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Familiarity-aware POI Recommendation in Urban Neighborhoods

Jungkyu Han[1,a) Hayato Yamana[1,b)

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Abstract: Users' visiting patterns to POIs (Points-Of-Interest) varied with regard to the users' familiarity with their visited areas. For instance, users visit tourist sites in unfamiliar cities rather than in their familiar home city. Previous studies have shown that familiarity can improve POI recommendation performance. However, such studies have focused on the differences between home and other cities, and not among small urban neighborhoods in the same city where user activities frequently occur. Applying the studies directly to the areas is difficult because simple distance-based familiarity measures, or visit-pattern differences represented on topics, groups of POIs that share common functions such as Arts, French restaurants, are too coarse for capturing the differences observed among different areas. In the urban neighborhoods in the same city, user visit-pattern differences originate from more precise POI levels. In order to extend the previously proposed familiarity-aware POI recommendation to be adopted in different areas in the same city, we propose a method that employs visit-frequency-based familiarity and precise POI level of visit-pattern differentiation. In experiments on real LBSN data consists of over 800,000 check-ins for three cities: NYC, LA, and Tokyo, our proposed method outperforms state-of-the-art methods by 0.05 to 0.06 in *Recall@20* metric.

Keywords: familiarity, LBSN, POI recommendation, urban neighborhoods, Location-Based Social Network

1. Introduction

It is not easy for us to choose favorable POIs (Points-Of-Interest, places of interest) to visit without pre-investigation because there are many POIs nearby, but we do not have much knowledge about them. Personalized POI recommendations can mitigate the problem by advising on preferable POIs.

Individual user preference and spatiotemporal influence are the two most important building blocks for personalized POI recommendations [1], [2], [3], [4], [5]. In previous papers [1], [5], "user preference" is used as the individual user's probability of visiting each POI without external influence, such as spatiotemporal. Spatiotemporal influence, such as the distance from the current location or visit time, is a unique factor in POI recommendation for reducing the number of candidate POIs by exploiting the fact that people do not want to move far distances, or not visit POIs at improper times. Although considering spatiotemporal influence is powerful, user preference is still important, because we can rank the reduced candidates by employing user preference.

Considering familiarity, i.e., how much a user knows a given area, is one way to improve user preference inference. User preference varies in terms of his/her familiarity with the visited areas [6], [7], [8]. Baltrunas et al. [6] and Wang et al. [7] showed that considering familiarity improves POI recommendation performance with experiments that employ user visit-logs of both the familiar home city and unfamiliar non-home cities.

Inspired by the previous studies, we propose a familiarity-aware POI recommendation method applicable to relatively small sized areas: urban neighborhoods located in the same city. For a concise description, we will call "the small sized areas" as "urban neighborhoods" or simply "areas." Our work was carried out by extending the previous method to manage user familiarity difference between the areas in the same city. However, extending state-of-the-art methods [6], [7] to manage user-preference variations caused by the familiarity difference among the areas in the same city is not straightforward, because the previous methods adopt the POI topic-level-preference difference, which is too coarse to be applied to the "small areas in the same city" case.

Here, POI topics indicate groups of POIs with similar semantic functions. For instance, we can classify both a movie theater and museum into the "Arts" topic. Because the familiarity difference between home and other cities is huge, we can relatively easily observe user preference differences caused by familiarity at the topic level, as argued by previous studies [6], [7]. For example, assume that there is a user who loves POIs classified into the Arts topic, and often visits a movie theater in his/her home city. When he/she visits an unfamiliar city, he/she might go to a basketball stadium ("Sports" topic), regardless of his/her preference for movie theaters, because the city might be famous for basketball. As shown in this example, users tend to visit famous local POIs when they visit unfamiliar cities.

However, we found that the familiarity influence on topic-level user preference is relatively weak "in different areas in the same city" compared to "the home city and other city" case. Instead, individual POIs should be highlighted [8], [27]. This means that a user who loves Arts topic still visits Arts-related POIs when they visit unfamiliar areas in the city, but his/her visiting POIs are dif-

1 Waseda University, Shinjuku, Tokyo, 169–8555 Japan
a) han.jungkyu@akane.waseda.ac.jp
b) yamana@waseda.jp

ferent. For example, such users might go to a movie theater in familiar areas of the city, but visit a museum in unfamiliar areas of the same city. Here, both of the POIs are classified as Arts topic.

State-of-the-art methods [6], [7] manage and selectively use two types of topic-level user preferences according to user familiarity to each target region: preference of familiar users and preference of un-familiar users. However, these methods assume that user preferences to all individual POIs in the same topic stay the same regardless of familiarity. Therefore, it is difficult to manage the familiarity influence on visits observed in POI level.

To exploit the familiarity influence observed in different areas in the same city effectively, our proposed method manages the familiarity-caused user-preference variations in individual POI levels. More specifically, our method maintains several user-group preferences for individual POIs located in a given area. The user groups are constructed by classifying users with similar familiarity with the given area into the same group (e.g., users familiar with, and users unfamiliar with the given area). We refer to such group preference as *global preference* hereafter. Then, to make recommendations for user u in area a, our method combines u's individual user preference with the selected global preference that has a similar familiarity with that of user u about area a.

To infer each user's familiarity with each of the areas, we first divide a city into $2\,\mathrm{km} \times 2\,\mathrm{km}$ non-overlapped areas. Then we adopt the visit-frequency-based familiarity estimation proposed in our previous work [8], [27] to calculate each user's familiarity with each area.

Our contribution is as follows: we propose a familiarity-aware POI recommendation method applicable to areas with different familiarity in the same city. Through our proposed method, we show that visit-pattern differences with regard to familiarity exist even between the areas closely located each other. In addition, the difference that is difficult to capture with state-of-the-art methods can be exploited using our proposed method.

The rest of this paper consists of 6 sections. We explain related work in Section 2. Section 3 describes the preliminary knowledge. In Section 4, our proposed method is presented in detail. We evaluate our proposed method in Section 5 and discuss the results in Section 6. In Section 7, we conclude our research.

2. Related Work

We first describe works related to overall POI recommendations, and then analyze the studies related to the familiarity concept.

POI recommendations: Many previous POI recommendation studies have proposed effective ways for modeling and combining mobility patterns and user preferences [1], [2], [3], [4], [5], [9], [10]. Mobility patterns are represented by the density distribution of user activity over geographic areas. Activity density is inferred from the geo-locations of user check-ins (visit logs) using kernel density estimation [3], [9], topic model [4], Multi-center Gaussian model [10], or simply penalizing the POIs located far from the nearest already visited areas [1]. User preferences are inferred from user check-ins or opinions about the visited POIs using memory-based [1], [9] or model-based collaborative filtering, such as matrix factorization [2], [5] or topic model [3], [7].

Other research has studied the influence of external environmental factors. Gao et al. [11] and Yuan et al. [12] incorporated the concept of visit time. Cheng et al. [13] and Liu et al. [14] studied subsequent visit POI predictions based on the lastly visited POIs. Yang et al. [15] proposed POI recommendations that are aware of user sentiment with regard to POIs.

Some approaches have focused on mitigating the cold start problem: directly available data to infer user preference are not large enough to achieve accurate recommendations. Gao et al. [19] proposed a method that exploits "visit-patterns of neighbors" to recommend POIs to those users with insufficient visit logs. Bao et al. [16] and Yin et al. [17] studied the method for addressing the cold start problem that arises when users visit a non-home city. Bao et al. used the POIs that are popular among local experts with preferences similar to users who request recommendations. Yin et al. inferred user preferences and popularity distributions over POIs in the user's visited city by topic model, and combined them to generate recommendations.

Familiarity-aware POI recommendations: Familiarity-related studies have been performed by Lian et al. [18], Baltrunas et al. [6], and Wang et al. [7]. Lian et al. exploited user visit-pattern differences to areas in order to reduce ambiguity in their preferences. For example, if there exists an unvisited POI in an area visited frequently by a given user, the system determines that the user does not prefer the POI because we can assume that he/she knows the POI well. In contrast, in an area rarely visited by the user, the system assumes that he/she simply does not know about the POI. This way, Lian et al. focused on how to reduce "*static* user preference" ambiguity by treating un-visited POIs located in familiar and un-familiar areas differently, whereas our proposed method focuses on how to manage *changes* in user preferences with regard to the degree of familiarity. Baltrunas et al. studied familiarity influence on sightseeing recommendations as a part of user context. This is also different from our proposed method because it uses the familiarity degree explicitly given by users. On the contrary, our proposed method automatically infers the degree of familiarity from LBSN data without using any information explicitly given by users.

The study of Wang et al. [7] is the most closely related to our study. Similarly to Yin et al.'s study [17], Wang et al. studied an effective way for combining user preference with popularity distribution over POIs located in a given area. Unlike Yin et al.'s study, for each area, Wang et al. used two popularity distributions inferred from two separate user groups: natives to the city (familiar users) and tourists from another city (unfamiliar users). The system selects the popularity distribution according to the target user's familiarity with the city. Subsequently, it combines the selected popularity with the target user's preference. However, popularity difference with regard to familiarity is captured at a topic-level that is too coarse for capturing visit-pattern differences observed at POI level. Therefore, Wang et al.'s method does not work well in areas with different familiarity in the same city. In addition, both Baltrunas et al. and Wang et al. calculated user familiarity to each city, and then recommended POIs from candidate POIs located in the city. For instance, Wang et al. classified users into natives and tourists if their visited city is closer/farther than 100 km from their home city. If we consider the small areas located in the same city, it is difficult to measure familiarity using the simple distance from home. For example, a workplace area 10 km far from home is more familiar than unvisited areas 5 km far from home.

Limitations of POI recommendations: The performance improvement by adopting a new concept is generally small in POI recommendations [28]. Most improvement is under 3% [28]. The first reason for this is that user visits to POIs are influenced by many factors. Therefore, the newly introduced single concept, which is the subject of each study, cannot consider all influential factors. The second reason is data sparseness. Most POI visit logs are generated voluntarily by users, i.e., users generate their visit logs only when they want to. Therefore, it is difficult to procure sufficient data to precisely model and evaluate user visit-pattern.

3. Preliminaries

In this section, we define the concepts required to explain our proposed method. Then, we describe the most related method, GeoSAGE (Wang et al. [7]), to explain how we extend the idea of GeoSAGE to manage user visit-pattern differences caused by familiarity differences in different areas located in the same city.

3.1 Definitions

The notations defined here are listed in **Table 1**.

City and Area: A city is defined as the union of an exclusively divided area $a \in A$, where A represents entire areas of the city. 2 km × 2 km squared area is adopted in this paper.

User and Check-in History: User $u \in U$ can visit any POI $v \in V$ located in area $a \in A$. u can leave a check-in $c \in C$ as a visit log to v. Therefore, u has check-in set $C_u = \{c_{u,1}, c_{u,2}, c_{u,3}, \ldots\}$ whose elements are check-ins left by u. $c_{u,i}$ indicates the i-th check-in in C_u.

Check-in: Single check-in $c_{u,i}$ consists of six attributes: User u, Visit time $t_{u,i}$, Visited POI $v_{u,i}$, POI's name, POI's location $l_{u,i}$, and POI's tags $W_{u,i} = \{w_{u,i,1}, w_{u,i,2}, \ldots\}$. $w_{u,i,j}$ indicates the j-th tag in $W_{u,i}$. **Figure 1** shows a check-in example. POI's name is given by the POI owner. POI's location $l_{u,i}$ indicates the POI's geographic position. Such position is represented by a latitude-longitude pair. $W_{u,i}$ is the keyword set that represents the POI's characteristics. A tag $w_{u,i,j}$ is selected from the entire keyword set W that consists of user-defined keywords and the categories defined by LBSN providers. For example, "tasty coffee" is a keyword and "Coffee shop" is a category. Because a single check-in indicates a user's single visit to a POI, there is only one check-in that has the exact $\langle u, t_{u,i}, v_{u,i} \rangle$ triple. In this paper, we use $c_{u,i} = \langle u, t_{u,i}, v_{u,i}, l_{u,i}, W_{u,i} \rangle$ to show single check-in.

Table 1 Notations of variable.

Variable	Interpretation
U, A, V, C	The set of users, areas, POIs, Check-ins.
W	The vocabulary set of POI tags.
C_u	The set of check-ins left by user u.
u, a (or a'), c, v	Instance of user, area, check-in, POI.
$c_{u,i}$	User u's i-th check-in.
$f_{u,a}$, $f'_{u,a}$	User u's familiarity, familiarity degree to area a.
F	The set of familiarity degrees.
$v_{u,i}$	The POI of i-th check-in in C_u.
V_a	The set of all POIs located in area a.
$l_{u,i}$	The location of POI $v_{u,i}$.
$W_{u,i}$, W_v	The set of tags describing POI $v_{u,i}$, POI v.
$w_{u,i,j}$	The j-th tag describing POI $v_{u,i}$.

User	Time	POI			
		ID	Name	Location	Tags
Ice_lover	2015 10-12 17:39	23453	62 ice-cream	Latitude, Longitude	Ice-cream shop, Ice-cream, Sweet

Fig. 1 An example of check-in.

Activity Area: A user's activity area is the area where the user has left most of his/her check-ins. Typically, users have plural activity areas [10].

Familiarity and Familiarity degree: Familiarity $f_{u,a}$ indicates how much user u knows about area a, which has a range of [0.0, 1.0]; 0.0 indicates that u does not know about a, and 1.0 indicates that u knows much about a.

In this paper, instead of directly using $f_{u,a}$, we use familiarity degree $f'_{u,a}$, which is a discretized version of $f_{u,a}$ whose value is discretized to a set of pre-defined non-overlapped bins. For instance, if we have the set of two pre-defined bins F = {U: [0.0, 0.9), F: [0.9, 1.0]}, then $f_{u,a1} = 0.22$, $f_{u,a2} = 0.91$, and $f_{u,a3} = 0.35$ become $f'_{u,a1}$ = U, $f'_{u,a2}$ = F, and $f'_{u,a3}$ = U, respectively.

POI Recommendation: As shown in **Fig. 2**, a user can visit any of the areas with different familiarities in a city. When a user requests a POI recommendation, the system extracts a finite number of POIs from those located in the user's currently visiting area. In familiarity-aware recommendation, according to $f'_{u,a}$, different POIs can be extracted for the same user-area pair (u, a).

3.2 GeoSAGE [7]

GeoSAGE is the latest and most closely related work to our study. The algorithm attempts to capture individual user preference variations with regard to the user's familiarity with a visited area. The algorithm assumes that the area is as wide as the city. The idea of GeoSAGE is to exploit the global preference in order to estimate the target user's preference bias in the target area. For explanation simplicity, we call a user who wants a recommendation, the *target user*, and the area where the target user is currently visiting, the *target area*. To infer global preference, the algorithm uses those check-ins that meet two conditions. First, the check-ins are made by a public whose familiarity with the target area is similar to that of the target user. Second, the check-ins are made in the target area. The idea behind this is that people tend to show similar visiting preferences when under similar conditions.

As shown in **Fig. 3** (a), GeoSAGE maintains both "individual preference" and "global preference" in the form of probability distribution over topics. A topic is a type of POI group where POIs in the same topic share common functions, for in-

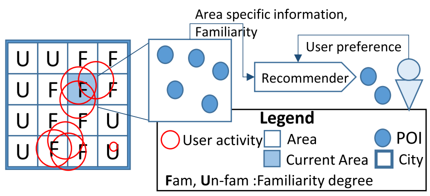
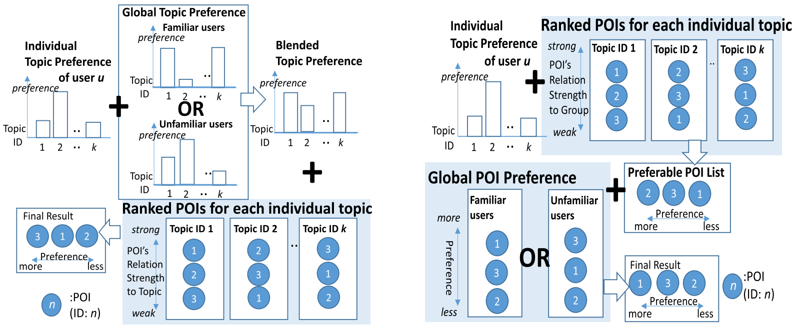


Fig. 2 POI recommendation.



(a) GeoSAGE[7] (b) Proposed Method

Fig. 3 Overview of GeoSAGE and proposed method.

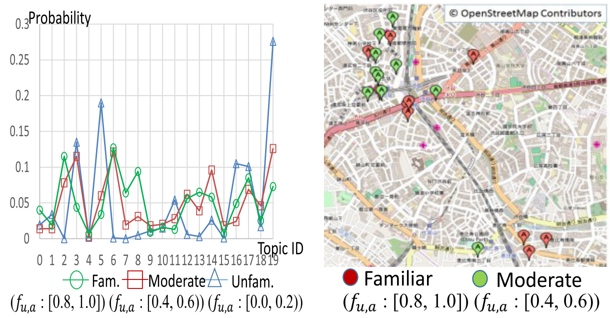
stance, POIs related to "dining." This topic-based preference was adopted to address the data sparseness problem in unfamiliar areas. Since users tend not to visit POIs in unfamiliar areas, the individual-POI-based model encounters difficulties when estimating the target user visit-patterns in unfamiliar target areas. In contrast, because GeoSAGE assumes that user visits are "visits to topics," the algorithm can mitigate the problem by recommending POIs with a strong relationship to the topic. In concrete, when target user u visits familiar (or unfamiliar) area a, GeoSAGE blends u's topic preference with the global topic preference of the public who are familiar (or unfamiliar) with a. Then, the recommended POIs are selected from all POIs in the target area based on the blended preference, followed by a ranking of both the POI relationship strength to each topic and the probability of each topic in the blended preference. If a given POI has higher relationship strength to the preferred topics, i.e., high probability in the blended preference, the POI has a higher probability of being ranked high as the recommended POI.

To infer the topics, blending ratio, and relationship strength between POIs and topics, GeoSAGE uses SAGE [20], a topic-learning algorithm. Simply speaking, a user is represented as a collection of POIs checked in by the user. In general, topic-learning algorithms classify those POIs that are commonly co-visited by many individual users into a single topic. For instance, movie lovers frequently visit "indie" (independent) movie theaters and multiplexes. Therefore, the two types of theaters are likely to be classified into the same topic. Because a user is represented by the POIs he/she has visited, individual and global topic preferences can be inferred using the POI-topic relationship strength of the visited POIs.

GeoSAGE does not work well when we changed the problem from "*inter-city"* to "*inter- urban neighborhoods* in the city".

First, GeoSAGE adopts an approximate delimiter (e.g., 100 km far from the home city) to classify user u as being familiar or unfamiliar with city a. The delimiter cannot be directly applicable to the classification of urban neighborhoods in the same city because, in the city, there are areas with different familiarity within the same distance from a user's active area such as the location of home. For example, when we set familiar areas as those areas within 4 km from home, other familiar areas, such as the workplace or frequently visited shopping areas, exist outside the 4 km range.

Second, there is a suspicion that the topic preference variation



(a) Global Topic Preference (b) Top 10 POIs in Topic ID 6

Fig. 4 Visit pattern variance w.r.t. familiarity in Roppongi [27].

caused by the familiarity difference is relatively weak in "areas in the same city" compared with the "inter-city" case [8], [27]. Therefore, we believe that individual POIs should obtain more highlights. We describe this issue in detail in Section 3.3.

3.3 Familiarity Observed in Areas Located in the Same City

In our previous paper [27], we confirmed that even in the home city, user visit-patterns represented by topic probability distribution varied with regard to the familiarity with the area but not sufficient to exploit in recommendation. Moreover, even if the topic distribution representing visit-patterns of familiar user group and that of unfamiliar user group are similar in a given area, visited POIs by the two user groups are different each other.

Figure 4 (a) show the global topic preferences with different familiarities in Roppongi. The preferences are learned by Gibbs sampling [21], a popular topic-learning algorithm. As shown in Fig. 4 (a), while clear differences can be detected between Fam. and Unfam., and between Moderate and Unfam., we cannot detect a definite preference difference between Fam. and Moderate.

Although the global topic preferences are similar, in the case of "Fam" and "Moderate" for Topic ID 6 in Fig. 4 (a), as shown in Fig. 4 (b), the POIs related to Topic ID 6, visited by "Fam" and "Moderate" are different.

4. Familiarity-aware POI Recommendation

In this section, we describe the actual familiarity used in our proposed method. Subsequently, our basic idea is described followed by its detailed explanation. Unless explicitly indicated, the notations used in this paper are those listed in Table 1 and **Table 2**.

Table 2 Model parameters.

Variable	Interpretation
z, Z	Topic, the set of topics.
φ_z^{word}, φ_z^{POI}	The probability distribution of topic z over keywords(φ_z^{word}), over POIs (φ_z^{POI})
$\theta_{*,u}^{pref}$	The user u's visit probability distribution over topics
$\theta_{f,u}^{pref}$	The user u's visit probability distribution over topics to areas of familiarity f
$\eta_{*,a}^{pop}$	The visit probability over POIs located in area a, of all users
$\eta_{f,a}^{pop}$	The visit probability over POIs located in area a, of users whose familiarity to area a is f
$d_{u,a}$	km distance between u's the center of the closest activity area and the center of area a, if $d_{u,a}$< 1km then set $d_{u,a}$ = 1.
$n_{u,a}$	The number of check-ins left by u in area a

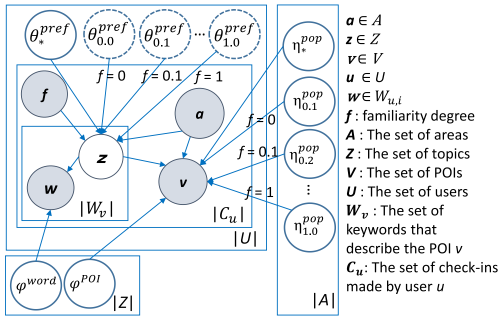


Fig. 5 Graphical representation of proposed method.

4.1 Familiarity calculation

Familiarity $f_{u,a}$ indicates how much user u knows about area a. In general, $f_{u,a}$ increases either when area a is one of the activity areas where user u has left many check-ins, or when area a is closer to one of the activity areas of user u. This is because we can assume that a person knows more about an area if the person frequently visits the area, or he has more opportunities to visit because of the area's geographic proximity to a frequently visited area.

We use Eqs. (1)–(3) [8], [27] to calculate $f_{u,a}$. $f_{u,a}$ has the range [0.0, 1.0], where 0.0 indicates that user u does not know about area a, and 1.0 indicates that user u knows much about area a.

$$f_{u,a} = \max\left(\frac{\log(n'_{u,a})}{\max\limits_{a' \in A}(\log(n_{u,a'}))}, \frac{\log(n_{u,a})}{\max\limits_{a' \in A}(\log(n_{u,a'}))}\right) \tag{1}$$

$$n'_{u,a} = (\max_{a' \in A} n_{u,a'}) \cdot p_{chk}(d_{u,a}) \tag{2}$$

$$p_{chk}(d_{u,a}) = z_1 \cdot {d_{u,a}}^{z_2} \tag{3}$$

Activity areas of user u are extracted from check-in set C_u by using DBSCAN algorithm [22]. If check-ins in C_u are located densely in n different geographic areas and there is no densely located check-ins between each areas, DBSCAN generates n different clusters. If area a includes the averaged geo-location of all the check-ins in one of the extracted clusters, we assume area a is an activity area of user u. Here, we allow a user to have multiple activity areas. We empirically use eps = 1, mitPts = 5 as the parameters for DBSCAN. $z_1 = 1$ and $z_2 = -1.1$ are constants. Interested readers can refer to Refs. [8], [27] for $f_{u,a}$ and Ref. [1] for the method for finding z_1 and z_2.

Our definition of familiarity is more robust than that of GeoSAGE [7], because 1) we are able to represent the familiarity by using a numerical value from 0 to 1, instead of using the binary representation used in GeoSAGE, i.e., familiar-or-unfamiliar, and 2) we are able to use multiple activity areas to calculate the familiarity, while GeoSAGE calculates the familiarity based on the distance from a single activity area.

4.2 Basic Idea

Our basic idea is to adopt individual POI-level preferences, i.e., global POI preferences, instead of using GeoSAGE's topic-level preference, global topic preference.

Since the preference difference between familiar users and unfamiliar users over topics is small in the areas located in the same city as described in Section 3.3, we utilize familiarity for the preference defined for individual POIs. As shown in Fig. 3 (b), our proposed method re-orders the POI order in a target user's preferable POI list using the global POI preference. POIs in the preferable POI list are ordered by the target user's preference degree for each POI. The global POI preference is the preference of individual POIs calculated from the check-ins of all users with a similar familiarity degree to the target user. By carrying out the re-ordering, we can calculate familiarity awareness while personalizing the POI recommendation list.

For a given area a, the proposed method maintains several global POI preferences. The number of preferences is predefined, such as two, based on the familiarity degree defined in Section 3.1, e.g., the global POI preference of familiar and unfamiliar users. "Area a's global POI preference with familiarity degree f" is calculated from the check-ins made by all users whose familiarity degree $f'_{u,a} = f$. If user u visits area a with $f'_{u,a} = f$, the proposed method first calculates u's familiarity-unaware preferable POI list with regard to a. The list is constructed using a method similar to GeoSAGE, but not using the global topic preference. Then the method combines the POI list with "a's global POI preference with familiarity degree f" to calculate recommended POIs.

4.3 Model Description

As described in Section 4.2, in order to calculate target user u's preference to a given POI v, our proposed method combines user u's preference to POI v with the familiarity-aware global POI preference to POI v. The combination is calculated with Eq. (4). This equation is used to calculate the case where user u visits area a, and the familiarity degree $f'_{u,a} = f$. The first term (in Σ's range) represents user u's preference to POI v. The second term represents area a's global POI preference with familiarity degree f. **Figure 5** shows a graphical representation of the proposed method.

To infer user preference, similarly to GeoSAGE, we adopt topic models because other popular methods, such as matrix factorization, cannot easily manage recommendations in unfamiliar areas [4]. User u's preference is represented by a probability distribution over topics. As shown in the first term of Eq. (4), user u's preference to POI v is calculated by accumulating POI v's relationship strength to each topic. When accumulating the relationship strength, we grant a weight to each topic based on user u's preference to the topic.

We linearly combine the two types of user preference distribution over topics (Eq. (5)). The first distribution is the general user preference distribution inferred by all the check-ins left by the user. The second distribution is the familiarity-aware user preference inferred from the check-ins left by the user in areas with the same familiarity degree. Combination weight b is automatically learned in learning phase.

POI v's relationship strength to topic z is calculated by taking both the relationship strength between POI v and z and the strength between the keywords that describe POI v and z (Eq. (6)). In this way, we can exploit both of POI's semantic closeness to a given topic and POI's popularity in the given topic. Because the number of describing keywords is different for each POI, we use the normalized version.

Area a's global POI preference with familiarity f is calculated with Eq. (7). Our method maintains the logged number of check-ins made to POI v in area a for each familiarity degree $\eta^{pop}_{f,a.v}$. In addition, our method maintains $\eta^{pop}_{*,a,v}$ that indicates the logged number of check-ins of all users, regardless of familiarity degrees. We combine $\eta^{pop}_{f,a.v}$ with $\eta^{pop}_{*,a,v}$ to mitigate the data sparseness problem. The assumption behind this is that in general, popular POIs attract people of all familiarity degrees to some extent.

The final recommendation list for user u is constructed by selecting the top-k POIs from the ordered candidate POI list. The candidate list is constructed by ordering the POIs in area a according to the recommendation score (Eq. (4)) in decreasing order. k is given by user u.

$$s(v|u, a, f, \boldsymbol{\Phi}) = \left(\sum_{z\in Z} p\,(z|u, f) \cdot p(v|z, a, \varphi^{POI}, \varphi^{word})\right) \cdot p(v|a, \eta^{pop}_{*}, \eta^{pop}_{f}) \tag{4}$$

where, $\Phi = \{\theta^{pref}_{*}, \theta^{pref}_{f}, \eta^{pop}_{*}, \eta^{pop}_{f}, \varphi^{word}, \varphi^{POI}\}$

$$p(z|u, f) = b \cdot \theta^{pref}_{*,u,z} + (1 - b) \cdot \theta^{pref}_{f,u,z} \tag{5}$$

$$p(v|z, a, \varphi^{POI}, \varphi^{word}) = \frac{1}{N_a} \cdot \left(\sqrt{\varphi^{POI}_{z,v} \cdot \frac{1}{|W_v|} \sum_{w\in W_v} \varphi^{word}_{z,w}}\right) \tag{6}$$

$$p\left(v|a, \eta^{pop}_{*}, \eta^{pop}_{f}\right) = \frac{1}{N'_a} \cdot \left(\frac{\exp\left(\eta^{pop}_{*,a,v} + \eta^{pop}_{f,a,v}\right)}{\sum_{v\in V_a} \exp\left(\eta^{pop}_{*,a,v} + \eta^{pop}_{f,a,v}\right)}\right) \tag{7}$$

where N_a and N'_a in Eqs. (6) and (7) are the normalization factors. Each factor is calculated by the summation of the second term (in parentheses) in each equation of all POIs located in area a (e.g., $\sum_{v\,located\,in\,a} 2nd\ term$).

4.4 Parameter Learning

In this sub-section, we describe how we learn parameters in Φ in Eq. (4) and b in Eq. (5).

We employed two-stage learning. In stage 1, we learn the topic model using the keywords that describe POIs to calculate the keyword-topic relationship strength. User u's preference over topics indicates the categories that user u likes. Then in stage 2, based on the keyword-topic relationship strength, we learn the POI-topic relationship strength. We calculate the POI-topic relationship strength by using both the assigned keywords and number of check-ins made to POIs, because some POIs are assigned to the same keywords. For example, if both POI v and POI v' have the same keyword "Coffee" that is strongly related to topic t and users made more check-ins to POI v than POI v', we can state POI v is more strongly related to topic t than POI v'.

Training Stage 1.
Input: U, C, F
Output: $\theta^{pref}_{*}, \theta^{pref}_{f}, \varphi^{word}$
set all counters to 0;
for (1 to maximum Iteration)
  for (each user u in U)
    for (each c in C_u)
      $v \leftarrow$ the POI where c made;
      $a \leftarrow$ the area where v located;
      $f \leftarrow$ ***getFamiliarity***(C_u, a, F);
      for (each w' in W_v)
        $z \leftarrow$ ***drawTopicP1***();
        updCounterP1(w, z, u, f);

Training Stage 2.
Input: $U, C, F, \theta^{pref}_{*}, \theta^{pref}_{f}\ \varphi^{word}$
Output: $\varphi^{POI}, \eta^{pop}_{*}, \eta^{pop}_{f}, b$
set all counters to 0;
for (1 to maximum Iteration)
  for (each user u in U)
    for (each c in C_u)
      $v \leftarrow$ the POI where c made;
      $a \leftarrow$ the area where v located;
      $f \leftarrow$ ***getFamiliarity***(C_u, a, F);
      $z \leftarrow$ ***drawTopicP2***(v, W_v);
      $s \leftarrow$ ***drawSrcPref***(z, $\theta^{pref}_{*,u}$, $\theta^{pref}_{f,u}$);
      updCounterP2(v, z, f, s);

Fig. 6 Learning algorithm.

We show the pseudocode for the learning algorithm in **Fig. 6**. In stage 1, similar to Liu et al.'s work [23], a user can be represented with the keywords that describe visited POIs and the POI visit frequency. This way, a user can be viewed as a single document that contains keywords. We can model user preference by LDA (Latent Dirichlet Allocation) [24] and infer user preference $\theta^{pref}_{*,u}$, $\theta^{pref}_{f,u}$, and topic-keyword relationship strength φ^{word}_{z} with Gibbs sampling [21]. The topic is sampled for each keyword in each check-in. Equation (8) shows the topic sampling probability used for *drawTopicP1*( ).

$$p(z_{u,i,j}|z_{\neg(u,i,j)}, w, u) \propto \frac{n^{\neg(u,i,j)}_{u,z_{u,i,j}} + \alpha_{z_{u,i,j}}}{\sum_{z\in Z}(n^{\neg(u,i,j)}_{u,z} + \alpha_z)} \cdot \frac{n^{\neg(u,i,j)}_{z_{u,i,j},w_{u,i,j}} + \beta_{w_{u,i,j}}}{\sum_{w\in W}(n^{\neg(u,i,j)}_{z_{u,i,j},w} + \beta_w)} \tag{8}$$

where $w_{u,i,j}$ represents an instance of the keyword that appears at the j-th position in keyword list $W_{u,i}$ that describes the POI checked in by $c_{u,i}$. $z_{u,i,j}$ represents an instance of the topic sampled for $w_{u,i,j}$. $n_{u,z}$ is the number of times topic z is sampled for user u. $n_{z,w}$ is the number of times topic z is sampled for keyword w. α_z and β_w are the hyper-parameters of Dirichlet prior for topic z and keyword w. $\neg(u, i, j)$ means excluding the result for $w_{u,i,j}$. For example, if topic z is sampled for $w_{u,i,j}$, the value for $n_{u,z} - n^{\neg(u,i,j)}_{u,z}$ equals 1; otherwise, equals 0.

Familiarity degree value f is calculated from *getFamiliarity*( ). As described in Section 3.1, we discretize the familiarity of Eq. (1) by grouping similar familiarity values into the same familiarity degree.

In *updCounterP1*( ), we count the topic sampling results to calculate user preferences (Eqs. (9) and (10)) and topic distributions over keywords (Eq. (11)).

$$\theta^{pref}_{*,u,z} = \frac{n'_{*,u,z} + \alpha_z}{\sum_{z'\in Z}(n'_{*,u,z'} + \alpha_{z'})}, \tag{9}$$

$$\theta^{pref}_{f,u,z} = \frac{n'_{f,u,z} + \alpha_z}{\sum_{z'\in Z}(n'_{f,u,z'} + \alpha_{z'})}, \tag{10}$$

$$\varphi^{word}_{z,w} = \frac{n'_{z,w} + \beta_w}{\sum_{w'\in W}(n'_{z,w} + \beta_w)} \tag{11}$$

where $n'_{*,u,z}$ and $n'_{f,u,z}$ are the number of times topic z is sampled for user u in all areas and in the areas of familiarity degree f. $n'_{z,w}$ is the number of times topic z is sampled for keyword w.

In stage 2, we calculate the topic probability distributions over

POIs (φ_z^{POI}), the area's global POI preference (η_*^{pop}, η_f^{pop}), and weight b in Eq. (5). In *drawTopicP2*( ), in order to calculate φ_z^{POI}, we sample topic z based on the topic probability to the keywords that describe POI v (Eq. (12)). Each sampled topic is counted and topic z's probability distribution over POIs is given by Eq. (13).

$$p(z|v, \varphi^{word}) = \frac{1}{|W_v|} \sum_{w \in W_v} \frac{\varphi_{z,w}^{word}}{\sum_{z'}^{Z} \varphi_{z',w}^{word}} \tag{12}$$

$$\varphi_{z,v}^{POI} = \frac{n'_{z,v} + \beta'_v}{\sum_{v' \in V}(n'_{z,v'} + \beta'_{v'})} \tag{13}$$

where $n'_{z,v}$ is the number of topic z sampled for POI v. β'_w is a hyper-parameter of Dirichlet prior for POI v.

We represent area a's global POI preference $\eta_{*,a,v}^{pop}$ and $\eta_{f,a,v}^{pop}$ as the logged frequency of check-ins for POI v (Eqs. (14) and (15)).

$$\eta_{*,a,v}^{pop} = log\left(\sum_{f \in F} n'_{f,v}\right), \tag{14}$$

$$\eta_{f,a,v}^{pop} = log(n'_{f,v}) \tag{15}$$

where $n'_{f,v}$ is the number of check-ins made for POI v by users with familiarity degree f.

Weight $\boldsymbol{b}$ is calculated with Eq. (16).

$$b = \frac{n'_{avg}}{(n'_{avg} + n'_{fam})} \tag{16}$$

where n'_{avg} and n'_{fam} are the number of topics sampled from the average preference ($\theta_{*,u}^{pref}$) and from the familiarity-aware preference ($\theta_{f,u}^{pref}$).

The probability of the sampled source selection used by drawSrcPref() follows Eq. (17).

$$p(s = avg|\theta_{*,u,z}^{pref}, \theta_{f,u,z}^{pref}) = \frac{\theta_{*,u,z}^{pref}}{\theta_{*,u,z}^{pref} + \theta_{f,u,z}^{pref}} \tag{17}$$

where term *avg* indicates that the source is the average preference.

5. Evaluation

5.1 Experimental Settings

Dataset: We evaluated our proposed method with check-in data from Foursquare [*1], one of the popular LBSNs. We tested the proposed method in three cities: New York City (NYC) and Los Angeles (LA) in the United States, and Tokyo in Japan. We selected these three cities because their residents have the most check-ins that we could gather. We first gathered Twitter [*2] users who left publicly available Foursquare check-ins in one of the cities. Subsequently, using both Twitter API [*3] and Foursquare API [*4], we gathered more publicly available check-ins from the users. We also collected keywords that describe POIs using the Foursquare API. The data were gathered from 2013.7 to 2014.12, and we collected over 1 million check-ins. Because the familiarity described in Section 4.1 needs information about activity areas, we only used the check-ins of users who have at least one activity area in the evaluation city. In **Table 3**, we list the statistics of the check-in data after filtering.

[*1] https://foursquare.com
[*2] https://twitter.com
[*3] https://dev.twitter.com/rest/public
[*4] https://developer.foursquare.com/

Table 3 Check-in data statistics.

City	Range (From, To, (latitude, longitude)) Width/Height	Target Users	POIs	Check-ins	Spatial Pyramid Height
NYC	(40.49,-74.27), (40.92,-73.67) 50.87/47.75 km	5,934	39,303	456,935	5
Tokyo	(35.59,139.50), (35.86,139.93) 38.97/29.96 km	3,139	38,030	178,206	5
LA	(33.68,-118.67), (34.34,-118.04) 58.42/73.21 km	2,264	23,843	174,373	6

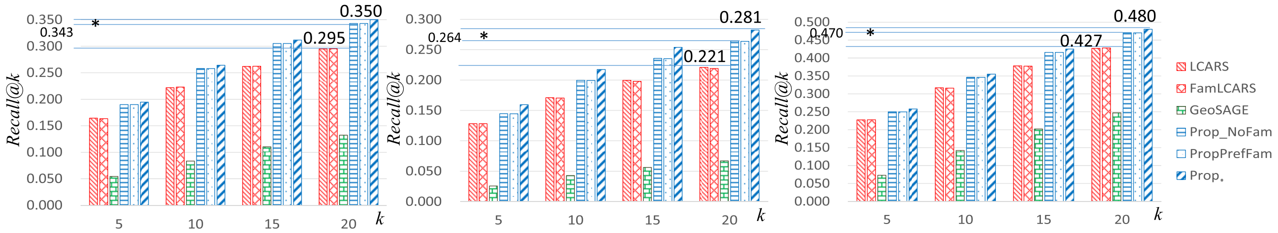
Table 4 Algorithms for comparison.

Algorithm	Description
LCARS [17]	**Similar to GeoSAGE. However, does not care familiarity.** $\vert Z\vert$= 40, α_z, α'_z=50/$\vert Z\vert$, β_v=0.01, and β_c=0.01, γ=0.5 for all cities.
FamLCARS	**Familiarity aware version of LCARS.** Similar to GeoSAGE. However, use additional latent switching variables instead of SAGE[20]. $\vert Z\vert$= 40, α_z, α'_z=50/$\vert Z\vert$, β_v=0.01, and β_c=0.01, γ= 0.5 for all cities.
GeoSAGE [7]	**State of the art.** Based on the source code shared by Wang *et al*. $\vert Z\vert$= 80 for all cities, Maximum height spatial pyramid: h = 5 for NYC, Tokyo. h = 6 for LA.
Prop_NoFam	**Proposed method but familiarity unaware.** b in Eq.(5) is always 1 & Uses $p(v\vert a, \eta_*^{pop})$ instead of Eq.(8). The other parameters used are the same to "Prop.".
PropPrefFam	**Proposed method but only use the familiarity captured by Eq.(5).** Use $p(v\vert a, \eta_*^{pop})$ instead of Eq.(8). The other parameters used are the same to "Prop.".
Prop.	**Proposed method.** $\vert Z\vert$= 40, α_z=50/$\vert Z\vert$, β_v=0.01, and β_w (β_c) =0.01 for all cities.

Methods: We evaluated the following six methods: LCARS, GeoSAGE, FamLCARS, our proposed method, and two variants of the proposed method. We set 2 km × 2 km as the area size for all the algorithms. Here, in GeoSAGE, the lowest spatial pyramid is set as 2 km × 2 km. The height of the pyramid is shown in Table 3. FamLCARS is a familiarity aware extension of LCARS implemented by us. FamLCARS maintains two global topic preferences to each area a: the preferences of familiar users, and unfamiliar users. In addition, it uses two latent switching variables for each user u to indicate the preference influenced to a given user visit: a variable for familiar area visits, and unfamiliar area visits. **Table 4**, we list the six algorithms and their parameters used in training phase to achieve the best performance. We evaluated the combination of (|Z|, h) for GeoSAGE, (|Z|) for the other methods. $|Z| \in \{10, 20, 40, 80, 100\}$ indicates the number of topics, $h \in \{0, 1, \ldots, max\}$ indicates the height of the spatial pyramid. We selected the combination that the *Racall@k* improvement started to be saturated. For priors $\alpha_z \sim \gamma$, we used the same value used in LCARS.

Evaluation: 5 × 2 cross-validation [25] was adopted. In a single two cross-validation, half of the randomly selected data were used to train the model, 20% of the last half was used to tune the parameter, and the remainder were used for testing. Then, we evaluated once more by exchanging the roles between the training and tuning/testing data. We repeatedly performed the two cross-validation five times to calculate the average as the results. In the 5 × 2 cross-validation, we are not concerned with the check-in time when constructing the training/tuning/testing sets because this is the methodology commonly used in POI-recommendation evaluations [7], [17], [23].

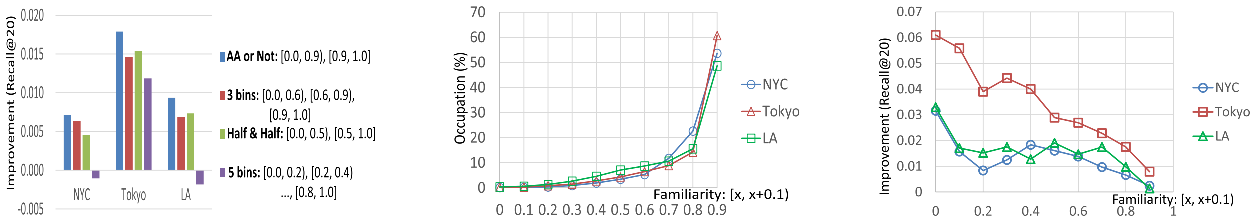
By following the evaluation setting descripted in Wang et al.'s work [7], for each user u, we construct ground truth POI set T_u by collecting every POI $v \in V$ that satisfies the two conditions: 1) POI v appears in at least one of user u's check-ins of the test data



* The difference between Prop and Prop_NoFam is statistically significant ($p < 0.01$) in all of three cities.

(a) NYC (b) Tokyo (c) LA

Fig. 7 Recommendation performance.



(a) Improvement to familiarity configuration (b) Check-in distribution over areas w.r.t. familiarity (c) Improvement over areas w.r.t. familiarity

Fig. 8 Performance improvement in areas in the same city after adopting familiarity.

set. 2) POI v does not appear in any of user u's check-ins of the training data set. Besides, we newly adopt the third condition: 3) POI v is located in area $a \in A$ that contains at least 120 identical POIs. The third condition was introduced to avoid the accidental occurrence of a good result that is originated in the small number of recommendation candidate POIs.

For each $v \in T_u$, the algorithms shown in Table 4 extract a list of top-k ranked POIs from the POIs located in the same area $a \in A$ where POI v is located, on the assumption that the algorithms do not know the ground truth POI v.

We used *Recall@k* shown in formula Eq. (18) as the evaluation metric employed by Wang et al. [7] and Yin et al. [17].

$$Recall@k = \frac{\sum_{u \in U} |R_{u,k}|}{\sum_{u \in U} |T_u|} \tag{18}$$

where $R_{u,k}$ indicates a set of successfully recommended POIs for user u. Here, if the ground truth POI v is included in the top-k recommended POI list, the recommendation is decided as successful. $|\,|$ indicates the set cardinality.

Unless explicitly indicated, we adopt the binary familiarity degrees {Uufam:[0.0, 0.9), Fam:[0.9, 1.0]} for familiarity classification with 2 km × 2 km area a for all the algorithms including GeoSAGE in Table 4. This indicates that the algorithms regard that area a is an unfamiliar area to user u if familiarity $f_{u,a}$ is less than 0.9.

5.2 Recommendation Performance

Recall@20: The results are shown in **Fig. 7**. The proposed method outperforms the two state-of-the-art methods. Compared to LCARS which is the best performing state of the arts, the proposed method achieved 0.05 to 0.06 improvement in *Recall@20*. Both of two statistical significance tests, t-test for 5 × 2 cross-validation [25] and Binary test [26], show that the performance difference between the proposed method (Prop.) and the familiarity-unaware version of the proposed method (Prop_NoFam) is statistically significant ($p < 0.01$) to all the cities.

It is interesting that the performance difference between each of the LCARS–FamLCARS pair, and Prop_NoFam–PropPrefFam pair is negligible. This implies that user preference variation with regard to familiarity degree cannot be easily captured at the topic level by using Gibbs Sampler. GeoSAGE showed the worst performance. It contradicts the result in Wang et al.'s work [7]. We will discuss these issues in Section 6.

Impact of Familiarity Degree Configuration: Figure 8 (a) shows the proposed method's *Recall@20* improvement achieved in comparison with the familiarity-unaware configuration (Prop_NoFam) by various familiarity degree configurations. Figure 8 (b) presents how the check-ins in each of the cities are distributed over the areas with different familiarity.

The binary classification, classifying areas into activity area or others, A.A. or not, which is concerned only with areas with familiarities in the range [0.9, 1.0] as familiar areas, shows the best performance improvement.

We divided the check-ins into "three bins" based on the check-in decreasing rate in NYC (three different slopes in blue line in Fig. 8 (b)). "Three bins" shows nearly the same performance as "A.A. or not" in NYC. However, in Tokyo and L.A., "Half & Half" configurations show better performance than "three bins."

"5 (the same sized) bins" shows the lowest improvement. Especially in NYC and LA, the performance decreased. The most probable reason is the data sparsity of the four bins with less than 0.8 familiarity.

Recall@20 improvement w.r.t. Familiarity: Figure 8 (c) shows the *Recall@20* improvement of our proposed method (Prop.) from the familiarity-unaware version of the proposed method (Prop_NoFam) calculated for each familiarity range. The performance is measured with the same configuration described in Section 5.1. The performance improvement is minimal in familiar areas (0.9 on the x-axis) in all three cities. We believe that the phenomenon is caused by the fact that most check-ins are left by familiar users, as shown in Fig. 8 (b). Therefore, in familiar ar-

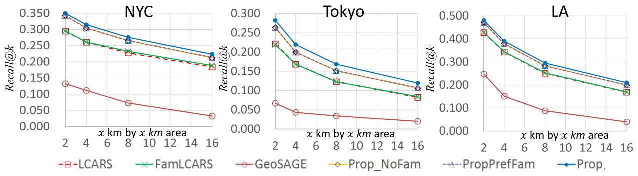


Fig. 9 Recommendation performance to various sized areas.

eas, there is no significant pattern difference between familiarity-unaware and familiarity-aware POI preference for familiar users, because the familiar users' check-ins govern both types of preferences.

For unfamiliar areas, we have a significant improvement because the familiarity-aware method (Prop.) can capture unfamiliar user visit-patterns normally diluted by massive check-ins made by familiar users in the familiar-unaware version (Prop_NoFam). It is worth noting that we have succeeded in performance improvement, especially in unfamiliar areas, which is not easily demonstrated by Fig. 7 because it only shows the average improvement.

Recall@20 w.r.t. the size of areas: *Recall@20* of the algorithms measured with various area size from 2 km × 2 km to 16 km × 16 km listed in **Fig. 9**. Our proposed method shows better performance with every area size. It shows that the proposed method is able to capture familiarity-caused-visit-pattern-variance in areas in the same city better than the other methods. We will discuss a possible reason in Section 6.

6. Discussion

In this section, we investigate why the familiarity-caused global topic preference difference captured by GeoSAGE does not contribute to high accuracy of recommendation. Then we examine why our proposed method works better in areas in the same city.

Differences of Global topic preferences: Figure 10 shows two kinds of global topic preferences - one for familiar and another for unfamiliar users, learnt by GeoSAGE, FamLCARS and our proposed method (shown as Prop.) for Roppongi in Tokyo, Japan. We omitted LCARS because the patterns of the preference and the performance is similar to FamLCARS. **Table 5** shows the human interpretation of each topic ID.

As for Prop., we calculated pseudo global topic preferences based on topic-venue strength ($\varphi^{POI}_{z,v}$) and the number of check-ins to venues as shown in Eq. (19) because our proposed method does not directly learn the global topic preference.

$$p\,(z|a,f) = \sum\nolimits_{\langle u,v,t\rangle\in C_{a,f}} \varphi^{POI}_{z,v} \Big/ \sum\nolimits_{z'\in|Z|} \sum\nolimits_{\langle u,v,t\rangle\in C_{a,f}} \varphi^{POI}_{z',v} \quad (19)$$

where, $\langle u, v, t\rangle$ is a triple representation of check-in that each symbol represents user, POI, and visit time. $z \in Z$, $a \in A$, $f \in \{Familiar, Un\text{-}familiar\}$, and $C_{a,f}$ represents the set of check-ins made in $a \in A$ by the users who have familiarity f with a.

In FamLCARS and Prop., the global topic preference distribution difference between familiar users and un-familiar users is minimal. This indicates that, in areas in the same city, preference differences caused by familiarity are difficult to be captured in topic level by Gibbs sampling.

On the other hand, GeoSAGE captures clearer preference difference between familiar users and un-familiar users than the other algorithms. However, the captured preferences are concentrated on a few topics. For instance, in Roppongi area, familiar users' preference is mostly concentrated on Restaurant topic (TID 1 and 5). On the other hand, un-familiar users' preference is concentrated on Theater and Music topic (TID 0). We think that phenomenon was caused by sparse distribution learning characteristic of SAGE [20] method. When recommending POIs in the cities far from home city as Wang et al. evaluated [7], GeoSAGE can capture user preferences more clearly than other algorithms because user preferences are concentrated on a few topics such as sightseeing. However, when GeoSAGE recommends POIs for areas with different familiarity in the same city, the deficiency of topic diversity results in poor accuracy.

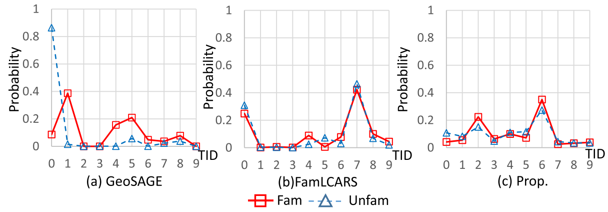


Fig. 10 Global Topic preferences in Roppongi in Tokyo, Japan.

Table 5 Topic interpretation.

TID	Interpretation		
	GeoSAGE	**FamLCARS**	**Prop**
0	Rock club, Theater, Music	Park, art	Rock club, Concert
1	Restaurant	Rock club, Theater	Theme park, Disney
2	Electronics, Bookstore	Restaurant, Park	Ramen, Fast food
3	Mall	Shinjuku	Department store, Mall
4	Tokyo Station	Electronics	Coffee shop
5	Restaurant 2	Museum, Art	Theater, Museum, Art
6	Park, Outdoor	Ramen, Bar	Restaurant, Bar
7	Department store, Mall2	Restaurant	Shrine, Temple
8	Coffee shop	Coffee shop	Park, Outdoor
9	Theme park, Disney	Restaurant, Disney	Electronics, Bookstore

For each area $a \in A$ where we made recommendations in Section 5 (55 areas in NYC, 58 areas in Tokyo, 41 areas in LA), we calculated the global topic preference of familiar users, and that of unfamiliar users. And then we calculated 1) *cosine similarity* [29] between the two global topic preferences, 2) *Shannon Entropy* [29] for each of the preferences (Eq. (20)).

$$ShannonEntropy(\vec{g}) = -\sum\nolimits_{t}^{|Z|} \vec{g}_t \cdot log_e(\vec{g}_t) \quad (20)$$

where, $\vec{g}$ is a global topic preference vector of |Z| dimension. *t-th* element of $\vec{g}$, $\vec{g}_t$ indicates the probability of topic ID t.

When the global topic preferences of familiar users and unfamiliar users in a given area are identical, the similarity is 1.0. And, if totally different (orthogonal), the similarity is 0. For the entropy, if the probability is concentrated on a single topic, then the value is 0.

For model parameters, we used the values described in Table 4 except for |Z|. We chose the same |Z| = 40 to compare all of the three algorithms in the same condition. We ran the same tests 10 times with the models trained from the 10 different training sets described in Section 5 and all of the test results led us to the same conclusion. Therefore, we list the results of one of the tests in **Table 6** and **Table 7**.

Table 6 Similarity and entropy of the global topic preference.

City		NYC			Tokyo			LA		
Algorithm		Geo SAGE	Fam LCARS	Prop.	Geo SAGE	Fam LCARS	Prop.	Geo SAGE	Fam LCARS	Prop.
Avg. Cosine similarity		0.66	0.97	0.95	0.31	0.90	0.88	0.35	0.99	0.95
Avg., Entropy	Fam.	0.65	0.74	3.27	0.74	2.05	2.99	0.58	0.76	3.31
	Un-fam.	0.69	0.67	3.25	0.81	1.90	2.80	0.48	0.65	3.27

*Cos.sim. difference between GeoSAGE and FamLCARS(or Prop.) has $p < 0.001$ (paired t-test) in all cities.
*Entropy of uniform probability distribution over 40 topics is 3.69.

Table 7 Similarity between top-20 relevant POI set for familiar user group and that for un-familiar user group.

City	NYC		Tokyo		LA	
Algorithm	Prop.	Fam LCARS	Prop.	Fam LCARS	Prop.	Fam LCARS
Avg. Jaccard index	0.59	0.93	0.43	0.71	0.61	0.95

*The difference between Prop. and FamLCARS has $p < 0.001$ (paired t-test) in all cities.

Table 6 showed the averaged values of all tested areas. We can see only GeoSAGE can capture differences between global preference of familiar and unfamiliar users with significant difference but the captured preferences have a narrow spectrum.

Differences of individual POIs: As we can see in Fig. 10, in FamLCARS and Prop., the global topic preferences between familiar users and unfamiliar users are similar. However, as expected in Section 3.3, the individual POI popularity between the two user-groups are different each other.

To validate our hypothesis, for each area $a \in A$ where we made recommendations in Section 5, we calculated the top 20 relevant POIs for familiar users and the top 20 relevant POIs for unfamiliar users. We prepared the two POI sets for each of FamLCARS and Prop. In FamLCARS, the sets are constructed by the top ranked POIs in the recommendation score calculated by the global topic preference without using individual user preference. In Prop., we used η^{pop}_{*} and η^{pop}_{f} because our method does not explicitly adopt the global topic preference. Instead, η^{pop}_{*} and η^{pop}_{f} were designed to be used for this purpose.

For each of FamLCARS and Prop., we calculated *Jaccard coefficient* [29] (Eq. (21)) by using the top-20 POI list of familiar users, and that of unfamiliar users calculated by each of the algorithms for each of the areas. The averaged results of all tested areas are shown in Table 7.

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \tag{21}$$

Even though the global topic preference distributions between familiar users and unfamiliar users are similar in Prop. as shown in Fig. 10 and Table 6, the values of *Jaccard coefficient* of Prop. in Table 7 are substantially low compared to those of FamLCARS. This indicates FamLCARS cannot capture the clear preference difference between familiar users and unfamiliar users because it adopts the same topic-POI relationship strength for both familiar and unfamiliar user groups, and the topic level preferences between familiar user group and unfamiliar user group captured by FamLCARS are similar to each other. This means, user preference to POI groups (topics) are not significantly changed by user familiarity with areas in the same city. Instead, visit attitudes to individual POIs change. For instance, ramen lovers eat ramen in any visited areas, but visit the ramen restaurants loved by the users whose familiarity with the visited area is similar to them.

Limitations of the experimental results: Our experimental results have two limitations. One of the limitations is related to generalization. Our results discussed in this paper were obtained from the data of only three big cities, from the single LBSN service: NYC, Tokyo, LA in Foursquare. In addition, we tested recommendation performance for users who have at least one activity area in the target city. By doing this, we implicitly expected that users have familiar areas and unfamiliar areas in the target city. However, the possibility that a tourist left many check-ins in a single area exists. As a result, the users who are equally unfamiliar to all of the areas in the target city may exist regardless of their familiarity value to areas, the value calculated by Eq. (1). Therefore, it is difficult to say the results are valid in all cities and all the logs could be obtained from LBSN services.

Second, we empirically defined *areas* are 2 km × 2 km squares on geographic space and used DBSCAN [22] with empirically tuned parameters to find activity areas of users. However, the shape and the size of *areas* might be different between cities because of user life-style difference between the different cities. One solution to finding optimal areas is using the method Cranshaw et al. [30] suggested. Cranshaw et al. used a spectral clustering method to find POI groups that have the POIs closely located and visited by the similar set of users. And then the areas that include the POIs for each group are defined. By doing this, we may capture the areas that can reflect user life-style in each city more precisely. However, this issue is still an open question. In activity area search, because users left check-ins in a voluntary manner, it is difficult to devise a general automated method applicable to every user.

Despite of the limitations we addressed, the experimental results showed that visit-pattern differences with regard to familiarity exist even between areas in the same city and there is a way to exploit the differences in POI recommendation.

7. Conclusion

In this paper, we proposed a familiarity-aware POI recommendation method. The method is designed to capture user preference differences with regard to familiarity differences in areas of the same city. Through experiments performed on real LBSN data, we showed that visit-pattern differences with regard to familiarity exist even between areas of the same city. In addition, the difference that cannot be easily captured by state-of-the-art methods can be exploited using the proposed method.

For future work, we will investigate if our findings described in this paper are still valid in small sized cities, because users' familiarity may be varied depending on the size of city. We will also study the suitable granularity of both POI category and recommended POIs. For example, in a large city that has many cafés, the questions, such as what kind of café and how many cafés should be recommended for familiar or un-familiar users, are interesting. The granularity issue is also related to the improvement of POI recommendation in familiar areas where lower improvement was achieved by our proposed method compared to un-familiar areas.

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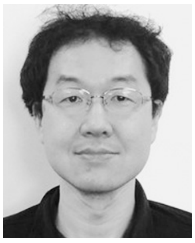

Jungkyu Han is a Ph.D. student at Waseda Univerisity. His research interests include data mining, artificial intelligence, distributed computing.

Hayato Yamana has been a Professor of Faculty of Science and Engineering at Waseda University since 2005. He is a member of IEEE and ACM and a senior member of IPSJ.