Scalable Network Distance Browsing in Spatial Databases

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Joint work with Jagan Sankaranarayanan and Houman Alborzi

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Outline

1. Overview
2. Spatial Networks
3. Precomputation and storage of shortest paths
4. k Nearest Neighbor Finding Algorithm
5. Experimental evaluation
6. Contributions
7. Future Work

Key to Nearest Neighbor Finding in Spatial Networks

1. Use distance along a graph rather than “as the crow flies”
2. Precompute and store shortest paths between all vertices in network
   - Reduce cost of storing shortest paths between all pairs of N vertices from $O(N^3)$ to $O(N^{1.5})$ using path coherence of destination vertices

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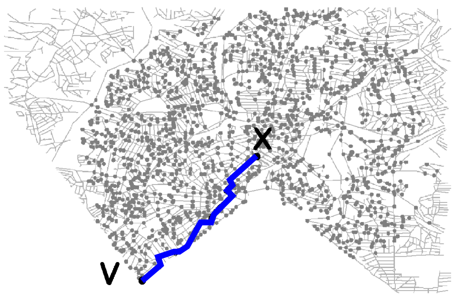

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   - Ex: Dijkstra's algorithm visits 3191 out of the 4233 ver tices in network to identify a 76 edge path from X to V

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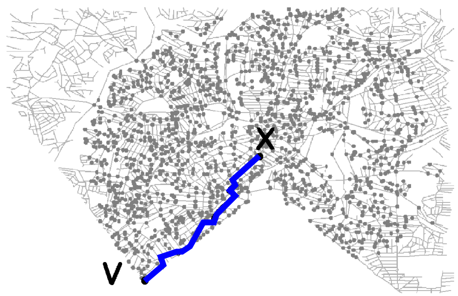
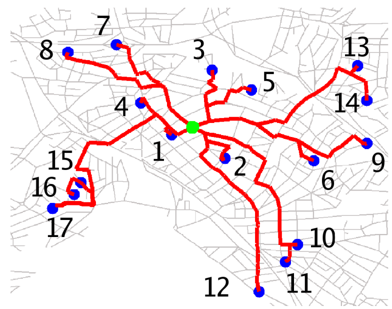


4. Avoids Dijkstra’s algorithm which visits too many vertices
   - Ex: Dijkstra’s algorithm visits 3191 out of the 4233 ver tices in network to identify a 76 edge path from X to V
5. Instead, only visit vertices on shortest paths to nearest neighbors



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Finding Nearest Neighbors in Spatial Networks

- Spatial Network: graph with spatial components at vertices and/or edges
- Involves shortest path computation
  1. Growing popularity of online mapping services (e.g., Google Maps, Microsoft MapPoint) has led to interest in real time query processing
  2. Finding nearest objects from a set S (e.g., gas stations, restaurants, markets, etc.)
  3. Should be able to make dynamic changes in query so that once found shortest path from A to B that passes through C, can change to pass through D
- Most transportation networks can be modeled as spatial networks. e.g.,
  - Road networks
    - Each intersection is a vertex of the graph, the position of the intersection is associated with the vertex
    - Each edge of the graph corresponds to a road segment. The weight of an edge corresponds to the cost of travel (i.e., distance or time) along the corresponding road segment
  - Airline routes
  - Waterways

Application – Find the closest Kinko's

- Let us compare the nearest neighbor (FedEx Kinkos) to a query point Piano store using both geodesic and exact distance measures

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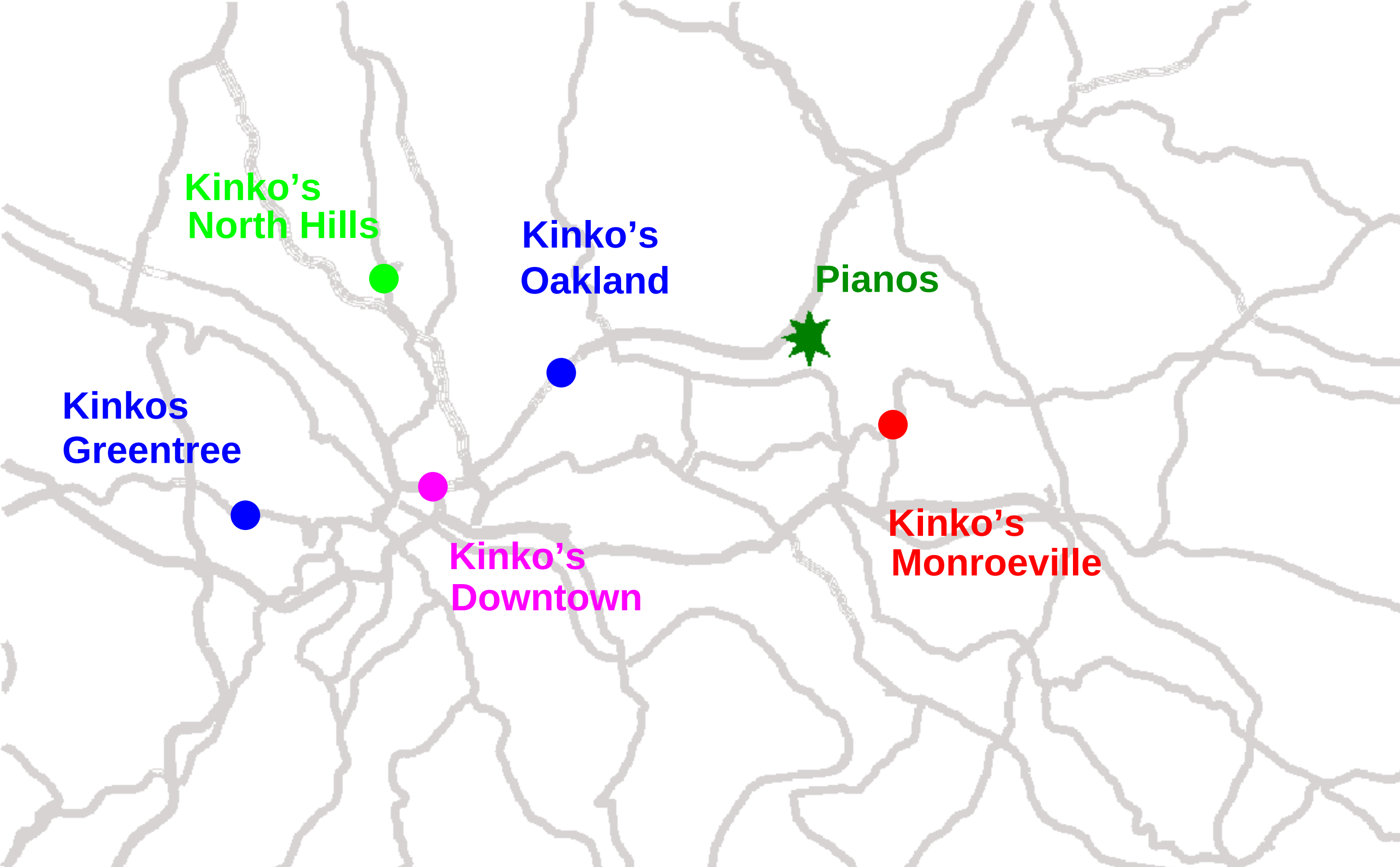

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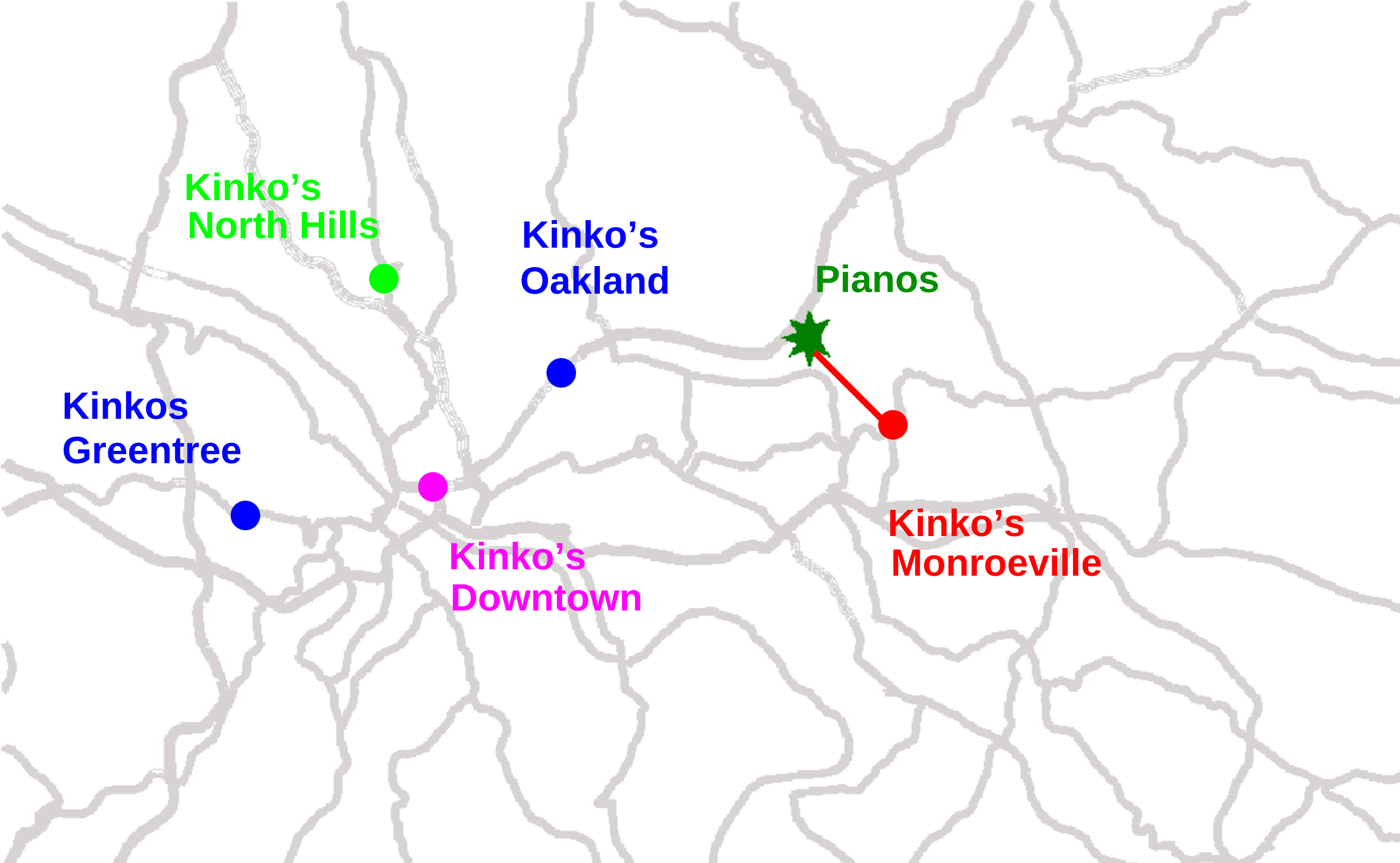

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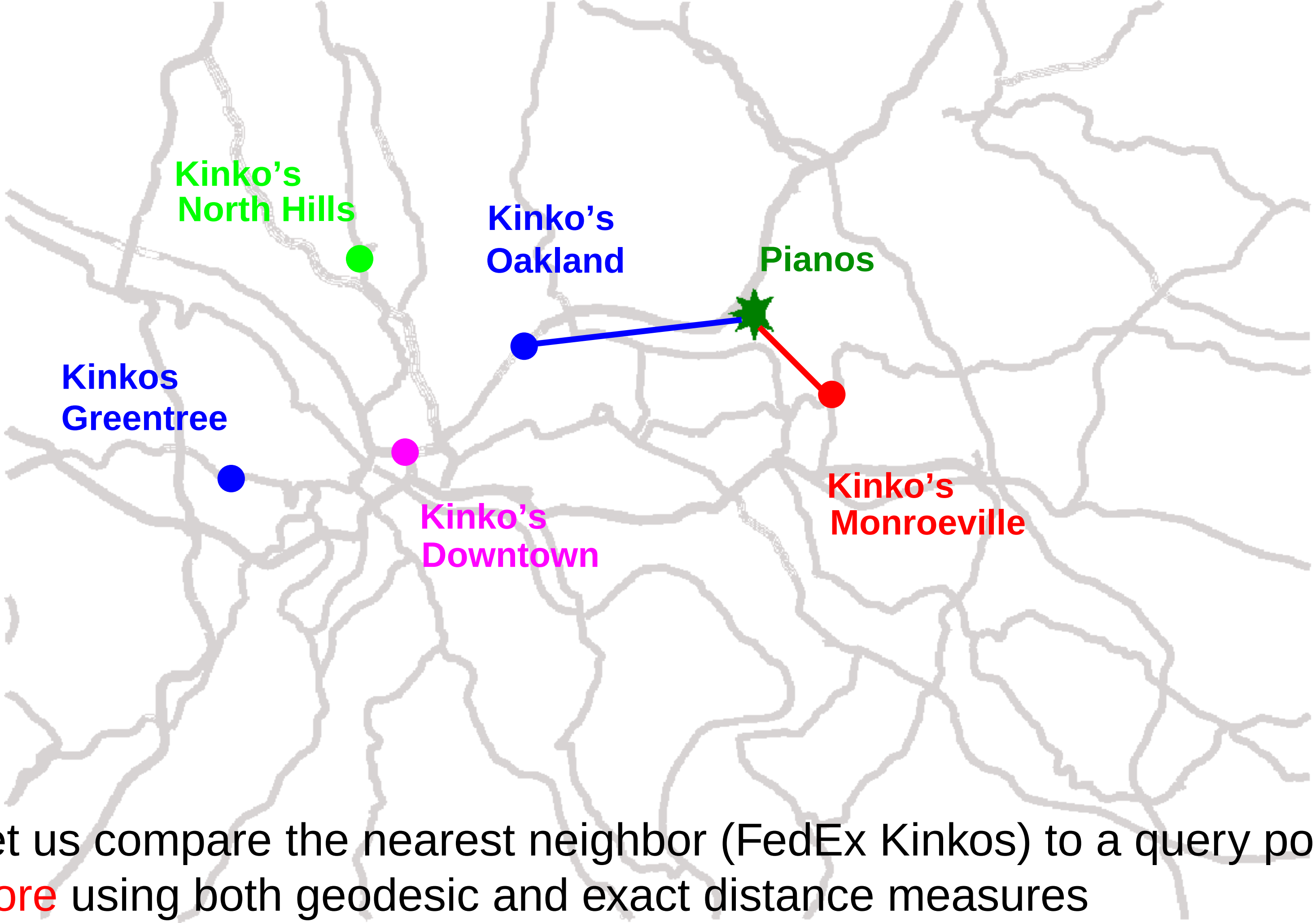

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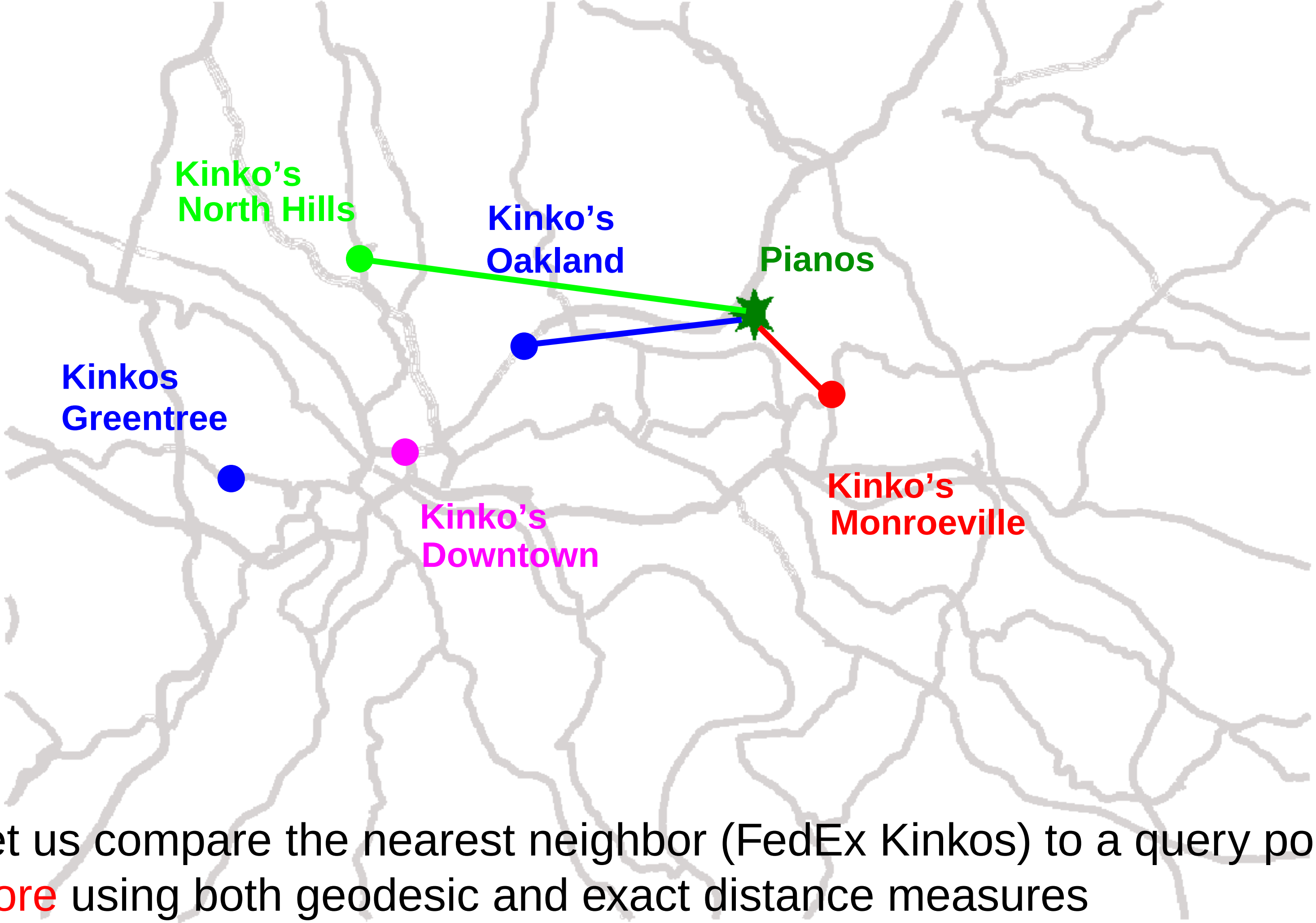

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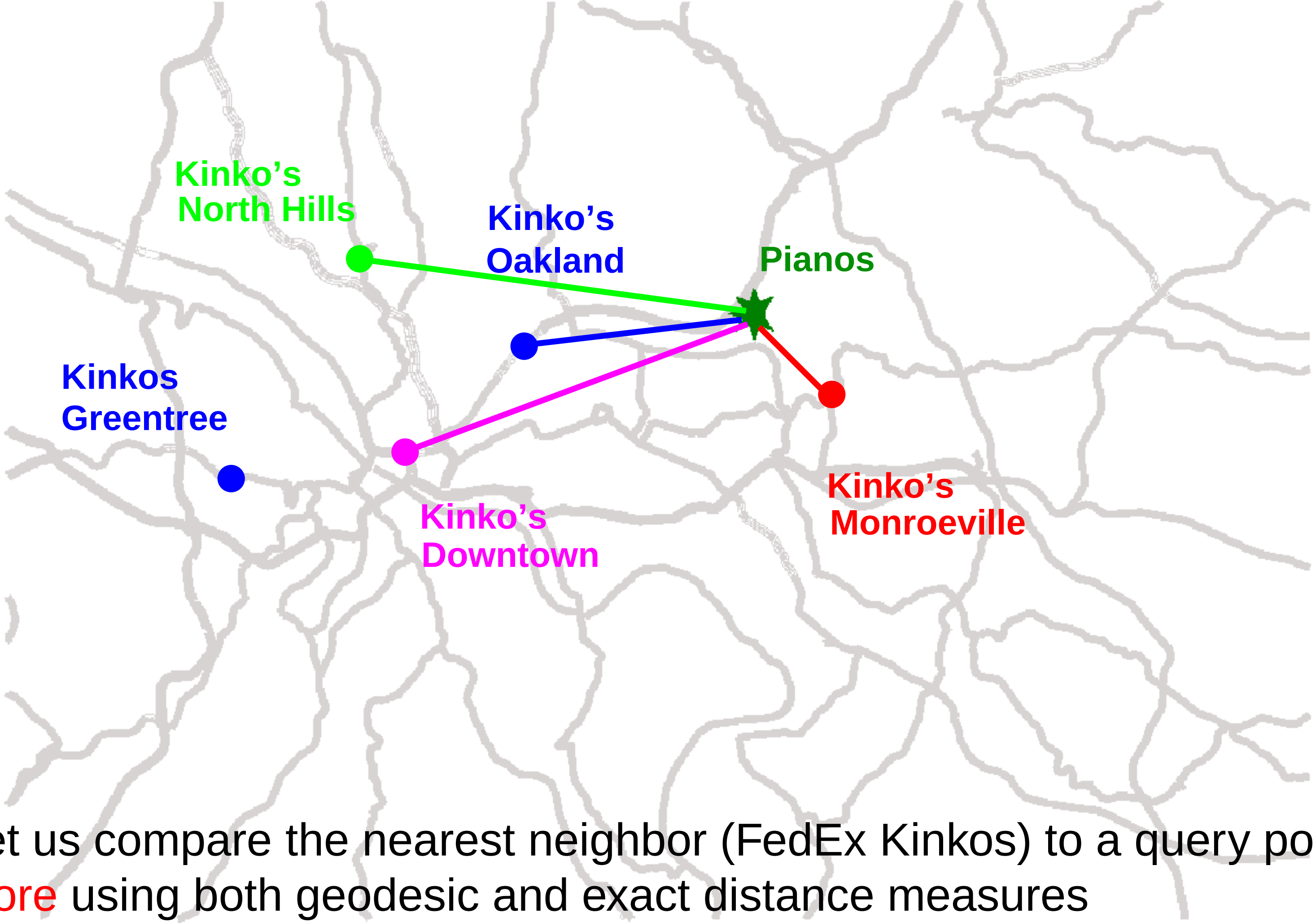

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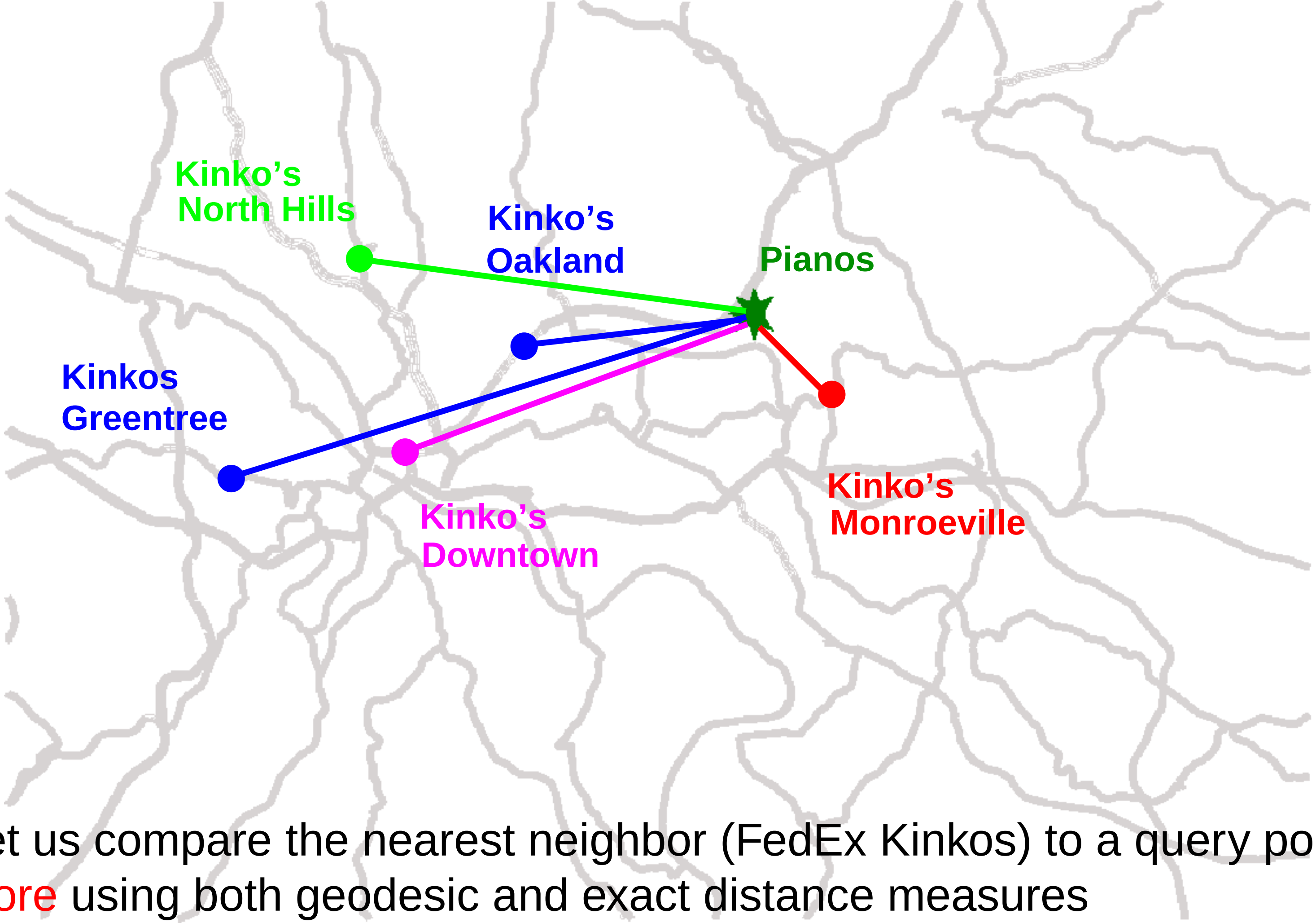

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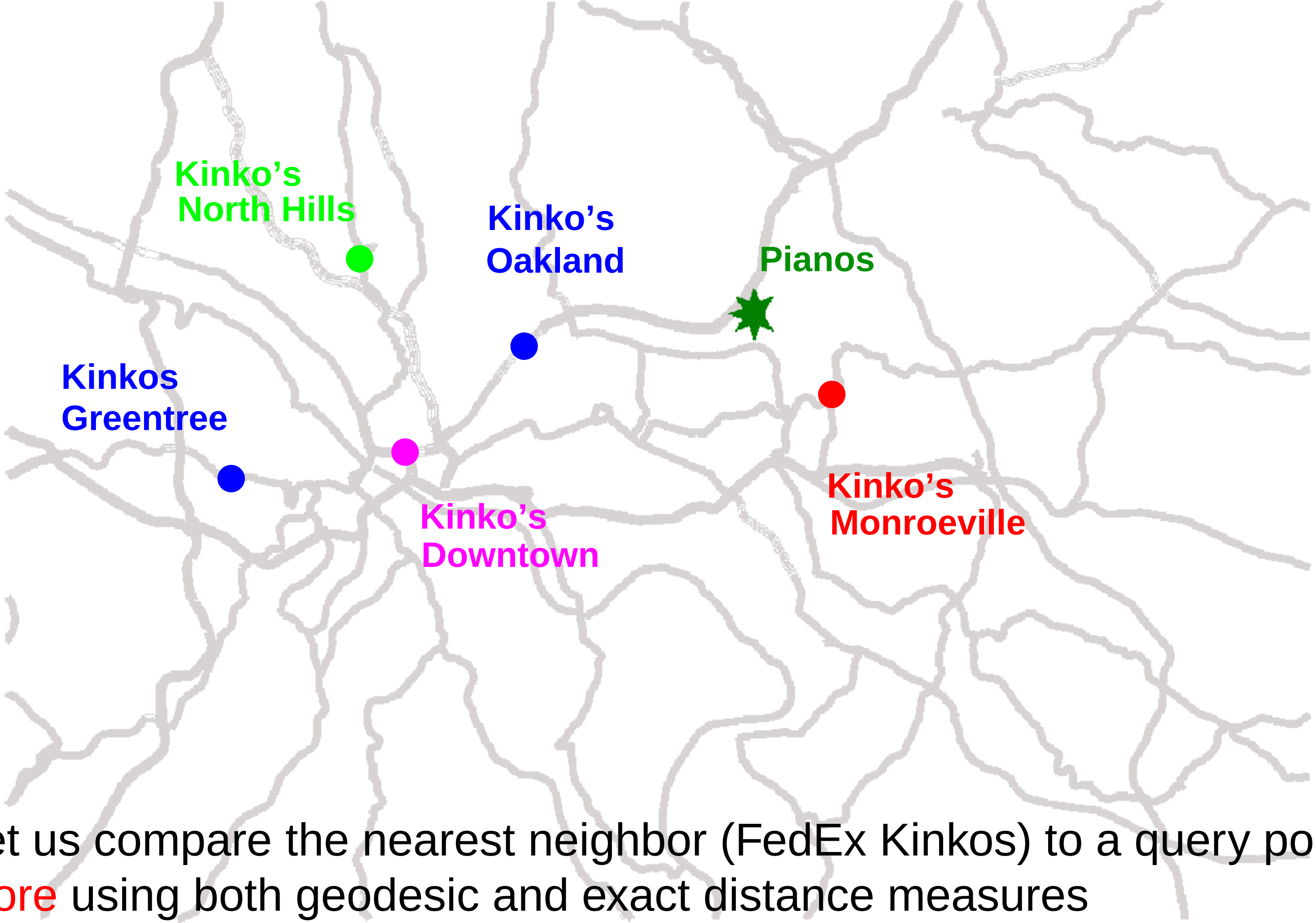

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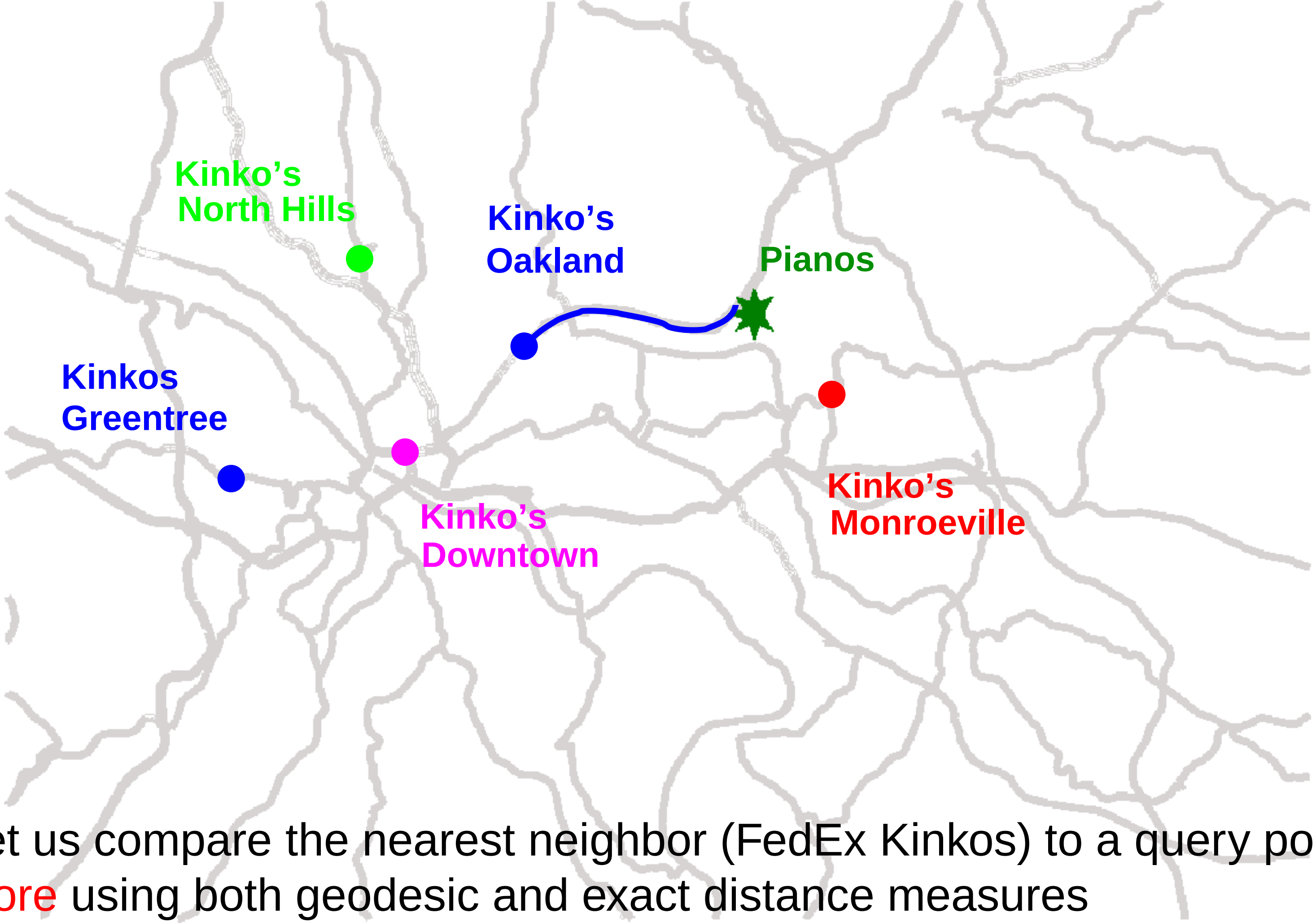

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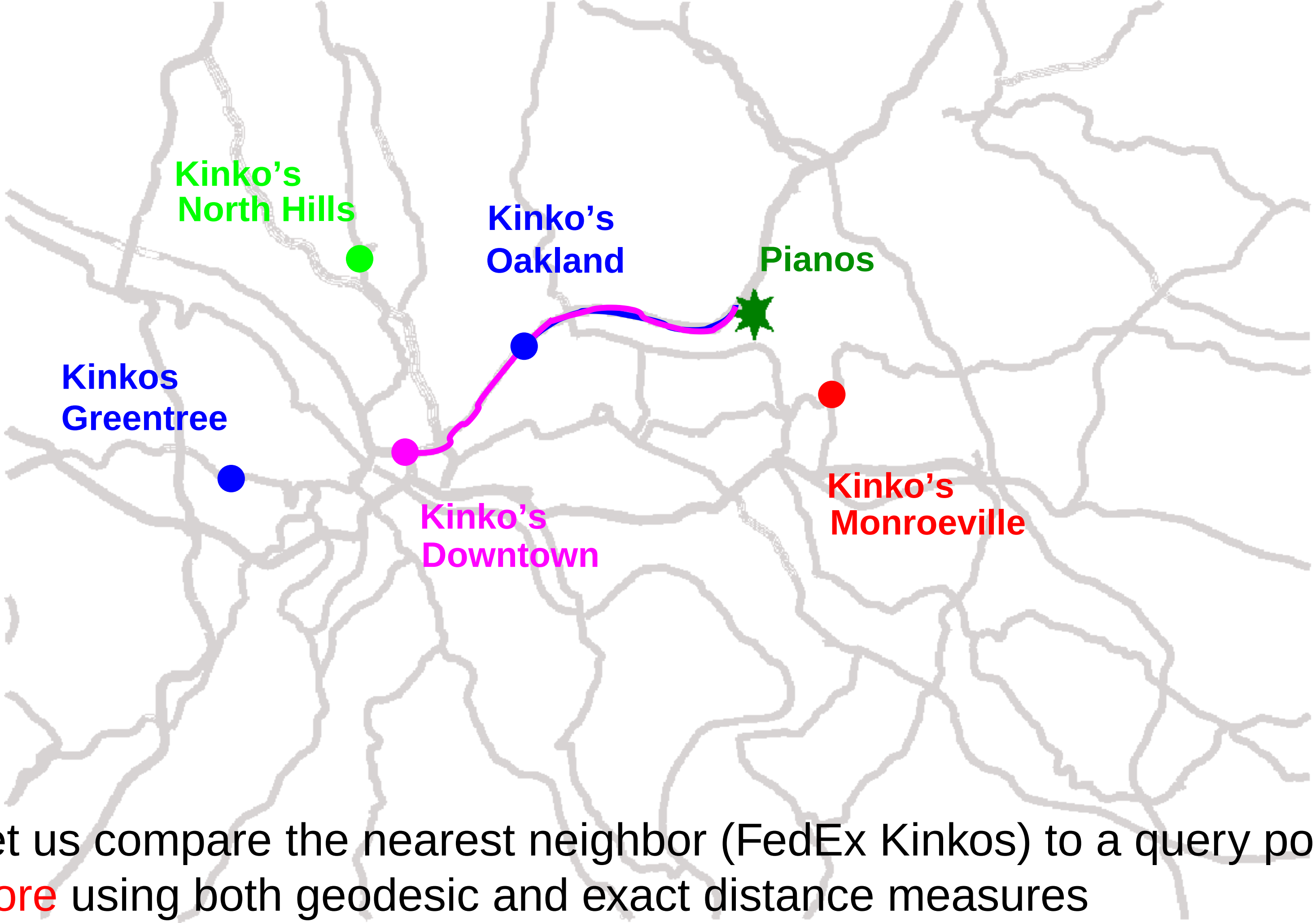

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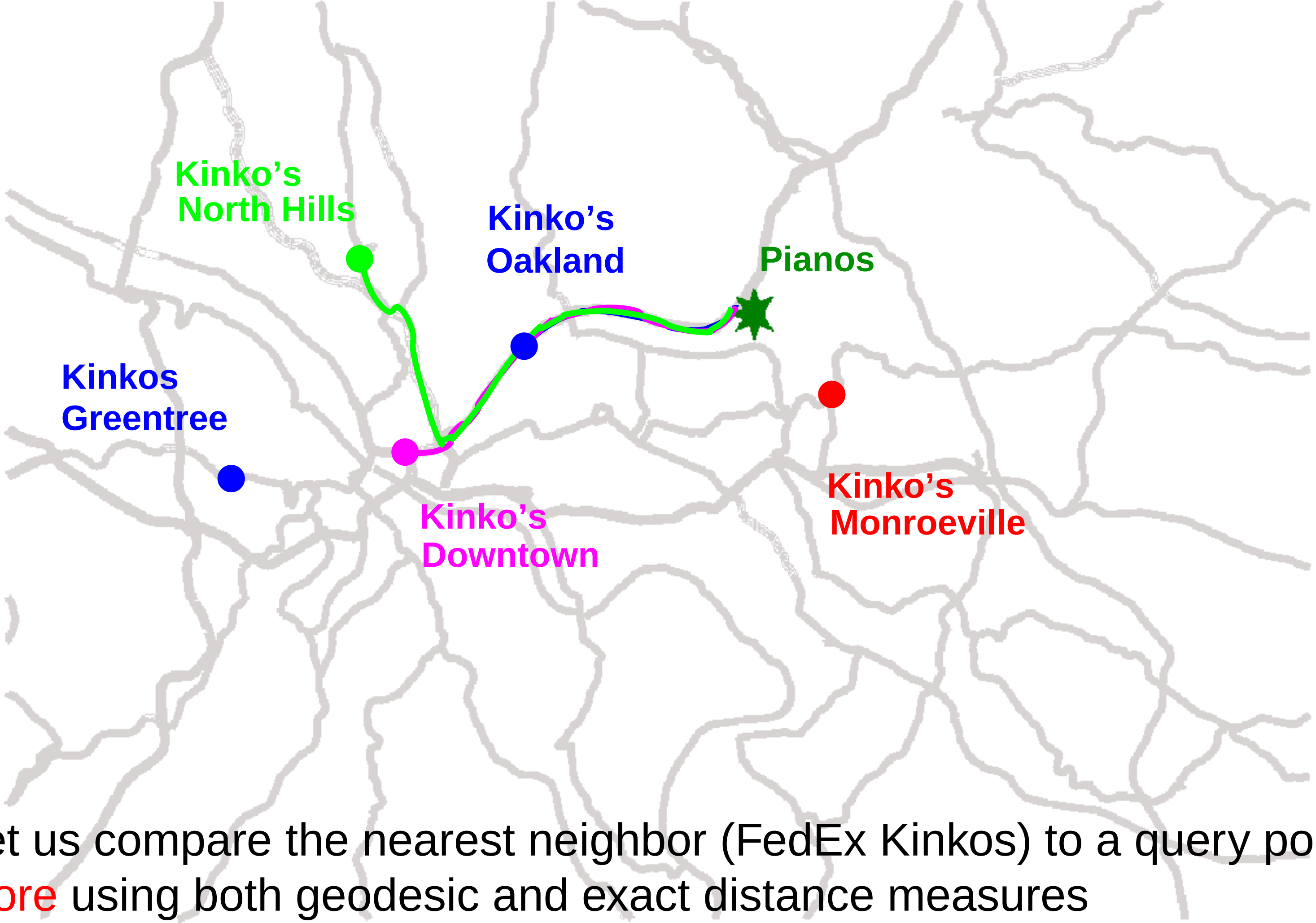

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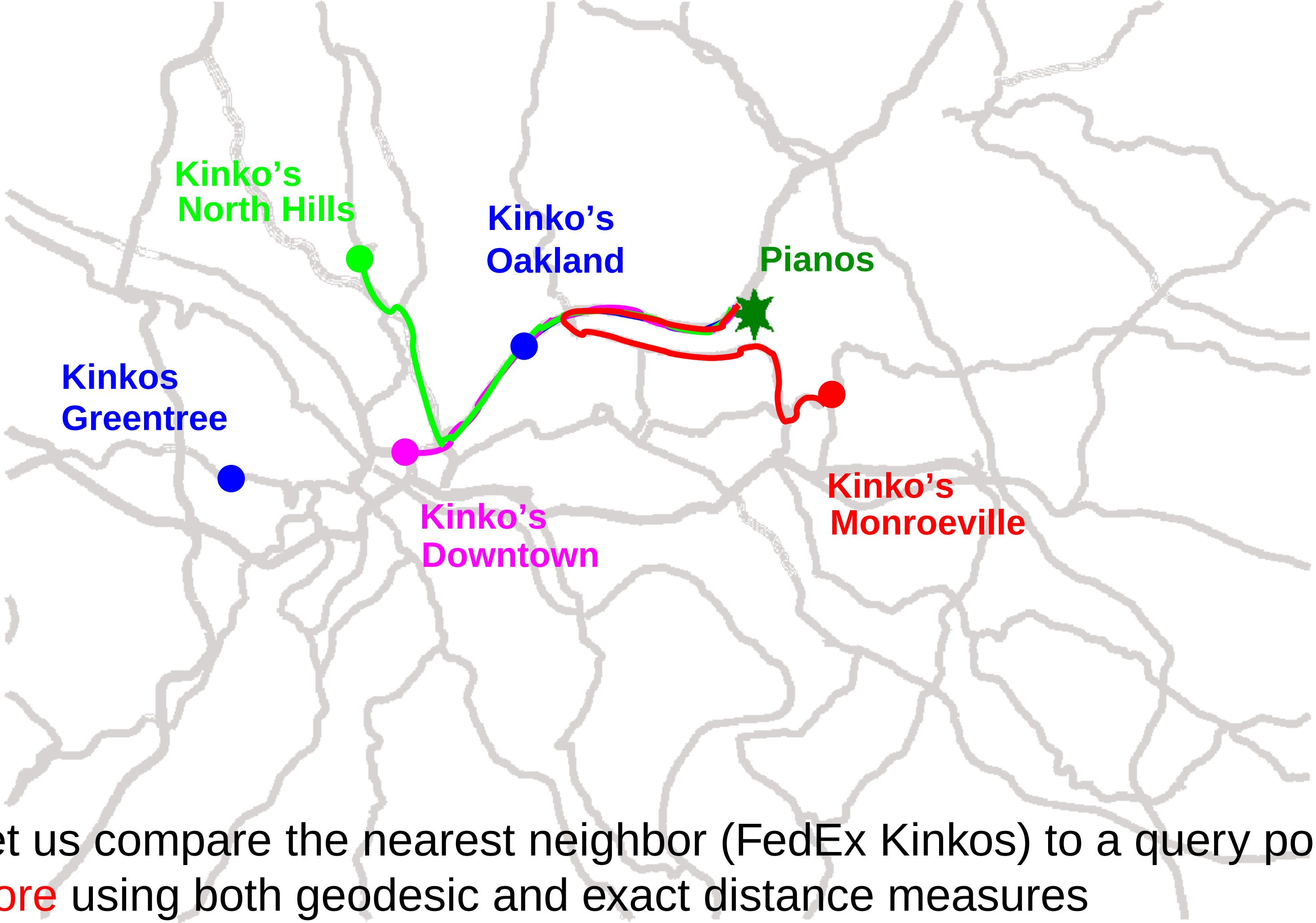

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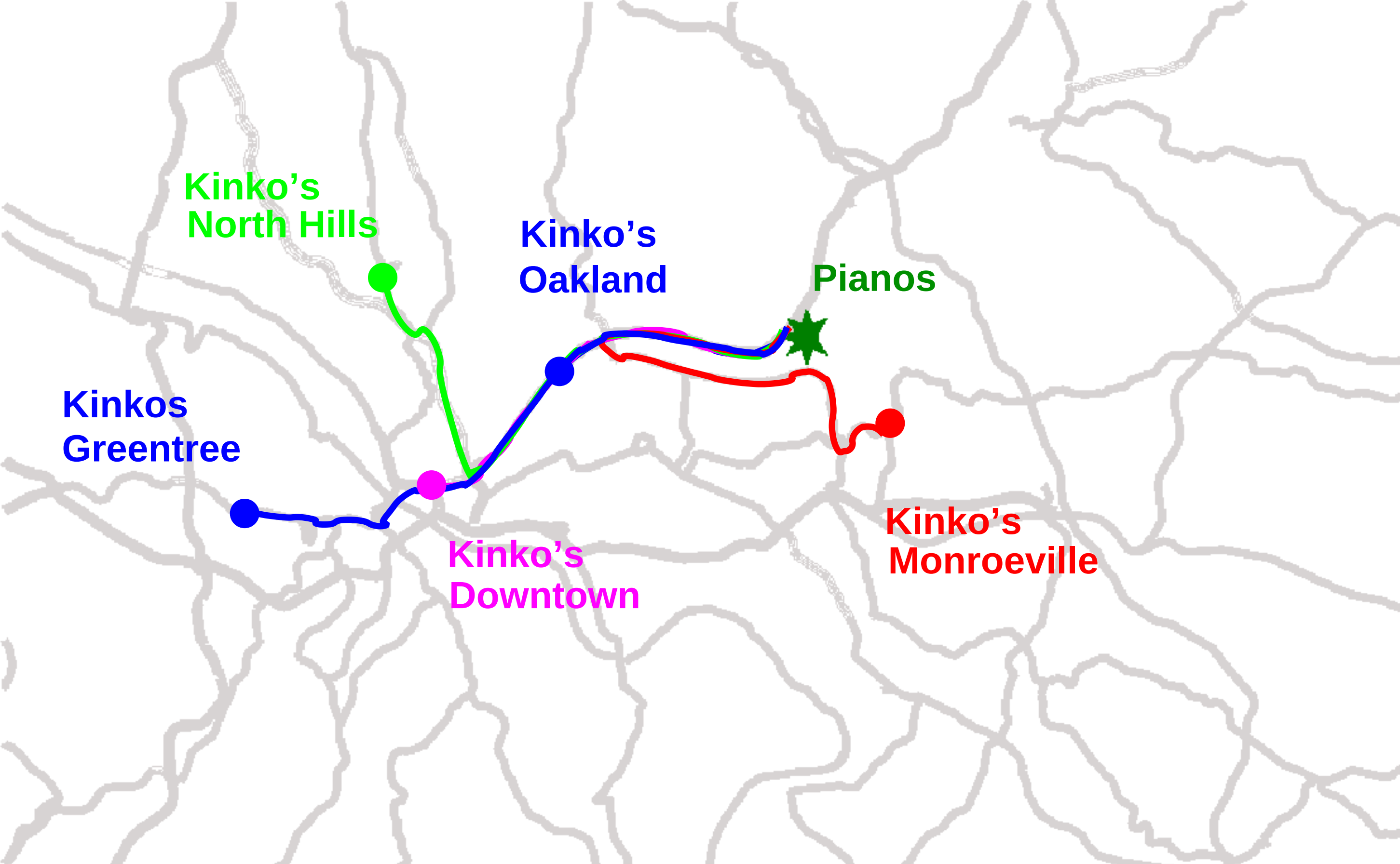

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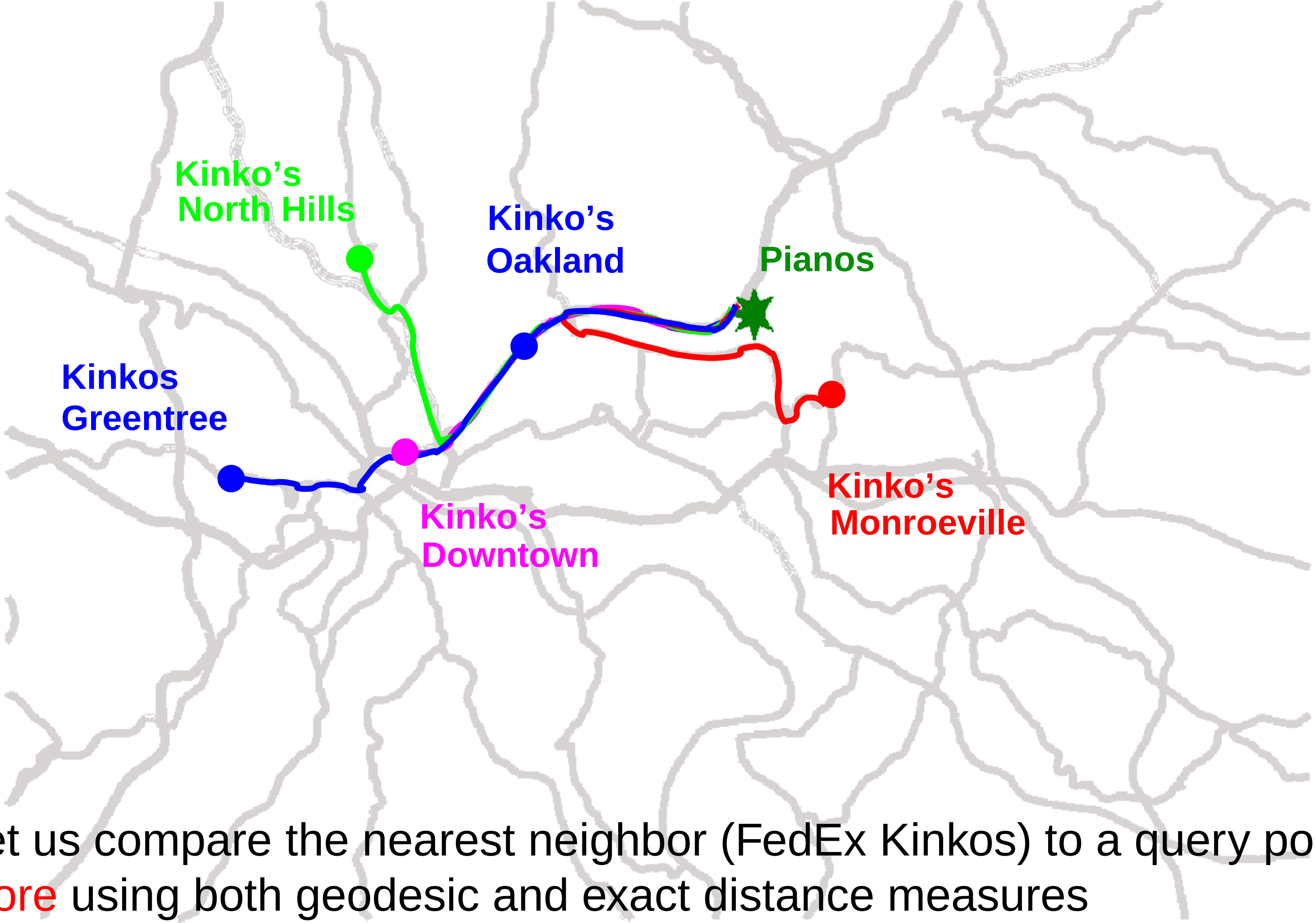

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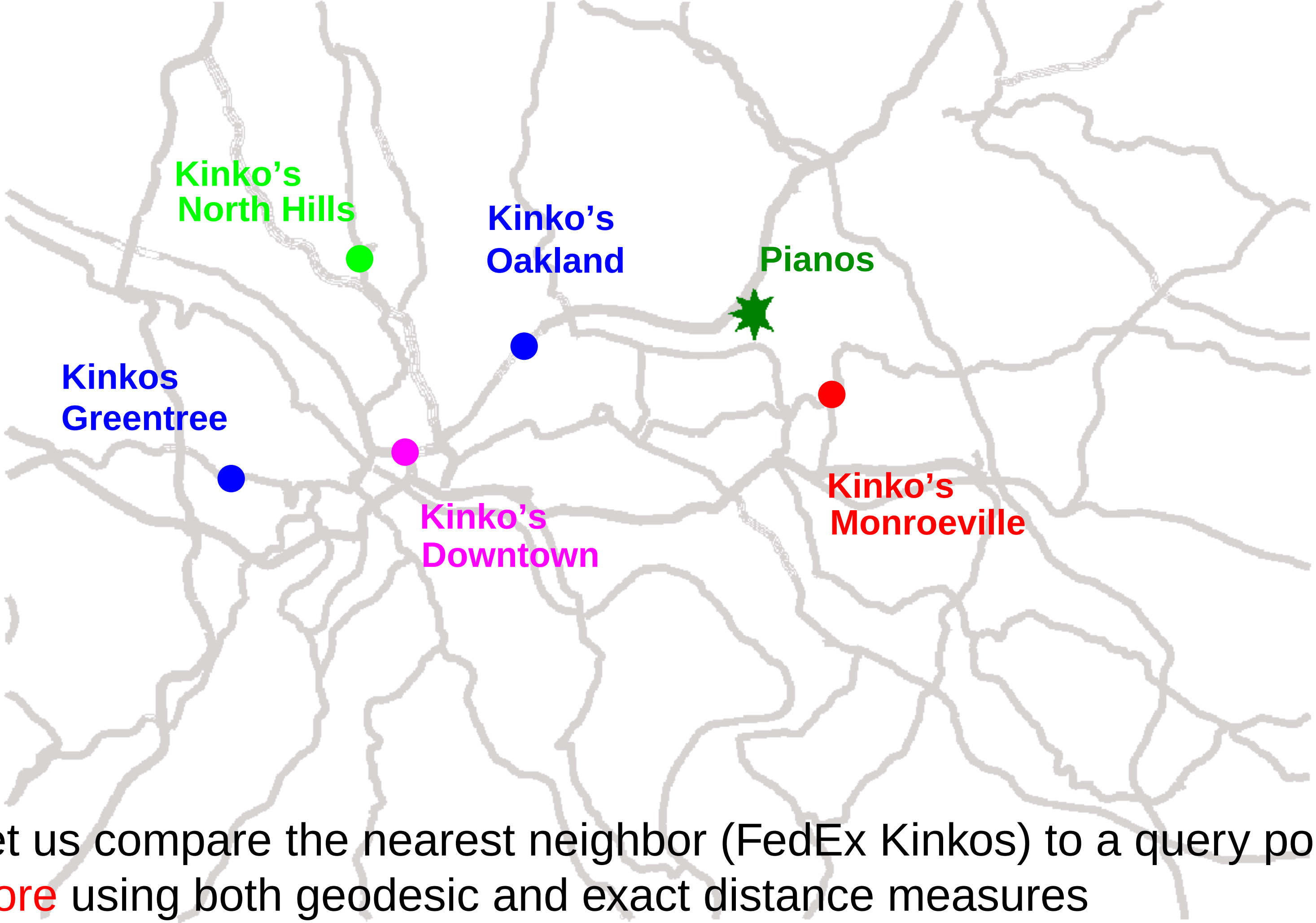

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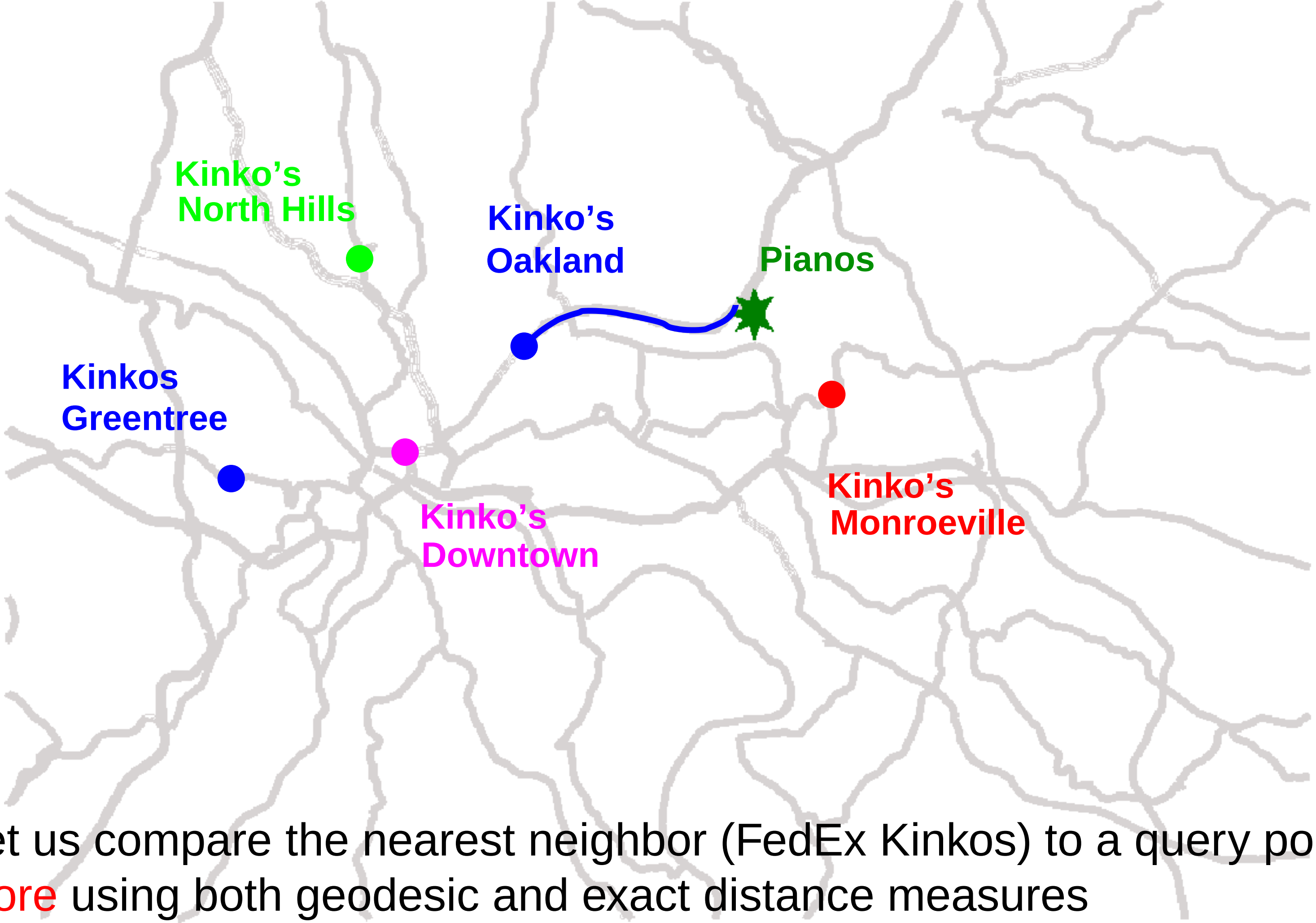

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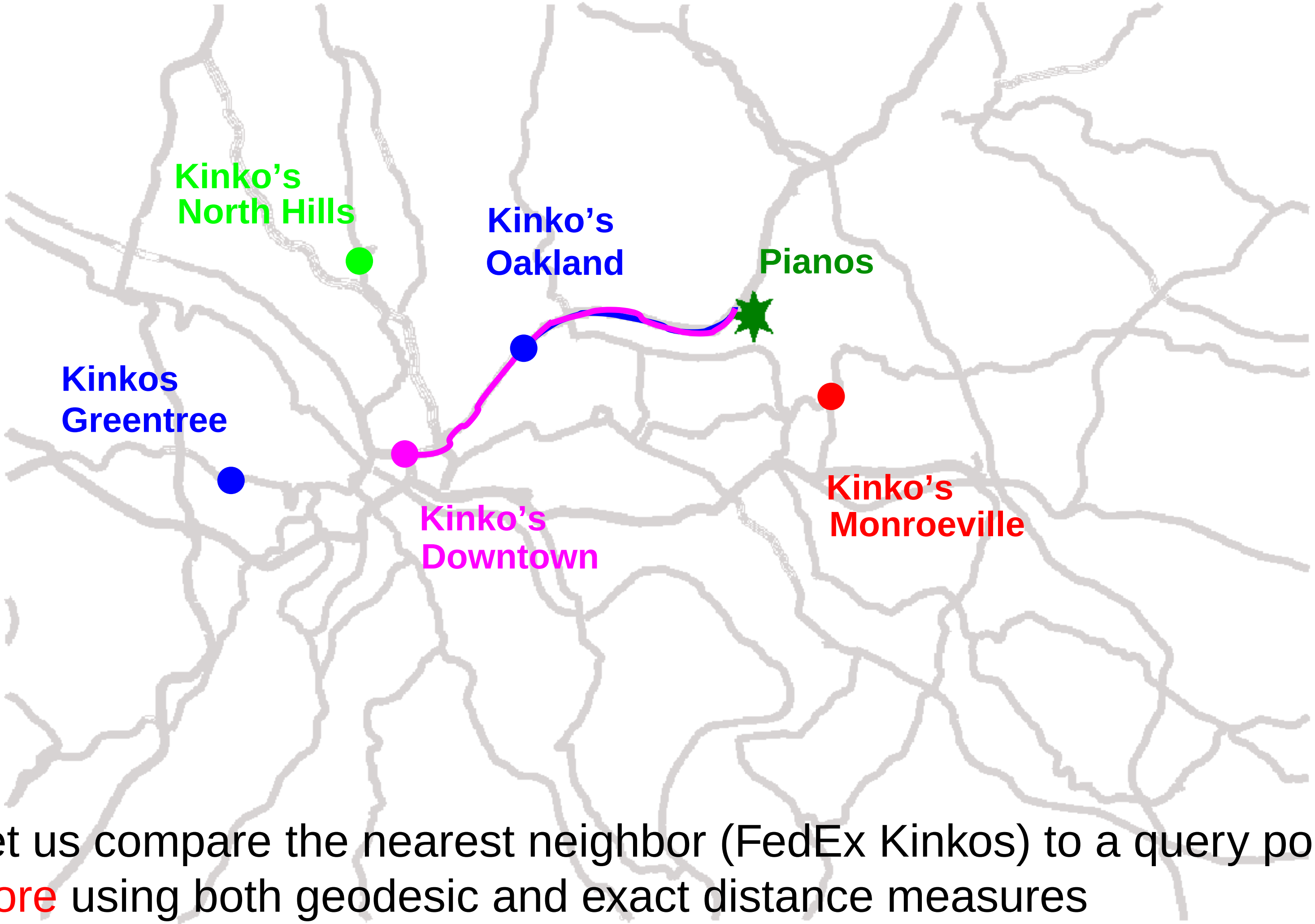

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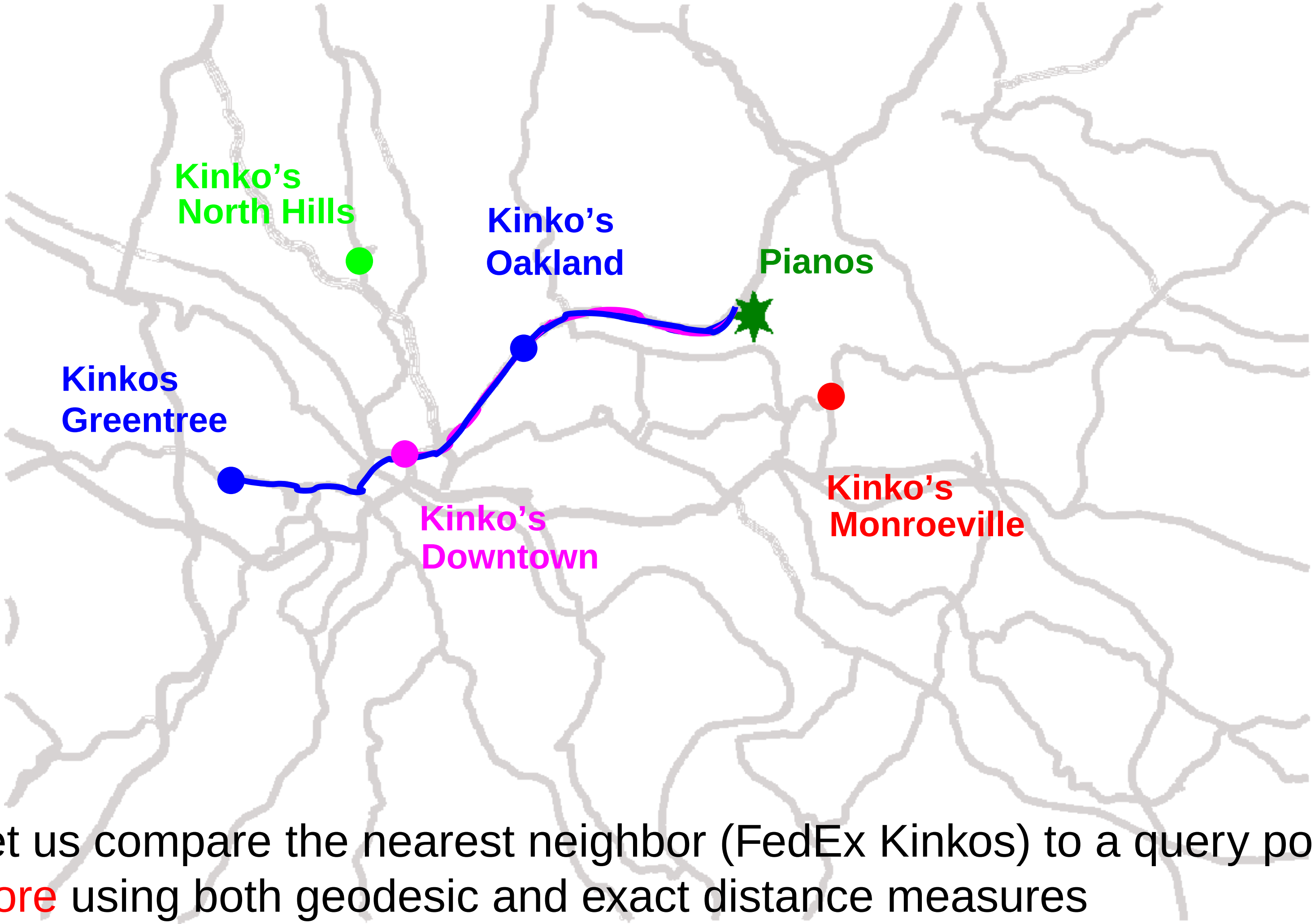

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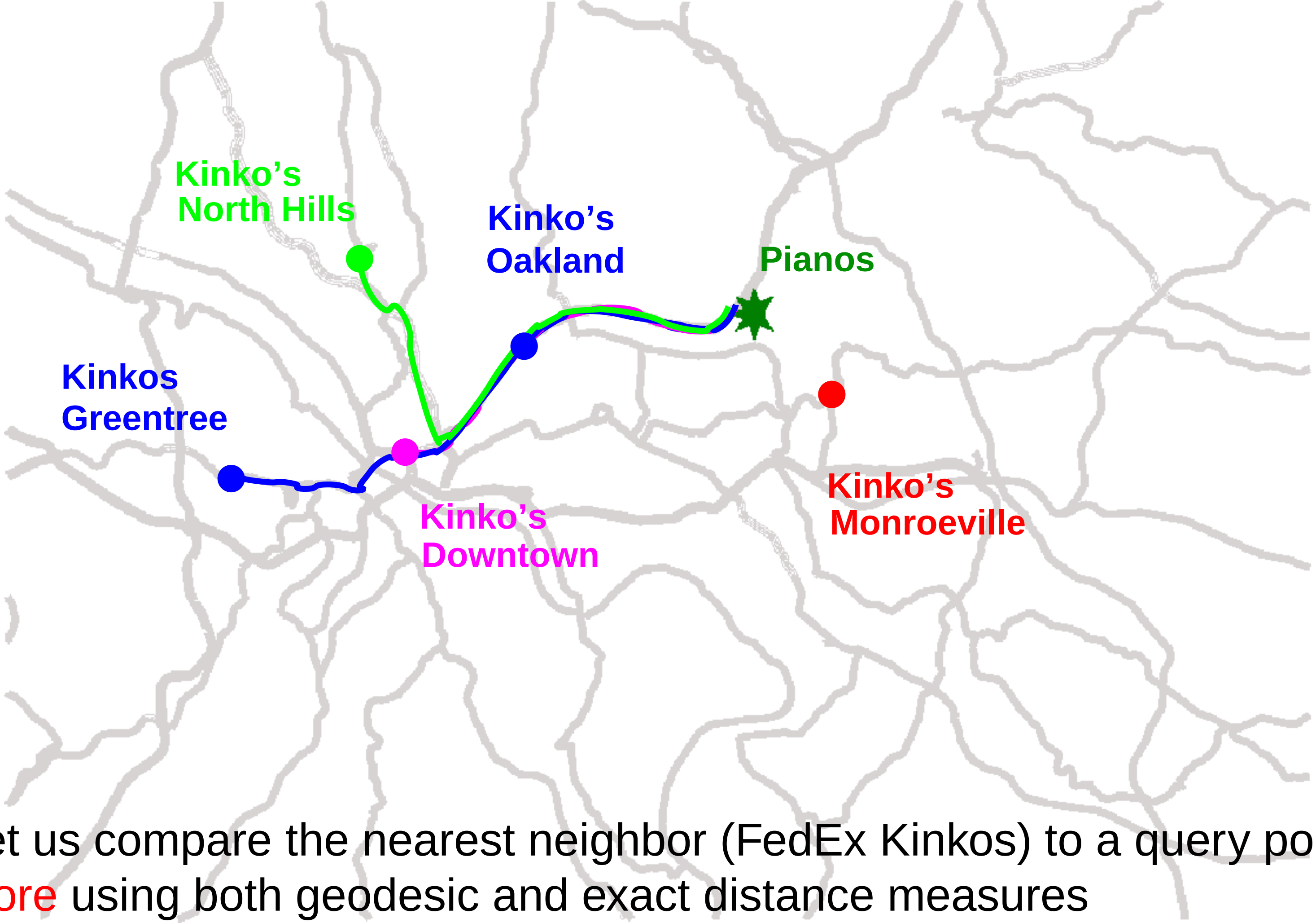

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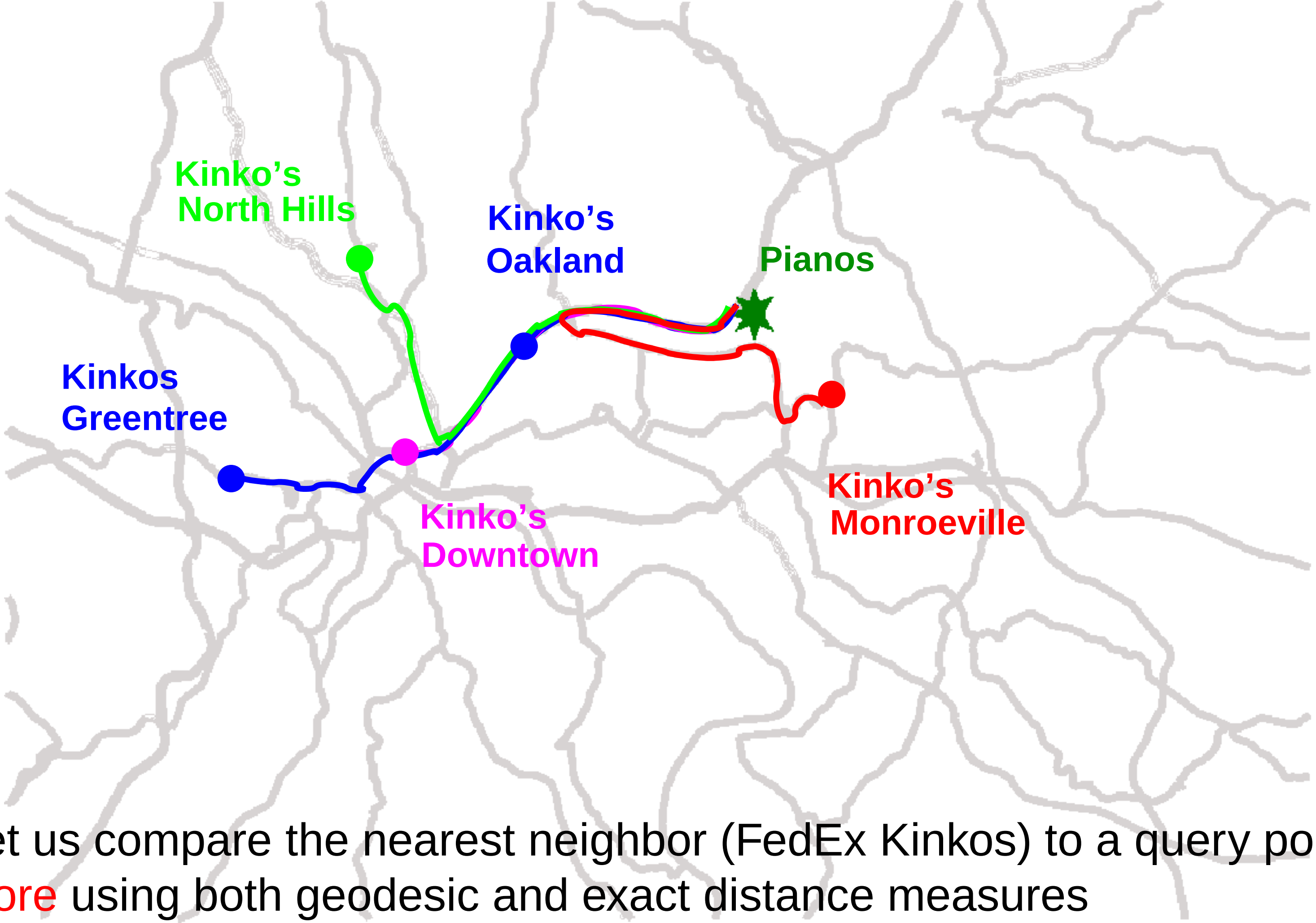

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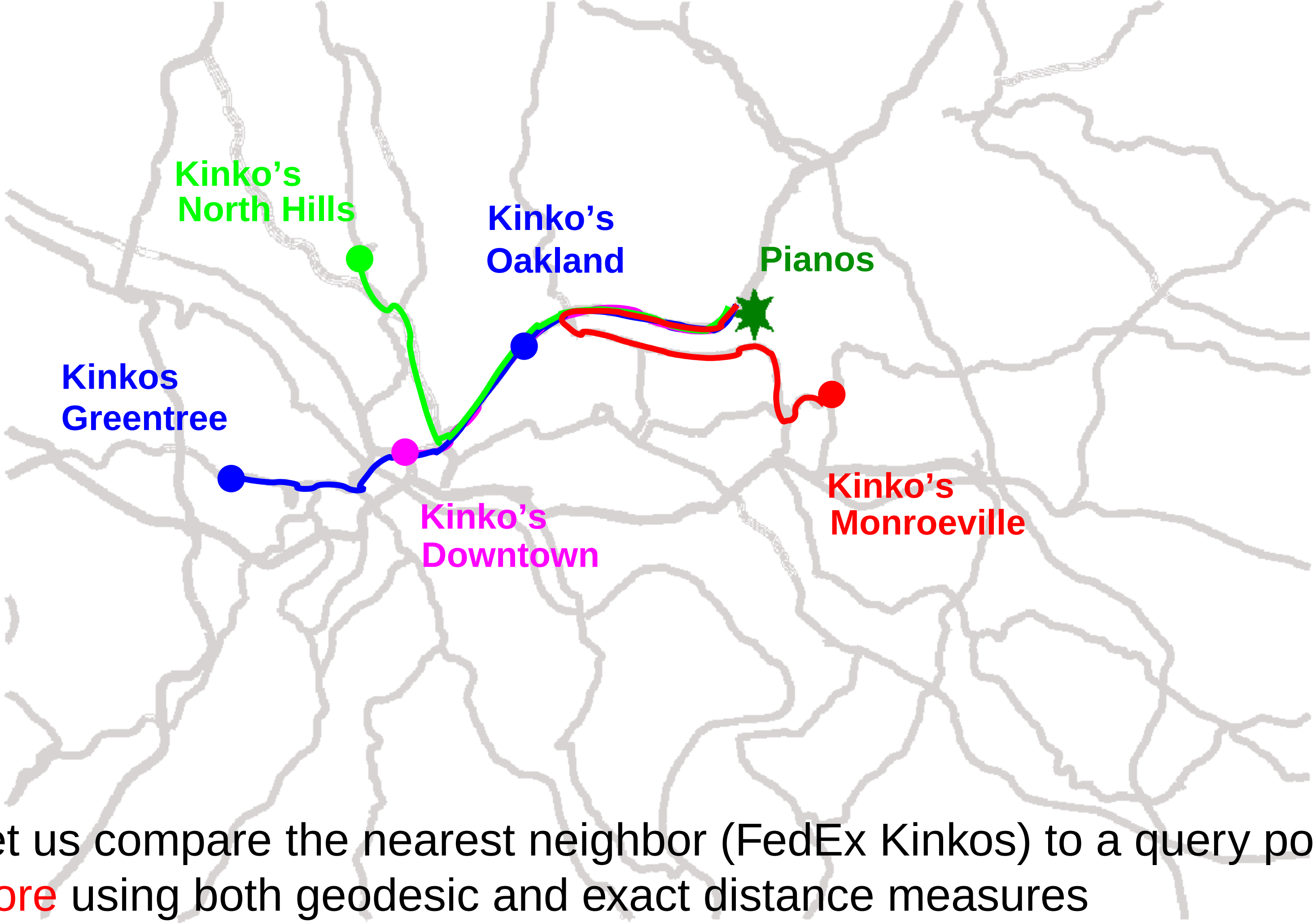

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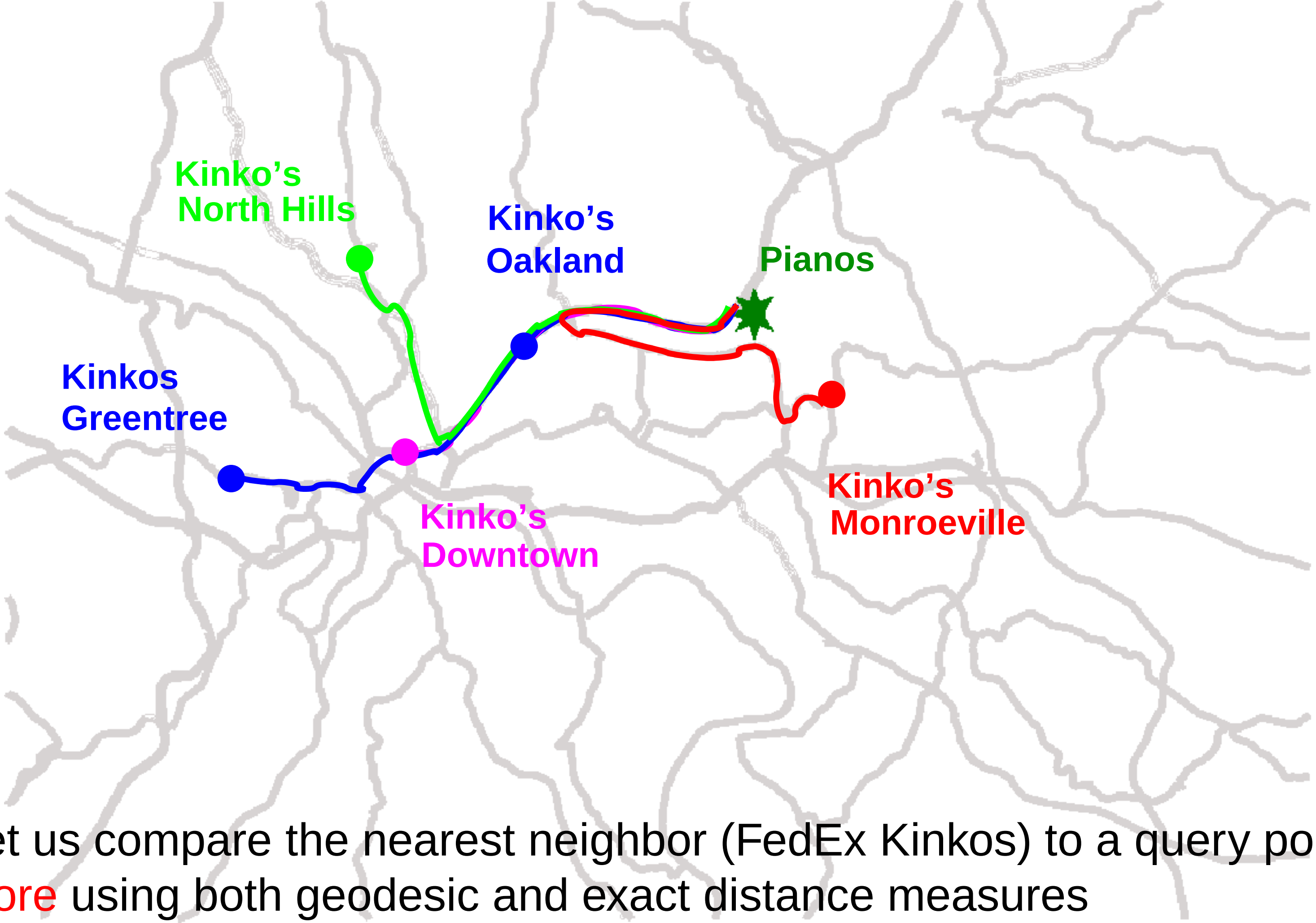

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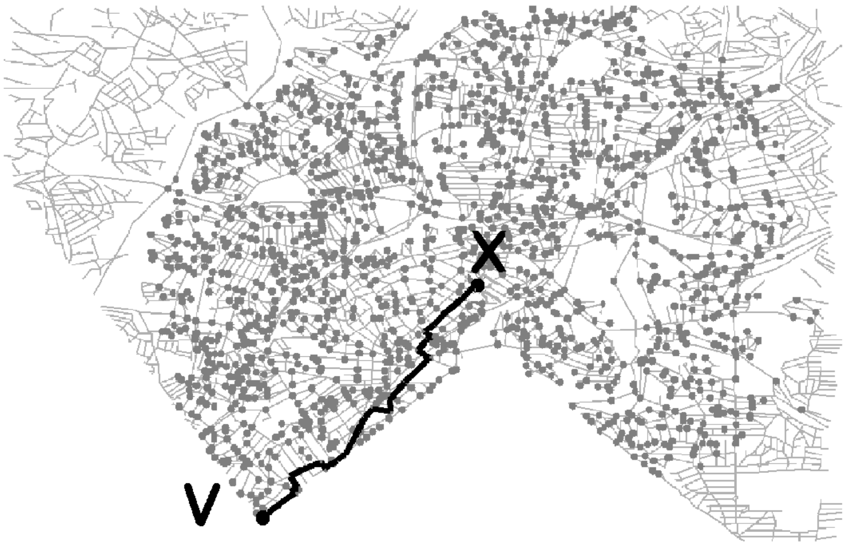
- Challenge: Real time + exact queries

Shortest Path Computation

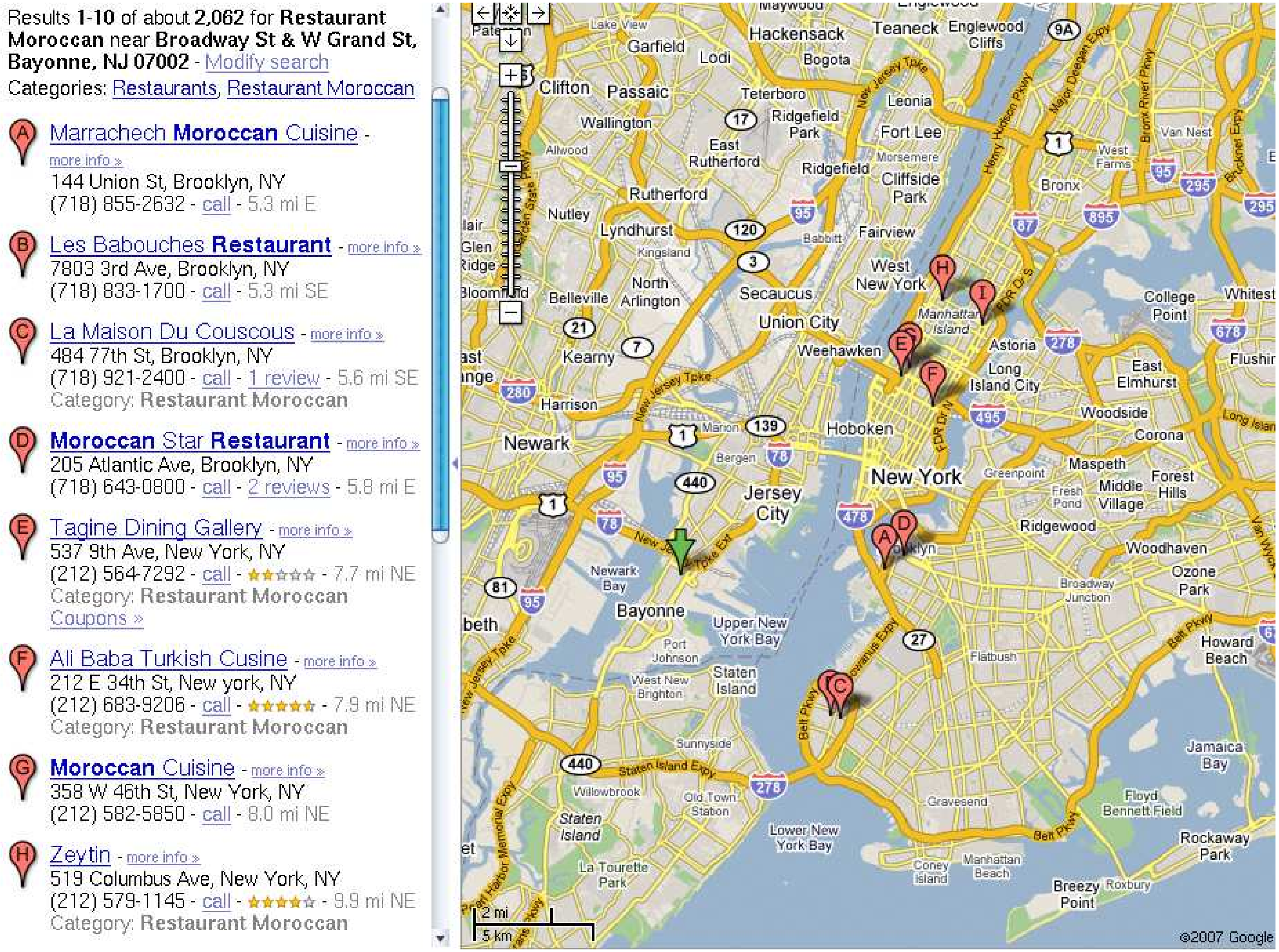
- Shortest path computation is a primitive operation
- Usually use Dijkstra's shortest path algorithm
  - Not feasible in real time for large spatial networks
  - Algorithm visits too many vertices during the search process
  - Ex: Dijkstra's algorithm visits 3191 out of a total of 4233 vertices in the spatial network to identify a path comprising 75 vertices between X and V



- Popular solution: Use "crow flying" (geodesic) distance

Proximity Search on “Google Local”

- Let us examine the errors between ordering by the spatial distance (“as the crow flies” used by Google) and by the network distance (used by us)



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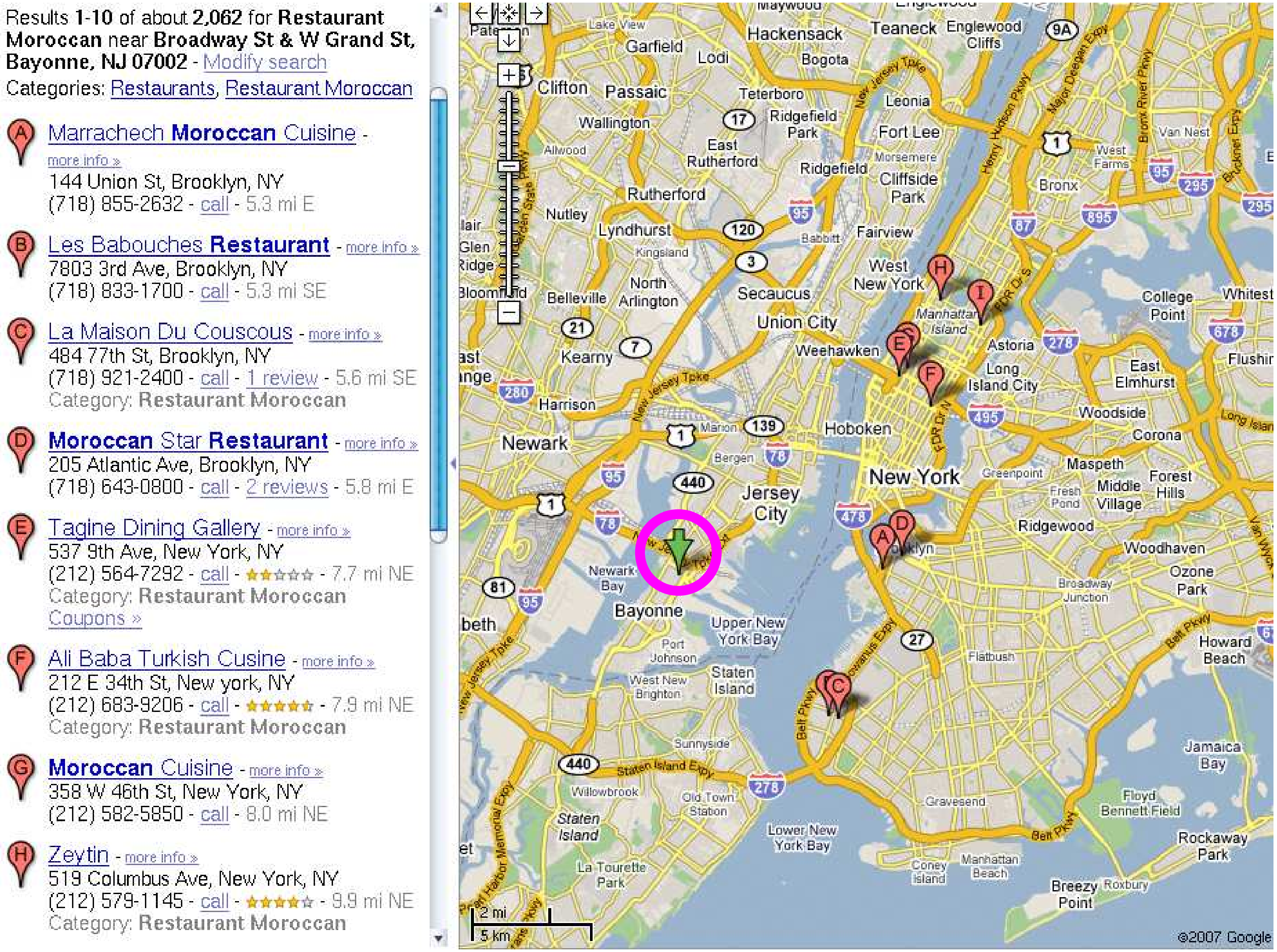

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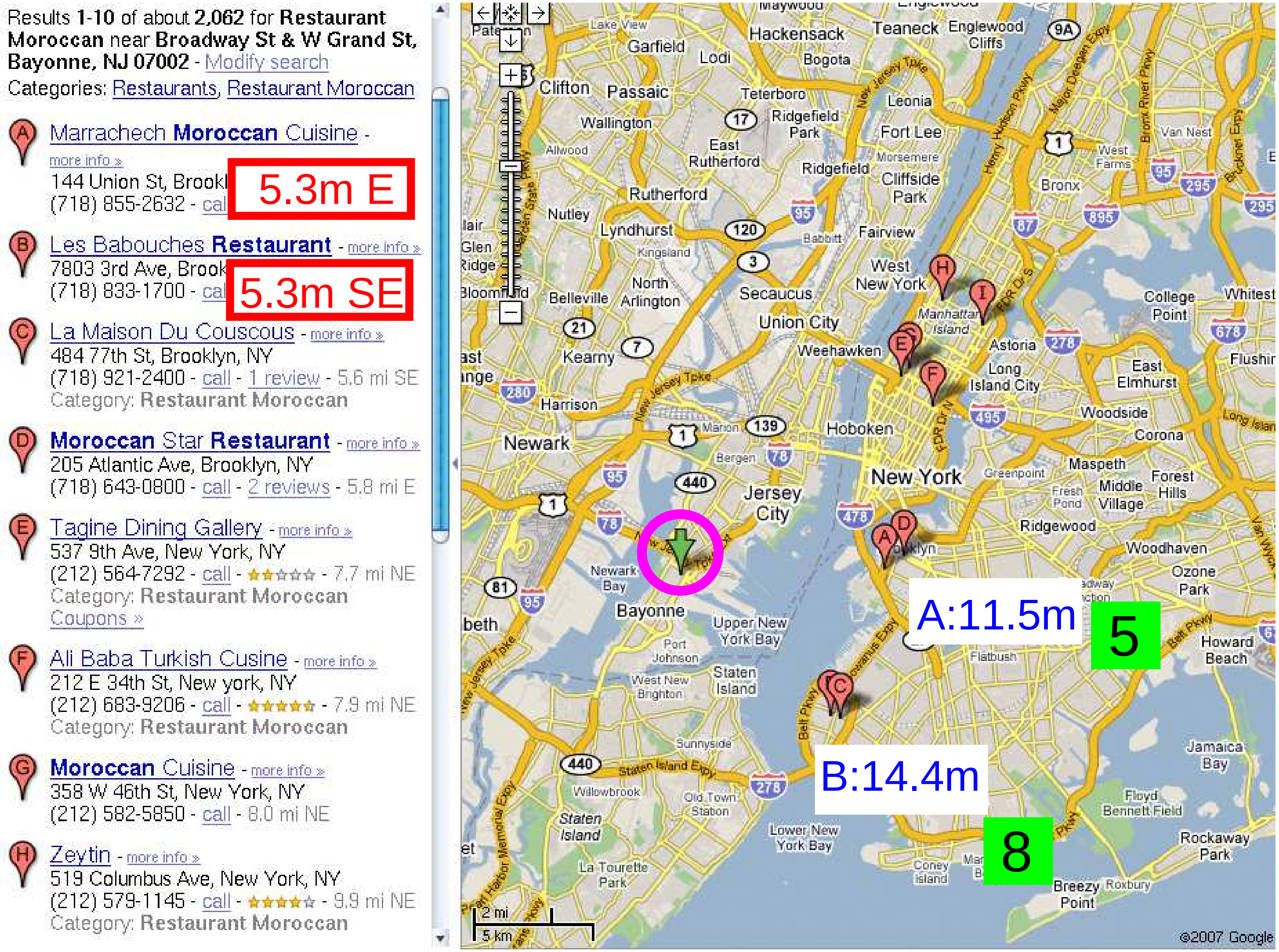

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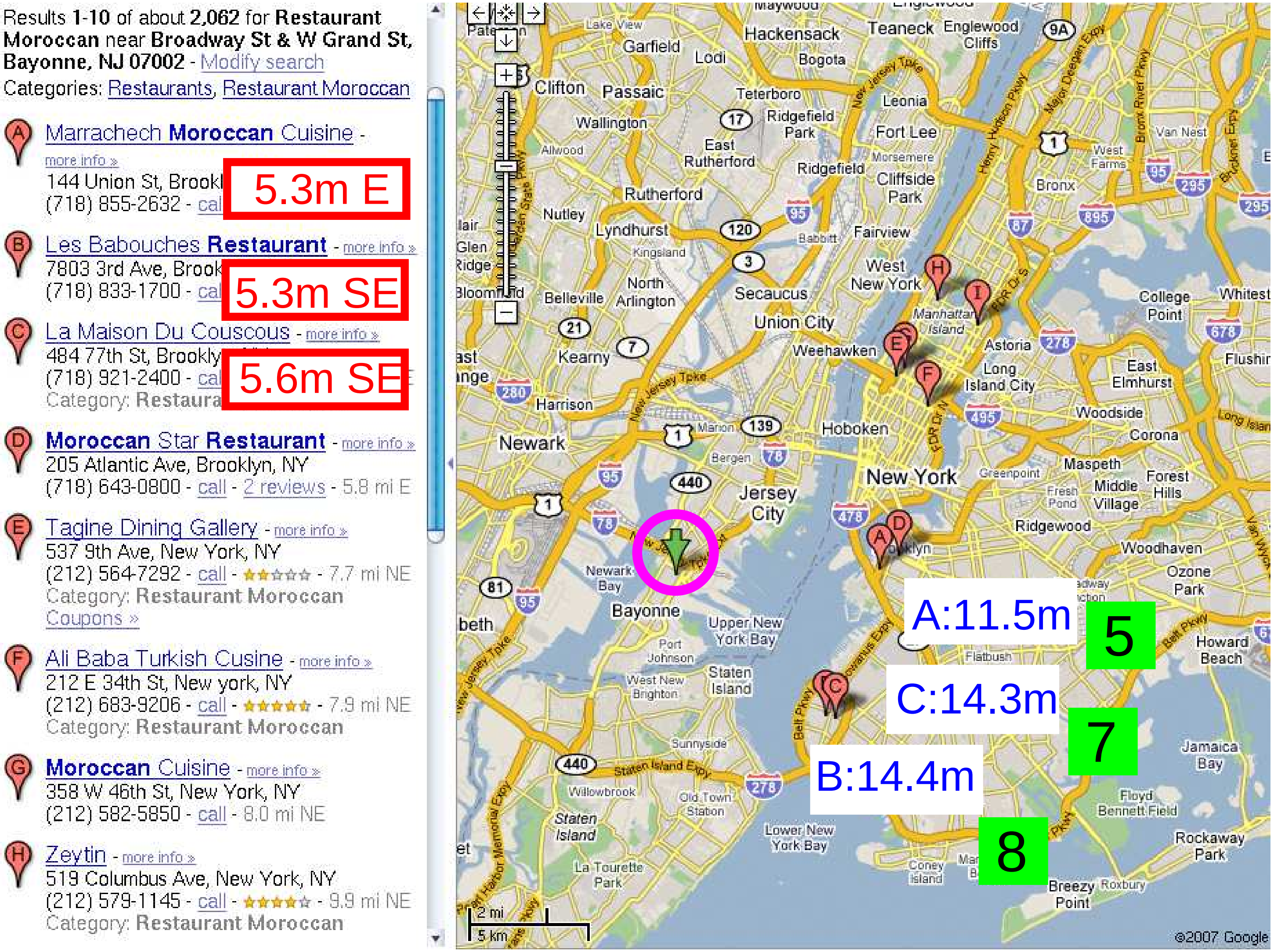

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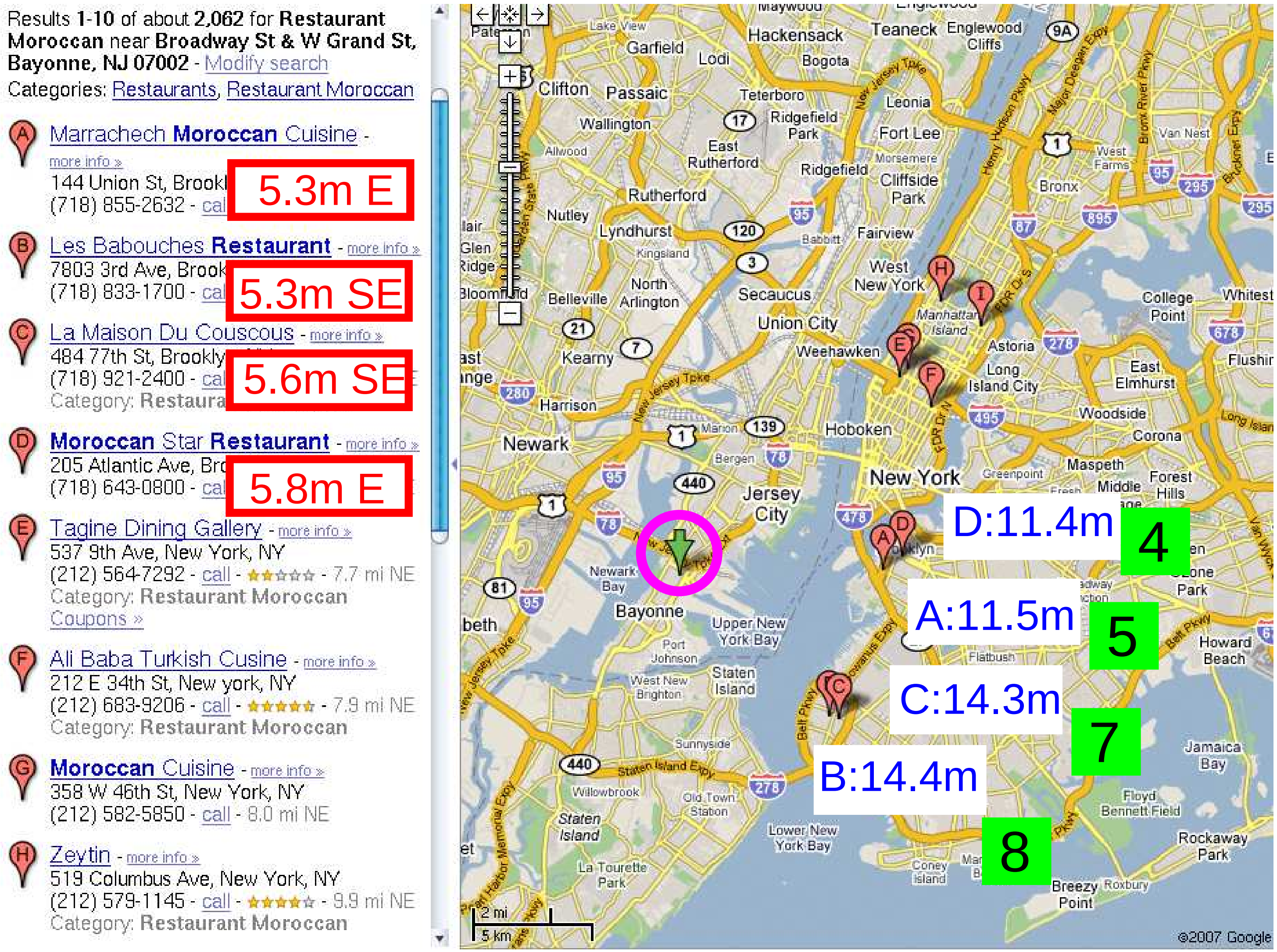

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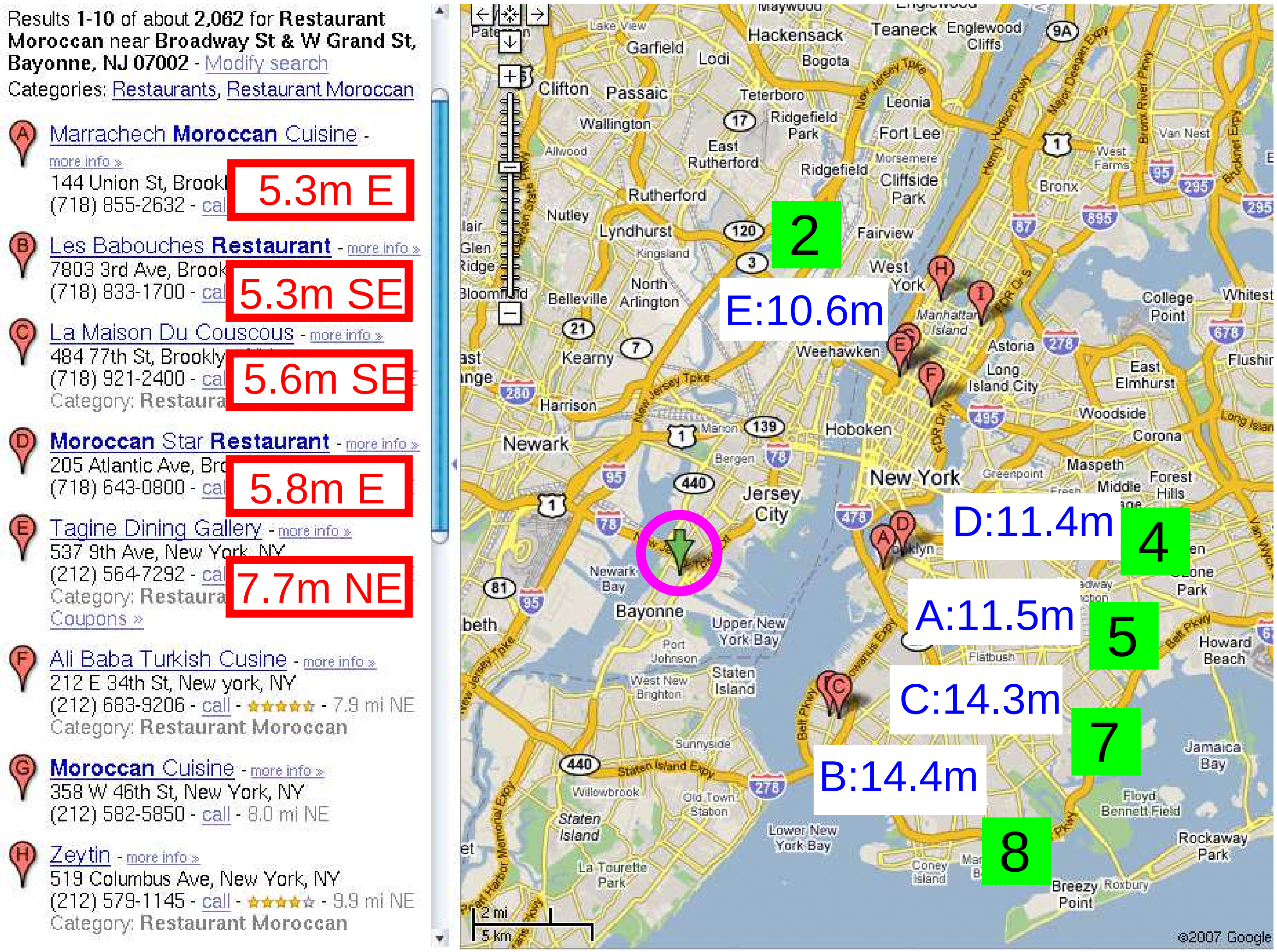

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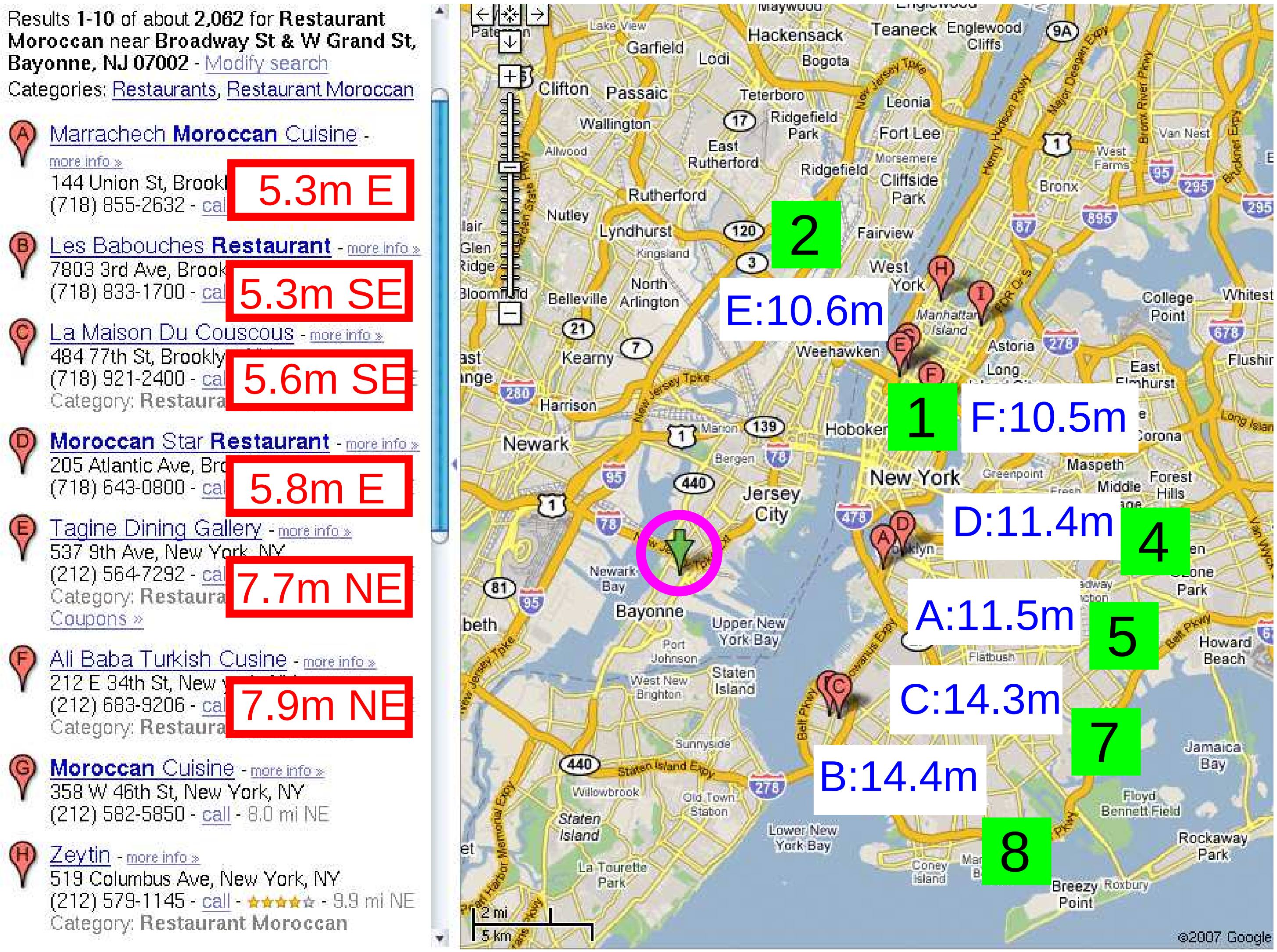

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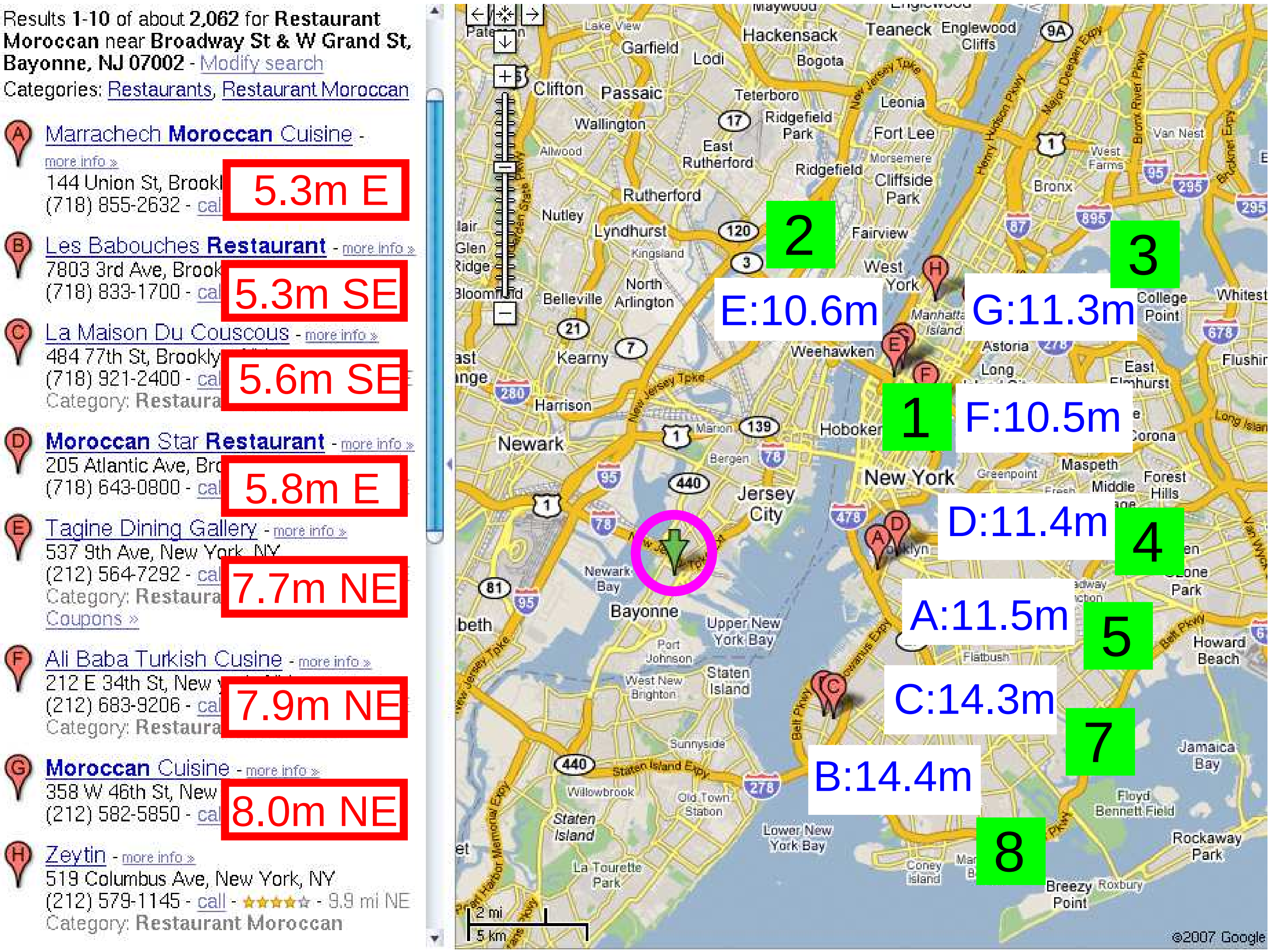

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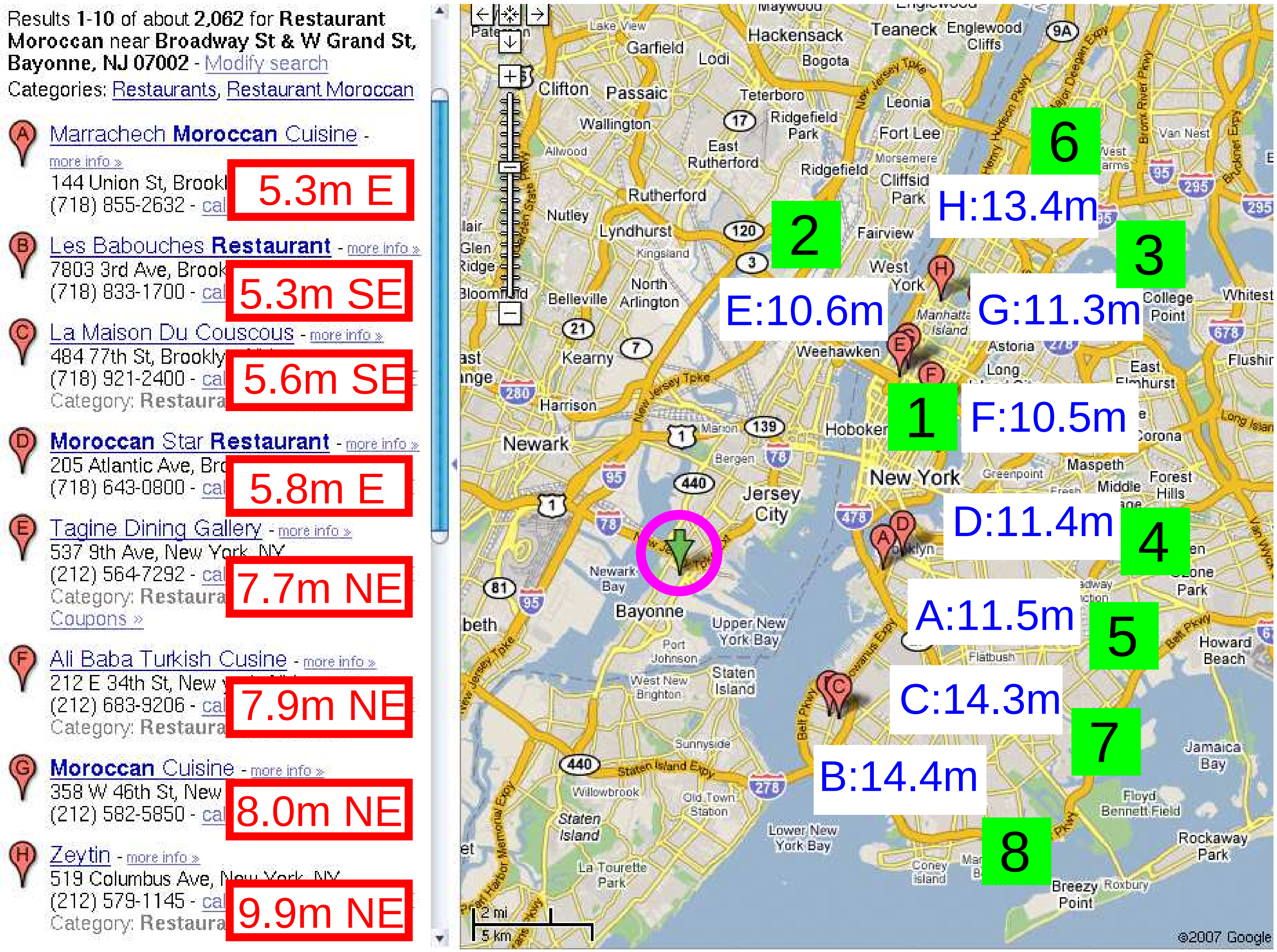

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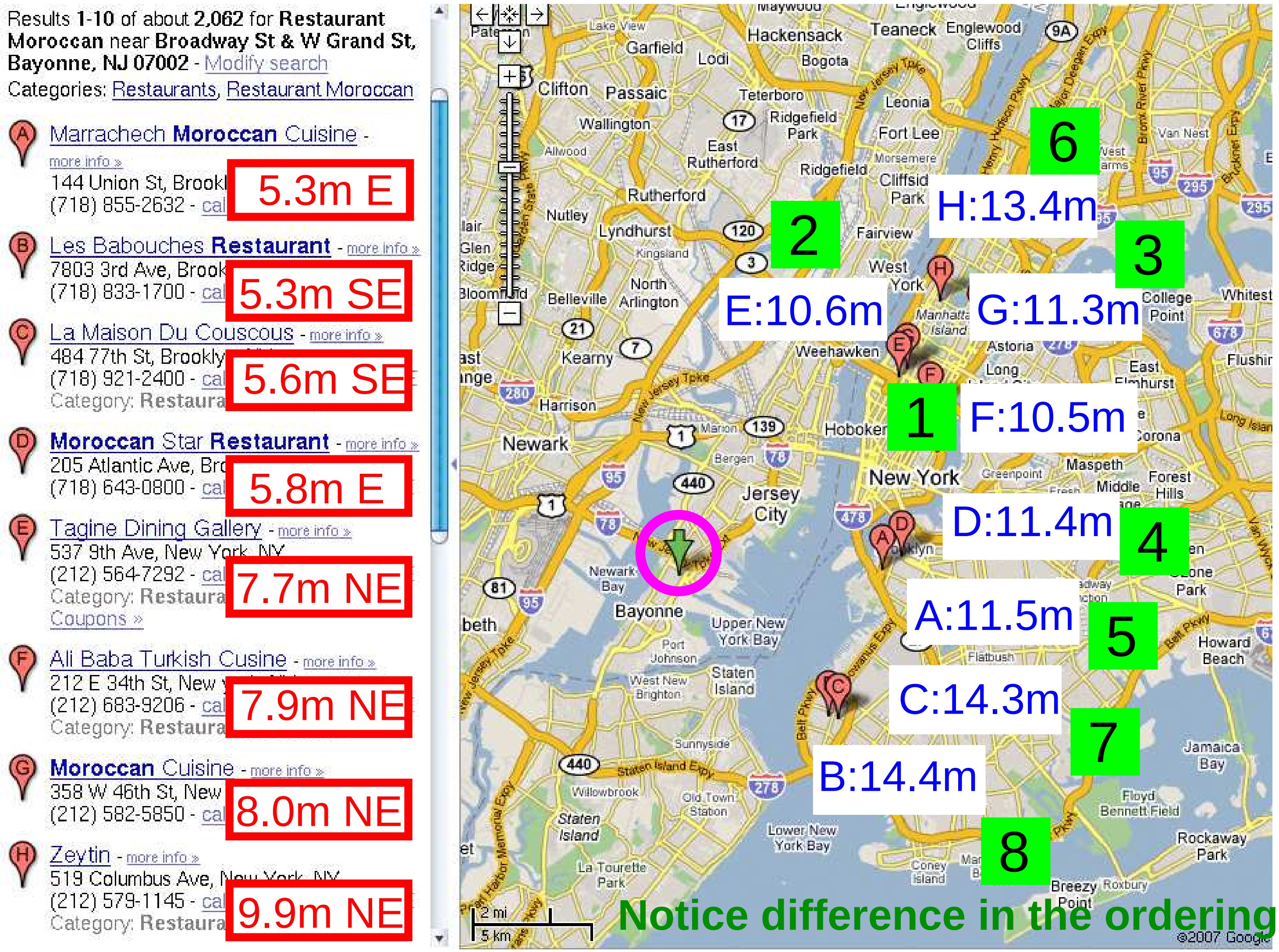

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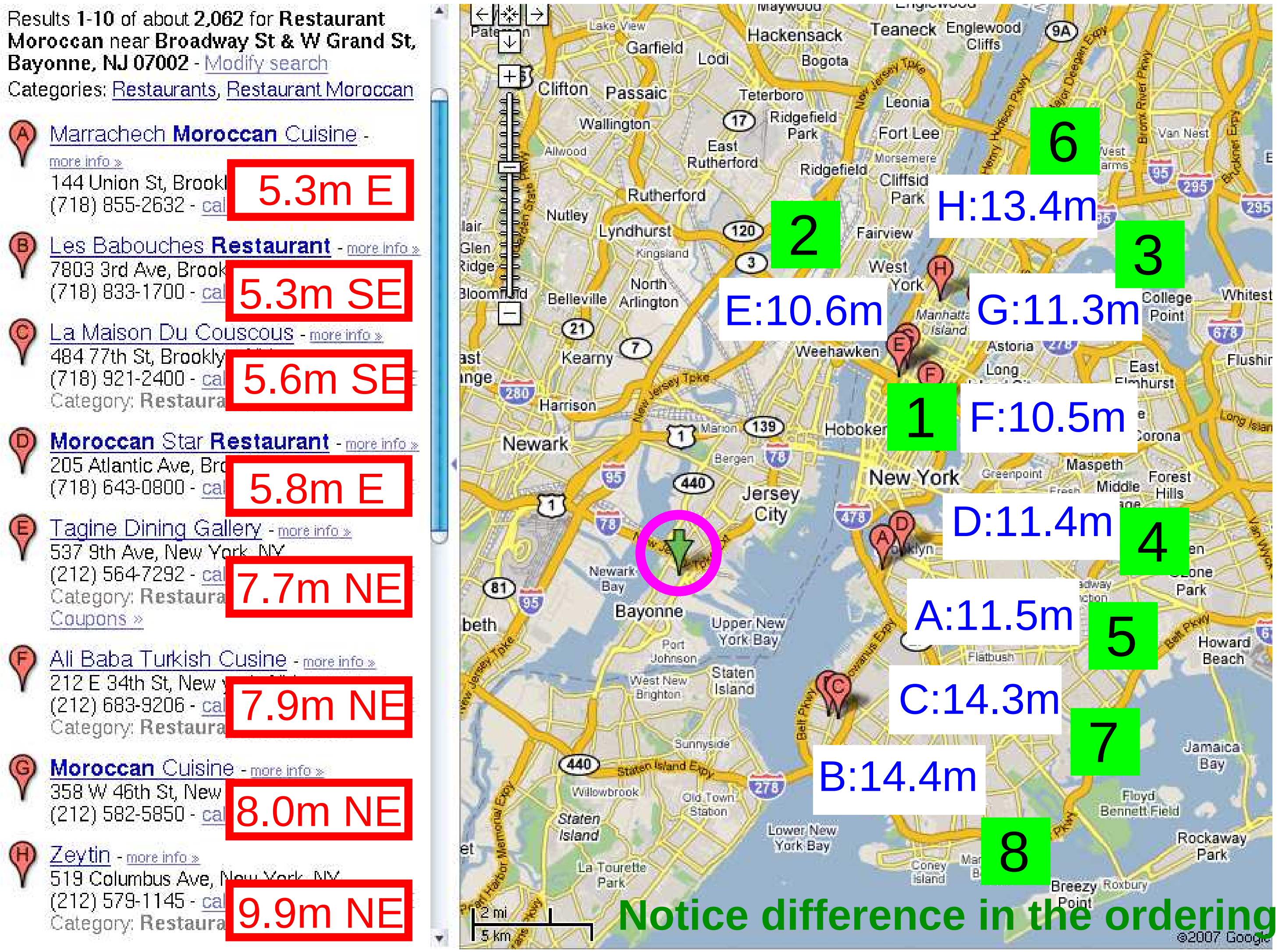

- Goal: Instant answers as well as accurate answers

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Precomputation of Shortest Paths

- By precomputing and storing all of the shortest paths, nearest neighbor queries could be answered instantly
  - How to effectively compute the shortest path?
  - How to effectively store the shortest path?
  - Challenge: very large network (approximately 24 million vertices)
- Result: Enables decoupling nearest neighbor and shortest path computation processes
  - Decouples domain S of query objects and objects from which the neighbors are drawn from domain V of the vertices of the spatial network
  - Implies no need to recompute shortest paths anew each time there are changes in q or S

Strategy: Precomputation

- Idea: Precompute and store all pairs shortest paths
  1. How to compute shortest paths?
  2. How to store shortest paths?
     - Challenge: Very large network (24,000,000 vertices)
- Trade-off: Space requirements vs. retrieval time

k=shortest path length   n=# vertices   m=# edges   constants $\delta > 1$ and $\epsilon > 0$

Approach	Space	Query Time	
		Path	Distance
Explicit Path Storage	$O(n^3)$	$O(1)$	$O(1)$
Next-Hop Storage	$O(n^2)$	$O(k)$	$O(1)$
Dijkstra's Algorithm	$O(m+n)$	$O(m+n\log n)$	$O(m+n\log n)$
SILC	$O(n\sqrt{n})$	$O(k\log n)$	Approx: $O(\log n)$
Distance Oracle–1	$O((\frac{1}{\epsilon})^2 n)$	—	ϵ-Approx:$O(\log n)$
Distance Oracle–2	$O((\frac{1}{\epsilon})^2 n\log n)$	—	ϵ-Approx:$O(1)$
Path Oracle	$O((2+\frac{1}{(\delta-1)})^2 n)$	$O(k\log n)$	—
Path-Distance Oracle	$O(\max((2+\frac{1}{(\delta-1)})^2, \frac{1}{\epsilon}^2)n)$	$O(k\log n)$	ϵ-Approx:$O(\log n)$

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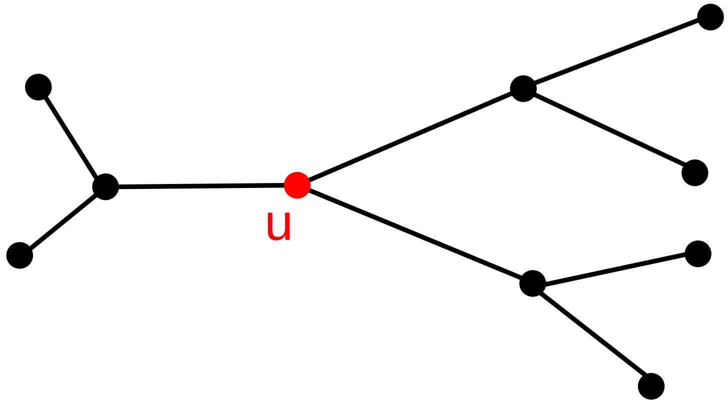

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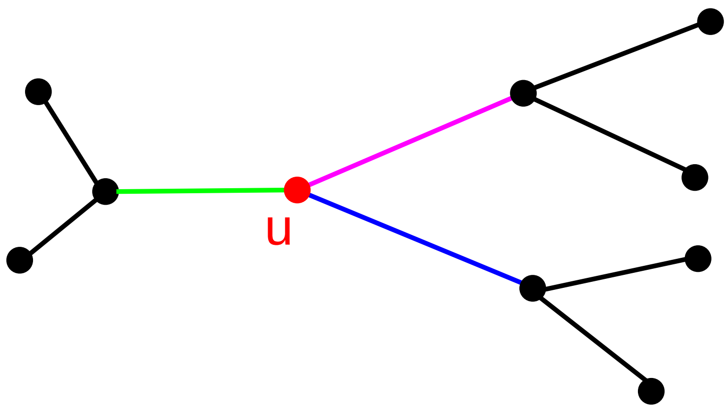
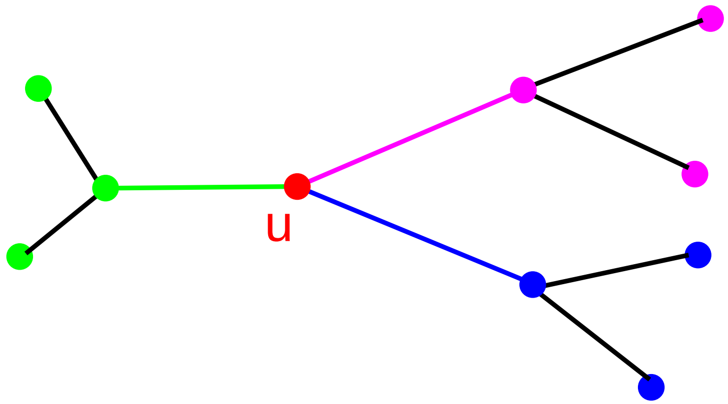


  - Source vertex u in a spatial network
  - Assign colors to the outgoing edges of u

SILC Path Encoding

- The SILC path encoding takes advantage of the path coherence
- How? Use a *coloring* algorithm



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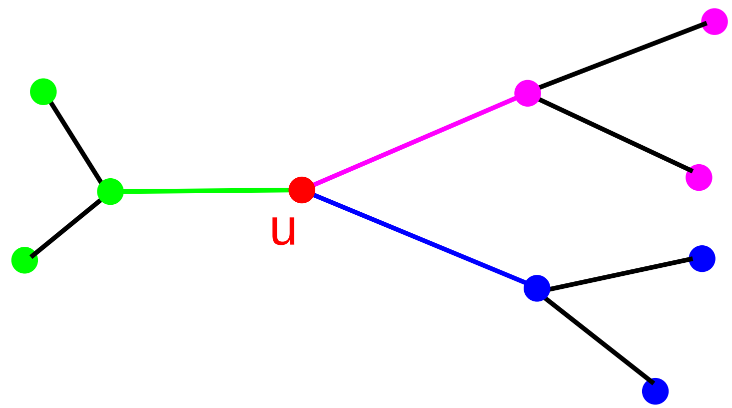

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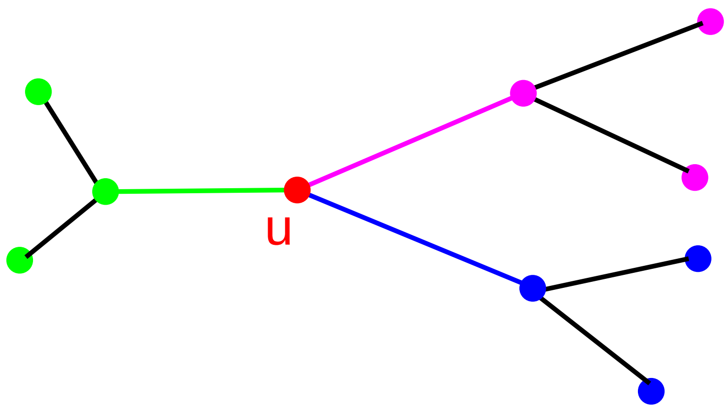

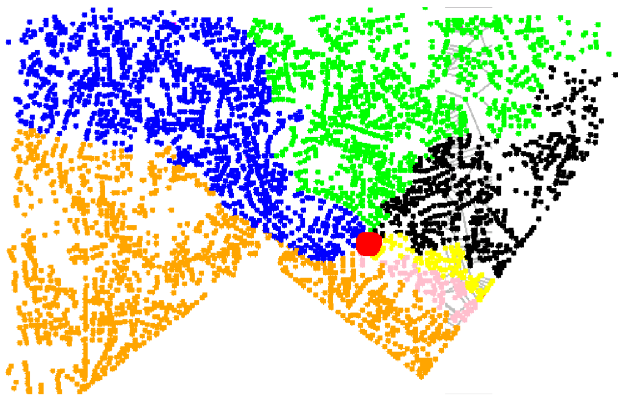

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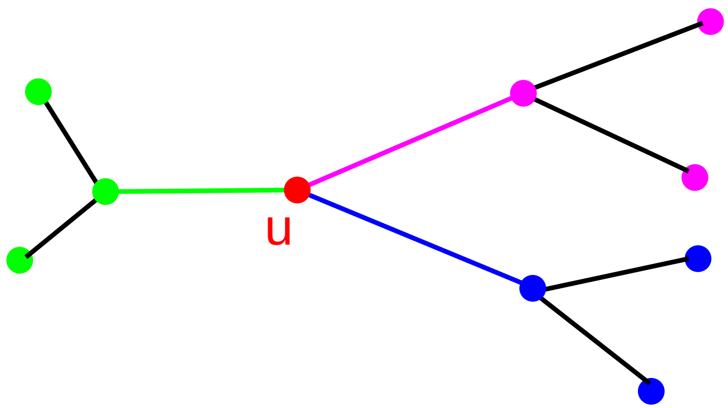

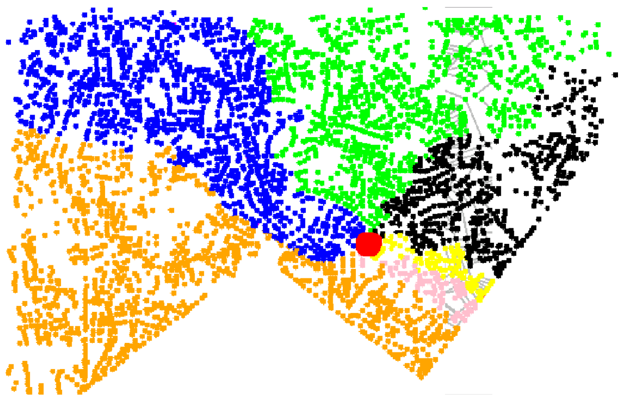

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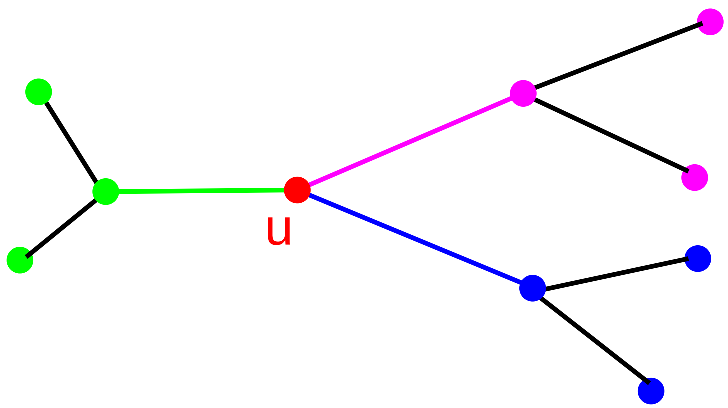

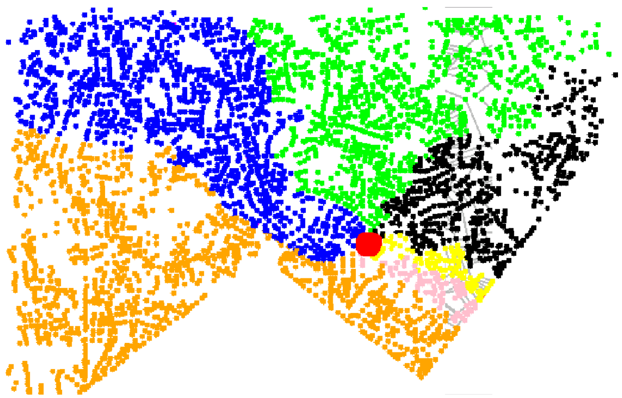

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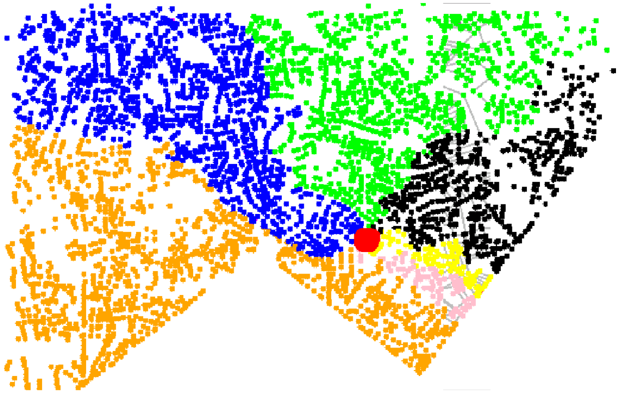
- Assuming planar spatial network graphs means that the coloring results in spatially contiguous colored regions due to path coherence

How to Store Colored Regions?



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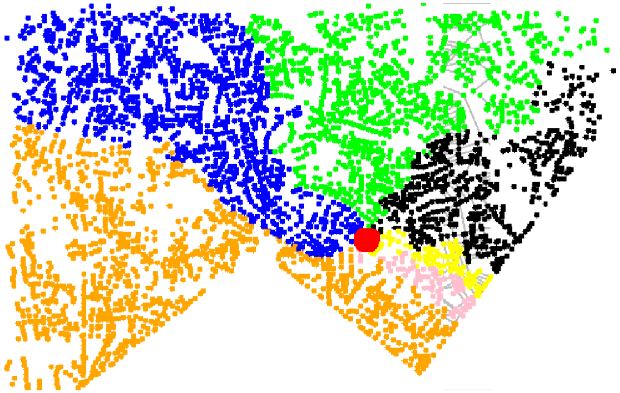
- Minimum bounding boxes (e.g., R-tree) [Wagn03]



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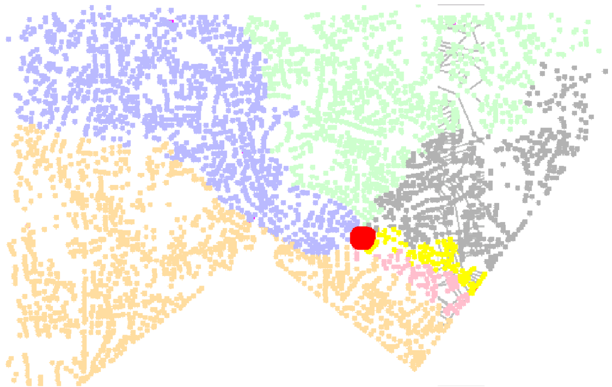

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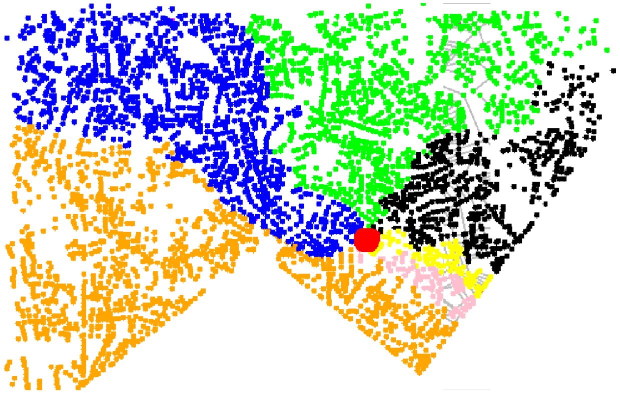

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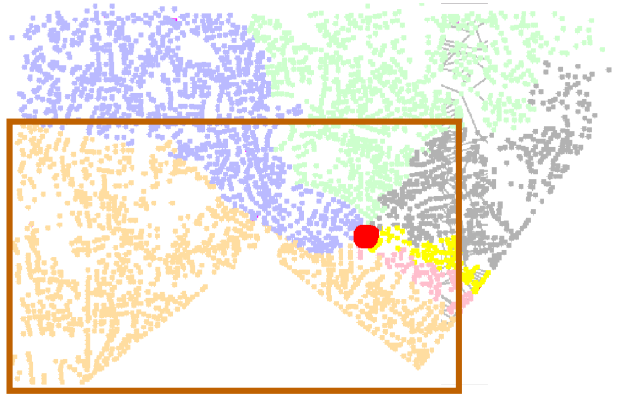

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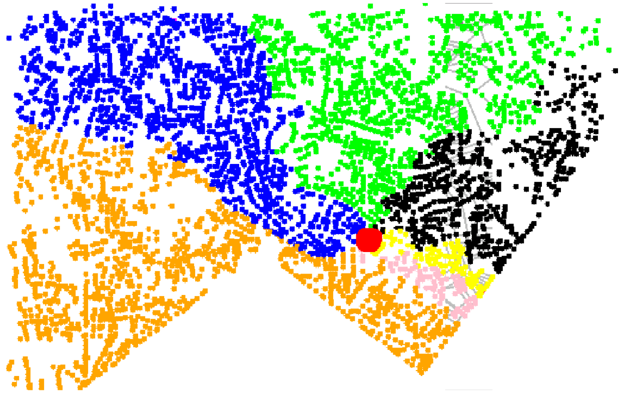

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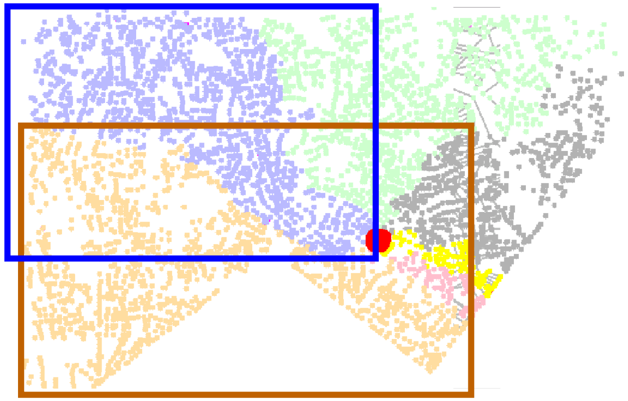

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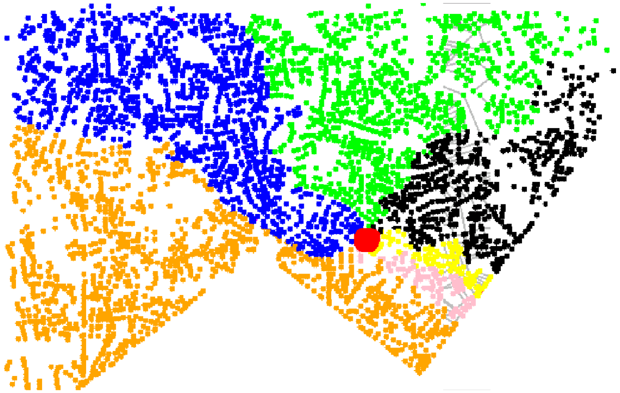

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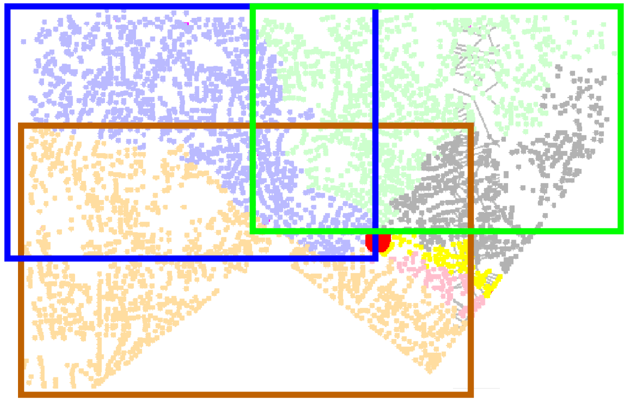

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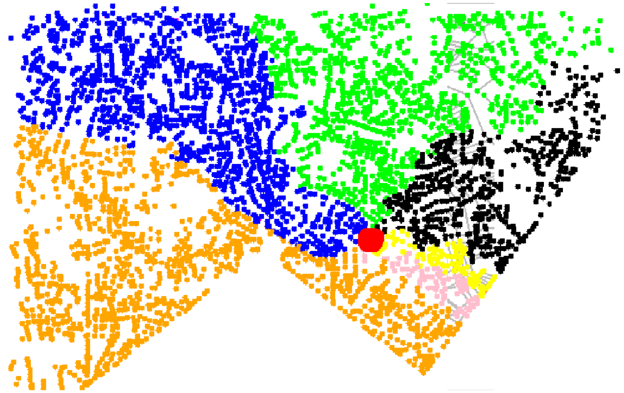

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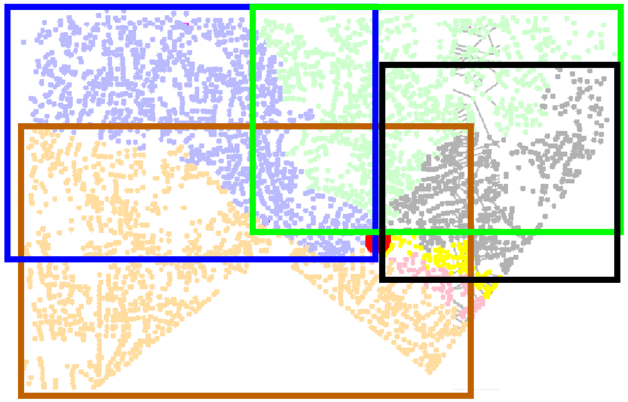

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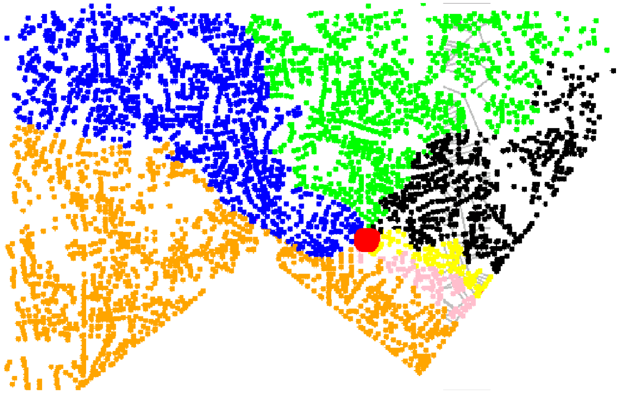

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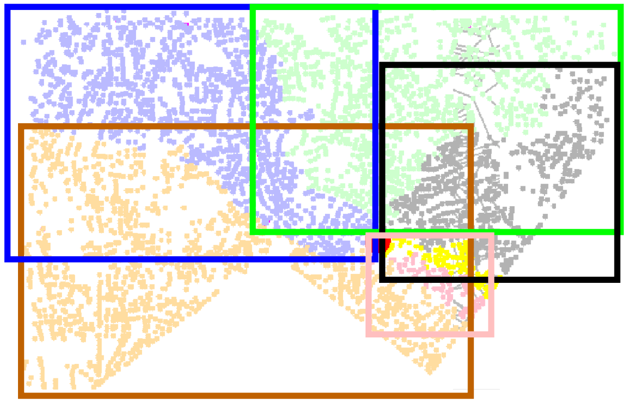

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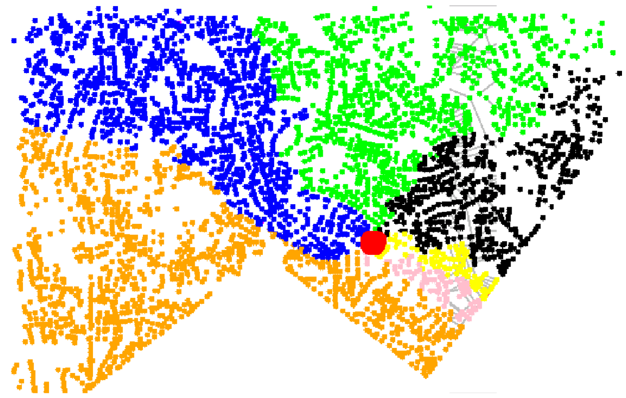

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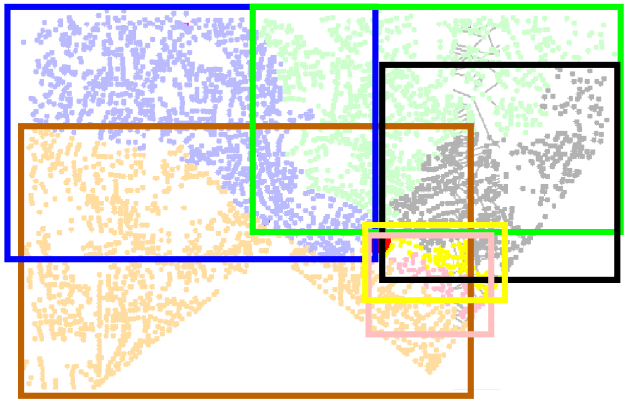

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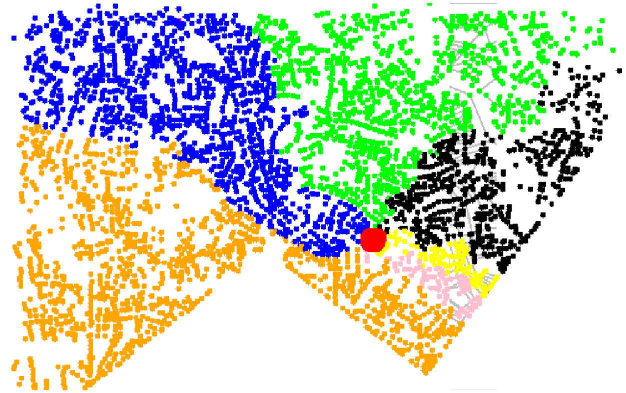

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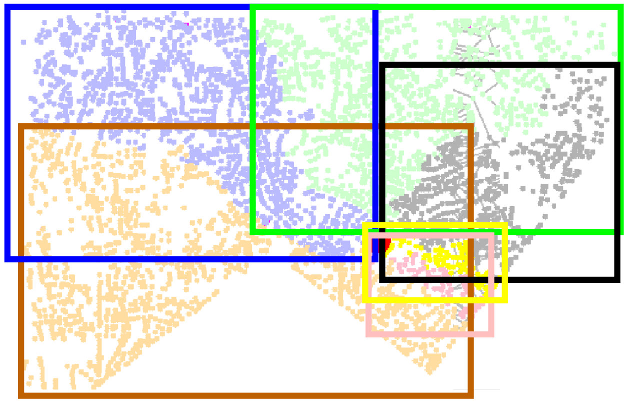

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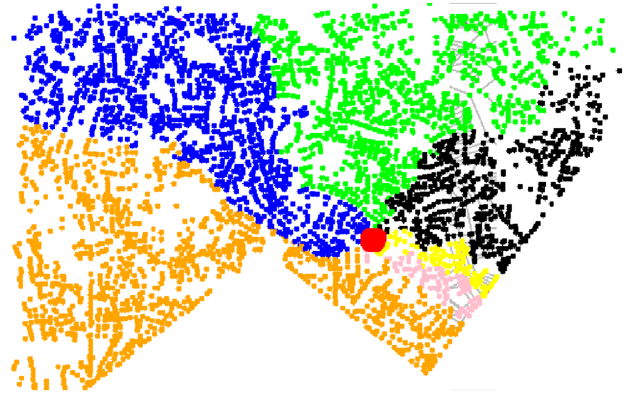

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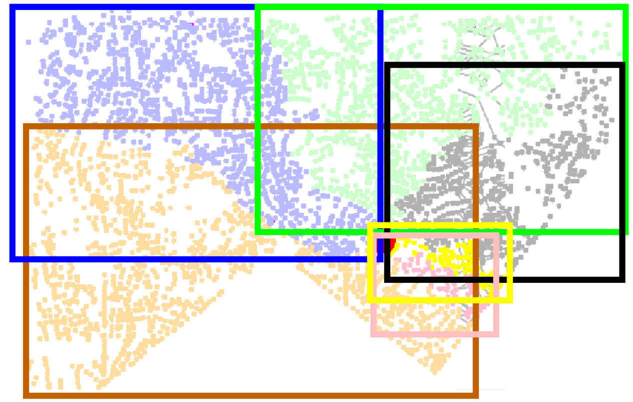

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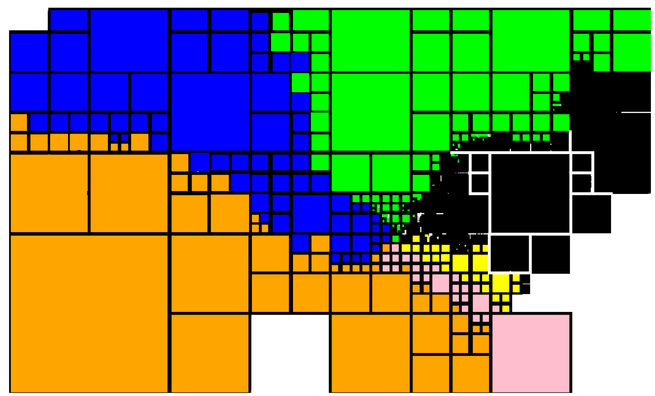

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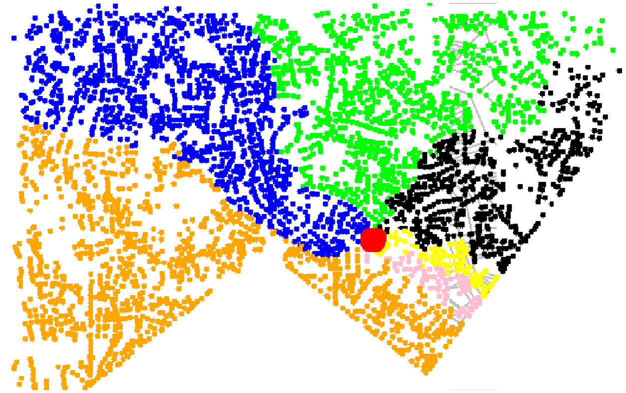

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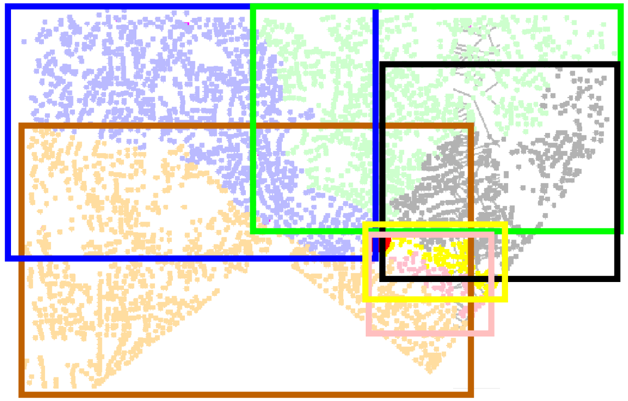

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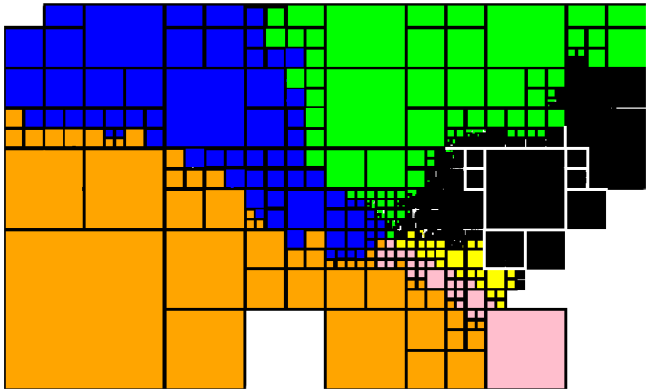

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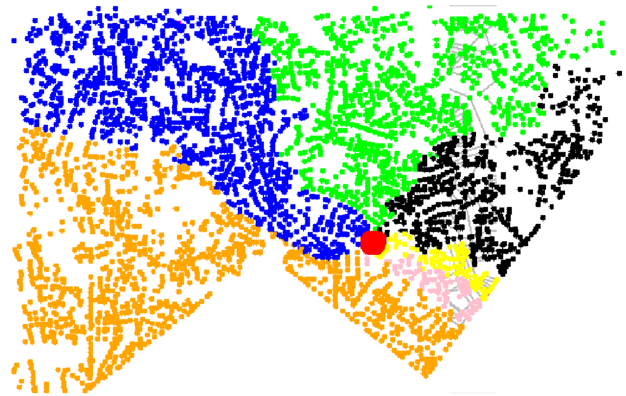

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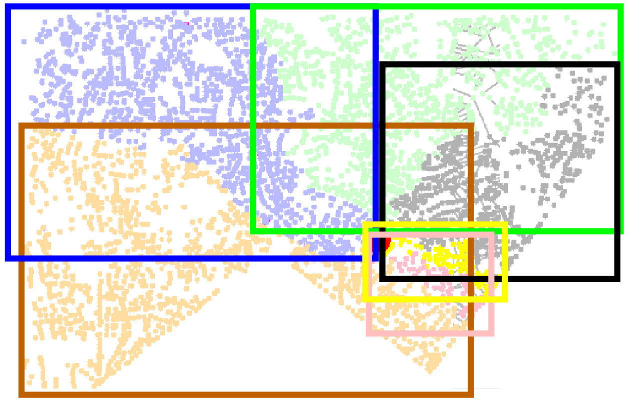

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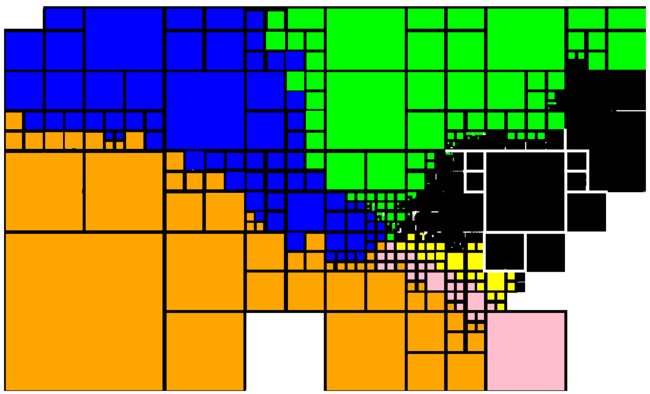

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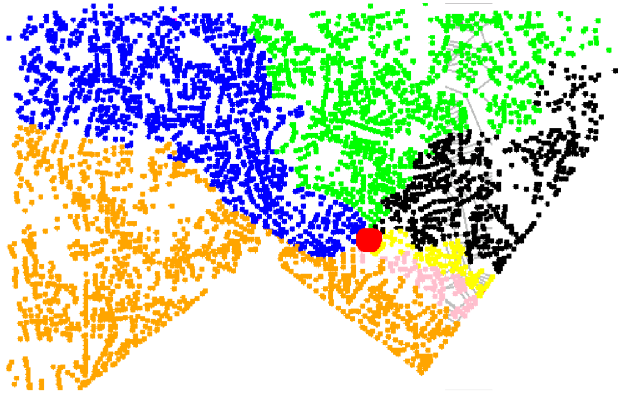

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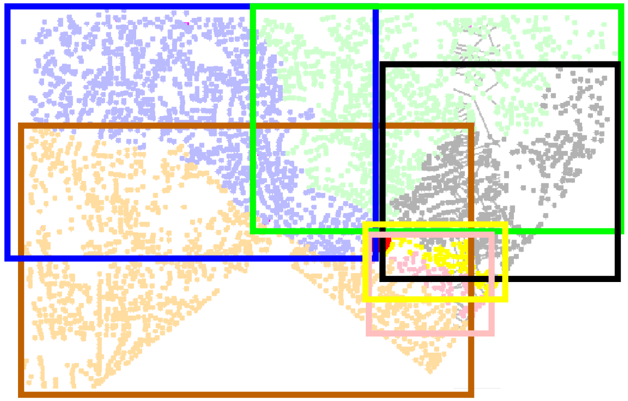

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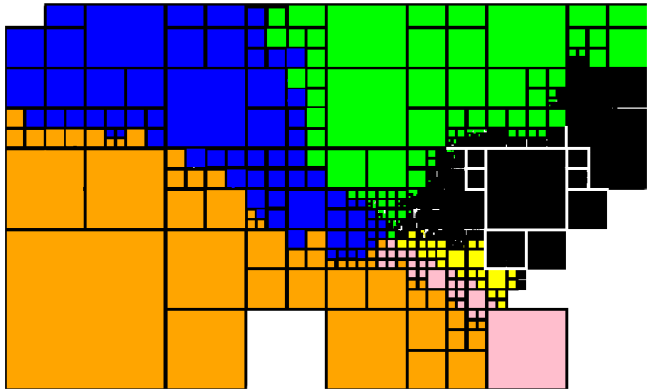

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- Proposed encoding leverages the dimensionality reduction property of MX and region quadtrees
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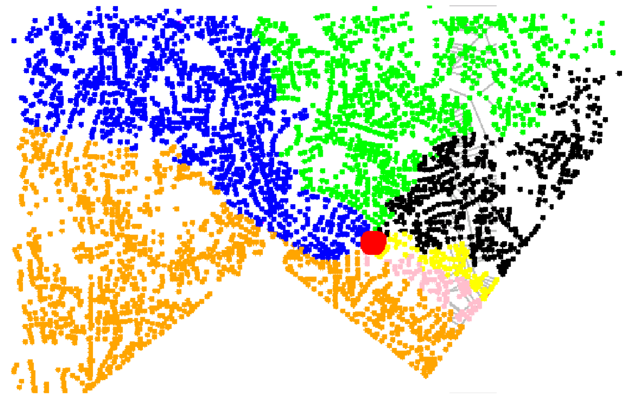

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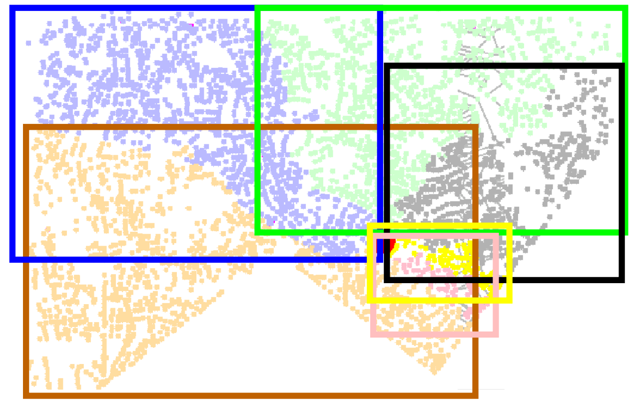

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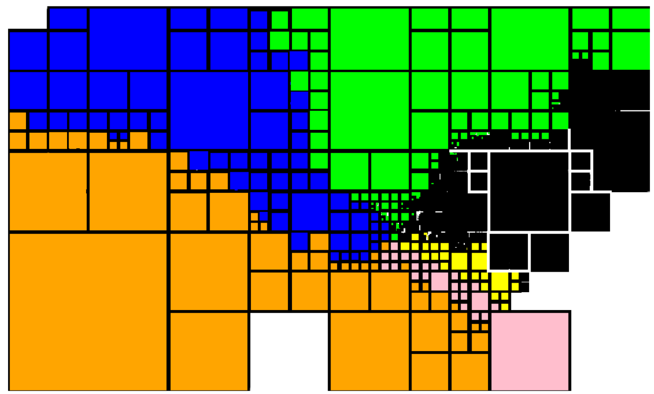
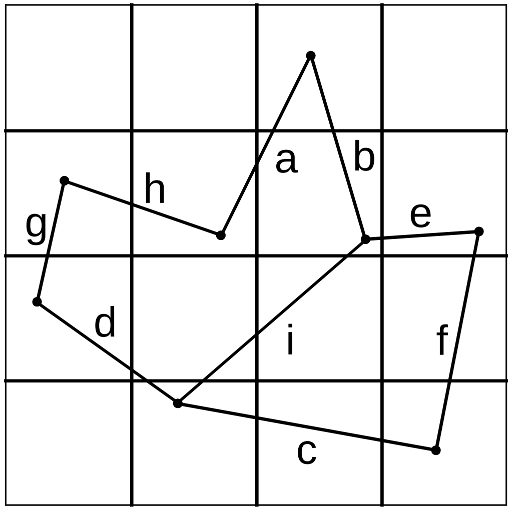


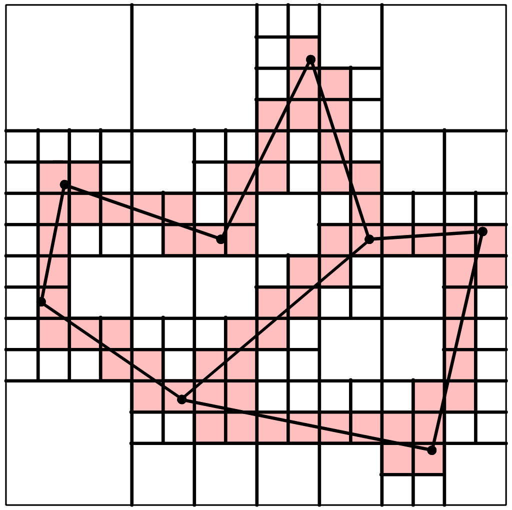
Shortest-Path Quadtree

Quadtree Complexity Theorem

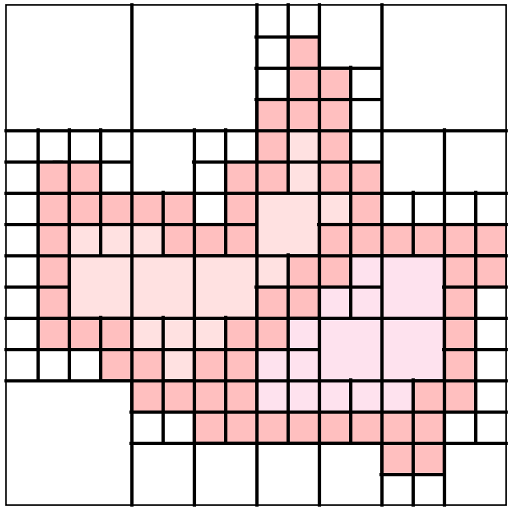
- Quadtree corresponding to a polygon of perimeter p embedded in a $2^q \times 2^q$ image has $O(p+q)$ nodes (Hunter)



Simple Polygons



MX−Quadtree



Region Quadtree

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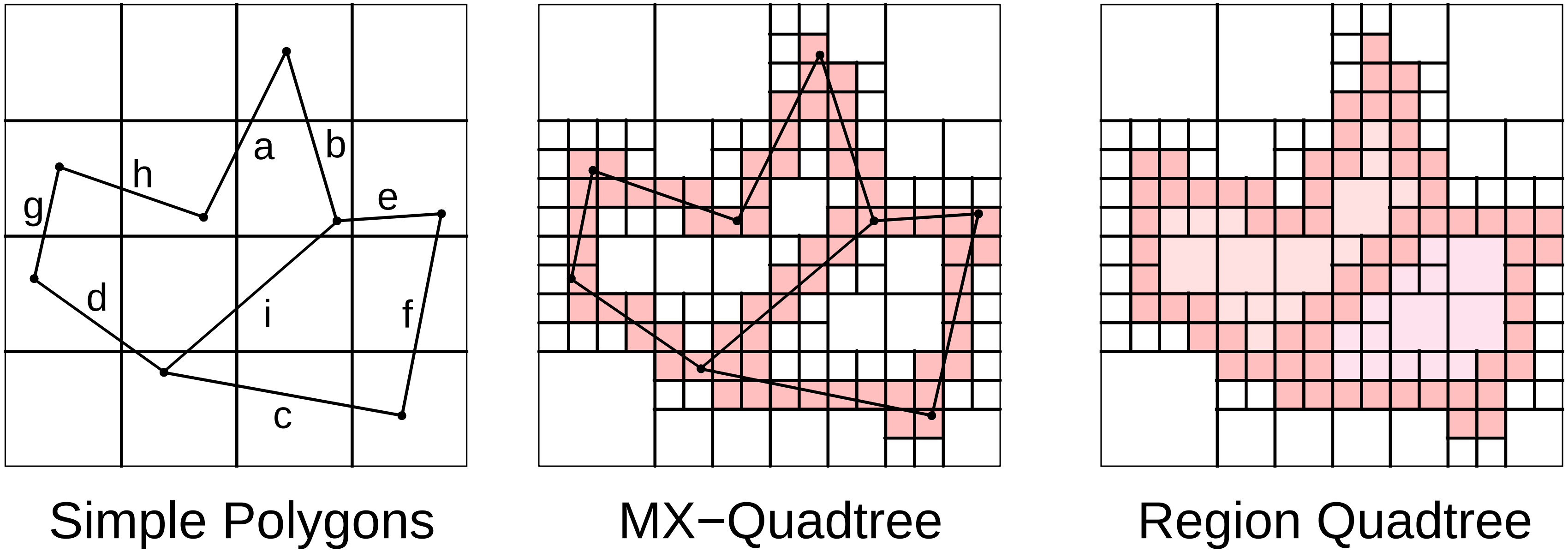

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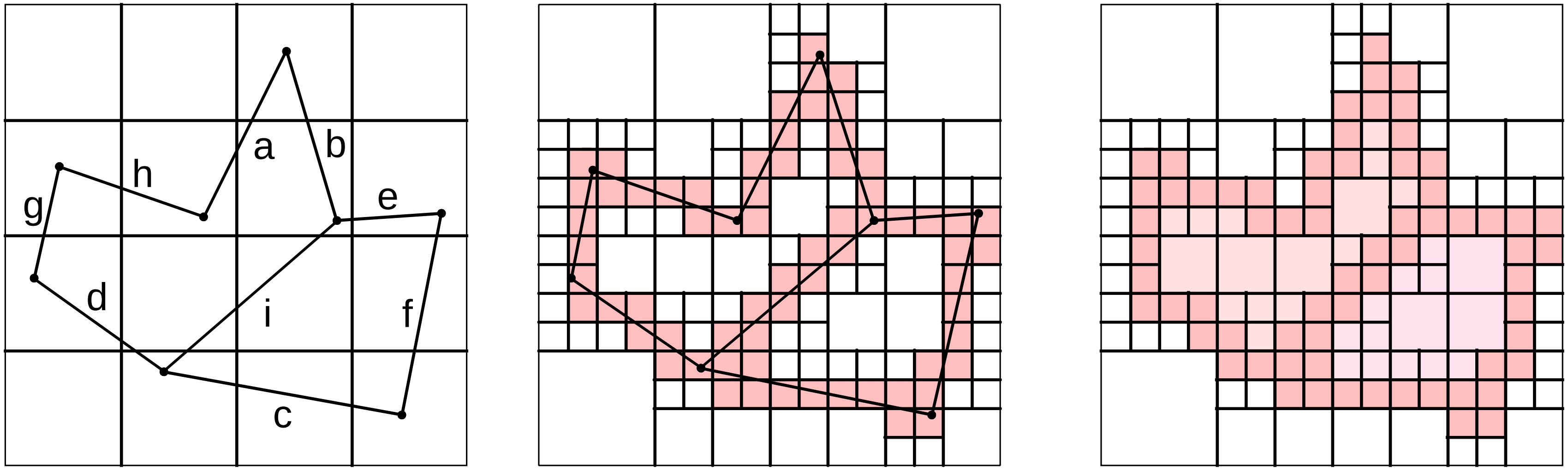

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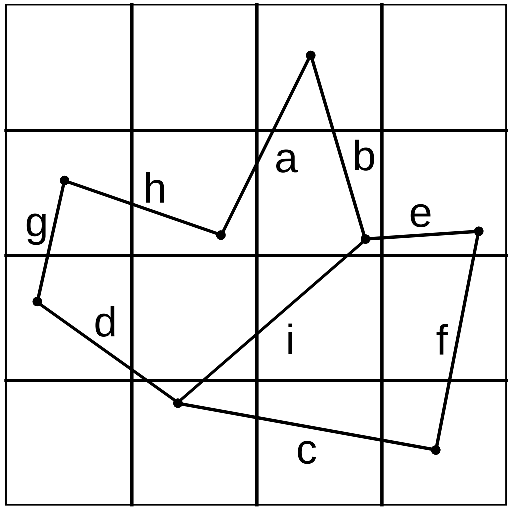

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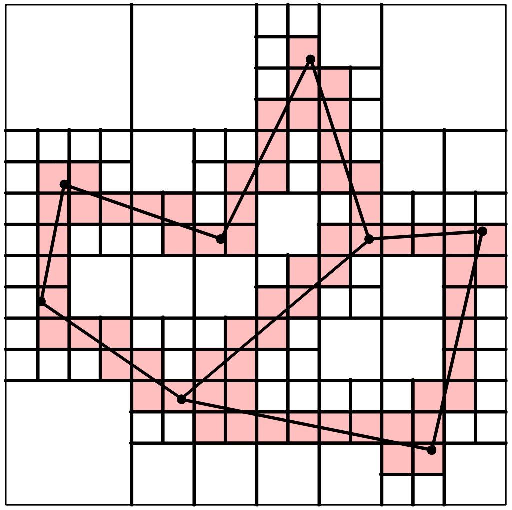

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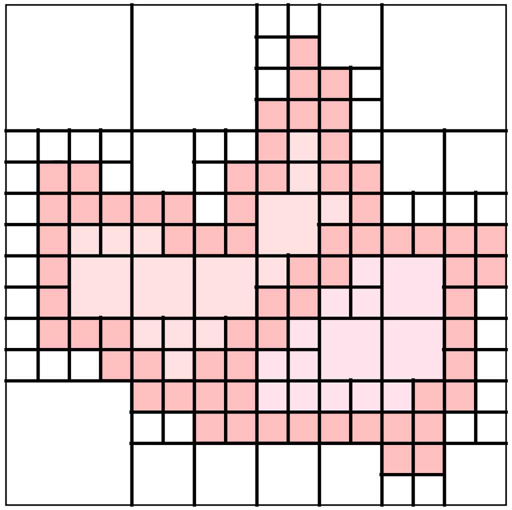

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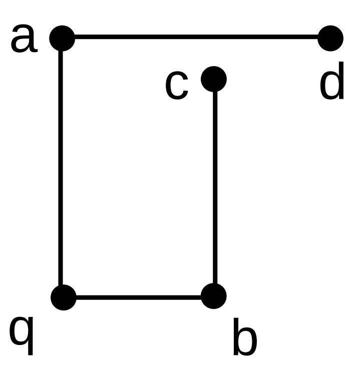

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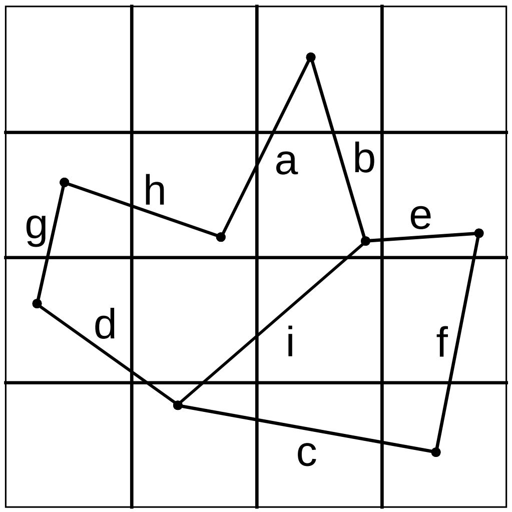

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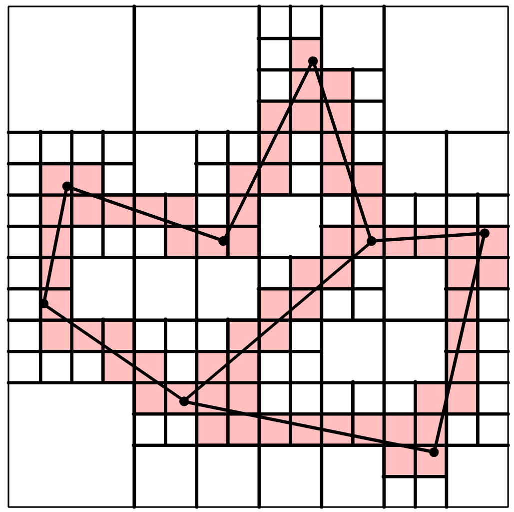

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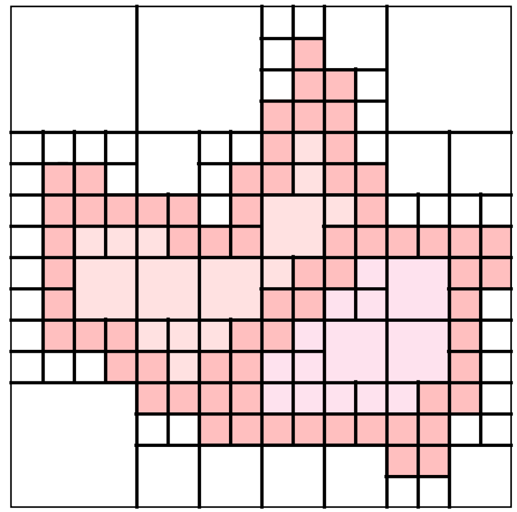

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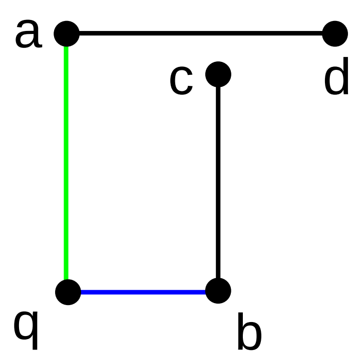

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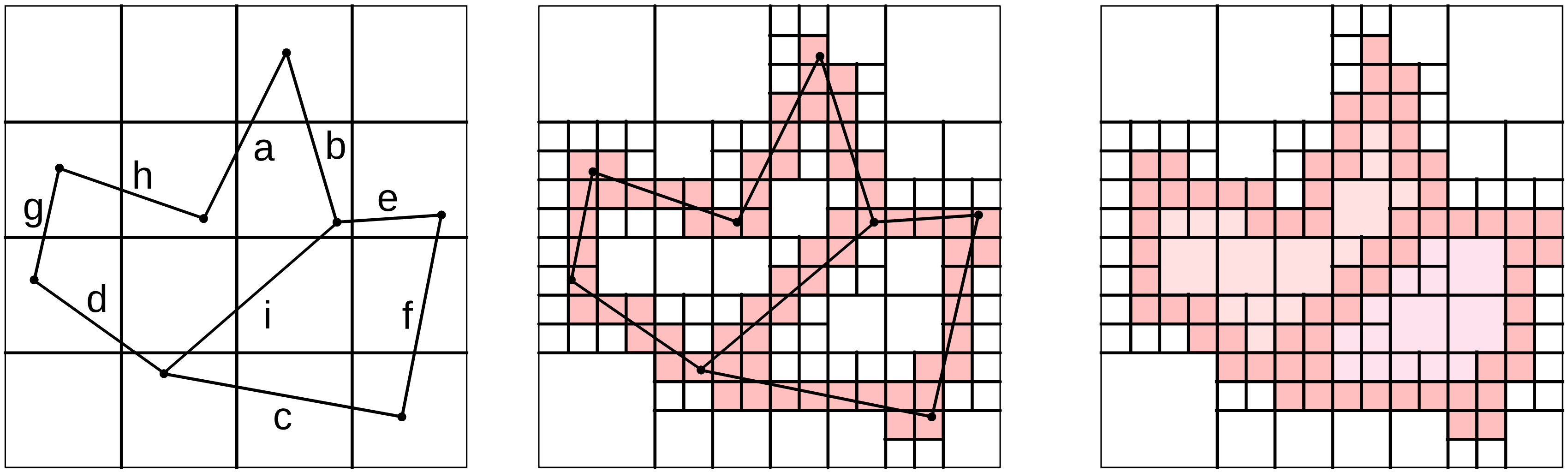

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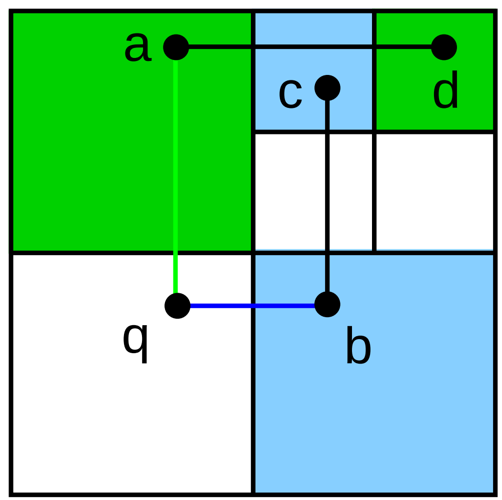

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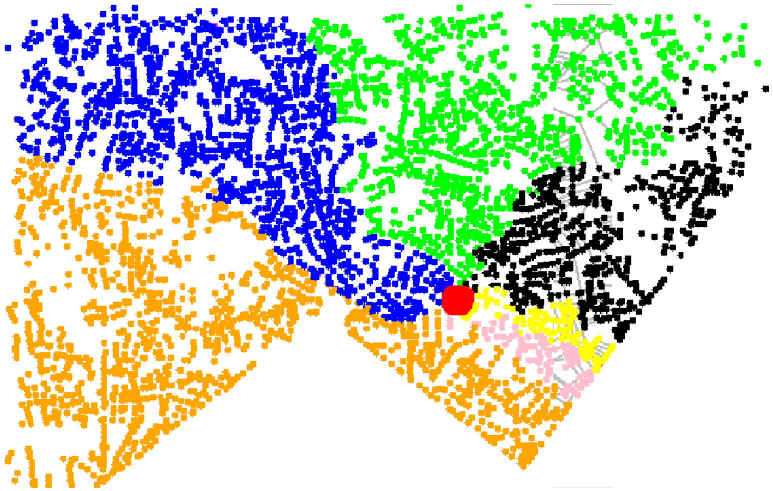

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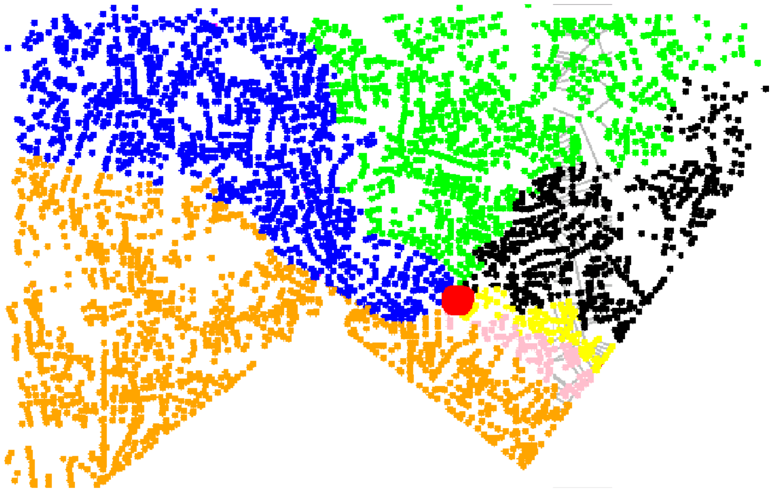

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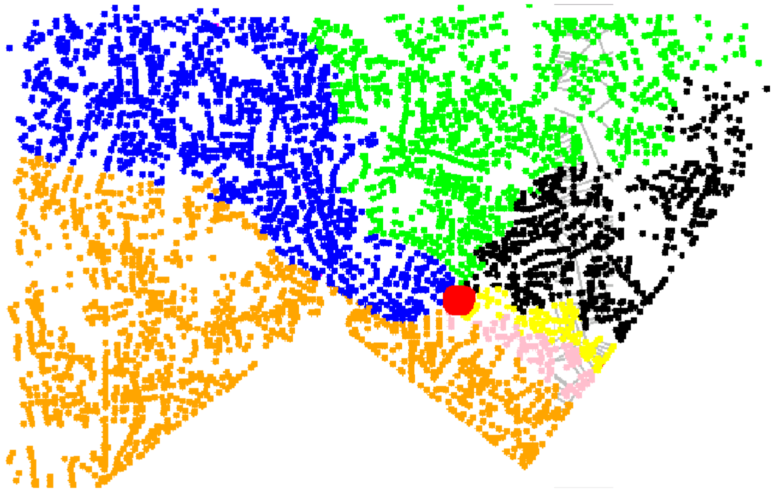

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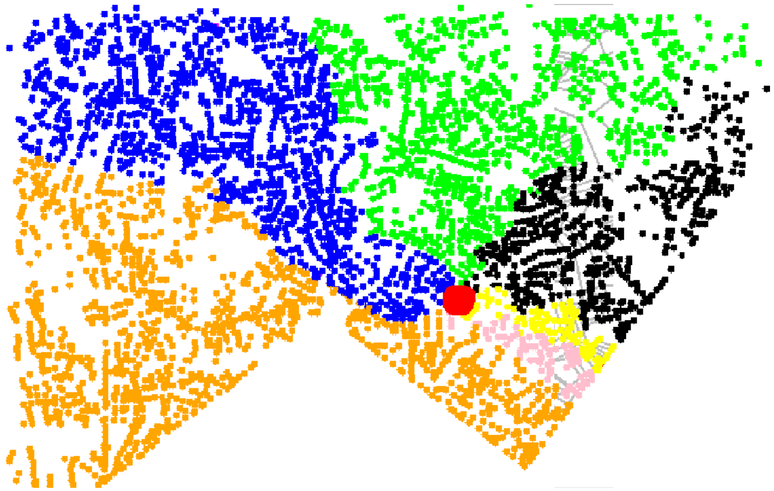

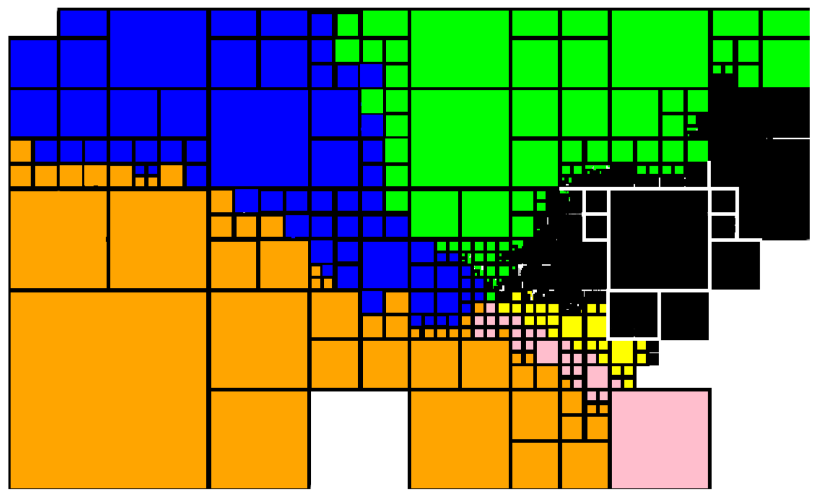

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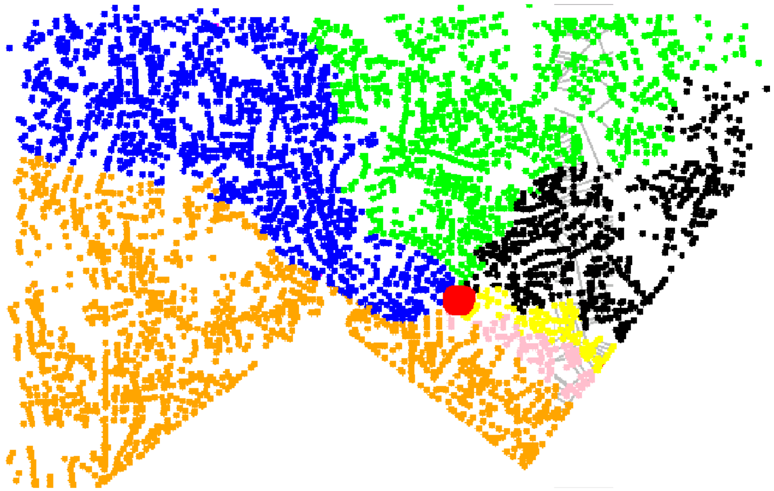
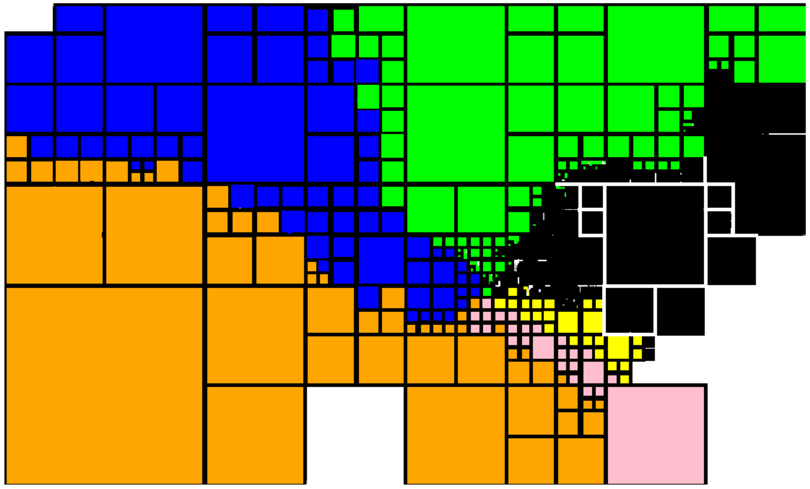
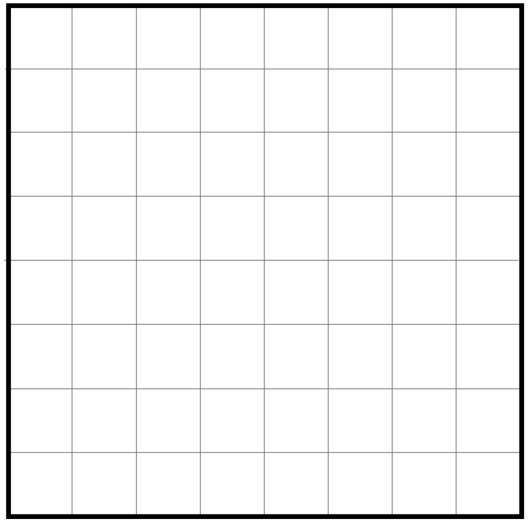
- Hence, shortest-path quadtrees are at worse O(perimeter) i.e., dimension reducing





Space Complexity Analysis of Shortest-Path Quadtrees

- Consider a spatial network containing N vertices



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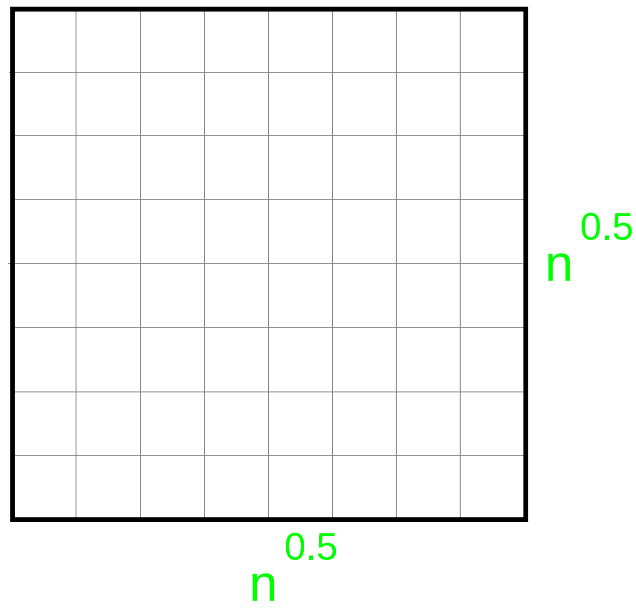

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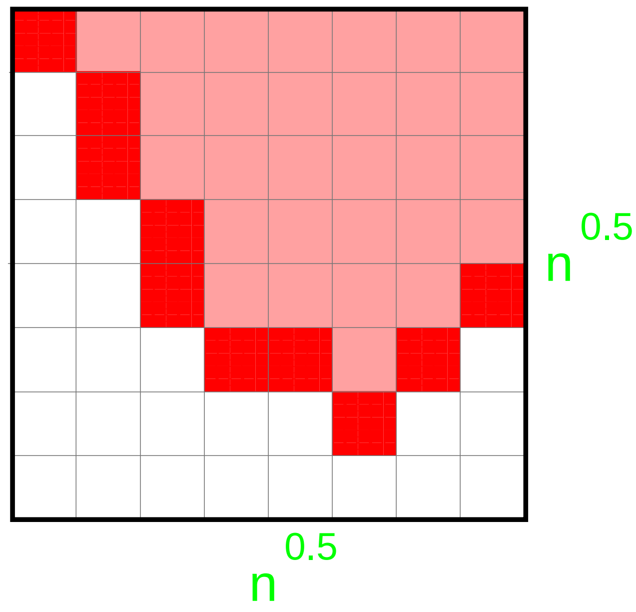

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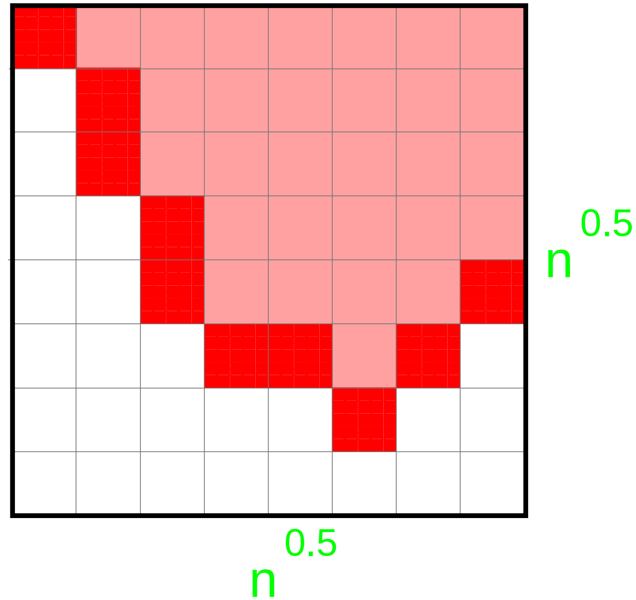

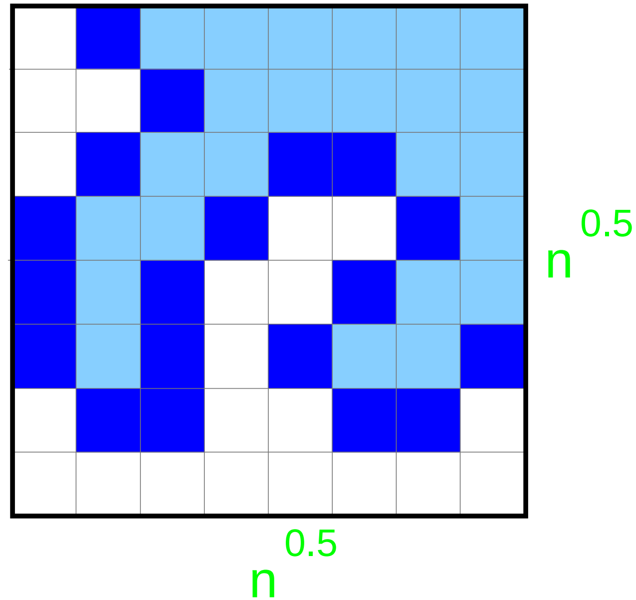

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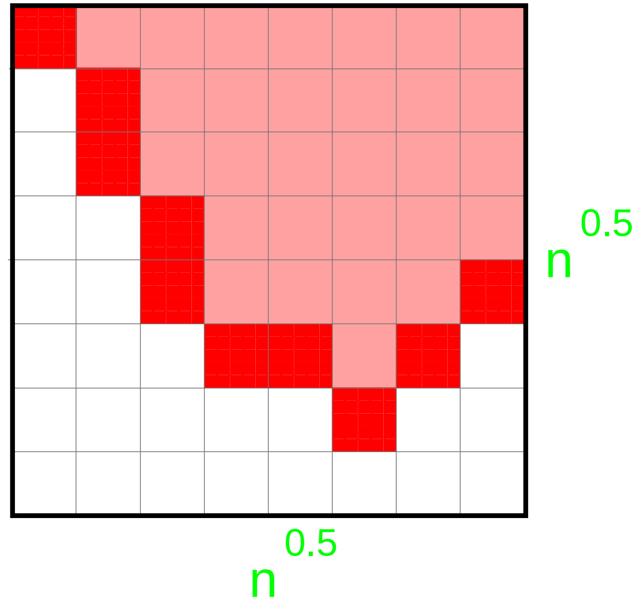

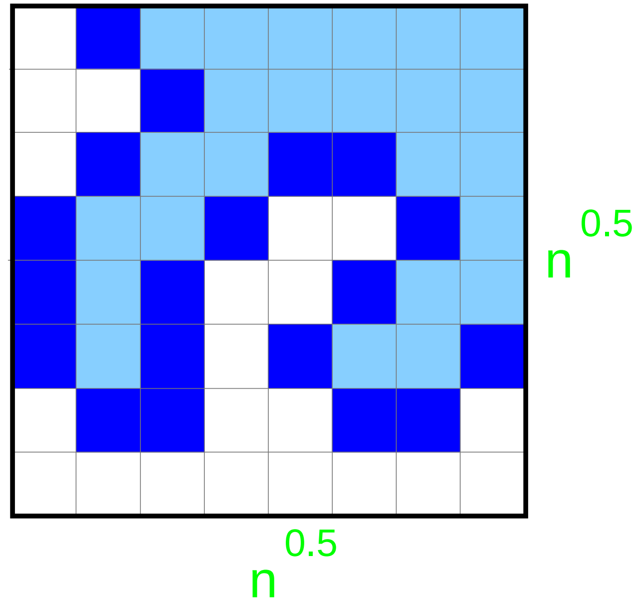

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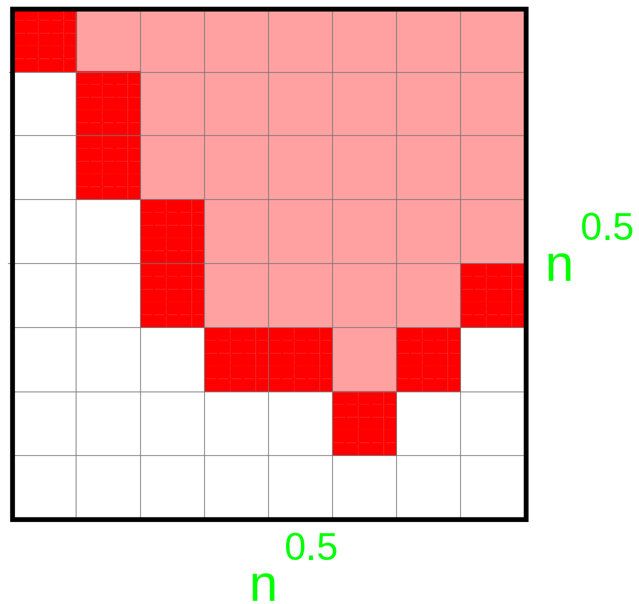

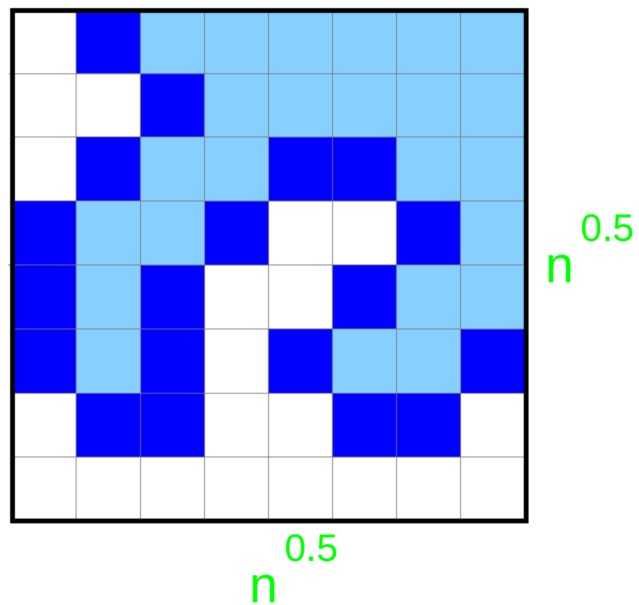

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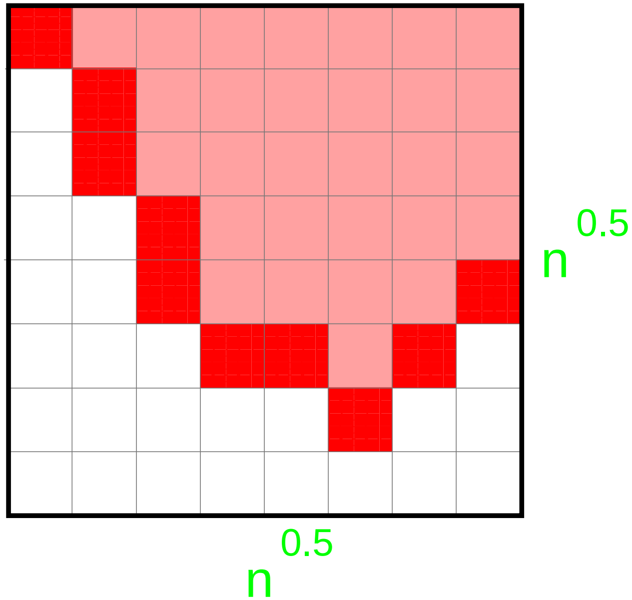

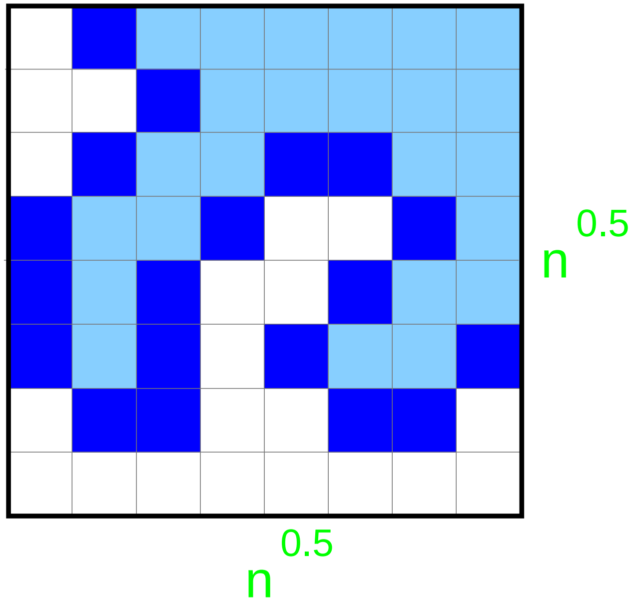

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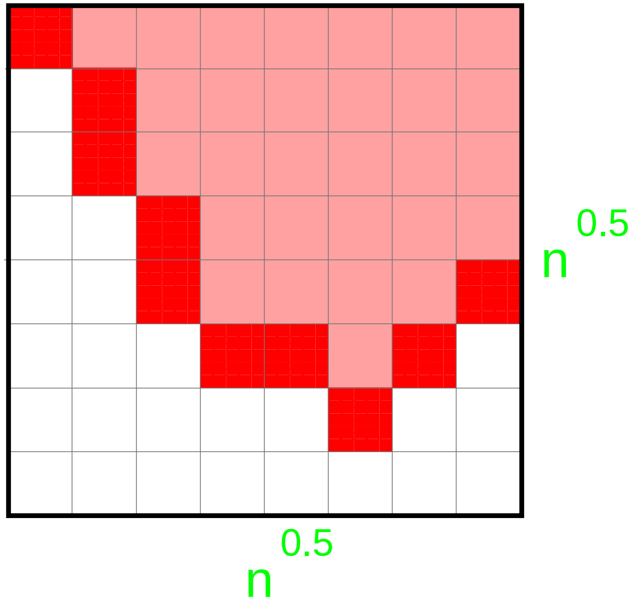
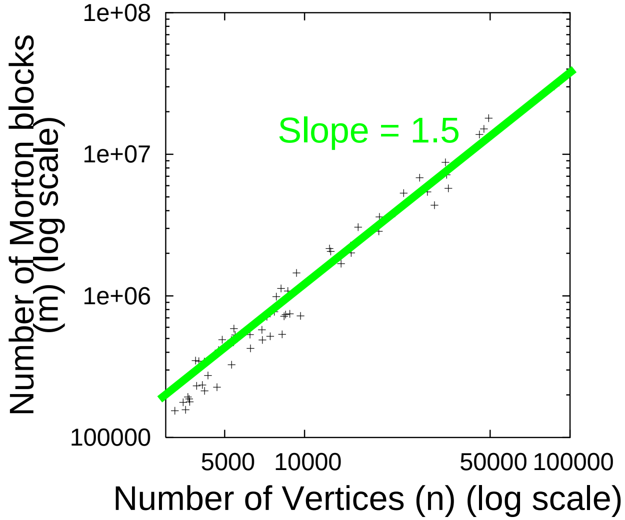
- Total storage complexity of the SILC framework is $O(N\sqrt{N})$; closely follows empirical results





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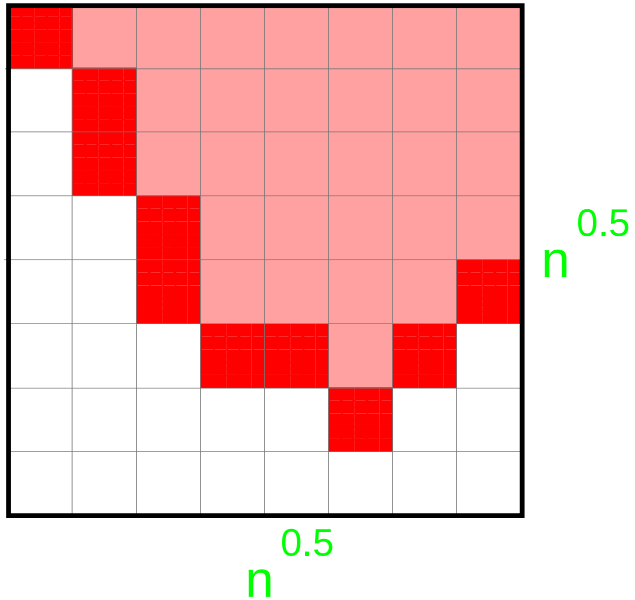
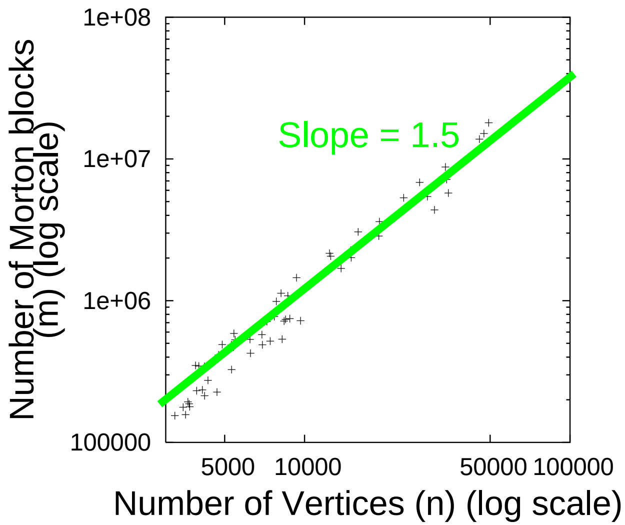
- Contribution: A mechanism to capture shortest paths in spatial networks based solely on geometry and independent of topology or connectivity





Path Retrieval

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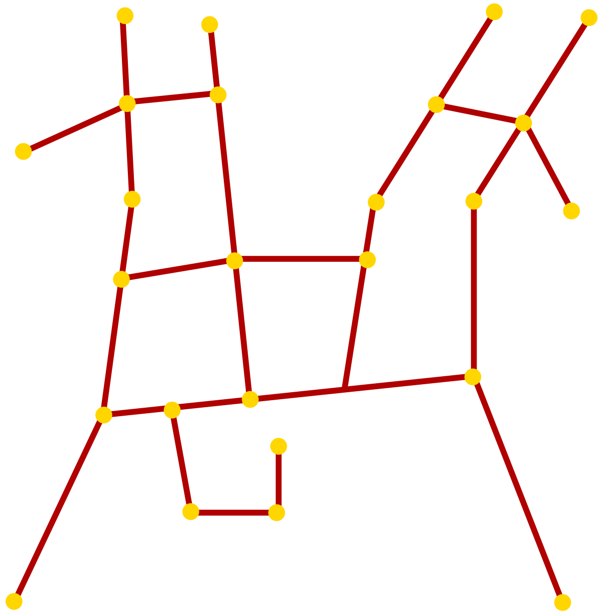
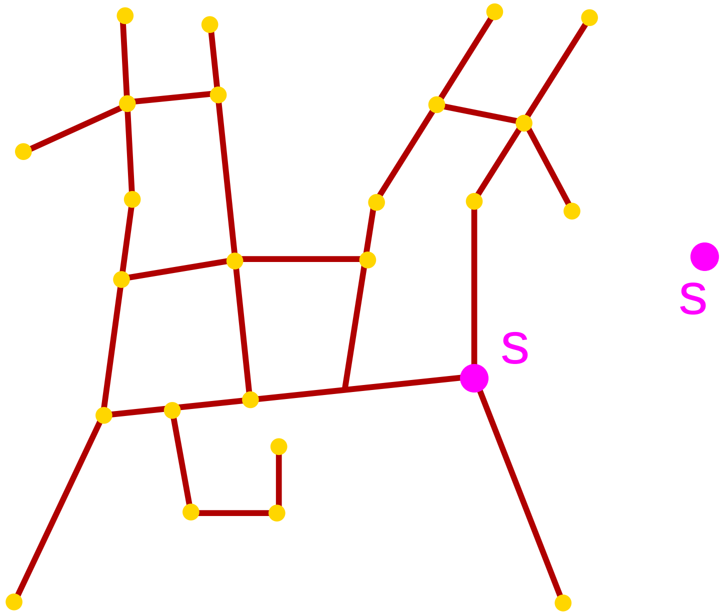


Path Retrieval

- Problem: How to retrieve the shortest path from a source s



Path Retrieval

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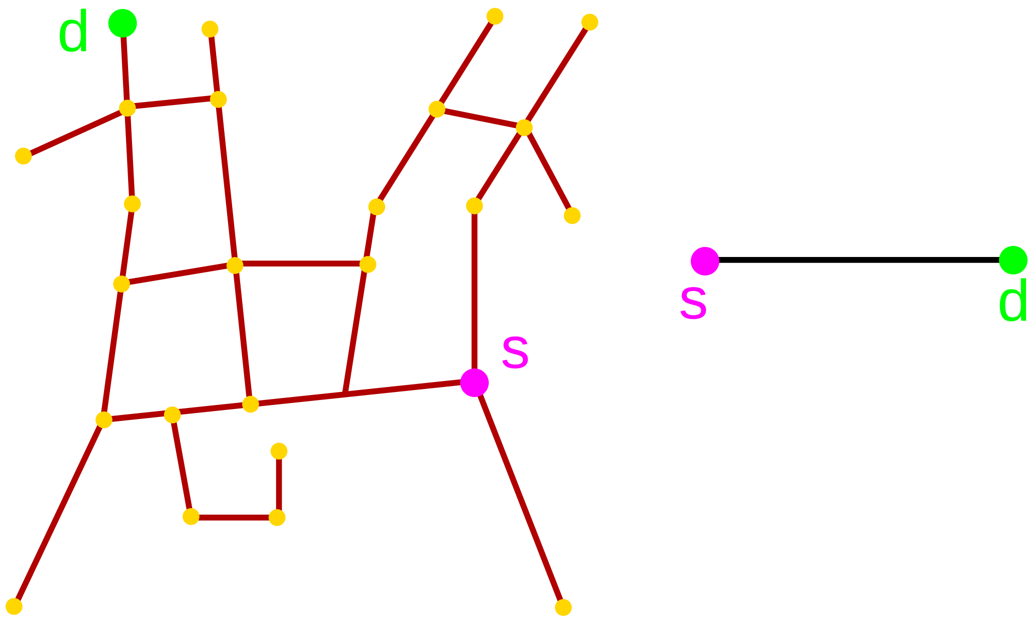

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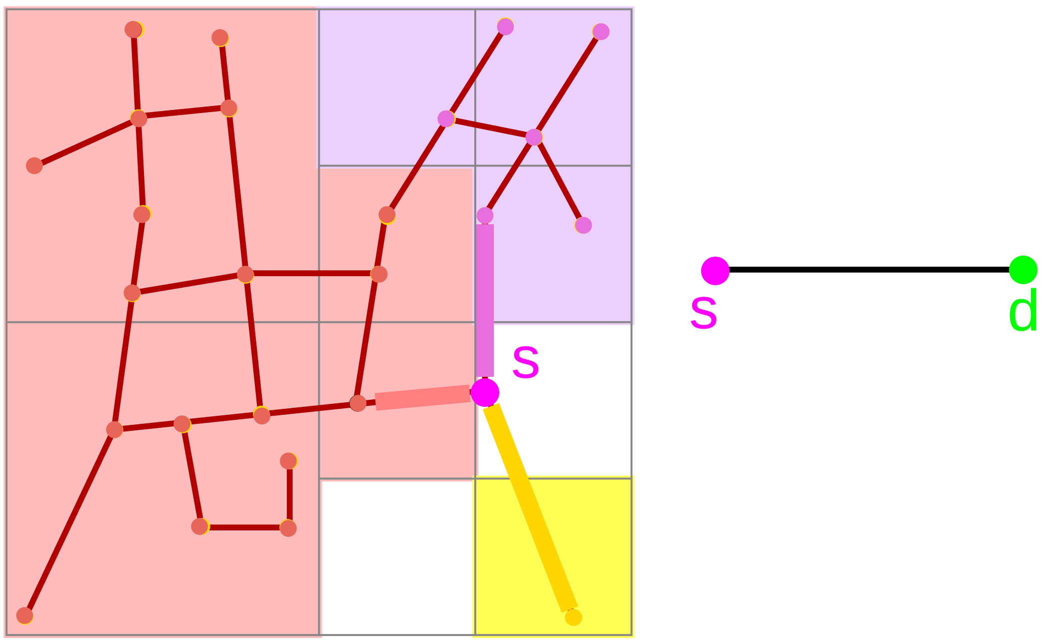

- Retrieve the shortest-path quadtree Q_s corresponding to s

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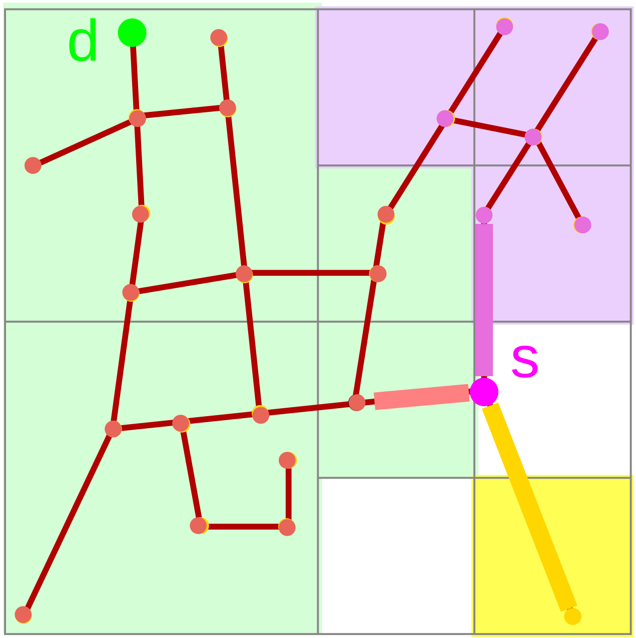

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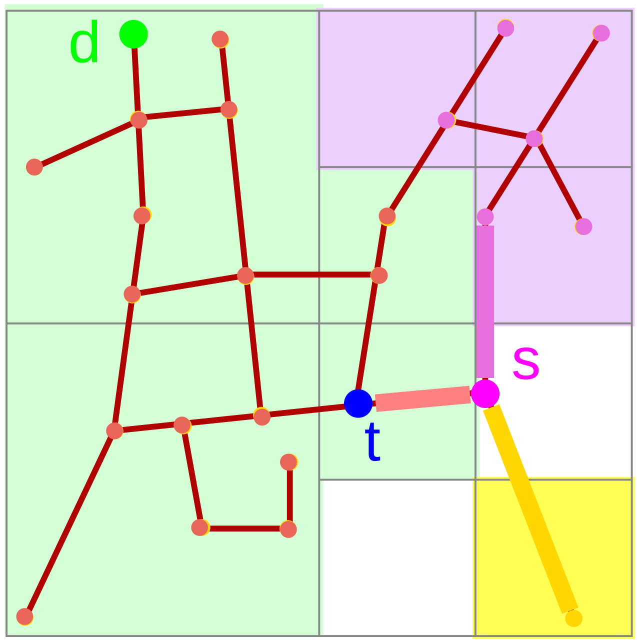

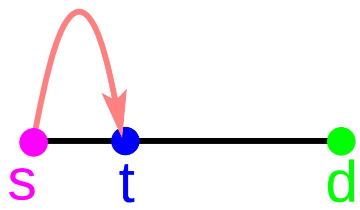

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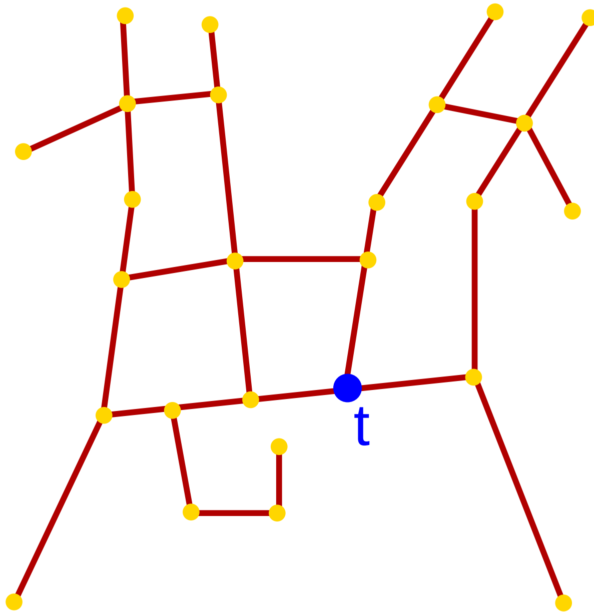

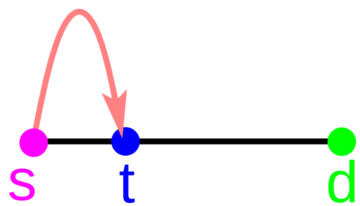

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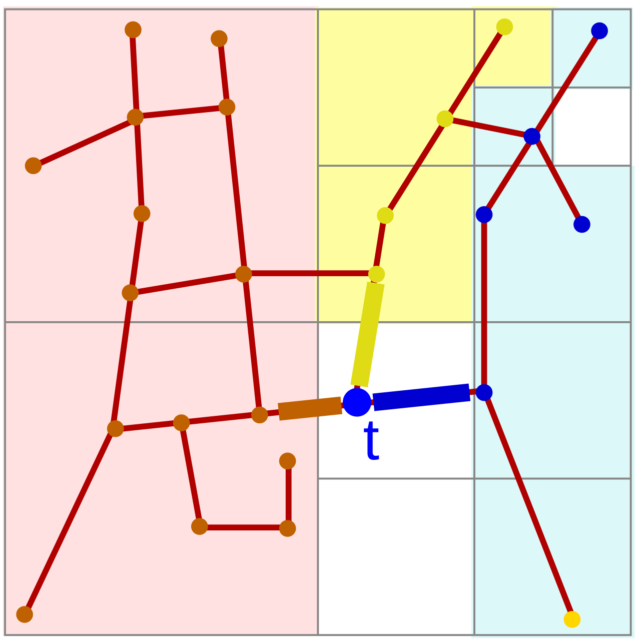

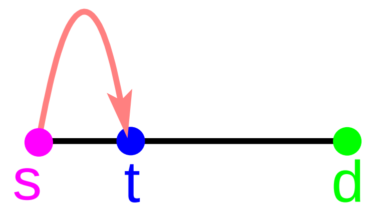

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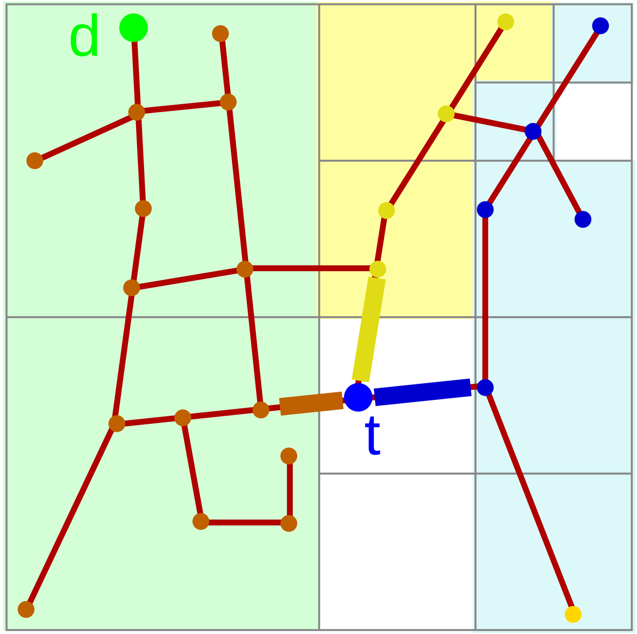

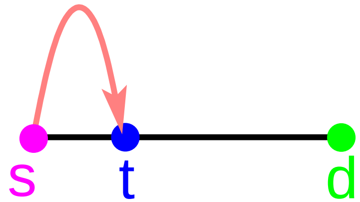

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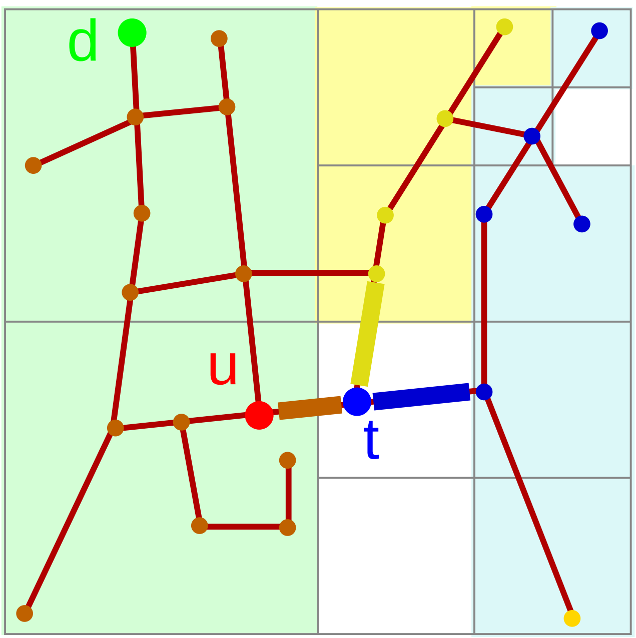

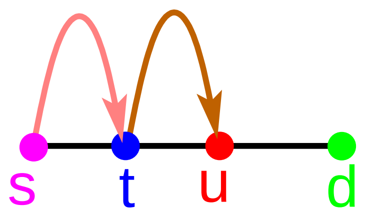

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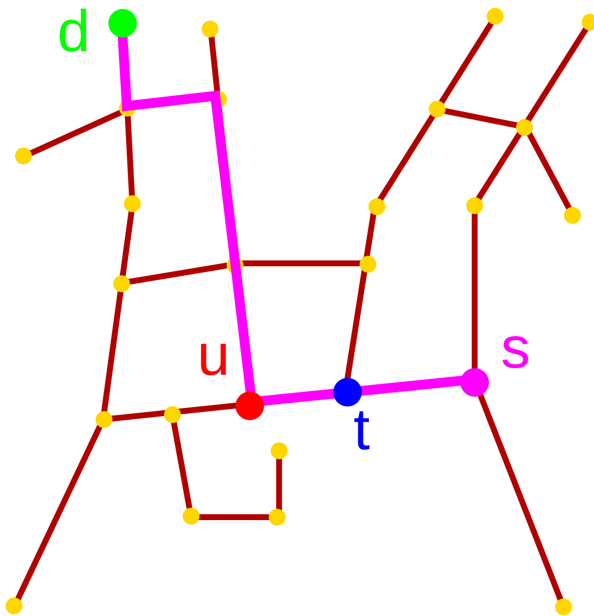

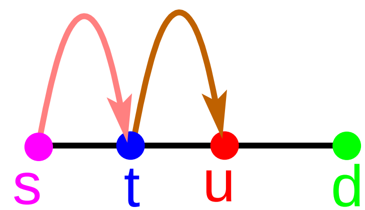

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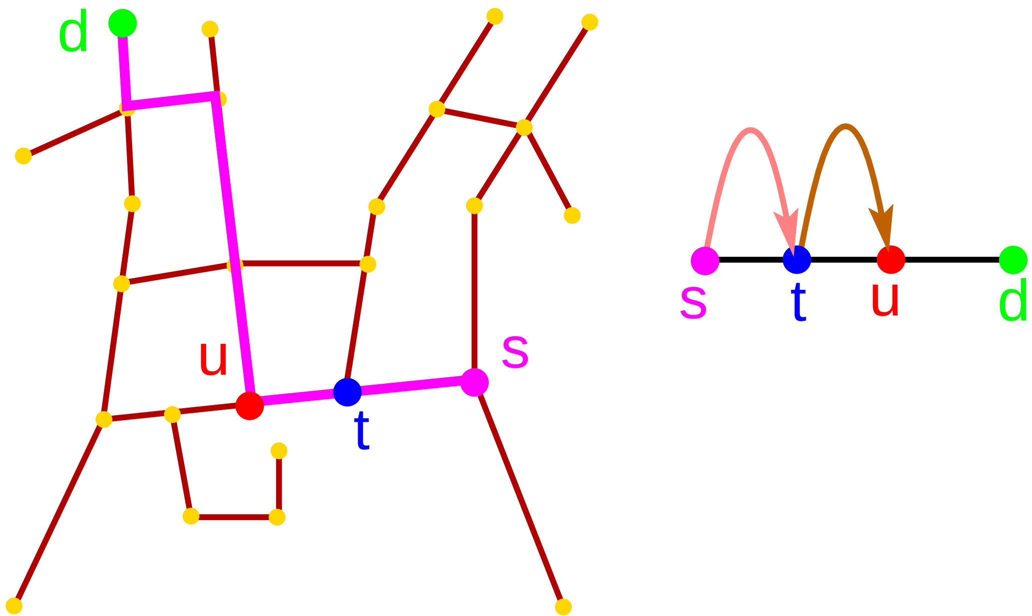

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Progressive Refinement of Distances

- Avoid full shortest path retrievals using progressive refinement
- Idea: Use distance intervals instead of the exact distance
- Progressive refinement: *Improve* interval if query cannot be answered
  - Associate Min/Max distance information with each Morton block
  - Refinement involves finding the next link in the shortest path
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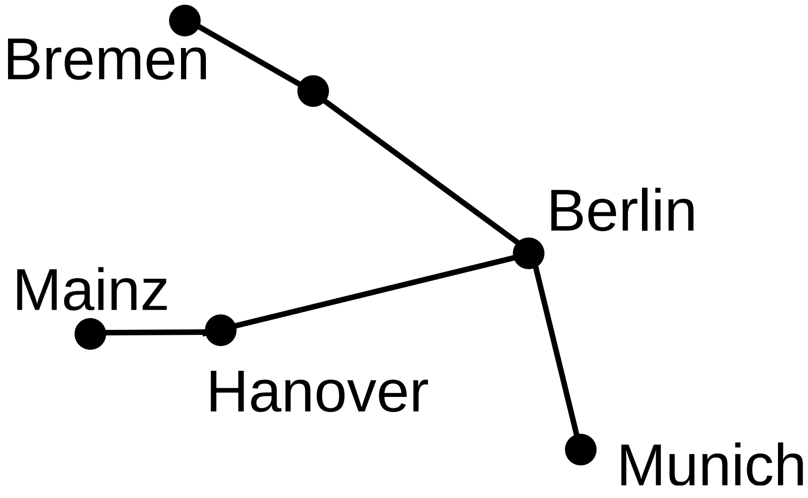

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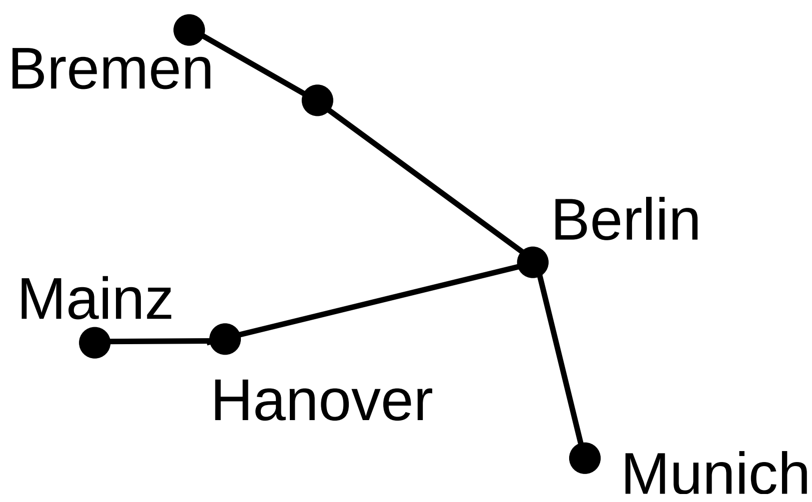

	Munich	Bremen
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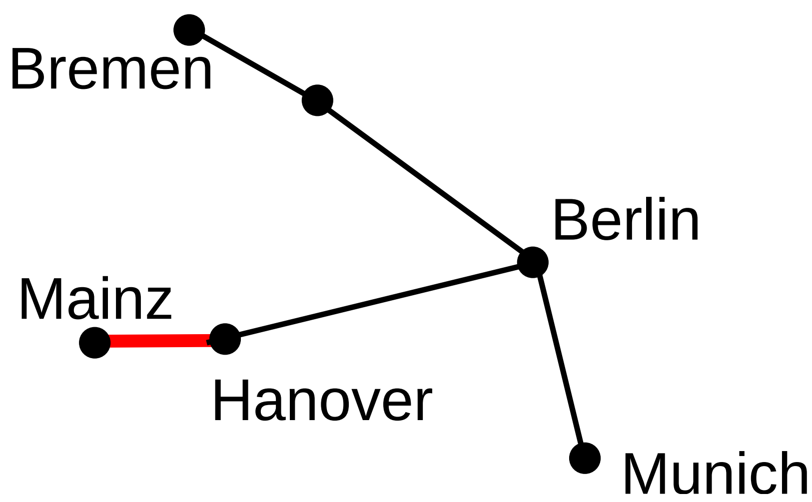

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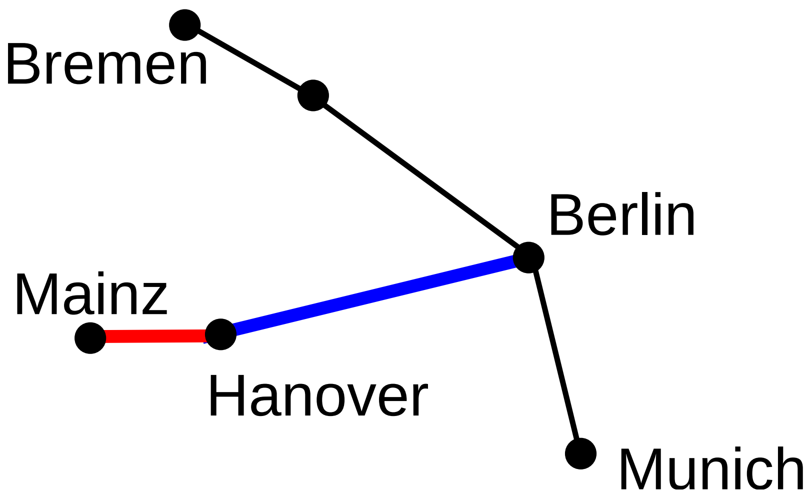

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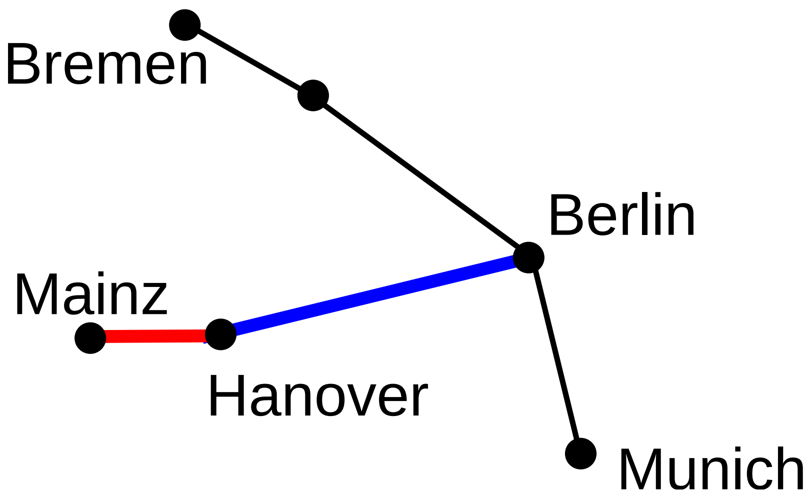

	Munich	Bremen
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- Munich is closer as distance interval via Berlin does not intersect distance interval to Bremen via Berlin

Outline

1. Overview
2. Spatial Networks
3. Precomputation and storage of shortest paths
4. k Nearest Neighbor Finding Algorithm
5. Experimental evaluation
6. Contributions
7. Future Work

Foundations of k Nearest Neighbor Finding (kNN)

- A non-incremental best-first algorithm
  - Set of objects (with spatial information)
  - A spatial data structure (e.g., a quadtree or R-tree) on objects
  - Shortest-path quadtrees for the spatial network
  - Note decoupling of data (objects) from domain (spatial network)
  - Cost Justification for Precomputing: Provision to reuse computations across queries and across datasets
- Primitive operations using Progressive Refinement

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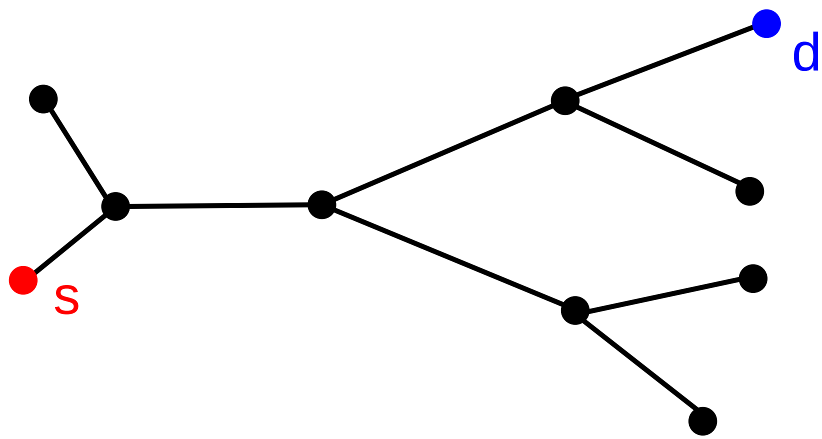

  - DISTANCE_INTERVAL(object,object)

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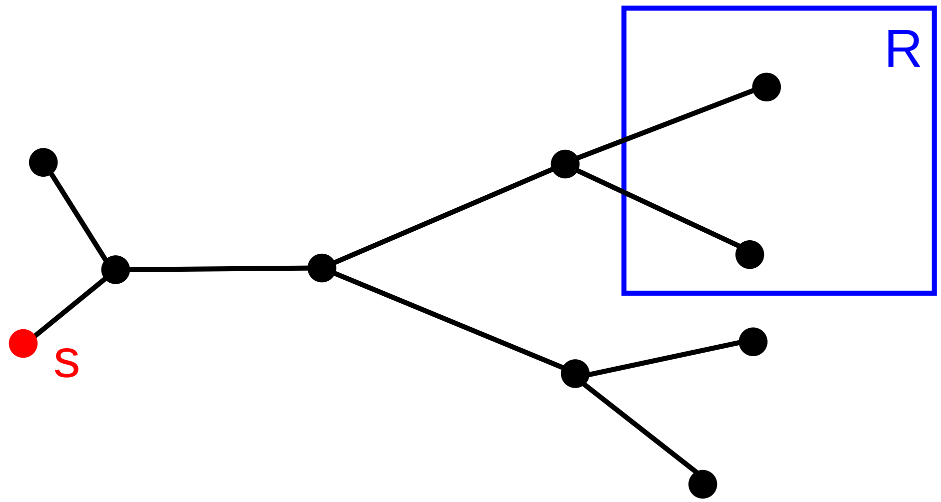

  - DISTANCE_INTERVAL(object,object)
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Type of Input Objects

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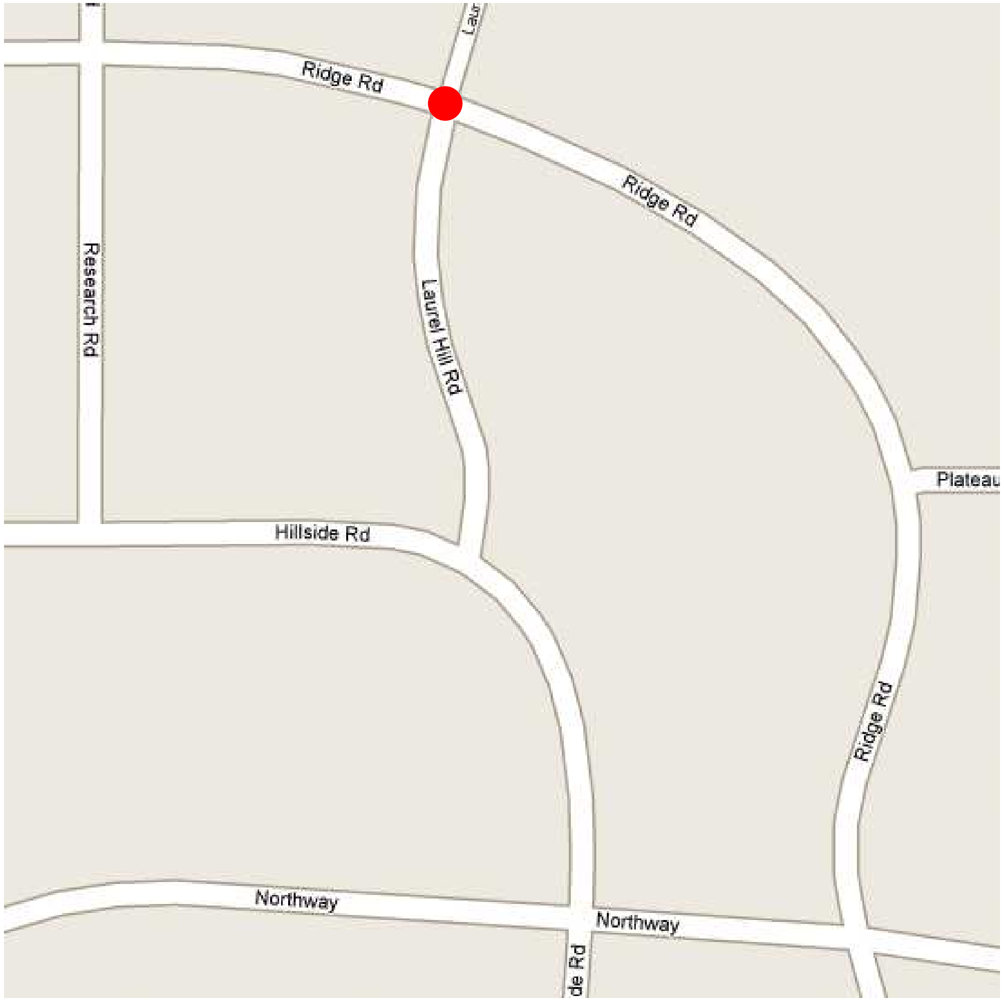

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- Types of objects on spatial networks
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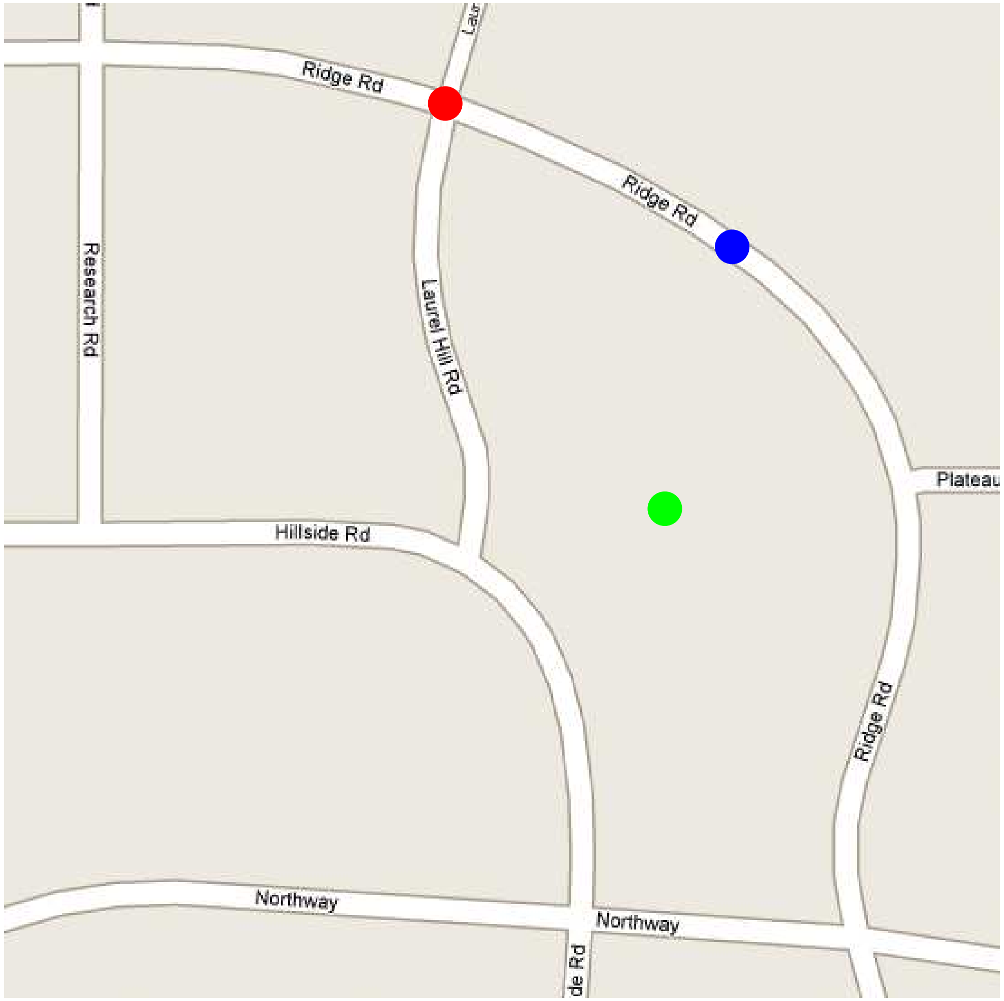

Type of Input Objects

- Types of objects on spatial networks
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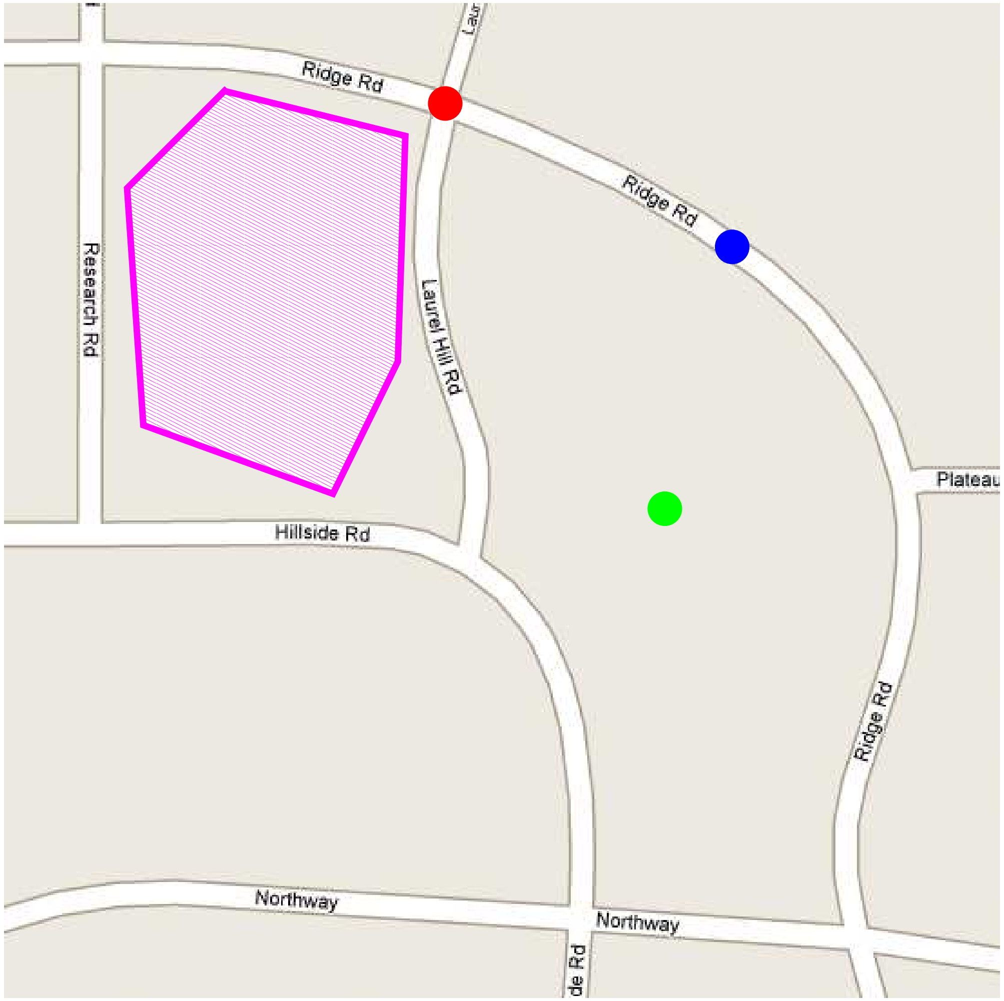
  - Object with extents



Type of Input Objects

- Types of objects on spatial networks
  - Vertex object
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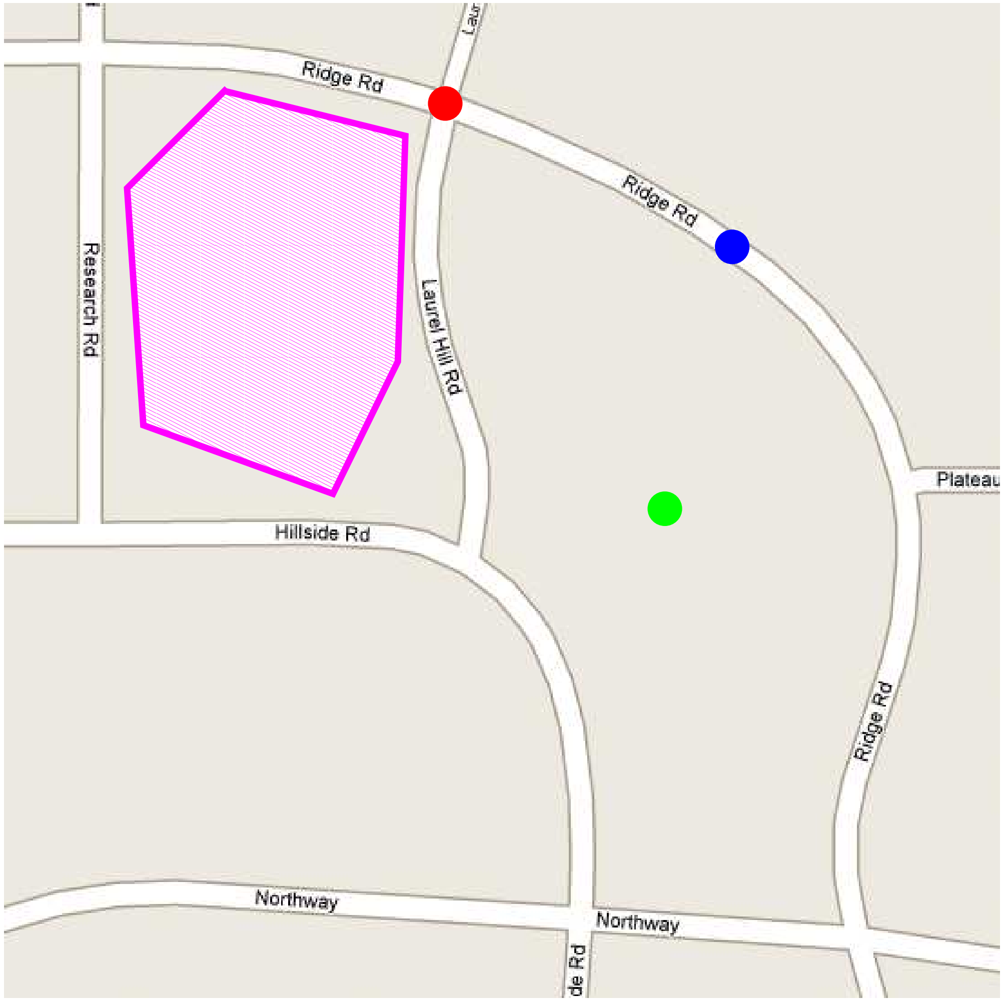
  - Face object
  - Object with extents
  - Any combination of the above



Properties of kNN Algorithm

- Neighbors produced in increasing order of distance from q
- Use a priority queue Q of objects and blocks
- Q contains network distance interval $[\delta^-, \delta^+]$ of objects from q
- Additional information stored with each object o in Q
  1. An intermediate vertex u in shortest path from q to u
  2. network distance d from q to u
- Uses another priority queue L in addition to Q
  - Stores k objects found so far in increasing order of δ^+
  - D_k is the maximum of the distance interval of the $k\mathrm{th}$ element in L
  - Idea: Prune elements e from Q such that $\delta_e^- \geq D_k$
- Elements are removed from Q in increasing order of the minimum of their distance interval δ^- from q
  - Objects may be reinserted in Q if $\delta^- < D_k$
  - Terminate when $\delta^- \geq D_k$
- Advantages over Incremental best-first kNN (INN)
  - Smaller size of Q
  - Faster than INN

kNN Algorithm

1. Initialize priority queue Q by inserting the root T
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   - Collision:
     - Remove p from L if $\delta^+ \leq D_k$
     - Apply refinement to improve distance interval of p and reinsert p in L if $\delta^+ \leq D_k$ and in Q if $\delta^- < D_k$ and go to Step 2
   - No collision:

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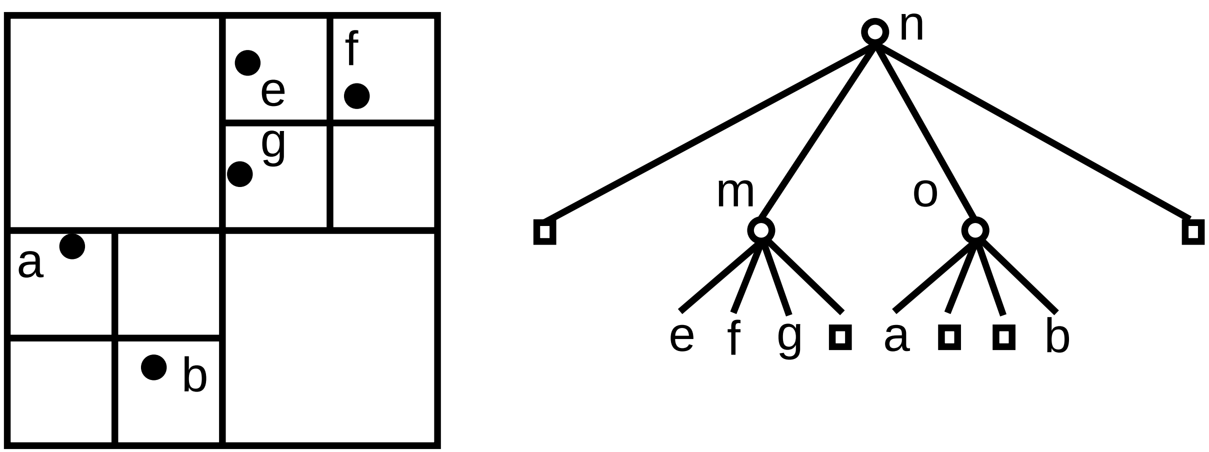
   - No collision: p is already one of k nearest neighbors in L (Theorem 1) and go to Step 2

Example of an Non-incremental k Neighbor Search

k = 2



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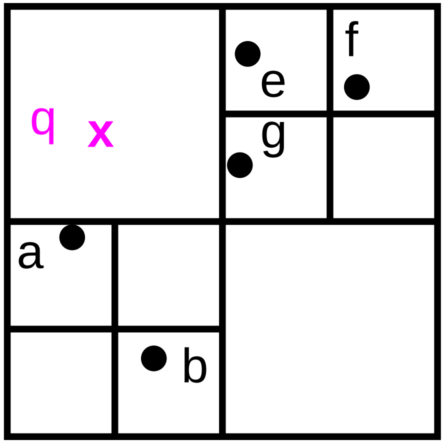

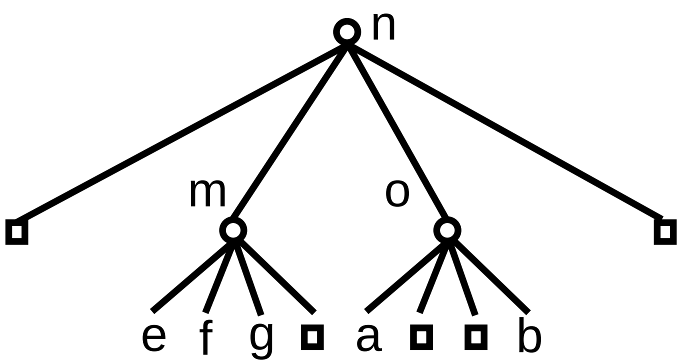

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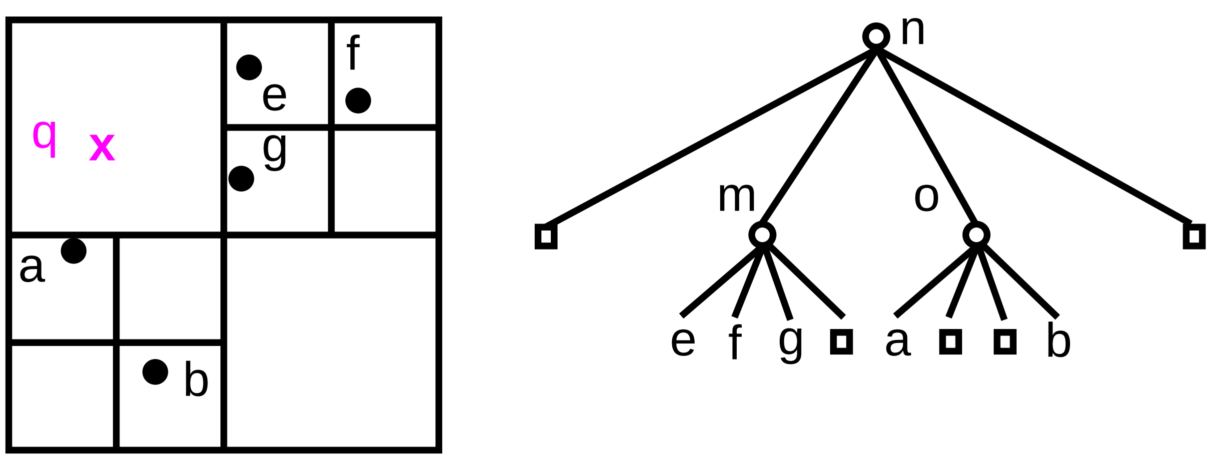

front

L Queue

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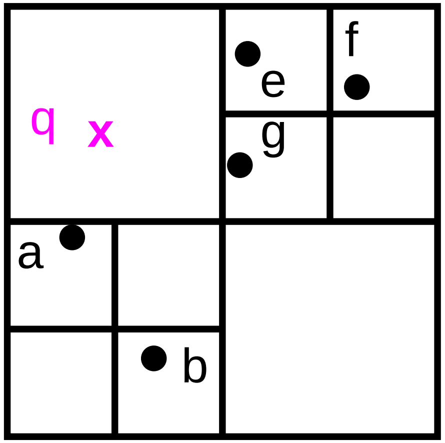
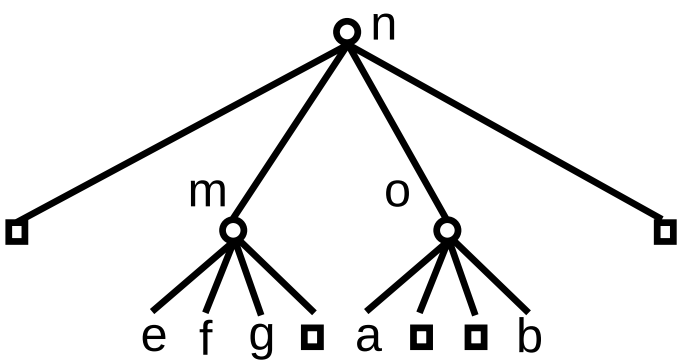
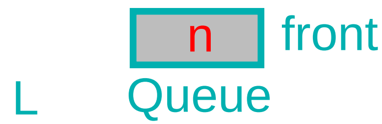




1. Insert n into Queue.



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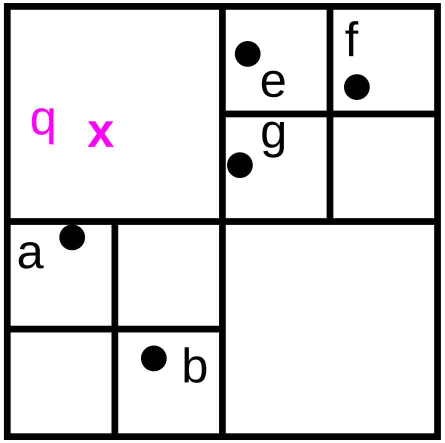

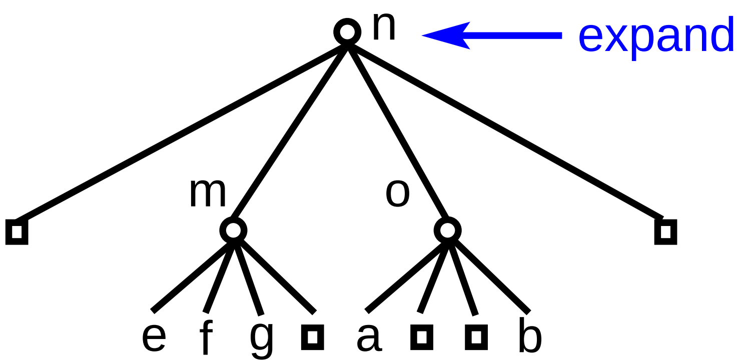

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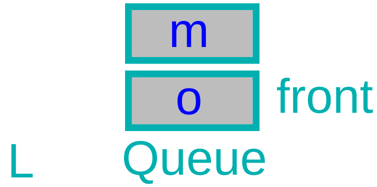

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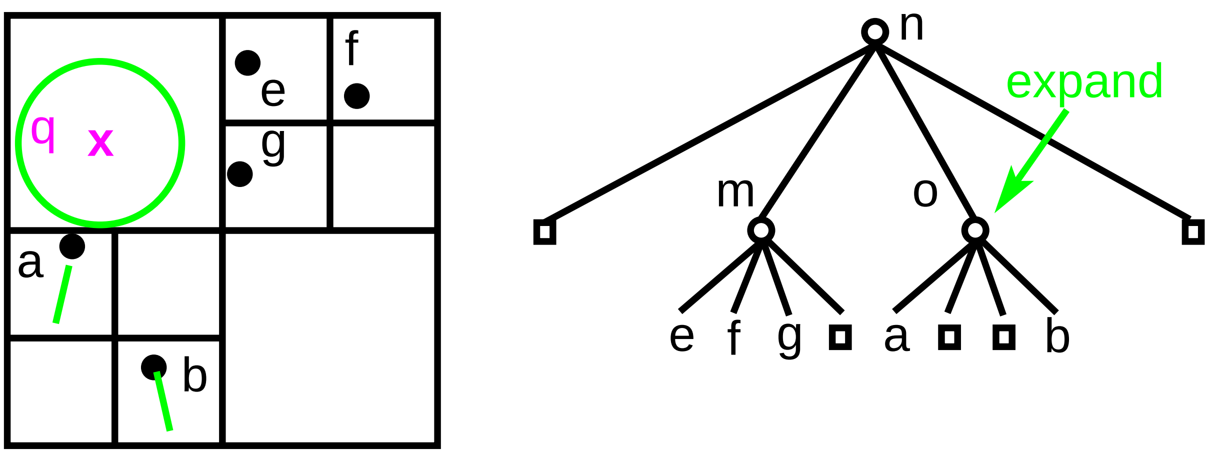

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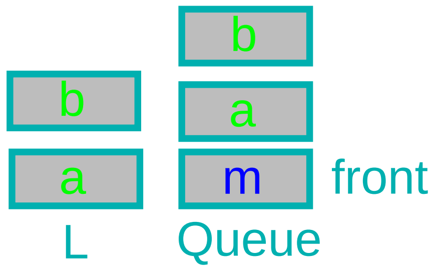

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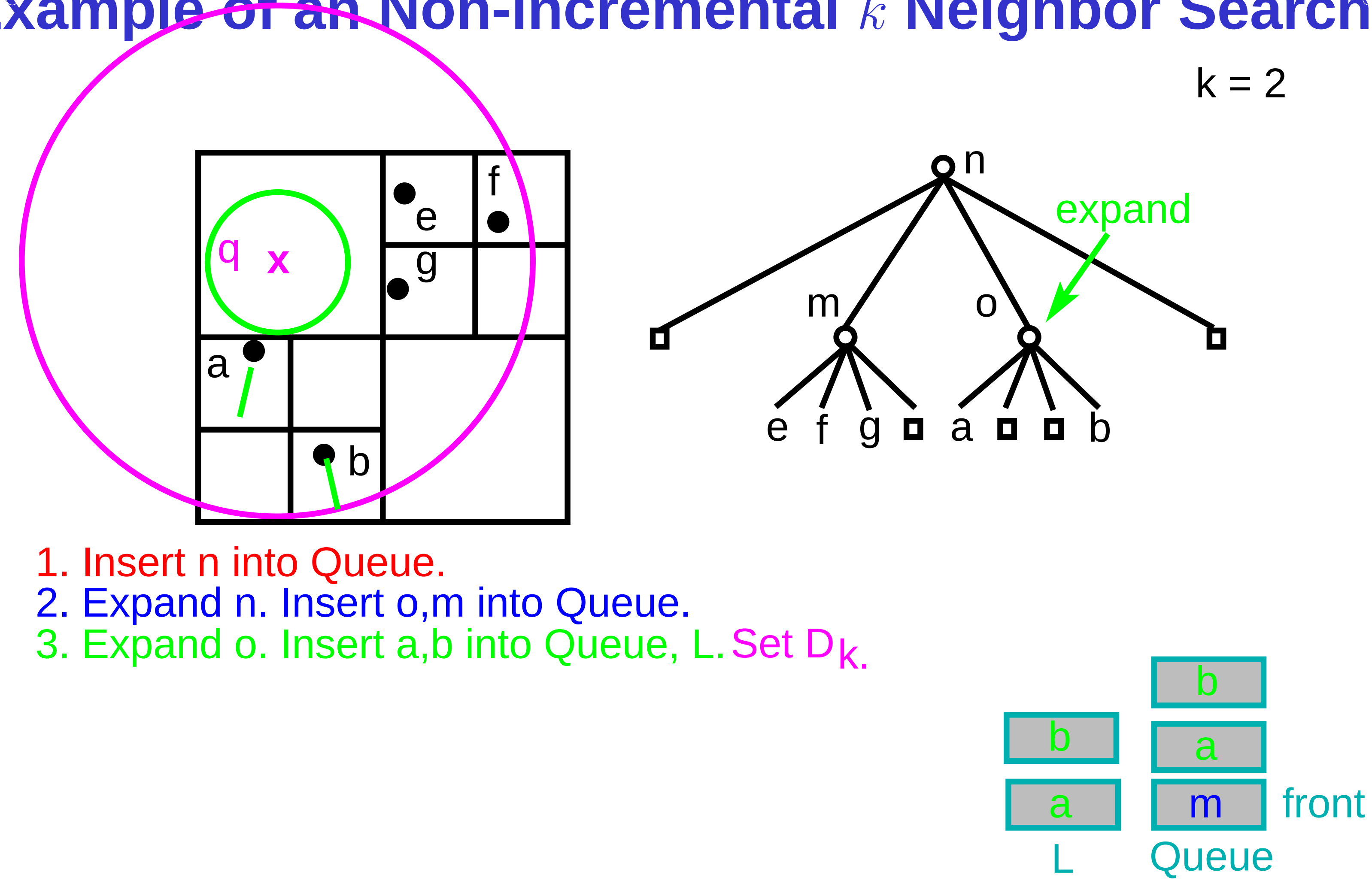

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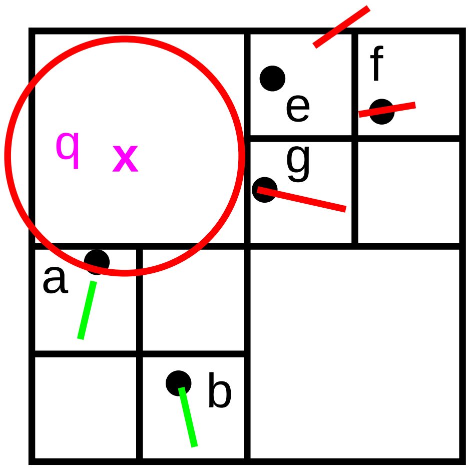

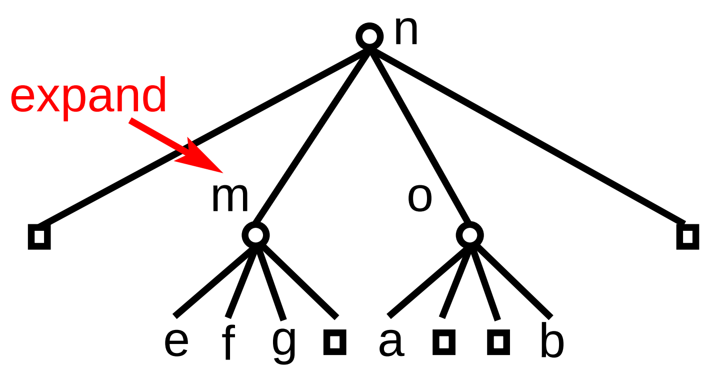

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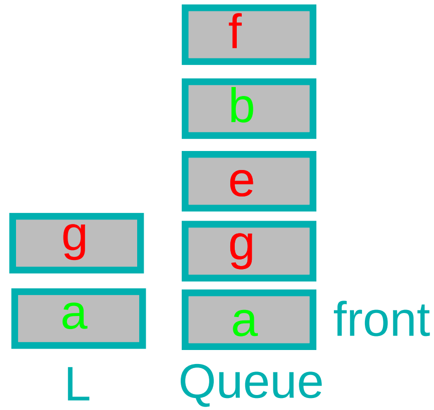

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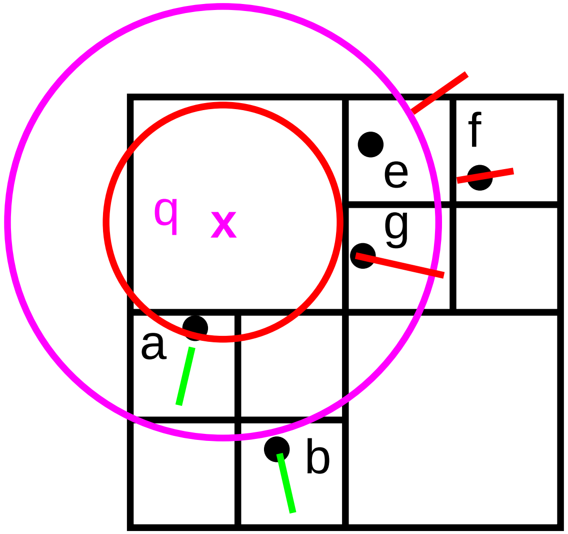

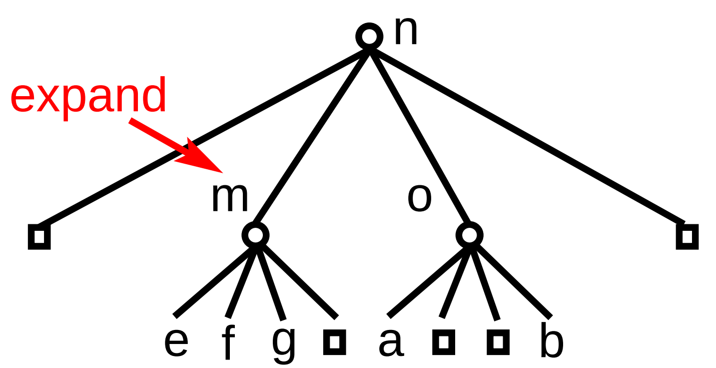

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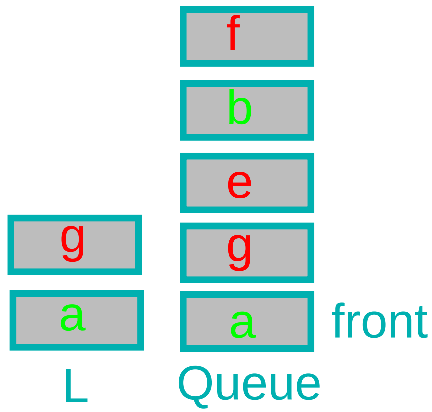

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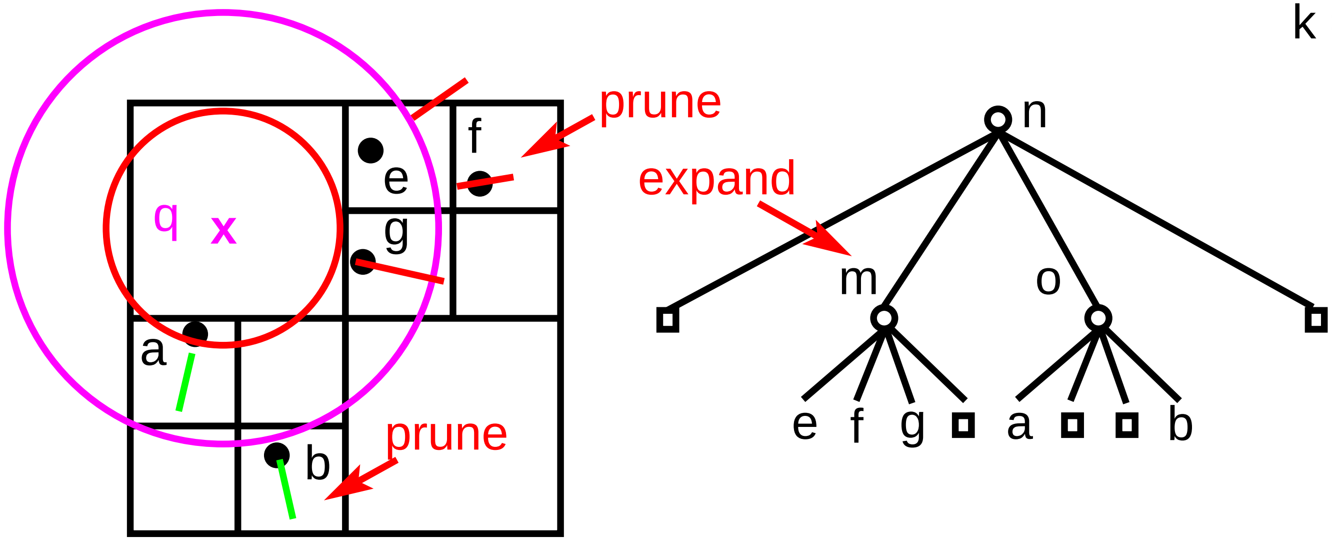

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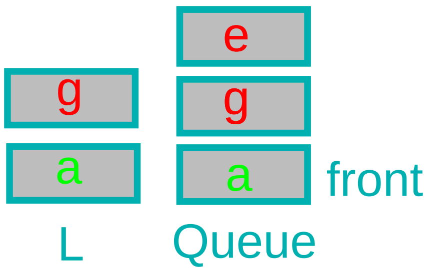

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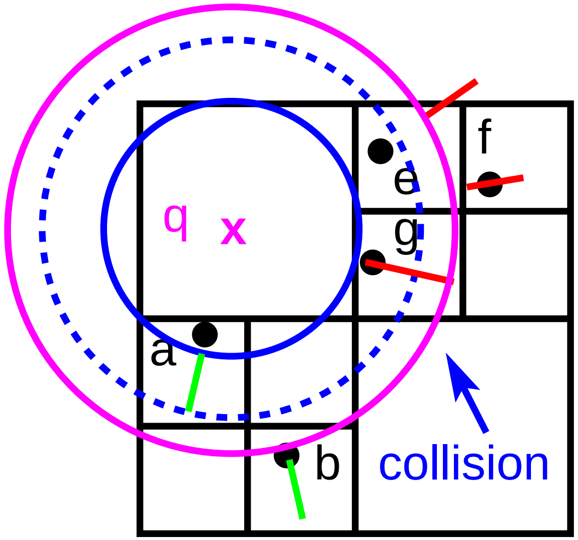

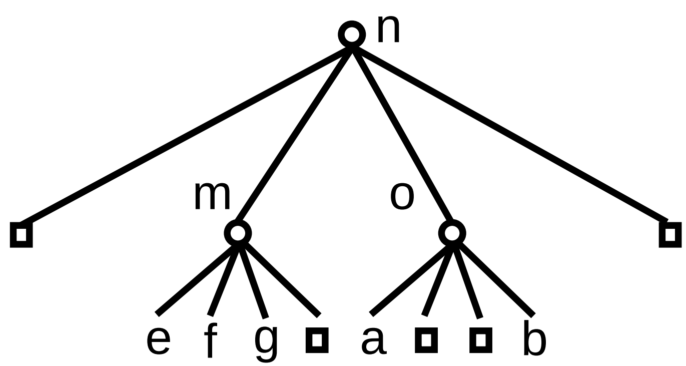

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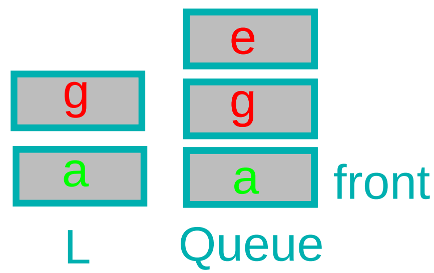

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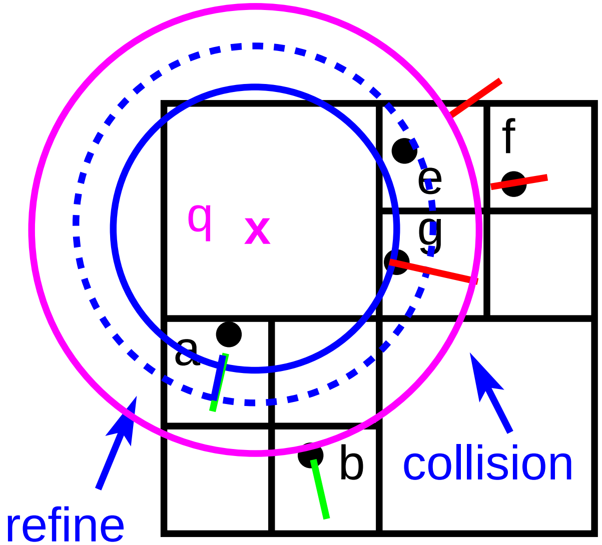
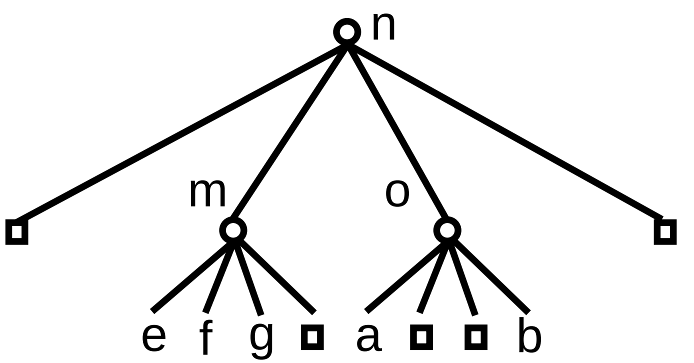
k = 2





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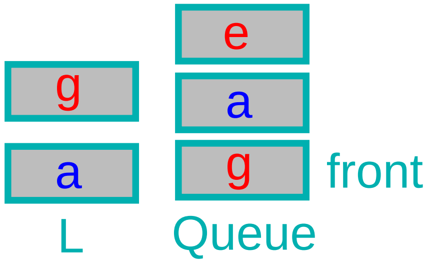

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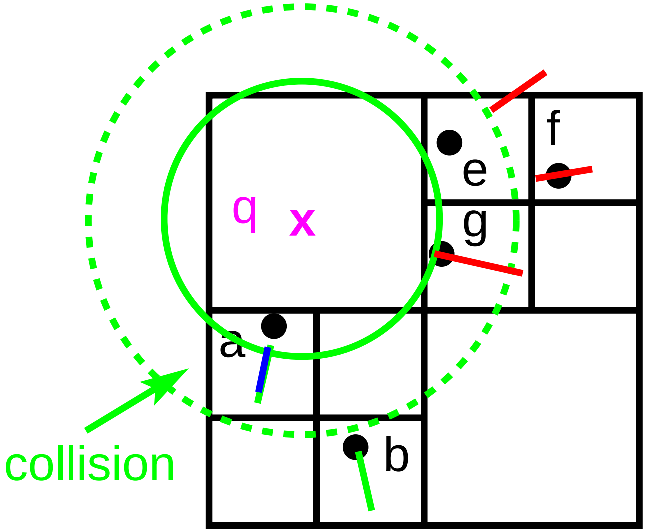

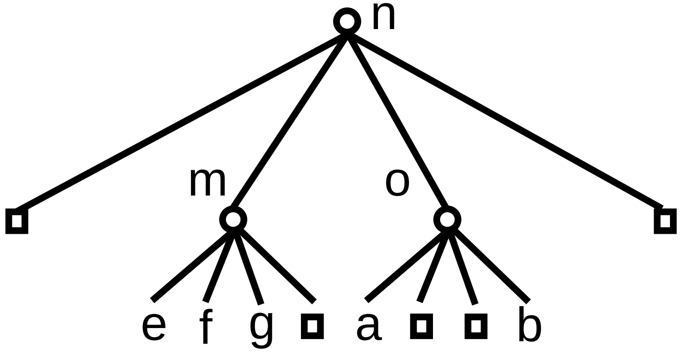

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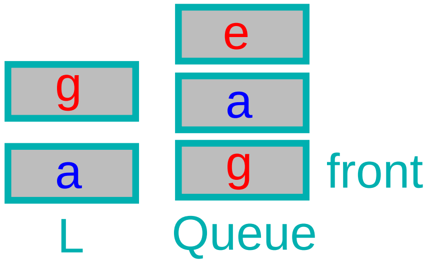

Example of an Non-incremental k Neighbor Search

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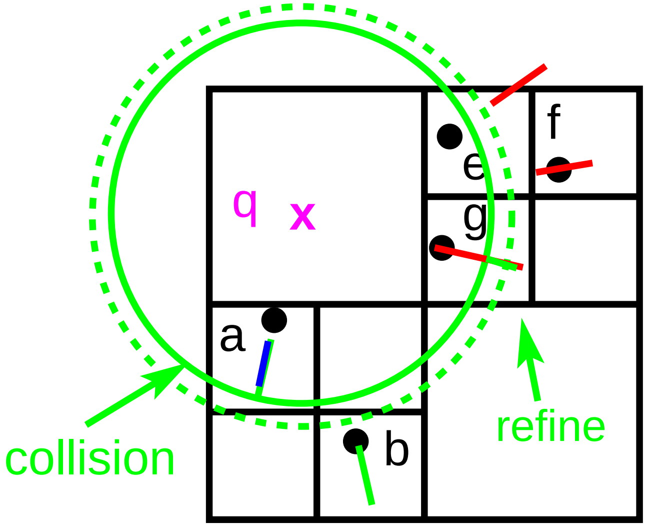

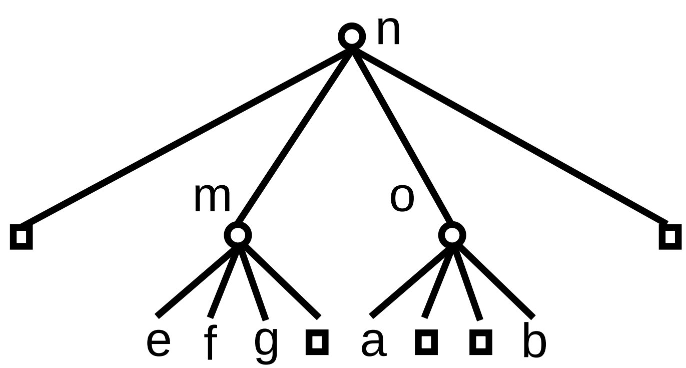

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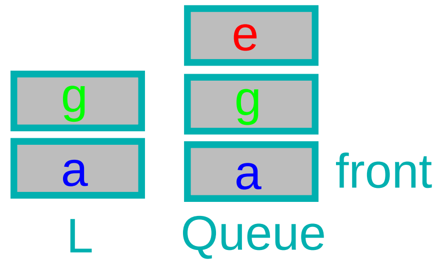

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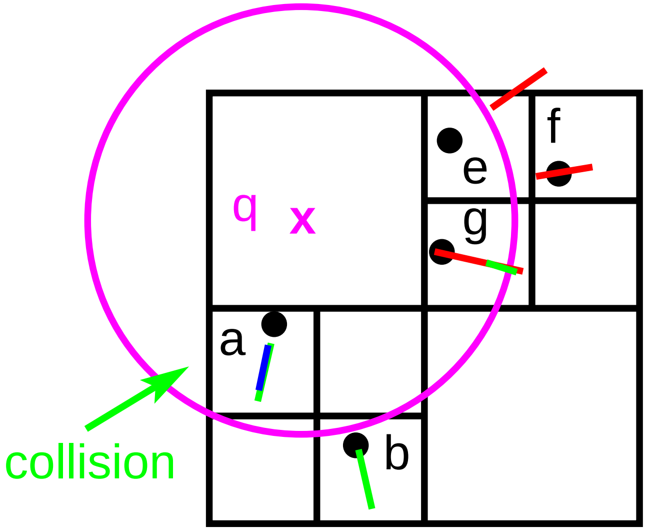

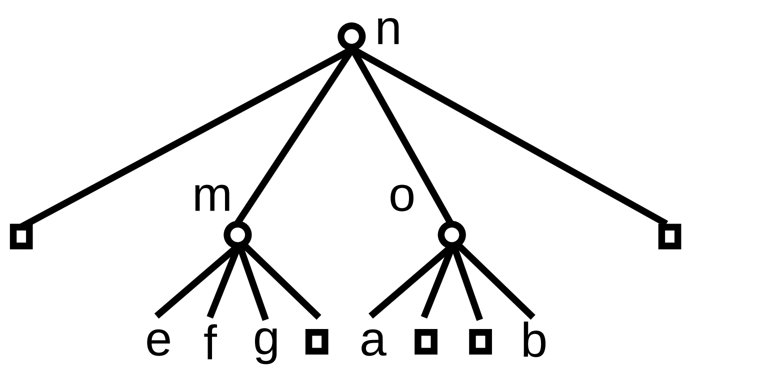

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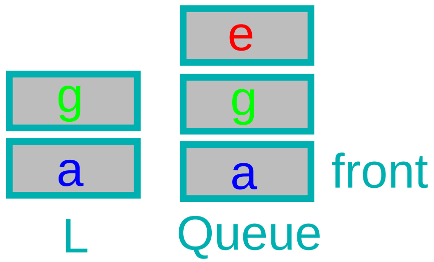

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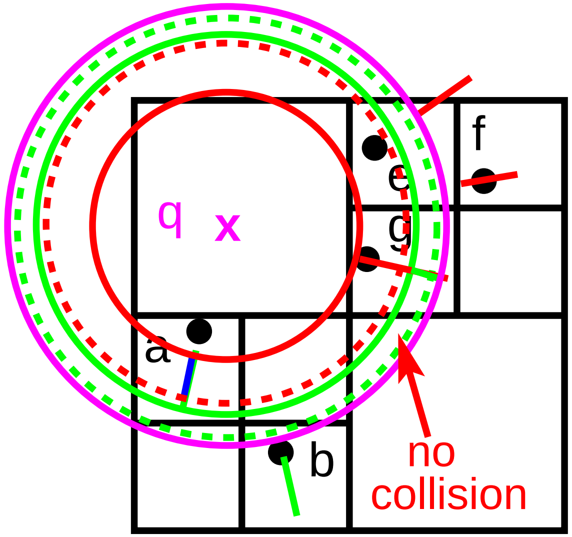

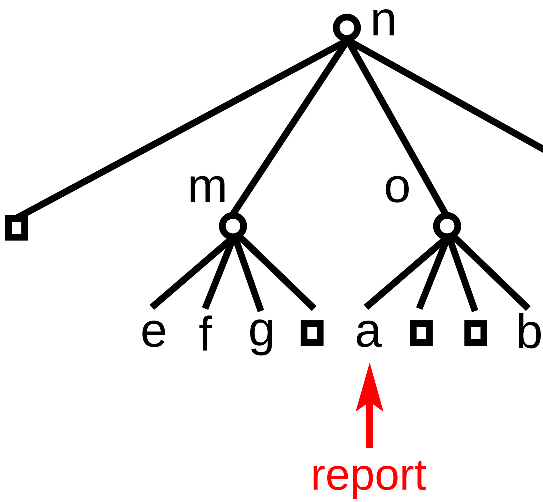

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3. Expand o. Insert a,b into Queue, L. Set D_k.
4. Expand m. Insert g,e,f into Queue and g into L.
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5. Process a. Collision of a with g.
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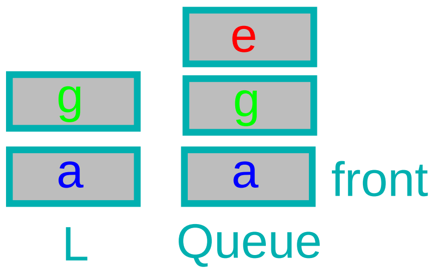
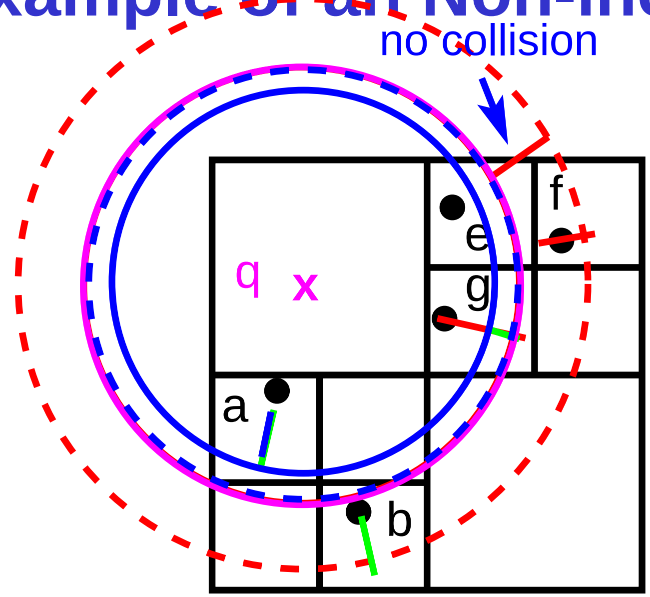
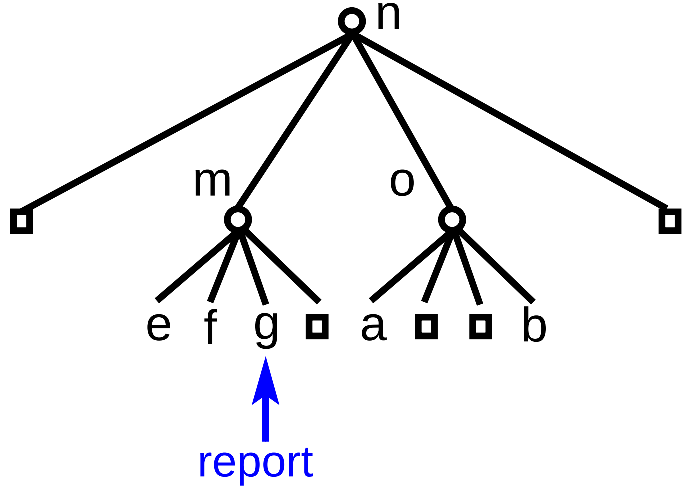
7. Process a. No collision of a with g. No need to refine a further.



Example of an Non-incremental k Neighbor Search



k = 2



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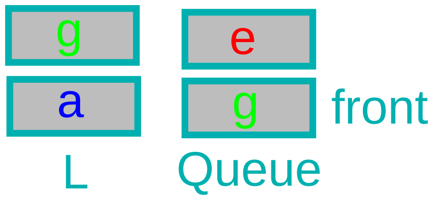
7. Process a. No collision of a with g. No need to refine a further.
8. Process g. No collision of g with e.
   No need to refine g further. Report L.



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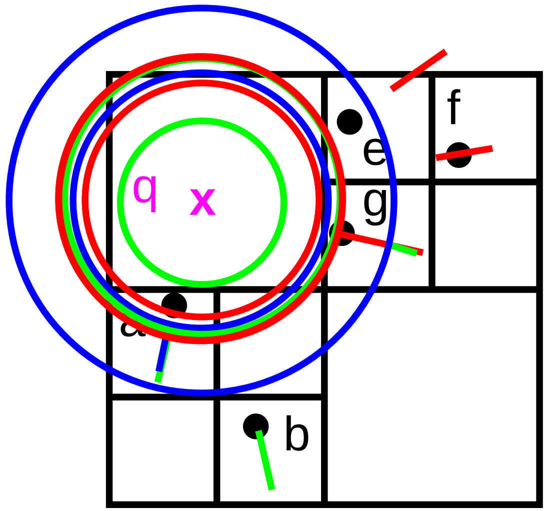

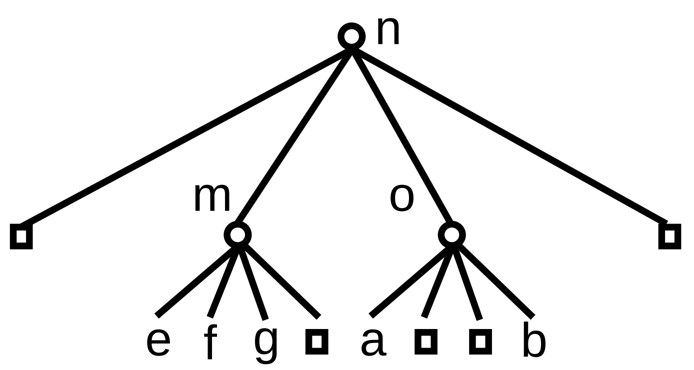

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8. Process g. No collision of g with e.
   No need to refine g further. Report L.
   Example of a best−first nearest neighbor algorithm.
   (Search radius to first element in Queue)

front

L Queue

Other Nearest Neighbor Methods

1. IER ("Incremental" Euclidean Restriction") method [Papa03]: not an incremental network distance algorithm
   - Use incremental nearest neighbor algorithm to find k nearest neighbors using Euclidean distance
   - Find the network distance of these k nearest neighbors using Dijkstra's algorithm and sort in increasing order
   - Apply incremental nearest neighbor algorithm using Euclidean distance until obtaining an object whose Euclidean distance is greater than the current network distance to the $k\mathrm{th}$ nearest neighbor
   - Need to apply Dijkstra's algorithm to obtain network distance to each additional object until termination
2. INE ("Incremental" Network Expansion) method [Papa03]: k-nearest neighbor network distance algorithm
   - Really Dijkstra's algorithm with a buffer L containing the k nearest neighbors seen so far in terms of network distance
   - Halt: current neighbor is farther than current k nearest neighbors in L
3. Advantage of our method is that Dijkstra's algorithm is only applied once per vertex in building the shortest-path quadtrees regardless of the number of queries instead of once for each query

Worst Case Comparison between INE and kNN

- Given a set of objects S on a spatial network

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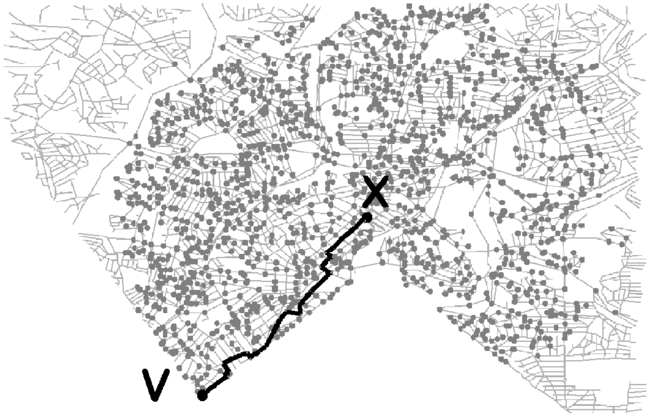

INE

Worst Case Comparison between INE and kNN

- Given a set of objects S on a spatial network
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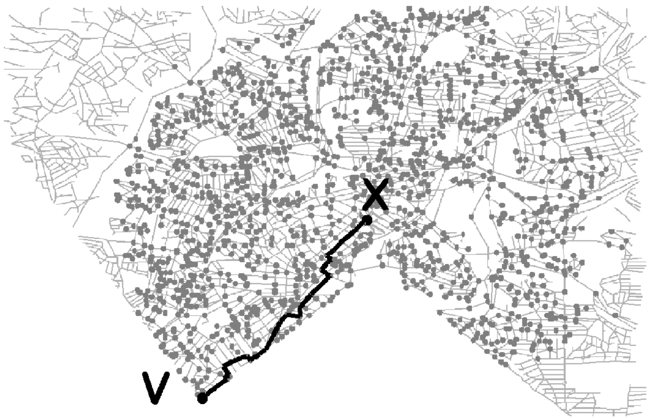

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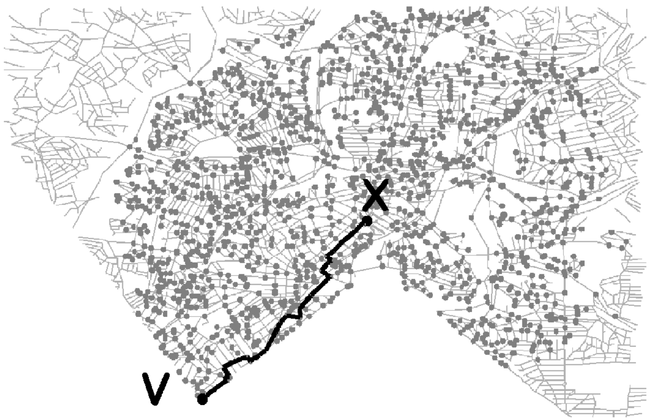

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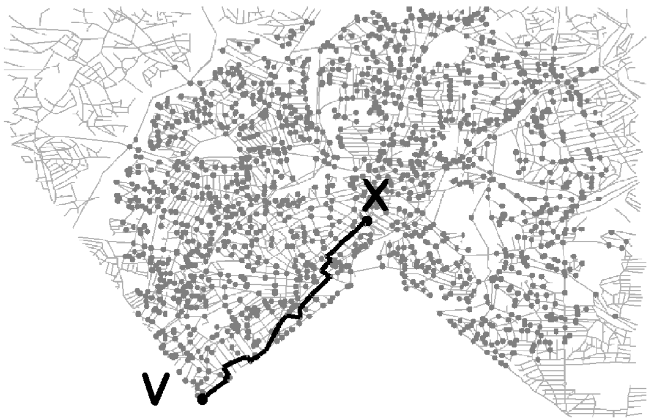

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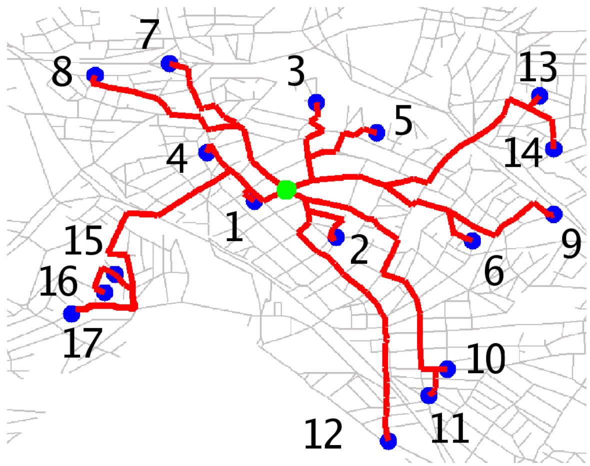

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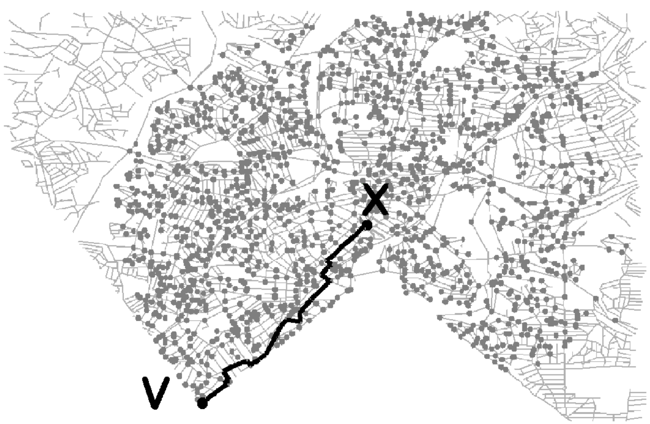

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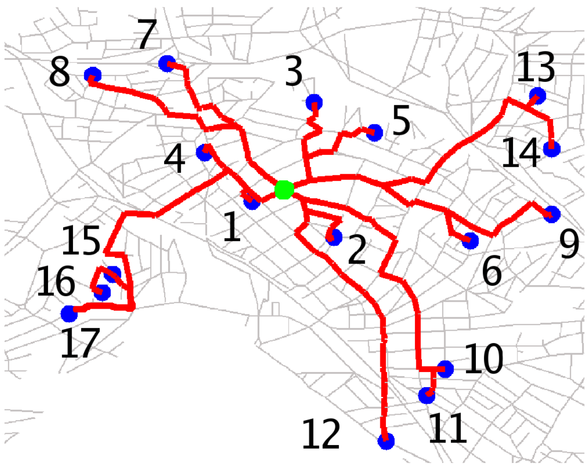

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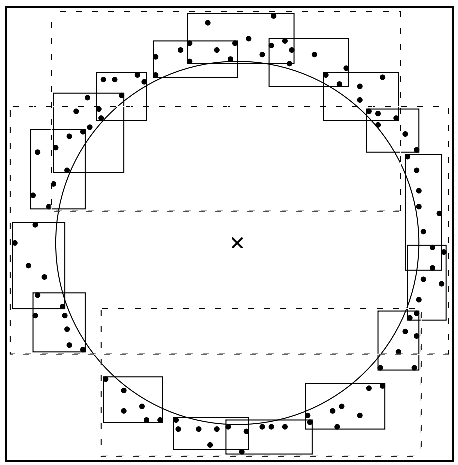

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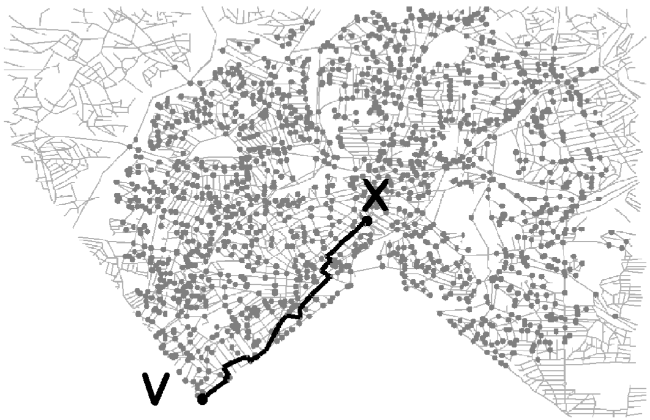
    - kNN's worst case occurs when data objects are all nearly equidistant from query object
    - Probability of worst case is low, as it depends on a particular configuration of both the data objects and the query object



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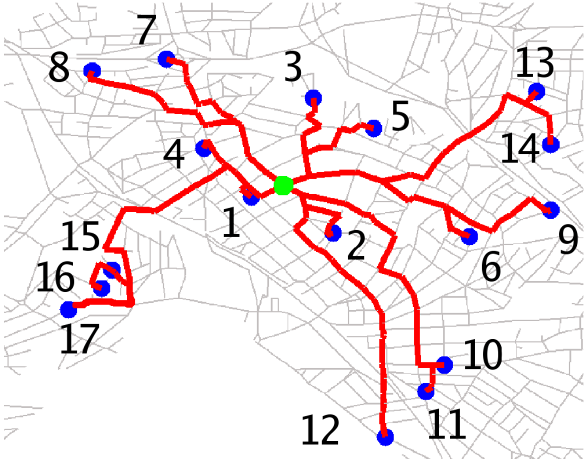

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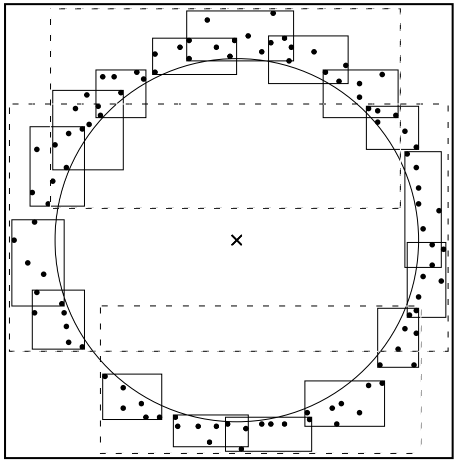

kNN

Musings on How Realistic is the Approach

- How about a system for the whole US?
  - 24 million vertices x 10 seconds (say) per shortest path
    - Single machine = 2777 days
    - Google with 0.5 million machines = 480 seconds
    - Modest Cluster of 2000 machines = 1 day, 10 hours
  - Storage shown to be $cN\sqrt{N}$ Morton Blocks
    - N = 24 million vertices, 8 bytes per Morton block, c = 2 from empirical analysis = 1.8 TB
  - Easily Parallelizable: data parallelism
  - Mostly a one-time effort (decoupling)
- Open Challenge: Updates!
  - Changes to spatial network (e.g., road closure)
  - Dynamic traffic information
  - Strategy: How to localize changes to minimize recomputation?
- Approximation Strategies: location based services
  - Shortest-path quadtree on proximal vertices only (say, 100 miles around a vertex)
  - Multiresolution spatial networks
    - Full resolution around a source vertex that gets sparse gradually

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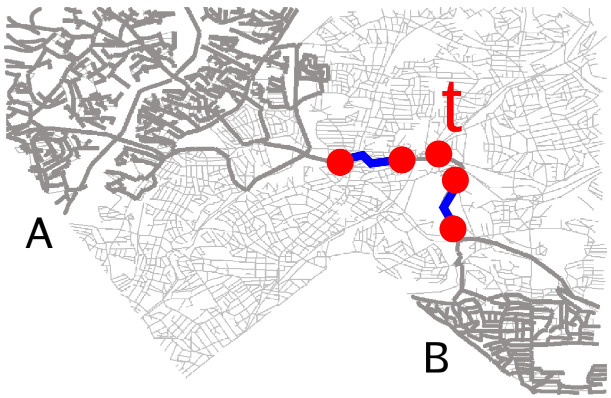

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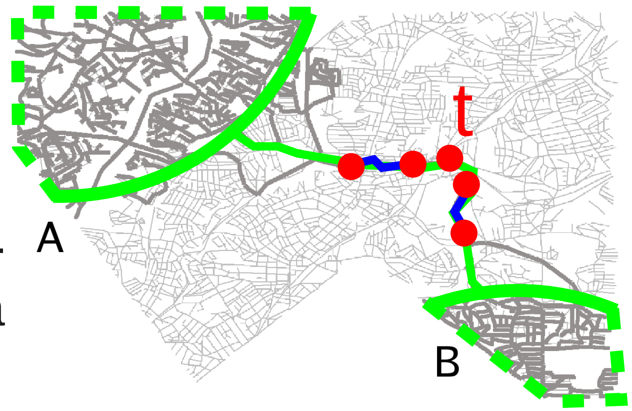
  3. Result has a structure of a dumbbell



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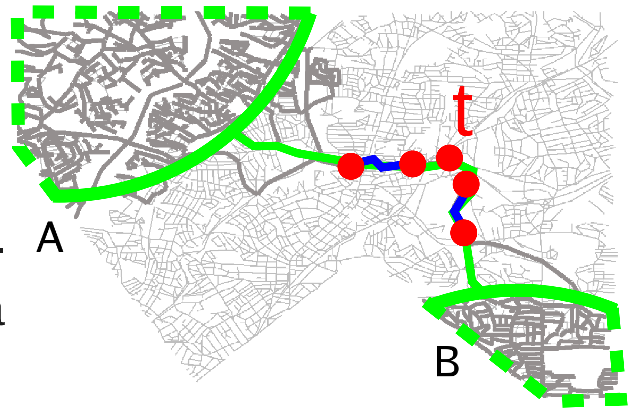

- Goal: Decompose spatial network into PCPs so that all n^2 shortest paths are captured

Finding Path Coherent Pairs in Spatial Networks

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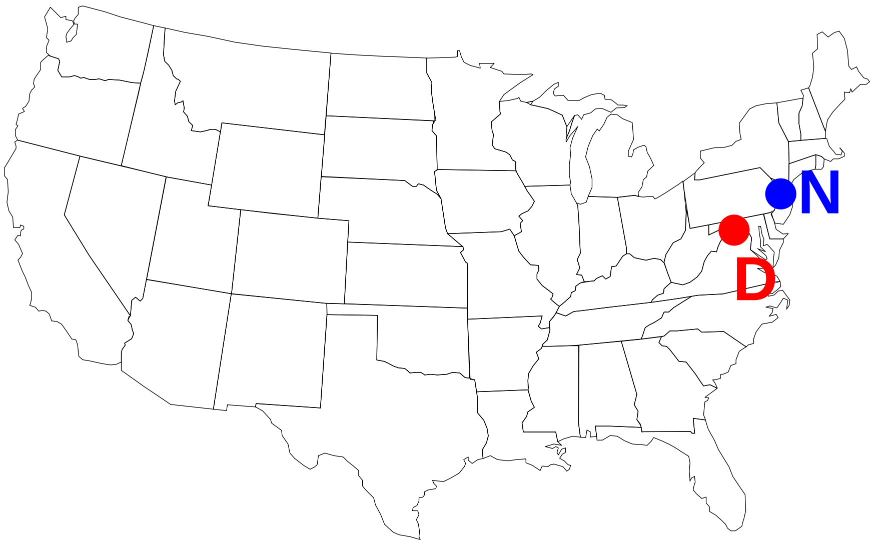
- Source Vertices:

Finding Path Coherent Pairs in Spatial Networks

- Source Vertices: Washington, DC (D)

Finding Path Coherent Pairs in Spatial Networks

- Source Vertices: Washington, DC (D) , New York (N)



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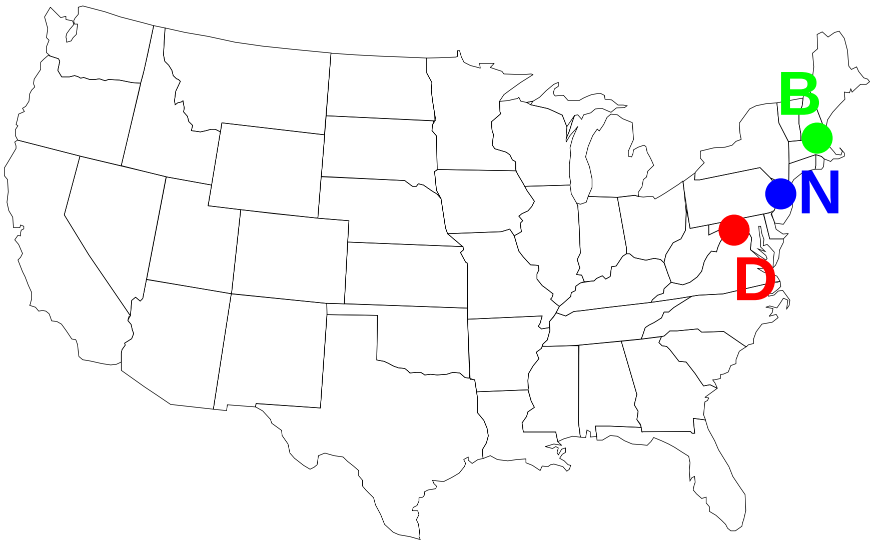
- Source Vertices: Washington, DC (D) , New York (N) , Boston (B)



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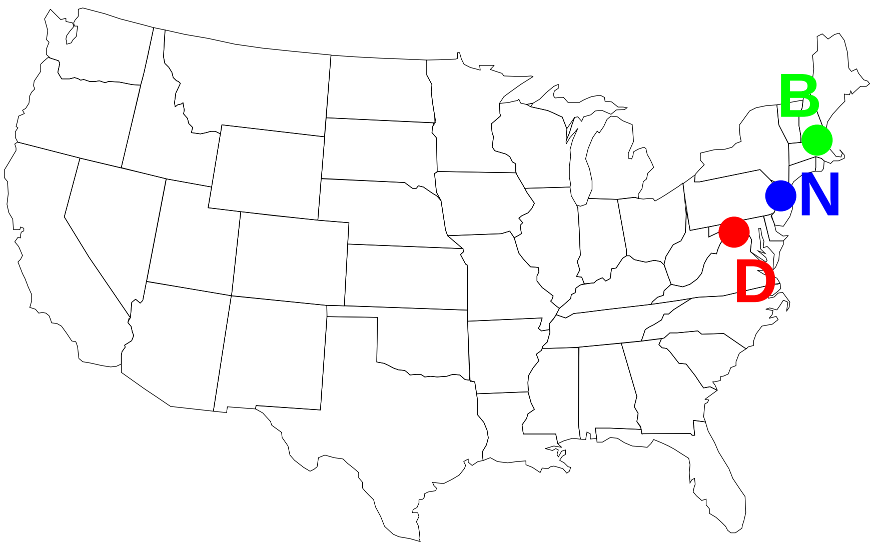

Finding Path Coherent Pairs in Spatial Networks

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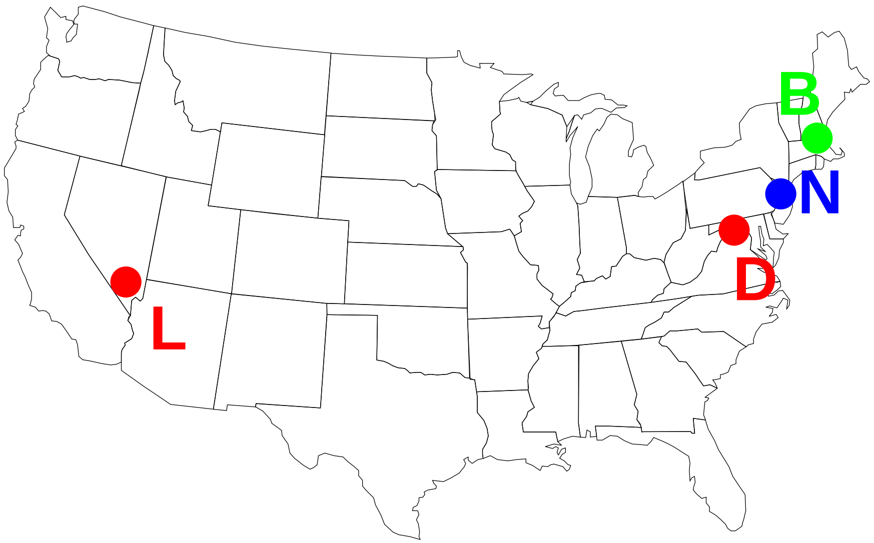
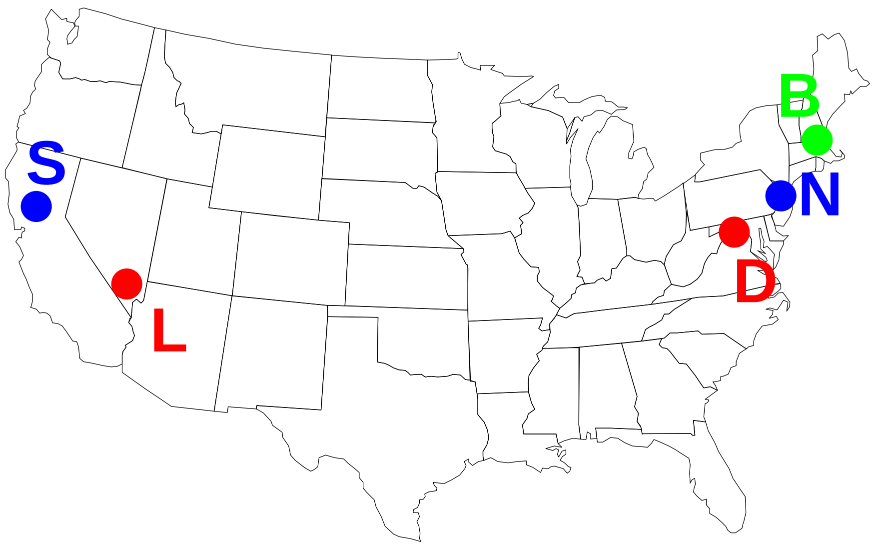


Finding Path Coherent Pairs in Spatial Networks

- Source Vertices: Washington, DC (D) , New York (N) , Boston (B)
- Destination vertices: Las Vegas (L) , Sacramento (S)



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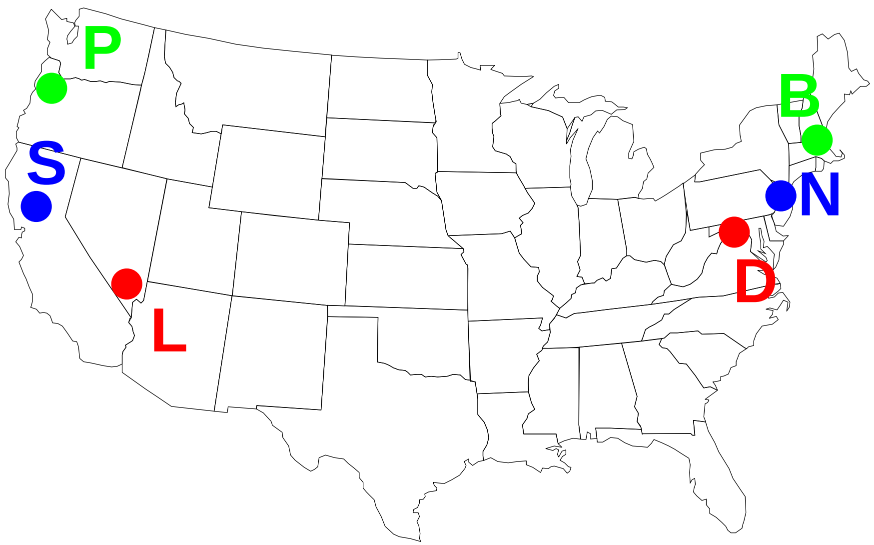

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- Source Vertices: Washington, DC (D) , New York (N) , Boston (B)
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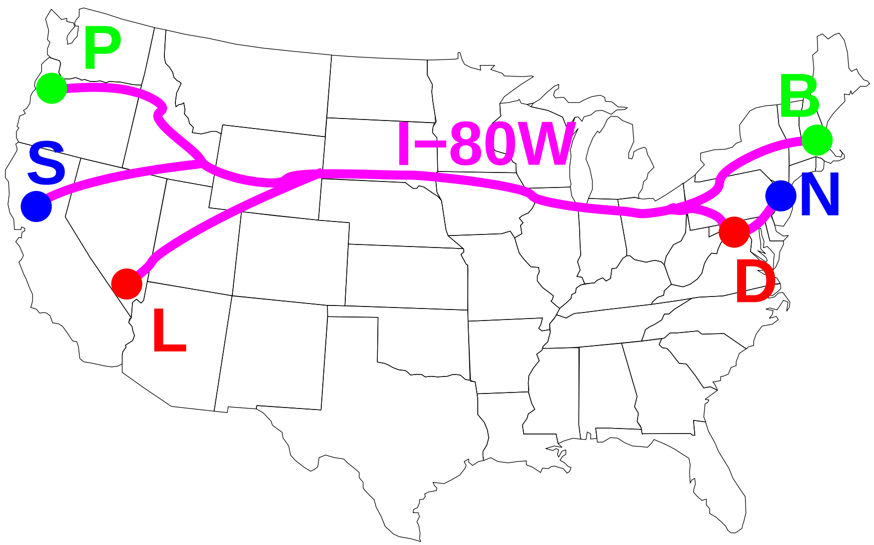
- Anyone driving from “North-East” to “North-West” US uses I-80W



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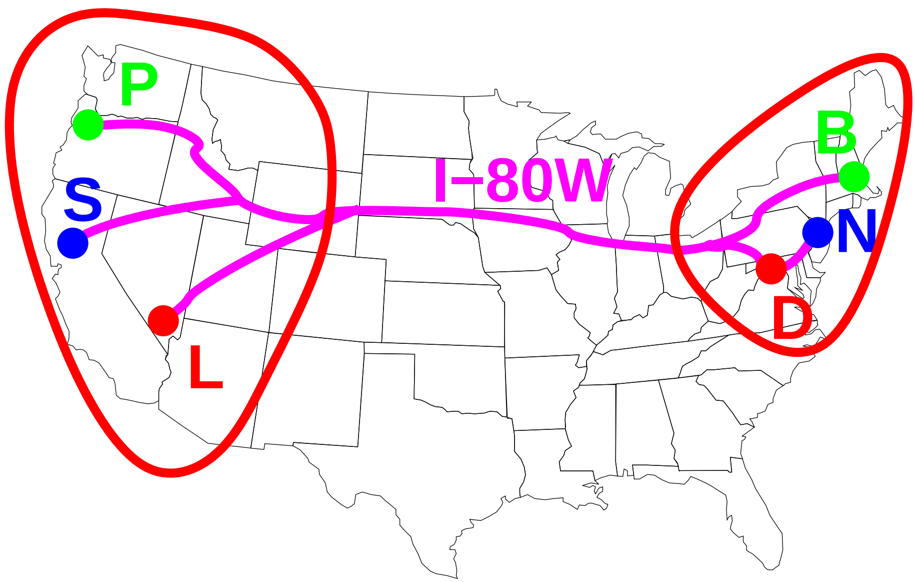

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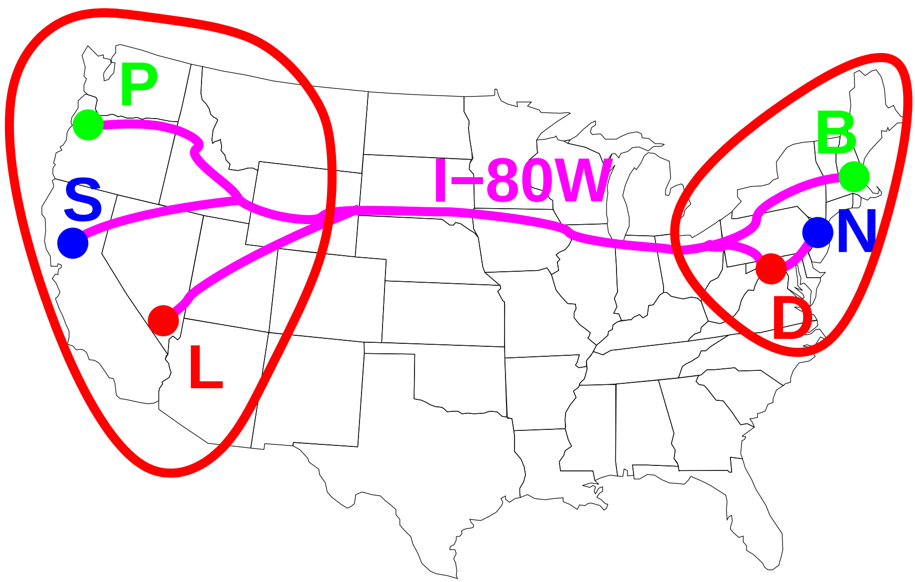

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- Decompose road network into PCPs:
  - Any vertex pair is contained in exactly one PCP
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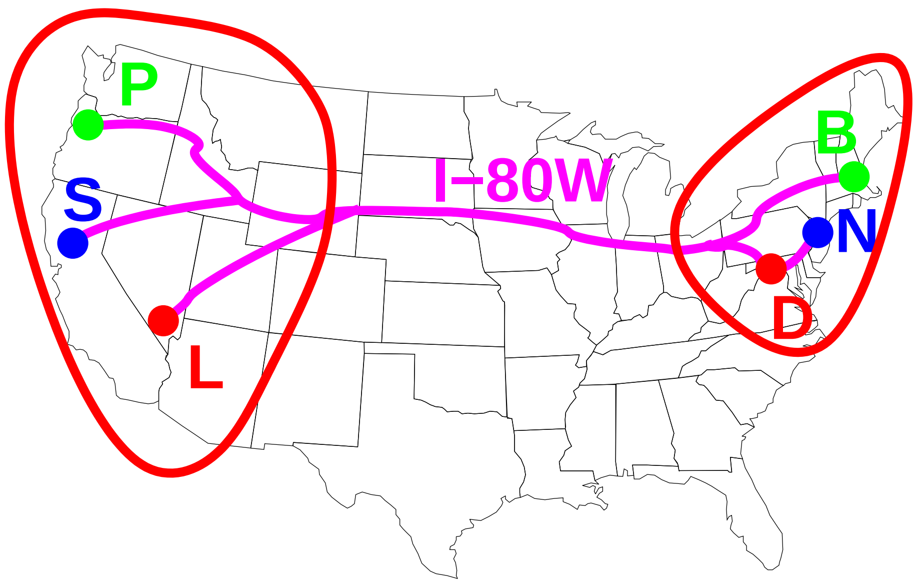

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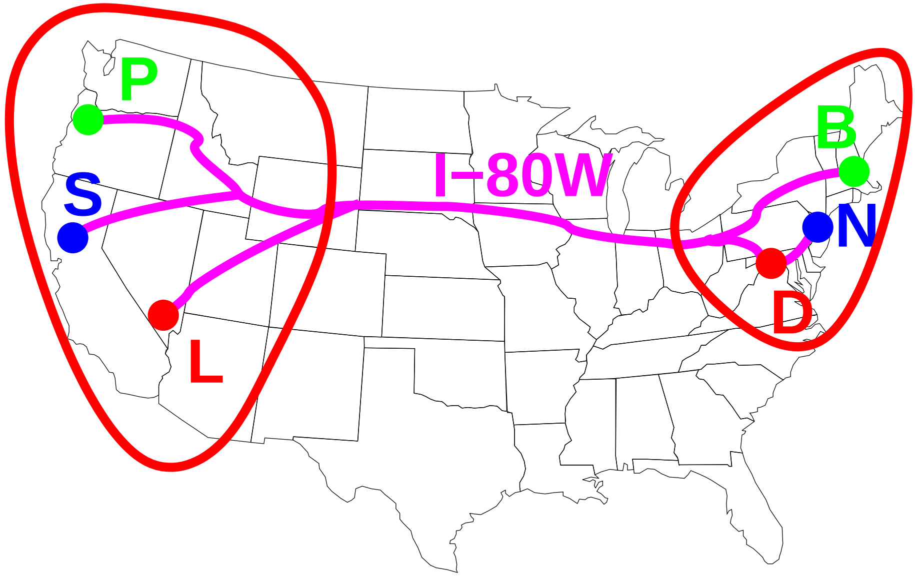


- Key idea is the analogy to the well-separated pairs in computational geometry

Is SILC Still Useful?

1. Type of refinement
   - Refinement in SILC finds the next intermediate vertex
   - Refinement in oracles fetches some intermediate vertex
2. Quality of refinement
   - SILC is superior as the network distance between source and destination is always expressed as an exact network distance from source to some intermediate vertex plus the network distance interval from the intermediate vertex to the destination
   - While in the case of distance oracles, the network distance between source and destination is always expressed as the sum of two network distance intervals

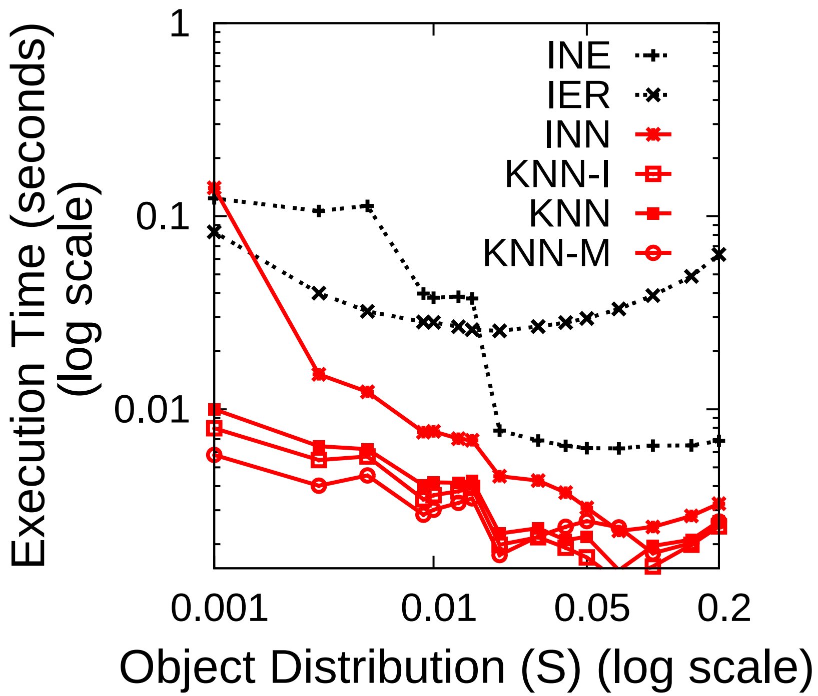
Outline

1. Overview
2. Spatial Networks
3. Precomputation and storage of shortest paths
4. k Nearest Neighbor Finding Algorithm
5. Experimental evaluation
6. Contributions
7. Future Work

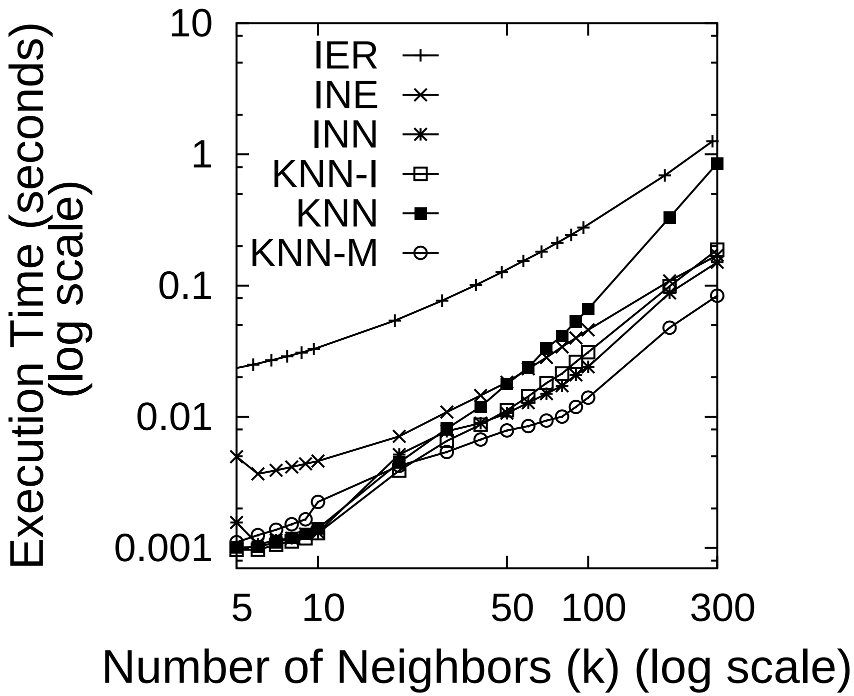
Experimental Evaluation

- Compared kNN with other algorithms including variants of kNN
  1. INE: Basically Dijkstra's algorithm [Papa03]
  2. IER: Using Euclidean distance as a filter [Papa03]
  3. INN: Incremental variant of kNN which invokes kNN k times
     - No priority queue, L, or D_k
  4. kNN-I: Use L to calculate D_k^0 using first k objects
     - Reduce size of *Queue* by not enqueueing elements with $\delta^- > D_k^0$
  5. kNN-M: Reduce number of refinements by dropping need for total ordering
     - KMINDIST keeps track of δ^- of object corresponding to D_k^0
     - *Queue*$_1$ contains all objects with $\delta^- \leq D_k^0$
     - Don't refine objects in *Queue*$_1$ with $\delta^+ <$ KMINDIST as automatically in L
- Linux (2.4.2 kernel), quad 2.4GHz Xeon server with 1GB of RAM, GNU C++
- LRU based cache that can hold 5% of the disk pages in main memory
- Test set is important roads on US eastern seaboard consisting of 91,113 vertices and 114,176 edges
- S is generated at random and stored in a PMR quadtree
- Each query run on at least 50 random input datasets of same size

Execution Time Comparison



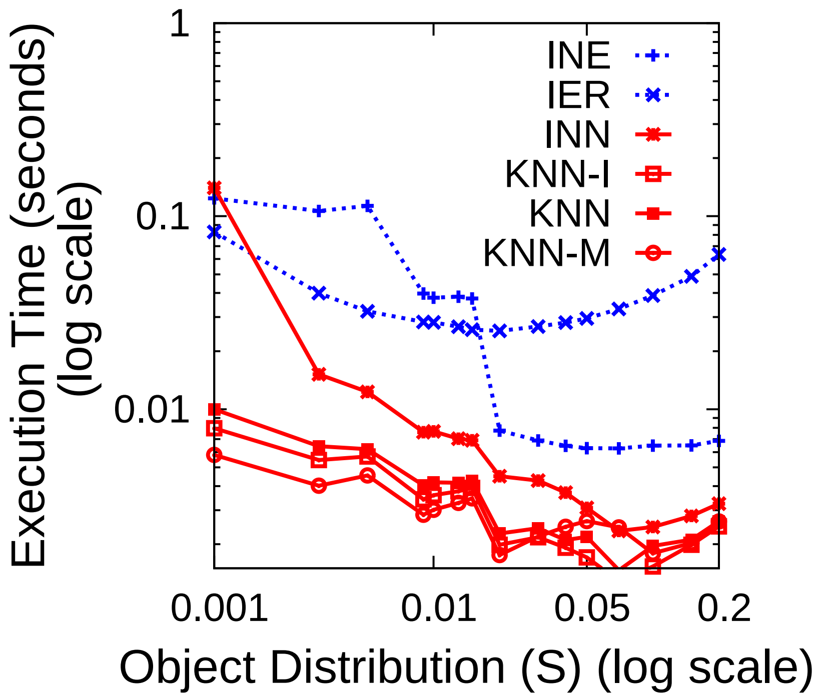
k=10 and varying sizes of S



$S = 0.07N$ and varying k

- kNN and Variants

Execution Time Comparison



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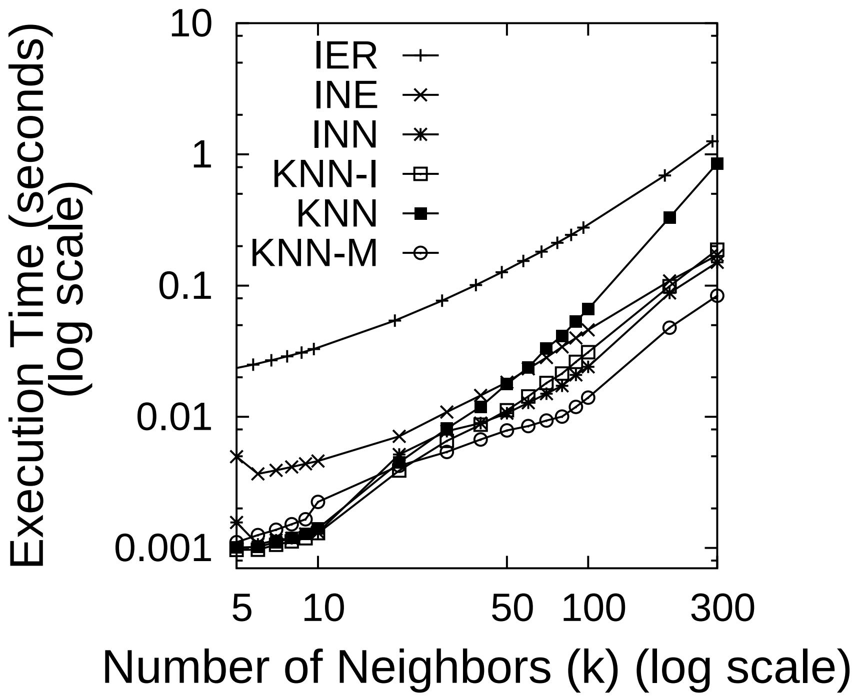
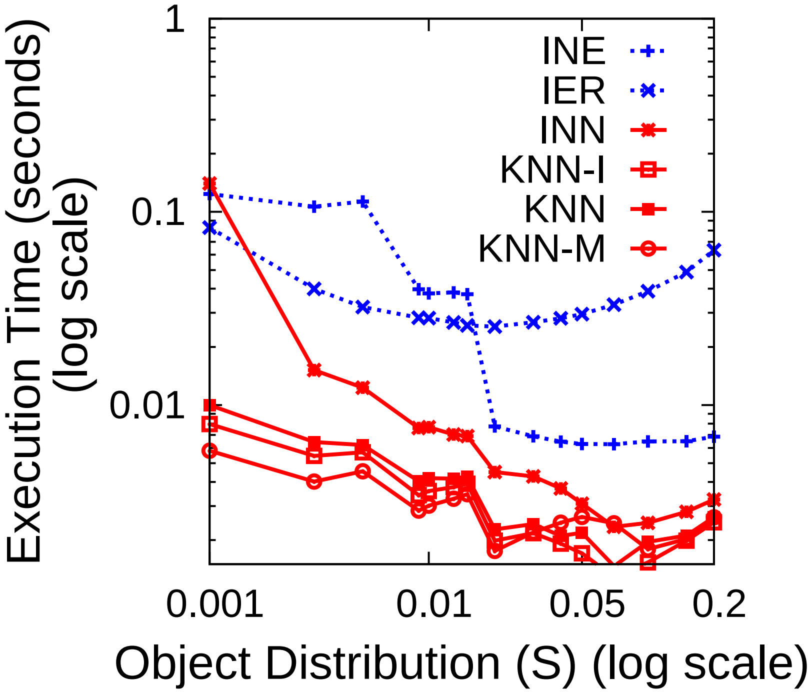


$S = 0.07N$ and varying k

- kNN and Variants are at least one order of magnitude faster than INE and IER for small values of k and moderate values of S

Execution Time Comparison



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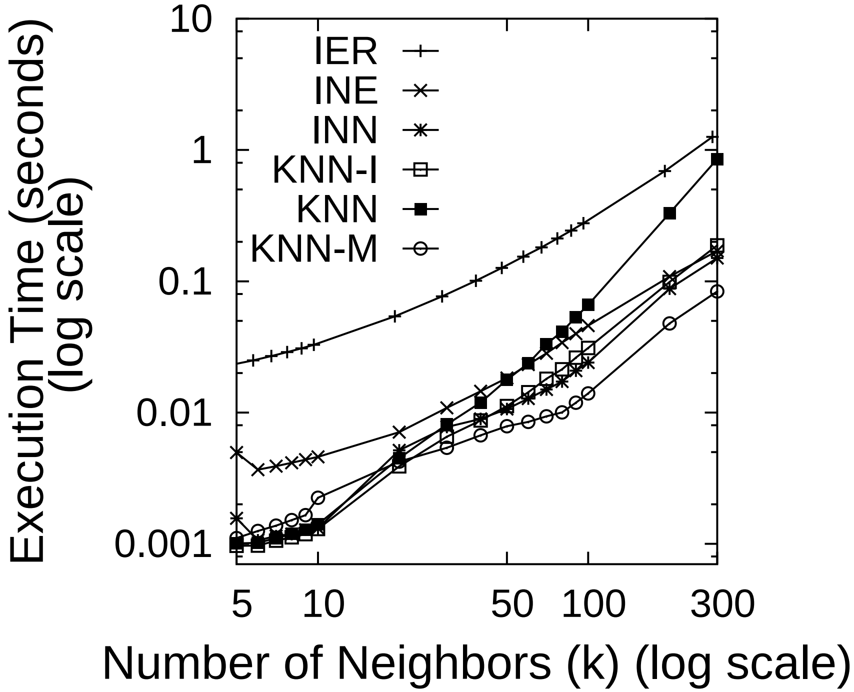

$S = 0.07N$ and varying k

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- INE and IER improve relatively for large values of S as easy to find k neighbors around q

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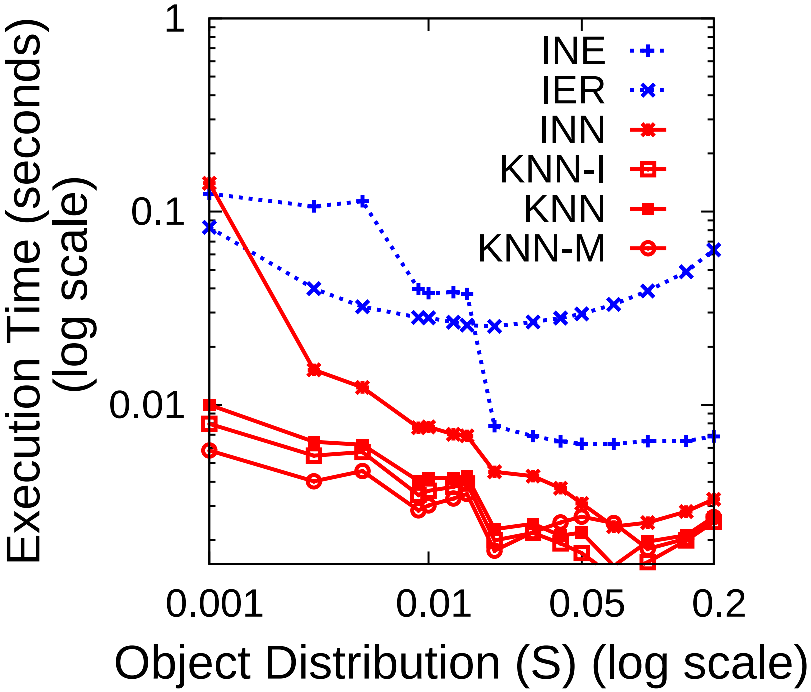

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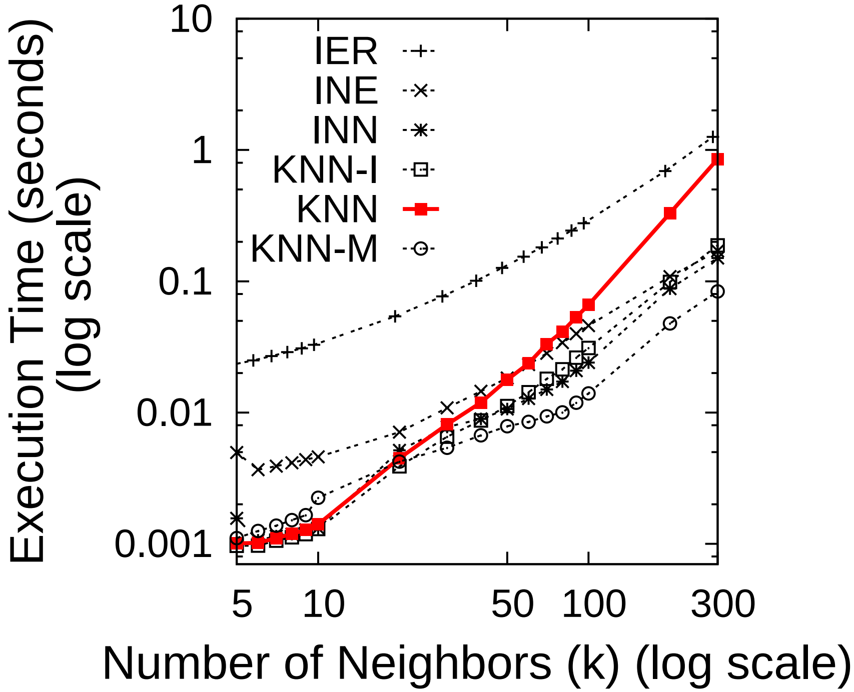

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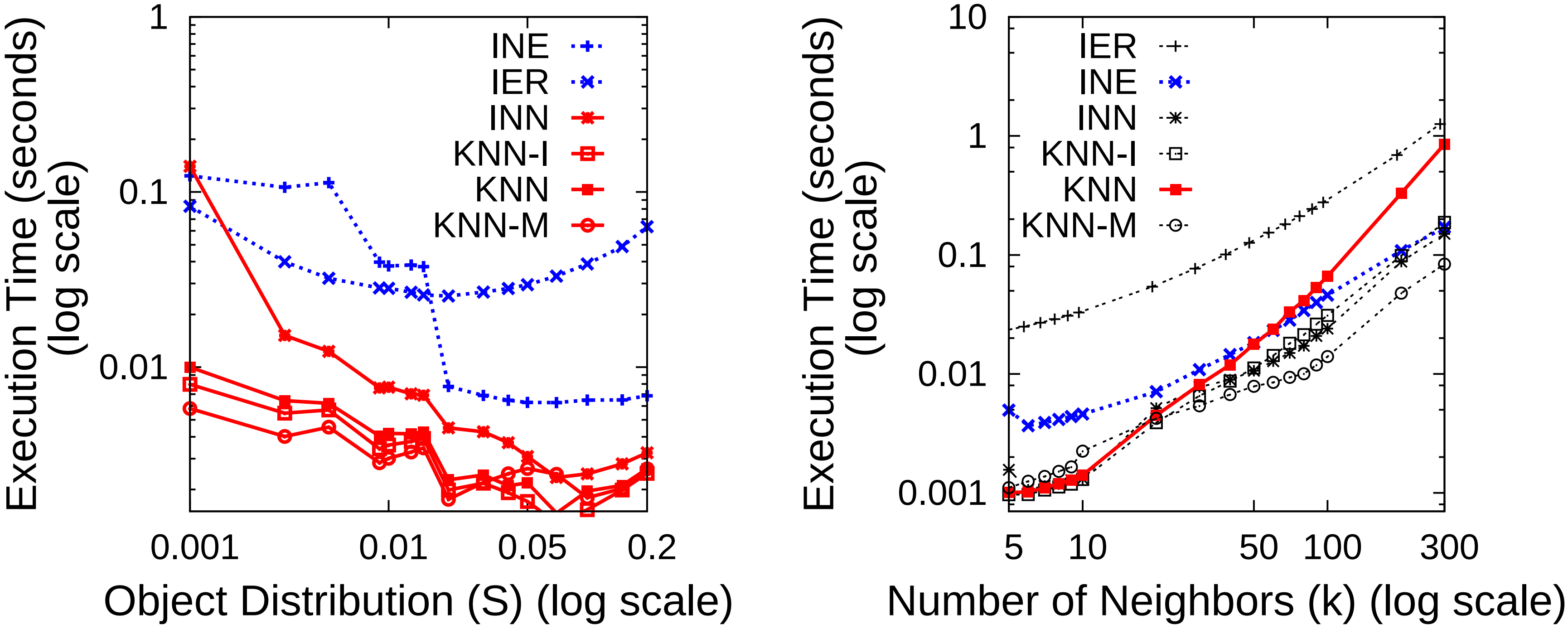

k=10 and varying sizes of S — $S = 0.07N$ and varying k

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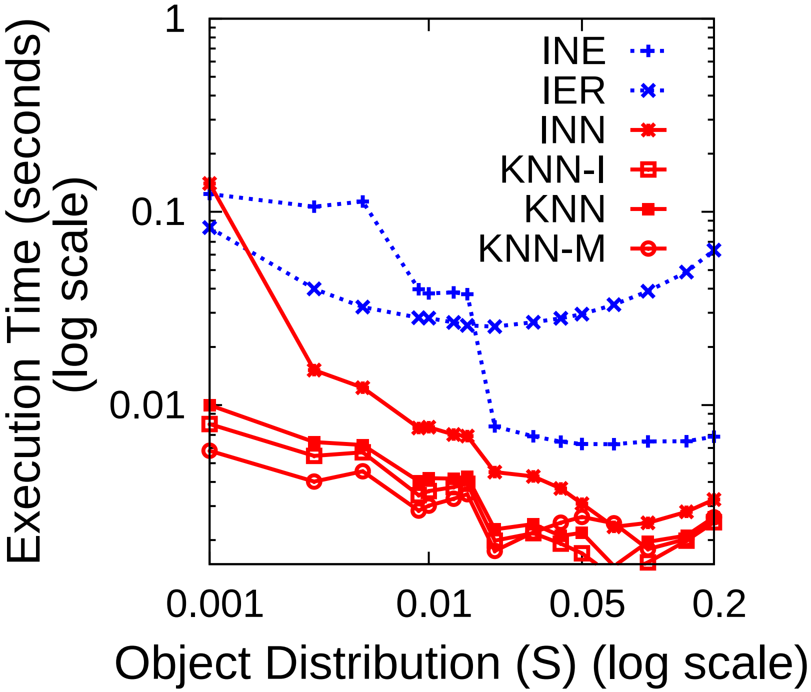
- As k increases, priority queue operations take more time and kNN performs worse than INE

Execution Time Comparison



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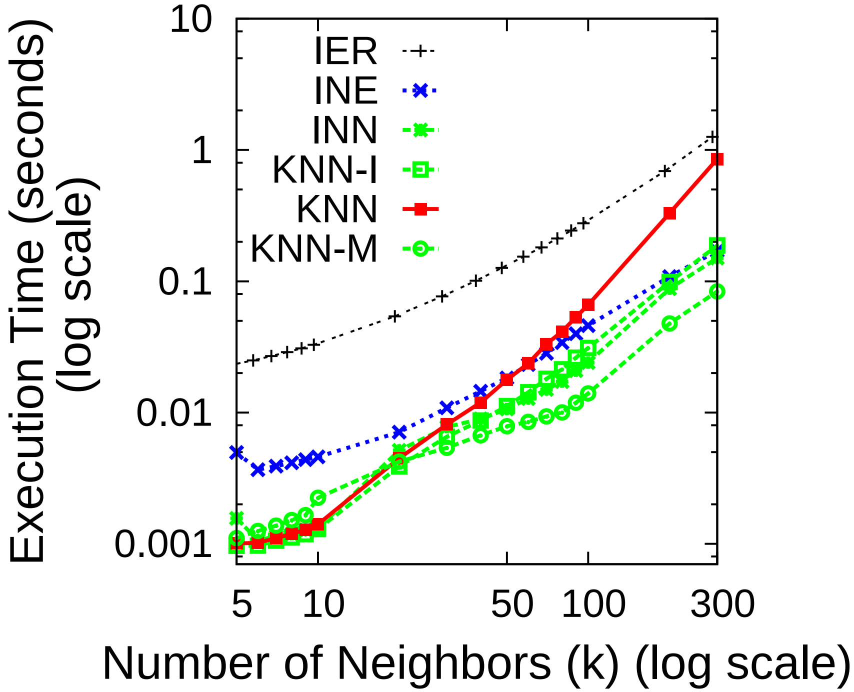

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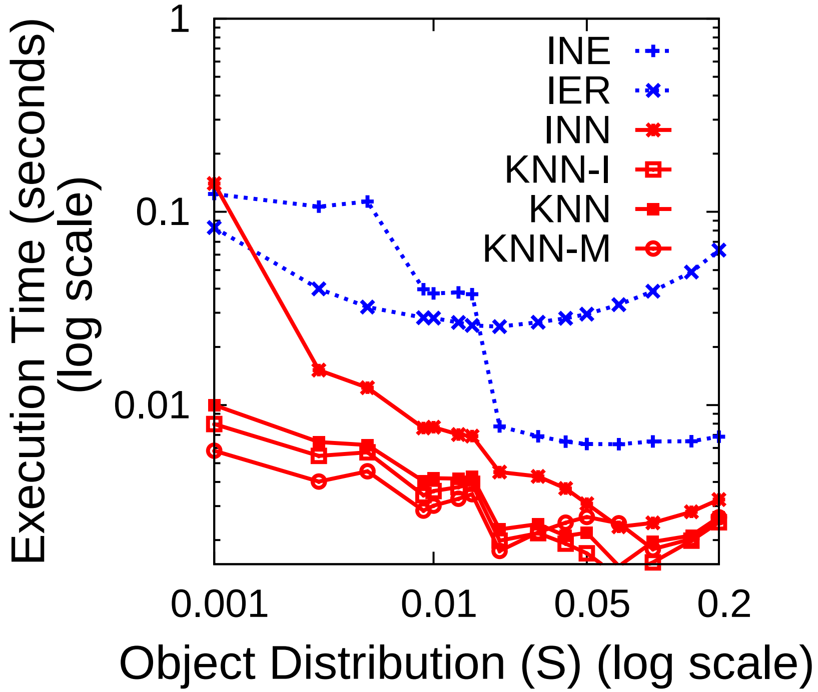

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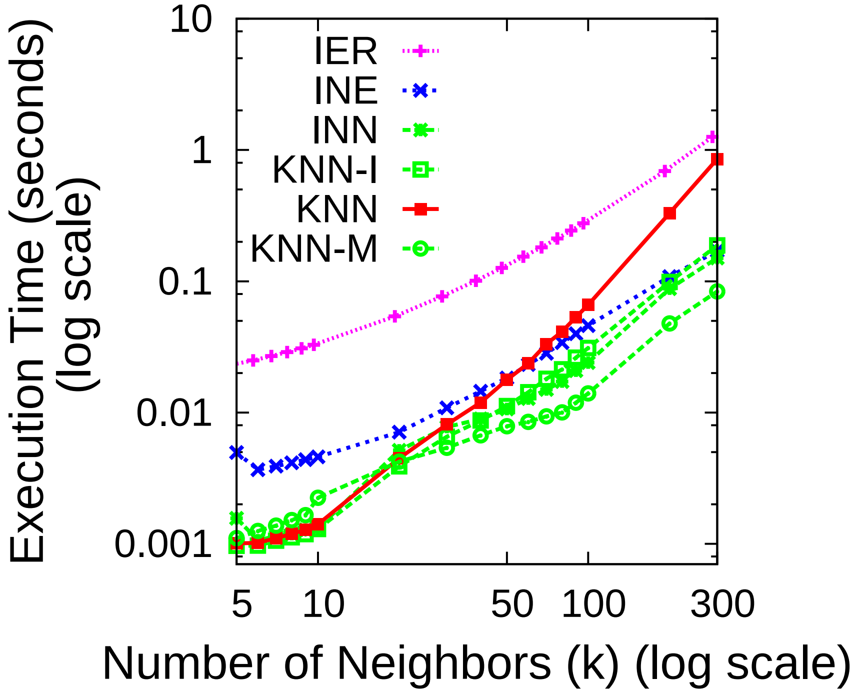

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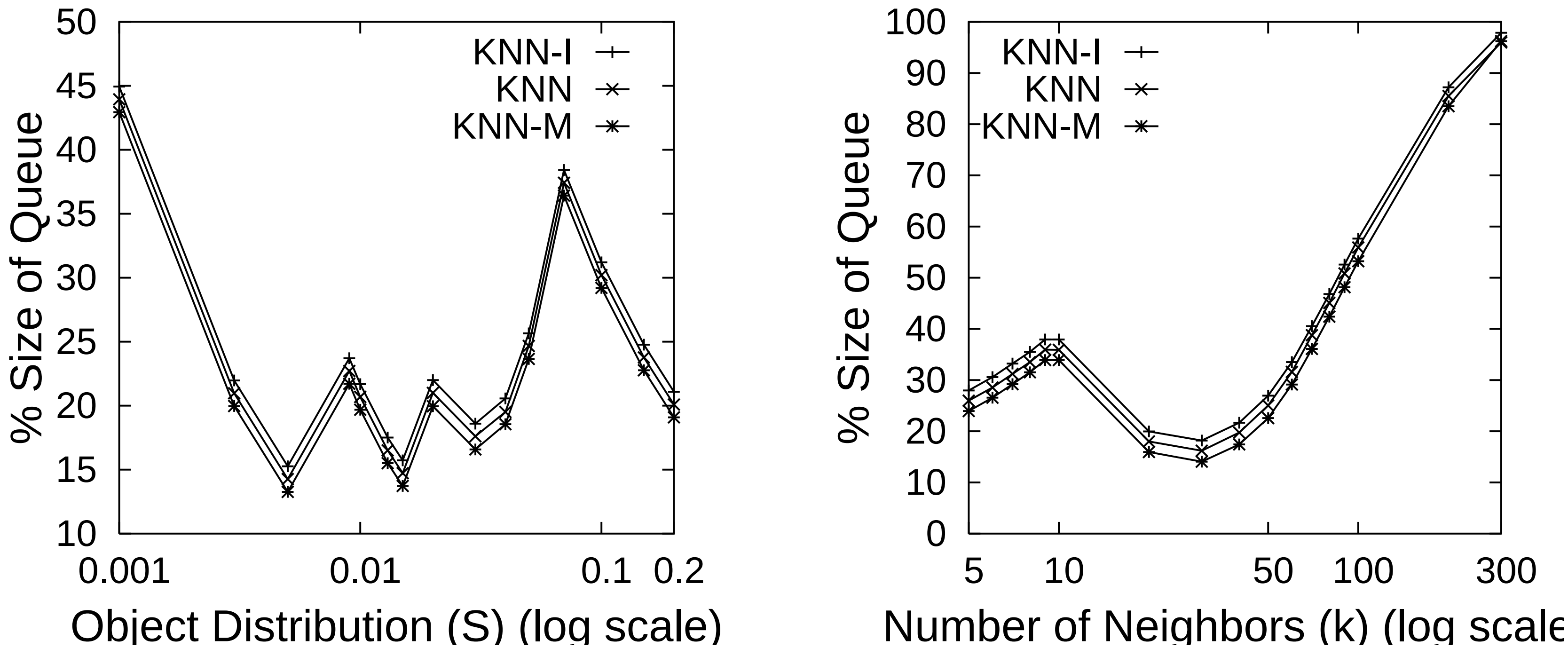
- IER always slowest

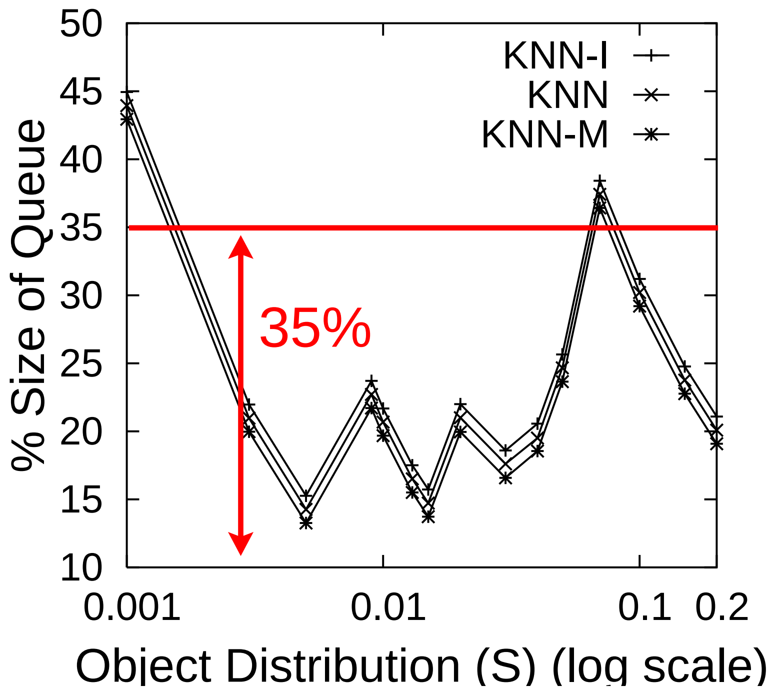
Maximum Priority Queue Size



k=10 and varying sizes of S $S = 0.07N$ and varying k

- Compared maximum size of priority queue of kNN and variants with INN which cannot use D_k to reduce insertions

Maximum Priority Queue Size



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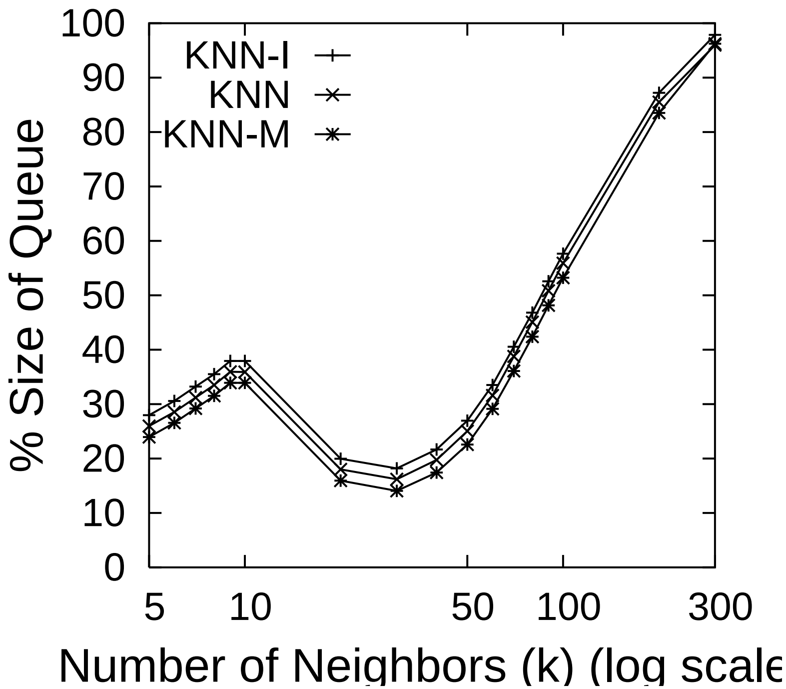

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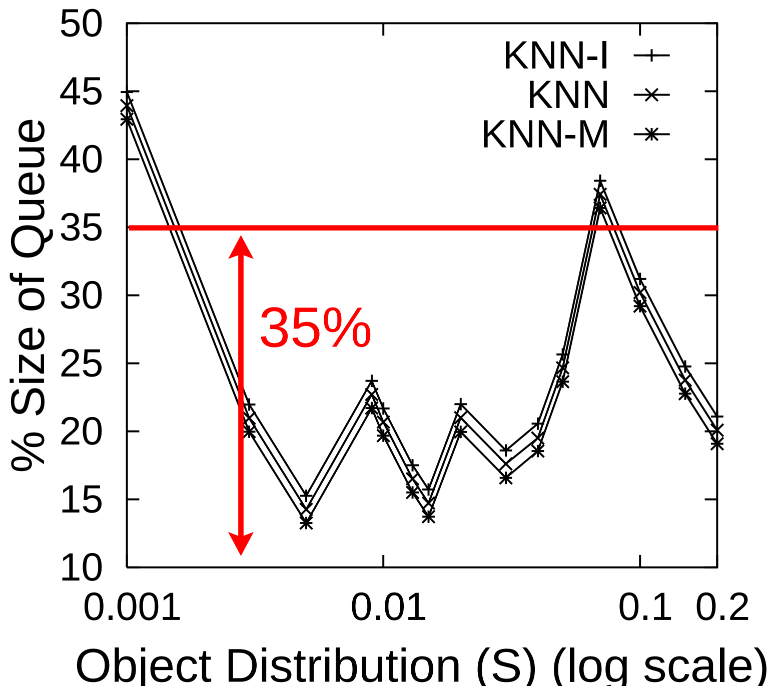
- 35% of INN on the average

Maximum Priority Queue Size



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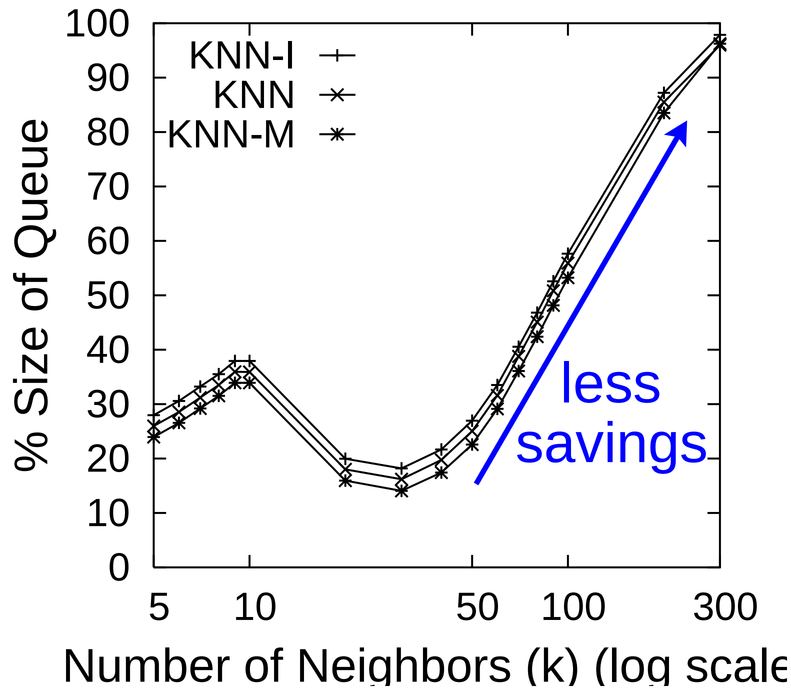
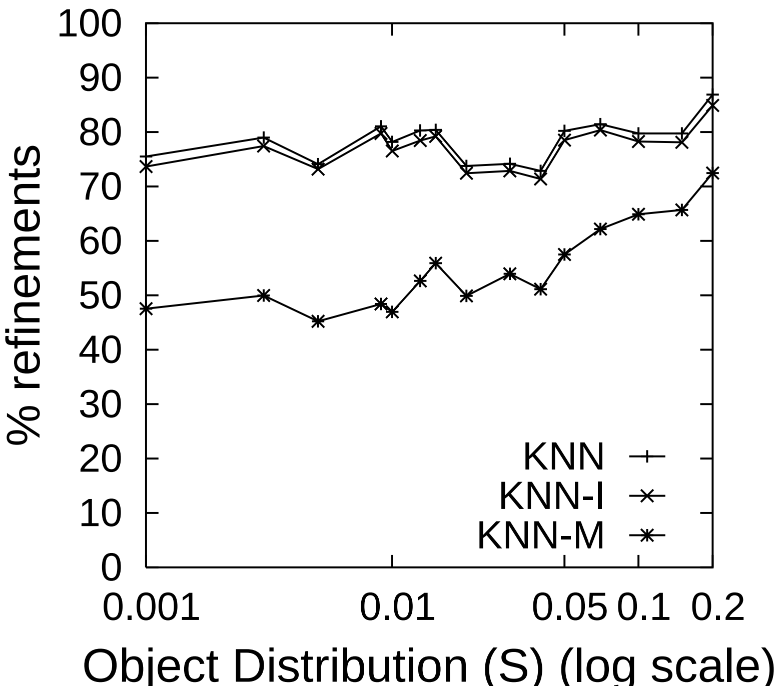


$S = 0.07N$ and varying k

- Compared maximum size of priority queue of kNN and variants with INN which cannot use D_k to reduce insertions
- 35% of INN on the average
- As k increases, savings in maximum queue size vanish
  - most likely due to an increase in the number of objects having overlapping distance intervals from q
  - Results in reducing pruning effectiveness of D_k

Number of Refinement Operations



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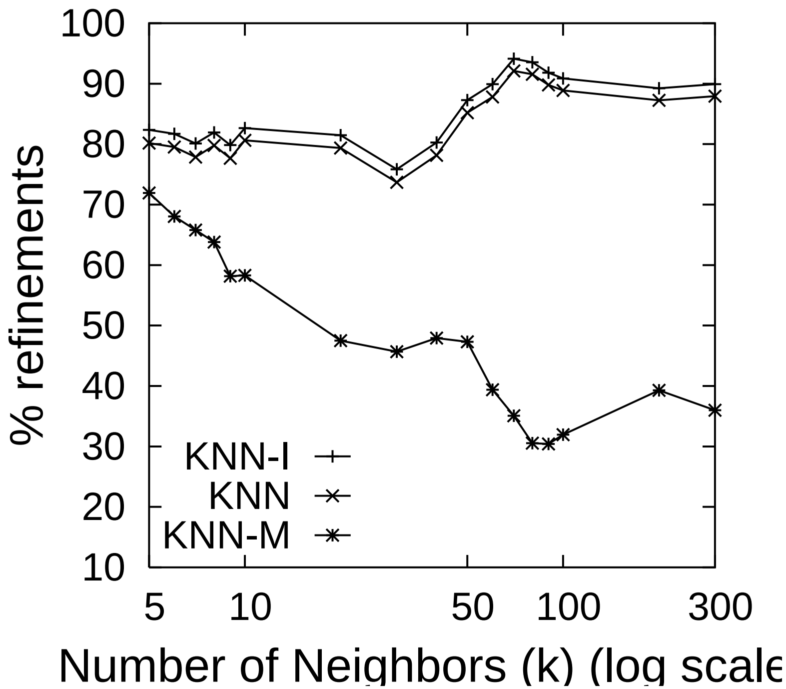
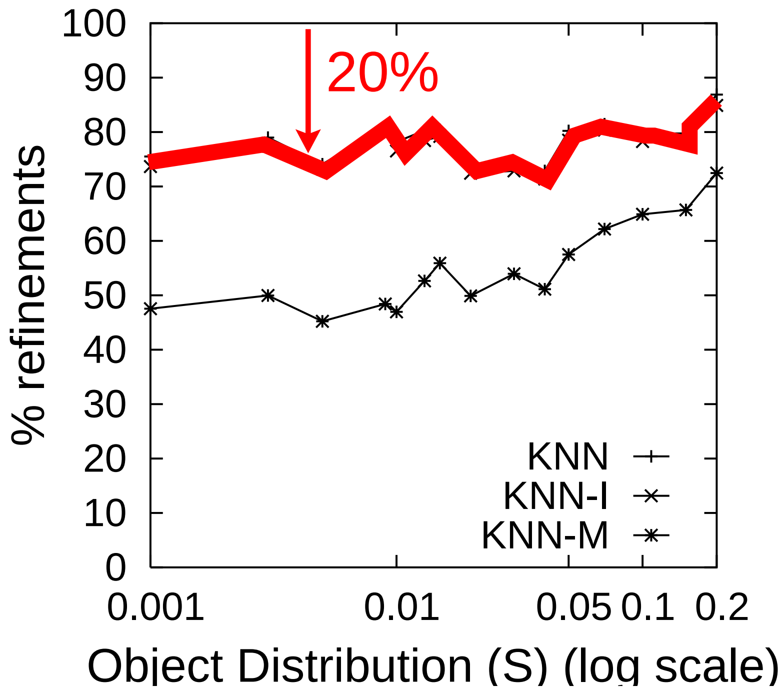


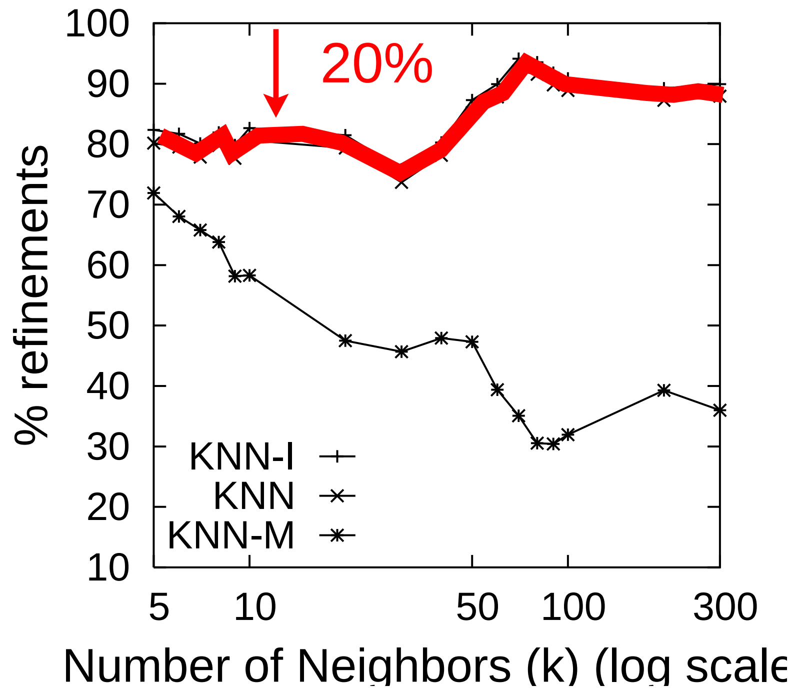
$S = 0.07N$ and varying k

- Compared reduction in refinements for

Number of Refinement Operations



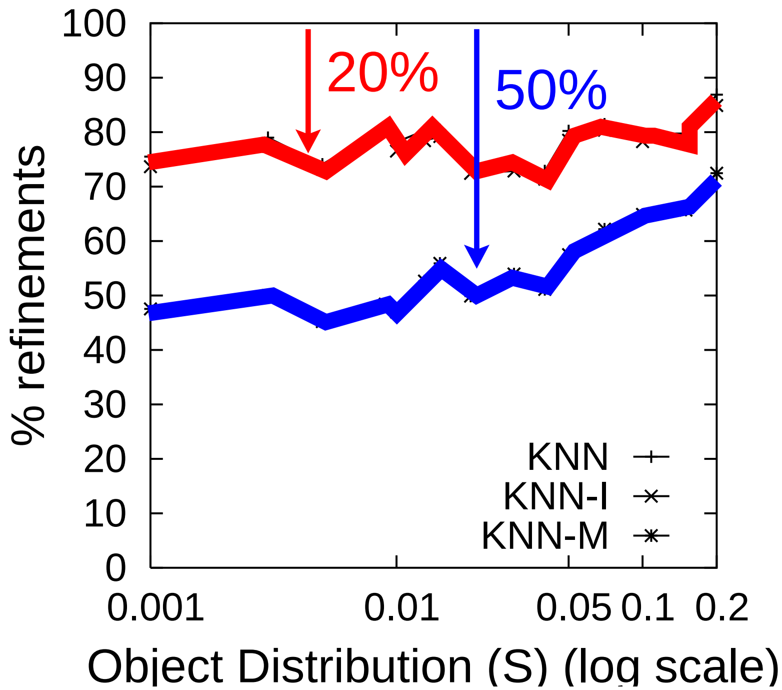
k=10 and varying sizes of S



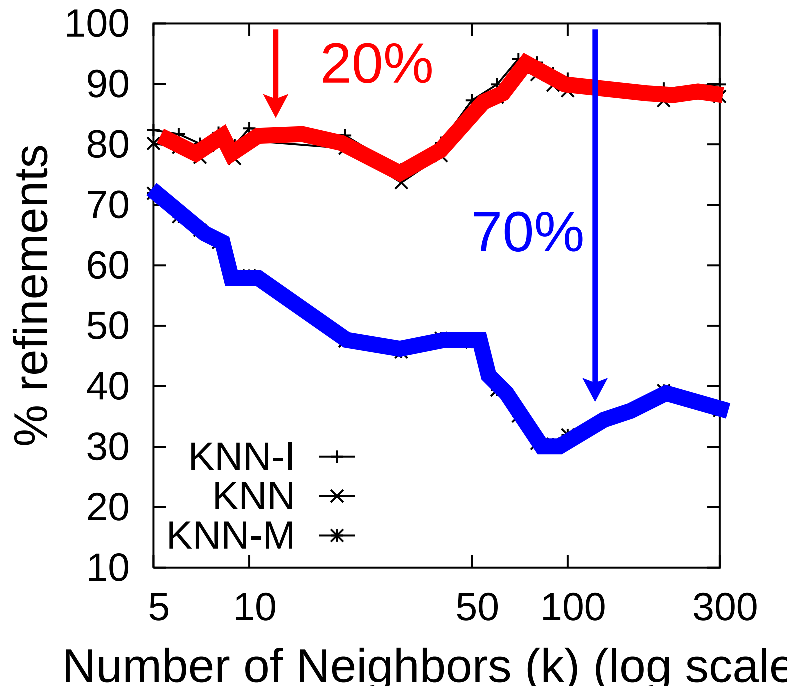
$S = 0.07N$ and varying k

- Compared reduction in refinements for kNN, kNN-I,

Number of Refinement Operations



k=10 and varying sizes of S



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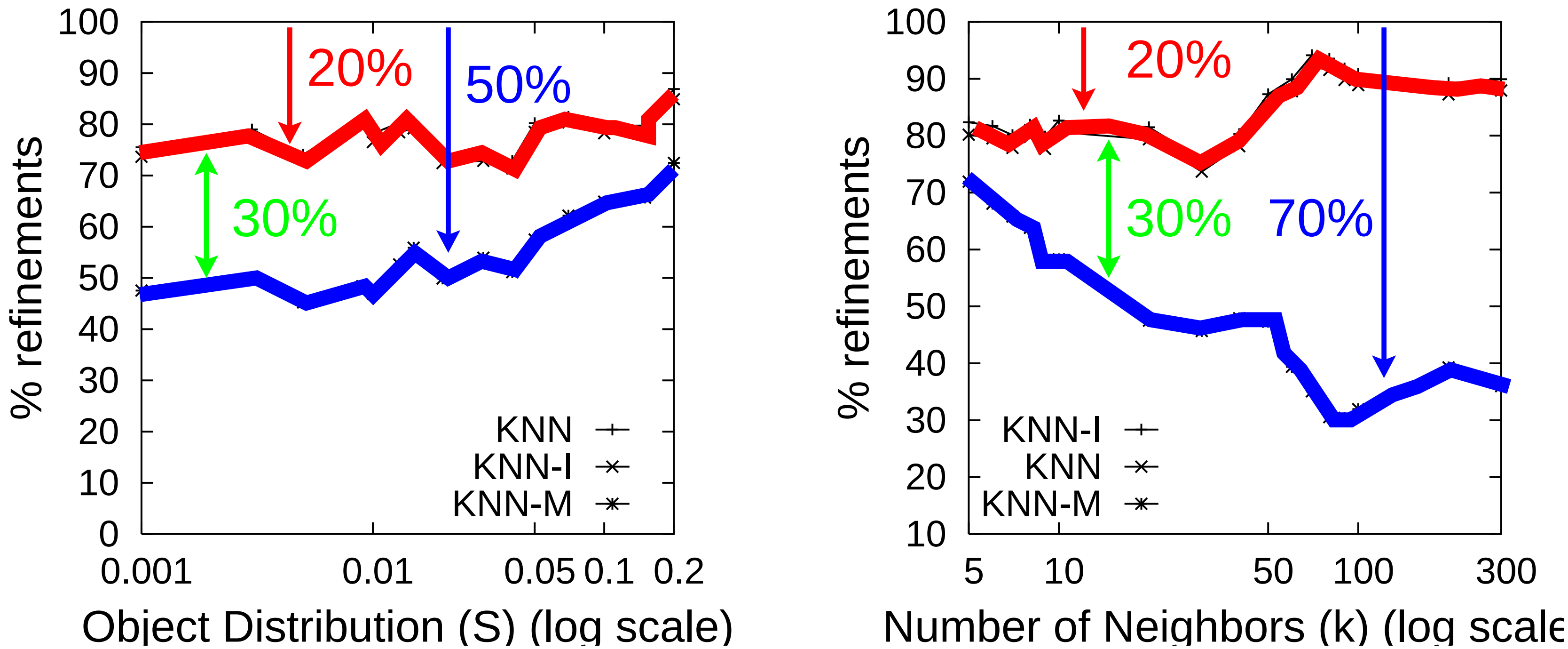
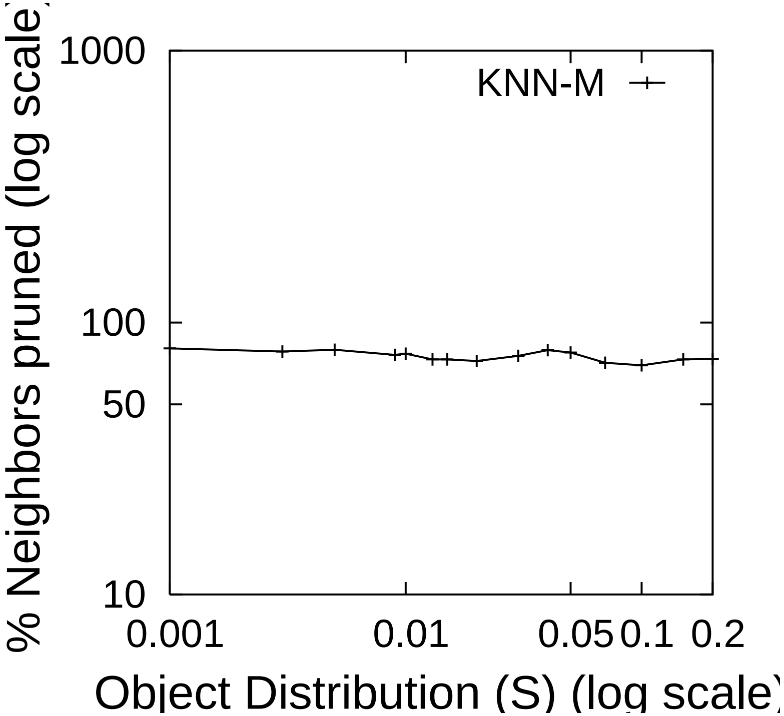


k=10 and varying sizes of S $\qquad$ $S = 0.07N$ and varying k

- Compared reduction in refinements for kNN, kNN-I, kNN-M with INN
- Large reduction for kNN-M which means that at least 30% of refinements in kNN are devoted to developing a total ordering

Roles of kMinDist in Pruning



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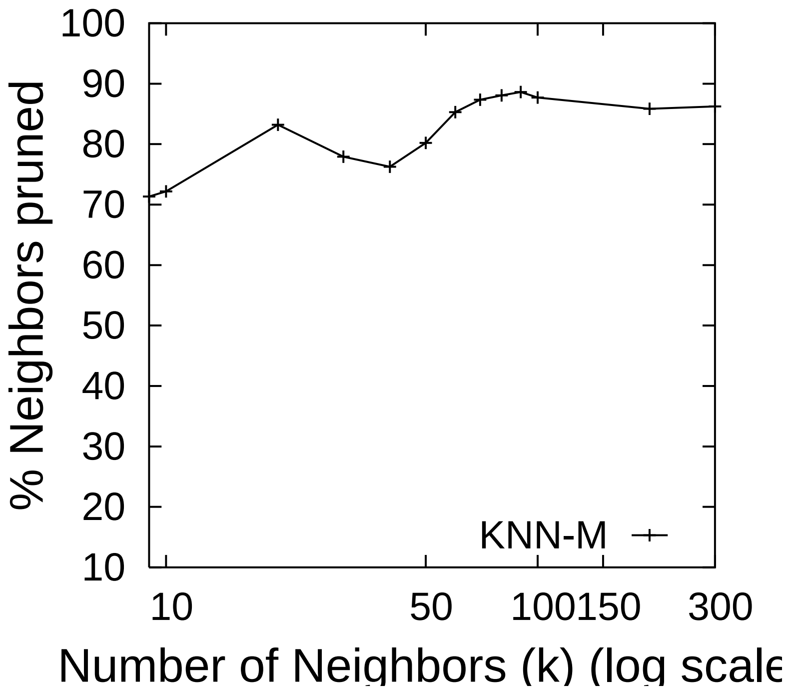

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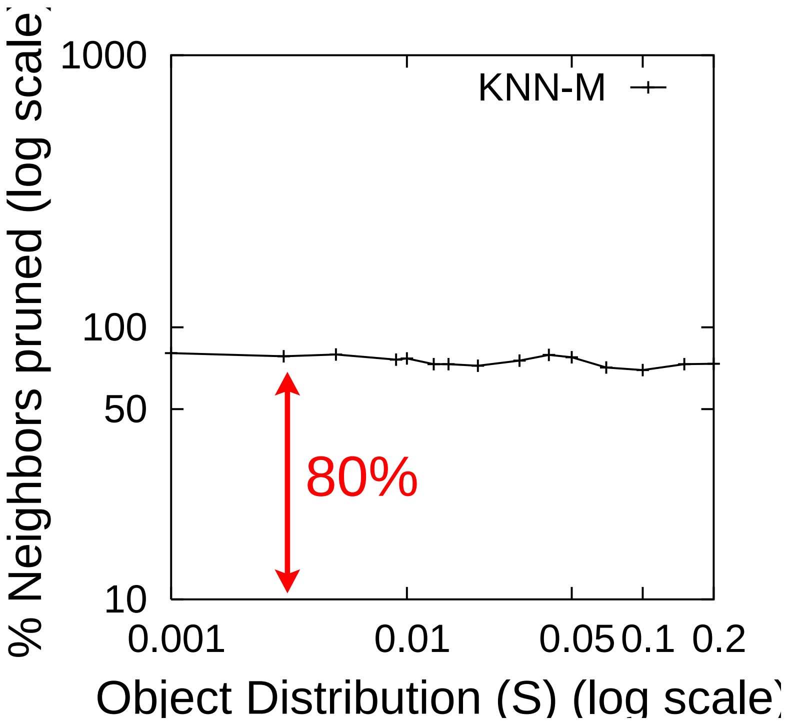
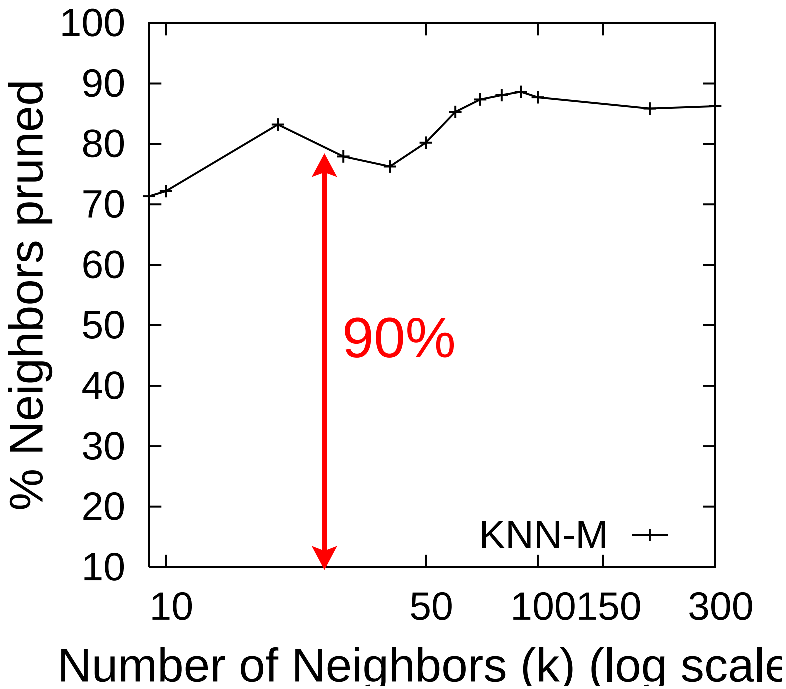


k=10 and varying sizes of S



$S = 0.07N$ and varying k

- Up to 90% of nearest neighbors in kNN-M were pruned against kMinDist
  - kMinDist yields minimum possible distance of $k\text{th}$ nearest neighbor
  - Means any object with $\delta^+ \leq$ kMinDist can be added directly to result
  - But output is no longer sorted

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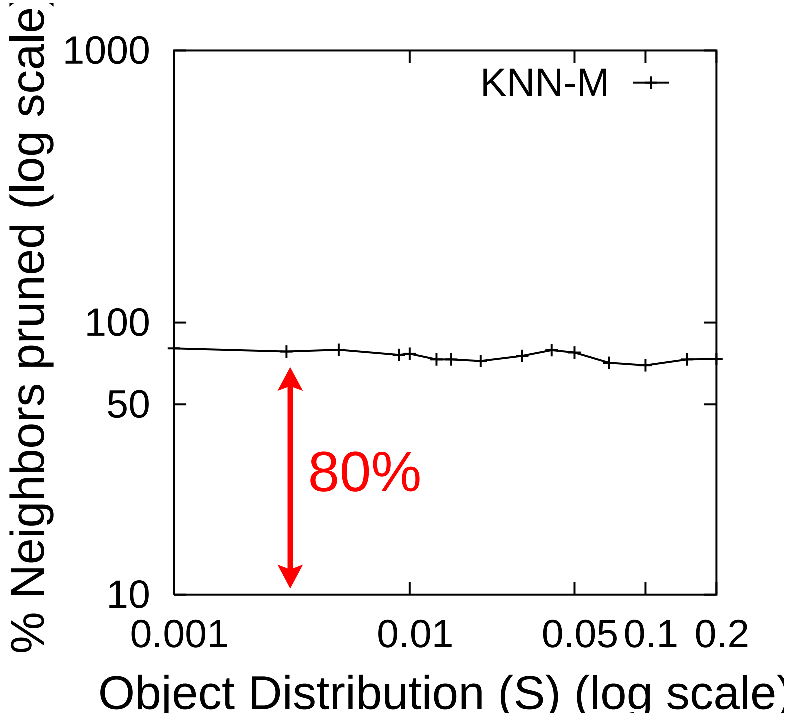

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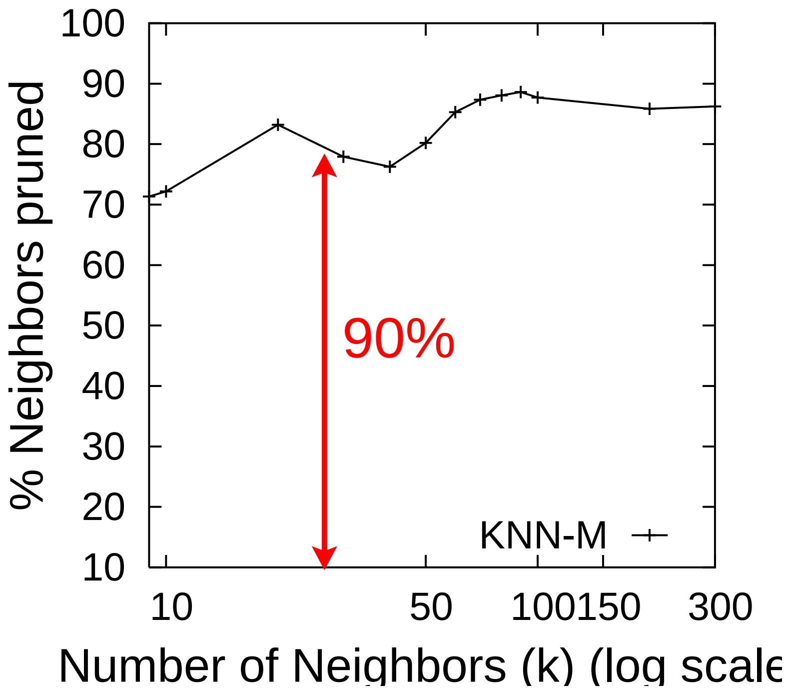

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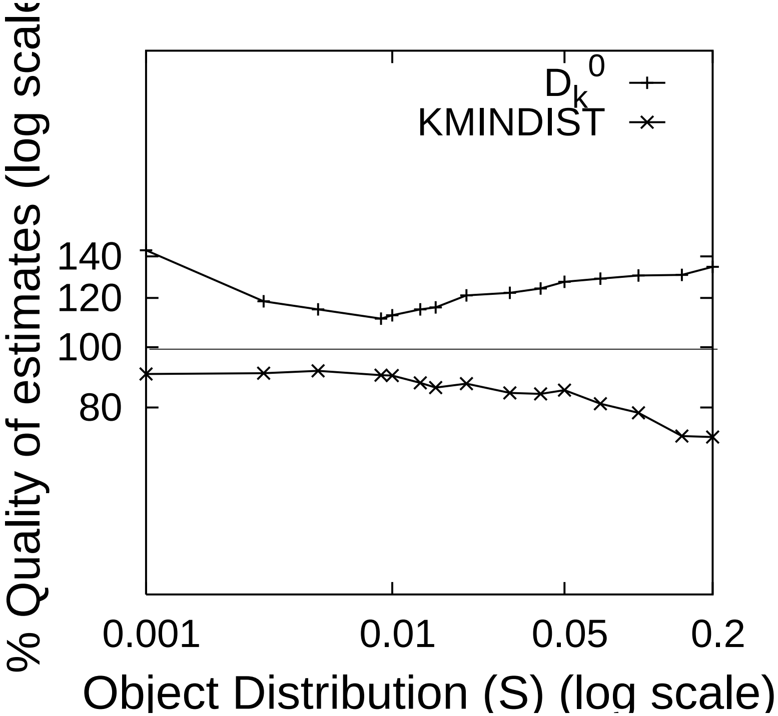
  - kMinDist yields minimum possible distance of $k\mathrm{th}$ nearest neighbor
  - Means any object with $\delta^+ \leq$ kMinDist can be added directly to result
  - But output is no longer sorted
- However, does not eliminate an equivalent number of refinements as most refinements are usually performed before pruning could take place

Role of KMINDIST and D_k^0 Vis-a-Vis D_k



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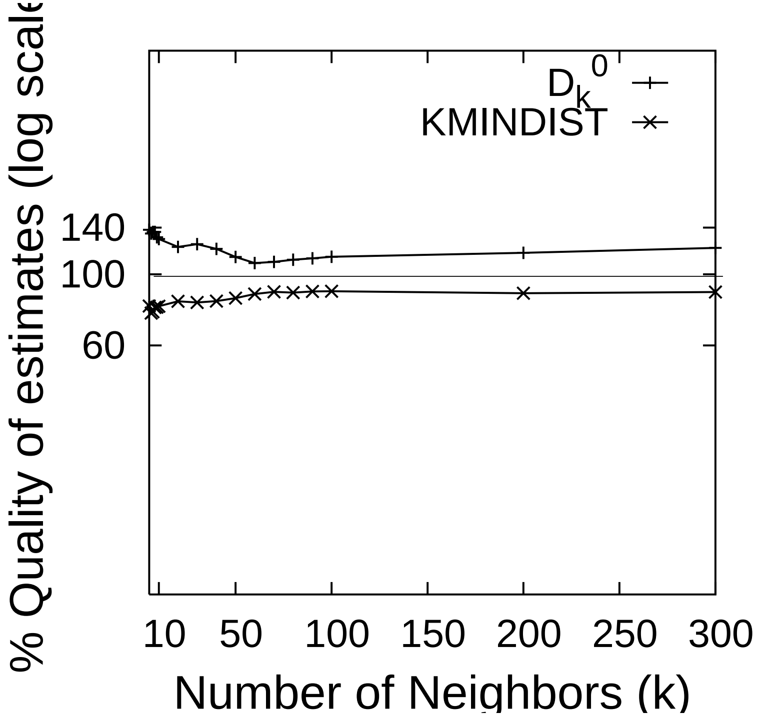

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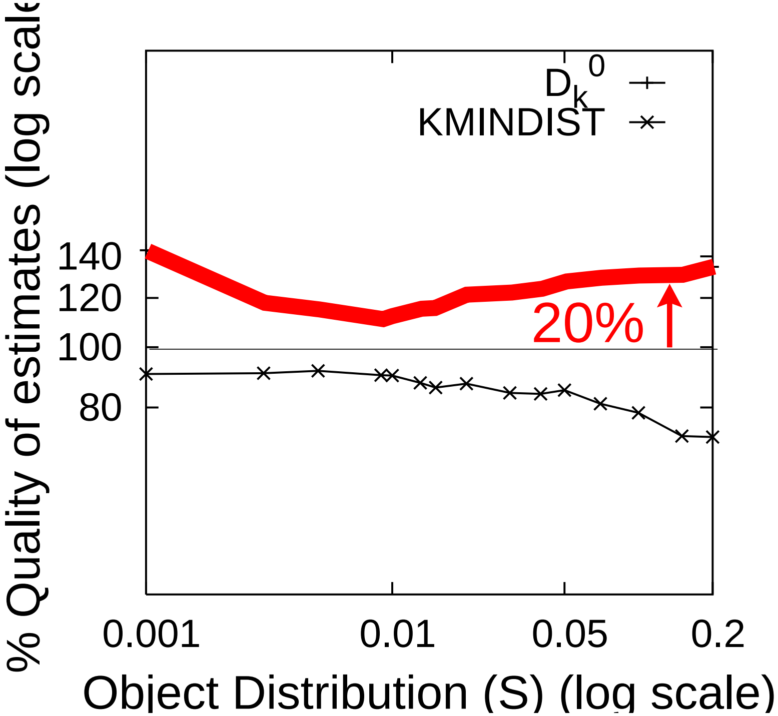

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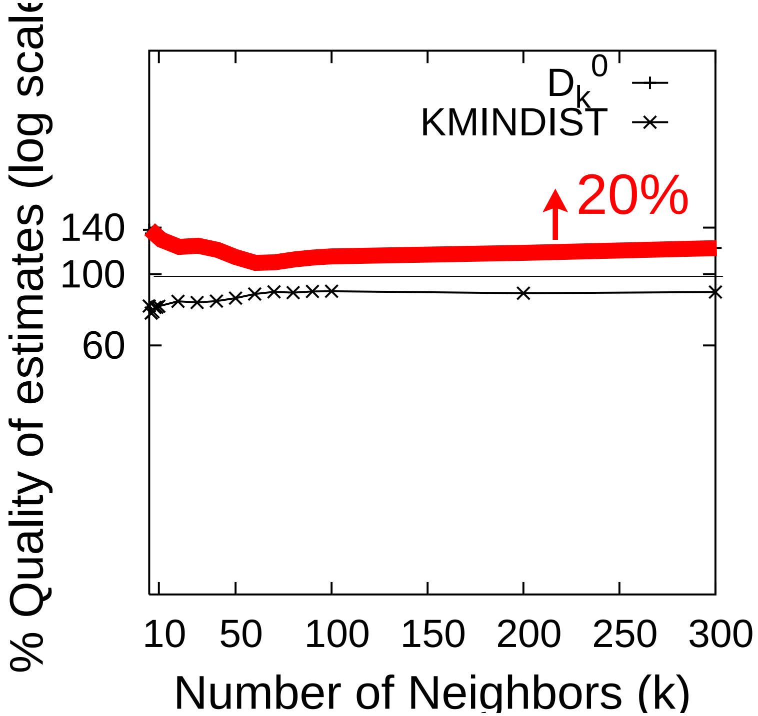

$S = 0.07N$ and varying k

- D_k^0 is about 20% larger than

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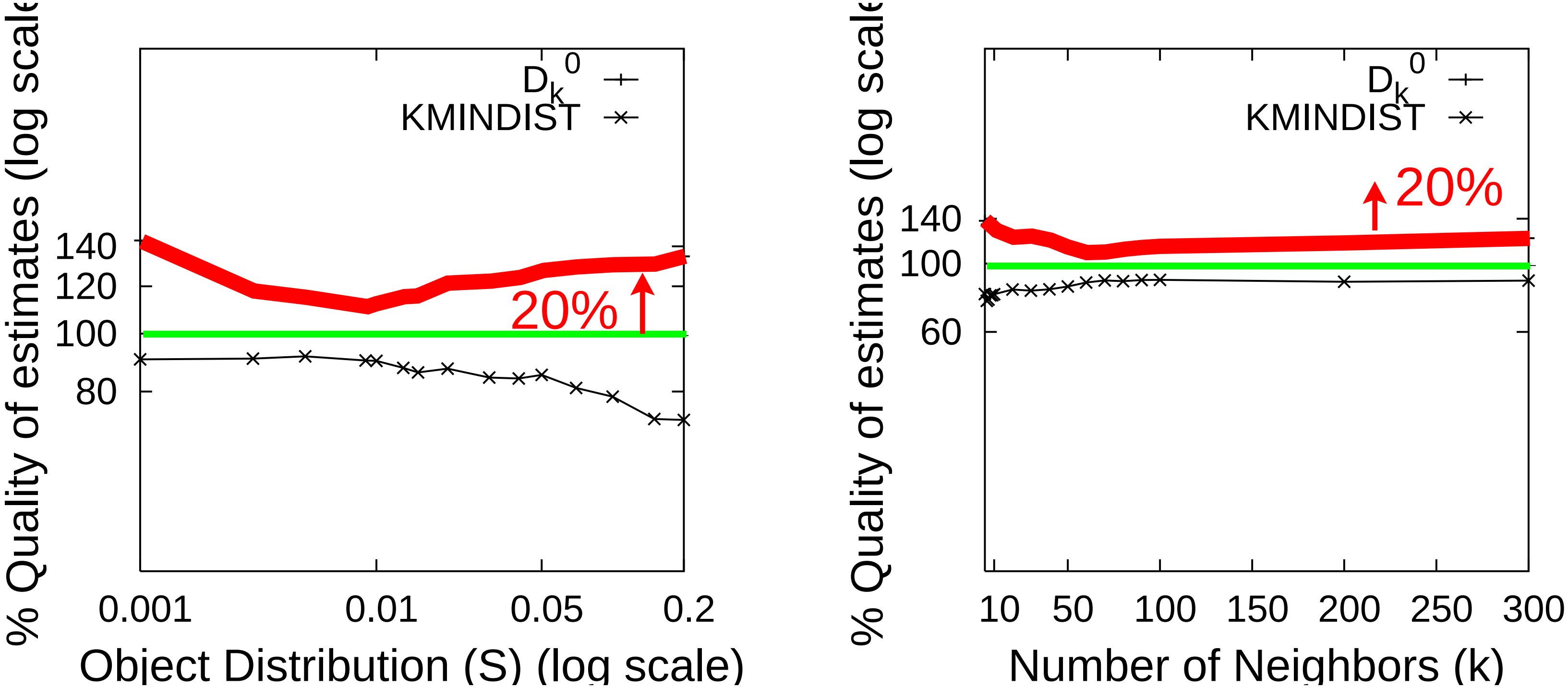

k=10 and varying sizes of S $\quad$ $S = 0.07N$ and varying k

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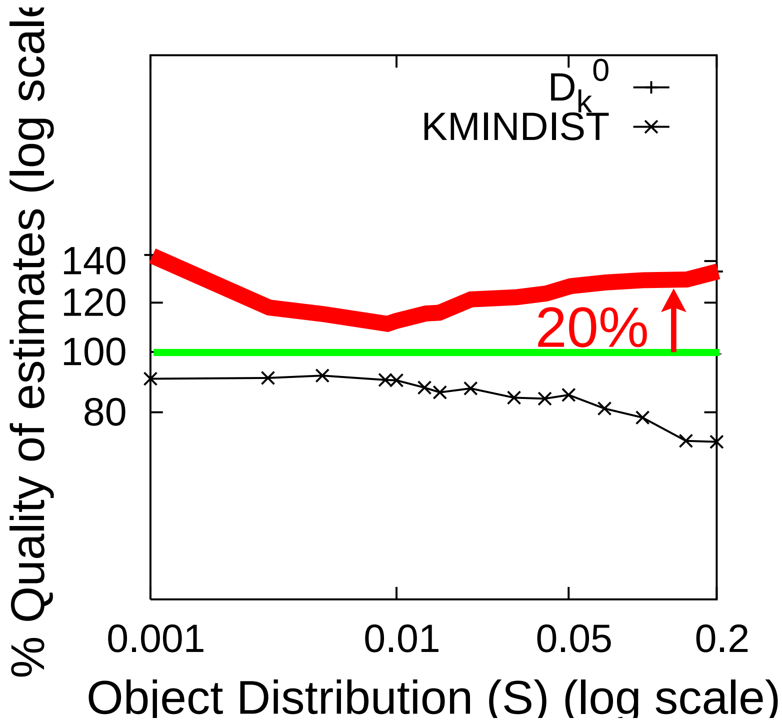

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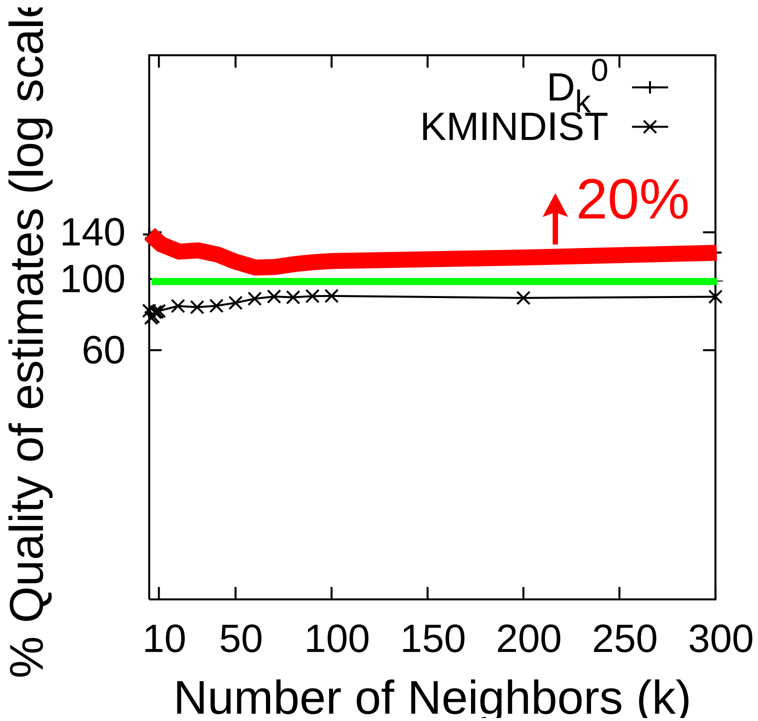

$S = 0.07N$ and varying k

- D_k^0 is about 20% larger than D_k
  - 20% means that D_k does not lead to much more pruning than D_k^0 explaining why the maximum sizes of the priority queues for kNN, kNN-I, and kNN-M are almost identical when compared to that for INN

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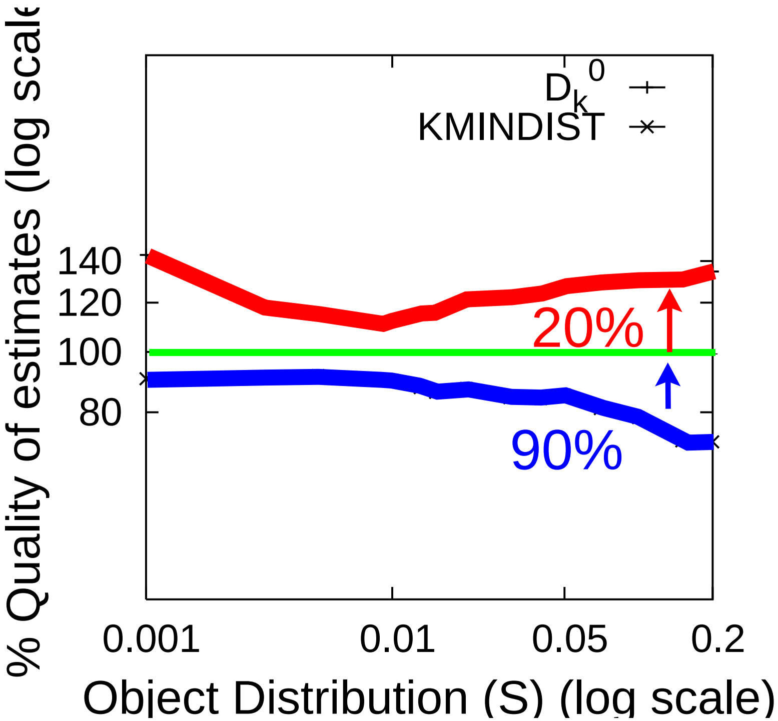

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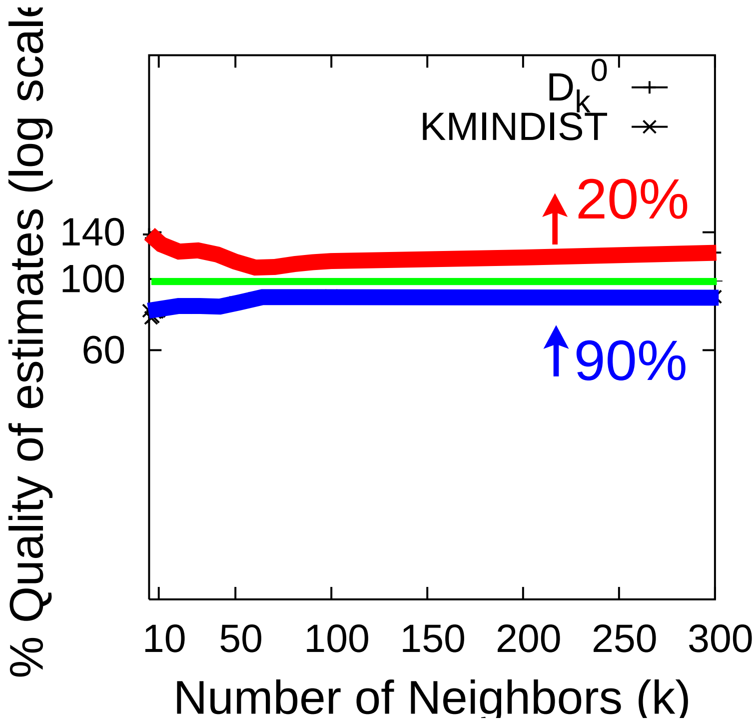

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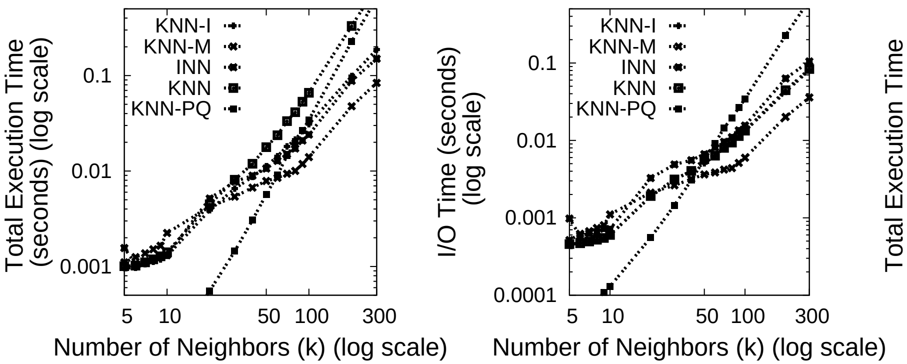
- KMINDIST is about 90% of D_k which may explain why many objects in kNN-M are added directly to the result set without need for further refinements (said to *pruned* against KMINDIST)

Comparison of kNN and variants



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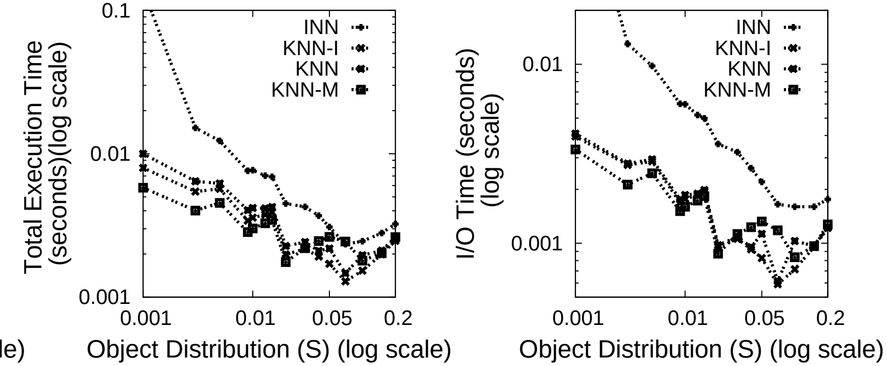

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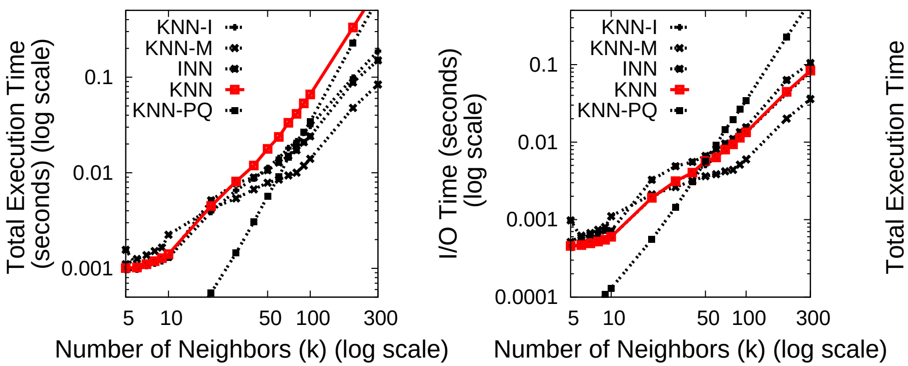

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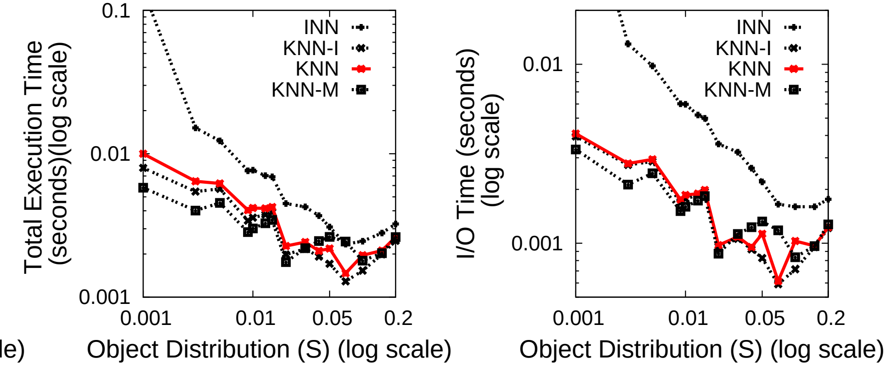

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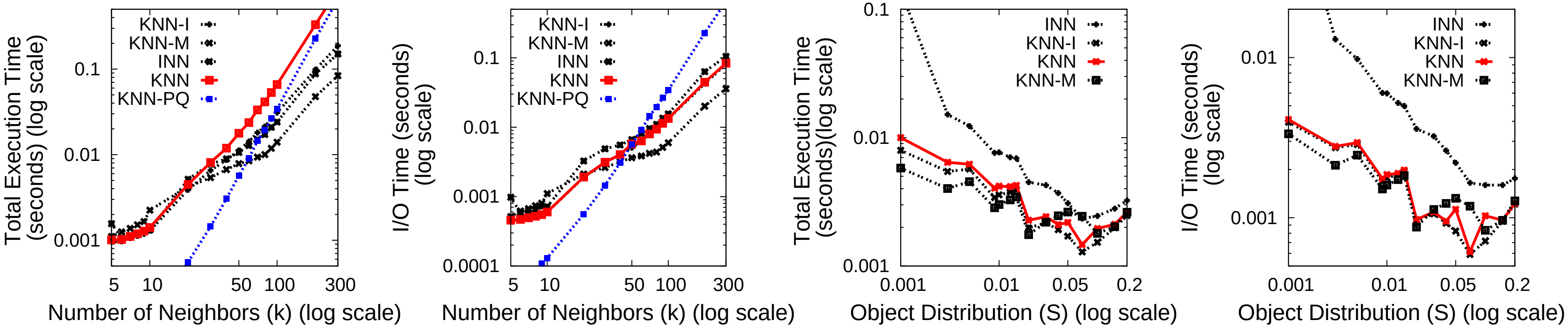

$S = 0.07N$ and varying k k=10 and varying sizes of S

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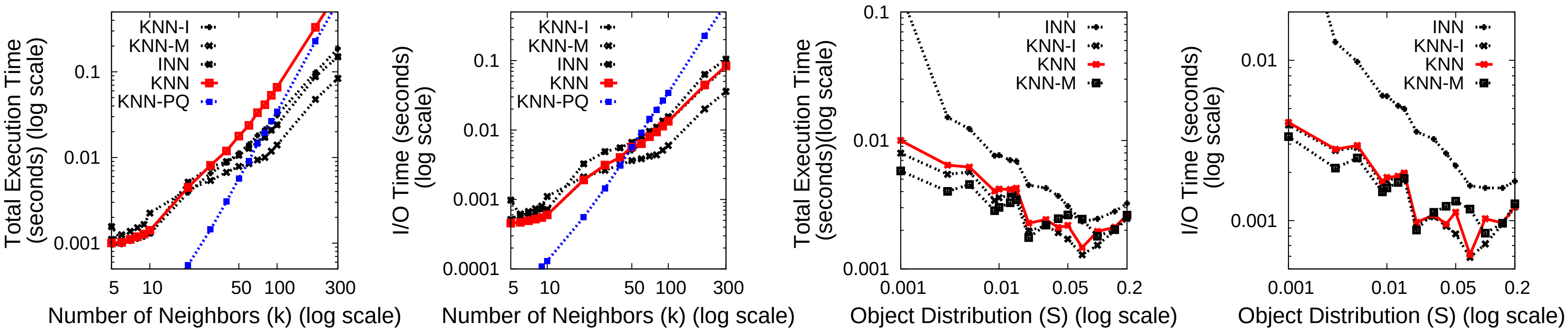

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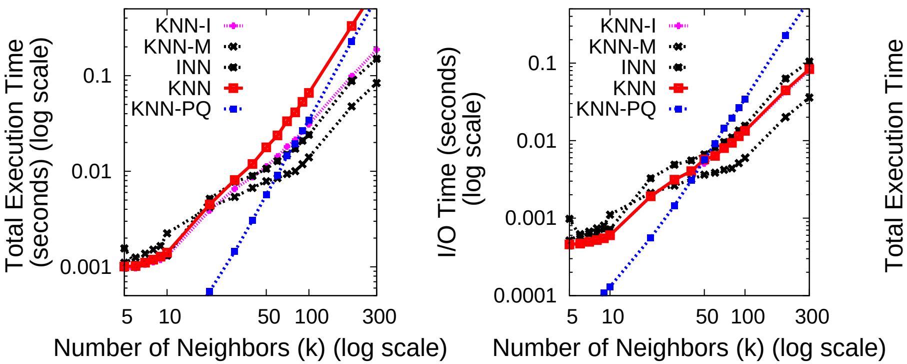

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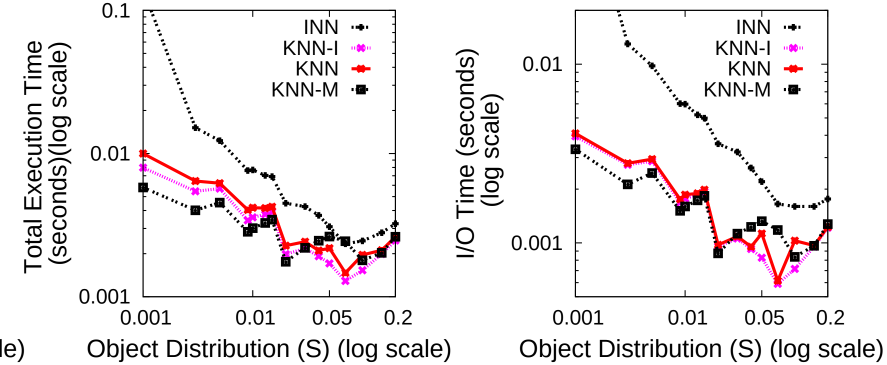

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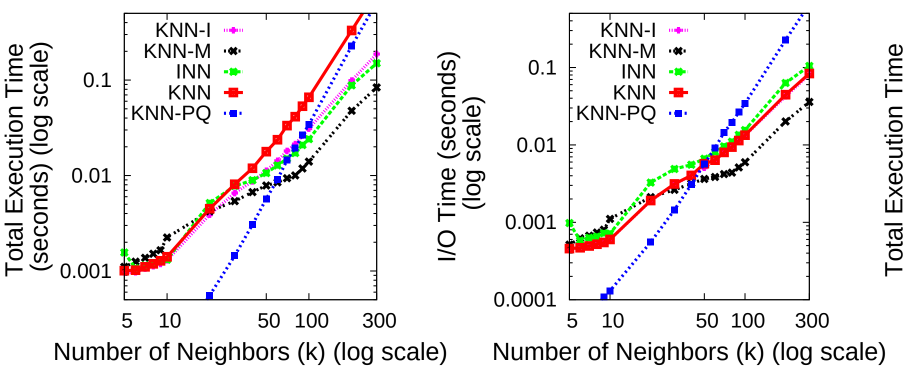

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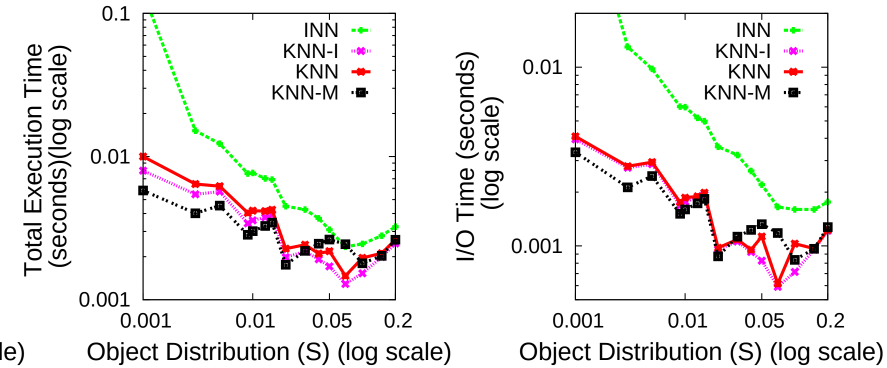

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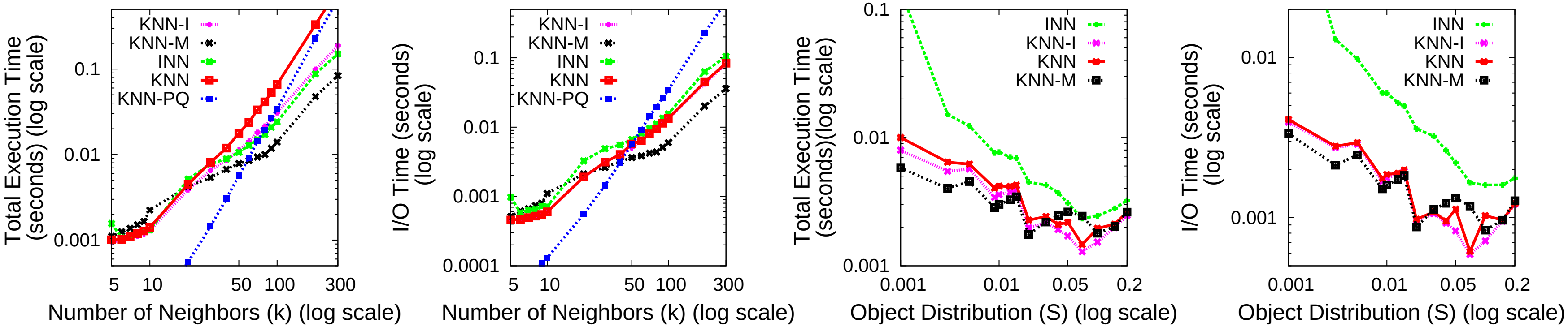

$S = 0.07N$ and varying k k=10 and varying sizes of S

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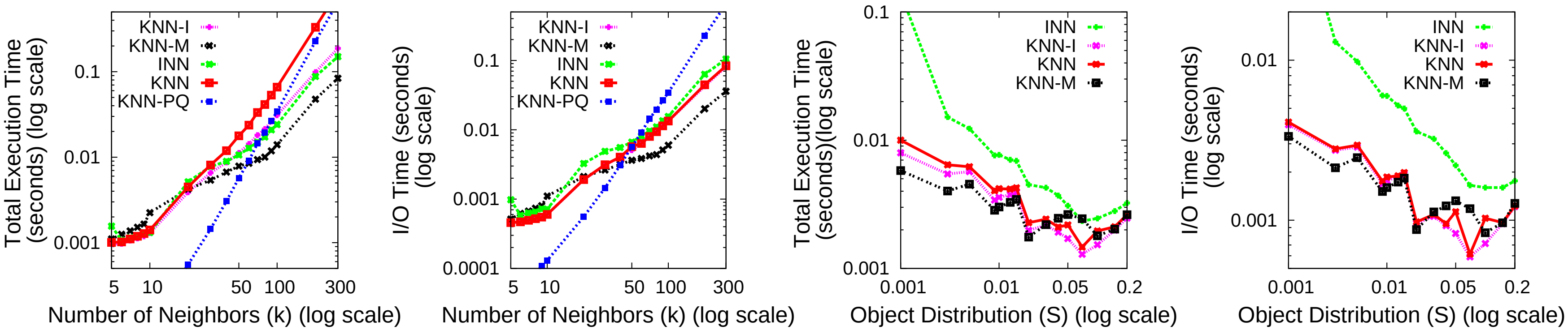

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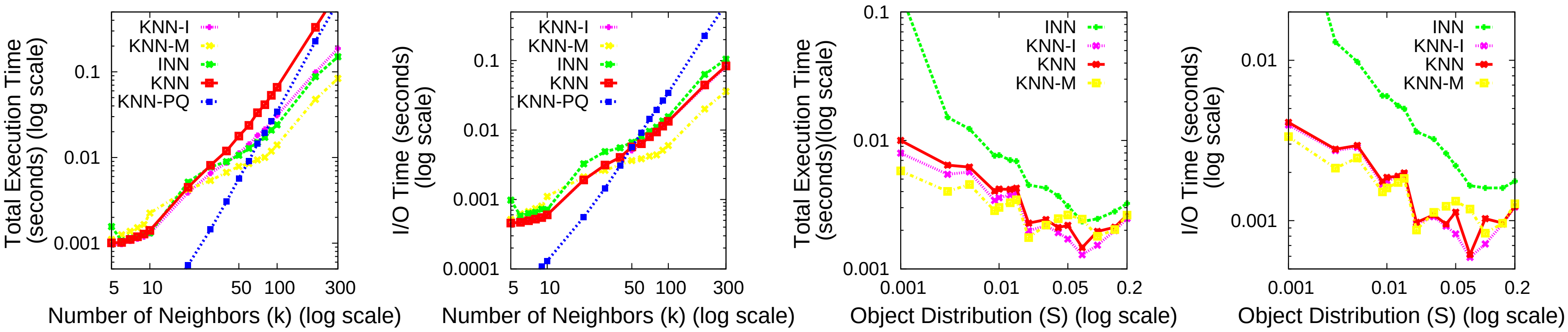
  - As k increases ($k > 20$), use kNN-I and INN as less or no manipulation of L
- I/O time dominates total execution time of kNN and variants
  - Each refinement may lead to a disk access

Comparison of kNN and variants



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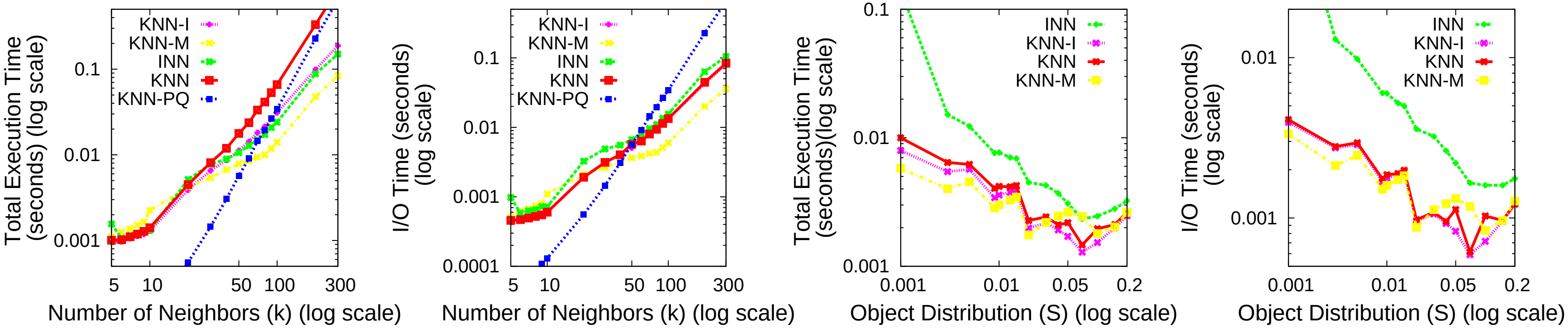
Comparison of kNN and variants



$S = 0.07N$ and varying k $\qquad$ k=10 and varying sizes of S

- Small value of k, kNN is best
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- Execution time for all variants of kNN decreases as size of S increases since objects are closer to query object and fewer refinement steps

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3. Precomputation and storage of shortest paths
4. k Nearest Neighbor Finding Algorithm
5. Experimental evaluation
6. Contributions
7. Future Work

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References

1. [Call95] P. B. Callahan and S. R. Kosaraju. Algorithms for dynamic closest pair and n-body potential fields. In *Proceedings of the 6th Annual ACM-SIAM Symposium on Discrete Algorithms*, pages 263–272, San Francisco, 1995.
2. [Filh02] G. G. Filho and H. Samet. A linear iterative approach for hierarchical shortest path finding. Computer Science Department CS-TR-4417, University of Maryland, College Park, MD, Nov. 2002.
3. [Gold05a] A. V. Goldberg and C. Harrelson. Computing the shortest path: A^* search meets graph theory. In *SODA '05: Proceedings of the 16th Annual ACM-SIAM Symposium on Discrete Algorithms*, pages 156–165, Vancouver, BC, Canada, Jan. 2005.
4. [Hjal95] G. R. Hjaltason and H. Samet. Ranking in spatial databases. In *SSD '95: Proceedings of the 4th International Symposium on Large Spatial Databases*, pages 83–95, Portland, ME, Aug. 1995.
5. [Hjal98] G. R. Hjaltason and H. Samet. Incremental distance join algorithms for spatial databases. In *SIGMOD '98: Proceedings of the International Conference on Management of Data*, pages 237–248, Seattle, WA, June 1998.

References

6. [Jing98] N. Jing, Y.-W. Huang, and E. A. Rundensteiner. Hierarchical encoded path views for path query processing: an optimal model and its performance evaluation. ons of Multidimensional and Metric Data Structures. Morgan-Kaufmann, San Francisco, CA, 2005.
7. [Papa03] D. Papadias, J. Zhang, N. Mamoulis, and Y. Tao. Query processing in spatial network databases. In *VLDB'03: Proceedings of the 29th International Conference on Very Large Databases*, pages 802–813, Berlin, Germany, Sept. 2003.
8. [Same05] H. Samet. *Foundations of Multidimensional and Metric Data Structures*. Morgan-Kaufmann, San Francisco, CA, 2005.
9. [Shah03] C. Shahabi, M. R. Kolahdouzan, and M. Sharifzadeh. A road network embedding technique for k-nearest neighbor search in moving object databases. *GeoInformatica*, 7(3):255–273, Sept. 2003.
10. [Shin00] H. Shin, B. Moon, and S. Lee. Adaptive multi-stage distance join processing. In *SIGMOD '00: Proceedings of the International Conference on Management of Data*, pages 343–354, Dallas, TX, May 2000.
11. [Wagn03] D. Wagner and T. Willhalm. Geometric speed-up techniques for finding shortest paths in large sparse graphs. In *ESA '03: Proceedings of the 11th Annual European Symposium on Algorithms*, pages 776–787, Budapest, Hungary, Sept. 2003.

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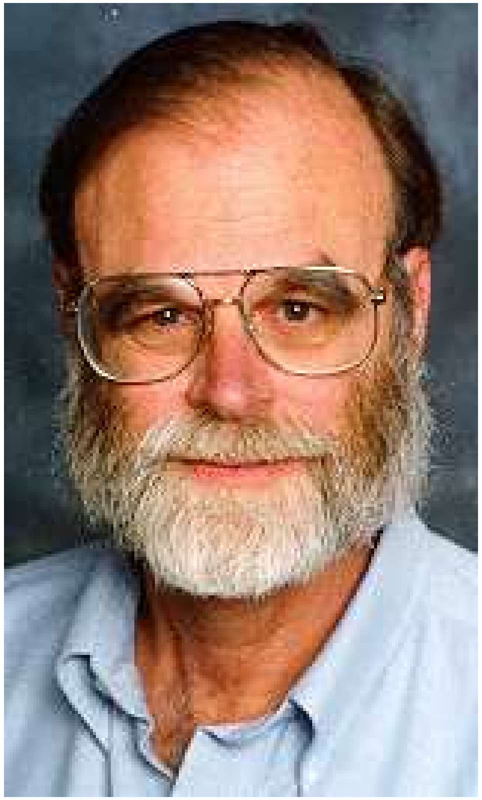

Questions and Comments?

Thank you!