Efficient Keyword-Aware Representative Travel Route Recommendation

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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, 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. Therefore, in this paper, 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 key words. 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.

Keywords: Location-Based Social Network, Text Mining, Travel Route Recommendation.

I. INTRODUCTION

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 [1], [2], [3], [4],[5] 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. However, the query results of existing travel route recommendation services usually rank the routes simply by the popularity or the number of uploads of routes. For such ranking, the existing works [6], [7], [8] derive a scoring function, where each route will have one score according to its features (e.g., the number of Places of Interest, the popularity of places). Usually, the query results will have similar routes. Recently, [9] aimed to retrieve a greater diversity of routes based on the travel factors considered. As high scoring routes are often too similar to each other, this work considers the diversity of results by exploiting Skyline query. In this paper, 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 data set could be built from the collection of low-sampling check-in records.

Definition 1 (Travel Route): 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 $\{T\} = \{T_0, T_1, \dots\}$ where $T_0 = (p_0, t_0), (p_1, t_1), \dots, (p_i, t_i)$ $T_1 = (p_{i+1}, t_{i+1}), (p_{i+2}, t_{i+2}), \dots$ and $t_{i+1} - t_i$ is greater than a route-split threshold. We set the route-split threshold to one day in this paper. Consider the example illustrated in Fig. 1, the related route information of which is stored in Table 1. For ease of illustration, each POI is associated with one keyword (though our model can support multiple keywords) and a two-dimensional score vector (each dimension represents the rank of a feature). Assume a tourist plans a date with a set of keywords ["Whisky" "Sydney Cove" "Sunset"]. First, we can find that these keywords vary in their semantic meaning: "Sydney Cove" is a geographical region; "Sunset" is related to a specific time period (evening) and locations such as beach; "Whisky" is the attribute of POI. We argue that knowing semantics is important, as some query keywords do not need to be matched in the POI keyword. For example, p9, even though its name does not include "Whiskey", is a good match, as it is an important attribute of Bar POIs. Similarly, "Sydney Cove" is not mentioned, but based on the location of Opera House, p8matches the requirement. As a result, T3 matches all the requirements, which could not be supported by existing simple keyword-based matches. In this example, the keyword "Sunset" can be easily matched. Although the other two words are not stored in the database, we want to correspond them to Drinking whisky at a bar and Opera House in Sydney Cove. Finally, T3 matches all the requirements. Meanwhile, there is still a possibility that no existing route is in accordance with the query keywords. For this challenge, we propose a candidate route generation algorithm to increase the number of routes. For instance, a travel sequence $T' = \{p_1 \rightarrow p_3 \rightarrow p_4 \rightarrow p_5 \rightarrow p_8 \rightarrow p_9\}$ which is aggregated from the route segments of T1 to T3, also matches all the keywords specified. Additionally, we have mentioned that the final results may have similar characteristics and be monotonous due to the fact that all of the factors are aggregated into one score for each travel route. Consequently, the system will retrieve the top-k routes with the highest score as the results. Users may not understand the characteristic of these routes through the final single score (e.g., Which one has the most interesting landmarks? Which one is well-connected to the place I want to go?) so it may be hard to choose a route from the final results. Furthermore, users need to pre-define the weight for each factor, although it is hard to select a suitable weight in most cases. Since travel route recommendation has to take several factors into consideration to emphasize the unique travel factors of travel routes, we borrowed the concept of Distance-based Representative Skyline [10] to retrieve travel routes.

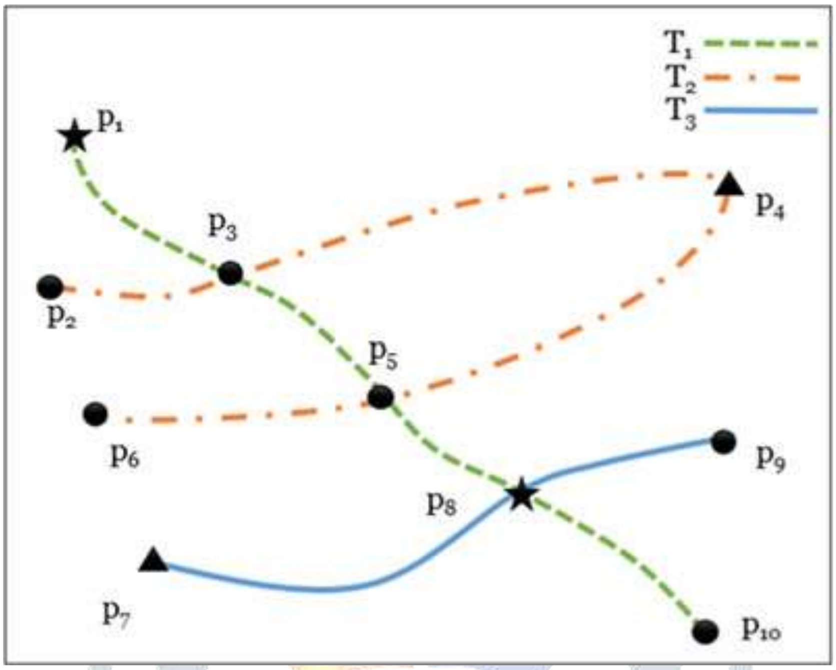

Fig.1. Keyword-aware travel routes query running example.

TABLE I: Example of Route Dataset

Tid	Uid	Pid	keyword	time	POI score vector
T_1	u_1	p_1	Opera House	10:00	(0.04, 0.2)
T_1	u_1	p_3	Bar	12:00	(0.25, 0.2)
T_1	u_1	p_5	Bar	15:30	(0.2, 0.8)
T_1	u_1	p_8	Opera House	17:30	(0.04, 0.3)
T_1	u_1	p_{10}	Bar	19:00	(0.04, 0.2)
T_2	u_2	p_2	Bar	10:30	(0.02, 0.2)
T_2	u_2	p_3	Bar	12:30	(0.25, 0.2)
T_2	u_2	p_4	Sunset	17:00	(0.05, 0.2)
T_2	u_2	p_5	Bar	19:00	(0.2, 0.8)
T_2	u_2	p_6	Bar	19:30	(0.25, 0.8)
T_3	u_3	p_7	Sunset	18:30	(0.4, 0.8)
T_3	u_3	p_8	Opera House	19:30	(0.04, 0.3)
T_3	u_3	p_9	Bar	20:00	(0.1, 0.1)

Distance-based Representative Skyline search on the travel routes also includes a small number k of skyline routes that best describe the full optimal (Skyline) results in terms of the features derived. Consider an example in Fig. 1, where the score vector of POIs represents the attractiveness score and the visiting time information. To compute the average POI score of T1, T2 and T3, we get the final score values (0.1, 0.34), (0.15, 0.44), and (0.18,0.3) respectively. For example, with k ¼ 3, the skyline points in Fig. 2 can be divided into three subsets {T4}, {T2; T5; T6}and {T3; T8}. Our representative skyline travel route solution will report fT2; T3; T4g. This paper builds on and significantly improves the KSTR framework [9] of recommending a diverse set of travel routes based on several score features mined from social media. KSTR then constructs travel routes from different route segments. Specifically, we extend KSTR to consider representative and approximate results under an optional k limit in Section 5. Additionally, resources including passive check-ins such as GPS-tagged photos are discussed in Section 6. This addition would enable KRTR to consider a larger input including active and passive checkins with high efficiency and scalability. The contributions of this paper are summarized as follows:

- We propose a KRTR framework in which 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 checkins to enrich the input data. GPS-tagged photos are larger in scale than foursquare check-ins. This mining thus improves the coverage of the input data.
- We propose a route reconstruction method to partition routes into segments by considering spatial and temporal features.
- Representative Skyline query for travel route search is adopted to combine the multi-dimensional measurements of routes, which increases the diversity of the recommended results. Moreover, a greedy method is designed for the efficiency of the online application.

To evaluate our proposed framework, we conducted experiments on real LBSN and photo datasets. The experiments show that KRTR is able to retrieve travel routes that are of interest to users. The rest of the paper is organized as follows. Section 2presents the overview of the KRTR framework. Section 3describes the feature scoring algorithms and how to extend KSTR to mine from both active and passive check-ins. In Section 4, we provide a travel routes exploration module of KRTR. The experiment results of the proposed methods are presented in Section 5. Section 6 summaries the related work. Finally, Section 7 concludes this paper.

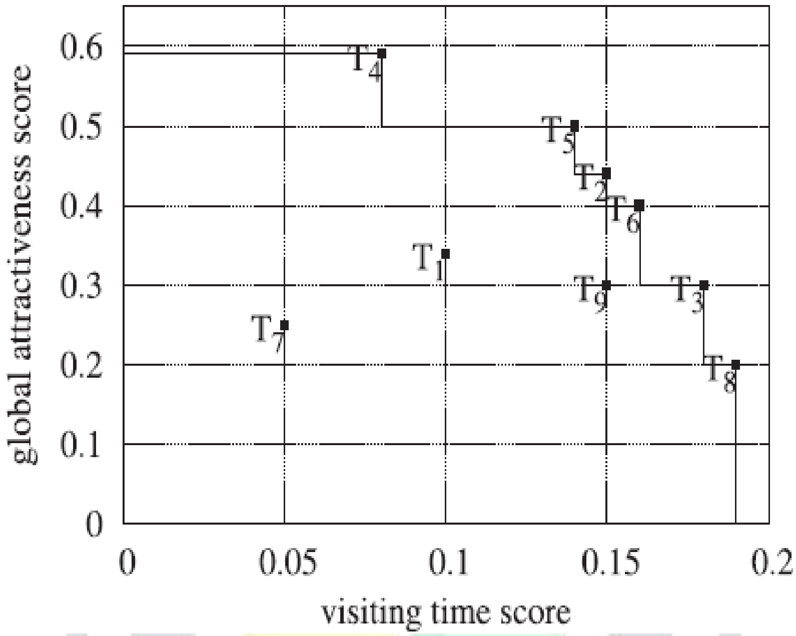

Fig.2. An extended example of skyline travel routes built by Table 1.

TABLE II: Symbols and Notations

Notation	Definition
p	location as Point-of-Interest (POI)
t	low-sampling route as travel sequence
w	tag that describes a POI
n	the number of routes in the dataset
$\mathcal{K}$	a set of query keywords
$GS(w)$	geo-specificity score of a tag w
$TS(w)$	temporal-specificity score of a tag w
$AT(w)$	attribute score of a tag w
$\mathcal{D}$	a set of d-dimensional featured routes
m	the number of routes in $\mathcal{D}$
$\mathcal{S}$	the full skyline of $\mathcal{D}$
k	maximum number of the returned travel routes
$\mathcal{R}$	the returned representative skyline travel routes

II. FRAMEWORK OVERVIEW

In this section, the proposed framework KSTR is presented. KSTR is comprised of two modules: the offline pattern discovery and scoring module and the online travel routes exploration module. The notations used throughout the paper are summarized below in Table 2.

Offline Pattern Discovery and Scoring Module: Given an LBSN dataset, 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 characteristics. Furthermore, we derive the feature scores of the POIs and generate proper candidate travel routes.

Online Travel Routes Exploration Modulez: In this module, we aim to provide an interface for users to specify query ranges and preference-related keywords. Once the system receives a specified range and time, the online module will retrieve those travel routes that overlap the query range and the stay time period. Then, it will compute a matched score of how well the travel route is connected to the keywords. Consequently, the online module returns the k most representative routes considering the aforementioned feature scores to the users.

III. EXISTING 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. 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.

IV. 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 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. 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 could be built from the collection of low -sampling check-in records.

A. Implementation of Modules

- Geo specific Keywords.
- Temporal Keywords.
- Candidate Route Generation.
- Travel Route Exploration

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 amount 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. Last, we design a Depth-first search-based procedure to generate possible routes.

4.Travel Route Exploration: With the featured trajectory dataset, our final goal 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. Next, 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.

V. SYSTEM ARCHITECTURAL DESIGN

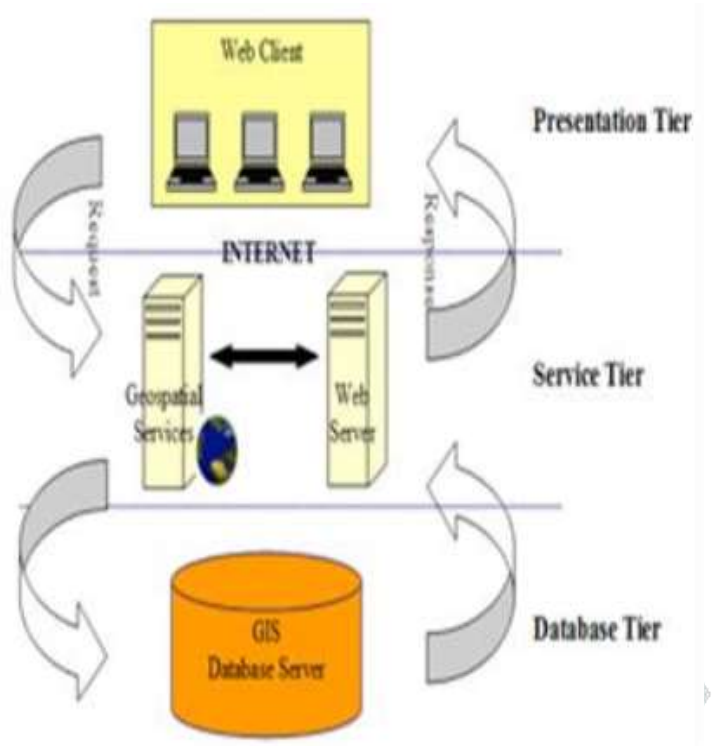

Fig.3. User Interface.

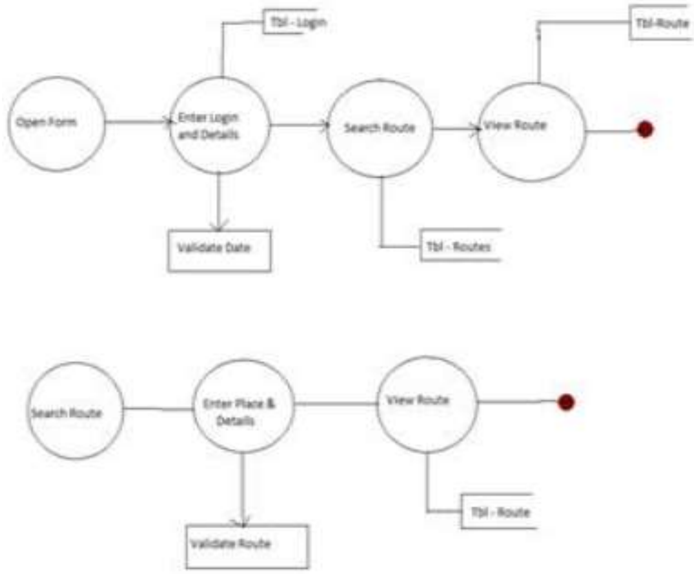

Fig.4.Data Flow Diagram.

VI. 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 user at a query region. Tools and Technologies used in this project:

- Asp.Net & SQL Management
- Server 2014 technologies.

Literature Survey: Efficient Keyword-Aware Representative Travel Route Recommendation Spatio-Temporal and Events Based Analysis of Topic Popularity in Twitter:

- In this paper we present a large-scale measurement study that attempts to describe and explain the processes that animate micro-blogging services.
- We study a large set of popular and non-popular topics derived from a comprehensive data set of tweets and user information taken from Twitter.
- A key strength of our study is that we observe both popular and not-so-popular topics.

In our In our view, T-patterns are a basic building block for spatio-temporal data mining, around which more sophisticated analysis tools can be constructed, including:

- integration with background geographic knowledge, such as road networks and other geographic information layers, at the level of trajectory pre-processing, POI discovery, T-patterns mining and post-processing.
- adequate visualization metaphors for T-patterns, as well as integrations into visual analytics methods and tools for exploratory trajectory pattern mining;
- adequate mechanisms for spatio-temporal querying and reasoning mechanisms on both input trajectories and extracted T-patterns, including refinements of interesting T-patterns.

VII. RESULTS

Results of this paper is as shown in bellow Figs.5 to 36.

Fig.5.

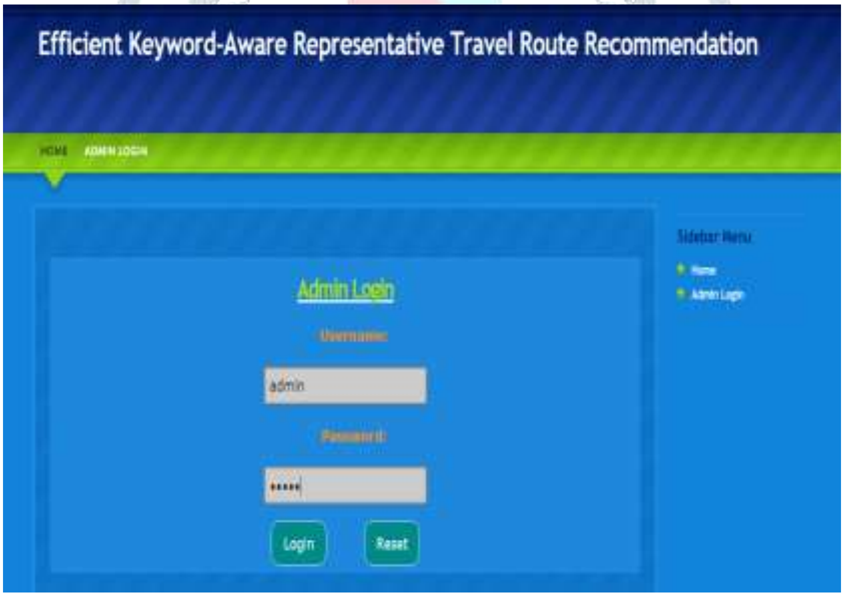

Fig.6.

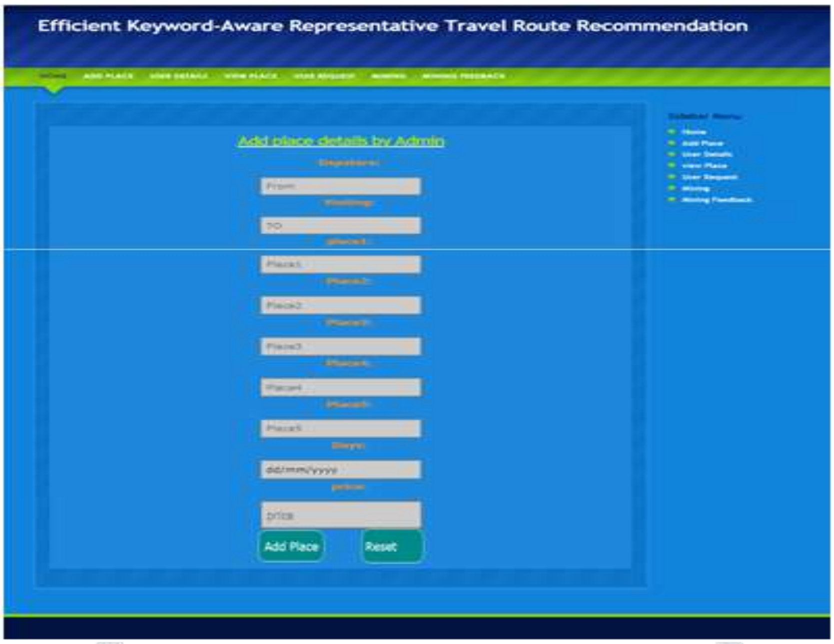
Efficient Keyword-Aware Representative Travel Route Recommendation
Add place details by Admin
From
TO
Place1
Place2
Place3
Place4
Place5
dd/mm/yyyy
price
Add Place
Reset

Fig.7.

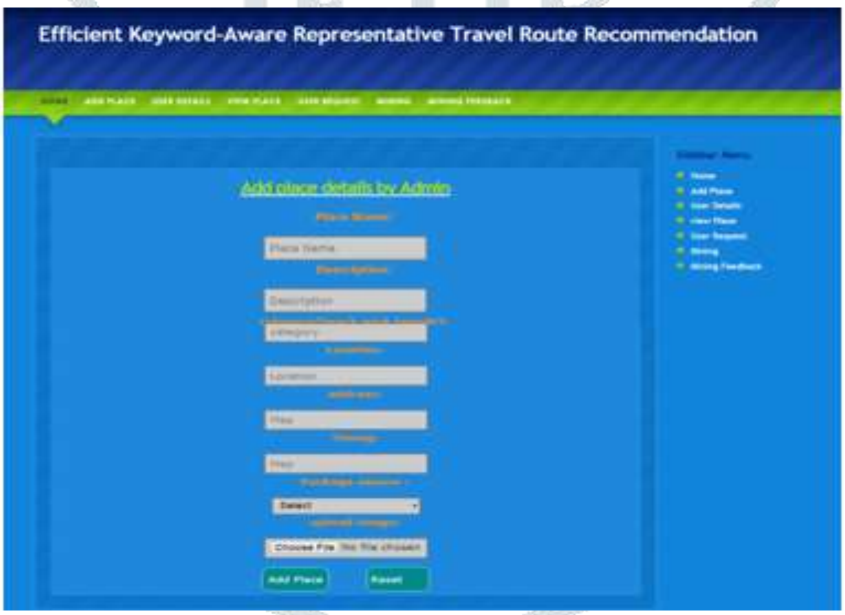
Efficient Keyword-Aware Representative Travel Route Recommendation
Add place details by Admin
Place Name
Description
Add Place
Reset

Fig.8.


Efficient Keyword-Aware Representative Travel Route Recommendation
User Registration Details
Profile
Username
User id
User Mail_id
Mobile
Location
Sidebar Menu

Fig.9.


Efficient Keyword-Aware Representative Travel Route Recommendation
View all places
Sidebar Menu

Fig.10.

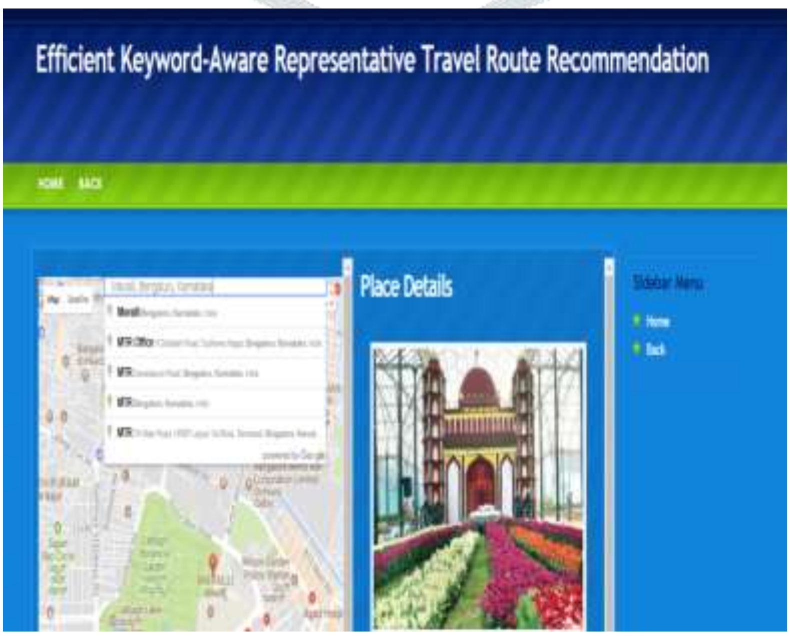
Efficient Keyword-Aware Representative Travel Route Recommendation
Place Details
Sidebar Menu

Fig.11.

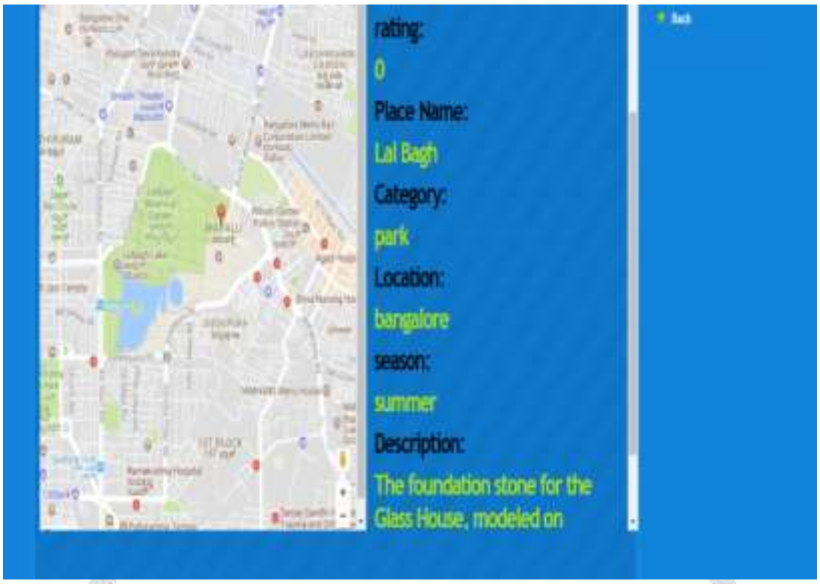

Fig.12.

Fig.13.

Fig.14.

Fig.15.

Fig.16.

Fig.17.

Fig.18.

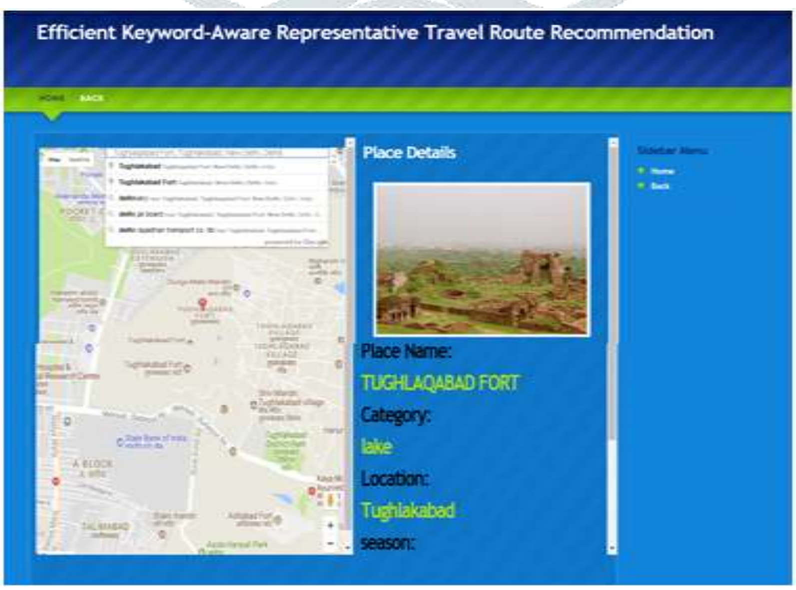

Fig.19.

Fig.20.

Fig.21.

Fig.22.

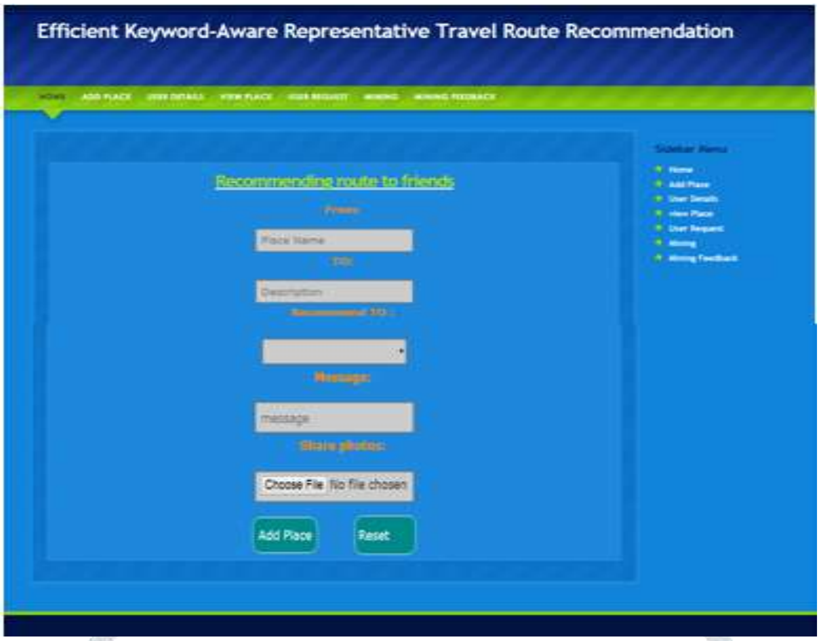
Efficient Keyword-Aware Representative Travel Route Recommendation
Recommending route to friends
Place Name
Description
message
Choose File No file chosen
Add Place
Reset

Fig.23.

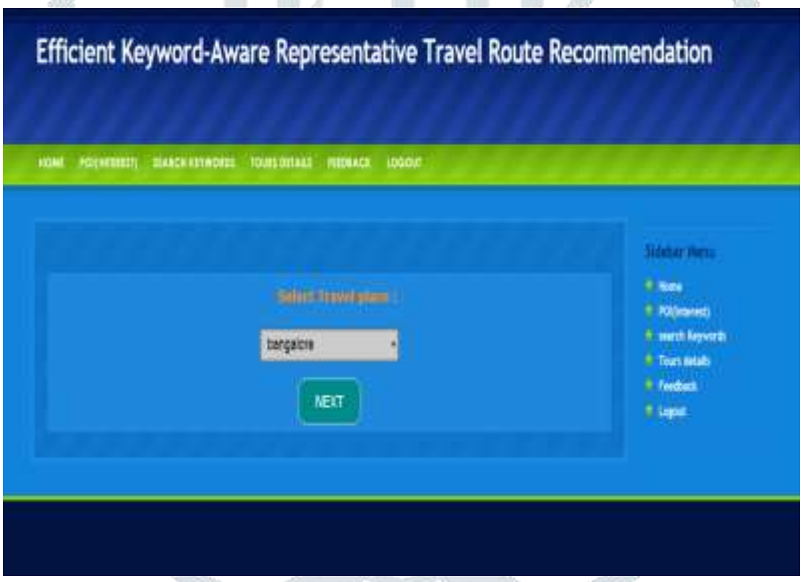
Efficient Keyword-Aware Representative Travel Route Recommendation
bangalore
NEXT

Fig.24.

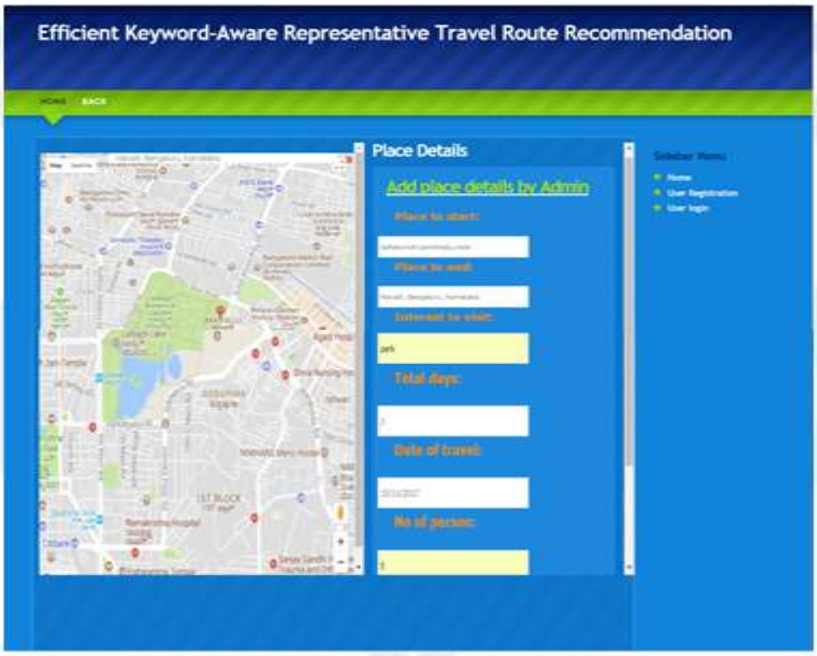
Efficient Keyword-Aware Representative Travel Route Recommendation
Place Details
Add place details by Admin

Fig.25.

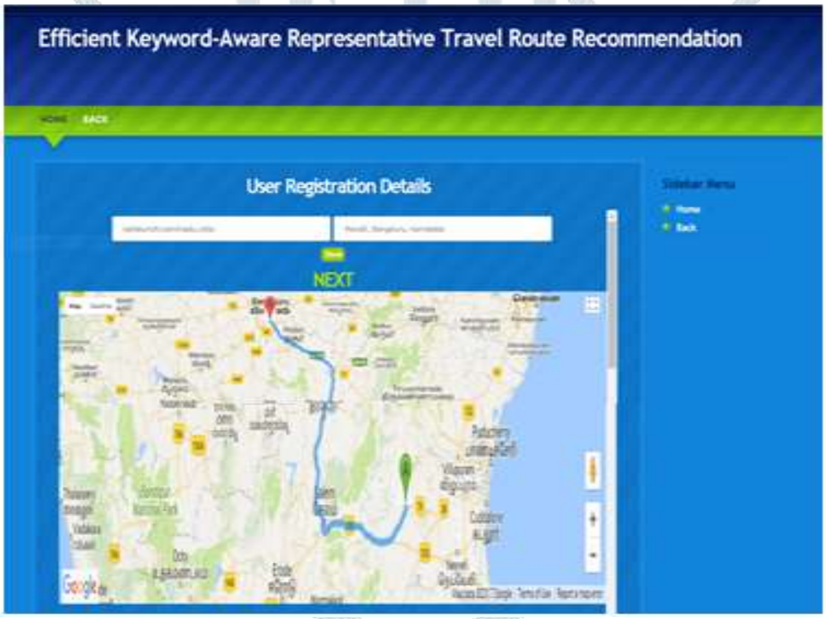
Efficient Keyword-Aware Representative Travel Route Recommendation
User Registration Details
NEXT

Fig.26.

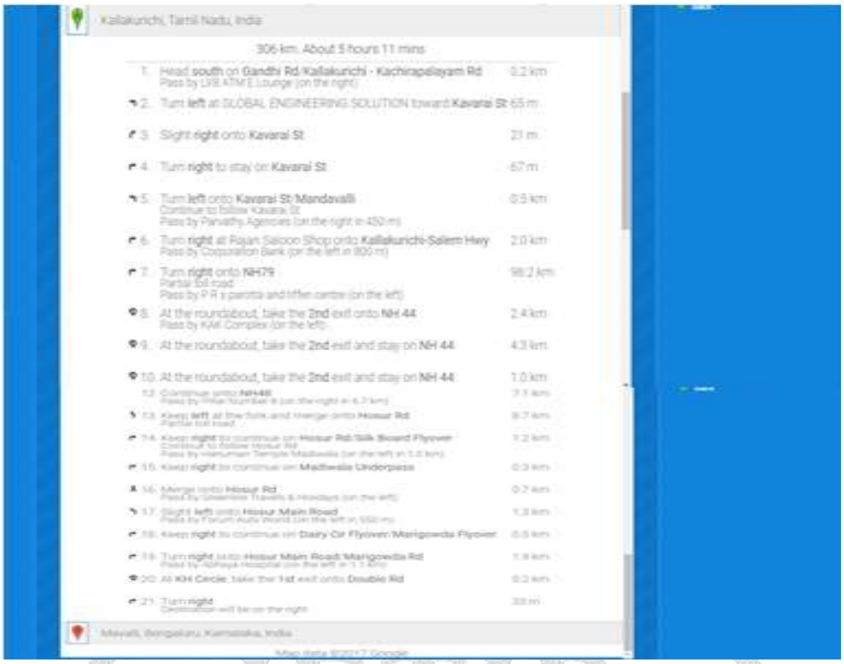

Fig.27.

Fig.28.

Fig.29.

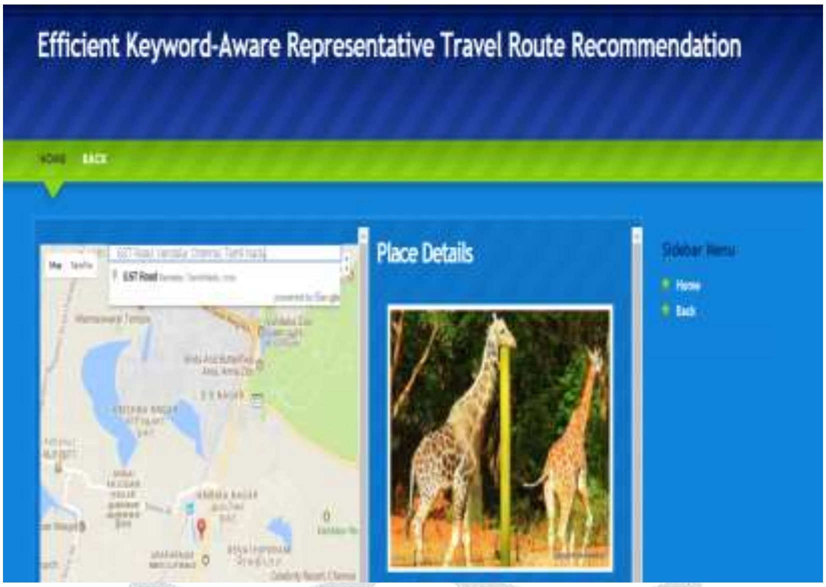

Fig.30.

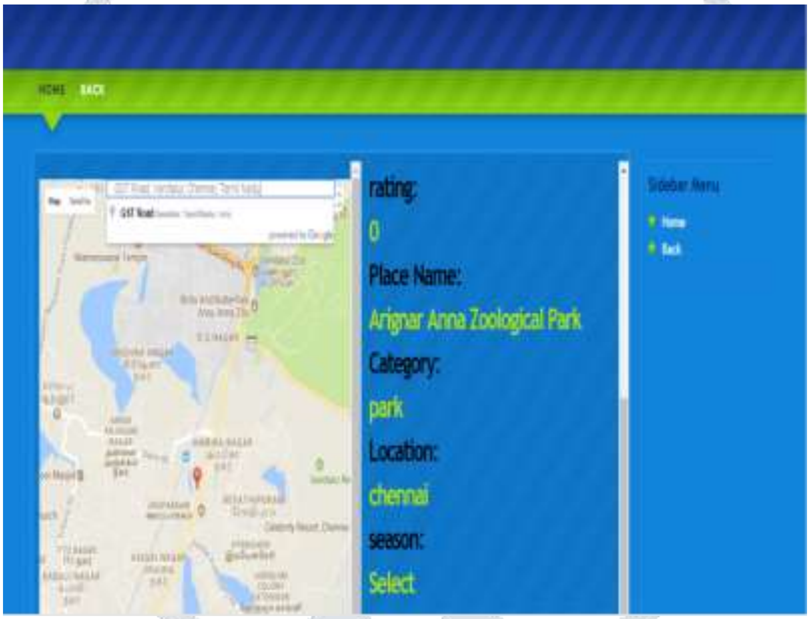

Fig.31.

Fig.32.


Efficient Keyword-Aware Representative Travel Route Recommendation
User Request Places
Sidebar Menu
Home
Add Place
User Details
view Place
User Request
Mining

Fig.33.


Efficient Keyword-Aware Representative Travel Route Recommendation
User Request Places
User Respond Places
Sidebar Menu
Home
Feedback
Logout

Fig.34.

Fig.35.

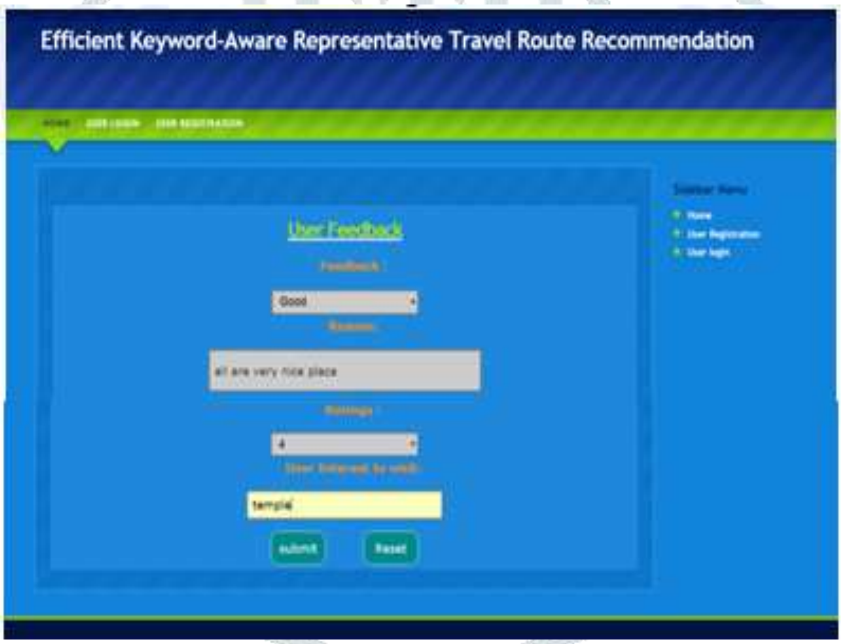

Fig.36.

VII. CONCLUSION

In this paper, we study the travel route recommendation problem. We have developed a KRTR framework to suggest travel routes with a specific range and a set of user preference keywords. These travel routes are related to all or partial user preference keywords, and are recommended based on (i) the attractiveness of the POIs it passes, (ii) visiting the POIs 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 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. The experiment results demonstrate that KRTR is able to retrieve travel routes that are interesting for users, and outperforms the baseline algorithms in terms of effectiveness and efficiency. Due to the real-time requirements for online systems, we aim to reduce the computation cost by recording repeated queries and to learn the approximate parameters automatically in the future.

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