

Alma Mater Studiorum - University of Bologna
LM Informatica
Data Analytics Project

Cotugno Giosué [983620] - Pruscini Davide [1007343]

July 11, 2022

Contents

1	Introduction	5
2	Methodology	7
2.1	Data Acquisition	7
2.2	Data Pre-process	7
2.3	Modeling	11
2.4	Performance Analysis	11

Chapter 1

Introduction

In this report we will discuss about the whole data pipeline of a project that uses different techniques of machine learning to classify some tabular data. In particular, we choose the first project proposal that aims to predict the average mark of a film from its features. The first step of the data pipeline requires to download, save and load in memory the MovieLens [1], TMDb [2] and IMDb [3] datasets. Consequently, the datasets were elaborated with the objective to generate a unified dataset that can be used as an input for some machine learning algorithms. Afterwards, during the modelling phase we built an MLP model thanks to the PyTorch framework [4]. In addition, we used other techniques like SVM, tree methods and naive bayes methods that are available into the Scikit-Learn library [5]. In order to find a good configuration during the performance analysis, it was mandatory to define a large enough hyperparameters space for all the models that we defined. Moreover, in the last phase, the cross validation technique was used to obtain more robust statistics results that has been compared between the trained models.

Chapter 2

Methodology

In the next chapter there will be the explanation of the data pipeline that the project followed. In particular, each subsection will focus on a specific task, except for the data visualization that has been used only when needed.

2.1 Data Acquisition

The used datasets are downloaded at runtime directly from the sources. These datasets come directly from MovieLens' page and provides 6 different files. More informations about the nature of the data are available [here](#).

Dataset	Features
ratings.csv	userId, movieId, rating, timestamp
tags.csv	userId, movieId, tag, timestamp
movies.csv	movieId, title, genres
links.csv	movieId, imdbId, tmdbId
genome-scores.csv	movieId, tagId, relevance
genome-tags.csv	tagId, tag

Most of these datasets provides information for approximately 60000 films. The links dataset provides two identifiers that allow to collect information from the IMDB and TMDB databases. Thanks to the links' features, it has been possible to collect some more information on the running times of the films that could provide more insight into them. Talking about the ground truth of the supervised models, the rating mean is missing. So the target feature will be computed during the pre-process phase thanks to the ratings dataset. Further information about the features usage and the cardinality of the datasets will be discussed in the Pre-Process section.

2.2 Data Pre-process

In this section, will be discussed the pre-process phase for each of the above presented datasets. In order to achieve a major clarity, the work on each dataset will be discussed in a specific subsection where the operation computed on them will be explained. At the beginning of each subsection the cardinality will be reported.

Movies - movies.csv

Cardinality: 58098×3

Inside this dataset, the title and genres features contains multiple information. In particular, the title has been splitted in two part, where on one hand there's only the title name, and on the other, there's the year of the film production. Since the title name is a string, that doesn't add more information to a classic machine learning model, this feature has been converted into its length meanwhile the production year just constitutes a new feature. The genres feature contains a pipe separated list of a fixed possible values. Since the list is just saying if a film has a specific genre or not, to each film, all the fixed values has been added as a feature, and if a genre appears into the genres feature, that column will result into 1 that indicate the presence of that genre, 0 otherwise. At the end of this initial phase, the first sample of movies dataset looks like:

movieId	title_len	year	action	adventure	...	Western	(no genres listed)
1	16	1995	0	1	...	0	0

In order to finish the data pre-process on this dataset, the data cleaning is required. First of all, there are some films where the year of the film production is missing. Analyzing the distribution of these, as showed in Figure 2.1, it is possible to see that the distribution is right skewed, so the missing values can be filled with the **median**, as suggested during the lectures.

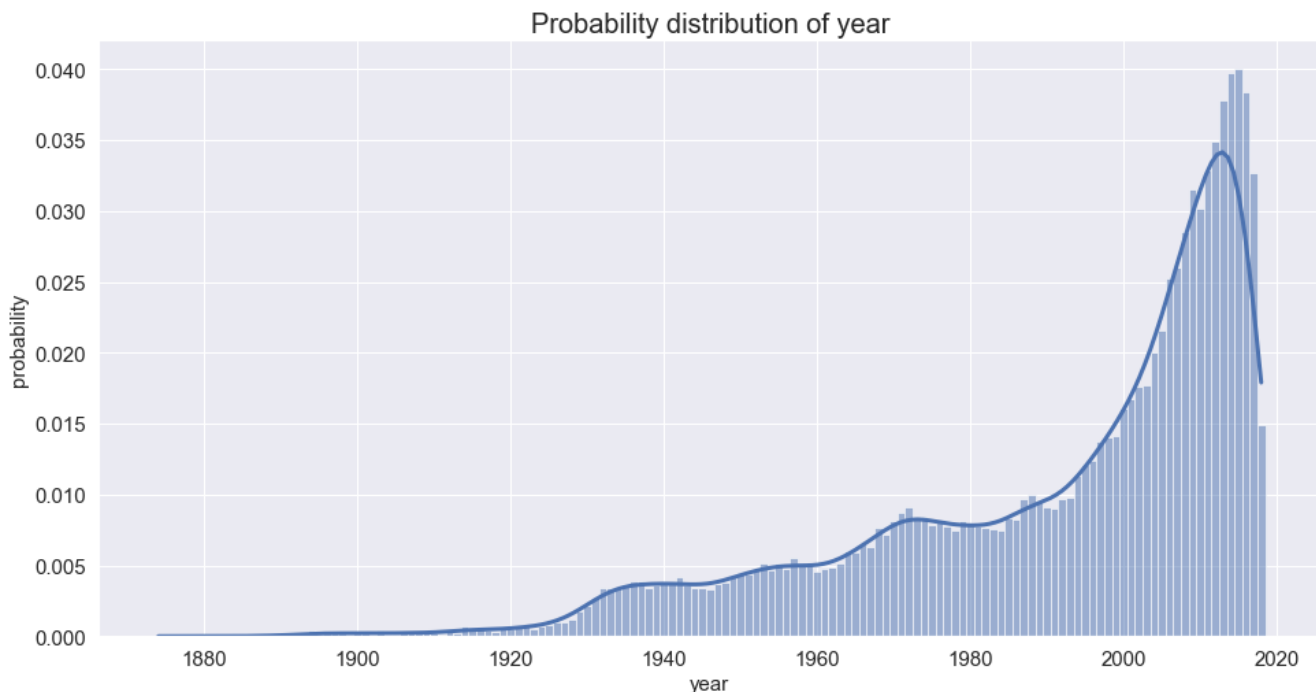


Figure 2.1: Right skewed probability distribution of the year feature

Since the feature (no genres listed) and the films that has no genres provide no information about the film, they will be removed obtaining a final cardinality of 53832×22 .

Tags - tags.csv

Cardinality: 1108997×4

In order to use the relevant data from this dataset the timestamp and userId features have been deleted because they don't explain anything more about the films. The information provided by each sample in the dataset are not very meaningful, for this reason it was decided to count the number of tags associated with each film, in order to understand how much interaction that film generated. When a film doesn't have any related tag, the tag_count can be setted to 0 because no users were interested on that film. After these operations the cardinality was reduced to 45981×2 .

Ratings - ratings.csv

Cardinality: 27753443×2

The features in this dataset were necessary to find the target column. In order to compute it, the average of each films' ratings has been calculated. In addition, the number of the rating on each film has been counted. However, the task of this project is the classification, for this reason the rating_mean has been discretized in 10 bins, where each of them covers a rating range of 0.45 as showed in Figure 2.2.

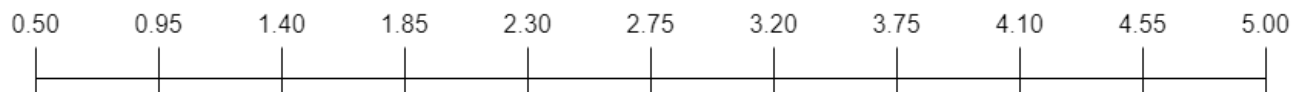


Figure 2.2: Discretization of the rating_mean feature

At the end, the final cardinality is 53889×4 .

Genome - genome-scores.csv and genome-tags.csv

Cardinality scores: 14862528×3

Cardinality tags: 1128×2

Talking about these two datasets, the merge operation over the tagId was needed because it was interesting to associate the tagId with its string name. After this union, on each sample there is the correspondence between a movieId, the tag name and the relevance of that tag. The final step consist on relate every film to the relevance of each tag, using the pivot function, with the following result:

movieId	007	18th century	action	absurd	...	addiction	adventure
1	0.02900	0.05425	0.66825	0.09725	...	0.07475	0.90700

The final dataset named genome.csv has the cardinality equal to 13176×1129 .

Links - links.csv

Cardinality: 58098×3

On this dataset no pre-processing was needed because for each movie it contains two identifier that provide a link to external sources. The interesting one is tmdbId because it has been used to retrieve information from the TMDB database. Using the TMDB Api it has been possibile to build a new dataset that contains some additional features:

- budget

- revenue
- adult
- runtime

In order to avoid the expensive operation of the Api calls, the resulted dataset has been saved in a GitHub release. Due to the insufficient amount of valid samples, the IMDb title-basics.csv dataset was downloaded to try to fill in all missing values. After a brief exploration and analysis it has been possible to see that only the runtime feature has an enough amount of samples. Since there continue to be some missing values, the distribution of this feature was analyzed in Figure 2.3. It is possible to see that the distribution is left skewed, so the missing values can be filled with the **median**.

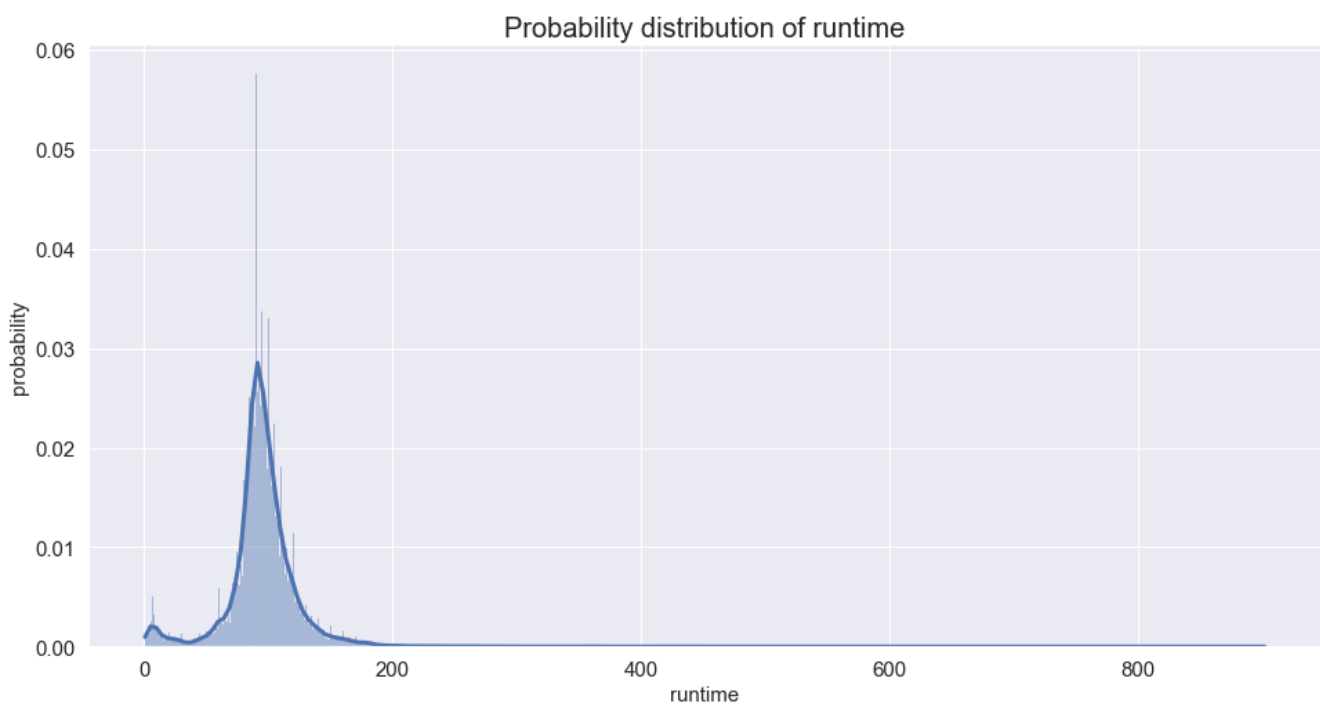


Figure 2.3: Left skewed probability distribution of the runtime feature

The final cardinality of the acquired external resources is 58098×2 .

Merged dataset

In this section it will be showed how the cardinality of the used dataset has been created, starting from all the previously processed datasets. In particular, the focus will be on the number of samples, because the number of features will increase by the addition of all the features in a single dataset. Since, for a classification task, it is interesting to know the information about a sample, the starting dataset will be the movies one then all the other will be merged, trying to preserve the maximum number of samples. The first merge has been between movies and ratings, because if a film doesn't have the target feature, it is useless to try to classify it. Moreover it has been discarded all the films that doesn't have a ratings means, obtaining a cardinality of: 50157×24 . The second merge is the one between the previously obtained

dataset and tags, where there was an important number of samples that hasn't a tag count. In this case, these samples hasn't been discarded because they has been considered as the film didn't have generated any interaction from the users, so all the missing values has been filled with 0, obtaining the cardinality 50157×25 . The third merge is between the previously generated dataset and the external resources. Since the external resources has a sample for each movie, the cardinality of this merge is 50157×26 . The final merge consider the genome dataset, where there is a big gap between the cardinality of this dataset, and the one that has build before. The choice on this merge was to discard all the data that didn't match with a sample on the genome dataset, because genome provides more and more interesting features with respect to the ones that the others dataset could provide. For this reason, the final cardinality of the dataset, after the merge operation is: 13147×1154

2.3 Modeling

2.4 Performance Analysis

Bibliography

- [1] GroupLens. MovieLens Latest Datasets. <https://grouplens.org/datasets/movielens/latest/>.
- [2] TMDb Community. Api Overview. <https://www.themoviedb.org/documentation/api/>.
- [3] IMDb.com. Imdb datasets. <https://www.imdb.com/interfaces/>.
- [4] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc., 2019.
- [5] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.