Finding Most Frequent Path based on Stratified Urban Roads

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Abstract: The path query based on big trajectory data has become a promising research direction due to the rapid development of the Internet. Previous studies mainly focus on searching paths in full road network and ignore the importance of stratified urban roads. It is observed that higher-level roads gather more trajectory points which means most drivers prefer the high-level road. In this paper, we study a new path query to find the most frequent path (MFP) based on road levels in large-scale historical trajectory data. We refer to this query as most frequent path based on road levels (RLMFP). Intuitively, selecting roads which are in line with local custom and choosing high-level roads such as high-way are people's two common sense notions. Our query not only satisfies aforementioned sense, but also has two advantages in algorithm implementation. First, the road hierarchy can speed up the path query. Next, the trajectory data can find more reasonable upgrade points (e.g., path query based on road levels need to find the intersection between low-level roads and high-level roads). Experiments show the effectiveness and the efficiency of our method.

1 INTRODUCTION

With the increasing amount of available information in Internet, our society has entered a new period of information technology. In our daily life, the number of Global Positioning System (GPS) and devices with wireless interactive system such as mobile phones, navigation systems and emergency communications are increasing quickly. These Location-Based Services (LBS) have become increasingly popular. The demand for such services is also rising, especially the requirements of recommended route. Specifically, given a source S, a destination D and a map, a recommended route system is able to find a path from S to D in a map.

In recent years, a large number of mobile devices and navigation devices also surge to generate trajectory data, so more and more people begin to focus on the study of path query with historical trajectory. Historical trajectory data can represent the users'driving habits which are very significant for the path query. For example, when tourists arrive in an unfamiliar place and get lost, what they want to do is to ask a local person rather than use navigation equipment. Though this path is not the fastest one or the shortest one, it is the most suitable in a combination of time, length and road conditions (Su et al., 2014). Thus if a path query system returns a route based on historical trajectory data, it also imply the local drivers' path selection habits. This is the first requirement that a navigation system must meet. Researchers (Luo et al., 2013)(Chen et al., 2011) have provided methods to solve it. Another requirement is that users wish to pass through fewer junctions and drive on better roads (e.g., freeway or highway). Figure 1 is a partial road network of Beijing. The set of purple points are the real trajectory data of taxi drivers, we get the trajectories from (Yuan et al., 2011). This is a sample of T-Drive trajectory data that contains one-week trajectories of 10,357 taxis. Some of them are presented on the map of Beijing in Figure 1. We can see that more drivers prefer higher level roads. Note that there are less intersections and traffic lights on higher level roads. Besides, when drivers use a navigation equipment which provides a path with many intersections and lanes, it is easy for them to take a wrong way or miss intersections they need to turn. Previous methods generally search a path on the whole map. Therefore, they may be insensitive to road levels and could not meet the second requirement. Note if an algorithm is searching based on the full map and the map contains a huge number of intersections and roads, the conventional methods would spend a large amount of search time.

We study a novel method named most frequent path based on road levels (RLMFP). Most frequent paths (MFP) (Luo et al., 2013) use trajectories to recommend path. Different from other algorithms, the

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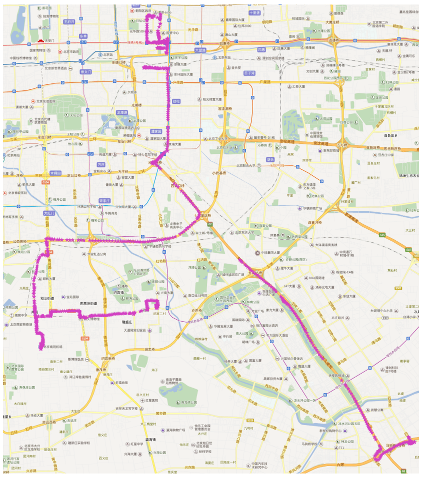


Figure 1: Partial map of Beijing.

weight of an edge in MFP is defined as counting the number of the trajectories passing through this edge. This weight of a map is named as edge frequently. And the weight of a path is a sequence obtained by sorting all the edge weights of P in non-decreasing order. For example, there are five edges in P and their weights are (5,3,6,4,7). So the weight of this path is (3,4,5,6,7). Similarly, another path P' is (2,6,7,8,9,11). P is better than P' in MFP because 3(the first weight of P) is bigger than 2(the first weight of P). It can well meet the first requirement of users for the path finding. This method of judging a better path is used by RLMFP. Here road level means the level of a road in a city. Many cities have their own plan and make roads into several levels according to their states, roles and traffic function. For instance, roads of China and Unites States are classified into 4 levels, and those of European Union are classified even into 13 levels. The roads of each level have different functions and properties. For example, the function of highways is to connect multiple large regions and the properties of highways define the design speed (60-80km / h), the number of one-way road ($\geq$4) and the width of total road (40-70m). In this paper we use the nature road levels to speed up the path searching and select high-level road segment to meet the second demand.

In brief, our algorithm first associate level properties to the vertexes and edges of road networks , then judges the area where the start point (end point) lies in and then determines the highest level of road network and the upgrade points (i.e., the points connecting edges in different levels). After that it uses MFP to find all sub-paths in the area. At last, we combine all sub-paths and chooses the best one. As shown in Figure 3, $A1,A2,A3$ and $A4$ are the upgrade points of S in $area(2-3)$. Similarly to S, $D1$ and $D2$ are the upgrade points of D. The rough(thin) edges represent high(low) level roads. Firstly, we get the $S.area$ and $D.area$. Here is $area(2-3)$ and $area(5-2)$. Then an index named FG(section 6) is used to find a set of best upgrade points from $area(2-3)$ to $area(5-2)$. Assuming $A3,A4$ and $D1$ is selected. Then we use MFP to compute the paths from A to $A3,A4$, D to $D1$ in low level road networks and $A3,A4$ to $D1$ in high level road. Then we combine these sub-paths. There are two paths which are $P1(A \to A3 \to D1 \to D)$ and $P2(A \to A4 \to D1 \to D)$. And finally, we select the better paths with Definition 2.11. The details of algorithm is given in following paragraphs.

So MFP algorithm considering road levels is feasible, effective and evidence-based. But existing hierarchical algorithm often layers for the convenience of calculation ignoring the delamination characteristics owned by the road itself. In this paper, aside from the function of building a new road network, the trajectory data is also used to determine the upgrade points. We also construct an index of all upgrade points. This can not only help correct direction, but also speed up the algorithm.

Above all, our method is justified in reality and validated in algorithm. The contributions of this paper are the following.

- We propose a novel path query named most frequent path based on road levels (RLMFP).
- We present a hierarchical algorithm to solve RLMFP problem.
- We present an algorithm to build the index structure of upgrade points (FG).
- We develop a new hierarchical algorithm to solve RLMFP problem using the index structure of upgrade points (RLMFPT).

The rest of this paper is organized as follows. First, we briefly introduce a four-step framework to solve the RLMFP problem in the context of very large trajectory data sets (Section 2). Second, we provide an algorithm to build a weighted road networks (Section 3). Third, we explain area division (Section 4). Fourth, we present a hierarchical algorithm to solve RLMFP (Section 5). Fifth, we propose a method to build the index structure of upgrade points. Sixth, we develop a new hierarchical algorithm to solve PLMFP utilizing the index structure of upgrade points (Section 6). Then we present the experimental results (Section 7). Next, we review the related work. We conclude the paper in (Section 8).

Table 1: Summary of Notations.

Notation	Description
G,P,Y	road network, path, trajectory
V,E	set of vertex(points), set of edge(roads)
$G(i)$,$V(i)$,$E(i)$	i–level of G,V,E
X	path or trajectory
$X.s/X.d$	starting/ending vertex of X
$X[i]$	the i–th element of X
T	set of trajectory
$F(u,v)$	frequency of edge (u,v)
$F(P)$	frequency of path P
$int(q)$	set of q–level upgrade vertices
NG	new graph with trajectory data
FG	an index for upgrade points set
$S.area(q)$	the area for point S in q–level graph
$P(area)/area(P)$	the area for point P
$Area[i]$	the i–th area of graph

2 THE RLMFP PROBLEM

2.1 Problem Formulation

In previous section, two key requirements for path query are provided from the users.

Property 2.1 (Local Drivers Path Selection). *Selecting roads which are in line with local custom.*

Property 2.2 (Better Roads). *The roads with less intersections and high-level road.*

We have showed that the path from trajectory data can meet Property 2.1 and the algorithm based on road levels can satisfy Property 2.2. The definition of RLMFP should satisfy the above 2 key requirements. Here follows the formal definition. For clarity, the main notations used in the rest of this paper are summarized in Table 1.

Definition 2.1 (Road Network). *A road network is a directed graph $G = (V,E)$ where V represents the set of road intersections and E represents the set of road segments.*

Figure 1 presents a partial road network of Beijing.

Definition 2.2 (Path). *Given G, path P is a set of consequent roads $E_Q = \{(x_1,x_2),(x_2,x_3),\ldots,(x_{k-1}, x_k)\}$ and intersections $V_Q = (x_1,x_2,\ldots,x_k)$ from x_1 to x_k. P is a subgraph of G and the x_i are all distinct.*

P.s, *P.e*, and $P[i]$ are used to denote the source vertex x_1, the ending vertex x_k, and the i-th vertex x_i, respectively. In addition, P is often represented by $P.s \to P.e$ or $P(x_1 \to x_2 \to \cdots \to x_k)$ in short, where *P.s* (or *P.e*) represent x_1(or x_k).

Definition 2.3 (Trajectory). *Given G, a trajectory Y is a sequence $((y_1,t_1),(y_2,t_2),\ldots,(y_k,t_k))$ such that there exists a path $y_1 \to y_2 \to \cdots \to y_k$ on G and t_i is a time stamp indicating the time when Y passes y_i.*

Similar to path, $Y.s$, $Y.e$, and $Y[i]$ are used to denote the source vertex y_1, the ending vertex y_k, and the i–th vertex y_i, respectively. In addition, Y is often represented by $Y.s \to Y.e$ in short, where $Y.s$(or $Y.e$) represent x_1(or x_k) or $Y(x_1 \to x_2 \to \cdots \to x_k)$. We denote T as the set of Y.

Definition 2.4 (Edge Frequency). *Given G, T, and an edge $(u,v) \in G$, the edge frequency $F(u,v)$ is the number of the trajectories containing (u,v).*

Definition 2.5 (Trajectory Network). *A road network is a directed graph $G = (V,E)$ where V represents the set of road intersections, E represents the set of road segments. We use W to represent the set of the weight of each edge. In this paper, W is a set of the edge frequency.*

Definition 2.6 (Edge Level). *Given a road network $G = (V,E)$, the level of an edge e is denoted as $e.level(i)$ according to the existing road network, where i is the level of the road.*

As shown in Figure 1, the yellow edges represent the highest level edges and each level of them is 1 written as $e.level(1)$.

Definition 2.7 (Vertex Level). *The level of a vertex v denoted v.level, is defined as the highest level of all edges to v. Vertex v is also written as $v.level(i)$ when the level of a vertex i is known.*

As shown in Figure 1, the level of yellow edges is $e.level(1)$ and the level of buff edges is $e.level(2)$. If one vertex v is the intersection of the yellow edge and the buff edge, the level of v takes the highest of edges and here is $v.level(1)$.

Definition 2.8 (Upgrade Vertex). *A vertex v is an upgrade vertex when the edges it connects are not in the same level. The set of upgrade vertices in same level is denoted as $int(q)$ where q is the level.*

As shown in Figure 3, $A1$ connected a 3-level edge and a 2-level edge, so $A1$ is an upgrade vertex. If we want to find the path from S to D, then the upgrade vertices $A1,A2,A3,A4$ belong to $S.int(1)$.

Definition 2.9 (Layered Graph). *Layered graph $G(i) = (V(i),E(i))$ is a subgraph of G, to $\forall e(or\ v) \in E(i)(or\ V(i))$, $e.level(or\ v.level) \leq i$.*

As shown in Figure 2, $G(2)$is a road network G, this is because the lowest level of $G(2)$ is 2,so $G(2)$ contains all vertices and edges. Thus $G(2)$ is G and $G(1)$, $G(2)$ represents the graph of level 1 and level 2.

Definition 2.10 (Area). *Given a graph $G(i) = (V(i),E(i))$,dividing the $G(i+1)$ into several subgraph through $E(i)$. Each area $Area(j)$ is one* *area of* $G(i+1)$ *where* $j \in (1,2,\ldots,k)$. $\forall e \in Area(j), e.level \geq i+1$.

As shown in Figure 2, $G(1)$ using its edges to cut $G(2)$ into five areas. For any area, the level of its edges is no smaller than 2.

Definition 2.11 (More-frequent-than Relation)**.** *Given two path frequencies* $F(P) = (f_1,\ldots,f_m)$ *and* $F(P') = (f'_1,\ldots,f'_n)$ *w.r.t. the same trajectory network,* $F(P)$ *is more-frequent-than* $F(P)$*, denoted as* $F(P) \succeq F(P)$*, if one of the following statements holds:*

- $F(P)$ *is a prefix of* $F(P')$*;*
- *there exists a* $q \in 1,\ldots,min(m,n)$ *such that 1)* $f_i = f_i$ *for all* $i \in 1,\ldots,q-1$*, if* $q > 1$*, and 2)* $f_q > f'_q$*.*

Particularly, $F(P)$ *is strictly-more-frequent-than* $F(P')$*, denoted as* $F(P) > F(P')$*, if* $F(P) \succeq F(P')$ *and* $F(P) \neq F(P')$*.*

Problem Statement: Given a graph G, trajectory set T, source S and a destination D, the recommended route system searches MFP based on road levels from S to D.

2.2 Solution Overview

Most frequent path based on road levels has four steps. It is shown in Algorithm 1. First, a large number of trajectory data should be matched to the road network so as to construct a new road network where the weight is edge frequency. Then we divide the graph into different areas according to the natural road levels. Next the trajectory data T and the stratified graph $G*$ are employed to build index FG (section 6). Finally, we use the algorithm to search the RLMFP and return the P.

The first step of this algorithm is to build $G*$, which means make the trajectory data match the road network. GPS data is a sequence of vertices made by users, therefore the path depending on the trajectory can reflect the choice of users. After building a new graph, some methods (Luo et al., 2013)(Chen et al., 2011) compute the path on whole road network directly. Though there are different ways in various algorithms, each of them should scan the full road network. Hence stratification is introduced in this paper. In step 2, G is divided into areas by road levels. For example, the first level road network $G(1)$ is the highest. Then we utilize the edge of first level to divide G into areas where any edge of areas is lower than 1. The existing algorithm (Bast et al., 2006) must traverse all upgrade vertices in the area. Here we employ the trajectory data to reduce the number of upgraded vertices. After that, the areas, road levels and upgrades vertices are determined according to detect which area the start vertex and end vertex lie in. Finally, we can perform the RLMFP.

Algorithm 1: Five steps for the RLMFP query.

Require:
G: road network; T: trajectory data set; S: start point; D: end point;
Ensure:
the RLMFP;
1: build a new road network $G*$ w.r.t. T;
2: divide G into areas w.r.t. road levels;
3: build an index FG w.r.t T and stratified graph in 2;
4: find the RLMFP P from S to D;
5: **return** P;

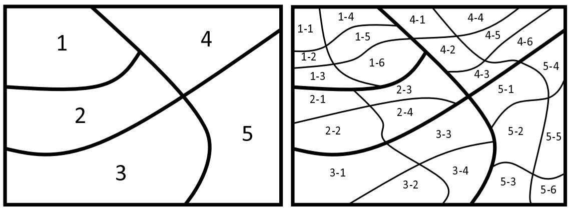
3 CONSTRUCT WEIGHTED ROAD NETWORK

In this section, we construct a weighted road network. According to the Definition 2.5, the weight of an edge is different in algorithms. The existing algorithms address the weight with Euclidean distance (Bellman, 1958)(Dijkstra, 1959), network distance and speed. In this paper the weight of one road segment is determined by the times that users passed. It is obvious that the path based on Euclidean distance means the nearest path and the path based on speed means the fastest path. However, in fact, some drivers may avoid aforementioned paths due to their experience, for example, when in a strange place, users prefer to believe the local people rather than the navigation system (Su et al., 2014).

Algorithm 2: Build weighted road network.

Require:
G: road network; T: trajectory data set;
Ensure:
$G*$: new road network;
$G* \leftarrow NG[VG][VG]$ matrix with all entries zeros;
for each Y in T **do**
  match Y to G ;
  get a path P corresponds Y in G ;
for each edge e in P **do**
  search e in $G*$;
  $NG.edge.weight++$;
return NG;

The idea is to find path depending on the history trajectory data of the local residents. It is because the local person drives in their familiar areas and trajectory data record their driving habits. So the first step is to build a trajectory network. It is shown in Algorithm



(a) $G(1) = E(1)$ (b) $G(1) = E(1) \cup E(2)$

Figure 2: Experiments of similarity, path points and query time in three algorithms.

2. First of all, we set the weight of each edge 0(line 1). Then we scan each trajectory and match them to G(line 2-3). Note that there will be a corresponding path produced(line 4). Next each edge section of the path are selected from NG and add 1 to the weight of them. We repeat the last steps until all the trajectory have been processed.

4 AREA DIVISION

Due to the idea based on stratification, after the completion of constructing the new road network $G*$, $G*$ needs to be divided into areas. Though road levels are used in previous researches, most of them do this for the convenience of the calculation. In fact, roads themselves have level property and they are produced by the traffic conditions, living areas, working areas, etc. As shown in Figure 2, $G(2)$ is a layered network.

Assuming that we divide road network into 2 levels in Figure 2. According to the function of different roads, the roads can be divided into first-level roads $E(1)$(e.g. highway, freeway)and second-level roads $E(2)$(e.g. city roads). In this way, $G*$ can be extracted into a two-level structure of network. Here $G(1) = E(1)$, $G(2) = E(1) \cup E(2)$. Those nodes located in the same position of different-level graphs and connect to edges in different levels become the upgrade vertices, which ensure the conversion of the roads between the different layers.

After the road stratification, low-level road networks should be divided into some smaller areas according to the level of the road network. In area-partition process, the high-level graph is cut by its edges and the areas from it are the ones of next graphs. We adopt a flood-filling algorithm (Gonzalez et al., 2007) to divide the graphs. Firstly, get a random vertex whose level is lower than the cutting edges. Then apply Breadth-First-Traversal(BFS) to the point. Note that if BFS encounters a vertex whose level equals to the level of cutting edges, the vertex would not become traversed one but would be an upgrade point of this area. We refer to the set of upgrade points as $int(q)$ in their area, where q is the level of their area. Process is repeated until there is no traversed point. As shown in Figure 2, $G(1)$ is dividing into several areas which named 1,2 etc. according to its edges. Here every area is the area of $G(2)$ and its edge-level is 2, its vertex-level is no lower than 2. Each area is named as (high-level)-(low-level). For example, the area which name is $1-2$ represents that it belongs to $area-1$ of $G(1)$ and $area-2$ of $G(2)$. This approach not only addresses the index direction and decides which level of network should be selected, but also helps build the structure of indexing in every two areas.

5 STRATIFICATION ALGORITHM

In this section, we explain a stratification algorithm to find path from start point to end point. We refer to this query as most frequent path based on road levels (RLMFP). First, assuming that the start point S and end point D are in different regions of the L_i and L_j. If S and D are in different levels, we judge higher level and upgrade the area of lower level to higher level graph until they are in the same level. Then we judge whether they are in same area. If not, we repeat this work till they are in same level and area. In this way, the highest level road network for S and D is determined. Next the vertices and graphs are upgraded according to the highest level road network for S and D. The algorithm is shown in Algorithm 3.

Initially, the algorithm traverses S and D in map to determine which areas they are in (line1-2). Then it addresses the highest level network they are both in and use level record the highest level (line 3-5). If $q == level$ which means their level is the highest, it can directly calculate the best path through the MFP in their common area and the path is saved by *P.max* (line 6-8). Otherwise, every path is computed from S (or D) to $S.int(q)$(or $D.int(q)$)(line9-12) and $level$ minus 1. This is one process of upgrading points. After the first upgrading, if S and D are still in different levels, continue to upgrade S and D in the same way. Here we should compute every *SP*(the most frequent path) from points in $S.int(q+1)$ to points in $S.int(q)$ till q equals $level$(line 13-17). At last, a set of paths P can be gotten by connecting each sub-path from S to D and *P.max* can be return through calculating the final weight of each path in P.

Assuming there are n vertices and m edges in a network with 2 levels of roads. Each time the average number of vertices of all the MFP to end is k. The area including most points has i upgrade points, n' vertices

Algorithm 3: Stratification algorithm.

Require:
$G*$: road network(including q levels, road levels is $E(1), E(2), \ldots, E(q)$, etc.); S: start point; D: end point;
Ensure:
the path RLMFP;
search S and D in $G*$;
get $S.area(q)$and $D.area(q)$;
$level, oldq \leftarrow q$;
while $S.area(level)! = D.area(level)$ **do**
  $level \leftarrow level - 1$;
if $q == level$ **then**
  get $SP(S-D)$ in $E(q)$;
  $P.max \leftarrow P(S,D)$;
else
  get every $SP(S, S.int(q))$ in $E(q)$;
  get every $SP(D, D.int(q))$ in $E(q)$;
  $q \leftarrow q-1$;
while $q > level$ **do**
  get every $SP(S.int(q+1), S.int(q)) inE(q)$;
  get every $SP(D.int(q+1), D.int(q)) inE(q)$;
  $q \leftarrow q-1$;
get every $SP(S.int(q), D.int(q))$ in $E(q)$;
for each $SP(1) \in SP(S, S.int(oldq)), \ldots, SP(k) \in SP(D, D.int(oldq))$ **do**
  $P \leftarrow \sum_{i=1}^{k} SP(i)$;
get $P.max$ from all P;
return $P.max$;

and m' edges at most. Each time the average number of vertices of all the MFP to end is k'. In the first layer, there are n'' points, m'' edges. Each time the average number of vertices of all the MFP to end is k''. If we take MFP algorithm directly, the time complexity is $O(kmn)$. If we adopt a stratification algorithm in this section, the time complexity of traversing each upgrade of S(or D) in $S.area(2)$ is $O(k'n'm')$, the time complexity of the second layer is $2O(k'n'm')$. In the second layer, we should compute S(or D) to every upgrade points in $S.area(1)$, so the time complexity of the second layer is $2iO(k'n'm')$. Similarly, the time complexity of the first layer is $O(k''n''m'')$. Finally, the road sections should be connected to a whole path. Here the path combines with three road sections and go through two upgrade points, so the number of paths is i^2 and its time complexity of selecting best paths is $O(i^2)$. Therefore the whole time complexity is $2iO(k'n'm') + O(''n''m'') + O(i^2)$. Due to property $(k'n'm', k''n''m'' \ll knm)$, it's easy to concluded that the time complexity of RLMFP is much smaller than MFP. But there may be a situation that is unsatisfied. If there are too many upgrade vertices with respect to the points in area are too many, they would affect the performance of the entire algorithm and i will affect the time complexity of this work.

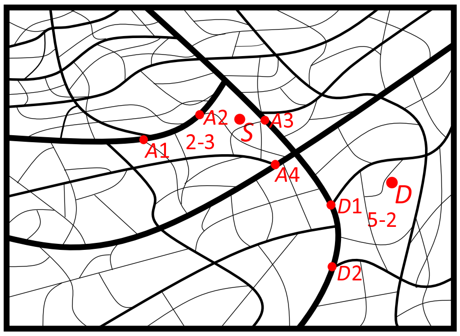


Figure 3: Upgrade points.

6 HIERARCHICAL OPTIMIZATION ALGORITHM

As shown in last section, RLMFP is more efficient than the MFP, but the number of upgrade points will affect the time complexity. Worse still, due to the global optimum road hierarchical algorithm, most of the upgrade points being traversed are inappropriate. As shown in Figure 3, $A1$, $A2$, $A3$ and $A4$ are the upgrades of S in $area(2-3)$. In stratification algorithm, we need to scan all paths from S to upgrade vertices. But it is obvious that, people would choose the $A3$ or $A4$ rather than $A1$ or $A2$. But the RLMFP in section 5 may upgrade road network through $A1$ or $A2$ because MFP has no sense of direction. So the stratification algorithm has considered all paths, but there may be a deviation for the best one and the number of upgrade points has an impact on the time complexity.

In order to solve the problem, this paper provides a hierarchical optimization algorithm RLMFPT, the last T means terminal. As we know, the weight of edge is based on trajectory, so we can simplify the algorithm by selecting upgrade points according to trajectory data.

The algorithm first establishes an index table to each of the two regions by storing a series of upgrade points of different levels. We refer to this index as FG. The storage structure is $(p_1, p_1.nub), (p_2, p_2.nub), \ldots, (p_n, p_n.nub)$. Here p_n means the id of vertex, $p_n.num$ means the number of being selected between the two areas. As shown in Figure 3, if there is a trajectory from S to D and its respect path pass the upgrade point $A3$, we plus 1 to the $A3.num$ in the index of $area(2-3)$ and $area(5-2)$. We repeat it until all the trajectory is handled. The algorithm is shown in Algorithm 4.

Firstly we construct an index structure and mark all memory locations empty (line 1). The algorithm then traverses all tracks and identifies the areas of starting point and destination point to determine where to store in the index (line 2-3). Next, Algorithm 4: Build area index structure.

Require:
G: road network; T: trajectory data set;
Ensure:
FG: Area index structure
1: set all $FG(area(G*)*area(G*))$ with null;
2: **for** each Y in T **do**
3: get $Y.s(area)$ and $Y.d(area)$;
4: match Y to G ;
5: get a path P corresponds Y in G ;
6: **for** each point p in P **do**
7: **if** point $p \in int$ **then**
8: push p to $FG(area(Y.s))(area(Y.d))$;
9: $area(Y.s)(Y.d).p.nub++$;
10: **return** FG;

each trajectory is matched to the network for obtaining the appropriate paths (line 4-5). Finally, the algorithm traverses every vertex on the path and judges whether it is the upgraded one. If it is true, this point will be stored in the position corresponding to the index construction. Assuming that the number of trajectory data is $|Y|$, the number of points in the path which each track corresponds to is $|P|$. The complexity of the algorithm is $O(|YP|)$, space complexity $|area(G*)|^2$.

Algorithm 5: Optimal Stratification algorithm.

Require:
$G*$: road network(including q levels, road levels is $E(1), E(2), \ldots, E(q)$, etc.); S: start point; D: end point; FG: Area index structure;
Ensure:
the path RLMFPT;
1: search S and D in $G*$;
2: get $S.area(q)$and $D.area(q)$;
3: get $FG(area(S)(D))$;
4: $level, oldq \leftarrow q$;
5: **while** $S.area(level)! = D.area(level)$ **do**
6: $level \leftarrow level - 1$;
7: **if** $q == level$ **then**
8: get $SP(S-D)$ in $E(q)$;
9: $P.max \leftarrow P(S,D)$;
10: **else**
11: get all $S.int$ and $D.int$ from $FG(area(S)(D))$
12: get every $SP(S, S.int(q))$ in $E(q)$;
13: get every $SP(D, D.int(q))$ in $E(q)$;
14: $q \leftarrow q-1$;
15: **while** $q > level$ **do**
16: get every $SP(S.int(q+1), S.int(q)) inE(q)$;
17: get every $SP(D.int(q+1), D.int(q)) inE(q)$;
18: $q \leftarrow q-1$;
19: get every $SP(S.int(q), D.int(q))$ in $E(q)$;
20: **for** each $SP(1) \in SP(S, S.int(oldq)), \ldots, SP(k) \in SP(D, D.int(oldq))$ **do**
21: $P \leftarrow \sum_{i=1}^{k} SP(i)$;
22: get $P.max$ from all P;
23: **return** $P.max$;

Different from the RLMFP, for the same condition, the algorithm determines the areas of start point and end point and then determines the set of upgrade vertices in FG. If upgrade vertices is in top 5 after sorting their number, they are the upgrade ones of this area. For example, $FG(2-3)(5-2)$ has 100 upgrade points($A1 - A100$). We sort the number of points, including $A1.num, A2.num, \ldots, A100.num$. Then the vertices in top 5 are selected as the upgrade ones.

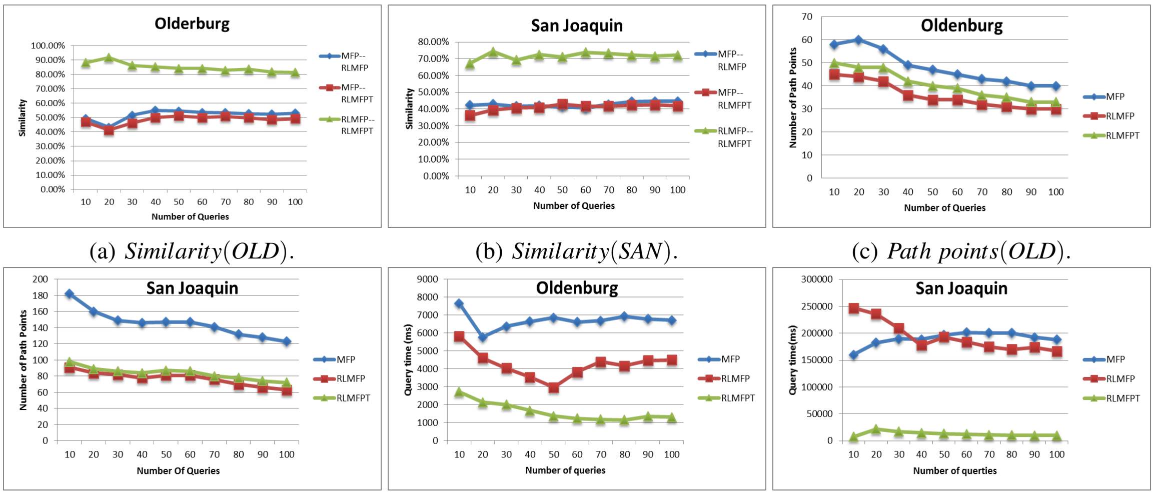
The Algorithm 5 is similar to Algorithm 3. The difference is getting the index in FG (line 3) and using the $int(q)$ in $FG(area(S)(D))$ replace the $int(q)$ in $area$(line 11). The remaining part of the idea is same as Algorithm 3.

Assuming the same condition of Algorithm 3, the number of upgrade points is i'. And we have proved that i' is among 5 to 10. The time complexity is $2iO(k'n'm') + O(k''n''m'') + O(i'^2)$. Since i' is smaller than i, thus the complexity is smaller than that of Algorithm 3. In addition, because i' is a defined low value, it will not affect the time complexity. For example, suppose each steps ratio of upgrade points is cut to 30%, $O(i'^2)$ is only 9% of $O(i^2)$. So the improved results to Algorithm 3 is obvious.

7 EXPERIMENT

In this section we conduct experiment to compare RLMFP, RLMFPT wiht MFP. In order to show advantages of RLMFPT, we design four experiments for these three algorithms. Similarity is designed to prove that RLMFPT has the advantages of MFP and RLMFP, which means it satisfies Property 2.1. There are more high-level roads in RLMFPT as a result of natural hierarchical policy. A comparison of path points is also done to prove that RLMFPT satisfies Property 2.2. In addition, we compare the query time of three algorithms to show the high query speed of RLFMPT. At last, feasibility of RLMFPT is displayed through the memory size of different algorithms.

In order to ensure the correctness and fairness of the experiments, the trajectories is under the same conditions. So We obtain trajectory data using the famous Network-based Generator of Moving Objects by Tomas Brinkhoff(Brinkhoff, 2002), which is a well known system of generating trajectory data. In addition, the maps are Oldenburg and San Joaquin. The smaller map Oldenburg has 6105 nodes and 7035 edges. The bigger map is San Joaquin with 18496 nodes and 24123 edges. In each map, we divide roads into 2 levels. All the experiments are conducted on a PC with an Intel CPU of 3.20GHz and 4GB memory.



(a) *Similarity*(*OLD*). (b) *Similarity*(*SAN*). (c) *Path points*(*OLD*).

(d) *Path points*(*SAN*). (e) *Query time*(*OLD*). (f) *Query time*(*SAN*).

Figure 4: Experiments of similarity, path points and query time in three algorithms.

7.1 Similarity

To evaluate the similarity of three path queries (MFP, RLMFP and RLMFPT), we compare the results of them through counting different quantities of the same starting point and destination point path queries.

Due to the different sizes of the two maps, we produce 70000 and 510000 trajectories by traffic simulator as the data set for each of them. Then we set the weights and build index FG for each graph with above data set. Next we apply 10 to 100 path queries from the same start point to the same end point for every algorithm.

We use the ratio of the number of same edges in two paths and the total number of edges in path which is being com-pared. As shown in Figure 4(a) and Figure 4(b), there are about 40% of similarity between MFP, RLMFP and RLMFPT, which indicates that the similarity is relatively high. The difference is because both RLMFP and RLMFPT traverse a high level map when they get upgrade points, do not adapt MFP all time. Because of the same principles and the high similarity, it is shown that both RLMFP and RLMFPT have the advantage of MFP and can satisfy the first demand of users. In addition, comparing RLMFP with RLMFPT, there is high similarity between them. Thus, RLMFPT (RLMFP with FG) has the advantages of RLMFP.

7.2 Path Points

In this experiment, to evaluate the less number of path points of RLMFP and RLMFPT, we compare the results of them through counting different quantities of the same starting point and destination point path queries. The conditions are set up the same as 7.1.

As shown in Figure 4(c) and 4(d), with the increasing number of queries, the number of points in algorithms (RLMFP and RLMFPT) remains stable between 30 and 35 in Figure 4(c) or 60 and 80 in Figure 4(d). The points of MFP gradually reduce with the growing queries, but they are 50% more than that of RLMFP or RLMFPT in Figure 4(d). It shows that RLMFP and RLMFPT select less path points than MFP, which satisfies the second demand of users.

7.3 Query Time

Algorithm proposed in this paper enjoy faster query speed. Therefore, in this experiment, we compare the results of the query time of three algorithms (MFP, RLMFP, RLMFPT) through counting different quantities of the same starting point and destination point path queries to evaluate the less query time of RLMFPT. The conditions are set up the same as 7.1.

As shown in Figure 4(e), with the increasing number of queries, the query time of MFP remains stable at 7000ms. To the end point that have large number of upgrade points, query time has ups and downs, because too many upgrade points would lead to a lot of stitching path and affect the query time. Thus the number of upgrade is an uncertain factor. But the query time in 4(e) is still better than MFP. Besides, because of the small number of upgrade points (less than 9), the factor of that in RLMFP will not affect RLMFPT. Therefore, the query time of RLMFPT still remains at a relatively low state.

In large map San Joaquin shown in Figure 4(f), as the number of queries increased, the query time of MFP is decreasing and that of RLMFP is increasing.

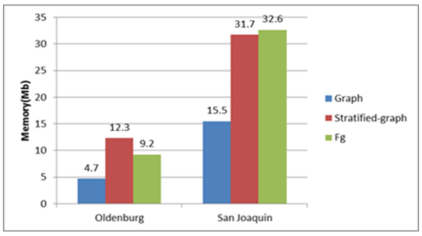


Figure 5: Memory size.

After stabilized,the query time of RLMFP is higher than that of MFP. The reason is that the scale of upgrade points is constantly increasing with the bigger map, which affects the query time directly. In addition, the query time of RLMFPT still remains at a short level. This is because the number of upgrade points does not affect RLMFPT. Thus in San Joaquin map, RLMFPT reflects the stable and short advantages and also shows the advantages of FG.

7.4 Memory Size

In this experiment, we compare the results of the memory size of common graph, stratified-graph and FG by counting two maps to evaluate the acceptable small extra memory size of RLMFPT.

As shown in Figure 5, regardless of the size of maps, the memory size of stratified-graph is twice as common graph. Besides, the memory size of FG is similar to stratified graph and also twice as common graph. Therefore, the memory size of RLMFPT is about four times as common graph. In reality, such additional storage is acceptable either on the client or the server.

8 RELATED WORK

The best path algorithms have been studied for many years. The most classic work is the shortest path algorithm in the graph theory. (Dijkstra, 1959)(Bellman, 1958) propose two shortest path algorithms. These algorithms have been studied for more than 50 years. On the basis of these algorithms, the later researchers develop some improved methods. (Pohl, 1971) proposes bidirectional Dijkstra's algorithm to improve the efficiency of the algorithm. New approaches (Hart et al., 1968) for fastest path finding are proposed aiming at using heuristic information to reduce the time complexity. In addition, if the weight on each edge represents travel time, shortest path finding becomes fastest path finding. (Kanoulas et al., 2006) raises an idea that speed is changing in different time periods. He estimates the optimal departure time and the shortest time depending on the property of each edge. (Ding et al., 2008) also makes a way to find the fastest path under large graph. Due to the changing information in some roads, it may lead to update whole road network so as to cause a huge waste of resources. (Shang et al., 2010) uses two tree of pruning map to solve the problems of update roads, which effectively improves the memory utilization. Considering that clients may make too many requests in the same period of time and lead to network congestion, (Leong et al., 2014) broadcasts packets of speed-changing weight. Then the client only accepts needed data packets and compute paths in local. Different from shortest/fastest path querying, we study the problem of finding the most frequent path. Thus their methods for determining the better path are different and shortest/fastest path are not suitable for this problem.

Finding a path utilizing the hierarchical road network is another related work. (Geisberger et al., 2008) offers CH algorithm, which first orders all points and compute this order to simplify the network gradually. After pretreatment, it queries a path following the order. Similar to (Geisberger et al., 2008), there are many other methods through pretreating data such as (Bast et al., 2006). (Bast et al., 2006) divides the graph into many areas. When a point comes out from the area, it should pass the access points. He preprocesses all shortest paths between every pair areas for optimization. But such approach has a defect that pretreatment time is too long. So (Akiba et al., 2013) presents a large map of the road network under the pruning techniques, resulting in great reducing of the processing time. (Jing et al., 1996) proposes a hierarchical road network to simplify algorithm. Though these algorithms are searching a path according the hierarchical idea, they are not focus on finding a path based on stratified urban roads.

Querying a path based on trajectory data is the most closely related work to this paper. Some approaches (Gonzalez et al., 2007)(Yuan et al., 2011)(Yuan et al., 2010)for fastest path finding are proposed aiming at using user-generated GPS trajectories to estimate the distribution of travel time on a given road network. (Chen et al., 2011) recommends a route by mining route preferences of the past visitors. Specially, this method constructs a graph only through trajectory clustering. He defines the possibility of next point from query point to destination point as the weight of graph. However, the method may contain infrequent sub-path. (Luo et al., 2013) proposes TPMFP to improve MPR. She utilizes edge frequency as weight of graph. In addition, edge frequency is computed in time of period, so the path do not contain infrequent sub-path. (Su et al., 2014) is the first one who put local drivers advices into query system. These methods are based on trajectories, but they will lead to a high responding time due to searching a path on a whole road network. In addition, a path based on trajectories which favors the high-level roads are ignored by these methods. They are therefore not a good method to find a way based on trajectory data.

9 CONCLUSION

In this paper, we propose two algorithms RLMFP and RLMFPT (RLMFP with FG) to solve the problem of path query. We observe two common sense notions, which are selecting roads in line with local customs and choosing high-level roads such as highway. Moreover, we study a four-step framework to solve the problem. The first step is to set the weight to the common graph with trajectory graph. The second step is to divide graph into several areas. The third step is to build an index named FG to speed up the query and find more reasonable upgrade points. The last step is to use RLMFPT to compute the paths. The experiment results demonstrate the efficiency, the effectiveness and the stability of our index FG and algorithm RLMFPT. The memory size of RLMFPT is also acceptable for customers or providers. In the future, we will extend our solution on real networks and recommand custum made route via allowing drivers to select preferable upgrade points.

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