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A Generative Model Approach for Geo-Social Group Recommendation

Peng-Peng Zhao[1], *Member*, *CCF*, *ACM*, *IEEE*, Hai-Feng Zhu[1], *Member*, *CCF*, Yanchi Liu[2], Zi-Ting Zhou[1]
Zhi-Xu Li[1], *Member*, *CCF*, *ACM*, *IEEE*, Jia-Jie Xu[1,*], *Member*, *CCF*, Lei Zhao[1], *Member*, *CCF*
and Victor S. Sheng[3]

[1]*School of Computer Science and Technology, Soochow University, Suzhou 215006, China*
[2]*Department of Management Science and Information Systems, Rutgers University, Piscataway, NJ 08854, U.S.A.*
[3]*Department of Computer Science, University of Central Arkansas, Conway 72035, U.S.A.*

E-mail: ppzhao@suda.edu.cn; hfzhu@stu.suda.edu.cn; yanchi.liu@rutgers.edu; carol_zhouzt@163.com
{zhixuli, xujj, zhaol}@suda.edu.cn; ssheng@uca.edu

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Abstract With the development and prevalence of online social networks, there is an obvious tendency that people are willing to attend and share group activities with friends or acquaintances. This motivates the study on group recommendation, which aims to meet the needs of a group of users, instead of only individual users. However, how to aggregate different preferences of different group members is still a challenging problem: 1) the choice of a member in a group is influenced by various factors, e.g., personal preference, group topic, and social relationship; 2) users have different influences when in different groups. In this paper, we propose a generative geo-social group recommendation model (GSGR) to recommend points of interest (POIs) for groups. Specifically, GSGR well models the personal preference impacted by geographical information, group topics, and social influence for recommendation. Moreover, when making recommendations, GSGR aggregates the preferences of group members with different weights to estimate the preference score of a group to a POI. Experimental results on two datasets show that GSGR is effective in group recommendation and outperforms the state-of-the-art methods.

Keywords group recommendation, topic model, social network

1 Introduction

Group activities (e.g., dining out, movie watching, traveling, and parties with friends or families) are essential ingredients of people's lives. With the fast development of two representative types of social network services, location-based social networks (LBSNs), e.g., Yelp① and Facebook②, and event-based social networks (EBSNs), e.g., Plancast③, Meetup④, and Douban⑤, it is easy for people now to organize and participate in group activities and share their experiences online. By exploiting the rich information from group activity data, group recommendation, which is to generate a set of recommendations that satisfy a group of users with potentially competing interests, not only helps groups make decisions but also helps web services improve their user experience.

During making significant progress in the recom-

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*Corresponding Author

①www.yelp.com, May 2018.

②www.facebook.com, May 2018.

③http://plancast.com, May 2018.

④www.meetup.com, May 2018.

⑤www.douban.com, May 2018.

mendation technology, individual recommendation[1-3], unfortunately, cannot be directly applied to group recommendation. Group recommendation is a much more challenging problem because of the different preferences of multiple users. The users in a group may or may not share similar tastes, and users usually change preferences due to other users in the group. How to make a trade-off among different preferences to recommend items for a group becomes the key to group recommendation. The early memory-based group recommender systems overlook the interactions between group members, and the group members' score aggregation or preference aggregation is regarded as group preference[4]. Different from that, model-based approaches exploit the interactions among members by modeling the generative process of a group[5-7]. However, the pre-defined static group has limited application. And users' influences are topic-dependent so that users have different weights in different groups. To consider members' topic-dependent influences, Yuan *et al.*[8] proposed a latent Dirichlet allocation based generative model (named Consensus Model (COM)), which provides a novel idea to construct a generative model of group members. However, COM does not consider social relationships. Several researches report that there is a correlation between items selected by a user and those selected by his/her friends[6,9]. The basic idea behind is that users' behaviors are usually influenced by friends and friends may share common interests. This phenomenon is more obvious in the group recommendation, e.g., you may choose the film your families like other than the film only you like when going out with families. Thus, social relationships have a positive impact on group recommendation.

In order to make group recommendations, we propose a generative geo-social group recommendation model (GSGR) based on the following four considerations. 1) Each group involves several topics with different degrees. For example, a swimming club is more about swimming-related topics, and some groups of female friends may be more relevant to shopping and dining related topics. 2) There are social relationships among users, such as friends and followers. To some extent, users' decisions are often influenced by the social relations of their friends and family. In addition, friends of a user may share common interests. 3) The selection of users in a group may be influenced by their personal preferences, the relevant topics of the group, and their social relations. Geographical distances to POIs can also affect the personal choice of POIs. 4) Each group is constituted of multiple users, and different users have different influences in making group decisions. In addition, the influence degree of a user in a group is topic-dependent. A user may have a significant influence on decision-making for a swimming group, while not for a dining group.

In this paper, we model the generative process of making decisions for a whole group. First, each group has a multinomial distribution over latent topics that attract users to join the group. Then, the POI selection of a member in the group is influenced by personal preferences, group topics, and social relationships. And the final decision of a group is made by aggregating the selections of all members in the group with different weights. Based on the generative model, we obtain a generative recommendation method to recommend POIs for a target group.

The major contributions of this paper are summarized as follows.

- We propose a generative model called GSGR to model the generative process of the POI selection for a target group, which considers the influential weights of multiple users with different topics and users' selections.
- We propose a new recommendation method to make group recommendations based on GSGR, which considers group topics, personal preferences, and social relationships.
- We conduct a comprehensive performance evaluation on two real-world datasets for group recommendation. Experimental results show that our method outperforms baselines and provides effective and meaningful recommendations for the members in a group.

The rest of this paper is organized as follows. In Section 2, we introduce our generative geo-social group recommendation model GSGR for POI recommendations. Experimental results are shown in Section 3. In Section 4, we briefly review related work. Finally, we conclude the paper in Section 5.

2 Generative Recommendation Model

In this section, we first introduce related definitions for group recommendation, and then explain our proposed generative model GSGR in detail. After that, we further explain the progress of parameter estimation for GSGR and how GSGR makes group recommendation.

2.1 Problem Statement

Let U, I, G and S be the user, POI, group and social sets, respectively. A group $g \in G$ consists of a set of users (group members) $u_g = \left\{u_g^1, u_g^2, \ldots, u_g^{|g|}\right\}$, where $u_g^i \in U$ and $|g|$ is the number of members in the group. And the social relationships of a user u can be expressed as $s_u = \{\langle u_1, u\rangle, \langle u_2, u\rangle, \ldots, \langle u_m, u\rangle\}$, where $\langle u_m, u\rangle$ shows u_m is a follower of u. In addition, if a group g selects a POI i_g, this group is relevant to this POI. Then, we can define a behavior of a group g as $\langle u_g, i_g\rangle$. The goal of group recommendation is that given a group g_t, we recommend it the POIs that this group has not visited but may be interested in.

For ease of reading, we list some key notations in Table 1.

2.2 Generative Group Model

GSGR is a probabilistic generative model for group recommendation. It aims to capture the following intuitions. 1) Each group has several topics and each user in the group has different degrees of relevance to these topics. 2) To some extent, users making decisions usually are affected by their social relations such as followers. Besides, the friends of a user may share common interests. 3) When making a selection, a user in a group would consider several factors, such as the group topic, his/her personal preference, and social selections. 4) Each group is constituted of multiple users; therefore the preference of a candidate POI is determined by different preferences of individual group members. In addition, the influence of each individual on making a group selection is topic-dependent.

The graphical representation of our GSGR model is shown in Fig.1. Then, we will describe the generative process in our model as follows.

1) Each group $g \in G$ is made up of members who are attracted by certain particular group topics; therefore we can use a multinomial distribution θ_g over latent topics to express the collective topic preference of group g.

2) Based on θ_g, group g chooses a single topic z and nominates a user u with the social relations s_u. We assume that each topic z has a multinomial distribution ϕ_z^{ZU}, which presents the relevance of all users to the topic z. Therefore, after sampling a latent topic z from its topic distribution θ_g, we sample a user u according to ϕ_z^{ZU}.

3) The basis of a user in a group making a selection is the topic of the group (which attracts him/her to join the group), his/her personal preference, and his/her social selections.

We use a topic-specific multinomial distribution ϕ_z^{ZI} to present the relevance of all POIs to the topic z, a user-specific multinomial distribution ϕ_u^{UI} to capture the personal consideration of user u, and a social-specific multinomial distribution $\phi_{s_u}^{SI}$ to show the social preference over all POIs of the user u. Moreover, a ternary switch c (with a value 0, 1 or -1) is designed to decide which one accounts for the POI selection of a user. If $c = 0$, the POI selection is based on the group topic-specific distribution ϕ_z^{ZI}; if $c = 1$, the POI selection is based on the user-specific distribution ϕ_u^{UI}; otherwise, the POI selection is drawn from the social-specific distribution $\phi_{s_u}^{SI}$. Here, the ternary switch c is drawn from the user-specific multinomial distribution ϕ_u^{UC}. In summary, the complete generative process of our GSGR model is shown in Algorithm 1. Note that different users in a group will sample different POIs,

Table 1. Definitions of Key Notations

Notation	Definition
U, I, G, S	User, POI, group and social sets
K, N	Numbers of latent topics and recommendation results respectively
u_g, s_g	Members and social relation of the group g respectively
$\alpha, \beta, \eta, \sigma, \rho, \gamma$	Dirichlet prior vectors
θ_g	Distribution of topics specific to group g
ϕ_z^{ZU}	Distribution of users specific to topic z
ϕ_z^{ZI}	Distribution of POIs specific to topic z
ϕ_u^{UI}	Distribution of POIs specific to user u
$\phi_{s_u}^{SI}$	Distribution of POIs specific to social graph of user u
ϕ_u^{UC}	Distribution of three values of the ternary switch c specific to user u
$n_{g,z,\neg j}$	Number of times topic z is assigned to group g, excepting the j-th user-POI pair
$n_{z,u,\neg j}$	Number of times user u is assigned to topic z, excepting the j-th user-POI pair
$n_{z,i,\neg j}$	Number of times POI i is assigned to topic z, excepting the j-th user-POI pair
$n_{u,(0),\neg j}$	Number of times switch c is drawn for user u, excepting the j-th user-POI pair

which is in accordance with our assumption that users have their personal preferences and make different selections. Thus, what we need to do is that we first let each member in a group express his/her personal opinion on the POI selection, and then aggregate all members' opinions with different weights to get final recommendation results. It is meaningful and important that the aforementioned generative process can be applied to make group recommendation for both the groups with and without pre-defined members.

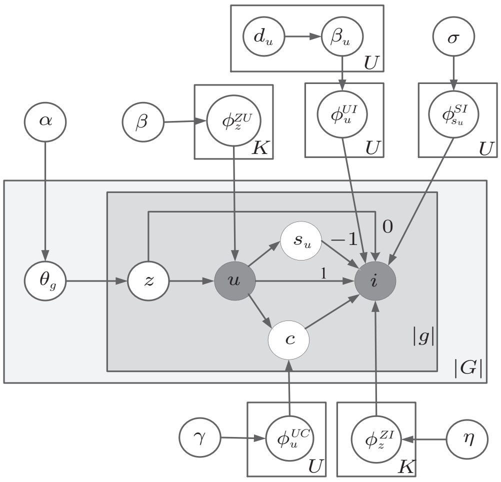

Fig.1. Graphical model of GSGR.

Algorithm 1 . Generative Process of GSGR

for each topic z_k, $k = 1, \ldots, K$ **do**
  Draw $\phi_k^{ZU} \sim Dirichlet\,(\beta)$
  Draw $\phi_k^{ZI} \sim Dirichlet\,(\eta)$
end for
for each user u_v, $v = 1, \ldots, |U|$ **do**
  Draw $\phi_v^{UI} \sim Dirichlet(\rho_v)$
  Draw $\phi_v^{UC} \sim Dirichlet(\gamma)$
  Draw $\phi_{s_u}^{UC} \sim Dirichlet(\sigma)$
end for
for each group g **do**
  Draw $\theta_g \sim Dirichilet\,(\alpha)$
  for each user-POI pair in group g **do**
    Draw $z \sim Multinomial\,(\theta_g)$
    Draw $u \sim Multinomial\,(\phi_z^{ZU})$
    Draw $c \sim Multinomial\,(\phi_u^{UC})$
    if $c = 0$ **then**
      Draw $i \sim Multinomial\,(\phi_z^{ZI})$
    end if
    if $c = 1$ **then**
      Draw $i \sim Multinomial\,(\phi_u^{UI})$
    end if
    if $c = -1$ **then**
      Draw $i \sim Multinomial\,(\phi_{s_u}^{SI})$
    end if
  end for
end for

2.3 Parameter Estimation

To learn the parameters in our GSGR model, an integrated likelihood is proposed, which contains four components and is shown as follows:

$$\begin{aligned}&P(z,u,c,i|\,\alpha,\beta,\eta,\gamma,\sigma)\\&=\int P(z\,|\theta)P(\theta\,|\alpha)\mathrm{d}\alpha\int P(u\,|z,\phi^{ZU})P(\phi^{ZU}\,|\beta)\mathrm{d}\phi^{ZU}\\&\int P(c\,|u,\phi^{UC})P(\phi^{UC}|\,\gamma)\mathrm{d}\phi^{UC}\\&\int\int\int P(i\,|u,z,s_u,c,\phi^{ZI},\phi^{UI},\phi^{SI})\\&P(\phi^{ZI}\,|\eta)P(\phi^{UI}\,|\beta)P(\phi^{SI}\,|\sigma)\mathrm{d}\phi^{ZI}\mathrm{d}\phi^{UI}\mathrm{d}\phi^{SI}. \qquad (1)\end{aligned}$$

In order to estimate the unknown parameters $\{\phi^{ZU},\phi^{ZI},\phi^{UI},\phi^{SI}\}$ in GSGR, we obtain samples from this high-dimensional distribution by employing collapsed Gibbs sampling. For ease of presentation and understanding, we utilize a user-POI pair $j = \langle u, i\rangle$ to indicate the POI i selected by a user u.

It is necessary to note that there exists a complex relationship between the latent topic variable z and the ternary switch variable c. To solve this problem, we employ a two-step Gibbs sampling procedure. In detail, we first sample topics z for all user-POI pairs, and then sample ternary switch c for all user-POI pairs. Unfortunately, in the process of Gibbs sampling, it is difficult to get a full conditional probability because of complex interdependencies between users, topics, switches, POIs and social relations. Therefore, we single out the POIs generated based on topics, personal preferences, and social preferences. Thus, we can decompose the last component of (1) into three components as follows:

$$\begin{aligned}&\int\int\int P(i\,|u,z,s_u,c,\phi^{ZI},\phi^{UI},\phi^{SI})\\&P(\phi^{ZI}\,|\eta)P(\phi^{UI}\,|\beta)P(\phi^{SI}\,|\sigma)\mathrm{d}\phi^{ZI}\mathrm{d}\phi^{UI}\mathrm{d}\phi^{SI}\\&=\underbrace{\int P(i^{(0)}\,|z,c,\phi^{ZI})P(\phi^{ZI}\,|\eta)\mathrm{d}\phi^{ZI}}_{\text{(A1)}}\\&\underbrace{\int P(i^{(1)}\,|u,c,\phi^{UI})P(\phi^{UI}\,|\beta)\mathrm{d}\phi^{UI}}_{\text{(A2)}}\\&\underbrace{\int P(i^{(-1)}\,|s_u,c,\phi^{SI})\mathrm{d}\phi^{SI}}_{\text{(A3)}}, \qquad (2)\end{aligned}$$

where $i^{(0)}$, $i^{(1)}$ and $i^{(-1)}$ are the sets of POIs sampled based on the value of the ternary switch c. In detail, the component (A1) of (2) corresponds to the switch $c = 0$, which expresses that the selection of POI is based on the group topic; the component (A2) corresponds to the switch $c = 1$, which expresses that the selection of POIs is based on the personal preference; the component (A3) corresponds to the switch $c = -1$, which expresses that the selection of POIs is based on the social selections.

The derivation of the collapsed Gibbs sampling equation for the topic-specific variable z_j and the switch-specific variable c_j for each user-POI pair j is similar to [8]. Then, we sample topic z_j according to the following posterior probability, when $c_j = 0$:

$$\begin{aligned}&P(z_j = k \,|\, z_{\neg j}, u, i^{(0)})\\ =\;& \frac{\int P(z\,|\theta)P(\theta\,|\alpha)\mathrm{d}\alpha}{\int P(z_{\neg j}\,|\theta)P(\theta\,|\alpha)\mathrm{d}\alpha} \times \\ & \frac{\int P(u\,|z,\phi^{ZU})P(\phi^{ZU}\,|\beta)\mathrm{d}\phi^{ZU}}{\int P(u\,|z_{\neg j},\phi^{ZU})P(\phi^{ZU}\,|\beta)\mathrm{d}\phi^{ZU}} \times \\ & \frac{\int P(i^{(0)}\,|z,c,\phi^{ZI})P(\phi^{ZI}\,|\eta)\mathrm{d}\phi^{ZI}}{\int P(i^{(0)}\,|z_{\neg j},c,\phi^{ZI})P(\phi^{ZI}\,|\eta)\mathrm{d}\phi^{ZI}}\\ \propto\;& \frac{n_{g_j,k,\neg j}+\alpha_k}{\sum\limits_{k^*\in Z}(n_{g_j,k^*,\neg j}+\alpha_k)} \times \frac{n_{k,u,\neg j}+\beta_u}{\sum\limits_{u^*\in U}(n_{k,u^*,\neg j}+\beta_u)} \times \\ & \frac{n_{k,i,\neg j}+\eta_i}{\sum\limits_{i^*\in I}(n_{k,i^*,\neg j}+\eta_i)}.\end{aligned}$$

If the POI of pair j is drawn based on a user's personal preference, i.e., $c_j = 1$, the probability can be obtained as follows:

$$\begin{aligned}&P(z_j = k \,|\, z_{\neg j}, u, i^{(1)})\\ \propto\;& \frac{n_{g_j,k,\neg j}+\alpha_k}{\sum\limits_{k^*\in Z}(n_{g_j,k^*,\neg j}+\alpha_k)} \times \frac{n_{k,u,\neg j}+\beta_u}{\sum\limits_{u^*\in U}(n_{k,u^*,\neg j}+\beta_u)}.\end{aligned}$$

Similarly, if the POI of j is drawn based on social preference, i.e., $c_j = -1$, the probability can be obtained as follows:

$$\begin{aligned}&P(z_j = k \,|\, z_{\neg j}, u, i^{(-1)})\\ \propto\;& \frac{n_{g_j,k,\neg j}+\alpha_k}{\sum\limits_{k^*\in Z}(n_{g_j,k^*,\neg j}+\alpha_k)} \times \frac{n_{k,u,\neg j}+\beta_u}{\sum\limits_{u^*\in U}(n_{k,u^*,\neg j}+\beta_u)}.\end{aligned}$$

After sampling topics, we draw a ternary switch c_j for each j. In the same way, we need to analyze three conditions.

$$\begin{aligned}&P(c_j = 0|c_{\neg j}, z, u, i)\\ \propto\;& \frac{n_{u,(0),\neg j}+\gamma_{(0)}}{\sum\limits_{c^*\in\{(-1),(0),(1)\}}(n_{u,c^*,\neg j}+\gamma_{c^*})} \times \\ & \frac{n_{z_j,i,\neg j}+\eta_i}{\sum\limits_{i^*\in I}(n_{z_j,i^*,\neg j}+\eta_{i^*})},\\ &P(c_j = 1|c_{\neg j}, z, u, i)\\ \propto\;& \frac{n_{u,(1),\neg j}+\gamma_1}{\sum\limits_{c^*\in\{(-1),(0),(1)\}}(n_{u,c^*,\neg j}+\gamma_{c^*})} \times \\ & \frac{n_{u,i,\neg j}+\beta_i}{\sum\limits_{i^*\in I}(n_{u,i^*,\neg j}+\beta_{i^*})},\\ &P(c_j = -1|c_{\neg j}, z, u, i)\\ \propto\;& \frac{n^{UC}_{u,(-1),\neg j}+\gamma_{(-1)}}{\sum\limits_{c^*\in\{(-1),(0),(1)\}}(n^{UC}_{u,c^*,\neg j}+\gamma_{c^*})} \times \\ & \frac{n^{SI}_{s_u,i,\neg j}+\sigma_i}{\sum\limits_{i^*\in I}(n^{SI}_{s_u,i^*,\neg j}+\sigma_{i^*})}.\end{aligned}$$

After having obtained a sufficient number of sampling iterations using the above Gibbs sampling rules, we calculate the parameters as follows:

$$\begin{aligned}&\hat{\phi}^{ZU}_{z,u} = \frac{n_{z,u}+\beta_u}{\sum\limits_{u^*\in U} n_{z,u^*}+\beta_{u^*}}, \quad \hat{\phi}^{ZI}_{z,i} = \frac{n_{z,i}+\eta_i}{\sum\limits_{i^*\in I} n_{z,i^*}+\eta_{i^*}},\\ &\hat{\phi}^{UI}_{u,i} = \frac{n_{u,i}+\rho_i}{\sum\limits_{i^*\in I} n_{u,i^*}+\rho_{i^*}}, \quad \hat{\phi}^{SI}_{s_u,i} = \frac{n_{s_u,i}+\sigma_i}{\sum\limits_{i^*\in I} n_{s_u,i^*}+\sigma_{i^*}},\\ &\hat{\phi}^{UC}_{u,c} = \frac{n_{u,c}+\gamma_c}{\sum\limits_{c^*\in\{(-1),(0),(1)\}} n_{u,c^*}+\gamma_{c^*}}.\end{aligned}$$

2.4 Recommendation

To make recommendation for a target group g, we need to learn the group-topic distribution θ_g based on the group members u_g. By performing Gibbs sampling on u_g, the distribution θ_g can be learnt as follows:

$$P(z_j = k\,|z_{\neg j}, u_{\neg j}, u_j = v) \propto \hat{\phi}^{ZU}_{k,v}(n_{g,k,\neg j}+\alpha_k).$$

Once we sample the topics for the target group, we define the recommendation score for a new POI as follows:

$$\begin{aligned}&P(i\,|u_g,\theta_g)\\ =\;& \prod_{u\in u_g}\Big(\sum_{z\in Z}(\theta_{g,z}\times\phi^{ZU}_{z,u}(\phi^{UC}_{u,(0)}\times\phi^{ZI}_{z,i}+\\ &\phi^{UC}_{u,(1)}\times\phi^{UI}_{u,i}+\phi^{UC}_{u,(-1)}\times\phi^{SI}_{s_u,i}))\Big).\end{aligned}$$

The above equation captures the following components when recommending a POI to a group: 1) each group has a topic distribution θ_g over all topics; 2) the user-specific distribution of a certain topic reflects the expertise of each user on this topic; 3) the opinion of a user to a POI may be influenced by the group topic, his/her own preference and social preference; 4) the group preference to a POI aggregates the preferences of all members.

2.5 Incorporation of Geographical Information

For POI group recommendation, geographical information is an influential factor of the behaviors of a user[10-11]. For example, users are usually willing to visit nearby locations, and the willingness to visit a POI decreases as the distance to the POI's location increases. Following [10], we use a power law distribution over the willingness of a user moving from one place to another as the distance function. The willingness of a user to visit a POI (dis km away) is defined as $w(dis) = a \times dis^{\kappa}$, where a and κ are the parameters.

Given a user u and the set of his/her historical POIs I_u, we can calculate the distance score $d(u,i)$ for each candidate POI i, and use this value for $\rho_{u,i}$, that is,

$$\rho_{u,i} = d(u,i) = p(i\,|I_u) \propto p(i) \prod_{i^* \in I_u} p(i^*\,|i), \qquad (3)$$

where $p(i^*\,|i)$ is proportional to $w(dis)$, the user's willingness to check in a POI with distance.

3 Experiments

In this section, we first describe the settings of experiments including datasets, evaluation metrics, and comparative methods. Then, we will show our experimental results to demonstrate the effectiveness of our group recommendation approach GSGR.

3.1 Experimental Settings

3.1.1 Datasets

We conduct experiments on two real-world datasets to evaluate the performance of our proposed method GSGR. The first dataset was collected from an event-based social network Plancast⑦, which is used in [12]. In Plancast, users can follow other people, and participate in various events. We treat the place of an event as a POI, which is associated with a geographical coordinate. Besides, an event is regarded as a group, and the users involved in this event are the members of this group. The second dataset[5] was collected from Whrrl⑧, an online location-based social network that helps people explore POIs. A group of users can check in POIs and share their experiences. The basic statistics of two datasets are shown in Table 2.

3.1.2 Evaluation Metrics

The performance of each method can be evaluated in terms of its capacity to find the locations of interest for each group. Following the previous work, we use two metrics to measure the performances, namely $Precision@N$ ($Pre@N$) and $Recall@N$ ($Rec@N$), where N is the number of recommended POIs. The former metric $Pre@N$ is defined as the percentage of POIs returned by the top N recommended POIs having been adopted by a group, while $Rec@N$ is defined as the percentage of POIs adopted by a group that are contained in the top N recommendations. Formally, we use $S_g(N)$ to denote the top N recommended POIs for group g, and G_g to denote the ground truth POIs for group g, then

$$Pre@N = \frac{1}{|G|}\sum_{g=1}^{|G|}\frac{|S_g\,(N) \cap G_g|}{N},$$

$$Rec@N = \frac{1}{|G|}\sum_{g=1}^{|G|}\frac{|S_g\,(N) \cap G_g|}{|G_g|},$$

where $|G|$ is the number of groups in the test set.

The above procedures just correspond to one trial. In our experiments, we conduct five independent trials.

3.1.3 Comparative Methods

We will compare our method GSGR with collaborative filtering variants (using various aggregation strategies) and probabilistic generative models as follows.

Table 2. Statistics of Datasets

	Number of Users	Number of Groups	Number of POIs	Average Group Size	Average Number of POIs of a Group	Average Number of Check-Ins of a User	Average Number of Friends of a User	Average Number of Check-Ins of a POI
Plancast	40 448	13 184	6 822	20.60	1.00	6.38	42.89	1.84
Whrrl	10 057	32 664	13 814	3.89	1.20	11.95	9.08	2.15

⑦http://plancast.com, May 2018.

⑧http://whrrl.com, April 2011.

• *Collaborative Filtering with the Averaging Strategy* (*CFA*)[13]. CFA first estimates the personal recommendation score of each group member for a candidate POI by user-based CF, and then calculates the average of these scores as the final recommendation score for the group.

• *Collaborative Filtering with the Least-Misery Strategy* (*CFL*)[14]. CFL first estimates the recommendation score of each member in a group for a candidate POI by user-based CF, and then uses the smallest score of each candidate POI as the final recommendation score for the group.

• *Collaborative Filtering with Relevance Disagreement* (*CFR*)[15]. This model estimates the recommendation score for each candidate POI based on the relevance and disagreement of a group. The relevance is calculated based on CFA or CFL, and the disagreement is calculated as the difference between the preference scores of individuals in a group.

• *Social Influence Based on Group Recommendation* (*SIG*)[6]. SIG is a topic model based approach, which assumes that when selecting items, a member in a group follows his/her friends' opinions. It aggregates the preferences of pairwise friends in the group for group recommendation, where one influences the other.

• *Personal Impact Topic Model* (*PIT*)[5]. The assumption of the PIT model is that different users in a group have different impact scores, and the user who has a larger impact score is more likely to be the representative of this group. The topic preference of the representative is regarded as the final topic preference of the group.

• *Consensus Model* (*COM*)[8]. COM is a state-of-the-art group recommendation model. When making recommendations, COM estimates the preference of a group to an item by aggregating the preferences of the group members with different weights. It is able to incorporate both users' selection history and personal considerations of content factors, such as geographic influence.

All the comparison methods are evaluated under corresponding optimal settings. For GSGR, we set fixed values for its hyperparameters, i.e., $\alpha = 50/K$, $\beta = \eta = \sigma = \gamma = 0.01$. ρ is set by following (3) introduced in Section 2.

3.2 Experimental Results

In this subsection, we will show our experimental results from different aspects, which are the average performance over five independent trials. In each run, we randomly choose 20% of group check-ins as a testing dataset to evaluate the performances of different methods. The remaining 80% of check-ins constitute a training dataset to learn the parameters in corresponding methods.

3.2.1 Overall Performance

To study the over performance under different numbers of recommendations of all methods, we fix the number of topics to be 250, i.e., $K = 250$. Our experimental results are shown in Fig.2. From Fig.2, we can see that the CF-based approaches with different aggregation strategies, i.e., CFA, CFL and CFR, do not perform well on both datasets. This is because the three methods do not take into account the difference of individuals and their interactions among group members. These methods have a common assumption that members in a group make selections independently. In addition, the performance of SIG is not satisfactory, since it only considers the interactions between pairs of friends in a group. However, the interactions among users are complex, and only several members or even none of the members in the same group are friends to one another.

It is obvious that the performances of model-based methods (SIG, PIT and COM) on both datasets are better than those of the three CF-based approaches (i.e., CFA, CFL and CFR) because of the consideration of group interactions by modeling the generative process of a group. Different from SIG, PIT and COM, we assume that different users have different impacts, and the selection of a user with a larger impact has greater influence in the group final selection. Nevertheless, PIT ignores the fact that the influence of a user is associated with a specific topic, while COM considers the topic-specific influences of users in a group and the behavior changes of users in the group. That is why COM obviously outperforms PIT on both datasets. Compared with all the state-of-the-art methods, our proposed method GSGR archives the best performance on both datasets. This is because that it considers not only user-specific influence in one group and topic-specific influence of a user in different groups, but also social relations among group members. As shown in Fig.2, it is obvious that our proposed GSGR outperforms COM, which proves that social relationships play a positive and significant role in improving the performance of group recommendation. However, unlike SIG, which only considers social influence in a group, GSGR

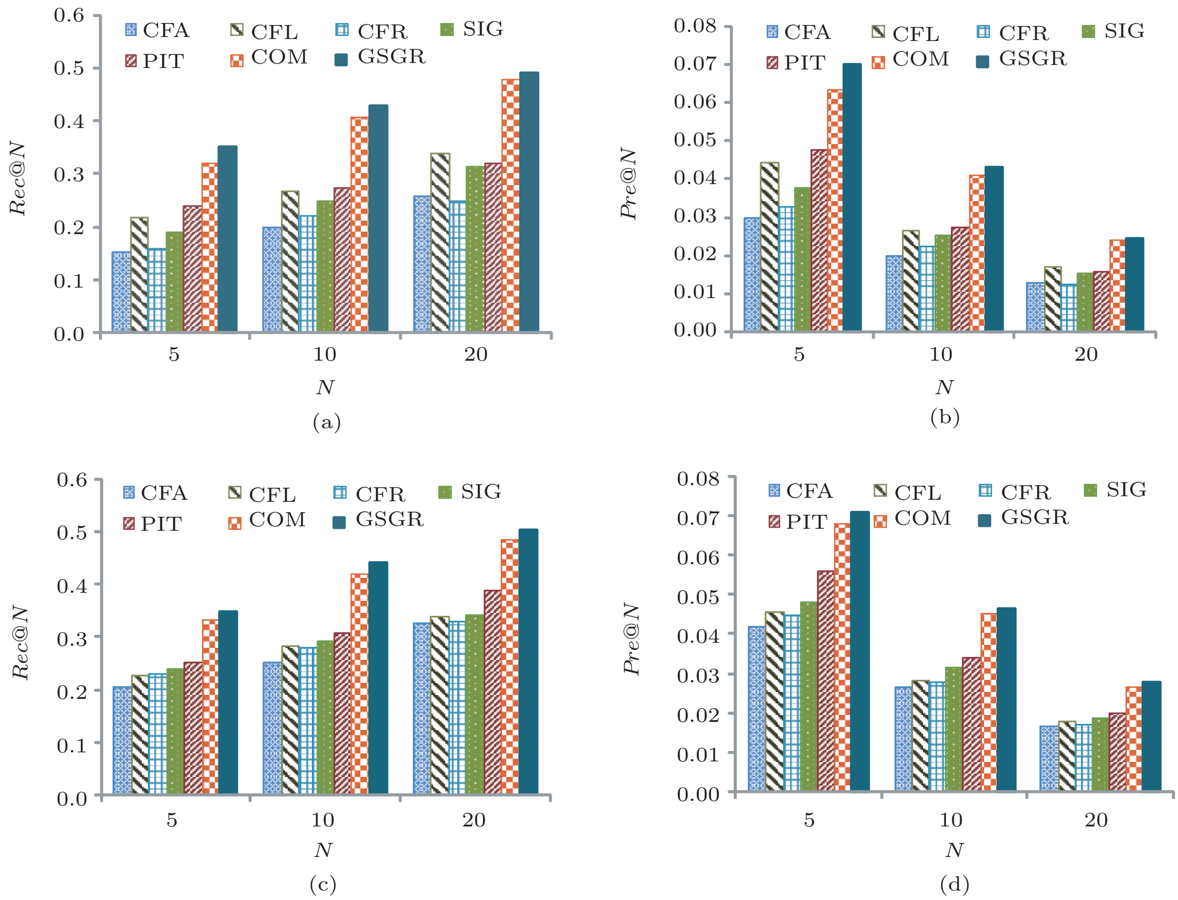

Fig.2. Performances under different numbers of recommendation results. (a) *Rec*@*N*-Plancast. (b) *Pre*@*N*-Plancast. (c) *Rec*@*N*-Whrrl. (d) *Pre*@*N*-Whrrl.

exploits more complex group interactions among group members. In addition, GSGR integrates the geographical influence for group recommendation, especially in POI recommended scenarios.

3.2.2 *Impact of Topic Size*

To investigate the impact of the number of topics, we vary the number of topics in our experiments, and experimental results are shown in Fig.3 with 10 recommendations. Fig.3 shows that the curves of precision and recall of all CF-based approaches under different numbers of topics are flat. That is, they have a constant precision and recall under different numbers of topics. This is because all CF-based approaches do not involve topics. The performances of other methods based on topic models have a common tendency: the performances first slowly increase with the increment of the number of topics, and then become stable after the number of topics reaches a certain point. Our proposed method GSGR always performs better than other comparison methods on both datasets. Compared with COM, GSGR enhances more when the group topic is less, which proves that social relationships play an important supplementary role when data is coarse-grained. Note that the average number of true POIs in the dataset Plancast is close to 1, and in this case, $Pre@N$ is proportional to $Rec@N$, since the number of recommendation results (N) is N times greater than the number of ground truth POIs. This is why Fig.3(a) is in accordance with Fig.3(b).

3.2.3 *Impact of Group Size*

To study the performance of every method for group recommendation with different group sizes, we set the number of recommendation results N and the number of topics K to 10 and 250, respectively. And groups are categorized into bins in terms of the size of each group. The performances of all methods under different sizes of groups are shown in Fig.4. From Fig.4, we can see that our proposed method GSGR performs the best on both datasets, followed by COM. Both GSGR and COM are significantly better than the other methods.

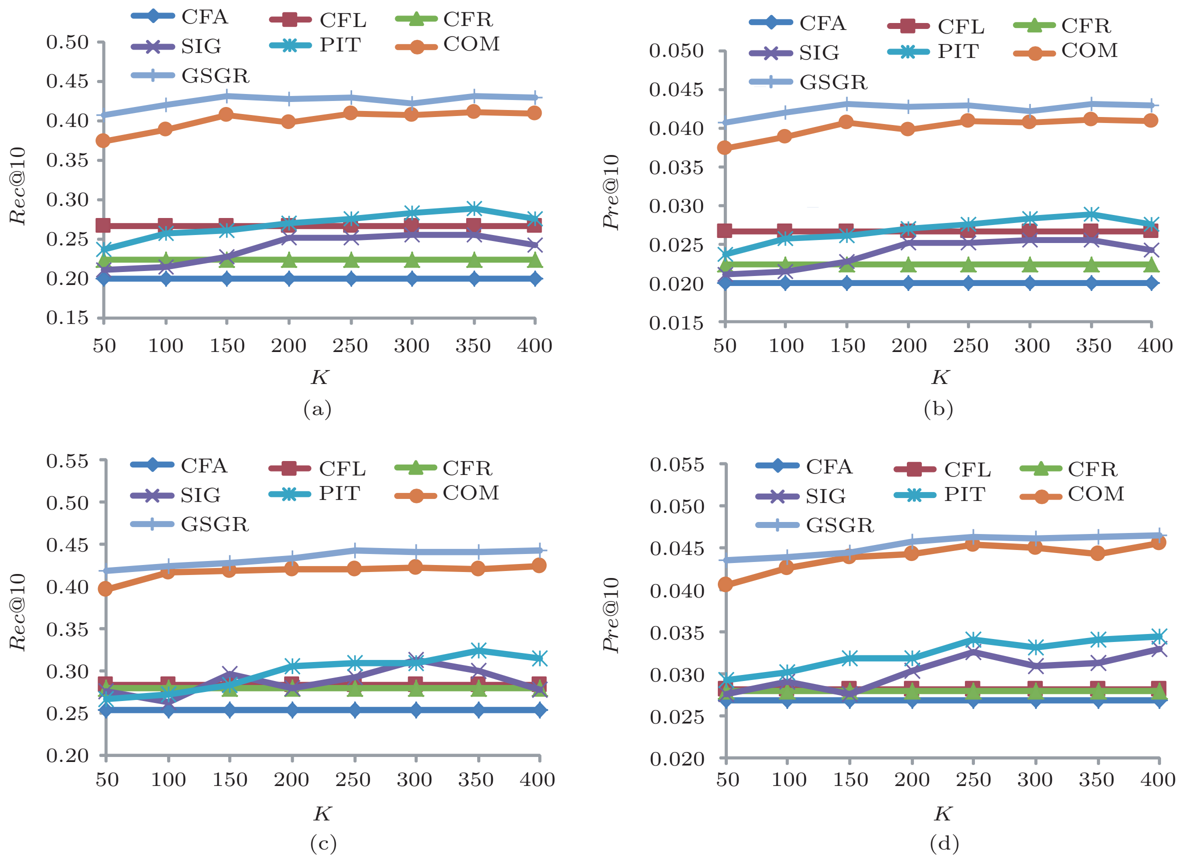

Fig.3. Performances under different numbers of topics. (a) *Rec*@10-Plancast. (b) *Pre*@10-Plancast. (c) *Rec*@10-Whrrl. (d) *Pre*@10-Whrrl.

Among all the comparison methods, the three CF-based approaches perform the worst.

4 Related Work

Different from conventional recommendation[16-23], group recommendation aims to recommend an item for a group of users. It is nature that group recommendation is more complicated than the conventional recommendation. Recently, group recommendation has attracted researchers' attention, and group recommendation techniques have been proposed for various domains, such as web/news pages[24], tourism[25], music[26], movies[14], and TV programs[27].

Specifically, two main categories of approaches have been proposed for group recommendation, i.e., preference aggregation approaches and score aggregation approaches. The preference aggregation approaches first create an aggregated profile for a group based on individual profiles of all members in the group, and then make group recommendations based on the aggregated group profile[27-28]. Nevertheless, the score aggregation approaches first produce the recommendation for each group individual respectively, and then aggregate the recommendation results of individual members into a single group recommendation[13,29]. Since score aggregation has higher flexibility and possibility than preference aggregation, it attracts more research attention. The popular and adopted methods of score aggregation mainly include the average strategy and the least misery strategy[13-14]. However, there are some limitations in both strategies. For the average strategy, the relevance of an item to different users might be diverse; therefore the final recommendation results may not be useful and meaningful for the whole group. For the least misery strategy, the recommendation score is decided by the minimum personal score of individual members[4]. In fact, the personality and the social status of group members can determine the impact of users' preferences group selections.

Recently, several model-based methods have been proposed to solve the group recommendation problem. For example, Seko *et al.*[30] assumed that the selection of a group is influenced by item genres and proposed

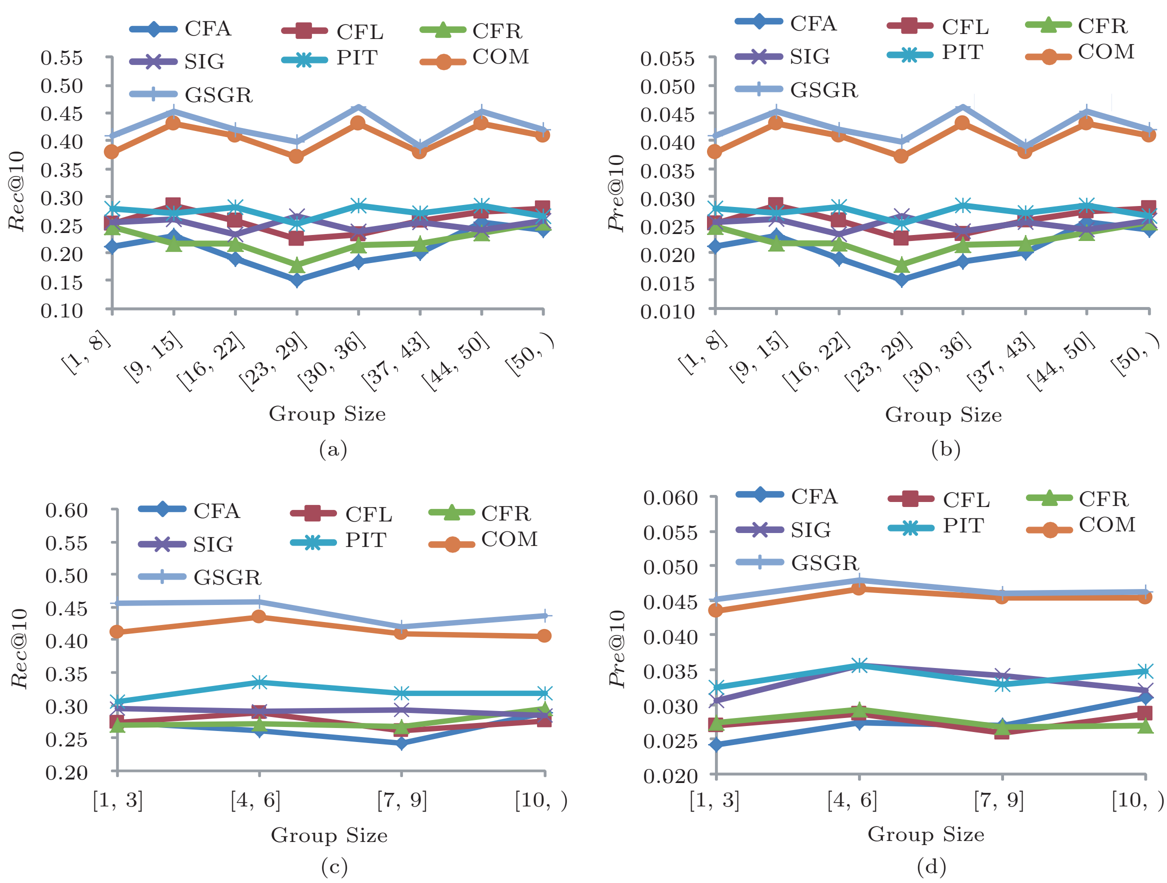

Fig.4. Performances under different sizes of groups. (a) *Rec*@10-Plancast. (b) *Pre*@10-Plancast. (c) *Rec*@10-Whrrl. (d) *Pre*@10-Whrrl.

a content-based group recommendation method. However, this method can only work for pre-defined groups. There are some existing model-based approaches that adopt similar settings as our method does. Ye *et al.*[6] considered that a user in a group activity selects an item due to two possible reasons, his/her own preference of the item and the influence from other group members. However, they assumed pairwise influences in a group, which may not stand. Liu *et al.*[5] developed a topic model approach based on an assumption that influential members are the representatives of a group. This assumption is too absolute to be true. In addition, users' influences are topic-dependent. Yuan *et al.*[8] proposed a generative model COM for group recommendation, which considers members' topic-dependent influences and members' group behaviors, and makes a trade-off among individual preferences. However, it ignores the social influence of a group, which can help improve the recommendation accuracy in group recommendation. Our method considers the social relationships in the group for group recommendation.

5 Conclusions

As location-based social networks have been growing rapidly in recent years, recommender systems need to adapt to this new trend to offer better services, particularly on group recommendation. In this paper, we studied the problem of group recommendation that aims at recommending POIs to a group of members and took different kinds of influential factors into consideration for group recommendation. We proposed a generative model, called geo-social group recommendation (GSGR) model, to model the generative process of the POI selection for a target group, which considers the influential weights of multiple users with different topics and users' selections. Besides, we proposed a new recommendation method to make group recommendations based on GSGR, which considers group topics, personal preferences and social relationships. Specifically, in our GSGR model, we introduced that different users have different topic-specific influences on making group selections. Moreover, the selection of a member in a group is affected by three factors, the group topics, his/her own preference of POIs, and his/her social relations. Our experimental results on two real-world datasets demonstrated the effectiveness of our proposed method. In the future, we would like to further extend our proposed GSGR method by integrating time information, an important factor for event recommendation and next POI recommendation to group recommendation, to improve the recommendation quality. In addition, we also plan to incorporate some other content factors (e.g., image) into our model.

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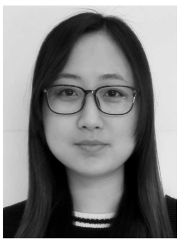
Peng-Peng Zhao is an associate professor in the School of Computer Science and Technology at Soochow University, Suzhou. He received his Ph.D. degree in computer science from Soochow University, Suzhou, in 2008. His main research interests are in the study of data integration, spatial data processing, data mining, machine learning and crowdsourcing.

Hai-Feng Zhu is a master candidate in the School of Computer Science and Technology at Soochow University, Suzhou. She got her B.S. degree in computer science from Soochow University, Suzhou, in 2016. Her main research interests are spatial data processing, recommendation system and data mining.

Yanchi Liu is currently a Ph.D. candidate in the Department of Management Science and Information Systems at Rutgers, the State University of New Jersey. He received his Ph.D. degree from the University of Science and Technology Beijing, Beijing, in 2012, and his B.S. degree from the Civil Aviation University of China, Tianjin, in 2005. His research interests include data mining, urban computing, business intelligence, and recommender systems.



Zi-Ting Zhou is a master student in the School of Computer Science and Technology at Soochow University, Suzhou. She got her B.S. degree in computer science from Soochow University, Suzhou, in 2014. Her main research interests are spatial data processing, recommendation system, and data mining.

Zhi-Xu Li is an associate professor in the School of Computer Science and Technology at Soochow University, Suzhou. He worked as a research fellow at King Abdullah University of Science and Technology, Thuwal. He received his Ph.D. degree in computer science from the University of Queensland, Brisbane, in 2013, and his B.S. and M.S. degrees in computer science from Renmin University of China, Beijing, in 2006 and 2009 respectively. His research interests include data cleaning, big data applications, information extraction and retrieval, machine learning, deep learning, knowledge graph and crowdsourcing.

Jia-Jie Xu is an associate professor at the School of Computer Science and Technology, Soochow University, Suzhou. He got his Ph.D. and M.S. degrees from the Swinburne University of Technology, Victoria, and the University of Queensland, Brisbane, in 2011 and 2006 respectively. Before joining Soochow University in 2013, he worked as an assistant professor in the Institute of Software, Chinese Academy of Sciences, Beijing. His research interests mainly include spatio-temporal database systems, big data analytics and workflow systems.

Lei Zhao is a professor in the School of Computer Science and Technology at Soochow University, Suzhou. He received his Ph.D. degree in computer science from Soochow University, Suzhou, in 2006. His research focuses on graph databases, social media analysis, query outsourcing, parallel and distributed computing. His recent research is to analyze large graph database in an effective, efficient, and secure way.

Victor S. Sheng is an assistant professor of computer science at the University of Central Arkansas, Conway, and the founding director of Data Analytics Lab (DAL). He received his M.S. degree in computer science from the University of New Brunswick, New Branswick, in 2003, and his Ph.D. degree in computer science from the Western University, Ontario, in 2007. After receiving his Ph.D. degree, he was an associate research scientist and NSERC Postdoctoral Fellow in information systems with the Stern Business School, New York University, New York. His research interests include data mining, machine learning, and related applications.