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Preference-Aware POI Recommendation with Temporal and Spatial Influence

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Abstract

POI recommendation provides users personalized location recommendation. It helps users to explore new locations and filter uninteresting places that do not match with their interests. Multiple factors influence users to choose a POI, such as user's categorical preferences, temporal activities and location preferences as well as popularity of a POI. In this work, we define a unified framework that takes all these factors into consideration. None of the previous POI recommendation systems consider all four factors: Personal preferences, spatial (location) preferences, temporal influences and POI popularity. This method aims to provide users with a list of recommendation of POIs within a geo-spatial range that should match with their temporal activities and categorical preferences. Experimental results on real-world data show that the proposed recommendation framework outperforms the baseline approaches.

Introduction

There have been vast advances and rapid growth in Location based social networking (LBSN) services in recent years. Foursquare[1], Yelp[2] and Facebook Places[3] are a few of the examples of LBSN services. LBSNs allow users to share their life experiences via mobile devices. A user posts his/her presence or arrival to a physical location, which is known as a process of "Check-in". She can also share her experiences by leaving comments or tips on that location. A *Point of Interest* (POI) location can be a "Restaurant", "Travel spot", "Park" and so on.

The task of *POI recommendation* is to provide personalized recommendation of POI locations to mobile users. Both LBSN users and POI owners can exploit the benefit from the recommendation service. Users can find better POIs and have better user experiences via the right recommendation. A POI owner could exploit this service to acquire more target customers (Liu et al. 2013). So, a POI recommendation system is a very important application in LBSN services.

User's movement data with location information provide us better knowledge about their activities and interests. For example, people who often visit a gym, must be interested in physical exercise. Also, people who visit the same place may share the same interest. Location histories and opinions of one user can be exploited to recommend an unvisited location to another user if they share the same interest.

A POI recommendation system provides users with list of locations that should match their personal interests within a geospatial range (Zheng and Zhou 2011). Here are some factors that may influence a user to make a decision to choose a POI.

1) *Personal preferences*: Personal preferences of different users are different. For example, a food lover is more likely to be interested in exploring better quality restaurants, whereas, a health conscious user may be interested in finding a better place for walking or running.

2) *Spatial Influence*: Geographical position of a POI location plays an important role. People often tend to visit nearby places. The probability of a user visiting a place is inversely proportional to the geographical distance of the POI from the current location of the user (Yuan et al. 2013).

3) *Temporal Influence*: User activities are significantly influenced by time (Yuan et al. 2013). For example, users are more likely to visit a restaurant rather than a bar at noon. Parks or other recreational places attract a lot of visitors in the weekend rather than weekdays.

4) *Popularity*: Choosing a POI can be influenced by the popularity or rank of a POI. People may visit a far away place if the place is very popular.

In this paper, we propose a preference-aware, location-aware and time-aware POI recommendation system that offers a particular user a set of POI locations incorporating time information and geo-spatial range. The contribution of this paper can be summarized as follows:

1) We incorporate time dimension to model time-specific user preferences, so our recommendation model aims to recommend POI locations that match the time-specific preferences of individual user.

2) We further exploit user's spatial behaviour using location histories to generate spatial-aware location preferences.

3) Our recommendation model uses the popularity factor of individual locations by calculating both time-specific popularity and regional popularity.

4) We model personal preferences of users based on the category information of their location histories. We estimate

[1]www.foursquare.com
[2]www.yelp.com
[3]www.facebook.com/places

the similarity between two users by computing similarity between their personal preferences rather than using user's location vector. There are 2 main reasons behind this. First, it handles the data sparsity problem of user-location matrix. Second, two users who do not visit the exact same venue may still share common interest if their preferences are the same.

5) We evaluate our system with a real-world dataset collected from Foursquare. The extensive experimental results with evaluation show that our method combining multiple factors (temporal, spatial, popularity, preferences) provide users better and effective recommendations than other baseline approaches.

Related Work

There have been many studies to design POI recommendation algorithms. Two popular approaches are Collaborative Filtering algorithm and Non-Negative Matrix Factorization algorithm.

Collaborative Filtering (*CF*) algorithms are divided into two major categories. 1) *Memory-based CF* and 2) *Model-based CF*. *Memory-based CF* methods are further divided into two categories. 1) *User-based CF* and 2) *Item-based CF*.

In (Ye et al. 2011), the *User-based CF* approach considers a combination of social influence and spatial influence. Their experiments report that geographical influence has a significant impact on the accuracy of POI recommendation, whereas the social friend link contributes little. Their results also indicate that *user-based CF* works much better than *Item-based CF*. In (Yuan et al. 2013), the authors exploit spatial influence as well as temporal influence for building a recommendation model. They incorporate time factors in the basic *CF based* model by computing similarity between two users by considering check-in information at a specific time t, rather than that of all times.

User similarity is computed based on check-in location history of two users. User's categorical preferences have not been considered in these works. In general, two users who do not visit the same venue may have similar preferences. Also, the large scale of user-location data suffered from data sparsity problem, which is a big challenge for CF based algorithm (Grčar et al. 2006).

In (Bao, Zheng, and Mokbel 2012), authors explore user preferences with social and geographical influence for POI recommendation. They model user preferences using predefined categorical information of location data. In (Liu et al. 2013), the authors propose a geographical probabilistic factor analysis framework for recommendation that takes various other factors into consideration, viz. user-item preferences, POI popularity and geographical preferences of individual users. In (Ye, Yin, and Lee 2010), the authors proposed a friendship based collaborative filtering (FCF) approach for POI recommendation.

Problem Definition

The problem of personalized POI recommendation is to recommend a set of POIs to a user. In this paper we used four key data structures: 1) User, 2) POI location, 3) Check-in and 4) Category hierarchy.

1) Each user u is represented by a unique id. Let $U = \{u_1, u_2, u_3, ...u_n\}$ be a set of users.

2) Each POI location is associated with a unique POI id, geographical position (latitude and longitude) and category information. Let $L = \{l_1, l_2, l_3, ..., l_m\}$ be set of POI locations.

3) "*Check-in*" is a process by which a user u announces his physical arrival or presence at a venue in location based social network. Let $Ch_{ij} = \{u_i, l_j, t\}$ be a *check-in* tuple, which represent that user u_i checked in POI l_j at time t.

4) Each POI location is associated with a category which represent its functionality. For example, a location can be a "Restaurant", "Museum", or "School" etc. In this paper, we use two level category hierarchy obtained from Foursquare[4]. In Foursquare, there are 8 primary categories. Each primary category includes other sub-categories. For example, "Food" is a primary category, it includes 78 sub-categories, such as "Chinese Restaurant", "Indian Restaurant", "Cafe" etc. Let $CT = \{ct_1, ct_2, ..., ct_8\}$ be a list of primary categories. Let $SCT = \{sct_1, sct_2, sct_3, ...sct_k\}$ be a list of sub-categories. Each sct_i is associated with only one primary category ct_m. Each POI location l_j is associated with exactly one primary category and one sub-category.

Baseline Preference-Aware Location Recommendation

In this section, we present the basic preference-aware location recommendation framework without incorporating temporal and spatial influence.

User-based Collaborative Filtering

User-based CF first finds similar users based on their interests or ratings on items using a similarity measure. Then the recommendation score for an item is computed by the weighted combination of historical ratings on the item from similar users (Su and Khoshgoftaar 2009).

Given a user $u \in U$, the recommendation score that u will check-in a POI l that she has not visited yet is computed with the following equation,

$$R_u(l) = \frac{\sum\limits_{v \in U} w_{uv}}{|v|} \tag{1}$$

Here $v \in U$ are the list of users who has visited the same location l and w_{uv} is the similarity score between u and v.

Preference-Aware Location Recommendation

Large-scale check-in data often faces the data sparsity problem, as a user only visits a limited number of locations (Scellato et al. 2011). For example, in user location matrix of NYC Foursquare data, data sparsity is 99.46%. To overcome the data sparsity problem, one paper proposed Preference-Aware location recommendation (Bao, Zheng, and Mokbel 2012). In this paper, we leverage the temporal properties

[4]https://developer.foursquare.com/categorytree

on LBSNs with baseline *Preference-Aware Location Recommendation* method.

Preference-Aware location recommendation method works in three major steps:

Step 1: Personal Preference Discovery In this step, we learn each individual user's categorical preferences from his/her check-in history and predefined *Category Hierarchy*. Categorical preference of a user u is a numerical score, denoted as $CP_{u,c'}$. It represents u's affinity as well as willingness to visit a venue with category c'. As we have two level *Category Hierarchy*, we calculate user's preference on two levels (Primary categories and their sub-categories).

In (Bao, Zheng, and Mokbel 2012), the authors used *TF-IDF* approach to calculate user preference. *TF-IDF* (*Term Frequency-Inverse Document Frequency*) is widely used in text mining, which reflects how important a word is in a corpus of documents (Sparck Jones 1972). Motivated by this idea, we use *TF-IDF* approach, where a user's location history is regarded as a document and categories are considered as terms in the document. We denote this approach as *CF-ILF (Category Frequency-Inverse Location Frequency).*

$CF(c', u.L)$ is the measure of how many times user u has visited the locations with a category c'. Intuitively, a user would visit more locations belonging to a category if he likes it. Here $u.L$ is the location set visited by u. ILF handles the *Rare-Item* problem (Sparck Jones 1972). Some locations are not visited by a user very often. For example, the number of visits to a restaurant is generally more than that of a museum. If a user visits location of a category that is rarely visited by other users, it means that the user could like this category more prominently (Bao, Zheng, and Mokbel 2012).

CF is calculated using eq. (2) and ILF is calculated using eq. (3).

$$CF(c', u.L) = \frac{|\{u.l_i : l_i.c = c'\}|}{|u.L|} \tag{2}$$

$$ILF(c', L) = \log \frac{|U|}{|\{u_j.l \in L : l_j.c = c'\}|} \tag{3}$$

Here, $|\{u.l_i : l_i.c = c'\}|$ is user u's number of visits in category c', $|u.L|$ is the total number of user's visit in all locations. $|U|$ is the number of total users in the system. $|\{u_j.l \in L : l_j.c = c'\}|$ is the number of users who visit category c' among all users in U.

$CP_{u,c'}$ is generated using following equation:

$$CP_{u,c'} = CF(c', u.L) \times ILF(c', L) \tag{4}$$

Then, we generate User-Preference matrix for a system with N users. The first matrix $A \in \mathbb{R}^{\mathrm{N} \times |\mathrm{CT}|}$ is based on primary category, with A_{ij} being the $CP(u_i, ct_j)$, preference of user u_i on primary category ct_j. The second matrix $B \in \mathbb{R}^{\mathrm{N} \times |\mathrm{SCT}|}$ is based on sub-categories, with B_{ij} being the $CP(u_i, sct_j)$ preference of user u_i on sub-category sct_j. Here, $|CT|$ = 8 and $|SCT|$ = 240.

Step 2: User Similarity We use *Cosine Similarity* (Tan and Steinbach 2006) to find the similarity (w_{uv}) between two users u and v based on their categorical preferences. Let $\vec{p_u}$ be the preference vector of u over primary category and $p_{u,ct}$ be the element of p_u. User similarity between u and v based on primary categorical preference is calculated as:

$$w_{uv}^{(pc)} = \frac{\sum_{ct=1}^{|CT|} p_{u,ct} p_{v,ct}}{\sqrt{\sum_{ct=1}^{|CT|} p_{u,ct}^2} \sqrt{\sum_{ct=1}^{|CT|} p_{v,ct}^2}} \tag{5}$$

Let $\vec{s_u}$ be the preference vector of u over the sub-categories and $s_{u,sct}$ be an element of s_u. User similarity between u and v based on sub-categorical preference is calculated as:

$$w_{uv}^{(sc)} = \frac{\sum_{sct=1}^{|SCT|} s_{u,sct} s_{v,sct}}{\sqrt{\sum_{sct=1}^{|SCT|} s_{u,sct}^2} \sqrt{\sum_{sct=1}^{|SCT|} s_{v,sct}^2}} \tag{6}$$

User similarity between u and v is calculated as:

$$w_{uv} = \frac{1}{2} * \left\{ w_{uv}^{(pc)} + w_{uv}^{(sc)} \right\} \tag{7}$$

Step 3: Preference-Aware Recommendation Given a user u, the recommendation score that u will visit location l that he has not visited yet is computed with the following equation:

$$R_u(l) = \frac{\sum_{v \in U} w_{uv}}{|v|} \times p_{u,ct_l} \times s_{u,sct_l} \tag{8}$$

Here v is the list of users who also visited l. ct_l is the primary category of location l and p_{u,ct_l} is the preference score of u and ct_l. sct_l is the sub-category of location l and s_{u,sct_l} is the preference score of u and sct_l.

Enhancement over Baseline By Incorporating Temporal Influence

Human movement is significantly influenced by time (Cho, Myers, and Leskovec 2011). People tend to arrive at work in the morning, check-in at a restaurant for lunch around noon. Again movement patterns on weekend are usually different than that of weekdays. People generally go to a travel spot on a weekend, whereas they go to work on a weekday. It is obvious that personal preference of a user is influenced by time. So a recommendation model should consider the time dimension for generating efficient recommendations.

To incorporate temporal influence, we introduce the time dimension to generate time-specific *User-Preference* matrix. We split a day into multiple equal time intervals (t_s) based on hour. Then we generate temporal preference of individual user on each time segment (t_s).

Temporal Categorical Preference

Given a user u, time segment t_s, category c', temporal preference of user u on category c', denoted as $CP_{u,c'}^{(t_s)}$ is calculated using the following equation:

$$CP_{u,c'}^{(t_s)} = CF^{(t_s)}(c', u.L^{(t_s)}) \times ILF(c', L^{(t_s)}) \quad (9)$$

Here $CF^{(t_s)}(c', u.L^{(t_s)})$ is the *Category Frequency* of user u for category c' at time segment t_s. $u.L^{(t_s)}$ is the location set visited by u at t_s. $ILF(c', L^{(t_s)})$ is the *Inverse Location Frequency* for category c'. $L^{(t_s)}$ is the list of all locations that has been visited at t_s by all users.

$$CF^{(t_s)}(c', u.L^{(t_s)}) = \frac{|\{u.l_i^{(t_s)} : l_i^{(t_s)}.c = c'\}|}{|u.L^{(t_s)}|} \quad (10)$$

$$ILF(c', L^{(t_s)}) = \log \frac{|U^{(t_s)}|}{|\{u_j.l \in L^{(t_s)} : l_j.c = c'\}|} \quad (11)$$

Here, $|\{u.l_i^{(t_s)} : l_i^{(t_s)}.c = c'\}|$ is the number of visits by user u at category c' at time segment t_s. $|u.L^{(t_s)}|$ is total visits by user u at time t_s. $|U^{(t_s)}|$ is the total number of unique users in the system that has checked-in at time t_s. $|\{u_j.l \in L^{(t_s)} : l_j.c = c'\}|$ is the total number of unique users that visit at category c' at time t_s.

For each time segment, we generate two User-Categorical Preference Matrix for N users. One is based on primary category $A^{(t_s)} \in \mathbb{R}^{\mathrm{N}\times|\mathrm{CT}|}$ and the second one is based on sub-categories $B^{(t_s)} \in \mathbb{R}^{\mathrm{N}\times|\mathrm{SCT}|}$.

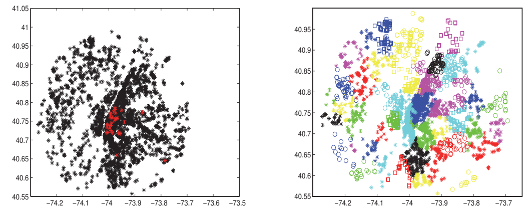
User similarity between two users is calculated based on the temporal categorical preference. If two users prefer to check in a POI with the same category during the same time, similarity between them will be high.

Temporal Popularity

Popularity of a location plays a significant role to attract users. People tend to visit a more popular POI for better satisfaction. However, popularity also varies over time. For example, a bar is more popular at night, whereas people tend to visit a museum during morning or afternoon. For better recommendation, we calculate the popularity score of each POI on each time segment. Popularity of a POI l at time t_s is calculated using the following equation:

$$P^{(ts)}(l) = \frac{1}{2} * \left\{ \frac{|U^{(t_s)}(l)|}{|U(l)|} + \frac{|Chk^{(t_s)}(l)|}{|Chk(l)|} \right\} \quad (12)$$

Here $|U^{(t_s)}(l)|$ is the number of users that visited l at time t_s, $|U(l)|$ is the total number of users who visited l. $|Chk^{(t_s)}(l)|$ is the number of check-ins at l at time t_s and $|Chk(l)|$ is the total number of check-ins at location l.



(a) POI locations (b) Regions

Figure 1: Check-in distribution in NY City

Incorporating Spatial Influence by POI Clustering

Geographical position of a POI plays a significant role to attract users (Ye et al. 2011; Yuan et al. 2013). People tend to visit nearby places. The propensity of a user to choose a POI decreases as the distance between the user and the POI increases (Liu et al. 2013). Consider the example in Figure 1a. Black points represent all the POI locations of NY City. Red points are the check-in distribution of a single user. It is obvious that, this person does not move all over the city, rather his movement data is limited to some geographical regions.

Spatial-Aware Candidate Selection

To incorporate spatial influence, we cluster all the POI locations into M number of regions. We use a modified version of DBSCAN (Ester et al. 1996) algorithm for clustering. DBSCAN is a density based clustering algorithm. It requires two parameters: ϵ and $MinPts$. Density of a point is defined as the total number of neighbours within a given radius (ϵ) of the point. A data point is considered dense if the number of its neighbours is greater than $MinPts$.

The drawback of this algorithm is that it is very sensitive to parameter ϵ. If ϵ is small, DBSCAN generates small sized clusters with a lot of outliers. If ϵ is big, a large number of points may merge together to form a big cluster. To overcome this problem, we used a modified version of DBSCAN. We introduced one extra parameter $maxD$. $maxD$ defines the maximum possible diameter of a cluster. Figure 1b shows the result of this algorithm on POI locations of NY City (see Figure 1a). The algorithm generates 44 regions.

Let $G = \{g_1, g_2, g_3, ...g_m\}$ be the list of all regions. Each region g_i is a collection of POI locations. Let $G^{(u)} = \{g_1, g_2, ...g_k\}$ be the list of regions that user u has visited. For each user, we project his check-in locations to G to generate $G^{(u)}$. All POI locations of $G^{(u)}$ are selected as candidate POI locations for recommendation of u.

Regional Popularity

In this section, we calculate popularity score of a location at the regional level. Two locations with the same terms can be rated differently in different regions (Liu et al. 2013). We calculate regional popularity of POI location l, denoted as

$P^{(g)}(l)$ using the following equation:

$$P^{(g)}(l) = \frac{1}{2} * \left\{ \frac{|U_l|}{max_{l\in g}\{U_l\}} + \frac{|Chk_l|}{max_{l\in g}\{Chk_l\}} \right\} \quad (13)$$

Here, U_l is the number of people who visited location l, $max_{l\in g}\{U_l\}$ is the maximum number of people who visited any location in region g. Chk_l is the number of total check-ins in location l and $max_{l\in g}\{Chk_l\}$ is the maximum number of check-ins in a location in region g.

POI Recommendation

Given a user u and check-in history of u, we first generate spatial-aware candidate location list $G^{(u)}$. Given time segment t_s, we calculate recommendation score $R_u^{(t_s)}(l)$ for each candidate location $l \in G^{(u)}$ using the following equation:

$$R_u^{(t_s)}(l) = \frac{\sum\limits_{v\in U} w_{uv}^{(t_s)}}{|v|} \times p_{u,ct_l}^{(t_s)} \times s_{u,sct_l}^{(t_s)} \times P^{(ts)}(l) \times P^{(g)}(l) \quad (14)$$

Here v is the list of users who also visited the location l at time t_s.

Experiments

Dataset

We use the real-world check-in dataset from Foursquare[5]. Dataset includes $227,428$ check-in data from New York City, USA. The dataset has data from 12 April 2012 to 16 February 2013 (10 months). We obtain the dataset from (Yang et al. 2015). Each check-in Ch_{ij} contains user (u_i), location id (l_j) and time (t). Each location id l_j is associated with geographical position (lat, lon), primary category (pc_{l_j}) and sub-category (sc_{l_j}). It contains check-in data of $1,083$ users and $38,383$ locations. To get more effective results, we removed POIs that have lower than 5 check-ins. After preprocessing, the dataset contains $4,597$ locations and $164,307$ check-ins. For each user, we randomly mark off 50% of his location histories as a training set to learn his temporal categorical preferences and location preferences. The other 50% is used as a test set.

Evaluation Method

To evaluate our proposed method, we use two well-established metrics: *precision* and *recall* (Powers 2011). We denote them as *Pre@N* and *rec@N* respectively.

$$pre@N = \frac{\textit{number of recovered ground truths}}{\textit{total number of recommendations (N)}} \quad (15)$$

$$rec@N = \frac{\textit{number of recovered ground truths}}{\textit{total number of ground truths}} \quad (16)$$

[5]www.foursquare.com

Here, N is the number of recommendation results. We use 3 values of N in our experiments: 5,10 and 20. Ground truth refers to the set of locations where user has visited. So, *pre@N* measures how many POIs in the top-N recommended POIs correspond to the ground truth POIs. *rec@N* measures how many POIs in the ground truths were returned as top-N recommendation. These two measures can be used together to evaluate the result, which is known as *f-measure*.

$$\textit{f-measure} = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (17)$$

Given time segment t_s, precision and recall for t_s are denoted as *precision(t_s)* and *recall(t_s)* respectively. The overall precision and recall are calculated by averaging the value over all time slots. Here, T is the number of time slots.

$$precision = \frac{1}{T} \sum_{t_s \in T} precision(t_s) \quad (18)$$

$$recall = \frac{1}{T} \sum_{t_s \in T} recall(t_s) \quad (19)$$

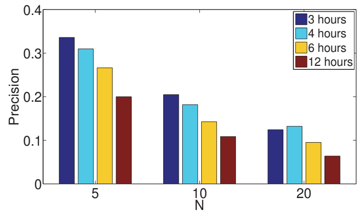
Experimental Results

In this experiment, we use different time slot lengths (Δ) to study how the experimental results change on varying time slot lengths. The value of Δ controls the granularity of time-aware recommendations. A lower value of Δ means that the result will be more time-specific. We use Δ = 3, 4, 6 and 12 hours, corresponding to number of slots T = 8, 6, 4 and 2 per day respectively. Figure 2a, 2b, 2c shows the *Precision@N*, *Recall@N* and *f-measure@N* with varying time slot length.

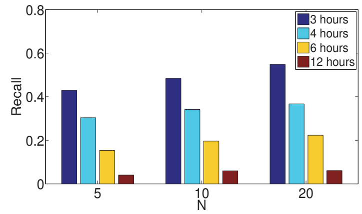
The experimental results show that smaller time slots give us better results. As Δ increases, precision value decreases slightly in most of the cases (see Figure 2a). But recall value improves dramatically with the lower Δ value (see Figure 2b). The reason is, with the lower value of time slot length, the recommendation method generates more focused and correct time-specific results.

As precision depends on N, precision gets slightly better as N increases. Because in many cases the number of time-specific ground truth value is less than N. Figure 2c shows the *f-measure@N* value that combines *precision* and *recall*. We can see that, for all N, *f-measure* value is better with lower Δ.

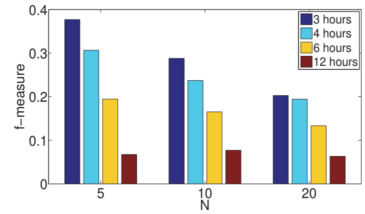
We evaluate the effectiveness of our *preference-aware, location-aware and time-aware (PLT)* method by comparing with two other methods: 1) *Preference-aware (P)*, and 2) *Preference-aware, location-aware (PL)*. *Preference-aware (P)* method is the base-line *preference-aware* recommendation method. *Preference-aware, location-aware (PL)* method combines baseline preference-aware and spatial influence. Neither uses temporal categorical preference and temporal POI popularity. Figure 2d, 2e and 2f shows the *precision*, *recall* and *f-measure* value of all three methods with N = 5, 10 and 20. We can see from the results that incorporating spatial influence gives us better results than baseline method (*P*) for all N. But the results of incorporating temporal influence with spatial influence (*PLT*) outperforms both of them (*PL* and *P*).



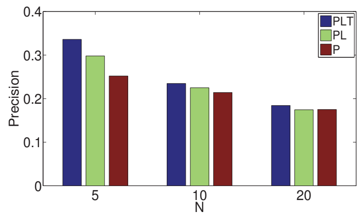
(a) *Precision@N*



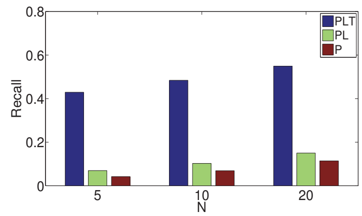
(b) *Recall@N*



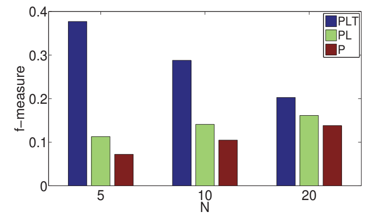
(c) *f-measure@N*



(d) *Precision@N*



(e) *Recall@N*



(f) *f-measure@N*

Figure 2: Experimental results

Conclusion

This paper presents a time-aware, location-aware and preference-aware recommendation system, which provides a user time-specific location recommendation based on user's personal categorical preferences and spatial preferences. This method also considers a combination of regional popularity and temporal popularity of a particular POI. To the best of our knowledge, this is the first work that combines all the 4 factors (temporal, spatial, categorical preferences, popularity) together to generate recommendations. Experimental results show that our method combining multiple factors is better than other baseline approaches. In the future, we plan to incorporate other time dimensions (day of the week, month/season of the year) in POI recommendation.

References

Bao, J.; Zheng, Y.; and Mokbel, M. F. 2012. Location-based and preference-aware recommendation using sparse geo-social networking data. In *Proceedings of the 20th International Conference on Advances in Geographic Information Systems*, 199–208. ACM.

Cho, E.; Myers, S. A.; and Leskovec, J. 2011. Friendship and mobility: user movement in location-based social networks. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, 1082–1090. ACM.

Ester, M.; Kriegel, H.-P.; Sander, J.; and Xu, X. 1996. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Kdd*, volume 96, 226–231.

Grčar, M.; Mladenič, D.; Fortuna, B.; and Grobelnik, M. 2006. *Data sparsity issues in the collaborative filtering framework*. Springer.

Liu, B.; Fu, Y.; Yao, Z.; and Xiong, H. 2013. Learning geographical preferences for point-of-interest recommendation. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, 1043–1051. ACM.

Powers, D. M. 2011. Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation.

Scellato, S.; Noulas, A.; Lambiotte, R.; and Mascolo, C. 2011. Socio-spatial properties of online location-based social networks. *ICWSM* 11:329–336.

Sparck Jones, K. 1972. A statistical interpretation of term specificity and its application in retrieval. *Journal of documentation* 28(1):11–21.

Su, X., and Khoshgoftaar, T. M. 2009. A survey of collaborative filtering techniques. *Advances in artificial intelligence* 2009:4.

Tan, P.-N., and Steinbach, M. 2006. Vipin kumar, introduction to data mining.

Yang, D.; Zhang, D.; Zheng, V. W.; and Yu, Z. 2015. Modeling user activity preference by leveraging user spatial temporal characteristics in lbsns. *Systems, Man, and Cybernetics: Systems, IEEE Transactions on* 45(1):129–142.

Ye, M.; Yin, P.; Lee, W.-C.; and Lee, D.-L. 2011. Exploiting geographical influence for collaborative point-of-interest recommendation. In *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval*, 325–334. ACM.

Ye, M.; Yin, P.; and Lee, W.-C. 2010. Location recommendation for location-based social networks. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, 458–461. ACM.

Yuan, Q.; Cong, G.; Ma, Z.; Sun, A.; and Thalmann, N. M. 2013. Time-aware point-of-interest recommendation. In *Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval*, 363–372. ACM.

Zheng, Y., and Zhou, X. 2011. *Computing with spatial trajectories*. Springer Science & Business Media.