Linear Regression: ¶

Linear Regression Practical implementaion on Algerian Forest Fires Dataset

Life cycle of Machine learning Project

In [ ]:

```
1.Understanding the Problem Statement
2.Data Collection
3.Exploratory data analysis
4.Data Cleaning
5.Data Pre-Processing
6.Model Training
7.Choose best model
```

1.Problem Statement

by using linear regression we have to predict the temperature

2.Data Collection

The Dataset is collected from UIC machine learning repository Dataset link :
[https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++ (https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++)](https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++)

Data Set Information:

The dataset includes 244 instances that regroup a data of two regions of Algeria,namely the Bejaia region located in the northeast of Algeria and the Sidi Bel-abbes region located in the northwest of Algeria.

122 instances for each region.

The period from June 2012 to September 2012. The dataset includes 11 attribues and 1 output attribue (class) The 244 instances have been classified into â€˜fireâ€™ (138 classes) and â€˜not fireâ€™ (106 classes) classes.

Attribute Information:

1.Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012) Weather data observations 2.Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42 3.RH : Relative Humidity in %: 21 to 90 4.Ws :Wind speed in km/h: 6 to 29 5.Rain: total day in mm: 0 to 16.8 FWI Components 6.Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5 7.Duff Moisture Code (DMC) index from the FWI system: 1.1

to 65.9 8.Drought Code (DC) index from the FWI system: 7 to 220.4 9.Initial Spread Index (ISI) index from the FWI system: 0 to 18.5 10.Buildup Index (BUI) index from the FWI system: 1.1 to 68 11.Fire Weather Index (FWI) Index: 0 to 31.1 12.Classes: two classes, namely â€œFireâ€ and â€œnot Fireâ€

2.1 importing data and required packages

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

2.2 import the dataset

Since data is in form of an csv file we have to use “pandas.read_csv” to load the data and store it in data frame as df.we are setting header = 1 means row 1 ,row 0 it will ignore

In [2]:

```
df=pd.read_csv(r"C:\Users\DHARAVATH RAMDAS\Downloads\Algerian_forest_fires_dataset_UPDATE.c
```

In [3]:

```
df
```

Out[3]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Class
0	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not f
1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not f
2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not f
3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not f
4	05	06	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not f
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
241	26	09	2012	30	65	14	0	85.4	16	44.5	4.5	16.9	6.5	f
242	27	09	2012	28	87	15	4.4	41.1	6.5	8	0.1	6.2	0	not f
243	28	09	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not f
244	29	09	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not f
245	30	09	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not f

246 rows × 14 columns

2.3 first 5 rows

In [4]:

```
df.head()
```

Out[4]:

	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

2.4 last 5 rows

In [5]:

```
df.tail()
```

Out[5]:

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

2.5 shape of the data

In [6]:

```
df.shape
```

Out[6]:

```
(246, 14)
```

observation : 246 rows and 14 columns

3.Data Cleaning

In [7]:

```
### we have to remove the unnecessary rows from dataset after observation
```

In [8]:

```
df[121:126]
```

Out[8]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FW
121	30	09	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1
122	Sidi-Bel Abbes Region Dataset	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	FW
124	01	06	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2
125	02	06	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2

observation: see the 122 row it contains the nan values see the 123 row it contains the categorical values we have to remove the 122 and 123 rows because it is different from the your data

remove unnecessary rows from dataset

In [9]:

```
df.drop(index=[122,123],inplace=True)
#it will give index gap so we reset index
df.reset_index(inplace=True)
df.drop('index',axis=1,inplace=True)
```

In [10]:

```
# check rows

df.loc[122:126]
```

Out[10]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classe
122	01	06	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not fi
123	02	06	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2	not fi
124	03	06	2012	29	80	14	2	48.7	2.2	7.6	0.3	2.6	0.1	not fi
125	04	06	2012	30	64	14	0	79.4	5.2	15.4	2.2	5.6	1	not fi
126	05	06	2012	32	60	14	0.2	77.1	6	17.6	1.8	6.5	0.9	not fi

Observation: we succesfully removed the nan values

adding new feature named Region in a dataset

In [11]:

```
# we add region new column in dataset
# 1.method
df['Region'] = 0
for i in range(len(df)):
    if i >= 122:
        df['Region'][i] = 1
```

In [12]:

```
# 2.method
# df.loc[:122,"region"] = 'bejaia'
# df.loc[122:, 'region'] = 'sidi-bel abbes'
```

In [13]:

```
df.head(3)
```

Out[13]:

	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

observation: we added new column sucessflly

In [14]:

```
### check the balanced data or not
df['Region'].value_counts()
```

Out[14]:

```
0    122
1    122
Name: Region, dtype: int64
```

observation :- see the above bejaia is 122 and sidi-bel abbes is 122 times both are same equal

In [15]:

```
df.columns
```

Out[15]:

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

observation: see the columns some have the extra spaces so we have to remove it

stripping the names of the columns

In [16]:

```
df.columns = [co.strip() for co in df.columns]
df.columns
```

Out[16]:

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

In [17]:

```
df['Classes'].unique()
```

Out[17]:

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

observation:- see the classes it contains some extra spaces so we have to remove it

stripping the classes features column

In [18]:

```
df['Classes'] = df.Classes.str.strip()
```

observation:- see we got nan value we have to identify it and set the correct

In [19]:

```
df.iloc[165]
```

Out[19]:

```
day                  14
month                07
year               2012
Temperature          37
RH                   37
Ws                   18
Rain                0.2
FFMC               88.9
DMC                12.9
DC               14.6 9
ISI                12.5
BUI                10.4
FWI              fire
Classes             NaN
Region                1
Name: 165, dtype: object
```

bservation :- see some miss match positions we have to reset it

In [20]:

```
df.at[165,'DC'] = 14.6
df.at[165,'ISI'] = 9
df.at[165,'BUI'] = 12.5
df.at[165,'FWI'] = 10.4
df.at[165,'Classes'] = 'fire'
```

In [21]:

```
df.loc[165]
```

Out[21]:

```
day              14
month            07
year           2012
Temperature      37
RH               37
Ws               18
Rain            0.2
FFMC           88.9
DMC            12.9
DC             14.6
ISI               9
BUI            12.5
FWI            10.4
Classes        fire
Region            1
Name: 165, dtype: object
```

In [22]:

```
## chaanging the classes
df['Classes'] = df['Classes'].replace('not fire','0')
df['Classes'] = df['Classes'].replace('fire','1')
```

Check the null values

In [23]:

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

Out[23]:

```
0
```

checking the datatype of each columns

In [24]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   day          244 non-null    object
 1   month        244 non-null    object
 2   year         244 non-null    object
 3   Temperature  244 non-null    object
 4   RH           244 non-null    object
 5   Ws           244 non-null    object
 6   Rain         244 non-null    object
 7   FFMC         244 non-null    object
 8   DMC          244 non-null    object
 9   DC           244 non-null    object
 10  ISI          244 non-null    object
 11  BUI          244 non-null    object
 12  FWI          244 non-null    object
 13  Classes      244 non-null    object
 14  Region       244 non-null    int64 
dtypes: int64(1), object(14)
memory usage: 28.7+ KB
```

observation:- see that day is object so its wrong data type so we have change its datatypes

Changing the datatype of the columns

In [25]:

```
Rain':'float', 'FFMC':'float','DMC':'float','FWI':'float', 'DC':'float','ISI':'float','BUI':
```

In [26]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   day          244 non-null    object 
 1   month        244 non-null    object 
 2   year         244 non-null    object 
 3   Temperature  244 non-null    int32  
 4   RH           244 non-null    int32  
 5   Ws           244 non-null    int32  
 6   Rain         244 non-null    float64
 7   FFMC         244 non-null    float64
 8   DMC          244 non-null    float64
 9   DC           244 non-null    float64
 10  ISI          244 non-null    float64
 11  BUI          244 non-null    float64
 12  FWI          244 non-null    float64
 13  Classes      244 non-null    int32  
 14  Region       244 non-null    int64  
dtypes: float64(7), int32(4), int64(1), object(3)
memory usage: 24.9+ KB
```

we are adding new feature named Day by replacing unnecessary feature like 'day','month','year'

In [27]:

```
df['date'] = pd.to_datetime(df[['day','month','year']])
df.drop(['day','month','year'],axis=1, inplace= True)
```

In [28]:

```
df
```

Out[28]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region	date
0	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0	0	2012-06-01
1	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0	0	2012-06-02
2	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0	0	2012-06-03
3	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0	0	2012-06-04
4	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0	0	2012-06-05
...	...	...	...	...	...	...	...	...	...	...	...	...	...
239	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	1	1	2012-09-26
240	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	0	1	2012-09-27
241	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	0	1	2012-09-28
242	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	0	1	2012-09-29
243	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	0	1	2012-09-30

244 rows × 13 columns

Exploring data

Shape of the datset

In [29]:

```
df.shape
```

Out[29]:

```
(244, 13)
```

Observation: there are 13 columns and 244 rows

Columns of dataset

In [30]:

```
df.columns
```

Out[30]:

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

Checking missing values in dataset

In [31]:

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

Out[31]:

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

Observation: don't have any null values

In [32]:

```
# uniwue value of classes feature

df['Classes'].unique()
```

Out[32]:

```
array([0, 1])
```

Describe is used for ststistics analysis

In [140]:

```
df.describe()
```

Out[140]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	
count	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	2
mean	32.172131	61.938525	15.504098	0.760656	77.887705	14.673361	49.288115	
std	3.633843	14.884200	2.810178	1.999406	14.337571	12.368039	47.619662	
min	22.000000	21.000000	6.000000	0.000000	28.600000	0.700000	6.900000	
25%	30.000000	52.000000	14.000000	0.000000	72.075000	5.800000	13.275000	
50%	32.000000	63.000000	15.000000	0.000000	83.500000	11.300000	33.100000	
75%	35.000000	73.250000	17.000000	0.500000	88.300000	20.750000	68.150000	
max	42.000000	90.000000	29.000000	16.800000	96.000000	65.900000	220.400000	

In [141]:

```
df.describe().T
```

Out[141]:

	count	mean	std	min	25%	50%	75%	max
Temperature	244.0	32.172131	3.633843	22.0	30.000	32.00	35.000	42.0
RH	244.0	61.938525	14.884200	21.0	52.000	63.00	73.250	90.0
Ws	244.0	15.504098	2.810178	6.0	14.000	15.00	17.000	29.0
Rain	244.0	0.760656	1.999406	0.0	0.000	0.00	0.500	16.8
FFMC	244.0	77.887705	14.337571	28.6	72.075	83.50	88.300	96.0
DMC	244.0	14.673361	12.368039	0.7	5.800	11.30	20.750	65.9
DC	244.0	49.288115	47.619662	6.9	13.275	33.10	68.150	220.4
ISI	244.0	4.759836	4.154628	0.0	1.400	3.50	7.300	19.0
BUI	244.0	16.673361	14.201648	1.1	6.000	12.45	22.525	68.0
FWI	244.0	7.049180	7.428366	0.0	0.700	4.45	11.375	31.1
Classes	244.0	0.565574	0.496700	0.0	0.000	1.00	1.000	1.0
Region	244.0	0.500000	0.501028	0.0	0.000	0.50	1.000	1.0

Analysis:

Numerical and Categorical Columns

Numerical features

In [33]:

```
# 1. Getting Numerical features from dataset
# 2. Creating Numerical dataframe
```

In [34]:

```
num_fea = [fea for fea in df.columns if df[fea].dtype != 'O']

print("len of numerical feature is : ",len(num_fea),", num features : ",num_fea)
```

```
len of numerical feature is :  13 , num features :  ['Temperature', 'RH', 'W
s', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'Region',
'date']
```

Categorical Features

In [35]:

```
# we are creating the categorical column from dataset

cat_fea = [fea for fea in df.columns if df[fea].dtype == 'O']

print("len of numerical feature is : ",len(cat_fea),", num features : ",cat_fea)
```

```
len of numerical feature is :  0 , num features :  []
```

Univariate Analysis

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

In [36]:

```
df.var()
```

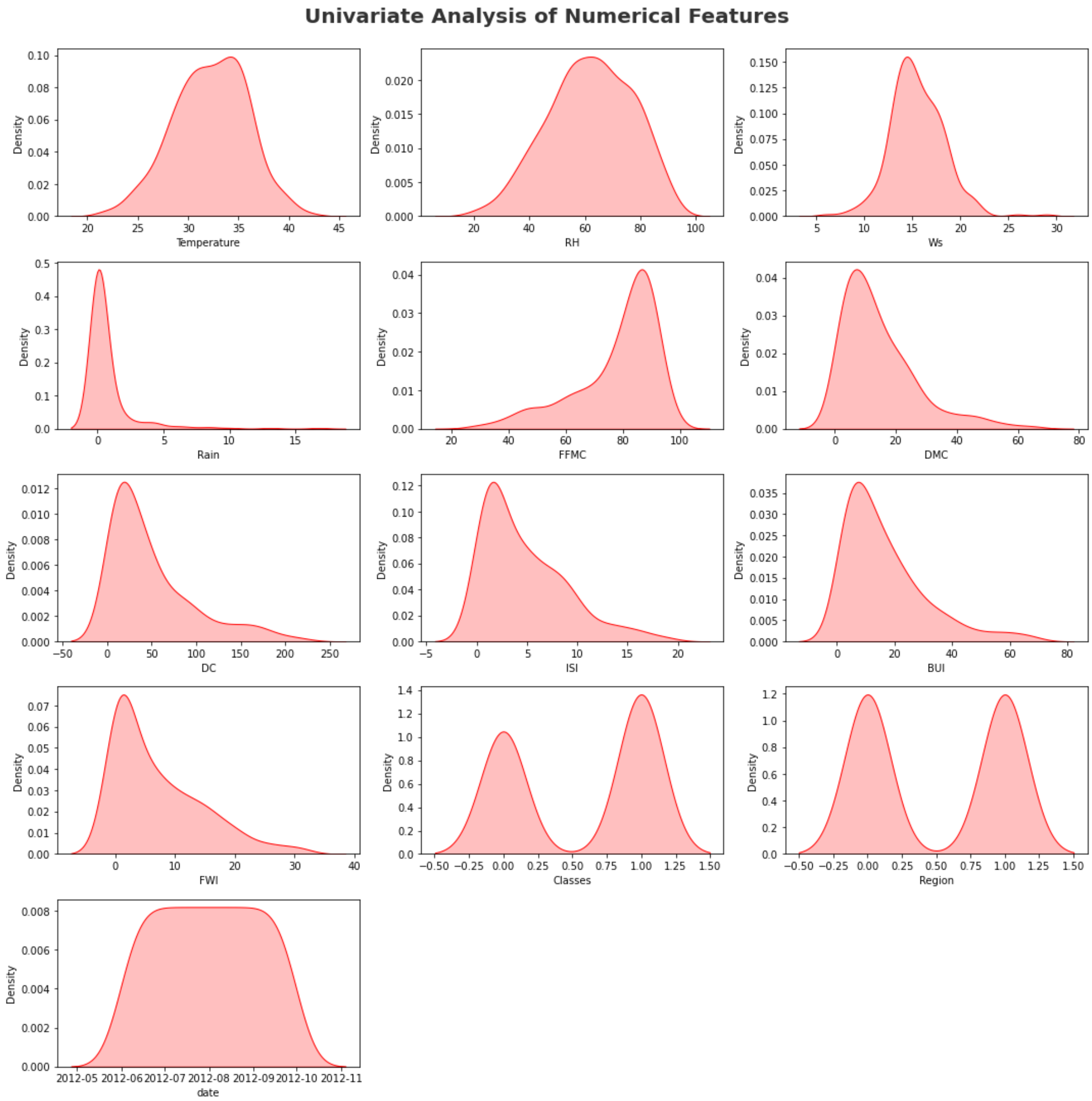
Out[36]:

```
Temperature      13.204817
RH              221.539415
Ws                7.897102
Rain              3.997623
FFMC            205.565939
DMC             152.968382
DC             2267.632245
ISI              17.260932
BUI             201.686818
FWI              55.180617
Classes           0.246711
Region            0.251029
dtype: float64
```

Numerical Feature Analysis

In [37]:

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

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

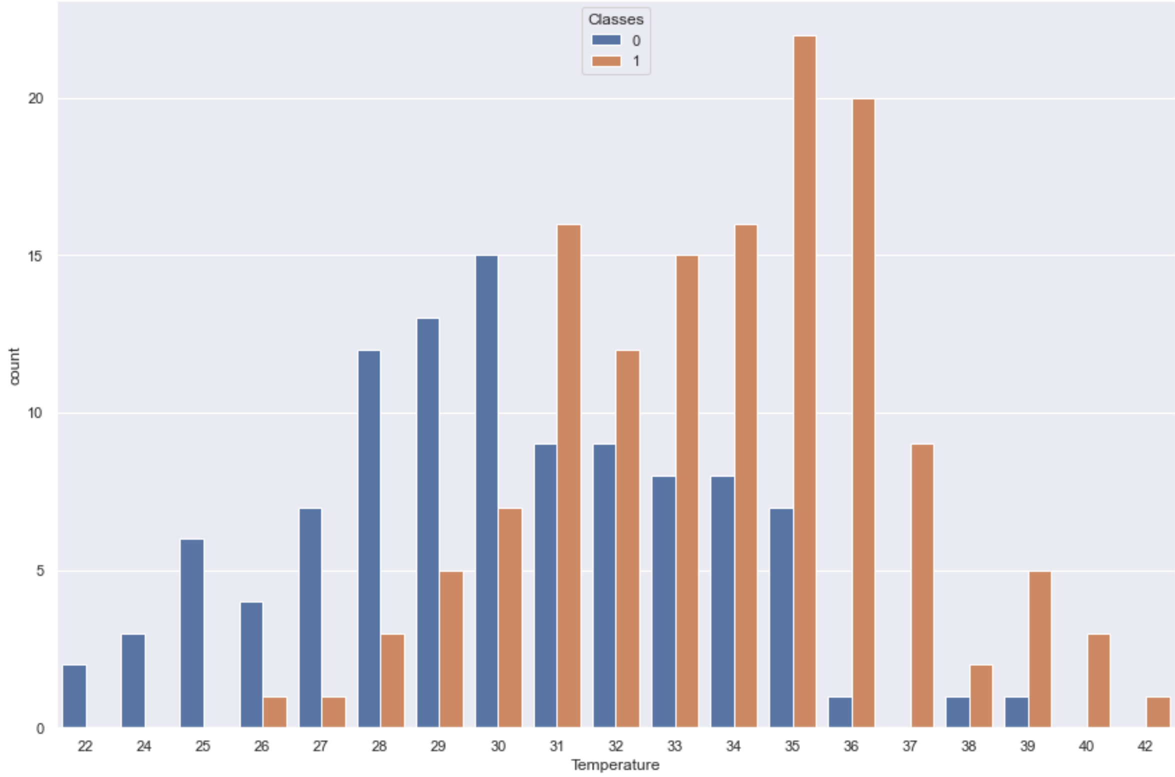


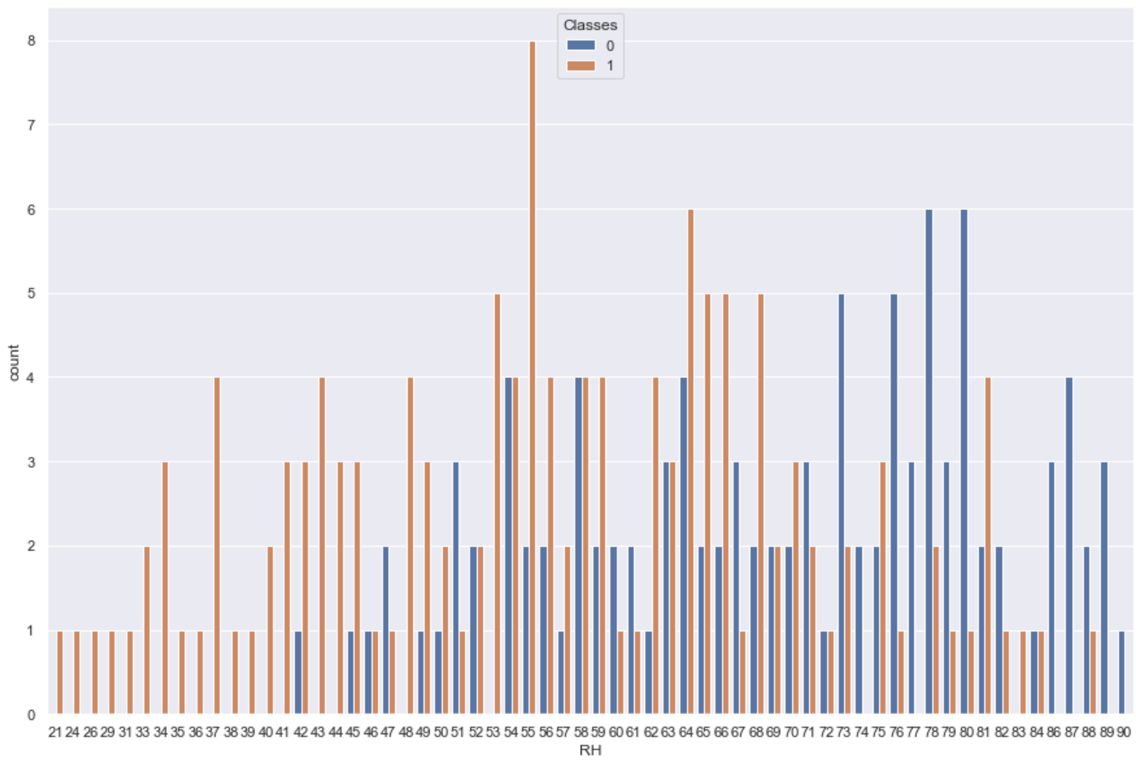
Observation: => Rain, DMC, DC, ISI, BUI, FWI are right skewed => FFMC is a left skewed => Temperature, RH, date are normal distribution

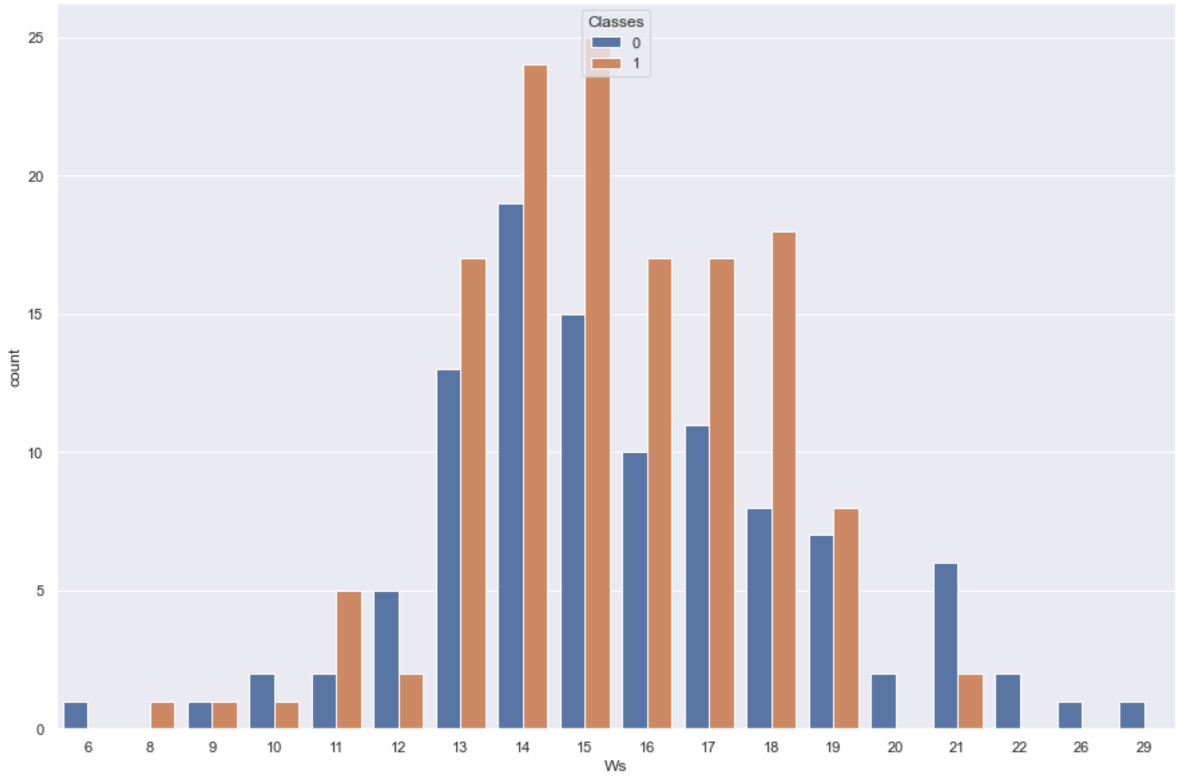
Count plot

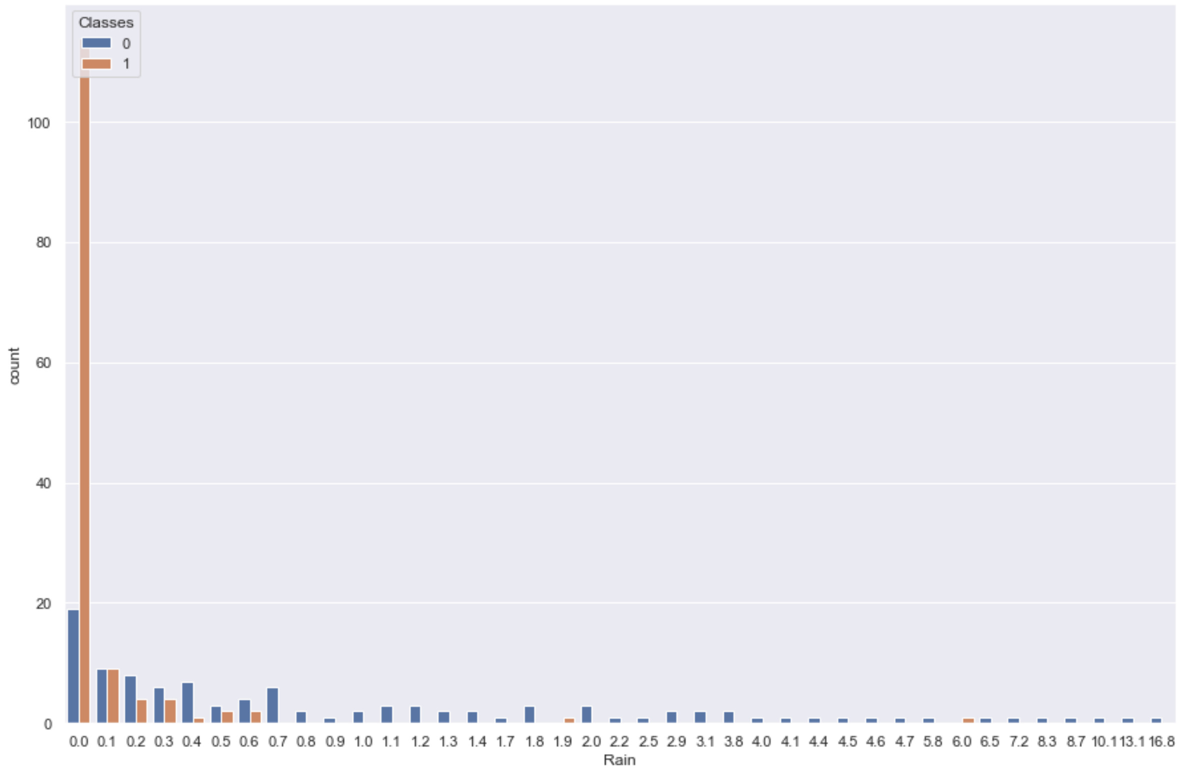
In [142]:

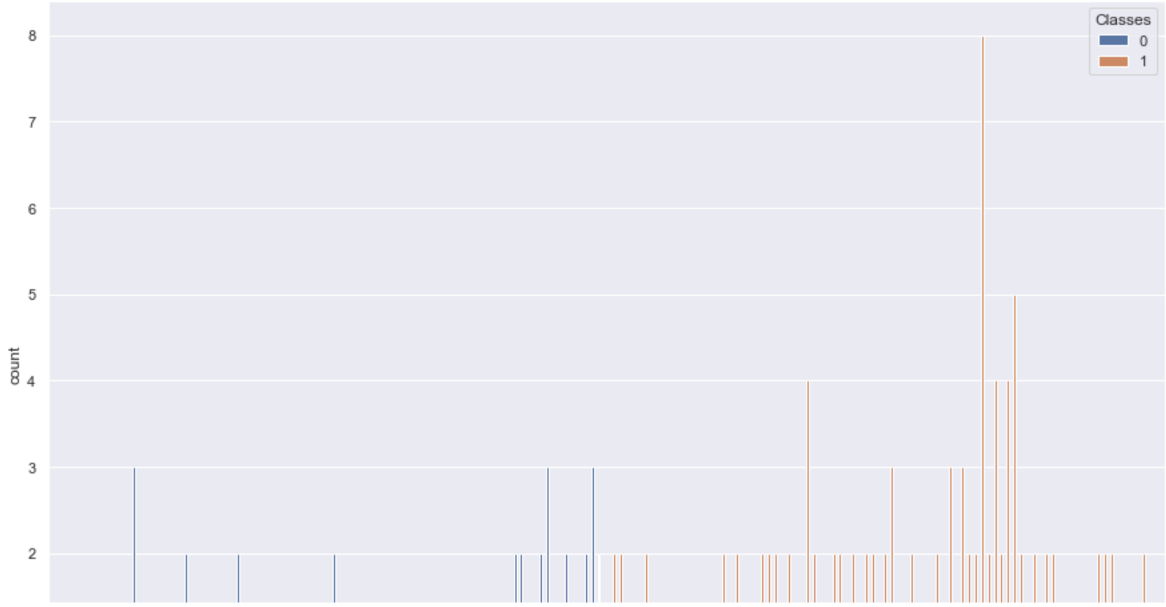
```
## we are analysing the bivariate analysis

for fea in num_fea:
    sns.countplot(data=df,x=fea,hue='Classes')
    plt.show()
```

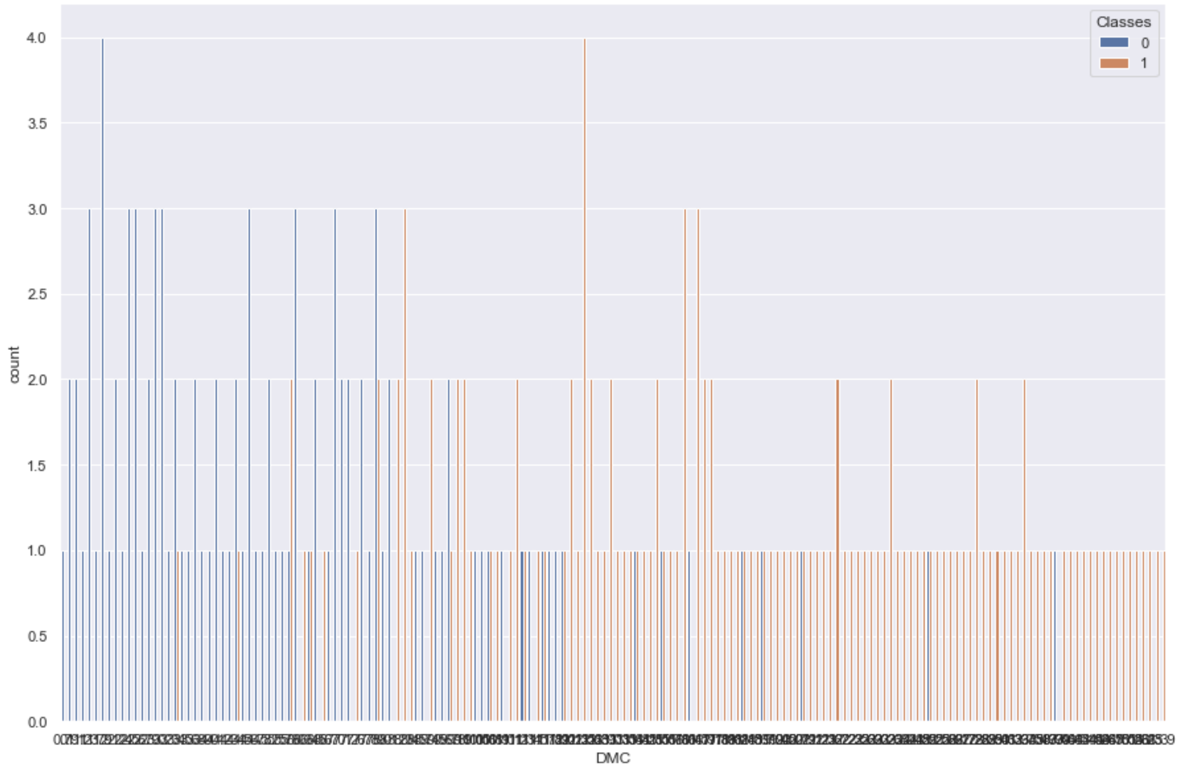


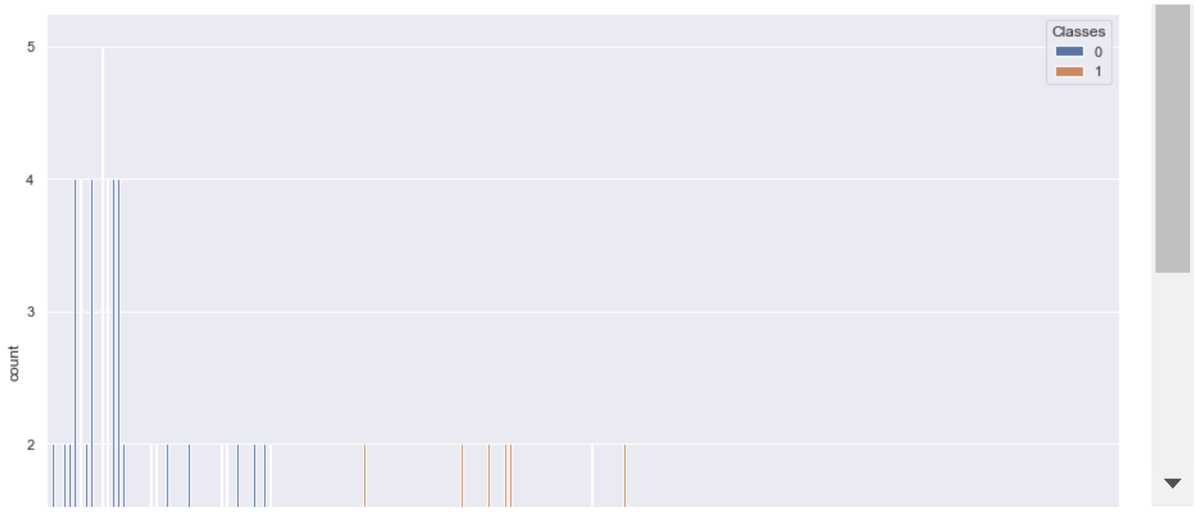


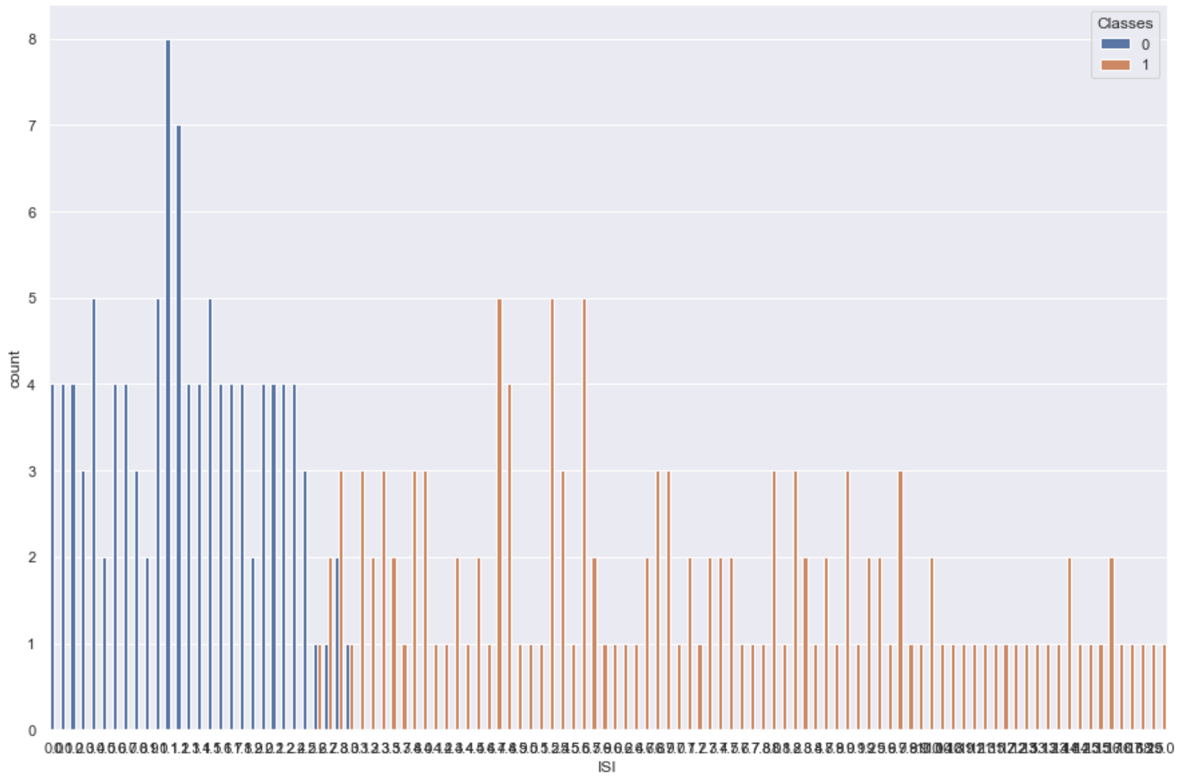

Classes
0
1
count
Ws
6
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
26
29

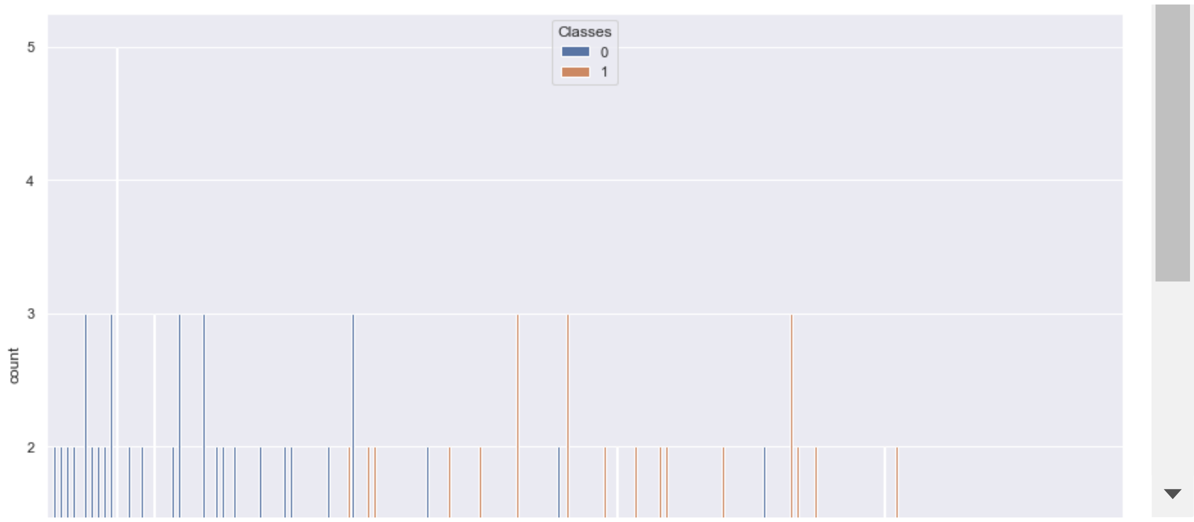

Classes
0
1
count
Rain

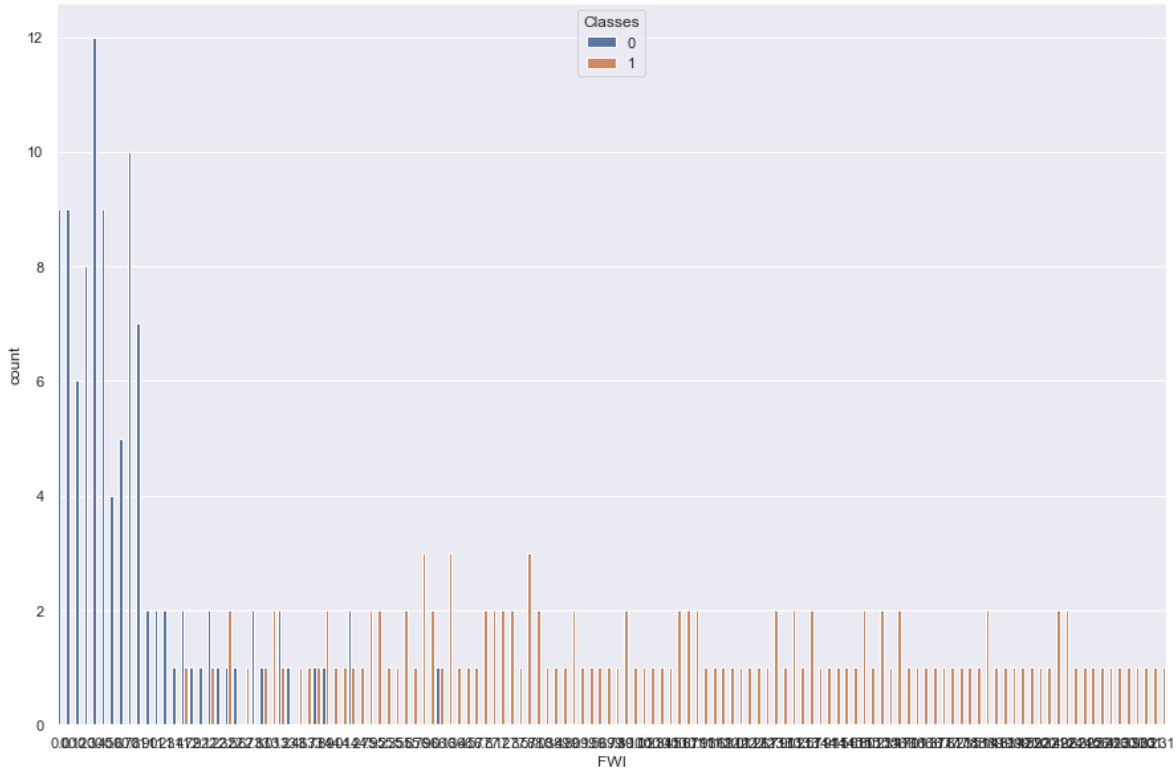

Classes
0
1
count
8
7
6
5
4
3
2

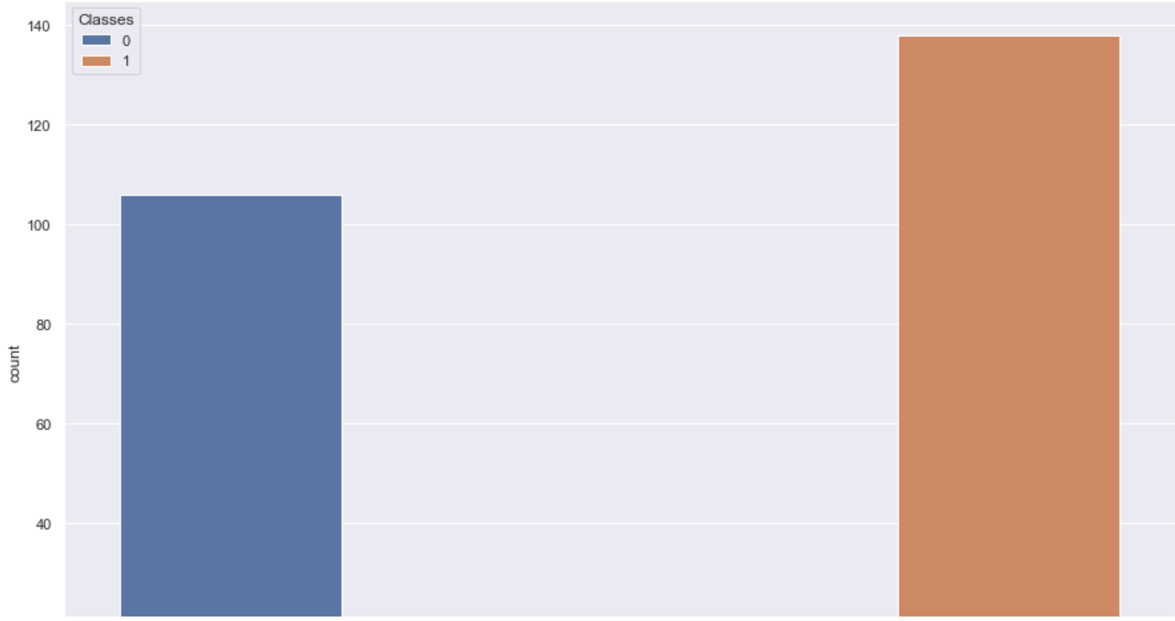

Classes
0
1
count
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
DMC

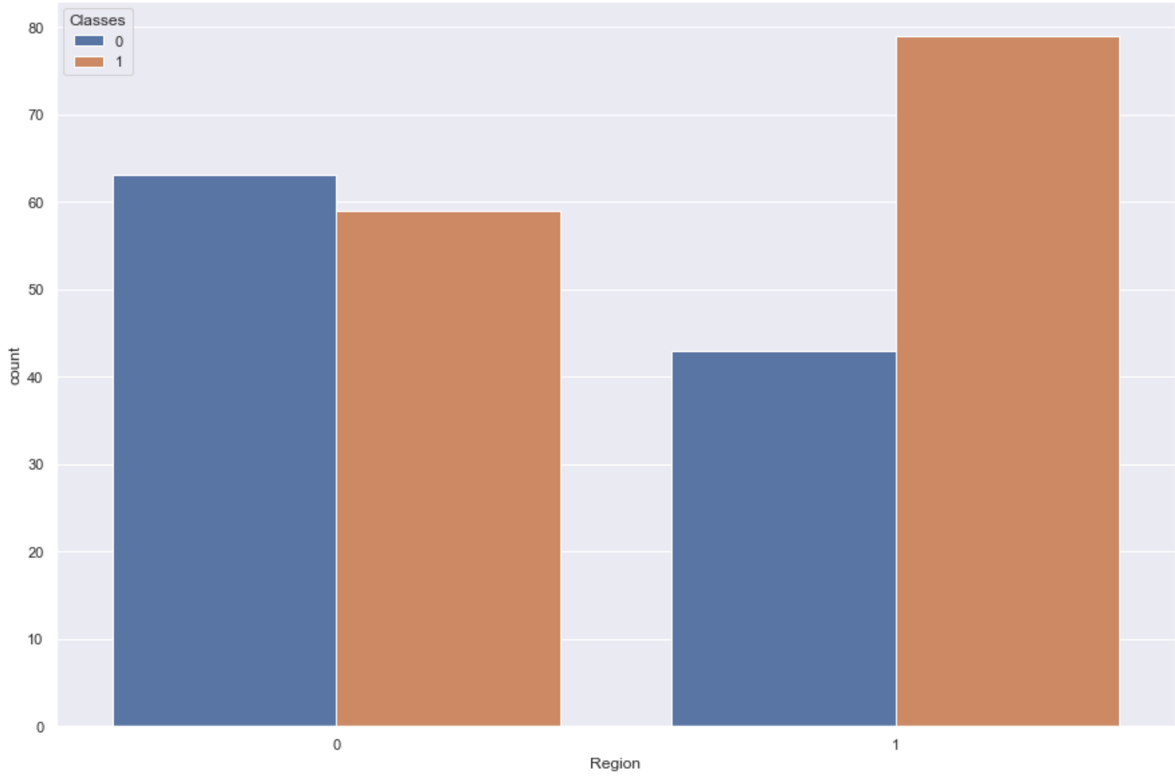

Classes
0
1
count
2
3
4
5

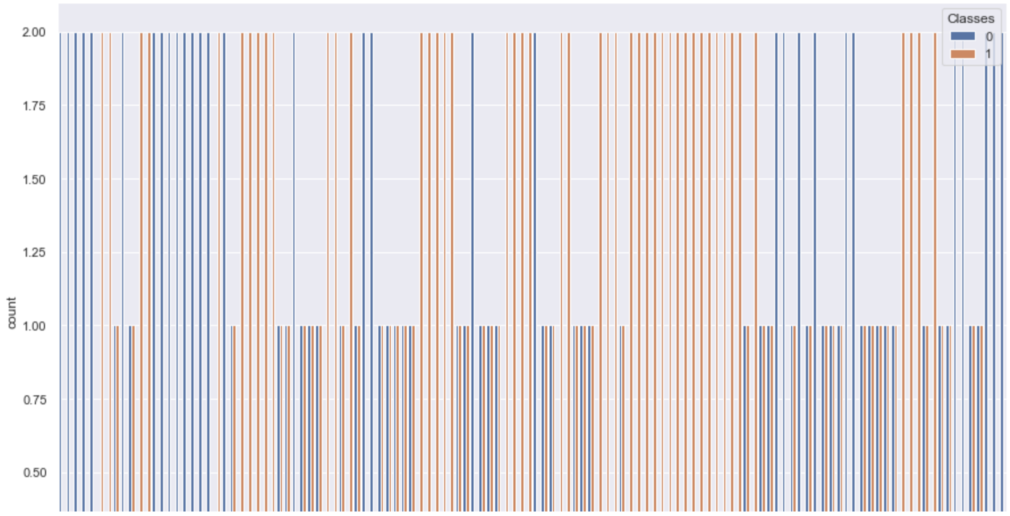

Classes
0
1
count
ISI
0
1
2
3
4
5
6
7
8


Classes
0
1
count
5
4
3
2


Classes
0
1
count
12
10
8
6
4
2
0
FWI


Classes
0
1
count
140
120
100
80
60
40

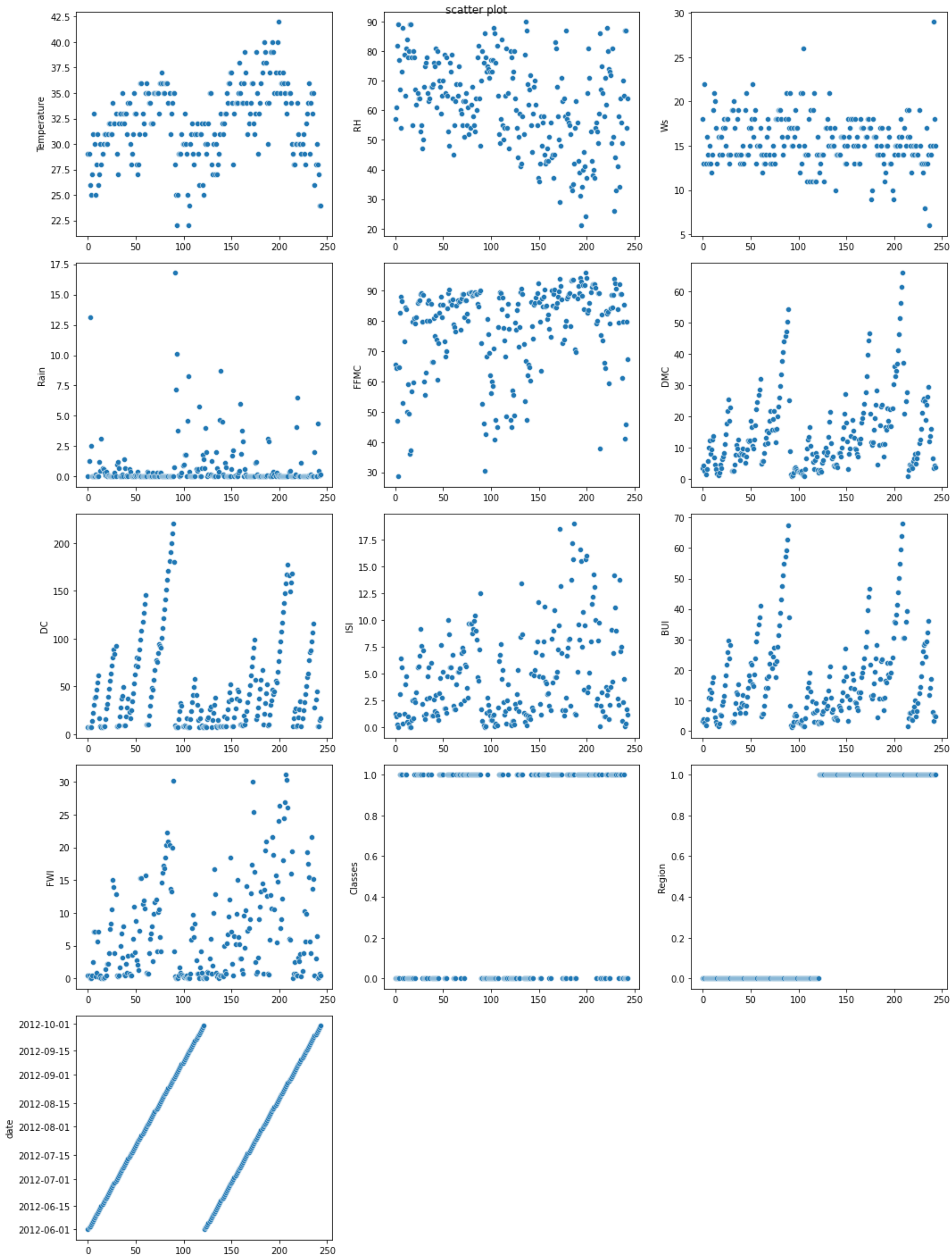

Classes
0
1
count
80
70
60
50
40
30
20
10
0
Region



Scatter plot to see the trends in each numeriacal columns

In [39]:

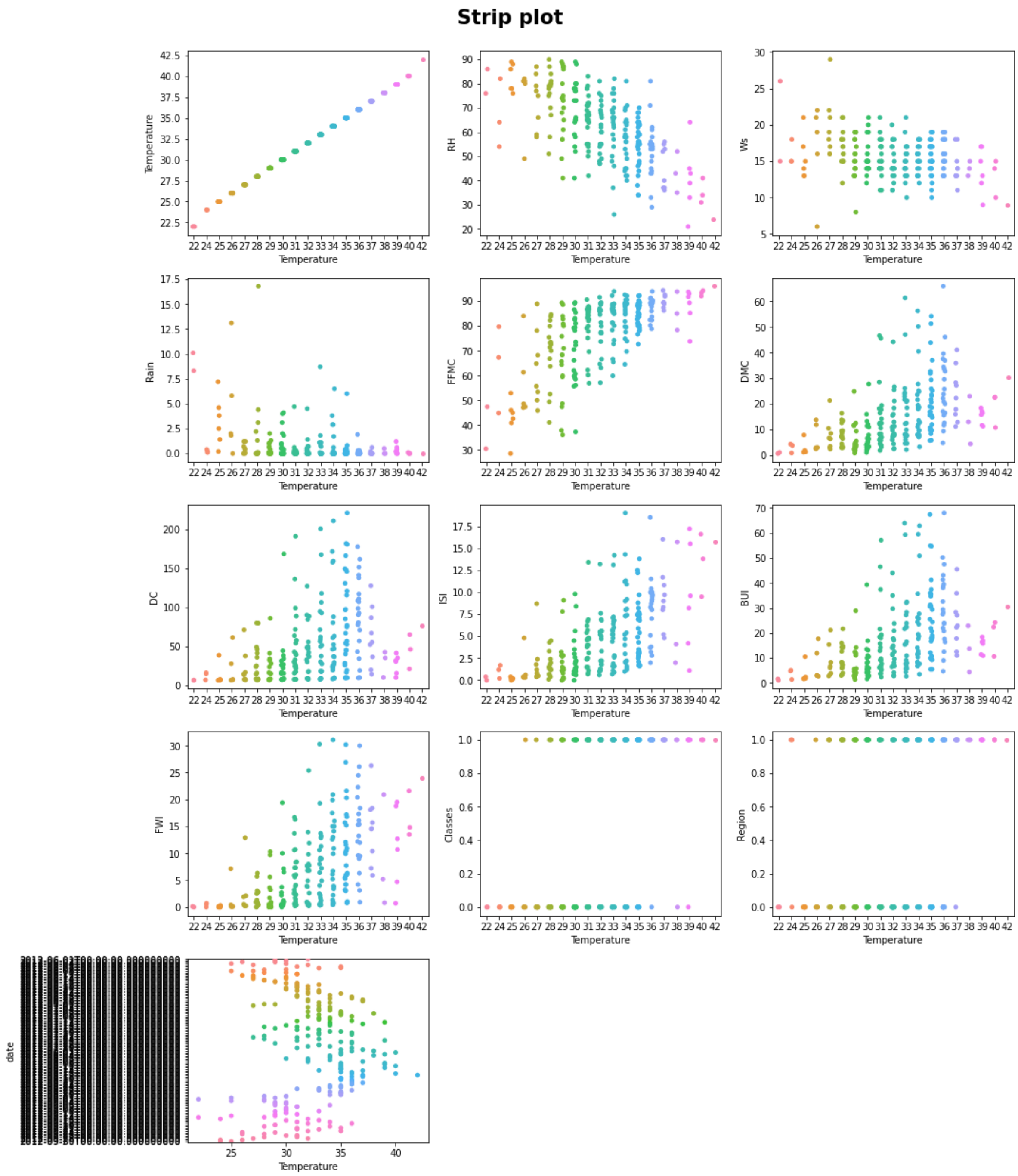
```
plt.figure(figsize=(15,20))
plt.suptitle('scatter plot ')

for i in range(0,len(num_fea)):
    plt.subplot(5,3,i+1)
    sns.scatterplot(x=df.index,y=num_fea[i],data=df)
    plt.tight_layout()
```



Strip plot

In [42]:

```
plt.figure(figsize =(15,20))
plt.suptitle('Strip plot', fontsize=21, fontweight='bold',alpha=1,y=1)

for i in range(0,len(num_fea)):
    plt.subplot(6,3,i+1)
    sns.stripplot(x='Temperature',y=num_fea[i],data=df)
    plt.tight_layout()
```



Box plot

In [43]:

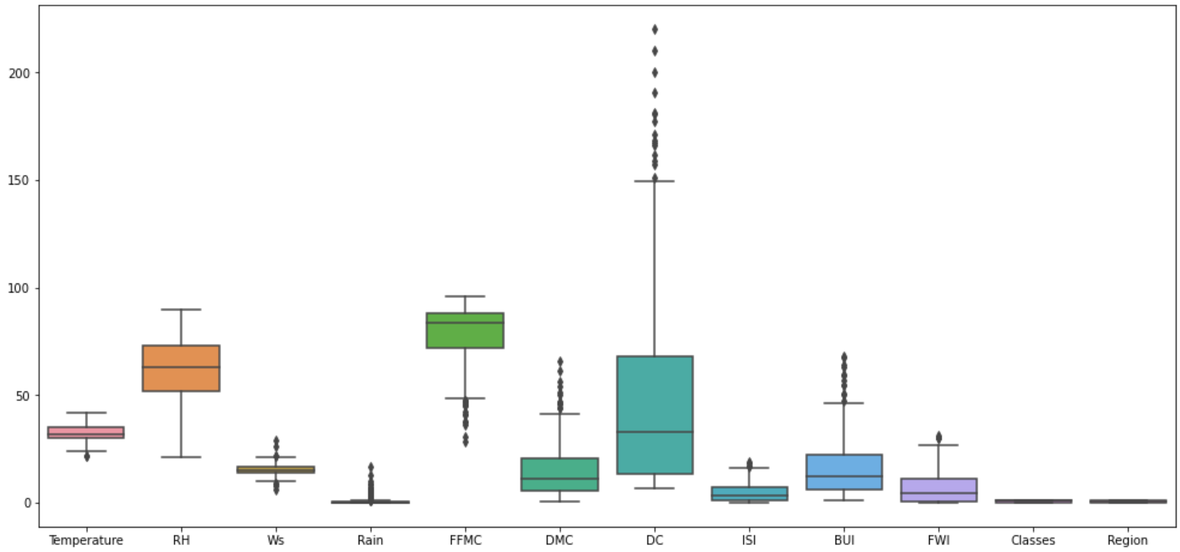
```
# boxplot to find out outliers
```

In [44]:

```
plt.figure(figsize = (17,8))
sns.boxplot(data = df)
```

Out[44]:

```
<AxesSubplot:>
```



Observation: RH, classes, region has no outliers temperature, ws, rain, ffmc, dmc, dc, isi, bui, fwi has more outliers

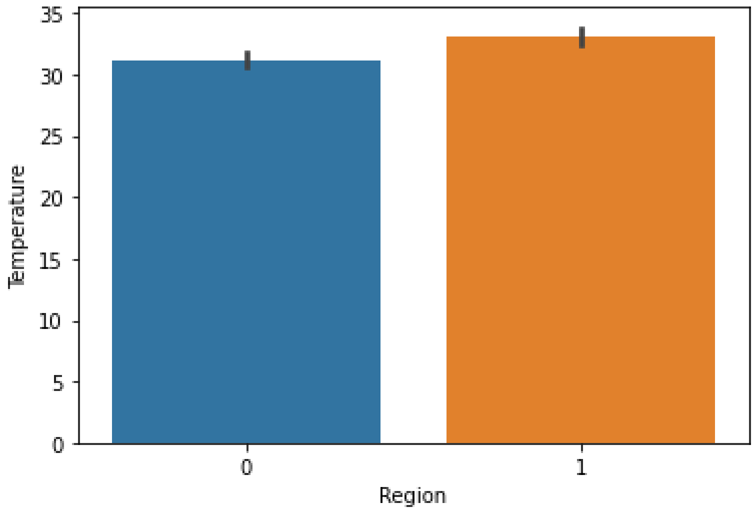
Barplot

In [45]:

```
sns.barplot(x="Region",y='Temperature',data=df)
```

Out[45]:

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



Observation: region 1 has more temperature region 0 has less temperature

Corr visualization

In [138]:

```
df.corr()
```

Out[138]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	
Temperature	1.000000	-0.654443	-0.278132	-0.326786	0.677491	0.483105	0.370498	0.6
RH	-0.654443	1.000000	0.236084	0.222968	-0.645658	-0.405133	-0.220330	-0.6
Ws	-0.278132	0.236084	1.000000	0.170169	-0.163255	-0.001246	0.076245	0.0
Rain	-0.326786	0.222968	0.170169	1.000000	-0.544045	-0.288548	-0.296804	-0.3
FFMC	0.677491	-0.645658	-0.163255	-0.544045	1.000000	0.602391	0.503910	0.7
DMC	0.483105	-0.405133	-0.001246	-0.288548	0.602391	1.000000	0.875358	0.6
DC	0.370498	-0.220330	0.076245	-0.296804	0.503910	0.875358	1.000000	0.5
ISI	0.605971	-0.688268	0.012245	-0.347862	0.740751	0.678355	0.503919	1.0
BUI	0.456415	-0.349685	0.030303	-0.299409	0.590251	0.982206	0.941672	0.6
FWI	0.566839	-0.580457	0.033957	-0.324755	0.691430	0.875191	0.737041	0.9
Classes	0.518119	-0.435023	-0.066529	-0.379449	0.770114	0.584188	0.507122	0.7
Region	0.273496	-0.406424	-0.176829	-0.041080	0.224680	0.191094	-0.081489	0.2

Pairplot

In [ ]:

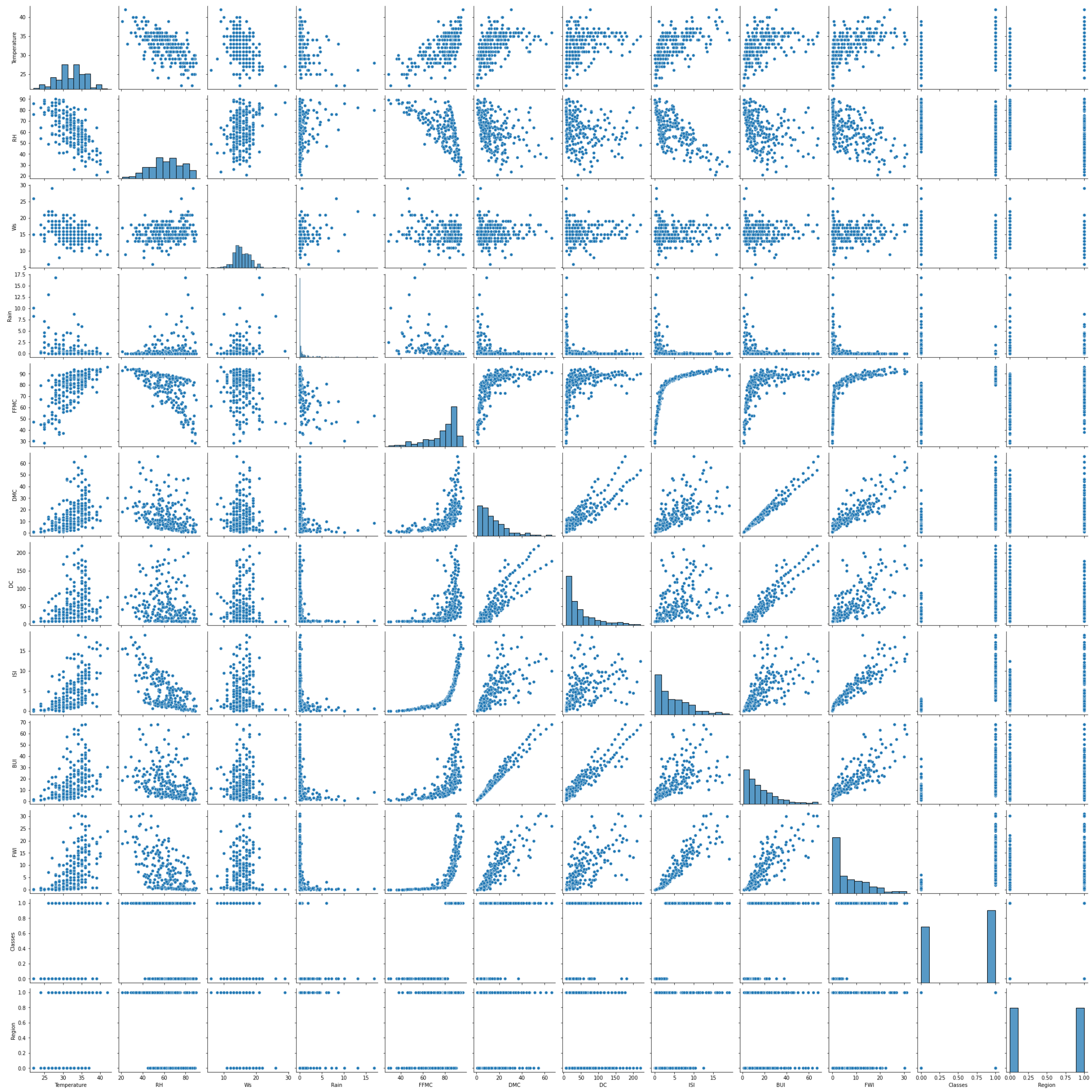
```
### corr visualization
```

In [46]:

```
sns.pairplot(df)
```

Out[46]:

<seaborn.axisgrid.PairGrid at 0x25f7b952730>



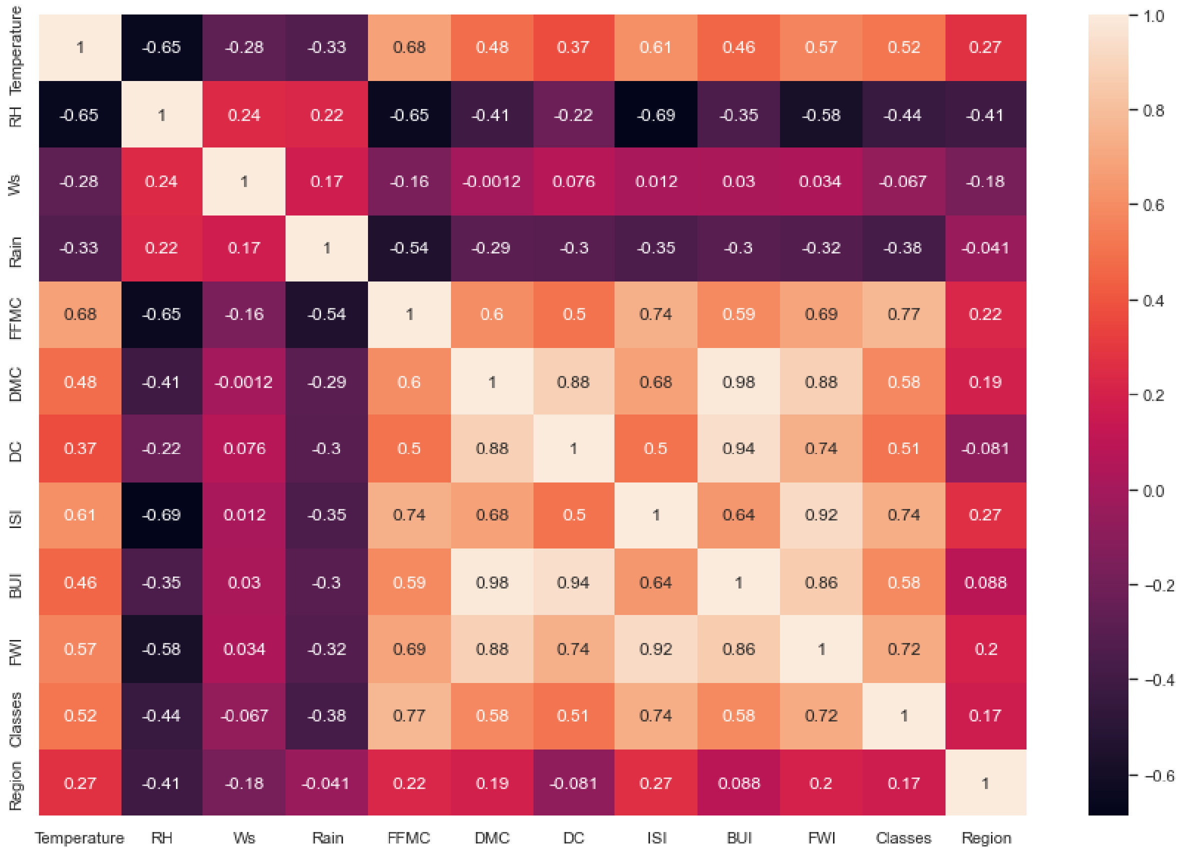
Heatmap

In [47]:

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

Out[47]:

<AxesSubplot:>



Plot data in linear regression

Regplot

In [48]:

```
# shaded region  in plot  is redge and lasso
# we see more points is there not shaped mean gap
# other have
# point is more the shade region is less
# point is less the shade region is high
```

rh vs temperatur

In [49]:

```
sns.regplot(x='RH',y='Temperature',data=df)
```

Out[49]:

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

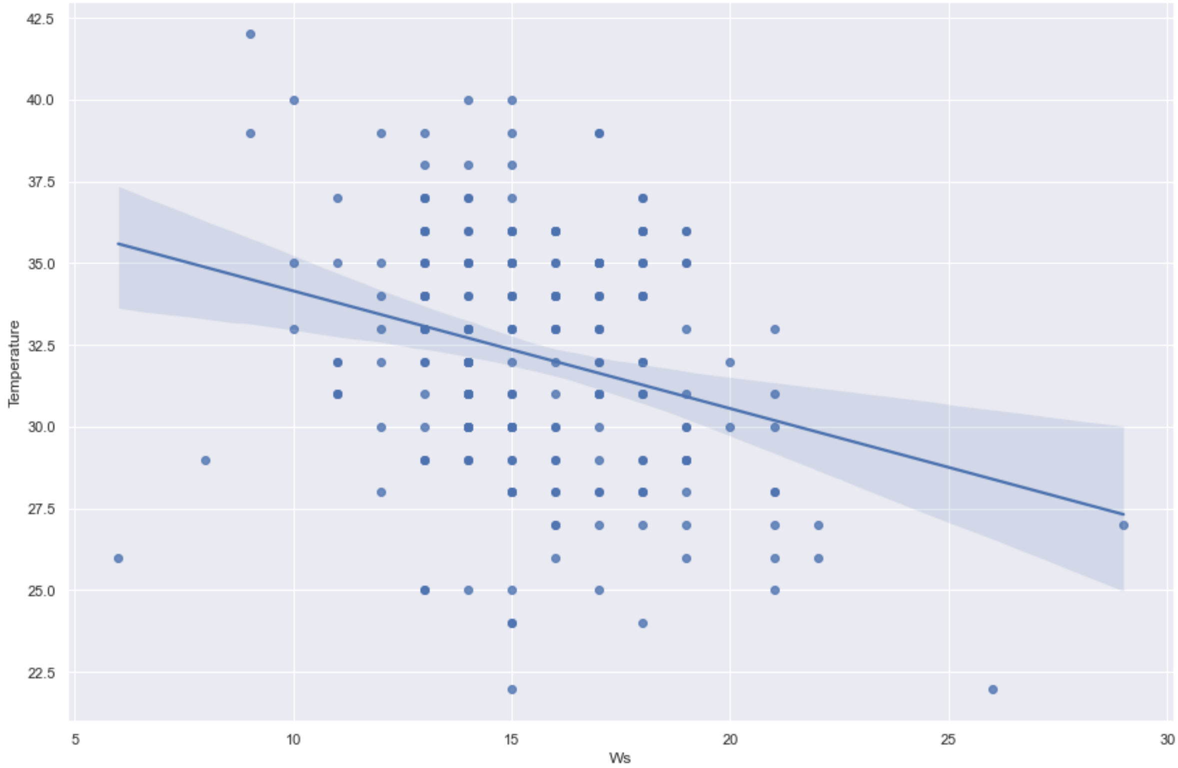
ws vs temperature

In [50]:

```
sns.regplot(x='Ws',y='Temperature',data=df)
```

Out[50]:

<AxesSubplot:xlabel='Ws', ylabel='Temperature'>



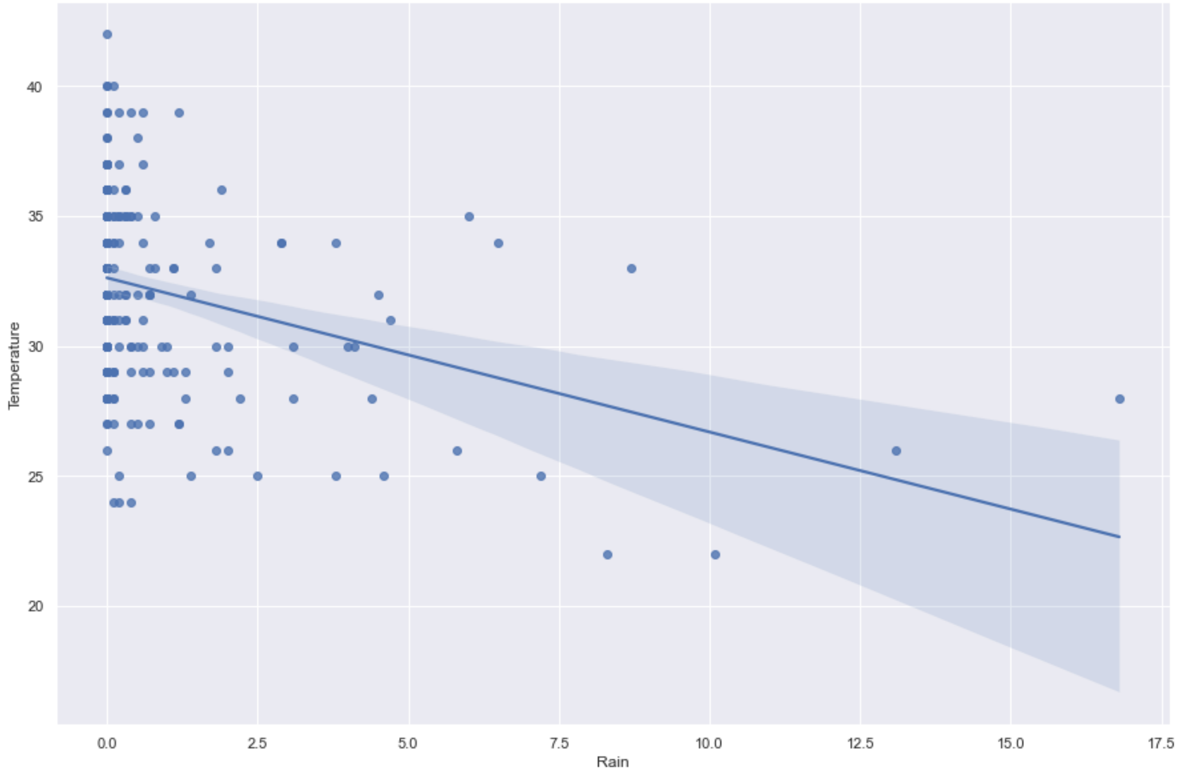
rain vs temperature

In [51]:

```
sns.regplot(x='Rain',y='Temperature',data=df)
```

Out[51]:

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



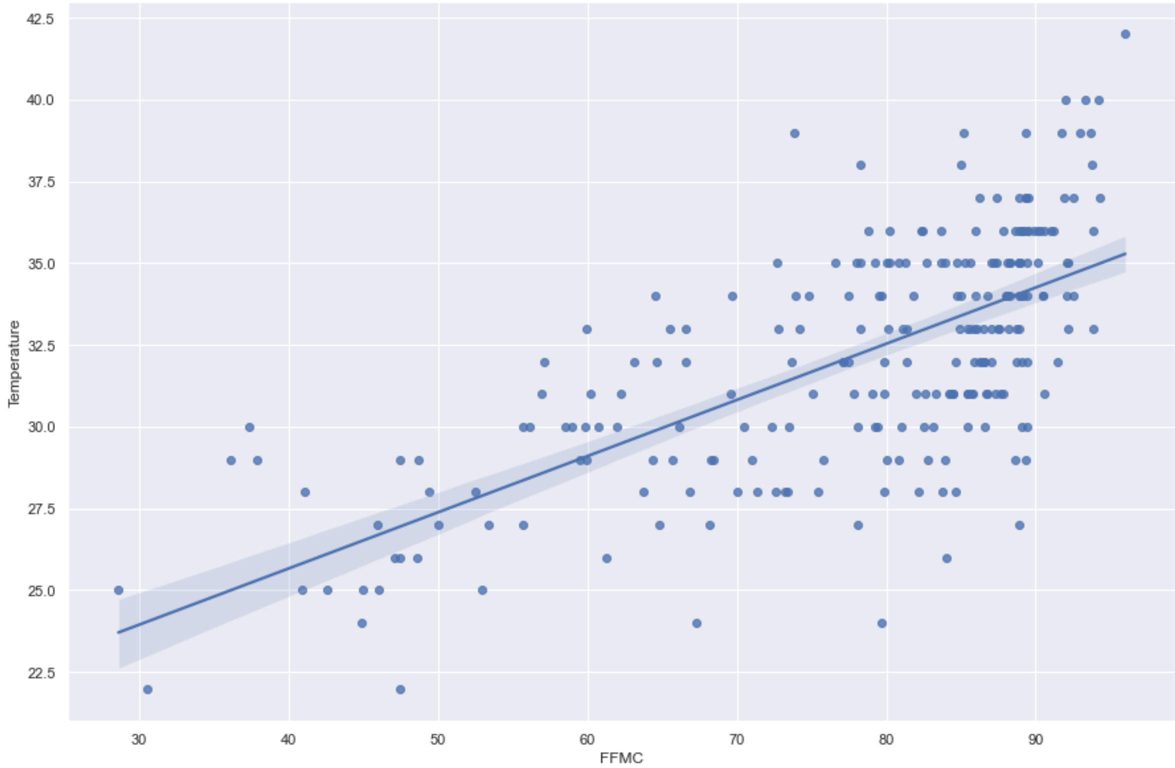
ffmc vs temperature

In [52]:

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

Out[52]:

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



dmc vs temperature

In [53]:

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

Out[53]:

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

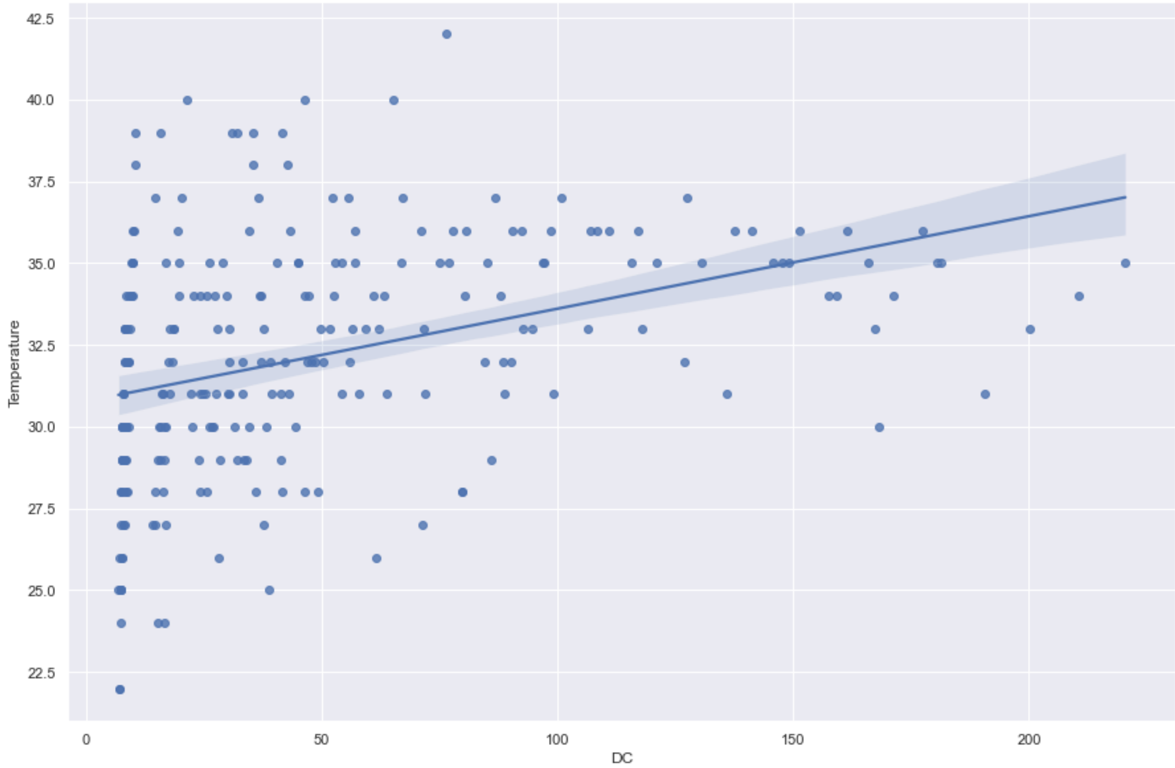
dc vs temperature

In [54]:

```
sns.regplot(x='DC',y='Temperature',data=df)
```

Out[54]:

<AxesSubplot:xlabel='DC', ylabel='Temperature'>



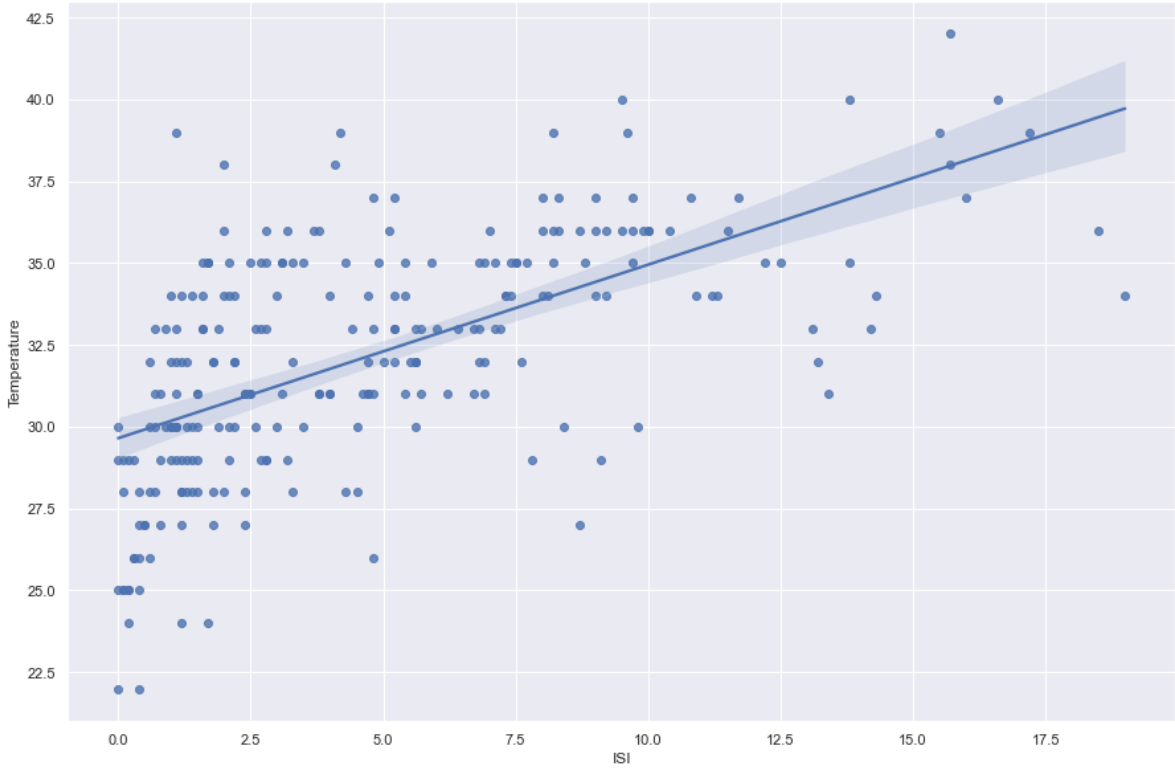
isi vs temperature

In [55]:

```
sns.regplot(x='ISI',y='Temperature',data=df)
```

Out[55]:

<AxesSubplot:xlabel='ISI', ylabel='Temperature'>



bui vs temperature

In [56]:

```
sns.regplot(x='BUI',y='Temperature',data=df)
```

Out[56]:

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

fwi vs temperature

In [57]:

```
sns.regplot(x='FWI',y='Temperature',data=df)
```

Out[57]:

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

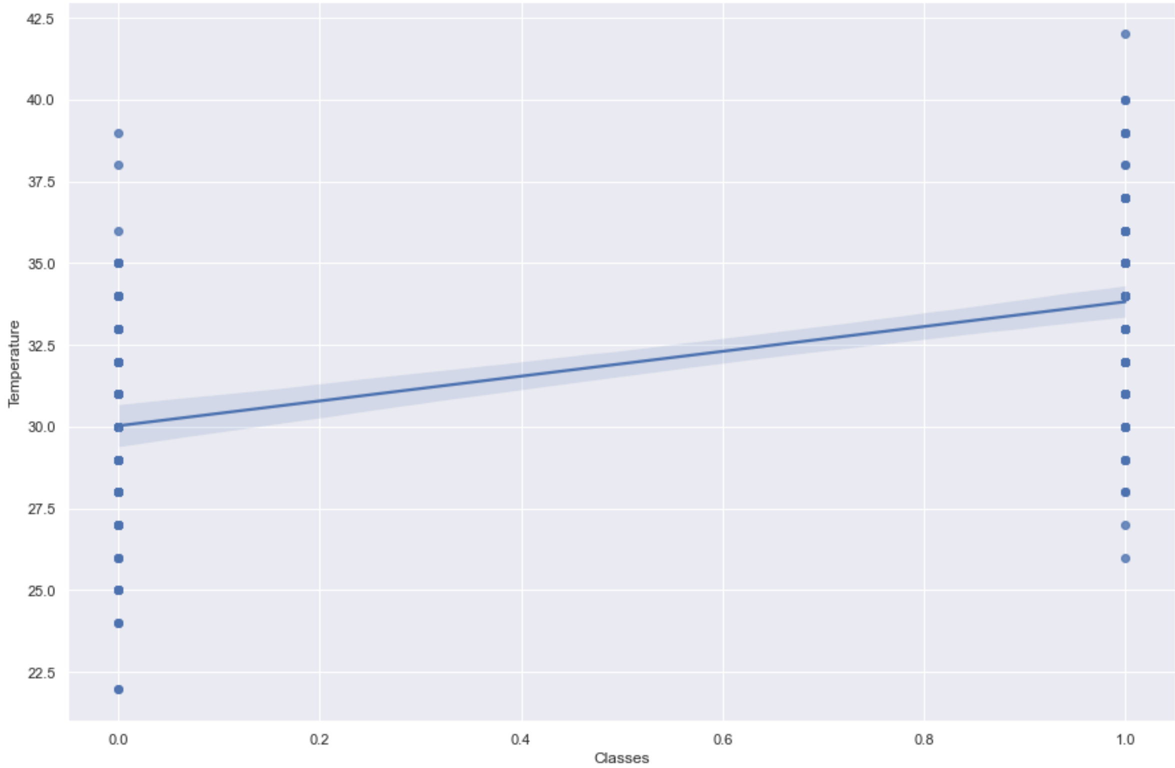
classes vs temperature

In [58]:

```
sns.regplot(x='Classes',y='Temperature',data=df)
```

Out[58]:

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



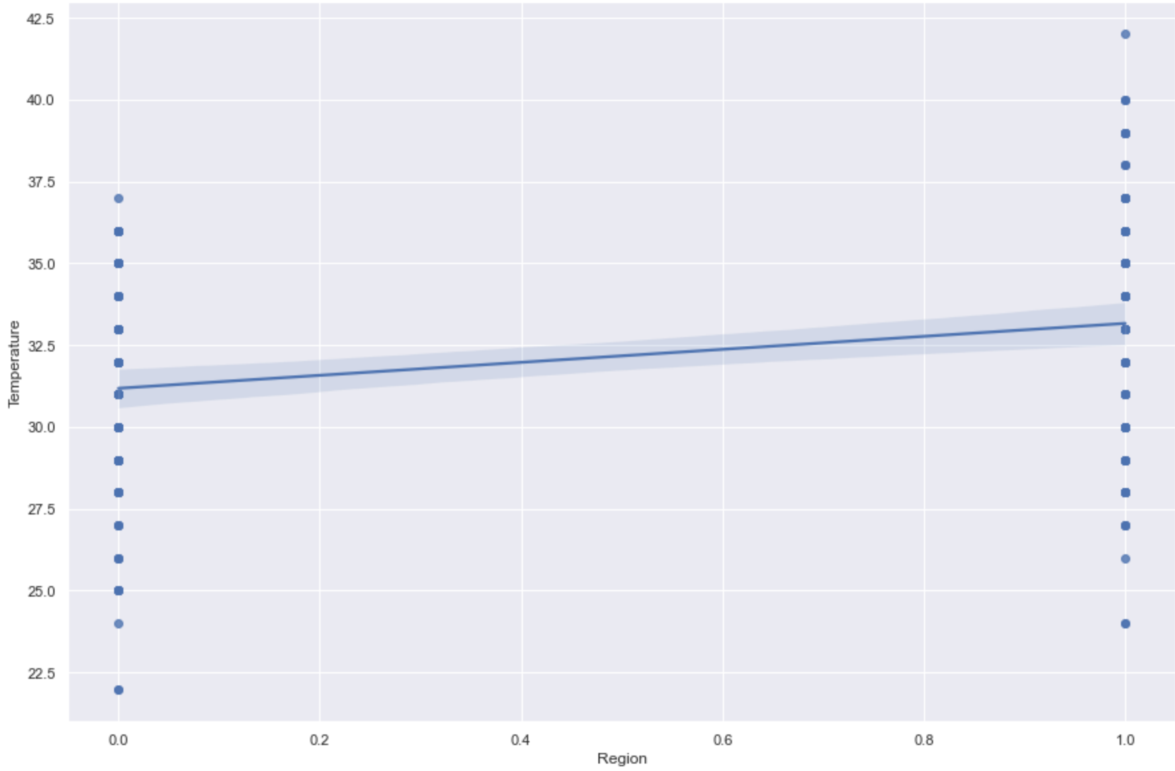
region vs temperature

In [59]:

```
sns.regplot(x='Region',y='Temperature',data=df)
```

Out[59]:

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



In [60]:

```
df.head()
```

Out[60]:

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

Independent and Dependent feature seperation

independent feature

In [61]:

```
X = df.iloc[:,1:-1]
```

dependent feature

In [62]:

```
y = df.iloc[:,0]
```

In [63]:

```
# checing
X.head()
```

Out[63]:

	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
0	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0	0
1	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0	0
2	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0	0
3	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0	0
4	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0	0

In [64]:

```
y.head()
```

Out[64]:

```
0    29
1    29
2    26
3    25
4    27
Name: Temperature, dtype: int32
```

Spliting the data into train and test split

In [65]:

```
# spliting the data into train test split
# it will return 4 different paremeters
# output feature of x train is y train and x test is y test
# test size = 0.25   if 1000 in 25% of data
# random state
```

In [66]:

```
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.33,random_state=42)
```

In [67]:

```
X_train.shape
```

Out[67]:

```
(163, 11)
```

In [68]:

```
y_train.shape
```

Out[68]:

```
(163,)
```

In [69]:

```
X_test.shape
```

Out[69]:

```
(81, 11)
```

In [70]:

```
y_test.shape
```

Out[70]:

```
(81,)
```

Standardizing or Feature scalling the dataset

In [71]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler
```

Out[71]:

```
StandardScaler()
```

In [72]:

```
# Apply data
```

In [73]:

```
X_train = scaler.fit_transform(X_train)
```

In [74]:

```
X_test = scaler.transform(X_test)
```

In [75]:

```
#data lekage we dont need to leak the data of test to train data
#avoid datalekage use transform
#example :
#    is eaxm paper is x_train if you get before exam is called parer lekage
# f to f' we convert mean and std in fit and transform
```

In [76]:

```
X_train
```

Out[76]:

```
array([[-0.60257784, -1.68484146, -0.17054229, ..., -0.8196431 ,
        -1.04390785, -0.99388373],
       [ 0.14460201, -0.93856657, -0.39436188, ..., -0.08219052,
         0.95793896, -0.99388373],
       [-1.41768313,  2.04653297, -0.39436188, ...,  1.36540157,
         0.95793896,  1.0061539 ],
       ...,
       [ 0.89178186,  0.5539832 ,  2.82864022, ..., -0.90158227,
        -1.04390785, -0.99388373],
       [-0.39880152,  0.18084575, -0.39436188, ...,  0.31384882,
         0.95793896,  1.0061539 ],
       [ 0.9597073 ,  2.04653297,  0.41138865, ..., -0.87426921,
        -1.04390785, -0.99388373]])
```

In [77]:

```
X_test
```

```
       [ 7.66765714e-02, -2.43111635e+00,  1.42805137e-01,
        -2.04288364e-01, -2.27949356e-01, -6.70454203e-01,
        -8.24177428e-01, -3.54056886e-01, -8.19643095e-01,
        -1.04390785e+00,  1.00615390e+00],
       [-1.62145945e+00, -1.92291688e-01, -3.04834043e-01,
         8.54449178e-01,  9.58307813e-02, -2.74901779e-01,
         8.82425788e-01, -5.19755172e-02,  5.46009818e-01,
         9.57938964e-01,  1.00615390e+00],
       [ 1.16348363e+00, -5.65429131e-01,  5.00916482e-01,
        -1.91876013e+00, -9.78171625e-01, -8.38817542e-01,
        -1.01647075e+00, -9.58219625e-01, -9.01582270e-01,
        -1.04390785e+00,  1.00615390e+00],
       [ 1.09555819e+00, -1.31170402e+00, -3.94361879e-01,
        -2.45271753e-01, -4.01685039e-01, -5.37981164e-02,
        -7.76104098e-01, -2.71671058e-01, -7.92330037e-01,
        -1.04390785e+00, -9.93883735e-01],
       [ 6.88005540e-01, -1.31170402e+00,  4.11388646e-01,
        -1.15373687e+00, -9.78171625e-01, -8.12447381e-01,
        -9.20324088e-01, -9.51354139e-01, -8.74269212e-01,
```

Model Training

In [78]:

```
from sklearn.linear_model import LinearRegression

regression = LinearRegression()
regression
```

Out[78]:

```
LinearRegression()
```

In [79]:

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

Out[79]:

```
LinearRegression()
```

Coefficient and Intercept

In [80]:

```
print(regression.coef_)
```

```
[-1.05126674 -0.48159084  0.11938767  1.82417191  0.94467874  0.67540664
  0.17325427 -1.25422021  0.0537007  -0.23927078 -0.00511072]
```

In [81]:

```
print(regression.intercept_)
```

```
31.98159509202454
```

Prediction

In [82]:

```
reg_pred = regression.predict(X_test)
reg_pred
```

Out[82]:

```
array([33.04281582, 34.18373317, 33.94262556, 33.12802489, 36.58081437,
       32.54990698, 35.21895989, 27.32175238, 30.96985655, 29.60339718,
       29.36216075, 33.3713269 , 33.9660541 , 33.37413504, 34.21146262,
       32.16667325, 37.06595141, 25.21346832, 32.29221418, 33.54538576,
       30.91440937, 28.43873771, 35.06373488, 28.67822485, 36.46752406,
       26.81905285, 32.74394806, 33.29778191, 32.84197893, 34.66821705,
       34.54137306, 31.59706773, 32.66796918, 33.31570383, 32.69911436,
       33.29613965, 30.40105147, 34.24122196, 31.8380836 , 23.73446099,
       33.60548737, 33.77838277, 32.43685622, 24.8281907 , 36.1657581 ,
       32.45334978, 31.14713505, 30.44305813, 35.30965237, 34.62074891,
       36.93021848, 30.95822914, 30.88244254, 34.35343577, 33.86159459,
       32.12780851, 36.88091527, 32.3288728 , 30.12070206, 36.49040274,
       33.13768817, 30.00109432, 33.98838284, 32.04060986, 31.81504287,
       24.80400402, 33.17469174, 30.59601544, 36.73404251, 34.58679402,
       32.78857774, 31.1503531 , 33.36867632, 34.75216207, 36.13928125,
       31.39844653, 33.53813822, 32.12231108, 35.42226323, 32.340719  ,
       34.10019406])
```

Assumption of Linear Regression

In [83]:

```
## assumption of linear regression
# we used to check model is good or not
# 1.linear relation between y test and
# 2.residuals we get normal distribution
# 3 get uniform distribution
```

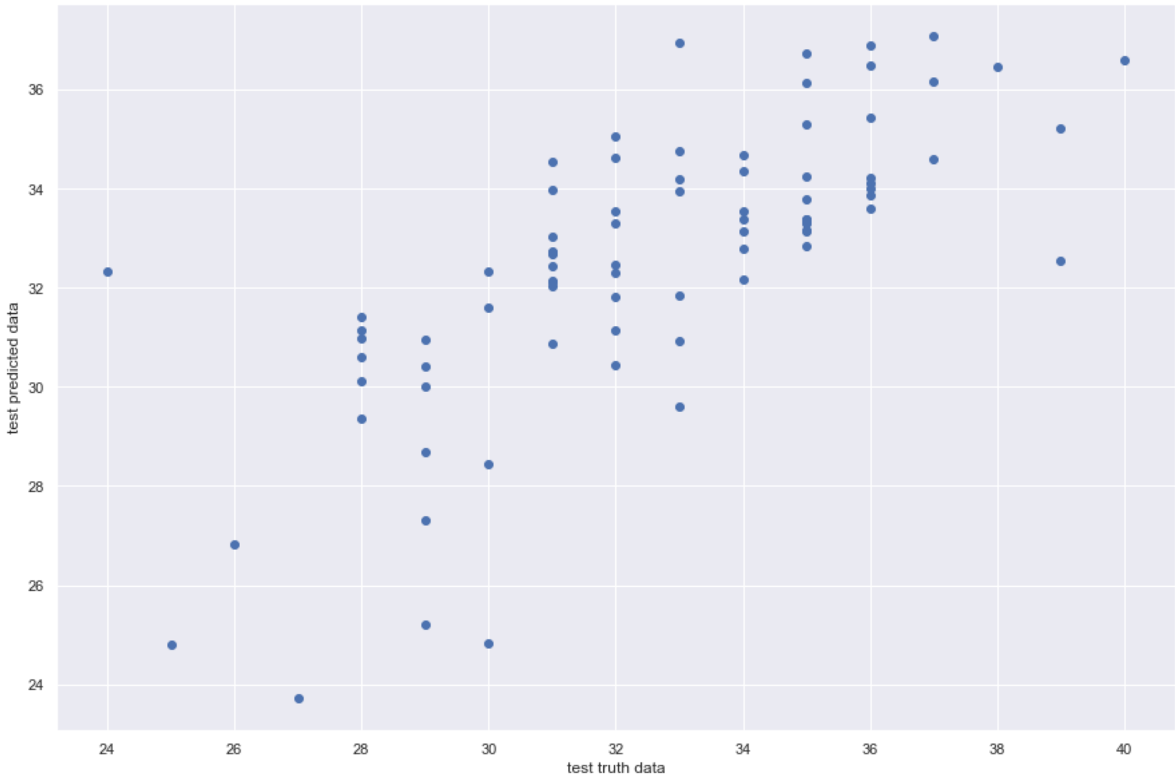
1.linear relationship between y_test and reg_prediction

In [84]:

```
plt.scatter(y_test,reg_pred)
plt.xlabel("test truth data")
plt.ylabel("test predicted data")
```

Out[84]:

```
Text(0, 0.5, 'test predicted data')
```



2.residual we get normal distributin

In [85]:

```
residuals = y_test - reg_pred
residuals
```

Out[85]:

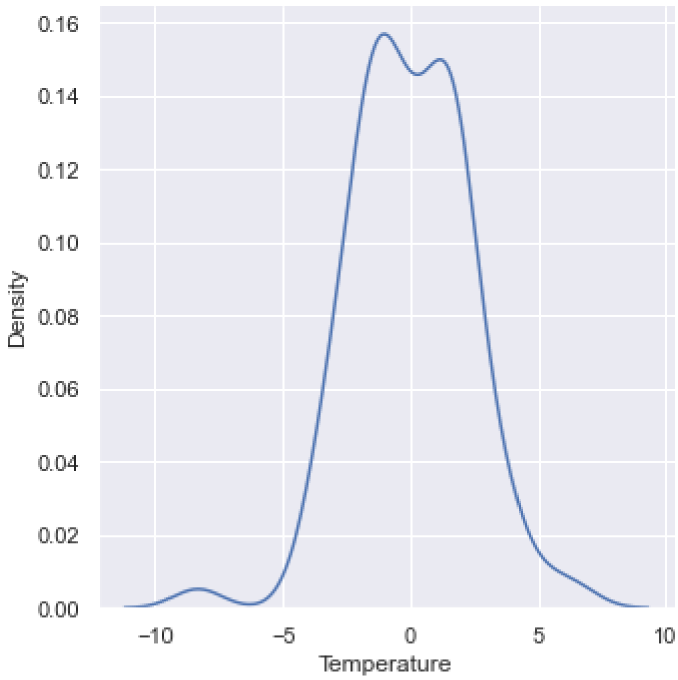
```
24    -2.042816
6     -1.183733
153   -0.942626
211    1.871975
198    3.419186
         ...
180    0.461862
5     -1.122311
56     0.577737
125   -2.340719
148    1.899806
Name: Temperature, Length: 81, dtype: float64
```

In [86]:

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

Out[86]:

```
<seaborn.axisgrid.FacetGrid at 0x25f05c07640>
```



3.uniform distributin

In [87]:

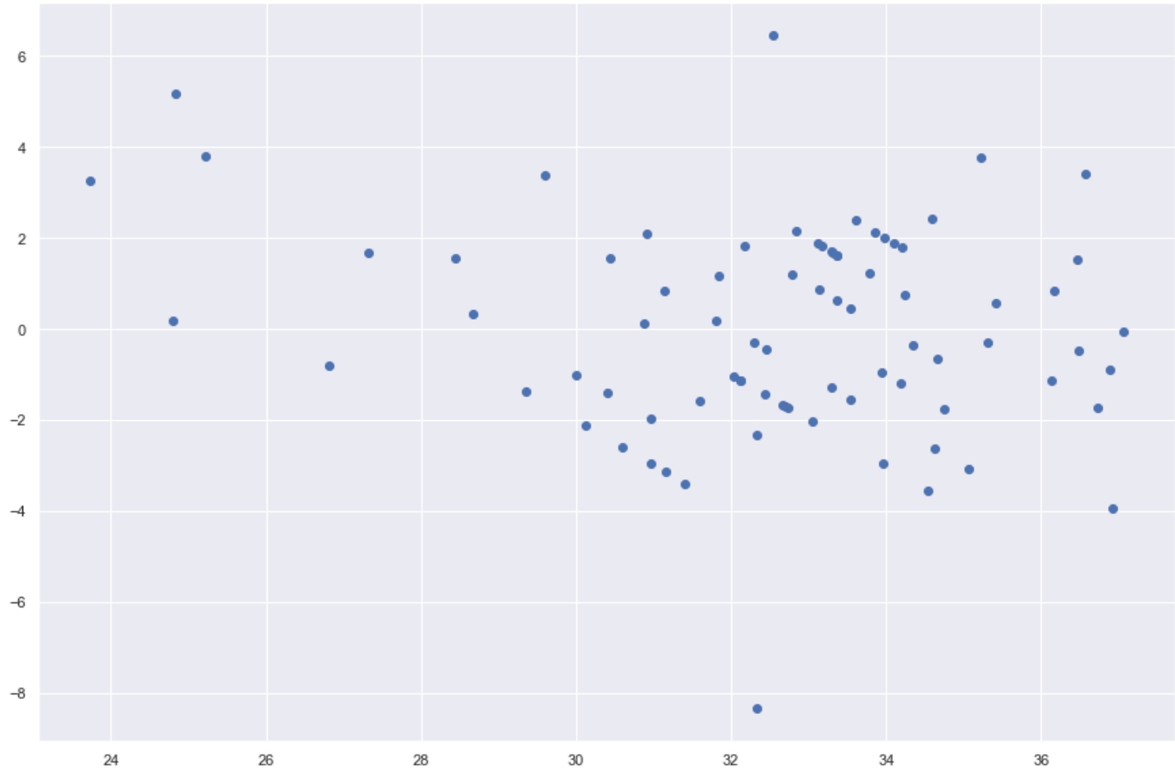
```
## scatter plot with prediction and residual
## uniform distribution  called below plo
```

In [88]:

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

Out[88]:

```
<matplotlib.collections.PathCollection at 0x25f0595de20>
```



Mean_squared_error, Mean_absolute_error, Root mean square error

In [89]:

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

```
5.208488116232257
1.8297548308020077
2.282211233920352
```

Performance Metrics

R Squared

In [90]:

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

```
0.5150717960749278
```

Adjusted R Squared

In [91]:

```
1 - (1-linear_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[91]:

```
0.437764401246293
```

Ridge Regression:

Train the Model

In [92]:

```
from sklearn.linear_model import Ridge
ridgeR = Ridge(alpha=.99)
ridgeR.fit(X_train,y_train)
```

Out[92]:

```
Ridge(alpha=0.99)
```

Coefficient and Intercept

In [93]:

```
print(ridgeR.coef_)
```

```
[-1.0603827  -0.48247028  0.103006    1.76997509  0.44896271  0.43633654
  0.2171534  -0.49095187 -0.01457222 -0.22989405  0.00997644]
```

In [94]:

```
print(ridgeR.intercept_)
```

```
31.98159509202454
```

Prediction

In [95]:

```
ridgeR_pred = ridgeR.predict(X_test)
ridgeR_pred
```

Out[95]:

```
array([33.03703532, 34.13986742, 33.9230024 , 33.1465684 , 36.55519553,
       32.58829202, 35.19676247, 27.38380412, 30.98064269, 29.60156146,
       29.34581086, 33.43754527, 33.91240038, 33.38918319, 34.25352319,
       32.14890454, 36.98229481, 25.29265754, 32.24261314, 33.52465167,
       30.87100591, 28.43359751, 35.03100492, 28.68653408, 36.47144325,
       26.84962548, 32.73580381, 33.30529063, 32.84489674, 34.61605839,
       34.52190817, 31.5919525 , 32.64407534, 33.36089243, 32.66605215,
       33.2821847 , 30.3432505 , 34.26694779, 31.80177943, 23.79831953,
       33.61803235, 33.77992474, 32.43218673, 24.89376354, 36.10493875,
       32.41168313, 31.13448973, 30.45274196, 35.28738503, 34.61534151,
       36.8740493 , 30.92310918, 30.89474016, 34.41553512, 33.84426077,
       32.24480798, 36.86813253, 32.32600243, 30.13700492, 36.48581499,
       33.10461989, 29.98703993, 33.93577532, 32.02760007, 31.81737762,
       24.83229543, 33.15596365, 30.57171511, 36.70933298, 34.61903868,
       32.77717507, 31.14460223, 33.36498358, 34.76465229, 36.17485522,
       31.39166017, 33.49065095, 32.09618419, 35.4327563 , 32.32729069,
       34.08011462])
```

Assumptions for ridgeRegression

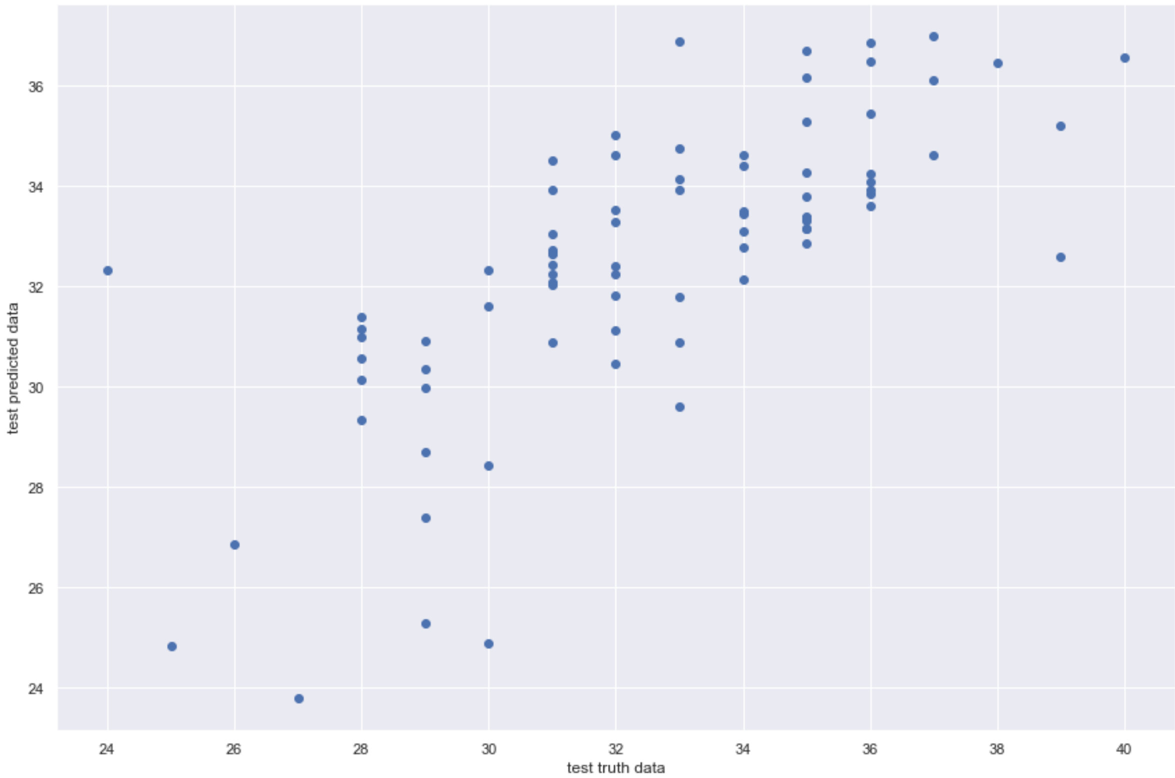
1.linear relationship between y_test and predicted y

In [96]:

```
plt.scatter(y_test,ridgeR_pred)
plt.xlabel("test truth data")
plt.ylabel("test predicted data")
```

Out[96]:

```
Text(0, 0.5, 'test predicted data')
```



2.residual we get normal distribution

In [97]:

```
residuals= y_test-ridgeR_pred
residuals
```

Out[97]:

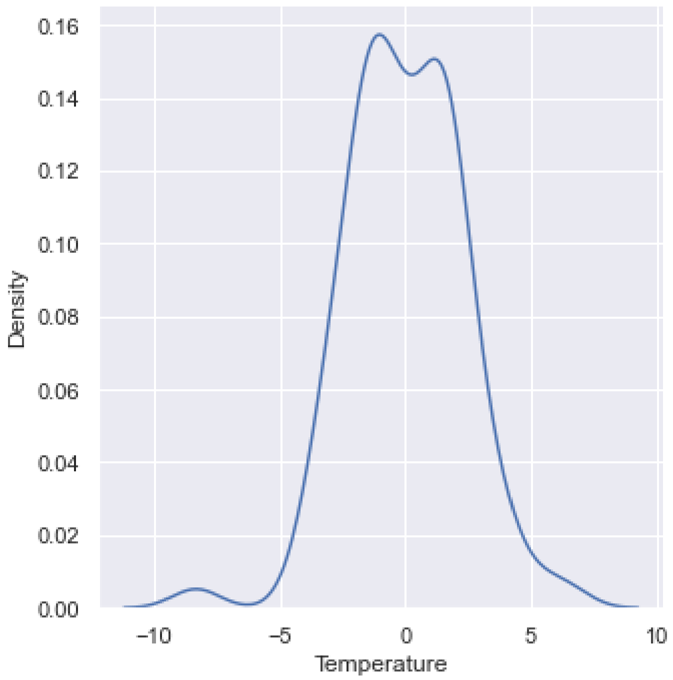
```
24    -2.037035
6     -1.139867
153   -0.923002
211    1.853432
198    3.444804
         ...
180    0.509349
5     -1.096184
56     0.567244
125   -2.327291
148    1.919885
Name: Temperature, Length: 81, dtype: float64
```

In [98]:

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

Out[98]:

```
<seaborn.axisgrid.FacetGrid at 0x25f059955e0>
```



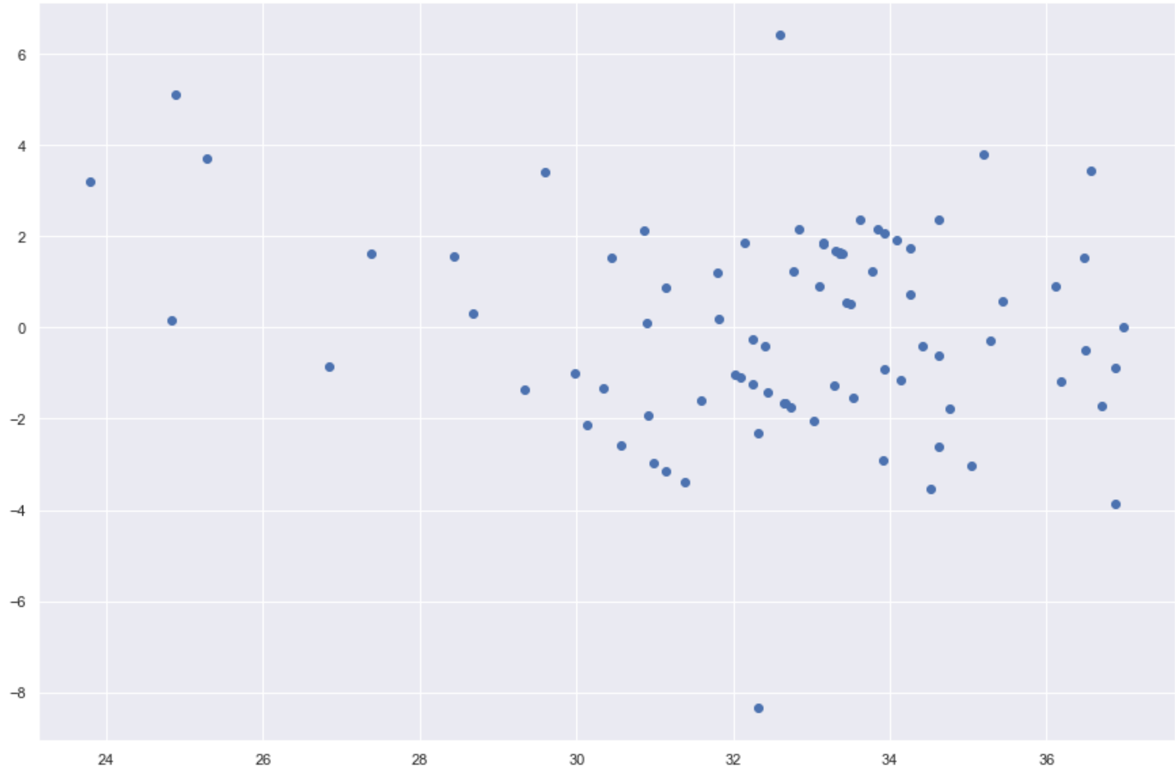
3.Uniform distribution

In [100]:

```
# scatter plot with prediction and residual
# uniform distribution called below plot

plt.scatter(ridgeR_pred,residuals)
```

Out[100]:

```
<matplotlib.collections.PathCollection at 0x25f066de2e0>
```



Performance Metrics

In [101]:

```
# mean squared error, mean absolute error, root mean square error
```

In [102]:

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

```
5.1609305484880625
1.8204108968922816
2.271768154651364
```

R Square

In [104]:

```
from sklearn.metrics import r2_score
ridgeR_score = r2_score(y_test,ridgeR_pred)
print(ridgeR_score)
```

```
0.5194995696235252
```

Adjusted R Squared

In [105]:

```
1-(1-ridgeR_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[105]:

```
0.4428980517374205
```

Lasso Regression:

Train the model

In [107]:

```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha = 0.05)
lasso.fit(X_train,y_train)
```

Out[107]:

```
Lasso(alpha=0.05)
```

Coefficient and Intercept

In [108]:

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

```
[-1.14351042 -0.38959936  0.          1.60766408  0.19021954  0.1505428
  0.01479416  0.          0.         -0.          0.        ]
```

In [109]:

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

```
31.98159509202454
```

Prediction

In [110]:

```
lasso_pred = lasso.predict(X_test)
lasso_pred
```

Out[110]:

```
array([33.10068594, 34.16909409, 34.06572152, 33.29832552, 36.33971798,
       32.35616345, 35.274234  , 27.45932539, 30.74954827, 29.52908042,
       29.50510865, 33.19552099, 33.66318829, 33.170849  , 34.19923109,
       32.2736529 , 36.61065379, 25.51342279, 32.26347727, 33.66045814,
       30.70453592, 28.46720366, 34.98784451, 28.90484174, 36.23620339,
       27.0366415 , 32.8662064 , 33.34916318, 33.09657046, 34.5920238 ,
       34.51750355, 31.40159905, 32.75760909, 33.38474096, 32.60458918,
       33.26775553, 30.27696818, 34.48550099, 31.32411804, 24.44832455,
       33.71986156, 33.91859271, 32.49506958, 25.20067319, 35.94108842,
       32.51738263, 31.29332202, 30.44740178, 35.45107045, 34.61058991,
       36.70605927, 31.15892409, 31.0733626 , 34.22273045, 33.81325237,
       32.33364388, 36.65215752, 32.36125976, 30.25480346, 36.45631965,
       33.19007592, 30.12692971, 33.95092625, 32.1368825 , 31.81374529,
       25.10459197, 33.26768874, 30.73357683, 36.54981286, 34.84529781,
       33.02908537, 31.33037755, 33.29481789, 34.77769489, 36.01641838,
       31.4525197 , 33.53238555, 32.30034485, 35.29687817, 32.14898629,
       34.10952059])
```

Assumptions of LassoRegression

In [ ]:

```
## assumption of linear regression
# we used to check model is good or not
# 1.linear relation between y test and
# 2.residuals we get normal distribution
# 3 get uniform distribution
```

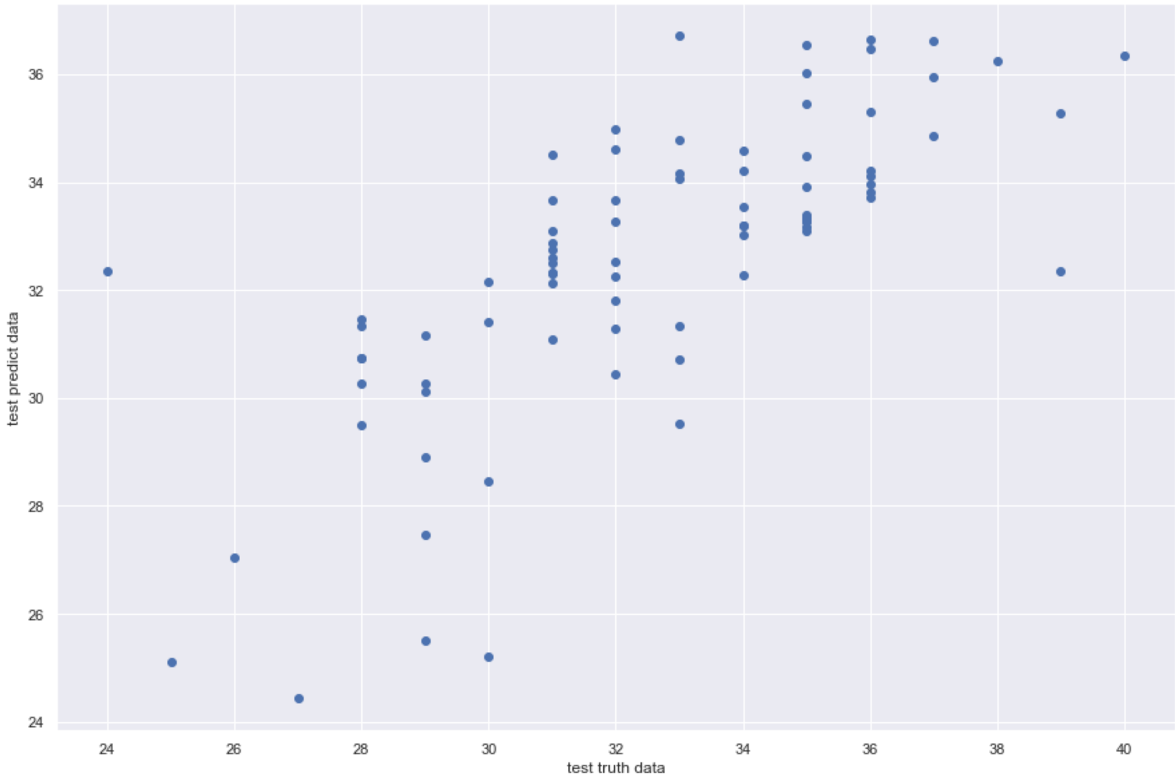
1.relationship between real y and predicted y

In [111]:

```
plt.scatter(y_test,lasso_pred)
plt.xlabel("test truth data")
plt.ylabel("test predict data")
```

Out[111]:

```
Text(0, 0.5, 'test predict data')
```



2.residual

In [112]:

```
residuals = y_test - lasso_pred
residuals
```

Out[112]:

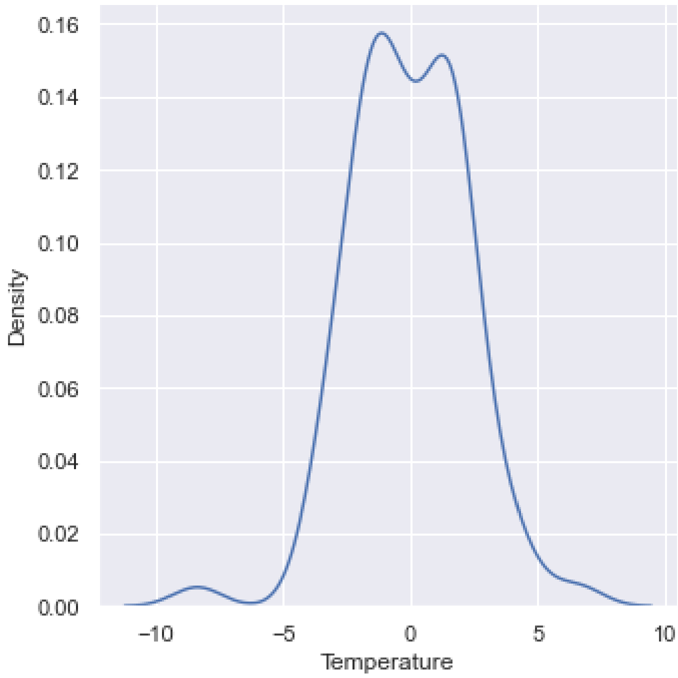
```
24    -2.100686
6     -1.169094
153   -1.065722
211    1.701674
198    3.660282
         ...
180    0.467614
5     -1.300345
56     0.703122
125   -2.148986
148    1.890479
Name: Temperature, Length: 81, dtype: float64
```

In [113]:

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

Out[113]:

```
<seaborn.axisgrid.FacetGrid at 0x25f063b4940>
```



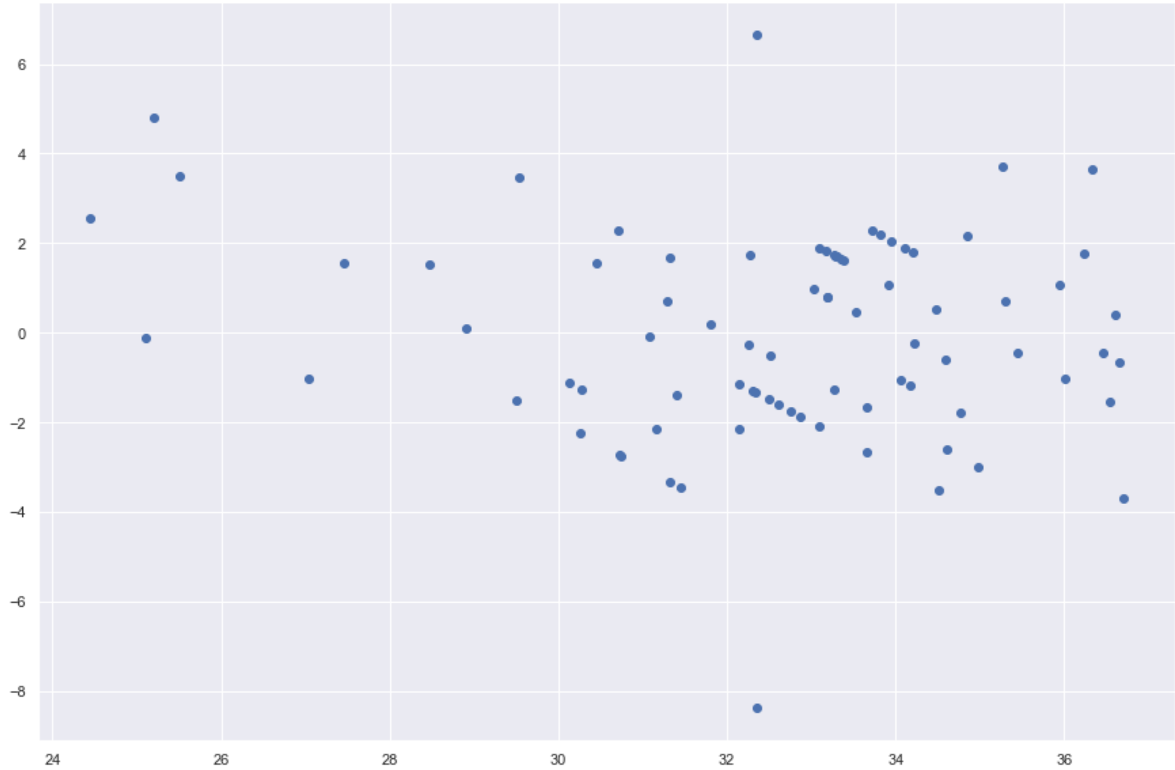
3.get uniform distribution

In [114]:

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

Out[114]:

```
<matplotlib.collections.PathCollection at 0x25f0692c1f0>
```



Performance Metrics

In [116]:

```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
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)))
```

```
5.117291412163739
1.8169325664744338
2.2621431016104485
```

R Square

In [117]:

```
from sklearn.metrics import r2_score
lasso_score = r2_score(y_test,lasso_pred)
print(lasso_score)
```

```
0.5235625236951003
```

Adjusted R Square

In [118]:

```
1 - (1-lasso_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[118]:

```
0.44760872312475397
```

ElasticNet Regression

Train the model

In [121]:

```
from sklearn.linear_model import ElasticNet
elas_net = ElasticNet(alpha=0.2,l1_ratio=.2)
elas_net.fit(X_train,y_train)
```

Out[121]:

```
ElasticNet(alpha=0.2, l1_ratio=0.2)
```

Coefficirnt and Intercept

In [122]:

```
print(elas_net.coef_)
```

```
[-0.99021193 -0.41392435 -0.06475598  1.21240385  0.15397277  0.12933095
  0.24656233  0.07999207  0.08206581  0.01988117  0.03843941]
```

In [123]:

```
print(elas_net.intercept_)
```

```
31.98159509202454
```

Prediction

In [124]:

```
elastic_pred = elas_net.predict(X_test)
elastic_pred
```

Out[124]:

```
array([32.94452846, 33.89800806, 33.8054905 , 33.06440211, 36.21155733,
       32.25235565, 35.01760209, 28.06235766, 30.76199791, 29.72842468,
       29.37429135, 32.97881163, 33.25040204, 32.93129519, 34.2691025 ,
       32.22059966, 36.85317988, 26.50163279, 32.18479724, 33.41277401,
       30.54995303, 28.7605909 , 34.67970073, 29.03554876, 36.36960064,
       27.58568589, 32.65807279, 33.21640402, 32.58004346, 34.56782142,
       34.25730231, 31.3070555 , 32.65626365, 33.37988341, 32.20674899,
       32.81146276, 30.12980252, 34.14902944, 31.1677371 , 25.11441012,
       33.46454815, 33.62865758, 32.08360603, 26.13049032, 35.85794742,
       32.39076583, 31.36983176, 30.44281863, 35.12107191, 34.44059646,
       36.91742207, 31.00642349, 31.16840354, 34.3976827 , 33.76311126,
       32.39266906, 36.97846166, 31.96453927, 30.23688726, 36.24163708,
       33.12120543, 30.04135076, 33.91855001, 32.04417237, 31.53187576,
       25.7508697 , 33.10508874, 30.74196754, 36.68216055, 34.59174287,
       32.79252885, 31.255731  , 33.35115765, 34.58237107, 36.07693106,
       31.4909129 , 33.47545565, 32.06411496, 35.15835858, 31.93499957,
       34.04358102])
```

Assumptions of ElasticNet Regression

In [ ]:

```
## assumption of linear regression
# we used to check model is good or not
# 1.linear relation between y test and predicted
# 2.residuals we get normal distribution
# 3 get uniform distribution
```

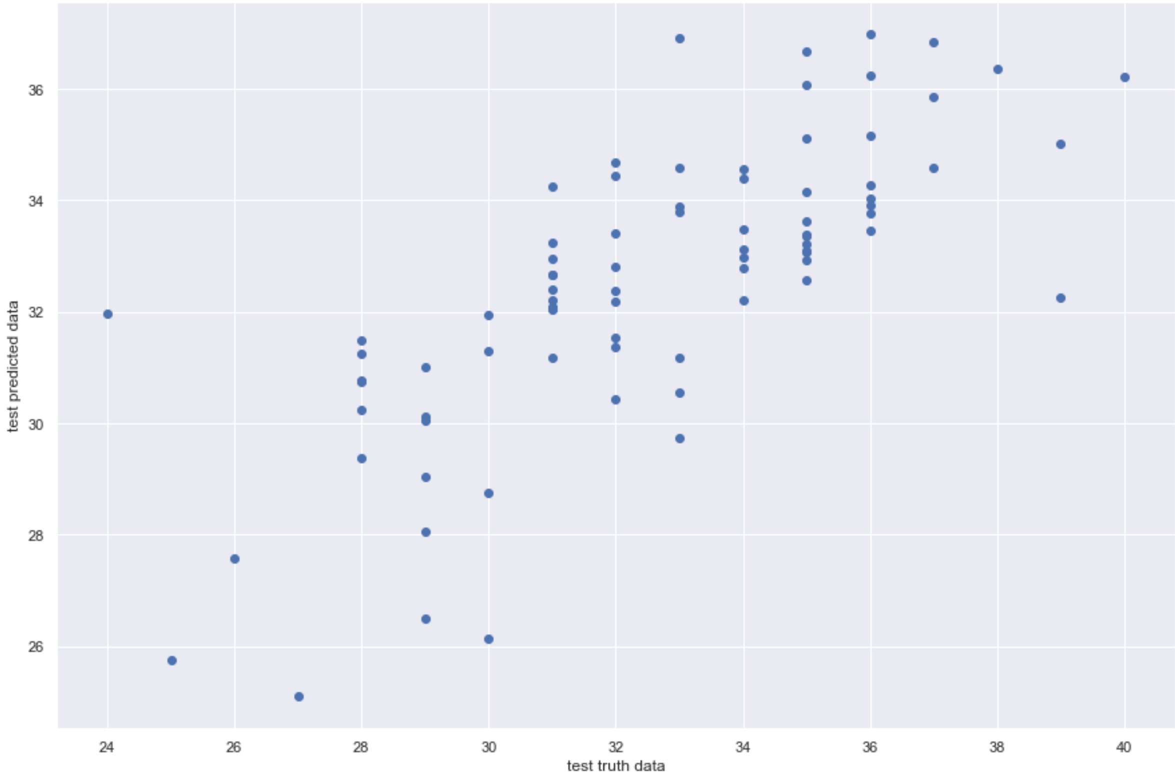
1.relationship between actual y test and y predicted

In [125]:

```
plt.scatter(y_test,elastic_pred)
plt.xlabel("test truth data")
plt.ylabel("test predicted data")
```

Out[125]:

```
Text(0, 0.5, 'test predicted data')
```



2.residual

In [126]:

```
residuals = y_test - elastic_pred
residuals
```

Out[126]:

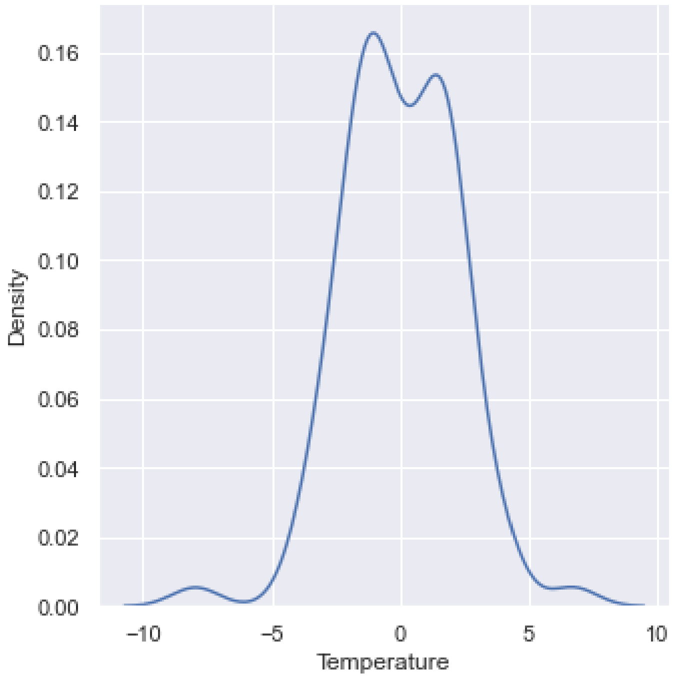
```
24    -1.944528
6     -0.898008
153   -0.805491
211    1.935598
198    3.788443
         ...
180    0.524544
5     -1.064115
56     0.841641
125   -1.935000
148    1.956419
Name: Temperature, Length: 81, dtype: float64
```

In [127]:

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

Out[127]:

```
<seaborn.axisgrid.FacetGrid at 0x25f06681610>
```



3.uniform distribution

In [131]:

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

Out[131]:

```
<matplotlib.collections.PathCollection at 0x25f070ed850>
```

Performance Metrics

In [129]:

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

```
4.816802294980992
1.7704639472804067
2.1947214618217483
```

R Square

In [132]:

```
from sklearn.metrics import r2_score
elastic_score = r2_score(y_test,elastic_pred)
print(elastic_score)
```

```
0.5515390966741835
```

Adjusted R Square

In [134]:

```
1 - (1-elastic_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[134]:

```
0.48004532947731415
```

```
Follow me on:
    linkedin link:   https://www.linkedin.com/in/dharavath-ramdas-a283aa213/
    GitHub link:  https://github.com/dharavathramdas101
```