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HOPE: a hybrid deep neural model for out-of-town next POI recommendation

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Abstract

Next Point-of-interest (POI) recommendation has been recognized as an important technique in location-based services, and existing methods aim to utilize sequential models to return meaningful recommendation results. But these models fail to fully consider the phenomenon of user interest drift, i.e. a user tends to have different preferences when she is in out-of-town areas, resulting in sub-optimal results accordingly. To achieve more accurate next POI recommendation for out-of-town users, an adaptive attentional deep neural model HOPE is proposed in this paper for modeling user's out-of-town dynamic preferences precisely. Aside from hometown preferences of a user, it captures the long and short-term preferences of the user in out-of-town areas using "*Asymmetric-SVD*" and "*TC-SeqRec*" respectively. In addition, toward the data sparsity problem of out-of-town preference modeling, a region-based pattern discovery method is further adopted to capture all visitor's crowd preferences of this area, enabling out-of-town preferences of cold start users to be captured reasonably. In addition, we adaptively fuse all above factors according to the contextual information by adaptive attention, which incorporates temporal gating to balance the importance of the long-term and short-term preferences in a reasonable and explainable way. At last, we evaluate the HOPE with baseline sequential models for POI recommendation on two real datasets, and the results demonstrate that our proposed solution outperforms the state-of-art models significantly.

Keywords Next POI recommendation · Out-of-town POI recommendation · Sequential recommendation

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1 Introduction

The widespread use of location-based social networks, such as Foursquare and Flickr, has attracted many users to share their locations and experiences, leading to a great amount of geo-tagged data to be accumulated. These data provide great opportunity to understand users' behaviors and preferences, and it becomes possible to answer next POI recommendation by inferring where a user will go next from their historical footprints [23, 34].

In recent years, the problem of next POI recommendation has been intensively studied. Classical models for next POI recommendation take advantage of the advances of sequential neural network, such as LSTM [9] and self-attention [20], to model dynamic user preferences from their check-in history. More recently, some spatio-temporal gating (e.g. STGCN [31] and LSTPM [19]) and attention mechanism [4] are further designed for more accurate recommendation. These models tend to obtain promising results for hometown user recommendation, since users tend to have relatively stable hometown preferences that can be learned precisely from historical interactions. However, according to [26], majority of them fail to effectively support the next POI recommendation for out-of-town users, which requires to capture both dynamic and region-specific out-of-town preferences of the user.

However, the next POI recommendation for out-of-town users faces several unique challenges. Firstly, as we can imagine, users tend to have completely different preferences when they are located in out-of-town (v.s. hometown) areas, known as the phenomenon of *out-of-town user interest drift* [26]. The reason behind this phenomenon is that when users go to out-of-town areas during personal or business trip, they may prefer to experience local attractions that do not match their original interests. Secondly, since users tend to have few or even no historical check-in record in out-of-town areas, especially in the target region, it is challenging to understand their out-of-town dynamic preferences , especially in a region-dependent approach, due to data sparsity problem. Besides, sequential patterns are considered to be important for next POI recommendation, including out-of-town recommendation. It is thus essential not only to explore useful sequential patterns, but also to consider the possible difference between hometown and out-of-town users.

Example 1 Considering the example in Figure 1, a tourist Jason has his historical check-ins in his hometown city A and out-of-town cities B and C. We can easily observe that this user prefers to visit a museum and other cultural in hometown city, but he tends to choose to visit natural landscape in other cities like B and C. By applying traditional models like [4, 23, 31], *Melbourne city museum* will be recommended to Jason since it is consistent with his hometown preference, which dominates in effects since the majority of check-ins are in hometown area. It thus requires to consider the user interest drift phenomenon, and model hometown and out-of-town preferences separately to remove noisy information. Moreover, we can observe that majority of visitors go to *lake Tyrrell* after *great ocean road* during their trips. It thus calls for a model to recommend more meaningful results like *lake Tyrrell*, instead of *Melbourne city museum*. However, it is more challenging to recommend for cold-start users like Patrick, who has insufficient check-in history, especially in out-of-town areas. At this time, it is essential to consider the crowd patterns of all other visitors in this area, so that a rational recommendation like *Phillip Island* can be recommended to Patrick since it is a popular local speciality preferred by many other visitors here. Therefore, the out-of-town recommendation needs to consider several factors, such as user interest drift, useful sequential pattern and region-based crowd pattern of all other visitors.

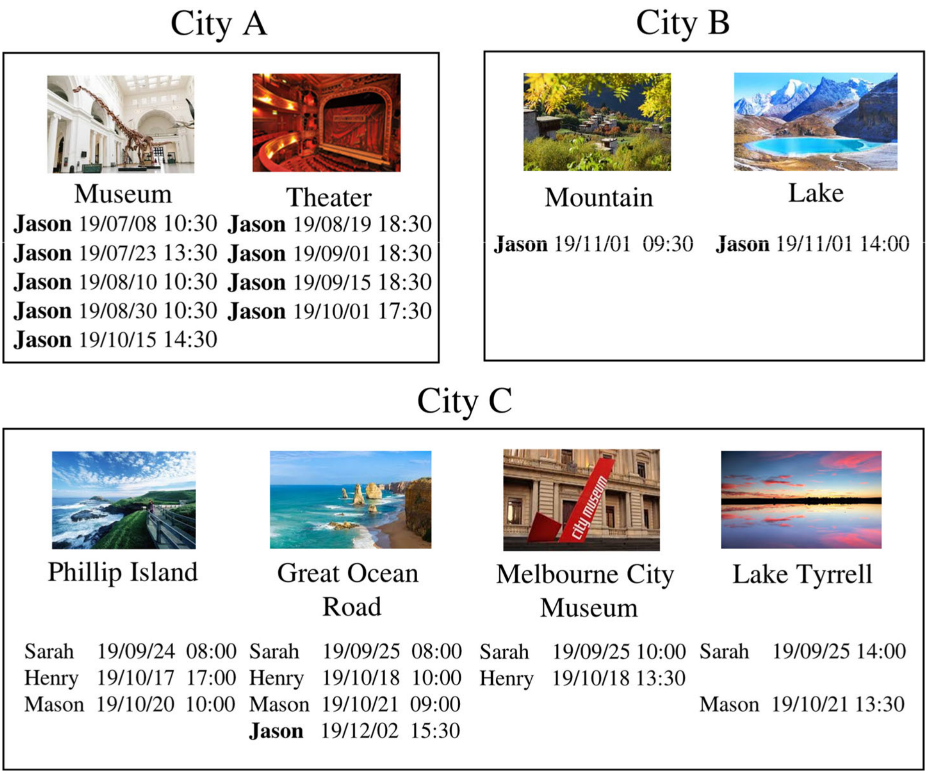


Figure 1 There are four check-in sequences to make recommendations for Jason: Jason's check-in sequence in his hometown(City A) and out-of-town areas(City B), Jason's check-in sequence in the current region(City C), other visitors' check-in sequences in City C

Although there have been some works considering out-of-town recommendation, they have significant deficiencies and fail to effectively solve all the above factors. Though some locality-aware models [7, 24] are designed to support out-of-town POI recommendation, they do not consider the phenomenon of out-of-town user interest drift, and merely return POIs based on user's general preferences, resulting in unsatisfactory results. To overcome this issue, user preference modeling is enhanced in [22, 32] by hometown and out-of-town granularities, and more rational POIs matching out-of-town preferences can be recommended. However, they require each user to have a large amount of check-in records, which is unrealistic, and thus suffer from data sparsity problem. Some other solutions utilize MF-based [3] and latent probabilistic generative model [21, 26] to incorporate preferences of this region. However, they neglect highly useful sequential pattern, thus unable to know where a visitor at current POI will go next. Besides, the probability-based model limits them to capture complex dependencies that can be learned by deep learning methods. Therefore, it calls for more advanced deep neural models to support more accurate next POI recommendation for out-of-town users.

To deal with this dilemma, we propose an adaptive attentional deep neural model called HOPE(**H**ybrid **O**ut-of-town **P**OI r**E**commendation model as short) that fully considers out-of-town user interest drift to achieve accurate next POI recommendation for out-of-town users. In order to make the recommendation explainable, we assume that users' preferences are affected by their own interests and the popularity among the crowd. Modeling users' personal preferences and exploring the region-based crowd pattern from check-in sequences separately, would lead to better user preference understanding and explainable recommendation. For users' personal preferences, both of their long and short-term preferences are captured from the check-in sequences in the out-of-town areas and using hometown preferences as a supplement. In order to overcome the data sparsity of user's personal preferences (especially out-of-town preferences), we further capture the region-based crowd preferences and patterns of all visitors in the target region. Specifically, we consider the crowd preferences, which are reflected as the POIs' popularity among visitors from different places. Moreover, we also model the patterns of POI transition in check-in sequences of visitors, which enables more accurate next POI recommendation. Meanwhile, for a better explanation, we use the attentive "Asymmetric-SVD" for capturing long-term preferences from the visited POIs of users and "TC-SeqRec" to capture short-term preferences considering the time interval. Furthermore, we note that the role of the above preferences in POI recommendation is restricted by contextual information. For example, different region and different category of POIs may lead to different weight distributions. We thus design an adaptive attention mechanism to integrate them. In this way, the data sparsity problem can be alleviated to achieve accurate out-of-town next POI recommendation. We finally conduct extensive experiments on two real datasets. Experimental results demonstrate that our proposed model outperforms several state-of-the-art models significantly. The contributions of this paper can be summarized as follows.

- We propose a novel deep neural model HOPE for the next POI recommendation of out-of-town users. It fully considers the phenomenon of user interest drift, such that both hometown and out-of-town user preferences are modeled separately for more meaningful user behavior understanding and explainable recommendation.
- We utilize region-based out-of-town pattern discovery to address the data sparsity problem in user preference modeling. For out-of-town recommendation, the HOPE model is the first deep neural model that consider capturing crowd preferences of all visitors in the target area, but also useful patterns of POI transition, such that the region-specific dynamic preferences of the user can be inferred rationally.
- We design an adaptive attention network to effectively integrate the information of hometown preferences, out-of-town preferences and region-based out-of-town patterns of visitors, such that their weights are reasonably balanced according to the contextual information (e.g. the target region, the visit time or the category of the target POI) for a rational recommendation.
- We conduct extensive experiments on two real datasets. Experimental results demonstrate that our proposed model outperforms several state-of-the-art models significantly.

The remainder of the paper is organized as follows. We first review related work from POI recommendation and sequential recommendation in Section 2. Afterwards, we define some important concepts used in this paper and formulate the problem in Section 3, before delving into details of the proposed method in Section 4. We perform extensive empirical research in Section 5 and conclude the paper in Section 6.

2 Related work

In this section, we review previous literatures in three aspects, including models for POI recommendation, next POI recommendation and out-of-town recommendation.

2.1 POI recommendation

POI recommendation has been extensively studied in recent years. Early studies in POI recommendation focus mainly on capturing users' static preferences by Collaborative Filtering (CF), especially Matrix Factorization (MF) based techniques [11, 25]. These models usurally utilize some side information, such as geographical influences [1], content information [17] or temporal effect [16, 33]. More recently, deep learning based methods have achieved excellent performance in many recommendation systems. In order to improve the performance of POI recommendation, some works have further optimized it based on deep learning models from different aspects, such as embedding learning, attention mechanism, deep latent factor and so on. Some works exploit the geographical latent representation [5, 24] or deep latent factor model [2] to enhance the learning of users and POIs for more accurate recommendation. Some work utilize improved attention mechanism, such as adaptive attention [4] and co-attention [5], to learn the influence of POIs on latent attributes, so that weight distribution can be balanced in a more reasonable way. Adversarial learning technique is used in [13] to better understand the interactions between users and POIs.

However, these models can only capture the user's long-term preferences, ignoring the sequential information between the pois, which can reflect the dependencies between the POIs. At the same time, the demands of users are constantly changing, which requires us to capture the short-term preferences of users. Therefore, it is crucial to take the sequential information into account.

2.2 Next POI recommendation

Aside from exploiting users' preferences on POIs, next POI recommendation requires to additionally consider the sequential information of users' check-in history, since people's movement exhibits sequential patterns. Some previous researches utilize Markov-based models [14, 30] to represent the sequential correlation between items based on check-in sequences of users. Recently, some models take advantage of deep learning to achieve more effective sequential recommendation. However, the original RNN cannot well model the geographic information. Some models equip LSTM with carefully designed gates, such as the temporal gate of Time-LSTM [34] and the spatio-temporal gate of ST-LSTM [31] for sequential pattern discovery. Moreover, attention mechanism is used to adaptively combine the long-term and short-term preferences of users for enhanced next item or POI recommendation [23, 27].

These models can work relatively well for next POI recommendation. However, all of these models ignored that human movement follows different sequential patterns when they have different roles (hometown and out-of-town). Therefore, no matter whether users are located in the hometown regions or travelling to out-of-town regions, they will be recommended in the same way, according to the same preferences.

2.3 Out-of-town POI recommendation

POI recommendation for out-of-town user faces the problem of user interest drift, and it is difficult to infer out-of-town preferences of users due to the data sparsity problem.

To overcome this issue, user preference modeling is enhanced in [22, 32] by hometown and out-of-town granularities, and more rational POIs matching out-of-town preferences can be recommended. However, they require each user to have a large amount of check-in records, which is unrealistic. Some efforts are made to consider side information, such as

POI content [12, 29] or [7] in locality-aware models for out-of-town recommendation. These works infer user preferences through side information and force the model to return the POI based on the user's current location through geographic constraints. However, these models do not consider different behavior patterns of users in different roles (i.e., hometown or out-of-town). Considering the *out-of-town user interest drift* phenomenon, some works based on probabilistic generative models are proposed. To relieve the sparsity problem, they combine out-of-town preferences with crowd preferences [26] and sentiment influences [21].

Unfortunately, these existing solutions for out-of-town recommendation are probabilistic model-based, thus fail to take advantage of deep learning, resulting in suboptimal results. Also, they fail to consider the sequential patterns required for the next POI recommendation. Therefore, we need to consider both users'preferences and their behavior pattern for next POI recommendation when located in out-of-town areas. To this end, in this paper, we aim to propose a model that can not only integrate person-based (hometown and out-of-town) preferences and region-based crowd preferences, but also to balance these factors in an effective way for enhanced next POI recommendation.

3 Problem formulation

Let U={u_1, u_2, ..., u_n} denote a set of users, and G={g_1, g_2, ..., g_m} denote a set of region, where $g_j (1 \leqslant j \leqslant m)$ represents a region in the administrative sense (e.g. a city or suburb). Although we use latitude and longitude to express the accurate location, users often only reach the administratively divided region when querying. The summary of all the notations in this paper is listed in Table 1.

Definition 1 (POI) A POI item i is defined as a uniquely identified specific site (e.g., a restaurant or a museum). In our model, a POI item has three attributes: geographical location, category and region. We use l_i to denote its corresponding geographical attribute in terms of longitude and latitude coordinates. Besides, we use c_i to denote the category for describing the POI item i generally, g_i to represente POI's region.

Definition 2 (User Hometown) For each user u, we define where she lives now as the user's hometown. However, it is hard to directly obtain a user's home location. Therefore, we

Table 1 Summary of notations

Symbol	Desciption
U, G, I	the set of users, regions, POIs
$B(u)$	the check-in sequence of user u
r_j^u	the j-th check-in record in $B(u)$
t_j^u	the occurrence time of r_j^u
i_j^u	the j-th POI in $B(u)$
l_i, c_i, g_i	the location, category, region of POI i
h_u	the hometown region of user u
g_p	the target region
$H(u), O(u)$	the check-in sequence of user u in hometown areas, out-of-town areas
$V(g)$	the set of check-in sequences of all visitors that occurred in region g

use the method developed by [18], such that we regard the region where a user frequently checks in as his home location, denoted as h_u. In Section 5.1 of experimental study we will introduce how the user hometown h_u is defined based on the datasets.

Definition 3 (Check-in Records) A user's check-in record r is represented by a triple (u, i, t), which denotes that user u visits POI item i, at time t.

Definition 4 (Check-in Sequence) A user's check-in sequence is represented by an ordered list: $B(u) = \{r_1^u, r_2^u, ..., r_j^u, r_k^u, ..., r_{|B(u)|}^u)\}$, $|B(u)|$ denotes the number of actions in the user's check-in sequence. In this list, $j < k$ means $t_j < t_k$, which indicates that behavior r_j^u is occurred before r_k^u . According to the location of the visited POIs in $B(u)$ and the user's hometown, $B(u)$ can be divided into a check-in sequence in hometown area $H(u)$ and a sequence in out-of-town area $O(u)$.

Definition 5 (Crowd Check-in Sequences Set) The check-in sequences set of crowd in region g is represented by a set: $V(g) = \{O(u_1), O(u_2), ..., O(u_j), O(u_{|V(u)|})\}$, which is collected from users' check-in records that occured in region g. $|V(u)|$ denotes the number of visitors who have visited region g, while $O(u_j)$ denotes the check-in sequence of user u_j in the region g.

Problem formalization Given a historical check-in sequence $B(u)$ of user u, target time t and a target region g_p, our goal is to recommend top-k POIs located in the target region g_p, which user u may be interested at time t, where $p = |B(u)| + 1$.

Although we use latitude and longitude to express the accurate location, users often only reach the administratively divided region when querying. Therefore, when a user u's target region g_p is different from her hometown h_u, we consider it to be an out-of-town recommendation problem, otherwise, we consider it to be a hometown recommendation problem.

4 HOPE model

In this section, we propose a hybrid deep neural model HOPE to support accurate next POI recommendation for out-of-town users. Figure 2 shows the architecture of the model, which contains two modules to capture *user-based personal preferences* and *region-based crowd pattern*, described in Sections 4.1 and 4.2 respectively. Then we introduce adaptive fusion of above preferences in different perspective in Section 4.3, and integrate both users' personal preferences and the region-based crowd pattern of visitors. Finally in Section 4.4, we introduce the detail of top-k recommendation for out-of-town users.

4.1 Personal preference modeling

This subsection aims to capture user's personal long-term and short-term preferences for next POI recommendation. Due to the phenomenon of *out-of-town user interest drift*, we model users' hometown and out-of-towm preferences simultaneously. It is thus able to enhance the out-of-town recommendation by an adaptive fusion to integrate these two user preferneces.

As shown in Figure 2 (left part), users' out-of-town and hometown preferences are captured by two attentional networks with the same structure. User's out-of-town(hometown)

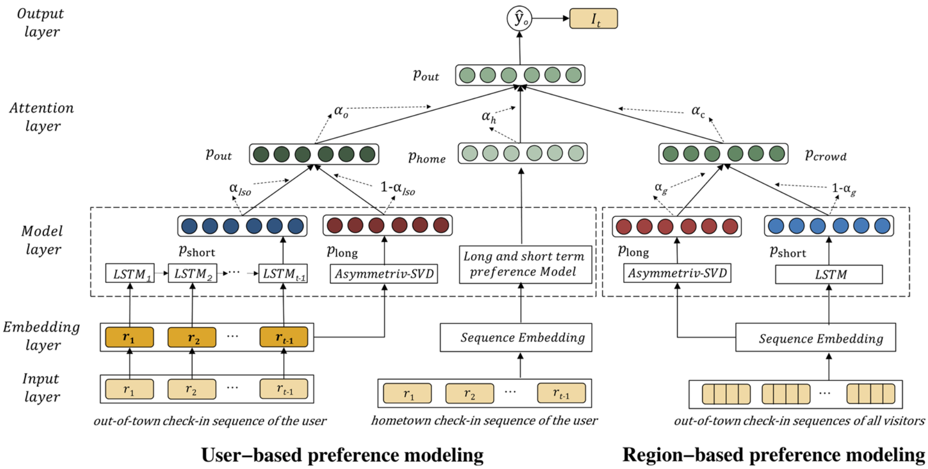


Figure 2 The Overall Architecture of HOPE Model: In the personal preference modeling module, we split the check-in sequence of each user as hometown check-in sequence and out-of-town check-in sequences and model the corresponding preferences separately. In the region-based preference modeling module, we collect the check-in sequences of visitors in the target region and model the crowd preferences. Finally, we merge all the preferences by an adaptive attention mechanism according to the temporal and spatial context

check-in sequence is inputted, and further embedded into a low-dimensional space in the embedding layer. In the model layer, we use LSTM with temporal gating to capture the short-term preferences, and derive the long-term preferences using "Asymmetric-SVD". At last, we use adaptive fusion to balance the importance of long-term and short-term preferences in a reasonable way. The details of the model layer are presented as follows.

4.1.1 Out-of-town preference modeling

Although users' interests may be region-varying, there are still some inherited habits across the regions, which can be regarded as their long-term preferences. As the rapid development of social media and the Internet, people are more easily influenced by others' successful experiences, and then check in some instagrammable places. Therefore, it is necessary to jointly model the long-term and short-term preferences of users in the out-of-town areas.

Long-term preference modeling In this module, we aim to model the preferences that users supposed to be static or changed slowly in the out-of-town areas. In the context of learning users' static preferences, matrix factorization techniques are often used to obtain the implicit vectors of users and POIs. Instead of employing the parameterization of users as their long-term preferences directly, we adopt the attentive "Asymmetric-SVD" paradigm [10] following the work in [28]. It represents users through the POIs they have visited, which makes the recommendation explainable. We utilize the POIs set that the user has visited in the out-of-town areas without considering sequentiality in this paper. In this way, long-term user preferences are represented by the aggregated properties of the POIs that have been visited, denoted as $p_u^{long_o}$:

$$\boldsymbol{p}_u^{long_o} = \sum_{j=1}^{|O(u)|} a_j^{lo} \boldsymbol{x}_j \tag{1}$$

1 where $\boldsymbol{x}_j$ is the embedding vector of j-th POI in the out-of-town check-in sequence $O(u)$, a_j^{lo} is the long-term out-of-town weighting score for $\boldsymbol{x}_j$. Since not all the POIs in the visited set are related to users' long-term preferences, it makes sense to assign higher weights to corresponding POIs with more information. The weighting score is computed as:

$$v_j = \phi(W_{lo}^{l}\boldsymbol{x}_j + b_{lo}) \tag{2}$$

$$a_j^{lo} = \frac{exp(v_j \tau_{lo})}{\sum_{k=1}^{|O(u)|} exp(v_k \tau_{lo})} \tag{3}$$

where W_{lo}, τ_{lo} are the parameters we need to train, b_{lo} is the bias, ϕ denotes the $tanh$ function.

Short-term user preference modeling In this module, we aim to model users' dynamic preferences that tend to change over time. Recently, LSTM has become the most important tools for sequential recommendation, including next item recommendation. However, general LSTM model cannot describe the spatial relations between two adjacent check-ins, which is nevertheless important for capturing users' short-term interests in next POI recommendation. We believe that there is a stronger connection between POIs within short time intervals.

Therefore, we employ the "*TC-SeqRec*" model [28] to handle sequential information. Different from other LSTM models, it is equipped with temporal gating to make it sensitive to time changes, which introduces a time interval feature δ_{t_k} as follows:

$$\delta_{t_k} = \phi(W_\delta log(t_k - t_{k-1}) + b_\delta) \tag{4}$$

$$T_\delta = \sigma(W_{x\delta}\boldsymbol{x}_k + W_{t\delta}\delta_{t_k} + b_{t\delta}) \tag{5}$$

where W_* is the parameter we need to train, b_* is the corresponding biases. The time interval feature δ_{t_k} encodes the temporal distance between two adjacent states. We add a fully connected layer to convert the time interval feature into dense vectors $W_{t\delta}\delta_{t_k}$, then compute time gates T_δ accordingly. σ denotes the $sigmoid$ function. After putting the time gate into the initial LSTM model, we can get the equations as follows:

$$f_k = \sigma(W_f\boldsymbol{x}_k + U_f h_{k-1} + b_f) \tag{6}$$

$$i_k = \sigma(W_i\boldsymbol{x}_k + U_f h_{k-1} + b_i) \tag{7}$$

$$c_k = f_k \odot T_\delta \odot c_{k-1} + i_k \odot \phi(W_c\boldsymbol{x}_k + U_c h_{k-1} + b_c) \tag{8}$$

$$o_k = \sigma(W_{xo}\boldsymbol{x}_k + W_{\delta o}\delta_{t_k} + W_{ho}h_{k-1} + b_o) \tag{9}$$

$$h_k = o_k \odot \phi(c_k) \tag{10}$$

where f_k, i_k, o_k stand for the forget gates, input gates and output gates respectively, c_k represents the cell status, h_{k-1} is the last hidden feature vector. U_* is the parameter we need to train, $\odot$ denotes the elementwise product.

Furthermore, instead of using the last hidden state as user's short-term preferences, we formulate it as the weighted average of all the hidden states:

$$a_j^s = \frac{exp(W_s h_j \boldsymbol{e}_p)}{\sum_{k=1}^{|O(u)|} exp(W_s h_k \boldsymbol{e}_p)} \tag{11}$$

$$\boldsymbol{p}_u^{short_o} = \sum_{j=1}^{|O(u)|} a_j^s h_j \tag{12}$$

where $\boldsymbol{e}_p$ represents another embedding vector of POI we want to make prediction, we call it prediction embedding in contrast to the input embedding vector $\boldsymbol{x}_p$.

Adaptive fusion of long-term and short-term preferences Next POI recommendation requires to consider long-term and short-term preferences simultaneously. Instead of using a naive way to combine them, e.g., $\boldsymbol{p}_u^{out} = \boldsymbol{p}_u^{short_o} + \boldsymbol{p}_u^{long_o}$, we adopt an adaptive way for information fusion. In fact, which part of the preferences should play a more important role depends on the specific contextual information, such as when (if the next travel occurs shortly after the previous one, then the short-term preferences may be more informative) and what (those POIs of classic attractions are better inferred from the long-term preferences, while POIs like new shopping malls are better inferred from the short-term preferences). As shown in Figure 2, we propose the following attention-based adaptive fusion method for combining the short-term preferences and long-term preferences for each user:

$$\alpha_{lso} = \sigma(W_o[\boldsymbol{p}_u^{short_o}, \boldsymbol{p}_u^{long_o}, \boldsymbol{x}_{context}] + b_o) \tag{13}$$

$$\boldsymbol{p}_u^{out} = \alpha_{lso} * \boldsymbol{p}_u^{short_o} + (1 - \alpha_{lso}) * \boldsymbol{p}_u^{long_o} \tag{14}$$

where $[\boldsymbol{p}_u^{short_o}, \boldsymbol{p}_u^{long_o}, \boldsymbol{x}_{context}]$ represents a concatenation of short-term information, long-term information, and the contextual information of a out-of-town user u. The contextual information include the category and the check-in time of the target POI.

However, out-of-town preference modeling is suffering from the condition of data sparsity, since users may have few or even no out-of-town check-in records in history.

4.1.2 Hometown preference modeling

Considering that some users do not have check-in records in out-of-town areas, we can employ their hometown check-ins to infer the out-of-town preferences. This is because some preferences that are independent of the region can also be found from the user's check-in record in their hometown areas.

We know that users' behaviors are influenced by their long-term preferences, which reflect their static habits in everyday life. Meanwhile, they are also affected by short-term preferences, such as their instant demands or decisions influenced by the Internet or TV Ads. Therefore, we aim to model both long-term and short-term user preferences w.r.t. the POIs in their hometown.

Similar to the long-term preferences modeling in Section 4.1, we can obtain users' long-term preferences in the hometown areas as:

$$\boldsymbol{p}_u^{long_h} = \sum_{j=1}^{|H(u)|} a_j^{lh} \boldsymbol{x}_j \tag{15}$$

where $\boldsymbol{x}_j$ is the embedding vector of j-th POI in the check-in sequence $H(u)$, and the weighting score a_j^{lh} is computed as:

$$v_j = \phi(W_{lh}^l \boldsymbol{x}_j + b_{lh}) \tag{16}$$

$$a_j^{lh} = \frac{exp(v_j \tau_{lh})}{\sum_{k=1}^{|H(u)|} exp(v_k \tau_{lh})} \tag{17}$$

where W_{lh}, τ_{lh} are the parameters we need to train, b_{lh} is the bias, ϕ denotes the $tanh$ function.

And users' short-term preferences $p_u^{short_h}$ in hometown areas is also modeled by the "*TC-SeqRec*". Then, the daptive fusion is also used for the combination for users' preferences in hometown areas:

$$\alpha_{lsh} = \sigma(W_h[\boldsymbol{p}_u^{short_h}, \boldsymbol{p}_u^{long_h}, \boldsymbol{x}_{context}] + b_h) \tag{18}$$

$$\boldsymbol{p}_u^{home} = \alpha_{lsh} * \boldsymbol{p}_u^{short_h} + (1 - \alpha_{lsh}) * \boldsymbol{p}_u^{long_h} \tag{19}$$

where $[\boldsymbol{p}_u^{short_h}, \boldsymbol{p}_u^{long_h}, \boldsymbol{x}_{context}]$ represents a concatenation of short-term information, long-term information, and the contextual information of a hometown user u. The contextual information include the category and the check-in time of the target POI.

Although we integrate users' hometown preferences into out-of-town preferences, we still cannot make accurate recommendations for out-of-town users. One is that cold-start users lack check-in records in both hometown and out-of-town areas, and the other is that users with similar hometown preferences may have different preferences in different regions. We further explore the region-based crowd pattern to improve the model.

4.2 Region-based crowd pattern discovering

In order to further improve the accuracy of the next POI recommendation, we explore the crowd preference of visitors in the target region. When modeling crowd preferences, an intuitive idea is to calculate the popularity of POI among visitors, which can be reflected as the long-term preference of visitors. In addition, we found that visitors' behaviors in out-of-town areas also follow some sequential patterns, which can be regarded as the short-term preference of visitors. So we need to jointly learn the long-term and short-term preferences of visitors.

As shown in the Figure 2 (right part), we collected all the check-ins of visitors that occurred in the target region as input. The region-based crowd pattern module incorporates the joint effects of visitors' crowd preferences and behavior pattern in the target region. It also has four layers in total.

4.2.1 Region-based crowd preference modeling

In this component, we aim to model the region-based crowd preferences of visitors in the target region g_p. We gather all the check-ins in $V(g_p)$ without considering sequentiality and identity of visitors, denoted as $v(g_p)$. Then we formulate the region's crowd long-term preferences as follows:

$$\boldsymbol{p}_g^{long} = \sum_{j=1}^{|v(g_p)|} \boldsymbol{x}_j \tag{20}$$

where $\boldsymbol{x}_j$ is the embedding vector of j-th POI in the region POIs set that checked by visitors, $|v(g_p)|$ is the number of the check-ins in the $V(g_p)$.

4.2.2 Region-based behavior pattern exploration

In this component, we explore the behavior pattern of visitors in the target region g_p. We use the above attentional network "*TC-SeqRec*" in Section 4.1 to capture short-term preferences. based on the check-ins of all visitors in the target region:

$$\boldsymbol{p}_g^{short} = \sum_{j=1}^{|F(g_s)|} \boldsymbol{p}_j^{short} \tag{21}$$

where $F(g_s)$ represent the union of each visitor j's short-term preferences $\boldsymbol{p}_j^{short}$ in the region g. At last, an attention mechanism is used to combine the long-term preferences and the short-term preferences:

$$\alpha_g = \sigma(W_g[\boldsymbol{p}_g^{long}, \boldsymbol{p}_g^{short}] + b_g) \tag{22}$$

$$\boldsymbol{p}_g^{crowd} = \alpha_g * \boldsymbol{p}_g^{long} + (1 - \alpha_g) * \boldsymbol{p}_g^{short} \tag{23}$$

where $[\boldsymbol{p}_g^{long}, \boldsymbol{p}_g^{short}]$ represents a concatenation of long-term information, short-term information of crowd.

4.3 Adaptive fusion of personal preferences and crowd preferences

Although users' preferences may drift in different regions, they are not absolutely unpredictable. This is due to the fact that personal preferences of users still influence their choices, even when they are in out-of-town areas. Therefore, out-of-town recommendation considers the joint effects of users' personal preferences and region-based crowd preferences. When fusing the crowd and personal preferences, it is important to balance their importances in an adaptive way, similar to long-term and short-term preference fusion. This is due to the fact that some users tend to choose local specialty (e.g. spicy food) when visiting a new city, while some users may persist in their personal preferences (e.g. light diet).

To this end, we propose the following attention-based adaptive fusion method to combine a user's personal preferences and region-based crowd preferences in the target region, such that:

$$[\alpha_h, \alpha_o, \alpha_c] = \psi(W_m[\boldsymbol{p}_u^{home}, \boldsymbol{p}_u^{out_p}, \boldsymbol{p}_g^{crowd}, x_{con}] + b_m) \tag{24}$$

$$\boldsymbol{p}_u = \alpha_h * \boldsymbol{p}_u^{home} + \alpha_o * \boldsymbol{p}_u^{out} + \alpha_c * \boldsymbol{p}_g^{crowd} \tag{25}$$

where ψ denotes the $softmax$ function. x_{con} represents the contextual information, which includes the check-in time and the category of target POI.

4.4 Prediction

4.4.1 Out-of-town recommendation

When people want to obtain a recommendation for where to go next, they would like to type some information such as the category of the target POI. Therefore, we adopt a Multi-Layer Perceptron (MLP) to make the best of these information for a more accurate recommendation. We use a two-layer MLP to predict the probability of each POI which is located in the target region g and recommend the top-k POIs to users, and all compared models in the experiment section will share this design:

$$\hat{y}_{ux_g} = MLP(\boldsymbol{p}_u, \boldsymbol{x}_g) \tag{26}$$

where $\boldsymbol{x}$ represents the embedding vector of a POI in the target region g. We formulate the loss as the distance between 1 and our predict value of the target POI:

$$\mathcal{L} = -\frac{1}{N_S}\sum_{j=1}^{N_S} log\sigma(1 - \hat{y}_j) \tag{27}$$

where N_S represents the number of the test data, y_j represents the predicted value. Furthermore, we use Adam to optimize the parameters in HOPE:

$$\mathcal{J} = \mathcal{L} + \lambda_* ||\Theta||_2 \tag{28}$$

4.4.2 Hometown recommendation

Although our proposed model focuses on improving recommendation performance for out-of-town users, it can simultaneously make recommendation for hometown users through separate hometown module. It is similar to the above prediction and optimization methods for out-of-town recommendation. We use the two-layer MLP

$$\hat{y}_{ux_h} = MLP(\boldsymbol{p}_u^{home}, \boldsymbol{x}_h) \tag{29}$$

to predict the probability of all the POIs in hometown areas and recommend the top-k POIs which get a higher scores. Also, all compared models in the experiment section will share this design. Then, we use the (28) to minimize the loss function (27).

5 Experiment

In this section, we first briefly depict the dataset, followed by baseline methods. Finally, we present our experimental results and discussions.

5.1 Datasets

We conduct our experiments on two real-world datasets, which have user-POI interactions of users and locations of POIs.

- **Foursquare** The Foursquare Dataset contains 117,329 POIs and 472,637 check-ins generated by 4,152 users who live in California, USA. Additionally, these records distributed in 5,858 cities.
- **Yelp** The Yelp dataset contains 129,114 check-in histories with short annotations that occurred in 464 cities.

In this experiment, we consider the administrative city as a region. Since it is hard to directly obtain a user's home location, we regard the region where a user frequently checks in as his home location, follow the work in [26]. Specially, we use the linear distance between the user's h_u and the location l_i of POI from check-in sequence of users to determine whether the check-in is occured in his' hometown area. When $|h_u - l_p|$ is greater than the given distance threshold d, we consider this check-in records is occured in the out-of-town area, otherwise, we consider it to be a hometown check-in records. In line with [7, 15], we set $d = 100km$ in this paper, which takes more than one hour to drive, because the distance of about $100km$ is the approximate range of human daily physical activity.

Furthermore, we transform each check-in record into a sequence of user-ID, POI-ID, POI-location in the form of latitude and longitude, check-in timestamp, and POI-category. Besides, we eliminate users' data which include fewer than 5 check-in records.

Both two datasets will be processed through the above methods. We use the first 80% of each users' trajectories for training and the rest for testing. The statistics of them are listed in Table 2.

Table 2 Basic statistics of yelp and foursquare

	Users	POIs	Cities	Check-ins	Hometown check-ins	Out-of-town check-ins
Yelp	7,228	247,920	464	129,114	94,426	34,688
Fs	4,152	117,329	5,858	472,637	383,318	89,319

5.2 Compared methods and settings

We compare our proposed model HOPE with the following baseline methods.

- **LSTM** [9], as a variant of RNN, is a classical sequential model that captures both long-term and short-term dependencies. It can be directly used for next POI recommendation.
- **PRME-G** [6] is a personalized ranking metric embedding algorithm that models the sequential transition of POIs and user preferences. It is widely recognized as a classical method for sequential POI recommendation.
- **STLDA** [26] is a probabilistic generative model that learns region-dependent user preferences based on the POI content, social relationship, temporal and spatial correlation information.
- **T-LSTM** [34] models users' sequential actions by LSTM with time gates, so as to accurately capture users' short-term and long-term interests simultaneously for prediction and recommendation tasks.
- **DeepMove** [4] is an attentional recurrent network to predict the next POI by modeling historical and current check-in sequences of users. It learns user's long-term preferences from the history with the attention mechanism and learns short-term preferences from the current trajectory using a RNN module.
- **STGCN** [31] is the state-of-the-art sequential POI recommendation model, which models spatio-temporal intervals between check-ins under the LSTM network architecture for next POI recommendation. It captures time and distance intervals between consecutive POI visits in user's check-in history.

We implement the models with Tensorflow. Follow the work in [28], dimension for POI embedding and RNN hidden layers is 18, while the dimension for MLP is 50. Optimal settings for our model are: learning rate is 0.001; L2 regularizataion is 0.0001; no dropouts; batch normalization is used only after the concatenation of the users' embedding; maximum length for user check-ins is set to 100; Optimizer is Adam. Moreover, all the baseline methods make a prediction for all POIs and return top-k POIs in the target region g only, which is equivalent to our HOPE model to ensure fair comparisons.

5.3 Evaluation metrics

In this paper, we use $Accuracy@k$ and MAP to measure the performance of our proposed model and baselines. These two popular metrics are used for next POI/item recommendation tasks, such as [6, 8, 28]. The overall $Accuracy@k$ is computed as the hit ratio in the test as follows:

$$Accuracy@k = \frac{\#Hit@k}{N_{test}} \tag{30}$$

where $\#Hit@k$ denotes the total hits of the top-k results for next POI recommendation and N_{test} represents the total number of ground truth results. In this paper, we choose k ={1, 5, 10} to illustrate different results of $Acc@k$ (short for $Accuracy@k$). If the next visited POI appears in the top-k POIs recommended, meaning that the next POI recommendation is successful for this case, and then, the value of $hit@k$ for a single test case will be defined as 1, or 0 otherwise.

5.4 Performance

In this section, we evaluate and compare our proposed HOPE model with the baseline methods. The performance of HOPE and the baseline methods on out-of-town data is shown in Table 3. From the experimental results, we can have the following observations.

Firstly, LSTM performs better than embedding method PRME-G, due to its capability in modeling sequential data and user interests using LSTM cells. Secondly, both T-LSTM and STGCN improve the performance compared with LSTM, which indicates that it is reasonable to capture temporal feature from the sequence information. Thirdly, ST-LDA ,as a non-deep model, outperforms LSTM and T-LSTM on Foursquare dataset, since it takes into account the users' out-of-town preferences and visitors' preferences. At last, our proposed model significantly outperforms all the baseline methods on both datasets in terms of the $Acc@K$ and MAP metric. It indicates the effectiveness of the HOPE model, due to the way of learning both users' personal preferences and region-based crowd pattern. More specifically, our model outperforms the other baseline methods by a large margin. The performance gains over the state-of-the-art counterparts are about 95.82% in terms of the $Acc@1$ metric on Foursquare. It demonstrates that our model can work well for out-of-town recommendation. Moreover, the improvement on Foursquare outperforms the improvement on Yelp. Such a phenomenon might be attributed to the data sparsity of the dataset. This further verifies that the mechanism to model personal preferences and region-based crowd pattern in HOPE can address the problem of data sparsity in out-of-town recommendation. .

5.4.1 Effictiveness of each component

In order to investigate the impact of data sparsity and *out-of-town user interest drift* for out-of-town recommendation, we further conduct the experiment by using the different parts of our out-of-town preference model.

Table 3 Performance comparison on out-of-town data w.r.t. $Acc@K$ and MAP

	Foursquare				Yelp			
	$Acc@1$	$Acc@5$	$Acc@10$	MAP	$Acc@1$	$Acc@5$	$Acc@10$	MAP
PRME-G	0.0258	0.0461	0.0644	0.0381	0.0979	0.1722	0.2132	0.1275
STLDA	0.0440	0.0886	0.1097	0.0455	0.1105	0.1957	0.2537	0.1464
LSTM	0.0334	0.0617	0.0872	0.0463	0.1065	0.2113	0.2654	0.1519
T-LSTM	0.0342	0.0749	0.0919	0.0506	0.1209	0.2254	0.2707	0.1649
DeepMove	0.0448	0.0862	0.1091	0.0584	0.1280	0.2216	0.2601	0.1668
STGCN	0.0526	0.0986	0.1236	0.0722	0.1324	0.2540	0.2976	0.1867
HOPE	**0.1030**	**0.1553**	**0.1793**	**0.1076**	**0.1687**	**0.3003**	**0.3517**	**0.2106**
Improvement	95.82%	57.51%	45.06%	49.03%	27.42%	18.23%	18.18%	12.80%

- **HOPE-H** This version removes the crowd preferences pattern and users' out-of-town preferences module of HOPE and only capture users' personal preferences in hometown areas.
- **HOPE-P** This version considers users' personal preferences, including users' preferences in hometown areas and out-of-town areas.
- **HOPE-D** This version aims to exploit those dense check-in data. It ignores users' personal preferences in out-of-town areas, and captures user's personal preferences in hometown areas and visitors' preferences in the target region.

The results of the degraded versions of HOPE on two datasets are shown in Figure 3.

As shown in the Figure 3, we can observe that HOPE-D and HOPE-P always perform better than HOPE-H, showing that both users' personal preferences and crowd pattern have positive impacts on the user's choice to the next POI in the out-of-town areas. Since HOPE-D is always significantly better than HOPE-P, we can draw the conclusion that the impact of data sparsity (in out-of-town areas) is more significant than the phenomenon of *out-of-town user interest drift*.

As mentioned above, the region-based crowd pattern of visitors makes a huge contribution to the results of out-of-town POI recommendation. To explore the contributions of the crowd preferences and behavior patterns in the model, we further implement two simplified versions of the HOPE-D model:

- **HOPE-DL** This version captures users' hometown preferences and the crowd preferences of visitors in the target region.
- **HOPE-DS** This version captures users' hometown preferences and the behavior pattern of visitors in the target region.

The results of the degraded versions of HOPE-D on two datasets are shown in Figure 4.

As shown in the Figure 4, we can observe that HOPE-DS always has a better performance than HOPE-DL, even closes to the HOPE model. The reason may be that users tend to follow some visit pattern according to the current status when travelling in the out-of-town areas, instead of visiting the POIs that most people are interested in. This clearly demonstrates the benefit of our modeling of behavior patterns of visitors.

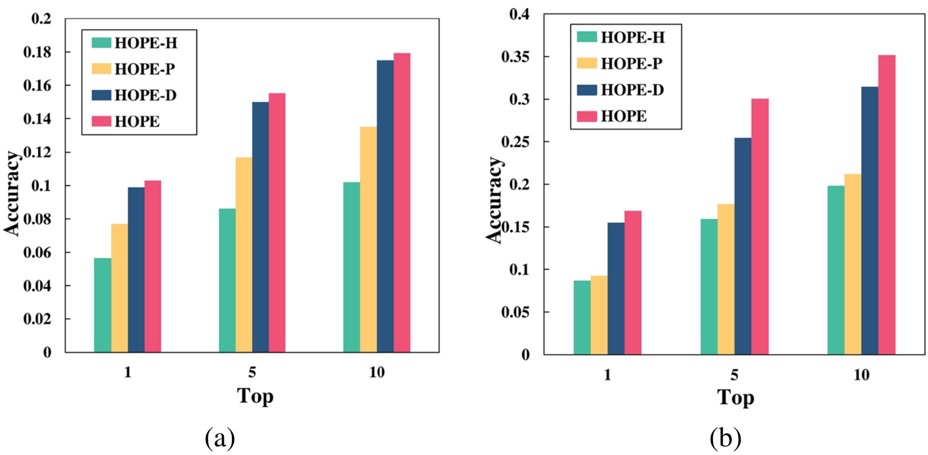
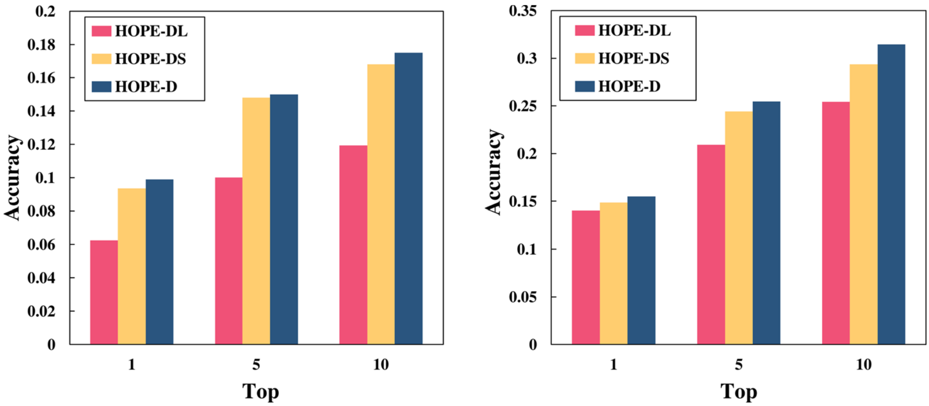


Figure 3 Performance comparison of different HOPE variants



(a) (b)

Figure 4 Performance comparison of different HOPE-D variants

The complete model HOPE, which is the combination of users' personal preferences and region-based crowd pattern, achieves the best performance on both datasets. It shows that all components of HOPE have positive impacts on users' choices to the next POI.

5.4.2 Hometown recommendation

Although our model focuses on improving recommendation performance for out-of-town users, we also report the performance of all recommendation models for the hometown scenario, and our HOPE also achieves the highest recommendation accuracy, which indicates that the combination of long-term and short-term preferences of users is effective.

Compared with the result in Table 4, we observe that all methods perform better than the out-of-town scenario. Because the user-POI matrix is not sparse in the hometown areas. In addition, our model's improvement over the best competitor STGCN on out-of-town recommendation is higher than that of hometown recommendation, which indicates that the optimization of our model for out-of-town recommendation is effective.

Table 4 Performance comparison on hometown data w.r.t. $Acc@K$ and MAP

	Foursquare				Yelp			
	$Acc@1$	$Acc@5$	$Acc@10$	MAP	$Acc@1$	$Acc@5$	$Acc@10$	MAP
PRME-G	0.0871	0.1166	0.1318	0.0869	0.1703	0.2682	0.3080	0.2073
STLDA	0.1087	0.1778	0.2292	0.1527	0.1894	0.2937	0.3402	0.2683
LSTM	0.1208	0.1792	0.2025	0.1521	0.1994	0.3437	0.3969	0.2662
T-LSTM	0.1248	0.1878	0.2168	0.1455	0.2076	0.3460	0.4120	0.2670
DeepMove	0.1447	0.2108	0.2403	0.1672	0.2070	0.3443	0.4100	0.2574
STGCN	0.1590	0.2338	0.2570	0.1915	0.2440	0.4075	0.4644	0.3146
HOPE	**0.2066**	**0.2633**	**0.2878**	**0.2141**	**0.2844**	**0.4148**	**0.4780**	**0.3633**
Improvement	29.94%	12.62%	11.98%	11.80%	16.56%	1.79%	2.93%	15.48%

Table 5 Comparison of different fusing method of HOPE on foursquare dataset

	Hometown		Out-of-town	
	$Acc@1$	$Acc@5$	$Acc@1$	$Acc@5$
Fixed	0.1569	0.2196	0.0446	0.0756
Adaptive	**0.2066**	**0.2633**	**0.1030**	**0.1553**

5.4.3 Effectiveness of adaptive fusion

To verify whether adaptive fusion is necessary for next POI recommendation, we conduct the experiments with different fusing method. We compared two selection of the tuple[$\alpha_h, \alpha_o, \alpha_c$] in (25). "Adaptive" means our complete HOPE model, "fixed" means that we empirically search a fixed optimal value for each dataset. As shown in Table 5, we can observe that the fixed fusion way of HOPE achieves much lower performance than either the personal preferences model or the crowd preferences model. It shows that the adaptive combination is effective for the next recommendation in the out-of-town areas.

5.4.4 Effectiveness of the combination

To verify whether the combination of the long-term and short-term preferences is necessary for next POI recommendation, we conduct the experiments with different variants of HOPE. "Short" means that we only capture the sequential preferences of both personal preferences and crowd preferences and "Long" means that we only capture the long-term preferences of both personal preferences and crowd preferences. As shown in Table 6, we can observe that both the long-term and short-term preferences have lower performance than HOPE. It shows that both long-term and short-term preferences are effective and necessary to achieve good performance in out-of-town recommendation and hometown recommendation.

5.4.5 Effectiveness of temporal gating

To verify the importance of temporal-gating, we conduct the experiments with different short-term preference model. As a comparison, we use the original LSTM model to capture users' short-term preferences. As shown in Table 7, it is clear that our HOPE model with *TC-SeqRec* yields better performance than the original LSTM on both datasets. It shows that the temporal gating is effective for the next recommendation in the out-of-town areas.

Table 6 Comparison of the combination of HOPE on Foursquare dataset

	Hometown		Out-of-town	
	$Acc@1$	$Acc@5$	$Acc@1$	$Acc@5$
Long	0.0929	0.1756	0.0528	0.0659
Short	0.1641	0.2274	0.0869	0.1477
HOPE	**0.2066**	**0.2633**	**0.1030**	**0.1553**

Table 7 The effectiveness of *TC-SeqRec*

	Foursquare		Yelp	
	$Acc@1$	$Acc@5$	$Acc@1$	$Acc@5$
LSTM	0.0949	0.1181	0.1464	0.2833
TC-SeqRec	**0.1030**	**0.1553**	**0.1687**	**0.3003**

6 Conclusion and future work

In this paper, we study the next POI recommendation for out-of-town problem and propose a deep neural model which learns users' personal preferences and the region-based crowd pattern of visitors. In personal preference modeling, we adopt an attentional network to effectively capture users' long-term and short-term preferences in both hometown areas and out-of-town areas. In region-based crowd pattern modeling, we adopt a carefully designed network structure to capture the crowd preferences and POI transitions of all visitors in this region. Therefore, the problem of data sparsity and *our-of-town user interest drift* for the out-of-town recommendation can be well tackled. Experimental results on real datasets demonstrate the effectiveness of our model, which outperforms several state-of-the-art models significantly. Moreover, we found that the region-based behavior pattern of visitors plays an important role for next out-of-town POI recommendation.

In the future, we would like to consider useful side information, such as user's reviews, photos and social relationship, so that more accurate POI recommendation can be achieved.

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