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観光行動の不確定性を考慮したルート推薦

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Abstract Tour planning system automatically recommends travel routes for tourists visiting unfamiliar cities, which is a very helpful application. Several web and mobile tour planning systems have been proposed in research and industry but they are still far from available for real tourists. Conventional work are mainly modeled with Orienteering Problem (OP), which maximize tourists' profits under the giving constraints. However, it is very hard to define the optimal travel route and the recommended routes are usually not applicable since real tourists' behaviors are not sufficiently considered. To address this issue, we proposed a heuristic method to recommend travel routes upon the understanding of real users' uncertain travel behaviors.

Key words Sightseeing, Tour Planning, Travel Route Recommendation

1 Introduction

In recent years, tourism has become one of the most important industries in the whole world. At the same time, benefiting from the rapid development of location-based social networks, there are many user generated contents (UGC) (e.g., photos, check-ins, and ratings) available on the Internet. Various research and services are aiming to help tourists with a better tourism experience when they travel in an unfamiliar urban area (e.g., point of interest (POI) recommendation). One of the important tasks is tour planning or recommendation that aims to automatically recommend travel routes that meet users' requirements, which is addressed in this paper.

Currently, most existing research and services on tour planning are based on the model of Orienteering Problem (OP) and it's variants [12]. OP is a classical route planning problem, which the objective is to maximize the score of a subset of ordered nodes without exceeding the time budget on an undirected graph with weighted nodes and travel time between these nodes [14]. Mapping to our tour planning task, an urban area is a graph, a POI is a node on the graph, the time cost to travels from one POI to another is the travel time between nodes, and users' satisfaction is represented as the score (i.e., tourists visit a POI to collect the score). The output is an optimal travel route by maximizing the user satisfaction score under the given total travel time budget.

With the above OP model, there are mainly two research areas interested in this tour planning task:

（1） Operational Research (OR). Since OP can be built as an OR problem and it is NP-hard complexity, they are interested in proposing heuristic algorithms for adding much more complicated realistic constraints. For example, In [6], Ander et al. integrated public transportation services and multi-day tour planning is considered in [9].

（2） Data Mining. To provide a better travel experience for tourists, they use data mining methods to analysis POIs' attributes and user preferences that mined from UGC and OP-based methods are applied for tour planning. For example, In [10], Lim et al. estimated tourists' personalized preferences through social images and machine learning methods were proposed in [3]. Also, like [17], the most representative travel route was recommended by retrieving all other tourists' travel history.

However, with higher demand for tour planning, there is still no efficient method or system widely applied online right now. One possible reason could be the drawback of OP-based model, which assumes an optimal travel route is a score-maximized route under the given constraints. Different from refuge or rescue route planning tasks that also can be modeled with OP, it is very hard to define what is an optimal travel route. Furthermore, tourists do not always visit popular attractions one by one and there are many factors that can let tourists change their plan. For instance, some tourists might wander around a popular attraction before moving to a next far away poplar attraction or visit some less well-known attraction on the way to the next popular attraction. As a result, we should model various user mobility's uncertainty into the tour planning task.

In this paper, we studied a tour planning task by introducing the mobility uncertainty and proposed a heuristic algorithm to recommend travel route.

2 Related Work

As we introduced in the last section, there are various tour planning methods and systems have been proposed from views of different research fields. One of the earliest OP-based method [4] mined POIs from social images. Similar ideas have been extended by Lim et al. and Zhao et al. in [10], [19], which using social images' metadata information and visual features to estimate users' preferences. Other personalized methods or systems have been proposed in different ways. For instance, in [15], [18], the authors developed an interactive web system that users can manually select travel preferences. Personalization was automatically estimated in [20] with a feature-centric collaborative filtering method. Tour planning also has been proposed as an information retrieval task in several studies. In [2], [17], the authors modeled the tour planning task as a max cover problem that finds the most suitable travel routes from other tourists travel history.

OP-variant models were leveraged as basic models to apply for taking more realistic constraints into account. Team OP (TOP) extends OP by allowing multiple tours, which is applied for multi-day tour planning in [4], [7]. Different from the TOP, a recent study [5] proposed a multi-day tour planning algorithm by maximizing the utility of the worst day. The most studied extension of OP-based tour planning model is TOP with Time Windows (TOPTW). It adds open and close time for each node (i.e., POIs' opening hours) on TOP and was solved with Iterated Local Search (ILS) algorithm in [13]. Based on this extension, public transportation services were integrated into [6]. [8] is probably the most complete study for tour planning that based on TOPTW and jointly modeled various settings mentioned in previous studies. In [16], the authors defined super-POI for the large sightseeing areas which contain smaller sightseeing spots and split into outer and inner route planning.

3 A Heuristic Tour Planning Method

In this section, we introduce our proposed heuristic tour planning method. Given a set of POIs with their profits (e.g., popularity) and a user query (i.e., start, destination, travel time budget), the algorithm outputs a travel route.

To take user mobility's uncertainty into consideration, we add a random mechanism inspired by the concept of Exploration and Exploitation (E&E) [1] in information retrieval research filed into the tour planning procedure. E&E is a trade-off between exploring unknown search space and maximizing rewards that already found. We borrow this concept to model users' uncertain decision behaviors. For instance, we treat top-popular POIs as known knowledge, and other less well-known POIs as unknown knowledge. This is because top-popular POIs' information is always easier to obtain and recommended, while those less well-known POIs' profits are relatively lower. Therefore, we split all POIs into two parts, and normalize the popularity with the maximum value in each part as the assigned profit value for each POI.

$\epsilon-greedy$ is a simple and efficient algorithm for E&E problems. It uses a simple trade-off ratio ϵ to control the balance between exploration and exploitation. For instance, a popular POI is selected for a proportion $1-\epsilon$, and a random exploration is selected for a proportion ϵ. It ensures the recommended route is mainly composed of popular POIs but also includes a little exploration.

However, tourists are unlikely to visit less well-known POIs exclusively and are more likely to visit them on the way. This limits the exploration not on the entire graph, but a small set of POIs. For example, tourists might wander around a popular attraction before moving to a next far away poplar attraction. With this assumption, we add a constraint that exploration only allows those less well-known POIs in the region of the last visited POI. Therefore, we need to divide the POI graph into different regions to represent potential explorable areas. Several strategies can be considered in this step. For example, we use clustering methods to automatically divide regions, or define the scope centered on popular POIs, or directly use the administrative area division. Figure 1 shows a result of using K-Means clustering algorithm, which divides the whole Kyoto city to different areas according to their distances.

After the region division, a Greedy Randomized Adaptive Search Procedure [11] with $\epsilon-greedy$ algorithm is proposed for tour planning. For each solution, a greediness parameter is initiated by drawing a value from a uniform distribution, which the value is between 0 and 1 and represents the balance between greediness and randomness. At each insert iteration, another value is drawn from a uniform distribution, which is ϵ to decide whether the top-popular or less well-known POIs should be inserted. If $\epsilon > ExpRatio$, all top-popular POIs are initialed into candidate list, otherwise,

Figure 1 A region divide example of Kyoto city

all less well known POIs inside the region of last inserted node is initiated into the candidate list. For all POIs in the candidate list a heuristic value h_i is calculated as the following:

$$h_i = \frac{profit_i}{shift_i}, \qquad (1)$$

where $profit_i$ is the normalized profit value of the POI and $shift_i$ is the total time cost of inserting POI i (i.e., the travel time and visit duration). A threshold value is computed by multiplying the difference between the maximum and minimum heuristic values by the greediness parameter. Then an insertion is done by randomly select a POI which the heuristic value should be larger than the heuristic value. The insertion step is over when no feasible POI can be inserted into the recommended list and this is a complete search. Until the max number of search is reached, then a local search procedure (e.g., 2-Opt, remove and replace two arcs in a sub-tour) is applied to the best-found tour and return it as the final solution. Algorithm 1 concludes the whole procedure.

Algorithm 1: GRASP with $\epsilon - greedy$

while $IterationNumber < MaxIteration$ **do**
  $Solution = \{\}$
  $Greediness$ = random(0, 1)
  $CandidateList$ = GenerateCandidates($Solution$)
  repeat
    ϵ = random(0, 1)
    $CandidateList$ = UpdateCandidateList($\epsilon, ExpRatio, Greediness$)
    $CurrentNode$ = RandomlySelect($CandidateList$)
    $Solution$ = Insert($CurrentNode$)
  until *no feasible insertion available*
  $SolutionSet \leftarrow Solution$
$BestFound$ = LocalSearch($BestFound$)
return $BestFound$

4 Experiments and Results

A Real Tourism Dataset. To evaluate our proposed tour planning framework, we prepared a real tourism dataset of Kyoto city. This dataset originally contains 450 foreigner tourists and 406 students' school excursion one-day tour GPS trail data. According to the GPS trails, we first map all GPS points to 123 POIs that represent sightseeing attractions. Then other attributes about POIs, such as location, visit duration and visit popularity can be computed. For simplicity, the travel speed between POIs is set as an average speed $12km/h$.

Results and Case Study. There are two queries are tested: $Query_1('KyotoMuseum', 'SanjoStation', 4h)$ and $Query_2('KyotoUniversity', 'SanjoStation', 7h)$. For each

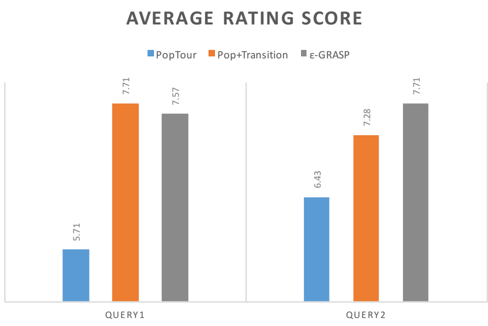

Figure 2 Average user rating scores

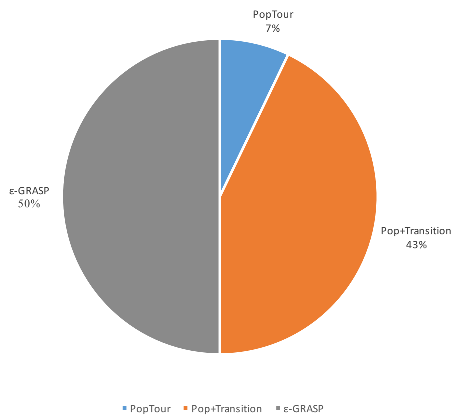

Figure 3 Percentage of user selected as helpful

query, we use the following methods to compare the performances:

- PopTour: A simple OP-based method that only takes POI popularity as the profit.
- Pop+Transition: A mixed OP-based method that takes both POI popularity and transition probability as the profit.
- $\epsilon-$GRASP: Our proposed GRASP with $\epsilon - greedy$ method in this paper.

We asked 7 foreigner tourists to rate all recommended travel routes of different methods. We also asked them which result is the most helpful solution. The results is summarized in 2 and 3.

From the results, we found that after considering user mobility' uncertainty, it not only did not reduce the quality of the recommended routes but made users feel more helpful.

5 Conclusion and Future Work

In this paper, we studied the tour planning task that aims to automatically recommend a travel route for tourists. We introduced a concept about user mobility's uncertainty and take it into the tour planning task. A heuristic tour planning with $\epsilon - greedy$ is proposed in this paper and has been evaluated by real tourists.

Since we our current proposed method is still very simple, we need to further improve it in our future work. For instance, we cannot automatically decide the value of *ExpRatio* but manually set it. Also, different regions should have their own *ExpRatio* which represent different potential explorable sightseeing resources.

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