Frequent Trip Mining Through Geo Tagged Photos

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A Mini-project Report

on

FREQUENT TRIP MINING THROUGH GEO TAGGED PHOTOS

carried out as part of the course Advanced Web Technologies (IT702)

Submitted by

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ABSTRACT

Photograph sharing is without a doubt one of the most trending and popular web services over the Internet. Photograph sharing sites like Flickr provide functions to add tags and geo-tags to photographs to form photo organization simple and easy. People take photographs to record those things that draws attention, geo-tagged photos are a rich source of data for data scientists and programmers for mining as these photos reflects people's unforgettable events related to locations where they have travelled. In this project, I have worked on how we can utilize publicly available geo-tagged photos to mine the frequent trips and places visited by people. This project contains five phases – firstly segmenting the photos into Collections, then detecting the city name of that segment of photos. After that we will classify the Photo Trips using machine learning tools in its type like – nature, landmark etc. The fourth phase is to mining the Photo trips using an appropriate mining algorithm. The last phases is to retrieve the description of photo trips using tags provided on photos. To implement this project, I have crawled 2500 geo-tagged photos from Flickr using *Flickr.photos.search* API for implementation. Finally, after successfully implementing this project, we got the frequent visited photo trips by the user and using this mined data, we developed a Desktop application to search for the frequently visited queries of an Area.

1. INTRODUCTION

Due to a lot of improvement in technology, now a days everyone has access to digital cameras or smartphones, which enables them to take the photographs on the go where ever they find the things or places that are attractive. So, due to reach of Camera to majority of people, individuals take the photographs very frequently to capture their memories. Moreover, due to a sudden rise in social media usage in almost all countries, people are uploading and sharing their photographs publicly in social networking sites like Instagram, Flickr, and Picasa etc. In most popular photo sharing sites like in Instagram about 40 million photos are uploaded per day while in Flickr around 2 million photos are uploaded each day. To make picture organization simple and easy, well- popular and liked photo sharing sites offer functions to assign information in the form of meta data to photos, i.e., tags and geo-tags. Tags will add descriptions that are understood by humans and geo-tags convey locations wherever the photos were captured described by their latitudes and longitudes.

Figure 1

As these geo-tagged photographs are related to locations due to longitude and latitude in them, we are able to trace people's journeys from them. We define trip as a person's movement from his/her base residence to at least one or many distant locations and returns, and define a photo trip as a collection of geo-tagged photos taken throughout their journeys. In different words, a photo trip is his/her trajectory consisting of locations and durations of stay. We conjointly define photo trip pattern that consists of a sequence of often visited locations, visit durations, and typical descriptions of the trip (represented by tags). Moreover, we estimate trip themes, i.e., people's chief objectives on their journeys like visiting a landmark or going to meeting for business purpose. Such info becomes a helpful attribute once recommending a trip to different users. So, in this project we have derived a method to find the frequently travelled places by people using publicly available photographs on social networking and photo sharing sites which contains geo-data.

In current scenario, Trip mining is very much helpful for tourism industry as we can detect what places are mostly liked by people as their holiday or travel destination. Trip mining is also useful for travellers who don’t have much time to search for places to visit during their holidays. They can check other people’s frequently visited travel destinations and from that data they can plan their tour for holidays.

2. Literature Survey

2.1 Background

During earlier phases of research, the focus was to make the collection of photos of similar events automatically using the captured time between two consecutive images. For the same, in the year 2002, Platt, J.C., Czerwinski, M. and Field, has given a method to classify user's photos into set of events through the help of captured timestamps of photographs in the research paper PhotoTOC: Automatic Clustering for Browsing Personal Photographs. PhotoTOC was an application to which user can give a collection of photographs taken during different time intervals at different places. So, based on the captured time gap between images, PhotoTOC used to classify the photographs into event sets., i.e. if captured time gap between a set of images is very small then they will come into one set of event and and then for next set of images captured time gap is huge than average local, then these images will be classified into another set of event. Loui in the year 2003 also proposed a technique for picture classification utilising a k-means algorithm based on photo captured time on his research paper. Naaman et al. and Song, Y. J., Paepcke, in the year 2004 given emphasis on the geographical vicinity of pictures for the task of photo organization and segmentation. They first of all over-segment a photograph collection using captured times, then merge segments based on the geographical property of every picture.

Similarly, in the year 2005 Cooper, M., Foote and J., Girgensohn, asked a famous photographer to categorise his five hundred photos into events, and then showed that these events partition photos contiguously in captured instances/times. The fundamental criterion of event detection of those works is common; they regard noticeable captured time gaps as the sign of a transformation of events between the two set of photographs.

2.2 Outcome of Literature survey

On all the above discussed research work, we found that there is not much efficient algorithm to classify the images more accurately based on the captured time gaps, geo-location associated with the photos in the form of latitude and longitude and additionally using the tags information of individual photos as similar type of photos may have a common tag For example a wedding ceremony may have 'wedding' or 'marriage' as a common tag in every photograph of that event. So, based on these three criteria, we came with a much more robust and better method for classifying the images of same events. After classifying the set of events with our proposed method, we can see in the literature survey that there is no much useful effort done to use these set of publicly available images to design any useful application by mining the publicly available meta data of a set of large scale images. So, in this project we have suggested few trip classifying techniques followed by mining of those trips into frequently travelled trips, so that all user's data who have shared in the form of geo-tagged photos in social media and photo sharing sites can be utilized to build a new application, which will show the travellers interest and most frequently places visited by them.

2.3 Problem Statement

In this project, using information retrieval techniques, we have to firstly collect a huge amount of source of information from large collection of geo-tagged photos uploaded by users in the photo sharing sites. The information in these photographs is stored in the form of meta data as shown below:


```
▼<photo id="2938436341" owner="66538459@N00" secret="3531ea25a6" server="3163" farm="4" title="Blue Angels" ispublic="1" isfriend="0" isfamily="0" datetaken="2008-10-11 15:37:26"
 datetakengranularity="0" datetakenunknown="0" tags="show blue san francisco air angels f18 2008" latitude="37.806473" longitude="-122.438979" accuracy="16" context="0"
 place_id="21gEXUtTVr77GYiR" woeid="2445714" geo_is_family="0" geo_is_friend="0" geo_is_contact="0" geo_is_public="1">
   <description/>
 </photo>
▼<photo id="2938432979" owner="66538459@N00" secret="d59ec2eea0" server="3147" farm="4" title="Blue Angels" ispublic="1" isfriend="0" isfamily="0" datetaken="2008-10-11 15:26:32"
 datetakengranularity="0" datetakenunknown="0" tags="show blue san francisco air angels f18 2008" latitude="37.806473" longitude="-122.438979" accuracy="16" context="0"
 place_id="21gEXUtTVr77GYiR" woeid="2445714" geo_is_family="0" geo_is_friend="0" geo_is_contact="0" geo_is_public="1">
   <description/>
```


Figure 2

From this source of information, we have to make the cluster or group of images which share common property like captured date, time, geographical location along with the common tags (if available) into one event and then using various classifying and data mining techniques, we have to make a platform in which we can access this data in a generalized manner.

2.4 Objectives

The objective of this project is to utilize the large scale publicly available information uploaded by billions of users in the form of images over Internet in social networking and photograph sharing sites like Flickr, Picasa etc. and use this source of information to build a new application which may be a desktop application or web application to answer the frequently travelled destinations on entering the home location of the user.

3. Methodology

3.1 Photo Collection Segmentation

The common concept of conventional strategies for event/occasion detection from a photograph collection is to use the gaps of captured times. Which may be due to the fact that the location information of photos was unobtainable at that time. The transition of photograph capturing locations instantly reflects individual's movement, and therefore can be an important major to strengthen the accuracy of event Detection algorithm. In addition, tags assigned to every photograph well describe the travel trip, like reminiscent of landmarks and folks captured. Furthermore, users tend to assign identical tags on a number of consecutive snap shots, which ought to enforce the photo collection segmentation algorithm.
As a result, we tend to use captured time gaps, location gaps between photos, and tags on photo collection segmentation.

Furthermore, PhotoCollectionSegmentation algorithm can be divided into three parts:

i. Calculating the value of time gaps between the photographs :
    - Sort the photos according to time and date taken either in ascending or descending order.
    - Time gap between two consecutive photos pk and pk+1 is given by :
      TimeGap = $\log(t_{pk+1} - t_{pk})$,
      Where, t_{pk+1} = capture time of pk+1 photo
      t_{pk} = capture time of pk photo.

ii. Now calculating the value of distance gaps between two images through the help of longitude and latitude between them.

$$distance_{gap} = log\ (D\varphi),$$

$$\varphi\ [rad] = 2\,arcsin\left(\sqrt{\sin^2\frac{\Delta\delta}{2} + \cos\delta_{p_{k+1}}\cos\delta_{p_k}\sin^2\frac{\Delta\lambda}{2}}\right).$$

iii. After that we can calculate the value of Tag gap as below :

$$tag_{gap} = 1 - \begin{cases} \frac{|\mathbb{L}_{p_k} \cap \mathbb{L}_{p_{k+1}}|}{|\mathbb{L}_{p_k}|} & (\text{if } |\mathbb{L}_{p_k}| > 0) \\ 0.5 & (\text{else if } |\mathbb{L}_{p_k}| = |\mathbb{L}_{p_{k+1}}| = 0) \\ 0 & (\text{otherwise}) \end{cases}$$

Here is an example of how sets are formed while photo collection segmentation phase from the large collection of photos. In first set and second set there are photos of two difference events. First event is of an International conference while second event is a cluster of photos of research lab. Here our algorithm has clustered the photos into two different sets even though as there are many common tags between two events but the distance and time gap is very huge between them. Moreover, in the third event, there is a very less time and distance gap in comparison to first two events, but here tags are different and that's why our Photo Collection and Segmentation algorithm has clustered those set of images into a new event, in which the same user has gone to some family nature trip.

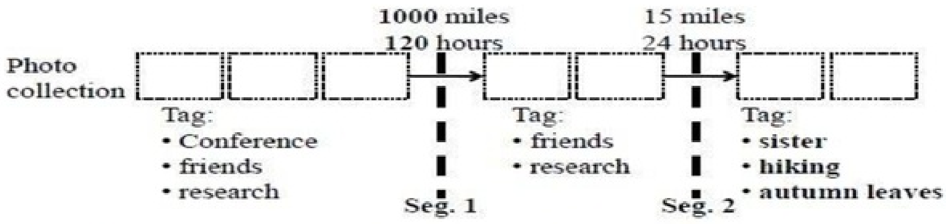

Figure Example of photo collection segmentation

Figure 3

3.2 City Name Detection

As the photos that we have crawled here are only geo-tagged photos, so from the meta description of the photos, we already have the longitude and latitude of each photograph. Using the longitude and latitude of every photograph, we can easily detect the name of the place where that photo has been taken, but here through longitude and latitude we will get a lot of information using any API including local address of location, street and Parish followed by the name of Town and City. And at last we can also get state name along with country name as shown in the figure below. But here for our frequent trip classifier application we are only considering the name of the city where that photograph was taken either using Google's API or through any other freely APIs.

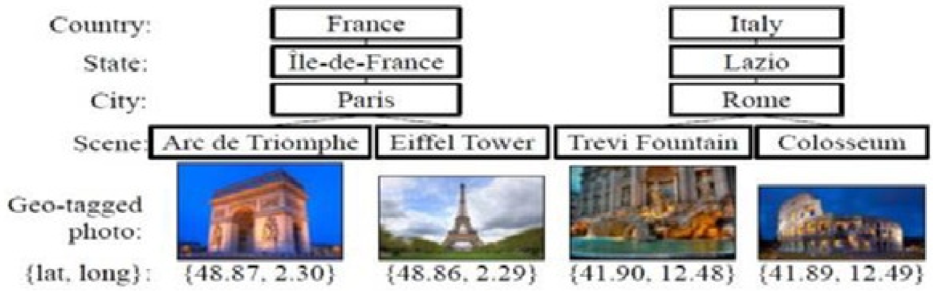

Figure Geographical hierarchy of photo trip: a trip from Paris to Rome

Figure 4

3.3 Photo Trip Classification

i. Categorizing the trips into their respective theme.

We have classified a trip in basically six categories to detect the type of trip visited by users, though these trips may be classified into more category other than discussed here.

Landmark: visiting famous landmarks, *e.g.*, famous sightseeing spots and world heritages, such as the Louvre museum and the Great Wall of China.

Nature: visiting places famous for rich nature, such as Niagara Falls in Toronto and national parks, to commune with nature.

Gourmet: visiting places to taste delicious foods, such as Pizza in Napoli.

Event: visiting places to attend an event, such as Zombie Walk in Vancouver and a wedding ceremony.

Business: visiting places with business oriented aims.

Local: including small and daily trips to nearby areas, such as getting together with friends at a local bar and taking a daughter to a nearby beach.

After defining the various types of user trips, we implement a classifying algorithm which can detect the type of trip automatically given a set of photo trips. Also make sure that, Trips visiting the same city or location may come under different type of themes, for example, suppose we have a location Chandni Chowk in New Delhi, then there people may go to any famous Gourmet (that should be categorize under Gourmet category) or people may come for shopping (which should be categorize under local event category) while few people may come for any business work (under business category).

But in the implementation of our project, we are classifying one trip into only a single category, which means there is a one-to-one mapping among a photo trip and trip type. Classifying a trip into with multiple types of themes is not covered in this project but it can be extension of our project if we add the same. Moreover, is it also possible that few people travel to a place with multiple objectives, for example – if any IEEE conference is organize at NITK Surathkal, then people may come here for attending the conference but after attending the conference they may visit to NITK beach. So, here there is a possibility to visit a place with more than one trip theme, but in our algorithm we have not considered this situation. In future work, we may include these additional features in our project.

ii. Classifier Used :

To classify the trip themes into its type, we are using linear Support Vector Machines (SVMs). Here we are using the multi class SVM classifier as the trip themes are more than two, so sequential minimal optimization (SMO) algorithm proposed by Platt's is used here to classify the events using a machine learning tool – Weka. Firstly, to train the Support Vector Machines (SVMs), we manually assigned the class label to a chosen set of dataset. Considering we tend to classify trip journeys into six classes, we tend to train a separate SVM for each of the trip themes. To perform image trip classification on a test set, we tend to run each of the six classifiers on a photo trip and select the class with the absolute best ranking (finest confident distance from the SVM's separating hyper-plane). We split the labelled pic visits into training and testing sets by partitioning pic visits of the same users so as to avoid the likelihood that similar pic visits of the same person seem in each test and training sets.

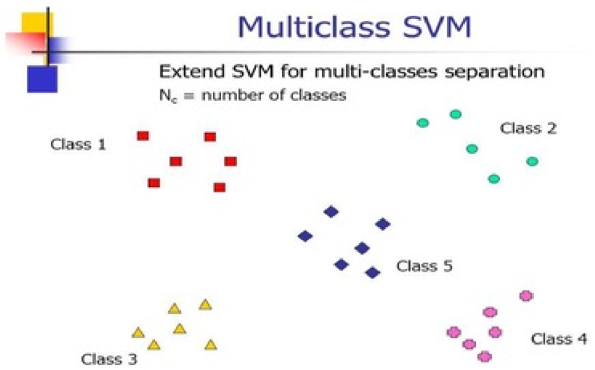

FIGURE 5

3.4 Photo Trip Pattern Mining

To mine the frequent trips travelled by users, we have used a very popular frequent pattern mining algorithm known as Apriori algorithm. Apriori is a very useful algorithm for mining frequent item sets and association rule learning over transactional databases. It proceeds by distinguishing the frequent character objects within the database and extending them to bigger and bigger item sets as long as these item sets seems sufficiently most often within the database. The pseudo code for the Apriori algorithm is given below:

Apriori(T, ϵ)

    $L_1 \leftarrow \{\text{large } 1 - \text{itemsets}\}$

    $k \leftarrow 2$

    while $L_{k-1} \neq \emptyset$

        $C_k \leftarrow \{a \cup \{b\} \mid a \in L_{k-1} \wedge b \notin a\} - \{c \mid \{s \mid s \subseteq c \wedge |s| = k-1\} \nsubseteq L_{k-1}\}$

        for transactions $t \in T$

            $C_t \leftarrow \{c \mid c \in C_k \wedge c \subseteq t\}$

            for candidates $c \in C_t$

                $count[c] \leftarrow count[c] + 1$

        $L_k \leftarrow \{c \mid c \in C_k \wedge \ count[c] \geq \epsilon\}$

        $k \leftarrow k + 1$

    return $\bigcup_k L_k$

Apriori Algorithm pseudo code

3.5 Trip Description Detection

It is the last phase of our algorithm, in which we extract the typical descriptions of each photo trip pattern using the tags assigned to the group of photos. Our algorithm is based on the TF/IDF technique, assuming that tags that primarily occur in photos captured in a trip pattern and do not frequently occur in others are more representative to the pattern. Since we associate tags with locations visited during the trip pattern, tags have geographical scales to cover, where some tags cover specific areas (they can also be termed as local tags) while others cover a global area (which can be termed as as global tags). For e.g., a local tag "wegas" covers Las Wegas, while a global tag "bakery" covers almost all of the world. We aim to detect trip descriptions, which represent characteristics of a trip pattern, and thus global tags are not appropriate as trip descriptions. Furthermore, excessively popular local tags, such as an abbreviation of a city name, are not informative. Therefore, we design the algorithm to filter out overly common local tags and select characteristic tags for the pattern.

4. Implementation

4.1 Work Done:

1) For implementing this project, we have implemented many parts in phases. First part is to collect the data set by crawling Flickr images using the Flickr API manually. After collecting the dataset we pre-processed it by converting xml file into a complete CSV file and we removed unwanted attributes which were containing irrelevant information with respect to our project. After pre-processing the data set we moved for implementation of our first algorithm knows as Photo Collection Algorithm, which we have discussed above in detail. Through the help of this algorithm, we got multiple sets of images of many events.

2) Then at second step we determined the city name of each event where the photographs are taken through the help of latitude and longitude of images.

3) After detecting the events and associating the city names with all the events, our next work was to detect the trip theme of every event. For detecting the trip

theme of each event, we used open source tool Weka, and classified the trip themes through SMO (which is already predefined in Weka tool) for trip theme classification.

4) Now we have a set of events, name of cities associated with those events and the type of trip theme for each event in a city. Our next work is to mine the frequently occurring events from the set of events. To do this task, we used Apriori algorithm and we done our apriori algorithm implementation in Python language whose pseudo code is already given above. Through Apriori algorithm we got a set of most frequently visited travel destinations (locations) when we given an appropriate support value.

5) Now from the above set of frequently visited locations, we extracted the meta tags and description from the collection of photographs taken at that places.

4.2 Results and Analysis

After implementing all the algorithm above, we discovered the knowledge from mined data, in which we got all the frequent trips visited by the users that were present in our data set. So, this information can be very useful for building our desktop application in which user gives a query entering his/her home location or the location from where user wants to check the frequently travelled destinations by the other users. So for the same purpose we build and GUI based desktop application as shown below in which user can search for the frequently travelled trips from any city that are available in database and after that user can select the theme type i.e. the the type of trips in which he is interested to search.

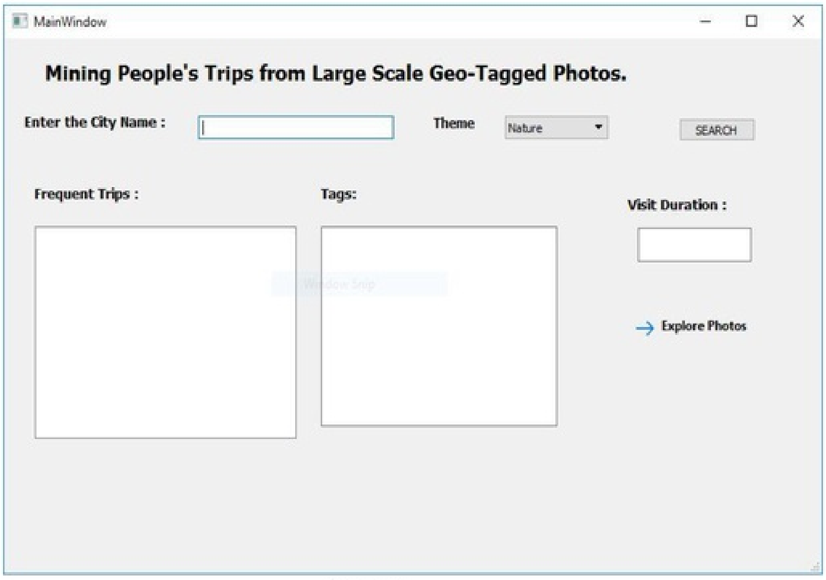

Figure 6

After executing the search query, user can get a set of results fetched from database of frequently travelled destinations or trips from user's home location, which are mined from publicly available photographs over the social networking and photo sharing web sites. Below is a screen shot of our application in which a user has entered his home location as "San Francisco County" and after that he has selected the theme as "Nature". On clicking on the search button, Frequent trips travelled by different users from his location are generated in a text box whose label is Frequent Trips. On selecting any frequent trip from the text box, in the next field it will display the common tags associated with most of the photos of that trip or event. These tags are also retrieved from the meta data of publicly available photographs. Furthermore, along with Tags associated with that particular trip, our application is also displaying the number of visit durations for that particular trip.

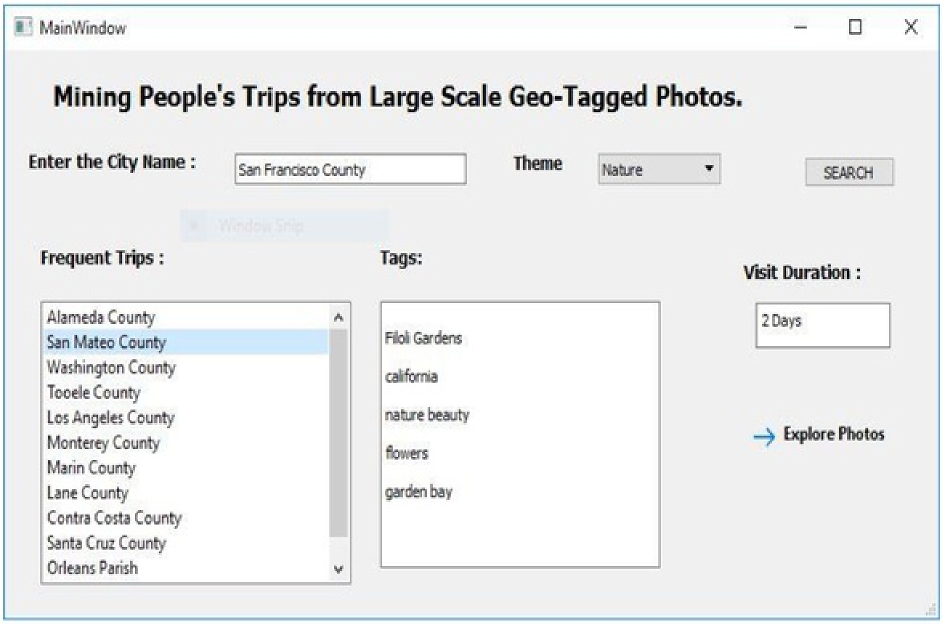

Figure 7

In our Trip Mining application as shown in the above demo image, we have also added the option of exploring the photographs of any trip. For that, we have called the default web browser of user to display the photographs of that place in web browser in accordance with the type of theme automatically on clicking the "Explore Photos" button, as shown in the below image. Here we can see that our application has automatically called the default web browser and applied a search query whose values are taken from the frequent trip box and nature of theme. In our query, we have taken the theme type as "nature", so in the below it is displaying the nature's images related to that particular city or location.

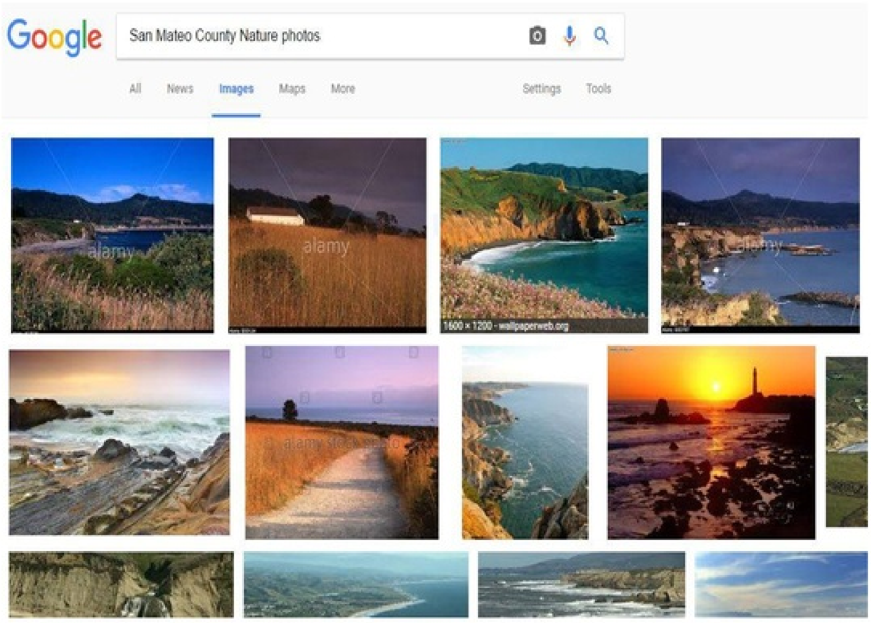

Figure 8

5. Conclusion and Future Work

In this project we crawled 2500 Flickr images manually from the Flickr website manually and after applying various algorithms like Photo Collection and Segmentation, Support Vector Machines for classifying the type of theme detection, Apriori Algorithm for finding frequent patterns we mined the publicly available data and came with useful result.

Taking trip on vacation or taking journeys is a wellknown global leisure endeavor. Nonetheless, it's challenging to arrange a satisfactory trip. Individuals might discuss with travel agencies and search the Internet to survey what to ascertain and what to try and do to fulfill their wishes on journeys. At this stage, journey blogs and comments on travel forums are sensible info, since they're based on actual trip experiences. Nevertheless, such data isn't organized, and so individuals have to be compelled to check several blogs and comments to verify these experiences are reliable and match with their needs. Our frequent photograph trip patterns will give a better solution for this drawback.

The above given Figures shows an example application built in Python. Users will search frequent picture trip patterns , that are supported people's real trip experiences, by querying their home city address, preferred trip period, and choosing their trip themes, i.e., what they expect on their journeys. The above application shows frequent trip patterns well-mined from geo-tagged photos collections as visited cities, typical visit durations, and descriptive tags to point out their excessive spots or popular spots.

In future work, we can expand our work to include the multiple trip objectives while visiting a place or city. Along with that, we can also consider on categorizing the trip themes of a place into more than one trip theme type. We can also discover further contexts of trips from photographs, that aren't associated by tags, from physical contexts (such as weather of the place and current temperature is appropriate for visiting or not) to situational contexts (such as how many percentage people are there and who is the main character within the trips). For future work, we might wish to extend our algorithms to create use of exposure contents to complement the detected trip information.

References

Frequent Trip Mining Through Geo Tagged Photos

ORIGINALITY REPORT

%15	%0	%15	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Arase, Yuki, Xing Xie, Takahiro Hara, and Shojiro Nishio. "Mining people's trips from large scale geo-tagged photos", Proceedings of the international conference on Multimedia - MM 10 MM 10, 2010. Publication	%15

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