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# Keyword Aware Representative Travel Route Recommendation with Places of Interest

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**ABSTRACT:** With the popularity of social media (e.g. Facebook and Flicker), users can easily share their check-in records and photos during their trips. In view of the huge number of user historical mobility records in social media, proposed work aim to discover travel experiences to facilitate trip planning. When planning a trip, users always have specific preferences regarding their trips. Instead of restricting users to limited query options such as locations, activities or time periods, proposed system consider arbitrary text descriptions as keywords about personalized requirements. Moreover, a diverse and representative set of recommended travel routes is needed. Prior works have elaborated on mining and ranking existing routes from check-in data. To meet the need for automatic trip organization, this work claim that more features of Places of Interest (POIs) should be extracted. Therefore, an efficient keyword-aware representative travel route framework is proposed that uses knowledge extraction from users' historical mobility records and social interactions. Explicitly, keyword extraction module have designed to classify the POI-related tags, for effective matching with query keywords. A route construction algorithm is used to construct route candidates that fulfil the requirements. To provide befitting query results, association mining concept have used. To evaluate the effectiveness and efficiency of the algorithms, proposed system have conducted experiments on location-based social network datasets.

**KEYWORDS**: GPS(Global Positioning System), LBSNs (Location Based Social Networks), points-of-interest (POIs), checking in, Association rule mining, Apriori algorithm

### I. INTRODUCTION

Even though there are numerous tourism websites and travel agencies to provide various travel packages, tourists just become puzzled about how to make a choice and neither could they adjust the travel plan. Besides, if tourists try to arrange the travel route by themselves, tremendous information is easy to exhaust them when considering the location interest, visiting time, price, etc. So it is desirable if a travel recommender could help a tourist to find places matching his interests. Location based social network (LBSN)services allow users to perform check in and share their check in data with their friends.In particular, when a user is traveling, the check-in data are in fact a travel route withsome photos and tag information. As a result, a massive number of routes are generated, which play an essential role in many well-established research areas, such as mobilityprediction, urban planning and traffic management. However, the query results ofexisting travel route recommendation services usually rank the routes simply by thepopularity or the number of uploads of routes. With the rapid development of location based social networking services, e.g. Loopt, Brightkite, Foursquare have emerged in recent years. These LBSNs allow users to establish cyber links to their friends or other users, and share tips and experiences of their visits to plentiful places-of-interests (POIs), e.g. restaurants, stores, cinema theaters, etc. Users and POIs are two essential types of entities in LBSNs.



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Vol. 6, Issue 5, May 2018

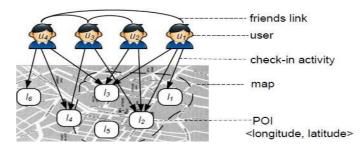


Fig. 1. User-location check-in activity in a Location based social network

As illustrated in Figure 1, users in an LBSN denoted as *u*1, *u*2, *u*3, *u*4, are interconnected via social links to form a social network. Moreover, POIs denoted as *l*1, *l*2,....,*l*6, are connected with users via their "check-in" activities, which generally reflects the users' tastes on various POIs. The POIs are geocoded by <longitude, latitude>, are constrained geographically [1].To make recommendations of travel routes to users, obviously the records of previous user check-in activities are very useful. With the availability of such information in LBSNs, an intuitive idea for supporting travel route recommendations based on POI is to employ the association rules mining. Association rules mining is one of the most important research methods in data mining which can obtain some useful knowledge to describe the association rules have been presented recently, among which Apriori algorithm is one of typical algorithm. The basic argument for this idea is that users' tastes can be deduced by other users who exhibit similar visiting behaviors to POIs in previous check-in activities.

#### II. RELATED WORK

Mao Ye, et al., aimed to provide a point-of-interests (POI) recommendation service for the rapid growing location based social networks (LBSNs), e.g., Foursquare, Whrrl, etc. The idea was to explore user preference, social influence and geographical influence for POI recommendations. In addition it put a special emphasis on geographical influence due to the spatial clustering phenomenon exhibited in user check-in activities of LBSNs. The geographical influence among POIs plays an important role in user check-in behaviors and model it by power law distribution. Accordingly, they proposed a unified POI recommendation framework, which fuses user preference to a POI with social influence and geographical influence based on naive Bayesian [2].

Yu Zheng, et al., proposed system based on multiple users' GPS trajectories. The increasing availability of GPSenabled devices is changing the way people interact with the Web, and brings us a large amount of GPS trajectories representing people's location histories. This system aimed to mine interesting locations and classical travel sequences in a given geospatial region. Here, interesting locations mean the culturally important places, such as Tiananmen Square in Beijing, and frequented public areas, like shopping malls and restaurants, etc. Such information can help users understand surrounding locations, and would enable travel recommendation [3].

Wan-Ting Hsu, et al., proposed system with given a spatial range Q and a set of query points specified by users, the goal of this system is to return the travel routes that fulfill two requirements: 1.) travel routes should contain all those query points specified, and 2.) travel routes should be within the spatial range Q. Furthermore, each query point may have its proper visiting time. As such, the travel routes should go through these query points at their corresponding proper visiting time. To avoid some redundant information in the travel routes, they utilized the skyline concept to retrieve travel routes with more diversity. Specifically, system considered some factors, such as the visiting time information of POIs and the set of query points, in retrieving travel routes [4].



(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

### Vol. 6, Issue 5, May 2018

Dingqi Yang et al., examined users' digital footprints on social networks and brought features in location search i.e. user feedback and preferences [5].

#### **III. PROBLEM DEFINITION**

Even if there are plentiful websites and companies to provide various plans for the arrangement of trips, traveller just becomes clueless about how to choose and fix the travel plan. If the person attempt to sort the travel route by themselves, they find difficulties as below:

- Sometimes travel agencies provide plans, which is not matched to users' need.
- > Often packages are too expensive, which is not economical to tourist.
- > Usually, travel agencies reassuring worthy service to tourist, but that does not occur indeed.

In this paper, we proposed a scheme that could help a traveler to find places corresponding his/her interests. The basic logic of this idea is that users' desire can be derived byother users who exhibit similar visiting behaviours to POIs in previous check-in activities.

#### IV. PROPOSED SYSTEM

Location-based social network (LBSN) services allow users to perform check-in and share their check-in data with their friends. In particular, when a user is traveling, the check-in data are in fact a travel route with some photos and tag information. In this proposed system, we focus on trip planning and intend to discover travel experiences from shared data in location based social networks. To facilitate trip planning, the prior works in provide an interface in which a user could submit the query region and the total travel time. In contrast, we consider a scenario where users specify their preferences with keywords. For example, when planning a trip in Goa, one would have "Beach". As such, we extend the input of trip planning by exploring possible keywords issued by users. Accordingly, we develop a user similarity andcollaborative route recommendation system based on geographical influence based on geographical influence based on association mining. Association rule is an important research in the knowledge discovery research. In large amounts of data, some interesting correlation would find in itemsets or related links. Association rules are a group of objects in the database which associated with the relationship between the rules. It is widely used in data mining. It can be divided into two sub problems .One is to find the frequent item sets which meet the minimum support. The other one is using the frequent item sets to generate association rules, according to the minimum credibility.

Supportive degree of the itemset Sup(X) is the proportion how much transaction X included in the entire database D. Confidence Conf (A  $\Rightarrow$ B) of association rule A $\Rightarrow$ B is the conditional probability that itemset B occurred in the condition that itemset A have occurred. Minimum support threshold minSup is the minimum one which item sets must be met in the mining process. The example illustrates the Apriori algorithms Transaction database as shown in Table 1, min Sup =50%, minConf =70%. Request the frequent association rules in transaction database D.

Tid	Itemsets
1	ABCDE
2	ABC
3	CDEF
4	ABE

Table 1.	Transaction	Database
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The implementation process is as follows:

The first step: Find the frequent itemsets

- 1) Frequent 1  $-itemsets\{\{A\}, \{B\}, \{C\}, \{D\}, \{E\}\}.$
- 2) Frequent 2 –itemsets{{AB}, {AC}, {AE}, {BC}, {BD}, {CD}, {CE}}.
- 3) Frequent 3 itemsets { ABC }.

Summary: L=L1UL2UL3 = {{A}, {B}, {C}, {D}, {E}, {AB}, {AC}, {AE}, {BC}, {BD}, {CD}, {CE}, {ABC}}.



(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

### Vol. 6, Issue 5, May 2018

The step two: seeking association from {ABC}

Only  $\{AC\} \rightarrow \{B\}, \{BC\} \rightarrow \{A\}, \{A\} \rightarrow \{B\}, \{B\} \rightarrow \{A\}$  meet the requirements. Where confidence level is 100%.

#### V. FLOWCHART OF PROPOSED SYSTEM

In proposed work, the aim is to develop keyword aware representative travel route framework to retrieve several recommended routes where keyword means the personalized requirements that users have for the trip. The route dataset collected from Foursquare. This dataset includes check-ins, tips and tags data of restaurant venues in New York City.

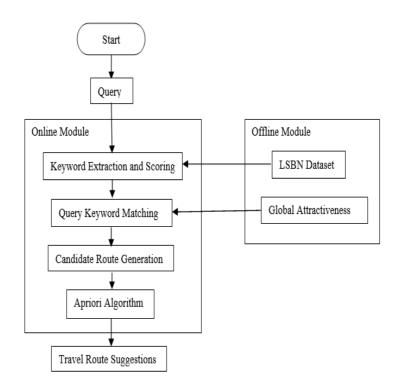


Fig. 2. Flowchart of proposed method

As can be seen in Figure 2, proposed wokis comprised of two modules: the offline pattern discovery also the online scoring and travel routes exploration module. Offline pattern discovery module: Given an LBSN dataset, we define the attractiveness scores and the proper visiting time of the POIs. Online travel routes exploration module: In this module, we provide an interface for users to specify query ranges and preference-related keywords. With the map interface provided, users could simply input their query range as a rectangle. Once it receives a specified range, we first analyze the tags of each POI to determine the semantic meaning of the keywords, which are classified into (i) Geo-specific keywords, (ii) Temporal keywords and (iii) Attribute keywords according to their features then online module will retrieve those trajectories that overlap the query range and reconstruct proper travel routes in the stay time period. Then, the online module will compute a matched score of how well the trajectory is connected to the keywords.

#### VI. MODIFICATION WITHIN EXISTING SYSTEMS

Location based social network (LBSN) services allow users to perform check-in and sharetheir check-in data with their friends. In particular, when a user is traveling, the check-in data are in fact a travel route with some photos and tag



(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

### Vol. 6, Issue 5, May 2018

information. As a result, a massive number of routes are generated, which play an essential role in many wellestablished research areas, such as mobility prediction, urban planning and traffic management. In proposed work, we focus on trip planning and intend to discover travel experiences from shared data in location based social networks. In contrast to prior work, proposed work considered a scenario where users specify their preferences with keywords. Also apriori algorithm is used which can obtain some useful knowledge to describe the association between different valuable data items out of a great amount data.

Proposed system:

- Proposed system developed a keyword-aware representative travel route framework to retrieve several recommended routes where keyword means the personalized requirements that users have for the trip. The route dataset is collected from Foursquare.
- In proposed system users are able to issue a set of keywords and a query region, and for which query results contain diverse trip routes.
- Check-in information is mined from passive check-ins to enrich the input data. This dataset includes check-ins, tips and tags data of restaurant venues in New York City.
- > Propose system used a route construction method to partition routes into segments.

Proposed system is comprised of two modules: offline module also online scoring and travel routes exploration module. 1. Offline Module:

Given an LBSN dataset, we define the attractiveness scores and the proper visiting time of the POIs

2. Online travel routes exploration module:

In this module, the system provide an interface for users to specify query ranges and preference related keywords. With the map interface provided, users could simply input their query range, and add keywords for personalized preference. Given an LBSN dataset, the system first analyze the tags of each POI to determine the semantic meaning of the keywords which are provided in user query, which are classified into:

- Geo-specific keywords
- Temporal keywords
- > Attribute keywords according to their features.

Then the online module will retrieve those trajectories that overlap the query range and reconstruct proper travel routes.

### VII. **Results**

Consider a traveller decided an outing along the keywords ["Diner", "Ice-cream"]. Earlier, we can encounter that the specified keywords are differ in their meaning. We represent how we bring out the semantic implication of the specified keywords which outline the level of alliance among keywords and route. The keyword extraction module figure out whether the keyword is related to the geographical area, specific time or virtue of some POI and derive scores for every keyword 'w' accordingly.

1. Geo-specific Score: Some tags are specific to a location, which represents its spatial nature. To quantify the geo-specificity of a tag, an external database identifies geoterms in the overall tag set and then the tag distribution on the map rates the identified geo-terms. Figure 3 shows geo-specific score of given keywords.

Query	is Geospeci	fic GeoScore
tea	Yes	5.416068141873617
coffee	Yes	21.68959609680893
diner	Yes	45.2240958132008
	Fig. 3.	Geo-specific Score

2. Temporal Score: Some tags are specific to a time interval, which represents its temporal nature. To quantify the temporal-spatiality of a tag, time distribution on a tag rates the identified temporal-terms.



(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: <u>www.ijircce.com</u>

### Vol. 6, Issue 5, May 2018

Word	TS(w) Temporal Specificity	
tea	0.001311111111111111	
coffee	0.0023210526315789472	
diner	0.0028620689655172414	

- Fig. 4. Temporal Score
- 3. Attribute Score: To find attribute keywords, we consider tags frequently associated with a POI (TF), while not with so many other POIs (IDF). User frequency is the number of users that assign 'w' to various POIs.

Word	User Frequency(U
tea	26
coffee	25
diner	7
Fig. 5.	Attribute Score

4. Route Formation in Existing System: In the previous work candidate routes are built up by merging the progression of paths. Connected POIs in the paths are arranged using time parameter. Figure 6 shows route formed using existing methodology and time required for it.

Route Path	Generated
	ee Tea & Spices>RiteAid>Hanco's Bubble Tea & Vietnamese Sandwich>Southside tarbucks Coffee>Carroll Gardens Classic Diner
Total	Route Generated : 1
Estim	ated Time : 5104791141939144 NS

Fig. 6. Route Formation in Existing System

5. Route Formation in Proposed System: Here we announce the apriori method for route formation. Data mining is a way to find out the significant information from the bulky databases.



Fig. 7. Route Formation in Proposed System

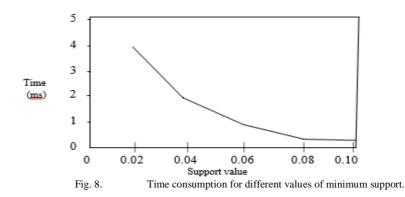
First practice analyzes the time spent on Apriori algorithm by employing the one group of transactions over diverse values for minimum support. The result is shown in Figure 8.



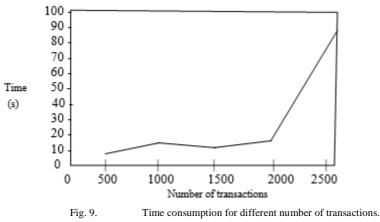
(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: <u>www.ijircce.com</u>

Vol. 6, Issue 5, May 2018



Second practice analyzes the time spent on Apriori algorithm by employing the one group of transactions over diverse number of transactions. The result is shown in Figure 9.



#### VIII. CONCLUSION AND FUTURE WORK

The conclusions of Travel Route Recommendation System are:Social media provides user facility to share their experiences via activities like checking in. These activities can provide rich information about best places to visit using users shared past experiences. So the goals in this work were (1) to bring out novel information by analyzing bulky databases, (2) to consolidate users experience to find magnetism of places-of-interest (3) to use an apriori algorithm for identifying hidden association among itemsets from large databases of user checking in data and to construct the route analogous to the key terms provided by user. Previous methods already tried to find travel routes. However proposed scheme built afeature score for places and leverage association mining to find the best route relevant to user need. Thus, people would know about the best route to accomplish their needs during visits in a specific geographical area.

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