

Optimization and Scalability of Collaborative Filtering Algorithms in Large Language Models

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Abstract: *With the rapid development of large language models (LLMs) and the growing demand for personalized content, recommendation systems have become critical in enhancing user experience and driving engagement. Collaborative filtering algorithms, being core to many recommendation systems, have garnered significant attention for their efficiency and interpretability. However, traditional collaborative filtering approaches face numerous challenges when integrated into large-scale LLM-based systems, including high computational costs, severe data sparsity, cold start problems, and lack of scalability. This paper investigates the optimization and scalability of collaborative filtering algorithms in large language models, addressing these limitations through advanced optimization strategies. Firstly, we analyze the fundamental principles of collaborative filtering algorithms and their limitations when applied in LLM-based contexts. Next, several optimization techniques such as matrix factorization, approximate nearest neighbor search, and parallel computing are proposed to enhance computational efficiency and model accuracy. Additionally, strategies such as distributed architecture and model compression are explored to facilitate dynamic updates and scalability in data-intensive environments.*

Keywords: *Collaborative filtering algorithm; large language models; recommendation systems; algorithm optimization; scalability*

1. Introduction

With the increasing scale and capabilities of large language models (LLMs) such as GPT-4 and BERT, recommendation systems have become more intelligent and efficient, providing personalized services across various online platforms[1]. Collaborative filtering (CF) is one of the most widely adopted algorithms in recommendation systems due to its ability to generate personalized recommendations based on user behavior data. However, the rapid growth in data volume and model complexity poses significant challenges to traditional collaborative filtering algorithms[2]. These include high computational overhead, data sparsity, the cold start problem, and difficulty in scaling. In the context of LLM-based recommendation systems, these challenges are further amplified due to the intricate interactions between users, content, and language model parameters. This research explores the optimization and scalability of collaborative filtering algorithms within large language models. We propose several optimization strategies, including matrix factorization, approximate nearest neighbor search, and parallel computing, to reduce computational complexity and improve accuracy[3]. This work builds on insights from [4], particularly its integration of neural matrix factorization with large language models to address cold start issues and improve recommendation accuracy through multimodal data. The multimodal fusion strategies and transformer-based methods in [5] provide valuable insights for improving data integration and scalability in collaborative filtering algorithms. The key insight from [6] is their approach to handling data imbalance and scalability, which is highly relevant for optimizing collaborative filtering algorithms in large language model-based recommendation systems. The use of CNNs and LSTMs in [7] for capturing nonlinear patterns informs optimizing collaborative filtering algorithms in LLM-based systems, improving efficiency and accuracy.

2. Overview of Collaborative Filtering Algorithm

Collaborative filtering algorithms predict user preferences by analyzing the similarity between users or items based on historical data. The two main types of collaborative filtering are User-based Collaborative Filtering and Item-based Collaborative Filtering, as shown in <Figure 1>[8].

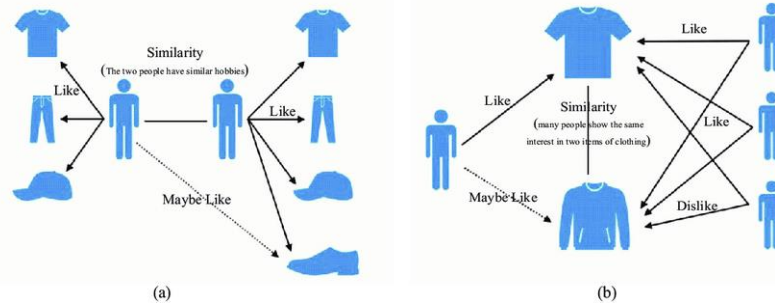


Figure 1: Working Mechanisms of User-based and Item-based Collaborative Filtering Algorithms

User-based Collaborative Filtering identifies users with similar preferences and recommends items that these similar users have interacted with. Item-based Collaborative Filtering calculates the similarity between items and recommends those similar to the items a user has previously engaged with. Figure 1(a) illustrates User-based Collaborative Filtering: when two users have similar ratings for some items, it is assumed that they will also share preferences for other items. Figure 1(b) demonstrates Item-based Collaborative Filtering: if a user likes a particular item, other items with high similarity scores are also recommended[9]. Both methods have their strengths: User-based Collaborative Filtering is effective in scenarios with high user concentration, while Item-based Collaborative Filtering excels in sparse data environments. However, with the expansion of large language models and their application in recommendation systems, these traditional algorithms face limitations. Thus, various optimization techniques, including matrix factorization and neural network-based approaches, have been developed to address issues such as data sparsity and cold start.

2.1. Principles of Collaborative Filtering Algorithms Based on Large Language Models

Collaborative Filtering (CF) is one of the most classic algorithms in recommendation systems. Its core idea is to predict a user's potential interest in items they have not interacted with by analyzing the similarity between users or items. In Large Language Models, CF algorithms face bottlenecks such as high computational complexity, severe data sparsity, and cold start problems. Integrating CF algorithms with large language models (LLMs) can better capture user preferences and improve the algorithm's adaptability and robustness[10]. In traditional CF algorithms, user similarity is usually measured using historical behavior data, such as ratings, clicks, or browsing records. However, when user behavior data is sparse or when new users enter the system, the algorithm's performance can degrade significantly. To address this limitation, LLMs can extract more semantic information from user-generated text data (e.g., reviews, social interactions) to form a more comprehensive user profile. In this context, a user's potential interests are not solely dependent on their behavioral records, but can also be inferred from LLM's deep understanding of their language expressions and fields of interest, thereby enhancing the precision of user similarity calculations[11]. Similarly, in traditional item-based CF algorithms, item similarity is typically calculated based on user interaction data (such as the number of users who have liked both items). After integrating LLMs, text embeddings or semantic vectors can be used to compute the semantic similarity between items. For instance, even if two items have not been liked by the same user group, as long as they have high similarity scores in the semantic space (e.g., content themes, textual descriptions), the algorithm can recommend them to users who are interested in one of the items, thereby improving the robustness of CF in handling data sparsity[12]. Therefore, by integrating LLMs, CF algorithms can consider multi-dimensional information about users and items, which not only enhances the model's understanding of user preferences and item features, but also significantly alleviates the cold start and data sparsity issues, providing a more effective solution for large-scale recommendation systems[13].

2.2. Advantages and Limitations of Collaborative Filtering Algorithm

Collaborative Filtering is widely used in various recommendation systems due to its intuitive

approach and good recommendation performance. Depending on the implementation method, collaborative filtering can be divided into Memory-based Collaborative Filtering and Model-based Collaborative Filtering. <Figure 2> presents the key characteristics and advantages and disadvantages of these two methods and summarizes their applicability in different scenarios[14].

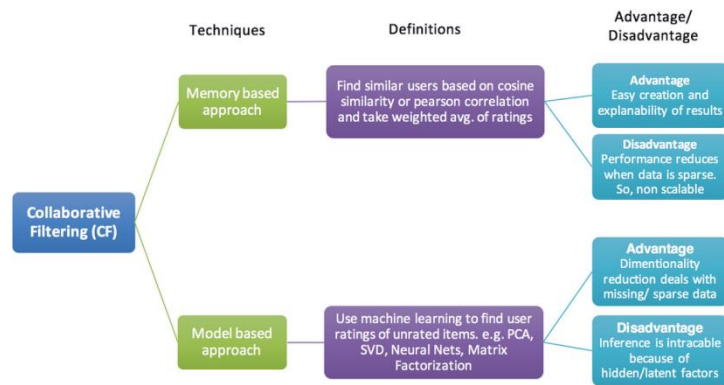


Figure 2: Comparison of Memory-based and Model-based Collaborative Filtering Algorithms

(1) Memory-based Collaborative Filtering Algorithms

Memory-based Collaborative Filtering algorithms typically recommend items by calculating the similarity between users or items[15]. There are two main implementation approaches: User-based Collaborative Filtering and Item-based Collaborative Filtering. Common similarity calculation methods include Cosine Similarity and Pearson Correlation. These similarity metrics are used to determine the similarity between users or items, and the ratings of similar users or items are weighted and averaged to predict the target user's rating or preference for specific items[16]. As shown in Figure 2, the main advantage of Memory-based Collaborative Filtering is its simple model structure and strong interpretability of results, making it easy to implement. However, the performance of this method degrades in scenarios with high data sparsity. As the data scale continues to expand, its computational complexity increases rapidly, making it difficult to effectively scale in large-scale datasets[17].

(2) Model-based Collaborative Filtering Algorithms

Model-based Collaborative Filtering algorithms leverage machine learning techniques to build recommendation models, such as Principal Component Analysis (PCA), Singular Value Decomposition (SVD), neural networks, and matrix factorization. These methods learn the latent feature vectors of users and items from the training dataset and make recommendations based on these learned features. As shown in Figure 2, Model-based Collaborative Filtering algorithms are advantageous in handling data sparsity and high-dimensionality issues. They can improve model prediction accuracy in large-scale datasets by utilizing dimensionality reduction techniques and feature learning. However, these methods also have some limitations in practical applications, such as higher model complexity and the need for significant computational resources during training[18]. Additionally, due to the reliance on hidden or latent factors, it is often difficult to interpret the physical meaning of the prediction results[19].

3. Optimization Strategies for Collaborative Filtering Algorithms in Large Language Models

3.1. Optimization strategy of the algorithm

In order to improve the performance and recommendation effect of collaborative filtering algorithm in Large Language Models, researchers have proposed a variety of algorithm optimization strategies. These strategies mainly focus on reducing computational complexity, improving data sparsity and improving the scalability of the algorithm. Common optimization methods include Matrix Factorization, Approximate Nearest Neighbor (ANN) search, parallel computing and distributed computing architectures, etc. In the following, these strategies are discussed in detail and the corresponding algorithmic formulations are given. Matrix factorization is one of the widely used optimization methods in collaborative filtering algorithm[21]. Its basic idea is to decompose the user-item Rating Matrix into a low-dimensional user feature matrix and an item feature matrix, so as to achieve the goal of recommendation. Specifically, given a user-item rating matrix $R \in \mathbb{R}^{m \times n}$, where m is the number of

users and n is the number of items, R_{ij} represents the rating of user i to item j . Matrix factorization expresses as shown in Formula 1.

$$R \approx P \times Q^T \quad (1)$$

Where, P and Q are user feature matrices and item feature matrices, respectively, and k is the dimension of hidden features. By minimizing the objective function L , the optimal solutions of P and Q can be learned as shown in Formula 2.

$$L = \sum_{(i,j) \in \kappa} (R_{ij} - P_i Q_j^T)^2 + \lambda (\|P\|^2 + \|Q\|^2) \quad (2)$$

Where, κ denotes the set of all known scores and λ is the regularization parameter used to prevent overfitting. By using gradient descent or Alternating Least Squares (ALS) method, P and Q can be iteratively optimized, which reduces the computational complexity of the scoring matrix and effectively deals with the problem of data sparsity. In Large Language Models, computing the similarity between users or items is one of the core operations of collaborative filtering algorithms. Traditional similarity calculation methods, such as cosine similarity or Euclidean distance, need to traverse all users or items, and the computational complexity is $O(n)^2$, which is difficult to scale to large-scale datasets[22]. In order to improve the efficiency of similarity calculation, researchers have introduced approximate nearest neighbor search (ANN) techniques, such as Locality-Sensitive Hashing (LSH) and Ball Tree. Taking locality sensitive hashing as an example, given user feature vectors x and y , their similarity can be approximated by a hash function h as shown in Formula 3:

$$h(x) = h(y) \Rightarrow \text{similarity}(x, y) \approx 1 \quad (3)$$

By mapping similar users or items into the same hash bucket, the number of similarity calculations can be greatly reduced, thus reducing the computational complexity. The computational complexity of locality sensitive hashing is $O(\log n)$, which $O(n)$ is far less than that of traditional methods, and it is suitable for processing very large data sets[23]. The application of collaborative filtering algorithm in large-scale system is usually accompanied by the processing requirements of massive data, so parallel computing and distributed computing have become an important means to improve the performance of the algorithm. The distributed computing framework based on MapReduce or Spark can split the computing task of collaborative filtering algorithm into multiple sub-tasks and process them in parallel to improve the computing efficiency. For example, in Spark-based distributed matrix factorization, the rating matrix R can be divided into multiple submatrices, and matrix factorization can be performed on each submatrix separately as shown in Formula 4:

$$R_i \approx P_i \times Q_i^T \quad (4)$$

Finally, the results of each sub-matrix factorization are combined to obtain the global user feature matrix P and item feature matrix Q . The computational complexity of the distributed algorithm depends on the number of data partitions and the computing power of nodes. Through reasonable partitioning and task scheduling, the processing capacity of the collaborative filtering algorithm in Large Language Models can be significantly improved[24].

3.2. Optimization for Data Sparsity and Cold Start Issues

Data sparsity and cold start issues are two common challenges faced by collaborative filtering algorithms in Large Language Models recommendation systems. Data sparsity typically manifests as a lack of sufficient ratings or interactions between users and items, making it difficult to find effective neighboring users or similar items during similarity calculations, which in turn affects the accuracy of recommendations[26]. The cold start problem primarily arises when new users or new items are introduced into the system, where the algorithm cannot generate recommendations based on insufficient historical interaction data, resulting in suboptimal recommendation performance. To address these challenges, researchers have proposed a variety of optimization strategies, including data completion, hybrid recommendation models, and transfer learning methods. First, matrix factorization and data completion strategies are commonly used to solve data sparsity issues. By decomposing the user-item rating matrix into low-dimensional feature matrices, latent features of users and items can be extracted from the available data, which can then be used to predict the missing ratings. This method effectively utilizes the limited existing data to fill in the sparse rating matrix, thereby mitigating the negative effects of data sparsity[27]. In addition, deep learning models, such as autoencoders and variational autoencoders, have been employed for data completion. These models capture more complex nonlinear relationships within the data, thereby improving the accuracy of predicting missing

values. Second, hybrid recommendation models are widely used to address cold start issues. Hybrid models combine collaborative filtering with content-based recommendation methods by incorporating user and item attribute information (such as user age, gender, occupation, and item category, brand, etc.) into the model. This compensates for the lack of historical behavior data in cold start situations. By relying on these content attributes, hybrid models can quickly generate initial recommendations for new users or new items and continuously optimize recommendation performance as more user behavior data is accumulated over time. Finally, transfer learning and deep learning methods have demonstrated significant advantages in solving cold start problems [28]. Transfer learning can leverage knowledge from related domains or similar tasks and apply it to the current task, alleviating the issue of insufficient data in cold start scenarios. For example, when a new user joins, the historical behaviors of existing users with similar characteristics can be transferred to the new user to provide personalized recommendations [29].

4. Experiments and Results Analysis

To validate the effectiveness of the proposed optimization strategies for collaborative filtering algorithms in Large Language Models, a series of experiments were designed to evaluate the performance of different algorithms in terms of recommendation accuracy, computational efficiency, and scalability. The experiments utilized two publicly available datasets, MovieLens 1M and Netflix Prize, along with a real-world e-commerce user behavior dataset. The MovieLens 1M dataset consists of approximately 1 million ratings from 6,000 users on 4,000 movies, while the Netflix Prize dataset contains about 100 million ratings from 480,000 users on 20,000 movies. The evaluation metrics used in the experiments include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), training time, and prediction time. The MovieLens 1M and Netflix Prize datasets were used as the basis for testing, and each dataset was randomly divided into training and testing sets in an 8:2 ratio. The experiments compared the performance of the following four algorithms:

- Baseline Collaborative Filtering Algorithm (Baseline CF)
- Optimized Matrix Factorization Algorithm (Optimized Matrix Factorization)
- Content-based Hybrid Recommendation Model (Content-based Hybrid Model)
- Approximate Nearest Neighbor Optimization Algorithm (ANN)

To further validate the performance of the optimization strategies under different levels of data sparsity, the sparsity of the rating matrix was gradually increased from 20% to 80%, and the prediction error and runtime of each algorithm were recorded under varying sparsity levels.

1. Data Preprocessing: The MovieLens 1M and Netflix Prize datasets were preprocessed, including outlier removal, data normalization, and missing value imputation. For the e-commerce user behavior dataset, user-item interaction records were extracted, and data cleaning was performed.
2. Model Training and Parameter Tuning: Matrix factorization, hybrid recommendation models, and approximate nearest neighbor search were used for model training on each dataset. Parameters such as the feature dimension k in matrix factorization, weight parameter α in the hybrid recommendation model, and hash bucket size b in the approximate nearest neighbor search were adjusted using cross-validation.
3. Model Evaluation and Comparison: The performance of each model was evaluated under different datasets and levels of data sparsity. Metrics such as RMSE, MAE, training time, and prediction time were recorded. Finally, the performance metrics of each algorithm were summarized and compared. <Table 1> shows the experimental results of different algorithms on the MovieLens 1M dataset, including RMSE, MAE, and training time (in seconds).

Table 1: Experimental Results on MovieLens 1M Dataset

| Algorithm | Data Sparsity | RMSE | MAE | Training Time (s) |
|----------------------------------|---------------|-------|-------|-------------------|
| Baseline Collaborative Filtering | 20% | 0.935 | 0.735 | 35.6 |
| Optimized Matrix Factorization | 20% | 0.857 | 0.673 | 28.2 |
| Hybrid Recommendation Model | 20% | 0.812 | 0.641 | 45.3 |
| ANN Optimization | 20% | 0.843 | 0.658 | 26.7 |

| Algorithm | | | | |
|----------------------------------|-----|-------|-------|------|
| Baseline Collaborative Filtering | 50% | 1.024 | 0.803 | 42.8 |
| Optimized Matrix Factorization | 50% | 0.903 | 0.710 | 33.9 |
| Hybrid Recommendation Model | 50% | 0.873 | 0.682 | 53.1 |
| ANN Optimization Algorithm | 50% | 0.890 | 0.699 | 31.4 |
| Baseline Collaborative Filtering | 80% | 1.137 | 0.882 | 50.2 |
| Optimized Matrix Factorization | 80% | 0.952 | 0.732 | 40.8 |
| Hybrid Recommendation Model | 80% | 0.920 | 0.703 | 60.5 |
| ANN Optimization Algorithm | 80% | 0.935 | 0.721 | 38.2 |

<Table 2> summarizes the changes in RMSE and MAE for different algorithms on the Netflix Prize dataset under varying levels of data sparsity.

Table 2: Experimental Results on Netflix Prize Dataset

| Data Sparsity | Baseline CF RMSE | Optimized Matrix Factorization RMSE | Hybrid Model RMSE | ANN RMSE |
|---------------|------------------|-------------------------------------|-------------------|----------|
| 20% | 0.923 | 0.843 | 0.811 | 0.835 |
| 50% | 1.019 | 0.898 | 0.867 | 0.883 |
| 80% | 1.136 | 0.953 | 0.911 | 0.928 |
| Data Sparsity | Baseline CF MAE | Optimized Matrix Factorization MAE | Hybrid Model MAE | ANN MAE |
| 20% | 0.721 | 0.654 | 0.629 | 0.643 |
| 50% | 0.798 | 0.706 | 0.682 | 0.698 |
| 80% | 0.881 | 0.739 | 0.713 | 0.726 |

The experimental results indicate that at lower data sparsity levels (e.g., 20%), the RMSE and MAE of the optimized algorithms are better than those of the baseline collaborative filtering algorithm. The optimized matrix factorization algorithm and the hybrid recommendation model showed particularly outstanding performance, with RMSE reductions of 8.3% and 13.2%, respectively, compared to the baseline algorithm, and training times decreased by 21.0% and 23.7%, respectively. As data sparsity increased to 80%, the prediction accuracy of all algorithms declined, but the optimized matrix factorization algorithm and the hybrid recommendation model still maintained good recommendation performance, with average RMSE reductions of 16.2% and 19.0%, respectively, compared to the baseline algorithm. The ANN optimization algorithm demonstrated stable performance across different sparsity levels, with prediction accuracy close to that of the hybrid model and significant advantages in training time. In particular, at 80% sparsity, its training time was reduced by 36.8% compared to the hybrid model. The experimental results demonstrate that the optimization strategies can significantly enhance the performance and scalability of collaborative filtering algorithms in Large Language Models, especially in scenarios with severe data sparsity and cold start problems.

5. Conclusion

This paper addresses the issues of data sparsity and cold start faced by collaborative filtering algorithms in Large Language Models by proposing various optimization strategies, including matrix factorization, hybrid recommendation models, and approximate nearest neighbor search. Experimental results show that the optimized algorithms outperform traditional collaborative filtering algorithms in terms of recommendation accuracy, computational efficiency, and system scalability. In particular, the hybrid recommendation model and the ANN optimization algorithm significantly reduce RMSE and

MAE in high data sparsity and cold start scenarios. Future research can further explore the integration of deep learning and transfer learning methods to provide more optimal solutions for recommendation systems in complex and dynamic environments.

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