POINT-OF-INTEREST RECOMMENDATION FOR LOCATION PROMOTION IN LOCATION-BASED SOCIAL NETWORKS

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***Abstract:* With the wide application of location-based social networks (LBSNs), point-of-interest (POI) recommendation has become one of the major services in LBSNs. The behaviors of users in LBSNs are mainly checking in POIs, and these checkingin behaviors are influenced by user's behavior habits and his/her friends. In social networks, social influence is often used to help businesses to attract more users. Each target user has a different influence on different POI in social networks. This paper selects the list of POIs with the greatest influence for recommending users. Our goals are to satisfy the target user's service need, and simultaneously to promote businesses' locations (POIs). This paper defines a POI recommendation problem for location promotion. Additionally, we use submodular properties to solve the optimization problem. At last, this paper conducted a comprehensive performance evaluation for our method using two real LBSN datasets. Experimental results show that our proposed method achieves significantly superior POI recommendations comparing with other state-of-the-art recommendation approaches in terms of location promotion.**

***Index Terms:* Location-based social networks; location promotion; POI recommendation; social influence**

I. INTRODUCTION

With the rapid development of the mobile internet, locationbased social networks (LBSNs) have become a new type of social network, for example, Foursquare, Gowalla, and Jiepang. Recently, many researchers have been engaged in location-aware services. In LBSNs, users can post comments on locations or activities, upload photos, and share check-in locations in which users are interested with friends. These locations are called points-of-interest (POIs). Currently, POI recommendation has become one of main location-aware services in LBSNs. POI recommendation approaches mostly involve recommending users with some locations in which users may be interested based on users' characters, preferences, and behaviorial habits. In view of POIs, POIs (e.g.restaurants, hotel, markets) have to explore checking-in records to attract more users to visit; more users (e.g., friends of users that checked in these POIs) will be influenced to check in these locations. In this paper, we regard the influence on the business as a maximization location promotion problem. The essential goals of recommendation system are to satisfy users' service demands and merchants' advertising needs. We formulate the problem as a POI recommendation problem for location promotion, in which, given a target region and the POI set in this region, a constant *K*, the

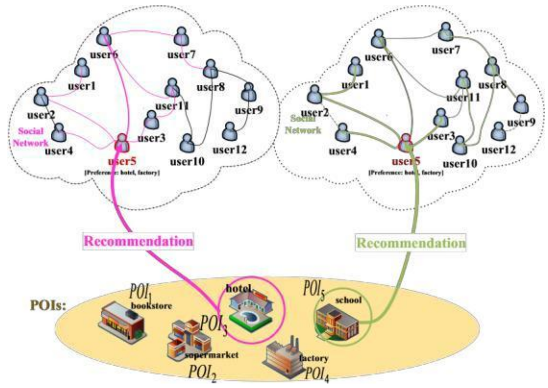

Fig. 1: An POI recommendation example

aim is to maximize the number of influenced users through recommending these recommended POIs to the target user, for which the number of recommended POIs is *K*. In the previous study [1], the authors formulated a location-aware influence maximization problem to find a set of seed users in social network for maximizing influence spreads, and it does not apply to our POI recommendation problem. The output result of our problem is a set of POIs.

Existing POI recommendations are categorized based on the data source used as follows [2]: 1) user profiles; 2) user location histories; and 3) user trajectories. POI recommendations are categorized by the methodologies employed as follows [2]: 1) content-based; 2) link analysis-based; and 3) collaborative filtering (CF)-based. Some researchers [3][4] have calculated the similarity between users according to the regions in which users lived, then researchers have made the similarity the input of traditional CF. Most existing research takes into account mainly the accuracy of the recommendation. However, recommendation system is equally important for users and merchants. It not only helps a business to attract more customers, but also recommends users with places in which they are interested. Social Survey by Marketing Letter stated the following: when accessing to information in the real world, people are more likely to obtain it from their friends. Businesses use social relationships to expand their influence scope (IS) and improve profit. Information dissemination and online marketing are the full use of the interaction influence between users or friends, for example, viral marketing. Existing researches [4][5][6] use social relationship to help solving the sparsity and cold-start problem in recommendation systems.

Through the detailed analysis above, we observe traditional POI recommendations rarely focus on the effect of social relationships for businesses location promotion through the POI recommendation process. Compared with existing works, we consider an example, as shown in Fig.1, in which there is a heterogeneous network that includes users and POIs (e.g., a bookstore $POI1$, supermarket $POI2$, hotel $POI3$, factory $POI4$, and school $POI5$). Because people's influence and authority under different information categories are different, the social influence about different POI categories is also different. When $user5$ is the target user, traditional recommendation approaches analyze users' checking-in behavior to infer the individual preferences and character. Then, the system's recommendation result is a list of POIs in which the user may be interested in the guarantee of recommendation accuracy. Because friends are directly affected by each other, this paper supposes friends of the target user is influenced by the target user under certain POI category/POI successfully.

As the left side of Fig.1 shown, users by the pink line connection are influenced successfully by $user5$ when the system recommends $user5$ with $POI3$. We state the IS of $user5$ in social network about $POI3$ is the user set $\{user1,user2,user3,user4,user6,user7,user8,user11\}$, and the number of influenced users is eight. However, $user5$'s IS about $POI3$ is not the maximum. In this paper, we call the users' IS about a special POI (POI category) as the individual POI's IS. Thus, $POI3$'s IS is the above user set, and its influence scope gain (ISG) without considering $user5$'s friends is $\{user7,user8,user11\}$. According to the right side of Fig. 1, $POI5$'s IS is greater than that of $POI3$, and its ISG is $\{user7,user8,user9,user11,user12\}$. Considering promoting businesses' products and services, the system should recommend the target user with the $POI5$. Thus, this paper proposes POI recommendation method for promoting POIs. Our proposed method is not only a tool for businesses to use to promote their products and attract more customers to visit their stores, but also recommends users with some POIs satisfying users preferences.

To summarize, our major contributions are as follows:

1.We define the user's IS under special POI categories in an entire social network, and model user mobility to describe the geographical influence between users.

2.Because of overlaps between IS under different POI categories, we propose a POI recommendation algorithm. The algorithm eliminates the overlaps effectively.

3.At last, we conduct comprehensive experiments on two massive real datasets, and experimental results show our algorithm on accuracy is the consistency as state-ofthe-art techniques. In terms of location promotion, our method has significant advantages.

II. POINT-OF-INTERESTS RECOMMENDATION

In this section, we define POI recommendation problem for location promotion (POILP) in LBSNs.

A. Definition

Definition 1. (LBSN) A LBSN $< G,C >$ consists of a social network $G = < U,E >$, where U is users set, $E = \{(ui,uj)|$ one social connection from ui to uj, $ui,uj \in U, u_i \neq u_j\}$, and check-in records $C = \{(u,l,t)\}$, (u,l,t) represents one check-in record where user u checks in a location l at time t. $l = (lon,lat,a)$, lon is longitude, lat is latitude, a is one POI category, POI set in a given region $POI_{region} = \{\ell_1, \ell_2, \cdots, \ell_M\}$, POI category set in a given region $POICregion = \{a1,a2,\cdots,am\}$.

Definition 2. (POILP) Given a LBSN $< G,C >$, a target user uT, a target location region $Rtarget$, the geography center of R_{target}: ℓ_{center}: $< lon, lat, POI_{region} >$, and a constant value K, the POI recommendation problem is to select a list of POIs $POIre,POIre \subseteq POIregion$, $|POIre| = K$, and the system recommends the target user uT with $POIre$, in order to maximize the number of expected influenced users who will check in $Rtarget$.

Since existing researches [9] indicate different topics have different diffusion results. Similarly, every users' IS in LBSNs is different under different POI categories, since users have different topic preferences. This paper firstly discovers users' top-N influential POI categories in LBSNs.

B. Top-N Influential POI category Extraction

Definition 3. (Top-N IPOIC) Give a LBSN $< G,C >$, the target user $uT \in U$ and his/her POI category preferences set $POIuT = \{a(1),a(2),\cdots\}$, a constant N, this problem is to select a list of POIs $pre,pre \subseteq POIuT$. The number of the expected influenced users $\phi(uT,ai)$ by uT (as information source) is the maximum under POI category $\forall ai \in pre$. Then, we select top$-N$ POI categories $pre = \{a(1),a(2),\cdots,a(N)\}$ according to the arrangement of the size of $\phi(uT,ai)$.

Learning influence between users This paper researches two aspects of influences between users in LBSNs : (1) geography influence; (2) topic-aware influence. The user u influences user v $(u \neq v)$ to check in the POI , which may denote: $P_{u,v}(\ell) = \beta \cdot P^G_{u,v}(\ell) + (1-\beta) \cdot P^T_{u,v}(\ell)$ and the parameter $\beta(\in [0,1])$ is a tradeoff between geographical influence $P^G_{u,v}(\ell)$ and semantic influence $P^T_{u,v}(\ell)$, when v prefers to go the nearby place, β is bigger; when v prefers to go to places of interest, β is smaller.

The geographical influence [8] between users denotes $P^G_{u,v}(\ell) = \sum_l p_l^{(v)} f^{(v)}(d(l,\ell))$, wherein $f^{(v)}(d(l,\ell)) =$ l and ℓ. The topic-aware influence between users denotes $P^T_{u,v}(\ell) = \sum_{a_i \in POI_u} \gamma_\ell^{a_i} P_{u,v}^{a_i}$. For each POI category ai, the influence on ai denotes $Pu,vai = \omega u,v \cdot Puai \cdot Pvai$. $Puai$ is the probability of POI category a_i. $\gamma_\ell^{a_i} = P(T = a_i|\ell)$. Moreover, for each in LBSNs, we have a probability distribution covering the POI categories.

Computing User's Influence Scope This paper focuses on user's IS under special POI category. Thus, the definition of computing user's IS problem is that given a LBSN $< G,C >$, user $u, v, u \neq v$, if $\exists$ a path from u to v, so that called as the user u can arrive at the user v, and $Path(u,S)$ denotes the set of users who u can arrive at. Our goal is to compute u's influence scope under special POI category.

Actually, comparing with strangers, people are more easily influenced by friends. $Path(uT,S)$ also represents the user uT influence scope of social network without considering POI category preferences. $Path(uT,S)$ is the results of the ideal state. Considering the influence between users in $Path(uT,S)$,

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we firstly identify users that are successfully influenced. paper supposes each user has an activated threshold value λuj uniformly at random from [0,1]. When $P^a_{(Path(u_T,S),u_j)} \geq \lambda uj$, the user uj is very likely to visit the POI *belong* to the category ai. We regard this situation as uj is affected completely. In this paper, we set λuj as the probability expectation based on uj's history check-in POI categories recorders in advance. This paper selects the influenced users satisfying $P^a_{(Path(u_T,S),u_j)} \geq \lambda_{u_j}$ into the user set $U^a_{u_T}$. Next, we select POI category a with the maximization IS about $POIuT$. Then, we select top $-N$ $\{U^{a(1)}_{u_T}, U^{a(2)}_{u_T}, \cdots, U^{a(N)}_{u_T}\}$based on the order of IS. Solving User Overlaps Problem Since each user has different influence scopes in social network under different POI categories, these different influence scopes have overlaps. The overlaps result in these top-N POI categories' ISG is not the maximum. The key is that how to design an appropriate objective function $\mathcal{F}(U^a_{u_T})$ to eliminate these overlaps. $\mathcal{F}(U^a_{u_T})$ represents ISG of the recommended POI category a.

$\mathcal{F}(U^a_{u_T}) = \sigma(U^a_{u_T} - U^S_{u_T})$, wherein $\sigma(\cdot)$ denotes the number of the user set, and $U^S_{u_T}$ represents the friends of the target user uT.

C. POI Recommendation Algorithm

Firstly, POILP problem could be formulated as an optimization problem:

$$POI_{re} = \arg \max_{\ell_j \in POI_{region}} \gamma^{a_i}_{\ell_j}, \ \forall a_i \in RC_{u_T}$$

$$s.t. \quad |POI_{re}| = K.$$

For the problem, we find out the recommended POI categories

RCuT as the following: RCuT = argmax$^{a_i \in POI_{u_T}}$ $\mathcal{F}(U^{a_i}_{u_T})$ s.t.|RCuT | = K. Wherein POIuT = {a(1),a(2),⋯ ,a(K)}, K is a constant in advance. Since the function F(·) is monotone and submodular [9]. We give a greedy algorithm with a (1−1e) approximation [10]. It is stated by the Algorithm 1 in detail.

Algorithm 1 POILP algorithm

Input: An LBSN < G,C >, the target user u_T, T_{uT} , K, POI_{uT} = $\{a_1,a_2,\cdots\}$

Output: A list of POIs, $POIre$, and the corresponding recommended POI categories $RCre$, $|POIre|$ = $|RCre|$ = K

1: Initialize $RCre \Leftarrow \varphi$
2: Compute $\mathcal{F}(U^{a_i}_{u_T})$ for each $ai \in POIuT$;
3: for j = 1 to K do
4: $aj \leftarrow$ arg max ;
5: $\ell_j \leftarrow \arg \max_{\ell_j \in POI_{region}} \{P_{\ell_j}\}$
6: $RC_{re} \leftarrow RC_{re} \cup a_j$
7: $POI_{re} \leftarrow POI_{re} \cup \ell_j$
8: return $POIre$, $RCre$.

III. PERFORMANCE EVALUATION

This paper utilizes the two real LBSN Foursquare, Gowalla datasets. These datasets respectively record 36,907 users and 4,163 users' checking-in behaviours including the location information, checking-in time, the times of checking-in and friend relationship.

A. Comparative Approaches

This paper compares POILP with existing better POI recommendation methods. Ye .etc [4] provided location recommendation method based on users' interests, social and geographical influence. This approach is called as location recommendation based on USG, and its technique is collaborative filtering (CF) and the power-law probabilistic model. Bao .etc [2] proposed the category-based k-Nearest Neighbors algorithm (CKNN), and this method computed the similarity between users in CKNN according to their weights in the category hierarchy with user-based CF. Yin.etc [11] focused on location features and users' preferences for POI recommendation with LDA, called as UP-based method. However, the above methods rarely consider users' influence under a special POI category for an entire social network. This influence is useful for location promotion.

B. Evaluation Method

Influence Scope Gain Comparison: $POIre$ based on the function F(·) can maximize uT's ISG under the special POI categories of $POIre$. Effectiveness of Methods: We verify the effectiveness of the proposed method comparing with the above-mentioned methods. We utilize the recall ratio: and the precision ratio: $Pre@K = \frac{|\{RC_{re} \cap POI_{u_T}\}|}{K}$ to evaluate the recommendation quality of every method. The three metrics are computed by averaging the values of the above three metrics for 2000 users (as the target users uT) respectively.

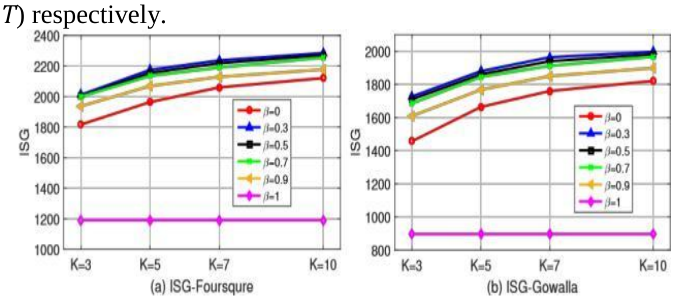

Fig. 2: Influence Scope Gain with Different β Values

C. Experimental Results

Fig.2 shows the performance of our method on two datasets. K is set in the range [3,5,7,10]. To determine whether a user really wants to check in the given region or not, we set the given target region range of the target geography center or location. The region range is used by computing the visiting regional probability. In our experiments, the radius of the target center or location is set in advance. Fig.2 reports ISG of

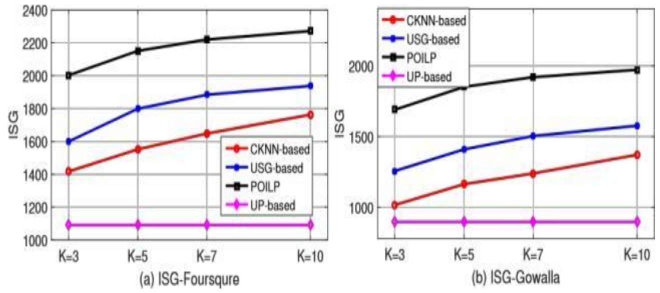

Fig. 3: Influence Scope Gain for Different Methods

algorithms with β = {0,0.3,0.5,0.7,0.9,1} on two datasets. β = 0 represents users are only influenced by POI preferences; β
1 represents users are only influenced by spatial distance.

In Fig. 2, we know ISG with β = 0.3 is the maximum. The performance of β = 0.5 is closed to β = 0.3. As our method is based on both geographical and topic influence, we give the two aspects of influences the same weight. Thus, this paper sets β = 0.5 throughout the following experiments. Our approach has significant advantages in the aspect of ISG under the lists of recommended POIs in Fig.3. In Fig.4, UP-based

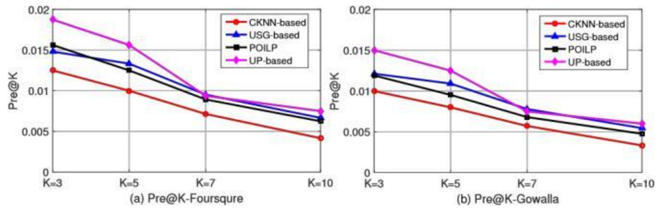

Fig. 4: Pre@K for Different Methods

method achieves better recommendation accuracy than the other methods. Since UP-based method mainly focused on the target user's preference, its recommendation performance has better advantage. POILP and USG-based method have similar recommendation precision, and our method is better than CKNN-based method in terms of recommendation precision. The comparison results about recall ratio are reported in Fig.5.

The POILP, UP-based and USG-based method are all better

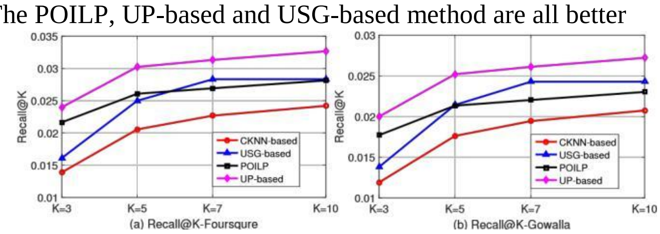

Fig. 5: Recall@K for Different Methods

than CKNN-based method. These results demonstrate our proposed method has the similar recall ratio as the USG-based method. Because our method is based on both geographical and topic-aware influence, the effectiveness of our approach is slightly worse than the UP-based method. But most of all, our POILP's ISG is superior to the state-of-the art methods.

IV. CONCLUSIONS

In this paper, we addressed on the location promotion problem in LBSNs. But most of all, the problem is formulated as one optimization problem, and ISG maximization problem under special POI category. The experimental evaluation shows our method achieves significantly superior POI recommendation comparing with other state-of-the-art methods in terms of location promotion.

V. ACKNOWLEDGMENTS

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