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Personify Search for Travel Proposal from High Dimensional Databases

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Abstract:
The Paper discusses Recommendation system to give high preferred tourist locations by analyzing social networks users shared information the objectives of this study: To utilize the publicly available data from the social networking websites for understanding and analyzing the mobility behaviors of the users from different parts of the world. To present novel system architecture that is capable of addressing dynamic queries for semantically meaningful and personalized tourist location recommendations using geotagged social media. More specifically, the queries may include any or all of the contexts. To recognize the mobility patterns among the users from their travelling routines and covered distances. And furthermore, recommend the places to users based on their history of geo tagging and their travels without affecting their privacy.

Keywords: network, tourist places, history.

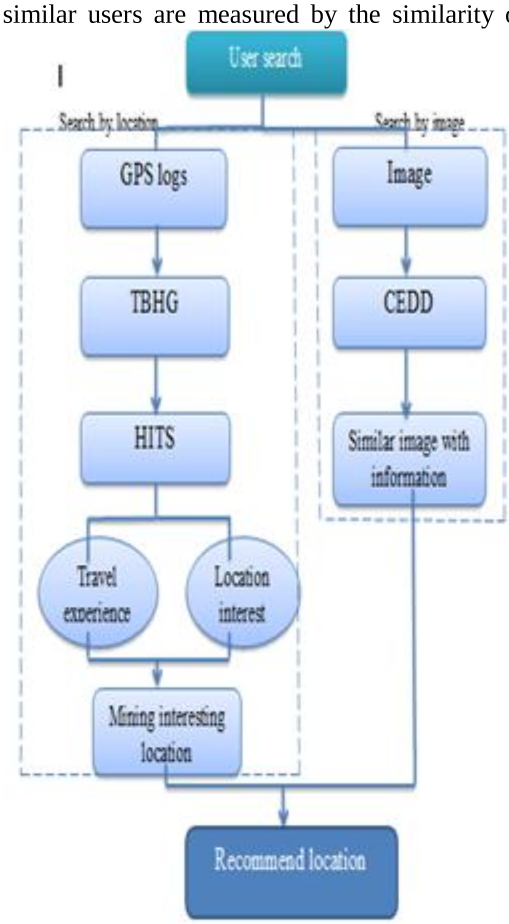
I. INTRODUCTION

The objective of data mining is to identify valid novel, potentially useful, and understandable correlations and patterns in existing data. Finding useful patterns in data is known by different names (including data mining) in different communities (e.g., knowledge extraction, information discovery, information harvesting, data archeology, and data pattern processing)[1]. Today data mining is primarily used by companies such as banking, insurance, medicine, retailing, and health care commonly use data mining to reduce costs, enhance research, and increase sales. The medical community sometimes uses data mining to help predict the effectiveness of a procedure or medicine.

The huge amounts of data generated by healthcare transactions are too complex and voluminous to be processed and analyzed by traditional methods. Data mining can improve decision-making by discovering patterns and trends in large amounts of complex data. Such analysis has become increasingly essential as financial pressures have heightened the need for healthcare organizations to make decisions based on the analysis of clinical and financial data. Data mining techniques are being increasingly implemented in healthcare sectors in order to improve work efficiency and enhance quality of decision making process.

II. METHODLOGY

We combine user topical interest and the cost, time, season distribution of each topic to mine users consumption capability, preferred visiting time and season. After user package mining, we rank famous routes through measuring user package and routes package. At last, we optimize the top ranked routes through social similar users' travel records in this city. Social similar users are measured by the similarity of user packages.



III. SEARCH BY LOCATION

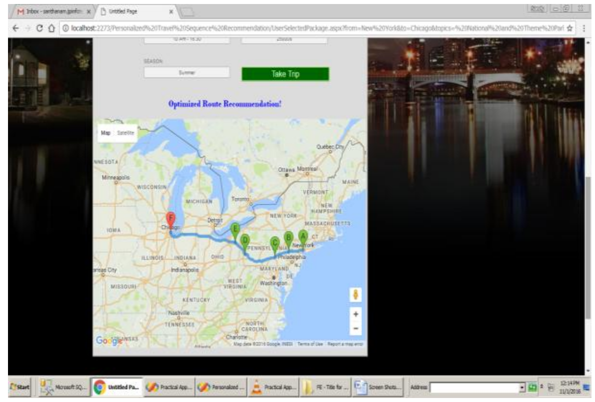
The latest GPS enabled devices allow the individual to as certain their location histories with GPS records, which means human behaviour and preferences based on travel. In this paper, two sorts of travel recommendations are given by casting off multiple users' GPS traces. The first kind recommends the 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 (HITS) search 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.

IV. SEARCH BY IMAGE

Content based image retrieval (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.



Automated Travel recommendation based on user preferences

V. DATA AND EVALUTION PARAMETERS

RESULT AND DISCUSON CONTEXT-AWARE PERSONALIZED RECOMMENDATION

In this section, we describe the effectiveness of our proposed context-aware personalized recommendation method. We explain our evaluation methodology and compare the results of our work with the existing approaches. For evaluation, we select users who have visited at least two distinct cities {Co, Ct} ∈ C, where Co represents training city and Ct is the test city. To evaluate only those users who have provided a decent amount of preference information, we consider users who have visited at least five locations in training city Co. We predict the locations actually visited by test user up∈ U in Ct, based on preferences derived from the locations visited by that user in Co. We use visits made by the test user to tourist locations in Ct to obtain (1) number of relevant locations denoted as k from total number of visits and temporal and weather contexts associated with visits to build list of contextual constraints. We use these contextual constraints to filter the tourist locations by our context-aware personalized recommendation method. We recommend k number of ranked locations using our and baseline methods. To evaluate the performance of recommendation methods for user up, we match the recommended list with the actual list of locations visited by the user in Ct. We compare the following baseline methods to show the effectiveness of our proposed personalized context-aware recommendation (PCR) method. Two baseline methods, that is, popularity rank (PR) and classic rank (CLR), result in static ranking and generate the same list of tourist locations to all users without considering individual preferences, whereas collaborative filtering rank (CFR) baseline method results in personalized ranking that generates recommendations based on individual's preferences. 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

7.2. FINDING TOURIST LOCATIONS

To detect locations from photos, we set the value of minPts= 50 photos, ε (epsilon) = 100 m, and density ratio ω = 0.5 for P-DBSCAN. The boundaries of locations in different cities summarize the information regarding the popularity of locations based on unique number of visits and visitors. To detect visits from photo taken activities, we use value of visit duration threshold visitthr = 6 hours

VI. CONCUSION

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 tourists 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.

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