MovieLens_Report

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03/06/2019

Introduction

Overview

The web site http://www.movielens.org/ allows users to rate films from one to five stars, with half-star ratings allowed. This project aims to use the large number of movies, ratings and users available to find a method to predict movie ratings.

This report describes the process and methodology adopted by this project to analyze the existing movie ratings and to devise a method to predict ratings. The accuracy of the various methods will be compared, the accuarcy being indicated by the RMSE of the predictions of each method.

The project will analyze a dataset of movie ratings to predict what ratings a particular user would give a movie.

The users are randomly selected and are only identified by a uniquely assigned user id; there is no demographic and geopgraphic location information used.

Dataset

Source

The source dataset was created by the University of Minnesota from the online movie recommendation service MovieLens (https://movielens.org).

It is a large dataset and contains:

- 10000054 ratings
- 95580 tags
- 10681 movies by
- 71567 users

The source files can be obtained from this location:

- https://grouplens.org/datasets/movielens/10m/

This link shows further details, including usage rights provided by the license:

- http://files.grouplens.org/datasets/movielens/ml-10m-README.html

Sample Size for Analysis

This is a very large dataset and for the sake of managability a 10% sample of the source dataset will be used by the project. The source dataset is circa 1M ratings so the sample dataset will be approximately 100K ratings.

Shape of the Data

The source data contains three data sets:

- Movies
- Ratings
- Tags

Training and Test Data Partitions

The full approach is described later in this report but in summary the sample data is split into two partitions. A *training partition* will be allocated *80%* of the sample data and will be used to create (or *train*) the algorithm. A *test partition* will be allocated the remaining *20%* of the sample data and will be used to validate the predictions of the algorithm.

Goal

The objective of the project was to find a movie recommendation algorithm. Its success will be measured by reference to the RMSE produced when the algorithm is validated against the test dataset. The RMSE will be graded against a predfined set of thresholds to determine the overall quality of the algorithm (described later).

Approach

Data Cleansing

Modelling Techniques

The algoritm will start from a naive position and then be refined as further insights into the data are gained. The effect of each refinement will be accessed using a loss function. The RMSE (*residual mean squared error*) will be used as the loss function for this project.

Version 1 : Naive Implementation

The first attemp will use the average movie rating of the training data to predict the rating in the test data. The RMSE will then be measured. The formula for this is described as follows, where u is the user, i is the movie, μ is the average and ϵ is the error.

$$Y_{u,i} = \mu + \epsilon_{u,i}$$

Version 2 : Coinsider the individual movie effect

This modification will use the mean with the addition of a movie effect to take into account that some movies are rated more favourably then others. For example, the top 5 rated movies are:

Table 1: Top 5 Rated Movies

title	n	average
Pulp Fiction (1994)	31336	4.161731
Forrest Gump (1994)	31076	4.010265
Silence of the Lambs, The (1991)	30280	4.205086
Jurassic Park (1993)	29291	3.658189
Shawshank Redemption, The (1994)	27988	4.456928
The bottom 5 rated movies include:		

title	n	
Where A Good Man Goes (Joi gin a long) (1999)	1	
Wings of Eagles, The (1957)	1	
Women of the Night (Yoru no onnatachi) (1948)	1	
Won't Anybody Listen? (2000)	1	
Zona Zamfirova (2002)	1	
We can see that some movies are rated very often	and	have a large number of ratings. For example Pulp Fiction (1994)

$$Y_{u,i} = \mu + b_i + \epsilon_{u,i}$$

Version 3

Use the mean with the addition of a user effect to take into account that some users rate movies more generously then others.

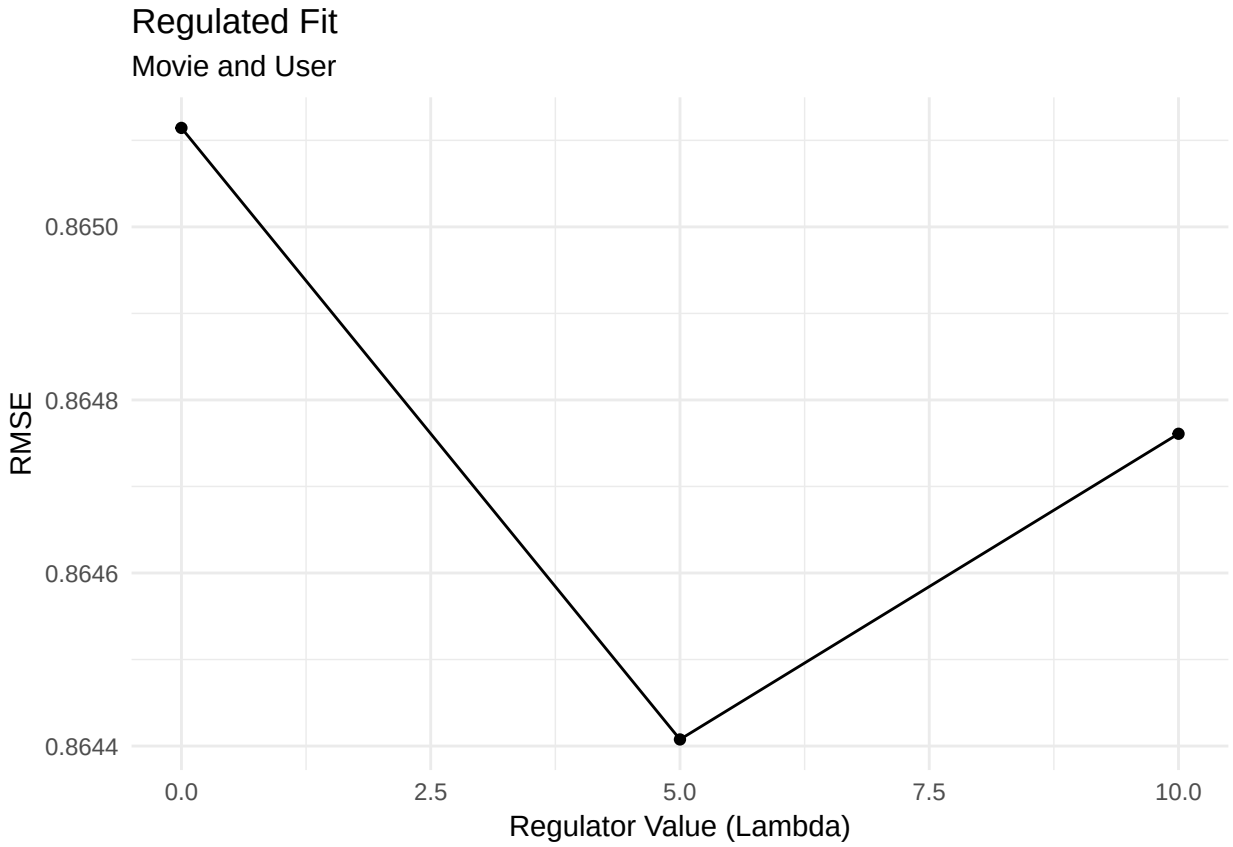
$$Y_{u,i} = \mu + b_u + \epsilon_{u,i}$$

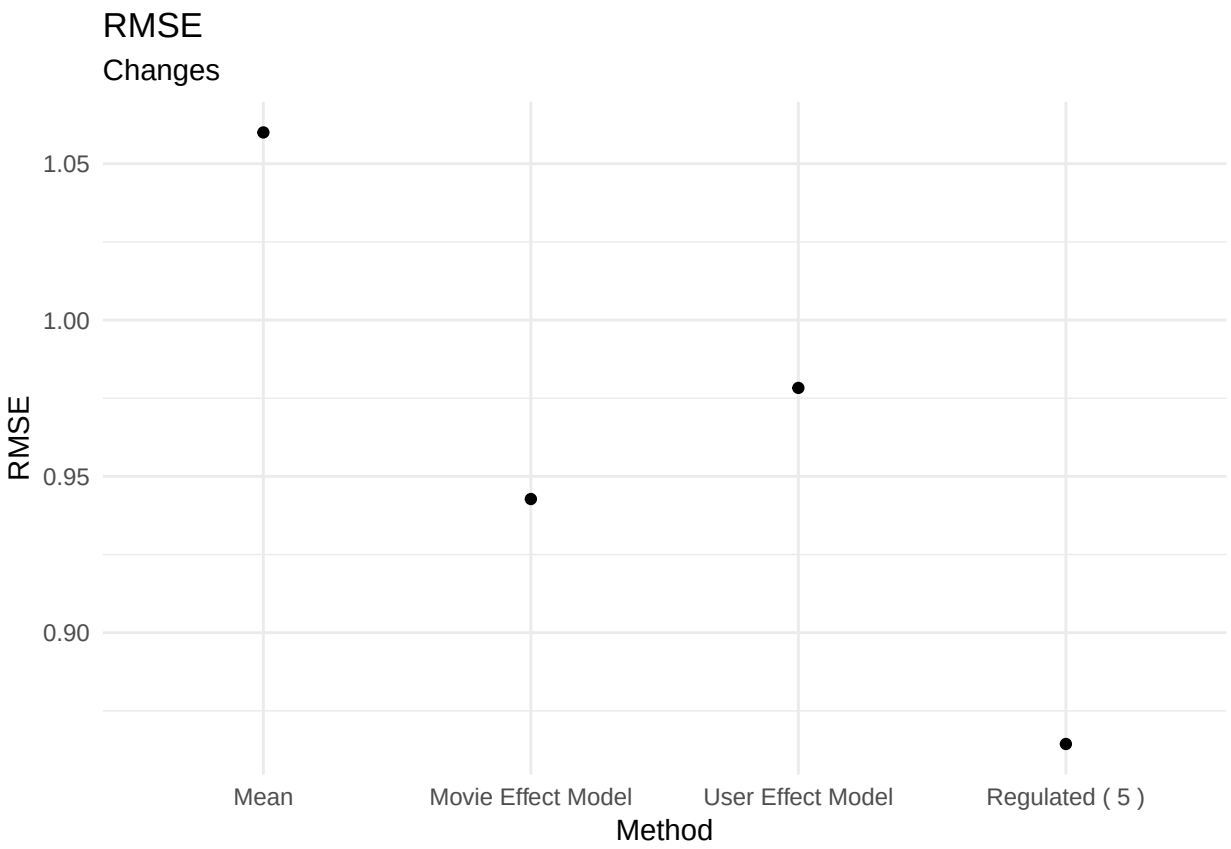
Version 4

Use the mean with the regulated movie and user effect.

$$Y_{u,i} = \mu + b_i + b_u + \epsilon_{u,i}$$

Results


Regulated Fit
Movie and User
RMSE
0.8650
0.8648
0.8646
0.8644
0.0
2.5
5.0
7.5
10.0
Regulator Value (Lambda)


RMSE
Changes
1.05
1.00
0.95
0.90
RMSE
Mean
Movie Effect Model
User Effect Model
Regulated (5)
Method

Conclusion

Bibliography and References

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. DOI=http://dx.doi.org/10.1145/2827872