Personalized Recommendation Of Travel Itineraries Based On Tourist Interests And Preferences

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Abstract- *Travel itinerary recommendation is an important but chal- lenging problem, due to the need to recommend captivating Places-of-Interest (POI) and construct these POIs as a con- nected itinerary. Another challenge is to personalize these recommended itineraries based on tourist interests and their preferences for starting/ending POIs and time/distance bud- gets. Our work aims to address these challenges by propos- ing algorithms to recommend personalized travel itineraries for both individuals and groups of tourists, based on their interest preferences. To determine these interests, we first construct tourists' past POI visits based on their geo-tagged photos and then build a model of user interests based on their time spent visiting each POI. Experimental evaluation on a Flickr dataset of multiple cities show that our proposed algorithms out-perform various baselines in terms of recall, precision, F1-score and other heuristics-based metrics.*

Keywords- Personalization; Tour Recommendations; Trip Planning; Group Recommendations; User Interests

I. INTRODUCTION

Holiday travelling and touring are popular leisure activities around the world, as shown by the 1.1 billion tourists world- wide who travelled in 2014 [22]. Economically, tourism is also an important and lucrative industry with an annual rev- enue of more than US$1.2 trillion in 2014. The importance of tourism has led to the creation of many tour planning re- sources such as online travel guides and tour agencies. From a tourist's perspective, their main purpose would be to visit captivating Places-of-Interest (POI) within the duration of their stay in the visited city.

Despite the availability of online travel guides and ser- vices provided by tour agencies, tourists still face challenges in tour planning due to the following reasons: (i) online travel guides are effective in recommending popular POIs but these POIs may not cater to the unique interest prefer- ences of individual tourists; (ii) in a foreign city, a tourist would require a customized trip itinerary with personalized POI recommendations, starting/destination points and time constraints (instead of a simple list of popular POIs without an itinerary); (iii) for groups of tourists, tour agencies offer standard group tours which may not cater to the diverse interest preferences of individuals within the tour group.

Research Goals

Our main research goal is to recommend personalized travel itineraries based on the unique preferences of tourists. This personalization of travel itineraries include the following as- pects of preferences, namely: (i) tourist interests; (ii) start- ing and ending POIs; and (iii) available length of travel du- ration. More specifically, we aim to investigate the following research questions:

R1: How can we model the interest preferences of *indi- vidual tourists* and personalize tour recommendations for these tourists based on their interests, time budgets and preferences for starting/ending points?

R2: Building upon R1, how can we model the interest preferences for *groups of tourists* and make tour recom- mendations that best satisfy the interest preferences of all tourists in a tour group?

State-of-the-Art Work

Many works on travel recommendation for individual tourists are based on combinatorial optimization problems such as the Orienteering problem [21, 23] or Generalized Maximum Coverage problem [8]. For example, Choudhury et al. [7] and Brilhante et al. [3, 4] modelled the itinerary recommen- dation problem based on the Orienteering problem and Gen- eralized Maximum Coverage problem, respectively. In par- ticular, Brilhante et al. [3, 4] optimized the recommended tour itineraries using both POI popularity and user interests, which is based on the (normalized) visit counts to POIs by individual tourists. Others such as Kurashima et al. [12, 13] and Chen et al. [5] also optimized for user interests, in addi- tion to their respective considerations for different transport modes and traffic conditions. Similar to that of [3, 4], Chen et al. also determined user interests based on a similar nor- malized POI visit count, while Kurashima et al. utilized a probabilistic framework based on a combined topic and Markov model. As part of R1, we extend upon these state- of-the-art by recommending personalized tours using a more fine-grained definition of user interests, which is based on the tourists' past POI visit duration.

Thus far, most travel recommendation research focus on recommending itineraries to a single tourist, whereas tourists frequently travel in groups in real-life. While there are in- teresting research that aim to recommend top-*k* POIs to groups [19], these works recommend individual POIs, in- stead of an itinerary of connected POIs, and constructing individual POIs into an itinerary is not a trivial scheduling problem due to various constraints, e.g., time and distance.

Similarly, there has been several interesting applications [9, 2] that recommend tours to groups of tourists based on user interests and group membership, which are explicitly pro- vided by the tourists. However, it is a challenging task to determine the interest preferences for multiple tourists and cluster these tourists into groups that best align their in- terests. As part of R2, we aim to explore the problem of group tour recommendation from the perspectives of tourist grouping, itinerary planning, and tour guide assignment.

Outline of Paper. This paper is structured as follows: Section 2 describes our current progress and contributions; Section 3 highlights our plans for future work; and Section 4 summarizes and concludes this paper.

II. PROGRESS TO DATE

In the following sections, we discuss our progress and con-

Modeling User Interests using Past Visits

After defining our basic tour recommendation problem, we now describe the approach we use to: (i) obtain the past visit history of tourists; and (ii) determine the interests of these tourists based on their past interest. These approaches were also used in various of our works [15, 14, 16].

Obtaining Past Visits

We use geo-tagged photos as a proxy for tourist real-life visits. In particular, we select geo-tagged photos taken near POIs as these photos imply that the tourist was physically at that POI (hence he/she was able to take that photo). From the series of geo-tagged photos taken by a tourist *u*, we are then able to determine the *past travel history* of this tourist, which is represented as:

$$H_u = .(p_1, t^a_{p_1}, t^d_{p_1}), ..., (p_n, t^a_{p_n}, t^d_{p_n})\Sigma \qquad (5)$$

recommendation problem; (ii) modeling of user interests;
(iii) developing various algorithms for recommending tours to individuals and groups; and (iv) evaluating our proposed algorithms against various baselines.

2.1 General Problem Formulation

Our basic tour recommendation problem is based on vari- ants of the Orienteering problem [21, 23] and we restate the formal problem definition used in [15]. Consider a particular city with *N* POIs, and a tourist *t* with the constraints of a time/distance budget and preferences to start and end at specific POIs *p*1 and *pN* , respectively. In this case, our main goal is to recommend a travel itinerary *I* = (*p*1, ..., *pN*) that optimizes the following:

$N-1$ N

where H_u is an ordered sequence comprising a series of triplets (p_x, $t^a_{p_x}$, $t^d_{p_x}$). This triplet consists of the visited POI p_x, arrival time t^a and departure time t^d at POI p_x. The visited POI p_x is determined based on geo-tagged photos taken near (e.g., within 100m) that POI p_x. As the geo-tagged photos include their taken time, we can determine the ar- rival and departure time, t^a and t^d based on the first and last photo consecutively taken at POI p_x.

Modeling of User Interests

Each POI is also tagged with a POI category (e.g., shopping, museum, beach, etc), which we determine using information from Wikipedia. Given that $\bar{D}(p_x)$ is the average amount of time that all tourist spent at POI p_x, we define the interest level of a tourist *u* in POI category *c* as follows:

$$Max \sum \sum x_{i,j}\ Utility(i) \qquad (1)$$

$$Int_u(c) = \Sigma \quad (t^d_{p_x} - t^a_{p_x})\delta(Cat_{p_x} = c) \qquad (6)$$

$$i=2\ j=2$$

where $x_{i,j} = 1$ if the travel itinerary includes a travel path

$p_x \in H_u$

$\bar{D}(p_x)$ *x*from POI *i* to *j*, and $x_{i,j} = 0$ otherwise. We then solve for Eq. 1, such that:

where $\delta(Cat_{p_x} = c) = 1$ if POI p_x belongs to category c, and $\delta(Cat_{p_x} = c) = 0$ otherwise. Eq. 6 determines the interest level of tourist *t* based on the amount of time he/she spends at POIs of category *c*, relative to the average amount of

$$\sum_{j=2}^{N} x_{1,j} = \sum_{i=1}^{N-1} x_{i,N} = 1 \quad (2)$$

time spent by other tourist at the same POIs. Thus, our intuition is that the more (less) time a tourist spends at a POI, the more (less) interested he/she is. This modeling of user interests is discussed further in [15].

$$\Sigma\, x_{i,k} = \Sigma\, x_{k,j} \leq 1,\ \forall\, k = 2, ..., N-1 \ (3)$$

Personalized Travel Recommendation for

$$\sum_{i=1}^{N-1} \sum_{j=2}^{N} Cost(i, j)x_{i,j} \leq B \quad (4)$$

Individual Tourist

Building upon our definition of interest in Eq. 6, we de- veloped the PersTour algorithm that aims to recommend personalized tours to individual tourists [15]. This person- alization takes place in terms of two aspects, namely: (i) Eq. 1 is our main objective function, which aims to max- imize a certain *utility* that can be obtained from the rec- ommended travel itinerary. This *utility* could be a value unique to individual tourists (e.g., interest preferences) or common to all tourists (e.g., POI popularity). Eq. 2 to 4 are constraints that are applied to the recommended itinerary, namely: (i) Constraint 2 ensures that the travel itinerary starts at $p1$ and ends at POI pN ; (ii) Constraint 3 ensures no POIs in the itinerary are disconnected or visited more than once; and (iii) Constraint 4 ensures that the entire itinerary can be completed within the budget *B*, based on the time or distance cost of travelling between POIs. the POIs are recommended based on tourist interest, with a varying emphasis on POI popularity as determined by the tourist; and (ii) the recommended visit duration is deter- mined based on the tourist interest level, i.e., more time spent at POIs that the tourist is more interested in.

For the personalization of recommended POIs, we modi- fied Eq. 1 such that the *utility* is based on both user interest alignment and POI popularity, that is:

$$Utility(i) = \eta Intu(Cati) + (1 - \eta)Pop(i) \qquad (7)$$

where $Intu(Cati)$ is defined previously in Eq. 6 and $Pop(i)$ is the popularity of POI *i*, which we define as the number oftimes POI *i* has been visited by all tourists. The parameter $\eta = [0, 1]$ allows tourists the flexibility to emphasize on either the user interest or POI popularity components, at varying levels.

For the personalization of POI visit duration, we utilize the interest level of tourist *u* in POI *i* (i.e., Eq. 6) and the average visit duration of all tourists at POI *i* (i.e., $\bar{D}(i)$). Thus, this personalized visit duration/time is defined as:

$$T\, ime_u(i) = Intu(Cati) \times \bar{D}(i) \qquad (8)$$

In short, we determine the personalized visit duration for tourist *u* based on how interested (uninterested) this tourist is in POI *i*, and accordingly recommend a longer (shorter) visit duration relative to the average visit duration. By fac- toring in the average visit duration, we are able to adapt to POIs of difference sizes, e.g., less time at a smaller museum but more time at a larger one. We refer readers to [15] for more details on this work.

Travel Recommendation with Mandatory Category

Extending upon our basic tour recommendation problem (Section 2.1), we proposed the TourRecInt algorithm that aims to recommend tours with a mandatory POI category, which is the POI category that a tourist is most interested in. In this work, we examine a tourist's past POI visit history and define the POI category that this tourist is most inter- ested in based on the most frequently visited POI category. In addition to this mandatory POI category, TourRecInt also personalizes tours based on other tourist preferences such as specific starting and ending points, and any time or distance budgets. Apart from tourism-related applica- tions, TourRecInt can also be extended to consider mul- tiple mandatory POI categories and be generalized to other path planning problems, e.g., John travelling from his office to home but having to drop by a supermarket, restaurant and petrol station to buy some groceries, take-out dinner and top-up petrol, respectively, before heading home. We refer readers to [14] for more details on this work.

Group Travel Recommendation for Mul- tiple Tourists

Recommending tours for groups of tourists involve addi- tional challenges, compared to recommending tours for indi- vidual tourists. Some of these challenges include customiz- ing tours to appeal to the interest preferences of the group as a whole and assigning tour guides with the appropriate ex- pertises to lead each group. We termed this the Group Tour Recommendation (GroupTourRec) problem, which we in- troduced in [16]. Technically, GroupTourRec is a chal- lenging problem that is NP-hard as it comprises variants of the Orienteering problem and clustering problem, which are also NP-hard [10, 1]. To solve this NP-hard problem, we di- vide GroupTourRec into more manageable sub-problems, and propose approaches to solve each sub-problem, which include:

For the sub-problem of recommending tour itineraries to groups, we first determine the group interest prefer- ences based on the average interest among all tourists in a group, then use a variant of the Orienteering prob- lem that considers both POI popularity and group in- terest preferences to recommend tours. For the sub-problem of allocating tour guides to lead each group, we first model the expertises of tour guides based on past tours they have led, then use an Inte- ger programming approach to assign tour guides whose expertises best match the tour recommended to each group.

We refer readers to [16] for more details on this work.

Evaluation of Proposed Approaches

Datasets. As mentioned in Section 2.2.1, we use geo-tagged photos to determine a tourist's past visits to POIs. For this purpose, we utilized the Yahoo! Flickr Creative Commons 100M dataset [25, 20], which includes 100M Flickr photos and videos along with their geographical coordinates and date/time taken. Apart from building a model of tourist interest preferences, we are able to use these past POI visits as a ground truth of real-life POI visits, which in turn is used to evaluate our proposed algorithms and various baselines.

Baseline Algorithms. In our research, we compared our proposed algorithms against various baselines, including:

StdTour: Standard tour itineraries that are offered by real-life tour agencies such as www.viator.com and local travel websites in the respective cities.

GNear: A distance-based greedy algorithm that ran- domly selects the next POI to visit from the three *near- est*, unvisited POIs.

GPop: A popularity-based greedy algorithm that ran- domly selects the next POI to visit from the three *most popular*, unvisited POIs.

Rand: A baseline that *randomly selects* the the next POI to visit from all unvisited POIs.

We selected these baselines as they reflect real-life tourist behaviours, such as signing up for an organized tour (Std- Tour) or simply visiting POIs that are nearby (GNear) or popular (GPop). In contrast, Rand shows us the perfor- mance of the various algorithm against a random recom- mendation

Performance Metrics and Results. Using past POI vis- its as a ground truth, we utilize various Information Re- trieval (IR) metrics such as Recall, Precision and F1-score to compare the performance of our proposed algorithms against the various baselines, in terms of how well the recommend tours reflect the real-life tours taken by tourists. In addition to these IR-based metrics, we also use various heuristics- based metrics such as POI popularity, tourist interest align- ment, tour guide expertise and group interest similarity to evaluate the performance of our proposed algorithms in terms of these utility scores. Using a Flickr dataset spanning mul- tiple touristic cities across the world, we evaluated our pro- posed algorithms against these baselines, with results show- ing that our proposed algorithms out-perform these base- lines for all cities, based on the above-mentioned metrics. Due to limited space, we refer readers to [15, 14, 16] for a more detailed discussion on the results.

III. FUTURE RESEARCH PLAN

Our future research plan includes the following:

1. Utilizing a game-theoretic approach to tour recommen- dations such that we try to minimize a global utilityof "crowdedness", while trying to personalize tours to individuals. In a museum setting, this would involve recommending an exhibit visit sequence that consid-

ers visitor interests but do not over-crowd a particular exhibit by sending all visitors there at the same time.

2. In addition to POI visit duration, we intend to explore other models of user interests using features based on textual contents of social media posts, number of pho- tos posted and user tags.
3. Refining our evaluation methodology by: (i) using Ama- zon Mechanical Turk for a qualitative study of user opinions on our recommended travel itineraries, such as in [7, 18]; and (ii) using online controlled experi- ments to better understand user behaviour and their fine-grained actions when deciding between our recom- mended travel itineraries and other baselines, such as in [11, 17].
4. Other potential ideas for future work include incorpo- rating image recognition techniques [6], considering the current user context (time, location, weather, etc) [24], and modelling the different levels of influence among users in a tour group [26].

IV. CONCLUSION

In this paper, we described the problem of travel itinerary recommendation and proposed the PersTour, TourRecInt and GroupTourRec algorithms for recommending itineraries that are personalized based on tourist interests and their preferences for starting/ending POIs and time/distance bud- gets. We also illustrated our approach of using geo-tagged photos to construct tourists' POI visit history and to build a model of user interests based on these visits. Using a Flickr dataset spanning multiple cities, experimental results show that our proposed algorithms out- perform various baselines in terms of tourist interests, POI popularity, recall, preci- sion, F1-score and other relevant metrics.

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