Nicholas De Santos

DSC 680

Final Project 1

Background/History and our Business Problem

```
Great films have always influenced society. And vise versa. Films
tell us a lot about the time in which they were
released. You see things like Godzilla which on surface level is just
a giant lizard terrorizing a city but in behind
the scenes you see a comment on the unfortunate horrors of the
attomic bomb attack against Japan. The event in turn
influenced a lot of Japenese film. Especially horror. This just goes
to show the power of movies. More importantly, the
power of understanding how audiences feel about certain movies.
Understanding what types of movies tend to be popular
among the public also shines a light on what interests people the
most. The purpose of this project is to investigate
what sort of attributes and features a major film could have that
would boost the film's ratings from its viewers.
```

Data Explanation (Data Prep, Data Dictionary, etc)

```
The data that we will be using a data set found on Kaggle.com titled
"IMDb 5000+ Movies & Multiple Genres Dataset".
This dataset has over 5000 different movie titles all containing
informating on the movie title, release year,
director, actors, ratings, runtime in minutes, censor rating, rotal
gross revenue, main genre and side genres
(G, 2022). Below are the descriptions for each of the varaibles in
the dataset.

'Movie_Title' : Consist of 5000+ Movie Titles (5000+ Unique Values)
'Year' : Ranging from 1920s to 2022 (99 Unique Values)
'Director' : Names the Director (2000+ Unique Values)
'Actors' : Names the Actors (5000+ Unique & Multiple Values)
'Rating' : Titles rated for 10 by 25k+ Voters (74+ Unique Values)
'main_genre' : Main Genre of the Title (13+ Unique Values)
'side_genre' : Side / Multiple Genre of the Movie (144+ Unique &
Multiple Values)
'Runtime(Mins)' : Total duration of the movie in Minutes (156+ Unique
Values)
'Censor' : Censorship of the Movie (25+ Unique Values)
```

```
'Total_Gross' : Total Box-Office Collection of the Movie (3500+
Unique Values)

Since the main goal of our investigation is to see what attributes
and features aare associated with more popular
films, we will use the user rating variable "Rating" as our target
variable when we get into our model building process.
```

Importing Data and Main Packages

```
Before we can begin to build our model we must first load our data. A
view of what the data looks like can be found
in the appendix at the end of this report. Our data will be saved
into a dataframe object 'movies'.
```

In [1]:

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

#Loading Data
movies = pd.read_csv('movies.csv')
movies = pd.DataFrame(movies)
original_data = movies
```

Examining and Cleaning Data

```
Once our data has been loaded and saved in a dataframe, we can start
examining the data more closely. Then we can
see what we need to do in order to clean and prepare the data for our
analysis.

The first thing that we did was we noticed that the total gross
revenue variable was not a numeric varaible so we
took just the numbers and then turned the column into a numeric
object. We can then check that the object conversion
was successful as well.
```

In [2]:

```
#Convert "Total_Gross" value to numerical variable
import re
movies['Total_Gross'] = movies['Total_Gross'].str.extract(r'(\d+\.\d+)')
movies['Total_Gross'] = pd.to_numeric(movies['Total_Gross'])
print(movies['Total_Gross'].dtype)
```

```
float64
```

```
In this next portion of the code we want to see all the different
unique values for each of the categorical
variables. This helps us decide to exclude the director variable
later on in our model building process due to too many
unique values. It no longer served as a category and was deemed
unecessary in the model building process as well. It
```

can also be useful in pointing out errors/misspelled strings in the categorical data.

In [3]:
```
#Unique Values for Director
print(movies['Director'].value_counts())
```

```
Director
Woody Allen                                                        40
Clint Eastwood                                                     32
Steven Spielberg                                                   28
Ron Howard                                                         24
Steven Soderbergh                                                  23
                                                                   ..
Directors:Mike Judge, Mike de Seve, Brian Mulroney, Yvette Kaplan   1
Directors:Aaron Blaise, Robert Walker                               1
Stephen J. Anderson                                                 1
Directors:Byron Howard, Chris Williams                              1
Gökhan Gök                                                          1
Name: count, Length: 2320, dtype: int64
```

In [4]:
```
#Unique Values for Censor Rating
print(movies['Censor'].value_counts())
```

```
Censor
UA           1118
A            1101
U            1023
R             926
Not Rated     495
PG-13         405
18            136
PG            120
16             71
13             53
UA 16+         22
15+            18
7              17
UA 13+         12
G               9
(Banned)        8
UA 7+           7
12+             5
All             5
Unrated         4
U/A             2
18+             2
12              1
M/PG            1
NC-17           1
Name: count, dtype: int64
```

In [5]:
```
#Unique Values for Main Genre
print(movies['main_genre'].value_counts())
```

```
main_genre
Action       1577
Comedy       1350
Drama        1027
Crime         447
Biography     355
Animation     321
Adventure     296
Horror        142
Mystery        26
Fantasy        13
Western         4
Film-Noir       3
Musical         1
Name: count, dtype: int64
```

```
In this portion of the code we are able to remove any duplicate rows
in our dataset, remove any missing values
within the dataset and removed both the actor, side genre and
director our of our dataset. We also do some renaming
of the columns within the dataset to make it easier to read and use
within the code. We can finally have a look at
what the final dataset looks like and move onto our data exploration
and analysis.
```

In [6]:
```
#Getting Rid of Duplicates: keeping first duplicate row
movies = movies.drop_duplicates()

#Getting Rid of Missing Value Rows: Based on NA values
movies = movies.dropna()

#Getting Rid of Actor and Side Genre columns
movies = movies.drop(columns=['side_genre'])
movies = movies.drop(columns=['Actors'])

#Renaming Columns
movies.rename(columns = {'Runtime(Mins)':'Runtime'}, inplace = True)
movies.rename(columns = {'Movie_Title':'Title'}, inplace = True)
movies.rename(columns = {'Total_Gross':'GrossRev'}, inplace = True)
movies.rename(columns = {'main_genre':'Genre'}, inplace = True)

movies
```

Out[6]:

	Title	Year	Director	Rating	Runtime	Censor	GrossRev	Genre
1	The Dark Knight	2008	Christopher Nolan	9.0	152	UA	534.86	Action
2	The Lord of the Rings: The Return of the King	2003	Peter Jackson	9.0	201	U	377.85	Action
3	Inception	2010	Christopher Nolan	8.8	148	UA	292.58	Action
4	The Lord of the Rings: The Two Towers	2002	Peter Jackson	8.8	179	UA	342.55	Action
5	The Lord of the Rings: The Fellowship of the Ring	2001	Peter Jackson	8.8	178	U	315.54	Action
...	...	...	...	...	...	...	...	...
5555	Son of the Mask	2005	Lawrence Guterman	2.2	94	U	17.02	Comedy
5557	Disaster Movie	2008	Directors:Jason Friedberg, Aaron Seltzer	1.9	87	PG-13	14.19	Comedy
5558	The Hottie & the Nottie	2008	Tom Putnam	1.9	91	PG-13	0.03	Comedy
5559	From Justin to Kelly	2003	Robert Iscove	1.9	81	PG	4.92	Comedy
5560	Superbabies: Baby Geniuses 2	2004	Bob Clark	1.5	88	PG	9.11	Comedy

4694 rows × 8 columns

Methods

```
Before getting into the model building process, we first conducted
some exploratory data analysis on our data to
investigate what kind of patterns and relationships we can find in
the data before we create a model. It is in this
state that we explored each varaible's relationship with our target
varaible, including categorical variables. The
purpose of those steps was to be able to give us a hint as to what
varaibles should or shouldn't be included in
the model building process as well as to shine a light on what
varaibles are most important in the model.

After our data exploration, we finally get into our model creation
process. Before we could use our data to train
a model we first had to convert all of our categorical varaibles to
dummy varaible in order to be used for linear
regression in the model building process.

We then split that new dataframe with dummy varaibles instead of
```

categorical varaibles into training and testing
sets of the original data. We built our model with the training
dataset and then later evaluated that model using
the RMSE value of our testing set compared to the model predictions.

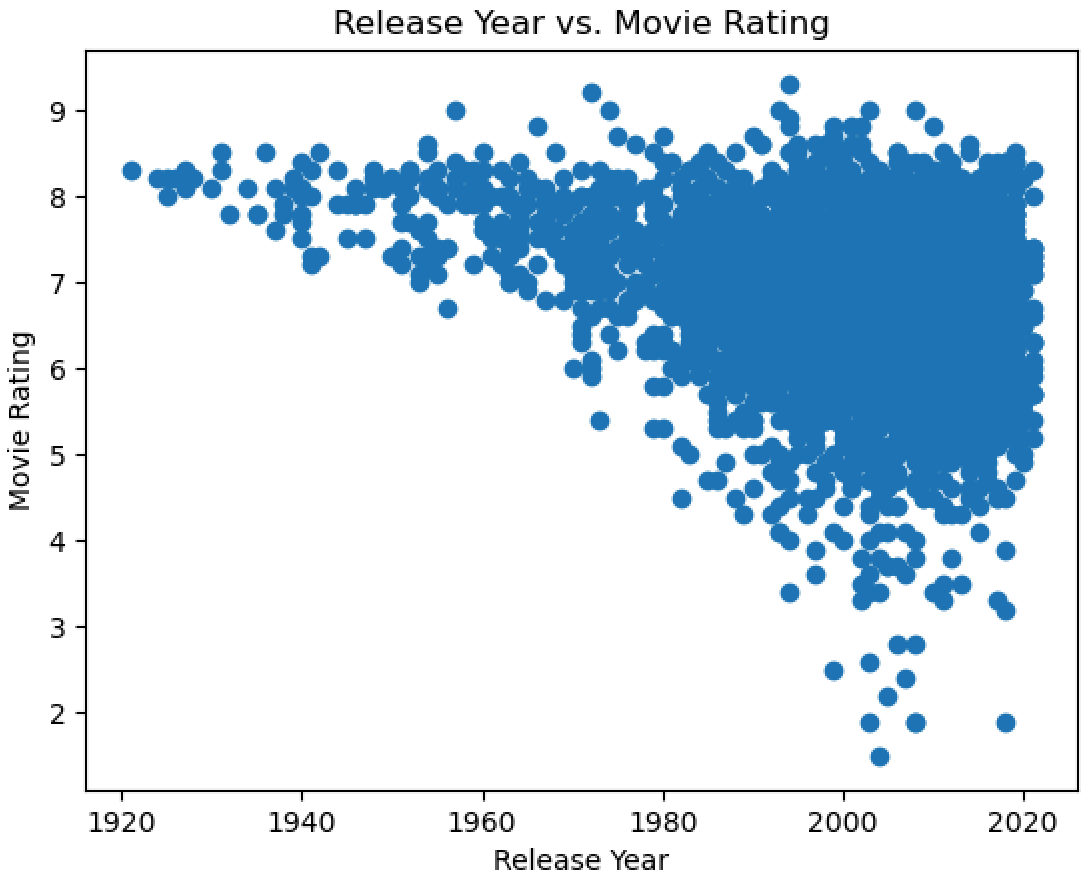
Analysis

Data Exploration

Next we move onto exploring any possible relationships between the
variables. To do so we look at both the scatter
plot graph of each variable along with our target variable "Rating"
along with the correlation coreficient between
those two variables.

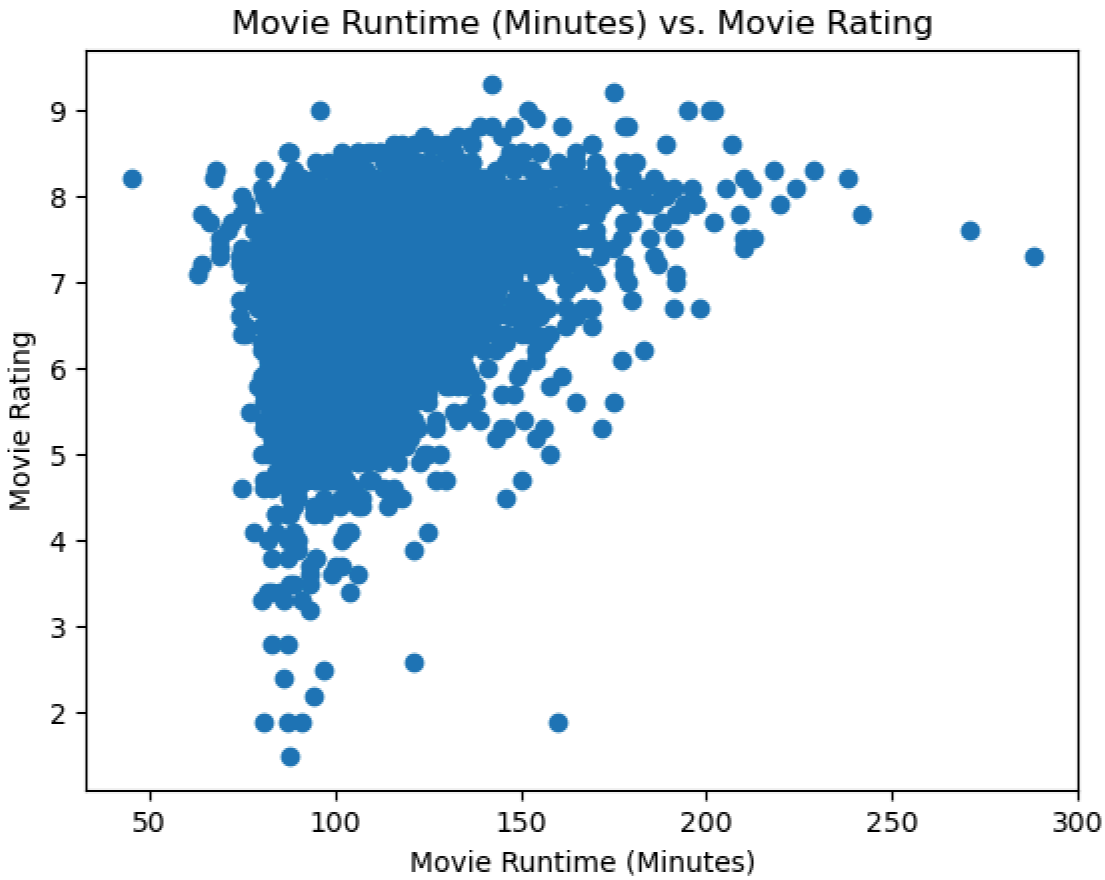
Numerical Varaibles

In [7]:
```
#Exploring Relationships: Year vs Rating

fig, ax = plt.subplots()
plt.scatter(movies.Year, movies.Rating)
plt.xlabel("Release Year")
plt.ylabel("Movie Rating")
plt.title("Release Year vs. Movie Rating")

plt.show()

import scipy.stats as stats

#correlation coefficient and PValue
correlation = stats.pearsonr(movies.Year, movies.Rating)
print(correlation)
```



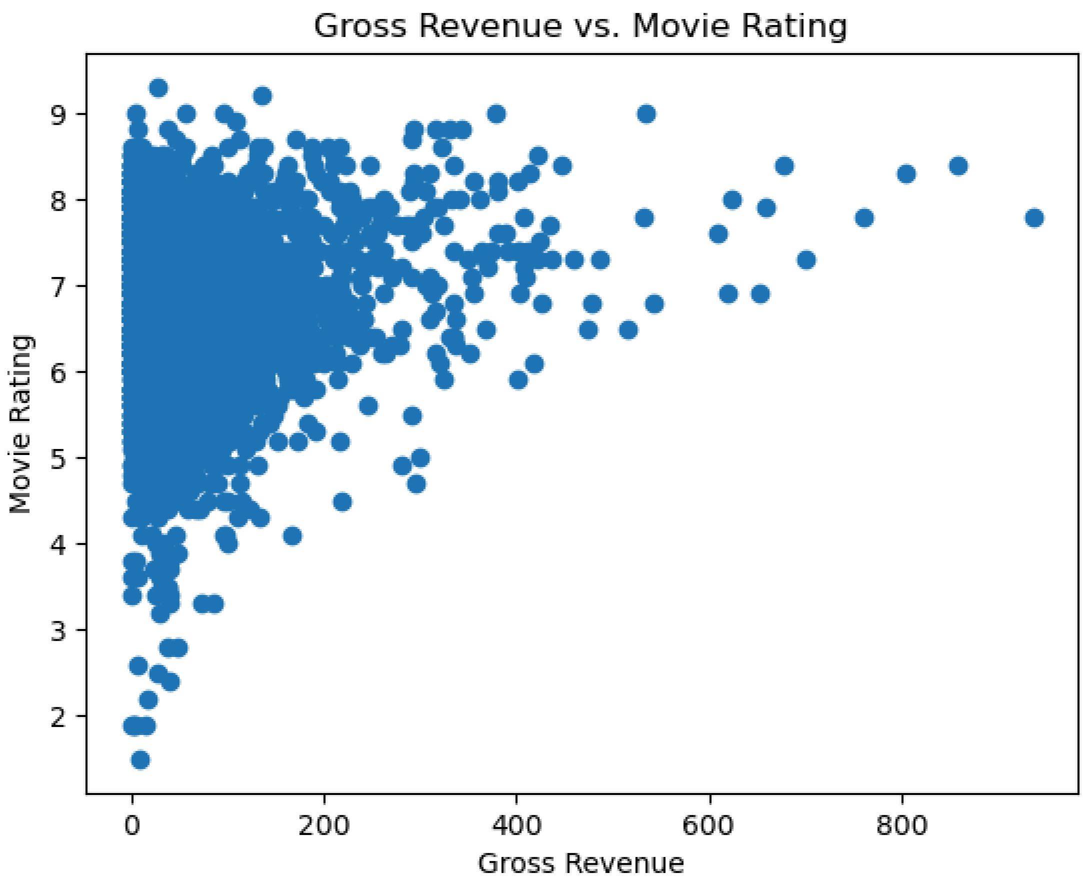

```
PearsonRResult(statistic=-0.2631474562741687, pvalue=3.3952118104659924e-75)
```

In [8]:
```
#Exploring Relationships: Runtime vs Rating

fig, ax = plt.subplots()
plt.scatter(movies.Runtime, movies.Rating)
plt.xlabel("Movie Runtime (Minutes)")
plt.ylabel("Movie Rating")
plt.title("Movie Runtime (Minutes) vs. Movie Rating")

plt.show()

#correlation coefficient and PValue
correlation = stats.pearsonr(movies.Runtime, movies.Rating)
print(correlation)
```




```
PearsonRResult(statistic=0.35976408087247, pvalue=1.944673821726563e-143)
```

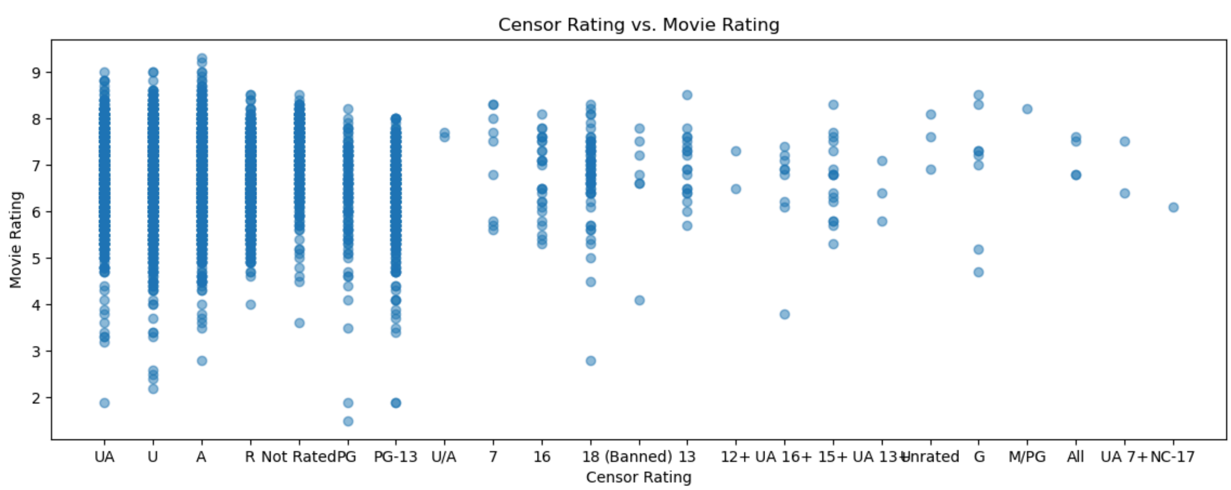
In [9]:
```
#Exploring Relationships: Year vs Rating

fig, ax = plt.subplots()
plt.scatter(movies.GrossRev, movies.Rating)
plt.xlabel("Gross Revenue")
plt.ylabel("Movie Rating")
plt.title("Gross Revenue vs. Movie Rating")

plt.show()

#correlation coefficient and PValue
correlation = stats.pearsonr(movies.GrossRev, movies.Rating)
print(correlation)
```



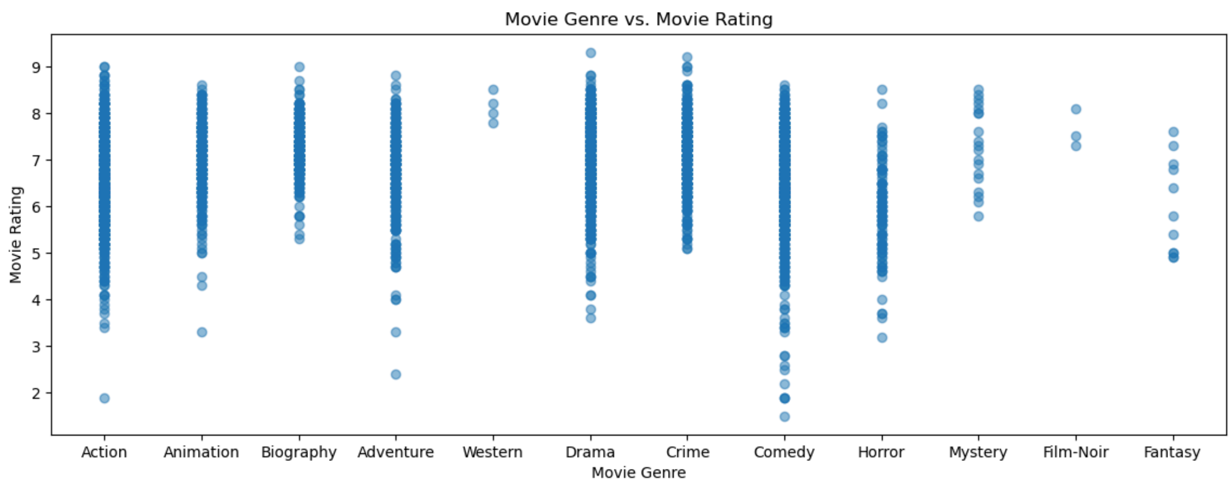

```
PearsonRResult(statistic=0.07276128277732986, pvalue=6.026534178753546e-07)
```

Categorical Varaibles

In [13]:
```python
#Exploring Relationships: Censor Rating vs Movie Rating

fig, ax = plt.subplots()
fig.set_figwidth(14)
plt.scatter(movies.Censor, movies.Rating, alpha = 0.5)
plt.xlabel("Censor Rating")
plt.ylabel("Movie Rating")
plt.title("Censor Rating vs. Movie Rating")

plt.show()
```



In [12]:
```
#Exploring Relationships: Genre vs Movie Rating

fig, ax = plt.subplots()
fig.set_figwidth(14)
plt.scatter(movies.Genre, movies.Rating, alpha = 0.5)
plt.xlabel("Movie Genre")
plt.ylabel("Movie Rating")
plt.title("Movie Genre vs. Movie Rating")

plt.show()
```



Model Creation and Testing

Finally, we get to our model building process in order to try and predict the viewer rating of a film. Before we start the process we first want to get the correct formatting and object types for model creation. We first start with turning our categorical variables into dummy varaibles that we can use for linear regression.

In [14]:
```
#Turn categorical varaibles to dummy varaibles for model creation process
moviemod = movies
from sklearn.preprocessing import LabelBinarizer

label_binarizer = LabelBinarizer()
label_binarizer_output = label_binarizer.fit_transform(moviemod['Censor'])
censord = pd.DataFrame(label_binarizer_output, columns = label_binarizer.classes_)

label_binarizer_output = label_binarizer.fit_transform(moviemod['Genre'])
genred = pd.DataFrame(label_binarizer_output, columns = label_binarizer.classes_)

moviemod = moviemod.drop(['Title', 'Director', 'Censor', 'Genre'], axis=1)
moviemod = pd.concat([moviemod, censord, genred], axis=1, join='inner')
moviemod
```

Out[14]:

	Year	Rating	Runtime	GrossRev	(Banned)	12+	13	15+	16	18	...	Animation	Biography
1	2008	9.0	152	534.86	0	0	0	0	0	0	...	0	0
2	2003	9.0	201	377.85	0	0	0	0	0	0	...	0	0
3	2010	8.8	148	292.58	0	0	0	0	0	0	...	0	0
4	2002	8.8	179	342.55	0	0	0	0	0	0	...	0	0
5	2001	8.8	178	315.54	0	0	0	0	0	0	...	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
4689	2003	6.1	92	36.92	0	0	0	0	0	0	...	0	0
4690	2002	6.1	117	9.68	0	0	0	0	0	0	...	0	0
4691	2001	6.1	109	13.73	0	0	0	0	0	0	...	0	0
4692	2000	6.1	103	37.17	0	0	0	0	0	0	...	0	0
4693	1999	6.1	122	22.36	0	0	0	0	0	0	...	0	0

3936 rows × 39 columns

```
Next we split our data into two different sets. The first set is the
trianing set that we will use to make our
model. The other set is the testing set. The testing set is used to
test the model's performance.
```

In [15]:
```python
#Splitting Training and Testing Sets

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

# get the locations
X = moviemod.drop(['Rating'], axis=1)
y = moviemod['Rating']

# split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.05, random_state
```

Results and Conclusion

In [16]:
```python
#Creating Linear Regression Model
import sklearn.metrics as metrics
from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

```
# RMSE
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
0.6971517528316209
```

As you can see, we used our training x variables of our data to create our model which later produced viewer rating predictions for the various attributes in our testing x variables. We then used those predictions and compared them to the actual target varaible values (y_test) and got an RMSE value of about 0.6972. The cut off of what is an "acceptable" RMSE value is typically 0.5 so you can see that we were close but not quite there. This might be a good reason to future the investigation and work on an improved model.

Assumptions

For our data we assume that the information about the films listed in the dataset are completely accurate and up to date as far as the documentation states in the Kaggle description. We also assume all the necessary assumtion to use linear regression in our model building process. The assumptions include the assumption that the chosen sample is representative of the population. The assmtion that there is a linear relationship between the independent variable(s) and the dependent variable. And the assumption that all the variables are normally distributed.

Limitations

Some limitations to this project and investigation was the data that we were able to use, the time given to hold the investigation and get our results, and our technical skills with Python as a programming language.

Challenges

The main challenges that we faced was mostly the data preparation and cleaning. It was difficult deciding what columns/varaibles we would keep in our model as well.

Future Uses/Additional Applications

In terms of what this model could be used for, the model we created can be used to predict the popularity of new films based on given features which was one of our original goals.

```
The model can also be used to compare films
actual performance to what the model predicted and use those results
to continue to better our model and increase
the accuracy.
```

Ethical Assessment

```
In terms of how ethical this process was. I don't belive there was
much of a breach in private information. we
beleive because the information provided for all the movie titles can
be easily found online there are no ethical
concerns for the names of actors or directors listed in the dataset.
There could be some copyright and property issues
if this model were to be used in some kind of business advancement in
the film industry without addressing the rightful
owners that intelectual property. That is a valid concern.
```

References

G, R. A. (2022, October 29). IMDB 5000+ movies & multiple genres dataset. Kaggle. https://www.kaggle.com/datasets/rakkesharv/imdb-5000-movies-multiple-genres-dataset?resource=download

Appendix

Table 1: Original Dataframe

In [23]:
```
original_data
```

Out[23]:

	Movie_Title	Year	Director	Actors	Rating	Runtime(Mins)	Censor	Total_Gross	mai
0	Kantara	2022	Rishab Shetty	Rishab Shetty, Sapthami Gowda, Kishore Kumar G...	9.3	148	UA	NaN	
1	The Dark Knight	2008	Christopher Nolan	Christian Bale, Heath Ledger, Aaron Eckhart, M...	9.0	152	UA	534.86	
2	The Lord of the Rings: The Return of the King	2003	Peter Jackson	Elijah Wood, Viggo Mortensen, Ian McKellen, Or...	9.0	201	U	377.85	
3	Inception	2010	Christopher Nolan	Leonardo DiCaprio, Joseph Gordon-Levitt, Ellio...	8.8	148	UA	292.58	
4	The Lord of the Rings: The Two Towers	2002	Peter Jackson	Elijah Wood, Ian McKellen, Viggo Mortensen, Or...	8.8	179	UA	342.55	
...	...	...	...	...	...	...	...	...	
5557	Disaster Movie	2008	Directors:Jason Friedberg, Aaron Seltzer	Carmen Electra, Vanessa Lachey, Nicole Parker,...	1.9	87	PG-13	14.19	
5558	The Hottie & the Nottie	2008	Tom Putnam	Paris Hilton, Joel David Moore, Christine Laki...	1.9	91	PG-13	0.03	
5559	From Justin to Kelly	2003	Robert Iscove	Kelly Clarkson, Justin Guarini, Katherine Bail...	1.9	81	PG	4.92	
5560	Superbabies: Baby	2004	Bob Clark	Jon Voight, Scott Baio,	1.5	88	PG	9.11	

	Movie_Title	Year	Director	Actors	Rating	Runtime(Mins)	Censor	Total_Gross	mai
	Geniuses 2			Vanessa Angel, Skyler ...					
5561	Cumali Ceber: Allah Seni Alsin	2017	Gökhan Gök	Halil Söyletmez, Doga Konakoglu, Emre Keskin, ...	1.0	100	Not Rated	NaN	