Extracting, Searching and Mining Semantic Annotations on the Web
Tutorial T10-F, WWW 2009

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High-level TOC

Annotation:
- Identifying token segments as entity mentions
- Ditto for relations
- Annotation vs. extraction
- Closed vs. open domain

Disambiguation:
- Supervised: against entities in a catalog
- Unsupervised: cluster mentions referring to same entity

Search:
- Relational
- XML, trees, twigs
- Proximity in text and general graphs
Timeline view

1992  Hearst patterns
1998  DIPRE (duality in pattern-relationship extraction)
2000  Snowball = DIPRE + confidence scores
2001  Turney’s PMI
2001  SemTag and Seeker
2000–now  Many systems for labeling token spans or 2d regions with entity types
2004  KnowItAll ≈ Hearst patterns + list extraction + a few more tricks
2007  TextRunner and ExDB

Supervision view

Detailed, domain-specific supervision: All sequential and tree labeling tasks

Limited domain, query by example:
  ▶ Fixed is-a relation: KnowItAll [8]
  ▶ Broader set of binary relations: DIPRE [2], Snowball [3]

Open-domain, only linguistic supervision: Arbitrary unnamed relations: TextRunner [9]
Tagging entities

- Restricted set of types or domains
- E.g., person, place, organization, date, paper title, conference venue, journal name, page range, number and street name
- *Closed domain* means positive and negative examples available for each type
- Test data is unlabeled token sequences
- The job is to mark some token segments with one or the trained types

Markov models

- System is in one of $M$ states $y_t$
- In each state, emits $x_t$ one of $N$ symbols
- Then moves to one of $M$ states $y_{t+1}$
- Many state transitions disallowed
Viterbi decoding

Limitations of generative models

- Would like to think of $x_t$ not as a symbol
- But as a feature vector
  - hasCap, isAllCap, isXxx, hasDigit, isAllDigits, isDDDD
    - isAllCap $\implies$ hasCap
    - isDDDD $\implies$ isAllDigits
- Correlated features – same issue as naive Bayes vs. logistic regression
- Prefer to model $Pr(y|x)$ rather than model $Pr(x|y)$ and use Bayes rule
Markov sequence features

- $x = (x_t : t = 1, \ldots, T)$ is the sequence of visible symbols
- Suppose there are $N$ symbols
- $y = (y_t : t = 1, \ldots, T)$ is the label/state sequence
- Suppose there are $M$ states
- Define a feature vector $\phi(x, y) \in \mathbb{R}^d$
- From training data $x^i, y^i : i = 1, \ldots, n$, learn a model $w \in \mathbb{R}^d$
- Given test sequence $x$, predict label sequence $\arg \max_y w^T \phi(x, y)$

Designing $\phi(x, y)$

- $N$ symbols, $M$ states
- Think of $\phi(x, y)$ as a $M \times (N + M)$ matrix

\[
\begin{array}{cc}
\Lambda & \Psi \\
\in \mathbb{R}^{M \times N} & \in \mathbb{R}^{M \times M}
\end{array}
\]

- $\Lambda[m, n]$ is the number of times symbol $n$ was emitted while in state $m$
- $\Psi[m, m']$ is the number of times a transition was made from state $m$ to $m'$
- Model $w$ also has $M(N + M)$ elements
Training $w$

- For each sequence $x^i$, there is (say) one correct labeling $y^i$; all other (exponentially many) labelings $y \neq y^i$ are incorrect
- Want to fit $w$ such that
  \[ \forall i, \forall y \neq y^i : w^\top \phi(x^i, y) > w^\top \phi(x^i, y^i) \]
- The worse $y$ is compared to $y^i$ the bigger we want the gap to be
- **Loss function** $\Delta(y^i, y) \geq 0$; $\Delta(y, y) = 0$
- E.g., Hamming loss
- $\forall i, \forall y \neq y^i : w^\top \phi(x^i, y) \geq w^\top \phi(x^i, y^i) + \Delta(y^i, y)$

**B-I-O state model**

- Our definition of $\Lambda$ limits interaction between $x$ and $y$ to individual positions, e.g., $x_t$ and $y_t$
- But this can be easily extended: we can define features between $x_{t-1}$ and $y_t$, or $x_{t+1}$ and $y_t$
- States none, person, place, epoch
  - Roy went to Boston in 1994
- “at” or “to” often precede place, “on” or “in” often precede epoch
- But the state of at, to, on, in are all ‘none’
Pattern-relationship duality

- Start with a small table of known facts
  - Isaac Asimov: The Robots of Dawn
  - David Brin: Startide Rising
  - James Gleick: Chaos: Making a New Science
  - Charles Dickens: Great Expectations
  - William Shakespeare: The Comedy of Errors

- Find mentions of known authors and books in the corpus:

- Induce and evaluate patterns on known data
  - *prefix, author, middle, title, suffix*

Pattern-relationship duality (2)

- `<LI><B>title</B>` by author (  
- `<I>title</I>` by author (  

- Find matches to patterns over corpus (scan/index?)  
- Import confident extractions into database  
- Rinse and repeat  
- Brin bootstrapped as follows: 5 facts → 199 occurrences → 3 patterns → 4047 proposed facts → 105 more patterns → 9369 proposed facts  
- Quality control needed
More pattern examples

<table>
<thead>
<tr>
<th>Organization</th>
<th>Location of headquarters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microsoft</td>
<td>Redmond</td>
</tr>
<tr>
<td>Exxon</td>
<td>Irving</td>
</tr>
<tr>
<td>IBM</td>
<td>Armonk</td>
</tr>
<tr>
<td>Boeing</td>
<td>Seattle</td>
</tr>
<tr>
<td>Intel</td>
<td>Santa Clara</td>
</tr>
</tbody>
</table>

- $e_1$’s headquarters in $e_2$
- $e_2$-based $e_1$
- $e_1$, $e_2$

Generic bootstrapping pseudocode

1. input seed tuples \( \{(e_{i1}, e_{i2}), i = 1, \ldots, n\} \)
2. while database not big enough do
3. find snippets in corpus where seed tuples are mentioned
4. tag entities in snippets
5. generate new patterns $L, t_1, C, t_2, R$ or $L, t_2, C, t_1, R$
6. apply new patterns over whole corpus
7. import newly extracted tuples into database

- Which patterns are sufficiently reliable and useful?
- Which extracted tuples are likely to be correct?
### How to represent patterns

<table>
<thead>
<tr>
<th>Organization $e_1 \in t_1$</th>
<th>Headquarter location $e_2 \in t_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microsoft</td>
<td>Redmond</td>
</tr>
<tr>
<td>Exxon</td>
<td>Irving</td>
</tr>
<tr>
<td>IBM</td>
<td>Armonk</td>
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<td>Seattle</td>
</tr>
<tr>
<td>Intel</td>
<td>Santa Clara</td>
</tr>
</tbody>
</table>

- $L = \{(\text{the}, 0.2)\}$
- $t_1 = \text{organization}$
- $C = \{(-, 0.5), (\text{based}, 0.5)\}$
- $t_2 = \text{location}$
- $R = \{\}$

### How to induce and evaluate patterns

- Pattern generated by clustering contexts of known facts
- Keep a held-out set of verified true and false is-a statements
- Apply pattern $P$ on held-out statements
- Use some notion like precision or $F_1$ as pattern confidence $\text{Conf}(P)$, e.g.,

\[\text{Conf}(P) = \frac{n^+}{n^+ + n^-},\]

where $n^+$ ($n^-$) is the number of known true (false) statements matched by $P$
Pattern match

- Two patterns $P_1 = (L_1, a_1, C_1, b_1, R)$ and $P_2 = (L_2, a_2, C_2, b_2, R_2)$ have nonzero match only if $a_1 = a_2$ and $b_1 = b_2$
- In that case, the match score is

$$\text{Match}(P_1, P_2) = L_1 \cdot L_2 + C_1 \cdot C_2 + R_1 \cdot R_2$$

i.e., sum of dot products of word bags
- Can scale to make it a belief between 0 and 1, or threshold it

Confidence of match

$$1 - \prod_{P} (1 - \text{Conf}(P) \cdot \text{Match}(P, S))$$

- $P$ is a pattern
- $S$ is a snippet containing $e_1 \in t_1, e_2 \in t_2$
- A soft-or formulation
- Can iterate between match and pattern confidence using EM
Dependency parsing

- Links tokens in sentence
- Edges encode purpose of syntax
- Often used for slot filling [14]:
  - Which company bought out which company?
  - For how much money?
  - How much in stocks vs. cash?
  - Where did the accident happen?
  - How many were injured?

Shortest path kernel
Visual/Xpath extraction

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Hearst patterns

- "The bow lute, such as the Bambara ndang, is plucked and has an individual curved neck for each string."
  - What is a Bambara ndang?
  - Can answer without knowing what a bow lute is!
- Source pattern: NPO such as \{NP1, NP2 \ldots , (and|or)\} NPn
- Target inference: for all NPi, i = 1, \ldots , n, hyponym(NPi, NPO)

More patterns

- such NP as NP, *(or|and) NP
  - "\ldots works by such authors as Herrick, Goldsmith, and Shakespeare."
  - Let us infer hyponym(‘‘author’’, ‘‘Herrick’’), hyponym(‘‘author’’, ‘‘Goldsmith’’), hyponym(‘‘author’’, ‘‘Shakespeare’’)
- NP, NP*, *(or|and) other NP
- NP, (especially|including) NP, *(or|and) NP
- NP1 is a NP2
Caveats

- Garth Brooks is a country singer
- gift such as wall
- person like Paris
Caveats

- Garth Brooks is a country singer
- gift such as wall clock
- person like Paris Hilton
Caveats

- Garth Brooks is a country singer
- gift such as wall clock
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- Need noun phrase chunking, e.g. “country singer” or “wall clock”
- Also need disambiguation, because “Hilton” may not be mentioned explicitly
- Cannot depend on simple phrase queries on a text index

KnowItAll

- Specific binary relation: is-a
- Use Hearst patterns to get high-confidence facts
- Pick random subsets (say, of size 3–4)
- Ask Web query with subset
- Locate HTML lists mentioning most elements of subset
- Judge if list is of entities of same type (how?)
- Extract other candidate entities from list
- Use global stats to validate candidates
List/table extraction

Direct Flights from/to Toulouse - Casablanca International Airport

<table>
<thead>
<tr>
<th>City</th>
<th>Flight hours</th>
<th>Company</th>
<th>Frequency</th>
<th>Fare (Euro)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amsterdam</td>
<td>2.00</td>
<td>KLM</td>
<td>Daily</td>
<td>3500.0</td>
</tr>
<tr>
<td>Barcelona</td>
<td>2.00</td>
<td>Iberia</td>
<td>Daily</td>
<td>3000.08</td>
</tr>
<tr>
<td>Brussels</td>
<td>1.40</td>
<td>Sabena</td>
<td>Daily</td>
<td>3000.75</td>
</tr>
<tr>
<td>Dusseldorf</td>
<td>2.00</td>
<td>Lufthansa</td>
<td>Daily</td>
<td>3200.10</td>
</tr>
<tr>
<td>Frankfurt</td>
<td>1.15</td>
<td>Lufthansa</td>
<td>Daily</td>
<td>3200.75</td>
</tr>
<tr>
<td>Lisbon</td>
<td>3.30</td>
<td>AirPortug</td>
<td>No Saturday</td>
<td>3500.1050</td>
</tr>
<tr>
<td>London</td>
<td>2.00</td>
<td>RyanAir</td>
<td>Daily</td>
<td>Online Only</td>
</tr>
<tr>
<td>Madrid</td>
<td>2.10</td>
<td>Iberia</td>
<td>Daily</td>
<td>3000.83</td>
</tr>
<tr>
<td>Munich</td>
<td>2.00</td>
<td>Lufthansa</td>
<td>Daily</td>
<td>3000.95</td>
</tr>
</tbody>
</table>

Open information extraction¹

- Traditional heavily-supervised IE is narrow
- Applied to small, homogeneous corpora
- On the Web
  - No parser is sufficiently accurate
  - No pre-trained named-entity taggers
  - Supervised learning is impractical
- Semisupervised learning needs a few hand-labeled examples per concept
- Concepts themselves are pre-specified

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¹From Etzioni slides at WSDM 2008
TextRunner

- Use a simple model of relationships in English to label extractions
- Bootstrap a general model of relationships in English sentences, encoded as a CRF
- Using a shallow parser, decompose each sentence into one or more (NP1, VP, NP2) chunks
- Use CRF model to retain relevant parts of each NP and VP


TextRunner example

- Extract Triple representing binary relation (Arg1, Relation, Arg2) from sentence.
  - Internet powerhouse, EBay, was originally founded by Pierre Omidyar.
  - Internet powerhouse, EBay, was originally founded by Pierre Omidyar.
  - RDF-like triple (Ebay, Founded by, Pierre Omidyar)


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TextRunner example\textsuperscript{3}

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From Etzioni slides at WSDM 2008

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Entity disambiguation

- ... book by Mike Jordan on graphical models ...
- ... chance to see Michael Jordan play without Dean Smith ...
- Which entity catalog to use? (Wikipedia, TAP, OpenCYC, WordNet, ...)
- What about the many Mike Jordans not in the catalog?
- Different from anaphora: Every dog has its day

Some distinctions from WSD

- Word sense disambiguation (WSD) is largely about common words, not references to specific entities
  - 42 senses of “run” in WordNet
  - Part of speech helps a fair bit
- Entity catalog typically richer info source than dictionary
  - Broader category system
  - Part of speech is largely “proper noun” and not as helpful
Why annotate?

- Make raw text look like Wikipedia with definitional and informational links (most systems)
  - Annotate first occurrence only
  - Annotate only on-topic entities
  - Use discretion to avoid “hyperlink fatigue”
- Index the annotations to enable advanced search (our focus)
  - Exhaustive annotation
  - Make no whole-document topic judgment

Notation

- book by Mike Jordan on graphical models and chance to see Michael Jordan play without Dean Smith are spots $s$
- Mike Jordan and Michael Jordan are mentions, other tokens form context
- $\gamma$ is an entity ID or label from the catalog
- Goals:
  - Identify that a sequence of tokens is a potential mention
  - Capture suitable context around to form spot $s$
  - Assign $s$ to a suitable entity $\gamma$ in catalog
  - Or claim that there is no suitable $\gamma$
- $n$ spots on a page
Notation (2)

- $y_s$ is the entity label assigned to spot $s$
- $y$ is a vector of $n$ label variables
- $\Gamma_s$ is the set of labels admissible for spot $s$

Catalog representation

- Pattern after WordNet, Wikipedia, TAP, . . .
- Each entity $\gamma$ as an associated description
- Descriptions link to other related entities $\gamma'$
- Entities belong to one or more categories
- Categories (physicist) are subcategories of others (scientist)
- Links may be "incidental"
- Categories and super-categories may be noisy: *Machine learning researcher* more meaningful than *Living people* or *Year of birth missing*
- Cycles in is-a "hierarchy"?
Local compatibility between $s$ and $\gamma$

- Feature vector $f_\gamma(s) \in \mathbb{R}^d$ expresses local textual compatibility between (context of) spot $s$ and candidate label $\gamma$.
- One element of $f_\gamma(s)$ might be the TFIDF cosine similarity between tokens from the context of spot $s$ (say $\pm 10$ tokens) and whole page of description for entity $\gamma$.
- Another element may be derived of “anchor text” match:
  - Find all links to $\gamma$ from within Wikipedia.
  - Collect anchor text from all these links in a bag of words.
  - Find TFIDF cosine similarity between this bag and the spot context $s$.

Node score

- Node scoring model $w \in \mathbb{R}^d$.
- Node score defined as $w^\top f_\gamma(s)$.
- $w$ is trained to give suitable relative weights to different compatibility measures and aggregate the evidence.
- During test time, greedy choice local to $s$ would be $\text{arg max}_{\gamma \in \Gamma_s} w^\top f_\gamma(s)$.
- Early algorithms are variations on this theme.
Two-phase process
- First identify token spans “worthy of annotation”
- Then choose entity labels

Sample annotations

In 1834, Sumner was admitted to the [[bar (law)|bar]] at the age of twenty-three, and entered private practice in Boston.

It is danced in 3/4 time (like most waltzes), with the couple turning approx. 180 degrees every [[bar (music)|bar]].

Vehicles of this type may contain expensive audio players, televisions, video players, and [[bar (counter)|bar]]s, often with refrigerators.

Jenga is a popular beer in the [[bar (establishment)|bar]]s of Thailand.

This is a disturbance on the water surface of a river or estuary, often cause by the presence of a [[bar (landform)|bar]] or dune on the riverbed.
Choosing token spans to annotate

- Wikify! follows the Wikipedia philosophy
- Use some score to rank candidate spans
- TFIDF of a token in a document
  \[
  \text{count of token in doc} \quad \text{count of all other tokens in doc}
  \]
- \( \chi^2 \) test:
  \[
  \begin{array}{c|c}
  \text{count of token in other docs} & \text{count of all other tokens in other docs} \\
  \end{array}
  \]
- “Keyphraseness” — In how many Wikipedia documents is the same term made a link anchor?
- (They only consider as candidates words which appear at least five times in Wikipedia)

Disambiguation

Wikify! compares two local techniques:

- “Knowledge-based approach” — similarity between Wikipedia page text of entity \( \gamma \) and context words in spot \( s \)
- “Data-driven approach” — similarity between context of known links to \( \gamma \) and context words in spot \( s \)
- “Context” consists of ±3 words around mention, their parts of speech, salient words chosen from whole document
Results

- “Data-driven” better than “knowledge-based”
- Consensus (agreement) has highest precision

<table>
<thead>
<tr>
<th>Method</th>
<th>Words</th>
<th>Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(A)</td>
<td>(C)</td>
</tr>
<tr>
<td>Baselines</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random baseline</td>
<td>6,517</td>
<td>4,161</td>
</tr>
<tr>
<td>Most frequent sense</td>
<td>6,517</td>
<td>5,672</td>
</tr>
<tr>
<td>Word sense disambiguation methods</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge-based</td>
<td>6,517</td>
<td>5,255</td>
</tr>
<tr>
<td>Feature-based learning</td>
<td>6,517</td>
<td>6,055</td>
</tr>
<tr>
<td>Combined</td>
<td>5,433</td>
<td>5,125</td>
</tr>
</tbody>
</table>
Relatedness info from entity catalog

- How related are two entities $\gamma, \gamma'$ in Wikipedia?
- Embed $\gamma$ in some space using $g : \Gamma \rightarrow \mathbb{R}^c$
- Define relatedness $r(\gamma, \gamma') = g(\gamma) \cdot g(\gamma')$ or related
- Cucerzan’s proposal: $c =$ number of categories; $g(\gamma)[\tau] = 1$ if $\gamma$ belongs to category $\tau$, 0 otherwise

$$r(\gamma, \gamma') = \frac{g(\gamma) \cdot g(\gamma')}{\sqrt{g(\gamma) \cdot g(\gamma)} \sqrt{g(\gamma') \cdot g(\gamma')}}$$

(standard cosine)

Relatedness info from entity catalog (2)

- Milne and Witten’s proposal: $c =$ number of Wikipedia pages; $g(\gamma)[p] = 1$ if page $p$ links to page $\gamma$, 0 otherwise

$$r(\gamma, \gamma') = \frac{\log |g(\gamma) \cap g(\gamma')|}{\log \frac{c}{\min\{|g(\gamma)|, |g(\gamma')|\}}}$$

- Related to Jaccard
- With voice of small inlink sets attenuated
Leave-one-out disambiguation

- Let $\Gamma_0$ be all possible entity disambiguations for all spots on a page
- Precompute the average vector $g(\Gamma_0) = \sum_{\gamma \in \Gamma_0} g(\gamma)$
- Score of candidate label $\gamma$ for spot $s$ depends on two factors multiplied together
- The local compatibility score as before
- $g(\gamma)^T g(\Gamma_0 \setminus \{\gamma\}) = g(\gamma)^T \sum_{\gamma' \in \Gamma_0 \setminus \gamma} g(\gamma')$
- Note that $\Gamma_0 \setminus \gamma$ still contains contributions from entities that cannot be used simultaneously to label the page
- $g(\Gamma_0 \setminus \gamma)$ may not be a representative feature vector

The need for collective disambiguation

- Premise: coherent doc refers to entities about related categories
- Optimize wrt $y$ an objective with two parts:
  - Local compatibility between $s$ and $y_s$
  - Global coherence between $y_s$ and $y_{s'}$ for all spot pairs
Two-part objective to maximize

Node potential:

\[ \text{NP}(y) = \prod_s \text{NP}_s(y_s) = \prod_s \exp (w^\top f_s(y_s)) \]

Clique potential:

\[ \text{CP}(y) = \exp \left( \sum_{s \neq s'} g(y_s)^\top g(y_{s'}) \right) \]

After taking logs and rescaling terms

\[ \frac{1}{|S_0|} \sum_s w^\top f_s(y_s) + \frac{1}{\binom{|S_0|}{2}} \sum_{s \neq s'} g(y_s)^\top g(y_{s'}) \]
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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
- 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

Web search←IR
- 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
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
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 \( \text{TF}(d,t) \)
  - Absolute term count or scaled by max term count
- Downplay frequent terms: \( \text{IDF}(t) = \log(1+|D|/|D_t|) \)
  - Better model: document vector \( d \) has component \( \text{TF}(d,t) \text{IDF}(t) \) for term \( t \)
- Query is like another “document”; documents ranked by cosine similarity with query

Map

<table>
<thead>
<tr>
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- “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
WHIRL (Cohen 1998)

- 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
  - $score(B_1 \land \ldots \land B_m; \theta) = \Pi_{1 \leq i \leq m} score(B_i, \theta)$
  - $score(B_1 \lor \ldots \lor B_m; \theta) = 1 - \Pi_{1 \leq i \leq m} (1 - score(B_i, \theta))$
Query execution strategy

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

- Start with `place(U1,S)` and `job(U2,D)`

  - 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
- Path expressions

```xml
<dishes_with_flour> { FOR $r IN document("recipes.xml")
  //recipe[//ingredient[@name="flour"]]
  RETURN <dish>{$r/title/text()}</dish> }
</dishes_with_flour>
```
Early text support in XQuery

- Title of books containing some para mentioning both “sailing” and “windsurfing”
  
  ```xml
  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”
  
  ```xml
  FOR $a IN view("text_table") WHERE
  numMatches($a/text_document,"stocks") > 3
  RETURN
  <text>{$a/text_title}{$a/text_document}</>}
  ```

Tutorial outline

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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)
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
  for $vi$ in
document("vldb.xml")/issue[@volume>24], $si$ in document("macbeth.xml")//speech
  where $vi$//article/title ~ $si$
  return <similar><title>$vi$//article/title</title>$si</speech></similar>

How ELIXIR works

ELIXIR query → ELIXIR Compiler → VLDB.xml → Macbeth.xml → Base XML documents
XQuery filters/transformers

→ Flatten to WHIRL → WHIRL select/join filters → Rewrite to XML → Result
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
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”
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)
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 $\text{score}(r) = \sum_{a \in A} b(a, r)$
- Belief $\text{score}(r) = 1 - \prod_{a \in A} (1 - b(a, r))$
- 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 ($|V|^3$)?
  - Prune unpromising candidates?
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 $|A| \approx |B|$
- 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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- 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’

<table>
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Chakrabarti
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
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
“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

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 \(u, v\)
- Proximity search must traverse edges in both directions ... what should \(w_B(u, v)\) be?
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, \( w_B(u,v) = s(R(v), R(u)) \cdot \text{IN}_v(u) \)
  - \( \text{IN}_v(u) \) 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., \( R \rightarrow S \rightarrow T \) relation path-based 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)
- Popularity or prestige
  - E.g. "mohan transaction"
  - Indegree
  - PageRank

\[
p(v) = \frac{d}{N} + (1 - d) \sum_{u \rightarrow v} \frac{p(u)}{\text{OutDegree}(u)}
\]
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
- $N(\nu) =$ node weight of $\nu$
- Overall NodeScore = $\sum_{\nu \in A} \log\left(1 + \frac{N(\nu)}{N_{\text{max}}} \right) / \# \text{nodes}$
- Overall EdgeScore = $1 / \left(1 + \sum_{e \in A} \log\left(1 + \frac{w(e)}{w_{\text{min}}} \right) \right)$
- Overall score = $\text{EdgeScore} \times \text{NodeScore}^\lambda$
  - $\lambda$ 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 $S_t$
- 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 $\nu$ maintains for each $t$ a set $\nu.R_t$ of nodes in $S_t$ which have reached $\nu$
Generic expanding search

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

Search example (“Vu Kleinberg”)

Quoc Vu
writes
Organizing Web pages by “Information Unit”
cites
writes
writes
Divyakant Agrawal
author
cites
writes
papers
Eva Tardos
writes
A metric labeling problem
Authoritative sources in a hyperlinked environment
writes
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
Random walk formulations

- Generalize PageRank to treat outlinks differently
  - $\tau(u,v)$ is the "conductance" of edge $u \rightarrow v$
- $p(v)$ is a function of $\tau(u,v)$ for all in-neighbors $u$ of $v$
  - $p_{\text{guess}}(v)$ ... at convergence
  - $p_{\text{user}}(v)$ ... user feedback

Gradient ascent/descent:

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

Prototypes and products

- DTL DataSpot $\rightarrow$ Mercado Intuifind [www.mercado.com/](http://www.mercado.com/)
- EasyAsk [www.easyask.com/](http://www.easyask.com/)
- ELIXIR [www.smi.ucd.ie/elixir/](http://www.smi.ucd.ie/elixir/)
- XIRQL [ls6-www.informatik.uni-dortmund.de/ir/projects/hyrex/](http://ls6-www.informatik.uni-dortmund.de/ir/projects/hyrex/)
- Microsoft DBXplorer
- BANKS [www.cse.iitb.ac.in/banks/](http://www.cse.iitb.ac.in/banks/)
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
References


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References (3)


References (4)


References (5)


References (6)


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