Point-of-interest (POI) Recommender Systems for Social Groups in Location Based Social Networks (LBSNs) – Proposition of an Improved Model

Saranyu Ngamsa-ard, Mahsa Razavi, P.W.C. Prasad, Amr Elchouemi

ABSTRACT— Point-of-interest (POI) recommendation systems provide recommendation of places to users based on their behavior or activities. Checking behavior features from many Location Based Social Network (LBSN) applications combined with POI recommendation systems, provides better location-based services and benefits consumers and businesses in many areas. For users, they assist consumers in discovering interesting places, while for industries, they distribute commercials to target consumers and increase industry benefits. LBSNs may also use a POI recommendation system to have more target customers in return. This research aims to improve the precision of the POI recommender system for individuals as well as social groups in LBSNs by overcoming limitations of current models. The revised model was designed to support individual as well as group recommendations. In terms of individual recommendations, the proposed model is intended to take friendships between users into consideration and their impact on LBSNs and their POI ratings. Furthermore, for group recommendations, consideration was given to the aggregation of individual user recommendations. The improved model was implemented on a Gowalla dataset and results were compared with current models. The experimental results showed higher precision in POI recommendations for individuals in LBSNs.

***Index Terms*— Point-of-Interest; Group Recommendation Systems; Individual Recommendation System; Location Based Social Networks (LBSN);**

I. Introduction

THE growth of technology and tourism has led to the emergence of Location Based Social Networks (LBSNs) and Point of Interest (POI) recommendation systems. LBSNs are location-based services that take advantage of location information to support social networking (Fusco, Abbas, Micheal & Aloudat, 2012). It allows consumers to share their favorite locations on a social network as well as adding new locations to an existing social network. There are many social media applications such as Foursquare or Facebook that use LBSNs to help their consumers explore chosen locations and identify potential POIs for recommendations (Gottapu & Monangi, 2017). The POI recommendation system provides a recommendation for places to users based on their behavior or activities. These POIs may be public places that people usually visit, such as tourist attractions, hotels, parks or restaurants, but exclude private properties. Check-in behavior features from many social media applications provide new lifestyles for millions of consumers by sharing places, reviews and experiences about POIs (Cheng, Yang, Lyu & King, n.d.).

The POI recommendation system plays a significant role in LBSNs since it provides better location-based services (Liu & Xiong, n.d.). They assist consumers in discovering interesting places and organizations in distributing commercials to target consumers and improve industry benefits (Zhang & Chow, 2015). Furthermore, LBSNs can use POI recommendation systems to attract targeted customers in return.

This research provides an overview of different techniques available in POI recommendation systems to identify those techniques that provide the most accurate results. Based on these, an improved model is proposed, evaluated on a sample dataset.

There is a substantial body of research for POI recommendations for individual users rather than for social groups (Gottapu & Monangi, 2017). This may be due to the fact that recommendations for social groups are more complex, taking into account the number of people (Gottapu and Monangi, 2017), their relationships (Quijano-Sánchez, Díaz-Agudo & Recio-García, 2014) and weighted member contributions (Wang, Zhang & Lu, 2016).

To address the problem of accuracy and be able to provide recommendations for groups of users, our proposed model uses a CTF-ARA algorithm as the base for developing and extending the work on POI recommendations. The CTF-ARA algorithm (Si, Zhang & Liu, 2017) provides POI recommendation to individuals in LBSNs. It was chosen because it has proven recommendation performance when compared with other algorithms for individual POI recommendations.

The proposed model considers relationships between LBSN users as one of the factors that can improve overall accuracy. Thus, direct friendship between users in LBSNs has been considered as an added factor for identifying users

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close to the target user. People are more likely to have the same interest if they are related on LBSNs.

A further contribution of our proposed model is the provision of a group POI recommendation rank by aggregating individual recommendation ranks and considering group profiles. In addition, the proposed method allows users to select larger locations such as cities or countries.

In this study, a framework has been developed that sets out steps to facilitate POI recommendations for individuals and social group users in LBSNs, tested on Gowalla and Brightkite datasets and compared with the output of the CTF-ARA algorithm. The results show that considering 'direct friendship' as part of the process can improve the accuracy of the POI recommendation. Furthermore, applying the process to social groups in LBSNs led to an acceptable level of performance precision.

This paper is structured as follows: In section 2, different approaches to POI recommendation systems for individuals and user groups are reviewed. Section 3 details the proposed model and section 4 contains an analysis of results from the application of the proposed model to sample data from Gowalla and Brightkite datasets. The conclusion can be found in section 5.

II. Related Work

In this section, we have provided brief information about current POI recommendations for individuals (section 2.1) and groups (section 2.2).

A. Recommendations for individuals

To provide POI recommendations in LBSNs, many researchers focus on accuracy as a major result. Chen, Li, Cheung and Li (2016) proposed a new two-step technique which predicts the category preference from users' successive location searches and then ranks these under a selected location category using a distance-weighted algorithm. The researchers combined individual preference, group preference and spatial restrictions for the recommendation task. Dokuz and Celik (2018) proposed an interest measure to discover socially important locations that consider historical user data and preferences. They found that identifying socially important locations was essential for analyzing spatial preferences of user groups. This model outperforms naïve algorithms. However, it still has some limitations in terms of temporal analysis, automatic labeling of discovered locations and a location labeling problem. Nevertheless, the idea has been useful for our proposed model.

Si, Zhang and Liu (2017) provided a new methodology based on check-in and temporal features by using collaborative filtering and probability statistics. They extracted four features from historical check-in data in LBSNs: user activity, similarity, temporal variability and consecutiveness. Moreover, they divided user activity and the improvement of recommendation method by combining user check-in and temporal features. This method has been incorporated into the proposed model. Rehman, Khalid and Madani (2017) reviewed location-based recommendation systems (LBRS) and summarized them in terms of performance and improvement. They concluded that the results could be improved by considering check-ins, social relationships, and temporal and geographical information. The researchers also believed that the rapidly growing amount of data (i.e. number of users, location, POIs etc.) would cause major scalability problems for LBRSs. Ren, Song, and Song (2017) proposed a matrix factorization method for POI recommendations that considered probability. They identified interest, geographical, social and categorical relevance scores of users through applying mining of textual information associated with POIs, the kernel estimation method and power-law distribution, and integrated these into a probabilistic matrix factorization model (PMF). Results showed that this approach outperformed other existing state-of-the-art methods. However, it has insufficient information in the data set which is a major limitation. Logesh and Subramaniyaswamy (2017) presented a model for location recommendation through exploiting the emotions of users from online social media. Users' online posts and check-ins were used to infer an emotional context which is useful in relevant POI prediction. However, sparsity of online posts and noise are issues. Nevertheless, prediction of users' preferences based on emotional context enhances user satisfaction. Capdevila, Arias an Arratia (2016) presented a hybrid recommender system that allows users to write reviews on the locations they visited. The result showed that pairing recommendation or balancing data sets alter the results of recommendations. Hawashin, Abusukhon and Mansour (2015) presented a method that can extract multipolar interests, time interval interests and dislikes. This is interesting but time consuming. Kefalas, Symeonidis and Manolopoulos (2016) and Bao, Zheng, Wilkie and Mokbel (2015) compared different LBSNs and state-of-the-art recommendation algorithms with the algorithm used in their investigation. They concluded that there is no standard data set for testing recommendation algorithms which makes it hard to make a comparison. Eirinaki, Gao, Varlamis and Tserpes (2018) reviewed facets of large-scale social recommender systems, summarizing challenges and interesting problems and discussing solutions. As the list of possible recommendations grows, the importance of algorithms that can make valid as well as novel recommendation increases. Apart from accuracy, diversity, novelty of recommended items, user familiarity and avoidance of user boredom are some of the new criteria for evaluation of quality. This has been useful for the proposed model. Gao, Li, Li, Song and Zhou (2018) proposed a novel POI recommendation approach which achieves three key goals: (1) it models the geographical influence between POIs; (2) it predicts explicit trust values between users; (3) it combines user preference from each POI with the geographical influence and established social correlations. Experimental results pointed to superior performance compared to existing state-of-the-art models. Limitation are that computation is expensive and a large amount of storage is required. Nevertheless, this approach has been useful for the proposed model.

B. Recommendation for groups

The main factor that makes group recommendation different from individual recommendation is the compilation that is required of individual results to produce group results (Flores–Parra, Castañón–Puga, Martínez, Rosales–Cisneros & Gaxiola–Pacheco, 2017). Gottapu and Monangi (2017) suggested using a signature to identify places suitable for group events based on six different parameters, using a similar signature for each new group. Through calculating the similarity between the proposed signatures, recommendations for groups can be identified. This provides recommendations for groups of different sizes and composition. However, this model does not consider social relation or similarity within groups that can impact on satisfaction of users within the group. Li, Chou & Lin (2014) proposed a recommender system for advertising products based on location. They considered three major factors: interest, geo-graphic availability and friend's weight. The result showed that this mechanism could increase the advantage of group advertisements by reducing expenses and improving location, although the researchers did not overcome the cold start problem. Quijano-Sánchez, Díaz-Agudo & Recio-García (2014) proposed an approach that considered cognitive modeling and a social approach to elicit social factors related to people's way of thinking and their relationships which leads to their reaction to group recommendations. The researchers simulated the process by using modules that measure social knowledge, estimate the individual and group preferences and include knowledge management regarding user satisfaction with previous recommendations. Kaššák, Kompan and Bieliková (2016) identified the problem of recommendation performance for groups by focusing on Top-N recommendations. They proposed hybrid recommendations for groups combining content-based and collaborative strategies, thus reducing the shortcomings of both approaches when used separately (collaborative – not enough information about user preferences - and content-based – problem of locking the user into a bubble of very similar items). Wang, Zhang & Lu (2016) proposed a model that weighted members' contribution by degree of importance. They proposed a score model which employs a separable non-negative matrix factorization technique on a group rating matrix to analyze the degree of importance of each member. Moreover, a Manhattan distance-based local average rating model was developed to refine predictions by addressing the 'fat tail' problem. The limitation of this model is the difficulty to define the degree of importance. Wang, Liu, Lu, Xiong and Zhang (2019) presented a TruGRC aggregation that is a combination between results and profile aggregation. This method resolved conflicting preferences in terms of group members and generated group preferences using an average aggregation method. Villavicencio, Schiaffino, Andres, Diaz-Pace and Monteserin (2019) proposed an approach that combined individual recommendations with group recommendations by using agents that acted on behalf of the users, protected their interests and represented them in negotiations. This aggregation can improve the quality of the recommendation as a whole and individually. We have included some ideas from recent group recommendation approaches in our proposed model.

III. Proposed Model

Our proposed model extends the CTF-ARA algorithm proposed by Si, Zhang and Liu (2017). This algorithm provides better recommendation performance in comparison with other studies by considering user activity. However, improvements can be made by combining user activity with social relations. The CTF_ARA algorithm combined user check-in and temporal features to create a POI recommendation system for individuals based on LBSNs. This model considered geographical features and temporal properties extracted from LBSN datasets. Si et al. (2017) used statistical probability analysis to mine user activity, similarity features of check-in behavior and features of variability and consecutiveness of temporal factors. They also filtered users by different levels of activity and applied smoothing technology to make POI recommendations. The results were then returned to the target users by Top-N location recommendation ranked by probabilistic value. The resulting POIs came from groups of people who showed similarity to the target user, specifically for places which the target user had never visited (Si, Zhang & Liu ,2017).

The proposed solution takes useful features from the CTF-ARA model and enhances these with social relationships to recommend POIs for individuals. Moreover, the proposed solution can recommend POIs for groups by considering group profiles and aggregation. In addition, this proposed method allows users to select larger locations such as cities or countries.

Our proposed model can be applied to individuals and groups of users. As shown in Figure 1, the proposed model for individuals and groups consists of 'features extraction' and 'adaptive recommendation'

In the first step, features are extracted from LBSNs datasets, beginning with user check-in features and temporal features as for the CTF-ARA algorithm proposed by Si et al. (2017). In addition, user activity features are extracted by finding a group of similar users based on the number of common locations checked for, to provide new locations for a target user.

In terms of 'adaptive recommendations', based on the idea of Si et al. (2017), the users are grouped into active and inactive users through a K-mean algorithm. If the target user is active, dissimilar users are eliminated from similar groups of users, and user similarity is calculated based on consecutive time slots. For inactive users, dissimilar users are not eliminated, and user similarity is calculated based on all time slots. Further, the Top-N location recommendations to the target user are returned based on calculated probability. In addition, for groups of users, the results from each member are aggregated and the Top-N location recommendations compiled.

A. Process Steps of the Proposed Model

In this section, the proposed model is explained in detail which includes the steps extracted from Si et al. (2017) and our proposed steps. For consistency, we have included all parts in this section, but given only a brief explanation for the steps extracted from Si et al. (2017).

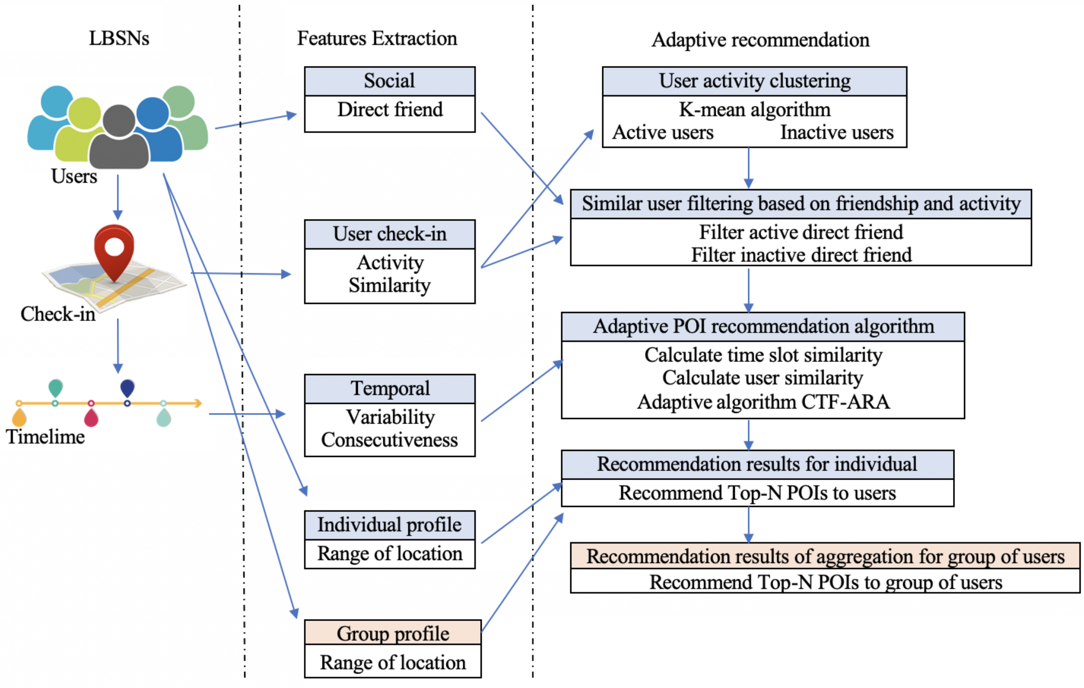

Fig. 1. Proposed framework for POI recommendation system in LBSNs for individuals and social groups

1) Feature extraction

- *Direct friend feature*

Social networks are considered a factor in improving POI recommendations based on the assumption that friends have common preferences (Pan, Hou, Liu & Niu, 2018). 'Direct Friend' relationships have been used in our proposed model as an added factor for identifying and filtering a cluster of similar users for each target user.

Definition 1 (Direct Friend, DF). For u∈U, the direct friend of users u, DFu is defined as the group of people who are friends of user u on social network.

DF can recommend locations that the target user has never visited before. In this way, the system can reduce the time of computation and recommendation noise.

- *Activity feature*

As defined by Si et al. (2017), user similarity manifests itself when users have the same interest in visiting a certain location. This can be measured by user similarity. Therefore, to achieve better accuracy, we filter out users who have low similarity.

- *Similarity feature*

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- *Variability feature*

Temporal features consider the time slot for user check-in within a 24-hour period. Variability refers to the fact that user check-in differs significantly (Si et al., 2017).

- *Consecutiveness feature*

Si et al. (2017) also found that users have similar check-in preferences in consecutive time slots. Statistical results encourage us to also use adjacent continuous time slots instead of only one time slot.

- *Range of location feature*

Gottapu and Sriram (2017) proposed signatures based on group size, location, time and other parameters. Based on this, we generated a user profile in which the target user can select desired locations in a specific range. The system will then recommend locations in the same area.

2) Adaptive recommendation

To provide the recommendation, we separate users into active users and inactive users according to Si et al. (2017). We then select groups of users that have common preferences with a direct friend and check-in locations before applying an adaptive POI recommendation algorithm.

- *User activity clustering*

The User Activity Clustering Algorithm (UAC) (Si, Zhang & Liu, 2017) has been used in this step to cluster users into active and inactive users.

- *Similar user filtering based on friendship and activity*

To select a group of similar users from a dataset for the target group, we apply algorithm 1 to find the direct friends who check-in for the same locations as target user u. Given a target user u and all check-in sets U_{All}, algorithm 1 is to find similarity for each user and make a judgement based on similarity value $SU_{u,v}$ that is greater than a threshold. Thus, a user v is like the target active user u if $SU_{u,v} > m_1$ (m_1 is an integer); otherwise, v is not a similar friend user and is filtered out. The description of this algorithm which is an improved version of the FSUA algorithm (Si, Zhang & Liu, 2017) is given as follows.

Algorithm 1 Filtering Similar Friend User Algorithm (FSFUA)
Input: The user check-in dataset U_{all}, the user relationship dataset UR_{all}, the target user u, The location dataset Lid and the location that user u ever visited L_u
Output: The similar user set SFU
for i = 1 to $|U_{all}|$ **do**
  if UId = u **then**
    add LId to L_u
    add UId who check-in Lid to LU
  end if
end for
for each v∈LU **do**
  compute $SFU_{u,v}$
  if (v is an active user, is direct friend with user u and $SFU_{u,v} > m_1$) or
    (v is an inactive use, is direct friend with user u and $SFU_{u,v} >$ m2) **then**
    add v to SFU
  end if
end for
return SFU

These results achieve the highest accuracy when $m_1 = 2$ for active users, because they have many check-in records, and similar users and similar user filtering through the CTF-ARA can produce better performance (Si et al., 2017). On the other hand, inactive users reach a peak when $m_2 = 0$, because inactive users have fewer check-in records.

- *Similarity calculation with temporal smoothing technology*

To increase accuracy of the recommendation, we extend user similarity by consecutive time slots based on cosine similarity and the temporal feature. According to Si et al. (2017), if users always visit the same POI in continuous periods of times, their similarity will be high.

In order to recommend adaptively, user similarity based on k a consecutive time slots concept is applied to active users. However, user similarity based on all time slots is applied to inactive users (Si et al., 2017). The similarity calculation combined with temporal influence solves the problem of low user similarity in the POI recommendation algorithm.

- *Adaptive POI recommendation algorithm*

This algorithm is combining user activity, similar user filtering based on friendship and activity, and a smoothing similarity calculation (Si, Zhang & Liu, 2017). The algorithm used in this step is the same as the CTF-ARA algorithm but the input in our proposed model is the SFU instead of the SU.

Strategy 1: For active users in AU, who have enough check-ins and similar users, we calculate the similarity $sim_{u,v}^{(kt)}$ between the target user u and similar user v based on k consecutive time slots. The recommendation probabilistic value $p_{u,t,l}^{(kt)}$ of user u visiting location l at time t is calculated as follows:

$$p_{u,t,l}^{(kt)} = \frac{\sum_{v \in SU}(sim_{u,v}^{(kt)} \cdot \sum_{t' \in T} r_{v,t',l} sim_{t',t})}{\sum_{v \in SU} sim_{u,v}^{(kt)}} \quad (1)$$

Strategy 2: For inactive users in IAU, who have less check-ins and similar users, we calculate the similarity $sim_{u,v}^{(at)}$ between the target user u and similar user v based on all time slots. The recommendation probabilistic value $p_{u,t,l}^{(at)}$ of user u visiting location l at time t is calculated as follows:

$$p_{u,t,l}^{(at)} = \frac{\sum_{v \in SU}(sim_{u,v}^{(at)} \cdot \sum_{t' \in T} r_{v,t',l} sim_{t',t})}{\sum_{v \in SU} sim_{u,v}^{(at)}} \quad (2)$$

The CTF-ARA algorithm is described as follows.

Algorithm 2 CTF-ARA
Input: The user check-in dataset UC, the target user u and time slot t
Output: The recommended Top-N POIs
call Algorithm 1 to get active user set AU and inactive user set IAU
call Algorithm 2 to get similar user set SU of u
if u∈AU then // Strategy 1
  for each l∈L and t'∈[t-k, t+k] **do**
    compute $sim_{t,t'}$ and compute $\hat{r}_{u,t,l}$
  end for
  for each v∈SU and l∈L and t∈T **do**
    compute $sim_{u,v}^{(kt)}$
  end for
  for each v∈SU and t' ∈[t-k, t+k] **do**
    computer $p_{u,t,l}^{(kt)}$
  end for
else // Strategy 2
  for each l∈L and t'∈T **do**
    compute $sim_{t,t'}$ and compute $\tilde{r}_{u,t,l}$
  end for
  for each v∈SU and l∈L and t∈T **do**
    compute $sim_{u,v}^{(at)}$
  end for
  for each v∈SU and t' ∈T **do**
    compute $p_{u,t,l}^{(at)}$
  end for
end if
sort $p_{u,t,l}^{(kt)}$ or sort $p_{u,t,l}^{(at)}$
return Top-N POIs

According to the model (Si, Zhang & Liu, 2017), results with the highest accuracy for active user were achieved when calculated on nine adjacent time slots. This means the target time t is the center of nine adjacent time slots. The reason is that users are more willing to visit correlated locations in the nearest time slots. Performance declines with the distance from t. Thus, we compute the similarity in the CTF-ARA algorithm for active users, using parameter k=4.

- *Recommendation results for individual*

To increase accuracy of the recommendation, we consider the range of locations that target users select at the beginning. Target users may select a city or country of POIs. The system filters the POIs before making recommendations.

- *Recommendation results of aggregation for group of users*

The adaptive POI recommendation algorithm returns Top-N POIs to users individually. There are many aggregation techniques and change results to POIs recommendation for groups of users, such as ‘borda’, ‘average’, ‘least misery’, ‘footrule’ or ‘random aggregation’. As shown in Figure 2, there is no significant difference between aggregation techniques. The performance of each technique depends on the group size and inner group similarity. Generally, the ‘average aggregation’ produced the most accurate group recommendations, because this method aggregates preferences and recommendations in an intuitive way. Moreover, this method corresponds to one of the ways in which a group of people naturally make choices. Thus, we decided to apply average aggregation with our POI recommender system.

Definition 2 (Average aggregation) the location l group score is equal to the average of the predicted rating for individuals

$$\text{score}_g\,(l) = \frac{\sum_{u \in g} \hat{r}_{ul}}{|g|} \qquad (3)$$

Where $\hat{r}_{ul}$ is the predicted rating for user u, location l combination and g is number of users in the target group. Subsequently, the ranking is computed accordingly (increasing values of group score).

To recommend locations for groups of users, average aggregation was applied in definition 2 to find the rank of each location for the target group. The results for the target group depend on the location recommendation for each user. This method will produce a POI recommendation that satisfies every user in the target group.

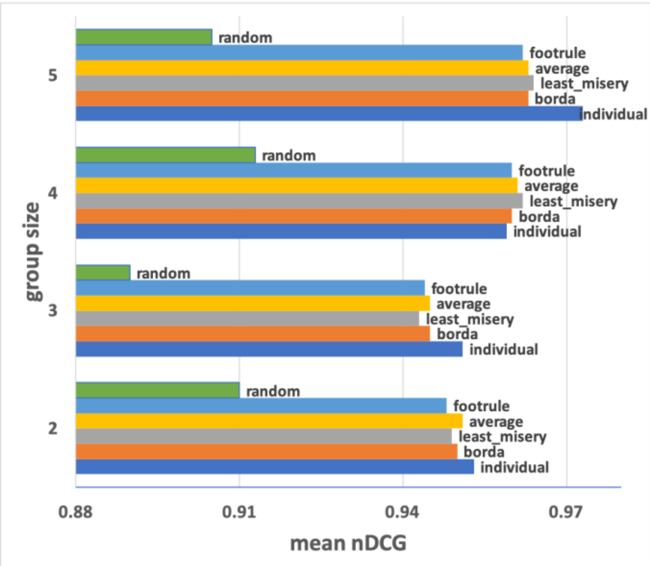

Fig. 2 Effectiveness of group recommendation with rank aggregation techniques. © L. Baltrunas, T. Makcinskas and F. Ricci 2010. This is a minor revision of the work published in Group recommendations with rank aggregation and collaborative filtering. In Proceedings of the fourth ACM conference on Recommender systems (RecSys '10), http://dx.doi.org/10.1145/1864708.1864733

IV. Calculations and Results

A. *Dataset and setting*

The model has been implemented using RapidMiner, a software platform for data science teams which unites data prep, machine learning and predictive model deployment. The Gowalla dataset was selected because we wanted to compare our results with the results of Si et al. (2017). Moreover, we applied our model and that of Si et al. (2017) to the Brightkite dataset for better comparison. These datasets collected information about friendships between users which was used for the DF feature of our model. These datasets consist of the undirected friendship network and locations of users from check-in (Cho, Myers & Leskovec, 2011). Statistics using the Gowalla dataset, collected over the period February 2009 to October 2010, are shown in table 1.

Table I: Statistics of Gowalla dataset

Items of datasets	Gowalla
Number of check-ins	6,442,890
Number of locations	1,280,969
Number of users	196,591
Number of relationships	950,327

The results from Brightkite, collected over the period of April 2008 to October 2010, are shown in table 2.

Table II: Statistics of Brightkite dataset

Items of datasets	Brightkite
Number of check-ins	4,491,143
Number of locations	772,966
Number of users	58,228
Number of relationships	214,078

Each check-in record on these datasets contains a user ID, a date and the time of check-in, a location-based latitude and longitude and a location ID. Each relationship record on the Gowalla and Brightkite datasets contains a user and a friend ID. To allow a comparison, we separated the check-in dataset into 16% for testing data and 84% for training data.

B. *Evaluation metrics*

- *Evaluation for individuals*

To compare our results with the model paper, we used the same metric (i.e. precision). This metric shows how many POIs in the Top-N recommended POIs correspond to the POIs in the testing data. Precision metrics are calculated as follows:

$$precision@N = \frac{1}{N}\sum_{t \in T}\left(\frac{\sum_{u \in U}|T_{u,t} \cap R_{u,t}|}{\sum_{u \in U}|R_{u,t}|}\right) \qquad (4)$$

where $T_{u,t}$ denotes the set of corresponding ground truth POIs in the testing data, $R_{u,t}$ is the set of Top-N recommended POIs and N is the number of location recommendation.

- *Evaluation for groups of users*

To evaluate performance of our proposed model for groups of users, we selected users randomly with group sizes of 5, 10 and 15 and used the same metric as in eq.4 to measure the performance of our POI recommender system on different size groups.

C. *Results*

Temporal information in LBSNs is highly significant for POI recommendation at a specific time. For analysis purposes, the VT values on the Gowalla dataset were computed using variability of time (Si, Zhang & Liu, 2017). Figure 3 shows that the user check-in differs significantly for each time slot, which demonstrates that users have different preferences at different times which confirms the findings of Si et al. (2017).

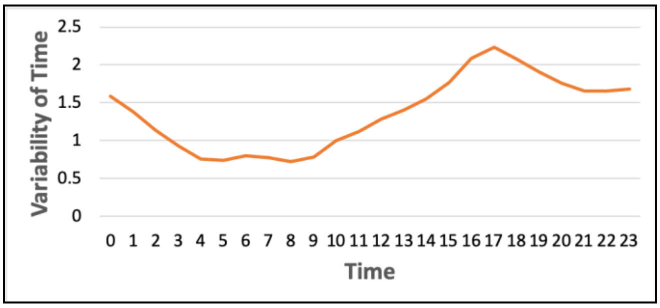

Fig. 3. VT values at different time on Gowalla dataset.

In the first step of the experiment, we divided all users in the Gowalla dataset into active and inactive users with Algorithm 1. In Figure 4, the number of users and their number of check-ins on the Gowalla are shown.

User activities differ significantly, and a small number of individuals make a high number of contributions. We found that, for the Gowalla dataset with a total number of 196,591 users, only a small number checked in frequently, particularly those checking-in more than 500 times (1,488) while 3,438 users checked-in more than 300 times.

This result indicates that the majority of LBSN user's check-in occasionally.

We also selected users from the dataset that are direct friends and have a common check-in time to the target user. The result of Algorithm 2 for user id 2 is shown in figure 5.

As shown in Figure 5 (a), the group of similar users with user id 2 was selected. The x-axis refers to user id and y-axis refers to the number of common check-ins between other users and user id 2. However, earlier results showed that user id 2 is an active user. Therefore, we eliminated the group of users who have less than 2 common check-ins with user id 2. As mentioned in section 5.1.2, if a target user is an active user, we eliminate these direct friends This is because selecting users with high similarity reduces computational overheads and noise in recommendations. If a target user is an inactive user, all direct friends are retained as a group of similar users. As a result, the group of similar users in the proposed model is smaller than that in the model paper which reduces processing time and improves accuracy of the POI recommendation. The results are shown in Figure 5 (b).

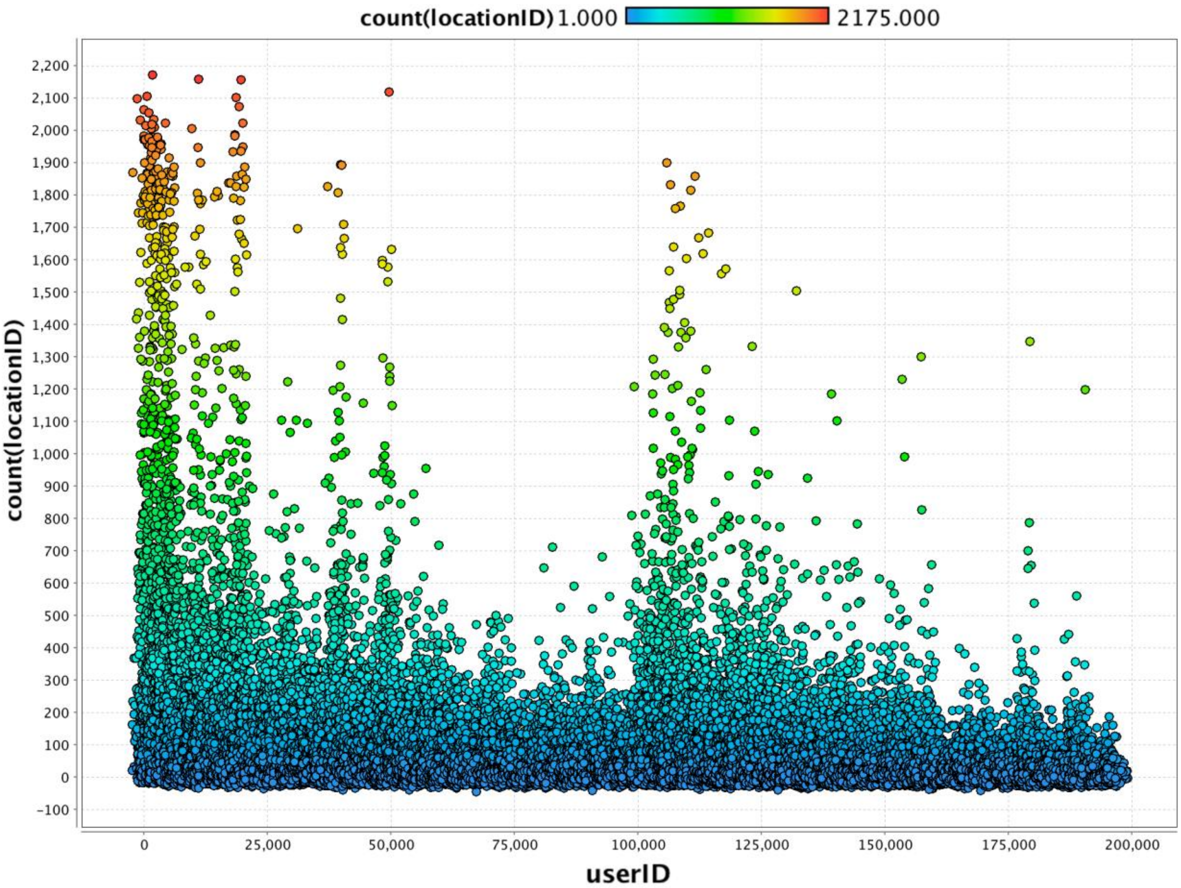

Fig. 4 Graph between user ID (x axis) and number of check-in (y axis)

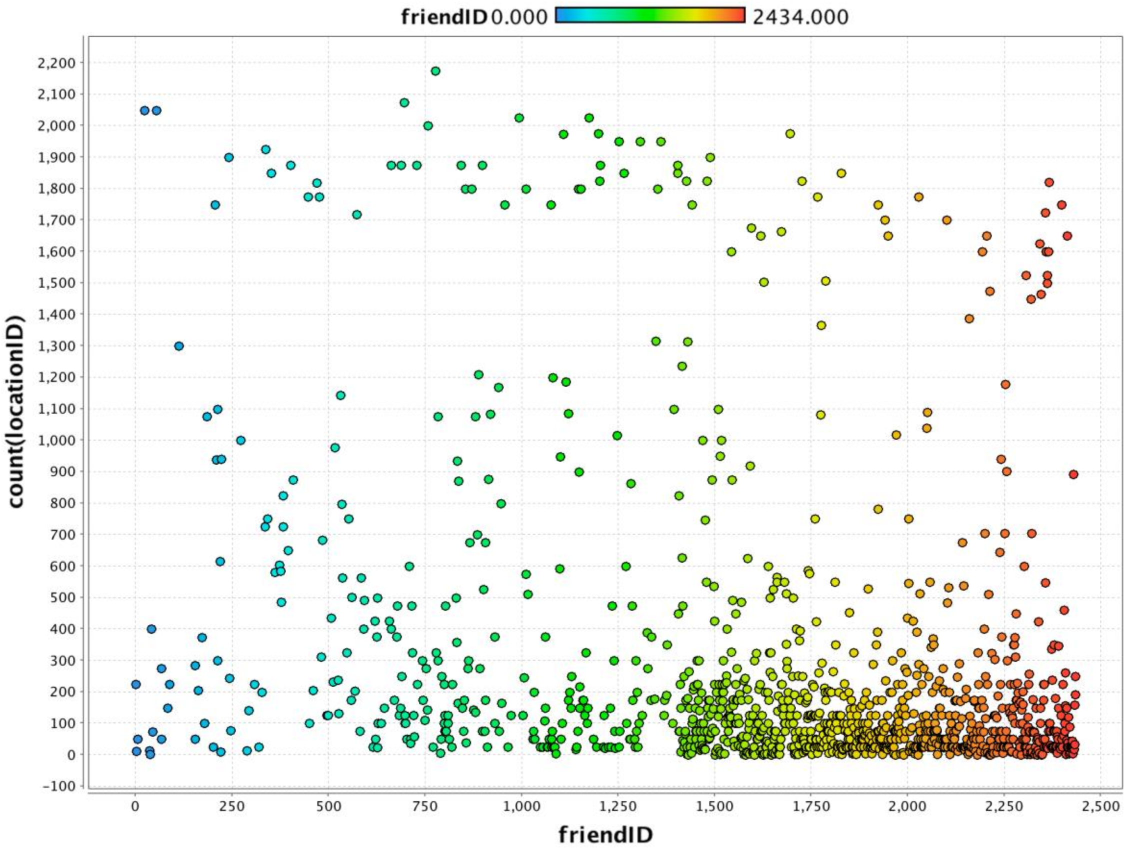

Fig. 5(a). Group of similar users with user id 2

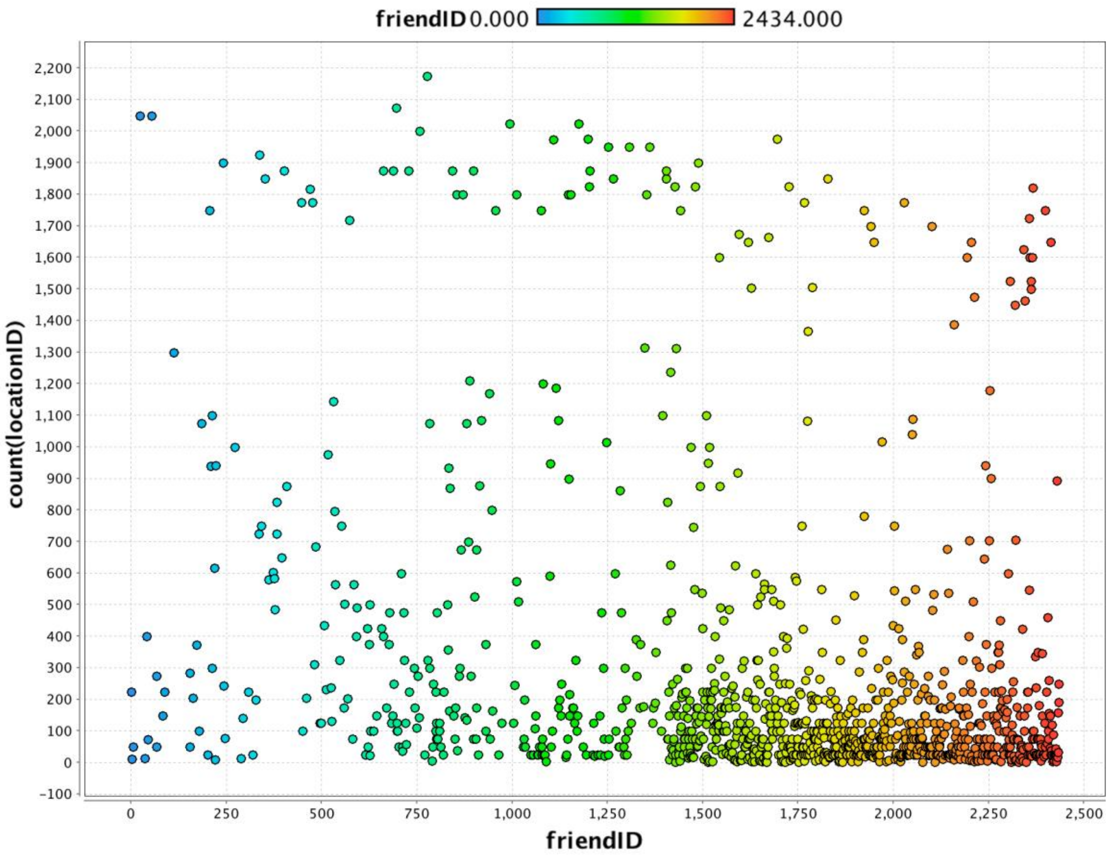

Fig. 5(b). Group of similar users with user id 2 for active user

Furthermore, we identified the location of countries and cities from their latitude and longitude in the Gowalla dataset. As shown in Table 3, each location id corresponds to a country and city.

The system allows target users to select countries or cities they would like to visit. The POI recommender system only recommends locations that are identical to the target user's selection, thus improving accuracy.

Lastly, we applied algorithm 3 which calculates user similarity based on nine adjacent time slots for active users and based on all time slots for inactive users. The results are shown in Tables 4 and 5. Table 4: user id 0 checked-in at different times. Since user id 0 is an active user, algorithm 3 was applied to nine adjacent time slots, before calculating rank or probability of location recommendation that came from a friend of the target user. Table 5: The POI recommender suggested location id 10190 as the first rank to user id 0, because this location had the highest ranking/probability among other locations.

TABLE III EXAMPLE OF LOCATION'S COUNTRY AND CITY.

LocationID	Country name	City name
22857	United States	Austin
420315	United States	Austin
316637	United States	Austin
16516	United States	Austin
5535878	United States	Austin
15372	United States	Austin
21714	United States	Austin
420315	United States	Austin
153505	United States	Austin
420315	United States	Austin
23261	United States	Rosedale
16907	United States	New York
12973	United States	New York
341255	United States	New York
260957	United States	New York
1933724	United States	New York

TABLE IV EXAMPLE OF CHECK-IN FROM USER ID 0 IN DIFFERENT TIME SLOT.

Row No.	Time slot	Number of check-in
1	0	18
2	1	16
3	2	18
4	3	5
5	4	4
6	5	1
7	6	2
8	7	1
9	11	1
10	13	3
11	14	16
12	15	6
13	16	16
14	17	15
15	18	16
16	19	13
17	20	15
18	21	18
19	22	23
20	23	18

TABLE V EXAMPLE OF LOCATION RECOMMENDATION TO USER ID 0, 1 & 2.

Row No.	user_id	location_id	rank
1	0	10190	1
2	0	9222	2
3	0	9246	3
4	0	14128	4
5	0	9247	5
6	1	9410	1
7	1	19542	2
8	1	23261	3
9	1	9241	4
10	1	10190	5
11	2	9410	1
12	2	19542	2
13	2	23261	3
14	2	10190	4
15	2	21714	5

Similarly, location id 9222, 9246, 14128 and 9247 were recommended to user id 0 respectively. Each user received recommendations for the top 5 locations that considered friendship, activity and temporal features and was calculated from previously used algorithms.

For group recommendations, we aggregated the individual results to group results by applying the average aggregation from definition 2. The results shown in Table 6, a group of 3 users, including user id 0, 1 and 2 received 10 locations recommendations sorted by score that calculated from average aggregation in definition 2. The lower score refers to the higher probability. The group of users received locations recommendation that satisfied overall users in that group, to an extent more than it satisfied only one user.

To evaluate the accuracy of the POI recommendation for individuals, we compared performance between the model paper and the individual model in our approach. Figure 6 shows the results from eq.4 which is the Top-N precision of two algorithms on the Gowalla dataset. The precision values of our proposed model are higher than those of the model paper in top 5 and 10 location recommendations. Our proposed model performed slightly better than the CTF-ARA algorithm in the top-5 of precision. However, our proposed model performed better by 0.07 in the top-10 of precision. The reason is that the proposed model combines relationship information with the model paper.

As shown in Figure 7, we also compared performance on the Brightkite dataset. The results showed that our precision values are better than those of the model paper in both top 5 and 10 location recommendations.

To evaluate the accuracy of POI recommendations for groups of users, we selected users randomly in groups of 5, 10 and 15 and used the same metric as POI recommendation as for the individuals in eq.4.

TABLE VI EXAMPLE RESULT OF LOCATION RECOMMENDATION FOR GROUP OF USER ID 0, 1 AND 2.

Row No.	location_id	average(rank)
1	9410	1
2	9222	2
3	19542	2
4	9246	3
5	23261	3
6	10190	3.333
7	9241	4
8	14128	4
9	9247	5
10	21714	5

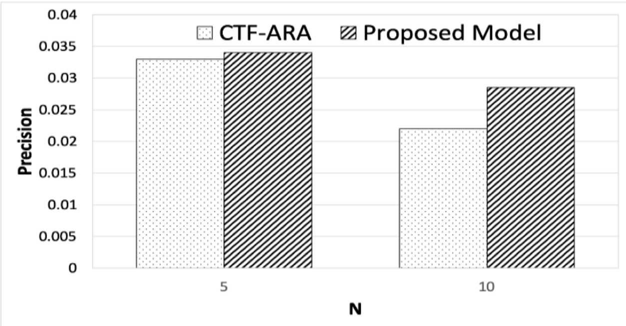

Fig. 6. Bar chart compared performance between model paper and proposed model on Gowalla dataset.

As shown in Figure 8, the precision performance for groups of 5 users reached 0.2, 0.1 and 0.067 for precision@5, precision@10 and precision@15 respectively.

However, as shown in Figure 9, the precision performance for groups of 10 users was slightly lower than for groups of 5 users: precision@5, precision@10 and precision@15 performed 0.156, 0.078 and 0.052 respectively.

Furthermore, as shown in Figure 10, the precision performance for groups of 15 users showed the lowest performance when compared with groups of 5 and 10 users. The precision performance reached 0.123, 0.162 and 0.041 for precision@5, precision@10 and precision@15 respectively.

These group precision tests demonstrate that groups of 5 users had the highest precision while groups of 15 users had the lowest in all precision@k. Moreover, precision@5 performed better than precision@10 and precision@15 in every group size. We conclude that our POI recommendation for groups of users based on LBSNs achieved the most accurate result when recommending top 5 locations to groups of 5 users.

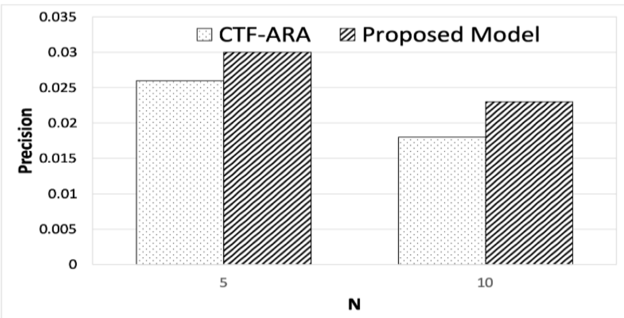

Fig. 7. Bar chart compared performance between model paper and proposed model on Brightkite dataset.

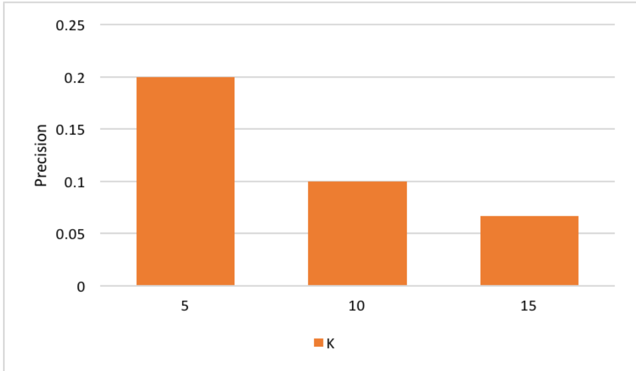

Fig. 8. Group performance for group of 5 users

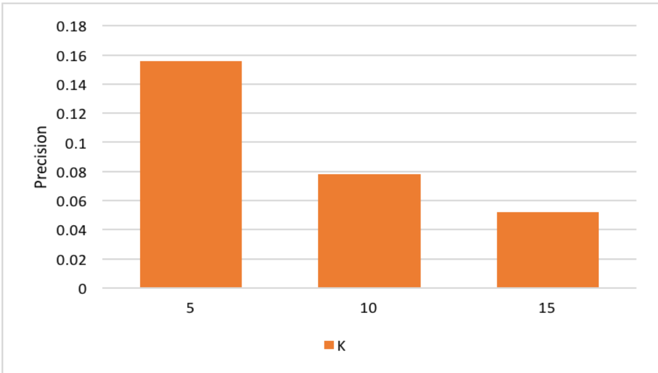

Fig. 9. Group performance for group of 10 users

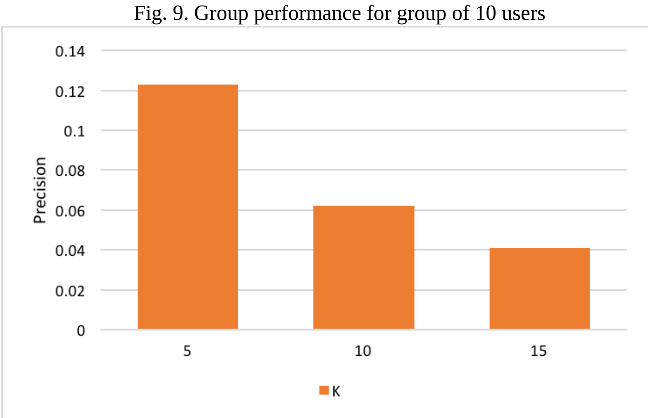

Fig. 10. Group performance for group of 15 users

V. CONCLUSION

In this study, an extension of the CTF-ARA algorithm (Si, Zhang & Liu, 2017) was proposed. We considered the friendship relationship between users in social networks, in addition to the factors considered in the above-mentioned algorithm, to identify target groups of related users. This improved the accuracy of the recommendation system in both top 5 and 10 POI recommendations. The proposed model is suitable also for groups of users as opposed to the CTF-ARA which is a POI recommendation method for individuals only. The performance of the proposed model for groups of users of different sizes and number of recommended locations were also analyzed. The results showed that the model had the highest accuracy when recommendations were made to groups of 5 users and most effective when the system recommended the top 5 locations for every size of group.

In conclusion, the proposed method has three major advantages. Firstly, the system allows users to select a range of locations, cities or countries, based on individual or group profiles. The system recommends locations in the area selected by the target users. Secondly, the proposed method is based on a smaller group of users with similarity to the target users but has higher accuracy. This was achieved through consideration of the friendship factor and by only selecting direct friends of the target users, thus reducing the size of groups of similar users. This reduces processing time and overheads. Lastly, the proposed method is effective for individuals and groups of users. The system aggregates the individual results to create a group result that satisfies everyone in the target group.

However, although the performance of the proposed model has improved POI recommendations, it has limitations. One of these is the sparsity of the LBSN dataset which leads to low POI recommendation performance. Furthermore, future research needs to focus on ratings, text reviews and location categorization which have the potential to improve the performance of POI recommendation systems.

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