Leveraging multi-aspect time-related influence in location recommendation

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Abstract Point-Of-Interest (POI) recommendation aims to mine a user’s visiting history and find her/his potentially preferred places. Although location recommendation methods have been studied and improved pervasively, the challenges w.r.t employing various influences including temporal aspect still remain unresolved. Inspired by the fact that time includes numerous granular slots (e.g. minute, hour, day, week and etc.), in this paper, we...
define a new problem to perform recommendation through exploiting all diversified temporal factors. In particular, we argue that most existing methods only focus on a limited number of time-related features and neglect others. Furthermore, considering a specific granularity (e.g. time of a day) in recommendation cannot always apply to each user or each dataset. To address the challenges, we propose a probabilistic generative model, named after Multi-aspect Time-related Influence (MATI) to promote the effectiveness of the location (POI) recommendation task. We also develop an effective optimization algorithm based on Expectation Maximization (EM). Our MATI model firstly detects a user’s temporal multivariate orientation using her check-in log in Location-based Social Networks (LBSNs). It then performs recommendation using temporal correlations between the user and proposed locations. Our method is applicable to various types of the recommendation models and can work efficiently in multiple time-scales. Extensive experimental results on two large-scale LBSN datasets verify the effectiveness of our method over other competitors.

**Categories and Subject Descriptors:** H.3.3 [Information Search and Retrieval]: Information filtering; H.2.8 [Database Applications]: Data mining; J.4 [Computer Applications]: Social and Behavior Sciences

**Keywords** Multi-aspect time-related influence · Hybrid location recommendation · Location-based service

1 Introduction

With the ubiquity of GPS-enabled smartphones, using Location-based Social Networks (LBSNs) has become an essential part of the daily life. People can easily socialize and share their check-in data through such mediums (e.g. Foursquare, Yelp, Gowalla, Loopt and Google places). Specifically, when an LBSN user presses the check-in button, she actually reveals her location and enclosed information including the time, textual contents, photos, videos, and so on [26, 51]. On the one hand, LBSN users share such valuable spatio-temporal information generously. On the other hand, by mining the rich user check-in data, the Point-Of-Interest (POI) recommendation systems assist the users in exploring new attractive venues which affirm numerous benefits for all stakeholders in the LBSN ecosystem.

A check-in in LBSNs is interpreted as a digit entry in the user-location matrix where it can indicate the frequency of a user’s visit to a location [2] or a binary value (e.g. [34, 40]) to denote whether she has visited the location or not. In a positive-only manner, missing an entry signifies that we don’t know whether the user does not like the venue or is basically unaware of it. Nevertheless, the primary problem in location recommendation is to propose a list of new interesting POIs to the query user. Owing to excessive sparsity (or scarcity) observed in user-location matrices [30], POI recommendation in LBSN environments is extremely challenging.

The challenges regarding location recommendation have already been tackled through different traditional methods [28, 32] such as Random Walk and Restart and the popular Collaborative Filtering (CF) [16, 34, 39, 40]. CF methods have two categories; memory-based and model-based [3] and study a user’s interest regarding each proposed POI. In reality, numerous approaches [9, 16, 34, 35] attempt to demote sparsity in user-location matrix. Moreover, a growing line of research has recently been dedicated to employing various kinds of effects to enhance recommender systems. Geographical [21, 34, 40], social [2, 10],
context-oriented [36, 39] (e.g. text contents and word-of-mouth) and temporal effects are among commonly utilized factors [39]. Despite the vital beneficial role of temporal influence [47], an insufficient amount of research work has been devoted to the time factor in location recommendation. As a matter of fact, regular User-Time-POI hexahedron (UTP) is more scattered compared to the User-Location matrix. While we have an insufficient number of records regarding a user’s check-in at a particular location, predicting the time of the visit seems more problematic. Anyhow, we consider time-related information to enhance the effectiveness of location recommendation systems.

With respect to time, POI recommenders have so far employed the three temporal attributes of periodicity, consecutiveness, and non-uniformness [3, 4, 8, 9, 40, 48]. Periodicity [4] states that a user’s movement at different locations has an approximate periodical replication. For example, a typical user would mostly perform check-ins near her workplace during the day and near her home at night. Consecutiveness or Successive attribute [3, 44] claims that there are certain locations which are visited in a sequential order during a limited time constraint. Finally, non-uniformness declares that the check-in behavior of LBSN users vary in different temporal periods (i.e. one’s activity pattern is work-oriented during weekdays and related to entertainment throughout the weekends) [9]. Inspired by the fact that the time dimension comprises numerous granular slots (e.g. minutes, quarters, hours, and days), while some are subsets of the others, we propose that the fourth attribute be named Temporal Subset Property (TSP).

Some other research also reveals that the time factor can be treated as either discretized [6, 8, 9, 35, 40, 48] or continuous [39, 43]. Those using time in a continuous manner claim that choosing the proper time interval is not feasible [39]. However, discrete-time constitutes the basis of our daily lives. We set our appointments, meetings, and events using predefined time slots. Additionally, urban arrangements are planned by discretized values (e.g. a sample supermarket chains in Australia close at 6 pm except on Thursdays when they serve the customers until 9 pm), hence it makes sense for us to use discrete-time in our paper. However, previous work [6, 8, 9, 35, 40, 43, 44, 48] that integrated discretized temporal information such as the hour of the day or day of the week cycles into POI recommendations considered only single or two temporal granularities to avoid complexity and overfitting issues [44]. In reality, time is multi-aspect and user check-in behaviors are simultaneously influenced by multiple temporal effects with different cycles or granularities. Also rather than configuring the method (e.g. [9]) to work under specific time-related intervals, it is better to devise a solution which can include multiple temporal factors to promote recommendation systems.

Accordingly, our observation of two public LBSN data sets (Section 4.1) shows more than 40% of locations, explored by at least 8 users, are mostly visited at their popular times (e.g. a bar is mostly visited during after hours). Hence, a location $l_j$’s probability of being visited by a user $u_i$ increases when $u_i$ owns prior check-ins during the times when $l_j$ is visited more. As the time of a visit can be declared through several dimensions (minute of hour, hour of the day, and the day of the week), we can conclude that LBSN users and locations correlate with each other temporally in a multi-aspect way. To summarize, what we are seeking throughout this paper is as follows: “What kind of model do we have to choose to comprise all temporal dimensions in POI recommendation systems? How to reduce sparsity in a hierarchical set of UTP matrices where each one is associated with a single temporal dimension? Finally, how can we use this perception to enhance POI recommendation systems?”

To this end, we initially aim to reduce sparsity. We select an optimum number of users via non-replacement stratified sampling model [20]. Where the size of the dataset is huge,
processing of the whole set of users can be time-consuming. Therefore, we utilize the stratified sampling model to infer the stable temporal patterns in each dimension using a minimum number of users. We choose the users from various categories - with low, medium, and high number of check-ins - in multiple rounds. When the check-in temporal behaviour of a user is learned, it will be excluded in the next sampling round(s) (non-replacement). We then extract a list of user-time-POI matrices for every sampled user. Each of these cubes is associated with a temporal dimension. We then apply similarity metrics to find homogeneous parts in each dimension (e.g. similar hours, days and etc). Consequently, through aggregating the evidence captured from every user, we can reach the final similarity maps for each temporal granularity. We also utilize matrix factorization to compute missing values in similarity maps (e.g. we may not have enough evidence to find the similarity between 2 am and 3 am in the hour of a day dimension). Subsequently, we use the Bottom-up Hierarchical Agglomerative Clustering (HAC) \cite{5} to merge similar partitions in various granularities. This constructs primary multi-aspect Temporal Slabs. Each temporal slab includes a set of similarly merged parts from various scales. Such preprocessing mitigates sparsity involved in UTP matrices as the user’s check-in at a given time can be estimated from her check-ins at other similar times.

Moreover, we propose a probabilistic generative model, named Multi-aspect Time-related Influence (MATI) which consumes constructed temporal slabs to recommend a temporally correlated list of new POIs to the query user. As each user’s location history is insufficient, we utilize a Expectation Maximization algorithm to infer latent parameters and subsequently compute both the depth and extent of temporal similarity between the query user and each of proposed locations. While the depth of correlation is computed through aggregation of the joint probabilities of the user, location, and all latent temporal factors, the extent of the correlation is calculated via Jaccard coefficient among temporal slabs associated with the query user and the proposed location. We theoretically prove that the model can simultaneously integrate multiple latent temporal impacts in the recommendation task. Nonetheless, not necessarily all users would follow leveraged temporal patterns. For instance, owing to holidays, a user may go to a restaurant on Monday at 10 am and go to a bar following this; however, such behaviour has the least likelihood for the majority of other users who are at work. Therefore, in a hybrid framework, we firstly detect whether each query user is adequately affected by the time factor or not. Our method mimics how the user and the set of top N proposed locations share a commonly acceptable check-in behavior. If the value for the computed metric is in the well-tuned range, the multivariate temporal influence will be implanted, and vice versa.

To summarize, this paper focuses on the problem of enhancing location recommendation task in social networks. We have previously presented a study regarding the effects of a single temporal granularity in Hosseini et al. \cite{12}. This article extends Hosseini et al. \cite{12} through utilizing various dimensions of temporal influence and in-depth performance analysis. Specifically, this article provides the following new contributions: first, our previous model addresses the role of a single temporal effect in the recommendation, while in this work, our proposed method takes an unlimited number of concurrent dimensions into consideration; second, we propose an optimized approach to retrieve multi-aspect similarity maps, which also mitigates sparsity; third, MATI as a latent generative model can predict user’s time-oriented mobility patterns. Moreover, the ultimate advantage of our model in capturing all temporal aspects can enhance various user-item based recommendation systems disregarding the level of density; We also review temporal trends of location recommendation systems in related work. To the best of our knowledge, no prior work attempted
to take into account both multi-aspect(MATI) and subset(TSP) temporal features to enhance location recommendation.

To sum up, the main contributions of this paper are listed as follows:

– Our method exploits *multi-aspect temporal slabs* through merging similar temporal slots in various scales.\(^1\) The size of the dataset can be huge and the users’ check-ins during certain slots might be low in number. Therefore, in a novel procedure, our method estimates proper slabs through the processing of a minimum subset of the dataset by employing both stratified sampling and matrix factorization.

– Our proposed generative model (MATI) in this paper can incorporate as many latent temporal granularities as required where each of them represents a temporal scale. The model enhances the results of the recommender framework through leveraging the multi-aspect temporal correlation between LBSN users and POIs. While the MATI model can comprise multiple temporal dimensions to collectively infer the visiting pattern among user-location pairs, our previous work (Section 2) could only include a single temporal dimension (e.g. weekday/weekend).

The rest of this paper is structured as follows. We start with a review of our prior work [12] in Section 2 which exploits a univariate time-related influence. We then continue with the extension which considers the multivariate aspect of time and using a comprehensive probabilistic approach devised based on temporal latent factors. Subsequently, Section 4 provides experimental results. Related research work is surveyed in Section 5. We finally close this paper in Section 6 which offers promised future directions and concluding remarks.

### 2 Single slot temporal influence

Intuitively, selecting a specific temporal granularity (e.g. hour of the day) and leaving others (e.g. minute of hours, and the day of the week) unattended is not legitimate. In addition, there is not a clear reason why one scale can be preferred versus others. Such an argument justifies the necessity of the model proposed in Section 3. Since the method proposed in this section cannot compensate the data loss caused through considering a single aspect, we propose our main method in Section 3 which can handle multiple temporal dimensions and prevent the data loss. However, in this section, we will review our previous work [12].

From a univariate temporal perspective, as visited locations during weekday and weekend are substantially different, we can study weekly intervals to see how this idea can promote the effectiveness of POI recommendation systems. People usually visit entertainment venues during weekends and work-related places throughout weekdays. Hence, we can develop a new method to perform recommendations, based on temporal weekly alignments of users and POIs. In our prior work [12], we developed a probabilistic model which detects a user’s temporal orientation based on visibility weights of POIs visited by her during weekday/weekend cycles. Consequently, the system proposes locations based on either her weekday or weekend interests.

To this end, we firstly set up two observations based on primary definitions to verify that certain POIs and users are aligned toward either weekday or weekend.

\(^1\) A temporal slot, scale, and dimension (e.g. Hour, Day and etc.) are used interchangeably in this paper unless noted otherwise.
Definition 1 (POI Act) Given a set of POIs $P = \{p_1, p_2, \ldots, p_n\}$, each $p_j (\forall p_j \in P)$ has a POI Act denoted as $p_j^a$ (1), which is the margin value ($[-1, 1]$) between its probabilities to be visited during weekday ($w_d$) and weekend ($w_e$).

$$p_j^a = \frac{W_d^j}{N_j} - \frac{W_e^j}{N_j}$$

(1)

Here, $W_d^j$ and $W_e^j$ denote the number of visits at $p_j$ during $w_d$ and $w_e$. Also, $N_j$ is its total number of visits. If $p_j^a$ is greater than zero, it will exhibit an alignment toward $w_d$ and if it is less than zero, it will show that $p_j$ is visited more during $w_e$. Otherwise (if $p_j^a = 0$), $p_j$ will be neutral (not temporally aligned). In short, POI act studies whether a location is mostly visited during either of weekdays or weekends. The number of days utilized in (1) follows the people’s weekly visiting patterns (i.e. work-related venues during the weekdays and recreational places during the weekends).

Definition 2 (User Act) Given a set of users $U = \{u_1, u_2, \ldots, u_n\}$, we define that each $u_i (\forall u_i \in U)$ has a User Act denoted as $u_i^a$ (2) which is the margin value ($[-1, +1]$) between probabilities of her $w_d$ and $w_e$ visits.

$$u_i^a = \text{Avg}_{i}^d - \text{Avg}_{i}^e$$

(2)

$\text{Avg}_{i}^d$ and $\text{Avg}_{i}^e$ are probabilities for $u_i$ to visit locations during $w_d$ and $w_e$ respectively. If $u_i^a$ is greater than 0, it reflects $u_i$’s temporal preference toward $w_d$ and if it is less than 0, it indicates that she is more interested in $w_e$.

Subsequently, we continue with observations to perceive the single aspect of weekday/weekend cycles in LBSN users’ behavior. As certain POIs and users can be oriented toward $w_d$ or $w_e$, we can use threshold $T$ to reflect the extent of alignment. $T$ is set to $17 \approx 15\%$ which follows the uniform distribution of locations for each day throughout the week. On the other hand, the temporal influence of every day in a week will be the same and the threshold $T$ is subjected to more than one day of alignment toward either weekday or weekend.

1. Absolute POI Act Observation: From a single temporal aspect, Absolute POI Act Observation clarifies that many of POIs are frequently visited either during $w_d$ or $w_e$. Therefore, for each $p_j$, visited by a set of users $U_j$, we computed $p_j^a^*$ (3) as an absolute rate of temporal $w_d/w_e$ deviation. In the inspection, we chose those locations which were visited by at least 5 users.

$$p_j^a^* = \frac{\sum_{u_i \in U_j} |p_{i,j}^d - p_{i,j}^e|}{|U_j|}$$

(3)

$p_{i,j}^d$ and $p_{i,j}^e$ are the probabilities of each $u_i \in U_j$ to visit $p_j$ during $w_d$ and $w_e$ (4):

$$p_{i,j}^d = \frac{W_{i,j}^d}{W_{i,j}}, \quad p_{i,j}^e = \frac{W_{i,j}^e}{W_{i,j}}$$

(4)

Here $W_{i,j}$ is the total number of times that each $u_i \in U_j$ has visited $p_j$. Also, $W_{i,j}^d$ and $W_{i,j}^e$ record the number of visits performed during $w_d$ and, respectively.

The probabilities regarding locations’ weekly deviations in various ranges (e.g. 0.3 - 0.4) are displayed in Figure 1a and b. This shows that more than 70% of the venues in both
datasets gain an average absolute orientation greater than threshold $T$. As highlighted in dark orange, we observe that most of the locations in both datasets are mainly visited either during the weekend or weekday.

2. **Absolute User Act Observation**: Similar to POI Act Observation, considering single weekday/weekend cycle, we computed $u_{i}^{a*}$ (5) as the average rate of absolute temporal $w_d/w_e$ deviation for each user $u_i$ with $L_i$ as her visiting record. We selected users who have visited at least 8 POIs ($\{\forall u_i \in \mathbb{U} | |L_i| > 8\}$). Figure 2a and b illustrate relevant probabilistic bins which reflect to what extent each user is temporally oriented toward either $w_d$ or $w_e$. $|p_{i,j}^a|$ is $p_j$’s absolute POI act limited to $u_i$’s visits.

$$u_{i}^{a*} = \frac{\sum_{p_j \in L_i} |p_{i,j}^a|}{|L_i|}$$ (5)

If $u_{i}^{a*}$ is less than $T(15\%)$, we can ensure that $u_i$ is not oriented toward $w_d$ or $w_e$. However, as highlighted in dark orange (Figure 2), 57.3% and 61.6% of users in Foursquare and Brightkite have an absolute temporal deviation more than the $T$. Also, more than 10% of users are highly aligned toward either weekday or weekend ($u_{i}^{a*} > 45\%$). The second bar from left in Note that both Figure 2a and b cover the range of 10% to 20% for absolute rate and also include a 5% portion that is bigger than the threshold $T(15\%)$.

Based on aforementioned observations, we can conclude that weekly temporal influences exist for both users and POIs.

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**Figure 1** Observation on Absolute POI Act

**Figure 2** Observation on Absolute User Act
2.1 User act single factor model

As shown in observations, the effect of single temporal influence regarding weekly periods has been witnessed in the visibility patterns of users and POIs. Hence, in this section, we review the method which was used in our previous work [12] to compute user acts. In reality, primary user act (Definition 2, (2)) treats all the locations the same, while they differ based on their importance (Weekday/Weekend visiting influence). Therefore, we propose a more efficient model to compute the user act. We first need to obtain user’s visiting orientation toward \( w_d \) or \( w_e \). Therefore, we compute the POI act for every location visited by \( u_i \) \((p_j \in L_i)\). We use (6) to find positive or negative impacts.

\[
\hat{p}_{i,j}^d = (p_{i,j}^d - \lambda), \quad \hat{p}_{i,j}^e = (p_{i,j}^e - \lambda)
\]

\( \lambda \in (0, 1) \) distinguishes \( w_d/w_e \) margins. If we assume \( \lambda = 0.5 \), \( p_{i,j}^d = 0.75 \), and \( p_{i,j}^e = 0.25 \), then \( \hat{p}_{i,j}^d = 0.75 - 0.5 = 0.25 \), which indicates that \( p_j \) has a positive impact on user \( i \)'s weekday act. For computation of a user’s act, we assume that as higher the visiting probability of a location, it will be more significant in the final value of the user’s act. In our previous work we utilized [34] to compute non-temporal visiting influences for each location \((p_j)\). we removed each \( p_j \) from \( L_i \), we then obtained \( c_{i,j}^* \) which represents the probability of \( u_i \) to visit \( p_j \) comprising all modules of Collaboration, Friendship, and Vicinity. We then normalized the results \((\in (0,1))\) using feature scaling (7):

\[
\tilde{c}_{i,j}^* = \frac{c_{i,j}^* - Min_{ci}}{Max_{ci} - Min_{ci}}
\]

where \( Max_{ci} = \arg \max (c_{i,k}^*), \) \( Min_{ci} = \arg \min (c_{i,k}^*), \forall p_k \in L_i \). To get the final weekday orientation probability for each \( p_j \in L_i \) we use (8):

\[
Pr_{i,j}^d = \tilde{c}_{i,j}^* \cdot \hat{p}_{i,j}^d = \frac{c_{i,j}^* - Min_{ci}}{Max_{ci} - Min_{ci}} \cdot (p_{i,j}^d - \lambda)
\]

The higher \( \tilde{c}_{i,j}^* \) is, the more likely this location will be visited by \( u_i \) and will be more influential on \( u_i \)'s act. Similarly, the weekend orientation probability \((Pr_{i,j}^e)\) can be computed as follows:

\[
Pr_{i,j}^e = \tilde{c}_{i,j}^* \cdot \hat{p}_{i,j}^e = \frac{c_{i,j}^* - Min_{ci}}{Max_{ci} - Min_{ci}} \cdot (p_{i,j}^e - \lambda)
\]

Finally, the user act orientation based on the single temporal influence is obtained through (10):

\[
\tilde{u}_i^a = \left| \tilde{Avg}_{i}^d - \tilde{Avg}_{i}^e \right|
\]

While \( \tilde{Avg}_{i}^d \) (11) and \( \tilde{Avg}_{i}^e \) (12) are respective \( w_d/w_e \) average ratios.

\[
\tilde{Avg}_{i}^d = \frac{\Sigma p_{j \in L_i} Pr_{i,j}^d}{|L_i|}
\]

\[
\tilde{Avg}_{i}^e = \frac{\Sigma p_{j \in L_i} Pr_{i,j}^e}{|L_i|}
\]

If the value of \( \tilde{Avg}_{i}^d - \tilde{Avg}_{i}^e \) is greater than zero, this will denote that the user is aligned toward \( w_d \) and if it is less than zero, she will be aligned toward \( w_e \).
2.2 Uni-variate temporal framework

Univariate Temporal Framework developed in our recent work [12] proposes a ranked list of candidate POIs to the query user. The method only depends on the extent of the user’s univariate (weekday/weekend) temporal orientations. As Figure 3 depicts, we can imagine the input of a recommender system as a continuous stream of query users in the course of time. Utilizing check-in history, the system aims to find top @Num unvisited venues for each user. A basic POI recommender system does not differentiate $w_d/w_e$ temporal preferences, however, we used the threshold $T$ as a single temporal influence margin to discretise stream of query users based on their effective user acts (Section 2.1). If they exceed the threshold, univariate temporal influence will be employed to enhance the results. Otherwise, they will be proposed with non-temporal influences. For example, $u_m$ and $u_v$ are oriented to do the check-ins during $w_d$. However, unlike $u_m$, $u_v$ does not surpass $T$ and is not adequately oriented toward $w_d$ so the framework does not apply the temporal method for her. While the user act reflects how a user performs the check-ins in weekly cycles, POI act is used in recommendation process to suggest right POIs to the right users through utilizing of single slot time-related effect.

$$f(L_i) = \begin{cases} M_{avg}(\rho, \delta) \quad \text{if } \hat{u}_i^w \geq T \\ usg_w \quad \text{otherwise} \end{cases}$$  

As formulated in (13), the system receives $u_i$’s check-in history ($L_i$). If the user act computed based on $L_i$ exceeds threshold $T$, the system will utilize temporal influence. Otherwise, we use $usg_w$ [34]. The method proposed by Ye et al. [34] fuses a user’s preference toward each location through employing the collaborative filtering along with social and geographical influences. In the temporal case, $\rho$ is the initial list of recommending POIs computed by USG and $\delta$ resembles the POI act for each item in the primary recommendation list. $\rho$ and $\delta$ are the input of $M_{avg}$ function which performs recommendation as described in Section 2.3.

2.3 Uni-variate temporal recommendation

If the user act is greater than threshold ($\hat{u}_i^w \geq T$), we need to follow the univariate temporal recommendation approach ($M_{avg}$). The method has two inputs: $\rho$ which is the primary
decently sorted recommendation list and $\delta$ which includes the univariate temporal acts for each of POIs in $\rho$. We first retrieve top $K*@Num$ items from $\rho$ where $@Num$ is the number of final list (denoted as $R$). $R$ is formed by three subsets of Weekday aligned($R_d$), Weekend oriented($R_e$) and Neutral ($R_n$) where $R = \{R_d, R_e, R_n\}$ and $|R| = @Num$. The final proportion of each category will follow relevant ratios from proper POIs which are computed based on efficient user act (14).

$$M_{avg}(\rho, \delta) = \begin{cases} |R_d| = (\tilde{Avg}_d + \lambda - \frac{\xi}{2}) \times @Num \text{ if } p^d_y > \theta \\ |R_e| = (\tilde{Avg}_e + \lambda - \frac{\xi}{2}) \times @Num \text{ if } p^e_y < \theta \\ |R_n| = \xi \times @Num \text{ otherwise} \end{cases}$$

(14)

($\tilde{Avg}_d + \lambda - \frac{\xi}{2}$) and ($\tilde{Avg}_e + \lambda - \frac{\xi}{2}$) are respective $w_d$ and $w_e$ proportions from the final recommendation list. Also, $\theta$ is the threshold to distinguish $w_d/w_e$ oriented POIs. For example, if $\theta = 0$, the weekday portion from the final list will comprise the POIs whose acts are greater than 0 ($\forall p^d_y \in \delta | p^d_y > 0$) and for the weekend ratio the POI acts should be less than 0 ($\forall p^e_y \in \delta | p^e_y < 0$). In fact, Neutral POIs are not likely to have high scores in $w_d/w_e$ lists. However, we still need to propose them when they gain high probabilities. Therefore we reserve a minor portion ($\xi$) for POIs which are not temporally aligned.

The recommendation system explained in Section 2 merely considers a single temporal aspect. It can also be adapted to any of the temporal dimensions. However, selecting a specific temporal granularity (e.g. hour of the day) and ignoring others (e.g. minutes of an hour, days of a week, and week of the month) is not legitimate. For instance, a user may go to a restaurant at 12 pm only on weekends. If we only consider the hour, the model may mistakenly treat the user the same during the weekdays and the weekend. Moreover, there is not a clear reason why one dimension should be preferred over others. Hence, we devise a new model in Section 3 which is capable to simultaneously integrate infinite number of temporal scales into the location recommendation methods.

3 Multi-aspect time-related influence

Jointly with collaborative filtering methods, effects such as Geographical [21, 34, 40], social [2, 10] and context-oriented including text contents and word-of-mouth [36, 39] are already employed to improve the effectiveness of spatial item recommendation. A growing line of research has also utilized temporal influence to foster the same purpose. However, the majority of prior works merely consider the univariate temporal granularities like hour of the day [6, 8, 9, 35, 40, 44], day of the week or weekday/weekend cycles [9, 41, 43, 48]. Selecting one temporal dimension and leaving others unattended is problematic, even if it is owing to complexity or overfitting issues [44].

Practically, LBSN based location recommendation systems consider bigger granularities such as the hour, day, week owing to sparsity issues. However, in other dense datasets such as user-item feedback matrices generated in online social networking spheres (e.g. Facebook), smaller granularities can be taken into account to study users’ mobility behaviors more precisely. In fact, all temporal granularities follow the Temporal Subset Property (TSP) which means some of the time slots are the subset of the others($\text{minute} \subset \text{hour} \subset \text{day} \subset \text{week}$). Hence, rather than reconfiguring a method [9] to make it work using another single time slot, it is better to develop an approach which can include multiple temporal factors in a unified way. In short, we believe there is a multivariate compound temporal correlation between visibility patterns of LBSN users and locations. Inspired by this perception, we
propose our Bayesian model (Figure 4) which is capable of employing an infinite number of temporal scales in location recommendation systems which we name it MATI, standing for Multi-aspect Time-related Influence. As illustrated in Figure 4, each user \( u_i \in U \) can visit any location \( l_j \in L \) affected under certain constraints that we can categorize them into multiple temporal latent factors defined as \( T = \{ z_1, z_2, \ldots, z_t \} \) and non-temporal impacts (denoted as \( \nu_{i,j} \)). \( \nu_{i,j} \) represents the visibility impact of the user \( u_i \) to visit location \( l_j \) disregarding the temporal influence. Such an impact is involved with friendship, geographical, and context-oriented influences.

In order to clarify our method, we demonstrate latent temporal parameters using two scales of \( z_h \) regarding time of the day and \( z_d \) for the day of the week. Yet, our model can be generalized to dealing with multiple time-related granularities as proven in Section 3.2.

Apparently, LBSN users mostly own a limited number of check-ins, which results in a sparse user-POI matrix. Adding the time dimension provokes the User-Time-POI (UTP) cube that is even more dispersed. While User-POI matrix reports whether a user has visited a location or not, UTP cube further provides the time information. In reality, UTP cubes can be defined in various levels of granularity where each scale is associated with a temporal latent factor.

As our approach aims to utilize multiple temporal factors to improve the effectiveness of location recommendation systems, we propose our method for sparseness demotion and exploiting of temporal slabs in Section 3.1 and continue with the parameter inference algorithm in Section 3.2.

### 3.1 Exploiting multi-aspect temporal slabs

Each temporal scale owns a distinguished User-Time-POI matrix as well as an associated level of sparsity. The UTP cube is certainly dispersed and the level of sparsity has an indirect

![Figure 4](image-url) Figure 4  The graphical representation of Multi-aspect Time-related Influence in location recommendation
connection to the size of discretised temporal granularity. For instance, associated UTP cube with the minute interval is far more scattered than hourly time slot. We assign a latent factor for each temporal granularity.

Definition 3 (Latent Temporal Factors) Given a set of users $U = \{u_1, u_2, \ldots, u_n\}$ and POIs $P = \{p_1, p_2, \ldots, p_n\}$, we define that each $u_i$ ($\forall u_i \in U$) can visit a location $p_j$ under a predefined set of Latent Temporal Factors $T = \{z_1, z_2, \ldots, z_t\}$. On the other hand, a user’s visit to a location simultaneously represents multiple temporal dimensions.

Deferring to Definition 3, if there is only one latent factor merely defined for hour (i.e. $T = \{z_h\}$), then $u_i$ will own 24 vectors. Each of them will report the locations that the user has visited during every 24 hours of day/night cycle. As a matter of fact, check-in activity of the user during certain hours will be similar [40]. Given $V_{u_i,t_i}$ and $V_{u_i,t_j}$ as the pair of check-in vectors for user $u_i$ at time slots $t_i$ and $t_j$ (e.g. 5 am and 6 am), we can apply Cosine or Pearson (with similar results) metric to compute the similarity between two hours based on the visits on the same locations. The final similarity value among two hours will be the average value that is gained from all the users who performed check-ins during both temporal slots (i.e. hours). Intuitively, if two hours are similar, a check-in during each of them can also be counted for the other one. Therefore, we can combine similar hours and make a block of hours that we name it the uni-aspect temporal slab.

Definition 4 (Uni-Aspect Temporal Slab) Given a latent temporal factor $z_h$ comprising $m$ default intervals (e.g. 24 hourly slots) $z_h = \{c_h^1, c_h^2, \ldots, c_h^m\}$, we can construct a sample Uni-Aspect Temporal Slab $\tilde{z}_h^t$ through merging similar slots from $z_h$’s intervals.

For instance, considering $z_h$ as the hour latent factor, $z_h^t = \{21, 22, 23\}$ can be the hourly slab which is made up of 3 hours (i.e. from 9 pm, 10 pm, and 11 pm). Nevertheless, this is a one dimension temporal slab. If we consider two latent features regarding hour and day (i.e. $T = \{z_h, z_d\}$), we can witness the subset feature as $z_h \subset z_d$. While we have already exploited distinguished uni-aspect slabs with regard to $z_h$ and $z_d$, we can imagine a multi-aspect temporal slab $\tau^s_o$ as a combination of two vectors of $z_h^t$ and $z_d^t$ respective to the hourly and daily slabs.

Definition 5 (Multi-Aspect Temporal Slab) Given the set of Uni-Aspect Temporal Slabs extracted for $n$ latent factors, a Multi-Aspect Temporal Slab $\tau^s_o$ is formed via combining $n$ Uni-Aspect Temporal Slabs where each of them is retrieved from a distinguished latent factor.

We can now formulate the problem regarding extraction of multi-aspect temporal slabs

Problem 1 (Exploiting Multi-Aspect Temporal Slabs) Given a set of predefined temporal latent factors ($T$) as well as the set of users ($U$) and their check-in logs $L = \{L_1, L_2, \ldots, L_n\}$ (e.g. $L_1$ is $u_1$’s check-in log), our goal is to extract all possible Multi-Aspect Temporal Slabs.

We aim to reduce sparsity in UTP cubes through extracting multi-aspect temporal slabs (Definition 5). We first need to leverage uni-aspect temporal slabs (Definition 4) that are constructed through computing the similarity between each pair of temporal slots for every latent time-related feature. Due to sparsity, finding the similarity value between two
temporal slots is also challenging. Hence, in this section, we propose our method to solve the Problem 1. We provide the solution for two factors of \(zh\) and \(zd\), but the same method can be applied to multiple latent features.

Considering latent factors with smaller scales (e.g. minutes) the sparsity condition may get even worse. Since we aim to merge similar slots (e.g. 5 am and 6 am in the hour dimension) to reduce the sparsity, the first task is to find the level of similarity between each pair of slots. Where the size of the dataset is huge, it may not be feasible to study the temporal behaviour of all dataset users. Therefore, random sampling of a subset of users and relying on the average similarity metrics can be the first solution. However, this sampling model suffers from two pitfalls. Firstly it cannot provide a comprehensive picture of the entire data set. Secondly, the sample number of users may miss the similarity value for some of the slot pairs. Owing to the common limited number of check-ins performed by LBSN users, given a sample user \(ui\), she might not have generated a check-in at all hour slots of a day/night (\(zh\)) nor every day in week cycles(\(zd\)). Therefore, we considered an alternative approach which utilizes an iterative process that takes random \(n\%\) of the users in each round and subsequently computes similarity values for each chosen user. We employed non-replacement stratified sampling model [20]. This method splits the data into several partitions based on the variety of users including passive, semi-active, and active and subsequently draws random samples from each partition. We then repeated the procedure until we collected a minimum of \(m\) similarity samples between each pair of slots for selected latent factors.

While the similarity pairs are more reliable, this finally obtains a better view of the whole dataset. Exceptionally, for the small datasets (i.e. Foursquare), even after completing the sampling process on all of the training pilot set (80% for four iterations), the entries in both of similarity matrices (regarding \(zd\) and \(zh\)) were either incomplete or unreliable. In order to predict missing similarity values between some of the temporal slots, we utilized matrix factorization [11].

Figure 5 illustrates the similarity maps associated with twin latent variables in our both datasets. The primary discoveries in Figure 5 are three-fold: (i) Neighboring temporal slots are more similar which affirms observations performed by Yuan et al. [40]. (ii) Due to the high sampling rate of \(zh\) factor, Brightkite’s similarity map is smoother. However, the hour based (\(zh\)) similarity patterns in both datasets (Figure 5b, d) are quite similar. (iii) While the similarity map regarding \(zh\) in Brightkite dataset is similar to the Foursquare counterpart, the figures regarding \(zd\) (Figure 5a, c) are obviously different. This implies that on the one hand, including more latent parameters can better reveal time-oriented mobility patterns and on the other hand a single temporal scale can not be applicable to all datasets.

---

2We created matrices of \(h\times h\) using LINQ queries in which \(h\) is the number of slots in each temporal scale (i.e. 7 for \(zd\) and 24 for \(zh\)).
Nevertheless, in order to generate uni-aspect temporal slabs regarding each latent feature, we were required to partition adjacent similar slots through various distance thresholds. We had to consider scalability features in mind to eventually mitigate the sparsity impact. Hence, we opted for bottom-up Hierarchical Agglomerative Clustering (HAC) which has gained a good reputation in maximizing similarity [5]. HAC employs a likeness function to verify that similar pairs will be included in the same cluster. We used complete linkage to ensure that all the time slots inside each of the merging clusters have similar visiting patterns.

Figure 6 exhibits the dendrogram regarding each of the latent variables in both datasets. The red line demonstrates the threshold value corresponding to the correlation among complete linkage. A final multi-aspect temporal slab will have the merging vertices regarding both temporal parameters. For example, as Figure 6 (a) shows, Tuesday and Thursday are similar enough to be merged as a $z_d$ block in the foursquare dataset. In addition, Figure 6b indicates that three hours of 21, 22, and 23 can be merged into a $z_h$ uni-aspect temporal slab. Hence, we can denote $\tau_i^z$ as an independent multi-aspect temporal slab that has two vector attributes, representing both latent aspects of $z_d = \{Tuesday, Thursday\}$ and $z_h = \{21, 22, 23\}$. Now that we have proposed the solution to exploit multi-aspect temporal slabs, we can formulate the main problem as follows:

**Problem 2 (Recommendation Via Multi-Aspect Temporal Slabs)** Given the check-in log dataset $D$, a predefined set of latent temporal factors $\mathbb{T}$, set of exploited multi-aspect temporal slabs $\tau^z$ based on $\mathbb{T}$ and the query user $u_i$, our goal is to suggest a list of new POIs that $u_i$ would likely visit, while proposed locations are correlated with $u_i$ according to $|\mathbb{T}|$ temporal aspects.

### 3.2 Parameter inference algorithm in recommendation

The problem of suggesting unvisited places to a user $u_i$ can be undertaken by computing the probability for $u_i$ to visit a spatial item $l_j$ denoted as $Pr(l_j|u_i)$ and formulated by (15). While all users are of the same importance, a set of highly ranked locations will be proposed to $u_i$.

\[
Pr(l_j|u_i) = \frac{Pr(u_i, l_j)}{Pr(u_i)} \propto Pr(u_i, l_j)
\] (15)

According to the MATI model, we can include as many latent temporal variables as required. Alongside other impacts (i.e. Geographical, Social and Context-oriented influences), the probability of $u_i$ visiting location $l_j$ must also include multi-variate temporal correlation.
between the user and the locations that are being appraised for recommendation. Such correspondence is two-fold that has been taken into account in (3.2). From one side, it should reflect the extent of shared temporal activity among user and locations (17). From another perspective, the depth of the temporal visibility pattern between \(ui\) and \(lj\) must be assessed.

Initially, the probability for a \(ui\) to visit \(lj\) is proportionate to the sum of the joint probabilities which include the temporal latent factors. Nonetheless, we compute the temporal impact through the average value of the joint probability for \(ui\) to visit \(lj\) involving time-related latent features denoted as \(\sum\sum P \(r\(ui,lj,zh,zd\))\). For clarity purposes, we have modeled two latent factors \((Z = \{zh, zd\})\), however, we will generalize the joint probability to incorporate multiple parameters later in this section.

\[
Pr(ui, lj) \propto \phi_t \Psi(ui, lj) + (1 - \phi_t) \sum\sum P \(r\(ui,lj,zh,zd\))
\]  

(16)

Note that we have already exploited multi-aspect temporal slabs as unfolded priorly (Section 3.1).

\[
\Psi(ui, lj) = \frac{|ui \cap lj|}{|ui \cup lj|}
\]

(17)

As denoted in (17), \(\Psi(ui, lj)\) represents the temporal similarity coefficient for the pair of user \(ui\) and location \(lj\). Also, \(ui\) and \(lj\) are the set of multi-aspect temporal slabs associated with \(ui\) and \(lj\) respectively. On the other hand, in (17) we aim to compute how the check-in pattern of user \(ui\) and location \(lj\) are temporally relevant.

As formulated in (16), a set of bi-module impacts is tuned in a mixture model using \(\phi_t\) parameter, ranging within \([0,1]\). We have included the tuning process in Section 4.4. In addition, as the scales concerning \(\Psi(ui, lj)\) and \(\sum\sum P \(r\(ui,lj,zh,zd\))\) differ, we normalized the values via dividing each probability by the maximum value proposed for every query user. This method is better than feature scaling [27] because the minimum value will not be converted to zero - having the null value in the recommendation.

Similar to [41], we don’t treat user and locations independently conditioned on temporal latent variables. Also, the parameters should be formulated following the TSP feature. Due to the fact that \(zh\) is a subset of \(zd\) (i.e. hour of a day is contained by day of the week) as (16) denotes, \(zh\) is mentioned before \(zd\) in the joint probability and is placed in the inner loop of the average summation (i.e. \(\sum\sum \ldots\)).

Logically, we now need to explain (18), which represents the joint probability of user \(ui\) to visit \(lj\) constrained by the twin temporal latent parameters of \(zh\) and \(zd\):

\[
Pr(ui, lj, zh, zd) \propto Pr(ui) Pr(v(lj|ui) Pr(zh|zd, ui, lj) Pr(zd|ui, lj)
\]

(18)

Primarily, \(Pr(ui)\) is assigned by one, because all the users are treated equally. Also, \(Pr(v(lj|ui)\) comprises total non-temporal influences for \(ui\) to visit \(lj\). It is also worth mentioning, that if the resulting value regarding multiplication of probabilities is less than the decimal minimum, the joint probability will be ignored as having the value of zero. Hence, in implementation, we take the log from both side of this equation which converts multiplication to summation and prevents missing values to be imputed incorrectly.

**Proof** We can prove (18) through applying Bayes theorem to \(Pr(zh, zd|ui, lj)\). As illustrated in Figure 4, users and locations form distinctive graphs while connecting to initial
influences \((v_{i,j})\) and temporal preferences (here assumed as \(z_h, z_d\)). Therefore we can reorder \(Pr(u_i, l_j, z_h, z_d)\) as follows:

\[
Pr(u_i, l_j, z_h, z_d) \propto Pr(u_i, l_j) Pr(z_h, z_d|u_i, l_j) 
\]

\[
Pr(u_i, l_j) \propto Pr(u_i) Pr(v(l_j|u_i))
\]

(19)

(20)

\(Pr_v(l_j|u_i)\) is proportionate to the joint probability of \(u_i\) and \(l_j\). Also, (21) paraphrases \(Pr(z_h, z_d|u_i, l_j)\) through the joint probability of \(z_h, z_d\) and rendering \(u_i, l_j\) as a single parameter:

\[
Pr(z_h, z_d|u_i, l_j) = Pr(z_h|z_d, u_i, l_j) Pr(z_d|u_i, l_j)
\]

(21)

By substituting (21) and (20) into (19,) we can reach (18).

Now that we have formulated both partitions of (3.2), we need to consider that the data is incomplete due to two reasons. Firstly, LBSN users mostly perform a limited number of check-ins and the information regarding their visiting behavior on POIs at various times is insufficient. Secondly, our evaluation method urges data compensations as we exclude certain percentage from one’s check-in history and assess how they are retrieved using various methods. Such an embargo makes the data even more defective. Therefore, we propose a model which can reflect a user’s behavior based on her imperfect visiting log during exploited multi-aspect temporal slabs.

Apparently, the model owns a set of parameters denoted by \(\psi\) including \(Pr_v(l_j|u_i)\), \(Pr(z_h|z_d, u_i, l_j)\) and \(Pr(z_d|u_i, l_j)\). Here \(z_h\) and \(z_d\) are the latent variables and \(Pr_v(l_j|u_i)\) can be computed using nontemporal approaches to include other effects. Hence, we aim to maximize the log-likelihood of \(\mathcal{L}(\psi)\).

\[
\mathcal{L}(\psi) = \sum_{<u_i, l_j> \in <U, L>} \log(Pr(u_i, l_j; \psi))
\]

(22)

We use Expectation-Maximization (EM) to find parameters \(\psi\) that can maximize the log-likelihood of the historical data.

- In the **E-step**, since there are two latent variables \(z_h\) and \(z_d\) in MATI, we update their joint expectation \(Pr(z_h, z_d|u_i, l_j)\) according to Bayes rule as formulated in (23).

\[
Pr(z_h, z_d|u_i, l_j) = \frac{Pr(u_i, l_j, z_h, z_d)}{\sum_{z_d} \sum_{z_h} Pr(u_i, l_j, z_h, z_d)}
\]

(23)

- In the **M-step**, we find the new \(\psi\) that can maximize the log-likelihood as follows:

\[
Pr(z_h|z_d, u_i, l_j) = \frac{Pr(z_h, z_d|u_i, l_j)}{\sum_{z_h} Pr(z_h, z_d|u_i, l_j)}
\]

(24)

\[
Pr(z_d|u_i, l_j) = \frac{\sum_{z_h} Pr(z_h, z_d|u_i, l_j)}{\sum_{z_d' \sum_{z_h}} Pr(z_h, z_d'|u_i, l_j)}
\]

(25)

The value for \(\sum_{z_d'} \sum_{z_h} Pr(z_h, z_d'|u_i, l_j)\) equates to one. Therefore, we consider \(Pr(z_d|u_i, l_j) \propto \sum_{z_h} Pr(z_h, z_d|u_i, l_j)\).

**Proof** Including infinite number of temporal latent factors
Subject to the TSP feature (i.e. \( z_1 \subset z_2 \subset z_3 \ldots z_{t-1} \subset z_t \)), we can generalize (21) to integrate an infinite number of temporal latent factors (i.e. \( z_1, z_2, z_3, \ldots, z_t \)) as shown in (26).

\[
Pr(z_1, z_2, z_3, \ldots, z_t | u_i, l_j) = Pr(z_1 | z_2, z_3, \ldots, z_t, u_i, l_j)Pr(z_2 | z_3, z_4, \ldots, z_t, u_i, l_j) \\
\ldots Pr(z_{t-1} | z_t, u_i, l_j)Pr(z_t | u_i, l_j)
\]

By substituting (26) and (20) into (27) which is the multi-aspect version of (19), we can reach (28) which includes multiple latent time-related variables proposed as the generalized version of the bi-variate model proposed in (18).

\[
Pr(u_i, l_j, z_1, z_2, z_3, \ldots, z_t) \propto Pr(u_i)Pr_{\nu}(l_j | u_i)Pr(z_1 | z_2, z_3, \ldots, z_t, u_i, l_j) \\
Pr(z_2 | z_3, z_4, \ldots, z_t, u_i, l_j) \ldots Pr(z_{t-1} | z_t, u_i, l_j)Pr(z_t | u_i, l_j)
\]

3.3 Hybrid decision method

Our recommendation system relies on multivariate time-related latent factors. However, such mechanism is not applicable to all scenarios. We can imagine a two-fold storyline as follows:

1. **Cold start case**: When a location has been visited for a limited number of times or a user owns a small number of visits in her check-in log, the temporal influence will gain an adequate weight to distinguish time-related metrics neither for the user nor for the location. In other words, when an LBSN user has only few check-ins that are also scattered in various temporal slabs, we cannot strongly predict her time-related mobility pattern.

2. **Erratic mobility pattern**: At times, recommender systems can embrace certain users whose temporal behaviors are inconsistent with dataset features. In our work, we learn the joint temporal and mobility patterns that are observed in the dataset. We then leverage the multi-aspect temporal slabs. However, not necessarily all the users would follow such influences. For instance, owing to holidays a user may go to a restaurant on Monday at 10 am and go to a bar afterward. Such a behavior has the least probability for most of the business-oriented people. This affirms a meaningless temporal correlation between a user and LBSN venues.

Due to aforementioned two-fold scenarios, not all the users can be treated the same by the MATI approach. Hence, we propose a hybrid framework based on the MATI model that can initially recognize whether each query user is temporally sensitive or not. The model can subsequently propose proper unvisited POIs based on the query user’s temporal sensitivity.

As denoted in (17), \( \Psi(u_i, l_j) \) can mimic how a query user \( u_i \) and a sample location \( l_j \) share temporal check-in activities. On the other hand, \( \Psi(u_i, l_j) \) can indicate the extent of temporal correlation between each user/location pair via considering the exploited temporal slabs. We firstly compute the average value of \( \Psi(u_i, l_j) \) for the query user \( u_i \) and any of the recommended locations. On this way, we can comprehend whether or not the user temporally synchronizes with the list of suggested POIs. From the hybrid perspective, if the value for the computed average metric passes the threshold or is in the properly trusted range, we can decide to apply our multi-aspect time-related influence. Otherwise, we can simply exclude temporal features and utilize the primary metrics alongside other non-temporal attributes (e.g. geographical influence). As elucidated in (18), \( Pr_{\nu}(l_j | u_i) \) represents the
non-temporal version of the CF-based probability for the user $u_i$ to visit each location $l_j$. Furthermore, we would need to evaluate our system to see under what threshold, we can attain the best effectiveness. Therefore, via a study on pilot set (Section 4.4), we choose the best range for the average value of $\Psi(u_i, l_j)$. Finally, we can utilize the threshold to lodge our hybrid decision model.

4 Experimental evaluation

In this section, through releasing multiple experiments, we compare our proposed method with various competitors, explained in Section 4.3. Firstly, we check under what tuning metrics, our proposed temporal hybrid framework will achieve its best performance. Secondly, we study how the Multi-aspect time-related perception can improve baseline methods which merely rely on non-temporal or uni-aspect temporal effects. We need to take into consideration the point that effectiveness of POI recommendation systems on LBSN datasets is always affected by the low density of User-POI and User-time-POI matrices. However, considering the results, we demonstrate that while the MATI model can be utilized to reveal the comprehensive temporal correlation in a general user-item relationship, it can also promote the location recommendation systems in the LBSN sphere.

4.1 Dataset

Similar to our previous work [12], we perform the experiments on the same wide-reaching LBSN datasets [4]. Both (Foursquare\(^3\) and Brightkite\(^4\)) are publicly available. While, the map (Figure 7) shows the spatial distribution of dataset check-ins, pertinent stats are also manifested in Table 1. Simply, we can find a high volume of cold start users in Brightkite dataset which comprises more than 50% of the dataset check-ins. We can witness that the data is scattered (Density: $2.7 \times 10^{-5}$). In addition, we observe that owing to the fact that merely 8% of twin users share a minimum of 5 locations, the Foursquare dataset suffers from scarcity which is a common practice in all LBSN data sources.

4.2 Evaluation metrics

Presumably, a POI recommendation task returns top $N$ (i.e. 5, 10 and 20) highly ranked locations for each query user. Two methods can evaluate the effectiveness: (i) The survey-based

\(^3\)http://www.public.asu.edu/~hgaol6/
\(^4\)https://snap.stanford.edu/data/loc-brightkite.html
Table 1  Statistics of the datasets

|                      | Brightkite | Foursquare |
|----------------------|------------|------------|
| Number of users      | 58,228     | 4,163      |
| Number of locations  | 772,967    | 121,142    |
| Number of check-ins  | 4,491,143  | 483,813    |
| Number of social links | 214,078    | 32,512     |
| Cold start ratio     | 53.36%     | 14.17%     |
| Avg. visited POIs per user | 20.93    | 64.66      |
| User-POI matrix density | $2.7 \times 10^{-5}$ | $5.33 \times 10^{-4}$ |

normalized Discounted Cumulative Gain (ndCG) [23] and (ii) F1-score ratios [3, 34] which is also used in this paper. Initially, we exclude x% (e.g. 30%) of the locations from the query user’s visiting history. Subsequently, we run the recommendation models using the remaining POIs. Finally, we count on the truly recovered items. As denoted in (29), considering recommendation@N, the evaluation indicators are the total Number of recovered POIs ($R_p$) and the number of initially excluded POIs ($E_p$). Precision, Recall, and F1-score metrics are firstly calculated for each query user in the test subset (20% of all dataset users) and the final metric is calculated through the total average. $F1 – score@N$ will be the final performance balance to find the best among all recommendation models.

$$\text{Precision@N} = \frac{R_p}{N}, \text{Recall@N} = \frac{R_p}{E_p}, F1 – score@N = \frac{2 \times \text{Precision@N} \times \text{Recall@N}}{\text{Precision@N} + \text{Recall@N}}$$  (29)

4.3 Recommendation methods

We compare five recommendation methods in the experiments. Among them, the first two are non-temporal and the middle two merely consider one aspect of the time, while the last one is our model which integrates multiple time-aspects. The ultimate aims of the experiments are to signify that our proposed approach outperforms other adversaries as follows.

– **UBCF**: The primary collaborative filtering method which excludes enhancing influences.

– **USG**: This method takes advantage of the collaborative filtering method alongside enhancing effects such as social and geographical where $0 < \alpha < 1$ and $0 < \beta < 1$ [34]. UTP-based model [40] proposes locations at a query time which is a various problem.

– **USGT**: Uni-aspect Time-related model [12] which is reviewed in Section 2.

– **UBCFT**: Another version of [12] which treats all the locations the same in the computation of the user act.

– **LRT**: Location Recommendation system with Temporal effects [9] utilizes the matrix factorization model. LRT can only adapt one temporal dimension (e.g. day, week/day/weekend or month of the year).

– **MATI**: Is the proposed model in this paper. While prohibiting any conflict with other effects, this method is capable of integrating Multi-Aspect Time-related Influences into

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5 We used Microsoft SQL Server 2012 relational databases. In expense of the disk space, both non-clustered and clustered indexes which were advised via Microsoft SQL Server Profiler accelerated the process speed exceptionally.
CF methods, no matter whether they are model-based or memory-based. We target to substantiate its supremacy.

4.4 Parameter settings

Basically, proposing a recommendation model to comprise multiple aspects of the time is inevitable. Nevertheless, the time factor involves a trade-off process among advantages and defects where parameter settings play a key role in maximizing the effectiveness of recommendation systems. Accordingly, in this section, we explain the way we analyzed temporally influencing parameters for our proposed method (MATI) through a set of tuning experiments. Also, note that we adopted another series of evaluations to ensure our method overtakes other competitors based on the performance metrics. Notable parameters to adjust are two-fold. (i) $\phi_t$ (ii) $\sum_{l_j \in U_i} \Psi(u_i, l_j)$.

It is also worth mentioning that the visiting histories possessed by cold start users are not reliable for supplying adequate evidence concerning multi-aspect temporal slabs. This stems from unreal results in the spatial item recommendation. For instance, owing to excessive data incompleteness, such users can be associated with a specific temporal slab and pretermit others. Hence, while choosing to analyze the parameters using active and semi-active users (at least 15 check-ins in the log $|L_i| \geq 15$), we selected a random set of 20% from both datasets.

Adjusting $\phi_t$: with regard to (3.2), we tuned $\phi_t$ (ranging within [0,1]) as the significant parameter in the recommendation mixture model. The essential aim was to figure out the importance coefficient of the binary factors including the depth of temporal visibility pattern ($\sum_{z_d} \sum_{z_h} Pr(u_i, l_j, z_h, z_d)$) as well as the extent of shared temporal activity($\Psi(u_i, l_j)$).

Figures 8 and 9 illustrate the parameter tuning results for $\phi_t$ considering the exclusion rate of 30% while we perform recommendation @5. In fact, F1-Score measure integrates

![Figure 8](image1.png)
![Figure 9](image2.png)
both precision and recall. Therefore, it is used to make the final decision. Note that for every value of $\phi_t$, a separate experiment based on a random set of users has been executed. Hence, the highest performance has been used to judge the best value for $\phi_t$ threshold. When the value for $\phi_t$ is set to 0.7 in both datasets, we obtain the best performance. This affirms that a bigger number of temporal slabs a pair of user-location share, the more likely the user may visit the location. On the other hand, as higher the number of shared temporal slabs, the more significant the level of temporal influence will be.

During tuning, we firstly fixed the value of $\phi_t$ for the mixture model. Subsequently, we continued by exploiting the best range in which we could make the proper decision for the hybrid recommendation system.

Adjusting $\sum_{l_j \in u^P_t} \Psi(u_t, l_j)$: From another perspective, we explored the best decimal range (e.g. [0.4-0.9]) in which the average value for the shared temporal activity could reach the highest performance in the recommendation. Here, $u_t$ is the query user who is proposed with the set of locations denoted as $u^P_t$. The selected range can maximize the performance of our proposed hybrid framework (discussed in Section 3.3). On the other hand, if the computed average metric for a user is between the selected range, the hybrid system can enforce multi-aspect temporal influence. Otherwise, while debarring the time-related latent factors, it can merely rectify the non-temporal method (i.e. CF based plus non-temporal effects).

As shown in Figures 10 and 11, the best ranges in which we can apply the temporal influence are [0.4-0.9] and [0.4-0.8] (Union of the two best ranges of [0.4-0.7] $\cup$ [0.6-0.8])
for respective Brightkite and Foursquare datasets. Moreover, we provide some information about parameter settings of the baseline models. For USGT, with regard to (6), we assume $\lambda = 0.5$ to equalize $w_d$ and $w_e$ treatments. Similar to our prior work, we chose a random set of 20% from users in both datasets and evaluated the rate of neutral POIs ($\forall p_y \in \rho | p^a_y = 0$) among top $K^*@Num$ proposed locations. owing to the fact that the rate of them was less than 10%, we set the value for $\xi$ to 0.1 in both datasets. In addition, we set $K$ to 10.

Subsequently, in order to set the parameters for USG [34], unlike rank learning (e.g. SVM-pairwise and EM), we iterated the values of $\alpha$ and $\beta$ through 0 and 1, while aiming to obtain the best performance @5 (Table 2). Finally, the best parameters of $\alpha$ and $\beta$ were selected based on the highest F1-score@5.

### 4.5 Performance comparison

In this subsection, we describe the comparison outcomes among our proposed model and other competitive rivals via utilizing well-tuned parameters. While theoretically, it is appealing to propose a model which can simultaneously comprise multiple temporal scales in a recommendation task, we additionally report the evaluation results to show how our novel model excels others.

The evaluation aspects are two-fold: (i) Firstly, Figures 12 and 13 illustrate respective performance results regarding the recommendation methods on Foursquare and Brightkite datasets. Practically, as a limited number of top-N items are commonly desirable in a recommendation process, we merely compare the performance where $N$ is set to 5, 10, and 20. The figures clearly confirm that our method (MATI) performs better than other models in terms of top-N recommendations. (ii) Secondly, we have evaluated how our method can alleviate the rate of failure by proposing one or more true suggestions (i.e. the POIs which are retrieved after exclusion in pre-processing) to every query user in test pilot set. The number of failures in recommendation@5 is bigger than both recommendations at 10 and 20. Hence, considering recommendation@5, as Table 3 demonstrates, our method has been able to increase the rate of relative success in both Brightkite and Foursquare datasets. Our proposed method (MATI) and LRT perform better than other baselines. Since LRT employ

### Table 2  USG Optimized values

|          | $\alpha$ | $\beta$ |
|----------|----------|---------|
| Foursquare | 0.2      | 0.6     |
| Brightkite | 0.3      | 0.4     |

F1-Score @5
the state-of-the-art matrix factorization method, except MATI, it gains better effectiveness versus other rivals. However, as it can only integrate a single temporal dimension, our temporal multi-aspect approach excels LRT in location recommendation process.

Densities concerning User-POI and User-Time-POI matrices are extremely low, which is common in LBSN datasets. Therefore, the effectiveness of POI recommendation systems does not reach high. For instance, Precision in [40] and recall in [22] are less than 4% while [9] achieves less than 3.5% for both metrics. Consequently, algorithms are evaluated relatively (i.e. rate of improvement for one versus the baselines).

As a matter of fact, where a test user owns a higher number of check-ins in her visiting history, more evidence regarding her temporal activity pattern will be mined and subsequently, our model can better detect temporal correlations between the user and proposed locations. We observe that the recall rate for many users is promoted less than precision. The reason for this is that the MATI model proposes true recommendations for many active or semi-active users for whom the prior memory-based models fail. Accordingly, for a sample test user, precision@5 elevates by 20% merely due to a single correct proposed POI. But, for Recall@5, as most of such users possess a high number of visits, the value does not increase considerably. For instance, if the user has 100 check-ins, then his recall will be approximately improved by 0.033 (1 recovered from 30 excluded POIs). Ultimately, as the recall is still a small value, the overall f1-score will not be inflated either.

5 Related work

Nowadays, LBSN platforms (e.g. Foursquare, Gowalla, Google places, and etc) shape the essential part of people’s daily lives. Accordingly, POI recommendation via such mediums has become a ubiquitous task [1]. Some traditional methods like HIT-based [49] and Random Walk & Restart [28, 32] have already been used for location recommendation [12]. Furthermore, various factors [39] such as geographical, social, context-oriented (e.g. text contents and word-of-mouth) and temporal influences have been recently integrated into Collaborative Filtering (CF) to improve the performance. In this paper, we have also considered the time as a multi-aspect influential parameter.

Table 3 Comparing the methods - Rate of failures in recommendation process

| Rate of failures @5 | Brightkite | Foursquare |
|---------------------|------------|------------|
| MATI                | 52.3%      | 51.6%      |
| Best case of other methods | 55.7%      | 58.2%      |
Collaborative filtering (CF) While CF-based methods [16, 34, 39, 40] are dominantly employed in location recommendation systems, they infer the query user’s preference regarding every proposing unvisited POI. Collaborative Filtering is categorized into memory-based and model-based approaches [3]. Memory-based approaches have two types of user-based [34] and item-based [7] which propose unvisited locations to a user based on similarity weights (e.g. Cosine and Pearson metrics) computed among users and items respectively. Like our prior work [12], we also utilize user-based collaborative filtering. From data perspective, CF-based methods have been commonly used to perform recommendation task on various data types such as semantics [13], Trajectories [14, 15, 50], and check-in logs [1]. However, as original CF methods fail to achieve a reasonable performance, other components (e.g. Social and Geographical influence) are jointly amended to enhance recommendation results.

Social link The correlations among network friends affect any user-item matrix [33]. In reality, we may visit a POI which has already been promoted by a friend on the network [18]. Accordingly, the social links in LBSN sphere [2, 10, 44] influence users’ visibility patterns. Goyal et al. [11] study how the social link can affect an individual’s decision to visit a location. They also model how the influence is propagated in social networks in a course of time. Ye et al. [34] study the Jaccard similarity coefficient with regard to both locations and friends. However, the parameter settings on their recommendation task confirm that the number of shared locations among two users has a bigger impact on visibility patterns than the number of friends they have in common [34]. While, Cheng et al. [2] similarly claim a minor influence for the social factor in location recommendation, LTSCR [44] and [4], concurrently model social data jointly with spatio-temporal information.

Geographical influence (GI) Geographical influence has already been studied in several previous works [21, 29, 34, 40, 43, 45] and explains why LBSN users tend to visit the POIs which are near to the venues where they have already visited [12]. Such effect has already been modeled using Power law distribution [29, 34, 40] and Multi-Center Gaussian Model [2] and personalized Kernel Density Estimation [45]. We have also utilized geographical influence jointly with social and multi-aspect temporal factors. Similar to our prior work [12], we have employed the Normal Equation to minimize the error function and exploit optimized parameters of the distribution function.

Temporal influence The time factor can be employed to promote the effectiveness of the location recommendation task either in general or the time-aware manner (proposing a new POI to the user at a specific query time)(e.g. [19, 31, 40]). In fact, time has numerous attributes such as recency, periodicity, consecutiveness, and non-uniformness [3, 4, 8, 9, 40, 48]. Based on Recency, the recommendation task [17] gives higher priority to the newly visited locations. Similarly, [25, 32] outline that some locations are visited steadily (e.g. people go to the bar after the dinner). Moreover, non-uniformness declares that the check-in behavior drifts continuously during various periods (e.g. People work and amuse during weekdays and weekend respectively) [9]. From another perspective, the time factor includes a set of granular slots (e.g. minutes, quarters, hours,
days and etc.) while some are the subset of the others. Hence, we bring another aspect of the time to the recommendation which is called Temporal Subset Property (TSP).

In addition, the temporal influence can be considered either discretized or continuous. Continuous manner [39, 43] is used owing to the fact that selecting a proper time interval is not viable [39]. On the contrary, as people set their schedules (e.g appointments, meetings, and etc) in a discrete style, a growing line of research [6, 8, 9, 35, 40, 48] has also adopted discrete-time in location recommendation. However, many works in the prior literature [6, 8, 9, 35, 40, 43, 44, 48] integrated merely a single or two discrete intervals to avoid complexity and overfitting issues [44]. Some methods like [9] require further configurations to make the recommendation task work under specific temporal granularity. Prior works include Matrix Factorization [9], Collaborative Filtering [40], Graph-based [42], and Density estimation [43]. In addition, we devise a probabilistic generative model named after Multi-aspect Time-related Influence (MATI) that can include multiple temporal slots in location recommendation and subsequently promote the performance.

This work distinguishes itself from our previous work [30, 36–39] in the following aspects. First, we project a user’s check-in behavior into a temporal latent space which predicts future visits based on current time-aware mobility patterns; Second, we retrieve multi-aspect temporal similarity maps which both mitigates data sparsity and represents the temporal state of the user-item dataset; Third, instead of taking into account a limited number of temporal dimensions, we leverage all time-related aspects among the query user and each of proposed locations. Disregarding the level of density, this model can promote various recommendation systems through encapsulating all temporal aspects.

6 Conclusions

In this paper, inspired by the fact that the discrete-time entity comprises numerous granular slots such as minute, hour, day and etc, we proposed a novel probabilistic model, named after Multi-aspect Time-related Influence (MATI) which simultaneously takes multiple latent temporal parameters into consideration to improve location recommendation systems. While most of the prior works utilize merely one or two limited aspects of the time, we proposed a multivariate model. On the one hand, it denotes the sparsity involved in user-location matrices in Location-based Social Networks (LBSN) and on the other hand, it employs a Expectation-Maximization method to compensate incomplete data w.r.t. to each latent temporal scale. Eventually, through a generalized Bayesian model, stimulated by Temporal Subset Property (TSP), we affirmed that our approach is applicable to various types of the recommendation models.

To evaluate the effectiveness of our proposed approach in POI recommendation, we conducted two series of experiments. Firstly, we applied various parameter adjustments to maximize the performance of all competitive models. Consequently, we assured the effectiveness of our proposed method, both in location recommendation and succeeding the recommendation task where it is failed via the baselines. In short, we approved supremacy of our method versus various temporal and non-temporal state-of-the-art rivals.

The restriction involved with our proposed MATI model is that it assumes that users’ temporal behavior are stable across their check-in history. But in reality, users show various temporal mobility patterns (e.g. during travel, holidays and etc). In our future work, we will adapt our approach to studying the dynamic multivariate temporal aspect through a correlation network among each of proposing POIs and the set of previously visited location.
by the query user. Moreover, in order to carry out the smoothing, we will consider the fact
that each temporal slot is affected by its containing latent factor. On the other hand, during
hours of a day, people’s behavior is different on various days of the week.

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