Automated Adaptive and Sequential Recommendation of Travel Route

Swaroopa V Dugani[#1], Dr. Sunanda Dixit[*2]

[#]M. Tech in CSE, DSCE Bangalore
Dayanand Sagar College of Engineering, Bengalore, India

Abstract *Big data has deeply rendered into both research and commercial fields such as health care, business and banking sectors. Automated Adaptive and Sequential Recommendation of Travel Route handovers automated and adaptive travel sequence recommendation from large amount of travel data. Unlike any other travel recommendation methods, this method is not only automated but it is personalized to user's travel interest and also it is able to recommend a travel sequence rather than individual Points of Interest (POIs). This method has large amount of travel data which includes different places, the distributions of cost, visiting time and visiting season of each topic is mined to bridge the gap between user travel preference and travel routes and we also have topical package space. In order to get extensive impression and much better view points of the user topical package model and user travel route, we have made use of the community contributed photos in addition to travel data.*

Keywords — *Points of Interest (POIs), Topical Package Space, Community Contributed Photos, User Topical Package, GPS, DFD, BTV.*

I. Introduction

Automatic travel recommendation is important problem in different industries like research, big media, social media etc. especially in the field of social media which offers great chances to address many challenging problems like GPS location estimation, and constraint based travel recommendation. Different Travel websites (e.g., www.holidify.com) offer rich descriptions about places which includes best time to visit, estimated cost of the travel, distance and user experience written on blog pages. Community-contributed photos on social media include the metadata which involves tags, date taken, latitude, longitude etc. it maintains the record of users' daily life and travel experience. These data are useful for mining POIs (points of interest), travel routes mining as well as this information provides an opportunity to recommend personalized travel POIs and routes based on user's interest.

There are two main challenges for Automated Adaptive and Sequential Recommendation of Travel Route. First recommended POIs must be personalized to user. These POIs can be mined by mapping POIs with user interest. Each user may prefer different POIs hence it is important to understand the user interest. Take Bangalore as an example. Some people may prefer places like the Museums, while others may prefer the places of adventures or activities. Along with places, route recommendation also includes attributes like location, best time to visit, opening and closing times, category, cost and distance. These may also be helpful to provide personalized travel recommendation [1].

Second challenge is it is important that recommended POIs must be in sequential order rather than individual POIs. It is time consuming and far more difficult for users to plan travel sequence based on their interests and opening, closing times this is because relationships between interested POIs and opening times of the location are considered. Existing studies on travel recommendations mine travel POIs and routes from GPS trajectory, check-in data, geo-tags and blogs (travelogues) these are four kinds of big social media.

However, existing travel route planning cannot well meet users' personal requirements. Whereas this method recommends the POIs and routes by mining user's travel records, Co-occurrence of previously visited POIs, and user interests. The existing methods related to travel sequence recommendation did not consider the personalization and popularity of travel routes at the same time. Routes (e.g., consumption capability, preferred season, etc.) have not been mined automatically. To solve these problems, in this paper, first, topical package is modelled to get users' and routes' multi attributes (i.e., interest, cost, best time to visit).

Following figure shows the results of existing system. Here user is provided with ser of personalised roots based on time constraint keeping it as first priority. User interested POIs are grouped together and named as user topical model.

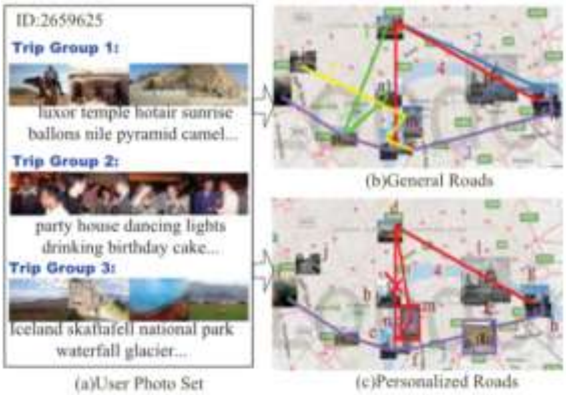

Fig 1. Output of existing system architecture

II. Literature Survey

Always social media have emerged continuous needs for automatic travel recommendations. Collaborative filtering (CF) is the most well-known approach. However, existing methods generally suffer from various weaknesses. For example, sparsity can significantly degrade the performance of traditional CF. If a user only visits very few locations, accurate similar user identification becomes very challenging due to lack of sufficient information for effective inference. Moreover, existing recommendation approaches often ignore rich user information like textual descriptions of photos which can reflect users' travel preferences. The topic model (TM) method is an effective way to solve the "sparsity problem," but is still far from satisfactory. In this paper, an author topic model-based collaborative filtering (ATCF) method is proposed to facilitate comprehensive points of interest (POIs) recommendations for social users. In our approach, user preference topics, such as cultural, cityscape, or landmark, are extracted from author topic model instead of only from the geo-tags (GPS locations) [2].

In case of recommending friends and locations based on individual location history, focus is on personalized friends and geographical information system (GIS). First, a particular user's visits to a geo-space region in the real world are used as their ratings on that region. Second, Similarity between users is measured in terms of location histories. Third, Individual's interests of unvisited places are estimated. This is called as hierarchical-graph-based similarity measurement (HGSM) which is used to model individual's location history and to effectively measure the similarity between the users [3].

User check-in data is available in large volume through local based social networks (LBSN) that gives information about different places. Here aim is to recommend the POIs which user has not visited before. Based on the observation made (i) users tend to visit nearby places and (ii) user tend to visit different places at different time slots and in same time slots they tend to repeatedly visit same places. Focus is on the problem of time-aware POI recommendation. Geographical-Temporal influences Aware Graph (GTAG) is used to model user records, geographical influence and temporal influence [4].

Trip planning is time consuming due to trip requirements and lack of tools to assist the planning. Even if tools are available they do not meet the user requirements. Here travel path search is made with the help of geo-tagged images to assist the tour planning not only where to visit but also how to visit. Geo-tagged images include large amount of metadata which can be used to mine travel path from previous user history. Search system involves various queries like (i) a destination name, (ii) a user specified region on map, (iii) a user preferred locations. Users are made to interact with system to specify region or interest point [5].

In current days it is common for people to share sightseeing experience through blogs. These blog entries contain valuable information with which one can learn the various aspects which is not specified in the website. Bloggers post text, images and videos this helps to extract the popular places. This system works as automatically generated travel guide [6].

User interest matters when it comes to visiting the tour spots. These travel spots are geo-graphically distributed under different atmospheric conditions. Topic extraction involves location, season, and mode of transport. Locations are filtered by season (summer, winter etc) this filtered set is again estimated by mode of travelling. This package goes one step near to customer satisfaction [7].

Problem of automatic travel route is solved by using large amount of geo-tagged images. With this customized trip plan can be provided to users this is well known destinations to visit, order of visiting the destinations, time arrangement in the destination. Users are also allowed to specify time, season, and preferred locations of visiting in an interactive manner to guide the system [8].

In case of Mining and Visualizing Local Experiences from Blog Entries, visitor's web blogs are extracted in order to visualize the activities of visitors at sightseeing spots. Association rules are used between locations, time periods and experiences. Local information search system enables user to specify a location, type experiences and time period in a search query and find relevant wed content [9].

III. Working Module

DFDs are used to represents the work of entire system at a glance. This demonstrates the interactions between process and external entities. Following figure shows the overall system DFD.

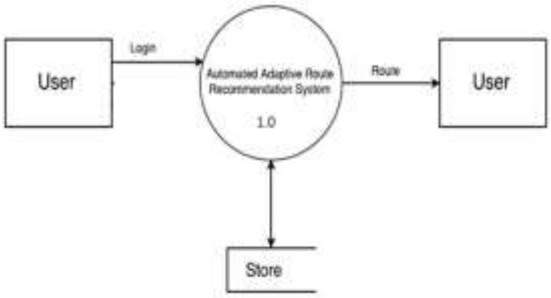

Fig 2. Context Level DFD

Travel route recommendation is automatic and adaptive because it meets the user expectations means that all the recommended routes will be according to user point of interests these rotes can be called as personalized rotes this is important to focus on user POIs because different users have different preferences.

This is also Sequential Route recommendation as it follows sequential pattern to recommend routes. It is far more difficult and time consuming for users to plan travel sequence than individual POIs because the relationship between the locations and opening time of different POIs should be considered. For example, it may still not be a good recommendation if all the POIs recommended for one day are in four corners of the city and not in sequential pattern, even though the user may be interested in all the individual POIs.

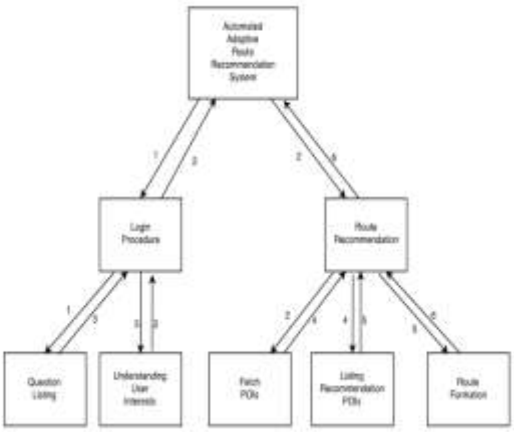

Fig 3. Structure Chart (1: Login, 2: Interests, 3: Q Results, 4: POIs, 5: Personalised POIs, 6: Route)

Structure chart is used to document the structure that makeup the system. It is a tool used to guide developers to ensure that all parts of the system work as intended in relation to all the other parts. All the nodes at the bottom of the chart are the working modules. If the problem is complex, the problem is sub-divided into sub problem. If the sub-problem is still complex then the problem is still divided into sub problems.

IV. Existing System Vs Proposed System Architecture

Following figure shows the existing system architecture. This has offline module and online module. In offline module topical package space is mined from social media and then route package is mined by mapping travelogues related to POIs on the route of the topical package space. Route package mining itself is online module [10].

Fig 4. Existing System

In existing system routes are mined by formulating the mapping between travelogues' POI and topical package module in order to recommend the personalised route [11]. Since the POIs are mined from travelogues based on the popularity, recommended POIs does not well meet the user's personal interests.

.

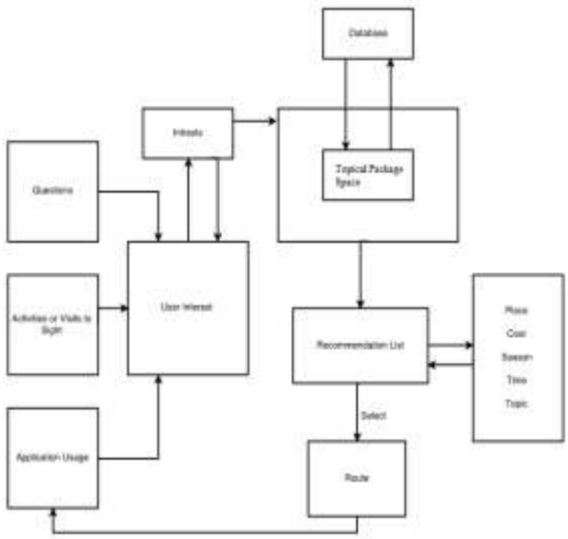

Fig 4. Proposed System Architecture

In our work, User interests are gathered by interacting with users. Users will be given with set of questions; these Q Results are mapped with database to obtain the personalised POIs. Following figure shows the architecture of proposed system

In existing system topical package space includes only route mining but in proposed system topical package includes readily available mapped results. These results can be further used formulation of Recommendation List.

V. CONTRIBUTION OF TOPICAL PACKAGE AND POIS MAPPING

Topical package model includes the mapped results. Actual mapping is performed between Qresults and different places that are priorly stored in the database.

Whereas this database includes many aspects such as location, time of opening and closing, best time to visit (BTV), cost, category, image of the particular place and description of the place.

Intern category has varieties like sightseeing, hillstation, resorts, heritages, waterfronts, shopping, adventurous places etc. Similarly BTV represents best time to visit the place it has aspects such as early morning, morning, evening, summer, winter or rainy etc.

Qresults include Y/N type of answers these are mapped with categories in order to understand the user interested categories. Then observation is performed which includes retrieving the places of selected categories. Based on this recommendation list is prepared. Out of this list used is again asked to select the places where he wishes to visit. Then the optimized route is returned.

Routes are recommended keeping time of opening as first priority. Consider an example: if Vidhan Soudha's opening time is 1:00 pm and Lalbagh's opening time is 9:30 am, user is first directed to Lalbagh and then to Vidhan Soudha. Second priority is given to distance. We make use of Google Maps. Places coordinates are stored priorly in the database and user is allowed to enter the current location. Current location's coordinates are formulated against pre-stored coordinates of places. Then the final route is obtained.

Flow chart is visual representation of the sequence of steps and decisions needed to perform a process. User details are collected from the user and then fed into User Topical Package Modelling. In User Topical Package Modelling stage User will be asked with set of questions and defined Q Results will be mapped with travel data to understand the user interest. Based on interests POIs are fetched. POIs are then displayed onto recommendation list to obtain the Personalised POIs. Personalised POIs are used in route formation to output the personalised route. This method may not hold good if all interested POIs are in four different corners of the city even though the user is interested to visit POIs.

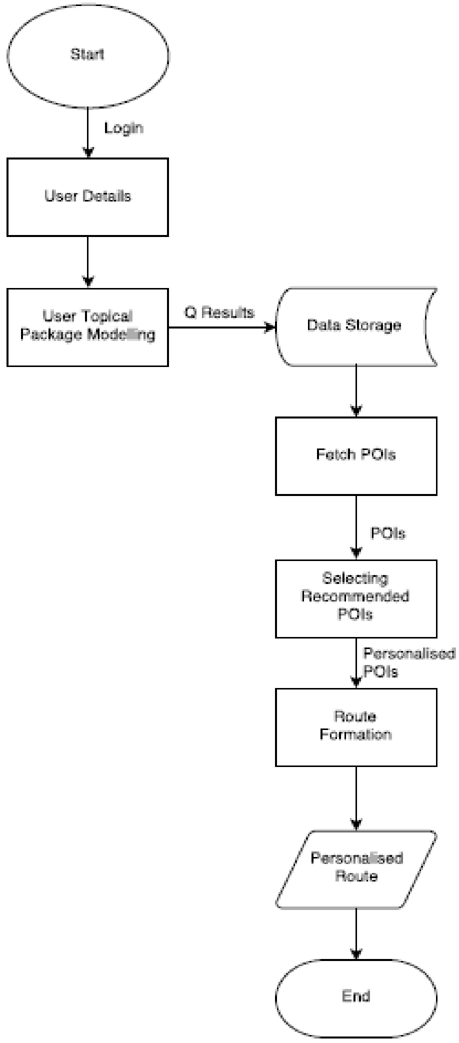

Fig 5. Flow Diagram

VI. CONCLUSION

Extensive experiments on fixed dataset show the effectiveness of the proposed framework. In this paper, we understood the working of a personalized travel sequence recommendation system by learning topical package model. Advantages of our work are 1) the system automatically mines user's topical preferences including the cost, time and season, 2) Along with POIs, travel sequences are also recommended considering time and user's travel preferences at the same time. But there are still some limitations of the current system. First, the visiting time of POI mainly presented the open time through travelogues, and it was hard to get more precise distributions of visiting time. Second, the current system only focused on POI sequence recommendation and did not include detailed information, which would be more convenient for travel planning. In the future, we aim to enlarge the dataset, and thus we could leverage the recommendation system to different cities. We plan to utilize more kinds of social media to provide more precise distributions of visiting time of POIs and the context-aware recommendation.

REFERENCES

[1] Shuhui Jiang, Xueming Qian, "Personalized Travel Sequence Recommendation on Multi-Source Big Social Media", IEEE Transaction on big data, vol 2, no-1, january-march 2016

[2] S. Jiang, X. Qian, J. Shen, Y. Fu, and T. Mei, "Author topic model based collaborative filtering for personalized POI recommendation, "IEEETrans.Multimedia,vol.17,no.6, pp.907–918,Jun.2015.

[3] Y. Zheng, L. Zhang, Z. Ma, X. Xie, and W. Ma, "Recommending friends and locations based on individual location history," ACM Trans. Web, vol. 5, no. 1, p. 5, 2011.

[4] Q. Yuan, G. Cong, and A. Sun, "Graph-based point-of-interest recommendation with geographical and temporal influences," in Proc. 23rd ACM Int. Conf. Inform. Knowl. Manage., pp. 659–668, 2014.

[5] H. Yin, C. Wang, N. Yu, and L. Zhang, "Trip mining and recommendation from geo-tagged photos," in Proc. IEEE Int. Conf. Multimedia Expo Workshops, pp. 540–545, 2012.

[6] H. Kori, S. Hattori, T. Tezuka, and K. Tanaka, "Automatic generation of multimedia tour guide from local blogs," in Proc. 13th Int. Conf. Adv. Multimedia Modeling, pp. 690–699, 2006.

[7] M. Clements, P. Serdyukov, A. de Vries, and M. Reinders, "Personalised travel recommendation based on location co-occurrence," arXiv preprint arXiv:1106.5213, 2011.

[8] X. Lu, C. Wang, J. Yang, Y. Pang, and L. Zhang, "Photo2trip: Gen- erating travel routes from geo-tagged photos for trip planning," in Proc. Int. Conf. Multimedia, pp. 143–152, 2010.

[9] Y. Pang, Q. Hao, Y. Yuan, T. Hu, R. Cai, and L. Zhang, "Summarizing tourist destinations by mining user-generated travelogues and photos," Comput. Vis. Image Understanding, vol. 115, no. 3, pp. 352–363, 2011.

[10] The IEEE website. [Online]. Available: http://www.ieee.org/.

[11] L. Cao, J. Luo, A. Gallagher, X. Jin, J. Han, and T. Huang, "A worldwide tourism recommendation system based on geotagged web photos," in Proc. IEEE Int. Conf. Acoust. Speech Signal Process. pp. 2274–2277, 2010.