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Dynamic metric embedding model for point-of-interest prediction

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HIGHLIGHTS

- We first study temporal factors systemically and utilize spatial information for POI prediction.
- Based on metric embedding, our model combines temporal and spatial factors into a unified models.
- Evaluations prove that DME-TS outperforms state-of-the-art methods and our model's flexibility.

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ABSTRACT

POI (Point-of-interest) prediction is a significant issue in recent years. It can not only enhance user experience in location-based service and apps but also promote the perceived ability of business to potential consumers. However, the accuracy of POI prediction is seriously dragged down by data sparsity. To remedy the problem, recent researches studied various context factors. But their models only focus on part of context factors and are not well compatible for new factors. To address these challenges, in this paper, we first propose a unified flexible model 'Dynamic Metric Embedding with temporal (T) and spatial (S) factors' (DME-TS), since it is based on metric embedding (ME), which can map various factors into a unified Euclidean space and learn them collectively to resolve data sparsity. At the same time, temporal factors are studied systemically from three aspects: dynamic personal interest, temporal non-uniformness, temporal sequentiality. In order to represent each factor in Euclidean space, we propose several targeted methods. First, Long Short Term Memory is brought into metric embedding to depict user's dynamic interest. Then, to character temporal non-uniformness, we develop a self-attention method, which can estimate the temporal relationship between user's behaviors. Besides, to depict temporal sequentiality and spatial influence, Euclidean distance and spatial distance of successive check-ins are utilized. Next, these factors are combined into metric embedding, forming our model DME-TS. Finally, experiments are conducted on two publicly available datasets. The experimental results demonstrate the effectiveness of DME-TS, which improves the state-of-the-art method performance nearly 10%.

1. Introduction

Recently, more and more mobile applications collect massive individuals' check-in information, including POI (sometime also called location) and time. Users expect mobile applications, which can provide more personalized service and especially can apperceive their evolving preference. For instance, if users are provided potential favorite restaurants, they need not to spend much time to seek favorite restaurant from all the candidates. At the same time, service providers, such as restaurant, transportation and mobile game, also eager to catch users' behavior pattern, so they can provide better service. Such as, hotel booking application could predict users' next behavior, and attract the potential users in advance. Additionally, by predicting individuals' next behavior, government could learn crowds' behavior trends and do a good job in traffic grooming work ahead of time. All of these urge better models to predict users' behavior from plentiful check-in history.

In POI prediction, data sparsity of individual's check-in history affects the accuracy heavily. At the same time, POI prediction is a complex task. Many factors influence it collectively, such as dynamic personal preference, temporal non-uniformness, temporal sequentiality and spatial influence. There needs a model to

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consider all of the factors above together. In the past few years, though part of these context information has been widely studied, none of them can consider all the factors together or are compatible for new factor. In 2013, Yuan et al. [1] first proposed users' behavior is time-aware, they considered user may have different behaviors during different hours in a day, which is also called temporal non-uniformness, and they employed a unified framework, UTE+SE, integrating the temporal and spatial factors to improve location prediction performance. They demonstrated the significance of temporal non-uniformness in POI prediction. Nevertheless, other temporal factors are ignored in their model, such as temporal sequentiality. Subsequently, Liu et al. [2] provided an ingenious model based on Recurrent Neural (RNN), called ST-RNN, which not only can learn user's sequential behavior but also can character different temporal intervals and spatial distances by transition matrices. However, the relationships between transition matrices are neglected, and much more parameters need to be learned in their model. Besides, the temporal non-uniformness is also unconsidered. Meanwhile, Liu et al. [3] proposed a recommender system WWO, which learns the distributions of the temporal intervals between two historical check-ins by assuming user's behavior is effected by several behaviors before. However, temporal non-uniformness is also left out in their model. We can discovery that recent researches only focused on part of context factors above. Meanwhile, the models they proposed are only good at special scene. When considering more factors, the models will not work very well, since they do not have good flexibility.

In this paper, to address data sparsity and utilize various factors collectively for POI prediction, metric embedding framework is introduced. It was first proposed in playlist prediction [4]. The framework provides a generalizing representation of items into Euclidean space, which is good at depicting the transition between items by Euclidean distance. Therefore, context features can be fused into the transition model intuitively. To make full use of context information, we extract four factors from temporal information systemically and spatial information: (1) User's dynamic interest. Because user's state will evolve by the time in fact, but early researches [5] assumed user's state is changeless. For example, if a user prefers culture this month. He/She would like to visit theater or museum. But in next month, he/she may be inclined to entertainment, then he/she would like to visit amusement park or bar. Therefore, we would consider user's dynamic nature by temporal information. To represent user's dynamic nature, Long Short Term Memory (LSTM) is first introduced into metric embedding. (2) Temporal non-uniformness. It is an important factor, which is usually ignored by recent researches. Since user may have different behaviors during different hours in a day, POIs also have different popularities during different hours in a day. For example, office, museum and beach are preferred in the daytime. Hotel, restaurant and bar are popular in the night. To character temporal non-uniformness, we propose a self-attention method, which can distinguish each POI's liveness from an intuitive perspective. (3) Temporal sequentiality. It is also a significant factor. By way of illustration, after shopping in market, user tends to visit a restaurant for diet. There exists underlying sequential pattern in users' behavior. Based on metric embedding, we utilize Euclidean distance between POIs to depict the temporal sequentiality. (4) Spatial Influence. Since spatial information plays a key role in POI prediction, spatial influence will also be included in our model. Finally, to combine these factors above, we propose a model named Dynamic Metric Embedding with Temporal and Spatial factors (DME-TS). Through metric embedding, these factors are easier to be integrated, which makes our model more flexible.

Table 1
Details of two datasets.

Dataset	#user	#loc	#check-in	Time range
Foursquare	2,321	5,596	194,108	08/2010–07/2011
Gowalla	10,162	24,250	456,988	11/2009–10/2010

In this paper, our contributions are listed as follows:

- To address the problem of data sparsity, we first study temporal factors systemically and make full use of temporal and spatial information for POI prediction. The targeted methods are proposed to depict temporal and spatial factors in Euclidean space.
- To combine temporal and spatial factors into a unified model, our model DME-TS is proposed. It is based on metric embedding, which makes our model more flexible for various context factors.
- Extensive evaluations are conducted on two benchmark datasets for POI prediction. The empirical results prove that DME-TS outperforms other state-of-the-art methods. They also demonstrate our model's flexibility for combining various factors.

2. Analysis of context factors

To analyze the effect of context factors, we will observe two publicly available datasets. One is Foursquare dataset, the other is Gowalla dataset [1]. These datasets are widely used in POI prediction. In Foursquare dataset, 194,108 check-ins are made within Singapore from August 2010 to July 2011. And in Gowalla dataset, 456,988 check-ins are produced within California and Nevada in America from February 2009 to October 2010. Each check-in includes three parts, $\langle user, loc, time \rangle$. *loc* means POI or location. Each *loc* is associated with geographic coordinate. The details about datasets are listed in Table 1. Since text information is not included in both datasets, we cannot show user's dynamic interest by analysis of two datasets. To observe the influence of other context factors on users behavior, we will analyze them from three perspectives: temporal non-uniformness, temporal sequentiality and spatial influence.

2.1. Temporal non-uniformness

Temporal non-uniformness means POI has different popularity in different hours of one day. Since different POIs provide different service, they will have their popular temporal spans in a day. Fig. 1 shows two POIs' checked-in distribution in different hours. From the figure, we can observe that POI *a* is popular in midnight, location *b* is popular in afternoon. And the distributions of check-in frequency in consecutive hours are very similar. This is in accordance with the observation in [1]. When making prediction, the locations which are popular in target hour will be prior to others.

2.2. Temporal sequentiality

Fig. 2 illustrates the cumulative distribution function (CDF) of two successive check-ins. After visiting a POI, nearly 50% of continuous check-ins happen in less than 12 h on Gowalla, and 45% check-ins happen in less than 12 h on Foursquare. This is almost consistent with [5]. From these observations, we can discovery that nearly half of continuous check-ins happen in a continuous period of time, there would be relationships between them more or less. And from Fig. 2(a), we could also find the cumulative distributions grow fast in less than 6 h for both datasets. So we guess that as the temporal interval is less, the sequential influence would be more important.