Data Set Information:

This archive contains 2075259 measurements gathered in a house located in Sceaux (7km of Paris, France) between December 2006 and November 2010 (47 months). Notes: 1.(global_active_power*1000/60 - sub_metering_1 - sub_metering_2 - sub_metering_3) represents the active energy consumed every minute (in watt hour) in the household by electrical equipment not measured in sub-meterings 1, 2 and 3. 2.The dataset contains some missing values in the measurements (nearly 1,25% of the rows). All calendar timestamps are present in the dataset but for some timestamps, the measurement values are missing: a missing value is represented by the absence of value between two consecutive semi-colon attribute separators. For instance, the dataset shows missing values on April 28, 2007.

Attribute Information:

1.date: Date in format dd/mm/yyyy 2.time: time in format hh:mm:ss 3.global_active_power: household global minute-averaged active power (in kilowatt) 4.global_reactive_power: household global minute-averaged reactive power (in kilowatt) 5.voltage: minute-averaged voltage (in volt) 6.global_intensity: household global minute-averaged current intensity (in ampere) 7.sub_metering_1: energy sub-metering No. 1 (in watt-hour of active energy). It corresponds to the kitchen, containing mainly a dishwasher, an oven and a microwave (hot plates are not electric but gas powered). 8.sub_metering_2: energy sub-metering No. 2 (in watt-hour of active energy). It corresponds to the laundry room, containing a washing-machine, a tumble-drier, a refrigerator and a light. 9.sub_metering_3: energy sub-metering No. 3 (in watt-hour of active energy). It corresponds to an electric water-heater and an air-conditioner.

Dataset Link: https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption

In [1]:

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

from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.svm import SVR
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
import sklearn.metrics as skm
from sklearn.model_selection import train_test_split
import operator as op

from sklearn.impute import SimpleImputer

import seaborn as sns
sns.set(rc={'figure.figsize': (12,8)})
```

In [2]:

```
df = pd.read_csv('household_power_consumption.txt',sep=";")
df.head()
```

```
C:\Windows\Temp\ipykernel_10028\3697064285.py:1: DtypeWarning: Columns (2,3,4,5,6,7) have
mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv('household_power_consumption.txt',sep=";")
```

Out[2]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_
0	16/12/2006	17:24:00	4.216	0.418	234.840	18.400	0.000	1.0(
1	16/12/2006	17:25:00	5.360	0.436	233.630	23.000	0.000	1.0(
2	16/12/2006	17:26:00	5.374	0.498	233.290	23.000	0.000	2.0(

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_
3	16/12/2006	17:27:00	5.388	0.502	233.740	23.000	0.000	1.0
4	16/12/2006	17:28:00	3.666	0.528	235.680	15.800	0.000	1.00

In [3]:

```
# Count the number of null values
df.isnull().sum()
```

Out[3]:

```
Date                         0
Time                         0
Global_active_power          0
Global_reactive_power        0
Voltage                      0
Global_intensity             0
Sub_metering_1               0
Sub_metering_2               0
Sub_metering_3           25979
dtype: int64
```

In [4]:

```
# Check the shape of dataset (No. of rows and No. of Columns)

df.shape
```

Out[4]:

```
(2075259, 9)
```

In [5]:

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

Out[5]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_mete
count	2075259	2075259	2075259	2075259	2075259	2075259	2075259	2
unique	1442	1440	6534	896	5168	377	153	
top	6/12/2008	17:24:00	?	0.000	?	1.000	0.000	
freq	1440	1442	25979	472786	25979	169406	1840611	1
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
...	...	...	...	...	...	...	...	
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

In [6]:

```
df.isnull().any(axis = 1).sum()
```

Out[6]:

```
25979
```

There are some options for dealing with with missing values 'nan'.

1: Fill NaN with Outlier or Zero.

2: Fill NaN with Mean Value or other values.

3: Fill NaN with Last Value with .ffill()

4: Fill NaN with Linearly Interpolated Value with .interpolate().

In [7]:

```
# fill missing values row wise and making the changes permanent in the original dataframe

df.ffill(axis=0,inplace=True)
```

In [8]:

```
# Cross check whether all missing values are filled

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

Out[8]:

```
Date                     0
Time                     0
Global_active_power      0
Global_reactive_power    0
Voltage                  0
Global_intensity         0
Sub_metering_1           0
Sub_metering_2           0
Sub_metering_3           0
dtype: int64
```

In [9]:

```
df.shape
```

Out[9]:

```
(2075259, 9)
```

In [10]:

```
# Feature Modification
df['Date'] = df['Date'].astype(str)
df['Time'] = df['Time'].astype(str)
df.replace(['?', 'nan', np.nan], -1, inplace=True)
num_vars= ['Global_active_power', 'Global_reactive_power', 'Voltage',
           'Global_intensity', 'Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3']
```

In [11]:

```
for i in num_vars:
    df[i] = pd.to_numeric(df[i])
imp = SimpleImputer(missing_values=-1, strategy='mean')
df[num_vars] = imp.fit_transform(df[num_vars])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2075259 entries, 0 to 2075258
Data columns (total 9 columns):
 #   Column                 Dtype
---  ------                 -----
 0   Date                   object
 1   Time                   object
 2   Global_active_power    float64
 3   Global_reactive_power  float64
 4   Voltage                float64
 5   Global_intensity       float64
 6   Sub_metering_1         float64
 7   Sub_metering_2         float64
 8   Sub_metering_3         float64
```

```
 8   Sub_metering_3         float64
dtypes: float64(7), object(2)
memory usage: 142.5+ MB
```

In [12]:

```python
# Target Variable
eq1 = (df['Global_active_power']*1000/60)
eq2 = df['Sub_metering_1'] + df['Sub_metering_2'] + df['Sub_metering_3']
df['power_consumption'] = eq1 - eq2
df.head()
```

Out[12]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_
0	16/12/2006	17:24:00	4.216	0.418	234.84	18.4	0.0	1
1	16/12/2006	17:25:00	5.360	0.436	233.63	23.0	0.0	1
2	16/12/2006	17:26:00	5.374	0.498	233.29	23.0	0.0	2
3	16/12/2006	17:27:00	5.388	0.502	233.74	23.0	0.0	1
4	16/12/2006	17:28:00	3.666	0.528	235.68	15.8	0.0	1

In [13]:

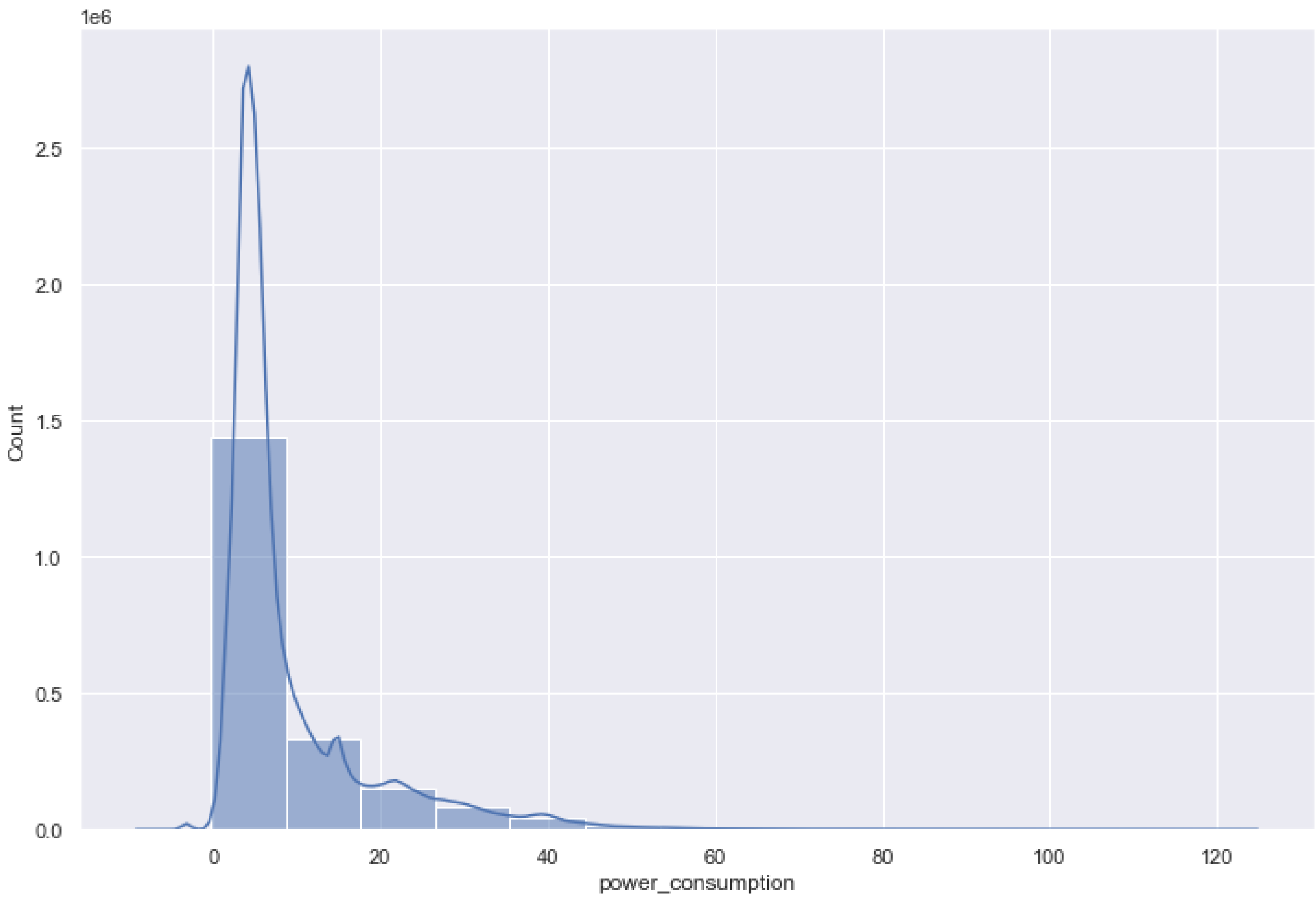
```python
df.columns
```

Out[13]:

```
Index(['Date', 'Time', 'Global_active_power', 'Global_reactive_power',
       'Voltage', 'Global_intensity', 'Sub_metering_1', 'Sub_metering_2',
       'Sub_metering_3', 'power_consumption'],
      dtype='object')
```

In [14]:

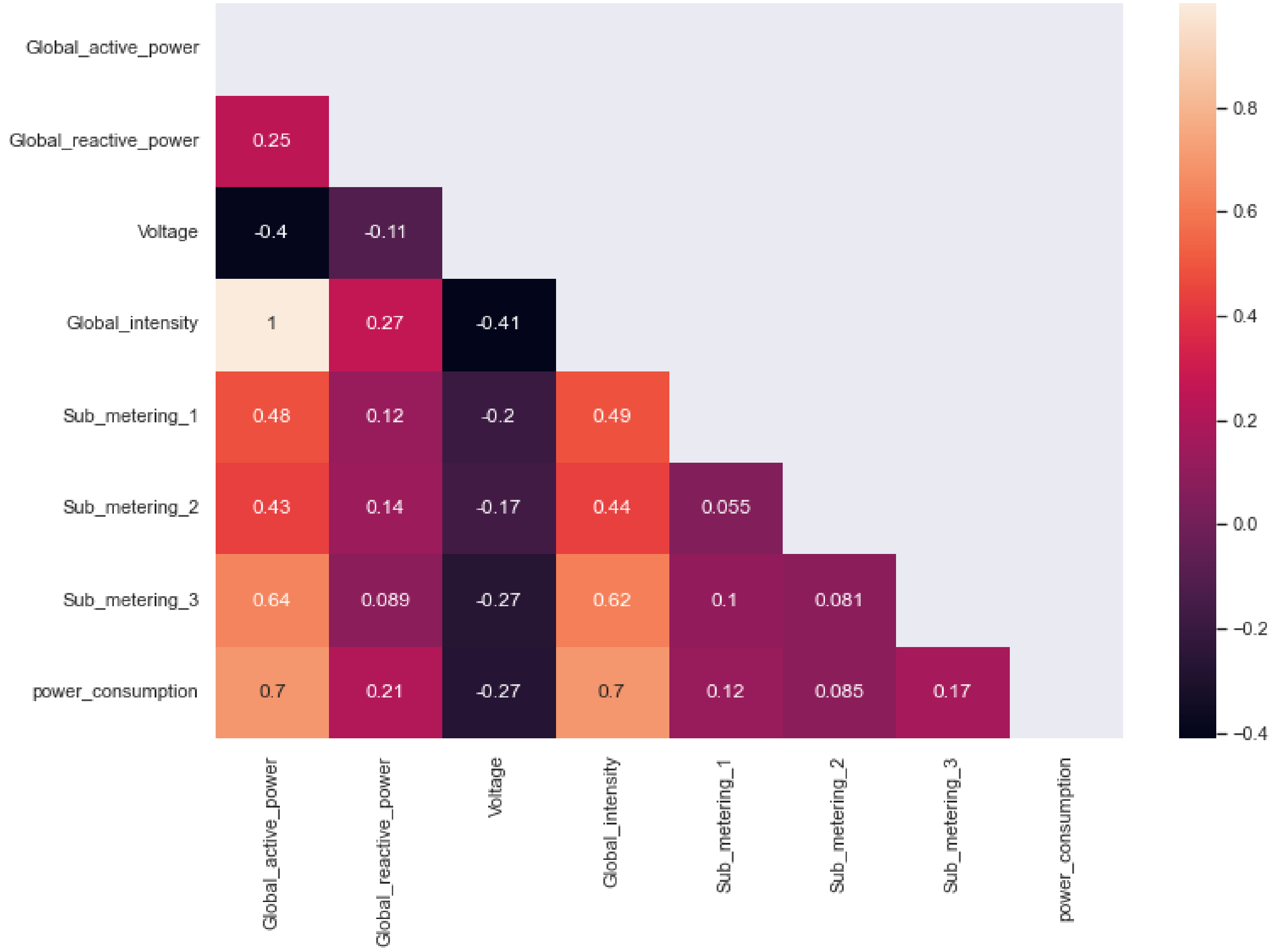
```python
# Distribution of the target variables
sns.histplot(data=df, x='power_consumption', bins=15, kde=True)
plt.show()
```



Heatmap

In [15]:

```
corr = np.corrcoef(df.corr())
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(df.corr(), annot=True, mask=mask)
plt.show()
```



In [16]:

```
corr = df.corr(method='pearson')
print("Correlation of the Dataset:",corr)
```

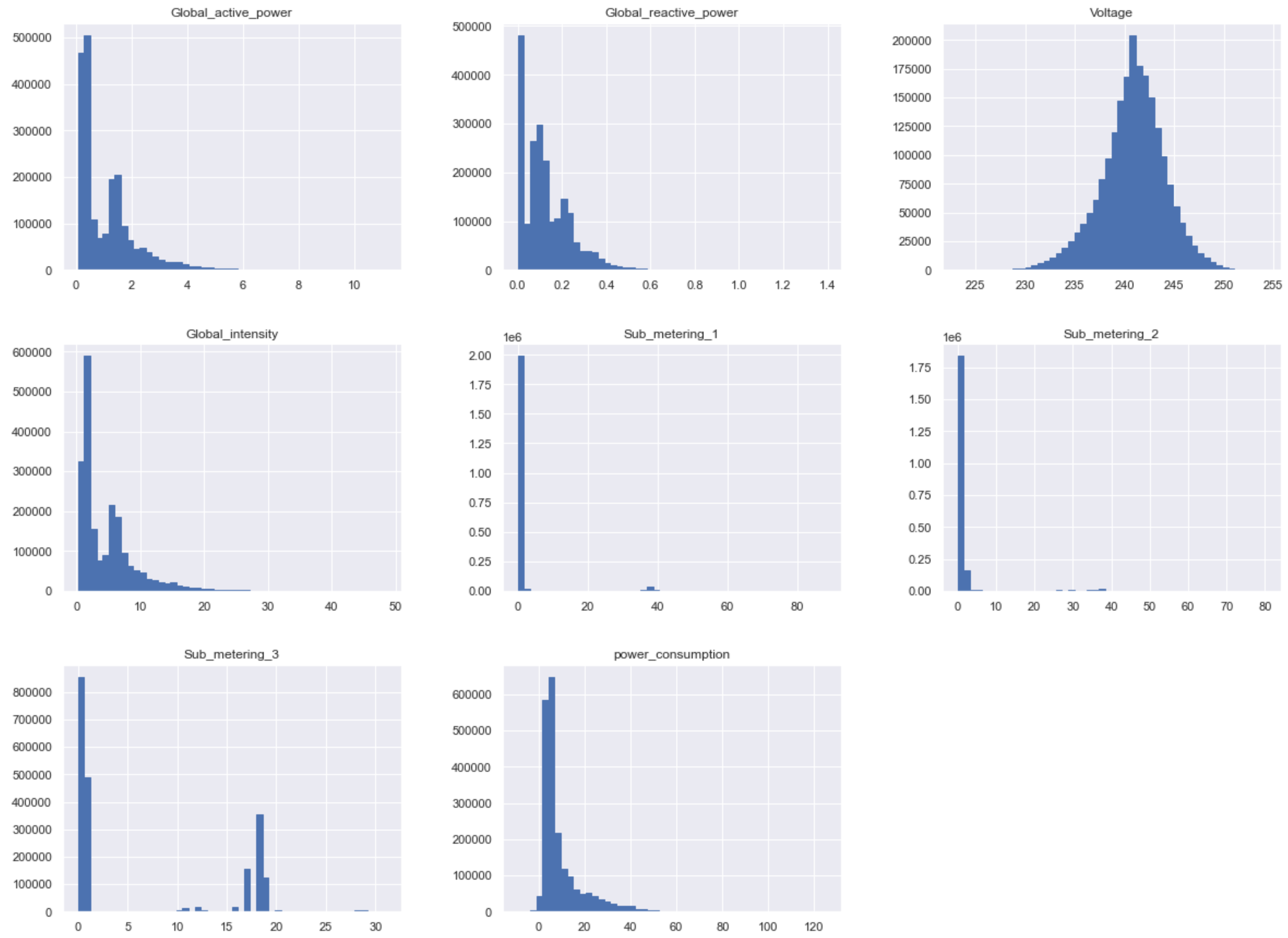
```
Correlation of the Dataset:                        Global_active_power  Global_reactive_p
ower   Voltage  \
Global_active_power              1.000000               0.247017 -0.399762
Global_reactive_power            0.247017               1.000000 -0.112246
Voltage                         -0.399762              -0.112246  1.000000
Global_intensity                 0.998889               0.266120 -0.411363
Sub_metering_1                   0.484401               0.123111 -0.195976
Sub_metering_2                   0.434569               0.139231 -0.167405
Sub_metering_3                   0.635876               0.089240 -0.267047
power_consumption                0.699097               0.210935 -0.270488

                       Global_intensity  Sub_metering_1  Sub_metering_2  \
Global_active_power            0.998889        0.484401        0.434569
Global_reactive_power          0.266120        0.123111        0.139231
Voltage                       -0.411363       -0.195976       -0.167405
Global_intensity               1.000000        0.489298        0.440347
Sub_metering_1                 0.489298        1.000000        0.054721
Sub_metering_2                 0.440347        0.054721        1.000000
Sub_metering_3                 0.623914        0.102141        0.080533
power_consumption              0.700969        0.124660        0.084923
```

```
                       Sub_metering_3  power_consumption
Global_active_power          0.635876           0.699097
Global_reactive_power        0.089240           0.210935
Voltage                     -0.267047          -0.270488
Global_intensity             0.623914           0.700969
Sub_metering_1               0.102141           0.124660
Sub_metering_2               0.080533           0.084923
Sub_metering_3               1.000000           0.170017
power_consumption            0.170017           1.000000
```

In [17]:

```
df.hist(bins=50, figsize=(20,15), ec = 'b')
plt.show()
```



In [18]:

```
# sns.regplot(data=df,x="Global_reactive_power",y="Voltage")
```

In [19]:

```
X = df.drop(['power_consumption','Date','Time'], axis=1).values
Y = df['power_consumption'].values
```

In [20]:

```
X
```

Out[20]:

```
array([[  4.216,   0.418, 234.84 , ...,   0.   ,   1.   ,  17.   ],
       [  5.36 ,   0.436, 233.63 , ...,   0.   ,   1.   ,  16.   ],
       [  5.374,   0.498, 233.29 , ...,   0.   ,   2.   ,  17.   ],
       ...,
       [  0.938,   0.   , 239.82 , ...,   0.   ,   0.   ,   0.   ],
       [  0.934,   0.   , 239.7  , ...,   0.   ,   0.   ,   0.   ],
```

```
[ 0.932,    0.    , 239.55 , ...,    0.    ,    0.    ,    0.    ]])
```

In [21]:

```
Y
```

Out[21]:

```
array([52.26666667, 72.33333333, 70.56666667, ..., 15.63333333,
       15.56666667, 15.53333333])
```

In [22]:

```
from sklearn.model_selection import train_test_split
```

In [23]:

```
X_train,X_test,y_train,y_test = train_test_split(X,Y,test_size=0.33,random_state=42)
```

In [24]:

```
X_train
```

Out[24]:

```
array([[1.7780e+00, 2.1000e-01, 2.4374e+02, ..., 0.0000e+00, 0.0000e+00,
        0.0000e+00],
       [4.9000e-01, 6.2000e-02, 2.3772e+02, ..., 0.0000e+00, 0.0000e+00,
        0.0000e+00],
       [2.9800e+00, 4.3600e-01, 2.3805e+02, ..., 0.0000e+00, 7.0000e+00,
        1.8000e+01],
       ...,
       [2.1160e+00, 2.3200e-01, 2.3967e+02, ..., 9.0000e+00, 0.0000e+00,
        0.0000e+00],
       [2.0120e+00, 2.5800e-01, 2.3599e+02, ..., 0.0000e+00, 3.0000e+00,
        0.0000e+00],
       [2.5620e+00, 5.4000e-02, 2.3839e+02, ..., 0.0000e+00, 0.0000e+00,
        0.0000e+00]])
```

In [25]:

```
y_train
```

Out[25]:

```
array([29.63333333,  8.16666667, 24.66666667, ..., 26.26666667,
       30.53333333, 42.7       ])
```

In [26]:

```
reg = LinearRegression()
reg.fit(X_train,y_train)
reg_pred = reg.predict(X_test)
```

In [27]:

```
## residuals
residuals=y_test-reg_pred
residuals
```

Out[27]:

```
array([6.78923584e-12, 6.29452046e-12, 5.71098724e-12, ...,
       4.70201655e-12, 6.71018796e-12, 6.25277607e-13])
```

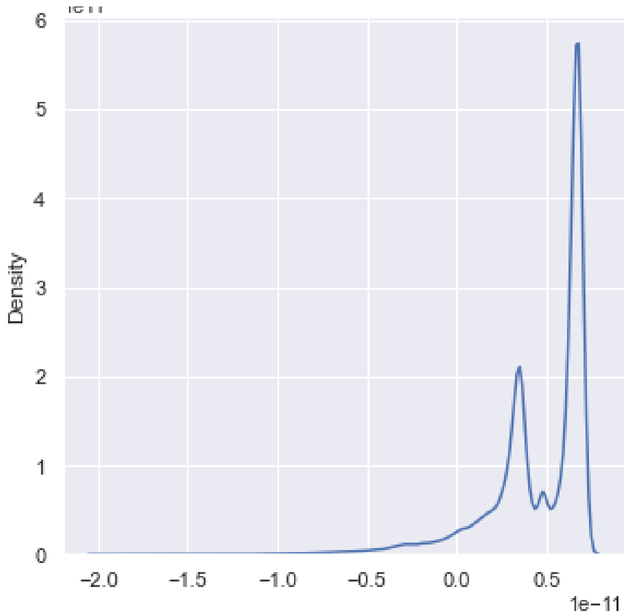
In [28]:

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

Out[28]:

```
<seaborn.axisgrid.FacetGrid at 0x1e6a7e24910>
```

1e11

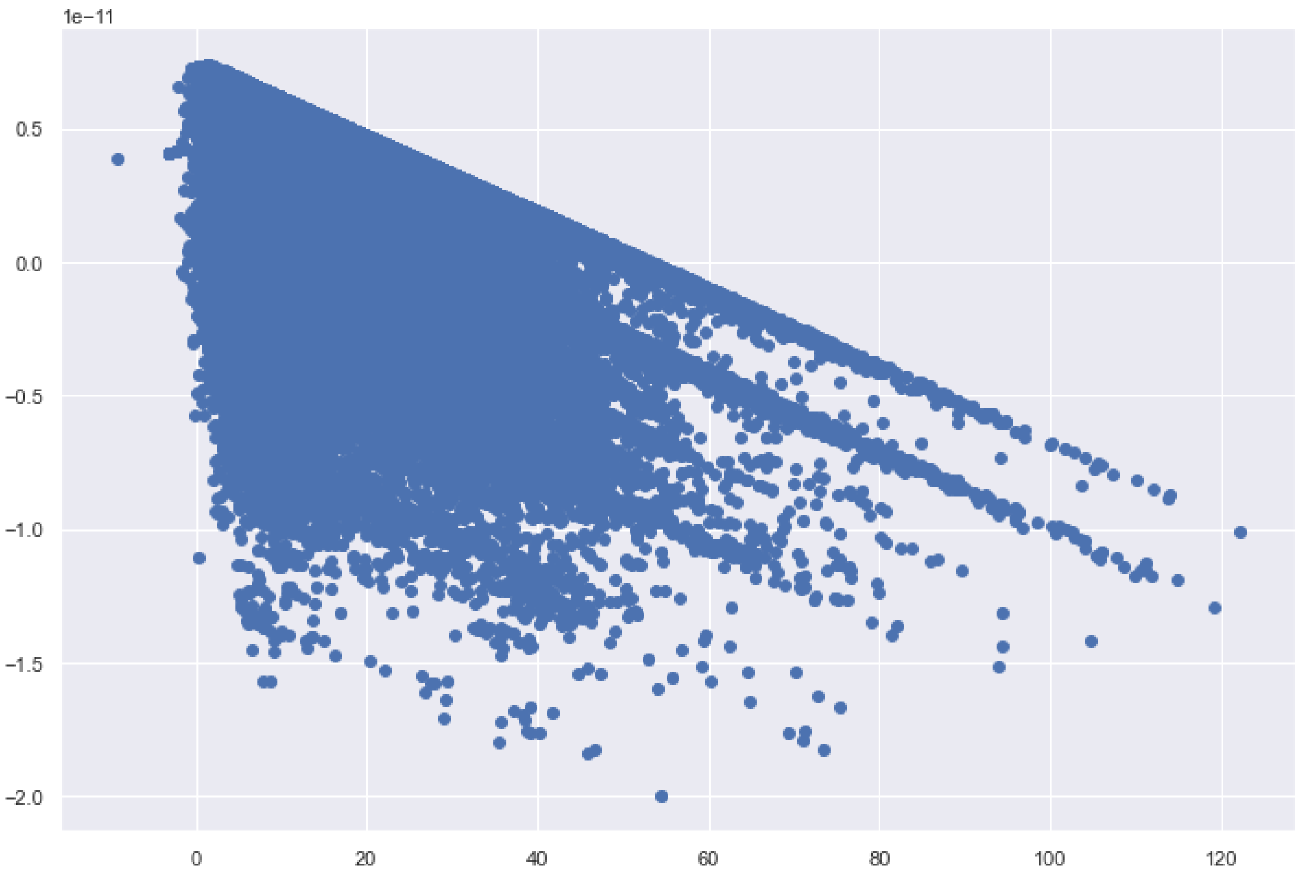


In [29]:

```
plt.scatter(reg_pred,residuals)
```

Out[29]:

```
<matplotlib.collections.PathCollection at 0x1e6a7ecc9d0>
```

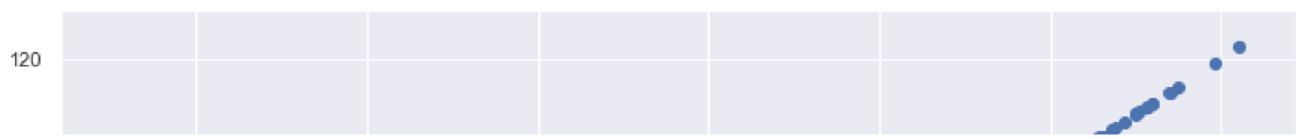


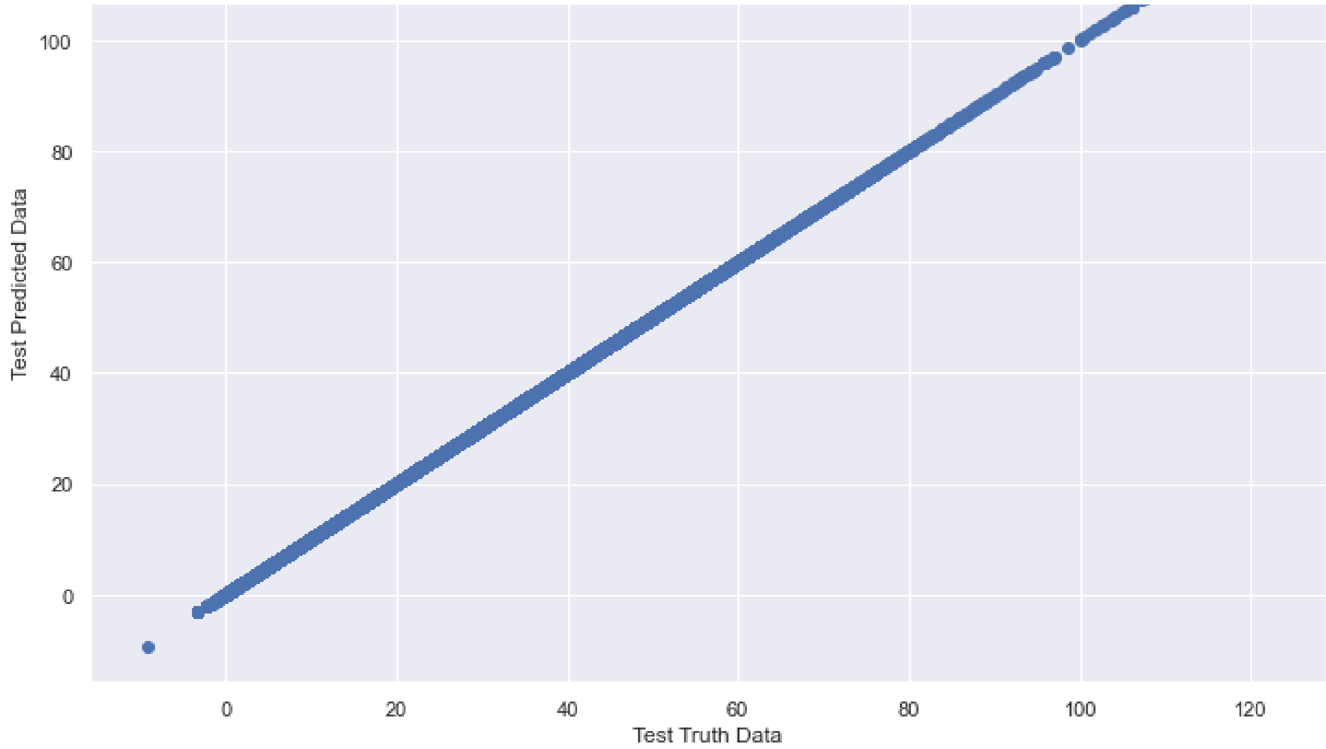
In [30]:

```
plt.scatter(y_test,reg_pred)
plt.xlabel("Test Truth Data")
plt.ylabel("Test Predicted Data")
```

Out[30]:

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





In [31]:

```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import explained_variance_score
from sklearn.metrics import r2_score

## Performance Metrics
from sklearn.metrics import mean_squared_error    ## MSE
from sklearn.metrics import mean_absolute_error   ## MAE
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)))
```

```
2.8924933491049666e-23
4.9745488309973314e-12
5.378190540604681e-12
```

In [32]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

In [33]:

```
X_train_scaled = scaler.fit_transform(X_train)
```

In [34]:

```
X_test_scaled = scaler.fit_transform(X_test)
```

In [35]:

```
reg.fit(X_train_scaled,y_train)
```

Out[35]:

```
▾ LinearRegression
LinearRegression()
```

In [36]:

```
## Prediction for the test data
reg_pred_scaled=reg.predict(X_test_scaled)
```

```
reg_pred_scaled
```

Out[36]:

```
array([ 3.263697  ,  5.76045433, 11.62476027, ...,  3.98306037,
        3.86310887, 46.43417263])
```

In [37]:

```
print(reg.intercept_)
```

```
9.350838967230835
```

In [38]:

```
print(reg.coef_)
```

```
[ 1.75071861e+01  3.28626015e-14 -3.17523785e-14 -2.13695728e-12
 -6.11662905e+00 -5.78695987e+00 -8.42111736e+00]
```

In [39]:

```
## Performance Metrics
from sklearn.metrics import mean_squared_error   ## MSE
from sklearn.metrics import mean_absolute_error  ## MAE
print(mean_squared_error(y_test,reg_pred_scaled))
print(mean_absolute_error(y_test,reg_pred_scaled))
print(np.sqrt(mean_squared_error(y_test,reg_pred_scaled)))
```

```
0.0007220358598308842
0.01736824147593707
0.02687072495916111 7
```

In [40]:

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

```
1.0
```

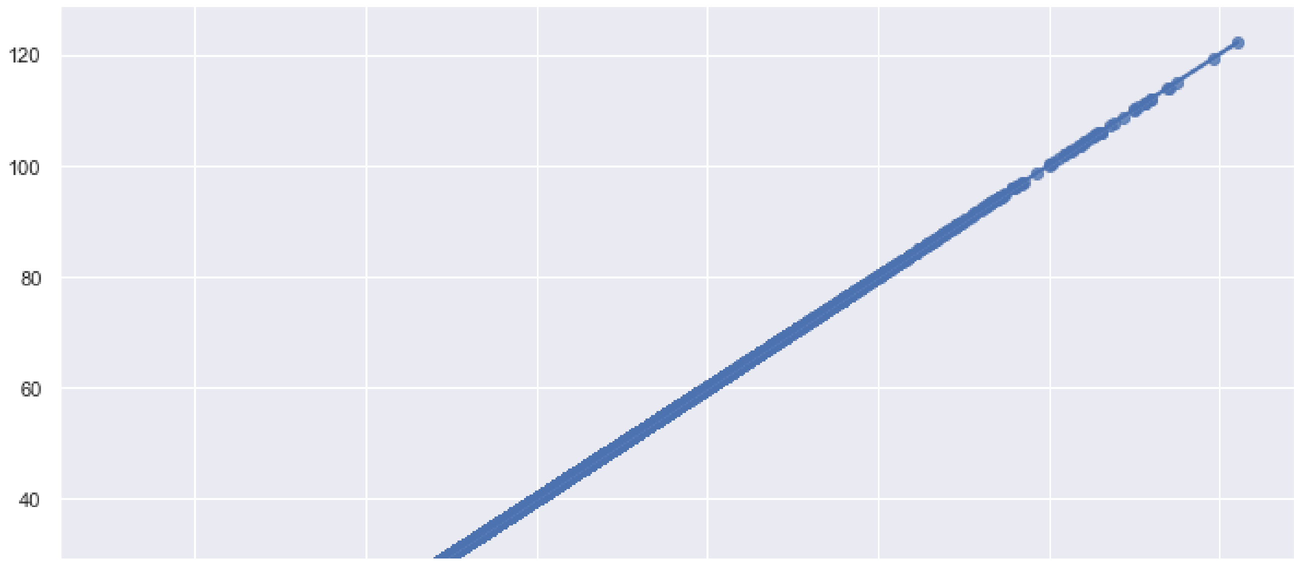
In [41]:

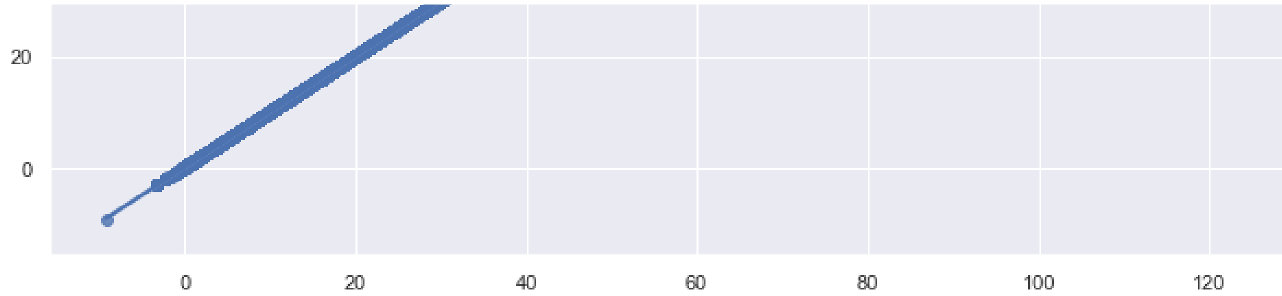
```
sns.regplot(y_test,reg_pred)
```

```
C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_de
corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[41]:

```
<AxesSubplot:>
```





In [42]:

```
## Adjusted R square
#display adjusted R-squared
1 - (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[42]:

```
1.0
```

In [43]:

```
from sklearn.metrics import r2_score
score_scaled=r2_score(y_test,reg_pred_scaled)
print(score_scaled)
```

```
0.9999921215620882
```

In [44]:

```
## Adjusted R square
#display adjusted R-squared
1 - (1-score_scaled)*(len(y_test)-1)/(len(y_test)-X_test_scaled.shape[1]-1)
```

Out[44]:

```
0.9999921214815584
```

In [45]:

```
print("----------------------------------------------Lasso Regression------------------
------------------------------")
lasso = Lasso()
lasso.fit(X_train,y_train)
prediction_lasso = lasso.predict(X_test)
score = explained_variance_score(y_test, prediction_lasso)
mae = mean_absolute_error(prediction_lasso,y_test)

print("Score:", score)
print("Mean Absolute Error:", mae)
```

```
----------------------------------------------Lasso Regression-------------------------
-----------------------
Score: 0.9860306565490398
Mean Absolute Error: 0.7568967353570939
```

In [46]:

```
from sklearn.metrics import r2_score
R2_score_lasso=r2_score(y_test,prediction_lasso)
print(R2_score_lasso)
```

```
0.986030654475905
```

In [47]:

```
from sklearn.metrics import r2_score
R2_score_lasso=r2_score(y_test,prediction_lasso)
print(R2_score_lasso)
```

```
0.986030654475905
```

In [48]:

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

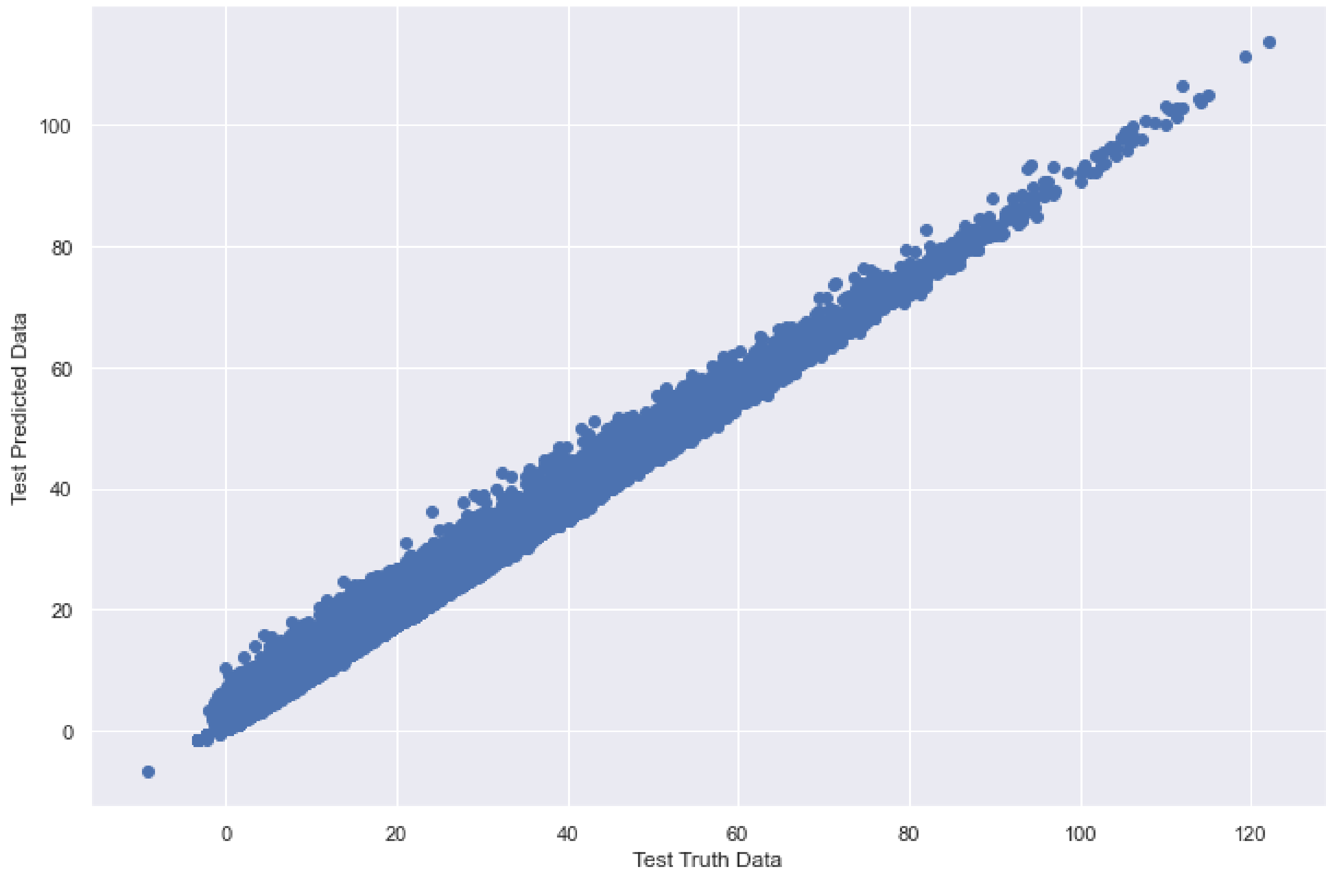
```
[ 0.         -0.          0.          3.5853411  -0.88014215 -0.88428731
 -0.85229769]
```

In [49]:

```
plt.scatter(y_test,prediction_lasso)
plt.xlabel("Test Truth Data")
plt.ylabel("Test Predicted Data")
```

Out[49]:

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



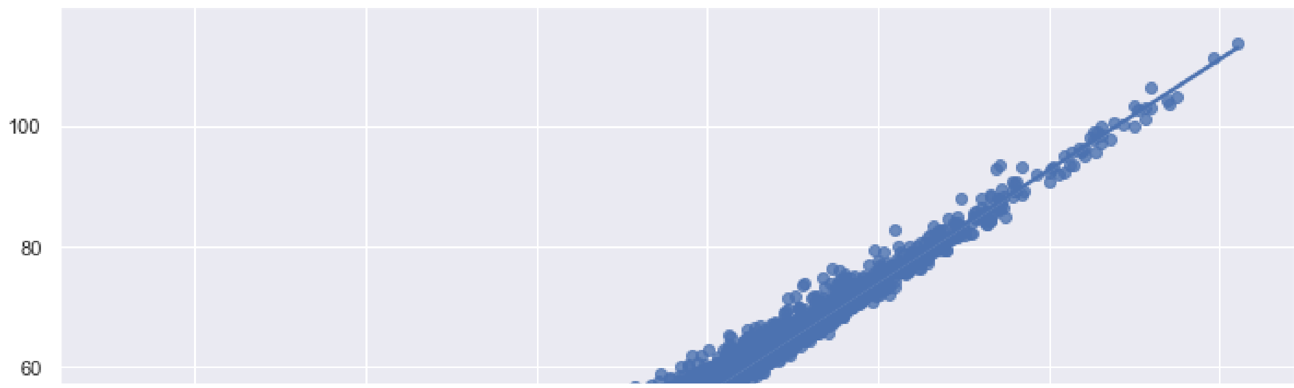
In [50]:

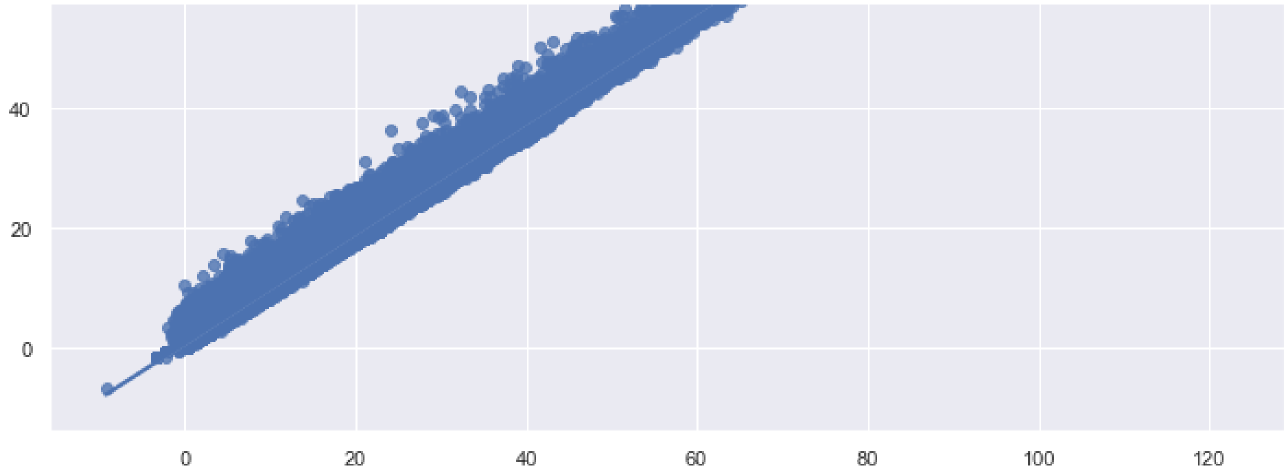
```
sns.regplot(y_test,prediction_lasso)
```

```
C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_de
corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[50]:

```
<AxesSubplot:>
```





In [51]:

```
## Adjusted R square
#display adjusted R-squared
1 - (1-R2_score_lasso)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[51]:

```
0.9860305116876156
```

In [52]:

```
print("----------------------------------------------Lasso Regression With Scaled Data-
-----------------------------------------------")
lasso = Lasso()
lasso.fit(X_train_scaled,y_train)
prediction_lasso_scaled = lasso.predict(X_test_scaled)
score_scaled = explained_variance_score(y_test, prediction_lasso_scaled)
mae = mean_absolute_error(prediction_lasso_scaled,y_test)

print("Score:", score_scaled)
print("Mean Absolute Error:", mae)
```

```
----------------------------------------------Lasso Regression With Scaled Data---------
---------------------------------------
Score: 0.7615292349686844
Mean Absolute Error: 3.0248244125903123
```

In [53]:

```
print("------------------------------------------------Ridge Regression----------------
----------------------------------")
ridge = Ridge()
ridge.fit(X_train,y_train)
prediction_ridge = ridge.predict(X_test)
score = explained_variance_score(y_test, prediction_ridge)
mae = mean_absolute_error(prediction_ridge, y_test)

print("Score:", score)
print("Mean Absolute Error:", mae)
```

```
------------------------------------------------Ridge Regression-----------------------
---------------------------
Score: 0.9999999990291548
Mean Absolute Error: 0.00018966115846728577
```

In [54]:

```
from sklearn.metrics import r2_score
R2_score_ridge=r2_score(y_test,prediction_ridge)
print(R2_score_ridge)
```

```
0.9999999990291499
```

In [55]:

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

```
-0.007872900713653763
```

In [56]:

```
print(ridge.coef_)
```

```
[ 1.66593043e+01 -1.29543539e-03  3.26525166e-05  1.75304534e-03
 -1.00000253e+00 -1.00000338e+00 -9.99984287e-01]
```

In [57]:

```
## Adjusted R square
#display adjusted R-squared
1 - (1-R2_score_ridge)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[57]:

```
0.99999999902914
```

In [58]:

```
print("-----------------------------------------------ElasticNet Regression-----------
---------------------------------------")
elasticnet = ElasticNet()
elasticnet.fit(X_train,y_train)
prediction_elasticnet = elasticnet.predict(X_test)
score = explained_variance_score(y_test, prediction_elasticnet)
mae = mean_absolute_error(prediction_elasticnet,y_test)

print("Score:", score)
print("Mean Absolute Error:", mae)
```

```
-----------------------------------------------ElasticNet Regression------------------
--------------------------------
Score: 0.9758464362189964
Mean Absolute Error: 0.9978200825917457
```

In [59]:

```
print(elasticnet.intercept_)
```

```
0.7877319724716898
```

In [60]:

```
print(elasticnet.coef_)
```

```
[ 0.0946939  -0.         -0.          3.36708172 -0.82384712 -0.83067903
 -0.79701427]
```

In [61]:

```
from sklearn.metrics import r2_score
R2_score_elasticnet=r2_score(y_test,prediction_elasticnet)
print(R2_score_elasticnet)
```

```
0.9758464140759413
```

In [62]:

```
## Adjusted R square
#display adjusted R-squared
1 - (1-R2_score_elasticnet)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[62]:

```
0.9758461671889836
```

In [63]:

```
print("-----------------------------------------------Ridge Regression with Scaled Dat
```

```
print("-----------------------------------------------Ridge Regression with Scaled Dat
a---------------------------------------------")
ridge = Ridge()
ridge.fit(X_train_scaled,y_train)
prediction_ridge_scaled = ridge.predict(X_test_scaled)
score_scaled = explained_variance_score(y_test, prediction_ridge_scaled)
mae = mean_absolute_error(prediction_ridge_scaled, y_test)

print("Score:", score_scaled)
print("Mean Absolute Error:", mae)
```

```
------------------------------------------------Ridge Regression with Scaled Data-------
---------------------------------------
Score: 0.9999954102873931
Mean Absolute Error: 0.017368250085188313
```

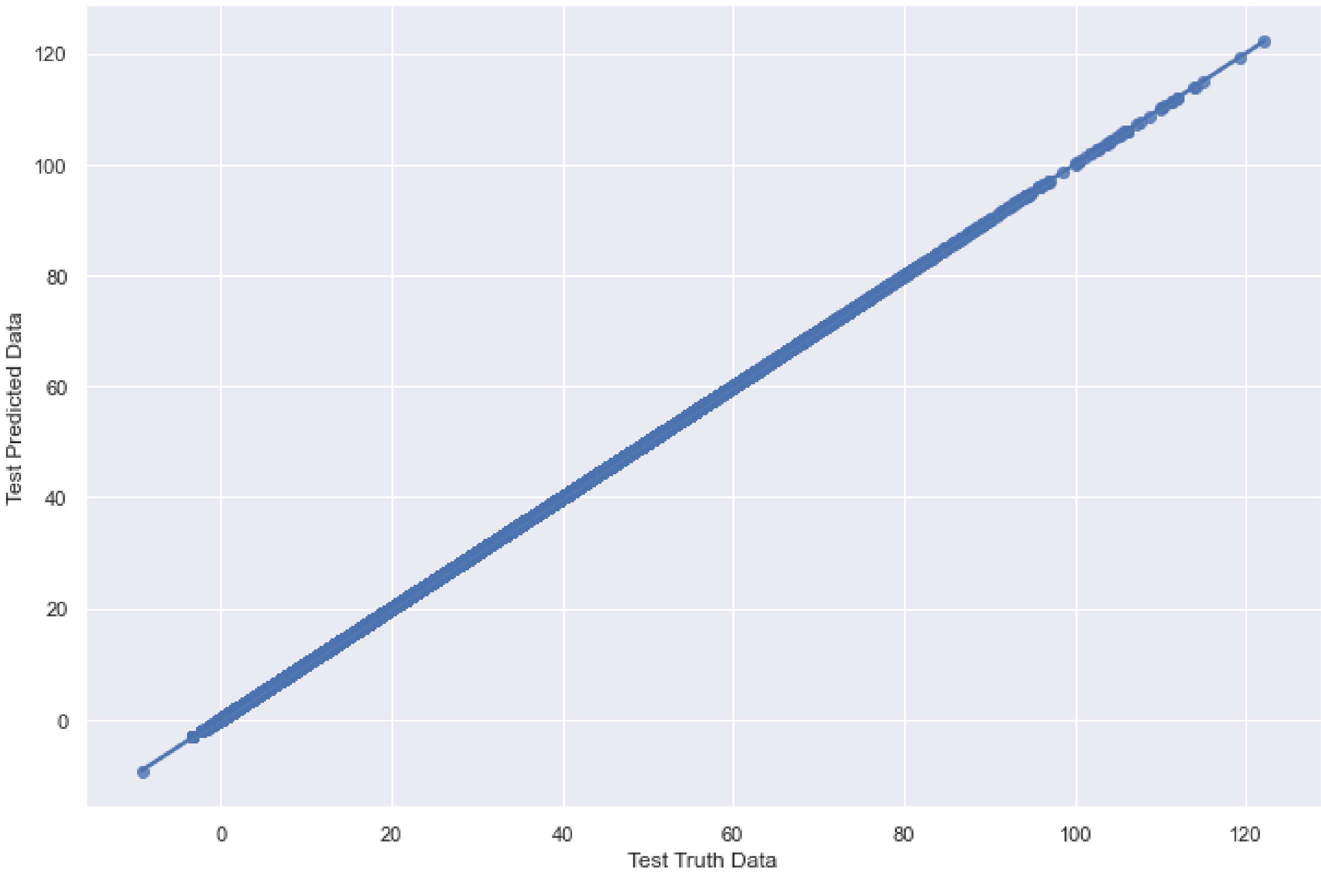
In [64]:

```
sns.regplot(y_test,prediction_ridge)
plt.xlabel("Test Truth Data")
plt.ylabel("Test Predicted Data")
```

```
C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_de
corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[64]:

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



In [65]:

```
print("-------------------------------------ElasticNet Regression with Scaled Data------
--------------------------------------------")
elasticnet = ElasticNet()
elasticnet.fit(X_train_scaled,y_train)
prediction_elasticnet_scaled = elasticnet.predict(X_test_scaled)
score_scaled = explained_variance_score(y_test, prediction_elasticnet_scaled)
mae = mean_absolute_error(prediction_elasticnet_scaled,y_test)

print("Score:",score_scaled)
```

```
print("Mean Absolute Error:", mae)
```

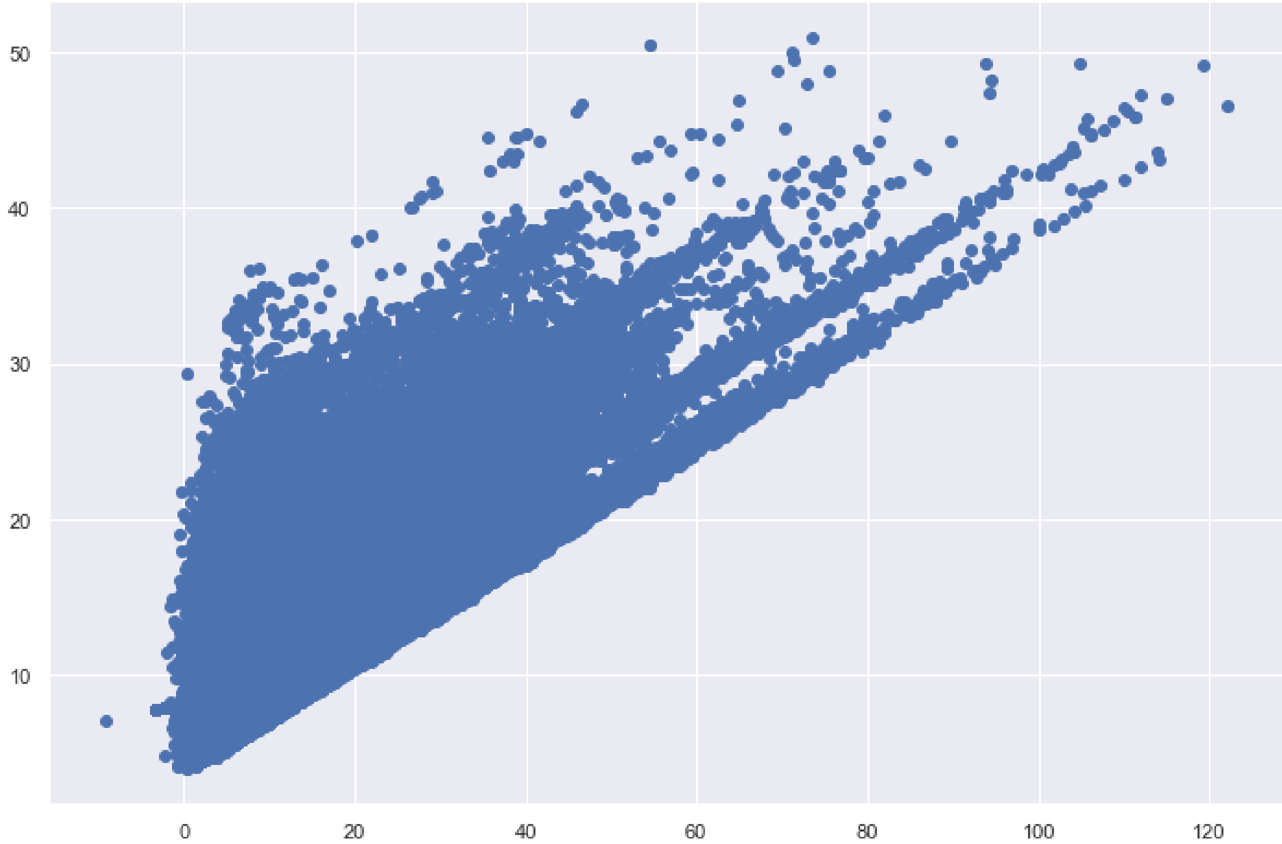
```
------------------------------------ElasticNet Regression with Scaled Data-------------
------------------------------------
Score: 0.5690312144535741
Mean Absolute Error: 4.150381323410036
```

In [66]:

```
plt.scatter(y_test,prediction_elasticnet_scaled)
```

Out[66]:

```
<matplotlib.collections.PathCollection at 0x1e6a737f940>
```



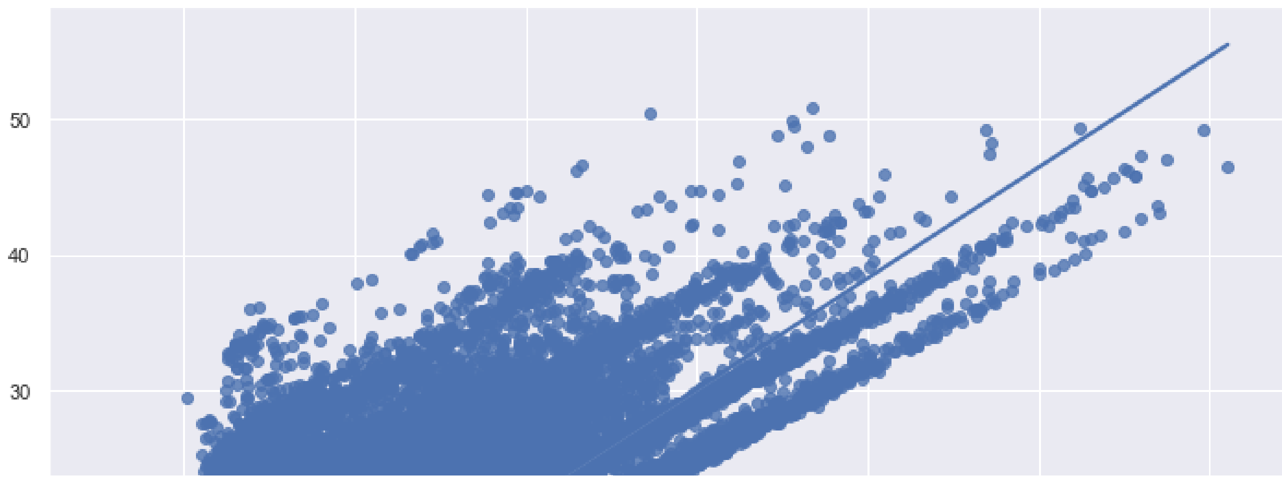
In [67]:

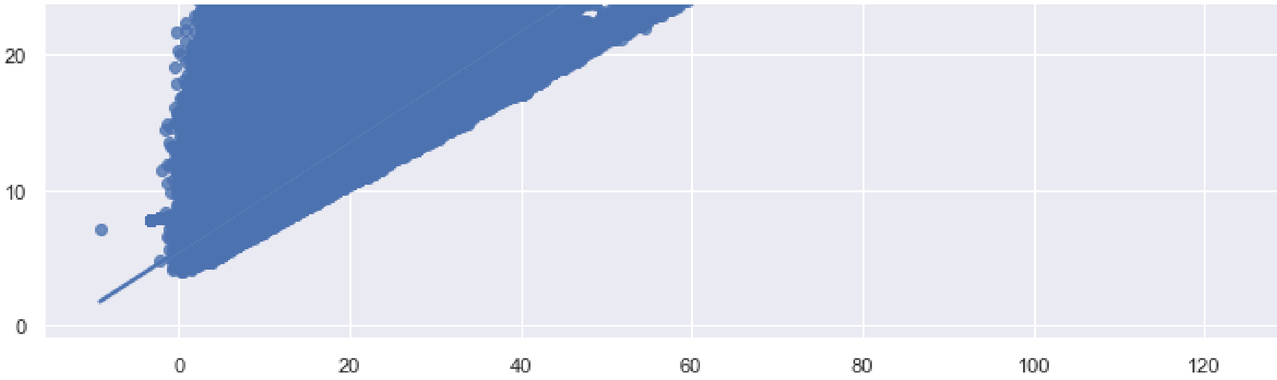
```
sns.regplot(y_test,prediction_elasticnet_scaled)
```

```
C:\Users\Shobhandeb\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\_de
corators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From v
ersion 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[67]:

```
<AxesSubplot:>
```





In [ ]: