

Movie Revenue Prediction

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```
[1]: import pandas as pd
import numpy as np
import matplotlib as plt
import matplotlib.pyplot as pyplot
import seaborn as sns
import datetime
import calendar
import statistics
```

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```
[2]: # Read the data from the file, and create a DataFrame object.
raw_data_movies = pd.read_csv("tmdb_5000_movies.csv")
```

```
[3]: # Reformat the columns contain dictionaries as a string list.
raw_data_movies["genres"] = raw_data_movies["genres"].apply(lambda x :
    ↪[i["name"] for i in eval(x)])
raw_data_movies["keywords"] = raw_data_movies["keywords"].apply(lambda x :
    ↪[i["name"] for i in eval(x)])
raw_data_movies["production_companies"] =
    ↪raw_data_movies["production_companies"].apply(lambda x : [i["name"] for i in
    ↪eval(x)])
raw_data_movies["production_countries"] =
    ↪raw_data_movies["production_countries"].apply(lambda x : [i["name"] for i in
    ↪eval(x)])
raw_data_movies["spoken_languages"] = raw_data_movies["spoken_languages"].
    ↪apply(lambda x : [i["name"] for i in eval(x)])
```

```
[4]: # Read the data from the file, and create a DataFrame object.
raw_data_credits = pd.read_csv("tmdb_5000_credits.csv")
```

```
[5]: # Reformat the columns contain dictionaries as a string list.
raw_data_credits["cast"] = raw_data_credits["cast"].apply(lambda x : [i["name"]
    ↪for i in eval(x)])
```

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raw_data_credits["crew"] = raw_data_credits["crew"].apply(lambda x : [i["job"]_
↳+ " : " + i["name"] for i in eval(x)])
```

```
[6]: # Merge two datasets base on the movies' id number, and drop the duplicated_
↳columns.
raw_data = pd.merge(raw_data_movies, raw_data_credits.drop("title", 1), left_on_
↳= "id", right_on = "movie_id").drop("movie_id", 1)
```

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[7]: # Clean the dataset, and remove the outliers.
data = raw_data[(raw_data["budget"] > 0) &
                (raw_data["original_title"] is not np.nan) &
                (raw_data["popularity"] > 0) &
                (raw_data["production_companies"].apply(len) != 0) &
                (raw_data["production_countries"].apply(len) != 0) &
                (raw_data["release_date"] is not np.nan) &
                (raw_data["revenue"] > 0) &
                (raw_data["runtime"] > 0) &
                (raw_data["cast"].apply(len) != 0) &
                (raw_data["crew"].apply(len) != 0)]
```

In the process of cleaning the data, the outliers that are caused by artifacts have to be removed. The purpose of this project is to build the model of predicting the revenue of movies, so the values of budget and revenue are not supposed to be zero. Also, the runtime of the movies cannot be zero because it does not make sense. In addition, the columns, “original_title”, “cast”, and “crew”, are necessary since they demonstrate the convincingness of the data. Furthermore, in the other columns, “production_companies” and “production_countries”, all these data are required in the model that we are going to build. And now, we are able to begin our data analysis.

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

```
[8]:
```

	budget	id	popularity	revenue	runtime \
count	3.183000e+03	3183.000000	3183.000000	3.183000e+03	3183.000000
mean	4.113039e+07	44878.875589	29.415936	1.229086e+08	110.859881
std	4.450600e+07	75046.011568	36.283411	1.871212e+08	20.991509
min	1.000000e+00	5.000000	0.037073	5.000000e+00	41.000000
25%	1.100000e+07	4884.500000	10.812450	1.770142e+07	96.000000
50%	2.600000e+07	11361.000000	20.786616	5.693230e+07	107.000000
75%	5.500000e+07	45038.500000	37.689512	1.487174e+08	121.000000
max	3.800000e+08	417859.000000	875.581305	2.787965e+09	338.000000

	vote_average	vote_count
count	3183.000000	3183.000000
mean	6.315112	991.026076
std	0.868237	1419.826830

min	0.000000	0.000000
25%	5.800000	189.000000
50%	6.300000	484.000000
75%	6.900000	1161.000000
max	8.500000	13752.000000

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```
[9]: data['release_date']
```

```
[9]: 0      2009-12-10
      1      2007-05-19
      2      2015-10-26
      3      2012-07-16
      4      2012-03-07
      ...
      4773     1994-09-13
      4788     1972-03-12
      4792     1997-11-06
      4796     2004-10-08
      4798     1992-09-04
      Name: release_date, Length: 3183, dtype: object
```

```
[10]: days = []
      for date in data['release_date']:
          day = calendar.day_name[datetime.datetime.strptime(date, '%Y-%m-%d').
          ↪weekday()]
          days.append(day)
      data["release_day_of_week"] = days
      data
      groupby_day = data.groupby('release_day_of_week').budget.count()
      print(groupby_day.sort_values())
```

```
release_day_of_week
Sunday      112
Saturday    129
Monday      157
Tuesday     223
Wednesday   593
Thursday    665
Friday     1304
      Name: budget, dtype: int64
```

<ipython-input-10-4c2d22df4d15>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
data["release_day_of_week"] = days

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```
[11]: # Gets all genres in the dataset
unique_genre = {genre for l in data["genres"] for genre in l}
unique_genre
```

```
[11]: {'Action',
      'Adventure',
      'Animation',
      'Comedy',
      'Crime',
      'Documentary',
      'Drama',
      'Family',
      'Fantasy',
      'Foreign',
      'History',
      'Horror',
      'Music',
      'Mystery',
      'Romance',
      'Science Fiction',
      'Thriller',
      'War',
      'Western'}
```

```
[12]: # Gets the popularity of all genres including repeats different genres
all_info = {}
for ug in unique_genre:
    list = []
    for l in range(0, len(data["popularity"])):
        nextList = data["genres"].get(l)
        if (nextList is not None and ug in nextList):
            list.append(data["popularity"].get(l))
    all_info[ug] = list
```

```
[13]: # Removes any genre with no popularity
new_all_info = {key:val for key, val in all_info.items() if val}
```

```
new_all_info
```

```
[13]: {'Animation': [48.681969,  
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39.744242,  
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62.341073,  
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27.990284,  
106.815545,
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1.623338,
2.993939,
32.523573,
45.072136,
56.805781,
11.227087,
19.231507,
7.559192,
14.282314,
3.495758,
4.12064,
2.259537,
7.722021,
7.063053,
9.371811,
1.187671,
4.519523,
12.792446,
0.037073,
10.892398,
14.754281,
8.9876,
5.882208,
8.932837,
26.598884,
25.929893,
21.258991,
5.699058,
7.499639,
4.928777,
20.452449,

14.543435,
3.290639,
9.559737,
11.350382,
18.289303,
17.592299,
4.207456,
5.647538,
18.366362,
6.736274,
5.671691,
14.038512,
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14.105392,
14.905357,
0.518056,
16.318608,
10.409155,
19.263477,
3.988432,
14.979375,
4.570043,
9.805551,
0.666218,
1.728816,
1.617943,
19.978021,
9.337388,
14.562991,
19.747809,
7.720692,
3.951041,
18.514292,
34.022209,
2.062087,
8.738737],
'Action': [150.437577,
139.082615,
107.376788,
112.31295,
43.926995,
115.699814,
134.279229,
155.790452,
57.925623,
107.928811,

145.847379,
49.046956,
99.398009,
144.448633,
135.413856,
52.035179,
120.965743,
89.866276,
37.668301,
61.22601,
198.372395,
64.928382,
418.708552,
93.004993,
35.149586,
77.68208,
3.857526,
21.939663,
116.840296,
89.270217,
73.79505,
51.872839,
71.862892,
102.322217,
81.834855,
118.078691,
78.291018,
43.349855,
62.169881,
56.523205,
28.529607,
75.674458,
125.114374,
65.352913,
22.57178,
45.274225,
85.36908,
42.741719,
187.322927,
120.725053,
40.748915,
60.034162,
90.23792,
79.456485,
44.640292,
32.852443,
77.300194,

110.620647,
243.791743,
41.796339,
72.225265,
203.73459,
48.775723,
69.405188,
481.098624,
167.58371,
9.476999,
108.849621,
6.909942,
3.195174,
127.284427,
35.580815,
21.133748,
63.148529,
202.042635,
25.468493,
39.019229,
56.758411,
70.867401,
115.040024,
81.781591,
5.954334,
73.313918,
70.78591,
99.499595,
434.278564,
86.493424,
26.710398,
114.522237,
33.769336,
63.079003,
39.004588,
54.159392,
66.21806,
58.485967,
91.332849,
35.601665,
56.747978,
77.77477,
52.341226,
101.599427,
73.616808,
82.502566,
100.21391,

17.88953,
64.798873,
24.855701,
34.981698,
59.325589,
21.605568,
26.074908,
74.506246,
39.604363,
62.898336,
45.381501,
120.09361,
76.310119,
38.068736,
20.678787,
48.829437,
42.840582,
68.757242,
39.448066,
271.972889,
2.871739,
7.255718,
81.499621,
47.686442,
43.129703,
27.220157,
90.33681,
50.073575,
41.380094,
54.931334,
60.810723,
51.328145,
46.834704,
62.641286,
33.616115,
67.33767,
27.835436,
66.757869,
17.060695,
44.906918,
67.698004,
44.108427,
43.987061,
15.953444,
54.035265,
18.714197,
60.467984,

143.350376,
16.90444,
39.873791,
38.126095,
48.780039,
100.412364,
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23.657284,
44.635452,
31.703608,
71.510596,
37.195046,
23.336875,
45.94834,
48.93337,
138.049577,
22.643776,
95.914473,
44.490453,
37.68056,
52.995628,
95.301296,
65.948959,
88.935165,
51.188633,
101.74155,
38.729418,
24.399642,
24.507987,
53.732892,
58.849256,
30.863434,
41.426678,
20.652943,
52.792678,
48.205606,
58.782359,
32.271938,
76.842247,
61.025639,
33.507289,
50.767332,
12.092241,
30.254021,
41.862983,
19.224754,
44.455166,
109.528572,
123.630332,
106.914973,
41.498631,
1.859364,
138.433168,

```
[14]: all_info = new_all_info
genres = [*all_info]
genres
```

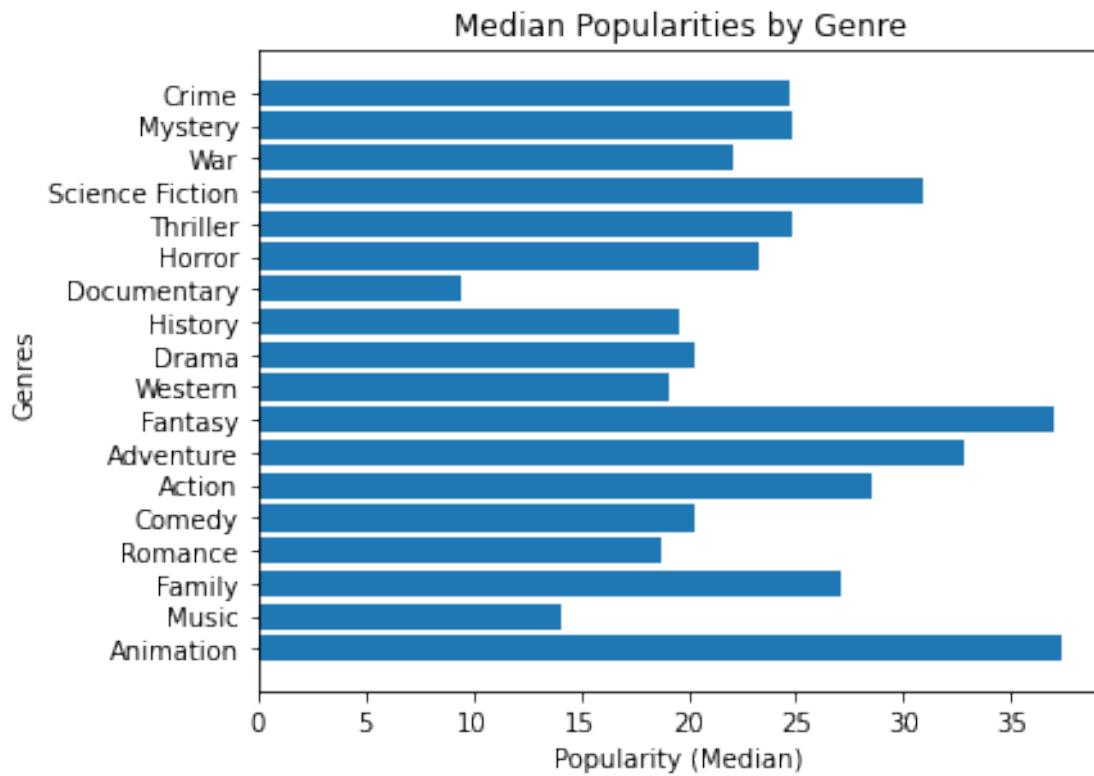
```
[14]: ['Animation',
      'Music',
      'Family',
      'Romance',
      'Comedy',
      'Action',
      'Adventure',
      'Fantasy',
      'Western',
      'Drama',
      'History',
      'Documentary',
      'Horror',
      'Thriller',
      'Science Fiction',
      'War',
      'Mystery',
      'Crime']
```

```
[15]: # Uses previous dictionary to get medians and means for each genre
medians = {}
means = {}
```

```
[16]: for g in genres:
      list = all_info.get(g)
      if(list):
          medians[g] = statistics.median(list)
          means[g] = statistics.mean(list)
median_values = [*medians.values()]
mean_values = [*means.values()]
median_val_rounded = [round(num,2) for num in median_values]
mean_val_rounded = [round(num,2) for num in mean_values]
#len(median_val_rounded)
#len(mean_val_rounded)
```

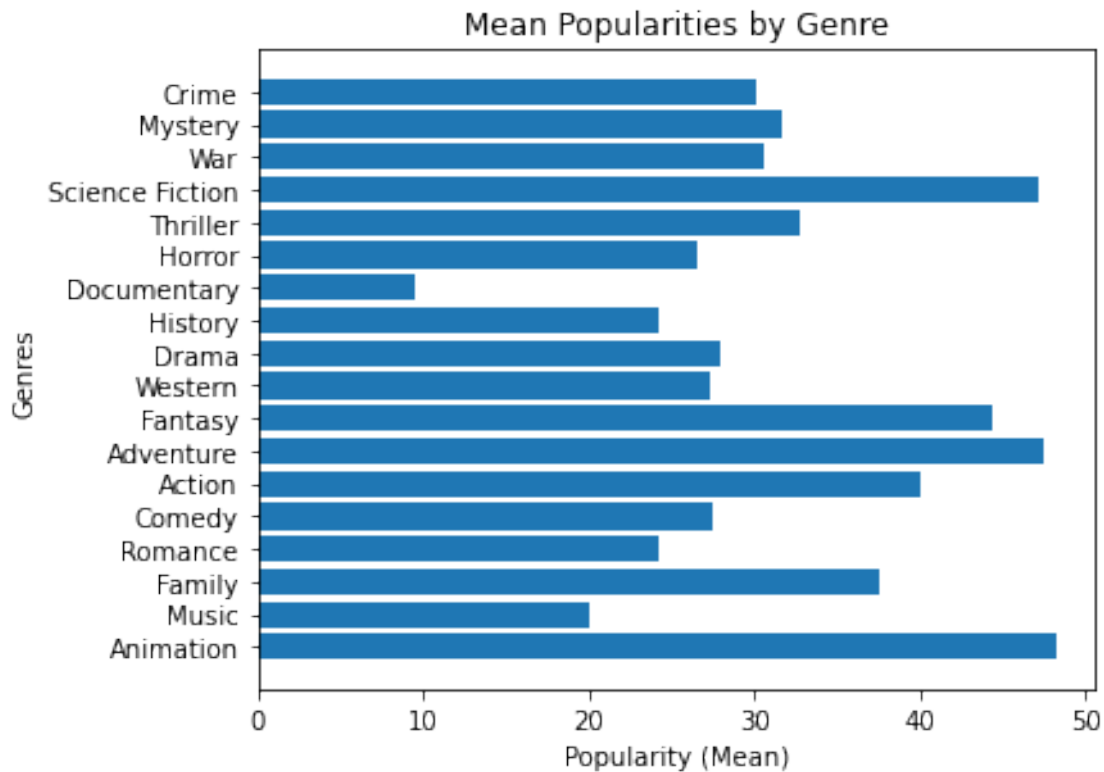
```
[17]: # Plot data
pyplt.barh(y=genres,width=median_val_rounded)
pyplt.tight_layout()
pyplt.xlabel("Popularity (Median)")
pyplt.ylabel("Genres")
pyplt.title("Median Popularities by Genre")
```

```
[17]: Text(0.5, 1.0, 'Median Popularities by Genre')
```



```
[18]: pyplot.barh(y=genres,width=mean_val_rounded)
pyplot.tight_layout()
pyplot.xlabel("Popularity (Mean)")
pyplot.ylabel("Genres")
pyplot.title("Mean Popularities by Genre")
```

```
[18]: Text(0.5, 1.0, 'Mean Popularities by Genre')
```



Via my interpretation of the question, “What are the movie genre trend shifting patterns that you can observe from the dataset?”, I started by understanding what trends are which are usually the most popular object which means dictates that trend shifting would imply an object in this case our object being movie genre that is farthest away from the mean and medians. To get this information, I used the dataset to find all unique genres to find the popularity means and medians for each genre. Afterwards I used the median and means by genre to visualize the results which displays that documentaries are the movie genre that shifts the movie genre trend pattern the most since it is by far the lowest in both median and mean compared to all other moviegenres.

•

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

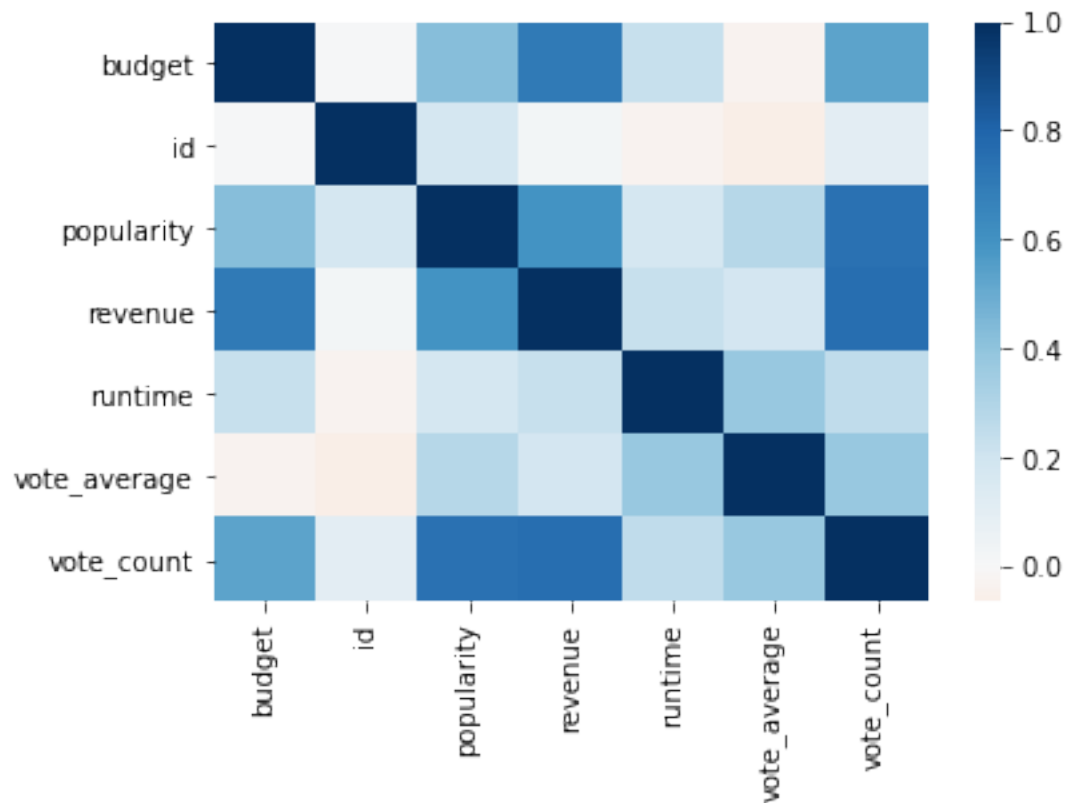
```
[19]:
```

	budget	id	popularity	revenue	runtime	\
budget	1.000000	0.012717	0.427822	0.703984	0.226795	
id	0.012717	1.000000	0.178044	0.029373	-0.033730	
popularity	0.427822	0.178044	1.000000	0.599706	0.179201	
revenue	0.703984	0.029373	0.599706	1.000000	0.231085	
runtime	0.226795	-0.033730	0.179201	0.231085	1.000000	
vote_average	-0.034135	-0.064647	0.286779	0.187030	0.382346	
vote_count	0.537224	0.106548	0.747323	0.754761	0.255873	

	vote_average	vote_count
budget	-0.034135	0.537224
id	-0.064647	0.106548
popularity	0.286779	0.747323
revenue	0.187030	0.754761
runtime	0.382346	0.255873
vote_average	1.000000	0.379500
vote_count	0.379500	1.000000

```
[20]: sns.heatmap(data.corr(), cmap='RdBu', center=0)
```

```
[20]: <AxesSubplot:>
```



```
[21]: groupby_day_rev = data.groupby('release_day_of_week').revenue.agg(['count',
↪ 'median'])
print(groupby_day_rev.sort_values('median'))
```

count	median
-------	--------

release_day_of_week		
Saturday	129	41158757.0
Friday	1304	42185535.5
Sunday	112	44367120.5
Monday	157	49469904.0
Tuesday	223	68896829.0
Thursday	665	77000000.0
Wednesday	593	86658558.0

By ranking, we see budget is the most correlated with revenue, followed by popularity and vote count. Runtime is not very strongly correlated with revenue. Correlation with vote average is surprisingly low. Correlation with id is, as expected, very low.

0.1.2 Modeling and Question Answering

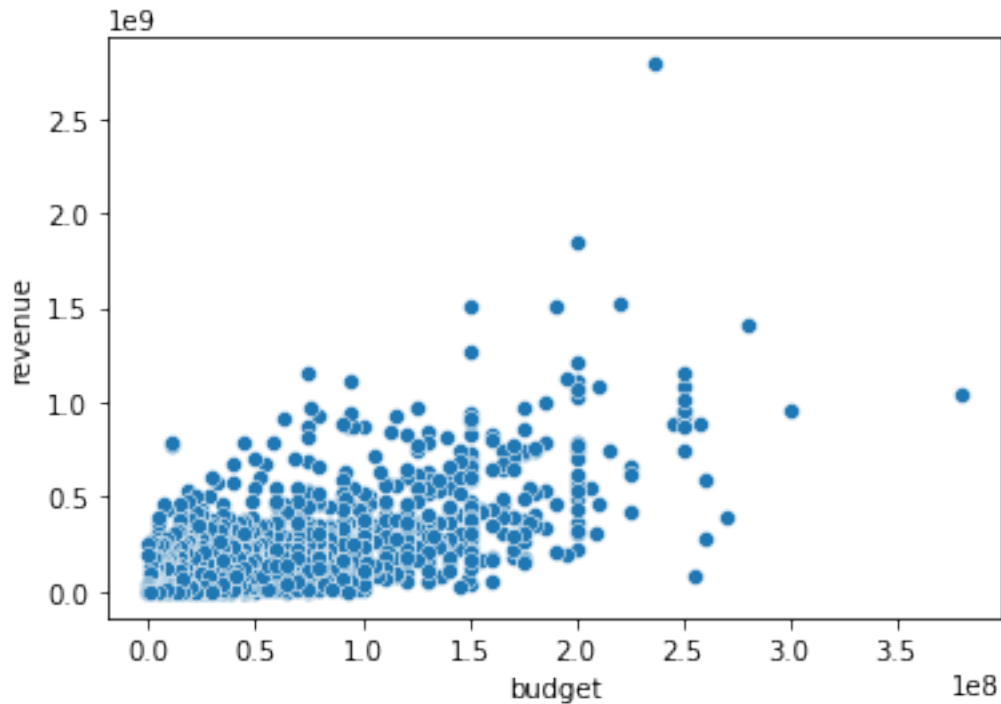
```
[22]: from sklearn.linear_model import LinearRegression
      from sklearn.model_selection import train_test_split
      from sklearn.model_selection import KFold
```

•

```
[23]: # Create a scatter plot between budget and revenue to find out outliers.
      sns.scatterplot(data["budget"], data["revenue"])
```

```
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-
packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```

```
[23]: <AxesSubplot:xlabel='budget', ylabel='revenue'>
```

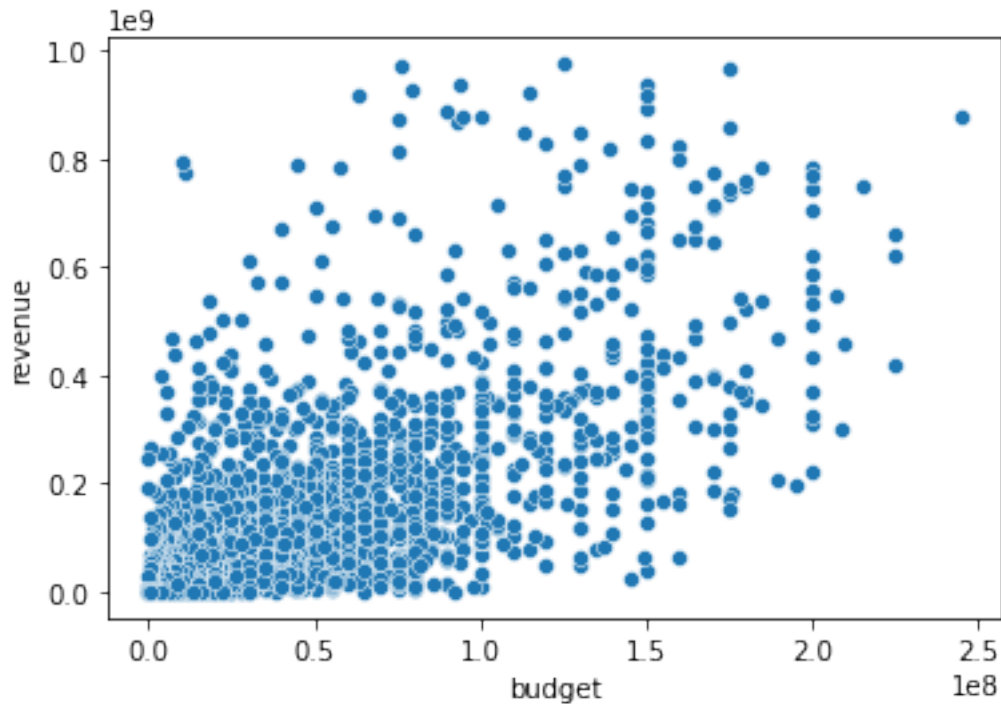


```
[24]: # Remove the outliers according to the scatter plot.
data_without_outliers = data[(data["budget"] < 2500000000) & (data["revenue"] < 10000000000)]
```

```
[25]: # Create a scatter plot again, and check if there are any outliers else.
sns.scatterplot(data_without_outliers["budget"], data_without_outliers["revenue"])
```

```
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

```
[25]: <AxesSubplot:xlabel='budget', ylabel='revenue'>
```



Build model without the Cross-Validation

```
[26]: # Create a LinearRegression object.
model_1 = LinearRegression()
# Create some empty lists to store values.
coef = []
intercept = []
MSE = []
# Create a loop.
times = 0
while (times <= 100):
    # Separate the dataset to training set and test set.
    train, test = train_test_split(data_without_outliers)
    # Fit the dataset to the model.
    model_1 = model_1.fit(train["budget"].to_numpy().reshape(-1, 1),
    ↪ train["revenue"].to_numpy())
    # Store the value of slope (coefficient) in each loop.
    coef.append(model_1.coef_[0])
    # Store the value of intercept in the model of each loop.
    intercept.append(model_1.intercept_)
    # Calculate predicted values by the values of budget for each movie.
    predictions = model_1.predict(test["budget"].to_numpy().reshape(-1, 1))
    # Store the value of mean square value in the model of each loop.
    MSE.append(np.mean((test["revenue"] - predictions) ** 2))
```



```

        times = times + 1
    # Use the average of the value of slope (coefficient) as the slope of the final
    ↪ model.
    model_1.coef_ = np.array([np.mean(coef)])
    # Use the average of the value of intercept as the intercept of the final model.
    model_1.intercept_ = np.mean(intercept)
    # Print the final linear regression model.
    print("The final linear model is: Revenue = " + str(model_1.coef_[0]) + " *
    ↪ Budget + " + str(model_1.intercept_))

```

The final linear model is: Revenue = 2.565989921721056 * Budget + 12151647.736499479

```

[27]: # Calculate the average of each linear regression model's MSE in the loop.
      MSE_average = np.mean(MSE)
      # Print out the average.
      print("Average MSE:", MSE_average)

```

Average MSE: 1.3211146352793626e+16

Here we use standard linear regression. With some outliers removed, RMSE comes out to be 113 million USD, a 32 percent improvement from guessing median only.

The equation is roughly Revenue = 2.571 * Budget + 12 Million USD

Without removing the outliers, we get a RSME 132 million.

```

[28]: # By the model, calculate the predicted values of revenue.
      predictions = model_1.predict(data["budget"].to_numpy().reshape(-1, 1))

```

```

[29]: # Create a scatter plot between budget and revenue.
      sns.scatterplot(data["budget"], data["revenue"])
      # Create a scatter plot between budget and predictions.
      sns.scatterplot(data["budget"], predictions)

```

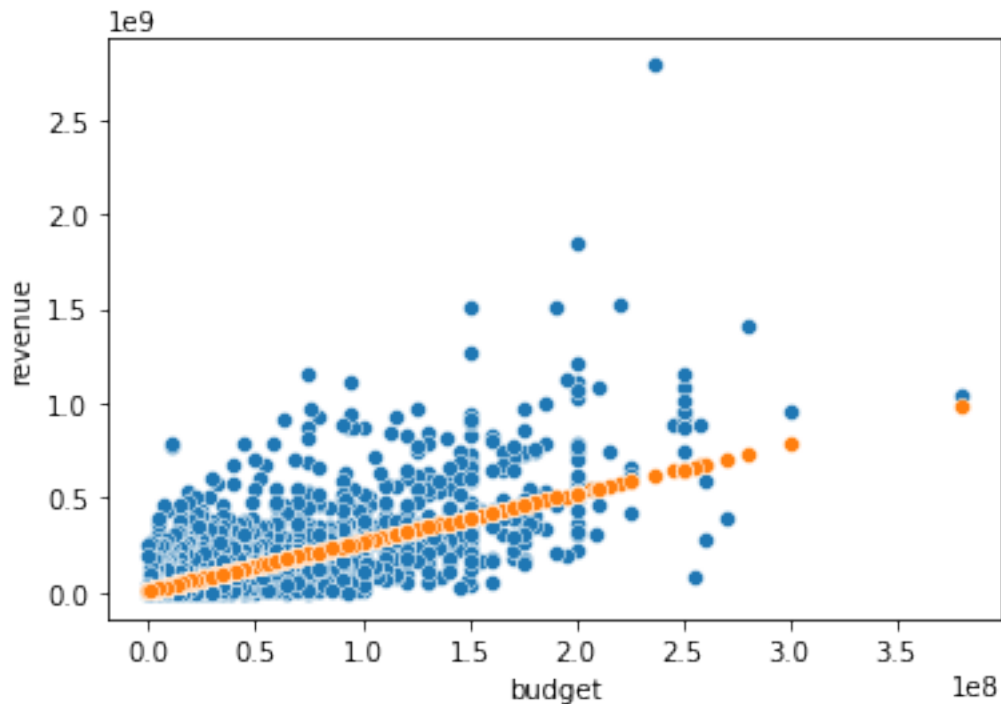
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will
```

```
result in an error or misinterpretation.  
warnings.warn(  

```

```
[29]: <AxesSubplot:xlabel='budget', ylabel='revenue'>
```



Build model with the Cross-Validation

```
[30]: # Create a LinearRegression object.  
model_1 = LinearRegression()  
# Create some empty lists to store values.  
coef = []  
intercept = []  
MSE = []  
# Create a KFold object to separate the data to the Cross-Validation set.  
kf = KFold(n_splits = 10, shuffle = True)  
# Create a loop to do the Cross-Validation.  
for train_index, test_index in kf.split(data_without_outliers):  
    # Get a train set.  
    train = data_without_outliers.iloc[train_index]  
    # Get a test set.  
    test = data_without_outliers.iloc[test_index]  
    # Fit the dataset to the model.
```

```

    model_1 = model_1.fit(train["budget"].to_numpy().reshape(-1, 1),
↪train["revenue"].to_numpy())
    # Store the value of slope (coefficient) in each loop.
    coef.append(model_1.coef_[0])
    # Store the value of intercept in the model of each loop.
    intercept.append(model_1.intercept_)
    # Calculate predicted values by the values of budget for each movie.
    predictions = model_1.predict(test["budget"].to_numpy().reshape(-1, 1))
    # Store the value of mean square value in the model of each loop.
    MSE.append(np.mean((test["revenue"] - predictions) ** 2))
# Use the average of the value of slope (coefficient) as the slope of the fianl
↪model.
model_1.coef_ = np.array([np.mean(coef)])
# Use the average of the value of intercept as the intercept of the fianl model.
model_1.intercept_ = np.mean(intercept)
# Print the final linear regression model.
print("The final linear model is: Revenue = " + str(model_1.coef_[0]) + " *
↪Budget + " + str(model_1.intercept_))

```

The final linear model is: Revenue = 2.5713786556233975 * Budget + 12124050.399081381

```

[31]: # Calculate the average of each linear regression model's MSE in the loop.
MSE_average = np.mean(MSE)
# Print out the average.
print("Average MSE:", MSE_average)

```

Average MSE: 1.2933494929720106e+16

```

[32]: # By the model, calculate the predicted values of revenue.
predictions = model_1.predict(data["budget"].to_numpy().reshape(-1, 1))

```

```

[33]: # Create a scatter plot between budget and revenue.
sns.scatterplot(data["budget"], data["revenue"])
# Create a scatter plot between budget and predictions.
sns.scatterplot(data["budget"], predictions)

```

/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

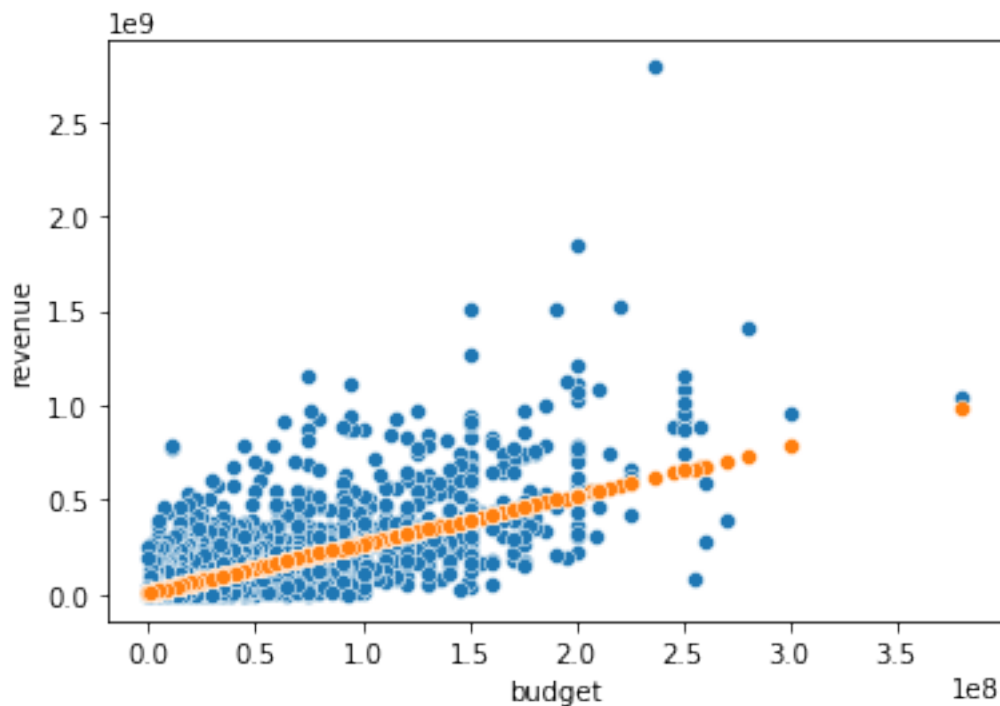
```

    warnings.warn(
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-

```

```
packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
warnings.warn(
```

```
[33]: <AxesSubplot:xlabel='budget', ylabel='revenue'>
```



From the table and heat map, we find the correlation coefficient between budget and revenue is highest. Therefore, we want to build a linear regression model between them.

Before training the model, we have to separate the dataset into a training set and a test set, and then we need to use the fit function to generate an appropriate linear regression model. But, we find the value of MSE is unsteady and inaccurate each time we generate a linear regression. Since there existing extreme cases which will impact our linear model, we repeat the process of fitting the training set a hundred times and record the value of coefficient (slope) and intercept. And then, we use the mean of coefficient (slope) and intercept as the final model. In order to evaluate the performance of the model, we calculate MSE according to the test set and record value each time we generate the linear regression model. And then, we use the mean as Mean Square Error to the final model.

However, after evaluating the performance of this model, we find that the value of MSE is very large, so it implies that the final model's predictions are not so accurate. But, we wonder if the Cross-Validation can help increase the model's accuracy even though we have applied a similar

method. After using the Cross-Validation, we calculate the MSE again. Unfortunately, the MSE doesn't have an obvious decrease.

Therefore, the final model cannot provide accurate predictions, and we think the reason is that we do not apply other features such as genres, production companies to the model. Hence, we guess these variables also play significant roles in movies' revenue.

•

Baseline Model - Guessing the mean of "training set"

If we do this, then our avg RMSE will be, in essence, the standard deviation of the revenue, which is 187 million USD. Although out of order, we also calculated the RMSE if we guess the median, which is shown a few lines below, rather than the mean. It was using a somewhat unconventional coding style. The RMSE for median came out to be 165 million USD

Code for RMSE for predicting median

```
[34]: # BASELINE MODEL - MEDIAN
basem1 = LinearRegression()
# Create some empty lists to store values.
coef = []
intercept = []
MSE = []
# Create a loop.
times = 0
while (times <= 100):
    MSE.append(np.mean((test["revenue"] - np.
    ↪median(data_without_outliers['revenue']))) ** 2))
    times = times + 1
# Use the average of the value of slope (coefficient) as the slope of the fianl
    ↪model.
basem1.coef_ = 0
# Use the average of the value of intercept as the intercept of the fianl model.
basem1.intercept_ = np.median(data_without_outliers['revenue'])
# Print the final linear regression model.
print("predicting median every time is: Revenue = " + str(np.
    ↪median(data_without_outliers['revenue']))) )
```

predicting median every time is: Revenue = 55707411.0

```
[35]: # Calculate the average of each linear regression model's MSE in the loop.
MSE_average = np.mean(MSE)
# Print out the average.
print("Average MSE, for basem1:", MSE_average)
print("Average RMSE:", MSE_average ** 0.5 / 1000000, 'million')
```

Average MSE, for basem1: 3.084953711419822e+16

Average RMSE: 175.64036299836724 million

```
[36]: # Create a scatter plot between budget and revenue.
sns.scatterplot(data["budget"], data["revenue"])
# Create a scatter plot between budget and predictions.
sns.scatterplot(data["budget"], np.median(data_without_outliers['revenue']))
```

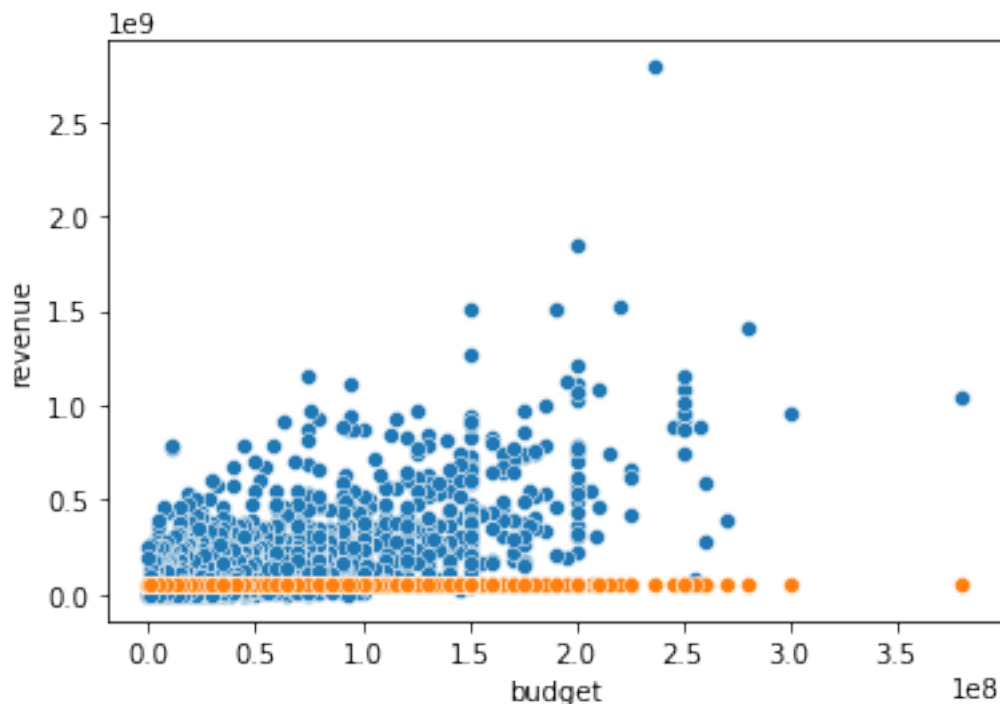
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

```
[36]: <AxesSubplot:xlabel='budget', ylabel='revenue'>
```



Advanced Model - Applying a non-linear function to budget

Here we try training by applying a non-linear function to budget, to see if we can obtain a better model. For simplicity, we have called all the non-linear transformations 'budgetSquared'. We used the original dataset, without removing outliers. First off, is an identity transformation, so same as the standard linear regression, except without removing any outliers. RMSE: 132.77 million USD

After trying several functions, including squared, cubed, square root... The best one came out to be raising budget to the 1.25th power. That resulted in a RMSD of 129 million USD, not a big improvement from 132 million, not enough to pass Occam's Razor's test.

```
[37]: data["budgetSquared"] = data["budget"]
      # Create a LinearRegression object.
      model_2 = LinearRegression()
      # Create some empty lists to store values.
      coef = []
      intercept = []
      MSE = []
      # Create a loop.
      times = 0
      while (times <= 100):
          # Separate the dataset to training set and test set.
          train, test = train_test_split(data)
          # Fit the dataset to the model.
          model_2 = model_2.fit(train["budgetSquared"].to_numpy().reshape(-1, 1),
          →train["revenue"].to_numpy())
          # Store the value of slope (coefficient) in each loop.
          coef.append(model_2.coef_[0])
          # Store the value of intercept in the model of each loop.
          intercept.append(model_2.intercept_)
          # Calculate predicted values by the values of budget for each movie.
          predictions = model_2.predict(test["budgetSquared"].to_numpy().reshape(-1, 1)
          →1))
          # Store the value of mean square value in the model of each loop.
          MSE.append(np.mean((test["revenue"] - predictions) ** 2))
          times = times + 1
      # Use the average of the value of slope (coefficient) as the slope of the final
      →model.
      model_2.coef_ = np.array([np.mean(coef)])
      # Use the average of the value of intercept as the intercept of the final model.
      model_2.intercept_ = np.mean(intercept)
      # By the model, calculate the predicted values of revenue.
      predictions = model_2.predict(data["budgetSquared"].to_numpy().reshape(-1, 1))
      # Print the final linear regression model.
      print("The final linear model is: Revenue = " + str(model_2.coef_[0]) + " *
      →BudgetSquared + " + str(model_2.intercept_))
```

```

# Calculate the average of each linear regression model's MSE in the loop.
MSE_average = np.mean(MSE)
# Print out the average.
print("Average MSE:", MSE_average)
print("Average RMSE:", MSE_average ** 0.5 / 1000000, 'million')
sns.scatterplot(data["budget"], data["revenue"])
sns.scatterplot(data["budget"], predictions)

```

```

<ipython-input-37-025ba891d088>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```

data["budgetSquared"] = data["budget"]

```

The final linear model is: $\text{Revenue} = 2.959983869894621 * \text{BudgetSquared} + 1278862.4659905878$

Average MSE: 1.7779793678443568e+16

Average RMSE: 133.34089274653732 million

```

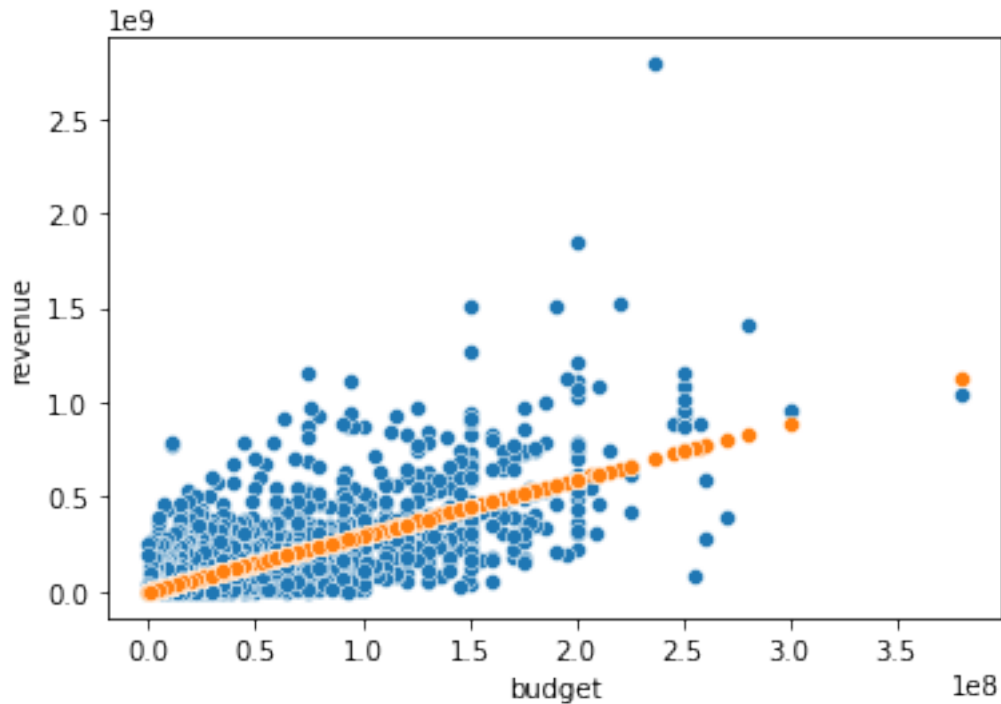
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-
packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-
packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(

```

```

[37]: <AxesSubplot:xlabel='budget', ylabel='revenue'>

```

```
[38]: data["budgetSquared"] = data["budget"] ** 1.25
# Create a LinearRegression object.
model_2 = LinearRegression()
# Create some empty lists to store values.
coef = []
intercept = []
MSE = []
# Create a loop.
times = 0
while (times <= 100):
    # Separate the dataset to training set and test set.
    train, test = train_test_split(data)
    # Fit the dataset to the model.
    model_2 = model_2.fit(train["budgetSquared"].to_numpy().reshape(-1, 1),
    ↪ train["revenue"].to_numpy())
    # Store the value of slope (coefficient) in each loop.
    coef.append(model_2.coef_[0])
    # Store the value of intercept in the model of each loop.
    intercept.append(model_2.intercept_)
    # Calculate predicted values by the values of budget for each movie.
    predictions = model_2.predict(test["budgetSquared"].to_numpy().reshape(-1,
    ↪ 1))
    # Store the value of mean square value in the model of each loop.
```

```

MSE.append(np.mean((test["revenue"] - predictions) ** 2))
times = times + 1
# Use the average of the value of slope (coefficient) as the slope of the final
→model.
model_2.coef_ = np.array([np.mean(coef)])
# Use the average of the value of intercept as the intercept of the final model.
model_2.intercept_ = np.mean(intercept)
# By the model, calculate the predicted values of revenue.
predictions = model_2.predict(data["budgetSquared"].to_numpy().reshape(-1, 1))
# Print the final linear regression model.
print("The final linear model is: Revenue = " + str(model_2.coef_[0]) + " *
→BudgetSquared + " + str(model_2.intercept_))
# Calculate the average of each linear regression model's MSE in the loop.
MSE_average = np.mean(MSE)
# Print out the average.
print("Average MSE:", MSE_average)
print("Average RMSE:", MSE_average ** 0.5 / 1000000, 'million')
sns.scatterplot(data["budget"], data["revenue"])
sns.scatterplot(data["budget"], predictions)

```

<ipython-input-38-bd3cf0b8d27f>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
data["budgetSquared"] = data["budget"] ** 1.25

The final linear model is: Revenue = 0.02578263943398939 * BudgetSquared +
25075765.488036998
Average MSE: 1.7421227007868844e+16
Average RMSE: 131.98949582398154 million

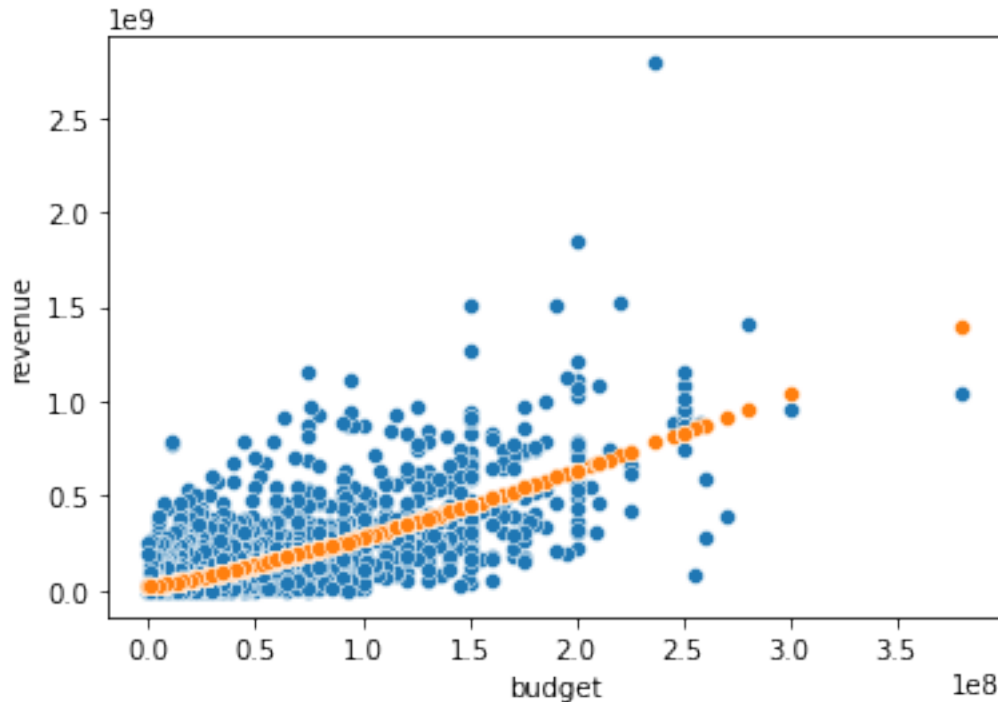
```

/Users/zhezhou/opt/anaconda3/lib/python3.8/site-
packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
    warnings.warn(
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-
packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.

```

```
warnings.warn(
```

```
[38]: <AxesSubplot:xlabel='budget', ylabel='revenue'>
```



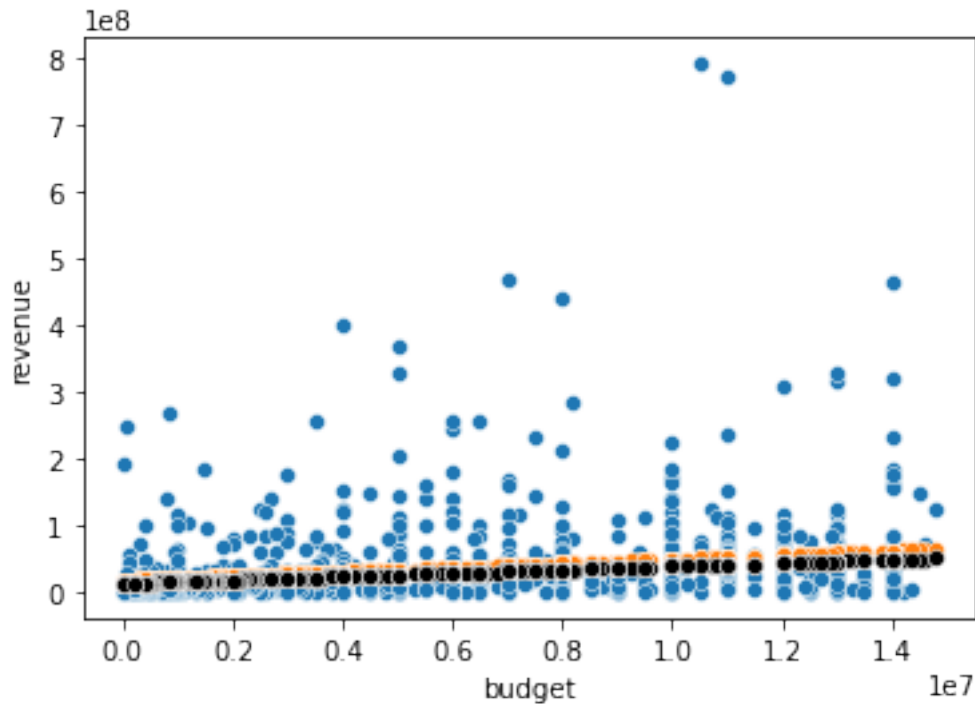
Advanced model - classifying by budget, then applying linear regression

We created three budget classes, under 15 million USD, 15 million - 105 million USD, and Over 105 million USD, as data1, data2, data3, respectively. We then applied standard linear regression to those three classes, and compared it to the original model 1. As it turned out, model 1 was nearly identical to what data1 and data2 training separately, but for model 3, Model 1 RMSE: 312 million, where training on data3 alone 292 million, so that gave a 6.4 percent improvement, perhaps still not enough to pass Occam's Razor Test.

```
[39]: data1 = data[(data["budget"] < 15000000)]
data2 = data[(data["budget"] > 15000000) & (data["budget"] < 105000000)]
data3 = data[(data["budget"] > 105000000)]
# data4 = data[(data["budget"] > 200000000)]
# data1.describe()
# data2.describe()
# data3.describe()
# data4.describe()
# pyplot.hist(data1.budget, bins=10)
# pyplot.hist(data2.budget, bins=10)
# pyplot.hist(data3.budget, bins=10)
```

```
# pyplot.hist(data4.budget, bins=10)
```

```
[40]: # Create a LinearRegression object.
model_31 = LinearRegression()
# Create some empty lists to store values.
coef = []
intercept = []
MSE = []
# Create a loop.
times = 0
while (times <= 100):
    # Separate the dataset to training set and test set.
    train, test = train_test_split(data1)
    # Fit the dataset to the model.
    model_31 = model_31.fit(train["budget"].to_numpy().reshape(-1, 1),
    ↪train["revenue"].to_numpy())
    # Store the value of slope (coefficient) in each loop.
    coef.append(model_31.coef_[0])
    # Store the value of intercept in the model of each loop.
    intercept.append(model_31.intercept_)
    # Calculate predicted values by the values of budget for each movie.
    predictions = model_31.predict(test["budget"].to_numpy().reshape(-1, 1))
    # Store the value of mean square value in the model of each loop.
    MSE.append(np.mean((test["revenue"] - predictions) ** 2))
    times = times + 1
# Use the average of the value of slope (coefficient) as the slope of the final
    ↪model.
model_31.coef_ = np.array([np.mean(coef)])
# Use the average of the value of intercept as the intercept of the final model.
model_31.intercept_ = np.mean(intercept)
# Print the final linear regression model.
print("The final linear model is: Revenue = " + str(model_31.coef_[0]) + " *
    ↪Budget + " + str(model_31.intercept_))
# Calculate the average of each linear regression model's MSE in the loop.
MSE_average = np.mean(MSE)
# Print out the average.
data1["predictions"] = model_31.predict(data1["budget"].to_numpy().reshape(-1,
    ↪1))
print("Average MSE:", MSE_average)
print("Average RMSE:", MSE_average ** 0.5 / 1000000, 'million')
model1mse = (data1['revenue'] - (data1["budget"] * 2.5666456407290505 +
    ↪12245913.01169521)) ** 2
print("Model 1 RMSE:", np.mean(model1mse) ** 0.5 / 1000000, 'million')
sns.scatterplot(data1["budget"], data1["revenue"])
sns.scatterplot(data1["budget"], data1["predictions"])
sns.scatterplot(data1["budget"], data1["budget"] * 2.5666456407290505 +
    ↪12245913.01169521, color='Black')
```

```
[41]: # Create a LinearRegression object.
model_32 = LinearRegression()
# Create some empty lists to store values.
coef = []
intercept = []
MSE = []
# Create a loop.
times = 0
while (times <= 100):
    # Seperate the dataset to training set and test set.
    train, test = train_test_split(data2)
    # Fit the dataset to the model.
    model_32 = model_32.fit(train["budget"].to_numpy().reshape(-1, 1),
    ↪train["revenue"].to_numpy())
    # Store the value of slope (coefficient) in each loop.
    coef.append(model_32.coef_[0])
    # Store the value of intercept in the model of each loop.
    intercept.append(model_32.intercept_)
    # Calculate predicted values by the values of budget for each movie.
    predictions = model_32.predict(test["budget"].to_numpy().reshape(-1, 1))
    # Store the value of mean square value in the model of each loop.
    MSE.append(np.mean((test["revenue"] - predictions) ** 2))
    times = times + 1
```

```

# Use the average of the value of slope (coefficient) as the slope of the final
    ↪ model.
model_32.coef_ = np.array([np.mean(coef)])
# Use the average of the value of intercept as the intercept of the final model.
model_32.intercept_ = np.mean(intercept)
# Print the final linear regression model.
print("The final linear model is: Revenue = " + str(model_32.coef_[0]) + " *
    ↪ Budget + " + str(model_32.intercept_))
# Calculate the average of each linear regression model's MSE in the loop.
MSE_average = np.mean(MSE)
# Print out the average.
data2["predictions"] = model_32.predict(data2["budget"].to_numpy().reshape(-1,
    ↪ 1))
print("Average MSE:", MSE_average)
print("Average RMSE:", MSE_average ** 0.5 / 1000000, 'million')
model1mse = (data2['revenue'] - (data2["budget"] * 2.5666456407290505 +
    ↪ 12245913.01169521)) ** 2
print("Model 1 RMSE:", np.mean(model1mse) ** 0.5 / 1000000, 'million')
sns.scatterplot(data2["budget"], data2["revenue"])
sns.scatterplot(data2["budget"], data2["predictions"], color='Red')
sns.scatterplot(data2["budget"], data2["budget"] * 2.5666456407290505 +
    ↪ 12245913.01169521, color='Black')

```

The final linear model is: Revenue = 2.3831947433719782 * Budget +
 12391098.004415099
 Average MSE: 1.4650249976505202e+16
 Average RMSE: 121.03821700812186 million
 Model 1 RMSE: 119.67720459015753 million

<ipython-input-41-da807a79bab6>:32: SettingWithCopyWarning:
 A value is trying to be set on a copy of a slice from a DataFrame.
 Try using .loc[row_indexer,col_indexer] = value instead

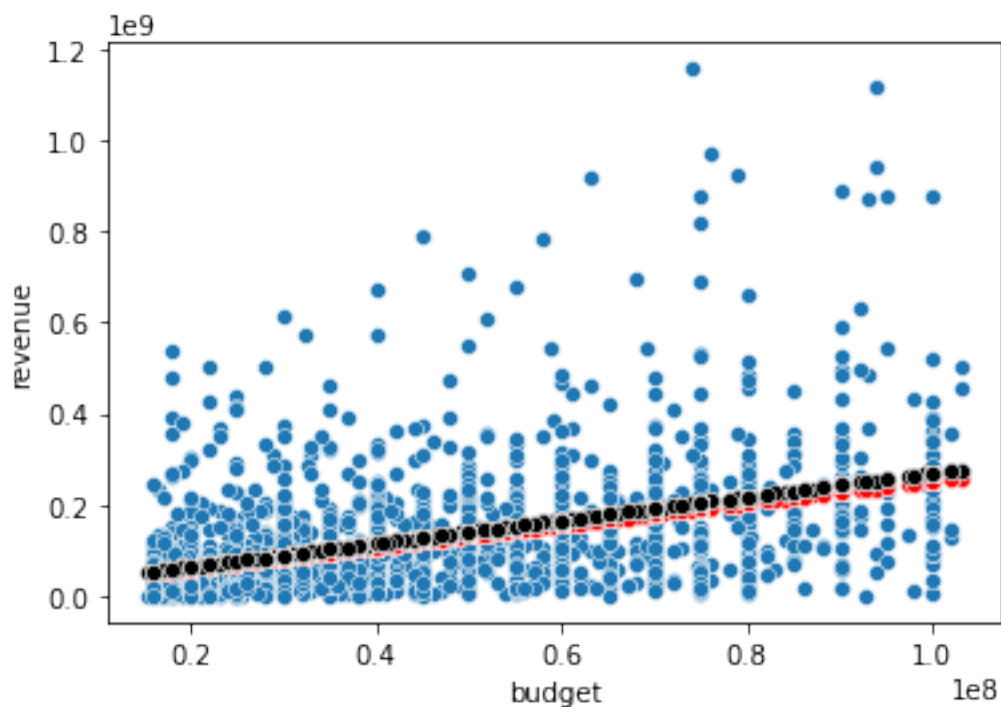
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 data2["predictions"] = model_32.predict(data2["budget"].to_numpy().reshape(-1,
 1))
 /Users/zhezhou/opt/anaconda3/lib/python3.8/site-
 packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables
 as keyword args: x, y. From version 0.12, the only valid positional argument
 will be `data`, and passing other arguments without an explicit keyword will
 result in an error or misinterpretation.
 warnings.warn(
 /Users/zhezhou/opt/anaconda3/lib/python3.8/site-
 packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables

as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

```
warnings.warn(  
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-  
packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables  
as keyword args: x, y. From version 0.12, the only valid positional argument  
will be `data`, and passing other arguments without an explicit keyword will  
result in an error or misinterpretation.  
warnings.warn(  

```

```
[41]: <AxesSubplot:xlabel='budget', ylabel='revenue'>
```



```
[42]: # Create a LinearRegression object.  
model_33 = LinearRegression()  
# Create some empty lists to store values.  
coef = []  
intercept = []  
MSE = []  
# Create a loop.  
times = 0  
while (times <= 100):  
    # Separate the dataset to training set and test set.
```



```

train, test = train_test_split(data3)
# Fit the dataset to the model.
model_33 = model_33.fit(train["budget"].to_numpy().reshape(-1, 1),
↳train["revenue"].to_numpy())
# Store the value of slope (coefficient) in each loop.
coef.append(model_33.coef_[0])
# Store the value of intercept in the model of each loop.
intercept.append(model_33.intercept_)
# Calculate predicted values by the values of budget for each movie.
predictions = model_33.predict(test["budget"].to_numpy().reshape(-1, 1))
# Store the value of mean square value in the model of each loop.
MSE.append(np.mean((test["revenue"] - predictions) ** 2))
times = times + 1
# Use the average of the value of slope (coefficient) as the slope of the final
↳model.
model_33.coef_ = np.array([np.mean(coef)])
# Use the average of the value of intercept as the intercept of the final model.
model_33.intercept_ = np.mean(intercept)
# Print the final linear regression model.
print("The final linear model is: Revenue = " + str(model_33.coef_[0]) + " *
↳Budget + " + str(model_33.intercept_))
# Calculate the average of each linear regression model's MSE in the loop.
MSE_average = np.mean(MSE)
# Print out the average.
data3["predictions"] = model_33.predict(data3["budget"].to_numpy().reshape(-1,
↳1))
print("Average MSE:", MSE_average)
print("Average RMSE:", MSE_average ** 0.5 / 1000000, 'million')
model1mse = (data3['revenue'] - (data3["budget"] * 2.5666456407290505 +
↳12245913.01169521)) ** 2
print("Model 1 RMSE:", np.mean(model1mse) ** 0.5 / 1000000, 'million')
sns.scatterplot(data3["budget"], data3["revenue"])
sns.scatterplot(data3["budget"], data3["predictions"], color = 'Red')
sns.scatterplot(data3["budget"], data3["budget"] * 2.5666456407290505 +
↳12245913.01169521, color='Black')
# The final linear model is: Revenue = 2.5666456407290505 * Budget + 12245913.
↳01169521

```

The final linear model is: Revenue = 3.8596046196373326 * Budget +
 -113868041.15420528
 Average MSE: 9.347146775003493e+16
 Average RMSE: 305.7310382510008 million
 Model 1 RMSE: 312.82331489501627 million

<ipython-input-42-94de11f952c7>:32: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
data3["predictions"] = model_33.predict(data3["budget"].to_numpy().reshape(-1, 1))
```

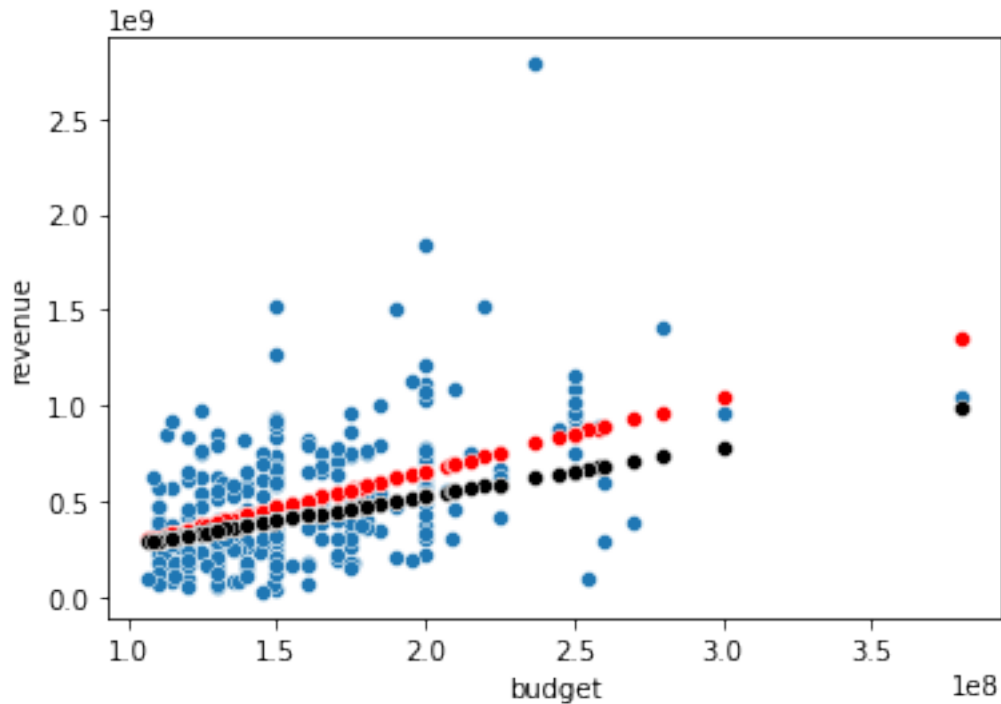
```
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
```

```
warnings.warn(  
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
```

```
warnings.warn(  
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
```

```
warnings.warn(  
/Users/zhezhou/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
```

```
[42]: <AxesSubplot:xlabel='budget', ylabel='revenue'>
```



•

```
[43]: # My code starts here
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
import math

allX = {}
allY = {}
for ug in unique_genre:
    x = []
    y = []
    for l in range(0, len(data["genres"])):
        if (data["genres"].get(l) and data["revenue"].get(l) and ug in
            ↳data["genres"].get(l)):
            x.append(math.log(data["budget"].get(l)))
            y.append(math.log(data["revenue"].get(l)))
    allX[ug] = x
    allY[ug] = y
```

Here we sort all values of budgets (X) and revenue (Y) into two dictionaries with key values of the specific genre and the values of budget or revenue as lists depending on dictionary. In this process,

repeats of the same movie does occur since most movies have more than a single genre. Additionally, using these lists would better allow us to plot the scatter plot in the future. In hindsight after the first run, the points and the line's visualization did not give a good understanding of approximation, hence the application of Napier Logarithms permitted a better visualization of data. This is why the log budget and revenue is used.

```
[44]: for g in unique_genre:
        if allX.get(g) == []:
            allX.pop(g)
        if allY.get(g) == []:
            allY.pop(g)
```

Here, we make sure that all genres have budgets and revenues by discarding the entire genre since an empty list of budget and revenues would result in an empty scatter plot.

```
[45]: coef = []
        intercept = []
        MSE = []
        sum_MSE = 0
        sum_RMSE = 0

        for g in unique_genre:
            if(allX.get(g) and allY.get(g)):
                # Gets all coordinates for x and y
                x = np.array(allX.get(g)).reshape((-1, 1))
                y = np.array(allY.get(g))
                # Creates LinearRegression object
                m4 = LinearRegression()
                m4.fit(x,y)
                # Creates regression line based off coordinates
                y_pred = m4.predict(x)
                pyplot.scatter(x,y)
                # Labels and organization
                pyplot.plot(x, y_pred, color="red")
                pyplot.xlabel("Log(Budget)")
                pyplot.ylabel("Log(Revenue)")
                title = "Linear Regression by Genre: " + g
                pyplot.title(title)
                pyplot.show()

                # Gets variables for solving RMSE and MSE
                m4 = m4.fit(x,y)
                coef.append(m4.coef_[0])
                intercept.append(m4.intercept_)
                predictions = m4.predict(data["budget"].to_numpy().reshape(-1, 1))
                MSE.append(np.mean((data["revenue"] - predictions) ** 2))
                m4coef_ = np.array([np.mean(coef)])
                m4intercept_ = np.mean(intercept)
```

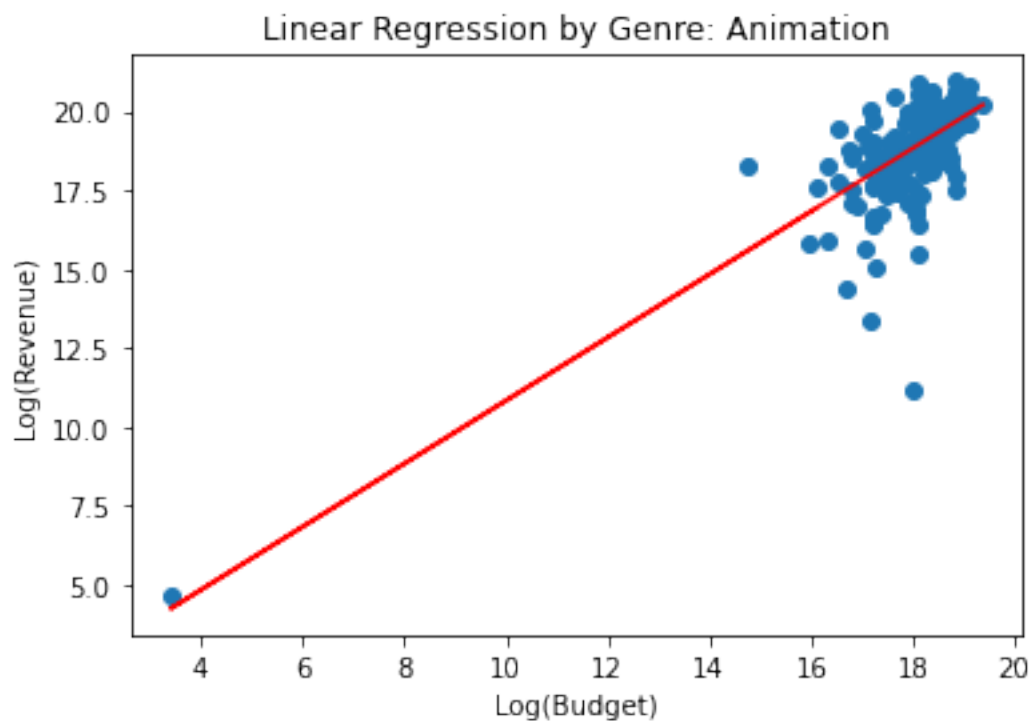
```

print("The " + g + " movie linear regression model is: Revenue = " +
↪str(m4.coef_[0]) + " * Budget + " + str(m4.intercept_))

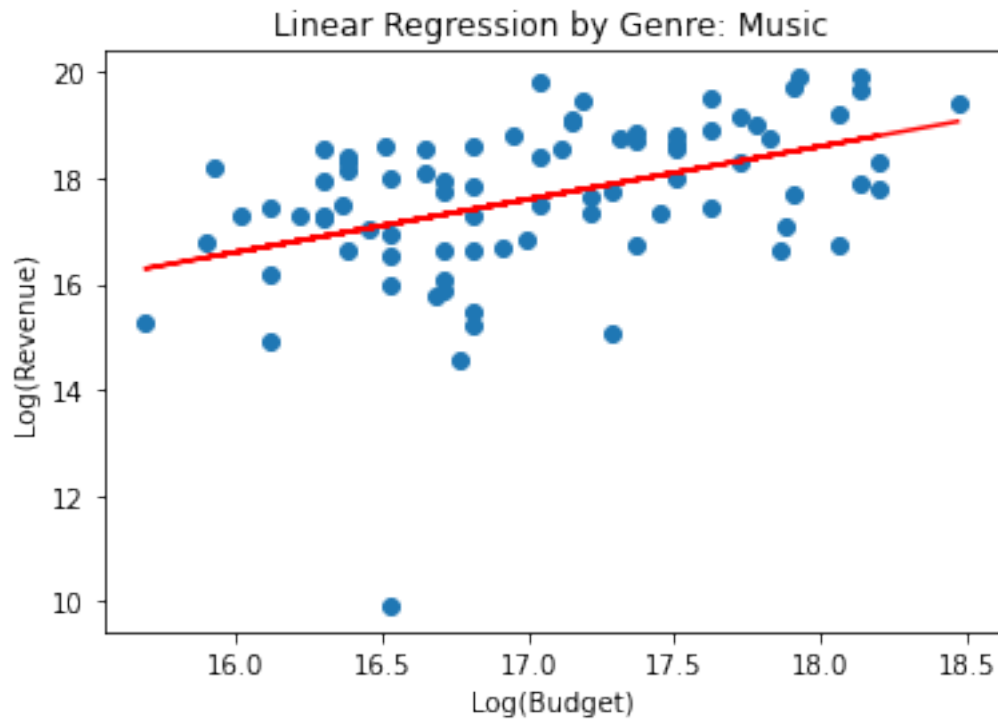
MSE_average = np.mean(MSE)
print("Average MSE, for model #4:", MSE_average)
print("Average RMSE:", MSE_average ** 0.5 / 1000000, 'million\n')
sum_RMSE += MSE_average ** 0.5 / 1000000
sum_MSE += MSE_average

print("Average MSE across all genres is " +str(sum_MSE/len(allX)))
print("Average RMSE across all genres is " +str(sum_RMSE/len(allX)) + "
↪million")

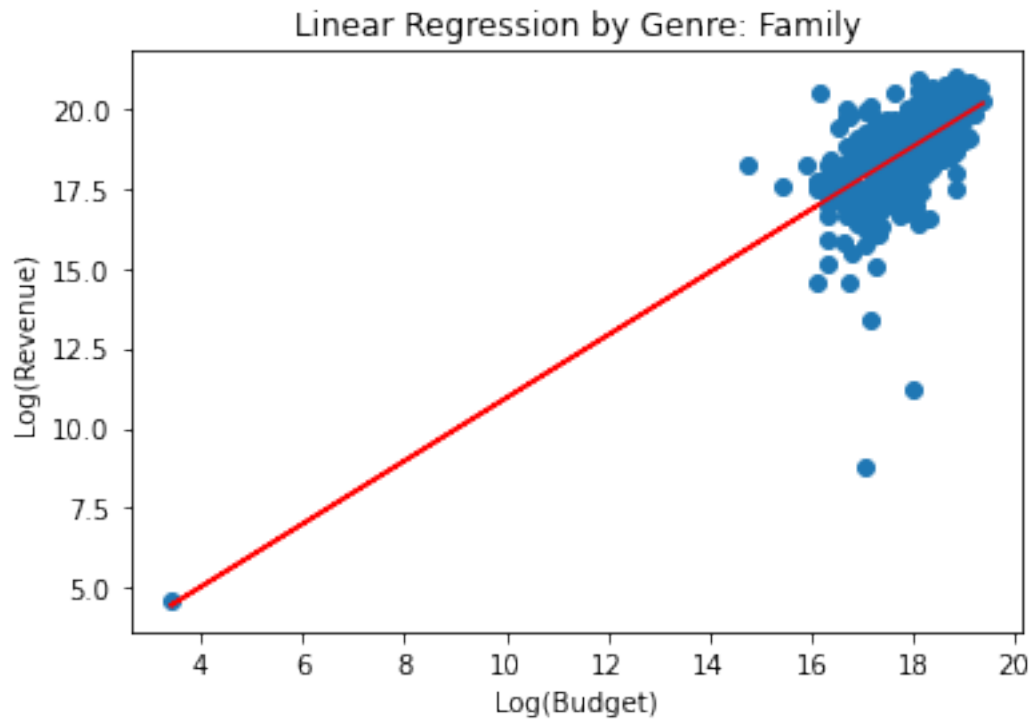
```



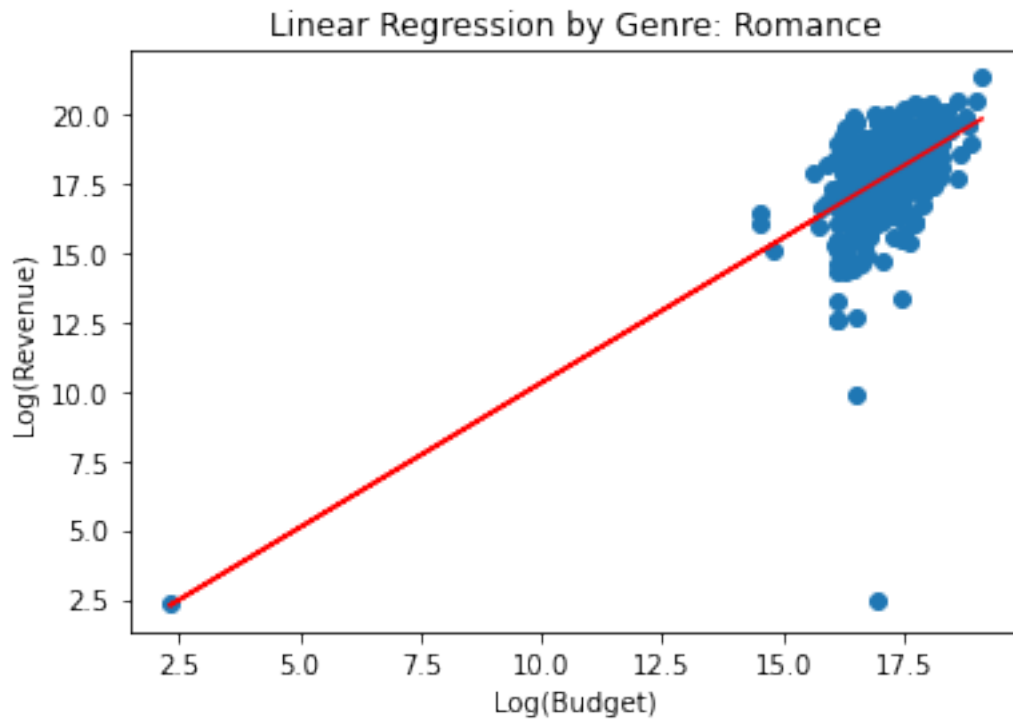
The Animation movie linear regression model is: Revenue = 0.9996253746508537 * Budget + 0.8440999753806153
Average MSE, for model #4: 3.195472169694911e+16
Average RMSE: 178.75883669611724 million



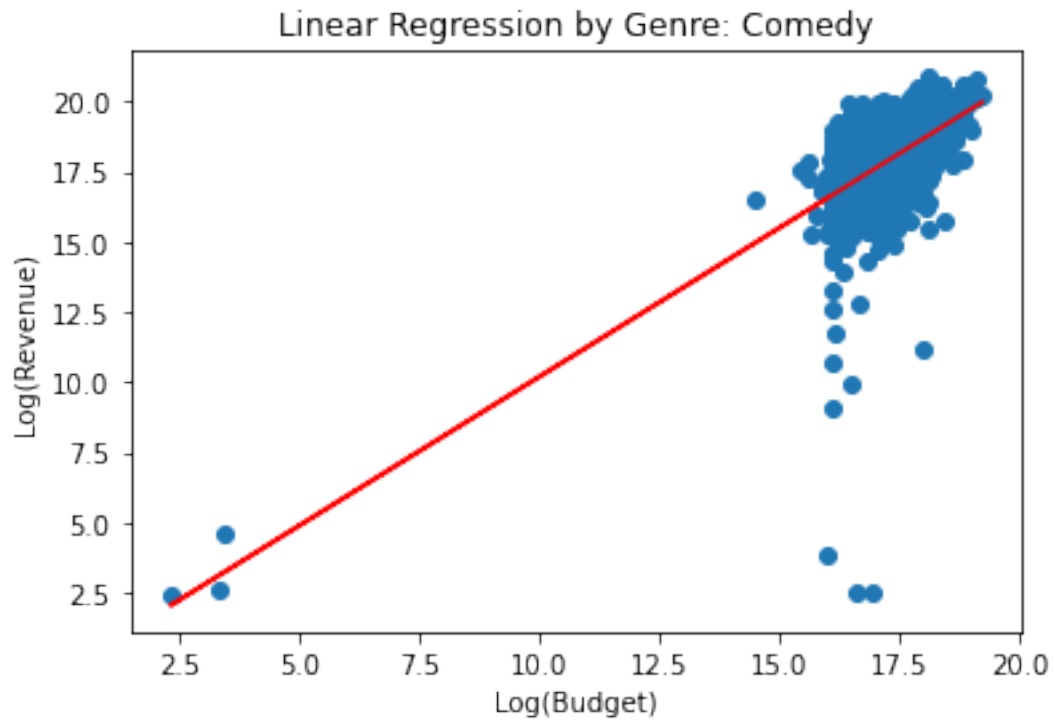
The Music movie linear regression model is: $\text{Revenue} = 0.999738134287128 * \text{Budget} + 0.6080134153163286$
Average MSE, for model #4: $3.195390471400805e+16$
Average RMSE: 178.756551527512 million



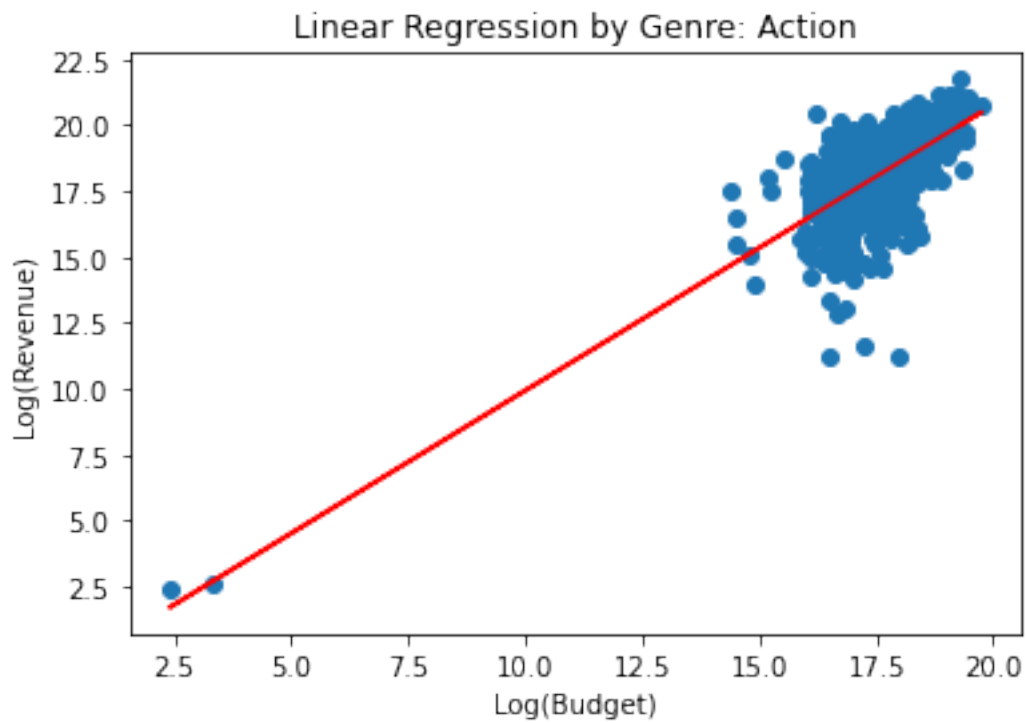
The Family movie linear regression model is: $\text{Revenue} = 0.9822522774321161 * \text{Budget} + 1.1175693113031606$
Average MSE, for model #4: $3.203846693194387e+16$
Average RMSE: 178.9929242510549 million



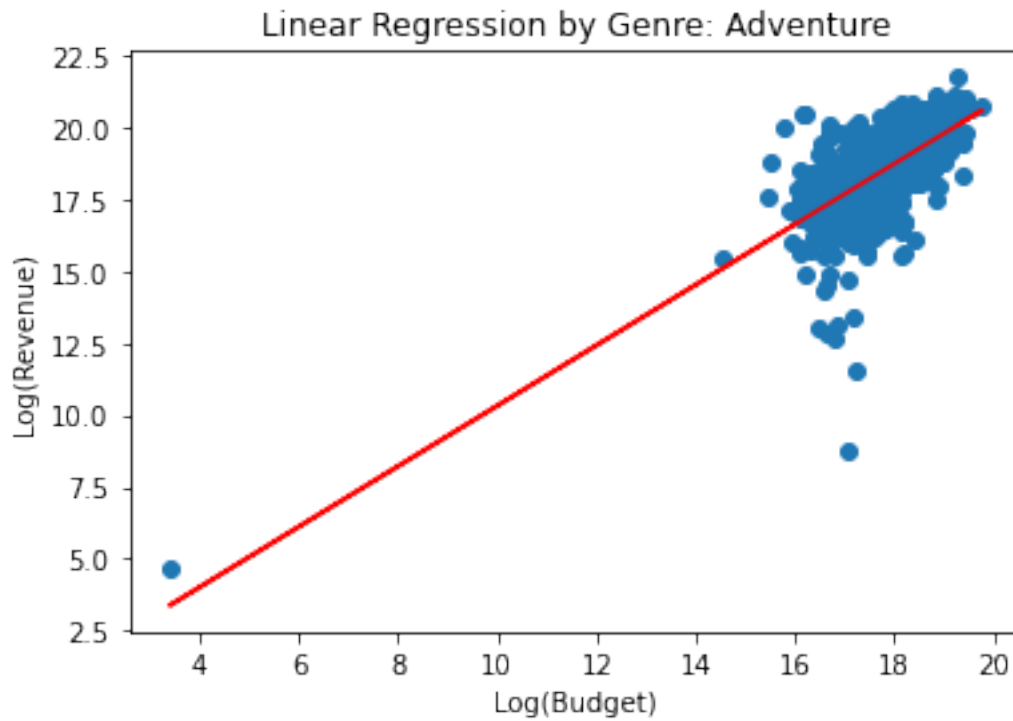
The Romance movie linear regression model is: $\text{Revenue} = 1.0444788139833783 * \text{Budget} + -0.13285509357041647$
Average MSE, for model #4: $3.185687955939429e+16$
Average RMSE: 178.4849561150583 million



The Comedy movie linear regression model is: $\text{Revenue} = 1.0603135683664549 * \text{Budget} + -0.4112974517280641$
Average MSE, for model #4: $3.17032607235656e+16$
Average RMSE: 178.05409493624572 million



The Action movie linear regression model is: $\text{Revenue} = 1.0833032120928778 * \text{Budget} + -0.9009172232818798$
Average MSE, for model #4: $3.1547353724129164e+16$
Average RMSE: 177.61574739906695 million



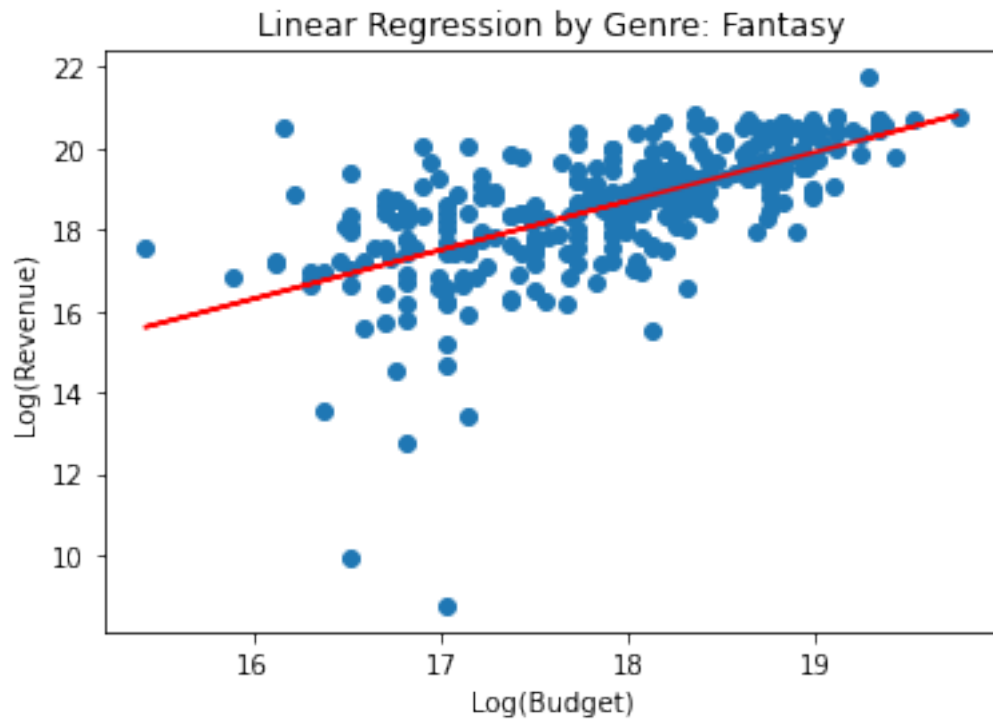
The Adventure movie linear regression model is: $\text{Revenue} = 1.052670509615493 * \text{Budget} + -0.2041529481709965$

Average MSE, for model #4: $3.1497210697909724e+16$

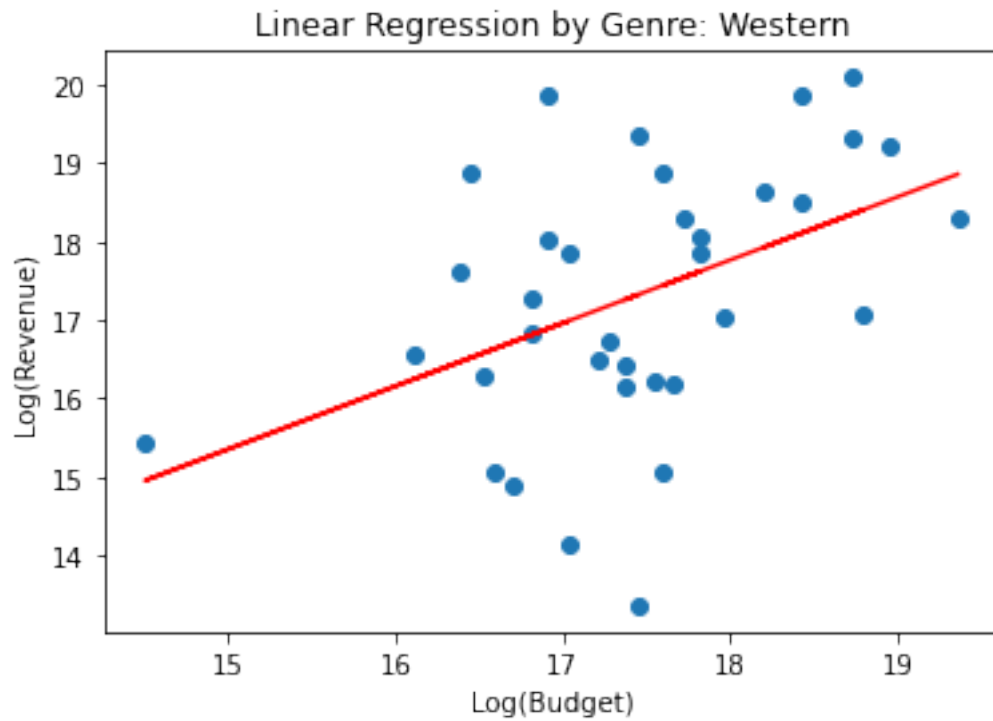
Average RMSE: 177.47453535059535 million

Average MSE, for model #4: $3.1497210697909724e+16$

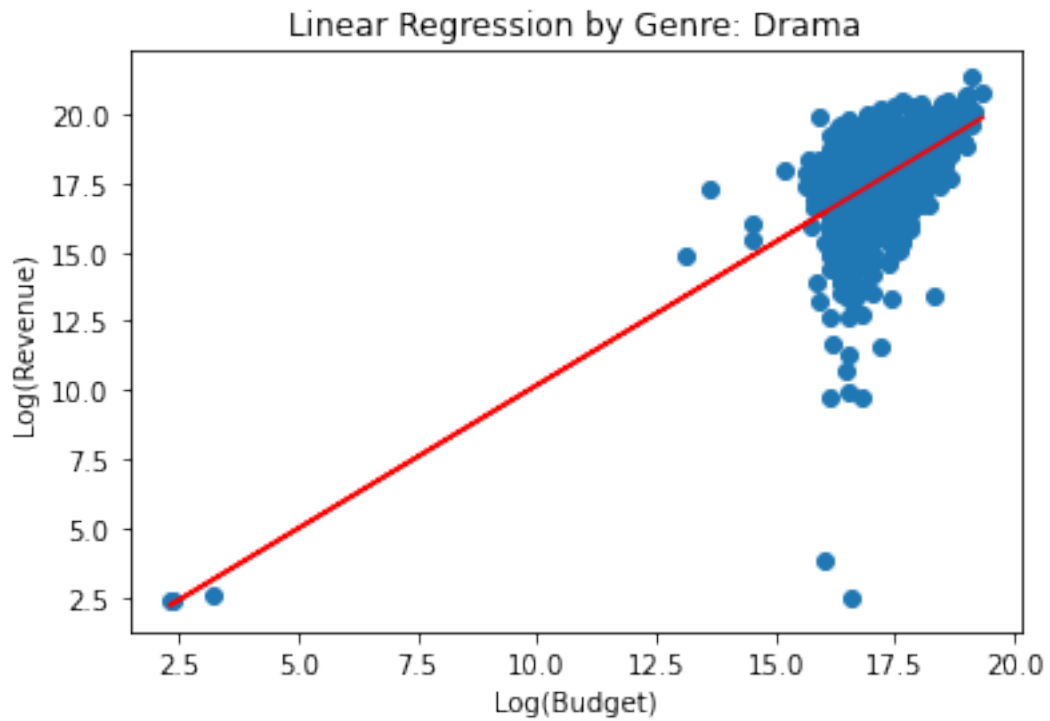
Average RMSE: 177.47453535059535 million



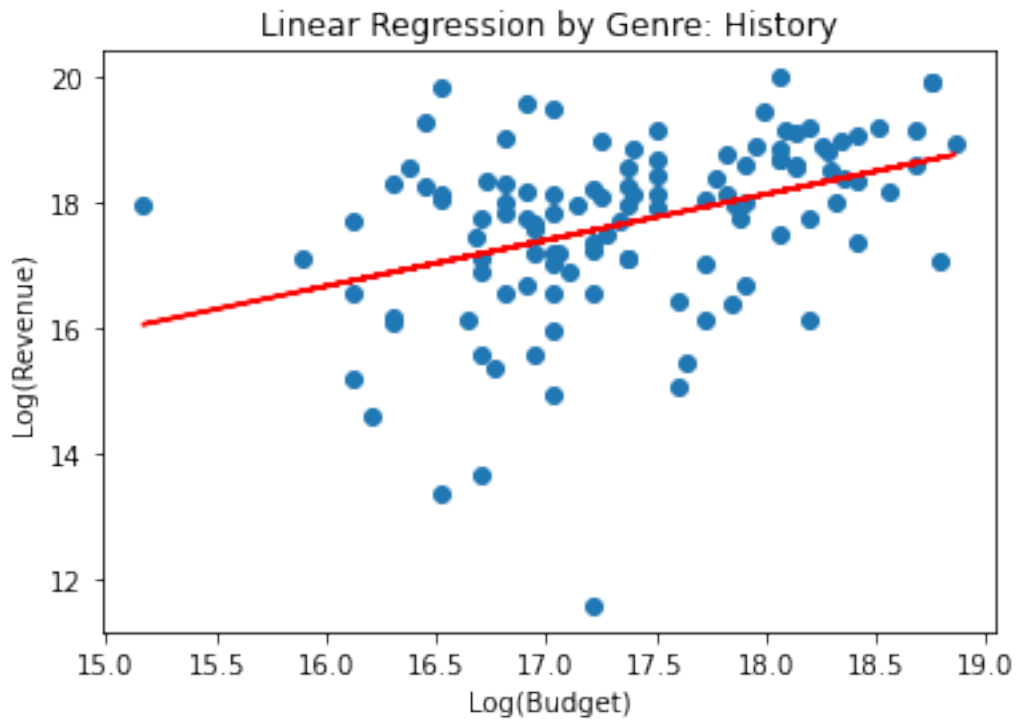
The Fantasy movie linear regression model is: $\text{Revenue} = 1.2045125377912622 * \text{Budget} + -2.974201891438412$
Average MSE, for model #4: $3.120252807395184e+16$
Average RMSE: 176.64237338179038 million



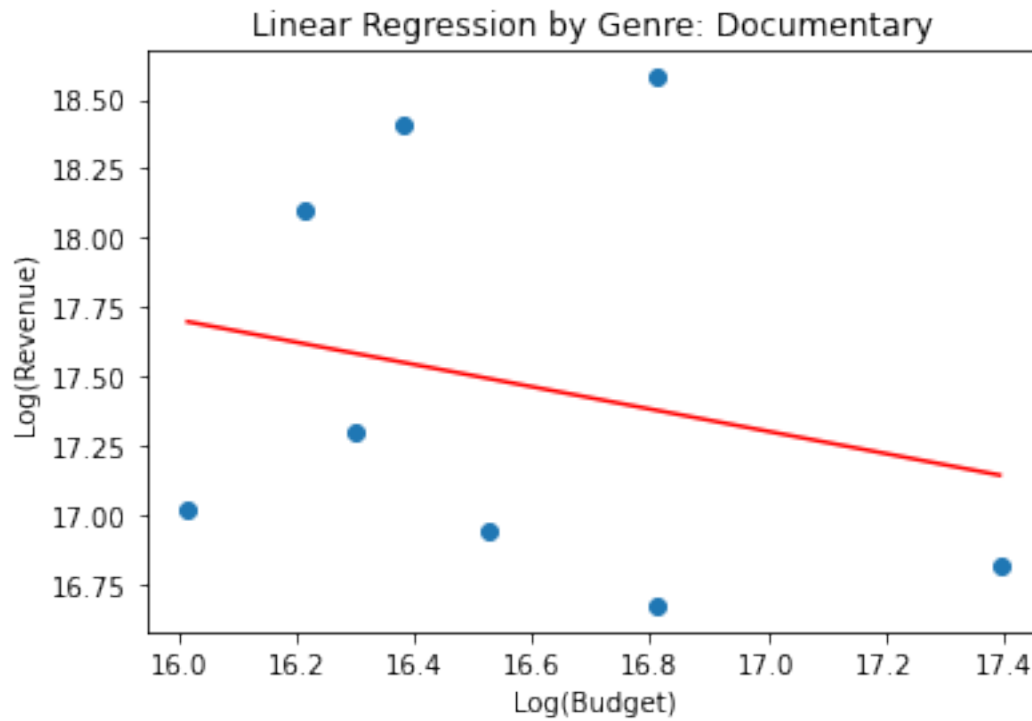
The Western movie linear regression model is: $\text{Revenue} = 0.8050776197153847 * \text{Budget} + 3.2734492825158608$
Average MSE, for model #4: $3.1614800209055576e+16$
Average RMSE: 177.80551231347013 million



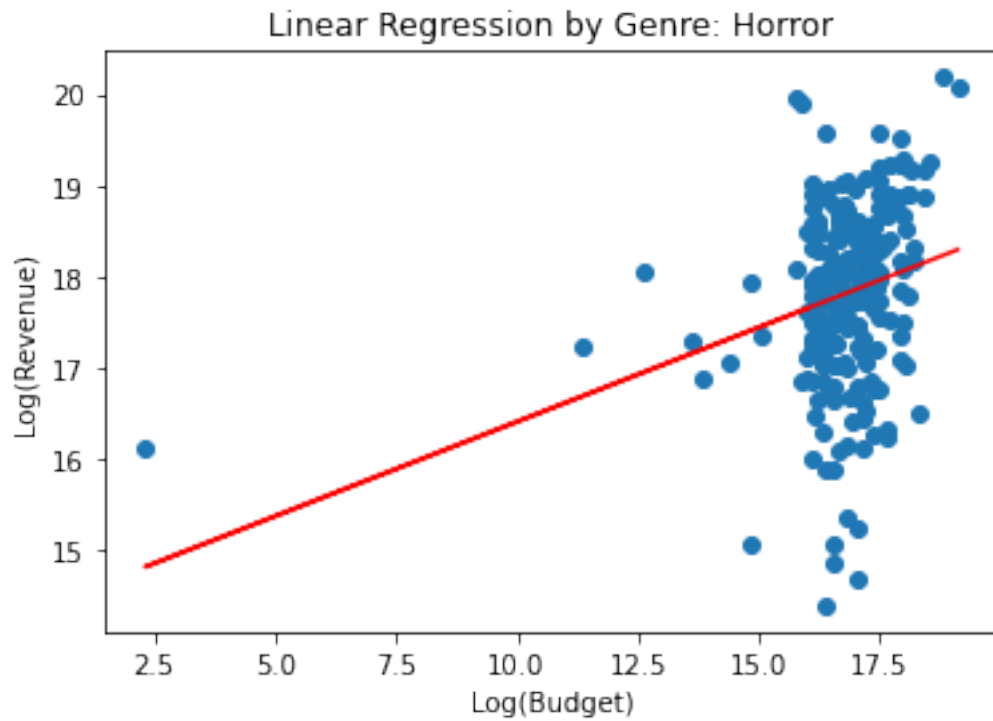
The Drama movie linear regression model is: $\text{Revenue} = 1.0374826098906231 * \text{Budget} + -0.19515802100759316$
Average MSE, for model #4: $3.159445797426479e+16$
Average RMSE: 177.74829949753328 million



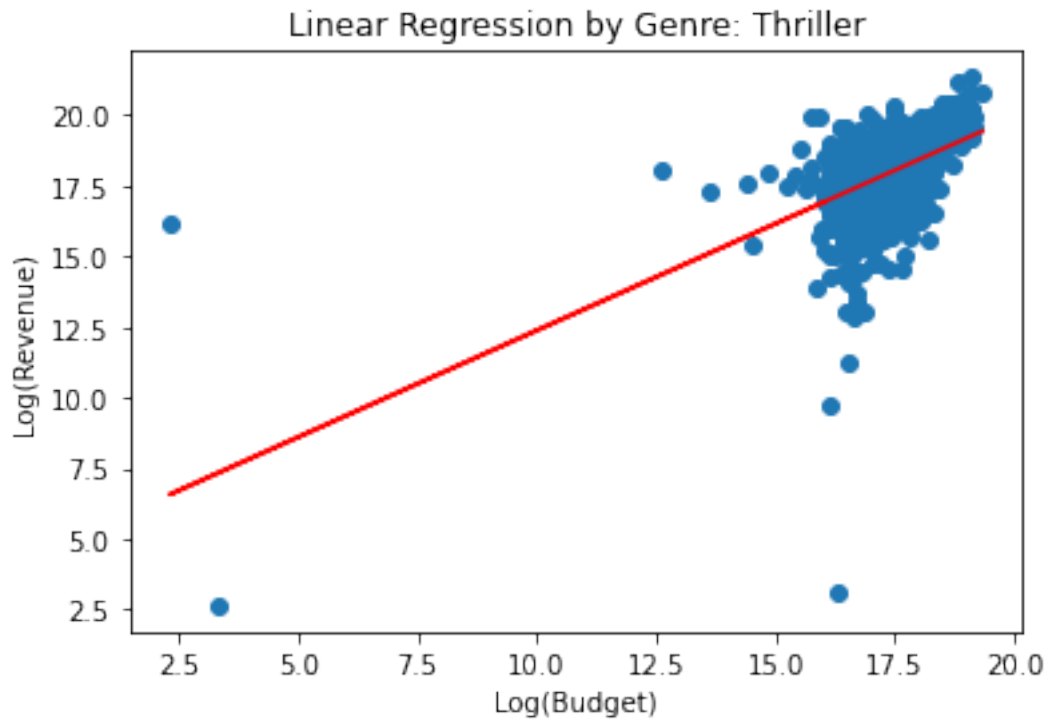
The History movie linear regression model is: $\text{Revenue} = 0.7306690597077001 * \text{Budget} + 4.980669121426153$
Average MSE, for model #4: $3.2005680266624012 \times 10^{16}$
Average RMSE: 178.9013143233554 million



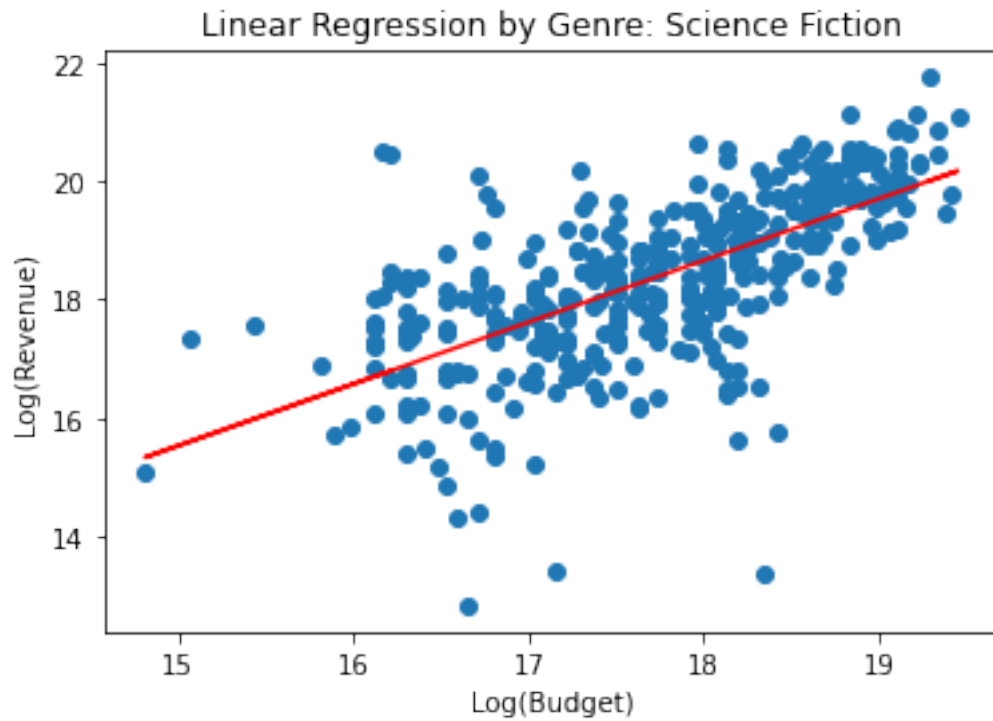
The Documentary movie linear regression model is: $\text{Revenue} = -0.40035544983285326 * \text{Budget} + 24.10859408985679$
Average MSE, for model #4: $3.429180221552374e+16$
Average RMSE: 185.18045851418486 million



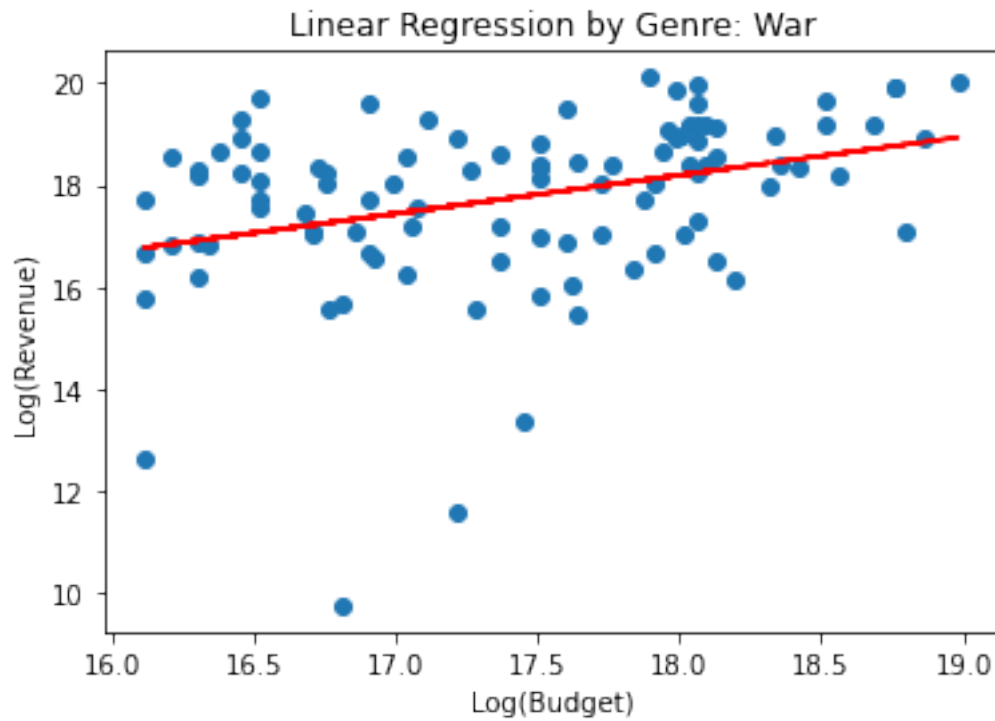
The Horror movie linear regression model is: $\text{Revenue} = 0.2069959942669641 * \text{Budget} + 14.340269563947485$
Average MSE, for model #4: $3.5173045578801536e+16$
Average RMSE: 187.5447828621248 million



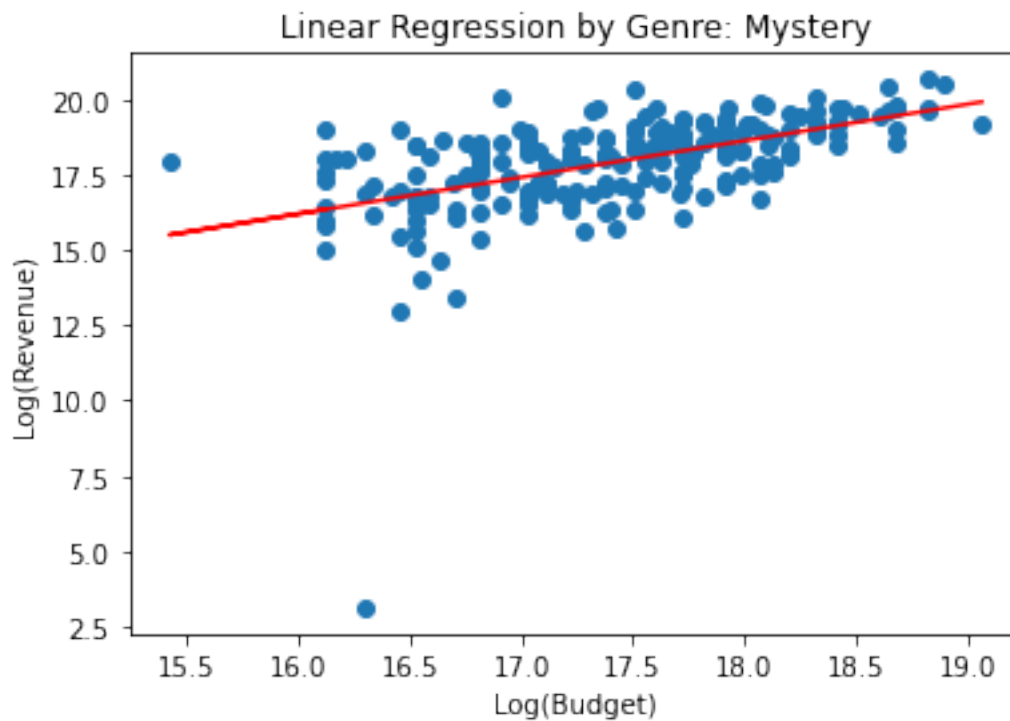
The Thriller movie linear regression model is: $\text{Revenue} = 0.7550352027182395 * \text{Budget} + 4.8258111787455995$
Average MSE, for model #4: $3.52120320164082e+16$
Average RMSE: 187.64869308473268 million



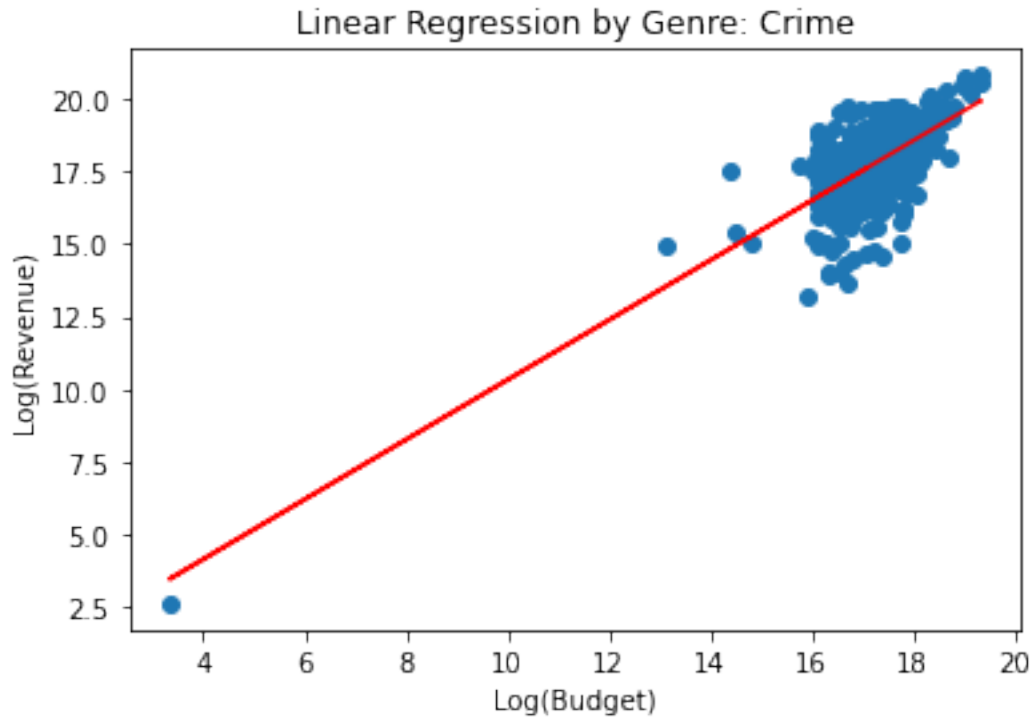
The Science Fiction movie linear regression model is: $\text{Revenue} = 1.0416826093657396 * \text{Budget} + -0.09309070378832018$
Average MSE, for model #4: $3.495467962669365e+16$
Average RMSE: 186.96170631092787 million



The War movie linear regression model is: $\text{Revenue} = 0.7533500753430058 * \text{Budget} + 4.632812389028199$
Average MSE, for model #4: $3.50041567095266e+16$
Average RMSE: 187.09397828237712 million



The Mystery movie linear regression model is: $\text{Revenue} = 1.2132649141311718 * \text{Budget} + -3.2207001264247346$
Average MSE, for model #4: $3.4652521933290148e+16$
Average RMSE: 186.15187867247042 million



The Crime movie linear regression model is: $\text{Revenue} = 1.0281119104877938 * \text{Budget} + 0.05093834362745042$

Average MSE, for model #4: $3.4479875722225756e+16$

Average RMSE: 185.687575573127 million

Average MSE across all genres is $3.467969939289863e+16$

Average RMSE across all genres is 191.2765974690189 million

Since we have so many genres, we loop through all key values of both dictionaries to plot the scatterplot as well as labeling both axes and the name of the plot. Additionally, we use the loop to calculate the MSE as well as the RMSE to visualize the accuracy of the models. As demonstrated by the above data, average MSE and average RMSE of each genre are about $1.86e+16$ and 140 million respectively. With this information and the information from other models, we can determine that the MSE and RMSE are mediocre to poor. To improve on this, one method can be to remove all outliers so the distance between predicted and actual values are less drastic, in other words resulting in smaller MSE and RMSE. Moreover, with this result, this is an example of a linear regression algorithm which sorts the data into categories to achieve a better idea of what the revenue would be like per genre since each genre's basis of revenue and budget is different. This is much like how splitting the demographic of an out of school income by major would give a better idea of how much a student is suppose to earn compared to an average for the entire school.

```

[46]: coef = []
intercept = []
MSE = []
sum_MSE = 0
sum_RMSE = 0

for g in unique_genre:
    # Gets all coordinates for x and y
    if(allX.get(g) and allY.get(g)):
        x = np.array(allX.get(g)).reshape((-1, 1))
        y = np.array(allY.get(g))
        # Creates LinearRegression object
        m4 = LinearRegression()
        m4.fit(x,y)
        # Creates regression line based off coordinates
        y_pred = m4.predict(x)
        pyplot.scatter(x,y)
        # Labels and organization
        pyplot.plot(x, y_pred, color="red")
        pyplot.xlabel("Log(Budget)")
        pyplot.ylabel("Log(Revenue)")
        title = "Linear Regression by Genre: " + g
        pyplot.title(title)
        pyplot.show()

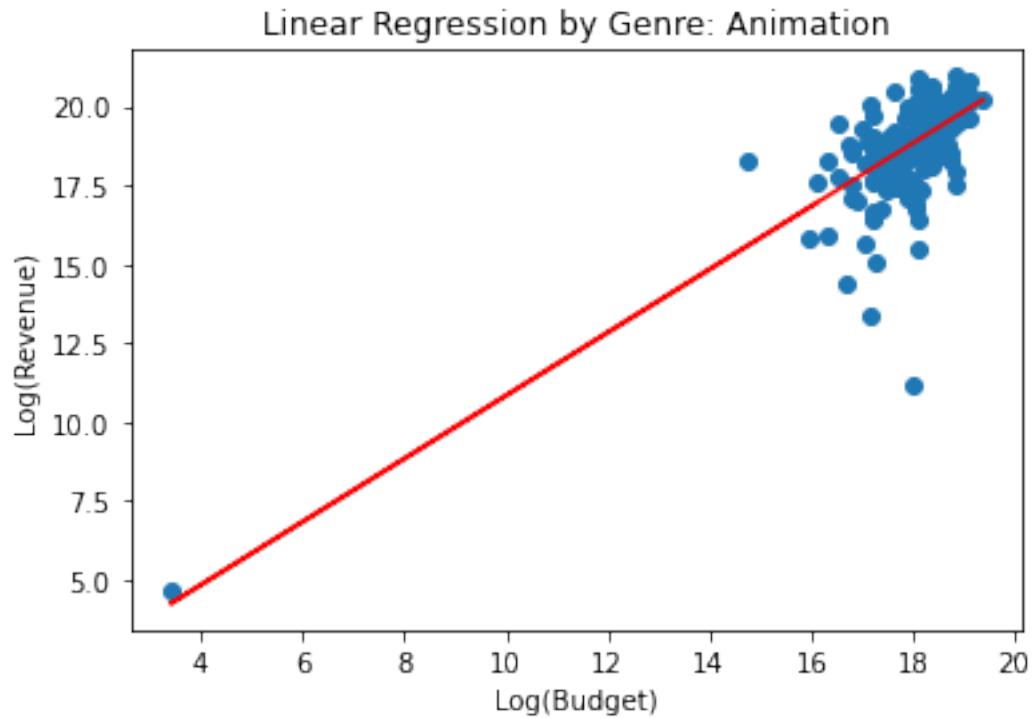
        # Applies cross-validation by splitting data
        kf = KFold(n_splits = 10, shuffle = True)
        for train_index, test_index in kf.split(data):
            train, test = train_test_split(data)
            m4 = m4.fit(train["budget"].to_numpy().reshape(-1, 1),
↪train["revenue"].to_numpy())
            coef.append(m4.coef_[0])
            intercept.append(m4.intercept_)
            predictions = m4.predict(test["budget"].to_numpy().reshape(-1, 1))
            MSE.append(np.mean((test["revenue"] - predictions) ** 2))
        m4coef_ = np.array([np.mean(coef)])
        m4intercept_ = np.mean(intercept)
        print("The " + g + " movie linear regression model is: Revenue = " +
↪str(m4.coef_[0]) + " * Budget + " + str(m4.intercept_))

        MSE_average = np.mean(MSE)
        print("Average MSE, for model #4:", MSE_average)
        print("Average RMSE:", MSE_average ** 0.5 / 1000000, 'million\n')
        sum_RMSE += MSE_average ** 0.5 / 1000000
        sum_MSE += MSE_average

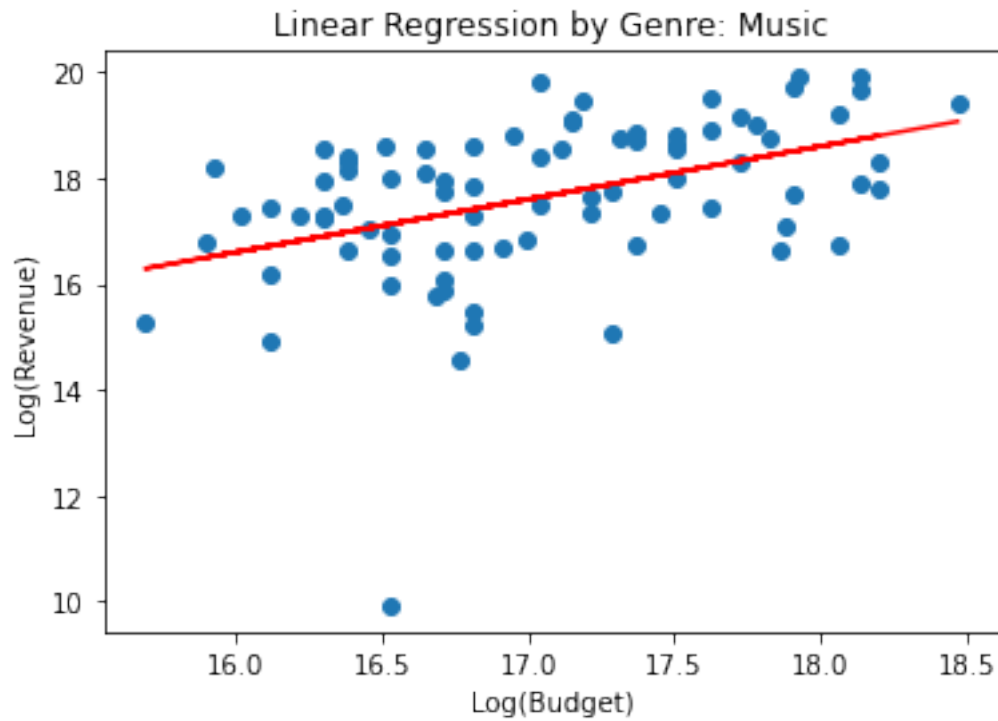
print("Average MSE across all genres is " +str(sum_MSE/len(allX)))

```

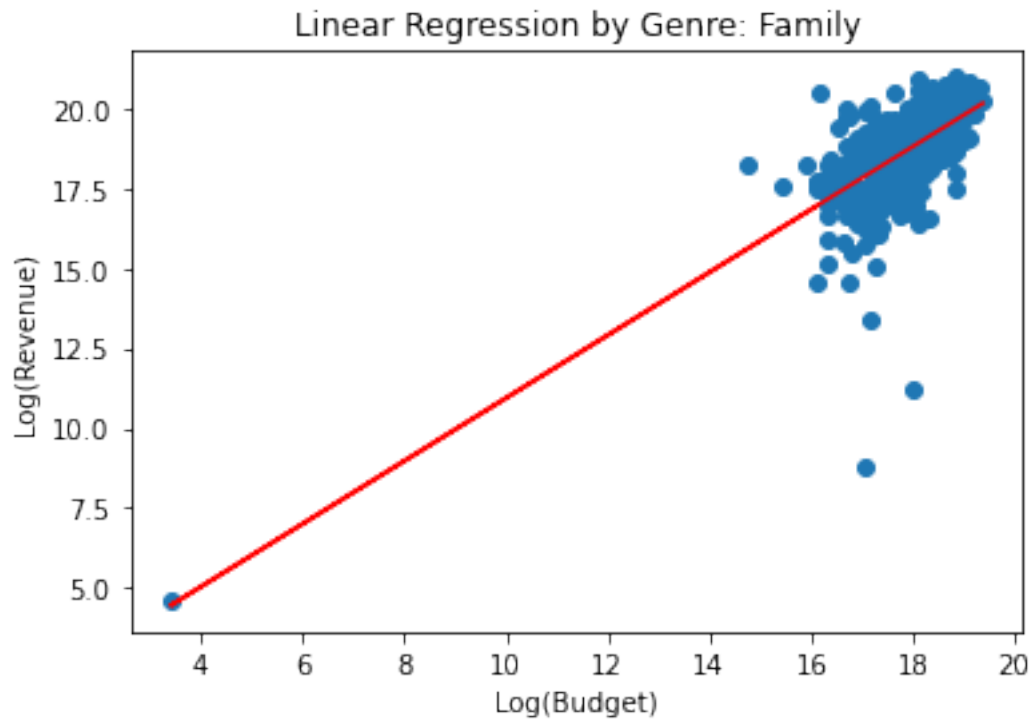
```
print("Average RMSE across all genres is " +str(sum_RMSE/len(allX)) + "␣  
↪million")
```



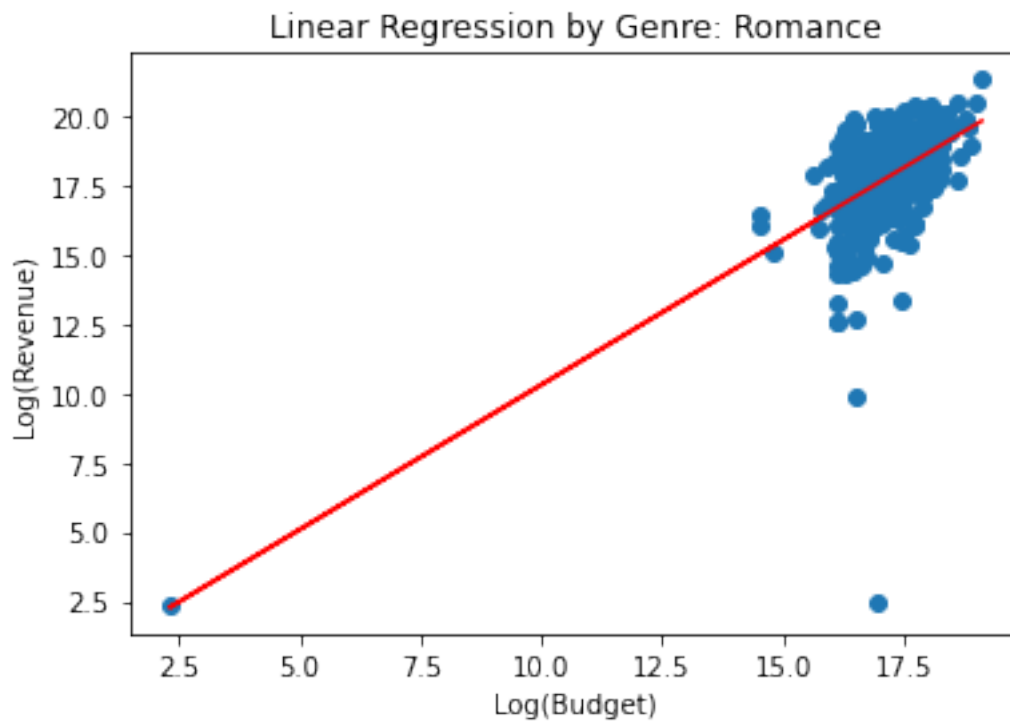
The Animation movie linear regression model is: $\text{Revenue} = 2.8637635365566276 * \text{Budget} + 3098560.186215684$
Average MSE, for model #4: $1.6993226590611046 \times 10^{16}$
Average RMSE: 130.35807067692835 million



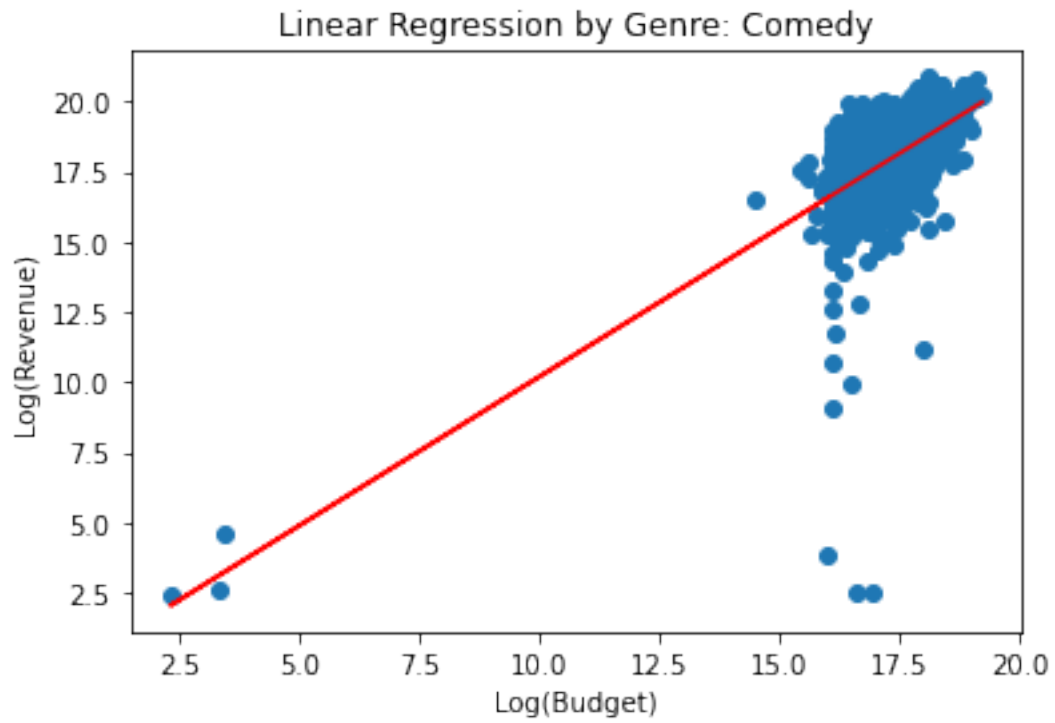
The Music movie linear regression model is: $\text{Revenue} = 3.0210554137341497 * \text{Budget} + -799255.1879631728$
Average MSE, for model #4: $1.635356376757887e+16$
Average RMSE: 127.88105320014716 million



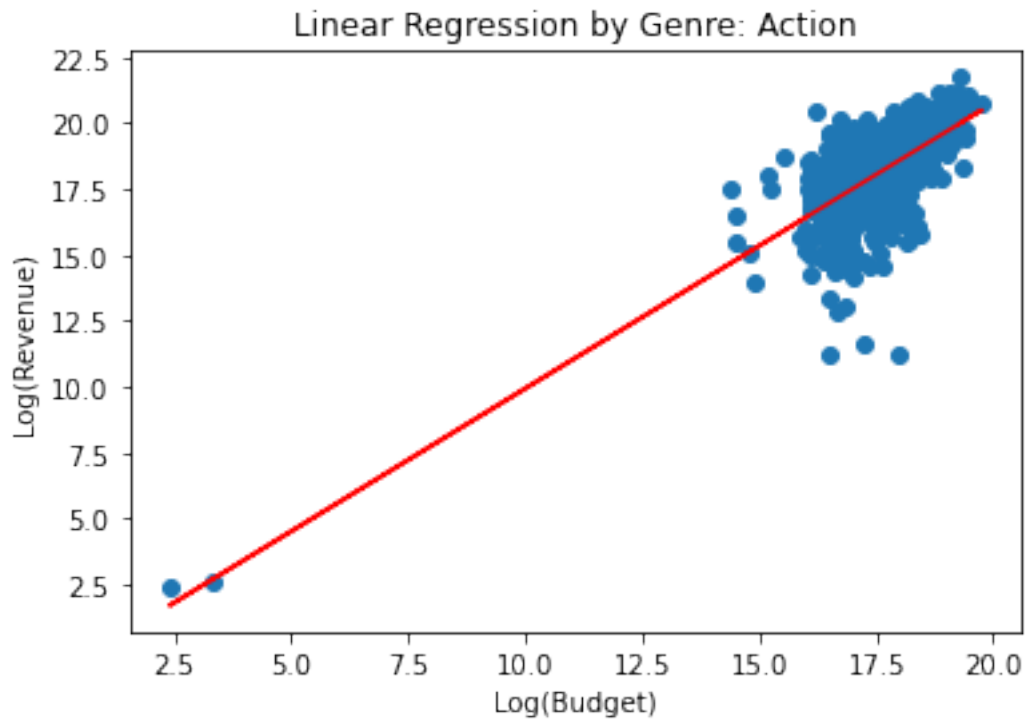
The Family movie linear regression model is: $\text{Revenue} = 3.0168631076545847 * \text{Budget} + -1063080.591673404$
Average MSE, for model #4: $1.6790654017291932e+16$
Average RMSE: 129.57875604161327 million



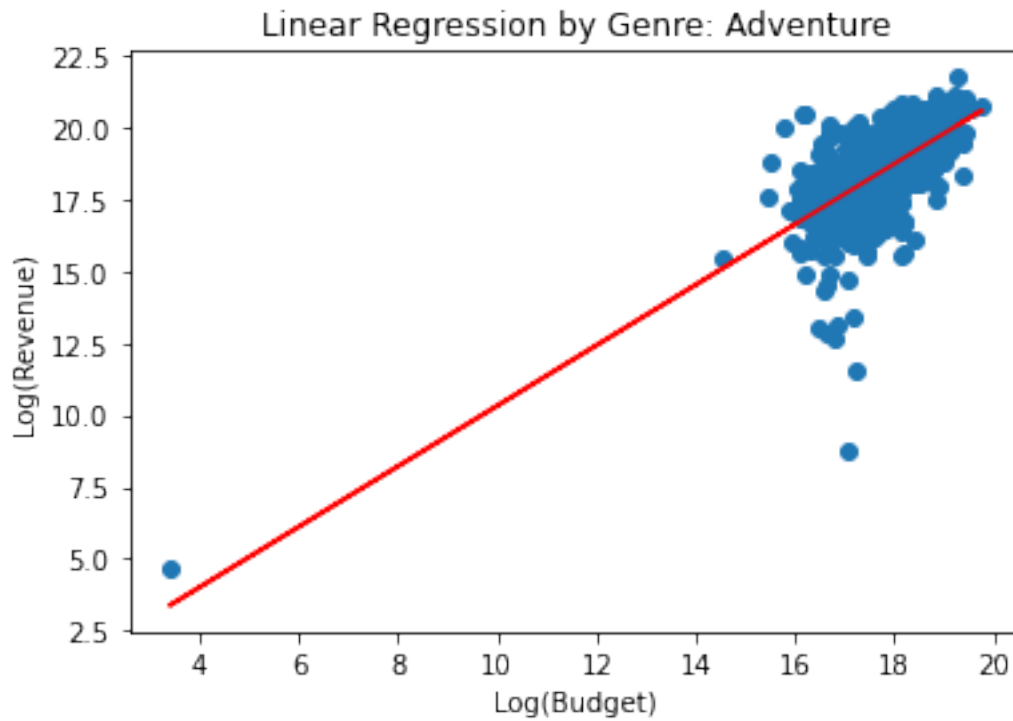
The Romance movie linear regression model is: $\text{Revenue} = 2.968707283130696 * \text{Budget} + 1179260.5576811433$
Average MSE, for model #4: $1.6933706202477676e+16$
Average RMSE: 130.129574664938 million



The Comedy movie linear regression model is: $\text{Revenue} = 2.956006875647089 * \text{Budget} + 2468763.8328278065$
Average MSE, for model #4: $1.6918827347771438e+16$
Average RMSE: 130.0723927194831 million



The Action movie linear regression model is: $\text{Revenue} = 3.010564135716209 * \text{Budget} + -166689.70156021416$
Average MSE, for model #4: $1.7034759186696102e+16$
Average RMSE: 130.51727543392906 million



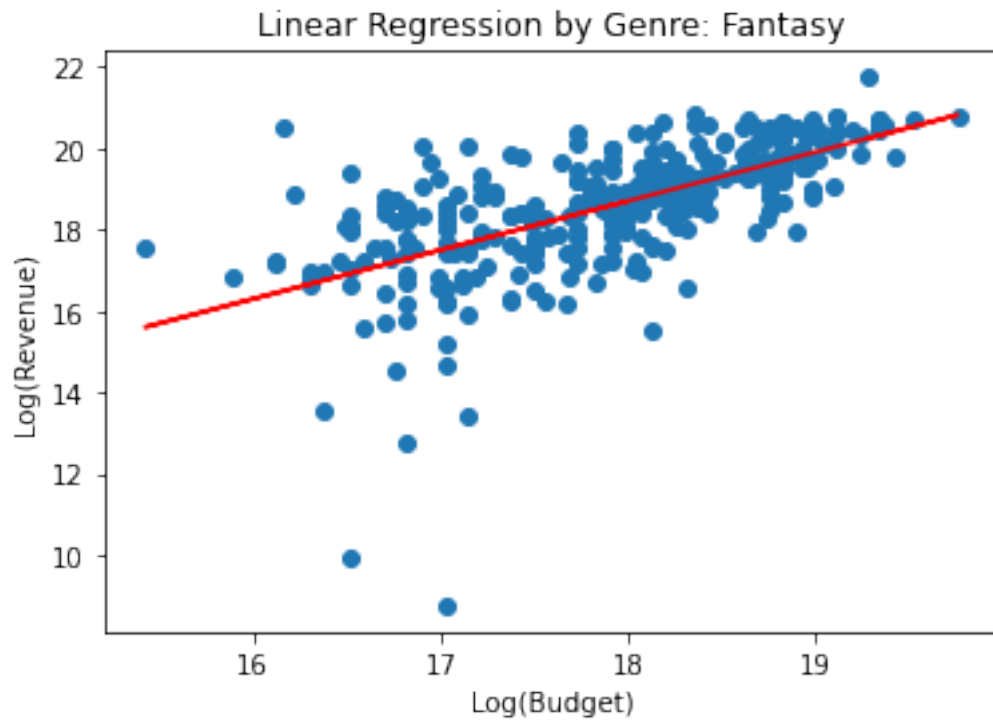
The Adventure movie linear regression model is: $\text{Revenue} = 2.9120650753473956 * \text{Budget} + 1987302.8563117683$

Average MSE, for model #4: $1.7323807536909798e+16$

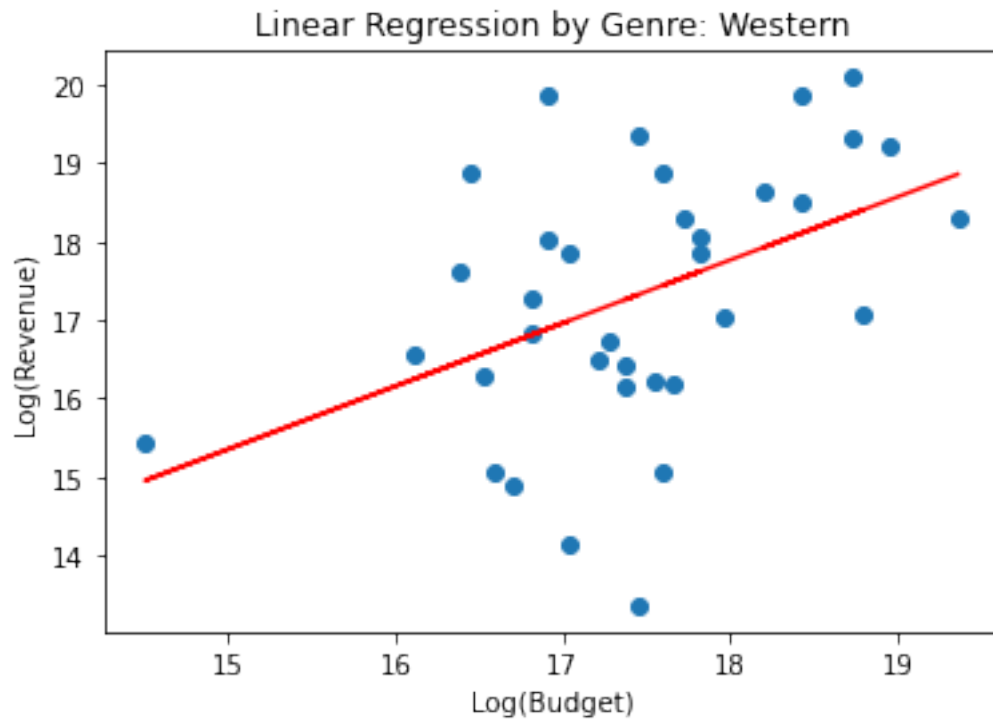
Average RMSE: 131.6199359402283 million

Average MSE, for model #4: $1.7323807536909798e+16$

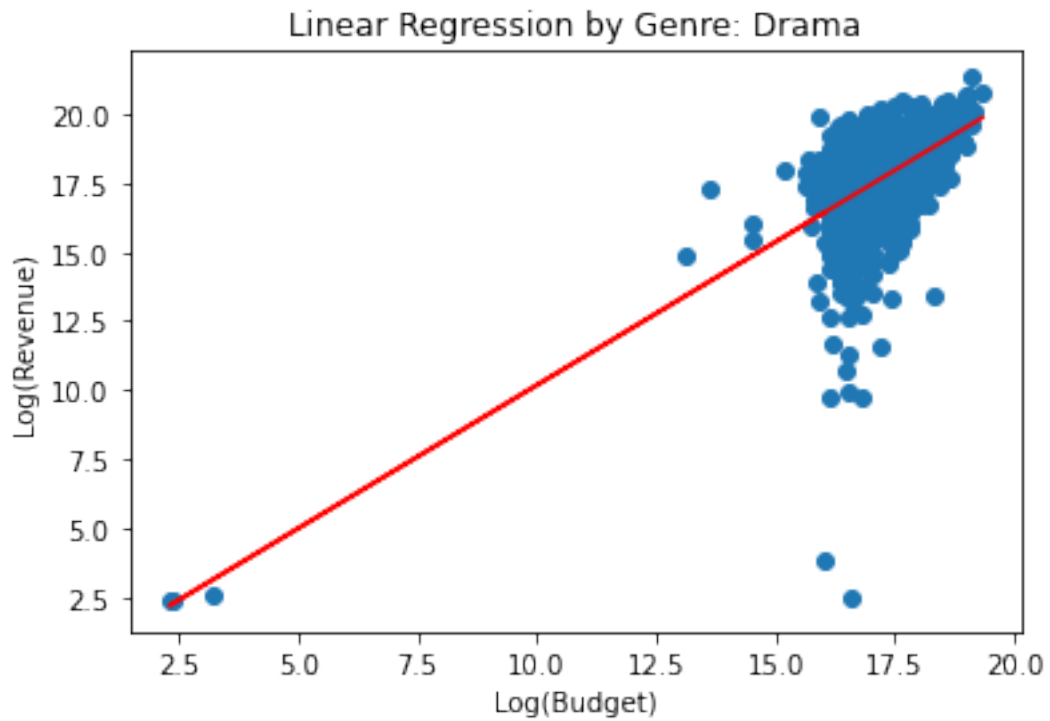
Average RMSE: 131.6199359402283 million



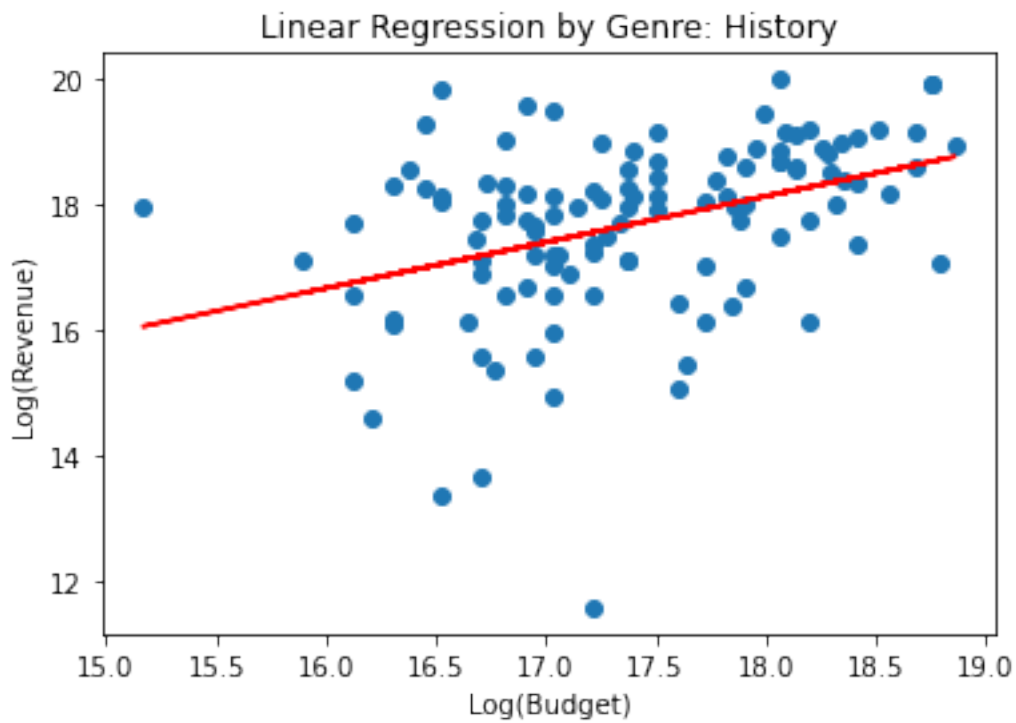
The Fantasy movie linear regression model is: $\text{Revenue} = 2.9708051727239884 * \text{Budget} + 1203317.747117594$
Average MSE, for model #4: $1.7350676889483732e+16$
Average RMSE: 131.72196813547743 million



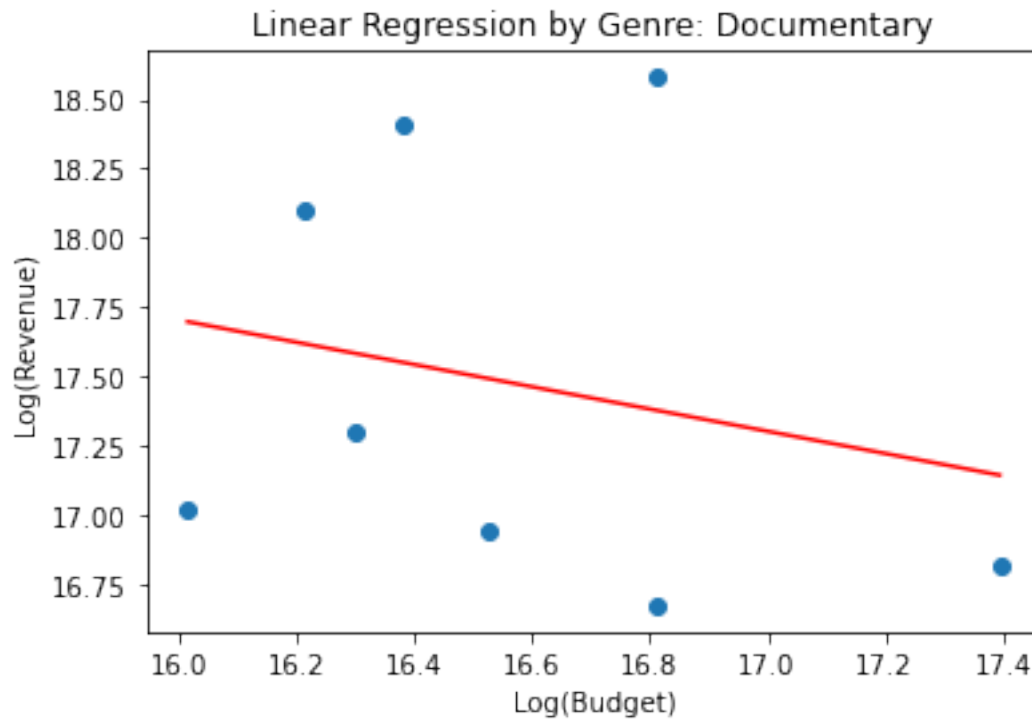
The Western movie linear regression model is: $\text{Revenue} = 2.926058396597216 * \text{Budget} + 1347649.497195825$
Average MSE, for model #4: $1.7370247110030754 \times 10^{16}$
Average RMSE: 131.79623329227113 million



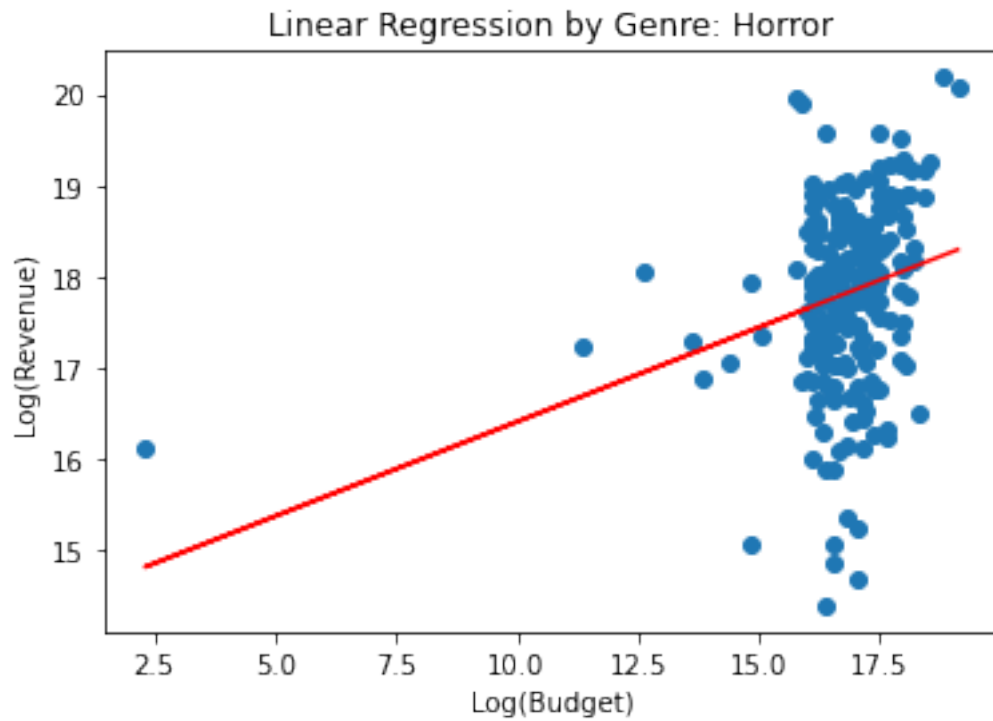
The Drama movie linear regression model is: $\text{Revenue} = 2.8945770539482534 * \text{Budget} + 4471614.5070246905$
Average MSE, for model #4: $1.7417824419012764e+16$
Average RMSE: 131.97660557467285 million



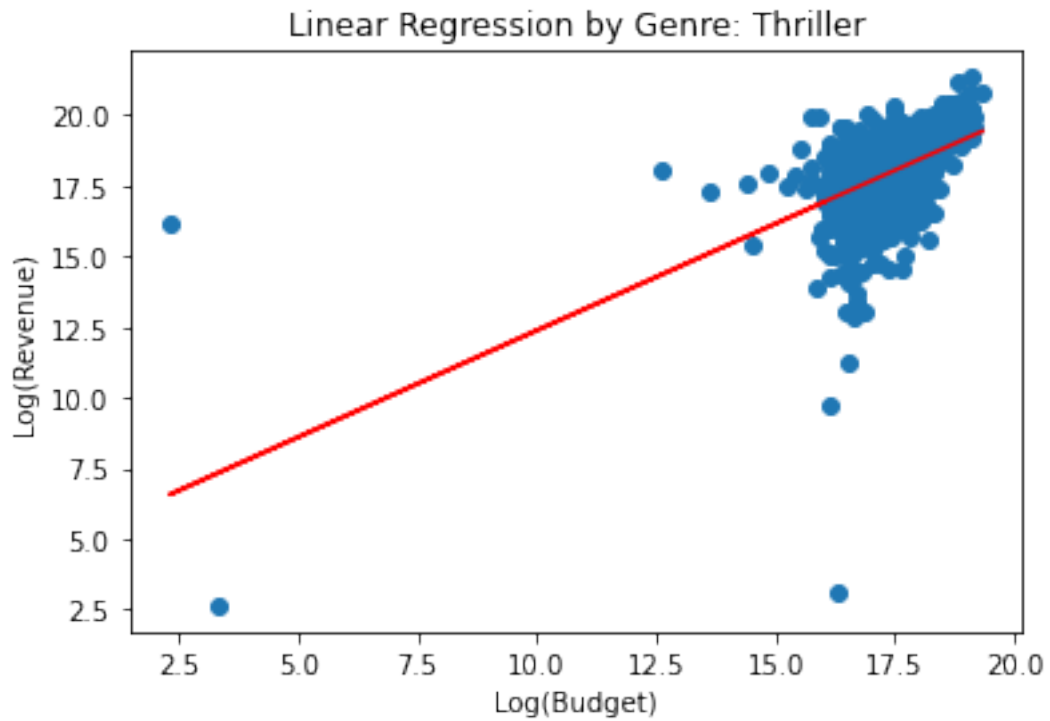
The History movie linear regression model is: $\text{Revenue} = 2.85357520998209 * \text{Budget} + 3242229.65944688$
Average MSE, for model #4: $1.7438709903074764e+16$
Average RMSE: 132.05570757477605 million



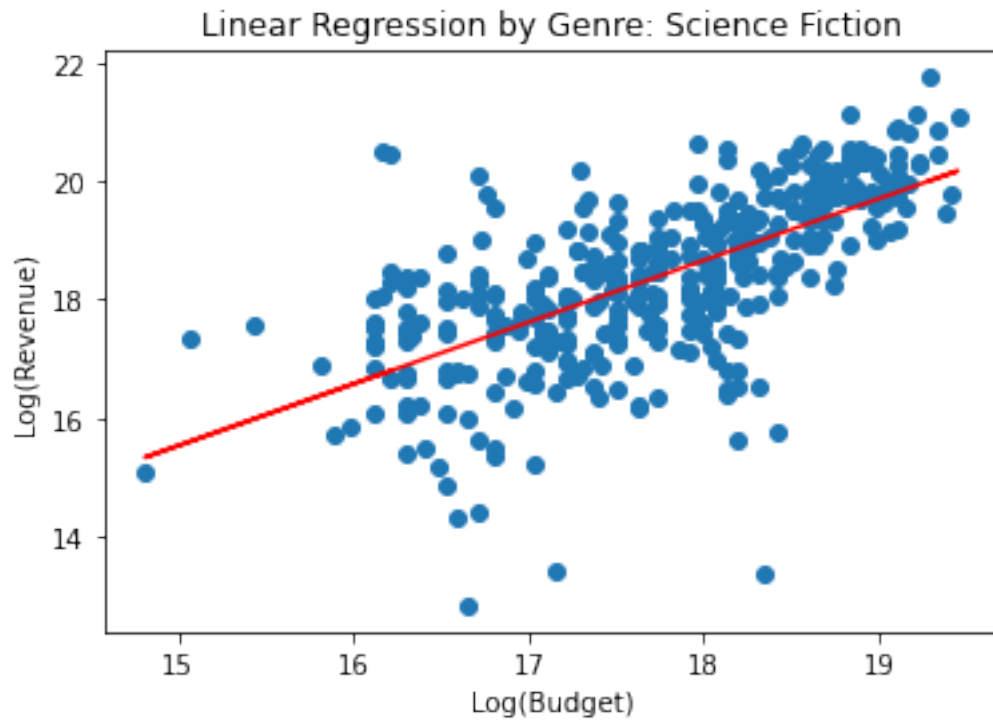
The Documentary movie linear regression model is: $\text{Revenue} = 2.8609469964996066 * \text{Budget} + 4541362.440034643$
Average MSE, for model #4: $1.7538407446663342e+16$
Average RMSE: 132.43265249425212 million



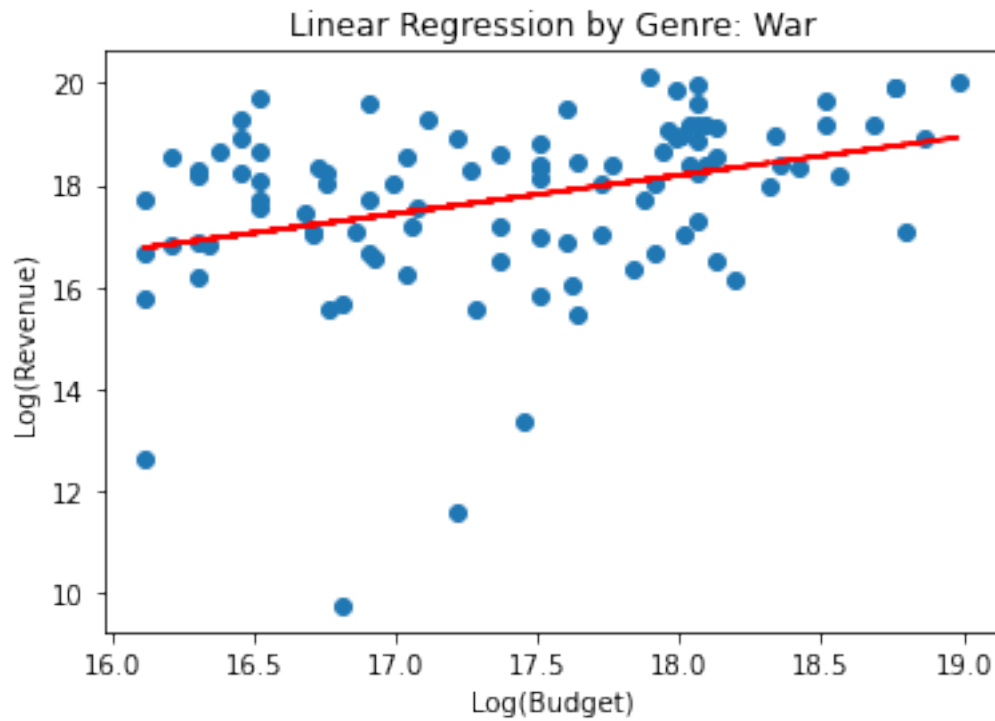
The Horror movie linear regression model is: $\text{Revenue} = 2.9513514860145427 * \text{Budget} + 3702741.271984011$
Average MSE, for model #4: $1.7410590618203186e+16$
Average RMSE: 131.94919711086985 million



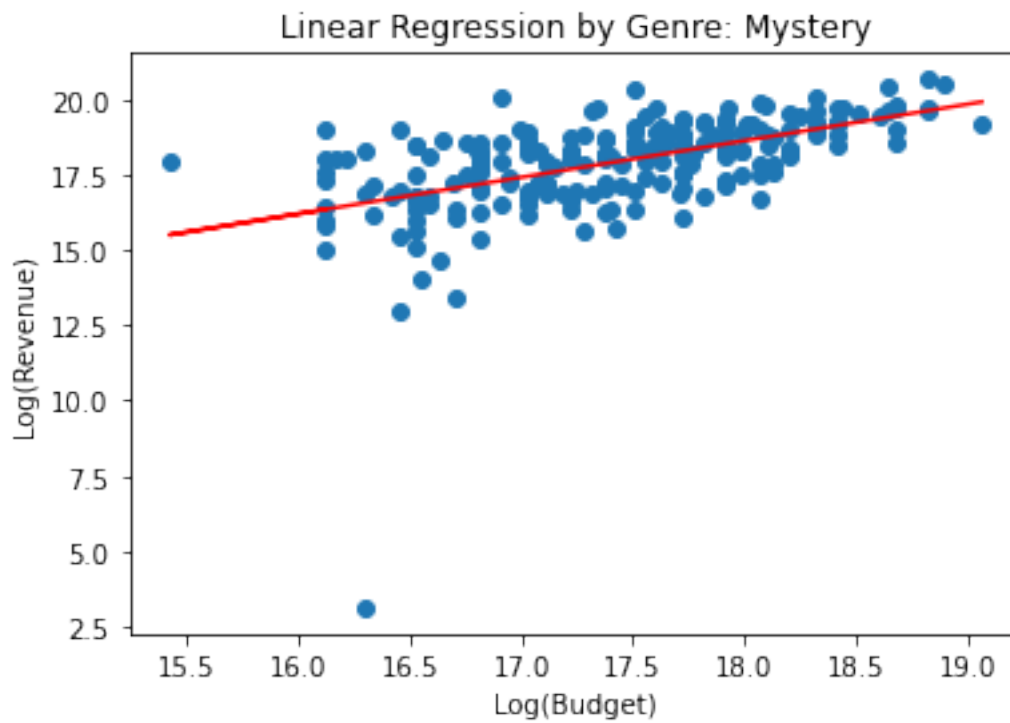
The Thriller movie linear regression model is: $\text{Revenue} = 3.0103702779199484 * \text{Budget} + 1409821.0873937309$
Average MSE, for model #4: $1.7364205093111456e+16$
Average RMSE: 131.7733094868284 million



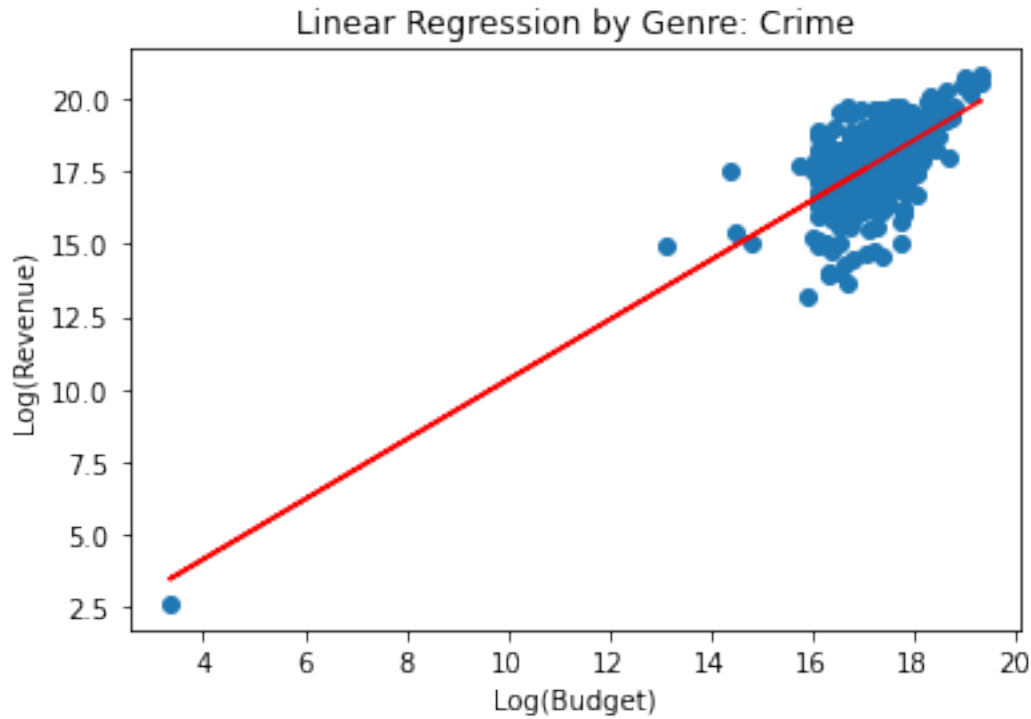
The Science Fiction movie linear regression model is: $\text{Revenue} = 2.9470690243017135 * \text{Budget} + 1416551.0724271983$
Average MSE, for model #4: $1.7381555446870426e+16$
Average RMSE: 131.83912714695293 million



The War movie linear regression model is: $\text{Revenue} = 3.0275604751890617 * \text{Budget} + -1084219.3206533939$
Average MSE, for model #4: $1.7356922222817196e+16$
Average RMSE: 131.74567250129013 million



The Mystery movie linear regression model is: $\text{Revenue} = 3.011859642641984 * \text{Budget} + -15542.013239726424$
Average MSE, for model #4: $1.734993791424026e+16$
Average RMSE: 131.71916304866298 million



The Crime movie linear regression model is: $\text{Revenue} = 2.906373692474324 * \text{Budget} + 3234639.4060617685$

Average MSE, for model #4: $1.736732000406586e+16$

Average RMSE: 131.78512815968978 million

Average MSE across all genres is $1.8167708291878908e+16$

Average RMSE across all genres is 138.47620884129108 million

Here we have cross-validation using the applications of k-folding. As a result of k-folding and cross validation, the average MSE and average RMSE has decreased slightly but not by much hence rendering this an unsuccessful alteration. The cross validation results to around $1.82e+16$ and 138 million respectively.