Data Acquisition

Importing Libraries

For dealing with file, I have imorted "pandas" libray, for numbers "numpy", for visualization purposes "seaborn and matplotlib is being used

In [46]:

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

Read Data

We use `pandas.read_csv()` function to read the csv file. In the bracket, we put the file path along with a quotation mark, so that pandas will read the file into a data frame from that address.

In [2]:

```
df=pd.read_csv("C:/Users/a/Downloads/dataframe_.csv")
```

In [5]:

```
df.head(10)
```

Out[5]:

	input	output
0	-122.740667	-130.572085
1	-121.531419	-129.938929
2	-134.917019	-130.141832
3	-120.605951	-125.760932
4	-129.894781	-112.785214
5	-134.366669	-116.000000
6	-115.563739	-126.267621
7	-132.080161	-132.032206
8	-133.366669	-114.000000
9	-119.524112	-94.419855

In [4]:

```
df.tail(10)
```

Out[4]:

	input	output
1687	41.117227	-107.611418
1688	26.692772	-111.741529
1689	42.929340	-93.571967
1690	24.633331	-91.000000
1691	11.632918	-72.708790
1692	25.410184	-76.380902
1693	29.537304	-82.796934
1694	31.633331	-87.000000
1695	29.091458	-104.943052
1696	17.145296	-101.726894

In [6]:

```
df.dtypes
```

Out[6]:

```
input      float64
output     float64
dtype: object
```

In [10]:

```
df.describe
```

Out[10]:

```
<bound method NDFrame.describe of             input      output
0    -122.740667 -130.572085
1    -121.531419 -129.938929
2    -134.917019 -130.141832
3    -120.605951 -125.760932
4    -129.894781 -112.785214
...          ...         ...
1692   25.410184  -76.380902
1693   29.537304  -82.796934
1694   31.633331  -87.000000
1695   29.091458 -104.943052
1696   17.145296 -101.726894

[1697 rows x 2 columns]>
```

In [12]:

```
df.info
```

Out[12]:

```
<bound method DataFrame.info of            input      output
0     -122.740667 -130.572085
1     -121.531419 -129.938929
2     -134.917019 -130.141832
3     -120.605951 -125.760932
4     -129.894781 -112.785214
...           ...         ...
1692    25.410184  -76.380902
1693    29.537304  -82.796934
1694    31.633331  -87.000000
1695    29.091458 -104.943052
1696    17.145296 -101.726894

[1697 rows x 2 columns]>
```

In [11]:

```
df.describe()
```

Out[11]:

	input	output
count	1696.000000	1696.000000
mean	1.159933	-34.088017
std	79.005970	65.771112
min	-134.962839	-132.422167
25%	-63.386506	-80.026767
50%	10.195194	-50.470981
75%	70.264109	-11.000000
max	134.605775	134.425495

Data Wrangling

Identifying and handling missing values

We are going to search for null values. Sometimes null values are represented by "?" so for searching this I have used "isin" function.

In [14]:

```
df.isin(['?']).any()
```

Out[14]:

```
input     False
output    False
dtype: bool
```

In [25]:

```
missing_data=df.isnull()
```

In [24]:

```
df.isnull().sum(axis=0)
```

Out[24]:

```
input     1
output    1
dtype: int64
```

Count missing values in each column

In [26]:

```
for column in missing_data.columns.values.tolist():
    print(column)
    print (missing_data[column].value_counts())
    print("")
```

```
input
False    1696
True        1
Name: input, dtype: int64

output
False    1696
True        1
Name: output, dtype: int64
```

Based on the summary above, each column has 1697 rows of data, two columns containing missing data:

1. "input": 1 missing data
2. "output": 1 missing data

Dealing with missing data

1. drop data
   a. drop the whole row
   b. drop the whole column
2. replace data
   a. replace it by mean

b. replace it by frequency
c. replace it based on other functions

Replace by mean

In [29]:

```
avg_input = df["input"].astype("float").mean(axis=0)
print("Average of input:", avg_input)
```

```
Average of input: 1.159932645006416
```

In [30]:

```
avg_output = df["output"].astype("float").mean(axis=0)
print("Average of output:", avg_output)
```

```
Average of output: -34.08801719326943
```

In [31]:

```
df['input'].replace(np.nan, avg_input, inplace=True)
df['output'].replace(np.nan, avg_output, inplace=True)
```

In [32]:

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

Out[32]:

```
input     0
output    0
dtype: int64
```

In [33]:

```
norm_input= df['input']/df['input'].max()
norm_output = df['output']/df['output'].max()
```

In [36]:

```
# print(norm_input)
# print(norm_output)
```

```
0      -0.971334
1      -0.966624
2      -0.968134
3      -0.935544
4      -0.839017
          ...
1692   -0.568202
1693   -0.615932
1694   -0.647199
1695   -0.780678
1696   -0.756753
Name: output, Length: 1697, dtype: float64
```

In [39]:

```
df.corr()
```

Out[39]:

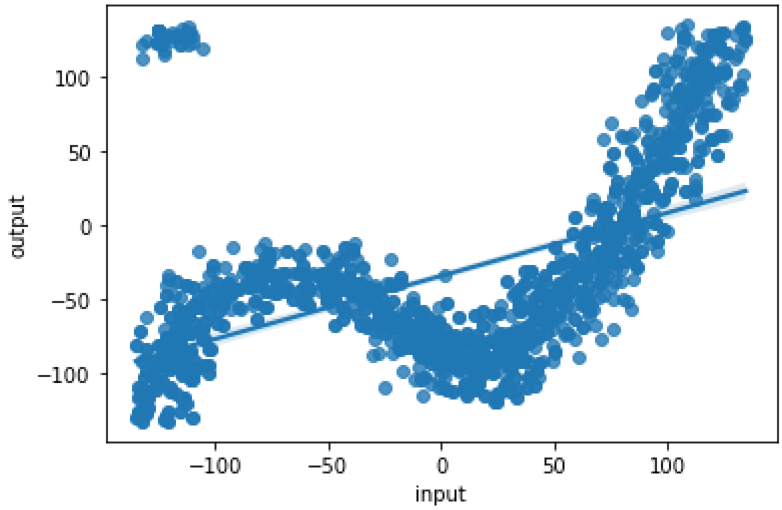
	input	output
input	1.000000	0.511776
output	0.511776	1.000000

In [41]:

```
sns.regplot(x="input", y="output", data=df)
```

Out[41]:

```
<AxesSubplot:xlabel='input', ylabel='output'>
```



This curve concludes that if input is less than zero than the output goes high but when the input is nearly equal to zero but as the input goes away from zero in positive direction the output again increases.
The group near (-100,100) are the outliers

In [43]:

```
df.head()
```

Out[43]:

	input	output
0	-122.740667	-130.572085
1	-121.531419	-129.938929
2	-134.917019	-130.141832
3	-120.605951	-125.760932
4	-129.894781	-112.785214

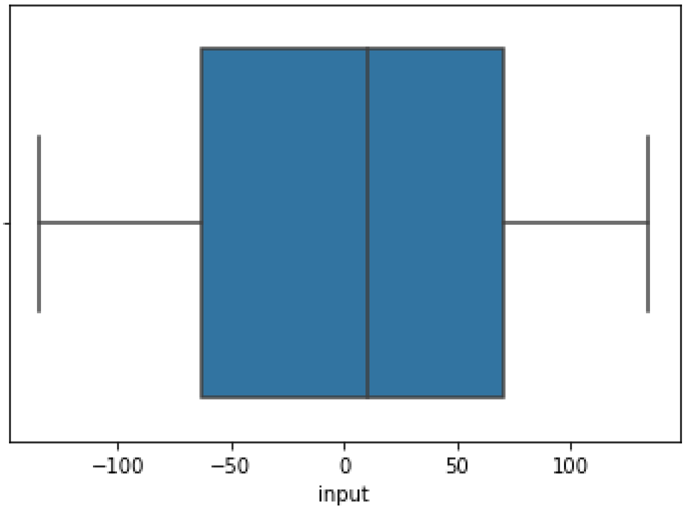
In [50]:

```
sns.boxplot(df['input'])
```

```
C:\Users\a\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWa
rning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpretat
ion.
  warnings.warn(
```

Out[50]:

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



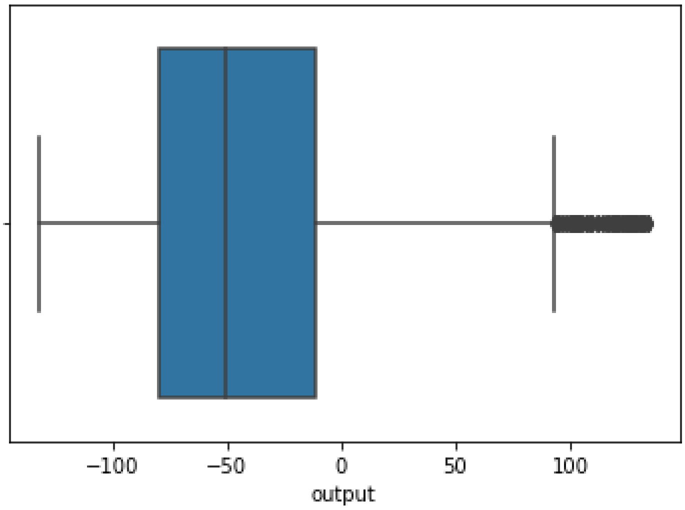
In [49]:

```
sns.boxplot(df['output'])
```

```
C:\Users\a\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWa
rning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argum
ents without an explicit keyword will result in an error or misinterpretat
ion.
  warnings.warn(
```

Out[49]:

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



In [55]:

```
Z_Score = df['input'].mean() / df['input'].std()
# df['input'].mean()
# df['input'].std()
```

In [59]:

```
Z_Score
```

Out[59]:

```
0.014685912403244402
```

P Value

In [44]:

```
from scipy import stats
```

In [45]:

```
pearson_coef, p_value = stats.pearsonr(df['input'], df['output'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a P-value of P =", p
```

```
The Pearson Correlation Coefficient is 0.5117757004836778  with a P-value
of P = 6.280078800910794e-114
```

Since the p-value is < 0.001, the correlation between input and output is statistically significant, although the linear relationship isn't extremely strong (~0.5117)

Linear Regression

In [47]:

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

In [48]:

```
lm = LinearRegression()
lm
```

Out[48]:

```
LinearRegression()
```

In [62]:

```
X = df[['input']]
Y = df['output']
```

In [63]:

```
lm.fit(X,Y)
```

Out[63]:

```
LinearRegression()
```

In [64]:

```
Yhat=lm.predict(X)
Yhat[0:5]
```

Out[64]:

```
array([-86.87518319, -86.35998977, -92.06285051, -85.96569911,
       -89.92315363])
```

In [65]:

```
lm.intercept_
```

Out[65]:

```
-34.58220008713727
```

In [66]:

```
lm.coef_
```

Out[66]:

```
array([0.42604447])
```

.

$$Y : Response\ Variable$$
$$X : Predictor\ Variables$$

Linear function:

$$Yhat = a + bX$$

- a refers to the **intercept** of the regression line0, in other words: the value of Y when X is 0
- b refers to the **slope** of the regression line, in other words: the value with which Y changes when X increases by 1 unit

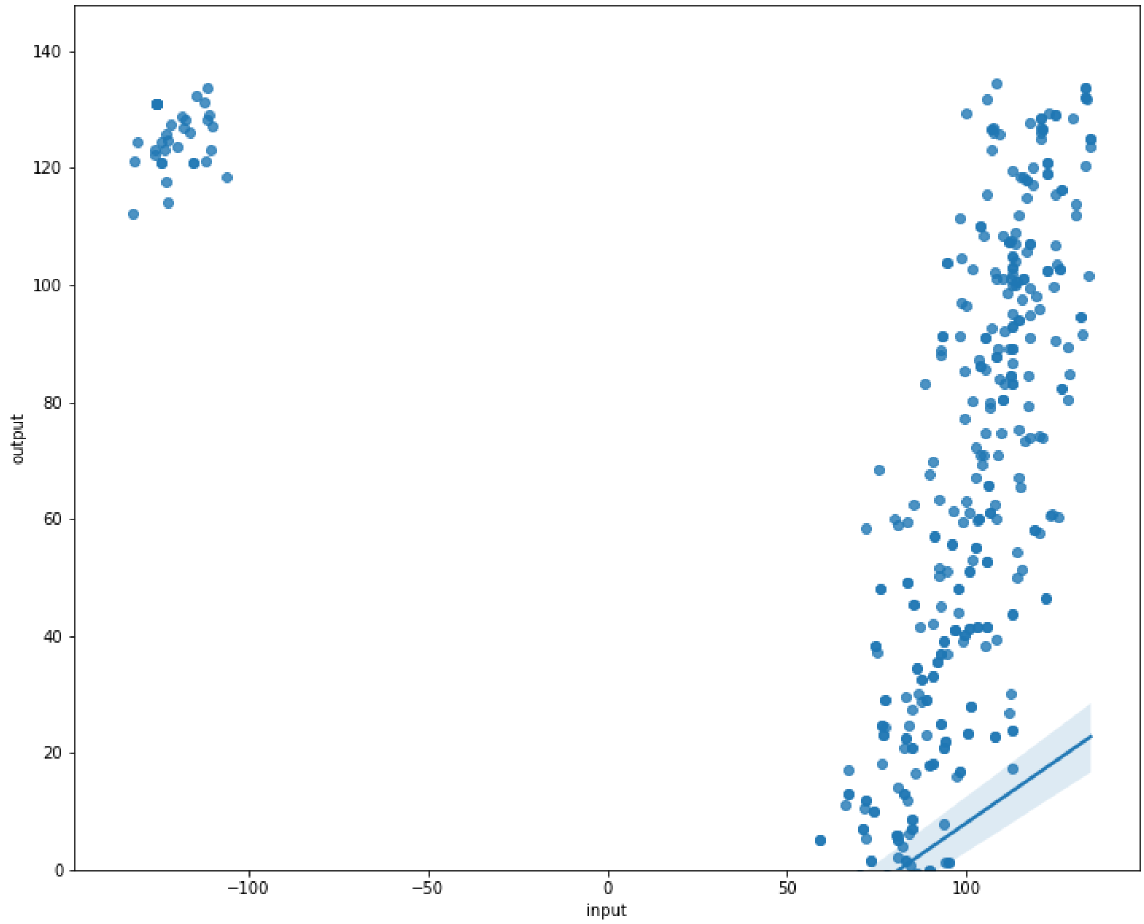
This plot will show a combination of a scattered data points (a **scatter plot**), as well as the fitted **linear regression** line going through the data. This will give us a reasonable estimate of the relationship between the two variables, the strength of the correlation, as well as the direction (positive or negative correlation).

In [67]:

```
width = 12
height = 10
plt.figure(figsize=(width, height))
sns.regplot(x="input", y="output", data=df)
plt.ylim(0,)
```

Out[67]:

```
(0.0, 147.76787831000001)
```



The difference between the observed value (y) and the predicted value (Yhat) is called the residual (e). When we look at a regression plot, the residual is the distance from the data point to the fitted regression line.

A residual plot is a graph that shows the residuals on the vertical y-axis and the independent variable on the horizontal x-axis.

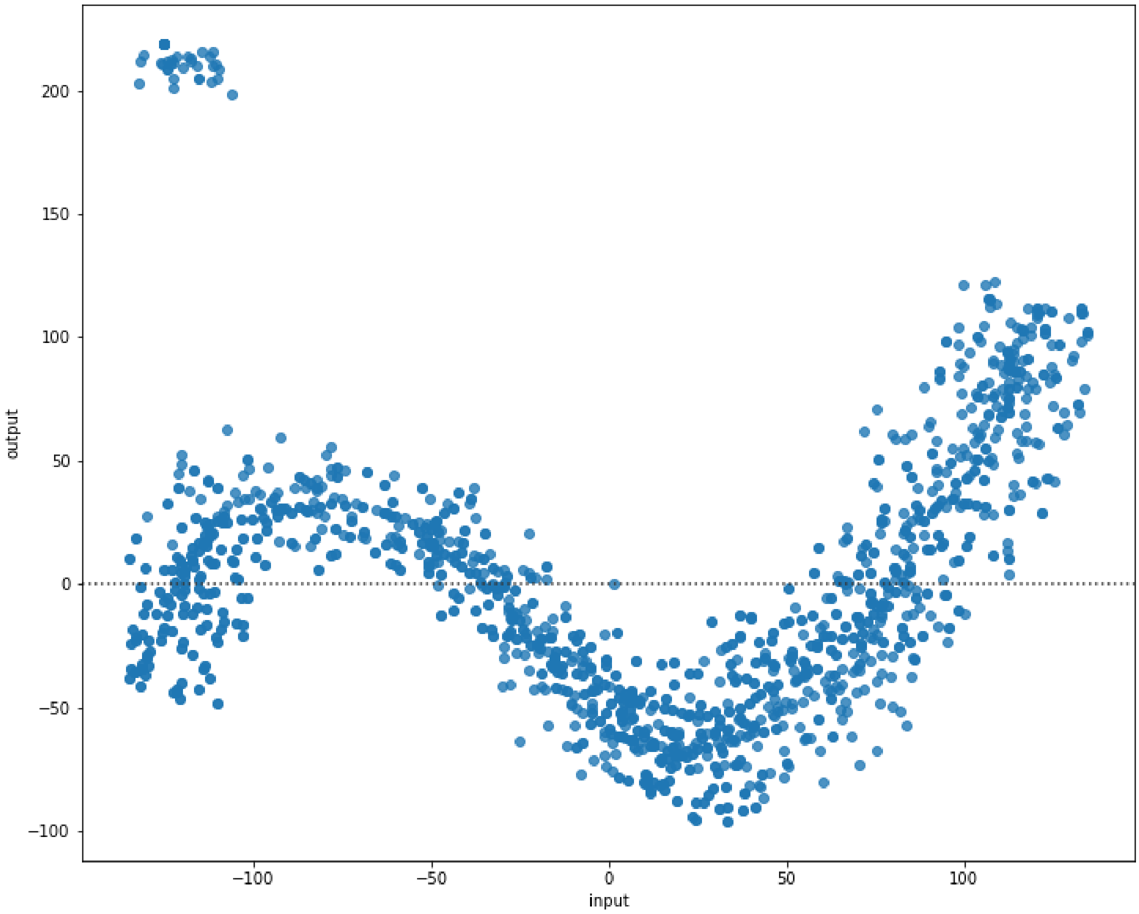
We look at the spread of the residuals:

- If the points in a residual plot are **randomly spread out around the x-axis**, then a **linear model is appropriate** for the data. Why is that? Randomly spread out residuals means that the variance is constant, and thus the linear model is a good fit for this data.

In [68]:

```
width = 12
height = 10
plt.figure(figsize=(width, height))
sns.residplot(df['input'], df['output'])
plt.show()
```

```
C:\Users\a\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWa
rning: Pass the following variables as keyword args: x, y. From version 0.
12, the only valid positional argument will be `data`, and passing other a
rguments without an explicit keyword will result in an error or misinterpr
etation.
  warnings.warn(
```



In [69]:

```
def PlotPolly(model, independent_variable, dependent_variabble, Name):
    x_new = np.linspace(15, 55, 100)
    y_new = model(x_new)

    plt.plot(independent_variable, dependent_variabble, '.', x_new, y_new, '-')
    plt.title('Polynomial Fit with Matplotlib for input-output')
    ax = plt.gca()
    ax.set_facecolor((0.898, 0.898, 0.898))
    fig = plt.gcf()
    plt.xlabel(Name)
    plt.ylabel('output')

    plt.show()
    plt.close()
```

Polynomial Regression

Polynomial regression is a particular case of the general linear regression model or multiple linear regression models.

We get non-linear relationships by squaring or setting higher-order terms of the predictor variables.

There are different orders of polynomial regression:

In [70]:

```
x = df['input']
y = df['output']
```

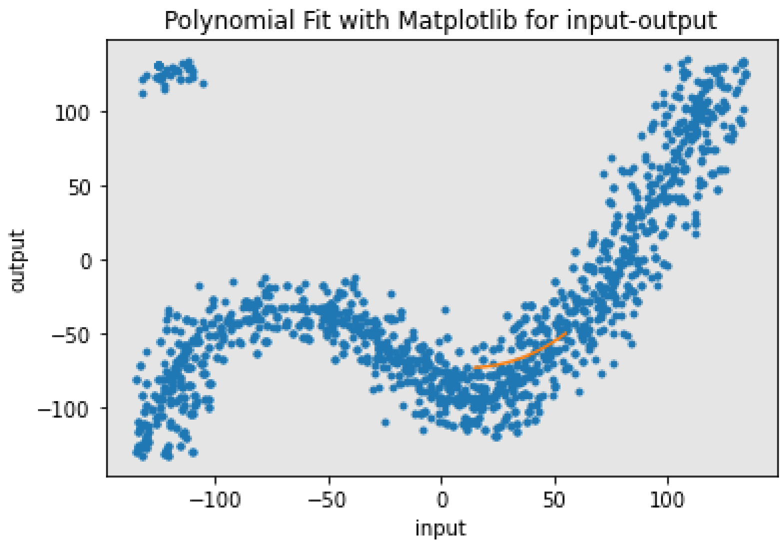
In [71]:

```
f = np.polyfit(x, y, 3)
p = np.poly1d(f)
print(p)
```

```
           3            2
6.004e-05 x + 0.006994 x - 0.1567 x - 72.82
```

In [72]:

```
PlotPolly(p, x, y, 'input')
```



In [73]:

```
np.polyfit(x, y, 3)
```

Out[73]:

```
array([ 6.00410571e-05,  6.99436862e-03, -1.56663023e-01, -7.28234061e+0
1])
```

R-Squared for linear

In [126]:

```
print('The R-square for linear regression is: ', lm.score(X_test, Y_test))
```

```
The R-square for linear regression is:  0.2645711041890637
```

In [81]:

```
Yhat=lm.predict(X)
print('The output of the first four predicted value is: ', Yhat[0:4])
```

```
The output of the first four predicted value is:  [-86.87518319 -86.359989
77 -92.06285051 -85.96569911]
```

In [82]:

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

Mean Squared error for linear Regression

In [127]:

```
mse = mean_squared_error(df['output'], Yhat)
print('The mean square error of price and predicted value is: ', mse)
```

```
The mean square error of price and predicted value is:  3189.076841478018
```

In [85]:

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

R-Squared value for poly

In [86]:

```
r_squared = r2_score(y, p(x))
print('The R-square value of Polynomial Regression is: ', r_squared)
```

```
The R-square value is:  0.6549316129206045
```

Mean Squared error for Polynomial Regression

In [87]:

```
mean_squared_error(df['output'], p(x))
```

Out[87]:

```
1490.9511222852
```

In [88]:

```
new_input=np.arange(1, 100, 1).reshape(-1, 1)
```

In [89]:

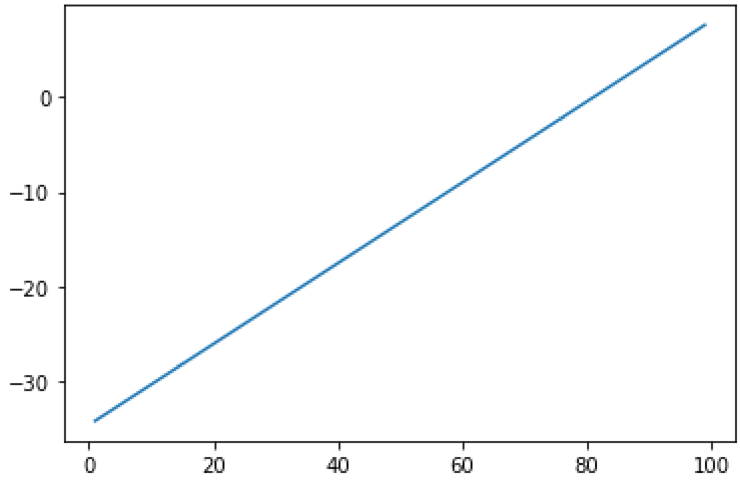
```
yhat=lm.predict(new_input)
yhat[0:5]
```

Out[89]:

```
array([-34.15615561, -33.73011114, -33.30406666, -32.87802219,
       -32.45197772])
```

In [90]:

```
plt.plot(new_input, yhat)
plt.show()
```



The model with higher R-Squared value is a better fit for the data.

The model with the smallest MSE value is a better fit for the data

Decision Trees

In [105]:

```
from sklearn.tree import DecisionTreeRegressor
```

In [111]:

```
dc=DecisionTreeRegressor()
dc
```

Out[111]:

```
DecisionTreeRegressor()
```

In [109]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y)
```

In [112]:

```
dc.fit(X_train, Y_train)
```

Out[112]:

```
DecisionTreeRegressor()
```

In [113]:

```
dc.score(X_test, Y_test)
```

Out[113]:

```
0.7144256652803515
```

The testing score for Decision Trees is 71.4%

In [121]:

```
Yhat_dc=dc.predict(X)
Yhat_dc[0:5]
```

Out[121]:

```
array([-130.5720846, -129.9389289, -130.1418321, -125.7609321,
       -112.7852137])
```

In [122]:

```
mse_dc = mean_squared_error(df['output'], Yhat_dc)
print('The mean square error of price and predicted value is: ', mse_dc)
```

```
The mean square error of price and predicted value is:  373.0123870891099
```

Neural Network

In [134]:

```
from sklearn.neural_network import MLPRegressor
from sklearn.datasets import make_regression
```

In [135]:

```
ml=MLPRegressor()
ml
```

Out[135]:

```
MLPRegressor()
```

In [136]:

```
ml.fit(X_train,Y_train)
```

```
C:\Users\a\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_
perceptron.py:614: ConvergenceWarning: Stochastic Optimizer: Maximum itera
tions (200) reached and the optimization hasn't converged yet.
  warnings.warn(
```

Out[136]:

```
MLPRegressor()
```

In [137]:

```
ml.score(X_test, Y_test)
```

Out[137]:

```
0.583198962850687
```

The testing score for Neural Network is 58.31%

For the given dataset I have used foloowing Algorithms:

1. Algorithms
   a. Linear Regression
   b. Poly Regression
   c. Decision Trees
   d. Neural Network Regressor.

Among the four algorithms the Rsquared for Decision Trees is maximum with 0.71442. Higher the value best is the model

```
a. Linear Regression R-Squared:  0.2645711041890637
b. Poly Regression R-Squared:0.6549316129206045
c. Decision Trees R-Squared:0.7144256652803515
d. Neural Network Regressor R-Squared:0.583198962850687.
```

Hence the best algorithm for given dataset is decision Trees.