Photography and Exploration of Tourist Locations Based on Optimal Foraging Theory

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***Abstract*—Animals search for food in their environment with a decision strategy which keeps them fit. Optimal Foraging Theory models this foraging behavior to determine the optimal decision strategy followed by animals. This theory has been successfully applied for humans as they search for information and is termed as Information Foraging. When people visit a tourist location, they follow a similar strategy to move from one spot to another and collect information by capturing photographs. This behavior has similarities with the foraging behavior of animals which has been widely studied by researchers. In this work, we propose to employ Optimal Foraging Theory to help tourists explore a location and capture photographs in an optimal way. We determine a decision strategy for tourist which provides a list of interesting spots to visit in a tourist location along with corresponding stay time. Finally, we solve an optimization problem to find a path through these spots which can be followed by tourists. Experimental results on a public dataset demonstrate the effectiveness of the proposed method [1].**

I. Introduction

A tourist location usually has multiple points of interest. We follow some trajectory through these points of interest as we explore and take photographs. There can be multiple ways in which we visit these points of interest, and it depends upon a lot of factors, such as visit time, user preference, etc. If we are not familiar with a tourist location, then usually we use our intuition or follow other tourists to explore these points of interest. This strategy is not always successful, and we end up spending a lot of time exploring the location rather than enjoying the points of interest.

Animals face a similar problem when they search for food and move from one food patch to another. Researchers have extensively studied the problem of animal foraging behavior and observed that animals follow optimal foraging behavior for their survival. Optimal Foraging Theory (OFT) [1] is a study which tries to model the animal behavior for foraging which ensures their survival. Although the consumption of food provides energy to animals, the involved search takes both energy and time. The animal has to optimize the search by minimizing travel time and maximizing the gain in energy by food consumption to remain fit. OFT models this behavior and helps in determining which food patches are most beneficial and involves low energy consumption. OFT also models the optimal navigation behavior of animals from one food patch to another.

The search for food patch by animals is analogous to the search of photography spots by tourists. Different food patches provide a different amount of energy to the animals, and similarly, different photography spots may provide a different experience to users. The animals observe loss of energy when they move from one food patch to another, and it is analogous to the time and energy spent by the tourists as they move from one photography spot to another. Inspired by this analogy, we propose a novel problem in which we attempt to identify the optimal tourist behavior at a tourist location. More specifically, we want to find an optimal path and the amount of time to spend at each point of interest in the path for a given user context at any given tourist location.

We leverage social media images captured at tourist locations and associated meta-data to understand the past tourist behavior and the location environment. We termed the points of interest at any tourist location as micro-poi. We employ concepts from Optimal Foraging Theory to find an optimal path to follow between the micro-pois and the amount of time to spend at each of the visited micro-pois. Although a list of micro-pois can be determined and used to construct a recommended path using traditional methods, it would be a general solution and will not be optimal for different user scenarios. The micro-pois and corresponding stay times could be different for different users. This may depend upon their time of visit, duration of visit and also their personal preferences. We propose to make use of the OFT which can optimize the user experience in exploring a tourist location considering all these factors.

The availability of a large number of geo-tagged photos shared on the social media platform has motivated the research in location recommendation. This available source of information has been widely utilized by researchers to identify Points-of-Interests [2–5] and recommend tourist locations to users [6–11]. The works in [12–14] focused on photography hot-spots and recommend points-of-interests which are good from photography perspective. These methods do not provide any particular order or strategy in which these locations should be visited. To overcome this limitation, the authors in [15–18] proposed methods to recommend travel routes which guide users to follow a path as they visit different attractions. However, the existing methods of route recommendation generate a path from one attraction to another and do not provide any guidance on how each particular attraction should be explored.

In this work, we focus on the recommendation to explore a

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[1]Code available at https://github.com/vyzuer/foraging_theory

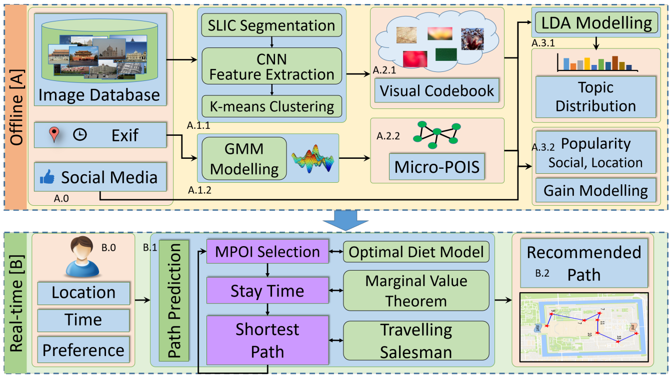


Fig. 1: Overview of the proposed method. The top block (A) shows offline preprocessing and the bottom block (B) shows real-time path recommendation process. The social media data (A.0) is first utilized to learn a visual codebook (A.2.1) via image processing (A.1.1) and micro-poi identification (A.2.2) via GMM modeling (A.1.2). This information is then utilized for topic modeling (A.3.1) and gain modeling (A.3.2). In real-time recommendation (B) the performed modeling on social media data is utilized to generate real-time path recommendation (B.2) using OFT (B.1).

particular tourist attraction from the photography perspective. We make use of social media images to learn previous patterns in the environment and employ Optimal Foraging Theory to determine an optimal path for exploring the attraction and capturing photographs. The proposed method provides a personalized recommendation, and the use of OFT helps in determining a path and corresponding stay time which is based on the current context of a user. It is important to note that we have focused on the photography experience of a user at a tourist location. However, since we are leveraging on the sequential time-stamp of the social media images, other factors corresponding to user experience are also integrated into the recommendation. The overview of the proposed method is outlined in Fig. 1. We make the following contributions in this work,

1) We propose a novel method which dynamically generates a route to explore a tourist location from the photography perspective. The route includes a list of micro-pois to visit along with a recommended stay time at each micro-poi.
2) We extended the Optimal Foraging Theory for photography to determine the most profitable micro-pois to visit and corresponding optimal stay time. The recommendation takes into account multiple factors such as user preference, visit time, trip duration and start/end location.
3) We demonstrate the effectiveness of the proposed method with extensive evaluation on a large-scale dataset form nine different tourist locations and the proposed method can generate recommendations in real-time.

The rest of the paper is organized as follows. In section II we will discuss the related work. We will introduce the Optimal Foraging Theory and discuss how we adapt it for exploring tourist attractions in section III. Section IV and V will present the proposed method in detail and the experimental results will be discussed in section VI. Finally, we will conclude this paper in section VII.

II. Related Work

A. POI Identification

The sharing of geo-tagged photographs by users on social media platforms such as Flickr, FourSquare, etc. has increased tremendously in the last decade [19]. This has motivated researchers to exploit this data for various kinds of recommendations [20–24]. Point-of-interest (POI) recommendation to users is one such area which has recently received a lot of attention from the community. In [25–29], the authors employed collaborative filtering for providing personalized location recommendation to the users. To make the recommendation process more personalized, the authors of [30, 31] presented an interactive framework where the user can provide real-time feedback regarding his or her choices. To further improve the relevance of recommendation, the authors of [6–10] also take into account the geographical, temporal and sequential influence of location and user movements. As the semantic and contextual information also plays an important role in users preferences, the authors of [32–35] incorporate venue semantics and user-context for making the recommendation.

Most of the methods discussed so far assume that the POI recommended to the user are known beforehand which may not always be true. Therefore, to overcome this problem researchers have proposed methods to automatically identify points of interests in a location utilizing user-contributed photographs. In [2–5, 36] the authors proposed to use clustering based algorithms to identify the points-of-interest which helped in detecting popular locations. Recently, researchers have focused their interest on identifying points-of-interests which are good from photography perspective [12–14, 37, 38]. Different from these methods our work is focused on determining an optimal stay time and a path through identified micro-pois.

B. Route Identification

The movement of tourists from one location to another is captured as a footprint in the geo-tags associated with the photos shared by users. This has been exploited by the researchers to identify various travel patterns followed by the tourists for recommendation [39–45]. One of the major limitations of these methods for intra-city recommendation is that they provide generalized recommendations which are independent of user preferences.

To overcome this limitation, the authors of [15–18, 46–49] also incorporated user preferences for making route recommendation. Lu et al. [15] proposed a method to identify tourist locations and then generate a personalized trip route to travel between identified attractions. Chen et al. [17] proposed to use people attributes (gender, age, and race) extracted from captured photos for personalized route recommendation. The proposed method identifies popular travel routes and recommends the next best location to visit based on the current user location. Yamasaki et al. [50] proposed a Markov model approach for route recommendation and incorporated personalization using collaborative filtering. The authors in [47] proposed a recommendation method which also takes into account the waiting time at different points of interests.

The existing methods for route recommendation are mainly focused on traveling from one attraction to another. Lu et al. [15] proposed a method to identify popular trajectories followed by visitors within an attraction. However, their method determines only the most popular paths without any knowledge of micro-pois and corresponding stay time. In this work, we focus on personalized route recommendation within an attraction where the routes are dynamically created based on the user-context and provide details such as which micro-pois to visit and corresponding stay time for taking photographs.

III. OFT FOR PHOTOGRAPHY

Optimal Foraging Theory is a model which is used to predict the foraging behavior of animals as they search for their food [1]. The energy gain from the food depends not only on the acquired food item but also on the foraging behavior as searching for food also require energy and time. Therefore, animals want to maximize energy gain as they forage in their environment to remain fit. OFT aims at predicting the best foraging strategy to achieve this goal.

OFT has also been successfully applied to develop Information Foraging Theory (IFT) [51] which models human behavior as they search for information. IFT is based on the assumption that humans use an inbuilt foraging mechanism that evolved from animal foraging behavior as they search for information. We observe that capturing photographs at tourist locations and moving from one spot to another is analogous to gathering information for capturing the experience. However, in IFT there is no notion of travel time as a user moves from one source of information (web pages) to another which is different than photo capture as moving from one photo spot to another involves time. Therefore, we have time as another constraint in photo capture which counts towards cost during the assessment of overall gain. This changes the formulation of overall gain as it is not just about the choice of information source (photography spots) but the gain it incurs and the order in which they are visited is also important.

Modeling of animal foraging behavior requires a currency variable, such as energy gain per unit time. The animals are trying to maximize this variable under the constraints of the environment. OFT aims at predicting the best foraging strategy for a given currency and environmental constraints. The average rate of gain (R) is the key factor that characterizes the efficiency of a forager. It is defined as a ratio of the net gain G and the total time spent,

$$R = \frac{G}{T_B + T_W} \tag{1}$$

here T_B is the between patch and T_W is the within patch time. The average rate of patch encounter is defined as,

$$\lambda_i = \frac{1}{t_{Bi}} \tag{2}$$

where t_{Bi} is average time for finding patch of type i. For X types of patches, the gain can be represented as,

$$G = \sum_{i=1}^{X} \lambda_i T_B g_i(t_{Wi}) \tag{3}$$

where g_i is the expected gain function from a patch i in terms of stay time t_{Wi}. Similarly, the total amount of time spent within patches is represented as,

$$T_W = \sum_{i=1}^{X} \lambda_i T_B t_{Wi} \tag{4}$$

Now, after substituting equation 3 and 4 in equation 1, we get the overall average rate of gain as,

$$R = \frac{\Sigma_{i=1}^{X} \lambda_i g_i(t_{Wi})}{1 + \Sigma_{i=1}^{X} \lambda_i t_{Wi}} \tag{5}$$

This is known as Holling's Disk Equation [52] which serves as the basis for deriving several optimal foraging models. In this work, we consider micro-pois as patches. The net gain is determined in terms of visual information in the captured photographs as a function of time spent by the users in a tourist location. We employ Optimal Diet Selection [1] and Marginal Value Theorem [53] from OFT to find the best strategy for taking photographs at a tourist location (Figure 1:B.1). We will present these two models in the following section and discuss how they can be used to solve the proposed problem.

A. Optimal Diet Model

Optimal Diet Model helps in deciding whether a predator should consume the prey at hand or search for a more profitable prey. If a prey item can provide an energy gain g with a handling time of t_W, then its profitability is defined as,

$$\pi = \frac{g}{t_W} \tag{6}$$

Based on the Optimal Diet Model, a predator should consume a prey item only if its profitability is greater than the overall profitability during foraging. We use this model to select micro-pois in a tourist location. The act of photo capture is associated with energy gain and the goal is to predict a strategy to maximize this gain in an optimal amount of time. We utilize the shared social media images to determine the profitability of micro-pois and selection of micro-pois is predicted using the Optimal Diet Model (Figure 1:A.3.2).

B. Marginal Value Theorem

Marginal Value Theorem [53] is used to determine whether an organism searching for food should stay in the current patch or search for a new patch. The model helps in predicting when it is economically favorable to leave the current patch. When the animal forages within a patch, finding food becomes more difficult, and it experiences the law of diminishing returns. Finding new patch also involves cost as the animal loses foraging time as well as energy while searching.

Marginal Value Theorem optimizes the net energy gain per unit time (Equation 3) in the foraging strategy. Figure 2 shows a plot of diminishing returns in terms of experience gain as a user capture photographs. If net experience gain is the currency, then it can be represented as the slope of the

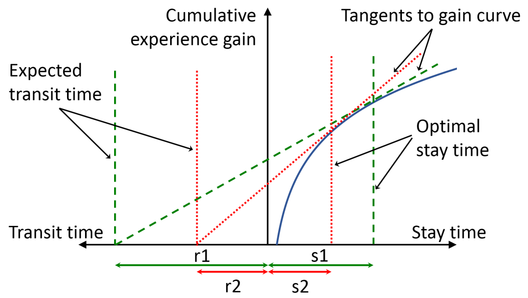


Fig. 2: Marginal Value Theorem adapted from [53]. The y-axis represents cumulative experience gain in terms of captured visual concepts in the photograph and x-axis represents travel time. The green and red lines corresponds to two different transit times (r1 and r2) and, s1 and s2 are the predicted optimal stay time for r1 and r2. A longer travel time lead to a longer stay as compared with shorter stay time.

line which starts at the search start time and intersects the gain curve. Marginal Value Theorem states that in order to maximize the net energy gain, one should leave the patch when this line touches the diminishing curve. In order to determine the optimal stay time at a micro-poi we utilize shared social media images to compute the diminishing gain curves. The act of photo capture measures energy gain. If a user continues to capture photographs at the same location, then the gain from each successive photograph will diminish due to redundancy. Based on this assumption we model the diminishing gain curve for each of the micros-poi and utilize it to determine the optimal stay time (Figure 1:A.3.2).

IV. Micro-POI Modeling

There are usually multiple hot-spots for photography at any tourist location. In this work, we term these locations as micro-pois (Figure 1:A.2.2). Tourists explore a location by visiting these micro-pois in some order as they capture photographs along their way. Therefore to generate a path for a recommendation we first need to identify these micro-pois.

A. Micro-POI Identification

We utilize the social media images shared by users to identify these micro-pois. We observe that each micro-poi may not be suitable for photography throughout the day because of the changing lighting conditions. Therefore we also incorporate the time factor as we identify these micro-pois. The *Exif* meta-data associated with the shared photographs can be used to determine the location as well as the time of image capture. We utilized YFCC100M dataset [54] in which the images have associated meta-data which can be used to extract the required information. We use the geo-coordinates and the time-stamp to develop a generative model to determine the micro-pois at a tourist location. The spatial distribution of location and time pair is assumed to be a Gaussian Mixture Model (GMM). For each photograph i we define $\mathbf{x}(i) = (latitude, longitude, time)^T$, where $(latitude, longitude)$ and $time$ represents the geo-location and time of capture respectively. The probabilistic distribution of location and time pair at an attraction can be expressed as

$$P(\mathbf{x}) = \sum_{i=1}^{N} w_i \mathcal{N}(\mathbf{x}|\mu_i, \Sigma_i) \tag{7}$$

where $\mathcal{N}(\mathbf{x}|\mu, \Sigma)$ denotes a Gaussian component, N is the no. of Gaussian components and w_i indicates the prior for each component. We make use of Bayesian information criterion (BIC) [55] to estimate the number of Gaussian components and the parameters $(\mu^k, \Sigma^k$ and $w^k)$ of GMM are estimated using expectation-maximization (EM) algorithm [56]. The components of the obtained generative model represent the identified micro-pois. Each micro-poi has a geo-location and a time-stamp associated with it. We associate each of the captured photographs at the corresponding attraction to one of the micro-poi.

B. Micro-POI Profiling

We compute a set of properties for each of the identified micro-poi which we will use later for recommendation. The total number of photographs captured at any micro-poi indicates its popularity among the visitors. We denote this as location-popularity ($LPop$) and it is computed as,

$$LPop(i) = \frac{N_i}{N_{max}} \tag{8}$$

where N_i is the total number of photos captured at i^{th} micro-poi and N_{max} is the maximum number of photographs captured at any micro-poi.

The social media images have associated social media cues such as, likes and views, which indicates their popularity on social media. We utilize these cues to compute the popularity of each of the image as well as the popularity of each micro-poi. The image popularity (q^i) for an image i is computed as proposed by [57] which assigns a score between 0-1.

$$q^i = 1 - e^{-(\lambda_v \times N_{views} + \lambda_l \times N_{likes})} \tag{9}$$

where N_{views} is the number of views and N_{likes} is the number of likes for an image i. λ_v and λ_l are corresponding weights and we use $\lambda_v = 0.1$ and $\lambda_l = 1$ in our experiments. The social media popularity ($SPop$) for a micro-poi i is computed as an average of the quality score assigned to the photographs captured at that micro-poi,

$$SPop(i) = \frac{1}{N_i} \sum_{j=1}^{N_i} q^j \tag{10}$$

where q^j is the popularity of a photograph and N_i is the total number of photographs captured at i^{th} micro-poi.

To determine a visual representation of micro-pois, we utilize the pixel information from the images captured at that micro-poi (Figure 1:A.1.1). First, we build a dictionary of visual words for a tourist location based on the captured images. We perform segmentation [58] on images and collect all the visual patches. Each patch is represented using a visual feature extracted using AlexNet Convolutional Neural Network (CNN) [59]. A network trained on the ImageNet dataset is used and visual features are extracted from the fully-connected layer (fc7), prior to the prediction layer, in the

AlexNet network. Then, we employ clustering on these patches to build a dictionary of visual words. We employ the k-means algorithm with a dictionary size of 1000. Each photograph can be represented as a feature vector using this dictionary to indicate the presence of visual words.

The micro-pois can be categorized into different groups based on the presence of visual words in the photos captured at any micro-poi. We perform topic modeling with Latent Dirichlet Allocation (LDA) [60] to determine the latent categories of the micro-poi. Each micro-poi is represented as a document, where the captured photos are considered as sentences and the visual words correspond to the words in the sentence. The topic model determines a set of latent topics for the tourist location along with the association of each topic with the identified micro-pois. The utilized parameters for LDA modeling are discussed in the experiment section. This work relies on images for micro-poi profiling. We can also make use of other sources such as videos, text [28], and sound [61], for micro-poi profiling.

C. Modeling Information Gain

Modeling and automatic quantification of the information gain as a tourist move from one micro-poi to another is a very difficult task. However, taking photographs as we explore a tourist location is a common practice followed by most of us. Therefore, we associate information gain with the photographs captured by the users along the exploration (Figure 1:A.3.2). As discussed in section IV-B, each photograph can be represented as a set of visual words. A micro-poi location will be associated with a subset of these visual words which is based on the photos which are captured at this micro-poi.

Now, as a user takes a photo, there will be a gain associated with it which will depend on the visual words present in the photograph. With each consecutive photograph captured at any micro-poi, this gain will follow a diminishing curve as some of the visual words might already be captured in previous photographs. Finally, the gain will saturate at a certain level when the user has captured all the visual words. The cumulative information gain as a user captured i^{th} photograph is computed as,

$$G^i = \sum_{j=1}^{T} max(v_j^i, g_j^{i-1}) \tag{11}$$

where T is the total number of visual words in the dictionary, $v_j^i \in (0, 1)$ indicates the presence of the visual word j in the i^{th} photo and g_j^{i-1} is gain from the visual word j in the previous photo which is computed as $max(v_j^{i-1}, g_j^{i-2})$. The gain corresponding to each of the visual words before capturing any photograph is initialized to 0.

This information gain will be different for different users based on their photo-taking behavior. We perform a regression analysis on the gain observe for earlier captured photos to determine the gain pattern for each micro-poi. We utilize a logarithmic diminishing gain function as proposed by [1] for modeling information gain,

$$G(t) = \alpha ln(t + \beta) + \gamma \tag{12}$$

where $G(t)$ is the information gain after time t, α and γ are constants which are determined using regression analysis, and

ALGORITHM 1: OPT_PATH

Input: Graph G(V, E), start(m_s), end(m_e), trip duration (td)
Output: Recommended path $\{m_s, m_1, ..., m_e\}$ and stay time $\{s_s, s_1, ..., s_e\}$

```
tt := 0.0                                          // current trip time
P := {m_s, m_e}                                    // initialize path
Π := sort(Π)        // sort the profitability in decreasing order
for π_i in Π do
    P.append(m_i)  // add the node corresponding to π_i to path
    P := TSP(P)          // find shortest path through these
     micro-pois
    S := {}                                  // initialize stay time
    for m_i in P do
        s_i := MVT(m_i, P)                     // update stay time
        S.append(s_i)                           // maintain a list
    end
    tt := update_trip_time(P, S)               // update trip time
    if tt > td then
        break
    end
end
```

$beta$ indicates the amount of time before capturing the first photograph. We set this to 60 secs for our experiments. The constants for equation 12 can be determined using least-square linear regression analysis. We also compute average gain (G_a) and average stay time (T_a) for each micro-poi which will be used to compute profitability.

D. User Profiling

The previous photographs captured by a user can be used to determine the preference corresponding to the semantic visual categories. To quantify the user interest, we represented each user as a document, and the personal image collection corresponds to sentences with the detected visual patches as words in each sentence. The trained LDA model as described in section IV-B is used to determine the preference of a user for the identified categories.

E. Graph Modeling

We represent a location as a graph (V, E) in 3-D space to determine the optimal path for a user (Figure 1:A.2.2). Here, V represents a set of nodes in the graph which corresponds to the identified micro-poi in the location, and E is the set of edges corresponding to the path connecting these micro-pois. The three dimensions refer to the latitude, longitude and time.

The photos captured at a location are first utilized to identify the tours which people have followed in the past. A tour is defined as a set of photographs which are captured in a sequence within a day. Each photograph in the sequence has associated geo-location and time-stamp. Each tour will pass through a set of micro-pois and we can determine the stay time as well as transit time between different micro-pois from each tour. Stay time at each micro-poi is computed as a difference between the time-stamp of the first captured photograph and the last captured photograph in that micro-poi. The transit time is computed as the difference between the time-stamp of the first captured photograph at a micro-poi and the last captured photograph at the previous micro-poi in the sequence. Finally, an average stay time for each micro-poi and average transit time between two micro-pois is computed using all the tours traveled in the past.

V. Path Prediction

The 3-dimensional graph of a tourist location is used to find an optimal path for a given user-context (Figure 1:B.1). The user-context indicates the current location, visit time, trip duration and final location, and are used to determine the start and last node in the path from the graph. The location and time information is used to identify the graph node closest to the user. The trip duration is added to the current time to identify the last node in the path. If the user does not provide destination location, a round trip is computed.

We employ Optimal Diet Algorithm to determine the micro-pois which should be included in the path. The location popularity ($LPop$), social media popularity ($SPop$), average gain (G_a) and average stay time T_a is utilized to compute profitability for Optimal Diet Algorithm. The profitability of a micro-poi i (Π_i) is computed as,

$$\Pi_i = \delta * \frac{G_a^i}{T_a^i} + \kappa * SPop_i + \theta * LPop_i \tag{13}$$

where G_a^i is the average information gain, T_a^i is the average stay time, $SPop_i$ is the social media popularity, $LPop_i$ is the location popularity and δ, κ and θ are constants to assign weights to these parameters. The stay time at each micro-poi in the path is predicted using Marginal Value Theorem (MVT). MVT maximize the net-gain to determine the optimal stay time (Figure 2). The goal is to determine the tangent from the start of transit point to the gain curve which will maximize the net-gain. This is equivalent to maximizing the slope of the line from start of transit point to $(t_s, G(t_s))$ which can be computed as $\frac{G(t_s)}{t_r+t_s}$, where t_s is the stay time to be optimized, $G(t_s)$ is the estimated gain at time t_s and t_r is the estimated reach time. We want to maximize this with t_s as an argument which will provide us the optimal stay time,

$$t_{opt} = \underset{t_s}{\operatorname{argmax}} \frac{G(t_s)}{t_r + t_s} \tag{14}$$

where t_{opt} is the predicted stay time. Finally, an optimal path is constructed through the selected micro-pois by solving a Traveling Salesman Problem. A path through the micro-pois is constructed to minimize the total travel time,

$$t_{total} = \min \sum_{i=1}^{N_{mpoi}} (t_{opt}^i + t_r^i) \tag{15}$$

where N_{mpoi} is the total number of micro-pois in the path, t_{opt}^i is the predicted stay time for i^{th} micro-poi and t_r^i is the estimated reach time for i^{th} micro-poi. We employ Simulated Annealing to determine the path in real-time. The path prediction process is presented in Algorithm 1.

A. Personalization

Personalization in route recommendation can be incorporated by taking into account the user preference for the visual content of each micro-poi. As discussed in section IV-D, we determine the user preference based on the past captured photographs using the trained LDA model for visual topics. We find the preference of a user for each micro-poi by computing a cosine similarity measure between the topics present in the user preference with the topics present at micro-poi. The similarity between user preference (TD_u) and i^{th} micro-poi's topic distribution (TD_i) is computed as,

$$Sim(u, i) = \frac{\sum_{j=1}^{K} TD_u^j * TD_i^j}{||TD_u|| \cdot ||TD_i||} \tag{16}$$

where TD_u is the topic distribution for user, TD_i is the topic distribution for i^{th} micro-poi and K is the total number of topics present in the LDA model. Now, for personalized recommendation, the profitability equation is updated as,

$$\Pi_i = \delta * \frac{G_a^i}{T_a^i} + \kappa * SPop_i + \theta * LPop_i + \eta * Sim(u, i) \tag{17}$$

where η is the weight given to personal preference.

TABLE I: Details of the dataset along with the average R2 scores for the linear regression modeling of gain curves at each of the tourist location. A-total images, B-unique users, C-average photos per user, D-total trips, E-identified micro-pois, F-average trip time in seconds.

Location	A	B	C	D	E	F	R2 score
BG	3914	229	17	305	69	3291	0.64
CP	127858	6269	20	10631	265	2267	0.59
ET	41303	4716	8	4678	90	2172	0.57
FC	3481	317	10	278	82	2384	0.68
GC	20310	1155	17	1491	160	3085	0.61
LP	6854	681	10	594	128	2416	0.65
SL	6974	1222	5	663	116	1897	0.66
TM	6152	487	12	406	87	3649	0.64
WM	113931	3917	29	7746	271	2716	0.55

VI. Experiments and Results

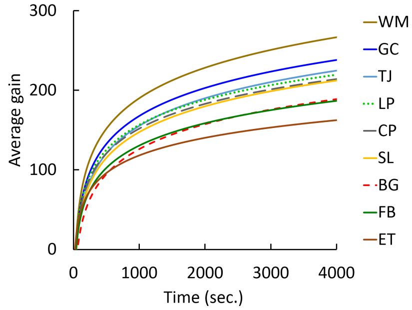
In this section, we will discuss the evaluation of the proposed method in terms of route recommendation.

A. Dataset

We use Flickr YFCC100M [54] to create a dataset of around 330K images from 9 tourist locations around the world including Botanical Gardens, Singapore (BG), Central Park, New York, USA (CP), Eiffel Tower, Paris, France (ET), Forbidden City, Beijing, China (FC), Grand Canyon, Arizona, USA (GC), Leaning Tower of Pisa, Pisa, Italy (LP), Statue of Liberty, New York, USA (SL). Taj Mahal, Agra, India (TM), Washington Monument, DC, USA (WM). The details of the dataset are provided in table I.

B. Micro_POI Identification

We employ generative model (GMM) to identify the micro-pois present in each location. The BIC score was measured to determine the number of micro-pois and we tested it for a range of 10-400 components. Table I presents the number of micro-poi identified at each of the locations in the dataset. The dictionary of visual words was created using k-means clustering algorithm where we set the dictionary size to 1000. A topic modeling using LDA was performed to determine the visual content distribution of the micro-pois. We set the number of topics to 50, prior of document topic distribution to 0.02 and prior of word topic distribution to 0.02 for topic distribution learning. Table I also shows the total number of trips for each tourist location. A trajectory is considered a trip only if it passes through at least 2 micro-pois.



(a) Average gain curves

Fig. 3: Average gain curve for all the locations.

C. Modeling Experience Gain

The gain curve for each micro-poi is determined using equation 11. Equation 11 is converted to a linear equation by setting the value of β and taking log of the time (t) dimension. We employ Linear Regression to identify the parameters of the gain curve. Table I shows the average Coefficient of Determination (R2 score) for each of the micro-poi for this regression analysis. The gain curves are further utilized to determine the optimal stay time at each of micro-poi as we predict a tour for exploring a tourist location.

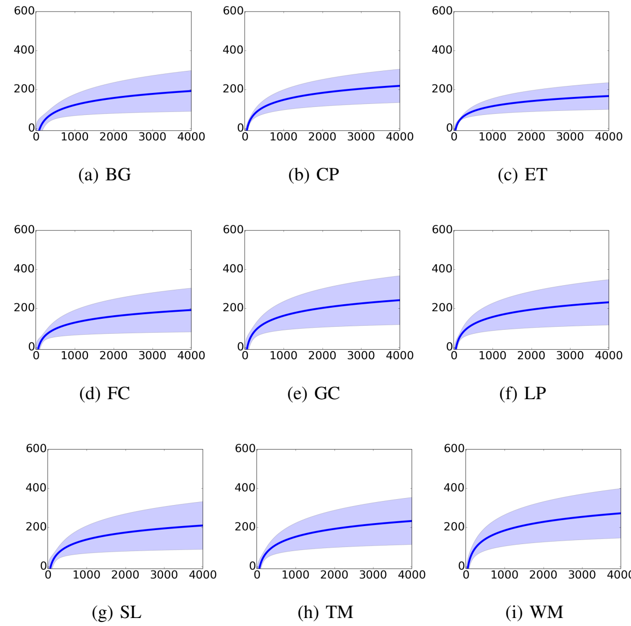
In figure 3 we have shown an average of all the gain curves corresponding to different micro-pois at each location for all tourist locations in our dataset. The variation in average gain curves corresponding to different tourist location shows different photography behavior of people at these locations.

We further analyze the variation in the gain pattern for different tourist locations. The plot of average gain curves along with corresponding standard deviation is shown in Figure 4. We observe that the variation in the gain pattern varies from one location to another. This indicates the variation in the information gain among different micro-pois within a location. We observe a higher variation in the gain pattern at Grand Canyon (GC) in comparison with Eiffel Tower (ET). This shows that some micro-pois in GC location are much better than others. On the other hand, a less variation at ET location shows that most of the locations are equally important from information gain perspective. Apart from this, we also observe that there is some consistency between gain curves from different locations which demonstrate the robustness of the proposed method across different locations. We will discuss the correlation between gain and visual diversity in section VI-E4 to get more insights in information gain pattern.

D. Path Recommendation

A tour recommendation is generated based on user visit time and trip duration. The tour includes a list of micro-pois, which should be visited in order, and corresponding stay time at each micro-poi included in the path. Equation 13 is utilized to determine the list of micro-pois to include in the tour and corresponding stay time for each micro-poi is computed using Marginal Value Theorem (section III-B).

Fig. 6 shows the recommended tours for different visit time and trip duration at Taj Mahal. We can observe how the trip path changes with a change in visit time and also a larger trip with more number of micro-pois is recommended for longer trip durations. In Fig. 5, we have shown the recommended tour along with sample images captured at each of the micro-poi present in the tour (Fig 6b) for TM.



(a) BG (b) CP (c) ET

(d) FC (e) GC (f) LP

(g) SL (h) TM (i) WM

Fig. 4: Plots of average gain curves along with standard deviation for each of the location. The average gain pattern and standard deviation is varying among different locations.

In Fig. 7 and 8, we have shown recommended tours for Forbidden City and Leaning Tower of Pisa. For Forbidden City, we have predicted recommendations for different visit time with variation in trip durations. We can observe how the recommended path changes with a change in both the parameters. Similarly, Figure 8 shows a recommended path for two different visiting times and same trip duration. We observe that some of the predicted micro-pois are different for these two recommendations. We also observe that the average stay time at each micro-pois is around 4 minutes for Leaning Tower of Pisa which is relatively lower as compare to Forbidden City and Taj Mahal where the average stay time at each micro-pois location is around 13 minutes and 12 minutes respectively. This information can be useful for tourists in making their selection for visiting tourist locations.

E. Quantitative Evaluation

Quantitative evaluation of the recommended tours is a challenging task due to the unavailability of ground truth. In addition, obtaining ground truth for varying user context (visit time and trip duration) is a non-trivial task. To overcome this difficulty, we make use of social media cues to determine the tours which are popular on social media.

We extract user trips at a tourist location which are popular on social media and meet certain criteria to establish ground truth trips. The criteria include minimum trip duration, which

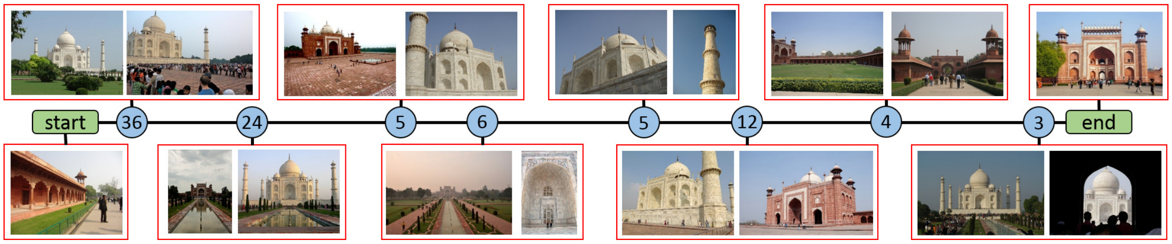
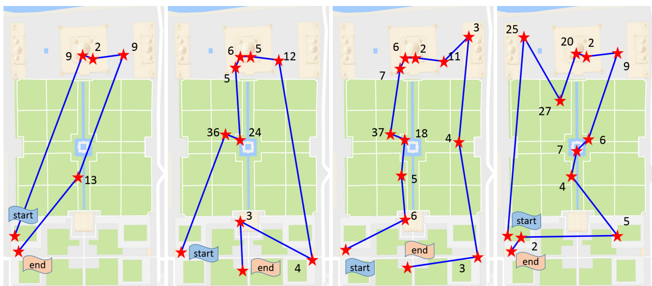
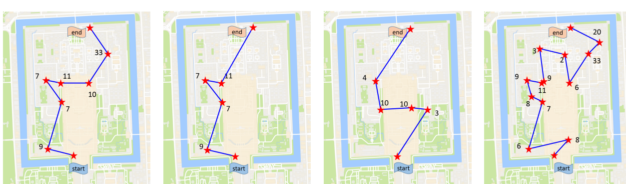


Fig. 5: Visualization of a recommended tour showing sample images captured at each of the micro-poi locations in the path for Taj Mahal.



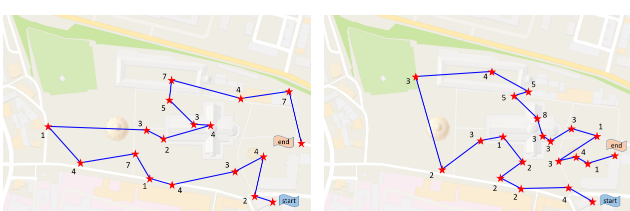
(a) 1pm,1.5hrs (b) 10am,3hrs (c) 10am,4hrs (d) 1pm,4hrs

Fig. 6: Sample tour recommendations at Taj Mahal. The star marks are micro-pois in the predicted tour and the number indicates a recommended stay time in minutes.



(a) 1pm, 1.5hrs (b) 1pm, 1hrs (c) 10am, 1hrs (d) 10am, 3hrs

Fig. 7: Sample recommendations at Forbidden City. The first two paths shows recommendation at 1pm for two different time durations and similarly, the next two paths shows recommendation at 10am for two different time duration.



(a) 10am, 2hrs (b) 4pm, 2hrs

Fig. 8: Sample tour recommendations at Leaning Tower of Pisa. The two paths shows path recommendations for two different visiting time for the same trip duration.

was set to 1 hour, and a minimum number of micro-pois in the tour, which was set to 8. To determine the popularity of a trip, a quality score is computed for each of the photographs in the trip. Then, an average score is computed for the complete trip using corresponding photographs and trips with a score of >0.6 are considered popular. The photographs in these ground truth trips are kept for testing and excluded from the training dataset.

The proposed method is used to predict tour recommendations corresponding to the extracted ground truth trips. The user context of the ground truth trip is utilized to generate the recommended tour. The generated tour is evaluated based on its similarity to the ground truth trip. We propose three different metrics, micro-poi similarity, edge similarity and path similarity, for the evaluation.

Micro-poi similarity is measured based on the number of overlapping micro-pois in the ground truth trip and recommended trip. It is computed as,

$$mpoi\_sim = \frac{n_{common}}{N_{mpoi}} \tag{18}$$

where n_{common} is the number of common micro-pois in ground truth and recommended trips and N_{mpoi} is the total number of micro-pois in the recommended trip. Edge similarity between the two trips is computed as,

$$edge\_sim = \frac{e_{common}}{E_{mpoi}} \tag{19}$$

where e_{common} is the number of common edges in ground truth and recommended trips and E_{mpoi} is the total number of edges in the recommended trip. An edge is defined as the path from one micro-poi to another in the trip. We compute the coefficient of determination (R2 score) to measure path similarity. For each micro-poi (poi_i) in the recommended trip, its closest micro-poi (poi_i^g) from the ground truth trip is determined. Then, the path similarity is computed as,

$$path\_sim = 1 - \frac{\sum_i^{N_{mpoi}} (poi_i^g - poi_i)^2}{\sum_i^{N_{mpoi}} (poi_i^g - \overline{poi^g})^2} \tag{20}$$

where $(poi_i^g - poi_i)$ represents the distance between corresponding micro-pois in the 3-D space of latitude, longitude and time and $(\overline{poi^g})$ is the mean position of the identified micro-pois in the ground truth. Finally, the average of these three similarity measures is computed for evaluation.

1) Baseline: We propose three baseline methods to compare the generated recommendation results. The first method (BL1) performs a random selection of micro-pois for path generation. In the second baseline (BL2), the social media popularity score $SPop$ is used for micro-poi selection and finally, in the third baseline (BL3), the micro-pois are selected

TABLE II: Quantitative comparison of the results for proposed and baseline methods. BL1, BL2 and BL3 are described in section VI-E1. [15] is the method proposed by Lu et al. for internal path discovery. PR-A1 is the proposed method which used only social popularity and average stay time and similarly PR-A2 used only location popularity and average stay time. PR1 is the proposed method without using social and location popularity, PR2 is the proposed method which also make use of social and location popularity and PR3 is the proposed personalized recommendation. (MS: micro-pois similarity, ES: edge similarity, PS: path similarity, SS: Similarity score, ST ratio is the stay time and travel time ratio, and time is the average computation time in seconds to generate the recommendation.)

Method	MS	ES	PS	SS	net-gain	ST ratio	time
BL1	0.12	0.01	0.09	0.07	0.02	0.31	0.93
BL2	0.26	0.04	0.23	0.18	0.04	0.43	1.18
BL3	0.21	0.03	0.17	0.14	0.05	3.42	1.07
[15]	0.30	0.05	0.25	0.19	0.05	0.45	0.34
PR-A1	0.42	0.07	0.24	0.25	0.04	0.52	1.14
PR-A2	0.27	0.04	0.18	0.16	0.05	2.94	1.15
PR1	0.34	0.06	0.22	0.21	0.12	0.64	2.24
PR2	0.39	0.09	0.29	0.26	0.12	0.69	2.53
PR3	**0.43**	**0.09**	**0.30**	**0.27**	**0.13**	0.70	2.86

based on the location-popularity score ($LPop$). In addition, we also compare the proposed method with the internal paths discovered using [15]. For all the baselines and [15], average stay time of each micro-pois is considered as a predicted stay time and TSP is utilized to determine the predicted path.

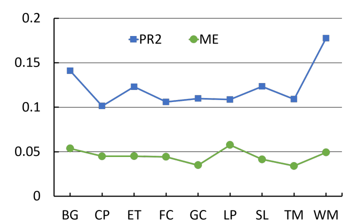
2) Comparison: The comparison results for the proposed and baseline methods is shown in table II. We generate four different types of recommendation for the evaluation. The first method (PR-A1) is based on social media popularity for micro-poi selection with $\delta = 0, \kappa = 1$ and $\theta = 0$ in equation 13 and the second method (PR-A2) uses location popularity for micro-poi selection with $\delta = 0, \kappa = 0$ and $\theta = 1$ in equation 13. Both PR-A1 and PR-A2 use average stay time instead of MVT. The third method (PR1) is based only on the gain of micro-pois and uses the parameter settings of ($\delta = 1, \kappa = 0$ and $\theta = 0$) for selecting micro-pois in equation 13. The fourth method (PR2) is based on gain, social media popularity and location popularity with a parameter setting of ($\delta = 1, \kappa = 1$ and $\theta = 1$). We observe that the method based on social media popularity PR-A1 performs better than PR1 in terms of path similarity. However, it has low ST-ratio. The low ST-ratio means shorter stay times, and it allows inclusion of a large number of micro-pois which leads to a high path similarity. However, after integrating the social and location popularity (PR2) we observe a higher similarity score.

To further investigate the quality of the recommended path, we compute net-gain for each of the predicted trips and compare with the baseline methods. We observe that the proposed methods (PR1 and PR2) outperform the other baselines in terms of net-gain. In addition, we also measure the ratio of stay time and travel time. Although this ratio will be location dependent, a more favorable tour should have a balanced travel and stay time for a user to enjoy the trip better. The results are shown in column 6 and 7 of Table II.

In addition, we also observe that the method based on location popularity have a higher ST ratio as compared to other methods. The location popularity is computed based on the number of photographs captured at any micro-poi and hence the corresponding micro-poi may have a longer stay time. To validate this, we compute Spearman's rank correlation between stay time and location popularity and found a weak positive correlation of 0.37 between the stay time and location popularity. However, a longer stay time is not always desirable as it indicates spending too much time at any point of interest. The average ST-ratio of the ground truth trips at all the locations was found to be 0.81.

3) Personalization: We generate personalized recommended trips for each of the ground truth trips to evaluate personalized recommendation which employs equation 17 for selecting micro-poi locations. The personal preference of a user is determined by considering the photographs captured by the user as discussed in section IV-D and section V-A. The evaluation results are shown in table II (PR3). We can observe that adding personalization improves the performance in terms of path similarity with the ground truth trips while maintaining a higher net-gain and stay/travel ratio.

4) Gain and Stay Time Analysis: To validate the experience gain modeling at each of the micro-poi, we compare the actual gain observed in ground truth trips with the gain predicted using the models learned from social media images. We use the trained model to predict estimated gain at each micro-poi location in a ground truth trip based on the observed stay time. The quality of prediction is validated by computing a Mean Squared Error (MSE) using the actual net-gain (total-gain/trip-time) and predicted net-gain. We observe an average MSE score of 0.002 for the predicted net-gain as compared to the actual net-gain in the ground truth trips of all the locations.



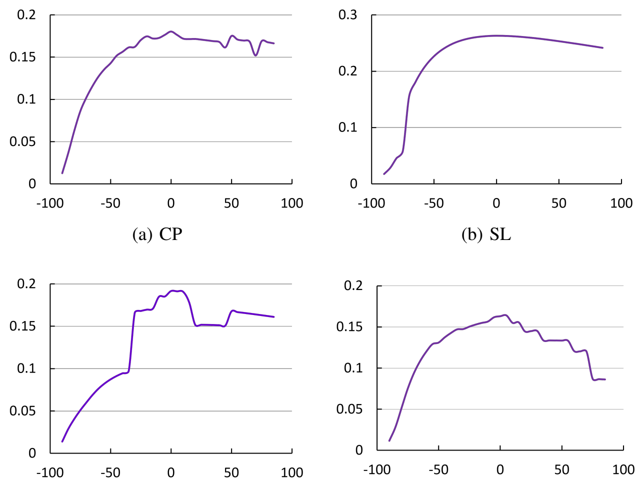
(a)

Fig. 9: Advantage of using OFT. Comparison of net-gain (y-axis) observed using proposed method (PR2) with the mean values (ME) for different locations (x-axis)

We further analyze the recommended stay time at each of the micro-poi location included in the predicted path. An optimal stay time is predicted for each of the micro-poi in the ground truth trips using the proposed method (PR2). Then, a net-gain is computed for the trip based on predicted stay time at each of the micro-poi location. We also computed a net-gain estimation when average stay time is used and observe that the net-gain estimated using the proposed method (PR2) is better as compared with the estimation where mean stay time is utilized. The comparison is shown in Figure 9a for all the nine locations.

We also study the effect of estimated stay time on observed information gain from a recommended trip. We monitor the information gain as we vary the stay time for each of the micro-poi in the recommended trip. The stay time estimated using MVT for each of the micro-poi in the recommended tour is varied as follows,

$$st^* = st_0 \times (1 - \frac{\Lambda}{100}) \tag{21}$$



(a) CP (b) SL

(c) TM (d) WM

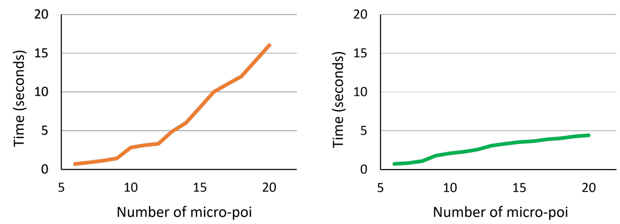
Fig. 10: Variation of information gain (y-axis) from the recommended trip, as we change the estimated stay time (x-axis, % of variation) at micro-pois in the trip, corresponding to sample ground truth trips for different locations.

where st_0 is the estimated stay time using MVT, st^* is the updated stay time and Δ is varied from -90 to +90. We observe that the information gain goes down as we move away from the estimated stay time for each of the micro-pois in the recommended trip. Figure 10 shows the variation of estimated net-gain with a change in stay time for some of the recommended trips from four different locations. We also observe that the gain consistently reduces to zero for all the trips when the stay time approaches close to zero. This is the scenario when the user will have to move from one micro-poi to another without any stay and all the time will be spent in traveling.

We observed varying gain patterns at different micro-pois. Since each micro-poi has different visual topic distribution, it can be one of the reasons for this variation. Therefore, we investigate the relationship between gain and diversity of topic distribution at a micro-poi to understand the variation in gain patterns across different micro-pois in a location. To quantify the diversity of topic distribution at a micro-poi, we employ Shanon's diversity index which is computed as,

$$H = -\sum_{i}^{N_t} p_i ln(p_i) \tag{22}$$

where N_i is the number of topics in the model (50 in our experiments) and p_i is the distribution of i^{th} topic at a micro-poi. We compute Spearman's rank correlation coefficient to find the correlation between gain and diversity of a micro-poi. We observe a weak positive correlation of 0.37 between the gain and diversity which indicates that visual diversity of a location has some impact on the observed gain. We also observe a moderate positive correlation of 0.56 between the stay time and observed gain which was expected as the gain at a location increases as we increase the stay time.



(a) (b)

Fig. 11: Running time analysis of the proposed method. The plot shows variation of average running time with number of micro-poi in the path. (a) Exponential running time when TSP is invoked with every step, (b) Optimized running time.

F. Running-time Analysis

The experiments for the proposed system were performed on an 8 core Intel processor running at 3.40 GHz and 8 GB of RAM using python code. Solving TSP is the most time-consuming step in the recommendation process. The time required to determine an optimal path also depends on the total number of micro-pois in the path. The average computation time to generate a recommendation for the Leaning Tower of Pisa was much higher in comparison with other locations. This was mainly due to the smaller stay time at each of the micro-poi for this location which leads to a large number of micro-pois in the path.

We further analyze the computational complexity of the proposed method to understand the effect of the number of micro-poi in computation time. We use our method to generate trip recommendations corresponding to the ground truth trips. For each ground truth trip, we generate multiple recommendations by varying the trip time. We use the minimum and maximum trip time from the same location and increment the target trip time with 15 minutes. The variation of running time with a different number of micro-pois in the trip is shown in Figure 11 (a). We observe that the computation time increases with the increase in the number of micro-pois. The exponential increase in computational cost is due to the repetitive invocation of TSP in each iteration of the proposed algorithm. The algorithm tries to find the shortest path after determining the next most profitable micro-poi in each step. However, estimation of the shortest path after each step is not required.

We modified the proposed algorithm to reduce the computational cost incurred due to the repetitive invocation of TSP. In the modified version, the TSP is invoked only when the total trip time is close (90%) to the expected total trip time. We use the average reach time for each micro-poi instead of the estimated reach time. This does not affect the final recommendation as estimated reach time will be available for the step which performs TSP. This significantly reduces the computation time for the trips with a large number of micro-pois. We observe that the average running-time was improved to almost linear with this optimization (Figure 11 (b)). The modified algorithm takes on an average around 1-3 seconds to generate a trip recommendation in the full test set.

A comparison of running-time with different variations of the proposed method is shown in Table II. We observe that the average computation time for small locations, such as Forbidden City, was much lower (0.56 seconds) as compared to large locations, such as Central Park (3.53 seconds). The computation time for the baselines (BL1, BL2, and BL3), PR-A1 and PR-A2 are almost similar as they all require TSP to find the shortest path. The computation time increases for PR1 and PR2 as they also need to optimize the stay time. The running time for PR3 increases further as it requires the computation of personal preference in addition to stay-time. However, we observe that the computation time reduces significantly with the modified algorithm.

VII. Conclusion and Future Work

In this work, we propose a trip recommendation method for photography and exploration of tourist locations based on OFT. The recommended trip includes a list of micro-poi locations a user should visit and corresponding stay time to spend at each micro-poi for capturing photographs. The recommendation can also be personalized based on the past photography behavior of a user. We evaluated the proposed method on a dataset drawn from YFCC100M [54] for nine different tourist locations. The experimental results demonstrated the effectiveness of the proposed method. The current work focuses on providing a recommendation based on optimal foraging behavior. However, different users may have different behavior for photography and understanding individual user behavior is also important. Therefore, understanding the photography behavior of users and employing it for personalized recommendations can be a future research direction.

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