

Comparing Critics to the General Public: Who is a better predictor of a movie's success?

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1 Overview

This report analyzes the relationship between different aspects of a movie and its gross income. These aspects include director list, actor list, runtime and so on. To investigate these relationships, we looked at a comprehensive dataset compiled by the movie ranking website IMDB.com. This dataset includes information about a movie like the director, the actors, the genre.

We found ..

2 Introduction

Context and motivation The global movie industry is immense, with a total of 629,807 titles listed on IMDb as of December 2022 [1], some dating as far back as 1894 [2]. With such a vast selection, it is impossible for all movies to become successful blockbusters. This raises the question: what factors contribute to a movie's success? There is an abundance of data available regarding movies, their cast, crew, and even their audiences. This data can be used to gain insight into the production, reception, and overall success of films. This study aims to explore how different metrics can predict the success of a movie before it gets released to the general public. Success in this context is defined as the amount of revenue generated by the movie.

When it comes to movie ratings, there are often two different scores available: one from the general public and the other from professional movie critics. At times, scores may be nearly identical. For instance, "The Godfather" [3] received nearly identical scores from both groups. On the other hand, "The Last Jedi" [4] saw a significant difference between the two. The disparity between ratings for certain movies can make it challenging to determine whether they were successful.

Previous work Recent research has explored the various factors that contribute to the success or failure of films. Several studies and papers have been conducted in this field, examining a range of elements. Previous research has investigated the potential of utilizing IMDb data to predict the success of films [5]. Other studies have sought to identify the factors that contribute to the making of a blockbuster movie [6]. Moreover, further studies have attempted to develop their own mathematical models to predict the success of upcoming movies [7].

Objectives This study seeks to identify the most influential factors in determining a movie's success. With the multitude of factors that could potentially affect a movie's performance at the box office, it is not feasible to investigate them all. Therefore, we will focus our research on the director, actors, genre and runtime of a movie, and compare these with its viewer rating, critic score and box office revenue. We will be exploring the following question in depth: who is more accurate in predicting a movie's success, critics or the general public? Additionally, we will investigate the influence of a movie's director and actors on its success, as well as the genres that are most likely to produce successful films.

3 Data

Data provenance We used two movie datasets for our investigation: an IMDb dataset [8] and The Movie Dataset (TMD) [9]. The IMDb dataset contains data about movies released between 2006 and 2016, while the TMD dataset contains data about movies released on or before July 2017. Both datasets were obtained from Kaggle.com and are shared under the CC0 1.0 Universal Public Domain Dedication. TMD is a merged dataset from TMDb (The Movie Database) and grouplens.org, a movie ranking site. We only used the part of the dataset that was obtained from TMDb. It is worth noting that the provenance of the IMDb dataset has been subject to controversy as it was scraped from IMDb.com. However, for this investigation, we used only a sample of this dataset which is publicly available on Kaggle.com.

Data description The IMDb movie dataset contains 12 columns with string or floating point values. The only column of note is the Genre column, which can only take on 12 distinct values, shown in Table 1. A summary of the columns is provided in Table 1.

Column Name	Description	Data Type
Rank	The rank the movie has in the IMDb database	Integer
Title	The name of the movie	String
Genre	The genres that apply to the movie, there can be anywhere from 1-3 genres. A genre can be any from: Action, Adventure, Sci-Fi, Thriller, Animation, Comedy, Family, Fantasy, Drama, Music, Romance, History, Crime, Western, War, Musical, Sport, Horror, Mystery, Biography.	Genre
Description	The description of the movie	String
Director	The person who directed the movie	String
Actors	The lead roles in the movie	String
Year	The year the movie was released	Integer
Runtime (Minutes)	The runtime in minutes of the movie	Integer
Rating	The mean rating of the movie, taken from IMDb.com	Float
Votes	The amount of users that voted on a movie to give it that rating	Integer
Revenue (Millions)	The gross income the movie made at the US box office	Float
Metascore	The rating of movie, determined using aggregated weighted Critics scores	Integer

Table 1: The different columns in the IMDb-Movie-Data.csv file

We worked exclusively with the Crew table in TMD, which is a small part of the entire database. This table contains three columns - Cast, Crew, and ID. However, the Cast and Crew columns are not composed of discrete data points, but rather JSON files representing the entire cast or crew list. As a result, we extracted the data using string parsing methods. A summary of the columns is provided in Table 2.

Column Name	Description	Data Type
cast	The cast list of the movie, including all actors who appeared in it.	.json file
crew	The entire crew list of the movie, including all the people who made it.	.json file
id	The movie id - used in the larger dataset to connect tables together	Integer

Table 2: The different columns in the credits.csv file

Data processing We used a Python script to parse the TMD dataset and count the number of movies each director and actor has been involved in. The resulting datasets were saved as CSV files named `actor_counts.csv` and `director_counts.csv`. We then merged this data with the original IMDb dataset. This involved dropping the Description column and replacing the Director and Actor columns with Director Exp. and Mean Lead Roles Exp. A summary of the merged datasets columns is shown in Table 3.

Column Name	Description	Data Type
Rank	See table 1	Integer
Title	See table 1	String
Genre	See table 1	Genre
Director Exp.	The number of movies that the director of the movie has made	Float
Mean Lead Roles Exp.	The mean number of movies that the lead actors have been in	Float
Year	See table 1	Integer
Runtime (Minutes)	See table 1	Integer
Rating	See table 1	Float
Votes	See table 1	Integer
Revenue (Millions)	See table 1	Float
Metascore	See table 1	Integer

Table 3: The different columns in the merged data set

We checked that the data had been properly normalized by creating a histogram plot of all the numeric variables, as shown in Figure 1. As anticipated, some variables were not normally distributed, including Revenue (Millions), Votes, Runtime (Minutes), Director Exp., and Rating.

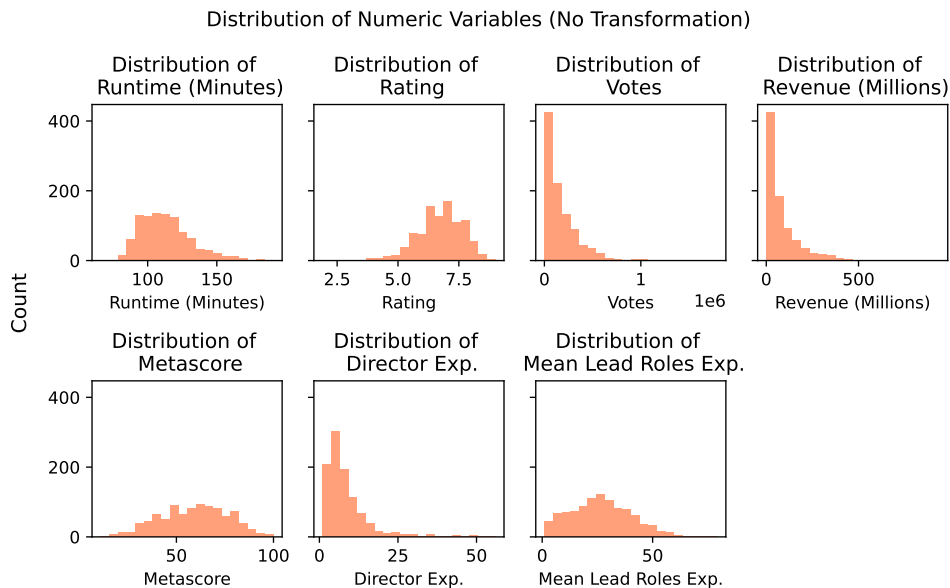


Figure 1: The distributions of the numeric variables in the merged dataset

Figure 1 shows that Revenue (Millions) and Votes are severely right-skewed, implying an exponential distribution. Runtime (Minutes) and Director Exp. appear to be less severely right-skewed, implying a lognormal distribution. Rating seems to be left-skewed. The transformations that give the best approximations to a normal distribution are cube root transform for Revenue (Millions) and Votes, log transform for Runtime (Minutes) and Director Exp., and square transform for Rating.

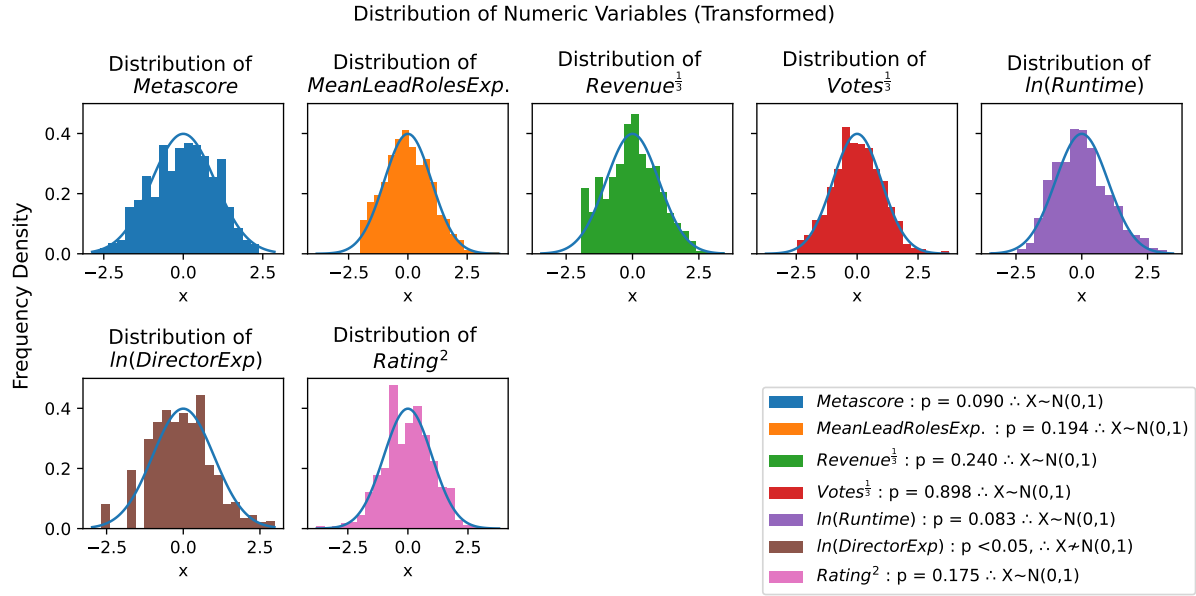


Figure 2: The distributions of the standardised and normalised numeric variables in the merged dataset, the legend has the p-values from testing with $H_0 : X \not\sim N(0,1)$. Also shown on the plots is the Gaussian Distribution with the columns mean and standard deviation

Figure 2 shows the standardised and normalised numeric variables. The legend contains the p-values from the Kolmogorov-Smirnov normality test [10], which was used to test the data against the null hypothesis $H_0 : X \not\sim N(0,1)$. It is worth noting that the Director Exp. column failed the test, however, there is missing data present in the histogram. Despite this, the histogram follows a normal distribution curve, providing convincing evidence that $\ln(\text{Director Exp.})$ has a normal distribution. Ultimately, these transformations helped to normalize the dataset and improve its suitability for further analysis.

To make use of the Genre column, one-hot encoding was used. We added a column for each Genre and set each entry to 1 if the corresponding movie fit that genre and 0 otherwise. Genres with less than 100 movies made were excluded to ensure a large enough sample size was present, such that we could draw meaningful conclusions

4 Exploration and Analysis

In order to further analyze the correlations between the various movie details and the revenue they generated, we created a multiple regression model using the normalized data we collected. The target variable was the normalised revenue, with the rest of the dataset as the predictor variables, excluding Genre and Title. $Votes^{1/3}$ was excluded as it is causally linked to Revenue; the more votes, the more people bought movie tickets. The model uses Ordinary Least Squares regression and a constant column has been added to show y-intercept. The summary results are provided below.

Dep. Variable:	<i>Revenue</i> ¹ ₃	R-squared:	0.404
Model:	OLS	Adj. R-squared:	0.393
Method:	Least Squares	F-statistic:	36.60
No. Observations:	826	AIC:	1921.
Df Residuals:	810	BIC:	1996.
Df Model:	15	Prob (F-statistic):	1.35e-80
Covariance Type:	nonrobust	Log-Likelihood:	-944.32

	coef	std err	t	P> t	[0.025	0.975]
<i>const</i>	114.0116	19.712	5.784	0.000	75.319	152.705
<i>Rank</i>	-0.0006	0.000	-5.654	0.000	-0.001	-0.000
<i>Year</i>	-0.0565	0.010	-5.770	0.000	-0.076	-0.037
<i>Metascore</i>	0.0416	0.038	1.093	0.275	-0.033	0.116
<i>MeanLeadRolesExp.</i>	0.1125	0.030	3.793	0.000	0.054	0.171
<i>ln(Runtime)</i>	0.1705	0.033	5.203	0.000	0.106	0.235
<i>ln(DirectorExp)</i>	0.0507	0.029	1.756	0.079	-0.006	0.107
<i>Rating</i> ²	0.0816	0.041	2.013	0.044	0.002	0.161
<i>Action</i>	0.1824	0.070	2.598	0.010	0.045	0.320
<i>Adventure</i>	0.4765	0.074	6.452	0.000	0.332	0.621
<i>Sci – Fi</i>	0.0318	0.087	0.364	0.716	-0.140	0.203
<i>Thriller</i>	-0.0395	0.078	-0.504	0.615	-0.193	0.114
<i>Comedy</i>	0.1145	0.072	1.599	0.110	-0.026	0.255
<i>Drama</i>	-0.5579	0.071	-7.877	0.000	-0.697	-0.419
<i>Romance</i>	-0.0243	0.084	-0.288	0.773	-0.190	0.141
<i>Crime</i>	-0.0545	0.082	-0.664	0.507	-0.216	0.107

Omnibus:	2.065	Durbin-Watson:	2.048
Prob(Omnibus):	0.356	Jarque-Bera (JB):	1.964
Skew:	-0.055	Prob(JB):	0.375
Kurtosis:	2.788	Cond. No.	1.53e+06

Table 4: Multiple Regression results summary

This model performs respectably, explaining about 40% of the variance in user ratings. It is also statistically significant, getting a very small $P(F - statistic)$. This indicates that the revenue of a movie can be predicted from the data present in the dataset, albeit not extremely well. However, the relatively good R^2 value does indicate a well performing model, as such we can postulate that at least some of these factors are impactful on the revenue a movie makes. There are also a few interesting observations that can be made about this data.

One such observation is that the experience of lead actors has a statistically significant effect on movie ticket sales ($p < 0.05$), while the experience of directors does not ($p > 0.05$). This raises the question of whether the director has as much of an impact as the actors when it comes to selling tickets. A possible explanation is the fact that promotional posters for movies often focus on the actors [label], with their faces being the first thing a consumer sees. Actors who have been in many movies tend to be more recognisable, making potential consumers more likely to see a movie they are in and thus improving ticket sales. In contrast, the director's name is usually the only thing featured on the poster, drawing little attention and thus being less impactful. This idea is inline with previous research [label].

Another insight is that while critic scores are not reliable predictors of a film's revenue user ratings are, with $p > 0.05$ and $p < 0.05$ respectively. This raises the question of why there is a difference between these two forms of rating; they both correlate strongly with each other (see fig ??) so it is reasonable to assume they would have similar strength as predictor variables. A possible explanation could be due to

the relatively short time movies appear in box office for. With revenue only being calculated during this time, consumers would have more reliance on friends and family than a review that would be published a while after the movie came out. With this in mind, it is reasonable to say that critics do not appear to be able to predict the Likelihood of a movie becoming a blockbuster.

Finally, there are some interesting notes about the impact of genre has on the box office success of a movie. Adventure seems to have the biggest positive impact on box office success, its coefficient is ~ 0.48 . Drama appears to have the largest negative impact on box office success, with a coefficient of ~ -0.56 .

Dep. Variable:	Metascore	R-squared:	0.310
Model:	OLS	Adj. R-squared:	0.297
Method:	Least Squares	F-statistic:	24.27
Date:	Fri, 31 Mar 2023	Prob (F-statistic):	1.31e-55
Time:	13:03:30	Log-Likelihood:	-1015.1
No. Observations:	826	AIC:	2062.
Df Residuals:	810	BIC:	2138.
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
<i>const</i>	-37.7720	24.738	-1.527	0.127	-86.330	10.786
<i>Rank</i>	-0.0004	0.000	-3.375	0.001	-0.001	-0.000
<i>Year</i>	0.0189	0.012	1.536	0.125	-0.005	0.043
<i>MeanLeadRolesExp.</i>	-0.0651	0.033	-1.989	0.047	-0.129	-0.001
<i>Revenue^{1/3}</i>	-0.1491	0.047	-3.178	0.002	-0.241	-0.057
<i>Votes^{1/3}</i>	0.5023	0.052	9.610	0.000	0.400	0.605
<i>ln(Runtime)</i>	0.0445	0.036	1.246	0.213	-0.026	0.115
<i>ln(DirectorExp)</i>	-0.0509	0.031	-1.624	0.105	-0.113	0.011
<i>Action</i>	-0.4852	0.075	-6.462	0.000	-0.633	-0.338
<i>Adventure</i>	-0.0360	0.082	-0.436	0.663	-0.198	0.126
<i>Sci – Fi</i>	-0.1184	0.097	-1.217	0.224	-0.309	0.072
<i>Thriller</i>	0.0131	0.086	0.154	0.878	-0.155	0.181
<i>Comedy</i>	0.0876	0.078	1.122	0.262	-0.066	0.241
<i>Drama</i>	0.5179	0.078	6.676	0.000	0.366	0.670
<i>Romance</i>	-0.5286	0.090	-5.853	0.000	-0.706	-0.351
<i>Crime</i>	-0.2394	0.090	-2.675	0.008	-0.415	-0.064

Omnibus:	10.156	Durbin-Watson:	2.001
Prob(Omnibus):	0.006	Jarque-Bera (JB):	6.613
Skew:	-0.038	Prob(JB):	0.0366
Kurtosis:	2.568	Cond. No.	1.76e+06

Dep. Variable:	<i>Rating</i> ²	R-squared:	0.298
Model:	OLS	Adj. R-squared:	0.286
Method:	Least Squares	F-statistic:	24.58
Date:	Fri, 31 Mar 2023	Prob (F-statistic):	2.43e-53
Time:	13:05:09	Log-Likelihood:	-1006.0
No. Observations:	826	AIC:	2042.
Df Residuals:	811	BIC:	2113.
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
<i>const</i>	139.5777	21.098	6.616	0.000	98.164	180.991
<i>Rank</i>	-0.0008	0.000	-7.280	0.000	-0.001	-0.001
<i>Year</i>	-0.0692	0.010	-6.608	0.000	-0.090	-0.049
<i>MeanLeadRolesExp.</i>	-0.0040	0.032	-0.124	0.901	-0.067	0.059
<i>Revenue</i> ^{1/3}	0.1256	0.038	3.344	0.001	0.052	0.199
<i>ln(Runtime)</i>	0.2477	0.035	7.129	0.000	0.180	0.316
<i>ln(DirectorExp)</i>	-0.0810	0.031	-2.612	0.009	-0.142	-0.020
<i>Action</i>	-0.3401	0.074	-4.582	0.000	-0.486	-0.194
<i>Adventure</i>	0.0261	0.082	0.320	0.749	-0.134	0.186
<i>Sci – Fi</i>	-0.0072	0.094	-0.077	0.939	-0.192	0.177
<i>Thriller</i>	0.0722	0.084	0.856	0.392	-0.093	0.238
<i>Comedy</i>	0.1158	0.077	1.502	0.133	-0.036	0.267
<i>Drama</i>	0.4943	0.076	6.462	0.000	0.344	0.644
<i>Romance</i>	-0.2747	0.089	-3.078	0.002	-0.450	-0.100
<i>Crime</i>	-0.0274	0.088	-0.311	0.756	-0.200	0.146
Omnibus:	30.769	Durbin-Watson:	2.011			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	35.962			
Skew:	-0.416	Prob(JB):	1.55e-08			
Kurtosis:	3.594	Cond. No.	1.52e+06			

5 Discussion and Conclusions

Summary of findings

Evaluation of own work: strengths and limitations

Comparison with any other related work E.g. “Anscombe has also demonstrated that many patterns of data can have the same correlation coefficient”.

Wikipedia can also be cited but it is better if you find the original reference it for a particular claim in the list of references on the Wikipedia page, read it, and cite it.

The golden rule is always to cite information that has come from other sources, to avoid plagiarism.

Improvements and extensions

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