Keyword Searching on Databases

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Outline

Motivation

BANKS - Introduction

BANKS - Bidirectional Expanding Search

SphereSearch

Summary
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Summary
Motivation

► For searching db
  ► Knowledge of detailed schema, SQL needed
  ► Need to create separate UI forms for searching relations

► IR seems to be appropriate:
  ► But cannot be directly applied to databases
  ► Answer to a query typically split across multiple tuples
  ► Alternative: combine db data into a “document"
  ► Disadvantage: Duplication of data; Sync with db
DBLP Example

- Normalization $\Rightarrow$ multiple tuples (through fk)
Note: 1 paper spread across 7 tuples
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Summary
BANKS

- BANKS = Browsing and Keyword Searching
- Convergence of IR and searching structured databases
- User specifies keyword(s)
  - no SQL, no detailed schema knowledge required
- Answers are ranked
  - Further user interaction may be needed to narrow down info
- Useful for publishing data on web: no coding required!
System Architecture

- Java Servlets (for web interface)
- JDBC to communicate with the RDBMS
- Configuration by administrator
BANKS : Browsing

- Browsable view of database relations
  - no content programming / user intervention required
- Drop-down menu with operations on column headers
- Projections, selections
- Joins for fk columns (or for pk used by a referencing fk)
- Grouping of results; drill-down
- Sorting
- Pagination and Schema browsing
BANKS : Templates

- Templates can be used for formatting display of tuples
  - Can contain HTML code snippets
  - Hyperlinks to attributes
  - Relationships to be folded in
- Cross-tabs
- Group-by template
- Folder-tree views
- Pie, bar, line charts (with drill down)
- Templates can be composed together in visual manner
<table>
<thead>
<tr>
<th>SNAME</th>
<th>EMAIL</th>
<th>TITLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nand Kumar Singh</td>
<td><a href="mailto:sudhakar@aero.iitb.ernet.in">sudhakar@aero.iitb.ernet.in</a></td>
<td>Get column info and drop column. Sort in Ascending and Descending order. Group by and Group by prefix. Join (FACULTY). Select.</td>
</tr>
<tr>
<td>N. Shama Rao</td>
<td><a href="mailto:mujumdar@aero.iitb.ernet.in">mujumdar@aero.iitb.ernet.in</a></td>
<td>THROUGH THICKNESS ELASTIC CONSTANTS AND STRENGTHS OF ADVANCED FIBRE COMPOSITES</td>
</tr>
<tr>
<td>Mini N Balu</td>
<td><a href="mailto:sys@math.iitb.ernet.in">sys@math.iitb.ernet.in</a></td>
<td>Some Preservation Results in Mathematical Theory of Reliability</td>
</tr>
</tbody>
</table>
Specify keywords to be searched for
Answers to query in relevance order
Each answer displayed in hierarchical form
Example answer tree
Indentation and color used to depict the tree structure
BANKS Query Model

- DB as a directed graph
  - Graph is in-memory
- Each tuple in the db corresponds to a node in the graph
- Each fk-pk link is a directed edge between the corr. tuples
  - Can be easily extended for other types of connections
Keyword query has \( n \geq 1 \) terms \((t_1, t_2, t_3, \ldots, t_n)\)

- Locate the nodes matching the search terms
  - Matching on attribute value or metadata (col name, tbl name, view name)
  - Use disk-resident indices to map keywords to RIDs
  - Another (in-memory) index to map RIDs to graph nodes

- \( S_i \): set of nodes matching keyword \( t_i \)

- \( S_i \)'s may overlap
An answer is a subgraph connecting a set of nodes that cover the keywords.

Important to identify a “central” node that connects all the keyword nodes.

An answer is then a rooted directed tree:
- at least one node from each $S_i$
- edges are directed away from the root.

Tree may also contain nodes that are not in $S_i$ (a Steiner tree).
Two types of weights:
- Edge weights
- Node weights (Prestige ranking, such as PageRank)
Edge weights

- Importance of a link depends on the type of link (relations, semantics)
  - link between Paper and Writes v/s link between Paper and Cites
- Semantically stronger links given lower weights
- Wt. of a tree $\propto$ sum of its edge weights
- Relevance of a tree inversely $\propto$ to its weight
  - Sort Answer trees in increasing order of weight
Need for directionality

- Consider earlier example: some links point toward root of tree, others away (e.g., Writes to Author and to Paper)
  - we require paths from Paper to Author; that is, traverse edge in opposite direction

- Can we ignore directionality?
  - If we do, problem of “hubs"
  - E.g., a dept. with large # of faculty and students
  - Many nodes would be within a short distance of many other nodes
  - Reduces the effectiveness of tree-wt based scoring mechanism
Backward Edges

- For each edge \((u, v)\), create a backward edge \((v, u)\)
- This ensures that a directed tree exists that is rooted at the “paper” with a path to each leaf
- To solve the hub problem
  - wt. of \((v, u)\) = wt. of \((u, v)\) * f(# of links to \(v\) from the nodes of the same type as \(u\))
  - if an edge already exists from \(v\) to \(u\), set the edge weight to the lower of the 2 weights
- Experiments indicate that the function \(\log(1 + x)\), where \(x\) is the # of inlinks, provides good results.
Node Weights

- Inspired by prestige rankings (Google PageRank)
- Nodes with more inlinks get higher node weight (higher prestige)
  - DBLP: More citations for paper, more inlinks
- Node weight function could be $\log(1 + x)$, where $x$ is the in-degree
Overall relevance score

- Combine node weights and tree weights (total of edge weights)
- Additive or multiplicative combination
  - $\lambda$ controls relative weightage
  - Additive:
    \[(1 - \lambda)Escore + \lambda Nscore\]
  - Multiplicative:
    \[Escore \cdot Nscore^\lambda\]
- Both $+$ and $\ast$ work well when relative weights are appropriately chosen
First, for each keyword
  - find the set of nodes $S_i$ that satisfy the keyword term $t_i$

Let $S = \bigcup S_i$

Backward Expanding Search algo (Heuristic incremental solution)
  - Concurrently run $|S|$ copies of Djikstra’s single src shortest path algo
  - One copy for each node $n$ in $S$, with $n$ as the source
Algo...contd

- Each copy of the single src SP algo traverses the graph edges in the reverse direction
- Try to find a common vertex from which forward path exists to at least one node in each set $S_i$
- Rooted directed tree (connection tree):
  - info node as root
  - keyword nodes as leaves
Connection trees approximately sorted in increasing order of weights

All connection trees could be generated and then sorted in decreasing relevance order

Better alternative:

- When output heap is full, output highest relevance tree and replace it
- No guarantees trees sorted in decreasing relevance order, but works well
Isomorphic trees

- Trees with similar structure modulo direction ("duplicate trees")
- These represent the same result, with diff. info. nodes.
- Retain only one with the highest relevance
  - Note: Results are output when the heap is full
Implementation

- Efficiency of graph traversals important
- Entire db graph is stored in memory. Acts as an index on the db
- Graph stores only id for each node and edge plus pointers
  - Each graph node: 30 bytes
  - No strings in memory
- Tens of millions records using modest amount of memory
Results

- Most intuitive answers ahead of less intuitive ones in almost all cases
- Space and Time:
  - For a bib. db with 100K nodes and 300K edges, mem. util around 120 MB
  - 2 minutes initial loading time
  - Once loaded, queries take a second / few seconds
  - Feasible to use BANKS for moderately large db
Effect of Parameters : Settings

- 7 different queries; for each, \( \sim 4 \) ideal answers were listed
- Each query run with diff. param combinations (10 answers)
- Rank diffs computed for each run
- Raw error score = \( \sum rankdiffs \)
- For missing answers
  - rank diff = 11
Effect of Parameters

- Important to keep the effect of node ranking relatively small, but non-zero
  - $\lambda = 0.2$, $EdgeLog = 1$ did best with error score of 0.0
  - $\lambda = 0.5$, $EdgeLog = 1$ - almost well with error scores of around 3
  - $\lambda = 1$, (ignore edge weights) - error score 15
- Conclusion: $\lambda = 0.2$, $EdgeLog = 1$ - does best
Effect of Parameters...contd

![Graph showing the effect of parameters on Scaled Error](image-url)

- The x-axis represents Lambda and EdgeLog.
- The y-axis represents Scaled Error.

The graph illustrates how changes in Lambda and EdgeLog affect Scaled Error.
Reducing edge wt. range by log scaling important
- else
  - back edges from some popular nodes get high weights
  - some intuitive answers got a very poor relevance ranking

Mode of score combination has almost no impact on the ranking

For node weights, log scaling gave same results as no log scaling
Extensions

- Extended to handle XML???
- Selection conditions \((\text{year} = 2007), (\text{year} \sim 2007)\)
- Ranking function: “near” movies (near hitchcock, reagan)
- User Feedback:
  - Disambiguation of nodes
  - Selecting answer tree patterns
  - Re-scoring
Related Work

- **DataSpot system**
  - similar model, relevance scores, trees of max relevance returned
  - Back edges based on in-degree and node weights not present in DataSpot

- **Proximity search in db - Goldman**
  - find object near object

- **EasyAsk:**
  - keyword search on data stored in RDBMS
  - but details are not available publicly
BANKS and related work

- BANKS differs from prior work:
  - Techniques for edge wt. computation and prestige ranking
  - Use of an in-memory graph structure for very efficient searching
Future Work

- Improved user feedback
- Querying across multiple data sources using different data models
- XML data
- attribute:keyword queries (e.g., author:Levy)
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Issues with Backward Expanding Search Algo

- Travel backwards from keyword nodes till you hit a common node
- Performs poorly if:
  - Some keywords match many nodes
  - Some node has a very large indegree
- In these cases, a large number of nodes must be examined
- Wasteful exploration of graph
- Longer time to generate answers
Bidirectional Expanding Search Algo

Backward search

How about searching in forward direction?

Backward search doesn't seem useful because of so many keyword nodes

Keyword 1

Keyword 2
Bidirectional Expanding Search Algo

- Basic idea:
  - Do not explore backward if:
    - Next node is a hub
    - Keyword matches a large number of nodes

- But, at what number do we switch over?
Bidirectional Expanding Search Algo

- Prioritize on the basis of *spreading activation*
  - Like propagating "scent" spread from keyword nodes
  - Edge weights as well as spread of the next node(s)
- Nodes with the highest activation explored first
- Higher the spread, lower the activation
Bidirectional Expanding Search Algo

- Initial activation:
  \[ a_{u,i} = \frac{\text{nodePrestige}(u)}{|S_i|}, \forall u \in S_i \]

- For spreading, use an "attenuation factor" \( \mu \)
- Each node keeps \( \mu \) fraction of the activation it receives
- Rest \( (1 - \mu) \) is divided amongst its neighbors
- Overall activation of a node \( u \) is:
  \[ a_u = \sum_{i=0}^{n} a_{u,i} \]
Bidirectional Expanding Search Algo
Bidirectional Expanding Search Algo

- Use a single combined iterator for all nodes in each direction
- Lesser state maintenance overhead than the Backward Expanding Search Algo
- Also, the iterator is not a single source shortest path iterator
- So,
  - need to update path lengths as they become known
  - need to worry about output of answers in relevance order
Bidirectional Expanding Search Algo

- Activate matching nodes; insert into backward iterator
- while (iterators are not empty)
  - Choose iterator for expansion in best-first manner
  - Explore node with highest activation
  - Spread activation to neighbors
  - Update path weights (and other datastructures)
  - Propagate values to ancestors if necessary
  - Insert nodes explored in the backward dir into fwd iterator // for future forward exploration
- Stop when top-k results are produced
Top-k results

- Naïve approach:
  - Store results in an intermediate heap
  - Output top $k$ results after $mk$ total results have been generated ($m \sim 10$)

- Can do better:
  - Compute upper bound on score of next result
  - Output answers with a higher score
Experimental Results

- Bidirectional Expanding Search outperforms Backward Expanding Search
- Current BANKS demo on site has flexibility
  - User can choose which algo to use for searching
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SphereSearch: Motivation

- Web search engines use mostly keyword query paradigm
  ⇒ less expressive querying capabilities
- Example
  - Web search: researcher Max Planck
  - We want to say: researcher person="Max Planck"
- We want:
  - Concept-aware search (Tag-aware querying)
  - Context-aware search
    - Answers to queries might be a set of pages, than a single page
  - Abstraction-aware search (Ontology-enabled search)
SphereSearch Features

- Uniform treatment for XML as well as present Web data
- Structured queries on semistructured data without a global schema
  - Heterogeneous XML
- Relevance-ordered results using ranked retrieval paradigm
SphereSearch Query Language

- Query Groups and Joins
  A(gift, vendor)
  B(courier, vendor)
  A.location = B.location

- Similarity operator, ~, used for:
  - Ontology
  - For numeric, "approximately" (year ~ 2007)
SphereSearch Transformation and Annotation

- Convert HTML, PDF, plain text to XML

  <H1>Experiments</H1>  <Experiments>
  ...Text1...
  ...Text1...
  <H2>Settings</H2>  =>  <Settings>
  ...Text2..
  ...Text2..
  <H1>...
  </Settings>
  </Experiments>

- Then, annotate data (e.g., identify places and tag them <places> )
Spheres
Spheres

- Sphere of node \( n \) at distance \( d \) is \( S_d(n) \): set of all nodes at distance \( d \) from node \( n \).
- Sphere Score at distance \( d \) of node \( n \) wrt condition \( t \) is:
  \[
  s_d(n, t) = \sum_{v \in S_d(n)} ns(v, t)
  \]
- Sphere Score of node \( n \) wrt \( t \) is:
  \[
  s(n, t) = \sum_{i=1}^{D} s_i(n, t) \star \alpha^i
  \]
  - \( D \): Sphere size limit
  - \( \alpha \): Damping coefficient
For $\alpha = 0.5$ and $D = 3$, we get:

$$s(1, t) = 1 + 4 \cdot 0.5 + 2 \cdot 0.5^2 + 5 \cdot 0.5^3 = 4.175$$
$$s(2, t) = 3 + 0 \cdot 0.5 + 0 \cdot 0.5^2 + 1 \cdot 0.5^3 = 3.125$$

Node 1 is a better result for “t” than node 2.
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- BANKS: useful for web publishing of data
- Bidirectional Expanding Search outperforms Backward Expanding Search
- SphereSearch: More expressive query language
