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PERFORMING TRAJECTORY SEARCH QUERY USING POINT OF INTEREST

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Abstract: The geographical data set by sensible phone bridges the gap between physical and digital worlds. Location data functions as a result of the affiliation between user's physical behaviors and virtual social internet works structured by the sensible phone or net services user gives ratings to that place and this place becomes popular with the help of rating prediction and user is used social media for rating. Nowadays, social media becomes popular. This paper is enhancement of a region based point of interest using TSR query processing models. The proposed model assists the user in precised manner. With the help of analyzed regions, spatial density correlations to the searched queries are estimated. Thus, a heuristic search model is arranged with the queries and then prioritized according to the user's rating. By doing so, we achieved reduced searching complexity and the spatial outliers. Experimental analysis has shown the efficiency of the proposed systems.

Keywords: Geographical data, Point of interest, Searching query, Location based searches, Spatial analysis, and Correlations.

I. INTRODUCTION

The availability of GPS-equipped devices and online map-based services to catch their present area what's more, to share their directions by methods trajectories by means of services, for example, Bikely4, GPS-Way-points5, ShareMy-Routes6, and Microsoft GeoLife7. Likewise, and more social networking sites, including Twitter8, Four square9, and Facebook10, bolster the sharing of trajectories. The accessibility of enormous trajectory data empowers novel portable applications. Such applications may use trajectory search, which discovers trajectory that are comparable in some particular sense to query [1]. This sort of inquiry can profit well known administrations, for example, travel arranging and proposal, and location-based services in general. For instance, when arranging an excursion to various spots in a new city, a traveler may profit by the experience of past guests. Specifically, guests with comparative interests may have gone by close-by points of interest that the client may not know, in any case, might be occupied with. Or, then again others may have maintained a strategic distance from a particular street since it is upsetting, in spite of the fact that it might appear like a decent decision as far as separation. Such encounters are caught in trajectory shared by past guests. In existing examinations, all directions are dealt with the same, paying little mind to their frequencies of utilization. For instance, some less traveled trajectories might be new or quite recently less popularity since the district they are in is less traveled. Such trajectories may even now bear some significance with users.

The proliferation of trajectory data has spawned many novel applications. One example is searching trajectories by locations [2]. Location-based trajectory search was first proposed as the k Best-Connected Trajectories (k-BCT) query. Given a few query locations, a k-BCT query finds k trajectories that are close to all query points from a trajectory database. Location-based trajectory search can benefit users in many real life applications. For example, it can help travelers who are planning a trip to multiple places of interest in an unfamiliar city, by providing similar routes traveled by other people for reference. Location-based trajectory search [3] is also useful in human behavior analysis, where the query locations can be tourist attractions (specified by a travel agency) or the stops of a new metro line (specified by the transport department).

The k-BCT query [4], however, considers only the spatial aspect of trajectories, which is inadequate for many real applications. Consider a travel agency that queries a database of tourist trajectories for market analysis. For simplicity, we assume the data space to be 1D rather than 2D, and we only mark the relevant trajectory samples using Δ. For example, Tom spent 15 minutes at the airport (for check-out), 1 hour at Outlet A (for shopping), 8 seconds at Outlet B (just passing by), and 30 minutes at the hotel (for check-in and taking a rest). Unfortunately, a 2-BCT query over the database with query locations, {Airport, Outlet B, Hotel}, would return the trajectories of Tom and Mary (who actually went shopping at Outlet A), since the 5-th sample in the trajectories of Tom and Mary is closer to Outlet B than any of the samples in the trajectories of Peter and Alice. As a result, the travel agency may make a wrong arrangement: when a tourist bus picks up a group of middle-aged tourists at the airport and goes to the hotel, it would stop at Outlet B for the tourists to go shopping [5].

The rest of the paper is organized as follows: Section II presents the related work; Section III presents the proposed work; Section IV presents the experimental analysis and results and finally concludes in Section V.

II. RELATED WORK

This section presents the prior works of the trajectories search models. S. Shang et al propose and investigate the methods to find and recommend the best trajectory to the traveler, and mainly focus on a novel technique named User Oriented Trajectory Search (UOTS) query processing. In contrast to conventional trajectory search by locations (spatial domain only), they considered both spatial and textual domains in the new UOTS query. In [6], they investigated the problem of discovering similar trajectories of moving objects. The trajectory of a moving object is typically modeled as a sequence of consecutive locations in a multidimensional (generally two or three dimensional) Euclidean space. Such data types arise in much application where the location of a given object is measured repeatedly over time. Examples include features extracted from video clips, animal mobility experiments, sign language recognition, mobile phone usage, multiple attribute response curves in drug therapy, and so on.

In [7], the authors proposed a novel map-matching algorithm called Pass by to work on most simplified road networks. The storage size of digital road map in disk or memory can be greatly reduced after the simplification. Even under the most simplified situations, i.e., each road segment only consists of a couple of junction points and omits any other information of it, the experimental results on real dataset show that our Pass by algorithm significantly maintains high matching accuracy. Benefiting from the small size of map, simple index structure and heuristic filter strategy, Pass by improves matching accuracy as well as efficiency. In [8] studied a new type of query that finds the k Nearest Neighboring Trajectories (k-NNT) with the minimum aggregated distance to a set of query points. Such queries, though have a broad ranges of application like trip planning and moving object study, cannot be handled by traditional k-NN query processing techniques that only find the neighboring points of an object. To facilitate scalable, flexible and effective query execution, we propose a k-NN trajectory retrieval algorithm using a candidate-generation and-verification strategy. The algorithms utilize a data structure called global heap to retrieve candidate trajectories near each individual query point.

In [8] proposed two such techniques. The idea here is to make use of the given distance measures to map sequences into points in k-d space. The other technique we propose defines a new distance function which uniformly underestimates the original distance function. This function can be computed much faster than the original distance so that it can be used. The other technique suggested new distance function which uniformly underestimates the original distance function. This function can be computed much faster than the original distance so that it can be used as alter to help us discard quickly non-qualifying sequences. The author in [9] suggested techniques that enable the construction of a multi-cost, time-dependent, uncertain graph (MTUG) model of a road network based on GPS data from vehicles that traversed the road network. Based on the MTUG, Author define stochastic skyline routes that consider multiple costs and time-dependent uncertainty, and Author propose efficient algorithms to retrieve stochastic skyline routes for a given source-destination pair and a start time. Empirical studies with three road network in Denmark and a substantial GPS data set offer insight into the design properties of the MTUG and the efficiency of the stochastic skyline routing algorithms.

The author in [10] studied a Top-k Spatial Keyword (TkSK) query for activity trajectories, with the objective to find a set of trajectories that are not only close geographically but also meet the requirements of the query semantically. Such kind of query can deliver more informative results than existing spatial keyword queries for static objects, since activity trajectories are able to reflect the popularity of user activities and reveal preferable combinations of facilities. In [11] study a new problem of searching the k Best-Connected Trajectories from a database by using a set of locations with or without an order constraint. Since the number of query locations is typically small, it enables us to adopt a spatial method for answering a similarity search query. They started the study based on a simple IKNN algorithm and then analyze the efficiency of different variants. As a conclusion, we would say that the BF-O achieves the best query performance although involving a risk of high memory usage. The pure DF-C algorithm, although guarantees a low memory consumption, performs poorly in efficiency.

In [12], the author studied a new type of query that finds the k Nearest Neighboring Trajectories (k-NNT) with the minimum aggregated distance to a set of query points. Such queries though have broad ranges of application like trip planning and moving object study cannot be handled by traditional k-NN query processing techniques that only find the neighboring points of an object. To facilitate scalable, flexible and effective query execution, we propose a k-NN trajectory retrieval algorithm using a candidate-generation and-verification strategy. The algorithms utilize a data structure called global heap to retrieve candidate trajectories near each individual query point. B. Yang et al propose techniques that enable the construction of a multi-cost, time-dependent, uncertain graph (MTUG) model of a road network based on GPS data from vehicles that traversed the road network. Based on the MTUG, Author define stochastic skyline routes that consider multiple costs and time-dependent uncertainty [13], and Author propose efficient algorithms to retrieve stochastic skyline routes for a given source-destination pair and a start time. Empirical studies with three road network in Denmark and a substantial GPS data set offer insight into the design properties of the MTUG and the efficiency of the stochastic skyline routing algorithms.

In [14], they investigated mechanisms to perform NN search on R-tree-like structures storing historical information's about moving object trajectories. The proposed (depth-first and best-first) algorithms vary with respect to the type of the query object (stationary or moving point) as well as the type of the query result (historical continuous or not), thus resulting in four type of NN queries. They also suggested a novel metrics to support our search ordering and pruning strategies. Using the implementation of the proposed algorithm on two members of the R-tree family for trajectory data [15] (namely, the TB-tree and the 3DR-tree), and demonstrated their scalability and efficiency through an extensive experimental study using large synthetic and real dataset.

III. PROPOSED WORK

This section presents the proposed model of our study. The proposed model composes of four phases, namely,

A) Network formation:

The spatial network is composed by the associated and undirected graph of G(V, E, F and W) where Vis the set of vertex with the edge E. In some cases, the vertex v_i also represents the intersection or termination of the road. These set of vertex and edge groups are denoted in geometries model F: V U E→ Geometries. It also represents the geometrical information of the spatial network. In general cases, it maps with the vertex and edge of its corresponding and polyline representing the load segment. The length of each road segment with its corresponding weight is computed. Spatial objects of the systems are matched using map-matching algorithms. Each spatial object are denoted by its p which is further assigned attribute of p and denoted as p.g. A vertex and its assigned spatial objects constitute the smallest unit in spatial-object density computations, and thus we need not access individual spatial objects during TSR query processing.

B) Data users & Data administrator:

Initially, the user has to register with the spatial network so as to proceed with the spatial objects. Once the user is registered with the environment, the location is added to the database. In addition to, the user can search the relevant data using appropriate keywords. The keyword analysis is done which stores the point of interest and also recommends the location for the users. The main task of data administrator is to perform all the data operations based on given user's details. In some cases, the user can add or delete the places. With the help of point of interest, the user can perform the searched operations. It can be done by the graphical analysis of the places and locations.

C) Query search processing:

In conventional search systems, the lack of scheduling model leads to poor performance. If any of the cases, the query systems found to be closer, then the query sources is highly utilized. Trajectory search region query takes a set of regions of interest as a parameter and returns the trajectory in the argument set with the highest spatial-density correlation to the query regions. This type of query is useful in many popular applications such as trip planning and recommendation, and location based services in general. TSR query processing faces three challenges: how to model the spatial-density correlation between query regions and data trajectories, how to effectively prune the search space, and how to effectively schedule multiple so-called query sources.

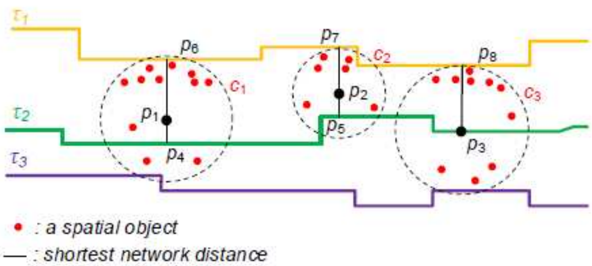

Fig.3.1 System Architecture

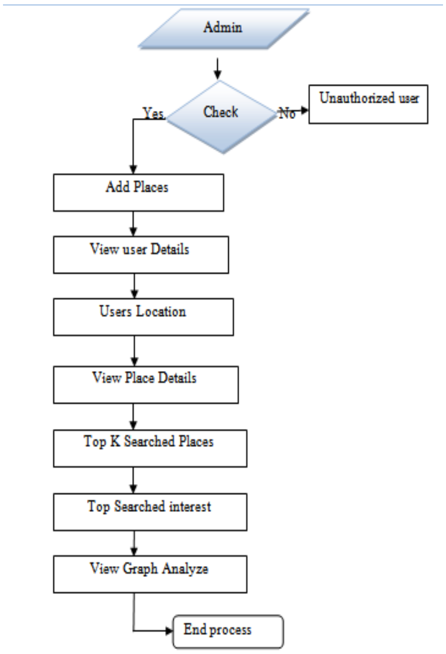

Fig.3.2 Workflow of data administrator

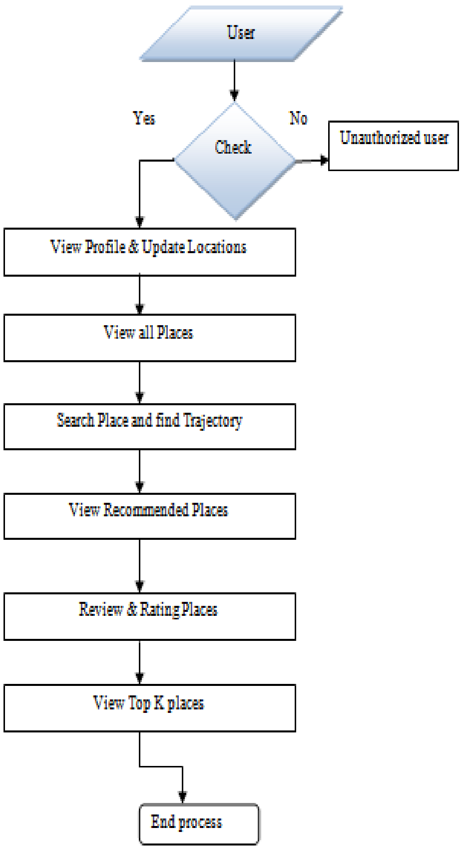

Fig..3.3 Workflow of data administrator

IV. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents experimental analysis of our proposed work.

Fig. 4.1 Discovery of user's location

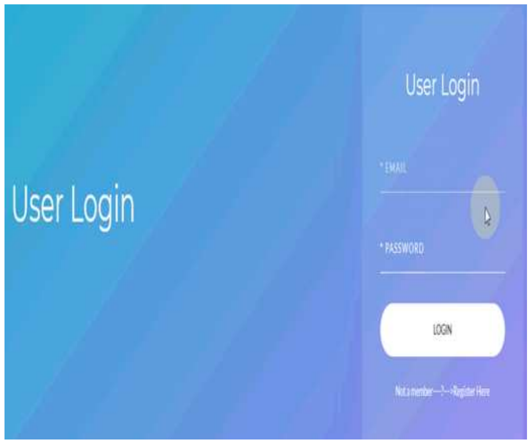

Fig. 4.2 User's login

Fig.4.3 Signed in users is verified via OTP systems

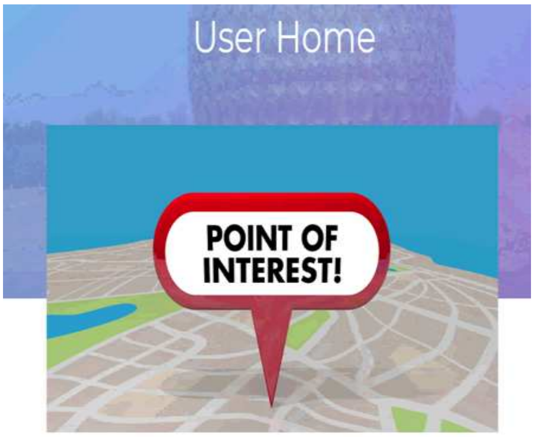

Fig.4.4 Users searching process is carried using point of interest

Fig. 4.5 User's profile is viewed

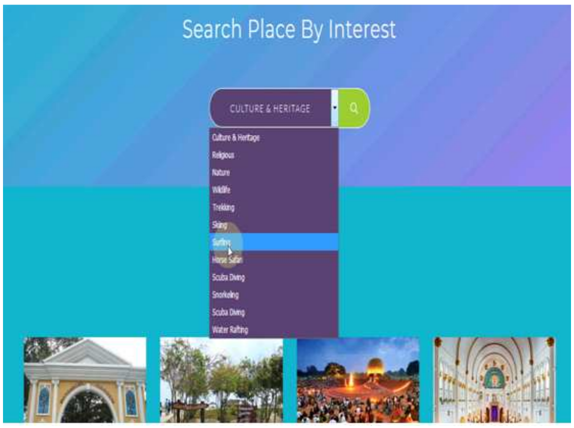

Fig.4.6 Searching places using point of interest

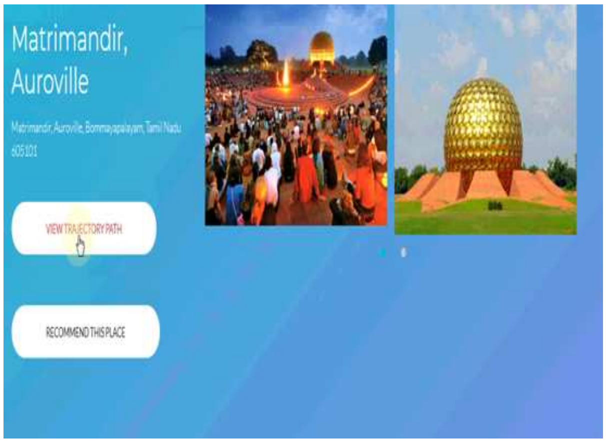

Fig.4.7 Discovery of places via trajectory models

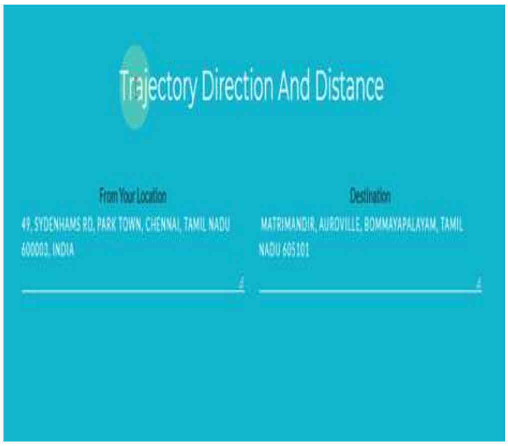

Fig.4.8 Information about the source and destination region

Fig.4.9 Recommending the places for users

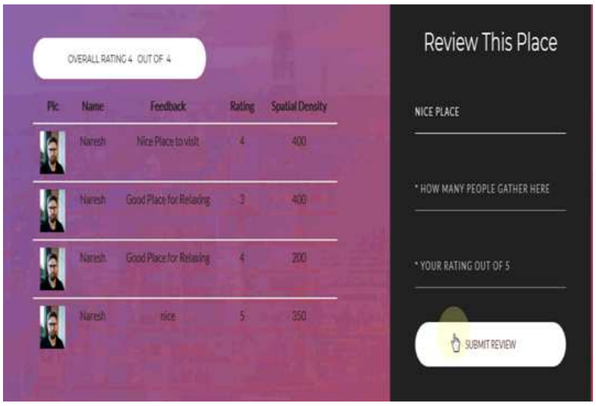

Fig.4.10 Reviewing the recommended places

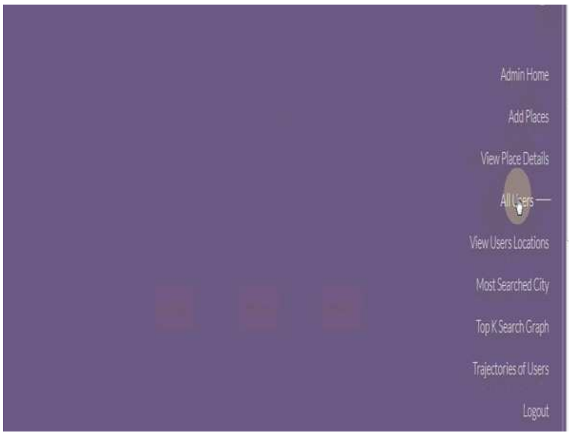

Fig.4.11. Role of Admin

Fig.4.12 Viewing the user's details

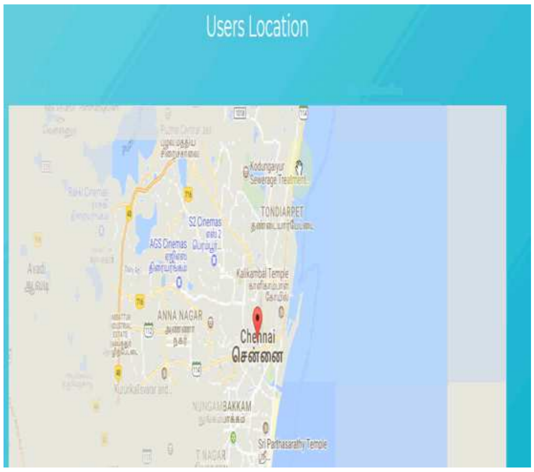

Fig.4.13 Predicting the user's location

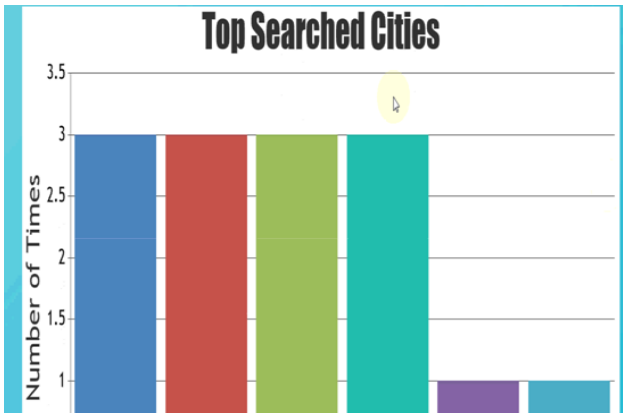

Fig. 4.14 Performance analysis of the proposed systems

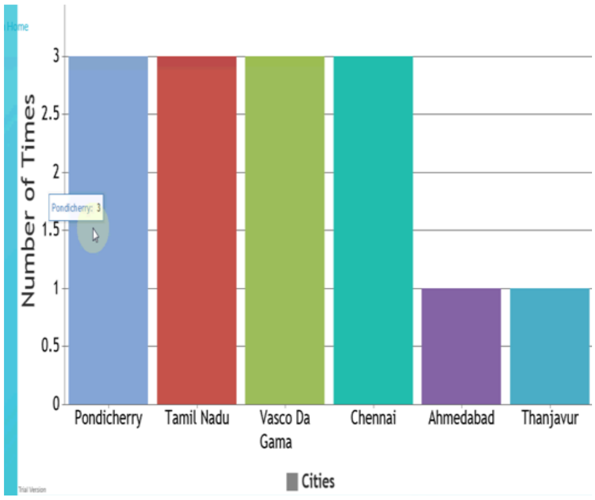

Fig.4.15 Analysis of the Recommender systems

Trajectories Details

Place Id	User Id	User Name	Source	Destination	View Trajectory
1	1	Naresh	49, Sydenhams Rd, Park Town, Chennai, Tamil Nadu 600003, India	South Boulevard (near old Bus Stand), Puducherry 605001	Trajectory Path
2	1	Naresh	49, Sydenhams Rd, Park Town, Chennai, Tamil Nadu 600003, India	40, Goubert Avenue, Puducherry, Tamil Nadu 605 001	Trajectory Path
3	3	Sabari	49, Sydenhams Rd, Park Town, Chennai, Tamil Nadu 600003, India	Matrimandir, Auroville, Bommayapalayam, Tamil Nadu 605101	Trajectory Path

Fig. 4.16 Trajectory path of the details

V. CONCLUSION

Trajectory outliers can be very useful in traffic analysis. This type of movement analysis between regions of interest is useful to help to understand the flow of people that move between the regions, how this flow is distributed and what are the characteristics of the movements. In high traffic areas outliers can show alternative paths that can reduce the volume of cars, or reveal the best or worst path that connects two regions. Moreover, the outliers can be interesting to discover suspicious behaviors, like company cars that scope from their normal route. In this paper, we propose a region based point of interest using TSR query processing models. This query process executes on set of region of interest with high spatial density correlation of the query regions. The proposed model resolves the queries issues like searching complexity, correlation between query regions and the multiple query sources. By efficiently finding the correlations, the queries are analyzed and then priority ranking is done. Experimental analysis has shown the efficiency of the systems.

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