POI Recommendation with Geographical and Multi-Tag Influences

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***Abstract*—In this paper, we propose a method for point of interest (POI) recommendation by extracting the multi-tag influence and modeling the geographical influence. First of all, we extract a user-tag matrix from the initial user-POI rating matrix by analyzing the relations between POI and the related bag of tags. Secondly, we use the probabilistic factor model to predict the missing data of the extracted matrix. Thirdly, an effective method to model the geographical influence is proposed by considering the location of user and POI and the related region center. Finally, the multi-tag and geographical influence are fused in the process of making prediction of missing value of every POI. Then we will get a great result for POI recommendation. The experimental analysis on the large dataset Yelp demonstrates that our method outperform the state-of-art methods.**

Keywords—POI recommendation; multi-tag; geographical influence; probabilistic factor;

Introduction

Recently, location-based social networks (LBSNs) [1, 2], such as Gowalla, Foursquare, DianPing, and Yelp, etc., have attracted millions of users to share their preference about a certain point of view via the 'check in' action, such as a famous restaurant. In LBSN services, user may (1) give rating to a POI after visiting it.; (2) tag a POI to let people know what they can expect from it; (3) share their comments of POI with others.

Indeed, providing personalized recommendations of places of interest is the task of POI recommendation [3]. The POI recommender system plays an important role in providing better location based services in LBSN. Traditionally, the POIs can be treated as ordinary items, therefore, conventional recommendation methods can be adopted in generating POI recommendation. Thus, many traditional models, such as model-based [4-6] and collaborative filtering (CF) based [7, 8] approaches can be utilized seamlessly. Such approaches mainly relay on handling the user-POI rating matrix to make a recommendation. However, there are several unique characteristics of LBSNs which distinguish POI recommendations from traditional recommendation tasks. These characteristics are also the motivations that inspire us to do this research. More specifically:

- Many users may like the same POI but for different reasons. Let's take the Hilton Hotel for example, a user may like it because of its star, but another user may like the same one because of its distance from airport. In POI recommendation, a lot of POIs can be marked or described by some specific tags [9]. In most cases, a user selects a POI because of those significant tags. In other words, different users will pay close attention to different tags of the same POI, even if the POI gets the same ratings from different users. If the above observation holds, the recognized principle “if two users select the same item, they may select more same items in the future” practiced by the standard collaborative filtering may not work well. Therefore, we can't just focus on the POI itself, the multi-tag factors of POIs cannot be ignored in the process of generating recommendation. Although user selects an POI according to his preference of the tags, he did not give ratings to POIs but the tags. Therefore, we need to mining the multi-tag influence.

- The POI recommendation is location-aware depended [10]. Due to geographical constraints and the cost of traveling large distances, the famous Tobler’s first law of geography states that the propensity of a user for a POI is inversely proportional to geographic distance between the user and the POI. This implies that if a place is too far away from the location a user lives, although he may like that place, he would probably not go there. Therefore, the geographical influence should not be ignored, because everything is related to everything else, but near things are more related than distant things [11].

The recommender systems have to infer the user preference by analyzing implicit user feedback and side information. In this paper, the extracted multi-tag information will be used as the implicit feedback and the geographical influence will be treated as the side information. We propose a probabilistic factor based method to predict missing ratings of user-POI rating matrix by combining the extracted multi-tag influence and geographical influence. More specifically, we made the following contributions:

- We extract a user-tag rating matrix from the initial user-POI rating matrix by analyzing the relations between POI and the POI's related bag of tags.
- According to the current location of user , POI, and POI's related region center, we propose a normalized algorithm to model the geographical influence.
- By using the probabilistic factor model, the missing ratings of the extracted user-tag matrix are predicted. Based on the selected times of each tag for the target POI, we assign each related tag a weight value. We call the weighted values of the bag of tags of the POI as multi-tag influence. Finally, the missing value of the POI will be predicted through fusing multi-tag influence and geographical influence.

The rest of this article is organized as follows: Section 2 introduces the related work of the previous studies of POI recommendation. The proposed method is stated in section 3, followed by experiments and results in section 4. Finally, section 5 concludes this paper.

Related Work

POI recommendation has attracted much research interest in recent years [12, 13]. In the following, we review several approaches in collaborative filtering communities.

A. *Latent Factor Models for POI Recommendation*

Recent works use the latent factor models, such as matrix factorization (MF) [14, 15], probabilistic matrix factorization (PMF) [16], probabilistic factor model (PFM) [17] and many other variants [18-21] to predict the missing values of the user-item matrix. The factorization machine (FM) [22] models multidimensional variable interactions through latent vectors. All these methods only concern on the item and no preference is captured on tags.

B. *Tag-Based Recommendation*

[23] predicts users' ratings for items based on inferred preferences for tags. The work in [24] predicts tag preference in the context of an item. All these methods are of two limitations: (1) the tag preferences are global for all items; (2) all the tag preference are the user's own tags, no prediction can be made for the new item.

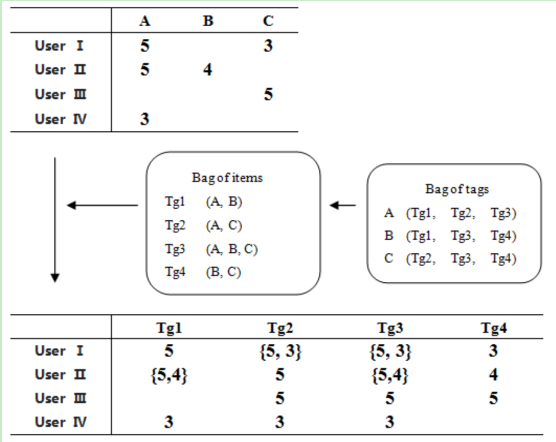


Fig. 1 Extract the user-tag matrix

C. *Model Geographcial Influence*

A key difference from traditional recommender systems is that the distance between the location of the user and the location of a POI will influence the user's adoption of the recommended POI [13]. In [25], geographical influence is considered by assuming a power-law distribution between the check-in probability and the distance along the whole check-in history. Many previous works partition the whole geographical space into some regions, but they ignore the relations between user and the POI's region center.

Methodology

A. *Extracting User-Tag Matrix*

In this section, we use the initial user-POI rating matrix to extract a related user-tag matrix. We define that $Q=\{q_1, q_2, \dots ,q_n\}$ stands for n users, and $I=\{i_1, i_2, \dots ,i_m\}$ stands for m POIs. Then we have a sparse rating matrix $R^{n\times m}$, where the rows correspond to users and columns correspond to POIs. Like the observation before, every POI can be expressed by a bag of tags, we assume $G^i=\{q^i_1, q^i_2, \dots ,q^i_h\}$ to stands for h tags of POI i. Different POI consists of different kinds of tags, the total number of tags will be defined as k. Now we have a set of n users and a set of k tags, then we extract another sparse matrix $T^{n\times k}$, where the rows correspond to users and columns correspond to tags to stands for the relationship between users and tags.

The matrix $T^{n\times k}$ is also a rating matrix, where the ratings are extracted from user-POI matrix $R^{n\times m}$. In order to clearly explain the process of the extraction, we show an example in Fig. 1.

There are 4 total tags in this example. Every POI can be described by a subset of tags. Such as POI A, it can be described by tag1, 2 and 3. Every tag can express different POIs. Such as tag1, both POI A and B can be partly expressed by the tag1. user Ⅰ gave rating to POI A 5, and didn't give rating to POI B. Therefore, according to the user-POI rating matrix, for user Ⅰ, the rating set of tag1 is {5,0}, which can be shorted as {5}. In a similar way, the rest ratings of each tag rated by each user will be extracted from

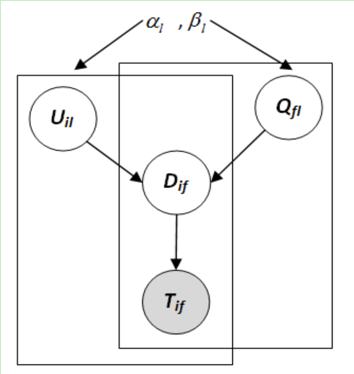


Fig. 2 Graphical model of Probabilistic Factor

the user-POI rating matrix. Finally, we can get a new matrix, which is called user-tag rating matrix. We define $tg_i^j=\{a_1, a_2, \ldots, a_t\}$ as the extracted rating set (the total number is t) of tag i (for user j), then the final rating of tag i can be computed as:

$$tg_i^j = \sum_{n=1}^{t} a_n / t \tag{1}$$

After extracting the user-tag matrix, a learning method will be used to make it possible to effectively to predict and recover the missing data of the rating matrix by learning the extracted ratings.

B. Probabilistic Factor Model in POI Recommendation

We use the Probabilistic Factor Model (PFM) discussed in [17] to predict the missing ratings of user-tag matrix. The PFM is a generative probabilistic model, which can be represented by the graphical model in Fig. 2. Matrix $T^{n\times k}$ be the extracted user-tag matrix whose rating t_{if} is the extracted tag j's rating rated by user i. The matrix T will be factorized into two low dimension matrices U and Q, where U is an $m \times d$ matrix, Q is $k \times d$ matrix and usually, $d<<m$, k. The factorization formula is $T^{n\times k} = D^{n\times k} \approx U^{n\times d} Q^{k\times d^T}$, where D is the predicted matrix, and every predicted rating D_{if} in D is assumed to follow Poisson distribution with the mean T_{if} in T.

Every U_{il} and Q_{fl} are following the Gamma distributions with parameters α and β as the empirical priors. The two gamma distribution will be defined as two probabilistic functions

$$P(\mathrm{U}|\alpha,\beta)=\prod_{i=1}^{m}\prod_{l=1}^{d}\frac{U_{il}^{\alpha_l-1}e^{(-U_{il}/\beta_l)}}{\beta_l^{\alpha_l}\Gamma(\alpha_l)} \tag{2}$$

$$P(\mathrm{Q}|\alpha,\beta)=\prod_{f=1}^{k}\prod_{l=1}^{d}\frac{Q_{fl}^{\alpha_l-1}e^{(-Q_{fl}/\beta_l)}}{\beta_l^{\alpha_l}\Gamma(\alpha_l)} \tag{3}$$

where $\Gamma(\mathrm{x})$ is the Gamma function. $\alpha=\beta$.

The Poisson distribution of T is defined as the follow formula

$$P(\mathrm{T}|\mathrm{D})=\prod_{i=1}^{m}\prod_{f=1}^{k}\frac{D_{if}^{T_{if}}e^{-D_{if}}}{T_{if}!} \tag{4}$$

where $D=UQ^T$, the posterior distribution of U and Q will be computed as

$$P(\mathrm{U},\mathrm{Q}|\mathrm{T},\alpha,\beta)\propto P(\mathrm{T}|\mathrm{D})\mathrm{P}(\mathrm{U}|\alpha,\beta)\mathrm{P}(\mathrm{Q}|\alpha,\beta) \tag{5}$$

By inferring Eq. (5) and using the method proposed in [17] (for more details, please see the techniques proposed in [17]), we have the multiplicative updating rules of each U_{il} and Q_{fl}

$$U_{il}^{new}\leftarrow U_{il}^{old}\frac{\sum_{f=1}^{k}T_{if}Q_{fl}/D_{if}+(\alpha_l-1)/U_{il}^{old}}{\sum_{f=1}^{k}Q_{fl}+1/\beta_l} \tag{6}$$

$$Q_{fl}^{new}\leftarrow Q_{fl}^{old}\frac{\sum_{i=1}^{m}T_{if}U_{il}/D_{if}+(\alpha_l-1)/Q_{fl}^{old}}{\sum_{i=1}^{m}U_{il}+1/\beta_l} \tag{7}$$

After the ratings of matrix are predicted through PFM, we use the fine tuning method proposed in [26] to make the improve prediction accuracy. Then the final predicted user-tag matrix D will be used to predict the missing ratings of user-POI matrix.

C. Geographical Influence

The geographical space can be partitioned into V regions. where a region covers the locations within a close proximity. Each region has an unique center.

An important factor in POI recommendation is user's current location. An effective POI recommendation depends on the distance between the location of POI and the location user. Based on the Tobler's first law of geography [13], we can draw the following assumptions:

- If user i and POI j are in the same region d, the geographical influence will have an effect on the user's POI preference.
- If user i and POI j are in different regions, the user's preference of POI will be effected by the factor of geographical location.

Therefore, a normalized distance function between use i and POI j is defined to model the geographical influence.

$$g(i,j)=\begin{cases}1 & i,j \text{ in same region}\\ 1+\dfrac{dis(i,j)+dis(c(i),c(j))}{2\bullet\min} & \text{otherwise}\end{cases} \tag{8}$$

where $dis(i,j)$ stands for the distance between user i and POI j, $c(i)$ and $c(j)$ stand for the region center of user i and POI j. And 'min' is the minimum pairwise distance (the minimum distance between different region centers). Then based on the user's current location, the proposed geographical influence will be used to estimate the user's rating on the location POI. More detail will be show in the next section.

D. *Predicting Preferences of POIs*

As we discussed before, the missing ratings of user-tag matrix can be predicted using the mentioned probabilistic factor model (section B). The final purpose of this paper is to predict the missing data of user-POI matrix. Let's reconsider the example in Fig. 1, the POI B can be expressed by tag1, 3, and 4, then the missing rating value, which is not rated by user I, is able to be computed by aggregating all the related tag ratings (tag 1,3, and 4). In real situation, some tags are occasionally selected by chance, but some will be consistently selected. Considering such difference, we use the strategy proposed in [9] for giving different weights to different relative tags. By using the Wilson score [9] (for more details, please see the mentioned paper), the weight of selecting tag *f* by user *i* can be measured by

$$w_{if} = c - \frac{1}{2}\delta \tag{9}$$

where

$$c = \frac{1}{1+\frac{1}{N}Z^2}\left(\frac{S}{N}+\frac{1}{2N}Z^2\right)$$

$$\delta = \frac{1}{1+\frac{1}{N}Z^2} z\sqrt{\frac{S}{N^2}\left(1-\frac{S}{N}\right)+\frac{1}{4N^2}z^2}$$

More precisely, all the tags are selected *N* times by user *i*, among them, tag *f* is selected *S* times. Z is the $1-\alpha/2$ percentile of a standard normal distribution and α is the error percentile. α is 5%,and Z=1.96.

Finally, the predicted rating of POI *j* by user *i* then be computed as

$$\tilde{R}_{ij} = \sum_{f\in\Omega_j} w_{if} D_{if} \bullet \frac{1}{g(i,j)} \tag{10}$$

where *g(i,j)* is quantified the index of the geographical influence discussed in previous section. Ω_j stands for the set of tags, which can describe the target POI *j*.

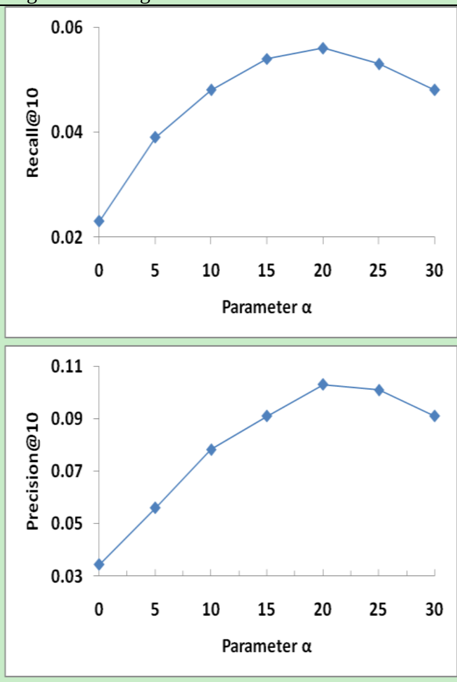
EXPERIMENT

A. *Dataset*

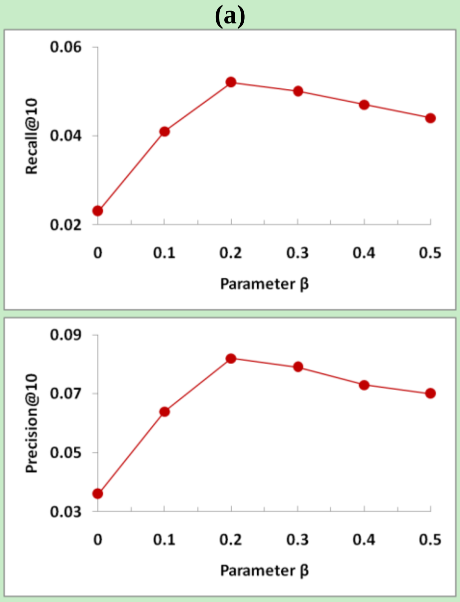
To test the proposed method, we use the standard data sets Yelp in our experiments. The datasets were previously used for recommendation evaluation in [27]. We use the subsets of Yelp (We filter out users who have less than 15 ratings from the raw data), which contains 2463 users, 50323 1-5 ratings, 3689 POIs and reviews of POIs. We use the similar method proposed in [13] to extract 685 keywords as tags. We use the clustering algorithm proposed in [28] to partition the space into regions. The statistics is shown in Table 1.

TABLE I. STATISTICS OF DATESETS

Statistics	***User***	***POI***
Max. Num of Ratings	1639	1824
Min. Num of Ratings	18	9
Avg. Num of Ratings	20.4	13.6
Max. Num of Tags	126	82
Min. Num of Tags	6	8
Avg. Num of Tags	46.4	28.6



(a)



(b)

Fig. 3 The impact of parametersαand β

B. *Metics*

Basically a recommendation algorithm estimates a ranking score for each POI and return the top-K highest ranked POIs. Two standard metrics, Recall@K and Precision@K will be employed to measure the prediction accuracy. These two well-known metric are defined as follows:

$$Recall@K = \frac{|\#K \cap T|}{|T|} \tag{11}$$

$$Precision@K = \frac{|\#K \cap T|}{|K|} \tag{12}$$

Where #K denotes the top K recommended POIs and T is the true visited POIs in the testing set. Higher Recall and Precision value means higher prediction accuracy.

C. Models for comparison

In this section, the following five models will be used for the comparison. In order to show the effectiveness of the proposed method, we compare the recommendation results with these models.

- **PMF:** the probabilistic matrix factorization [16] model is proposed by in , This method adopts matrix factorization on the user-item rating matrix and controlled by an additive updating rule.
- **NMF:** the non-negative matrix factorization model is proposed in [29] , all the predicted ratings are considered as an non-negative value. Different from the PMF, this model has a multiplicative updating rule.
- **FCR:** This is the feature-centric solution proposed in [9]. The influence of features of items are analyzed in this paper.
- **BPR:** It was proposed in [30] by modeling user preference as a ranking problem. It provides a generic learning algorithm based on stochastic gradient descent with bootstrap sampling.

D. Results

We randomly select 90% of the observed data as the trainging data to predict the remaining 10%. The random selection was carried out 5 times independently, we show the average results. Plus, the low dimension *d* will be setted as 20 in this paper.

The impact of parameters α and β. Parameters α and β are two important parameters since they control the prediction accracy of user-tag matrix. We set top $K = 10$ in our simulations. Fig. 3 shows the impact of the mentioned two parameters. From Fig. 3(a), we can see that the best Recall@10 and Precision@10 are obtained when $\alpha = 20$**.** Similarly, the method achieve the best performance when $\beta = 0.2$ (see Fig.3(b)).

Comparation with state-of-art methods. We examine the performance of different methods with respect to the number of recommened number K (K=5,10,15,20,25,30). We set $\alpha = 20$ and $\beta = 0.2$. The result is shown in Fig. 4. For all methods, the performance of Recall@K improves as K increases, to the contrary, the performance of Precision@K drops. Note that our method outperforms other models. Our method improves the global accuracy. The overall performance comparison will give promising results for the future.

CONCLUSIONS AND FUTURE WORK

Traditional recommender systems are item-centric in which all steps including rating collection, model extraction, and

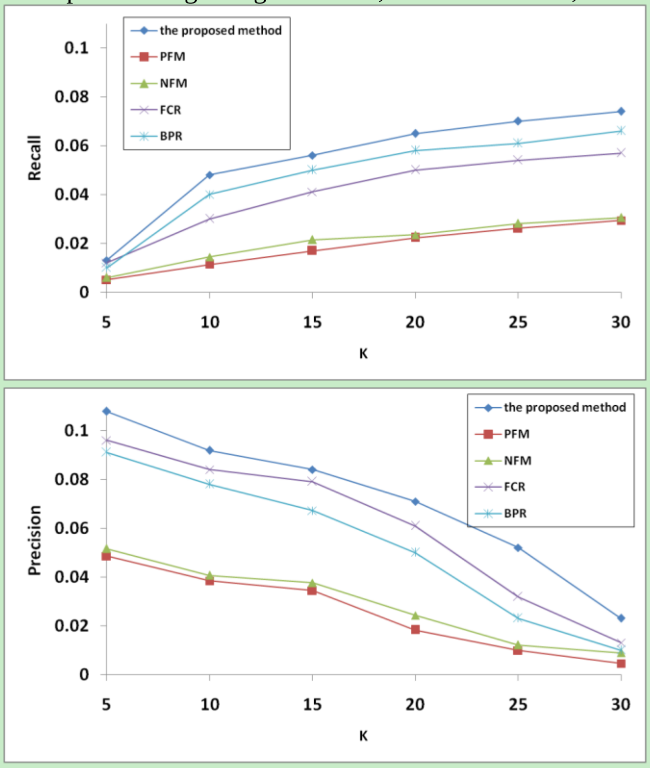


Fig.4 The performance of different methods

rating prediction are all centered around items. For POI recommendation, a POI can be described by some specific tags and a user selects the POI because he/she likes the certain tags of the POI. Moreover, the result of POI recommendation is also influenced by geographical factor. The above observations motivate us to propose a probabilistic factor based method by combing the multi-tag influence and geographical influence. We make two main contributions including extracting user-tag matrix from the initial user-POI matrix to make the final prediction and modeling the geographical influence by considering the current location of POI and the related region center of user and POI. Experiments conducted on the real world dataset have demonstrated that our approach outperform existing methods.

For the future work, we will study more proper methods for learning geographical preferences of POI recommendation and text analysis of content recommender. In addition, user mobility can greatly affect POI recommendation as an important characteristic in LBSNs. Therefore, We will take comments and user mobility into full consideration in future.

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