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PERSONALIZED SEARCH FOR TRAVEL RECOMMENDATION MODEL FROM HIGH DIMENSIONAL DATABASES

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***Abstract*— The proliferation of digital cameras and the growing practice of online photo sharing using social media sites such as Flickr have resulted in huge volumes of geotagged photos available on the Web. Based on users' traveling preferences elicited from their travel experiences exposed on social media sites by sharing geotagged photos, we propose a new method for recommending tourist locations that are relevant to users (i.e., personalization) in the given context (i.e., context awareness). We obtain user-specific travel preferences from his/her travel history in one city and use these to recommend tourist locations in another city. Our technique is illustrated on a sample of publicly available Flickr dataset containing photos taken in various cities. Results show that our context-aware personalized method is able to predict tourists' preferences in a new or unknown city more precisely and generate better recommendations compared to other state-of-the-art landmark recommendation methods.**

Index Terms*— *Travel recommendation, geo-tagged photos, social media, multimedia information retrieval.

I. Introduction

The enormous growth of web and its user base has become source for large amount of information available online. This information may be helpful for users, to suggest items or services as per their preferences. Recommender system plays the role of generating suggestions by collecting user information such as preferences, interests, and locations. The research on recommender systems gained importance after the emergence of collaborative filtering [1, 2].

Various researches led to the implementation of recommender systems to different domains such as e-commerce [3], advertising [4], and tourism [5]. Generating suggestions according to user preferences is a complex task for recommender systems. Semantic web technologies help recommender systems to resolve those tasks easily [6]. Recommender system uses information from many sources to make predictions and to suggest an item for a user. Factors such as novelty, stability, and accuracy are balanced in the generated recommendations. Filtering mechanisms play an important role in the recommendation process [7].

The most commonly used filtering techniques are collaborative filtering, content-based filtering, knowledge-based filtering, and social filtering [8]. Alreadymany researches had contributed to the development of various recommender systems such asmovie [9, 10],music [11, 12], books [13], e-commerce [14–16], e-learning [17, 18], web search [19], and tourism [20]. The main aim of using personalization techniques is to generate customized recommendation according to the user preferences and interests [21]. The recommender system has an objective to filter unwanted information and to provide specific results for the particular user [22].

In the travel recommender systems [20], proposed model learns the user preferences and generates places of attractions according to the user interests. This paper focuses on the recommender systems and their application in tourism. To make this paper useful to all, including new readers of recommender systems, it covers topics from evolution to applications along with the challenges in it. Since more research is required to improve the effectiveness and efficiency of recommender systems, this paper will be more useful to the upcoming researchers to develop a user specific recommender system [14].

This paper contributes clear review of recommender systems published in scientific journals and conferences with a special focus on travel recommender systems. These systems are analyzed through the recommendation mechanism, interface, data source, and functionalities used. The paper also provides some guidelines to develop efficient, user specific travel recommender systems [16]. As a description about the methodology of collection and organization of articles for the analysis on the travel recommendation problem, a starting study was performed to focus on the most illustrative subjects and terms in the recommender system field. Initially, 105 recommender system papers were chosen from various journals and conference publications, with a higher need for current and frequently referred to articles. Next, we extricated from these papers the most considerable terms. We gave the most accentuation to decisive words, less accentuation to titles, and, at last, the minimum accentuation to modified works [5].

The paper gives a clear view on recommender systems and explains the various problems in the traditional recommender systems. Then, we have explained the development of travel recommender systems along with the techniques and interface types. Later, the location based social network was introduced and its needs and issues were explained in detail [21]. As for the part of proposed model, we have explained in depth about SPTW (social pertinent trust walker) model for category of location recommendations. For the enhancement of the proposed location recommendation model, we have introduced SPTW based group recommendation model (SPTW-GRM) for group of users. The proposed models have proved their efficiency and accuracy through evaluation metrics. The paper is organized as follows [9].

The remainder of this paper is organized as follows. Related studies on travel recommendation are reviewed in Section 2. Section 3 describes the overview of existing system. Then Section 4 introduces the proposed system and the advantages of it. The implementation and discussion of the results are analyzed in the section 5. In Section 6 the conclusions and scope for future works are drawn.

II. LITERATURE SURVEY

J. Bao, et.al., [2] learns the preferences of the users from her location history and models the preferred ideas with a weighted category hierarchy (WCH) and further approximately calculating the similarity between the two users' preferences by calculating the similarity of WCHs between the two users. This method adds to user preference modeling and managing the data sparseness problem for location recommendations.

D. M. Blei, et.al, [3] described latent Dirichlet allocation, a versatile generative probabilistic model for collecting discrete information. LDA is established on an easy exchangeability assumption for the various words and topics in a document. It is so accomplished by a straightforward application of de Finetti's illustration theorem. LDA is considered as a dimensionality reduction technique within the principle of LSI however with proper basic generative probabilistic semantics that's logical for the kind of information that it models.

A. Cheng, et.al, [4] focuses on the customized recommendation framework to provide not solely a context-aware recommendation system however also a route planning application before the journey is initiated. The personalization is achieved by adopting specific user profiles with the automatically detected people attributes (e.g., gender, age and race) along with the trips undertaken.

M. Clements, et.al, [5] predicts similar locations based on the users' geotags in a geographically remote location and view statistical enhancements over all users that visited largest cities and provides an example of efficient recommendation based on an artificial user profile and define a resemblance between the geotag distributions of two users based on a Gaussian kernel convolution. The geotags of most of the similar users are then combined to relocate the popular locations in the destined city personalized for this user.

H. Gao, et.al, [7] systematically studied the content information on LBSNs for POI recommendation and investigated various kinds of content data on LBSNs in terms of sentiment indications, user interests, and POI properties and model them below a unified POI recommendation framework. As a result, the experiment demonstrated the importance of content data in explaining the user behavior and improvement of POI recommendation performance on LBSNs.

Zheng et.al. [20] has proposed to deploy the activity correlation and location correlation of the user with regard to the location features to regularize the factorization of a location-activity matrix for location and activity recommendation.

All these approaches target issues associated with the overall plan and optimization of travel guides by relying on the available resources of knowledge. In contrast, this paper addresses a customized POI recommendation task. That is to mention those recommendations are generated by the individual preference of every user.

III. EXISTING SYSTEM

Existing studies on travel recommendation mining famous travel POIs and routes are mainly from four kinds of big social media, GPS trajectory, check-in data, geo-tags and blogs (travelogues) [25]. However, general travel route planning cannot well meet users' personal requirements. Personalized travel recommendation recommends the POIs and routes by mining user's travel records. The most famous method is location-based collaborative filtering (LCF). To LCF, similar social users are measured based on the location co-occurence of previously visited POIs. Then POIs are ranked based on similar users' visiting records [1].

A. DISADVANTAGES OF EXISTING SYSTEM

Existing studies haven't well solved the two challenges. For the first challenge, most of the travel recommendation works only focused on user topical interest mining but without considering other attributes like consumption capability [17]. For the second challenge, existing studies focused more on famous route mining but without automatically mining user travel interest. It still remains a challenge for most existing works to provide both personalized and sequential travel package recommendation [4].

IV. PROPOSED SYSTEM

We propose a Topical Package Model (TPM) learning method to automatically mine user travel interest from two social media, community-contributed photos and travelogues. To address the existing first challenge, we consider not only user's topical interest but also the consumption capability and preference of visiting time and season. As it is difficult to directly measure the similarity between user and route, we build a topical package space, and map both user's and route's textual descriptions to the topical package space to get user topical package model (user package) and route topical package model (route package) under topical package space. Online module focuses on mining user package and recommending personalized POI sequence based on user package. First, tags of user's photo set are mapped to topical package space to get user's topical interest distribution. It is difficult to get user's consumption capability directly from the textual descriptions of photos. But the topics user interested in could somehow reflect these attributes. For example, if a user usually takes part in luxurious activities like Golf and Spas, he is more likely to be rich.

We combine user topical interest and the cost, time, season distribution of each topic to mine user's consumption capability, preferred visiting time and season. After user package mining, we rank famous routes through measuring user package and routes package.

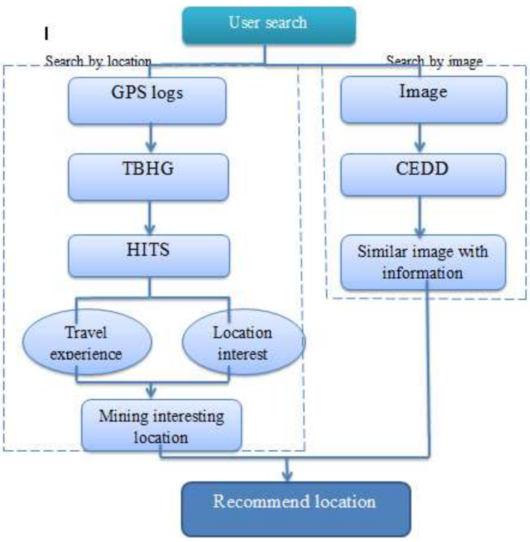

Fig.1 Architecture of proposed work

A. SEARCH BY LOCATION

The latest GPS enabled devices allow the individual to as certain their location histories with GPS records, which means human behavior and preferences based on travel. In this paper, two sorts of travel recommendations are given by casting off multiple users' GPS traces. The first kind recommends the user with prime fascinating locations and travel sequences in an exceedingly given geospatial region. The second may be a personalized recommendation that offers the user with locations matching her/his travel preference.

To model multiple user location history, Tree-Based Hierarchical Graph (TBHG) is employed. Tree based hierarchy is constructed by collecting multiple GPS logs and cluster them using density based clustering‖ so that similar points will come under same cluster.

Based on tree based hierarchical graph, Hypertext Induced Topic Search (HITS) model is developed. This is a search-query dependent ranking algorithm for information retrieval and predicts various levels of location and knowledge about travel experiences. When the user enters a probe query, in the first instance, the HITS method lists out the relevant pages returned by a probe engine and then it brings out two sorts of rankings for the enlarged set of pages. Those rankings are called authority ranking and hub ranking. In the expanded set, HITS assigns them an authority score (location that's visited by most variety of user is given higher authority score) and a hub score (user who have visited most variety of places is given higher hub score).

There are two links that are discussed—in-links and out-links. An authority is a page with a number of in-links, and a hub is a page with a number of out-links. The main idea of HITS is that it will have good hub points to many good authorities, and a good authority is referred to a number of good hubs. Thus, both authorities and hubs have a mutual reinforcement relationship.

To be very precise, the authority score of a page is the sum of the hub scores of the pages pointed to it and its hub score is the integration of authority scores of the pages pointed to it. The authority and hub scores of every page can be calculated by using a power iteration method. According to the query topic, the main strength of HITS is ranking pages, which may provide more relevant authority and hub pages.

B. SEARCH BY IMAGE

Content Based Image Retrieval (CBIR) or Query by Image Content (QBIC) is the application of computer vision technique to the image retrieval problem from the large dataset. Content-based means analyzing the data of the image rather than the metadata such as keywords, tags or description associated with the image. Content refers to colors, texture or any other information that can be derived from the image. CBIR use query technique which involves an example image that it will then base its search upon. A pre-existing image can be used by the user to search. The result images should all share common elements with the provided example. The average of color layout and edge histogram descriptor for all images is found and stored in the database. Calculate the distance of query image with that of images in the database using Euclidian distance,

H1 = Average histogram (image1)

H2 = Average histogram (image2)

Distance = sqrt [(sum (H1-H2)2)]

Examining images based on the colors is one of the commonly used methods because it does not depend on image size or orientation. Thus it will retrieve similar image with the tag information associated with it.

C. ADVANTAGES OF PROPOSED SYSTEM

1. Our work is a personalized travel recommendation rather than a general recommendation. We automatically mine user's travel interest from user contributed photo collections including consumption capability, preferred time and season which is important to route planning and difficult to get directly.
2. We recommend personalized POI sequence rather than individual travel POIs. Famous routes are ranked according to the similarity between user package and route package, and top ranked famous routes are further optimized according to social similar users' travel records.
3. We propose Topical Package Model (TPM) method to learn users and route's travel attributes. It bridges the gap of user interest and routes attributes. We take advantage of the complementary of two big social

media to construct topical package space.

V. IMPLEMENTATION

The system proposed in this paper is divided into five major modules and described as below.

1. Finding tourist locations from geotagged photos.
2. Annotation of locations with semantic.
3. Profiling locations and building a database of tourist locations.
4. Modeling users' traveling preferences and similarities among users based on their traveling preferences.
5. Making recommendations.

A. FINDING TOURIST LOCATIONS

Finding tourist locations from a collection of geotagged photos can be viewed as a clustering problem of identifying highly photographed locations. Clustering algorithms such as k-mean and mean-shift have been used to cluster photos using associated geotags for the identification of locations. However, density-based clustering algorithms such as DBSCAN have several advantages over other types of clustering algorithms: they require minimum domain knowledge to determine the input parameters and can find clusters with arbitrary shape. In addition, they can filter outliers and work effectively when applied to large databases. TPM requires only two parameters: ε (epsilon) and the minimum number of points required to form a cluster (minPts). TPM randomly selects an object and forms a range search with radius ε and iteratively finds subsequent density-reachable objects to make the cluster. DBSCAN clustering works with generic points having a unified density threshold for all clusters; however, the locations extracted by clustering the given collection of photos can have varying sizes and densities.

The extended the definition of directly density-reachable object by adding an adaptive density technique. In TPM, an object O is directly density reachable from another object O_ if it is not farther away than a given density radius ε and the ratio of surrounding objects between O and O_ must be less than a density ratio ω. Given a collection of photos P, we use TPM, in order to cluster photos to identify tourist locations based on the photos' geotags.

The output of a TPM is a set of locations (clusters of photos) L = {l1, l2, . . . , ln}. Each element l = {Pl, gl}, where Pl is a group of geographically clustered photos, and gl are geographical coordinates to represent the centroid of photos' cluster Pl and are computed from a group of geotags associated with the photos in the cluster Pl.

B. SEMANTIC ANNOTATION OF LOCATIONS

The tourist locations, identified by using a clustering algorithm on spatial proximity of photos, can be visualized on a map interface where icons or convex hull polygons can be drawn to show the position and boundaries of locations. To give semantic meanings, we provide a method that uses textual tags annotated to photos in combination with the information provided by online Web services, to automatically generate textual descriptions for each tourist location. Our method as described by algorithm-1 contains three steps.

Considering each location l = (Pl, gl) and set of tags Xl that appear with group of photos Pl, they used a method based on term frequency-inverse document frequency (TF-IDF) to score each tag x ∈ Xl. Note that, TFIDF is a popular ranking method and is widely used for information retrieval. At the end of step 1, for location l = (Pl, gl), we have a list of tags X_ l and each tag x_ ∈ X_ l has a score s(x). The higher the score, the more distinctive the tag is within a group Xl. In the second step (line 3), we use Web services, that is, Google Places (google.com/places) to extract the information about the POIs in a certain geographical area. These services work in this way: we provide them a geographical coordinate g and a radius r in meters and in response they return the metadata of places that are present within r of g. We use centroid gl of location l to represent g. The output of step 2 is the set PLACES = {place} for location l.

C. PROFILING LOCATIONS AND ACQUISITION OF USER PREFERENCES

Once the photos have been clustered using their spatial proximity to find the tourist locations, and the locations have been annotated with semantic, we are interested in formulating the profiles of locations and build a database of locations. It illustrates the method for locations' profiling. First step is to identify visits made by different users from photos taken by them on these locations (lines 1–10).

For each location l ∈ L, we sort photos of each user u according to photos' taken time.We infer visit v from a photo p taken by a user u at location l at time t. Note that a user u can take more than one photo in same visit at same location. For this, if the difference between the time-stamps of two photos taken by same user at same location in less than visit duration threshold visitthr, we consider that both photos belong to same visit. We use the median of time-stamps associated with photos (belong to visit v) as the visit time v.t.

D. MODELING USERS' TRAVELING PREFERENCES

To derive the interest of users U in a set of locations L, we use the links (set of visits V) between users U and locations L to build a weighted undirected graph GUL = (U; L; EUL; WUL), where U and L are nodes to represent users and locations, respectively. EUL and WUL are sets of edges and edge weights between U and L to represent users' visits and the number of visits to particular locations. We calculate the similarities among users based on their traveling preferences using the Pearson correlation metric and build users' similarity matrix MUU. Note that, we will use this similarity matrix MUU for personalized recommendation based on state-of-the-art user-based collaborative filtering recommendation method. Each entry in MUU represents the similarity between up and uq.

E. TRAVEL RECOMMENDATIONS

When a tourist asks for travel assistance using a tourist-assisting service in a new city, a context-aware query is generated on the basis of tourist's current contexts. We assume, when a tourist makes a request, this request can either come from a mobile device or a query is posted against the Web search engine for which local results shall be returned together with regular results. Furthermore, we suppose two scenarios for the probable contexts of query.

First, a tourist is in the target city and asking for immediate assistance. Second, he or she is planning to visit target city in the future. For both scenarios, it is required to augment the query with context. For the first case, current system time can be used to represent temporal context, whereas the current weather conditions of geographical area (target city) for which the tourist is making the request can be retrieved from weather Web services.

For the latter case, user can provide temporal information explicitly, and on the basis of that temporal information, forecasted weather conditions published by weather Web services can be retrieved. As this augmented query contains contextual information in the form of time-stamp and weather variables, it cannot be addressed directly.

We use similarity, sim (up, uq), between users up and uq as a weight to calculate the rank score for each location li. That is, the more similar up and uq are, the more weight rqi will carry in the prediction of li. Instead of using the absolute values of ratings, we use the deviations from the average rating of the corresponding user. One problem with using the weighted sum is that it does not take into account the fact that different users may use the rating scale differently. Therefore, we use an adjusted weighted sum here.

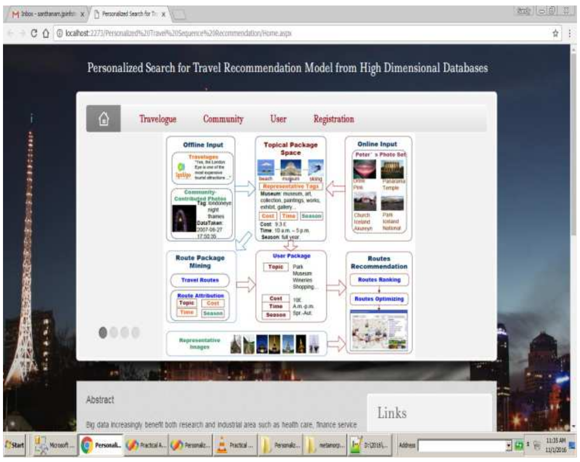

Figure 2. Home page of personalized Travel recommendation model

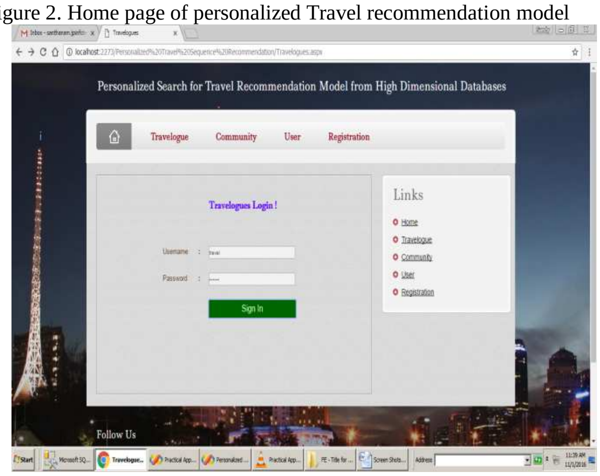

Figure 3. Traveler login page

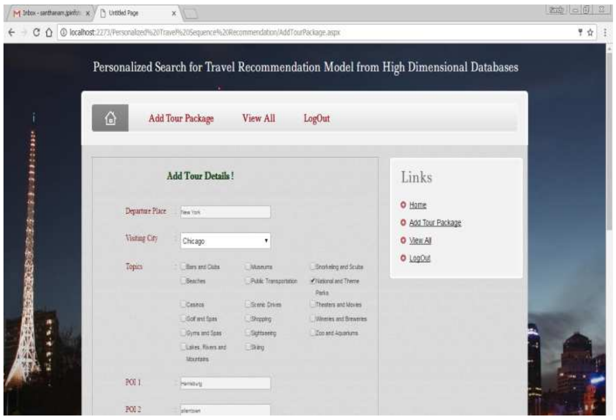

Figure 4. Search engine of personalized Travel recommendation model

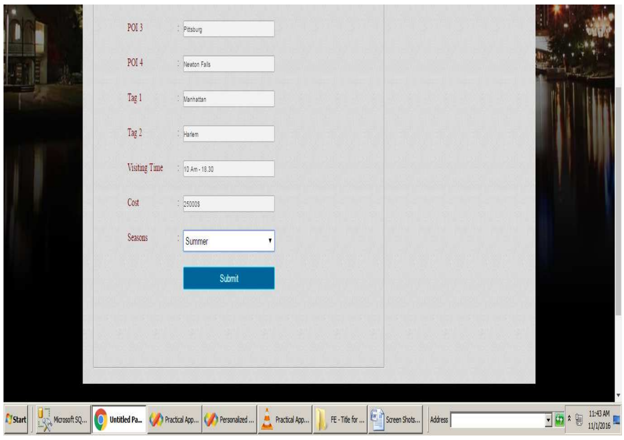

Figure 5. Searching travel data

Figure 6. Retrieved data based on Travel recommendation model

We use the public API of Flickr to collect metadata of 736,383 geotagged photos that were taken in six cities in China between 1 January 2001 and 1 July 2011. Historical weather data of these cities are collected using the public API of Wunderground. We removed the metadata of photos that were collected in the result of search based on text containing name of a city in their metadata, that is, tags, title, and description but their spatial context (latitude, longitude) did not match the geographical context of that city, and photos with incorrect temporal context. For example, we removed any photo whose upload time was identical to its taken time, because Flickr assigns a default value to photo without the taken time recorded by the camera. Statistics about photos' metadata, and spatial distribution of photos in different cities

VI. CONCLUSION

In this article, we put forward an approach to extract semantically meaningful tourist locations from geotagged social media such as photos for tourist travel recommendations. We have contributed a method that applies a collaborative filtering approach to obtain tourist's preferences from his or her publicly contributed photos and takes into account the current context of user for personalized recommendations. We presented the evaluation of our methods on a sample of publicly available photos from the Flickr dataset. It contains metadata of photos taken in various cities in China. Results show that our context-aware personalized method is able to predict tourists' preferences in a new or unknown city more precisely and generate better recommendations compared to other state-of-the-art landmark recommendation methods. We found that people's preferences with short and targeted visits are easier to predict by methods based on popularity. Performance of collaborative filtering methods based on tourist preferences improves in the case of long and real tourist visits. Moreover, considering contexts gives a substantial improvement in the precision of prediction.

A. FUTURE WORK

Our future work includes extending the same analysis to data collected from Panoramic and potentially other online social networks that allow fetching public data through their APIs. Comparisons could then be made between results obtained from Flickr and Panoramic. In addition, we consider learning more details about the users and their photo content to get further insight of the observed patterns. For example, examining users' habits like, which camera(s) they use (mobile phone/tablet vs. compact camera vs. DSLR). This might help us to categorize and qualify user behavior further to differentiate between the commuter on the way to work, the professional at work, and the tourists. Photo content analysis might contribute here as well.

We would also like to gain insight, e.g., on the number and visiting frequency of favorite spots for users of a certain class. This could assist in confirming and extending mobility models (for example, community mobility models) but also to infer behavioral context from types of places visited, and to classify users further. Finally, we are curious if the proliferation of better quality cameras in mobile phones and the continued popularity growth of photo sharing services (and maybe apps that foster virtually continuous uploading) will lead to denser data sets and thus, ultimately, allowing us to infer closer to microscopic mobility characteristics for the users after all.

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