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A Lightweight Representative Grid Framework for Sparse Recommendation Systems

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Abstract.

Recommendation systems rely on user-item interaction data that is usually sparse. There are numerous methods to deal with sparsity, but with limitations. Matrix factorization is a widely used method. It demands high computations and is limited by low interpretability. This work introduces a low-complexity approach that preserves structural information while avoiding latent factor optimization. This approach first identifies a grid band that captures significant user and item interaction patterns and uses it as a basis to make predictions. Experiments were conducted on the MovieLens 100K benchmark dataset using five-fold cross-validation. The results demonstrate competitive prediction performance and top- K recommendation quality compared with existing approaches. The proposed approach offers a computationally efficient alternative for recommendation tasks in sparse data situations.

Keywords. Representative Grid Recommender (RGR), Matrix Factorization, Structural Recommendation, Top- K Recommendation, Sparse Rating Prediction.

1. INTRODUCTION

Sparse matrices are data sources for recommendation systems, with much of the data remaining unobserved. The primary goal of a recommendation algorithm is to process this data to derive useful recommendations. Matrix Factorization (MF) has emerged as one of the most influential approaches owing to its ability to estimate missing ratings using a latent feature space [1]– [3]. However, sparsity limits accuracy, and learning through latent factors limits interpretation. Moreover, MF performs iterative parameter tuning, with high computational complexity for large-scale recommendation tasks [1], [4].

This paper presents a lightweight recommendation approach for sparse rating prediction that uses a grid structure to pick representative users and items to guide the estimations. Prediction performance and recommendation quality are assessed using appropriate metrics.

The major contributions of this work are summarized as follows.

1. A novel Representative Grid Recommender (RGR) is proposed instead of latent factor optimization.
2. A three-case prediction strategy is developed to improve recommendation robustness under highly sparse rating conditions.
3. The proposed framework preserves the structural characteristics of the observed rating matrix during the prediction process.
4. An experimental setup is presented to demonstrate the effectiveness, stability, and practical applicability of the proposed model.

2. RELATED WORK

Existing recommendation approaches can be classified into 4 categories.

2.1. *Neighbourhood-based collaborative filtering*

These approaches exploit similarities among users or items. They study similar users or relationships among similar items. Recommendation neighbourhoods are constructed using similarity metrics [5]–[8]. However, these techniques often exhibit reduced performance on large-scale sparse datasets where the neighbourhoods are also sparse [6], [9].

2.2. *Matrix Factorisation recommender*

Matrix Factorization constructs a product of low-dimensional latent user and item matrices to estimate unknown ratings [1], [3]. Numerous variants have evolved, ranging from biased Matrix Factorization to Neural Collaborative Filtering [4], [10]–[12]. However, these approaches are computationally expensive and less interpretable, particularly when sparseness is too high.

2.3. *Hybrid and deep models*

Hybrid frameworks combine collaborative filtering with content information, knowledge graphs, graph neural networks, transformer architectures, and large language models [13]–[15]. The hybridisation benefited from the positive elements of the constituent models. However, large computational resources, complex training pipelines, and extensive parameter optimization remain their major limitations.

2.4. *Sparse rating prediction*

Matrix completion, graph-guided recommendation, trust-aware recommendation, and low-rank approximation belong to this category [11], [12],[15]. However, these approaches generally rely on iterative parameter optimization, demanding significant computational resources.

All these observations motivate the design of better strategies to mitigate the problems associated with the existing methods. The proposed design is constrained by low computational complexity and better interpretability.

3. PROPOSED REPRESENTATION GRID RECOMMENDER

The observed rating matrix is of the form $R = [r_{ui}]_{m \times n}$, (1),

where

$$r_{ui} = \begin{cases} 1, \dots, k, & \text{if user } u \text{ rated item } i, \text{ in the range 1 to } k \\ 0, & \text{otherwise.} \end{cases}$$

The objective is to estimate the rating $\hat{r}_{ui}$. A grid is a subset of the rating matrix, with a minimal binary disjunction of rows forming a one-vector row band. Similarly, a minimal collection of columns forms a column band of the grid. This grid beam is a combination of representations of users (U_R) and items (I_R) that guide our prediction. These users and items are significant contributors to the user-item interaction behaviour.

Let b_u is a vector corresponding to user u . Starting from an all-zero vector, $W^{(0)} = 0$, successive logical disjunctions form

$$W^{(t)} = W^{(t-1)} \vee b_{u_t}, \quad t = 1, 2, \dots, p, \quad (2)$$

The process continues until one vector is formed. The corresponding user set $U_R = \{u_1, u_2, \dots, u_p\}$ forms the representative user set.

Similarly, a dual procedure is applied to the binary item vectors to obtain the representative item set $I_R = \{i_1, i_2, \dots, i_q\}$. The Cartesian intersection of U_R and I_R constitutes the Representative Grid.

The complete prediction model is

$$\hat{r}_{ui} = \begin{cases} \hat{r}_{ui}^{(1)}, & u \in U_R \wedge i \notin I_R, \\ \hat{r}_{ui}^{(2)}, & u \notin U_R \wedge i \in I_R, \\ \hat{r}_{ui}^{(3)}, & \text{otherwise.} \end{cases} \quad (3)$$

If the target cell comes under the representative user set (U_R), the missing rating is estimated from representative neighbors $N_u = \{v_1, v_2, \dots, v_k\}$ who rated the target item. Therefore

$$\hat{r}_{ui}^{(1)} = \frac{1}{k} \sum_{v \in N_u} r_{vi}. \quad (4)$$

If the target cell comes under the representative item set (I_R), the missing rating is estimated from representative neighbors $N_i = \{j_1, j_2, \dots, j_l\}$ who were rated by the target user.

$$\text{Therefore } \hat{r}_{ui}^{(2)} = \frac{1}{l} \sum_{j \in N_i} r_{uj}. \quad (5)$$

If the target cell is out of the grid, the prediction falls under user-item statistics.

$$\hat{r}_{ui}^{(3)} = \frac{E_u + E_i}{2}. \quad (6)$$

, where E_u and E_i are average observed ratings of similar users and items. The similar users are those who rated other items similarly to the targeted user. Similar items also follow the similar criterion.

4. EVALUATION, RESULTS AND DISCUSSION

4.1. Prediction accuracy

The proposed Representative Grid Recommender (RGR) was evaluated against existing baselines using five-fold cross-validation on the MovieLens 100K dataset. Each fold has a train-to-test ratio of 80:20. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are the metrics for the evaluation. Table 1 presents the prediction accuracy results given by the proposed process in comparison with Matrix Factorization, user KNN, and item KNN models.

Table 1
Prediction Accuracy Comparison Between MF and RGR

Method	RMSE	MAE
MF	0.9376	0.7256
RGR	1.006267	0.806471
User KNN	1.005402	0.780696
Item KNN	0.98	0.899

It can be noticed that RGR achieves a matching prediction error with existing methods. The closeness of RMSE and MAE indicates that the proposed structural prediction mechanism provides a significant estimate of missing ratings under sparse conditions using a non-iterative, low-cost process. Unlike MF, RGR directly uses the observable interaction structures in the rating matrix.

4.2. Ranking performance

In recommendation systems, the quality of recommendations is also a significant contribution of a recommendation model. Table 2 presents the ranking performance comparison.

Table 2
Top-10 Ranking Performance Comparison on MovieLens 100K

Method	Precision@10	Recall@10	Hit Ratio@10	MAP@10	NDCG@10
User-KNN	0.019822	0.026241	0.167996	0.009718	0.025243
Item-KNN	0.007501	0.007300	0.066316	0.003210	0.008927
MF	0.043858	0.033038	0.287108	0.020119	0.049430
RGR	0.016214	0.014526	0.133400	0.011232	0.024597

RGR reached a Precision@10 of 0.016214, Recall@10 of 0.014526, Hit Ratio@10 of 0.133400, MAP@10 of 0.011232, and NDCG@10 of 0.024597. Although these values are lower than those of the MF model, the proposed method consistently outperformed Item-KNN in all ranking metrics. Compared with User-KNN, RGR got a higher MAP value, indicating improved ranking quality. The NDCG value of RGR (0.024597) is also comparable to that of User-KNN (0.025243), demonstrating that the proposed

representative-grid strategy preserves the relative ordering of relevant recommendations with a lighter processing framework.

It can be observed that the proposed method was evaluated for competitive recommendation performance. RGR showed better recommendation metric values in some sub-cases and was competitive in others. Without high-level computations or latent factors, the proposed approach can provide reliable recommendations. Therefore, RGR is a practical and interpretable recommendation framework.

Recommendation quality can be further improved by adopting structural extraction methods like Hyperlink Induced Topic Search (HITS).

5. CONCLUSION

As a structural representation model, RGR provides interpretable knowledge for recommendation without learning latent factors. By identifying users and items that contribute a significant basis for interaction behavior, this grid-based approach made predictions without iterative computations, reducing complexity. The proposed method is a lightweight alternative to complex matrix imputation methods. As with other existing methods, the proposed method has limitations when the data is too sparse. This limitation can be mitigated by adopting lightweight structural methods like HITS. The idea introduced in this paper motivates further lightweight approaches that reduce the burden on computing resources and improve interpretability and reliability.

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Biographies



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