

08_MovieMining_Part2

Discovering Trends in Film Runtime

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Problem Statement / Motivation

Group 8's project goal is the mining of data from a repository with information on over 950,000 films. The mining will have a focus primarily on the runtime feature of the data. It will look at both its impact on other features and the way other features impact it.

Some questions that will be answered via data examination include whether it is possible to predict the runtime of a film based on its genre, country of origin, and/or date of release. Another goal is to identify the ideal film length associated with high ratings.

The intent of determining if these relationships exist, and to what extent, is that this information could be applied within the film industry. This application would theoretically help produce movies with a greater likelihood of positive public reception, resulting in an increased box office.

Literature Survey

A survey of existing literature suggests that some work has been done to examine the impact of runtime on other facets of films. However, the work has been minimal.

A piece in Cognitive Research Journal [1] speaks to runtime tangentially as it related to trends in the pacing of films throughout history. However, the author examines a limited 210 films and only includes films within an arbitrary runtime cutoff at the two-and-a-half-hour mark.

Another article from Film and Digital Media [2] does focus on runtime but is a shallow piece. The intent of

this project is to mine further information than is presented in this strictly topical article.

IMDBPro [3] published an article that focuses on how the success of a film is measured, which is related to this project, but it does not speak to runtime at all. This may lead one to believe that runtime is an overlooked aspect of success.

Proposed Work

This project will begin with EDA, including concurrent data cleaning and preprocessing.

As part of the EDA process outliers in the data will be identified and handled. For instance, a cursory glance at the data shows that there are movies over the 7-hour mark in the data set. Both whether these are actual movie lengths or bad data, and how the outlier is handled needs to be determined. Some of the outliers may be determined from area expertise instead of raw data. Such as the fact that the data set was last updated in July 2024, meaning that any films with release dates past June 2024 likely have bad or limited ratings data as only select viewers may have seen it. This kind of outlier will also need to be determined and handled.

Not only will outliers need to be either removed, transformed, or replaced depending on the type of feature but the overall data characteristics will be recorded and documented. During EDA visualization will be leveraged to help determine if any patterns arise. Visualizing the data and documenting characteristics will help understand the distributions and relationships between features and may influence which features are kept for which parts of the project.

In an earlier iteration of this project, it was discussed that other data sets may be brought in to get additional information on box office, budget, and ratings for films. Since the initial planning it has been decided to abstain from these additions. The primary data set from Letterboxd includes viewer ratings which can be indexed as a success metric. It was determined that there is already a large sum of literature on the analysis of the box office and budgets of films [3] and additional research would be less impactful than that pertaining to runtime. As there are no other data sets being leveraged there is less data preprocessing and integration than initially planned.

Some integration is still required however, as the Letterboxd data set is split into ten separate sub-sets in CSV format. A primary key is shared across all these sub-sets allowing for merging during data frame creation. Other steps in the preprocessing will include transforming categorical data into numerical, using one-hot encoding, so that the information can be more easily parsed. Depending on which evaluation techniques are being leveraged there may also be instances of classification occurring, e.g. the assignment of ratings to categories such as great, good, okay, poor, and bad.

The evaluation stage comes after the EDA, cleaning, and preprocessing, wherein primary features and correlations will be discovered. Mean Squared Error (MSE), regression analysis, Mean Absolute Error (MAE), precision, recall, F1 scores, and lift are just some of the measurements that will be used to determine the strength of correlation and general relationships between the features mined.

Data Set

The data set is sourced from the website / app Letterboxd and hosted on Kaggle [4]. Letterboxd is a social media film site that aggregates film data and viewer interactions such as ratings, likes, and views with said films. The data set has been downloaded locally in case of an unforeseen event where it is no longer available via the web.

The data set is quite large. It includes 10 sub-sets of data and has information on over 950,000 films. Each

of these films can have many entries across the sub-sets of data. For instance, one film may have 3 genres (rows) of data in the genre sub-set alone. The sub-sets include information on genres, country of origin, actors, crew, studios, languages, poster urls, release type and date information, themes, and the movies themselves. The sub-sets vary in size. As mentioned above each film can have many rows in each sub-set other than the movies sub-set. No sub-set has more than seven columns (including the primary key).

The data set is updated annually. It was last updated July 2024, meaning the runtime data included is very up to date for current research. However, when looking at some features, such as ratings, it may be important to note that this feature may not have stabilized for a movie that came out close to the data set update. This is another candidate for domain knowledge-based outliers for certain features.

It is important to note that most of the data in these data sets is categorical. Therefore, if regression is to be done on any of these subsets or the final monolithic set then some encoding will be required.

Evaluation Methods

For evaluation accuracy measurements will be used when looking at the success of classification prediction. Lift will be measured to look at the performance and importance of the associations found. MSE will be used for regression analysis such as the prediction of runtimes. Precision and recall will be used to measure the success of model predictions. F1 scores will be leveraged for tasks such as genre classification. Matplotlib and Seaborn will also be used to create visual plots to aid in evaluation, such as providing a comparison between predicted and known values.

Tools

Python, and its associated libraries will be the primary tools for this project. The following associated libraries will be used for mining the data; Pandas for producing and manipulating data frames, NumPy to aid in calculations, Seaborn and Matplotlib to produce plots and other visualizations, Scikit-learn to help build regression models. There was initial discussion around

the use of Orange, but due to the size of the data set it was determined to not be ideal for this project.

Milestones

1.1 Identification

Expected completion date: 10/01/24

1. Identification of viable datasets
2. Identification of the primary and secondary features.

2.1 EDA – Cleaning

Expected completion date: 10/15/24

Cleaning of data:

Removal of NaN and bad data

Identification and potential removal of outliers (by both domain expertise and statistical determination)

2.2 Data Preprocessing

Expected completion date: 10/31/24

Data has been combined into a singular set containing all pertinent data.

Transformation of data – e.g. one-hot encoding

Trend analysis and precursory evaluations

3.1 Analysis

Expected completion date: 11/30/24

Complete research and analysis on the data. Apply evaluation methods and add visualizations.

Build a predictive model and compare model to test data.

Apply methodologies to the following big questions (more may arise during EDA):

1. What is impact of runtime on rating? / What is the ideal runtime?
2. What is impact of genre on runtime?

3. What is impact of country of origin on runtime?

4. What is the impact of runtime on rating by country of origin?

5. What is the impact of runtime on rating by genre?

4.1 Finalize Results

Expected completion date: 12/6/24

1. Finalize evaluation
2. Synthesize results – determine if there are new questions to be asked
3. Produce final presentation.

REFERENCES

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- [3] *How is the success of films and TV shows measured?*, IMDBPro DOI: <https://pro.imdb.com/content/article/entertainment-industry-resources/featured-articles/how-is-the-success-of-films-and-tv-shows-measured/GLFTC8ZLBBSNTM3>
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