HoST: Exploiting Heterogeneous Spatial-Temporal Graph for Next POI Recommendation

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ABSTRACT

Next Point-Of-Interest (POI) recommendation focuses on recommending next POIs for users to visit based on their historical check-in sequences. Recent work leverages graph structures (e.g., predefined POI graphs) and Graph Neural Networks to capture global user preference, which have brought significant improvements. However, there are still several under-explored challenges. *(C1) How to construct fine-grained spatial-temporal context graphs?* Most existing methods construct large global graphs as model input, which is neither efficient nor informative for a single user. *(C2) How to build a unified spatial-temporal model?* Most existing approaches follow the Sequence Augmented by Graph (SAG) paradigm, which uses sequential models as backbones and graph models as supplements. Their overall frameworks are usually overly complex. *(C3) How to model multi-granular temporal periodicity?* Users naturally have multi-granular movement patterns.

To address these challenges, we introduce a novel heterogeneous spatial temporal method called HoST. For *(C1)*, we introduce HoST-Graph to first construct a fine-grained global Heterogeneous Spatial Temporal Graph (HSTG) by exploiting all check-in sequences and the inherent spatial-temporal dynamics, and then sample a relative spatial-temporal context (i.e., ego-graph) for the target user and time. For *(C2)*, we propose to directly use the sampled ego-graph as the context to refine user embeddings regardless of distant past check-ins. We refer to this new paradigm as Spatial-Temporal Context (STC) paradigm. Under the STC paradigm, we introduce a simple unified model HoST-GNN$_{\text{base}}$ based on Graph Attention Network, which is equipped with trainable edge type embeddings and spatial-temporal slot embeddings. To further address *(C3)*, multi-granular temporal slot embeddings are introduced and thus we have our full model HoST-GNN. Comprehensive experiments on benchmark datasets demonstrate the effectiveness of HoST.

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KEYWORDS

Point-of-Interest; Heterogeneous Spatial-Temporal Graph

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1 INTRODUCTION

With the widespread applications of positioning technology and mobile internet, Location-Based Services (LBS) have become an indispensable part of people's daily lives. LBS providers, such as Google Map, Yelp and Foursquare, enable users to share information on Point-Of-Interests (POIs) and record their movement trajectories. To improve users' experience and relevant services such as advertising strategies [15], the next Point-Of-Interest recommendation systems have been developed to model users' mobility patterns and recommend them attractive POIs based on their historical check-ins and current spatial-temporal context.

Most existing approaches make recommendations based on users' own historical check-in sequences. Earlier works use Markov chains to capture the dependencies between observed visits and next POI decisions [3, 8]. Later, spatial-temporal aware Recurrent Neural Network (RNN) based methods [7, 19, 38, 55] become mainstream due to their strong capability of handling sequential data. Recently, several spatial-temporal-aware self-attention based and Transformer based methods are proposed to model both successive and non-successive transition patterns within individual check-in sequences [24, 28, 31, 49]. However, most users only have a few check-in records in real-world datasets. The highly sparse user-POI interaction data cannot provide sufficient supervision signals, and thus it is difficult to make satisfying recommendations solely based on users' own check-in sequences. To tackle the data sparsity issue, several graph-augmented approaches have been proposed recently, which leverage global user-POI collaborative information to learn general user mobility patterns [22, 25, 26, 32, 33, 46, 51]. Specifically, they construct global graphs (e.g., user-POI and POI-POI graphs) based on all users' check-in sequences such that relevant users' records could complement each other.