  -0.08348215  0.21115453  0.67213177  0.04275862  1.29003041]]
2. Intercept of best fit hyper plane is [32.16049383]
```

Prediction of test data

[58]:
```
linear_reg_pred=linear_reg.predict(X_test)
```

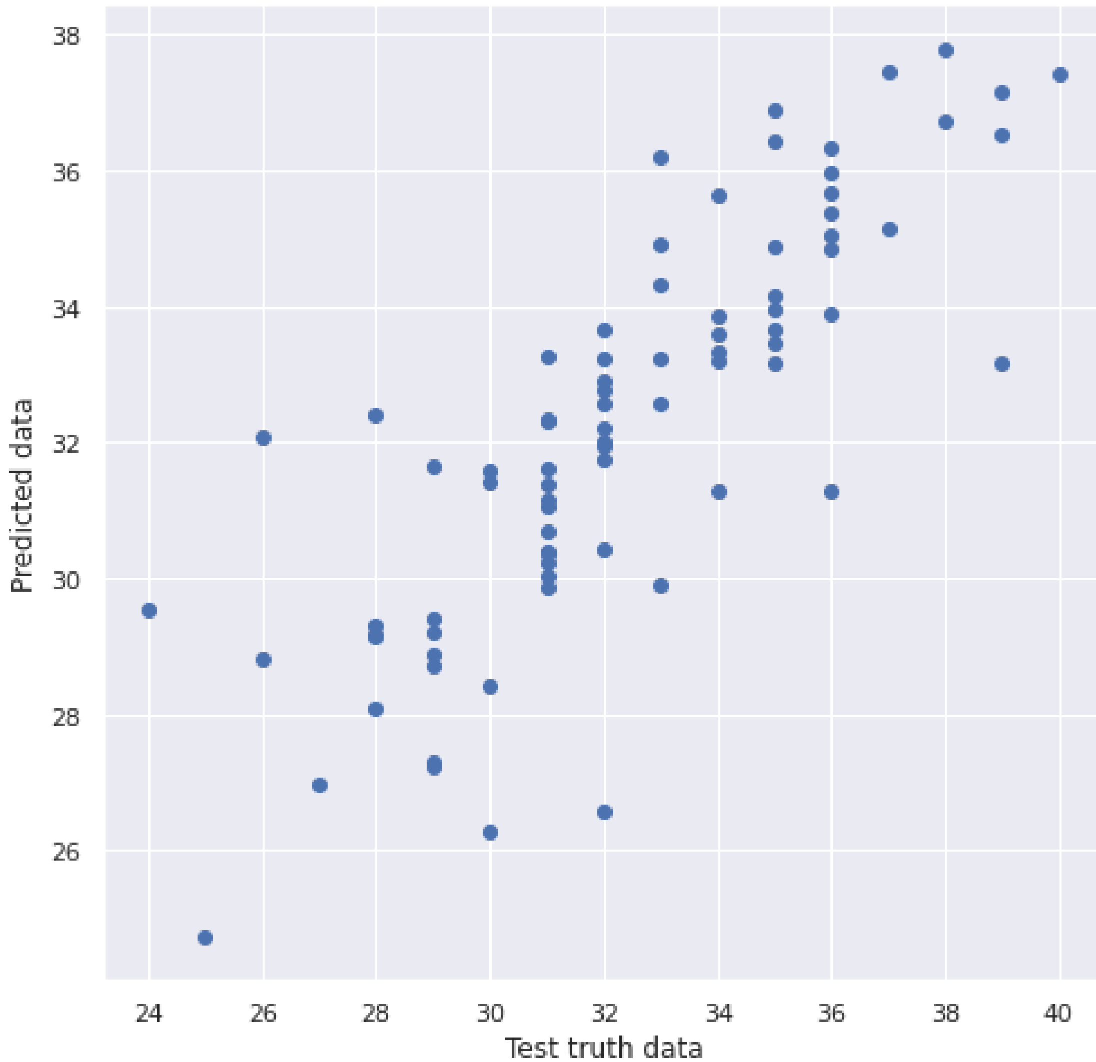
[59]:
```
residual_linear_reg=y_test-linear_reg_pred
residual_linear_reg = pd.DataFrame(residual_linear_reg)
```

8.1 Validation of Linear Regression assumptions

1. Linear Relationship

[60]:
```
plt.scatter(x=y_test,y=linear_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

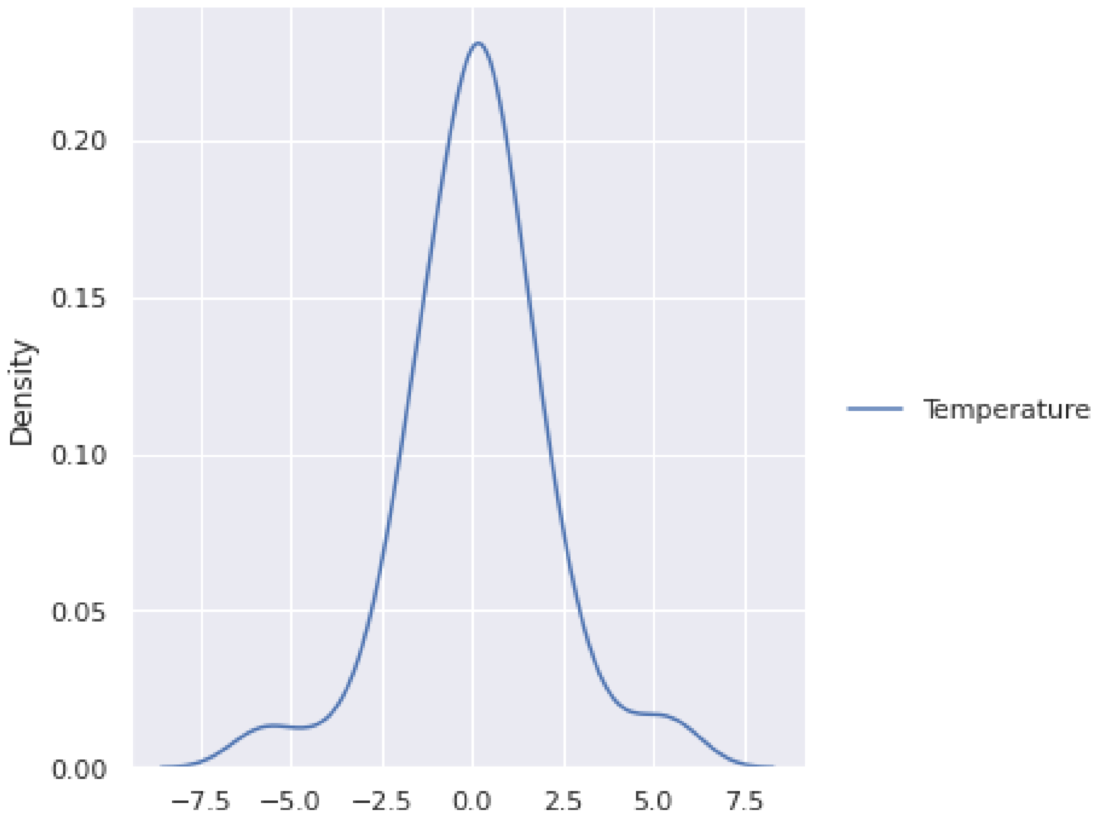
[60]:
```
Text(0, 0.5, 'Predicted data')
```



2. Residual should be normally distributed

[61]:
```
sns.displot(data=residual_linear_reg, kind='kde')
```

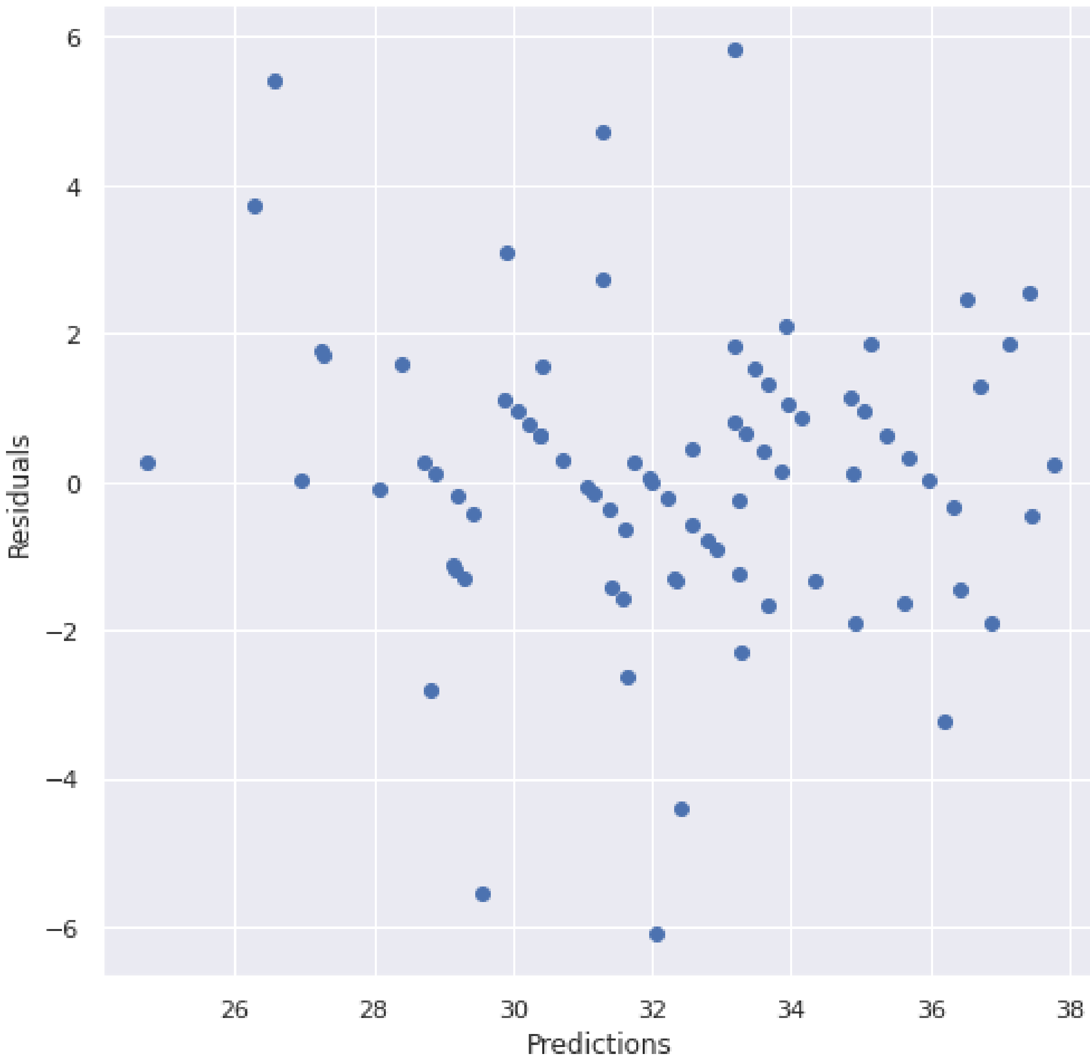
[61]: <seaborn.axisgrid.FacetGrid at 0x7f5c47a24e90>



3. Residual and Predicted values should follow uniform distribution

[62]:
```
plt.scatter(x=linear_reg_pred, y=residual_linear_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

[62]: Text(0, 0.5, 'Residuals')



8.2 Cost Function Values

[63]:
```
print(f"MSE : {round(mean_squared_error(y_test, linear_reg_pred),2)}\nMAE :
↪{round(mean_absolute_error(y_test, linear_reg_pred),2)}\nRMSE : {round(np.
↪sqrt(mean_squared_error(y_test, linear_reg_pred)),2)}")
```

```
MSE : 3.97
MAE : 1.42
RMSE : 1.99
```

8.3 Performance Metrics

[64]:
```
linear_reg_r2_score=r2_score(y_test, linear_reg_pred)
linear_reg_adj_r2_score=1-((1-linear_reg_r2_score)*(len(y_test)-1)/
 ↪(len(y_test)-X_test.shape[1]-1))
print(f"R-Squared Accuracy : {round(linear_reg_r2_score*100,3)} % \nAdjusted␣
 ↪R-Squared Accuracy : {round(linear_reg_adj_r2_score*100,2)}%")
```

```
R-Squared Accuracy : 65.577 %
Adjusted R-Squared Accuracy : 60.09%
```

9 Ridge Regresion Model

[65]:
```
## creating Ridge regression model
ridge_reg=Ridge()
ridge_reg
```

[65]: Ridge()

[66]:
```
### Passing training data(X and y) to the model
ridge_reg.fit(X_train, y_train)
```

[66]: Ridge()

[67]:
```
### 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.intercept_))
```

```
1. Co-efficients of independent features is [[-1.5220595  -0.69660965
0.14190643 -0.54059873  0.39066657  0.23783093
  -0.08099752  0.21234668  0.65289177  0.04621455  1.27989004]]
2. Intercept of best fit hyper plane is [32.16049383]
```

Prediction of test data

[68]:
```
ridge_reg_pred=ridge_reg.predict(X_test)
```

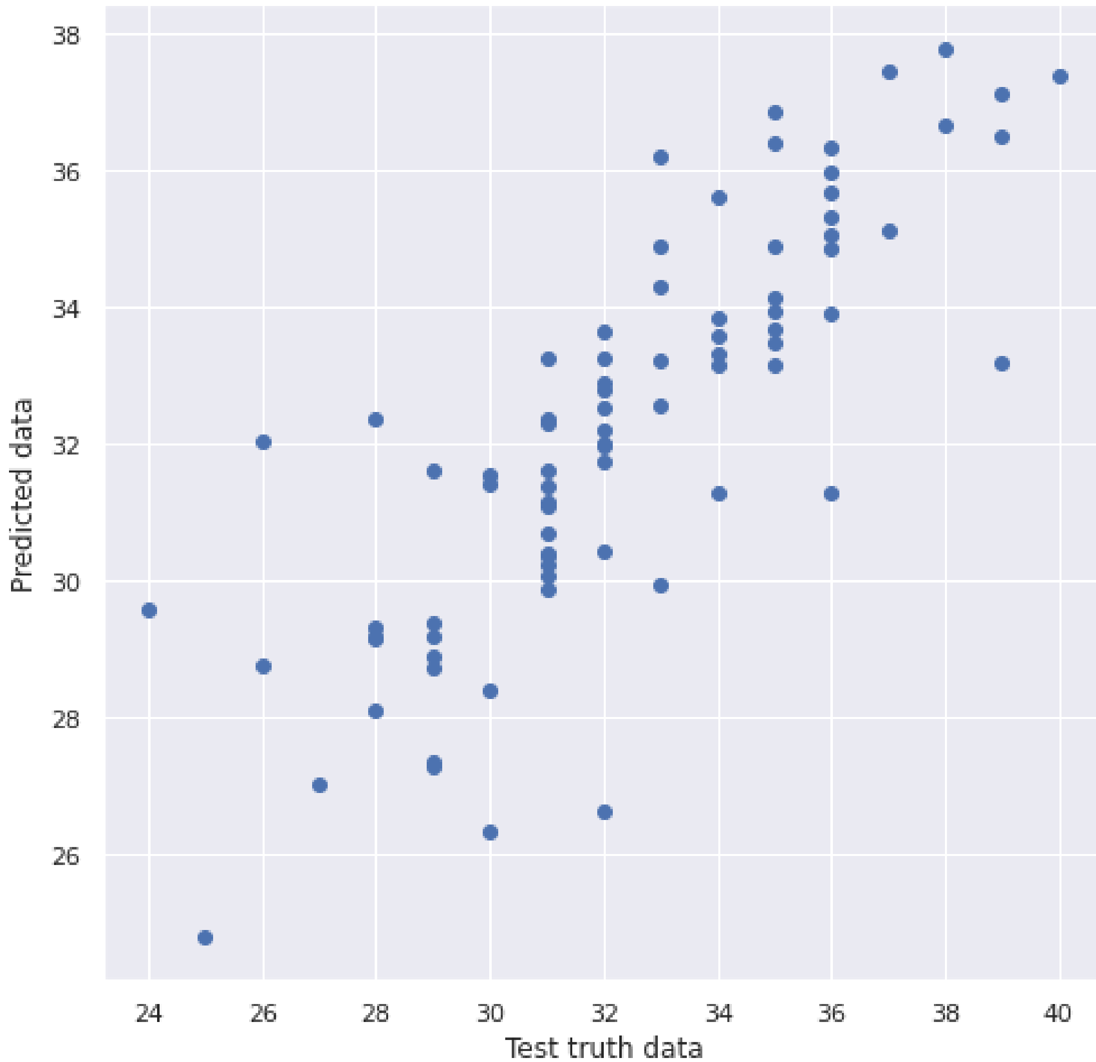
[69]:
```
residual_ridge_reg=y_test-ridge_reg_pred
residual_ridge_reg = pd.DataFrame(residual_ridge_reg)
```

9.1 Validation of Ridge Regression assumptions

1. Linear Relationship

[70]:
```
plt.scatter(x=y_test,y=ridge_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

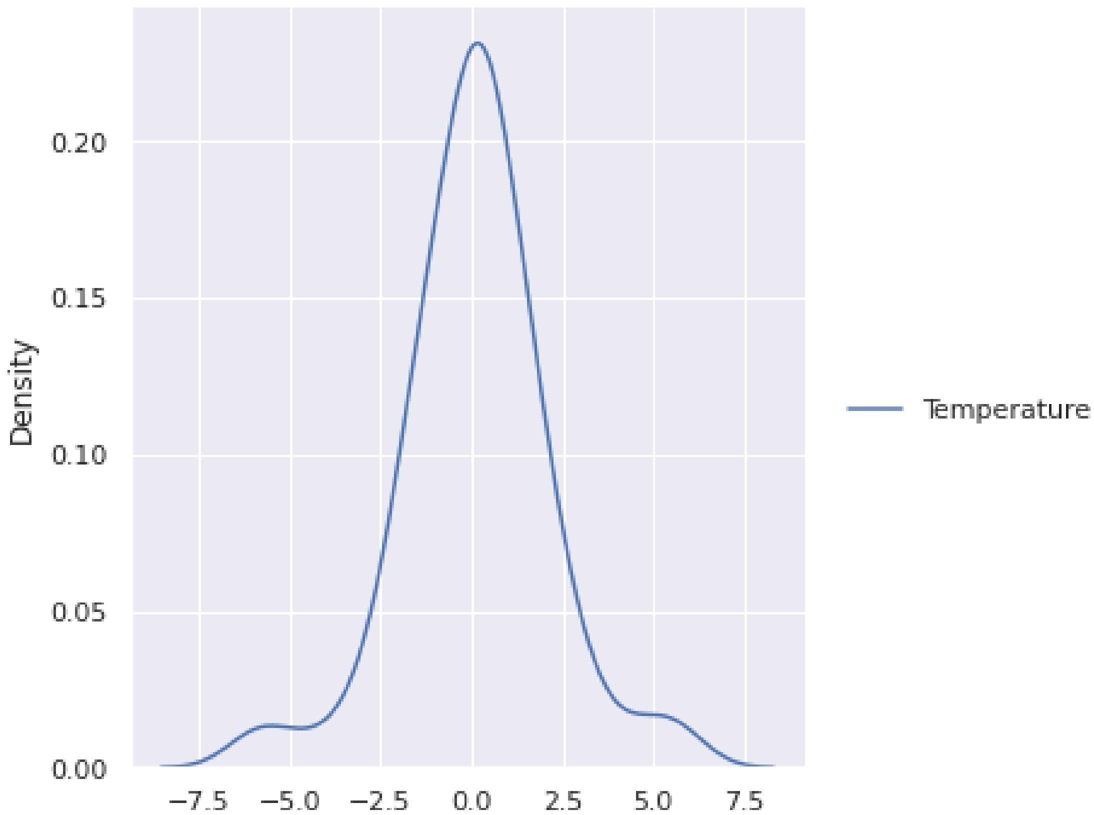
[70]: Text(0, 0.5, 'Predicted data')



2. Residual should be normally distributed

[71]:
```
sns.displot(data = residual_ridge_reg, kind='kde')
```

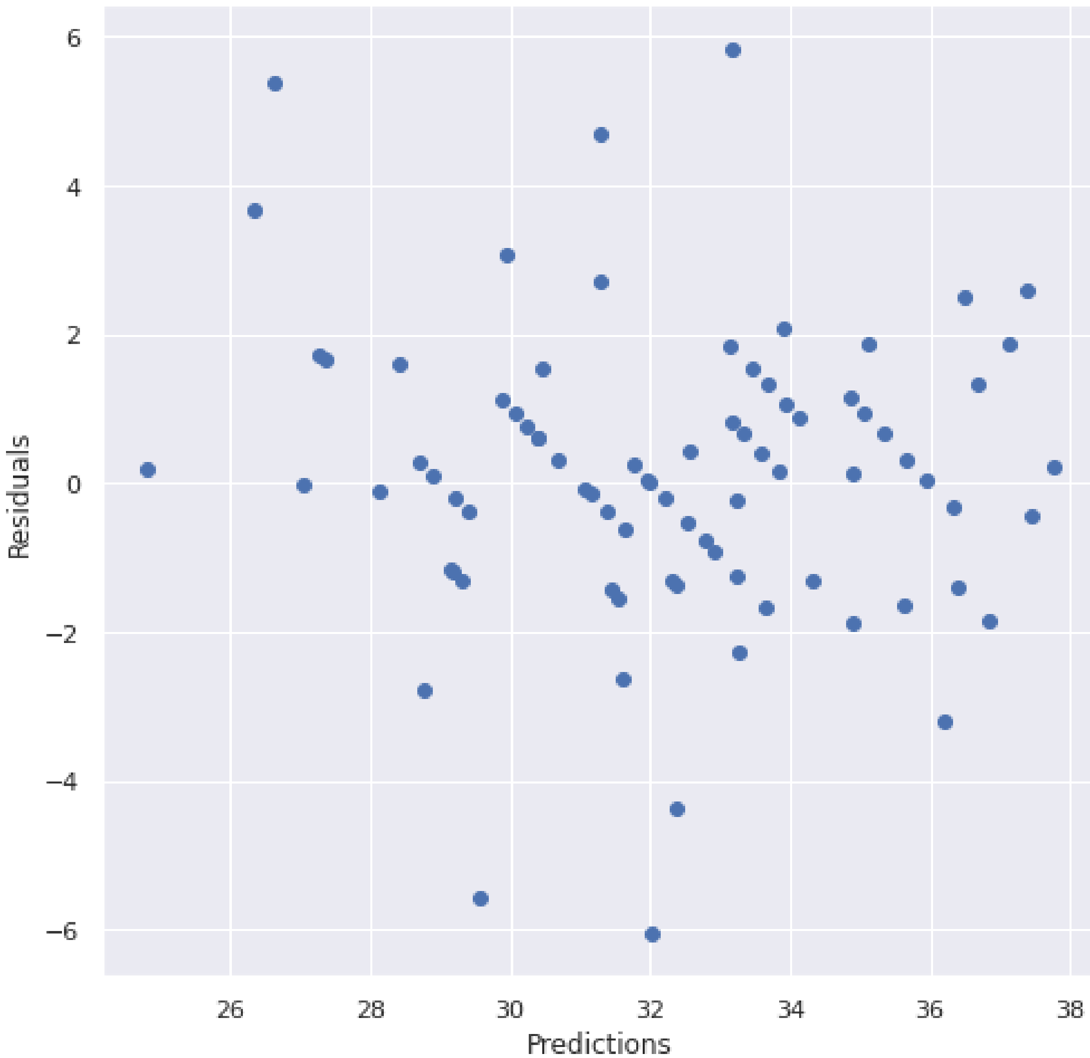
[71]: <seaborn.axisgrid.FacetGrid at 0x7f5c4787bd90>



3. Residual and Predicted values should follow uniform distribution

[72]:
```
plt.scatter(x=ridge_reg_pred, y=residual_ridge_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

[72]: Text(0, 0.5, 'Residuals')



9.2 Cost Function Values

[73]:
```
print(f"MSE : {round(mean_squared_error(y_test, ridge_reg_pred),2)}\nMAE :␣
↪{round(mean_absolute_error(y_test, ridge_reg_pred),2)}\nRMSE : {round(np.
↪sqrt(mean_squared_error(y_test, ridge_reg_pred)),2)}")
```

```
MSE : 3.93
MAE : 1.41
RMSE : 1.98
```

10 Performance Metrics

[74]:
```
ridge_reg_r2_score=r2_score(y_test, ridge_reg_pred)
ridge_reg_adj_r2_score=1-((1-ridge_reg_r2_score)*(len(y_test)-1)/
 ↪(len(y_test)-X_test.shape[1]-1))
print(f"R-Squared Accuracy : {round(ridge_reg_r2_score*100,3)} % \nAdjusted␣
 ↪R-Squared Accuracy : {round(ridge_reg_adj_r2_score*100,2)}%")
```

```
R-Squared Accuracy : 65.852 %
Adjusted R-Squared Accuracy : 60.41%
```

11 Lasso Regression Model

[75]:
```
## creating Lasso regression model
lasso_reg=Lasso()
lasso_reg
```

[75]: Lasso()

[76]:
```
### Passing training data(X and y) to the model
lasso_reg.fit(X_train, y_train)
```

[76]: Lasso()

[77]:
```
### 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.intercept_))
```

```
1. Co-efficients of independent features is [-1.08734742 -0.         -0.
0.          0.07431697  0.
  0.          0.14897177  0.          0.          0.53109976]
2. Intercept of best fit hyper plane is [32.16049383]
```

Prediction of test data

[78]:
```
lasso_reg_pred=lasso_reg.predict(X_test)
```

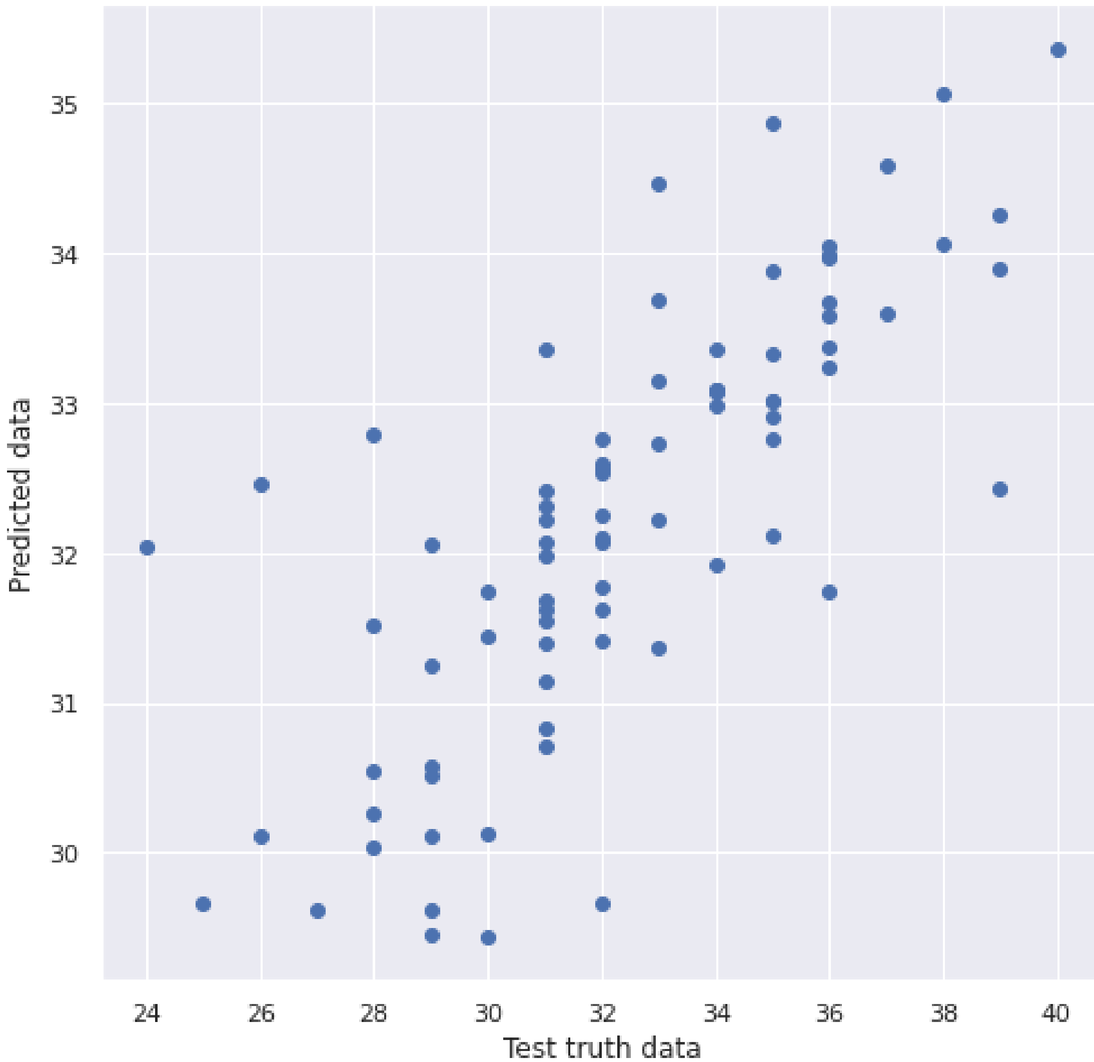
[79]:
```
y_test = y_test.squeeze()
residual_lasso_reg = y_test-lasso_reg_pred
residual_lasso_reg = pd.DataFrame(residual_lasso_reg)
```

11.1 Validation of Lasso Regression assumptions

1. Linear Relationship

[80]:
```python
plt.scatter(x=y_test,y=lasso_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

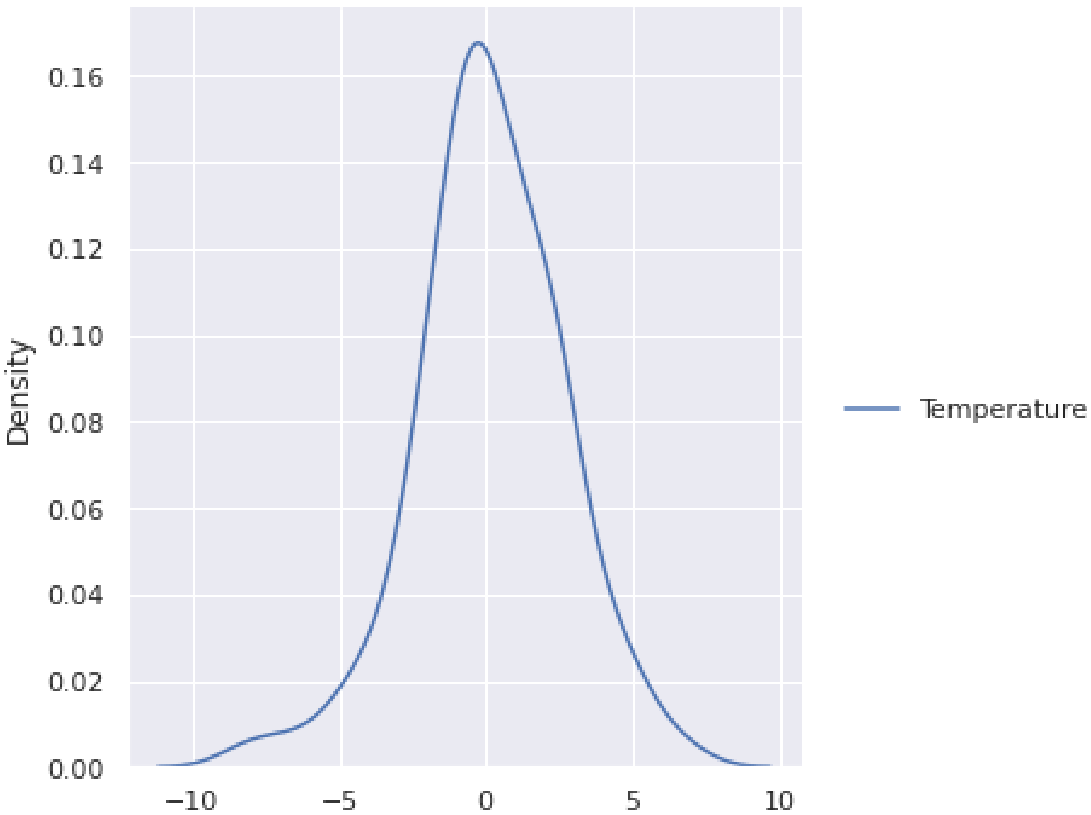
[80]: Text(0, 0.5, 'Predicted data')



2. Residual should be normally distributed

[81]:
```python
sns.displot( data = residual_lasso_reg, kind='kde')
```

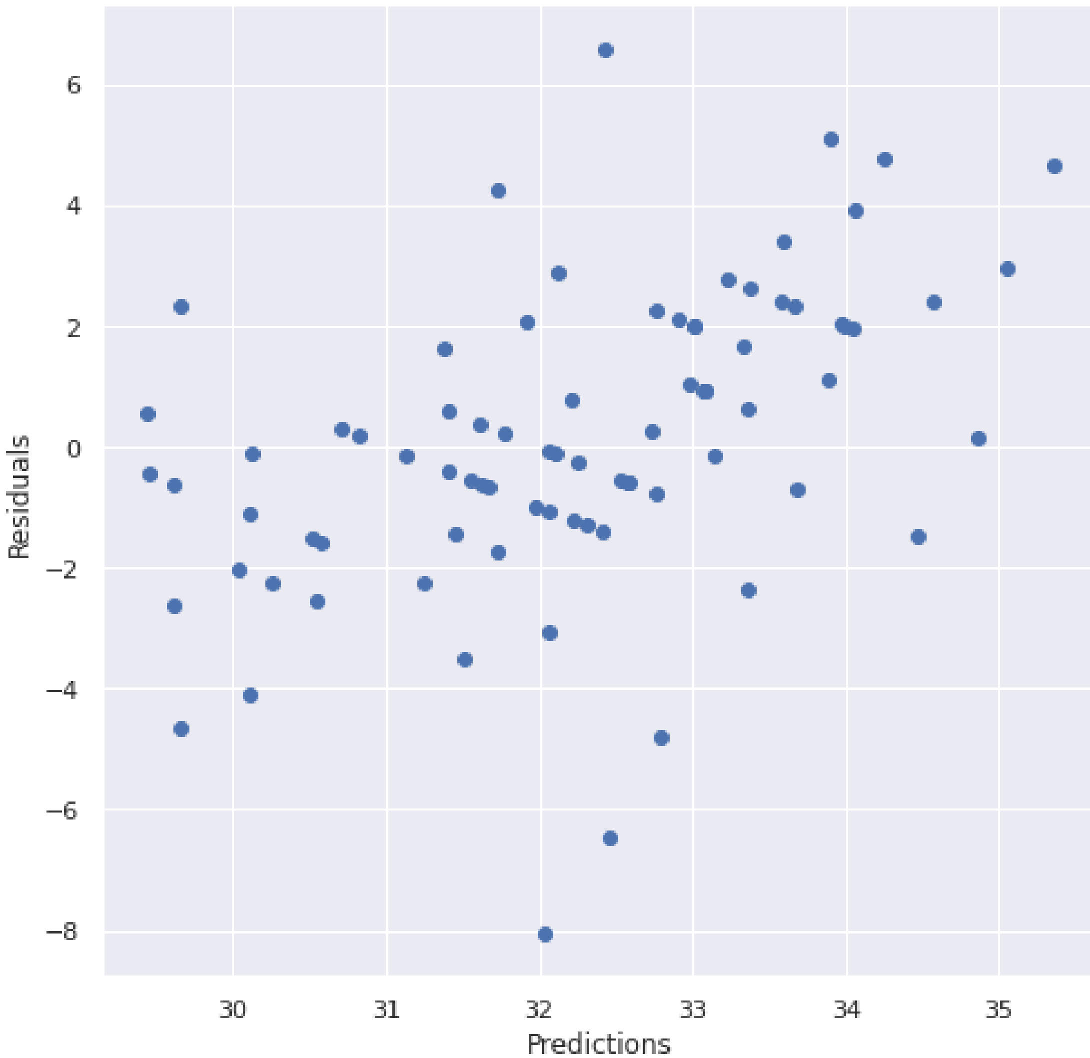
[81]: <seaborn.axisgrid.FacetGrid at 0x7f5c47630950>



3. Residual and Predicted values should follow uniform distribution

[82]:
```
plt.scatter(x=lasso_reg_pred, y=residual_lasso_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

[82]: Text(0, 0.5, 'Residuals')



11.2 Cost Function Values

[83]:
```
print(f"MSE : {round(mean_squared_error(y_test, lasso_reg_pred),2)}\nMAE :␣
↪{round(mean_absolute_error(y_test, lasso_reg_pred),2)}\nRMSE : {round(np.
↪sqrt(mean_squared_error(y_test, lasso_reg_pred)),2)}")
```

```
MSE : 6.25
MAE : 1.89
RMSE : 2.5
```

11.3 Performance Metrics

[84]:
```
lasso_reg_r2_score=r2_score(y_test, lasso_reg_pred)
lasso_reg_adj_r2_score=1-((1-lasso_reg_r2_score)*(len(y_test)-1)/
 ↪(len(y_test)-X_test.shape[1]-1))
print(f"R-Squared Accuracy : {round(lasso_reg_r2_score*100,3)} % \nAdjusted␣
 ↪R-Squared Accuracy : {round(lasso_reg_adj_r2_score*100,2)}%")
```

```
R-Squared Accuracy : 45.787 %
Adjusted R-Squared Accuracy : 37.14%
```

12 Elastic Net Regression Model

[85]:
```
## creating Elastic-Net regression model
elastic_reg=ElasticNet()
elastic_reg
```

[85]:
```
ElasticNet()
```

[86]:
```
### Passing training data(X and y) to the model
elastic_reg.fit(X_train, y_train)
```

[86]:
```
ElasticNet()
```

[87]:
```
### Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent features is {}".format(elastic_reg.
 ↪coef_))
print("2. Intercept of best fit hyper plane is {}".format(elastic_reg.
 ↪intercept_))
```

```
1. Co-efficients of independent features is [-0.80490282 -0.0858647   0.
0.0089834   0.24763801  0.25455999
  0.          0.21308972  0.16777268  0.          0.58280977]
2. Intercept of best fit hyper plane is [32.16049383]
```

Prediction of test data

[88]:
```
elastic_reg_pred=elastic_reg.predict(X_test)
```

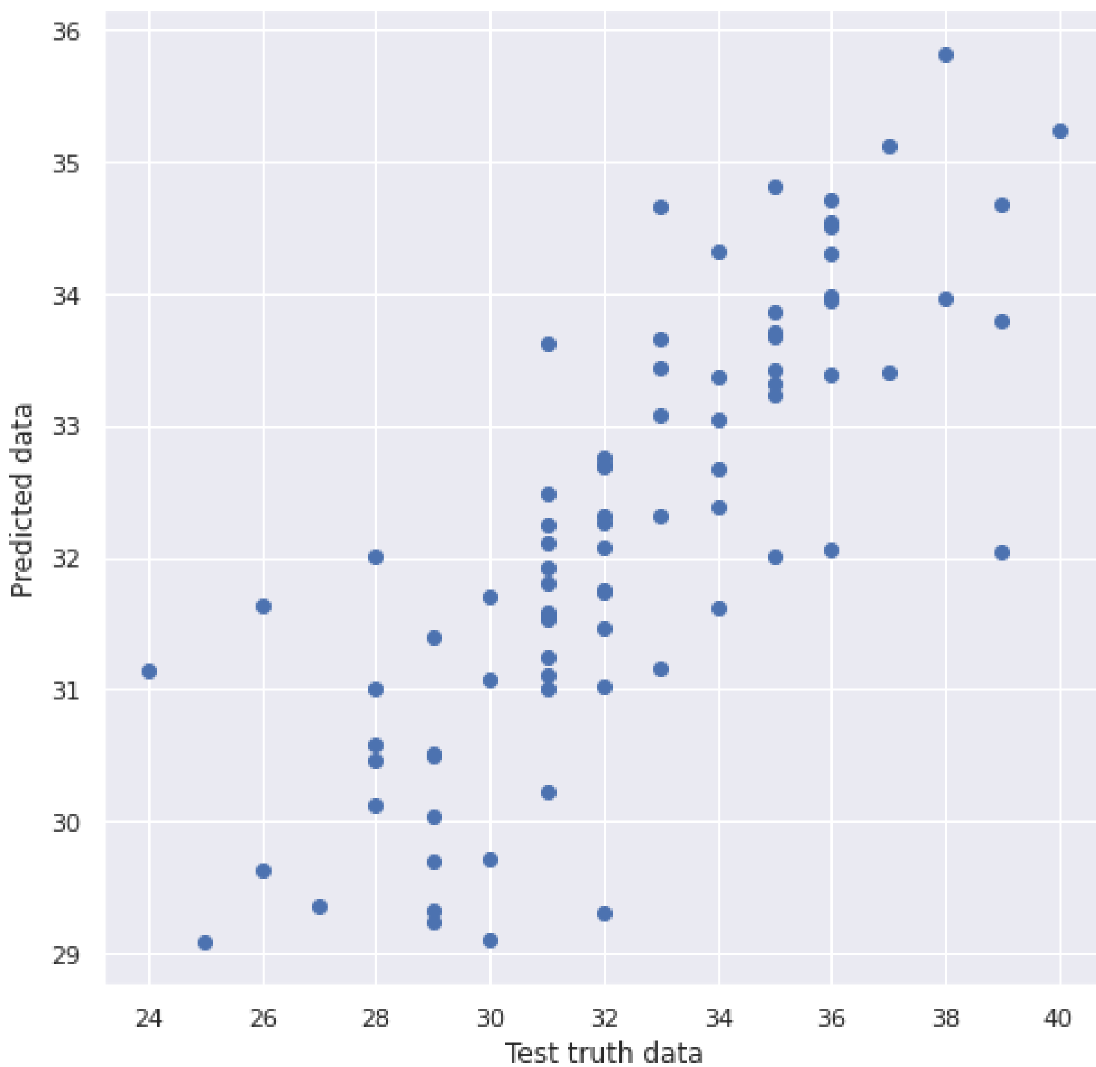
[89]:
```
residual_elastic_reg=y_test-elastic_reg_pred
residual_elastic_reg = pd.DataFrame(residual_elastic_reg)
```

12.1 Validation of Elastic Regression assumptions

1. Linear Relationship

[90]:
```
plt.scatter(x=y_test,y=elastic_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

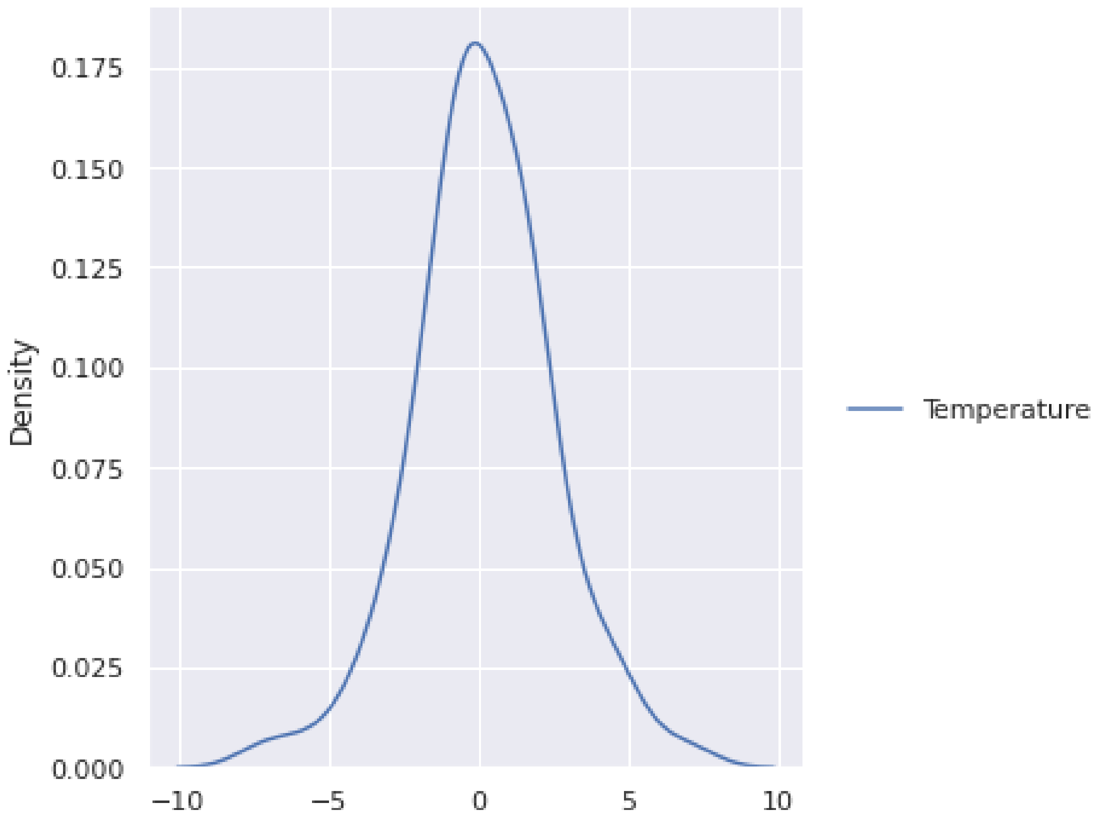
[90]:
```
Text(0, 0.5, 'Predicted data')
```



2. Residual should be normally distributed

[91]:
```
sns.displot( data = residual_elastic_reg, kind='kde')
```

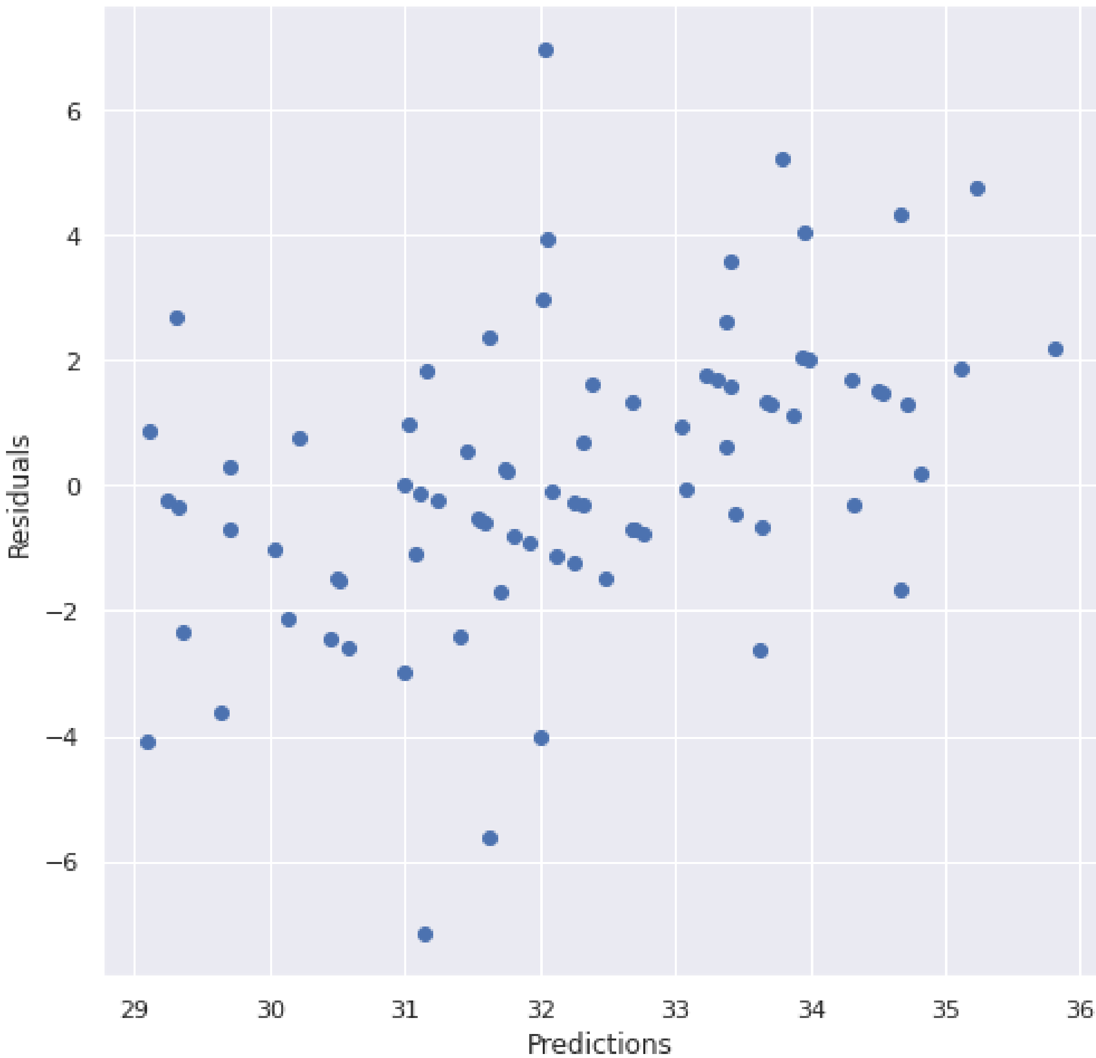
[91]:
```
<seaborn.axisgrid.FacetGrid at 0x7f5c4d1b1e50>
```



3. Residual and Predicted values should follow uniform distribution

[92]:
```
plt.scatter(x=elastic_reg_pred, y=residual_elastic_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

[92]: Text(0, 0.5, 'Residuals')



12.2 Cost Function Values

[93]:
```
print(f"MSE : {round(mean_squared_error(y_test, elastic_reg_pred),2)}\nMAE :␣
↪{round(mean_absolute_error(y_test, elastic_reg_pred),2)}\nRMSE : {round(np.
↪sqrt(mean_squared_error(y_test, elastic_reg_pred)),2)}")
```

```
MSE : 5.41
MAE : 1.75
RMSE : 2.33
```

12.3 Performance Metrics

[94]:
```
elastic_reg_r2_score=r2_score(y_test, elastic_reg_pred)
elastic_reg_adj_r2_score=1-((1-elastic_reg_r2_score)*(len(y_test)-1)/
↪(len(y_test)-X_test.shape[1]-1))
print(f"R-Squared Accuracy : {round(elastic_reg_r2_score*100,3)} % \nAdjusted␣
↪R-Squared Accuracy : {round(elastic_reg_adj_r2_score*100,2)}%")
```

```
R-Squared Accuracy : 53.05 %
Adjusted R-Squared Accuracy : 45.56%
```

13 Comparisions of all Models

13.1 Cost Function Values

[95]:
```
print(f"--------------------------------------")
print(f"MSE:\n1. Linear Regression : {round(mean_squared_error(y_test,␣
↪linear_reg_pred),2)}\n2. Ridge Regression :␣
↪{round(mean_squared_error(y_test, ridge_reg_pred),2)}\n3. Lasso Regression :␣
↪{round(mean_squared_error(y_test, lasso_reg_pred),2)}\n4. Elastic Net␣
↪Regression : {round(mean_squared_error(y_test, elastic_reg_pred),2)}")
print(f"---------------------------------------")
print(f"MAE:\n1. Linear Regression : {round(mean_absolute_error(y_test,␣
↪linear_reg_pred),2)}\n2. Ridge Regression :␣
↪{round(mean_absolute_error(y_test, ridge_reg_pred),2)}\n3. Lasso Regression :
↪ {round(mean_absolute_error(y_test, lasso_reg_pred),2)}\n4. Elastic Net␣
↪Regression : {round(mean_absolute_error(y_test, elastic_reg_pred),2)}")
print(f"--------------------------------------")
print(f"RMSE:\n1. Linear Regression : {round(np.sqrt(mean_squared_error(y_test,␣
↪linear_reg_pred)),2)}\n2. Ridge Regression : {round(np.
↪sqrt(mean_squared_error(y_test, ridge_reg_pred)),2)}\n3. Lasso Regression :␣
↪{round(np.sqrt(mean_squared_error(y_test, lasso_reg_pred)),2)}\n4. Elastic␣
↪Net Regression : {round(np.sqrt(mean_squared_error(y_test,␣
↪elastic_reg_pred)),2)}")
print(f"--------------------------------------")
```

```
--------------------------------------
MSE:
1. Linear Regression : 3.97
2. Ridge Regression : 3.93
3. Lasso Regression : 6.25
4. Elastic Net Regression : 5.41
---------------------------------------
MAE:
1. Linear Regression : 1.42
2. Ridge Regression : 1.41
```

```
3. Lasso Regression : 1.89
4. Elastic Net Regression : 1.75
--------------------------------------
RMSE:
1. Linear Regression : 1.99
2. Ridge Regression : 1.98
3. Lasso Regression : 2.5
4. Elastic Net Regression : 2.33
--------------------------------------
```

13.2 Performance Metrics

[96]:
```
print(f"--------------------------------------")
print(f"R-Squared Accuracy:\n1. Linear Regression :␣
↪{round(linear_reg_r2_score*100,3)} %\n2. Ridge Regression :␣
↪{round(ridge_reg_r2_score*100,3)} %\n3. Lasso Regression :␣
↪{round(lasso_reg_r2_score*100,3)} %\n4. Elastic Net Regression :␣
↪{round(elastic_reg_r2_score*100,3)} %")
print(f"--------------------------------------")
print(f"Adjusted R-Squared Accuracy:\n1. Linear Regression :␣
↪{round(linear_reg_adj_r2_score*100,3)} %\n2. Ridge Regression :␣
↪{round(ridge_reg_adj_r2_score*100,3)} %\n3. Lasso Regression :␣
↪{round(lasso_reg_adj_r2_score*100,3)} %\n4. Elastic Net Regression :␣
↪{round(elastic_reg_adj_r2_score*100,3)} %")
print(f"--------------------------------------")
```

```
--------------------------------------
R-Squared Accuracy:
1. Linear Regression : 65.577 %
2. Ridge Regression : 65.852 %
3. Lasso Regression : 45.787 %
4. Elastic Net Regression : 53.05 %
--------------------------------------
Adjusted R-Squared Accuracy:
1. Linear Regression : 60.089 %
2. Ridge Regression : 60.408 %
3. Lasso Regression : 37.145 %
4. Elastic Net Regression : 45.565 %
--------------------------------------
```

14 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.