Explore A Recommendation System

Xuanzhe Han, Radhegovind Sriram, Akash Pulinthanathu, Liang-Chun Chen

May 7, 2025

Abstract

Recommendation systems are a crucial component of many modern platforms. From social networks to online shopping sites, recommendation systems work to maintain a high level of user interest and generate revenue by showing users content they are interested in. For this project, we will be exploring the effectiveness of different probabilistic models in predicting user preference. We use various techniques to implement recommendation systems using Anime Recommendations Database, a dataset containing real information on user preference data from 73,516 users on 12,294 anime. We plan on using three techniques, Probabilistic Matrix Factorization (PMF), Bayesian Personalized Ranking (BPR), and Latent Dirichlet Allocation (LDA), and compare the resulting models and analyze their performance. The project will involve data processing, model implementation using PyTorch and Scikit-Learn, and evaluation, using RMSE, precision, and recall. We hope to gain insights into the uncertainty and expressiveness of the resulting models, and ultimately determine which technique is more suitable for a real-world recommendation system.

1 Motivation and Introduction

Recommendation systems are a prevalent real-world application of probabilistic modeling. They are widely used in various online services, from social networks such as Instagram, YouTube, and Twitter, to online shopping sites such as Amazon, Aliexpress, and eBay. They are vital to these services, showing users content they enjoy to keep them using the service, and generating sales by pushing relevant advertisements that attract potential consumers. By implementing such systems using probabilistic techniques, we will gain insights into how they are used practically, their strengths, and weaknesses.

2 Course Relevance

This is one of the recommended projects. With the course being about probabilistic programming, this project allows us to apply theoretical models we learned in class and see their performance in a real-life workload. We will be able to gain an understanding of PMF, LDA, and BPR if we are able to implement all three, and compare the three using objective results.

3 Background

PMF [1],BPR [2], LDA [3] are three wilderly used methods in recommendation systems, they are based on different assumption and are suitable in different types of data. PMF relies on the assumption that the data is in a Gaussian distribution, and it can perform well when the dataset is large and sparse, e.g. Netflix dataset. On the other hand, BPR directly optimizes the pair-wire ranking loss, but it also assumes that the behavior between each user is independent. LDA is a topic modeling algorithm, we can use it to retrieve the user preference from the dataset and predict the the recommendation.

We decided to use the Anime Recommendations Database [4] since it contains data with less noise, we are easier to extract the information from the data.

4 Measures of Success

At a baseline, we will preprocess the dataset, implement PMF, BPR, and LDA, and evaluate them using metrics like RMSE, precision, and recall. We will optimize models and conduct a detailed comparison of their performance. As a stretch goal, we hope to integrate additional features like genre data, explore more advanced probabilistic techniques, and assess model calibration to better understand how well the models capture uncertainty.

5 Planning and Timeline

Since our group has four people, we can initially start by branching out and splitting up the implementations of our different recommendation systems. One person will work on PMF, one on BPR, and two on LDA. We want to use the first few weeks to deepen our understanding of the various models as well as our dataset. Our goal is to have baseline implementations completed by the end of week 9. Week 10 and finals week will be used for model comparison, optimizations, and report writing.

References

[1] A. Mnih and R. R. Salakhutdinov, "Probabilistic matrix factorization," *Advances in neural information processing systems*, vol. 20, 2007.

[2] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "Bpr: Bayesian personalized ranking from implicit feedback," *arXiv preprint arXiv:1205.2618*, 2012.

[3] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *Journal of machine Learning research*, vol. 3, no. Jan, pp. 993–1022, 2003.

[4] CooperUnion and B. Dweller, "Anime recommendations database," Kaggle, 2017. [Online]. Available: https://www.kaggle.com/datasets/CooperUnion/anime-recommendations-database/data