User similarity-based gender-aware travel location recommendation by mining geotagged photos

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Abstract: The popularity of camera phones and photo sharing websites, e.g., Flickr and Panoramio, has led to huge volumes of community-contributed geotagged photos, which could be regarded as digital footprints of photo takers. Thus, mining geotagged photos for travel recommendation has become a hot topic. However, most existing work recommends travel locations based on the knowledge mined from photo logs (e.g., time, location), and largely ignores the knowledge implied in the photo contents. In this paper, we propose a geotagged photos mining-based personalised gender-aware travel location recommendation approach, which considers both photo logs and photo contents. Firstly, it uses an entropy-based mobility measure to classify geotagged photos into tour photos or non-tour photos. Secondly, it conducts gender recognition based on face detection from tour photos. Thirdly, it builds the gender-aware profile of travel locations and users. Finally, it recommends personalised travel locations considering both user gender and similarity. Our approach is evaluated on a dataset, which contains geotagged photos taken in eleven cities of China. Experimental results show that our approach has the potential to improve the performance of travel location recommendation.

Keywords: geotagged photos; gender recognition; travel location recommendation.

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1 Introduction

With the popularity of smart phones and GPS-enabled digital cameras, people can casually take photos with geotags and share these photos on websites such as Flickr and Panoramio. These community-contributed geotagged photos on the Web are publicly available and cover most of the lands in the world. The geotagged photos can be utilised by many applications, e.g., searching, advertising, annotation, and recommendation (Chen et al., 2013; Liu et al., 2013; Luo et al., 2011; Zheng et al., 2011c; Wohrer et al., 2009; Anand et al., 2014; Che et al., 2012; Gao et al., 2014; Xiang et al., 2015; Wu et al., 2015).

Since tourists usually take photos while on travel, geotagged photos mining-based travel recommendation has recently drawn the attention of the research community. These researches can be roughly divided into two categories depending on what kind of information from geotagged photos is considered during mining and recommendation: photo log-based and photo content-based. For the former category, existing methods extract travel locations and sequences, and then cluster, index, and recommend these travel locations (Arase et al., 2010; Kurashima et al., 2013; Lu et al., 2010; Majid et al., 2013; Popescu and Grefenstette, 2009). However, these methods only use photo logs (e.g., time, location), ignoring the rich knowledge implied in the photo contents to mine user travel preferences.

For the latter category, existing methods take the user attributes information (e.g., race, gender, age) implied in the photo contents into account, so these methods can provide more accurate recommendation results (Cheng et al., 2011; Chen et al., 2013). For example, Cheng et al. (2011) and Chen et al. (2013) leveraged the automatically detected user profiles in the photo contents for travel recommendation, which shows promising results. However, these works do not distinguish tour and non-tour photos during geotagged photos mining, and do not take user similarity mined from photo logs into consideration during travel recommendation.

To this end, we propose a personalised gender-aware travel recommendation approach based on the knowledge mined from both logs and contents of geotagged photos. The knowledge mined from photo logs is travel preference similarity between users, and the knowledge mined from photo contents is user gender information. These two aspects of knowledge are integrated by a recommendation model to give more accurate results.

The main contributions of this paper are summarised as follows:

1 Build the gender-aware profile of travel locations and users by exploiting gender information implied in the photo contents. Especially, we classify locations into three types (male-favoured, neutral, female-favoured) to build the profiling of locations.

2 Propose a travel recommendation method that integrates user travel preference similarity mined from photo logs and gender information mined from photo contents. We calculate the probability of next travel location using the theorem of Bayes based on travel histories of the top N most similar users U' for user u_p. It is more natural to make preference predictions for u_p via the travel histories of the most correlated users than all users.

3 Conduct experiments based on geotagged photos collected from eleven major cities in China, and show that our approach has the potential to improve the performance of travel location recommendation.

The remainder of this paper is structured as follows. In Section 2, we review the related work. Section 3 gives preliminaries and problem definition. Section 4 introduces the framework and details of our method. Section 5 reports the experimental results. Section 6 concludes and discusses future research directions.

2 Related work

Depending on what kind of data source is considered, we classify the existing travel recommendation researches into three categories: GPS trajectories-based methods, travelogues-based methods and geotagged photos-based methods.

2.1 GPS trajectories-based methods

The GPS trajectories-based methods are mainly used at the early stage by researchers based on the GPS trajectory data. Zheng et al. (2011a, 2009) utilised GPS trajectory data to mine interesting locations and classical travel sequences, and provided a personalised location recommender utilising the similarity of users in terms of their location histories. Yoon et al. (2011) built an itinerary model in terms of attributes extracted from user-generated GPS trajectories and presented a social itinerary recommendation framework to find and rank itinerary candidates. Zheng et al. (2010) used the location data based on GPS and users' comments at various locations to discover interesting locations and possible activities that could be performed there for recommendations. The main obstacle for GPS trajectories-based methods is that the data resources are comparatively difficult to obtain from a large number of users due to their privacy concerns, and therefore are still not readily available.

2.2 Travelogues-based methods

For travelogues-based methods, researchers are mainly focus on mining trip-related knowledge from blogs. Kori et al. (2007) extracted typical travel patterns by analysing blog text and aggregating travel data using the local blogs. Ji et al. (2009) emphasised on the mining of the famous sightseeing spots from cities by a graph-based method. Gao et al. (2010) mainly focused on automatically recognising and ranking the landmarks for travellers. Hao et al. (2009) proposed a location overview generation method which firstly mined location-representative terms from travelogues and then utilised such terms to retrieve Web photos. Hao et al. (2010) proposed a probabilistic topic model which mined topics from travelogues and then represented locations by appropriate topics for further destination recommendation and summarisation. Subramaniyaswamy et al. (2014) proposed a novel approach based on topic ontology for tag recommendation based on Wikipedia categories and WordNet semantic relationship to make the ontology more meaningful and reliable. The main obstacles of travelogues-based methods are:

1 it is difficult for researches to judge whether the bloggers really visited the locations

2 it is difficult for these methods to determine the actual location of travelogues and show the information about the location, since the travelogues are usually unstructured and contain much noisy information.

2.3 Geotagged photos-based methods

The geotagged photos-based methods can be roughly divided into two kinds: photo log-based and photo content-based.

2.3.1 Photo log-based methods

For the photo log-based methods, researches usually extract travel locations and sequences from geotagged photos, and then cluster, index, and recommend these travel locations and sequences (Arase et al., 2010; Kurashima et al., 2010; Majid et al., 2012, 2013; Popescu and Grefenstette, 2009; Popescu et al., 2009; Kurashima et al., 2013; Lu et al., 2010). Popescu and Grefenstette (2009) and Popescu et al. (2009) focused on the query with temporal constraints in terms of duration of the trip. Lu et al. (2010) proposed an interactive tourist recommendation approach which took into account a number of factors, e.g., duration of the trip and travelling cost, to help the tourist for trip planning. Kurashima et al. (2010, 2013) incorporated present location information and preference of user into the probabilistic behaviour model to make recommendations. The method recommended a set of personalised travel plans that matched the preference of user, present location, spare time and transportation means. Majid et al. (2012, 2013) considered weather context for travel recommendations. Arase et al. (2010) focused on the detection of frequent trip patterns of people. However, these methods only use photo logs (e.g., time, location), ignoring the rich knowledge implied in the photo contents to mine user travel preferences.

2.3.2 Photo content-based methods

For photo content-based methods, researches take the attributes information (e.g., race, gender, age) of users into account, so these methods can provide more accurate recommendation results (Cheng et al., 2011; Chen et al., 2013). Cheng et al. (2011) extracted people attributes in the photo contents, and leveraged these attributes to recommend travel locations. They demonstrated that people attributes were informative and effective for travel recommendation by the information-theoretic measures. Chen et al. (2013) extended their previous work, and considered not only individual user attributes but also travel group types (e.g., family, friends, couple) during making recommendation. These works show promising recommendation results. However, they do not distinguish tour and non-tour photos during geotagged photo mining, and do not take user similarity mined from photo logs into consideration during travel recommendation. Therefore, in this paper, we propose a personalised gender-aware travel recommendation approach based on the knowledge mined from both logs and contents of geotagged photos. The knowledge mined from photo logs is travel preference similarity between users, and the knowledge mined from photo contents is user gender information. These two aspects of knowledge are integrated by a recommendation model to give more accurate results.

3 Problem definition

Definition 1 (geotagged photo): A geotagged photo p can be defined as $p = (id, t, g, X, u)$, where id is the photo's unique identification, g is its geotag (i.e., the location where p was taken), t is its time-stamp, and u is the identification of the user who contributed the photo. Each photo p can be annotated with a set of textual tags X.

Definition 2 (photo collection): The collection of photos contributed by all user can be represented as $P = \{P_1, P_2, ..., P_n\}$, where P_u (u = 1, ..., n) is the collection of photos contributed by user u.

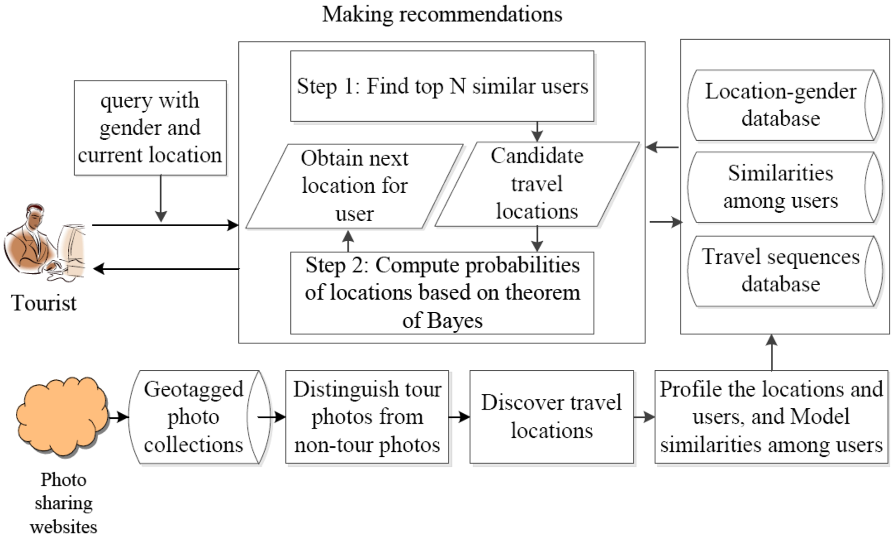
Definition 3 (travel location): A travel location l which is popular for users to visit and take photos is a specific geographic area within a city, such as a sightseeing spot, a park, a building, a bridge, etc.

Definition 4 (visit): A visit v can be described as $v = (l, u, t)$, where user u has visited travel location l at time t.

Definition 5 (gender-aware query): A gender-aware query Q is defined as $Q = (u_p, g, c, d)$, where u_p is the user who issues the query, g and c is the gender and current location of the user, and d is the city that u_p is visiting. The output of query is a recommended travel location from city d.

Our research problem can be formulated as: suppose that we have a photo collection $P = \{P_1, P_2, ..., P_n\}$, our task is to locate and summarise travel locations and build a travel profile of each user based on the user's gender and travel preference similarity, and the aim is to recommend next travel location to answer the gender-aware query $Q = (u_p, g, c, d)$.

Figure 1 Architecture of proposed recommendation method (see online version for colours)



4 Travel location recommendation method

The framework of our method is configured into various modular tasks as depicted in Figure 1. First, an entropy-based measure is adopted to distinguish tour photos from non-tour photos, and then travel locations are discovered by clustering tour photos. Second, gender-aware profile of travel locations is constructed to distinguish a travel location as male-favoured, neutral or female-favoured. The gender information can be obtained by face detection and facial gender recognition from photo contents. We also build the profiling of users based on the gender recognition. Third, a user-user similarity matrix is built by mining travel histories recorded in photo logs. Fourth, a recommend method that integrates gender-aware travel location profile and user travel preference similarity is used to recommend travel locations that can fit the gender-aware query of the user. The following subsections detail each task.

4.1 Discovering travel locations

4.1.1 Distinguishing tour photos from non-tour photos

A large proportion of geotagged photos are not for tour. Therefore, it is necessary for us to filter out non-tour photos. We apply an entropy-based mobility measure to classify photos into tour or non-tour photos for the following reasons.

1 Entropy is a measure of unpredictability of information content. In a probabilistic perspective, the mobility during a tour is usually more complex and leads to a geospatial distribution with reasonably high entropy (Zheng et al., 2011b).

2 In entropy context, Shannon entropy is usually used. The Shannon entropy is easy to implement, and its threshold can be obtained empirically. In order to employ Shannon entropy to discriminate between tour and non-tour photos, let $p(x, y)$ denote the geospatial density of photos with geospatial coordinate (x, y) pertaining to the photographer. The Shannon entropy $H(s)$ of a sequence $s = <(x_1, y_1, t_1), \ldots, (x_k, y_k, t_k)>$ is calculated by equation (1)

$$H(s) = -\sum_{i=1}^{n}\sum_{j=1}^{m} p_{ij}(x, y)\log p_{ij}(x, y) \tag{1}$$

where $p_{ij}(x, y)$ is a discrete geospatial distribution of photos in grid (i, j) and is estimated by the number of photos in grid (i, j). A city is partitioned into $n \times m$ grids, and the size of the grid is equal to 1 km × 1 km. The photo sequence s is classified as a tour sequence if $H(s)$ is no less than mobility entropy threshold H_0.

4.1.2 Clustering geotagged photos

Once the geotagged photos are classified into tour or non-tour photos, we utilise the tour photos to discover travel locations. Travel location discovery can be regarded as a clustering problem of identifying frequently photographed locations. Existing clustering algorithms include mean shift (Kennedy et al., 2007; Yin et al., 2011), k-mean (Rana et al., 2011; Li et al., 2009) and DBSCAN (Ester et al., 1996), etc. In these algorithms, DBSCAN has several advantages over others:

1 it requires minimum domain knowledge to determine the input parameters and can identify clusters with arbitrary shape

2 it can filter outliers and has good efficiency on large-scale data.

DBSCAN algorithm works with generic points and has a unified density threshold for all clusters. However, the locations extracted by clustering the given collection of photos, can have varying sizes and densities. In order to address this problem, Kisilevich et al. (2010) proposed P-DBSCAN algorithm, which extends the definition of directly density reachable by adding an adaptive density technique.

In our work, given a collection of photos P, we use P-DBSCAN algorithm to cluster photos to discover travel locations based on the photos' geotags. The output of a P-DBSCAN is a set of travel locations (clusters of photos) $L = \{l_1, l_2, ..., l_n\}$. Each element is a pair $l = \{P_l, g_l\}$, where P_l is a group of clustered photos, and g_l is the geographical coordinates of the centroid of cluster P_l.

4.2 Profiling travel locations and users

Gender of a user is an intrinsic factor. It could affect the user decision of visiting a location. For example, a female is more likely to visit a silk museum instead of a military museum. Thus, it is necessary to build the gender-aware profile of travel locations. The approach for profiling travel locations and users is summarised as follows.

1. We identify all the geotagged photos taken at a location.
2. We detect faces and discriminate their gender. The approach for face detection and gender recognition is summarised as follows. First, we construct a training dataset containing rich and diverse photos that involve human face, and extract facial region from the photos based on the face detection algorithm proposed by Kumar et al. (2008). Second, we employ local binary patterns (LBP) to describe faces (Shan, 2012). The LBP operator labels the pixels of a photo by thresholding a 3 × 3 neighbourhood of each pixel with the centre value and considering the results as a binary number. Formally, given a pixel at (x_c, y_c), the LBP can be expressed by equation (2), where m runs over the eight neighbours of the central pixel, i_c and i_m are the grey-level values of the central pixel and the surrounding pixel, and $b(x)$ is 1 if x is no less than zero, and 0 otherwise. Third, we train a support vector machines (SVM) classifier using the manually labelled faces detected from training photos. We classify face into two categories: male and female.
3. We compute the male and female proportions of locations and label it with a favour attribute (i.e., male-favoured, neutral, female-favoured). For example, if there are 200 male and 800 female faces detected in the geotagged photos of a location, the male and female proportions of the location are 0.2 and 0.8, respectively. Then, this location is labelled as female-favoured. Note that there are some travel locations very popular with both male and female. Therefore, if the difference between the proportions of male and female is less than a threshold *diffGender*, we consider that the travel location is favoured by both male and female, and is labelled as neutral. After finishing this step, we build a travel location database LDB = $\{l_1, l_2, ..., l_n\}$. Each travel location $l_i = \{g_i, pop_i\}$, where g_i and pop_i are the location and favour attribute of the travel location l_i.
4. Using the travel location database LDB, we can obtain the proportions of male-favoured and female-favoured locations of a user based on the travel history and build user-gender database UDB = $\{u_1, u_2, ..., u_m\}$. Each user $u_i = \{ID_i, G_i\}$, where ID_i and G_i are the ID of user u_i and the gender of user u_i. For instance, if many female-favoured locations are detected in travel history of a user, the gender of the user is probably female.

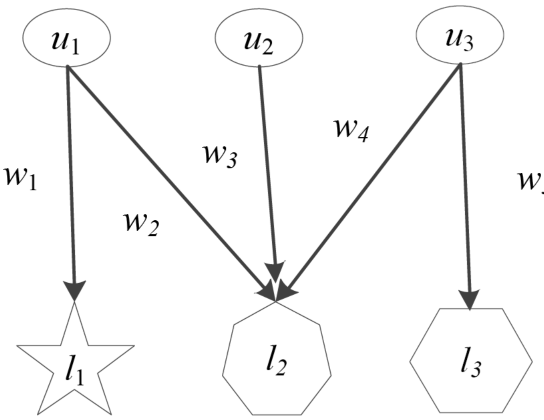
$$LBP\left(x_c, y_c\right) = \sum_{m=0}^{7} b\left(i_m - i_c\right)2^m \tag{2}$$

4.3 Modelling the similarities among users

4.3.1 Building user-location matrix

To obtain the preferences of users U in a set of travel locations L, the links between U and L are exploited to build a weighted undirected graph $G_{UL} = (U, L, E_{UL}, W_{UL})$, where U and L are nodes to represent users and travel locations, respectively. E_{UL} and W_{UL} are sets of edges and edge weights between U and L to represent the visits of users and the number of visits to particular travel locations. The relationship between users and travel locations is depicted in Figure 2.

Figure 2 The relationship between users and locations



Given m users and n travel locations, we construct an $m \times n$ adjacency matrix M_{UL} for graph G_{UL}. Formally, $M_{UL} = [T_{ij}]$, where T_{ij} represents how many times that the i^{th} user has visited the j^{th} travel location.

4.3.2 Building user-user similarity matrix

After we build the user-location matrix M_{UL}, the similarity between users is calculated by equation (3), and the similarity matrix M_{UU} among users is built. Each entry S_{pq} in M_{UU} represents the similarity between users u_p and u_q. A large value means that two users are more similar in terms of travelling preferences.

$$Sim(u_p, u_q) = \frac{\sum_{i \in S(R_p) \cap S(R_q)} \left(r_{pi} - \overline{R_p}\right) \cdot \left(r_{qi} - \overline{R_q}\right)}{\sqrt{\sum_{i \in S(R_p) \cap S(R_q)} \left(r_{pi} - \overline{R_p}\right)^2} \cdot \sqrt{\sum_{i \in S(R_p) \cap S(R_q)} \left(r_{qi} - \overline{R_q}\right)^2}} \quad (3)$$

where the $S(R_p)$ and $\overline{R_p}$ are defined and calculated based on the user-location matrix. From the user-location matrix, the travel history record of user up can be described as $R_p = <r_{p0}, r_{p1}, ..., r_{pn}>$, where r_{pi} is the number of visits made by up in a travel location i, $S(R_p)$ is the subset of R_p (any element of $S(R_p)$ is not zero), and the average value in R_p is denoted as $\overline{R_p}$. For example, if

$R_1 = <2, 3, 2, 0, 3, 1, 2, 0, 1>$,

$R_2 = <2, 3, 0, 3, 3, 4, 4, 2, 0>$, then

$S(R_1) = <2, 3, 2, 3, 1, 2, 1>$,

$S(R_2) = <2, 3, 3, 3, 4, 4, 2>$,

$\overline{R_1} = 2$, $\overline{R_2} = 3$.

4.4 Recommendation

When a tourist, who has visited some travel locations before, is visiting a new city, a query $Q = (u_p, g, c, d)$ is generated on the basis of the preferences of the tourist. To recommend a travel location for user u_p based on the gender g and current location c of the user in the city d, the query Q is processed by the following three steps:

1 find the top N most similar users U' for user u_p from user-user similar matrix M_{UU}

2 calculate the probability of next travel location using equation (4) based on travel histories of the top N most similar users U' for user u_p

3 return a travel location with the highest probability as the query result in city d for user u_p.

$$P(l_{i-1\to i} \mid g) = \frac{P(g \mid l_{i-1\to i}) P(l_{i-1\to i})}{P(g)} \quad (4)$$

$$P(l_{i-1\to i}) = P(l_{i-i}) P(l_i \mid l_{i-1\to i}) \quad (5)$$

$$P(g \mid l_{i-1\to i}) = \frac{count(l_{i-1\to i} \wedge g)}{count(l_{i-1\to i})} \quad (6)$$

$$P(g) = \frac{\text{Number of users with gender } g}{N} \quad (7)$$

$$P(l_i \mid l_{i-1}) = \frac{count(l_{i-1\to i})}{count(l_{i-1})} \quad (8)$$

where $count(l_{i-1\to i})$ represents the total number of users that start at travel location l_{i-1} and end at travel location l_i. Similarly, $count(l_{i-1\to i} \wedge g)$ represents the total number of users that start at travel location l_{i-1} and end at travel location l_i with gender g. Note that equations (4) to (8) are based on theorem of Bayes which has shown effective in recommendation systems (Cheng et al., 2011).

5 Experiments

5.1 Dataset

The dataset utilised in the experiments is collected by downloading geotagged photos from Flickr using the public API. We collect the geotagged photos that were taken in eleven popular tour cities in China between 1 January 2001 and 27 May 2014. Samples and records of the geotagged photos are given in Figure 3 and Table 1, respectively. The statistics of geotagged photos is given in Table 2.

5.2 Data preprocessing

Due to the noise of the raw geotagged photos downloaded from Flickr, outliers need to be removed. The method for removing the outliers from geotagged photo collection is summarised in the following steps:

1 Apply the entropy-based measure to filter out photos that are not for tour.

2 Use the combination of geographic coordinates, user ID and captured timestamp of photos to remove the duplicate records.

3 Remove the photos with incorrect temporal information. For example, we remove a photo whose upload time is identical to its taken time, because Flickr assigns a default value to photo that misses the taken time.

4 Remove the photos whose spatial information (latitude, longitude) does not fall inside the geographical boundary of the city.

Figure 3 A sample of the geotagged photos (see online version for colours)

Table 1 Records of the geotagged photo in Figure 3

Item	*Information*
PhotoID	8492985260
Owner	68288326@N04
Title	Beijing Trip 2003
DateTaken	2003-08-23 10:14:01
DateUpload	1361382172
Tags	University Beijing Tufts Igl
Latitude	39.993955
Longitude	116.301269

Table 2 The statistics of geotagged photos

Cities	*Users (raw)*	*Geotagged photos (raw)*	*Users (filtered)*	*Geotagged photos (filtered)*
Shanghai	85,768	295,463	53,302	244,123
Beijing	52,221	335,702	32,168	239,053
Hangzhou	3,216	106,042	1,589	53,424
Hongkong	30,260	348,716	18,187	257,519
Guangzhou	1,102	23,974	648	14,672
Chengdu	1027	29,476	437	18,731
Shenzhen	535	15,195	337	10,467
Wuhan	249	7,711	115	3,509
Nanjing	1984	56,736	644	39,925
Qingdao	230	7,544	118	3,304
Tianjin	224	7,727	126	3,421

5.3 Experimental settings

5.3.1 Parameter settings and method for evaluation

To detect travel locations from geotagged photos, we set *minPts* = 50, ε (epsilon) = 100, and density ratio $w = 0.5$ for P-DBSCAN. To classify photos into tour or non-tour photos and build the profile of travel locations, we set the threshold of entropy $H_0 = 0.25$ and *diffGender* = 0.20, respectively.

For evaluation, we select users who have visited at least two distinct cities. We use leave-one-city-out method for evaluation: for user u_p, we pick out the locations from one city which has been actually visited as testing dataset, and the locations from other visited cities as training dataset. We match the recommended travel locations with the actual visited travel locations in the testing dataset to evaluate the recommendation performance.

5.3.2 Baseline methods

In experiment, we verify the effectiveness of our method by comparing it with the following baseline methods.

- popularity method (PM), that recommends travel locations based on the general popularity score determined by the number of unique visits made to them
- distance method (DM), that recommends travel locations based on the distance between the current location and the locations of the candidate travel locations
- frequency and attributes method (FAM) (Cheng et al., 2011), that considers the frequency of movements between travel locations and the attributes of users when making recommendation
- personalised context-aware method (PCM) (Majid et al., 2013), that considers weather as an extra condition for collaborative filtering to calculate user similarity.

5.4 Results

Precision (P), recall (R) and F1 are utilised as performance metrics, which can be calculated by equations (9) to (10). Figures 4 to 6 depicts the performance of different methods in terms of precision, recall and F1 of one-step prediction in eleven cities in China. Figure 7 gives the average precision of prediction based on the prediction of all cities.

$$P = \frac{\text{Number of correct prediction}}{\text{Number of total prediction}} \tag{9}$$

$$R = \frac{\text{Number of correct prediction}}{\text{Number of total visited locations}} \tag{10}$$

$$F1 = \frac{2 * P * R}{P + R} \tag{11}$$

In Figures 4 to 6, we can find that PM gives the worst result. It might be because that it predicts the next travel location only based on its popularity, not considering the current location or preference of user. DM obtains better result than PM. It might be because it considers the distance among locations. For FAM and PCM, we find that they obtain better results than PM and DM. FAM and PCM consider the attributes or similarity of users when making recommendation, respectively. For our method, it outperforms other methods. It might be because our method obtains gender attributes by face detection and facial gender recognition from geotagged photos, and considers user preference similarity mined from photo logs. Thus, our method could be viewed as a combination of FAM and PCM.

Figure 4 Comparison of precision

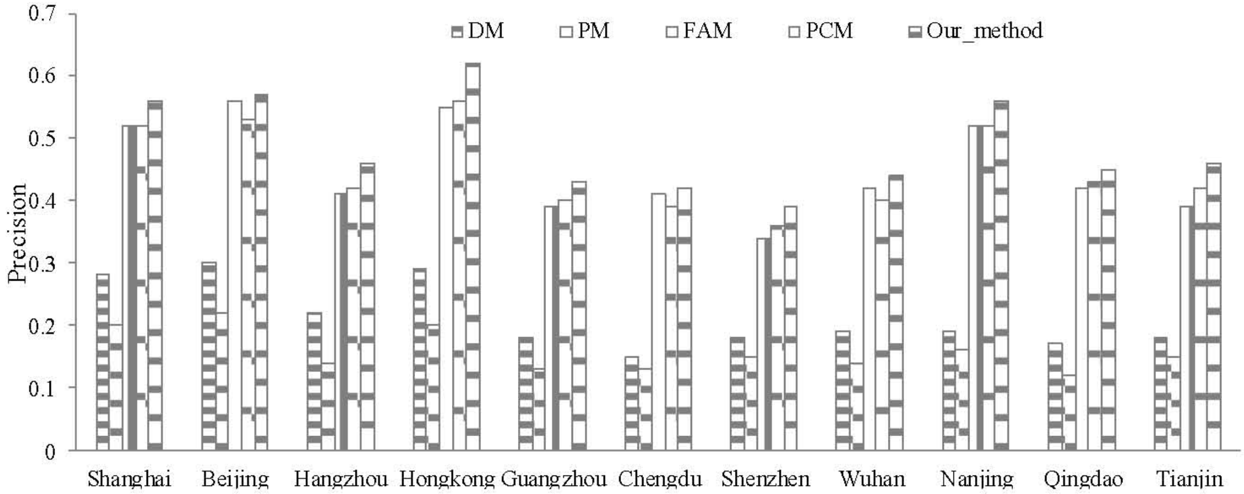


Figure 5 Comparison of recall

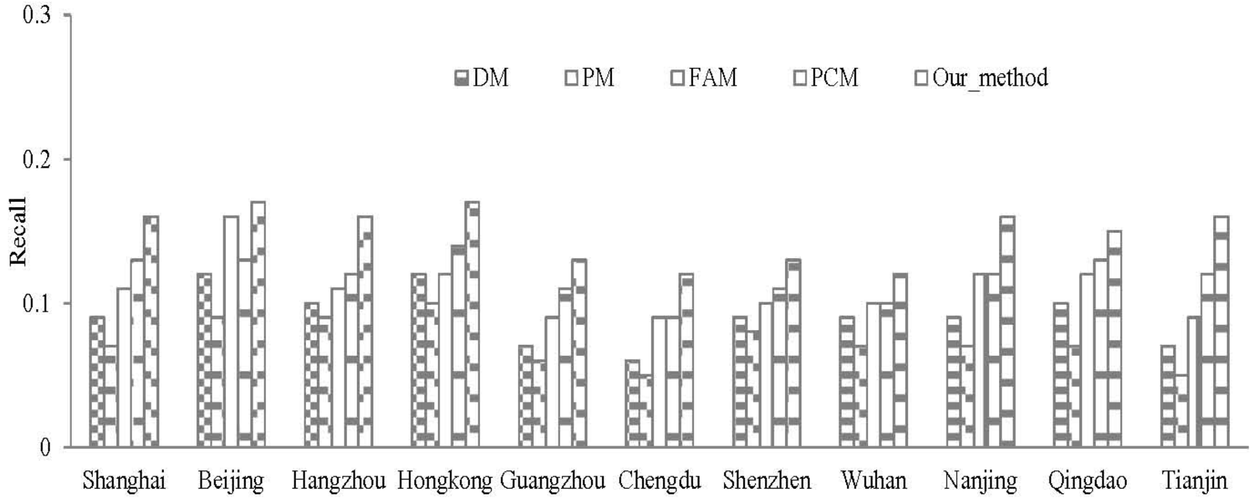
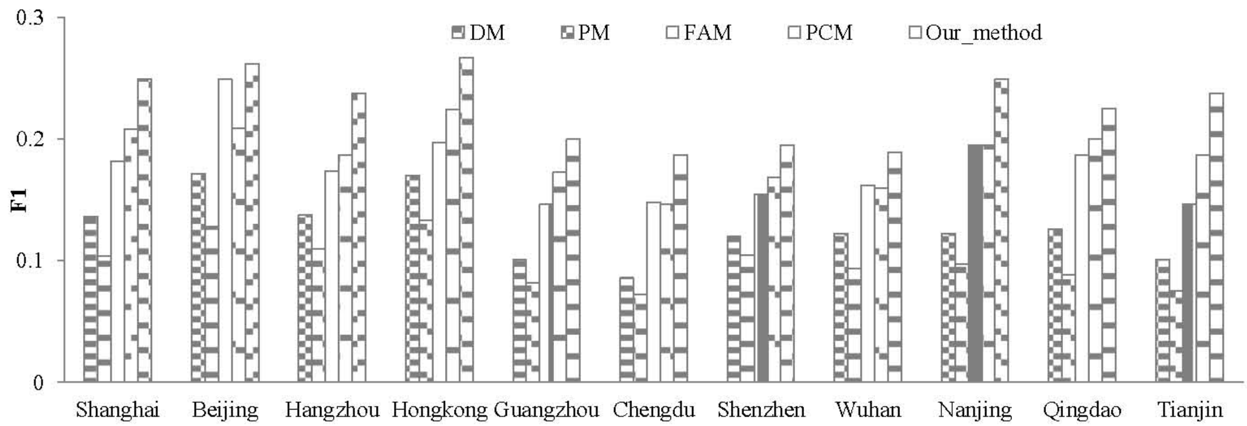
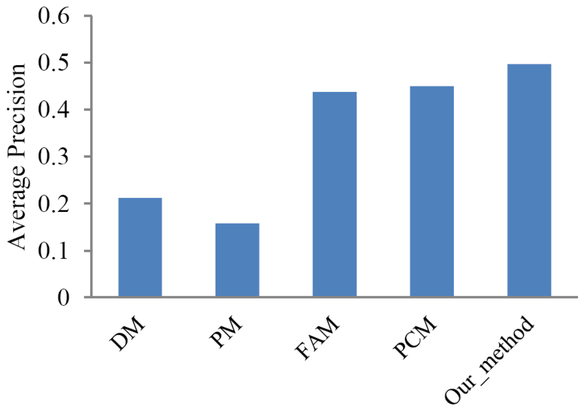


Figure 6 Comparison of F1



In Figure 7, the results show the performance of each method in terms of average precision of prediction. PM and DM give worse result, and the average precisions are less than 30%. FAM and PCM offer the similar result, and the result is better than PM and DM. The average precisions are more than 40%. These results show that considering user information (e.g., user gender or similarity information) during recommendation is better than PM and DM, which just used location information. For our method, it offers the best result. It shows our method which combines the advantage of FAM and PCM is able to find similar uses and mine the preferences of user when making recommendation.

Figure 7 Comparison of average precision (see online version for colours)



6 Conclusions

In this paper, we propose a personalised gender-aware travel locations recommendation method based on geotagged photos. First, we utilise an entropy-based measure to distinguish tour photos from non-tour photos, and discover travel locations by clustering tour photos. Second, user gender information mined from photo contents is used to build the gender-aware profile of travel locations. Third, a user-user similarity matrix is built by mining travel histories recorded in photo logs. Fourth, a recommend method that integrates gender-aware travel location profile and user travel preference similarity is used to recommend travel locations that can fit the gender-aware query of the user. The evaluation of our method is presented on a sample of publicly available photos from the Flickr dataset that contains logs and contents of photos taken in popular tour cities in China. Results show that our method is able to generate better recommendation as compared to other location recommendation methods.

In the future, our major work is to combine other users' contributed datasets (e.g., microblog) to mine richer travel knowledge. A combination with other datasets is helpful for mining the detailed descriptions of travel histories of users. It will give the tourist a substantial improvement in the precision of prediction. Additionally, more competitive recommender models need to be investigated.

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