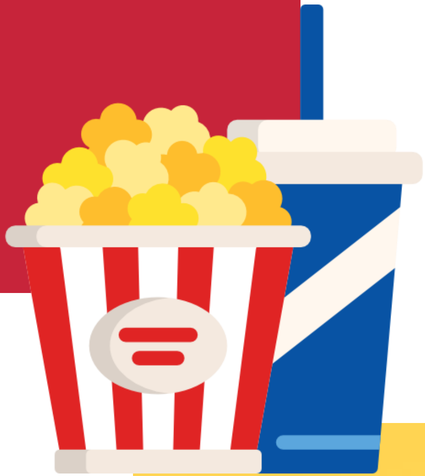
Data Science Use Case Scenario: How good is a movie?



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Overview

- **How good is the movie?**
- Datasets descriptions
- Descriptive analytics
- Feature Engineering
- ML Algorithm and results
- Next Steps

How good is the movie?

- The presented use case scenario tries to predict how good is the movie base on 6 different datasets available on kaggle. See git repo
- https://github.com/nonameforpirate2/Prediction-Movie-Good-or-Bad

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Datasets Descriptions

The six datasets available are the next ones

- **genome_scores**: contains a list of tags assign to each movie with its corresponding relevance.
- **Genome_tags**: contains the list of the different tags created by users with its corresponding ID.
- **Link**: it has an homologation of the ids between movieId, imdbId and tmdbId.

Datasets Descriptions

The six datasets available are the next ones

- **Movie**: it has information about the movies, title, movieId and genre assign to the movie.
- **Rating**: it is the most important dataset. It contains the activity rating of users to movies with its corresponding timestamp. It has the user id, movie id, timestamp and the rating.
- **Tag**: it has the tagging activity of users to movies with its corresponding timestamp.

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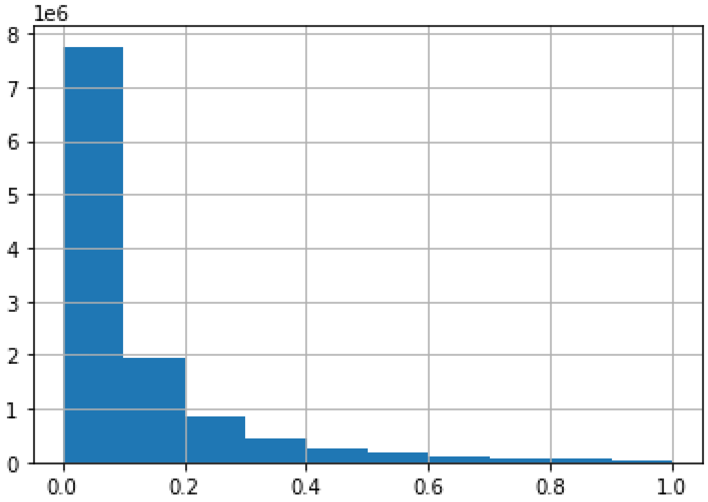
Descriptive Analytics

From the available datasets, it was possible to describe the next information:

- The most of the movies do not have a big relevance, very few movies are quite relevant.
- People create so far 1128 different tags to assign to movies.
- There are 27278 movies, most of them contain the "year" in the title. However, around the 19.2% do not have a year asign (5218).
- There are movies from the year 1913 to the year 2013.The year with more movies is 2013.

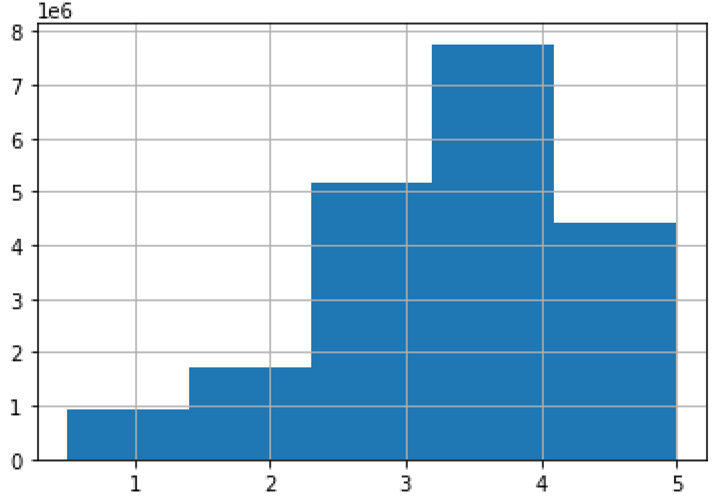


Relevance Histogram

Descriptive Analytics

From the available datasets, it was possible to describe the next information:

- There are 20 different genres.
- From the rating asignation the time took place between 1995-2015.
- Most of the movies have a 4 + rating.
- It was found that not all the movies have a tag assign, only 71.6% (19545) have a tag.
- Customers present a tendency to assign around 10-15 tags per movie.



Rating Histogram

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Feature Engineering

From the available datasets, it was possible to describe the next information:

- **Relevance feature**. The feature describes the average relevance that a movie has given the tags available on it.
- **Movie Year feature**. Text mining was done on the movie titles to get the year from each movie.
- **Movie Genre feature**. Text mining was done to create label columns with each of the 20 genres.
- **Movie tag feature**. Represents the amount of tags presented in a movie.
- **User tag feature**. Represent the amount of tags that a user has use.
- **User movie feature**. Represents the amount of tags that a user use in a movie

Feature Engineering

- **Month feature**. User behavior intention by seasonality. Represents the month of the year when the user rated the movie. Weather influence on human behavior.

- **Day feature**. User behavior intention by day. Represents the day of the month when the user rated a movie. Paycheck effect/friday and beers etc.

- **Hour feature**. User behavior intention by hour. Represents the hour in the day when the user rated a movie. Before going to sleep efect, student, house wife etc.

- **Year rating feature**. Represents the years that passed by from the moment of the rating and the movie creation.

- **Y_lag**: the rating of the user in the previous movie. Intuition, how is my humor while I do rate movies.

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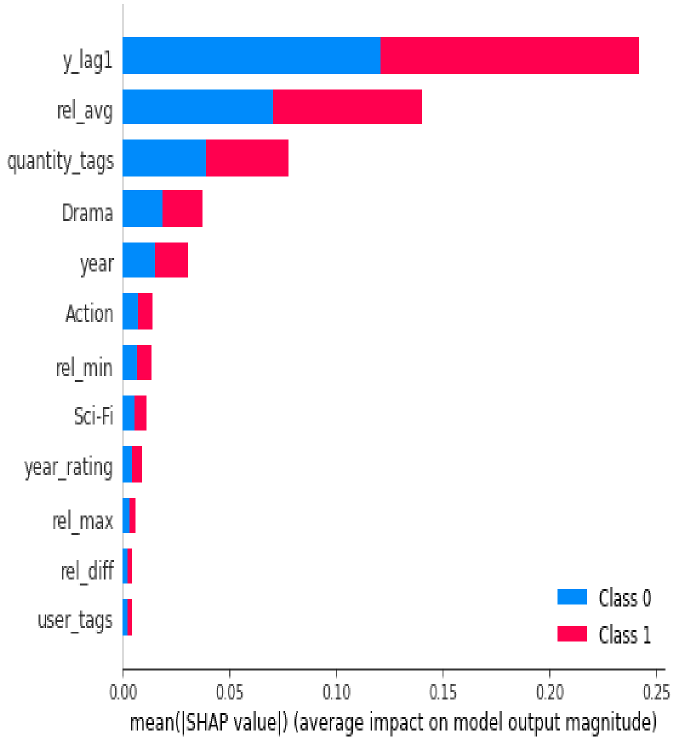
ML Algorithm and Results

A machine learning algorithm was trained to predict whether the movie was good or bad, it takes into account a +4 stars rating as a good movie.

- The selected algorithm was a random forest with 50 trees, entropy criterion, depth = 10.

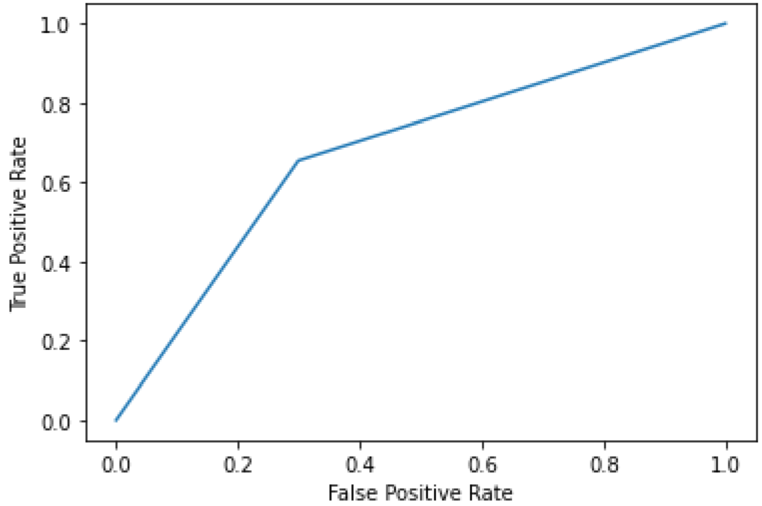
- The attributes with more influence over the model can be appreciated in the graph.

- The relevance related to the tags, the amount of tags in a movie, the time between the rating moment and the movie creation and the previous rating of the user are the features with most importance.



ML Algorithm and Results

- Its performance was measure with a 5 k-fold cross validation and it gave as a result a ~70% accuracy.



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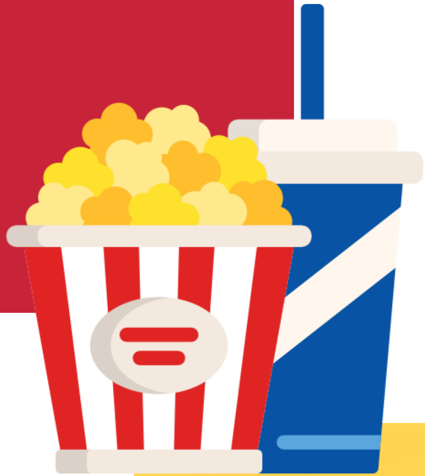
Next Steps

This data science model is a baseline and there is a lot to be done to improve it.

- There is plenty of room to work with NER (name entity recognition) in the part of the tagging / More feature engineering with text mining.
- More feature engineering.
- More hyper parameter tuning.
- Test more algorithms.

Thanks!



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