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# Itinerary recommender system with semantic trajectory pattern mining from geo-tagged photos

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ABSTRACT

A large number of geo-tagged photos become available online due to the advances in geo-tagging services and Web technologies. These geo-tagged photos are indicative of photo-takers' trails and movements, and have been used for mining people movements and trajectory patterns. These geo-tagged photos are inherently spatio-temporal, sequential and implicitly containing aspatial semantics. and recommender systems are collaborative filtering based. There have been some studies to build itinerary recommender systems from these geo-tagged photos, but they fail to consider these dimensions and share some common drawbacks, especially lacking aspatial semantics or temporal information. This paper proposes an itinerary recommender system with semantic trajectory pattern mining from geo-tagged photos by discovering sequential points-of-interest with temporal information from other users' visiting sequences and preferences. Our system considers spatio-temporal, sequential, and aspatial semantics dimensions, and also takes into account user-specified preferences and constraints to customise their requests. It generates a set of customised and targeted semantic-level itineraries meeting the user specified constraints. The proposed method generates these semantic itineraries from historic people's movements by mining frequent travel patterns from geo-tagged photos. Experimental results demonstrate the informativeness, efficiency and effectiveness of our proposed method over traditional approaches.



## 1. Introduction

Travel itinerary recommender systems attempt to assist users on travel planning (Yoon, Zheng, Xie, & Woo, 2012). They provide useful suggestions on a tour about popular places to visit and ideas on a travel route of places and corresponding stay times for users who travel an unfamiliar destination. Intelligent recommender systems play an important role in decision-making and intelligent systems, and require a mixture of knowledge in expert systems, intelligent decision-making systems, and data mining. An itinerary is a detailed trip plan with a travel route associated with stay time information, where the travel route is a sequence of places. With the advance of social media platforms, a large number of online users generates and shares photos they have taken during their trips with their lovers, friends, and families. These photos are about their travel, activities and life, and are indicative of their movements and activities during their travel. Through the geo-tagging service, a large number of photos is becoming tagged with geographic locations. A photo together with geographic information and time stamp indicates a user's footprint, the place the user visits and the time the user spends there. A series of geo-tagged photos reflects the user's movement and trajectory. Consequently, the enormous amount of online photo data has become a potential data repository for discovering useful travel information and building travel recommender systems (Beel, Gipp, Langer, & Breitinger, 2016; Bobadilla, Ortega, Hernando, & Gutiérrez, 2013), like location recommendation (Popescu & Grefenstette, 2011; Waga, Tabarcea, & Fränti, 2012; Yamasaki, Gallagher, & Chen, 2013) and travel route recommendation (Okuyama & Yanai, 2013).

Existing itinerary recommender systems generate specific itineraries with geographic location information from available geo-tagged photos. Typically, they generate popular Points-of-Interest (PoIs) where a number of photos taken, and map-match PoIs with specific geographic place types to construct a suggestive itinerary. However, traditional approaches share a common major drawback. They are mainly based on geographic spatial information only when they recommend an itinerary. That is, they do not take any aspatial semantic information into account in the recommender system. In many real world scenarios, a user wants to visit a certain place type for instance "zoo" in a given trip. This specific semantically enhanced request is not considered at all in the traditional approaches. Instead, they accommodate this aspatial seman-

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tic information as a post-processing stage for their spatial information only recommender systems. Therefore, the traditional recommender systems are not able to accommodate users' semantically enhanced requests to generate meaningful and semantically enhanced itineraries.

The semantic place type request is an important feature in the user's travel planning. For users who are unfamiliar with specific geographic locations and PoIs in a certain destination, they prefer to list some place types (categories) they would like to visit (Gionis, Lappas, Pelechrinis, & Terzi, 2014). For instance, a user may want visit "Great Barrier Reef", "Rain Forest" and "Cultural aboriginal park" in a trip to Cairns, a popular gateway to rain forest and Great Barrier Reef in Australia. In addition, the user may want to visit "Great Barrier Reef" in a clear day to enjoy swimming with fish and exploring the beauty of reefs, whilst "Rain Forest" in a rainy day. The recommended itineraries are expected to contain a set of these requested place types. However, existing itinerary recommender systems fail to consider this constraint considering semantic information in the recommender system. This study presents an itinerary recommender system that considers users' predefined semantic spatial and aspatial constraints on place types, weather conditions and travel duration time. A semantic-level itinerary is a detailed journey planning with semantic spatial and aspatial information incorporated. It is more detailed and specific than the general spatial location alone itinerary. It shows a sequence of movements among different place types with certain weather conditions and certain stay times. This semantic-level itinerary provides users with flexible choices (rain forest in Kuranda or rain forest in Port Douglas) of specific geographic level route that satisfy their actual requests (Chen, Ku, Sun, & Zimmermann, 2011).

Note that, trajectories generated from geo-tagged photos are inherently spatio-temporal and sequential, and implicitly containing aspatial semantics. Therefore, itineary recommender systems from these spatio-temporal trajectories should incorporate: locational spatial dimension, temporal dimension, sequence and aspatial semantics in addition to two basic features Collaborative Filtering (CF) to benefit from other users and user-specified constraints to refine search result. These six are important features in this type of recommender system, and to the best of our knowledge, there is no known itinerary recommender system that produces a semantic-level itinerary with a set of spatial and aspatial user-specified constraints meeting this set of requirements.

This study develops a semantic-level itinerary recommendation system from geo-tagged photos. This system considers users' semantic spatial and aspatial requests, and travel duration constraints, and generates semantic-level itineraries that meet the user constraints. The proposed semantic-level itinerary recommendation system aims to provide users with higher level advice on place types, weather conditions and stay times. We generate itineraries based on mining semantic trajectory patterns from geo-tagged photos. We construct people trajectories from geo-tagged photos (raw trajectories), enhance the raw trajectories with required semantics to build semantically enhanced trajectories (semantic trajectories), and mine semantic trajectory patterns that will be basically used to build semantic-level itineraries. We test our algorithm with real datasets from Flickr[1] against traditional spatial only recommender systems. The experimental results support the effectiveness and efficiency of our recommendation system.

The rest of paper is organised as follows. Section 2 reviews current studies in itinerary recommender systems, and Section 3 formulates problems and provides problem statements derived from the literature review. Section 4 introduces a framework of our proposed itinerary recommender system based on trajectory pattern mining from geo-tagged photos whilst Section 4 outlines our experimental design and datasets used. Section 6 provides experimental results to demonstrate the effectiveness and efficiency of our framework over traditional approaches, and analyses the results. Section 7 draws conclusion and provides future work.

## 2. Literature review

On-line user generated massive databases have become a potential and useful resource for tourism related research community to build collective intelligence and to generate collectively filtered and recommended travel itineraries (De Choudhury et al., 2010). Advances of Web technologies promote a speedy increase of online user generated photo data, and people are uploading and storing their photos on-line to share their experience and moments with their friends, colleagues and families. Photos are also associated with various metadata including title, tags, description, comments and geographic locations. This large user-contributed data contains useful travel experiences and people's movements behaviors (Girardin, Fiore, Ratti, & Blat, 2008; Xiang & Gretzel, 2010). Various studies have attempted to discover valuable knowledge from geo-tagged photos, such as the detection of landmark (Kennedy & Naaman, 2008), extraction of PoIs (Lee, Cai, & Lee, 2014), and discovery of people's dynamic travel mobility behaviors (Cai, Hio, Bermingham, Lee, & Lee, 2014; Girardin et al., 2008; Zheng, Zha, & Chua, 2012). Another popular research topic is to use these volumes as a collective indication of sequential movement experiences to generate travel recommendations.

### 2.1. PoIs recommendation

The first type of recommender system is to provide users with suggestions of sets of popular and interesting places. Cao et al. (2010) recommend generic popular locations of interest associated with representative sample images. Another group focuses on personalised recommendations that consider users' preferences and recommend locations that match with their interest learned from past travel histories. Popescu and Grefenstette (2011) recommend users with landmarks in the destination that have been visited by similar users. Yamasaki et al. (2013) recommend personalised landmarks to users across cities. Shi, Serdyukov, Hanjalic, and Larson (2011) measure a similarity between users by using an additional category of landmarks in order to provide personalised recommendations. Chen, Cheng, and Hsu (2013) recommend personalised next destinations to users based on their gender, age, and travel group types which are detected from photo images. Majid et al. (2013) and Memon et al. (2015) recommend personalised tourist locations which are relevant to the temporal and weather context environments. Bujari, Ciman, Gaggi, and Palazzi (2017) uses gamification to identify cultural heritage PoIs, and similarly many approaches (Feick & Robertson, 2015; Gaggi, 2013; Shi, Serdyukov, Hanjalic, & Larson, 2013; Su, Wan, Hu, & Cai, 2016; Xu, Chen, & Chen, 2015; Yuan & Medel, 2016) explore local landmarks, attractions or PoIs from geo-tagged photos.

All these belong to the location recommendation system that suggests a set of discrete but interesting locations (PoIs). A common drawback of these stand-alone location recommendation systems is the deficiency of important sequential feature of these places.

[1] http://www.flickr.com.

### 2.2. A sequence of PoIs recommendation

Some studies have been proposed to build recommendation systems for a travel route, the visit sequence of locations. Okuyama and Yanai (2013) recommend travel routes for target destinations to users that are reconstructed from the trajectory data formed from geo-tagged photos. Sun, Fan, Bakillah, and Zipf (2015) recommend a set of most popular landmarks with the best travel routing between the landmarks based on the road network. However, these route recommendations are lack of temporal stay information. Time is a significant information for travel that tells people how long they are planning to stay in a particular place (Lu, Lin, & Tseng, 2011). The time information provides a better advice to people who have predefined travel duration time and let them plan their travel itinerary better.

### 2.3. A sequence of PoIs with temporal information recommendation

A number of recommender systems generates travel routes with time constraint to help people plan a travel itinerary. Generally, this kind of recommender system accepts a pre-defined a travel duration constraint from users and provides appropriate itineraries that fit the time constraint. One kind of time information is a typical transit time between neighboring locations in the route. Kurashima, Iwata, Irie, and Fujimura (2013) produce a sequence of locations with a transit time between two locations. Another kind of time information is the duration time spent in the destination. Lu, Wang, Yang, Pang, and Zhang (2010) and Lim, Chan, Leckie, and Karunasekera (2015) generate recommendations of sequence of locations with a stay time at each location. De Choudhury et al. (2010) generate a sequence of locations with both stay time and transit time. These previous studies consider various users' travel requirements and constraints, like travel duration and distance, and recommend a sequence of specific geographic spatial locations. However, they fail to deal with semantic-level requirements such as place types, weather conditions and others. In addition to specific geographic locations, travellers who plan to visit an unfamiliar area do not know any specific place, but may want to visit some place types at certain weather conditions, and customise these requirements as a constraint, like restaurant, beach, and cultural park. And, they may want that the recommended itineraries would contain some of these required place types. Previous itinerary recommender systems are unable to deal with these semantic-level requests. Symeonidis, Ntempos, and Manolopoulos (2014) consider additional semantic categories of landmarks, but their study focuses on a landmark only recommendation.

### 2.4. A sequence of semantic PoIs with temporal information recommendation

Higher semantic-level itinerary is another kind of important suggestion for users' travel planning. Chen et al. (2011) and Gionis et al. (2014) allow a user to customise a visit sequence of categories they prefer, and then generate specific geographic routes that match the visit sequence and the user's actual situation. This work proves that the higher semantic-level itinerary is useful for users who are unfamiliar with travel destinations and who have no idea what sequence of place categories is popular. However, there exist no current work to recommend this higher semantic-level itinerary. Previous itinerary recommendation systems produce a final specific geographic itinerary that does not meet this requirement.

As for the itinerary generation, previous methods use original travel sequences formed from photo data to build people's travel sequences as a probabilistic-model (Kurashima et al., 2013) and graph-model (De Choudhury et al., 2010; Lim et al., 2015; Lu et al., 2010; Quercia, Schifanella, & Aiello, 2014), and then they reconstruct itineraries from the travel model based on various criteria such as the popularity-maximisation.

However, the main drawback is that these itineraries are not guaranteed that they have been taken by previous people (not CF based). CF is an important concept in itinerary recommendation systems, it is to extract people's "frequent" movement patterns from their historic data and to use these extracted patterns to provide recommendations to users. Being "frequent" means that the itinerary is regularly occurring in and supported by a certain number of people's travel movements. These frequent movement patterns in people' trajectories guarantee the validity and trustfulness of recommended itineraries. Recently, Memon et al. (2015) investigate a user's travel preference considering spatial, temporal and semantic dimensions while ignoring sequential dimension with CF whilst Huang (2016) makes recommendations based on sequential dimension with CF but failing to consider user-driven constraints.

In summary, a set of sequential geo-tagged photos is indicative of people's movements, and a solid candidate for CF-based itinerary recommendation systems. Note that, these geo-tagged photos are inherently spatio-temporal and sequential, and implicitly containing aspatial semantics, thus it is crucial for CF-based itinerary reommender systems to consider all these dimensions. In addition, user-provided constraints could refine users' requests and they are useful means to provide user-specific and user-preferred recommendations. Past studies are fail to meet all these requirements, and this study focuses on this semantic-level itinerary recommendation considering spatial, temporal, sequential dimensions along with CF and user-driven constraints. Moreover, our system produces itineraries with additional useful recommendations with richer meaningful movement contextual information.

## 3. Problem statements and definitions

This study is to build a semantic itinerary recommender system using massive on-line geo-tagged photos. The problem could be described as follows: given a query including a set of required place types and travel duration, $query = \{< Types >, Duration\}$, our system replies a list of semantic-level candidate itineraries. An itinerary is a sequence of place types with interval time information, that contains some of required place types and satisfies the travel duration. A stop of place type is associated with several additional semantic contextual information like day time, day type and weather condition. An itinerary is expressed as shown below:

$$semantic\ itinerary = Stop_0 \xrightarrow{\alpha_1} Stop_1 \xrightarrow{\alpha_2} \cdots \xrightarrow{\alpha_n} Stop_n.$$

We generate itineraries based on previous people's semantic trajectory patterns. These patterns are extracted from their historic trajectories formed from geo-tagged photos. Using basic place type semantics, a semantic trajectory pattern is a sequence of visited place type stops with an interval time between two stops. Geo-tagged photos indicate people's mobility trajectories and they serve as a rich travel experience repository. These data contain potentially useful travel behaviors which are useful to help other users to plan their travels (De Choudhury et al., 2010). We mine people's semantic trajectory patterns from massive on-line photo data.

A geographic trajectory is represented as a sequence of geographic coordinates with time stamp as defined in Definition 1.

**Definition 1.** A trajectory is a sequence of geographic coordinates with time information $T = < (x_1, y_1, t_1), (x_2, y_2, t_2), \cdots, (x_n, y_n, t_n) >$, where $x_i$ and $y_i$ (for $1 \le i \le n$) are attached geographical coordinates of a geo-tagged entity, and $t_i$ is the corresponding time stamp.

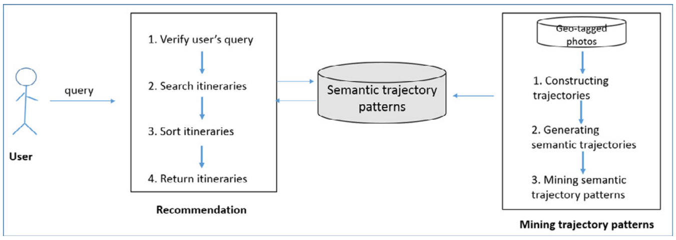



**Fig. 1.** Framework of semantic itinerary recommender system.

The raw geographic trajectory contains spatial and time information. We then build people aspatial semantically enhanced trajectories. We enrich these raw trajectories with application-dependent contextual aspatial semantics to present movements at the semantic-level A semantic trajectory is defined as a sequence of semantic stops. A semantic trajectory is formally defined as below:

**Definition 2.** Semantic trajectory: $SemT = \langle(SemA_0, t_0), \cdots, (SemA_n, t_n)\rangle$, where $SemA_i$ is a set of semantic annotations of a Region-of-Interest (RoI) and $t_i$ is the corresponding time stamp for $1 \le i \le n$. A semantic element $SemA_i$ is denoted by $(e_i, V_i)$, where $e_i$ is a set of basic semantics, and $V_i$ is a set of additional semantic annotations.

From these semantic trajectories, semantic trajectory pattern mining is to find frequent sequences of semantic elements with transit times that are frequent from semantic trajectories. These mobility behaviors are named as semantic trajectory patterns in this paper. A *semantic trajectory pattern* contains a sequence of semantic elements and a sequence of transit times where each demonstrates a frequent time interval between two consecutive elements. Adopting the spirit of trajectory pattern (Giannotti, Nanni, Pinelli, & Pedreschi, 2007), we represent semantic trajectory pattern (SemT-pattern) as a pair of sequences of semantic elements and time annotation sequence. When an element is the basic geographic semantic annotation only, SemT-pattern will be called *basic SemT-patterns*, while when element is associated with multiple other semantics, SemT-pattern will be called *multidimensional SemT-patterns*.

**Definition 3.** (SemT-pattern) A semantic trajectory pattern is a pair $(SemS, A)$, where $SemS = \langle(SemA_0), \cdots, (SemA_n)\rangle$ is a sequence of semantic elements, and $A = \langle\alpha_1, \cdots, \alpha_n\rangle$ is the (temporal) annotations of the sequence.

## 4. Semantic itinerary recommender system and methods

Fig. 1 shows our architecture of semantic itinerary recommender system. The framework includes two main components which are "offline" semantic trajectory pattern mining from geo-tagged photos and "online" itinerary recommendation. In the offline component, we construct people trajectories from geo-tagged photos, generate semantic trajectories associated with basic place type semantics and additional other contextual environment semantics, and extract previous users' semantic trajectory patterns. This part contains three steps: construction of basic trajectories from geo-tagged photos; building enhanced semantic trajectories using additional spatial and aspatial databases; and extraction of semantic trajectory patterns. These patterns are used for itinerary recommendations. In the online component of recommendation, our system verifies user's query, searches for related candidate itineraries, and sorts and displays them. The following content of this section describes details of methods step by step. It first presents methods for extracting semantic trajectory patterns in the offline part and then illustrates methods for recommendation in the online part.

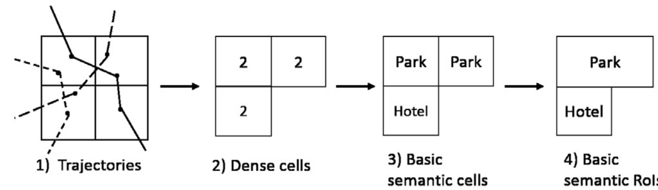



**Fig. 2.** Process of semantic RoI mining ($minimum\ density = 2$).

### 4.1. Constructing trajectories

In the offline part, the first step is to build people trajectories from geo-tagged photos data. A geo-tagged photo is associated with geographic information which points out the spatial position where the photo-taker visited. And, the time stamp of photo indicates the time information of the visit. Consequently, for a photo taker, chronologically connecting all geo-tagged photos implies a dynamically moving geographic trajectory. Given a dataset of geo-tagged photos, we first preprocess and remove noise, faults and redundancies, and we group them by photo owner *id* as each photo taker has a set of geo-tagged photos. For each photo-taker, we construct a trajectory from geo-tagged photo data. Trajectories with more than 2 points are considered to be useful in this study.

### 4.2. Building semantic trajectories

We then generate people semantic trajectories from geographic trajectories at the second step. A semantic trajectory is a sequence of stops with place type and additional other dimensions including contextual temporal day type and day time, city and weather condition. The method of building semantic trajectories is mining basic semantic RoIs from raw geographic trajectories first, transforming them into basic semantic trajectories next, and enriching trajectories with additional environmental contextual semantics at last.

We apply a semantic RoI mining algorithm to detect basic semantic RoIs from trajectories (Cai, Lee, & Lee, 2016b). A semantic RoI is a dense region with basic place type semantics where a number of trajectories passes through. Fig. 2 shows the brief process of semantic RoI mining approach. At first, the space is divided into girds and the algorithm finds out dense spatial grids. These cells are then annotated with basic place type to show place categories of cells by using external geographic information databases. At last, the neighboring cells having the same place type are merged into a final semantic RoI. Output of the algorithm is a set of semantic RoIs where each RoI is associated with basic place type semantics. In the next step, based on these RoIs with place type annotations, a raw trajectory is transformed into a sequence of place types. The transformed semantic trajectory shows people's mobility at the contextual place type semantics level.

We then add additional environmental semantics to these transformed trajectories. We add day type (weekday or weekend), day time (time period in a day), city (city name), and weather condition (clear or rainy etc). As a result, our final semantic trajectories are attached with multiple spatial and aspatial semantics.

### 4.3. Semantic trajectory pattern mining

At last, we mine semantic trajectory patterns from these semantically enhanced trajectories. A semantic trajectory pattern is a sequence of semantic stops with typical interval time between stops. We utilise a semantic trajectory pattern mining algorithm (a collection of semantic trajectories as input; a set of semantic trajectory patterns as output) (Cai, Lee, & Lee, 2016a). Given a dataset of semantic trajectories, this algorithm finds all semantic trajectory patterns. The semantic trajectory pattern mining algorithm is based on $\mathcal{TAS}$ algorithm (Giannotti, Nanni, & Pedreschi, 2006) which is a projection based method built on the PrefixSpan method (Pei et al., 2001) designed for sequential patterns. $\mathcal{TAS}$ algorithm uses T-sequence data type instead of normal sequence used in projections. A T-sequence is a projected sequence enriched with an annotation sequence where the annotation sequence includes records of occurrences of the prefix in the original sequence. The semantic trajectory pattern method shown in Algorithm 1 adopts the T-sequence data type, but it uses a progressively increasing approach to calculate frequent interval time and semantic trajectory patterns. For an actual projection, algorithm extracts frequent time interval sequences in Step 7, and generates semantic trajectory patterns by integrating prefixes and frequent interval sequences in Step 8. Step 10 removes the occurrences of prefixes that do not contribute to the frequent interval sequences. Steps 11–13 extend actual projection that generates sub-projection for each newly extracted frequent item of actual projection. This algorithm progressively finds longer patterns. Note that, the semantic trajectory pattern mining framework utilities arbitrary combination of dimensions when it generates trajectory patterns. It finds not only trajectory patterns associated with a set of all dimensions used, but also patterns with subsets of dimensions. These results contain two kinds of SemT-patterns. One is basic semantic pattern which is a sequence of basic semantics whilst the other is a sequence of basic semantics with several additional semantics.

**Algorithm 1** Semantic trajectory pattern mining.

**Require:** A set of semantic trajectories $T$, a min sup *minSup*, a temporal threshold *tau*;
**Ensure:** A set of semantic trajectory patterns (SemT-patterns);

1: $L \leftarrow 0$;
2: $P_0 \leftarrow \{T \times \{ \langle \ \rangle \} \}$;
3: **while** $P_L \neq \emptyset$ **do**
4: $\quad P_{L+1} \leftarrow \emptyset$;
5: $\quad$ **for all** $P \in P_L$ **do**
6: $\quad\quad$ **if** P.prefix $\geq 2$ **then**
7: $\quad\quad\quad$ ExtractFrequentIntervalAnnotations($P$);
8: $\quad\quad\quad$ *patterns* $\leftarrow$ GeneratingTrajectoryPatterns(P);
9: $\quad\quad\quad$ Output(*patterns*);
10: $\quad\quad\quad$ $P \leftarrow$ PruneAnnotations($P$,*Intervals*);
11: $\quad\quad$ **end if**
12: $\quad\quad$ **for all** element $e \in P$ **do**
13: $\quad\quad\quad$ **if** support(e) $\geq$ minSup **then**
14: $\quad\quad\quad\quad$ $P_{L+1} \leftarrow P_{L+1} \cup$ {ExtendProjection($P$,$e$)};
15: $\quad\quad\quad$ **end if**
16: $\quad\quad$ **end for**
17: $\quad$ **end for**
18: $\quad L++$;
19: **end while**

### 4.4. Semantic itinerary recommendation

At the online itinerary recommendation component, for a given user query, the proposed system recommends appropriate semantic itineraries through a series of processes including verifying query, searching and filtering candidate itineraries from semantic trajectory pattern database, and ranking itineraries. At last, a set of semantic itineraries is extracted and displayed.

The first step is to verify a user' query to check its correctness and validity. A query should include a set of place types and travel duration. Each place type is a textual word of place category such as hotel, beach, park and etc. We check to ensure that the query contains correct and valid category words. Travel duration indicates the number of days a user will spend for the travel. We check to ensure the number is a valid positive integer number.

The second step is to search and filter itineraries from the semantic trajectory pattern database. We search every semantic trajectory pattern, and then a pattern could be considered as a candidate itinerary if the pattern contains some of required place types, and the total duration is no greater than the user specified time constraint. Once found, the computed candidate itineraries are stored based on their degree of satisfaction of the user specified constraints. If there is no pattern containing any of the required types, we choose a set of long patterns that matches the travel duration.

The last step is to sort candidate itineraries. We need to place the most satisfied candidate itinerary meeting the most user constraints at the top. A satisfaction is defined based on the number of required place types a candidate itinerary meets and contains. We sort candidate itineraries based on the number of required types they meet and contain. The final outcome of recommendation system is a list of sorted candidate itineraries.

## 5. Experimental design

We conduct experiments to evaluate the efficiency and effectiveness of the proposed recommender system. The first evaluation mainly focuses on the effectiveness of our system. Specifically, we validate the performance of recommended semantic itineraries that the number of user's requests the recommended itineraries contains. The second experiment is about evaluations for the informativeness of recommendations. We present what additional useful information our recommendations can provide with a comparison to previous traditional methods.

### 5.1. Baseline methods

We choose two previous popular traditional methods (popularity-based method De Choudhury et al., 2010; Lim, 2015 and random-based method Lim, 2015) as baseline comparative studies. They reconstruct itineraries from people's historical travel routes generated from geo-tagged photos. A travel route is a sequence of PoIs with transit time information. A PoI is a geographical location where a great number of users visits. In the implementation of baseline methods in this experiment, PoIs are extracted from people geo-tagged photos by clustering photo points. We store PoIs and create a PoI database. Then, we generate people travel routes using these PoIs. For each sequence, we collect transit time between each pair of sequential PoIs, and compute an average transit time database. Two baseline methods use the PoI database and average transit time database to construct itineraries. Each itinerary is a sequence of geographic PoIs with transit time between two PoIs.

- **Random selection method** (Lim, 2015): This method randomly selects a PoI from the PoI database as the next destination, and finds out the average time between these two PoIs from the transit time database as the recommended interval time. This process continues until the total duration time of recommended itinerary reaches to the user specified travel duration constraint.
- **Popularity-based method** (De Choudhury et al., 2010; Lim, 2015): This method aims to recommend itineraries with maximum popularity. The popularity of a PoI is the number of people who visit and take a photo at this PoI. This is one of the most popular approach used in previous recommendation system that the basic assumption is that a route with maximum

popularity will be preferred by users. From the PoI database and the average transit time database, this method finds out all potential itineraries that the total duration is not greater than the user's queried travel duration constraint. Then, these potential itineraries are sorted in a descending order based on the total popularity. At last, a list of top itineraries is recommended to users.

As baseline methods produce specific spatial itineraries without any basic place type semantics information, we conduct an extra post-processing step in order to add place types to the spatial itineraries for the baseline methods for a fair comparison with our approach. We find a place type for every PoI to transform each spatial only itinerary into a place type semantic-level itinerary. We record statistics about place type in the recommended itineraries for a comparison with our itinerary results.

### *5.2. Evaluation approaches*

We introduce the metrics to measure the effectiveness of itinerary recommendation results. We measure how the recommendations satisfy the user's query. Specifically, when a user searches for a travel itinerary with a set of customised place type and travel duration, each system generates multiple candidate itineraries. Each candidate is considered as a potential selection to users. To evaluate the effectiveness of recommender systems, we measure the following aspects:

1. Given a user query $q$, a system generates a list of $n$ candidate itineraries $I = \{i_i, i_2, \ldots, i_n\}$. If a candidate itinerary $i_k \in I$ contains some of user's queried types (user's customised constraints $C = \{c_1, c_2 \ldots, c_m\}$), it is called **positive**. For $n$ candidates, there are $n+1$ situations from where no candidate contains any queried type (0 positive) to where all candidates contain some queried types ($n$ positive). Higher positive values mean better performance. That is, it is formally defined as: $|I'|$ for $I' \subset I$ where $i' \in I'$, $\exists c \in C$ such that $i'$ contains $c$. $|I'|$ varies between 0 and $n+1$. Given a set of itinerary recommender systems $R = \{R_1, R_2, \ldots, R_l\}$, $R_i$ is said to be better than $R_j$ in performance, for $R_i$ and $R_j \in R$ iff $|I'_{R_i}| > |I'_{R_j}|$.
2. Let us assume there are $n$ candidature itineraries $I$ for a given query $q$. For a candidate itinerary $i_k \in I$, let us assume that it has $x$ unique types (place types no other candidate itineraries contain), and contains $y$ common types (place types other candidate itineraries contain). The **percentage** of common types in the candidate $i_k$ is $per_k = y/x$. the higher percentage, the better performance. For all $n$ candidates, we calculate the average percentage for $I$, that is $aver\_per = (per_1 + per_2 + \cdots + per_n)/n$. For a given set of $m$ testing routes, we record the average percentage for each route. At last, we count the number of testing routes in each average percentage range, that is the metric we use to measure the degree of concentration. The more number of routes with higher average percentage range, the better quality of candidate itineraries.
3. The efficiency of each system, how fast the system generates a list of recommendations.

We also compare the degree of **additional meaningful semantics information** in the itinerary recommendation results. This comparison is about the aspect of information richness. Specifically, the comparison mainly focuses on what information our approach and the baseline systems recommend. We conduct these evaluation experiments by simulating user queries for test travel routes.

### *5.3. Datasets for experiments*

#### *5.3.1. Training dataset*

This study uses real Flickr photos as a training dataset for all three methods. We collect 62,899 photos in Queensland area of Australia for April 2014 to March 2015. We use a geographic information database from Geonames to annotate place types to geographic locations. For each method, the photo data are used for different purposes. The statistics about the training dataset are as follows:

- For our recommender system, we generate 1404 trajectories, find 49 semantic RoIs with 12 place types, and extract 65 basic semantic trajectory patterns (each one has a set of multiple multi-dimensional semantic patterns). Most of the patterns are 2 to 4 length long;
- For two baseline methods, we apply the DBSCAN clustering method (Ester, Kriegel, Sander, & Xu, 1996) to photo data and validate final PoIs based on the number of users. Finally, we obtain 46 PoIs with 17 unique place types.

#### *5.3.2. Testing dataset*

We simulate user travel routes as our testing dataset. We use a combination set of unique types from our method and unique types from the baselines methods (12 and 17, respectively). The final type dataset for simulation includes 22 unique types. We then generate travel routes by randomly selecting types from the type set and randomly generating an interval time between two types. We keep a total duration of each route less than 16 days since the popularity-based baseline method will cost much more time to construct itineraries when a query travel duration constraint is more than 16 days. Finally, we create a testing dataset of 300 simulated travel routes which has the following statistics:

- Including 300 travel routes;
- Containing total 22 unique types;
- Nearly half routes are 2-length while containing 2 unique types;
- Common types with training dataset (our system: 12/22, baseline 17/22);
- Higher diversity than real Flickr travel route testing dataset.

## 6. Results and discussions

### *6.1. Effectiveness of recommendation results*

We use each testing route as a user query. A query includes a set of place types and a travel duration constraint. In evaluation experiments for the effectiveness of itinerary recommendation results, we choose top five candidate itineraries as final recommendations because the top five candidates provide a temperate diversity and number of recommendations for all three methods. When using more than five candidates, the redundancy of itineraries increases.

The first experimental result is about how many candidate itineraries contain the user queried types in the recommendation results. If a candidate itinerary contains any user required type, it is noted as positive. When all five candidate itineraries contain any required type, it becomes 5-positive. Fig. 3 shows the performance of itinerary recommendation results from three systems. For 300 testing queries, the figure presents the distribution of queries for each positive situation.

Obviously, the random selection method generates the worst quality of recommendations. It is not able to generate 5-positive for any testing route, whilst the popularity-based method and our method can produce 5-positive for more than half testing routes. The number of routes the popularity-based method generates a

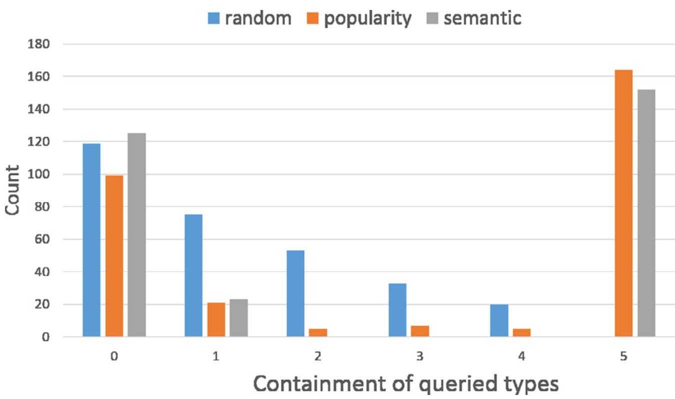



**Fig. 3.** Number of routes for each different containment for user queried types.

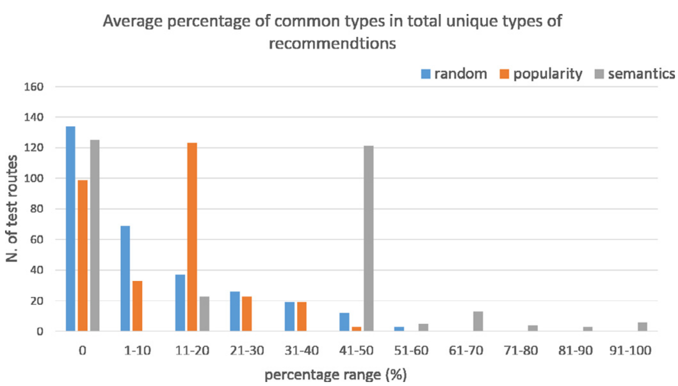



**Fig. 4.** Average percentage (*N.comtypes*/*N.uniqueTypes*).

high positive situation is a little more than that of our method. The reason is that extracted patterns of our system are mostly in short length. As a result, our recommended itineraries are in short length while the popularity-based method constructs itineraries by finding PoIs and connecting PoIs as long as possible until the total time duration reaches to the user defined duration constraint. The long itinerary has a higher probability to contain the user queried types. However, the gap is not significant but trivial. A positive value indicates the system's ability to generate valuable and useful candidates. The higher positive value, the higher performance. Both our method and the popularity-based method are able to produce high positive itineraries.

The second result is the average percentage of common types in the recommendations. A candidate containing a high percentage of user queried types exhibits high concentration on queried types and thus it is useful to users. The average percentage indicates the quality and concentration of whole recommendation results. Fig. 4 shows the distribution of routes with different average percentage ranges. Our system produces better itinerary recommendations since it is able to generate higher concentration recommendation results for more than half queries. However, two baseline methods can only generate low concentration itineraries.

The third experiment is to measure the running time of system. The total duration time for testing route is used as a queried travel duration constraint. Fig. 5 shows running time requirements for the three systems. As shown in Fig. 5, the popularity-based method exhibits the worst efficiency that is not scalable to large datasets. For larger travel duration queries, the popularity-based method costs much more time to generate recommendations than the other two. The random-based method and our method cost much less time, which is scalable to the large dataset. However, please note that our method requires consistently little time for

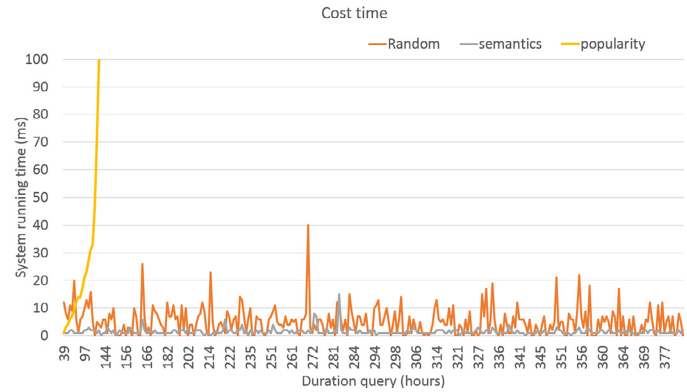



**Fig. 5.** Specific running time of probability-based, random-based and semantic-based recommendation systems.

**Table 1**
Performance comparison of recommendation results.

| | Positiveness | Concentration | Efficiency |
|---|---|---|---|
| Random-based | Bad | Bad | Good |
| Popularity-based | Good | Bad | Bad |
| Semantic-based | Good | Good | Good |

**Table 2**
Example of itinerary recommendations.

| Method | Itinerary recommendation |
|---|---|
| Our system | route: PIER–[0 to 2 days]–ISL<br>— additional info —-<br>* PIER[weekday][Cairns]–[0 to 2 days]–ISL[weekday][Cairns]<br>* PIER[Clear][Cairns]–[0 to 2 days]–ISL[Clear][Cairns] |
| Random-based & Popularity-based | route : P45 - 4days - P31 |

all travel duration queries and exhibits the best efficiency performance.

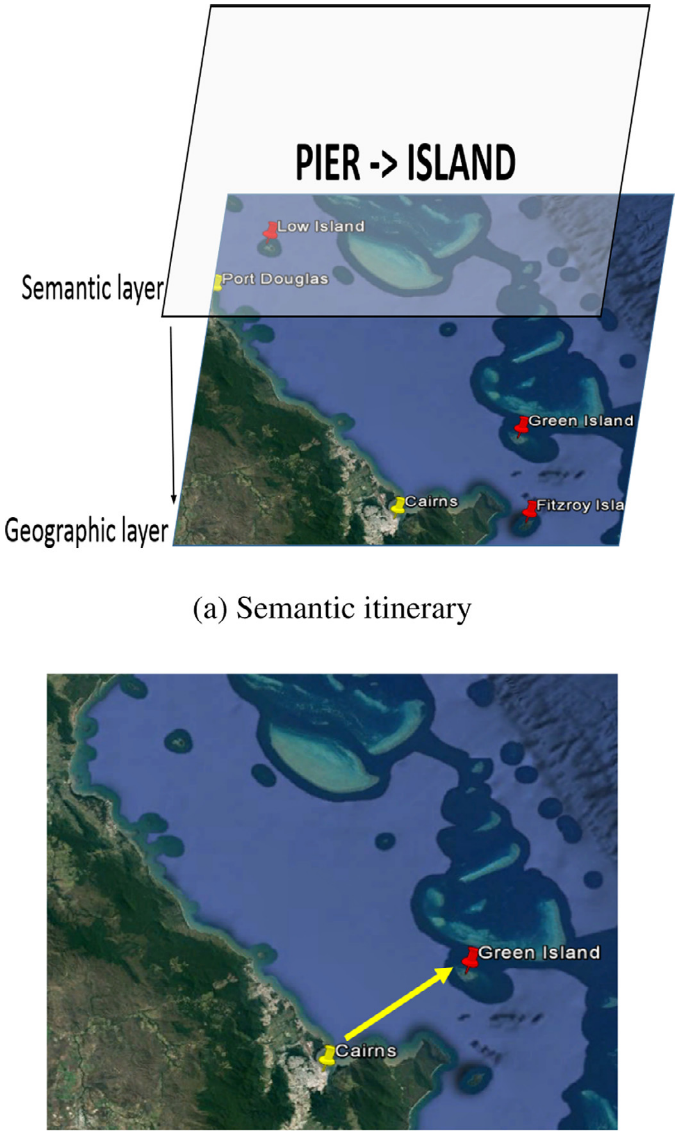
In summary, Table 1 presents the performance comparison of three recommender systems under study. The random-based method is good at efficiency that costs less time to generate candidate itineraries, but the quality of candidates is poor since it contains fewer user required place types. The popularity-based method is able to generate good positive candidate itineraries containing the user required place types. However, this method costs much more time to generate candidate itineraries, and the percentage of required types in the candidate is small. Our proposed semantic-based approach exhibits effective performance in positiveness and concentration while requiring an efficient time.

### 6.2. Comparative results of information aspect

#### 6.2.1. Higher layer semantic-level vs. lower layer geographic-level

Our system produces semantic-level itineraries including basic semantic itineraries, and itineraries with additional semantics. The baseline methods produce geographic itineraries with specific geographic places. Table 2 lists one example of typical itinerary recommendations from three systems, for query: set of types = ISL, travel duration = 15 days. This sample selects a route from PoI Cairns pier to PoI Green Island in Cairns area.

One main difference between itineraries of our system and itineraries of the baseline systems is in the layer of the recommended itinerary. For the sample shown in Table 2, the baseline systems recommend a user a specific geographic layer travel route which is from Cairns pier to the Green Island. It is one of popular travel routes for visiting the Great Barrier Reef. Our system




(a) Semantic itinerary

(b) Geographic itinerary

**Fig. 6.** Semantic-level itinerary and geographic-level itinerary.

recommends a user a higher layer semantic route which is from pier to the island. Fig. 6 shows the semantic-level itinerary and geographic-level itinerary.

The higher semantic-level itinerary is better than the lower specific geographic route. The semantic layer itinerary enables users to freely choose various optional geographic routes according to their preferences and actual environments such as the geographic location where they are, whilst the baseline systems recommend specific routes, and users receive these routes only but are unable to obtain other optional routes. For the semantic-level route, pier to island, there are many piers and islands. We find several specific piers and islands in Cairns shown in Fig. 6(a). Users can choose a route from Port Douglas pier to the Low Island, or a route of from Cairns pier to either the Green Island or the Fitzroy Island. All these three routes are popular travel routes of visiting the Great Barrier Reef. Compared to this additional availability of various choices, the baseline systems recommend a specific geographic route that limits the selection of other popular routes. The semantic-level itinerary provide a higher layer perspective and guidance to users on how to travel and also they can select a specific geographic route of their choice.

**Table 3**
Information from itinerary recommendation results.

| | Basic information | Other information |
|---|---|---|
| Itinerary recommendations of baseline systems | Interval time for a route of specific PoIs | N/A |
| Itinerary recommendations of our system | A route with place types; Interval time | Recommended contextual information: temporal (day time, day type), weather condition |

### 6.2.2. Other additional semantics information

Our system recommends more useful travel context information than the baseline systems. Table 3 lists specific information the recommended itinerary results can provide. The baseline systems supply basic information on travel route among specific geographic PoIs and interval time. Our system can provide basic information on frequent travel routes among place types and interval time. Moreover, our results can provide additional and useful information about travel context environment including temporal information about day time and day type, and weather condition. In particular, our system recommends itineraries based on previous people' frequent trajectory patterns mined from their historic trajectories. The trajectory patterns are associated with additional semantic information. The additional information shows the frequent contextual environment at which frequent trajectories occur. As a result, this information in the itinerary recommendation results, provides users with useful advice on environmental contexts in which people travel the destination. Moreover, this useful information can be potentially further used as for context-aware recommendation services that recommend itineraries to users based on their contextual environment like day time and weather condition.

## 7. Conclusion

In this study, we present an itinerary recommender system using on-line geo-tagged photos. Our system allows user to customise a set of place types and travel duration in the query. The system generates itinerary recommendations based on the previous people semantic trajectory patterns extracted from their historic photo data. Experimental results show that our system is able to produce itinerary recommendations which satisfy user's predefined requirements. Our system recommends semantic-level itineraries to users that show higher place type layer route suggestions compared to specific geographic-level ones. The higher layer routes provide users with more flexible selections of potential spatial routes. Moreover, our system generates itinerary recommendations with additional and useful environmental semantics information.

Our current system considers 6 dimensions: spatial, temporal, aspatial semantics, sequential, CF and user-provided constraints, and it can be further extended with the following future directions:

1. Its extension to incorporate more semantic databases to further explore semantic-level itinearies;
2. Comparison with real-world travel agency-based recommendations in order to validate our system;
3. Incorporation of more user constraints such as "dislikes" to avoid certain places;
4. Evaluation of our system with a questionnaire with real users with quantitative and qualitative analysis;
5. Incorporation of photo images to itinerary recommendations in order to reflect users' preferences.

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