Temporal and Spatial Data Management
Fall 2017

Query Processing in Spatial Network Databases
SL06

- Spatial network databases
- Shortest Path
- Incremental Euclidean Restriction
- Incremental Network Expansion

Spatial Network Databases (SNDB)/1

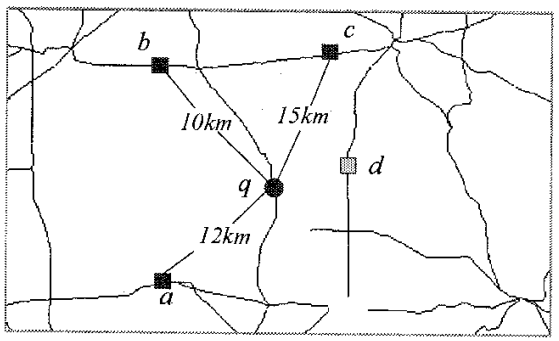
Definition (Spatial network databases)

In a **spatial network database** objects can move only on pre-defined trajectories as specified by the underlying network (representing e.g., roads, railways, rivers, etc.)

- The distance between two objects is the shortest trajectory between the two rather than the Eucledian distance

Example

- Query "Find the hotels within a 15km range" returns $\{a, b, c\}$
- Query "Find the closest hotel" returns $\{b\}$
  - Eucledian nearest neighbor is d (which is the farest in the network)



Spatial Network Databases (SNDB)/2

Definition (Network distance)

- For each edge connecting n_i and n_j, the network distance, $d_N(n_i, n_j)$, is stored with the edge.
- For nodes n_i and n_j that are not directly connected, the network distance, $d_N(n_i, n_j)$, is the length of the shortest path from n_i to n_j.

Euclidean Lower-Bound Property: For any two nodes, the Euclidean distance, $d_E(n_i, n_j)$, lower bounds the network distance, $d_N(n_i, n_j)$, i.e.,

$$d_E(n_i, n_j) \leq d_N(n_i, n_j)$$

Shortest Path

- Much of the work on spatial network databases is on **shortest path**, **nearest neighbor** and **range search**.
- Dijkstra's incremental network expansion is a greedy algorithm and the most basic solution to the shortest path problem.
- Dijkstra's algorithm influenced much of the later work in spatial network databases.

- Starting point: directed weighted graph
- $G = (V, E)$ with weight function $W : E \rightarrow \mathbb{R}$
- Weight of path $p = v_1 \rightarrow v_2 \rightarrow ... \rightarrow v_k$ is

$$w(p) = \sum_{i=1}^{k-1} w(v_i, v_{i+1})$$

- Shortest path = a path of minimum weight (cost)

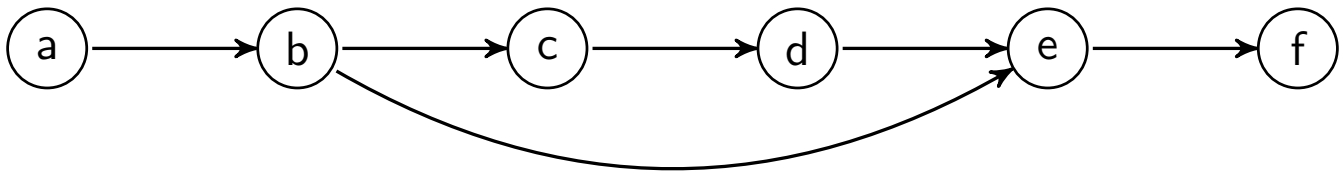
Shortest Path Problems

- **Single-source**
  Find a shortest path from a given source vertex s to all other vertices.
- **Single-pair**
  Given two vertices, find a shortest path between them. Solution to single-source problem solves this problem efficiently, too.
- **All-pairs**
  Find shortest-paths for every pair of vertices. Dynamic programming algorithm.
- **Unweighted shortest-paths**
  BFS.

Optimal Substructure

- **Theorem**:
  Subpaths of shortest paths are shortest paths

- Proof: if some subpath were not the shortest path, one could substitute the shorter subpath and create a shorter total path

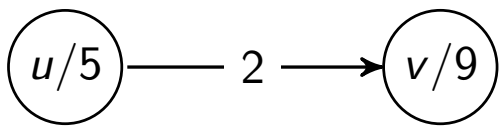


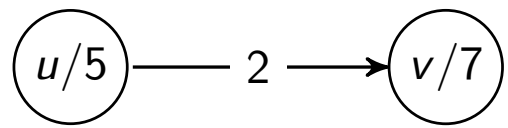
Shortest Path Tree

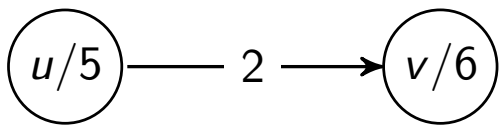
- The result of the algorithms is a **shortest path tree**.
  For each vertex v it
  - records a shortest path from the start vertex s to v
  - v.pred is the predecessor of v in this shortest path
  - v.dist is the shortest path length from s to v

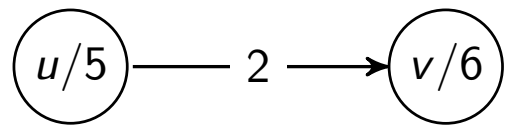
Relaxation

- For each vertex v in the graph, we maintain v.dist, the estimate of the shortest path from s. It is initialized to ∞ at the start.
- Relaxing an edge (u,v) means testing whether we can improve the shortest path to v found so far by going through u.







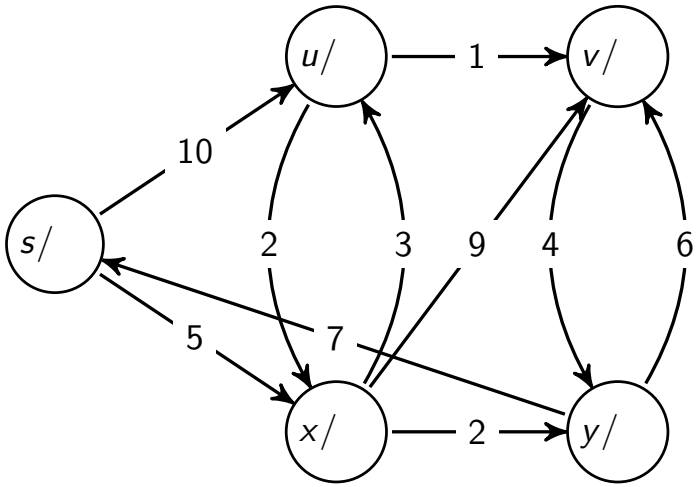


Dijkstra's Algorithm

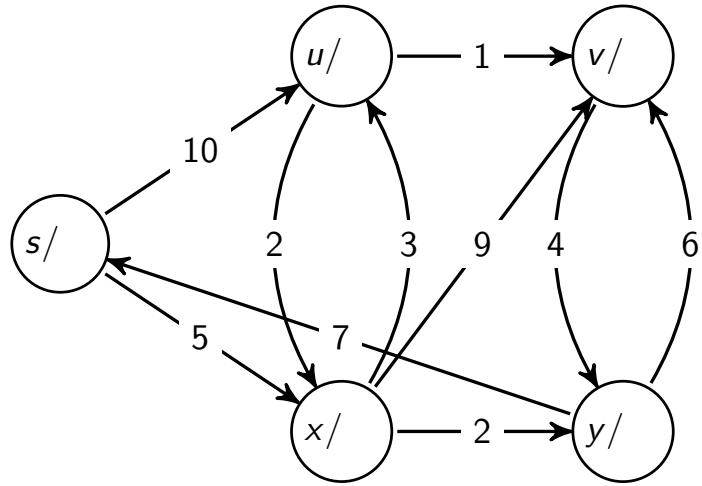
- Basic idea of Dijkstra's algorithm:
  - maintains a set S of solved vertices
  - at each step select closest vertex u, add it to S, and relax all edges from u
- Greedy algorithm that gives optimal solution
- Similar to breadth-first search (if all weights $= 1$ then one can simply use BFS)
- Use a priority queue Q with keys v.dist, which is re-organized whenever some dist decreases

Dijkstra's Algorithm

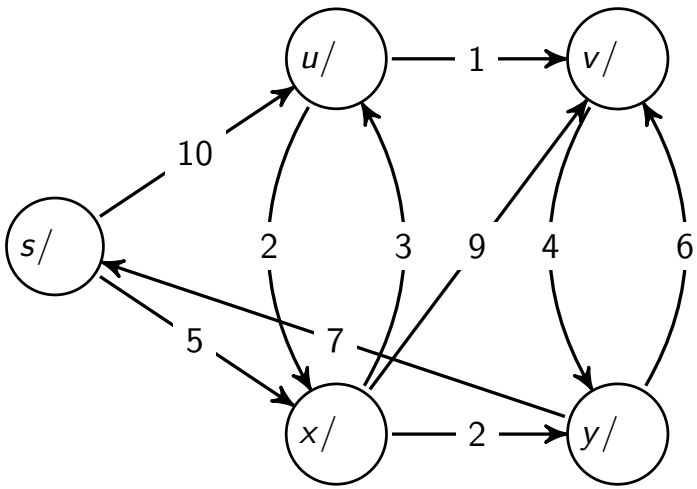
```
foreach u ∈ G.V do
    u.dist := ∞ ;
    u.pred := NIL;
s.dist := 0;
init(Q, G.V) // priority queue Q;
while ¬isEmpty(Q) do
    u := extractMin(Q);
    foreach v ∈ u.adj do
        Relax(u, v, G);
        modifyKey(Q, v);
```



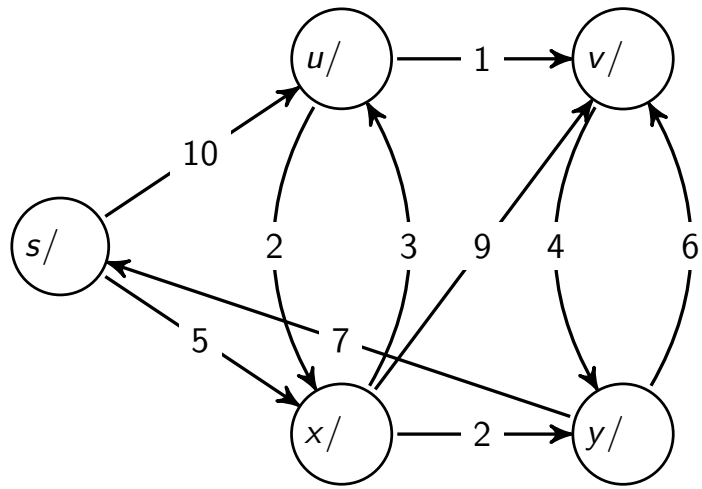
$Q = \{s(0,-), u(\infty,-), u(\infty,-),$
$u(\infty,-), u(\infty,-)\}$



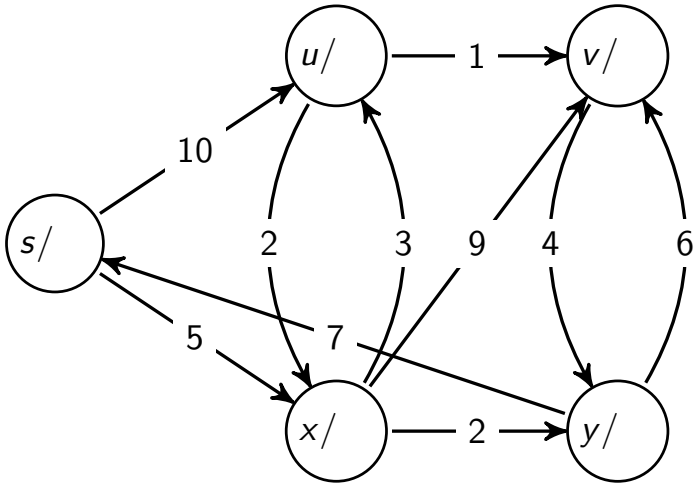
$Q = \{x(5,s), u(10,s), v(\infty,-), y(\infty,-)\}$



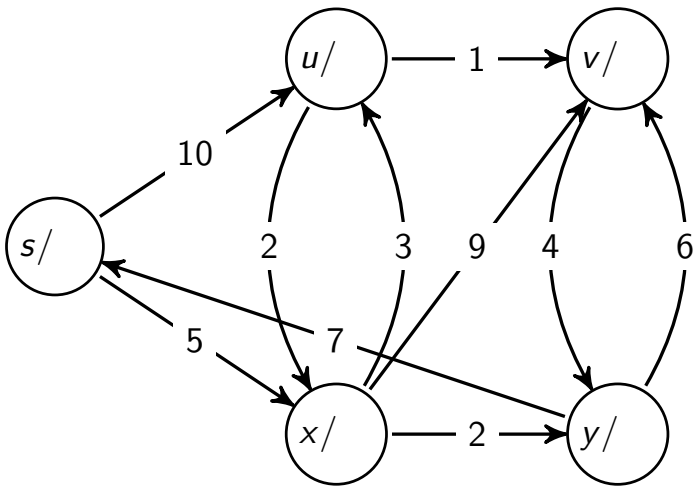
$Q = \{y(7,x), u(8,x), v(14,x)\}$



$Q = \{u(8,x), v(13,x)\}$



$Q = \{y(9, u)\}$



$Q = \{\}$

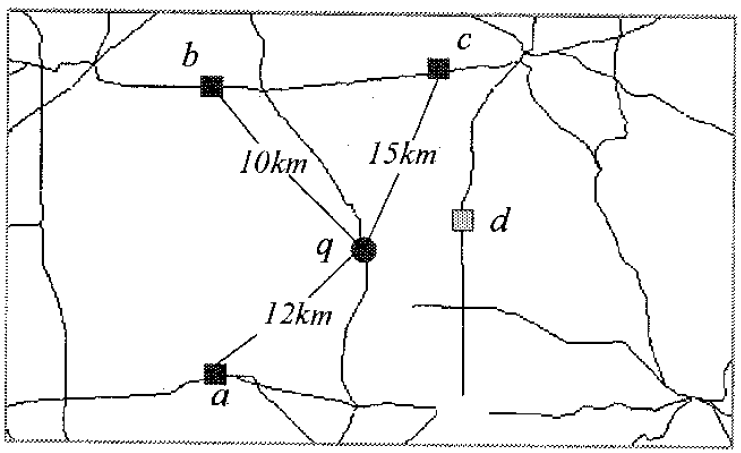
Nearest Neighbors in SNDB

Definition

Given a source point q and an entity dataset S, a k-**nearest neighbor** (kNN) query retrieves the k (≥ 1) objects of S closest to q according to the network distance.

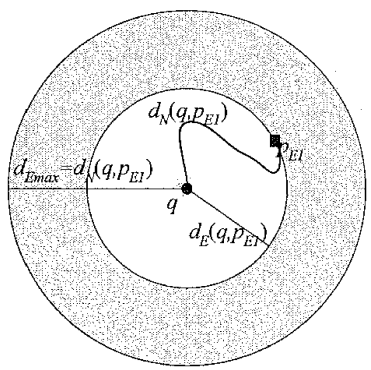
Example

- $S = \{a, b, c, d\}$
- 1-NN is $\{b\}$
- 2-NN is $\{b, a\}$

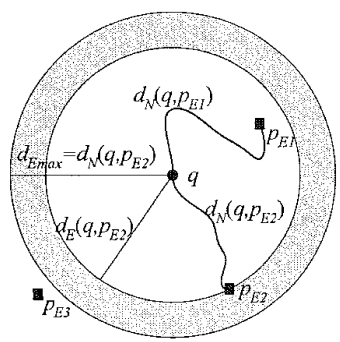


Incremental Euclidean Restriction (IER)/1

- Applies the Euclidean distance to reduce the search space in combination with the Euclidean lower bound
- Basic idea for 1-NN search
  - Retrieve the Euclidean NN p_{E1} using an incremental kNN algorithm on the R-tree built on S
  - Compute the network distance $d_N(q, p_{E1})$
  - Due to the lower-bound property, objects closer to q should be within Euclidean distance $d_{Emax} = d_N(q, p_{E1})$ (shaded area in figure below).
  - The second Euclidean NN, p_{E2}, is retrieved with $d_N(q, p_{E2}) < d_N(q, p_{E1})$; thus p_{E2} becomes the new NN and $d_{Emax} = d_N(q, p_{E2})$.
  - Repeat last step until no more Eulidean NN is found in search region.



(a) 1st Euclidean NN



(a) 2nd Euclidean NN

Incremental Euclidean Restriction (IER)/2

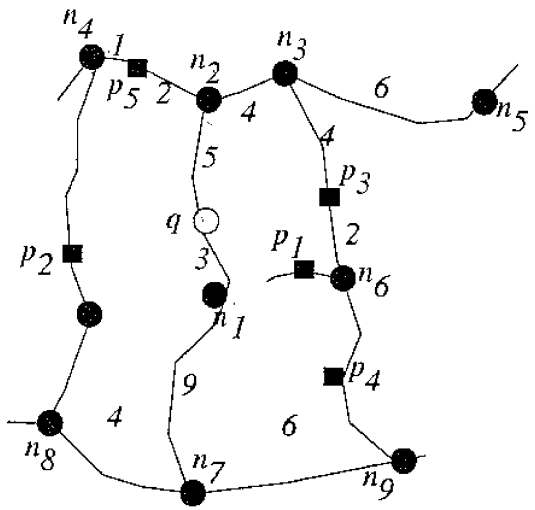
$\{p_1, \ldots, p_k\} = Euclidean\_NN(q, k)$;
foreach *entity* p_i **do**
  $d_N(q, p_i) = compute\_ND(q, p_i)$;
Sort $\{p_1, \ldots, p_k\}$ in ascending order of $d_N(q, p_i)$;
$d_{Emax} = d_N(q, p_k)$;
repeat
  $(p, d_E(q, p)) = next\_Euclidean\_NN(q)$;
  if $d_N(q, p) < d_N(q, p_k)$ **then**
    Insert p in $\{p_1, \ldots, p_k\}$;
    $d_{Emax} = d_N(q, p_k)$;
until $d_N(q, p) > d_{Emax}$;

Incremental Euclidean Restriction (IER)/3

- IER performs well if Euclidean distance is similar to network distance; otherwise, many Euclidean NNs are inspected before the network NN.

Example

- The nearest entity to query point q is the entity p_5
- The subscripts in $p_1, \ldots, p_5$ are in ascending order of $d(q, p_i)$
- p_5 will be examined after $p_1, \ldots, p_4$, since it has the largest Euclidean distance

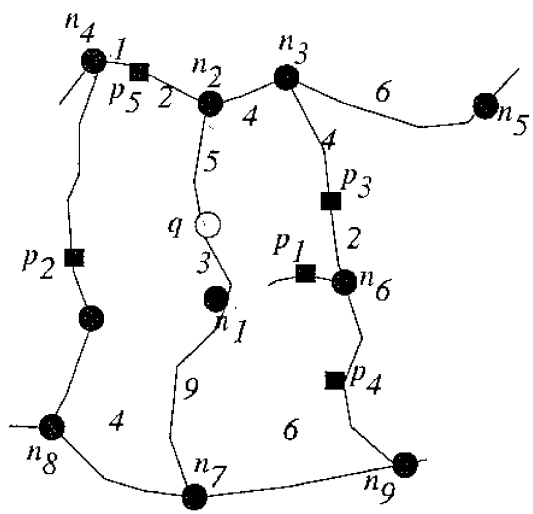


Incremental Network Expansion (INE)/1

- Performs network expansion starting from query point q and examines entities in the order they arrive
- Nodes not yet explored are stored in a queue Q which is sorted according to the network distance from q

Example

- Locate the edge (n_1, n_2) that covers q and add n_1 and n_2 to the queue; $Q = \{(n_1, 3), (n_2, 5)\}$.
- No entity is on (n_1, n_2), and the closest node n_1 is expanded; $Q = \{(n_2, 5), (n_7, 12)\}$
- No entity is on (n_1, n_7) and n_2 is expanded; $Q = \{(n_4, 8), (n_3, 9), (n_7, 12)\}$
- p_5 is discoverd on (n_2, n_4)
- $d_N(q, p_5) = 7$ provides a bound to restrict the search space



Incremental Network Expansion (INE)/2

Algorithm: INE(q, k)
$n_i n_j = find\_segment(q)$;
$S_{cover} = find\_entities(n_i n_j)$;
$\{p_1, \ldots, p_k\}$ = the k network nearest entities in S_{cover};
Sort $\{p_1, \ldots, p_k\}$ in ascending order of $d_N(q, p_i)$;
if $p_k \neq \emptyset$ **then** $d_{Nmax} = d_N(q, p_k)$;
else $d_{Nmax} = \infty$;
$Q = \langle (n_i, d_N(q, n_i)), (n_j, d_N(q, n_j)) \rangle$;
De-queue the node n in Q with the smallest $d_N(q, n)$;
while $d_N(q, n) < d_{Nmax}$ **do**
  foreach *non-visited adjacent node* n_x *of* n **do**
    $S_{cover} = find\_entities(n_x n)$;
    Update $\{p_1, \ldots, p_k\}$ from $\{p_1, \ldots, p_k\} \cup S_{cover}$;
    $d_{Nmax} = d_N(q, p_k)$;
    En-queue $(n_x, d_N(q, n_x))$;
  De-queue next node n in Q;

Summary

- Network databases consider the street network, which constrains the positions and movements of objects.
- The Euclidean distance lower bounds the network distance.
- Most network expansion algorithms are based on Dijkstra's shortest path algorithm.
- Incremental Euclidean Restriction (IER)
- Incremental Network Expansion (INE)
- The addition of schedules (start and end times, multimodal networks) complicates network algorithms significantly.