A COLLABORATIVE METHOD FOR ROUTE DISCOVERY USING TAXI DRIVERS' EXPERIENCE AND PREFERENCES

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Abstract- This paper presents a collaborative route discovery method that leverages the experience and preferences of taxi drivers in urban areas. The proposed method is mainly comprised of two phases: collaborative preference discovery (CPD) and intelligent driver network generation (IDNG). In the first phase, given an origin–destination (O–D) pair and provided that the cluster is a road segment set within a time-reachable range, we propose CPD which involves cluster-to-cluster retrieval to capture the top-k routes that are not only frequently traversed by taxis but also neighboring to the O–D pair. In the second phase, to support route computation, an IDNG algorithm is devised to generate an experiential graph for each specific O–D pair. In empirical studies, using the period-based experiential route database, sensitivity analysis is employed to select optimal parameters of intelligent driver networks.

KEYWORDS:- driver network generation (IDNG)., O–D pair, CPD

1 INTRODUCTION

A. Route Recommendation With the increasing demand of human mobility, technological innovations such as location-based services hint at a promising approach to explore the power of informationoriented routing [1]. In recent years, a large number of GPS-equipped vehicles such as taxis have become common in urban areas worldwide. In terms of both experience and preference, the intelligence of taxi drivers is hidden in their historical trajectories. Availability of trajectory could foster a number of route recommendation applications which are categorized into follows.

(1) Driving direction enhancement: the fastest route [4]–[6], the shortest route [7], the popular route (i.e., the most frequent route, and sometimes, the top-k frequent routes) [8], [9]–[11], easy- driving route [12], cost-effective route (i.e., shorter travel time, lower costs, and more frequent) [13], [14], and others [15]–[18] are recommended in response to users' (mainly private car drivers [45], [46]) queries.

(2) Taxis' profitable route recommendation [19]–[21]: using drivers' picking-up and dropping-off behaviors, previous studies have attempted to maximize drivers' profit, while some methods intend to recommend locations where passengers can easily find vacant taxis [19]. Relying on crowdsourcing data and crowd knowledge, TripPlanner [24] and CrowdPlanner [25], [26] employed a combination of the social network (i.e., POI network) and taxis' trajectories to achieve personalized, interactive, and traffic-aware routing. Furthermore, [27] aimed to characterize both the dynamics and the uncertainty of road conditions to implement adaptive routing. In [28], [41], and [42], a derivation skyline concept was utilized to retrieve travel routes.

2 REVIEW THE LITERATURE

Rapid urbanization and increasing demand for transportation burdens urban road infrastructures. The interplay of number of vehicles and available road capacity on their routes determines the level of congestion. Although approaches to modify demand and capacity exist, the possible limits of congestion alleviation by only modifying route choices have not been systematically studied. Here we couple the road networks of five diverse cities with the travel demand profiles in the morning peak hour obtained from billions of mobile phone traces to comprehensively analyze urban traffic. We present that a dimensionless ratio of the road supply to the travel demand explains the percentage of time lost in congestion. Finally, we examine congestion relief under a centralized routing scheme with varying levels of awareness of social good and quantify the benefits to show that moderate levels are enough to achieve significant collective travel time savings.

2.1 Finding and Evaluating Community Structure in Networks:

We propose and study a set of algorithms for discovering community structure in networks-natural divisions of network nodes into densely connected subgroups. Our algorithms all share two definitive features: first, they involve iterative removal of edges from the network to split it into communities, the edges removed being identified using any one of a number of possible "betweenness" measures, and second, these measures are, crucially, recalculated after each removal. We also propose a measure for the strength of the community structure found by our algorithms, which gives us an objective metric for choosing the number of communities into which a network should be divided. We demonstrate that our algorithms are highly effective at discovering community structure in both computer-generated and real-world network data, and show how they can be used to shed light on the sometimes dauntingly complex structure of networked systems.

This paper presents a smart driving direction system leveraging the intelligence of experienced drivers. In this system, GPS-equipped taxis are employed as mobile sensors probing the traffic rhythm of a city and taxi drivers' intelligence in choosing driving directions in the physical world. We propose a time-dependent landmark graph to model the dynamic traffic pattern as well as the intelligence of experienced drivers so as to provide a user with the practically fastest route to a given destination at a given departure time. Then, a Variance- Entropy-Based Clustering approach is devised to estimate the distribution of travel time between two landmarks in different time slots. Based on this graph, we design a two-stage routing algorithm to compute the practically fastest and customized route for end users. We build our system based on a real-world trajectory data set generated by over 33,000 taxis in a period of three months, and evaluate the system by conducting both synthetic experiments and in-the-field evaluations. As a result, 60-70 percent of the routes suggested by our method are faster than the competing methods, and 20 percent of the routes share the same results. On average, 50 percent of our routes are at least 20 percent faster than the competing approaches.

3 implementation Study

EXISTING SYSTEM

Taxis' profitable route recommendation: using drivers' picking-up and dropping-off behaviors, previous studies have attempted to maximize drivers' profit, while some methods intend to recommend locations where passengers can easily find vacant taxis. Relying on crowdsourcing data and crowd knowledge, Trip-Planner and CrowdPlanner employed a combination of the location-based social network (i.e., POI network) and taxis' trajectories to achieve personalized, interactive, and traffic-aware routing.

Disadvantages:

However, to the best of our knowledge, few studies have considered the following two aspects.

Collaborative preference. We use the taxis' trajectories with the consideration of its travel frequency in specific time period and spatial distance to a certain O-D pair. To some extents, O-D purpose-oriented and cluster-to-cluster route discovery can covert collective intelligence into a collaborative formula while capturing top-*k* routes.

O-D purpose-oriented partial graph. Once experiential routes are well-organized, we can achieve appropriate route recommendations by only considering refined partial graph with highly collaborative routes rather than a global graph.

PROPOSED SYSTEM

The route planning, as a classical problem, can also be accomplished by leveraging experience of taxi drivers' route decisions. To this end, this study presents a collaborative route planning method with the latent knowledge from experienced drivers in urban areas. In general, the proposed method makes the route planning can be solved by a query-like solution

Time-evolving traffic patterns may cause a taxi driver make different route choices. Thus, we construct a period-based database. In this study, days of the week are roughly divided into weekdays and weekends, further, time periods of the day include morning peak hours, evening peak hours and other off-peak hours.

When using taxis' trajectory, an inevitable issue is sparseness, meaning that it is impossible to always have experiential routes matching to a given O-D pair directly. However, by means of the collaborative preference discovery, routes between two physical regions can be retrieved.

Advantages:

Empirical studies demonstrate that our proposed method performs favorably in terms of efficiency, reliability, andeffectiveness while comparing with the conventional fastest path and shortest-path methods.

The routes recommended by the proposed method tend to better express the latent experience and preferences of taxi drivers. Last but not least, with the proposed threshold free method in selecting a suitable *tc*, the cluster-to-cluster retrieval based method can address the existing sparseness issue to some extent.

ARCHITECTURE DIAGRAM

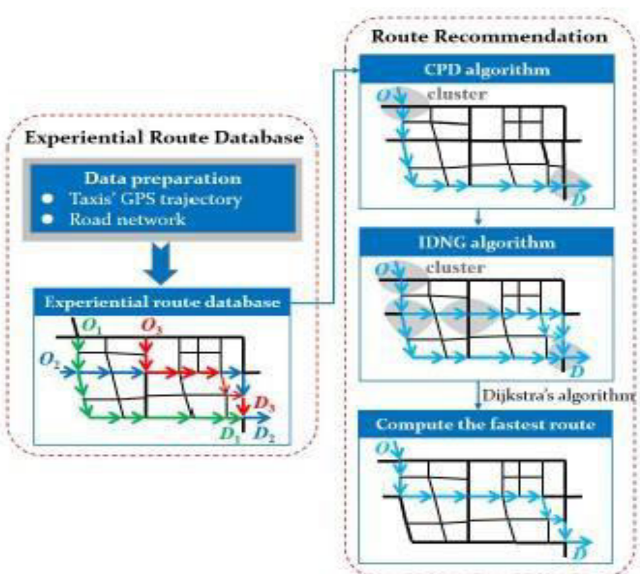

Fig 1:-proposed model

4 Methdology

ADMIN:

Admin is the main module for this application which has features for viewing drivers and users and check bookings and assign bookings and admin has feature to look after all bookings and route information for each taxi driver traveling from source to destination and routes they are choosing and time taken for traveling from source to destination.
Admin will use this information of each taxi driver paths and times and recommend best route based on clustering in to three types cs,cl,cd and recommend best route form source to destination for new taxi user. This is done using Collaborative Preference Discovery (CPD) algorithm

1) Cluster: A cluster can be regarded as the road segment set within a time-reachable region. Specifically, as shown in Fig. 3, the clusters are classified into three types, i.e., source cluster (*cs)*, destination cluster (*cd)*, and extended cluster (*ce)*.Starting from a source, the road segments in the source cluster and the extended cluster are reachable within a prescribed time threshold. Likewise, the destination is required to be reachable within the same time threshold starting from any road segment in the destination cluster.

2) Time-Reachable Threshold tc: To avoid an abnormal cluster arising via the inclusion of too many road segments, we set a time-reachable threshold *tc*as a condition. In the following studies, all clusters are restricted by the same *tc*.

3) Cluster-to-Cluster Retrieval*:* In Fig. 3, the cluster-to cluster retrieval from *cs*to*cd* covers *r*1, *r*2, and *r*3, while *r*4is the retrieval result from *ce*1 to *cd* . Given a route ranking scheme, the top-*k* routes can be selected from the source cluster *cs*(or extended cluster *ce)* to the destination cluster *cd* .

4) Query Experiential Route Rq *:*A query experiential routes one that proceeds from *cs*to*cd* such as *r*1, *r*2, and *r*3 shown

5) Extended Experiential Route*: Re*: The extended experiential route is captured from an extended cluster to the destination cluster. In Fig. 3(b), *r*4 is an extended experiential route from *ce*1 to *cd*

6) Transfer Route: Rt: From *cs*(or *ce)* to *cd* , the start road segment (or end road segment) of an derived experiential route may not be the source (or the destination). In this vein, a transfer route is necessary to connect the source (or destination) with the start road segment (or end road segment), and the experiential route can be completely matched to a journey. Here, the transfer route is the fastest option and has been previously traversed by taxis.

USER:

User module is used for collecting data to verify CPD algorithm. In this module user can select source and destination and send request for taxi drivers and check accepted requests from taxi drivers and conform.

DRIVER:

Taxi driver module is used for taking bookings from users and select route form source to destination and conform users bookings. Details of path drivers followed from source to destination and time taken for drivers to reach destination is stored in database.

RESULTS

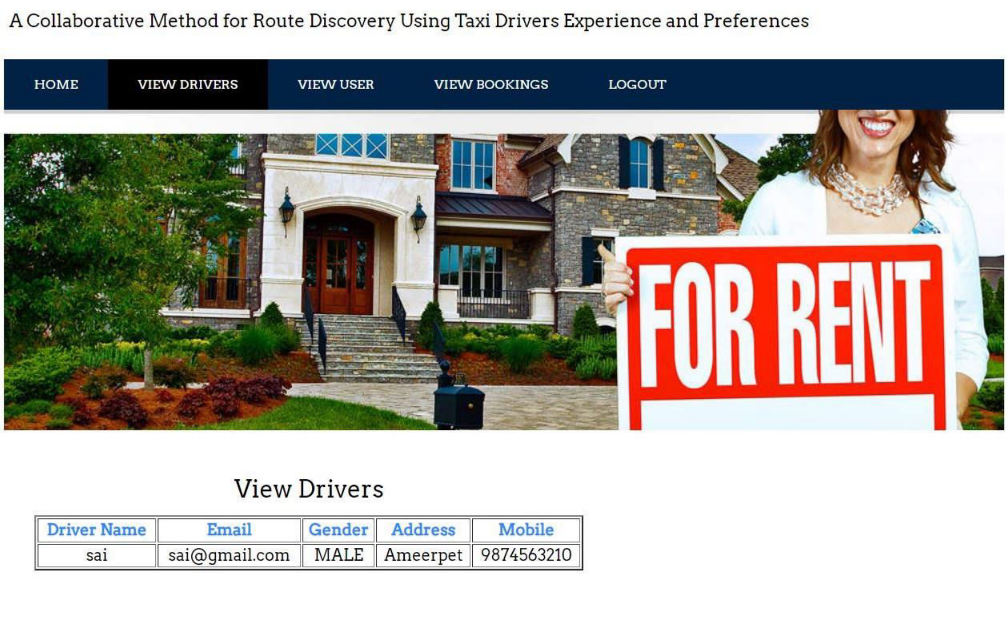

Fig 2:-view drivers

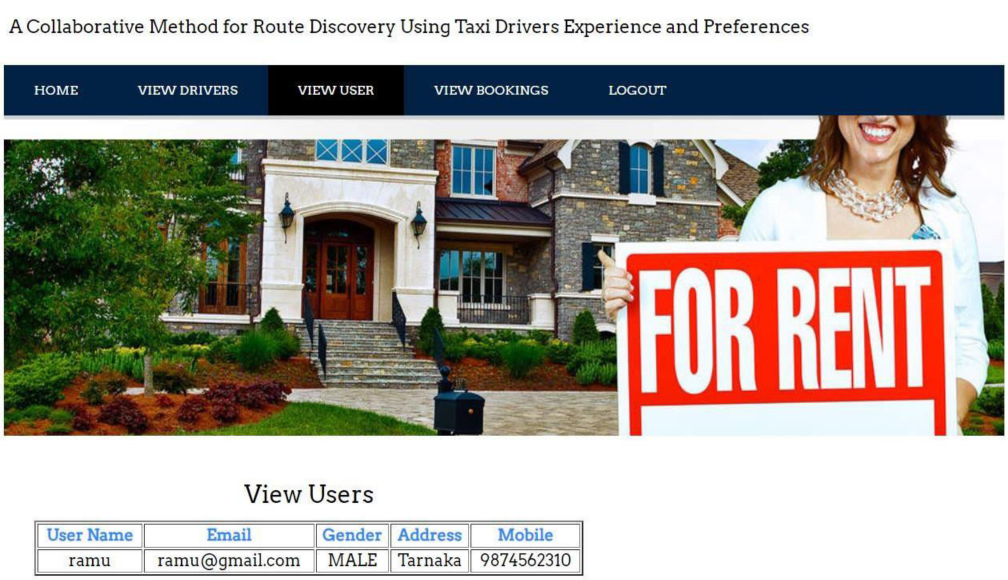

Fig 3:- view users

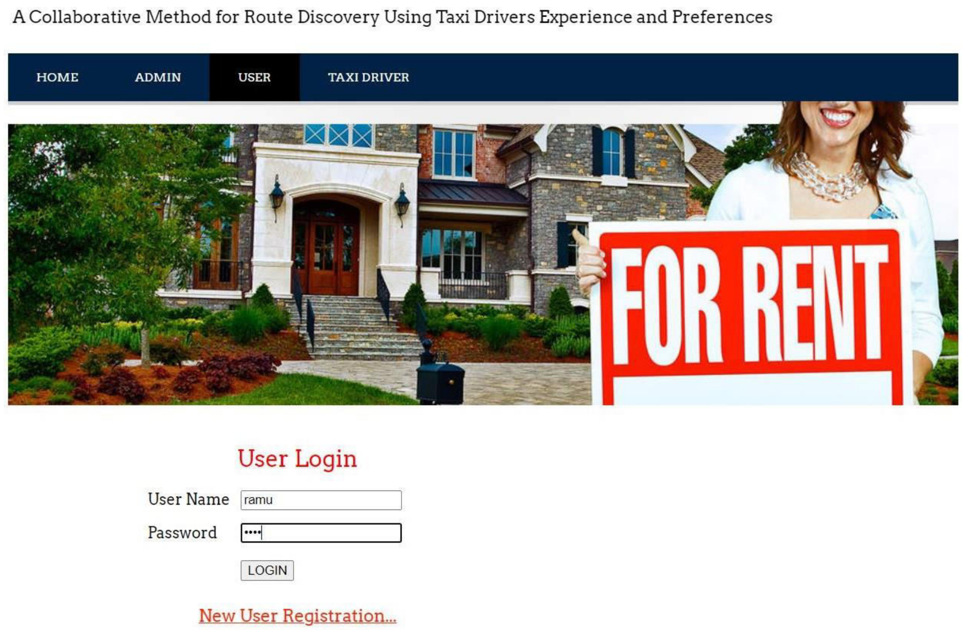

Fig 4:- user login

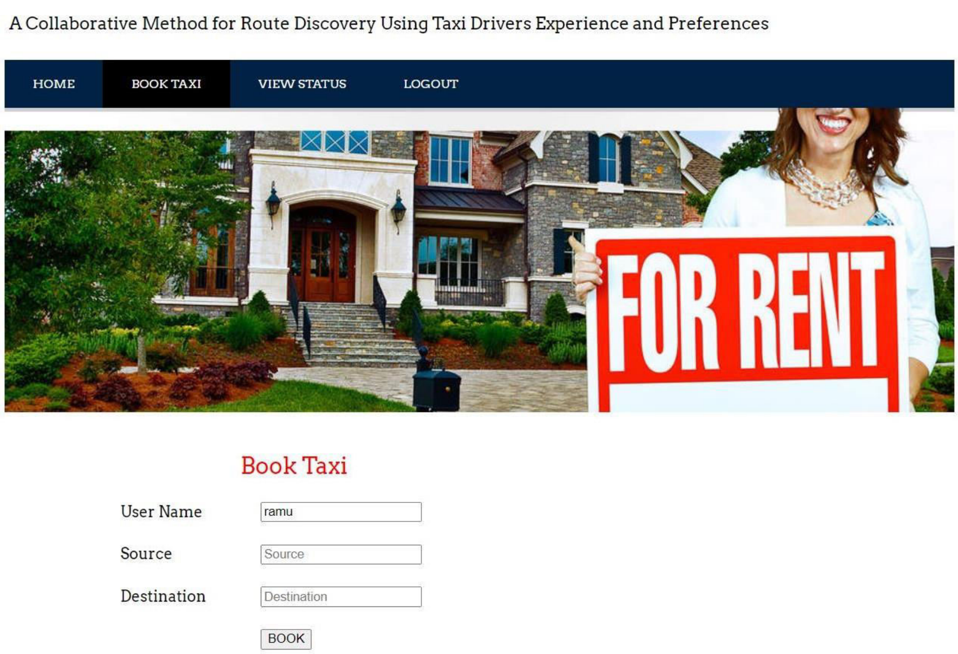

Fig 5 :- book taxi

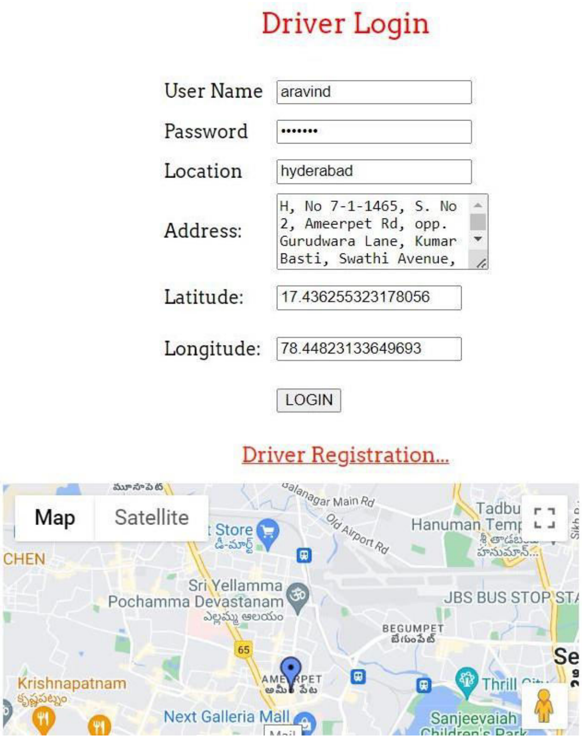

Fig 6:- driver registration page

CONCLUSION

In big data era, discovering knowledge such as experience and preference from human trajectory for better travelling is an interesting topic. Thus, how to harness the large-scale trajectory data and unlock their power is rather meaningful. The route planning, as a classical problem, can also be accomplished by leveraging experience of taxi drivers' route decisions. To this end, this study presents a collaborative route planning method with the latent knowledge from experienced drivers in urban areas. In general, the proposed method makes the route planning can be solved by a query-like solution, rather than the traditional graph-labelling method. Given an O- D pair, a rank-threshold k, and a time-reachable threshold tc, the CPD and IDNG algorithms can be used to capture several experiential routes and generate an IDN.

Empirical studies demonstrate that our proposed method performs favorably in terms of efficiency, reliability, and effectiveness while comparing with the conventional fastestpath and shortest-path methods. Furthermore, the routes recommended by the proposed method tend to better express the latent experience and preferences of taxi drivers. Last but not least, with the proposed threshold free method in selecting a suitable tc, the cluster-to-cluster retrieval based method can address the existing sparseness issue to some extent. There also exist some limitations and requirements for the proposed method. First, due to the sparseness issue, the experiment area must have enough taxis and taxis' trajectory data. Second, if we apply the proposed method in a large-scale road network, the time-reachable threshold should be highly correlated with the distance of a given O-D pair (i.e., a distant O-D pair should set a larger tc, while a near O-D pair corresponds to a smaller tc).

REFERENCES:

[1] S. Çolak, A. Lima, and M. C. González, "Understanding congested travel in urban areas," Nature Commun., vol. 7, Mar. 2016, Art. no. 10793.

[2] Y. Zheng and X. Zhou, Eds., Computing Spatial Trajectories. New York, NY, USA: Springer- Verlag, 2011.

[3] Y. Zheng, "Trajectory data mining: An overview," ACM Trans. Intell. Syst. Technol., vol. 6, no. 3, pp. 1–41, May 2015.

[4] J. Yuan et al., "T-drive: Driving directions based on taxi trajectories," in Proc. ACM GIS, 2010, pp. 99–108.

[5] J. Yuan, Y. Zheng, X. Xie, and G. Sun, "T-drive: Enhancing driving directions with taxi drivers' intelligence," IEEE Trans. Knowl. DataEng., vol. 25, no. 1, pp. 220–232, Jan. 2013.

[6] J. Yuan, Y. Zheng, X. Xie, and G. Sun, "Driving with knowledge fromthe physical world," in Proc. ACM SIGKDD, 2011, pp. 316–324.

[7] J. Zhang, W. Meng, Q. Liu, H. Jiang, Y. Feng, and G. Wang, “Efficientvehicles path planning algorithm based on taxi GPS big data,” Optik-Int.J. Light Electron Opt., vol. 127, no. 5, pp. 2579– 2585, 2016.

[8] Z. Chen, H. T. Shen, and X. Zhou, “Discovering popular routes fromtrajectories,” in Proc. 27th IEEE Int. Conf. Data Eng., Apr. 2011,pp. 900–911.