Data Analytics - Project Presentation
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Musical Instruments Recommendation

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Introduction

For my Data Analytics Project, my task is to **build two recommendation systems** using a Musical Instruments dataset and to use them to **predict the product ratings** for some users based on other users' ratings.

Two datasets have been given to me: the first one contains information about **user preferences** on musical instruments (ratings); the second one contains information about each rated item (**metadata**).

Exploration and description of data (1)

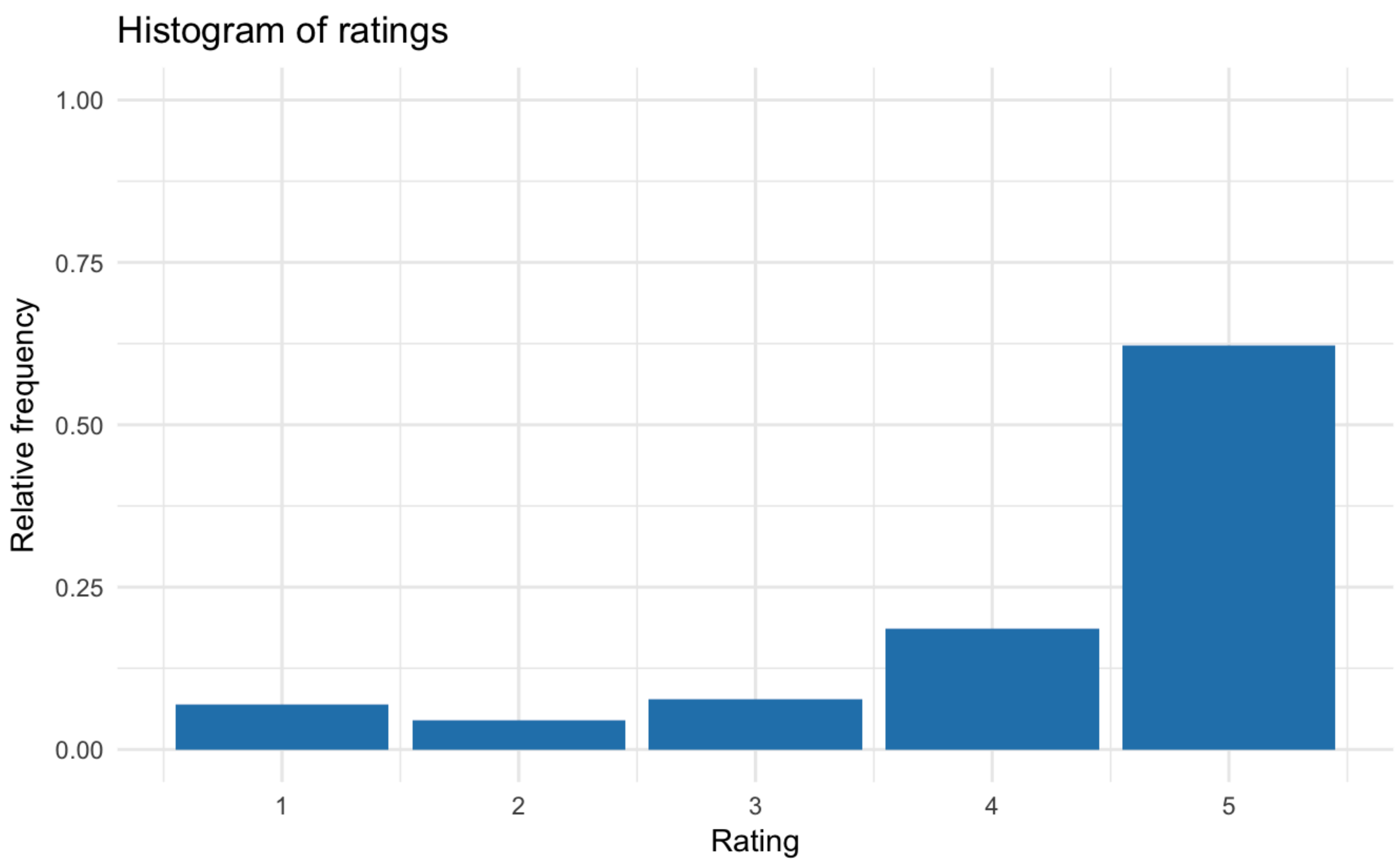
The **main dataset** contains four attributes, which are *user*, *item*, *rating* and *timestamp*, and 500,175 observations, each one representing an item's rating given by a user. This is the most interesting dataset, since it relates users and items by the corresponding rating.

The **second dataset** contains nine attributes and 84,901 observations, each one representing the metadata of one item. This dataset doesn't contain very interesting data for my purpose, furthermore more than a half of the metadata values are NA and can't be used.

Exploration and description of data (2)

Ratings' **standard descriptive statistics**:

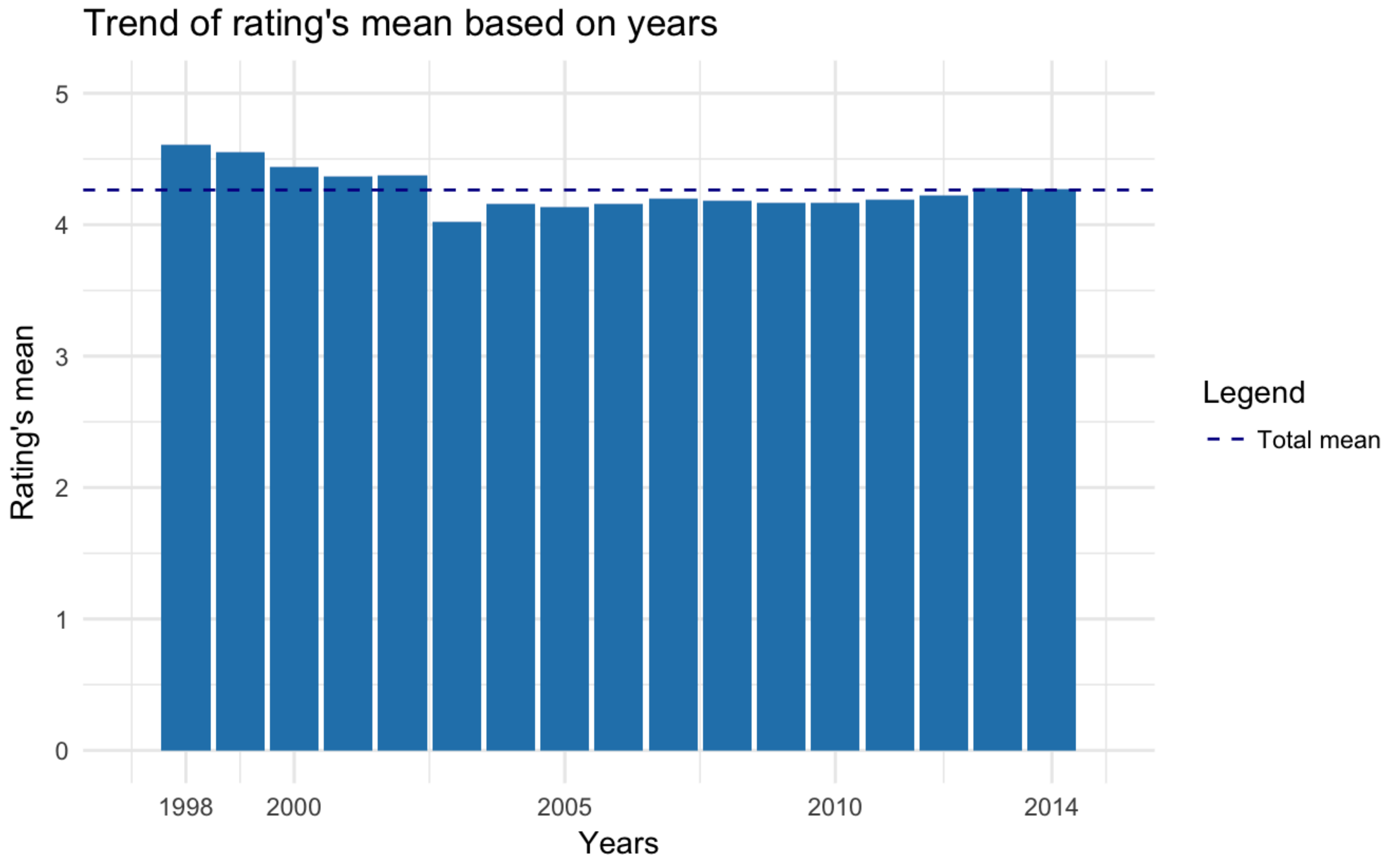
Min.	1.000
1st Qu.	4.000
Median	5.000
Mean	4.244
3rd Qu.	5.000
Max.	5.000
St. Dev.	1.203

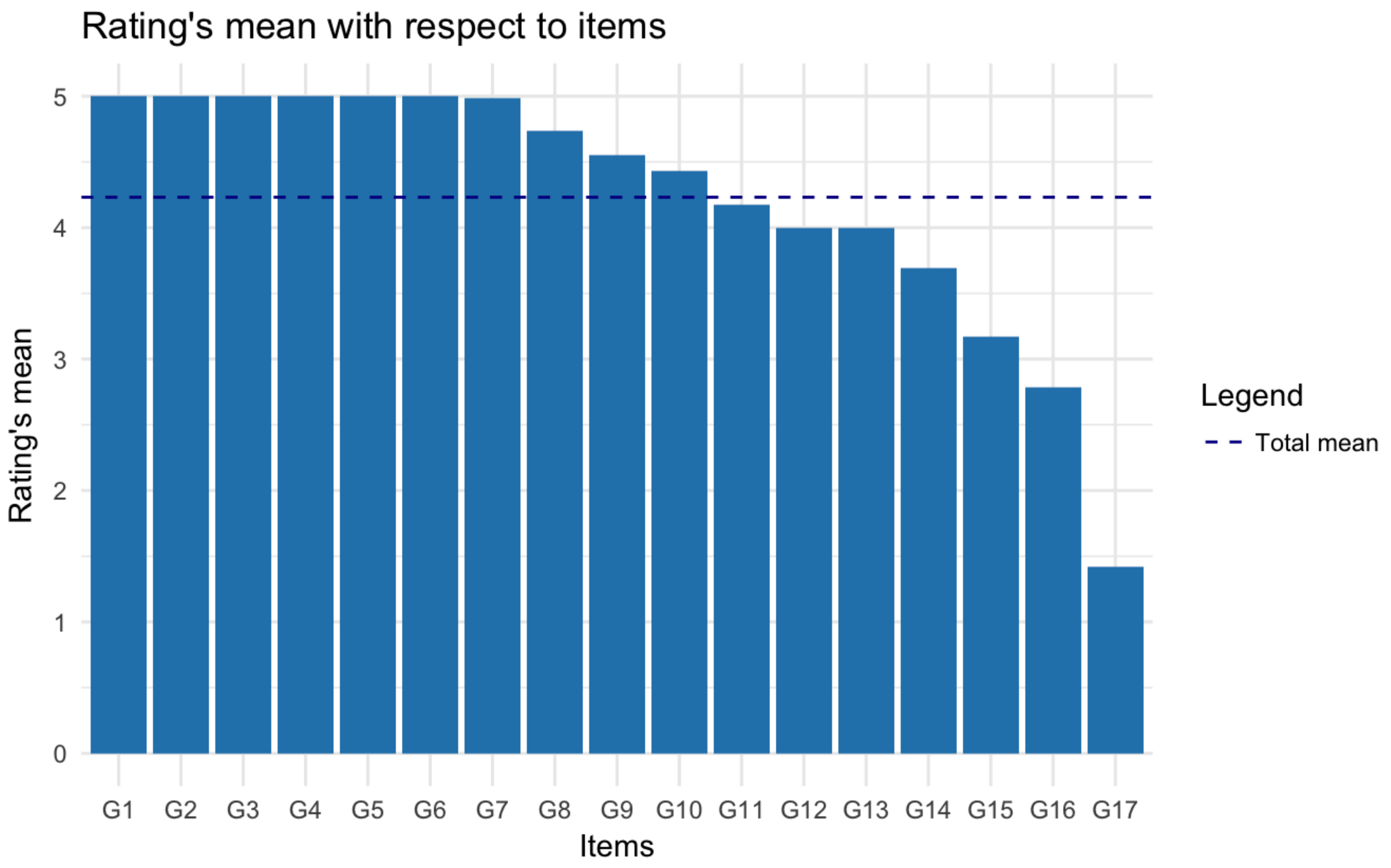


1	2	3	4	5
7.0%	4.5%	7.7%	18.7%	62.1%

Exploration and description of data (3)

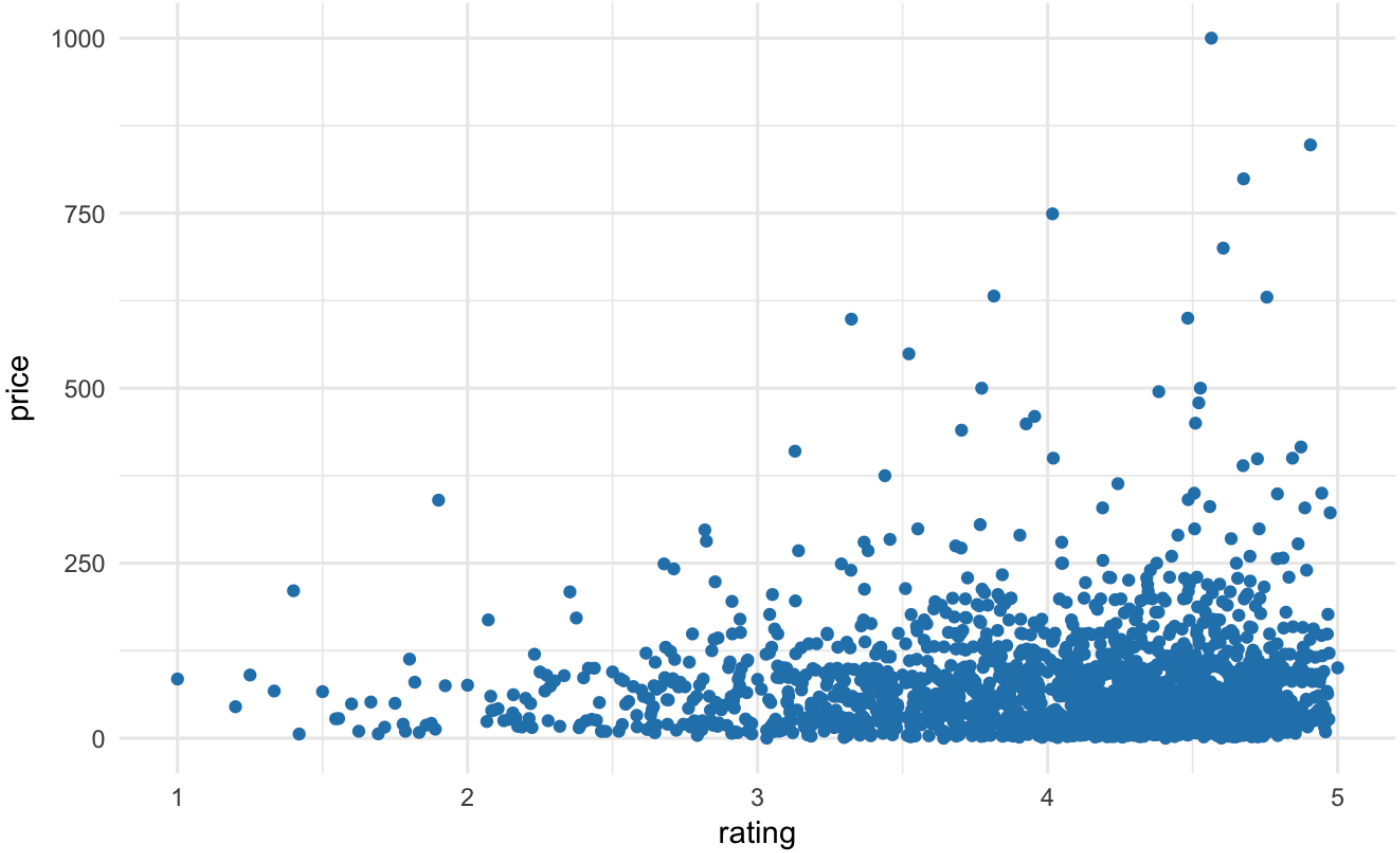
Some other **data representations**:





Exploration and description of data (4)

Relation between the ratings and the prices of items:



	rating	price
rating	1.0000	0.0097
price	0.0097	1.0000

The **correlation matrix** shows that there is no linear correlation between the variables *rating* and *price*. However, from the graph we can deduct the presence of a **non-linear relation** between the two variables.

Recommendation systems (1)

In order to build the two recommendation systems required, I used **collaborative filtering** (CF) in both cases: one of them makes use of the *user-based collaborative filtering* (UBCF), the other makes use of the *item-based collaborative filtering* (IBCF).

Collaborative filtering is an algorithm that uses given rating data by many users for many items as the basis for predicting missing ratings or for creating a list of items with the top-N items to recommend to a given user, called the active user.

The **UBCF** algorithms bases the recommendations on the similarity between users, while the **IBCF** algorithms bases the recommendations on the similarity between items.

Recommendation systems (2)

First, I **pre-processed data** by filtering users and items in order to speed up computation and reduce the sparsity of the utility matrix. Then, I build the **utility matrix**, where each row represents a user, each column an item and into each user-item cell it is stored the rating of that user for that item.

```
utility_matrix = dcast(rating, formula = user~item, value.var = 'rating')
```

After that, I created an **evaluation scheme** that determines what and how data is used for training and testing and that allows me to evaluate the two models at the end. I split the dataset using 75% of users for the training set and 25% for the test set, I considered good ratings only the ratings equal to 5 and I set to 4 the value of given ratings for each user in the test set.

```
e = evaluationScheme(utility_m, method = "split", train = 0.75, given = 4, goodRating = 5)
```

Recommendation systems (3)

I created the **two recommendation systems** by using the training set and setting the method, depending on whether the UBCF or the IBCF has to be used. Then, I used the created *Recommenders* in order to predict the missing ratings in the test set through the function *predict*.

```
# --- Recommendation system using UBCF
rUBCF = Recommender(getData(e, "train"), method = "UBCF")
pUBCF = predict(rUBCF, getData(e, "known"), type = "ratings")
# --- Recommendation system using IBCF
rIBCF = Recommender(getData(e, "train"), method = "IBCF")
pIBCF = predict(rIBCF, getData(e, "known"), type = "ratings")
```

Finally, I **evaluated the predictions** of the two models through an evaluation matrix.

```
# Error between prediction and unknown part of the test data
error = rbind(UBCF = calcPredictionAccuracy(pUBCF, getData(e, "unknown")),
                            IBCF = calcPredictionAccuracy(pIBCF, getData(e, "unknown")))
```

Recommendation systems (4)

	RMSE	MSE	MAE
UBCF	0.9631215	0.9276031	0.6462931
IBCF	1.3906379	1.9338738	0.9206462

In general, **the UBCF works better than the IBCF** with every configuration I tried, since all the three measures of error are higher in the UBCF than in the IBCF .

In all the different configurations I tried for the data filtering, obviously the higher the minimum number of ratings for each user and item, the lower the error of the predictions.

Thank you for your attention

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