I. INTRODUCTION

Internet Movie Database (IMDb) is an online database dedicated to all kinds of information about a wide range of motion picture contents such as films, TV and onlinestreaming shows, series, etc. The information which is presented on the IMDb portal includes cast, production crew, personal biographies, plot summaries, trivia, ratings, and fan and critical reviews and much other similar information which are mostly provided by volunteer contributors. To contribute, registration is required, however since no legal document is required, one is able to use an arbitrary name. Being a user-regulated website could be a shortcoming as it would be vulnerable to malicious attempts from a certain group to bias information. However, taking advantage of a large community not only overpower these attempts but also create a cornucopia of valuable data that analyzing them may shed light on many hidden factors that help movie industries and other related businesses in content production.

There are various studies have been done on IMDb data. Oghina and et al. investigated the possibility of prediction of IMDb rating using social media contents such as tweets and YouTube comments. Otterbacher showed there is a tangible difference between men and women’s review writing style using the IMDb review section. In the connection between user voting data and economic film characteristics such as budget and box office data has been investigated by Wasserman et al. Hsu et al., using linear combination, multiple linear regression, neural networks predicted the IMDb rating from other movie’s attributes using 32968 titles; and In Nithin et al. used Logistic Regression, SVM Regression and Linear Regression to predict box office data. In, using available demographic information on IMDb Baes et al. created a demographic movie recommender system. Ramos et al. showed the distribution of votes showed a scale-free behavior.

There various datasets available each with a different policy. IMDb itself discloses a subsets their data for personal use. Furthermore there are more dataset available freely on kaggle such as IMDb movies extensive dataset, IMDb Dataset of 50K Movie Reviews, Also there are other which are required corresponding with the owner.

Seeing that many datasets available online usually do not cover some important information or they are not large enough, we determined to create a dataset that covers some drawbacks that exist in the available sets. Still, the other datasets could be used as a complement. The present paper is the first paper in a series of papers aiming to create a suitable dataset, analyze it, and predict some information using those data.

II. AVAILABLE DATA

The created dataset is based on the data available on IMDb website and some third-party datasets and resources to provide some additional information on the available data on IMDb, such as similarity of countries and languages or how much a certain actor is talked about comparing other using the number of google results. The data mainly extracted from IMDb Portal, IndexMundi, Elinguistics, and Google results in a specific field of data. This section is dedicated to the description of gathered data from the IMDb database. The full description of the data is available at https://help.imdb.com. To learn about the gathered and processed data from IndexMundi and Elinguistics you may refer to Appendix.

To access each title, we used the code which IMDb assigned uniquely to each title. The code started with a double t - “tt”- followed by some numbers, for example this code for the title Logan (2017) is “tt3315342”. Using this code one can have access to the title’s main page, for example the address for the title Logan (2017) would be like https://www.imdb.com/title/tt3315342. The main portion of extracted data is from the title’s page and some relative addresses from that page, for instance, the rating data extracted from the relative address of /ratings of each title page.
A. Movie Name

The Movie name is the name which was given to each title by the producer, we found a few minor discrepancies on the titles from different part of IMDb. Here our reference is the name on the designated page for each title.

B. Poster

There are several posters associated with each title. Here the main poster which has been presented on the title page, is stored.

C. Alternate titles (AKAs)

Alongside the original title, every film may have other titles or names that are known with, either in different countries and/or languages; in this case, alternate titles may be listed. Default Alternate title is the same as the primary one. The alternate titles could be a small deviation from the original name and/or be in other languages rather than the film’s language[s], for example for the movie Logan (2017) the alternate titles are mainly the original title plus Wolverine which is sometimes in different languages rather than its original language, English. In this case, the regular NLP analysis may not give any insightful results, however, the number of the alternated title could be an interesting factor. It could somehow show how much people and/or different nations care to give the movie their own names. Thus, the number of Alternate titles could be an important factor.

D. IMDb ratings and Number of votes

Every user can vote from 1 to 10 for the rating of each title, there is no need to writing a review upon giving the score. A weighted average of the registered users will be shown as the title rate. IMDb’s intention is to reduce the intended attempts to change the title rating from actual worth. Various filters are applied for this propose and IMDb does not disclose the math. However the arithmetic mean is also available in the relative address of [ratings] for each title. Moreover, the voting distribution histogram and demographic information of rating and number of votes are also available. Here demographic information contains the top 1,000 voters information, US and none-US users, and different age and genders. The top 1,000 voters are the top 1,000 who have voted the most titles and are unknown. For the rating section, the IMDb’s rating, the arithmetic mean of rating, median, and all the demographic information about the rating (by age, sex, and being top 1000 users, US and Non-US) and the number of votes have been gathered.

E. Metacritic Score and User/Critics reviews

Besides the rating, the [metacritic score] and user reviews professional critics are available, so one could be informed of other viewer opinions. At first glance, the semantic analysis of each review seems to be the only way to use this information. However the number of reviews could be a helpful factor to validate the user’s ratings. Despite the reviews could be biased, ignoring various drawbacks of the title, especially the one written by users rather than renown critics, the number of them could be showing how much the title worth to people dedicate their time to write about, after watching the movie. On the other side, the votes could be blind votes which are given by particular groups very high or low, without seeing the movie as it happened for The interview (2014) which at the beginning of release get a near-perfect score. Not only blind voting causes a problem, but also die-hard fans of some genres like Sci-Fi, ignoring major flaws, could also have very biased voting. However, after a given period of time the effect this attempt will smooth out. On the other hand, writing a review is less impulsive action and needs more contemplation, and of course being a fan of a genre won’t be enough to write the reason why an individual liked/disliked a title.

F. Popularity and change

The popularity ranking on a title separately compares movie titles with each other.

G. Motion Picture Rating, IMDb Certificates

To specify the appropriate audience for each title IMDb provides the Motion Picture Rating (MPAA) certificate. Explanations for the available entries are available at. Each county has its own MPAA system and/or age restriction for each title. Here the rating certificate given to each title within the United States has been considered as the reference. The information about other countries also extracted from relative url of /parentalguide for each title.

H. Parent Guide

IMDb includes parent guide entry to provide the parents with additional information by describing some scenes to determine the appropriateness of each title. All the information is available in the relative address of /parentalguide of each title. The entries include Sex and Nudity, Violence and Gore, Profanity, Alcohol, Drugs, and Smoking, and Frightening, and Intense Scenes. Here just the number of scenes (and not the description) and, if it is available, the degree of severity (Mild, Moderate, Severe) are extracted.
I. Genres

There are several genres, which each title may associate with one and more. For the full description you may refer to [15].

J. Countries and Languages

Country is defined as the country where the production company is based. It is possible multiple companies are associated with each title [16]. The languages which are spoken in each title are listed in order of frequency [17].

K. Release Dates and Locations, Filming Dates and Locations

Release dates and locations have been gathered from the relative address /releaseinfo of each title. One of the importance of this portion of data is the potential popularity. For example, if the title released in different countries in a small time window it may be a sign for its popularity.

Moreover, the filming dates and locations have been extracted from relative address of /locations. The filming locations could be a good indicator for the budget class of the movie especially when no data is available on the budget.

L. Box Office data - may need to add

The extracted data here are: Budget, Opening Weekend USA Income, Opening Weekend USA, Gross USA, Cumulative Worldwide Gross.

M. Director, Writers, Stars

Director, Writers, Stars, and roles are also extracted. There is an elaborate list for each of them available but at this point, for the sake of simplicity, the first names on the main page of each title are stored. To machine they are some random string. Plus, there are not a lot of data to assign them a value or a vector with techniques such as Word2Vec. Some datasets are containing the number of Facebook page’s likes for each actor or similar information like this dataset on kaggle. However the size of these datasets is limited and does not cover all the names that are needed here. Here we have taken another strategy and used the number of google results. To avoid name similarity we used the profession alongside the name to narrow down the results as much as possible: for example we searched Tom Hanks actor, or Steven Spielberg director.

N. Production Companies

The list of production companies has been extracted from the relative address of /companycredits of each title.

O. Related movies

Up to twelve similar titles are suggested under the “More like this” entry. These titles are generated based on various information such as genres, country, stars, etc [18]. Here we also extracted the IMDb rating, number of votes, the IMDb code for each related title.

P. Keywords and Storyline

There are also storyline plot and keywords available. This data is valuable to this extent that reveals the special things that stand out of other things which are presented in the movie. The keywords are offered by users and other users can vote if they are relevant or not. Here we gather all the keywords sorted by a relevancy score from the relative address of /keywords which is calculated by this relation:

\[
\text{Number of votes} \times \frac{\text{Number of positive votes}}{\text{Number of votes}}
\]

III. DATA CLEANING AND PROCESSING

Here we briefly describe the pre-processes and labeling format that is essential to know before using the data.

A. Structure of the Data

1. Data Format

Data is packed according to the release year of each title for better management. All the data are stored in a CSV file with UTF-8 encoding. The index of the table has been set to its unique IMDb code. Using the IMDb code as the index could be beneficial during the model training since it uniquely determines the title it does not contain specific information that could be used during the analysis or model training to be a part of the table. Moreover, there is a sub-directory for each year containing the film’s poster in jpg format each with the dimension of 182×268, 72 DPI. The size of the data is around 5-25 Mb for the CSV file and 10-15 kb for each poster image.
2. Columns' names

Since heavily relying on column numbers in the middle of analysis could be confusing, especially here which data are packed according to the release date of the titles and the number of columns may vary. Here we introduce a specific semi-wildcard format to access columns without heavily relying on the column number. Including those patterns enable the users to search with Regular Expressions (RegEx) to narrow down the column to the specific part of the table. Here we used capital letters at the end of each column name to distinguish them from the actual name of the column; since the multi-parted names are accompanied by underscore, using python regular expression has been made easy. If you are using the Pandas library you may filter the DataFrame keys according to these sets of characters.

B. Wildcards

Here we will briefly describe the wildcards’ meaning.

C. *GS

GS stands for General Set, which contains general information about the title such as the name and alternate names, technical information like runtime sound mixing, the plot, keywords and etc.

D. *GENRE

This wild card is related to information about the genre. Since each title’s genre does not necessarily fall into one category, here we created two sub-wildcard of *SET_GENRE for a complete set of genre and *HOTVECTOR_GENRE for their hot vector representation.

E. *COUNTRY

With this wildcard you may access the country information of each title. There are two sub-wildcards are also available *SET_COUNTRY *HOTVECTOR_COUNTRY for list of country and hot vectors of countries respectively. Here we included two quantized information about the country; the reference of comparison has been chosen the United States as the creator of the most titles each year. In NonGeographical_DIFF_COUNTRY the mean Manhattan distance between 106 parameters has been calculated, for more information about this analysis please refer to Appendix I. Geographical_DIFF_COUNTRY provides information about the geographical distance by calculating the great-circle distance between the country’s capital from Washington DC using haversine formula.

1. *LANGUAGE

This wildcard related to languages which are spoken in the original version of each title. *SET_LANGUAGE includes list of spoken languages with descending order of usage frequency. *HOTVECTOR_LANGUAGE is the hot vector of languages. Language comparison to English is stored in *ENGLISH_DIFF_LANGUAGE column. *GOOLERESULTS_LANGUAGE contains the number of google search results. It is abundantly clear that the exact number is not a good reference but its order of magnitude would give an idea of how much a language is spoken about relative to another. Although the number of people who are speaking a certain language as the first and/or second language also might be a good option to assign a meaningful value to each language, however, we hadn’t found any resource for all the languages.

2. *BOXOFFICE

This wildcard is the data related to Boxoffice, Please note that the Currency is not converted to their today’s value.

3. *DWS

This wildcard is related to Directors, Writes, and Stars and their roles. There is a comprehensive list for each field but here the list of names is restrained to the names which are appeared on the main title page. Also the number of google results for directors, writers and stars are included in sub-wildcard of *GOOGLE_RESULT_DWS.

4. *RATING

*RATING is associated with the voting, the rate and the number of votes. The general information such as the total number of votes, arithmetic mean rating, and IMDb rating and median of votes can be found using *G_RATING wildcard. The sub-wildcard related to the distribution of voting of *NUM_DIST_RATING, *PERCENT_DIST_RATING for number of specific vote and the percentage respectively. US and Non US voters, sore and number of vote are accessible using the wildcards of *SCORE_GIS_RATING and *NUM_GIS_RATING. Top users score and number of votes are Top1000_Voters_*SCORE_DEMOGRAPHIC_TOP_RATINGS, Top1000_Voters_*NUM_DEMOGRAPHIC_TOP_RATING columns. For all Ages and gender and/or separately sorted by age intervals and gender the wildcards of *SCORE_DEMOGRAPHIC_AG_RATING, *NUM_DEMOGRAPHIC_AG_RATING are used to access the score and number of votes respectively.
IV. PRELIMINARY ANALYSIS

Although a full analysis is beyond the scope of this paper. The intention of this section is not to draw any conclusion about the results, but to show a glimpse of how the analysis looks like, a small part of the analysis has been shown here. This analysis will be conduction on IMDb Ratings and Parent Guide information on a portion of about 3,000 items.

A. The highest rates and movie certificate

Tables 1-3 summarized mean of IMDb rating of each certificate rating given by each age range. As it can be inferred here, usually the movies with more near-general-audience certificate receive better ratings.

| Certificate | All Ages | under 18 | 18 - 29 | 30 - 44 | over 45 |
|-------------|----------|----------|---------|---------|---------|
| G           | 6.25     | 6.27     | 6.32    | 6.07    | 6.23    |
| NC-17       | 6.70     | 6.00     | 6.50    | 6.70    | 6.80    |
| PG          | 6.15     | 6.06     | 6.29    | 6.03    | 6.16    |
| PG-13       | 5.95     | 5.91     | 6.02    | 5.85    | 5.88    |
| R           | 5.90     | 5.97     | 6.00    | 5.82    | 5.80    |

B. IMDb rating, Arithmetic mean of ratings, Ratings Demographic Information, Parent Guide Information

Another interesting information that could be extracted from this data is the voting distribution of each group according to their age and gender [1] or how much they are correlated, which makes it possible to figure out how the rating of each group is related to another Fig [1] or how much parent guide items such as “Sex and Nudity” or “Violence and Gore” would affect on each age/sex group voting [2].

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[1] A. Oghina, M. Breuss, M. Tsagkias, M. de Rijke “Predicting IMDB Movie Ratings Using Social Media”. Advances in Information Retrieval. ECIR 2012. Lecture Notes in Computer Science 7220: 360–371.
Third-party data compliments

Since part of data is in form of text, we needed to utilize an appropriate approach to turn them into numbers so we can use it in training of machine learning models. Despite turning them into hot-vectors might sound like the only option, we used other approaches to assign each entry a suitable value. Here we briefly discuss about the datasets and the process of preparation. As the results of some policy we are not allow to reshare some of these third-party data, thus only our results after the processing will be disclosed.

1. Third-party data compliments

All the data are available [https://www.indexmundi.com/factbook/compare](https://www.indexmundi.com/factbook/compare) Please read carefully the **Term of use** before using their data. Here we mainly used demographics information, and some information from geography and economy table. In total, 106 Fields of data extracted. All fields of data are normalized to so they are ranged from 0-1. Since we need to assign each country a value we calculate the geographical distance and non-geographical distance using extracted data from United States. The missing information was another issue; Antarctica, for instance, does not possess 96 out of 106 our data columns. Here we take the availability of data as similarity factor, therefore the number of missing data will increase the distance of two country. Since each column was unrelated to the most of other data we report the mean Manhattan distance as the non-geographical distance of countries. In this process the most similar, excluding geographical distance, countries was United Kingdom and the least similar was Antarctica, which sounds reasonable.

2. Elinguistics

This database used to compare different languages to English.Despite their similarity to English, the most spoken language, could be consider as an important factor, this analogy could be misleading since two different languages from English might be highly similar. The reported values are from 1 to 100. Highly related languages, Related languages, Remotely related languages, Very remotely related languages, and No recognizable relationship receive score Between 1 and 30, Between 31 and 50, Between 51 and 70, Between 71 and 78, and Between 71 and 100 respectively. You may learn more about their analogy from their methodology.

3. Number of Google Results

The number of google results also used to compare how much the searched key is talked about on the web. For the languages, stars, directors, writers, and production companies, we used number of google results.
FIG. 2: Heat map of all $\ast$RATING sub-wildcards correlations
FIG. 3: The correlation of rating demographic information and parent guide items