Efficient Point-of-Interest Recommendation Services With Heterogenous Hypergraph Embedding

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Abstract—Point-of-interest (POI) recommendation service has drawn growing attention with the widespread popularity of location-based social networks (LBSNs). Recent research methods on POI recommendation based on graph embedding have mainly focused on explicit interactions of LBSN objects such as user s check-ins on POIs and social relationships, while neglecting implicit relationship that cannot be directly observed but may notably contribute to the POI recommendation. This paper presents VirHpoi, a heterogeneous hypergraph embedding method for POI recommendation in LBSNs with three original contributions. First, we model the LBSNs as a hypergraph to capture the complex interactions in LBSNs and learn the hypergraph by preserving homophily and interaction attribute affinity of the LBSNs. Second, we introduce the notion of "virtual hyperedges" to capture the intrinsic correlations of POIs. Virtual hyperedges incorporate implicit yet informative connections of the check-in patterns in LBSNs in terms of geographical and semantic characteristics. Third, we propose techniques to learn heterogenous hypergraph embedding on the complex LBSN graph with both homogenous edges and heterogenous hyperedges with dual objectives: we aim to preserve the homophily of objects intra domain by maximizing the co-occurrence probability of all homogenous edges, and we want to learn the interaction attribute affinity across domains by maximizing the probability of predicting the target object in the hyperedges. As a result, our approach can preserve both the intra domain homophily of objects and the interaction attribute affinity across domains by learning low-dimensional embeddings of LBSN objects and then make more effective recommendations based on the embeddings. Extensive experiments on four real-world datasets show the effectiveness and superiority of VirHpoi compared with the state-of-the-art methods.

Index Terms—Graph embedding, heterogeneous hypergraph, location-based social networks, POI recommendation

1 Introduction

Location-based social networks (LBSNs) [1], [2], [3] continue to receive growing attention with the popularity of smart mobile devices and the advancement of location acquisition technologies. Millions of users engage in LBSN services like Facebook, Foursquare, to name a few. In order to improve service experience for users, the point-of-interest (POI) recommendation service [4], [5], [6] which aims to recommend new and potentially attractive POIs to users has gained great research interest, as it can benefit not only users, but also advertising agencies for effective advertisements.

Studies on POI recommendation mainly consider four influencing factors: geographical influence, social relations, temporal dynamics and activity categories. Early works usually consider these factors separately, and combine their corresponding results together to perform recommendation [7], [8], [9], [10]. Recent advances of representation learning in networks (a.k.a. graph embedding) provide an opportunity to exploit and integrate these influencing factors [11], [12], [13], by modeling the LBSNs as a graph and embedding each node of the network into a low-dimensional latent space while preserving the key topological information.

While most of existing graph embedding works [14], [15], [16] model the LBSNs as several relational bipartite graphs or regard the LBSNs as a graph with only pair-wise connections (c.f. Fig. 1a), LBSNs are inherently heterogenous which have various types of relations and objects including users, POIs, categories and time slots. Therefore, simplifying the essential tuple-wise relationship into pair-wise one cannot fully capture the information from the check-ins, and may degrade the joint interactions of all objects from four domains in a check-in record into the interactions of several pair-wise objects, which will inevitably lead to the loss of structure information [17], [18].

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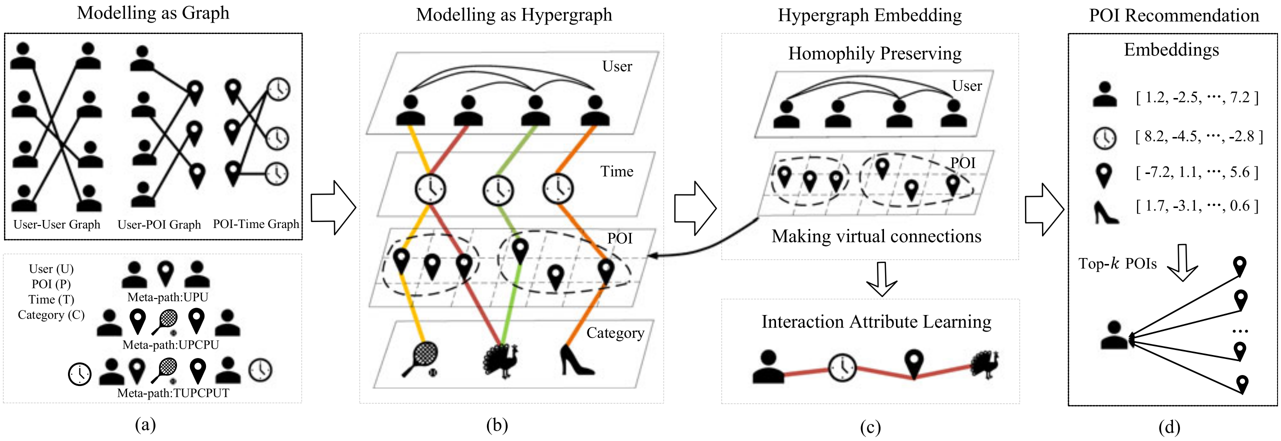

Fig. 1. (a) The LBSNs are modeled as bipartite graphs or heterogenous graphs with only pair-wise connections, where the joint interactions of all objects from four domains (user-time-POI-category) in a check-in record are degraded into the interactions of several pair-wise objects. (b) We model the LBSNs as a heterogenous hypergraph and introduce virtual hyperedges (clusters containing multiple objects) to incorporate implicit relationships in the LBSNs. Friendships are represented by classical edges (black lines) linking two users, while check-ins are modeled as hyperedges (colored thick line) linking four nodes, one from each domain. (c) We learn heterogenous hypergraph embedding by preserving both the homophily of objects intra domain and the interaction attribute affinity across domains. (d) Top-k unvisited POIs are recommended to each user based on the heterogenous hypergraph embeddings.

To rectify such drawbacks, recent works [19], [20] propose to adopt the hypergraph to better describe the tuple-wise relationship, where check-ins are modeled as hyperedges and friendships are modeled as classical edges. In their designs, however, they only concentrate on explicit check-ins and friendships, while neglecting implicit relationships that cannot be directly observed but may notably contribute to the recommendation. In particular, there are classical edges in social domain and hyperedges linking four nodes, one from each domain, but no direct connection exists in other domains. In practice, there often exists correlation between POIs and they are not completely independent. For example, a classroom is more related to a library than a gym. Some POIs may be of different categories, but they have correlations and similar appeals to users. Therefore, the correlations of POIs are much useful for recommendation tasks and should be taken into consideration. The existing works only concentrate on explicit interaction links. We aim to leverage these enriched correlations for improving new POI recommendation.

In this paper, we address the above problems by developing a novel heterogeneous hypergraph embedding method for POI recommendation in LBSNs, coined as VirHpoi. Our key idea is to model the LBSNs as a heterogenous hypergraph and introduce the notion of the "virtual hyperedges" to incorporate implicit yet informative connections of the LBSNs. Intuitively, users are more likely to check in on new POIs that have a higher degree of relationship with their previously visited POIs, and new POI recommendation would benefit from the embeddings of POIs with high correlations. Moreover, the virtual connections are conducive to shorten the distance between users and potentially appealing but unvisited POIs and thus help make more precise recommendation. Besides, the graph based methods are potentially more vulnerable to data sparsity. The virtual connections will help deal with the data sparsity issue to an extent.

Although the idea sounds simple, there are two technical challenges to be addressed. The first challenge is how to make effective virtual connections, which plays an important role in improving the performance of the POI recommendation. To tackle this issue, we analyze and reveal the check-in patterns in terms of geographical and semantic characters using real-world data, and further propose two kinds of similarity metrics to quantify the corresponding two factors, based on which we can perform valid virtual connections. The constructed virtual hyperedges contain multiple objects which have implicit relatedness. They are in fact potential neighbors that may not be directly reachable on graphs. The second challenge is how to learn the heterogenous hypergraph graph embedding on such complex graph with both homogenous edges and heterogenous hyperedges. To cope with this problem, we maximize the co-occurrence probability of all homogenous edges to preserve the homophily of objects intra domain, and learn the interaction attribute affinity across domains by maximizing the probability of predicting the target object in the hyperedges. As such, we can preserve interaction information of the LBSNs by learning low-dimensional embeddings of the objects and then conduct effective POI recommendations.

Our major contributions are summarized as follows:

- We propose a heterogenous hypergraph embedding based POI recommendation method, which models the LBSNs as a hypergraph to capture the complex interactions in the LBSNs and learns the hypergraph by preserving homophily and interaction attribute affinity of the LBSNs.
- We incorporate implicit connections of POIs by establishing virtual hyperedges in the LBSN heterogenous hypergraph, which enables more efficient embedding from latent geographical and semantic characters in the LBSN hypergraph.
- We conduct extensive experiments to evaluate the performance of VirHpoi on four real-world datasets. The results show the effectiveness and superiority of VirHpoi compared with the state-of-the-art methods.

We should emphasize that our virtual hyperedges are not limited to the POI domain. In other domains, such as

TABLE 1
Statistic of Datasets

Dataset	Users	POIs	Check-ins	Friendships
New York	12,062	11,422	443,284	14,346
Tokyo	14,441	16,265	1,311,614	40,252
Istanbul	16,925	12,780	650,451	2,466
Jakarta	11,407	11,184	502,540	14,998

user or category domain, we can also design appropriate metrics to establish virtual hyperedges, so as to incorporate more implicit correlations which introduce latent patterns of objects in the LBSNs to recommendation model and further improve the recommendation performance.

The remainder of this paper is organized as follows. In Section 2, we analyze the geographical and semantic characters of the LBSNs for better establishing virtual connections. Section 3 details the design of the heterogenous hypergraph embedding. We report our experiment results in Section 4. Section 5 reviews some related works, and finally Section 6 concludes the paper. The code of VirHpoi has been released for reproducibility purposes[1].

2 Empirical Data Analysis

In this section, we conduct an empirical data analysis to reveal check-in patterns of the LBSNs in terms of geographical and semantic factors for incorporating implicit relationships in the hypergraph embedding, using the global-scale check-in data collected in [21], [22] from Foursquare between Apr. 2012 and Jan. 2014. In our analysis, we take cities as basic units and select four different datasets with large numbers of check-ins from the raw check-ins: New York City (NYC), Tokyo (TKY), Istanbul (IST) and Jakarta (JK). Each check-in record contains a user, a POI, and a corresponding timestamp; descriptive information of POIs such as longitude, latitude and categories are also available. Each dataset also contains a snapshot of socially connected friendship. Following previous work [16], we select users who have check-ins at least 5 times and POIs with more than 10 visitors to avoid very inactive users and POIs. The detail statistics of the datasets are shown in Table 1.

2.1 Geographical Characters of the LBSNs

Geography is an important factor that distinguishes POI recommendation from traditional item recommendation, as the check-in behavior is closely related to locations geographical features. Intuitively, people tend to visit neighboring POIs subject to geographical constraints. We can infer that the influence of geographical adjacent on user check-ins follows a certain pattern, which can be utilized for POI recommendation. We perform a spatial analysis on the four datasets by measuring the likelihood that two of a user's check-ins are within a given distance. Specifically, to obtain the likelihood, we calculate the geographical distances between all pairs of check-ins by the same user and plot a histogram to show the statistics.

1. https://www.dropbox.com/s/ey79crqa0xrdg8l/VirHpoi-Code.zip?dl=0

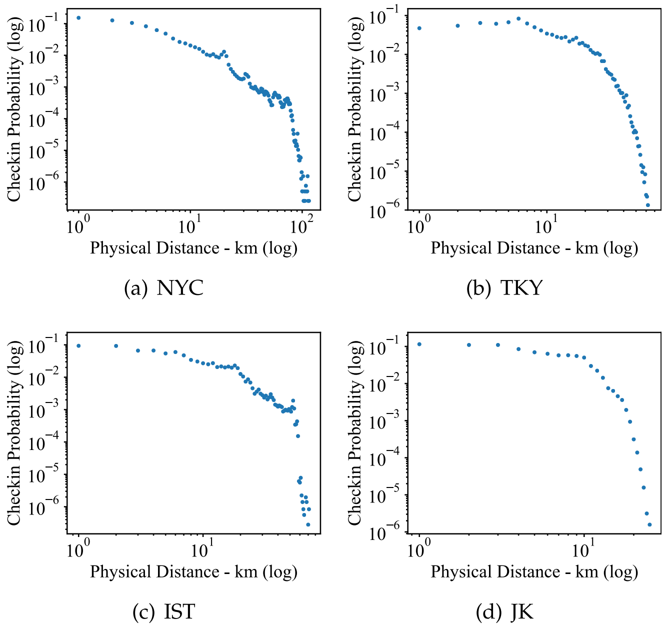

Fig. 2. Geographical influence probability distribution on four datasets. Our piece-wise function can fit the city-scale large datasets better.

Fig. 2 shows the results of geographical influence on check-ins on the four datasets. From the results, we can observe an obvious geographical clustering phenomenon. As the distance between two POIs increases, the probability of a user checking in from one POI to another decreases. Comparing to distant places, users are more inclined to visit closer POIs or POIs near those already being visited.

Considering the data characteristics, we propose to employ the power-law distribution to model the geographical influence of the user's check-in behavior on POIs [23]. It can be observed from Fig. 2, however, that the check-in probability of POIs visited by the same user over distance is not a standard power-law distribution. That is because our datasets include POIs within the city range, and the geographical range is not very large. Therefore, unlike existing works [24], [25], [26] which usually directly use power-law distribution to fit all check-ins of a platform, we test it on city-scale large datasets and design a piece-wise function according to the tendency in our results, which is formulated as follows:

$$f_g(p_n, p_m) = \begin{cases} a_1 \cdot d(p_n, p_m)^{b_1} & 0 < d(p_n, p_m) < d_1 \\ a_2 \cdot d(p_n, p_m)^{b_2} & d_1 \le d(p_n, p_m) < d_2 \\ a_3 \cdot d(p_n, p_m)^{b_3} & d_2 \le d(p_n, p_m) \end{cases} \quad (1)$$

where a_i, b_i and d_i are parameters to be learned, and $d(p_n, p_m)$ refers to the physical distance between POI p_n and p_m. Physical distances less than 0.01 km are treated as 0.01 km. $f_g(p_n, p_m)$ represents the calculated probability of a user checking in from p_n to p_m. From the decreasing curve in Fig. 2, we can infer that the calculated parameter $b < 0$. So, when $d(p_n, p_m)$ is small enough, the calculated $f_g(p_n, p_m)$ may vary in a large scale.

The probability $f_g(p_n, p_m)$ that a user checks in from one POI to another can be used to quantify the geographical similarity of POIs. For our POI recommendation task, if a