EDA(Algerian Forest Fires Dataset)

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Linkedin:https://lnkd.in/gu7QnXPV (https://lnkd.in/gu7QnXPV)

Github: https://github.com/Rajeshsekar1504/EDA_Algerian_Data_Set (https://github.com/Rajeshsekar1504/EDA_Algerian_Data_Set)

EDA

```
1.Data Profiling
2.Statistical Analysis
3.Graphical Analysis
```

Dataset:https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++ (https://archive.ics.uci.edu/ml/datasets/Algerian+Forest+Fires+Dataset++)

Importing all the required the Libraries

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import warnings

warnings.filterwarnings("ignore")
%matplotlib inline
pd.set_option('display.max_columns', 500)
```

Importing dataset and cleaning data

In [2]:

```
df= pd.read_csv('Algerian_forest_fires_dataset_UPDATE.csv',header=1)
df.iloc[121:].head(4) #index 122,123 need to be removed from dataset
```

Out[2]:

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

Dropping rows which have no information

In [3]:

```
df.drop(index=[122,123], inplace=True) # droping row 122,123 from dataset
df.reset_index(inplace=True)
df.drop('index', axis=1, inplace=True)
df.iloc[121:].head()
```

Out[3]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classe
121	30	09	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1	not fi
122	01	06	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not fi
123	02	06	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2	not fi
124	03	06	2012	29	80	14	2	48.7	2.2	7.6	0.3	2.6	0.1	not fi
125	04	06	2012	30	64	14	0	79.4	5.2	15.4	2.2	5.6	1	not fi

Creating Region feature

In [4]:

```
### creating feature called Region 0 for Bejaia region and 1 for Sidi Bel-abbes region
df.loc[:122,'Region']=0
df.loc[122:, 'Region']=1
df.iloc[120:].head(8)
```

Out[4]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classe
120	29	09	2012	26	80	16	1.8	47.4	2.9	7.7	0.3	3	0.1	not fi
121	30	09	2012	25	78	14	1.4	45	1.9	7.5	0.2	2.4	0.1	not fi
122	01	06	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not fi
123	02	06	2012	30	73	13	4	55.7	2.7	7.8	0.6	2.9	0.2	not fi
124	03	06	2012	29	80	14	2	48.7	2.2	7.6	0.3	2.6	0.1	not fi
125	04	06	2012	30	64	14	0	79.4	5.2	15.4	2.2	5.6	1	not fi
126	05	06	2012	32	60	14	0.2	77.1	6	17.6	1.8	6.5	0.9	not fi
127	06	06	2012	35	54	11	0.1	83.7	8.4	26.3	3.1	9.3	3.1	fi

Datatypes and describe

In [5]:

```
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    float64
dtypes: float64(1), object(14)
memory usage: 28.7+ KB
```

Describing the dataset

In [6]:

```
df.describe(include='all')
```

Out[6]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FW
count	244	244	244	244	244	244	244	244	244	244	244	244	24
unique	31	4	1	19	62	18	39	173	166	198	106	174	12
top	01	07	2012	35	64	14	0	88.9	7.9	8	1.1	3	0.
freq	8	62	244	29	10	43	133	8	5	5	8	5	1
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

Data Cleaning

In [7]:

```
# here it is visible that some columns have spaces in the names like RH, Ws
df.columns
```

Out[7]:

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

stripping spaces from column names

In [8]:

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

Out[8]:

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

In [9]:

```
### converting all feature values to string so that we can do data cleaning as shown below.
df=df.astype(str)
```

In [10]:

```
### Some values in columns also have space
for feature in ['Rain','FFMC','DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes']:
    df[feature] = df[feature].str.replace(" ","")
```

In [11]:

```
## index no 165 for feature name FWI has value fire
df[df['FWI']== 'fire'].index
```

Out[11]:

```
Int64Index([165], dtype='int64')
```

In [12]:

```
### replacing fire value witha float value
df.loc[165,'FWI'] ='0.1'
```

In [13]:

```
### replacing nan value wit fire to make data equal to the info given in dataset
df[df['Classes']== 'nan'].index
df.loc[165,'Classes']='fire'
```

In [14]:

```
## encoding classes feature
df['Classes']=df['Classes'].str.replace('notfire','0')
df['Classes']=df['Classes'].str.replace('fire','1')
```

Changing datatypes

In [15]:

```
### changing datatypes of features to numerical for numerical features as all are in object
datatype_convert={'day':'int64','month':'int64','year':'int64','Temperature':'int64','RH':'
'FFMC':'float64', 'DMC':'float64', 'DC':'float64', 'ISI':'float64', 'BUI':'float64', 'FWI':
'Classes':'int64', 'Region':'float64'}
df=df.astype(datatype_convert)
df.dtypes
```

Out[15]:

```
day              int64
month            int64
year             int64
Temperature      int64
RH               int64
Ws               int64
Rain           float64
FFMC           float64
DMC            float64
DC             float64
ISI            float64
BUI            float64
FWI            float64
Classes          int64
Region         float64
dtype: object
```

Info about dataset and its attributes

1. The dataset includes 244 instances that regroup a data of two regions of Algeria,namely the Bejaia region located in the northeast of Algeria and the Sidi Bel-abbes region located in the northwest of Algeria.
2. 122 instances for each region.
3. The period from June 2012 to September 2012.
4. The dataset includes 11 attribues and 1 output attribue (class)
5. The 244 instances have been classified into fire (138 classes) and notfire (106 classes) classes.

Attributes

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

Weather data observations

1. Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
2. RH : Relative Humidity in %: 21 to 90
3. Ws :Wind speed in km/h: 6 to 29
4. Rain: total day in mm: 0 to 16.8

FWI Components

1. Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
2. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
3. Drought Code (DC) index from the FWI system: 7 to 220.4
4. Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
5. Buildup Index (BUI) index from the FWI system: 1.1 to 68
6. Fire Weather Index (FWI) Index: 0 to 31.1
7. Classes: two classes, namely fire and not fire

In [16]:

```
df.shape
```

Out[16]:

```
(244, 15)
```

Checking Null values

In [17]:

```
### checking for null values

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
```

Observation

1. There is no null value in dataset.
2. Total 244 rows and 15 columns is present.

Numerical and continuous features

In [18]:

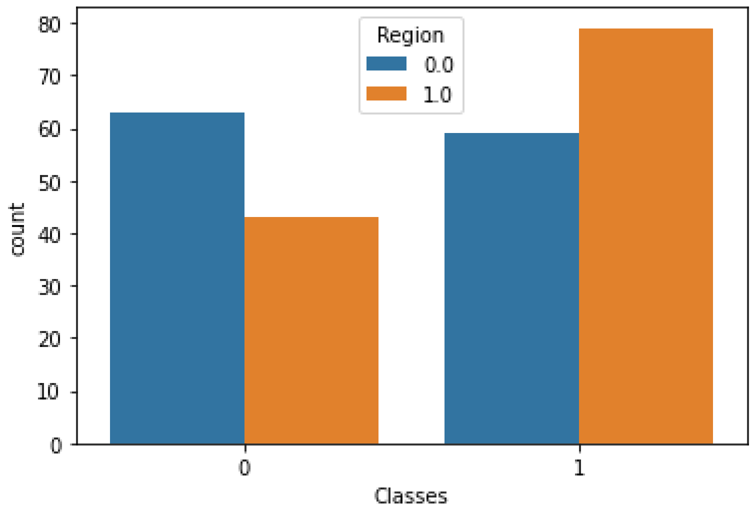
```
# categorical features

categorical_feature=[feature for feature in df.columns if df[feature].dtypes=='O']

#getting to know different categories in cateogrical features with its count.
for feature in categorical_feature:
    print(df.groupby(feature)['Region'].value_counts())
```

In [19]:

```
sns.countplot(data=df, x='Classes',hue='Region')
```

Out[19]:

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



Observation

1.It is evident that Sidi Bel-abbes region has more occurance of fire than Bejaia region.

Numerical features

In [20]:

```
### Getting list of numerical features
numerical_features=[feature for feature in df.columns if df[feature].dtypes!='O']
print(numerical_features)
```

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

In [21]:

```
### Getting uniques values in each numerical features

df[numerical_features].nunique()
```

Out[21]:

```
day             31
month            4
year             1
Temperature     19
RH              62
Ws              18
Rain            39
FFMC           173
DMC            166
DC             198
ISI            106
BUI            174
FWI            125
Classes          2
Region           2
dtype: int64
```

Seggregating discrete and continuous variables

Discrete Numerical Features

In [22]:

```
#here the assumption to consider a feature discrete is that it should have less than 35 uni
#considered continuous feature

discrete_features = [feature for feature in numerical_features if len(df[feature].unique())
discrete_features
```

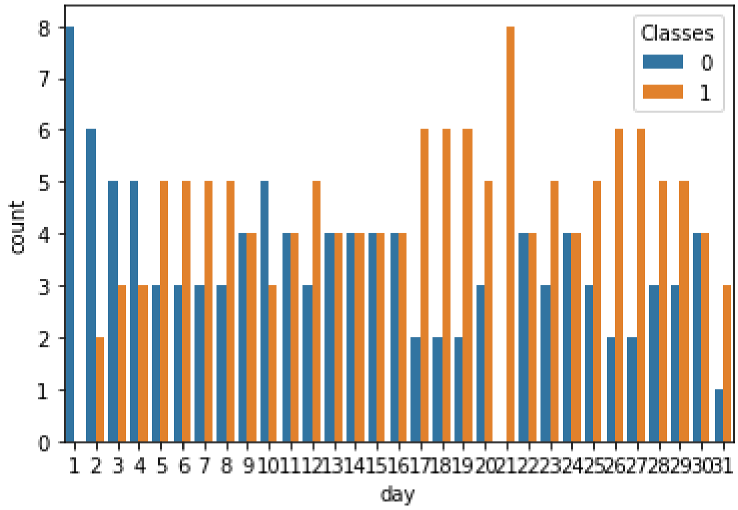
Out[22]:

```
['day', 'month', 'year', 'Temperature', 'Ws', 'Classes', 'Region']
```

Discrete Numerical Feature vs Target Feature

In [23]:

```
### this is bivariate analysis between target feature classes and discrete numerical featur

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



Observations

1. From day vs Classes plot it is visible that on almost all days the occurance of fire is there, and its count is more than or equal to the count of no fire cases.
2. From month vs Classes plot it is visible that july and august month have more cases of occurance of fire as compared to other two months of june and september where occurance of fire is less as compared to no fire .
3. The month of august has highest no of cases of occurance of fire.
4. Overall cases of occurance of fire is more than the cases of no occurance of fire.
5. From temperature vs Classes plot it is visible that temperature between 30 to 37 degree celcius have most no of cases of occurance of fire.
6. From windspeed vs Classes plot it is visible that for wind speed between 13 to 19 Km/hr range there is most no of occurance of fire.
7. From Region vs Class plot it is visible that in Bejaia region, the no of cases of occurance of fire is less compared to no fire.
8. In Sidi Bel-abbes region the no of cases of occurance of fire is more compared to no fire. Also Overall no of cases of occurance of fire is more in Sidi Bel-abbes region as compared to Bejaia region.

Continuous Numerical Features

In [24]:

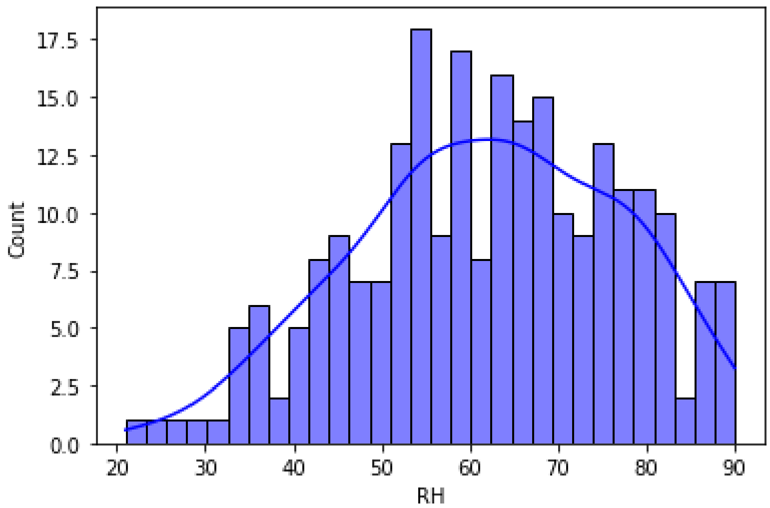
```
continuous_features=[feature for feature in numerical_features if feature not in discrete_f
print(continuous_features)
```

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

Distribution of Continuous Numerical Features

In [25]:

```
for feature in continuous_features:
    sns.histplot(data=df,x=feature,kde=True,bins=30,color='blue')
    plt.show()
```



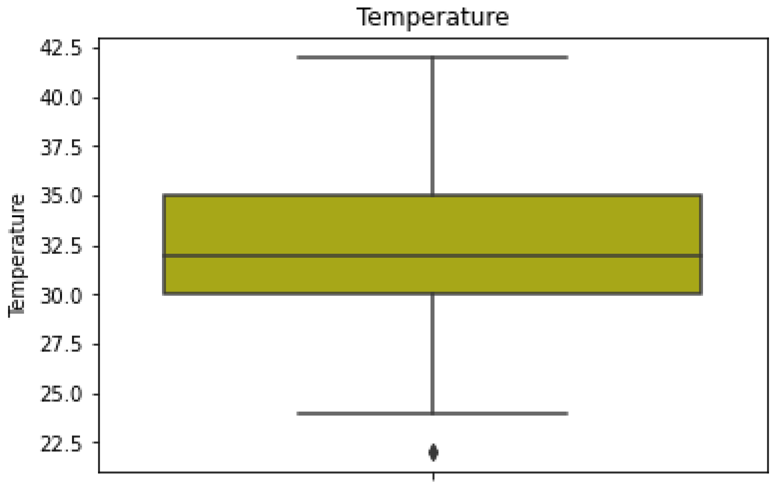
Observations

1. Relative humidity is following gaussian distribution
2. Rain,DMC,DC,ISI,BUI,FWI are following right skewed distribution(Log-Normal distribution)
3. FFMC feature follows left skewed distribution

Checking for outliers

In [26]:

```
### excluding 'day','month','year','Region'

for feature in [feature for feature in numerical_features if feature not in ['day','month',
    sns.boxplot(data=df,y=feature,color='y')
    plt.title(feature)
    plt.show();
```



Observations

1.Relative Humidity RH feature doesnt have outliers. 2.Temperature and FFMC have outliers in low boundary side. 3.Wind Speed, Ws has outliers on both sides(Upper and lower boundary). 4.Rain,DMC,ISI,BUI and FWI have outliers in upper boundary side.

Correlation between each Numerical features

In [27]:

```
data = round(df[[feature for feature in numerical_features if feature not in ['day','month'
data
```

Out[27]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
Temperature	1.00	-0.65	-0.28	-0.33	0.68	0.48	0.37	0.61	0.46	0.56	0.52
RH	-0.65	1.00	0.24	0.22	-0.65	-0.41	-0.22	-0.69	-0.35	-0.57	-0.44
Ws	-0.28	0.24	1.00	0.17	-0.16	-0.00	0.08	0.02	0.03	0.03	-0.07
Rain	-0.33	0.22	0.17	1.00	-0.54	-0.29	-0.30	-0.35	-0.30	-0.32	-0.38
FFMC	0.68	-0.65	-0.16	-0.54	1.00	0.60	0.50	0.74	0.59	0.69	0.77
DMC	0.48	-0.41	-0.00	-0.29	0.60	1.00	0.88	0.67	0.98	0.87	0.58
DC	0.37	-0.22	0.08	-0.30	0.50	0.88	1.00	0.50	0.94	0.74	0.51
ISI	0.61	-0.69	0.02	-0.35	0.74	0.67	0.50	1.00	0.64	0.91	0.74
BUI	0.46	-0.35	0.03	-0.30	0.59	0.98	0.94	0.64	1.00	0.86	0.58
FWI	0.56	-0.57	0.03	-0.32	0.69	0.87	0.74	0.91	0.86	1.00	0.71
Classes	0.52	-0.44	-0.07	-0.38	0.77	0.58	0.51	0.74	0.58	0.71	1.00

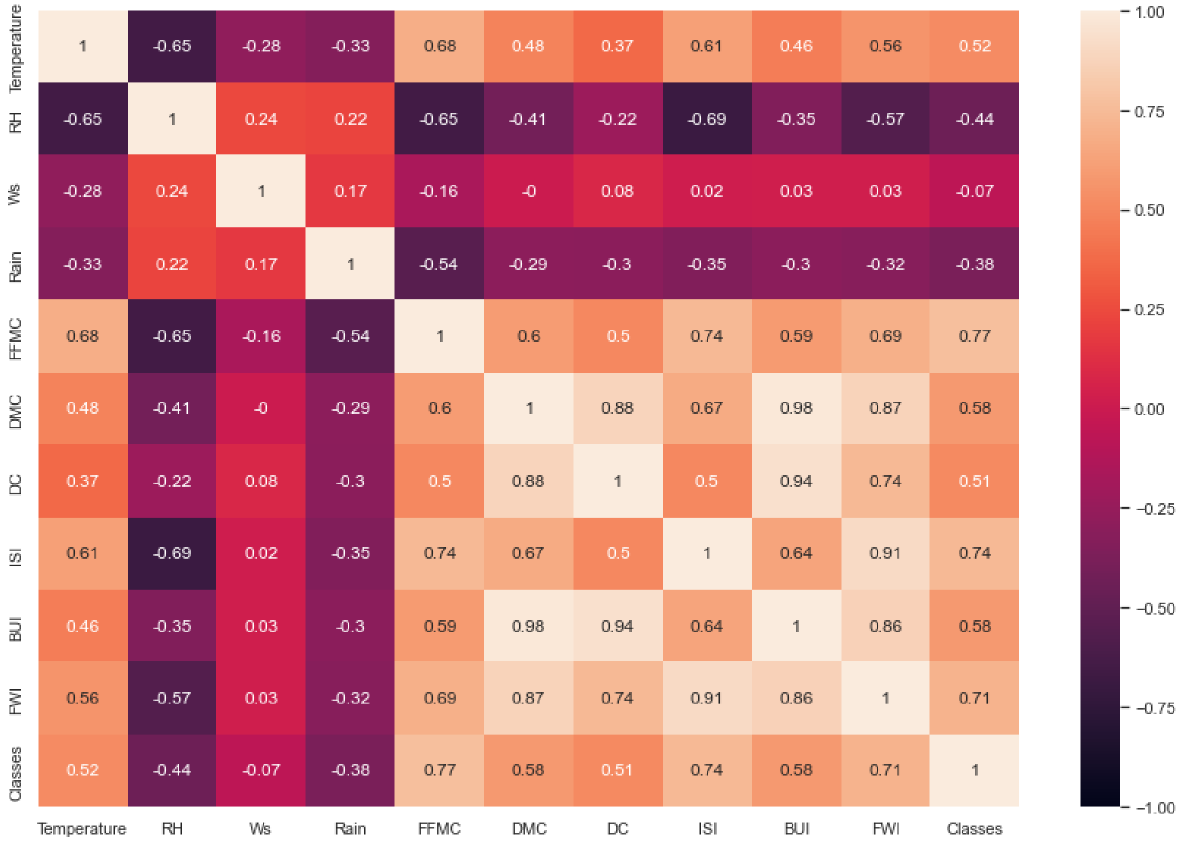
Heatmap to visualise the Correlation

In [28]:

```
### Plotting heatmap for visualising the correlation between features
sns.set(rc={'figure.figsize':(15,10)})
sns.heatmap(data=data,annot=True, vmin=-1, vmax=1)
```

Out[28]:

```
<AxesSubplot:>
```



Note(For both positive and negative side)

1. Correlation coefficients between 0.9 and 1.0,very highly correlated.
2. Correlation coefficients between 0.7 and 0.9, highly correlated.
3. Correlation coefficients between 0.5 and 0.7, moderately correlated.
4. Correlation coefficients between 0.3 and 0.5, low correlation.
5. Correlation coefficients less than 0.3, little correlation.

Observations

1. Very highly Corrleated feature:DMC-BUI,DC-BUI,ISI-FWI
2. Highly correlated features:FFMC-ISI,DC-DMC,FWI-DMC,FWI-DC,FWI-BUI Note: Features with very hihg and high correlation are more linearly dependent and hence have almost the same effect on the dependent variable. So, we can drop one of the two features.

Feature VS target

day

In [29]:

```
sns.scatterplot(data=df,x='day',y='Temperature',hue='Classes')
```

Out[29]:

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

Observation

1. Most cases of fire occur for temperature more than 30 degree celicus

In [30]:

```
df
```

Out[30]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Class
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
239	26	9	2012	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	
240	27	9	2012	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	
241	28	9	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	
242	29	9	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	
243	30	9	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	

244 rows × 15 columns

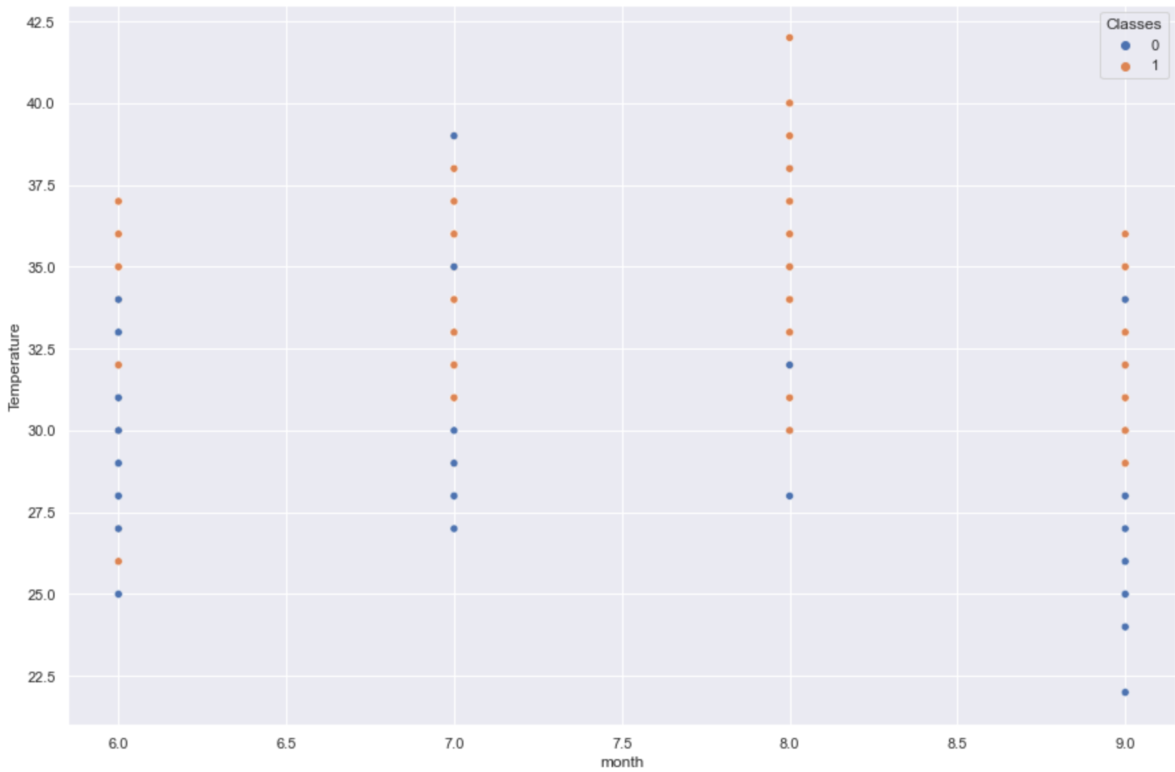
Month

In [31]:

```
sns.scatterplot(data=df,x='month',y='Temperature',hue='Classes')
```

Out[31]:

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



Observations

1. July and august have more cases of fire as compared to no fire.
2. june and september have more cases of no fire as compared to fire.

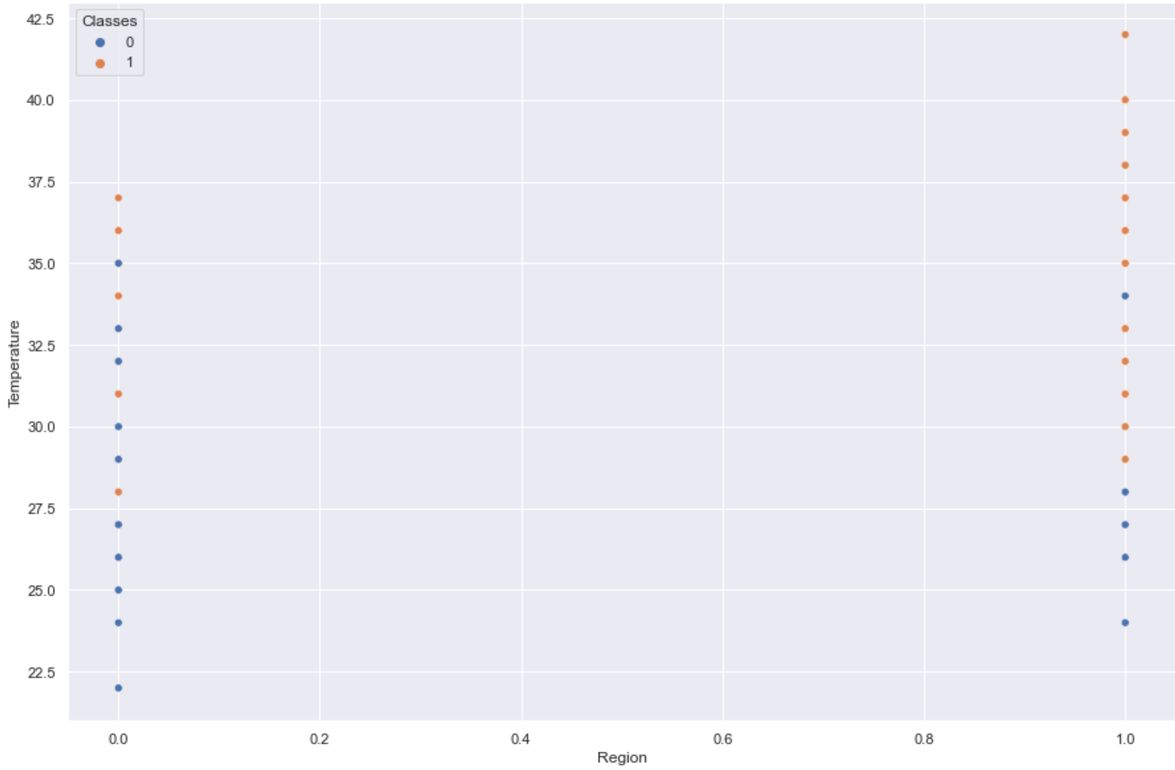
Region

In [32]:

```
sns.scatterplot(data=df,x='Region',y='Temperature',hue='Classes')
```

Out[32]:

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

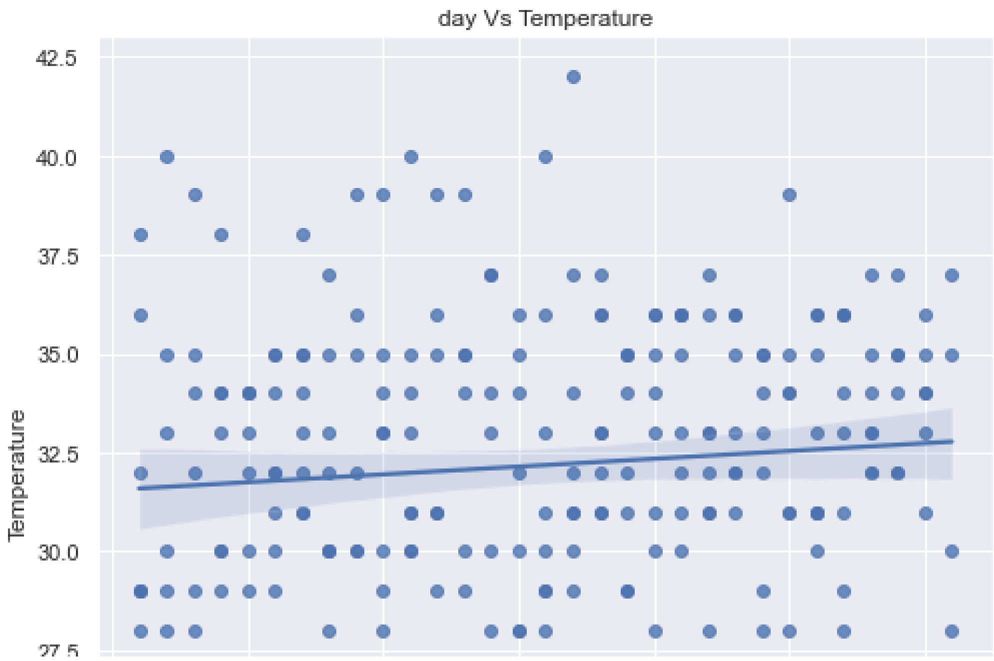


Observations

1. In Bejaia region, the no of cases of occurance of fire is less compared to no of cases of occurance of no fire.
2. In Sidi Bel-abbes region the no of cases of occurance of fire is more compared to no fire.
3. Also Overall no of cases of occurance of fire is more in Sidi Bel-abbes region as compared to Bejaia region.

In [33]:

```
#### shaded region is basically with respect to ridge and lasso (lambda)
for feature in [feature for feature in df.columns if feature not in ['Temp']]:
    sns.set(rc={'figure.figsize':(8,8)})
    sns.regplot(x=df[feature], y=df['Temperature'])
    plt.xlabel(feature)
    plt.ylabel('Temperature')
    plt.title('{} Vs Temperature'.format(feature))
    plt.show();
```



Final Report

1. very highly correlated features:DMC-BUI,ISI-FWI
2. Highly correlated features:FFMC-ISI,DC-DMC,FWI-DMC,FWI-DC,FWI-BUI
3. Temperature between 30 to 37 degree celcius have most no of cases of occurance of fire.
4. Wind speed between 13 to 19Km/hr range there is most no of occurance of fire.
5. Almost all cases of occurance of fires is for region having rain less than 1mm i.e, dry regions are more prone to forest fires.
6. For FFMC(Fine Fuel Moisture Code) greater that 80, almost all cases of fire is reported.
7. DMC (Duff Moisture Code) >30 and DC (Drought code) >100, almost all cases of occurance of fire reported, this means drought affected areas are more prone to forrest fires.
8. In Bejaia region, the no of cases of occurance of fire is less compared to no of cases of occurance of no fire.
9. In Sidi Bel-abbes region the no of cases of occurance of fire is more compared to no fire.
10. Also Overall no of cases of occurance of fire is more in Sidi Bel-abbes region as compared to Bejaia region.
11. Most no of cases of fire occured are in the month of august and least no of cases of fire occured is in month of september.
12. July and august have more cases of fire as compared to no fire.
13. June and september have more cases of no fire as compared to fire.
14. Relative Humidity, RH feature doesnt have outliers whereas Temperature, FFMC, wind speed, Rain, DMC,DC, ISI, BUI and FWI have outilers.
15. There is no null vales in dataset.

Note EDA and basic feature engineering is done its time to seperate independent and dependent features.

1. For demonstrating linear regression taking Temperature as Dependent feature.
2. dropping year feature as dataset contains only 2012 year

In [34]:

```
df.drop('year',axis=1,inplace=True)
```

In [35]:

```
df['Temp']=df['Temperature']
```

In [36]:

```
df.drop('Temperature',axis=1,inplace=True)
```

In [37]:

```
df
```

Out[37]:

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

244 rows × 14 columns

Starting Model Building Preparatin

In [38]:

```
### Getting Independent features in dataset and Dependent feature in Series object
```

In [39]:

```
df.head()
```

Out[39]:

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

In [40]:

```
### X independent features and y dependent feature
X = df.iloc[:,:-1]
y = df.iloc[:,-1]
```

In [41]:

```
X.head()
```

Out[41]:

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

In [42]:

```
y.head()
```

Out[42]:

```
0     29
1     29
2     26
3     25
4     27
Name: Temp, dtype: int64
```

Splitting data into Training and Test data

In [43]:

```
## Splitting data into Training and Test da
from sklearn.model_selection import train_test_split
```

In [44]:

```
### random state train test split will be same with all people using random state =42
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.33,random_state=42)
```

In [45]:

```
X_train.head()
```

Out[45]:

	day	month	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
114	23	9	54	11	0.5	73.7	7.9	30.4	1.2	9.6	0.7	0	0.0
65	5	8	65	13	0.0	86.8	11.1	29.7	5.2	11.5	6.1	1	0.0
132	11	6	42	21	0.0	90.6	18.2	30.5	13.4	18.0	16.7	1	1.0
207	25	8	40	18	0.0	92.1	56.3	157.5	14.3	59.5	31.1	1	1.0
162	11	7	56	15	2.9	74.8	7.1	9.5	1.6	6.8	0.8	0	1.0

In [46]:

```
y_train.head()
```

Out[46]:

```
114    32
65     34
132    31
207    34
162    34
Name: Temp, dtype: int64
```

In [47]:

```
X_test.head()
```

Out[47]:

	day	month	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
24	25	6	64	15	0.0	86.7	14.2	63.8	5.7	18.3	8.4	1	0.0
6	7	6	54	13	0.0	88.2	9.9	30.5	6.4	10.9	7.2	1	0.0
153	2	7	48	16	0.0	87.6	7.9	17.8	6.8	7.8	6.4	1	1.0
211	29	8	53	17	0.5	80.2	20.7	149.2	2.7	30.6	5.9	1	1.0
198	16	8	41	10	0.1	92.0	22.6	65.1	9.5	24.2	14.8	1	1.0

In [48]:

```
y_test.head()
```

Out[48]:

```
24     31
6      33
153    33
211    35
198    40
Name: Temp, dtype: int64
```

In [49]:

```
### both will have same shape
X_train.shape,y_train.shape
```

Out[49]:

```
((163, 13), (163,))
```

In [50]:

```
### both will have same shape
X_test.shape,y_test.shape
```

Out[50]:

```
((81, 13), (81,))
```

Feature Engineering

Standardisation/feature scaling the dataset

In [51]:

```
from sklearn.preprocessing import StandardScaler
```

In [52]:

```
### creating a StandardScalar object
scaler = StandardScaler()
scaler
```

Out[52]:

```
StandardScaler()
```

In [53]:

```
### Using fit_transform to standardise train data
X_train = scaler.fit_transform(X_train)
X_train
```

Out[53]:

```
array([[ 0.84447703,  1.3826723 , -0.60257784, ..., -0.8196431 ,
        -1.04390785, -0.99388373],
       [-1.19310159,  0.48116996,  0.14460201, ..., -0.08219052,
         0.95793896, -0.99388373],
       [-0.51390872, -1.32183472, -1.41768313, ...,  1.36540157,
         0.95793896,  1.0061539 ],
       ...,
       [-1.64589683,  1.3826723 ,  0.89178186, ..., -0.90158227,
        -1.04390785, -0.99388373],
       [ 1.41047108, -0.42033238, -0.39880152, ...,  0.31384882,
         0.95793896,  1.0061539 ],
       [-0.51390872,  1.3826723 ,  0.9597073 , ..., -0.87426921,
        -1.04390785, -0.99388373]])
```

In [54]:

```
### Here using only transform to avoid data leakage
### (training mean and training std will be used for standardisation of test when we use tr
X_test=scaler.transform(X_test)
X_test
```

Out[54]:

```
array([[ 1.07087465, -1.32183472,  0.07667657, ...,  0.23190965,
         0.95793896, -0.99388373],
       [-0.96670396, -1.32183472, -0.60257784, ...,  0.0680313 ,
         0.95793896, -0.99388373],
       [-1.53269802, -0.42033238, -1.01013048, ..., -0.04122093,
         0.95793896,  1.0061539 ],
       ...,
       [ 1.29727227, -0.42033238, -1.01013048, ...,  1.17421016,
         0.95793896, -0.99388373],
       [-1.3063004 , -1.32183472,  0.07667657, ..., -0.77867351,
        -1.04390785,  1.0061539 ],
       [ 1.29727227, -1.32183472, -0.5346524 , ...,  0.7235447 ,
         0.95793896,  1.0061539 ]])
```

Model Buliding

Linear Regression

In [55]:

```
from sklearn.linear_model import LinearRegression
```

In [56]:

```
### creating Linear regression model
linear_reg = LinearRegression()
linear_reg
```

Out[56]:

```
LinearRegression()
```

In [57]:

```
### passing training data(X and y ) to the model
linear_reg.fit(X_train,y_train)
```

Out[57]:

```
LinearRegression()
```

In [58]:

```
## Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent features is {}".format(linear_reg.coef_))
print("2. Intercept of best fit hyperplane is {}".format(linear_reg.intercept_))
```

```
1. Co-efficients of independent features is [-0.62994684 -0.33080692 -0.9681
523  -0.55769053  0.23645285  1.90585623
  0.93380592  1.17296981  0.044581   -1.35995788  0.19772494 -0.25230922
  0.08345626]
2. Intercept of best fit hyperplane is 31.98159509202454
```

Using model to get predictions of test data

In [59]:

```
linear_reg_pred = linear_reg.predict(X_test)
linear_reg_pred
```

Out[59]:

```
array([32.86982262, 34.97907511, 34.71895423, 32.93220734, 36.64866482,
       32.00281859, 35.27819508, 28.49312857, 31.84450923, 29.27704091,
       29.06704133, 33.07364481, 32.4667427 , 32.7008168 , 34.32599535,
       31.80453584, 37.01042617, 25.23211237, 32.73196597, 33.38253854,
       31.55571716, 28.30699286, 34.23615097, 29.30603632, 36.93126913,
       24.98756128, 33.51228222, 33.57587507, 33.35705604, 35.40329932,
       33.767112  , 31.85221582, 32.40507656, 33.11736397, 32.44972087,
       31.46599605, 30.34784931, 34.2239929 , 32.37589956, 21.74277219,
       33.82900884, 34.85103093, 31.20651563, 24.69868309, 36.17424894,
       32.81796744, 31.22635993, 30.67357508, 35.1950892 , 34.29311524,
       36.98975313, 30.97884914, 30.95678802, 34.6655222 , 33.46814569,
       32.38222097, 36.65227179, 30.589826  , 30.97603618, 36.10290928,
       33.94615809, 28.43783118, 33.17776773, 31.78923636, 31.99593987,
       24.12810241, 33.39123143, 29.76320324, 36.80847578, 34.30376941,
       33.61696277, 31.49444654, 33.44085947, 34.43788629, 35.59708798,
       31.17211416, 32.72579793, 32.96039667, 35.20161022, 33.43024933,
       33.69316482])
```

Validating model using assumptions of Linear regression

Linear relatioship

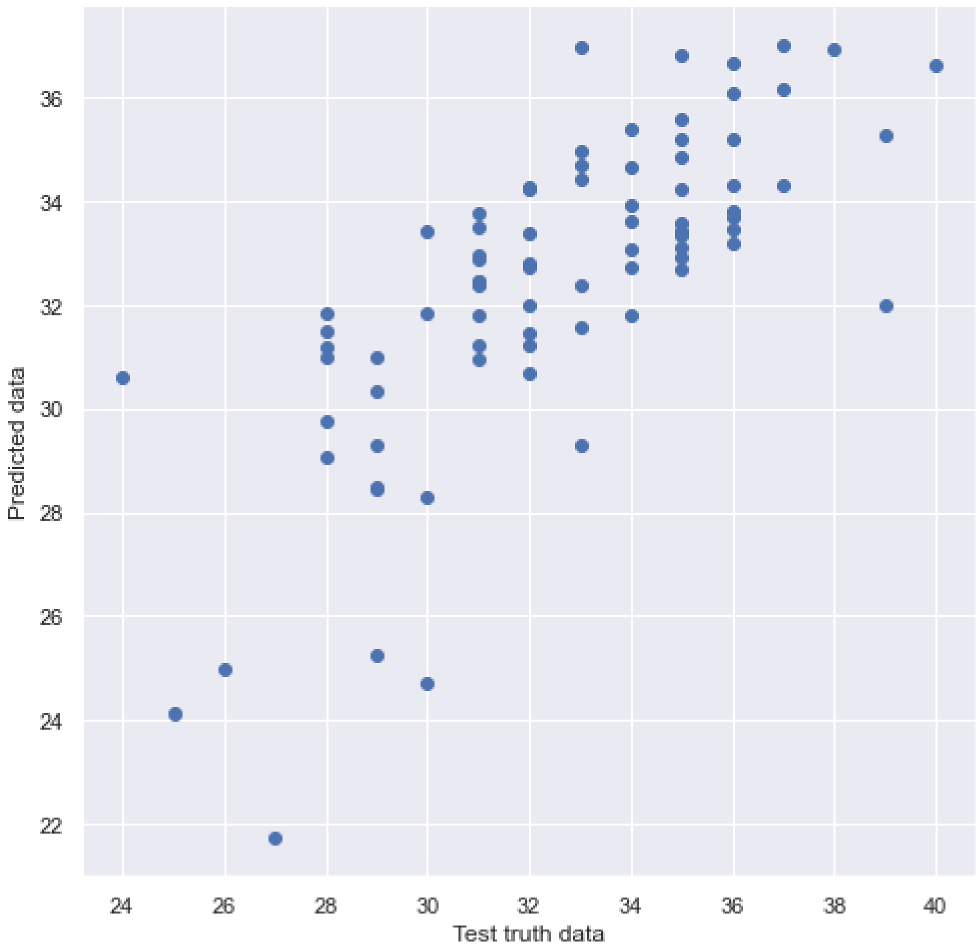
1. Test truth data and Predicted data should follow linear relationship.
2. This is an indication of a good model.

In [60]:

```
plt.scatter(x = y_test, y = linear_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

Out[60]:

```
Text(0, 0.5, 'Predicted data')
```



Residual distribution

1. Residuals should follow normal distribution.
2. if residuals follow normal distribution,it indicates we have a good model.

In [61]:

```
residual_linear_reg=y_test-linear_reg_pred
residual_linear_reg.head()
```

Out[61]:

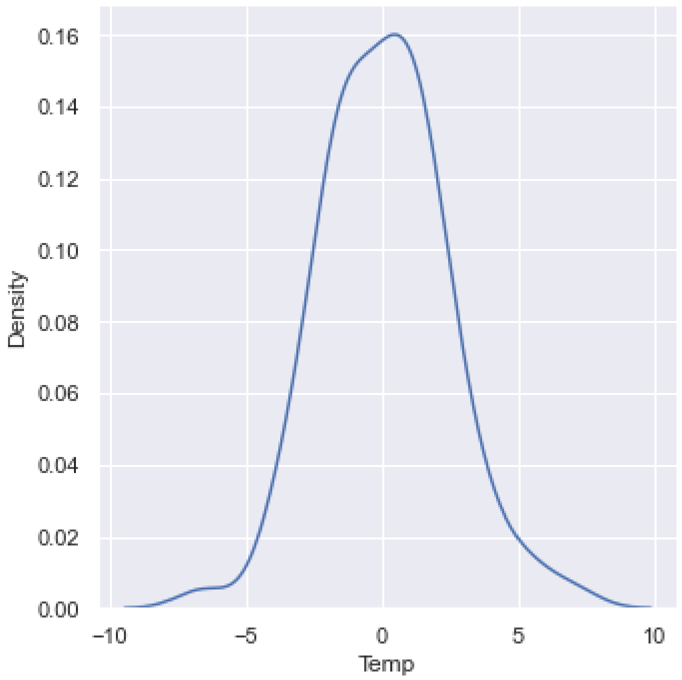
```
24    -1.869823
6     -1.979075
153   -1.718954
211    2.067793
198    3.351335
Name: Temp, dtype: float64
```

In [62]:

```
sns.displot(x=residual_linear_reg, kind='kde')
```

Out[62]:

```
<seaborn.axisgrid.FacetGrid at 0x126c8ff1820>
```



Uniform distribution

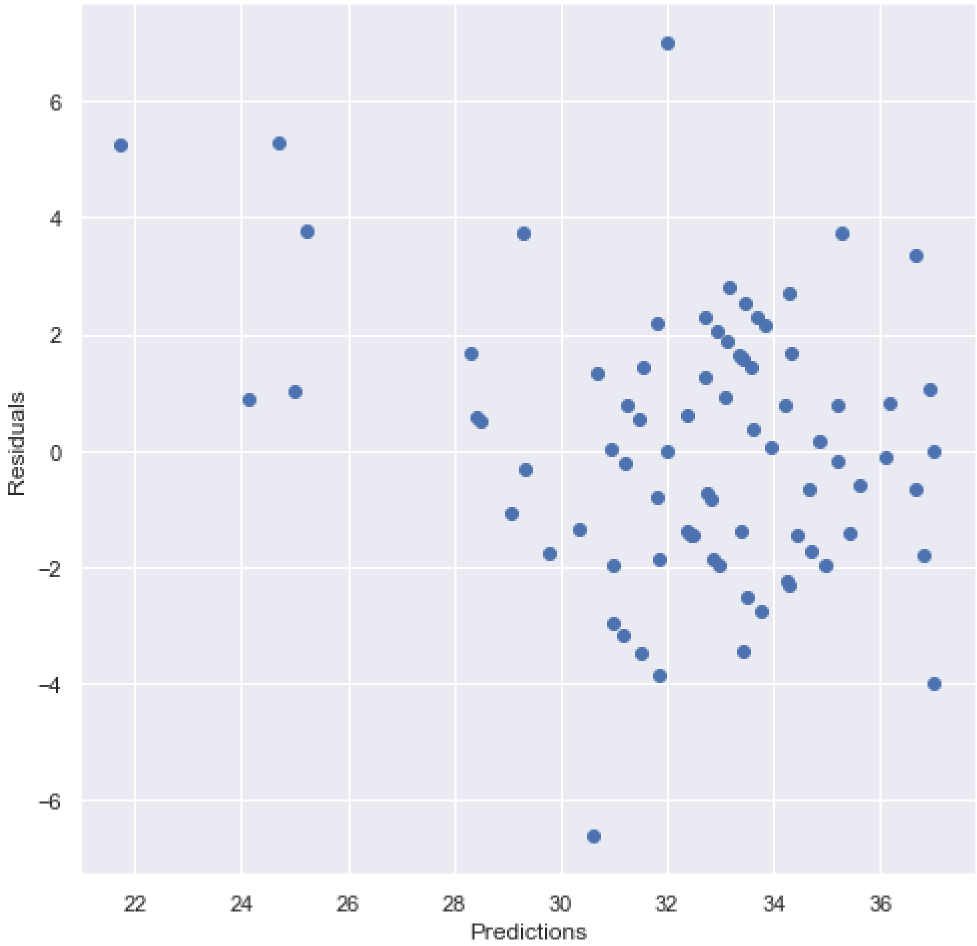
1. Residuals vs Predictions should follow a uniform distribution.
2. If Residuals vs Predictions follow uniform distribution, it indicates we have a good model.

In [63]:

```
plt.scatter(x=linear_reg_pred,y=residual_linear_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

Out[63]:

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



Performance Matrix

Cost function values

In [64]:

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

MSE, MAE and RMSE

In [65]:

```
print("Mean squared error is {}".format(round(mean_squared_error(y_test,linear_reg_pred),2)
print("Mean absolute error is {}".format(round(mean_absolute_error(y_test,linear_reg_pred),
print("Root mean squared error is {}".format(round(np.sqrt(mean_squared_error(y_test,linear
```

```
Mean squared error is 5.25
Mean absolute error is 1.81
Root mean squared error is 2.29
```

R Square and Adjusted R Square values

In [66]:

```
from sklearn.metrics import r2_score
```

In [67]:

```
linear_reg_r2_score=r2_score(y_test,linear_reg_pred)
print("Our Linear regression model has {} % accuracy".format(round(linear_reg_r2_score*100,

linear_reg_r2_score=1-((1-linear_reg_r2_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]
print("Adjusted R square accuracy is {} percent".format(round(linear_reg_r2_score*100,2)))
```

```
Our Linear regression model has 51.089 % accuracy
Adjusted R square accuracy is 41.6 percent
```

Ridge Regression

In [68]:

```
from sklearn.linear_model import Ridge
```

In [69]:

```
## Creating Ridge regression model
ridge_reg = Ridge()
ridge_reg
```

Out[69]:

```
Ridge()
```

In [70]:

```
### Passing training data(X and y) to the model
ridge_reg.fit(X_train,y_train)
```

Out[70]:

```
Ridge()
```

In [71]:

```
### Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent features is {}".format(ridge_reg.coef_))
print("2. Intercept of best fit hyperplane is {}".format(ridge_reg.intercept_))
```

```
1. Co-efficients of independent features is [-0.61752995 -0.3207458  -0.9821
8457 -0.55467826  0.21315492  1.84131702
  0.40094067  0.87094221  0.11396182 -0.48465778  0.08466793 -0.24063909
  0.09187935]
2. Intercept of best fit hyperplane is 31.98159509202454
```

Using model to get predictions of test data

In [72]:

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

Out[72]:

```
array([32.85982748, 34.9149207 , 34.6801255 , 32.92998132, 36.61056862,
       32.05917754, 35.25499575, 28.51988807, 31.83679288, 29.28276684,
       29.06439442, 33.15037313, 32.44677748, 32.7322483 , 34.35814975,
       31.78754571, 36.91567124, 25.31324295, 32.67492302, 33.35526777,
       31.49765658, 28.29644553, 34.22316335, 29.30830796, 36.93224783,
       25.06526261, 33.48461631, 33.57641555, 33.35387649, 35.32860357,
       33.76792408, 31.83362797, 32.37993338, 33.16010038, 32.42109455,
       31.5078178 , 30.28919718, 34.25440049, 32.3007279 , 21.86171205,
       33.83192673, 34.81983629, 31.24261825, 24.76831106, 36.10419592,
       32.77320818, 31.21807666, 30.69260083, 35.1742616 , 34.29037291,
       36.93483074, 30.9447582 , 30.97755205, 34.71719979, 33.43904851,
       32.52070875, 36.64973602, 30.62216011, 30.9696123 , 36.10416977,
       33.88939183, 28.47020463, 33.13493675, 31.7769902 , 32.00695307,
       24.17731957, 33.37004249, 29.76297127, 36.78001537, 34.44394437,
       33.58457247, 31.47437138, 33.41857278, 34.45102238, 35.62964268,
       31.16568509, 32.68759611, 32.91480612, 35.20066129, 33.38322692,
       33.67748654])
```

Validating Model using assumptions of Ridge regression

Linear relationship

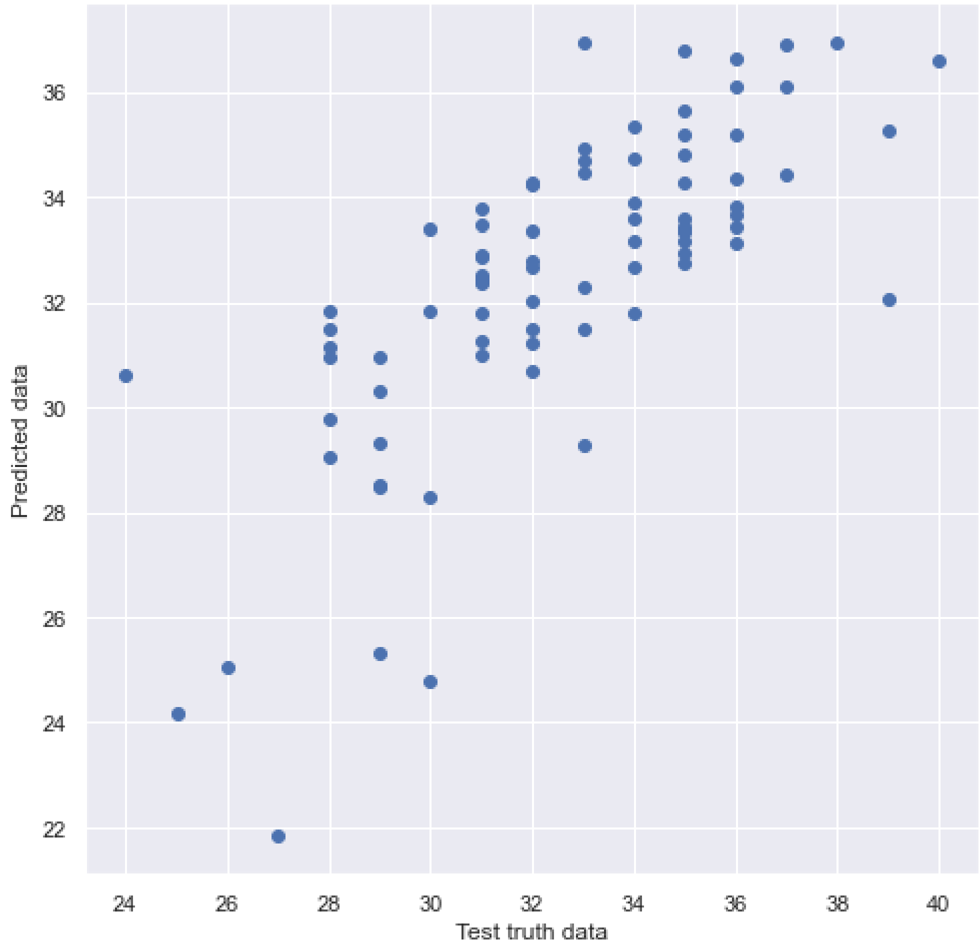
1. Test truth data and Predicted data should follow linear relationship.
2. This is an indication of a good model.

In [73]:

```
plt.scatter(x=y_test,y=ridge_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

Out[73]:

```
Text(0, 0.5, 'Predicted data')
```



Residual distribution

1. Residuals should follow normal distribution.
2. If residuals follow normal distribution, it indicates we have a good model.

In [74]:

```
residual_ridge_reg = y_test-ridge_reg_pred
residual_ridge_reg.head()
```

Out[74]:

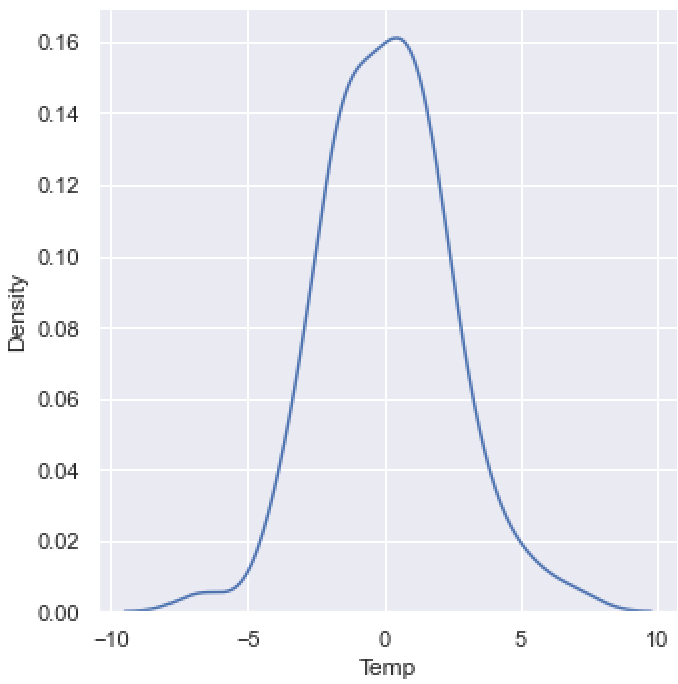
```
24    -1.859827
6     -1.914921
153   -1.680125
211    2.070019
198    3.389431
Name: Temp, dtype: float64
```

In [75]:

```
sns.displot(x=residual_ridge_reg, kind = 'kde')
```

Out[75]:

```
<seaborn.axisgrid.FacetGrid at 0x126cb105d60>
```



Uniform distribution

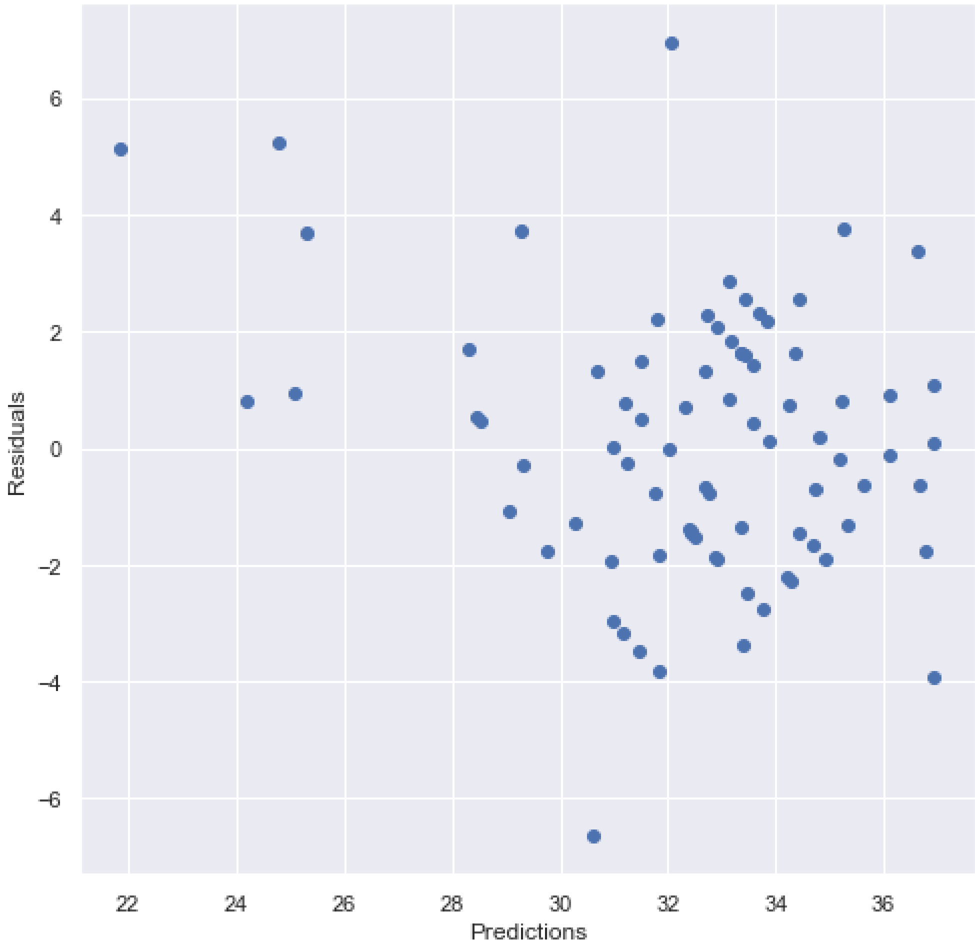
1. Residuals vs Predictions should follow a uniform distribution.
2. If Residuals vs Predictions follow uniform distribution , it indicates we have a good model.

In [76]:

```
plt.scatter(x=ridge_reg_pred,y=residual_ridge_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

Out[76]:

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



Performance Matrix

Cost function values

MSE, MAE, RMSE

In [77]:

```
print("Mean squared error is {}".format(round(mean_squared_error(y_test,ridge_reg_pred),2))
print("Mean absolute error is {}".format(round(mean_absolute_error(y_test,ridge_reg_pred),2
print("Root Mean squared error is {}".format(round(np.sqrt(mean_squared_error(y_test,ridge_
```

```
Mean squared error is 5.19
Mean absolute error is 1.8
Root Mean squared error is 2.28
```

R Square and Adjusted R Square values

In [82]:

```
ridge_reg_r2_score = r2_score(y_test, ridge_reg_pred)
print("Our Ridge regression model has {} % accuracy".format(round(ridge_reg_r2_score*100,3)
ridge_reg_adj_r2_score = 1-((1-ridge_reg_r2_score)*(len(y_test)-1)/(len(y_test)-X_test.shap
print("Adjusted R squre accuracy is {} percent".format(round(ridge_reg_adj_r2_score*100,2))
```

```
Our Ridge regression model has 51.709 % accuracy
Adjusted R squre accuracy is 42.34 percent
```

Lasso Regression

In [83]:

```
from sklearn.linear_model import Lasso
```

In [84]:

```
## Creating Lasso regression model
lasso_reg = Lasso()
lasso_reg
```

Out[84]:

```
Lasso()
```

In [85]:

```
### Passing training data(X and y) to the model
lasso_reg.fit(X_train,y_train)
```

Out[85]:

```
Lasso()
```

In [86]:

```
### Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent feautures is {}".format(lasso_reg.coef_))
print("2. Intercept of best fit hyperplane is {}".format(lasso_reg.intercept_))
```

```
1. Co-efficients of independent feautures is [-0.         -0.         -0.623
24302 -0.         -0.          1.25581509
  0.          0.          0.          0.          0.          0.
  0.         ]
2. Intercept of best fit hyperplane is 31.98159509202454
```

Using model to get predictions of test data

In [87]:

```
lasso_reg_pred = lasso_reg.predict(X_test)
lasso_reg_pred
```

Out[87]:

```
array([32.78381104, 33.3358205 , 33.53835729, 32.69192045, 34.21212444,
       31.67725854, 34.06518855, 28.84685412, 30.99078013, 30.10392027,
       31.06631475, 32.42020469, 32.80398907, 32.31726957, 33.37068778,
       32.46976122, 34.57875298, 27.38502889, 32.29240264, 33.12192792,
       31.62499111, 29.79900395, 33.65042591, 30.31559056, 34.62053146,
       28.73534108, 32.5527626 , 32.85187888, 32.99739235, 33.91411932,
       33.25917474, 31.27076256, 32.79238897, 32.82670067, 32.58151856,
       32.71432078, 31.4254765 , 33.30564213, 31.04995877, 28.31033379,
       32.79596672, 32.94981382, 32.61305239, 27.48796401, 34.24588058,
       32.5549849 , 31.88399562, 30.89031162, 34.19107957, 33.50571231,
       34.39861652, 31.81203876, 31.79074958, 32.97252542, 33.46393383,
       32.11393291, 34.88311373, 32.60669677, 31.06489233, 34.43070593,
       33.14932842, 31.16313854, 33.31119788, 32.23069043, 32.12966634,
       27.92377153, 33.05552681, 31.68837004, 34.34770454, 34.11554496,
       32.95092497, 31.93212973, 33.10008317, 33.54804636, 34.5256187 ,
       31.88399562, 33.11557229, 32.30511389, 33.7699613 , 32.15762242,
       33.37068778])
```

Validating model using assumptions of Lasso regression

Linear relationship

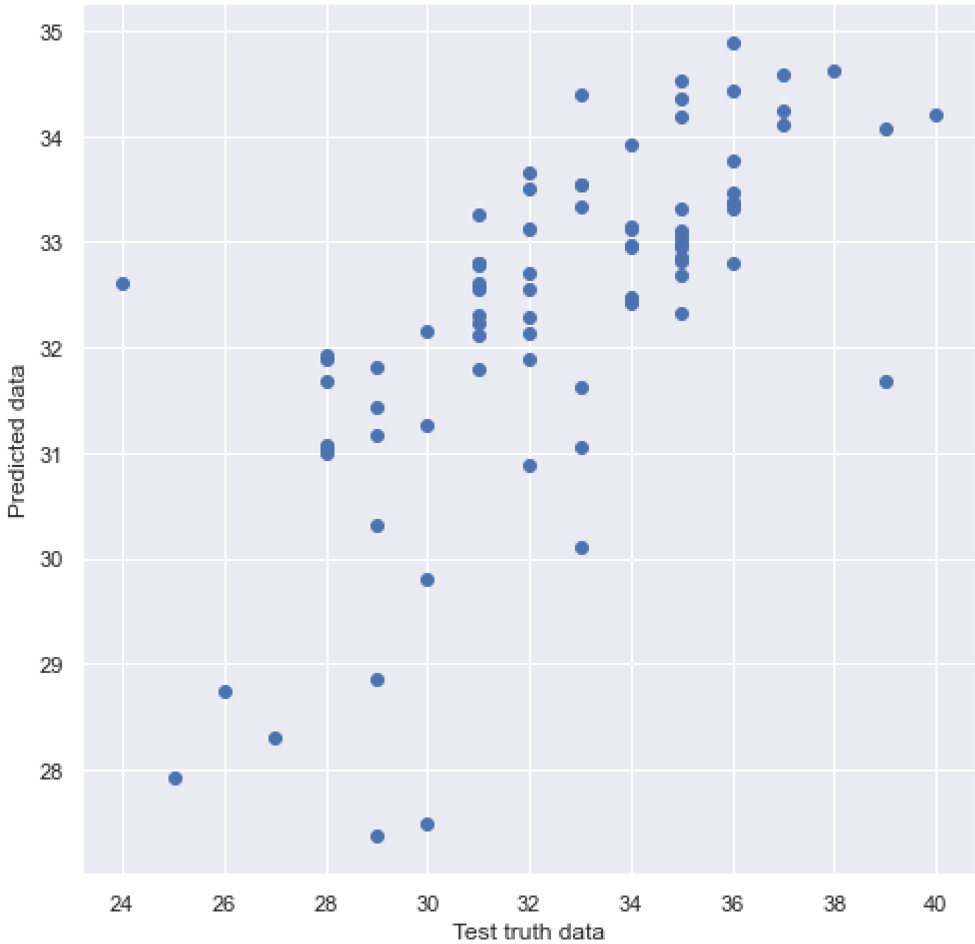
1. Test truth data and predicted data should follow linear realtionship.
2. This is an indication of a good model.

In [89]:

```
plt.scatter(x=y_test, y=lasso_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

Out[89]:

```
Text(0, 0.5, 'Predicted data')
```



Residual distribution

1. Residuals should follow normal distribution
2. If residuals follow normal distribution,it indicates we have a good model.

In [91]:

```
residual_lasso_reg=y_test-lasso_reg_pred
residual_lasso_reg.head()
```

Out[91]:

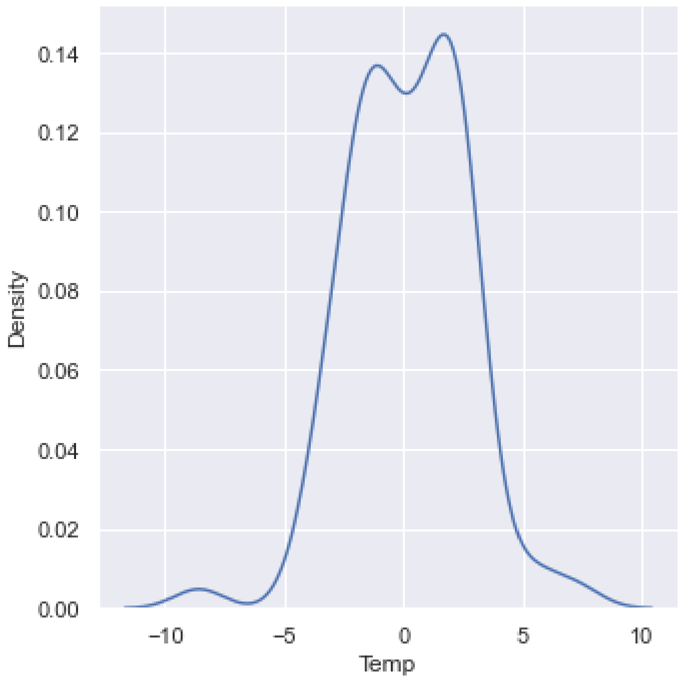
```
24    -1.783811
6     -0.335821
153   -0.538357
211    2.308080
198    5.787876
Name: Temp, dtype: float64
```

In [92]:

```
sns.displot(x=residual_lasso_reg, kind='kde')
```

Out[92]:

```
<seaborn.axisgrid.FacetGrid at 0x126cc6d27f0>
```



Uniform distribution

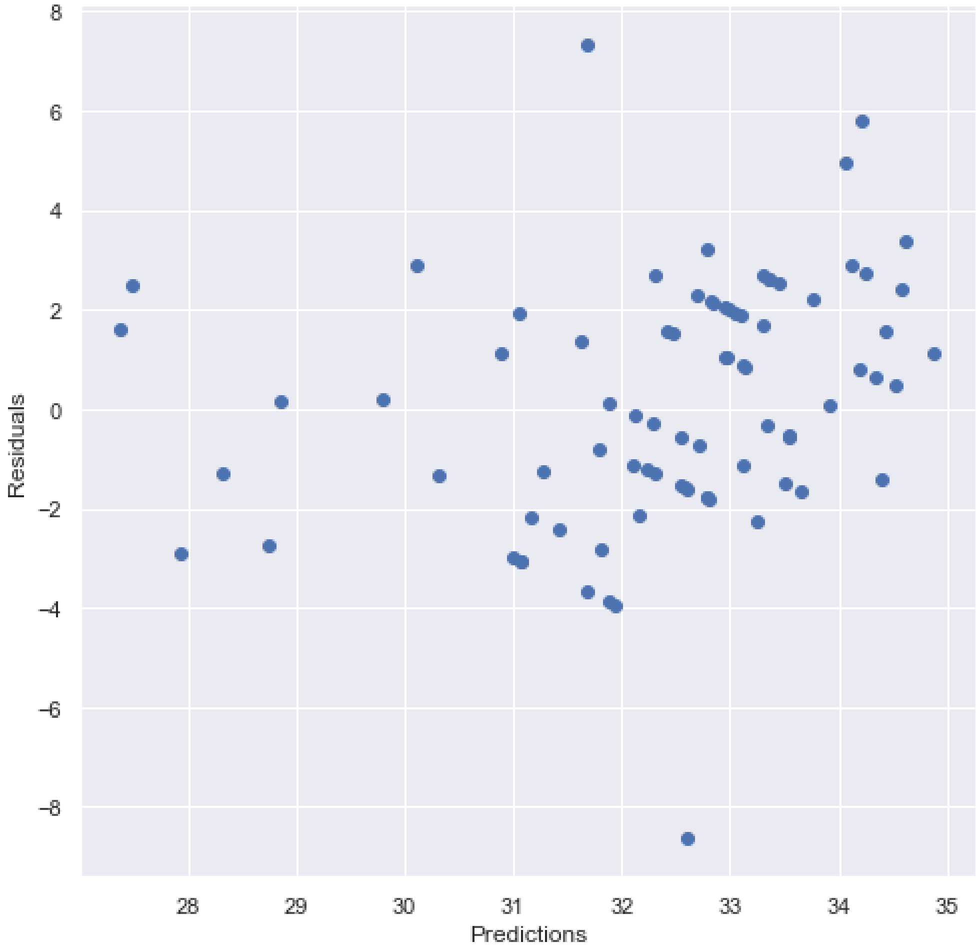
1. Residuals vs Predictions should follow a uniform distribution.
2. If Residuals vs Predictions follow uniform distribution,it indicates we have a good model.

In [93]:

```
plt.scatter(x=lasso_reg_pred, y=residual_lasso_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

Out[93]:

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



Performance Matrix

Cost function values

MSE, MAE and RMSE

In [96]:

```
print("Mean squared error is {}".format(round(mean_squared_error(y_test, lasso_reg_pred),2)
print("Mean absolute error is {}".format(round(mean_absolute_error(y_test, lasso_reg_pred),
print("Root Mean squared error is {}".format(round(np.sqrt(mean_squared_error(y_test, lasso
```

```
Mean squared error is 6.09
Mean absolute error is 2.0
Root Mean squared error is 2.47
```

R Square and Adjusted R Square values

In [97]:

```
lasso_reg_r2_score=r2_score(y_test, lasso_reg_pred)
print("Our Lasso regression model has {} % accuracy".format(round(lasso_reg_r2_score*100,3)
lasso_reg_adj_r2_score=1-((1-lasso_reg_r2_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[
print("Adjusted R square accuracy is {}".format(round(lasso_reg_r2_score*100,2)))
```

```
Our Lasso regression model has 43.342 % accuracy
Adjusted R square accuracy is 43.34
```

Elastic-Net Regression

In [98]:

```
from sklearn.linear_model import ElasticNet
```

In [99]:

```
## creating Elastic-Net regression model
elastic_reg = ElasticNet()
elastic_reg
```

Out[99]:

```
ElasticNet()
```

In [100]:

```
### Passing training data(X and y) to the model
elastic_reg.fit(X_train, y_train)
```

Out[100]:

```
ElasticNet()
```

In [101]:

```
### Printing co-efficients and intercept of best fit hyperplane
print("1. Co-efficients of independent features is {}".format(elastic_reg.coef_))
print("2. Intercept of best fit hyperplane is {}".format(elastic_reg.intercept_))
```

```
1. Co-efficients of independent features is [-0.          -0.          -0.6880
8933 -0.10544712 -0.00834786  0.85162206
  0.10376148  0.          0.23158765  0.02547021  0.15362153  0.07372069
  0.        ]
2. Intercept of best fit hyperplane is 31.98159509202454
```

Using model to get predictions of test data

In [102]:

```
elastic_reg_pred=elastic_reg.predict(X_test)
elastic_reg_pred
```

Out[102]:

```
array([32.70014869, 33.29910099, 33.41026626, 32.61092932, 34.7047485 ,
       31.58360838, 34.21527053, 29.02563256, 30.73347022, 30.11039166,
       30.41277398, 32.24275851, 32.49689882, 32.11572726, 33.82943086,
       32.26602144, 35.60101706, 27.89264401, 32.12951491, 32.95265792,
       31.02735367, 29.65251053, 33.71392821, 30.09882338, 35.36763797,
       28.87850096, 32.39310489, 32.86323328, 32.70140428, 34.17896096,
       33.34379291, 31.19918174, 32.72501691, 33.05000354, 32.11073799,
       32.39596102, 30.82655691, 33.29618332, 31.03905163, 27.97071052,
       32.81078878, 32.83085009, 32.18944481, 27.83881794, 34.71347157,
       32.40467835, 31.69547324, 30.73847724, 34.32027173, 33.61283179,
       35.5799204 , 31.38989764, 31.57088417, 33.58592157, 33.61999323,
       32.2560815 , 36.04767586, 32.00594323, 30.83622131, 34.89715148,
       33.0854042 , 30.78738109, 33.49083492, 31.9555529 , 31.71431021,
       27.98432489, 32.99835463, 31.35802614, 35.34742765, 34.15121761,
       32.70498873, 31.52572086, 33.29706361, 33.77686044, 35.16781422,
       31.6287495 , 33.16854289, 32.00367904, 34.13279424, 31.72123893,
       33.52323673])
```

Validating model using assumptions of Elastic-Net regression

Linear relationship

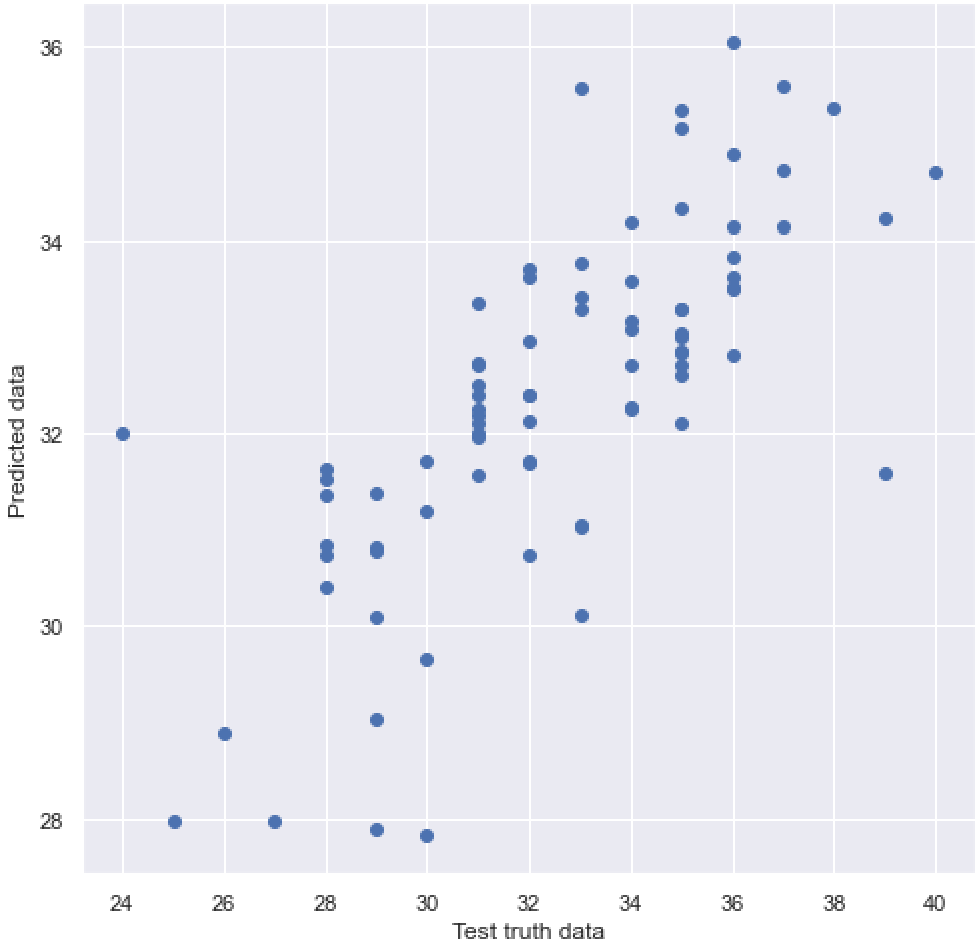
1. Test truth data and Predicted data should follow linear relationship.
2. this is an indication of a good model.

In [103]:

```
plt.scatter(x=y_test,y=elastic_reg_pred)
plt.xlabel("Test truth data")
plt.ylabel("Predicted data")
```

Out[103]:

```
Text(0, 0.5, 'Predicted data')
```



Residual distribution

1. Residuals should follow normal distribution.
2. if residuals follow normal distribution, it indicates we have a good model.

In [105]:

```
residual_elastic_reg = y_test-elastic_reg_pred
residual_elastic_reg.head()
```

Out[105]:

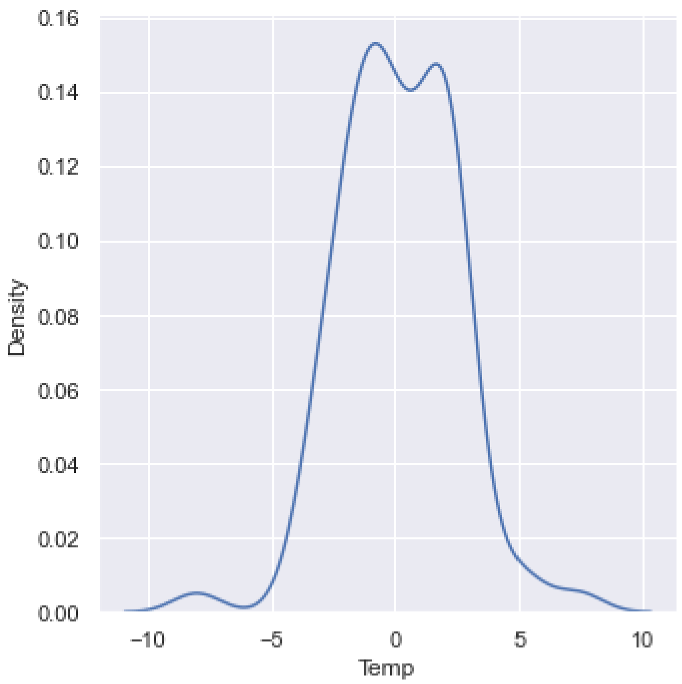
```
24    -1.700149
6     -0.299101
153   -0.410266
211    2.389071
198    5.295251
Name: Temp, dtype: float64
```

In [106]:

```
sns.displot(x=residual_elastic_reg, kind='kde')
```

Out[106]:

```
<seaborn.axisgrid.FacetGrid at 0x126cd4cfc70>
```



Uniform distribution

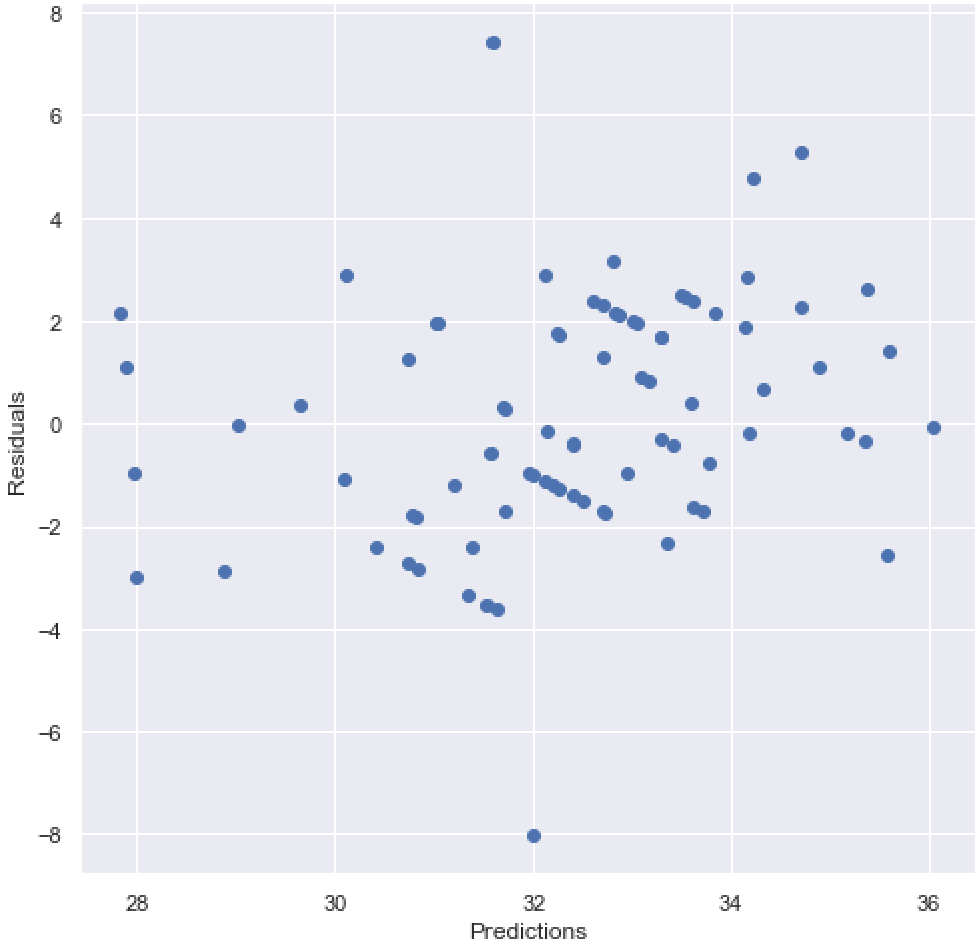
1. Residuals vs Predictions should follow a uniform distribution.
2. If Residuals vs Predictions follow uniform distribution, it indicates we have a good model.

In [107]:

```
plt.scatter(x=elastic_reg_pred, y = residual_elastic_reg)
plt.xlabel('Predictions')
plt.ylabel('Residuals')
```

Out[107]:

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



Performance Matrix

Cost function values

MSE, MAE and RMSE

In [108]:

```
print("Mean squared error is {}".format(round(mean_squared_error(y_test, elastic_reg_pred),
print("Mean absolute error is {}".format(round(mean_absolute_error(y_test,elastic_reg_pred)
print("Root Mean squared error is {}".format(round(np.sqrt(mean_squared_error(y_test,elasti
```

```
Mean squared error is 5.39
Mean absolute error is 1.85
Root Mean squared error is 2.32
```

R Square and Adjusted R Square values

In [109]:

```
elastic_reg_r2_score=r2_score(y_test, elastic_reg_pred)
print("Our Elatic-Net regression model has {} % accuracy".format(round(elastic_reg_r2_score
elastic_reg_adj_r2_score=1-((1-elastic_reg_r2_score)*(len(y_test)-1)/(len(y_test)-X_test.sh
print("Adjusted R square accuracy is {} %".format(round(elastic_reg_adj_r2_score*100,2)))
```

```
Our Elatic-Net regression model has 49.812 % accuracy
Adjusted R square accuracy is 40.07 %
```

Comparisions of all Models

MSE

In [148]:

```
print("MSE for Linear Regression Model is '{}'\nMSE for Ridge Regression Model is '{}'\nMSE
.format(round(mean_squared_error(y_test, linear_reg_pred),2), round(mean_squared_error(y_te
 round(mean_squared_error(y_test, lasso_reg_pred),2), round(mean_squared_error(y_test, elas
```

```
MSE for Linear Regression Model is '5.25'
MSE for Ridge Regression Model is '5.19'
MSE for Lasso Regression Model is '6.09'
MSE for Elastic-Net Regression Model is
```

In [146]:

```
rint("MAE for Linear Regression Model is '{}'\nMAE for Ridge Regression Model is '{}'\nMAE
format(round(mean_absolute_error(y_test, linear_reg_pred),2), round(mean_absolute_error(y_t
ound(mean_absolute_error(y_test, lasso_reg_pred),2), round(mean_absolute_error(y_test, elas
```

```
MAE for Linear Regression Model is '1.81'
MAE for Ridge Regression Model is '1.8'
MAE for Lasso Regression Model is '2.0'
```