Zone-Enhanced Spatio-Temporal Representation Learning for Urban POI Recommendation

En Wang, Yuanbo Xu, Yongjian Yang, Yiheng Jiang, Fukang Yang, and Jie Wu, *Fellow, IEEE*

***Abstract*—Points-of-interest (POIs) recommendation plays a vital role in location-based social networks (LBSNs) by introducing unexplored POIs to consumers and has drawn extensive attention from academia and industry. Existing POI recommender systems usually learn fixed latent vectors to represent both consumers and POIs from historical check-ins and make recommendations under the spatio-temporal constraints. However, we argue that the existing works still suffer from the challenges of explaining consumers' complicated check-in actions. To this end, we first explore the interpretability of recommendations from the POI aspect, i.e., for a specific POI, its function usually changes over time, so representing a POI with a single fixed latent vector is not sufficient to describe the dynamic nature of POIs. Besides, check-in actions to a POI are also affected by the zone where it is located. In other words, the zone's embedding learned from POI distributions, road segments, and historical check-ins could be jointly utilized to enhance POI embeddings. Along this line, we propose a Time-zone-space POI embedding model (ToP), which integrates multi-knowledge graphs and topic model to introduce not only spatio-temporal effects but also sentiment constraints into POI embeddings for strengthening interpretability of recommendation. Specifically, ToP learns multiple latent vectors for a POI in a different period with spatial constraints via knowledge graph learning. To add sentiment constraints, ToP jointly combines these vectors with the zone's representations learned by topic models to make explainable recommendations. ToP considers the time, space, and sentiment of POI in a unified embedding framework, which benefits the POI recommendations. Extensive experiments on real-world Changchun city datasets demonstrate that ToP achieves state-of-the-art performance in terms of common metrics and provides more insights for consumers' POI check-in actions.**

***Index Terms*—Embedding, interpretability, POI recommendation, zone-enhanced model.**

I. Introduction

LOCATION-BASED social networks (LBSNs), such as Foursquare[1] and Yelp,[2] are increasingly important as they bridge the gap between the physical world and online social networking services based on personal preferences [1], [2]. In LBSNs, consumers usually check in a Point of Interest (POI), with a high probability for them to share the check-in experience with real/virtual friends [3], [4]. These interaction data between consumers and POIs are growing at an unprecedented speed, which makes it difficult to accurately extract their preferences on POIs. To deal with the huge amount of data in LBSNs and understand consumers' personal preferences, POI recommender systems, aiming to recommend the POIs to consumers, which they may be interested in but have no check-in records yet, have attracted increasing attention from both academia and industry.

Unlike traditional personalized recommender systems, which push goods (e.g. news, music, and movies) based on prior knowledge/inputs of each consumer, POI recommendation aims at providing consumers (in this paper, consumers can be substituted by users) unexplored POIs according to their preferences [5]. Specifically, POI recommendations can be seriously affected by users' personal preferences, POIs' functions, and other real-world spatio-temporal factors. Considering these complicated factors, existing POI recommendation models [2], [6], [7], [8] usually learn fixed latent vectors to model users' preferences and POIs' functions by embedding historical check-in data and other side information (users' natural characters, POIs' descriptions, and check-in feedback ratings.). Then they utilize these latent vectors to make a POI recommendation under various spatio-temporal restrictions, which are widely applied in neural network based models, e.g. deep generative models [9], [10].

Although POI recommender systems have achieved great success, we are still facing many vital challenges: 1) **Interpretability**: most POI recommendation models concentrate on precision improvement and lack explainable formulations to understand the complicated user-POI check-in actions. Hence,

[1]https://foursquare.com/
[2]https://www.yelp.com/

Manuscript received 28 January 2021; revised 8 August 2022; accepted 27 January 2023. Date of publication 8 February 2023; date of current version 8 August 2023. This work was supported by the National Natural Science Foundations of China under Grants 61772230, 61976102, U19A2065, and 61972450, in part by the Natural Science Foundation of China for Young Scholars under Grants 61702215 and 62002132, in part by the China Postdoctoral Science Foundation under Grant 2020M681040, and in part by the Changchun Science, and Technology Development Project under Grant 18DY005, and in part by the National Defense Science and Technology Key Laboratory Fund Project under Grant 61421010418, and in part by the Science Foundation of Jilin Province under Grant 20190201022JC, and in part by the China National Postdoctoral Program for Innovative Talents under Grant BX20180140. An earlier version of this work appeared as a 10-page regular paper in IEEE INFOCOM 2021. However, this journal version has added the principles, details, analysis of our design, the case study, the related work, as well as substantial illustrations and revisions. [DOI: 10.1109/INFOCOM42981.2021.9488726]. Recommended for acceptance by N. Zhang. *(Corresponding author: Yuanbo Xu.)*

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Digital Object Identifier 10.1109/TKDE.2023.3243239

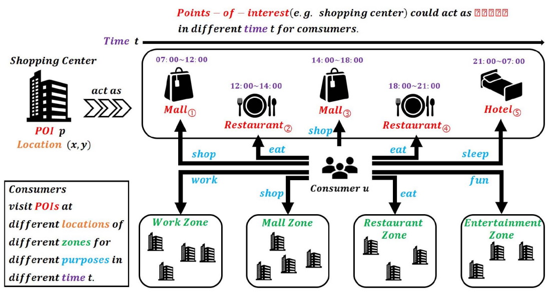


Fig. 1. An example to illustrate the **dynamic function** of POI over time and the chanllenge to explain the consumers' different **purposes** to check in POIs at different **location** of different **zones** at different **time**.

their recommendation results are usually unexplainable. In the real-world, different users usually visit the same POI for different purposes. For example, in Fig. 1, the consumer u may visit POI p repeatedly with different reasons for each time. He may visit p for sleep at midnight or just for a meal at noon. To enhance the performance of the POI recommendation, the interpretability of the model should be taken into consideration. 2) **Dynamic POI representation**: not only users' visiting purposes but also POI's functions are changing over time. In the real world, a POI may be multi-functional, but its representation in existing works is usually fixed, which limits the model's performance of POI recommendation. As shown in Fig. 1, POI p could act as a hotel, a mall, or a restaurant at different time t. A fixed latent vector learned by embedding models is not sufficient to explain the reason that a user visits a POI. Instead, a time-dependent representation of POI will be more meaningful and explainable for recommendations. 3) **Zone effect**: the functions of the zone where the POI locates may enhance or weaken the POI's recommendation priority. Specifically, a zone is a small urban area that has an obvious function, such as a work zone, mall zone, and entertainment zone. For example, when users enter mall zones, their visiting purposes may be affected by the zones' function, so they perhaps prefer visiting the malls rather than a hotel or a restaurant (Fig. 1). Hence, how to define the suitable zone area to learn a reasonable zone representation for enhancing POI recommendation is a more challenging problem.

To jointly address the above challenges, in this paper, we propose a **T**ime-z**o**ne-space **P**OI embedding model (**ToP**), which is an end-to-end framework for personalized and explainable POI recommendations. Specifically, a spatio-temporal knowledge graph embedding (STKGE) is employed to model the spatio-temporal representations of POIs' functions from side information and check-in data. Moreover, we propose a Topic Zone Embedding component (TZE) to learn meaningful representations for zones, where a road network-based zoning method is employed to define the reasonable zone areas from the physical map. Then the zone effect, combined with spatial and temporal effects, could be used to improve POI recommendations and understand users' check-in actions. Cooperating with these representations (POIs and zones), a unified knowledge graph-based recommendation model is devised to capture the dynamic of POI functions and zone effect, and further make short and long time-term explainable POI recommendations. Specifically, comparing to our prior work, we add spatial relations for POI representation learning, which improves ToP to a comprehensive embedding model that considers space, time, and zone effect simultaneously for POI recommendations.

Our primary contributions can be summarised as follows:

- We explore the limitations of POI representations, and address POI recommendation issues with knowledge graph embedding, which adds interpretability, the dynamic of POIs' functions, and zone effect into POI recommendations,
- According to the embedding results, we propose an end-to-end recommender system - ToP - to jointly learn both dynamic POIs,' and zones' representations, which significantly improves the recommendation performance. Besides, because ToP is a knowledge graph embedding-based model, it can make an explainable POI recommendation.
- Specifically, for learning representations from POI graphs in ToP, we propose a structural RotatE (sRotatE), which maps the entities and relations to the complex vector space and defines each relation as a rotation from the source entity to the target entity. With sRotatE, ToP can tackle different types of graphs and learn a proper set of representations.
- We evaluate ToP on the Changchun city dataset with several state-of-the-art recommendation models. The results show that ToP not only achieves stable performance compared with baselines in terms of common metrics (e.g., HR and NDCG) but also provide more insights into users' check-in actions and POIs' dynamic functions.

II. Preliminaries

A. Definitions

In POI recommender systems, U denotes a set of m users $U = \{u_1, u_2, \ldots u_m\}$, and P denotes a set of n POIs $P = \{p_1, p_2, \ldots p_n\}$. In our proposed model, we define a user-POI check-in action as a triplet Tr_{upt} $<u, p, t>$, which means u has checked in p at time t.

Definition 1. POI-POI Category Graph (C-graph): To consider the relation between POIs from a global view, we build a global POI-POI category graph $G^P = (V^P, E^P)$, in which vertexes V^P are the POIs' categories, and the edges E^P are the global relations between different POI categories. In this paper, we integrate check-in frequency (the overlap percentage or the transfer actions between different POI categories) as the weights of edges and build a weighted graph. This graph is fixed through all of the procedures, aiming at learning a global representation $\mathbf{p}^g$ for each POI category.

Definition 2. Spatial POI-POI Graph (S-graph): To consider the spatial relation between POIs, we built a spatial POI-POI graph, $G^S = (V^S, E^S)$, in which vertexes V^S are the POI sets, and the edges E^S are the spatial relations between different POIs. In this paper, we integrate distances as the weights of edges and build a weighted graph. This graph is fixed through all procedures, aiming to learn a spatial representation $\mathbf{p}^s$ for each POI.

Definition 3. Temporal User-POI Graph (T-graph): A user's check-in actions in a time period T are represented as a temporal

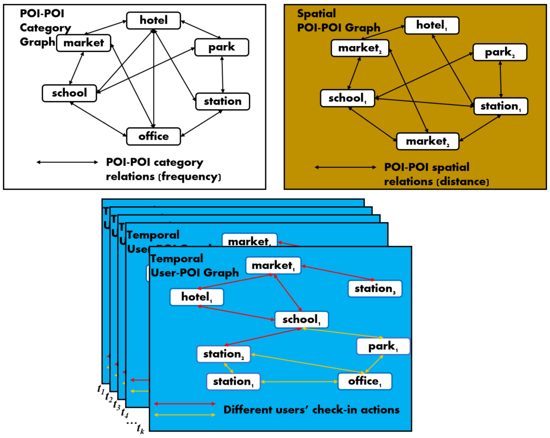


Fig. 2. POI-POI category graph, spatial POI-POI graph and temporal User-POI graph. All three knowledge graphs extract the users' different check-in action patterns jointly.

TABLE I
NOTATION LIST

Notation	Description
G^P	C-graph, POI-POI category graph
G^T	T-graph, Temporal user-POI graph
G^S	S-graph, Spatial POI-POI graph
p, z	Point of Interest/Zone
(h,r,t)	Triplet from graphs, **h,t** are embeddings
$\mathbf{p}^g, \mathbf{p}^t, \mathbf{p}^s$	Global/Temporal/Spatial embeddings of p
$\mathbf{z}^t$	Zonel embeddings of z at time t
$\mathbb{C}^k$	k-dimension latent space
$\mathbf{w}^t, \mathbf{w}^s$	Temporal/Spatial attention weights
$\mathbf{p}^c$	Spatio-temporal representation of p at time c
τ	Embedding margin in Loss function
n_n, n_k	Negative sampling number in STKGE/TZE
$\#(p_k, p_e)$	Frequency of POI pair $< p_k, p_e >$ occurence
$\mathbf{p}^s_{can}$,$\mathbf{p}^l_{can}$	Short term/Long term candidate POIs
$\mathbf{p}^s_{rec}$,$\mathbf{p}^l_{rec}$	Short term/Long term POI recommendations
η, α	Trade-off weights in STKGE/TZE

user-POI graph G^T=(V^P, E^T, T), in which vertexes V^P are the POIs, and the edges E^T are the check-in frequencies between these POIs at this period T. With many Tr_{upt}, this graph can completely describe users' check-in actions with structural information representation, to learn a dynamic POI representation $\mathbf{p}^t$. We give an example of all three knowledge graphs in Fig. 2.

The differences among T-graph, C-graph, and S-graph are: S-graph and C-graph are global stable graphs, which means that there is only one S-graph and one C-graph in our scenario, respectively. Note that the C-graph contains the POI category relations, weighted by the check-in frequency, while the S-graph contains the spatial relations between POIs, weighted by the geographical distance. Unlike the above graphs, the T-graph denotes the users' check-in actions at time T. So the T-graph is a time-dependent graph. C-graph, S-graph, and T-graph describe the complex city-scale POI check-in actions.

Definition 4. Zone Embedding: We define a zone as a small urban area that has an obvious function, such as a mall zone, work zone, and entertainment zone. To cooperate with the zone effect for POI recommendation, we study the zone's attributes, including POI distributions and historical user-POI check-ins, to learn a zone embedding vector **z** for representing the zone's functional attributes. Note that in the real world, the zone's functions are also varying with time. In this paper, zone embedding **z** is represented as $\mathbf{z}^t$ for zone's dynamic functions.

B. Problem Statement

Problem Statement: In this paper, we study the POI recommendation problem cooperating with dynamic POI representation and zone effect. For learning dynamic POI representation, we aim to automatically learn a time-dependent spatio-temporal latent vector to represent the POI's attributes, adding the model's interpretability. We extract three graphs (C-graph, S-graph, and T-graph) from multi-source data (e.g., check-in data, POI locations, and side information), from where we learn to represent the dynamic of POIs' functions. We formulate this problem as a task of multiple spatio-temporal knowledge graph embedding problems with multi-source data.

Meanwhile, for zone effect, we first divide the map into several fine-grained no-overlap zones and learn the zone embedding vectors from historical check-in data and POI distributions. Hence, this task is a joint embedding learning of dynamic POI and zone for an explainable POI recommendation with multi-source data.

Formally, we formulate the POI recommendation problem as a two-stage task:

1) Embedding stage: given a C-graph G^P, a S-graph G^S and a c set of T-graphs $G^T_{t_1}, G^T_{t_2}...G^T_{t_c}$, we aim to find a map function for each $G^T_t \rightarrow \mathbf{p}^t$ that takes each temporal user-POI graph G^T_t and G^S as input, and outputs the spato-temporal vectorized embedding $\mathbf{p}^t$ of the POI. Meanwhile, compare $\mathbf{p}^t$ with global representation $\mathbf{p}^g$, we can add insights into the dynamic of POIs' functions. Also we need get zone embedding $\mathbf{z}^t$ in this stage.
2) Zone-enhanced Recommendation: given zone embedding $\mathbf{z}^t$ learned by proposed model, we aim to enhance the POI recommendation with $\mathbf{p}^g$, $\mathbf{p}^t$, and $\mathbf{z}^t$, and explain why these users check-in these POIs at this time t. The notations in this paper are listed in Table I.

III. Time-Zone-Space POI Embedding

A. Framework Overview

Fig. 3 demonstrates the overview of our proposed model ToP, including the following tasks: 1) Learning dynamic POIs' representations to explain the purpose of users' check-in actions. 2) Learning dynamic zone embeddings with multi-source data. 3) Adding interpretability to enhance POI recommendations with dynamic POIs' representations and zone effect. In the first task, we build a POI-POI category graph (C-graph) to learn the global representation of POIs. we also build a spatial POI-POI graph (S-graph) and a set of temporal user-POI graphs

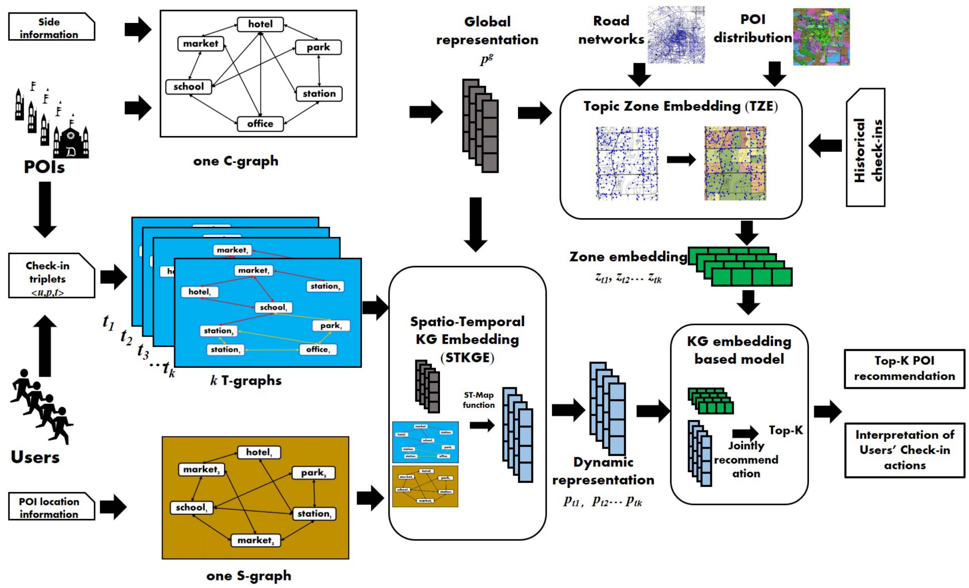


Fig. 3. An overview of learning dynamic POI presentation and explainable Top-k POI recommendation via the proposed ToP model. The inputs of ToP are side information, check-in triplets, and location information. These data form one C-graph, k T-graphs, and one S-graph. ToP utilizes the C-graph to obtain global representation and the T-graph and S-graph to obtain dynamic representation. Then combining the results of Topic Zone Embedding, ToP can output the Top-k recommendations and the interpretations.

(T-graphs) and propose spatio-temporal knowledge graph embedding (STKGE) to learn dynamic POI representations with global representations. In the second task, a topic zone embedding model is developed to learn zone embeddings with road networks, POI distribution, and historical check-in data. In the last task, we apply a knowledge graph embedding-based model with dynamic POI representations and zone embeddings to recommend Top-K POIs and analyze users' check-in actions.

B. Spatio-Temporal Knowledge Graph Embedding

In this section, we represent a POI with a set of time-dependent dynamic embedding vectors. We develop a spatio-temporal knowledge graph embedding (STKGE) model with the following intuitions:

Intuition 1. Global representation: A POI should have its basic attributes about categories, e.g., a school or a hospital. Specifically, we learn global representation from the transfer patterns extracted in POI-POI category graph. Thus, the global representation should be a part of the dynamic POI representation and contribute to POI recommendations. Our model should also input global representation as the initial POI representation through the learning process.

Intuition 2. Spatio-temporal constraints/relations: Learning POI representation in latent vector space should consider spatio-temporal constraints/relations. Because timestamps and coordinates are continuous variables, existing work usually discretizes them into temporal windows and spatial cells. However, in this paper, we transfer coordinates into euclidean distance between POIs to build a spatial POI-POI graph (S-graph) for modeling spatial constraints while using a set of temporal user-POI graphs (T-graphs), which are divided by time interval, to capture the temporal relations.

Intuition 3. Time-dependent dynamic: Unlike other methods with a fixed embedding for POI representation, we explore the insights on POIs' time-dependent dynamic functions. We argue that the temporal user-POI graph built from check-in triplets is different at different periods. Along this line, the representation of POI should be also dynamic at different periods. We need to capture the varying of POIs' functions to learn explainable representations.

1) Methodology for ST-KG Embedding: We first analyze the three different graphs. There exists two special relations except for the normal check-in relations: 1) circle visit: users may visit from p_1 to p_2 and return from p_2 to p_1, which means ($\mathbf{h}_{p_1}$, $\mathbf{r}$, $\mathbf{h}_{p_2}$) => ($\mathbf{h}_{p_2}$, $\mathbf{r}$, $\mathbf{h}_{p_1}$), it is a symmetry relation. 2) combine visit: users may visit p_3 passed by p_1 and p_2, which means ($\mathbf{h}_{p_1}$, $\mathbf{r}^1$, $\mathbf{h}_{p_2}$) $\wedge$ ($\mathbf{h}_{p_2}$, $\mathbf{r}^2$, $\mathbf{h}_{p_1}$) => ($\mathbf{h}_{p_1}$, $\mathbf{r}^3$, $\mathbf{h}_{p_3}$), $\mathbf{r}^3$ is a composed relation of $\mathbf{r}^2$ and $\mathbf{r}^1$. Existing knowledge graph embedding models, such as TransE [11] and TransD [12], cannot achieve a satisfying result according with the special relations above in a graph.

To learn the global representations from the POI-POI graph, inspired by RotatE [13], we propose **structural RotatE** (sRotatE) as the knowledge graph embedding method. Motivated from Euler's identity $e^{i\theta} = \cos\theta + i\sin\theta$, sRotatE model maps the entities and relations in KGs into the same complex vector space and defines each relation as a rotation from the source entity to the target entity. Different from Trans Embedding series, sRotatE models the weighted relation as rotations in a complex plane instead of a translation in a real line, which could solve the circle visit and combine visit issues in the embedding procedure. Moreover, sRotatE considers limited relation types and the connection between different graphs (S-graph and T-graph) to model the graph's structure, which is an improvement on RotatE.

2) Global Representation Learning: In our proposed model, given a POI-POI graph $G^P = (V^P, E^P)$ with triplets $(\mathbf{h}^p, \mathbf{r}^p, \mathbf{t}^p)$ ($\mathbf{h}^p$, $\mathbf{t}^p$ both are POIs' global representations $\mathbf{p}^g$, which can be switched according to the relations), we expect that $\mathbf{t}^p = \mathbf{h}^p \circ \mathbf{r}^p$, where $\mathbf{h}^p, \mathbf{t}^p \in \mathbb{C}^k$ are the embeddings and $\circ$ denotes the Hadamard (element-wise) products. Specifically, for each dimension i of embeddings we expect that:

$$t_i^p = h_i^p r_i^p, \tag{1}$$

where $h_i^p, r_i^p, t_i^p \in \mathbb{C}$ and the modulus $|r_i^p| = 1$. It turns out that this simple but useful operation can effectively model all three relation patterns: symmetric/antisymmetric, inversion, and composition. For example, if a relation $\mathbf{r}$ is symmetric (circle visit), each element of $\mathbf{r}$, i.e. r_i should only satisfy $r_i = e^{0/i\pi} = \pm 1$; if $\mathbf{r}^3$ is a combination of the other two relations $\mathbf{r}^1$ and $\mathbf{r}^2$, $\mathbf{r}^3$ should only satisfy $\mathbf{r}^3 = \mathbf{r}^1 \circ \mathbf{r}^2$ ($\mathbf{r}^1 = e^{i\theta_1}, \mathbf{r}^2 = e^{i\theta_2}, \mathbf{r}^3 = e^{i\theta_3}$, and $\theta_3 = \theta_1 + \theta_2$).

According to the above definitions, for each relation $(\mathbf{h}^p, \mathbf{r}^p, \mathbf{t}^p)$ in POI-POI graph, we define the distance function:

$$d_r = (\mathbf{h}^p, \mathbf{t}^p) = \|\mathbf{h}^p \circ \mathbf{r}^p - \mathbf{t}^p\|. \tag{2}$$

Negative sampling has been proved quite effective for both learning knowledge graph embedding [14] and word embedding [15]. To learn the representations, we need to minimize the distance of positive relations $(\mathbf{h}^p, \mathbf{r}^p, \mathbf{t}^p)$, and maximize the negative ones. In our proposed model, we employ a loss function with negative sampling like [13] for effectively optimizing distance-based models:

$$L^p = -\log\sigma(\tau_1 - d_r(\mathbf{h}^p, \mathbf{t}^p)) - \sum_{i=1}^{n_n} \frac{1}{k} \log\sigma(d_r(\hat{\mathbf{h}}_i^p, \hat{\mathbf{t}}_i^p) - \tau_1), \tag{3}$$

where τ_1 is a fixed margin, σ is a sigmoid function. $(\hat{\mathbf{h}}_i^p, \hat{\mathbf{t}}_i^p)$ is the i-th negative relation, and n_n is the negative sample number. Different from RotatE, for dynamic POI representation learning, we add two structural restrictions: $\sum_{i=1}^k h_i^p = 1$, $\sum_{i=1}^k t_i^p = 1$ to accelerate the processing and avoid overfitting.

After this processing, we can get the global representation $\mathbf{p}^g \in \mathbb{C}^k$ for each POI category.

3) Spatial-Temporal KG Representation Learning: To learn spatial-temporal dynamic representations from a set of user-POI graphs (T-graphs) and a spatial POI-POI graph (S-graph), we need to measure the change of POIs' functions over time explicitly, with the combination of spatial restrictions, and also the interpretability of representations. To solve the problem, we add both time and space restrictions for sRotatE.

Time restrictions: We restrict the dynamic temporal POI representation $\mathbf{p}^t$ with the attention weight vector $\mathbf{w}^t$ as the following form:

$$\begin{aligned} \mathbf{p}^t &= \mathbf{w}^t \otimes \mathbf{p}^g = w_1^t \mathbf{p}_1^g + w_2^t \mathbf{p}_2^g \ldots w_s^t \mathbf{p}_s^g \\ &= w_1^t \begin{bmatrix} p_{11}^g \\ p_{12}^g \\ \cdots \\ p_{1k}^g \end{bmatrix} + w_2^t \begin{bmatrix} p_{21}^g \\ p_{22}^g \\ \cdots \\ p_{2k}^g \end{bmatrix} + \cdots w_s^t \begin{bmatrix} p_{s1}^g \\ p_{s2}^g \\ \cdots \\ p_{sk}^g \end{bmatrix}, \end{aligned} \tag{4}$$

where s is the category number of POIs, k is the embedding dimension. $\sum_{i=1}^s w_i^t = 1$. With this form, our model can reveal the dynamic of POIs' functions by analyzing the weight vector $\mathbf{w}^t$. Note that at the beginning of this processing, the initialization of POI weight vectors should be one-hot style because all of the POIs have their own category information. e.g., $\mathbf{w}^{in}$ of a hotel is initialized as [0-restaurant,1-hotel,0-bar]. And after dynamic POI representation learning for time t, $\mathbf{w}^t$ could be [0.1, 0.2, 0.7], which reveals that this hotel changes to a bar at this specific time t.

Given a c set of temporal user-POI graphs $G_{t_1}^T, G_{t_2}^T \ldots G_{t_c}^T$, we can apply sRotatE on each user-POI graph at time t, like we did on POI-POI graph:

$$d_r = (\mathbf{h}^t, \mathbf{t}^t) = \left\|\mathbf{h}^t \circ \mathbf{r}^t - \mathbf{t}^t\right\|, \tag{5}$$

$$L^t = -\log\sigma(\tau_2 - d_r(\mathbf{h}^t, \mathbf{t}^t)) - \sum_{i=1}^{n_n} \frac{1}{k} \log\sigma(d_r(\hat{\mathbf{h}}_i^t, \hat{\mathbf{t}}_i^t) - \tau_2), \tag{6}$$

where τ_2 is a fixed margin, σ is a sigmoid function, $(\hat{\mathbf{h}}_i^t, \hat{\mathbf{t}}_i^t)$ is the i-th negative relation, and n_n is the negative sample number, $\sum_{i=1}^k h_i^t = 1$, $\sum_{i=1}^k t_i^t = 1$.

Spatial restrictions: We should consider the limitation of traditional spatial restrictions for POI recommendations. Basically, spatial relations are modeled with two styles: 1) Grid style, which divides the map into grids, and utilizes the hops between the grids where POIs locate as the spatial relations. 2) Distance style, which utilizes the euclidean distance as the spatial relations. We argue that the grid style may lose some personality of POI relations (different POIs located at the same grid may get the same spatial characters in embedding.). Additionally, employing distance style directly may ignore the road assignment effect on spatial relation (two POIs located at the different ends of highways may have a long euclidean distance but closer spatial relations.).

To overcome the limitations, we employ attention weights on euclidean distance to model the dynamic spatial relations, which consider the road assignment effects. Moreover, we notice that some spatial relations also change with time, which leads to specific spatial relations in a short time, and dynamic relations over a long time.

Associated with the time restriction, given a spatial POI-POI graph G^s, the style of spatial restrictions is:

$$\mathbf{p}^s = \mathbf{w}^s \otimes \mathbf{p}^g, \tag{7}$$

$$d_r = (\mathbf{h}^s, \mathbf{t}^s) = \|\mathbf{h}^s \circ \mathbf{r}^s - \mathbf{t}^s\|, \tag{8}$$

$$L^s = -\log\sigma(\tau_3 - d_r(\mathbf{h}^s, \mathbf{t}^s)) - \sum_{i=1}^{n_n} \frac{1}{k} \log\sigma(d_r(\hat{\mathbf{h}}_i^s, \hat{\mathbf{t}}_i^s) - \tau_3), \tag{9}$$

where τ_2 is a fixed margin, σ is a sigmoid function. $(\hat{\mathbf{h}}_i^s, \hat{\mathbf{t}}_i^s)$ is the i-th negative relation, and n_n is the negative sample number, $\sum_{i=1}^k h_i^s = 1$, $\sum_{i=1}^k t_i^s = 1$.

4) United Spatial and Temporal Map Representation Learning and Optimizations: To consider the overfitting problem in embeddings, we apply dropout [16] on global representation

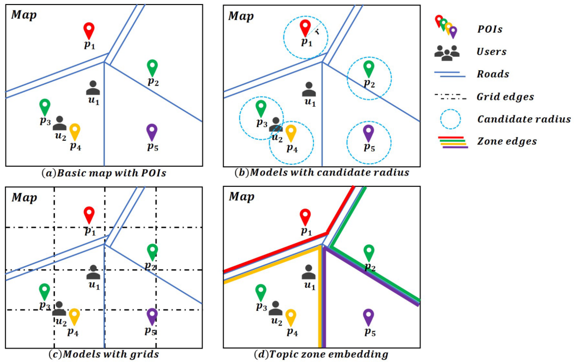


Fig. 4. (a) is the basic map with POIs. (b) (c) indicate the limitations of traditional POI recommendations. In (b), for u_1, no POI is selected as his candidates; for u_2, models are confused by choosing p_3 or p_4 for u_2. In (c), models ignore the road network between grids. In (d), we consider the road network and recommend POIs with different zone effects (different edge colors).

with POI-POI category graph:

$$'\mathbf{p}^g = \text{dropout}(\mathbf{p}^g), \tag{10}$$

where we replace all the $\mathbf{p}^g$ with $'\mathbf{p}^g$ in time restriction and space restriction loss functions as optimizations.

To learn the spatio-temporal representation from KGs efficiently, we co-train the POI embeddings with the time restriction and the space restriction in a weighted loss function:

$$L^{st}(c) = \eta L^s(c) + (1-\eta)L^t(c), \tag{11}$$

Where c is a specific time, η is a space-time trade-off parameter (0,1). Finally, instead of combining two representations directly, we employ a gate mechanism to cooperate with the learned temporal vector $\mathbf{p}_c^t$ and $\mathbf{p}_c^s$ to achieve the spatio-temporal representation:

$$\mathbf{v}^c = \sigma(\mathbf{W}_t\mathbf{p}^t + \mathbf{W}_s\mathbf{p}^s), \tag{12}$$

$$\mathbf{p}^c = \mathbf{v}^c\mathbf{p}^t + (1-\mathbf{v}^c)\mathbf{p}^s. \tag{13}$$

With these loss functions on each temporal user-POI graph, POI-POI category graph, and spatial POI-POI graph (T-graph, C-graph, and S-graph) at time c, we can get the temporal dynamic representations $\mathbf{p}^1$, $\mathbf{p}^2 \ldots \mathbf{p}^c \in \mathbb{C}^k$, which are the input of the recommendation model.

C. Topic Zone Embedding

In this section, we explore the zone effect on POI recommendations. For POI recommendations, the spatial effect is important for candidate filtering and recommend models, and some existing models have done some effective work on spatial effect. However, we argue that it is still insufficient without considering the zone effect: 1) Candidate selection problem: Existing models usually utilize a radius as the POIs' candidate metric. As shown in Fig. 4, they set a radius r to be 100 meters from POIs, and only recommend these POIs to the users within the radius. Recommendation models may be confused or misled, when a user is not covered by any POI-centered circular areas or a user is just located in the intersecting region of several POI-centered circular areas. 2) Ignoring road networks: Some models split the map with grids and consider the effect between grids [17], [18]. This is also limited by ignoring connections between grids. In the real world, locations are split naturally by road networks. Without considering the road networks, the neighbor grids' spatial effect is not convincing.

To solve the problems, we propose topic zone embedding (TZE), which considers the road network in the real world and recommends POIs with zone effect. In TZE, we divide the map with the road networks and learn the embeddings of each zone from the POI distributions and historical check-in data. TZE has some advantages: the model splits the map into no-overlap subsections (zones) according to the road networks, where all the users will be covered and only covered by one zone, which solves the candidate selection problem. Meanwhile, because the zone has its function attributes represented by its embeddings, the POIs are enhanced or weakened in each zone, which leads to an accurate recommendation (as shown in Fig. 4(d), p_4 should be recommended to u_2 rather than p_3 at this time because the zone embedding is yellow, which means the zone's attribution matches p_4's function, thus enhances p_4).

In TZE, we first split the map with road networks with ARCMAP, which is the map editing tool used to extend and correct the selected roads and divide the city areas into fine-grained natural zones (shown in Fig. 6(a). Inspired by the probabilistic latent topic model in text analysis, we formulate TZE as follows:

Given a zone set z_1, z_2,... z_c, and POIs in each zone, TZE learns the zone's embedding from two aspects: temporal zone relations and spatial zone relations. We first define POI pair: a POI pair $< p_k, p_e >$ is two POIs that are both checked by one user at time t and $t \pm 1$, respectively. A user's check-in historical data $(p_1, p_2, p_3, \ldots .p_k ...)$ can be treated as a combination of many POI pairs $(< p_1, p_2 >, < p_2, p_3 > ...)$. TZE extracts the temporal zone relations:

$$\text{TC}_{ij}^t = \sum_{p_k \in z_i} \sum_{p_e \in z_j} \left(\mathbf{p}_k^t\right)^{\text{T}} \mathbf{p}_e^{t\pm1}, p_k, p_e \in < p_k, p_e >, \tag{14}$$

where $\mathbf{p}$ is the POI's dynamic representation $\mathbf{p}^c$ learned in STKGE, $\mathbf{p}^{t\pm1}$ is the previous or next check-in of one trajectory of a user. In this way, TC_{ij}^t measures the time correlation among zone z_i and z_j.

We define spatial neighbor zones as follows: if two zones z_i and z_j share two or more zone edges, they are spatial neighbor zones, $z_i \in N_{z_j}$. For spatial zone relation, TZE model utilizes the statistic of historical check-ins:

$$\text{sc}_{ij} = \sum_{p_k \in z_i} \sum_{p_e \in z_j} \log\left(\frac{\#(p_k, p_e) \cdot |L|}{\#(p_k) \cdot \#(p_e)}\right), z_i \in N_{z_j}, \tag{15}$$

where $\#(p_k, p_e)$ denotes the frequency of POI pair $< p_k, p_e >$ occurence. $\#(p_k)$, $\#(p_e)$ denote the frequency of single check-in on p_k and p_e, respectively. $|L|$ is the ratio of $< p_k, p_e >$ from all POI pairs. Considering the noise problem and negative sampling, we utilize SC_{ij} to measure spatial zone relations as:

$$\begin{aligned}\mathrm{SC_{ij}} &= \max\left(\sum_{\mathrm{p_k}\in \mathrm{z_i}}\sum_{\mathrm{p_e}\in \mathrm{z_j}} \log\left(\frac{\#(\mathrm{p_k},\mathrm{p_e})\cdot|\mathrm{L}|}{\#(\mathrm{p_k})\cdot\#(\mathrm{p_e})}\cdot\frac{1}{\mathrm{n_k}}\right), 0\right) \\ &= \max\left(\sum_{p_k\in z_i}\sum_{p_e\in z_j}\log\left(\frac{\#(p_k,p_e)|L|}{\#(p_k)\cdot\#(p_e)}\right) - \log n_k, 0\right)\end{aligned}, z_i \in N_{z_j}, \tag{16}$$

where n_k is the negative sampling number.

We utilize temporal zone relation TC^t_{ij} and spatial zone relation SC_{ij} to build zone relation triplets. Considering TC^t_{ij} and SC_{ij} jointly, we formulate spatio-temporal zone relations:

$$\mathbf{r}^z = \alpha \mathrm{TC}^t_{ij} + (1-\alpha)\,\mathrm{SC}_{ij}, \tag{17}$$

where α is a spatio-temporal weight. Hence, we can achieve a zone-zone graph with triplets $(\mathbf{h}^z, \mathbf{r}^z, \mathbf{t}^z)$.

Finally, we learn zone embedding from this zone-zone graph with sRotatE:

$$L^z = -\log\sigma(\tau_4 - d_r(\mathbf{h}^z, \mathbf{t}^z)) - \sum_{i=1}^{n_n}\frac{1}{k}\log\sigma(d_r(\hat{\mathbf{h}}^z_i, \hat{\mathbf{t}}^z_i) - \tau_4), \tag{18}$$

where τ_4 is a fixed margin, σ is a sigmoid function, $(\hat{\mathbf{h}}^z_i, \hat{\mathbf{t}}^z_i)$ is the i-th negative relation, and n_z is the negative sample number. Specially, we restrict $\mathbf{z}$ like we did on dynamic POI representation $\mathbf{z} = \mathbf{w}^z \otimes \mathbf{p}^g$, same as (4), and achieve a zone weight vector $\mathbf{w}^z$ for each time t.

D. ToP for Explainable POI Recommendation

1) Short Time-Term and Long Time-Term POI Recommendations: After we get the global POI representation $\mathbf{p}^g$, dynamic POI representation $\mathbf{p}^t$ and zone embeddings $\mathbf{z}^t$, ToP model can make an explainable recommendation for different time t. Specifically, ToP can achieve two different time-term recommendation tasks:

Short time-term POI recommendation: For POI recommendation in the same time period t, we employ a knowledge embedding-based recommendation model [19] to make recommendations with zone effect. Note that in this task, POIs' representations are different from initializations, but stable during the recommendation processure.

Given user's check-in location p_u at time t, we can apply the following function to get the accurate representation of users' potential next check-in POI:

$$\mathbf{p}^s_{rec} = \mathbf{p}_u \circ \mathbf{r}^t, \tag{19}$$

where $\mathbf{p}_u$ is the POI representation of p_u at time t, $\mathbf{r}^t$ is the POI-POI relation at time t. Note that we utilize a set of time-dependent vectors to represent the dynamic function of POI, but at each time the representation is stable. We select the zone where p_u is located, and its neighbor zones as candidate zones, calculate the similarity between $\mathbf{p}^s_{rec}$ and $\mathbf{p}^s_{can}$:

$$\mathbf{sim}(\mathbf{p}^s_{rec}, \mathbf{p}^s_{can}) = |\mathbf{p}^s_{rec}, \mathbf{p}^s_{can}|_E, p^s_{can} \in z_u \cup N_{z_u}, \tag{20}$$

where $\mathbf{p}^s_{can}$ is the candidate POI p^s_{can}'s representation, and p^s_{can} is located in z_u or z_u's neighbour zones. $|*|_E$ is the euclidean distance of $*$.

Long time-term POI recommendation: For POI recommendations in the different time period t and $\tilde{t}$, we notice that the POIs' functions are dynamic over time, which reveals the time effect; the candidate should be more than which in short-time term POI recommendation, which is under the spatial restriction. So, the user's potential next POI's representation for long-time term recommendation is:

$$\mathbf{p}^l_{rec} = \mathbf{p}_u \circ \mathbf{r}^{\tilde{t}}. \tag{21}$$

Note that we use POI-POI relation $\mathbf{r}^{\tilde{t}}$ to replace $\mathbf{r}^t$ in (19). Then we consider spatial restrictions when computing similarity, which adds candidate zones according to the time span $(\tilde{t} - t)$:

$$\mathbf{sim}(\mathbf{p}^l_{rec}, \mathbf{p}^l_{can}) = |\mathbf{p}^l_{rec}, \mathbf{p}^l_{can}|_E, p^l_{can} \in z_u \cup N^{\tilde{t}-t}_{z_u}, \tag{22}$$

We sort the similarity in ascending order and make a Top-K POI recommendation with short time-term, or long time-term restriction.

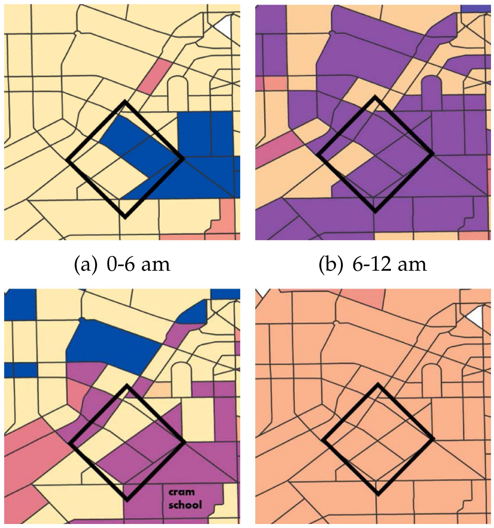
2) Zone-Enhanced Explainable Ranking for Recommendations: We add zone effect by computing a ranking score for each candidate POI p_{can} in candidate sets as:

$$\mathbf{score}(p_{can}) = \frac{1}{\mathbf{sim}(\mathbf{p}_{rec}, \mathbf{p}_{can})} + \frac{\lambda}{\mathbf{sim}(\mathbf{p}_{rec}, \mathbf{z}_{p_{can}})}, \tag{23}$$

where λ is the balance weight for the zone effect. If λ=0, it omits all the zone effects for POI recommendations. $\mathbf{z}_{p_{can}}$ is the zone embedding for where p_{can} locates. By this formula, if the candidate POI is similar to the object user's potential POI, and the function of the zone where it locates is more like the object user's potential POI's function, the candidate POI will achieve a higher score. By ranking these scores descending, we can achieve spatio-temporal zone-enhanced Top-K POI recommendations.

3) Interpretability: A Simple Case Study: ToP can not only learn dynamic POI and Zone representations from graphs for accurate POI recommendation but also give some explainable insights into recommendations. We introduce the interpretability with an example in Fig. 5: This marked area is a park (the park is not only a point on the map, so we mark it with a rectangle, it is a POI that contains different areas.) With our model, first, we can analyze the time effect on POI by computing the similarity of its temporal representation with POI global representations ($\mathbf{sim}(\mathbf{p}^t, \mathbf{p}^g)$), and achieve a clear change of its attributes over time dimension, as the visual function change from (a)-(d). Hence, the purpose of a user's check-in action on POIs at a different time can be achieved, which can explain POI recommendations.

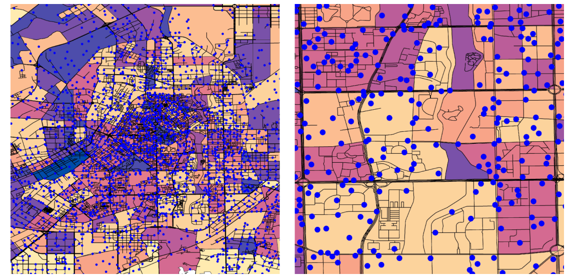
Second, by analyzing the zone embedding's dynamic function (17), (18), we can also understand the city's pulse and give introductions to urban computing. As shown in Fig. 5, the park's function is changed from park (0-6 am) to tourist area (6-12 am) to school area (12-6 pm) to the void area (6-0 am). Note that during weekends, people may go to the park for morning exercise (a), while some people who work on weekdays may go to the park for entertainment at the noon (b). The most interesting phenomenon is that (c) marks the park as a school area, which is not intuitive. After analysis, we notice that the neighbor of this



(a) 0-6 am (b) 6-12 am

(c) 12-6 pm (d) 6-0 pm

Fig. 5. A visual example to explain the model's interpretability (weekends). Blue-park, Purple-tourist area, Madder-school area, and Orange-void area.



(a) City-scale dataset (b) Region-scale dataset

Fig. 6. Changchun Datasets with different scales. The blue points are the POI distribution. The black lines are the road networks. The different colour are the zones. Note that zone distributions may be dynamic at different time.

TABLE II
DESCRIPTION OF CHANGCHUN DATASETS

Datasets	c-wd	c-we	r-wd	r-we
#Users	2,239,529	1,839,685	544,414	321,524
#POIs	2,185	2,193	67	66
#Check-ins	49,716,815	19,041,478	4,138,466	1,501,011
Sparsity	98.9%	99.5%	88.6%	92.9%

part is a cram school, and parents always pick the students up close to the park, which affects the park's function.

IV. EXPERIMENT

In this section, we first describe the experimental settings, including datasets, baselines, and other details. Subsequently, we conduct extensive experiments to answer the following research questions:

RQ1: How is the effectiveness of ToP? Can it provide a competitive Top-K POI recommendation compared with the state-of-the-art baselines?

RQ2: How does the proposed model enhance the interpretability of POI embeddings? How does this interpretability benefit the POI recommendation?

RQ3: How do the POIs' dynamic representations capture the temporal effect? How do zone embeddings capture spatial effect?

RQ4: What is the impact of three different graphs (C-graph, T-graph, and S-graph)? Which graph is more important for deducing people's check-in actions on weekdays/at weekends?

RQ5: How do the hyper-parameters affect the performance of ToP? Which are the optimal values?

A. Experimental Settings

1) Datasets and Preprocessing: We self-collect two raw datasets of Changchun city:

a) *Trajectory dataset:* It contains billions of raw trajectories collected by GPS devices in smartphones, from July to December in 2017.

b) *POI dataset:* It covers 3,402 POIs with 159 sub-categories of 12 main-categories. We delete the POIs with less than 200 check-ins in six months and the trajectory without any mobility in 24 hours as data pre-filtering.

Specifically, we use the trajectories from 3 rd July (Monday) to 9th July (Sunday), which contains 2,394,096 trajectories, and 2,198 POIs with 68,758,293 check-ins to learn POIs embeddings. First, we filter the POIs with no check-ins and rebuild two datasets to validate our algorithm in different scales LeftTop (longitude, latitude) - BottomRight (longitude, latitude), including city scale LT (125.319,43.862) - BR (125.358,43.832) and region scale LT (125.201,43.977) - BR (125.416,43.777), which are shown in Fig. 6.) We split a day into 4 time periods (6 hours for a time period. c=4). We also consider the check-in diversity between weekdays and weekends. Finally, we use four datasets to validate our model; City-scale Weekdays (c-wd), City-scale Weekends (c-we), Region-scale Weekdays (r-wd), and Region-scale Weekends (r-we). The dataset details are shown in Table II.

2) Baselines: To evaluate our proposed model on POI recommendations, we compare ToP with several representative recommendation models, including:

NCF [20] This model is a general framework, which replaces describing the interaction between users and items by the inner product with a neural architecture that can learn an arbitrary function from data. NCF is generic and can express and generalize CF and MF models under its framework. **GeoMF** [21] This model integrates spatial effect in user geographical regions and its propagation. **RGeoFM** [22] This model is a ranking based geographical factorization method incorporating the spatial-temporal factors, and give a rank score to make recommendations. **PACE** [23] This model builds a word2vec-based architecture to jointly learn the embeddings of users and POIs to predict both user preference over POIs and context associated with users and POIs. **KTUP** [24] This model especially accounts for various preferences in translating a user to an item, and then jointly trains it with a KG completion model by combining several transfer schemes. We treat POI recommendation as a 1 to N relation completion problem and solve it with KTUP.

TABLE III
PERFORMANCE EVALUATION COMPARED WITH BASELINE METHODS ON HR@N AND NDCG@N (CITY-SCALE DATASETS)

Dataset	Changchun c-wd						Changchun c-we					
Model	NCF	GeoMF	RGeoFM	Pace	KTUP	ToP	NCF	GeoMF	RGeoFM	Pace	KTUO	ToP
H@5	0.222	0.231	0.203	0.264+	0.143	0.275*	0.194	0.191	0.231	0.261+	0.079	0.289*
H@10	0.274	0.216	0.254+	0.250	0.162	0.381*	0.234	0.292	0.301	0.311+	0.161	0.397*
N@5	0.221	0.220	0.201	0.333+	0.194	0.412*	0.195	0.222	0.234	0.323+	0.103	0.383*
N@10	0.179	0.274	0.231	0.301+	0.131	0.346*	0.164	0.194	0.222+	0.213	0.089	0.251*

TABLE IV
PERFORMANCE EVALUATION COMPARED WITH BASELINE METHODS ON HR@N AND NDCG@N (REGION-SCALE DATASETS)

Dataset	Changchun r-wd						Changchun r-we					
Model	NCF	GeoMF	RGeoFM	Pace	KTUP	ToP	NCF	GeoMF	RGeoFM	Pace	KTUO	ToP
H@5	0.197	0.214	0.297+	0.291	0.098	0.351*	0.127	0.131	0.232	0.264+	0.101	0.321*
H@10	0.211	0.472	0.465	0.513+	0.201	0.589*	0.313	0.421	0.444+	0.397	0.201	0.516*
N@5	0.333	0.354	0.397	0.421+	0.201	0.541*	0.214	0.379	0.423+	0.411	0.272	0.512*
N@10	0.231	0.377	0.411+	0.400	0.132	0.501*	0.222	0.214	0.402+	0.311	0.203	0.491*

CT-ToP [25] This model is the former version of our proposed method, which utilizes only user-POI check-in actions to make POI recommendations. We compare and discuss CT-ToP and ToP in the ablation study section.

In the experiment, we split the datasets into two non-overlapping sets: for each user, the earliest 80% of check-ins are the training set and the remaining 20% check-ins are testing set. We initialize $\lambda = 0.6$ and $\alpha = 0.6$ for city-scale data, and $\lambda = 0.7$ and $\alpha = 0.5$ for region-scale data. We tune all the baselines to the best performance according to references where they were proposed. All the evaluations are performed on an x64 machine with Intel E5-1680 3.40 GHz CPU and 128 GB RAM. The operating system is CentOS 7.4.

3) Metrics: We evaluate the model performance in terms of two common ranking metrics: *Hit Ratio* (**HR@N**) and *Normalised Discounted Cumulative Gain* (**NDCG@N**). Specifically, HR measures whether the POIs in test datasets show within the top N in the ranked list, and the NDCG takes the position of the POIs in test datasets into account and penalizes the score if they are ranked lower in the list.

B. Overall Performance: POI Recommendation Accuracy (RQ1)

We compare our methods with the baseline methods in terms of two accuracy metrics: **HR@N** and **NDCG@N**. We give the general comparison in Tables III and IV on POI recommendation accuracy. Encouragingly, it is clear that the performance of our proposed model ToP is consistently better than all of the baselines under different datasets by a relatively large margin.

Note that RGeoFM and Pace are competitive to our proposed ToP. Then we explore the ToP's ability to make short-term ($t_c, c = 0$) and long-term ($t_c, c = 1, 2, 3$) POI recommendations, compared with RGeoFM and Pace on region-scale datasets (weekdays) in Fig. 7. The performance of RGeoFM and Pace recedes sharply when making the long-term recommendation. Because ToP considers the POIs' and zones' dynamic attributes, it can maintain stable performance for both short and long time recommend scenarios.

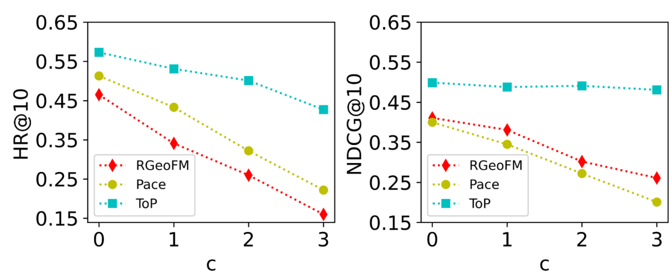


Fig. 7. Comparison of short-term ($t_c, c = 0$) and long-term ($t_c, c = 1, 2, 3$) POI recommendations with baselines.

C. Interpretability of Dynamic POI Learning: Attention Visualization (RQ2)

We explore the interpretability of POI dynamic functions with attention visualization. To take insights into POI representations learned by ToP, we visualize the attention weight w of two POIs at a different time on weekdays and weekends. As shown in Fig. 8, p_1 is with label **Cafe** in POI category data, so the initialization of w is one-hot style where the dimension **Cafe** is set to 1, the other dimensions are set to 0. Then we apply our proposed model ToP on p_1, to learn the dynamic POI representations. On weekdays, the most important features of p_1' representations at different time t are **Living**, **Office**, **Finance**, and **Public**, which reveals that p_1 should be a cafe that locates in an office building, and users often visit this location for work on weekdays. However, at weekends, the most important features change to **Leisure**, **Cafe**, **Media**, and **Public**, which reveals that there exists many entertainments among p_1 and users visit this location for leisure and entertainment at weekends. To validate our insights, We check the location of p_1 and find that there is a Wanda Plaza around p_1. The users often visit Wanda Plaza for work on weekdays and entertainment during weekends, which is consistent with our inference from dynamic POI representations.

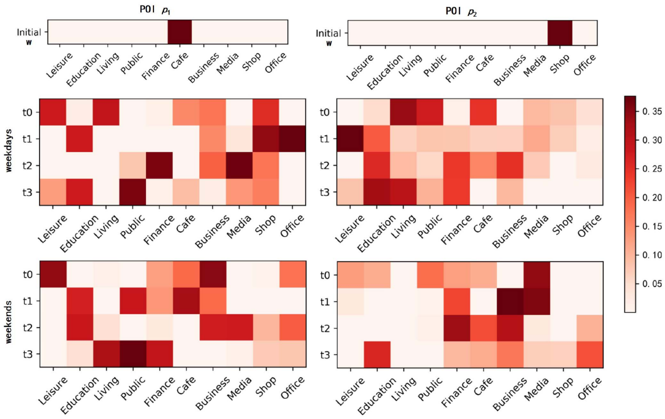
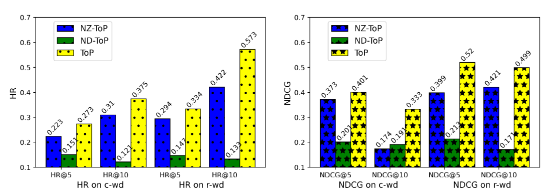


Fig. 8. Visualization of dynamic POI representations through weekdays and weekends. The color indicates the importance of dimensions in vectors.



(a) City-scale dataset (b) Region-scale dataset

Fig. 9. Validation of spatial/temporal effect of ToP on HR@N and NDCG@N.

We can also see the dynamic from p_2, and many other POIs with our proposed model.

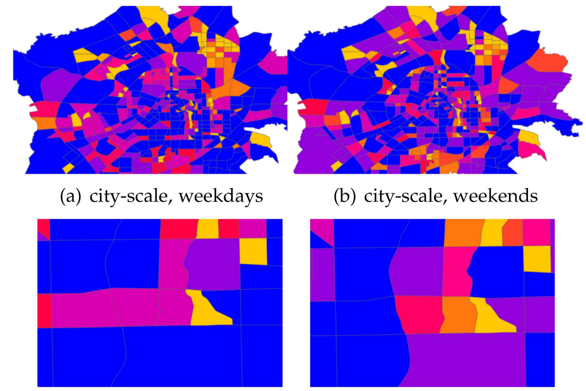
With these insights, we can give explainable recommendations. For example, if users are in the zone near p_1 on weekdays at time t_1, we should recommend some workplaces for them because p_1' most important feature at t_1 is office. While if users are in the zone near p_2 on weekends at t_2, we should give recommendations about finance or business instead of shops, according to the p_2' dynamic representations.

D. Impact of Spatial/Temporal Factors: Structure Ablation Validation (RQ3)

We explore the impact of spatial/temporal factors in ToP with the structure ablation validation. Note that in ToP, we use zone embeddings to capture the spatial effect and dynamic POI embedding to capture the temporal effect. Specifically, we build two sub-models: NZ-ToP: No-Zone enhanced ToP, which ignores the zone embeddings in (23). ND-ToP: No-Dynamic POI representation ToP, which uses global POI representation $\mathbf{p}^g$ to replace $\mathbf{p}^t$.

The results are shown in Fig. 9. The great performance improvement over NZ-ToP and ND-ToP indicates the effect of spatial/temporal factors in ToP.

Moreover, according to the zone's dynamic embeddings learned by ToP, we explore the dynamic of the zone's function through weekdays and weekends on city-scale and region-scale data, as shown in Fig. 10.



(a) city-scale, weekdays (b) city-scale, weekends

(c) region-scale, weekdays (d) region-scale, weekends

Fig. 10. Visualization of dynamic zone embedding through weekdays and weekends on city-scale and region-scale data at a time period.

Note that we merge the zones with similar embeddings. From Fig. 10(a) and (b), we can find that the zone's embeddings on city-scale datasets are different between weekdays and weekends at the same time, which reveals the necessity of TZE in ToP for POI recommendations. While in the lower part of Fig. 10(c), the blue zone (weekday) is an office function zone according to the embeddings learned by TZE, while it changes to a purple zone (weekend) which is a leisure zone. When validating this pattern in historical check-ins, users would work in this zone on weekdays and rest for fun during weekends, which inducts the recommendations. As a result, the dynamic of zone functions also gives explanations for users' check-in actions for POI recommendations. Moreover, we can see the varying of zones' functions to deduce the city's pulse for smart cities, such as population mobility and urban planning.

E. Impact of Multiple Graphs: Input Ablation Validation (RQ4)

We explore the impact of different graphs (POI-POI category graph C-graph, Temporal user-POI graph T-graph, and Spatial POI-POI graph S-graph) in ToP. To consider the possible combinations with three comprehensively, we build five sub-models based on ToP: 1) T-ToP: T-ToP utilizes $\mathbf{p}^t$ learned from T-graph as input $\mathbf{p}^c$; 2) S-ToP: S-ToP utilizes $\mathbf{p}^s$ learned from S-graph as input $\mathbf{p}^c$; 3) CT-ToP, CS-ToP, and TS-ToP: they are sub-models with different combinations of three graphs ($\mathbf{p}^p$ and $\mathbf{p}^t$, $\mathbf{p}^p$ and $\mathbf{p}^s$, and $\mathbf{p}^t$ and $\mathbf{p}^s$) as input $\mathbf{p}^c$, respectively. Note that the sub-model with only C-graph ($\mathbf{p}^p$) as input performs quite weak for not considering any dynamic relationships for POI recommendations, so we omit this sub-model. The results across all the five sub-models and proposed model ToP are listed as Tables V and VI.

From the experimental results, we can see that our proposed models achieve superior performance over all the sub-models with all metrics in both city-scale and region-scale datasets.

TABLE V
INPUT ABLATION VALIDATIONS ON HR@N AND NDCG@N (CITY-SCALE DATASETS)

Dataset	Changchun c-wd						Changchun c-we					
Model	T-ToP	S-ToP	CT-ToP	CS-ToP	TS-ToP	ToP	T-ToP	S-ToP	CT-ToP	CS-ToP	TS-ToP	ToP
HR@5	0.222	0.241	0.273^{+}	0.244	0.267	0.275*	0.177	0.142	0.246	0.264^{+}	0.234	0.289*
HR@10	0.316	0.320	0.375	0.376^{+}	0.346	0.381*	0.313	0.312	0.374^{+}	0.360	0.351	0.397*
NDCG@5	0.300	0.324	0.401	0.379^{+}	0.403	0.412*	0.316	0.370	0.377^{+}	0.361	0.372	0.383*
NDCG@10	0.291	0.301	0.333	0.354^{+}	0.312	0.346*	0.231	0.236	0.249^{+}	0.239	0.245	0.251*

TABLE VI
INPUT ABLATION VALIDATIONS ON HR@N AND NDCG@N (REGION-SCALE DATASETS)

Dataset	Changchun r-wd						Changchun r-we					
Model	T-ToP	S-ToP	CT-ToP	CS-ToP	TS-ToP	ToP	T-ToP	S-ToP	CT-ToP	CS-ToP	TS-ToP	ToP
HR@5	0.201	0.333	0.334	0.321	0.350^{+}	0.351*	0.226	0.254	0.289	0.271	0.293^{+}	0.321*
HR@10	0.472	0.534	0.573	0.563	0.580^{+}	0.589*	0.391	0.451	0.471	0.461	0.479^{+}	0.516*
NDCG@5	0.433	0.517	0.520	0.516	0.531^{+}	0.541*	0.414	0.444	0.483	0.496	0.500^{+}	0.512*
NDCG@10	0.412	0.464	0.499^{+}	0.481	0.499^{+}	0.501*	0.432	0.461	0.478	0.476	0.481^{+}	0.491*

While single graph-based sub-models perform weak, which validates the impact of cooperating three graphs (C-graph, S-graph, and T-graph) for POI recommendations.

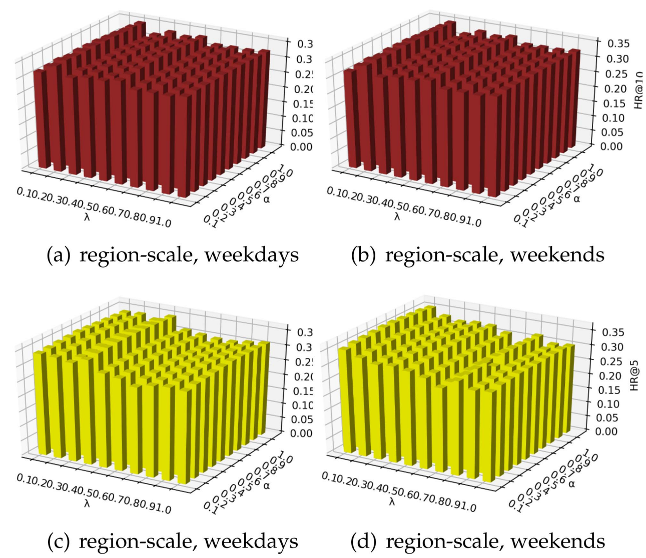
Besides, ToP improves our proposed model in CT-ToP [25], where we have considered the time factor and zone factor for POI recommendation. In ToP, three aspects of effects are utilized to learn a dynamic POI representation: Time, Space, and Zone. Specifically, we add a Spatial POI-POI graph, cooperating with a POI-POI category graph and a set of Temporal User-POI graphs to jointly extract the users' different check-in action patterns, which aims at achieving a comprehensive embedding for POIs. The experimental results also indicate the effectiveness of ToP. This is the core improvement and the changes of the CT-ToP compared to ToP.

Taking into deep insight, we notice some interesting phenomena: first, on Changchun c-wd, CS-ToP achieves the best performance among the sub-models, while CT-ToP achieves the best on Changchun c-we. Hence, we conclude that for city-scale datasets, people's interests in POI are severely touched by POI categories and Locations on weekdays, while during weekends, people may be more sensitive to time segment and POI categories.

While for region-scale datasets, we notice that TS-ToP achieves the best performance among baselines, and its performance is close to our proposed model ToP, especially on NDCG. In a relatively small region, spatio-temporal relationships make more effort on people's check-in actions. We can conclude many useful application rules for real-world scenarios by analyzing the results and proposing a personalized, efficient POI recommendation model. Note that CT-ToP is the former model we proposed. ToP is more practical and effective than CT-ToP and achieves a better POI recommendation.

F. Impact of Parameters: Parameter Space Analysis (RQ5)

We explore the effect of ToP's hyperparameters λ and α on region-scale data, as shown in Fig. 11. Note that the best performance of HR@10 (weekdays) is achieved when $\lambda = 0.3$ and $\alpha = 0.4$ and NDCG@10 (weekdays) when $\lambda = 0.4$ and $\alpha = 0.5$. While at weekends, ToP achieves best HR@10 when $\lambda = 0.2$ and $\alpha = 0.5$, NDCG@10 when $\lambda = 0.1$ and $\alpha = 0.5$. Note that α is relatively stable, and the smaller λ achieves better performance at weekends. The reason is that the users' check-in actions are regular on weekdays, where a larger λ can enhance the zone effect and improve the performance. While during weekends, users' check-in actions are more irregular, where the POI's dynamic representations play a more important role in POI recommendations.



(a) region-scale, weekdays (b) region-scale, weekends

(c) region-scale, weekdays (d) region-scale, weekends

Fig. 11. Analysis of hyperparameter λ and α.

V. RELATED WORK

Our work is closely related to recommendation models and knowledge graph models. Traditional recommendation models are designed for applications, such as CTR tasks [26] and Next-item [27]. These tasks usually utilize ratings, reviews, or text [28], [29] to deduce users' preferences for accurate recommendations. However, POI recommendation [30] is quite different from traditional recommendation issue, since temporal and spatial effects have been incorporated into existing POI recommender systems [5], [31]. Some groups of researchers have treated POI recommendation as a sequential prediction problem, which takes the temporal period patterns [32], [33] or sequential effects [23], [34] into considerations. Another group of researchers has focused on the spatial effects on user profiling and action pattern analysis for POI recommendations [35]. For instance, GeoMF [21] integrates the spatial effect of user geographical regions and its propagation into a weighted matrix factorization framework. RankGeoFM [22] proposes a ranking based geographical factorization method incorporating the spatial-temporal factors. Besides spatio-temporal effects, other types of information have also been explored to enhance POI recommendation performance, such as social influence [4], [36], POI category information [37], [38], and text information [39], [40] of POIs. However, existing models can not learn the dynamic function of a POI, which leads to a biased recommendation.

From the angle of knowledge graph embedding models, some effective recommendation models have been proposed by researchers to enhance accuracy. The basic idea of embedding models for recommendation is to learn the user's and item's representations respectively, input them into a model, and make a prediction [20]. TransX (TransE [11], TransD [12], etc.) series of knowledge graph embedding are popular in recommendations. [41] considers the nodes and edges of multiple types with different attributes and jointly learns the embeddings for each node and edge. [42] deals with distinctive challenges in predicting node importance in KGs, and analyzes the diversity of KG embeddings.

The combination of KG embedding and POI recommendation has recently boosted. For POI recommendation, KG embedding can learn proper latent vector spaces for representing POIs and users, which adds the interpretability for recommendations. For KG embedding models, POI recommendation is a reasonable application area because the user-POI check-in actions can be formulated as a sparse knowledge graph. PACE [23] builds a word2vec-based architecture to jointly learn the embeddings of users and POIs to predict both user preference over POIs and context associated with users and POIs. KTUP [24] especially accounts for various preferences in translating a user to an item and then jointly trains it with a KG completion model by combining several transfer schemes. However, it is still challenging to utilize knowledge graph embedding methods to learn dynamic POI representations for recommendations.

VI. Conclusion

In this paper, we study the effect of POI's dynamic functions on POI recommendations. We proposed an end-to-end knowledge graph embedding recommendation framework, called ToP, to tackle this dynamic function learning problem for POIs. The proposed framework contains three components: spatio-temporal knowledge graph embedding (STKGE), topic zone embedding (TZE), and unified KG based recommendation model. The three components could jointly learn a dynamic representation for each POI at different periods, and a dynamic zone embedding for each zone. Then by considering the time, space, and zone effect comprehensively, ToP can add interpretability into users' check-in actions and make an explainable POI recommendation. Also, we proposed a zone splitting method based on road networks data and historical check-in data for combining POI candidate selections with zone effect. We conducted extensive experiments to demonstrate the effectiveness of our proposed framework on city-scale and region-scale data, and give a discussion about the interpretability of ToP and its superior performance compared with the state-of-the-art baselines.

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