Introduction

The objective of this assignment is to develop a movie recommendation system aimed at proposing movie suggestions for users.
Movie recommendation systems represent intelligent algorithms designed to propose films for users based on their prior viewing patterns and preferences. These systems examine various user-related data, including ratings, reviews, and viewing histories, to create tailored suggestions. The impact of movie recommender systems is transformative, reshaping the way individuals explore and engage with films, offering a more streamlined approach to navigating extensive film catalogs.

Data analysis

The primary three data files are u.data, u.genre, and u.user.

User data

User data file consists of 100000 rows and 4 columns: user_id, item_id, rating and timestamp (unix seconds). I found several important facts about this file:

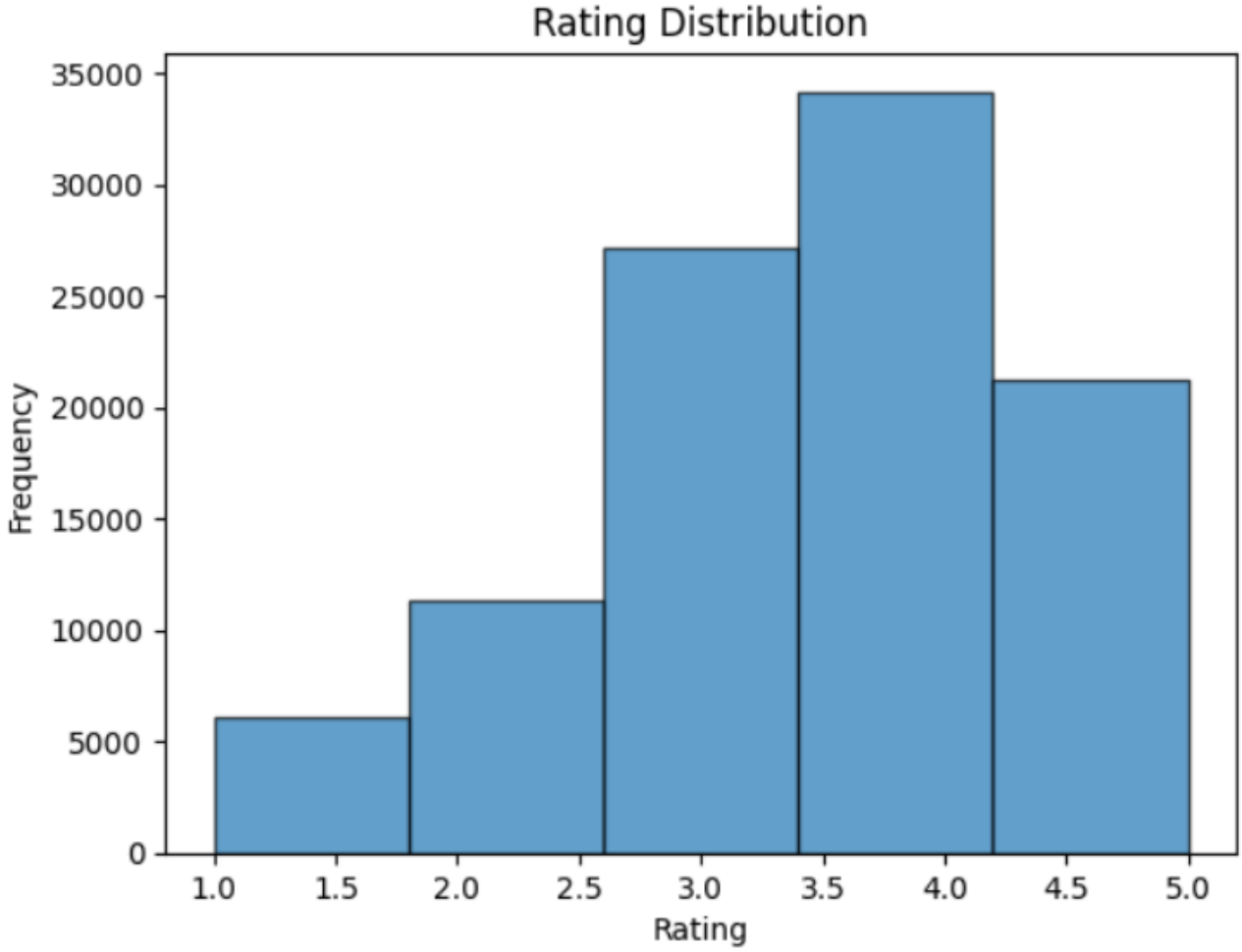
- User data does not contain nan values.
- Average rating of the movie is equal to 3.53
- Standard deviation of the rating is equal to 1.13
- Minimal rating equals to 1.0
- Maximum rating equals to 5.0

User item

This file contains information about movies: movie_id, movie_title, release_date, video_release_date, IMDB_URL and genres. Important moment is that each movie can be of several genres at once. u.genre file consists information about genres. User item:

- Has 1 nan value in release date, 1682 nan values in video release date and 3 nan values in imdb url column. I think that I will drop those columns.

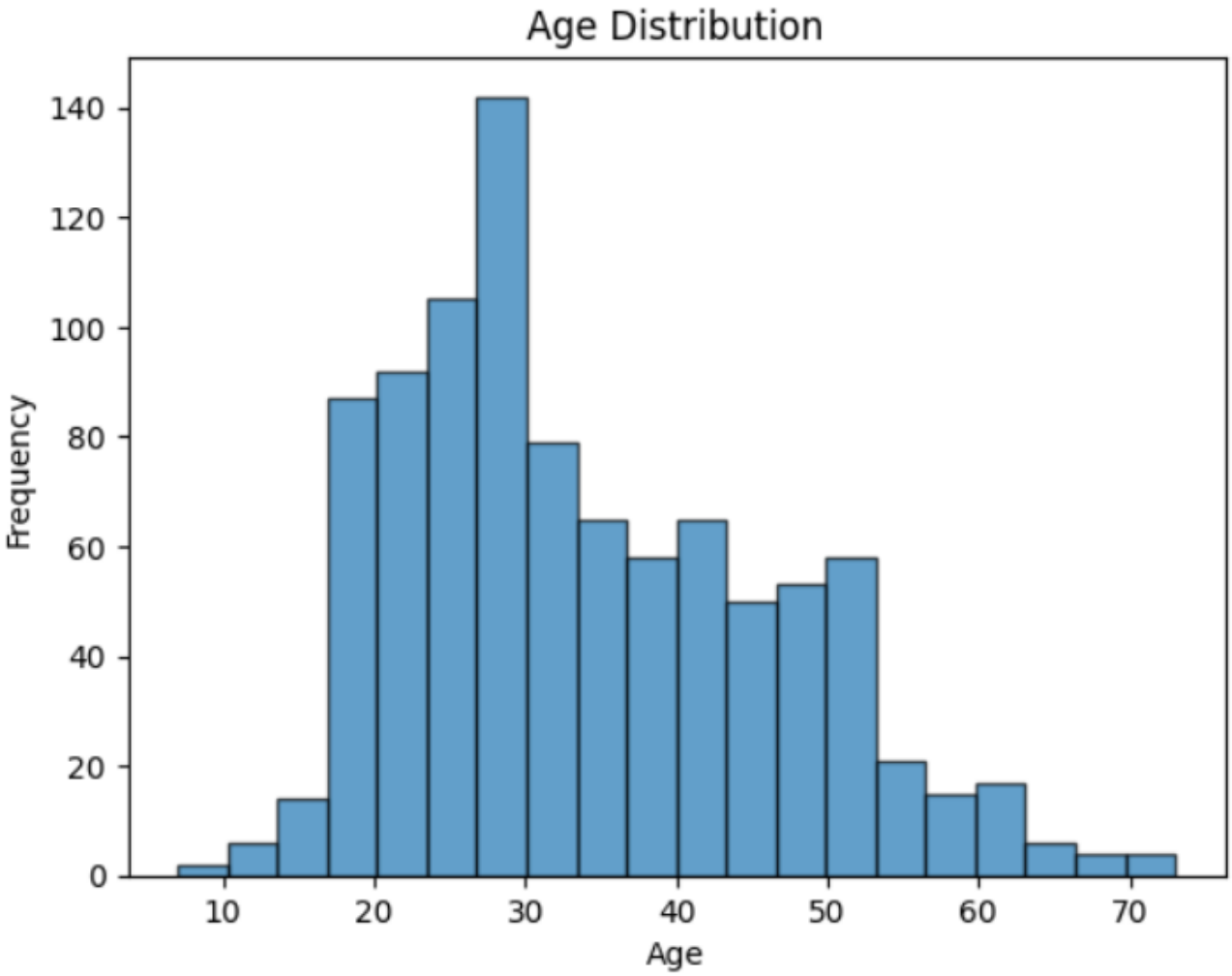
- The most popular genres are Drama, Comedy and Action

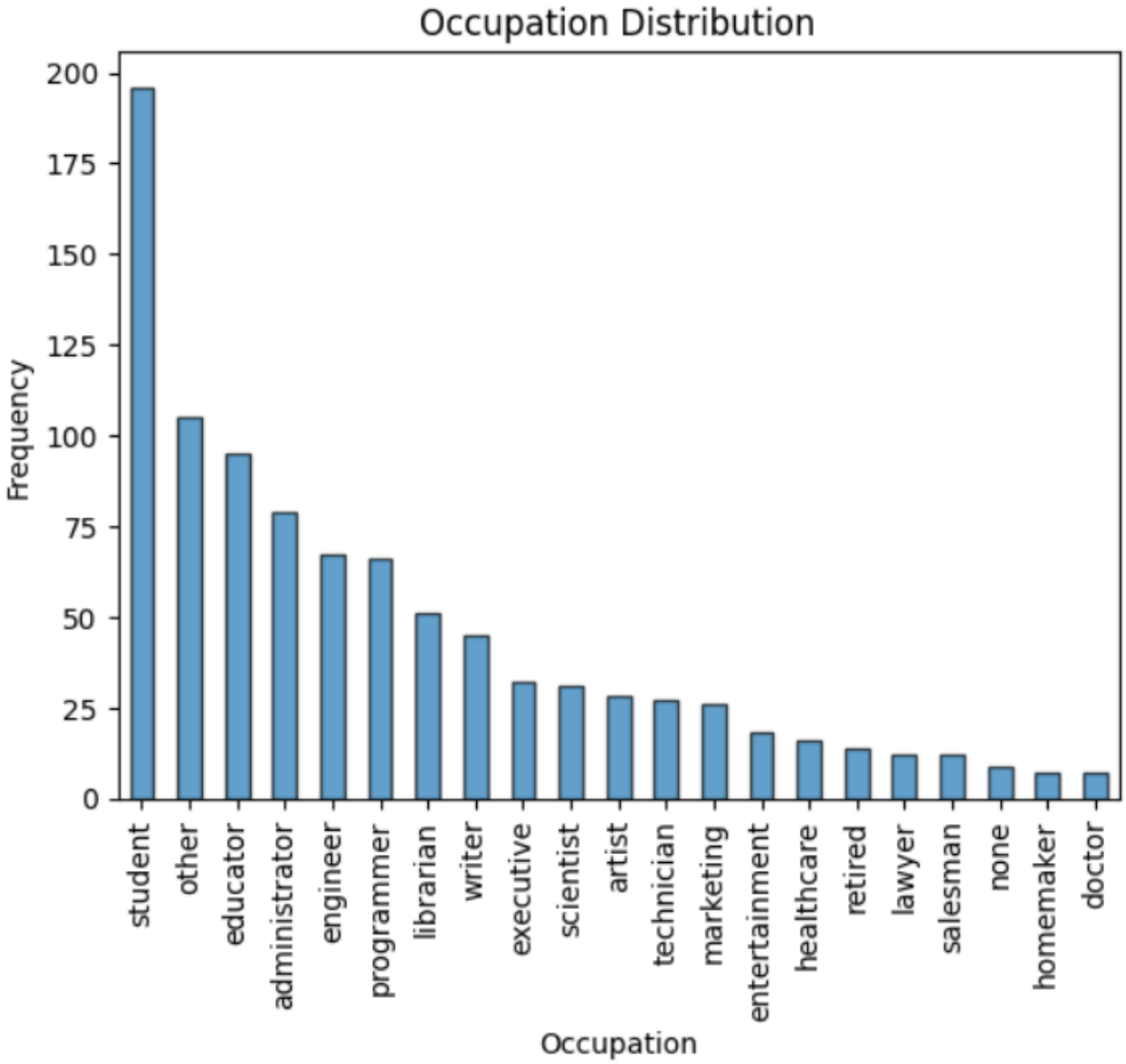


User user

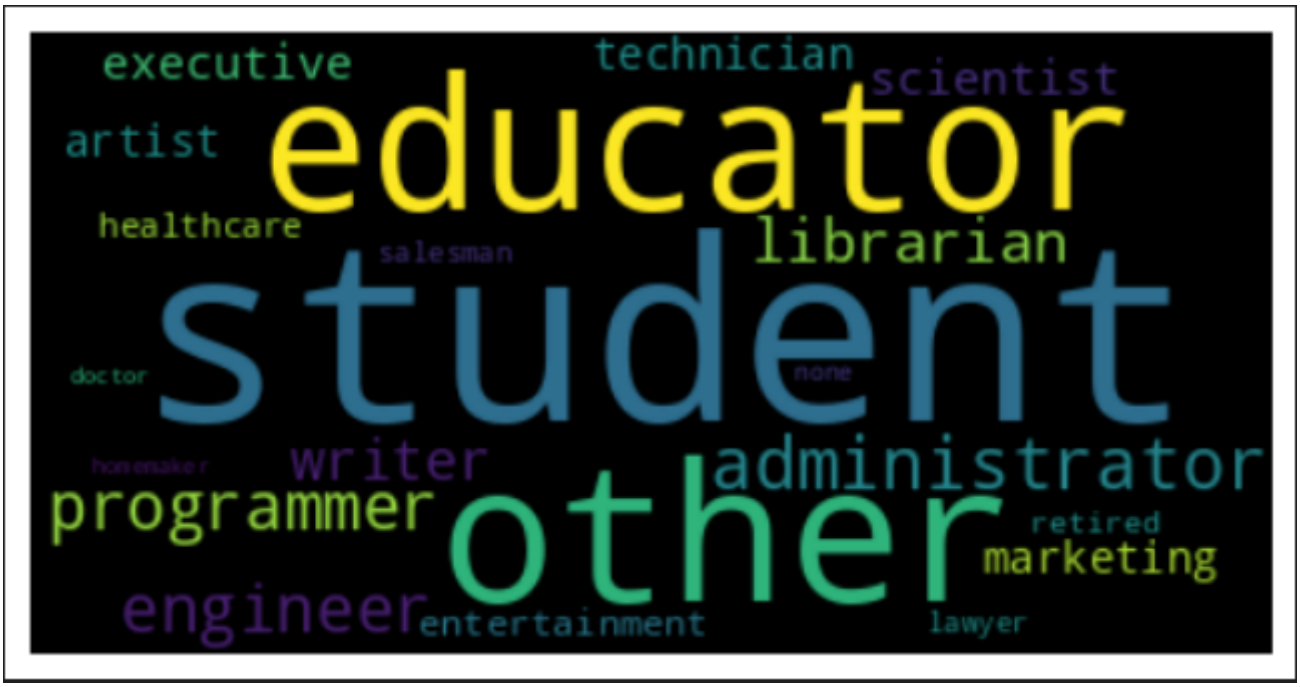
This file contains demographic information about the users (user_id, age, gender, occupation, zip code)

- File does not have non values
- Average age of the user equals to 34
- Standard deviation of the age 12.19
- Minimal age 7
- Maximal age 73
- Student, other, educator, administrator, engineer, programmer are the most frequent occupations


Age Distribution
Frequency
Age
0
20
40
60
80
100
120
140
10
20
30
40
50
60
70



The most popular occupations

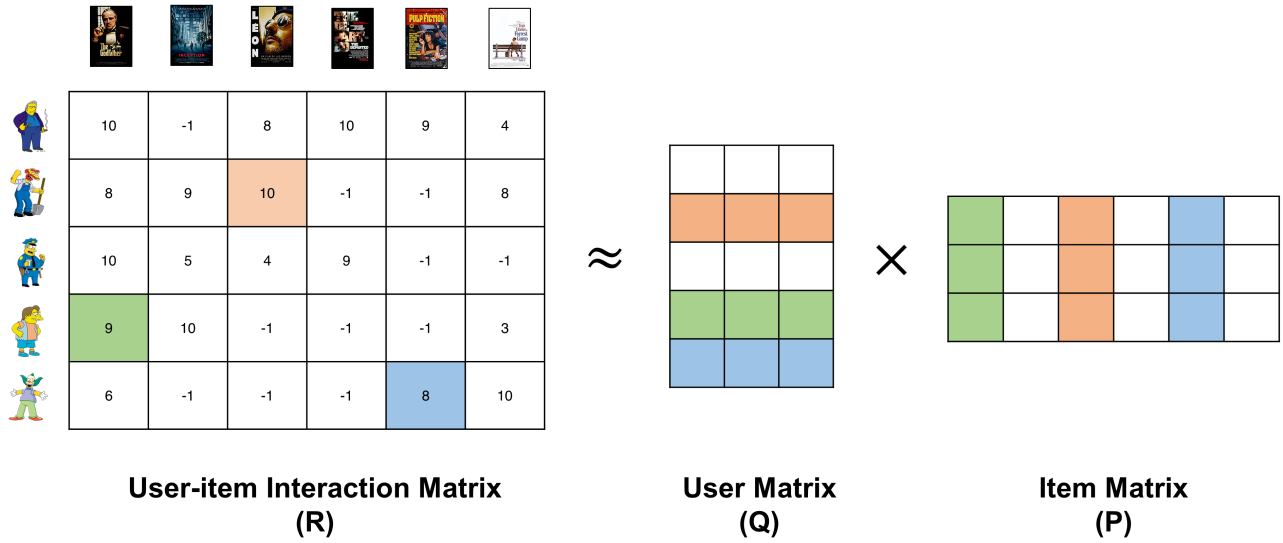


Model implementation

My model was inspired by collaborative filtering. Collaborative filtering is a technique that finds item that a user might like based on the theory that similar users like the same items. In this recommender systems, user ratings or suggestions are combined, user commonalities are discovered based on ratings, and new recommendations are created based on user comparisons. The primary benefit of collaborative techniques is that they can be utilized for complex issues where a significant amount of the variation in preferences is due to differences in taste. Collaborative filtering is predicated on the idea that people who have previously chosen to favor similar items would continue to do so.[4]

Matrix factorization

Matrix factorization uses linear algebra for recommendation.



User-item Interaction matrix can be decomposed into User Matrix and Item Matrix. The User Matrix contains learned features about users, Item Matrix contains features about items (in our case about movies). The algorithm defines the low-dimensional latent features in a way that captures correlated patterns from past user-item interactions. When accurately calculated, the matrices representing users and items can effectively mimic prior user-item interactions, enabling the prediction of unknown entries in the rating matrix. In the picture each row of matrix Q contains information about user, and each row of matrix P contains information about movie. Dot product of user matrix row and item matrix row is the predicted rating for the corresponding movie.

Model optimization

I used root mean squared error as the loss function.

$$\mathrm{RMSE}(y, \hat{y}) = \sqrt{\frac{\sum_{i=0}^{N-1}(y_i - \hat{y}_i)^2}{N}}$$

Model advantages and disadvantages

Our model based on idea of collaborative filtering.

Advantages

- **Personalization:**

    - Collaborative filtering considers the preferences and behaviors of similar users to make personalized recommendations. This leads to more accurate and relevant suggestions for individual users.
- **No Dependency on Item Metadata:**
    - Collaborative filtering relies on user-item interactions, making it less dependent on item metadata. This can be advantageous when dealing with a large number of items with limited metadata.
- **Scalability**
    - It is often scalable as the system grows, as the recommendations are based on user behavior rather than the entire item catalog.

Disadvantages

- **Cold start problem**
    - Collaborative filtering struggles when dealing with new items or new users with limited interaction history. It requires a sufficient amount of data to provide accurate recommendations.
- **Sparsity**
    - The user-item matrix is often sparse, meaning that users typically interact with only a small fraction of the available items. This sparsity can lead to challenges in finding meaningful patterns.

Training process

- **Data preprocessing**
    - The final dataset consists of user IDs, movie IDs and corresponding ratings. There were no nan values in these columns.
- Batch size
    - I trained model with various batch sizes: 8, 16, 32, 64. The best batch size for my model is 16
- Dataset splitting
    - Dataset was splitted into train, valid and test subsets
- Loss function
    - Root Mean Squared Error is used as a loss function
- Optimizer
    - Adam optimizer with learning rate equals to 1e-4
- Training
    - The model had been trained for 20 epochs, however after 5-7 epochs model was overfitted. I decided to train model for 5 epochs

Evaluation

- **Root mean squared error**
  Root mean squared error provides a quantitative measure of how well the recommendation system's predicted ratings align with the actual ratings given by users.
  It measures the average magnitude of the errors, giving you an indication of how accurate the system's predictions are across the entire dataset.
  * Root mean squared error penalizes large prediction errors more heavily than smaller errors. This is particularly relevant in recommendation systems, where accurately predicting highly-rated or disliked items is often more crucial than accurately predicting moderately-rated items.

$$\mathrm{RMSE}(y, \hat{y}) = \sqrt{\frac{\sum_{i=0}^{N-1}(y_i - \hat{y}_i)^2}{N}}$$

- **Precision@k**
  * Precision at k is the proportion of recommended items in the top-k set that are relevant. Precision is important when you want to ensure that the recommended items are highly relevant and minimize the number of irrelevant recommendations.

$$P@k = \frac{\text{Number of recommended items @k that are relevant}}{\text{Number of relevant items}}$$

- Recall@k
  * Recall at k is the proportion of relevant items found in the top-k recommendations. Recall is crucial when you want to make sure that the system captures as many relevant items as possible, even if it means including some irrelevant ones.

$$P@k = \frac{\text{Number of recommended items @k that are relevant}}{\text{Total number of relevant items}}$$

Results

Precision @ 10 (P@10): 0.67
A precision of 0.67 means that, on average, 67% of the items recommended in the top 10 are relevant to the user.
Recall @ 10 (R@10): 0.53
A recall of 0.53 means that your model is capturing 53% of all relevant items in the top 10 recommendations.
Root Mean Square Error (RMSE) : 0.934
RMSE is often used in regression problems to measure the difference between predicted values and actual values. In the context of recommendation systems, it's common to use it to evaluate the accuracy of predicted ratings. A lower RMSE value (closer to 0) indicates better

predictive performance.

Let's look how model suggests movies.

User Id: 10

movie_id	movie_title	rating
11	Seven (Se7en) (1995)	4.7906
482	Some Like It Hot (1959)	4.72725
1448	My Favorite Season (1993)	4.64087
317	In the Name of the Father (1993)	4.63857
63	Santa Clause, The (1994)	4.5784
179	Clockwork Orange, A (1971)	4.5458
312	Midnight in the Garden of Good and Evil (1997)	4.53887
356	Client, The (1994)	4.53327
512	Wings of Desire (1987)	4.52927
171	Delicatessen (1991)	4.50101