



Graph Query Processing

When it comes to Graphs

- Semi-structured
 - No schema
 - No constraints yet
- No standard query languages
 - A variety of queries used in practice
 - Nontrivial
- What is the complexity of the following problems?
 - Subgraph isomorphism
 - Simple path: given a graph G , a pair (s, t) of nodes in G , and a regular expression R , it is to decide whether there exists a simple path from s to t that satisfies R .
- Query optimization techniques, indexing, updates, ...

Basic Graph Queries And Algorithms

- Graph search (traversal)
- PageRank
- Nearest neighbors
- Keyword search
- Graph pattern matching (a full treatment of itself)

Path Query

- Reachability

- Input: A directed graph G and a pair of nodes s and t in G
- Question: Does there exist a path from s to t in G ?

- Distance

- Input: A directed weighted graph G , and a node s in G
- Output: The length of shortest paths from s to all nodes in G

- Regular Path

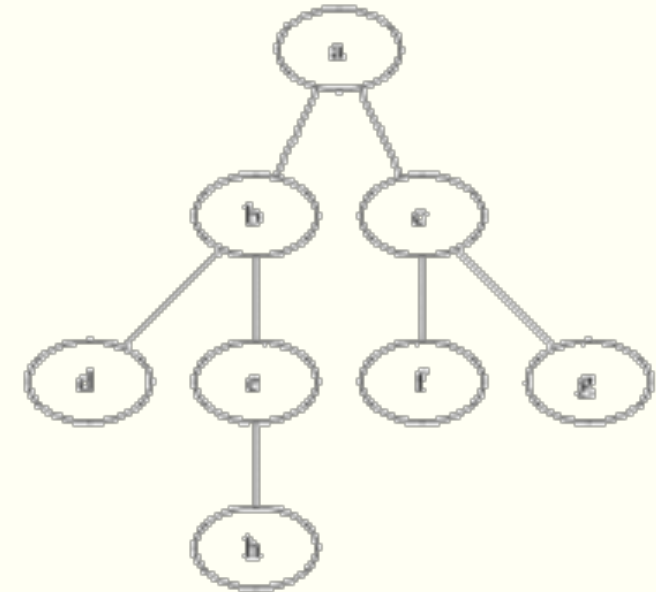
- Input: A node-labeled directed graph G , a pair of nodes s and t in G , and a regular expression R
- Question: Does there exist a (simple) path p from s to t that satisfies R ?

Reachability Queries

- Reachability
 - Input: A directed graph G and a pair of nodes s and t in G
 - Question: Does there exist a path from s to t in G ?
- Application: (a routine operation)
 - Social graph: Are two people related for security reasons?
 - Biological Networks: find genes that are (directly or indirectly) influenced by a given molecule
 - Nodes: Molecules, reactions or physical interactions
 - Edge: Interactions

Breadth-first Search

- BFS (G, s, t):
 - Let Q be a queue
 - Q.enqueue(s)
 - ▪ While Q is not empty
 - $v = Q.dequeue()$
 - If v is the goal (i.e. t), return **True**
 - For all edges from v to w in G.adjacentEdges(v) do
 - If w is not labelled as discovered:
 - Label w as discovered
 - w.parent = v
 - Q.enqueue(w)
 - Return **false**



BFS Complexity

- **BFS** (G, s, t):
 - Let Q be a queue
 - Q.enqueue(s)
 - While Q is not empty
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Class: **NL-Complete**

Complexity:

Space: $O\left(\underbrace{|V|} + \underbrace{|E|}\right)$

Time: $O\left(\underbrace{|V|} + \underbrace{|E|}\right)$

If you want to review complexity theory, here is a video
<https://www.youtube.com/watch?v=ZADqzLRDIOQ>

2-Hop Covers: Strike a balance

■ 2 Hop Labels

- Let $G = (V, E)$ be a directed graph.

- A 2-hop reachability labeling of G assigns to each vector $v \in V$ a label

$$L(v) = (\underline{L_{in}(v)}, \underline{L_{out}(v)})$$

- such that $\underline{L_{in}(v)}, \underline{L_{out}(v)} \subseteq V$ and there is a path from every $\underline{x \in L_{in}(v)}$ to \underline{v} and from \underline{v} to every $\underline{x \in L_{out}(v)}$.

- Thus, node ~~s~~ u can reach node v iff.

$$L_{out}(\uparrow u) \cap L_{in}(\uparrow v) \neq \phi$$

- Testing:

- Better than $O(|V| + |E|)$
- Space: $O(|V| \cdot |E|^{\frac{1}{2}})$

Distance Queries

- Distance
 - Input: A directed weighted graph G, and a node s in G
 - Output: The length of shortest paths from s to all nodes in G
- Application: Transportation Networks

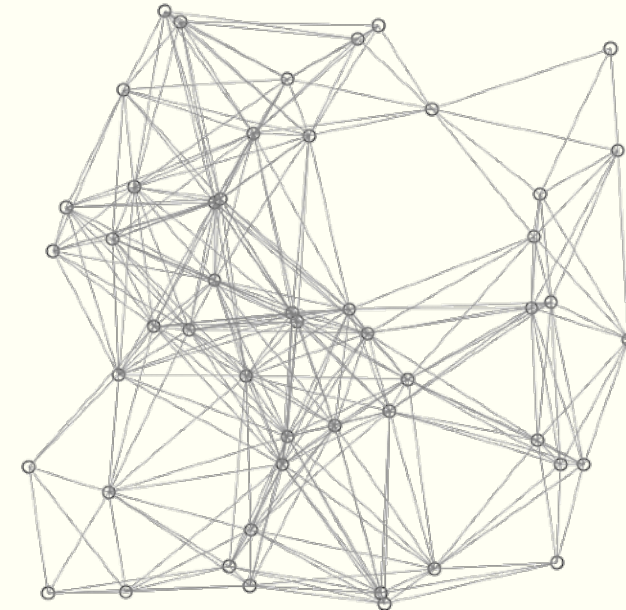
Distance Queries

■ Dijkstra (G, s, w):

- Create vertex set Q
- For each vertex $v \in V$
 - $dist[v] = \infty$
 - $prev[v] = undefined$
 - $Q.add(v)$
- $dist[\underline{s}] = 0$
- While Q is not empty:
 - \underline{u} = vertex in Q with minimum distance $dist[u]$
 - Remove \underline{u} from Q
 - Update the distance of each neighbor v of u to (if it is smaller) $dist[v] = dist[u] + w(u, v)$

■ Complexity: If \underline{Q} is a list, $O(|E| + |V|^2)$

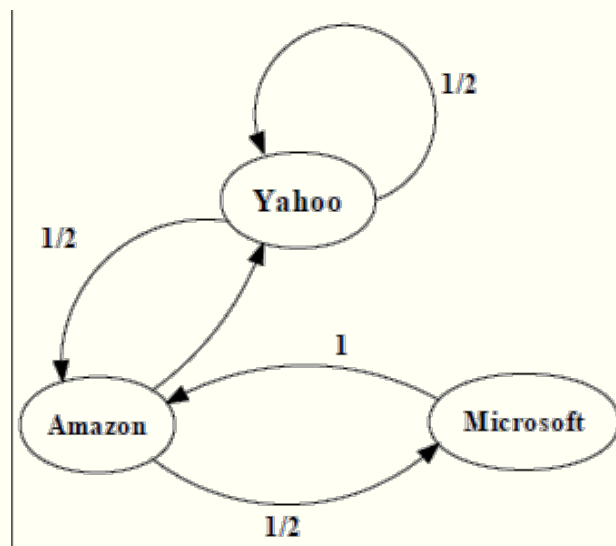
■ Complexity with the right data structure: $O(|E| + |V| \log |V|)$



Page Rank

- To Measure the “Quality” of a web page
 - Input: A directed graph G modeling the web, in which nodes represent Web pages, and edges indicate hyperlinks
 - Output: For each node v in graph G , $\underline{P(v)}$ is the likelihood that a random walk over G will arrive at v
- Intuition: How a random walk can reach v
 - The more pages link to v
 - The more popular those pages that link to v
 - Then, v has a higher chance to be visited

An example of Simplified PageRank



$$\overline{M} = \begin{matrix} & \begin{matrix} Y & A & M \end{matrix} \\ \begin{matrix} Y \\ A \\ M \end{matrix} & \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix} \end{matrix}$$

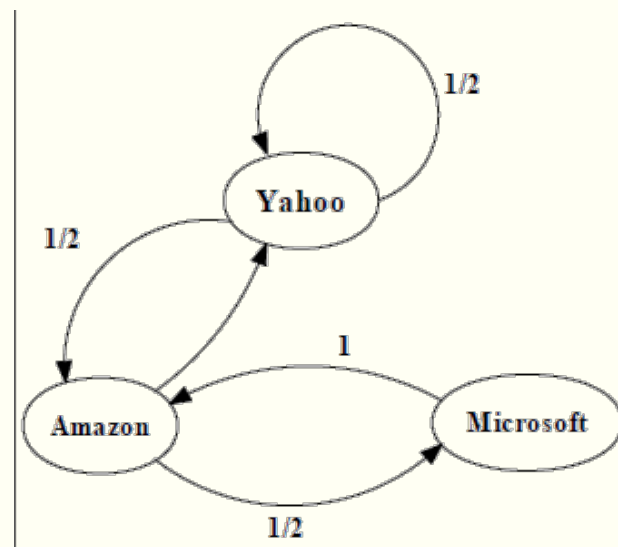
$$\begin{bmatrix} \underline{\text{yahoo}} \\ \text{Amazon} \\ \text{Microsoft} \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} \underline{1/3} \\ 1/2 \\ 1/6 \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

\overline{M}

X

An example of Simplified PageRank (Cont'd)



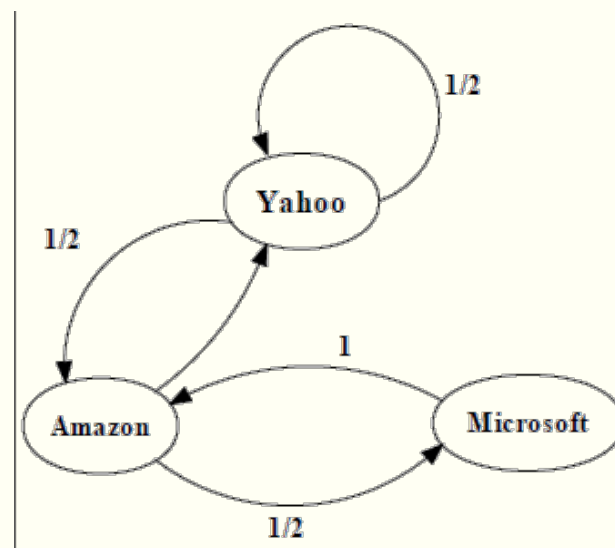
$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix}$$

$$\begin{bmatrix} \text{yahoo} \\ \text{Amazon} \\ \text{Microsoft} \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} \underline{5/12} \\ 1/3 \\ 1/4 \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} 1/3 \\ 1/2 \\ 1/6 \end{bmatrix}$$

\uparrow
 \underline{M}
 \uparrow

An example of Simplified PageRank (Cont'd)

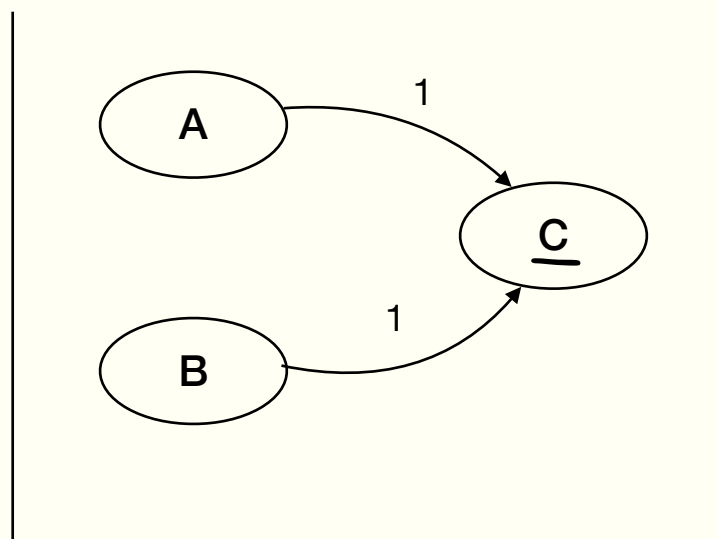


$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix}$$

$$\begin{bmatrix} \text{yahoo} \\ \text{Amazon} \\ \text{Microsoft} \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} 3/8 \\ 11/24 \\ 1/6 \end{bmatrix} \quad \begin{bmatrix} 5/12 \\ 17/48 \\ 11/48 \end{bmatrix} \quad \dots \quad \underbrace{\begin{bmatrix} 2/5 \\ 2/5 \\ 1/5 \end{bmatrix}}$$

Example of Simplified PageRank



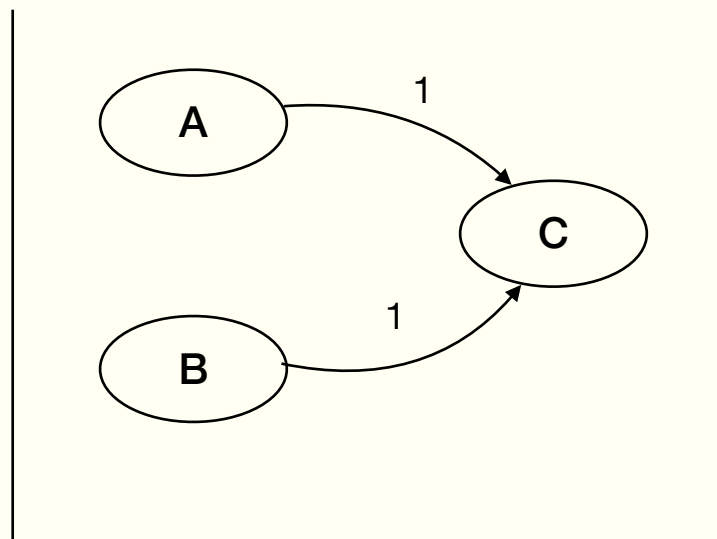
$$M = \begin{matrix} \begin{matrix} A \\ B \\ C \end{matrix} \end{matrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ \underline{1} & \underline{1} & 0 \end{bmatrix}$$

$$\begin{bmatrix} A \\ B \\ C \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ \underline{1/3} \end{bmatrix}$$

$$\begin{bmatrix} A \\ B \\ C \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ \underline{1} & \underline{1} & 0 \end{bmatrix} \begin{bmatrix} 1/3 \\ 1/3 \\ \underline{1/3} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \uparrow 2/3 \end{bmatrix}$$

$$\begin{bmatrix} A \\ B \\ C \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ \underline{1} & \underline{1} & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ \underline{2/3} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \underline{0} \end{bmatrix}$$

Example of PageRank - Damping Factor



$$M = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} A \\ B \\ C \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} A \\ B \\ C \end{bmatrix} = \underline{(1 - \alpha)} \underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 1 & 0 \end{bmatrix}} + \alpha \underbrace{\begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}}$$

$(1 - \alpha)$: Damping factor

Page Rank: (Cont'd)

- Random jump to v : $\alpha \left(\frac{1}{|V|} \right)$
 - i.e. The chance of hitting node v among all pages
 - α : random jump factor (teleportation factor)
- Hyperlink to v : $(1 - \alpha) \sum_{u \in L(v)} \frac{P(u)}{C(u)}$
 - $(1 - \alpha)$: Damping factor
 - $L(v)$: The set of page that link to v
 - $C(u)$: The out-degree of node u (the number of links on u)
 - $P(u)$: The probability of u being visited itself
 - $\sum_{u \in L(v)} \frac{P(u)}{C(u)}$: The chances of one to click a hyperlink at a page u and reach v

Page Rank: (Cont'd)

- According to intuition, the likelihood that a page v is visited by a random walk:

$$\alpha \left(\frac{1}{|V|} \right) + (1 - \alpha) \sum_{u \in L(v)} P(u)/C(u)$$

- Recursive computation: For each page $v \in V(G)$,
 - Compute $P(v)$ by using $P(u)$ for all $u \in L(v)$
- Until
 - Converge: no change to any $P(v)$
 - After a fixed number of iterations

K-Nearest Neighbor

- Nearest neighbor (kNN)

- Input: A set S of points in a space M , a query point p in M , a distance function $dist(u, v)$, and a positive integer k
- Output: Find top-k points in S that are closest to p based on $dist(p, u)$
- Note: The distance can be Euclidean distance, hamming distance, Cosine distance, etc.

- Applications

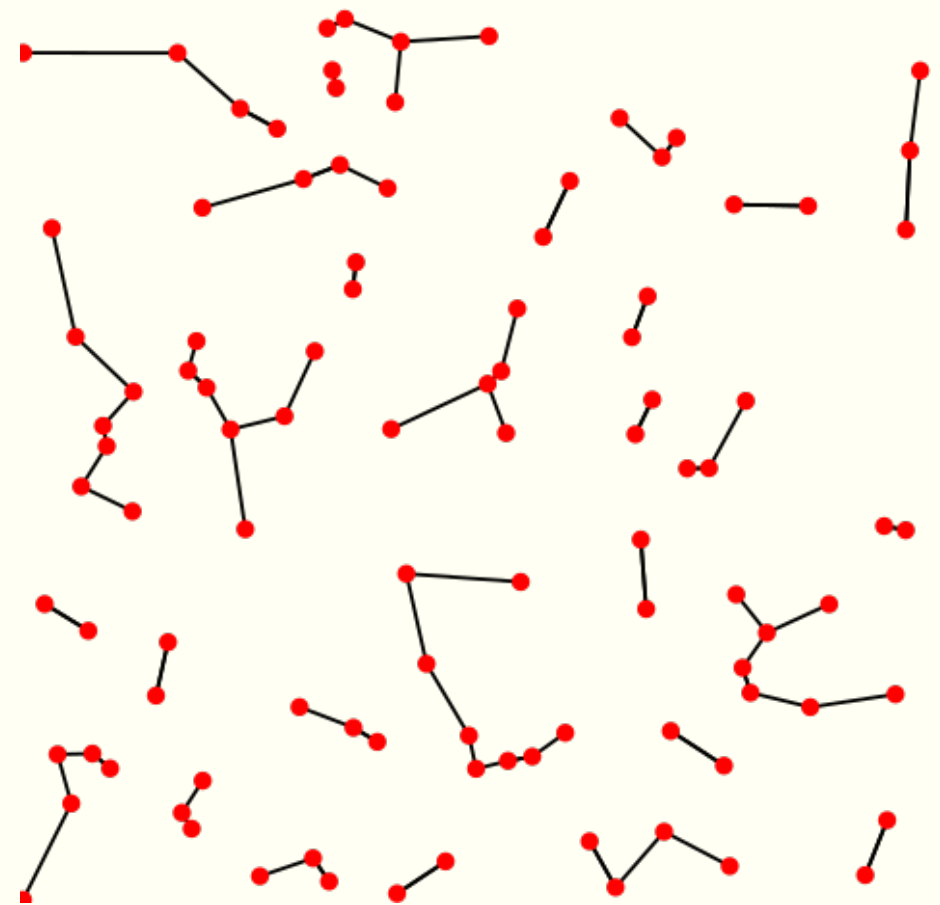
- POI recommendation: Find me top-k restaurants close to where I am
- Classification: classify an object based on its nearest neighbors
- Regression: property value as the average of the values of its k nearest neighbors

- Methods:

- Linear search, space partitioning, locality sensitive hashing, compression/clustering based search

K-Nearest Neighbor Graph

- Graph constructed based on k -nearest neighbor nodes
- Node p is connected to node q if $\text{dist}(p, q)$ is among the k -smallest distances of node p to all other nodes.
- NNG (Nearest Neighbor Graph) is a special case of k -NNG with $k=1$

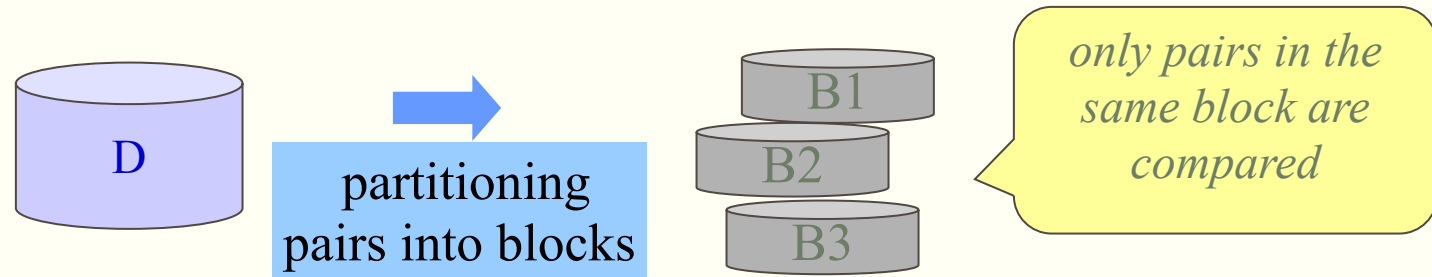


kNN Join

- Input: Two datasets \underline{R} and \underline{S} , a distance function $\underline{dist(R, S)}$, and a positive integer k
- Output: $\underset{\uparrow}{pairs} (r, s)$, for all $\underline{r} \in \underline{R}$ and $\underline{s} \in \underline{S}$, and s is one of the k -nearest neighbors of r .
- A naïve algorithm
 - Scanning \underline{S} once for each object in \underline{R}
 - $O(\underline{|R|} \cdot \underline{|S|})$: expensive when both datasets are large

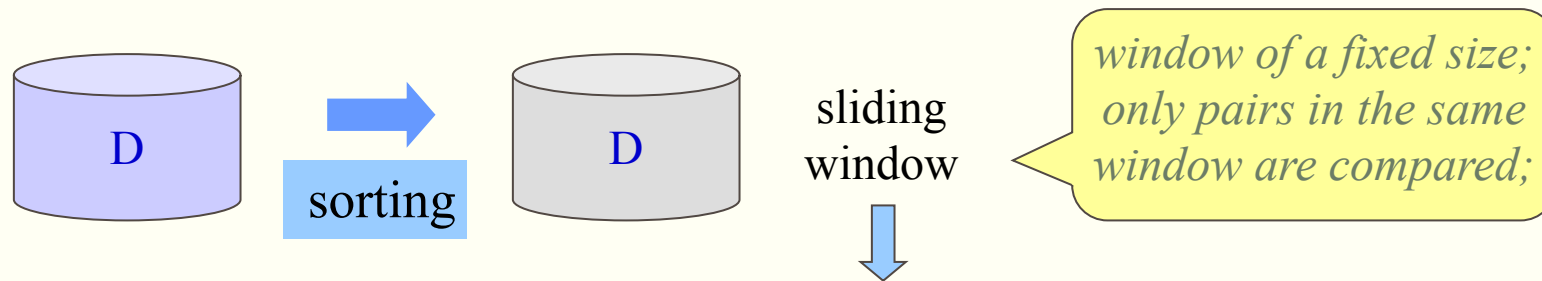
Blocking and Windowing

- Blocking



GORDER: An Efficient Method for KNN Join Processing. VLDB 2004.

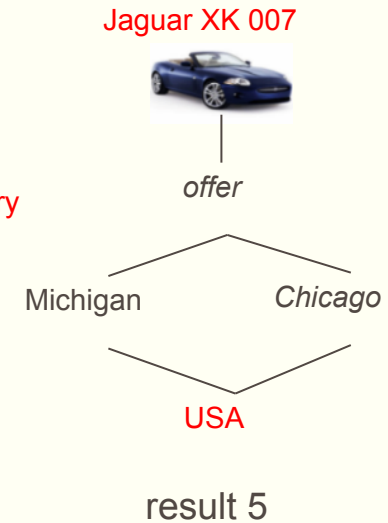
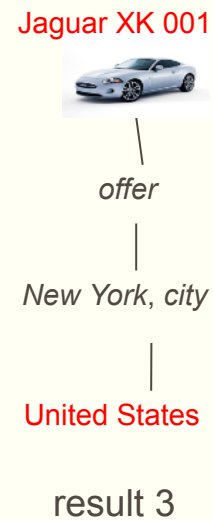
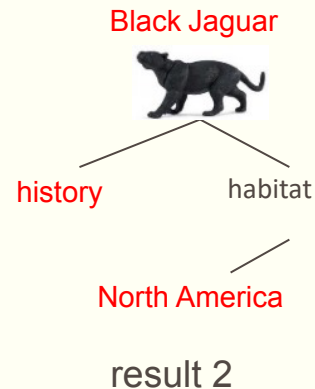
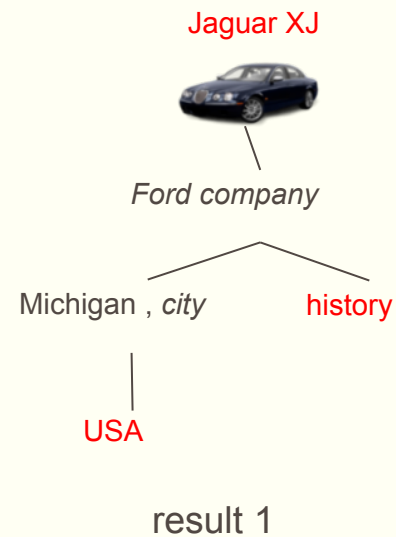
- Windowing



Keyword Search

- Input: A list Q of keywords, a graph G , a positive integer k
- Output: top-k “matches” of Q in G
- Example: Query: [Jagur, America, history]

- ✓ What makes a match?
- ✓ How to sort the matches?
- ✓ How to efficiently find top-k matches?



Keyword Search: Steiner Tree (Semantics)

- Input: A list Q of keywords, a graph G , a weight function $w(e)$ on the edges on G , and a positive integer k
- Output: top-k Steiner trees that match Q
- Match: a subtree T of G such that
 - Each keyword in Q is contained in a leaf of T
- Ranking:
 - The total weight of T (the sum of $w(e)$ for all edges e in T)
- Complexity:
 - NP-Complete

Semantics: distinct-root (tree)

- Input: A list Q of keywords, a graph G , a weight function $w(e)$ on the edges on G , and a positive integer k
- Output: top-k distinct trees that match Q
- Match: a subtree T of G such that
 - Each keyword in Q is contained in a leaf of T
- Ranking:
 - Dist(r,q): from the root of T to a leaf q
 - The sum of distances from the root to all leaves of T
- Diversification:
 - Each match in the top-k answer has a distinct root
- Complexity:
 - $O\left(|Q|\left(|V|\log|V| + |E|\right)\right)$

Semantics: Steiner graphs

- Input: A list Q of keywords, an undirected (unweighted) graph G , a positive integer r , and a positive integer k
- Output: find all r -radius Steiner graphs that match Q
- Match: a subgraph G' of G such that it is
 - r -radius: the shortest distance between any pair of nodes in G is at most r (at least one pair with the distance)
 - Each key word is contained either in a content node (containing the key word) or a Steiner node (on a simple path between a pair of content nodes)
- Computation: M^r , the r -th power of adjacency graph of G

Answering Keyword Queries

- A host of techniques
 - Backward search
 - Bidirectional search
 - Bi-level indexing
- References:
 - G. Bhalotia, A. Hulgeri, C. Nakhe, S. Chakrabarti, and S. Sudarshan. Keyword searching and browsing in databases using BANKS. ICDE 2002.
 - V. Kacholia, S. Pandit, S. Chakrabarti, S. Sudarshan, R. Desai, and H. Karambelkar. Bidirectional expansion for keyword search on graph databases. VLDB 2005.
 - H. He, H. Wang, J. Yang, and P. S. Yu. BLINKS: ranked keyword searches on graphs. SIGMOD 2007.

Reading List

- SoQL: an SQL-like language to retrieve paths
- CRPQ: extending conjunctive queries with regular path expressions
 - R. Ronen and O. Shmueli. SoQL: A language for querying and creating data in social networks. ICDE, 2009.
 - P. Barceló, C. A. Hurtado, L. Libkin, and P. T. Wood. Expressive languages for path queries over graph-structured data. In PODS, 2010
- SPARQL: for RDF data
 - <http://www.w3.org/TR/rdf-sparql-query/>
- Unfortunately, no “standard” query language for graphs, yet