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Comparative Analysis of Item-Based Collaborative Filtering and Alternating Least Squares on Implicit Feedback Recommender Systems

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Abstract

This study addresses the challenge of predicting user preferences using implicit feedback data. We compared Popularity-Based and Item-Based Collaborative Filtering (IBCF) baselines against the Alternating Least Squares (ALS) method, evaluating performance via Mean Average Precision at 10 (MAP@10). Results show that ALS-Tuned achieved the highest score (MAP@10 = 0.012788), showing best performance compared to the baseline model. This indicates that hyperparameter tuning affects the most in model performance.

1. Introduction

This chapter outlines the fundamental background and motivation for conducting research on the comparative analysis of recommender systems. The discussion begins with the background underlying the selection of the research topic, identification of problems arising in the processing of implicit interaction data, and the formulation of research objectives and scope. Through this chapter, readers are provided with a comprehensive overview of the importance of comparing Item-Based Collaborative Filtering and Alternating Least Squares methods within the context of the Recommender System 2023 Challenge.

1.1 Background

The rapid growth of digital transformation has significantly changed how users interact with information services and electronic commerce platforms. In these interactions, most of the data generated takes the form of implicit feedback, such as click history, purchasing patterns, and visit duration, which is far more abundant than explicit rating data. To process this large volume of data effectively, recommender systems are required to accurately identify user preference patterns in order to mitigate the problem of information overload.

In practice, two main approaches are commonly used to process such interaction data. The first is Item-Based Collaborative Filtering (IBCF), which analyzes similarities between items based on collective user behavior.

IBCF is well known for its stability and interpretability; however, it often faces scalability challenges when applied to very large and sparse datasets.

As an alternative, matrix factorization techniques using the Alternating Least Squares (ALS) algorithm offer a more efficient solution. ALS maps user–item interactions into a low-dimensional latent factor space, enabling the model to capture hidden relationships that may not be detected by item-similarity-based methods. The advantages of ALS become more pronounced in handling implicit feedback through a specialized confidence-weighting scheme that differentiates the reliability of each interaction. Furthermore, numerical optimization through matrix decomposition allows ALS to achieve high computational efficiency when processing large-scale matrices.

Although both algorithms have been widely studied, comparative analyses of their performance on specific implicit feedback dataset characteristics remain a relevant research topic. Therefore, this study compares the effectiveness of IBCF and ALS using a dataset from the Recommender System 2023 Challenge – Polimi. The evaluation focuses on ranking precision measured using the Mean Average Precision at 10 (MAP@10) metric. The results are expected to provide guidance on selecting the most optimal algorithm for implicit interaction data scenarios.

1.2 Problem Formulation

Based on the background described above, the research problems addressed in this study are as follows:
1. How effective are Item-Based Collaborative Filtering and Alternating Least Squares algorithms when applied to implicit feedback datasets?
2. To what extent does hyperparameter tuning improve the performance of both models?
3. Which algorithm achieves the highest precision based on the MAP@10 metric on the Polimi 2023 competition dataset?

1.3 Research Objectives

The objectives of this study are:
1. To implement recommender models based on IBCF and ALS using an implicit feedback dataset.
2. To analyze and compare the performance of both methods in generating relevant recommendations for users.
3. To identify optimal parameter configurations to maximize model accuracy in accordance with competition evaluation standards.

2. Literature Review

2.1 Recommender Systems

A recommender system is a data processing mechanism designed to predict a user's interest in items or services with which they have not previously interacted. This technology functions as an information filter that helps users discover relevant content amid massive data volumes. The primary objective of recommender systems is to add value to digital platforms by increasing user engagement through personalized suggestions [1].

2.1.1 Implicit Feedback

Implicit feedback refers to interaction data collected passively from user activities on a platform. This data includes click history, viewing duration, search history, and purchasing patterns. Unlike explicit feedback, implicit data is typically more abundant but presents challenges due to the absence of clear negative signals. The lack of interaction does not necessarily imply user disinterest; instead, the item may simply not have been exposed to the user[1].

2.1.2 Explicit Feedback

Explicit feedback refers to data where users consciously provide evaluations of items. Common examples include star ratings (1–5), textual reviews, and like or dislike buttons. Although explicit feedback provides clearer and more accurate interpretations of user preferences, its availability is often limited because not all users are willing to provide ratings manually[1]

2.2 Popularity Based

The popularity-based method is a non-personalized approach in recommender systems. This algorithm recommends items with the highest interaction counts or rising popularity trends to all users without considering individual preferences. Despite its simplicity, this method is highly effective as a baseline model and is frequently used to address the cold-start problem for new users who lack interaction history[2][3].

2.3 Item-Based Collaborative Filtering (IBCF)

Item-Based Collaborative Filtering (IBCF) is a collaborative filtering algorithm that focuses on item-to-item similarity relationships. The core assumption of this method is that if a user likes an item, the system should recommend other items with similar characteristics based on overall user consumption patterns. Item similarity is typically computed using similarity measures such as cosine similarity. IBCF is considered more stable and efficient for platforms where item relationships evolve more slowly than individual user behavior [4][5].

2.4 Alternating Least Squares (ALS)

Alternating Least Squares (ALS) is an optimization algorithm used in matrix factorization techniques to decompose large and sparse interaction matrices into two smaller latent factor matrices. In the context of implicit feedback, ALS applies a confidence-weighting scheme to determine the reliability of each interaction. The algorithm operates iteratively by optimizing one factor matrix while holding the other constant, and vice versa. The primary strengths of ALS lie in its scalability for parallel processing of large datasets and its ability to capture latent relationships that are not explicitly observable [6][7].

2.5 Evaluation

Evaluation is a crucial stage in measuring how effectively a recommender system provides accurate and useful recommendations. The evaluation process compares model-generated predictions against actual user interactions that were withheld during training. Various evaluation metrics are used to assess model performance from both accuracy and ranking quality perspectives[2].

2.5.1 Precision

Precision measures the system's ability to deliver recommendations that are truly relevant to users. This metric is calculated as the ratio of relevant items recommended to the total number of items recommended. High precision indicates that most items appearing in the recommendation list are items that users actually prefer [8].

2.5.2 Mean Average Precision (MAP@10)

Mean Average Precision (MAP) is a metric that emphasizes the quality of ranking order. MAP@10 specifically computes the average precision of the top ten recommended items. This metric assigns greater importance to relevant items appearing at higher ranks. A higher MAP@10 value indicates better capability of the system in placing the most relevant items at top positions, which is critical for real-world user experience [8][9].

3. Results and Discussion

In this section, we present the results of developing a recommender model capable of generating Top-10 ranked item lists for each user. The evaluation includes baseline models, namely the popularity-based model and Item-Based Collaborative Filtering (IBCF), as well as an advanced model based on Alternating Least Squares (ALS) that was specifically tuned for implicit feedback data. Performance comparison is conducted using the Mean Average Precision at 10 (MAP@10) metric, highlighting performance improvements and factors influencing each model.

Model	MAP@10	Improvment
Popularity	0.004362	-
IBCF	0.010915	150.22%
ALS - Initial Config	0.011806	170.64%
ALS - Best Tuned	0.012788	193,1%

The popularity-based recommendation model was used as the first baseline, where items are recommended to all users based solely on global popularity without considering individual preferences, specific interaction histories, or contextual information. As such, this baseline serves as a lower bound for evaluating more sophisticated recommendation models. Evaluation using MAP@10 yielded a score of 0.004362, which is relatively low, indicating the limited ability of global popularity-based recommendations to place relevant items at top ranks for individual users.

The IBCF model demonstrated a significant performance improvement, achieving a MAP@10 score of 0.010915, representing a substantial increase compared to the popularity-based model. This improvement confirms that item-similarity-based approaches are more effective in capturing user preferences than non-personalized popularity-based methods.

Meanwhile, the ALS model achieved the best overall performance with a MAP@10 score of 0.011806, corresponding to a 170.64% improvement over the baseline. This result indicates that matrix factorization in

ALS is more effective in modeling latent relationships between users and items, thereby producing more relevant recommendations

📊 HYPERPARAMETER TUNING RESULTS

Rank	Factors	Alpha	Reg	Iter	MAP@10	vs IBCF	Time(s)
🏆 1	64	20	0.10	5	0.012788	+17.16%	1633.10
🏆 2	64	60	0.01	8	0.012456	+14.12%	2341.53
🏆 3	48	40	0.05	8	0.011550	+5.81%	1431.08
🏆 4	48	80	0.05	8	0.011057	+1.30%	3443.97
5	48	20	0.10	5	0.010816	-0.91%	1033.06
6	32	40	0.10	8	0.010727	-1.73%	990.72
7	32	40	0.01	10	0.010356	-5.12%	2118.56
8	48	40	0.01	5	0.009867	-9.61%	944.90
9	48	40	0.10	5	0.009859	-9.68%	941.42
10	32	20	0.10	5	0.009797	-10.25%	729.15
11	32	40	0.05	5	0.009238	-15.37%	3517.39
12	32	40	0.10	5	0.009164	-16.04%	4430.92
13	32	40	0.01	5	0.009124	-16.41%	661.61
14	32	60	0.10	5	0.008802	-19.36%	661.10
15	16	20	0.10	5	0.007942	-27.24%	373.76

In addition to model comparison, this study conducted hyperparameter tuning on the ALS model to obtain the optimal configuration. The tuning process evaluated various combinations of key parameters, including the number of latent factors, regularization value, alpha parameter, and number of iterations. Each configuration was evaluated using MAP@10, with the IBCF model serving as the reference benchmark. The best-performing configuration was achieved at Rank 1 with 64 latent factors, alpha = 20, regularization = 0.10, and 5 iterations, producing a MAP@10 score of 0.012788. This configuration yielded a 17.16% improvement over IBCF and represented the highest performance among all tested configurations.

The tuning results also revealed that not all parameter combinations led to performance gains. Some ALS configurations exhibited lower performance than IBCF, indicating that hyperparameter selection plays a critical role in recommendation quality. Additionally, substantial variation in computational time across configurations highlights the importance of balancing accuracy and efficiency. Overall, the hyperparameter tuning process confirms that ALS can outperform IBCF when appropriately configured, and the best-performing configuration was therefore selected as the final ALS model for subsequent evaluation stages.

4. Conclusion

This study presents a comparative analysis of recommender system approaches based on implicit feedback, focusing on Popularity-based recommendation, Item-Based Collaborative Filtering (IBCF), and Alternating Least Squares (ALS). The experimental results demonstrate that simple popularity-based recommendations provide limited personalization capability, as reflected by the lowest MAP@10 score. In contrast, IBCF significantly improves recommendation quality by leveraging item–item similarity, showing more than a 150% improvement over the popularity baseline.

Furthermore, the ALS model exhibits the strongest overall performance when appropriately configured. Through systematic hyperparameter tuning, ALS can effectively capture latent relationships between users and items, resulting in the highest MAP@10 score among all evaluated models. These findings highlight that matrix factorization techniques, when carefully tuned, are well suited for handling large-scale implicit feedback datasets and can outperform traditional similarity-based methods.

Overall, this research confirms that both IBCF and ALS are viable approaches for implicit feedback recommender systems, with ALS offering superior performance under optimal parameter settings. The results provide practical insights for selecting and configuring recommendation algorithms in real-world scenarios where ranking accuracy is critical. Future work may explore hybrid models, additional regularization strategies, or the integration of contextual features to further enhance recommendation performance.

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