Jonathan Bunch

20 November, 2021

DSC550-T301--Final Project

Predicting Disney Movie Profits With Movie Attributes and Societal Development Indicators

Introduction

Movie production is a long and expensive process that necessitates careful planning and extensive risk mitigation. The factors that influence the opinion, interest, and motivation of movie-goers are as diverse as the people themselves, but there are some logical hypotheses that we can make. For example, many leisure activities are influenced by the weather. Indoor activities may become more popular as the weather becomes less agreeable, or perhaps less popular due to generally lower motivation to leave home.

It also seems reasonable to assume that the overall health and prosperity of a society could influence the desire and ability to pursue leisure activities. Unemployment rates, for example, could logically be expected to impact the availability of disposable income. influence the popularity of leisure activities such as visiting the theater. Fertility and mortality rates are recognized as general measures of societal health and development, which may well influence public interests. Disney movies in particular have the connotation of being family-oriented, so it stands to reason that fertility rate could impact the target audience of these films.

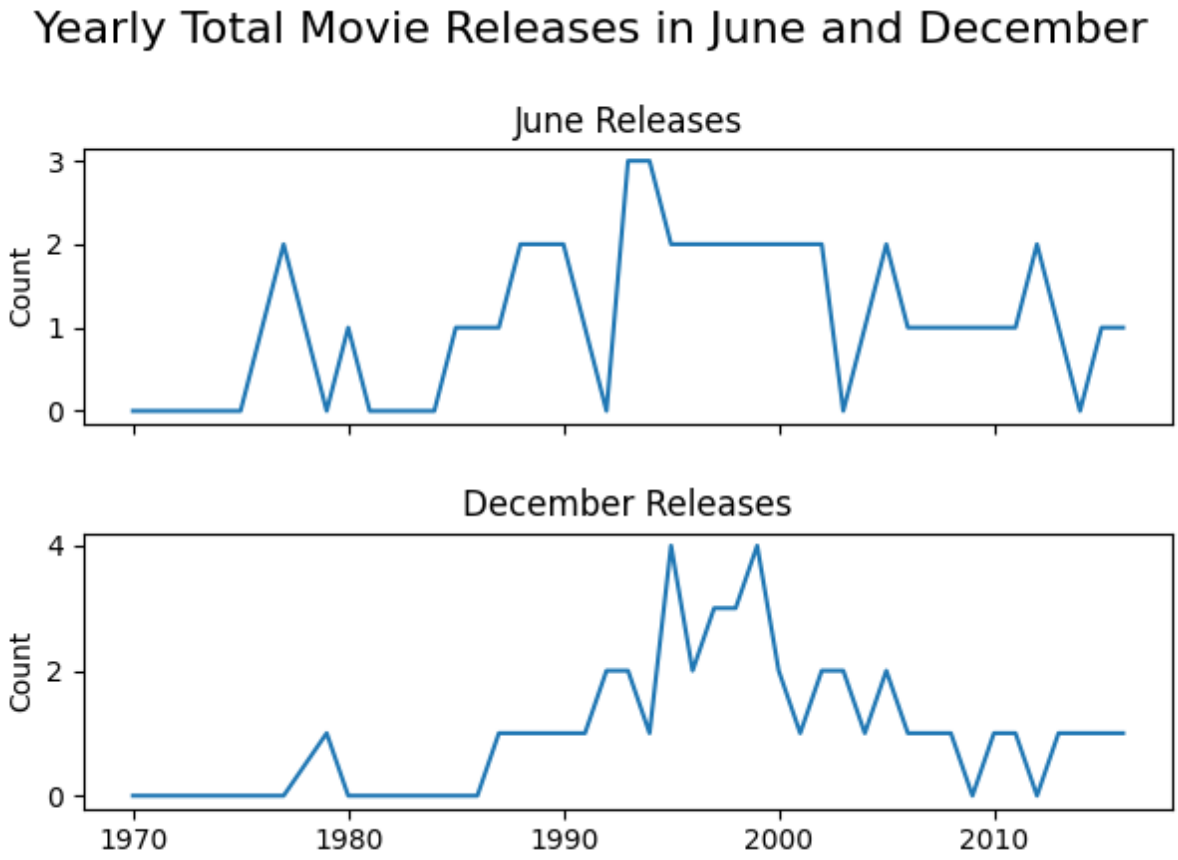
The objective of this analysis is to help mitigate the risks involved in investing in film production by providing insight into factors that can impact the total profits earned from those investments.

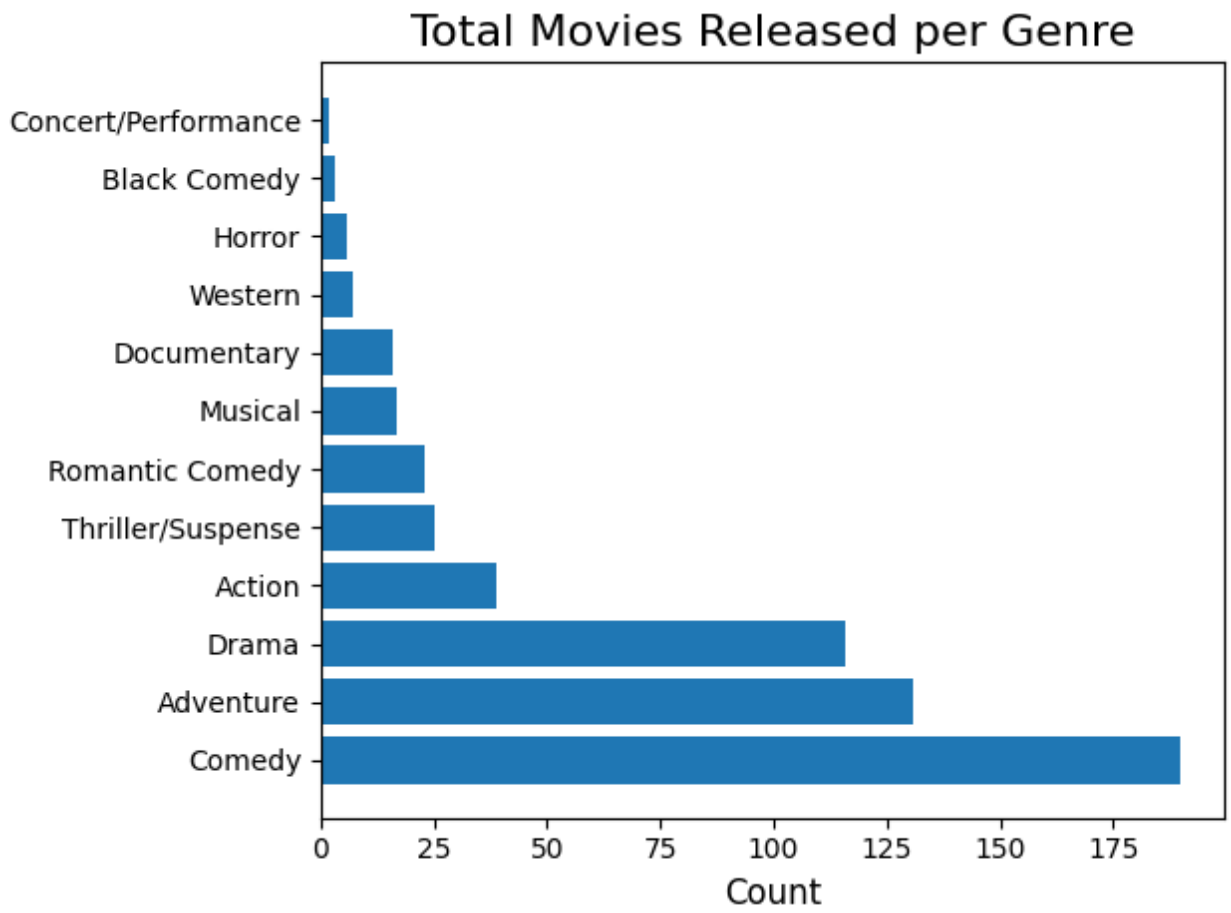
Process Summary

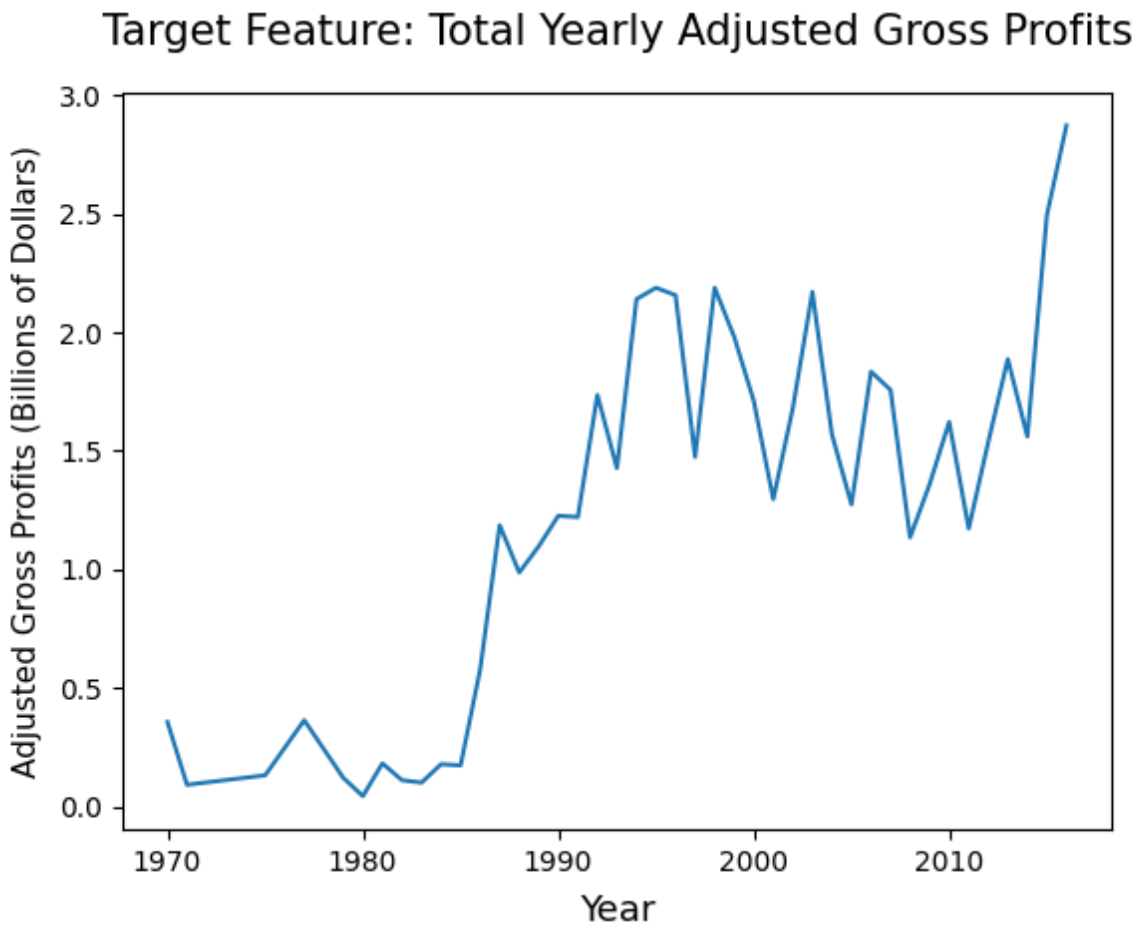
Milestones One & Two: Data Exploration, Visual Analysis, and Feature Engineering.

The goal of this analysis was to predict the total gross profits of a Disney movie based on aspects of the movie itself and/or broader social indicators. The Disney movie dataset included some potentially useful information about the movies themselves, while information regarding societal development indicators provided broader information about health and society in the United States.

The primary dataset provides information about movies produced by Disney, with historical data back to about 1940. Features of interest included the date of release, genre, and inflation adjusted total gross profits, which represents the target feature for this analysis.



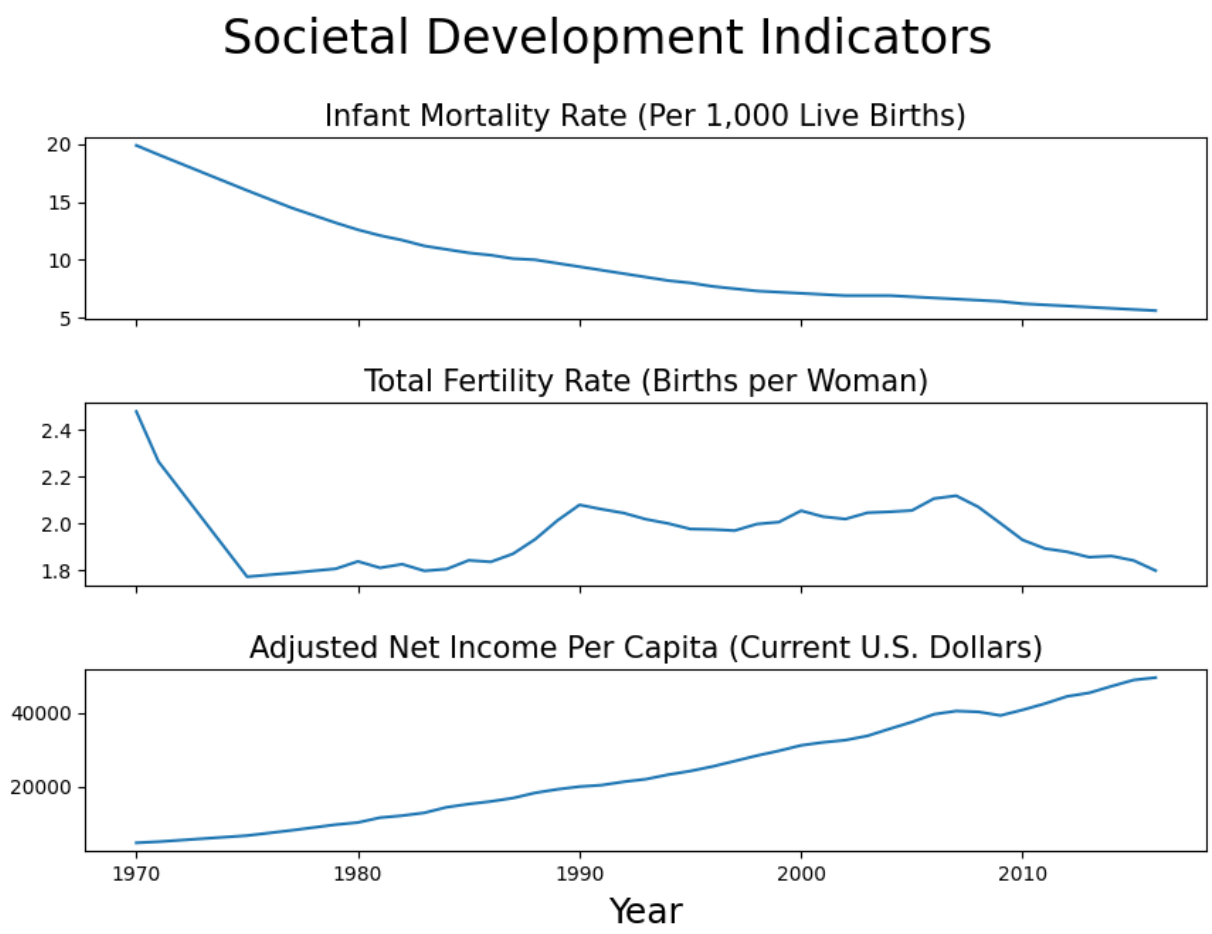

Total Movies Released per Genre
Concert/Performance
Black Comedy
Horror
Western
Documentary
Musical
Romantic Comedy
Thriller/Suspense
Action
Drama
Adventure
Comedy
0
25
50
75
100
125
150
175
Count



This dataset was fairly well organized and complete, with less than 10 missing values in most of the features. The only exception was the MPAA Rating feature (G, PG, R, etc.). This feature had to be discarded due to the large number of missing values and the lack of a conceptually appropriate fill method.

New features were created to represent the month and year of release, which were then one-hot encoded to create a feature for each month of release. The genre feature was also one-hot encoded, and all features were aggregated by sum to create yearly totals. The finished dataset contained one feature for each movie release month, one feature for each genre, and one feature for the adjusted total gross profits, with the row index representing the year.

The second dataset provided societal development indicators by country and year, including fertility rate, mortality rate, and per capita income. This dataset was oddly organized, with only one row per country and columns for each year-indicator combination. The dataset was reorganized to match the desired format, with the row index representing the year and one feature for each of the three indicators. The data appeared otherwise sound and complete, but was lacking any data for years prior to 1970.



These two datasets were joined by year to create a dataset with yearly observations for all features. While the movie dataset did contain observations for years prior to 1970, they represented a very small proportion of the total observations. Therefore, observations before 1970 were dropped, and the dataset ultimately spanned from 1970 to 2016, with a few observations missing from the 1970s. The finished dataset contained 29 features, including the target feature, and 42 observations. The target feature was then separated from the predictive features, yielding the conventional "X" and "y" datasets required for model building.

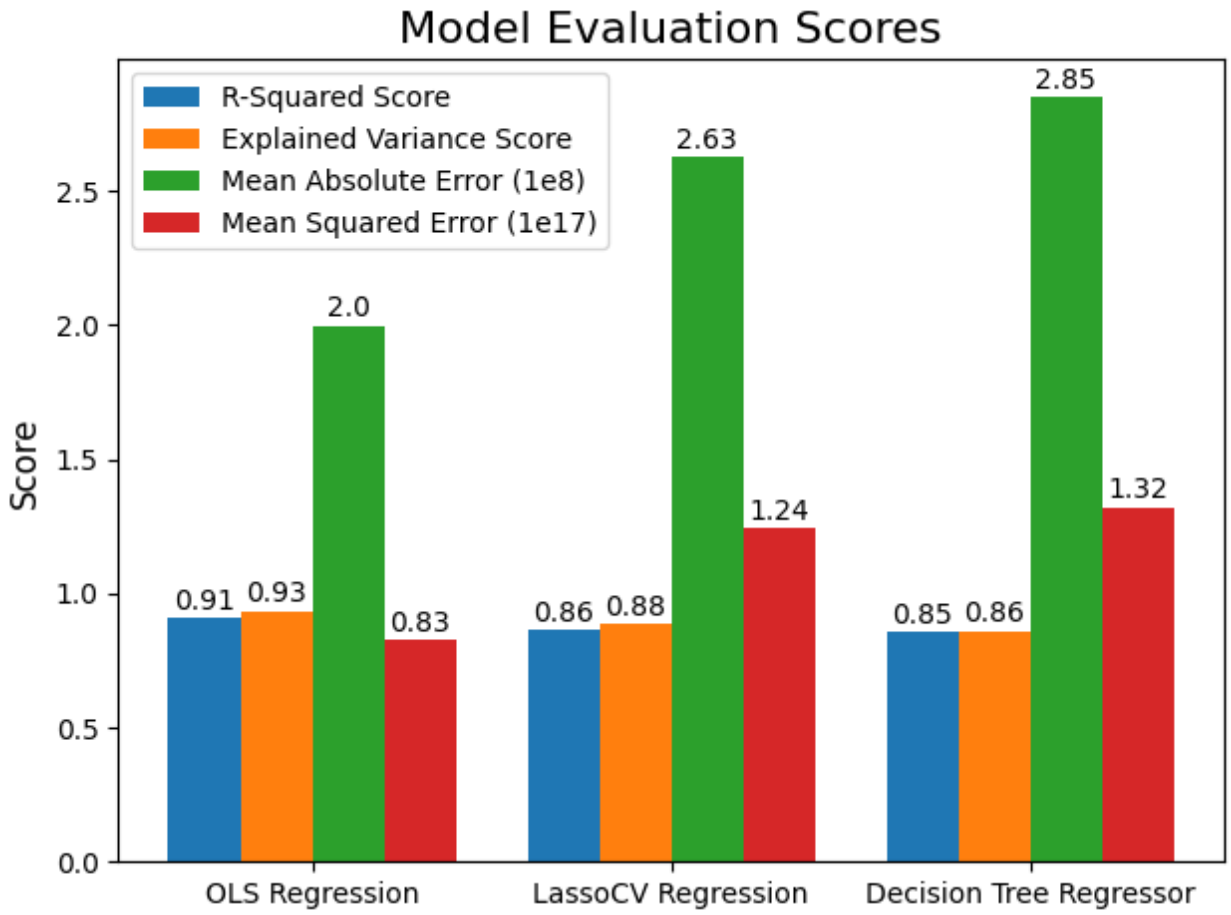
Milestone Three & Four: Model Selection, Creation, and Evaluation.

The model building process began with the completion of the feature reduction process. Feature reduction was required to prune deleterious features and improve model performance. The datasets were split into training and testing sets, and feature reduction was applied to the predictive training and predictive testing datasets. An iterative modeling process was employed to determine the ideal number of features to keep, and the best features were identified using a

univariate linear regression and F-statistic based testing method. This resulted in a reduction from 27 to 16 predictive features and improved regression scores. The reduced feature dataset contained features representing: - Movie releases in the months of January, February, March, April, May, June, August, October, and December. - Movies in the genres of action, adventure, comedy, drama, and thriller/suspense. - Mortality rate and per capita income.

Next, a standard scaler was incorporated with several model types to create pipelines for OLS Linear Regression, LassoCV Regression, and Decision Tree Regressor models. These pipelines could then easily be fitted to the data, and the evaluation results from each model could be compared.

As shown in the figure below, model performance was fairly strong with all three models, with OLS Linear Regression taking a slight edge. However, it should be considered that this model was used in the feature selection process, so the data may have been overfitted to this model.



Conclusion

This analysis resulted in some evidence that these factors could have predictive power for the

profits a movie will earn. Certain times of year when a movie is released, the genre of the movie, and general societal development indicators produced models with high R-Squared and Explained Variance scores, which may indicate some type of relationship between these features.

While the results are promising, I would not recommend relying on these results for several reasons. First, there were correlations between some of the predictive features, indicating potential confounding explanations for these relationships. Also, the sample sizes involved in this analysis were extremely small, making the statistical power of these predictions dubious.

In conclusion, while this analysis undoubtedly had some flaws, it did reveal some interesting patterns that justify further investigation.

Data Sources: https://www.kaggle.com/burhanykiyakoglu/infant-mortality-fertility-income
https://www.kaggle.com/rashikrahmanpritom/disney-movies-19372016-total-gross/metadata