A List-wise Matrix Factorization Based POI Recommendation by Fusing Multi-Tag, Social and Geographical Influences

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Abstract

In this paper, a list-wise matrix factorization method is proposed for point of interest (POI) recommendation that fuses multi-tag, social and geographical influences. Based on the relevance of location information in the physical world, location-based networks (LBSN) contain a new social structure. Firstly, we extract and model mutil-tag, social and geographical influences separately from three layers of LBSN. For multi-tag influence, 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. For social influence, we model the social influences by using social regularization method and considering distance factor between trusted users. For geographical influence, an effective method to model the geographical influence is proposed by considering the location of user and POI and the related region center. Secondly, in order to improve the performance of point of interest (POI) recommendation, we include multi-tag influences and fuse the social information and geographical influences into a list-wise matrix factorization (MF) framework for making prediction of recommendation list. The experimental evaluation is conducted on Yelp datasets with different scales. Our experiments show the proposed method significantly outperforms other state-of-the-art recommendation approaches and achieve a great result for POI recommendation

Keywords: POI recommendation, Multi-tag, Social, Geographical influences, List matrix factorization

1 Introduction

Location-based social networks (LBSNs) [1-2], such as Gowalla, Foursquare, DianPing, and Yelp, etc., are the most useful platforms to allow users to explore some certain point of interests (POI) through sharing past ‘check in’ activities and opinions on the POIs they have checked in.

In LBSNs services, after visiting some locations (POIs), user may give rating to his favorite POI or share their comments of POI with others, (in most cases, users will add tags to the POIs) . In addition, as a kind of social network, LBSNs services also attracted millions of users to share their social friendship and their locations via check-ins. Providing personalized recommendations of place of interest is the main task of POI recommendation [1]. If the POIs are treated as ordinary items, many traditional recommendation models can be adopted, such as model-based [2-3] and collaborative filtering (CF) based [4-6] approaches can be utilized seamlessly. Such approaches are of some shortcomings in the field of POI recommendation, because the decision process of a user choose a POI is complex and can be influenced by various characteristics. Based on the relevance of location information in the physical world, location-based networks contain a new social structure. As shown in Figure 1, location-based social networks can be composed of geographic space layer, social relation layer, content information layer, and the correlation between them. Among the structure, the trust relations between users will guide or affect other uses to share their comments and ratings about some locations. Meanwhile, each POI contain a wealth of information about its location-related tags, content descriptions, comments, etc. Much of those information is actively posted or tagged by users through the interaction between users and location-based social networks. Therefore, the inner correlation of these three layers forms a new social network structure. Three important characteristics which will influences user’s geographical location preference are extracted and analyzed in this paper. This paper is inspired by the mentioned characteristics.

1.1 Content

First of all, a user likes an item because of some specific features of the item. When a user likes an item, she may like some features of the item but is not impressed with other features. Let’s take the HolidayInn Hotel for example, services of HolidayInn

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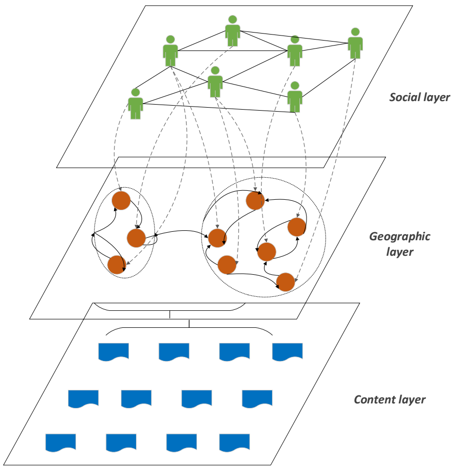

Figure 1. Three layers in LBSNs

are the main attraction for a user rather than its star, while cleanliness may be the main attraction for another user. A lot of features in POI RS are described or marked by a few of useful specific tags in most cases [3, 7]. Even if two different users give same rating to a target POI, they way have different reasons. 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. In the study of POI recommendations, we usually collect an explicit user-POI rating matrix, but the explicit feedback of tags or features can not be achieved directly. Therefore, as an important influence factor, the mentioned content-related influences should analyzed in this paper. We extract a user-tag rating matrix from the initial user-POI rating matrix to model users' deep preferences about different tags by analyzing the relations between POI and the POI's related bag of tags. Then the predicted user-tag matrix can be utilized in the next step of recommendation. 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 POIs as multi-tag influences.

1.2 Social

Secondly, social relations have a big impact on users location preferences. For example, Bob is more likely to choose a restaurant which has been rated, visited or recommended by his trust friend. That is to say, the preference of POI will pass to other users through the social relations. A great chance of having the same preferences among trusted friends. Meanwhile, the most important feature of location-based social network is to map user's behavior in virtual networks to real life through location. In the real circumstances, each POI is located in a fix location and each user has a fixed area of activity, if a user is too far away from another user, the social relations between them will decay. Therefore, the social relations among users are constrained by geographic space. We utilize the social regularization and incorporate multi-district distance factors between trusted users to model the social relations. This is different from an early work in modeling social relations [8], which ignored distance factors.

1.3 Geographic

Thirdly, the POI recommendation is location-aware depended [9-10]. For example, recommending a Chinese restaurant in Beijing to a user who is currently visiting New York City will fail, even if the user loves Chinese food very much. Users tend to check in around several centers, they may unwilling to go far places, although they like the places. Near things are more related than distant things, geographical influences are the key points in POI recommendation [11]. According to the current location of user, POI, and POI's related region center, a normalized algorithm was proposed to model the geographical influences in this paper.

The main idea of POI recommendation is to infer the probability of visiting a POI based on the observed implicit user feedback and some side information. In order to provide more accurate and efficient POI recommendation, we propose a fused list-wise matrix factorization method to take into account the mentioned content, social and geographic influences.

The rest of the paper is organized as follows: Section 2 includes a brief description of previous related work. Section 3 describes the proposed fusion model. Section 4 describes the evaluation procedure, and provides encouraging results. Finally, Section 5 gives conclusions and outlook for further research in this area.

2 Related Work

Location-based service research becomes prevalent due to a wide range of potential applications. Recently, the increasing pervasiveness of location-acquisition technologies, like GPS and LBSNs, are leading to the collection of large spatio-temporal datasets. POI recommendation in LBSNs bring the opportunity of discovering valuable knowledge about users' preference [13]. In the following, we review some related methods in the field of POI recommendation.

Like we discussed before, after users visit some POIs, the recommender system will collect an initial user-POI rating matrix. Many methods have been proposed to solve the POI recommendation. One important line of approaches includes latent factor models [12-15] to predict the missing values of the user-item matrix. Matrix factorization models have been generalized into a proposed probabilistic matrix factorization [13], which analyze the matrix factorization problem through a Bayesian version. Lee and Seung [16] propose the non-negative matrix factorization model (NMF), in which all the predicted ratings are considered as an non-negative value. Different from MF and PMF, this model has a multiplicative updating rule. The factorization machine (FM) [17] models multidimensional variable interactions through latent vectors. Generally, MF-based techniques learn latent features of users and items from the observed ratings in the user-item matrix, which are further used to predict unobserved ratings. The final purpose of predicting unobserved ratings of initial matrix is to generate a proper recommendation result according to the rating values. But optimizing the objective function in conventional matrix factorization based recommendation methods, which is the sum-of-square of factorization errors with regularization terms, does not ensure that the obtained recommendation results are consistent with the preference orders of the users. MF is equivalent to a pointwise ranking model, while not modeling ranking directly. High accuracy of rating prediction does not mean that the recommended result (top N recommendation or recommendation list) is accurate. To address this problem, some MF based learn to rank model was proposed in the past decade years. Sui *et al.* [18] propose a lit-wise MF by using the cross-entropy of top one probabilities of the items in the training example lists and the ranking lists from MF model. URM model is proposed in [19] by combing a rating oriented MF model and a ranking-oriented list-wise MF model. Future more, ListPMF is proposed in [20], which take the preference orders of the users indicated by observed ratings as a whole instance, ListPMF maximize the log-posterior over the predicted preference order with the observed preference orders. All these methods only concern on the collected user-item ratings but no deep preferences about a target user are captured on side information (such as tags, comments or social relations).

In fact, the decision process of a user choose a POI is complex and can be influenced by many factors. A majority of POI recommendation works utilize the geographical influences [21]. Lian *et al.* [22] have proposed a geographical matrix factorization (GeoMF) to integrate this influence directly into the factorization model of WMF. Cheng *et al.* [23] employ a power-law distribution to model the distance between locations visited by the same user. Zhang *et al.* [24] extract locations of interest and travel sequences based on multiple users' trajectories. Cheng *et al.* propose a personalized Multi-center Gaussian Model (MGM) to capture the geographical influence on a user's check-ins but not ratings. Many previous works partition the whole geographical space into some regions, but they ignore the relations between user and the POI's region center.

After a user visits a POI, the user may rate the POI and select some features or create tags or comments for it . The users' preference can be reflected by these features. User's preferences on features are available in many real life rating systems. However, few literatures concern on analyzing the tags selected by users for a POI. Sen *et al.* [25] predicts users' ratings for items based on inferred preferences for tags. The work in [26] 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. The method proposed in this study does not have this problem because it employs collaborative filtering on extracted tag ratings, which can predict a rating for any pair of user and tag.

3 Methodology

3.1 List-wise Matrix Factorization Framework

An efficient and effective approach to recommender systems is to factorize the user-item rating matrix, and utilize the factorized user-specific and item-specific matrices to make further missing data prediction [27], which is rating prediction. Matrix Factorization (MF)-based Collaborative Filtering (CF) method has been proved to be an useful model to improve the performance of rating prediction. MF consider an $m \times n$ rating matrix R describing m users' numerical ratings on n items. A low-rank MF approach seeks to approximate the rating matrix R by a multiplication of f-rank factors:

$$R^{n\times m} \approx P^{n\times f} Q^{f\times m}, \tag{1}$$

where $P^{n\times f}$ and $Q^{f\times m}$ stand for user-specific and item-specific matrices, respectively, and f is f-dimensional specific potential feature of user and item, usually, $f \ll n,m$. Traditionally, the MF method is utilized to approximate the rating matrix R by minimizing:

$$\ell = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{m} I_{\mathrm{ij}}^{R}(R_{ij}-\hat{R}_{\mathrm{ij}})^2 + \frac{\lambda_P}{2}\|P\|_F + \frac{\lambda_Q}{2}\|Q\|_F \ , \tag{2}$$

where $\hat{R}^{n\times m} = P^{n\times f} Q^{f\times m}$, $\|\bullet\|$ is the Frobenius norm, that is, $\|P\|_F = \sqrt{\sum_{a=1}^{n}\sum_{b=1}^{f}|P_{ab}|^2}$. $\frac{\lambda_P}{2}\|P\|_F$ and $\frac{\lambda_Q}{2}\|Q\|_F$ are regularization terms. I_{ij}^{R} is the indicator function that is equal to 1 if user i rates item j and equal to 0 otherwise. The parameters λ_P and λ_Q are regularizing coefficients for P and Q respectively, which are used to prevent over-fitting.

Note that MF, and also some other matrix factorization approaches as in [28], are rating prediction oriented optimizing the objective function in conventional matrix factorization based recommendation methods, which is the sum-of-square of factorization errors with regularization terms, does not ensure that the obtained recommendation results are consistent with the preference orders of the users. Although we can use the predicted ratings to rank the items (the real user preference), the quality of ranking is not directly related to the purpose of MF. Therefore, in order to model the user's preference from her ranked list of rated items, a list-wise MF model is proposed in [18]. List-wise MF introduces the top one probability [29] for the transformation from ratings of each user to ranking scores, the top one probability indicates the probability of a graded item being ranked in the top position from all the graded items. the top one probability for an item rated R_{ij} in user I's ranking list can be expressed as:

$$p(R_{ij}) = \frac{\exp(R_{ij})}{\sum_{k=1}^{n} \exp(R_{ik})}, \quad \textbf{(3)}$$

in which exp(x) denotes the exponential function of x. Different from [18], we do not formulate the List-wise MF by using the cross-entropy of top one probabilities of the items, we will use top one probabilities of the items in the training example lists and the ranking lists from the ranking model instead of training rating R_{ij} and predicted rating $(PQ)_{ij}$. We change function (2) to:

$$\ell = \frac{1}{2}\sum_{i,j} I_{\mathrm{ij}}^{R} (p(R_{ij}) - p(\hat{R}_{ij}))^2 + \frac{\lambda}{2}(\|P\|_F + \|Q\|_F)\ , \quad \textbf{(4)}$$

Eq.(4) is the basic list-wise MF framework in this paper. It's worth noting that the traditional List-wise MF framework is not suitable to make POI recommendation, because the list-wise matrix factorization method only model users' preference order on items, content, social and geographical influences are not included in the framework. Hence, we will model content, social and geographical influences in the rest three sections, and finally we incorporate these influences into the fused List-wise MF framework.

3.2 Extracting User-Tag Rating Matrix

In order to analyze the influences of content, which has been discussed in section 1, we use the initial user-POI rating matrix to extract a related user-tag matrix to model the a multi-tag influences in LBSNs. Assuming that we have an initial user-item matrix $R^{n\times m}$, where the rows correspond to a set of n users and columns correspond to a set of m POIs, r_{ij} is the rating of user i on POI j. Like the observation before, every POI is associated with a bag of tags, we assume that POI j can be described by h tags. For all POIs, we define the total number of all tags as k. Now we have a set of n users and a set of k tags, In this paper, our goal is to get a user-tag matrix $T^{n\times k}$ through analyze initial user-POI matrix $R^{n\times m}$.

In order to clearly explain the process of the extraction, we show an example in Figure 2.

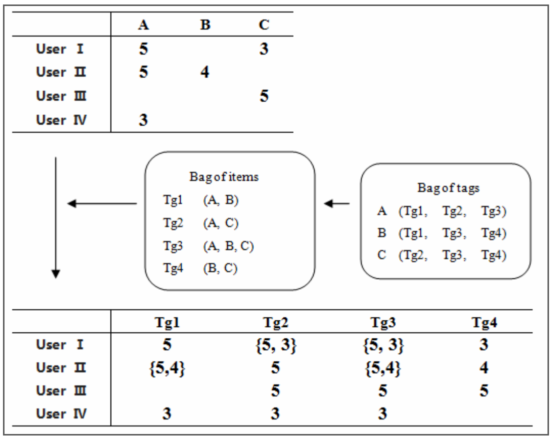

Figure. 2 Extracting a user-tag matrix

In this example, we totally collect 4 tags. Note that each POI is described by a subset of tags. Let's take POI A for example, which can be described by tag1, 2 and 3. In addition, different POIs can be partly expressed by same tag. For example, both POI A and B can be partly expressed by tag1. Note that POI A achieve a rating value from userⅠ but didn't achieve a rating value from user III. Therefore, for user I, the rating set of tag1 can be extracted as {5,0}, which can be shorted as {5}. The rest rating sets of each tag rated by each user can be extracted from the initial user-POI rating matrix in a similar way. Let's take tag 3 and user II for example, the rating set will be {5,4}. Finally, a new user-tag rating matrix can be collected through the above method. We define $tg_j^i=\{a_1, a_2, ..., a_t\}$ as the extracted rating set (the total number is t) of tag j (for user i), then the final rating of tag j in user-tag matrix can be defined as:

$$\mathrm{tg}_{\mathrm{j}}^{\mathrm{i}} = \sum_{n=1}^{t} a_n / t\ , \quad \textbf{(5)}$$

In real situation of location-based social networks, some tags are very macro. Such as "hotel", "restaurant", they have little meaning for analyzing POI preferences, but they occur frequently as tags. In order to avoid the problem, we define equation to embody the uniqueness of the useful tags.

$$\mathrm{p_j} = 1 - \frac{\sum_{\mathrm{j}\in\Theta(\mathrm{tg})} tg_{\mathrm{j}}}{m}\ , \quad \textbf{(6)}$$

where p_j is the weight of tag j, m is the total number of all tags, numerator means total number of tag j.

It's worth noting that 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 [30] for giving different weights to different relative tags. By using the Wilson score [30] (for more details, please see the mentioned paper), the weight of selecting tag j by user i can be measured by:

$$w_{ij} = c - \frac{1}{2}\delta\,, \tag{7}$$

where

$$c = \frac{1}{1+\frac{1}{N}Z^2}\left(\frac{S}{N} + \frac{1}{2N}Z^2\right), \tag{8}$$

$$\delta = \frac{1}{1+\frac{1}{N}Z^2}\, z\sqrt{\frac{S}{N^2}\left(1-\frac{S}{N}\right) + \frac{1}{4N^2}z^2}\,, \tag{9}$$

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.Then the missing value of POI j, which is not rated by user i, is able to be computed by aggregating all the related tag ratings:

$$t_{ij} = \sum_{f\in\Omega(j)} w_{if}\, p_f\, tg_f^{\;i}\,, \tag{10}$$

where t_{ij} is user i's final predicted rating for tag j, tag f belongs to POI j, $tg_f^{\;i}$, p_f, w_{if} can be computed by Eq. (3)-(7). We call formula (8) as extracted multi-tag influences, which will be incorporated into MF framework to make future POI recommendation.

3.3 Geographical Influences

In LBSNs, the geographical space can be divided into some regions based on POIs' longitude and latitude. Usually, each region has an unique center and users tend to check in around the center.

Based on the Tobler's first law of geography [31], assuming that user i is in some region k, we want to estimate the user's rating on the location of POI j, where j is not necessarily in the region k. Clearly, this rating may not be the same as the observed rating r_{ij} generated when user i actually visited POI j where both the user and the POI j are in the same region. In this paper, we define the geographical influences between i and j through the following normalized distance formula:

$$g(i,j) = \begin{cases} 1 & i,j \text{ in same region} \\ 1 + \dfrac{dis(i,j) + dis(c(i),c(j))}{2} & \text{otherwise} \end{cases} \tag{11}$$

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). Function (11) follows the following assumptions:

- User i's POI preferences are not affected by geographical location when user i and POI j are in the same region.
- User i's POI preferences will be effected by the factor of geographical location when user i and POI j are in different regions.

Finally, the proposed geographical influences will be used to estimate the user's preference on the location POI.

3.4 Social Influences

Previous work [8, 32] states that social relationship has effect on users' behaviors in social network, users are not independent and identically distributed. This article draw lessons from the idea of social regularization to dealing with social influences. We use the similarity function proposed in [8] to calculate the trust relation between users. Since we have the rating information of all the users, the evaluation of similarities between user i and user f can be calculated by measuring the issued ratings of these two users:

$$S_{\text{if}} = \frac{\sum_{p\in I(i)\cap I(\text{f})} (r_{ip} - \overline{r}_i)(r_{fp} - \overline{r}_f)}{\sqrt{\sum_{p\in I(i)\cap I(f)} (r_{ip} - \overline{r}_i)^2}\sqrt{\sum_{p\in I(i)\cap I(f)} (r_{fp} - \overline{r}_f)^2}}\,, \tag{12}$$

Where user i and user f are trusted friends in LBSNs, $I(i)$ is the location set that user i has checked in, $I(f)$ is the location set that user f has checked in, then p belongs the subset of items which user i and user f both rated. r_{ip} stands for rating of user i on item p, $\overline{r}_{\text{i}}$ is the average rating of user i. The range of S_{if} is [-1, 1], we employ a mapping function f (x) = (x + 1)/2 to bound the range of social similarities into [0, 1]. A larger value means users i and f are more similar.

However, in location-based social network, the trust relationship between users is also affected by geographical location. For example, each person has their own fixed area of activity, which also shows a stronger preference for the locations of the fixed area. If the distance between two trusted users is too far away, their preference for the same location will be weakened by the distance, meanwhile, the trust relation between users will be weakened accordingly. Therefore, the traditional conclusion "trusted users share same preference" should be taken seriously when facing POI recommendation problems, the distance factor cannot be ignored. Finally, we redefine the trust social relation between user i and f:

$$S_{\text{if}} = P(i,f) \bullet \frac{\sum_{p\in I(i)\cap I(\text{f})} (r_{ip} - \overline{r}_i)(r_{fp} - \overline{r}_f)}{\sqrt{\sum_{p\in I(i)\cap I(f)} (r_{ip} - \overline{r}_i)^2}\sqrt{\sum_{p\in I(i)\cap I(f)} (r_{fp} - \overline{r}_f)^2}}\,, \tag{13}$$

where p(i,f) stands for the trust weight between user i and f. Drawn on the definition of formula 7, p(i,f) can be computed as follows:

$$P(i,f) = \begin{cases} 1 & i,f \text{ in same region} \\ \dfrac{2 \bullet \max - [dis(i,f) + dis(c(i),c(f))]}{\max} & \text{otherwise} \end{cases} \tag{14}$$

where 'max' stands for the maximum pairwise distance (the maximum distance between different region centers), $dis(i,f)$ stands for the distance between user i and user f, $c(i)$ and $c(j)$ stand for the region center of user i and user f.

3.5 Fusion Framework

As introduced above, we have collect the multi-tag, social and geographical influences. Our motivation of fusion framework is then straightforward so that all the modeled influences can be exploited simultaneously, by which the knowledge encoded in individual ratings is expected to improve the latent features of users and POIs from the fusion model to achieve better ranking performance. Whole framework is shown in Figure 3.

More specifically, by adding the multi-tag and geographical influences, we change the predicted rating (Eq. 2) to

$$\hat{\mathrm{R}}_{ij} = P_i Q_j + \frac{t_{ij}}{g(i,j)}, \tag{15}$$

where t_{ij} and $g(i,j)$ are carefully discussed in section 3.2 and 3.3. Then, by adding the social influences, the fused new model is utilized to approximate a rating matrix R by minimizing the following loss function:

$$\begin{aligned}\ell_{(\mathrm{P,Q})} &= \frac{1}{2}\sum_{\mathrm{i,j}}(\mathrm{p}(\mathrm{R}_{\mathrm{ij}}) - \mathrm{p}(\hat{\mathrm{R}}_{\mathrm{ij}}))^2 \\ &+ \frac{\delta}{2}\sum_{\mathrm{i=1}}^{n}\sum_{f\in F^+(i)} s_{if}\left\|P_i - P_f\right\|^2 + \frac{\lambda}{2}(\|P\|^2 + \|Q\|^2)\end{aligned}, \tag{16}$$

where $F+(i)$ stands for the set of all user i's trusted social friends, s_{if} is the social influences and can be computed by Eq. (13).

Since the loss function (16) is not convex jointly over P and Q, for the model optimization problems, we use gradient based approaches to search for local minima. We set

$$e_{ij} = \sum_{\mathrm{i,j}}[p(R_{\mathrm{ij}}) - p(\hat{R}_{\mathrm{ij}})], \tag{17}$$

$$m_i = \sum_{f\in F^+(i)} s_{if}\left|P_i - P_f\right|, \tag{18}$$

then the gradients of u_i,u_j will be achieved by

$$\begin{cases} g_i = \dfrac{\partial \ell}{\partial P_i} \\ \quad = -e_{ij}[\sum_j (Q_j \cdot p(\hat{R}_{\mathrm{ij}}) + p(\hat{R}_{\mathrm{ij}}) \cdot \dfrac{\sum_{k=1}^{N} Q_k \exp(\hat{R}_{ik})}{\sum_{k=1}^{N}\exp(\hat{R}_{ik})})] + m_i + \lambda P_i \\ l_j = \dfrac{\partial \ell}{\partial Q_j} \\ \quad = -e_{ij}[\sum_i P_i \cdot p(\hat{R}_{\mathrm{ij}}) + p(\hat{R}_{\mathrm{ij}}) \cdot \dfrac{P_i \exp(\hat{R}_{ij})}{\sum_{k=1}^{N}\exp(\hat{R}_{kj})} + \lambda Q_j \end{cases} \tag{19}$$

over the negative gradient direction, we can update $u_{i,}u_j$ to

$$\begin{cases} P_i \leftarrow P_i - \eta g_i \\ Q_j \leftarrow Q_j - \eta l_j \end{cases}, \tag{20}$$

where η is the learning rate. In our experiments, the value of λ is set to 0.01. Our experiments showed that the algorithm usually converges after no more than 300 iterations.

4 Evaluation

4.1 Dataset

A real-world LBSN datasets Yelp are collected in our experiments to test the performance of the proposed fusion model. We preprocess the subsets of Yelp by filtering out users who have less than 20 ratings from the raw data, then the subsets contains 47624389 ratings (with the rating score range from 1 to 5) from 1059 users on 1628 POIs. The similar method proposed in [31] will be conducted to extract 26 keywords as tags. The statistics of data source is summarized in Table 1.

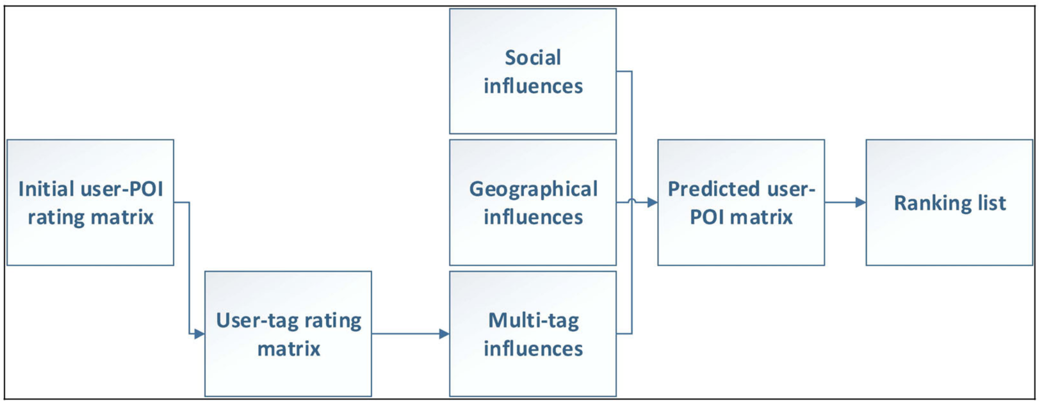

Figure. 3 the proposed recommendation framework

Table 1. Statistics of datesets

Statistics	User	POI
Max. Num of Ratings	1059	1628
Min. Num of Ratings	24	16
Max. Num of Tags	8	18
Min. Num of Tags	4	6

4.2 Experiment Setup and Evaluation Metrics

A cross-validation technique will be used in the paper. we randomly select 10, 30, 50 rated items for each user for training, and use the remaining user ratings for testing. In order to evaluate on at least 10 rated items (test ratings) per user, we remove users with less than 20, 40, and 60 ratings under different conditions of training set length. We report the average performance attained across all users and 10 test runs. We measure the recommendation performance only based on the rated items from each user. For each user, we form a topK recommendation ranking list by ordering all the POIs according to his predicted ratings in the test-sets. We consider the performance of a recommender algorithm to be good if it ranks items with high ratings in the test set to higher positions in the ranked list than those having low ratings. The algorithm should also emphasize the accuracy of highly ranked items, since users usually expect highly relevant items to be recommended as early as possible. Traditional measures RMSE and MAE are not considered in this paper because they are employed to compute the rating prediction accuracy. We are interested in the final recommendation list based on the predicted ratings. the evaluation metrics as Hit Ratio, Mean reciprocal rank(MRR) and Recall@K satisfies the requirement and they are sensitive to the result of ranked items. Another metric is widely used in RS is Precision@K, which is equal to Recall@K*|T|/|K|, Since all methods are compared for the same K, it suffices to consider Recall@n.

Hit Ratio can be computed as follows:

$$HitRatio = \frac{\sum_u I(T(u) \in R(u))}{|\mathrm{u}|}, \quad \textbf{(21)}$$

In Hit Ratio, T means a recommendation list generated by the proposed model form training sets, R means the real recommendation list in test sets. I(*) is a judgement function. If an item of T belongs to R, a hit happens. If we consider the order of recommendation list, Hit Ratio will be replaced by :

$$HitRatio = \frac{\sum_u I(T(u) \cap R(u))}{|\mathrm{u}|}, \quad \textbf{(22)}$$

if an item of T belongs to R in the same position, a hit happens. Higher Hit Ratio value means higher prediction accuracy.

MRR focus on the performance of the top one recommendation. It can be computed as:

$$MRR = \frac{1}{|\mathrm{U}|} \sum_{(i) \in U} \frac{1}{toprank(i)}, \quad \textbf{(23)}$$

In formula (23), *toprank*(i) denotes the ranking position of the top one recommendation of user i's recommended list in the test sets. For example, if user i's top one recommendation is in the first position of test list, toprank() value will be 1, if user i's top one recommendation is in the nth position of test list, toprank() value will be n. Higher Hit Ratio value means higher prediction accuracy. In the experiment, we evaluate MRR in the case of recommendation list size =10.

The definition of Recall@K at the top-K ranked items for a target user can be given as:

$$Recall@K = \frac{|\#K \cap T|}{|T|}, \quad \textbf{(24)}$$

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

4.3 Models for Comparison

We use the following seven models for the comparison.

MF. The matrix factorization model is proposed by [15], which is the baseline model in this paper. This method adopts matrix factorization on the user-item rating utility matrix where POIs are treated as items, which ignores the content, social and geographical information of POIs.

NMF. The non-negative matrix factorization model is proposed by [16], which is another baseline model in this paper. Different from the MF, all the predicted ratings are considered as an non-negative value and NMF is guided by a multiplicative updating rule. NMF also ignores the content, social and geographical information of POIs.

List MF. The list-wise MF is proposed by [18]. In list-wise MF, latent matrix P and Q that is not optimized for rating prediction, but for ranking positions of items in the users lists. Note that list-wise MF also ignores the content, social and geographical information of POIs.

T-list MF. Only the multi-tag influences is incorporated into the fused MF framework, the multi-tag influences can be achieved by section 3.2. T-MF model ignores the social and geographical information of POIs.

S-list MF. Only the social influences is incorporated into the fused MF framework, the social influences can be achieved by section 3.4. S-MF model ignores the content and geographical information of POIs.

G-list MF. Only the geographical influences is incorporated into the fused MF framework, the geographical influences can be achieved by section 3.3.

G-MF model ignores the social and content information of POIs.

TSG-list MF This is a fusion model proposed in this paper that integrates mutli-tag, social and geographical information of POIs.

4.4 Results

Hit Ratio. In this section, we will evaluate the prediction accuracy of each model under the following two conditions: 1. considering the order of recommendation list (evaluated by formula (21)); 2. the order of recommendation list is not considered (evaluated by formula (22)). 30 rated POIs are randomly selected for each user in this section.

Table 2 states the comparison results of Hit Ratio in condition 1. Note that the fused list MF (T-list MF, S-list MF, G-list MF, TSG-list MF) model outperformances the traditional MF, NMF and List MF model. TSG-list MF achieves the best performance, because TSG-list MF fuse all the related influences in LBSN. As shown in Table 2, the proposed fused model achieves a performance improvement of ca. 16.5%-25.6% over traditional List MF, and 9.6%-11.1% over T-list MF, S-list MF and G-list MF.

Table 2. Evaluation of Hit Ratio (consider the order of recommendation list)

List size	1	2	3	4	5	10
MF	0.1460	0.1015	0.0706	0.0563	0.0322	0.0184
NMF	0.1542	0.1163	0.0735	0.0595	0.0311	0.0143
List MF	0.2234	0.1577	0.1044	0.0811	0.0587	0.0233
T-list MF	0.2579	0.1643	0.1192	0.0998	0.0611	0.0207
S-list MF	0.2588	0.1698	0.1135	0.0923	0.0626	0.0205
G-list MF	0.2640	0.1687	0.1180	0.0908	0.0609	0.0216
TSG-list MF	**0.2827**	**0.1822**	**0.1302**	**0.1006**	**0.0662**	**0.0288**

Table 3 states the comparison results of Hit Ratio in condition 2. Different from the result shown in Table 4, if the order of recommendation list is not considered in the experiment. The hit ratio will increase as the recommendation list increases. TSG-list MF achieves the best performance compared with traditional MF, NMF, List MF, T-list MF, S-list MF and G-list MF, because all useful influences of LBSN are fused into list MF model. TSG- list MF achieves a performance improvement of ca. 6.9%-25.6% over traditional List MF.

Table 3. Evaluation of Hit Ratio (the order of recommendation list is not considered)

List size	1	2	3	4	5	10
MF	0.1460	0.2115	0.2826	0.3576	0.4634	0.5771
NMF	0.1542	0.2163	0.2835	0.3595	0.4687	0.5723
List MF	0.2234	0.3077	0.3244	0.3811	0.5758	0.6704
T-list MF	0.2579	0.3143	0.3292	0.3898	0.5904	0.6895
S-list MF	0.2588	0.3198	0.3335	0.3823	0.5926	0.6825
G-list MF	0.2640	0.3187	0.3380	0.3908	0.5989	0.6896
TSG-list MF	**0.2827**	**0.3272**	**0.3502**	**0.4000**	**0.6042**	**0.7168**

MRR. Table 4 states the comparison results of MRR. 10 rated POIs are randomly selected for each user in this section. Note that the proposed fusion model TSG-list MF achieve the best performance compared with other models. MRR value of TSG-list MF is 0.7139, which leads the performance improvement of ca. 6.4% over List MF, ca. 3.1% over T-list MF, ca.2.9% over S-list MF and ca.2.7% over G-list MF. We can get the same conclusion that by considering the content, social and geographical influences, the proposed fusion list MF model is able to enhance the performance of preference prediction, especially when it is the top one recommendation.

Table 4. Evaluation of MRR

model	MRR
MF	0.6525
NMF	0.6582
List-MF	0.6745
T-list MF	0.6961
S-list MF	0.6979
G-list MF	0.6992
TSG-list MF	**0.7182**

Recall@K. Figure 4 reports the effect of recommendation list size K on Recall@K for the five models. X axis states the length of recommendation list (the value of K) and y axis stands for the value of Recall@K. 50 rated POIs are randomly selected for each user in this section. Under the circumstances of different length of recommendation list, TSG- list MF is the clear overall winner, followed by T-list MF, S-list MF, G-list MF and list MF and traditional MF and NMF has the worst performance. The reason for the higher Recall@K of TSG-MF is the same as for the higher Hit Ratio and MRR discussed above, which is the superiority of TSG-list MF comes from combining the content preference of users, social trust and geographical influences, but T-list MF, S-list MF and G-list MF only pay close attention to one aspect of the complex influences.

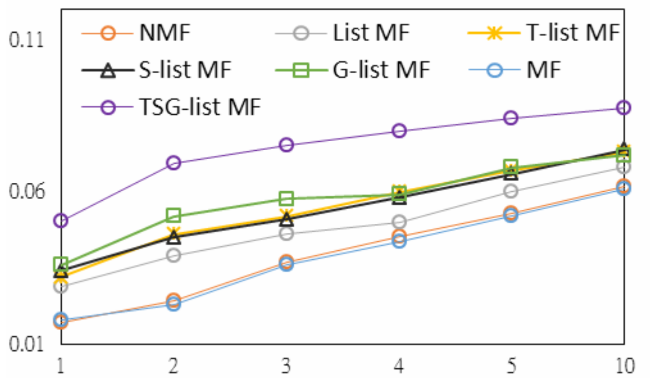

Figure 4. evaluation of Recall@K

5 Conclusions

In this paper, we have introduced the a fused List MF approach, an approach that fuses multi-tag, social and geographical influences in order to realize improvement over the performance of the state-of-the art matrix factorization techniques for the task of recommendation. Our experimental results indicate that the proposed model substantially outperforms both traditional MF based approaches (rating-oriented approaches), i.e., MF and NMF, and other traditional list-wise recommendation approaches (ranking-oriented approaches). i.e. list MF.

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 work.

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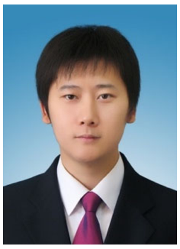
Biographies



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