Towards Next Generation Touring: Personalized Group Tours

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Abstract

Recommending and planning tour itineraries are challenging and time-consuming for tourists, hence they may seek tour operators for help. Traditionally tour operators have offered standard tour packages of popular locations, but these packages may not cater to tourist's interests. In addition, tourists may want to travel in a group, e.g., extended family, and want an operator to help them. We introduce the novel problem of group tour recommendation (GROUPTOURREC), which involves many challenges: forming tour groups whose members have similar interests; recommending Points-of-Interests (POI) that form the tour itinerary and cater for the group's interests; and assigning guides to lead these tours. For each challenge, we propose solutions involving: clustering for tourist groupings; optimizing a variant of the Orienteering problem for POI recommendations; and integer programming for tour guide assignments. Using a Flickr dataset of seven cities, we compare our proposed approaches against various baselines and observe significant improvements in terms of interest similarity, total/maximum/minimum tour interests and total tour guide expertise.
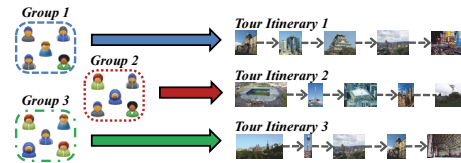
1 Introduction

Tourism is an important industry, with a visitor rate of 1.1 billion tourists in 2014, who generated more than US$1.2 trillion in revenue (UNWTO 2015). In particular, both tourists and tour operators play important roles in tourism. A major objective of such tourists is to visit captivating Points-of-Interest (POI) in foreign cities, but they often lack the expertise, familiarity and/or time to plan a suitable tour itinerary. As such, many of these tourists engage the services of tour operators. In turn, tour operators conduct organized tours to multiple POIs for groups of tourists, and assign tour guides to lead each tour group. However, tour operators typically offer standard tour packages of popular POIs, which may not cater to a tourist's interests. Although tour packages can be customized, it is challenging to construct tours that are interesting to multiple tourists in each tour group and assign tour guides with the right expertise to lead these customized tours. We term this the customized Group Tour Recommendation (GROUPTOURREC) problem (Fig. 1).

1.) Cluster Tourists into Different Tour Groups

Tourists with diverse interests *Different Tour Groups*
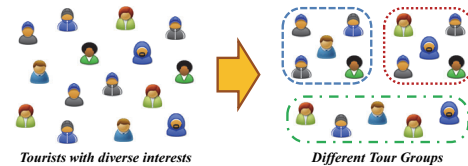
2.) Recommend Tour Itinerary to Tour Groups

Group 1 *Tour Itinerary 1*
Group 2 *Tour Itinerary 2*
Group 3 *Tour Itinerary 3*

3.) Assign Tour Guides to Lead Tour Groups

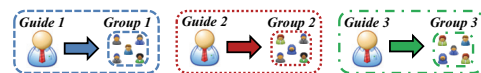*Guide 1* *Group 1* *Guide 2* *Group 2* *Guide 3* *Group 3*

Figure 1: Group Tour Recommendation

Technically, GROUPTOURREC is a non-trivial problem due to its NP-hard complexity, which is discussed in later sections. Thus, we decompose GROUPTOURREC into a series of more manageable sub-problems, namely:

1. How do we divide the tourists into tour groups, maximizing the interest similarity of all tourists in a group?

2. How do we plan a tour itinerary comprising a subset of POIs that are most interesting to each tour group?

3. How do we assign a tour guide to each tour group, matching the expertise of each guide to the recommended tour?

While there are various works that investigate group recommendations (Boratto and Carta 2011) or tour recommendations (Gavalas et al. 2014) separately, there has been a lack of work on group tour recommendations as a holistic problem. GROUPTOURREC is an important problem for tourism as most tourists travel in groups and there is increasing demand for customized tours (Cogswell 2014).

In this paper, we make the following contributions:

- We introduce and formulate the novel GROUPTOURREC problem, which involves recommending tours to groups of tourists with diverse interests and assigning tour guides with the right expertise to lead these tours. (Section 3)

- To overcome the NP-hard complexity of GROUPTOUR-REC, we propose a decomposition of GROUPTOURREC into a series of more manageable sub-problems, comprising tourist grouping, POI recommendation and tour guide assignment. (Section 4)

  - For tourist grouping, we model user interest based on their visit duration at specific POI categories, relative to their total visit duration. Thereafter, we use k-means and hierarchical clustering to group these users into different tour groups. (Section 4.1)

  - For POI recommendation, we optimize a variant of the Orienteering problem, with considerations for user interests, POI popularity, starting/destination POIs and available time budget. We determine user interests and POI popularity using geo-tagged photos. (Section 4.2)

  - For tour guide assignment, we model tour guide expertise based on the number of times they led a tour to a specific POI, relative to the number of visits by an average user. Thereafter, we use integer programming to assign tour guides to tour groups. (Section 4.3)

  - We also utilize geo-tagged photos as a form of crowd-sourcing to determine real-life POI visits by users, which is then applied to our model of user interests, POI popularity and tour guide expertise. (Section 5.1)

- We evaluate our proposed approaches against various baselines, using a Flickr dataset comprising seven cities. Results show that our proposed approaches out-perform these baselines using measures based on tour interest, group interest and tour guide expertise. (Sections 5 and 6)

For the remaining paper: Section 2 discusses related work; and Section 7 concludes this paper.

2   Related Work

Most earlier work has examined either group recommendations or tour recommendations as distinct research problems, instead of group tour recommendation as an integrated problem. Thus, we discuss the key literature in each of these two areas, before highlighting the differences with our work.

Group Recommendations (Retail). Group recommendations on retail items (e.g., movies, books, music) have been well-studied in recent years, such as by (Amer-Yahia et al. 2009) that performed group recommendations using a consensus score that maximizes the item relevance to the entire group, while trying to minimize disagreement within the group. Others such as (Hu et al. 2014) used collective deep belief networks and dual-wing restricted Boltzmann machines to model group preferences as high level features, which are not biased towards specific individuals within the group. In contrast, (Roy, Lakshmanan, and Liu 2015) studied a complementary problem of constructing groups in ways such that recommended items are most relevant to members within these groups. For a more in-depth discussion, (Boratto and Carta 2011) provides a comprehensive survey on group recommendation systems.

Group Recommendations (Tourism). There also exists many interesting applications of group recommendations to the tourism domain. For example, *e-Tourism* (Garcia, Sebastia, and Onaindia 2011; Garcia et al. 2009), which extends (Sebastia et al. 2009), allows users to explicitly indicate their interests and whether they belong to a specific group. Based on these user-defined groups, *e-Tourism* then considers the preference of individual users and recommend tours that best satisfy the entire group. Others such as *Intrigue* (Ardissono et al. 2003) and *Travel Decision Forum* (Jameson, Baldes, and Kleinbauer 2003) serve similar functions but require users to respectively indicate POI preferences instead of interests preferences and actively discuss online to reach a mutual agreement.

Tour Recommendations. There have also been numerous works related to recommending tours for a single tourist, and we highlight various key works. (Choudhury et al. 2010) recommended tours with specific starting and ending POIs based on the Orienteering problem (Tsiligirides 1984), while (Gionis et al. 2014) extended the Orienteering problem with an additional constraint of a specific POI category visit sequence (e.g., shopping → museum → park). Other works consider both POI popularity and user interests for tour recommendations, such as (Brilhante et al. 2013; 2015) and (Lim et al. 2015; Lim 2015) that are based on variants of the Generalized Maximum Coverage problem (Cohen and Katzir 2008) and Orienteering problem, respectively. There are also numerous web and mobile-based applications for single tourist recommendations (Brilhante et al. 2014; Refanidis et al. 2014; Castillo et al. 2008), which apply variations of the earlier works. For a more comprehensive discussion, (Gavalas et al. 2014) provides a good overview of tour recommendation algorithms targeted at a single tourist.

These earlier works are the state-of-the-art in their respective and distinct areas of group recommendations and tour recommendations. However, our work differs from these earlier works in the following ways: (i) most group recommendations for retail applications attempt to recommend (top-k) items such as movies, books and music, whereas recommending tour itineraries requires different considerations such as starting/ending POIs, time/distance budget, POI popularity and user interest preferences, constructed as a complete itinerary instead of only the top-k items; (ii) although traditional tour recommendation methods are effective for a single tourist, group tour recommendations need to address the additional challenges of grouping tourists, group interest alignment, and assignment of tour guides; (iii) however, group recommendations in tourism assume that tour groups are pre-defined by tourists, whereas we model tourist interests then cluster tourists into groups based on their interests. (iv) in addition, group recommendations for tourism do not consider the assignment of tour guides to lead tour groups, whereas we model tour guides' expertise and assign tour guides to tour groups based on their expertise; and (v) moreover, group recommendations for tourism require users to explicitly enter their demographics details and general interests or select specific POIs, whereas we automatically determine user interests based on their past visits. To the best of our knowledge, there has been no earlier work that investigates group tour recommendations as a holistic problem.

3 Background and Problem Definition

In this section, we introduce some preliminaries and formalize the GROUPTOURREC problem.

3.1 Preliminaries

For each city, let $T = \{t_1, ..., t_l\}$ be the set of tourists, $U = \{u_1, ..., u_m\}$ be the set of tour guides, $G = \{g_1, ..., g_m\}$ be the set of tour groups, and $P = \{p_1, ..., p_n\}$ be the set of POIs. In other words, there are l tourists, m tour guides and tour groups, and n POIs. Given that $C = \{c_1, ..., c_o\}$ denotes the set of all POI categories, each POI p belongs to a category $Cat_p \in C$. A future extension could include classifying POIs under multiple categories with different weightings for each category.

Definition 1: Tourist and Tour Guide Travel History. We represent the travel history of a tourist t as an ordered sequence $S_t = ((p_1, t_{p_1}^a, t_{p_1}^d), ..., (p_n, t_{p_n}^a, t_{p_n}^d))$, where $t_{p_x}^a$ and $t_{p_x}^d$ respectively denote the arrival and departure time at POI p_x.[1] Based on this travel history S_t, we can determine the duration a tourist t spends at POI p_x by calculating the difference between the arrival time $t_{p_x}^a$ and departure time $t_{p_x}^d$. Similarly, we define the total visiting time a tourist t spends at all POIs as: $V(t) = \sum_{p \in S_t} (t_p^d - t_p^a)$.

Definition 2: POI Popularity and Tourist Interest Preference. Like many earlier works (Brilhante et al. 2013; 2015; Lim 2015), we adopt a simple but effective representation of POI popularity based on the number of times a POI is visited. The popularity of a POI p is defined as:

$$Pop(p) = \sum_{t \in T} \sum_{p_x \in S_t} \delta(p_x = p), \quad \forall p \in P \quad (1)$$

where $\delta(p_x = p) = \{^{1, \ p_x = p}_{0, \ otherwise}$.

Unlike POI popularity, which is the same for all tourists, interest preferences are unique to each tourist, i.e., different tourists will have different interest preferences for various POI categories. Thus, we calculate the interest level of a tourist t in POI category c using:

$$Int_t(c) = \sum_{p \in S_t} \frac{(t_p^d - t_p^a)}{V(t)} \delta(Cat_p = c), \quad \forall c \in C \quad (2)$$

where $\delta(Cat_p = c) = \{^{1, \ Cat_p = c}_{0, \ otherwise}$. That is, the interest level of a tourist t in a POI category c is based on the amount of time he/she spends at POIs of category c, relative to the total time he/she spends visiting all POIs. The basic intuition is that a tourist is more likely to spend more (less) time at a POI category that interests (uninterests) him/her.

Definition 3: Tourist Interest Preferences. Given the interest function $Int_t(c)$ introduced in Eqn. 2, we represent the interest vector of a tourist t as:

$$\vec{v_t} = \langle Int_t(c_1), ..., Int_t(c_o) \rangle, \quad \forall \{c_1, ...c_o\} \in C \quad (3)$$

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[1] $S_t = ((p_1, t_{p_1}^a, t_{p_1}^d), ..., (p_n, t_{p_n}^a, t_{p_n}^d))$ is also written as $S_t = (p_1, ..., p_n)$, for brevity of representation. Similarly, we use S_u to represent the travel history of a tour guide.

Definition 4: Tour Guide Expertise. Next, we model the expertise level of a tour guide u in a specific POI p as:

$$Ept_u(p) = \frac{\sum_{p_x \in S_u} \delta(p_x = p)}{\frac{1}{|T|} \sum_{t \in T} \sum_{p_y \in S_t} \delta(p_y = p)}, \quad \forall p \in P \quad (4)$$

where $\delta(p_x = p) = \{^{1, \ p_x = p}_{0, \ otherwise}$. In short, Eqn. 4 determines the expertise of a tour guide u in POI p based on the number of times he/she has visited this POI, relative to the number of visits by an average user. The basic intuition is that the more times a tour guide has led a tour to POI p, the more experienced this tour guide will be about POI p. We then represent the expertise vector of a tour guide u as:

$$\vec{v_u} = \langle Ept_u(p_1), ..., Ept_u(p_n) \rangle, \quad \forall \{p_1, ...p_n\} \in P \quad (5)$$

It should be noted that $|\vec{v_u}| = |P|$, i.e., the total number of possible points of expertise of a tour guide corresponds to the total number of POIs in the city. Another possible representation of tour guide expertise is based on his/her expertise in POI categories, instead of specific POIs. However, we chose the representation in Eqn. 5 as this measure is more fine-grained and representative of real-life, i.e., a tour guide is more likely to be an expert in various distinct POIs, rather than having the same level of expertise across all POIs of a certain category.

3.2 Problem Definition

We aim to address the GROUPTOURREC problem in terms of its sub-problems of tourist grouping, POI recommendation and tour guide assignment. Given that $T = \{t_1, ..., t_l\}$, $U = \{u_1, ..., u_m\}$, $G = \{g_1, ..., g_m\}$, and $P = \{p_1, ..., p_n\}$ are respectively the set of tourists, tour guides, tour groups, and POIs, our main goal is find $x_{t,g}$, $y_{g,p}$, and $z_{u,g}$ that maximize the following objective function:

$$\alpha \sum_{g \in G} \sum_{t \in T} \sum_{p \in P} x_{t,g} y_{g,p} \Big(\eta Int_t(Cat_p) + (1 - \eta) Pop(p) \Big)$$
$$+ (1 - \alpha) \sum_{g \in G} \sum_{u \in U} \sum_{p \in P} z_{u,g} y_{g,p} Ept(u, p)$$
$$(6)$$

where:

$$x_{t,g} = \{^{1, \ \text{tourist } t \text{ is assigned to group } g}_{0, \ \text{otherwise}}$$
$$y_{g,p} = \{^{1, \ \text{group } g \text{ is recommended POI } p}_{0, \ \text{otherwise}}$$
$$z_{u,g} = \{^{1, \ \text{tour guide } u \text{ is assigned to group } g}_{0, \ \text{otherwise}}$$

such that:

$$x_{t,g}, y_{g,p}, z_{u,g} \in \{0, 1\} \quad (7)$$

$$\sum_{g \in G} x_{t,g} = 1, \quad \forall t \in T \quad (8)$$

$$\sum_{g \in G} z_{u,g} = 1, \quad \forall u \in U \quad (9)$$

$$\sum_{u \in U} z_{g,u} = 1, \quad \forall g \in G \quad (10)$$

$$\sum_{p \in P} Cost(p_i, p_{i+1})y_{g,p} \leq B, \quad \forall\, g \in G \quad (11)$$

In Eqn. 6, the parameter $\alpha \in [0, 1]$ controls the weighting between the components of: (i) user grouping and POI recommendation; and (ii) tour guide assignment. Thus, Eqn. 6 is maximized when the two components are maximized. We use $\alpha = 0.5$ to give a balanced emphasis on both components. Constraint 8 ensures that each tourist is assigned to exactly one tour group. Constraint 9 ensures that each tour guide leads exactly one tour group, and Constraint 10 ensures that each tour group is led by only one tour guide. For each tour group g, Constraint 11 ensures that the total time required to complete the tour itinerary is within a budget B (more details are provided in Section 4.2).

While we use Eqn. 6 to formalize the GROUPTOURREC problem, it can be easily generalized to other problems. Consider the application of Eqn. 6 to a project management problem comprising of members, teams, projects and managers. The idea would be to: (i) assign members to teams to either diversify or specialize their skill-set, i.e., $x_{t,g}$; (ii) assign projects that best match the skill-set of specific teams, i.e., $y_{g,p}$; and (iii) assign managers to lead each team based on their experience with the projects, i.e., $z_{u,g}$. Similarly, instead of optimizing for tourist interests, POI popularity and guide expertise in Eqn. 6, we will optimize for the member's skill-set, project requirements and manager's experience.

Eqn. 6 is an instance of a non-linear integer programming problem, resembling multiple quadratic assignment problems that are also dependent on each other. Quadratic programming problems are NP-hard (Loiolaa et al. 2007; Burkard 1984), thus Eqn. 6 as a whole is also NP-hard. Hence we propose a decomposition of GROUPTOURREC into more manageable sub-problems and use greedy approaches to solve each sub-problem separately.

4 Group Tour Recommendation Framework

Due to the NP-hard complexity of GROUPTOURREC, solving Eqn. 6 optimally is not feasible. As such, we divide GROUPTOURREC into more manageable sub-problems of tourist grouping, POI recommendation and tour guide assignment (as stated in Section 1), and we describe our approaches to solving each of these sub-problems.

4.1 Tourist to Tour Group Allocation (Tourist2Group)

Given that the l tourists are divided into m tour groups, let $G = \{g_1, ..., g_m\}$ be the set of tour groups, and $g_k = \{t_1, ..., t_q\}$ denote the kth tour group that comprises q tourists. Formally, our goal is to find a grouping G that:

$$Max \sum_{g \in G} \sum_{t_i \in g} \sum_{t_j \in g, t_j \neq t_i} \frac{\vec{v_{t_i}} \cdot \vec{v_{t_j}}}{||\vec{v_{t_i}}||\ ||\vec{v_{t_j}}||} \quad (12)$$

where $\frac{\vec{v_{t_i}} \cdot \vec{v_{t_j}}}{||\vec{v_{t_i}}||\ ||\vec{v_{t_j}}||}$ is the cosine similarity of two tourists t_i and t_j. This cosine similarity tells us how similar two users are in terms of their interest preferences. Thus in Eqn. 12, we are maximizing the interest preference among all user pairs in each tour group g_k, and for all m tour groups.

Optimal solutions to this clustering problem have been shown to be NP-hard (Aloise et al. 2009). As such, we employ the following algorithms to obtain approximate solutions to this problem. The algorithms are:

- **k-means clustering (KMEAN).** An iterative algorithm that assigns points (users) to their nearest centroid (group) (Hartigan and Wong 1979). This assignment then leads to an update of the centroid, and the assignment and update steps are repeated until the algorithm converges.

- **Hierarchical clustering (HIERA).** An agglomerative, hierarchical clustering algorithm that aims to minimize the variance within groups, using Euclidean distances (based on interests) between users in a group (Ward 1963).

Given POI categories $C = \{c_1, ..., c_o\}$ and two users i and j, their Euclidean distance is defined as: $\sqrt{(Int_i(c_1) - Int_j(c_1))^2 + ... + (Int_i(c_o) - Int_j(c_o))^2}$.

4.2 POI Recommendation to Tour Group (POI2Group)

One main challenge in recommending and planning tours for a group is the diverse interest preferences among members of the tour group. To address these diverse interest preferences, we construct a collective group interest preference based on the average interest preference of all group members. For a tour group $g = \{t_1, ..., t_q\}$, this collective group interest preference is defined as:

$$\vec{v_g} = \frac{1}{|g|} \sum_{t \in g} \vec{v_t}, \quad \forall\, g \in G \quad (13)$$

Similar to $Int_t(c)$ (Eqn. 2), we define a function $Int_g^{group}(c)$ that determines the interest level of tour group g in POI category c, based on $\vec{v_g}$.

Thereafter, we approach this tour recommendation problem as an instance of the Orienteering problem (Tsiligirides 1984; Vansteenwegen, Souffriau, and Oudheusden 2011; Lim et al. 2015), with a time budget B, starting POI p_1 and destination POI p_N. Our main goal is to recommend a tour itinerary $I = (p_1, ..., p_N)$ that maximizes POI popularity and tourist interest, while staying within the time budget B. As described in Section 3.1, POI popularity and tourist interest are defined based on the functions $Pop(p)$ (Eqn. 1) and $Int_t(c)$ (Eqn. 2), respectively. Formally, we want to plan a tour itinerary $I = (p_1, ..., p_N)$ for a tour group g that:

$$Max \sum_{i=1}^{N-1} \sum_{j=2}^{N} r_{i,j}\Big(\eta Int_g^{group}(Cat_i) + (1-\eta)Pop(i)\Big)$$
$$(14)$$

where $r_{i,j} = \{^{1,\ \text{travel from POI } i \text{ to } j}_{0,\ \text{otherwise}}$, such that:

$$\sum_{j=2}^{N} r_{1,j} = \sum_{i=1}^{N-1} r_{i,N} = 1 \quad (15)$$

$$\sum_{i=1}^{N-1} r_{i,k} = \sum_{j=2}^{N} r_{k,j} \leq 1, \quad \forall\, k = 2, ..., N-1 \quad (16)$$

$$\sum_{i=1}^{N-1} \sum_{j=2}^{N} Cost(i,j)r_{i,j} \leq B \qquad (17)$$

Eqn. 14 aims to maximize the POI popularity $Pop(i)$ and tour group interest $Int_g^{group}(Cat_i)$ of the recommended tour, with $\eta \in [0,1]$ as the weight assigned to POI popularity and group interest. Constraint 15 ensures that the recommended tour starts and ends at POI 1 and N, respectively. Constraint 16 ensures that no POIs are re-visited and all paths are connected. Constraint 17 ensures that the total time needed to visit all POIs in the recommended tour is within the budget B based on the function $Cost(p_x, p_y)$, which considers the travelling time between POIs and visit duration at each POI. To eliminate sub-tours, we adapted the constraints from (Miller, Tucker, and Zemlin 1960). We then proceed to solve this tour recommendation problem as an integer programming problem, using the lpsolve linear programming package (Berkelaar, Eikland, and Notebaert 2004).

4.3 Tour Guide to Tour Group Assignment (Guide2Group)

Given that $U = \{u_1, ..., u_m\}$ is the set of tour guides and $I_g = (p_1, ..., p_N)$ is the tour itinerary recommended to a tour group $g \in G$, our goal is to find a tour guide u for tour group g that:

$$Max \sum_{g \in G} \sum_{u \in U} \sum_{p \in I_g} z_{u,g} y_{g,p} Ept(u,p) \qquad (18)$$

In short, we want to best match tour guides to tour groups based on the tour guides' expertise and the POIs recommended to the tour groups. Similar to Section 4.2, we solve this as an integer programming problem and denote this approach **OPTIM**.

5 Experimental Methodology

In this section, we describe our experimental dataset, the various baseline algorithms and our evaluation methodology.

5.1 Dataset

We perform our experiments using the publicly available Yahoo! Flickr Creative Commons 100M (YFCC100M) dataset (Yahoo! Webscope 2014; Thomee et al. 2015). This dataset comprises 100M Flickr photos and videos, along with their meta-data such as the date/time taken and latitude/longitude coordinates. The latitude/longitude coordinates are associated with a geo-location accuracy ranging from 1 to 16 (least to most accurate). Such geo-tagged photos serve as a good approximation for real-life tourist visits and are used in similar tour recommendation works (Choudhury et al. 2010; Brilhante et al. 2015; Lim et al. 2015; Lim 2015).

For our experiments, we pre-processed the YFCC100M dataset by extracting geo-tagged photos that were taken in seven different cities, namely: Toronto, Vienna, Osaka, Budapest, Glasgow, Delhi and Edinburgh. We selected these seven touristic cities around the world to ensure the generalizability of our experimental results. In addition, we

Table 1: Summary Statistics of Dataset

City	No. of Photos	No. of Users	# POI Visits	# Travel Sequences
Toronto	157,505	1,395	39,419	6,057
Vienna	85,149	1,155	34,515	3,193
Osaka	392,420	450	7,747	1,115
Budapest	36,000	935	18,513	2,361
Glasgow	29,019	601	11,434	2,227
Delhi	13,919	279	3,993	489
Edinburgh	82,060	1,454	33,944	5,028

only considered photos with the highest geo-location accuracy of 16 to ensure the accuracy of our results. These geo-tagged photos are then mapped to a list of POI locations (obtained from Wikipedia), thus providing us with a proxy of users' real-life POI visits, which is then formulated as Definitions 1 to 4 (Section 3.1). Based on Definition 1, we use the time taken of a user's first and last photo at a POI to determine his/her POI visit duration. Table 1 summarizes the main statistics of our dataset, which is available at https://sites.google.com/site/limkwanhui/datacode#icaps16.

Using this dataset, we first construct the interest preference vector $\vec{v_t}$ for all tourists $t \in T$, as stated in Eqn. 3. Next, we construct the expertise vector $\vec{v_u}$ for all tour guides $u \in U$, as stated in Eqn. 5. In our experiments, we define tour guides as users who visited the most number of POIs and thus have the highest expertise level in the most POIs.[2]

5.2 Baseline Algorithms

Tourist2Group Baselines. For the Tourist2Group allocation, we compare the KMEAN and HIERA algorithms against the following baselines:

- **First-Come-First-Allocated (FCFA).** Tourists are assigned into tour groups based on their time of arrival.

- **Random Allocation (RAND).** Tourists are randomly assigned into each tour group.

FCFA reflects the modus operandi of tour operators, where they allocate tourists into tour groups based on the order in which they signed up for the tours. RAND shows the effectiveness of a random-based approach.

POI2Group Baselines. After the Tourist2Group allocation using the KMEAN, HIERA, FCFA and RAND algorithms, we next determine the tour group interest (Eqn. 13) and then proceed to make POI2Group recommendations for each tour group. As described in Section 4.2, the POI2Group recommendations can be customized based on the value of η, and we use the following variants:

- **POI2Group with η=0.5 (I.5).** Compute POI2Group recommendations with a balanced weighting on both POI

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[2]Due to a lack of explicitly identified tour guides, we use the most well-visited users as a proxy for tour guides. Our assumption is that tour guides are the most well-visited (compared to the average tourist), due to the tour guide having led many previous tours. In real-life, a tour agency is likely to have a profile of its tour guides or be able to obtain their expertises directly from their tour guides.

popularity and group interest.

- **POI2Group with $\eta=1$ (I1).** Compute POI2Group recommendations with a full weighting on group interest, with no consideration for POI popularity.

We use KMEAN-I.5 to denote the allocation of tourists to tour groups using the KMEAN algorithm, and the recommendation of POIs to these tour groups using $\eta=0.5$ (I.5). We use a similar notation for the other Tourist2Group allocations (KMEAN, HIERA, FCFA and RAND) combined with the different POI2Group recommendations (I.5 and I1).[3] Thus for the POI2Group recommendations, we are essentially comparing the {KMEAN, HIERA}-{I.5, I1} algorithms against the {FCFA, RAND}-{I.5, I1} baselines.

In addition, we also compare against a baseline of standard tour packages offered by tour operators, defined as:

- **STDTOUR.** Actual tour itineraries offered by the following tour operators: viator.com (Toronto and Osaka), budapest.com (Budapest), viennacitytours.rezgo.com (Vienna), scottishtours.co.uk (Glasgow), delhitourism.gov.in (Delhi), and edinburghtour.com (Edinburgh).

The main purpose of this baseline is to determine how our customized tours perform against standard tour packages, in terms of satisfying the interest preferences of tourists. In order to ensure a fair comparison between our algorithms and the STDTOUR baseline, we only evaluate with travel sequences that comprise the same number of POIs as that in STDTOUR (for each city in our dataset).

Guide2Group Baselines. For the Guide2Group assignment, we compare our OPTIM approach (Section 4.3) against a **Random Assignment (RANDA)** baseline where each tour group is randomly assigned a tour guide. As our GROUPTOURREC problem comprises the Tourist2Group, POI2Group and Guide2Group components, our overall evaluation involves comparing the {KMEAN, HIERA}-{I.5-OPTIM, I1} algorithms against the {FCFA, RAND}-{I.5, I1}-RANDA baselines.

5.3 Evaluation

Our experimental evaluation is based on all travel sequences with ≥ 3 POI visits in our dataset.[4] For each of these travel sequences, we perform the following evaluations:

1. **Tourist2Group Evaluation.** Based on the entire set of users for each city, we randomly select 100 users and group these users into five tour groups using the various Tourist2Group allocation algorithms. We evaluate each Tourist2Group allocation using the following metrics:

   - **Jaccard Similarity:** $Jac(g)$. The average Jaccard similarity of all pair-wise combinations of tourists in group g. Let $g = \{t_1, ..., t_q\}$ denote a tour group g that comprises q tourists, then Jaccard similarity is defined as:

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[3]Note that we do not use $\eta=0$, which results in POI2Group recommendations based only on POI popularity. Such recommendations ignore user interests and is not the focus of this work.

[4]Rather than pick random POIs to construct artificial itineraries, we use these travel sequences as they reflect real-life itineraries and serve as a more realistic evaluation.

$Jac(g) = \frac{1}{|g|} \sum_{t_i \in g} \sum_{t_j \in g, t_j \neq t_i} \frac{|v_{t_i} \cap v_{t_j}|}{|v_{t_i} \cup v_{t_j}|}$, where v_{t_i} is the binary version of $\vec{v_{t_i}}$ (non-zero values converted to 1s).

- **Cosine Similarity:** $Cos(g)$. The average cosine similarity of all pair-wise combinations of tourists in group g. Let $g = \{t_1, ..., t_q\}$ denote a tour group g that comprises q tourists, then cosine similarity is defined as: $Cos(g) = \frac{1}{|g|} \sum_{t_i \in g} \sum_{t_j \in g, t_j \neq t_i} \frac{\vec{v_{t_i}} \cdot \vec{v_{t_j}}}{||\vec{v_{t_i}}|| \, ||\vec{v_{t_j}}||}$.

- **Common Top Interest:** $Com(g)$. The largest proportion of tourists in group g with the same interest $c \in C$. Let $g = \{t_1, ..., t_q\}$ denote a tour group g that comprises q tourists, then common top interest is defined as: $Com(g) = \max_{c \in C} \frac{1}{|g|} \sum_{t_i \in g} \delta(Int_{t_i}(c))$, where

$\delta(Int_{t_i}(c)) = \{^{1, \, Int_{t_i}(c) \neq 0}_{0, \, otherwise}$.

These similarity measures show how similar users in the allocated group are in terms of their interest, and allow us to determine the effectiveness of our Tourist2Group allocation algorithms against the baselines. As there is no ground truth on the real-life groups, we use these heuristics to measure the effectiveness of the group allocations.

2. **POI2Group Evaluation.** Based on each allocated tour group (from Step 1 above), we run the various POI2Group recommendation algorithms using the starting POIs and destination POIs of these real-life travel sequences. Thus the POI2Group recommendation results in a tour itinerary $I_g = (p_1, ..., p_N)$ of N POIs that is recommended to a group g. We evaluate each POI2Group recommendation using the following metrics:

   - **Tour Total Interest:** $Tot_I(t)$. The total interest of all POIs in the recommended itinerary I to a tourist t in group g. Tour total interest is defined as: $Tot_I(t) = \sum_{p \in I_g} Int_t(Cat_p)$.

   - **Tour Maximum Interest:** $Max_I(t)$. The maximum interest out of all POIs in the recommended itinerary I to a tourist t in group g. Tour maximum interest is defined as: $Max_I(t) = \max_{p \in I_g} Int_t(Cat_p)$.

   - **Tour Minimum Interest:** $Min_I(t)$. The minimum interest out of all POIs in the recommended itinerary I to a tourist t in group g. Tour minimum interest is defined as: $Min_I(t) = \min_{p \in I_g} Int_t(Cat_p)$.

Total interest allows us to determine how interested all tourists in a tour group are regarding the recommended tour. In addition, we also use maximum and minimum interests to determine the best and worst case of a recommended tour, respectively, i.e., akin to the most interested and least interested tourist in each group.

3. **Guide2Group Evaluation.** Based on the POI2Group recommendations to each tour group (from Step 2 above), we run the various Guide2Group assignment algorithms using the tour guide expertise and recommended tour for each group. We evaluate each Guide2Group assignment using the following metric:

Table 2: Tourist2Group comparison of the KMEAN, HIERA algorithms against the FCFA, RAND baselines, in terms of Jaccard Similarity (Jac), Cosine Similarity (Cos) and Common Top Interest (Com). † denotes a significant difference with both FCFA and RAND, based on two-sided t-tests with p<.0001.

	Toronto				**Vienna**				**Osaka**				**Budapest**		
Algo.	*Jac*	*Cos*	*Com*	*Algo.*	*Jac*	*Cos*	*Com*	*Algo.*	*Jac*	*Cos*	*Com*	*Algo.*	*Jac*	*Cos*	*Com*
RAND	.383±.002	.263±.001	.355±.002	RAND	.495±.002	.338±.001	.422±.002	RAND	.414±.004	.373±.003	.459±.005	RAND	.561±.003	.319±.001	.357±.001
FCFA	.382±.002	.263±.001	.356±.002	FCFA	.494±.002	.336±.001	.421±.002	FCFA	.409±.004	.373±.003	.456±.005	FCFA	.559±.003	.320±.001	.359±.001
KMEAN	.723±.003†	.836±.004†	**.893±.004†**	KMEAN	.788±.004†	.816±.004†	.856±.004†	KMEAN	.908±.013†	.921±.008†	.902±.012†	KMEAN	.816±.004†	.837±.003†	**.898±.003†**
HIERA	**.738±.002†**	**.853±.005†**	.882±.005†	HIERA	**.815±.003†**	**.860±.005†**	**.870±.005†**	HIERA	**.923±.013†**	**.929±.008†**	**.911±.012†**	HIERA	**.830±.003†**	**.870±.004†**	.887±.004†

Table 3: POI2Group comparison of the {KMEAN, HIERA}-{I.5, I1} algorithms against the {FCFA, RAND}-{I.5, I1} baselines, in terms of Tour Total Interest (Tot_I), Tour Maximum Interest (Max_I) and Tour Minimum Interest (Min_I). † denotes a significant difference with both FCFA and RAND, based on two-sided t-tests with p<.0001.

	Toronto				**Vienna**				**Osaka**				**Budapest**		
Algo.	*Tot_I*	*Max_I*	*Min_I*	*Algo.*	*Tot_I*	*Max_I*	*Min_I*	*Algo.*	*Tot_I*	*Max_I*	*Min_I*	*Algo.*	*Tot_I*	*Max_I*	*Min_I*
RAND-I1	0.82±.005	.530±.003	.054±.001	RAND-I1	1.59±.007	.663±.002	.139±.001	RAND-I1	1.52±.023	.658±.007	.172±.005	RAND-I1	1.51±.007	.639±.002	.102±.001
FCFA-I1	0.82±.005	.531±.003	.054±.001	FCFA-I1	1.59±.007	.664±.002	.137±.001	FCFA-I1	1.52±.022	.676±.007	.163±.005	FCFA-I1	1.51±.007	.640±.002	.102±.001
KMEAN-I1	**1.26±.006†**	**.737±.002†**	**.092±.001†**	KMEAN-I1	**2.21±.007†**	**.886±.001†**	**.200±.002†**	KMEAN-I1	**2.05±.021†**	.871±.005†	**.239±.006†**	KMEAN-I1	**2.46±.008†**	**.875±.001†**	**.167±.001†**
HIERA-I1	1.22±.006†	.728±.002†	.084±.001†	HIERA-I1	2.15±.007†	.863±.001†	.186±.002†	HIERA-I1	2.05±.021†	**.872±.005†**	.231±.006†	HIERA-I1	2.36±.008†	.845±.001†	.154±.001†
RAND-I.5	0.69±.004	.497±.003	.038±.001	RAND-I.5	1.41±.006	.665±.002	.139±.001	RAND-I.5	1.36±.019	.691±.007	.137±.005	RAND-I.5	1.39±.006	.634±.002	.086±.001
FCFA-I.5	0.69±.004	.496±.003	.038±.001	FCFA-I.5	1.40±.006	.662±.002	.141±.001	FCFA-I.5	1.35±.019	.692±.007	.133±.005	FCFA-I.5	1.38±.006	.635±.002	.086±.001
KMEAN-I.5	**1.12±.005†**	**.701±.002†**	**.074±.001†**	KMEAN-I.5	**2.10±.007†**	**.867±.001†**	**.225±.002†**	KMEAN-I.5	**2.01±.021†**	**.872±.005†**	**.249±.006†**	KMEAN-I.5	**2.16±.007†**	**.830±.002†**	**.138±.001†**
HIERA-I.5	1.10±.005†	.698±.002†	.069±.001†	HIERA-I.5	2.04±.007†	.852±.002†	.210±.002†	HIERA-I.5	2.01±.021†	.871±.005†	.247±.006†	HIERA-I.5	2.13±.007†	.812±.002†	.133±.001†

- ***Guide Total Expertise:*** $Tot_E(t)$**.** The total expertise of a tour guide u in all POIs of an itinerary I recommended to group g. Guide total expertise is defined as:
$$Tot_E(t) = \sum_{p \in I_g} Ept_u(p)$$

4. **Overall Evaluation.** To evaluate GROUPTOURREC as a whole (i.e., Tourist2Group Allocation, POI2Group Recommendation and Guide2Group Assignment as an integrated component), we use an evaluation metric that is based on our main objective score (Eqn. 6).

- ***Objective Score:*** $ObjScore$**.** Refer to Eqn. 6.

As we focus more on user interests than POI popularity, we use $\eta = 1$ in this objective score to better measure user interests in the recommended POIs.[5] As stated in Eqn. 6, the α parameter determines the emphasis between the two components of: (i) user grouping and POI recommendation; and (ii) tour guide assignment. In this experiment, we evaluate the performance of the algorithms based on multiple α values from 0 to 1, in intervals of 0.05.

Each of the above-mentioned evaluations (1 to 4) are then repeated multiple times for each city, based on the number of travel sequences in that city (Table 1). In the following sections, we report the average score and standard error of each metric, and conduct t-tests to determine if the improvements of our proposed approaches are statistically significant.

6 Results and Discussion

Overall Evaluation of GroupTourRec. Fig. 2 shows the objective score (described in Section 5.3) of our proposed algorithms and baselines at multiple α values. While there are different trends for different cities, our proposed algorithms

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[5]Furthermore, POI popularity is the same for all tourists, while user interests are unique to each tourist. As a result, any evaluation based solely on POI popularity ($\eta = 0$) results in the same score for all tourists.
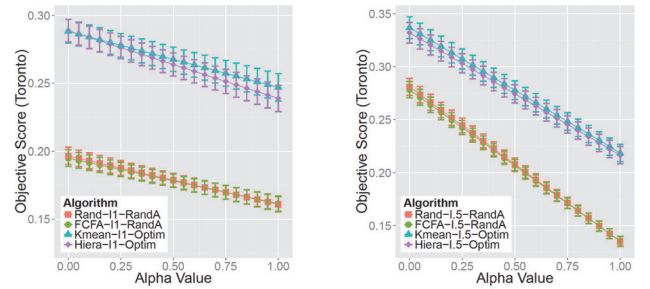

Figure 2: Overall comparison of the {KMEAN,HIERA}-{I.5, I1}-OPTIM algorithms against the {FCFA, RAND}-{I.5, I1}-RANDA baselines for Toronto, in terms of our main objective score (described in Section 5.3).

({KMEAN, HIERA}-{I.5, I1}-OPTIM) consistently out-perform the baselines ({FCFA, RAND}-{I.5, I1}-RANDA) in all cases and for all cities, regardless of α values. The consistent out-performance at all α values also shows that our proposed algorithms offer better performance in terms of both components of user grouping and POI recommendation, and tour guide assignment, regardless of the emphasis that a tourist might place on either component. We observe similar results for Vienna, Osaka, Budapest, Glasgow, Delhi and Edinburgh. Our proposed algorithms out-perform the various baselines for GROUPTOURREC as a whole, and we further investigate its performance for the sub-problems of Tourist2Group, POI2Group and Guide2Group.

Evaluation of Tourist2Group Allocation. We now study the effectiveness of Tourist2Group allocations using our proposed approaches of using the KMEAN and HIERA algorithms, compared to the FCFA and RAND baselines, as shown in Table 2. The results show that KMEAN and HIERA consistently out-perform the baselines of FCFA and RAND with relative improvements of more than 45.4%, 141.4% and 96.5% in terms of Jac, Cos and Com scores, respectively.

Table 4: POI2Group comparison of the {KMEAN, HIERA, FCFA, RAND}-{I.5, I1} algorithms against the STDTOUR baseline, in terms of Tour Total Interest (Tot_I), Tour Maximum Interest (Max_I) and Tour Minimum Interest (Min_I). † denotes a significant difference with the STDTOUR baseline, based on two-sided t-tests with p<.0001, ‡ denotes the same with p<.01.

	Toronto				Vienna				Osaka				Budapest		
Algo.	Tot_I	Max_I	Min_I	*Algo.*	Tot_I	Max_I	Min_I	*Algo.*	Tot_I	Max_I	Min_I	*Algo.*	Tot_I	Max_I	Min_I
STDTOUR	1.33±.002	.644±.001	.007±.000	STDTOUR	1.90±.003	.800±.001	.022±.000	STDTOUR	1.09±.006	.630±.003	.032±.001	STDTOUR	2.31±.003	.792±.001	.005±.000
RAND-I1	1.59±.032†	.722±.011†	.016±.002†	RAND-I1	2.17±.020†	.738±.005†	.097±.003†	RAND-I1	1.25±.025†	.668±.011‡	.155±.008†	RAND-I1	3.06±.046†	.781±.008	.051±.003†
FCFA-I1	1.59±.033†	.717±.011†	.023±.003†	FCFA-I1	2.16±.020†	.743±.005†	.093±.003†	FCFA-I1	1.25±.024†	.671±.011‡	.151±.008†	FCFA-I1	3.04±.044†	.772±.008	.048±.003†
KMEAN-I1	**3.10±.030†**	.955±.005†	**.071±.006†**	KMEAN-I1	**3.34±.015†**	**.966±.002†**	**.157±.004†**	KMEAN-I1	**1.79±.020†**	**.918±.006†**	**.204±.009†**	KMEAN-I1	**5.66±.034†**	**.980±.003†**	**.092±.005†**
HIERA-I1	3.04±.028†	**.973±.004†**	.063±.006†	HIERA-I1	3.14±.017†	.929±.003†	.137±.004†	HIERA-I1	1.77±.020†	.902±.007†	.198±.009†	HIERA-I1	5.33±.040†	.944±.004†	.078±.005†
STDTOUR	1.33±.002	.644±.001	.007±.000	STDTOUR	1.90±.003	.800±.001	.022±.000	STDTOUR	1.09±.006	.630±.003	.032±.001	STDTOUR	2.31±.003	.792±.001	.005±.000
RAND-I.5	1.28±.024	.745±.011†	.007±.001	RAND-I.5	2.12±.021†	.782±.006†	.069±.003†	RAND-I.5	1.25±.027†	.656±.012	.143±.009†	RAND-I.5	2.98±.042†	.769±.008‡	.049±.003†
FCFA-I.5	1.29±.025	.736±.011†	.008±.001	FCFA-I.5	2.14±.021†	.787±.006	.072±.003†	FCFA-I.5	1.25±.029†	.653±.013	.152±.009†	FCFA-I.5	2.95±.043†	.757±.008†	.051±.003†
KMEAN-I.5	2.31±.027†	**.978±.004†**	.012±.002‡	KMEAN-I.5	**3.34±.019†**	**.955±.003†**	**.181±.005†**	KMEAN-I.5	1.97±.020†	**.952±.006†**	.232±.011†	KMEAN-I.5	**4.62±.033†**	**.973±.003†**	.068±.004†
HIERA-I.5	**2.34±.028†**	.943±.006†	**.014±.002†**	HIERA-I.5	3.26±.020†	.948±.003†	.159±.005†	HIERA-I.5	**2.00±.020†**	.944±.006†	**.239±.011†**	HIERA-I.5	4.55±.037†	.934±.005†	**.072±.004†**

Furthermore, the t-test results show that these improvements are statistically significant with p<.0001. We observe similar results for Glasgow, Delhi and Edinburgh. These results show how KMEAN and HIERA result in groups comprising members whose interests are more similar to one another, compared to the FCFA and RAND baselines. In the next section, we further examine the effects of a good Tourist2Group allocation on the subsequent POI2Group recommendations.

Evaluation of POI2Group Recommendation. Next, we evaluate the effectiveness of the various POI2Group recommendations of the {KMEAN, HIERA}-{I.5, I1} algorithms, against the {FCFA, RAND}-{I.5, I1} baselines. Table 3 shows that the {KMEAN, HIERA}-{I.5, I1} algorithms out-perform the {FCFA, RAND}-{I.5, I1} baselines for all cases, with relative improvements of more than 34.8%, 25.8% and 33.8% based on measures of Tot_I, Max_I and Min_I, respectively. Similarly, these improvements are statistically significant as indicated by t-test results with p<.0001. The experiments on Glasgow, Delhi and Edinburgh show similar results. These results show that our proposed algorithms successfully recommend tour itineraries that are more aligned to the interests of tourists in each tour group, compared to those of the baseline methods.

Table 4 shows the comparison of the {KMEAN, HIERA, FCFA, RAND}-{I.5, I1} algorithms against the STDTOUR baseline, in terms of $Tot_I(t)$, $Max_I(t)$ and $Min_I(t)$. The results shows that the {KMEAN, HIERA}-{I.5, I1} algorithms out-perform the STDTOUR baseline for all cities, with relative improvements of more than 62.3%, 16.1% and 71.4% based on measures of Tot_I, Max_I and Min_I, respectively. Results from t-tests also show that these improvements are statistically significant with p<.0001.[6]

In contrast, the {FCFA, RAND}-{I.5, I1} algorithms (our previous baselines) show mixed results against the STDTOUR baseline in terms of Tot_I and Max_I scores, while showing general improvements in terms of Min_I scores. However, some of the improvements by the {FCFA, RAND}-{I.5, I1} algorithms are not statistically significant. On the whole, these results show that our {KMEAN, HIERA}-{I.5, I1} algorithms are the best performers in all cases and that recommending customized tours better satisfy the interest preferences of tourists, compared to recommend-

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[6]Except for Toronto in terms of Min_I scores, which show statistically significant improvements at p<.01.

Table 5: Guide2Group comparison of the OPTIM algorithm against the RANDA baseline, in terms of Guide Total Expertise (Tot_I). † denotes a significant difference with RANDA, based on two-sided t-tests with p<.0001.

Guide Total Expertise (Tot_E)				
Algo.	*Toronto*	*Vienna*	*Osaka*	*Budapest*
RANDA	149.53±1.17	269.36±1.63	50.29±1.08	105.00±0.65
OPTIM	**174.78±1.33†**	**321.22±1.74†**	**60.40±1.23†**	**119.51±0.68†**

ing standard tour packages offered by tour operators.

Evaluation of Guide2Group Assignment. We next evaluate the effectiveness of the Guide2Group assignment using the OPTIM algorithm compared to the RANDA baseline. Based on the Tot_E scores, Table 5 shows that OPTIM out-performs RANDA with relative improvements of 13.8% to 20.1%. Similarly, the t-test results show that these improvements are statistically significant with p<.0001. The experiments on the Glasgow, Delhi and Edinburgh datasets show similar results. On the whole, the results for the Tourist2Group, POI2Group and Guide2Group evaluations show that our proposed approaches significantly out-perform the various baselines, for all seven cities.

7 Conclusion

We introduced and formulated the novel GROUPTOURREC problem, which involves recommending tours to groups of tourists and assigning tour guides to lead these tours. Our approach to solve this NP-hard GROUPTOURREC problem involves decomposing it into more manageable sub-problems of Tourist2Group allocation, POI2Group recommendation and Guide2Group assignment. For Tourist2Group allocations, we modeled the interests of tourists based on their past POI visits (extracted from geo-tagged photos) and proposed the use of k-means and hierarchical clustering to allocate these tourists into tour groups. For POI2Group recommendations, we recommended tours to these tour groups based on their collective group interest and using a variant of the Orienteering problem, which also considers various trip constraints. For Guide2Group assignments, we proposed a model of tour guide expertise which is then matched to the recommended tour for each tour group as an Integer programming problem. Lastly, experimental results on a Flickr dataset of seven cities show that our proposed approaches significantly out-perform the various baselines,

based on measures of Jaccard/Cosine/top interest similarity, total/max./min. tour interests and total tour guide expertise.

Our work currently considers a single transport mode, i.e., walking, which is easily generalizable to other transport modes (e.g., train, bus or taxi) by modifying the $Cost(p_x, p_y)$ function in Eqn. 17. For future work, we intend to include the option to switch among multiple transport modes (e.g., train→walk→taxi→bus) in the same spirit as (Flórez et al. 2011; Botea, Nikolova, and Berlingerio 2013; Botea and Braghin 2015), and also consider uncertainty in POI visit durations due to crowds and long queues.

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