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Tourist Traveller Guide and Suggestion System for Easy Tourism

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Abstract — *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. As a result, a massive number of routes are generated, which play an essential role in many well-established research areas, such as mobility prediction, urban planning and traffic management. In this paper, 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 Sydney, one would have "Opera House". As such, we extend the input of trip planning by exploring possible keywords issued by users.*

Keywords* - *Spatial keyword query , spatial objects, spatial database, best keyword cover query.

I. INTRODUCTION

With the emerging development of location-based social net-work (LBSN) services such as Yelp and Foursquare, users are able to "check in" at a certain point of interest (POI), such as restaurant/museum/park, via their mobile devices. A user may rate and make comments after visiting a POI and other users may consider those ratings and comments to select the POIs for their visits at a later time. The availability of such rating data and LBSN service open up an array of new research problems in both academia and industry, such as user behavior analysis, movement pattern study, and various real-world applications. Among them, POI recommendation and trip recommendation are hot topics and require a location sensitive solution. For example, recommending a highest rated Chinese restaurant in Beijing to a user who is currently visiting New York City will fail, even if the user loves Chinese food. Recommending a nearby Chinese restaurant with a reasonable rating score makes more sense in this case. In this paper, we focus on the personalized trip recommendation problem. In this problem, a user travels to a new region (e.g., on a business trip to a new city) and wants to visit several POIs within a limited amount of time. The goal is to recommend a trip route visiting several POIs according to not only the temporal-spatial constraints (more details shortly), but also the user specific preferences on POIs

II. MOTIVATION

The trip recommendation is not trivial because of the following challenges:

(Personalization)
First, while a user has its own interests, explicitly soliciting this information does not work in large scale applications because the user often does not know what POIs are available and where they are. Modeling user preferences by learning from historical rating and check-in behaviors of users and their peers to predict the user's preferences on unvisited POIs would be a preferred solution.

(Sequence of POIs)
Second, the traditional POI recommendation recommends individual POIs with highest scores, such POIs may not form a feasible trip due to the spatial and time constraints.

(POI availability and uncertain traveling time)

Third, the traditional trip recommendation assumes that POIs are always available any time and the traveling time between two POIs are known in advance, but in practice, a POI may be available only at certain times (say, due to opening hours and closing hours) and traveling time is uncertain due to traffic conditions at the time of travel. As a result, whether a POI can be visited will depend on its available time and predictability of the time traveling to the POI. If the timeliness of finishing the trip is important to the user, a trip with a more predictable traveling time would be preferred. For example, the user may give up one more POI to visit in order to ensure a high probability of visiting another more preferred POI or arriving at the specified destination on time.

(Large search space)

Finally, the POI availability and uncertain traveling time imply each order of visiting a set of POIs may have a different consequence; thus, a brute-force search of all candidate trips is prohibitive. For example, with 150 POIs in total, the number of trips that consist of 5 POIs can reach billions (i.e., 150!).Most of these candidate trips do not follow the POI availability match user's preferences, or cannot be finished within a given time limited. A strategy that prunes such infeasible and non-optimal trips based on user preferences, POI availability, traveling time uncertainty is essential for scaling a solution to large applications. Trip recommendation has been studied recently. Analyzed the characteristics of travel packages and proposed a graphical model to extract the topics conditioned on tourists, areas and travel seasons for personalized travel package recommendation. Developed a Bayesian learning model to extract travel paths from photos and conducted personalized travel recommendation according to user-specific profiles. All these works, however, adopt probabilistic models to generate a possible travel package or path but do not consider the objective function to maximize the user's happiness under the trip and other constraints. The recent work formulated the trip recommendation as a constrained objective function and presented a dynamic programming solution. Their assumption is that POIs can be grouped into several types or categories and the user knows the order of visiting POI types and likes to visit POIs of each type exactly once in a predetermined order. The restriction of visiting each type exactly once in a pre-determined orders significantly reduces the search space. For example, for 150 POIs falling into 5 types equally, the original 150! Possible routes are reduced to 305 if the order is fixed. In real world applications, however, the user may not provide this order either because she does not care about the order or because she is concerned that such a fixed order may restrict her options. In addition, their work does not consider the POI availability and the uncertainty of traveling time

III. EXISTING SYSTEM

In existing system, 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, we 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, we 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, we claim that more features of Places of Interest (POIs) should be extracted

IV. PROPOSE SYSTEM

We propose an efficient Keyword-aware Representative Travel Route framework that uses knowledge extraction from users' historical mobility records and social interactions. Explicitly, we have designed a keyword extraction module to classify the POI-related tags, for effective matching with query keywords. We have further designed a route reconstruction algorithm to construct route candidates that fulfill the requirements. To provide befitting query results, we explore Representative Skyline concepts, that is, the Skyline routes which best describe the trade-offs among different POI features. To evaluate 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 methods do indeed demonstrate good performance compared to state-of the art works.

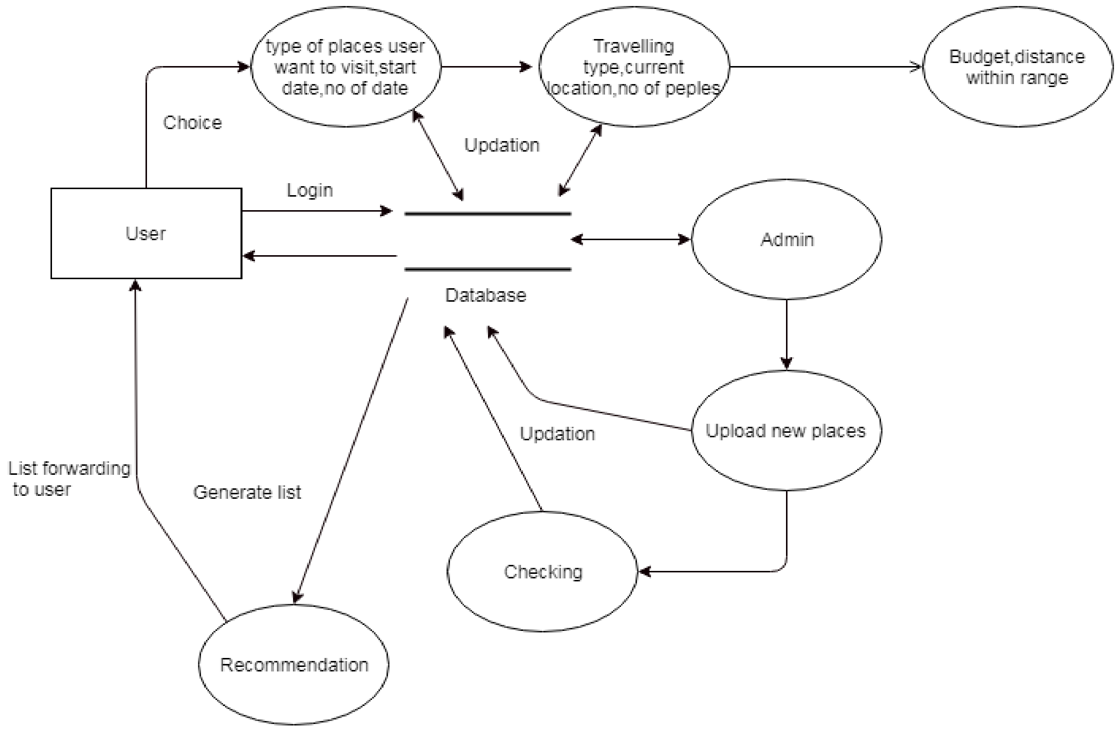


Fig.1 System Architecture

V. CONTRIBUTIONS

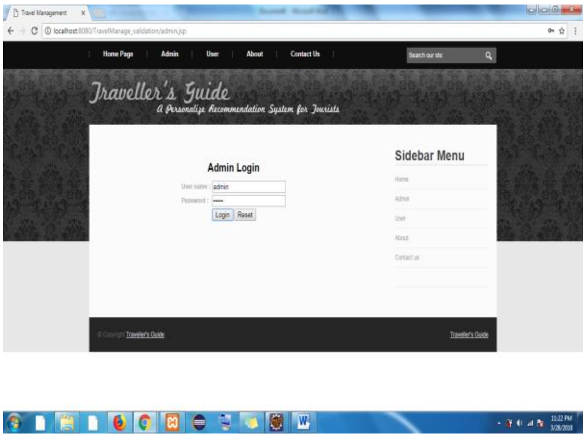
In this paper, we address the trip recommendation by taking into account the following information and constraints:
(1) the user's personalized preferences on POIs;
(2) the user's time budget that constrains the total traveling and visiting time;
(3) the time window for the POI availability;
(4) the uncertainty of traveling time between POIs.

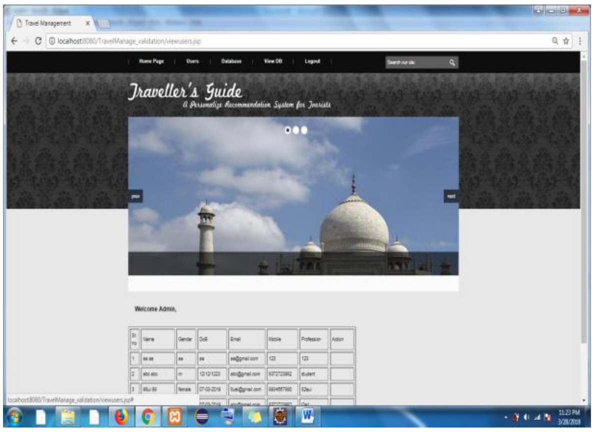
We formulate the above requirements in our Trip problem. The goal of the problem is to find an optimal trip that maximizes user happiness under the constraint that all the POIs in the trip can be visited and the trip can be completed within the user time budget with a probability not less than a user specified threshold. This problem is NP-hard as it is a special case of either the Knapsack problem or the Orienteering problem we solve this problem by using the information and constraints in (1)-(4) to prune unpromising candidate trips. Our algorithm has an offline step and an online step. In the offline step, we apply collaborative filtering adopted to items with features to estimate user's preferences on unvisited POIs based on available check-in data. This step is performed only once as it applies to all users. In the online step Where the user's time budget constraint and start/destination locations are provided, we search for the optimal trip route under the various constraints discussed above. We present two optimal solutions that guarantee to find the optimal trip if it exists. One is based on a state expansion approach and one is based on a pre- fix based depth-first search strategy. We also present two heuristic solutions that find "good trips" with a significantly better runtime than the optimal solutions. We evaluated all solutions on two real life LBSN data sets, Yelp and Foursquare, and demonstrated the superiority over previous trip recommendation algorithm.

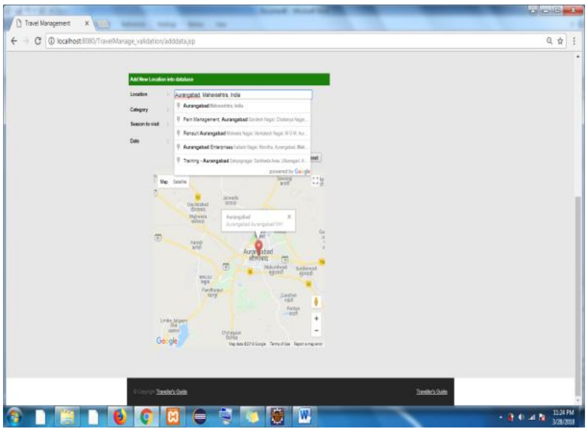
VI. HARDWARE AND SOFTWARE USED

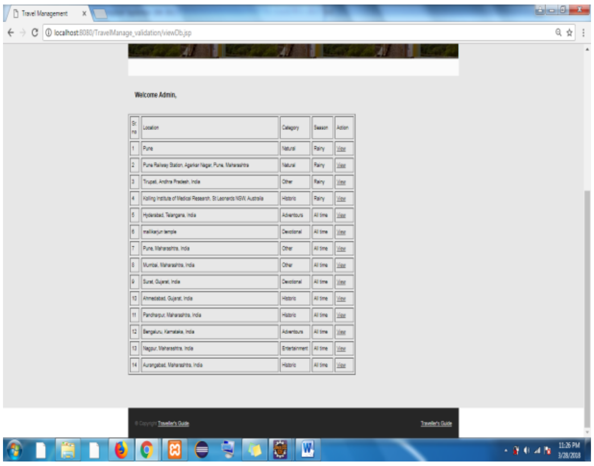
System : Pentium IV 2.4 GHz.
Hard Disk : 40 GB.
Ram : 512 Mb.
Operating system : Windows XP/7.
Coding Language : JAVA/J2EE
IDE : Eclipse Jee oxygen
Database : MYSQL

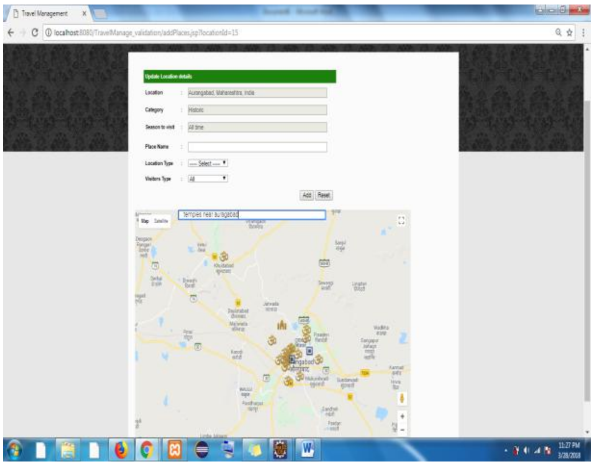
VII. SCREENSHOTS











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