

PROJECT:1

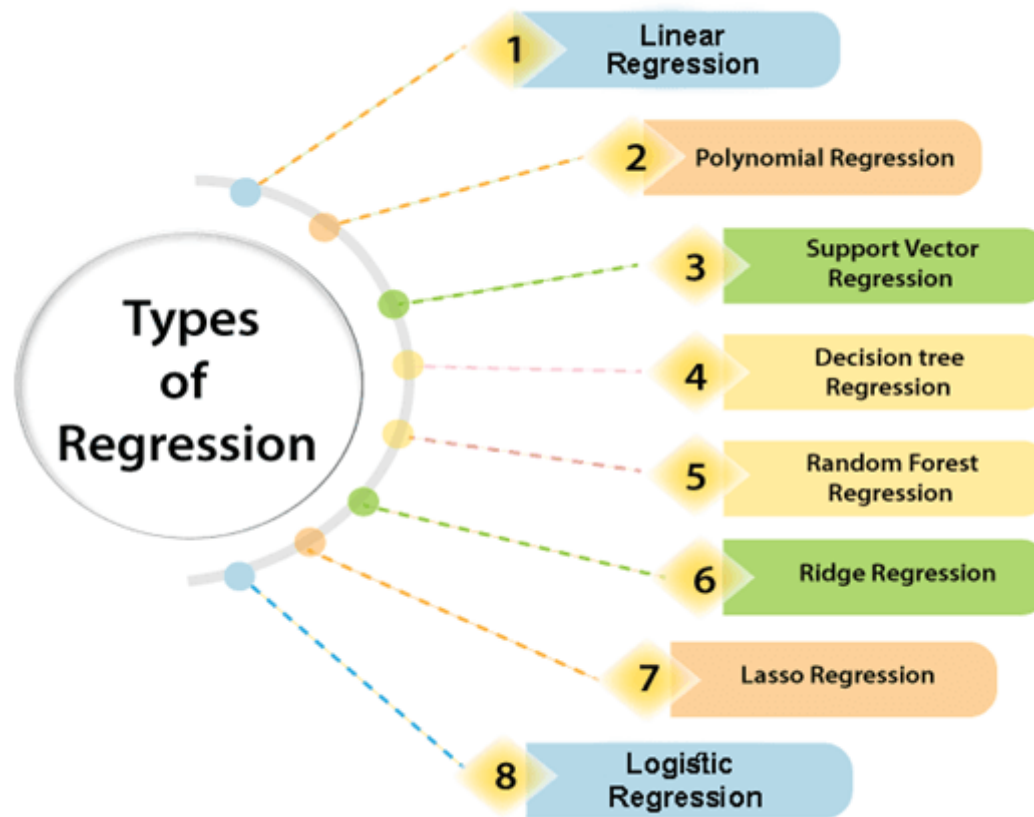
Estimating Movie Box Office Revenue :

Estimating Movie Box Office Revenue : Problem Statement: Estimating Movie Box Office Revenue
Project Description: Build a regression model to estimate the box office revenue of movies based on factors such as genre, production budget, release date, and marketing efforts.
Domain: Film Industry
Dataset Link: <https://www.kaggle.com/datasets/kalilurrahman/top-box-office-revenue-data-english-movies?select=bomojobrandindices.csv>

- Regression analysis is a statistical method to model the relationship between a dependent (target) and independent (predictor) variables with one or more independent variables.
- More specifically, Regression analysis helps us to understand how the value of the dependent variable is changing corresponding to an independent variable when other independent variables are held fixed.
- It predicts continuous/real values such as temperature, age, salary, price, etc.

REGRESSION PROBLEM:

- Linear Regression
- Logistic Regression
- Polynomial Regression
- Support Vector Regression
- Decision Tree Regression
- Random Forest Regression
- Ridge Regression
- Lasso Regression:



LINEAR REGRESSION:

```
In [1]: import pandas as pd
```

```
In [66]: data = pd.read_csv("bomojobrandindices.csv")
```

In [67]: data

Out[67]:

	Brand	Total Releases	#1 Release	Lifetime Gross	
0	Marvel Comics	15806336901	69	Avengers: Endg...	
1	Legendary Pictures	7018798067	56	Jurassic W...	
2	Lucasfilm	6325022918	39	Star Wars: Episode ...	
3	Pixar	6078217662	28	Incredibles 2	608581744
4	DC Comics	5815645953	46	The Dark Knight	53...
5	DreamWorks Animation	5792217737	41	Shrek 2	...
6	Vertigo Entertainment	3154664176	41	It	327...
7	Bad Robot	3077078931	15	Star Wars: Episode ...	
8	Walt Disney Animation Studios	2774912904	15	...	
9	Illumination Entertainment	2759505881	13	Th...	
10	Blumhouse Productions	2451844676	49	Get Out...	
11	Hasbro	2079485824	17	Transformers: Revenge ...	
12	Nickelodeon	1930746182	26	Teenage Mutant Ni...	
13	Sony Pictures Animation	1918763863	21	Spide...	
14	Walden Media	1842852183	38	The Chronicles o...	
15	Blue Sky	1740428763	13	Ice Age 3: Dawn of t...	
16	Stephen King	1729648950	49	It	327481748
17	MTV	1520456359	36	The Longest Yard	158119460
18	Platinum Dunes	1422911399	19	Teenage Mutant...	
19	Saturday Night Live - Alumni Debuts	102359603	...		
20	Dark Horse Comics	947671338	16	300	210614939
21	Tim Burton-Johnny Depp	889955830	8	Alice in...	
22	Warner Animation Group	786497181	8	The Lego...	
23	Tyler Perry	765635362	16	Madea Goes to Jail...	
24	CBS Films	652824187	29	Scary Stories to Tel...	
25	John Grisham	645661825	10	The Firm	158348367

	Brand	Total	Releases	#1 Release	Lifetime Gross
26	Robert Ludlum	645459186	6	The Bourne Ultima...	
27	MonsterVerse	580145113	4	Godzilla	200676069
28	Hanna-Barbera	578586146	10	Scooby-Doo	1532...
29	Nicholas Sparks	574728259	11	The Notebook	
30	Philip K. Dick	495237720	14	Minority Report...	
31	Dark Castle	454625110	16	Unknown	63686397
32	National Lampoon	436669213	21	National Lamp...	
33	Disney Channel	359952780	8	High School Musi...	
34	Roald Dahl	356238494	7	Charlie and the Choc...	
35	Saturday Night Live	346533876	11	Wayne's Wo...	
36	DisneyToon Studios	337576791	8	Planes	9028...
37	Aardman	333777829	16	Chicken Run	106834564
38	Laika	300158323	6	Coraline	75286229
39	Alan Moore	276088604	4	Watchmen	107509799
40	Amazon Studios	204376048	43	Manchester by t...	
41	Clive Barker	171686009	10	Candyman	61186570
42	Disney	151620585	8	Earth	32011576
43	Broken Lizard	73338237	5	Super Troopers 2	
44	Studio Ghibli	70666453	26	The Secret World ...	

```
In [68]: data = pd.read_csv("bomojobbrandindices.csv", sep = '\t')
```

In [28]: data

Out[28]:

	Brand	Total	Releases	#1 Release	Lifetime Gross
0	Marvel Comics	15806336901	69	Avengers: Endgame	858373000
1	Legendary Pictures	7018798067	56	Jurassic World	652270625
2	Lucasfilm	6325022918	39	Star Wars: Episode VII - The Force Awakens	936662225
3	Pixar	6078217662	28	Incredibles 2	608581744
4	DC Comics	5815645953	46	The Dark Knight	533345358
5	DreamWorks Animation	5792217737	41	Shrek 2	441226247
6	Vertigo Entertainment	3154664176	41	It	327481748
7	Bad Robot	3077078931	15	Star Wars: Episode VII - The Force Awakens	936662225
8	Walt Disney Animation Studios	2774912904	15	Frozen II	477373578
9	Illumination Entertainment	2759505881	13	The Secret Life of Pets	368384330
10	Blumhouse Productions	2451844676	49	Get Out	176040665
11	Hasbro	2079485824	17	Transformers: Revenge of the Fallen	402111870
12	Nickelodeon	1930746182	26	Teenage Mutant Ninja Turtles	191204754
13	Sony Pictures Animation	1918763863	21	Spider-Man: Into the Spider-Verse	190241310
14	Walden Media	1842852183	38	The Chronicles of Narnia: The Lion the Witch a...	291710957
15	Blue Sky	1740428763	13	Ice Age 3: Dawn of the Dinosaurs	196573705
16	Stephen King	1729648950	49	It	327481748
17	MTV	1520456359	36	The Longest Yard	158119460
18	Platinum Dunes	1422911399	19	Teenage Mutant Ninja Turtles	191204754
19	Saturday Night Live - Alumni Debuts	1023596031	30	Bridesmaids	169106725
20	Dark Horse Comics	947671338	16	300	210614939
21	Tim Burton-Johnny Depp	889955830	8	Alice in Wonderland	334191110
22	Warner Animation Group	786497181	8	The Lego Movie	257760692
23	Tyler Perry	765635362	16	Madea Goes to Jail	90508336
24	CBS Films	652824187	29	Scary Stories to Tell in the Dark	68947075
25	John Grisham	645661825	10	The Firm	158348367

	Brand	Total	Releases	#1 Release	Lifetime Gross
26	Robert Ludlum	645459186	6	The Bourne Ultimatum	227471070
27	MonsterVerse	580145113	4	Godzilla	200676069
28	Hanna-Barbera	578586146	10	Scooby-Doo	153294164
29	Nicholas Sparks	574728259	11	The Notebook	81001787
30	Philip K. Dick	495237720	14	Minority Report	132072926
31	Dark Castle	454625110	16	Unknown	63686397
32	National Lampoon	436669213	21	National Lampoon's Animal House	120091123
33	Disney Channel	359952780	8	High School Musical 3: Senior Year	90559416
34	Roald Dahl	356238494	7	Charlie and the Chocolate Factory	206459076
35	Saturday Night Live	346533876	11	Wayne's World	121697323
36	DisneyToon Studios	337576791	8	Planes	90288712
37	Aardman	333777829	16	Chicken Run	106834564
38	Laika	300158323	6	Coraline	75286229
39	Alan Moore	276088604	4	Watchmen	107509799
40	Amazon Studios	204376048	43	Manchester by the Sea	47695371
41	Clive Barker	171686009	10	Candyman	61186570
42	Disneynature	151620585	8	Earth	32011576
43	Broken Lizard	73338237	5	Super Troopers 2	30617396
44	Studio Ghibli	70666453	26	The Secret World of Arrietty	19202743


```
In [69]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45 entries, 0 to 44
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype  
---  -
0   Brand            45 non-null    object  
1   Total            45 non-null    int64   
2   Releases         45 non-null    int64   
3   #1 Release       45 non-null    object  
4   Lifetime Gross   45 non-null    int64   
dtypes: int64(3), object(2)
memory usage: 1.9+ KB
```

```
In [30]: data.isna().sum()
```

```
Out[30]: Brand            0
Total              0
Releases           0
#1 Release         0
Lifetime Gross     0
dtype: int64
```

```
In [31]: data.dropna(inplace = True)
```

```
In [32]: data.isna().sum()
```

```
Out[32]: Brand            0
Total              0
Releases           0
#1 Release         0
Lifetime Gross     0
dtype: int64
```

```
In [33]: data.describe()
```

```
Out[33]:
```

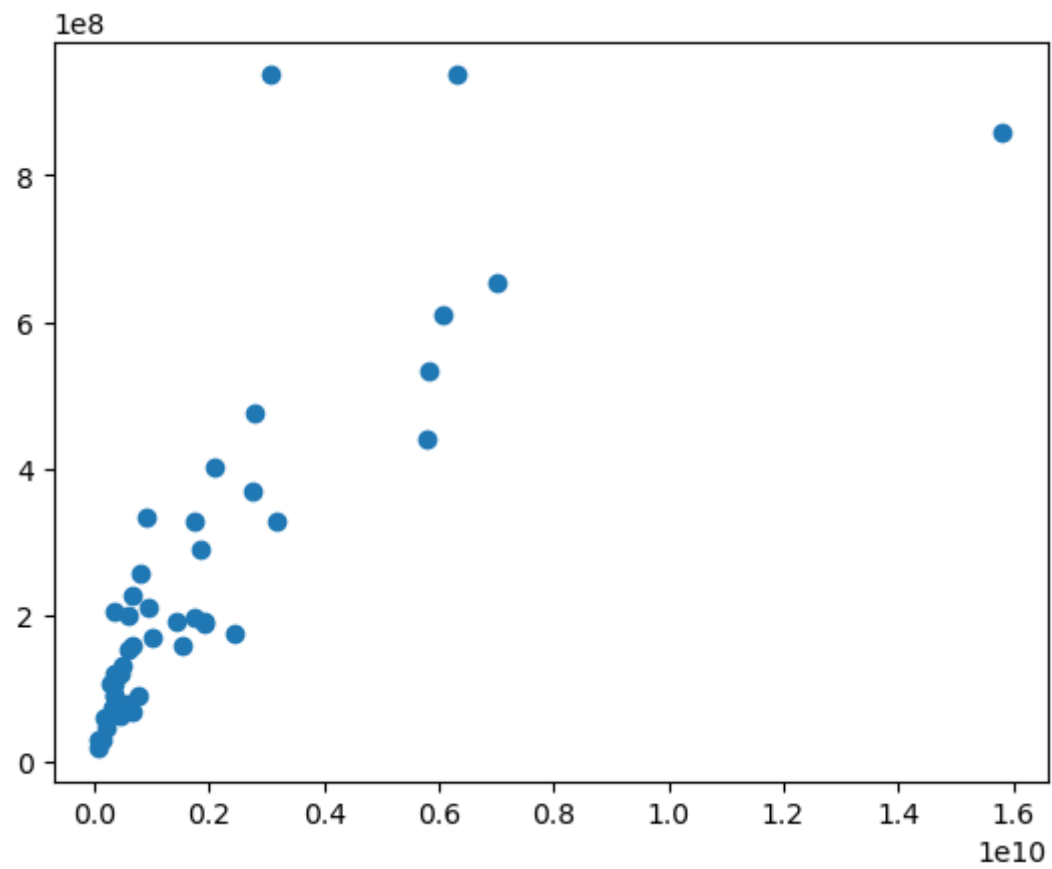
	Total	Releases	Lifetime Gross
count	4.500000e+01	45.000000	4.500000e+01
mean	1.948863e+09	21.822222	2.560482e+08
std	2.806106e+09	16.035881	2.336907e+08
min	7.066645e+07	4.000000	1.920274e+07
25%	3.599528e+08	10.000000	9.055942e+07
50%	7.864972e+08	16.000000	1.902413e+08
75%	2.079486e+09	30.000000	3.274817e+08
max	1.580634e+10	69.000000	9.366622e+08

```
In [36]: import matplotlib.pyplot as plt
```

```
In [37]: data.columns
```

```
Out[37]: Index(['Brand', 'Total', 'Releases', '#1 Release', 'Lifetime Gross'], dtype='object')
```

```
In [40]: plt.scatter((data["Total"]),data["Lifetime Gross"])  
plt.show()
```



```
In [45]: for i in data.columns[:-1]:  
        plt.xlabel(i)  
        plt.ylabel("Total")  
        plt.scatter(data[i],data["Total"])  
        plt.show()
```



```
In [47]: import numpy as np  
x = np.array(data["Releases"]).reshape(-1,1)  
y = np.array(data["Total"]).reshape(-1,1)
```

```
In [49]: from sklearn.linear_model import LinearRegression
```

```
In [50]: linear = LinearRegression()
```

```
In [51]: linear.fit(x,y)
```

```
Out[51]: LinearRegression()
```

```
In [52]: linear.predict([[34]])
```

```
Out[52]: array([[3.47997776e+09]])
```

multiple Linear Regression

```
In [70]: len(data.columns)
```

```
Out[70]: 5
```

```
In [71]: data.columns
```

```
Out[71]: Index(['Brand', 'Total', 'Releases', '#1 Release', 'Lifetime Gross'], dtype='object')
```

```
In [73]: x.head()
```

```
Out[73]:
```

	Total	Releases	#1 Release	Lifetime Gross
0	15806336901	69	Avengers: Endgame	858373000
1	7018798067	56	Jurassic World	652270625
2	6325022918	39	Star Wars: Episode VII - The Force Awakens	936662225
3	6078217662	28	Incredibles 2	608581744
4	5815645953	46	The Dark Knight	533345358

```
In [74]: y.head()
```

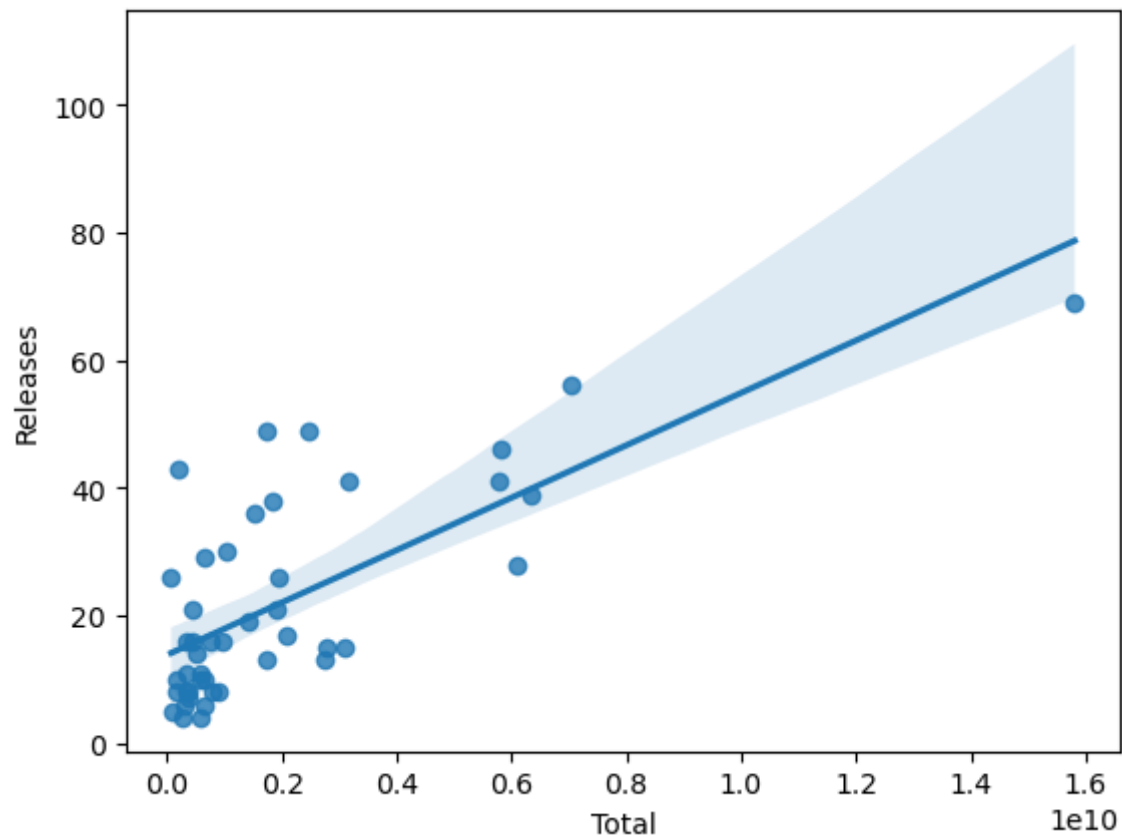
```
Out[74]: 0      Marvel Comics
1  Legendary Pictures
2      Lucasfilm
3          Pixar
4          DC Comics
Name: Brand, dtype: object
```

```
In [75]: model = LinearRegression()
```

```
In [92]: import seaborn as sns  
data = pd.read_csv("bomojobbrandindices.csv", sep = '\t')
```

```
In [99]: sns.regplot(x = "Total",  
                    y = "Releases",  
                    data = data)
```

```
Out[99]: <AxesSubplot:xlabel='Total', ylabel='Releases'>
```



split the data into testing and training

```
In [121]: from sklearn.model_selection import train_test_split
```

```
In [124]: xtrain,xtest,ytrain,ytest = train_test_split(data.drop("Total",axis=1),data["Total"],train_size = .75)
```

```
In [125]: xtrain.shape
```

```
Out[125]: (33, 4)
```

```
In [126]: ytrain.shape
```

```
Out[126]: (33,)
```

```
In [127]: xtest.shape
```

```
Out[127]: (12, 4)
```

```
In [128]: ytest.shape
```

```
Out[128]: (12,)
```

```
In [129]: model.fit(xtrain,ytrain)
```

```
Out[129]: LinearRegression()
```

```
In [113]: # One hot encoding for the columns  
data_onehot = pd.get_dummies(data, columns=['Brand', '#1 Release'])
```

In [114]:

```
# Import LabelEncoder
from sklearn.preprocessing import LabelEncoder

# Instantiate LabelEncoder
le = LabelEncoder()

# Apply le on categorical feature columns
data[['Brand', '#1 Release']] = data[['Brand', '#1 Release']].apply(lambda col: le.fit_transform(col))
```

In [116]: data.sketch.howto("ValueError: could not convert string to float: 'Vertigo Entertainment'")

```
# Replace the string value with a numeric value
data['Brand'] = data['Brand'].replace('Vertigo Entertainment', 0)
```

Copy

In [117]:

```
# Replace the string value with a numeric value
data['Brand'] = data['Brand'].replace('Vertigo Entertainment', 0)
```


In [120]: data

Out[120]:

	Brand	Total	Releases	#1 Release	Lifetime Gross
0	24	15806336901	69	2	858373000
1	21	7018798067	56	16	652270625
2	22	6325022918	39	26	936662225
3	30	6078217662	28	14	608581744
4	9	5815645953	46	31	533345358
5	15	5792217737	41	24	441226247
6	41	3154664176	41	15	327481748
7	3	3077078931	15	26	936662225
8	43	2774912904	15	9	477373578
9	18	2759505881	13	36	368384330
10	5	2451844676	49	10	176040665
11	17	2079485824	17	38	402111870
12	28	1930746182	26	28	191204754
13	36	1918763863	21	25	190241310
14	42	1842852183	38	30	291710957
15	4	1740428763	13	13	196573705
16	37	1729648950	49	15	327481748
17	23	1520456359	36	34	158119460
18	31	1422911399	19	28	191204754
19	35	1023596031	30	3	169106725
20	11	947671338	16	0	210614939
21	39	889955830	8	1	334191110
22	44	786497181	8	33	257760692
23	40	765635362	16	17	90508336
24	7	652824187	29	22	68947075
25	19	645661825	10	32	158348367

	Brand	Total	Releases	#1 Release	Lifetime Gross
26	33	645459186	6	29	227471070
27	25	580145113	4	11	200676069
28	16	578586146	10	23	153294164
29	27	574728259	11	35	81001787
30	29	495237720	14	19	132072926
31	10	454625110	16	39	63686397
32	26	436669213	21	20	120091123
33	12	359952780	8	12	90559416
34	32	356238494	7	5	206459076
35	34	346533876	11	41	121697323
36	13	337576791	8	21	90288712
37	0	333777829	16	6	106834564
38	20	300158323	6	7	75286229
39	1	276088604	4	40	107509799
40	2	204376048	43	18	47695371
41	8	171686009	10	4	61186570
42	14	151620585	8	8	32011576
43	6	73338237	5	27	30617396
44	38	70666453	26	37	19202743

```
In [130]: model.fit(xtrain,ytrain)
```

```
Out[130]: LinearRegression()
```

```
In [131]: y_pred = model.predict(xtest)
```

```
In [132]: ytest.head(10)
```

Out[132]: 3 6078217662
44 70666453
13 1918763863
41 171686009
15 1740428763
4 5815645953
19 1023596031
33 359952780
0 15806336901
32 436669213
Name: Total, dtype: int64

```
In [133]: xtest.head()
```

Out[133]:

	Brand	Releases	#1 Release	Lifetime Gross
3	30	28	14	608581744
44	38	26	37	19202743
13	36	21	25	190241310
41	8	10	4	61186570
15	4	13	13	196573705

```
In [134]: for i in y_pred[:10]:  
          print(i)
```

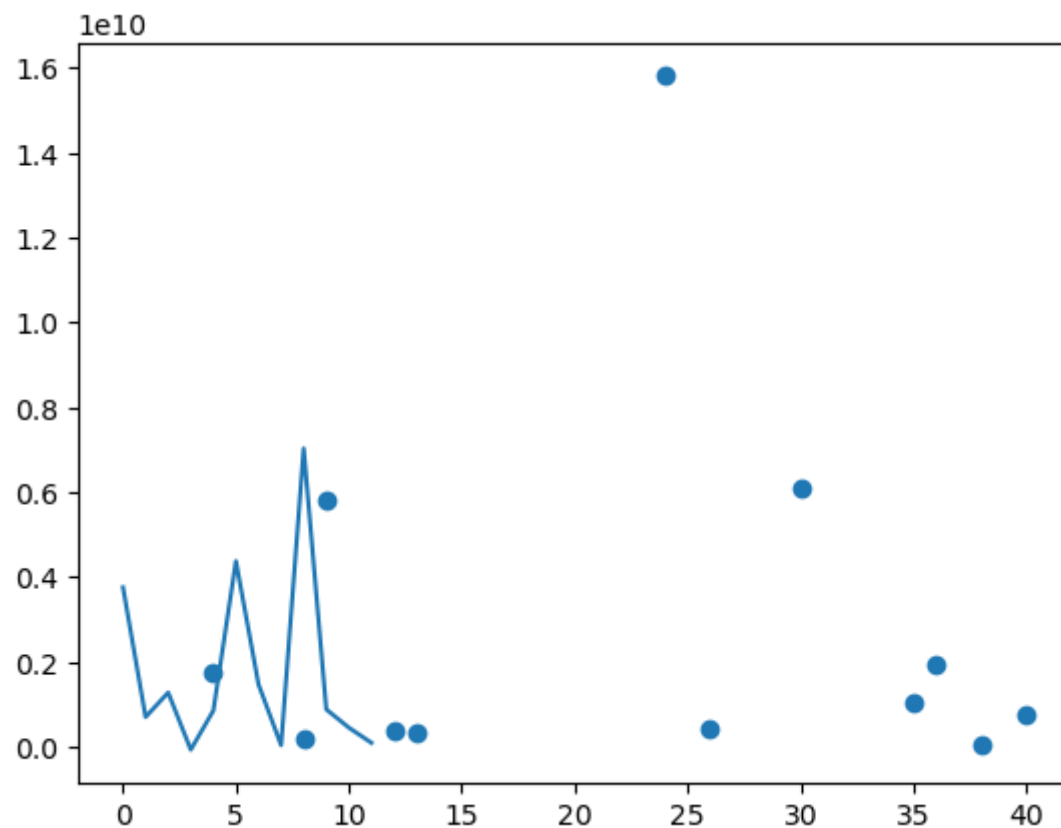
```
3759981527.9100475  
703903546.8336082  
1279417825.7516363  
-66796223.29696846  
854936214.8594639  
4377559329.549724  
1472205887.3786857  
38449329.33133459  
7032576530.735122  
882981429.5428896
```

```
In [135]: model.score(xtrain, ytrain )
```

```
Out[135]: 0.8177496414203069
```

```
In [141]: plt.scatter(xtest["Brand"],ytest)
plt.plot(y_pred)
```

```
Out[141]: [<matplotlib.lines.Line2D at 0x12e0b00cb80>]
```



```
In [142]: from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_squared_log_error
```

```
In [143]: mean_absolute_error(ytest, y_pred)
```

```
Out[143]: 1391561105.1962876
```

```
In [144]: mean_squared_error(ytest, y_pred)
```

```
Out[144]: 7.227713975573045e+18
```

```
In [145]: model.score(xtrain,ytrain) #r2 score
```

```
Out[145]: 0.8177496414203069
```

Polynomial Regression

```
In [146]: import numpy as np  
import matplotlib.pyplot as plt
```

```
In [147]: from sklearn.preprocessing import PolynomialFeatures
```

```
In [150]: lin = LinearRegression()
```

```
In [152]: x_train = poly.fit_transform(x)
```

```
In [153]: poly.fit(x_train,y)
```

```
Out[153]: PolynomialFeatures()
```

```
In [155]: lin = LinearRegression()
```

logistic regression:

```
In [159]: from sklearn.linear_model import LogisticRegression
```

```
In [160]: log = LogisticRegression()
```

```
In [162]: import pandas as pd
```

```
In [163]: data = pd.read_csv("bomojobbrandindices.csv")
```

```
In [164]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45 entries, 0 to 44
Data columns (total 1 columns):
#   Column
---  ---
0   Brand      Total   Releases      #1 Release      Lifetime Gross  45 non-null    object
dtypes: object(1)
memory usage: 488.0+ bytes
```

```
In [165]: data = pd.read_csv("bomojobbrandindices.csv",sep = "\t")
```

```
In [166]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45 entries, 0 to 44
Data columns (total 5 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   Brand      45 non-null    object
1   Total      45 non-null    int64
2   Releases   45 non-null    int64
3   #1 Release  45 non-null    object
4   Lifetime Gross  45 non-null    int64
dtypes: int64(3), object(2)
memory usage: 1.9+ KB
```



```
In [173]: data["Lifetime Gross"].unique()
```

```
Out[173]: array([858373000, 652270625, 936662225, 608581744, 533345358, 441226247,
                327481748, 477373578, 368384330, 176040665, 402111870, 191204754,
                190241310, 291710957, 196573705, 158119460, 169106725, 210614939,
                334191110, 257760692, 90508336, 68947075, 158348367, 227471070,
                200676069, 153294164, 81001787, 132072926, 63686397, 120091123,
                90559416, 206459076, 121697323, 90288712, 106834564, 75286229,
                107509799, 47695371, 61186570, 32011576, 30617396, 19202743],
                dtype=int64)
```

```
In [174]: for i in data.columns:
            print(f"{i}          {data[i].dtype}")
```

```
Brand          object
Total          int64
Releases       int64
#1 Release     object
Lifetime Gross int64
```

```
In [175]: data.isna().sum()
```

```
Out[175]: Brand          0
Total          0
Releases       0
#1 Release     0
Lifetime Gross 0
dtype: int64
```

```
In [176]: for column in data.columns:
            if data[column].dtype == "object":
                print(column)
```

```
Brand
#1 Release
```

```
In [177]: le = LabelEncoder()
         for column in data.columns:
             if data[column].dtype == "object":
                 data[column] = le.fit_transform(data[column])
```

```
In [178]: data.head()
```

```
Out[178]:
```

	Brand	Total	Releases	#1 Release	Lifetime Gross
0	24	15806336901	69	2	858373000
1	21	7018798067	56	16	652270625
2	22	6325022918	39	26	936662225
3	30	6078217662	28	14	608581744
4	9	5815645953	46	31	533345358

```
In [179]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45 entries, 0 to 44
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Brand           45 non-null    int32
1   Total           45 non-null    int64
2   Releases        45 non-null    int64
3   #1 Release      45 non-null    int32
4   Lifetime Gross  45 non-null    int64
dtypes: int32(2), int64(3)
memory usage: 1.5 KB
```

```
In [180]: from sklearn.linear_model import LogisticRegression
```

```
In [181]: log = LogisticRegression()
```

```
In [182]: x = data.drop("#1 Release",axis=1)
          y = data["#1 Release"]
```

In [183]:

x

Out[183]:

	Brand	Total	Releases	Lifetime Gross
0	24	15806336901	69	858373000
1	21	7018798067	56	652270625
2	22	6325022918	39	936662225
3	30	6078217662	28	608581744
4	9	5815645953	46	533345358
5	15	5792217737	41	441226247
6	41	3154664176	41	327481748
7	3	3077078931	15	936662225
8	43	2774912904	15	477373578
9	18	2759505881	13	368384330
10	5	2451844676	49	176040665
11	17	2079485824	17	402111870
12	28	1930746182	26	191204754
13	36	1918763863	21	190241310
14	42	1842852183	38	291710957
15	4	1740428763	13	196573705
16	37	1729648950	49	327481748
17	23	1520456359	36	158119460
18	31	1422911399	19	191204754
19	35	1023596031	30	169106725
20	11	947671338	16	210614939
21	39	889955830	8	334191110
22	44	786497181	8	257760692
23	40	765635362	16	90508336
24	7	652824187	29	68947075
25	19	645661825	10	158348367

	Brand	Total	Releases	Lifetime Gross
26	33	645459186	6	227471070
27	25	580145113	4	200676069
28	16	578586146	10	153294164
29	27	574728259	11	81001787
30	29	495237720	14	132072926
31	10	454625110	16	63686397
32	26	436669213	21	120091123
33	12	359952780	8	90559416
34	32	356238494	7	206459076
35	34	346533876	11	121697323
36	13	337576791	8	90288712
37	0	333777829	16	106834564
38	20	300158323	6	75286229
39	1	276088604	4	107509799
40	2	204376048	43	47695371
41	8	171686009	10	61186570
42	14	151620585	8	32011576
43	6	73338237	5	30617396
44	38	70666453	26	19202743

In [184]:

y

```
Out[184]: 0      2
          1     16
          2     26
          3     14
          4     31
          5     24
          6     15
          7     26
          8      9
          9     36
         10     10
         11     38
         12     28
         13     25
         14     30
         15     13
         16     15
         17     34
         18     28
         19      3
         20      0
         21      1
         22     33
         23     17
         24     22
         25     32
         26     29
         27     11
         28     23
         29     35
        30     19
        31     39
        32     20
        33     12
        34      5
        35     41
        36     21
        37      6
        38      7
        39     40
        40     18
```



```
41      4
42      8
43     27
44     37
Name: #1 Release, dtype: int32
```

```
In [185]: log.fit(x,y)
```

```
C:\Users\munep\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html> (<https://scikit-learn.org/stable/modules/preprocessing.html>)

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
n_iter_i = _check_optimize_result(
```

```
Out[185]: LogisticRegression()
```

```
In [186]: log.intercept_
```

```
Out[186]: array([ 2.86285554e-17, -1.85914091e-16, -1.39181778e-15,  8.32407369e-17,
  8.58631258e-16,  4.45867324e-16,  5.76586802e-16,  6.56153836e-16,
  9.19305777e-16, -9.44390716e-16, -2.41915921e-16,  2.34424915e-16,
  5.73761593e-16, -1.50758715e-16, -1.32956516e-15, -1.58356233e-16,
 -1.44823536e-15,  3.04579637e-16,  8.16519469e-16,  4.09619835e-16,
  4.82188874e-16,  5.93281141e-16,  3.77671048e-16,  3.01878487e-16,
 -9.43093054e-16, -1.73660675e-16, -3.05455765e-15,  1.05629418e-15,
  5.73632089e-16,  1.49254454e-16, -3.78566823e-16, -1.15632182e-15,
  2.48736620e-16,  2.37871516e-17, -3.32495489e-17,  4.11783452e-16,
 -6.55909867e-16,  1.06091036e-15, -6.67713766e-16,  5.36489387e-16,
  6.45832090e-16,  5.44968108e-16])
```

In [187]: log.coef_

```
Out[187]: array([[ -1.37451387e-14, -4.27565812e-09, -1.22503283e-15,
                  4.77516077e-08],
                 [ 1.54403560e-14, -4.22568594e-08, -1.10156011e-14,
                  1.58297380e-07],
                 [-2.77565405e-14,  2.68044808e-08, -2.82443164e-14,
                  -2.59151363e-07],
                 [ 1.84203299e-14,  4.26109300e-09,  1.62829232e-14,
                  1.58170000e-09],
                 [ 2.11955779e-15, -1.23251079e-09,  6.50137180e-15,
                  2.89592603e-08],
                 [ 2.31560063e-14, -3.86034575e-08, -2.57614029e-15,
                  1.43904027e-07],
                 [-1.44204536e-14, -4.41500921e-09,  9.83508234e-15,
                  4.38612941e-08],
                 [ 1.31374216e-14,  1.09575809e-09, -2.02122511e-15,
                  1.62488557e-08],
                 [ 1.10700274e-14,  2.25647880e-09,  4.70400558e-15,
                  -3.74222515e-10],
                 [ 3.73928229e-15, -5.41147036e-10, -2.56453549e-14,
                  3.42568848e-08],
                 [-2.65134460e-14,  1.96890880e-08,  2.52135266e-14,
                  -1.46119819e-07],
                 [ 9.32996985e-15, -1.83039926e-08, -1.07697920e-14,
                  9.23072693e-08],
                 [ 9.10462009e-16,  6.88237880e-10, -8.68060303e-16,
                  2.14492248e-08],
                 [-2.69961390e-14,  1.10324343e-08, -1.41743138e-14,
                  -5.33939481e-08],
                 [-1.97572627e-14,  1.31786969e-08, -3.82723649e-14,
                  -7.21600381e-08],
                 [ 3.61439698e-14,  4.98082200e-09,  4.99283010e-14,
                  2.62437452e-10],
                 [-3.29912443e-14,  1.56806940e-08, -9.87434156e-15,
                  -9.84728320e-08],
                 [ 3.03047126e-14,  9.74167937e-09,  2.62299326e-15,
                  -4.30630174e-08],
                 [-6.52688628e-15,  2.20784317e-09,  4.82064518e-14,
                  5.65056270e-09],
                 [ 1.88440988e-14, -4.72136905e-09,  3.99009336e-15,
                  4.13181108e-08],
                 [ 1.67281468e-14, -3.36708113e-09,  1.43095932e-14,
```

4.00211425e-08],
[2.68161848e-15, -1.48679304e-10, -4.36179740e-16,
2.51823806e-08],
[-1.04299433e-14, 9.84359155e-09, 2.10906461e-14,
-5.10945678e-08],
[-4.81455733e-16, -4.51794847e-09, -2.99196969e-15,
4.78797014e-08],
[-2.78516663e-14, 2.08819125e-08, -1.50468659e-14,
-1.59284754e-07],
[1.39350677e-14, 1.35185002e-08, -5.66203867e-15,
-7.84753691e-08],
[-9.55712233e-14, -1.80970647e-10, -3.96928108e-14,
3.49634789e-08],
[3.40154561e-15, -1.08132358e-08, 3.01142586e-15,
1.50809019e-08],
[3.06047297e-14, 1.00631858e-08, 9.22893142e-15,
-4.22710883e-08],
[1.73654805e-14, -2.32637457e-08, -9.37872508e-15,
1.05854718e-07],
[1.59062932e-14, 2.73617599e-09, 1.52154479e-14,
1.36807108e-08],
[-4.18169197e-14, 1.62778925e-08, -1.17579186e-14,
-1.05314706e-07],
[2.05754506e-15, -3.29656670e-09, -4.22695212e-15,
4.20375773e-08],
[2.82957545e-14, -2.43227845e-08, -9.05288864e-15,
1.10082436e-07],
[3.60059418e-16, 1.23262042e-08, 1.84170910e-14,
-6.63084428e-08],
[1.61946236e-14, 7.68558725e-09, -9.20136980e-16,
-2.59275846e-08],
[-2.15006522e-14, 6.29201452e-09, -2.68411440e-14,
-1.00143741e-08],
[4.47037283e-14, -1.27800771e-08, 3.01288104e-14,
7.88374997e-10],
[-2.28561422e-14, -5.06110869e-09, -1.47843719e-14,
5.07064474e-08],
[-2.74441810e-15, 7.14421063e-09, 8.02931210e-15,
-2.42334692e-08],
[-1.15303316e-14, -8.27673868e-09, -4.28102685e-15,
5.63297131e-08],

```
[ 2.86390763e-14, -8.00764112e-09,  3.04356538e-15,  
 5.72033971e-08]])
```