Long- and Short-term Preference Learning for Next POI Recommendation

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ABSTRACT

Next POI recommendation has been studied extensively in recent years. The goal is to recommend next POI for users at specific time given users' historical check-in data. Therefore, it is crucial to model users' general taste and recent sequential behavior. Moreover, the context information such as the category and check-in time is also important to capture user preference. To this end, we propose a long- and short-term preference learning model (LSPL) considering the sequential and context information. In long-term module, we learn the contextual features of POIs and leverage attention mechanism to capture users' preference. In the short-term module, we utilize LSTM to learn the sequential behavior of users. Specifically, to better learn the different influence of location and category of POIs, we train two LSTM models for location-based sequence and category-based sequence, respectively. Then we combine the long and short-term results to recommend next POI for users. At last, we evaluate the proposed model on two real-world datasets. The experiment results demonstrate that our method outperforms the state-of-art approaches for next POI recommendation.

CCS CONCEPTS

• **Information systems → Recommender systems**;

KEYWORDS

Next POI recommendation, Attention mechanism, User preference

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1 INTRODUCTION

Recent years have witnessed significant development of location-based social networks (LBSNs), such as Foursquare, Gowalla, Facebook, and Yelp, etc. Particularly, users can share their locations and experiences with their friends by checking-in points-of-interest (POIs). A check-in record usually contains the visited POI with its associated contexts that describe user movement, including the timestamp, GPS and semantics (e.g., categories, tags, or comments). The massive check-in data generated by millions of users in LBSNs provide an excellent opportunity to explore the intrinsic pattern of user check-in behavior. For example, based on users' historical check-in records, we can analyze and further recommend POIs for them, which not only help users to explore their interested places but also benefit for business to attract more potential customers[1, 2].

Recently, next POI recommendation has received significant attention in research community. Excepted for users' general preference (long-term preference), next POI recommendation additionally considers the sequential patterns of users' check-in records (short-term preference).

Our work is motivated by the following inspirations: (1) Users' long- and short-term preference on POIs codetermine where they will go next time. Therefore, it is necessary to consider the two factors together. (2) A user's check-in behavior is autonomous and elusive, leading it difficult to capture users' long-term regularity. At different time, location and situation, users may prefer different POIs. Therefore, to better learn users' long-term preference for personalized recommendation, it is important to consider the context information of POIs. (3) The activity purpose and check-in locations are inseparable. The location-based sequences and category-based sequences have different influence on the decisions of users. Since sometimes a user may hesitate about where to go after having decided what to do. Therefore, it is crucial to learn what users will do and where they will go at specific time.

To this end, we propose a Long- and Short-term Preference Learning (LSPL) model for next POI recommendation. Concretely, we integrate the long- and short-term preference together to calculate the ranked probability list of candidate POIs. In long-term module, to better capture users' long-term preference, we learn contextual features of POIs in their check-in history and utilize attention mechanism to learn users' preference on these POIs. In short-term module, we leverage LSTM to model the short-term sequential preference of users. To model the different influence of locations and categories, we learn location-level and category-level preference by training two parallel LSTM models. Finally, we fuse the long-term and short-term together with weighed summarization to obtain the final probabilities of candidate POIs.

The main contributions of this paper are summarized as follows:

1) We propose a unified model to learn the long-term and short-term preference of users. The long-term preference reflects the general tastes of users, which is helpful to obtain personalized recommendation for users. The short-term behaviors reflect the recent preference of users at current time. Therefore, combination of long- and short-term preference is essential to better capture users' preference of next POI at specific time.

2) For long-term preference, it is of importance to learn users' behavior from different aspects. Therefore, we extract the contextual features of POIs in users' check-in history and utilize attention mechanism to further characterize the general taste of users.

3) For short-term preference, we integrate the location-level and category-level preference together to better capture user activity purpose. We leverage two parallel LSTM models to learn the short-term check-in sequence of users. The outputs of them are merged together as the final ranked list.

2 RELATED WORK

In this section, we give a brief review about next POI recommendation. Different from general location recommendation that mainly exploit users' preferences on POIs, next POI recommendation additionally considers the sequential information of users' check-in history. Therefore, it is crucial to take the sequential information in to account. In the literature, effective methods have been widely applied for sequential data analysis and next item recommendation. Generally, the widely used approaches of next POI recommendation are Markov Chains, ranking-based method and recurrent neural networks-based method.

Markov-based methods model the sequential correlation between POIs based on users' check-in sequences. FPMC [3] applies personalized Markov chains and matrix factorization to learn the transition matrix and the general taste of users, respectively. In terms of ranking-based method, Bayesian Personalized Ranking (BPR) [4] is a widely studied method with promising performance. It is a pairwise approach, which takes the implicit feedback as the relative preference rather than absolute one.

Recently, Recurrent Neural Networks (RNNs) such as Long Short-term Memory (LSTM) [5] have demonstrated ground-breaking performance on modeling sequential data. However, the original RNN cannot well model the contextual information. Therefore, existing studies focus on exploiting users' sequential preference on POIs by integrating various context information into RNNs framework. Therefore, Liu et al.[6] proposed Spatial Temporal Recurrent Neural Networks (ST-RNN) model to capture the periodical spatial and temporal contexts. Recently, attention mechanism has been widely used in image caption and machine translation and recommendation. Ying et al. [7] proposed Sequential Hierarchical Attention Network(SHAN) which combined long-term and short-term preferences to recommend next item for users. But they failed to consider the sequential behavior of ours. Feng et al. [8] proposed an attentional recurrent model named DeepMove to predict human mobility. A historical attention module was designed to capture the multi-level periodical nature of human mobility by jointly selecting the most related historical trajectories under the current mobility status.

3 PROBLEM DESCRIPTION

Let $U = \{u_1, u_2, \cdots, u_M\}$ be a set of users, and $L = \{l_1, l_2, \cdots, l_N\}$ be a set of locations, where M and N are the total number of users and locations, respectively. In our work, the categories of locations are also considered. We denote $C = \{c_1, c_2, \cdots, c_K\}$ as the categories of all the locations, where K is the total number of categories. For each user, we define the check-in sequence as follows.

Definition 1 (check-in sequence). The check-in sequence for a user $u \in U$ with n records is a time-ordered sequence $Q^u = \{q_1^u, q_2^u, \cdots, q_n^u\}$. Each record $q_i^u \in Q^u$ contains three attributes (l_i, c_i, t_i), where $l_i \in L$ is the location visited by user u at time; $c_i \in C$ is the category of l_i; t_i is the timestamp.

Definition 2 (long-term sequence). In this paper, we utilize the data in training set to represent the long-term sequence for a user u, which is regarded as prior information of each user. We set the long-term sequence as $L^u = \{q_1^u, q_2^u, \cdots, q_L^u\}$

Definition 3 (short-term sequence). Given the raw sequence Q^u of user u, we split it into a set of sequences as short-term sequence. Suppose the length of short-term sequence is k, we set the short-term sequence as ${S_j}^u = \{q_j^u, q_{j+1}^u, \cdots, q_{j+k-1}^u\}$ s.t. $\forall 1 < k < n$.

Formally, given the short-term sequence ${S_j}^u$ and the corresponding long-term sequence L^u of a user u, our goal is to recommend the next POI l_{j+k} from the location set L at time t_{j+k}.

4 OUR MODEL

4.1 The Overall Architecture

The illustration of the overall framework is shown in Fig. 1. The basic idea of our approach is to recommend a ranked list of POIs for users by jointly learning the long- and short-term preferences. More specifically, we learn the long-term preference of user u from the long-term sequence $L^u = \{q_1^u, q_2^u, \cdots, q_L^u\}$ with the attention mechanism similar to [7]. Meanwhile, we utilize the short-term sequence ${S_j}^u = \{q_j^u, q_{j+1}^u, \cdots, q_{j+k-1}^u\}$ of user u to capture the short-term inference of users' activity pattern. Specially, we feed the location-based and category-based sequences into two LSTM models respectively to learn the location-level and the category-level preference. Finally, in the output layer, we combined the output of the long- and short-term together to generate the final probabilities of candidate POIs in the location set L.

4.2 The Long-term Preference Learning

In this section, we introduce the learning method for long-term preference of users. The long-term sequence of a user u reflect the general taste of the check-in behavior of user, thus we utilize it to learn the long-term preference. The main idea is to capture the

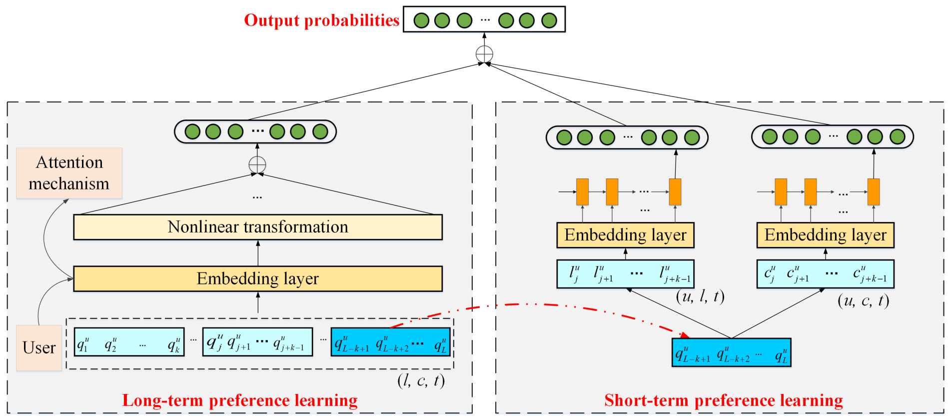

Figure 1: The overall architecture of LSPL model.

different preferences of each POI in long-term sequence for every user.

4.2.1 Embedding layer. For the long-term check-in sequence of user u , we learn the latent embedding vectors of user u and the contextual feature of every record. Firstly, they are represented as one-hot vectors, where the non-zero entry denotes the indexes. Then we transform them into D^u, D^l, D^c, D^t dimensional dense vectors, respectively. The compositive feature of each POI is calculated as follows:

$$h_i = \phi(W_l v_i^l + W_c v_i^c + W_t v_i^t + b). \tag{1}$$

where v_i^l, v_i^c and v_i^t represent the embedding vectors of the tuple (l_i, c_i, t_i) of every POI in the long-term sequence. W_l , W_c, W_t and b are the weights and corresponding bias parameters. ϕ is the nonlinear activation function.

4.2.2 The Attention Mechanism. To learn the long-term preference of user, we leverage the attention mechanism to calculate the contextual features of POIs in long-term sequence. The importance of each POI is calculated as the normalized similarity between latent vector of the user u and the POI q_i :

$$a_j = \frac{\exp(u^T h_i)}{\sum\limits_j \exp(u^T h_i)}, \tag{2}$$

$$u_{long} = \sum_i a_i [v_i^l; v_i^c; v_i^t]. \tag{3}$$

where $[v_i^l; v_i^c; v_i^t]$ represent the concatenation of the embedding vector of the tuple (l_i, c_i, t_i) of each POI. a_i denotes the importance of each POI. u_{long} is the final representation of the long-term preference of user u. Then u_{long} is fed into a fully connected layer to calculate the probability of next POI.

4.3 The Short-term Preference Learning

We leverage LSTM model to learn the short-term preference of users. For the check-in sequence of user u , the latent vectors of user u and the tuple of every record (l_i, c_i, t_i) are in the same way as the section 4.2.1. Then the embedding vectors of locations (u, t_i, l_i) and categories (u, t_i, c_i) are simultaneously fed into two LSTM models to learn the location-level and category-level preference. Finally, the output vectors of the two LSTM models are fed into a fully connected layer to calculate the probability of next POI.

4.4 The output layer

In the out-put layer, we integrate the results of long- and short-term learning with weighed summarization as follows:

$$P_i = \alpha \cdot P_L^i + \beta \cdot P_l^i + \gamma \cdot P_c^i, \tag{4}$$

where P_L^i represents the output probability of long-term preference learning. P_l^i and P_c^i are the output of location-based LSTM and category-based LSTM, respectively. α, β, γ are the weights to be learned. The final output probability is determined as follows:

$$O_i = \frac{e^{P_i}}{\sum_{j=1}^{N} e^{P_j}}. \tag{5}$$

where N is the total number of candidate POIs.

5 EXPERIMENTS

5.1 Datasets

We evaluate our model on public Foursquare check-in datasets collected from New York City (NYC) and Tokyo (TKY) [9]. The check-in records were collected from April 2012 to February 2013. Each record contains user ID, POI ID, category name, GPS and timestamp. In following experiments, we split the records of each user into several sessions keeping each session as the same length. Then we take the first 80% check-ins as the training set, the latter 20% as the test set.

5.2 Baselines

Several baselines and state-of-the-art methods on next POI recommendation are used for comparison. **FPMC** [3] modeled both general taste and sequential behavior by integrating Matrix Factorization and Markov Chain method. **SHAN** [7] applied a nonlinear two-layer hierarchical attention network to capture users' dynamic preference including long-term preference and short-term preference. **DeepMove** [8]learned user preference using recurrent neural networks for historical sequence and short-term current sequence. Then an attention mechanism is used to compute the similarity of current state and historical states.

5.3 Parameter Setting

The key parameters in our model include: the embedding dimensions of latent vector for users D^u, locations D^l, categories D^c

Table 1: Performance Comparation With Baselines

Data	Method	P@1	P@5	P@10	P@20	MAP@20
NYC	FPMC	0.0892	0.2262	0.2943	0.3895	0.1483
	SHAN	0.1353	0.1779	0.1896	0.2019	0.1545
	DeepMove	0.1408	0.2946	0.363	0.4052	0.2101
	LSPL	**0.1501**	**0.3204**	**0.3901**	**0.4461**	**0.2257**
TKY	FPMC	0.0655	0.1725	0.2385	0.2944	0.1128
	SHAN	0.1084	0.1527	0.1684	0.1813	0.1296
	DeepMove	0.1282	0.2488	0.2923	0.3289	0.1820
	LSPL	**0.1497**	**0.3281**	**0.3986**	**0.4596**	**0.2162**

and time D^t, the dimension of the hidden state and the batch size. Considering the vocabulary size of them, we set the dimensions of users, POIs, categories and time to be $D^u = 50$, $D^l = 300$, $D^c = 100$ and $D^t = 20$ respectively. The batch size is set to be 32, and the learning rate is 0.001.

5.4 Comparative Results

In this paper, we use precision@k (P@k) and MAP@k to evaluate the performance of different methods. P@k indicates that whether the ground truth POI appears in the top-k recommended POIs and MAP@k measures the order of our recommendation list. The performance is illustrated in Table 1.

We can observe that SHAN and DeepMove show an increase of 4.61% and 5.16% compared with FPMC under P@1 on the NYC dataset. However, SHAN shows poor performance under P@k with k = 5, 10, and 20. Compared with SHAN, DeepMove shows an increase of 0.5%-20% under all k of P@k, and 5.56% under MAP@20. Moreover, our model outperforms the compared methods on both datasets measured by all the metrics. Concretely, for P@k on the NYC dataset, our method is almost 5%-9% higher than FPMC, 1%-24% higher than SHAN, and 1%-4% higher than DeepMove. For MAP@20, our method outperforms FPMC, SHAN and DeepMove by 7.74%, 7.12% and 1.56% respectively. For P@k on the TKY dataset, our method is almost 8%-16% higher than FPMC, 4%-28% higher than SHAN, and 2%-13% higher than DeepMove. For MAP@20, our method outperforms FPMC, SHAN and DeepMove by 10.34%,8.66% and 3.42% respectively.

5.5 Discussions

Besides the performance comparison of the proposed model with the existing FPMC, SHAN and DeepMove, we also discuss some variants of our method to demonstrate the importance of each part of our model.

1) **LSPL_long**: variant model with only the long-term module.
2) **LSPL_loc**: variant model with only location-level module.
3) **LSPL_cate**: variant model with only category-level module.
4) **LSPL_loc+cate**:variant model with only the location- and category-level preference learning module.

Due to space limitation, we just investigate the performance on NYC dataset. The performance is illustrated in Fig.2. We can conclude that the models with only one module show poor performance. LSPL_long is the worst one under P@1 and P@5 in both datasets. That's because there's no sequential information for long-term preference learning. Meanwhile, the models with merged modules such as LSPL_loc+cate show better performance, and our LSPL model shows the best performance. It indicates that it is effective to integrate users' long-term and short-term preference.

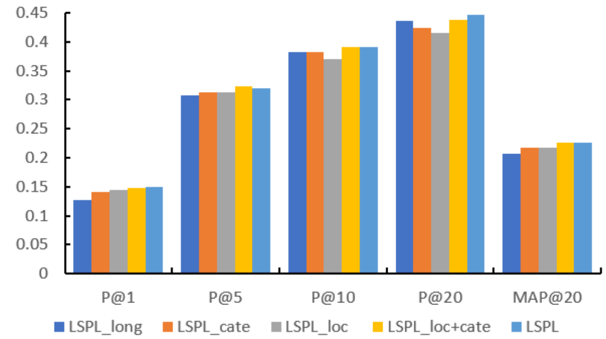

Figure 2: Comparison results of variant models.

6 CONCLUSION AND FUTURE WORK

In this paper, we proposed a unified model jointly learning users' long- and short-term preference for next POI recommendation. In long-term module, we characterize contextual features of POIs and capture the long-term preference via attention mechanism. In short-term module, we learn the location- and category-level preference by two parallel LSTM models. At last, we integrate the outputs of long- and short-term module to obtain the ranked list of candidate POIs. The experiments demonstrate that our model outperformed the state-of-the-art methods on real-world datasets. In future work, we would incorporate more context information into the model to further improve the performance.

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