PERSONALIZED SEQUENTIAL CHECK-IN PREDICTION: BEYOND GEOGRAPHICAL AND TEMPORAL CONTEXTS

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ABSTRACT

Check-in prediction is an important task for location-based systems, which maps a noisy estimate of a user's current location to a semantically meaningful point-of-interest (POI), such as a restaurant or store. In this paper, we leverage the personalized preference and sequential check-in pattern to improve the traditional methods that base on the geographical and temporal contexts. In our approach, we propose a Gaussian mixture model and a histogram distribution estimation model to learn the contextual features from relevant spatial and temporal information, respectively. Furthermore, we employ user and POI embeddings to model the personalized preference and leverage a stacked Long-Short Term Memory (LSTM) model to learn the sequential check-in pattern. Combining the contextual features and the personalized sequential patterns together, we propose a wide and deep neural network for the check-in prediction task. Experimental evaluations on two real-life datasets demonstrate that our proposed method outperforms state-of-the-art models.

Index Terms— Deep Learning, Recurrent Neural Network, Location-based Services, Check-in Prediction

1. INTRODUCTION

Location-based services are very popular now, owing to the explosive increase of smart-phones. On the one hand, traditional online social networks such as Facebook and Twitter allow users to tag geographical information when reporting states and twitts. On the other hand, professional location-based social networks such as Yelp and Foursquare arouse to provide special location-aware services, such as restaurant recommendation. In order to acquire the user location information, location-based services encourage users to check-in where the users are. The check-in activity records users' geographical information, which delivers significance in three aspects: 1) providing opportunities for location-based applications such as POI recommendation [1, 2, 3]; 2) increasing user viscosity in the social networks; and 3) helping researchers understand the human mobility behavior.

The check-in service in location-based systems aims to label where the user locates given the GPS information. Correspondingly, the task of check-in prediction arouses, i.e., mapping a noisy estimate of a user's current location to a semantically meaningful POI. In practice, the location-based systems yield a POI list according to the user's current geographical information (i.e., latitude and longitude). And the generated POI list is expected to contain the POI where the user wants to check-in and rank the POI as highly as possible.

Two issues make the check-in prediction task very challenging. First, each POI's geographical information recorded from users' check-ins encounters a high variance, resulted from the following reasons: 1) a POI may correspond to a big region, for instance, a university covers a large region; and 2) GPS on current mobile devices is not accurate. The high variances on POIs make the check-in prediction far from an easy one-one map task. Second, the places in urban areas are highly dense, for instance, many companies are located in the same office building and different shops are in the same shopping mall. From the 2D perspective, POIs in the same building are highly contiguous, even overlapping in GPS information. Moreover, inaccurate GPS for POIs especially in the indoor scenarios deteriorates to find the desirable POI from its spatial neighbors.

In this paper, we propose the personalized sequential check-in prediction problem, which mines users' personalized check-in preferences and mobility patterns to improve the prediction results. Our proposed personalized sequential check-in prediction problem is similar to the next POI prediction task [1, 4, 5]. Both tasks mine users' check-in records to predict POIs. The difference lies in that the predicted POIs for the personalized sequential check-in prediction problem should satisfy the specified context, namely the GPS information, because predicting POIs far away from the fetched GPS is meaningless. Inspired by the work in POI prediction [1, 4, 5], we leverage users' check-in preferences and sequential patterns to improve the check-in prediction task. We propose a deep neural network model to learn the personalized sequential check-in prediction problem. In particular, we represent the user and POI in embedding spaces and learn the user preference from the check-in history records. Furthermore, we employ a stacked Long-Short Term Memory (LSTM) model to effectively acquire the check-in sequential pattern. Finally, we propose a wide and deep neural network to incorporate the personalized sequential features along with the context information to infer a POI list for each user given the specific context, i.e., GPS and time stamp. We conduct elaborated experiments on two real-life datasets. Experimental results demonstrate that our proposed model effectively captures the personalized sequential features and improves the check-in prediction.

We summarize the contributions of this paper as follows.

- This is the first work for personalized check-in prediction. Compared with general check-in prediction based on context information (i.e., the geographical information and time stamp), personalized check-in prediction incorporates the user mobility pattern and provides better check-in services.

- We propose a deep neural network model to learn the user preference and sequential pattern in the check-in activity, which significantly improves the check-in prediction. In particular, we employ user and POI embeddings to model the personalized preference and propose a stacked LSTM model to learn the sequential check-in pattern.

- We conduct elaborated experiments on two real-life datasets. Experimental results show that our model outperforms state-of-the-art check-in prediction methods.

2. RELATED WORK

In this section, we review the related work in three aspects: check-in prediction, POI prediction and recommendation, and Recurrent Neural Network (RNN) models.

The problem of check-in prediction is first proposed in [6], which introduces the framework in Foursquare to create a POI list for users' check-in activities. The work in [6] analyzes the POI features (e.g., popularity, spatial characteristic) and user feature (e.g., the number of visits on POIs), and then leverages the LambdaMART [7] to learn a ranked POI list. Check-in prediction resembles the POI identification task [8, 9, 10], which maps a user's current location to a POI in a database with unique GPS information. Compared with POI identification, the check-in prediction problem is more complicated due to the uncertain GPS information for each POI.

POI prediction (or recommendation) in LBSNs has been well studied recently [1, 4, 5, 11, 12, 13], which aims to predict where the user will visit in the future via mining the check-in records. The major difference between POI prediction and check-in prediction lies in the predicted POIs for check-in prediction must satisfy the querying context GPS and predicting POIs far away from the querying GPS is meaningless. Studies in POI prediction indicate that, 1) personalization improves prediction accuracy [12, 13, 14], and 2) user check-ins exhibit sequential pattern: next checked-in POI can be inferred from a user's recent check-ins to some extent [1, 4, 5]. Inspired by these observations, this paper proposes personalized sequential check-in prediction, which leverages the personalized user preference and sequential mobility pattern to improve the check-in prediction task.

Recurrent Neural Network (RNN) model and its variants, i.e., Long-Short Term Memory (LSTM) model [15] and Gated Recurrent Unit (GRU) model [16] have been successfully utilized for sequence modeling. Particularly, the power of RNN models for sequence modeling inspires researchers to employ RNN models for recommendation systems [17, 5]. The work in [17] exploits GRU for session-based recommendations. The work in [5] leverages the RNN for next POI prediction. However, the proposed models in [5, 17] cannot handle the long dependency in a sequence for the check-in prediction task, so we employ a stacked LSTM to model the check-in sequence.

Connection to prior work. Our proposed personalized check-in prediction model takes both the user behavior understanding and the context information to infer a user's check-in. Although previous work [6, 9] considers the personal check-in history to infer possible POIs, the proposed models in [6, 9] simply assume that prior checked-in POIs are preferred rather than learning the personalized check-in preferences. Moreover, the important characteristic, i.e., check-in sequential pattern, is ignored in prior check-in prediction model [6] and POI identification systems [8, 9, 10].

3. PROBLEM DESCRIPTION

Definition 1 *(Check-in prediction) The task of check-in prediction aims to map the fetched GPS information $\langle g_x, g_y \rangle$ to a semantically meaningful POI p for user u at time t.*

Practically, the location-based system yields a POI list according to the user's current geographical information for the check-in prediction task. Supposing L denotes the POI set, the check-in prediction task aims to estimate the probability, $P(l|g_x, g_y), \forall l \in L$.

Estimating the probability $P(l|g_x, g_y)$ is challenging. Each POI contains geographical information collected from historical check-ins with high variance. Moreover, different POIs may share overlapping GPS information. Fig. 3 shows two POIs' geographical information: both POIs' geographical information contains variance and overlaps with each other. To overcome such challenges, this paper proposes a personalized sequential check-in prediction, exploiting users'

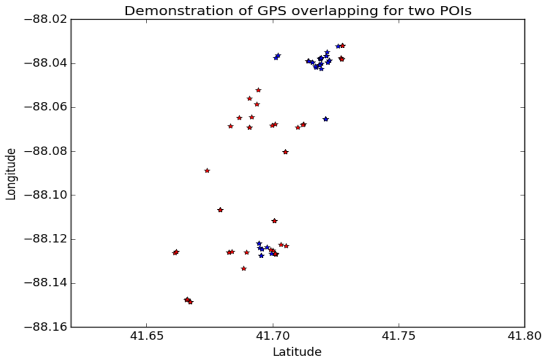


Fig. 1. Demonstration of geographical information for two different POIs

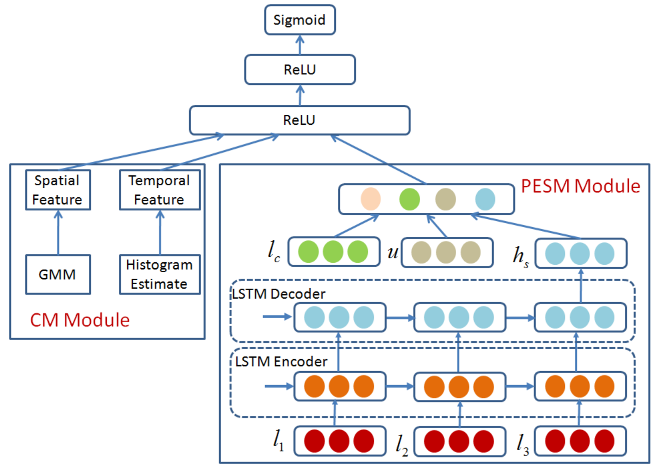


Fig. 2. Personalized sequential check-in prediction model

personalized preference and sequential check-in pattern to improve the check-in prediction accuracy.

Definition 2 *(Personalized sequential check-in prediction) Personalized sequential check-in prediction aims to predict a POI list L_c given the check-in context information $\langle g_x, g_y, t\rangle$ and a user u's check-in sequential records L_s.*

Here, given by $L_s = (l_1 \rightarrow l_2 \rightarrow \cdots \rightarrow l_s)$ a user u's previous check-in sequence before time t, the personalized sequential check-in prediction aims to calculate the probability $P(l|g_x, g_y, t, u, L_s), \forall l \in L$.

4. MODEL

We propose a wide and deep neural network as a unified framework to jointly learn the context information and personalized sequential mobility pattern for the personalized sequential check-in prediction task, shown in Fig. 2. In the wide neural network part, we build the context modeling (CM) module, aiming to predict the check-in from the geographical and temporal information. In the deep neural network part, we establish a personalization enhanced sequence modeling (PESM) module. In particular, we learn user and POI embeddings from the check-in records to model the personized preference and use a stacked Long-Short Term Memory (LSTM) network to model the sequential mobility. Furthermore, we engage a two-layer fully connected Rectified Linear Units (ReLU) [18] to learn the combined contextual features and personalized sequential features, where the second ReLU layer contains half hidden neurons of the first ReLU layer. Finally, we use a sigmoid activation layer to map the function value as a probability estimation.

4.1. Context Modeling (CM) Module

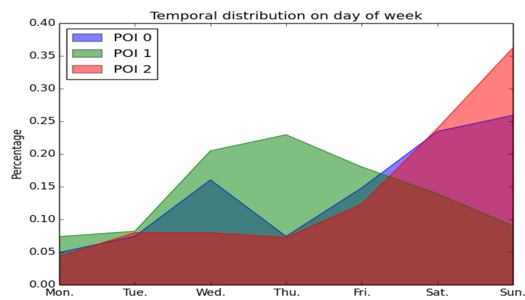
The CM module leverages the domain knowledge to analyze the relations between the context information and POIs, and predict the check-ins. This module establishes models to infer the possible check-in POI from the geographical context (i.e., GPS information) and the temporal context (i.e., time stamp), respectively.

Learning from Geographical Context. The key of check-in inference from the geographical context is to estimate a distribution $P(g_x, g_y|l)$ for prior check-ins happening at l. As shown in Fig. 3, a POI corresponds to multiple GPS records. We assume Gaussian noise on the observed GPS information, and propose a Gaussian mixture model to estimate the GPS distribution,

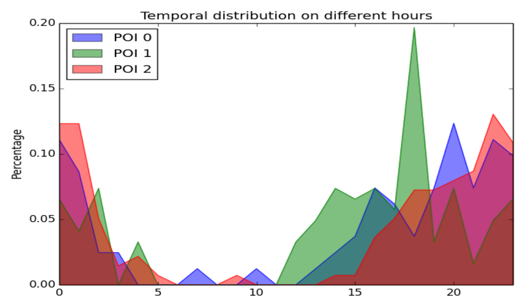
$$P(g_x, g_y|l) = \sum_k \pi_k \mathcal{N}(l|\mu_k, \sigma_k), \tag{1}$$

where $\mathcal{N}(l|\mu_k, \sigma_k)$ represents a Gaussian distribution with mean μ_k and covariance σ_k evaluated at location l, where π_k denotes the mixing proportions. Different locations need different k values. For example, an outdoor coffee shop may only needs a center, while an airport is too huge to be satisfied by one center. In this paper, we use Dirichlet Process GMM to automatically choose k.

Learning from Temporal Context. We have the intuition that POIs enjoy different probabilities to be checked-in at the different time. For example, nightclubs are more likely to be visited at night while the office tends to be visited in the day time. Figure 3 demonstrates the normalized distribution for three randomly selected POIs on two temporal scales: day of week and hour in one day. We observe, 1) POI 0 and POI 2 are more likely to be checked-in on weekends while POI 1 gets higher probability on weekdays; 2) POI 0 and POI 2 are more likely to be checked-in in the evening while POI 1 gets higher probability in the afternoon. The observation verifies our intuition POIs enjoy different probabilities to be checked-in at the different time. Hence, we model the temporal context using the histogram probability in two scales: day of week and hour in one day.



(a) Temporal distribution on day of week



(b) Temporal distribution on different hours

Fig. 3. Temporal distribution for three randomly selected POIs

4.2. Personalization Enhanced Sequence Modeling (PESM) Module

The most challenging issue is to learn the personalized and sequential features, which are beyond explicit context information. Inspired by the success of deep learning, especially the RNN models for sequence modeling, we propose a deep neural network to learn the personalized and sequential features.

Referring to the work [19], we use a two-layer stacked LSTM to learn a user's sequential mobility pattern. The first layer is used to encoder the check-in sequence L_s, and the second layer is used to model the sequential dynamics. Given L_s as input, the stacked LSTM (SLSTM) model outputs a vector $\mathbf{h}_s$ to represent the sequence information. Omitting the details of LSTM model, we use SLSTM to represent this module,

$$\mathbf{h}_s = \mathrm{SLSTM}(L_s). \tag{2}$$

Motivated by the success of embedding learning [20, 21], we further employ the embedding representations to express the user and POI latent features and learn the personalized check-in preference.

4.3. Model Interpretation

Our personalized sequential check-in prediction model aims to calculate the probability $P(l|g_x, g_y, t, u, L_s), \forall l \in L$. Our neural network model can be interpreted as follows. We assume that the context information (i.e., geographical information and time stamp) and personalized sequential features independently affect the check-in activity. Furthermore, we assume the two kinds of context information are independent from each other. Then, we can leverage a Bayesian rule to deduce the probability of a candidate POI l,

$$P(l|g_x, g_y, t, u, L_s) \propto P(g_x, g_y|l)P(t|l)P(l, u, L_s), \tag{3}$$

where $P(g_x, g_y|l)$ denotes the probability (g_x, g_y) belonging to location l, $P(t|l)$ denotes the probability of l is checked-in at time t, $P(l, u, L_s)$ denotes the personalized check-in probability of user u given the previous check-in sequence L_s. Specifically, $P(g_x, g_y|l)$, $P(t|l)$, and $P(l, u, L_s)$ represent the geographical feature, temporal feature, and personalized sequential feature, respectively. Finally, we use linear neural connections to combine different features and predict the check-ins.

5. EXPERIMENTS

In this section, we conduct experiments on two real-life LBSN datasets to evaluate our proposed method. In particular, we aim to seek the answers to the following questions. 1) How does our proposed method comparing with state-of-the-art methods? 2) How does each component in our joint deep neural network take effect?

5.1. Experimental Settings

We use two check-in datasets crawled from real-life LBSNs: Foursquare data provided in [22] and Gowalla data in [23]. We preprocess the data based on the following two reasons: 1) POIs with a few records can be affected by the noisy check-ins adversely, especially the collected GPS information for the POI, and 2) the sequential pattern is not obvious for those users with a few check-ins. Hence, we filter the POIs checked-in by less than five users and users whose check-ins are less than ten times. After the preprocessing, the datasets contain the statistical properties as shown in Table 1. In order to make our model satisfactory to the scenario of future check-in prediction, we choose the first 80% of each user's check-ins as training data and the remaining 20% for test data.

Following [6], we use the precision@1, abbreviated as $P@1$ for evaluation. This is an important metric measuring the accuracy of the first predicted POI. $P@1$ is the most important metric for check-in prediction, especially for auto check-in in location-based systems.

5.2. Model Comparison

We compare our model with the following baselines.

- **Geographical Nearest Neighbor (GNN)**. This method recommends geographically nearest N POIs to the

Table 1. Statistics of datasets

Source	**Foursquare**	**Gowalla**
#users	10,180	3,318
#POIs	16,561	33,665
#check-ins	867,107	635,600
Avg. #check-ins each user	85.2	191.6

fetched GPS for check-in prediction. Because each POI corresponds to multiple GPS pairs, we use an averaged GPS to estimate each POI's geographical location.

- **RankList**. This is a ranking method used in [9] for POI identification, mapping the context information, i.e., geographical feature and temporal feature, to the most possible POI.
- **LambdaMART**. This is state-of-the-art learning to rank method, which is used for check-in prediction in [6], delivering state-of-the-art check-in prediction result.
- **LSTM** and **stacked LSTM (SLSTM)**. These two methods are state-of-the-art RNN models for sequence learning, which can be used to predict the check-in from the sequential patterns.

5.3. Experimental Results

Table 2 shows the experimental results for model comparison. We obtain the following observations. First, the context information, especially the geographical information plays an important role in the check-in prediction task. The baselines including GNN, RankList, and LambdaRank demonstrate decent results. Compared with the sequential models LSTM and SLSTM, the context inference models (i.e., RankList and LambdaRank) show better performance because of the direct relations between the context information and the checked-in POI. Second, the sequential models, LSTM and SLSTM, can predict the check-ins without the context information, only mining users' check-in patterns. In addition, according to our extra calculation the overlapping corrected predictions in sequential models (i.e., LSTM and SLSTM) and context inference models (i.e., GNN, RankList, and LambdaRank) are less than 50%. Hence, the sequential models and context inference models predict the check-ins from two perspectives to some extent. Third, our proposed model achieves the best performance. Through combining the contextual information and the personalized sequential information, our model delivers better performance. Hence, our proposed personalized sequential check-in prediction can improve the traditional check-in prediction task. Moreover, the higher P@1 value turns out our model can be used to improve the auto check-in function in location-based systems that are usually based on traditional check-in prediction methods.

Moreover, we conduct experiments to learn how each module in our model contributes to the check-in prediction task, shown in Fig. 4. We predict the check-ins only based on the features generated from CM module and PESM module respectively. Our model only based on the context information shows comparable performance with the prior ranking methods. Our PESM module shows better performance than the SLSTM, because we also incorporate the personalized information. Moreover, the experimental results demonstrate the effectiveness of our model—the wide and deep neural framework absorbs each module's information and shows significant improvements.

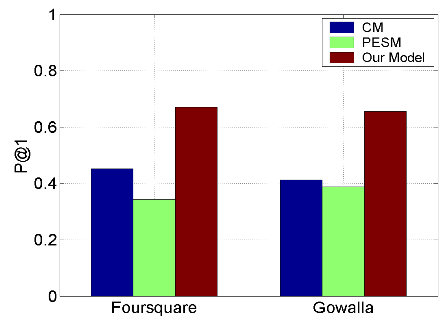


Fig. 4. Comparison of different module learning

6. CONCLUSION AND FUTURE WORK

In this paper, we attempt to resolve the personalized check-in prediction task. In particular, we predict check-ins through a wide and deep learning framework, which subsumes two modules: the CM module for context (i.e., geographical and temporal information) inference and PESM module for personalized sequential pattern learning. Moreover, we conduct experiments on two real-life datasets. The experimental results show that our model outperforms state-of-the-art check-in prediction models. Because our model predicts the check-in beyond the geographical and temporal contexts and benefits from the personalized sequential pattern learning as well. In the future, we may consider using users' social information to improve the check-in prediction. We independently model each user in this paper. In fact, friends in LBSNs share similar preference such that we can use this kind of social information to enhance our model.

Acknowlegement

The work described in this paper was partially supported by the Research Grants Council of the Hong Kong Special Administrative Region, China (No. CUHK 14208815 and No. CUHK 14234416 of the General Research Fund), and 2018 Microsoft Research Asia Collaborative Research Award.

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Table 2. Comparison of different methods

	GNN	RankList	LambdaRank	LSTM	SLSTM	Our Model
Gowalla	0.144	0.421	0.510	0.215	0.351	**0.656**
Foursquare	0.152	0.453	0.532	0.191	0.310	**0.671**

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