# Project Name : - Algerian Forest Fire Dataset EDA , FE &Temperature Prediction using Linear Regression,Ridge,Lasso,Elastic Net .

## 1) Problem statement .

- This dataset comprises of Algerian Forest Fire Dataset taken from UCI .
- Link of the dataset is as follows :- https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++ .

## 2) Data Collection.

- This dataset includes 244 instances that regroup a data of 2 regions of Algeria,namely the Brjajia region located in the northeast of Algeria and the Sidi Bel-abbes region located in the northwest of Algeria .
- 122 instances for each region .
- The Period is from June 2012 to September 2012.The Dataset includes 11 attributes and 1 output attribute i.e. Temperature
- The data consists of 14 column and 246 rows.

### 2.1 Import Data and Required Packages

**Importing Necessary Libraries**

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

**Loading the Algerian Forest Fire Dataset**

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

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 |

| | day | month | year | Temperature | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **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 |

### Attribute Information :-

### Period Covered

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

### Weather data observations

- 1. Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
- 1. RH : Relative Humidity in %: 21 to 90
- 1. Ws :Wind speed in km/h: 6 to 29
- 1. 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
- 1. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
- 1. Drought Code (DC) index from the FWI system: 7 to 220.4
- 1. Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
- 1. Buildup Index (BUI) index from the FWI system: 1.1 to 68
- 1. Fire Weather Index (FWI) Index: 0 to 31.1
- 1. Classes: two classes, namely â€œFireâ€ and â€œnot Fireâ€

In [4]:

```
df.tail()
```

Out[4]:

| | day | month | year | Temperature | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **241** | 26 | 09 | 2012 | 30 | 65 | 14 | 0 | 85.4 | 16 | 44.5 | 4.5 | 16.9 | 6.5 | fire |
| **242** | 27 | 09 | 2012 | 28 | 87 | 15 | 4.4 | 41.1 | 6.5 | 8 | 0.1 | 6.2 | 0 | not fire |
| **243** | 28 | 09 | 2012 | 27 | 87 | 29 | 0.5 | 45.9 | 3.5 | 7.9 | 0.4 | 3.4 | 0.2 | not fire |
| **244** | 29 | 09 | 2012 | 24 | 54 | 18 | 0.1 | 79.7 | 4.3 | 15.2 | 1.7 | 5.1 | 0.7 | not fire |
| **245** | 30 | 09 | 2012 | 24 | 64 | 15 | 0.2 | 67.3 | 3.8 | 16.5 | 1.2 | 4.8 | 0.5 | not fire |

In [5]:

```
df.shape
```

Out[5]:

```
(246, 14)
```

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 246 entries, 0 to 245
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: 27.0+ KB
```

In [7]:

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

Out[7]:

```
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 [8]:

```
df.describe()
```

Out[8]:

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

In [9]:

```
df.iloc[121:125,:]
```

Out[9]:

| | day | month | year | Temperature | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **121** | 30 | 09 | 2012 | 25 | 78 | 14 | 1.4 | 45 | 1.9 | 7.5 | 0.2 | 2.4 | 0.1 | not fire |
| **122** | Sidi-Bel Abbes Region Dataset | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **123** | day | month | year | Temperature | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes |
| **124** | 01 | 06 | 2012 | 32 | 71 | 12 | 0.7 | 57.1 | 2.5 | 8.2 | 0.6 | 2.8 | 0.2 | not fire |

In [ ]:

In [ ]:

# 2.2 Data Cleaning

#### Dropping row no 122 specifying region name & 123 respecifying the header

In [10]:
```
df.drop([122,123],inplace=True)
```

#### Resetting the index and dropping the index column

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

In [ ]:
```
```

#### Creating a new column called Region reprenting [0:- Bejaia and 1- Sidi Bel-abbes]

In [12]:
```
df.loc[:122,"Region"]=0
df.loc[122:,"Region"]=1
```

#### Checking the Column Headers

In [13]:
```
df.columns
```

Out[13]:
```
Index(['day', 'month', 'year', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes  ', 'Region'],
      dtype='object')
```

#### Removing unnecessary space in column headers using str.strip()

In [14]:
```
df.columns=df.columns.str.strip()
df.columns
```

Out[14]:
```
Index(['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'Region'],
      dtype='object')
```

#### Dropping rows with null values

In [15]:
```
df.dropna(inplace=True)
```

#### Converting the necessary column dataye to int

In [16]:
```
df.dtypes
```

Out[16]:
```
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         object
Region         float64
dtype: object
```

In [17]:

```
df[['day', 'month', 'year', 'Temperature', 'RH', 'Ws',"Region"]]=df[['day', 'month', 'year
```

In [18]:

```
df.dtypes
```

Out[18]:

```
day              int32
month            int32
year             int32
Temperature      int32
RH               int32
Ws               int32
Rain            object
FFMC            object
DMC             object
DC              object
ISI             object
BUI             object
FWI             object
Classes         object
Region           int32
dtype: object
```

**Values in df[Classes] has unnecessary spaces that are removed by str.strip()**

In [19]:

```
df.Classes.unique()
```

Out[19]:

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

In [20]:

```
df.Classes=df.Classes.str.strip()
df.Classes.unique()
```

Out[20]:

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

**Converting the Necessary Column Datatype to Float**

In [21]:

```
df.columns
```

Out[21]:

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

In [22]:

```
df[['Rain', 'FFMC','DMC', 'DC', 'ISI', 'BUI', 'FWI']]=df[['Rain', 'FFMC','DMC', 'DC', 'ISI
```

In [23]:

```
df.dtypes
```

Out[23]:

```
day               int32
month             int32
year              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
```

**Dropping the year column as the data is for the same year**

In [24]:
```
df1=df.drop(['year'],axis=1)
```

**DataFrame Description**

In [25]:
```
df1.describe().T
```

Out[25]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **day** | 243.0 | 15.761317 | 8.842552 | 1.0 | 8.00 | 16.0 | 23.00 | 31.0 |
| **month** | 243.0 | 7.502058 | 1.114793 | 6.0 | 7.00 | 8.0 | 8.00 | 9.0 |
| **Temperature** | 243.0 | 32.152263 | 3.628039 | 22.0 | 30.00 | 32.0 | 35.00 | 42.0 |
| **RH** | 243.0 | 62.041152 | 14.828160 | 21.0 | 52.50 | 63.0 | 73.50 | 90.0 |
| **Ws** | 243.0 | 15.493827 | 2.811385 | 6.0 | 14.00 | 15.0 | 17.00 | 29.0 |
| **Rain** | 243.0 | 0.762963 | 2.003207 | 0.0 | 0.00 | 0.0 | 0.50 | 16.8 |
| **FFMC** | 243.0 | 77.842387 | 14.349641 | 28.6 | 71.85 | 83.3 | 88.30 | 96.0 |
| **DMC** | 243.0 | 14.680658 | 12.393040 | 0.7 | 5.80 | 11.3 | 20.80 | 65.9 |
| **DC** | 243.0 | 49.430864 | 47.665606 | 6.9 | 12.35 | 33.1 | 69.10 | 220.4 |
| **ISI** | 243.0 | 4.742387 | 4.154234 | 0.0 | 1.40 | 3.5 | 7.25 | 19.0 |
| **BUI** | 243.0 | 16.690535 | 14.228421 | 1.1 | 6.00 | 12.4 | 22.65 | 68.0 |
| **FWI** | 243.0 | 7.035391 | 7.440568 | 0.0 | 0.70 | 4.2 | 11.45 | 31.1 |
| **Region** | 243.0 | 0.497942 | 0.501028 | 0.0 | 0.00 | 0.0 | 1.00 | 1.0 |

# 3. Exploratory Data Analysis

**Encoding not fire as 0 and Fire as 1**

In [26]:
```
df1['Classes']=np.where(df1['Classes']=='not fire ',0,1)
```

In [27]:
```
df1.head()
```

Out[27]:

| | day | month | Temperature | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes | Region |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 6 | 29 | 57 | 18 | 0.0 | 65.7 | 3.4 | 7.6 | 1.3 | 3.4 | 0.5 | 1 | 0 |
| **1** | 2 | 6 | 29 | 61 | 13 | 1.3 | 64.4 | 4.1 | 7.6 | 1.0 | 3.9 | 0.4 | 1 | 0 |
| **2** | 3 | 6 | 26 | 82 | 22 | 13.1 | 47.1 | 2.5 | 7.1 | 0.3 | 2.7 | 0.1 | 1 | 0 |

| | day | month | Temperature | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes | Region |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **3** | 4 | 6 | 25 | 89 | 13 | 2.5 | 28.6 | 1.3 | 6.9 | 0.0 | 1.7 | 0.0 | 1 | 0 |
| **4** | 5 | 6 | 27 | 77 | 16 | 0.0 | 64.8 | 3.0 | 14.2 | 1.2 | 3.9 | 0.5 | 1 | 0 |

In [28]:

```
df1.corr()
```

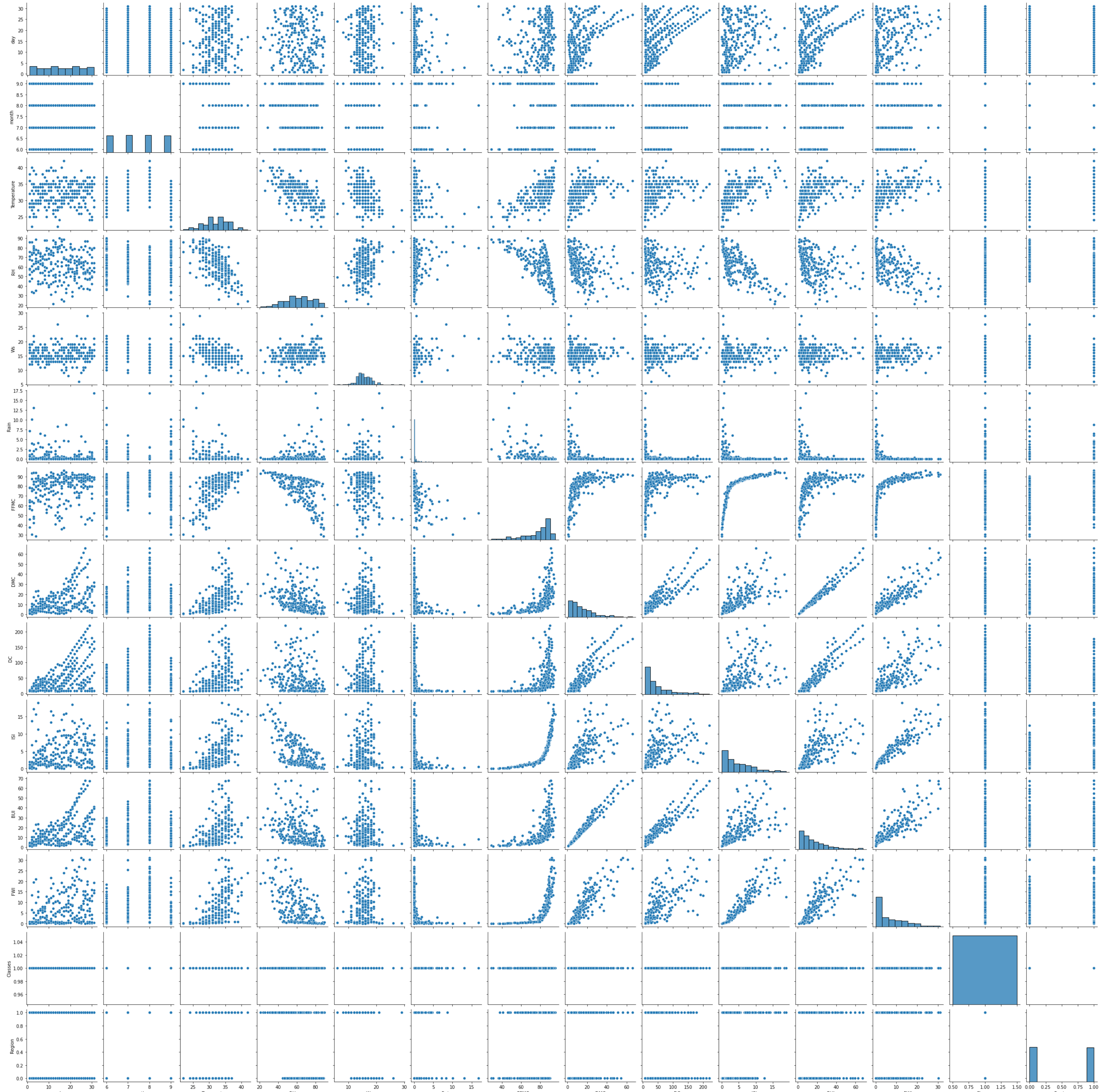
Out[28]:

| | day | month | Temperature | RH | Ws | Rain | FFMC | DMC | DC | |
|---|---|---|---|---|---|---|---|---|---|---|
| **day** | 1.000000 | -0.000369 | 0.097227 | -0.076034 | 0.047812 | -0.112523 | 0.224956 | 0.491514 | 0.527952 | 0.1 |
| **month** | -0.000369 | 1.000000 | -0.056781 | -0.041252 | -0.039880 | 0.034822 | 0.017030 | 0.067943 | 0.126511 | 0.0 |
| **Temperature** | 0.097227 | -0.056781 | 1.000000 | -0.651400 | -0.284510 | -0.326492 | 0.676568 | 0.485687 | 0.376284 | 0.6 |
| **RH** | -0.076034 | -0.041252 | -0.651400 | 1.000000 | 0.244048 | 0.222356 | -0.644873 | -0.408519 | -0.226941 | -0.6 |
| **Ws** | 0.047812 | -0.039880 | -0.284510 | 0.244048 | 1.000000 | 0.171506 | -0.166548 | -0.000721 | 0.079135 | 0.0 |
| **Rain** | -0.112523 | 0.034822 | -0.326492 | 0.222356 | 0.171506 | 1.000000 | -0.543906 | -0.288773 | -0.298023 | -0.3 |
| **FFMC** | 0.224956 | 0.017030 | 0.676568 | -0.644873 | -0.166548 | -0.543906 | 1.000000 | 0.603608 | 0.507397 | 0.7 |
| **DMC** | 0.491514 | 0.067943 | 0.485687 | -0.408519 | -0.000721 | -0.288773 | 0.603608 | 1.000000 | 0.875925 | 0.6 |
| **DC** | 0.527952 | 0.126511 | 0.376284 | -0.226941 | 0.079135 | -0.298023 | 0.507397 | 0.875925 | 1.000000 | 0.5 |
| **ISI** | 0.180543 | 0.065608 | 0.603871 | -0.686667 | 0.008532 | -0.347484 | 0.740007 | 0.680454 | 0.508643 | 1.0 |
| **BUI** | 0.517117 | 0.085073 | 0.459789 | -0.353841 | 0.031438 | -0.299852 | 0.592011 | 0.982248 | 0.941988 | 0.6 |
| **FWI** | 0.350781 | 0.082639 | 0.566670 | -0.580957 | 0.032368 | -0.324422 | 0.691132 | 0.875864 | 0.739521 | 0.9 |
| **Classes** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **Region** | 0.000821 | 0.001857 | 0.269555 | -0.402682 | -0.181160 | -0.040013 | 0.222241 | 0.192089 | -0.078734 | 0.2 |

In [29]:

```
sns.pairplot(df1)
```

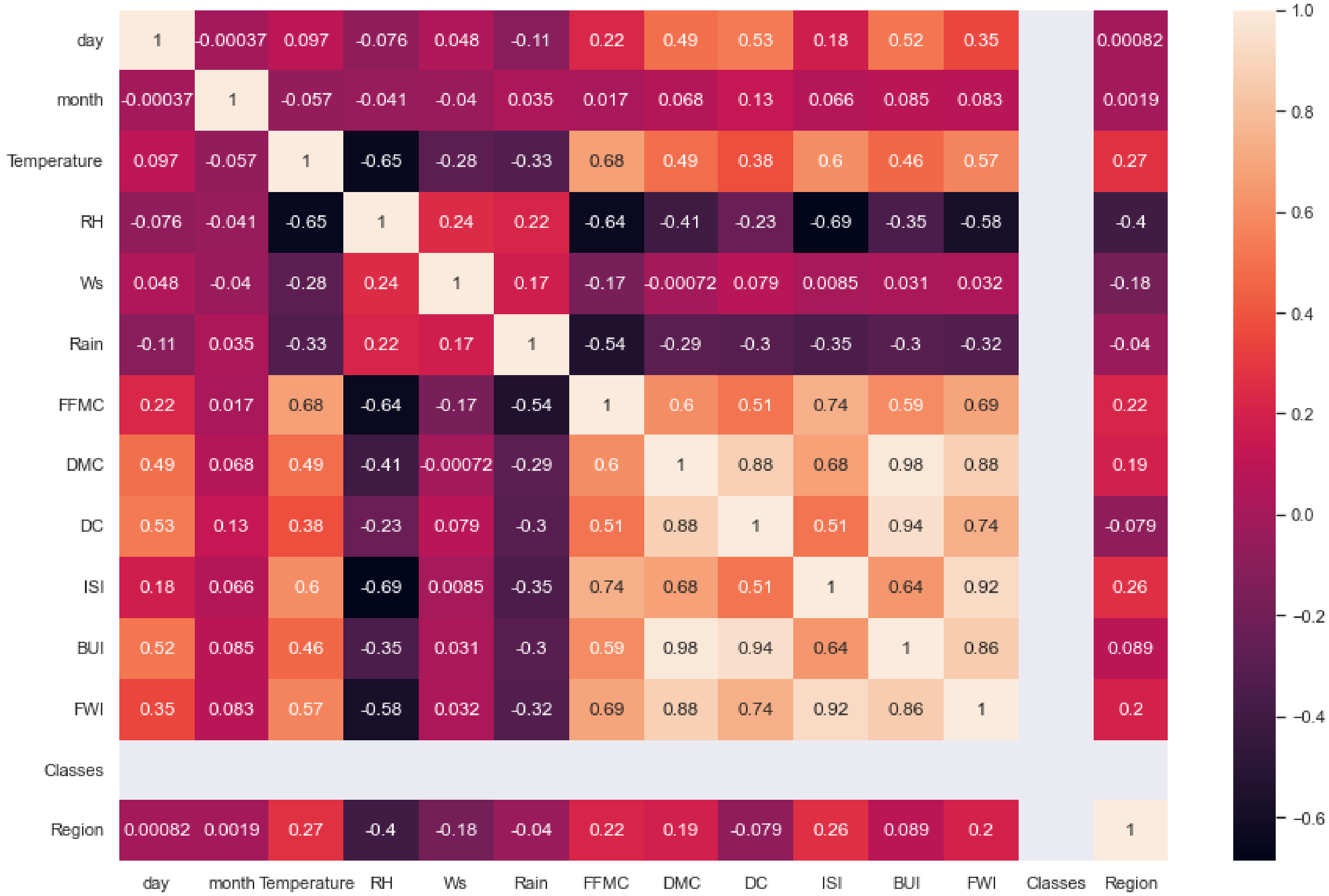
Out[29]: <seaborn.axisgrid.PairGrid at 0x1e875ab4190>




In [30]:

```
sns.set(rc={'figure.figsize':(15,10)})
sns.heatmap(df1.corr(),annot=True)
```

Out[30]: <AxesSubplot:>




**Report**

- RH is negatively corelated with Temperature, FFMC and ISI
- Rain is negatively correlated with Temperature and FFMC,DMC, ISI and BUI

In [31]:

```
df1.columns
```

Out[31]:

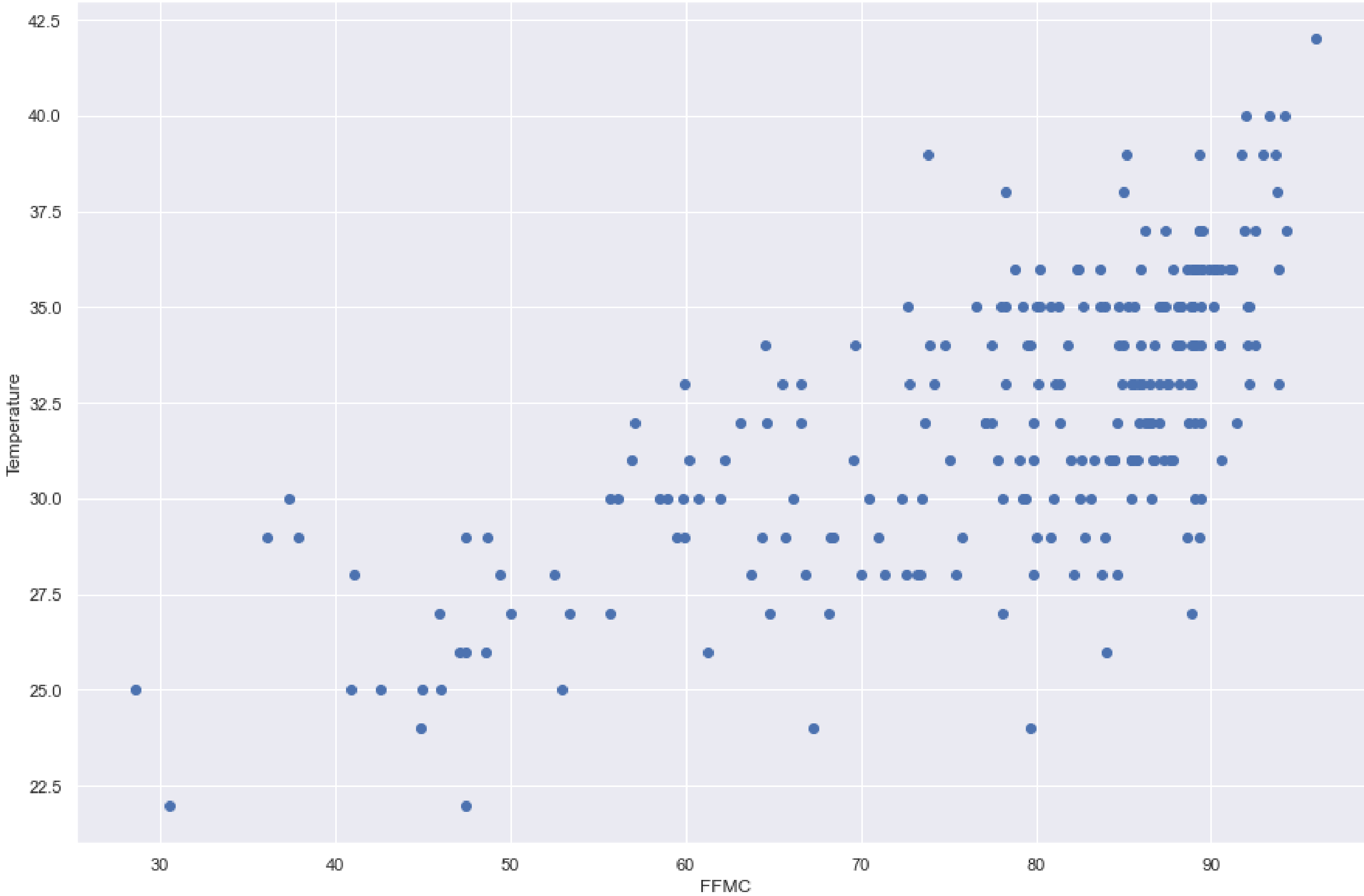
```
Index(['day', 'month', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC',
       'ISI', 'BUI', 'FWI', 'Classes', 'Region'],
      dtype='object')
```

In [32]:

```
plt.scatter(df1['FFMC'],df1['Temperature'])
plt.xlabel("FFMC")
plt.ylabel("Temperature")
```

Out[32]:

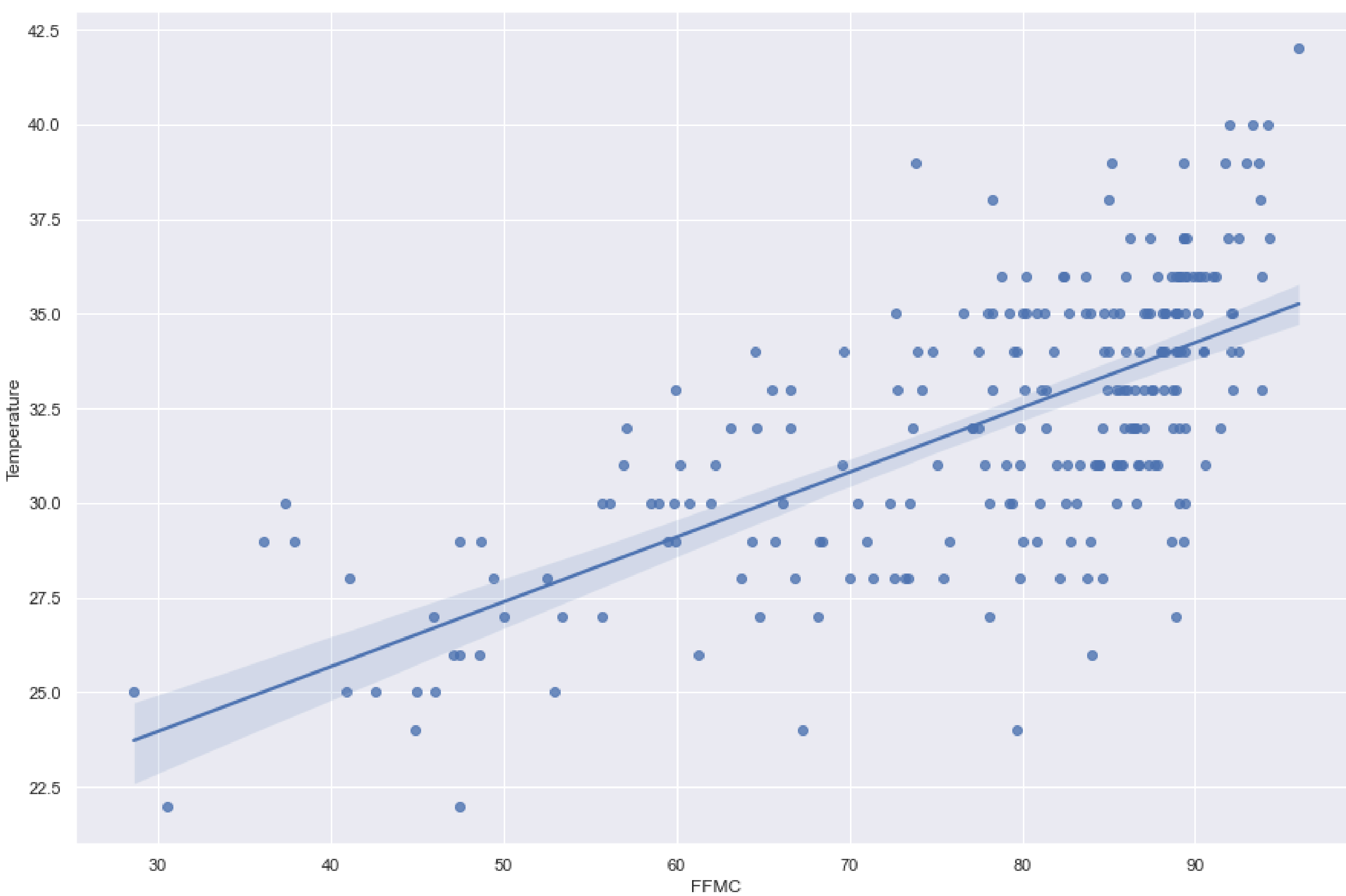
```
Text(0, 0.5, 'Temperature')
```




In [33]:

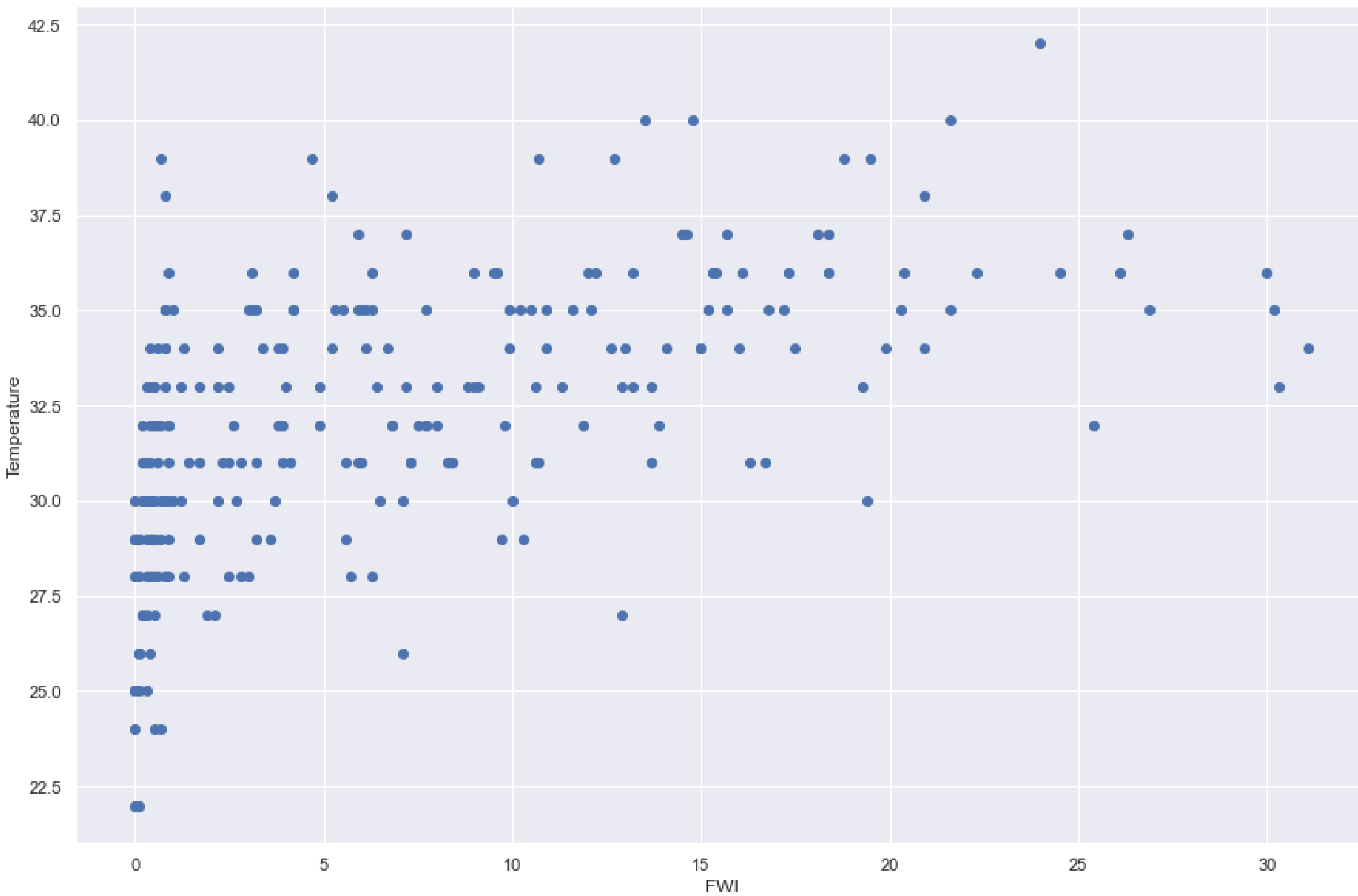
```
sns.regplot(x='FFMC',y='Temperature',data=df1)
```

Out[33]: <AxesSubplot:xlabel='FFMC', ylabel='Temperature'>



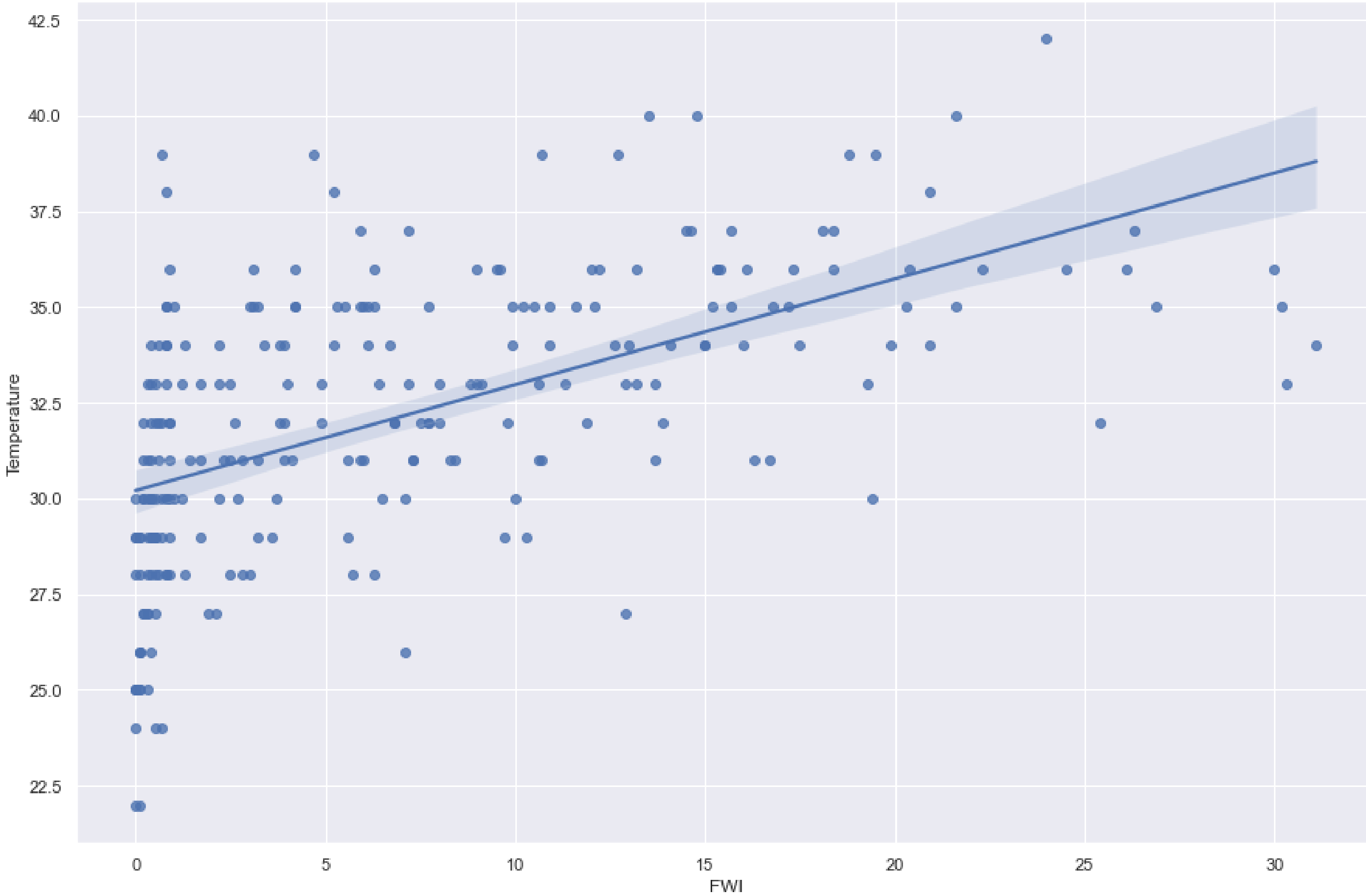
In [34]:
```
plt.scatter(df1['FWI'],df1['Temperature'])
plt.xlabel("FWI")
plt.ylabel("Temperature")
```

Out[34]:
```
Text(0, 0.5, 'Temperature')
```




In [35]:
```
sns.regplot(x='FWI',y='Temperature',data=df1)
```

Out[35]:
```
<AxesSubplot:xlabel='FWI', ylabel='Temperature'>
```

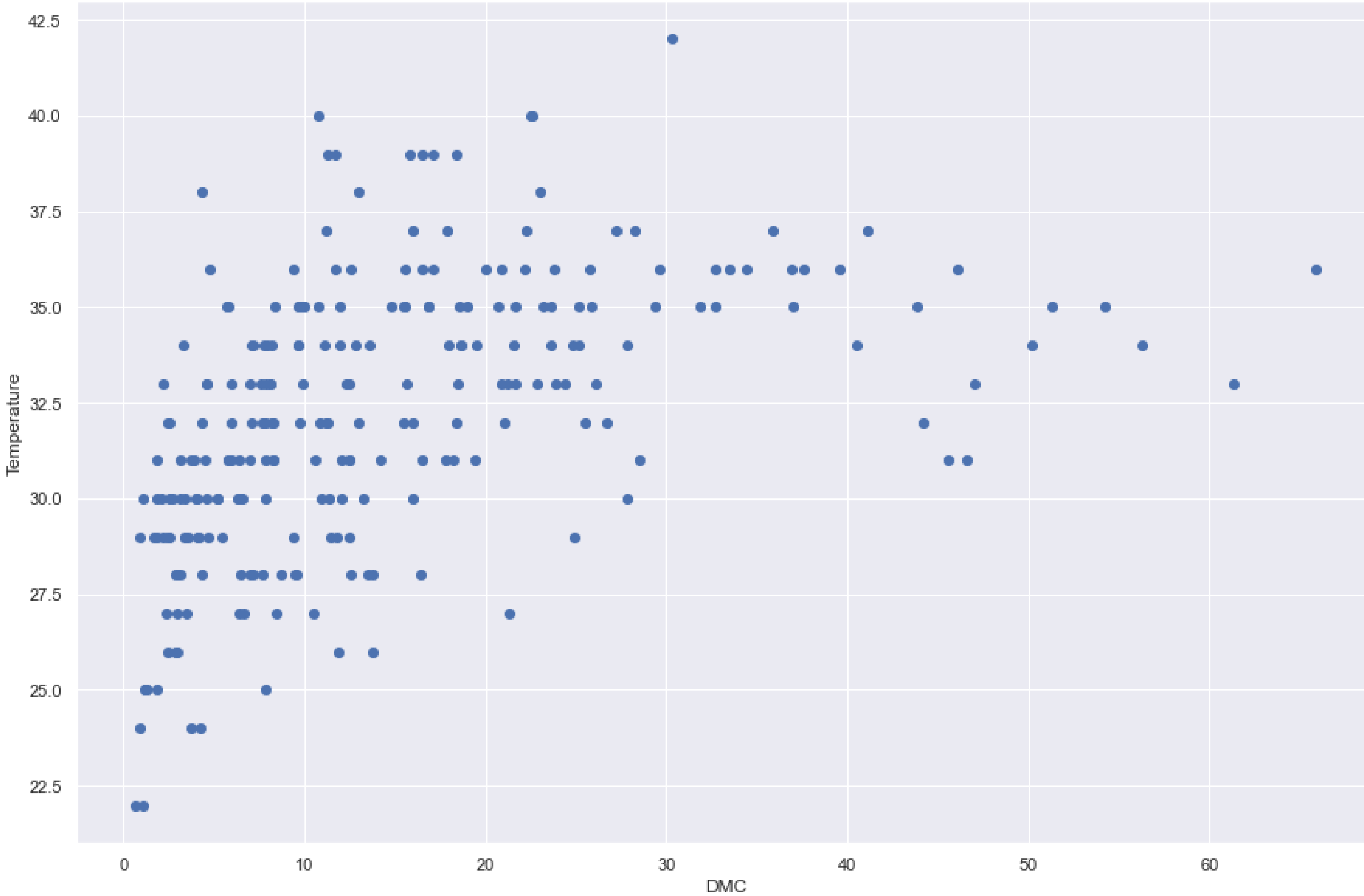



In [36]:

```
plt.scatter(df1['DMC'],df1['Temperature'])
plt.xlabel("DMC")
plt.ylabel("Temperature")
```

Out[36]:

```
Text(0, 0.5, 'Temperature')
```




In [37]:

```
sns.regplot(x='DMC',y='Temperature',data=df1)
```

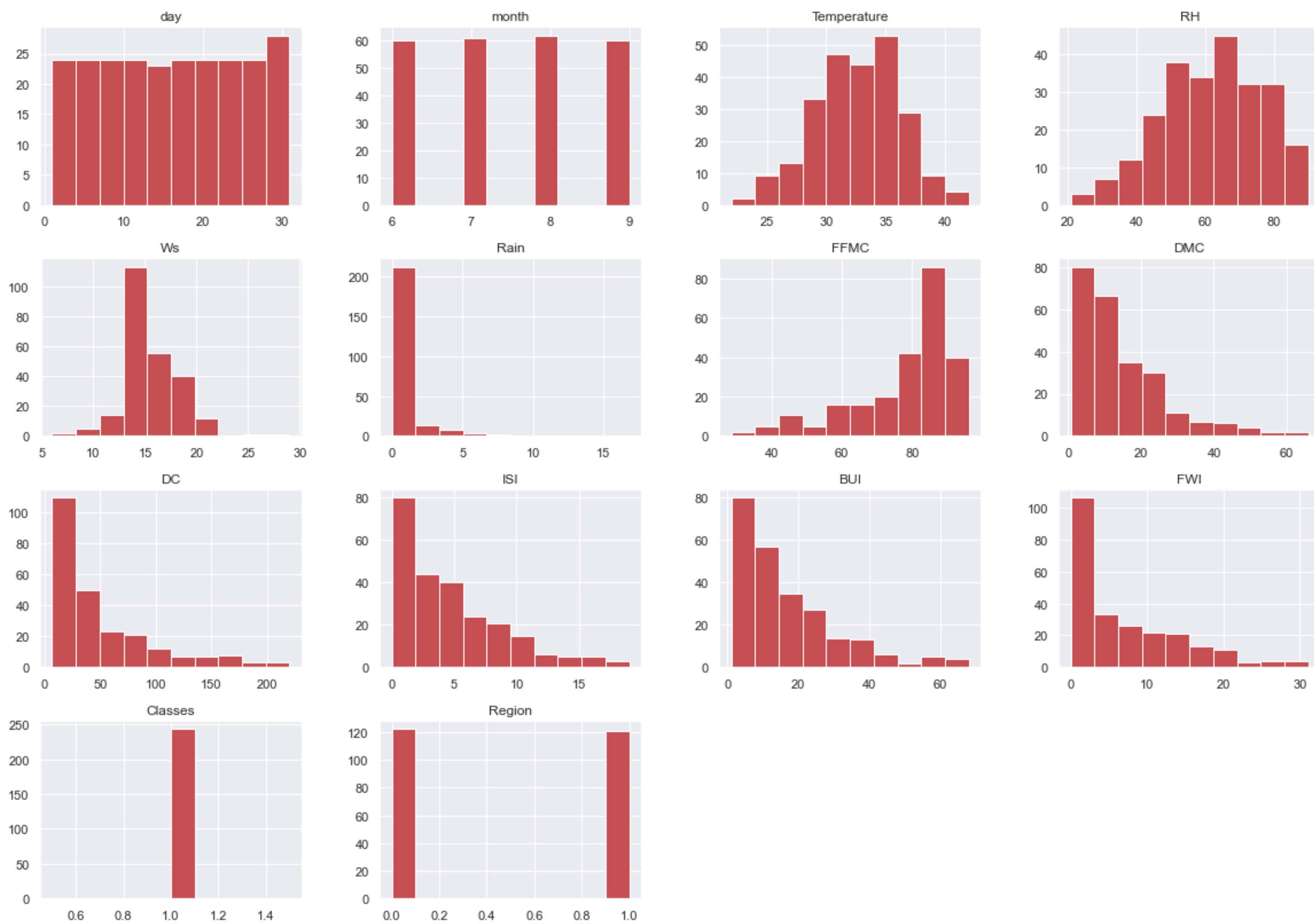
Out[37]: <AxesSubplot:xlabel='DMC', ylabel='Temperature'>

**Histogram**

**-A histogram is basically used to represent data provided in a form of sme groups**

In [38]:
```
df1.hist(figsize=(20,14),color='r')
```

Out[38]:
```
array([[<AxesSubplot:title={'center':'day'}>,
        <AxesSubplot:title={'center':'month'}>,
        <AxesSubplot:title={'center':'Temperature'}>,
        <AxesSubplot:title={'center':'RH'}>],
       [<AxesSubplot:title={'center':'Ws'}>,
        <AxesSubplot:title={'center':'Rain'}>,
        <AxesSubplot:title={'center':'FFMC'}>,
        <AxesSubplot:title={'center':'DMC'}>],
       [<AxesSubplot:title={'center':'DC'}>,
        <AxesSubplot:title={'center':'ISI'}>,
        <AxesSubplot:title={'center':'BUI'}>,
        <AxesSubplot:title={'center':'FWI'}>],
       [<AxesSubplot:title={'center':'Classes'}>,
        <AxesSubplot:title={'center':'Region'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



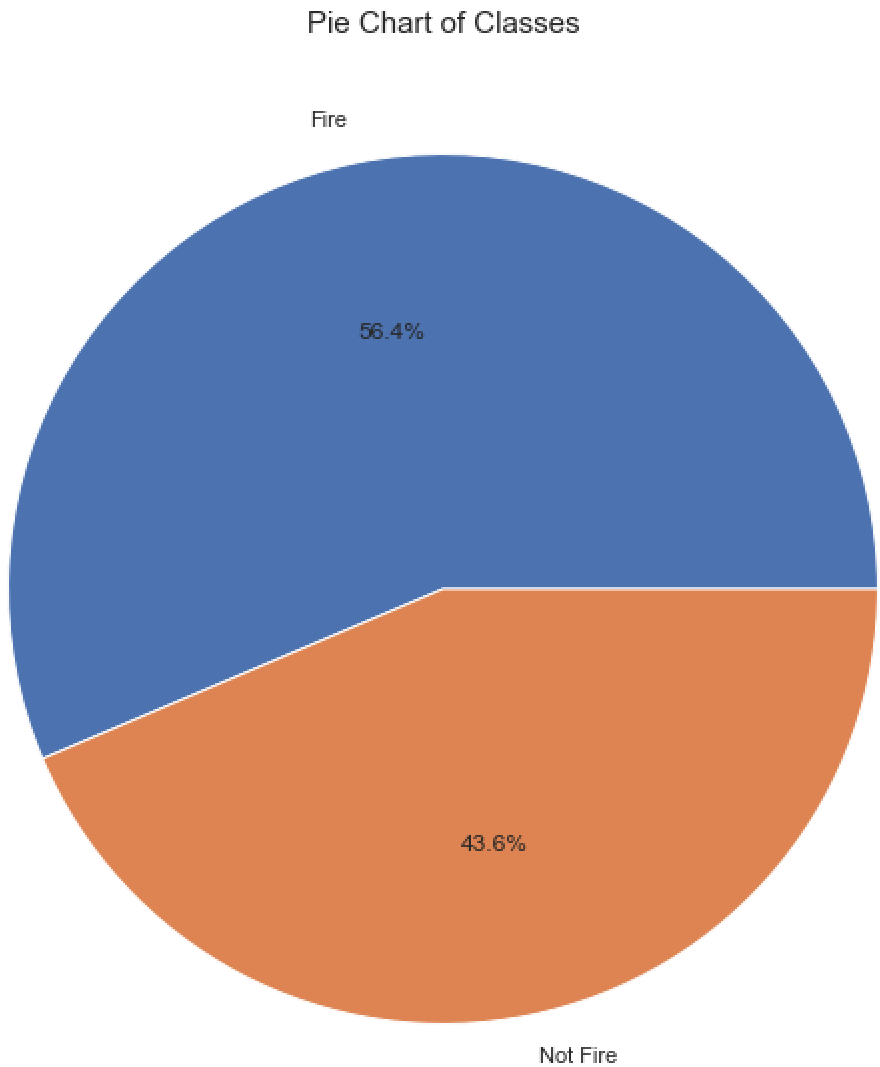

**Percentage for Pie Chart**

In [39]:
```
percentage=df.Classes.value_counts(normalize=True)*100
percentage
```

Out[39]:
```
fire        56.378601
not fire    43.621399
Name: Classes, dtype: float64
```

**Plotting Pie chart**

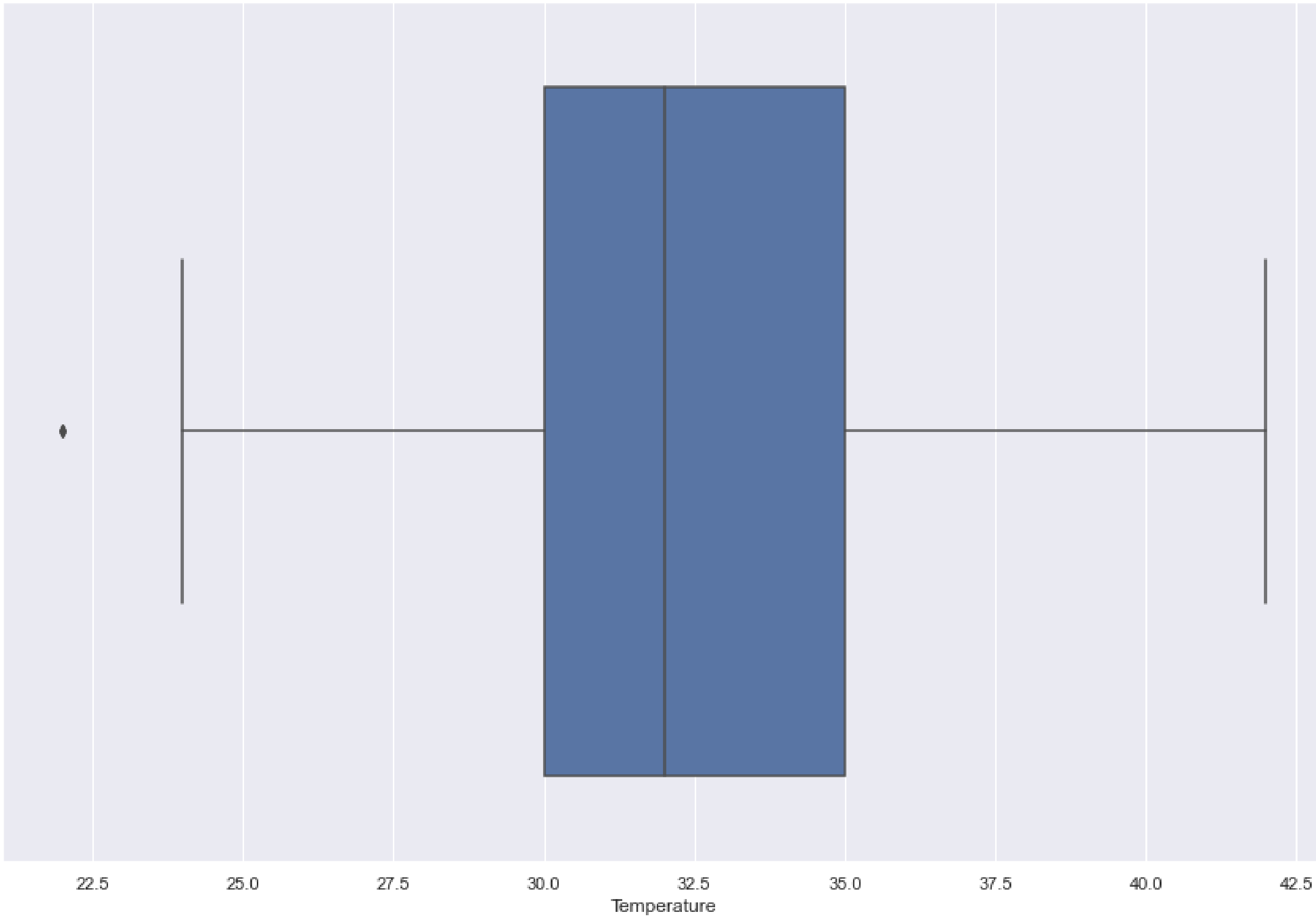
In [40]:
```
classes_labels=['Fire','Not Fire']
plt.figure(figsize=(15,10))
plt.pie(percentage,labels=classes_labels,autopct="%1.1f%%")
plt.title("Pie Chart of Classes",fontsize=15)
plt.show()
```




**Forest Fire Temperature Box Plot**

In [41]:
```
sns.boxplot(df1['Temperature'])
```

Out[41]:
```
<AxesSubplot:xlabel='Temperature'>
```



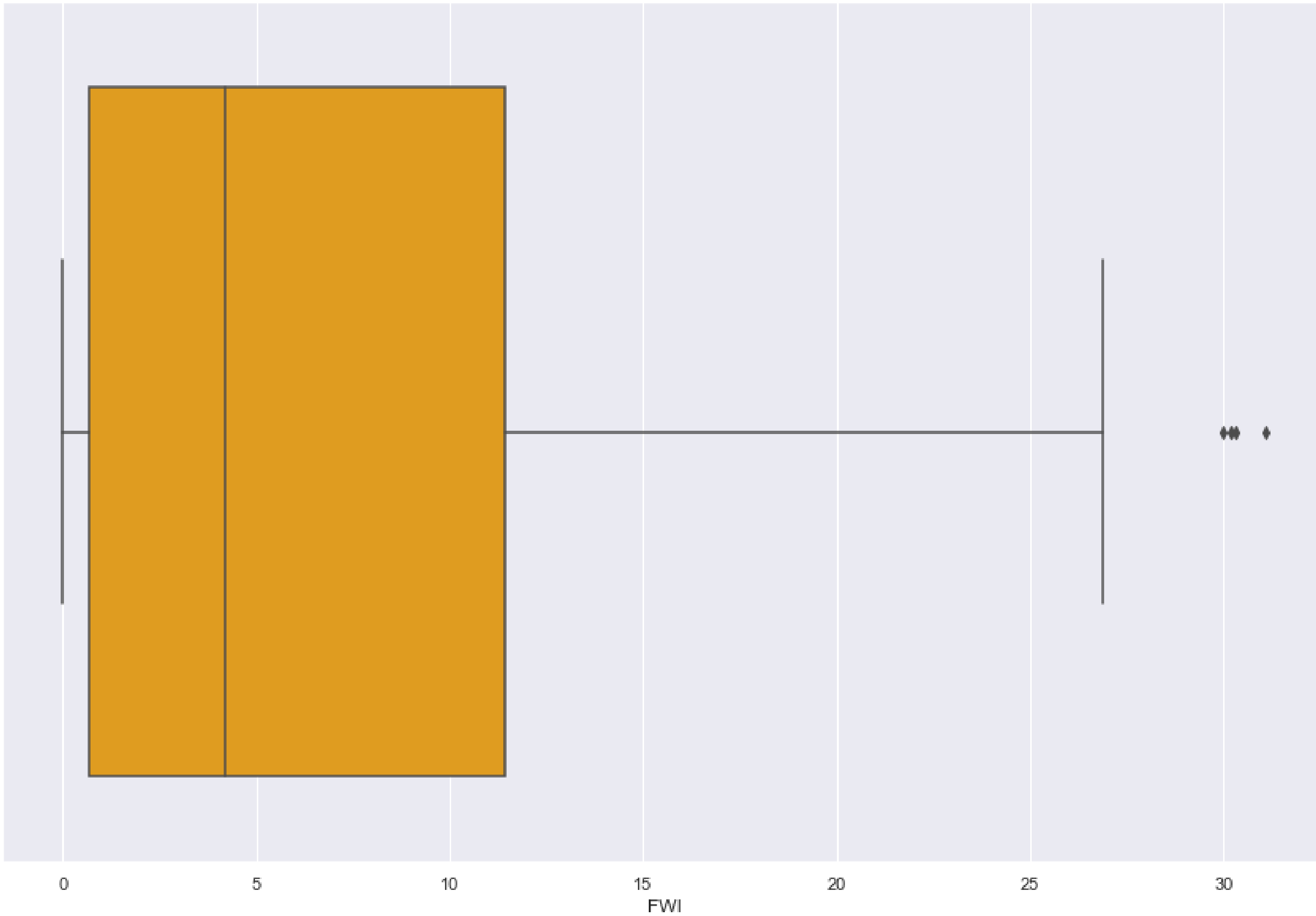

### Forest Fire Weather Index System[FWI] Boxplot

In [42]:

```
sns.boxplot(df['FWI'],color='orange')
```

Out[42]:

```
<AxesSubplot:xlabel='FWI'>
```




# 4. Building Linear Regression Model

In [43]:
```
df1
```

Out[43]:

| | day | month | Temperature | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes | Region |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 6 | 29 | 57 | 18 | 0.0 | 65.7 | 3.4 | 7.6 | 1.3 | 3.4 | 0.5 | 1 | 0 |
| **1** | 2 | 6 | 29 | 61 | 13 | 1.3 | 64.4 | 4.1 | 7.6 | 1.0 | 3.9 | 0.4 | 1 | 0 |
| **2** | 3 | 6 | 26 | 82 | 22 | 13.1 | 47.1 | 2.5 | 7.1 | 0.3 | 2.7 | 0.1 | 1 | 0 |
| **3** | 4 | 6 | 25 | 89 | 13 | 2.5 | 28.6 | 1.3 | 6.9 | 0.0 | 1.7 | 0.0 | 1 | 0 |
| **4** | 5 | 6 | 27 | 77 | 16 | 0.0 | 64.8 | 3.0 | 14.2 | 1.2 | 3.9 | 0.5 | 1 | 0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **239** | 26 | 9 | 30 | 65 | 14 | 0.0 | 85.4 | 16.0 | 44.5 | 4.5 | 16.9 | 6.5 | 1 | 1 |
| **240** | 27 | 9 | 28 | 87 | 15 | 4.4 | 41.1 | 6.5 | 8.0 | 0.1 | 6.2 | 0.0 | 1 | 1 |
| **241** | 28 | 9 | 27 | 87 | 29 | 0.5 | 45.9 | 3.5 | 7.9 | 0.4 | 3.4 | 0.2 | 1 | 1 |
| **242** | 29 | 9 | 24 | 54 | 18 | 0.1 | 79.7 | 4.3 | 15.2 | 1.7 | 5.1 | 0.7 | 1 | 1 |
| **243** | 30 | 9 | 24 | 64 | 15 | 0.2 | 67.3 | 3.8 | 16.5 | 1.2 | 4.8 | 0.5 | 1 | 1 |

243 rows × 14 columns

In [44]:
```
x=df1.drop('Temperature',axis=1)
```

In [45]:
```
y=df1['Temperature']
```

In [46]:
```
X_train, X_test, y_train, y_test = train_test_split(x,y,test_size=0.33, random_state=10)
```

In [47]:
```
X_train
```

Out[47]:

| | day | month | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes | Region |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **25** | 26 | 6 | 64 | 18 | 0.0 | 86.8 | 17.8 | 71.8 | 6.7 | 21.6 | 10.6 | 1 | 0 |
| **121** | 30 | 9 | 78 | 14 | 1.4 | 45.0 | 1.9 | 7.5 | 0.2 | 2.4 | 0.1 | 1 | 0 |
| **174** | 23 | 7 | 71 | 17 | 0.0 | 87.3 | 46.6 | 99.0 | 6.9 | 46.5 | 16.3 | 1 | 1 |
| **72** | 12 | 8 | 51 | 13 | 0.3 | 81.3 | 15.6 | 75.1 | 2.5 | 20.7 | 4.2 | 1 | 0 |
| **186** | 4 | 8 | 35 | 15 | 0.0 | 93.8 | 23.0 | 42.7 | 15.7 | 22.9 | 20.9 | 1 | 1 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **64** | 4 | 8 | 69 | 13 | 0.0 | 85.0 | 8.2 | 19.8 | 4.0 | 8.2 | 3.9 | 1 | 0 |
| **15** | 16 | 6 | 89 | 13 | 0.7 | 36.1 | 1.7 | 7.6 | 0.0 | 2.2 | 0.0 | 1 | 0 |
| **229** | 16 | 9 | 26 | 13 | 0.0 | 93.9 | 21.2 | 59.2 | 14.2 | 22.4 | 19.3 | 1 | 1 |
| **125** | 4 | 6 | 64 | 14 | 0.0 | 79.4 | 5.2 | 15.4 | 2.2 | 5.6 | 1.0 | 1 | 1 |
| **9** | 10 | 6 | 79 | 12 | 0.0 | 73.2 | 9.5 | 46.3 | 1.3 | 12.6 | 0.9 | 1 | 0 |

162 rows × 13 columns

In [48]:
```
X_test
```

Out[48]:

| | day | month | RH | Ws | Rain | FFMC | DMC | DC | ISI | BUI | FWI | Classes | Region |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **46** | 17 | 7 | 70 | 14 | 0.0 | 82.8 | 9.4 | 34.1 | 3.2 | 11.1 | 3.6 | 1 | 0 |
| **226** | 13 | 9 | 49 | 19 | 0.0 | 88.6 | 11.5 | 33.4 | 9.1 | 12.4 | 10.3 | 1 | 1 |
| **181** | 30 | 7 | 56 | 16 | 0.0 | 88.9 | 23.8 | 57.1 | 8.2 | 23.8 | 13.2 | 1 | 1 |
| **116** | 25 | 9 | 81 | 21 | 5.8 | 48.6 | 3.0 | 7.7 | 0.4 | 3.0 | 0.1 | 1 | 0 |
| **124** | 3 | 6 | 80 | 14 | 2.0 | 48.7 | 2.2 | 7.6 | 0.3 | 2.6 | 0.1 | 1 | 1 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **127** | 6 | 6 | 54 | 11 | 0.1 | 83.7 | 8.4 | 26.3 | 3.1 | 9.3 | 3.1 | 1 | 1 |
| **242** | 29 | 9 | 54 | 18 | 0.1 | 79.7 | 4.3 | 15.2 | 1.7 | 5.1 | 0.7 | 1 | 1 |
| **208** | 26 | 8 | 37 | 16 | 0.0 | 92.2 | 61.3 | 167.2 | 13.1 | 64.0 | 30.3 | 1 | 1 |
| **102** | 11 | 9 | 77 | 21 | 1.8 | 58.5 | 1.9 | 8.4 | 1.1 | 2.4 | 0.3 | 1 | 0 |
| **78** | 18 | 8 | 54 | 18 | 0.0 | 89.4 | 20.0 | 110.9 | 9.7 | 27.5 | 16.1 | 1 | 0 |

81 rows × 13 columns

In [49]:
```
y_train
```

Out[49]:
```
25     31
121    25
174    31
72     35
186    38
       ..
64     34
15     29
229    33
125    30
9      28
Name: Temperature, Length: 162, dtype: int32
```

In [50]:
```
y_test
```

Out[50]:
```
46     29
226    29
181    36
116    26
124    29
       ..
127    35
242    24
208    33
102    30
78     36
Name: Temperature, Length: 81, dtype: int32
```

In [51]:
```
scaler=StandardScaler()
```

In [52]:
```
x_train_scaled=scaler.fit_transform(X_train)
```

In [53]:
```
x_train_scaled
```

Out[53]:
```
array([[ 1.30705791, -1.39305207,  0.06835876, ...,  0.52024214,
         0.        , -1.01242284],
       [ 1.77217242,  1.29354835,  0.99672801, ..., -0.93452011,
         0.        , -1.01242284],
       [ 0.95822202, -0.4975186 ,  0.53254338, ...,  1.30997022,
         0.        ,  0.9877296 ],
       ...,
       [ 0.14427163,  1.29354835, -2.45150064, ...,  1.72561657,
         0.        ,  0.9877296 ],
       [-1.2510719 , -1.39305207,  0.06835876, ..., -0.8098262 ,
         0.        ,  0.9877296 ],
       [-0.55340014, -1.39305207,  1.0630401 , ..., -0.82368108,
         0.        , -1.01242284]])
```

In [54]:
```
x_test_scaled=scaler.transform(X_test)
```

In [55]:
```
x_test_scaled
```

Out[55]:
```
array([[ 0.26055026, -0.4975186 ,  0.46623129, ..., -0.44959936,
         0.        , -1.01242284],
       [-0.20456425,  1.29354835, -0.92632258, ...,  0.4786775 ,
         0.        ,  0.9877296 ],
       [ 1.77217242, -0.4975186 , -0.46213796, ...,  0.88046898,
         0.        ,  0.9877296 ],
       ...,
```

```
[ 1.30705791,  0.39801488, -1.72206765, ...,  3.24965322,
  0.        ,  0.9877296 ],
[-0.43712151,  1.29354835,  0.93041592, ..., -0.90681035,
  0.        , -1.01242284],
[ 0.37682889,  0.39801488, -0.59476213, ...,  1.28226046,
  0.        , -1.01242284]])
```

**Model Training**

In [56]:
```
regression=LinearRegression()
```

In [57]:
```
regression.fit(x_train_scaled,y_train)
```

Out[57]:
```
▾ LinearRegression
LinearRegression()
```

In [58]:
```
#print the coefficients & intercept
print(regression.coef_)
#regression.score(x_test_scaled,y_test)
```

```
[-0.36440793 -0.22635361 -1.44134283 -0.7142619  -0.23278709  0.96421264
 -0.01542755  0.65162217  0.13076922  0.26277398 -0.28088408  0.
  0.24272792]
```

In [59]:
```
print(regression.intercept_)
```

```
32.074074074074076
```

In [60]:
```
reg_pred=regression.predict(x_test_scaled)
```

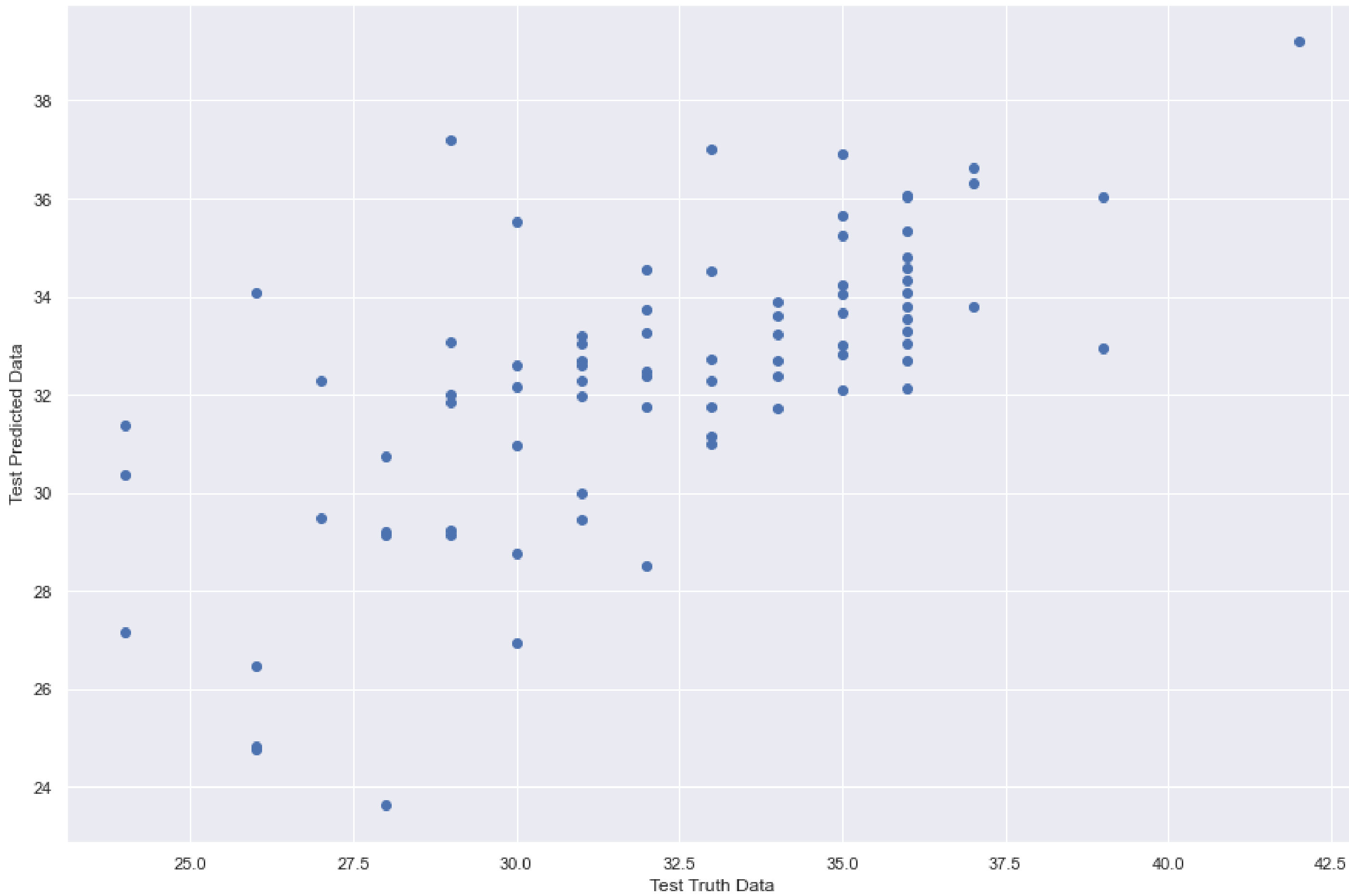
In [61]:
```
reg_pred
```

Out[61]:
```
array([31.84063173, 33.08286672, 33.29508782, 24.75854227, 29.24684893,
       33.62257975, 31.75352242, 34.58358479, 31.72328528, 32.36866716,
       33.67767751, 33.25839479, 35.65738396, 31.97503396, 34.04296478,
       33.22479669, 26.47624061, 36.04714436, 33.19344089, 23.64162513,
       32.1343707 , 32.60093493, 33.02495519, 32.94209422, 29.99121682,
       32.68893888, 33.04332061, 32.27268269, 32.09347766, 34.07041738,
       34.51057574, 33.74628677, 34.33569821, 32.69179752, 31.163211  ,
       28.76146317, 32.70115088, 31.76403503, 33.04719502, 34.07436881,
       33.80864285, 35.5411224 , 34.22166608, 37.18514799, 32.83625502,
       36.64474361, 32.38777677, 35.33018647, 30.75190986, 30.94859328,
       32.28439034, 39.1982583 , 32.58656685, 34.55522617, 27.14324627,
       36.9254135 , 33.79514082, 33.90475288, 29.13300329, 32.27931989,
       32.48201446, 32.01342537, 24.82170293, 36.32093954, 36.06160239,
       29.12469145, 29.4759838 , 29.4409954 , 36.02022222, 28.49852589,
       29.20955152, 32.15466961, 30.3678962 , 30.98622517, 34.80797612,
       32.73436681, 35.23626121, 31.37326569, 37.001972  , 26.92983473,
       33.55759223])
```

**ASSUMPTIONS OF LINEAR REGRESSION**

In [62]:
```
#if we are plotting  y_test,reg_pred relation should be linear
plt.scatter(y_test,reg_pred)
plt.xlabel("Test Truth Data")
plt.ylabel("Test Predicted Data")
```

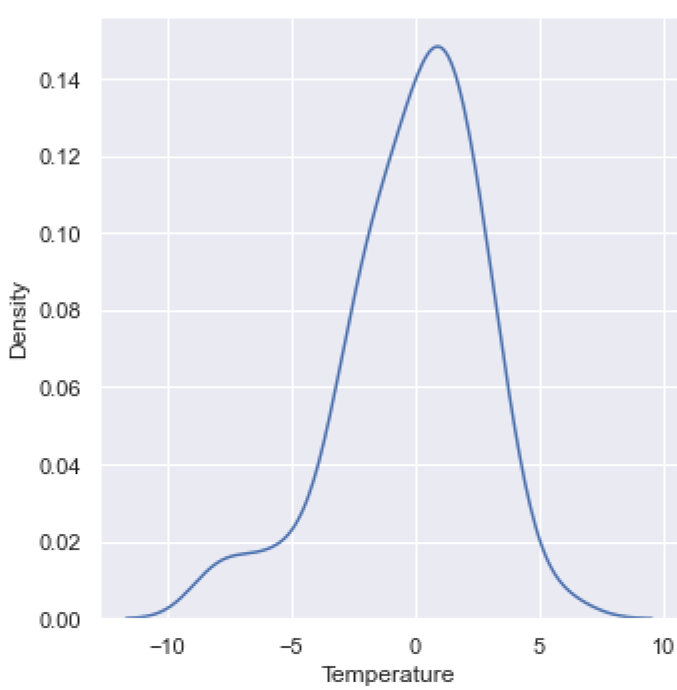
Out[62]: Text(0, 0.5, 'Test Predicted Data')




In [63]:
```
residuals=y_test-reg_pred
```

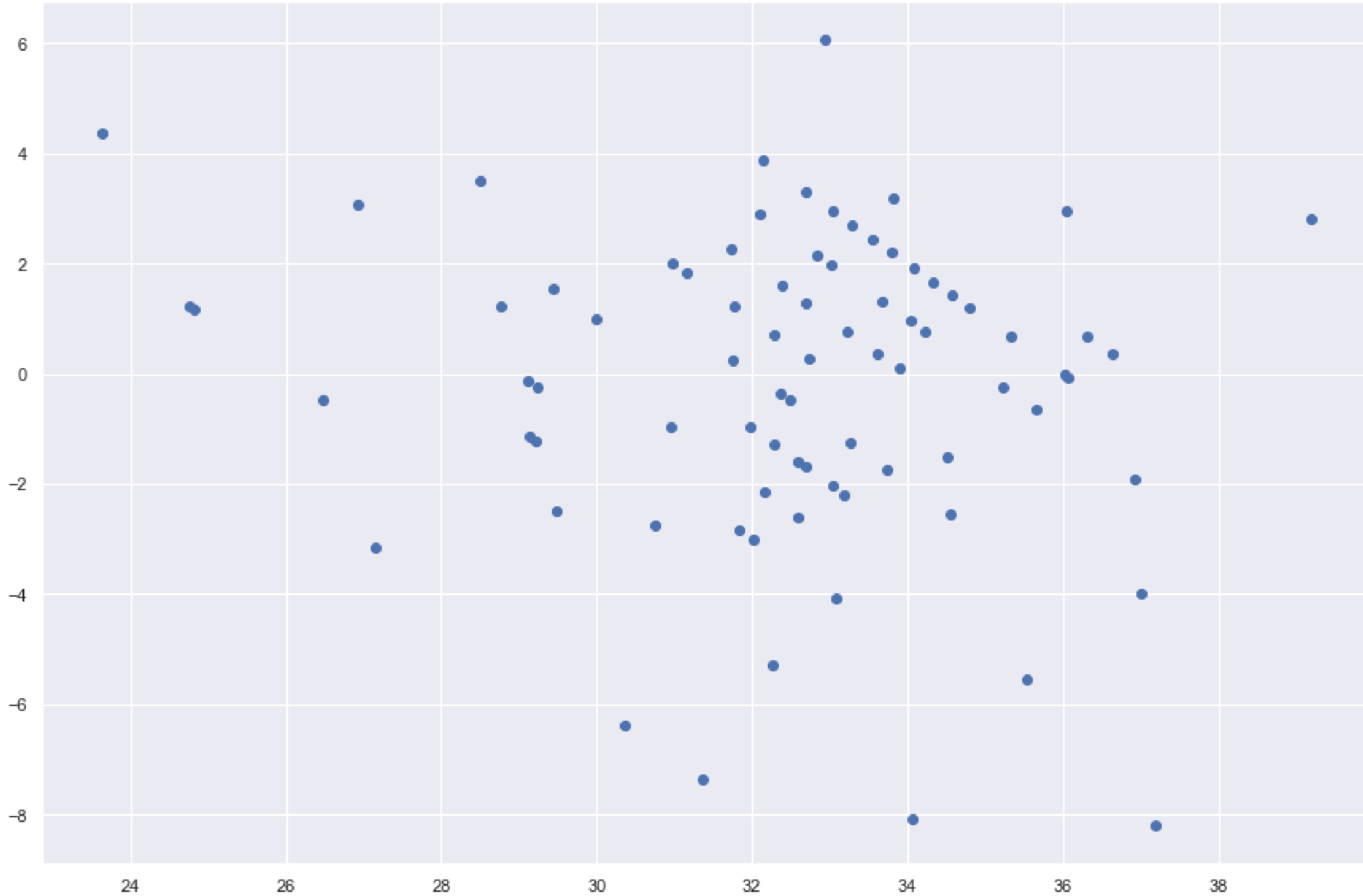
In [64]:
```
sns.displot(residuals,kind="kde")
```

Out[64]: <seaborn.axisgrid.FacetGrid at 0x1e804eb1130>




In [65]:
```
plt.scatter(reg_pred,residuals)
```

Out[65]: <matplotlib.collections.PathCollection at 0x1e806189ca0>




**Performance Metrics**

In [66]:
```
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)))
```

```
7.718372490369679
2.1359729920427832
2.7781959056858603
```

**R SQUARE & ADJUSTED R SQUARE**

In [67]:
```
score=r2_score(y_test,reg_pred)
score
```

Out[67]: 0.442435458586767

**Now we test the accuracy of the model using Adjusted R2**

**But why to test the accuracy of the model using Adjusted R2,when we have already tested the accuracy of the model using R2,**

**It is because the accuracy of the model under R2 will increase as and when we increase the no of features(x)**

**But the Adjusted R2 will remain unaffected inspite of No of features(x) we take , so R2 is less reliable then Adjusted R2**

In [68]:
```
## Adjusted R square
```

```
#display adjusted R-squared
1 - (1-score)*(len(y_test)-1)/(len(y_test)-x_test_scaled.shape[1]-1)
```

Out[68]:
```
0.3342512938349457
```

# 5. Ridge Regression

**Ridge Regression (also called as L2 Regularization),the main aim of ridge regression is to reduce overfitting**

In [109…:
```
ridge=Ridge()
```

In [70]:
```
ridge.fit(x_train_scaled,y_train)
```

Out[70]:
```
▾ Ridge
Ridge()
```

In [71]:
```
print(ridge.coef_)
```

```
[-0.35859242 -0.22361881 -1.4246319  -0.71357223 -0.23419537  0.96377519
  0.02101355  0.62937949  0.10421058  0.21661456 -0.22339104  0.
  0.23878478]
```

In [72]:
```
print(ridge.intercept_)
```

```
32.074074074074076
```

In [73]:
```
print(ridge.intercept_)
```

```
32.074074074074076
```

In [74]:
```
ridge_pred=ridge.predict(x_test_scaled)
```

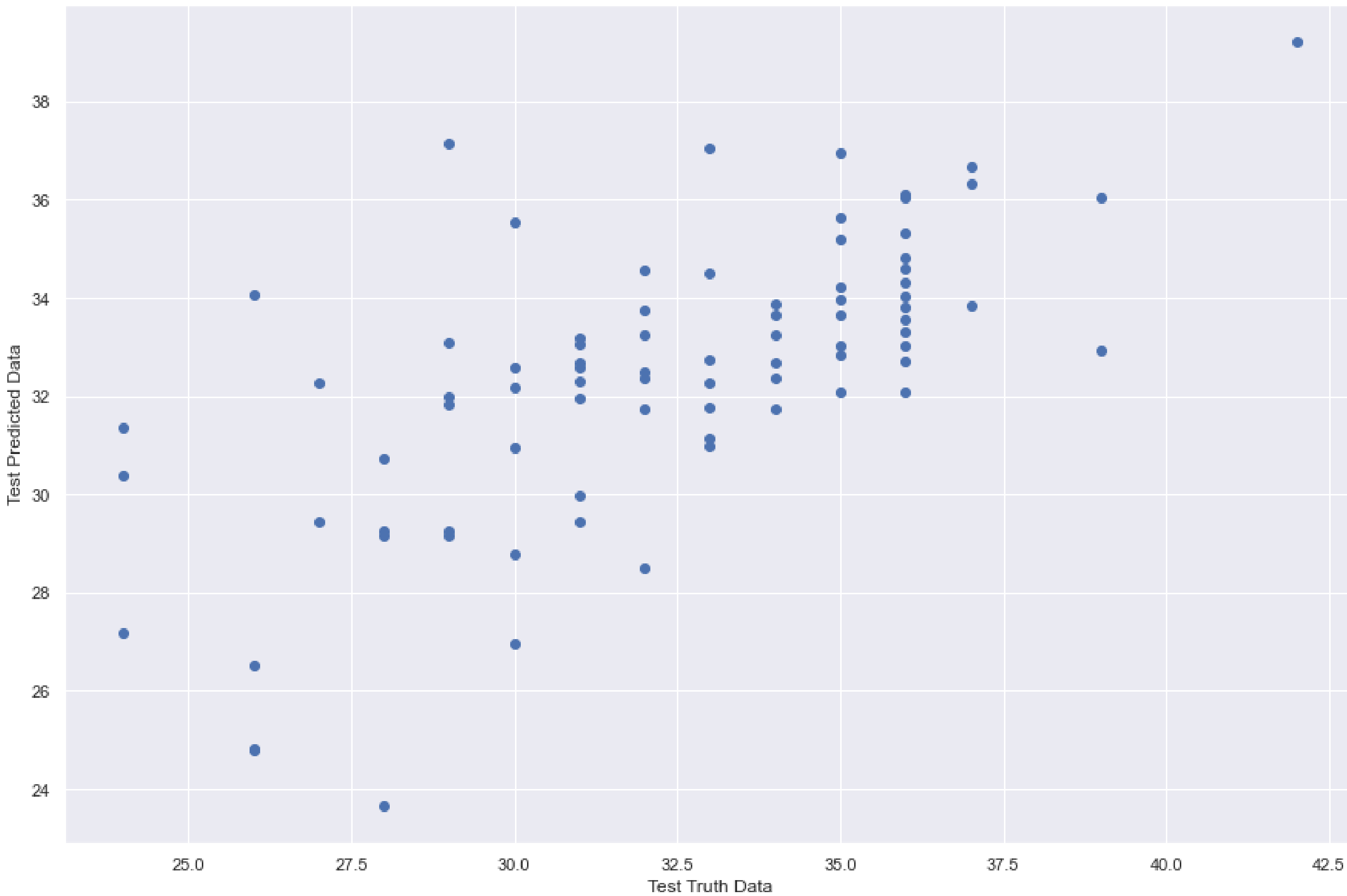
In [75]:
```
ridge_pred
```

Out[75]:
```
array([31.84522025, 33.07801866, 33.32143372, 24.79311009, 29.25112242,
       33.64529216, 31.73250629, 34.61248132, 31.74324356, 32.36616109,
       33.66795511, 33.25653199, 35.63844353, 31.96899817, 33.96914585,
       33.23538038, 26.51482354, 36.03947803, 33.1811996 , 23.66716673,
       32.09793728, 32.58109242, 33.0232019 , 32.94038806, 29.98560291,
       32.70770994, 33.04393524, 32.25760392, 32.08900203, 34.04925765,
       34.50009163, 33.73910985, 34.31012523, 32.69207555, 31.13817866,
       28.77144618, 32.67740941, 31.75746455, 33.04099284, 34.04747401,
       33.83814527, 35.52736647, 34.22117957, 37.13751492, 32.83627381,
       36.68161808, 32.36960708, 35.31854183, 30.73882088, 30.95562496,
       32.291368  , 39.20825907, 32.57797449, 34.55202448, 27.17475543,
       36.9522104 , 33.81487792, 33.86236693, 29.15322938, 32.26413039,
       32.47914425, 32.00320521, 24.82974268, 36.34245785, 36.10298328,
       29.15073976, 29.45086263, 29.43904153, 36.0418111 , 28.50689289,
       29.24000588, 32.16520447, 30.37216231, 30.99205138, 34.80964697,
       32.7546397 , 35.207702  , 31.36583658, 37.04199234, 26.94898166,
       33.54871979])
```

**ASSUMPTIONS OF LINEAR REGRESSION**

In [76]:
```
#if we are plotting  y_test,reg_pred relation should be linear
plt.scatter(y_test,ridge_pred)
plt.xlabel("Test Truth Data")
plt.ylabel("Test Predicted Data")
```

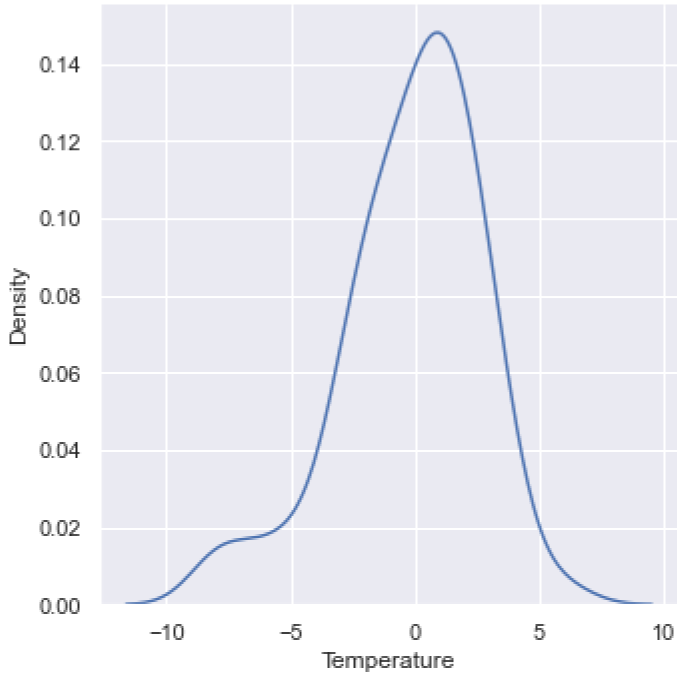
Out[76]: Text(0, 0.5, 'Test Predicted Data')




In [77]:
```
residuals=y_test-ridge_pred
```

In [78]:
```
sns.displot(residuals,kind="kde")
```

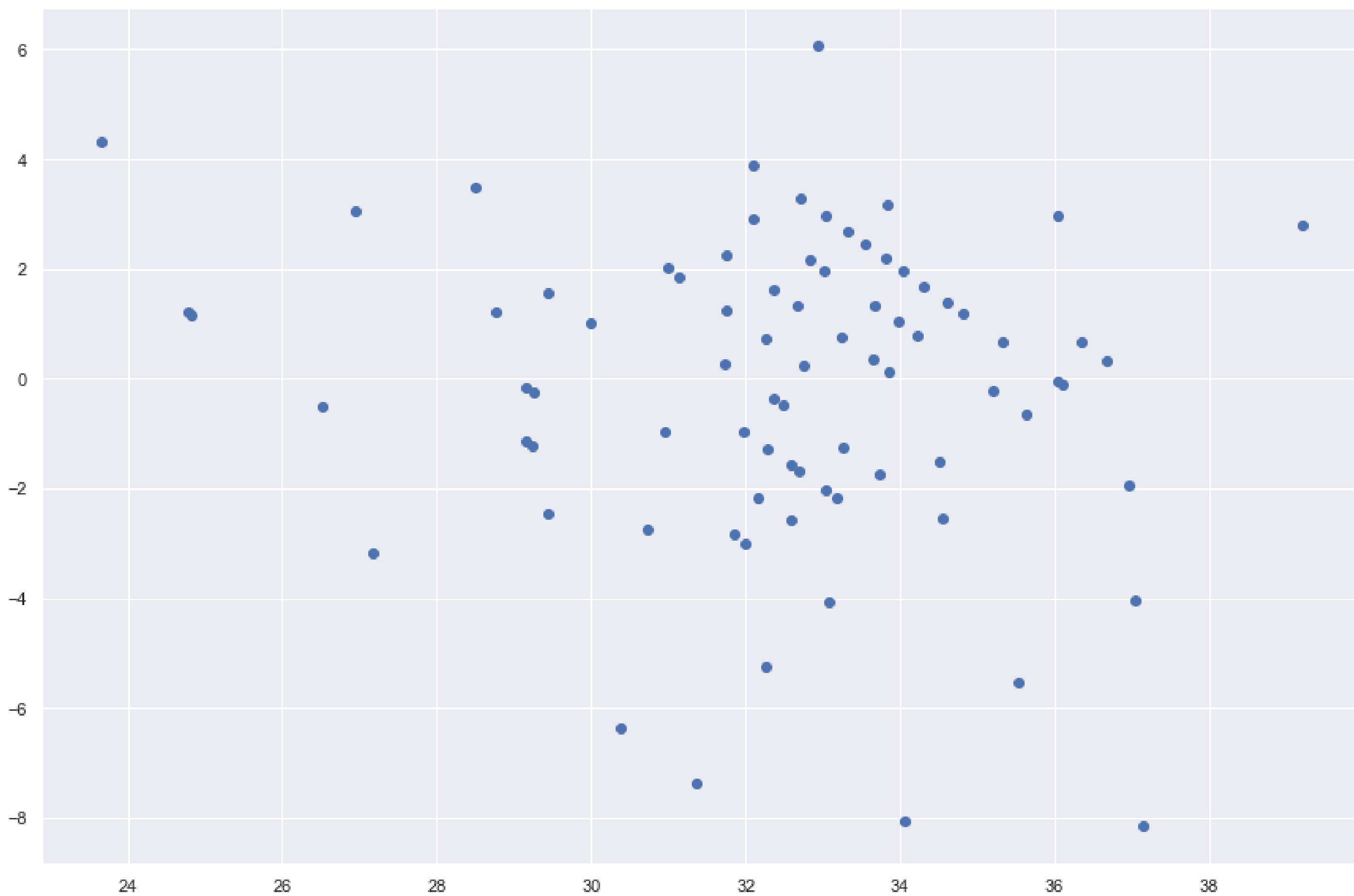
Out[78]: <seaborn.axisgrid.FacetGrid at 0x1e8061e60a0>




In [79]:

```
plt.scatter(ridge_pred,residuals)
```

Out[79]: <matplotlib.collections.PathCollection at 0x1e8066e2400>




**Performance Metrics**

In [80]:

```
print(mean_squared_error(y_test,ridge_pred))
print(mean_absolute_error(y_test,ridge_pred))
print(np.sqrt(mean_squared_error(y_test,ridge_pred)))
```

```
7.700169527845219
```

```
2.1363570878417484
2.774917931731535
```

**R SQUARE & ADJUSTED R SQUARE**

In [81]:
```
score=r2_score(y_test,reg_pred)
score
```

Out[81]:
```
0.442435458586767
```

**Now we test the accuracy of the model using Adjusted R2**

**But why to test the accuracy of the model using Adjusted R2,when we have already tested the accuracy of the model using R2,**

**It is because the accuracy of the model under R2 will increase as and when we increase the no of features(x)**

**But the Adjusted R2 will remain unaffected inspite of No of features(x) we take , so R2 is less reliable then Adjusted R2**

In [82]:
```
## Adjusted R square
#display adjusted R-squared
1 - (1-score)*(len(y_test)-1)/(len(y_test)-x_test_scaled.shape[1]-1)
```

Out[82]:
```
0.3342512938349457
```

# 6. LASSO

- LASSO Regression(also called as L1 Norm/L1 Regularization),the main aim of LASSO regressio is to reduce the features which are least correlated with dependent variables .
- If our datasets has outliers we should use LASSO .

In [83]:
```
lasso=Lasso()
lasso
```

Out[83]:
```
▾ Lasso
Lasso()
```

In [84]:
```
lasso.fit(x_train_scaled,y_train)
```

Out[84]:
```
▾ Lasso
Lasso()
```

In [85]:
```
print(lasso.coef_)
```

```
[ 0.         -0.         -0.88423537 -0.         -0.          0.88313134
  0.          0.          0.          0.          0.          0.
  0.        ]
```

In [86]:
```
print(lasso.intercept_)
```

```
32.074074074074076
```

In [87]:
```
lasso_pred=lasso.predict(x_test_scaled)
```

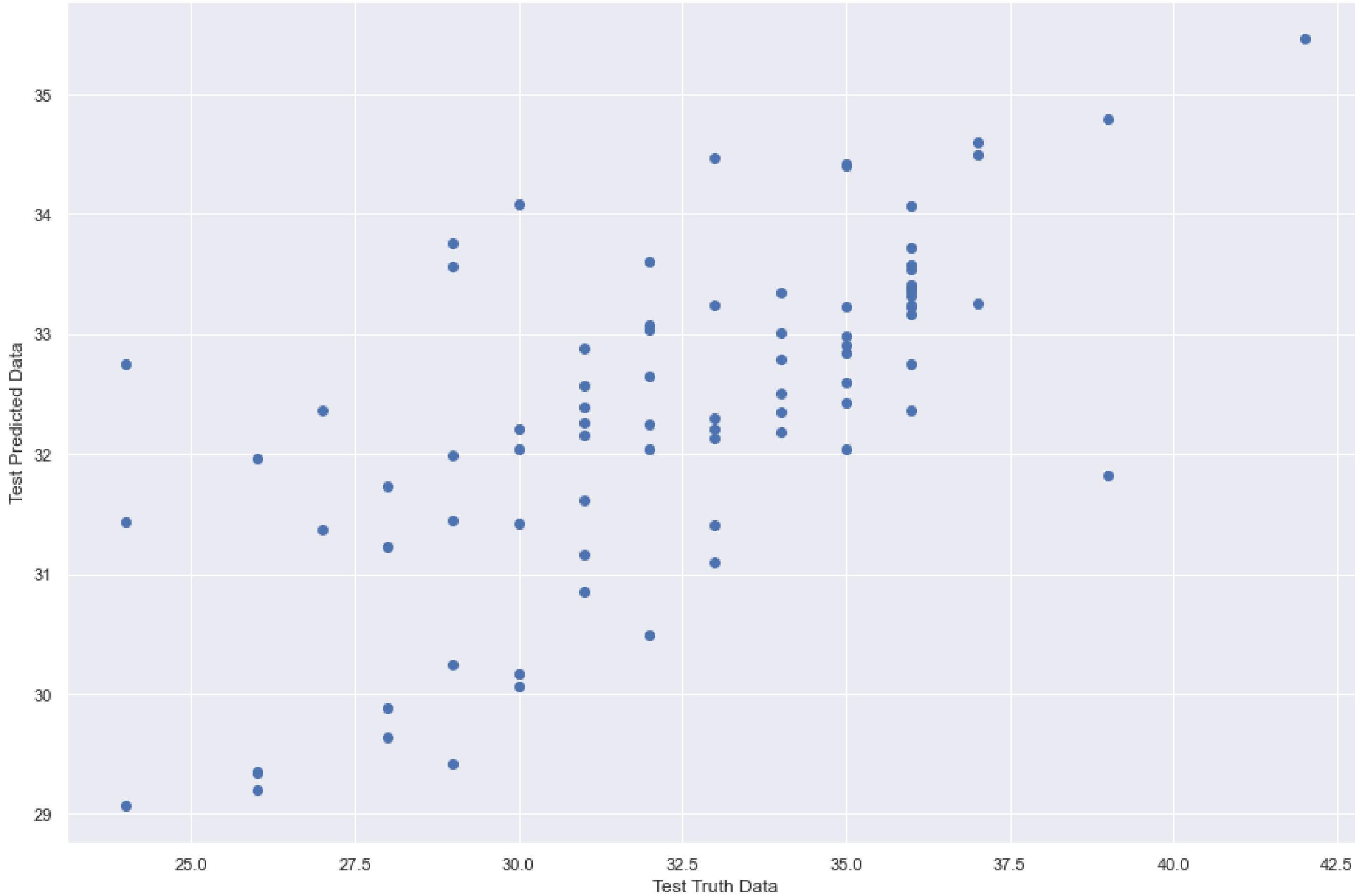
In [88]:
```
lasso_pred
```

Out[88]:
```
array([31.99263189, 33.56261409, 33.16968133, 29.35085197, 29.41532603,
       33.00570181, 32.24618859, 33.57987995, 32.17946599, 33.03180429,
       32.43352237, 32.64830012, 34.42463082, 31.61671515, 32.83763259,
       33.35142638, 29.33942467, 34.79854886, 32.38506498, 29.63719153,
       32.36854863, 32.21265622, 32.60134175, 31.81897394, 31.16330572,
       32.75364414, 32.88409128, 32.36320974, 32.04108928, 31.96868565,
       33.24608236, 33.07067555, 33.54659742, 32.57214892, 31.41161583,
       30.06340682, 32.79726231, 32.13550568, 33.36310351, 33.22497663,
       33.25167109, 34.07840658, 33.22831682, 33.75728546, 32.90619636,
       34.59903828, 32.34644356, 33.72050521, 31.73648451, 31.41845375,
       32.26170559, 35.46055533, 32.15686124, 33.60932262, 29.07618954,
       34.41195434, 33.23999395, 32.50358516, 29.88575148, 32.20406944,
       32.0385909 , 31.44605525, 29.20463799, 34.49394409, 33.4095622 ,
       30.24824223, 31.37474327, 30.84852284, 34.06622977, 30.49062147,
       31.23012062, 32.0385909 , 31.43946717, 31.10541974, 33.38061921,
       32.30257555, 32.9833469 , 32.74980427, 34.4764284 , 30.16341195,
       33.31614515])
```

**ASSUMPTIONS OF LINEAR REGRESSION**

In [89]:
```
#if we are plotting  y_test,reg_pred relation should be linear
plt.scatter(y_test,lasso_pred)
plt.xlabel("Test Truth Data")
plt.ylabel("Test Predicted Data")
```

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



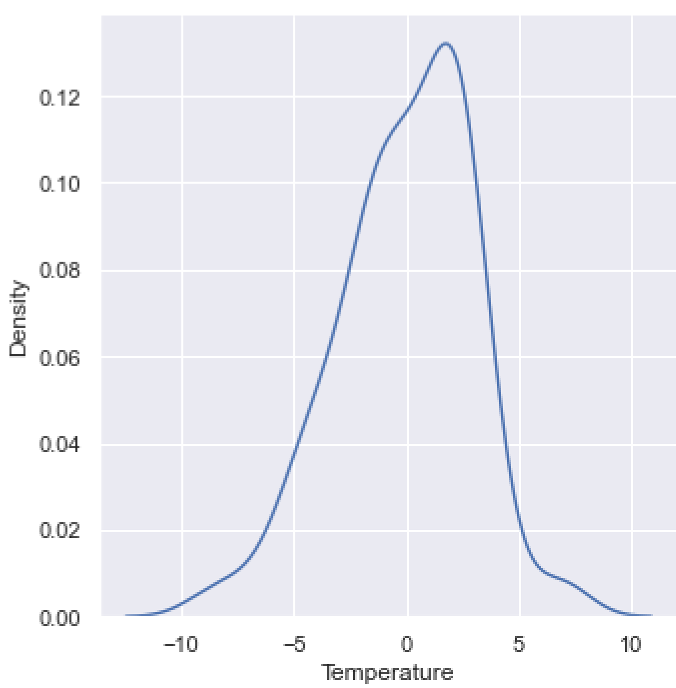

In [90]:

```
residuals=y_test-lasso_pred
```

In [91]:

```
sns.displot(residuals,kind="kde")
```

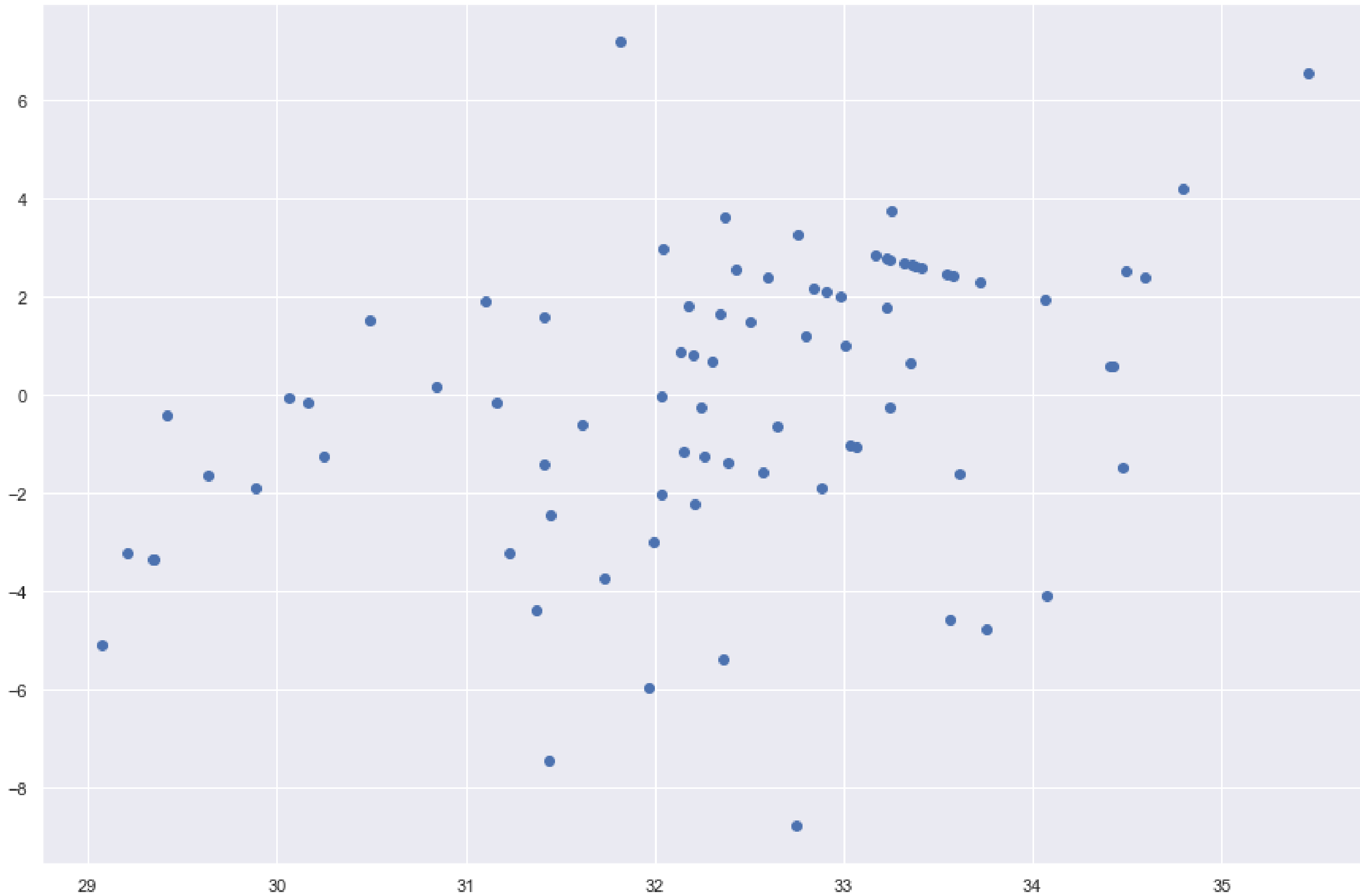
Out[91]: <seaborn.axisgrid.FacetGrid at 0x1e875aaa4c0>




In [92]:

```
plt.scatter(lasso_pred,residuals)
```

Out[92]: <matplotlib.collections.PathCollection at 0x1e806c50ac0>




**Performance Metrics**

In [93]:
```
print(mean_squared_error(y_test,lasso_pred))
print(mean_absolute_error(y_test,lasso_pred))
print(np.sqrt(mean_squared_error(y_test,lasso_pred)))
```

```
8.69462464944341
2.370968686727018
2.9486648927003234
```

**R SQUARE & ADJUSTED R SQUARE**

In [94]:
```
score=r2_score(y_test,lasso_pred)
score
```

Out[94]:
```
0.3719123543887275
```

In [95]:
```
## Adjusted R square
#display adjusted R-squared
1 - (1-score)*(len(y_test)-1)/(len(y_test)-x_test_scaled.shape[1]-1)
```

Out[95]:
```
0.250044602255197
```

# 7. ElasticNet

**ElasticNet is a combination of Ridge & LAASO Regression**

In [96]:
```
elastic_net=ElasticNet()
```

In [97]:
```
elastic_net.fit(x_train_scaled,y_train)
```

Out[97]:
```
▾ ElasticNet
ElasticNet()
```

In [98]:
```
print(elastic_net.coef_)
```

```
[-0.         -0.         -0.77155493 -0.27327033 -0.02945645  0.70980198
  0.11177449  0.          0.20914599  0.04593431  0.12829249  0.
  0.        ]
```

In [99]:
```
print(elastic_net.intercept_)
```

```
32.074074074074076
```

In [100…
```
elastic_net_pred=elastic_net.predict(x_test_scaled)
```

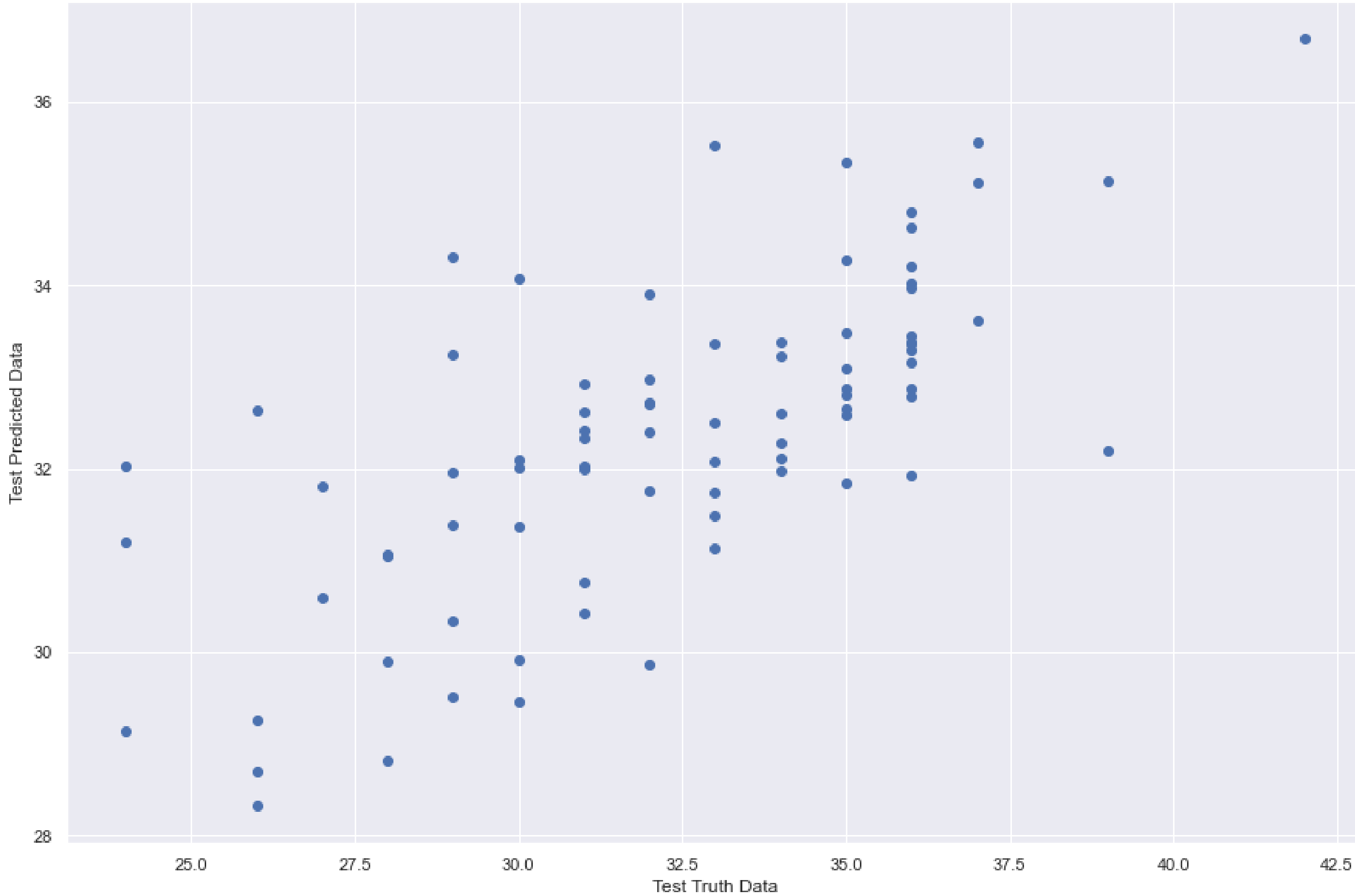
In [101…
```
elastic_net_pred
```

Out[101…
```
array([31.9573208 , 33.23686908, 33.35699564, 28.69175409, 29.50702659,
       33.21952486, 31.75246849, 33.96237735, 32.10800305, 32.71913539,
       32.6464949 , 32.70818669, 34.28160866, 31.98757886, 32.58127398,
       33.38088877, 29.25544946, 35.1329971 , 32.41345187, 28.81942678,
       31.92062398, 32.01321369, 32.87611371, 32.19248582, 30.76147509,
       32.77885483, 32.9241576 , 31.80574265, 31.84088675, 32.63570681,
       33.35824365, 32.97725238, 33.16526411, 32.6259555 , 31.48228091,
       29.90876877, 32.28704956, 31.73349961, 33.28556103, 32.87586141,
       33.61368581, 34.06687234, 33.48616338, 34.31378768, 32.80354959,
       35.56194932, 31.98083723, 34.20080511, 31.06352775, 31.3703163 ,
       32.33015611, 36.68465163, 32.02910227, 33.90164802, 29.13016242,
       35.33664404, 33.44975962, 32.59500157, 29.89482886, 32.07728159,
       32.39209933, 31.39172713, 28.33121558, 35.11153428, 34.62534381,
       30.33956758, 30.58992082, 30.41863187, 34.79501455, 29.86618003,
       31.0520072 , 32.09680635, 31.20338706, 31.12722538, 34.01998343,
       32.49121998, 33.0901132 , 32.02987963, 35.52196854, 29.45679071,
       33.38350807])
```

**ASSUMPTIONS OF LINEAR REGRESSION**

In [102…
```
#if we are plotting  y_test,reg_pred relation should be linear
plt.scatter(y_test,elastic_net_pred)
plt.xlabel("Test Truth Data")
plt.ylabel("Test Predicted Data")
```

Out[102…
```
Text(0, 0.5, 'Test Predicted Data')
```




In [103…

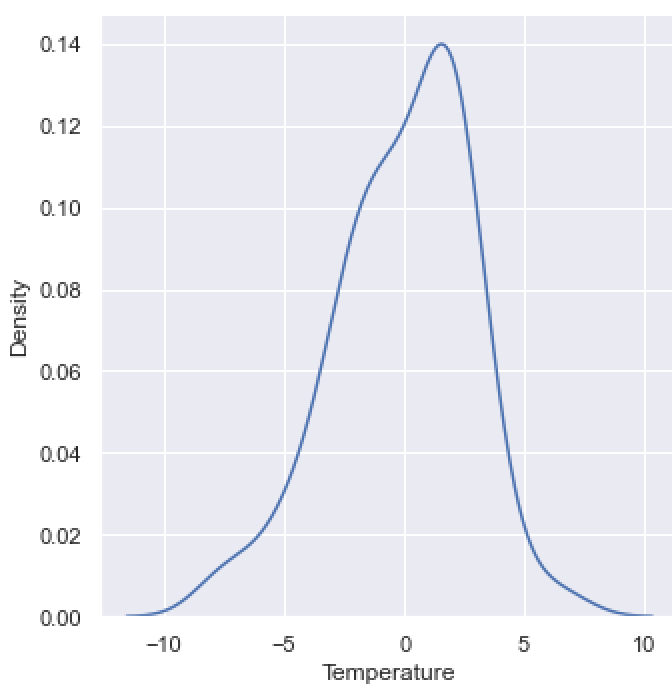
```
residuals=y_test-elastic_net_pred
```

In [104…

```
sns.displot(residuals,kind="kde")
```

Out[104…

```
<seaborn.axisgrid.FacetGrid at 0x1e806949280>
```

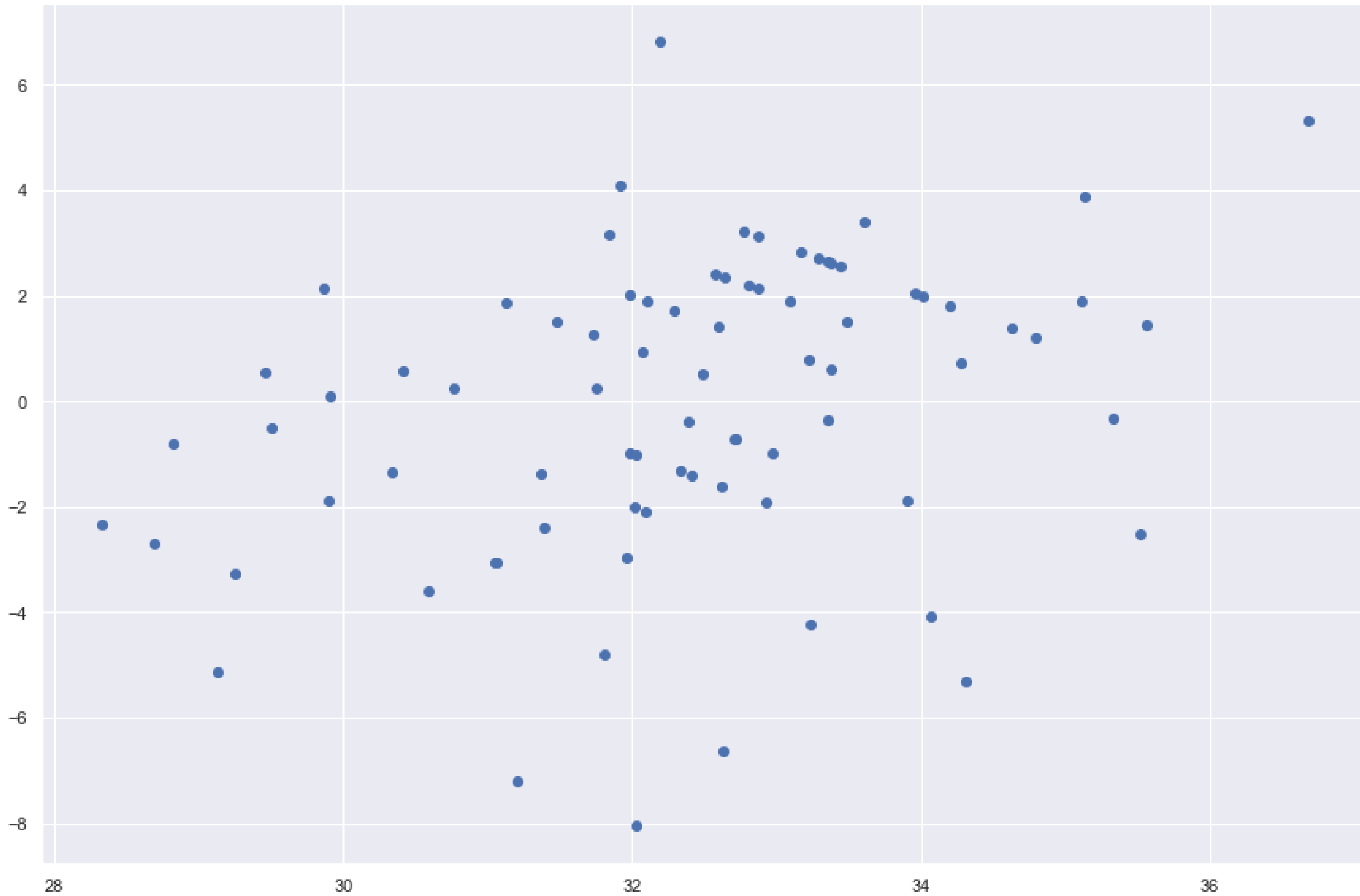



In [105…

```
plt.scatter(elastic_net_pred,residuals)
```

Out[105…

```
<matplotlib.collections.PathCollection at 0x1e80715d2b0>
```




**Performance Metrics**

In [106…

```
print(mean_squared_error(y_test,elastic_net_pred))
print(mean_absolute_error(y_test,elastic_net_pred))
print(np.sqrt(mean_squared_error(y_test,elastic_net_pred)))
```

```
7.918267418307838
2.2796482511865195
2.813941616009088
```

**R SQUARE & ADJUSTED R SQUARE**

In [107…

```
score=r2_score(y_test,elastic_net_pred)
score
```

Out[107…

```
0.42799532577823 34
```

**Now we test the accuracy of the model using Adjusted R2**

**But why to test the accuracy of the model using Adjusted R2,when we have already tested the accuracy of the model using R2,**

**It is because the accuracy of the model under R2 will increase as and when we increase the no of features(x)**

**But the Adjusted R2 will remain unaffected inspite of No of features(x) we take , so R2 is less reliable then Adjusted R2**

In [108…

```
## Adjusted R square
#display adjusted R-squared
1 - (1-score)*(len(y_test)-1)/(len(y_test)-x_test_scaled.shape[1]-1)
```

Out[108…

```
0.317009344212816
```