Cross-Platform Item Recommendation for Online Social E-Commerce

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Abstract—Social e-commerce, as a new concept of e-commerce, uses social media as a new prevalent platform for online shopping. Users are now able to view, add to cart, and buy products within a single social media app. In this paper, we address the problem of *cross-platform recommendation for social e-commerce*, i.e., recommending products to users when they are shopping through social media. To the best of our knowledge, this is a new and important problem for all e-commerce companies (e.g., Amazon, Alibaba), but it has never been studied before. Existing cross-platform and social-related recommendation methods cannot be applied directly to this problem since they do not co-consider the social information and the cross-platform characteristics together. To study this problem, we collect two real-world datasets from social e-commerce services. We first investigate the heterogeneous shopping behaviors between traditional e-commerce app and social media. Based on these observations from data, we propose *CROSS* (**C**ross-platform **R**ecommendation for **O**nline **S**hopping in **S**ocial Media), a recommendation framework utilizing not only user-item interaction data on both platforms, but also social relation data on social media. The framework is general, and we propose two variants, CROSS-MF and CROSS-NCF. Extensive experiments on two real-world social e-commerce datasets demonstrate that our proposed CROSS significantly outperforms existing state-of-the-art methods.

Index Terms—Recommender systems, collaborative filtering, social media, social e-commerce

1 Introduction

Increasing penetration and rapid development of social media [1] have significantly changed the lifestyle of humans. Social media like Facebook and Wechat possess most of our spare time nowadays. Chatting, watching videos, news, live streaming, *etc.*, we can now do almost anything in a single social media app. Social e-commerce, as defined by the ability to make a product purchase from a third-party company within the native social media experience [2], is one of the most popular topics recently. As opposed to the traditional e-commerce app, social media is becoming one of the leading platforms for online shopping. When a user wants to buy a product, there is no need to install another e-commerce app. Instead, we can now view, add to cart, make a purchase, all within a social media app.

To sum up, users now have two platforms to shop online: traditional e-commerce app and social media. Fig. 1 presents the screenshots of a mobile phone when shopping on these two platforms. Given the increasing number of users shopping in these ways, designing a recommender system specifically for users' shopping on social media becomes important and urgent. Besides, to our knowledge, this problem is very prevalent for all e-commerce companies (e.g., Amazon, Alibaba) but has never been studied before.

In this paper, we investigate the problem of *cross-platform recommendation for social e-commerce*, which aims to recommend products to users when they are shopping through social media, given their user-item interaction data on both platforms. Apparently, in the literature, cross-platform recommendation [3], [4], [5] and social recommendation [6] are related to this problem.

In terms of social recommendation, it considers only one platform with social information. Thus, existing methods [6], [7], [8], [9], [10], [11] are not suitable for our task since they would fail to model the cross-platform characteristics of user behavior. On the other hand, existing cross-platform recommendation methods consider user-item interactions on multiple platforms [3], [4], [5]. [4] focuses on the task of app recommendation in smartphones, tablets, and computers. [3] performs the recommendation task on multiple video websites. They share the same user (or item) embedding across platforms and learns a separate item (or user) embedding for each platform. However, social information, a crucial component of social media, has never been taken into consideration.

Furthermore, the problem of cross-platform recommendation for social e-commerce is challenging in the following two aspects.

- *Cross-platform user behavior modeling*. Since we aim to design a recommender system for users' shopping in social media with the data from both platforms, we should first know how the difference and heterogeneity of the shopping behaviors are on two platforms. To this end, how to model the heterogeneity of user behaviors, and subsequently utilize them to

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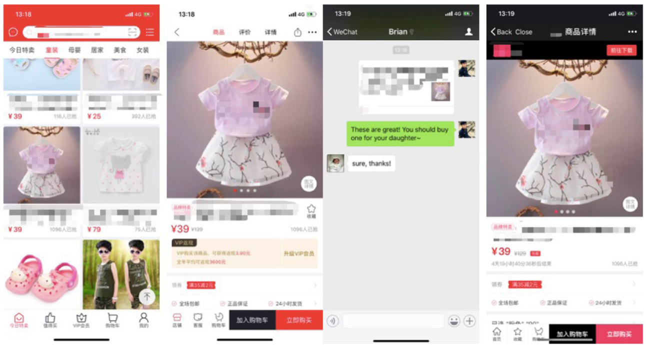


(a) Traditional e-commerce app (b) Social media (Wechat)

Fig. 1. Online shopping through traditional e-commerce app, and through social media. Users can buy products conveniently on both platforms.

design a specialized recommender system is the first challenge we need to solve.

- *Complex social behaviors in social media.* Existing social recommendation methods follow the idea that the user's embeddings should be similar to her friends, which forces the L_2 distance between friends to be small [7], [8], [9], [10]. However, they only maintain one embedding for each user, which means there is an assumption that all user's interests are influenced by their friends. We argue that this is not reasonable. Although a user is influenced by her friends in social media, there should always be some part of her interest that is constant and irrelevant to her friends. How to explicitly design a social influence model to address the above problem is also very challenging.

To address the above two challenges, we first systematically analyze the distinct shopping behaviors on two platforms, and then we propose a novel method named CROSS (short for **C**ross-platform **R**ecommendation for **O**nline **S**hopping in **S**ocial Media) according to the observations. For the cross-platform characteristics of this problem, we jointly learn from user-item interactions on two platforms by performing a co-optimization task. For the utilization of social information, we split users' interest in social media into two parts: one constant part and one social-bias part. The constant part represents a user's static interests, which are shared with that on the traditional e-commerce app platform. The social-bias part represents a user's interests shared with friends, which is limited by a social regularization term. To summarize, the main contributions of this work are as follows.

- To our knowledge, we are the first to consider the problem of *cross-platform recommendation for social e-commerce*, which recommends items to users when they are shopping through social media. We argue that this problem is very important since it is faced by all e-commerce platforms but has never been studied before.
- We systematically analyzed the shopping patterns of users on traditional e-commerce app and social media. More specifically, we find users more hesitant (or decisive) on traditional e-commerce app (or social media) and that they buy different categories of products on different platforms. In addition, their shopping behaviors on social media are selectively affected by their friends. This is a finding different from researches on traditional social recommendation, which assumes a user's all interests are influenced by her friends. These observations provide valuable insights for a better understanding of user behaviors and pave the way for designing recommender systems in this scenario.
- We propose CROSS to explicitly model user's interest in social media as two parts: one constant part and one social-bias part. CROSS is a general framework, and we formulate two variants, CROSS-MF and CROSS-NCF. Extensive experiments on two precious real-world datasets, Beibei and Beidian, demonstrate the superior performance of our CROSS compared with other state-of-the-art methods. The relative improvements in terms of HR and NDCG are about 8.40% and 5.20% for the Beibei dataset and 16.22% and 25.17% for the Beidian dataset. Further studies show that CROSS can achieve steady performance improvement for sparse interactions and social relations.

An earlier version of this work was published in the SIGIR conference [12].

2 Related Work

Cross-Platform Recommendation. Distinct from traditional cross-domain recommendation, which is defined to utilize interaction data from multiple domains [13], [14], [15], [16], [17], [18], cross-platform recommendation concentrates on a specific recommendation task when a user can interact with an item in multiple platforms. Collective Matrix Factorization (CMF) [5] is an intuitive way to deal with such a cross-platform recommendation task. It maintains separate user (or item) embeddings on different platforms, and shares the same item (or user) embeddings across all platforms. Cao *et al.* [4] focuses on the task of App recommendation and assumes that user embeddings can be shared while item embeddings are various. Yan *et al.* [19] studies the problem of video recommendation on multiple video sites. It proposed an extension of CMF via a specially designed user embedding vector, which is made up of a global part and a local part. There are some works [20], [21], [22] on the traditional cross-domain recommendation that use the term of cross-platform since they utilize data from multiple so-called platforms. Nevertheless, in our work, the definition of "cross-platform" refers to that users can interact with the same item in multiple platforms. Thus, we study a different problem compared with these works. However, none of the above methods have considered social information when designing their systems, and thus they are not suitable for the task in this paper.

Social Recommendation. Social recommendation aims to exploit users' social relations to improve a recommender system [6]. Existing social recommendation approaches are based on the fact that users' behaviors can be affected by their friends. As a result, users tend to have similar tastes and preferences with friends. Some works [7], [8], [9], [10], [23], [24] apply the regularization techniques [25] to matrix factorization. These works integrate social information to

TABLE 1
Statistics of Beibei Dataset's Interaction Logs

#User	#Item	#Friendship
2,623,433	1,194,766	76,491

Platform	App (Trad. E-Com. App)	Social Media (Wechat)
#View	34,595,001	22,104,620
#Cart	4,389,796	5,493,643
#Buy	2,006,887	3,923,367

recommender system via a social regularization term which can limit the distance in latent space of users' embedding vectors with their friends when performing the optimization task. Such regularization term can be adapted to tasks for both explicit data [7], [9] and implicit data [8], [10], [23], [24]. Some other works [11], [26], [27] rely on CMF to co-factorize matrices of multiple relations. These works extend CMF to the field of social recommendation since the social relation can also be regarded as an auxiliary matrix. These researches follow a narrow definition of social recommendation; that is, only social relation data serves as the auxiliary knowledge from social networks. While following a broader definition, more complicated forms of data can be collected from social networks to enhance recommendation [28], [29], [30], [31]. Zhang *et al.* [28] introduce text data to help mining communities in social relations based on the topic model. Jiang *et al.* [29] built a star-structured hybrid graph centered on the social network, which connects with other item domains, and then knowledge extracted from social relations can be transferred. Wang *et al.* [30] considered strong and weak ties in social relations and incorporated them into the social recommendation task. Zhao *et al.* [31] extracted various features from social networks to help build user vector and utilize it in feature-based matrix factorization on user-item interaction of an e-commerce website. Despite their effectiveness in extracting knowledge from social networks, the critical problem in our task, how to integrate social information with cross-platform characteristics, has never been studied. Recently, there are some works [32], [33], [34] utilizing graph representation learning [35], [36] or graph neural networks [37] to capture the social influence in social recommendation. There are some works [38], [39], [40] leveraging social-relation data to perform special recommendation tasks, such as inductive recommendation [38], long-tail recommendation [39], session recommendation [40], etc.

3 Data & Preliminary Study

3.1 Dataset and Observations

The Beidian dataset[1] is collected from one of the largest e-commerce platforms in China. As shown in Fig. 1, users have two main channels to buy products on this e-commerce platform. First, they can use a traditional e-commerce app. On the other hand, after a friend has shared a product link to them on Wechat[2] (a social media), they can also directly buy the product and browse other products in Wechat. Our dataset is collected within the time period from 2017/06/01 to 2017/06/30, the statistics of which are shown in Table 1.

1. https://www.beibei.com
2. Wechat is the largest Social Network Service Provider in China.

User Behaviors. The dataset records three types of interaction on both platforms, including view, adding to cart, and buy. Fig. 2 shows the cumulative distribution function (CDF) for the number of the three behaviors on two platforms, respectively.

Friendships. As mentioned earlier, users can share links to products with their friends on social media (*cf.* Fig. 1b). During the sharing operation, the user's unique identifier is contained in the URL of the shared link. Thus, when another user clicks this link, we are able to infer that they are friends on social media.

3.2 Preliminary Study

Is it necessary to design a recommender system specifically for social media? To answer this, we start by investigating the following questions to study whether users are really demonstrating diverse behaviors on these two different platforms.

Q1. Are Users Really Buying Products Through Social Media? First, we might be wondering if users are really buying this way, or they are just viewing products in the social media and still return back to the app when finally buying the product. First, we can observe in Table 1 that the total number of buy behaviors on social media has already exceeded that on the app, indicating that users have already got accustomed to buying through social media. To further study this point, we calculate the percentage of behaviors on social media for each user, which is defined as follows.

$$\% \text{ of } \# \text{ on social media} = \frac{\# \text{ on social media}}{\# \text{ on App} + \# \text{ on social media}}. \tag{1}$$

We show the box-plot of % of #behavior on social media in Fig. 3. For each type of behavior, it presents five values: the lowest data point Q_0, the median of the lower half of the data Q_1, the middle value of the data Q_2, the median of the upper half of the dataset Q_3, and the largest data point Q_4. As we can observe that there is an increasing-trend of three more important points, Q_1, Q_2, and Q_3. That is, although users still tend to view products on app (23%), when it comes to adding to cart (42%) and buying (50%), they treat two platforms nearly equally. These findings indicate that social media has become one of the main platforms to buy products.

Q2. Are Users Shopping With Different Patterns on Two Platforms? In order to investigate user's shopping patterns on each platform, we define a metric called view-buy-ratio. For user u, the view-buy-ratio is defined by the number of views divided by the number of buys

$$\text{view-buy-ratio} = \frac{\#\text{view}}{\#\text{buy}}. \tag{2}$$

A larger (or smaller) view-buy-ratio means a more hesitant (or decisive) user. We present the CDF of view-buy-ratio of each user on two platforms in Fig. 4. We can observe that the view-buy-ratio on app is significantly higher than that of social media. This indicates that when users are buying on app, they tend to shop around and compare products in different shops. When users are buying on social media, they make the buying decision much more quickly. On

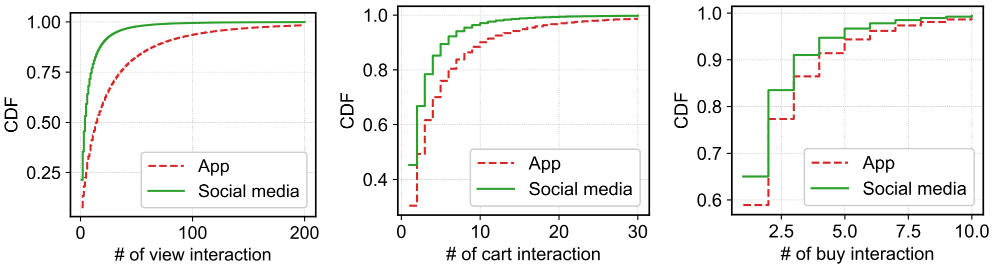


Fig. 2. CDF of behaviors on two platforms.

average, users buy one product after viewing 3 products on social media, while they buy one product after viewing 12 products on app.

Furthermore, we want to investigate if some categories are prevalent among users on each platform; we display the fractions of categories users have bought on app and social media in Fig. 6. Since some categories possess a very high fraction on both platforms, solely displaying their respective fractions cannot distinguish the difference between the two platforms. To address this issue, we also calculate the difference between fractions on social media and app. A fraction difference larger (or smaller) than 0% indicates this category is more prevalent on social media (or app).

From the results, we can observe that at the top 5 categories, social media-prevalent categories are: Household supplies and Food & Fruit, app-prevalent categories are: Baby clothes, Baby supplies, Women clothes, Makeup, Baby shoes. Other categories have little difference that we cannot distinguish; they are prevalent on which platform. This finding shows that users do buy different categories of products on different platforms. It is also reasonable since in real life, buying clothes requires more comparison, which is usually done on an e-commerce app. On the contrary, for buying products like household supplies, food, and fruit, comparison between products are needless; we can quickly make the buying decisions on social media without hesitation.

Q3. Are Friends Affecting Our Buying Behaviors on Social Media? In order to investigate whether friends are affecting our buying decisions, we plot the number of friends of users with the different number of buys on app and social media in Fig. 5. From the results, we can observe a very strong positive correlation between the number of friends and the number of buys on social media, while it is very weak on the app. This indicates that if more friends are sharing products with a user, she would be very likely to buy more on the social media, instead of the app.

To sum up, we have the following findings.

- Social media is becoming one of the main platforms to buy products. A specialized recommender system for social media is in demand.
- Users demonstrate distinct shopping behaviors on two platforms. More concretely, users are more hesitant on app, and more decisive on social media. In addition, users buy different categories of items on two platforms. These observations indicate the irrationality of adopting the same recommendation strategy across these two platforms and further demonstrate the necessity of designing a recommender system specifically for social media.

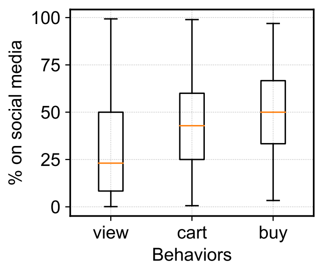


Fig. 3. Fraction of #behavior on social media.

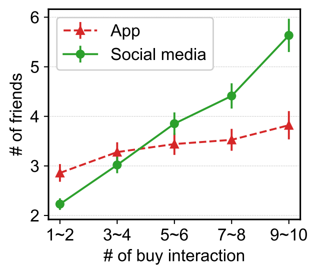


Fig. 5. The number of friends with different number of buys.

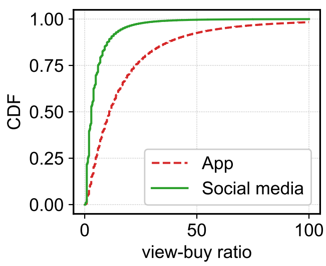


Fig. 4. CDF of view-buy-ratio on two platforms.

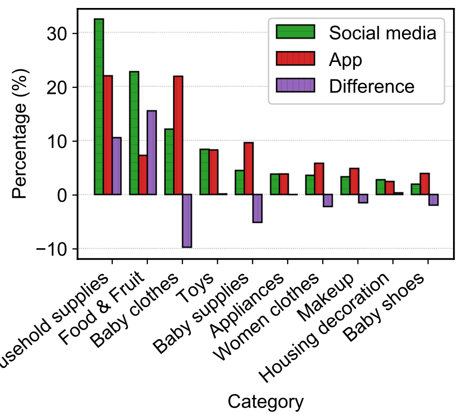
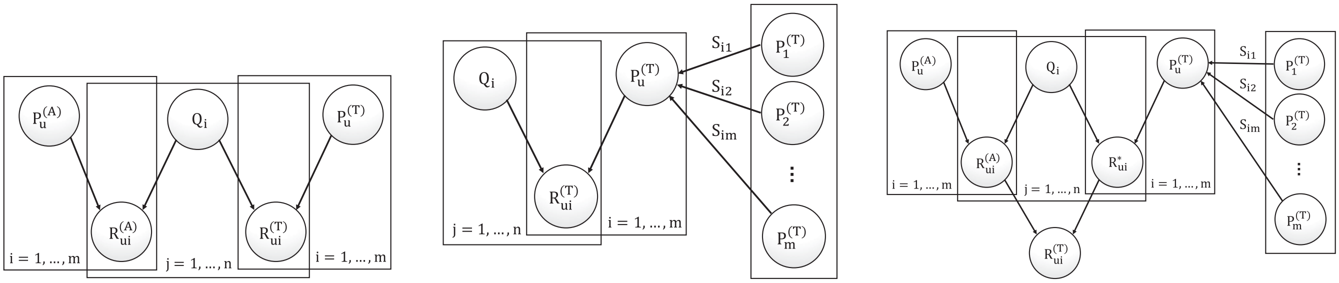


Fig. 6. Percentage of Top 10 categories bought on two platforms.



(a) CMF [5] (b) SocialMF [7] (c) CROSS (ours)

Fig. 7. Graphical models.

- A user with more friends will have more buying behaviors on social media, but not on the app, which indicates that when modeling user behaviors on the social media, we need to consider social information.

Given the above findings, why we need to design cross-platform recommendation is well motivated. Note that it does not only exists in Beibei or Beidian. There are similar social platforms, such as Instagram[3], on which the user can purchase products via embedded-URL in images or group-purchase platforms as Pinduoduo[4]. Answering these three questions helps us clarify the difference and relation across these two platforms, which supports our method design in the following sections.

4 Preliminaries

In this section, we first formulate the investigated problem to solve. Then we recapitulate the ideas and drawbacks of existing cross-platform and social recommendation methods since they are related to our task.

4.1 Problem Formulation

Social e-commerce is a kind of e-commerce service where users can purchase items through two platforms: social media and traditional e-commerce. The users and items can be overlapped on these two platforms. Social influence plays a significant role in social e-commerce. First, we introduce some symbols and notations used in this paper. Suppose we have two platforms, an *auxiliary* platform A (traditional e-commerce app), and a *target* platform T (social media). Note that in our scenario, users and items on two platforms are fully overlapped. We denote M and N as the number of users and items. Then the historical user-item interaction can be denoted as matrices: $R^{(A)} \in \mathbb{R}^{M\times N}$ in the *auxiliary* platform and $R^{(T)} \in \mathbb{R}^{M\times N}$ in the *target* platform. The corresponding indicator matrices are $I^{(A)}$ and $I^{(T)}$, respectively. The user and item matrices are $P^{(A)} \in \mathbb{R}^{K\times M}$, $P^{(T)} \in \mathbb{R}^{K\times M}$ and $Q^{(A)} \in \mathbb{R}^{K\times N}$, $Q^{(T)} \in \mathbb{R}^{K\times N}$, where K is the dimensionality of the latent space in the matrix factorization model. From the perspective of representative learning, user and item matrices represent user interests and item features, respectively. We also define the social relation matrix in social media platform as $S \in \mathbb{R}^{M\times M}$. Specifically, s_{uv} will be 1 if user u and v are friends, and $s_{uv} = 0$ otherwise. Finally, the problem of cross-platform recommendation in social media is formulated as follows.

3. https://instagram.com
4. https://www.pinduoduo.com

Problem 1. Cross-Platform Recommendation for Social E-Commerce

Input: *An app platform A with* $\{R^{(A)}\}$;
Social media platform T with $\{R^{(T)}, S\}$.
Output: *Missing values in* $R^{(T)}$.

4.2 Collective Matrix Factorization

Collective Matrix Factorization (CMF) (shown in Fig. 7a) is originally proposed to factorize multiple data matrices that have common entities simultaneously [5]. For example, it can be used to co-factorize a user-item matrix and a user-attribute matrix. In this way, user attributes will also be considered when learning user and item embeddings.

CMF can also be easily adapted to solve a cross-platform recommendation problem by co-factorizing user-item interaction matrices from different platforms. When performing the co-factorization, item embeddings are shared across all platforms, while user embeddings are various across domains. The objective function to be optimized can be formulated as follows.

$$\min_{P^{(A)},P^{(T)},Q} \sum_{u=1}^{M}\sum_{i=1}^{N} I_{ij}^{(T)}(R_{ui}^{(T)} - p_u^{(T)} \cdot q_i)^2 + I_{ij}^{(A)}(R_{ui}^{(A)} - p_u^{(A)} \cdot q_i)^2. \tag{3}$$

Note that here and in the following paper, L_2 regularization term for embedding matrices are omitted for simplification. As argued earlier in the introduction, in our social media scenario, a user's behaviors are largely influenced by her friends. Settings of CMF are clearly unreasonable since it fails to utilize social information.

4.3 SocialMF

SocialMF [7] (*cf.* Fig. 7b) is a prevalent method to solve a social recommendation problem. SocialMF adds a social regularization term to the loss function to limit the L_2 distance of the user's embedding and her friends' average embeddings. Its main idea is that a user's interest should be similar to her friends. SocialMF's objective function to be optimized can be formulated as follows.

$$\min_{P^{(T)},Q} \sum_{u=1}^{M}\sum_{i=1}^{N} I_{ij}(R_{ui} - p_u \cdot q_i)^2 + \sum_{u=1}^{N}\left(p_u - \sum_{v\in N_u} S_{uv} p_v\right)^2. \tag{4}$$

As argued earlier in the introduction, this setting is unreasonable since it assumes all user's interests are influenced by their friends. A more rational assumption would be part of the user's interests are influenced by her friends, and she should always contain a constant part of her interests that would not be influenced. In addition, how to utilize social information in a cross-platform recommender system is still an unstudied question.

5 Our CROSS Solution

Fig. 7c illustrates our proposed CROSS model. Following a standard setting of cross-platform methods like CMF [5], we jointly model user behaviors on two platforms. We define our loss function as follows,

$$L = L^{(A)} + L^{(T)}, \tag{5}$$

where $L^(A)$ and $L^{(T)}$ denote the loss function on app platform and social media platform, respectively. In what follows, we will introduce our design of CROSS for each platform.

5.1 Learning From App Platform

For learning from user behaviors on the app platform, we assign latent embeddings for users and items, which are not affected by the social network. This assumption is also justified by the observation in Section 3.2. Therefore on the app platform, user u's rating on item i can be learned via the interaction of MF or NCF as follows.

$$\hat{R}_{ui}^{(A)} = p_u^{(A)} \cdot q_i, \tag{6}$$

$$\hat{R}_{ui}^{(A)} = \mathbf{h}^{(A)}([p_u^{(A)} \odot q_i; \mathrm{MLP}([p_u^{(A)}; q_i])]), \tag{7}$$

where $[\cdot;\cdot]$ denotes the concatenation operation, $\odot$ denotes the element-wise product, $\mathbf{h}$ denotes the function that maps vectors to predicted scores, and MLP denotes multi-layer perceptrons. The loss function of App platform can be formulated as follows,

$$L^{(A)} = \sum_{u=1}^{M}\sum_{i=1}^{N} I_{ij}^{(A)} (R_{ui}^{(A)} - \hat{R}_{ui}^{(A)})^2. \tag{8}$$

5.2 Learning From Social Media Platform

To learn from user behaviors on social media, we model users' interests as two parts, one part that represents their own interests and another part that is influenced by their friends. Since friends cannot influence user behaviors on the app platform, user behaviors on the app platform can be regarded as the user's own interests. User u's rating on item i can be modeled as the sum of two parts: user u's rating on App platform $\hat{R}_{ui}^{(A)}$, plus a social-bias $\hat{R}_{ui}^{*}$ that is influenced by friends. Thus two platforms are co-related by the embedding sharing, which is a kind of transfer learning [41]. Similarly, we adopts the interaction function of MF or NCF to obtain the prediction results, formulated as follows,

$$\hat{R}_{ui}^{(T)} = \hat{R}_{ui}^{(A)} + \hat{R}_{ui}^{*} = p_u^{(A)} \cdot q_i + p_u^{(T)} \cdot q_i. \tag{9}$$

$$\begin{aligned} \hat{R}_{ui}^{(T)} &= \hat{R}_{ui}^{(A)} + \hat{R}_{ui}^{*} \\ &= \mathbf{h}^{(A)}([p_u^{(A)} \odot q_i; \mathrm{MLP}([p_u^{(A)}; q_i])]) \\ &\quad + \mathbf{h}^{(T)}([p_u^{(T)} \odot q_i; \mathrm{MLP}([p_u^{(T)}; q_i])]), \end{aligned} \tag{10}$$

where $\mathbf{h}^A$ and $\mathbf{h}^T$ are two mapping function for two parts of predictions respectively. Note that two parts of MLP layers are different and here we use the same notations to simplify the presentation. To further model the social-bias part $\hat{R}_{ui}^{*}$ in (9), we add a social regularization term to the loss function, similar to the idea of SocialMF [7]. More concretely, we expect this part of embedding of user u dependent on her friends. Such influence can be formulated as follows,

$$\hat{p}_u^{(T)} = \frac{\sum_{v\in N_u} S_{uv} p_v^{(T)}}{\sum_{v\in N_u} S_{uv}} = \frac{\sum_{v\in N_u} S_{uv} p_v^{(T)}}{|N_u|}, \tag{11}$$

where N_u is the friends of user u, and $\hat{p}_u^{(T)}$ is the estimated embedding of user u given the embeddings of the friends. Note that social relation matrix S is a binary matrix in our scenario (friends or not friends), this method would be more expressive if strength of social influence is also taken into consideration. Here, we only focus on a binary social relation, and leave that as future work. For convenience, we normalize each row of the social relation matrix so that $\sum_{v=1}^{N} S_{uv} = 1$ and have

$$\hat{p}_u^{(T)} = \sum_{v\in N_u} S_{uv} p_v^{(T)}, \tag{12}$$

where $\sum_{v\in N_u} S_{uv} = 1$.

To sum up, the loss function of social media platform can be formulated as follows.

$$\begin{aligned} L^{(T)} = &\sum_{u=1}^{M}\sum_{i=1}^{N} I_{ij}^{(T)} (R_{ui}^{(T)} - \hat{R}_{ui}^{(T)})^2 \\ &+ \lambda_S \sum_{u=1}^{M} (p_u^{(T)} - \sum_{v\in N_u} S_{uv} p_v^{(T)})^2, \end{aligned} \tag{13}$$

where λ_S is the weight of the social regularization term controlling the strength of social influence.

5.3 Training

Loss Function. In the training process, loss functions for each part are added together for joint optimization. The overall loss function can be expressed as follows,

$$\begin{aligned} \min_{P^{(A)},P^{(T)},Q} L = &\sum_{u=1}^{M}\sum_{i=1}^{N} I_{ij}^{(A)} (R_{ui}^{(A)} - \hat{R}_{ui}^{(A)})^2 \\ &+ \sum_{u=1}^{M}\sum_{i=1}^{N} I_{ij}^{(T)} (R_{ui}^{(T)} - \hat{R}_{ui}^{(T)})^2 \\ &+ \lambda_S \sum_{u=1}^{M} \left(p_u^{(T)} - \sum_{v\in N_u} S_{uv} p_v^{(T)} \right)^2. \end{aligned} \tag{14}$$

Learning With Gradient Descent. We optimize parameters with stochastic gradient descent (SGD) and implement it on Tensorflow [42], which provides the function of automatic differentiation; thus, we omit the derivation of the objective function.

Extend to Pairwise Case. Pairwise learning [43], [44], [45], [46] is a widely used method for solving implicit feedback recommendation problem. When solving a implicit feedback problem, our proposed CROSS can also be learned in a pairwise manner [44] by easily changing the loss function to

$$\min_{P^{(A)},P^{(T)},Q} L = \sum_{(u,i,j)\in D_S^{(A)}} \ln\sigma(\hat{x}_{uij}^{(A)}) + \sum_{(u,i,j)\in D_S^{(T)}} \ln\sigma(\hat{x}_{uij}^{(T)}) + \lambda_S \sum_{u=1}^{M} \left(p_u^{(T)} - \sum_{v\in N_u} S_{uv} p_v^{(T)} \right)^2, \tag{15}$$

where

$$\hat{x}_{uij}^{(A)} = \hat{R}_{ui}^{(A)} - \hat{R}_{uj}^{(A)}, \quad \hat{x}_{uij}^{(T)} = \hat{R}_{ui}^{(T)} - \hat{R}_{uj}^{(T)}, \tag{16}$$

and σ is the sigmoid function, $(u,i,j) \in D_S$ is the triplet set that user u prefer i over j.

5.4 Discussion

As mentioned above, when learning from user-item interaction data, we can use different interaction functions. Therefore, our CROSS is a general and flexible framework with two variants CROSS-MF and CROSS-NCF.

Matrix factorization (MF), of which the core is an inner-product-based interaction function, is the widely-used recommendation method. It is simple yet very effective. Recently some deep learning-based methods are proposed, but however, they cannot replace matrix factorization due to two aspects. First, it has been shown that neural methods do not necessarily outperform MF [47], [48]. On the contrary, MF is still a very competitive method nowadays. In our experiments of Section 6, both CROSS-MF and CROSS-NCF are very effective. Second, for the learned embeddings by MF and MF-based methods, the inference stage can be faster. This is because the inner product has no extra parameter besides the embeddings, and it is easy to calculate [48], [49]. It makes MF-based methods have better scalability and easier to deploy in industrial systems.

Now, we summary some desirable properties of CROSS. First, CROSS jointly optimizes user behaviors on two platforms, which gains benefit from cross-platform learning. Second, for modeling user's interest on social media, we carefully design two parts: one constant part that is not influenced by friends, and another social-bias part that is fully influenced by friends. Thus, our model is more expressive and more reasonable compared to other traditional social recommendation methods.

6 Experiments

6.1 Experimental Settings

Evaluation Dataset

Besides the Beibei dataset mentioned above, to approach the problem of cross-platform recommendation for social media, we collect another real-world dataset, Beidian,[5] from another social e-commerce service. Note that although they are operated by the same company, these two services are two different mobile Apps and have completely different targeting users. Beidian is a website similar to Taobao, and there are various kinds of products. Thus, they can be considered as two independent datasets for evaluating models' performance. Without losing generality, and also due to the commercial regulations, we unbiasedly sample the subset of users from the original dataset for efficiency. We also make sure that each user has at least one friend and at least four interaction records, which is a commonly accepted manner [18]. In Section 3.2, we have conducted a careful preliminary study by investigating three problems and presenting data-analysis figures. Let's recap them and study whether the conclusions from the original dataset still hold in the pre-processed and filtered dataset. There are three conclusions, corresponding to three questions in Section 3.2 as follows.

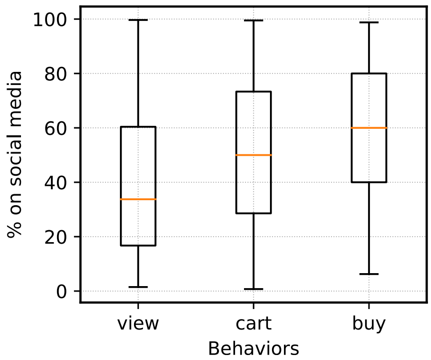


Fig. 8. Fraction of #behavior on social media in the pre-processed Beibei evaluation dataset.

- In Q1 of Section 3.2, we present the box-plot in Fig. 3 illustrating the ratios of three types of behaviors in the Beibei dataset. The conclusion is that when it is closer to buying behaviors, the ratio of the social media platform grows. For the pre-processed and filtered Beibei dataset, we also present the box-plot of the ratios in Fig. 8. We can observe that there is the same conclusion that from viewing, to carting behavior, to buying behavior, the ratio of social media out of two platforms gradually increases. In short, the conclusion of Q1 still holds.
- In Q2 of Section 3.2, we present the view-buy-ratio of two platform in Fig. 4 The conclusion is that users tend to browse/view more items before making the purchase decision. For the pre-processed and filtered Beibei dataset, we also present the view-buy-ratio in Fig. 9. We can also observe that there is the same conclusion.
- In Q3 of Section 3.2, we present the the relation between number of friends and number of purchase in Fig. 5. The major conclusion is that in the social media, the purchase is more likely to be affected by friends. For the pre-processed and filtered Beibei dataset, we also present the curves in Fig. 10 (we redefine the thresholds of each group to make sure each group has enough users).. We can also observe that the conclusion still holds for the experimental dataset: the curve of social media is far steeper, and the curve of App is relatively more stable. Please note that our focus is "steep or stable", and thus although the shape of curves seems quite different compared with Fig. 5, our conclusion still holds.

The statistics of the two evaluated datasets are as follows. For the Beibei dataset, there are 2,620 users with 1,902

5. https://www.beidian.com

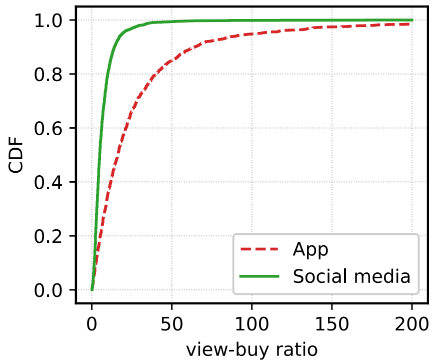


Fig. 9. CDF of view-buy-ratio on two platforms in the pre-processed Beibei evaluation dataset.

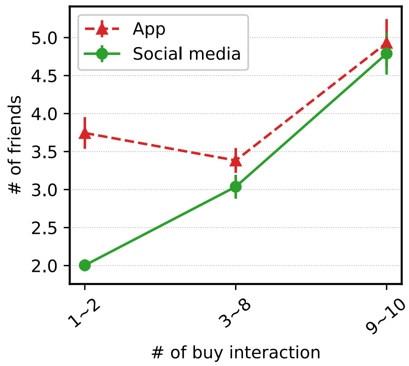


Fig. 10. The number of friends with different number of buys in the pre-processed Beibei evaluation dataset.

friendships, interacting with 6,701 items; the total numbers of buys are 5,904 and 3,687 on the app and social media, respectively. For the Beidian dataset, there are 8327 users with 8,984 friendships, interacting with 5,045 items; the total numbers of buys are 52,398 and 24,510 on the app and social media, respectively. There are no other publicly-available datasets, and we release these two datasets at this link[6] to benefit the community.

Besides, the interaction data of this dataset, the buy log, is in the implicit form. Considering the different scale and sparsity of the two utilized datasets, As introduced in Section 5.3, our CROSS model can be adapted to implicit datasets by training it in a pairwise manner. Therefore, here we train CROSS based on a pairwise loss [44].

Evaluation Protocol. To evaluate the performance, we adopted the *leave-one-out* [50] evaluation method with the following metrics widely used in existing works [8], [44], [51]. For each user, we choose the last-interacted item as the test item and randomly sample one item from others as the validation item.

- *HR: Hit Ratio* (HR) measures whether the test item is contained by the top-K item ranking list (1 for yes and 0 for no).
- *NDCG: Normalized Discounted Cumulative Gain* (NDCG) complements HR by assigning higher scores to the hits at higher positions of the ranking list.

For each user, we randomly choose an item in the training set as the validation set.

*Baselines.*Our compared baselines can be divided into two groups. The first group contains three methods that do not consider cross-platform characteristics.

- *BPR [44].* This is a widely-used method that optimizes the matrix factorization model with a pairwise loss when dealing with implicit feedback data. This is a widely used and competitive model for collaborative filtering.
- *NeuMF* [51]. This is a state-of-the-art collaborative filtering method that fuses a generalized matrix factorization (GMF) model and a multi-layer perceptron (MLP) model together as the interaction function.
- *SocialBPR [8].* This famous and competitive social recommendation method extends BPR by adding a social regularization term to limit the L_2 distance of friends' embeddings. This method can also be regarded as training SocialMF [7] in a pairwise manner.
- *SoRec [11]* This is a competitive method for social recommendation based on social network matrix factorization and interaction matrix factorization.
- *DiffNet [33]* This is the state-of-the-art graph neural network-based social recommendation model, which utilizes graph convolutional layers to capture social influence.

Since the above methods have not considered the cross-platform characteristics of the problem, they can be trained in two manners. The first way applies the same recommender system to both platforms, and the system is trained via aggregated data from both platforms without a difference. The second way trains a separate recommender system for each platform, which only uses data from that specific platform. In our scenario, we only use data from social media to train a recommender system. In the following paper, without special notice, baselines with a (social media) or (both) suffix mean this algorithm is trained using data on the social media platform or both two platforms, respectively.

Note that here we do not compare with those social recommendation methods with complicated interaction functions [32], [33], [34], [35], [36] since our CROSS is a general framework that can be adapted to various interaction functions.

The second group contains the methods considering cross-platform characteristics and jointly learning user behaviors on two platforms.

- *CMF [5].* This is a widely-used cross-domain recommendation method that can utilize multi-source user-item interaction matrices. CMF factorize multiple matrices simultaneously, sharing item embeddings across two platforms and learning separate user embeddings for each platform. Note that for a fair comparison, we also train CMF in a pairwise manner [44], which is proved to achieve a better performance compared to the original element-wise version.

Parameter Settings. For our model and all baselines, we set the weights of regularization terms λ_P and λ_Q for P and Q to a trivial value 0.01 following common settings [7], [9],

6. https://github.com/tsinghua-fib-lab/Social-E-Commerce-Dataset

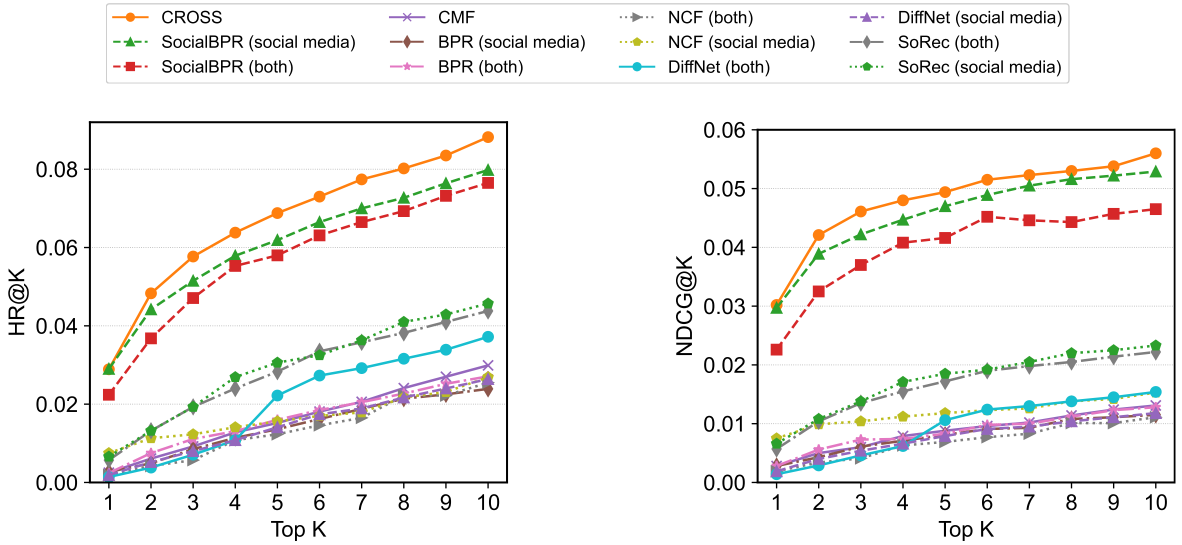


Fig. 11. Evaluation of Top K item recommendation on the Beibei dataset, where baselines with a '(social media)' (or '(both)') suffix means this algorithm is trained using data on social media (or both) platform as described in Section 6.1.

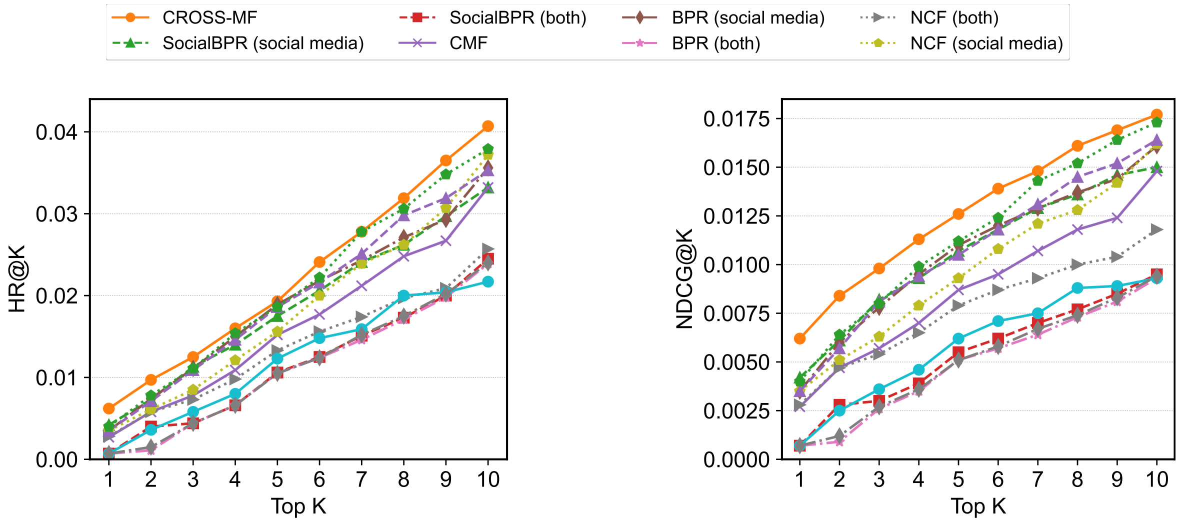


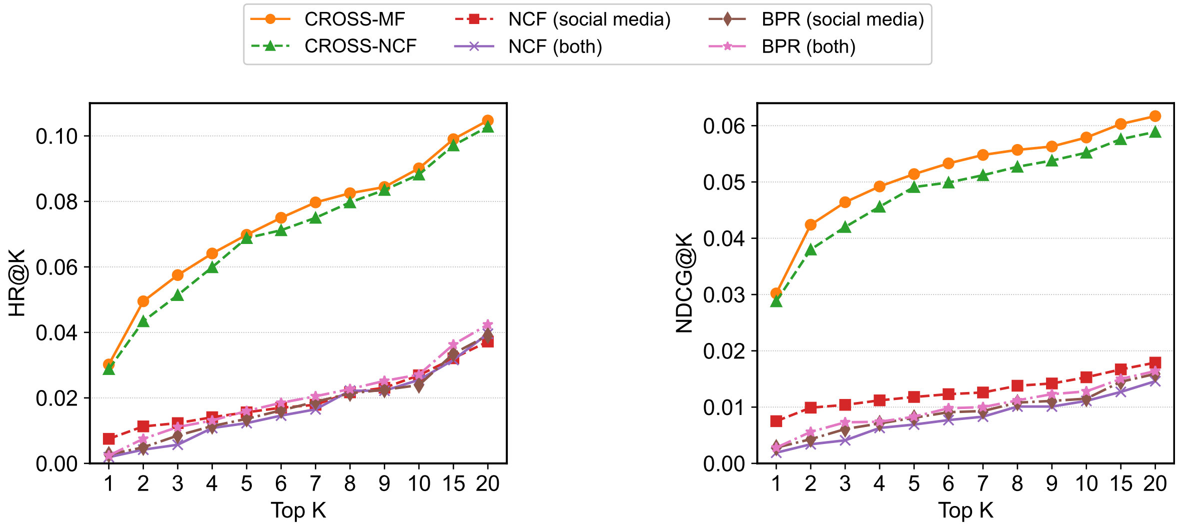
Fig. 12. Evaluation of Top-K item recommendation on the Beidian dataset, where baselines with a '(social media)' (or '(both)') suffix means this algorithm is trained using data on social media (or both) platform as described in Section 6.1.

[11]. To make the experiments fair and reasonable, the weight of social regularization term λ_S for CROSS and SocialBPR, and dimensionality K for all methods were searched in [0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.25, 0.5, 1, 1.25, 1.5, 1.75, 2, 3, 4, 8, 10] and [32, 64, 128, 256], respectively. For the Beibei dataset, we find that values near 2 of λ_S can achieve the best performance, and for the Beidian dataset, we find that setting λ_S to a value near 0.1 can achieve the best performance. In the following sections, we report the performance of the best hyper-parameter settings for each model.

6.2 Performance Comparison (RQ1)

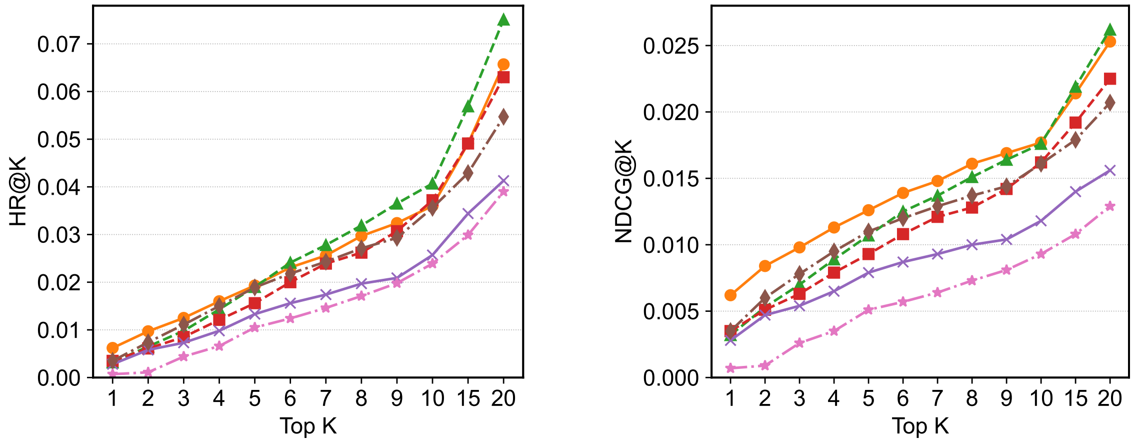
We choose top-K from 1 to 10, a commonly-used range in existing works, since users tend to focus on top-ranked items in a recommendation list. We present the top-K recommendation performance of our CROSS and state-of-the-art baselines in Figs. 11 and 12 for Beibei and Beidian dataset, respectively. For all these results, we conduct five repetitive experiments with different random seeds and report the averaged values. From the results, we have the following findings.

- *Our CROSS can achieve the best recommendation performance on two utilized datasets.* First, we can observe that our proposed CROSS outperforms all baseline methods substantially and consistently *w.r.t* all *HR* and *NDCG* metrics. For the Beibei dataset, the average relative improvement for CROSS to the best baseline is 8.40% and 5.20% for HR and NDCG, respectively; For the Beidian dataset, the average relative improvement for CROSS to the best baseline is 16.22% and 25.17% for HR and NDCG, respectively; These results justify the effectiveness of our CROSS model.
- *Social modeling is challenging.* For the Beibei dataset, methods that can utilize social information, CROSS, SocialBPR(both), and SocialBPR(social media), outperforms the other best baselines significantly by 247%, 188%, 226% in terms of HR, and 305%, 228%, 287% in terms of NDCG. This demonstrates the importance



(a) HR Performance (b) NDCG Performance

Fig. 13. Top-K recommendation performance of different CROSS variants on the Beibei dataset. We also present the base models, MF (BPR) and NCF, for a clearer observation. We also study the performance with larger top-Ks.



(a) HR Performance (b) NDCG Performance

Fig. 14. Top-K recommendation performance of different CROSS variants on the Beidian dataset. We also present the base models, MF (BPR) and NCF, for a clearer observation. We also study the performance with larger top-Ks.

and necessity of social modeling in this task. However, for the Beidian dataset, SocialBPR's performance is poor. This can be explained that in Beidian dataset, users' interaction records are denser, and thus roughly utilizing social-relational data is not reasonable. Another finding is that DiffNet cannot outperform SoRec on both two datasets, although it adopts graph neural networks. This may be explained by the overfitting of too complicated models.

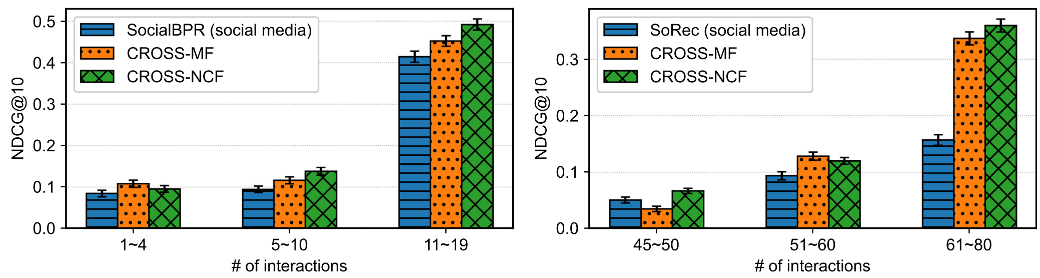
- *Cross-platform modeling is challenging.* When considering using only social media or both platform data to train for baselines, SocialBPR(social media) performs 9.46% and 15.36% on the Beibei dataset and 117.63% and 140.51% on the Beidian dataset better than SocialBPR(both) on HR and NDCG in average. This is reasonable since if user behaviors existing on two platforms differ a lot, naively leveraging users' interaction data on the app platform to evaluate data on the social media platform would undoubtedly have a negative effect. In addition, this observation further justifies the heterogeneity of user behaviors on two platforms, as analyzed in Section 3.2.

  We further studies the performance of two variants. We present the top-K recommendation performance of CROSS-NCF, CROSS-MF, BPR, and NCF on both the Beibei and Beibian dataset in Figs. 13 and 14. The experimental setting is the same as the above results. The difference is that here we report the results of two extra top-Ks, 15 and 20. We can observe CROSS-NCF performs better for larger top-K, especially for HR performance on the Beidian dataset, which can be explained by that NCF has good performance when setting top-K to a relatively larger value.

In summary, our proposed CROSS-MF and CROSS-NCF can achieve the best performance on two real-world datasets.

6.3 Data Sparsity Issue (RQ2)

Data sparsity issue is one of the most critical issues in recommender systems. Specifically, when an item has few



(a) Beibei (b) Beidian

Fig. 15. Performance comparison on the Beibei dataset and Beidian dataset for items with different sparsity.

interaction records, it is hard to predict users who have high interests in it precisely. On the other hand, whether a recommendation model can achieve good performance on sparse items or not is an important criterion. In this section, we study the recommendation performance of items with different sparsity. To be more precise, we divide items into several groups according to sparsity, i.e., the number of records in the training set. We also make sure that each group has enough items to avoid biasing results. For each item, we calculate the average performance if it has been selected as a test item. It helps evaluate whether an item can be successfully recommended to a promising target user. In other words, it is evaluated in an item-centered manner. Then for each group, we report the average values of NDCG. The experimental settings are completely the same as the settings in Section 6.2. We present the results on the Beibei and Beidian dataset in Fig. 15. From these results, we can observe that our CROSS, especially for CROSS-NCF, can steadily outperform the best baseline for items with different sparsity levels. Since a model that can only achieve performance improvement for dense items has low application value in the real world, the observed stable and consistent improvement of CROSS demonstrate its effectiveness. It is worth mentioning that since we utilize the strict full-ranking evaluation metrics, the absolute performance values for sparse items in the Beidian dataset are relatively small. Thus our conclusion of CROSS's effectiveness still holds.

6.4 Study of Dimensionality K (RQ3)

Dimensionality, which has a huge impact on models' capacity, is a significant hyper-parameter for embedding-based recommendation models [44], [51], [52], [53]. To study its impact, we compare the performance of all methods in different dimensionality K[7] of the latent space and present the results of the Beibei and Beidian dataset in Figs. 16 and 17. The following findings are observed.

- *Effectiveness.* We can observe that our proposed CROSS method outperforms all the other baselines substantially and consistently regardless of the dimensionality K. On the Beibei dataset, the average performance improvement compared with the best baseline is 17.78% and 20.17% for HR and NDCG, respectively; on the Beidian dataset, the average improvement is 14.84% and 13.34%, respectively. These results demonstrate that with the same embedding size, our CROSS can have a stronger ability to capture user interests and social influence. This further justifies the effectiveness of our model.
- *Expressiveness.* First, we can observe better performance with larger dimensionality K for CROSS, SocialBPR(both), and SocialBPR(social media). This is intuitive since larger dimensionality means more expressiveness for models. However, this observation does not stand for BPR(both), BPR(social media), and CMF. This indicates that BPR(both), BPR(social media), and CMF have already reached the limit of their expressiveness with a very small dimensionality K (16, 64, 32, respectively).
- *Computational cost.* Our proposed CROSS method can achieve much better performance than the baselines even if the dimensionality is very small. Since the computational cost is in proportion to dimensionality K, this observation indicates that CROSS can achieve decent performance with much lower computational cost.

6.5 Impact of Social Relation Density (RQ4)

Section 3.2 has analyzed the correlation between the number of buy and the number of friends, and we further analyze how our model performs for users with different numbers of friends. We name it social relation density. For the Beibei dataset, we divide users into three groups according to the number of their friends: [1-4, 5-8, 9-12]. For the Beidian dataset, we divide users into two groups according to the number of their friends: [1-4, 5-20]. The studies on different groups can help validate whether the proposed method can work well with different densities of social relations. Such dividing manners can make sure each group has

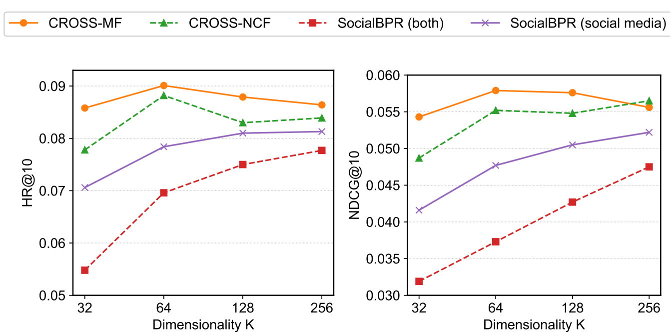


Fig. 16. Performance with different dimensionality K on the Beibei dataset. The best baseline, SocialBPR, is chosen for comparison.

7. Note that dimensionality K and top-K are completely different and irrelevant, although using the same symbol.

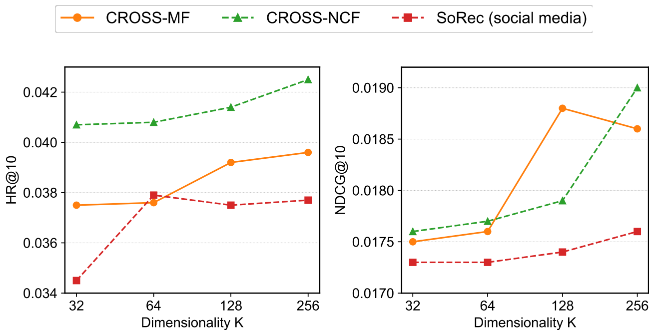


Fig. 17. Performance with different dimensionality K on the Beidian dataset. The best baseline, SocialRec (social media), is chosen for comparison.

enough users. The recommendation performance for each group of our CROSS-MF, CROSS-NCF and the best baseline are shown in Fig. 18.

First, we can observe a trend of better performance with users having more friends. This is intuitive and shows the importance of social relation information for recommendation. Second, our CROSS, especially CROSS-NCF, outperforms the best baseline significantly for each group on both two datasets. This further justifies that our method can utilize social information more effectively. Last, our method is able to achieve promising performance, even if users have only a few friends. That is, our method can well alleviate the data sparsity issue, which is a major concern in recommendation tasks [54], [55], [56].

7 Discussion of Contribution

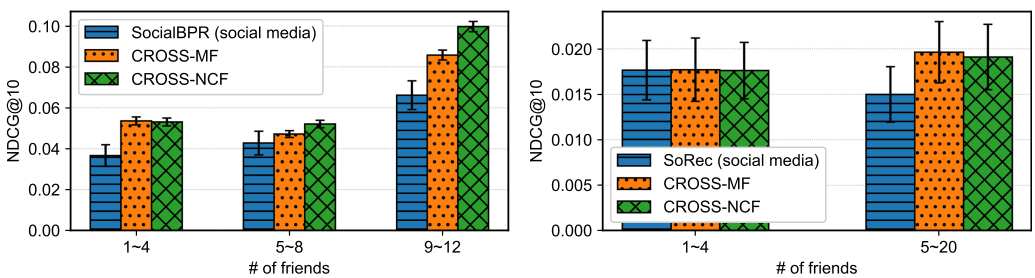
The proposed method CROSS in this work is the first approach to solve the problem of *cross-platform recommendation for social e-commerce*. CROSS is elegant and general, showing promising performance. Here we would to emphasize the contribution of this work, especially for its extra contribution compared with the earlier conference version [12].

7.1 CROSS: CROSS-MF, CROSS-NCF, and More

MF and NCF belong to two kinds of interaction functions, parameter-free interaction function, and parameterized interaction function. Specifically, MF is a model that does not have any other parameters besides the embedding parameters. It uses the inner product as the interaction function, and the matching results are only determined by the embeddings. Different from MF, NCF is a typical and representative model of parameterized interaction function, introducing the auxiliary neural network parameters. Our CROSS plays a role in regularizing and guiding the learning of embedding parameters. In other words, it does not explicitly affect the learning of auxiliary parameters. Therefore, bringing the success of CROSS from CROSS-MF to CROSS-NCF means a lot, of which there are two important insights as follows. First, the CROSS method based on only explicitly regularizing the learning of embedding parameters can also work well for parameterized interaction functions with auxiliary parameters. The wall between parameter-free interaction functions and parameterized interaction functions has been broken by the success of CROSS-NCF. Second, more parameterized interaction functions not restricted to NCF can also be potential good choices. As recent works [48], [57] have shown that no single interaction function can always be the best model when choosing different datasets or metrics. As CROSS can serve as a general framework rather than a single model, the application value of CROSS can be largely broadened.

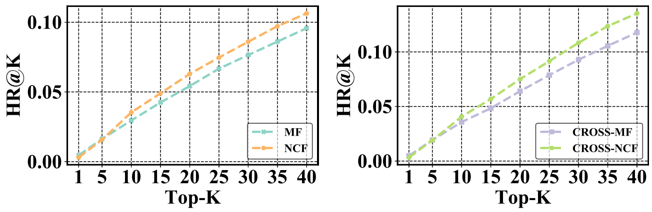
7.2 New Insights From New Results: From the Real-World Perspective

Let's revisit a standard two-phase paradigm of today's real-world recommender systems, matching and ranking. At the matching phase, collaborative filtering (CF) [44], [51], [58] models are deployed to fast recall tens or hundreds of items from a larger pool of item candidates; at the ranking phase, the feature-based recommendation models, also known as click-through rate (CTR) prediction [59], [60], [61] models, take the output of the matching stage as input and present a few items to the users, which are the final recommendation results. The recall phase uses Recall, NDCG, Hit Ratio, etc., as metrics and the ranking phase uses AUC or LogLoss as metrics. This work focuses on the matching stage, and for these metrics, there is a controllable Top-K. Due to the different requirements in real-world use cases, the Top-K can be various, and there is no fixed choice for Top-K. Therefore, it becomes a commonly accepted manner to test the performance under the different Top-K values. The experimental results in Fig. 14 validate that MF cannot perform very well for relatively larger Top-Ks in Beidian dataset. This also causes the CROSS-MF's performance not so well. On this occasion, NCF achieves better performance than MF, and thus, CROSS-NCF outperforms CROSS-MF. Therefore it is essential to adopt NCF rather than MF as the interaction model when setting Top-K to 20 is the required choice in the real-world case. We have added a detailed illustration in Fig. 19 for further analysis. An insightful finding from it, which is also a piece of good news, is that



(a) NDCG (b) Beidian

Fig. 18. Performance comparison for users with different sparsity of social relations on the Beibei and Beidian datasets.



(a) Base Interaction Models (b) CROSS Models

Fig. 19. Further studies on CROSS-MF and CROSS-NCF on Beidian dataset with a wide range of Top-Ks.

CROSS's performance is generally consistent with the performance of the base interaction model. This helps us quickly adapt the experience of interaction model selection to our CROSS and significantly reduces the efforts of engineers and researchers in model selection.

8 Conclusion

In this work, we systematically investigate the task of *cross-platform recommendation for social e-commerce*. To the best of our knowledge, this is a practical task but has rarely been studied previously. We have proposed an elegant framework, CROSS, which seamlessly integrates social information into the cross-platform recommendation. Our CROSS is a general framework that can have different choices of the interaction function. We collect two precious real-world datasets from social e-commerce service providers, which we hope can benefit the community. To evaluate our proposed method, we have conducted extensive experiments on these datasets, showing that our proposed CROSS method significantly outperforms existing state-of-the-art methods. The experimental results on CROSS-MF and CROSS-NCF reveal the impact of interaction function. Further experiments show that our CROSS can achieve the best performance with different dimensionality and sparsity.

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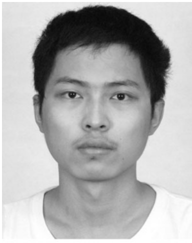

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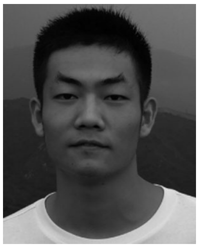

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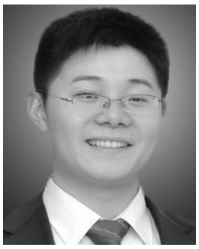

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