



# RCFC: A Region-Based POI Recommendation Model with Collaborative Filtering and User Context

Jun Zeng<sup>(✉)</sup>, Haoran Tang, and Xin He

School of Big Data and Software Engineering, Chongqing University, Chongqing, China  
{zengjun, tanghaoran, hexin}@cqu.edu.cn

**Abstract.** In the past few years, mobile application has been innovated by leaps and bounds, which leads the prevalence of location-based social networks (LBSNs). Point of interest (POI) recommendation aims to recommend satisfactory locations to users in mobile environment and plays an important role in LBSNs. However, there are still two challenges to be solved. One is the data sparseness caused by users who just visit a few POIs. The other is that it's hard to make reasonable explanation of recommendation from the perspective of real world. Hence, firstly we propose a region-based collaborative filtering to alleviate the data sparseness by clustering locations into regions. Secondly, we model the impact of two kinds of user contexts like geographical distance and POI category to make POI recommendation more reasonable. Finally, we present a joint model called RCFC which combines the two parts mentioned above. Results of experiments on two real-world datasets demonstrate the model we propose outperforms the popular recommendation algorithms and is more in line with the situation in real world.

**Keywords:** Recommendation system · Point of interest · Region · Context · Collaborative filtering

## 1 Introduction

Recent years have witnessed the rapid prevalence of location based social networks (LBSNs) such as Facebook, Twitter and Foursquare, which facilitate people's outdoor activities by recommending nearby POIs in real time [1]. LBSNs encourage users to share their experiences and locations by check-ins [20]. These check-ins embed abundant hints of users' preferences on locations. Implicit user preferences can provide better recommendation diversity [2]. Moreover, utilizing these check-ins helps users to explore new locations and bring more benefits to the third-parties like advertisers [12]. Therefore, it's still worth studying POI recommendation system in terms of its value [11].

Collaborative filtering (CF) is extensively investigated in recommendation system and widely used in industry [3]. It's based on a simple intuition that if users have similar rating records in the past, they are likely to rate new items similarly in the future [4]. It takes the full advantages of the similarity or correlations among user behaviors [5].

In most real-world applications, there are a huge number of users and locations. However, most users only visit a few of these locations, which causes thorny data sparseness [18]. Facing the data sparseness, CF can't calculate the similarity between users appropriately. Even though matrix factorization is an effective way to solve data sparseness [6], its mathematical nature makes explain recommendation from real-world perspective become much difficult. The key of reasonable explanation is to make full use of user context, as it greatly influences the user's decision on visiting a location [7]. Geographical distance is extremely important in user context. Users are more willing to visit locations closer to their current location [8]. For instance, if a user wants to watch a new movie that just comes out, he may tend to choose a nearby cinema, instead of going to one 20 kilometers away from home. In addition to the geographic distance, user daily activities usually present category-level transition patterns [9]. For example, user who loves stage plays may often go to locations classified as theater.

In this paper, inspired by CF and user context, we propose a novel region-based CF with the impact of context, which simulates the situation of users visiting POIs from real-world perspective. Our region-based CF is different from grid-based model which divide map into rectangular grids. We focus on the geographical relevance that can be regarded as irregular regions. For simplicity, we also call POI location.

The main contributions of this paper can be summarized as follows.

- Firstly, in order to alleviate the negative impact caused by data sparseness of CF, we cluster locations into many regions and figure out the preferences of users on regions instead of just locations. Then, we incorporate region factor into the CF.
- Secondly, since the full use of user context can explain recommendation well, we construct a probability model of geographic distance in a region and capture category level transition pattern between locations by a new category pairing method.
- Thirdly, we integrate our region-based CF with the impact of context by combining them in a linear way and propose our model called RCFC.
- Experimental results on two real-world datasets collected from Foursquare demonstrate our proposed model RCFC is superior to other popular recommendation models.

The rest of the paper is organized as follows. Related works are reviewed in Sect. 2. Section 3 describes in detail the design of RCFC model. Experiments are presented in Sect. 4 to analyze RCFC model and demonstrate its effectiveness compared to other recommendation algorithms. Finally, the Sect. 5 gives conclusion of this paper.

## 2 Related Work

POI Recommendation aims to obtain users' personal preferences according to their historical records such as check-ins, so as to recommend satisfactory locations to users in the future for saving time in making choices. To the best of our knowledge, there are many studies that extend CF or adopt user context for the sake of improving POI recommendation.

CF that is widely-used in industry is a classic popular algorithm in recommendation system. Liu [8] defines three types of friends in LBSNs and develop a two-step framework to leverage information brought by friends, which improves the quality of CF. Furthermore, Yang [10] proposes a general principled semi-supervised learning framework to alleviate data sparseness in CF via regularizing user preference and smoothing among neighboring users and POIs. The methods mentioned above focus on positive preferences of users. Tran [6] constructs a joint model which combines user embedding, user positive preference embedding and user negative preference embedding to complete recommendation from different perspectives. Therefore, it can be seen that the CF still plays a significant role today. However, the data sparseness is a great challenge for CF. Matrix factorization is an effective method. Xue [5] presents a deep matrix factorization structure to calculate the similarity between users and recommendations by learning a common low dimensional space for them.

User context always indicates the preferences of users explicitly and it can constrain predictions correctly no matter in recommendation system or other fields. Ye [13] argues that influence of geographical distance among two POIs is able to decide users' check-in behaviors and model it by power law distribution. Many geo-based POI recommendation models refer to his work so far. In contrast, Liu [14] considers the geographical influence from the location perspective rather than preferences of users and then models geographical neighborhoods of locations. Liu [15] proposes an adversarial learning model based on geographic information to dig deeper geographic representations. While most existing works discover the spatial, temporal and social patterns of user behavior, the information of context itself is often ignored [16]. To a large extent, location's category that represents its attribute can be regarded as expression of context itself. He [9] uses a third-rank tensor to predict the next preferred category that user may visit and then fuse distance to filter out POI candidates. These studies on user context are consistent with real world and give us great inspiration to our work.

In our previous work, we propose a deep recommendation framework by combining restricted Boltzmann machine with non-negative matrix factorization [18]. Furthermore, we construct a recurrent neural network based on self-attention to predict the next locations of users [20]. We also try some explorations by modeling geographical and social influence [19]. In this paper, different from our previous work, we focus on the region factor that could improve CF in POI recommendation. Moreover, we still consider the user context such as geographical distance and location category.

### 3 Region-Based POI Recommendation Model with Collaborative Filtering and User Context

#### 3.1 Framework of RCFC

POI recommendation aims to recommend satisfactory locations to users by mining users' historical records of visiting locations. Now we introduce our recommendation model RCFC on the whole. RCFC is a joint model that combines region-based CF and the impact of user context. The whole framework of RCFC is shown in Fig. 1. Firstly, we cluster locations into different regions for capturing users' preference on regions and

then incorporate that into CF. The goal of first step is to alleviate the negative impact caused by data sparseness. Secondly, after obtaining regions, we search the activity areas for users in order to find limited candidate locations and next use a non-linear model to calculate the probability of geographic distance. Thirdly, we capture the category-level transition pattern between locations by a novel category pairing method. The goal of second and third steps is to make recommendation more reasonable by adopting user context. Finally, we are able to recommend suitable locations to users by combination of all the steps mention above. The details of each step will be presented in following subsections.

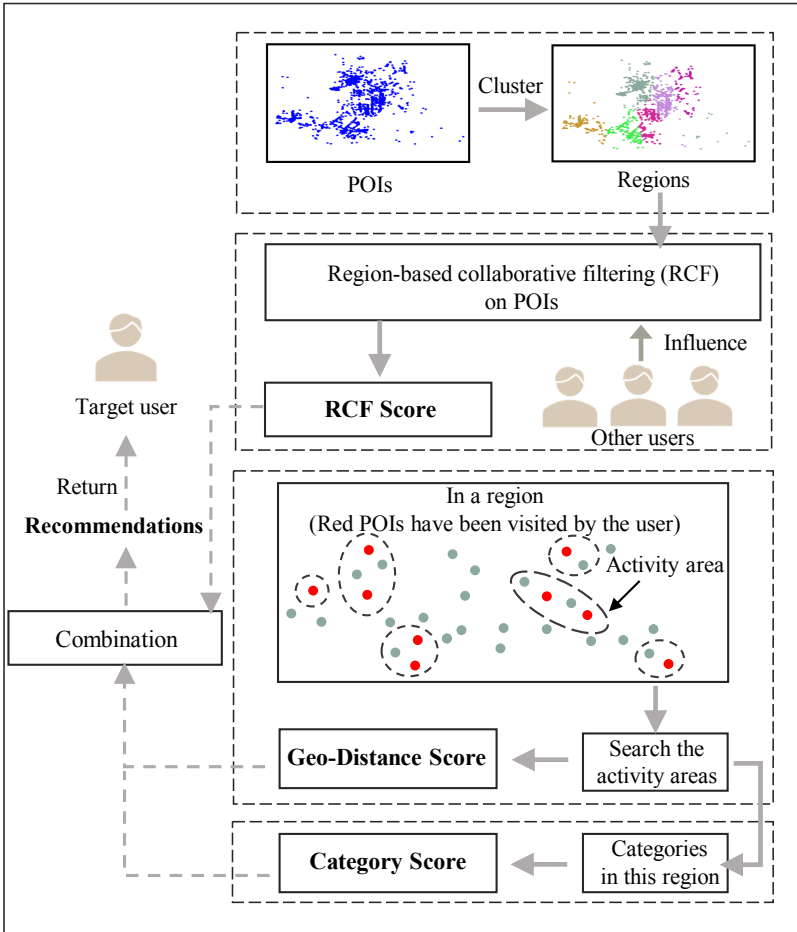


Fig. 1. The framework of RCFC

### 3.2 Region-Based Collaborative Filtering

For widely distributed locations, clustering them into regions is benefit for alleviating the data sparseness since there is a huge number of locations. We have a set  $U$  of users  $\{u_1, u_2, \dots, u_m\}$ , a set  $L$  of locations  $\{L_1, L_2, \dots, L_n\}$ , and a set  $C$ , of categories  $\{c_1, c_2, \dots, c_p\}$ . Each location is denoted by a triple  $l = (lon, lat, c)$ , which includes the longitude and latitude of the location and the category it belongs to. Before clustering locations, we use  $\mathbf{u}^L = (u^{l_1}, u^{l_2}, \dots, u^{l_n})$  to denote the corresponding vector of user  $u$ , where  $u^{l_j}$  represents the number of times user  $u$  has visited the location  $l_j$ .

It's intuitive and realistic to cluster locations in terms of distance. The more adjacent two locations are, the more likely they will gather to a region. Therefore, we adopt classic K-means algorithm in this paper because the goal of K-means is exactly to minimize the sum of the distances. Suppose there are  $q$  regions  $R = \{r_1, r_2, \dots, r_q\}$  where  $|R| \ll |L|$  and  $\mu_i$  is the center location of region  $r_i$ , which is updated by K-means dynamically. The objective function is defined as follows:

$$\min \sum_{i=1}^q \sum_{l_j \in r_i} \|dis(l_j, \mu_i)\|^2 \tag{1}$$

where  $dis$  calculates the distance between two locations according to their latitudes and longitudes. After obtaining regions that is shown in Fig. 2, it's easy to know the overall check-ins of each region.

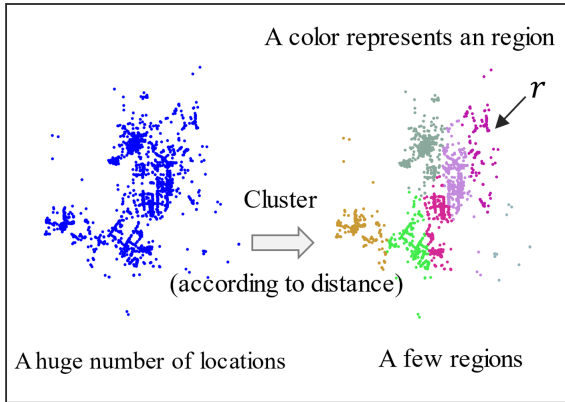


Fig. 2. Cluster locations into regions

Based on region, we use  $\mathbf{u}^R = (u^{r_1}, u^{r_2}, \dots, u^{r_q})$  to denote the corresponding vector of user  $u$ , where  $u^{r_j}$  represents the number of times user  $u$  has visited the region  $r_j$ . In order to compare with the overall regional visits, we have adopted a normalization on  $\mathbf{u}^R$  in advance. The region similarity between a user and the whole is shown as follows:

$$sim(u, R) = \frac{\sum_{z=1}^q u^{r_z} \times cnt(r_z)}{\sqrt{\sum_{z=1}^q (u^{r_z})^2} \times \sqrt{\sum_{z=1}^q cnt^2(r_z)}} \tag{2}$$

where  $cnt(r_z)$  denotes the ratio of the total number of check-ins in the region  $r$  to the maximum of all regions.  $sim(u, R)$  indicates whether the user will follow others while choosing a region. If  $sim(u, R)$  is large, it means the user is more willing to visit the regions that other users tend to visit. Otherwise, the user may have his own unique taste on visiting regions that is different from others. Then, the score  $u^{r_z}$  of user visiting region  $r_z$  is defined as follows, which considers both the public and the user himself:

$$u^{r_z} = sim(u, R) \times cnt(r_z) + (1 - sim(u, R)) \times u^{r_z} \quad (3)$$

Our goal is to enhance CF by clustering all locations into regions. The original CF is shown as follows:

$$cf(u_i, l_j) = \frac{\sum_{z=1}^{SU(u_i)} sim(u_i, u_z) \times u_z^{l_j}}{\sum_{z=1}^{SU(u_i)} sim(u_i, u_z)} \quad (4)$$

$$Score_{u_i, l_j}^{RCF} = u_i^{r_z} + \frac{cf(u_i, l_j)}{\max_{l_z \in L} (cf(u_i, l_z))} \quad (5)$$

where  $r_z$  is corresponding region of  $l_j$ . Unlike geographical and category contexts, region is a further strategy for CF so we don't adopt weighted calculation for them. Note that the user vectors in (4) and (5) are based on location and region respectively.  $r_z$  is corresponding region of  $l_j$ . Next, we will explore the impact of user context.

### 3.3 Geographical Distance Context

The major user context for POI recommendation is geographical distance. Users tend to visit locations that are closer to their current location. For the sake of modeling geographical distance, inspired by [13], we adopt a power law distribution that is shown as follows:

$$p(l_i|l_j) = a \times (dis(l_i, l_j))^b \quad (6)$$

where  $p(l_i|l_j)$  denotes the probability of visiting location  $l_i$  while the current location is  $l_j$ .  $a$  and  $b$  are the parameters of the power law distribution.

For obtaining suitable  $a$  and  $b$ , firstly we convert it to a linear model by using logarithmic representation, which is defined as follows:

$$\log p(l_i|l_j) = \log a + b \log dis(l_i|l_j) \quad (7)$$

$$y(x, \mathbf{w}) = a' + bx \quad (8)$$

where  $y(x, \mathbf{w})$  denotes  $\log p(l_i|l_j)$  and  $\mathbf{w}$  is the parameter set.  $a'$  is equal to  $\log a$ .  $x$  denotes the pair of two adjacent locations  $l_i$  and  $l_j$ .

We adopt the least squares method in terms of its simplicity and the loss function that needs to be minimized is defined as follows:

$$\min_{\mathbf{w}} \frac{1}{2} \sum_{x \in D} (y(x, \mathbf{w}) - t(x))^2 + \frac{\lambda}{2} \|\mathbf{w}\|^2 \quad (9)$$

where  $D$  is our real-world dataset and  $t(x)$  is the logarithmic value of the true distance probability derived from  $D$ . Moreover, the last term is a regularization that is controlled by its weight  $\lambda$ .

Generally, a user has visited a few locations in a region but they denote the user’s activity areas that are shown in Fig. 3. Hence, in order to filter out candidate locations, we set 0 to those locations that is out of user’s activity areas. We only calculate geographical score for locations belong to user’s activity area.

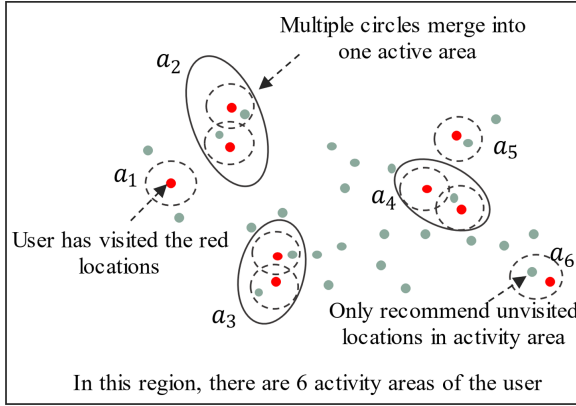


Fig. 3. Activity areas

In a region  $r$ , centered by location the user has visited, the circle with a radius of 0.5 kilometers composes an activity area. If two circles overlap, then merge them into one activity area. For a user, we have a set  $A_u$  of his activity areas  $\{a_1, a_2, \dots, a_z\}$ , where  $a_0$  represents the locations that the user has visited in this activity area. The geographical probability of a candidate location  $l_j$  is calculated as follows:

$$p(l_j|a_o) = \prod_{l_i \in a_o} p(l_i, l_j) \tag{10}$$

where  $a_o$  is the corresponding activity area of  $l_j$  and  $l_i$  is the location user has visited in  $a_o$ . Next, the geographical score of unvisited  $l_j$  is defined as follows:

$$S_{u_i, l_j}^{Geo} = \frac{count(a_o)}{\max_{a_x \in A_{u_i}} count(a_x)} \times \frac{p(l_j|a_o)}{\max_{l_x \in a_o} p(l_x|a_o)} \tag{11}$$

where  $count(a_o)$  is the function that counts the total number of check-ins of the user in  $a_o$ . Even in the same region, user has different check-in behaviors in different activity areas. In order to make all candidate locations comparable, we decide to normalize the geographical scores of them according to activity areas they belong to and also take the weight of each activity area into account.

### 3.4 Category Context

Categories usually have semantic information, reflecting functions of locations. In this paper, we present a novel pair-wise method to model the impact of category. If a user has visited both category  $c_i$  and  $c_j$ , then we can say there is a transition relationship between  $c_i$  and  $c_j$ . This kind of transfer has symmetry. Let  $T$  denote the category transition matrix, where its size is  $p \times p$ .  $T_{ij}$  represents value of the transition between  $c_i$  and  $c_j$ , which means the number of users who has visited both the two categories.

We use  $C_{u_i, r_z}$  to denote the set of categories that user  $u_i$  has visited in region  $r$ . For the category  $c_x$  of a candidate location  $l_j$ , its category score is defined as follows:

$$S_{u_i, l_j}^{Cate} = \begin{cases} \frac{\text{count}(c_x)}{\sum_{c_v \in C_{u_i, r}} \text{count}(c_v)}, c_x \in C_{u_i, r} \\ f(c_x), c_x \notin C_{u_i, r} \end{cases} \quad (12)$$

If user has visited the category before, then we calculate its probability according to user's check-ins in this region. Otherwise, we adopt function  $f$  to get its category score, which is shown as follows:

$$f(c_x) = \frac{\frac{1}{|C_{u_i, r}|} \sum_{c_v \in C_{u_i, r}} T_{c_v, c_x}}{\sum_{c_s \in C_{u_i, r}} f(c_s)} \quad (13)$$

Note that in both (12) and (13),  $c_v$  denotes the category user has visited and  $c_s$  denotes the unvisited category. After obtaining geographical distance score and category score, the final context score of location  $l_j$  is defined as follows:

$$Score_{u_i, l_j}^{Context} = \beta \times S_{u_i, l_j}^{Geo} + (1 - \beta) \times \frac{S_{u_i, l_j}^{Cate}}{\max_{l_z \in r} S_{u_i, l_z}^{Cate}} \quad (14)$$

where  $l_z$  and  $l_j$  belong to the same region  $r$  and  $\beta \in [0, 1]$ . We have adopted normalization when calculating geographical score, so now we only have to normalize category score.

### 3.5 Joint Recommendation

We have introduced the region-based CF and obtain  $Score_{u_i, l_j}^{RCF}$ . RCF alleviates the data sparseness by clustering locations into regions and incorporating them into CF. Then, we combine the geographical and category context to get  $Score_{u_i, l_j}^{Context}$ , which models the impact of two major user context for explaining the recommendation more reasonable. Now we propose our final model called RCFC. It contains the  $Score_{u_i, l_j}^{RCF}$  and  $Score_{u_i, l_j}^{Context}$ . RCFC is defined as follows:

$$Score_{u_i, l_j}^{RCFC} = \alpha \times Score_{u_i, l_j}^{RCF} + (1 - \alpha) \times Score_{u_i, l_j}^{Context} \quad (15)$$

where  $\alpha \in [0, 1]$ . Finally, we sort the scores of all candidate locations and recommend top-K locations to users.

## 4 Experiments

In this section, we choose the optimal parameters of our proposed model and evaluate that with other popular POI recommendation models on two real-world datasets.

### 4.1 Datasets

We employ two real-world datasets that are collected from two cities on Foursquare, one is Los Angeles, the other is London. There are 48460 check-ins made with Los Angeles. They are made by 4746 users on 7135 POIs and the average check-ins of each user is 10. As for London dataset, there are 43912 check-ins. They are produced by 3470 users on 7941 POIs and the average check-ins of per user is 12. Both two datasets are much sparse. We randomly select 70% of the locations of each user as training data and the remaining 30% as test data. In addition, for the effectiveness of our experiments, the users who have visited less than 5 POIs and the POIs that have been visited by less than 5 users are removed.

### 4.2 Evaluation Metrics

We adopt precision, recall and F1-score to evaluate the performance. F1-score combines precision with recall and we use that to find the best values of parameters of our model. Precision and recall are used in comparing with other algorithms. All evaluation metrics are defined as follows:

$$Precision@K = \frac{1}{|U|} \sum_{u \in U} \frac{|rec^u \cap test^u|}{|rec^u|} \quad (16)$$

$$Recall@K = \frac{1}{|U|} \sum_{u \in U} \frac{|rec^u \cap test^u|}{|test^u|} \quad (17)$$

$$F1 - score@K = 2 \frac{Precision@K \times Recall@K}{Precision@K + Recall@K} \quad (18)$$

where F1-score is based on the overall precision and recall.  $K$  is the number of recommended POIs, which is always set to 10, 15 and 20.  $rec^u$  is the recommendation list for user  $u$  and  $test^u$  is the test data of user  $u$ .

### 4.3 Study on Parameters

There are three parameters of our model.  $Q$  determines how to cluster locations into regions.  $\alpha$  weights the region-based CF and the impact of context and  $\beta$  weights the geographical distance and category. We do experiments on different parameter combinations.

The results of  $\alpha$  are shown in Fig. 4. For the LA dataset, the optimal  $\alpha = 0.7$  while  $\alpha = 0.6$  is most suitable for the LON dataset. From the figure, it's observed that all curves first go up and then go down in both datasets. This indicates that with the increase of  $\alpha$ , the performance of our model can be improved by region-based CF but then excessively

ignoring the user context will cause the performance to decrease.  $\alpha = 0.0$  means our model depends only on the impact of user context while  $\alpha = 1.0$  means there is only region-based CF. However, the latter is better than the former on both datasets, which proves the effectiveness of clustering locations into regions for POI recommendation.

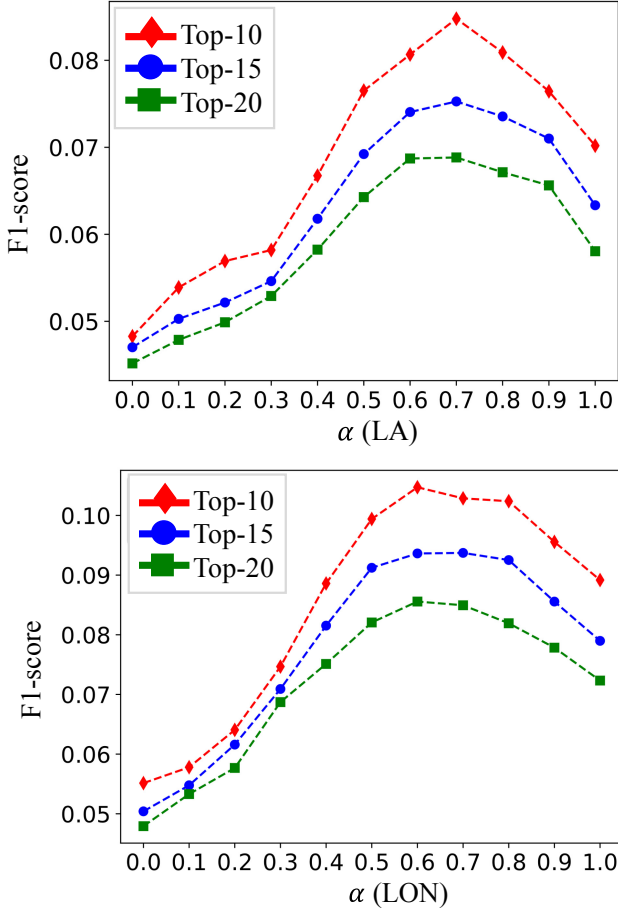


Fig. 4. F1-score under different  $\alpha$

The results of  $\beta$  are shown in Fig. 5. For the LA dataset, the optimal  $\beta = 0.9$  while  $\beta = 0.5$  is most suitable for the LON dataset. On one hand, the curves of LA dataset have clear upward trends before  $\beta = 0.5$  but then become flat gradually, which reveals that geographical distance has a limited improvement. On other hand, while Top-K = 10 and 15, the curves of LON dataset go down significantly after reaching their peaks, which shows that too much consideration of geographical distance will bring negative effect. However, for both datasets, region-based CF with only geographical context where  $\beta = 1.0$  outperforms that with only category context where  $\beta = 0.0$ . This fully demonstrates that geographical distance is the most important context for POI

recommendation and it's worth studying. Moreover, even though category context dose not play the equal impact as geographical distance, it can still improve the performance of POI recommendation based on geographical distance.

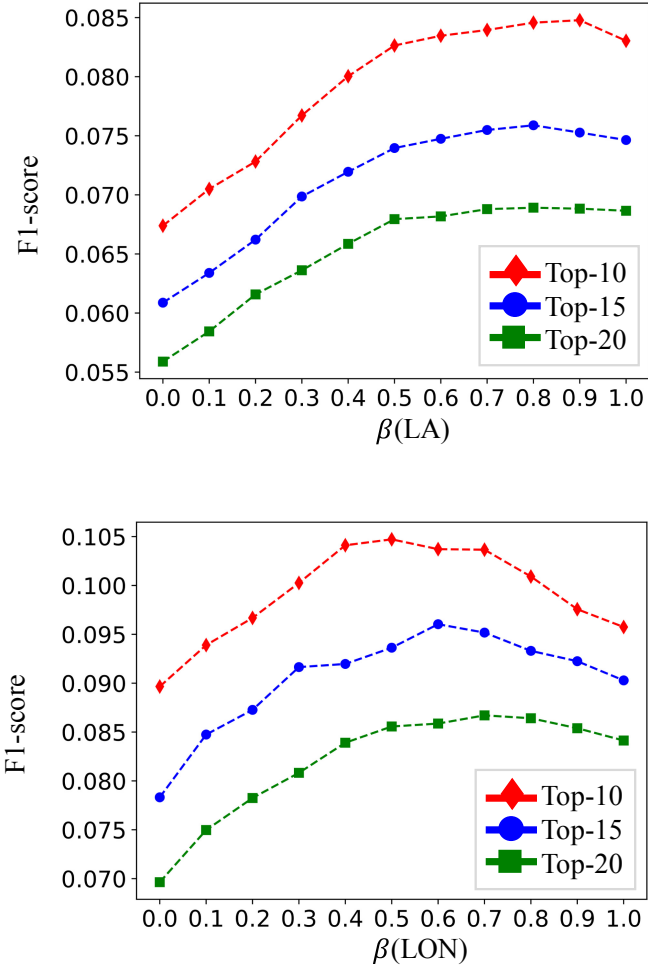


Fig. 5. F1-score under different  $\beta$

As shown in Fig. 6, for the LA dataset, the optimal  $Q = 11$  while  $Q = 16$  is most suitable for the LON dataset. There are significant differences between two datasets. A huge decline happens for LA dataset when  $Q = 2$ , which indicates that few regions may result in insufficient clusters especially at the beginning. With the increase of  $Q$ , the advantage of region comes into play gradually. In contrast, for LON dataset,  $Q = 2$  doesn't destroy the performance. That may be due to characteristics of the dataset because each city has different distributions of locations. Overall, there are many obvious fluctuations on both datasets. One possible reason is that, for each  $Q$ , the K-means method clusters locations

into regions dynamically. In general, a larger region number can improve our model even though fluctuations exist. Meanwhile, a larger region number help us understand the regional behaviours of users.

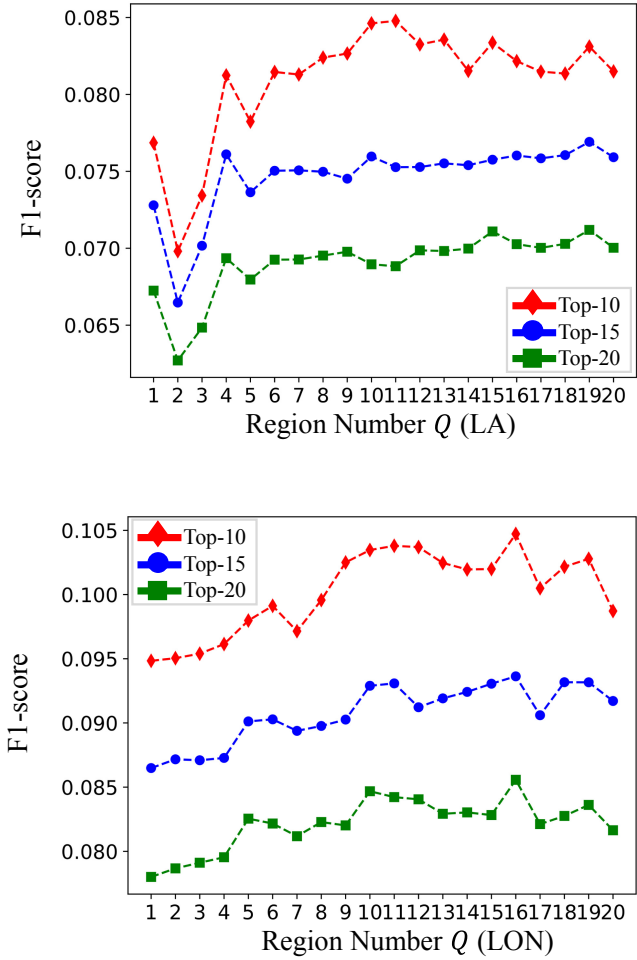


Fig. 6. F1-score under different region number

#### 4.4 Performance Comparison

To comprehensively demonstrate the effectiveness of our model, we compare them with following popular models:

**POP:** A basic model that recommends popular POIs.

**CF:** User-based collaborative filtering, which is widely-used in industry.

**NMF**: A classic non-negative matrix factorization. It aims to fill in unknown items in user-POI matrix.

**BPR** [17]: Bayesian personalized ranking via optimizing the ordering relationship of users and POIs.

**DMF** [5]: A novel deep matrix factorization for recommendation system, which aims to learn a common low dimensional space for users and recommendations.

**RCF**: The region-based collaborative filtering we propose before, which only takes region factor into account

Our final model that consists of the region-based CF and the impact of context is called **RCFC**. We conduct comparison experiments on two datasets respectively. For the LA dataset, we set  $Q = 11$ ,  $\alpha = 0.7$  and  $\beta = 0.9$ . For the LON dataset, we set  $Q = 16$ ,  $\alpha = 0.6$  and  $\beta = 0.5$ . The performance comparison is shown in Fig. 7 and then we summarize the following observations.

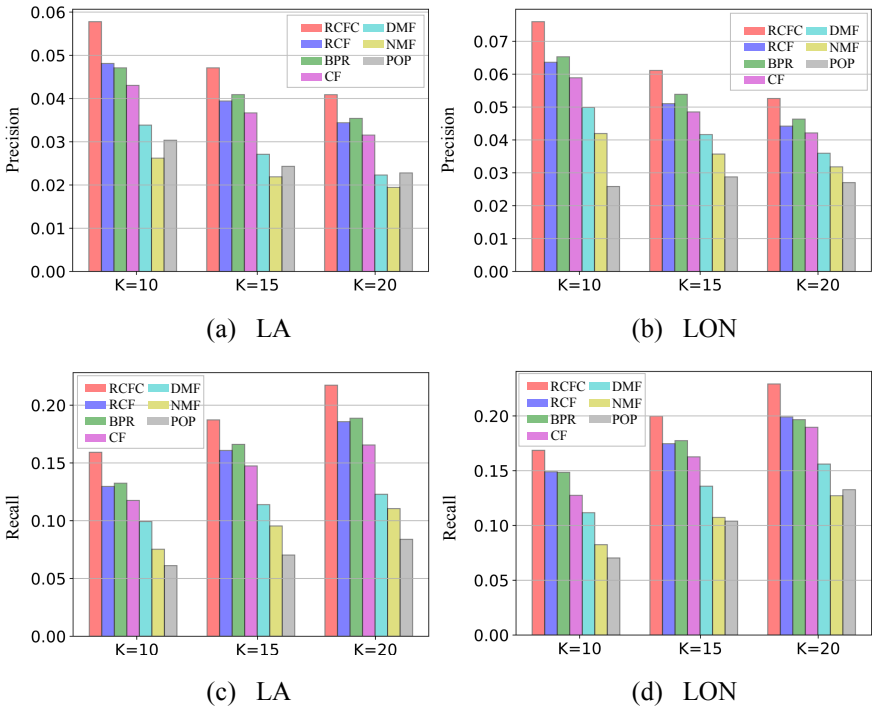


Fig. 7. Performance comparison in terms of precision and recall

Firstly, from a whole perspective, RCFC is obviously superior to other recommendation models in terms of both precision and recall. This result is due to clustering locations into regions and modeling the impact of context. RCF doesn't outperform BPR, which indicates BPR still has an excellent performance at present. BPR that aims to match the users and POIs can mine the correlations between them effectively. Although DMF is a

state-of-art deep model for recommendation system, it's not as good as CF, only better than NMF and POP. One possible explanation can be that DMF depends on the structure of neural network to a great extent and it's also very sensitive to different datasets. Besides, DMF does not consider any unique characteristics of POI recommendation, such as geographical distance.

Secondly, the classical CF model performs well on both datasets, which fully proves why it can become the widely-used recommendation model in industry. This is why we are interested in it and proposed our own model. Our RCFC achieves excellent improvement by incorporating region and context into it. RCF only considers the region factor and ignores the impact of user context. Hence, it doesn't outperform RCFC. In terms of precision, NMF outperforms POP on LON dataset while POP is better than NMF on LA dataset. However, the recall of NMF basically is superior to POP on both datasets. In short, it's obvious that RCFC outperforms the popular recommendation models since it is based on region and user context. Meanwhile, RCFC can make reasonable explanation for recommendation according to region and context.

## 5 Conclusion

In this paper, we put forward two challenges in POI recommendation. One is the data sparseness caused by users who just visit a few locations and the other is that it's hard to make reasonable explanation for recommendation from the perspective of real world. Therefore, for the sake of alleviating data sparseness, we firstly present a region-based CF by clustering locations into different regions. Secondly, we explore the impact of two user context like geographical distance and location category to enhance the explanation of recommendation. Finally, we propose our joint model RCFC that combines region-based CF and user context. We construct experiments on two real-world datasets collected from two cities on Foursquare and the results demonstrate RCFC is superior to some popular POI recommendation models.

For future work, on one hand, we will compare different clustering methods to make the regions more accurate. On the other hand, we will take more contexts into account since there are still many useful contexts such as time and weather. We will continue our work of the model RCFC.

**Acknowledgements.** This research is Sponsored by Natural Science Foundation of Chongqing, China (No.cstc2020jcyj-msxmX0900) and the Fundamental Research Funds for the Central Universities (Project No.2020CDJ-LHZZ-040).

## References

1. Li, H., Ge, Y., Lian, D., Liu, H.: Learning user's intrinsic and extrinsic interests for point-of-interest recommendation: a unified approach. In: The 26th International Joint Conference on Artificial Intelligence, IJCAI 2017, pp. 2117--2123 (2017)
2. Fletcher, K.K.: Regularizing matrix factorization with implicit user preference embeddings for web API recommendation. In: IEEE SCC, pp. 1-8 (2019)

3. Xue, H., Dai, X., Zhang, J., Huang, S., Chen, J.: Deep matrix factorization models for recommender systems. In: The 26th International Joint Conference on Artificial Intelligence, IJCAI 2017, pp. 3203–3209 (2017)
4. Sarwar, B.M., Karypis, G., Konstan, J.A., Riedl, J.: Item-based collaborative filtering recommendation algorithms. In: ACM WWW, pp. 285–295 (2001)
5. Hu, S., Tu, Z., Wang, Z., Xu, X.: A POI-sensitive knowledge graph based service recommendation method. In: IEEE SCC, pp. 197–201 (2019)
6. Tran, T., Lee, K., Liao, Y., Lee, D.: Regularizing matrix factorization with user and item embeddings for recommendation. In: ACM CIKM, pp. 687–696 (2018)
7. Liu, Q., Wu, S., Wang, L., Tan, T.: Predicting the next location: a recurrent model with spatial and temporal contexts. In: The 30th AAAI Conference on Artificial Intelligence, AAAI 2016 (2016)
8. Li, H., Ge, Y., Hong, R., Zhu, H.: Point-of-interest recommendations: learning potential check-ins from friends. In: ACM KDD, pp. 975–984 (2016)
9. He, J., Li, X., Liao, L.: Category-aware next point-of-interest recommendation via listwise bayesian personalized ranking. In: The 26th International Joint Conference on Artificial Intelligence, IJCAI 2017, pp. 1837–1843 (2017)
10. Yang, C., Bai, L., Zhang, C., Yuan, Q., Han, J.: Bridging collaborative filtering and semi-supervised learning: a neural approach for POI recommendation. In: ACM KDD, pp. 1245–1254 (2017)
11. He, J., Li, X., Liao, L., Song, D., Cheung, W.K.: Inferring a personalized next point-of-interest recommendation model with latent behavior patterns. In: The 30th AAAI Conference on Artificial Intelligence, AAAI 2016, pp. 137–143 (2016)
12. Cheng, C., Yang, H., King, I., Lyu, M.R.: Fused matrix factorization with geographical and social influence in location-based social networks. In: The 26th AAAI Conference on Artificial Intelligence, AAAI 2012, pp. 17–23 (2012)
13. Ye, M., Yin, P., Lee, W., Lee, D.L.: Exploiting geographical influence for collaborative point-of-interest recommendation. In: ACM SIGIR, pp. 325–334 (2011)
14. Liu, Y., Wei, W., Sun, A., Miao, C.: Exploiting geographical neighborhood characteristics for location recommendation. In: ACM CIKM, pp. 739–748 (2014)
15. Liu, W., Wang, Z., Yao, B., Yin, J.: Geo-ALM: POI recommendation by fusing geographical information and adversarial learning mechanism. In: The 28th International Joint Conference on Artificial Intelligence, IJCAI 2019, pp. 1807–1813 (2019)
16. Gao, H., Tang, J., Hu, X., Liu, H.: Content-aware point of interest recommendation on location-based social networks. In: The 29th AAAI Conference on Artificial Intelligence, AAAI 2015, pp. 1721–1727 (2015)
17. Rendle, S., Freudenthaler, C., Gantner, Z., Schmidtthieme, L.: BPR: Bayesian personalized ranking from implicit feedback. In: The 25th Conference on Uncertainty in Artificial Intelligence, UAI 2009, pp. 452–461 (2009)
18. Zeng, J., Tang, H., Li, Y., He, X.: A deep learning model based on sparse matrix for point-of-interest recommendation. In: The 31st International Conference on Software Engineering & Knowledge Engineering, SEKE 2019, pp. 379–492 (2019)
19. Zeng, J., Li, F., He, X., Wen, J.: Fused collaborative filtering with user preference, geographical and social influence for point of interest recommendation. *Int. J. Web Serv. Res. (IJWSR)* 16(4), 40–52 (2019)
20. Zeng, J., He, X., Tang, H., Wen, J.: A next location predicting approach based on a recurrent neural network and self-attention. In: The 15th International Conference on Collaborative Computing: Networking, Applications and Worksharing, CollaborateCom 2019, pp. 309–322 (2019)