## **Linear Regression on Algerian Fire Forest Dataset**

from IPython import display
display.Image("D:\\220818074357-02-algeria-fires-0817.jpg",
width=1000)



#### **Life Cycle of Machine Learning Project**

- Understanding the Problem Statement
- Data Collection
- Exploratory data analysis
- Data Cleaning
- Data Pre-Processing
- Model Training
- Choose best model

Dataset Link: 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 Belabbes 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 'fire' (138 classes) and 'not fire' (106 classes) classes.

#### Attribute Information:

•

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

.

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

.

a. RH: Relative Humidity in %: 21 to 90

•

a. Ws:Wind speed in km/h: 6 to 29

•

a. Rain: total day in mm: 0 to 16.8 FWI Components

•

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

•

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

•

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

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

•

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

•

a. Fire Weather Index (FWI) Index: 0 to 31.1

•

a. Classes: two classes, namely Fire and not Fire

#### **Problem Statement**

• Predict the tempreture using Linear Regression Algorithm

## # Importing necessary libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import cufflinks as cf
cf.go_offline
import plotly.express as px
%matplotlib inline
```

```
import warnings
warnings.filterwarnings('ignore')
# Importing dataset
df=pd.read csv("D:\Algerian forest fires dataset UPDATE (1).csv",
header=1)
df.head()
  day month
            year Temperature
                                 RH
                                     Ws Rain
                                                FFMC
                                                      DMC
                                                             DC
                                                                  ISI
                                                                       BUI
FWI
0 01
                                 57
                                               65.7
                                                            7.6
                                                                  1.3
         06
             2012
                            29
                                     18
                                            0
                                                      3.4
                                                                       3.4
0.5
1 02
             2012
                            29
                                 61
                                               64.4
         06
                                     13
                                          1.3
                                                      4.1
                                                            7.6
                                                                    1
                                                                       3.9
0.4
2 03
             2012
                            26
                                 82
                                     22
                                         13.1
                                               47.1
                                                      2.5
                                                            7.1
                                                                       2.7
         06
                                                                  0.3
0.1
3
                            25
  04
         06
             2012
                                 89
                                     13
                                          2.5
                                               28.6
                                                      1.3
                                                            6.9
                                                                    0
                                                                       1.7
0
4
             2012
                            27
                                 77
                                     16
                                             0
                                               64.8
                                                        3
                                                           14.2
                                                                       3.9
  05
         06
                                                                 1.2
0.5
     Classes
0
   not fire
   not fire
1
2
   not fire
3
   not fire
   not fire
df.shape
(246, 14)
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 246 entries, 0 to 245
Data columns (total 14 columns):
 #
     Column
                   Non-Null Count
                                    Dtype
                                    object
 0
     day
                   246 non-null
 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
                   245 non-null
                                    object
     Rain
 7
     FFMC
                   245 non-null
                                    object
 8
     DMC
                                    object
                   245 non-null
 9
     DC
                   245 non-null
                                    object
                   245 non-null
 10
     ISI
                                    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
df.columns
Index(['day', 'month', 'year', 'Temperature', ' RH', ' Ws', 'Rain ',
'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes '],
      dtype='object')
# We hav few extra space in column name
for feature in df.columns:
    df.rename(columns= {feature : feature.strip()}, inplace=True )
df.columns
Index(['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain',
'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes'],
      dtype='object')
df.isnull().sum()
day
month
               1
year
               1
Temperature
               1
RH
               1
               1
Ws
               1
Rain
FFMC
               1
DMC
               1
DC
               1
ISI
               1
BUI
               1
FWI
               1
Classes
               2
dtype: int64
#Deleting uneccesary rows
df.drop([122,123], axis=0, inplace=True)
# There is till one missing value present in dataset
df.isnull().sum()
day
month
               0
vear
               0
Temperature
               0
RH
               0
               0
Ws
```

```
FFMC
               0
DMC
               0
DC
               0
ISI
               0
BUI
               0
FWI
               0
Classes
               1
dtype: int64
#Checking which index have NaN value
df[df['Classes'].isna()]
                                                               DC
                                                                     ISI
    day month year Temperature RH Ws Rain
                                               FFMC
                                                      DMC
BUI
                                      18 0.2 88.9 12.9 14.6 9 12.5
167
     14
           07 2012
                             37 37
10.4
         FWI Classes
167
     fire
                 NaN
Observation
     At index 167 few column values are shifted towards left
# WE need range that enitities correctly
df.at[167, 'DC']=14.6
df.at[167, 'ISI']=9
df.at[167, 'BUI']=12.5
df.at[167, 'FWI']=10.4
df.at[167, 'Classes']='fire'
df.head()
  day month year Temperature
                                        Rain FFMC
                                                    DMC
                                                           DC
                                                               ISI BUI
                               RH
                                   Ws
FWI \
0 01
                               57
                                              65.7
                                                          7.6 1.3
         06
            2012
                           29
                                    18
                                           0
                                                    3.4
                                                                    3.4
0.5
1 02
         06
             2012
                           29
                               61
                                    13
                                         1.3 64.4
                                                    4.1
                                                          7.6
                                                                 1
                                                                    3.9
0.4
                               82
                                    22
                                                   2.5
2 03
         06
             2012
                           26
                                        13.1 47.1
                                                          7.1 0.3
                                                                    2.7
0.1
3
  04
         06
             2012
                           25
                               89
                                    13
                                         2.5
                                              28.6
                                                    1.3
                                                          6.9
                                                                 0
                                                                     1.7
0
4 05
         06
             2012
                           27
                               77
                                           0 64.8
                                                      3
                                                         14.2 1.2 3.9
                                    16
0.5
       Classes
   not fire
1
   not fire
   not fire
3
   not fire
   not fire
```

Rain

0

```
df.isna().sum()
day
                0
month
                0
                0
year
Temperature
               0
RH
                0
Ws
                0
                0
Rain
FFMC
                0
               0
DMC
DC
               0
ISI
               0
BUI
                0
FWI
                0
Classes
                0
dtype: int64
#Adding new column in dataset because we have two region present in
dataset
# From index 0-122 we have Bajaija region
# From index 122 onwards we have Sidi-Bel Abbes region
df.loc[:122, 'Region']='Bajaia'
df.loc[122:, 'Region']='Sidi-Bel Abbes'
Observtaion
     We added region columns for better understanding
df.dtypes
               object
day
month
               object
               object
year
Temperature
               object
RH
               object
Ws
                object
Rain
                object
FFMC
                object
DMC
                object
DC
               object
ISI
               object
BUI
                object
FWI
                object
Classes
               object
Region
               object
dtype: object
#here we combined day, month and year column together
df['date']=(df['day']+('/')+df['month']+('/')+df['year'])
df.date
```

```
0
       01/06/2012
1
       02/06/2012
2
       03/06/2012
3
       04/06/2012
4
       05/06/2012
241
       26/09/2012
242
       27/09/2012
243
       28/09/2012
244
       29/09/2012
245
       30/09/2012
Name: date, Length: 244, dtype: object
#Dropping day, month, year column
df.drop(['day', 'month', 'year'], axis=1, inplace=True)
df.head()
  Temperature
               RH
                   Ws
                       Rain
                             FFMC
                                    DMC
                                           DC
                                               ISI
                                                    BUI
                                                         FWI
Classes \
0
           29
               57
                   18
                          0
                             65.7
                                   3.4
                                          7.6
                                               1.3
                                                    3.4
                                                         0.5
                                                              not fire
1
           29
               61
                   13
                        1.3 64.4 4.1
                                          7.6
                                                 1
                                                    3.9
                                                         0.4
                                                               not fire
2
           26
               82
                   22
                       13.1
                             47.1 2.5
                                          7.1
                                               0.3
                                                    2.7
                                                         0.1
                                                               not fire
3
           25
               89
                   13
                        2.5
                             28.6
                                    1.3
                                          6.9
                                                 0
                                                    1.7
                                                               not fire
                                         14.2 1.2 3.9 0.5
           27
              77
                   16
                          0 64.8
                                      3
                                                              not fire
4
   Region
                 date
  Bajaia
           01/06/2012
0
1
  Bajaia
           02/06/2012
  Baiaia
           03/06/2012
3
   Bajaia
           04/06/2012
  Bajaia
           05/06/2012
df['Classes'].unique()
array(['not fire ', 'fire ', 'fire', 'fire ', 'not fire', 'not
fire '
       'not fire ', 'not fire
                                      '], dtype=object)
Observation
     Here we have few uneccesary spaces between classes entities
#striping uneccessary spaces
df['Classes']= [i.strip() for i in df['Classes']]
df.Classes.unique()
```

```
array(['not fire', 'fire'], dtype=object)
# Changing important columns datatypes
df.dtypes
Temperature
               object
RH
               object
Ws
               object
Rain
               object
FFMC
               object
DMC
               object
DC
               object
ISI
               object
BUI
               object
FWI
               object
Classes
               object
Region
               object
date
               object
dtype: object
Observation
     Few numeric columns have dtype as object
df.columns
Index(['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI',
'BUI',
       'FWI', 'Classes', 'Region', 'date'],
      dtype='object')
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['DC']=df['DC'].astype(float)
df['ISI']=df['ISI'].astype(float)
df['BUI']=df['BUI'].astype(float)
df['FWI']=df['FWI'].astype(float)
df['Temperature']=df['Temperature'].astype(int)
df.dtypes
Temperature
                  int32
RH
                  int32
Ws
                  int32
               float64
Rain
FFMC
               float64
               float64
DMC
DC
               float64
ISI
               float64
               float64
BUI
```

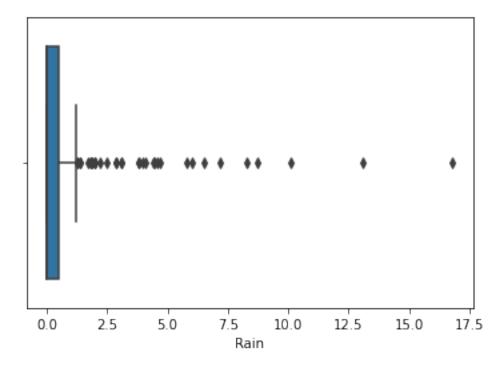
```
FWI
                float64
Classes
                 object
                 object
Region
date
                 object
dtype: object
df.head()
   Temperature
                 RH
                     Ws
                          Rain
                                 FFMC
                                       DMC
                                               DC
                                                   ISI
                                                         BUI
                                                              FWI
                                                                     Classes
\
                 57
                                              7.6
                                                   1.3
0
             29
                     18
                           0.0
                                 65.7
                                       3.4
                                                         3.4
                                                              0.5
                                                                    not fire
                           1.3
1
             29
                 61
                     13
                                 64.4
                                       4.1
                                                                    not fire
                                              7.6
                                                   1.0
                                                         3.9
                                                              0.4
2
             26
                 82
                     22
                          13.1
                                47.1
                                       2.5
                                              7.1
                                                   0.3
                                                         2.7
                                                              0.1
                                                                    not fire
3
             25
                 89
                     13
                           2.5
                                 28.6
                                       1.3
                                              6.9
                                                   0.0
                                                         1.7
                                                              0.0
                                                                    not fire
4
             27
                 77
                     16
                           0.0
                                64.8
                                       3.0
                                             14.2
                                                   1.2
                                                        3.9
                                                              0.5
                                                                    not fire
   Region
                  date
   Bajaia
            01/06/2012
   Bajaia
            02/06/2012
1
2
   Bajaia
            03/06/2012
3
   Bajaia
            04/06/2012
4
   Bajaia
            05/06/2012
df.shape
(244, 13)
#Checking duplicate values
df.duplicated().sum()
0
df.describe()
       Temperature
                              RH
                                           Ws
                                                       Rain
                                                                    FFMC
                                                                          \
                      244.000000
                                                244,000000
                                                             244.000000
        244.000000
                                   244.000000
count
                       61.938525
                                    15.504098
                                                  0.760656
                                                              77.887705
mean
         32.172131
          3.633843
                       14.884200
                                                              14.337571
std
                                     2.810178
                                                  1.999406
         22.000000
                       21.000000
                                     6.000000
                                                  0.000000
                                                              28.600000
min
          30.000000
25%
                       52.000000
                                    14.000000
                                                  0.000000
                                                              72.075000
50%
         32.000000
                       63.000000
                                    15.000000
                                                  0.000000
                                                              83.500000
75%
         35.000000
                       73.250000
                                    17,000000
                                                  0.500000
                                                              88.300000
         42.000000
                       90.000000
                                    29.000000
                                                 16.800000
                                                              96.000000
max
               DMC
                             DC
                                          ISI
                                                       BUI
                                                                    FWI
       244.000000
                                  244,000000
count
                    244.000000
                                               244.000000
                                                            244.000000
```

mean	14.673361	49.288115	4.759836	16.673361	7.049180
std	12.368039	47.619662	4.154628	14.201648	7.428366
min	0.700000	6.900000	0.000000	1.100000	0.000000
25%	5.800000	13.275000	1.400000	6.000000	0.700000
50%	11.300000	33.100000	3.500000	12.450000	4.450000
75%	20.750000	68.150000	7.300000	22.525000	11.375000
max	65,900000	220.400000	19.000000	68,000000	31.100000

• As we can see min, max, 24th, 50th and 75th percentile surely we have some outliers in few features

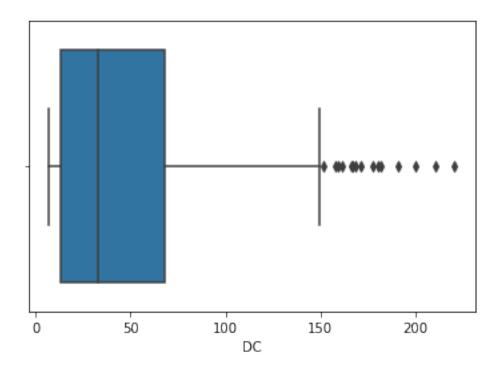
sns.boxplot(x=df['Rain'])

<AxesSubplot:xlabel='Rain'>



sns.boxplot(x=df['DC'])

<AxesSubplot:xlabel='DC'>



## **EDA and Feature Engineearning**

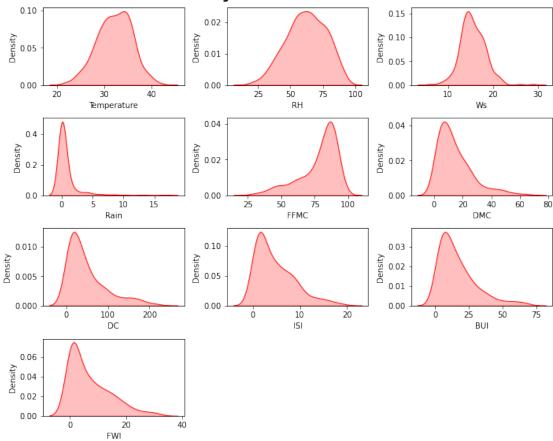
```
Num_col=[feature for feature in df.columns if df[feature].dtypes!='0']
Num_col

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

plt.figure(figsize= (10,10))
plt.suptitle('Univariate analysis on Numeric features', fontsize=30)

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

## Univariate analysis on Numeric features



#### Observation

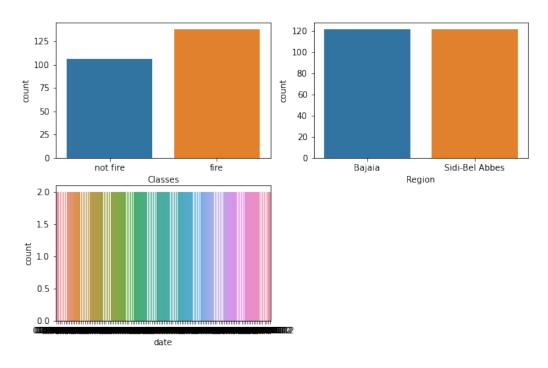
- Feature Tempreture, RH, WH are normally distrubuted
- Feature Rain, DC, ISI, BUI, FWI are right skewed and have outliers
- Feature FFMC, DMC are left skewed and have outliers

Cat\_col=[feature for feature in df.columns if df[feature].dtypes=='0']
Cat\_col

```
['Classes', 'Region', 'date']
plt.figure(figsize= (10,10))
plt.suptitle('Univariate analysis on Catogerical features',
fontsize=30)

for i in range(len(Cat_col)):
    plt.subplot(3, 2, i+1)
    sns.countplot(x=df[Cat_col[i]])
    plt.xlabel(Cat_col[i])
```

# Univariate analysis on Catogerical features



#### Observation

- In Classes feature there are more count of fire compared to no fire

## df.corr()

Temperature	RH	Ws	Rain	FFMC	
1.000000	-0.654443	-0.278132	-0.326786	0.677491	
-0.654443	1.000000	0.236084	0.222968	-0.645658	-
-0.278132	0.236084	1.000000	0.170169	-0.163255	-
-0.326786	0.222968	0.170169	1.000000	-0.544045	-
0.677491	-0.645658	-0.163255	-0.544045	1.000000	
0.483105	-0.405133	-0.001246	-0.288548	0.602391	
0.370498	-0.220330	0.076245	-0.296804	0.503910	
0.605971	-0.688268	0.012245	-0.347862	0.740751	
0.456415	-0.349685	0.030303	-0.299409	0.590251	
	1.000000 -0.654443 -0.278132 -0.326786 0.677491 0.483105 0.370498 0.605971	1.000000 -0.654443 -0.654443 1.000000 -0.278132 0.236084 -0.326786 0.222968 0.677491 -0.645658 0.483105 -0.405133 0.370498 -0.220330	1.000000 -0.654443 -0.278132 -0.654443 1.000000 0.236084 -0.278132 0.236084 1.000000 -0.326786 0.222968 0.170169 0.677491 -0.645658 -0.163255 0.483105 -0.405133 -0.001246 0.370498 -0.220330 0.076245 0.605971 -0.688268 0.012245	1.000000 -0.654443 -0.278132 -0.326786 -0.654443 1.000000 0.236084 0.222968 -0.278132 0.236084 1.000000 0.170169 -0.326786 0.222968 0.170169 1.000000 0.677491 -0.645658 -0.163255 -0.544045 0.483105 -0.405133 -0.001246 -0.288548 0.370498 -0.220330 0.076245 -0.296804 0.605971 -0.688268 0.012245 -0.347862	1.000000 -0.654443 -0.278132 -0.326786 0.677491 -0.654443 1.000000 0.236084 0.222968 -0.645658 -0.278132 0.236084 1.000000 0.170169 -0.163255 -0.326786 0.222968 0.170169 1.000000 -0.544045 0.677491 -0.645658 -0.163255 -0.544045 1.000000 0.483105 -0.405133 -0.001246 -0.288548 0.602391 0.370498 -0.220330 0.076245 -0.296804 0.503910 0.605971 -0.688268 0.012245 -0.347862 0.740751

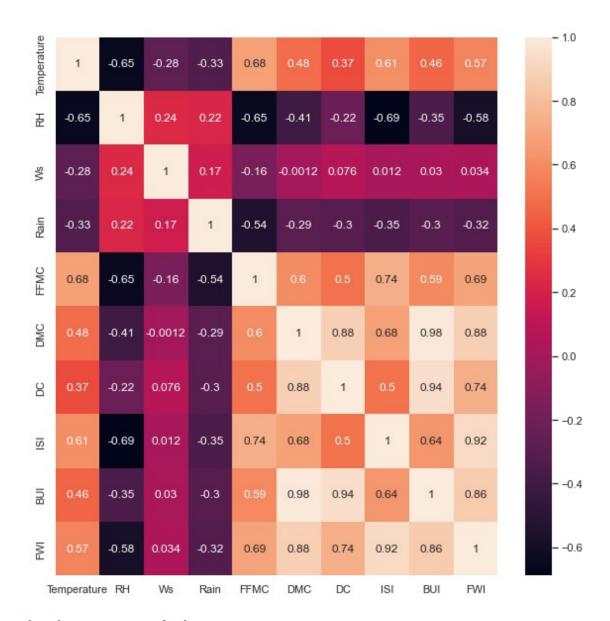
FWI 0.566839 -0.580457 0.033957 -0.324755 0.691430 0.875191

DC ISI BUI FWI

```
0.566839
Temperature 0.370498 0.605971 0.456415
RH
           -0.220330 -0.688268 -0.349685 -0.580457
Ws
            0.076245 0.012245 0.030303 0.033957
Rain
           -0.296804 -0.347862 -0.299409 -0.324755
            0.503910 0.740751 0.590251
FFMC
                                         0.691430
DMC
            0.875358 0.678355 0.982206
                                         0.875191
DC
            1.000000 0.503919 0.941672
                                         0.737041
ISI
            0.503919 1.000000 0.641351
                                         0.922422
BUI
            0.941672 0.641351 1.000000
                                         0.856912
FWI
            0.737041 0.922422 0.856912
                                         1.000000
```

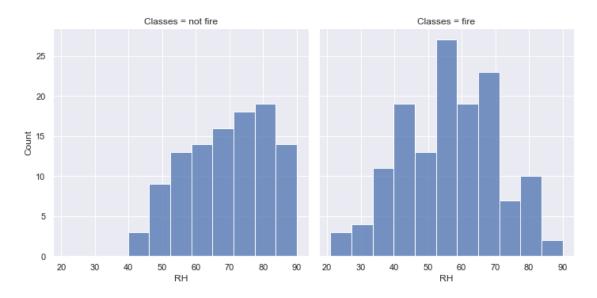
sns.set(rc={'figure.figsize':(10,10)})
sns.heatmap(df.corr(), annot=True)

<AxesSubplot:>



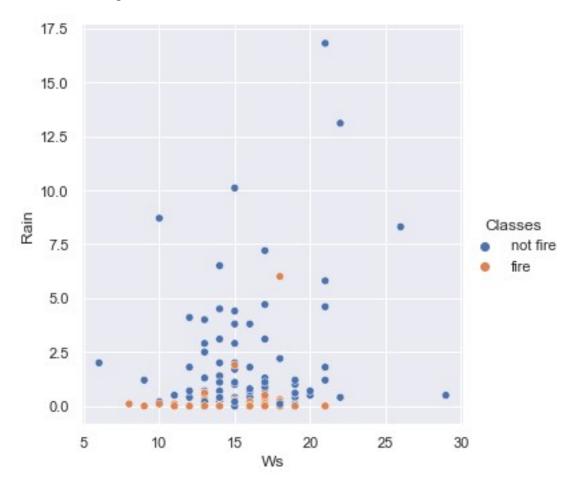
#### **Bivariate Data Analysis**

```
df.columns
```



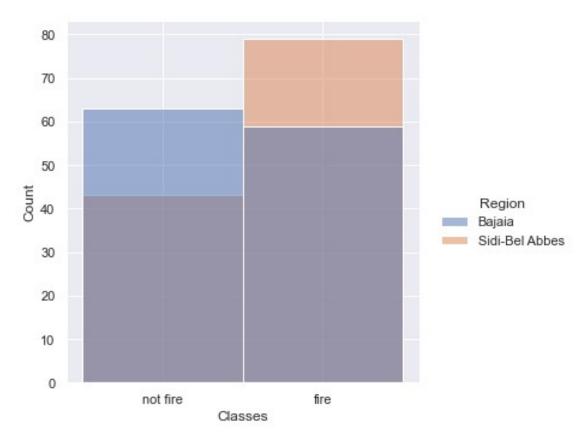
• RH(relative humidity) between range 40% - 70% rate of catching fire is high sns.relplot(data=df, x="Ws", y="Rain", hue="Classes")

<seaborn.axisgrid.FacetGrid at 0x213f73d4a60>



- Whenever there is less Ws(Wind speed) the chances of rain are less, so chances of catching fire is high (most of fire shown in this phase)
- $\bullet$  Whenever there is high Ws(Wind speed) the chances of rain are high, so chances of catching fire is less

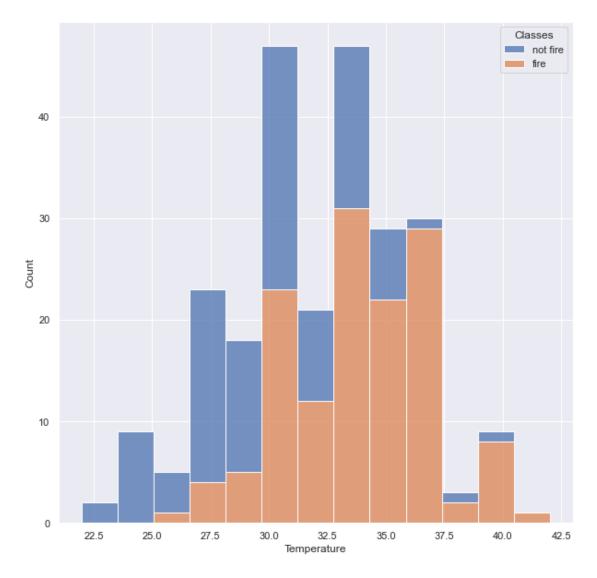
```
sns.displot(df, x='Classes', hue='Region')
<seaborn.axisgrid.FacetGrid at 0x213f6d697f0>
```



#### Observation

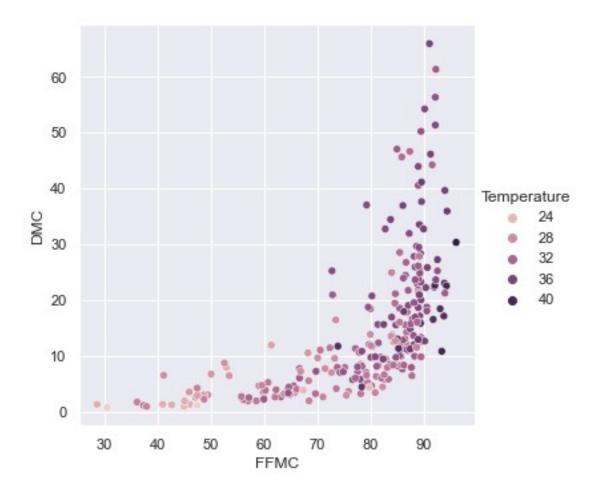
 As compared to Sidi-Bel Abbes region Bajaija region has more fire cases sns.histplot(data=df, x="Temperature", hue="Classes", multiple="stack")

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



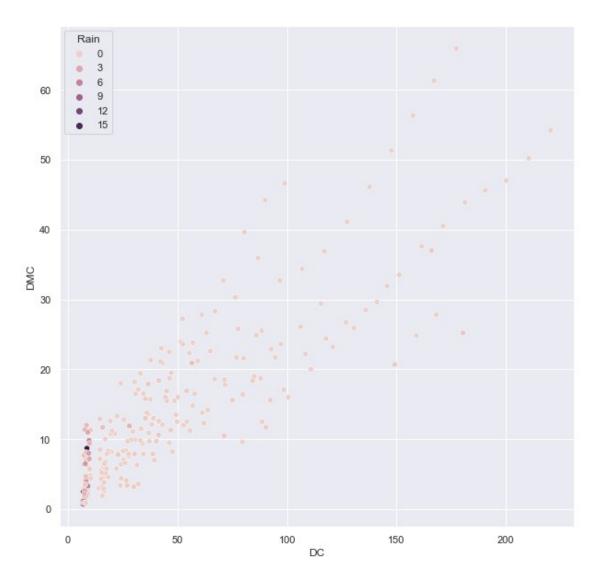
• The relationship between Temperature and Classes are directly propotional sns.relplot(data=df, x="FFMC", y="DMC", hue="Temperature")

<seaborn.axisgrid.FacetGrid at 0x213f842a310>



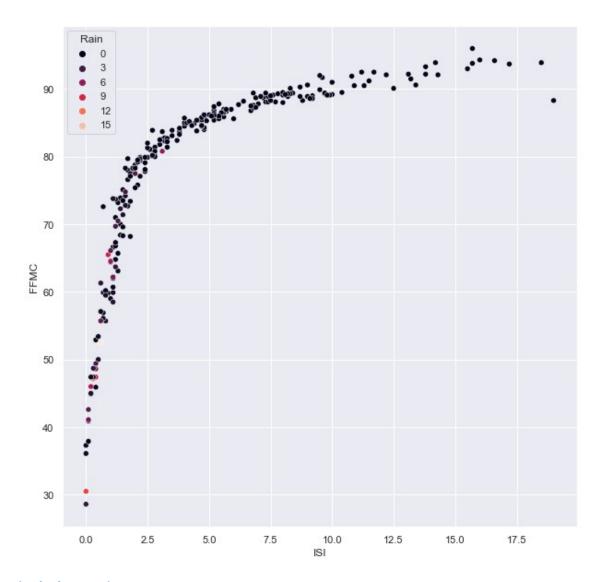
• Feature FFMC(Fine Fuel Moisture Code), DMC(Duff Moisture Code) increses exponentially with respect to Temperature

df.columns



• As we can see when DC(Drought Code) increses along with DMC(Duff Moisture Code ) chances of Rain are very less

```
sns.scatterplot(data=df,x='ISI', y='FFMC', hue='Rain',
palette='rocket')
<AxesSubplot:xlabel='ISI', ylabel='FFMC'>
```



#### **Final Observation**

- As compared to Sidi-Bel Abbes region Bajaia region have more fire cacthed cases
- Increase in feature Tempreture, Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC) showns more fire cases
- While feature like Increase in Ws (Wind speed), Rain showns less chances of fire catched

df.columns

```
ISI
   Temperature
                 RH
                     Ws
                         Rain
                                FFMC
                                      DMC
                                             DC
                                                       BUI
                                                            FWI
                                                                  Classes
Region
                           0.0
                                65.7
                                                                 not fire
             29
                 57
                     18
                                      3.4 7.6
                                                 1.3
                                                       3.4
                                                            0.5
Bajaia
df.Classes.unique()
array(['not fire', 'fire'], dtype=object)
df["Classes"]=df["Classes"].map({'not fire':0, 'fire':1})
df.Region.unique()
array(['Bajaia', 'Sidi-Bel Abbes'], dtype=object)
df['Region']=df["Region"].map({'Bajaia':0, 'Sidi-Bel Abbes':1})
df
     Temperature
                            Rain
                                  FFMC
                                          DMC
                                                 DC
                                                     ISI
                                                            BUI
                   RH
                       Ws
                                                                 FWI
Classes \
               29
                   57
                       18
                             0.0
                                  65.7
                                          3.4
                                                7.6
                                                                 0.5
                                                     1.3
                                                            3.4
0
                             1.3 64.4
1
               29
                       13
                                                7.6
                                                                 0.4
                   61
                                          4.1
                                                     1.0
                                                            3.9
0
2
               26
                   82
                       22
                            13.1 47.1
                                          2.5
                                                7.1
                                                     0.3
                                                            2.7
                                                                 0.1
0
3
               25
                   89
                       13
                             2.5
                                  28.6
                                          1.3
                                                6.9
                                                     0.0
                                                            1.7
                                                                 0.0
0
4
               27
                   77
                       16
                                          3.0
                                               14.2
                             0.0
                                  64.8
                                                      1.2
                                                            3.9
                                                                 0.5
0
                             . . .
                                          . . .
. .
                   . .
                        . .
                                   . . .
                                                . . .
                                                      . . .
              . . .
                                  85.4
                                               44.5
241
               30
                   65
                       14
                             0.0
                                         16.0
                                                     4.5
                                                           16.9
                                                                 6.5
1
242
               28
                   87
                       15
                             4.4
                                  41.1
                                          6.5
                                                8.0
                                                            6.2
                                                                 0.0
                                                     0.1
243
               27
                   87
                       29
                             0.5
                                 45.9
                                          3.5
                                                7.9
                                                     0.4
                                                            3.4
                                                                 0.2
244
               24
                   54
                       18
                             0.1
                                  79.7
                                          4.3
                                               15.2
                                                     1.7
                                                            5.1
                                                                 0.7
               24
                   64
                       15
                             0.2 67.3
                                          3.8
                                               16.5
                                                     1.2
                                                            4.8
                                                                 0.5
245
0
     Region
0
          0
1
          0
2
          0
3
          0
4
          0
241
          1
```

```
242
           1
243
           1
244
           1
245
           1
[244 rows x 12 columns]
#### Independant and dependant feature
X=df.iloc[:, 1:]
Χ
     RH
          Ws
              Rain
                     FFMC
                             DMC
                                    DC
                                         ISI
                                                BUI
                                                     FWI
                                                           Classes
                                                                     Region
                     65.7
                                         1.3
0
     57
          18
               0.0
                                   7.6
                                                3.4
                                                     0.5
                             3.4
                                         1.0
1
     61
                     64.4
                                                     0.4
                                                                  0
          13
               1.3
                             4.1
                                   7.6
                                                3.9
                                                                           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
241
     65
          14
               0.0
                     85.4
                            16.0
                                  44.5
                                         4.5
                                               16.9
                                                     6.5
                                                                  1
                                                                           1
                     41.1
242
     87
          15
                             6.5
                                   8.0
                                         0.1
                                                6.2
                                                                  0
                                                                           1
               4.4
                                                     0.0
                                                                           1
243
     87
          29
               0.5
                     45.9
                             3.5
                                   7.9
                                         0.4
                                                3.4
                                                     0.2
                                                                  0
244
     54
          18
               0.1
                     79.7
                             4.3
                                  15.2
                                         1.7
                                                5.1
                                                     0.7
                                                                  0
                                                                           1
245
          15
               0.2
                     67.3
                                  16.5
                                                                           1
     64
                             3.8
                                         1.2
                                                4.8
                                                     0.5
                                                                  0
[244 rows x 11 columns]
y=df.iloc[:, :1]
У
     Temperature
0
               29
1
               29
2
               26
3
               25
4
               27
241
               30
242
               28
243
               27
244
               24
               24
245
[244 rows x 1 columns]
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=30)
X_train
```

	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	
Regi	on										
231	26	13	0.0	93.9	21.2	59.2	14.2	22.4	19.3	1	
1											
159	42	15	0.3	84.7	15.5	45.1	4.3	16.7	6.3	1	
1											
227	72	14	0.0	84.2	8.3	25.2	3.8	9.1	3.9	1	
1											
87	82	21	0.0	84.9	47.0	200.2	4.4	59.3	13.2	1	
0											
6	54	13	0.0	88.2	9.9	30.5	6.4	10.9	7.2	1	
0											
•										_	
142	67	14	4.5	64.6	4.4	8.2	1.0	4.2	0.4	0	
1											
45	/6	21	0.0	72.6	7.0	25.5	0.7	8.3	0.4	0	
0										_	
175	48	18	0.0	91.5	44.2	90.1	13.2	44.0	25.4	1	
1										_	
167	37	18	0.2	88.9	12.9	14.6	9.0	12.5	10.4	1	
1											
37	68	19	0.0	85.6	12.5	49.8	6.0	15.4	8.0	1	
0											

[163 rows x 11 columns]

y\_train

	Temperature
231	33
159	35
227	31
87	33
6	33
142	32
45	28
175	32
167	37
37	33

[163 rows x 1 columns]

X\_test

	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
51	79	18	0.1	73.4	16.4	79.9	1.8	21.7	2.8	0	0
224	80	15	0.0	83.1	7.9	34.5	3.5	10.0	3.7	1	1
41	75	13	0.1	75.1	7.9	27.7	1.5	9.2	0.9	0	Θ
192	56	11	0.0	87.4	11.2	20.2	5.2	11.0	5.9	1	1

```
67
                   86.5 15.5
                                48.6 5.5
                                                   8.0
     69
         16
              0.0
                                            17.2
                                                               1
              . . .
                                                    . . .
                                                             . . .
245
     64
         15
              0.2
                    67.3
                           3.8
                                16.5
                                       1.2
                                             4.8
                                                   0.5
                                                               0
172
     58
         16
              0.0
                   88.1
                          27.8
                                61.1
                                       7.3
                                            27.7
                                                  13.0
                                                               1
                                       8.2
                   88.9
                          23.8
                                                               1
183
     56
         16
              0.0
                                57.1
                                            23.8
                                                  13.2
199
     46
         13
              0.3
                    83.9
                          16.9
                                54.2
                                       3.5
                                            19.0
                                                   5.5
                                                               1
                                                               0
125
     73
         13
              4.0
                   55.7
                           2.7
                                 7.8
                                       0.6
                                             2.9
                                                   0.2
[81 rows x 11 columns]
y_test
     Temperature
51
              28
224
              30
41
              31
192
              37
67
              32
245
              24
172
              34
183
              36
199
              35
125
              30
[81 rows x 1 columns]
#### Model Training
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
X train=scaler.fit transform(X train)
X train
array([[-2.27212014, -0.90068636, -0.36944043, ..., 1.66828808,
         0.90061707,
                       1.03116009],
       [-1.24886175, -0.22413393, -0.22001415, \ldots, -0.08645353,
         0.90061707,
                       1.031160091,
       [0.66974773, -0.56241015, -0.36944043, \ldots, -0.41040582,
         0.90061707,
                      1.03116009],
                       0.79069471, -0.36944043, ...,
                                                       2.49166684,
       [-0.86513986,
         0.90061707,
                       1.03116009],
                       0.79069471, -0.26982291, ...,
       [-1.56863]
                                                       0.46696498.
                       1.03116009],
         0.90061707,
       [ 0.41393313,
                       1.12897092, -0.36944043, ..., 0.14301268,
         0.90061707, -0.96978152]
```

0

1

1

1

1

1

. . .

```
X test=scaler.transform(X_test)
X test
array([[ 1.11742327, 0.79069471, -0.31963167, -0.28472323,
0.16888849,
         0.70985894, -0.6911055 , 0.38668233, -0.55888396, -
1.11034982,
        -0.96978152],
       [ 1.18137692, -0.22413393, -0.36944043, 0.37189273, -
0.55043215,
        -0.27510311, -0.29616771, -0.45610838, -0.43740185,
0.90061707,
         1.03116009],
       [ 0.86160868, -0.90068636, -0.31963167, -0.16964621, -
0.55043215,
        -0.42263047, -0.76080041, -0.5137351 , -0.8153462 , -
1.11034982,
        -0.96978152],
       [-0.35351066, -1.57723878, -0.36944043, 0.6629699 , -
0.27116649,
        -0.58534446, 0.09877008, -0.38407499, -0.14044558,
0.90061707,
         1.03116009],
       [0.47788678, 0.11414228, -0.36944043, 0.60204677,
0.09272513.
         0.0307992 , 0.16846498, 0.06253206, 0.14301268,
0.90061707,
        -0.96978152],
       [ 0.92556232, 0.45241849, 3.21679024, -2.13949408, -
1.10896348,
        -0.8608735 , -1.06281166, -1.04678222, -0.92333029, -
1.11034982,
        -0.96978152],
       [ 0.54184043, 0.45241849, 0.02902964, -0.33210789,
0.91359693,
         2.89022647, -0.71433714, 1.51760663, -0.36991179, -
1.11034982,
        -0.96978152],
       [-0.67327891, 0.45241849, 0.27807344, -0.42010796, -
0.56735734.
        -0.86304302, -0.76080041, -0.65059855, -0.82884421, -
1.11034982,
         1.03116009],
       [-1.37676905, 0.79069471, -0.36944043, 0.98112403,
3.54546423,
         2.39340641. 2.21284884. 3.10954465. 3.26105354.
0.90061707,
         1.03116009],
       [ 0.92556232, -0.56241015, -0.36944043,  0.23650799, -
0.53350696,
```

```
-0.61788726, -0.50525242, -0.59297183, -0.63987203, -
1.11034982,
       -0.96978152],
       [ 0.47788678, 0.45241849, 1.97157126, -1.04287774, -
0.88893599.
        -0.8500259 , -0.85372694, -0.90271543, -0.88283626, -
1.11034982.
         1.03116009],
       [-0.54537161, 0.79069471, -0.36944043, 0.77127769,
0.60894348.
         0.71853702, 1.02803547, 0.68201925, 1.08787355,
0.90061707,
        -0.96978152],
       [ 0.79765503, -0.22413393, 0.17845592, -1.22564713, -
0.82123522,
        -0.84568686, -0.92342185, -0.84508872, -0.89633427, -
1.11034982,
        1.03116009],
       [ 0.22207218, 0.79069471, -0.36944043, 0.45312357, -
0.16115275,
         0.90077669, 0.00584354, 0.15617547, 0.0485266,
0.90061707,
        -0.96978152],
       [-1.56863 , 0.11414228, -0.36944043, 0.98789326,
3.96859402,
         2.60384984, 1.93406922, 3.43369493, 3.15306944,
0.90061707,
         1.03116009],
       [ 0.09416488, -0.56241015, -0.22001415, -0.06810766, -
0.73660926,
        -0.8066355 , -0.71433714, -0.78025866, -0.82884421, -
1.11034982,
        -0.969781521,
       [-0.99304716, -0.56241015, 0.17845592, 0.04696937, -
0.53350696.
        -0.84351734, -0.66787387, -0.62178519, -0.77485216, -
1.11034982,
         1.03116009],
       [-0.60932526, 0.79069471, -0.36944043, 0.7915854 ,
0.13503811,
         1.16111908, 1.14419364, 0.47312241, 1.0338815,
0.90061707,
        -0.96978152],
       [ 1.69300612, -0.90068636, -0.26982291, -1.67241675, -
0.55043215,
        -0.18181376, -1.01634839, -0.42009169, -0.89633427, -
1.11034982,
        -0.969781521,
       [-0.80118621, -0.22413393, -0.36944043, 0.78481616,
0.87974654.
```

```
2.42811873, 0.77248749, 1.39514986, 1.22285367,
0.90061707,
         1.03116009],
       [ 0.09416488, -0.56241015, -0.36944043, 0.63589296, -
0.29655428.
        -0.22086512, 0.19169662, -0.2760249, -0.01896347,
0.90061707,
        -0.96978152],
       [-0.16164972, 0.45241849, -0.36944043, 0.71035456, -
0.20346572.
         0.12191903, 0.67956095, 0.13456545, 0.53445504,
0.90061707,
        -0.96978152],
       [-0.03374242, -0.90068636, 0.27807344, -0.89395453, -
0.87201079,
        -0.85870398, -0.87695858, -0.89551209, -0.88283626, -
1.11034982,
        -0.96978152],
       [ 1.69300612, -0.90068636, -0.36944043, -0.44718491, -
0.99894973.
        -0.66344718, -0.83049531, -0.90991877, -0.86933824, -
1.11034982,
       -0.96978152],
       [-0.22560336, -0.90068636, -0.26982291, 0.12820021, 0.3635282]
         0.88559005, -0.6214106, 0.5811725, -0.42390384, -
1.11034982,
         1.03116009],
       [ 0.34997948, 1.12897092, -0.36944043, -0.1493385 , -
0.97356194,
        -0.66995574, -0.64464223, -0.88830875, -0.82884421, -
1.11034982,
         1.031160091,
       [-0.41746431, -1.57723878, -0.36944043, 0.69004685,
0.17735109.
         0.23256455, 0.14523335, 0.20659885, 0.18350672,
0.90061707,
        -0.96978152],
       [ 0.15811853, 0.45241849, -0.36944043, 0.64943143,
1.48059085,
         2.13740306, 0.47047623, 1.79133353, 1.18235964,
0.90061707,
        -0.96978152],
       [ 0.60579408, -0.22413393, -0.36944043,  0.56820059,
1.90372064,
         1.51692035, 0.07553844, 1.79853687, 0.7099292,
0.90061707,
         1.031160091,
       [ 0.28602583, -1.57723878, -0.36944043, 0.54789288, -
0.51658177.
```

```
-0.48337703, -0.18000954, -0.52814178, -0.3834098,
0.90061707,
        -0.96978152],
       [ 1.05346962, -0.56241015, -0.36944043, 0.22973876, -
0.68583369,
        -0.33801919, -0.50525242, -0.57136182, -0.63987203,
0.90061707,
        -0.96978152],
       [-0.73723256, 0.11414228, -0.36944043, 0.83220082,
1.54829161.
         0.51677166, 1.09773037, 1.17184634, 1.39832783,
0.90061707,
         1.03116009],
       [-0.80118621, 1.12897092, -0.36944043, 0.74420074, -0.2457787]
        -0.29896783, 1.00480383, -0.28322824, 0.45346697,
0.90061707,
         1.03116009],
       [ 0.86160868, 0.11414228, -0.36944043, 0.3109696 , -
0.84662301.
        -0.49639415, -0.34263098, -0.74424196, -0.599378
0.90061707,
         1.03116009],
       [-0.22560336, 0.45241849, -0.36944043, 0.76450845,
0.58355569,
        -0.20350896, 0.91187729, 0.35066564, 0.80441529,
0.90061707,
         1.031160091,
       [ 0.73370138, 0.45241849, 0.0788384 , -1.05641621, -
0.99894973,
        -0.84134782, -0.85372694, -0.96034215, -0.88283626, -
1.11034982,
        -0.969781521,
       [ 1.82091342, -0.22413393, -0.36944043, -0.73149285, -
0.60967032.
        -0.70466806, -0.83049531, -0.66500523, -0.85584023, -
1.11034982,
         1.031160091.
       [ 0.98951597, -0.22413393, 0.12864716, -1.45580117, -
1.04126271,
        -0.84134782, -0.94665348, -0.98915551, -0.90983228, -
1.11034982,
        -0.96978152],
       [-0.16164972, 1.12897092, -0.36944043, 0.77804693,
1.13362442,
         2.62554504, 1.16742528, 1.65447008, 1.68178609,
0.90061707,
         1.031160091,
       [\ 0.60579408,\ -1.23896257,\ -0.02077911,\ -1.38810881,\ -
1.00741233.
```

```
-0.84568686, -0.96988512, -0.97474883, -0.90983228, -
1.11034982,
         1.03116009],
       [-0.09769607, -0.22413393, -0.36944043, 0.76450845,
2.49610234,
         2.90975215, 0.79571912, 2.76378436, 1.80326821,
0.90061707,
        -0.96978152],
       [-1.24886175, 1.80552335, -0.36944043, 0.87958548,
0.32121522.
        \hbox{-0.36188391,} \quad \hbox{2.00376413,} \quad \hbox{0.12015877,} \quad \hbox{1.31733976,}
0.90061707,
         1.03116009],
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```

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```

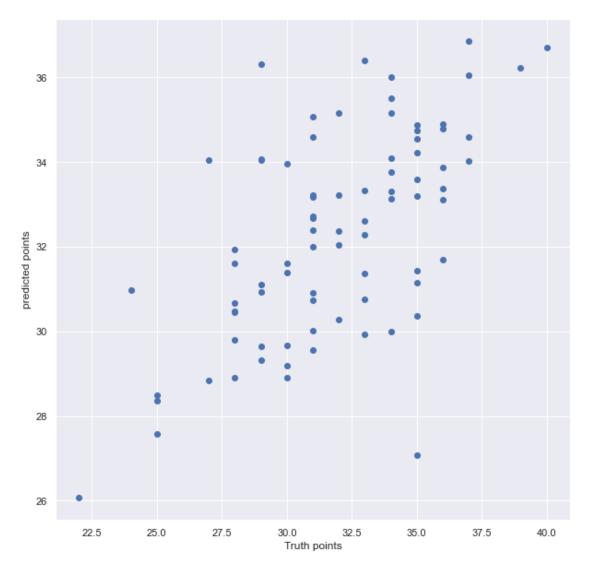
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```

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```

```
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1.11034982.
         1.03116009]])
#### Model Training
from sklearn.linear model import LinearRegression
regression=LinearRegression()
regression
LinearRegression()
regression.fit(X train, y train)
LinearRegression()
print(regression.coef )
[[-1.21117536 \ -0.56706065 \ -0.12035252 \ 0.79369256 \ -3.55532765 \ -
1.72320298
   0.49361804 5.46481362 -0.04530436 0.31041538 0.1591916 ]]
print(regression.intercept )
[32.3190184]
#### Prediction for the test data
reg pred=regression.predict(X test)
reg pred
array([[29.80432572],
       [31.61071065],
       [30.73014592],
       [34.58491894],
       [32.35863837],
       [27.58007776],
       [30.36907285],
       [31.94145267],
       [36.01307871],
       [30.75069173],
       [29.54877507],
       [34.09509279],
       [29.64882182],
       [32.00585198],
       [36.40617546],
       [31.42711725],
```

```
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[33.12666656],
[30.4810564],
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[33.1030309],
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[31.60202042],
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[28.89787311],
[33.96700741],
[30.28273097],
[34.8669716],
[35.06170097],
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[31.68988943],
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[33.3634101],
[34.07017095],
[34.89172421],
[33.29372785],
[33.2248847],
[36.84607614],
[30.91854501],
[31.36269269],
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[32.27919608],
[32.60007873],
[32.38141252],
[35.50179954],
[36.70607581],
[29.92935775],
[26.08386059],
[36.22513487],
[30.66696089],
[31.11362841],
[31.14057926],
```

```
[36.05348884],
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       [30.44540749],
       [35.14557424],
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       [33.18585853],
       [32.71730626],
       [30.01110205],
       [27.06618946],
       [34.22490375],
       [30.98029946],
       [33.7562864],
       [33.87397263],
       [34.74045167],
       [29.65709425]])
#### Assumption of linear Regression
plt.scatter(y_test, reg_pred)
plt.xlabel("Truth points")
plt.ylabel("predicted points")
Text(0, 0.5, 'predicted points')
```

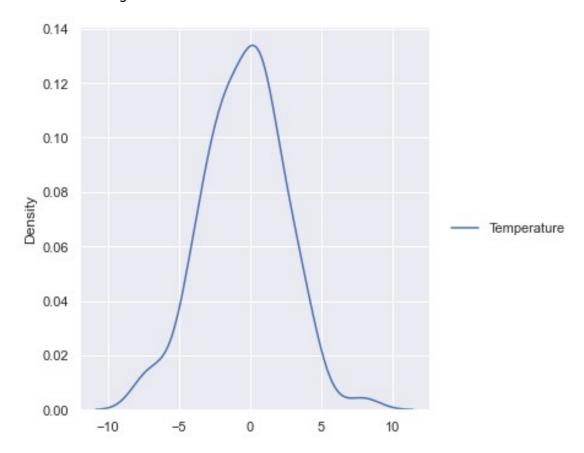


With respect to test data and predicted data our scatter plot should be linearly disrubuted residuals=y\_test-reg\_pred

## residuals

51 224 41 192 67	Temperature -1.804326 -1.610711 0.269854 2.415081 -0.358638
245	-6.980299
172	0.243714
183	2.126027
199	0.259548
125	0.342906

[81 rows x 1 columns]
sns.displot(residuals, kind='kde')
<seaborn.axisgrid.FacetGrid at 0x213f72e4c70>

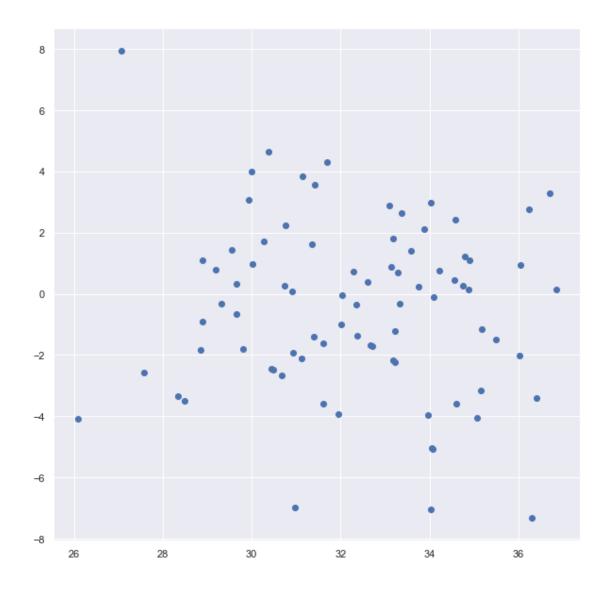


With respect to residuels our graph should be normally distrubuted and if there is outliers in dataset it will be skewed

## Scatter plot of residuels and predicted points
## Uniform distrubution

plt.scatter(reg\_pred, residuals)

<matplotlib.collections.PathCollection at 0x213f926f880>



## Graph of reg\_pred and residuals should be uniformally distrubuted #### Performance Metrics

```
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))) 8.016503622543366  
2.2234819896738385  
2.831343077506392  
from sklearn.metrics import r2_score  
R-squared score
```

score=r2\_score(y\_test, reg\_pred)

```
0.356305467292779
```

[29.87478071], [32.25061527],

```
Adjusted R squared
1 - (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
0.25368749831046844

conclusion: Adjusted R squared will be always less than R-squared
```

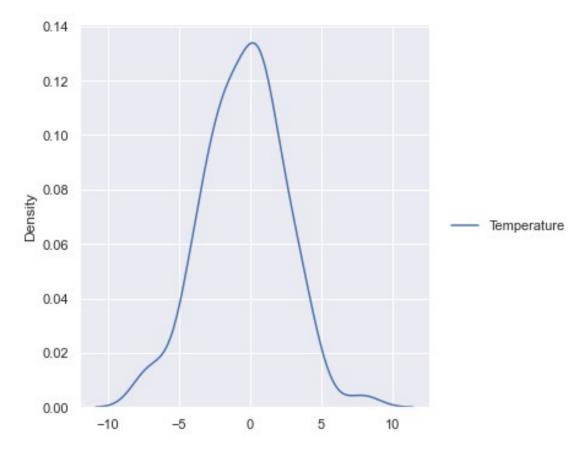
```
Ridge Regression
##Ridge
from sklearn.linear model import Ridge
from sklearn.model selection import GridSearchCV
ridge regressor=Ridge()
parameters={'alpha':[1,2,3,5,6,47,8,9,89,5,2,10]}
ridgecv=GridSearchCV(ridge regressor,parameters,scoring='neg mean squa
red error', cv=5)
ridgecv.fit(X train, y train)
GridSearchCV(cv=5, estimator=Ridge(),
             param grid={'alpha': [1, 2, 3, 5, 6, 47, 8, 9, 89, 5, 2,
10]},
             scoring='neg mean squared error')
print(ridgecv.best params )
{'alpha': 47}
print(ridgecv.best score )
-5.696939972304345
ridge pred=ridgecv.predict(X test)
ridge pred
array([[29.94108029],
       [31.76255471],
       [30.791717],
       [34.31117955].
       [32.51369767],
       [27.85978095],
       [30.92874271].
       [31.54199374],
       [36.8475654],
       [30.9651734],
       [29.68408041],
       [33.9444298],
```

```
[37.33647968],
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[26.64592561],
[35.8183171],
[30.987609
```

```
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[31.90231119],
[32.53703286],
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[30.25262092],
[33.07540182],
[33.89602943],
[30.93970635],
[34.10848385],
[34.27794362],
[34.36227647],
[29.82794407]])
```

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

<seaborn.axisgrid.FacetGrid at 0x213f68c98b0>



score=r2\_score(ridge\_pred, y\_test)

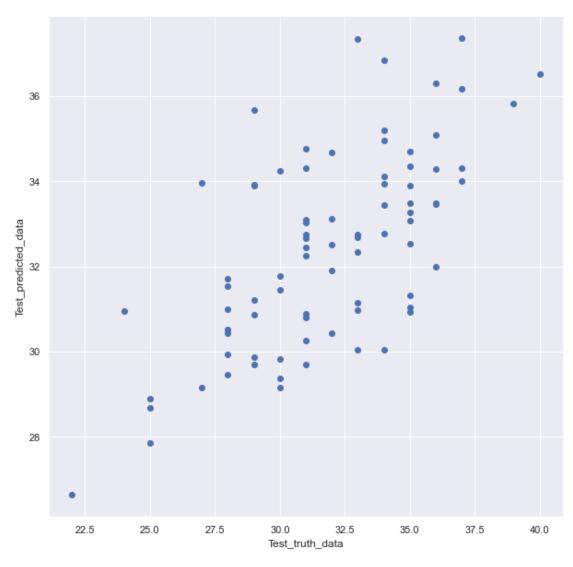
score

## **Assumptions of ridge regression**

## y\_test and ridge\_pred should be linearlly increasing

```
#y_test and ridge_pred should be linearlly increasing
plt.scatter(y_test, ridge_pred)
plt.xlabel("Test_truth_data")
plt.ylabel("Test_predicted_data")
```

Text(0, 0.5, 'Test\_predicted\_data')

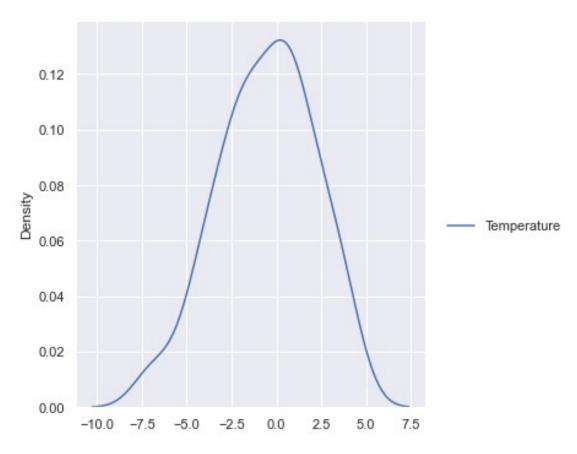


#### #residuel/error

```
ridge_residual=y_test-ridge_pred
ridge_residual
```

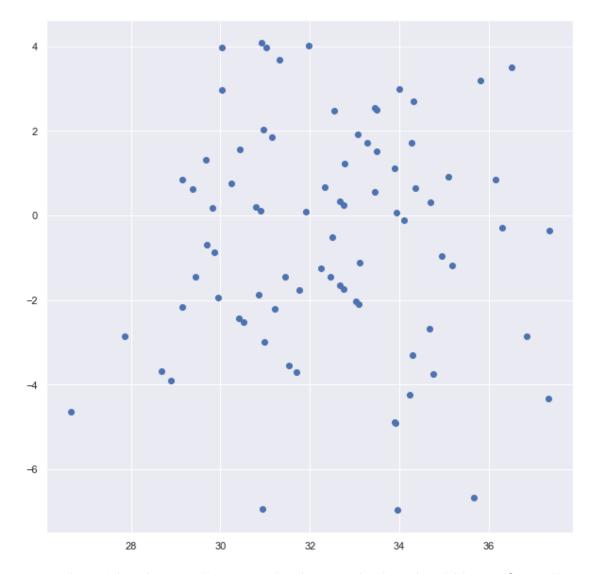
Temperature 51 -1.941080

```
224
       -1.762555
41
        0.208283
        2.688820
192
67
       -0.513698
245
       -6.939706
172
       -0.108484
183
        1.722056
199
        0.637724
125
        0.172056
[81 rows x 1 columns]
sns.displot(ridge_residual, kind='kde')
<seaborn.axisgrid.FacetGrid at 0x213f92d7b20>
```



residual plot is normally distrubuted and little skewed beacause of outliers #scatterplot with ridge\_pred and ridge\_residual plt.scatter(ridge\_pred, ridge\_residual)

<matplotlib.collections.PathCollection at 0x213f93e92e0>



# Scatterplot with ridge prediction and ridge residual, it should be uniformally distrubtion (it should not have any shape)

```
#performance metrix
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)))
7.339619547763014
2.1835739336118043
2.7091732221773888

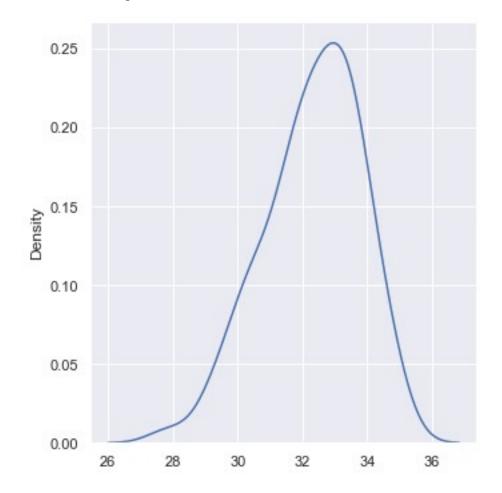
## R squard and adjusted R square
from sklearn.metrics import r2_score
score=r2_score(y_test, ridge_pred)
```

print(score)

```
0.41065666561163705
#Adiusted R squared
1 - (1-score)*(len(y test)-1)/(len(y test)-X test.shape[1]-1)
0.31670338041928936
Lasso Regression
from sklearn.linear model import Lasso
lasso=Lasso()
lasso
Lasso()
parameters={'alpha':[1,2,3,5,6,47,8,9,89,5,2,10]}
lassocv=GridSearchCV(lasso,parameters,scoring='neg_mean_squared_error'
lassocv.fit(X_train, y_train)
GridSearchCV(cv=5, estimator=Lasso(),
             param grid={'alpha': [1, 2, 3, 5, 6, 47, 8, 9, 89, 5, 2,
10]},
             scoring='neg mean squared error')
print(lassocv.best params )
{'alpha': 1}
print(lassocv.best score )
-7.305375337514984
lasso pred=lassocv.predict(X test)
lasso_pred
array([31.06500611, 31.6929418 , 31.37273876, 33.25264037,
32.53495303,
       29.38956497, 31.47868541, 32.36389873, 34.63408271,
31.74292057,
       30.82932091, 33.62246138, 30.38837138, 32.57748256,
34.76114641,
       32.09211617, 33.08122523, 33.70729096, 29.22852024,
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       32.87835676, 33.21395045, 31.3805652, 30.42986749,
32.54888306,
       31.81695348, 33.33561581, 32.8735165, 32.38854412,
32.5950227 ,
       31.63372511, 33.84347762, 33.79897898, 31.88544081,
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       30.61093 , 30.05359843, 30.01008413, 33.33766721,
```

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32.81026343,
       34.97883206, 32.06912862, 31.39808898, 29.72594618,
29.2217436 .
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31.78029808,
       32.29293423, 34.52342663, 32.84467117, 31.49456821,
33.7869353 ,
       32.2814977 , 33.22620675, 32.48953551, 30.53665078,
32.63202256,
       33.7570561 , 31.42102746, 33.25413369, 33.43403145,
33.49063868,
       30.186601731)
sns.displot(lasso pred, kind='kde')
```

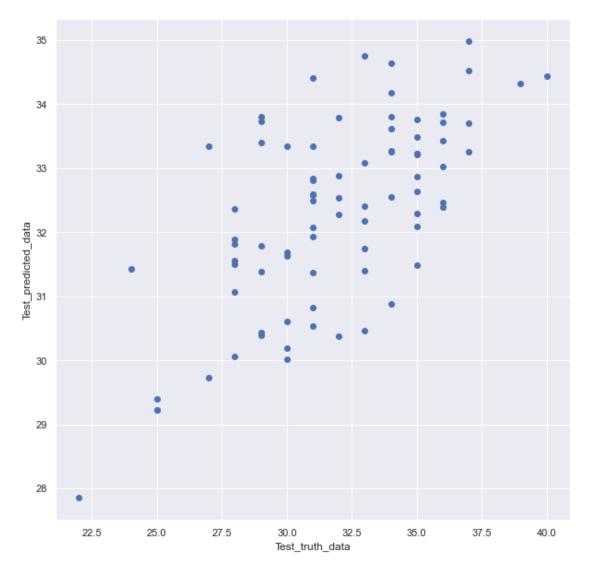




## **Assumption of Lasso regression**

```
#y_test and lasso_pred should be linearlly increasing
plt.scatter(y_test, lasso_pred)
plt.xlabel("Test_truth_data")
plt.ylabel("Test_predicted_data")
```

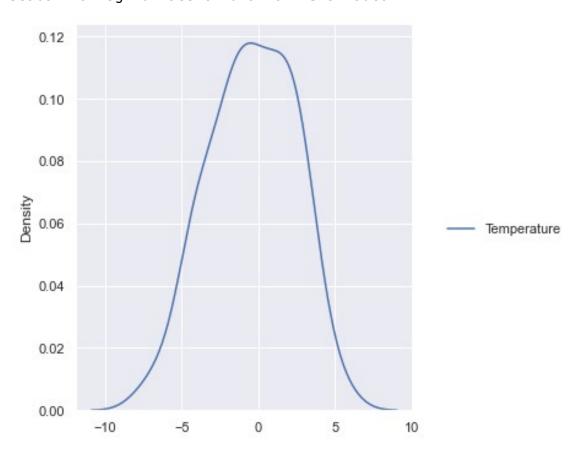
Text(0, 0.5, 'Test\_predicted\_data')



## y\_test and lasso\_pred should be linearlly increasing

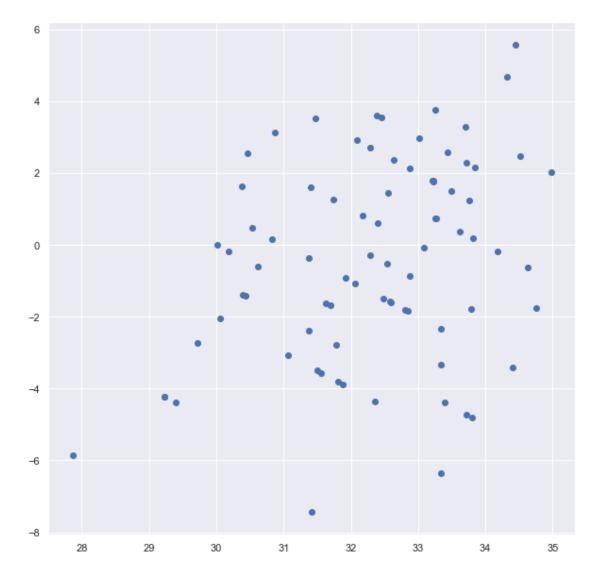
```
lasso_pred=lasso_pred.reshape(81,1)
lasso_residuals=y_test-lasso_pred
lasso_residuals
         Temperature
51          -3.065006
```

```
224
       -1.692942
41
       -0.372739
        3.747360
192
67
       -0.534953
245
       -7.421027
172
        0.745866
183
        2.565969
199
        1.509361
125
       -0.186602
[81 rows x 1 columns]
sns.displot(lasso_residuals, kind="kde")
<seaborn.axisgrid.FacetGrid at 0x213f947adc0>
```



## residuels are normally distrubuted

plt.scatter(lasso\_pred, lasso\_residuals)
<matplotlib.collections.PathCollection at 0x213fa6f7340>



#### performance metrix

```
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)))
```

- 7.8696515835539005
- 2.317044907898472
- 2.8052899286087882

#### R-squared

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

0.368097123489204

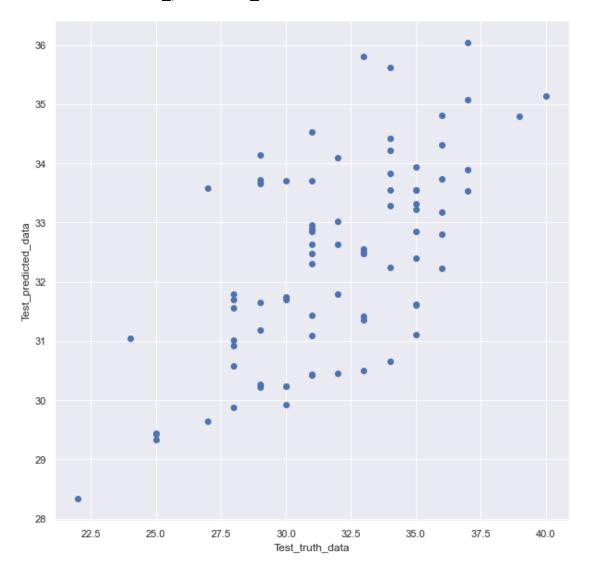
```
Adjusted R-squared
1 - (1-score)*(len(y test)-1)/(len(y test)-X test.shape[1]-1)
0.26735898375559874
Elastic Net Regression
from sklearn.linear model import ElasticNet
elasticnet=ElasticNet()
elasticnet
ElasticNet()
elasticnet.fit(X train, y train)
ElasticNet()
elasticnet pred=elasticnet.predict(X test)
elasticnet pred
array([30.58233822, 31.74586174, 31.09445454, 33.53022515,
32.63419427,
       29.32869664, 31.11079064, 31.70167753, 35.6154579,
31.35850018.
       30.43450915, 33.83885723, 30.2240347, 32.475088,
35.81421841.
       31.62292661, 32.49882967, 33.89578669, 29.44833766,
34.21716181,
       33.02648884, 33.31803187, 31.18767492, 30.27232433,
32.23581132,
       31.01871744, 33.70732584, 33.22936002, 32.80188594,
32.84543675,
       31.6976918 , 34.3135809 , 33.72355759, 31.78543796,
33.58215229,
       30.23996414, 29.87392299, 29.91891528, 33.70900631,
30.45500239,
       33.9437523 , 34.53407031, 34.14547336, 32.22330939,
30.66281449.
       33.17190122, 33.6626742 , 34.8057206 , 33.28279936,
32.965061
       36.03624783, 31.42861309, 31.414447 , 29.64474524,
29.42816641.
       32.48118908, 32.54893688, 32.29866047, 34.42618513,
35.14097454,
       30.49554117, 28.34188711, 34.7989069, 31.55191832,
31.65671625,
       31.59752962, 35.07922341, 32.90263715, 30.92382263,
34.10327908,
       31.79145966, 32.85482119, 32.63669002, 30.41606874,
32.39651287,
       33.54428462, 31.04246852, 33.55023753, 33.73096224,
```

```
33.55844474,
30.22928558])
```

## **Assumption of Elastic-Net regression**

```
plt.scatter(y_test, elasticnet_pred)
plt.xlabel("Test_truth_data")
plt.ylabel("Test_predicted_data")
```

Text(0, 0.5, 'Test\_predicted\_data')



## y\_test and elasticnet\_pred should be linearlly increasing

elasticnet\_pred=elasticnet\_pred.reshape(81,1)
elasticnet\_residuals=y\_test-elasticnet\_pred
elasticnet\_residuals

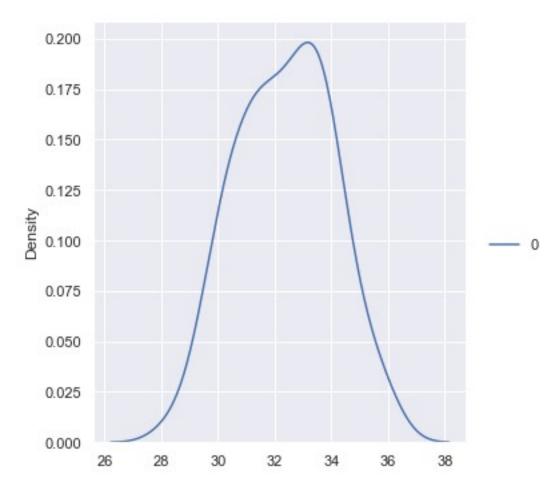
```
Temperature
51
       -2.582338
224
       -1.745862
41
       -0.094455
192
        3.469775
67
       -0.634194
       -7.042469
245
172
        0.449762
183
        2.269038
199
        1.441555
125
       -0.229286
```

#### [81 rows x 1 columns]

## ## residual plot

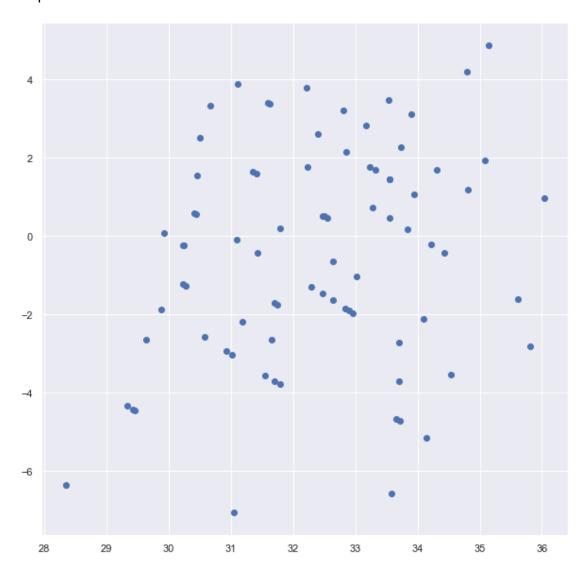
sns.displot(elasticnet\_pred, kind="kde")

<seaborn.axisgrid.FacetGrid at 0x213fa714370>



Residual plot is normally distubuted #scatterplot with elasticnet\_pred and EN\_residuel plt.scatter(elasticnet\_pred, elasticnet\_residuals)

#### <matplotlib.collections.PathCollection at 0x213fa847d30>



Scatterplot of elasticnet\_pred and elasticnet\_residuals is uniformally distrubuted

#### Performance metrics

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

- 7.736339628192311
- 2.2886972607562712
- 2.781427624115413

```
R-squared
```

```
from sklearn.metrics import r2_score
score=r2_score(y_test, elasticnet_pred)
print(score)
```

0.3788015628372323

## Adjusted R-squared

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

0.2797699279272259