An Analysis of Film Industry Performance

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Introduction and Motivation

The main purpose of this project is to do an analysis of what kind of factors and characteristics (if any) of different movies can help us determine how successful a movie will be. Specifically, two measures of success that we might be looking at during this analysis is first and foremost the amount of gross revenue the movie brought in as well as how popular the movie was with audiences. For the latter we will consider an IMDb rating as our variable to help measure this.

Background: The Data

The dataset that we are working with is a movie dataset containing information about 6820 different movie titles. The data was scraped from IMDb databases. There are movies from different years between 1986 and 2016. There are 220 movies per year and each movie has the following information included in the dataset:

Name: name of the movie

Rating: what was the movie rated (PG,

PG-13, R etc)

Genre: what genre does the movie belong

to

Year: year the movie was released

Released: release date

Score: IMDb score

Votes: count of IMDb votes

<u>Director</u>: who directed the movie

Writer: who wrote the movie

Star: major stars in the movie

Country: what country was the movie

made

Budget: budget used to make movie

Gross: how much did the movie make

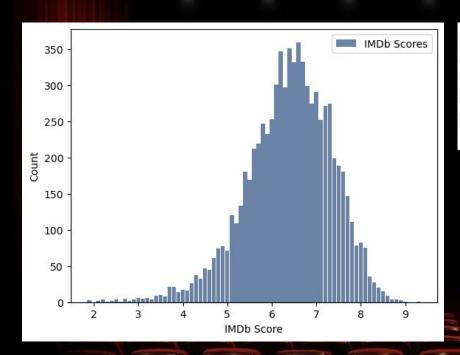
<u>Company</u>: what production company

Runtime: how long was the movie



I selected "score" and "gross" as variables because there are the variables I am planning to use as a measure of success in this analysis of the film industry. Similarly, votes could also be used as a measure of success but the amount of votes can also be an indicator on how much revenue a movie will make. Other variables that I chose to include in this analysis are the budget of the movie and the runtime for each movie. The movie genre is the only variable that is a categorical one, hence it is the only one in which we cannot create a histogram for.

Histogram: "Score" Variable Analysis



Score Mean: 6.390410958904109

Score Median: 6.5

Score Mode: 0 6.6

Name: score, dtype: float64

Score Standard Dev: 0.9688416402530576

Score Varience: 0.9386541238882352

<u>Outliers</u>: There doesn't seem to be any extreme outliers in the distribution. Possibly on the left side.

Spread: There seems to be a slight skew to the left.

Behavior: Distribution appears to be more or less symmetrical. Majority of observations between 5 and 8.

Histogram: "Votes" Variable Analysis

Votes Mean: 88108.50476190477

Votes Median: 33000.0

Votes Mode: 0 13000.0

Name: votes, dtype: float64

Votes Standard Dev: 163323.7639095057

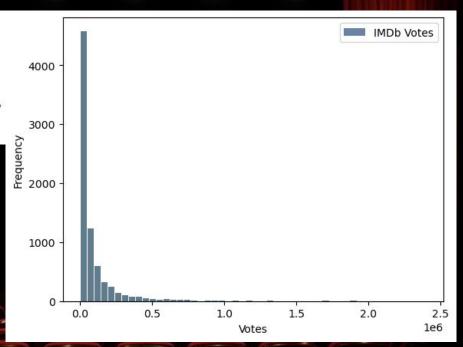
Votes Varience: 26674651857.567955

Outliers: There are definitely outliers on the right side of this distribution but it's likely some movies are just more popular so there isn't a reason to get rid of any outliers since the observations are possible.

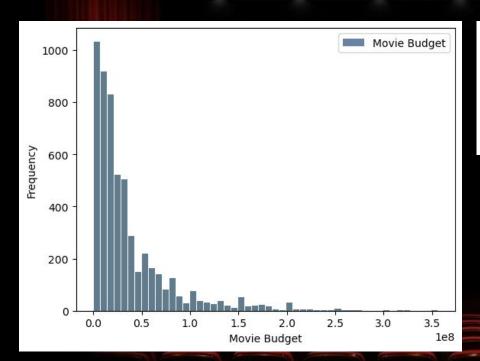
Spread: Significant skew to the right

Behavior: Largest density on left side of

distribution



Histogram: "Budget" Variable Analysis



Budget Mean: 35589876.192650534

Budget Median: 20500000.0

Budget Mode: 0 20000000.0

Name: budget, dtype: float64

Budget Standard Dev: 41457296.60193096 Budget Varience: 1718707441540476.5

Outliers: Possible outliers on the right of the distribution but it's possible movies could've had a large budget so no outliers will be removed.

Spread: Significant skew to the right **Behavior**: Largest density at the left side of the distribution.

Histogram: "Gross" Variable Analysis

Gross Mean: 78500541.01778312

Gross Median: 20205757.0

Gross Mode: 0 14000000.0

Name: gross, dtype: float64

Gross Standard Dev: 165725124.31875733

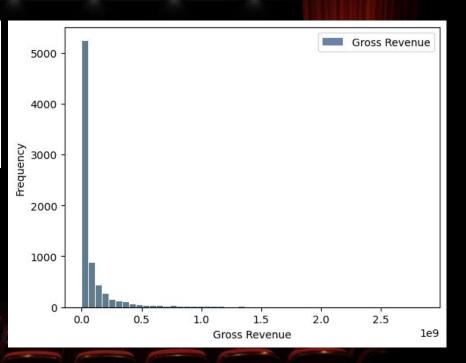
Gross Varience: 2.746481683046757e+16

<u>Outliers</u>: Possible outliers to the right. Won't be removed since it is not unlikely for some movies to make significantly more gross revenue than other movies.

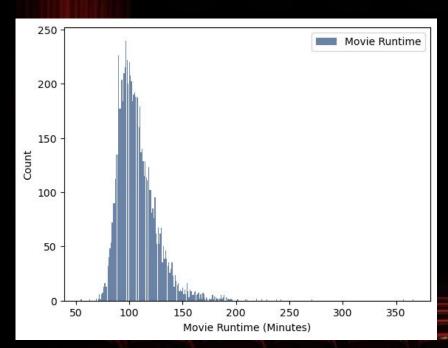
Spread: Significant skew to the right

Behavior: Largest density to the left of the

distribution.



Histogram: "Runtime" Variable Analysis



Gross Mean: 78500541.01778312

Gross Median: 20205757.0

Gross Mode: 0 14000000.0

Name: gross, dtype: float64

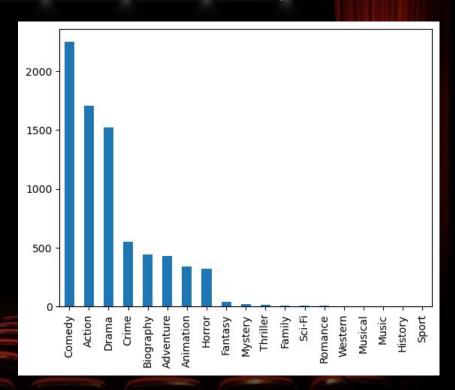
Gross Standard Dev: 165725124.31875733 Gross Varience: 2.746481683046757e+16

<u>Outliers</u>: It looks like there are some possible outliers but they won't be removed as they are real movies. Ex: There is a movie that is actually 6 hours long (The Best of Youth).

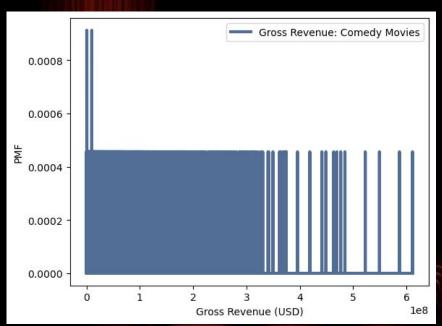
Spread: Slightly skewed to the right **Behavior**: Biggest density around 75 to 125 minutes.

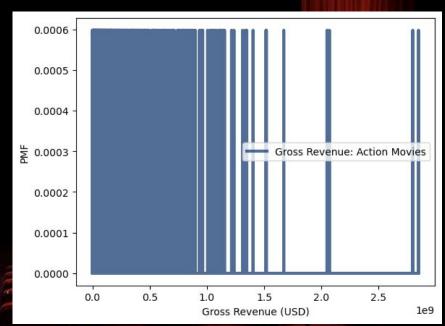
Bar Plot: "Genre" Variable Analysis

Because this is a categorical variable, there is no way to find a traditional average. We can only analyze the frequency of which each type of observation is observed. Based on the data, we see that there are more Comedy movies than any other genre. The least popular movie genre is "Sport". In order, the top movie genres here are Comedy, Action, Drama, Crime, Biography, Adventure, Animation and Horror.

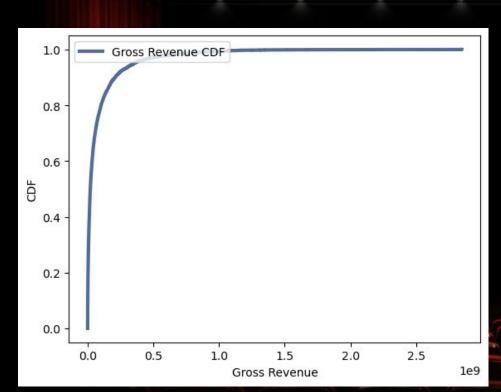


Analysis of Gross Revenue of Different Movie Genres (PMFs)





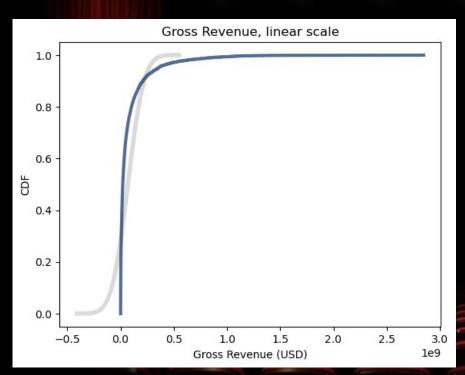
CDF of Gross Revenue

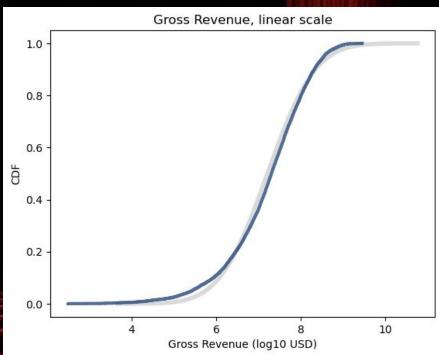


What does this tell us?

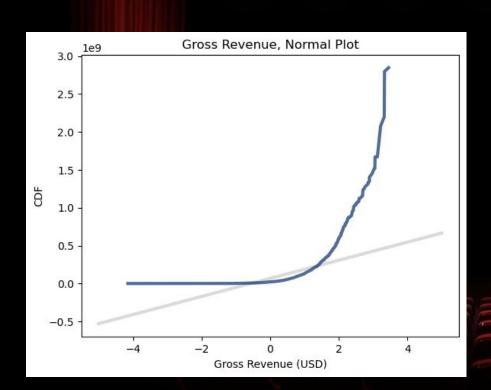
As you can see above, the CDF of the gross revenue for our data appears to follow a logarithmic path as it progresses. It's highly possible that the distribution for this variable is a lognormal distribution. If we look back to the histogram of this variable, it does appear to support this claim.

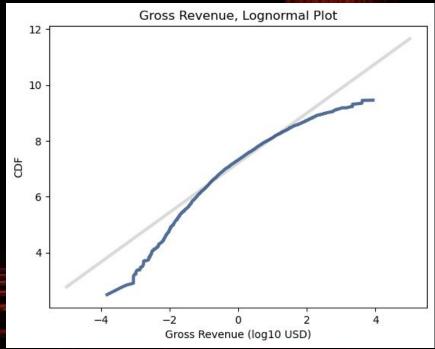
Analytical Distribution Plot





Analytical Distribution Plot

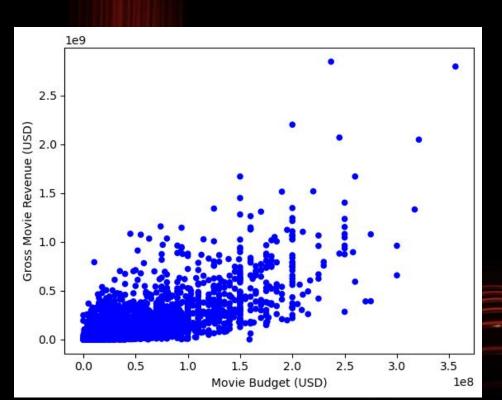






Previously I mentioned that the distribution of the Gross Revenue for the Movie Industry data set could possibly follow a log-normal distribution. Considering the figures above, it's clear to see that a log-normal distribution fits the data better than just a normal distribution. Through the graphs we see an improvement when we apply a logarithmic transformation to our data.

Variable Relationships: Scatter Plot of Budget and Gross Revenue



Variables: Budget and Gross

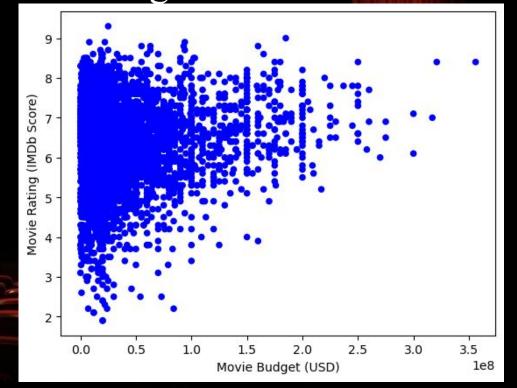
Covarience: 5754614010107631.0

Correlation: 0.7403948929894826

Variable Relationships: Scatter Plot of Budget and Movie Rating

Variables: Budget and Score Covarience: 2872497.4451108794

Correlation: 0.0717919879816616



Hypothesis Testing

```
#separatina data again
gross comedy = moviedf.gross[moviedf.genre == "Comedy"]
gross action = moviedf.gross[moviedf.genre == "Action"]
#cleaning data of any missing or invalid values
gross comedy = gross comedy[-gross comedy.isnull()]
gross_action = gross_action[-gross_action.isnull()]
#putting data together
data = [gross_comedy, gross action]
#Hypothesis test and result
gross ht = DiffMeansPermute(data)
gross pv = gross ht.PValue()
#resulting pvalue
print(gross pv)
```

As you can see we got a resulting p-value of 0.0. This is of course not possible for an observed p-value but this could be a minor error due to the fact that there could have been some rounding off in some of our calculations. Because of this, if we resulting in a relatively small p-value, the computer system could have rounded the small value to zero. As we recall from previous lessons, when the p-value of a hypothesis test is extremely small, it's safe to say that we can reject the null hypothesis that the means of the two samples are the same and accept the alternative hypothesis that there is a difference between the gross revenue of Comedy movies and the gross revenue of Action movies.

Regression Analysis

inter, slope = LeastSquares(moviedf.budget, moviedf.gross)
inter, slope

(-16825009.95297028, 3.3342796500711454)

Variables: Budget and Gross

Covarience: 5754614010107631.0

Correlation: 0.7403948929894826

Our model for our Gross income is a linear model in the form of (approximately) f(x) = 3.3342x - 16825009.9530. Here f(x) represents the gross revenue generated as a function of x where x is the budget the movie had. In the end, these two variables had a correlation of 0.74 which makes this a decent model.

