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April 16, 2023

1 Algerian Forest Fire Dataset linear regression modelling

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pylab as plt
%matplotlib inline
```

[2]:
```
data = pd.read_csv("Algerian_forest_fires_dataset_UPDATE.csv",header=1)
data
```

[2]:
```
     day month  year Temperature  RH  Ws Rain   FFMC  DMC    DC  ISI   BUI  \
0     01    06  2012          29  57  18     0  65.7  3.4   7.6  1.3   3.4
1     02    06  2012          29  61  13   1.3  64.4  4.1   7.6    1   3.9
2     03    06  2012          26  82  22  13.1  47.1  2.5   7.1  0.3   2.7
3     04    06  2012          25  89  13   2.5  28.6  1.3   6.9    0   1.7
4     05    06  2012          27  77  16     0  64.8    3  14.2  1.2   3.9
..    ..   …   …          …  ..  ..   …    …    …    …   …     …
241   26    09  2012          30  65  14     0  85.4   16  44.5  4.5  16.9
242   27    09  2012          28  87  15   4.4  41.1  6.5     8  0.1   6.2
243   28    09  2012          27  87  29   0.5  45.9  3.5   7.9  0.4   3.4
244   29    09  2012          24  54  18   0.1  79.7  4.3  15.2  1.7   5.1
245   30    09  2012          24  64  15   0.2  67.3  3.8  16.5  1.2   4.8

     FWI    Classes
0    0.5  not fire
1    0.4  not fire
2    0.1  not fire
3      0  not fire
4    0.5  not fire
..   …          …
241  6.5      fire
242    0  not fire
243  0.2  not fire
244  0.7  not fire
245  0.5 not fire
```

```
[246 rows x 14 columns]
```

[3]:
```python
data[data.isna().any(axis=1)]
```

[3]:
```
                               day month year Temperature   RH   Ws Rain   \
122  Sidi-Bel Abbes Region Dataset   NaN   NaN          NaN  NaN  NaN   NaN

    FFMC  DMC   DC  ISI  BUI  FWI Classes
122  NaN  NaN  NaN  NaN  NaN  NaN       NaN
```

[4]:
```python
data.iloc[121:125,:]
```

[4]:
```
                               day  month  year  Temperature   RH   Ws  Rain   \
121                             30     09  2012           25   78   14    1.4
122  Sidi-Bel Abbes Region Dataset    NaN   NaN          NaN  NaN  NaN    NaN
123                            day  month  year  Temperature   RH   Ws  Rain
124                             01     06  2012           32   71   12    0.7

     FFMC  DMC   DC  ISI  BUI  FWI    Classes
121    45  1.9  7.5  0.2  2.4  0.1  not fire
122   NaN  NaN  NaN  NaN  NaN  NaN          NaN
123  FFMC  DMC   DC  ISI  BUI  FWI    Classes
124  57.1  2.5  8.2  0.6  2.8  0.2  not fire
```

[5]:
```python
data.drop([122,123],inplace=True)
data.reset_index(inplace=True)
data.drop(['index',"day","month","year"],axis=1,inplace=True)
data = data.iloc[:,:-1]
data
```

[5]:
```
    Temperature  RH  Ws Rain   FFMC  DMC    DC  ISI   BUI  FWI
0            29  57  18     0  65.7  3.4   7.6  1.3   3.4  0.5
1            29  61  13   1.3  64.4  4.1   7.6    1   3.9  0.4
2            26  82  22  13.1  47.1  2.5   7.1  0.3   2.7  0.1
3            25  89  13   2.5  28.6  1.3   6.9    0   1.7    0
4            27  77  16     0  64.8    3  14.2  1.2   3.9  0.5
..          …  ..  ..   …    …    …    …    …   …   …
239          30  65  14     0  85.4   16  44.5  4.5  16.9  6.5
240          28  87  15   4.4  41.1  6.5     8  0.1   6.2    0
241          27  87  29   0.5  45.9  3.5   7.9  0.4   3.4  0.2
242          24  54  18   0.1  79.7  4.3  15.2  1.7   5.1  0.7
243          24  64  15   0.2  67.3  3.8  16.5  1.2   4.8  0.5

[244 rows x 10 columns]
```

1.1 EDA for data set

[6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Temperature  244 non-null    object
 1    RH          244 non-null    object
 2    Ws          244 non-null    object
 3   Rain         244 non-null    object
 4   FFMC         244 non-null    object
 5   DMC          244 non-null    object
 6   DC           244 non-null    object
 7   ISI          244 non-null    object
 8   BUI          244 non-null    object
 9   FWI          244 non-null    object
dtypes: object(10)
memory usage: 19.2+ KB
```

[7]:
```
data = data.astype("float64")
```

[8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Temperature  244 non-null    float64
 1    RH          244 non-null    float64
 2    Ws          244 non-null    float64
 3   Rain         244 non-null    float64
 4   FFMC         244 non-null    float64
 5   DMC          244 non-null    float64
 6   DC           244 non-null    float64
 7   ISI          244 non-null    float64
 8   BUI          244 non-null    float64
 9   FWI          244 non-null    float64
dtypes: float64(10)
memory usage: 19.2 KB
```

[9]:
```
from pandas_profiling import ProfileReport
profile = ProfileReport(data, explorative=True)

#Saving results to a HTML file
```

```
profile.to_file("pandas_profiling.html")
```

```
Summarize dataset: 100%|      | 123/123 [00:13<00:00,  9.03it/s, Completed]
Generate report structure: 100%|      | 1/1 [00:02<00:00,  2.75s/it]
Render HTML: 100%|      | 1/1 [00:01<00:00,  1.44s/it]
Export report to file: 100%|      | 1/1 [00:00<00:00, 20.16it/s]
```

[10]:
```
import sweetviz as sv

#EDA using Autoviz
sweet_report = sv.analyze(data)

#Saving results to HTML file
sweet_report.show_html('sweet_report.html')
```

```
Done! Use 'show' commands to display/save.   |      | [100%]   00:00 ->
(00:00 left)
```

```
Report sweet_report.html was generated! NOTEBOOK/COLAB USERS: the web browser
MAY not pop up, regardless, the report IS saved in your notebook/colab files.
```

[11]:
```
data.describe()
```

[11]:

	Temperature	RH	Ws	Rain	FFMC
count	244.000000	244.000000	244.000000	244.000000	244.000000
mean	32.172131	61.938525	15.504098	0.760656	77.887705
std	3.633843	14.884200	2.810178	1.999406	14.337571
min	22.000000	21.000000	6.000000	0.000000	28.600000
25%	30.000000	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
max	42.000000	90.000000	29.000000	16.800000	96.000000

	DMC	DC	ISI	BUI	FWI
count	244.000000	244.000000	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

[12]:
```
data.corr()
```

[12]:

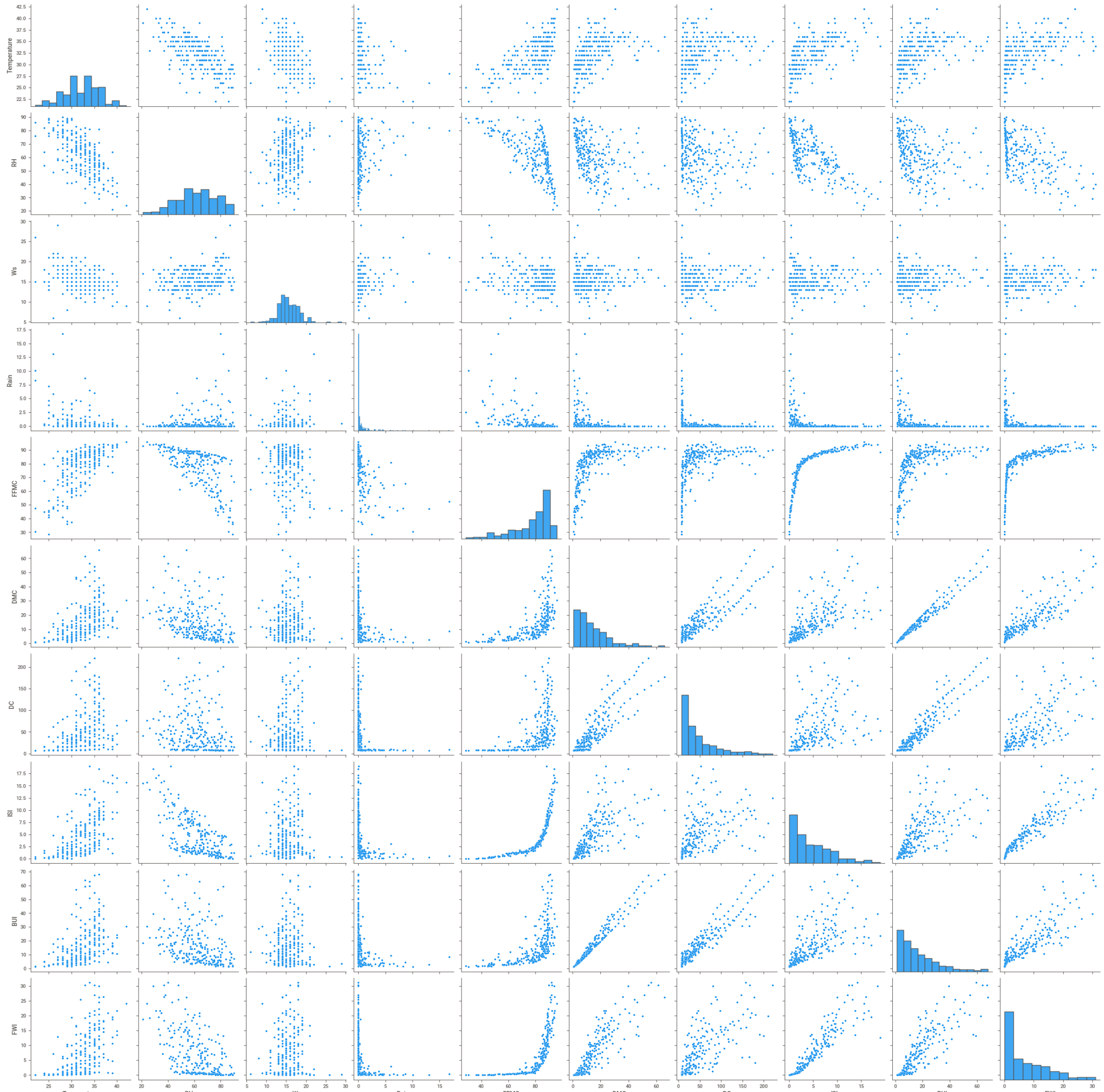
	Temperature	RH	Ws	Rain	FFMC	DMC
Temperature	1.000000	-0.654443	-0.278132	-0.326786	0.677491	0.483105
RH	-0.654443	1.000000	0.236084	0.222968	-0.645658	-0.405133

```
 Ws            -0.278132  0.236084  1.000000  0.170169 -0.163255 -0.001246
Rain           -0.326786  0.222968  0.170169  1.000000 -0.544045 -0.288548
FFMC            0.677491 -0.645658 -0.163255 -0.544045  1.000000  0.602391
DMC             0.483105 -0.405133 -0.001246 -0.288548  0.602391  1.000000
DC              0.370498 -0.220330  0.076245 -0.296804  0.503910  0.875358
ISI             0.605971 -0.688268  0.012245 -0.347862  0.740751  0.678355
BUI             0.456415 -0.349685  0.030303 -0.299409  0.590251  0.982206
FWI             0.566839 -0.580457  0.033957 -0.324755  0.691430  0.875191

                   DC       ISI       BUI       FWI
Temperature  0.370498  0.605971  0.456415  0.566839
 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
FFMC         0.503910  0.740751  0.590251  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
```

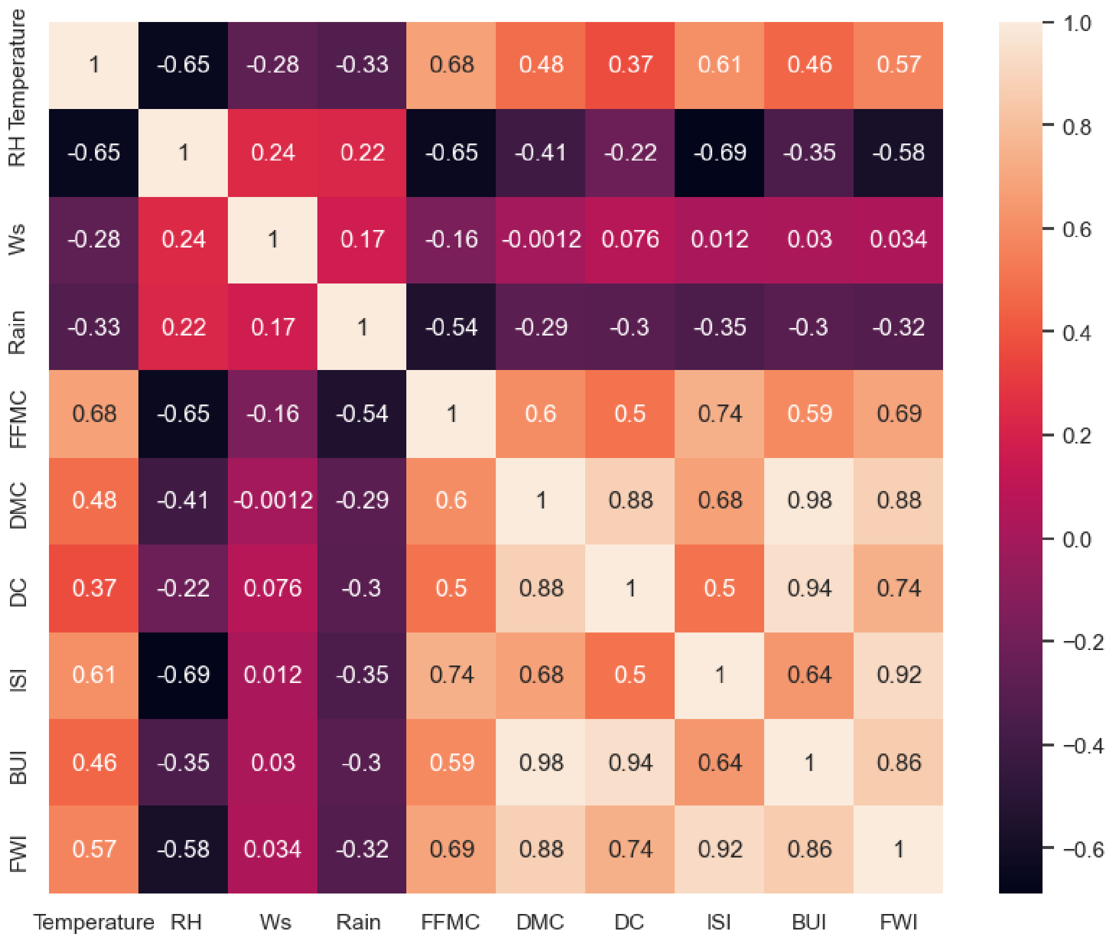
[13]:
```
sns.pairplot(data)
```

[13]: <seaborn.axisgrid.PairGrid at 0x7ff5a1885370>



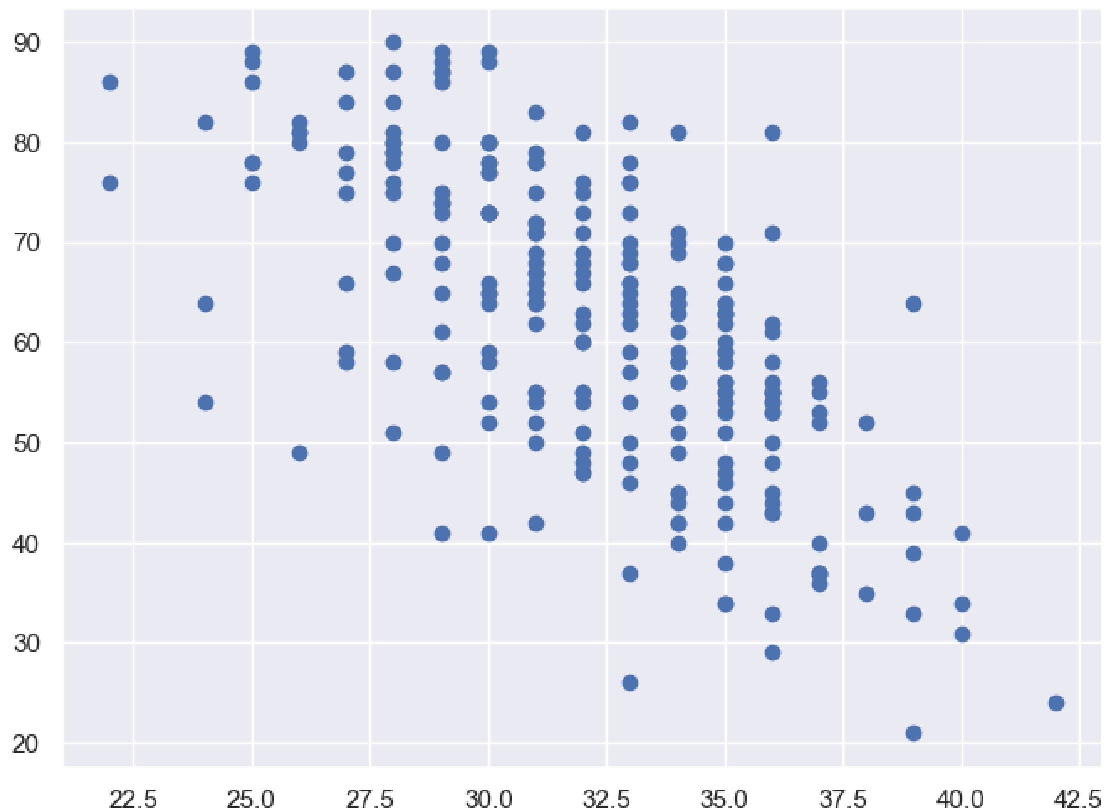

```
[14]: sns.set(rc={'figure.figsize':(10,8)})
      sns.heatmap(data.corr(),annot=True)
```

```
[14]: <AxesSubplot:>
```



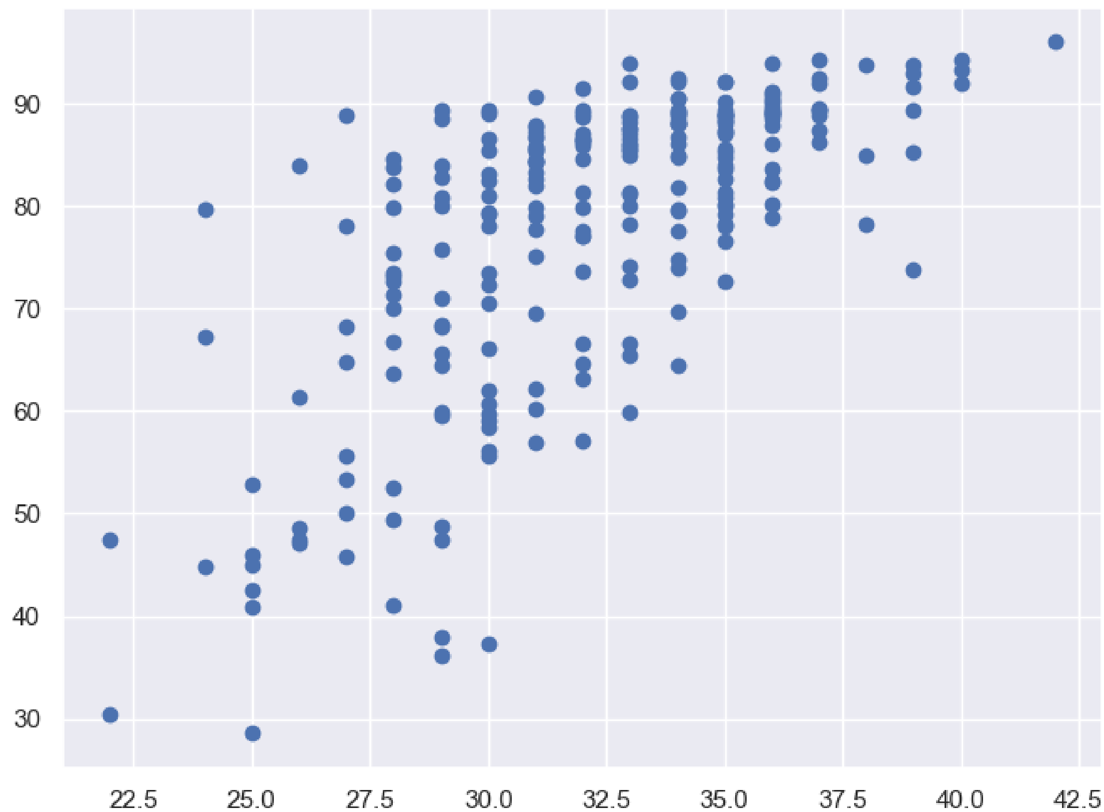
[15]:
```
sns.set(rc={'figure.figsize':(8,6)})
plt.scatter(data["Temperature"],data[" RH"])
```

[15]: <matplotlib.collections.PathCollection at 0x7ff5c0269520>



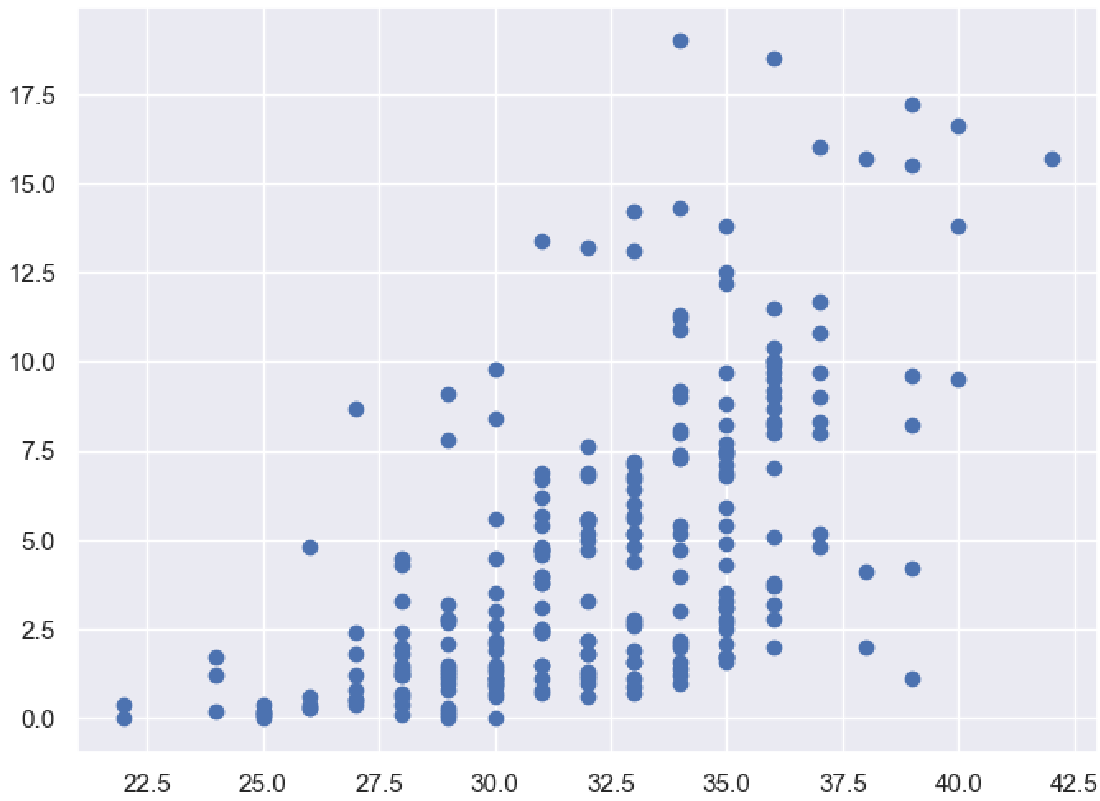
[16]:
```
sns.set(rc={'figure.figsize':(8,6)})
plt.scatter(data["Temperature"],data["FFMC"])
```

[16]: <matplotlib.collections.PathCollection at 0x7ff5c00854c0>



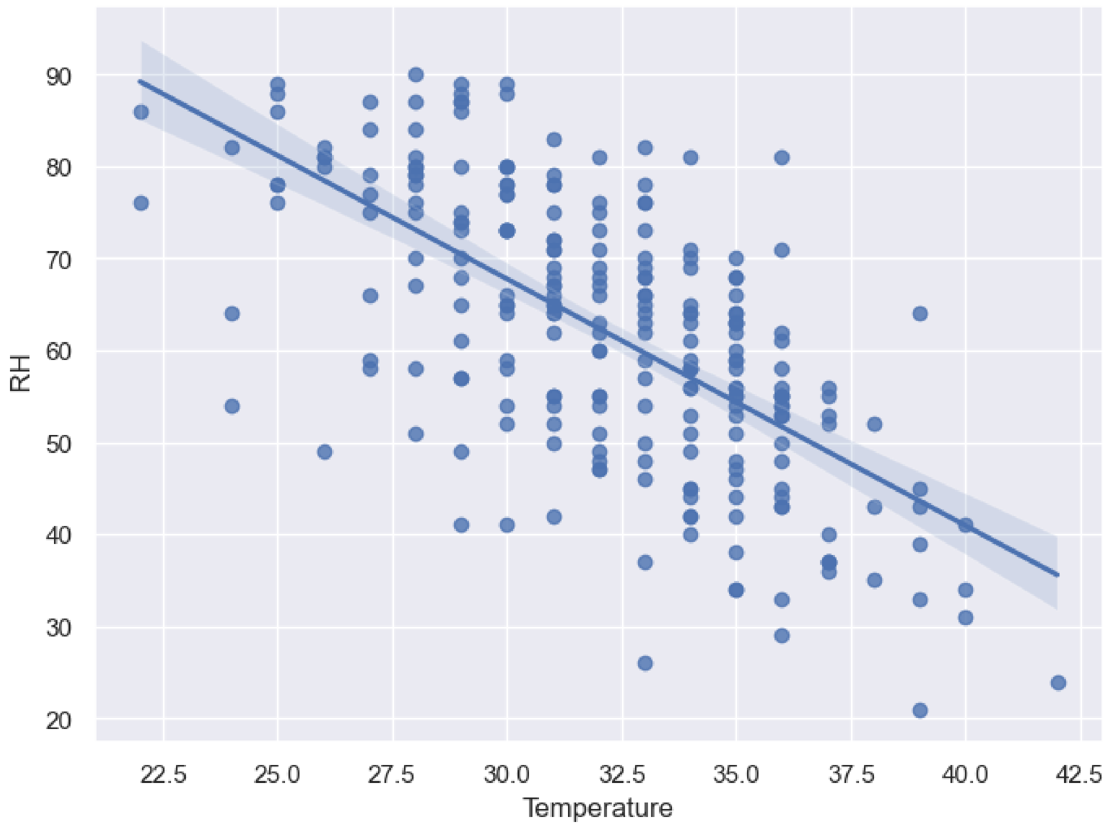
[17]:
```
sns.set(rc={'figure.figsize':(8,6)})
plt.scatter(data["Temperature"],data["ISI"])
```

[17]: <matplotlib.collections.PathCollection at 0x7ff5c0020e80>



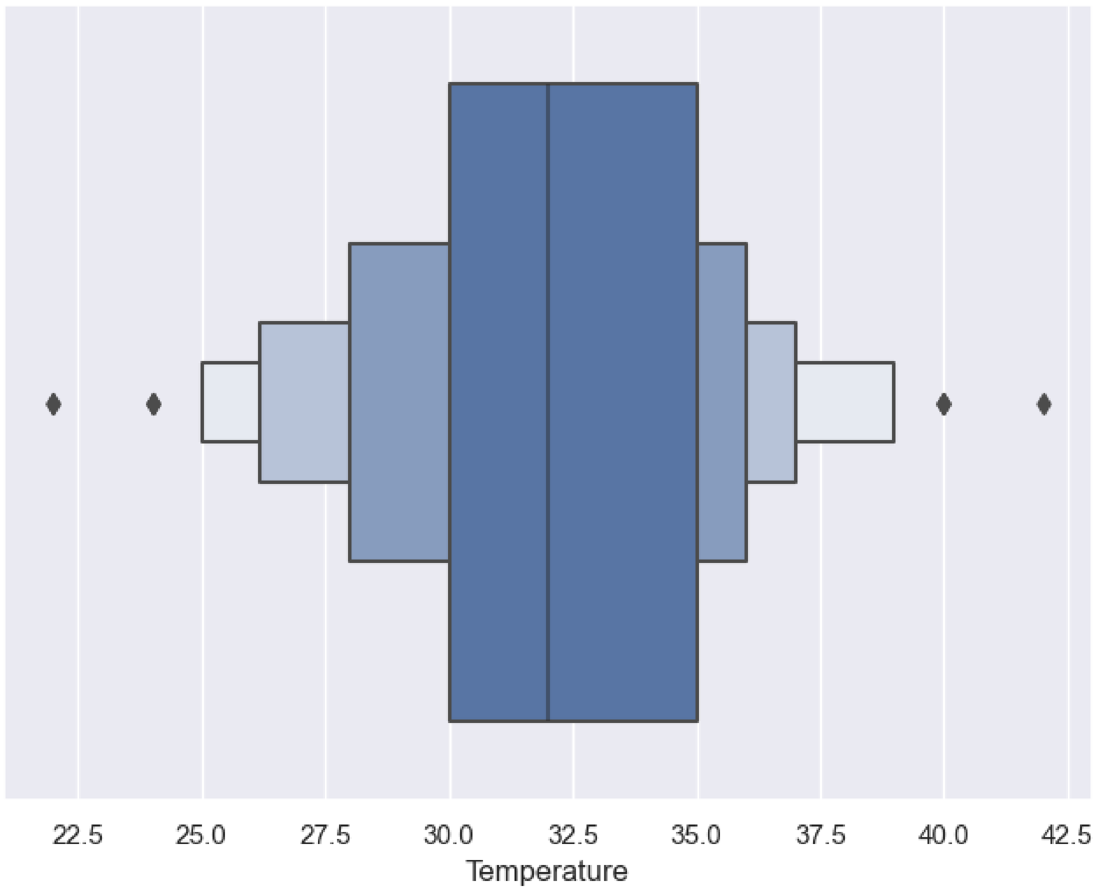
[18]:
```
sns.regplot(data=data,x="Temperature",y=" RH")
```

[18]: <AxesSubplot:xlabel='Temperature', ylabel=' RH'>



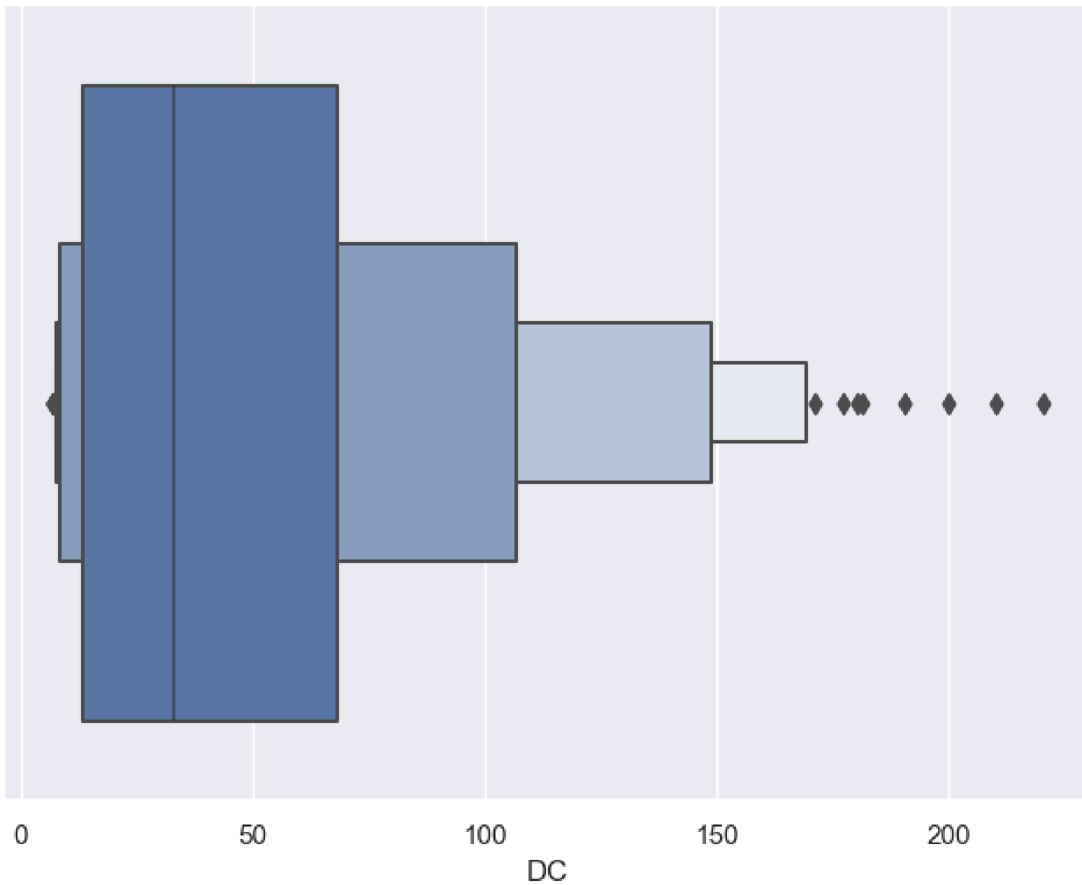
[19]:
```
sns.boxenplot(x=data["Temperature"],data=data)
```

[19]: <AxesSubplot:xlabel='Temperature'>



[20]:
```
sns.boxenplot(x=data["DC"],data=data)
```

[20]: <AxesSubplot:xlabel='DC'>



[21]:
```
x = data.iloc[:,1:]
x.head()
```

[21]:

	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI
0	57.0	18.0	0.0	65.7	3.4	7.6	1.3	3.4	0.5
1	61.0	13.0	1.3	64.4	4.1	7.6	1.0	3.9	0.4
2	82.0	22.0	13.1	47.1	2.5	7.1	0.3	2.7	0.1
3	89.0	13.0	2.5	28.6	1.3	6.9	0.0	1.7	0.0
4	77.0	16.0	0.0	64.8	3.0	14.2	1.2	3.9	0.5

[22]:
```
y = data.iloc[:,0]
y.head()
```

[22]:
```
0    29.0
1    29.0
2    26.0
3    25.0
4    27.0
Name: Temperature, dtype: float64
```

[23]:
```
from sklearn.model_selection import train_test_split
```

[24]:
```
X_train,X_test,y_train,y_test = train_test_split(x,y,test_size=0.
  ↪33,random_state=42)
```

[25]:
```
X_train.shape
```

[25]:
```
(163, 9)
```

[26]:
```
X_test.shape
```

[26]:
```
(81, 9)
```

[27]:
```
y_train.shape
```

[27]:
```
(163,)
```

[28]:
```
y_test.shape
```

[28]:
```
(81,)
```

[29]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

[30]:
```
X_train = scaler.fit_transform(X_train)
```

[31]:
```
X_test = scaler.transform(X_test)
```

1.2 linear model

[32]:
```
from sklearn.linear_model import LinearRegression
regg = LinearRegression()
regg.fit(X_train,y_train)
```

[32]:
```
LinearRegression()
```

[33]:
```
print(regg.coef_)
```

```
[-1.11905525 -0.45739521  0.09691421  1.67893862  1.07917612  0.72319354
  0.11814242 -1.39324802 -0.05262333]
```

[34]:
```
print(regg.intercept_)
```

```
31.98159509202454
```

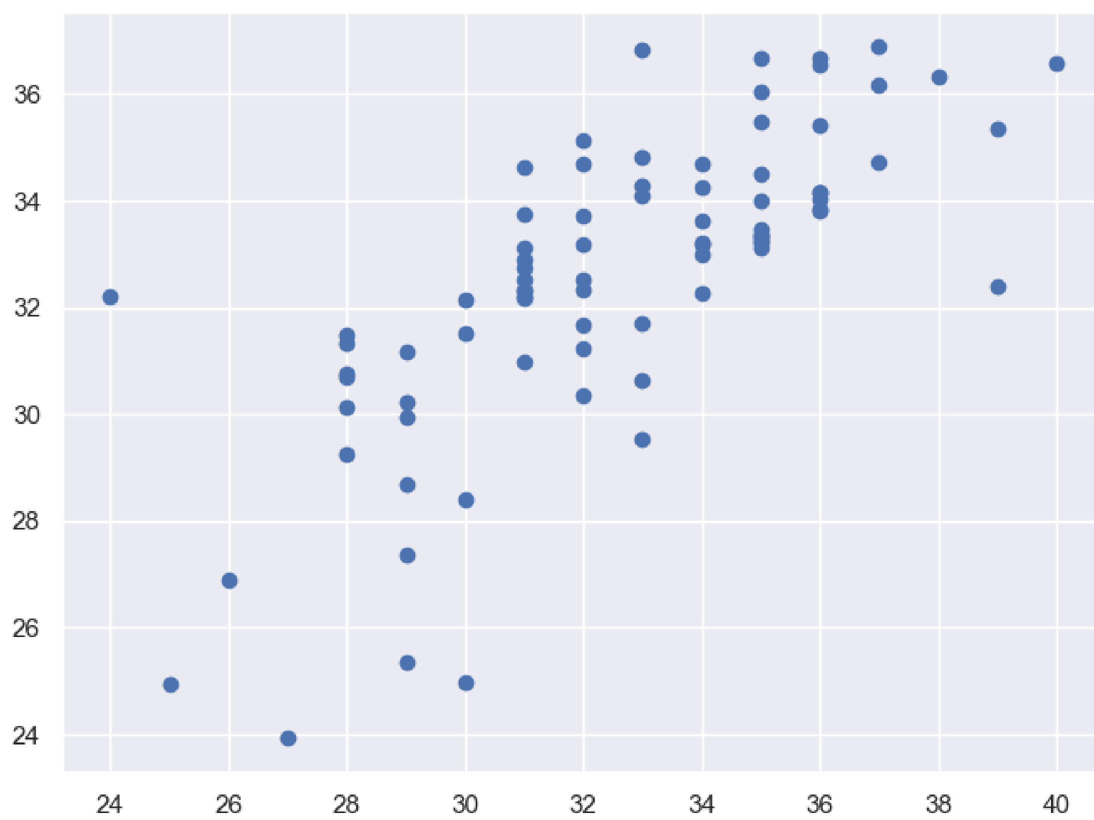
[35]:
```
predict = regg.predict(X_test)
predict
```

[35]:
```
array([33.12113277, 34.27599153, 34.1081232 , 33.4551817 , 36.56742968,
       32.38680838, 35.34162102, 27.3654293 , 30.76167063, 29.53403578,
       29.26453111, 33.18737898, 33.74397562, 33.20293714, 34.15771284,
       32.27376808, 36.88282294, 25.33846086, 32.34613028, 33.72112033,
       30.64422533, 28.39171201, 35.13413644, 28.69736813, 36.33429667,
       26.88918698, 32.89023041, 33.36234711, 33.13267513, 34.69072521,
       34.6296513 , 31.52410657, 32.74168095, 33.33535668, 32.53412299,
       33.19055268, 30.2321709 , 34.50328733, 31.69115187, 23.92788304,
       33.8111882 , 34.00495789, 32.33564172, 24.96891784, 36.16141483,
       32.53768689, 31.24732598, 30.35652666, 35.49132159, 34.70573285,
       36.84582014, 31.16185778, 30.96947655, 34.24806396, 33.85580631,
       32.20004503, 36.68678969, 32.21851926, 30.13805868, 36.56085853,
       33.22333782, 29.95567173, 34.04112054, 32.18632508, 31.67567942,
       24.92633321, 33.25306646, 30.68494645, 36.66003733, 34.72400965,
       33.0037378 , 31.33439708, 33.31162289, 34.80593026, 36.05684966,
       31.48685955, 33.61476731, 32.316884  , 35.40290519, 32.14618976,
       34.1510535 ])
```

1.2.1 Assumptions Of Linear Regression

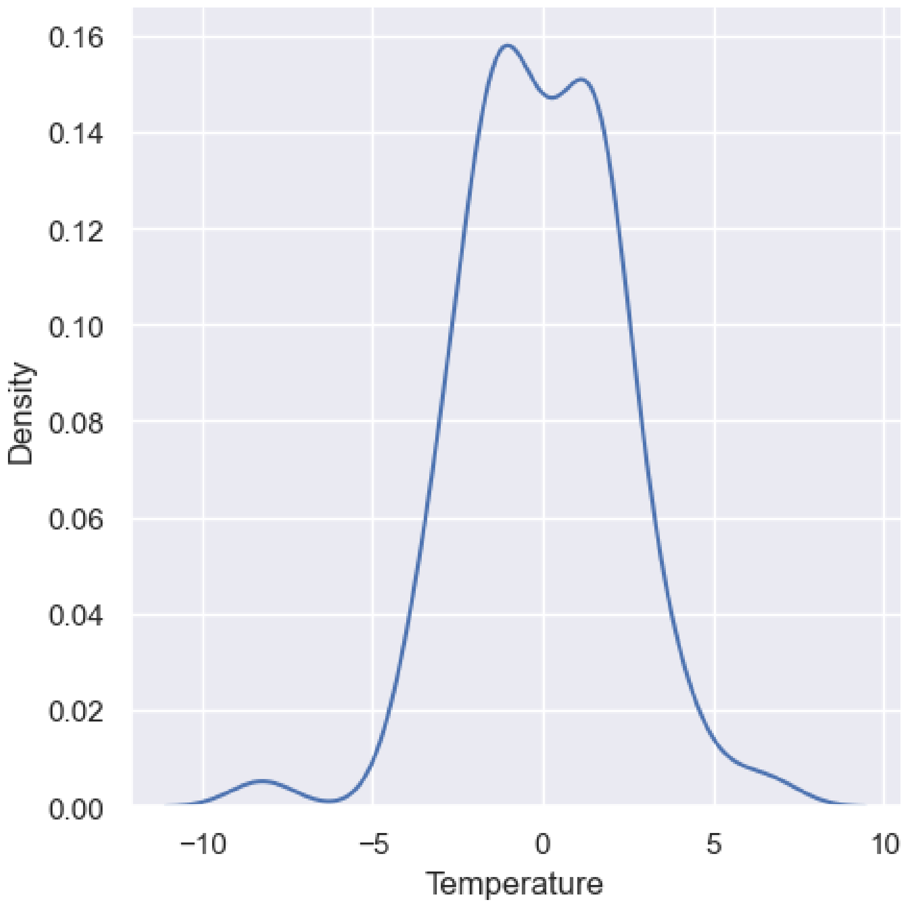
[36]:
```
plt.scatter(y_test,predict)
```

[36]: <matplotlib.collections.PathCollection at 0x7ff568e1b6a0>



[37]:
```
residual = y_test-predict
sns.displot(residual,kind="kde")
```

[37]: <seaborn.axisgrid.FacetGrid at 0x7ff5a364efd0>



[38]:
```
residual.kurtosis()
```

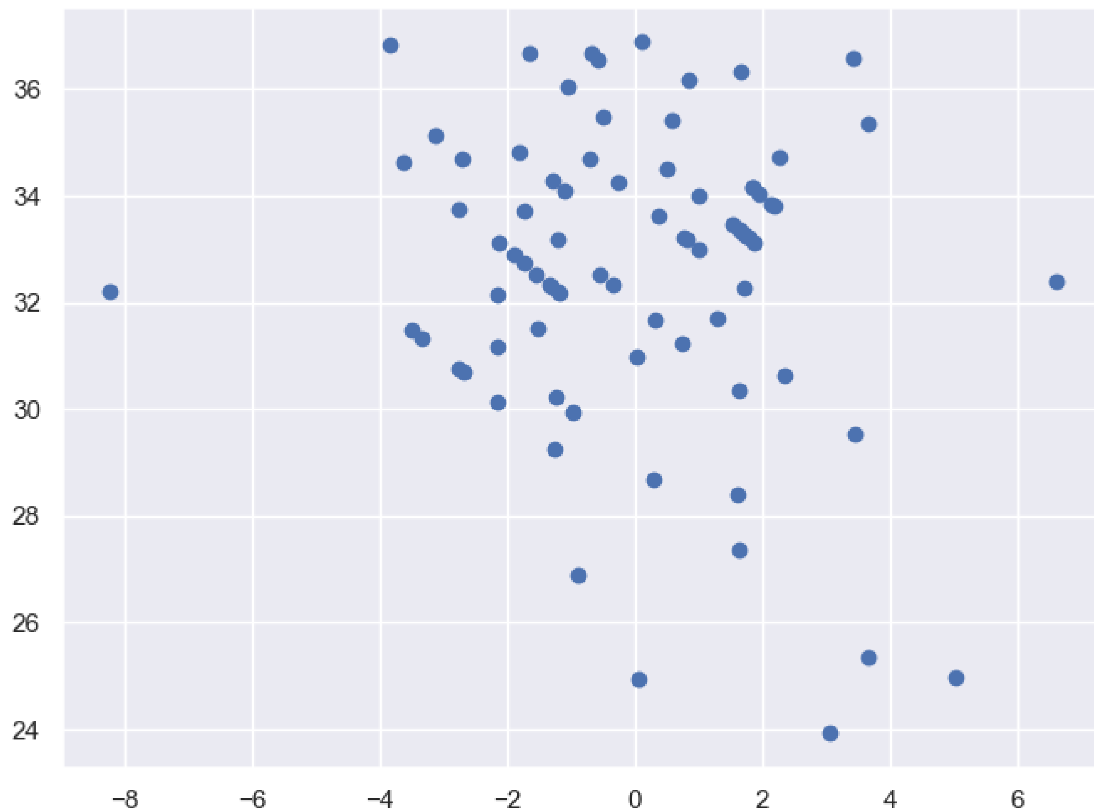
[38]: 1.4665473844478676

[39]:
```
residual.skew()
```

[39]: -0.1724108863462388

[40]:
```
plt.scatter(residual,predict)
```

[40]: <matplotlib.collections.PathCollection at 0x7ff568d72be0>



1.2.2 Performance Metrics

[41]:
```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
print(mean_absolute_error(y_test,predict))
print(mean_squared_error(y_test,predict))
print(np.sqrt(mean_squared_error(y_test,predict)))
```

```
1.8166245543075037
5.144034073423941
2.268046312010392
```

[42]:
```
from sklearn.metrics import r2_score
score = r2_score(y_test,predict)
print(score)
```

```
0.5210726897157021
```

1.3 Ridge regression

[43]:
```
from sklearn.linear_model import Ridge
ridge = Ridge()
ridge.fit(X_train,y_train)
```

[43]:
```
Ridge()
```

[44]:
```
predict_ri = ridge.predict(X_test)
predict_ri
```

[44]:
```
array([33.12618992, 34.24674   , 34.06922682, 33.42510732, 36.53814134,
       32.42996174, 35.30762891, 27.4057252 , 30.79261446, 29.54793777,
       29.25913293, 33.24772941, 33.71838792, 33.21993484, 34.21546555,
       32.23843379, 36.80045992, 25.41971491, 32.30821218, 33.6815395 ,
       30.62048363, 28.39123683, 35.11991037, 28.71361891, 36.34377989,
       26.9248708 , 32.8908782 , 33.38172768, 33.12033053, 34.62363441,
       34.62800665, 31.51025782, 32.7258902 , 33.39246733, 32.52281669,
       33.20470157, 30.18157071, 34.51169763, 31.65133631, 23.9500916 ,
       33.82657625, 33.98804714, 32.34987969, 25.03226483, 36.09250024,
       32.50666047, 31.21803583, 30.38934469, 35.45342925, 34.68761049,
       36.79108503, 31.12578978, 30.96863631, 34.33251422, 33.84410339,
       32.32887485, 36.68517508, 32.20456918, 30.13608325, 36.54981854,
       33.17022939, 29.95378642, 33.97467454, 32.15149675, 31.69665969,
       24.95146106, 33.24563787, 30.66575481, 36.63611759, 34.74939874,
       32.96905953, 31.29991731, 33.31582773, 34.83624989, 36.08518219,
       31.4585751 , 33.55076018, 32.29725788, 35.43083938, 32.12534116,
       34.12227596])
```

[45]:
```
ridge.coef_
```

[45]:
```
array([-1.128844  , -0.46133629,  0.08183743,  1.6314207 ,  0.53993679,
        0.44532083,  0.16303925, -0.55090562, -0.11702728])
```

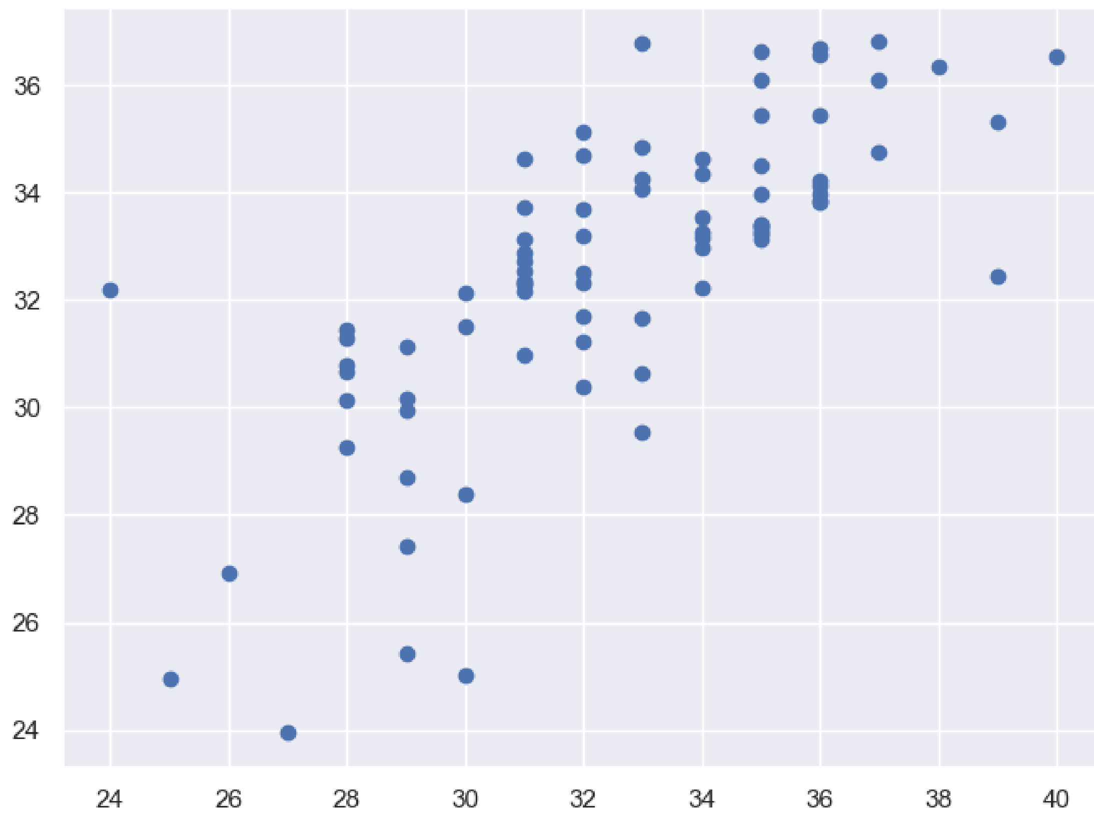
[46]:
```
ridge.intercept_
```

[46]:
```
31.98159509202454
```

1.3.1 Assumptions Of ridge regression

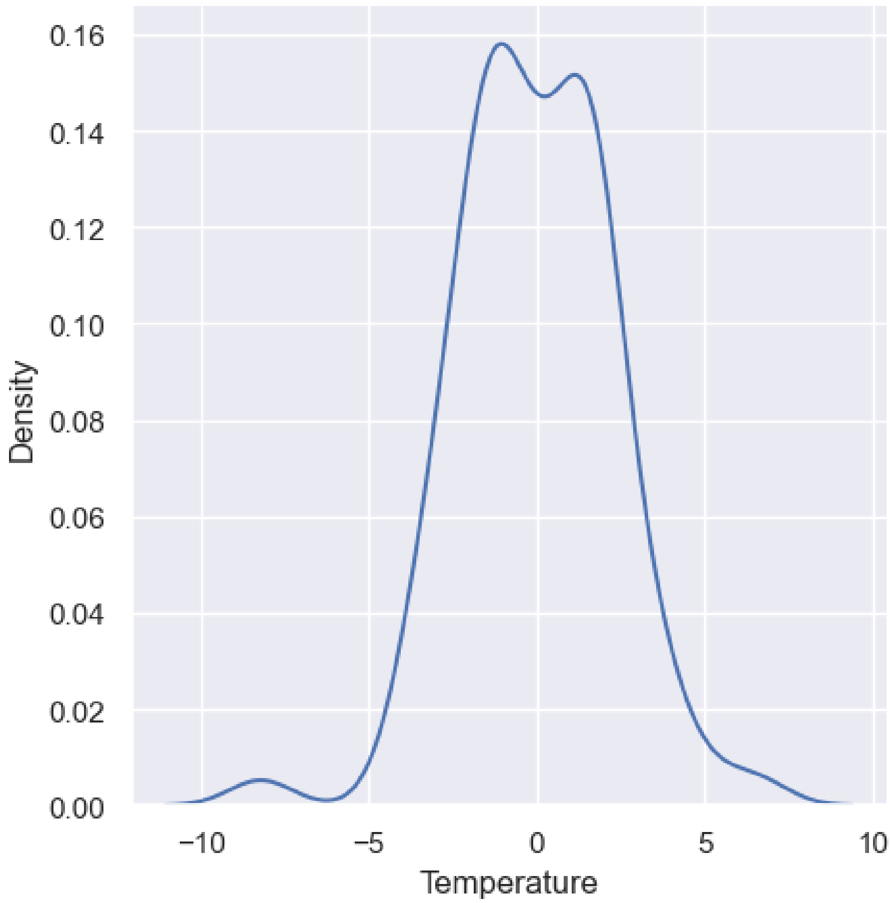
[47]:
```
## asumption
plt.scatter(y_test,predict_ri)
```

[47]:
```
<matplotlib.collections.PathCollection at 0x7ff568cdaf10>
```



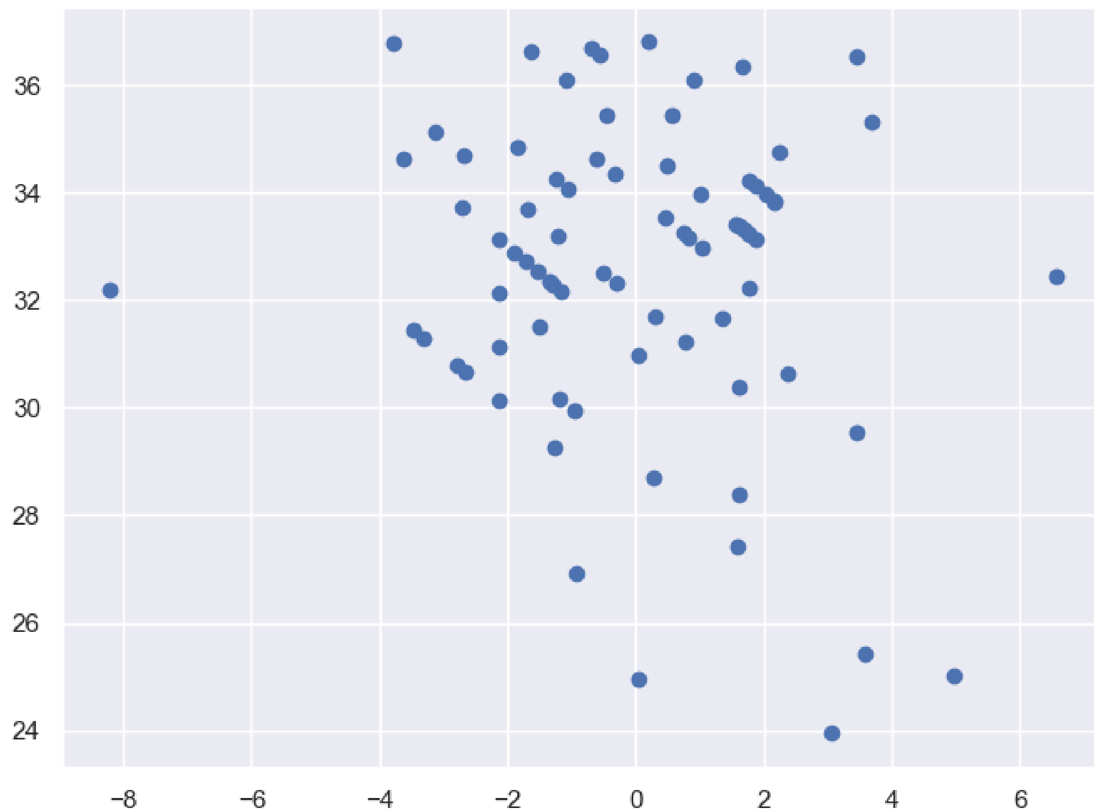
[48]:
```
residual_ri = y_test - predict_ri
sns.displot(residual_ri,kind="kde")
```

[48]: <seaborn.axisgrid.FacetGrid at 0x7ff568d4a160>



[49]:
```
plt.scatter(residual_ri,predict_ri)
```

[49]: <matplotlib.collections.PathCollection at 0x7ff568c3c940>



1.3.2 Performance Metrics

[50]:
```
## Performance Metrics
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,predict_ri))
print(mean_absolute_error(y_test,predict_ri))
print(np.sqrt(mean_squared_error(y_test,predict_ri)))
```

```
5.10441260465425
1.812177855113185
2.2592947139880293
```

[51]:
```
from sklearn.metrics import r2_score
score=r2_score(y_test,predict_ri)
print(score)
```

```
0.5247615850839147
```

1.4 lasso regression

[52]:
```
from sklearn.linear_model import Lasso
lasso = Lasso()
lasso.fit(X_train,y_train)
```

[52]:
```
Lasso()
```

[53]:
```
predict_la = lasso.predict(X_test)
predict_la
```

[53]:
```
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])
```

[54]:
```
lasso.coef_
```

[54]:
```
array([-0.62324302, -0.        , -0.        ,  1.25581509,  0.        ,
        0.        ,  0.        ,  0.        ,  0.        ])
```

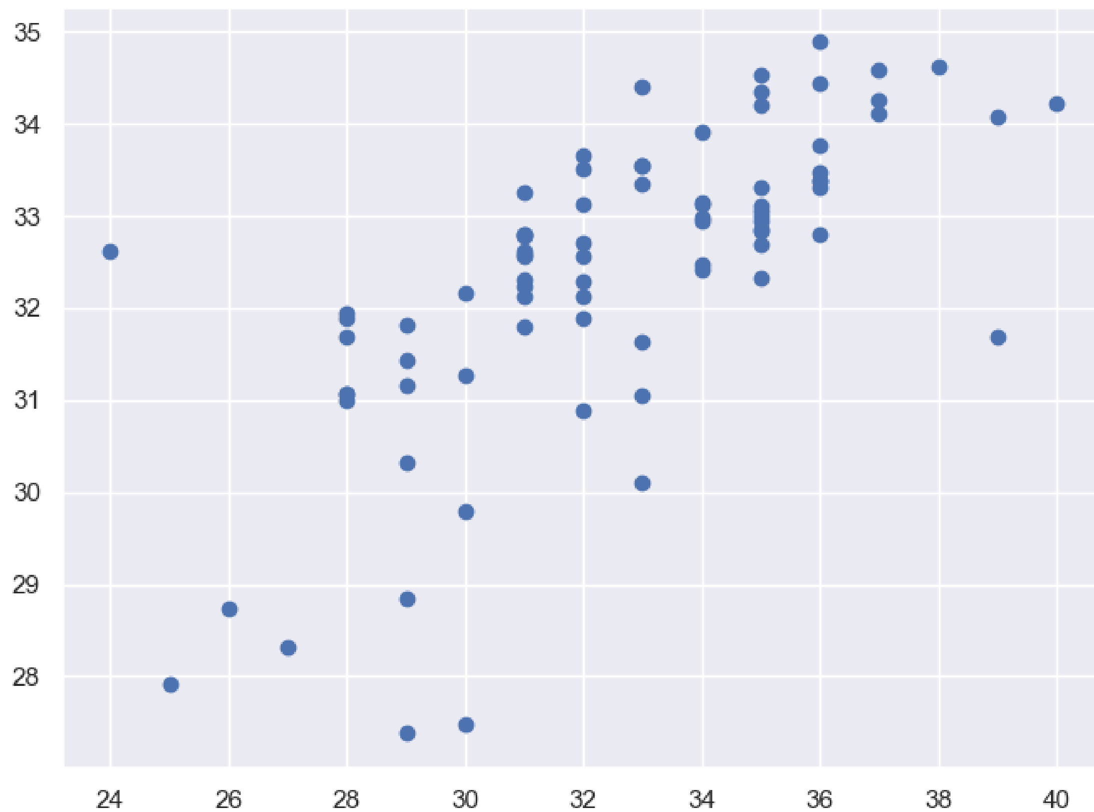
[55]:
```
lasso.intercept_
```

[55]:
```
31.98159509202454
```

1.4.1 Assumptions Of lasso regression

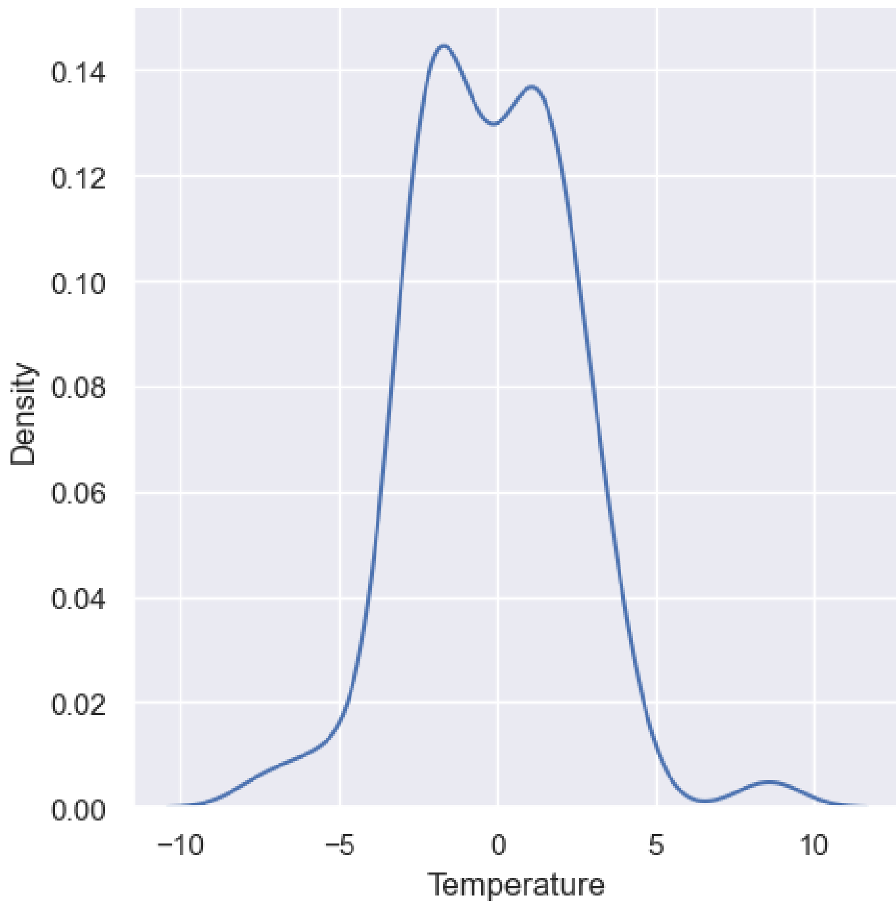
[56]:
```
### Assumptions Of ridge regression
plt.scatter(y_test,predict_la)
```

[56]:
```
<matplotlib.collections.PathCollection at 0x7ff568ba3a00>
```



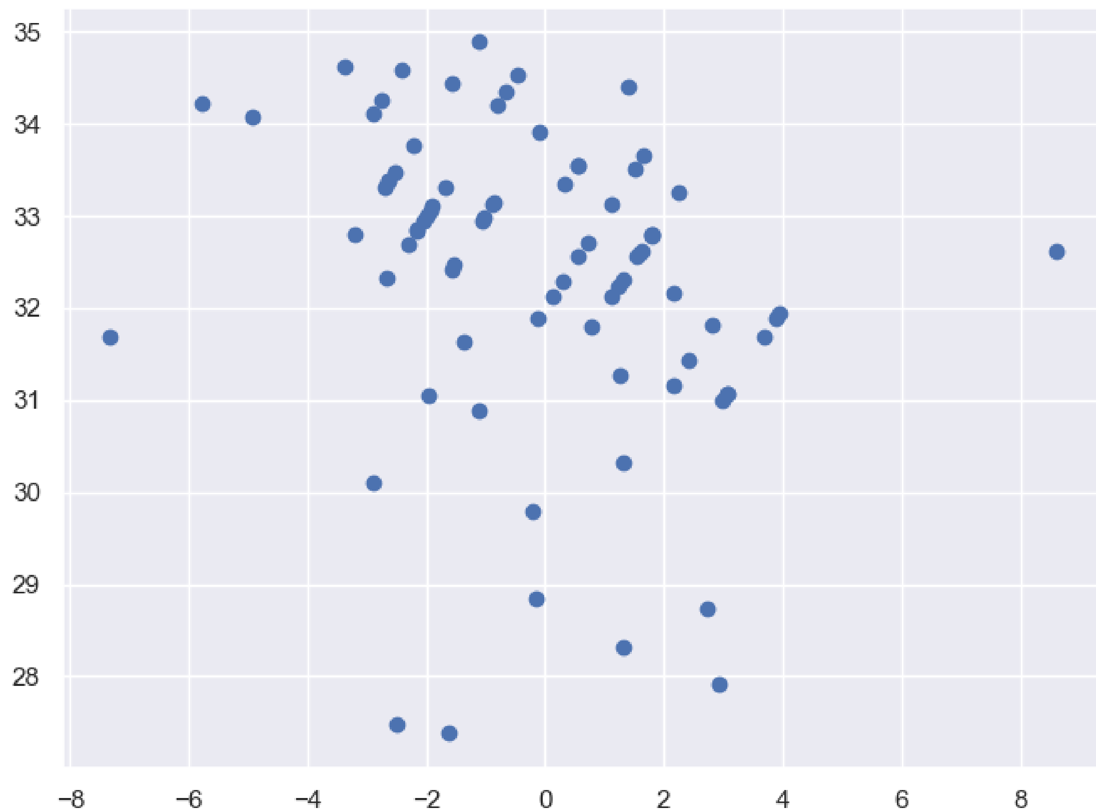
[57]:
```
residual_la = predict_la - y_test
sns.displot(residual_la,kind="kde")
```

[57]: <seaborn.axisgrid.FacetGrid at 0x7ff568bea550>



[58]:
```
plt.scatter(residual_la,predict_la)
```

[58]:
```
<matplotlib.collections.PathCollection at 0x7ff568b031f0>
```



1.4.2 Performance Metrics

[59]:
```
print(mean_squared_error(y_test,predict_la))
print(mean_absolute_error(y_test,predict_la))
print(np.sqrt(mean_squared_error(y_test,predict_la)))
```

```
6.085458745527471
1.9978776414662658
2.4668722596696147
```

[60]:
```
score=r2_score(y_test,predict_la)
print(score)
```

```
0.4334228064508907
```

1.5 ElasticNet Regression

[61]:
```
from sklearn.linear_model import ElasticNet
elasticnet = ElasticNet()
```

[62]:
```
elasticnet.fit(X_train,y_train)
```

[62]: ElasticNet()

[63]:
```
predict_en = elasticnet.predict(X_test)
predict_en
```

[63]:
```
array([32.65256996, 33.25056558, 33.35664726, 32.54205018, 34.69525792,
       31.63470292, 34.18134196, 29.02965354, 30.78570894, 30.13252743,
       30.45231109, 32.31544376, 32.56189723, 32.17489562, 33.83320104,
       32.21088442, 35.64395188, 27.8812157 , 32.07683621, 32.8901327 ,
       31.08820729, 29.67645915, 33.67039069, 30.11852367, 35.39011198,
       28.87997656, 32.33069454, 32.82341449, 32.61035675, 34.16641541,
       33.29924587, 31.22742866, 32.68528639, 33.03186089, 32.16811667,
       32.44762109, 30.87567129, 33.23168415, 31.06207802, 27.9644791 ,
       32.74801743, 32.75694081, 32.24725645, 27.82670749, 34.70745611,
       32.35515881, 31.6432799 , 30.77367885, 34.28175003, 33.57529939,
       35.63209843, 31.30433666, 31.51696316, 33.59539218, 33.60290528,
       32.23503043, 36.10463476, 32.05723319, 30.86007637, 34.88440778,
       33.04643393, 30.82269541, 33.46716217, 31.88611065, 31.77279988,
       27.9685264 , 32.95696894, 31.29725359, 35.38485687, 34.13985105,
       32.63887317, 31.44594133, 33.28775087, 33.75081985, 35.18328968,
       31.56817229, 33.13431113, 31.9250291 , 34.11941938, 31.7788403 ,
       33.49568181])
```

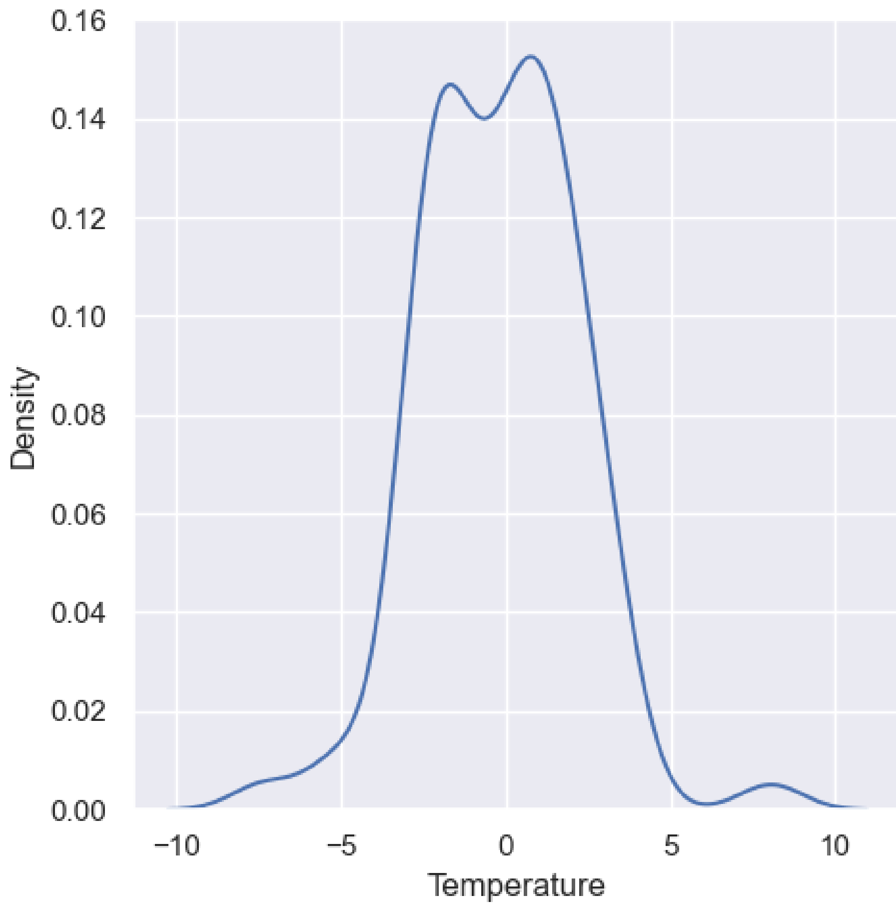
1.5.1 Assumptions Of ElasticNet regression

[64]:
```
plt.scatter(predict_en,y_test)
```

[64]: <matplotlib.collections.PathCollection at 0x7ff568a67e80>

[65]:
```
residual_en = predict_en - y_test
sns.displot(residual_en,kind="kde")
```

[65]: <seaborn.axisgrid.FacetGrid at 0x7ff568a1a490>



[66]:
```
plt.scatter(predict_en, residual_en)
```

[66]: <matplotlib.collections.PathCollection at 0x7ff5689bcac0>

1.5.2 Performance Metrics

[67]:
```
print(mean_absolute_error(y_test,predict_en))
print(mean_squared_error(y_test,predict_en))
print(np.sqrt(mean_squared_error(y_test,predict_en)))
```

```
1.8487698991824761
5.402378245642594
2.3243016683818376
```

[68]:
```
print(r2_score(y_test,predict_en))
```

```
0.4970199564401724
```