



Data Mining II Project:

Analyzing Data Insights from the IMDb Platform

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Introduction

The goal of this report is to illustrate the characteristics of the given IMDb dataset, and to show key insights that can be obtained from it. In particular, the focus of many of the observations is based on aspects that could be useful for a product’s creation and marketing, in order to optimize the chances of success of a product in the market.

1 Data Understanding and Preparation

TODO: distrib graphs The dataset contains around 1.6 million of titles of different types. For each title, the dataset contains information regarding many different aspects. Table 1 lists the initial categorical features.

Feature	Description
<code>originalTitle</code>	Original title, in the original language (?)
<code>isAdult</code>	Whether or not the title is for adult
<code>canHaveEpisodes</code>	Whether the title can have episodes
<code>isRatable</code>	Whether the title can be rated by users
<code>titleType</code>	Type of the title (e.g., movie, tvseries)
<code>countryOfOrigin</code>	Countries where the title was primarily produced
<code>genres</code>	Genres associated with the title
<code>regions</code>	Regions for this version of the title
<code>soundMixes</code>	Technical specification of sound mixes
<code>worstRating</code> (ordinal)	Worst title rating
<code>bestRating</code> (ordinal)	Best title rating
<code>rating</code> (ordinal)	IMDB title rating class

Table 1: Initial categorical features of the IMDb dataset

Of the initial categorical attributes, the following were removed:

- `originalTitle`, as it did not provide particularly useful information;
- `isAdult`, as it was almost completely correlated with the *Adult* genre, so a logical OR operation was performed, and the genre only was kept; **Interesting to note the fact that in our representation, being that the genres are represented through freq enc, we don’t have the info**
- `canHaveEpisodes`, as it was completely correlated with the title type being *tvSeries* or *tvMiniSeries*;
- `isRatable`, as it was always true;
- `worstRating` and `bestRating`, as they were always 1 and 10, respectively;
- `rating`, as it was obtainable from the `averageRating` continuous attribute, through a simple discretization.

`soundMixes` was also removed, as it required some domain knowledge to be understood, as well as having issues with the values it contained.

Because of their very similar meaning, `regions` and `countryOfOrigin` were merged through a simple union operation. The resulting feature was then represented through frequency encoding on the entire list, as well as counts of the number of countries from each continent. This resulted in eight new features (six continents, one for unknown country codes, and the last for the frequency encoding).

While inspecting the `genre` attribute, it was observed that each record contained up to three genres, listed in alphabetical order—indicating that the order did not convey any semantic information about the title. To represent this information, three separate features were created, each corresponding to one of the genres. These features were encoded using frequency encoding, sorted in descending order of frequency across the dataset. A value of 0 was used to indicate missing genres—either when no genres were present or to fill the remaining slots when fewer than three were available.

The initial numerical features are listed in Table 2.

`endYear` was removed due to it not being meaningful for non-Series titles, and having around 50% of missing values for *tvSeries* and *tvMiniSeries*.

`totalImages`, `totalVideos` and `quotesTotal` were merged through a simple sum operation into a single feature

Feature	Description
startYear	Release year of the title (series start year for TV)
endYear	TV Series end year
runtimeMinutes	Primary runtime of the title, in minutes
numVotes	Number of votes the title has received
numRegions	Number of regions for this version of the title
totalImages	Total number of images for the title
totalVideos	Total number of videos for the title
totalCredits	Total number of credits for the title
criticReviewsTotal	Total number of critic reviews
awardWins	Number of awards the title won
awardNominations	Number of award nominations excluding wins
ratingCount	Total number of user ratings submitted
userReviewsTotal	Total number of user reviews
castNumber	Total number of cast individuals
CompaniesNumber	Total number of companies that worked for the title
averageRating	Weighted average of all user ratings
externalLinks	Total number of external links on IMDb page
quotesTotal	Total number of quotes on IMDb page
writerCredits	Total number of writer credits
directorCredits	Total number of director credits

Table 2: Initial numerical features of the IMDb dataset

(totalMedia) because of their similar semantic meaning, as well as heavy right skewness. The same was true for awardWins and awardNominations, as well as userReviewsTotal and criticReviewsTotal, merged with the same procedure into totalNominations and reviewsTotal, respectively.

castNumber, writerCredits, directorCredits with and without totalCredits; deltacredits

runtimeMinutes had a very high number of missing values (add %). Since the feature had high relevance in the domain, it was imputed with random sampling from a interquartile range, separately for each title type.

eventually, add description of the imputation procedure for tasks which involved titleType

2 Outliers

2.1 COF

2.2 Isolation Forest

2.3 ABOD

3 Imbalanced Learning

3.1 Undersampling

3.2 Oversampling

3.2.1 SMOTE

4 Advanced Classification

5 Advanced Regression