Sequential-knowledge-aware Next POI Recommendation: A Meta-learning Approach

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Accurately recommending the next POI has become a fundamental problem with the rapid growth of location-based social networks (LBSNs). However, sparse, imbalanced check-in data and diverse user check-in patterns pose severe challenges for POI recommendation tasks. Knowledge-aware models are known to be primary in leveraging these problems. However, as most knowledge graphs are constructed statically, sequential information is yet integrated. In this work, we propose a meta-learned sequential-knowledge-aware recommender (Meta-SKR), which utilizes sequential, spatio-temporal and social knowledge to recommend the next POI for an LBSN user. The framework mainly contains four modules. First, in graph construction module, a novel type of knowledge graph, sequential knowledge graph (SKG), which is sensitive to the check-in order of POIs, is built to model users' check-in patterns. To deal with the problem of data sparsity, a meta-learning module based on latent embedding optimization is then introduced to generate user-conditioned parameters of the subsequent sequential-knowledge-aware embedding module, where representation vectors of entities (nodes) and relations (edges) are learned. In this embedding module, gated recurrent units are adapted to distill intra- and inter-SKG sequential information. We also design a novel knowledge-aware attention mechanism to capture information surrounding a given node. Finally, POI recommendation is provided by inferring potential links of knowledge graphs in the prediction module. Evaluations on three real-world check-in datasets show that Meta-SKR can achieve high recommendation accuracy even with sparse data.

CCS Concepts: • **Information systems → Recommender systems**; *Location based services.*

Additional Key Words and Phrases: POI recommendation, knowledge graphs, meta-learning

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1 INTRODUCTION

Proliferation of GPS enabled devices and location based social networks (LBSNs) has promoted users to check-in at points of interest (POIs) so as to keep mementos and share life experience with friends. One of the most fundamental techniques maintaining LBSNs is POI recommendation, which assist users' decision making when they face huge volumes of information. For example, a travel recommendation system can help a user arrange trips and discover next places to visit based on her own preference.

As an important feature, people's mobile behavioral patterns can be significantly influenced by their own historical experiences [7, 20, 29, 44, 48, 50]. As a consequence, POI recommendation based on historical spatio-temporal data has proven to be effective. Traditionally, LRT [10] incorporates temporal feature as one of the properties of user behavior in LBSNs. It models users' check-in temporal patterns $weekly/monthly/yearly$ with check-in matrix $C^{(t)}$ and then implements matrix factorization to learn user and POI representation vectors, in which user vectors are of time slots. More recently, machine learning methods have POI recommendation accuracy greatly increased. To capture temporal patterns of user preference, [17, 19, 44, 50] jointly learn users' long- and short-term preferences via attention mechanism for next POI recommendation with sequential and contextual information considered. ST-RNN [18] models local temporal and spatial contexts with recurrent neural networks (RNNs), where there are time-specific transition matrices for different time intervals and distance-specific transition matrices for different geographical distances in each layer. DeepMove [7] learns user preference using recurrent neural networks for historical sequence and short-term current sequence. [48] profiles the temporal popularity of POIs and then incorporates the degree of temporal matching between users and POIs into personalized POI recommendations. [54] hierarchically learns user's check-in patterns with state-based stacked RNNs. Despite superior results those models get, massive training data is required to obtain such a performance, which is probably inaccessible for the majority of LBSNs in real practice.

The recent advances in meta-learning has made it prevalent in instantiating a model with limited training data [3, 9, 23, 30, 47]. Meta-learned predictions based on sequential data has proven to be effective in domains including traffic forecasting [28, 47], taxi demand prediction [28], resource quality prediction [47], on-line item recommendation of E-commerce [6] and so forth. However, there have been several differences between above tasks and POI recommendation, which make it hard to implement those approaches directly. **1) Temporally imbalanced data.** In problem settings such as traffic prediction, it is easier to obtain continuous temporal sequences, while in LBSNs, people's check-ins are discrete and unevenly distributed, which makes it rather unpredictable. For example, a user may create extensive check-in records during national holidays while rarely visit POIs on work days. **2) Complex interactions.** Sequential relation is the primarily consideration of those tasks. However, given the explicit and potential interactions between users and/or POIs, in the task of POI recommendation, side information in LBSNs is also of great significance.

In this paper, to tackle the above challenges, we take two special considerations:

- **Sequential knowledge.** Interactions between users and/or POIs can be utilized to give accurate recommendations. [24] These interactions are hidden in spatial, temporal and social context of LBSNs. There have been works taking advantage of knowledge graphs to build context-aware recommender [27, 29, 32, 35, 51]. However, most of them ignore sequential information, which might lead to the problem of either forgetting past experience or "over recommendation". For example, a well trained model that has accurately learned the preference of a user might continuously recommend the same type of POI to her, which is definitely an unpleasant experience. Thus, it is desirable to incorporate user's sequential check-in behaviors when building such a knowledge-aware recommender.

- **Sparse data with large number of null intervals.** Predicting user behavior from limited and sparse data is one of the fundamental research problems in POI recommendation. To remedy the problem of data sparsity, some works ignore the exact physical time of check-in and deal with sequential pattern merely. However, this practice spoils the check-in patterns hidden in "null intervals", which refers to the intervals in a check-in graph when user does not make any check-in. Consider a scenario where two users have visited the same POIs during a certain period of time, while the first has regular check-in patterns (e.g. everyday) while the other finished all the check-ins in a few days but stays off-line for the rest of the time. Apparently the recommender should not make the same recommendations to them though they share the same check-in sequence. A recommender should be able to capture the difference between the two users. Therefore, a model that is adaptive to various check-in habits on sparse data is required.

In this work, we propose a meta learning framework, named **Meta**-learned **S**equential-**k**nowledge-aware **R**ecommender (Meta-SKR) for next POI recommendation. We deal with the first consideration by constructing sequential knowledge graphs (SKGs) from users' check-in sequences, which is a novel type of knowledge graph that jointly models sequential, geographical, temporal and social information. Specifically, we take users and POIs as entities (nodes) and link them with five types of relations (edges) that capture check-in features hidden in POI visiting orders and null check-in intervals. Each SKG is constructed on the basis of the check-in order a user made and thus sequential information can be integrated and users' dynamic and evolving preferences can be distilled. Regarding the second consideration, to fast learn from sparse training data, we introduce a meta-learner that can generate user-specific parameters based on the input check-in sequence, which are then used in subsequent embedding network to learn representation vectors of entities and edges of SKGs. Finally, the task of POI recommendation can be accomplished by predicting links between user and POI nodes.

Our contributions are summarized as follows:

- We propose a novel meta-learned framework that leverages both fine-granularity sequential patterns and spatial-temporal-social context information for POI recommendation. To the best of our knowledge, this is the first work to jointly model these factors into a shared knowledge graph and adopt meta-learning to address the challenges of user behavior modeling and data sparsity in POI recommendation tasks.
- To learn representations vectors of users and POIs from sequential knowledge graphs, we develop an attention-based graph embedding method that first extracts intra- and inter-SKG information for a node and then propagates the information to the node with edge directions considered.
- We conduct extensive experiments on three public real-world check-in datasets to evaluate the performance of our model. The favorable results verify our expectation that the proposed framework can reach a high accuracy even with sparse data.

2 PRELIMINARIES

In this section, we briefly introduce a set of preliminary concepts in the context of spatio-temporal social-based knowledge graph, and then give an overview of our framework.

2.1 Definitions and Notations

Definition 1. Check-in Sequence. *Each check-in c includes user ID u, POI ID p_c, check-in time τ_c and check-in location in terms of (latitude, longitude). Given the overall check-in sequence of user u, i.e. $C_u = [c_1, c_2, ..., c_n]$, where the check-ins are ordered in time, a set of subsequences,*

Table 1. Summary of Notations.

Notation	Description
c	A check-in.
u, U	A user and a set of users.
p, P	A POI and a set of POIs.
$s, \mathcal{S}$	A check-in sequence and a set of sequences.
$e, \mathcal{E}$	An entity and a set of entities.
$r, \mathcal{R}$	A relation and a set of relations.
$G, \mathcal{G}$	A sequential knowledge graph (SKG) and a set of sequential knowledge graphs.
$t = (e_i, r_k, e_j)$	A triple with head entity e_i, tail entity e_j and relation r_k of a knowledge graph.
$\mathcal{M}^{tr}$,$\mathcal{M}^{val}$,$\mathcal{M}^{ts}$	The meta-training, meta-validation, meta-test set.
($\mathcal{D}^{tr}$, $\mathcal{D}^{ts}$)	A meta learning task, composed of training set and test set.
τ	A time instance.
l_p	The location of POI p.
$d_i^{+/-}$	The out/in degree of node i.
$\mathcal{N}_i$	The set of neighbors of node i.
λ	The length of a check-in sequence s
T	The number of SKGs in $\mathcal{D}^{tr}$.
$\mathbf{h}$	The representation vector of an entity.
$\mathbf{g}$	The representation vector of a relation.
$\mathbf{x}$	The representation vector of a triple.
Θ	General notation for parameters in SKR network.
$\hat{y}_t$	The estimated probability of triple t being valid in a knowledge graph.

$\mathcal{S}_u = \{s_1, ..., s_m\}$, can be built by continuously sampling λ-length subsequences from C_u with stride r, i.e. $s_i = [c_{i1}, c_{i2}, ..., c_{i\lambda}]$.

Definition 2. Sequential Knowledge Graph (SKG). *Given a sequence s_i, a sequential knowledge graph (SKG) denoted as $G_i = (\mathcal{E}, \mathcal{R})$ can be constructed by generating triples that retrieving certain check-in patterns in s_i, where $\mathcal{E}$ is the set of entities (nodes) and $\mathcal{R}$ is the set of relations (edges). A triple in a SKG can be denoted as $t = (e_i, r_k, e_j)$, which describes entities e_i and e_j are connected by relation r_k. The set containing all SKGs that constructed from $\mathcal{S}_u$ is denoted as $\mathcal{G}_u = \{G_1, ..., G_m\}$.*

Table 1 summarizes the major notations of this paper.

2.2 Problem Statement

Before mathematically defining the problem, we first introduce the meta training paradigm used in this paper, which is based on the mainstream episodic formulation [40]. Suppose we have a group of users and their check-in history, we split each user's check-in data into meta-training set $\mathcal{M}_u^{tr}$, meta-validation set $\mathcal{M}_u^{val}$ and meta-test set $\mathcal{M}_u^{ts}$, for model training, selection and final test respectively. Each task sampled from the meta set has two components: $\mathcal{D}^{tr}$ and $\mathcal{D}^{ts}$. $\mathcal{D}^{tr}$ is composed of T successive check-in sequences and is used for user-specific parameter generation, i.e. $\mathcal{D}^{tr} = \{s_{i1}, ..., s_{iT}\}$. $\mathcal{D}^{ts}$, a randomly chosen sequence with $\mathcal{D}^{tr} \cap \mathcal{D}^{ts} = \emptyset$, is used for evaluating the generated parameters and making predictions.

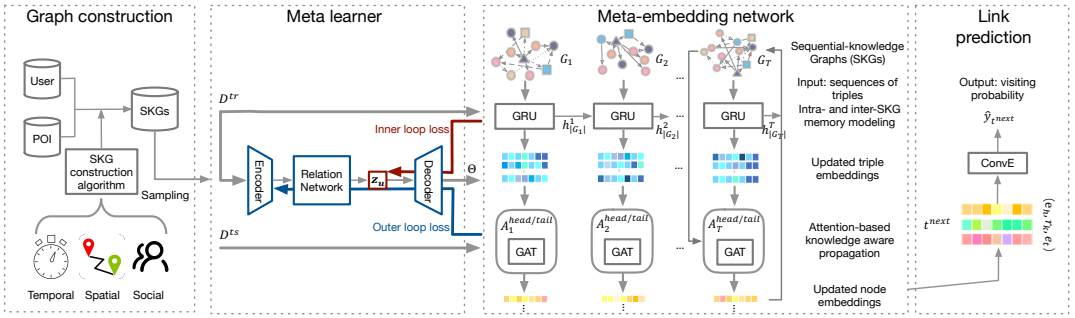


Fig. 1. Overview of Meta-SKR. In the meta-embedding network, for limited space, only data-flow of G_T is fully depicted, while the same flow exists in all SKGs.

Given a set of users $U = \{u_1, ..., u_n\}$ and their check-in sequences $\{\mathcal{S}_1, ..., \mathcal{S}_n\}$, we aim to recommend the next POI that might be visited by u_i after her most recent check-in sequence $s^r_{u_i}$ in the meta-test set, i.e.

$$t^{next}_{u_i} = \arg\max_{t^{next}_{u_i}} f(t^{next}_{u_i} | s^r_{u_i}, g_\Theta),$$

where $t^{next}_{u_i}$ is the next check-in of u_i in the form of triple, which consists of two entities (the user and a POI that is going to be visited) and a relation (a specific check-in pattern), f denotes meta-SKR that computes the probability of whether $t^{next}_{u_i}$ is a valid triple, g_Θ denotes the the initialized model with parameters adapted from $\mathcal{D}^{tr}$ of the task.

2.3 Framework Overview

As illustrated in Fig. 1, the proposed Meta-SKR contains four modules. **1) The Graph Construction Module**. In this module, to distill sequential, geographical, temporal and social information from user check-in history and model user check-in patterns, we design a novel type of knowledge graphs named sequential knowledge graphs (SKGs). The triples of SKGs are construed sequentially based on check-in sequences. Five types of relations are built to extract certain check-in patterns. **2) The Meta-learner**. We sample tasks in the form of ($\mathcal{D}^{tr}$, $\mathcal{D}^{ts}$) from SKGs of each user, which are then taken as inputs of the meta-learner, where user-dependent latent representations of parameters in subsequent meta-embedding module are learned. Gradient-based adaptation is performed in the latent space with training loss (the red flow). The meta-learner is optimized based on test loss (the blue flow). **3) The Meta-embedding Module**. In this module, nodes and edges embeddings are obtained. Intra- and inter-SKG sequential correlations are captured by adapting GRUs, and then graph attention networks (GATs) that use triple head/tail-dependent connection matrix to incorporate context-aware edges in the nodes' neighborhood. **4) The Link Prediction Module**. At last, we make recommendations on users' next POIs by computing the probability of whether potential triples are valid using ConvE [5], where a multi-layer convolutional network is adopted. The four modules can be categorized into two parts: the base model, SKR, which is composed of the Graph Construction Module, Meta-embedding Module and Link Prediction Module, and the meta learner.

3 PROPOSED METHOD

In this section, we describe the framework of Meta-learned Sequential-knowledge-aware Recommender (Meta-SKR) for POI recommendation. The section is organized as follows. In subsection 3.1, we introduce the algorithm for graph triple generation, where sequential, spatio-temporal and social

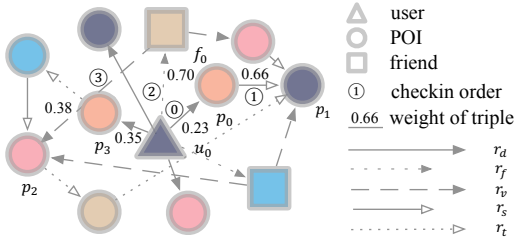


Fig. 2. Sequential knowledge graph: a running example (better viewed in color). In this example, the user u_0 (triangle) checked-in at $p_0 \rightarrow p_1 \rightarrow p_2 \rightarrow ...$ sequentially, while her friend f_0 (brown rectangle) checked-in at p_2 ahead of her. For simplicity, only edges related to the toy checkin sequence sample $p_0 \rightarrow p_1 \rightarrow p_2$ are labeled with weights, while for others only direction and edge type are illustrated. Weights of edges need to be normalized within edges of the same type.

relations are explored to generate triples from check-in sequence set $\mathcal{S}$. In subsequent subsection 3.2, an embedding network is designed to learn representations of users and POIs, followed by a discussion on how to make POI recommendations by inferring potential links in subsection 3.3. In subsection 3.4, we provide a description of the meta-learning strategy for advanced adaption of user-specific model parameters of the embedding network discussed in subsection 3.2.

3.1 Sequential-knowledge Graph Construction

For a given user u and one of her check-in sequence $s = \{c_1, ..., c_\lambda\}$, a sequential knowledge graph (SKG) can be constructed with the following entities and relations.

3.1.1 Entities of SKG. There are three kinds of entities in SKG:

- User. It represents the user who creates the current check-in sequence, denoted as u.
- POI. It represents a specific POI, denoted as p_i.
- Friend. It represents a friend of u, denoted as f_i .

There is friend entity in SKG, if existing check-in c_{f_i} in one of the friend's check-in sequences s_{f_i} such that:

i. $p_{c_{f_i}} = p_{c_u}$,
ii. $\tau_{c_{f_i}} \prec \tau_{c_u}$,

where $p_{c_{f_i}}$ denotes POI ID of check-in c_{f_i}. The intuition of above friend-based entity conditions is that the user and her friend check-in at the same location but the check-in time of her friend is earlier.

The reasons for leveraging this kind of interaction are twofold. First, people, especially friends, who check-in at similar POIs have greater similarities. Second, there is potential possibility that user visited the location is because a friend, who had been there before, explicitly or implicitly recommend it to her. By this way, we could make sure that the social effect imposed by friends sharing similar check-in behavior is incorporated in SKGs.

3.1.2 Relations of SKG. Five types of relations can be defined as follows. Note that all edge weights are normalized within their edge types.

- Temporal Sequential-check-in. If the time-interval between two successive check-ins in s_u is no longer than Δ_τ, then nodes of the two corresponding POIs can be linked by a temporal sequential-check-in edge, which is denoted as r_t, directed from the earlier check-in POI to the later one. The weight of r_t is defined as the time-interval between the two check-ins.

Algorithm 1: Sequential Knowledge Graph (SKG) Construction

Input: Check-in sequence $s = \{c_1, ..., c_\lambda\}$ of user u, F, P, Δ_s, Δ_t.
Output: A SKG in the form of ordered triples: $\{t_1, ..., t_m\}$.
Initialize SKG set G_s={};
$p^{prev} \leftarrow$ the POI in check-in c_1;
for *c in s* **do**
  $Size_{G_s} = |G_s|$;
  for *r in* $\{r_t, r_s\}$ **do**
    if *corresponding conditions could be satisfied* **then**
      $G_s \leftarrow ((p^{prev}, r, p^c), weight) \cup G_s$
    end
  end
  if *friend-visited check-in condition could be satisfied* **then**
    find the closest satisfied check-in record from friend f;
    $G_s \leftarrow ((u, r_f, f), weight) \cup G_s$;
    $G_s \leftarrow ((f, r_v, p^c), weight) \cup G_s$
  end
  if $Size_{G_s} == |G_s|$ **then**
    $G_s \leftarrow ((u, r_d, p^c), weight) \cup G_s$
  end
end

- Spatial Sequential-check-in. If the distance of two successive check-in records in s_u is no farther than Δ_d, then nodes of the two corresponding POIs can be linked by a spatial sequential-check-in edge, which is denoted as r_s, directed from the temporally checked-in earlier POI to the later one. The weight of r_s is defined as the Euclidean distance between the two POIs.
- Friend Visited. If a friend visited a POI earlier than the user with friend-based entity conditions satisfied, then the friend node and the POI node can be linked by a friend visited edge, denoted as r_v, directed from the friend node to POI node. The weight of r_v is defined as the frequency the friend visited the POI in her check-in history.
- Friendship. The friendship relation exists between the user and her friend, denoted as r_f, if friend-based entity conditions can be satisfied by certain check-in (s) of the friend. The edge is directed from the user to the friend. Weight of the edge is defined as:

$$\gamma \frac{|F_u \cap F_{f_i}|}{|F_u \cup F_{f_i}|} + (1-\gamma)\frac{|P_u \cap P_{f_i}|}{|P_u \cup P_{f_i}|},$$

  where F_u, P_u and F_{f_i}, P_{f_i} are the friend set and POI set of user u and her friend f_i respectively, γ is a manually set parameter for the trade off between the two factors.
  Friend visited and friendship relations (edges) always co-exist. In other words, if there is a POI, user and friend satisfying friend-based entity conditions, a friendship edge and a friend visited edge will be added to connect the three entities (nodes).
- Direct Check-in. For a given check-in, if all above relations can not be established, then a direct check-in edge will be built between the user and the POI, denoted as r_d, directed from the user to the POI. It represents an independent check-in. Edge weight is defined as the frequency the user visiting the POI in sequence s.

With the above defined entities and relations, we can now construct an SKG for the sequence s by sequentially traversing s, as described in Algorithm 1. For each check-in, we first try to construct the first four relations, if none of the four relations' conditions could be satisfied, a direct check-in relation will be added to the graph.

An example describing elements in a SKG is demonstrated in Fig. 2. Note that all edges are directed, from head entity e_h to tail entity e_t.

There are various advantages for constructing such sequential knowledge graphs. First, there can be multiple edges containing comprehensive information between two nodes since that triples are constructed sequentially in the order of check-ins. Second, information for why a triple is constructed (the relation) and how strong the connection is (the weight) are included in SKGs as well. Moreover, by defining r_t, r_s, r_v, r_f, r_d, null values in the check-in data can be translated into relations of SKGs, and is thus expected to provide more insights of user check-in behaviors.

3.2 Sequential Knowledge-aware Embedding

With SKGs obtained, we now discuss how to learn representation vectors for entities and relations.

Graph attention networks (GATs) [39] are extensions of graph convolutional networks (GCNs) [15], which learn to assign varying importances to a given node's neighbors rather than treat all neighboring nodes equally.

However, in KGs, entities play different roles depending on the relations they are associated with [25]. Though advanced in correlation modeling, GATs ignore context information in edges. To this end, Nathani et al. proposed an extension of GAT that incorporates relation and neighboring node features with attention mechanism [25]. This idea forms the basis of the embedding network we propose for sequential knowledge-aware recommender.

3.2.1 Intra- and Inter-SKG Memory Modeling. Inspired by [25], the representation of a triple $t_{ij}^k = (e_i, r_k, e_j)$, denoted as $\mathbf{x}^{ijk}$, can be calculated as linear transformation of the concatenation of its components' representation vectors, i.e.

$$\mathbf{x}^{ijk} = \boldsymbol{W_1}[\mathbf{h}_i \| \mathbf{h}_j \| \mathbf{g}_k], \tag{1}$$

where $\mathbf{h}_i$ and $\mathbf{h}_j$ are embeddings of e_i and e_j respectively and $\mathbf{g}_k$ denotes the representation vector of r_k, $\mathbf{h}_i, \mathbf{h}_j, \mathbf{g}_k \in \mathbb{R}^\kappa$ and $\boldsymbol{W_1} \in \mathbb{R}^{\kappa \times 3\kappa}$. Thus, with constructed SKGs, which can be treated as series of triples, we take the transformed representation vectors of triples as inputs of the embedding network.

Temporal correlation is an important factor affecting people's check-in behaviors. The order of check-in implies a user's check-in pattern and more recent items in a sequence may have larger impact on the next item [37]. However, to the best of our knowledge, very few knowledge-aware POI recommendation models take temporal correlations into account. To leverage information hidden in check-in orders, we model intra-SKG (sequence) and inter-SKG (sequence of sequences) memories with gated recurrent units (GRUs) [4].

GRUs have proven to be effective in processing sequential data because of the structure of update gates, denoted as a, and reset gates, denoted as r, which can effectively control information pipelines. We here adopt a standard GRU unit. Formally, for each current evaluated SKG G_i, the embedding update formulas can be written as:

	head					tail				
	t_0	t_1	t_2	t_3	...	t_0	t_1	t_2	t_3	...
u_0	0.23/6	0.66/6	0.70/6	0	...	0	0	0	0	…
f_0	0	0	0	0.38/2	...	0	0	0.70/1	0	…
p_0	0	0.66/1	0	0	...	0.23/1	0	0	0	…
p_1	0	0	0	0	...	0	0.66/3	0	0	…
p_2	0	0	0	0	...	0	0	0	0.38/3	…
...	…	…	…	...	...	…	…	…	…	…

Fig. 3. The connection matrix of SKG in Fig. 2. The connection matrix describes the role each node playing in all triples. Taking entry (u_0, t_0) as an example, its value 0.23/6 is resulted from: 1) u_0 is the head node of triple t_0; 2) the weight of the corresponding edge is 0.23 and the out degree of u_0 is 6.

$$\begin{aligned}
\mathbf{a}_\tau &= \sigma(\mathbf{W}_a \mathbf{v}_{\tau-1} + \mathbf{U}_a \mathbf{x}_\tau + \mathbf{b}_a), \\
\mathbf{r}_\tau &= \sigma(\mathbf{W}_r \mathbf{v}_{\tau-1} + \mathbf{U}_r \mathbf{x}_\tau + \mathbf{b}_r), \\
\hat{\mathbf{v}}_\tau &= \tanh(\mathbf{W}_v(\mathbf{r}_\tau \odot \mathbf{v}_{\tau-1}) + \mathbf{U}_v \mathbf{x}_\tau + \mathbf{b}_v), \\
\mathbf{v}_\tau &= (1 - \mathbf{a}_\tau) \odot \mathbf{v}_{\tau-1} + \mathbf{a}_\tau \odot \hat{\mathbf{v}}_\tau,
\end{aligned} \tag{2}$$

where $\mathbf{x}_\tau$ is the initial embedding of the τth triple in G_i, $\tau \in [0, |\mathcal{R}|]$, $\mathbf{W}_\epsilon$, $\mathbf{U}_\epsilon$, $\epsilon \in \{a, r, v\}$ are learnable parameters, $\mathbf{b}_\epsilon$, $\epsilon \in \{a, r, v\}$ are bias of the function, $\sigma(\cdot)$ is the sigmoid function and $\odot$ is the Hadamard product.

As discussed in Section 2, in each training set there are T SKGs, it is desirable and doable to make use of past experience for embedding learning of the current SKG. To capture long term correlations between SKGs and eliminate the problem of catastrophic forgetting in continual meta-learning tasks [23], we feed the embedding network with hidden state embedded in historical graphs. Therefore, the specific description of $\mathbf{v}_\tau$ can be written as follows. Note that the notation i has been omit in previous equations, which denotes the current graph (the i-th) we modeled.

$$\mathbf{v}_\tau^i = \begin{cases} \mathbf{v}_{|G_{i-1}|}^{i-1} & i \neq 1, \tau = 1; \\ \mathbf{0}, & i = 1, \tau = 1; \\ \textit{calculated recursively}, & \text{otherwise.} \end{cases} \tag{3}$$

where $\mathbf{v}_{|G_{i-1}|}^{i-1}$ denotes the last hidden state of previous SKG. Then the hidden state v_τ is taken as the updated embedding of x_τ.

3.2.2 Entity Embeddings Update. We propose an attention-based approach with graph neural networks (GNNs) to propagate information from triples to nodes, considering the role (head/tail) the node playing in triples. It is worth to mention that our approach shares some similarities with [43], where the in- and out-flowing features of a node's neighbors are modeled. However, connections in [43] are between homogeneous nodes, while in our problem setting, triple is the minimum operable unit. Therefore, their approach can not be directly adopted. To fit the natural instinct of SKGs, we adapt incidence matrix to model the connection between entities and triples. Moreover, in SKGs, an entity can be of different meanings given it is the head or tail in a triple. For example, a temporal sequential-check-in from POI A, a hot-pot restaurant in Chengdu, China to POI B, a bubble-tea shop would be less unusual if inversed. Thus, it is problematic to use a global representation of triples as [43] deals with nodes when propagating informations from a nodes' neighbors. To deal with this problem, we apply a linear transformation layer to expand the

representation vector of a triple into head and tail partitions. Mathematically, the approach can be described with the following formulas:

$$\mathbf{x}_{\tau}^{head/tail} = \mathbf{W}_2^{head/tail}\mathbf{x}_{\tau}^{T}, \tag{4}$$

where $\mathbf{W}_2^{head}, \mathbf{W}_2^{tail} \in \mathbb{R}^{\kappa\times\kappa}$ are the head- and tail-related triple transformation matrices and the calculated $\mathbf{x}_{\tau}^{head}$, $\mathbf{x}_{\tau}^{tail}$ are taken as outgoing and incoming representation vectors of the τth triple respectively.

Obtaining outgoing and incoming latent vectors of each triple, we get the absolute value of attention of a triple from the following formula:

$$\alpha_{\tau}^{head/tail} = LeakyReLU(\mathbf{W}_3\mathbf{x}_{\tau}^{head/tail}), \tag{5}$$

where $\mathbf{W}_3 \in \mathbb{R}^{1\times\kappa}$ is the shared weight matrix. Thus, the absolute graph attention for entity e_i over all triples can be described as:

$$\beta'_{i:} = A_{s,i:} \odot [(\alpha_1^{head}, ...\alpha_{\tau}^{head}, ..., \alpha_{|\mathcal{R}|}^{head})||(\alpha_1^{tail}, ...\alpha_{\tau}^{tail}, ..., \alpha_{|\mathcal{R}|}^{tail})], \tag{6}$$

where $A_s \in \mathbb{R}^{|\mathcal{E}|\times 2|\mathcal{R}|}$ is the connection matrix that describes incoming and outgoing neighbors of the unique entity set $\mathcal{E}$ of the evaluated SKG, $|2\mathcal{R}|$ is two times of the number of triples in the SKG, $A_{s,i:}$ is the specific row corresponding to entity e_i. A_s is defined as the concatenation of two weighted incidence matrices A_s^{head} and A_s^{tail}, which represent connections of outgoing and incoming edges in the SKG respectively and are calculated as:

$$A_{s,ij}^{head/tail} = w_{ij}\frac{1}{d_i^{+/-}}, \tag{7}$$

where w_{ij} is the weight of edge between entity e_i and e_j, and $d_i^{+/-}$ denotes the out/in degree of entity e_i. For example, in the running example of Fig. 2, A_s can be calculated as shown in Fig. 3, where t_0, t_1, t_2, t_3 are the first four generated triples as marked in Fig. 2.

Softmax is then applied over $\beta'_{i:}$ to get the relative attention values between a head (tail) entity and its tail (head) neighbors, i.e.,

$$\beta_{ij} = softmax_j(\beta'_{ij}) = \frac{exp(\beta'_{ij})}{\sum_{k=1}^{2|\mathcal{R}|} exp(\beta'_{ik})}. \tag{8}$$

Multi-head attention is first implemented by Valičković et al. [39] to stabilize the learning process and encapsulate more information of the neighbor. Inspired by [25, 39], we also adopt M independent attention layers to calculate the embeddings and then they are concatenated by the following formula:

$$\mathbf{h}'_i = \|_{m=1}^{M}\sigma(\sum_{k=1}^{2|\mathcal{R}|}\beta_{ik}^{m}\mathbf{x}_k^{m}), \tag{9}$$

where $\|$ denotes concatenation operation.

Multiple layers can be stacked to propagate information from a node's higher level neighbors. In the final layer, instead of concatenating output of different layers, we take the average of M layers to get the final embedding.

3.2.3 Edge Embeddings Update. Relations are far less complex than entities. For simplicity, linear transformation is then performed on relation embedding matrix $\mathbf{G}_R$, where $\mathbf{G}_R = [\mathbf{g_1}||\mathbf{g_2}||...||\mathbf{g_n}]$ and n is the number of relation types, to get further representation of relations in a similar fashion with [25], i.e.

$$\mathbf{G}_R^{'} = \mathbf{G}_R\mathbf{W}_R, \tag{10}$$

where $\mathbf{W_R}$ is a parameterized transformation matrix.

3.3 Recommendation Based on Knowledge Inference

Thus far we have obtained the embeddings of entities and relations. We then make recommendations by scoring potential triples using a link predictor. Given a triple $t = (e_i, r_k, e_j)$, where r_k is one of the possible check-in relation that the head entity e_i can generate, we predict the probability a user would take a specific POI as her next destination using the state-of-the-art relation inference method ConvE [5]. The scoring function is defined as:

$$\hat{y}_{t,next} = f(t) = f(vec(f[\overline{\mathbf{h}_i}; \overline{\mathbf{g}_k}] * \Omega)\mathbf{W}_4) \circ \mathbf{h}_j, \tag{11}$$

where $\overline{\mathbf{h}_i}$ and $\overline{\mathbf{g}_k}$ are 2D reshaping of $\mathbf{h}_i$ and $\mathbf{g}_k$, $*$ represents convolution operator. Accordingly to [5], the model first reshapes $\mathbf{h}_i$ and $\mathbf{g}_k \in \mathbb{R}^{\kappa}$ into $\overline{\mathbf{h}_i}$, $\overline{\mathbf{g}_k} \in \mathbb{R}^{\kappa_w \times \kappa_h}$, where $\kappa_w \times \kappa_h = \kappa$. Then the reshaped matrices are taken as inputs for 2D convolutional layer with filter Ω. The output tensors is then subsequently reshaped into a vector $vec()$ and be linearly transformed by $\mathbf{W}_4 \in \mathbb{R}^{|vec| \times \kappa}$. The returned vector of κ dimension is then used to compute the dot product, which is denoted by $\circ$, with tail entity embedding vector $\mathbf{h}_j$.

Parameters can be learned by minimizing the following binary cross entropy loss:

$$\mathcal{L}_{rec} = -\sum_{i}^{n} y_{t,next}^{i} log(\sigma(\hat{y}_{t,next}^{i})) + (1 - y_{t,next}^{i}) log(1 - \sigma(\hat{y}_{t,next}^{i})), \tag{12}$$

where $y_{t,next}^{i}$ is the ground-truth value of whether triple t is valid, which is 1 if t is in the generated triple set of the user's next check-in, 0 otherwise, and $\sigma(\cdot)$ denotes the sigmoid function.

The link predictor serves as a decoder of the encoded embeddings. Besides ConvE [5], there can be other implementations for this module, such as ConvKB [26] and so forth.

3.4 The Meta-learner

In the scenario of POI recommendation, it usually does not have massive data of users that could be used for training due to check-in sparsity. It is desirable to design a model that could fast learn with limited data. Additionally, people having different sequential check-in patterns may require different parameterized models for next check-in prediction. To this end, in this section, we present a meta-learner adapted from LEO [30], which automatically adjusts model weights of the embedding network of SKR by users instead of making predictions of all users' next check-ins with unified model weights.

As one of the state-of-the-art works on optimization-based meta-learning, LEO [30] proves that latent embedding optimization is beneficial to decouple optimization-based meta-learning techniques from high dimensional space of model parameters. We extend LEO for the problem of POI recommendation for that it is straightforward to feed embeddings of SKR to LEO and LEO can be extended to fit the graph-structured of SKGs.

The meta-learning approach is developed as a two-stage process. In the first stage, named the "inner loop", the meta-learner generates parameterized weights to its subsequent embedding

network of SKR and then update the weights based on the returned loss after training data passing through the initialized embedding network. After several iterations in "inner loop". The optimized SKR is believed to be fitted to the training data. In the subsequent stage, which is called "outer loop", we then use test data to evaluate the generated embedding network and then make predictions, and the returned loss will be used to update parameters of the meta-learner itself.

3.4.1 Generate Parameters—Optimization on Training Set (the "inner loop"). Let u represent a specific user, we encode user-specific latent vector $\mathbf{z_u}$ from embeddings of SKGs as:

$$\begin{aligned} \mu_{\mathbf{u}}^{\mathbf{e}}, \sigma_{\mathbf{u}}^{\mathbf{e}} = \frac{1}{T} \sum_{G_k \in \mathcal{D}_u^{tr}} \frac{1}{\sum_{i \in \mathcal{E}_{G_k}} d_i} \sum_{i \in \mathcal{E}_{G_k}} \sum_{j \in \mathcal{N}_i} \sum_{k \in \mathcal{R}_{ij}} g_{\phi_r}(g_{\phi_e}(\mathbf{h_i}), g_{\phi_e}(\mathbf{h_j}), g_{\phi_e}(\mathbf{g_k})), \\ \mathbf{z_u} \sim q(\mathbf{z_u}|\mathcal{D}_u^{tr}) = \mathcal{N}(\mu_u^e, diag(\sigma_u^{e\,2})), \end{aligned} \tag{13}$$

where T is the number of SKGs in $\mathcal{D}_u^{tr}$, d_i denotes the degree of node i, $\mathcal{N}_i$ denotes the neighborhood of entity e_i, $\mathcal{R}_i$ denotes the set of relations connecting entity e_i and e_j, g_{ϕ_e}, g_{ϕ_r} are encoder network and relation network respectively that are used to obtain data-dependent multivariate Gaussian distribution with a diagonal covariance $\mathcal{N} \sim (\mu_{\mathbf{u}}^{\mathbf{e}}, \sigma_{\mathbf{u}}^{\mathbf{e}})$, where e denotes encoder. $\mathbf{z_u}$ can then be sampled from the obtained distribution. As a common practice, we adopt re-parameterization trick to deal with the undifferentiable problem of sampling operation.

As the embedding network has multiple parameters to learn, it is unreasonable to define a single decoder and expect that it could fit all parameters. Thus, in a similar fashion to [28], after obtaining the latent vector $\mathbf{z_u}$ of a user, we then generate Gaussian distribution of parameters via parameter-specific decoders. For a given parameter θ, the decoding formulas are:

$$\begin{aligned} \mu_{\mathbf{n},\theta}^{\mathbf{d}}, \sigma_{\mathbf{n},\theta}^{\mathbf{d}} = g_{\phi_d}^{\theta}(\mathbf{z}_n), \\ \omega_n^{\theta} \sim p(\omega^{\theta}|\mathbf{z}_n) = \mathcal{N}(\mu_{n,\theta}^d, diag({\sigma_{n,\theta}^d}^2)), \end{aligned} \tag{14}$$

where $g_{\phi_d}^{\theta}$ is the decoder, ω_n^{θ} represents sampled user-specific weights of parameter θ, e.g. $\mathbf{W}_a$ in Equation 2, and d denotes the decoder.

The decoded parameters are taken as user-specific temporal model weights of SKR, using which we update triples, node and edge embeddings according to Equation 1-10. We define the "inner loop" training objective function using hinge loss:

$$L_u^{tr}(g_{\Theta_u}) = \sum_{t_{ij} \in \mathcal{T}} \sum_{t'_{ij} \in \mathcal{T}'} max\{l_{t_{ij}} - l_{t'_{ij}} + \zeta, 0\}, \tag{15}$$

where $l_{t_{ij}}$ is the L1-norm dissimilarity measure given by $l_{t_{ij}} = ||\mathbf{h}_i + \mathbf{g}_k - \mathbf{h}_j||$, $\zeta > 0$ is a marginal hyper-parameter, $\mathcal{T}$ is the valid triple set and $\mathcal{T}'$ is a set of randomly sampled invalid triples. Then, latent representation $\mathbf{z}_u$ can be updated with

$$\mathbf{z_u}' = \mathbf{z_u} - \eta \bigtriangledown_{\mathbf{z_u}} L_u^{tr}(g_{\Theta_u}), \tag{16}$$

where η is the learning rate. We adopt the architectures of encoder, decoder and relation networks similar as presented in [30]. The "inner loop" runs multiple times and finally reaches a new embedding network of SKR, g'_{Θ_u}.

3.4.2 Meta-learning Strategy—Optimization on Test Set (the "outer loop"). Parameters of the meta-learner hold through the optimization process in the "inner loop". We now discuss how to evaluate the parameter generating performance of the meta-learner. According to LEO [30], with a goal of

Algorithm 2: Framework of Meta-SKR.

Input: SKGs of users $\mathcal{G}_u$, $u \in U$; hyper parameters T, γ_1, γ_2, η, ζ.
Output: Topk recommended POIs.
Randomly initialize ϕ_e, ϕ_r, ϕ_d, hidden state of GRU;
Compute connection matrix A;
while *not converged* **do**
  Sample a batch of users from U;
  for *user u in batch* **do**
    Sample task instances ($\mathcal{D}_u^{tr}$, $\mathcal{D}_u^{ts}$) from $\mathcal{M}_u^{tr}$;
    Encode $\mathcal{D}_u^{tr}$ to $\mathbf{z}_u$;
    Decode $\mathbf{z}_u$ to Θ_u;
    $\mathbf{z}_u^{'} \leftarrow \mathbf{z}_u$, $\Theta_u^{'} \leftarrow \Theta_u$;
    /*Compute user specific parameters based on $\mathcal{D}_u^{tr}$.*/;
    for *number of adaption iterations* **do**
      Feed the SKR with $\mathcal{D}_u^{tr}$;
      Update node and relation embeddings with Equation 9 and Equation 10;
      Compute training loss $L_u^{tr}(g_{\Theta_u})$;
      Update Θ_u performing gradient steps w.r.t. Equation 16 to obtain $\mathbf{z}_u^{'}$;
      Decode $\mathbf{z}_u^{'}$ to $\Theta_u^{'}$;
    end
    /*Make predictions based on $\mathcal{D}_u^{ts}$*/;
    Feed the network with $\mathcal{D}_u^{ts}$ and compute test loss L_u^{ts};
    Make predictions with $\mathcal{D}_u^{ts}$;
    Compute recommendation loss $\mathcal{L}_{rec}$;
  end
  Update ϕ_e, ϕ_r, ϕ_d and the link prediction module by gradient descend;
  /* We ignore the validation process in this pseudo code */;
end
for *user u in U* **do**
  Sample task instances ($\mathcal{D}_u^{tr}$, $\mathcal{D}_u^{ts}$) from $\mathcal{M}^{test}$;
  Encode $\mathcal{D}_u^{tr}$ to $\mathbf{z}_u$ and then decode $\mathbf{z}_u$ to Θ_u;
  Make predictions with $\mathcal{D}_u^{ts}$;
end

fast adapting to new data, given a test set D^{tr} of user u, the optimization strategy of meta-learner can be defined as follows:

$$\min_{\phi_e, \phi_r, \phi_d^{\theta_1 \ldots, \theta_m}} L_u^{ts}(g_{\Theta_u}^{'}) + \gamma_1 D_{KL}(q(\mathbf{z_u}||D^{tr}), p(\mathbf{z_u})) + \gamma_2 ||stopgrad(\mathbf{z_u}^{'}) - \mathbf{z_u}||_2^2 + R, \tag{17}$$

where $p(\mathbf{z_u}) = \mathcal{N}(0, \mathcal{I})$, $D_{KL}(\cdot)$ denotes the KL divergence, $stopgrad(\cdot)$ is the function used to stop gradient computation, γ_1 and γ_2 are term importance hyper-parameters and R is a regularizer that calculated as L_2 regularization of all the weights in the encoder model with the layer-wise orthogonality constraint on decoder network weights. Similar to [12, 30], we use the second term to regularize the latent space and encourage the generative model to learn a disentangled embedding, and use the third term to encourage the encoder and relation net to output a parameter initialization that is close to the adapted code, which are beneficial to simplify the adaptation procedure [30].

The overall algorithm for Meta-SKR is shown in Algorithm 2.

4 EXPERIMENTS AND RESULTS

All the algorithms are implemented on an Intel(R) Xeon(R) CPU E5-2650 v4 @ 2.20GHz, two GeForce GTX 1080 GPUs and two TITAN XP GPUs.

4.1 Datasets

We use three real public location-based social network (LBSNs) datasets collected from Gowalla [1] and Weeplaces [1][22] and Yelp [2][21] respectively. The Gowalla dataset spans from January 1st, 2011 to May 31st, 2011. It contains user profiles, user friendship, location profiles, and users' check-in history. Each check-in is associated with user ID, POI ID, check-in time. Weeplaces is an application mapping an individuals' shared locations on other LBSNs such as Foursquare. In Weeplaces, users can login using their LBSN accounts and connect with their friends in the same LBSN who are also using this application [22]. The Weeplaces dataset, which contains user friendship and users' check-in history, spans from March 1st, 2010 to November 30th, 2010. For each check-in, user ID, POI ID, check-in time, latitude, longitude, city and category are recorded. Yelp dataset spans over several metropolitan areas in five years: January 1st, 2010 to August 1st, 2015. Each POI is tagged with category ID and location. Users' check-in history and social relations are also provided.

The statistics of preprocessed datasets are described in Table 2.

Table 2. Statistics of dataset.

Attribute	Gowalla	Weeplaces	Yelp
# of check-ins	1922604	1819632	473439
# of POIs	29976	37802	18990
# of users	22566	10287	6563

4.2 Implementation Details

Data Preprocessing. We divide each dataset into 6:2:2 for training, validation and test. We filter out users with less than 30 check-ins. The pre-trained embeddings of entities and relations are obtained via TransE [2], with random initialization and embedding size of $\kappa = 100$.

Hyper Parameter Settings. The embedding layer described in section 3.2 is set as 1. We optimize all models with Adam optimizer, where the batch size is fixed at 64, all learning rates are initialized as 1×10^{-3} and weight decay of 1×10^{-5}. The hyper parameters Δ_τ and Δ_d in Section 3.1 are set as 2h and 3km separately for graph construction. Trade off parameter γ is set as 0.5. We report the results with default parameter values $T = 4$ and $\lambda = 5$ to fit the size of our datasets. In all experiments, except when studying the effect of r in section 4.5.2, sampling stride r is set as $r = \lambda$. Unless otherwise stated, we choose the best settings for other hyper parameters regarding each dataset using random grid search.

4.3 Evaluation Metrics

Accuracy@k is commonly adopted to measure next POI recommendation results [13, 45]. Given a set of test users U, Accuracy@k can be described as:

$$Accuracy@k = \frac{\sum_{i=0}^{|U|} Avg\_hit_i@k}{|U|}$$

[1]https://www.yongliu.org/datasets/index.html
[2]http://spatialkeyword.sce.ntu.edu.sg/eval-vldb17/data/Yelp.zip

where $Avg\_hit_i@k$ is the average of $hit@k$, which is calculated as

$$Avg\_hit_i@k = \frac{|Topk_i \cap Ground - truth_i|}{min\{k, |Ground - truth_i|\}}$$

where $Topk_i$ is the set of top-k prediction results of user u_i and $Ground - truth_i$ is the ground-truth triple set of the user, which is generated in a similar strategy as described in Section 3.1, which means there might be multiple ones.

4.4 Performance Comparison

To evaluate the performance of our model, we first compare our Meta-SKR with the following models.

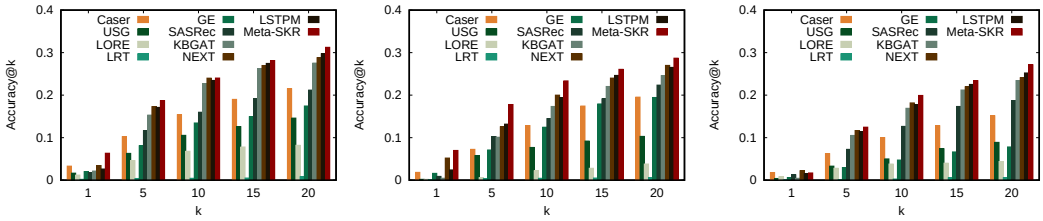
- **LRT** [10]: LRT is a variant of Matrix Factorization (MF) model, which makes POI recommendation based on both user features and users' temporal check-in patterns..
- **USG** [49]: It adopts the Collaborative Filtering (CF) framework for POI recommendation, which incorporates the geographical influence, social influence and user preference.
- **LORE** [52]: As a hybrid model, LORE employs Additive Markov Chain (AMC), CF and kernel density estimation to exploit the sequential influence, social and geographical influence between users and POIs.
- **GE** [45]: GE is a graph-based embedding POI recommendation model that integrally captures sequential effect, geographical influence, temporal cyclic effect and semantic effect into a shared low dimensional space.
- **SASRec** [13]: SASRec is a self-attention based sequential model that allows to capture long-term semantics (like an RNN), but, using an attention mechanism, makes its predictions based on relatively few actions.
- **Caser** [38]: Convolutional sequence embedding recommendation model (Caser) proposes a convolutional network structure for capturing both general user preferences and sequential behavior patterns.
- **KBGAT** [25]: The recent proposed KBGAT learns graph attention based embeddings that cater to relation prediction on KGs.
- **NEXT** [53]: NEXT Incorporates meta-data information and temporal contexts, i.e. time interval and visiting time, to predict user's next move.
- **LSTPM** [34]: The method LSTPM models user's long-term preference with a nonlocal network and short-term preference with a geo-dilated RNN.

4.4.1 Recommendation effectiveness. We first present comparison results on the three datasets in terms of Accuracy@k in Fig. 4, where $k \in \{1, 5, 10, 15, 20\}$, for that a greater value of k is usually ignored in top-k recommendation tasks [45].

As presented in Fig. 4, it can be observed that our proposed Meta-SKR outperforms other baselines in terms of Accuracy@k on all three datasets and nearly all cases. Some other interesting observations are in the following:

i. Meta-SKR achieves 84%, 34% relative improvements of Accuracy@1 on Gowalla, Weeplaces and 5.2%, 8.2%, 7.3% relative improvements of Accuracy@20 on Gowalla, Weeplaces and Yelp respectively over the best results of the baselines, which demonstrates the superiority of our model.

ii. Another observation is the evaluated models gain their best performances on Gowalla, while perform the worst on Yelp. An explanation could be that though Gowalla and Yelp is of similar dense in terms of the average number of check-in per user, data collected form Yelp is of a much longer time-span, which might lead to weak user behavior patterns.



(a) On Gowalla (b) On Weeplaces (c) On Yelp

Fig. 4. Recommendation effectiveness comparisons.

Table 3. Effect of data sparsity on Gowalla dataset (-20%). "-" denotes the method with reduced data.

Acc \ M / k	LRT	LRT-	USG	USG-	LORE	LORE-	GE	GE-	Caser	Caser-
1	0.0011	0.0005	0.0165	0.0125	0.0119	0.0081	0.0201	0.0134	0.0330	0.0149
5	0.0030	0.0005	0.0630	0.0535	0.0462	0.0211	0.0810	0.0622	0.1023	0.0558
10	0.0035	0.0010	0.1065	0.0799	0.0681	0.0342	0.1346	0.1101	0.1539	0.0887
15	0.0041	0.0011	0.1261	0.1095	0.0782	0.0460	0.1493	0.1354	0.1901	0.1187
20	0.0072	0.0020	0.1461	0.1250	0.0819	0.0527	0.1745	0.1563	0.2151	0.1421

Acc \ M / k	SASRec	SASRec-	KBGAT	KBGAT-	NEXT	NEXT-	LSTPM	LSTPM-	Meta-SKR	Meta-SKR-
1	0.0179	0.0112	0.0214	0.0089	0.0344	0.0101	0.0263	0.0131	**0.0634**	**0.0547**
5	0.1163	0.0674	0.1531	0.0976	0.1731	0.1109	0.1712	0.1129	**0.1869**	**0.1255**
10	0.1599	0.1012	0.2268	0.1426	0.2400	0.1402	0.2346	0.1671	**0.2403**	**0.1831**
15	0.1921	0.1259	0.2623	0.1670	0.2698	0.1837	0.2747	0.1972	**0.2815**	**0.2239**
20	0.2119	0.1459	0.2754	0.1812	0.2882	0.2120	0.2973	0.2250	**0.3126**	**0.2660**

iii. Though GE uses the same type of information as Meta-SKR, it performs significantly worse. This might be due to their different embedding strategies. To be more specific, different from Meta-SKR that jointly models context information, GE encodes sequential effect, geographical effect, temporal effect separately in different graphs (models) and then optimizes the embedding model together by a fusing objective function.

iv. LRT performs significantly worse than other algorithms. This might because LRT only considers temporal information and the explicit check-in behaviors while ignores geographical and other side information that is important as well in location recommendation.

4.4.2 Impact of data sparsity. In this part, we study the effect of data sparsity. To simulate datasets with different sparsity, we randomly reduce the training data by a ratio of 5%, 10%, 15% and 20%. For limited space, we only report the recommendation accuracy when 20% data is reduced on Gowalla and Yelp dataset, as listed in Table 3 and Table 4.

As expected, when more data is reduced, the recommendation accuracy of all methods drops. However, Meta-SKR still outperforms all the other methods in most of the cases. It could be observed that when evaluating Accuracy@1 on Yelp dataset, Caser performs slightly better than Meta-SKR. However, when it comes to relative accuracy drop, Meta-SKR is 4.1% less than Caser. It also worth mention that the relative advantage of Meta-SKR over other methods becomes more significant. For example, compared with the state-of-the-art baseline model LSTPM, Meta-SKR achieves 317.6%, 35% relative improvements of Accuracy@1 and 18.2%, 16.3% relative improvements of Accuracy@20 on the two reduced datasets, which indicates Meta-SKR is more robust on sparse data. This is probably

Table 4. Effect of data sparsity on Yelp dataset (-20%). "-" denotes the method with reduced data.

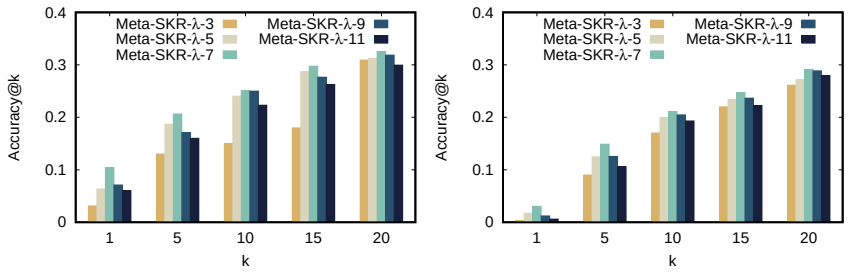
Acc \ M / k	LRT		USG		LORE		GE		Caser	
	LRT	LRT-	USG	USG-	LORE	LORE-	GE	GE-	Caser	Caser-
1	0.0002	/	0.0040	0.0021	0.0088	0.0014	0.0059	0.0032	0.0180	**0.0164**
5	0.0012	0.0005	0.0333	0.0180	0.0285	0.0042	0.0297	0.0101	0.0624	0.0470
10	0.0027	0.0017	0.0506	0.0289	0.0380	0.0141	0.0474	0.0229	0.1002	0.0728
15	0.0054	0.0029	0.0739	0.0375	0.0411	0.0223	0.0665	0.0400	0.1280	0.0972
20	0.0060	0.0043	0.0892	0.0433	0.0447	0.0284	0.0782	0.0683	0.1514	0.0984
Acc \ M / k	SASRec		KBGAT		NEXT		LSTPM		Meta-SKR	
	SASRec	SASRec-	KBGAT	KBGAT-	NEXT	NEXT-	LSTPM	LSTPM-	Meta-SKR	Meta-SKR-
1	0.0126	0.0040	0.0044	0.0031	**0.0221**	0.0092	0.0152	0.0120	0.0170	0.0162
5	0.0725	0.0597	0.1053	0.0400	0.1169	0.0418	0.1142	0.0857	**0.1247**	**0.0979**
10	0.1266	0.0735	0.1691	0.0790	0.1818	0.1043	0.1776	0.1248	**0.1993**	**0.1536**
15	0.1735	0.1017	0.2121	0.1116	0.2197	0.1345	0.2253	0.1723	**0.2342**	**0.1992**
20	0.1871	0.1273	0.2344	0.1380	0.2411	0.1376	0.2522	0.1892	**0.2716**	**0.2201**

resulted from two reasons. Firstly, accuracy on baseline models drops faster. On account of their data-driven nature, their advanced performances are heavily relied on large datasets. Once the dataset becomes sparser and smaller, the model might fail to draw a complete picture of users' behavior patterns. Second, with the implementation of meta-learning strategy, Meta-SKR is trained to leverage user-specific features from limited data, thus it is less sensitive to the reduction of data size.

As for the experiments on other reduction values (5%, 10%, 15%) and on Weeplaces dataset, we observe similar trends.

4.5 Study of Meta-SKR

In the above subsection we compare our Meta-SKR model with other approaches. To further study the benefits of hyper parameters and components of Meta-SKR, we design three groups of experiments to evaluate how they affect recommendation accuracy on datasets of Gowalla and Yelp.

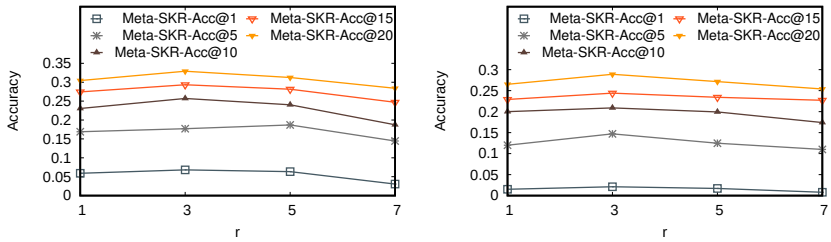


(a) On Gowalla (b) On Yelp

Fig. 5. Effect of check-in sequence length λ.

4.5.1 Effect of check-in sequence length λ. Parameter sequence length λ as defined in Definition. 1 of triple generator directly influences what knowledge graphs are consist of, and thus eventually effects Accuracy@k. Four comparison methods are designed to evaluate the impact of λ on recommendation accuracy: Meta-SKR-λ-3, Meta-SKR-λ-5, Meta-SKR-λ-7, Meta-SKR-λ-9, Meta-SKR-λ-11, which represents the Meta-SKR model with $\lambda = \{3, 5, 7, 9, 11\}$ respectively, and 5 is chosen to be the default value of λ in our Meta-SKR.

The results are depicted in Fig. 5. It can be observed that both a super short sequence and a super long sequence contribute negatively to model performance. From the figures we can tell that relatively longer sequence benefits recommendation (see, Meta-SKR-λ-5 and Meta-SKR-λ-7).



(a) On Gowalla (b) On Yelp

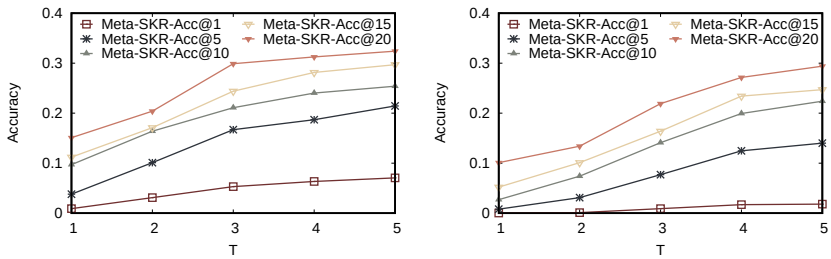
Fig. 6. Effect of sampling stride r.

4.5.2 Effect of sampling stride r. Sampling stride r not only influence the size of training data but also has effect on the granularity of the modeled user behavior patterns. With λ fixed as 5, we increase r from 1 to 7 with step size 2.

Some observations of Fig. 6 are as follows. Middle sized sampling stride benefits recommendation the most. This could be resulted from that for the current λ, which is set as 5, $r = 3$ and $r = 5$ covers all source data and the observed user behavior patterns are dynamic and coherent enough for the model to learn. Stride 7 gives the lowest accuracy probably because not all data is observed by the model thus the prediction of user's next move is based on incoherent patterns. Though model with stride 1 performs slightly worse than $r = 5$, it is worth mentioning that generating a set of SKGs with $r = 1$ is rather time consuming, given the large number of previous SKGs that need to be considered for the construction of the later ones.

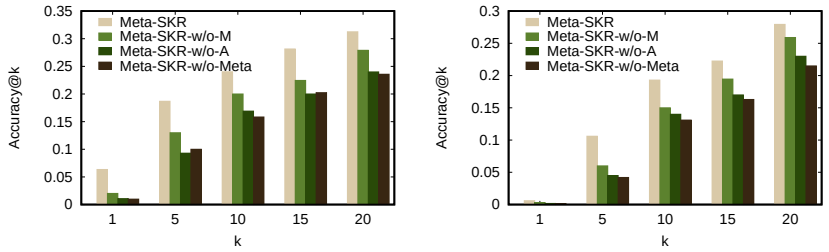
4.5.3 Effect of SKG number in D^{tr}. In order to study the impact of length of SKG sequence in the meta-training process, we increase the number of SKGs of D^{tr} from 1 to 5 by step size 1, where 4 is taken as the default value. The experiment results are shown in Fig. 7.

Overall, recommendation accuracy tends to raise as the number of SKGs increases. It can also be observed that with SKG number increasing, recommendation accuracy first increases significantly, then shows signs of slow-growth and finally becomes relatively stable when the SKG number is around 4. This might be resulted from: first, when more SKGs are fed into the model, more data can be utilized to obtain a comprehensive user profile; moreover, long-term preference can also be extracted with more SKGs. This trend indicates that making use of inter-SKG information is likely to be beneficial for good performance.



(a) On Gowalla (b) On Yelp

Fig. 7. Effect of SKG number in D^{tr}.



(a) On Gowalla (b) On Yelp

Fig. 8. Effect of model components.

4.5.4 Effect of model components. The major results of ablation study regarding Meta-SKR with different components on Gowalla and Yelp dataset are shown in Fig. 8. We design three variants of Meta-SKR, Meta-SKR-w/o-M, Meta-SKR-w/o-A and Meta-SKR-w/o-Meta.

Meta-SKR-w/o-M is a variant related to sequential memory extracting. To investigate the effect of retrieving memory from previous sequences, Meta-SKR-w/o-M reduces the hidden state initialization function (see Equation 3) by replacing the initialization when $i \neq 1, \tau = 1$ with vector $\mathbf{0}$ as well. It can be told from Fig. 8 that the performance of Meta-SKR-w/o-M is significantly worse than Meta-SKR. Without inheriting status from prior SKGs, only intra-sequence sequential information can be extracted for temporal correlation modeling, which inevitably leads to poor performance.

Meta-SKR-w/o-A represents a variant of attention-based knowledge propagation part. Instead of building head/tail-specific triple connection matrix, Meta-SKR-w/o-A treats head and tail related triples symmetrically. Specifically, if an entity e_i is of the triple t_j, regardless of whether it is the head or tail, e_i is considered connected with t_j. Direction information eliminated by this strategy. Accordingly, the recommendation accuracy suffers an even more significant drop.

Meta-SKR-w/o-Meta simply uses the sequential-knowledge-aware recommender defined in Section 3.1 - 3.3 to recommend next POIs, with shared model weight for all users. Comparing Meta-SKR-w/o-Meta with baseline models in Fig. 4, in most cases, the variant still outperforms most baseline models. Moreover, comparing Meta-SKR-w/o-Meta with other methods in Fig. 8, models with parameter generating, i.e. Meta-SKR, Meta-SKR-w/o-M and Meta-SKR-w/o-A, perform better in most cases, among which the performance improvement of Meta-SKR and Meta-SKR-w/o-M is more significant. These results indicate first, the proposed sequential-knowledge-aware recommendation network is effective; second, parameter adaptation significantly contributes to the model's performance.

5 RELATED WORK

5.1 POI Recommendation

POI recommendation can be deemed as one of the main enablers of location based social networks. As a special branch of context-aware recommendation [29], POI recommendation methods take (combinations of) geographical, temporal, social, sequential and categorical information into account. According to the utilized techniques, they can be categorized into Collaborative Filtering (CF) based [10, 11, 46], Matrix Factorization (MF) based [22, 49], Poisson Factor Models (PFM), Hybrid Models [8, 52], Embedding Based Models [29, 53] and deep models [7, 18, 34, 44].

The recent advances in knowledge graph embedding and completion [5, 25] have greatly helped with the problems of properly incorporating context-aware information and data sparsity [21, 29, 41, 45, 51]. For example, [29] proposes a spatio-temporal context-aware and translation-based recommender framework (STA) to model the third-order relationship among users, POIs, and

spatio-temporal contexts. [45] models sequential effect, geographical influence, temporal cyclic effect and semantic effect into four corresponding relational graphs. Although these methods have provided strong performance, most of them require rich types of side information and rely on massive training data, which are inaccessible in most real-world check-in datasets. Moreover, since the interactions are constructed in a statistic setting, they might not well model users' sequential check-in orders. Based on embedding based models, our model takes the idea of meta-learning and sequential knowledge-aware graph embeddings to solve the above problems.

5.2 Meta-learning

Meta-learning studies how to distill the prior knowledge from past experiences and enable fast adaptation to novel tasks with only a limited amount of samples [23]. The main researches in meta-learning include 1) learning a widely generalizable initialization or leveraging an optimizer as the meta-learner to adjust model weights [3, 9, 30]; 2) learning an embedding function that can embed inputs into a shared spaces where there are distance metrics serving as the meta-learner [14, 23, 33, 36, 40]; 3) learning with memories of previous task obtained from recurrent neural networks [31].

Meta-learning has been proven to be promising in recommender systems, especially in the task of cold-start recommendation. The most relevant work to our study includes [1, 6, 16, 42]. Compared to [1, 16, 42], which use MAML [9] for fast user adaptation, our work is adapted from latent embedding optimization (LEO) [30] since it well suits our problem where embeddings can be easily obtained and taken as inputs of the meta-learner and the original LEO model can be extended to adapt to our graph structured data. To make full use of sequential information, we also propose a memory transmission strategy to utilize inter-SKG interactions during meta-learning. From the perspective of problems, though a great number of algorithms have been proposed with meta-learning in recommender systems, e.g. [1, 16, 42] introduce meta-learning to the task of general recommendations and [6] is designed for e-commerce sequential recommendation, our work is the first to study the problem of meta-learning through knowledge-aware graph neural networks in the context of POI recommendation, which requires providing spatio-temporal-aware recommendations based on users and and items' spatio-temporal context.

6 CONCLUSIONS

In this work we study the problem of utilizing user sequential check-in and spatio-temporal-social information in SKGs for next POI recommendation. We propose a meta-learning framework named Meta-SKR, which contains four modules. Our solution starts with graph construction where triples of sequential knowledge graphs (SKGs) are built, followed by the embedding network with a meta-learning paradigm and at last we provide the next POI recommendation by scoring potential triples in the link prediction module. Extensive experiments based on real check-in datasets are conducted and the favorable results confirm the superiority of our framework with sparse training data.

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