ToP: Time-dependent Zone-enhanced Points-of-interest Embedding-based Explainable Recommender system

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IEEE INFOCOM 2021 - IEEE Conference on Computer Communications | 978-1-6654-0325-2/21/$31.00 ©2021 IEEE | DOI: 10.1109/INFOCOM42981.2021.9488726

***Abstract*—Points-of-interest (POIs) recommendation plays a vital role by introducing unexplored POIs to consumers and has drawn extensive attention from both academia and industry. Existing POI recommender systems usually learn 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. In this paper, 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 POIs dynamic function. Besides, check-in actions to a POI is also affected by the zone it belongs to. In other words, the zone's embedding learned from POI distributions, road segments, and historical check-ins could be jointly utilized to enhance the accuracy of POI recommendations. Along this line, we propose a Time-dependent Zone-enhanced POI embedding model (ToP), a recommender system that integrates knowledge graph and topic model to introduce the spatio-temporal effects into POI embeddings for strengthening interpretability of recommendation. Specifically, ToP learns multiple latent vectors for a POI in different time to capture its dynamic functions. Jointly combining these vectors with zones representations, ToP enhances the spatio-temporal interpretability of POI recommendations. With this hybrid architecture, some existing POI recommender systems can be treated as special cases of ToP. Extensive experiments on real-world Changchun city datasets demonstrate that ToP not only achieves state-of-the-art performance in terms of common metrics, but also provides more insights for consumers POI check-in actions.**

***Index Terms*—Recommender systems; knowledge graph; POI recommendation; interpretability**

I. Introduction

Location-based social networks (LBSNs), such as Foursquare[1] and Yelp[2], are increasingly important, bridging the gap between the physical world and online social networking services based on personal preferences [1] [2]. In LBSNs, consumers usually check in and share the experience with friends when visiting a Point of Interest (POI) [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 at recommending consumers the POIs which they may be interested in but haven't checked-in yet, have attracted increasing attention from both academia and industry.

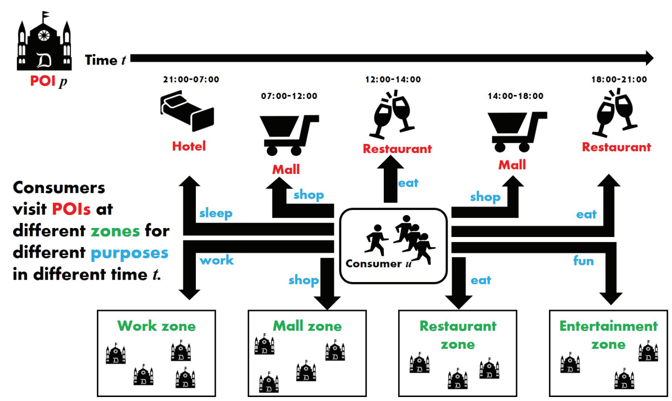

Fig. 1. An example to illustrate the dynamic function of POI over time and the chanllenge to explain the consumers' different purposes to check in POIs in different zones at different time.

Unlike traditional recommender systems that push goods on the websites, e.g. news, music, and movies, 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 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 deep generative models.

Although POI recommender systems have achieved great success, we are still facing many challenges: 1) **Interpretability**: most POI recommendation models concentrate on precision improvement and lack explainable formulations to under-

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

stand the complicated user-POI check-in actions. Hence, their recommendation results are usually unexplainable. In the real-world, different users usually visit the same POI for different purposes. For example, in Figure.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 recommendation, the interpretability of the model should be taken into consideration. 2) **Dynamic POI representation**: not only users' preferences 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 Figure.1, POI p could act as a hotel, a mall, or a restaurant in 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 POI locates may enhance or weaken the POI's recommendation priority. For example, when users are in commercial centers (zones), they perhaps prefer visiting the malls rather than visiting a hotel or a restaurant (Fig.1). Hence, how to define the suitable zone area and 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-dependent Z**o**ne-enhanced **P**OI embedding-based model (**ToP**), which is an end-to-end framework for personalized and explainable POI recommendations. Specifically, a temporal knowledge graph embedding (TKGE) is employed to model the time-dependent representations of POIs' functions from side information and check-in data. Then 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 effects, combining with spatial and temporal effects, could be used to improve POI recommendations and understanding 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 effects, and further make short and long time-term explainable POI recommendations.

Our primary contributions can be summarised as follows:

- We explore the limitation of POI representations, and address POI recommendation problems in an embedding way with knowledge graphs, which adds interpretability, dynamic of POIs' functions and zone effects into POI recommendations,
- According to the embedding results, we propose an end-to-end recommender system - ToP - to jointly learn both dynamic POIs', 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.
- We evaluate ToP on 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 for users' check-in actions and POIs' dynamic functions.

II. Related Work

Our work is closely related to knowledge graph embedding and POI recommendation models. In POI recommendations, temporal and spatial effects have been incorporated into existing POI recommender systems [5] [9]. Some groups of researchers have treated POI recommendation as a sequential prediction problem, which takes the temporal period patterns [10], [11] or sequential effects [12], [13] into considerations. Another group of researchers has focused on the spatial effects on user profiling and action pattern analysis for POI recommendations. For instance, GeoMF [14] integrates spatial effect of user geographical regions and its propagation into a weighted matrix factorization framework. RankGeoFM [15] 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 [16] [4], POI category information [17], and text information [18] 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 for enhancing 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 [19]. TransX (TransE [20], TransD [21], etc.) series of knowledge graph embedding are popular in recommendations. [22] considers the nodes and edges of multiple types with different attributes, and jointly learns the embeddings for each node and edge. [23] deals with distinctive challenges involved with predicting node importance in KGs, and analyze the diversity of KG embeddings.

The combination of KG embedding and POI recommendation is boosting in recent years. 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 [13] 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. However, it is still a challenge to utilize knowledge graph embedding methods to learn dynamic POI representations for recommendations.

III. Preliminaries

A. Definitions

In POI recommender systems, U denotes a set of m users $U = \{u_1, u_2, ...u_m\}$, and P denotes a set of n POIs $P = \{p_1, p_2, ...p_n\}$. 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. **Temporal User-POI Graph.** A user's check-in actions in a time period T are represented as a temporal 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 time. With many Tr_{upt}, this graph can completely describe users' check-in actions with structural information representation, to learn a dynamic POI representation $\mathbf{p}^t$.

Definition 2. **POI-POI Graph.** To consider the relation between POIs from a global view, we build a global POI-POI 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 and side information (e.g., the overlap percentage or the transfer actions between different POI categories) into edges between vertexes. This graph is fixed through all the procedures, aiming at learning a global representation $\mathbf{p}^g$ for each POI category. We give an example of POI-POI Graph and Temporal User-POI Graph in Figure.2.

Definition 3. **Zone Embedding.** To cooperate with 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 $\mathbf{z}$ for representing zone's functional attributes. Note that real-world, the zone's functions are also varying with time. In this paper, zone embedding $\mathbf{z}$ 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 latent vector to represent the POI's attributes, hence add the model's interpretability. We extract two graphs (temporal user-POI graph and POI-POI Graph) from multi-source data (e.g., check-in data and side information), from where we represent the dynamic of POIs' functions. Therefore we formulate this problem as a task of temporal knowledge graph embedding problem 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.

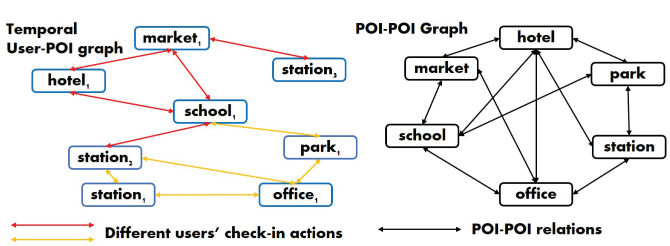


Fig. 2. Temporal User-POI graph and POI-POI graph. Both two kinds of knowledge graphs extract the users' dfferent check-in action patterns jointly.

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

1) Embedding stage: given a c set of temporal user-POI 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 as input, and outputs the time-dependent 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 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.

IV. Time-dependent Zone-enhanced POI Embedding

A. Framework Overview

Figure.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 effects. In the first task, we build a POI-POI graph to learn the global representation of POIs. we also build a set of temporal user-POI graphs, and propose temporal knowledge graph embedding (TKGE) 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. Temporal Knowledge Graph Embedding

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

Intuition 1: Global representation: A POI should have its basic attributes, e.g., a school or a hospital. The global representation learned from POI-POI graph should be part of the dynamic POI representation, and make its contribution to POI recommendations. In our model, we should input global representation as the initial POI representation through the learning process.

Intuition 2: Time-dependent dynamic: Unlike other methods with a fixed embedding for POI representation, we explore the insights on POIs' time-dependent dynamic functions. We

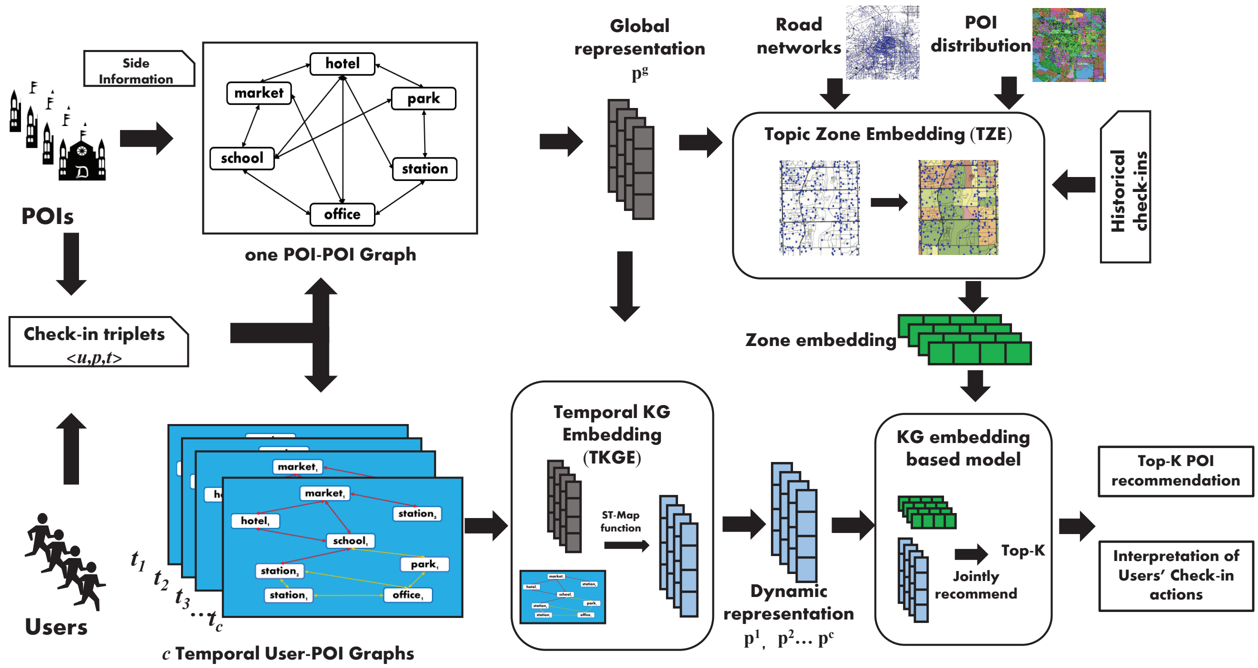


Fig. 3. An overview of learning dynamic POI representations and explainable Top-k POI recommendation via proposed model ToP.

argue that the temporal user-POI graph built from check-in triplets are different at different time. Along this line, the representation of POI should be dynamic at different time. We need to capture the varying of POIs' functions and learn explainable representations.

1) Global Representation Learning: We first analyze the POI-POI graph: 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 [20], TransD [21] 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 [25], 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 to the complex vector space and defines each relation as a rotation from the source entity to the target entity. In our proposd 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 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 the three relation patterns: symmetric/antisymmatric, 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 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 [26] and word embedding [27]. 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 as [25] 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 funtion. $(\hat{\mathbf{h}}_i^p, \hat{\mathbf{t}}_i^p)$ is th 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.

2) Temporal Dynamic Representation Learning: To learn temporal dynamic representations from a set of user-POI graphs, we need to measure the change of POIs' functions over time explicitly and also the interpretability of representations. To solve the problem, we add time restrictions for sRotatE.

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

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

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 $\mathbf{w}$. Note that at the beginning of this processing, the initialization of POI weight vectors should be one-hot style because all 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 time t.

Given a c set of temporal user-POI graphs $G_{t_1}^T, G_{t_2}^T ... G_{t_c}^T$, 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 funtion. $(\hat{\mathbf{h}}_i^t, \hat{\mathbf{t}}_i^t)$ is the i-th negative relation, and n_n is the negative sample number, $\sum_{i=1}^{k} h_i^t = 1$, $\sum_{i=1}^{k} t_i^t = 1$.

With these loss functions on each user-POI graph at time c, we can get the temporal dynamic representations $\mathbf{p}^1$, $\mathbf{p}^2 ... \mathbf{p}^c \in \mathbb{C}^k$, 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 methods, and some existing models have done some effective work on spatial effect. However, we argue that it is still insufficient: 1) Candidate selection problem: Existing models usually utilize a radius as the POIs' candidate metric. As shown in Figure 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 [28], [29]. 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.

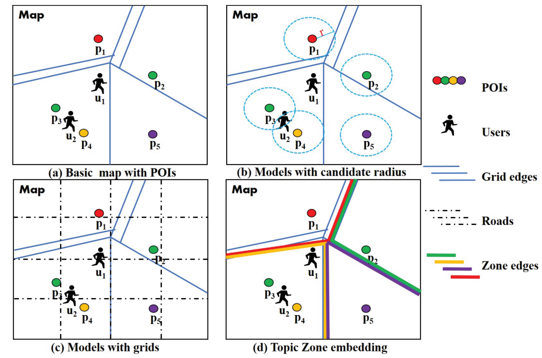


Fig. 4. (a) is the basic map with POIs. (b) (c) indicate the limitations of traditional POI recommendations. In (b), for u_1, no POI is selected as his candidates; for u_2, models are confused by choosing p_3 or p_4 for u_2. In (c), models ignore the road network between grids. In (d), we consider the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

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 Figure.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 to extend and correct the selected roads and divide the city areas into fine-grained natural zones (shown in Figure.5(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 learn 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 which 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,...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:

$$\mathrm{TC}_{ij}^t = \sum_{p_k \in z_i} \sum_{p_e \in z_j} \left(\mathbf{p}_k^t\right)^{\mathrm{T}} \mathbf{p}_e^{t \pm 1}, p_k, p_e \in < p_k, p_e >, \tag{7}$$

where $\mathbf{p}$ is the POI's dynamic representation learned in TKGE, $\mathbf{p}^{t \pm 1}$ 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: 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:

$$\mathrm{sc}_{ij} = \sum_{p_k \in z_i} \sum_{p_e \in z_j} \log\left(\frac{\#(p_k, p_e) \cdot |L|}{\#(p_k) \cdot \#(p_e)}\right), z_i \in N_{z_j}, \quad (8)$$

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:

$$\begin{aligned} \mathrm{SC}_{ij} &= \max\left(\sum_{p_k \in z_i} \sum_{p_e \in z_j} \log\left(\tfrac{\#(p_k,p_e)\cdot|L|}{\#(p_k)\cdot\#(p_e)} \cdot \tfrac{1}{n_k}\right), 0\right) \\ &= \max\left(\sum_{p_k \in z_i} \sum_{p_e \in z_j} \log\left(\tfrac{\#(p_k,p_e)\cdot|L|}{\#(p_k)\cdot\#(p_e)}\right) - \log n_k, 0)\right) \end{aligned}, z_i \in N_{z_j}, \quad (9)$$

where n_k is the negative sampling number.

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

$$\mathbf{r}^z = \alpha \mathrm{TC}_{ij}^t + (1-\alpha)\,\mathrm{SC}_{ij}, \quad (10)$$

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:

$$L^z = -\log\sigma(\tau_3 - d_r(\mathbf{h}^z, \mathbf{t}^z)) - \sum_{i=1}^{n_n} \frac{1}{k} \log\sigma(d_r(\hat{\mathbf{h}}_i^z, \hat{\mathbf{t}}_i^z) - \tau_3), \quad (11)$$

where τ_3 is a fixed margin, σ is a sigmoid function. $(\hat{\mathbf{h}}_i^z, \hat{\mathbf{t}}_i^z)$ 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 Eq.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 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 knowledge embedding based recommendation model [30] to give 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:

$$\mathbf{p}_{rec}^s = \mathbf{p}_u \circ \mathbf{r}^t, \quad (12)$$

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 locates, and its neighbor zones as candidate zones, calculate the similarity between $\mathbf{p}_{rec}^s$ and $\mathbf{p}_{can}^s$:

$$\mathbf{sim}(\mathbf{p}_{rec}^s, \mathbf{p}_{can}^s) = |\mathbf{p}_{rec}^s, \mathbf{p}_{can}^s|_E, p_{can}^s \in z_u \cup N_{z_u}, \quad (13)$$

where $\mathbf{p}_{can}^s$ is the candidate POI p_{can}^s's representation, and p_{can}^s locates 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; and 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:

$$\mathbf{p}_{rec}^l = \mathbf{p}_u \circ \mathbf{r}^{\tilde{t}}. \quad (14)$$

Note that we use POI-POI relation $\mathbf{r}^{\tilde{t}}$ to replace $\mathbf{r}^t$ in Eq.12. Then we consider spatial restrictions when computing similarity, which adds candidate zones according to the time span $(\tilde{t} - t)$:

$$\mathbf{sim}(\mathbf{p}_{rec}^l, \mathbf{p}_{can}^l) = \left|\mathbf{p}_{rec}^l, \mathbf{p}_{can}^l\right|_E, p_{can}^l \in z_u \cup N_{z_u}^{\tilde{t}-t}, \quad (15)$$

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:

$$\mathbf{score}(p_{can}) = \frac{1}{\mathbf{sim}(\mathbf{p}_{rec}, \mathbf{p}_{can})} + \frac{\lambda}{\mathbf{sim}(\mathbf{p}_{rec}, \mathbf{z}_{p_{can}})}, \quad (16)$$

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 as the object user's potential POI, and the functions 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 time-dependent zone-enhanced Top-K POI recommendations.

3) Interpretability: We can give some explainable insights into recommendations: first, we can analyze the time effect on POI by computing 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. Hence, the purpose of a user's check-in action on POIs at different time can be achieved, which can explain POI recommendations. Second, by analyzing zone embedding's dynamic function (Eq.10,11), we can also understand the city's pulse and give introductions for urban computing.

V. 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 does zone embeddings capture spatial effect?

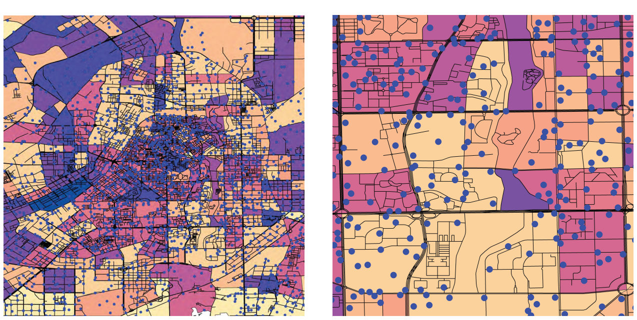
RQ4: How do the hyper-parameters affect the performance of ToP? Which are the optimal values?

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 device 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.

We use the trajectories from 3rd 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 Figure.5). We spilt 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 details of our datasets are shown in Table I.



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

Fig. 5. 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 I
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%

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

NCF [19] 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 [14] This model integrates spatial effect in user geographical regions and its propagation.

RGeoFM [15] This model is a ranking based geographical factorization method incorporating the spatial-temporal factors, and give a rank score to make recommendations.

PACE [13] 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.

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 3.40GHz CPU and 128GB 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 (RQ1)

We compare our methods with the baseline methods in terms of two metrics: **HR@N** and **NDCG@N**. We give the general comparison in Table II and Table III. Encouragingly, it is clear that the performance of our proposed model ToP is consistently better than all 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-

TABLE II
PERFORMANCE EVALUATION COMPARED WITH BASELINE METHODS ON HR@N AND NDCG@N (CITY-SCALE DATASETS). * IS THE BEST PERFORMANCE AND + IS THE BEST PERFORMANCE OF BASELINES.

Dataset	Changchun c-wd						Changchun c-we					
Model	NCF	GeoMF	RGeoFM	Pace	KTUP	ToP	NCF	GeoMF	RGeoFM	Pace	KTUO	ToP
HR@5	0.222	0.231	0.203	0.264+	0.143	0.273*	0.194	0.191	0.231	0.261+	0.079	0.264*
HR@10	0.274	0.216	0.254+	0.250	0.162	0.375*	0.234	0.292	0.301	0.311+	0.161	0.374*
NDCG@5	0.221	0.220	0.201	0.333+	0.194	0.401*	0.195	0.222	0.234	0.323+	0.103	0.377*
NDCG@10	0.179	0.274	0.231	0.301+	0.131	0.333*	0.164	0.194	0.222+	0.213	0.089	0.249*

TABLE III
PERFORMANCE EVALUATION COMPARED WITH BASELINE METHODS ON HR@N AND NDCG@N (REGION-SCALE DATASETS). * IS THE BEST PERFORMANCE AND + IS THE BEST PERFORMANCE OF BASELINES.

Dataset	Changchun r-wd						Changchun r-we					
Model	NCF	GeoMF	RGeoFM	Pace	KTUP	ToP	NCF	GeoMF	RGeoFM	Pace	KTUO	ToP
HR@5	0.197	0.214	0.297+	0.291	0.098	0.334*	0.127	0.131	0.232	0.264+	0.101	0.289*
HR@10	0.211	0.472	0.465	0.513+	0.201	0.573*	0.313	0.421	0.444+	0.397	0.201	0.471*
NDCG@5	0.333	0.354	0.397	0.421+	0.201	0.520*	0.214	0.379	0.423+	0.411	0.272	0.483*
NDCG@10	0.231	0.377	0.411*	0.400	0.132	0.499*	0.222	0.214	0.402+	0.311	0.203	0.478*

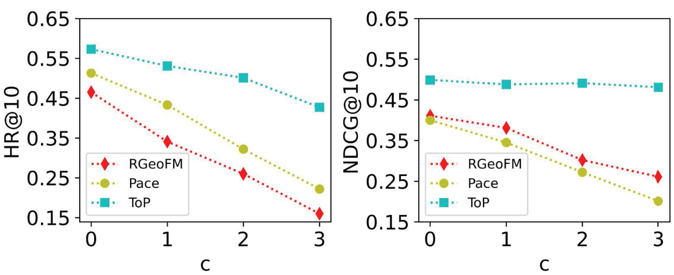


Fig. 6. Comparison of short-term ($t_c, c = 0$) and long-term ($t_c, c = 1, 2, 3$) POI recommendations with baselines.

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.6. 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.

C. Interpretability of POI dynamic functions (RQ2)

We explore the interpretability of POI dynamic functions. To take insights into POI representations learned by ToP, we visualize the attention weight w of two POIs at different time through weekdays and weekends. As shown in Fig.7, 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 a 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

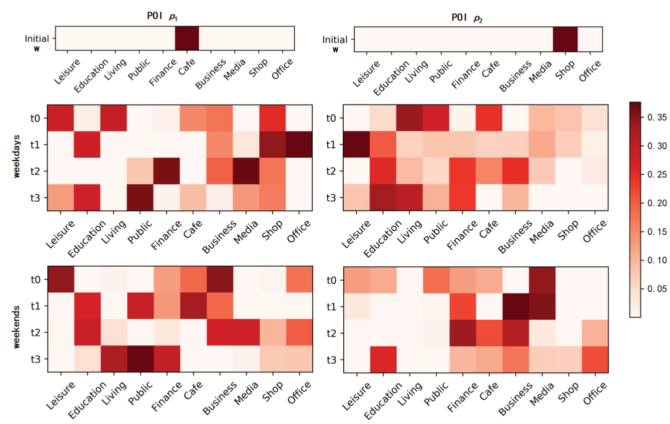


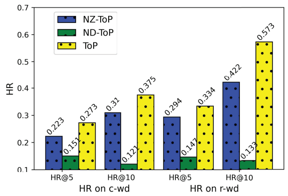
Fig. 7. Visualization of dynamic POI representations through weekdays and weekends. The color indicates the importance of dimensions in vectors.

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 at weekends, which is consistent with our inference from dynamic POI representations. We can also see the dynamic from p_2, and many other POIs with our proposed model.

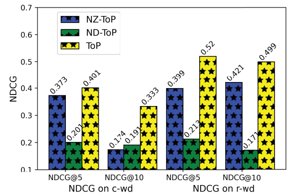
With these insights, we can give explainable recommendations. For example, if users are in the zone near p_1 on weekdays at time t_1, we should recommend some workplaces for them because p_1' most important feature at t_1 is office. While if users are in the zone near p_2 on weekends at t_2, we should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

D. Effect of spatial/temporal factor (RQ3)

We explore the effect of spatial/temporal factors in ToP. Note that in ToP, we use zone embeddings to capture the spatial effect and dynamic POI embedding to capture the

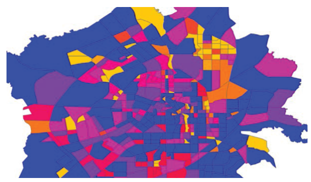


(a) City-scale dataset

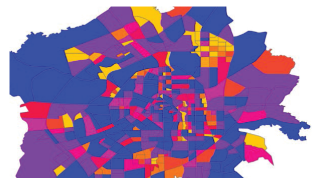


(b) Region-scale dataset

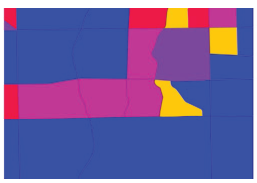
Fig. 8. Validation of spatial/temporal effect of ToP on HR@N and NDCG@N.



(a) city-scale, weekdays



(b) city-scale, weekends



(c) region-scale, weekdays

(d) region-scale, weekends

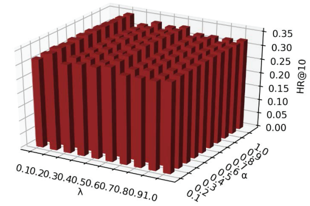
Fig. 9. Visualization of dynamic zone embedding through weekdays and weekends on city-scale and region-scale data at a time period.

temporal effect. Specifically, we build two sub models: No-Zone enhanced ToP (NZ-ToP), which ignores the zone embeddings in Eq.16. And No-Dynamic POI representation ToP (ND-ToP), which uses global POI representation $\mathbf{p}^g$ to replace $\mathbf{p}^t$. The results are shown in Fig.8. The great performance improvement over NZ-ToP and ND-ToP indicates the effect of spatial/temporal factors in ToP.

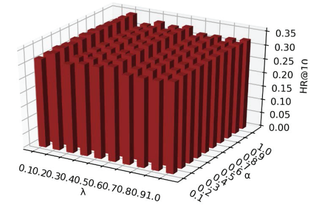
Moreover, according to the zone's dynamic embeddings learned by ToP, we explore the dynamic of zone's function through weekdays and weekends on city-scale and region-scale data, as shown in Fig.9. Note that we merge the zones with similar embeddings. From Fig.9(a), 9(b), we can find that the zone's embeddings 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.9(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 at weekends, which inducts the recommendations. As a result, the dynamic of zone' functions also gives explanations for users' check-in actions.

E. Parameter Analysis (RQ4)

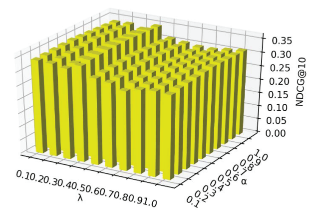
We explore the effect of ToP's hyperparameters λ and α on region-scale data. As shown in Fig.10. Note that the best performance of HR@10 (weekdays) is achieved when $\lambda = 0.3$



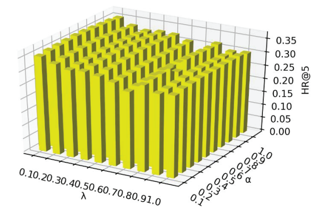
(a) region-scale, weekdays



(b) region-scale, weekends



(c) region-scale, weekdays



(d) region-scale, weekends

Fig. 10. Analysis of hyperparameter λ and α.

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 at weekends, users' check-in actions are more irregular, where the POI's dynamic representations play a more important role for POI 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. By considering the time, space, and zone effects comprehensively, ToP can add interpretability into users' check-in actions and make an explainable POI recommendation. 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.

Acknowledgment

This work is supported by the National Natural Science Foundations of China under Grant No. 61772230 and No. 61972450, Natural Science Foundation of China for Young Scholars No. 61702215 and No. 62002132, China Postdoctoral Science Foundation No. 2020M681040 and Changchun Science, and Technology Development Project No.18DY005, and National Defense Science and Technology Key Laboratory Fund Project No. 61421010418 and Science Foundation of Jilin Province No. 20190201022JC.

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