Event-centric Tourism Knowledge Graph—A Case Study of Hainan

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Abstract. Knowledge graphs have become increasingly important in tourism industry recently for their capability to power insights for applications like recommendations, question answering and so on. However, traditional tourism knowledge graph is a knowledge base which focuses on the static facts about entities, such as hotels, attractions, while ignoring events or activities of tourists' trips and temporal relations.

In this paper, we first propose an Event-centric Tourism Knowledge Graph (ETKG) in order to model the temporal and spatial dynamics of tourists trips. ETKG is centered on activities during the trip and regards tourists' trajectories as carriers. We extract valuable information from over 18 thousand travel notes crawled from Internet, and define an ETKG schema to model tourism-related events and their key properties. An ETKG based on touristic data in Hainan is presented which incorporates 86977 events (50.61% of them have complete time, activity, location information) and 7132 journeys. To demonstrate the benefits of ETKG, we propose an Event-centric Tourism Knowledge Graph Convolutional Network (ETKGCN) for POI recommendations, which facilitates incorporating tourists behavior patterns obtained from ETKG, so as to capture the relations between users and POIs more efficiently. The offline experiment results show that our approach outperforms strong recommender baselines, so that it validates the effectiveness of ETKG.

Keywords: Knowledge graph · Event evolutionary graph · Intelligent tourism · Recommendation system

1 Introduction

With the uprising of large scale knowledge graphs (KGs) like Wikidata, DBpedia, and YAGO, various knowledge-based applications, such as semantic search, question answering [12], recommendation system [14] and so on, can benefit from the substantial and valuable knowledge in the KGs, and achieve significant performance improvement. Recently, in the field of tourism, knowledge graphs are

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leveraged to recommend travel attractions or tour plans [2,6]. However, existing tourism knowledge graphs mainly focus on modeling static knowledge about tourists trips, such as opening hours of attractions, nearby restaurants, addresses of hotels and so on. This static knowledge may not provide enough information to meet the needs of tourists in some cases. We analyze these issues.

- Tourist activities have not received enough attention in the existing tourism knowledge graphs. In fact, various activities in travel have an important impact on the experience of tourists.
- In the current knowledge graphs, tourist attractions, which make up the entire trip, are described as separate entities, ignoring the transfer relationship between attractions. Therefore, it's difficult to recommend or answer questions about travel routes.
- It is difficult to answer questions concerned with most" and best" based on existing knowledge graphs since there is no relation strength or entity popularity provided. For example, when it comes to recommending the most suitable places to surf for a tourist, it's hard to get the best results with traditional knowledge graphs.

Inspired by the event-centric knowledge graph proposed by Rospocher [13] and event evolutionary graph by Liu [10], we turn the focus of knowledge graph into events. In the literature, an event refers to a specific occurrence at a certain time and location, involving one or more participants. In this study, we consider tourist activities as events in tourism scenario, such as rain forest rafting, water-skiing, and whale watching, etc., which happens sometime at certain places. Efficiently incorporating these events and spatial-temporal information into a variety of tourism applications will be very beneficial. So we propose an Event-centric Tourism Knowledge Graph (ETKG) that interconnects tourist activities using temporal relations in chronological order, and with spatial information at that time. In addition, features about tourist trips like trip type, trip consumption are integrated into ETKG to enrich it. In this work, we construct an ETKG based on a large number of travel notes about tourism in Hainan province, which is a popular tourist destination in China. The travel notes record where the tourists visited and what they did during the trips for the purpose of sharing their travel experiences, mostly in chronological order. The information about tourism activities included in travel notes is of high quality and suitable for generating the initial ETKG.

To verify the effectiveness of ETKG, we present an application of POI recommendation which can make use of information generated from ETKG so as to improve the accuracy of recommendation. We propose Event-centric Tourism Knowledge Graph Convolutional Networks (ETKGCN), which can better learn user and item representations by incorporating information inferred from ETKG. Through experiments on real-world datasets in the tourism, we demonstrate that ETKGCN achieves substantial gains over several state-of-the-art baselines.

In summary, our key contributions are presented as follows:

- We present an Event-centric Tourism Knowledge Graph (ETKG) which integrates tourism events and their temporal relations to represent tourists' activities in an efficient way. The schema of ETKG built upon the Simple Event Model [5] with additional properties and classes is also presented.
- We propose an efficient pipeline to construct ETKG. Event information can be extracted from travel notes accurately and organized in an appropriate form. Based on the pipeline, an ETKG about Hainan tourism is presented, which incorporates 86977 events, 680 locations, 7132 journey and 79845 temporal relations.
- A new recommendation system framework is proposed based on ETKG—ETKGCN, which demonstrates the effectiveness of ETKG.

The paper is organized as follows. In Sect. 2, we describe the related work. In Sect. 3, we present the pipeline to construct the graph. An application of ETKG for POI recommendation is shown in Sect. 4. Finally in Sect. 5, we provide a conclusion.

2 Related Work

Knowledge Graphs (KGs) are used extensively to enhance the results provided by popular search engines at first. These knowledge graphs are typically powered by structured data repositories such as Freebase, DBpedia, Yago, and Wikidata.

With the development of NLP technology, more and more knowledge graphs are constructed based on unstructured corpus [13], using named entity recognition [9] and relation extraction [8,11] technology. The most commonly used model of named entity recognition(NER) is BiLSTM+CRF [9]. As for relation extraction, there are also many new approaches in academia, such as distant supervision and transformer [3].

In the last few years, knowledge graphs have been used in many fields. In the tourism scene, some experts also begin to build knowledge graphs to solve tourists' problems during the travel [2,6]. DBtravel [2] is a tourism-oriented knowledge graph generated from the collaborative travel site Wikitravel. Jorro-Aragoneses and his team proposed an adaptation process to generate accessible plans based on the retrieved plans by the recommender system in 2018 [6]. A KG is a type of directed heterogeneous graph in which nodes correspond to entities and edges correspond to relations. The introduction of Graph Convolutional Networks [17] accelerates the application of knowledge graph in industry, especially in the field of recommendation [14].

Event-centric knowledge graphs (ECKG) [13] was proposed in 2016. Compared with traditional KG, the focus of ECKG turns into the events in real world. In 2018, Simon Gottschalk built EventKG, a multilingual knowledge graph that integrates and harmonizes event-centric and temporal information regarding historical and contemporary events [4]. Both ECKG and EventKG were constructed based on SEM [5] and supported W3C standard [15]. In the same year, Professor Liu Ting's team from Harbin Institute of Technology put forward the concept of event evolutionary graph [10]. Event evolutionary graph puts more emphasis on the logical relationship between events and achieved excellent result in script event prediction task. However, it didn't support W3C standard. Our goal is to define a KG with the features of EventKG and Event evolutionary graph.

3 Construction of ETKG

In contrast with existing tourism knowledge graphs, Event-centric Tourism Knowledge Graph (ETKG) is centered on events, i.e. tourism activities in this study, and interconnects events using temporal relations in chronological order. Moreover, some additional features such as spatial information, attributes of journeys are incorporated into ETKG. In this way, we can obtain not only static information of tourism, but also some hidden patterns of various tourist behaviors inferred from inter-event relationship, which can be utilized as prior knowledge for tourism applications. We design an ETKG schema based on the Simple Event Model [5].

3.1 Generation Pipeline of ETKG

The construction process of ETKG is shown in Fig. 1 which generally consists of the following three parts. Firstly, we crawl travel notes from the web page, for the reason that travel notes not only record the activities of tourists in various scenic spots, but also contain some important tags, such as trip consumption, travel companions, types of travel and so on. These tags are made by tourists themselves when their travel notes are published, which has a high credibility. Secondly, we extract valuable information from travel notes, including trajectories, activities and tags mentioned above. Finally, the information extracted from travel notes was organized based on ETKG schema we proposed in order to model events in RDF. The ETKG schema is given in Fig. 2.

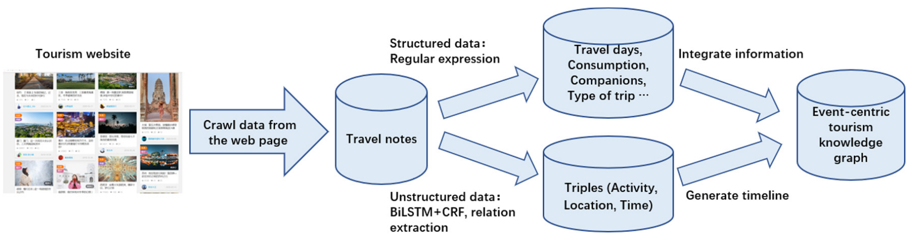

Fig. 1. ETKG generation pipeline.

In this work, we use a case study of Hainan tourism to illustrate the construction of ETKG and its application of POI recommendation. We crawl users' travel notes about Hainan from Ctrip, one of China's largest travel websites (https://www.ctrip.com). About 18 thousand travel notes related to Hainan are crawled. However, some of them just mention Hainan instead of recording the travel experiences in Hainan. After filtering these out, we get 7132 travel notes and then construct an Event-centric Tourism Knowledge Graph based on them.

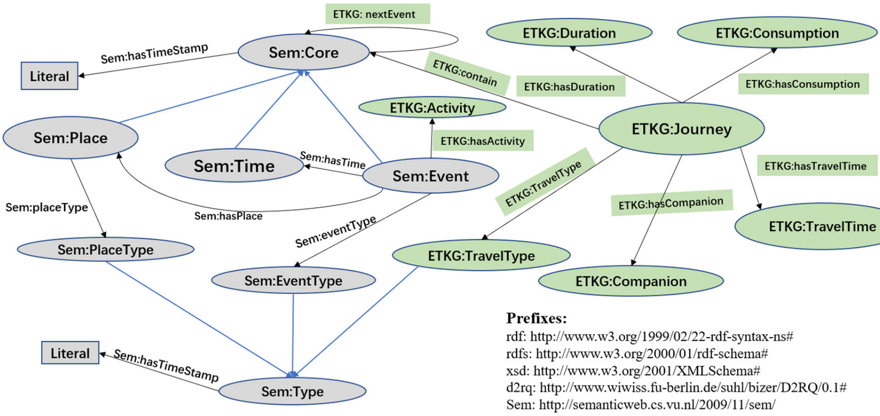

Fig. 2. Schema of Event-centric Tourism Knowledge Graph (*ETKG*). Our schema is based on *SEM* and the classes are colored gray. The blue arrows denote *rdfs:subClassOf* properties, while the black arrows visualize *rdfs:domain* and *rdfs:range* restrictions on properties. Classes and properties introduced in *ETKG* are colored green. (Color figure online)

Table 1. The examples of place type

Place type	Place
Shopping	Shopping mall, supermarket, store
Transportation	Airport, railway station, long-distance bus station, customs ports
Recreation	Park, gym, beach, soccer field, zoo, museum, scenic spots
Entertainment	Tea room, coffee shop, nightclub, pub, theater, beauty salon

Travel notes contain both structured and unstructured information. Structured information includes: travel days, trip consumption, travel companions, type of trip (self-driving travel, travel on a budget and so on) and month of travel. The structured information can be extracted by regular expression. As for unstructured information, this paper uses BiLSTM+CRF to extract events and entities from the body of travel notes, including: scenic spots visited by tourist, tourist's activities which correspond to events in this study, time for tourists to participate in activities.

The schema of the Event-centric Tourism Knowledge Graph is shown in Fig. 2. As we can see, the description of activity is inspired by SEM (Simple Event Model) [5]. SEM provides a generic event representation including topical, geographical and temporal dimensions of an event, as well as links to its actors. In ETKG, each Event contains three properties:*Activity*, *Place* and *Time*. The extracted activities are connected through the ***nextEvent*** relation in chronological order. Therefore, tourists' trajectories are included in the Event-centric Tourism Knowledge Graph. In Table 1 and Table 2, we give some examples of ***eventType*** and ***placeType*** [16]. We also define 5 attributes to describe tourists' journey, which can be seen in Table 3, including: ***travelType***, ***companion***, ***duration***, ***travelTime***, ***consumption***. Each activity is connected to the corresponding journey through relationship ***contain***.

Table 2. The examples of event type

Event type	Event
Dining	Eat BBQ, have a buffet, enjoy seafood, walk down the food court...
Sightseeing	See the sunrise, watch the sunset, go surfing, take a motorboat...
Rest	Sleep, have a rest, sunbathe
Entertainment	Go shopping, go to the spa, go to the coffee shop, go to nightclub...

Table 3. The definition of five attributes

Attribute	Meaning	Examples
TravelTime	The month when tourists went to Hainan	$1 \sim 12$
Duration	The number of days tourists visited Hainan	$2 \sim 20$
Consumption	Per capita consumption on the trip	$1000 \sim 10000$
TravelType	A brief summary of the journey	Self-driving, gourmet tour
Companion	The people who the user travel with	Parents, friends

3.2 Information Extraction and Organization

In this subsection, we give a detailed description how to extract events and entities from unstructured data. We have to extract three types of elements: activity, location, and time from the texts of travel notes. We turn the problem into a named entity identification task [9]. Our purpose is to tag every words of travel notes with labels: activity, location, time, None. BiLSTM+CRF [9] is selected to accomplish this task due to its high performance in this area.

To annotate travel notes and construct training and validation set, we built the dictionary of Hainan tourism after discussing with local tourism experts. The dictionary contains 79 kinds of activities, 680 locations and 5 types of time. The 79 kinds of activities are the most concerned by tourists and they are determined by experts. As the carrier of activity information, in the tourism scene, trajectories are often made up of places that tourists pay attention to during the trip, such as attractions, hotels and so on. The 680 locations almost cover all the scenic spots and hotels in Hainan. As for time, we divide a day into early morning, morning, noon, evening and late night after reading some travel notes to differentiate happening time for various activities.

After the processing of BiLSTM+CRF model, we get corresponding tags (activity, location, time, None) for each word in the travel notes. Then we need to organize them according to the ETKG schema we designed as shown in Fig. 2. There are two tasks to construct ETKG. First, an event is represented by a triple (activity, location, time) in the schema, so we have to match the time, location with the associated activity. Second, we need to get the temporal relations of events to interlink events within each specific journey. We propose an approach

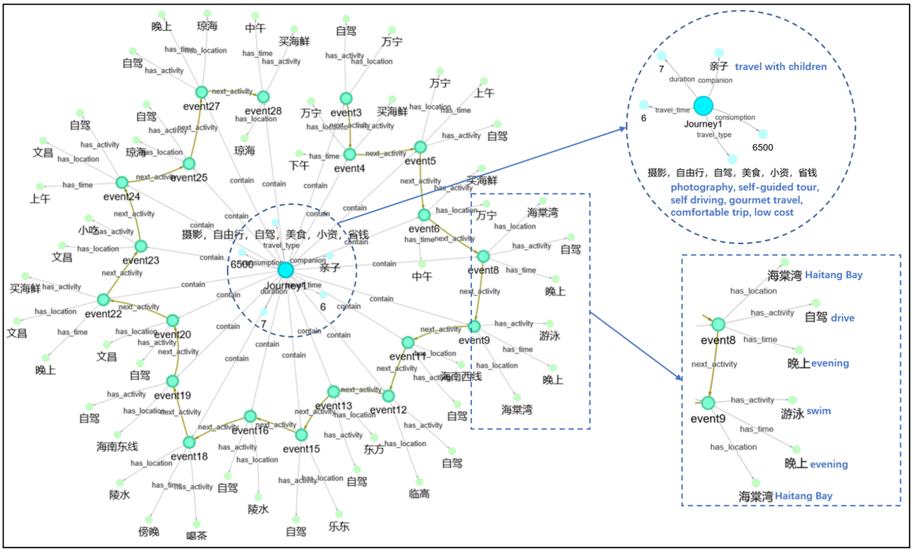

Fig. 3. Event-centric tourism knowledge graph of one journey.

to associate location and time with each activity and get relations between activities, which is shown in Algorithm 1. Based on an assumption that most tourists prefer to record their journey in chronological order, we get tourists' trajectories by the order of locations appearing in travel notes. Algorithm 1 generate a chain of events for each travel note tagged by BiLSTM+CRF model. And then combined with the attributes extracted from the structured data to construct an ETKG according to ETKG schema, so that it clearly describes the tourist's journey.

Through the above information extraction and organization methods, the Event-centric Tourism Knowledge Graph of 7132 journeys in Hainan is constructed which incorporates 86977 events, 140726 entities and 227703 relations (79845 temporal relations in it). 50.61% of these events contain time and location information. The ETKG of Hainan covers most of tourist attractions (680 sites) and most kinds of travel (26 types of journeys: self-driving tours, package tour and so on).

Algorithm 1. Approach to generate the chain of events

Input:
A travel note tagged by BiLSTM+CRF, T;
Trajectory of the tourist, $L\,(l_1, l_2, \ldots)$;
Output:
The chain of events in the travel note, $E\,(e_1, e_2, \ldots)$;

Initialize E with an empty list.
for all $l \in L$ **do**
  Find the paragraph P containing location l in T.
  Generate a sequence $A\,(a_1, a_2, \ldots)$ containing all the activity in P.
  if $len(A) = 0$ **then**
    Append triple $(None, l, None)$ to E
    continue
  end if
  for all $a \in A$ **do**
    Find the sentence S containing activity a in P
    if there is time t in S **then**
      Append triple (a, l, t) to E
    else
      Append triple $(a, l, None)$ to E
    end if
  end for
end for
return E

Figure 3 shows the ETKG of one journey. Obviously, we can learn most key information about this journey. The tourist came to Hainan with their children and have a seven-day road trip. Each person spent 6500 yuan during the trip and took many pictures. We can also know where the user had been and what activities they participated in at each location. With ETKG, the activities and travel routes for each journey can be obtain easily. After aggregations of each kind of journeys in ETKG, we can get event popularity and relation strength between events or entities, so as to answer questions about “most” or “best” by using SPARQL. Here is a case when tourists ask for best places for diving.

Question: Could you recommend suitable places for diving?
SPARQL: SELECT ?location WHERE {?e rdf:type:Event. ?e :hasActivity ”diving”. ?e :hasLocation ?location.}

We can get a list of scenic spots where other tourists choose to dive, and we would return the answer that appears most frequently to users.

4 An Application of ETKG for POI Recommendation

As mentioned above, from ETKG, some hidden patterns of tourist behaviors can be inferred, such as transfer relationship between different POIs, popularity indications of various tourist activities, etc. With the information obtained by ETKG, it offers an opportunity to improve the accuracy of POI recommendation. In this section, we propose a new knowledge-aware POI recommendation framework, ETKGCN (Event-centric Tourism Knowledge Graph Convolutional Network), which makes full use of the information in ETKG. Experimental results on a real world dataset show that when applied to the knowledge-aware POI recommendation, ETKG is superior to the traditional tourism KG.

We formulate our knowledge-aware recommendation problem as follows. A KG $\mathcal{G}$ is comprised of entity-relation-entity triples (h, r, t). Here $h, t \in \mathcal{E}$ denote the head entity and tail entity of a knowledge triple respectively. $r \in \mathcal{R}$ denotes the relation between h and t. $\mathcal{E}$ and $\mathcal{R}$ are the set of entities and relations in the knowledge graph. We have a set of M users $\mathcal{U} = \{u_1, u_2, \ldots, u_M\}$, a set of N POIs $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$. The user-poi interaction matrix $\mathbf{Y} \in \mathbb{R}^{M \times N}$ is defined according to users' historical trajectories, where $y_{uv} = 1$ indicates that user u has been to POI v, otherwise $y_{uv} = 0$. The POI set $\mathcal{V}$ is a subset of entity set $\mathcal{E}$. Our goal is to learn a prediction function $\hat{y}_{uv} = \mathcal{F}(u, v|\Theta, \mathrm{Y}, \mathcal{G})$, where $\hat{y}_{uv}$ $(0 \leq \hat{y}_{uv} \leq 1)$ denotes the probability that user u would go to POI v, and Θ denotes the model parameters of function $\mathcal{F}$.

4.1 Framework of ETKGCN

The framework is proposed to capture high-order structural proximity among entities in ETKG. In real life, tourists choose whether to go to a POI not only considering their personal preferences, but also referring to the opinions of most other tourists. We will take these two factors into account in ETKGCN framework.

Here we define π_r^u which characterizes the importance of relation r to user u in ETKG.

$$\pi_r^u = t_r g(\mathbf{u}, \mathbf{r}) \tag{1}$$

where $\mathbf{u} \in \mathbb{R}^d$ and $\mathbf{r} \in \mathbb{R}^d$ are the representations of user u and relation r. Function g is to compute the inner product of $\mathbf{u}$ and $\mathbf{r}$, which is used to model the tourist's travel preferences. As for the experiences from most other tourists, our framework introduces knowledge matrix $T \in \mathbb{R}^{|\mathcal{E}|\times|\mathcal{E}|}$ that is calculated from ETKG. t_r is the value of the element r in T which indicates the relation strength of its head and tail entities. As shown in Fig. 4, we compute t_{r1} as follows (with the help of ETKG):

$$t_{r1} = \frac{|E_{v,e1}|}{|E_v|} \tag{2}$$

Here, E_v is the event set that happened in Yalong Bay (v) while $E_{v,e1}$ is event set that represents tourists swam ($e1$) in Yalong Bay (v). So for a user loves swimming, if a large proportion of tourists go to Yalong Bay for swimming, π^u_{r1} will be high and it means the user would pay more attention to $r1$ in this subgraph. We consider both their own preferences and experience of others.

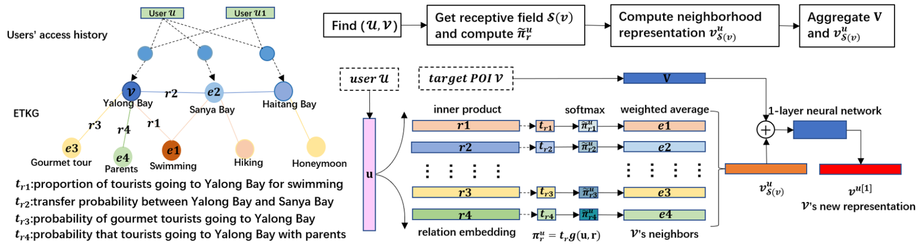

Fig. 4. The detail of an ETKGCN-layer.

As shown in Fig. 4, inspired by Graph Attention Network (GAT), consider a candidate pair of user u and POI v (an entity in ETKG). We first find the target entity v in ETKG and use $\mathcal{N}(v)$ denote the set of entities directly connected to v. In ETKG, the size of $\mathcal{N}(v)$ may vary significantly over all entities. We uniformly sample K neighbors and define the receptive field of v as $\mathcal{S}(v) \triangleq \{e|e \in \mathcal{N}(v)\}, |\mathcal{S}(v)| = K$. If we use $\mathbf{e}$ to denote the representation of an entity e, in order to characterize the topological proximity structure of POI v, we compute the linear combination of v's neighborhood through user-relation score π^u_r:

$$\tilde{\pi}^u_{r_{v,e}} = \frac{\exp\left(\pi^u_{r_{v,e}}\right)}{\sum_{e \in S(v)} \exp\left(\pi^u_{r_{v,e}}\right)} \tag{3}$$

$$\mathbf{v}^u_{\mathcal{S}(v)} = \sum_{e \in \mathcal{S}(v)} \tilde{\pi}^u_{r_{v,e}} \mathbf{e} \tag{4}$$

where $\tilde{\pi}^u_{r_{v,e}}$ denotes the normalized user-relation score, and it acts as personalized filters when computing vs neighborhood representation $\mathbf{v}^u_{\mathcal{S}(v)}$.

Then we would aggregate the target entity representation $\mathbf{v} \in \mathbb{R}^d$ and its neighborhood representation $\mathbf{v}^u_{\mathcal{S}(v)} \in \mathbb{R}^d$ to get the new representation of POI v.

$$\mathbf{v}^{u[1]} = \sigma\left(\mathbf{W} \cdot \left(\mathbf{v} + \mathbf{v}^u_{\mathcal{S}(v)}\right) + \mathbf{b}\right) \tag{5}$$

where $\mathbf{W}$ and $\mathbf{b}$ are transformation weight and bias, and σ is the activation function.

Here, we use $\mathbf{v}^{u[1]}$ to denote the 1-order representation of POI v for user u. If we want to get h-order representation, we should sample v's neighbors up to h hops away(in our framework, $h = 2$). After obtaining the final representation $\mathbf{v}^u$ of v, we can predict the probability of user u going to POI v:

$$\hat{y}_{uv} = f\left(\mathbf{u}, \mathbf{v}^u\right) \tag{6}$$

Function f can be a multilayer perceptron. If y_{uv} denotes whether user u intends to go to POI v, the loss function can be described as:

$$\mathcal{L} = \sum_{u \in \mathcal{U}} \left(\sum_{v \in h} \mathcal{J}\left(y_{uv}, \hat{y}_{uv}\right)\right) + \lambda \|\mathcal{F}\|_2^2 \tag{7}$$

$\mathcal{J}$ is cross-entropy loss and h denotes the training set coming from users' access history. The last term is the L2-regularizer.

4.2 Experiments

We obtain POI visit records of 6166 anonymous tourists of Hainan in 2015 which are generated from a call detail records (CDRs) data set, and carried out experiments on these data. To verify the effectiveness of ETKG, we compare the proposed ETKGCN with some classic recommendation algorithms, as well as those traditional entity-centric tourism KG-based models. The entity-centric tourism KG contain 10000 entities and nearly 87000 relations in Hainan, which covers the same tourist attractions as ETKG.

Baselines. We compare the proposed ETKGCN with the following baselines:

- **SVD** is a classic CF-based model using inner product to model user-item interactions.
- **LightFM** [7] is a feature-based factorization model in recommendation scenarios.
- **LightFM+KG** extends LightFM [7] by attaching an entity representation learned by TransE [1] using traditional tourism KG.
- **LightFM+ETKG** extends LightFM [7] by attaching an entity representation learned by TransE [1] using ETKG.
- **GCN+KG** [14] is a Graph Convolutional Neural Network method cooperating with traditional tourism KG.
- **GCN+ETKG** [14] is a Graph Convolutional Neural Network method cooperating with ETKG.

Results. The experiment results are shown in Table 4. We use AUC, F1score and Top-N precision to evaluate the performance of POI recommendation models. We have the following observations:

- ETKGCN performs best among all the methods. Specifically, ETKGCN outperforms baselines by 4.6% to 21.7% on AUC and 2.7% to 17.2% on F1score. ETKGCN also achieves outstanding performance in top-n recommendation.
- KG-aware models perform much better than KG-free baselines (like SVD, LightFM). It means that the information in KGs plays a positive role in building tourists' preferences.
- GCN-based models get better result than traditional graph representation learning method (such as transE). This demonstrates that GCN can make full use of information in KGs.
- The models cooperating with ETKG (GCN+ETKG and LightFM+ETKG) perform better than those with traditional tourism KG (GCN+KG and LightFM+KG). This demonstrates that ETKG may be more suitable for POI recommendation task, for the reason that ETKG integrates more information than the traditional tourism KG, especially transfer relationship between POIs in this case.

Table 4. The result of experiments.

Model	AUC	F1score	Top-n precision				
			1	2	5	10	15
SVD	0.754 (−21.7%)	0.746 (−17.2%)	0.280	0.232	0.241	0.212	0.234
LightFM	0.758 (−21.3%)	0.734 (−18.4%)	0.480	0.475	0.458	0.490	0.479
LightFM+KG	0.809 (−16.2%)	0.822 (−9.6%)	0.400	0.415	0.434	0.478	0.500
LightFM+ETKG	0.830 (−14.1%)	0.862 (−5.6%)	0.560	0.505	0.486	0.491	0.520
GCN+KG	0.903 (−6.8%)	0.889 (−2.9%)	0.602	0.602	0.572	0.577	0.592
GCN+ETKG	0.925 (−4.6%)	0.891 (−2.7%)	**0.607**	**0.613**	0.601	0.595	0.602
ETKGCN	**0.971**	**0.918**	0.592	0.610	**0.611**	**0.613**	**0.624**

5 Conclusion

This paper presented an Event-centric Tourism Knowledge Graph (ETKG) to interconnect events using temporal relations. We built an ETKG of Hainan and realized an application of POI recommendation based on it. Our evaluations show that ETKG performs very well in solving the problems related to routes and activities of tourists during the trip. The code and data of ETKGCN are available at: https://github.com/xcwujie123/Hainan_KG and we will constantly update the work on it.

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