# Text Search for Fine-grained Semi-structured Data

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Acknowledgments		
S. Sudarshan	Arvind Hulgeri	
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# Two extreme search paradigms

#### Searching a RDBMS

- Complex data model: tables, rows, columns, data types
- Expressive, powerful query language
- Need to know schema to query
- Answer = unordered set of rows
- Ranking: afterthought

#### Information Retrieval

- Collection = set of documents, document
   sequence of terms
- Terms and phrases present or absent
- No (nontrivial) schema to learn
- Answer = sequence of documents
- Ranking: central to IR

#### Convergence?

#### SQL→XML search Web search←IR

- Trees, reference links
- Labeled edges
- Nodes may contain
  - Structured data
  - Free text fields
     Data vs. document
- Query involves node data and edge labels
  - Partial knowledge of schema ok
- Answer = set of paths

- Documents are nodes in a graph
- Hyperlink edges have important but unspecified semantics
  - Google, HITS
- Query language remains primitive
  - No data types
  - No use of tag-tree
- Answer = URL list

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#### Outline of this tutorial

- Review of text indexing and information retrieval (IR)
- Support for text search and similarity join in relational databases with text columns
- Text search features in major XML query languages (and what's missing)
- A graph model for semi-structured data with "free-form" text in nodes
- Proximity search formulations and techniques; how to rank responses
- Folding in user feedback
- Trends and research problems

# Text indexing basics

- "Inverted index" maps from term to document IDs
- Term offset info enables phrase and proximity ("near") searches
- Document boundary and limitations of "near" queries
- Can extend inverted index to map terms to
  - Table names, column names
  - Primary keys, RIDs
  - XML DOM node IDs

My<sub>0</sub> care<sub>1</sub> is loss of care with old care done

Your care is gain of care with new care won

care D1: 1, 5, 8

D2: 1, 5, 8

new D2: 7

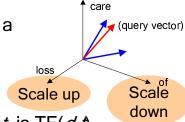
old D1: 7

loss D1: 3

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#### Information retrieval basics

- Stopwords and stemming
- Each term t in lexicon gets a dimension in vector space
- Documents and the query are vectors in term space



- Component of d along axis t is TF(d,t)
  - Absolute term count or scaled by max term count
- Downplay frequent terms:  $IDF(t) = log(1+|D|/|D_t|)$ 
  - Better model: document vector d has component TF(d,t) IDF(t) for term t
- Query is like another "document"; documents ranked by cosine similarity with query

#### Map

		Data model		
		Relational	XML-like	
IR support	None	SQL Datalog	XML-QL, Xquery	
	Schema(	WHIRL	ELIXIR, XIRQL	
	No schema	DBXplorer, BANKS, DISCOVER	EasyAsk, Mercado, DataSpot, BANKS	

- "None" = nothing more than string equality, containment (substring), and perhaps lexicographic ordering
- "Schema": Extensions to query languages, user needs to know data schema, IR-like ranking schemes, no implicit joins
- "No schema": Keyword queries, implicit joins

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# WHIRL (Cohen 1998)

place(univ, state) and job(univ, dept)

- Ranked retrieval from a RDBMS:
  - select univ from job where dept ~ 'Civil'
- Ranked similarity join on text columns:
  - select state, dept from place, job where place.univ ~ job.univ
- Limit answer to best k matches only
- Avoid evaluating full Cartesian product
  - "Iceberg" query
- Useful for data cleaning and integration

#### WHIRL scoring function

#### A where-clause in WHIRL is a

- Boolean predicate as in SQL (age=35)
  - Score for such clauses are 0/1
- Similarity predicate (job ~ 'Web design')
  - Score = cosine(job, 'Web design')
- Conjunction or disjunction of clauses
  - Sub-clause scores interpreted as probabilities
  - $score(B_1 \land ... \land B_m; \theta) = \prod_{1 \le i \le m} score(B_i, \theta)$
  - score( $B_1 \vee ... \vee B_m$ ;  $\theta$ )=1  $\prod_{1 \leq k \leq m} (1 \text{score}(B_k \theta))$

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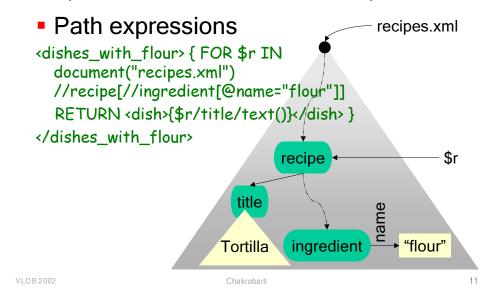
#### Query execution strategy

select state, dept from place, job where place.univ ~ job.univ

- Start with place(U1,S) and job(U2,D)
   where U1, U2, S and D are "free"
  - Any binding of these variables to constants is associated with a score
- Greedily extend the current bindings for maximum gain in score
- Backtrack to find more solutions

# **XQuery**

Quilt + Lorel + YATL + XML-QL



# Early text support in XQuery

 Title of books containing some para mentioning both "sailing" and "windsurfing"

```
FOR $b IN document("bib.xml")//book
WHERE SOME $p IN $b//paragraph SATISFIES
(contains($p,"sailing") AND
contains($p,"windsurfing"))
RETURN $b/title
```

 Title and text of documents containing at least three occurrences of "stocks"

```
FOR $a IN view("text_table") WHERE
  numMatches($a/text_document,"stocks") > 3
RETURN
  <text>{$a/text_title}{$a/text_document}</>>
```

#### **Tutorial outline**

		Data model		
		Relational	XML-like	
IR support	None	SQL,Datalog	XML-QL, Xquery	
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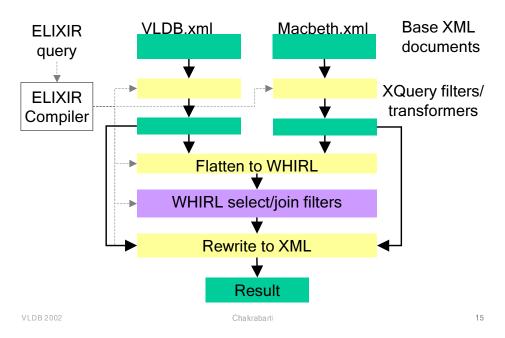
- Review of text indexing and information retrieval
- Support for text search and similarity join in relational databases with text columns (WHIRL)
- Adding IR-like text search features to XML query languages (Chinenyanga et al. Führ et al. 2001)

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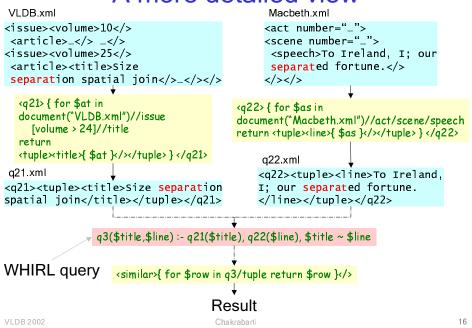
# **ELIXIR: Adding IR to XQuery**

- Ranked select for \$t in document("db.xml")/items/(book|cd) where \$t/text() ~ "Ukrainian recipe" return <dish>\$t</dish>
- Ranked similarity join: find titles in recent VLDB proceedings similar to speeches in Macbeth

#### How ELIXIR works



#### A more detailed view



#### **Observations**

- SQL/XQuery + IR-like result ranking
- Schema knowledge remains essential
  - "Free-form" text vs. tagged, typed field
  - Element hierarchy, element names, IDREFs
- Typical Web search is two words long
  - End-users don't type SQL or XQuery
  - Possible remedy: HTML form access
  - Limitation: restricted views and queries

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# Using proximity without schema

- General, detailed representation: XML
- Lowest common representation
  - Collection, document, terms
  - Document = node, hyperlink = edge
- Middle ground
  - Graph with text (or structured data) in nodes
  - Links: element, subpart, IDREF, foreign keys
  - All links hint at unspecified notion of proximity

Exploit structure where available, but do not impose structure by fiat

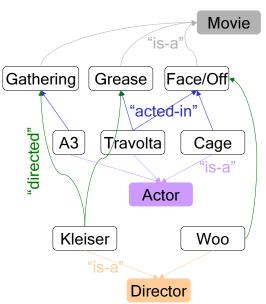
# Two paradigms of proximity search

- A single node as query response
  - Find node that matches query terms...
  - ...or is "near" nodes matching query terms
    (Goldman et al., 1998)
- A connected subgraph as query response
  - Single node may not match all keywords
  - No natural "page boundary"

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# Single-node response examples

- Travolta, Cage
  - Actor, Face/Off
- Travolta, Cage, Movie
  - Face/Off
- Kleiser, Movie
  - Gathering, Grease
- Kleiser, Woo, Actor
  - Travolta



#### Basic search strategy

- Node subset A activated because they match query keyword(s)
- Look for node near nodes that are activated
- Goodness of response node depends
  - Directly on degree of activation
  - Inversely on distance from activated node(s)

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#### Ranking a single node response

- Activated node set A
- Rank node r in "response set" R based on proximity to nodes a in A
  - Nodes have relevance  $\rho_R$  and  $\rho_A$  in [0,1]
  - Edge costs are "specified by the system"
- d(a,r) = cost of shortest path from a to r
- Bond between a and r  $b(a,r) = \frac{\rho_A(a)\rho_R(r)}{d(a,r)^t}$
- Parameter t tunes relative emphasis on distance and relevance score
- Several ad-hoc choices

# Scoring single response nodes

Additive

$$score(r) = \sum_{a \in A} b(a, r)$$

Belief

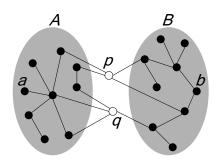
$$score(r) = 1 - \prod_{a \in A} (1 - b(a, r))$$

- Goal: list a limited number of find nodes with the largest scores
- Performance issues
  - Assume the graph is in memory?
  - Precompute all-pairs shortest path (|V|<sup>3</sup>)?
  - Prune unpromising candidates?

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# Hub indexing

- Decompose APSP problem using sparse vertex cuts
  - |A|+|B| shortest paths to p
  - |A|+|B| shortest paths to q
  - d(p,q)
- To find *d*(*a*,*b*) compare
  - $d(a \rightarrow p \rightarrow b)$  not through q
  - $d(a \rightarrow q \rightarrow b)$  not through p
  - $d(a \rightarrow p \rightarrow q \rightarrow b)$
  - $d(a \rightarrow q \rightarrow p \rightarrow b)$
- Greatest savings when |A|≈|B|
- Heuristics to find cuts, e.g. large-degree nodes



#### Connected subgraph as response

- Single node may not match all keywords
- No natural "page boundary"
- Two scenarios
  - Keyword search on relational data
    - Keywords spread among normalized relations
  - Keyword search on XML-like or Web data
    - Keywords spread among DOM nodes and subtrees

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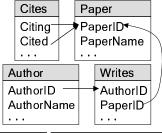
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	No.	DBXplorer,	EasyAsk, Mercado,	
	schema	BANKS,	DataSpot, BANKS	
		DISCOVER		

- Adding IR-like text search features to XML query languages
- A graph model for relational data with "free-form" text search and implicit joins
- Generalizing to graph models for XML

#### Keyword search on relational data

- Tuple = node
- Some columns have text
- Foreign key constraints = edges in schema graph→
- Query = set of terms
- No natural notion of a document
  - Normalization
  - Join may be needed to generate results
  - Cycles may exist in schema graph: 'Cites'

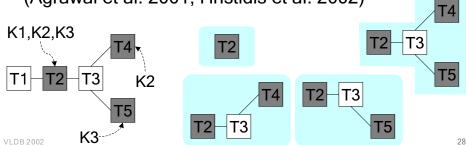


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	ļ		•	P2	BANKS

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# **DBXplorer and DISCOVER**

- Enumerate subsets of relations in schema graph which, when joined, may contain rows which have all keywords in the query
  - "Join trees" derived from schema graph
- Output SQL query for each join tree
- Generate joins, checking rows for matches (Agrawal et al. 2001, Hristidis et al. 2002)



#### **Discussion**

- Exploits relational schema information to contain search
- Pushes final extraction of joined tuples into RDBMS
- Faster than dealing with full data graph directly
- Coarse-grained ranking based on schema tree
- Does not model proximity or (dis) similarity of individual tuples
- No recipe for data with less regular (e.g. XML) or ill-defined schema

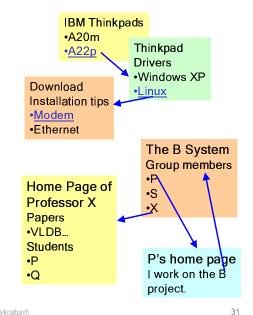
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# Generalized graph proximity

- General data graph
  - Nodes have text, can be scored against query
  - Edge weights express dissimilarity
- Query is a set of keywords as before
- Response is a connected subgraph of the database
- Each response graph is scored using
  - Node weights which reflect match, maximize
  - Edge weights which reflect lack of proximity, minimize

#### Motivation from Web search

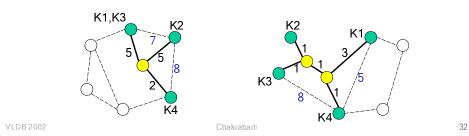
- "Linux modem driver for a Thinkpad A22p"
  - Hyperlink path matches query collectively
  - Conjunction query would fail
- Projects where X and P work together
  - Conjunction may retrieve wrong page
- General notion of graph proximity



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# "Information unit" (Lee et al., 2001)

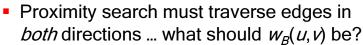
- Generalizes join trees to arbitrary graph data
- Connected subgraph of data without cycles
- Includes at least one node containing each query keyword
- Edge weights represent price to pay to connect all keyword-matching nodes together
- May have to include non-matching nodes



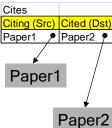
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# Setting edge weights

- Edges are generally directed
  - Foreign to primary key in relational data
  - Containing to contained element in XML
  - IDREFs have clear source and target
- Consider the RDMS scenario
- Forward edge weight for edge (u, v)
  - u, v are tuples in tables R(u), R(v)
  - Weight s(R(u),R(v)) between tables
    - · Configured heuristically based on semantics
    - $w_F(u, v) = s(R(u), R(v))$  all such tuple pairs u, v





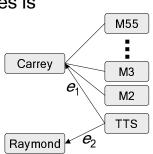


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#### Backward edge weights

 "Distance" between a pair of nodes is asymmetric in general

- Ted Raymond acted only in The Truman Show, which is 1 of 55 movies for Jim Carrey
- $w(e_1)$  should be larger than  $w(e_2)$  (think "resistance" on the edge)
- For every edge (u,v) that exists,  $w_B(u,v)=s(R(v),R(u))$  .  $IN_v(u)$ 
  - $IN_{\nu}(u)$  is the #edges from R(v) to u
- $w(u, v) = \min\{w_F(u, v), w_B(u, v)\}$
- More general edge weight models possible, e.g., R→S→T relation pathbased weights



# Node weight = relevance + prestige

- Relevance w.r.t. keyword(s)
  - 0/1: node contains term or it does not

Cosine score in [0,1] as in IR

 Uniform model: a node for each keyword (e.g. DataSpot)

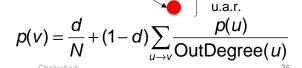


a random node

W.p. (1-d) jump to an

out-neighbor

- Popularity or prestige
  - E.g. "mohan transaction"
  - Indegree
  - PageRank



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# Trading off node and edge weights

- A high-scoring answer A should have
  - Large node weight
  - Small edge weight
- Weights must be normalized to extreme values
- N(ν)=node weight of ν

$$\frac{\sum_{v \in A} \log(1 + \frac{N(v)}{N_{\text{max}}})}{\text{\#nodes}}$$

Overall NodeScore =

• Overall EdgeScore = 
$$\frac{1}{1 + \sum_{e \in A} \log(1 + \frac{w(e)}{w_{min}})}$$

- Overall score = EdgeScore × NodeScore<sup>λ</sup>
  - λ tunes relative contribution of nodes and edges
- Ad-hoc, but guided by heuristic choices in IR

#### Data structures for search

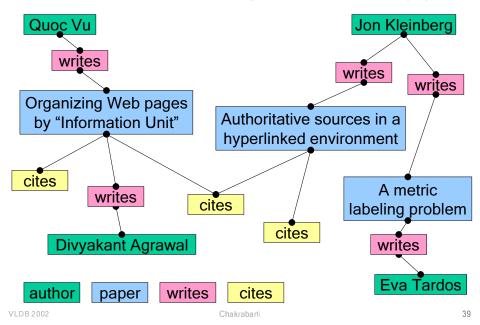
- Answer = tree with at least one leaf containing each keyword in query
  - · Group Steiner tree problem, NP-hard
- Query term t found in source nodes S<sub>t</sub>
- Single-source-shortest-path SSSP iterator
  - Initialize with a source (near-) node
  - Consider edges backwards
  - getNext() returns next nearest node
- For each iterator, each visited node ν maintains for each t a set ν.R<sub>t</sub> of nodes in S<sub>t</sub> which have reached ν

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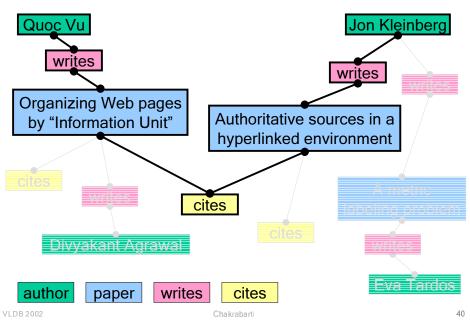
#### Generic expanding search

- Near node sets  $S_t$  with  $S = \bigcup_t S_t$
- For all source nodes  $\sigma \in S$ 
  - create a SSSP iterator with source σ
- While more results required
  - Get next iterator and its next-nearest node v
  - Let t be the term for the iterator's source s
  - crossProduct = {s}  $\times \prod_{t'\neq t} v.R_{t'}$
  - For each tuple of nodes in crossProduct
    - Create an answer tree rooted at v with paths to each source node in the tuple
  - Add s to v.R,

# Search example ("Vu Kleinberg")



# First response



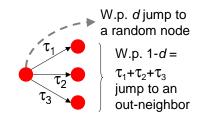
# Folding in user feedback

- As in IR systems, results may be imperfect
  - Unlike SQL or XQuery, no exact control over matching, ranking and answer graph form
  - Ad-hoc choices for node and edge weights
- Per-user and/or per-session
  - By graph/path/node type, e.g. "want author citing author," not "author coauthoring with author"
- Across users
  - Modifying edge costs to favor nodes (or node types) liked by users

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#### Random walk formulations

- Generalize PageRank to treat outlinks differently
  - τ(u,v) is the "conductance" of edge u→ v
- p(ν) is a function of τ(u, ν) for all in-neighbors u of ν
  - p<sub>guess</sub>(v) ... at convergence
  - puser(v) ... user feedback



$$p(v) = \frac{d}{N} + \sum_{u \to v} p(u) \ \tau(u, v)$$
$$\frac{\partial p(v)}{\partial \tau(u, v)} = p(u)$$

#### Gradient ascent/descent:

- For each  $u \rightarrow v$ , set (with learning rate  $\eta$ ):  $\tau(u,v) \leftarrow \tau(u,v) + \eta \operatorname{sgn}(p_{user}(v) p_{guess}(v)) \frac{p(u)}{\sum_{u' \rightarrow v} p(u')}$
- Re-iterate to convergence

#### Prototypes and products

- DTL DataSpot → Mercado Intuifind <u>www.mercado.com/</u>
- EasyAsk <u>www.easyask.com/</u>
- ELIXIR www.smi.ucd.ie/elixir/
- XIRQL <u>ls6-www.informatik.uni-dortmund.de/ir/projects/hyrex/</u>
- Microsoft DBXplorer
- BANKS www.cse.iitb.ac.in/banks/

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#### **Summary**

- Confluence of structured and free-format, keyword-based search
  - Extend SQL, XQuery, Web search, IR
  - Many useful applications: product catalogs, software libraries, Web search
- Key idiom: proximity in a graph representation of textual data
  - Implicit joins on foreign keys
  - Proximity via IDREF and other links
- Several working systems
- Not enough consensus on clean models

#### Open problems

- Simple, clean principles for setting weights
  - Node/edge scoring ad-hoc
  - Contrast with classification and distillation
- Iceberg queries
  - Incremental answer generation heuristics do not capture bicriteria nature of cost
- Aggregation: how to express / execute
- User interaction and query refinement
- Advanced applications
  - Web query, multipage knowledge extraction
  - Linguistic connections through WordNet

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