Box Office Revenue Prediction

Project Proposal Paper

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PROBLEM STATEMENT/MOTIVATION

As of 2018, it has been reported that the global box office is worth $41.7 billion. However, when the home entertainment revenue is included, the global film industry is worth over three times that at $136 billion. Despite the massive profits, movie industry is one of the riskiest markets for investors due to its uncertainty and unpredictability. Once a movie fails to meet expectation, it can potentially place a stress on the financial status of the movie studio, and lead to the withdrawal of funds from the investors. Therefore, through analyzing the performance of movies on the market, we could find the correlation between attributes of a movie and predict the revenue on release.

CCS CONCEPTS

• **Computing methodologies** → Retrieval model and ranking

KEYWORDS

Revenue, profitability, variables, data

ACM Reference format:

N. Nguyen, M. Pollich and B. Breyfogle. 2018. Box Office Revenue Prediction : Project Proposal Paper. In *Proceedings of ACM Woodstock conference (WOODSTOCK'18). ACM, New York, NY, USA, 2 pages.* https://doi.org/10.1145/1234567890

*Article Title Footnote needs to be captured as Title Note
†Author Footnote to be captured as Author Note

WOODSTOCK'18, June, 2018, El Paso, Texas USA

LITERATURE SURVEY

Galvão, M. and Henriques, R. (2018). Forecasting Movie Box Office Profitability. Journal of Information Systems Engineering & Management, 3(3), 22. https://doi.org/10.20897/jisem/2658

The revenue of a movie can be predicted by constructing a predictive model based on regression, decision trees or neural networks. The paper proposed 3 different variables to use: an interval variable for the value of profitability of individual movies, a categorial variable with multiple classes of profitability values, and a binary variable that shows whether the movie is profitable or not. Using these three variables can increase the accuracy of the prediction and help answer how the market behaves, what appeal to the audiences and the risk associated with movies production.

PROPOSED WORK

Overall, our proposed methodology has three components: Data Collection, Data Cleaning, Data Analysis and Prediction. Cleaning the dataset and discarding the irrelevant data from the datasets as well as thorough analysis of the data within these sets. We will compare the attributes that are provided across all of the datasets and build a brand a database that encompasses only the attributes that we care about.

1. Data collection: We plan to utilize three different datasets that all contain different attributes for all the

movies that were produced within the last decade or so. Within these selected datasets, some common attributes included: ratings (IMDB), title, actors, actresses, studio, and release date. We will explore in more detail which attributes we want to focus on in the Evaluation Methods section of this paper. Lastly, we chose not to collect data from the IMDB dataset due to multiple reviews expressing the difficulty with the formatting of the data.

2. Data Cleaning: In order to clean the data from all of the datasets, we will construct a relational database to make finding duplicates and unnecessary attributes easier. Moreover, with this database we will be able to write various SQL queries in order to narrow down relevant information.

3. Data Analysis and Prediction: After the data is cleaned and organized efficiently, we will analyze it and look for distinguishing patterns. As proven to be effective in the surveyed literature, our prediction model will use a classification system in order to separate the movies based off of the attributes that contribute the most to a higher box office revenue.

DATA SET

Boxofficemojo Alltime Domestic Data

The data contains 16223 unique values of the lifetime gross, ranking, title, studio and production year of Hollywood movies. They were scrapped from BoxofficeMojo's listing and based on domestic gross.

https://www.kaggle.com/eliasdabbas/boxofficemojo-alltime-domestic-data/version/3

The Movies Dataset

This dataset contains files containing metadata for all 45,000 movies listed in the Full MovieLens Dataset. The dataset consists of movies released on or before July 2017. Data points include cast, crew, plot keywords, budget, revenue, posters, release dates, languages, production companies, countries, TMDB vote counts and vote averages. This dataset also has files containing 26 million ratings from 270,000 users for all 45,000 movies. Ratings are on a scale of 1-5 and have been obtained from the official GroupLens website.

https://www.kaggle.com/rounakbanik/the-movies-dataset/downloads/the-movies-dataset.zip/7

MovieLens Dataset

This dataset contains six files: genome-scores.csv, genome-tags.csv, links.csv, movies.csv, ratings.csv and tags.csv and describes 5-star rating and free-text tagging activity from MovieLens, a movie recommendation service. It contains 20000263 ratings and 465564 tag applications across 27278 movies. These datasets were created by 138493 users between January 09, 1995 and March 31, 2015 and was generated on October 17, 2016. Users were selected at random for inclusion. All selected users had rated at least 20 movies. No demographic information is included. Each user is represented by an id, and no other information is provided.

https://grouplens.org/datasets/movielens/20m/

EVALUATION METHOD

We are looking for a high percent of support and confidence between revenue and studios, budgets, genre…

We will prepare a training set and a testing data set for our analyses. This will allow us to determine our models' accuracies.

We will be able to evaluate the relative contributions of different factors affecting movie revenue at the box office.

Most of the attributes that we will use in the project are adopted from previous studies that have found especially useful and relevant. Moveover, we will consider not only the most relevant studies with a higher success rate (sequel, actor, director, budget, nominations, genre), but also other attributes that are not as commonly considered (reviews, duration,

number of screens). Some of the attributes that we have found to be used across all studies include:

Budget

Previous studies have shown that the budget of a movie is strongly correlated with the predictability of its popularity and reception. However, while some argue that big budgets represent better quality and positive reviews from both the audience and movie critics, the studies have shown that a big budget does not ensure a high revenue. Despite this finding, this attribute could still prove valuable in our analysis and design of the prediction model.

Genre

While many authors and critics state through their studies that action movies and thrillers are the most significant and popular among audiences, the evaluation of each genre and its correlation to the film's overall success will ultimately help weed out variables that are not relevant.

Premier Date

The movies premiere date is a variable that influences box office revenue. This may be due to the fact that movie attendance, overall, tends to increase significantly on holidays or festive seasons.

TOOLS

Python – Pandas, Dataframe, Numpy, Sklearn, Seaborn

Github

MILESTONES

Milestone completed:

Data Collection:

Description: find datasets with movie data (the movies dataset was chosen).

Completed on: July 12, 2019

Asigned to: Melissa, Nhan

Data Cleaning:

Description:

Look at collected datasets and figure out important/relevant attributes.

Build/organize new database (remove duplicates and unnecessary data points).

Completed on: July 20, 2019

Assigned to: Nhan, Melissa

Data Analysis – Classification:

Description:

Construct classification system based off of new cleaned/organized dataset.

Divide dataset into training dataset and test dataset (these two are now merged together)

Completed on: July 26, 2019

Assigned to: Nhan, Melissa

Milestone Todo:

Data Analysis/Prediction – Build Prediction Model:

Description:

Code prediction model using the training dataset to develop models which can be used for the test dataset

Complete by: July 28, 2019

Assigned to: TBD

Data Analysis/Prediction – Test Prediction Model:

Description:

Test prediction model code using test dataset for analysis using these prediction algorithms:

Decision Tree

Regression

Neural networks

Complete by: August 2, 2019

Assigned to: TBD

Finalize Prediction Model:

Description: finalize prediction model and note all the changes.

Complete by: August 8, 2019

Assigned to: TBD

Figures and Prediction Summary:

Description: build graphs of the data from the prediction model test and summarize the results.

Complete by: August 9, 2019

ACKNOWLEDGMENTS

RESULTS SO FAR

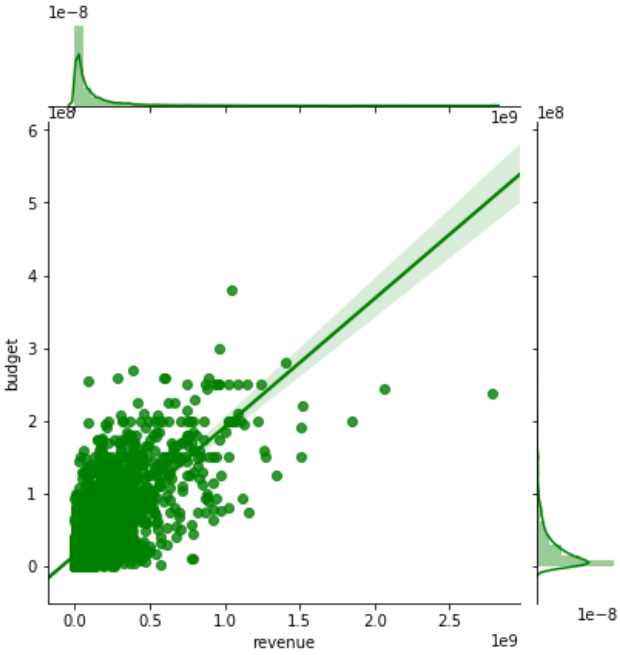
The movies dataset (more specifically, movies_metadata.csv) was chosen because in contains the necessary attributes like genres, budget, vote count, vote average, popularity… and revenue.

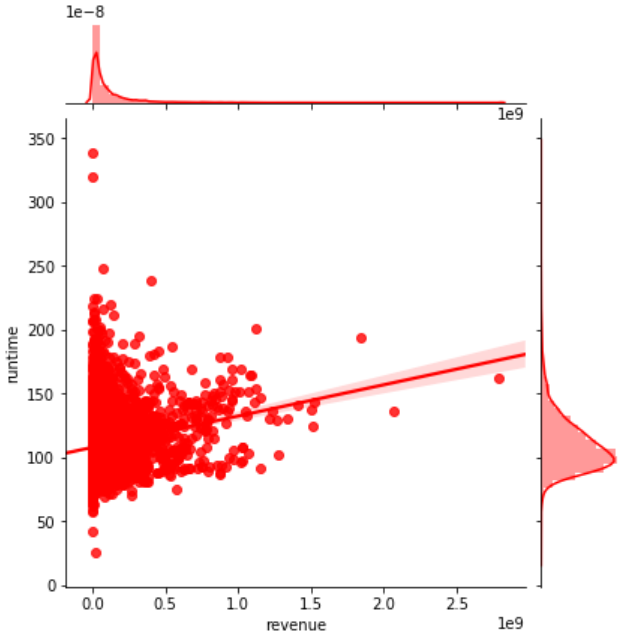
	adult	belongs_to_collection	budget	genres	homepage	id	imdb_id	original_language	o
0	False	{'id': 10194, 'name': 'Toy Story Collection', ...	30000000	[{'id': 16, 'name': 'Animation'}, {'id': 35, '...	http://toystory.disney.com/toy-story	862	tt0114709	en	T
1	False	NaN	65000000	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	NaN	8844	tt0113497	en	J
2	False	{'id': 119050, 'name': 'Grumpy Old Men Collect...	0	[{'id': 10749, 'name': 'Romance'}, {'id': 35, ...	NaN	15602	tt0113228	en	G C
3	False	NaN	16000000	[{'id': 35, 'name': 'Comedy'}, {'id': 18,	NaN	31357	tt0114885	en	W E

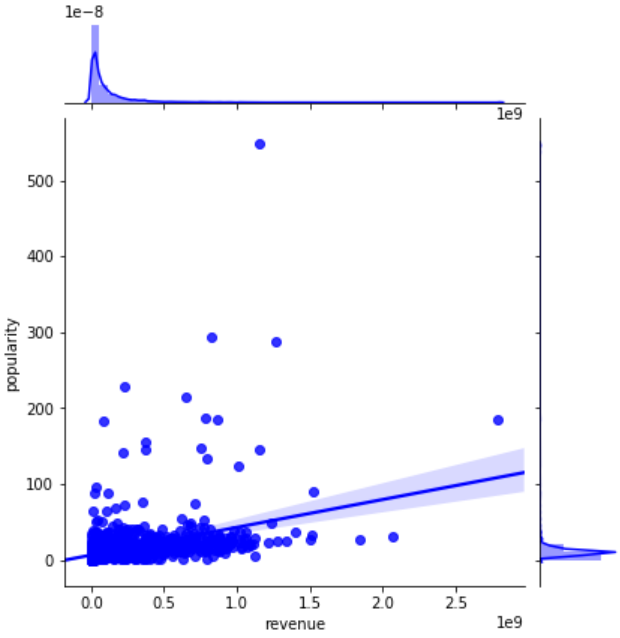
There were a lot of empty data in the original list (NaN value), and the values in budget and popularity was classified as string type instead of int and float type. Also, there was some movies with no budget, or no revenue, so they need to be removed as well. Some attributes like collections, homepage, status… are not required so they should also be dropped from the table. Therefore, data cleaning and processing are required, and the new dataset is as followed:

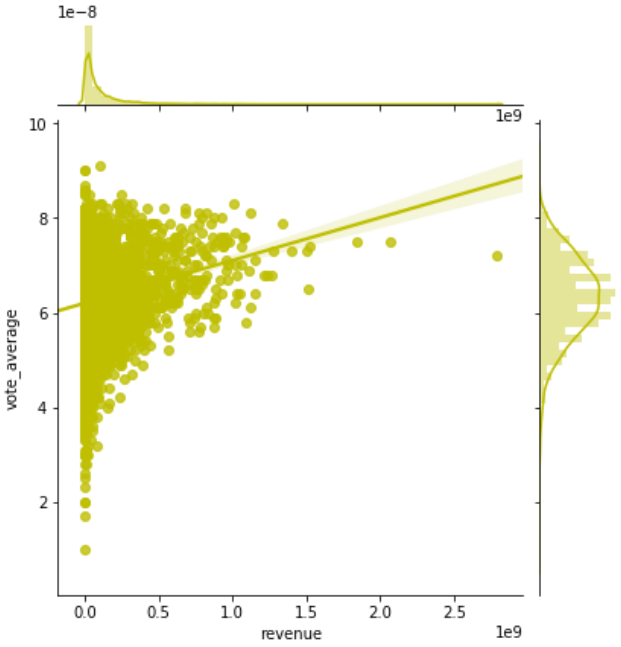
	adult	budget	genres	id	imdb_id	original_language	popularity	production_companies	production_countr
0	False	30000000	[{'id': 16, 'name': 'Animation'}, {'id': 35, '...	862	tt0114709	en	21.946943	[{'name': 'Pixar Animation Studios', 'id': 3}]	[{'iso_3166_1': 'US', 'name': 'United Stat o...
1	False	65000000	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	8844	tt0113497	en	17.015539	[{'name': 'TriStar Pictures', 'id': 559}, {'na...	[{'iso_3166_1': 'US', 'name': 'United Stat o...
3	False	16000000	[{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam...	31357	tt0114885	en	3.859495	[{'name': 'Twentieth Century Fox Film Corporat...	[{'iso_3166_1': 'US', 'name': 'United Stat o...
5	False	60000000	[{'id': 28, 'name': 'Action'}, {'id': 80, 'nam...	949	tt0113277	en	17.924927	[{'name': 'Regency Enterprises', 'id': 508}, {...	[{'iso_3166_1': 'US', 'name': 'United Stat o...
8	False	35000000	[{'id': 28, 'name': 'Action'}, {'id': 12, 'nam...	9091	tt0114576	en	5.231580	[{'name': 'Universal Pictures', 'id': 33}, {'n...	[{'iso_3166_1': 'US', 'name': 'United Stat o...

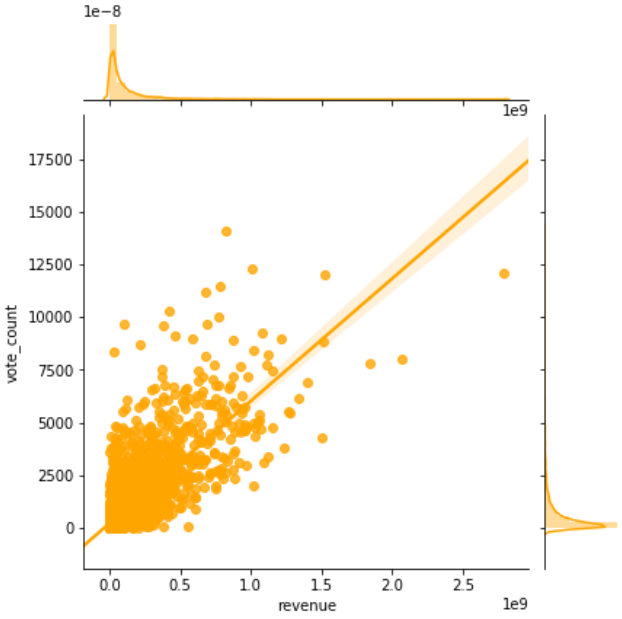
We then look at the relationship between revenue and some of the prominent attributes like budget, popularity, runtime, vote average, vote count. So far, budget and vote count show really positive result:


1e−8
1e8
1e9
budget
revenue
1e9
1e8
1e−8

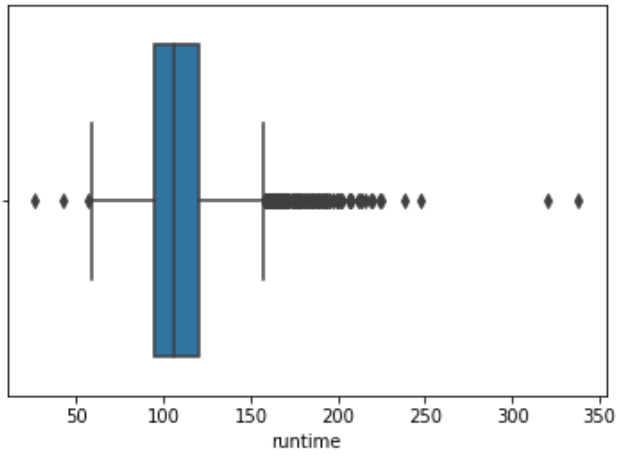

1e−8
1e9
runtime
revenue
1e9

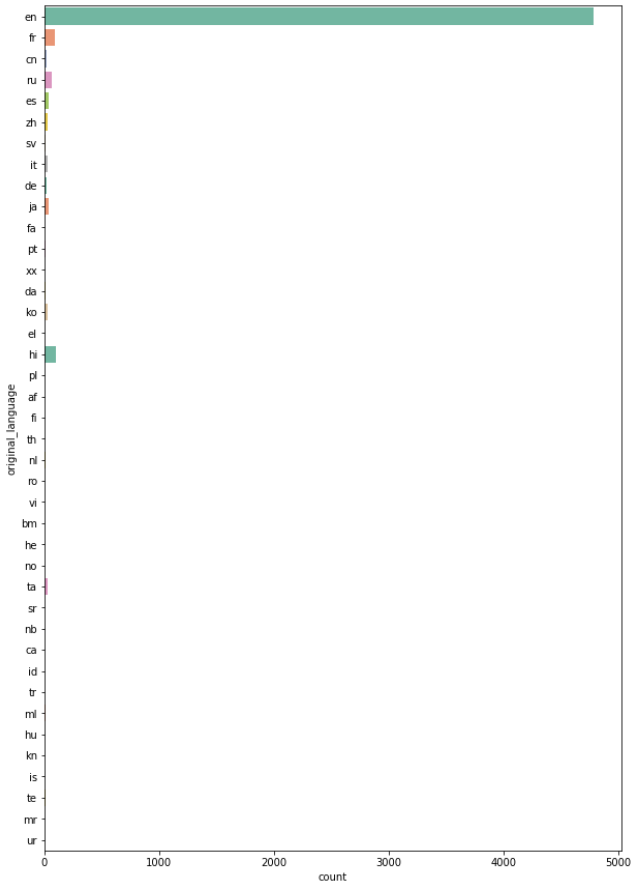

1e−8
1e9
popularity
revenue
1e9

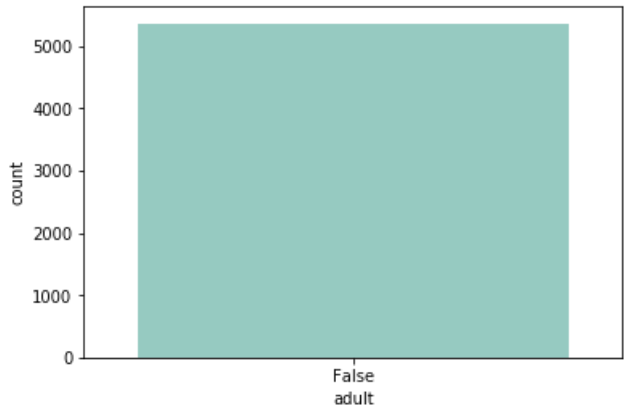

1e−8
1e9
vote_average
revenue
1e9



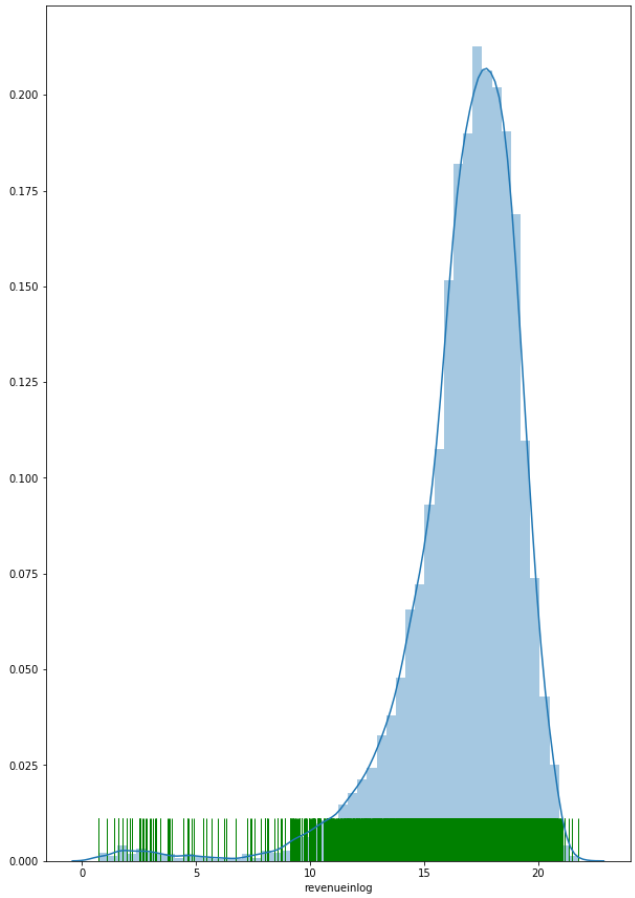
Some of the other attributes were also interesting. For examples, most movies have average runtime, are in English and none of the movies in the list are for adult:







The revenue was also changed to log for easier observation.



We planned to process genre, release day and production countries after this, and combine all the information to make a predictive model.

REFERENCES

[1] Galvão, M. and Henriques, R. (2018). Forecasting Movie Box Office Profitability. Journal of Information Systems Engineering & Management, 3(3), 22. https://doi.org/10.20897/jisem/2658

[2] F. Maxwell Harper and Joseph A. Konstan. 2015. The MovieLens Datasets: History and Context. ACM Transactions on Interactive Intelligent Systems (TiiS) 5, 4, Article 19 (December 2015), 19 pages. http://dx.doi.org/10.1145/2827872