Online POI Recommendation: Learning Dynamic Geo-Human Interactions in Streams

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Abstract—Online POI recommendation strives to recommend future visitable places to users over time. It is crucial to improve the user experience of location-based social networking applications (e.g., Google Maps, Yelp). While numerous studies focus on capturing user visit preferences, geo-human interactions are ignored. However, users make visit decisions based on the status of geospatial contexts. In the meantime, such visits will change the status of geospatial contexts. Therefore, disregarding such geo-human interactions in streams will result in inferior recommendation performance. To fill this gap, in this paper, we propose a novel deep interactive reinforcement learning framework to model geo-human interactions. Specifically, this framework has two main parts: the representation module and the imitation module. The purpose of the representation module is to capture geo-human interactions and convert them into embedding vectors (state). The imitation module is a reinforced agent whose job is to imitate user visit behavior by recommending next-visit POI (action) based on the state. Imitation performance is regarded as a reward signal to optimize the whole interactive framework. When the model converges, the imitation module can precisely perceive users and geospatial contexts to provide accurate POI recommendations. Finally, we conduct extensive experiments to validate the superiority of our framework.

Index Terms—Online POI recommendation, user modeling, geographical contexts modeling, reinforcement learning

1 INTRODUCTION

Online Point of Interest (POI) recommendation aims to dynamically recommend next POIs to users over time by modeling human spatiotemporal activities at various POIs. This kind of research can help users discover attractive places, provide personalized and user-centric human-technology interfaces (e.g., Google Maps, Foursquare, Yelp), improve user experiences and revenues in location-based social network applications, and, moreover, create a better geo-social community.

Most of the prior literature in POI recommendations takes a default setting: offline learning. With that being said, many offline-trained POI recommendation models [2], [9], [14], [15], [36] learn user visit preferences from historical check-in data and recommend next-visit POIs to users based on the static learned preferences. However, the preferences and activity patterns of humans do indeed change over time. Online recommendation, in contrast to offline recommendation, assumes that user activity data (e.g., POI visits) are generated in real time, and that human preferences and learning environments change over time. Moreover, by analyzing large-scale POI visit data, we observe that there is dynamic and mutual influence between users and geospatial contexts (e.g., POIs, POI categories, functional zones, etc.) in POI visit streams. For example, after visiting the New York City Metropolitan Museum, a user visits the Statue of Liberty in New York City. Each visit event will update the status of a user, as well as the status of the connected network of NYC tourism attractions. Users and the NYC tourism attraction network will mutually influence and be influenced over time, which we call geo-human interactions. In the scenario of POI recommendation, modeling such varying and influential interactions in streams can help us to better understand how users evolve and how users influence and are influenced by a geospatial contextual and networked environment. While there are studies in online recommendation [4], [22], [23], [34], [39], the integration of dynamic geo-human interactions and online recommendation with streams is still in early stage.

To fill this gap, in this paper, we focus on modeling the geo-human interactions in streams for online POI recommendation. We formulate the in-stream geo-human interaction modeling problem into a reinforcement learning task. The underlying idea is to regard a reinforcement learning agent as a recommender and regard the reinforcement learning environment as a joint composition of users and geospatial contexts (e.g., POIs, POI categories, and functional zones), so that we can leverage the agent-environment interactions in reinforcement learning to model the interactions between users and geospatial contexts. To that end, we propose a novel deep interactive reinforcement learning framework to unify both in-stream recommendation and geo-human interaction modeling.

Our proposed learning framework includes two major modules: representation module and imitation module. First, the representation module is to learn and track the representations of users and geospatial contexts. Second,
the imitation module will use the representations of users and geospatial contexts as state and recommended POIs as actions to mimic how users visit places. Third, the accuracy of the mimics of user visit patterns is fed back to the representation and imitation modules to help them optimize their parameters. When the imitation module perfectly mimics user visit patterns the representation module produces the most accurate embeddings of interactive users and geospatial contexts. Finally, the trained imitation module will choose the user-POI pairs with the highest Q value and make updated recommendations on the fly.

Based on the overarching idea, we have conducted a preliminary study [26]. To simplify online recommendation, we only focused on modeling a single-user POI visit stream, instead of a mixed-user POI visit stream. In particular, the representation module separately learned the representations of the user and the geospatial contexts. Then, we concatenated the representations of a user and geospatial contexts together as the state of the environment. The imitation module took the environment state as input and exploited its policy network to make a personalized next POI recommendation to the user.

However, the modeling of dynamic interaction in streams can be significantly improved. Specifically, user visit intents exhibit multi-level interaction dynamics: 1) Connected Dynamics: a user’s visit decision is impacted by other users and POI-related geographic entities through various types of visit events. Such a relationship forms a more comprehensive knowledge graph that includes not just spatial entities but also users. 2) Topological Dynamics: new POI visit events continue to add new entities (users) and edges (visit events) to the knowledge graph. 3) Semantic Dynamics: A user typically connects with POIs through various meta-path schemes based on distinct semantic relationships. Therefore, it is appealing to model multi-level interaction dynamics for improving online POI recommendation in streams.

To this end, in our journal version, we consider a new data environment setup: a mixed-user visit stream. Based on the mixed-user visit stream, we construct a new dynamic knowledge graph, in which nodes are both users and geospatial entities, edges stand for user-user, geo-user, and geo-geo relationships, and, moreover, edges and nodes are added and deleted over time. This setup is fundamentally different from the data environment setup of our preliminary study: (1) a single-user visit stream; (2) nodes are only geospatial entities; (3) nodes and edges will not be deleted.

However, the new data environment setup raises three algorithmic challenges. First, because there are millions of users, the new KG will grow exponentially larger over time. To address the exploding challenge, we create an exit mechanism for long-ago visit-events in order to remove obsolete records for KG refinement. Second, because the new KG will be larger and more sparse, it is challenging to identify POI candidates from a sparse and huge KG. To solve the problem of sparsity, we propose and use predefined meta-paths to choose the most relevant POI candidates for recommendation, taking into account semantics and the context of interests. Finally, because the node set of the new KG is dynamic, it creates dynamic action space and makes recommendation policy difficult to train. To address this challenge, we develop a new deep neural policy network architecture to support the dynamic action space.

In summary, in this paper, we propose a deep interactive reinforcement learning framework for online POI recommendation. Our unique perspective is to model the multi-level dynamics of geo-human interactions in data streams. Specifically, our contributions are: (1) Formulating the problem of modeling geo-human interactions in streams for online POI recommendation. We identify that human visit activities are an interactive, mutually-influenced process between users and geospatial entities. We propose a new perspective to attack online POI recommendation by unifying in-stream recommendation and dynamic geo-human interaction modeling.

(2) Proposing a representation-imitation based deep interactive reinforcement learning framework. To address the in-stream dynamic interaction modeling problem, we propose a novel deep interactive reinforcement learning framework. This framework has two main parts: the representation module and the imitation module. The former is to conduct dynamic knowledge graph learning to learn the state representations of users and geospatial entities. The latter is to perform online next-POI recommendations via policy networks. The two modules form a closed-loop interactive learning system.

(3) Developing technical solutions to tackle multi-level interaction dynamics in mixed-user data streams. We identify the difficulties that arise at three levels of dynamics in mixed-user data stream interactions: connected dynamics, topological dynamics, and semantic dynamics. To address these challenges, we propose effective technical solutions. First, we propose an exit mechanism to maintain the dynamic KG on a reasonable scale and reduce computational complexity. Second, we develop a meta-path based candidate generation method for overcoming the challenge caused by sparse KG; Third, we devise a new policy network that generates Q-values for selecting recommended user-POI pairs to address the challenge of dynamic action space.

(4) Extensive experiments with real-world data. To validate the superiority of our framework, we conduct extensive experiments using two real-world datasets in comparison to six state-of-the-art baseline models. Experimental results show that our method consistently outperforms baselines to justify our technical insights.

2 DEFINITIONS AND PROBLEM STATEMENT

We first introduce the key definitions, and then present the problem statement.

2.1 The Key Components of Our Framework

We aim to address the joint task of both online recommendation in streams and dynamic geo-human interaction modeling. We develop a deep interactive reinforcement learning framework that includes:

1) Agent. An agent is a recommender that predicts the next-visit POI of a given user, based on the current state of the environment (i.e., a knowledge graph of users and geospatial contexts).

2) Action. The action space refers to all possible visiting places (POIs). Let \( a_i \) denote the action at the \( i \)th time step, assuming a user will visit the POI \( P_i \) at the \( i \)th time step, we expect \( a_i = P_i \).
3) **Environment.** The environment is where the recommendation of next-visit POIs is carried out. The joint and networked composition of users and geographic contexts (e.g., POIs, POI categories, functional zones, and their semantic linkages) is therefore regarded as the reinforcement learning environment. We use a dynamic knowledge graph to represent the environment, with users, POIs, POI categories, and functional zones as nodes and visiting relations, affiliation relations, and locating relations as edges.

4) **State.** The state is a snapshot of the environment at a specific timestamp. Formally, the dynamic KG at the step \( l \) is denoted as \( G^l \). Then, the state \( s^l \) refers to the representation vector of the \( G^l \).

5) **Reward.** The effectiveness of next visit POI recommendation is evaluated from three perspectives: POI-POI geographic distance, POI-POI category similarity, and POI-POI identically equivalent indicator. We define the reward as the weighted sum of three parts: (1) \( r_d \), the reciprocal of the geographic distance between the real and predicted next-visit POI; (2) \( r_c \), the similarity between the real and predicted POI category. Here, we utilize GloVe\(^1\) embedding to calculate the cosine similarity between predicted and real POI categories as \( r_c \); (3) \( r_p \), the binary indicator shows whether the predicted visit POI is identically equivalent to the real one. In addition, to reduce the variance of the reward, we introduce the baselines \( (b_d, b_c, b_p) \) of the three elements into the reward. Formally we set a sliding window for \( r_d, r_c, r_p \), respectively. The mean value of each sliding window is regarded as the baseline values of \( b_d, b_c, b_p \). Thus, the reward function can be formulated as follows:

\[
r = \sigma(\lambda_d \times (r_d - b_d) + \lambda_c \times (r_c - b_c) + \lambda_p \times (r_p - b_p)),
\]

where \( \lambda_d, \lambda_c \) and \( \lambda_p \) are weights for \( r_d, r_c \) and \( r_p \) respectively. \( \sigma \) is the sigmoid function, which aims to smooth the distribution of the reward for better policy learning.

2.2 **Problem Statement**

We formulate the online POI recommendation problem into a joint task of recommendation in streams and dynamic geo-human interaction modeling. We propose a deep interactive reinforcement learning framework. In the framework, all users and geographic contexts (e.g., POIs, POI categories, functional zones) are considered as the environment, and a policy network is trained to replicate the decision-making process of user visits depending on the environment’s state. Formally, at the time step \( l \), given the state of the environment \( s^l \), our propose is to find a mapping function \( f: s^l \rightarrow a^{l+1} \). Here, \( a^{l+1} \) is the user next visit action in the time step \( l + 1 \). Thus, the function takes \( s^l \) as input, and outputs \( a^{l+1} \). During the mapping process, the state of the environment \( s \) evolves over time. The objective is to model user-user, user-geo, geo-geo interactions and maximize the recommendation reward.

3 **METHODOLOGY**

3.1 **Framework Overview**

Fig. 1 shows our framework includes two modules: representation and imitation. First, the representation module is to learn the state of the environment. In particular, this module focuses on preserving the dynamic mutual interactions between user and geospatial contexts when learning the state embedding vector. Second, the imitation module is to predict the next-visit POI and evaluate the reward value of this prediction. In particular, the imitation module takes the state of the environment as input, and predicts the next-visit POI (action) of a given user. The reward function is later exploited to evaluate the effectiveness of this recommendation. After that, we leverage the reward value as a feedback signal to optimize the parameters of the representation and imitation modules. The representation module and the imitation module enhance each other through iterative updates. When the representation module learns the most accurate representation of the dynamic knowledge graph of users and geospatial contexts, the imitation module perfectly mimics users’ next visit patterns. Finally, we
can be defined as \( r \), denoted by \( r_{\text{rel}} \). \( r \) is the representation of the relationship \( r \) is the representation of the tails (\( r_2 \)).

\[ l_{\text{cond}} = \text{max} \{ \text{KG} + Q, \text{rel} \} \quad \text{with probability} \quad \text{softmax} \]

\[ x_{t_r} = r^l. \]  

(2) Temporal Distance (TD)-based. The TD error is originally updated to use the policy network. A larger TD error for a data sample denotes that it contains more information not covered by the policy network. Thus, we may set the TD error as the priority score of the data sample to improve learning. The TD-error based priority score at the \( l \)th time step \( X_{TD} \) can be defined as

\[ x_{TD} = r^l + \gamma \max_{a^{l+1}} Q(s^{l+1}, a^{l+1}) - Q(s^l, a^l). \]  

After assigning the priority score for each data sample, we calculate the distribution of the priority score. Specifically, a softmax function takes the priority score as input and outputs the priority distribution. Then, we sample top \( K \) data samples based on the priority distribution as a batch to train the imitation module, where \( K \) is the data size of one batch.

We design two types of priority score: (1) Reward-based. In general, a larger reward value for a data sample indicates that it contributes more to policy learning. Thus, we may set the reward value as the priority score of the data sample to improve learning. The reward-based priority score at the \( l \)th time step \( X_{TD} \) can be defined as

\[ x_{TD} = r^l + \gamma \max_{a^{l+1}} Q(s^{l+1}, a^{l+1}) - Q(s^l, a^l). \]  

3.2 Simplified Version: Static Spatial Knowledge Graph

Our preliminary work [26] only considers geospatial contexts as a static spatial KG, learns the representations of users and geospatial contexts separately, and models the geo-human interactions exclusively in parameter updating rules. Below, we first introduce the simplified method in our preliminary work.

3.2.1 Imitation Module

Fig. 2 shows the framework overview of our preliminary work. The right part of this Figure shows that the imitation module takes the state of environment as input, recommends next-visit POIs, and evaluates the recommendation effectiveness as reward. We use a classical Deep Q-Network (DQN) [19] as the backbone of the policy network. The DQN takes the state at the time \( l \), denoted by \( s^l \), as input and outputs the most possible visit POI based on \( s^l \). The \( \epsilon - \text{greedy} \) method is used to integrate exploration and exploitation to capture user visit preferences sufficiently. In particular, the imitation module chooses a random POI \( a^l \) with probability \( \epsilon \), or selects the POI \( a^l_{\text{opt}} \) that owns the maximum Q value with probability \( 1 - \epsilon \), denoted by \( a^l_{\text{opt}} = \text{argmax}(Q(s^l, a^l)) \). After that, the predicted POI and real POI are input into the reward function to calculate the reward value. Finally, the imitation module updates its parameters based on the Bellman Equation. The learning process continues until the imitation module fully imitates the users’ visit behavior.

The imitation module has to search a large visiting POIs (action) space to learn user mobility patterns. Thus, the learning process will be difficult and computationally expensive. To alleviate this issue, we propose a training strategy to accelerate the learning procedure based on the prioritized experience replay [24]. Specifically, we first assign a priority score for each data sample \( (s^l, a^l, r^l, s^{l+1}) \). Then, we construct a priority distribution based on the priority score for sampling batch of data from the memory.

The left part of Fig. 2 shows that the representation module considers two types of information (1) the interactions between users and geospatial contexts; (2) the temporal dependency of user representations, in the updating rules.

First, the spatial knowledge graph (KG) indicates the geo-spatial contexts. We denote the spatial KG as \( g^l = < h^l, \text{rel}, t^l > \), where \( h^l \) is the representation of the heads (\( i.e., \) POIs), \( t^l \) is the representation of the tails (\( i.e., \) categories and functional zones), \( \text{rel} \) is the representation of the relationship between the heads and tails. Second, the temporal context \( T \in \mathbb{R}^{M \times 3} \) is the combination of inner traffic, in-flow traffic, and out-flow traffic in all areas of a city, where \( M \) represents the number of areas, and 3 represents the three kinds of traffic
flows. The interactions between users and geospatial KG occur concurrently with the temporal context. The users’ visit events change the representation of spatial KG, and a new spatial KG representation leads users to choose next-visit places. Meanwhile, new user representations are not just related to current user visit preference changes but also associated with the representative parts of old user visit interests.

**Updating Rules of User Representations.** Assuming a user \( u_i \) visits the POI \( P_j \) at the step \( l \), as an example to explain the whole process, the user representation will be updated for the step \( l + 1 \). We incorporate the user representation \( u_i \) and the interactions between the POI \( P_j \) and the user \( u_i \) into \( u_{i+1} \) such that:

\[
u_{i+1} = \sigma(a_i \cdot u_i + (1 - a_i) \cdot (W_u \cdot (h_{P_j})^T \cdot T)),\]

where \( W_u \in \mathbb{R}^{N \times 1} \) is the weight; \( a_i \) is a scalar that represents the proportion of old profiling information in \( u_{i+1} \), it is given by: \( a_i = \sigma(W_{a_i} \cdot u_i + b_{a_i}) \), where \( W_{a_i} \in \mathbb{R}^{1 \times N} \) is the weight and \( b_{a_i} \in \mathbb{R}^{1 \times 1} \) is the bias term; \( T \in \mathbb{R}^{N \times 1} \) is the temporal context vector adaptable with state update, it can be calculated by: \( T = \sigma(W_T \cdot T_1 \cdot W_T_2 + b_T) \), where \( W_T \in \mathbb{R}^{N \times M} \), \( W_T_2 \in \mathbb{R}^{1 \times 1} \) and \( b_T \in \mathbb{R}^{1 \times 1} \) are the weights and bias respectively.

**Updating Rules of Spatial KG Representations.** During the learning process of the representation of the spatial KG, we only focus on directly visited POI \( P_j \) and other POIs \( P_j \) that “belong to” the same category or “locate at” the same functional zones with the directly visited \( P_j \). Here, heads are POIs and tails are categories or functional zones. Formally, we need to update the spatial KG representation \( g' = < h', \text{rel}, t' > \). We update the information in \( h' \) and \( t' \), except \( \text{rel} \). In addition, \( \sigma(\cdot) \) denotes the sigmoid function in following formulas.

1. **Updating visited POI \( h_{P_j}^{t+1} \).** Similar to update \( u_{i+1} \), we incorporate the old visited POI representation \( h_{P_j}^{t+1} \) and the interactions between the use \( u_i \) and the POI \( P_j \) in a given temporal context: \( h_{P_j}^{t+1} = \sigma(a_p \cdot h_{P_j}^{t+1} + (1 - a_p) \cdot (W_p \cdot (u_i)^T \cdot T)) \), where \( W_p \in \mathbb{R}^{N \times 1} \) is the weight; \( a_p \) is a scalar that denotes the proportion of old POI information in \( h_{P_j}^{t+1} \), it is calculated by: \( a_p = \sigma(W_{a_p} \cdot h_{P_j}^{t+1} + b_{a_p}) \), where \( W_{a_p} \in \mathbb{R}^{1 \times N} \) is weight and \( b_{a_p} \in \mathbb{R}^{1 \times 1} \) is bias.

2. **Updating category and functional zones (tail) \( t_{P_j}^{t+1} \).** We update tail \( t_{P_j}^{t+1} \) by the combination of \( t_{P_j}^{t+1} \), \( h_{P_j}^{t+1} \) and \( \text{rel}_{P_j} \), it can be denoted as:

\[
t_{P_j}^{t+1} = \alpha_t \cdot t_{P_j}^t + (1 - \alpha_t) \cdot (h_{P_j}^{t+1} + \text{rel}_{P_j}).\]

where \( \alpha_t \) is scalar that denotes the proportion of old tail information in \( t_{P_j}^{t+1} \), it is calculated by: \( \alpha_t = \sigma(W_{a_t} \cdot t_{P_j}^t + b_{a_t}) \), where \( W_{a_t} \in \mathbb{R}^{1 \times N} \) is weight and \( b_{a_t} \in \mathbb{R}^{1 \times 1} \) is bias.

3) **Updating same category and location POIs \( h_{P_j}^{t+1} \).** We update the other POIs that belong to the same POI category and locate at the same functional zones of the visited \( P_j \) as:

\[
\begin{align*}
\{ h_{P_j}^{t+1} = t_{P_j}^{t+1} - \text{rel}_{P_j} \\
\text{rel}_{P_j} = \sigma(\alpha_h \cdot h_{P_j}^{t+1} + (1 - \alpha_h) \cdot h_{P_j}^h) \}
\end{align*}
\]

where \( \alpha_h \) is a scalar that is the proportion of \( h_{P_j}^{t+1} \) in \( h_{P_j}^t \), it is calculated by: \( \alpha_h = \sigma(W_{a_h} \cdot h_{P_j}^h + b_{a_h}) \), where \( W_{a_h} \in \mathbb{R}^{1 \times N} \) is weight and \( b_{a_h} \in \mathbb{R}^{1 \times 1} \) is bias. After the above updating and learning process, we concatenate \( u_{i+1} \) and \( g' \) as the state \( s^{t+1} \).

### 3.3 Enhanced Version: Dynamic Geo-Human Knowledge Graph

#### 3.3.1 Advancing Representation Module

The left part of Fig. 3 shows that, we propose an enhanced representation module that unifies both users and geospatial contexts (POIs, POI categories, functional zones) into a single dynamic attributed knowledge graph, in order to better model connected, topological, and semantic dynamics.

**Constructing A New Dynamic KG.** The dynamic KG construction includes two stages: 1) *initialization stage* and 2) *evolving stage*. In the initialization stage, we construct a classical knowledge graph to depict the semantic connectivity among different spatial entities. There are three types of spatial entities in the stage: POI, POI category, POI location (*i.e.*, *functional zones*), and two relations types: “belong to” and “locate at”. We organize two triple facts based on the entities and relations: (1) <POI, “belong to,” POI category >, which expresses the affiliation relation between POI and POI category; (2) <POI, “locate at,” functional zone >, which demonstrates the geographical relation between POI and function zone. In the evolving stage, we aim to add the
Among the joint embeddings of all objects (i.e., entity and relation) in the KG. Let \( o \) be an entity, the context of \( o \) is a sub-graph structure in the KG. We first input the context of \( o \) into graph convolutional networks (GCNs) with \( m \) layers. The embedding of the final layer can be represented as

\[
Z^m = \text{relu}(D^{-\frac{1}{2}}\hat{A}D^{-\frac{1}{2}}Z^{m-1}W^{m-1}),
\]

where relu is the activation function, \( \hat{A} = A + I, A \) is the adjacency matrix, \( I \) is the identity matrix, \( D \) is the degree matrix, and \( W^{m-1} \) is the weight matrix. For the learned embedding \( Z^m \in \mathbb{R}^{n \times d} \), \( n \) is the number of vertex in the sub-graph and \( d \) is the dimension of each row in \( Z^m \). Then, we employ an attention layer to aggregate \( Z^m \) into a graph-level embedding. The attention weight for each vertex in the sub-graph can be calculated by

\[
\alpha_i = \frac{\exp(score(Z^m_i, o))}{\sum_{i=1}^n \exp(score(Z^m_i, o))},
\]

where \( Z^m_i \) is the embedding of the \( i \)th vertex in the subgraph, \( o \in \mathbb{R}^d \) is the embedding of the object, \( score(\cdot) \) measures the relevance between \( Z^m_i \) and \( o \). Next, we obtain the context embedding \( cx(o) \) by calculating the weighted sum of all vertex embeddings, which can be denoted as

\[
 cx(o) = \sum_{i} \alpha_i Z^m_i.
\]

Later, we incorporate \( o \) with \( cx(o) \) as the joint embedding \( o^* \) through a gated neural cell as follows:

\[
o^* = \sigma(y) \odot o + (1 - \sigma(y)) \odot cx(o),
\]

where \( \sigma \) is the sigmoid function, \( \odot \) is element-wise multiplication, \( y \) is a trainable parameter vector. We minimize the following loss function during the training process:

\[
\mathcal{L} = \sum_{(h, r, t) \in S} \sum_{(h', r, t') \in \neg S} \max(0, f(h, r, t) + \varepsilon - f(h', r, t')),
\]

where \( f(h, r, t) = ||h + r - t||_1, \varepsilon \) is a tolerance margin value, \( S \) is the positive triple set that contains the correct semantic meaning, \( \neg S \) is the negative triple set that randomly replaces the head and tail entities in \( S \). After that, we apply the average pooling on both entity and relation embeddings to obtain the representation of the whole KG. We regard the representation as the initial state of the environment for the reinforced agent of the imitation module, denoted by \( s^0 \).

In the evolving stage of dynamic KG construction, we learn the KG embedding by partially updating \( s^0 \) according to the information of new events. In particular, we incrementally learn the dynamic KG embedding via a local updating strategy. The initial KG embedding has been obtained by the initialization stage. As new nodes are added or old nodes are removed, only the translation relationships of impacted items will be broken. Other items whose contexts are unaffected by the event still maintain original translation relations. Therefore, we pick up all objects that are affected by the node update event and utilize the same model structure that is used in the initialization stage to learn the embedding of these objects incrementally. In this case, the translation relationships are dynamically updated.
way, we avoid retraining the whole model from the scratch. The state evolves over time: $s^0 \rightarrow s^1 \rightarrow \cdots \rightarrow s^T$.

### 3.3.2 Advancing Imitation Module

**POI Candidates Generated by Meta-Path.** Intuitively, different users have different mobility patterns and visiting preferences. They decide where to go on their next trip for a variety of reasons, such as proximity, recommendations from friends, and how the POI works. So, we can generate POI candidates based on such prior knowledge to reduce the action space and improve the recommendation performance. To achieve this goal, we propose a meta-path based POI candidate generation method.

Fig. 5 shows how to select POI candidates by predefined meta-paths. Here, we define four kinds of meta-path scheme in the dynamic KG: (1) “user -> visit -> POI”; (2) “user -> visit -> POI -> also visit -> RPOI”; (3) “user -> visit -> POI -> belong to -> RPOI category -> belong to -> POI”; (4) “user -> visit -> POI -> locate at -> functional zone -> locate at -> POI”. These paths all start from the “user” entity and end with the “POI” entity. To simplify the discussion, we take the POI recommendation at the $l$th time step as an example. For a given user, we generate POI candidates by applying the four meta-paths on the dynamic KG. Each meta-path produces a POI set according to the corresponding schema. Then, the Top-K popular POIs of each predefined meta-path. In this way, we reduce the action space from all POIs to $K$.

**A New Policy Network Structure for Dynamic Action Space.** In our preliminary study, we exploit a vanilla DQN as a policy network. However, the vanilla DQN cannot deal with a dynamically varying action space, because it only learns a fixed point-wise mapping from a state to an action in a fixed action set. In the work of the journal version, the action space will change over time since different users have different POI candidates. To overcome the challenge of the varying action space, we propose a new policy network structure as shown in Fig. 6.

The underlying idea of this network structure is to learn a pairwise mapping function that maps a state-action embedding pair to a score. To simplify the description, we take the $l$th time step as an example. Specifically, we first obtain the state embedding $s^l$ and the POI candidates $\text{cand}^l = \{a_1, a_2, \ldots, a_K\}$. Then, we concatenate the state embedding with each action embedding in $\text{cand}^l$ respectively, then regard the concatenation as the input of the fully connected (FC) layers. The outputs of the FC layers are the Q-values of all state-action pairs in $\text{cand}^l$ based on the concatenated embedding. Finally, we feed all Q-values into a rank module for sorting them in a descending order, and the POI with the highest Q-value is selected as the action $a^l$.

**Fig. 6. The structure of the enhanced policy network.** The network learns the Q-value of the concatenation of the state and action embedding. The action with the highest Q-value will be regarded as the next-visit POI.

### 3.4 Recommending POIs

When the model has been well-trained, the imitation module is regarded as the POI recommendation engine. Specifically, we input the state of the environment (i.e., users, spatial KG) into the imitation module. Then, the imitation module provides the Q values of all actions (POIs). After that, the action with the highest Q value is output as the recommended POI for the user who is searching places.

### 3.5 Solving the Optimization Problem

Our method is a closed-loop learning system. We propose an adversarial training-like optimization method to train the model sufficiently.

We first interpret our method from an adversarial learning perspective. We regard the representation module as a generator to produce the state in real-time. Then, we treat the imitation module and reward function as a discriminator. When the discriminator always gives the highest score for quality, the best situation for the representation module is reached. As opposed to classical adversarial learning, the scoring criteria of our method are deterministic. The reward value of each imitation behavior indicates the imitated performance. Therefore, we regard the reward value as feedback to update the parameters of the representation module for improving representation learning capability. Specifically, we utilize the gradient that comes from the gap between the current reward and the expected reward value to update the parameters of the representation module. The Algorithm 1 shows the training process.

Without the loss of generality, we use the $i$th training iteration to explain Algorithm 1. Specifically, we first generate the state at the step $i$ by $R^i$. Then, the imitation module $I$ takes the state as input and outputs the predicted action
(POI). Next, we use the reward function $r$ to calculate reward value based on predicted POI and real-visit POI. Finally, we exploit the gradient that comes from the gap between 1 (maximum reward value) and the current reward to update the parameters $\theta_R$.

Algorithm 1. Stochastic Gradient Descent Training for the Representation Module

1: Denotation:
   $r$: reward function;
   $I$: imitation module;
   $R$: representation module;
   $a$: Real action (real POI).
2: for number of training iterations do
3: Assume the loop variable is $i$.
4: Update $\theta_R$ by descending the gradient:
   $\nabla_{\theta_R} \log(1 - r(I(R^i), a^i))$.

4 EXPERIMENTS

We conducted experiments on two real-world datasets to answer the following questions: Q1. Does our proposed recommendation framework outperform the existing methods? Q2. How about the robustness of the proposed framework? Q3. Is each part of the proposed framework effective for improving recommendation performance? Q4. How does the reward function impact the POI recommendation performance?

4.1 Experimental Setup

4.1.1 Data Description

Table 1 shows the statistics of two check-in datasets: New York and Tokyo [33]. Each dataset includes User ID, Venue ID, Venue Category ID, Venue Category Name, Latitude, Longitude, and Timestamp.

4.1.2 Evaluation Metrics

We evaluated recommendation performance in terms of four metrics:

1) Precision on Category (Prec_Cat). POI recommendation on the POI category level can be viewed as multi-classification. We used the weighted precision, denoted by

$$\text{Prec}_\text{Cat} = \frac{|c_k| \cdot I_{TP}^k}{\sum_k |c_k| (I_{TP}^k + I_{FP}^k)}.$$ (10)

where $c_k$ is the $k$th POI category, $|c_k|$ is the number of $c_k$, $I_{TP}^k$ is the number of true positive predictions, and $I_{FP}^k$ is the number of false positive predictions.

2) Recall on Category (Rec_Cat). We used the weighted recall on POI categories, denoted by

$$\text{Rec}_\text{Cat} = \frac{|c_k| \cdot I_{TP}^k}{\sum_k |c_k| (I_{TP}^k + I_{FN}^k)}.$$ (11)

where $I_{FN}^k$ is the number of false negative predictions for $c_k$.

3) Average Similarity (Avg_Sim). We expected that the semantic meaning of the predicted POI category should be similar to the actual goal of the user traveling. Thus, we evaluated the average similarity between the real and predicted POI category. We employed the pretrained Glove word embedding [21] to represent POI categories, then calculated the cosine similarity between the real POI category “word” and the predicted POI category “word”.

Formally, the average similarity is given by

$$\text{Avg}_\text{Sim} = \frac{\sum_{l} \text{cosine}(\text{word}^l, \hat{\text{word}}^l)}{L},$$ (12)

where $L$ denotes the total visit number. The higher value of $\text{Avg}_\text{Sim}$ is, the better the model performance is.

4) Average Distance (Avg_Dist). We evaluated the average geographic distance between the locations of predicted POIs and real visit POIs. $\text{Avg}_\text{Dist}$ can be defined as follows:

$$\text{Avg}_\text{Dist} = \frac{\sum_l \text{Dist}(P^l, \hat{P}^l)}{L},$$ (13)

where $\text{Dist}(P^l, \hat{P}^l)$ denotes the distance between the location of the real POI $P^l$ and the predicted POI $\hat{P}^l$ at the $l$th visit. The lower value of $\text{Avg}_\text{Dist}$ is, the better the model performance is.

4.1.3 Baseline Models

We compared the performance of our enhanced POI recommendation framework (namely “DRPR,” Dynamic Reinforced POI Recommendation) against the following baseline algorithms.

1) PMF recommends items based on the user-item interaction matrix through probabilistic matrix factorization [18].

2) PoolNet employs a deep neural network model to model the interaction between user embedding and item embedding for recommending items [5].

3) WaveNet is used to generate raw audio waveforms originally. It also can be used to recommend items by imitating the sequential decision-making process of users [20].

4) LSTMNet utilizes a recurrent neural network to mimic users’ behavior for recommending items [11].

5) LightFM utilizes user-item interaction matrix and user-item meta-data for recommending items [12].

6) APOIR proposes an adversarial POI recommendation framework, which learns the distribution of user latent preference via a minimax game optimization [38].

7) IMUP-r is a new POI recommendation framework with incorporating spatial KG and reinforcement learning to recommend items for users. The reward-based sampling strategy is used to improve model performance [27].

8) IMUP-TD is the same as the model structure of the IMUP-r. The only difference is that the sampling strategy of IMUP-TD is TD-based.
RIRL-r is our preliminary work, which utilizes the adversarial training skill to train the whole framework and employs the reward-based sampling strategy during the training phase [26].

RIRL-TD is a variant of RIRL-r, which utilizes TD-based sampling strategy during the training phase.

4.1.4 Hyperparameters, Source Code, and Reproducibility

In the experiment, we first selected the 15,000 continuous check-in records from New York and Tokyo datasets respectively. Then, for each city, we split the corresponding records into two non-overlapping sets: the earliest 80% for training and the remaining 20% for testing. During the learning process, we set the dimension of the state as 200 and the number of POI candidates as 20. For the implementation of baseline models, we evaluated PMF by adopting the implementation; we implemented PoolNet, WaveNet, and LSTMNet by adopting “spotlight” [13], where the learning rate is set as 0.1; we evaluated LightFM by adopting the implementation; we implemented IMUP by adopting the implementation. Finally, to make others reproduce the experiment easily, we release the code and data in Dropbox.

4.1.5 Environmental Settings

We conducted all experiments on Ubuntu 18.04.3 LTS, Intel (R) Core(TM) i9-9920X CPU@ 3.50 GHz, with Titan RTX and memory size 128 G. In addition, we implemented all models based on python 3.7.4, TensorFlow 2.0.0 GPU.

4.2 Overall Performance (Q1)

We compared our method (DRPR) with baseline algorithms in terms of Prec_Cat, Rec_Cat, Avg_Sim, and Avg_Dist. Figs. 7 and 8 show that our method outperforms other baseline models on both New York and Tokyo datasets. A potential interpretation for the improvement on Prec_Cat and Rec_Cat is that DRPR sufficiently captures the visit preferences of users by mining the sub-structure information in the dynamic KG. In addition, a possible reason for the improvement on Avg_Sim and Avg_Dist is that the evolving update strategy of the dynamic KG captures the change of user mobility patterns over time. Thus, not only from a semantic viewpoint, but also from a distance standpoint, DRPR achieves a high level of recommendation performance in comparison to baseline models.

4.3 Robustness Check (Q2)

We randomly divided the dataset into 5 subsets, and evaluated DRPR over these subsets to examine its robustness (low variance). As illustrated in Figs. 9 and 10, we can find that compared with our preliminary framework RIRL, the enhanced framework DRPR is more stable in terms of Prec_Cat, Rec_Cat, Avg_Sim, and Avg_Dist. Such an observation indicates that the model performance is more robust as capturing more user mobility patterns. In addition, another interesting observation is that DRPR outperforms RIRI under the same sampling strategy. Such an observation reflects that capturing connected, topological, and semantic interactions make DRPR have a more stable performance compared with RIRL. Moreover, after a careful inspection of Figs. 9 and 10, we can find that no matter in DRPR or RIRL, the TD-based sampling strategy is more superior to the reward-based sampling strategy. A possible interpretation for the observation is that the TD-based sampling strategy...
strategy enhances the comprehension of the reinforced agent for the data samples that are difficult to learn.

4.4 The Study of Dynamic Knowledge Graph (Q3)

We employed the dynamic KG to model the change of user mobility patterns in DRPR. To evaluate the contribution of the dynamic KG, we developed a variant of DRPR, namely DRPR*, as the control group. DRPR* only replaces the dynamic KG with a static KG and keeps other components stable. For the static KG, we first collected all training data samples to construct a KG that contains the semantic relations among spatial entities and user visit events. Then, we utilized the TransE model [1] to learn its representation, and regard the representation as the state vector to predict the next-visit POIs. During this process, the KG is static, which doesn’t change over time. Tables 2 and 3 show that DRPR outperforms DRPR* in terms of all evaluation metrics under on New York and Tokyo datasets. This observation indicates that compared with static KG, the dynamic updating process in the dynamic KG can not only capture the temporal intrinsic of the environment, but also grasp the change in user mobility preference accurately.

4.5 The Study of Exit Mechanism (Q3)

In our method, we designed an exit mechanism in DRPR to eliminate the outdated user visit events to maintain the dynamic KG in a reasonable scale. To validate its effectiveness, we developed a variant of DRPR, i.e., DRPR’, which removes the exit mechanism in DRPR and maintains the other components. Tables 2 and 3 show that the performance of DRPR’ drops significantly compared with DRPR, indicating the importance of the exit mechanism. A possible...
interpretation for the observation is that the exit mechanism discards the outdated and trivial user mobility interests, which avoids the learning process of DRPR from being disturbed by them.

4.6 The Study of POI Candidates Generation (Q3)
In our method, we generated a personalized POI candidate set for a given user by leveraging pre-defined meta-paths. The generated POI candidates aim to reduce the action space and improve the performance of POI recommendations. To justify its effectiveness, we developed a variant of DRPR, namely DRPR$^\perp$, which removes the POI candidate generation part. Tables 2 and 3 show that, DRPR exhibits a great improvement on both recommendation performance and convergence speed on two datasets. A potential explanation of this observation is that the personalized POI candidate set significantly reduces the action space for the agent, making the exploration on POI more efficient. Meanwhile, as the personalized POI candidate is more accurate and targeted for the user, the recommendation effectiveness can also be improved.

4.7 The Study of Reward Function (Q4)
Our reward function consists of three components, i.e., distance $r_d$, category similarity $r_c$, and prediction accuracy $r_p$ whose value is 1 if the predicted POI is identical to the real user visit event, and 0 otherwise. We combined the three components into our reward function by taking their weighted memorization, with three corresponding weights, i.e., $\lambda_d$, $\lambda_c$ and $\lambda_p$, w.r.t $\lambda_d + \lambda_c + \lambda_p = 1$. We set the learning rate as 1e-5, and project evaluation metrics into a 3D space, with $(r_d, r_c, r_p)$ as axes. The shade of color denotes the value of the metric. The darker the color is, the higher the performance will be.

Figs. 11 and 12 show an interesting observation: the contribution of $r_d$ is higher than $r_c$ and $r_p$ in terms of all evaluation metrics. The reason is that we have employed the meta-path-based POI candidate generation in DRPR to discover the POI and POI category subset that a given user is possibly interested in. This operation improves the importance of $r_d$: as long as DRPR predicts the POIs that are close to real visit POIs, the model performance can be improved from all sides. A careful inspection of Figs. 11 and 12 finds that although $r_d$ is more important than the other two factors for all metrics, the best model performance is achieved based on the balanced combination of $r_d$, $r_c$, and $r_p$. Such an observation reveals that balanced considering different factors can make model objective comprehend user visit preferences.

5 RELATED WORKS
POI Recommendation. POI recommendation plays an important role in location-based social networks (LBSNs). Accurate POI recommendations help users explore interesting places, which makes their lives more convenient. Thus, many researchers are attracted to the POI recommendation domain [7], [9], [17], [36]. For example, Lian et al. [14] explored user mobility preferences by a modified weighted matrix factorization method. Liu et al. proposed a novel geographical probabilistic factor analysis framework to study the user geographical interest [15]. In [8], the researchers exploited factorization-based approaches to construct user representation by integrating spatio-temporal influence of human mobility for POI recommendation. Compared with these works, our framework DRPR incorporates multiple factors...
that affect POI recommendation into a dynamic knowledge graph, and the exploration and exploitation modules of the reinforced agent in DRPR capture user visit preferences sufficiently.

**Knowledge Graph-Based Recommendation.** Knowledge graph (KG) demonstrates the semantic relations and reasoning structure among different entities. Owing to the rich semantic information in KG, many researchers adopt KG in the recommendation domain and achieve good performance [3], [25], [29], [35]. For instance, Sun et al. utilized a recurrent neural network to learn the semantic rich embedding of entities and relations for capturing the user preference [25]. Xian et al. proposed the PGPR framework that employs the meta-path in KG for explainable recommendations [32]. Wang et al. generated the path embedding by incorporating the semantics of both entities and relations and inferred reasonable recommendation based on meta-paths [28]. Fan et al. extracted rich meta-path structure information for user intent recommendation [6]. Compared with the previous works, we implement a dynamic knowledge graph to simulate the environment where users visit. Furthermore, we unify the dynamic KG’s embedding and meta-paths to sufficiently explore user mobility patterns and preferences.

**Reinforcement Learning for Online Recommendation.** Reinforcement learning-based recommendation systems formulate the user-item interaction into a sequential decision-making process for recommending items [10], [16], [30], [37]. For instance, Zheng et al. utilized reinforcement learning to capture implicit user feedback characteristics [37] for news recommendation. Zhao et al. proposed “DEERS” recommendation model, which leverages reinforcement learning to automatically mine users’ preferences on items. POI recommendation is different from traditional recommendation system, because its strong geographical constrains. Recently, in POI recommendation domain, Wang et al. incorporated reinforcement learning and a spatial knowledge graph to grab user mobility pattern [27]. Compared with [27], we leverage a dynamic KG to incorporate the interaction and information of users and a geographical environment. Meanwhile, we recommend attractive POIs for users by exploring the substructure information in the dynamic KG.

### 6 Conclusion Remarks

In this article, we propose a novel POI recommendation framework by integrating dynamic KG into a reinforcement learning setting. Since the common practice of KG-based recommendation cannot capture the multi-level dynamics of human mobility, we introduce dynamic KG as the environment. Specifically, we regard the representation of the dynamic KG as the state in reinforcement learning. To address the uncontrollable graph-scale issue, we develop an exit mechanism to remove outdated information. To reduce the action space, we devise a meta-path-based POI candidate generation method to select the most possible POIs to recommend. To solve the problem of the dynamic action space, we propose a new policy network that takes state-action pairs as input and outputs a Q value for each pair. We select the pair with the highest Q value as the recommendation. From extensive experiments, we can find that our proposed method can better capture the dynamic characteristics of user mobility patterns and preferences compared with other baselines. And the personalized POI candidates make the recommendation performance more accurate and efficient.

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