

Algerian Forest Fire Dataset - Temperature Prediction

- Data Collection
- Exploratory data analysis
- Data Cleaning
- Linear Regression Model Training
- Ridge Regression Model Training
- Lasso Regression Model Training
- Elastincet Regression Model Training

Importing the Libraries

```
In [63]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

Data Reading and Cleaning

```
In [64]: df = pd.read_csv(r"C:\Users\hrush\Downloads\Algerian_forest_fires_dataset_UPDATE (1).csv",header=1)
df.head()
```

```
Out[64]:
```

	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

Drop an row

```
In [65]: df.drop([122,123],inplace=True)
df.reset_index(inplace=True)
df.drop('index',axis=1,inplace=True)
```

```
In [66]: df.loc[:,122, 'region'] = 'bejaia'
df.loc[122:, 'region'] = 'Sidi-Bel Abbas'
```

Stripping the names of the columns

```
In [67]: df.columns = [i.strip() for i in df.columns]
df.columns
```

```
Out[67]: Index(['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC',
'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'region'],
dtype='object')
```

Dropping the Classes Feature

```
In [68]: df.drop('Classes',axis=1,inplace=True)
```

```
In [69]: df.head()
```

```
Out[69]:
```

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

Replacing the day,month,year feature with date feature

```
In [70]: df['date']=pd.to_datetime(df[['day','month','year']])
df.drop(['day','month','year'],axis=1,inplace=True)
```

```
In [71]: df.head()
```

```
Out[71]:
```

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

Checking the datatypes of feature

```
In [72]: df.dtypes
```

```
Out[72]: Temperature      object
RH                        object
Ws                        object
Rain                     object
FFMC                     object
DMC                      object
DC                       object
ISI                      object
BUI                      object
FWI                      object
region                   object
date                     datetime64[ns]
dtype: object
```

Checking the datatypes of features

```
In [73]: df['Temperature']=df['Temperature'].astype(int)
df['RH']=df['RH'].astype(int)
df['Ws']=df['Ws'].astype(int)
df['Rain']=df['Rain'].astype(float)
df['FFMC']=df['FFMC'].astype(float)
df['DMC']=df['DMC'].astype(float)
df['ISI']=df['ISI'].astype(float)
df['BUI']=df['BUI'].astype(float)
```

```
In [74]: df.dtypes
```

```
Out[74]: Temperature      int32
RH                        int32
Ws                        int32
Rain                     float64
FFMC                     float64
DMC                      float64
```

```

DC                object
ISI               float64
BUI               float64
FWI               object
region            object
date              datetime64[ns]
dtype: object

```

Applying Label encoding in DC,FWI,region features

```

In [75]: from sklearn.preprocessing import LabelEncoder
LabelEncoder=LabelEncoder()

```

```

In [76]: df['DC']=LabelEncoder.fit_transform(df['DC'])
df['FWI']=LabelEncoder.fit_transform(df['FWI'])
df['region']=LabelEncoder.fit_transform(df['region'])

```

```

In [77]: df.dtypes

```

```

Out[77]: Temperature      int32
RH                      int32
Ws                      int32
Rain                   float64
FFMC                   float64
DMC                    float64
DC                     int32
ISI                    float64
BUI                    float64
FWI                    int32
region                 int32
date                   datetime64[ns]
dtype: object

```

```

In [78]: df.head()

```

```

Out[78]:
   Temperature  RH  Ws  Rain  FFMC  DMC  DC  ISI  BUI  FWI  region  date
0           29  57  18   0.0   65.7   3.4  150  1.3  3.4   5     1  2012-06-01
1           29  61  13   1.3   64.4   4.1  150  1.0  3.9   4     1  2012-06-02
2           26  82  22  13.1   47.1   2.5  146  0.3  2.7   1     1  2012-06-03
3           25  89  13   2.5   28.6   1.3  136  0.0  1.7   0     1  2012-06-04
4           27  77  16   0.0   64.8   3.0   18  1.2  3.9   5     1  2012-06-05

```

Checking the null values

```

In [79]: df.isnull().sum()

```

```

Out[79]: Temperature      0
RH                      0
Ws                      0
Rain                   0
FFMC                   0
DMC                    0
DC                     0
ISI                    0
BUI                    0
FWI                    0
region                 0
date                   0
dtype: int64

```

Observation

Zero null value in the dataset

Univariate Analysis

```
In [80]: numeric_features = [feature for feature in df.columns if df[feature].dtype != 'O']
```

```
In [81]: numeric_features
```

```
Out[81]: ['Temperature',  
        'RH',  
        'Ws',  
        'Rain',  
        'FFMC',  
        'DMC',  
        'DC',  
        'ISI',  
        'BUI',  
        'FWI',  
        'region',  
        'date']
```

Features Information

*Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012) Weather data observations

*Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42

*RH : Relative Humidity in %: 21 to 90

*Ws :Wind speed in km/h: 6 to 29

*Rain: total day in mm: 0 to 16.8 FWI Components

*Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5

*Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9

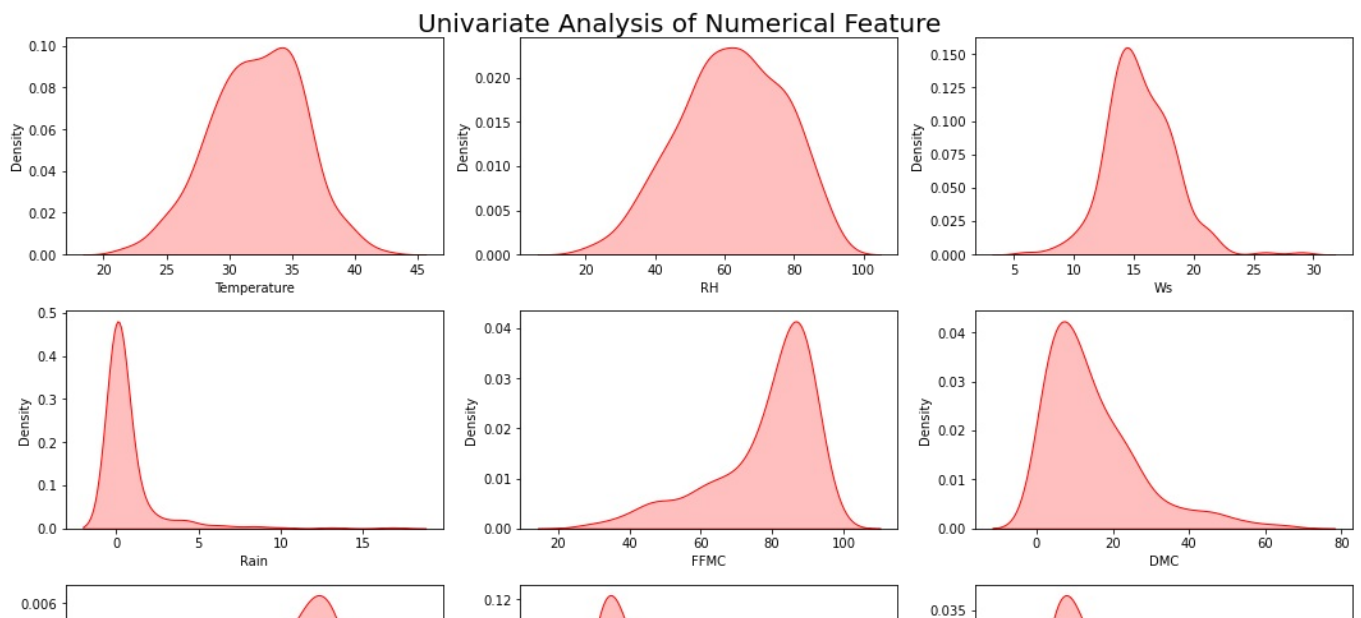
*Drought Code (DC) index from the FWI system: 7 to 220.4

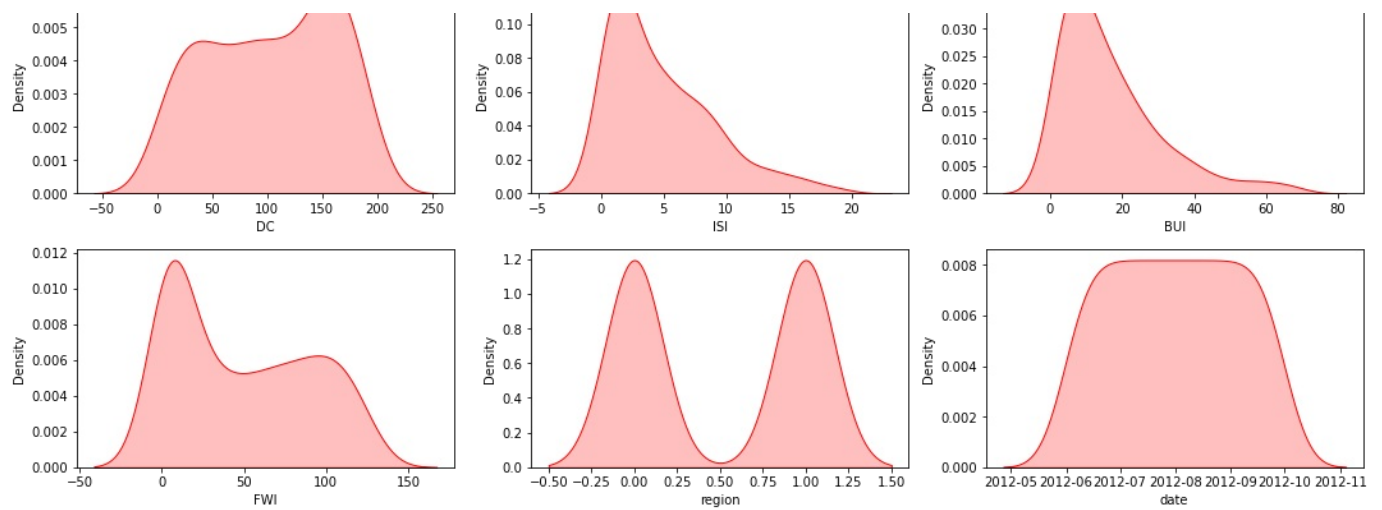
*Initial Spread Index (ISI) index from the FWI system: 0 to 18.5

*Buildup Index (BUI) index from the FWI system: 1.1 to 68

*Fire Weather Index (FWI) Index: 0 to 31.1

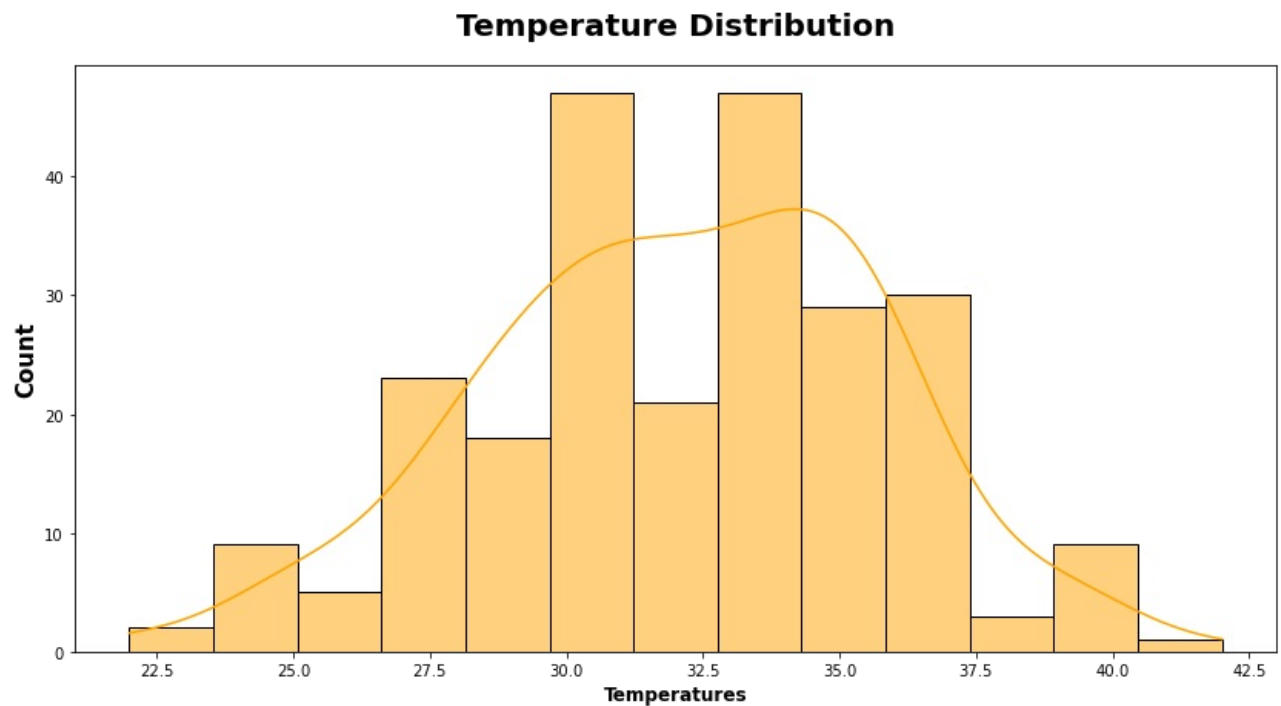
```
In [82]: plt.figure(figsize=(15,15))  
plt.suptitle('Univariate Analysis of Numerical Feature', fontsize=20, fontweight=20)  
  
for i in range(0, len(numeric_features)):  
    plt.subplot(5, 3, i+1)  
    sns.kdeplot(x=df[numeric_features[i]],shade=True, color='r')  
    plt.xlabel(numeric_features[i])  
    plt.tight_layout()
```





Visualization of Target Feature

```
In [83]: plt.subplots(figsize=(14,7))
sns.histplot(x=df.Temperature, ec = "black", color='orange', kde=True)
plt.title("Temperature Distribution", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count", weight="bold", fontsize=15)
plt.xlabel("Temperatures", weight="bold", fontsize=12)
plt.show()
```



Observation

Temperature occur most of the time in range 32.5 to 35.0

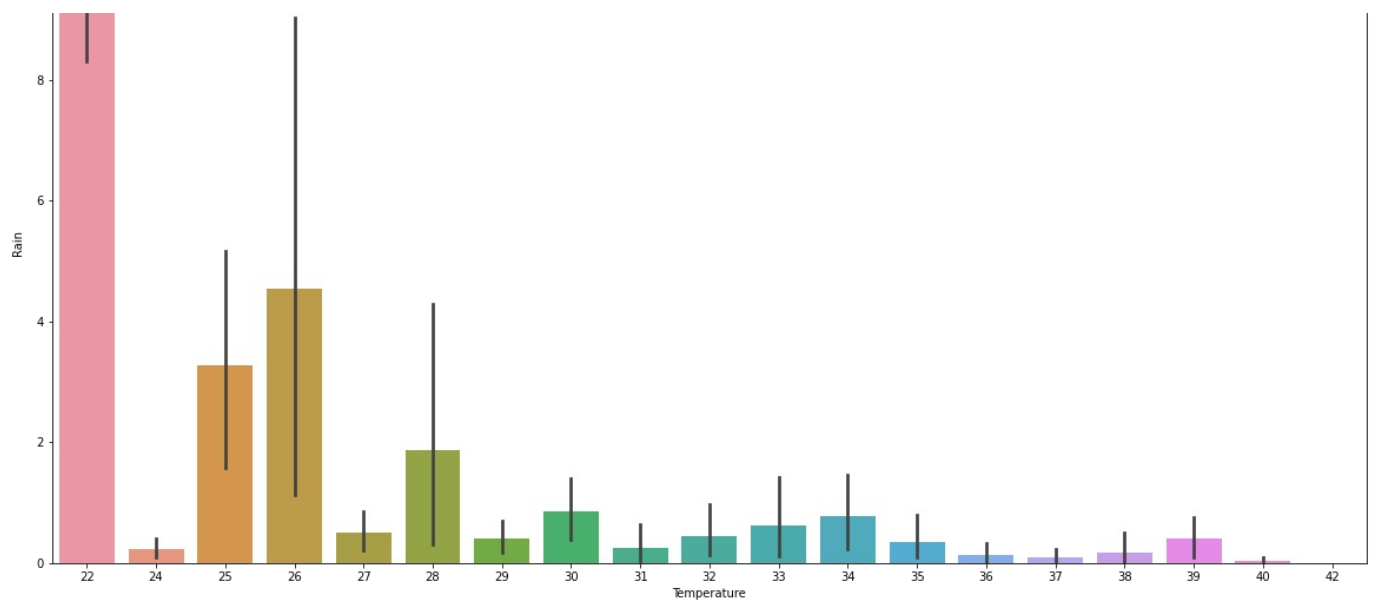
Temperature Vs Rain

```
In [84]: import matplotlib
matplotlib.rcParams['figure.figsize']=(20,10)

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

```
Out[84]: <AxesSubplot:xlabel='Temperature', ylabel='Rain'>
```





Observation

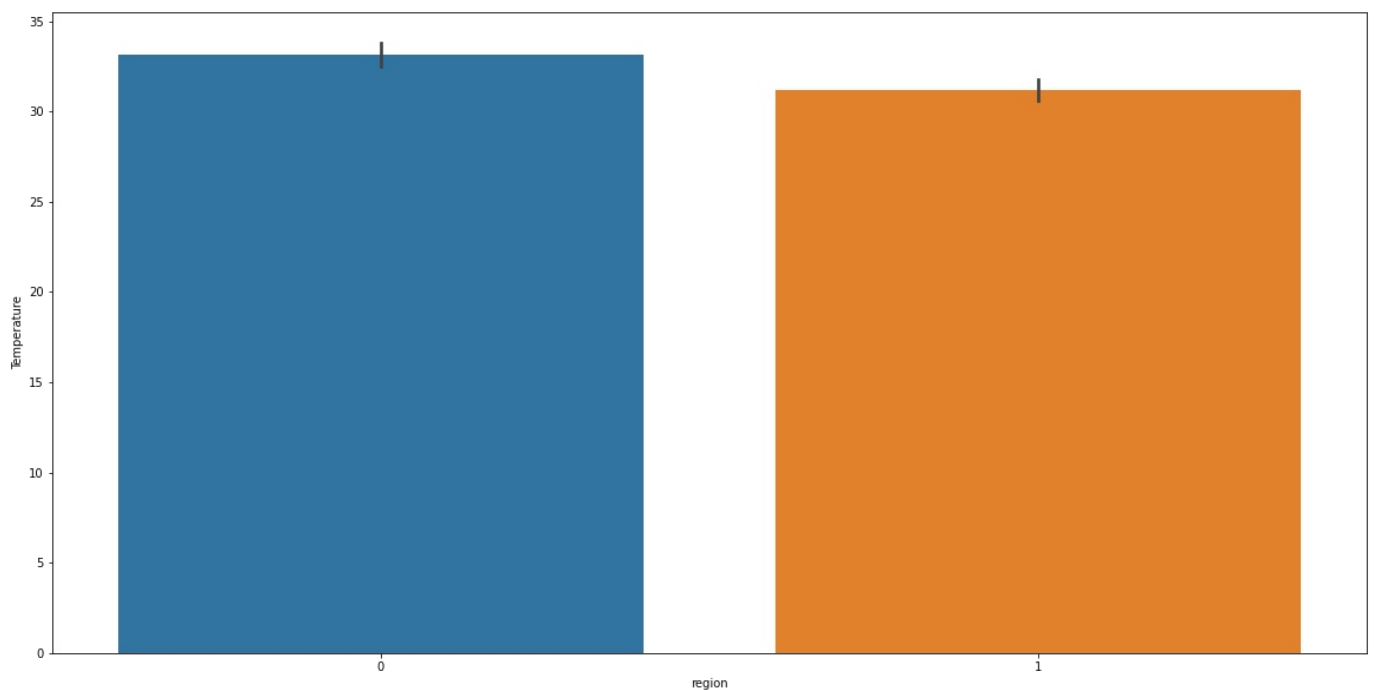
When the temperature is around 22, most of the rain occur

Which region has most temperature?

```
In [86]: import matplotlib
matplotlib.rcParams['figure.figsize']=(20,10)

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

```
Out[86]: <AxesSubplot:xlabel='region', ylabel='Temperature'>
```



Observation

Region represented by 0 i.e. 'Sidi-Bel Abbes' has highest temperature

Correlation of the features

```
In [87]: df.corr()
```

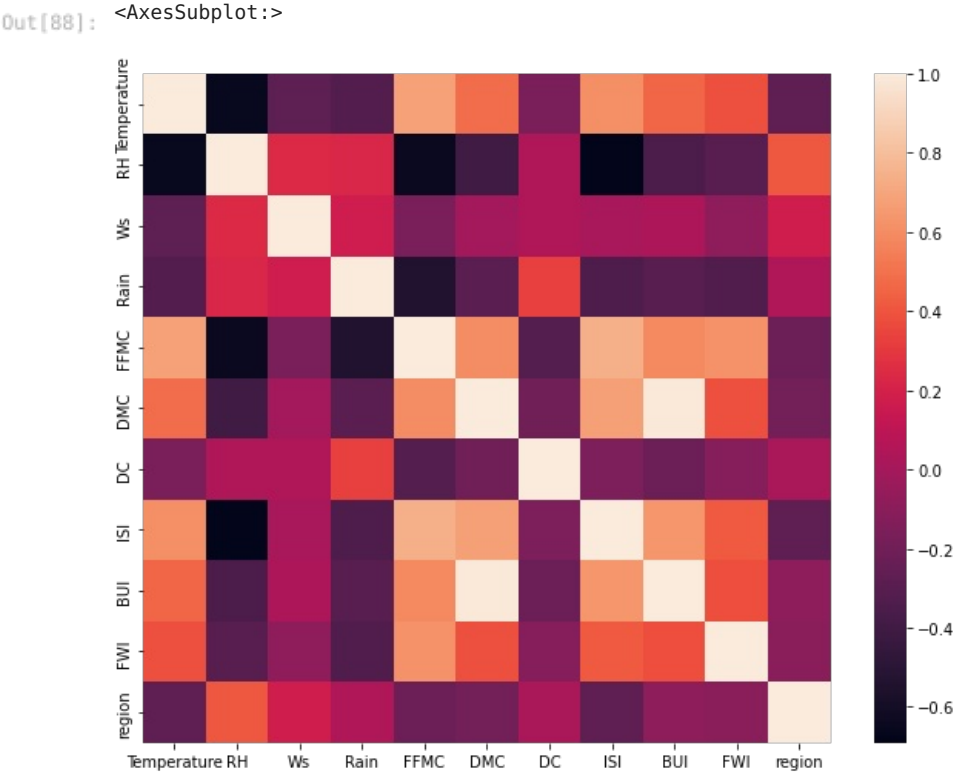
Out[87]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	region
Temperature	1.000000	-0.654443	-0.278132	-0.326786	0.677491	0.483105	-0.165840	0.607551	0.455504	0.380581	-0.273496
RH	-0.654443	1.000000	0.236084	0.222968	-0.645658	-0.405133	0.041651	-0.690637	-0.348587	-0.295093	0.406424
Ws	-0.278132	0.236084	1.000000	0.170169	-0.163255	-0.001246	0.040958	0.015248	0.029756	-0.081447	0.176829
Rain	-0.326786	0.222968	0.170169	1.000000	-0.544045	-0.288548	0.324748	-0.347105	-0.299171	-0.340412	0.041080
FFMC	0.677491	-0.645658	-0.163255	-0.544045	1.000000	0.602391	-0.319086	0.739730	0.589652	0.617445	-0.224680
DMC	0.483105	-0.405133	-0.001246	-0.288548	0.602391	1.000000	-0.200609	0.674499	0.982073	0.384628	-0.191094
DC	-0.165840	0.041651	0.040958	0.324748	-0.319086	-0.200609	1.000000	-0.152717	-0.226445	-0.118684	0.016293
ISI	0.607551	-0.690637	0.015248	-0.347105	0.739730	0.674499	-0.152717	1.000000	0.635891	0.412512	-0.268421
BUI	0.455504	-0.348587	0.029756	-0.299171	0.589652	0.982073	-0.226445	0.635891	1.000000	0.375234	-0.087370
FWI	0.380581	-0.295093	-0.081447	-0.340412	0.617445	0.384628	-0.118684	0.412512	0.375234	1.000000	-0.108099
region	-0.273496	0.406424	0.176829	0.041080	-0.224680	-0.191094	0.016293	-0.268421	-0.087370	-0.108099	1.000000

Multivariate analysis

In [88]:

```
import seaborn as sns
plt.figure(figsize=(10,8))
sns.heatmap(df.corr())
```



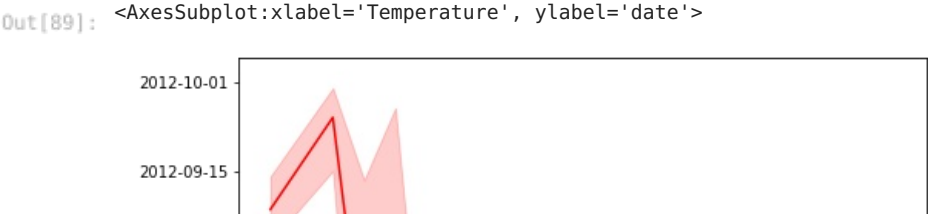
Observation

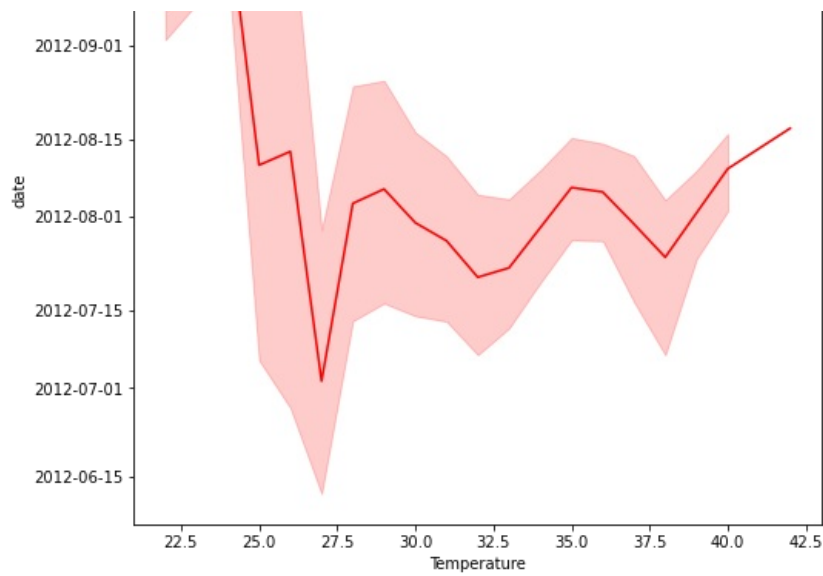
The target feature Temperature is highly positively correlated with FFMC,ISI

Temperature Vs date feature

In [89]:

```
plt.figure(figsize=(8,8))
sns.lineplot(x='Temperature',y='date',data=df,color='r')
```



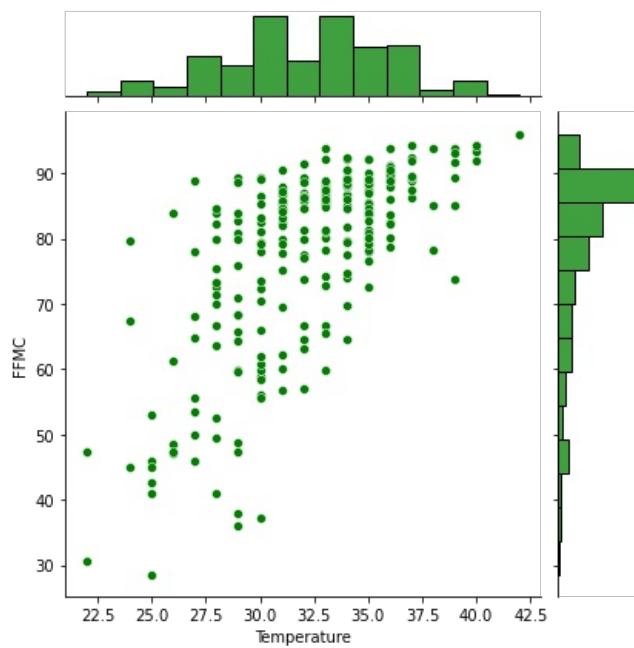


Temperature Vs FFMC

```
In [90]: plt.figure(figsize=(10,10))
sns.jointplot(x='Temperature',y='FFMC',data=df,color='g')
```

```
Out[90]: <seaborn.axisgrid.JointGrid at 0x1c390143d90>
```

<Figure size 720x720 with 0 Axes>

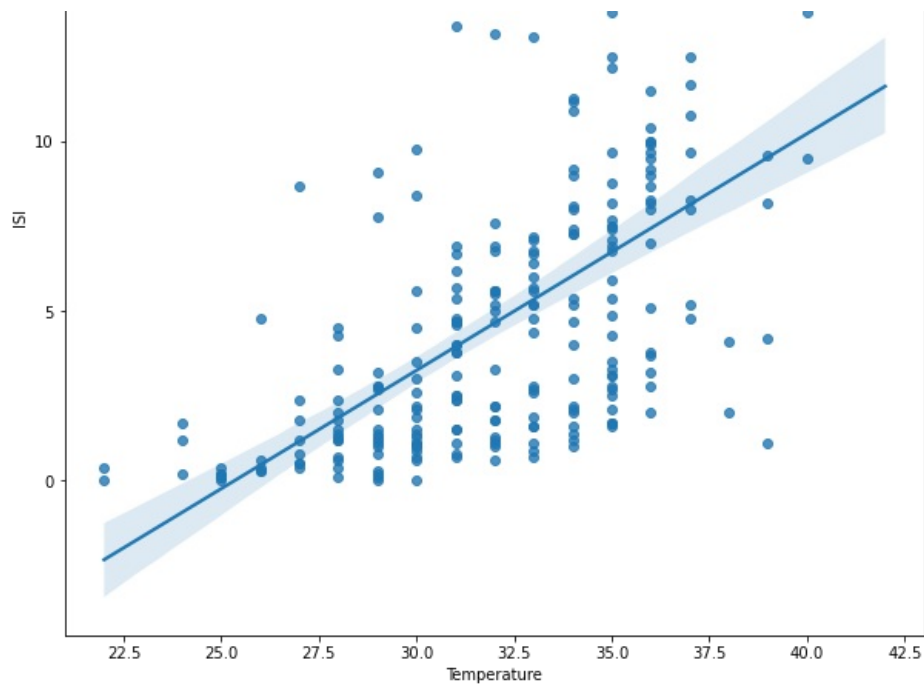


Temperature Vs ISI

```
In [91]: plt.figure(figsize=(10,10))
sns.regplot(x='Temperature',y='ISI',data=df)
```

```
Out[91]: <AxesSubplot:xlabel='Temperature', ylabel='ISI'>
```

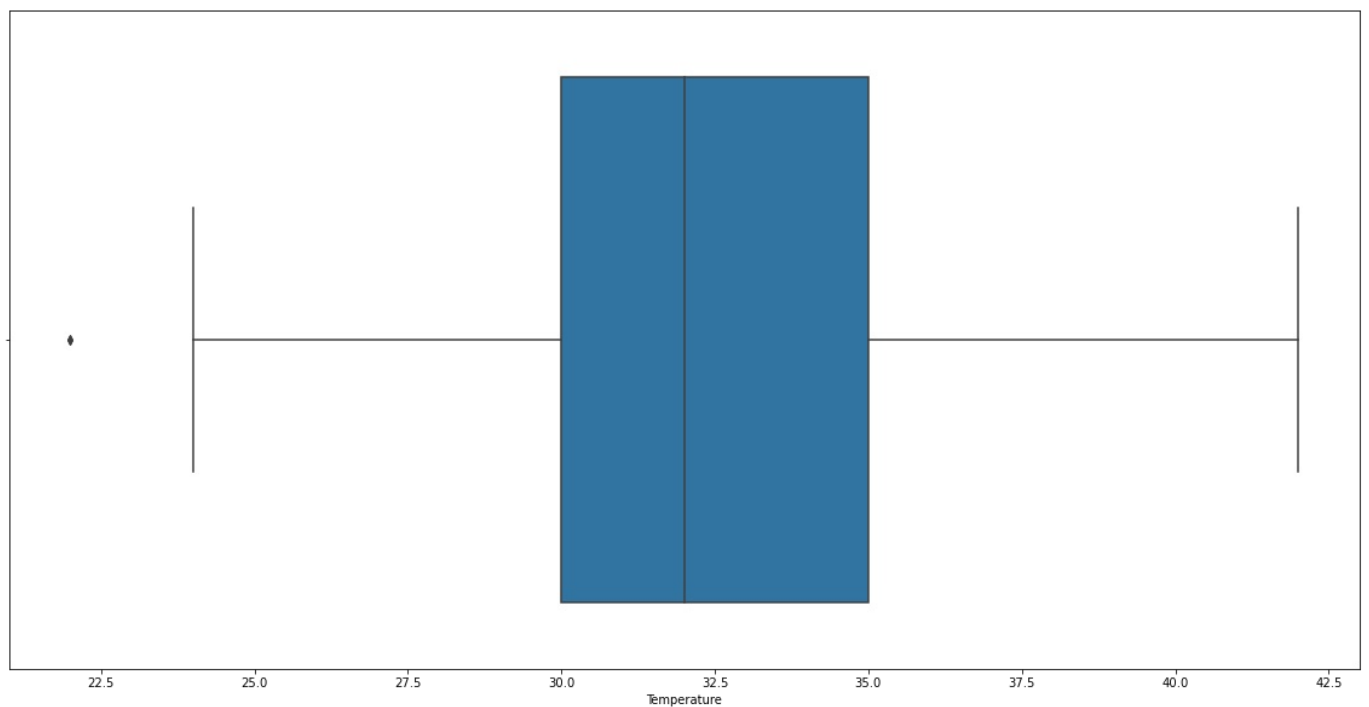




Checking the outliers of the target 'Temperature' feature

```
In [92]: sns.boxplot(df['Temperature'])
```

```
Out[92]: <AxesSubplot:xlabel='Temperature'>
```

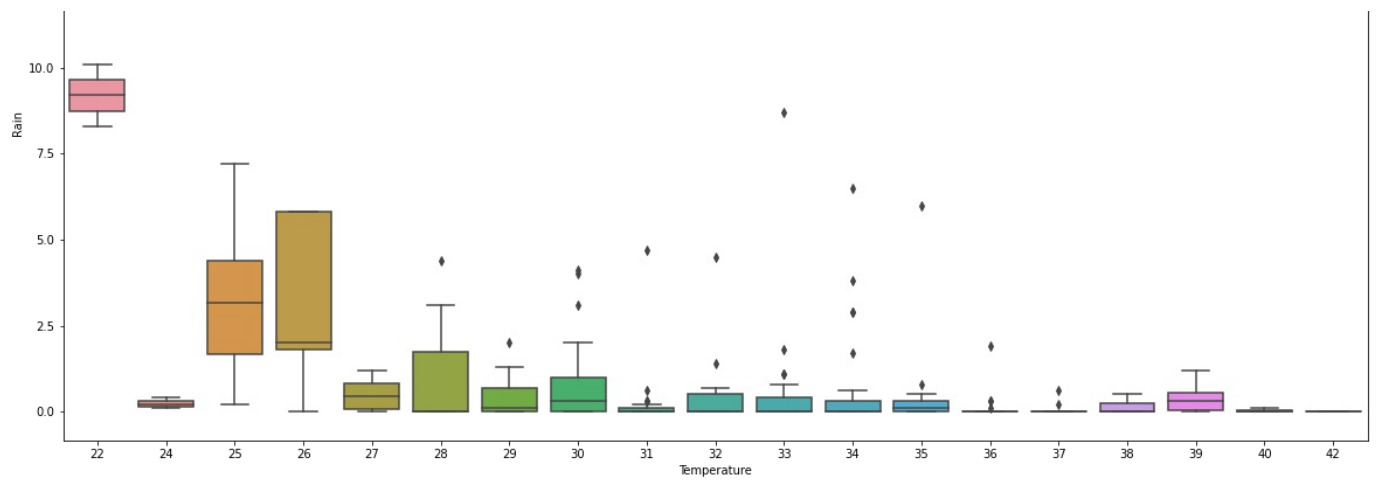


Boxplot of Rain Vs Temperature

```
In [93]: sns.boxplot(x='Temperature', y='Rain', data=df)
```

```
Out[93]: <AxesSubplot:xlabel='Temperature', ylabel='Rain'>
```

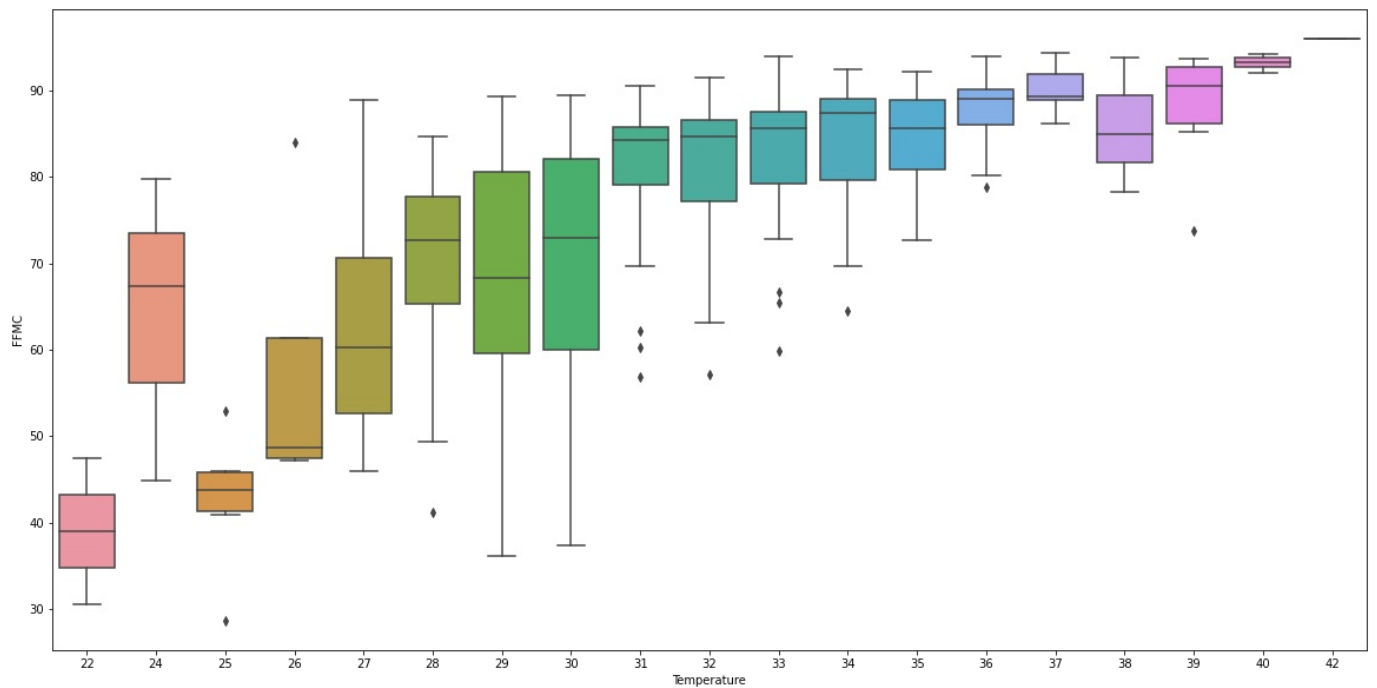




Boxplot of 'FFMC' Vs Temperature

```
In [94]: sns.boxplot(x='Temperature', y='FFMC', data=df)
```

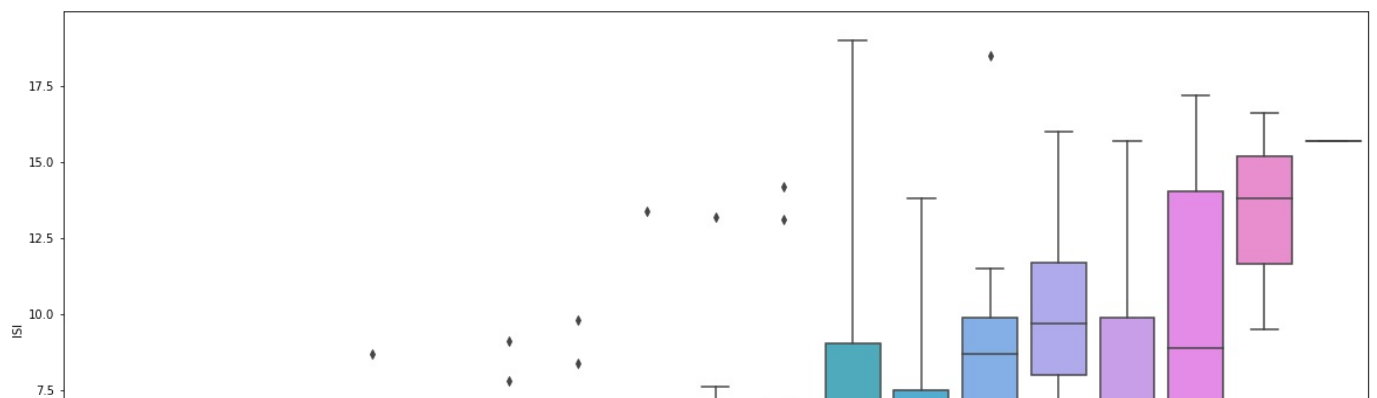
```
Out[94]: <AxesSubplot:xlabel='Temperature', ylabel='FFMC'>
```

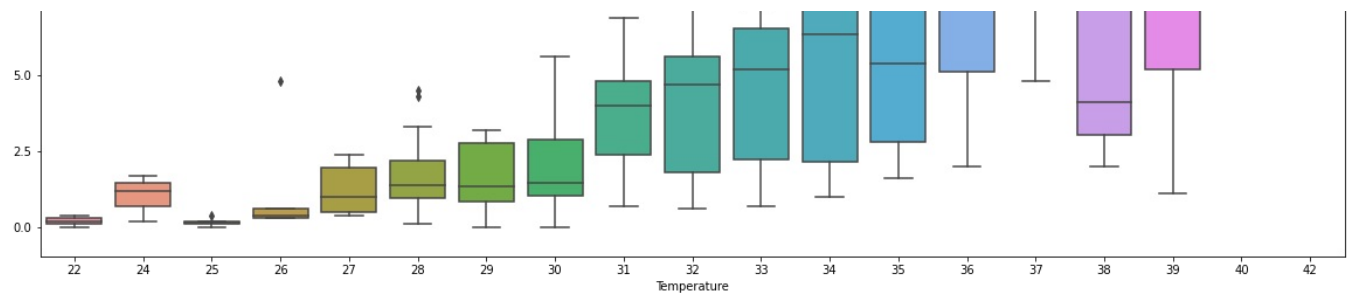


Boxplot of ISI Vs Temperature

```
In [95]: sns.boxplot(x='Temperature', y='ISI', data=df)
```

```
Out[95]: <AxesSubplot:xlabel='Temperature', ylabel='ISI'>
```

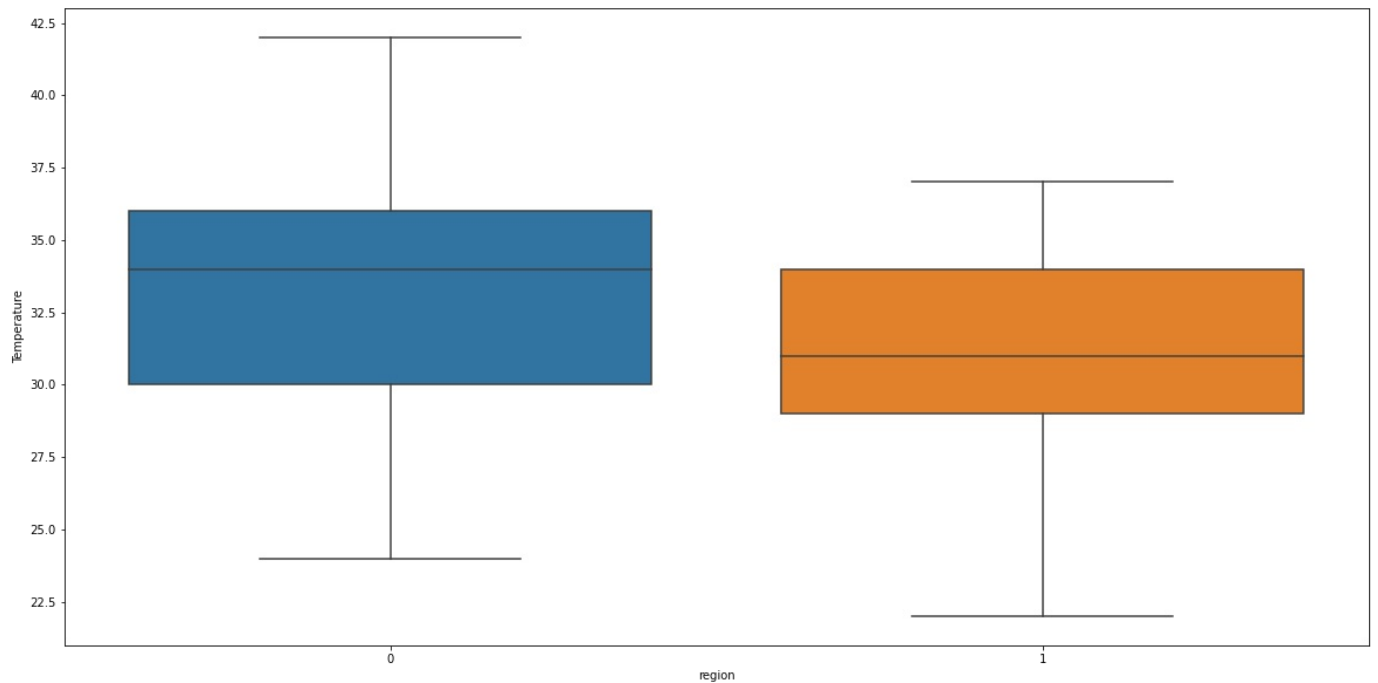




Boxplot of region Vs Temperature

```
In [96]: sns.boxplot(x='region', y='Temperature', data=df)
```

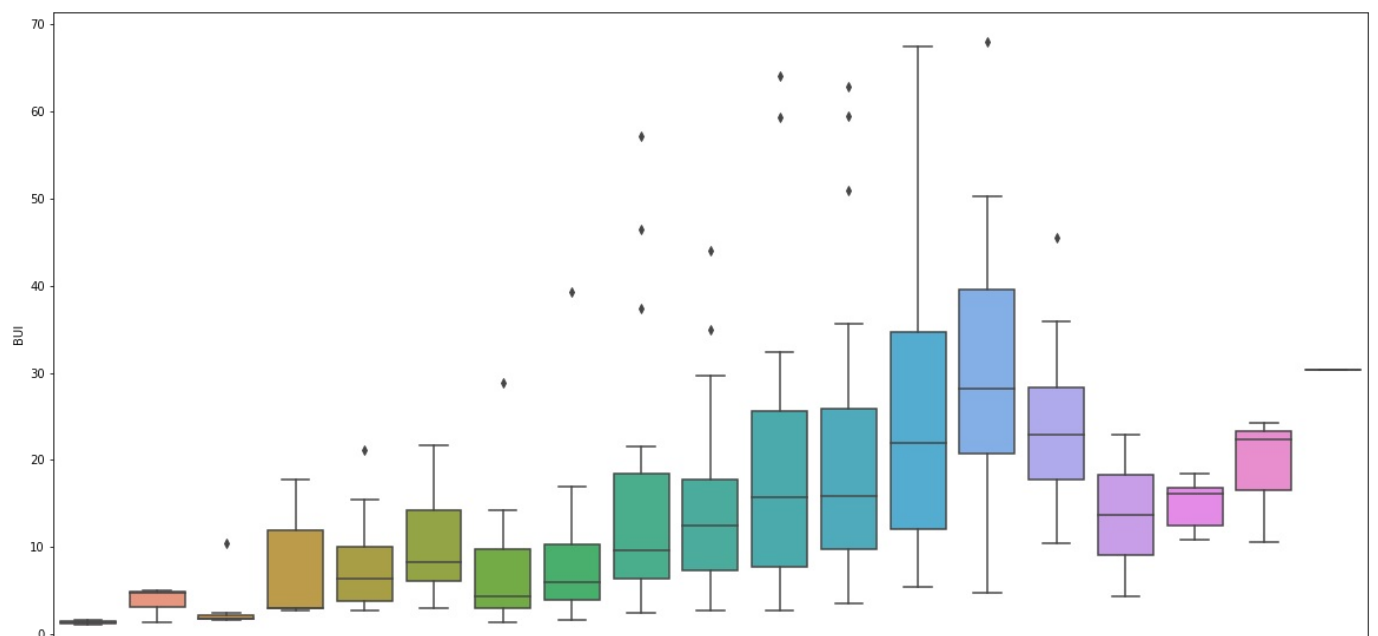
```
Out[96]: <AxesSubplot:xlabel='region', ylabel='Temperature'>
```

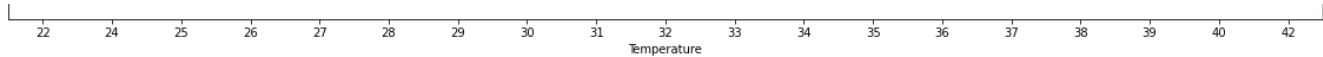


Boxplot of BUI Vs Temperature

```
In [97]: sns.boxplot(x='Temperature', y='BUI', data=df)
```

```
Out[97]: <AxesSubplot:xlabel='Temperature', ylabel='BUI'>
```

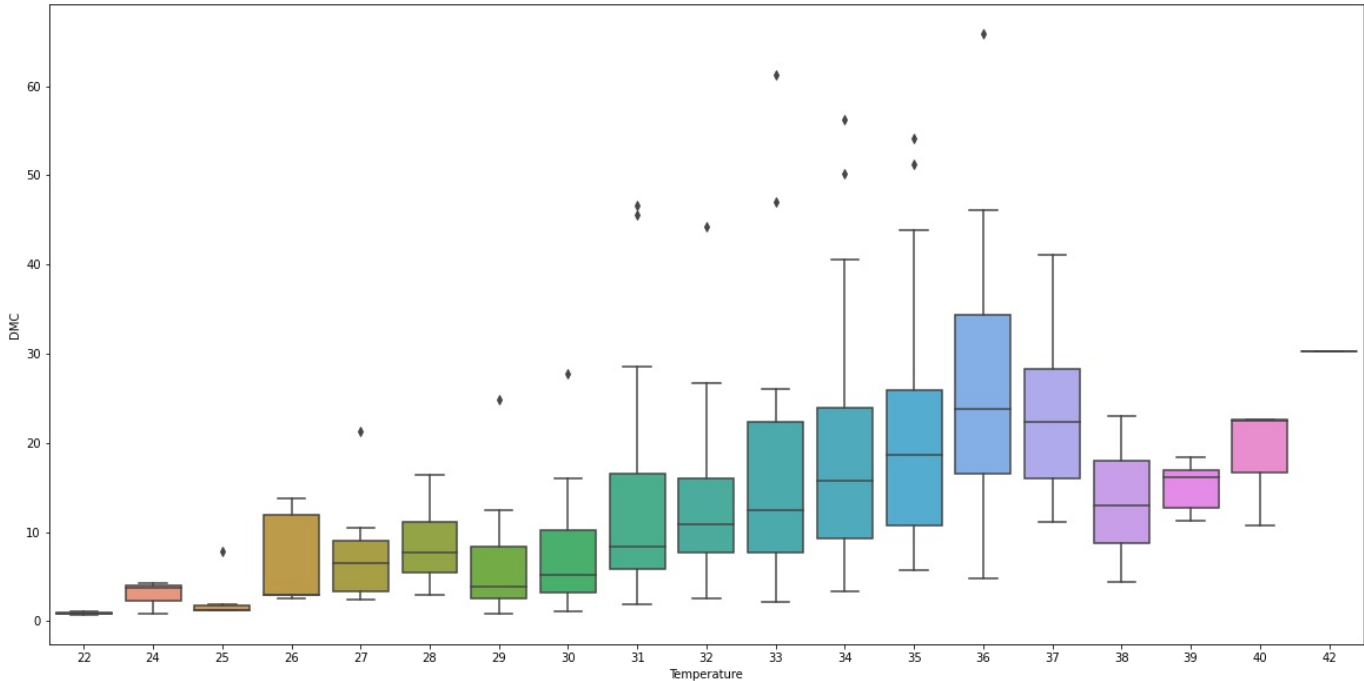




Boxplot DMC Vs Temperature

```
In [98]: sns.boxplot(x = 'Temperature', y = 'DMC', data = df)
```

```
Out[98]: <AxesSubplot:xlabel='Temperature', ylabel='DMC'>
```



Creating Dependent and Independent features

```
In [99]: df.columns
```

```
Out[99]: Index(['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'region', 'date'], dtype='object')
```

```
In [128]: ## Independent Features
x=pd.DataFrame(df, columns=['RH','Ws','Rain','FFMC','DMC','DC','ISI','BUI','FWI','region'])

## Dependent Features
y=pd.DataFrame(df,columns=['Temperature'])
```

Independent Features

```
In [129]: x
```

	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	region
0	57	18	0.0	65.7	3.4	150	1.3	3.4	5	1
1	61	13	1.3	64.4	4.1	150	1.0	3.9	4	1
2	82	22	13.1	47.1	2.5	146	0.3	2.7	1	1
3	89	13	2.5	28.6	1.3	136	0.0	1.7	0	1
4	77	16	0.0	64.8	3.0	18	1.2	3.9	5	1
...
239	65	14	0.0	85.4	16.0	112	4.5	16.9	106	0

240	87	15	4.4	41.1	6.5	164	0.1	6.2	0	0
241	87	29	0.5	45.9	3.5	153	0.4	3.4	2	0
242	54	18	0.1	79.7	4.3	25	1.7	5.1	7	0
243	64	15	0.2	67.3	3.8	34	1.2	4.8	5	0

244 rows × 10 columns

Dependent Features

In [130...

```
y
```

Out[130...

	Temperature
0	29
1	29
2	26
3	25
4	27
...	...
239	30
240	28
241	27
242	24
243	24

244 rows × 1 columns

TrainTest Split

In [131...

```
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=10)
```

In [132...

```
x_train.shape
```

Out[132...

```
(163, 10)
```

In [133...

```
x_test.shape
```

Out[133...

```
(81, 10)
```

In [134...

```
y_train.shape
```

Out[134...

```
(163, 1)
```

In [135...

```
y_test.shape
```

Out[135...

```
(81, 1)
```

Independent training dataset

In [136...

```
x_train
```

Out[136...

	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	region
237	49	6	2.0	61.3	11.9	77	0.6	11.9	4	0
78	54	18	0.0	89.4	20.0	8	9.7	27.5	47	1
25	64	18	0.0	86.8	17.8	157	6.7	21.6	20	1
124	80	14	2.0	48.7	2.2	150	0.3	2.6	1	0
176	64	9	1.2	73.8	11.7	28	1.1	11.4	7	0
...
64	69	13	0.0	85.0	8.2	53	4.0	8.2	86	1
15	89	13	0.7	36.1	1.7	150	0.0	2.2	0	1
228	51	13	0.0	88.7	16.0	122	6.9	17.8	124	0
125	64	14	0.0	79.4	5.2	26	2.2	5.6	10	0
9	79	12	0.0	73.2	9.5	114	1.3	12.6	9	1

163 rows × 10 columns

Independent Test Dataset

In [137...

x_test

Out[137...

	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	region
162	56	15	2.9	74.8	7.1	185	1.6	6.8	8	0
60	64	17	0.0	87.2	31.9	22	6.8	41.2	45	1
61	45	14	0.0	78.8	4.8	1	2.0	4.7	9	1
63	63	14	0.3	76.6	5.7	0	1.7	5.5	8	1
69	59	17	0.0	87.4	14.8	132	6.9	17.9	125	1
...
169	68	15	0.0	86.1	23.9	123	5.2	23.9	120	0
232	41	8	0.1	83.9	24.9	177	2.7	28.9	99	0
144	59	16	0.8	74.2	7.0	166	1.6	6.7	8	0
208	37	16	0.0	92.2	61.3	38	13.1	64.0	89	0
105	76	26	8.3	47.4	1.1	145	0.4	1.6	1	1

81 rows × 10 columns

Dependent Training Dataset

In [138...

y_train

Out[138...

	Temperature
237	26
78	36
25	31
124	29
176	39
...	...
64	34
15	29
228	32
125	30
9	28

163 rows × 1 columns

```
In [139... y_test
```

Temperature	
162	34
60	35
61	36
63	35
69	35
...	...
169	33
232	29
144	33
208	33
105	22

81 rows × 1 columns

Standardizing or Feature Scaling

```
In [140... from sklearn.preprocessing import StandardScaler
scaler=StandardScaler() ## Initialising
```

```
In [141... scaler
```

```
Out[141... StandardScaler()
```

```
In [142... x_train=scaler.fit_transform(x_train)
```

```
In [143... x_test=scaler.transform(x_test)
```

```
In [144... x_train
```

```
Out[144... array([[ -0.85631108, -3.36419461,  0.88853946, ..., -0.32535487,
          -1.03738328, -0.98176139],
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          -0.01141751,  1.01857744],
        [  0.13736742,  0.99944243, -0.441414  , ...,  0.35302912,
          -0.65562857,  1.01857744],
        ...,
        [ -0.72382061, -0.81873967, -0.441414  , ...,  0.08727045,
          1.825777  , -0.98176139],
        [  0.13736742, -0.45510325, -0.441414  , ..., -0.76595478,
          -0.89422526, -0.98176139],
        [  1.13104591, -1.18237609, -0.441414  , ..., -0.27639932,
          -0.91808493,  1.01857744]])
```

```
In [145... x_test
```

```
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          -7.33442383e-01, -6.82030988e-01, -9.41944600e-01,
          -9.81761387e-01],
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          -7.09829682e-01, -7.72948430e-01, -9.41944600e-01,
          1.01857744e+00],
        [ -1.93858749e-01,  6.35806011e-01, -4.41414004e-01,
```

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1.01857744e+00],
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1.01857744e+00],
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[-4.58839681e-01, -4.55103250e-01, -4.41414004e-01,
5.96262207e-01, -5.06751286e-01, -1.01912309e+00,
6.93894730e-02, -5.84119896e-01, 1.13384660e+00,
-9.81761387e-01],
[9.32310211e-01, 1.72671527e+00, 2.40697100e-02,
-9.81576073e-01, -9.62400778e-01, 1.38430259e+00,
-8.04280488e-01, -9.47789665e-01, -1.01352361e+00,
1.01857744e+00],

```
[ -5.25084914e-01,  9.99442431e-01, -3.74916331e-01,
  1.52281739e-01, -8.26505316e-01, -1.38753141e+00,
 -7.09829682e-01, -8.00923028e-01, -9.65804269e-01,
 -9.81761387e-01],
 [ 7.33574512e-01, -9.14668296e-02, -4.41414004e-01,
  6.23584082e-01, -2.02984958e-01, -7.17874223e-02,
  2.11065683e-01, -2.13456477e-01,  1.46788197e+00,
  1.01857744e+00],
 [ 1.37367416e-01, -9.14668296e-02, -3.08418657e-01,
 -6.94696386e-01, -8.66474569e-01, -1.22964213e+00,
 -8.27893190e-01, -8.21903976e-01, -1.01352361e+00,
 -9.81761387e-01],
 [ 4.68593580e-01, -8.18739670e-01,  2.40697100e-02,
 -7.42509667e-01, -6.90609853e-01,  1.40184584e+00,
 -8.51505892e-01, -7.51967482e-01, -1.01352361e+00,
  1.01857744e+00],
 [ 1.32978161e+00,  2.09035169e+00, -4.41414004e-01,
  5.07466114e-01,  2.58686895e+00, -8.43690560e-01,
 -7.22867370e-02,  2.98963495e+00, -3.45452876e-01,
  1.01857744e+00],
 [ 4.02348347e-01, -9.14668296e-02, -4.41414004e-01,
  5.89431738e-01,  7.40289429e-01,  3.31707400e-01,
  1.16614876e-01,  5.13883061e-01,  1.73033833e+00,
 -9.81761387e-01],
 [-1.38627294e+00, -2.63692177e+00, -3.74916331e-01,
  4.39161426e-01,  8.20227936e-01,  1.27904307e+00,
 -4.73702665e-01,  8.63565532e-01,  1.22928528e+00,
 -9.81761387e-01],
 [-1.93858749e-01,  2.72169591e-01,  9.05673835e-02,
 -2.23394042e-01, -6.10671346e-01,  1.08606728e+00,
 -7.33442383e-01, -6.89024637e-01, -9.41944600e-01,
 -9.81761387e-01],
 [-1.65125387e+00,  2.72169591e-01, -4.41414004e-01,
  1.00609033e+00,  3.72998960e+00, -1.15946912e+00,
  1.98201831e+00,  3.31833647e+00,  9.90688587e-01,
 -9.81761387e-01],
 [ 9.32310211e-01,  3.90853379e+00,  5.07789289e+00,
 -2.05395967e+00, -1.08230854e+00,  7.17658968e-01,
 -1.01679480e+00, -1.04570076e+00, -1.10896228e+00,
  1.01857744e+00]])
```

Model Training

```
In [146... from sklearn.linear_model import LinearRegression
```

```
In [147... regression=LinearRegression()
```

```
In [148... regression
regression.fit(x_train,y_train)
```

```
Out[148... LinearRegression()
```

Coefficient

```
In [149... print(regression.coef_)

[[-1.27500995 -0.53842199 -0.21205266  0.70886534 -1.02729123 -0.32455869
  0.2501139   1.35400654  0.21687466 -0.23115864]]
```

Intercept

```
In [150... print(regression.intercept_)

[32.17791411]
```

Predcition for Test Data

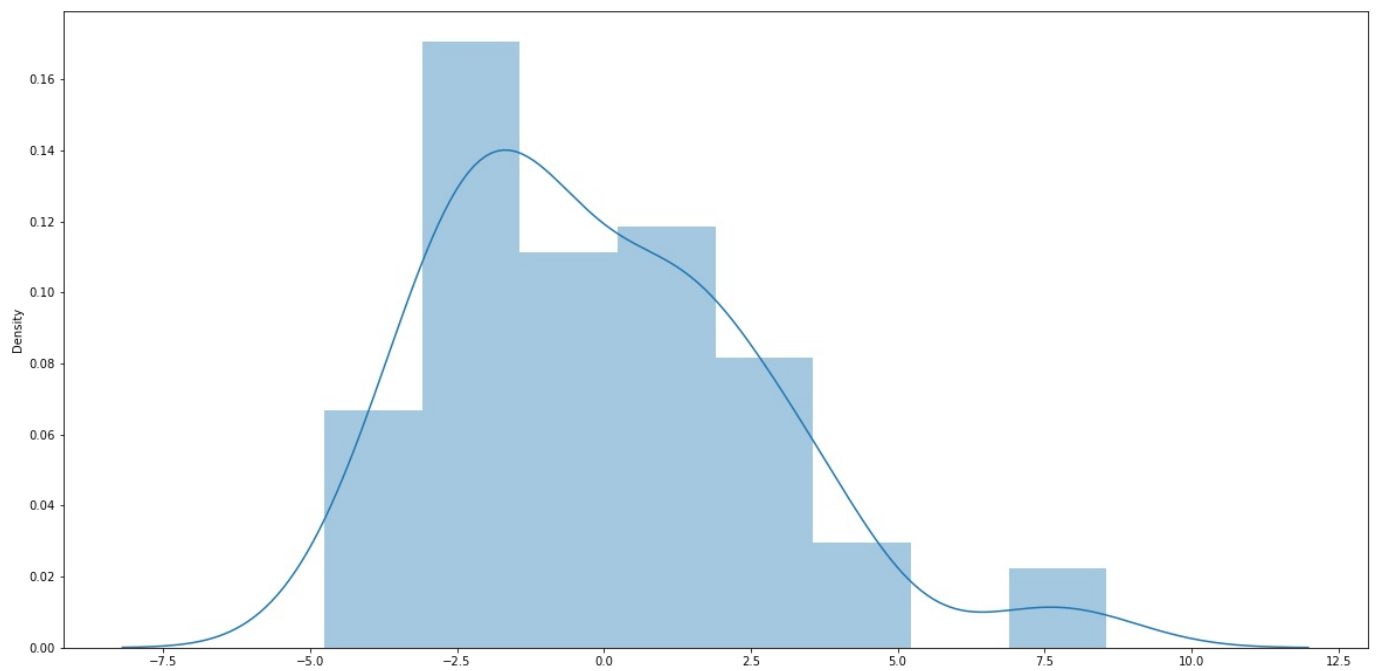
```
In [151... reg_pred=regression.predict(x_test)
```

```
In [152... reg_pred
```

```
Out[152... array([[31.35728286],
       [33.48448971],
       [33.68885621],
       [32.00434093],
       [32.90791395],
       [35.12184072],
       [32.88392257],
       [34.41877632],
       [31.94627835],
       [32.98721461],
       [33.30675698],
       [27.36975802],
       [35.07784211],
       [29.24028529],
       [31.85823402],
       [32.41802576],
       [34.37535576],
       [28.09756027],
       [36.26505018],
       [34.01992072],
       [32.55507349],
       [34.37404142],
       [32.95376928],
       [33.26908507],
       [36.11652279],
       [29.43281151],
       [31.64047533],
       [32.38849979],
       [27.56606986],
       [32.22728534],
       [25.99441341],
       [27.23155419],
       [34.06867619],
       [31.64327002],
       [32.76692249],
       [31.05185077],
       [29.01675218],
       [33.06175783],
       [27.69372403],
       [35.63560078],
       [32.8693709 ],
       [33.63210892],
       [34.17783984],
       [31.5433198 ],
       [36.08261913],
       [33.41675348],
       [24.66437356],
       [35.74882134],
       [33.62798919],
       [29.69949092],
       [31.06668332],
       [32.38004487],
       [36.25233174],
       [32.16965552],
       [30.17098904],
       [30.08639562],
       [32.50310102],
       [36.07831078],
       [31.40637145],
       [33.45272801],
       [32.10289562],
       [32.80364988],
       [30.70110717],
       [24.64737332],
       [31.51727723],
       [36.35580039],
       [29.95761627],
       [29.70472774],
       [35.38938777],
       [34.07489424],
       [27.95824128],
       [32.55161796],
       [31.90597354],
       [31.60138869],
       [30.05790994],
       [31.14615789],
       [32.6846203 ],
       [36.0426106 ],
       [31.28209795],
       [36.91863039],
       [25.08477191]])
```

```
In [154... import seaborn as sns
sns.distplot(reg_pred-y_test)
```

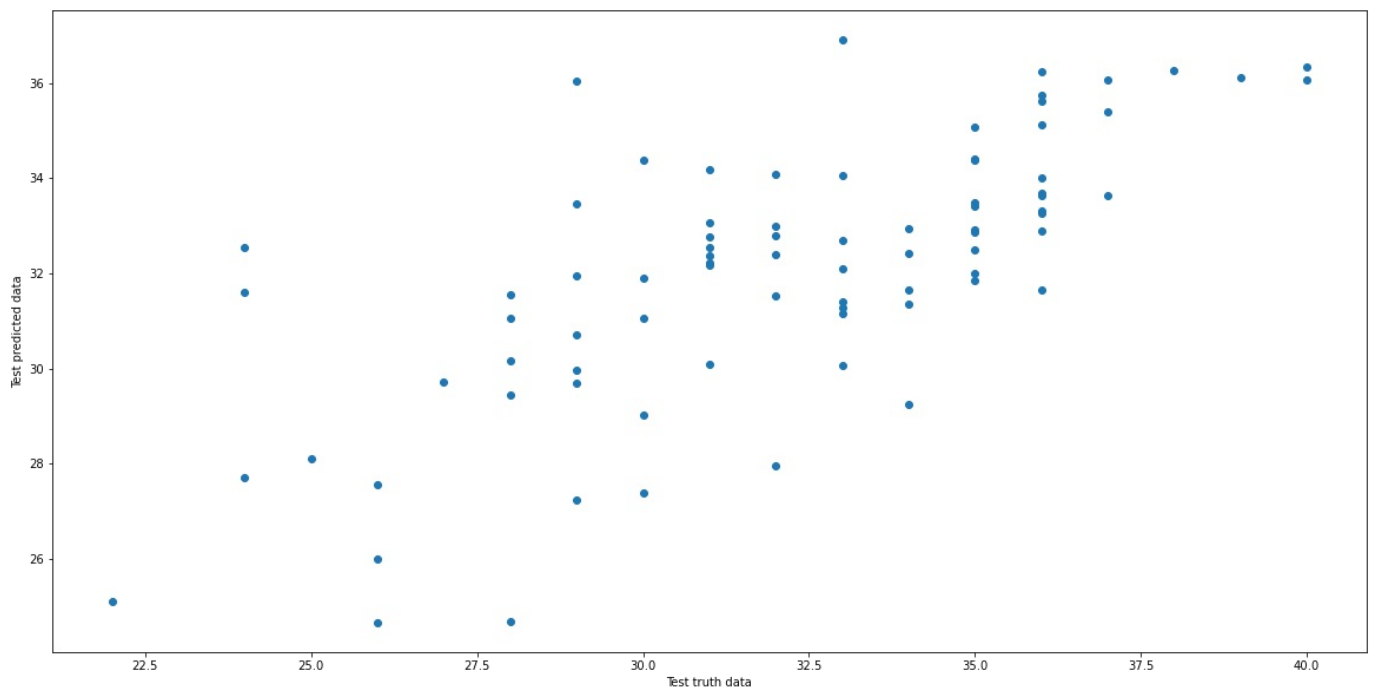
```
Out[154... <AxesSubplot:ylabel='Density'>
```



Assumption of Linear Regression

```
In [155... plt.scatter(y_test,reg_pred)
plt.xlabel("Test truth data")
plt.ylabel('Test predicted data')
```

```
Out[155... Text(0, 0.5, 'Test predicted data')
```



Residuals

```
In [156... residual=y_test-reg_pred
```

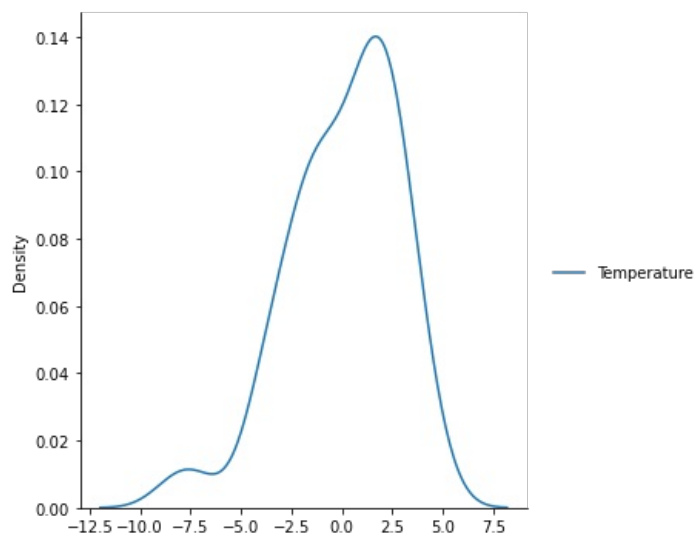
```
In [157...] residual
```

	Temperature
162	2.642717
60	1.515510
61	2.311144
63	2.995659
69	2.092086
...	...
169	0.315380
232	-7.042611
144	1.717902
208	-3.918630
105	-3.084772

81 rows × 1 columns

```
In [158...] sns.displot(residual,kind='kde')
```

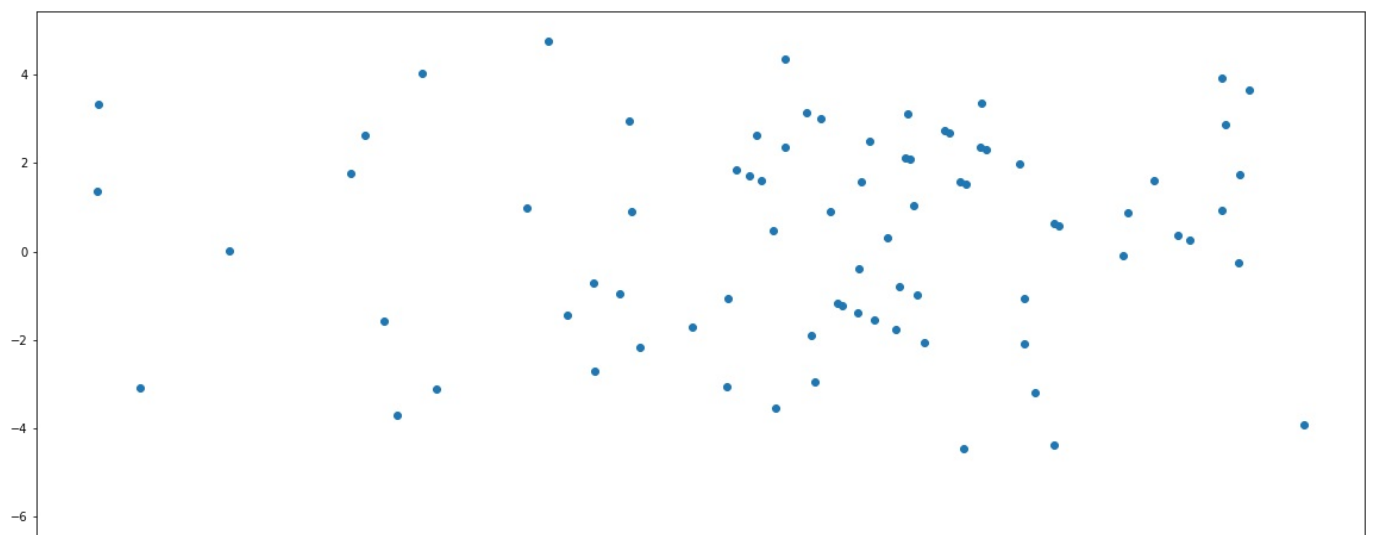
<seaborn.axisgrid.FacetGrid at 0x1c39909b550>

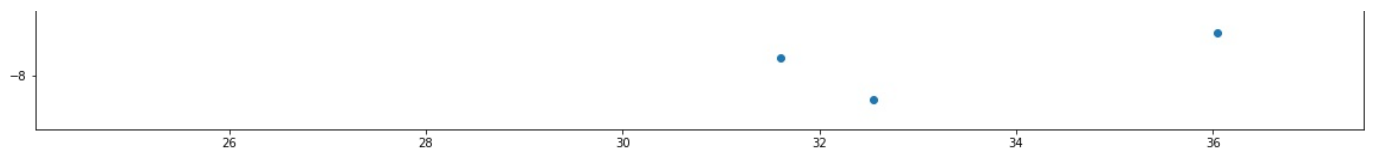


Scatterplot with prediction and residual

```
In [159...] plt.scatter(reg_pred,residual)
```

<matplotlib.collections.PathCollection at 0x1c39909a1c0>





Performance Metrics

```
In [160... 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)))
```

```
7.504766973062432
2.2354993752323624
2.739482975501478
```

R square and adjusted R square

```
In [161... from sklearn.metrics import r2_score
score=r2_score(y_test,reg_pred)
print(score)
```

```
0.5037314185907535
```

Adjusted R square

```
In [162... 1-(1-score)*(len(y_test)-1)/(len(y_test)-x_test.shape[1]-1)
```

```
Out[162... 0.43283590696086116
```

Ridge Regression Algorithm

```
In [163... from sklearn.linear_model import Ridge
```

```
In [164... ridge=Ridge()
```

```
In [165... ridge
```

```
Out[165... Ridge()
```

```
In [166... ridge.fit(x_train,y_train)
```

```
Out[166... Ridge()
```

```
In [167... ## Coefficient
print(ridge.coef_)
```

```
[[-1.25483718 -0.53296814 -0.20702885  0.72895886 -0.60290935 -0.32591751
  0.24045074  0.93900788  0.21118476 -0.1916003 ]]
```

```
In [168... ## Intercept
```

```
print(ridge.intercept_)
```

```
[32.17791411]
```

```
In [169]: ridge_pred=ridge.predict(x_test)
```

```
In [170]: ridge_pred
```

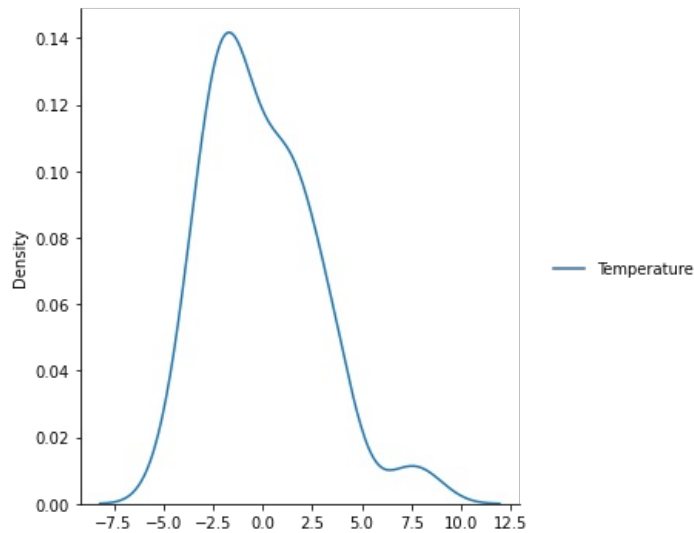
```
Out[170]: array([[31.35162743],  
 [33.40986612],  
 [33.72771064],  
 [32.07338971],  
 [32.90931259],  
 [35.0319983 ],  
 [32.79015818],  
 [34.17178646],  
 [31.97942736],  
 [33.01801414],  
 [33.36867288],  
 [27.41069432],  
 [35.06294721],  
 [29.21943029],  
 [31.86814167],  
 [32.4415311 ],  
 [34.32301905],  
 [28.10883976],  
 [36.28106232],  
 [34.1156651 ],  
 [32.5477257 ],  
 [34.12721932],  
 [32.95790766],  
 [33.29642758],  
 [36.10629748],  
 [29.45172695],  
 [31.55350828],  
 [32.44406184],  
 [27.6048532 ],  
 [32.16940933],  
 [26.0626233 ],  
 [27.15902083],  
 [34.09770279],  
 [31.64258349],  
 [32.74172122],  
 [31.00145744],  
 [29.02397313],  
 [33.02208479],  
 [27.70413671],  
 [35.54562191],  
 [32.78559985],  
 [33.71213911],  
 [34.19881056],  
 [31.48850848],  
 [36.06072934],  
 [33.43404309],  
 [24.81171141],  
 [35.7280546 ],  
 [33.67748084],  
 [29.73906751],  
 [31.08558962],  
 [32.40946204],  
 [36.27999474],  
 [32.1989361 ],  
 [30.22249483],  
 [30.08807274],  
 [32.52930384],  
 [36.1226345 ],  
 [31.43466997],  
 [33.42545678],  
 [32.07007099],  
 [32.74547017],  
 [30.74281953],  
 [24.73332347],  
 [31.51966611],  
 [36.32138028],  
 [30.00101555],  
 [29.64684244],  
 [35.40167579],  
 [34.05569841],  
 [28.00372035],  
 [32.50468393],  
 [31.96302548],  
 [31.53812647],  
 [30.11946542],  
 [31.09359251],
```



```
[32.75250885],
[35.95392448],
[31.27455865],
[37.0485867 ],
[25.1392405 ]])
```

```
In [171]: import seaborn as sns
sns.displot(ridge_pred-y_test, kind='kde')
```

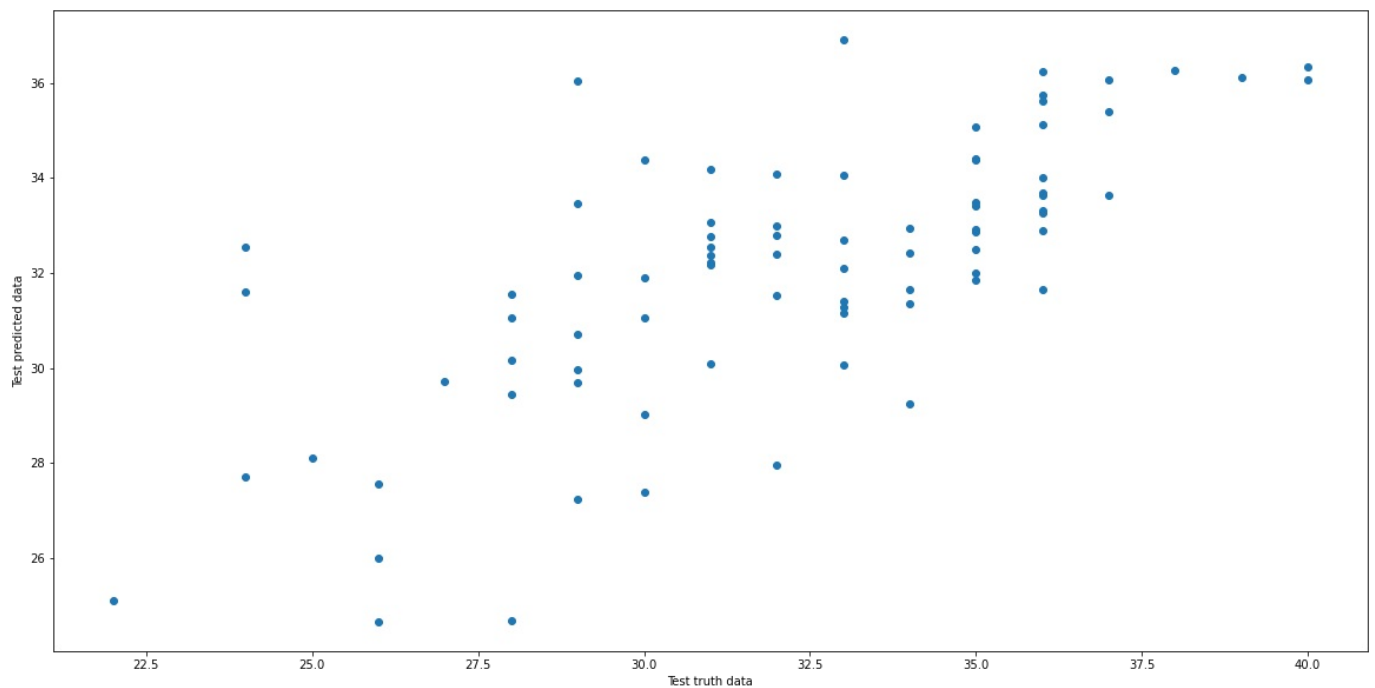
```
Out[171]: <seaborn.axisgrid.FacetGrid at 0x1c38911c880>
```



Assumption on Ridge Regression

```
In [172]: plt.scatter(y_test, reg_pred)
plt.xlabel("Test truth data")
plt.ylabel('Test predicted data')
```

```
Out[172]: Text(0, 0.5, 'Test predicted data')
```



```
In [173]: # Residual
residual=y_test-ridge_pred
```

```
In [174]: residual
```

Out[174...

	Temperature
162	2.648373
60	1.590134
61	2.272289
63	2.926610
69	2.090687
...	...
169	0.247491
232	-6.953924
144	1.725441
208	-4.048587
105	-3.139240

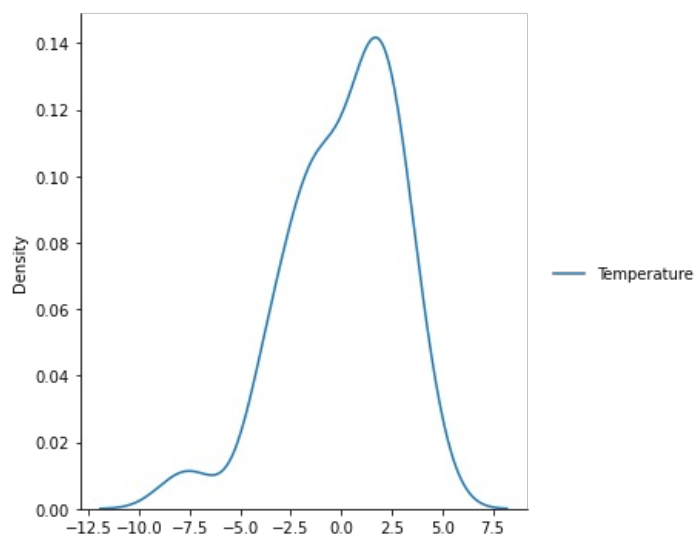
81 rows × 1 columns

In [175...

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

Out[175...

<seaborn.axisgrid.FacetGrid at 0x1c39956b520>



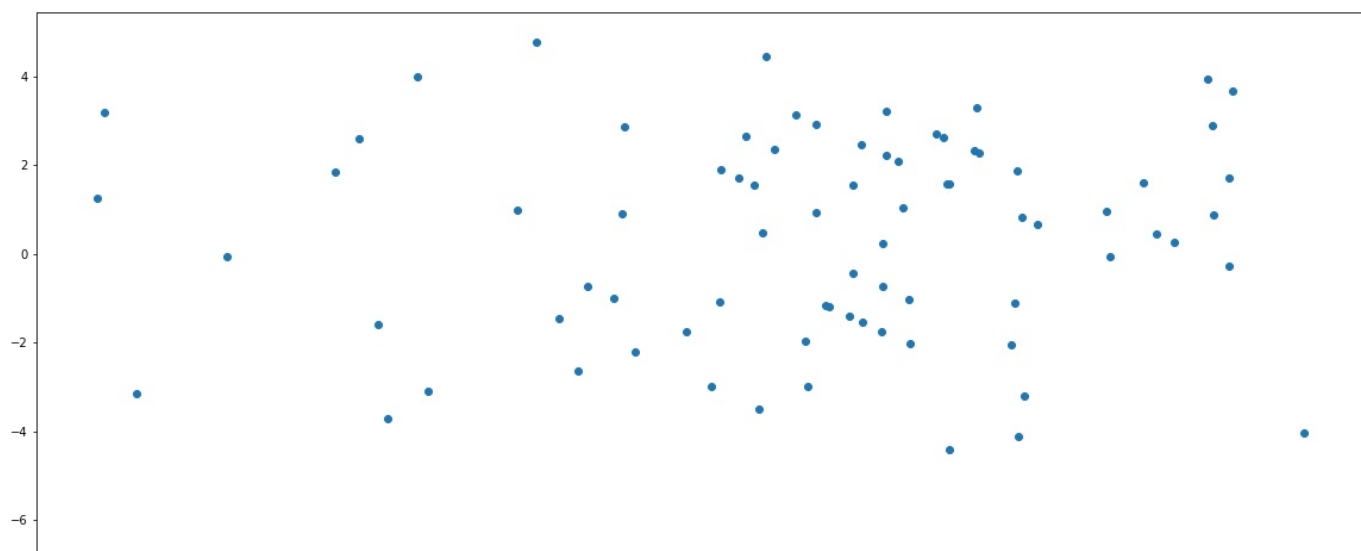
Scatter plot with residual and prediction

In [176...

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

Out[176...

<matplotlib.collections.PathCollection at 0x1c39c15e370>





Performance Matrics

```
In [177... from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
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)))
```

7.444528719288363
2.2355295943587614
2.728466367630058

R square

```
In [178... from sklearn.metrics import r2_score
ridge_score=r2_score(y_test,ridge_pred)
print(ridge_score)
```

0.5077148004671435

Adjusted R square

```
In [179... 1-(1-ridge_score)*(len(y_test)-1)/(len(y_test)-x_test.shape[1]-1)
```

Out[179... 0.43738834339102106

Lasso Regression

```
In [180... from sklearn.linear_model import Lasso
```

```
In [181... lasso=Lasso()
```

```
In [182... lasso
```

Out[182... Lasso()

```
In [183... lasso.fit(x_train,y_train)
```

Out[183... Lasso()

Coefficients and Intercepts

```
In [184... print(lasso.coef_)
```

```
[ -0.71955751 -0.          -0.          0.89582004  0.          -0.
  0.          0.          0.          -0.          ]
```

```
In [185... print(lasso.intercept_)
```

```
[32.17791411]
```

```
In [186...  ## Prediction for test data

lasso_pred = lasso.predict(x_test)
```

```
In [187... lasso_pred
```

```
Out[187... array([32.29700076, 32.6744027 , 33.06609539, 32.07346965, 32.92497671,
       33.33947653, 33.32111992, 32.77042154, 32.11916885, 32.70983221,
       33.15976154, 30.29861247, 34.17172792, 30.95174825, 33.0931383 ,
       32.31497272, 32.93691477, 29.42489766, 34.46059856, 33.50695377,
       32.46152593, 33.02899752, 33.30888217, 32.80645043, 34.5498142 ,
       30.18680443, 32.38908351, 32.89121556, 29.47641605, 31.8492542 ,
       29.50217524, 28.6091198 , 33.21226395, 32.70054654, 32.64380834,
       31.80937418, 30.23515603, 32.53110125, 29.22810977, 33.62676377,
       32.55104126, 33.23190428, 33.93112391, 31.84411936, 34.06445535,
       33.20742879, 29.78847846, 33.80519505, 33.21966653, 30.53913152,
       31.62769114, 32.373594 , 33.92016988, 32.24993288, 31.51301599,
       31.26381066, 32.303719 , 34.28571873, 31.84095256, 33.47507571,
       32.27184094, 32.20868418, 31.42230192, 29.36272493, 32.24706577,
       34.47767146, 31.13749714, 31.41648274, 33.33947653, 33.04221928,
       30.62774778, 32.69215994, 32.20868418, 31.45674741, 31.17557904,
       31.67565808, 32.4164261 , 33.56882682, 32.11728577, 34.26736212,
       29.66708507])
```

Performance Matrics

```
In [188... 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)))
```

```
9.10609532182792
2.4978660766652734
3.0176307464346794
```

R square

```
In [189... from sklearn.metrics import r2_score
lasso_score=r2_score(y_test,lasso_pred)
print(lasso_score)
```

```
0.39784019626969913
```

Adjusted R square

```
In [190... 1-(1-lasso_score)*(len(y_test)-1)/(len(y_test)-x_test.shape[1]-1)
```

```
Out[190... 0.31181736716537045
```

Elastic - Net regression

```
In [191... from sklearn.linear_model import ElasticNet
```

```
In [192... elastic=ElasticNet()
```

```
In [193... elastic
```

Out[193...] ElasticNet()

```
In [194...] elastic.fit(x_train,y_train)
```

Out[194...] ElasticNet()

Coefficients and Intercepts

```
In [195...] print(elastic.coef_)
```

```
[-0.69396083 -0.10315403 -0.01507374  0.6926462   0.10752205 -0.
 0.28392506  0.07544656  0.05920494 -0.          ]
```

```
In [197...] print(elastic.intercept_)
```

```
[32.17791411]
```

```
In [198...] ## Prediction for test data
elastic_pred = elastic.predict(x_test)
```

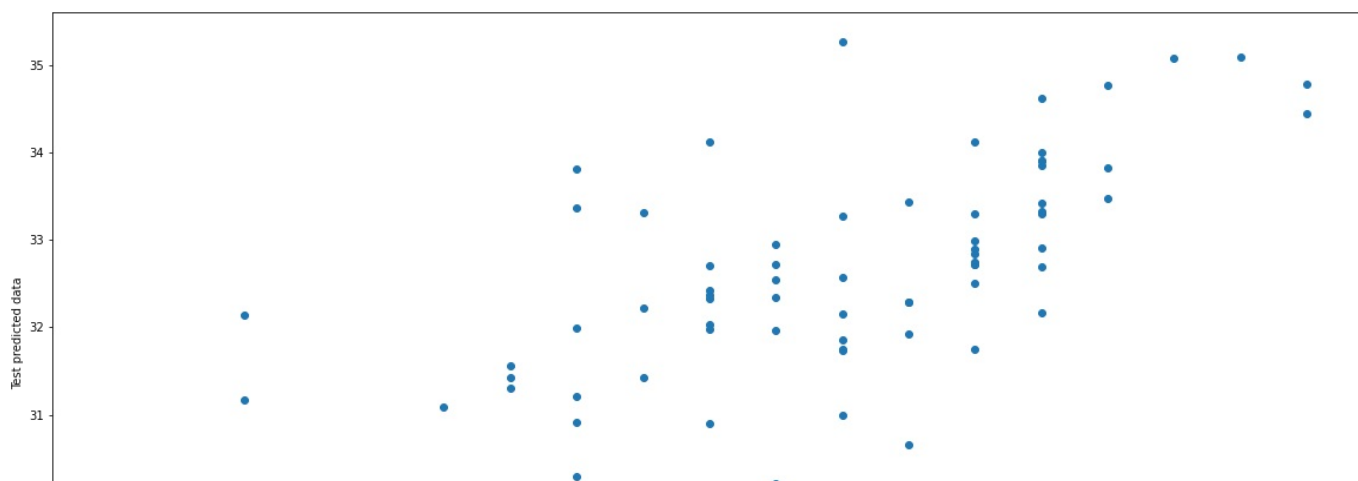
```
In [199...] elastic_pred
```

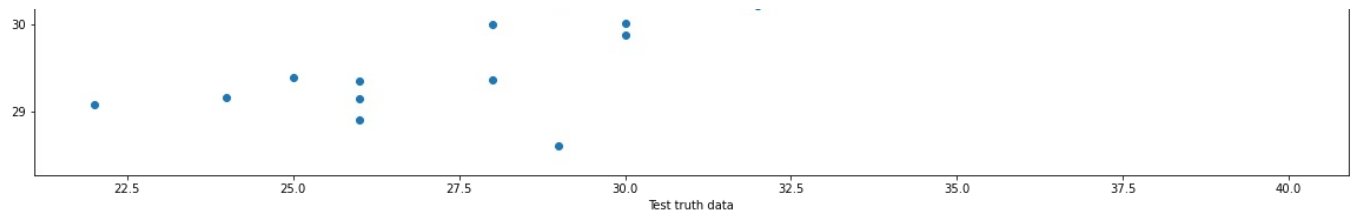
```
Out[199...] array([31.93076461, 32.89925279, 32.68965549, 31.74550697, 32.98836724,
        33.91299333, 33.41776043, 32.72078781, 31.98790062, 32.72490467,
        33.30044153, 29.87165926, 34.12217082, 30.65936304, 32.72255437,
        32.28333638, 32.84852051, 29.39040946, 35.0786389 , 33.86050655,
        32.42586731, 33.31820617, 33.43805315, 32.91463826, 35.09348452,
        29.99111145, 32.16696212, 32.5466324 , 29.35144729, 31.97557447,
        29.14216505, 28.60375228, 33.27376701, 32.28678221, 32.70561446,
        31.30843328, 30.01197805, 32.32347658, 29.15902087, 33.91042464,
        32.74766721, 33.47903767, 34.12940549, 31.56461381, 34.44958031,
        33.30036678, 29.35558024, 33.99794233, 33.3293338 , 30.2978916 ,
        31.4241864 , 32.36311525, 34.61701506, 32.03023331, 31.41948172,
        30.89419347, 32.508051 , 34.7691147 , 31.73370163, 33.3687946 ,
        32.1509131 , 32.34603101, 31.21296836, 28.90195873, 31.96458545,
        34.79046967, 30.91855019, 31.0841594 , 33.82121587, 32.95120309,
        30.20921418, 32.14232146, 32.22575701, 31.16525171, 30.98976689,
        31.86034438, 32.57697932, 33.81340658, 31.74661525, 35.27207415,
        29.07891997])
```

Assumption of Elastic Net Regression

```
In [200...] plt.scatter(y_test,elastic_pred)
plt.xlabel("Test truth data")
plt.ylabel('Test predicted data')
```

```
Out[200...] Text(0, 0.5, 'Test predicted data')
```





Performance Matrix

```
In [201... 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)))
```

```
8.34600759092681
2.3987645425349116
2.888945757698959
```

R square

```
In [202... from sklearn.metrics import r2_score
elastic_score=r2_score(y_test,elastic_pred)
print(elastic_score)
```

```
0.4481026043251144
```

Adjusted R square

```
In [204... 1-(1-elastic_score)*(len(y_test)-1)/(len(y_test)-x_test.shape[1]-1)
```

```
Out[204... 0.36926011922870217
```