A Personalized Trip Recommendation System Based on Field of Views

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ABSTRACT
In the past decades, many prior approaches have been proposed to address the issue of uncertainty issue and handle the dissatisfaction a user might experience about the trip recommendations. Generally, a trip recommendation is derived based on user-specified conditions and user preferences by analyzing their social activities such as check-in data that is retrieved from the social networks of a user and the user's friends. Alternatively, we propose a novel approach to infer personal preferences for trip recommendations by analyzing the photos taken by the user in the past. The photos continuously accumulated over time are tagged with sensor data such as geographical information. In this paper, we apply a probabilistic model to detect favored points of interest (POI) contained in the field-of-view (FOV) of the photos. Subsequently, each detected POI is classified into one or more corresponding categories, which are then used to build a user profile. Furthermore, by mining the geo-tagged photos taken by many users, we can extract the frequent travel patterns, which may reveal the user's travel habits. As a result, our approach returns a high-quality itinerary that considers both the user's preferences and personal habits.

Keywords: Geo-tagged photos, trip planning, user preference, recommendation

1. INTRODUCTION

The impressive advancement of communication technologies and the popularity of mobile devices have sparked intense development of location-based services (LBS). A LBS encompasses services (e.g., map services) that perform programs which use geographical data. Map services enables travelers to issue trip planning queries (TPQ) to search for the information around them and plan trips to his/her favorite destinations. A TPQ, firstly proposed by Li et al. [1], is one of the important functionalities of LBS, and it is also the core technique of our trip recommendation system. A high-quality itinerary for a trip depends on many aspects, such as travel cost (e.g., travel distance and travel time), user-specified constraints (e.g., one must go to a bank before going to a market), and user preferences for destinations.

In recent years, many research studies [4-6] have appeared to tackle the issue of trip recommendations as part of their answers for trip planning queries. User preferences and spatial/temporal features were analyzed to determine a desirable recommendation for users. Using social network data is one of the approaches used to model user preferences by reasoning about the association of social relationships among a user's friends of a user. However, accessing social network data might raise privacy issues simultaneously. On the other hand, an increasing number of people nowadays tend to record their trips by taking pictures with sensor-rich mobile devices (e.g., smart phones) and sharing them on the Internet. The photos capture the moments that a user experiences, thus revealing his/her possible personal preferences. Because a significant number of pictures taken by a user are continuously accumulated, we may further analyze them to learn the user's personal preferences that can then be utilized to support TPQs.

A POI indicates the object on which a user is interested in focusing so as to infer his/her preferences. To accurately obtain the POIs recorded by the user in a picture, we adopt the field of view (FOV), firstly proposed by Arslan Ay et al. [7], to formulate the visible region where POIs are likely placed for each picture. Furthermore, we apply a probabilistic model to detect the most likely POIs that a user intends to capture among all the POIs within the FOV. A detected POI is used to retrieve its corresponding categories, defined as the attributes of the POI, by which we can infer the user's preferences. For example, Bob took a lot of pictures of museums in the past. We may therefore infer that he likes arts and history and recommend to him other places that also fall into the similar categories (e.g., art exhibitions and galleries.) Additionally, we further analyze the consecutive pictures to extract the frequent travel patterns from detected POIs that were visited by a user. By combining the above-mentioned strategies, we then build a profile for each user to recommend an itinerary.

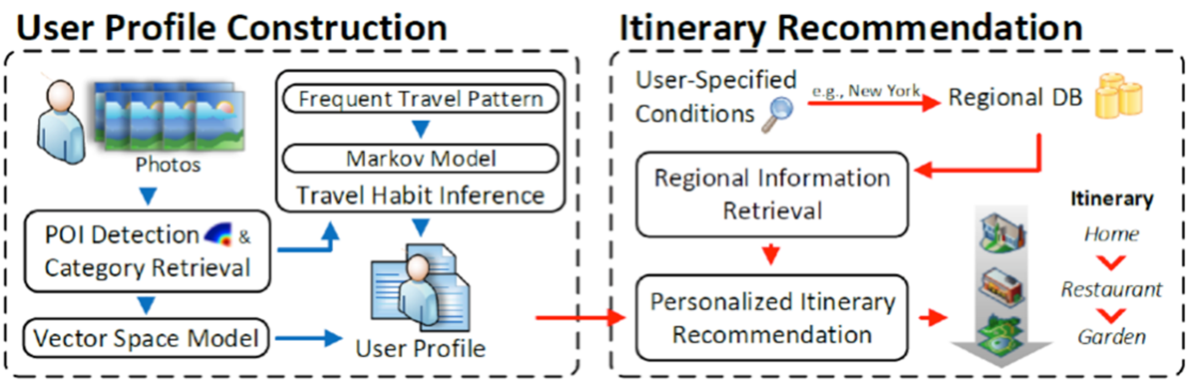


Fig 1. System Architecture

As shown in Figure 1, our system consists of *User Profile Construction* and *Itinerary Recommendation* modules. A user profile is constructed off-line, while the itinerary computations are performed on-line when our system receives a query. In the off-line phase, we detect favored POIs as well as their corresponding categories for each user. Then we leverage the *Vector Space* model and the *Travel Habit Inference* model to construct a user profile from these detected POIs. In the on-line phase, given a request from a user who specifies a region he/she would like to visit, our system returns a personalized itinerary to the user based one the user profile that was built in the off-line phase. We make the following major contributions in this paper:

- We extend the detection technique [8] to improve the accuracy of detecting the POIs of photos. Since these detected POIs of photos play an important role to infer the user preferences, the improvement further supports the inference of a user's preferences with higher precision.

- We combine the *Vector Space* and the *Travel Habit Inference* models as the user profile for personalized trip recommendation; therefore, our system could recommend an itinerary for a trip based on the user's query condition and preferences.
- We have built a web service and conducted extensive experiments based on a significant of geo-tagged photos collected from Flickr. The results empirically demonstrate that our personalized trip recommendation system can provide high-quality travel routes to users on the basis of their preferences.

The rest of this paper is organized as follows. In Section 2, we report our survey of related literatures. Section 3 defines the terminologies, symbolic notations, and problem statements. We then describe our approach in detail in Section 4. Section 5 shows the experimental results of our approach. Finally, we conclude this paper in Section 6.

2. Related Work

This section reports the survey of the related literatures related to our work in two categories: point of interest detection and trip planning queries.

2.1 Point of Interest Detection

In order to detect points of interest (POI) captured in the photos, the most conventional way is to analyze the image contents and match them to the landmark POI databases through the computer vision techniques [9-10]. However, regardless of the high computational cost that is incurred to extract low level media signal features, these techniques are more suitable for detecting well-known POIs (i.e., landmarks) than the personal POIs of a particular user as the latter may be any common object in geo-space. Additionally, it is common for users to capture the same object from diverse perspectives, but such diversity can hardly be matched in a POI database. Currently, it is common for a photo to be tagged with geographic properties that can provide additional information to detect POIs efficiently and accurately. For example, several existing approaches retrieve the objects that are located nearest to the camera location as POIs [11-12]. Cheng *et al.* [13] leveraged both GPS and compass information to narrow down the region where a POI may be located. However they assume that there exists only one POI in each photo and it is likely located nearby the camera location and around the central viewing direction. Therefore, Thomee [14] proposed another approach to locate POIs from geo-tagged photos by assuming in a photo there may exist multiple POIs which are distributed with different probabilities over the whole geo-space. However, all these studies ignore the fact that the viewable region of a photo is usually constrained within a small region. As a result, Zhang *et al.* [8] integrated the FOV model for POI detection to further reduce the investigation scope.

2.2 Trip Planning Queries

The Traveling Salesman Problem (TSP) is the underlying core problem of this research topic. Hsieh et al. [5] firstly discussed a new type of query called TPQ to formulate the problem clearly and proposed some solutions. TPQ is a generalization of the TSP problems (GTSP) [2-3]. The approaches proposed in [1] consider the factors such as distance and direction in a Euclidean space for solving problems. In our system, we do the same except we also consider user preferences and user-defined constraints. Chen et al. [15] proposed a Nearest Neighbor-based Partial Sequence Route query (NNPSR) algorithm that computes a recommended trip route with the consideration of multiple destinations as well as user-defined traveling rules specified by a user. Basu Roy et al. [16] further considered the user-defined constraints (e.g., travel duration and budget) to plan an itinerary.

Many existing studies have retrieved the trip planning features by utilizing crowd-sourced geo-tagged photos. Okuyama et al. [17] proposed a system that clusters pictures collected from the internet according to embedded GPS data and text-tags to detect hot spots, models travel trajectories based on time stamps, and then generates multiple trip routes for users. The system retains high flexibility for it allows users to choose the most favorite one trip listed on the user interface. Lu et al. [18] implemented a system that utilizes not only crowd-sourced geo-tagged photos but also travelogues and travel packages to generate travel routes. Nevertheless, none of the aforementioned methods provides a framework which uses the previously taken photos to infer the user preferences to recommend an itinerary. In this paper, we propose a novel approach to computing personalized trip planning queries with user-defined constraints.

3. Preliminaries

3.1 Field of Views

Because the meta-data can be collected by sensor-rich devices, we adopt the FOV model to represent the coverage areas for each photo in geo-space. Fig. 2(a) illustrates the FOV model in a 2D space. A FOV is fan-shaped and formed by the following parameters: picture taken location $\mathcal{L}$, maximum visible distance $\mathcal{R}$, viewing orientation θ, and viewable angle ϕ. Hence, FOV could be formulated as $FOV \equiv <\mathcal{L}, \mathcal{R}, \theta, \phi>$. Fig. 2(b) shows the coverage area and the captured objects when a user takes a photo at location $\mathcal{L}$ in a direction θ. As a result, the coverage area in the photo can be modeled as a ϕ degree fan with radius $\mathcal{R}$.

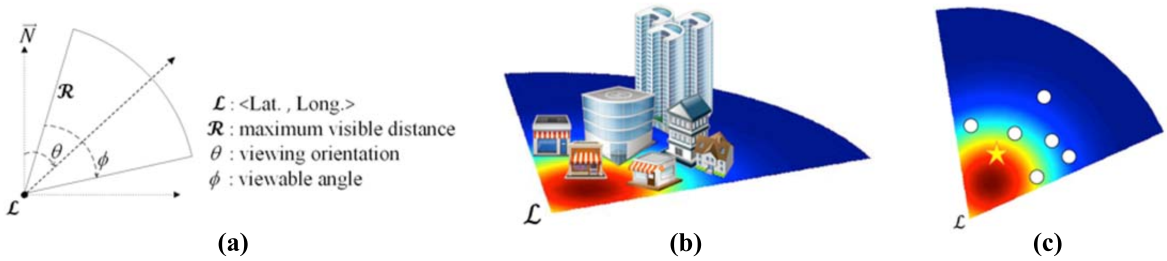


Fig. 2. **(a)** A FOV in a 2D space, **(b)** the coverage area of a photo, **(c)** the captured object location distribution within the FOV corresponding to **(b)**, and the yellow star representing the POI of this FOV.

The picture taken at location $\mathcal{L}$ consists of the latitude and longitude coordinates. The maximum visible distance $\mathcal{R}$ is the maximum distance at which an object within the FOV can be recognized by the human eye. The viewing direction θ is obtained by a digital compass. Finally, the viewable angle ϕ is derived based on the properties of the lens and zoom level. Therefore, based on the FOV model, we can detect the POI (i.e., the yellow star in Fig. 2(c)) in a photo more easily, precisely, and efficiently. Generally, people tend to take photos to record attractive objects (e.g., a brilliant museum) in their trips or in their daily life. Therefore, our conjecture is that a user is likely to captured favored objects in photos. Detecting POIs in photos may reveal the preference of the user.

3.2 Definitions and Problem Statement

In this section, we first introduce the definitions used throughout the paper. The objective of this work is also described as follows.

Definition 1 Category

A category $c_i \in \mathcal{C}$ $(1 \le i \le n)$ represents an attribute for a landmark p, a geographical object in space (e.g., a "*Monument*" for the Statue of Liberty). A category set for a landmark, $\mathbf{C}_{\mathcal{L}} = \{c_1, \dots, c_j\}$ $(c_j \in \mathcal{C};\ 1 \le j \le n)$, defines the attributes for the landmark (e.g., $Statue\ of\ Liberty.c = \{"Monument", "Outdoor\ Sculpture"\}$.)

Definition 2 User Preference

Historical travel data $\mathcal{D}$ for a user u is composed of photos taken by u. The frequencies of categories for POIs (a POI $h \in$ landmarks $\mathcal{P}$ bounded in a FOV for a photo d) obtained in $\mathcal{D}$ define the likelihood of the user preferences which the categories are related to.

Definition 3 Visiting Sequence

A user u may have his/her intent visiting sequence (e.g., u likes to take a walk in a park after having lunch). The intent visiting sequence could be obtained from $\mathcal{H}$ and induced to frequent visiting patterns $\{c_1 \to c_2, \dots, c_l \to c_m\}(1 \le l, m \le n)$.

Problem Statement

We aim to find a personalized solution for the TPQ problem on a graph. Our system selects a top-k subset category set $\mathcal{C}_s \subseteq \mathcal{C}$ $(\mathcal{C}_s = \{c_{s1}, \dots, c_{sk}\},\ c_{sk} \in \mathcal{C}_s)$ according to the user preferences. Each $c_{sk} \in \mathcal{C}_s$ consists of at least one landmark $\mathcal{L}$ bounded in a query region $\mathcal{R}$. Given a starting point S, an ending point E, and a graph $\mathrm{G} = (\mathcal{V}, \mathcal{E})$ with vertices $\mathcal{V} = \{v_1, \dots, v_x\}$ and edges $\mathcal{E} = \{e_1, \dots, e_y\}$, we denote that $v_x \in \mathcal{V}$ is a selected landmark contained in $\mathcal{C}_s$ and $e_y \in \mathcal{E}$ is a path that links up two vertices. A traveling path set $\mathcal{T} = \{\mathrm{S}, t_1, \dots, t_z, \mathrm{E}\}$ consists of the starting point S, sequence of consecutive paths t_z, and destination E.

4 Approach

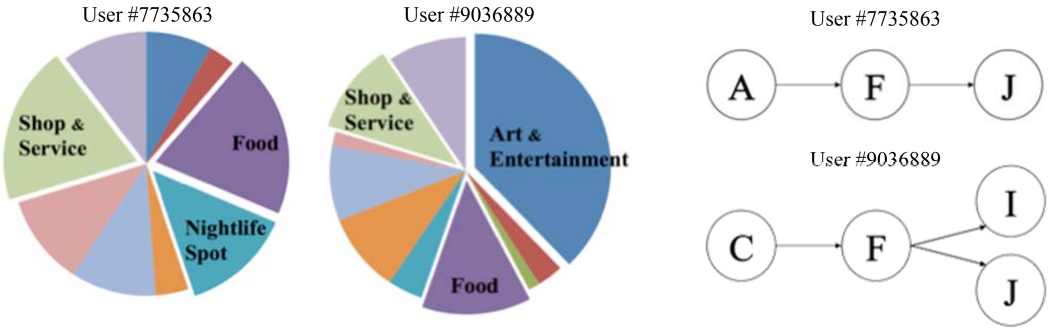
The personalized trip recommendation system is divided into the User Profile Construction and Itinerary Recommendation modules. We describe the details of each module in the following sections.

4.1 Offline Module: User Profile Construction

In our research, we use a photo's metadata including the geographical location $\mathcal{L}$, visible distance $\mathcal{R}$, and compass information (converted into viewing orientation θ, and viewable angle ϕ) to efficiently detect the POI within a FOV. An illustration of a FOV with the relevant parameters is shown in Fig. 2. In addition, we adopt the detection technique proposed in our early work [8] to further reduce the search scope for detecting the favored POI in a photo.

$$\frac{1}{2\pi\sigma_x\sigma_y}\exp\left(-\left(\frac{(x-x_o)^2}{2{\sigma_x}^2}+\frac{(y-y_o)^2}{2{\sigma_y}^2}\right)\right) \quad \textbf{(1)}$$

We apply a two-dimensional Gaussian model (Eq. 1) to a FOV to simulate the photography composition style of subject placement (e.g., place a POI in the middle of a picture) for a user such that we can infer the most likely favored object. For our dataset, we first collected the geo-tagged photos for a user by using Flickr APIs, and then extract all POIs for each photo by using the Foursquare APIs. Each returned POI h of a photo is assumed to be the favored POI of that user. Next, we estimate the relative location to $\mathcal{L}$ for all h (the star in Fig. 2(c)) to train the Gaussian model, which is used later to detect the user's favored POI. The formula of the model is shown in Eq. 1, where x_o vs. σ_x and y_o vs. σ_y are the means and standard deviations of the relative locations of all h corresponding to the x and y coordinates, respectively.



(a) User Preferences **(b) Visiting Sequence**

Fig. 3. Two examples of the user profiles of User #7735863 and User#9036889 retrieved from the Flickr data sets. A user profile contains the user preference (a) and a favorable travel sequences (b).

After the training process for constructing the Gaussian model, the system obtains the favorable degree of subject placement (shown as one of the heat maps in Fig. 4) in a FOV for different users. Subsequently, we construct a vector space model to represent the historical visiting records, represented as $\boldsymbol{U} = [u_1, u_2, u_3, \dots, u_n]$, for a user, where $u_i \in \boldsymbol{U}$ is the number of times the user has visited a category i. For the travel habit inference, given the frequent travel patterns mined from the user's historical travel data, we build a first-order Markov model to infer the visiting sequence that has the highest probability from the chosen categories. Fig. 3 shows two examples of the user profiles retrieved from the Flickr data sets. As shown in the pie charts (Fig. 3(a)) that represent user preferences, a bigger slice means a higher visiting frequency of the category a user likes to visit. The corresponding visiting sequences of these two users are illustrated in Fig. 3 (b), where each node represents the category of a visited location. Therefore, we can utilize the information to construct a user profile.

4.2 Online Module: Itinerary Recommendation

Our system first obtains the regional data of the user-specified region, which the user may not have visited before. To provide a personalized and localized itinerary, we consider both the user profile (see Section 4.1) and public POI categories obtained from the regional databases. Therefore, a score of category n_i is computed by the equation formulated as $n_i = u_i + \alpha \times r_i$, where α is a similarity weight and $u_i \in \boldsymbol{U}$ as well as $r_i \in \boldsymbol{R}$ are the number of times a category i has been visited by the user and the public, respectively. $\boldsymbol{U}$ is the user preference vector in the user profile and $\boldsymbol{R}$ is a regional information vector.The frequent travel pattern (e.g., going to a bank before going to a book store) retrieved from the off-line module is also accessed from the user profile. Finally, by performing a modified version of TSP algorithm [2-3], we compute an itinerary that contains the places of all corresponding recommended categories and visiting sequence based on the frequent travel patterns as well as the user-specified rules.

Fig. 4 shows the interface of our personalized trip recommendation system. When a user specifies a query range (e.g., starting point A, ending point B, and user-specified conditions), the system starts computing an itinerary based on the specified conditions and the user preferences. For example, when a user inputs New York City for a trip recommendation, according to his/her user profile which reveals personal preferences for museums & galleries and several visiting sequences, the system recommends attractions with the visiting sequences, accordingly.

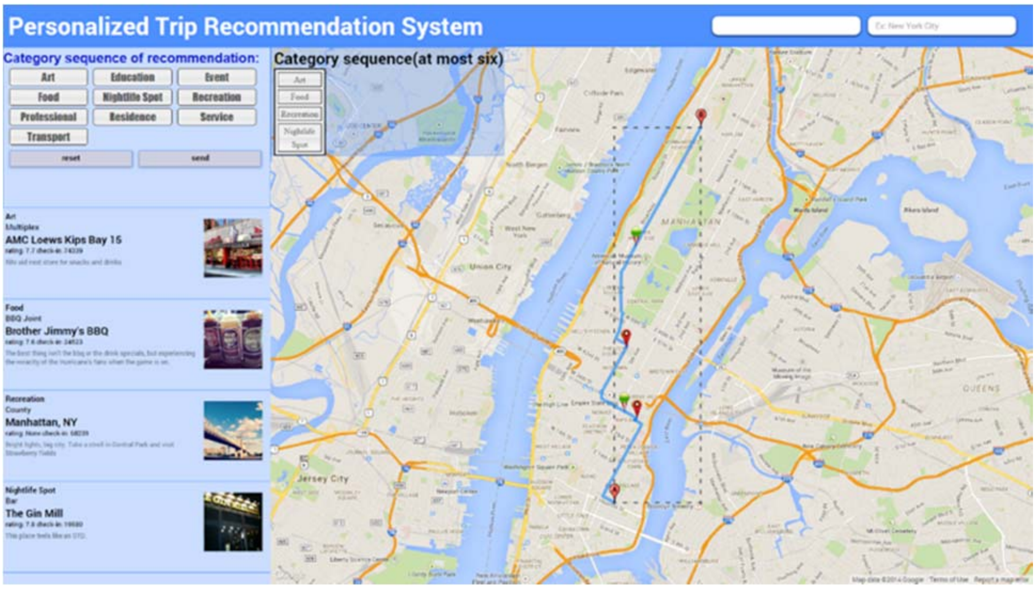


Fig. 4 The interface of the personalized trip recommendation system.

5 Experiments

We crawled geo-tagged photos taken in New York, known as one of the most popular travel cities, from Flickr to build the dataset. Each photo includes necessary meta-data, and we totally collected 133,198 photos uploaded by 456 users.

For user preference construction, we leverage the detecting technique [8] to improve the accuracy of POI detection. The detecting technique works based on the training process as well as the adoption of the Gaussian model, which is visualized as heap maps shown in Fig 5. The heap maps illustrate photography composition styles for different users.

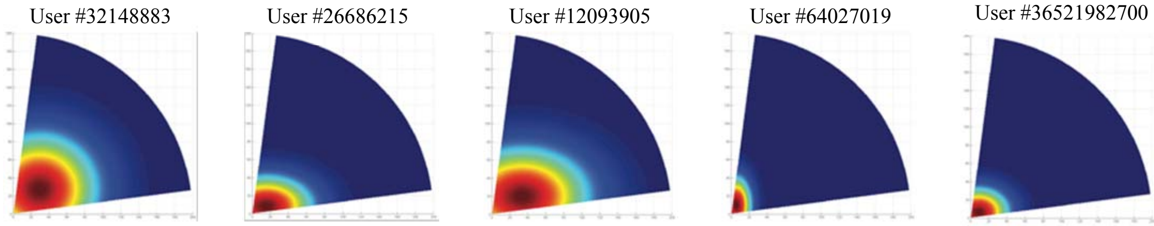


Fig. 5 Favorable degrees of the subject placement shown as heat maps for different users.

To check that whether our system can recommend a high-quality itinerary for a trip to a user, we performed a serial of experiments to test the utility of our novel approach. First, we separated the users into 5 groups according to the number of photos taken by the users. We used half of each user's historical travel data to train the user preference and leveraged the rest of the data for testing. The results are shown in Table 1, where Table 1, where five trips were computed for each group, on both training and testing data. The similarity degrees between the ground truths and the recommended itineraries were measured. A higher similarity was obtained as the number of photos increases.

Table 1. The Similarity degree (%) between the ground truths and the recommended itineraries.

Trips	0-50 photos	50-100 photos	100-500 photos	500-1000 photos	1000- photos
Trip 1	24.07	24.11	65.29	77.93	77.33
Trip 2	29.08	44.89	76.29	65.77	86.51
Trip 3	17.67	33.87	79.61	81.31	82.45
Trip 4	16.89	37.21	66.14	88.12	86.34
Trip 5	27.93	23.61	76.22	77.92	83.92
Average	23.13	39.29	72.71	78.21	83.31

6 Conclusions

In this paper, we propose a novel approach to infer personal preferences for trip recommendations by analyzing the photos taken by the user in the past. We apply a probabilistic model to detect favored POI contained in the FOV of the photos. Subsequently, each detected POI is classified into one or more corresponding categories, which are then used to build a user profile. Furthermore, by mining the geo-tagged photos taken by many users, we can extract the frequent travel patterns, which may reveal the user's travel habits. As a result, our approach returns a high-quality itinerary that considers both the user's preferences and personal habits.

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