Performing EDA and Implementing Linear Regression, Ridge, Lasso, Elastic Net Regressions with Assumptions and Performance Metrics on Algerian Forest Fires Dataset ¶

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [2]:

```
df = pd.read_csv('Algerian_forest_fires_dataset.csv')
df.head()
```

Out[2]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not fire
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not fire
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not fire
4	5	6	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not fire

In [3]:

```
df[121:130]
```

Out[3]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FW
121	30	9	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1
122	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
123	Sidi-Bel Abbes Region Dataset	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
124	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FW
125	1	6	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2
126	2	6	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2
127	3	6	2012	29	80	14	2	48.7	2.2	7.6	0.3	2.6	0.1
128	4	6	2012	30	64	14	0	79.4	5.2	15.4	2.2	5.6	1
129	5	6	2012	32	60	14	0.2	77.1	6	17.6	1.8	6.5	0.9

In [4]:

```
df.drop([122,123,124], inplace = True)
df.reset_index(inplace=True)
df.drop('index',axis=1,inplace=True)
```

In [5]:

```
df[121:130]
```

Out[5]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Class
121	30	9	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1	not f
122	1	6	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not f
123	2	6	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2	not f
124	3	6	2012	29	80	14	2	48.7	2.2	7.6	0.3	2.6	0.1	not f
125	4	6	2012	30	64	14	0	79.4	5.2	15.4	2.2	5.6	1	not f
126	5	6	2012	32	60	14	0.2	77.1	6	17.6	1.8	6.5	0.9	not f
127	6	6	2012	35	54	11	0.1	83.7	8.4	26.3	3.1	9.3	3.1	f
128	7	6	2012	35	44	17	0.2	85.6	9.9	28.9	5.4	10.7	6	f
129	8	6	2012	28	51	17	1.3	71.4	7.7	7.4	1.5	7.3	0.8	not f

In [6]:

```
# we adding a new column Region to dataset
# rows 1 = Bejaia Region and 0 = Sidi Bel-abbes Region
df['Region'] = 1
for i in range(len(df)):
    if i >= 122:
        df['Region'][i] = 0
```

```
C:\Users\Thanmai\AppData\Local\Temp/ipykernel_21028/3918257608.py:6: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  df['Region'][i] = 0
```

In [7]:

```
df
```

Out[7]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Class
0	1	6	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not f
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not f
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not f
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not f
4	5	6	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not f
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
239	26	9	2012	30	65	14	0	85.4	16	44.5	4.5	16.9	6.5	f
240	27	9	2012	28	87	15	4.4	41.1	6.5	8	0.1	6.2	0	not f
241	28	9	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not f
242	29	9	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not f
243	30	9	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not f

244 rows × 15 columns

1. Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012) Weather data observations
2. Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
3. RH : Relative Humidity in %: 21 to 90
4. Ws :Wind speed in km/h: 6 to 29
5. Rain: total day in mm: 0 to 16.8 FWI Components
6. Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
7. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
8. Drought Code (DC) index from the FWI system: 7 to 220.4
9. Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
10. Buildup Index (BUI) index from the FWI system: 1.1 to 68

11. Fire Weather Index (FWI) Index: 0 to 31.1
12. Classes: two classes, namely â€œFireâ€ and â€œnot Fireâ€

In [8]:

```
df.info()
```

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

In [9]:

```
df.columns
```

Out[9]:

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

In [10]:

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

Out[10]:

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

In [11]:

```
#let's check for missing values
df.isnull().sum()
```

Out[11]:

```
day            0
month          0
year           0
Temperature    0
RH             0
Ws             0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
Classes        1
Region         0
dtype: int64
```

We can see that there is a missing value in classes column

In [12]:

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

Out[12]:

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

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

In [13]:

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

Out[13]:

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

In [14]:

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

Out[14]:

```
fire        137
not fire    106
Name: Classes, dtype: int64
```

In [15]:

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

Out[15]:

```
day                14
month               7
year             2012
Temperature        37
RH                 37
Ws                 18
Rain              0.2
FFMC             88.9
DMC              12.9
DC             14.6 9
ISI              12.5
BUI              10.4
FWI            fire
Classes           NaN
Region              0
Name: 165, dtype: object
```

In [16]:

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

In [17]:

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

Out[17]:

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

In [18]:

```
, 'Ws':'int', 'Rain':'float', 'FFMC':'float','DMC':'float', 'DC':'float','ISI':'float', 'BU
```

In [19]:

```
# Statistical summary of dataset
df.describe().T
```

Out[19]:

	count	mean	std	min	25%	50%	75%	max
day	244.0	15.754098	8.825059	1.0	8.000	16.00	23.000	31.0
month	244.0	7.500000	1.112961	6.0	7.000	7.50	8.000	9.0
year	244.0	2012.000000	0.000000	2012.0	2012.000	2012.00	2012.000	2012.0
Temperature	244.0	32.172131	3.633843	22.0	30.000	32.00	35.000	42.0
RH	244.0	61.938525	14.884200	21.0	52.000	63.00	73.250	90.0
Ws	244.0	15.504098	2.810178	6.0	14.000	15.00	17.000	29.0
Rain	244.0	0.760656	1.999406	0.0	0.000	0.00	0.500	16.8
FFMC	244.0	77.887705	14.337571	28.6	72.075	83.50	88.300	96.0
DMC	244.0	14.673361	12.368039	0.7	5.800	11.30	20.750	65.9
DC	244.0	49.288115	47.619662	6.9	13.275	33.10	68.150	220.4
ISI	244.0	4.759836	4.154628	0.0	1.400	3.50	7.300	19.0
BUI	244.0	16.673361	14.201648	1.1	6.000	12.45	22.525	68.0
FWI	244.0	7.049180	7.428366	0.0	0.700	4.45	11.375	31.1
Region	244.0	0.500000	0.501028	0.0	0.000	0.50	1.000	1.0

In [20]:

```
# Printing all the categorical columns
categorical_col = [fea for fea in df.columns if df[fea].dtype == 'O']
categorical_col
```

Out[20]:

```
['Classes']
```

In [21]:

```
# Printing all the numerical columns
numerical_col = [fea for fea in df.columns if df[fea].dtype != 'O']
numerical_col
```

Out[21]:

```
['day',
 'month',
 'year',
 'Temperature',
 'RH',
 'Ws',
 'Rain',
 'FFMC',
 'DMC',
 'DC',
 'ISI',
 'BUI',
 'FWI',
 'Region']
```

Univariate Analysis:

The term univariate analysis refers to the analysis of one variable. You can remember this because the prefix “uni” means “one.” The purpose of univariate analysis is to understand the distribution of values for a single variable. These plots help in understanding the location/position of observations in the data variable, its distribution, and dispersion. Uni-variate plots are of two types:

1) Enumerative plots

2) Summary plots

1) Univariate enumerative Plots :

These plots enumerate/show every observation in data and provide information about the distribution of the observations on a single data variable. We now look at different enumerative plots.

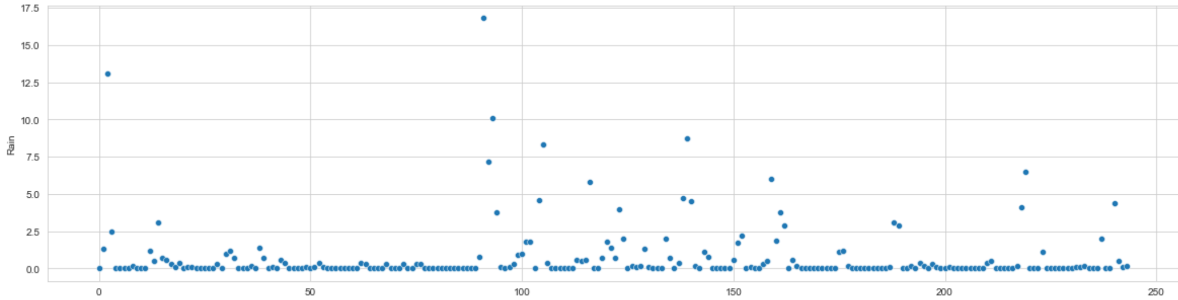
Scatter Plot:

This plots different observations/values of the same variable corresponding to the index/observation number. Use the plt.scatter() function of matplotlib to plot a univariate scatter diagram. The scatter() function requires two parameters to plot. So, in this example, we plot the variable ‘math score’ against the corresponding observation number that is stored as the index of the data frame (df.index).And we are considering the gender to make the plot more meaningful.

In seaborn, the hue parameter determines which column in the data frame should be used for color encoding. This helps to differentiate between the data values according to the categories they belong to. The hue parameter takes the grouping variable as it’s input using which it will produce points with different colors.

In [22]:

```
#Scatter Plot
sns.set_style('whitegrid')
plt.figure(figsize=(20,5))
sns.scatterplot(x=df.index,y=df['Rain'],data=df)
plt.show()
```

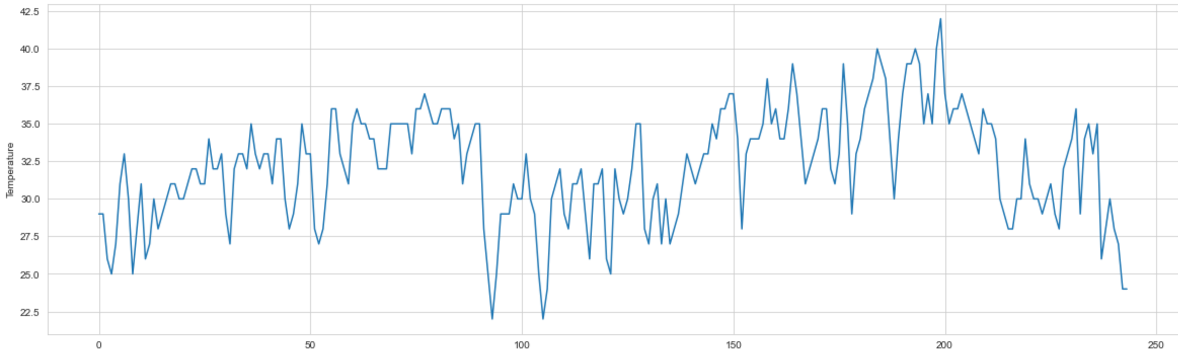


Line Plot:

A line plot visualizes data by connecting the data points via line segments. It is similar to a scatter plot except that the measurement points are ordered (typically by their x-axis value) and joined with straight line segments.

In [23]:

```
#Line Plot
plt.figure(figsize=(20,6))
fig=sns.lineplot(x=df.index,y=df['Temperature'],data=df)
plt.show()
```



Strip Plot:

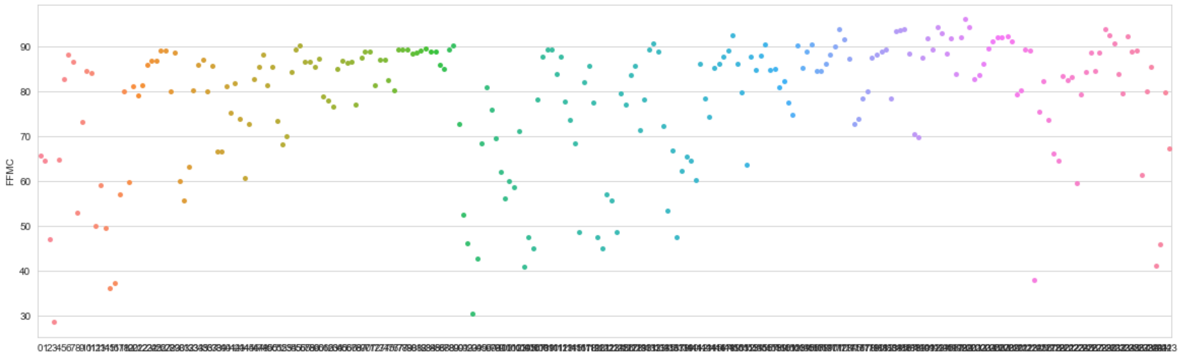
The strip plot is similar to a scatter plot. It is often used along with other kinds of plots for better analysis. It is used to visualize the distribution of data points of the variable.

In [24]:

```
#Strip Plot
plt.figure(figsize=(20,6))
sns.stripplot(x=df.index,y=df['FFMC'])
```

Out[24]:

```
<AxesSubplot:ylabel='FFMC'>
```



2) Uni-variate summary plots :

These plots give a more concise description of the location, dispersion, and distribution of a variable than an enumerative plot. It is not feasible to retrieve every individual data value in a summary plot, but it helps in efficiently representing the whole data from which better conclusions can be made on the entire data set.

Histogram:

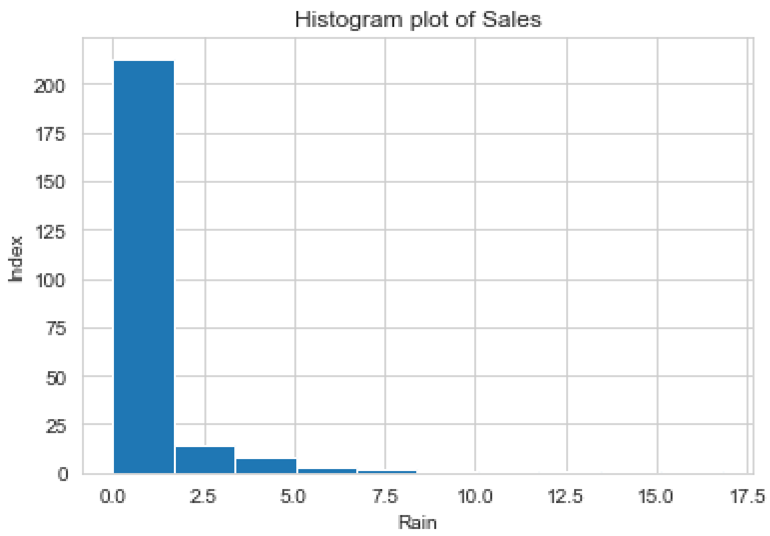
Histograms are similar to bar charts which display the counts or relative frequencies of values falling in different class intervals or ranges. A histogram displays the shape and spread of continuous sample data. It also helps us understand the skewness and kurtosis of the distribution of the data.

In [25]:

```
#Histogram / Distplot (in Seaborn)
plt.figure(figsize=(6,4))
plt.hist(df['Rain'])
sns.set_style('whitegrid')
plt.xlabel('Rain')
plt.ylabel('Index')
plt.title('Histogram plot of Sales')
```

Out[25]:

```
Text(0.5, 1.0, 'Histogram plot of Sales')
```



Density Plot:

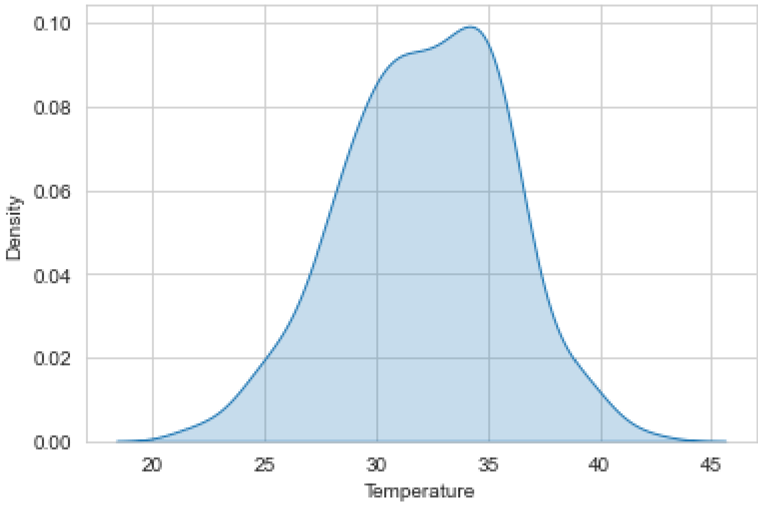
A density plot is like a smoother version of a histogram. Generally, the kernel density estimate is used in density plots to show the probability density function of the variable. A continuous curve, which is the kernel is drawn to generate a smooth density estimation for the whole data.

In [26]:

```
#Density plot/kde plot(in seaborn)
sns.kdeplot(df['Temperature'],shade=True)
```

Out[26]:

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



Box Plot:

A box-plot is a very useful and standardized way of displaying the distribution of data based on a five-number summary (minimum, first quartile, second quartile(median), third quartile, maximum). It helps in understanding these parameters of the distribution of data and is extremely helpful in detecting outliers.

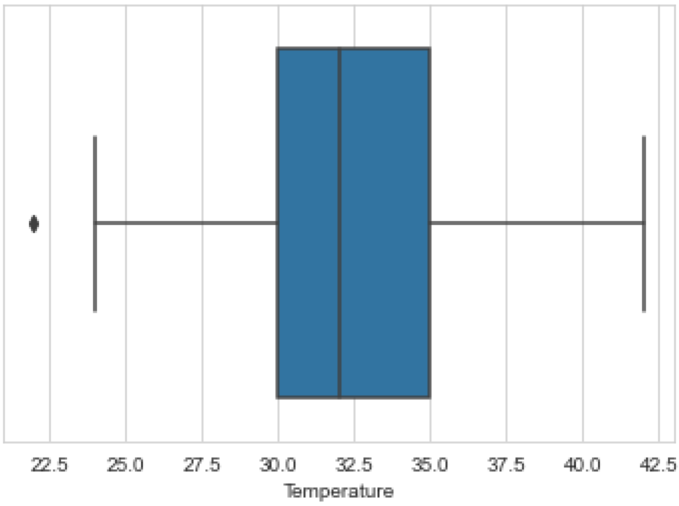
In [27]:

```
#Box Plot
sns.boxplot(df['Temperature'])
```

```
C:\Users\Thanmai\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futu
reWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretati
on.
  warnings.warn(
```

Out[27]:

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



Bivariate Analysis

Bivariate analysis is an analysis of two variables to determine the relationships between them. They are often reported in quality of life research. It is one of the simplest forms of quantitative (statistical) analysis. It involves the analysis of two variables (it is often denoted as X, Y), for the purpose of determining the empirical relationship between them.

Types of Bivariate Analysis Some of the common types of bivariate analysis include:

Scatter Plots:

Scatterplot provides you with a visual idea of the pattern that your variables follow.

Regression Analysis:

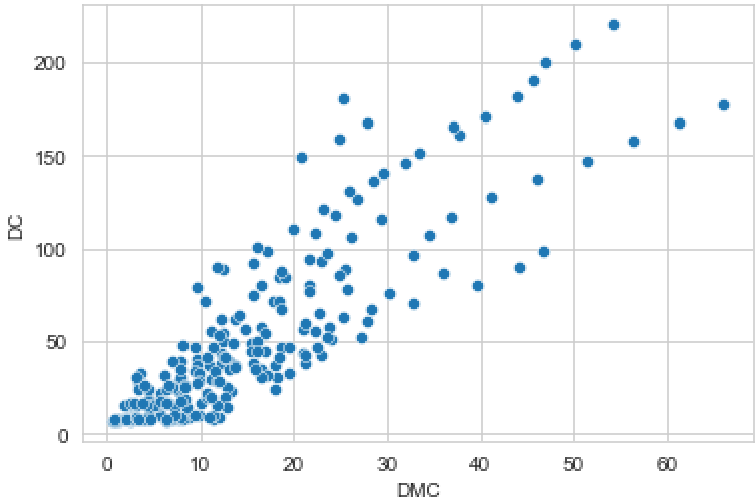
Regression analysis is a catch-all term for a wide variety of tools that can be used to determine how your data points might be related. The points in the image above seem like they could follow an exponential curve (as opposed to a straight line). Regression analysis not only provides you with an equation for that curve or line but also gives you the correlation coefficient.

Correlation Coefficients:

Calculation of values for correlation coefficients are performed using a computer, although here, you can find the steps to find the correlation coefficient by hand. This coefficient acknowledges you if the variables are related. Basically, by '0' means they aren't correlated (i.e. related in some way), while a '1' (either positive or negative) means that the variables are perfectly correlated (i.e. they are perfectly in sync with each other).

In [28]:

```
#Plotting correlation between DMC & DC features
sns.set_style('whitegrid')
plt.figure(figsize=(6,4))
sns.scatterplot(x=df['DMC'],y=df['DC'],data=df)
df['DMC'].corr(df['DC'])
#print("Correlation value is",df['DMC'].df['DC'])
plt.show()
```



Multivariate Analysis

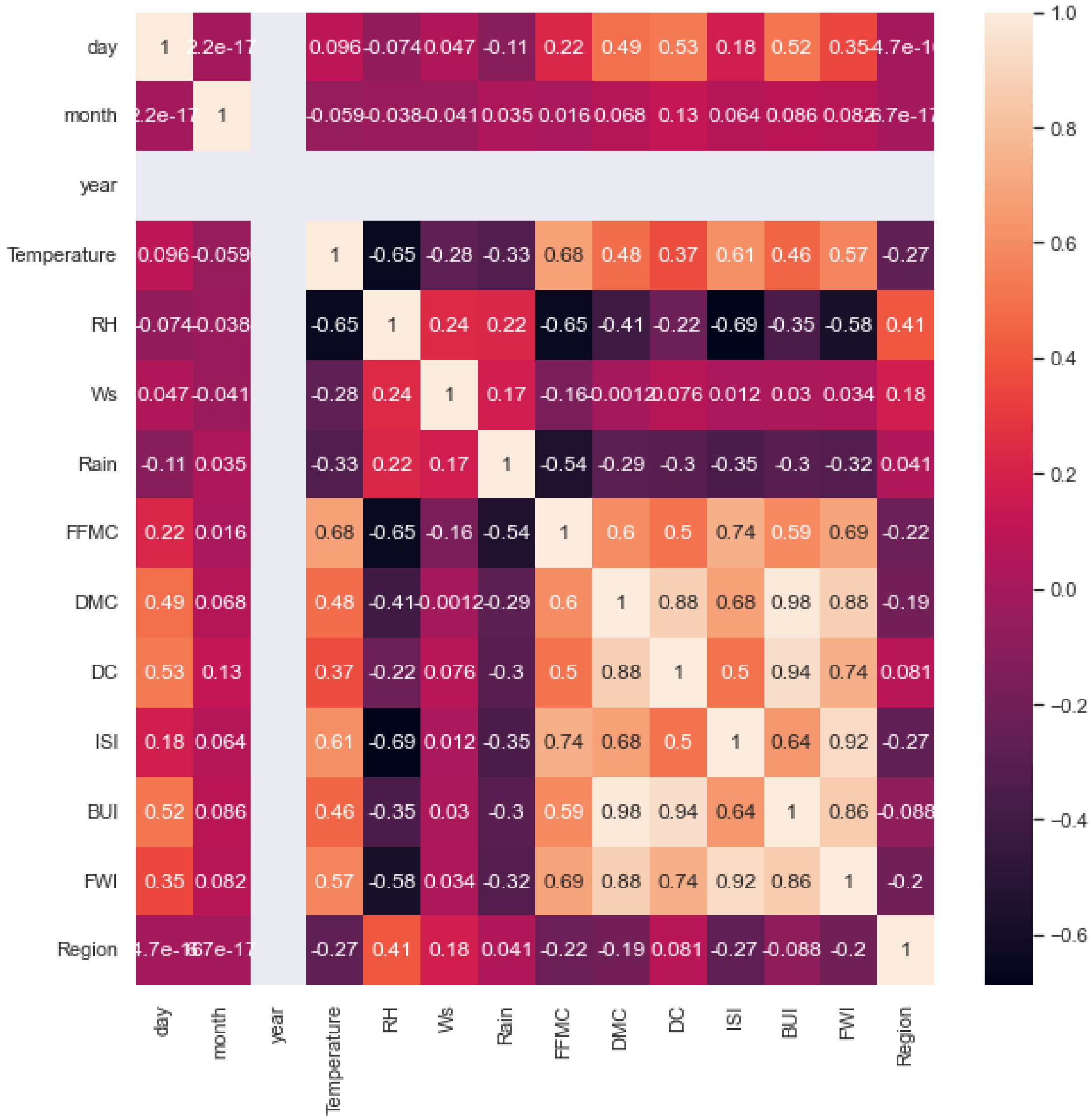
In data analytics, we look at different variables (or factors) and how they might impact certain situations or outcomes. For example, in marketing, you might look at how the variable "money spent on advertising" impacts the variable "number of sales." In the healthcare sector, you might want to explore whether there's a correlation between "weekly hours of exercise" and "cholesterol level." This helps us to understand why certain outcomes occur, which in turn allows us to make informed predictions and decisions for the future.

In [29]:

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

Out[29]:

```
<AxesSubplot:>
```

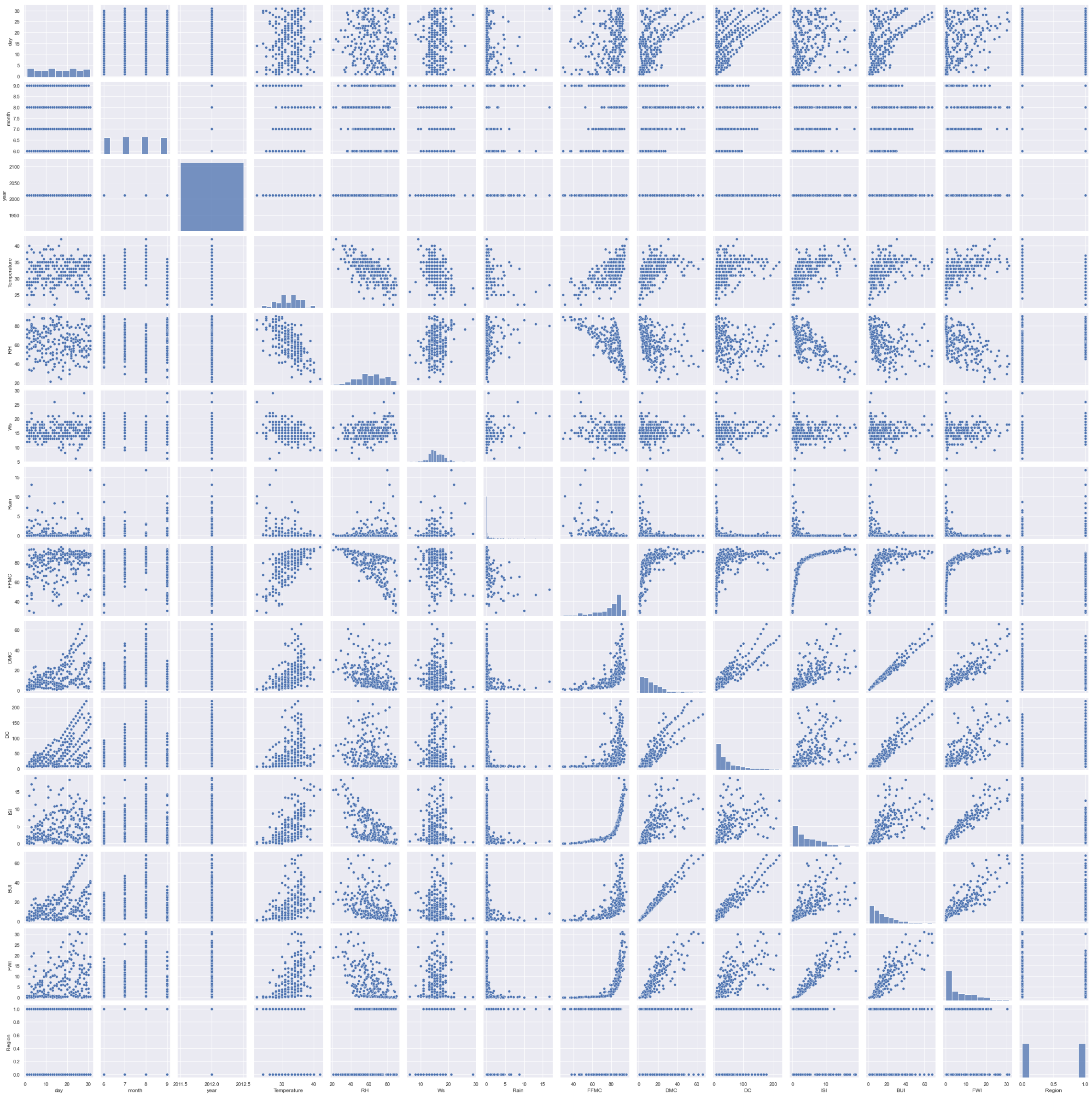


In [30]:

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

Out[30]:

```
<seaborn.axisgrid.PairGrid at 0x2e4dc521c70>
```



In [31]:

```
df.columns
```

Out[31]:

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

```
#Combining day, month, year to Date
df["Date"] = pd.to_datetime(df[['year','month','day']])
df
```

Train Test Splitting

In [41]:

```
#encoding the data values using one hot encoding techiniue
df = pd.get_dummies(df,columns=['Classes'],drop_first=True)
df.head()
```

Out[41]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Region
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	1
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	1
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	1
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	1
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	1

In [101]:

```
x_col = ['day', 'month','RH', 'Ws', 'Rain', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Region', 'Classes_not fire']
print(x_col)
y_col = ['Temperature']
print(y_col)
```

```
['day', 'month', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FW
I', 'Region', 'Classes_not fire']
['Temperature']
```

In [102]:

```
X
```

Out[102]:

	day	month	year	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Region	Classes_nc fir
0	1	6	2012	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	1	
1	2	6	2012	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	1	
2	3	6	2012	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	1	
3	4	6	2012	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	1	
4	5	6	2012	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	.
239	26	9	2012	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	0	
240	27	9	2012	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	0	
241	28	9	2012	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	0	
242	29	9	2012	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	0	
243	30	9	2012	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	0	

244 rows × 14 columns

In [103]:

```
y
```

Out[103]:

```
0      29
1      29
2      26
3      25
4      27
       ..
239    30
240    28
241    27
242    24
243    24
Name: Temperature, Length: 244, dtype: int32
```

In [104]:

```
# train test split
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 [105]:

```
print(len(X_train))
print(len(y_train))
print(len(X_test))
print(len(y_test))
```

```
163
163
81
81
```

In [106]:

```
# standarding the featues using Standard Scaler feature
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_train
```

Out[106]:

```
array([[ 1.0627621 ,  1.33562856,  0.        , ..., -0.86597829,
        -0.98176139,  1.06992376],
       [ 0.34495731,  0.44338489,  0.        , ...,  1.21371864,
         1.01857744, -0.93464604],
       [ 1.30203036, -1.34110244,  0.        , ...,  0.48516239,
         1.01857744, -0.93464604],
       ...,
       [-0.01394508,  1.33562856,  0.        , ...,  0.37919057,
        -0.98176139, -0.93464604],
       [-1.32992053, -1.34110244,  0.        , ..., -0.78649943,
        -0.98176139,  1.06992376],
       [-0.61211574, -1.34110244,  0.        , ..., -0.7997459 ,
         1.01857744,  1.06992376]])
```

Linear Regression

In [107]:

```
# Model Training
from sklearn.linear_model import LinearRegression
regression = LinearRegression()
```

In [108]:

```
regression.fit(X_train, y_train)#we are applying formula not changing data
```

Out[108]:

```
LinearRegression()
```

In [109]:

```
#print the coefficients and the intercept
print(regression.coef_)
print(regression.intercept_)
```

```
[-1.54702871e-01 -3.07343341e-01  1.11022302e-16 -1.21203430e+00
 -5.80039874e-01 -2.23702352e-01  1.00381362e+00 -1.54419211e-01
  1.07134593e+00 -4.99392889e-02 -5.57853940e-01  3.28177590e-01
 -2.83598389e-01 -1.44181128e-01]
32.17791411042945
```

In [110]:

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

Out[110]:

```
array([31.89343014, 33.45850542, 33.16243941, 31.43710015, 32.88168669,
       34.8669297 , 33.8942223 , 34.37067802, 32.02984529, 33.18602102,
       33.67809413, 27.06745096, 35.36651176, 29.35877503, 32.22558526,
       32.33418792, 34.92608865, 27.22763463, 36.08533571, 34.43514539,
       33.24253375, 34.61673357, 33.80293181, 33.19394862, 35.82598142,
       29.34648278, 32.44331073, 31.89524442, 26.73630937, 32.35108551,
       25.16025926, 27.05285188, 34.39426024, 32.12446729, 33.19996306,
       30.56626556, 29.13749234, 32.53449518, 27.1575937 , 35.57830841,
       32.73296049, 34.0292092 , 34.27847556, 31.43501508, 36.56354671,
       34.00949109, 23.78638114, 35.26468661, 34.10593886, 29.11023866,
       31.49805083, 32.48570204, 35.69147436, 32.62538514, 29.72811213,
       29.82534175, 32.71969495, 36.30264752, 31.17939635, 33.28070153,
       32.45840843, 32.88885861, 31.4095334 , 24.91571028, 31.27452007,
       36.23243437, 29.52256918, 29.80846347, 34.99178321, 34.04412555,
       28.52643877, 31.51552543, 32.37036319, 30.50611   , 30.52874488,
       31.06267388, 32.6843747 , 36.03865205, 31.74320213, 36.35570562,
       24.31888423])
```

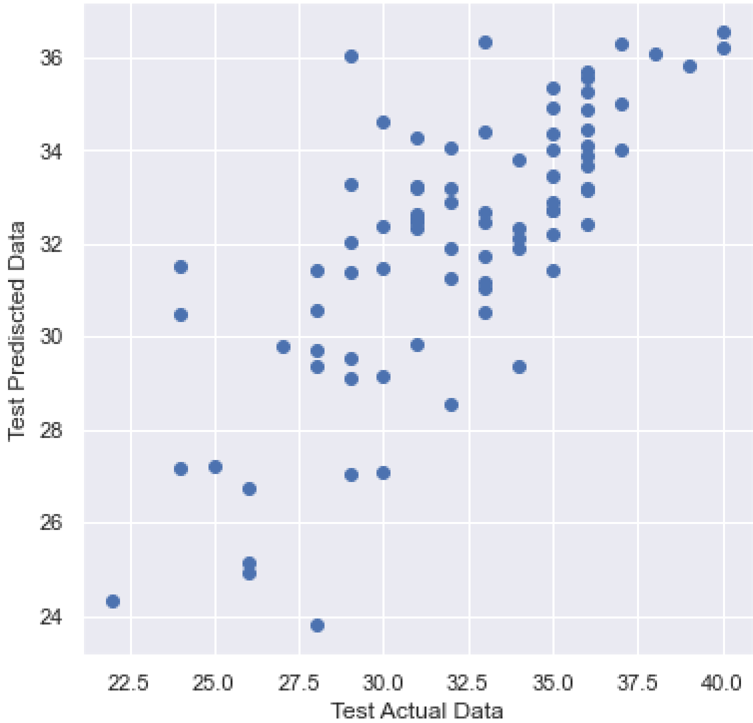
Assumptions

In [111]:

```
#The relationship between actual and predicted data should be linear
sns.set(rc = {'figure.figsize' : (6,6)})
plt.scatter(y_test,reg_pred)
plt.xlabel('Test Actual Data')
plt.ylabel('Test Prediscted Data')
```

Out[111]:

```
Text(0, 0.5, 'Test Prediscted Data')
```



We can see that the relationship between actual and predicted values is linear.

In [112]:

```
#Calculating residual
residuals = y_test - reg_pred
residuals
```

Out[112]:

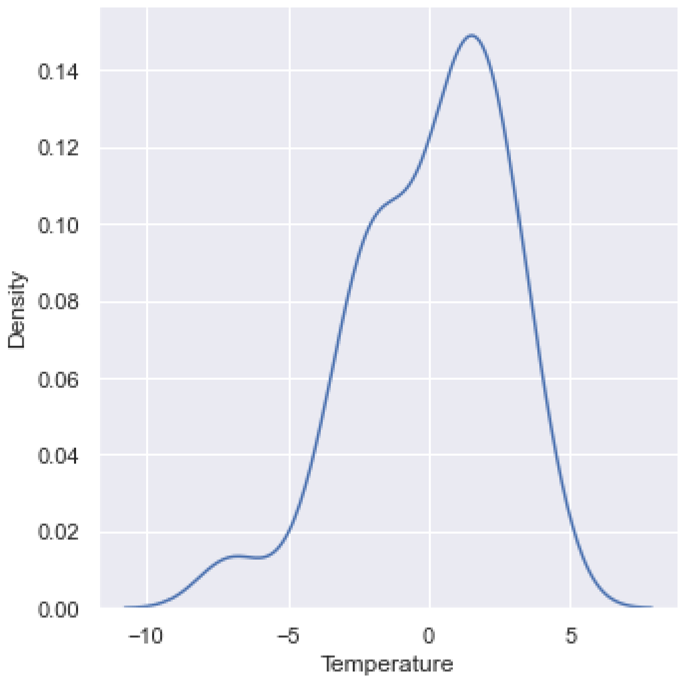
```
162    2.106570
60     1.541495
61     2.837561
63     3.562900
69     2.118313
         ...
169    0.315625
232   -7.038652
144    1.256798
208   -3.355706
105   -2.318884
Name: Temperature, Length: 81, dtype: float64
```

In [113]:

```
# distribution of residual are approxi normal fashion
sns.displot(residuals,kind='kde')    #little sked due to outliers
```

Out[113]:

```
<seaborn.axisgrid.FacetGrid at 0x2e4ebb721f0>
```



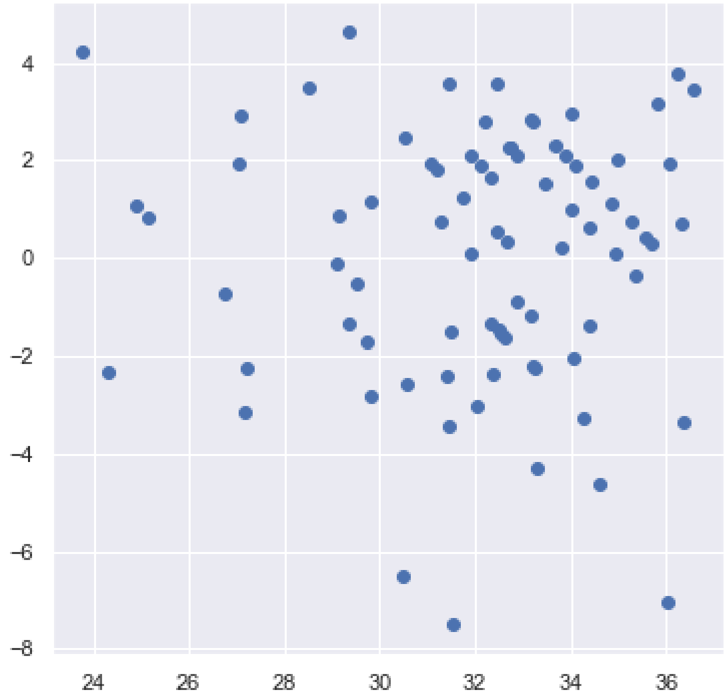
we can see that the distribution of data is little leftsked data distribued we can overcome this by hyperparameter tunning.

In [114]:

```
# The distribution should be uniform (Homoscedasticity)
plt.scatter(reg_pred, residuals)
```

Out[114]:

```
<matplotlib.collections.PathCollection at 0x2e4ebc43070>
```



Data b/w the reg_prd and residual are in random in nature

performance Metrics

In [115]:

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

```
6.731161507077733
2.1389715593305056
2.594448208594215
```

In [116]:

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

```
0.5548877154554919
```

In [117]:

```
## Adjusted R2 need to write
# need to perform
adjR = 1 - ( 1-score ) * ( len(y) - 1 ) / ( len(y) - X.shape[1] - 1 )
print(adjR)
```

```
0.5276756107235132
```

In [118]:

```
from sklearn.linear_model import Ridge
ridge_reg = Ridge(alpha=0.1)
```

In [119]:

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

Out[119]:

```
Ridge(alpha=0.1)
```

In [120]:

```
print(ridge_reg.coef_)
print(ridge_reg.intercept_)
```

```
[-0.15424289 -0.30624371  0.         -1.21186781 -0.579886   -0.22436748
  1.00021506 -0.18426142  1.04758895 -0.0389993  -0.49665107  0.31086336
 -0.28318329 -0.14430298]
32.17791411042945
```

In [121]:

```
rid_pred =ridge_reg.predict(X_test)
rid_pred
```

Out[121]:

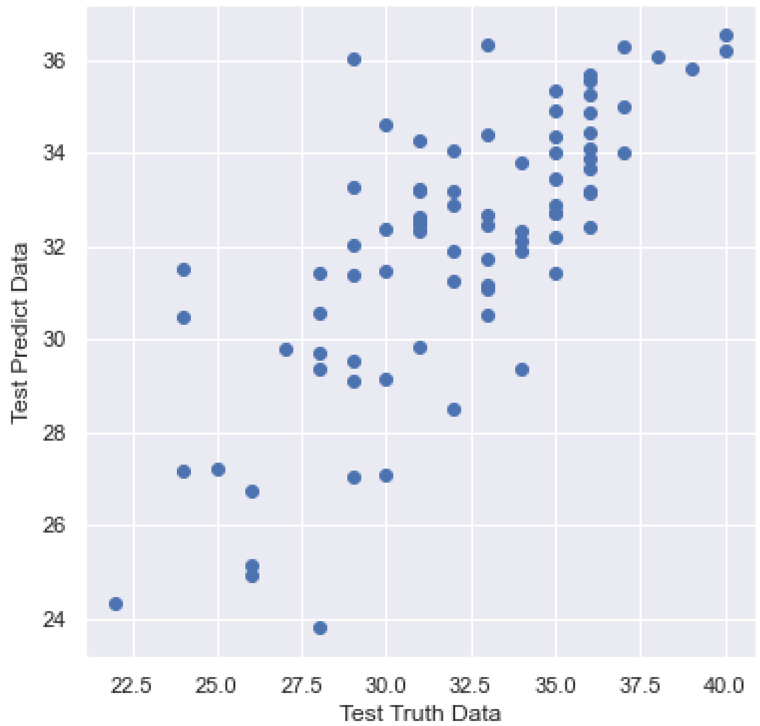
```
array([31.8934962 , 33.45884012, 33.16084694, 31.43705101, 32.88045238,
       34.86680184, 33.88771381, 34.3638284 , 32.0291461 , 33.18348471,
       33.67530269, 27.06932887, 35.36341495, 29.35606797, 32.22640251,
       32.33303055, 34.92181234, 27.2322376 , 36.08768485, 34.43499638,
       33.24021406, 34.60656969, 33.80061046, 33.19264072, 35.8291675 ,
       29.34728604, 32.43605834, 31.89983245, 26.74056853, 32.35453529,
       25.16254664, 27.05531756, 34.3902838 , 32.12501804, 33.19783753,
       30.56496392, 29.13489492, 32.53333239, 27.16037097, 35.57426371,
       32.73024019, 34.02708897, 34.28064089, 31.43274654, 36.55996311,
       34.00821491, 23.79084181, 35.265936  , 34.10506228, 29.10918315,
       31.49585056, 32.48488557, 35.69094053, 32.62233747, 29.73049296,
       29.82265016, 32.727771  , 36.30304316, 31.18517647, 33.28042796,
       32.45847576, 32.88998187, 31.40720265, 24.91099741, 31.27702408,
       36.2338036 , 29.52248208, 29.80872421, 34.99406499, 34.04056197,
       28.52576549, 31.5157757 , 32.36730395, 30.50777987, 30.5304353 ,
       31.07858176, 32.68621315, 36.04572845, 31.74452072, 36.35402198,
       24.3188669 ])
```

In [122]:

```
# relation between real and pred data
plt.scatter(y_test,rid_pred) # if you get linear manner it is good linear model
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predict Data')
```

Out[122]:

```
Text(0, 0.5, 'Test Predict Data')
```



In [123]:

```
## calculating residual
residuals = y_test-rid_pred
residuals
```

Out[123]:

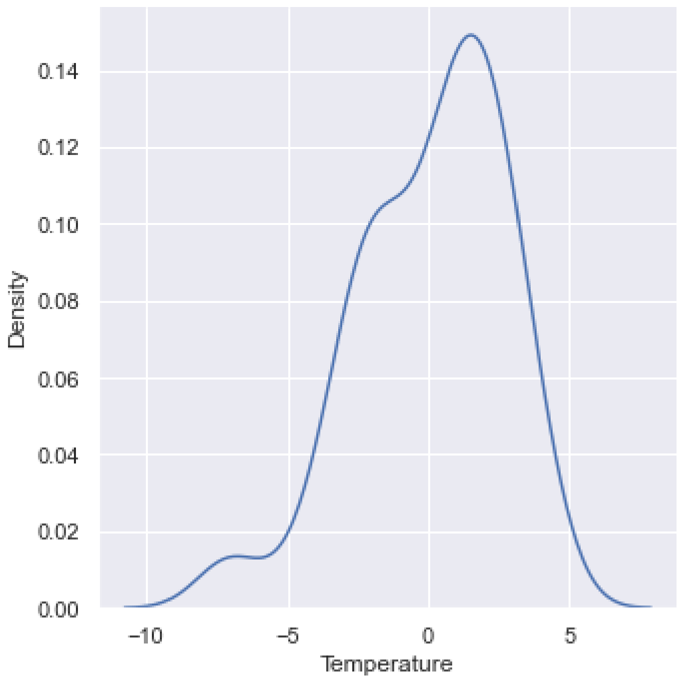
```
162    2.106504
60     1.541160
61     2.839153
63     3.562949
69     2.119548
         ...
169    0.313787
232   -7.045728
144    1.255479
208   -3.354022
105   -2.318867
Name: Temperature, Length: 81, dtype: float64
```

In [124]:

```
# distribution of residual are approxi normal fashion
sns.displot(residuals,kind='kde')    #little left-sked due to outliers
```

Out[124]:

```
<seaborn.axisgrid.FacetGrid at 0x2e4ebb72070>
```

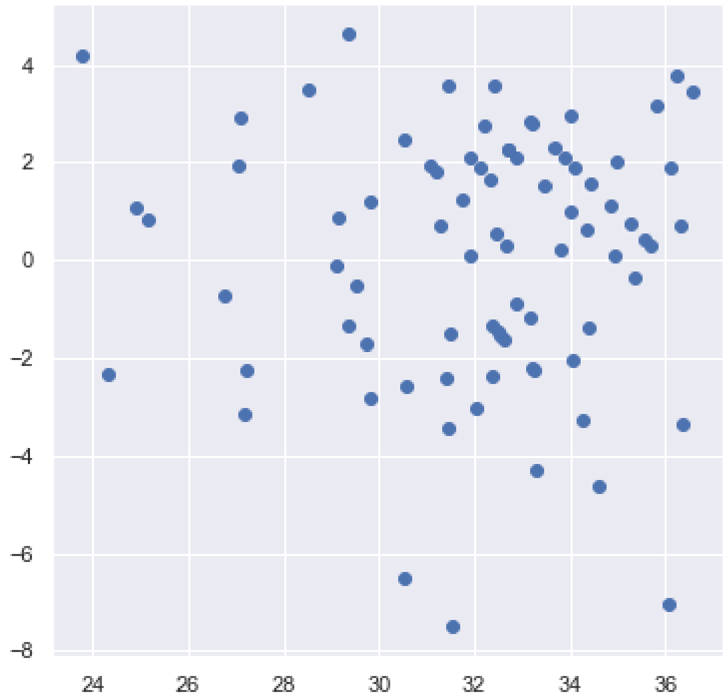


In [125]:

```
# The distribution should be uniform (Homoscedasticity)
plt.scatter(rid_pred,residuals)
```

Out[125]:

```
<matplotlib.collections.PathCollection at 0x2e4ebd9d910>
```



In [126]:

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

```
6.730570507988153
2.1387459536380713
2.594334309218485
```

In [127]:

```
score = r2_score(y_test,rid_pred)
print(score)
```

```
0.5549267965196811
```

In [128]:

```
adjR = 1 - ( 1-score ) * ( len(y) - 1 ) / ( len(y) - X.shape[1] - 1 )
print(adjR)
```

```
0.5277170810230678
```

Lasso Regression

In [129]:

```
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.1)
```

In [130]:

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

Out[130]:

```
Lasso(alpha=0.1)
```

In [131]:

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

```
[-0.         -0.13083314  0.         -1.19926931 -0.43044757 -0.11815794
  1.07190386  0.          0.37061052  0.02636961  0.          0.01903014
 -0.10390872 -0.1057482 ]
32.17791411042945
```

In [132]:

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

Out[132]:

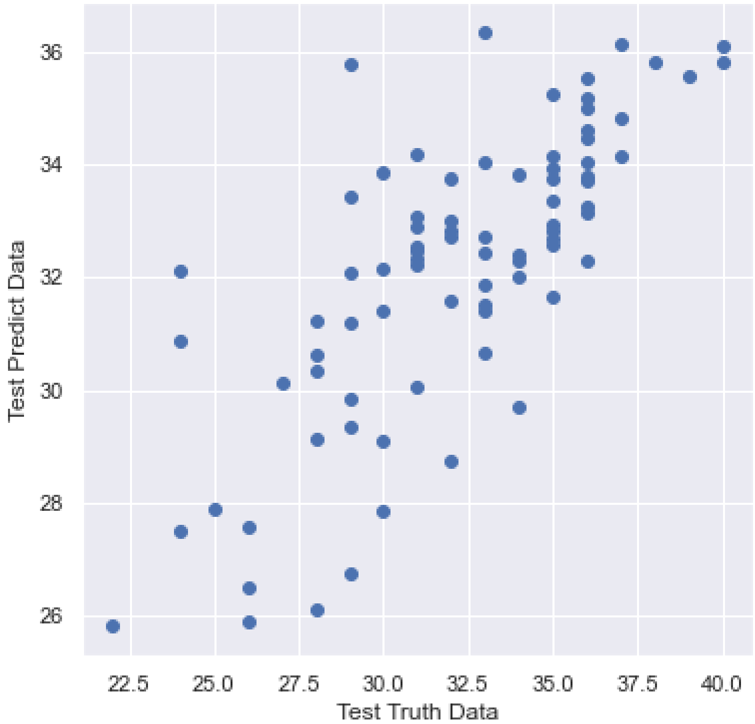
```
array([32.02526755, 33.34480955, 33.26003391, 31.64167363, 32.9368546 ,
       34.58886804, 33.70524233, 33.73480417, 32.09547487, 33.0047531 ,
       33.78337989, 27.85648846, 35.25038677, 29.71177096, 32.69491101,
       32.29687911, 34.15632818, 27.90259846, 35.80487346, 34.45974776,
       32.9008972 , 33.86215751, 33.8159162 , 33.15047181, 35.56691989,
       29.12035907, 32.29010472, 32.82209479, 27.57712451, 32.23325154,
       26.48924395, 26.75655737, 34.03641512, 32.39670811, 33.07641734,
       30.61891365, 29.10044563, 32.46085155, 27.49773337, 35.19092581,
       32.57578321, 34.1310085 , 34.18897878, 31.23736497, 36.09094216,
       33.91915165, 26.11619991, 34.99283468, 34.03924056, 29.3562621 ,
       31.41813935, 32.52947928, 35.54319282, 32.34005462, 30.3299199 ,
       30.06167567, 32.8307416 , 36.1412909 , 31.52129085, 33.42869921,
       32.44184598, 32.73653619, 31.19470952, 25.91478652, 31.58563549,
       35.80818946, 29.86108072, 30.12512377, 34.81999111, 33.75328103,
       28.7571279 , 32.10452875, 32.15207233, 30.87037216, 30.66471256,
       31.40559435, 32.70967005, 35.79073671, 31.85888805, 36.34692216,
       25.81411309])
```

In [133]:

```
# relation between real and pred data
plt.scatter(y_test,ls_prd) # if you get linear manner it is good linear model
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predict Data')
```

Out[133]:

```
Text(0, 0.5, 'Test Predict Data')
```



In [134]:

```
## calculating residuals
residuals = y_test-ls_prd
residuals
```

Out[134]:

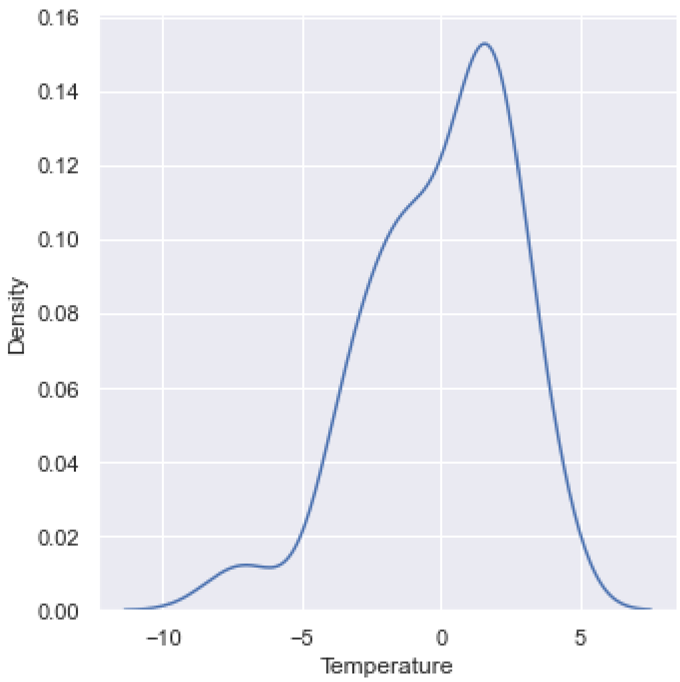
```
162    1.974732
60     1.655190
61     2.739966
63     3.358326
69     2.063145
         ...
169    0.290330
232   -6.790737
144    1.141112
208   -3.346922
105   -3.814113
Name: Temperature, Length: 81, dtype: float64
```

In [135]:

```
# distribution of residual are approxi normal fashion
sns.displot(residuals,kind='kde')
```

Out[135]:

```
<seaborn.axisgrid.FacetGrid at 0x2e4ebd388b0>
```

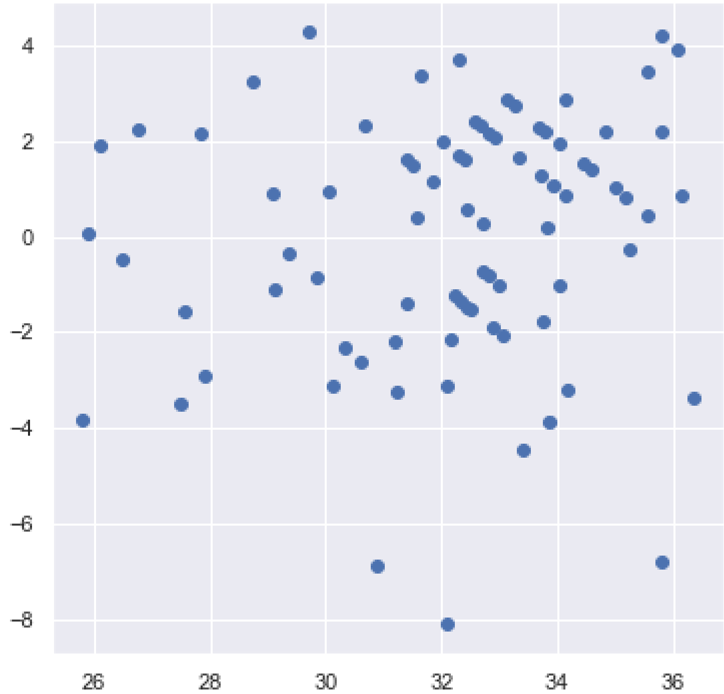


In [136]:

```
# The distribution should be uniform (Homoscedasticity)
plt.scatter(ls_prd,residuals)
```

Out[136]:

```
<matplotlib.collections.PathCollection at 0x2e4ebc3d130>
```



In [137]:

```
#performance Metrics
print(mean_squared_error(y_test,ls_prd))
print(mean_absolute_error(y_test,ls_prd))
print(np.sqrt(mean_squared_error(y_test,ls_prd)))
```

```
6.745755700162749
2.1398428556321805
2.5972592670279857
```

In [138]:

```
score = r2_score(y_test,ls_prd)
print(score)
```

```
0.5539226435851579
```

In [139]:

```
adjR = 1 - ( 1-score ) * ( len(y) - 1 ) / ( len(y) - X.shape[1] - 1 )
print(adjR)
```

```
0.5266515388261719
```

Elastic Net

In [140]:

```
from sklearn.linear_model import ElasticNet
el_reg = ElasticNet(random_state=0)
```

In [141]:

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

Out[141]:

```
ElasticNet(random_state=0)
```

In [142]:

```
print(el_reg.coef_)
print(el_reg.intercept_)
```

```
[ 0.         -0.          0.         -0.68644564 -0.10781129 -0.01366814
  0.67087773  0.06895291  0.          0.19946905  0.03908996  0.14549461
 -0.         -0.1081778 ]
32.17791411042945
```

In [143]:

```
el_prd = el_reg.predict(X_test)
el_prd
```

Out[143]:

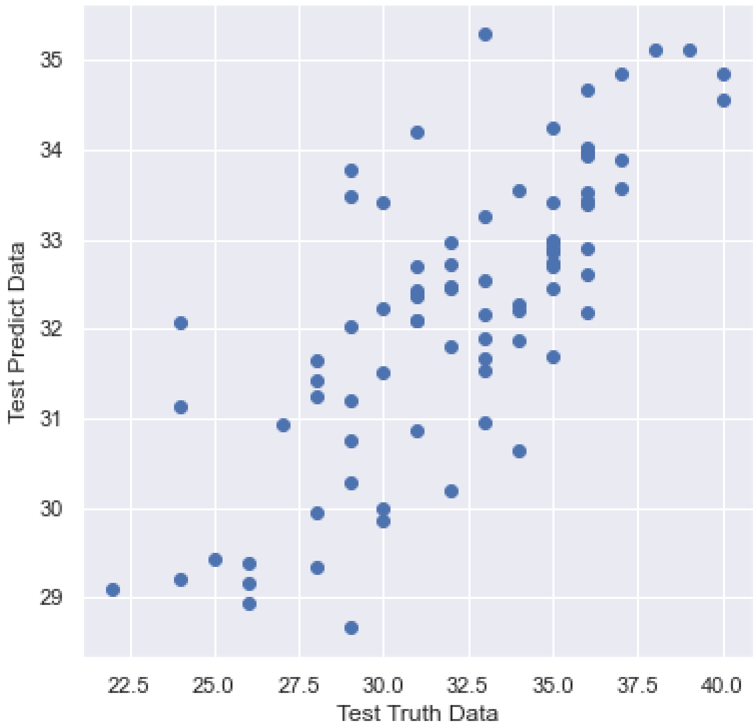
```
array([31.8659284 , 32.99980934, 32.61748317, 31.68640363, 32.97133107,
       33.99127101, 33.52848833, 32.70058551, 32.03261403, 32.73102985,
       33.40671458, 29.86476604, 34.23731503, 30.65217133, 32.75675926,
       32.28808467, 32.89332375, 29.43217613, 35.12277514, 33.93920094,
       32.44432598, 33.42168594, 33.54478947, 32.89474727, 35.1259888 ,
       29.95812513, 32.18623078, 32.46953345, 29.38105996, 32.08849583,
       29.16349431, 28.66243293, 33.27026445, 32.20567456, 32.70223675,
       31.2509238 , 30.00475117, 32.36817369, 29.20540962, 34.02296148,
       32.85515574, 33.57663149, 34.19266935, 31.64138001, 34.55218622,
       33.42794545, 29.34695893, 33.96772651, 33.44375187, 30.28336163,
       31.5064206 , 32.37874239, 34.67273523, 32.10287032, 31.43470396,
       30.85601515, 32.44873308, 34.84733754, 31.54349233, 33.48150748,
       32.17519927, 32.46567057, 31.1942968 , 28.93540971, 31.80171987,
       34.85089246, 30.74604222, 30.93384856, 33.88868711, 32.96698456,
       30.18907546, 32.07198548, 32.23388955, 31.13457905, 30.95911371,
       31.88974828, 32.55139635, 33.78501179, 31.6810708 , 35.30061812,
       29.10282975])
```

In [144]:

```
# Linear Relationship
plt.scatter(y_test,el_prd)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predict Data')
```

Out[144]:

```
Text(0, 0.5, 'Test Predict Data')
```



In [145]:

```
## calculating residuals
residuals = y_test-el_prd
residuals
```

Out[145]:

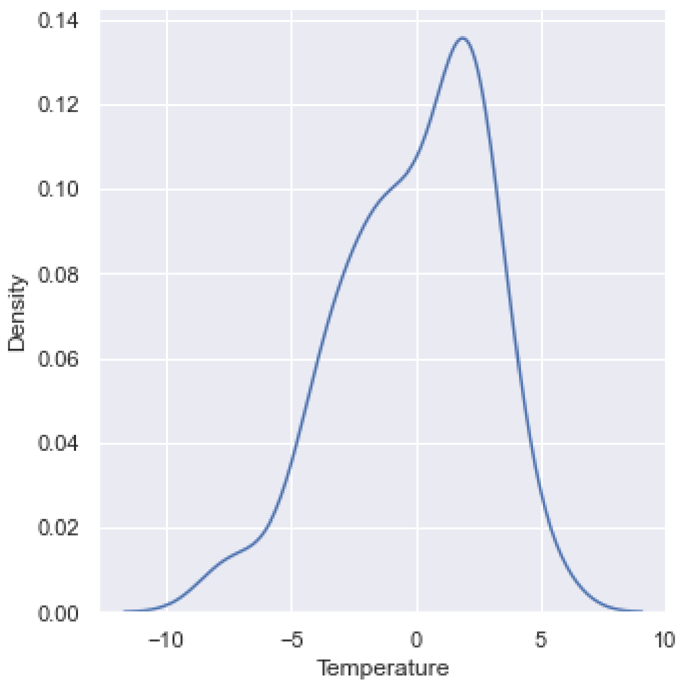
```
162    2.134072
60     2.000191
61     3.382517
63     3.313596
69     2.028669
         ...
169    0.448604
232   -4.785012
144    1.318929
208   -2.300618
105   -7.102830
Name: Temperature, Length: 81, dtype: float64
```

In [146]:

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

Out[146]:

```
<seaborn.axisgrid.FacetGrid at 0x2e4ebf603a0>
```

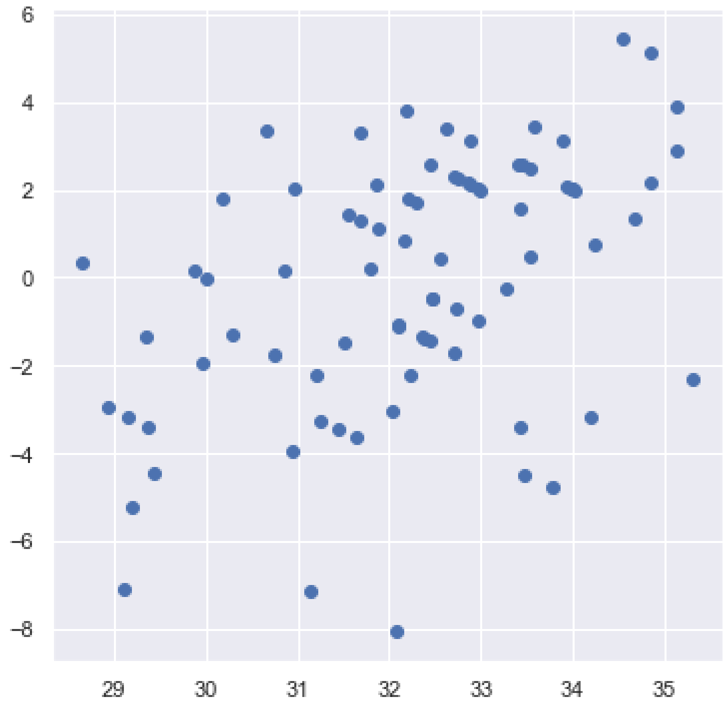


In [147]:

```
# Homoscedaticity
plt.scatter(el_prd,residuals)
```

Out[147]:

```
<matplotlib.collections.PathCollection at 0x2e4ec009d60>
```



In [148]:

```
#Performance Metrics
print(mean_squared_error(y_test,el_prd))
print(mean_absolute_error(y_test,el_prd))
print(np.sqrt(mean_squared_error(y_test,el_prd)))

score = r2_score(y_test,el_prd)
print(score)

adjR = 1 - ( 1-score ) * ( len(y) - 1 ) / ( len(y) - X.shape[1] - 1 )
print(adjR)
```

```
8.292252068870686
2.3928423520303443
2.879627071144923
0.45165730186195463
0.4181341674779693
```

In [ ]:

In [ ]:

In [ ]: