CROSS: Cross-platform Recommendation for 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 has never been studied before.

Existing cross-platform and social related recommendation methods cannot be applied directly for this problem since they do not co-consider the social information and the cross-platform characteristics together. To study this problem, 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 model utilizing not only user-item interaction data on both platforms, but also social relation data on social media. Extensive experiments on real-world online shopping dataset demonstrate that our proposed CROSS significantly outperforms existing state-of-the-art methods.

CCS CONCEPTS

• **Information systems → Recommender systems**; • **Human-centered computing → Social media**.

KEYWORDS

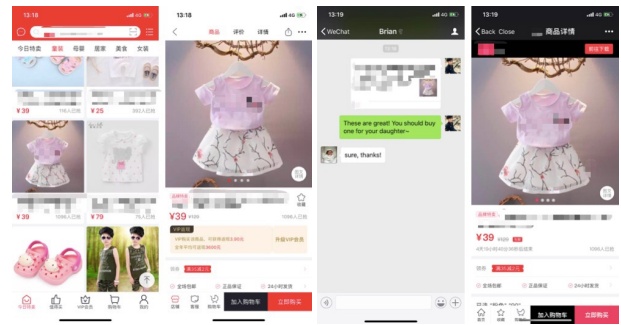Recommender systems, collaborative filtering, social media, social e-commerce

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

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

1 INTRODUCTION

Increasing penetration and rapid development of social media [34] have significantly changed the lifestyle of human. Social media like Facebook and Wechat possess most of our spare time nowadays. Chatting, watching videos, news, live streaming, *etc.*, we are now able to 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 in an article [21], are one of the most popular topics recently. As opposed to the traditional e-commerce app, social media is becoming one of the main platforms for online shopping. When a user wants to buy a product, there is no need to install another e-commerce app. Instead, we are now able to view, add to cart, make a purchase, all within a social media app.

To sum up, users now have two main platforms to shop online: traditional e-commerce app, and social media. Figure 1 presents the screenshots of a mobile phone when shopping on these two platforms. Given the increasing number of users shopping in these ways, how to design a recommender system specifically for users shopping in 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, 28, 35] and social recommendation [30] are related to this problem.

In terms of social recommendation, it considers only one platform with social information. Thus, existing methods [7, 10, 13, 19, 20, 30] 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, 28, 35]. [3] focuses on the task of app recommendation in smart phones, tablets, and computers. [35] performs their 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 modelling.** 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 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 user's embeddings should be similar to her friends, which forces the L_2 distance between friends to be small [7, 10, 13, 20]. 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 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 utilization of social information, we split users' interest on social media as two parts: one constant part, and one social-bias part. The constant part represents a user's static interests, which is shared with that on the traditional e-commerce app platform. While 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 that 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 with researches on traditional social recommendation, which assumes a user's all interests are influenced by her friends. These observations provide valuable insights for better understanding user behaviors and paves the way for designing recommender systems in this scenario.
- We propose CROSS to explicitly model user's interest on social media as two parts: one constant part, and one social-bias part. Extensive experiments demonstrate superior performance of our CROSS compared with other state-of-the-art methods. A relative improvement of 8.40% and 5.20% are reported in terms of HR and NDCG, two metrics for top-N recommendation. Furthermore, we give a thorough investigation to understand why our proposed method outperforms the baselines, which further demonstrates the rationality of our algorithm design.

The remainder of the paper is as follows. We first review our related work in Section 2. Then, we introduce our dataset with some preliminary analysis in Section 3. Afterward, we formalize the problem and introduce our proposed algorithm in Section 4 and Section 5. Experiments are conducted in Section 6. We describe our limitations, and point out some future research directions in Section 7. Finally, conclusions are drawn in Section 8.

2 RELATED WORK

Cross-platform Recommendation Distinct from traditional cross-domain recommendation which is defined to utilize interaction data from multiple domains [2, 8, 9, 12, 31], cross-platform recommendation concentrates on a specific recommendation task when a user can interact with an item in multiple platforms. Collective Matrix Factorization (CMF) [28] is a 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.* [3] focuses on the task of App recommendation and assumes that user embeddings can be shared while item embeddings are various. Yang *et al.* [35] studies the 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. 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 [30]. 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, 10, 13, 16, 20, 32] apply the regularization techniques [22] to matrix factorization. These works integrate social information to 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 [13, 20] and implicit data [7, 10, 16, 32]. Some other works [17, 19, 29] rely

on CMF to co-factorize matrices of multiple relations. These works extend CMF to the filed 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 network. While following a broader definition, more complicated forms of data can be collected from social network to enhance recommendation [14, 33, 37, 38]. Zhang *et al.* [37] introduce text data to help mining communities in social relations based on topic model. Jiang *et al.* [14] 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.* [33] considered strong and weak tie in social relations and incorporated it into social recommendation task. Zhao *et al.* [38] 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 key problem of our task that how to integrate social information with cross-platform characteristics, has never been studied.

3 DATA & PRELIMINARY STUDY

3.1 Dataset and Observations

Table 1: Statistics of our dataset

#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

Our dataset is collected from one of the largest e-commerce platform in China. As shown in Figure 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[1] (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 is shown in Table 1.

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

Friendships   As mentioned earlier, users can share links of products with their friends on social media (*cf.* Figure 1(b)). During the sharing operation, 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.

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[1]Wechat is the largest Social Network Service Provider in China.

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 social media, and still return back to app when finally buying the product. Firstly, we can observe in Table 1 that the total number of buy behaviors on social media has already exceeded that on 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.

$$\% \text{ of } \# \text{ on social media} = \frac{\# \text{ on social media}}{\# \text{ on App} + \# \text{ on social media}}, \quad (1)$$

We show the box-plot of % of #behavior on social media in Figure 3. From the results, we can observe that 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:

$$\text{view-buy-ratio} = \frac{\#\text{view}}{\#\text{buy}} \quad (2)$$

A larger (or smaller) view-buy-ratio means a more hesitant (or decisive) user. We present the CDF of view-buy-ratio of each users on two platforms in Figure 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 average, users buy one products after viewing 3 products on social media, while they buy one products 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 Figure 6. Since some categories possess very high fraction on both platforms, solely displaying their respective fractions cannot distinguish the difference between 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
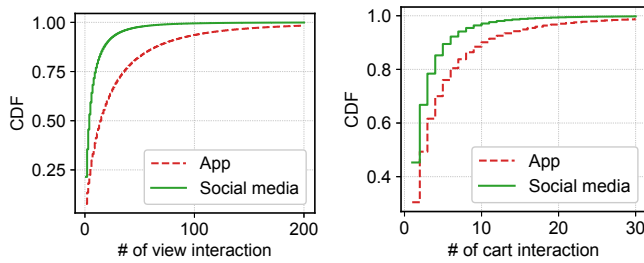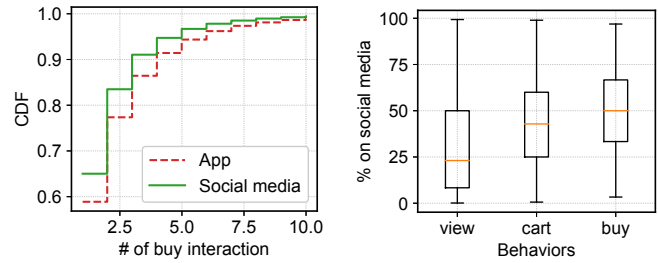
Figure 2: CDF of behaviors on two platforms

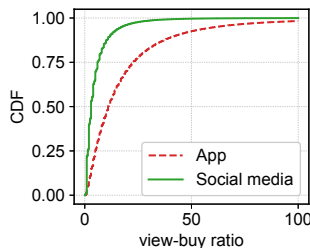Figure 3: Fraction of #behavior on social media

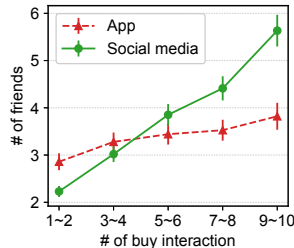Figure 4: CDF of view-buy-ratio on two platforms

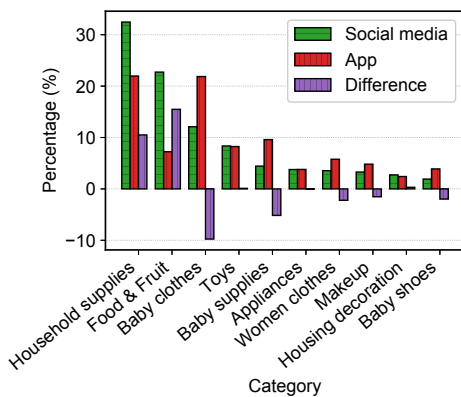Figure 5: The number of friends with different number of buys

Figure 6: Percentage of Top 10 categories bought on two platforms

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 different number of buys on app and social media in Figure 5. From the results, we can observe a very strong positive correlation between number of friends and number of buys on social media, while it

is very weak on the app. This indicates that if more friends are sharing products to a user, she would very likely to buy more on social media, instead of app.

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

Given the above findings, we argue that designing a recommender system specifically for social media is essential. It is also worth noting that, the above findings also give us important indications on how to design this recommender system.

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

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 $P^{(A)} \in \mathbb{R}^{K \times M}$, $P^{(T)} \in \mathbb{R}^{K \times N}$ 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.
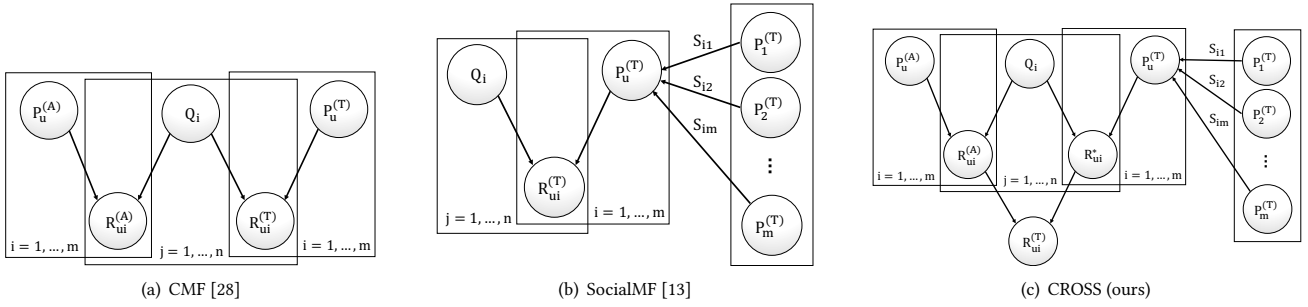
(a) CMF [28] (b) SocialMF [13] (c) CROSS (ours)

Figure 7: Graphical models

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.

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 Figure 7(a)) is originally proposed to factorize multiple data matrices that have common entities simultaneously [28]. For example, it can be used to co-factorize a user-item matrix and a user-attribute matrix. In this way, user's attributes will also be taken into concern 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.

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

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 is clearly unreasonable since it fails to utilize social information.

4.3 SocialMF

SocialMF [13] (*cf.* Figure 7(b)) 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 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.

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

As argued earlier in the introduction, this setting is unreasonable since it assumes all user's interests are influenced by her friends. A more rational assumption would be part of 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 the social information in a cross-platform recommender system is still an unstudied question.

5 OUR SOLUTION

Figure 7(c) illustrates our proposed CROSS model. Following a common setting of cross-platform method like CMF [28], we jointly model user behaviors on two platforms. We define our loss function as follows,

$$L = L^{(A)} + L^{(T)}. \quad (5)$$

In the training process, the loss function we want to optimize contains two parts: one models user behaviors on traditional e-commerce app, another models user behaviors on a social media. In what follows, we will introduce our design for each part of the loss function.

5.1 Learning from App Platform

For learning from user behaviors on the app platform, we use a simple MF (Matrix Factorization) model. We assume that user behaviors on app is not much influenced by her friends, so we do not need to take social information into consideration in this part. 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 a simple MF model.

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

The loss function of App platform can be formulated as follows.

$$L^{(A)} = \sum_{u=1}^{M} \sum_{i=1}^{N} I_{ij}^{(A)} (R_{ui}^{(A)} - p_u^{(A)} \cdot q_i)^2. \quad (7)$$

5.2 Learning from Social Media Platform

For learning from user behaviors on social media, we model users' interest as two parts: one part that represents own interest, and

another part that is influenced by the friends. Since user behaviors on app platform cannot be influenced by friends, user behaviors on the app platform can be regarded as 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. Both parts are modeled using the MF model, formulated as follows,

$$\hat{R}_{ui}^{(T)} = \hat{R}_{ui}^{(A)} + \hat{R}_{ui}^* = p_u^{(A)} \cdot q_i + p_u^{(T)} \cdot q_i. \tag{8}$$

To further model the social-bias part $\hat{R}_{ui}^*$.8, we add a social regularization term to the loss function, similar to the idea of SocialMF [13]. More concretely, we expect this part of embedding of user u dependent on her friends. Such influence can be formulated as follows,

$$\hat{p}_u^{(T)} = \frac{\sum_{v \in N_u} S_{uv} p_v^{(T)}}{\sum_{v \in N_u} S_{uv}} = \frac{\sum_{v \in N_u} S_{uv} p_v^{(T)}}{|N_u|}, \tag{9}$$

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:

$$\hat{p}_u^{(T)} = \sum_{v \in N_u} S_{uv} p_v^{(T)}, \tag{10}$$

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

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

$$L^{(T)} = \sum_{u=1}^{M} \sum_{i=1}^{N} I_{ij}^{(T)} (R_{ui}^{(T)} - p_u^{(A)} \cdot q_i - p_u^{(T)} \cdot q_i)^2$$
$$+ \lambda_S \sum_{u=1}^{M} (p_u^{(T)} - \sum_{v \in N_u} S_{uv} p_v^{(T)})^2, \tag{11}$$

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,

$$\min_{P^{(A)}, P^{(T)}, Q} L = \sum_{u=1}^{M} \sum_{i=1}^{N} I_{ij}^{(A)} (R_{ui}^{(A)} - p_u^{(A)} \cdot q_i)^2$$
$$+ \sum_{u=1}^{M} \sum_{i=1}^{N} I_{ij}^{(T)} (R_{ui}^{(T)} - p_u^{(A)} \cdot q_i - p_u^{(T)} \cdot q_i)^2 \tag{12}$$
$$+ \lambda_S \sum_{u=1}^{M} (p_u^{(T)} - \sum_{v \in N_u} S_{uv} p_v^{(T)})^2.$$

Learning with Gradient Descent   We optimize parameters with stochastic gradient descent (SGD), and implement it on Tensorflow [1], which provides the function of automatic differentiation, we omit the derivation of the objective function.

Extend to pairwise case   Pairwise learning [6, 18, 25, 26] 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 [26] by easily changing the loss function to

$$\min_{P^{(A)}, P^{(T)}, Q} L = \sum_{(u,i,j) \in D_S^{(A)}} \ln \sigma(\hat{x}_{uij}^{(A)}) + \sum_{(u,i,j) \in D_S^{(T)}} \ln \sigma(\hat{x}_{uij}^{(T)})$$
$$+ \lambda_S \sum_{u=1}^{M} (p_u^{(T)} - \sum_{v \in N_u} S_{uv} p_v^{(T)})^2, \tag{13}$$

where

$$\hat{x}_{uij}^{(A)} = \hat{R}_{ui}^{(A)} - \hat{R}_{uj}^{(A)} = p_u^{(A)} \cdot q_i - p_u^{(A)} \cdot q_j$$
$$\hat{x}_{uij}^{(T)} = \hat{R}_{ui}^{(T)} - \hat{R}_{uj}^{(T)} \tag{14}$$
$$= (p_u^{(A)} \cdot q_i + p_u^{(T)} \cdot q_i) - (p_u^{(A)} \cdot q_j + p_u^{(T)} \cdot q_j),$$

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

We note that a more complex interaction function (e.g. NCF [11]) can be easily integrated into our algorithm. Since this is not the core of this paper, we use the simplest matrix factorization model for demonstration in this work, and leave the exploration of other choices as the future work.

Now, we summary some desirable properties of CROSS. Firstly, CROSS jointly optimizes user behaviors on two platforms, which gains benefit from cross-platform learning. Secondly, 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

To evaluate our proposed CROSS method, we designed and conducted extensive experiments to answer the following four research questions.

- **RQ1:** How does our proposed model compared with state-of-the-art recommendation algorithms?
- **RQ2:** How do the hyper-parameters, such as dimensionality K of the latent space, affect the performance of our model?
- **RQ3:** How do social relations affect the recommendation performance in our proposed CROSS model?
- **RQ4:** How heterogeneity across the two platforms affect recommendation performance?

In what follows, we first describe the experimental settings, and then answer the above four research questions.

6.1 Experimental Settings

Evaluation Dataset   Without loss of generality, we unbiasedly sample a small subset of users from the original dataset for efficiency, and make sure that each user has at least one friend. This gives us 2,620 users with 1,902 friendships, interacting with 6,701 items. Total number of buys are 5,904, 3,687 on app and social media, respectively. Besides, the interaction data of this dataset, the buy log, is in the implicit form. As introduced in Section 5.3, our CROSS model can be adapted to implicit dataset by training it in a pairwise manner. Therefore, here we train CROSS based on a pairwise loss [26] for better performance.

Evaluation Protocol   To evaluate the performance, we adopted the *leave-one-out* [27] evaluation method with the following metrics.

- **HR@K:** *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@K:** *Normalized Discounted Cumulative Gain* (NDCG) complements HR by assigning higher scores to the hits at higher positions of the ranking list.

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

- **BPR [26].** This is a widely-used method which optimizes a pairwise loss when dealing with implicit feedback data.
- **SocialBPR [10].** This 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 [13] in a pairwise manner.
- **ItemPop.** This is a non-personalized method raking items base on their popularity, which is defined as the number of historical interactions.

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 one same recommender system to both platforms, and the system is trained via aggregated data from both platforms without 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 means this algorithm is trained using data on social media (or both) platform.

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

- **CMF [28].** This method shares item embeddings across the two platforms, and extends BPR by learning separate user embeddings for each platform. Note that for a fair comparison, we also train CMF in a pairwise manner [26], 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 [13, 19, 20]. 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 [8, 16, 32, 64, 128, 256], respectively. In the following sections, we report the performance of the best hyper-parameter settings for each model.

6.2 Performance Comparison (RQ1)

Figure 8 presents the performance comparison among all methods. From the results, we have the following findings.

- **Effectiveness.** Firstly, we can observe that our proposed CROSS outperforms all baseline methods substantially and consistently *w.r.t* all $HR@K$ and $NDCG@K$ metrics. The average relative improvement for CROSS to the best baseline is 8.40% and 5.20% for HR and NDCG, respectively, which justifies the effectiveness of our model.
- **Social modeling.** Methods which 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 and necessity of social modelling in this task.
- **Distinct user behaviors on two platforms.** When considering using only social media or both platform data to train for baselines, SocialBPR(social media) performs 9.46%, 15.36% better than SocialBPR(both) in HR and NDCG, respectively. This is reasonable since if user behaviors existing on two platforms differ a lot, naively leveraging users interaction data on app to evaluate data on social media platform would certainly have a negative effect. In addition, this observation further justifies the heterogeneity of user behaviors on two platforms as analyzed in Section 3.2.
- **Cross-platform modeling.** Our CROSS outperforms SocialBPR (both) and SocialBPR(social media), and also, CMF slightly outperforms BPR(both) and BPR(social media). These show the necessity of cross-platform modeling for shopping behaviors.

6.3 Study of Dimensionality K (RQ2)

We further compare the performance of all methods in Figure 9 *w.r.t* different dimensionality K of the latent space. Following findings are observed.

- **Expressiveness.** Firstly, 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).
- **Effectiveness.** We can observe that our proposed CROSS method outperforms all the other baselines substantially and consistently regardless of the dimensionality K. The average relative improvement for CROSS to the best baseline is 17.78% and 20.17% for HR and NDCG, respectively. This further justifies the effectiveness of our model.
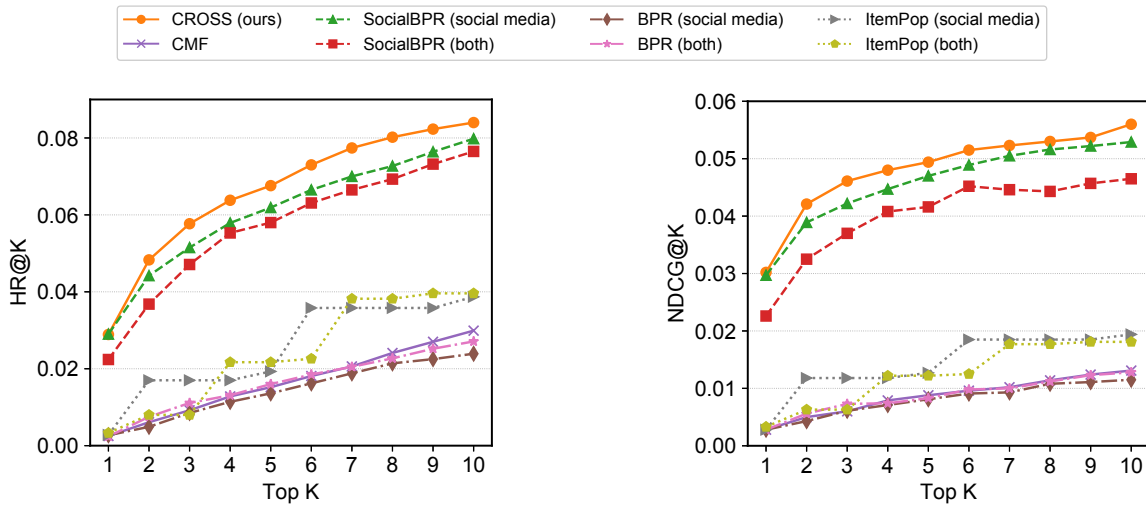
Figure 8: Evaluation of Top K item recommendation, where baselines with a '(social media)' (or '(both)') suffix means this algorithm is trained using data on social media (or both) platform as described in Section 6.1.
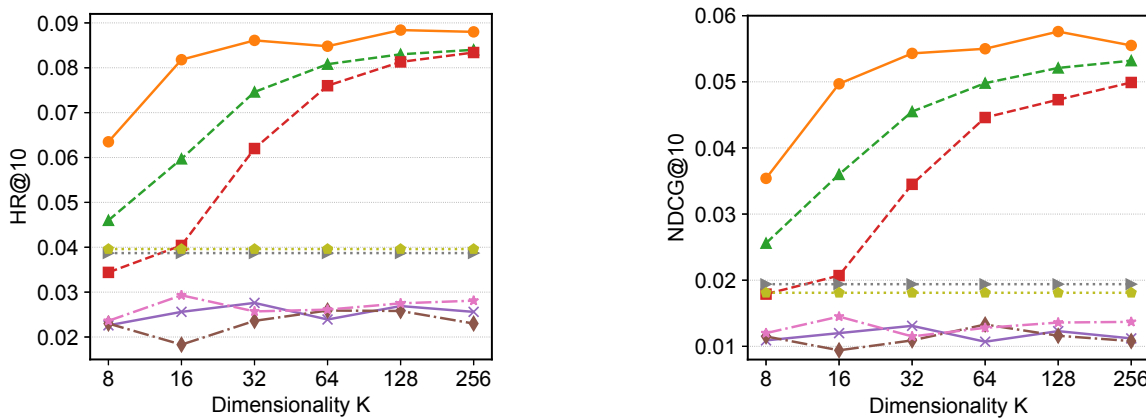

Figure 9: Performance with different dimensionality K. Legends are consistent with that of Figure 8.

- **Computational cost.** Our proposed CROSS method can achieve much better performance than the baselines even if the dimensionality is very small. Since computational cost is in proportion to dimensionality K, this observation indicates that we can gain decent performance with much lower computational cost.

6.4 Impact of Social Relations (RQ3)

Section 3.2 has analyzed the correlation between number of buy and number of friends, and we further analyze how our model performs for users with different number of friends. We divide users into 3 groups according to the number of their friends: [1-4, 5-8, 9-12]. The recommendation performance for each group of our CROSS method and other baselines which utilize social information are shown in Figure 10.

Firstly, we can observe a trend of better performance with users having more friends. This is intuitive, and shows the importance
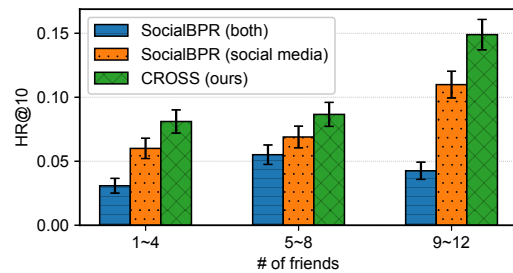

Figure 10: Performance with different number of friends

of social relation information for recommendation. Secondly, our method outperforms the best baselines significantly by 35.01%, 25.59%, 35.53% for each of the three groups. This further justifies

Table 2: Performance (HR@10) of Top 5 item categories, where *(or +) indicates algorithms trained on data from social media (or both) platform have better performance than the one trained on data from both (or social media) platform. For each category, top 2 performances are marked in bold.

Category	Fraction (social media)	Fraction (App)	Fraction (Diff)	BPR (both)	BPR (social media)	ItemPop (both)	ItemPop (social media)	SocialBPR (both)	SocialBPR (social media)	CMF	CROSS (ours)
Food & Fruit*	22.72%	7.24%	15.48%	0.000	**0.034***	0.000	0.000	0.000	0.017*	0.000	**0.022**
Household supplies*	32.46%	21.96%	10.50%	0.017	**0.035***	0.025	0.029*	0.017	**0.035***	0.017	**0.042**
Toys	8.35%	8.24%	0.11%	0.007	0.012*	0.021+	0.018	0.021	**0.043***	0.007	**0.034**
Baby supplies+	4.43%	9.59%	-5.17%	0.029+	0.021	0.151+	0.000	**0.169+**	0.052	0.035	**0.192**
Baby clothes+	12.10%	21.86%	-9.75%	0.020+	0.005	0.011+	0.000	0.026+	0.022	**0.029**	**0.057**

that our method can utilize social information more effectively. Lastly, our method is able to achieve decent performance even if users have only few friends. This demonstrates our method can address the problem of poor performance of users with sparse social relations. That is, our method can efficiently alleviate the data sparsity issue which is a major concern in recommendation tasks [5, 36, 39].

6.5 Impact of Item Categories (RQ4)

We further investigate how our model performs on different categories of products. Table 2 shows the performance on the top 5 categories (which has at least 4% fraction on social media). As analyzed in Section 3.2, a larger fraction difference between fraction on social media and fraction on app means this category is more prevalent on social media platform.

Thus, we can divide the top 5 categories into 3 groups by the fraction difference. The first group contains two social media-prevalent categories: Food & Fruit and Household supplies, which have a fraction difference much larger than 0%. The second group contains one category which are almost as popular on two platforms: Toys, which has a fraction difference about equal to 0%. The third group contains two app-prevalent categories: Baby supplies and Baby clothes, which have a fraction difference much smaller than 0%. Shown in Table 2, following findings are observed.

- **Specialty Trade-off.** For social media-prevalent (or app-prevalent) categories, using social media (or both) platform data to train will have better performance (Marked as * (or +) in Table 2). This shows that there is a trade-off between specialty in app-prevalent categories and specialty in social media-prevalent categories for the baseline methods. Compared to all the other baselines, our proposed CROSS method not only has decent performance on social media-prevalent categories, it also shows a significant improvement on app-prevalent categories. This indicates that our CROSS can alleviate the trade-off and improve both performance simultaneously.
- **Effect of Social modelling.** For social media-prevalent categories, there is no performance gain after adding social information (*i.e.* comparing CROSS, SocialBPR with other baselines). However, for app-prevalent categories, a large improvement is achieved after leveraging social information. This indicates that the habits of users buying app-prevalent categories products are largely influenced by their friends, which further justifies the need for social modelling.

- **Failure situation of CROSS.** In all our previous experiments, we find our proposed CROSS outperforms the other baselines consistently. However, after we have analyzed CROSS in depth, we find that in category Food & Fruit, CROSS cannot beat the baseline of BPR (social media). Our guess is that for Food & Fruit, we usually have our own thoughts, and do not refer to their friends too much.

7 DISCUSSION

Here, we would like to discuss some points of this work that we plan to address in the future. We also expect further efforts from the community in the following aspects.

Lack of publicly available dataset. Firstly, we test our algorithm on one private dataset. Due to the characteristic of the application scenario, no other publicly available data is suitable for evaluating it (i.e. lack of access platform information and social relationship between users). However, the problem we have proposed is very common and important. We will open our dataset[2] and expect further improvement for this problem on other suitable data in the industry in the future.

Performance in real scenario Secondly, we conduct our experiments offline for efficiency and convenience. We would like to evaluate our proposed method via online A/B testing with significantly more users and items in the future.

Understanding of user behaviors. In this paper, we conduct a preliminary analysis of the comparison of user behaviors on social media and traditional e-commerce app. Deeper understanding of user behaviors on two platforms are definitely crucial for further modelling of users. We expect in-depth study of this research topic in the future.

Exploration of model structure and richer information.
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, straightforward, and shows superior performance. We note that there are multiple improvements that can be made to further promote the performance. For instance, as mentioned in Section 5.4, we only use an MF element-wise product interaction function in this work, more complex interaction functions, such as neural network based ones [11, 23], can be easily integrated to our model. Also, when modelling user behaviors, we utilize buying behaviors. Multi-behavior recommendation is an

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[2]will be available in https://lzhbrian.me/sigir19-cross

emerging research topic [15, 24, 39] and it would be meaningful if we can utilize other types of behaviors, such as click or view, to solve this problem. In addition, extension for CROSS to model auxiliary information, such as product prices & information [4], user reviews [40], to name just a few, would be extremely interesting to develop. As this paper is the first attempt, we hope that our work and our dataset can elicit other reasonable and inspiring ideas from the community in the future.

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 model CROSS, which seamlessly integrate social information into cross-platform recommendation. To evaluate our proposed method, we have conducted extensive experiments on a real-world dataset, showing that our proposed CROSS method significantly outperforms existing state-of-the-art methods.

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