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Efficient Keyword-Aware Representative Travel Route Recommendation

Dr. G. Anandharaj*[1], R. Kavitha[2]

[1]Assistant Professor, PG & Research Department of Computer Science and Applications, Adhiparasakthi College of Arts and Science (Autonomous), G.B.Nagar, Kalavai, Vellore, Tamil Nadu, India

[2]M.Phil (CS) Research Scholar, PG & Research Department of Computer Science and Applications, Adhiparasakthi College of Arts and Science (Autonomous), G.B.Nagar, Kalavai, Vellore, Tamil Nadu, India

ABSTRACT

Location-based network (LBN) services enable users to perform check in and share their check-in data with their companions. In particular, when a user is traveling, the check-in data are in actuality a travel route with some photographs and tag data.As an outcome, a massive number of routes are generated, which assume an essential role in many well-established research areas, for example mobility prediction, urban planning and traffic management. In this paper, we focus on trip planning and plan to discover travel experiences from shared information in location based social networks. To encourage trip planning, the earlier works in give an interface in which a user could submit the query region and the total travel time.

Keywords: Location-based social network, text mining, travel route recommendation

I. INTRODUCTION

Location-based social network (LBSN) services enable users to perform check-in and offer their check-in data with their companions. Specifically, when a user is travelling, the check-in information is in reality fact a travel route with some photographs and tag information. Subsequently, a massive number of routes are generated, which play an essential role in many well-established research areas, for example mobility prediction, urban planning and traffic management. In this paper, we focus on trip planning and plan to find travel experiences from shared data in location-based social networks. To encourage 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 arranging an excursion in Sydney, one would have “Musical drama House”. All things considered, we extend the contribution of outing arranging by investigating conceivable keywords issued by users.

II. PROBLEM DEFINITION

We proposed a productive Keyword-aware Representative Travel Route framework which utilizes information extraction from user's historical mobility records and social communications between Users’s. By this, we have designed a keyword extraction module to group the POI-related tags so as to ensure effective matching with query keywords. We also explore Representative Skyline concepts, which is the Skyline routes describing the trade-offs among different POI features so as to provide befitting query results. The experiment results demonstrate that our techniques do indeed demonstrate better performance compared to state-of-the-art works.

III. LITERATURE SURVEY

3.1Efficient Keyword-Aware Representative Travel Route Recommendation

Authors: Yu-Ting Wen, Jinyoung Yeo, Wen-Chih Peng and Seung-Won Hwang

Description: Nowadays the users can easily share their check-in records and photos during their trips via social media (e.g., Face book and Twitter). We are planned to discover travel experiences of the users to facilitate trip planning by considering high number of user historical mobility records in social media. When arranging a trek, users dependably have particular preferences regarding their outings. Rather than restricting users to limited query options such as locations, activities, or time periods, we consider subjective content descriptions as keywords about personalized requirements. Furthermore, a diverse and representative set of recommended travel routes is required. Earlier works have explained on mining and ranking existing routes from check-in data. To guarantee the need for automatic trip organization, we claim that additional features of Places of Interest (POIs) should be extracted. So in this paper we suggest an efficient Keyword-aware Representative Travel Route framework that utilizes knowledge extraction from user's historical mobility records and social interactions. Specifically, we have designed a keyword extraction module to differentiate the POI-related tags, for effective matching with query keywords. In addition, we have designed a route reconstruction algorithm to construct route candidates that fulfil the requirements. To provide befitting query results, we explore Representative Skyline concepts, that is, the Skyline routes which describes the trade-offs among different POI features in better way. To examine the effectiveness and efficiency of the proposed algorithms, we have conducted extensive experiments on real location-based social network datasets, and the experiment results show that our techniques do indeed demonstrate better performance compared to state-of-the-art works.

3.2 Mining interesting locations and travel sequences from GPS trajectories

Authors: Y. Zheng, L. Zhang, X. Xie, and W.-Y. Ma

DESCRIPTION: The way users communicate with the Web is changed due to the increasing availability of GPS- empowered gadgets, which presents to us a considerable measure GPS trajectories representing to individuals' location histories. In this paper, in perspective of different user's GPS directions, we plan to mine interesting locations and traditional travel sequences in a predefined geospatial region. Here, interesting locations mean the socially critical spots, for example, Tiananmen Square in Beijing, and frequented open zones, such as shopping centres and eateries, and so on. Such data can enable users to comprehend encompassing areas, and would empower travel suggestion. In this work, we first model different user's area histories with a tree based hierarchical graph (TBHG).At that point, in light of the TBHG, we propose a HITS (Hypertext Induced Topic Search) based inference model, which respects a user's access on an zone as a guided association from the user to that region. This model deduces the enthusiasm of an area by considering the following three factors. 1) The interest of a territory relies upon not just the quantity of users going by this area yet in addition these users' travel experiences. 2) Users' travel experiences and area interests have a mutual reinforcement relationship. 3) The interest of an area and the travel experience of a user are relative values and are region-related. In addition, we mine the traditional travel sequences among areas considering the interests of these areas and users' travel experiences. We assessed our framework utilizing an expansive GPS dataset gathered by 107 users over a time of year in reality. Therefore, our HITS-based inference model outperformed baseline approaches like rank-by count and rank-by frequency. Then, when considering the users' travel experiences and area interests, we guarantee better execution past baselines, for instance, rank-by count and rank-by interest, etc.

3.2 Exploiting geographical influence for collaborative point-of-interest recommendation

Authors: M. Ye, P. Yin, W.-C. Lee, and D.-L. Lee

DESCRIPTION: We intend to give a point-of-interests (POI) suggestion benefit for the rapid developing location-based social networks (LBSNs), e.g., Foursquare, Whrrl, etc. Our design is to investigate user preference, social impact and geographical influence for POI recommendations. In addition to deriving user preference based on user-based collaborative filtering and exploring social influence from companions, we put a exceptional emphasis on geographical influence because of the spatial clustering phenomenon exhibited in user check-in activities of LBSNs. We contend that the geographical impact among POIs plays an important role in user check-in practices and model it by control law distribution. In like manner, we build up a collaborative recommendation algorithm based on geographical influence based on naive Bayesian. Moreover, we propose a brought together POI recommendation framework, which fuses user preference to a POI with social impact and geographical impact. Finally, we conduct a comprehensive performance evaluation over two large-scale datasets gathered from Foursquare and Whrrl. Assessment results with these real datasets demonstrate that the brought together collaborative recommendation approach to a great extent outperforms a wide spectrum of elective recommendation approaches.

3.3 Exploring social influence on location-based social networks

Authors: Y.-T. Wen, P.-R. Lei, W.-C. Peng, and X.-F. Zhou

DESCRIPTION: In recent years, with the popularization of mobile network, the location-based service (LBS) has made large strides, becoming an efficient marketing instrument for enterprises. In the retail business, good selections of store and appropriate marketing techniques are critical to increasing the profit. However, it is not easier to select the retail store because there are multiple considerations and the analysis was short of metadata in the past. Therefore, this study uses LBS, and provides a recommendation method for retail store selection by analyzing the relationship between the user track and point-of-interest (POI). This study also uses regional relevance analysis and human mobility construction to establish the feature values of retail store recommendation. This examination proposes (1) design of the information show accessible for retail store recommendation by influential layers of LBS; (2) System-based solution for recommendation of retail stores, adopts the influential factors with determined information in LBS and sifted by industrial types; (3) Industry density, area categories and region/ industry clustering methods of POIs. In addition the effect of regional functionality on the retail store selection is calculated by using KDE and KMeans, where similarity is used to calculate the industry category relation, and consumption capacity is considered to state.

IV. SYSTEM STUDY

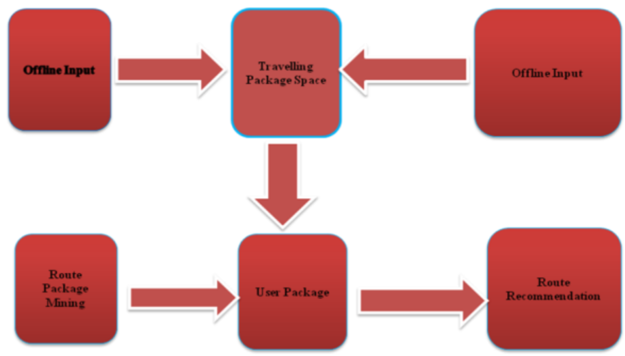

Figure 1. System Architecture

4.1 Existing system:

Location-based social network (LBSN) services allow users to perform check-in and share their check-in data with their friends. Specifically, when a user is traveling, the check-in data is a travel route with some 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, e.g., mobility prediction, urban planning and traffic management.

4.2 Proposed system:

In this project, 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 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 Sydney, one would have "Opera House". As such, we extend the input of trip planning by exploring possible keywords issued by users. In this system, we develop a Keyword aware Representative Travel Route (KRTR) framework to retrieve several recommended routes where keyword means the personalized requirements that users have for the trip. The route dataset can be built from the collection of low-sampling check-in records.

4.3 Proposed Algorithm:

Keyword-Aware Representative Travel Route Framework (KRTR): Given a set of check-in points recorded as a series of travel routes, each check-in point represents a POI p and the user's checked-in time t. The check-in records were grouped by individual users and ordered by the creation time. Each user could have a list of travel routes {T}={T0,T1,…}, where T0=(P0,T0),(P1,T1),…..(Pi, Ti), T1=(Pi+1,Ti+1), (Pi+2, Ti+2),….. And Ti+1-Ti are greater than a route split threshold. We set the route-split threshold to one day in this paper.

Implementation of Modules:

1) Geo specific Keywords.
2) Temporal Keywords.
3) Candidate Route Generation.
4) Travel Route Exploration
5) Similarity Route Search
6) Location Recommendation and Prediction

1) **Geo specific Keywords:** Some tags are specific to a location, which represents its spatial nature. To quantify the geo-specificity of a tag, an external database identifies geo-terms in the overall tag set and then the tag distribution on the map rates the identified geo-terms and shows some description about the specific POI.

2) **Temporal Keywords:** Some tags are specific to a time interval, which represents its temporal nature. To quantify the temporal-specificity of a tag, time distribution on a tag rates the identified temporal terms. Using the time distribution of tags, we can find tags associated with a specific time interval like 'sunset'. Tags independent of time like 'Taipei' are far more widely distributed in time than time-specific tags.

3) Candidate Route Generation: In this system we have introduced the methods for matching raw texts to POI features and mining preference patterns in existing travel routes. However, the route dataset sometimes may not include all the query criteria, and may have bad connections to the query keywords. Thus, we propose the Candidate Route Generation algorithm to combine different routes to increase the quantity and diversity. The new candidate routes are constructed by combining the sub sequences of trajectories. Here we introduce the preprocessing method first. We then utilize the pre-processing results to accelerate the proposed route reconstruction algorithm. At last, we design a Depth-first search-based procedure to generate possible routes.

4) **Travel Route Exploration:** With the featured trajectory dataset, our final aim is to recommend a set of travel routes that connect to all or partial user specific keywords. We first explain the matching function to process the user query. Then, we introduce the background of why we apply a skyline query, which is suitable for the travel route

recommendation applications, and present the algorithm of the distance based representative skyline search for the online recommendation system. Furthermore, an approximate algorithm is required to speed up the real time skyline query.

5) **Similarity Route Search:** Another pertinent region is the similarity course searches under particular properties. Research on this subject has concentrated on discovering courses as indicated by location, movement or keyword related queries. Characterize similitude work for estimating how well a direction connects the query locations thinking about both spatial separations. Moreover managed the issue of recognizing perfect courses considering an arrangement of client indicated keywords. In any case, those works concentrated on the proficient method to look for existing courses that cover all the pre characterized keywords. To the best of our insight, we are the first to handle keyword and social impact in trip arranging with registration information. This work is the most extensive model for a bland travel course proposal framework.

6) **Location Recommendation and Prediction:** In addition, a number of research ventures concentrated on proposal and forecast of single location. The errand of location recommendation is to prescribe new locations that the client has never gone, while the errand of location forecast is to anticipate the following locations that the client is liable to visit. The vast majority of the exploration has considered "Where, When, Who" issues to display client versatility. For the location proposal part, pointed out that individuals tend to visit close by locations however it might be intrigued by more removed locations that they are agreeable to. At last, it joined client inclination, land impact, also, verifiable directions to suggest registration locations. Suggested a rundown of POIs for a client to visit at guaranteed time by misusing both land and worldly influences. Concentrated on the connections amongst people and suggested the locations that compelling clients have been to. For the location expectation part, anticipated the most likely location of a person whenever for given the recorded directions of their companions.

4.4 ADMIN DFT

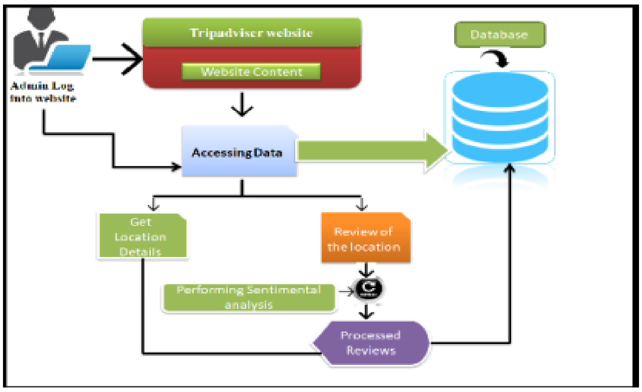

Figure 2 Admin DFT

4.5 USER DFT

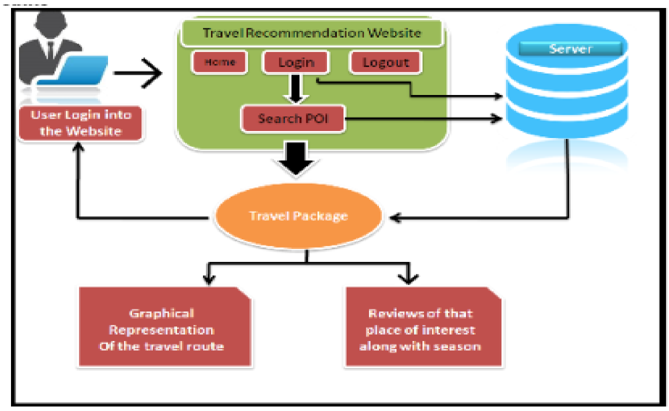

Figure 3. User DFT

V. RELATED WORK

Trip Planning: Trip planning has been intensively studied recently. The problem is to develop a collaborative recommendation model to recommend routes for a given

```
Algorithm 1. Candidate Route Generation
Input: Raw trajectory set T;
Output: New candidate trajectory set T_c.
Initialize a stack S;
Split each route r ∈ T into (head,tail) subsequences;
Reconstruct(headSet).
Procedure Reconstruct(Set):
foreach (head,tail) ∈ Set do
    endFlag = False;
    if S is empty or tail.time > S.pop().time then
        Push head in S;
        Push tail in S;
    else
        Push head in S;
        endFlag = True;
    if endFlag is False then
        Reconstruct(tailSet)
    Insert S in T_c;
Procedure End
```

Figure 4. Algorithm 1

user at a query region. Tools and Technologies used in this project I used: Asp.Net & SQL Management Server 2014 technologies.

```
Algorithm 2. Travel Routes Exploration
Input: User u, query range Q, a set of keywords K;
Output: Keyword-aware travel routes with diversity in
        goodness domains KRT.
Initialize priority queue CR, KRT;
Scan the database once to find all candidate routes covered
  by region Q;
  /* Fetch POI scores and check keyword matching
foreach route r found do
    r.kmatch ← 0;
    foreach POI p ∈ r do
        r.kmatch ← r.kmatch + KM(p,k);
    if r.kmatch ≤ ε then
        Push r into CR;
  /* Initialize an arbitrary skyline route, see Section 4.3
CR.r_0 ← route r with the largest value of an arbitrary
  dimension;
  /* Greedy algorithm for representative skyline, see
  Algorithm 3 */
KRT ← I-greedy(CR);
return KRT.
```

Figure 5. Algorithm 2

VI. RESULTS

6.1 Screenshot

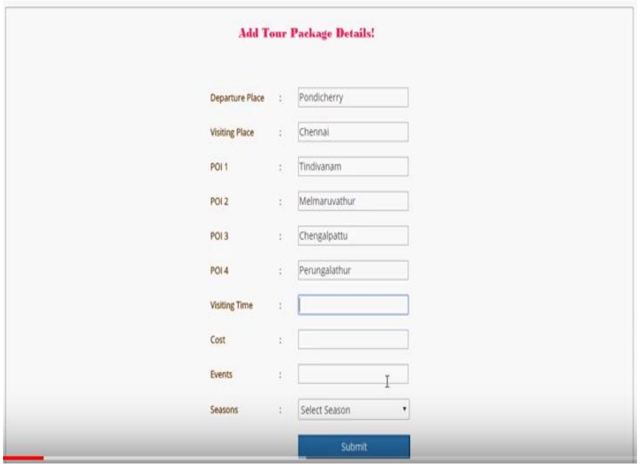

Figure 6. Add tour Package Details

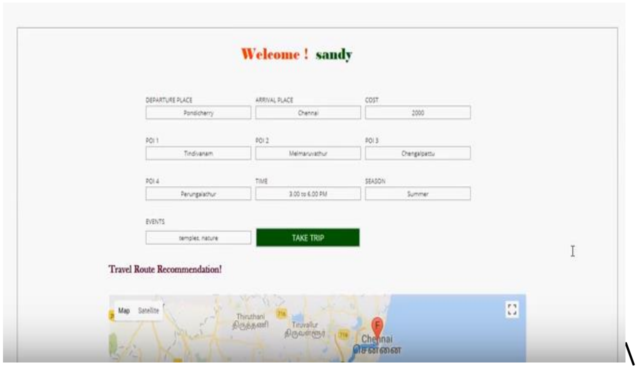

Figure 7. User Search Tour package

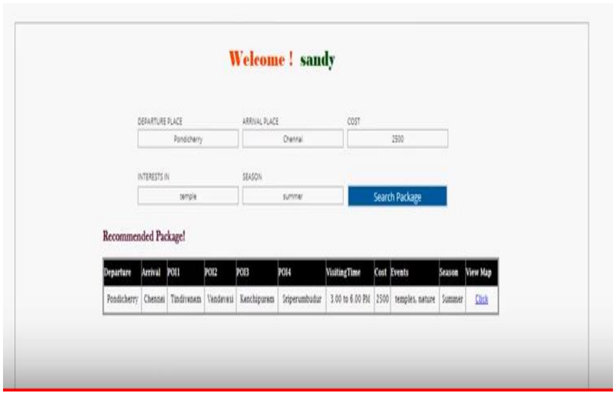

Figure 8. Travel route Recommendations

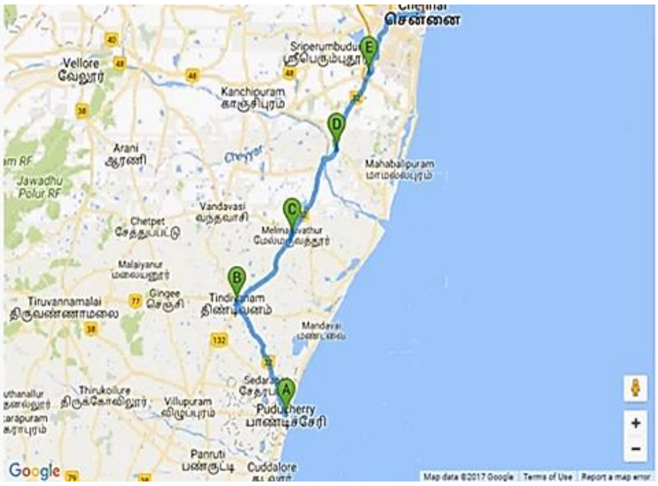

Figure 9. Travel Route Recommendation on Maps

VII. CONCLUSION

In this project we analyzed the travel route recommendation problem. We have developed a KRTR framework to suggest travel routes with a specific range and set of user preference keywords. These travel routes are related to all or partial user preference keywords and recommended based on

I. Attractiveness of the POI's it passes
II. Visiting the POI's at their corresponding proper arrival times, and
III. The routes generated by influential users

We propose a novel keyword extraction module to identify the semantic meaning and match the measurement of routes, and have designed a route reconstruction algorithm so as to aggregate route segments into travel routes in accordance with query range and time period.

VIII. FUTURE SCOPE

In this system we used a novel keyword extraction module to identify the semantic meaning and match the measurement of routes, and have designed a route reconstruction algorithm to aggregate route segments into travel routes in accordance with query range and time period. We leverage score functions for the three aforementioned features and adapt the representative Skyline search instead of the traditional top-k recommendation system.

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