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Maximum Recommendation in Geo-social Network for Business

Jing YU, Sanggyun NA, Zongmin CUI

Abstract: Most of existing methods do not consider the maximum recommendation issue. Meanwhile, the methods also do not consider the negative influence in recommendation model. These two shortcomings limit further application of the recommendation system. In another word, the shortcomings not only decrease the recommendation effect but also increase the recommendation cost in the business. To remove the shortcomings, we propose a Maximum Recommendation scheme in Geo-social network for business (called as MRG). On the one hand, we identify *k* nodes with maximum recommendation according to the expected paid node number *k*. On the other hand, we exclude the negative node from the geo-social network. Based on the above innovation, we effectively increase the recommendation effect and decrease the company's recommendation cost. Meanwhile, MRG considers the negative influence to enhance the recommendation efficiency. Experimental results show that our scheme has better performance than most of the existing methods in the maximum recommendation field.

Keywords: business policy; geo-social network; maximum recommendation; negative influence

1 INTRODUCTION

With the development of the geo-social network technology and the geo-social media platform [1], more and more companies are using the geo-social network to promote their products [2]. Therefore, the relevant business procedures become increasingly necessary in applications [3]. Maximum recommendation uses the spread influence of word-of-mouth effect in the geo-social network. Given a geo-social network G, a positive integer k and a recommended position r, our challenge is to find the k nodes in G, where the k nodes have the maximum recommendation effects on r. This allows r's company to pay minimum cost for maximum recommendation. The recommendation influence is based on trust among the family, close friends, colleagues, and so on. This business policy has a better effect than traditional advertising (like TV and newspaper [4]). The following is a running example of our motivation.

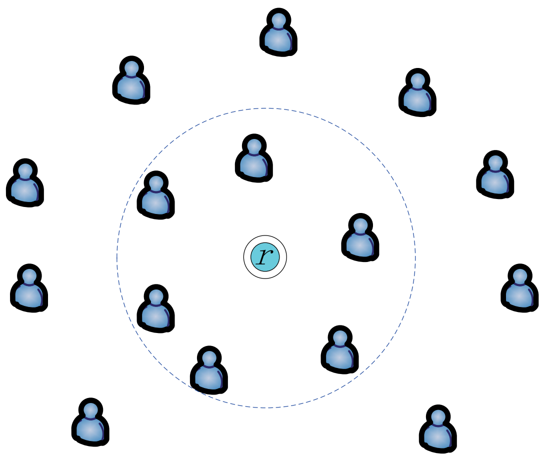


Figure 1 Motivation example

Example 1. As shown in Fig. 1, there is a newly opened restaurant "Cinky" in Beijing. The restaurant is located in position r. The company (i.e. the boss) wants to recommend his restaurant by using geo-social network (such as Facebook, WeChat, QQ, etc.). He intends to pay some recommendation costs (such as free meal voucher, home delivery, VIP discount card, etc.) to some customers who have enough influence on their friends. Consequently, these paid customers can recommend "Cinky" to their friends. In another word, the purpose of paying recommendation costs is to hope that these influential customers can disseminate information about the restaurant through geo-social networks. In addition, the recommendation is effective and efficient. The recommendation cost is limited. It is unlikely to pay recommendation costs to too many people. So he can only set a k value to pay the recommendation cost to k influential customers. Intuitively, if no other information about the customer is provided, people near the restaurant will be more likely to become a potential customer.

Most of existing methods [5-10] have two following shortcomings when they are applied in maximum recommendation scenarios.

(1) They do not consider maximum recommendation issue. They focus on maximum influence issue. The core challenge of this issue is to minimize the number of evaluated nodes (i.e. candidate nodes). In another word, they want to minimize the evaluated range. In addition, they want to maximize the influence of selected nodes in the evaluated range. However, the number of selected nodes is unrelated to the number of paid nodes. Therefore, they waste some of the company's costs in the face of maximum recommendation scenarios.

(2) They do not consider negative influence. For example, "Cinky"'s company provides free meal vouchers to customers. However, some customers do not feel good after eating. In this case, these customers may not only not recommend this restaurant to their friends, but also discourage their friends to spend on "Cinky". Therefore, it is necessary to add the negative influence to the maximum recommendation model. However, the negative influence is not taken into account in existing methods.

Therefore, to remove the above shortcomings, we propose a Maximum Recommendation scheme in Geo-social network for business, called MRG. MRG focuses on maximum recommendation issue. MRG not only decreases company's recommendation costs but also increases recommendation effects. In addition, MRG considers the negative influence to enhance the efficiency of the maximum recommendation. Experimental results show that our scheme has better performance than most of existing methods in the maximum recommendation scenarios. Our contributions are summarized as follows.

(1) We propose a new maximum recommendation model. According to the expected paid node number k, MRG identifies k nodes with maximum recommendation. Thus, we can save the company's recommendation costs and enhance the recommendation efficiency.

(2) We add the negative influence in the maximum recommendation model. Once we identify the negative node, we will exclude the negative node from the geo-social network. Consequently, the negative node cannot further influence the maximum recommendation model. Through removing the negative influence out of the geo-social network, we increase the recommendation effect.

The remainder of this paper is organized as follows. Section 2 discusses the related works. Section 3 shows our maximum recommendation model. Section 4 illustrates the experiment results. Finally, Section 5 concludes the paper.

2 RELATED WORKS

2.1 Maximum Recommendation

Shambour et al. [11] propose IMCCF algorithm. The algorithm can obtain the highest predictive accuracy and maximum recommendation coverage. Thus, IMCCF has a higher efficiency than the benchmark algorithm and reduces the effect of sparsity problem. Gephart et al. [12] consider the maximum recommendation calorie intake for an active individual to be 3200. Chavasit et al. [13] believe that the maximum recommendation proportion of fat in the energy distribution of macro-nutrient is 30%.

These works are different from our researches. Our maximum recommendation considers how to help companies to maximize the recommendation of their products. In another word, we want to minimize the recommendation cost with good recommendation effect. As far as we know, the maximum recommendation is put forward by us firstly.

2.2 Maximum Influence

The challenge of Maximum Influence (MI) issue is to select a set of nodes (called seed set) from a social network [6]. MI wants to maximize the number of nodes affected by this seed set (called influence spread) [14]. MI algorithm is a key problem in social influence analysis [15]. MI plays an important role in business policy and information spread [10]. There are a large number of references about the MI issue [6, 14, 15]. The classic MI model uses independent cascade and linear threshold techniques [16, 10].

Tong, etc. [10] study the strategy of adaptively selecting seed node. They present the concept of adaptively seeding strategy. Han et al. [14] propose a framework which minimizes the possible differences between the observed topology and the actual network. Based on the framework, they propose an algorithm to reduce the computational overhead by using the divide-and-conquer strategy. Cui et al. [15] analyze the reason of low efficiency of greedy algorithm. They propose a descending order search evolutionary algorithm (DDSE) which eliminates the time-consuming simulation of greedy algorithm. Therefore DDSE has higher efficiency than greedy algorithm in MI. Samadi et al. [16] achieve favorable optimality gaps of SASP (Seed Activation Scheduling Problem) by observing the pro-health discussion forum. Li et al. [10] expand the key challenge and research direction of MI boundary.

The above works focus on maximum influence, rather than maximum recommendation. Therefore, when they are applied in maximum recommendation scenarios, they may waste some company's recommendation costs. However, we focus on the maximum recommendation. Thus, our algorithm effectively decreases the company's recommendation costs.

2.3 Geo-social Network

With the development of geographical location equipment, geographical factors play an increasingly important role in the analysis of social networks. The TR tree index structure [7] is designed for users with themed and geographic preferences for promotional products. Each tree node stores the user's themed and geographic preferences. By traversing the TR tree in depth precedence, Su et al. [7] can find the target user effectively. Zhong et al. [8] propose an efficient location sampling method based on heuristic anchor selection and facility allocation technique. They improve the online and offline efficiency of DAIM (Distance-aware influence maximization).

The most relevant work to us is introduced by Wang et al. [5, 9]. They propose three algorithms PRI, PRII and PRIII. We use PRI to represent the related core idea of these three algorithms in this paper. Based on a greedy framework, the approximate ratio of PRI is $1-1/e$. Wang et al. [5, 9] build an offline index to meet online query requirements. They attempt to find a subset that maximizes the influence spread in the query area. When performing a location recommendation, these methods can determine an appropriate query scope, which is very important.

However, the above methods do not consider the negative influence, which results in the fact that the recommendation efficiency is not efficient enough. To remove this shortcoming, we consider the negative influence in maximum recommendation scenarios. As far as we know, the negative influence is put forward by us firstly. In this case, we exclude the negative node from the geo-social network. Thus, the negative node cannot further damage the maximum recommendation model. That is, we remove the negative influence out of the geo-social network to enhance the recommendation efficiency.

3 MAXIMUM RECOMMENDATION MODEL

To accurately and formally define our problem, we provide the following definitions of MRG.

Definition 1. (Geo-social network). We define a geo-social network as a directed graph $G = (C, E)$, where C denotes a set of customer nodes, and E denotes a set of directed edges (relationships between customers). Each node $c \in C$ has a geographic location (x, y), where x and y represent the longitude and latitude of c respectively. The weight function is shown in Eq. (1).

$$f{:}C{\times}r{\rightarrow}F \tag{1}$$

In Eq. (1), C denotes a set of customer nodes, r is a recommended location, and F denotes a set of weights. Eq. (1) indicates that each node is given a weight $f \in F$ corresponding to a given position r in the two-dimensional space.

Given an edge $< c_i, c_j > \in E$, we define that c_i points to c_j. It can also be understood that c_i can influence c_j.

For example, customer c_i thinks that the food in r is delicious. Thus c_i recommends r to his friends. In this case, c_i's influence is positive. We define c_i as a positive node. However, customer c_j feels not good, too expensive, etc. Thus, c_j criticizes r and discourages his friends from r. In this case, c_j's influence is negative. We define c_j as a negative node.

In general, a customer's feeling about the restaurant will not be changed casually. For example, it is almost impossible that customer A recommends r to customer B and discourages customer D from r synchronously. In addition, once customer A has a bad feeling about the restaurant, it is difficult to change his feeling. Therefore, it is necessary to exclude any negative nodes from the geo-social network.

The company wants to pay k customers for recommending his location. We define the paid customer as **cost-node** (labeled by **red color** in our maximum recommendation model). Our core idea is to identify the k cost-nodes that have the maximum recommendations.

Definition 2. (Recommendation value). Given a geo-social network G=(C, E), we assume that each edge $< c_i, c_j > \in E$ has an independent recommendation value $h < c_i, c_j > \in [-1,1]$. Positive values indicate positive influences, negative values indicate negative influences, and 0 means no influence (that is, if $h < c_i, c_j >= 0$, edge$< c_i, c_j >$ does not need to be painted in our maximum recommendation model).

Obviously, if c_i and c_j are good friends, the recommendation value could be 1 or -1. If c_i and c_j are just friends, the recommendation value may be just 0.1. If c_i just sends r to WeChat, friends circle, etc., the recommendation value may even be 0.

As discussed in Section1, people near the recommended location r will be more likely to become potential customers. Therefore, weight $f(c,r)$ is inversely proportional to the distance between c and r. In another word, closer between c and r leads bigger $f(c,r)$. Thus, we paint a set of recommendation rings, which take r as the center in our maximum recommendation model. Nodes in inner ring have bigger weights. Nodes in outer ring have smaller weights.

Fig. 1 is a maximum recommended model in timestamp 0. In this case, the company has not identified any cost-node for recommending location r. Our maximum recommendation model is from inside to outside. In another word, our algorithm gradually spreads from highest-weight nodes to lowest-weight nodes.

Example 2. To clearly illustrate our maximum recommendation model, we provide an example in timestamp 1 shown in Fig. 2.

In Fig. 2, customers $\{c_1, c_2, c_3\}$ in Ring 1 have the biggest weight 3. Customers $\{c_{11}, c_{12}, \ldots, c_{20}\}$ in Ring 3 have the smallest weight 1. Customers $\{c_4, \ldots, c_{10}\}$ in Ring 2 have the middleweight 2. Customer c_1 has negative influence on the other customers, i.e. $\{h < c_1, c_6 >= -1.0, h < c_1, c_{10} >= -0.4, h < c_1, c_{13} >= -0.7\}$. Customers c_2 and c_3 have the positive influences in Fig. 2.

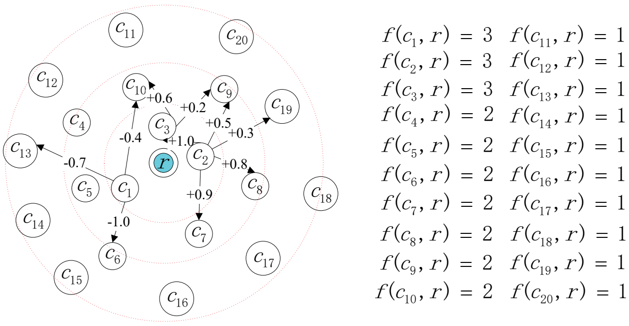


Figure 2 Themaximum recommendation model in timestamp 1

Definition 3. (Weighted recommendation). Given a geo-social network G=(C, E) and a recommended location r in the two-dimensional space. The weighted recommendation of node $c \in C$ on the other nodes in G is expressed as $I_r(c)$. The calculation process of $I_r(c)$ is shown in Eq. (2).

$$I_r(c) = \sum_{(<c,c_i>\in E)} h(c, c_i) \times f(c, r) \tag{2}$$

In Eq. (2), $f(c,r)$ is c's weight corresponding to r. $h(c, c_i)$ is c's recommendation value corresponding to c_i.

Before giving the core algorithm of this paper, we give a sub-algorithm shown in Algorithm 1: WR. Algorithm 1 is used to calculate the weighted recommendation of any one node c. Algorithm 1 takes a geo-social network G=(C, E) and a customer node c as input. Meanwhile, Algorithm 1 takes c's weighted recommendation $\boldsymbol{I_r}(c)$ as output.

Algorithm 1: WR	
Input: G, c Output: $\boldsymbol{I_r}(c)$	
1:	$\boldsymbol{I_r(c)}$:= **0**
2:	**For all** $< c, \boldsymbol{c_i} > \in E$ **do**
3:	**If** $\boldsymbol{h(c, c_i)}$**<0 then**
4:	Exclude$c$ from **G**
5:	Exit
6:	**Else**
7:	$\boldsymbol{I_r(c)}$:=$\boldsymbol{I_r(c)}$+ $\boldsymbol{h}(c, \boldsymbol{c_i}) \times \boldsymbol{f}(c, \boldsymbol{r})$
8:	**End if**
9:	**End for**
10:	**Return**($\mathrm{I_r}$(c))

In Algorithm 1, if node c has negative influence on the other nodes in G, we exclude c from the geo-social network (Steps 3-5). Otherwise, we calculate the weighted recommendation of c (Steps 6-7).

Giv threshold $\boldsymbol{\delta}$, we think that only when $\boldsymbol{I_r(c)} > \boldsymbol{\delta}$, customer c has enough influence to be considered as a candidate cost-node.

Based on Algorithm 1, our core idea is shown in Algorithm 2MAXR. Algorithm 2 takes a geo-social network G= (C, E), the expected paid cost-node number k, a threshold δ and the recommended location r as input. Meanwhile, Algorithm 2 takes k cost-nodes E_k with maximum recommendations as output.

In Algorithm 2, if the weighted recommendation $I_r(c)$ is bigger than the threshold δ, it is indicated that c is an influential node. Thus, we take c as a candidate cost-node (Steps 5-7). After finding the k candidate cost-nodes E_k (Steps 3-15), Algorithm 2 compares E_k with the remaining nodes to identify the k cost-nodes with maximum recommendations (Steps 17-27). If there exists a node c_j out of E_k that has bigger weighted recommendation than $c \in E_k$ which has minimum weighted recommendation in E_k, we exchange the two nodes (Steps 19-23). Following the same rule, we filter each remaining node to identify the k cost-nodes with maximum recommendations.

Algorithm 2: MAXR	
Input: G, k, δ, r Output: E_k	
1:	p:=1 // Recommended ring number
2:	E_k:= ∅
3:	**While** k>0 **do**
4:	**For all**c ∈Ring p **do**
5:	$\boldsymbol{I_r(c)}$:= $WR(\boldsymbol{G}$, c)//Calling Algorithm 1
6:	**If** $\boldsymbol{I_r}(c) > \delta$ **then**
7:	$\boldsymbol{E_k}$:=$\boldsymbol{E_k} \cup c$
8:	k--
9:	**If** k<1 **then**
10:	exit
11:	**End if**
12:	**End if**
13:	**End for**
14:	p++
15:	**End while**
16:	p--
17:	**While**p is in the recommended range**do**
18:	**For all**c ∈Ring $p \cap \boldsymbol{I_r}(c) \neq 0$ **do**
19:	$\boldsymbol{I_r(c)}$:= $WR(\boldsymbol{G}$, c)
20:	Select a node $c_j$from $E_k$with minimumweighted recommendation $\boldsymbol{I_r}(\boldsymbol{c_j})$
21:	**If** $\boldsymbol{I_r}(\boldsymbol{c_j}) < \boldsymbol{I_r}(\boldsymbol{c})$**then**
22:	Remove c_j from $\boldsymbol{E_k}$
23:	$\boldsymbol{E_k}$:=$\boldsymbol{E_k} \cup c$
24:	**End if**
25:	**End for**
26:	p++
27:	**End while**
28:	**Return**($\boldsymbol{E_k}$)

Example 3. The maximum recommendation model in Fig. 2 runs Algorithm 2. The running results are shown in Figs. 3 and 4.

First, we determine whether Ring 1's customers $\{c_1, c_2, c_3\}$ arethe candidate cost-node with enough influence.

(1) c_1. We call Algorithm 1 $WR(G, c_1)$. $h < c_1, c_6 >= -1.0$, thus we exclude c_1 from G.

(2) c_2 . $I_r(c_2) = h(c_2, c_3) \times f(c_2, r) + h(c_2, c_7) \times f(c_2, r) + h(c_2, c_8) \times f(c_2, r) + h(c_2, c_9) \times f(c_2, r) + h(c_2, c_{19}) \times f(c_2, r)$ =(+1.0) × 3+(+0.9) × 3+(+0.8) × 3+(+0.5) × 3+(+0.3) × 3=10.5. We assume δ=2 and k=3. Obviously,$I_r(c_2) > \delta$. Therefore, c_2 is an influential node. We take c_2 as a candidate cost-node.

Similarly, $I_r(c_3)$=2.4 also meets the condition. In this case, the maximum recommended model is shown in Fig. 3.

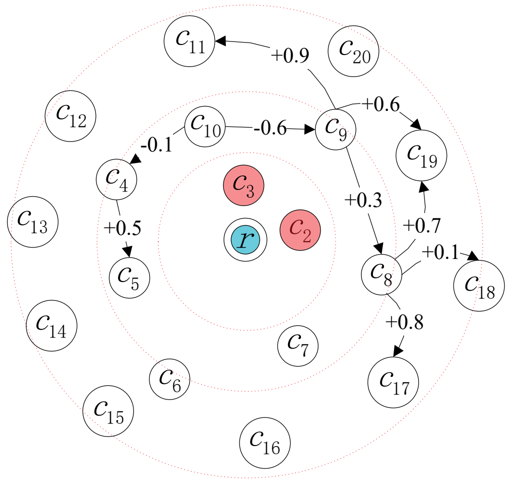


Figure 3 The maximum recommendation model in timestamp 2

After judging Ring 1, we begin to judge Ring 2 (p=2). After judgment, we find that c_{10} needs to be excluded from G. $I_r(c_4)$=1 $< \delta$, thus c_4 cannot be taken as a candidate cost-node. $I_r(c_9)$=3.6>$I_r(c_8)$=3.2>$I_r(c_3)$. As k=3, we can only identify 3 cost-nodes with maximum recommendations. Therefore, we remove c_3 from E_k and add c_8 and c_9 into E_k. That is, after judging Ring 2, the candidate cost-node set E_3={c_2, c_8, c_9} shown in Fig. 4.

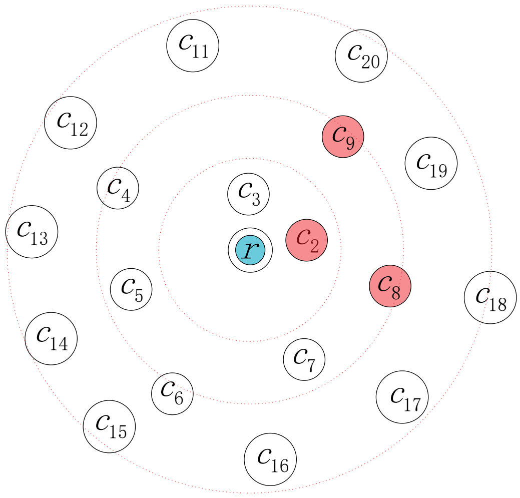


Figure 4 The maximum recommendation model in timestamp 3

In the above examples, the maximum number of recommended rings is 3. That is, p=3. When p=4, p is out of the recommended range. In this case, the algorithm ends. Following the same rule, the next running process is no longer described in this paper.

Let p be the maximum number of recommended ring, n be the maximum number of nodes in a recommended ring, and k be the expected paid node number. By analyzing our algorithms, the computing cost of the MRG is $O(k \times p \times n)$. PRI [5, 9] focuses maximum influence and does not consider negative influence. Consequently, PRI requires computing redundant nodes. Therefore, the computing cost of PRI is $O(k \times \log_2^k \times p \times n \times \log_2^n)$. Obviously, our approach is more efficient than PRI.

4 EXPERIMENTS

The PRI [5, 9] is the most classic and closely related approach to our scheme. Therefore, we compare our scheme, MRG, to PRI to verify the maximum recommendation effect with high efficiency.

4.1 Experiment Setup

We use Visual C++6.0 to achieve all experiments. The experiment uses a computer with 3.4 GHz dual-core CPU and 32 GB memory. Following the general settings of the traditional maximization system, we assume that the index is stored in memory to support real-time response [8].

Each recommendation value $h < c_i, c_j >$ is randomly selected in interval $[-1,\ 1]$. The weight $f(c, r)$ is determined by the maximum number p of recommended ring. For example, if the maximum number of recommended ring is 5, i.e. p=5. The weight of nodes in Ring 1 is 5 and the weight of nodes in Ring 5 is 1, and so on. The recommended position r is fixed. The position and number of other nodes are random. Threshold δ is the average of all positive weights. The number of negative nodes does not exceed 10% in the geo-social network. When PRI is compared with MRG, they are always based on the same dataset.

In our system, the cost-node (i.e. expected paid node) number k is from 10 to 50. The maximum number of nodes in a recommended ring n is from 1T to 5T (T represents thousand). The maximum number of recommended ring p is from 2 to 10. The specific parameters are shown in Tab. 1.

Table 1 Experimental parameters

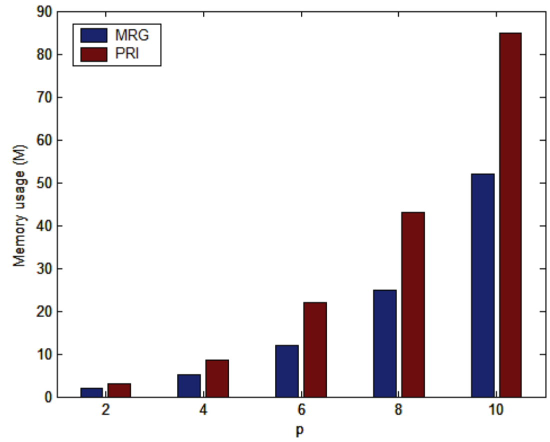
Illustration	Character	Range of changes
Cost-node number	k	10, 20, 30, 40, 50
Maximum number of nodes in a recommended ring	n	1T, 2T, 3T, 4T, 5T
Maximum number of recommended ring	p	2, 4, 6, 8, 10

4.2 Memory Consumption

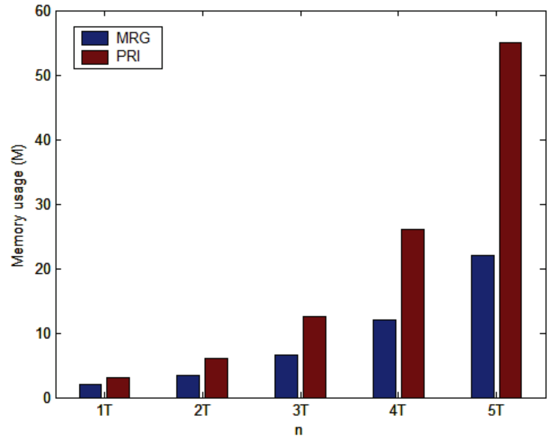
Our maximum recommended model is actually an index. As the index is resident in memory, the first experiment tests the memory consumption of MRG and PRI. There are two parameters that affect memory consumption: the maximum number of recommended ring p and the maximum number of nodes in a recommended ring n. Consequently, our experimental results are shown in Fig. 5, where the Y-axes represent memory consumption whose unit is M. The X-axes of Figs. 5(a) and 5(b) represent the maximum number of recommended ring p and the maximum number of nodes in a recommended ring n respectively.

(1) Fig. 5(a). When the maximum number of recommended ring p grows from 2 to 10, the memory consumption of our scheme MRG grows slower than PRI. PRI consumes 1.65 times as much memory as MRG. While recommended range increases, the negative node increases too. Increasing negative nodes consume much memory. We exclude negative node from the geo-social network. PRI does not consider negative nodes. As a result, MRG consumes significantly less memory than PRI.

(2) Fig. 5(b). When the maximum number of nodes in a recommended ring n grows from 1T to 5T, PRI consumes dramatically increasing memories. However, MRG consumes only slow increasing memories. PRI focuses on maximum influence. We focus on maximum recommendation. In maximum recommendation scenarios, we remove some redundant nodes from memory. Therefore, we have less memory consumption than PRI.



(a) Maximum number of recommended ring



(b) Maximum number of nodes in a recommended ring

Figure 5 The comparison of memory consumption

4.3 Index Building

Index building is primarily affected by the maximum number of recommended ring p and the maximum number of nodes in a recommended ring n. Consequently, our experimental results are shown in Fig. 6, where the X-axis represents the maximum number of recommended ring p, Y-axis represents the maximum number of nodes in a recommended ring n whose unit is T (Thousand) and

Z-axis represents the building time whose unit is ms (millisecond).

When p=2 and n=1T, the building time of PRI is almost 1.35-fold that of MRG. However, when p=10 and n=5T, the building time of PRI is almost 1.66-fold that of MRG. That is, when p and n grow synchronously, PRI's building time is growing faster than MRG. This is because that we remove all negative nodes from MRG’s index. Therefore, our index is simpler than PRI. MRG consumes less time during the building process. Meanwhile, our performance significantly increases with p and n growing.

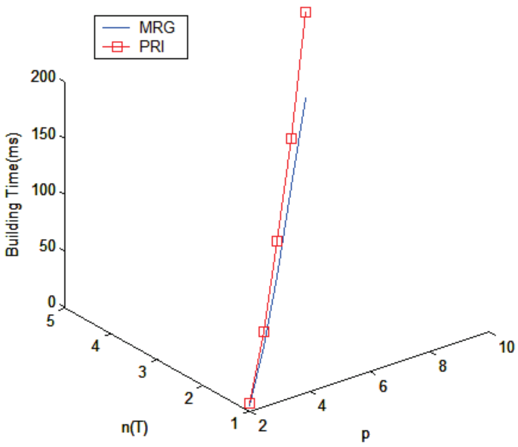


Figure 6 Comparison of index building

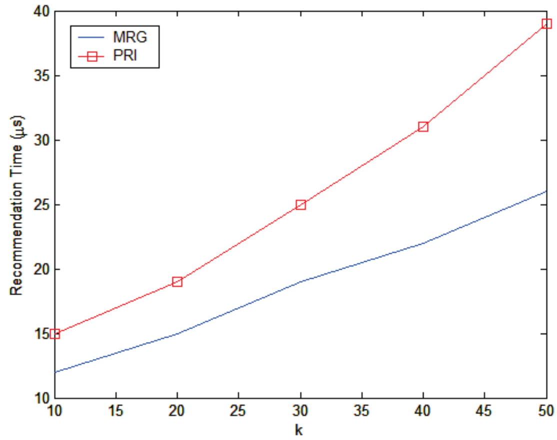
4.4 Recommendation Efficiency

The recommendation efficiency determines the query speed of identifying the k cost-nodes. Therefore, the recommendation efficiency is a key performance of maximum recommendation systems. The recommendation efficiency is mainly affected by the cost-node number k, the maximum number of recommended ring p and the maximum number of nodes in a recommended ring n. The experiment results are shown in Fig. 7, where the Y-axes denote the recommendation time, whose unit is μs (microsecond). Meanwhile, the X-axes denote the cost-node number, the maximum number of recommended ring, and the maximum number of nodes in a recommended ring, respectively.

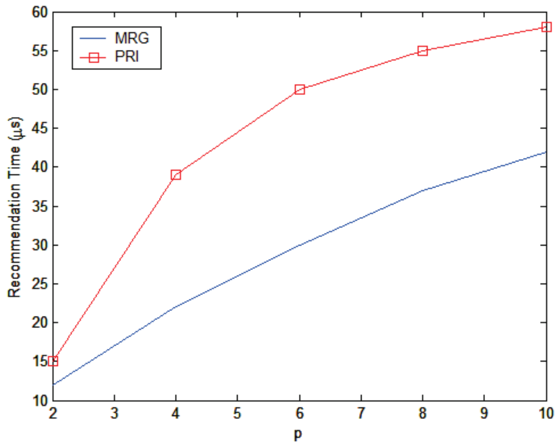
(1) Fig. 7(a). In the process of cost-node number k increasing from 10 to 50, the recommendation time of PRI is growing significantly faster than that of MRG. PRI focuses on maximum influence. We focus on maximum recommendation. Thus, PRI is more severely affected when the cost-node number changes. Meanwhile, the computational complexity of PRI based on threshold is higher than that of MRG. Therefore, the performance of MRG is significantly higher than that of PRI.

(2) Fig. 7(b). When p increases from 2 to 10, PRI determines which recommended rings have the maximum influence. Thus, the impact of p growth on PRI decreases significantly when p increases to a certain extent. In this case, PRI does not calculate the nodes out of the maximum influence range. Therefore, PRI’s recommendation time is growing slower than MRG.

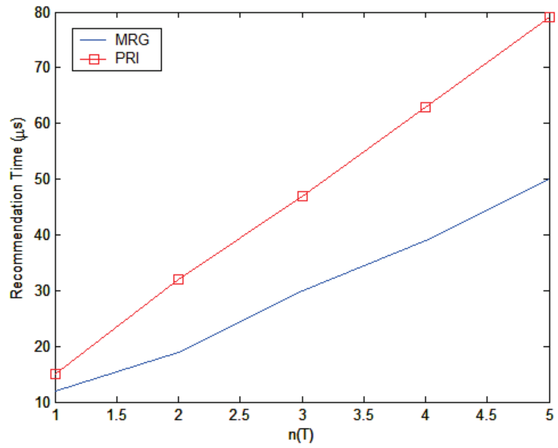
(3) Fig. 7(c). When n increases from 1T to 5T, PRI does not consider negative nodes. Thus, although PRI’s recommendation time is growing linearly, the growth rate is greater than MRG. MRG considers negative nodes. Each recommended ring has some nodes that do not have to be calculated. MRG effectively reduce the computational complexity. Thus, MRG is more efficient than PRI.



(a) Cost-node number



(b) Maximum number of recommended ring



(c) Maximum number of nodes in a recommended ring

Figure 7 Comparison of recommendation efficiency

4.5 Recommendation Effect

A node’s weighted recommendation is the actual effect of the node on other nodes. Thus, we take the sum of weighted recommendations of all cost nodes as the recommendation effect. This is the most key performance for the entire system. Obviously, the recommendation effect is mainly affected by cost-node number k. That is, we test the recommendation effect of both methods in the case where the company pays the same costs. The experiment results are shown in Fig. 8, where the *X*-axis represents the cost-node number *k* and the *Y*-axis represents the recommendation effect.

As MRG considers negative nodes, the recommendation effect increases significantly as the cost-node number grows. PRI do not consider the negative nodes. This results in that the recommendation model may be negatively influenced. The growth of recommendation effect is not obvious as MRG in Fig. 8. Meanwhile, in the maximum influence model of PRI, some nodes have a lower influence than the maximum recommendation threshold. Perhaps these nodes have sufficient influences, but do not have sufficient recommendation effects. This results in many omitted nodes, which may be good enough for maximum recommendation. Therefore, in the maximum recommendation scenarios, MRG obviously has a better recommendation effect than PRI.

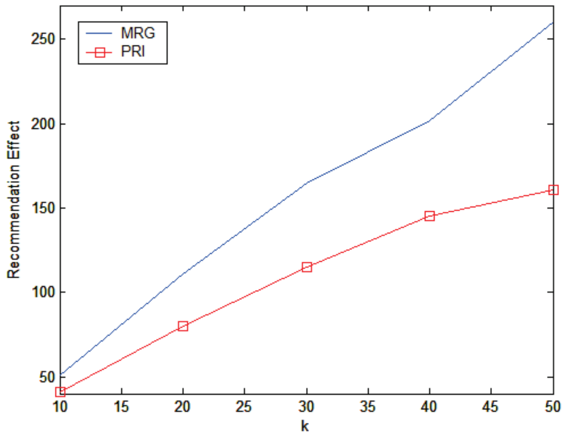


Figure 8 Comparison of recommendation effect

By analyzing all experimental results, we can draw the following conclusions.

(1) The comprehensive performance of our scheme is significantly better than that of most of related existing methods. We reduce the company's recommendation cost, enhance the recommendation efficiency and improve the recommendation result.

(2) Facing with a variety of parameters, MRG all have excellent performance. Thus, MRG can be widely applied in a variety of scenarios, such as geo-big data, geo-distributed computing, geo-e-commerce, geo-mobile platform and so on.

(3) We exclude all negative nodes from the geo-social network. If the geo-social network is updated, the negative node does not exist. It is not necessary to compute the negative node. Therefore, we enhance the update efficiency.

5 CONCLUSIONS

By analyzing the shortcomings in the existing methods, this paper puts forward a scheme to maximize the recommendation in the business-oriented geo-social network. We take the negative node into account and remove the negative influences from the recommendation system. At the same time, aiming at the problem of maximization recommendation, an efficient recommendation model is proposed. Our model can effectively reduce the company's recommendation cost and improve the recommendation effect. Meanwhile, we enhance the efficiency of updating geo-social network. Consequently, we improve the usability of the maximum recommendation system.

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Contact information:

Jing YU, PhD candidate
School of Information Science and Technology, Jiujiang University,
No. 551, Qianjin East Road, Jiujiang, Jiangxi 332005, China
College of Business Administration, Wonkwang University,
No. 460, Iksandae-ro, Iksan, Jeonbuk 54538, Korea
E-mail: yujingellemma@gmail.com

Sanggyun NA, Prof., PhD
(Corresponding author)
College of Business Administration, Wonkwang University,
No. 460, Iksandae-ro, Iksan, Jeonbuk 54538, Korea
E-mail: nsghy@wku.ac.kr

Zongmin CUI, Assoc. Prof., PhD
School of Information Science and Technology, Jiujiang University,
No. 551, Qianjin East Road, Jiujiang, Jiangxi 332005, China
E-mail: cuizm01@gmail.com