Geographical Constraint and Temporal Similarity Modeling for Point-of-Interest Recommendation

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Abstract. People often share their visited Points-of-Interest (PoIs) by "check-ins". On the one hand, human mobility varies with each individual but still implies regularity. Check-ins of an individual tend to localize in a specific geographical range. We propose a novel model to capture personalized geographical constraint of each individual. On the other hand, PoIs reflect requirements of people from different aspects. Usually, places of different functions show different temporal visiting distributions and places of similar function share similar visiting pattern in temporal aspect. Temporal distribution similarity can be used to characterize functional similarity. Based on the findings above, this paper introduces improved collaborative filtering models by jointly taking advantages of geographical constraint and temporal similarity. Experimental results on real data collected from Gowalla and JiePang demonstrate the effectiveness of our models.

Keywords: Recommendation system · Collaborative filtering · Geographical constraint · Temporal similarity

1 Introduction

The popularity of smart mobile devices with positioning technologies triggers the advent of Location-based Social Networks (LBSNs), such as Foursquare, Facebook Place and Yelp, which combine online services and offline activities. In traditional social networks, users build digital social connection. However, in LBSNs, with mobile communication devices now reaching almost every corner of planet earth, users are encouraged to share their location information and extend virtual social connection to real life by sharing their life experiences with "check-ins".

There are two kinds of participants playing important roles in LBSN, namely, *ordinary users* and *business owners*. Ordinary users play the part of consumers

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who consume services provided by business owners and LBSN platform developers. Users can choose services that satisfy their requirements or save expenses. Business owners provide information that draws attentions of users and favors profits of business owners themselves. Business owners partnering with LBSN platforms can publish advertisements or discount information. Based on users' historical behaviors, their interests can be explored, which makes it easy for business owners to provide corresponding services.

In this work, we focus on Point-of-Interest (PoI) recommendation in LBSNs. Both of users and business owners can benefit from recommendation systems. For business owners, they can make their services stand out. For users, good services matching their preferences can be provided. The key issue of achieving a successful PoI recommendation is to capture factors that influence users' decisions to visit PoIs and model these factors. Our work is based on exploiting **geographical constraint** and **temporal similarity**.

Geographical constraint of a user influences the possibility of visiting a PoI. It does not make sense to recommend the user a PoI out of her mobility range even though the PoI satisfies her requirements and matches her preferences. There have been several models developed for capturing human mobility pattern. For example, previous work [1,8,11,13] used a power law distribution to model geographical influence. Other work [3,4,14] modeled geographical constraint using Kernel Density Estimation (KDE) method. Gaussian Mixture Model (GMM) can also be adopted when capturing geographical clustering phenomenon [12].

Besides geographical influence, temporal influence should be noted from daily check-in behaviors as well. Human form repetitive behavior patterns, which provides predictability to human mobility, temporal preferences and temporal requirements. Work [1,12] demonstrated that geographical states of some users are influenced by the time factor. Exploring temporal proximity can also contribute to recommendation effectiveness [11,13]. In this work, we examine temporal similarity of PoIs' visiting distributions and use the similarity to characterize functional similarity.

This paper first investigates geographical constraint and temporal similarity separately, and then combines geographical influence with temporal influence in two different ways. The main contributions of our work are:

- We propose a novel geographical pattern model called Short-term Cluster-based Gaussian Mixture Model (SCBGMM) to capture a personalized check-in distribution for each individual.
- We measure functional similarity of PoIs by using temporal distribution. Temporal similarity is capable of explaining characteristics of a PoI.
- We demonstrate the effectiveness of geographical constraint, temporal similarity and two combinations of geographical and temporal influences by incorporating factors mentioned above with a basic model.

The remainder of the paper is organized as follows. We discuss previous studies related to PoI recommendation in Sect. 2. We introduce models based on geographical constraint and temporal similarity in Sects. 3 and 4, respectively. We present two ways to combine geographical and temporal influences in Sect. 5.

In Sect. 6, we verify the effectiveness of our proposal on two real datasets. We conclude our work in Sect. 7.

2 Related Work

Collaborative Filtering. There exist two basic flavors of *collaborative filtering* (CF), *user-based CF* (UCF) and *item-based CF* (ICF). UCF recommends items that users with similar preferences have visited, viewed or purchased. ICF recommends items which are similar to those having been visited, viewed or purchased by same user [5].

In this paper, ICF is used as the basic algorithm. The reasons of this in the context of LBSN are two-fold. First, in UCF, similarity between users is indicated by historical PoI records and is hard to extend to other respect of user behaviors. While in ICF, temporal similarity makes up for lacking of semantic information and provides another angle for evaluating PoI similarity beyond PoI visiting history. Second, in traditional CF application domains (e.g., e-commerce platforms), capturing users' preference is the main purpose. LBSNs bridge the gap between online communications and real life activities, which is an important distinction between LBSN and other virtual applications. In addition to preferences, users' physical and daily life related requirements must be satisfied. This needs more attentions from PoIs' perspective.

Let $N(i;u)$ be a set of PoIs visited by user u, and $N(u;i)$ be a set of users who have visited PoI i. Generally, notations like i, j denote PoIs and u, v denote users. We follow this convention. Given the rate (frequency) r_{uj} of PoI j visited by user u, the recommendation rate of some unvisited PoI is:

$$r_{ui} = \frac{\sum_{j \in N(i;u)} s_{ij} * r_{uj}}{\sum_{j \in N(i:u)} s_{ij}} \tag{1}$$

where s_{ij} represents the similarity of two PoIs. Cosine similarity is one of the most popular measures:

$$s_{ij} = \frac{\sum_{v \in N(u;i) \bigcup N(u;j)} r_{vi} * r_{vj}}{\sqrt{\sum_{j \in N(u;i)} r_{vi}^2} * \sqrt{\sum_{j \in N(u;j)} r_{vj}^2}} \tag{2}$$

Geographical Influences for PoI Recommendation. In previous work, difference approaches have been adopted to describe personalized geographical constraint in an individual's visiting records.

Power law distribution can model the distribution of distances of PoIs [1,11,13]. It is based on a global observation that the probability of people visiting PoIs decreases with the increase of their distance. Ye et al. [9] proposed a power law distribution of distances between PoIs to estimate check-in probability of an unvisited PoI. Yuan et al. [11,13] modeled the likelihood of a user's check-in at some PoI by using power law distribution of distance between the PoI and previously visited PoI. The distribution of distances of PoIs and current user's "home" location is observed to follow a power law distribution in [1].

KDE is adopted based on a more personalized assumption than power law distribution by modeling PoIs visited by same user. There are some variations when adopting KDE. In some context, KDE was proposed to capture the intuition that every PoI has an influence over nearby PoIs. For example, a famous scenic spot has a higher chance to attract tourists to visit surrounding restaurants or hotels. Capturing the influence spreading phenomenon can more reasonably explain choices of PoIs that users make. Lian et al. [3] proposed kernel density estimation to model the influence areas of a PoI which is fixed to be Gaussian distribution. Besides, KDE can model that the distances of PoIs visited by same user are subject to some kind of distribution, usually Gaussian distribution. A mixture kernel density method which has the ability to model global location data and personal location data is proposed in [4]. Zhang et al. [15] proposed a pilot estimation which is given by a weighed average of distance distribution between current PoI and visited PoIs. KDE is also used to model differences of distances of PoIs. A one-dimensional kernel density estimation to model difference distribution was investigated in [14].

GMM approach can also be used to model check-in distribution. Yuan et al. [12] proposed a probabilistic model based on the intuition that human mobility centers at predefined geographical regions (which is captured by a sampling Gaussian distribution) and influenced by current requirements. GMM describes a user's check-in distribution intuitively and the possibility of a PoI being visited from geographical perspective is represented by GMM value. The GMM describes geographical constraint from another angle.

We choose GMM as our basic model based on the analysis as follows. Power law distribution is often adopted in two aspects - indicating social intimacy [8] and modeling likelihood of users' geographical transfers between PoIs (which is represented by distance distribution of PoIs visited by a same user [9,11,13]). As mentioned above, we adopt ICF as the basic algorithm so that social intimacy has a limited influence. In addition, distance distribution is sensitive to noise spots. KDE is a non-parametric method, but it fails to resist interference of noise spots. GMM needs an assumption about the predefined number of human mobility centers for all users, which can be against the principle of personalization. Based on the global assumption of centers (e.g., "home" and "work"), personalized geographical constraint will take fewer effects. To avoid such global assumption, we use density-based clustering to automatically detect the number of centers to initialize GMM, so that GMM can start from a personalized, reasonable assumption about the number of an individual's mobility centers.

In our model, we adopt a density-based clustering algorithm for each user to capture kernels that the user's check-ins center at, which, at the same time, remove noise spots. However, not all check-in clusters are useful. For example, an individual may move from New York to San Francisco. Clusters in New York that the individual used to visited will be no longer visited. Only short-term clusters should be considered to build the individual's geographical mobility pattern. Thus, Short-term Cluster-based Gaussian Mixture Model (SCBGMM) is built and can be incorporated with ICF for recommendation. Note that we do not make the assumption that a user's check-in distribution is centered at "home" location (such as [1]).

Temporal Influences for PoI Recommendation. Human behaviors show strong periodicity in respect of time [1,11,13]. Temporal influence has been investigated from various aspects. Decisive influence of time on geographical mobility was examined in [1,12]. Cho et al. [1] modeled temporal movement between the "home" state and "work" state based on the Gaussian distribution of each state over the time of the day respectively. Yuan et al. [12] modeled a probabilistic graph, in which, geographical region of a user is decided by time factor. Different from the above studies, we exploit decisive influence of time on clusters to predict which clusters will be visited. Besides temporal influence on geographical information, we use the relationship between temporal similarity and PoIs' functional (categorial) similarity. Yin et al. [10] claimed that PoIs visited at similar time tend to belong to similar category. Ye et al. [7] proved temporal and semantic interaction of PoIs. Different from [7], we use cosine similarity to measure temporal similarity and consider temporal similarity as a factor that influences the possibility of a user's visit to a PoI. In our work, temporal similarity corresponds to current user's requirement rather than short-term preferences such as in [6].

3 Using Geographical Constraint

In our model, we first employ a density-based clustering method in geographical coordinate system to cluster an individual's check-ins. Clusters visited a long time ago are removed and those visited recently are retained. Then, we use remaining clustering centers to initialize parameters of GMM, such as the number of centers and positions of centers. Expectation Maximization (EM) algorithm is employed to learn GMM. Finally, SCBGMM is incorporated with ICF.

3.1 Density-Based Clustering

Yin et al. [10] claimed that PoIs visited by users tend to form several cluster centers and modeled each region with a Gaussian distribution. Different from [10], we assume that PoIs visited by each user are gathering into several centers and capture each region with a density-based clustering algorithm. DBSCAN [2] is capable of clustering a region with higher density than a predefined density value. It detects a kernel based on the principle that if there exist more than an fixed number ($minPts$) of points within an acceptable distance (ϵ), the point is considered as a kernel. Each kernel with neighbors within the acceptable distance forms a cluster. If a neighbor of a kernel is a kernel itself, it will be added into the current cluster with its neighbors. The iteration process continues until no point is added. Traditionally, DBSCAN is employed in two dimensional surface. Here, we extend DBSCAN to the earth surface by replacing Euclidean distance with geodesic distance.

3.2 Decisive Influence of Time

Unlike previous work [1] which uses time to decide which cluster current user to stay, in our work time factor is used to decide which cluster is useless. Firstly, we calculate time span which all check-ins of current user are within. Then check-ins visited after a time spot are marked as recently visited ones. The time spot is set to a value that can split the time span into two intervals with some proportion. Check-ins in the first interval are visited a relatively long time ago, and those in the second interval are visited recently. A cluster without any check-in marked as recently visited one will be removed. Remaining clusters are used to initialize the number of Gaussian components next.

3.3 Gaussian Mixture Model

Given the number of Gaussian model components K, GMM is represented as:

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k) \tag{3}$$

where $\mathcal{N}(x|\mu_k, \Sigma_k)$ is k^{th} Gaussian component, π_k is the weight of each Gaussian component, μ_k and Σ_k represent mean and standard deviation of k^{th} Gaussian component. The basic assumption of GMM is that each data point is generated from K Gaussian models jointly so that GMM can provide richer sorts of density models than only one Gaussian model. We use two steps to describe the data point generating process which provides us with a deeper insight into this distribution:

- Choosing one Gaussian model component from K components. The probability of each component being chosen is π_k.
- Picking one data point from the Gaussian model chosen in last step. The process follows a Gaussian distribution parameterized by μ_k and Σ_k.

Suppose N data points are in our dataset. We need to learn parameters mentioned above. EM algorithm is used to fit GMM by maximizing the probability that data points in the dataset are generated from GMM.

3.4 Expectation Maximization for GMM

EM algorithm offers an powerful method to find maximum likelihood solutions for models with latent variables. Parameters of GMM are unknown, and maximum likelihood provides a feasible solution by estimating parameters of the distribution and making the observed dataset fit the distribution most likely. The basic process of EM is: (1) finding the expected value of a maximization function, and (2) maximizing the expectation function.

We will introduce EM for GMM model as an example. For a dataset X, let x_n denote an observed value in X. The likely function of the observations is given by:

$$p(X) = \prod_{n=1}^{N} p(x_n) = \prod_{n=1}^{N} \sum_{k=1}^{K} \pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k) \tag{4}$$

To avoid the underflow of the production above, a log-likelihood function is adopted instead.

$$lnp(X|\pi, \mu, \Sigma) = \Sigma_{n=1}^{N} ln\{\Sigma_{k=1}^{K} \pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k)\} \tag{5}$$

Two-step iteration is implemented:

– **E-Step (Expectation):** Use values of the parameters from last iteration to evaluate the probability of generating an observation from K Gaussian models.

$$\gamma(n, k) = \frac{\pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j \mathcal{N}(x_n|\mu_j, \Sigma_j)} \tag{6}$$

– **M-Step (Maximization):** Re-estimate the distribution parameters to maximize the log-likelihood function.

$$\mu_k = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(n, k) x_n \tag{7}$$

$$\Sigma_k = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(n, k)(x_n - \mu_k)(x_n - \mu_k)^T \tag{8}$$

$$\pi_k = \frac{N_k}{N} \tag{9}$$

We need to reevaluate the log-likelihood function and check for the convergency. The **Expectation** and **Maximization** iteration will not stop until the convergency is achieved.

3.5 Incorporating SCBGMM with ICF

PoIs out of the geographical range described by SCBGMM are less likely to be visited. We propose an algorithm named **ICF-SG**. For each candidate PoI i, we calculate the possibility of i being visited by user u according to Short-term Cluster-based Gaussian Mixture Model (SCBGMM). Those PoIs with lower possibility than a threshold κ will not be recommended. Detailed ICF-SG is presented in Algorithm 1.

3.6 CBGMM

To understand decisive influence of time, we introduce another geographical model slightly different from SCBGMM. GMM is initialized by the clustering result of DBSCAN directly (without filtering clusters that are visited a relatively long time ago). After learning with EM, a simpler model called Cluster-based Gaussian Mixture Model (CBGMM) can be built. We can incorporate CBGMM with ICF in a similar way as Algorithm 1, and we call this algorithm **ICF-LG**. In the experiments, by comparing ICF-SG with ICF-LG, we can verify the effectiveness of decisive influence of time factor in filtering clusters.

Algorithm 1. ICF-SG Algorithm

$U \leftarrow$ user set;
$u \leftarrow$ current user;
$C_u \leftarrow$ queue of unvisited PoIs ranked by user's predicted preference calculated by ICF;
$R_u \leftarrow$ top-K recommended PoIs;
$\kappa \leftarrow$ threshold to filter;
for each user $u \in U$ **do**
  learn personalized SCBGMM;
  for each unvisited PoI $i \in C_u$ **do**
    if $p(i) = \sum_{k=1}^{K} \pi_{uk} \mathcal{N}(i|\mu_{uk}, \Sigma_{uk}) < \kappa$ **then**
      continue;
    end if
    if sizeOf(R_u)¡=K **then**
      add i to R_u;
    end if
  end for
end for

4 Using Temporal Similarity

PoIs satisfy individuals' requirements from various aspects, and normally these requirements are time-related and show periodicity. We propose a way to describe time-relevance and use this characteristic in our model. In this paper, we analyse temporal distribution similarity of PoIs and propose a model to take advantage of temporal similarity. A smoothing approach is discussed as well.

4.1 Characterizing Functional Similarity

People's visits to PoIs are often driven by their requirements. These requirements are different in category and show time-relevance. Here, time-relevance of PoIs does not mean short-term preference [6]. Short-term preference means a user's interest of PoIs with a specific style. For example, someone who is used to go to tidy, quite restaurants, may go to romantic restaurants since his girlfriend who has a long-distance relationship with him comes to visit him. In this work, time-relevance corresponds to an individual's requirements. For example, at mealtime we should pay attention to users' preferences for restaurants, whereas in the afternoon users' preferences for leisure-related spots such as cafes should be concerned.

An intuitive way is to analyse categories of PoIs which are often visited in a time interval and capture the requirements in this time interval. For example, if we analyse categorial information of PoIs often visited in 12 pm or 1 pm in a day, we can find they tend to be restaurants. However, without textual information or categorial annotation in PoI data, we find it hard to analyse users' preferences in PoIs' respect. Previous work [7] mined the relationship between temporal similarity and categorial information. We follow and apply the discovery in our work. We use temporal distribution over 24-hour slots to capture functional characteristic of a PoI. However, considering normalization, we use cosine similarity of temporal distributions to evaluate categorial similarity, which is different from [7].

4.2 Temporal Similarity Evaluation

Let T_{ik} and T_{jk} denote temporal distribution of PoIs i and j in k^{th} hour of a day time, temporal similarity of PoIs i and j is defined as:

$$s^t_{ij} = \frac{\sum_{k=0}^{23} T_{ik}T_{jk}}{\sqrt{\sum_{k=0}^{23} T^2_{ik}} * \sqrt{\sum_{k=0}^{23} T^2_{jk}}} \tag{10}$$

Both of users' time-related requirements and preferences for a PoI should be taken into consideration. PoIs which meet the time-related requirements and satisfy current user's preferences should have high possibilities to be recommended. In traditional ICF (Eq. 1), a user's preference for an unvisited PoI is evaluated by weighted average of the user's preferences for visited, similar PoIs.

4.3 Incorporating Temporal Similarity with ICF

We adopt a linear combination to balance requirement relevance of a PoI and a user' preference for the PoI (Eq. 2), which is called **ICF-T** and defined as follows.

$$\begin{aligned} s^T_{ij} &= (1-\alpha)s_{ij} + \alpha s^t_{ij} \\ &= (1-\alpha)\frac{\sum_{v\in N(u;i)\bigcup N(u;j)} r_{vi} * r_{vj}}{\sqrt{\sum_{j\in N(u;i)} r^2_{vi}} * \sqrt{\sum_{j\in N(u;j)} r^2_{vj}}} + \alpha\frac{\sum_{k=0}^{23} T_{ik}T_{jk}}{\sqrt{\sum_{k=0}^{23} T^2_{ik}} * \sqrt{\sum_{k=0}^{23} T^2_{jk}}} \end{aligned} \tag{11}$$

We substitute Eq. 11 into Eq. 1 and get

$$r^T_{ui} = \frac{\sum_{j\in N(i;u)} s^T_{ij} * r_{uj}}{\sum_{j\in N(i:u)} s^T_{ij}} \tag{12}$$

4.4 Smoothing

The idea of smoothing visiting frequency was proposed in [7,11]. Ye et al. [7] applied an empirical window to replace the PoI's visiting frequency in a hour slot with an weighted sum of visiting frequency in current hour, an hour earlier and an hour later. The weight is set to a fixed and empirical value. Yuan et al. [11] evaluated similarity between two time slots by averaging cosine similarity between PoI check-in frequency vectors in the two time slots for all users. In our work, we evaluate similarity between time slots by calculating cosine similarity of all PoIs' check-in frequency vectors in two time slots from a global respective. We use se_h to represent similarity between hour h with an hour earlier and sl_h to represent similarity between hour h with an hour later. We smooth each PoI's number of check-ins in some hour by

$$N(i;u)^s_h = N(i;u)_h + \frac{se_h}{se_h + sl_h} N(i;u)_{(h+23)/24} + \frac{sl_h}{se_h + sl_h} N(i;u)_{(h+1)/24} \tag{13}$$

5 Combination of both Factors

In this section, we will investigate combinations of geographical constraint and temporal similarity factors in two ways, in order to examine effectiveness of these combinations and a mutually reinforcement relationship of them.

Combinations of the two factors can be various for the reason that we set different values for parameter κ in ICF-SG and parameter α in ICF-T, separately. If we set parameter κ to a relatively higher value, PoIs having higher accordance with geographical constraint range will be recommended and vise versa. Parameter α can balance the relative importance between time-relevance of a PoI and current user's preference for the PoI. For simplification and significance, we choose two directions to investigate them in depth. We investigate influences of parameter α on condition that ICF-SG performs best, and influences of parameter κ when best performance of ICF-T is achieved.

5.1 Using Temporal Similarity on ICF-SG

By applying ICF-SG, PoIs which fit a user's preference and are possible to be visited from geographical aspect are recommended. Besides, current user's requirements need to be taken into consideration. When κ equals to a specific value, ICF-SG performs best. Based on ICF-SG, we investigate temporal influences by fixing parameter κ to the value mentioned above and balancing relative importance of time-relevance (by changing the value of α). We call this model as **ICF-GT**. If ICF-GT performs better than ICF-SG, we can conclude that this combination of the two factors is effective and temporal influence can reinforce geographical influence.

5.2 Using Geographical Constraint on ICF-T

ICF-T is capable to capture a user's preference and requirement both. However, only applying ICF-T lacks of filtering power to those PoIs out of geographical mobility range. Geographical constraint needs to be considered. In Eq. 11, we balance the importance of time-relevance and current user's preference using a parameter α. Similar to the method mentioned in Sect. 5.1, we analyse geographical influences through setting parameter α to a fixed value (the value that makes ICF-T achieve best performance) and changing the value of κ. We call this model as **ICF-TG**. If we observe better performances compared with ICF-T, we can prove the effectiveness of this combination of the two factors and the reinforcement of geographical influences to temporal influences.

6 Experiments

6.1 Experimental Setup

Datasets for Evaluation: We conduct our experiments using two datasets crawled from Gowalla [1] and JiePang [3]. The dataset from Gowalla contains

196,591 users and 6,442,890 check-ins from Feb. 2009 to Oct. 2010, and the sample dataset from JiePang (jiepang.com) contains 9,237 users and 1,556,636 check-ins from Mar. 2011 to Mar. 2013. Every check-in record in the test datasets contains *coordinates* and *timestamp* fields. Due to page limit, we mainly report results of experiments on Gowalla dataset. Results on JiePang exhibit similar trend. There are two ways to partition the datasets. Both of them need to divide training set and test set as 7 to 1 in portion. The first way is that we split all check-ins in portion of 7 to 1 in chronological sequence as training set and test set, separately. The second way is to add first 7/8 part according to check-in time of each individual into training set and the others into test set. The first approach cannot guarantee that every user has check-ins in test set. We therefore adopt the second approach so that we can evaluate algorithm effectiveness on every user.

Evaluation Metrics: *Precision*, *Recall* and *F1* are three most popular measures to evaluate the effectiveness of recommendation algorithms. *Precision* evaluates how many top PoIs recommended are actually visited. *Recall* measures how many PoIs which are visited later are recommended. Empirically, we consider top 7 returned results. Intuitively, stricter constraint condition means higher *Precision* but lower *Recall*, where constraint condition means a standard that we consider a PoI as one that should be recommended. *F1* incorporates both factors of *Precision* and *Recall* and gets a relatively fair measurement.

Evaluated Algorithms: We keep a list of top PoIs for each user in each algorithm tested. We show effects of geographical constraint (Sect. 3), temporal similarity (Sect. 4) and a combination of these factors (Sect. 5) by comparing proposed models with ICF [5]. We set every measurement of ICF as 1, and calculate the ratio of algorithm results of ICF-T, ICF-LG, ICF-SG, ICF-GT, ICF-TG to ICF for each measurement.

- **ICF:** Item-based CF [5] expressed in Eq. 1 predicts user's preference for an unvisited PoI by calculating weighted sum of user's preference for visited PoIs.
- **ICF-2G:** Some of previous studies (e.g., [1]) claimed that an individual's check-ins center at two locations ("home" and "work"). ICF-2G considers two clusters with most check-ins as "home" cluster and "work" cluster so that check-in distribution model for each individual is constituted of two Gaussian components.
- **ICF-LG:** In Sect. 3.6, a long-term check-in distribution is captured for an individual without filtering those clusters which may never be visited. GMM is initialized by clustering results of DBSCAN directly.
- **ICF-SG:** As described in Algorithm 1, ICF-SG filters out those PoIs out of range of personal geographical mobility with decisive influence of time.
- **ICF-T:** In ICF-T expressed by Eq. 12, time-relevance and current user's visiting preferences are combined to evaluate PoIs' similarity. The relative importance of each factor needs to be tuned.
- **ICF-GT, ICF-TG:** ICF-GT focuses on temporal influences on condition that the best performance of ICF-SG is attained, and ICF-TG investigates geographical influences when ICF-T performs best.

6.2 Experimental Results on Gowalla Dataset

Study of Geographical Constraint: We show the influence of κ by comparing *Precision*, *Recall* and *F1* for different κ. ICF-SG is meaningful when κ is between 0 and 0.9. Specially, when κ is set to 0, the model reduces to basic ICF model. We increase κ from 0 and take 0.1 as step length. The effect of κ is shown in Fig. 1. Overall, ICF-SG outperforms ICF, which proves that geographical constraint takes a promising effect. When κ increases, ICF-SG performs better. ICF-SG performs best when we set κ to 0.9, which confirms that PoIs having high accordance with our model SCBGMM are more likely to be visited.

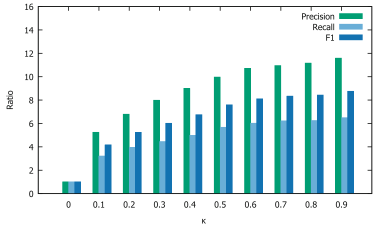
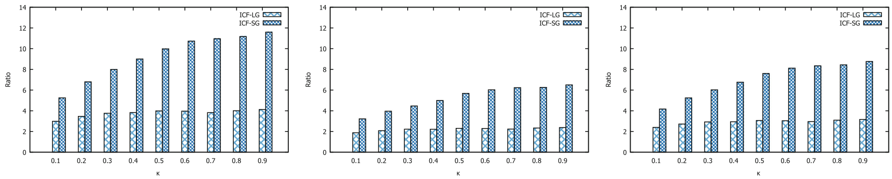


Fig. 1. Performance of ICF-SG

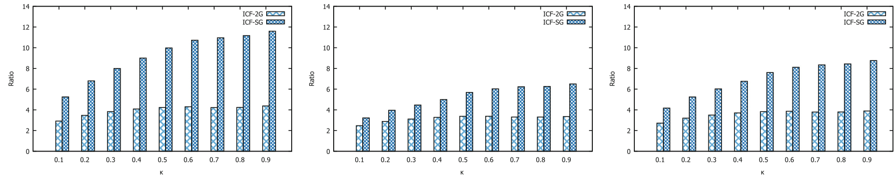
Study of Decisive Influence of Time in Geographical Constraint: We verify the effectiveness of filtering clusters based on time by comparing ICF-SG with ICF-LG. In Fig. 2, we observe clear improvements of ICF-SG in terms of three evaluation metrics and over all values of parameter κ.



(a) *Precision* (b) *Recall* (c) *F1*

Fig. 2. Comparison of performance between ICF-SG and ICF-LG

Study of Number of Gaussian Components: In our model ICF-SG, we do not make any assumption about the number of Gaussian components. However, in model ICF-2G, the number is fixed to 2. By comparison of ICF-SG and ICF-2G showing in Fig. 3, we observe better performance of ICF-SG, and this proves that our model is a more personalized one and can more properly describe individuals' check-in distribution.



(a) *Precision* (b) *Recall* (c) *F1*

Fig. 3. Comparison of performance between ICF-SG and ICF-2G

Study of Temporal Similarity: We tune α to leverage the importance of time-relevance and user's preference as shown in Eq. 11. Same as κ, α is set to be in the interval $[0.0, 0.9]$, with a step length of 0.1. The result is shown as in Fig. 4. When α increases, results fall after rising, and $\alpha = 0.5$ gets the best performance. That means time-relevance of a PoI is as important as current user' preference for the PoI. A large ($\alpha = 0.9$) or a small ($\alpha = 0$) weighted value of temporal similarity leads to poor performance. Compared with previous work in [7], we adopted a different way to smooth a PoI's check-ins distribution over time slots by using temporal similarity rather than a fix window. We calculate similarities between time slots in our dataset. The temporal distribution of each PoI's check-ins is smoothed by Eq. 13. However, smoothed ICF-T takes effect compared with ICF when α is in the interval $[0.1, 0.7]$ but performs worse than ICF-T. As we can see from Fig. 5, the results of smoothed ICF-T show similar tendency with results of original ICF-T when we increase parameter α. However, we only observe slight improvement of smoothed ICF-T compared with original ICF. The reason for the worse performance of smoothed ICF-T (compared with ICF-T) may be that, in our work, temporal distribution of a PoI is used to indicate distinguishing characteristics of PoIs. The number of check-ins in a time slot of a PoI represents an attribute of the PoI's visiting characteristic. Smoothing loses this capability to some extent by sharing the specificity of a time slot with its near time slot. In this way, a time slot may lose the ability to be a special attribute, and the effect of denoting categorial similarity by temporal similarity is reduced.

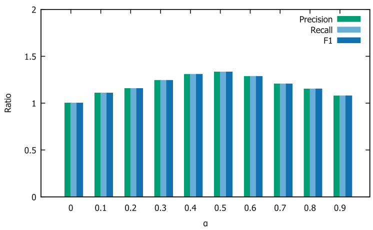


Fig. 4. Performance of ICF-T

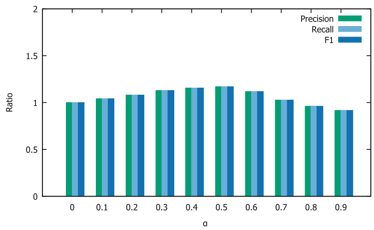


Fig. 5. Performance of smoothed ICF-GT

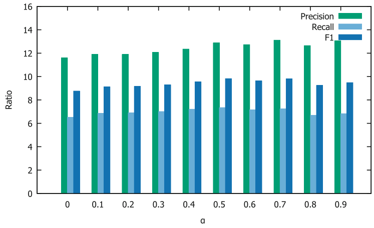


Fig. 6. Performance of ICF-GT

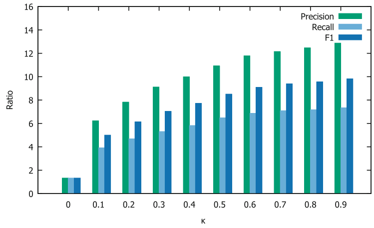
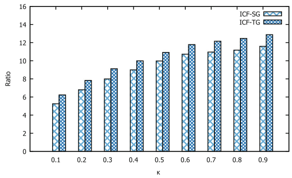


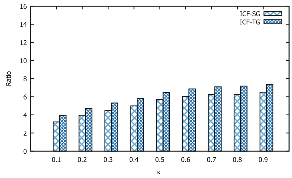
Fig. 7. Performance of ICF-TG

Combination of Geographical Constraint and Temporal Similarity: We test the relative importance of time-relevance of PoIs on condition that ICF-SG performs best by fixing parameter κ to 0.9. We set α to best performance value in ICF-T and tune κ to investigate geographical influence. Overall, compared with the best performance of ICF-SG, we observe an improvement of ICF-GT in Fig. 8 for every value of α. Similarly, as shown in Fig. 9 ICF-TG in terms of all values of κ outperforms the best performance of ICF-T, which indicates that with geographical influences, effectiveness of temporal influence is improved. According to the analysis above, we demonstrate mutual reinforcement of geographical and temporal influences and show the superiority of fusing geographical and temporal information.

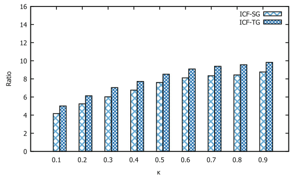
In the following, we demonstrate the effectiveness of geographical constraint with and without temporal similarity, by comparing ICF-TG with ICF-SG and



(a) *Precision*

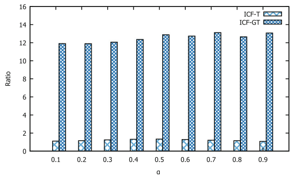


(b) *Recall*

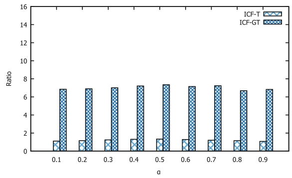


(c) *F1*

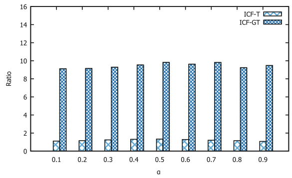
Fig. 8. Comparison of performance between ICF-SG and ICF-TG



(a) *Precision*



(b) *Recall*



(c) *F1*

Fig. 9. Comparison of performance between ICF-T and ICF-GT

the effectiveness of temporal similarity with and without geographical constraint, by comparing ICF-GT with ICF-T. Firstly, we compare ICF-TG with ICF-SG. Containing temporal similarity, ICF-TG outperforms ICF-SG for each value of κ in terms of each metric, as shown in Fig. 8. With the increase of κ, *Precision*, *Recall* and *F1* of ICF-TG change in a similar tendency with those metrics of ICF-SG. Both of ICF-TG and ICF-SG take best effect when κ is set to 0.9. Secondly, we compare ICF-GT with ICF-T. Involving geographical constraint, ICF-GT outperforms ICF-T clearly for each value of α in all evaluations, as shown in Fig. 9. Variations of three metrics with the increase of parameter α differ a lot between ICF-GT and ICF-T. We can owe this difference to the dominant position of geographical constraint. When comparing ICF-T with ICF-SG, we can draw similar conclusion because the improvement of ICF-SG is more noticeable than that of ICF-T. ICF-GT performs best when α equals to 0.5 in terms of two metrics. In ICF-GT, $\alpha = 0.5$ performs slightly worse than $\alpha = 0.7$.

7 Conclusion

SCBGMM adopts DBSCAN and remove clusters not recently visited to initialize GMM. The proposed ICF-SG based on SCBGMM attains good performance. By comparing ICF-SG with ICF-LG, we prove the effectiveness of filtering based on time. By comparing ICF-SG with ICF-2G, we prove the advantage of varying cluster numbers for individuals. In addition, we take advantage of temporal similarity to describe time-relevance of a PoI and show that time-relevance of a PoI has same importance as preference for the PoI in our model ICF-T. Finally, we combine geographical constraint and temporal similarity to build ICF-GT and ICF-TG, and our experiments show superiority over previous models without considering these two factors or considering only one of them.

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