CPT-S 415

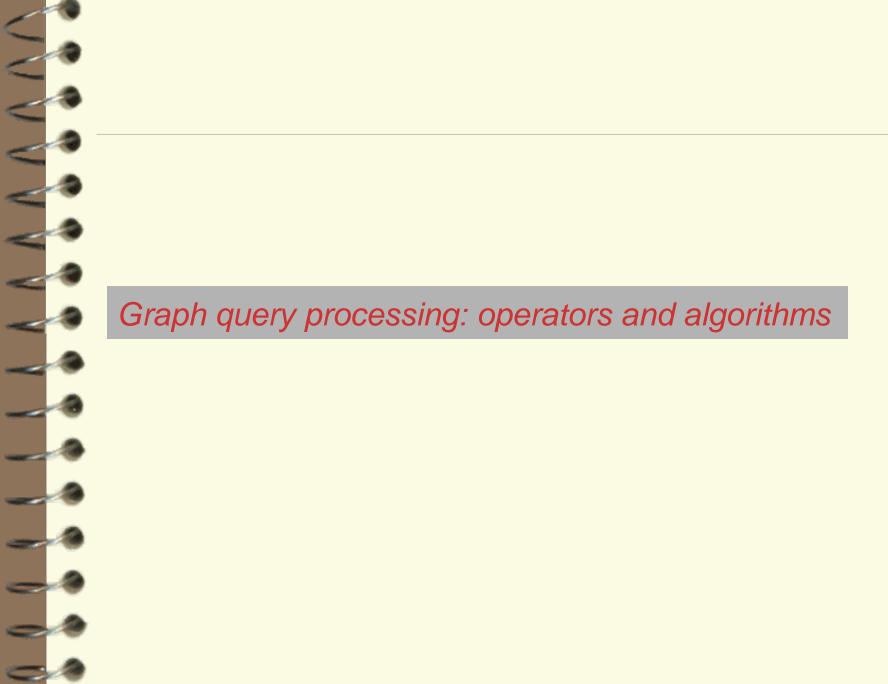
Big Data

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CPT-S 415 Big Data

Graph Query Processing

- ✓ Basics of Graph Algorithms
 - Graph search (traversal)
 - PageRank
 - Nearest neighbors
 - Keyword search
 - Graph pattern matching (next lecture)



When it comes to graphs ...

- ✓ Semistructured:
 - 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

NP-complete

- 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, ... preliminary

The study of graph queries is still in its infancy

Basic graph queries and algorithms

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

Widely used in graph algorithms



Path 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?

✓ Distance

- Input: A directed weighted graph G, and a node s in G
- Output: The lengths 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?
- Applications: a routine operation
 - Social graphs: 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

Edges: interactions

How to evaluate reachability queries?

Breadth-first search

- ✓ BFS (G, s, t):
 - 1. while Que is nonempty do
 - a. v ← Que.dequeue();
 - b. if v = t then return true;

Breadth-first, by using a queue

adjacency lists to store G

Use (a) a queue Que, initialized with s, (b)

flag(v) for each node, initially false; and (c)

- c. for all adjacent edges e = (v, u) of v do
- 2. return false

Complexity: each node and edge is examined at most once

What is the

Breadth-first search

Reachability: NL-complete

Too costly as a routine operation when G is large

- ✓ BFS (G, s, t): O(|V| + |E|) time and space
 - 1. while Que is nonempty do
 - a. v ← Que.dequeue();
 - b. if v = t then return true;
 - c. for all adjacent edges e = (v, u) of v do
 - a) if not flag(u)then flag(u) ← true; enqueue u onto Que;
 - return false
- \checkmark O(1) time? Yes, adjacency matrix, but O($|V|^2$) space

How to trike a balance?

2-hop cover

✓ For each node v in G,

$$2hop(v) = (L_{in}(v), L_{out}(v))$$

- •L_{in}(v): a set of nodes in G that can reach v
- L_{out}(v): a set of nodes in G that v can reach
- √ To ensure: node s can reach t if and only if

$$L_{out}(s) \cap L_{in}(t) \neq \emptyset$$

•Testing: better than O(1)/1 + IFI) on everage

•Space: O(|V| |E|^{1/2}) Find a minimum 2-hop cover? NP-hard

Maintenance cost in response to changes to G

A number of algorithms for reachability queries (see reading list)

Distance queries



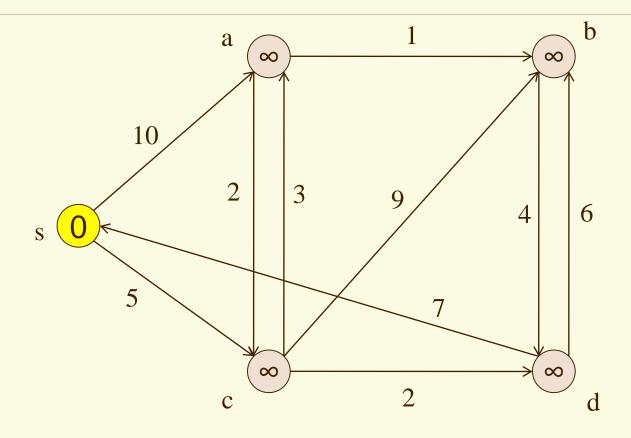
Edsger Wybe Dijkstra (1930-2002)

- ✓ Distance: single-source shortest-path problem
 - Input: A directed weighted graph G, and a node s in G
 - Output: The lengths of shortest paths from s to all nodes in G
- ✓ Application: transportation networks
- ✓ Dijkstra (G, s, w):
 - 1. for all nodes v in V do
 - a. $d[v] \leftarrow \infty$; \leftarrow
 - 2. $d[s] \leftarrow 0$; Que $\leftarrow V$;
 - while Que is nonempty do

Extract one with the minimum d(u)

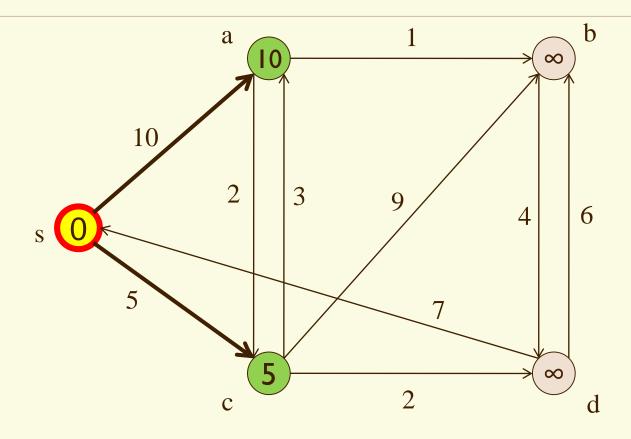
- a. u ← ExtractMin(Que);
- b. for all nodes v in adj(u) do
 - a) if d[v] > d[u] + w(u, v) then $d[v] \leftarrow d[u] + w(u, v)$;

Use a priority queue Que; w(u, v): weight of edge (u, v); d(u): the distance from s to u



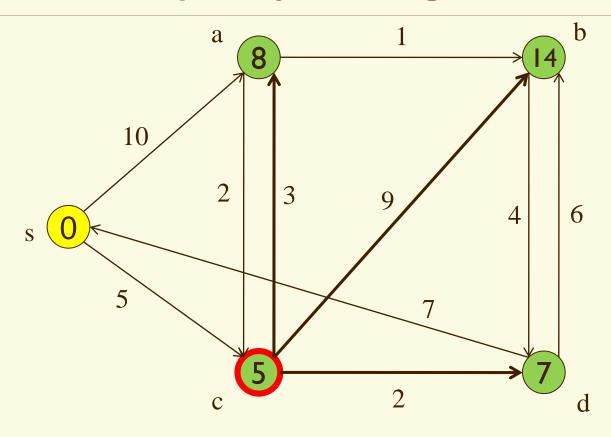
Q =
$$\{s,a,b,c,d\}$$

d: $\{(a,\infty), (b,\infty), (c,\infty), (d,\infty)\}$



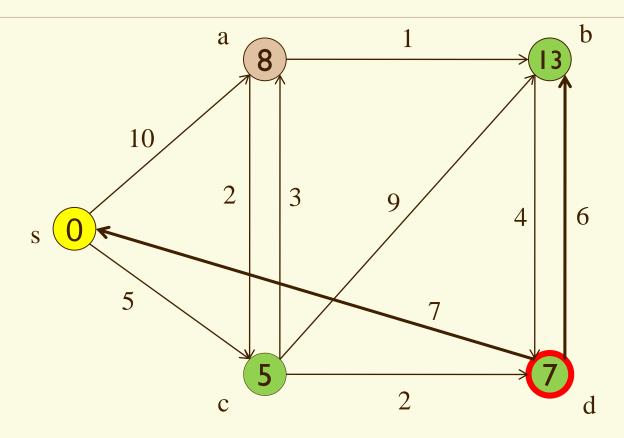
Q =
$$\{a,b,c,d\}$$

d: $\{(a,10), (b,\infty), (c,5), (d,\infty)\}$



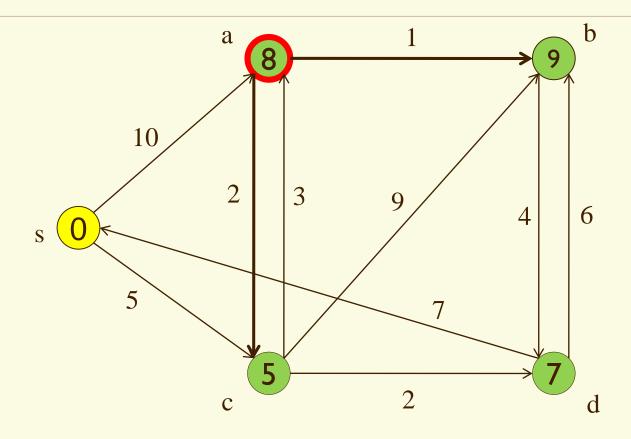
Q =
$$\{a,b,d\}$$

d: $\{(a,8), (b,14), (c,5), (d,7)\}$



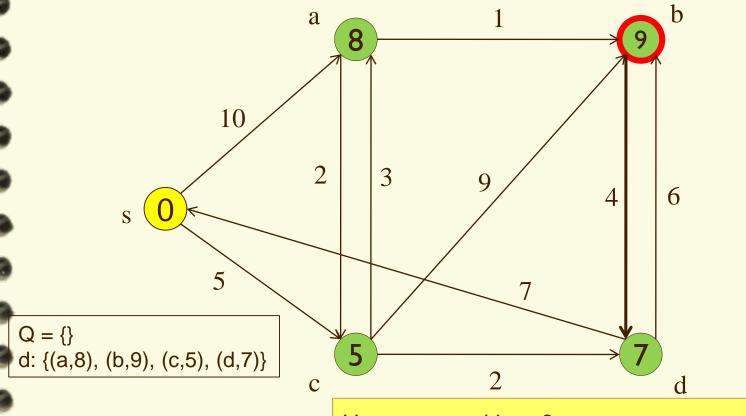
Q =
$$\{a,b\}$$

d: $\{(a,8), (b,13), (c,5), (d,7)\}$



$$Q = \{b\}$$

d: {(a,8), (b,9), (c,5), (d,7)}



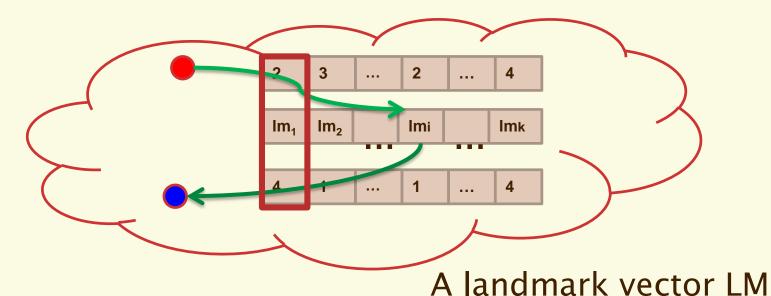
How to speed it up?

O(|V| log|V| + |E|). A beaten-to-death topic ?

Landmarks

✓ Landmark vectors

- A list of nodes L in a graph G, s.t for each pair (u,v) of nodes in G,
 there is an node in L on a shortest path from u to v
- Answering distance query: linear time



Regular path queries

- Regular simple 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 nath n from s to t such that the labels of a A. Mendelzon, and P. T. Wood. Finding Regular Simple Paths In Graph Databases.

 SICOMP 24(6), 1995
- ✓ NP-complete, even when R is a fixed regular expression (00)* or 0*10*.
- ✓ In PTIME when G is a DAG (directed acyclic graph)

Patterns of social links

Why do we care about regular path queries?

Regular path queries

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 path p from s to t such that the labels of adjacent nodes on p form a string in R?



a social voting network

Graph queries are nontrivial, even for path queries

Strongly connected components

- A strongly connected component in a direct graph G is a set V of nodes in G such that
 - for any pair (u, v) in V, u can reach v and v can reach u; and
 - V is maximal: adding any node to V makes it no longer strongly connected
- ✓ SCC

Find social circles: how large? How many?

- Input: A graph G
- Question: all strongly connected components of G

What is the complexity?

by extending search algorithms, e.g., BFS

$$O(|V| + |E|)$$

PageRank

Introduction to PageRank

- To measure the "quality" of a Web page
 - Input: A directed graph G modelling the Web, in which nodes represent Web pages, and edges indicate hyperlinks
 - Output: For each node v in G, P(v): the likelihood that a random walk over G will arrive at v.
- ✓ Intuition: how a random walk can reach v?
 - A random jump: α (1/|V|)
 The chances of hitting v among |V| pages
 - α: random jump factor (teleportation factor)
 - Following a hyperlink: $(1 \alpha) \sum (u \in L(v)) P(u)/C(u)$
 - (1α) : damping factor
 - (1 α) ∑(u ∈ L(v)) P(u)/C(u): the chances for one to click a hyperlink at a page u and reach v

Intuition

- ✓ Following a hyperlink: $(1 \alpha) \sum_{u \in L(v)} P(u)/C(u)$
 - L(v): the set of pages that link to v;
 - C(u): the out-degree of node u (the number of links on u)
 - - the probability of u being visited itself
 - the probability of clicking the link to v among C(u) many links on page u
- ✓ Intuition:
 - the more pages link to v, and
 - the more popular those pages that link to v,
 - v has a higher chance to be visited

One of the models

Putting together

The likelihood that page v is visited by a random walk:

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

random jump

following a link from other pages

- Recursive computation: for each page v in G,
 - compute P(v) by using P(u) for all u ∈ L(v)

until

too expensive; use an error factor

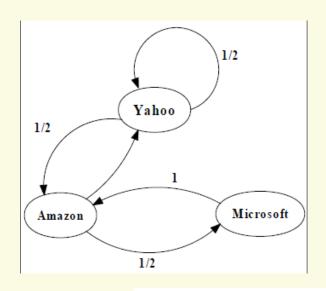
- converge: no changes to any P(v)
- after a fixed number of iterations

costly: trillions of pages

Parallel computation

How to speed it up?

An example of Simplified PageRank



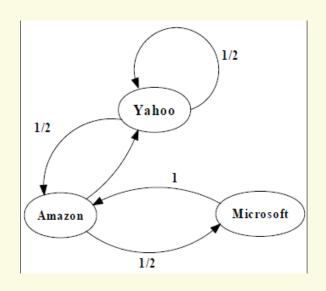
$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix}$$

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

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

PageRank Calculation: first iteration

An example of Simplified PageRank



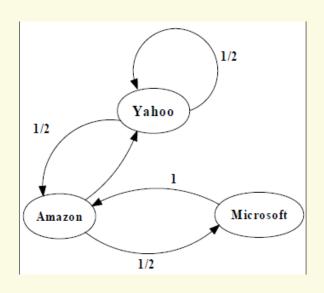
$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix}$$

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

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

PageRank Calculation: second iteration

An example of Simplified PageRank



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

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

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

Convergence after some iterations

Nearest neighbors

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) Euclidean distance, Hamming distance, continuous variables, ...
 - **Applications**
 - POI recommendation: find me top-k estaurants 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 neight Linear search, space partitioning, locality sensitive

hashing, compression/clustering based search, ...

A number of techniques

kNN join

✓ kNN join

- Input: Two datasets R and S, a distance function dist(r, s), and a positive integer k
- Output: pairs (r, s) for all r in R, where s is in S, and is one of the k-nearest neighbors of r

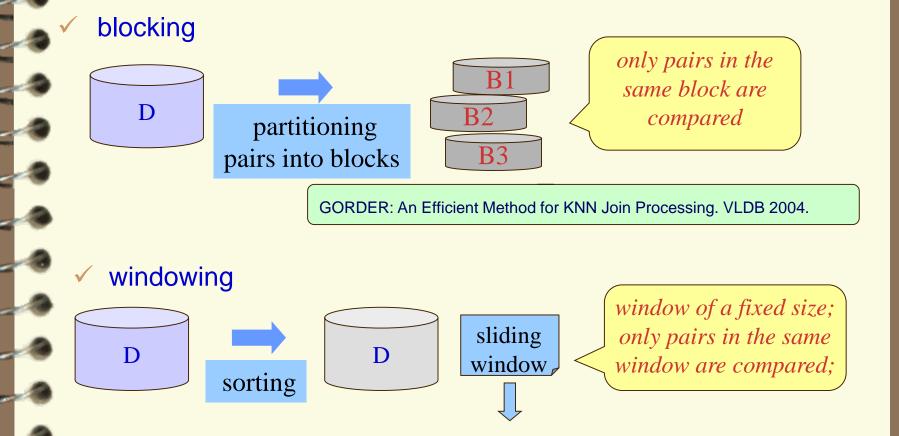
✓ A naive algorithm

Pairwise comparison

- Scanning S once for each object in R
- O(|R| |S|): expensive when R or S is large

Can we do better?

Blocking and windowing



Several indexing and ordering techniques



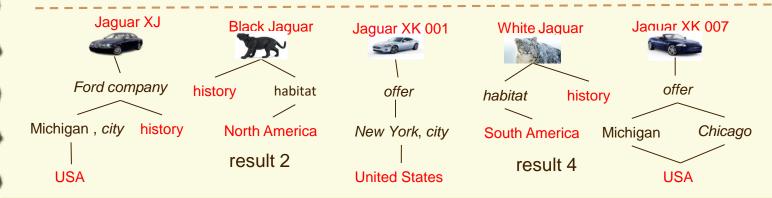
Keyword search

- ✓ Input: A list Q of keywords, a graph G, a positive integer k
- Output: top-k "matches" of Q in G

Information retrieval



Query Q: '[Jaguar', 'America', 'history']



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

Questions to answer

Semantics: Steiner 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 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)

 The cost to connect the keywords
- ✓ Complexity?

NP-complete

What can we do about it?

PageRank scores

Semantics: distinct-root (tree)

- ✓ Input: A list Q of keywords, a graph 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

 $O(|Q| (|V| \log |V| + |E|))$

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); and
 - each keyword is contained in either
 - a content node: containing the key word
 - 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

Revision: minimum subgraphs

Answering keyword queries

- A host of techniques
 - Backward search
 - Bidirectional search
 - Bi-level indexing
 - •
- ✓ 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.

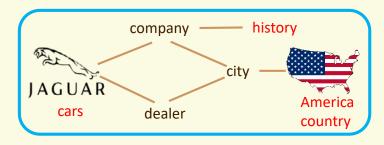
However, ...

The semantics is rather "ad hop

What does the user really want to find? Tree or graph? How to explain matches found?

Query Q: '[Jaguar', 'America', 'history']







Add semantics to keyword search

Summing up

Reading List 2: Graph query languages

There have been efforts to devel Querying topological structures

- 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

Read this

http://www.w3.org/TR/rdf-sparql-query/

Unfortunately, no "standard" query language for graphs, yet

Summary and review

- Review of searching RDBMS
 - Algorithms for selection/complex selection
 - Algorithms for joins: what are several common ways to compute joins? Design ideas?
- ✓ Why are reachability queries? Regular path queries? Connected components? Complexity? Algorithms?
- ✓ What are factors for PageRank? How does PageRank work?
- ✓ What are kNN queries? What is a kNN join? Complexity?
- ✓ What are keyword queries? What is its Steiner tree semantics?Distinct-root semantics? Steiner graph semantics? Complexity?
- ✓ Name a few applications of graph queries you have learned.
- Find graph queries that are not covered in the lecture.

Reading List 2 (graduate students)

- ❖ 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.
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- A. Fard, M. U. Nisar, J. A. Miller, L. Ramaswamy, Distributed and scalable graph pattern matching: models and algorithms. Int. J. Big Data. http://cobweb.cs.uga.edu/~ar/papers/IJBD_final.pdf
- W. Fan J. Li, S. Ma, and N. Tang, and Y. Wu. *Graph pattern matching: From intractable to polynomial time*, VLDB, 2010.
- W. Fan, F. Geerts, and F. Neven. Making Queries Tractable on Big Data with Preprocessing, VLDB 2013.