Fusing Dual Geo-Social Relationship and Deep Implicit Interest Topic Similarity for POI Recommendation

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Abstract

Nowadays, POI recommendation has been a hot research area, which are almost based on incomplete social relationships and geographical influence. However, few research simultaneously focuses on the refined social relationship and the user deep implicit topic similarity under a reachable region. Under this background, a novel Dual Geo-Social Relationship and Deep Implicit Interest Topic Similarity mining under a Reachable Region for POI Recommendation (DDR-PR) is proposed. DDR-PR first adopts kernel density estimation to compute the user checking-in reachable area. Under the reachable area, the combined relationship similarity based on the link relationship and common check-in social relationship is computed out. Then, the deep implicit interest topic similarity between users is mined out adopting the proposed topic model RTAU-TCP. We formulate the combined relationship similarity and implicit interest topic similarity as two regularization terms to incorporate into matrix factorization, which can recommend new POIs for a user under his or her reachable area. Extensive experiments prove the superiority of DDR-PR.

Keywords: POI recommendation, Geo-Social Relationship, Topic similarity

1 Introduction

In recent years, Web location acquisition technologies have developed rapidly, and some location-based social networks (LBSNs) such as Foursquare, Yelp, Gowalla have attracted many users [1-3]. Under these LBSNs, users usually check-in many POIs and leave their experiences on visiting these POIs. Currently, there has been much research on POI recommendation [4-8], among which, some studies find that people always visit POIs where they have reached before [6-7]. Therefore, POIs checked in by users generally present spatial clusters. Some other outstanding researches [9-10] focused on utilizing friendships to promote the recommendation performance, which mostly regarded relationships between the socially connected users as regularization terms to constrain matrix factorization. However, only taking into account explicit social information for recommendation may not be effective.

Aiming at the above-mentioned problems, we are thus motivated to simultaneously mine social link relationships, the common check-in relationships, and the deep implicit topic similarity under a reachable region in LBSNs. We intuitively demonstrate the significance of social relationships and the implicit interest topic similar relationship in Figure 1. In the direct social layer, there exists some users who have geo-social correlation through link relationships. Moreover, social relationships are based on the common check-in behavior of users, such as the users included in two eclipses. There are the common check-in behaviors between users u_1 and u_4, who both checked-in POI P_4. There are also the common check-in behaviors between users u_2 and u_3, who both checked-in POI P_2. In the areas where the target user arrived, the raised dual geo-social relationships recommend new POIs visited by these two kinds of friends, but the target user does not visit. In the lower part of Figure 1, it can be observed that there are some visited POIs and left some reviews. It not only demonstrates that some users have similar visiting behavior under a specific geographical area, but also implies that user reviews, user tags, and POI tags can also deeply reflect the implicit topic similarity between users. Hence, we mine the dual geo-social relationship and deep implicit topic similarity for POI recommendation. The main researches are as follows.

(1) Personalize location geographical influence is computed using the kernel density estimation, because there is not any assumption about the formation of distance distribution.

(2) We propose the dual geo-social relationship mining and deep implicit interest topic mining under a reachable region. The link relationship between users is calculated using SimRank similarity and the common check-in social relationship under a reachable region is computed adopting Cosine similarity. The deep implicit interest topic similarity between users is identified using our proposed RTAU-TCP model.

(3) Extensive experiments have been made to validate the proposed DDR-PR model, which show that our method is much better than the baselines on precision rate, recall rate, MAP and NDCG.

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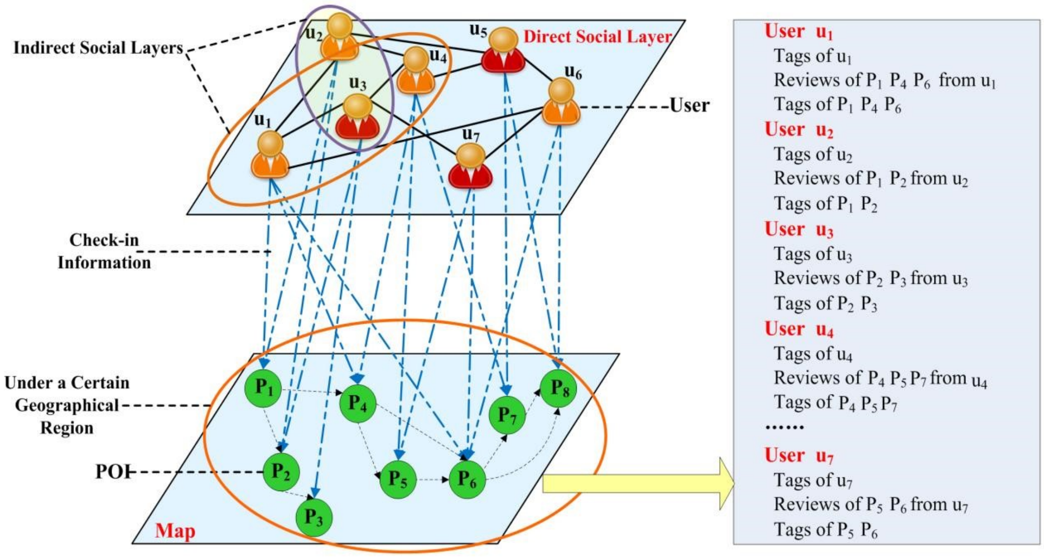


Figure 1. Influence of dual geo-social relationship and deep implicit interest topic similarity on POI recommendation

2 Related Work

Tobler's first Geography Law elaborated that "Everything is related to everything else, but near things are more related than distant things." [11]. For LBSNs, Tobler's first Geography Law shows users always enjoy reaching the nearby locations, relative to the distant place. Some studies show that the location geographical proximity greatly affects the user checking-in [12-13]. Liu et al. [12] observed that users tend to visit places close to their homes or workplace, and enjoy exploring the nearby locations of the visited. And they suppose that the distance between two locations reached by the same user obeys power-law distribution. Cheng et al. [13] proposed that users tend to visit locations around the most popular POIs and the check-in locations present a Gaussian distribution.

About social recommendation, Berjani et al. [14] utilized user-location check-in data to realize a regularized matrix factorization-based POI recommendation. Ye et al. [15] mined the common visited places of friends and designed a friend-based POI recommendation. Li et al. [1] developed a Social Friend Probabilistic Matrix Factorization (SFPMF) method. Specifically, in social friend space, users are assumed to repeat the historical POIs of their friends. In addition, user-generated contents play a very important role in POI recommendation, which can improve the check-in data sparsity to some extent in LBSNS. For example, Ye et al. [16] utilized the explicit pattern of individual location and the implicit correlation between similar positions to propose a semantic annotation with classified labels for POI recommendation. Liu et al. [6] put forward a POI recommendation method based on topic and location awareness, named TL-PMF.

From the above mentioned researches, it can be observed that user check-in behaviors are obviously influenced by geographical influence, social relationships, and user-generated contents. However, there are still not many researches which simultaneously and deeply consider link relationships between users, social relationships based on the common check-in POIs, and the detailed user generated contents. Therefore, we simultaneously incorporate link relationships between users, social relationships based on the common check-in POIs, and the detailed user-generated contents into matrix factorization and propose the DDR-PR (a new Dual Geo-Social Relationship and Deep Implicit Interest Topic Similarity mining under a Reachable Region for POI Recommendation) model.

3 Preliminaries

LBSNs contain rich information, we assume that $U=\{u_1,u_2,\ldots,u_M\}$ is use set and $P=\{p_1,p_2,\ldots,p_N\}$ denotes POI set, respectively. If user u_i has visited POI p_j, $r_{ij}\neq 0$, otherwise $r_{ij}=0$. C is check-in set, which includes the check-in activities in LBSNs. $c_{ij}=k$ denotes that user u_i has visited POI p_j for k times. F is the friend set and F_i denotes all friend set of user u_i. Then, the problem of POI recommendation is transformed into predicting the unvisited POIs in P and recommending them to user u_i [2]. To better depict the proposed DDR-PR model, five core concepts are defined as follows.

Definition 1. **POI:** POI is a uniquely identified specific event or a venue, the identifier and location are two attributes of POI, p represents a POI identifier and l expresses its corresponding location attribute according to the coordinates.

Definition 2. **Check-in activity:** User check-in activity is expressed using a four tuple *(u, p, l_v, W_v)*, in which, user u checks-in POI p at l, among which, l_v and Wv respectively denote the longitude and latitude coordinates of location l.

Definition 3. Check-in matrix: Given the historical user check-in data on POIs in an LBSN, we define a check-in matrix $R_{|u|\times|l|}$, in which each entry $R_{u\times l}$ represents the check-in frequency of user $u\in U$ on location $l\in L$. Most entries in R are zero, because users only visit a very small proportion of POIs in the LBSN.

Definition 4. Social link matrix: Given the social links between users from an LBSN, we construct a social link matrix $S_{|U|\times|U|}$, in which if there exists a social link between two different users u_i and u_j, $S_{u_i,u_j}=1$, otherwise $S_{u_i,u_j}=0$.

Definition 5. Topic distribution: Suppose a word set to denote *W*, the topic is a multinational distribution on word set *W*. Specifically, topic distribution of reviews on POIs from user u denotes $z_{u,r}=\{z_{u,r,w}, w\in W\}$, in which each $z_{u,r,w}$ represents the word w distribution generated by topics of user u reviewing on POIs.

4 Methodology

In this section, we first calculate the probability that user checks-in at a new place. Second, the dual Geo-social relationships are mined. Third, the deep implicit interest topic similarity is obtained using the proposed RTAU-TCP (All the Reviews and user Tags published by A User, all Tags from the Correlating POIs). Finally, we fuse the dual Geo-social relationships and deep implicit interest topic similarity to produce DDR-PR.

4.1 Probability of User Checking-in a New Location

Personalized geographical influence from locations plays a very important role in user checking-in. Specifically, we model the personalized distance distribution between any two locations visited by the user. Observation on geographical influence shows that users tend to visit nearby places. The willingness of visiting a place decays with the increase of distance from the current location. Hence, we use kernel density estimation of distance to deduce the user willingness moving from one place to another. The distance between locations is computed as follows:

$$d_{xo}=distance(l_x,l_o)\ \ \forall\, l_o\in L_i \tag{1}$$

in which, d_{xo} denotes the distance between l_x and l_o, l_x and l_o belong to the checked-in POI set L_i . We use d_{xo} to deduce $\hat{f}(d_{xo})$ based on Eq.(2):

$$\hat{f}(d_{xo})=\frac{1}{|D|h}\sum_{d'\in D}K\left(\frac{d_{xo}-d'}{h}\right) \tag{2}$$

in which, *D* denotes the distance sample for a certain user, which is drawn from some distribution with a density *f*. $K(\cdot)$ represents kernel function and *h* is bandwidth, denoting a path distance attenuation threshold. We apply the most popular normal kernel:

$$K(x)=\frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}} \tag{3}$$

h is denoted as follows:

$$h=\left(\frac{4\hat{\sigma}^5}{3n}\right)^{1/5}\approx 1.06\hat{\sigma}n^{-1/5} \tag{4}$$

in which, $\hat{\sigma}$ is the sample standard deviation of the sample, *n* represents the number of POIs, the path distance is less than or equal to *h* between the target user and these POIs.

After a distance distribution is deduced, based on Eq.(2), the probability of user u_i visiting a new location l_x is calculated given the visited locations L_i by user u_i as follows:

$$p(l_x|L_i)=\frac{1}{n}\sum_{i=1}^{n}f(\hat{d}_{xo}) \tag{5}$$

4.2 Dual Geo-social Relationship Mining

As Figure 1 shows, in social networks, there always exists the link relationships between users. Hence, we compute the user link relationship similarity using SimRank similarity $sim(u_i,u_t)_{link}$, the indirect social circles include the users who have the common check-ins and show that there may be an implicit social relationship between users in these circles. That is to say, if u_i and u_t both visited POI P_l, they may share similar interest. We utilize Cosine similarity $sim(u_i,u_t)_{CC}$ to evaluate the implicit check-in behavior similarity between u_i and u_t, Simultaneously, considering the above mentioned link relationship similarity and social relationship similarity between users, we get the general similarity in a unified way:

$$sim(u_i,u_t)_{LinkCC}=\lambda\cdot sim(u_i,u_t)_{link}+(1-\lambda)\cdot sim(u_i,u_t)_{cc} \tag{6}$$

The latent relationships between users have been found very useful in recommending new POIs for users, which provide a way for getting acquainted with users. We fuse the latent user relationships and their personalized mobility patterns in Eq.(5) to compute the probability that the target user u_i would check-in at POI l_x. The similarity between u_i and u_t is derived based on the social friendship and residence distance as follows.

$$sim(u_i,u_t)_{GLinkCC}=P(l_x|L_i)\cdot sim(u_i,u_t)_{LinkCC} \tag{7}$$

It is noted that Eq.(7) combines user preference, social relationships and geographical influence into POI recommendation. To sum up, the dual geo-social relationship mining algorithm is described below in pseudo code.

4.3 Modeling Deep Implicit Interest Topic Similarity

Analyzing the reviews on POIS from users in LBSNS, we find that user reviews are short and reviews generally do not contain any explicit POI information. The existing topic models are not adaptable for latent topic mining on sparse reviews of POIs. Hence, a novel topic model focusing on all Reviews and user Tags published by A User, and all Tags from the Correlating POIs (RTAU-TCP) is proposed. The graphical representation of RTAU-TCP is shown in Figure 2.

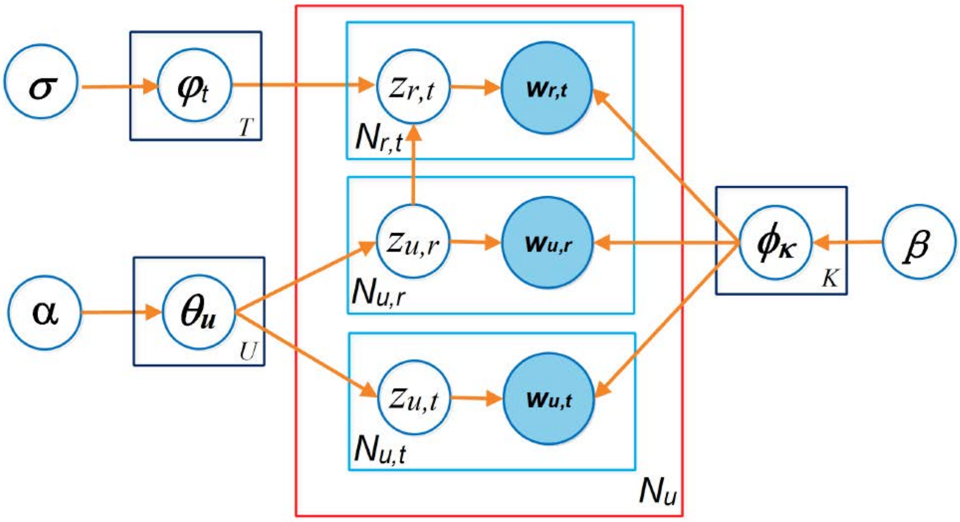


Figure 2. A graphical representation of RTAU-TCP

The preliminary problem of RTAU-TCP is to deduce user interest topic weights. All reviews and all tags from the same user and their corresponding POI tags are combined to produce a document. Assume that there are T topics, each topic is denoted by a multinomial distribution over words in the dictionary, and each user has some specific interests with the probability distributions over T topics. When a user would like to publish a review, this user selects a interesting topic. The topic words of the review are produced based on the topic word distribution. Each user review also corresponds to some tags, and these tag words reflect the topics than reviews. Combining all reviews and all tags from the same user, their relative POI tags can better embody the user interest topics. About the main idea of RTAU-TCP, please refer to our research [10], the interest topic similarity between u_i and u_r is shown in Eq.(8):

$$sim(u_i, u_r)_{topic} = 1 - D_{JS}(u_i, u_r) \quad \textbf{(8)}$$

Then, the implicit interest similarity between users u_i and u_r under a reachable region is computed as follows.

$$sim(u_i, u_r)_{GTopic} = P(l_x | L_i) \cdot sim(u_i, u_r)_{topic} \quad \textbf{(9)}$$

4.4 The Unified DDR-PR Model

DDR-PR model combines the dual geo-social relationships and the deep implicit interest topic similarity based on matrix factorization. We adopt $U_i \in R^{m\times k}$ to denote the user feature matrix of u_i, and $P_j \in R^{k\times n}$ to represent POI feature matrix of p_j, k denotes the number of latent factors and $k << (m,n)$. Main idea of DDR-PR is shown as the following Eq.(10). In Eq.(10), the objective function is defined considering influence from the dual geo-social relationships and deep implicit topic similarity, as shown below.

$$\begin{aligned}\min F(U,P,S,SC) = &\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij} - U_i^T P_j)^2 \\ &+ \frac{\mu}{2}\sum_{i=1}^{m}\sum_{u_t\in S} sim(u_i,u_t)_{GLinkCC} \|U_i - U_t\|_F^2 \\ &+ \frac{\gamma}{2}\sum_{i=1}^{m}\sum_{u_c\in SC} sim(u_i,u_c)_{GTopic} \|U_i - U_c\|_F^2 \\ &+ \frac{\alpha}{2}(\|U\|_F^2 + \|P\|_F^2 + \|S\|_F^2 + \|SC\|_F^2)\end{aligned} \quad \textbf{(10)}$$

in which, P_j is POI set visited by user $U_{i,}$, I_{ij} is an indicator function, S represents the user set having the dual social relationship with the target user $U_{i,}$ SC represents the user set having similar implicit interest topic with the target user. $sim(u_i, u_t)_{GlinkCC}$ denotes the similarity between u_i and u_t based on dual geo-social relationships. $sim(u_i, u_c)_{GTopic}$ is the similarity between u_i and u_r based on the implicit interest topic similarity under a certain geographical region. Parameter μ is used to balance the effect of the dual Geo-social relationship mining, and parameter γ balances the mutual influence of the implicit interest topic relationship mining. Stochastic Gradient Descent (SGD) is adopted to optimize the objective function.

5 Experimental Results and Discussion

5.1 Experimental Datasets and Experimental Setting

In our research work, we adopt the existed two real-world datasets crawled from Foursquare [2] and Yelp [13], respectively. The checking-in records in the datasets contain users' ID, users' check-in locations, users' social relationships, and location details, etc. The datasets are listed in Table 1.

Table 1. Information of the two datasets

Statistics	Foursquare	Yelp
Num. of users	29,117	70,817
Num. of POIs	364,259	15,585
Num. of check-ins	785,249	335,022
Num. of reviews	3,417	3,456
Num. of social links	89,693	151,516
User-location matrix density	0.0074%	0.0304%

In DDR-PR, several parameters affect its performance. First, all reviews from foursquare dataset and yelp dataset are preprocessed using natural language processing technology, then the meaningless stop words, lowercase conversion, symbolization and abbreviations are cut out, representative words are distilled from each review, and all preprocessed reviews are elaborated into one document. Interest topics of each user are extracted out by utilizing the proposed RTAU-TCP, and hyper topic modeling parameters are set to $\alpha = 50/K$, $\sigma = 50/K$ and $\beta = 0.01$. According to the features of the datasets, user interest topic K on Foursquare dataset is set to 40 and the user interest topic K on Yelp dataset is set to 60. Second, through experimental verification, the tuning parameter λ is set to 0.6, the dimension of latent matrix factor K is chosen from $\{10, 20, 30, 40, 50, 60, 70, 80\}$ and 30 is the best value. In addition, the acceptable parameter combination μ=0.05 and γ=0.05 are used for the two datasets, and the latent factors are obtained by SGD algorithm with initial learning rate ξ=0.001 and ρ is also set to 0.001.

Each dataset is randomly divided into the training set and the test set, the 80% of checking-in data are used to be the training set and the remaining data are regarded as the test set. In our experiments, we utilize the training set to learn the recommendation model, and the learned recommendation model is further used to predict the test data.

5.2. Baseline Comparative Methods

In order to prove the personalized ranking quality of DDR-PR, we compare it with the following state-of-the-art recommendation models.

(1) BasicMF [17]. BasicMF is a kind of traditional matrix factorization model, which only takes into account the impact of user interest on recommendation, without focusing on other auxiliary factors such as geographical and social information.

(2) PMFSR [18]. PMFSR is a kind of probabilistic matrix factorization model based on social regularization. Through incorporating social regularization, over-fitting problems of traditional probabilistic matrix factorization are alleviated to some extent and the accuracy of POI recommendation is improved.

(3) GeoCF [3]. GeoCF is a user-based collaborative filtering recommendation model, and it adopts the geographical influence factor to improve the recommendation performance.

(4) GeoMF [7]. GeoMF adopts weighted matrix factorization for recommendation, which introduces the spatial clustering phenomenon to solve the challenge from matrix sparsity.

(5) TL-PMF [6]. TL-PMF proposes a topic and location aware POI recommendation by using associated textual and context information. It exploits LDA model to learn user interest topics and and obtains the interest POIs through mining textual information. TL-PMF considers the extent to user interest matching POI according to topic distribution and the word-of-mouth POI opinions.

(6) ATCF [19]. ATCF is a kind of collaborative filtering method based on the author topic model, which facilitates comprehensive POI recommendations for users. ATCF extracts user interest topics from the geo-tag constrained textual description using the author topic model instead of only from the GPS locations.

(7) Algorithm 1: GLinkCC-PR. GLinkCC-PR is from our proposed DDR-PR. When recommending POIs, GLinkCC-PR only focuses on the dual social relationships containing the link relationships between users and the common checking-in social relationships under a reachable region.

(8) Algorithm 2: GTopic-PR. GTopic-PR is a special case of our proposed DDR-PR. When recommending POIs, GTopic-PR based on matrix factorization only takes into account the external influence from implicit interest topic similarity under a reachable region.

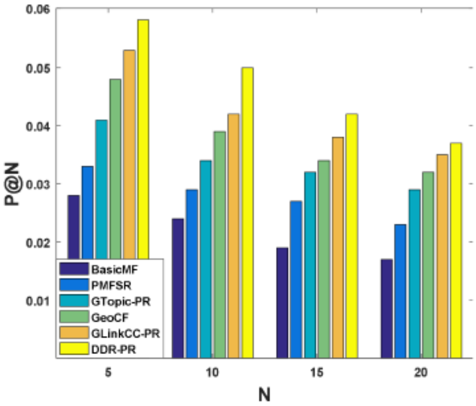
5.3 Methods Comparison on P@N, R@N, MAP@N and NDCG@N

(1) Research questions and evaluation metrics

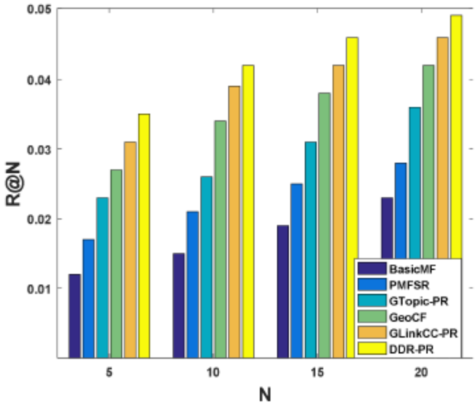
Predicting a POI recommendation list for the target user is our research central task. Four metrics Precision Rate *P@N*, Recall Rate *R@N*, *MAP* and *NDCG@N* are adopted to evaluate the performance of POI recommendation in a real scenario. And we further compare our DDR-PR to the above baseline methods on the Foursquare and Yelp datasets by using these four evaluation metrics.

(2) Experimental comparison and analysis

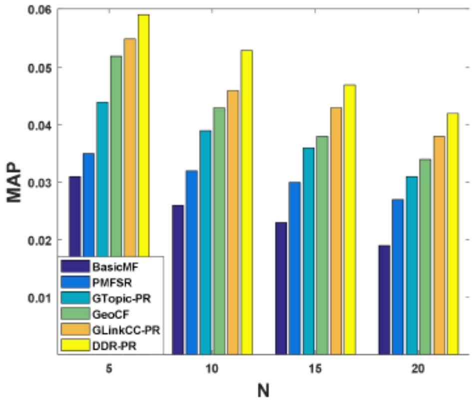
Comparative experiments are made as follows: we first study how *P@N*, *R@N*, *MAP@N* and *NDCG@N* are optimal with the change of the recommendation list size, that is top-N. N are set to 5, 10, 15 and 20, respectively. And the dimension of latent factor K is set to 30. Comparison results are shown in Figure 3 and Table 2 on the Foursquare dataset, Figure 4 and Table 3 are comparison results on the Yelp dataset. From Figure 3, it is found that DDR-PR consistently outperforms previous methods for different N. Specifically, it can be observed that PMFSR outperforms BasicMF and GeoCF further improves upon PMFSR. Moreover, our DDR-PR is obviously better than GeoCF. To better prove the advantages of DDR-PR, Table 2 presents the absolute improvements of DDR-PR compared to the best baseline method GeoCF. In Table 2, *P@N* has a 28.21% relative improvement, R@N has a 23.53% relative improvement. A 23.26% improvement for MAP and a 31.43% improvement for NDCG@N are also observed. Figure 4 and Table 3 show similar comparative results on Yelp dataset, which are similar to those presented in Figure 3 and Table 2 on the Foursquare dataset. The proposed DDR-PR has the best performance on P@N, R@N, MAP@N and NDCG@N.



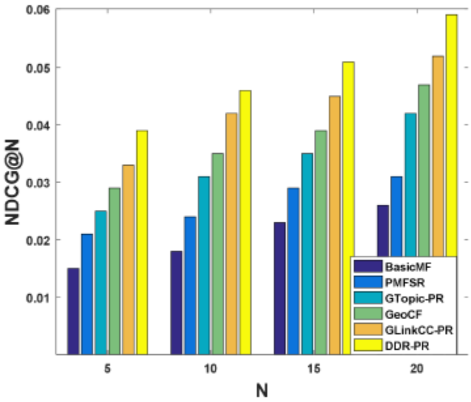
(a) Variation of *P@N* with *N*



(b) Variation of *R@N* with *N*



(c) Variation of *MAP@N* with *N*

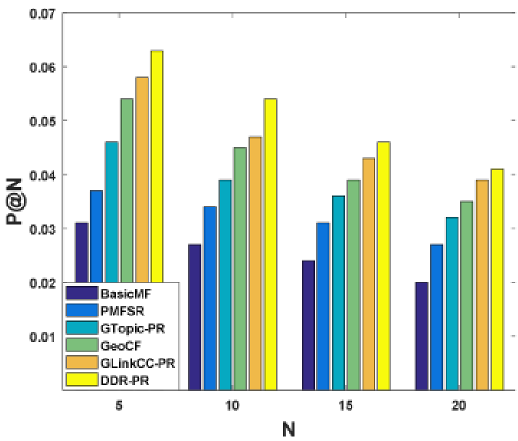


(d) Variation of *NDCG@N* with *N*

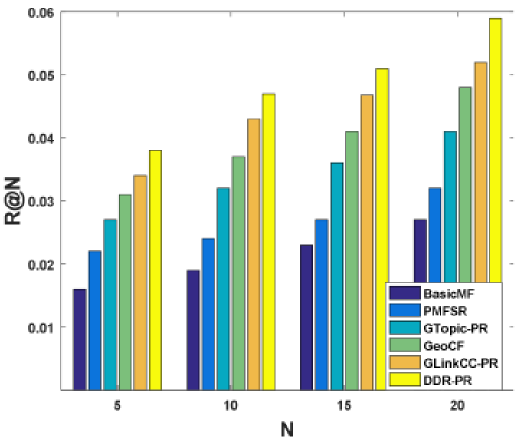
Figure 3. Top-N recommendation comparison on Foursquare dataset

Table 2. Absolute improvements of DDR-PR compared to the best baseline GeoCF on Foursquare dataset

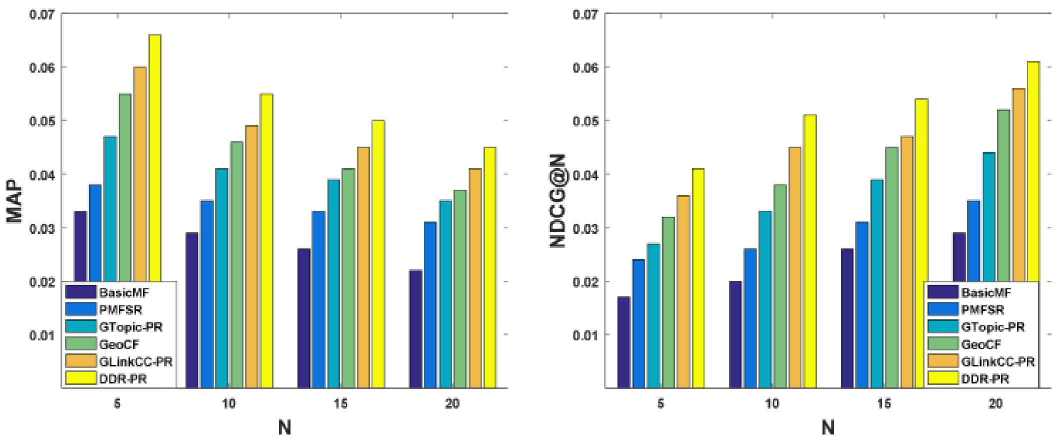
Metric	GeoCF	DDR-PR	Relative improvement
P@10	0.039	0.050	28.21% ↑
R@10	0.034	0.042	23.53% ↑
MAP@10	0.043	0.053	23.26% ↑
NDCG@10	0.035	0.046	31.43% ↑



(a) Variation of *P@N* with *N*



(b) Variation of *R@N* with *N*



(c) Variation of *MAP@N* with *N*　　(d) Variation of *NDCG@N* with *N*

Figure 4. Top-N recommendation comparison on Yelp dataset

Table 3. Absolute improvements of DDR-PR compared to the best baseline GeoCF on Yelp dataset

Metric	GeoCF	DDR-PR	Relative improvement
P@10	0.045	0.054	20% ↑
R@10	0.037	0.047	27.03% ↑
MAP@10	0.046	0.055	19.57% ↑
NDCG@10	0.038	0.051	34.22% ↑

From the above experimental comparison, it can be found that, when the tuning parameter λ is set to 0.6, the proportion setting of the link-based social relationships and the common checking-in behavior social relationships between users is very rational, our proposed DDR-PR show better performance. And it is also very reasonable that the dimension of latent factor K is set to 30, which not only strengthens the representation ability of latent factors, but also ensures that only a few number of latent factors affect user preferences and characterize the POI feature. In addition, experimental results show that when we consider the dual Geo-social relationships and deep implicit interest topic similarity under a certain geographical region, the performance of the proposed DDR-PR gets improved. To sum up, DDR-PR obviously outperforms all other baselines, which shows the advantage of DDR-PR.

6 Conclusion and Future Work

In this paper, a novel POI recommendation model DDR-PR based on the dual Geo-social relationship and deep implicit interest topic similarity under a reachable region is put forward. Its innovative ideas are the fusion of dual Geo-social relationships and deep implicit interest topic similarity mining. From the comparative experimental results, we can observe that the proposed DDR-PR outperforms other baselines. This is due to the fact that DDR-PR is a synthetic algorithm, and the proposed two deep potential geo-social relationships are from the user reachable area.

Several interesting directions need continuously to be explored. First, DDR-PR only considers the deep potential social relationship under a certain geographical region, however, user check-in behavior also vary with time. we would exploit time influence factor for POI recommendation. Second, sentiments contained in reviews contribute to precisely recommend POIs to users. Hence, analyzing sentiments contained in the reviews for POI recommendation is something worth looking forward to.

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