IPR: Interaction-level Preference Ranking for Explicit Feedback

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ABSTRACT

Explicit feedback—user input regarding their interest in an item—is the most helpful information for recommendation as it comes directly from the user and shows their direct interest in the item. Most approaches either treat the recommendation given such feedback as a typical regression problem or regard such data as implicit and then directly adopt approaches for implicit feedback; both methods, however, tend to yield unsatisfactory performance in top-k recommendation. In this paper, we propose *interaction-level preference ranking* (IPR), a novel pairwise ranking embedding learning approach to better utilize explicit feedback for recommendation. Experiments conducted on three real-world datasets show that IPR yields the best results compared to six strong baselines.

CCS CONCEPTS

• **Information systems** → Recommender systems.

KEYWORDS

collaborative filtering; matrix factorization; explicit feedback; top-k recommendation; high-order graph information

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1 INTRODUCTION

Recommendation systems have been developed to mitigate information overload and have been applied in many real-world scenarios [18]; they are now used by almost every online content provider and e-commerce platform. There are two main ways for a recommender to collect information: explicit feedback and implicit feedback. The former (also referred to as rating information) is user input regarding interest in items; this is more helpful, as it comes directly from the user and shows their direct interest in the item; the latter is produced based on observation of user behavior.

Although explicit feedback is the most helpful for recommendation, usually, it consists of a sparse matrix, as any single user is likely to have rated only a small percentage of possible items. Therefore, over the past decade, researchers have focused on recommendation algorithms for implicit feedback [15]. Conventionally, most studies treat recommendation with explicit feedback as a regression problem—numerous existing matrix factorization methods rely heavily on explicit feedback [4, 9, 10, 13, 16, 21]. Moreover, due to data sparsity, many studies enhance recommendation performance by incorporating content information such as user reviews and metadata from items into the modeling process [1, 3, 8].

Given the success of algorithms for implicit feedback, another type of approach simply regards explicit data as implicit data and directly adopts approaches for implicit feedback [5, 6, 17, 20], most of which either assume that different ratings are the same, or filter out ratings that fall below a predefined threshold, e.g., they keep only interactions with ratings larger than 3 as positive examples and regard the rest as negative examples [5, 20]. However, such simplified approaches either 1) neglect the magnitude information of ratings, or 2) disregard information embedded in low ratings. Other work addresses these shortcomings by incorporating rating importance into the learning process [7, 11, 19]; for example, Loni et al. propose MCBPR, which alters the sampling procedure in Bayesian preference ranking (BPR) [17] to prioritize different ratings, but at the same time injects predefined biases into the learning process [11].

In this study, we propose *interaction-level preference ranking* (IPR), a novel, lightweight embedding learning framework for explicit feedback that ensures both effective utilization of explicit feedback data and a learned model that is scalable. Specifically, using a concept similar to BPR [17], we fundamentally change the picture by altering the basic unit—the node triplet—to an *interaction triplet* for model training. Conceptually, instead of characterizing preferences between items for a given user as in other approaches, we model similarity between user-item interactions; for example, two interactions in which users A and B both rate a movie as

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one star are clustered together in the embedding space. This enables us to incorporate useful information distilled from all explicit feedback in a less assumptive, natural, and weight-free manner, as no importance is assumed and no weights are learned during the modeling process. The proposed IPR intuitively clusters similar user-item interactions in a self-supervised manner and automatically enables the learning of a universal embedding matrix for all users and items that naturally encodes information from different magnitude of user-item interactions. Note also that in contrast to many end-to-end recommendation models, IPR generates a set of user and item embeddings for recommendation, meaning that many calculations can be computed offline or approximated by nearest-neighbor search[1] to deal with large-scale data in practice. To attest the effectiveness of the proposed IPR model, we conduct extensive experiments on three publicly available rating datasets. Experimental results show that the proposed model consistently outperforms state-of-the-art baselines in top-k recommendation. For reproducibility, we will share our implementation of IPR at GitHub,[2] by which the learning process can be completed within an hour for each evaluated dataset.

2 METHODOLOGY

Definition 2.1 (Multi-rating User-item Graph). Let $\mathcal{U}$ and $\mathcal{I}$ denote the set of users and items, respectively. Given a set of ratings $\mathcal{R} = \{r_1, r_2, ..., r_T\}$, where T is the magnitude of the ratings, a multi-rating user-item graph $G_{\mathcal{R}}(\mathcal{U} \cup \mathcal{I}, \mathcal{E})$ is an indirect bipartite graph with an edge-type mapping function $\psi : \mathcal{E} \rightarrow \mathcal{R}$, where $\mathcal{E}$ denotes the set of all edges in the graph, and $(u, i) \in \mathcal{E}$ denotes an edge between $u \in \mathcal{U}$ and $i \in \mathcal{I}$.

Given the multi-rating user-item graph described in Definition 2.1, our goal is to learn an embedding matrix $\Theta \in \mathbb{R}^{|\mathcal{U} \cup \mathcal{I}| \times |d|}$ for all users and items such that for each user $u \in \mathcal{U}$, we generate the top-k recommended items by computing the dot products of Θ_u and Θ_i $\forall i \in \mathcal{I}$. Above, d denotes the dimension of the learned embeddings, and Θ_u and Θ_i are the row vectors of Θ, indicating the embeddings of user u and item i, respectively. It is expected that with our model, the learned embedding matrix Θ properly models user interaction w.r.t. different ratings.

2.1 Proposed IPR Framework

To better exploit the information encoded in different magnitudes of user preferences (ratings) for recommendation, we propose interaction-level preference ranking (IPR), a unified and interaction-level embedding learning framework for explicit feedback. In particular, IPR changes the main idea of many pairwise ranking recommendation algorithms from node-level modeling to interaction-level modeling and clusters interactions with similar (or same) ratings in a self-supervised manner for explicit feedback.

To construct the framework, we leverage Bayesian preference ranking (BPR) [2, 17], a prevalent concept in the recommendation literature for implicit feedback. The basic training unit for a typical BPR-based algorithm is the node triplet (u, i, j) and relation $i >_u j$, where $u \in \mathcal{U}$, $i, j \in \mathcal{I}$, and $i >_u j$ denotes that user u prefers item i over item j. Using a similar concept, we change the picture by altering the basic unit—the node triplet—to an *interaction triplet*. Let L be the set containing all user-item interactions from $G_{\mathcal{R}}(\mathcal{U} \cup \mathcal{I}, \mathcal{E})$, where each element $\ell^r_{ui} \in L$ denotes a user-item interaction in which user u interacts with item i with $r \in \psi((u, i))$ as the user rating. Formally speaking, we define the basic training unit of the proposed IPR as

$$(\ell^r_{ui}, \ell^{r^+}_{u^+i^+}, \ell^{r^-}_{u^-i^-}) \tag{1}$$

along with the relation between interactions

$$\ell^{r^+}_{u^+i^+} >_{\ell^r_{ui}} \ell^{r^-}_{u^-i^-}$$

where $\ell^{r^+}_{u^+i^+} >_{\ell^r_{ui}} \ell^{r^-}_{u^-i^-}$ denotes that $\ell^{r^+}_{u^+i^+}$ is "more similar" to ℓ^r_{ui} than $\ell^{r^-}_{u^-i^-}$. Note that we use a flexible "similarity" between interactions: so-called "positive" interaction $\ell^{r^+}_{u^+i^+}$ and "negative" interaction $\ell^{r^-}_{u^-i^-}$ in a triplet given ℓ^r_{ui}.

For such interaction-level preference ranking, with the triplet from (1), we create training data $D_L : L \times L \times L$ by

$$D_L := \left\{ (\ell^r_{ui}, \ell^{r^+}_{u^+i^+}, \ell^{r^-}_{u^-i^-}) \,\middle|\, \ell^{r^+}_{u^+i^+} \in L^+_{\ell^r_{ui}} \wedge \ell^{r^-}_{u^-i^-} \in L^-_{\ell^r_{ui}} \right\}, \tag{2}$$

where $L^+_{\ell^r_{ui}}$ $(L^-_{\ell^r_{ui}})$ denotes the set of all positive (negative, respectively) interactions regarding ℓ^r_{ui}. With D_L defined in (2), the objective of IPR is to find an embedding matrix Θ that maximizes the interaction-specific likelihood function from observed user-item interactions:

$$O_{\text{IPR}} = \prod_{t \in D_L} p(\ell^{r^+}_{u^+i^+} >_{\ell^r_{ui}} \ell^{r^-}_{u^-i^-} | \Theta),$$

where $t = (\ell^r_{ui}, \ell^{r^+}_{u^+i^+}, \ell^{r^-}_{u^-i^-})$.

For optimization, we define the individual probability that an interaction $\ell^{r^+}_{u^+i^+}$ is more similar to ℓ^r_{ui} than $\ell^{r^-}_{u^-i^-}$ as

$$\begin{aligned} & p(\ell^{r^+}_{u^+i^+} >_{\ell^r_{ui}} \ell^{r^-}_{u^-i^-} | \Theta) \\ & = \sigma\left(\langle g(\Theta_u, \Theta_i), g(\Theta_{u^+}, \Theta_{i^+}) - g(\Theta_{u^-}, \Theta_{i^-}) \rangle\right), \end{aligned} \tag{3}$$

where $\langle \cdot, \cdot \rangle$ denotes the dot product between two vectors, $\sigma(\cdot)$ denotes the sigmoid function, and $g(\cdot)$ refers to the function used to combine the embeddings of the given user and item. Note that $g(\cdot)$ is an arbitrary function; in this paper, we simply adopt $g(\Theta_u, \Theta_i) = \Theta_u + \Theta_i$.

With Eq. (3), we formulate the maximum posterior estimator to derive our optimization criterion for IPR as

$$\begin{aligned} & \text{IPR-OPT} \\ & := \ln p(\Theta | >_{\ell^r_{ui}}) \propto \ln p(>_{\ell^r_{ui}} | \Theta) p(\Theta) \\ & = \ln \prod_{t \in D_L} p(\ell^{r^+}_{u^+i^+} >_{\ell^r_{ui}} \ell^{r^-}_{u^-i^-}) p(\Theta) \\ & = \sum_{t \in D_L} \ln \sigma\left(\langle g(\Theta_u, \Theta_i), g(\Theta_{u^+}, \Theta_{i^+}) - g(\Theta_{u^-}, \Theta_{i^-}) \rangle\right) \\ & \qquad -\lambda_\Theta \|\Theta\|^2, \end{aligned} \tag{4}$$

where $t = (\ell^r_{ui}, \ell^{r^+}_{u^+i^+}, \ell^{r^-}_{u^-i^-})$, and λ_Θ is a model-specific regularization parameter.

[1] Faiss: https://github.com/facebookresearch/faiss
[2] https://github.com/seantheplug/SIGIR_2022_IPR

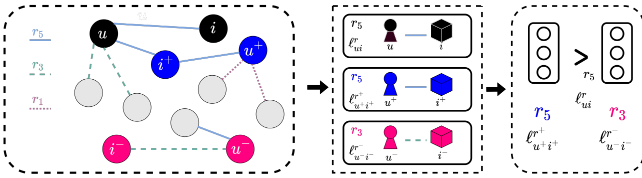

Figure 1: Interaction triplet sampling

2.2 Sampling Strategy and Optimization

We propose a strategy to construct the training data D_L in Eq. (2) for which, regarding ℓ^r_{ui}, we define the set of positive interactions, $L^+_{\ell^r_{ui}}$, as follows.

Definition 2.2 (Positive Interaction Set $L^+_{\ell^r_{ui}}$). Given ℓ^r_{ui} denoting an interaction between user u and item i with rating r, we define the positive interaction set regarding ℓ^r_{ui} as

$$L^+_{\ell^r_{ui}} := \left\{ \ell^{r^+}_{u^+i^+} \middle| (u^+, i^+), (u, i^+) \in \mathcal{E} \wedge \psi(u, i^+) = r^+ = r \right\}.$$

To elaborate the idea in Definition 2.2, we take Fig. 1 as an example. Given an interaction between user u and i with a specific rating r (the solid line in the figure), i.e., ℓ^r_{ui}, we first sample an item i^+ that user u has interacted with and to which he/she has assigned an identical rating r, according to which we further sample a user u^+ who has interacted with item i^+ and given the same rating r to construct a positive interaction $\ell^{r^+}_{u^+i^+}$ regarding ℓ^r_{ui}. (Note that the superscript r^+ in $\ell^{r^+}_{u^+i^+}$ equals r as it is restricted to sampling the same magnitude of the rating to construct a positive interaction.) For the set of negative interactions, we set $L^-_{\ell^r_{ui}} = L \backslash L^+_{\ell^r_{ui}}$. Recall that in our framework, "positive" interaction $\ell^{r^+}_{u^+i^+}$ and "negative" interaction $\ell^{r^-}_{u^-i^-}$ in a triplet given ℓ^r_{ui} can be freely defined to correspond to different application scenarios.

With the training data D_L and the objective function in (4), we optimize the embedding matrix as

$$\Theta \leftarrow \Theta + \alpha \left(\frac{\partial \text{IPR-OPT}}{\partial \Theta} \right), \tag{5}$$

where α denotes the learning rate. Following [2, 5, 6, 17, 20], we maximize the objective function in (4) using asynchronous stochastic gradient ascent (ASGD) [14] to efficiently update parameters Θ in a parallel manner. More specifically, for each given interaction ℓ^r_{ui}, we uniformly sample a positive interaction $\ell^{r^+}_{u^+i^+} \in L^+_{\ell^r_{ui}}$ and a negative interaction $\ell^{r^-}_{u^-i^-} \in L^-_{\ell^r_{ui}}$. Therefore, with triplet $(\ell^r_{ui}, \ell^{r^+}_{u^+i^+}, \ell^{r^-}_{u^-i^-})$, we update the model parameter matrix Θ with the gradient defined as

$$\begin{aligned} \frac{\partial \text{IPR-OPT}}{\partial \Theta} &= \frac{\partial}{\partial \Theta} \ln \sigma(\hat{x}) - \lambda_\Theta \frac{\partial}{\partial \Theta} \|\Theta\|^2 \\ &\propto \frac{e^{-\hat{x}}}{1 + e^{-\hat{x}}} \frac{\partial}{\partial \Theta} \hat{x} - \lambda_\Theta \Theta. \end{aligned} \tag{6}$$

Note that in this paper, we adopt $g(\Theta_u, \Theta_i) = \Theta_u + \Theta_i$; thus we have

$$\hat{x} := \langle \Theta_u + \Theta_i, (\Theta_{u^+} + \Theta_{i^+}) - (\Theta_{u^-} + \Theta_{i^-}) \rangle.$$

Algorithm 1 details the complete model training procedure.

Algorithm 1 Proposed IPR algorithm

Inputs $G_\mathcal{R}(\mathcal{U} \cup \mathcal{I}, \mathcal{E})$, K ▷ K denotes #(iterations).
Output Θ
Randomly initialize Θ
$L \leftarrow$ all user-item interactions in $G_\mathcal{R}(\mathcal{U} \cup \mathcal{I}, \mathcal{E})$
for $t = 1$ to K **do**
    Sample an user-item interaction ℓ^r_{ui} from L
    $L^+_{\ell^r_{ui}} \leftarrow$ positive interactions ▷ see Definition 2.2
    $L^-_{\ell^r_{ui}} \leftarrow L \backslash L^+_{\ell^r_{ui}}$
    Sample a positive interaction $\ell^{r^+}_{u^+i^+} \in L^+_{\ell^r_{ui}}$
    Sample a negative interaction $\ell^{r^-}_{u^-i^-} \in L^-_{\ell^r_{ui}}$
    Update Θ with Eqs. (5) and (6)
end for

Dataset	Users	Items	Interactions	Sparsity
Movielens-1M	6,040	3,687	1,000,188	95.5087%
AMZ BT	5,123	11,217	91,174	99.8413%
AMZ H-PC	38,609	18,525	346,310	99.9515%

Table 1: Dataset statistics

Dataset	Rating 1	Rating 2	Rating 3	Rating 4	Rating 5
Movielens-1M	5.61 %	10.76 %	26.12 %	34.91 %	22.57 %
AMZ BT	4.56 %	5.57 %	11.67 %	22.13 %	56.04 %
AMZ H-PC	4.71 %	4.87 %	9.67 %	19.73 %	61.00 %

Table 2: Rating composition of each dataset

3 EXPERIMENTS

3.1 Datasets and Preprocessing

We conducted extensive experiments on three real-world recommendation datasets. **(1) Movielens-1M:** a conventional recommendation dataset containing approximately one million user-item interactions with rating information.
(2)–(3) Amazon datasets [12]: these contain user-item ratings collected from the Amazon e-commerce website. We conducted experiments on two subsets for experimentation: Amazon Beauty (AMZ BT), and Amazon Health and Personal Care (AMZ H-PC).

For data preprocessing, we did not filter out lower rating interactions or "less-relevant" interactions, and in fact used no human engineering in our experiments. We believe that all types of interactions contain helpful information that should be modeled. For example, the fact that a user watches a sci-fi horror movie and assigns it a rating of 1 does not necessarily indicate that she dislikes horror movies. The movie's sci-fi aspect, for instance, could lead to such dissatisfaction; thus, arbitrarily removing such an interaction results in a loss of valuable insight. Therefore, to ensure a fair evaluation, all interactions were preserved; both the training and testing data were identical for all baseline and proposed models. The dataset statistics are given in Tables 1 and 2.

	Movielens-1M						AMZ H-PC						AMZ BT					
	Recall			nDCG			Recall			nDCG			Recall			nDCG		
	@1	@3	@10	@1	@3	@10	@1	@3	@10	@1	@3	@10	@1	@3	@10	@1	@3	@10
MF	0.0097	0.0287	0.0894	0.2241	0.2195	0.2169	0.0088	0.0178	0.0382	0.0151	0.0175	0.0254	0.0090	0.0242	0.0641	0.0378	0.0354	0.0499
MF-BPR	0.0133	0.0376	0.1061	0.2736	0.2676	0.2547	0.0117	0.0245	0.0477	0.0210	0.0240	0.0328	0.0110	0.0281	0.0711	0.0433	0.0405	0.0561
LightGCN	0.0209	0.0536	0.1316	0.4463	0.4100	0.3524	†0.0146	†0.0316	†0.0691	†0.0294	†0.0320	†0.0459	†0.0119	†0.0327	†0.0884	0.0496	†0.0458	†0.0669
DeepICF	†0.0221	†0.0562	0.1362	†0.4625	†0.4209	†0.3634	0.0052	0.0142	0.0389	0.0141	0.0153	0.0240	0.0112	0.0286	0.0726	†0.0511	0.0452	0.0590
CDAE	0.0204	0.0543	†0.1431	0.4241	0.3990	0.3581	0.0073	0.0186	0.0435	0.0131	0.0170	0.0269	0.0112	0.0267	0.0705	0.0457	0.0398	0.0552
MCBPR	0.0116	0.0288	0.0672	0.2793	0.2451	0.2015	0.0070	0.0146	0.0280	0.0137	0.0149	0.0197	0.0068	0.0165	0.0453	0.0308	0.0267	0.0359
IPR	**0.0270**	**0.0666**	**0.1564**	**0.5124**	**0.4610**	**0.3943**	**0.0163**	**0.0359**	**0.0713**	**0.0309**	**0.0353**	**0.0486**	**0.0132**	**0.0375**	**0.0909**	**0.0531**	**0.0518**	**0.0710**
Improv. (%)	22.17 %	18.50%	9.29%	10.78%	9.52%	8.50%	11.64 %	13.60%	3.18%	5.10%	10.31%	5.88%	10.92 %	14.67%	2.82%	3.91%	13.10%	6.12%

Table 3: Overall performance comparison

	Movielens-1M					
	recall@1	recall@3	recall@10	nDCG@1	nDCG@3	nDCG@10
IPR (rating>3)	0.0261	0.0645	0.1519	0.5009	0.4536	0.3869
IPR	**0.0270**	**0.0666**	**0.1564**	**0.5124**	**0.4610**	**0.3943**
Improv. (%)	3.44 %	3.25%	2.96%	2.29%	1.63%	1.91%

Table 4: Is lower rating data really informative?

3.2 Baselines

We compared the proposed IPR with six baselines listed as follows.
(1) MF [10]: a matrix factorization method optimized via a point-wise objective function (square loss).
(2) MF-BPR [17]: an MF method optimized via the Bayesian personalized ranking (BPR) loss function, a widely used pairwise learning framework that assumes all observed interactions are identical and superior to unobserved ones.
(3) LightGCN [5]: a state-of-the-art graph convolutional network (GCN) that simplifies the original GCN by removing the non-linear activation function and redundant feature transformation in the embedding propagation layers to achieve better performance on collaborative filtering tasks.
(4) DeepICF [22]: (deep item-based collaborative filtering) an item-based collaborative filtering model that incorporates neural networks to effectively learn high-order relations among items in a non-linear fashion.
(5) CDAE [21]: (collaborative denoising auto-encoder) a deep learning based model for top-k recommendation that uses denoising auto-encoders. The model is optimized via a square loss function to reflect different numeric ratings.
(6) MCBPR [11]: a pioneering work that utilizes different ratings for recommendation. The model uses modified negative sampling under the assumption that different ratings reflect different preference orders between users and items.

Note that while MF, and CDAE treat the recommendation as a regression problem, the remaining four baselines are with either pair-wise ranking (i.e., MF-BPR, LightGCN, MCBPR) or point-wise (i.e., DeepICF) losses. Among these four, MF-BPR, LightGCN, and DeepICF is initially designed for implicit feedback; therefore, in the experiments, they consider all interactions identical during model training. In contrast, MCBPR treats different magnitudes of interactions differently.

3.3 Evaluations and Settings

The embedding size of all the baselines and the proposed model was set to 100. To tune the baseline parameters, we followed the settings in the original papers and conducted a grid search to determine the parameters that yielded the best results on our datasets. For the proposed model, the learning rate for all the datasets was determined from the set of {0.1, 0.025, 0.0025}, and the regularization coefficient was determined from {0.01, 0.0001, 0.00001}. We evaluated each model's ranking result on two widely used metrics—recall and normalized discounted cumulative gain (nDCG).

3.4 Performance Analysis

Table 3 presents the performance of the proposed IPR in comparison to the six baselines on the three datasets. We evaluated the top-k recommendation performance with $k \in \{1, 3, 10\}$; the evaluation on a smaller k is to test the ability of first-glance recommendation and larger values of k are for "continuous scrolling" recommendation. The best results are set in boldface, and the † symbol indicates the best performing method among all the baselines.

- **Model effectiveness.** IPR yields the best results on all evaluation metrics across all datasets with performance improvements up to 22.17% and 14.67% in recall and nDCG, respectively, which attests the effectiveness of our model.
- **Significant performance improvements for top position recommendation.** Compared to the performance regarding positions like $k = 10$, IPR performs remarkably well for positions $k = 1, 3$, suggesting that the proposed interaction-level modeling to include all rating magnitudes is advantageous to top-position recommendation.
- **Negative correlation between IPR performance and data sparsity.** The performance of IPR has a negative correlation with the sparsity of the datasets: the performance improvement of IPR scales down with the increase of data sparsity. Furthermore, IPR performs best on Movielens-1M, which shows that a more balancing rating composition (see Table 2) helps for such fine-grained interaction modeling.
- **LightGCN/DeepICF is the strongest baseline in most cases.** In most cases, DeepICF (for Movielens-1M) and LightGCN (for the remaining two datasets) are the strongest baselines and mostly surpass CDAE, one of the state-of-the-art top-k recommendation models taking the different magnitude of user interactions into account.

To further determine whether the proposed IPR effectively encompasses lower rating data, we twist the original setting of IPR (which considers all ratings for model training) into "IPR (rating>3)." The experiments of IPR (rating>3) follow the conventional settings in which only ratings larger than three are included into the modeling process. The two are compared in Table 4, which attests to our hypothesis that all rating data represent valuable insight and thus should be included in the modeling process. Finally, by comparing the results of IPR and those of MF, CDAE and MCBPR, the baselines that also explicitly model the different magnitude of rating data (see Table 3), we confirm the effectiveness of our interaction-level approach for dealing with explicit data.

4 CONCLUSION AND FUTURE WORK

We propose interaction-level preference ranking (IPR), a simple yet effective embedding learning framework for explicit feedback data. IPR fundamentally changes the basic training unit of typical BPR-based algorithms from a node triplet to an interaction triplet and models the similarity between user-item interactions in an unsupervised manner. Such a reformulation enables us to better exploit explicit feedback in a less assumptive and weight-free manner. Extensive experiments on three real-world datasets demonstrate the superiority of IPR, and the ablation study further verifies the effectiveness and credibility of the unified user and item embeddings learned by IPR. For future work, as "positive" and "negative" interactions in a triplet can be freely defined in our framework, we could additionally leverage content information such as user reviews and item metadata to further refine the definition of positive and negative interactions to improve the performance.

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