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Intelligent travel recommendation system by mining attributes from community contributed photos

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Abstract

This paper purposes a system which helps user in finding tourist locations that he/she might likes to visit a place from available user contributed photos of that place available on photo sharing websites. This paper describes methods used to mine demographic information and provide travel recommendation to users. This paper also describes an algorithm adaboost to classify data and Bayesian Learning model for predicting desired location to a user based on his/her preferences.

Keywords: Personalized Travel Recommendation; geo-tagged photos; route planning; Adaboost; Naïve Bayesian Modeling

1. INTRODUCTION

Travel has become one of the hottest contenders of modern era. Users are interested to search for their favorite tourist destination places, so this domain has becoming a hot topic for researches to take up Research in Travel Recommendation System. In general, travel recommendation system consists of two aspects: generic recommendation and personalized recommendation. For the generic recommendation, it contains the suggested travel information for the destination given by user when he/she is planning a trip, which answers the question like "I want to go to Hyderabad, what are the attractions of this place?". The personalized recommendation consists of user's preferences such as user attributes such as male/female, group type (couple / family /friends) to create a user profile. It can provide a more appropriate recommendation result matching user's profile. Both aspects are to

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support route planning before the journey.

2. RELATED WORK

With advent globalization people are interested in looking for their favorite Travel destination which leads to increase in Trip mining and recommendation. Generally, the data sources for learning to recommend can be classified into three categories GPS trajectory data, travelogues (blogs) and Geo tagged photos. GPS trajectory data obtained by GPS are mainly used at the early stage. Zheng et al. (2011a) utilize GPS trajectory data to extract the interesting location, classical travel sequences and provide personalized friend and location recommender using the similarity of user profiles created from their location histories. The main drawback of this method is that it is impossible to collect data from a large number of people, as every person has a GPS Enabled device it becomes impossible to collect and analyses data from each device.

Some Travel Recommendation System analyses Travelogues (blogs) to obtain trip related knowledge. It analyse keywords in blogs and rank landmarks for travelers. The main drawback of this is some keywords relating to some Landmark in a city can be missed or Travelogues are usually unstructured and contain much noise metadata. Recently, there is an increasing tendency to adopt the information from geo-tagged photos. D. J. Crandall et al.(2009) systematically adopt large-scale photo database to discover important landmarks. They evaluate on many cities and indicate that the time-stamped and geo-tagged photos will construct the typical pathways of people movements. The major differences between our work and other related studies are that we bring in concept people attributes such as gender, group type, travel season in the travel photos and consider demographic information with the movements of photographer into a personalized travel recommendation framework.

Trip mining along with recommendation systems have seen a rise of interest and research in the recent past. The systems are designed incorporating appropriate relevant information from sources such as GPS trajectory data, travelogues and Geo tagged photos, or a combination of these. Initially the process of recommendation estimations involved GPS trajectory data largely. In [Y. Zheng et al. 2002, 2011a, 2011b] locations of interest are determined using GPS trajectory data along with location histories of similar users. Suggestions of popular travel routes are also provided along with location recommendation. The scarcity of data and complexities in building adequate information is a challenge in trajectory based systems. In [R. Ji et al. 2009, Q. Hao et al. 2010, Y. Gao et al. 2010], the recommender system is designed by suitable analysis of the blogs or travelogues of past users. City land marks are determined using graph search methods applied to appropriate features extracted from blogs in [R. Ji et al. 2009].

3. TRAVEL RECOMMENDATION

The topics in travelogues or blogs are mined in order to provide route recommendation and popular destinations using a probabilistic approach in the work [Q. Hao et al. 2010]. In the work [Y. Gao et al. 2010] recommendation is made through automation of recognition and ranking based on trajectory information, user profiles from online travel guides and metadata of photos. The use of travelogue or blog based data in recommendation is limited to providing location information as the systems faces the challenges of mining thorough unstructured data and large noise. The use of geo tagged photos has been made recently in some works. In [D. J. Crandall et al. 2009] large scale photos are used to mine import landmarks over many cities and claims geo tagged photos and time stamps can be utilized to provide better routes of travel to the user. Y. Arase et al.(2010) mines the trip pattern from the geo tagged photos to determine frequent trip patterns and recommendations based on similar information for inter city travel. X. Lu et al.(2010) concentrates on information from textual blogs along with geo tagged photos to establish landmarks and in turn discover paths and recommend route plans. This approach combines the incomplete paths and provides suggestion based on graph analysis and dynamic programming.

An-Jung Cheng et. al. (done a research in personalized travel recommendation by mining people attributes from geo tagged photos. Although existing system architecture is similar to proposed system but their work is restricted to people attributes such as gender, group type and age .Drawback of existing system is that it does not recommend which season is best for location to visit for gender or group type or age. As some locations may not be preferable for adults during winter season or some locations may be preferable only to couples during a particular season. This issue will be addressed in our proposed system.

4. SYSTEM ARCHITECTURE

Architecture of System is shown in **Fig 1**, it has four main steps. First step is to collect photos from photo sharing websites such as Facebook, Flickr where people share and tag their photos .After collecting photos identify destination in which photos are captured. In second step people attributes such as gender, race, age, and travel season are detected and Group types (friends, family, couple, solo) are predicted from detected people attributes. Trips are generated from detected people attributes by sorting out photos of users according to captured date and time and build a travel recommendation model which is further assisted by Probabilistic Bayesian model.

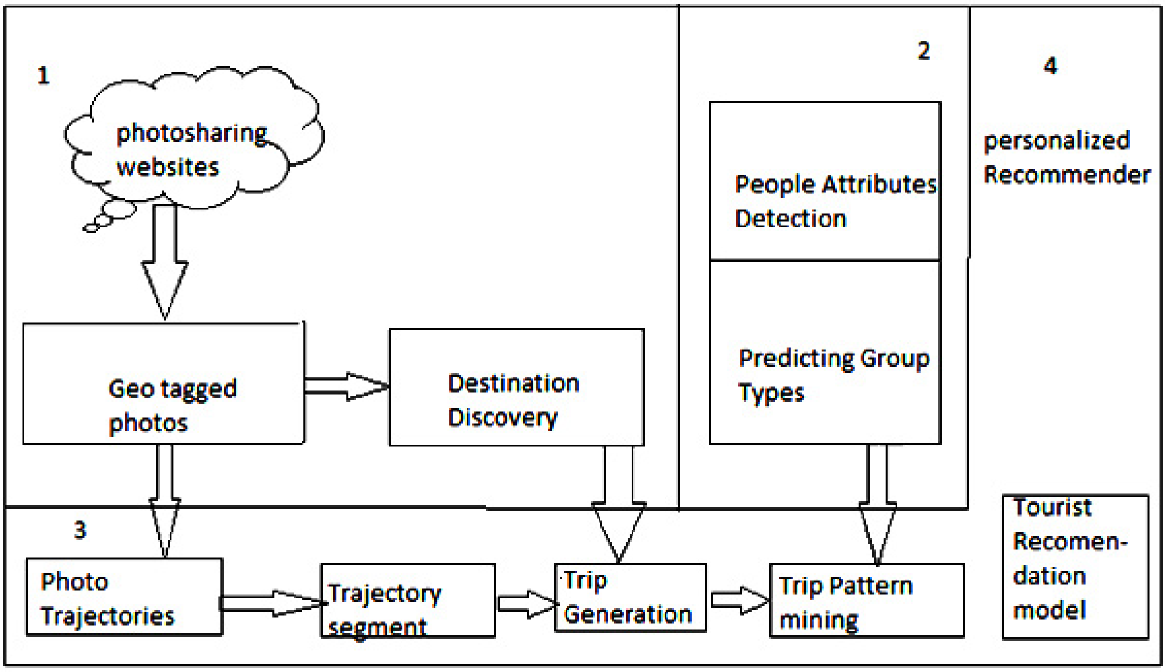


Fig 1: Architecture of a proposed travel recommendation system

Concept Definition

Destination: Destinations are the popular places in a country
for example Araku in Andhrapradesh, India, Manali in Uttar Pradesh, India

Trajectory: A collection of time series geo tagged photos of a specific user.

Trip: An individual user's trip is the route with attribute information.

Trip segment: A trip segment is a tuple with (start location, end location, attributes). They are considered as major knowledge resources for intelligent travel recommendation and route planning.

5. ANALYZING PEOPLE ATTRIBUTES FROM PHOTO CONTENTS

5.1 Geo tagged photos

The use of geo tagged photos has been made recently in some works. In D. J. Crandall et al.(2009) large scale photos are used to mine import landmarks over many cities and claims geo tagged photos and time stamps can be utilized to provide better routes of travel to the user. Y. Arase et al.(2010) mines the trip pattern from the geo tagged photos to determine frequent trip patterns and recommendations based on similar information for inter city travel. X. Lu et al.(2010) concentrates on information from textual blogs along with geo tagged photos to establish landmarks and in turn discover paths and recommend route plans. This approach combines the incomplete paths and provides suggestion based on graph analysis and dynamic programming. Geo-tagged and time-stamped photos now plays an increasing role for mining travel recommendation data as in [D. J. Crandall et al.(2009), Y. Arase et al.(2010), X. Lu et al.(2010), T. Mei et al.(2010)]. The availability and easier access of photo trajectories nowadays helps in mining travel movements and demographic information efficiently. This can be enhanced by the analysis of people attributes. It is evident from M. Ames et al.(2007) that people for organization and communication willingly tend to share travel related information especially photos. V. K. Singh et al.(2010) also points out that this photos can be considered as social pixels of travel locations.Previous works involving travel logs and geo tagged photos emphasizes in popularity of locations mining. Various people attributes and their constitution dimension are neglected. But in N. Kumar et al.(2008) it can be seen that photos used to learn facial attributes from social media photos provides a significant accuracy. Thus the proposed approach focuses on community contributed photos to provide travel recommendations by automated extraction of people attributes.

5.2 Correlation between Travel Patterns and People Attributes

Some locations and landmarks tend to be male or female favoured and some locations are favoured by attributes of people from different race and age. In order to determine the correlation between people attributes and next possible or likely travel location, entropy and mutual information [T. M. Cover et al.(1991)] is used. The mutual information I(X;Y) between two random variable X and Y is defined by:

$$I(X; Y) = H(X) - H(X|Y)$$

Here H(X) is the measure of uncertainty with respect to the random variable X. The mutual information I(X;Y) between the two random variables is obtained by introducing another random variable Y as the entropy reduction. The sample was from 5 major worldwide cities with travel patterns in 5 locations. Nearest five locations were taken into considerations with the starting location as i, the uniform choice entropy is $H(L_i \rightarrow_j) = 2.3219$. We will further see the reduction in the entropy for selecting next visiting location by the inclusion of knowledge mined from community tagged photos.

The visiting frequency F is calculated from the photo trips between I and j using only the gender attribute. This F is then determines the prediction entropy of the next location from the minded travel using $H(L_i \rightarrow_j | F)^2$. Thus the recommendation of the possible next location is aided by the determination of $H(L_i \rightarrow_j|F)$. The inclusion of people attributes(A) in the process improves the accuracy further by providing entropy reduction as in $H(L_i \rightarrow_j |A, F)$. Calculating the $I(L_i \rightarrow_j; A|F)$ on Madison Square in Manhattan 0.5329 is obtained indicating 25% reduction of entropy. Hence its evident that there is a significant correlations between the travel location predictions and the people attributes (A).

In this work, we utilize ten people attributes including gender (male, female), age (kid, teen, middle aged, elder) travel season (summer, winter, spring, autumn) to profile the travel preferences of users. Initially the system crawl the images of ten people who had visited Indian cities [N. Kumar et al. (2008)] then we detect attributes from training set of images, the facial region is extracted from whole image by face detection [P. Viola et al. (2001)] and further applied facial feature detection to locate important parts of a face such as eyes, philtrum and mouth. Therefore construct a mid level feature bank based on those facial components for providing better generalization capability to deal with various facial attributes.

5.3 Mid –level Features

A mid level feature is a SVM classifier with varying low-level features extracted from different face components. Those combinations constitute a feature bank to provide possible mid-level features required by facial attributes. Rather than using low level features mid-level features have better semantic meanings for describing facial attributes through multiple modalities.

We treat each mid level feature as a weak classifier and learn the best combination of mid level features for an attribute by Adaboost algorithm .The combined strong classifier represents the most important parts of that attribute for example (whole face, Gabor) is most effective for female attribute. These important mid-level feature set for the designed facial attribute is adaptively selected and weighted through the boosting scheme as the final strong classifier.

6. PREDICTING TRAVEL GROUP TYPES AND TRAVEL SEASON

Mining travel preferences for travel by people attributes of individuals can reduce the uncertainty of destination prediction. Beyond the preferences of an individual traveler, the preferences of a travel group and travel season which may comprise people of very diverse attributes have significant impact on travel planning. For example, recommending a place for holidaying may not be suitable for friends but suitable for family and couple and also recommending a place during summer may be feasible but same place cannot be feasible for all group types.

To consider the attributes of all group members in holistic members, we propose to exploit social contexts and relationship among a group of people example face size, relative distance, gender difference as features for travel group type prediction from sequence of travel photos. In this work we focus on four group types (family, friends, couple, solo traveler) because they are considered as important factors for travel planning. To predict travel group type we considered following:

Gender difference: It is measured by number of faces in a photo is less than 2 then difference is set to 0 else it is set to 1.

Age gap: It can be measured in 2 ways (1) standard deviation (2) average age detection scores in a photo.

Number of faces: It indicates the size of group. Since size of family and friends are larger than a couple and a solo traveler.

To predict travel season attribute, we have four season summer, winter, rainy, spring we consider the captured date of photo and extract month from date attribute and predict travel season attribute.

6.1 Photo Trip Generation

To generate trip from photos is a challenging problem because of the various trip types and different travel behaviors among people. To mine Trips from user contributed photo tags we use three main procedures Path extraction, destination discovery, and trip attribute mining to extract trip segments between destinations to be incorporated in the recommendation model. This paper focuses on the travel behavior which lasts for couple of days. Therefore the time stamped photos for each user taken on a particular location is considered as paths along with sequence of GPS logs. However, GPS logs are very dense as different GPS logs may indicate the same landmark. Paths can be extracted by the captured time for each user. These paths are mapped to higher informative level routes by associating paths with discovered destinations. These routes will then associate with detected people attributes resulting in informative trips. These trips can be separated into trip segments which will become inputs in our proposed travel recommendation model.

6.2 Path Extraction

The first step in path extraction involved sorting of the photos. The photos were typically sorted based on the captured time by the user. Then separation of sorted photos was carried out based on the date information. The path assignment based on the photos is made with handling of midnight trips by soft assigning boundary between two days. So the original date path and the previous date path share the boundary photo.

7. TRAVEL PLANNING

7.1 Destination Discovering and Route Mapping

Refinement of the paths generated is necessary to minimize the noise and to smooth the information mining process. This is done by organizing based on routes and quantizing to destinations. For each city the geo-tagged photos are analyzed using mean-shift clustering procedure to determine high photo density locations based on latitude and longitude coordinates. Flat kernel function with bandwidth parameter 0.001 is used by the mean shift procedure [Y. Li et al. (2009), M. Clements et al. (2010), D. J. Crandall et al. (2009)]. A threshold value is estimated based on the percentage of the photos in the city and the clustering. Then the destination sequences are generated from the path sequence. The used clusters consisted of 0.1% photos in city with photos as destinations above 100. As generated paths are too noisy and complicated to mine the information, we refine these paths to a more descriptive level by quantizing photos into the destinations. In order to do these we apply mean shift clustering procedure on the geo tagged photos for each city ,to discover the locations with high photo densities we use flat kernel function and set bandwidth parameter as 0.001 (roughly radius of a landmark). The path sequences of all users can be converted into destination sequences.

7.2 Trip Attribute Pattern Mining

Face detected in a photo can be considered as an observed people attribute as a photographer can be seen as a human sensor [V. K. Singh et al. (2010)]. Thus faces in photos can be used to get more than trip information. Also it has to be noted that the face shares the movement with the photographer. Hence the detected face and the photographer are confined to the same movements. Therefore the faces detected along the movements of the photographer produces a sequence of faces that can be used to find route sequences and possible trip routes. But the different attributes may be encountered from these sequences from the detected faces. The movement sequences obtained can be viewed as segments and can be used to recommend and learn possible trip sequences. The sequence of the location and the attributes detected is represented as

$$T_u = (L1_u \rightarrow L2_u \rightarrow \dots \rightarrow Ln_u, Au)$$

Where Li_u is the location traversed by the user u and Au is the set of detected attributes.

7.3 Tourist Recommendation Model

The model is designed in such a way that the user specifies the attributes and the current location and in turn be provided with possible destination suggestions. The user's attributes Au is matched with the similar people attributes along with the location Li and the recommendation Lj is suggested. The optimal destination that can be travelled next is determined by:

$$L^* = \text{argmax}_{Lj} P(L_j|A_u, L_i, \Theta)\ \Theta = \{F,A\}$$

Where L* is the optimal next destination, Θ represents the model of learned frequencies between locations (F), (A) is the detected attributes from the photos. Thus the trips with attribute patterns are represented as:

$$T_{u\varepsilon U} = (L1_u \rightarrow L2_u \rightarrow \dots \rightarrow Ln_u, Au)$$

$T_{u\varepsilon U}$, the sequence of trip segments can be added to dataset of the system. Further, the sequence correlation $P(L_i \rightarrow_j)$ or $P(L_{ij})$ between locations, the people attribute patterns on the movements $(P(A|L_{ij}))$ is calculated to learn the tourist knowledge.

8. INTELLIGENT TRAVEL RECOMMENDATION MODEL

We are building a recommendation model to solve the particular scenario like we friends are at araku. What is the next suggested destination for us? Obviously inputs for the following scenario will be users' profile which is composed of detected people attributes from geo tagged photos and output is the recommended next destination.

We adopt Bayesian learning model as our recommendation model because Bayesian is simple and most effective in recommendation systems. Bayes theorem states that the probability that the location Lj is suggested destination given a start location Li and attribute value PRu of a specific user u is

$$P(L_{i\text{->}j} / PR_u) = P(L_{i\text{->}j}, PR_u) / P(PR_u) \quad (1)$$

$$P(L_{i\text{->}j} / PR_u) = P(L_{i\text{->}j}) * P(PR_u | L_{i\text{->}j}) / P(PR_u)$$

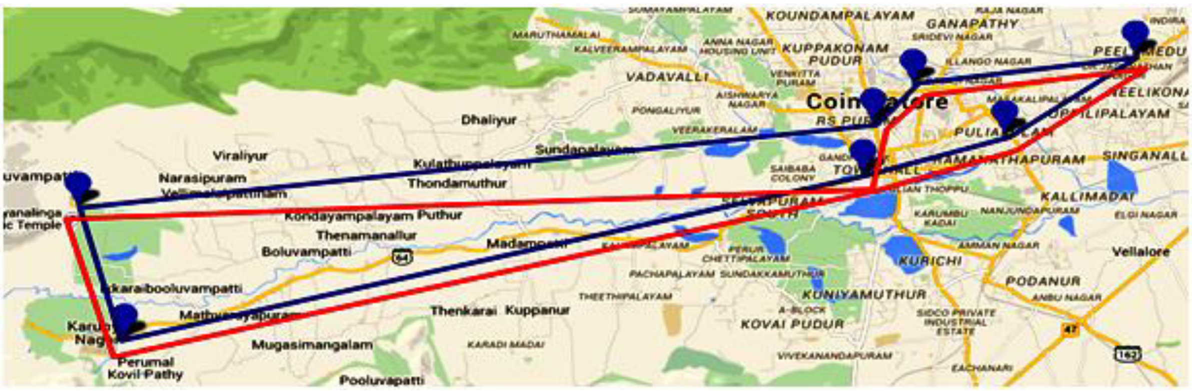
$L_{i\text{->}j}$ is a trip segment (L_i is starting location L_j is ending location).We need to predict the location L_j probabilities that the user might like to visit from a location L_i .To calculate L_j equation (1) can further be transformed into following equation

$$P(L_{i\text{->}j} / PR_u) = P(L_i) * P(L_j / L_i) * P(PR_u / L_{i\text{->}j}) / P(PR_u) \quad (2)$$

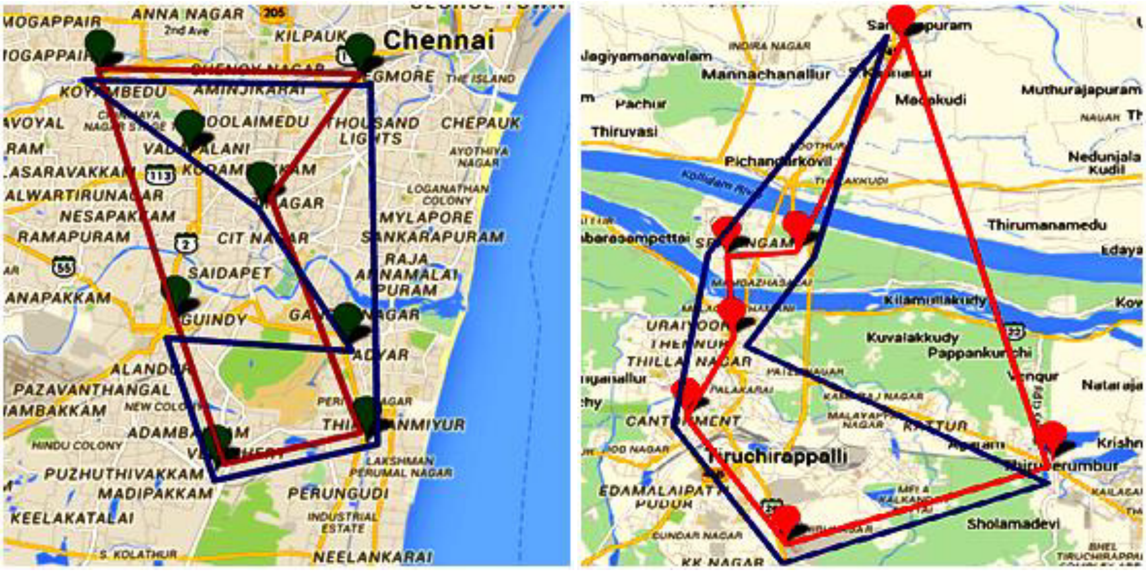
From the above equation We can suggest the location L_j from L_i using users profile attributes (PR_u).

8.1 Route Planning

Route planning is the situation in which the user with attributes Au, from location L_s decides to go to location Le through N locations. This problem can be solved using graph-based method. Graphs consist of a set of nodes connected by edges that may have weights associated with it. The locations are represented as nodes, the connecting path between locations as the edges of the graph. The edge weights are determined through the attribute set A from the learned model and user attributes Au. $P(L_i)$ is considered to place more importance to the popular landmarks. A penalty function manages the diminishing of overall route distance. Also the weights between locations are adjusted to avoid visiting a destination twice.



(a)



(b) (c)

Fig 2: The route planning samples, with designated profiles – male vs. female, in 3 cities: (a) Coimbatore, (b) Chennai, and (c) Tiruchirappalli. The blue route is for male, while the red one for female. Both routes in the same city are fixed at the same starting and end locations.

9. CONCLUSION

In this paper, we propose a probabilistic travel recommendation model which exploits automatically mined knowledge from user contributed photo tags as well as the detected people attributes, travel group types and travel group season in photo contents .For future work, we will implement real time application for Intelligent travel recommendation that will mine user's preferences from user contributed photo tags and recommend location to users.

References

1. An-Jung Cheng et al. Personalized Travel Recommendation by Mining People Attributes from Community-Contributed Photos. In ACM MM, 2011.
2. M. Ames et al. Why we tag: motivations for annotation in mobile and online media. In ACM CHI, 2007.
3. Y. Arase et al. Mining people's trips from large scale geo-tagged photos. In ACM MM, 2010.
4. M. Clements et al. Using flickr geotags to predict user travel behaviour. In ACM SIGIR, 2010.
5. T. M. Cover et al. Elements of Information Theory. Wiley, 1991.
6. *D. J. Crandall et al. Mapping the world's photos. In WWW, 2009.*
7. Y. Gao et al. W2go: a travel guidance system by automatic landmark ranking. In ACM MM, 2010.
8. *Q. Hao et al. Equip tourists with knowledge mined from travelogues. In WWW, 2010.*
9. R. Ji et al. Mining city landmarks from blogs by graph modeling. In ACM MM, 2009.
10. N. Kumar et al. Facetracer: A search engine for large collections of images with faces. In ECCV, 2008.
11. Y. Li et al. Landmark Classification in Large-scale Image Collections. In IEEE ICCV, 2009.
12. X. Lu et al. Photo2trip: generating travel routes from geo-tagged photos for trip planning. In ACM MM, 2010.
13. T. Mei et al. Knowledge discovery from community-contributed multimedia. IEEE MultiMedia, 17, October 2010.
14. V. K. Singh et al. Social pixels: genesis and evaluation. In ACM MM, 2010.
15. P. Viola et al. Rapid object detection using a boosted cascade of simple features. In IEEE CVPR, 2001.

16. Y. Zheng et al. Mining interesting locations and travel sequences from gps trajectories. In WWW, 2009.
17. Y. Zheng et al. Learning travel recommendations from user-generated gps traces. ACM Trans. Intell. Syst.Technol., 2011a.
18. Y. Zheng et al. Recommending friends and locations based on individual location history. ACM Trans. Web, 2011b.