Optimizing Movie Recommendations with User and Item Biases in Singular Value Decomposition.

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ABSTRACT

Movie recommendation systems aim to predict the ratings of unseen items for users, facilitating personalized suggestions. This paper evaluates the performance of collaborative filtering-based models, specifically Singular Value Decomposition (SVD) and SVD++, using the MovieLens dataset. We compare their performance based on traditional metrics like RMSE and MAE, as well as more complex metrics such as Precision, Recall, F-measure, and NDCG. Additionally, we assess model fairness using the Gini Index and analyze the potential impact of popularity bias in recommendations.

KEYWORDS

Recommender systems, Matrix factorization, SVD, Collaborative filtering, Movie recommendation, MovieLens

1 INTRODUCTION

Recommendation systems have become central to the digital economy, particularly in domains like streaming services, where personalized suggestions enhance user experience. In this paper, we focus on the MovieLens dataset, which contains user-movie ratings, and use collaborative filtering techniques to predict ratings for unseen movie-user pairs. Our primary goal is to develop a recommendation model capable of accurately predicting user preferences, offering insights into model performance, and evaluating fairness and bias.

2 RELATED WORK

Matrix factorization techniques outperform traditional methods like nearest-neighbor algorithms by capturing latent factors that represent user-item interactions. Koren, Bell, and Volinsky (2009) showed how these models improve recommendation accuracy by integrating implicit feedback, temporal effects, and confidence levels, as demonstrated in the Netflix Prize competition. In the Netflix Prize, collaborative filtering models achieved MAE values between 0.65 and 0.75, with RMSE ranging between 0.85 and 0.95, setting benchmarks for future recommender systems [1].

3 PROBLEM FORMALIZATION

The problem we aim to address is to predict user ratings for movies that a user has not yet rated. Given a user-item matrix, where rows represent users and columns represent movies, and the entries represent ratings, the task is to predict missing entries. This can be formalized as:
\hat{r}_{ui} = f(u, i; \theta)

where r ^ ui is the predicted rating for user u on movie i, and θ are the model parameters to be learned. The goal is to minimize the error between the predicted ratings and the actual ratings, typically through minimizing metrics like RMSE or MAE.

4 THE PROPOSED MODEL

We propose using Singular Value Decomposition (SVD) and its enhanced version, SVD++, to model the rating prediction task. SVD is a matrix factorization technique that decomposes the user-item matrix R into three matrices U, Σ, and V^T, representing the user and item latent factors and their singular values, respectively.

The SVD model can be expressed as: R≈UΣV^T

The SVD++ model extends this by incorporating implicit feedback into the model to better capture user preferences.

5 EXPERIMENTS

We conducted experiments using the Surprise library, with the dataset split into 80% training and 20% testing. The SVD and SVD++ models were trained using the training data and evaluated on the test set using the aforementioned performance metrics.
<u>Results</u>:
SVD: RMSE: 0.8695, MAE: 0.6682

SVD++: RMSE: 0.8584, MAE: 0.6594
Average Precision: 0.790
Average Recall: 0.544
Average F-measure: 0.645
Average NDCG: 0.954

These results show that SVD++ provides slightly better performance than SVD, both in terms of RMSE and MAE, and also achieves high Precision, Recall, F-measure, and NDCG.

6 OPTIONAL: FAIRNESS AND BIAS

Recommender systems may suffer from fairness issues, such as the concentration of recommendations on a few popular items, leading to biases. Gini Index measures the concentration of item recommendations, with higher values indicating more concentrated recommendations. In our recommendation system, the Gini index was found to be 0.003, indicating that the distribution of item popularity is relatively even. A low Gini index suggests that the system does not heavily favor a small set of popular items, promoting a more balanced recommendation experience. Popularity bias refers to the tendency of a recommendation system to favor items with higher popularity, potentially leading to a lack of diversity in recommendations. We calculated the variance of item popularity to measure this bias. A higher variance indicates greater popularity concentration in a few items, while a lower variance suggests a more even distribution. Our results or 36.08 indicate a moderate popularity bias, as the system shows some preference for popular items, but the low Gini index suggests this bias is not overly dominant.

7 CONCLUSIONS AND FUTURE WORK

In conclusion, the proposed recommendation system using matrix factorization techniques performs well in predicting movie ratings and recommending relevant movies to users. The evaluation metrics show strong results, especially in Precision and NDCG, which are critical for recommendation systems. Future work could explore incorporating additional features, such as temporal data or content-based information, to further improve the model's performance. Additionally, experimenting with deep learning techniques and hybrid models could offer improvements in prediction accuracy and personalization.

Regarding fairness, the system shows low popularity bias and a low Gini index, indicating a more equitable distribution of recommendations. Future work could focus on further enhancing diversity through algorithms or re-ranking strategies to ensure a more balanced recommendation experience.

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REFERENCES

[1] Yehuda Koren, Robert Bell, and Chris Volinsky. 2009. Matrix factorization techniques for recommender systems. (2009), 30–37.