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A general and effective diffusion-based recommendation scheme on coupled social networks

Xiaofang Deng[a,b], Yuansheng Zhong[a,*], Linyuan Lü[c,d], Naixue Xiong[a,e,*], Chiho Yeung[f]

[a] School of Information Technology, Jiangxi University of Finance and Economics, Nanchang, 330013, PR China
[b] School of Software, Jiangxi Normal University, Nanchang, 330022, PR China
[c] Institute of Fundamental and Frontier Sciences, University of Electronic Science and Technology of China, Chengdu, 610054, PR China
[d] Alibaba Research Center for Complexity Sciences, Hangzhou Normal University, Hangzhou, 310036, PR China
[e] Department of Mathematics and Computer Science, Northeastern State University, 74464, USA
[f] Department of Science and Environmental Studies, The Education University of Hong Kong, Hong Kong

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ABSTRACT

Online social networks and recommender systems are two of the most common internet applications, but due to their different nature, they are seldom considered under a single framework. Nevertheless we often rely on friends for advices before purchasing products or services. In other words, information embedded in the online social networks may be relevant to recommender systems and the combination of the two systems may benefit each other. In this paper, we introduce a simple recommendation algorithm based on a diffusion process which integrates the networks of friends and user-product relations. Our results show that social networks improve the accuracy of recommendation for inactive users, and increase the diversity of the recommended products for active users. In addition, our approach outperforms conventional popularity-based algorithms and provides personalized recommendations in the cold-start period. These results shed light on a new design of recommendation algorithms in integrating social information and recommendations.

1. Introduction

In order to overcome information overload, recommender systems [25] have become the key tool for providing users with personalized recommendations on items such as movies, music, books and news. In recent years, significant steps have been taken towards providing personalized services for a wide variety of web-based applications: E-commerce [17,47], E-government [32], E-education [40] and Electronic medical services [38,42]. Recommender systems can be generally classified into content-based analysis [1,33], collaborative filtering [8,11] and hybrid recommender systems [32]. Content-based analysis consists of suggesting items similar to those the user liked in the past. In order to fight overspecialization, researchers devised collaborative filtering - whose underlying assumption is that the active user will prefer those items which the similar users prefer, and even they combined content-based and collaborative filtering in hybrid recommender systems.

* Corresponding authors at: School of Information Technology, Jiangxi University of Finance and Economics, No. 168, Shuang-gang East Road, Economic and Technological Development district, Nanchang 330013, China.
E-mail address: xiongnaixue@gmail.com (N. Xiong).

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Just like recommender systems, online social networks [6] are also the most common internet applications. On one hand, recommender systems are implicitly implemented in many online applications, although most internet users are not aware of their presence. Recommended systems can significantly help to improve user engagement in social platforms because they can recommend new friends or interesting content. The user will be more actively engaged in social platform, because the more content he/she shares, the better it is for the recommender systems to understand his/her potential interests. On the other hand, online social networks have become an essential component of our daily life, largely supplemented or even replaced the conventional social network. Social platform transforms information consumers into active contributors, enabling them to share their status, comment or rate web content. Social platforms encourage interaction between users. Each interaction can be extracted and used as an input for the recommendation system because it helps to better understand user interests and information needs. In addition, the structure of social network can help to generate recommendations that are more trusted by the user. Although both online social networks and recommender systems play a crucial role in our daily life, they seem to be very different applications and are seldom studied under a single framework.

An interesting question to ask is whether the two applications are relevant to each other. An example of the integration of two systems is Facebook,[1] where a simple recommendation algorithm is applied to recommend new friends to users, which is an important feature offered by online social networks but not by conventional forms of social interaction. Online social networks present new opportunities as to further improve the accuracy of recommender systems. On the other hand, the information hidden in the social network is relevant, since friends usually share common interests, and examining friends' favors may identify relevant items for the target user. There have been many social-based recommender systems [28,44] which utilizes the relations between users in social network, for instance the similarity in taste between friends, to improve the recommendation accuracy.

In addition to improving recommendation accuracy and diversity [20], social information may help recommender systems to solve the cold-start problem [37], which corresponds to the difficulties in identifying relevant products for new users who have not shown their preferences. In this case, popularity-based approaches are widely used but always unable to provide personalized recommendations, they merely recommend the most popular products for every new user despite their intended functionality to match users to specific products [3]. Social networks thus provide an extra piece of information for the recommender system to explore, especially in the cold-start period for new users.

In this paper, we study two datasets, namely *Friendfeed* [3] and *Epinions* [29], where a social network is present on top of the user-item recommender systems. The network dataset extracted from the two applications integrated both social relations as well as user-product preference, and we will call these networks the friend-and-commodity network throughout the paper.

The main task of a recommender system is to generate a ranking list of the target user's uncollected items based on the observed information and to recommend the top-ranked items to the target user. Our proposed method, which is inspired by classic mass diffusion approach [51], aims to recommend items to the target user according to his preference on choices of friends and items. We apply the mass diffusion process to undirected friend-and-commodity network where a tuning parameter $p \in [0, 1]$ regulating the resources redistributed in the social network and user-commodity bipartite network. After the diffusion, items not yet collected by the target user are ranked according to their resources in descending order, and are recommended accordingly. The larger the parameter p, the less the amount of resources redistributed in the social network.

We then conduct comprehensive experiments on datasets *Friendfeed* and *Epinions* to validate our proposed scheme. Our results show that social information improves recommendation accuracy for inactive users and increases the diversity of recommended products for active users. In case of cold-start users who have never collected any items, we also compare our proposed algorithm against conventional global ranking algorithm.

To summarize, this paper makes the following contributions.

- We design a simple recommendation algorithm, which is an extension of classic mass diffusion method, based on a diffusion process on the friend-and-commodity network to integrate social information into recommendations. The idea of our method is intuitive to understand, and easy to implement.
- Our proposed algorithm is validated over two datasets: *Friendfeed* and *Epinions*. It is found that our proposed algorithm improves classic mass diffusion by $3.12-12.6\%$ for ranking score. We then examine those users who collect less than 5 items in *Friendfeed* and less than 13 in *Epinions*, respectively. They account for more than 20% of the users in these two datasets. The improvements on ranking score compared with the original mass diffusion are 43.11% and 9.92%, respectively.
- We also investigate the target users who had never chosen an item but made some friends. By comparing our proposed method to global ranking algorithm, we found that the improvement for ranking score and precision are $30.3-77.6\%$ and $29-179\%$, respectively.

The remainder of this paper is organized as follows. We provide an overview of social-based and diffusion-based recommendation approaches in Section 2. We introduce three baseline methods and then formally propose a social network based

[1] http://www.facebook.com/.

recommender algorithm in Section 3. Section 4 describes the utilised datasets and the performance metrics. The experimental results and discussion are presented in Section 5, followed by conclusions and future works in Section 6.

2. Related works

Recently, based on the homophily assumption that users linked with each other in social networks tend to have similar tastes, some social recommendation methods [28,39,44] have been proposed to improve recommendation accuracy by leveraging the social relationships between users. Social-based recommendation mainly includes memory-based social collaborative filtering, social-based matrix factorization and probabilistic models. However, almost all the existing social-based recommendation algorithms need additional information such as commodity ratings, social tags and user's profile. Since explicit ratings and use's profile are not always available [4], many diffusion-based approaches, which work with network structure, have been proposed in the literature.

2.1. Memory-based social recommender systems

Memory based social recommender systems use memory based collaborative filtering models, especially user-oriented methods as their basic models. Kautz et al. [14] modeled professional social networks through co-authorship in hopes of recommending experts on a certain topic that the users of the system are likely to know. Li et al. [18] employed user comments for dynamically suggesting related stories to a given news article, showing that suggestions improve when the content of user comment threads is considered. Due to the large size of a network, directly monitoring the status of all users cannot be feasible in a limited amount of time and is too expensive, Yu [45] categorized the existing recommendation algorithms and explained that these systems suffer from users' behavior and diversities of personal characteristics. They proposed a hybrid recommendation algorithm that is based on the multiple component algorithms. The use of resource-tag bipartite network typically results in more diverse and niche commendations, this is in accordance with the observation in the work [2]. The major limitations of collaborative filtering methods are the cold start problem for new users and new items, the sparsity problem, and the long tail problem. These problems have attracted much attention from researchers. A kernel-mapping recommender was proposed in [7], and the recommendation algorithm performs well in handling these problems.

2.2. Social-based matrix factorization

The social-based matrix factorization model addresses the transitivity of trust in social networks, as the dependence of a user's feature vector on the direct neighbors' feature vectors can propagate through the network, making a user's feature vector dependent on possibly all users. Recently, some model-based approaches have been proposed which use matrix factorization for recommendation in social networks [26,27]. Due to data sparsity, the number of commonly rated items between friends could be very small or even zero. To address this problem, authors of [46] improved the prediction accuracy by employing adaptive social similarities in the social regularization part. They calculate similarity between users based on their latent features. Jiang et al. [13] demonstrate that individual preference is also a significant factor in social network. Just like the idea of interpersonal influence, due to the preference similarity, user latent features should be similar to his/her friends' based on the probabilistic matrix factorization model. The primary latent factor model cannot effectively optimize the user-item latent spaces because of the sparsity and imbalance of the rating data, Authors of [12] introduced latent space regularization and provide a general method to improve recommender systems by incorporating latent space regularization.

2.3. Social-based probabilistic models

Social networks can be also modeled using Bayesian networks [10,16]. He and Chu [9] developed a probabilistic model to make item recommendations based on information in social networks, including user preferences, item's general acceptance and influence from social friends. In [15], the Markov process was used to model the purchasing process of market basket data and recommendations utilizing the probabilistic latent semantic indexing were also investigated. Different from trust-based recommendation, authors of [43] proposed to use conditional probability distributions to capture the similarity between friends in social networks. Rich information carried by probability distributions allows one to employ Bayesian networks to conduct multiple-hop recommendation in online social networks.

2.4. Diffusion-based approaches

Inspired by the network-based resource-allocation dynamics, Zhou et al. [51] proposed the mass diffusion method to extract the hidden information of networks. In the mass diffusion approach, resource is redistributed from one node to its neighbors equally. However, some objects are very popular while some objects are out of fashion in real recommendation systems. A similar heterogeneity also exists for users, i.e., some users collect many objects and some users collect only a few. Therefore, the authors in [21] assume that each node has an attraction that is proportional to the power of its degree, and then apply a diffusion process in which each node distributes its resource to its neighbors depending on their attractions.

Mass diffusion is demonstrated to give recommendation results with good accuracy but poor diversity. Because every user distributes the total resource he receives previously from objects, back averagely to his neighbor objects in mass diffusion. The niche objects will receive lower final resources because they have fewer neighbor users, thus rank in the bottom of the recommendation lists. In order to seek out novel items and enhance the personalization of individual user recommendations, heat spreading method is suggested in [50]. However, people found that accuracy and diversity seem to be two sides of the seesaw, heat spreading is found to be effective in providing a diverse recommendation lists at the cost of accuracy.

Motivated by the accuracy-diversity dilemma in the recommendation systems, various kinds of algorithms have been proposed. Zhou et al. [50] designed delicately a nonlinear hybrid model of mass diffusion and heat spreading, which achieves significant improvements in both accuracy and diversity of recommendation results. Qiu et al. [34] proposed an item-oriented recommendation algorithm by introducing an item-degree-dependent parameter in the hybrid model. The authors claim that the recommendation accuracy of the cold items can be significantly improved by appropriately tuning the item-degree-dependent parameter while keeping the recommendation accuracy of the popular items. The authors in [22] introduced an improved hybrid algorithm of mass diffusion and heat spreading by assigning the items with the initial resource values depending on the item degree. Another four effective methods modified respectively from original mass diffusion and heat spreading, named Preferential Diffusion [24], Weighted Heat Conduction [19], Biased Heat Conduction [23] and Balanced Diffusion [30], also make a good trade off on accuracy and diversity.

Different from the previous diffusion-based approaches, a novel social-based mass diffusion (SMD) algorithm [5] is introduced by our group, which focused only on the structure of social network and user-commodity bipartite network. The significant difference of our proposed method and SMD lies in the nodes to assign the initial resources. In SMD, every item collected by the target user is assigned one unit of resources. This step is similar to the original mass diffusion method. Different from SMD, our proposed method places one unit of resources on the target user and then redistributes the resources in user-user social network and user-commodity bipartite network Simultaneously, by tuning the parameter p to regulate the proportion of resources transferred in the social network and the bipartite network. Moreover, our proposed method is an extension of the classic mass diffusion algorithm while $p = 1$.

3. Our proposed scheme

In this section, we first introduce basic notations used throughout this paper. We consider a friend-and-commodity network denoted by $G(U, O, E_{UO}, E_{UU})$, where U denotes a group of n users, O denotes a group of m products, E_{UO} denotes the set of edges between users and products, and E_{UU} denotes the set of edges between users. The network merged two sub-networks, namely a user-commodity bipartite network $G_{UO}(U, O, E_{UO})$ and a social network $G_{UU}(U, E_{UU})$ between users.

The user-commodity bipartite network G_{UO} is characterized by an $n \times m$ adjacency matrix $\mathcal{A}_{UO}$, where the matrix element $a_{i\alpha} = 1$ if user i collected item α, and otherwise $a_{i\alpha} = 0$. Similarly, the social network G_{UU} is characterized by an $n \times n$ adjacency matrix $\mathcal{A}_{UU}$, where the matrix element $A_{ij} = 1$ if user i and j are friends, and otherwise $A_{ij} = 0$. For the user-commodity bipartite network, we denote the number of users collected item α to be k_α, and number of items collected by user i to be k_i; hence, the k_α and k_i are the degree of product α and user i in the user-commodity bipartite network respectively. On the other hand, we denote the number of friends of user i in the social network to be K_i, which we call the social degree of user i.

In the following, we explain three baseline algorithms. They are mass diffusion algorithm, heat spreading algorithm and hybrid method.

The original recommendation algorithm mimicking the mass diffusion process is called the MD algorithm, also referred to as Network-Based Inference(NBI) [51] and ProbS [50]. It works by assigning one unit of *resources* on the products collected by the target user, and subsequently spreads the resources on the user-commodity bipartite network to items potentially favored by the target user. In terms of mathematics, we denote the initial resources on all the items by $\vec{f}$, and the diffusion is described by the equation $\vec{f'} = W^{\mathrm{MD}}\vec{f}$, where $\vec{f'}$ is the final resources allocated to the items after the diffusion, such that W^{MD} is an $m \times m$ matrix with element $w_{\alpha\beta}^{\mathrm{MD}}$ given by

$$w_{\alpha\beta}^{\mathrm{MD}} = \frac{1}{k_\beta} \sum_{i=1}^{n} \frac{a_{i\alpha} a_{i\beta}}{k_i}. \tag{1}$$

After the diffusion, items not yet collected by the target user are ranked according to their resources in descending order, and are recommended accordingly.

The second classic diffusion-based method is called heat spreading (HeatS) in the literature [50]. The significant difference between MD and HeatS is the resource redistribution strategy: MD works by equally distributing the resource of each node to its nearest neighbors, the overall resource remains unchanged; while in HeatS every node absorbs equal proportion of the resource from the nearest neighbors, the overall resource increases in the process. Specifically, the difference of HeatS from MD lies in the transfer matrix W^{HeatS}, which is described as:

$$w_{\alpha\beta}^{\mathrm{HeatS}} = \frac{1}{k_\alpha} \sum_{i=1}^{n} \frac{a_{i\alpha} a_{i\beta}}{k_i}. \tag{2}$$

It has been pointed out that MD has high recommendation accuracy yet low diversity, while HeatS, which is designed specifically to address the challenge of diversity, succeeds in seeking out novel or niche objects and thus enhancing the personalization of individual user recommendations but with relative low accuracy [50]. To solve this diversity-accuracy dilemma, Zhou et al. [50] proposed a recommendation method to nonlinearly combine MD and HeatS, called the HHP algorithm, by introducing a tunable parameter λ into the transfer matrix W^{HHP}:

$$w_{\alpha\beta}^{\mathrm{HHP}} = \frac{1}{k_\alpha^{1-\lambda} k_\beta^{\lambda}} \sum_{i=1}^{n} \frac{a_{i\alpha} a_{i\beta}}{k_i}. \tag{3}$$

when $\lambda = 0$, HHP method reduces to the pure Heats and $\lambda = 1$ the pure MD. By tuning the parameter λ one can make a trade-off between diversity and accuracy.

Recommendations derived from the above diffusion process are merely based on the user-product relationship without considering the friends of the target users. In real life, people often resort to friends in their social networks for advice before purchasing a product or consuming a service. To recommend a product to a user utilizing the information in the social network, we apply the mass diffusion on the friend-and-commodity network. In addition to the diffusion on the user-commodity bipartite network, part of the resources is spread along the friendship network of the users. Since the social network of users is utilized, we call this method the social mass diffusion (SocMD for short). There are four steps in the SocMD method: (i) Initial stage: assignment of one unit of resources on the target user; (ii) Two-way diffusion: a ratio p of the resources are distributed to items collected by the target user while a ratio $1-p$ of the resources diffuse from the target user to his/her friends; (iii) Turn-round diffusion: resources are transferred from users to their friends in social network and redistributed among items' neighboring users in user-commodity bipartite network, respectively; (iv) Final diffusion, all the resources arrived at the users are allocated to their collected items. Mathematically, we denote the initial resources on all the users by $\vec{g}$, and use the equation $\vec{f'} = W^{SocMD}\vec{g}$ to describe the diffusion, where $\vec{f'}$ is the final resources allocated to the items after the diffusion, the modified diffusion matrix W^{SocMD} is an $m \times n$ matrix with element $w_{\alpha j}^{SocMD}$ reads

$$w_{\alpha j}^{SocMD} = p \sum\nolimits_{i=1}^{n} \sum\nolimits_{\beta=1}^{m} \frac{a_{i\alpha} a_{i\beta} a_{j\beta}}{k_i k_\beta k_j} + (1-p) \sum\nolimits_{i=1}^{n} \sum\nolimits_{l=1}^{n} \frac{a_{i\alpha} A_{il} A_{lj}}{k_i K_l K_j}. \tag{4}$$

where p is the ratio of resources which are spread merely on the user-commodity bipartite network, $1-p$ is the ratio of the resources which (i) are transferred from the target user to his friends, (ii) spread from the users to their friends, and (iii) finally transferred to the items in the user-commodity bipartite network. A simple example of these procedures is illustrated in Fig. 1. As in MD, items not yet collected by the target user are ranked according to their resources in descending order after the diffusion and those with the largest resources are recommended. As can be seen from Eq. (4), SocMD will reduce to the pure MD when $p = 1$.

4. Experimental setup

We conduct several experiments to compare the performance of our proposed method with different classic diffusion based methods. We evaluate our method on two real-world datasets: *Friendfeed* and *Epinions*.

4.1. Datasets

In this paper, we studied two datasets, namely *Friendfeed* and *Epinions*, to evaluate the algorithmic performance. These datasets are obtained in [31]. FriendFeed[2] was a real-time feed aggregator that consolidates updates from social media and social networking websites. Epinions.com[3] was a general consumer review website established in *1999*. Other than the conventional user-item relations, we can also extract social relations among the users in these networks. Specifically, we consider user A and user B are friends whenever A follows B or B follows A in the original social network, resulting in an undirected social network as our analyzed data. On the other hand, links in the user-commodity bipartite network are defined when a user collected an item. Finally, users who did not collect any items or had no friends and items which are not collected by any users were deleted from the friend-and-commodity network. The statistical properties of the two datasets are given in Table 1.

Moreover, the proportion of inactive users in *Friendfeed* is obviously greater than that in *Epinions*. Actually, the proportion of users with commodity degree $k_i \leq 7$ are 44.46% and 3.32% in *Friendfeed* and *Epinions*, respectively.

In addition, Fig. 2 shows that the percentages of pair of friends who collect at least one common item are 46.34% and 54.5% in *Friendfeed* and *Epinions*, respectively. It reveals that friends are more likely to collect items in common, and these social information would be useful for the recommendation systems.

[2] http://www.friendfeed.com/.
[3] http://www.epinions.com/.

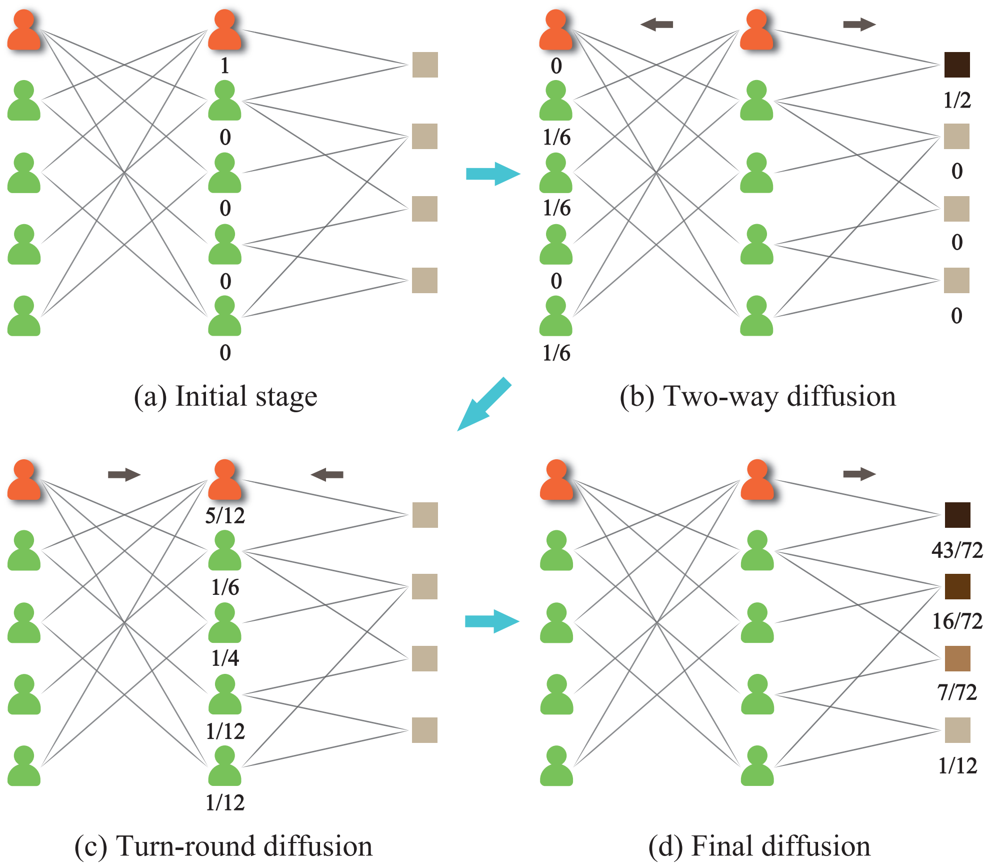

Fig. 1. A simple illustrative example of the SocMD algorithm with $p = 0.5$. The user in red is the target user, and squares denote items. The darker the squares, the greater the amount of resources they own. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
The statistical properties of the two studied datasets, namely *Friendfeed* and *Epinions*.

Datasets	Users	Objects	Links (G_{UO})	Links (G_{UU})	$\langle k_i \rangle$	$\langle K_i \rangle$	Sparsity (G_{UO})	Sparsity (G_{UU})
Friendfeed	4148	5700	96,942	265,497	23	128	4×10^{-3}	3×10^{-2}
Epinions	4066	7649	154,122	167,717	37	82	5×10^{-3}	2×10^{-2}

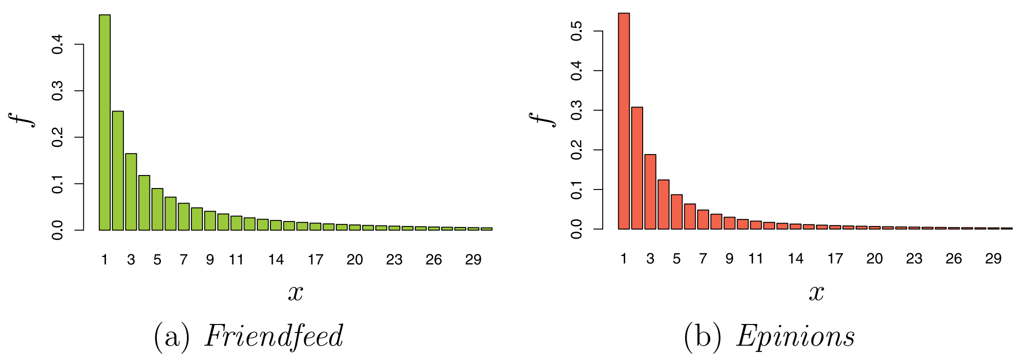

Fig. 2. The cumulative ratio $f = n_1/n_2$ as a function of x for *Friendfeed* and *Epinions*, x is the number of common objects collected by paired friends. The variable n_1 corresponds to the number of paired friends who collect at least x common objects, while n_2 corresponds to the total number of paired friends in social network.

4.2. Evaluation metrics

We employ seven metrics to fully characterize the performance of the recommendation algorithms studied:

(1) **Ranking score(*RS* for short)** [51]: Ranking score measures the ability of a recommendation algorithm to produce a good ordering of items that matches the user's preference. For a target user, the recommender system returns a list of all his uncollected item ranked according to his preference. For each user-item link in the probe set, we measure the rank of the item in the recommendation list of the user. A good algorithm is expected to give those items collected by the target user in the probe set a higher rank, and thus leads to a small *RS*. Averaging over all the user-object relations in the probe set, we obtain an average ranking score *RS* that quantify recommendation accuracy of the algorithm. Alternatively, for a target user i, RS_i is given by

$$RS_i = \frac{1}{|\{(i\alpha) \in E^P\}|} \sum_{(i\alpha)\in E^P} RS_{i\alpha}, \tag{5}$$

where $(i\alpha)$ denotes the probe link connecting user i and object α. By averaging the individual RS_i over all users we obtain the mean ranking score *RS* of the whole system. Clearly, the smaller the ranking score, the higher the accuracy of the algorithm, and vice versa.

(2) **Precision(*Prec*)** [11]: Precision is defined as the ratio of relevant items selected by a target user to the number of items found in the top-L positions of the recommendation list. For a target user i, the precision $P_i(L)$ is defined as

$$P_i(L) = \frac{d_i(L)}{L}, \tag{6}$$

where $d_i(L)$ is the number of relevant items (i.e. the items collected by i in the probe set) in the top-L positions of the recommendation list. By averaging the individual precisions over all users with at least one link in the probe set, we obtain the mean precision $P(L)$ of the whole system. Precision corresponds to the probability that a recommended item is relevant to a target user.

(3) **Inter-user diversity of recommended products(*H*)** [49]: it measures the diversity of recommendation lists among different users. Given two users i and j, the difference of their lists can be measured by the hamming distance:

$$H_{ij}(L) = 1 - \frac{C_{ij}(L)}{L}, \tag{7}$$

where $C_{ij}(L)$ denotes the number of common items in the top-L positions of their lists. Obviously, $H_{ij}(L) = 0$ if i and j obtain an identical recommendation list, while $H_{ij}(L) = 1$ if their lists are completely different. By averaging $H_{ij}(L)$ over all pairs of users, we obtain the average inter-user recommendation diversity $H(L)$ for the system. The greater the value of $H(L)$, the more personalized the recommendation list to individual users.

(4) **Intra-user diversity of recommended products(*I*)** [52]: it quantifies the similarity among the items within the recommendation list of individual users. For a target user i, the recommendation list can be denoted by $\{o_1, o_2, \ldots, o_L\}$, and the similarity of products in his/her recommendation list can be defined as:

$$I_i(L) = \frac{1}{L(L-1)} \sum_{\substack{\alpha\neq\beta \\ \alpha,\beta\in O_i(L)}} S^o_{\alpha\beta}, \tag{8}$$

where $S^o_{\alpha\beta}$ is the similarity between item α and β, and $O_i(L)$ is the item found in the top-L positions of the recommendation list of user i. There are many similarity indices which can be used to quantify the similarity between items. Here we employ the widely used cosine similarity index [36] to measure similarity between items. Given two items α and β, their similarity is defined as:

$$S^o_{\alpha\beta} = \frac{1}{\sqrt{k_{o_\alpha} k_{o_\beta}}} \sum_{l=1}^{n} a_{l\alpha} a_{l\beta}, \tag{9}$$

By, averaging $I_i(L)$ over all users, we obtain the average intra-user recommendation diversity $I(L)$ for the whole system. A good algorithm should be able to cover a sufficient area of interest for individual user and obtains a low intra-user recommendation diversity.

(5) **Coverage(*Cov*)** [24]: Coverage is the ratio of the number of distinct items included in all user's recommendation lists to the total number of items in the system. It can be defined as:

$$Cov = \frac{1}{m} \sum_{\alpha=1}^{m} \delta_\alpha, \tag{10}$$

here m is the total number of items in the system and $\delta_\alpha = 1$ only if item α appears in the recommendation list of at least one user, otherwise $\delta_\alpha = 0$.

(6) **Novelty(*N*)** [48]: A good recommendation algorithm should be able to identify niche or unpopular items that users are less likely find through other ways but match their preferences. The metric popularity quantifies the capability of an

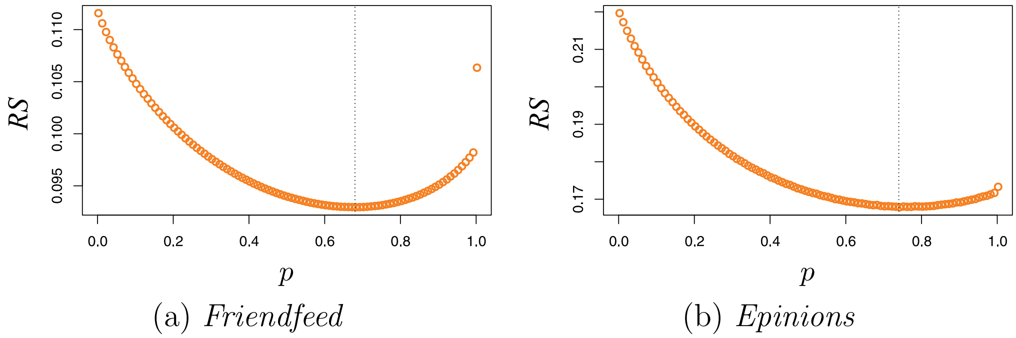

Fig. 3. The recommendation accuracy of the SocMD algorithm measured by the ranking score (*RS*) as a function of parameter *p*. The dotted lines mark the optimal parameters p^*, which are 0.68 and 0.74 in *Friendfeed* and *Epinions*, respectively.

algorithm to generate novel and unexpected results. The simplest way to calculate popularity is to average the recommended times of items, as

$$N_i(L) = \frac{1}{L} \sum_{\alpha \in O_i(L))} k_\alpha, \tag{11}$$

where $O_i(L)$ again denotes the set of items found in the top-L positions of the recommendation list of user i. Evidently, lower popularity means higher novelty and surprisal. By averaging $N_i(L)$ over all users, we obtain the average popularity for the system.

(7) **Congestion(*C* for short)** [35]: Congestion occurs while a few different items are recommended to numerous users. It can be quantified by the famous Gini coefficient which was used to measure the inequality of individual wealth distribution in an economy. Firstly, we rank items in ascending order according to the number of occurrences in the recommended lists of all users. Then the Lorenz curve, denoted by $R(x)$, is the normalized cumulative times of recommendation, and $x \in [0, 1]$ indicate the normalized rank. Finally, congestion is defined as:

$$C = 1 - 2\int_0^1 R(x)dx. \tag{12}$$

Obviously, $C = 0$ indicates that all items are recommended to users with the same probability.

4.3. Experimental settings

To evaluate the performance of the recommendation algorithm, we divide all the links in the user-commodity bipartite network into two sets randomly: the training set E^T which consists of 90% of all the links in the user-commodity bipartite network, and the remaining 10% of links are considered to be the probe set E^P. The training set is treated as the known information for the recommender systems to predict the existence of links in the probe set. In fact, the training set is a friend-and-commodity network which consists of integral social network and 90% of links in user-commodity bipartite network. We then run MD, HeatS, HHP and socMD method on the training sets of *Friendfeed* and *Epinions*, respectively. We vary λ and p from 0 to 1, the increment is 0.01, to compute all metrics defined in Section 4.2. All the numerical results are obtained by averaging over ten independent runs with random data division of training and probe set. Note that λ and p are the tuning parameters in Eqs. (3) and (4), respectively. The value of parameter p determines the amount of resources transported over the social network. The larger the parameter p, the less the amount of resources redistributed in the social network. In particular, our proposed socMD method will reduced to original MD method when $p = 1$.

5. Performance analysis

To examine the benefit of the cross-fertilization between social information and recommendation, we compare the recommendation results obtained by SocMD and MD on two real datasets, namely *Friendfeed* and *Epinions* (see Section 4.1 for details of the datasets). The metric *ranking score* (*RS*) (see Section 4.2 for definition) is used to measure the recommendation accuracy, and a lower *RS* implies a higher recommendation accuracy. Fig. 3 shows the *RS* obtained by applying the SocMD algorithms on the two datasets.

As shown in Fig. 3 for the *Friendfeed* dataset, *RS* reaches the minimum value of 0.093 at $p = 0.68$, corresponding to an improvement of 12.6% over the original MD, i.e. the result of SocMD at $p = 1$. On the other hand, as shown in Fig. 3 for the *Epinions* dataset, we can see that the *RS* obtained by SocMD improves by 3.12% compared to that obtained by MD, from 0.1678 at $p = 0.74$ to 0.1732 at $p = 1$. Besides, *RS* decreases sharply when p decreases from $p = 1$ for both datasets. In order to explain the sharp decrease, we compare the *RS* values of each target user in the cases of $p = 1$ and $p = 1 - \epsilon$, where $\epsilon = 1 \times 10^{-8}$ is a very small number to show the slightest impact of SocMD on the recommendation scores. We found that

Table 2
Recommendation performance obtained by SocMD and various diffusion methods including MD, HeatS and HHP method (see baseline methods in Section 3). The algorithmic performance is quantified in terms of seven metrics: *RS, Prec, N, H, I, Cov* and *C* (see definition in Subsection 4.2). For the HHP algorithm, the *RS* value reaches its minimal value at $\lambda = 0.67$ in *Friendfeed* and $\lambda = 0.51$ in *Epinions*, respectively. With respect to the SocMD method, the optimal *RS* is obtained at $p = 0.68$ in *Friendfeed* and $p = 0.74$ in *Epinions*, respectively. The length of recommendation list is 20 for computing the metrics *Prec, N, H, I, Cov* and *C*.

Metrics	*Friendfeed*				*Epinions*			
	MD	HeatS	HHP	SocMD	MD	HeatS	HHP	SocMD
RS	0.1063	0.1218	0.1047	**0.0929**	0.1732	0.2180	**0.1643**	0.1678
Prec	0.0200	0.0120	**0.0209**	0.0189	0.0208	0.0075	**0.0252**	0.0198
N	63.320	**11.196**	47.602	70.827	242.23	**8.7263**	151.33	254.84
H	0.9229	**0.9866**	0.9628	0.8821	0.6403	**0.9831**	0.8802	0.5798
I	0.1243	**0.0570**	0.1097	0.1276	0.1302	**0.0352**	0.1140	0.1326
Cov	0.6060	**0.7676**	0.7430	0.4873	0.2628	0.6447	**0.6678**	0.1926
C	0.8650	**0.6652**	0.7501	0.9204	0.9778	**0.7671**	0.8555	0.9857

a lower *RS* value is obtained for all target users in the cases of $p = 1 - \epsilon$ compared to the case of $p = 1$, implying that even the smallest spreading on the social network would be beneficial to the recommendation accuracy.

To better understand the sharp *RS* improvement when the parameter slightly changes from $p = 1$ to $p = 1 - \epsilon$, we compare the list of the recommended items in the two cases. An illustrative example is: user 3783 has collected three items, namely item 954, 4278 and 4771. Only the last item 4771 is included in the probe set. In the case with $p = 1$, the resource of item 4771 is zero and it is ranked at 4792th among all the other items with a zero resource. On the other hand, in the case with $p = 1 - \epsilon$, item 4771 obtained a small amount of resources from the diffusion on the social network by the SocMD procedure, and its resource becomes 2.1184×10^{-14}. This gives item 4771 a rank of 2277th, higher than most of the items with a zero resource due to the slightest diffusion on the social network, which is the origin of the great improvement over the case of $p = 1$.

Other than the ranking score, we also summarize in Table 2 the performance of SocMD and MD compared with the two other algorithms proposed in [50], and measured by other common metrics. These common metrics include precision, novelty, inter-user recommendation diversity, intra-user recommendation diversity, coverage and congestion (see Section 4.2 for their definitions). As we can see, SocMD outperforms all the previous diffusion methods on the *Friendfeed* dataset in terms of ranking score, but performs less favorably compared with the HHP method [50] on *Epinions*. This may be explained by the difference on the sparsity of the two datasets. As we can see from Table 1, *Friendfeed* has a denser social network compared to that of *Epinions*, which implies that there are more social information for SocMD to exploit in *Friendfeed*, and leads to its better performance compared with that of *Epinions*. On the other hand, since *Epinions* has a more comprehensive user-item network, the HHP method outperforms SocMD on *Epinions* by effectively exploring merely the user-item relations.

It is worth mentioning that trust-based approaches provide more accuracy and more diversity recommendation by incorporating social trust ensemble and ratings of products into recommender systems [41]. Moreover, The trust-based methods can significantly improve the proportion of ratings, which can be predicted, of the validation dataset [28]. Since explicit ratings and user's profile are always not available, our proposed method merely focuses on the user-user social relations and user-item selections. Therefore, the algorithm proposed in this paper is a simple, efficient and general scheme on coupled social network.

5.1. Evaluation for inactive users

Most real networks are sparse, in other words, there are many users who only collect a small number of items, and some items are collected by only a few users. Recommendation results on inactive users usually have a low accuracy since there is insufficient information for the recommendation algorithm to utilize. Therefore, it is particularly meaningful to improve the recommendation accuracy for these inactive users. We thus focus on inactive users, with commodity degree $k_i \le 35$ in *Friendfeed* and *Epinions*. As we can see from Fig. 4(a), the average *RS* of these users obtained by SocMD are all lower than that obtained by MD.

In order to investigate the relation between the commodity degree k_i and the parameter p, we compute the average *RS* as a function of p and the commodity degree k_i. Fig. 4(b) reveals a positive correlation between the commodity degree k_i and the parameter p^* when the ranking score is lowest, which suggests that the social information in the social network has a larger impact in providing accurate recommendations to inactive users than active users.

In addition, the less active the users, the more the resources should be redistributed on the social network for more accurate recommendations. We show the improvement on *RS* obtained by SocMD compared to MD in Fig. 4(c), which again suggests that SocMD is more beneficial for inactive users than active users.

To further demonstrate the effectiveness of SocMD on the most inactive users, we examine those users who collect less than 5 items in *Friendfeed* and less than 13 in *Epinions*. They account for more than 20% of the users in these two datasets.

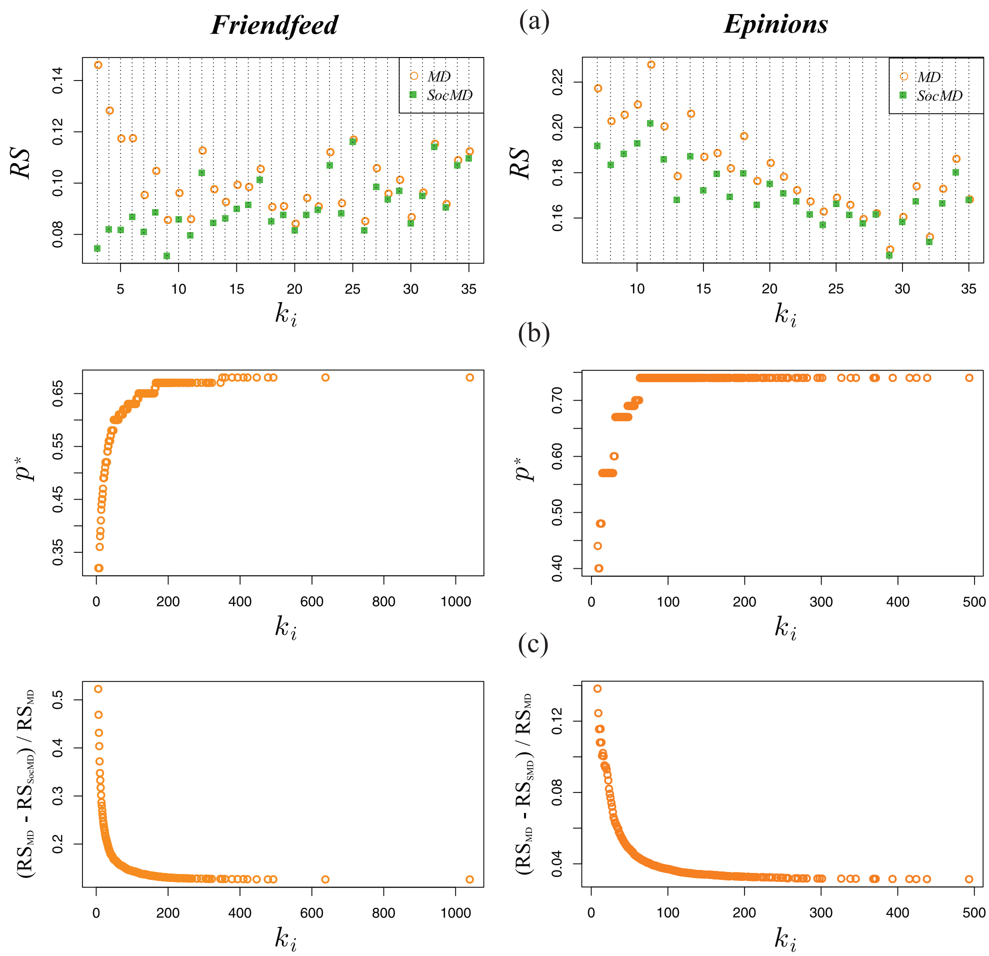

Fig. 4. (a) Comparison of optimal *RS* values under SocMD and MD with regard to inactive users, *RS* reaches its optimal value at $p = 0.68$ and $p = 0.74$ on *Friendfeed* and on *Epinions*, respectively; (b) Optimal parameter p^* as a function of commodity degree k_i. For each k_i, averaging *RS* reaches its optimal value at a p^* value in *Friendfeed* and *Epinions*, respectively; (c) Improvement on *RS* by comparing SocMD with MD concerning k_i. For each k_i, averaging *RS* reaches its optimal value at a p^* value, we calculate the improvement of optimal *RS* to the *RS* at $p = 1$ on *Friendfeed* and *Epinions*, respectively.

The results of SocMD and MD are shown in Fig. 5, As we can see, the minimum *RS* is achieved at $p = 0.32$ in *Friendfeed* and $p = 0.53$ in *Epinions* and the improvements on *RS* compared with the original MD are 43.11% and 9.92%, respectively. Furthermore, we can see from Fig. 5 that precision also improved by 14.44% in *Friendfeed*. Since inactive users collect only a few items, it is difficult to recommend the correct items to them by relying merely on the user-product network and in this case, one can infer the items they prefer by their friends' favors. In fact, the number of paired friends who collect at least one common item accounts for 46.34% and 54.5% in *Friendfeed* and *Epinions*, respectively.

To examine the fraction of common products shared by users with different degree, we compute the ratio n_1/k_i, where n_1 is the average number of products shared by a user and one of his/her neighbors who shared at least one product. Fig. 6 shows that common products are more popular among users with small degree then users with large degree. Therefore recommendation accuracy can be significantly improved for inactive users by combining diffusion mechanism on the user-product network with that on the social network.

For inactive users, we summarize *RS* and *Prec* in Table 3 to compare the performance of SocMD with MD, HeatS and HHP method. As can be seen from Table 3, SocMD outperforms MD, HeatS and HHP method on datasets *Friendfeed* and *Epinions* in terms of *RS*. Furthermore, precision of SocMD also has a greater increase compared with MD, HeatS and HHP method on the *Friendfeed* dataset.

5.2. Evaluation for active users

Most studies of recommender systems focus overwhelmingly on the accuracy as the only important performance measure, ignoring many other elements necessary for a good recommender system. For instance, there is often a tradeoff between recommendation accuracy and diversity [50]. While we have shown that SocMD increases the recommendation

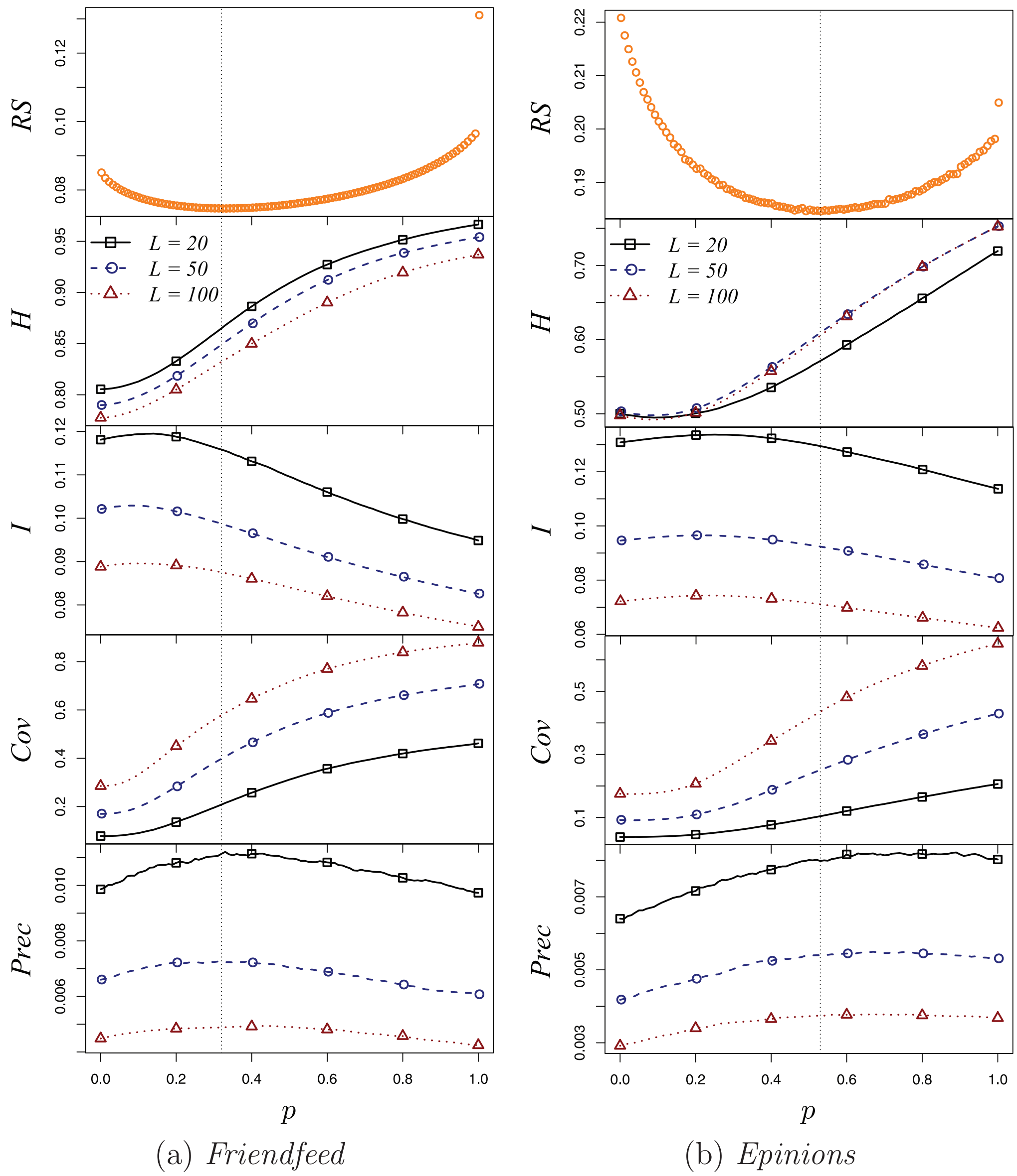

Fig. 5. The recommendation performance of the SocMD algorithm for the inactive users, measured by *RS, H, I, Cov, Prec* as functions of the parameter p of the algorithm. The results are averaged over users whose commodity degree k_i are less than 5 and 13 in *Friendfeed* and *Epinions*, respectively. The dotted lines mark the optimal parameters p^*, which are 0.32 and 0.53 in *Friendfeed* and *Epinions*,respectively.

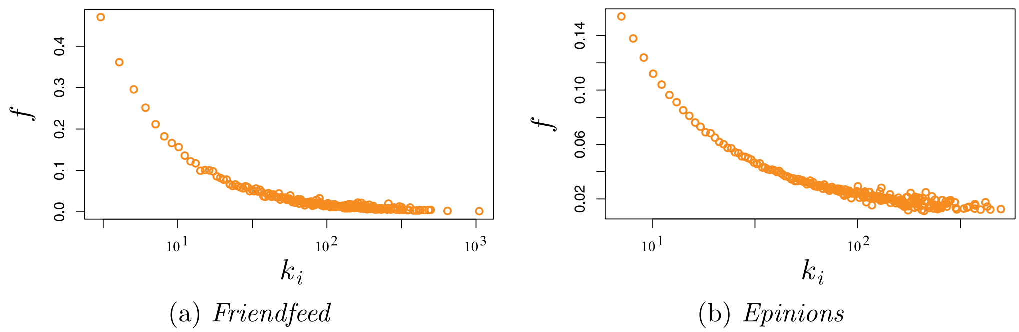

Fig. 6. The ratio $f = n_1/k_i$ as a function of commodity degree of a user for *Friendfeed* and *Epinions*. The variable n_1 corresponds to the average number of products shared by a user and one of his/her neighbors who shared at least one product.

Table 3
Recommendation performance obtained by SocMD and MD, HeatS and HHP method for inactive users. The algorithmic performance is quantified in terms of two metrics: *RS* and *Prec*. For the HHP algorithm, the *RS* value reaches its minimal value at $\lambda = 1$ in *Friendfeed* and $\lambda = 0.65$ in *Epinions*, respectively. With respect to the SocMD method, the optimal *RS* is obtained at $p = 0.32$ in *Friendfeed* and $p = 0.46$ in *Epinions*, respectively. The length of recommendation list is 20 for computing precision value.

Metrics	*Friendfeed*				*Epinions*			
	MD	HeatS	HHP	SocMD	MD	HeatS	HHP	SocMD
RS	0.1311	0.1515	0.1311	**0.0746**	0.2049	0.2514	0.2018	**0.1846**
Prec	0.0097	0.0057	0.0097	**0.0111**	0.0080	0.0025	**0.0087**	0.0080

accuracy for inactive users but not for active users, here we show that SocMD increases the diversity of the recommendations for active users while preserving recommendation accuracy. We consider active users with commodity degree $k_i \geq 28$ in *Friendfeed* and $k_i \geq 52$ in *Epinions*, which account for more than 20% of all users.

As shown in Fig. 7, for the *Friendfeed* and *Epinions* dataset, the optimal *RS* value is achieved at $p = 0.95$ and $p = 0.99$, respectively, i.e., almost no improvement on *RS* is obtained by applying SocMD compared to MD. On the other hand, as shown in Fig. 7, we can see that the intra-user recommendation diversity shows an improvement of 0.36% when *RS* achieves its minimum value at $p = 0.95$ for *Friendfeed*. And for *Epinions, RS* achieves its minimum value at $p = 0.99$ which corresponds to an improvement of 0.09% in terms of intra-user recommendation diversity. Regardless of the *RS* value, intra-user recommendation diversity achieves its optimal value at $p = 0$ which corresponds to an improvement of 23.17% and 8.48% from the case of MD in *Friendfeed* and *Epinions*, respectively. It can be easily seen that Intra-user diversity reaches its optimal value at $p = 0$ in both *FriendFeed* and *Epinions*. The above results suggest that the more the resources are redistributed through the social network, the more diverse the items are recommended to the active users.

5.3. Evaluation for cold-start users

For new users who do not collect any products, recommender systems do not have information about their favors and is not able to suggest a relevant product for them. This problem is known as the cold-start problem. As a result, most recommender systems recommend items to the new users based on the popularity of products, which we called the Global Ranking Method (GRM). Although GRM is not a personalized recommendation algorithm, since it provides the same recommendation for all users, it is widely used as it is simple and requires little computational resources. As SocMD makes use of the information in the social network to derive recommendations, it serves as an alternative to global ranking algorithm in providing personalized recommendation to users who do not collect any items. To demonstrate the effectiveness of SocMD in solving the cold-start problem, we remove all the existing user-product links for those users with small degree, and provide recommendations for them using SocMD. In other words, these users resemble new users since the system does not have any information on their preference for products, but have their information on their choice for friends. Specifically, for *FriendFeed*, we study a group of users with commodity degree less than 4, and move all his/her user-product links to the probe set while keeping the rest of the network as the training set. As shown in Fig. 8, the recommendation results obtained by applying SocMD show an extensive improvement over GRM for a wide range of metrics (except intra-user recommendation diversity). Especially, the inter-user product diversity is improved significantly since recommendations are now personalized instead of identical for every user. Similarly, the same comparison is conducted for a group of users with degrees less than 8 on the *Epinions* dataset. As shown in Fig. 8, SocMD outperforms GRM over all the tested metrics including the intra-user recommendation diversity.

The above results show that SocMD is a good candidate to substitute GRM for providing users with personalized recommendations in the cold-start period. This is particularly important for recommender systems to demonstrate their capability of providing customized recommendation to new users, or otherwise the new users may think that recommender systems are an alternative form of advertisement which only recommends the most popular items as in conventional advertisements.

6. Conclusions and future work

In summary, socMD provides a general way to integrate social information into recommender systems. socMD has the following three main advantages:

1. It is an extension of original mass diffusion method on the friend-and-commodity network and easily gives us the pure MD by assigning 1 to the parameter p.
2. By comparing with MD, socMD improves the recommendation accuracy for inactive users, as well as increases the diversity among the recommended items for the active users.
3. socMD provides personalized recommendations and hence outperform the conventional popularity-based algorithms in the cold-start period.

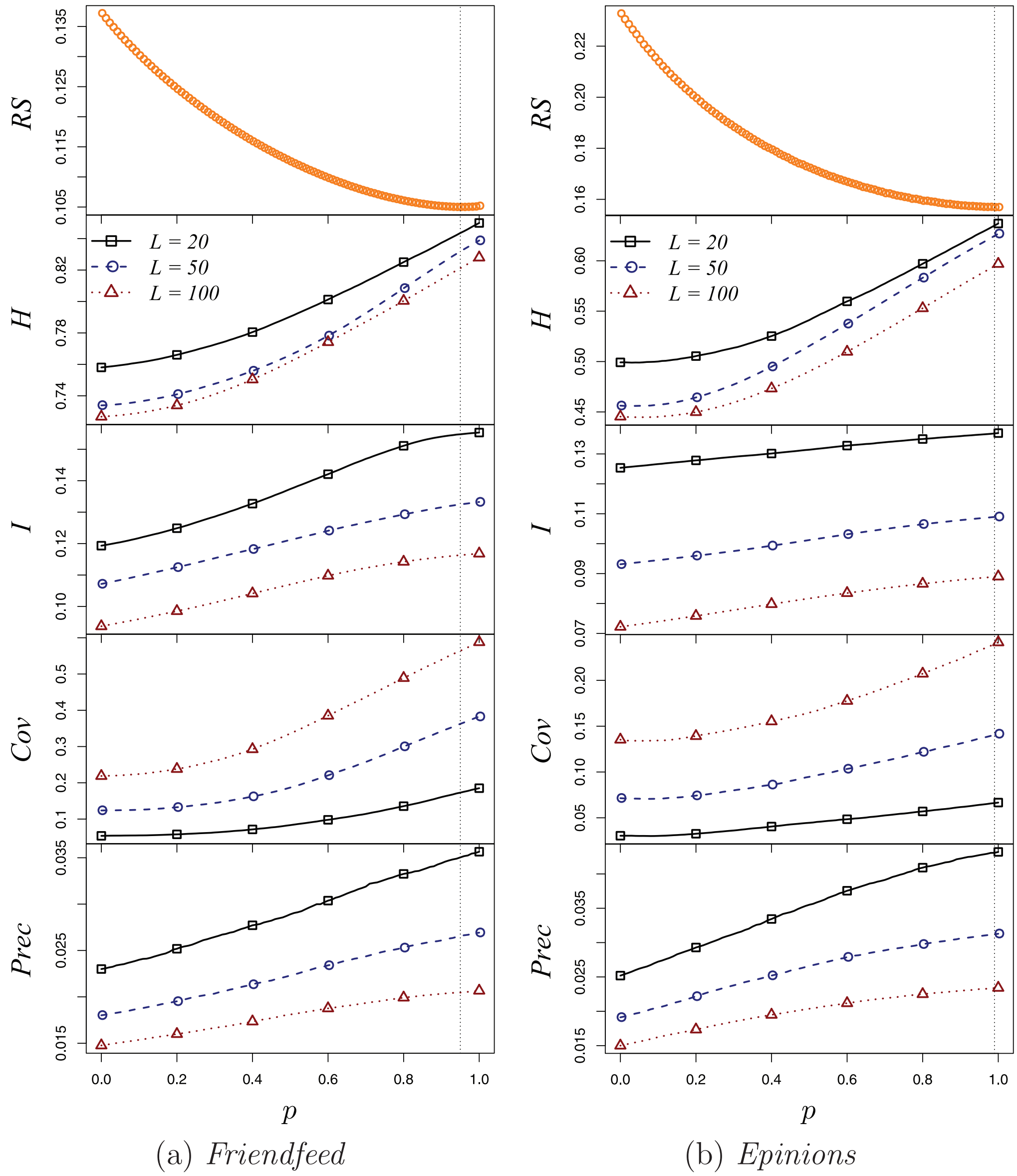

Fig. 7. Performance of socMD on active users. We average indices on users whose bipartite degree k_i are greater than 28 and 52 in *Friendfeed* and *Epinions*, respectively. The dotted lines are used to mark the parameter p corresponding to optimal *RS*, which is 0.95 and 0.99 in *Friendfeed* and *Epinions*, respectively.

Our experimental results shed light on a new design of recommendation algorithms which integrate online social networks and recommender systems. On top of improving recommendation accuracy and diversity, our work demonstrates an integration of different networks and information on the internet for the purpose of inference and information retrieval. As shown by our results, integrating data of different nature may extract information not assessable by considering individual datasets alone. This is consistent with the idea of big data for deeper and more complex data analysis.

Although our present work only focused on recommender systems, the potential of the method to extract other information using the integrated friend-and-commodity network will be further explored. In general, we hope that our work serves as an example to integrate data of different nature for the purpose of general inference. Incorporating heat spreading approach into our proposed scheme is part of future work. Considering importance of users in the network and then providing diverse resource allocation mode is another direction in which future work can be done.

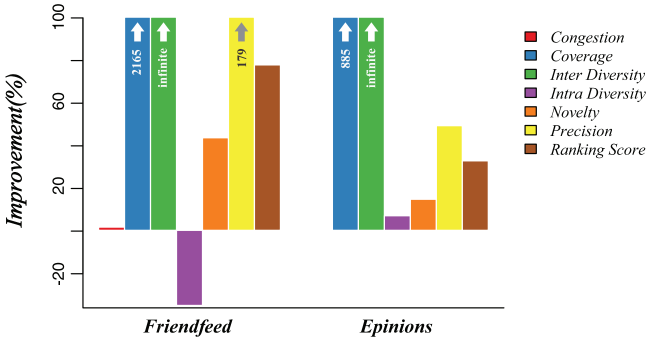

Fig. 8. Comparison between the recommendation results obtained by SocMD and GRM in an analogy with cold-start scenario by removing all the collected item of users with small degree. Specifically, we study users in *Friendfeed* with commodity degree less than 4, and users in *Epinions* with commodity degree less than 8, respectively. The length of recommendation list is fixed at 20. For the sake of illustration, we only represent the fractional improvement which is less than 100% by the bar chart, and the values of the fractional improvements which are larger than 100% are labeled on the corresponding bars.

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In this paper, Naixue Xiong and Yuansheng Zhong are the corresponding authors.

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