ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

A Novel Approach for Optimal Sequential Route Recommendation

M.Geethanjali
M.Tech Student,
Sreenidhi Institute of Science and Technology, Hyderabad.

Abstract:
The problem of mobile sequential recommendation is to recommend a route connecting a set of pick-up points for a vehicle driver so that he/she is more likely to get customers with a reduced amount of travel cost. Basically, the main challenge of this crisis is its high computational complexity. In this paper, we propose a novel dynamic programming based method to solve the mobile sequential recommendation problem consisting of two separate stages: an offline pre-processing stage and an online search stage. The offline stage pre-figures potential competitor successions from an arrangement of Pickup points. A backward incremental grouping era calculation is proposed taking into account the distinguished iterative property of the cost capacity. All the while, an incremental pruning arrangement is embraced during the time spent grouping era to lessen the search space of the potential arrangements viably. Also, a cluster pruning calculation is further connected to the created potential arrangements to expel some non-ideal successions of a given length. Since the pruning adequacy continues developing with the expansion of the grouping length, at the online stage, our technique can proficiently locate the ideal driving course for an emptied taxi in the remaining hopeful arrangements

Keywords:
Mobile Sequential Recommendation, Potential Travel Distance, Backward Path Growth, Sequence Pruning.

1. Introduction:

With the wide usage of the sensor, remote correspondence and data frameworks, for example, GPRS, WiFi and RFID, we can without much of a stretch get to the area follow information for an expansive number of moving items. Finding helpful learning from this direction information will give solid backing to the ongoing choice and the insight administrations in the related applications [1]. Decreasing cab cruising cost issue is a common illustration [2, 3]. An emptied taxi driving out and about not just prompts misuse of fuel and time additionally may bring about traffic congestion. Be that as it may, some high likelihood. derived from the given set of pick-up points of the high return drivers can be unearthed to manage new drivers to get travelers in a more temperate and efficient way. In this manner, high efficiency versatile example mining and suggestion calculation can enhance business execution of the drivers and decrease the vitality utilization. This is an issue having extensive hypothetical importance and appropriate qualities [3, 4].

In [2], Ge et al. have proposed a novel issue of Mobile Sequential Recommendation (MSR), which is to propose a course associating some pick-up points for a vacant taxi so that the driver will probably get travelers with less travel cost beginning from its current position. It is a testing errand, since we have to count and think about every compare all possible routes. Derived from the surrendered set of pick focuses which includes a somewhat high computational intricacy. To take care of the MSR issue, they gave a component of Potential Travel Distance (PTD) for assessing the expense of a driving course. Basically, the PTD estimation of a recommended course is the normal travel separation for an unfilled taxi before it effectively gets new travelers when it goes along the course. To diminish the computational cost, two eff ective potential grouping pruning calculations LCP and Sky Route, which depend on the monotone property of the PTD capacity, have been proposed in [2].

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Be that as it may, the time and space complexities of these two calculations both become exponentially with the quantity of pick-up points and the length of the proposed driving course, so they can just play out the driving course suggestion with a length requirement in a little number of pick-up points. In any case, in genuine applications, a driver dependably needs to acquire the optimal driving routes in a scope of length, so that he/she can choose a best driving course among them. In this paper, we consider a summed up versatile consecutive proposal issue with negligible and maximal length limitations. We propose an answer including an online stage and an online stage. The online organize effectively prunes the inquiry space and creates a little arrangement of succession hopefuls. The online stage is for acquiring the ideal driving course given the present position of an emptied taxi as the beginning stage. In particular, for the online pre-calculation, we have profoundly concentrated on the way of the PTD work and have found that it fulfills the iterative computation highlight.

This component permits us to incrementally develop a potential driving course in reverse from the terminal point to the beginning stage. In view of the above computation highlight of the PTD capacity, we have likewise found that an arrangement of potential successions with the same length and the same beginning stage fulfills the incremental and group pruning properties. At that point, we plan a novel portable consecutive proposal strategy which takes full favorable position of the iterative way of the PTD capacity. It incrementally produces potential arrangements and evacuates a ton of unthinkable inquiry space in the process which incredibly upgrades the time efficiency and decreases the memory utilization. Among the produced potential successions with the same length, we can in any case evacuate a substantial number of potential arrangements which can't shape the ideal course by utilizing a cluster pruning strategy. It can significantly decrease the quantity of the rest of the grouping hopefuls.

Test comes about demonstrate that the online pruning effect and the online hunt efficiency of our strategy are essentially enhanced contrasted with the current best in class techniques. The principle commitments of the paper are given as takes after 1) Our algorithm can generate all possible sequence candidates of arbitrary length which can be used to suggest the driving route with any length range constraint; 2) The recursive formula of the PTD function is presented which makes the incremental generation of the potential sequences possible; 3) A backward incremental sequence generation algorithm with less time and a smaller space complexity is proposed; 4) An efficient method for comparing the PTD cost of different potential sequences and driving routes is presented; 5) An effective sequence pruning method combining incremental pruning and batch pruning is adopted which significantly improves the online pruning effect.

Whatever is left of the paper is sorted out as takes after. Segment 2 presents the foundation and the related work. Segment 3 gives the iterative way of the PTD capacity and the proposed succession pruning standard. In Section 4, the online succession era and online pursuit calculations are depicted in point of interest. Area 5 gives the exploratory results and examination. Segment 6 talks about some augmentation of our technique. At long last, area 7 finishes up the paper.

2 BACKGROUND:

In this section, we first introduce the MSR problem and then describe the previous works.

2.1 Related Work:

In recent years, intelligent transportation systems and trajectory data mining have aroused widespread attentions [1, 7, 8, 9]. Mobile navigation and route recommendation have become a hot topic in this research field [2, 11, 12, 13, 14, 15, 21, 10, 22, 23]. The MSR problem presented by Ge et al. in [2] is rather different from the traditional problems such as Shortest-Path problem [16, 17], Traveling-Salesman problem [18] and Vehicle-Scheduling problem [19].

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Because for the shortest path computation problem, the source and destination nodes of an object are known in advance. However, for MSR problem, both of them are unknown. The traditional Traveling-Salesman Problem (TSP) gets a shortest path that includes all N locations while MSR problem is to find a path that consists of a subset of given N locations. In addition, the traditional Vehicle-Scheduling problem needs to determine a set of duties in advance while the pick-up routes (jobs) among several locations is uncertain for the MSR problem.

In [2], the authors focus on the MSR problem with a length constraint due to the high computational complexity of the unconstraint simple MSR problem. To reduce the search space, they proposed a route dominance based sequence pruning algorithm LCP. However, the proposed algorithm has difficulty in handling the problem with a large number of pick-up points. A novel skyline based algorithm Sky Route is also introduced for searching the optimal route which can service multiple cabs online. However, the skyline query is inefficient in handling, since it is processed online.

Yuan et al. proposed a probability model for detecting pick-up points [4]. It finds a route with the biggest pick-up probability to the parking position constrained by a distance threshold instead of the minimal cost of the route and provides location recommendation service both for the cab drivers and for the people needing the taxi services. In contrast, the problem solved in [21, 22] is deferent from the MSR problem which is to recommend a fastest route to a destination place with starting position and time constraints.

Powell et al. [3] proposed a grid-based approach to suggest profit locations for taxi drivers by constructing a spatiotemporal profitability map, on which, the nearby regions of the driver are scored according to the potential profit calculated by the historical data. However, this method only finds a parking place with the biggest profit in a local scope instead of a set of pick-up points with overall consideration.

Lu et al. [11] introduced a problem of finding optimal trip route with time constraint. They also proposed an efficient trip planning method considering the current position of a user. However, their method uses the score of attractions to measure the preference of a route.

MSR problem:

A set of potential pickup points C = {c1,c2,c3,…..cN};
A probability set P = { P(c1),P(c2),…..P(cN)};
A potential sequence set R={r1,r2,…rM};
The position c0 of cab which needs the service;
Recommending a optimal driving route d= (c0,r),s.t. min(r->R)F(c0,r,P(r)).

The main contributions of the paper are given below:

1) Our algorithm can generate all possible candidate sequences of arbitrary lengths.

2) The recursive formula of the PTD function is proposed which makes the incremental generation of the potential sequences possible.

3) A backward incremental sequence generation algorithm with less time complexity is proposed.

4) An efficient method for comparing the PTD cost of different potential sequences and driving routes is presented.

5) An effective sequence pruning method combining incremental pruning with batch pruning is adopted which significantly improves the offline pruning effect.

6) Our method can handle the optimal driving route search problem with a maximum cruising distance or a destination constraint that has never been examined by previous studies.

In this paper, we consider clusters and taken cluster heads as pickup points and cluster nodes as users and then server update the status.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Here we set the routing between cluster heads and users and data forwarded to server. The requests of user's are sent to the cluster heads. In this process, more data will be generated based on cluster head position. We maintain the request of users properly and setup as data moving to server.

We consider:

- pickup points pp1,pp2,pp3,…..ppN;
- Sequence r;
- Sequence length R;

Each group of cluster maintains proper communication with pickup point location.

3 PROPOSED METHOD:

To address the computational challenge of the generalized MSR problem, we first identify the iterative property of the PTD function, which makes the incremental generation of the potential sequences possible and then propose the pruning principle, which uses the iterative property to efficiently reduce the search space.

The Iterative Property of the PTD Function:

As described in section 2, the PTD function gives a computable measure for the cost of a route. In the following, we study the property of the PTD function. Actually, an iterative computational formula of the PTD function [5] can be obtained without considering the driving distance beyond the last pick-up point of a driving route. For this purpose, we introduce the concept of PTD sub-function.

The initial value:

$\forall\ c \in C, F1(c)=0, PE(c)=p(c)$

Iterative formula:

$F1(c_1,c_2,c_3,..c_L) = \overline{P}(c_2).F1(c_2,c_3\ldots c_L)+D_{C1,C2}.PE(c_2,c_3,\ldots..c_L)$

$PE(c_1,c_2,c_3,..c_L) = P(c_1)+\overline{P}c_1.PE(c_2,\ldots.c_L)$

Offline Processing:

The detail of our dynamic programming based algorithm BP-Growth is given in Algorithm 1. It generates the potential sequence candidates in the online stage when the position of a cab is not involved. In order to construct all possible potential sequence candidates incrementally and efficiently, a backward path growth procedure and an incremental sequence pruning process are employed which combines with the iterative calculation of the F 1 and P E values of the potential sequences. After the sequence generation and pruning process of Algorithm 1, we will obtain a set of sequence candidates with length from 1 to N . For the potential sequence candidates, we adopt the batch pruning algorithm to reduce the number of sequence candidates further. It generates the potential candidate sequences in the offline stage when the position of a cab is not involved. In order to construct all possible potential candidate sequences incrementally and Efficiently, a backward path growth procedure and an incremental sequence pruning process are employed which contain the iterative calculation of the F1 and PE values of the potential sequences[2].

BP-growth:

Input-> a set of potential pickup points C, the probability set P for all pickup-points, the pair wise driving distance matrix D of pickup points.
Output-> a set of potential sequences R with length L ranging from 1 to N

Batch pruning:

Input-> a set of potential sequence RL with length L
Output-> a set of remaining candidates sequences R1L length L

Online search processing:

This method is able to provide real-time driving route recommendation services for the empty cabs at various positions. When a cab at the position c0 requests the recommendation service, an online search algorithm, called Route Online, is adopted to find an optimal

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

driving route from the remaining potential sequences generated in the offline stage.

Route online:
Input-> a set of the candidate sequences R, the current position of a cab c0, the desired maximum crusing distance D_{max}
Output-> s set of the optimal driving routes Dop.

Algorithms used:
Algorithm 1: BP-Growth
Input: A set of the potential sequence candidates−→R with length L from 1 to N

1:−→R1 ← ∅;

2: for each ci ∈ C do

3: ~r ← hcii; F1(~r) ← 0; PE(~r) ← P(ci);−→R1 ←−→R1 ∪ {~r};

4: end for
5: for L = 2 to N do

6:−→RL ← ∅;

7: for each ~r ∈−−−→RL−1 do

8: for each ci ∈ (C − C~r) do
9: //Potential Sequence Generation

10: ~p ← hci, ~ri; c ← s(~r);

11: F1(~p) ← F1(~r) · P(c) + Dci,cPE(~r);

12: PE(~p) ← PE(~r) · P(ci) + P(ci);
13: //Incremental Sequence Pruning

14:−→RL~p = {~q|~q ∈−→RL, s(~q) = s(~p),C~q = C~p};

15: if−→ RL~p = ∅ then

16:−→RL ←−→RL ∪ {~p};
17: else
18: if ∀~q ∈−→RL~p (F1(~p) = F1(~q)) then

19:−→RL ←−→RL ∪ {~p};
20: end if
21: else
22: if ∀~q ∈−→RL~p (F1(~p) < F1(~q)) then

23:−→RL ←_−→RL −−→RL~p_∪ {~p};
24: end if
25: end if
26: end for
27: end for
28: end for
29: return−→R =N∪L=1−→RL;

Algorithm 2: Batch Pruning
Input: A set of the potential sequences−→ RL with length L.
Output: A set of the remaining sequence candidate's −→ R′L with length L.

1: for each c ∈ C do

2:−→RLc← ∅;
3: end for
4: for each ~r ∈−→RL do

5: c ← s(~r);

6:−→RL←−→RLc∪_−→r;

7: for each −→q ∈−→RLc∧ −→r 6= −→q do

8: if ~q ∝ ~r then

9:−→RLc←−→RLc−_−→r;
10: break;
11: else
12: if ~r ∝ ~q then

13:−→RLc←−→RLc−_−→q;
14: end if
15: end if
16: end for
17: end for
18: return−−→R′ L = ∪c∈C−→RLc;

Algorithm 3: Route Online
Input: A set of the sequence candidates−→R , the current position of a cab c0 and the minimum length

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Lmin and maximum length Lmax of the suggested driving route ($1 \leq Lmin \leq Lmax \leq N$).

Output: A set of the optimal driving routes——→Dmin.

1:−−−→Dmin ← ∅; Fmin ← +∞;

2: for L = Lmin to Lmax do

3: for each ~r ∈−→RL do

4: c = s(~r);

5: ~d = hc0, ~ri;

6: F(~d) = F1(~r) · (1 − P(c)) + Dc0,c · PE(~r) + D∞ · (1 − PE(~r));

7: if−−−→Dmin = ∅ ∨ F(~d) = Fmin then

8:−−−→Dmin ←−−−→Dmin ∪ {→d };

9: else

10: if F(~d) < Fmin then

11:−−−→Dmin ← {→d }; Fmin ← F(~d);

12: end if

13: end if

14: end for

15: end for

16: return−−−→Dmin;

4. EXPERIMENTAL EVALUATIONS:

In this section, we evaluate the performance of our method by comparing its pruning effect, Memory consumption and online search time with those of other state-of-the-art methods. All acronyms of evaluated algorithms are given in Table 2. LCP and Sky Route are two route dominance based pruning algorithms proposed in [2]. In particular, Sky Route is an online pruning algorithm, where two skyline computing methods BNL and D&C can be applied to prune potential sequences [6]. Its corresponding online search methods are denoted by SR(BNL)S and SR(D&C)S, respectively.

Data Sets:

The adopted experimental data sets are divided into two categories: real-world data and synthetic data.

Real-World Data:

In the experiments, we adopt real-world cab mobility traces used in [2], which are provided by Exploratorium - the museum of science, art and human perception. It contains GPS location traces of 514 taxis collected around 30 days in the San Francisco Bay Area. We extract 21,980 and 38,280 historical pick-up locations of all the taxi drivers on two time periods: 2PM-3PM and 6PM-7PM. In total, we obtain 10 and 25 clusters as well as their probabilities on these two real data sets using the same method adopted in [2].

Table 1: A comparison of search time (millisecond) on the real-world data set (2-3PM).

	L = 2	L = 3	L = 4	L = 5
BFS	0.0077	0.0286	0.1980	1.4341
LCPS	0.0073	0.0157	0.0371	0.1175
SR(D&C)S	10.3269	41.6794	182.0520	1520.3100
SR(BNL)S	1.9306	24.3543	139.0600	2333.1200
IPS	0.0070	0.0110	0.0165	0.0246
IBPS	0.0068	0.0069	0.0076	0.0085

Synthetic Data:

We also generate four synthetic data sets. Specifically, we randomly generate potential pick-up points and their pick-up probabilities within a special area by a standard uniform distribution. In total, we have four synthetic data sets with 10, 15, 20 and 25 pick-up points respectively. The Euclidean distance instead of the driving distance is adapted to measure the distances between pairs of pick-up points. For both real-world and synthetic data, we randomly generate the positions of the target cab for recommendation.

Table 2: A comparison of search time (millisecond) on the synthetic data set with |C| = 15 .

	L = 2	L = 3	L = 4	L = 5
BFS	0.0125	0.0925	1.3028	17.9584
LCPS	0.0120	0.0458	0.3002	1.9866
SR(D&C)s	24.7075	154.6790	1962.8100	31210.4000
SR(BNL)s	3.3707	109.5560	3612.4100	210161.0000
IPS	0.0089	0.0556	0.2317	0.7322
IBPS	0.0086	0.0095	0.0107	0.0119
	L = 2	L = 3	L = 4	L = 5
BFS	0.0125	0.0925	1.3028	17.9584
LCPS	0.0120	0.0458	0.3002	1.9866
SR(D&C)s	24.7075	154.6790	1962.8100	31210.4000
SR(BNL)s	3.3707	109.5560	3612.4100	210161.0000
IPS	0.0089	0.0556	0.2317	0.7322
IBPS	0.0086	0.0095	0.0107	0.0119

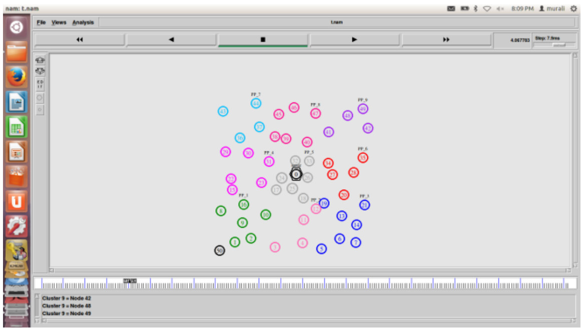

Fig1: The detected potential pick-up points

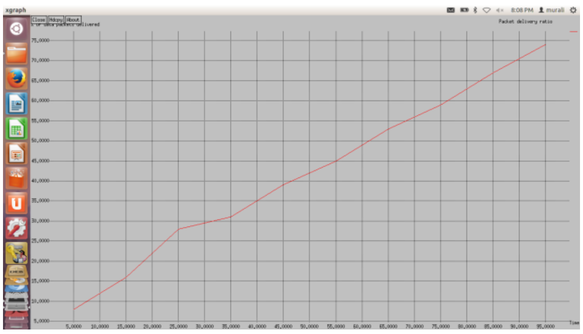

Fig 2: The Pruning Ratio Varying with the Number of Pick-up Points

5. Conclusion:

This paper presents a dynamic programming based method to solve the problem of mobile sequential recommendation. The proposed method utilizes the iterative nature of the cost function and multiple pruning policies which greatly improve the pruning effect. The overall time complexity for handling mobile sequential recommendation problem without length constraint has been reduced from O(N !) to O(N ^{2} · 2^{N}). Experimental results show that the pruning effect and the online search time are better than those of other existing methods. In the future, it will be interesting to use parallel algorithms for sequence generation and recommendation.

References:

[1]F. Giannotti, M. Nanni, F. Pinelli, and D. Pedreschi, "Trajectory pattern mining," in: KDD'07, pp. 330–339, 2007.

[2]Y. Ge, H. Xiong, A. Tuzhilin, K. Xiao, M. Gruteser, and M. Pazzani, "An energy-efficient mobile recommender system,“ in: KDD'10, pp. 899–908, 2010.

[3]J. Powell, Y. Huang, F. Bastani, and M. Ji, "Towards reducing taxicab cruising time using spatio-temporal profitability maps,“ in: SSTD'11, pp. 242–260, 2011.

[4]J. Yuan, Y. Zheng, L. Zhang, X. Xie, and G. Sun, "Where to find my next passenger,“ in: UbiComp'11, pp. 109–118, 2011.

[5]J. Kleinberg and E. Taros, "Algorithm design,“ Addison Wesley, 2005.

[6]S. B¨orzs¨onyi, K. Stocker, and D. Kossmann, "The skyline operator,“ in: ICDE'01, pp. 421–430, 2001.

[7]H. Kargupta, J. Gama, and W. Fan, "The next generation of transportation systems, green-house emissions, and data mining,“ in: KDD'10, pp. 1209–1212, 2010.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

[8]J. G. Lee, J. Han, X. Li and H. Cheng, "Mining discriminative patterns for classifying tra-jectories on road networks," IEEE Transactions on Knowledge and Data Engineering, vol. 23, no. 5, pp. 713-726, 2011.

[9]N. Pelekis, I. Kopanakis, E. Ramasso and Y. Theodoridis, "Segmentation and Sampling of Moving Object Trajectories based on Representativeness," IEEE Transactions on Knowledge and Data Engineering, 2011.

[10]EHC. Lu, CY Lin, VS. Tseng, "Trip-Mine: An Efficient Trip Planning Approach with Travel Time Constraints," in: MDM'11, pp. 152–161, 2011.

[11]H. Wang, "The strategy of utilizing taxi empty cruise time to solve the short distance trip problem," Master's Thesis, the University of Melbourne, 2009.

[12]K. Yamamoto, K. Uesugi, and T. Watanabe, "Adaptive routing of cruising taxis by mutual exchange of pathways," in: KES'08, pp. 559–566, 2008.

[13]Q. Li, Z. Zeng, B. Yang, and T. Zhang, "Hierarchical route planning based on taxi GPS-trajectories," in: Geoinformatics'09, pp. 1–5, 2009.

[14]S.F. Cheng and X. Qu, "A service choice model for optimizing taxi service delivery," in: ITSC'09, pp. 1–6, 2009.

[15]G. Hong-Cheng, Y. Xin, and W. Qing, "Investigating the effect of travel time variability on drivers' route choice decisions in Shanghai, China," Transportation Planning and Technology, vol. 33, no. 8, pp. 657–669, 2010.

[16]E.W. Dijkstra, "A note on two problems in connexion with graphs," Numerische mathematik, vol. 1, no. 1, pp. 269–271, 1959.

[17]E.V. Denardo and B.L. Fox, "Shortest route methods: 1. reaching, pruning, and buckets," Operations research, pp. 161–186, 1979.

[18]D.L. Applegatea, "The traveling salesman problem: a computational study," Princeton Univ Pr, 2006.

[19]M. Dell'Amico, M. Fischetti, and P. Toth, "Heuristic algorithms for the multiple depot vehicle scheduling problem," Management Science, pp. 115–125, 1993.

[20]R. Portugal, H.R. Louren¸co, and J.P. Paix˜ao, "Driver scheduling problem modellin," Public transport, vol. 1, no. 2, pp. 103–120, 2009.