Bridging the Structured-Unstructured Gap

Searching the Annotated Web

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Search engine evolution

- From brittle ranking and near-duplicate results (ca. 1995) …
- … to spam filtering, link-assisted ranking, result diversification, geosensitivity
- Limited type-awareness in verticals
  - 1 kg = ? lb, distance rome venice
  - Hotels near Brooklyn Bridge
- However, there remain information needs where cognitive burden is still very large
Challenging queries

- Artists who got Oscars for both acting and direction *(same movie?)*
- *(Typical price of)* Opteron motherboards with at least two PCI express slots
- Is the number of Oscars won directly related to production budget?
- How many justices serve in the International Criminal Court?
- Exxon Valdez cleanup cost
- How many papers submitted to SIGMOD?
Why difficult?

• Search engines provide excellent “low-level access methods to pages”, but ...

• No variables
  – \(?a\) acts, \(?a\) directs movies

• No types
  – \(?m \in Motherboard, ?p \in MoneyAmount\)

• No predicates
  – \(?m\) sells for \(?p\), \(?m\) costs \(?p\)

• No aggregates
  – Large variation in Exxon Valdez estimate
What if we could ask…

- $?f \in^+ \text{Category:FrenchMovie}
- $?a \in \text{QType:Number}
- $?b \in \text{QType:MoneyAmount}
- $?c1, $?c2 \text{ are snippet contexts}
- \text{InContext}( $?c1, $?f, $?a, +\text{oscar, won})$
- \text{InContext}( $?c2, $?f, $?p, +"production cost")
  \text{ or InContext}( $?c2, $?f, $?p, +\text{budget})$
- \text{Aggregate}( $?c1, $?c2)$
- \text{Answer: list of } \langle $?f, $?a, $?b \rangle \text{ tuples}
Disclaimers

- Esoteric
- Public domain
- May not work today
- Speculative, “what if”
- Ideas, prototypes

- Mainstream
- Proprietary
- Stable, practical
- Broad user base
- Traffic, revenue
Influences

Searching
the annotated
Web

Your
idea
here

Statistical info
extraction

NLP tagging,
WSD

Question
answering

WebKB,
KnowItAll,
Web Reading

Uncertain,
probabilistic
databases

XML search,
RDF, SPARQL

Semantic Web,
linked data
Pieces to the puzzle

Raw corpus

1. Spotter

2. Indexer

3. Query API provider

Catalog of types and entities

Query processor

Entity annotations

Composite index
Mentions and spots

The lack of **memory** and time efficient **libraries** in the **free software world** has been the main motivation to create the C **Minimal Perfect Hashing Library**, a portable **LGPL library**.

- A **mention** is any token segment that may be a reference to an entity in the catalog
- Mention + limited token context = **spot**
- Mentions and spots may overlap
- \( S_0 \): set of all spots on a page
- \( s \in S_0 \): one spot among \( S_0 \)
A massive similarity join

... the New York Times reported on school library budgets ...

York University
Duke of York ...

New York City
New York State
York University ...

New York Times
Time Magazine

Library, a collection of books...
Library (computing), a collection of subprograms...
Library (Windows 7), virtual folder that aggregates...
Library (electronics), a collection of cells, macros...
Library (biology), a collection of molecules...
Library Records, a record label
"The Library" (Seinfeld)
Library (UTA station), a transit station...
Library of Congress

Wikipedia:
2.5M entities
2.8M “lemmas”
7M lemma tokens
IDF, prefix/exact match, case, ...
Disambiguation

• $s$ is a spot with a mention of some entity
• $\Gamma_s$ is the set of candidate entities for $s$
• $\gamma \in \Gamma_s$ is one candidate entity for $s$
• $s$ may be best left unconnected to any entity in the catalog (“no attachment”, NA)
  – Most people mentioned on the Web

• Generalization of WSD in NLP
• SemTag/Seeker, Wikify!, Bunescu+Pasca, Cucerzan, Milne+Witten, [KSRC2009]
On first getting into the 2009 Jaguar XF, it seems like the ultimate in automotive tech. A red backlight on the engine start button pulses with a heartbeat cadence.
Encoding local compatibility

- $f_s(\gamma)$ is a vector of features
- Each feature is a function of $s$ and metadata associated with $\gamma$
- Learn $w$ from training data
- Choose
  $$\arg\max_{\gamma} w^T f_s(\gamma)$$
- Better than heuristics
Exploiting collective info

... **Michael Jordan** is also noted for his product endorsements. He fueled the success of Nike's **Air Jordan** sneakers.

...The **Chicago Bulls** selected Jordan with the third overall pick, ...

- Let \( y_s \in \Gamma_s \cup \text{NA} \) be the variable representing entity label for spot \( s \)
- Pick all \( y_s \) together optimizing global objective
Collective formulation

- Embed entities as vector $g(\gamma)$ in feature space
- Maximize local compatibility + global coherence
Collective model validation

- Local hill-climbing to improve collective obj
- Get F1 accuracy using ground truth annotations
- Very high positive correlation
Collective accuracy

- ~20,000 spots manually labeled in Web docs
- Local=training $W$
- Prior=bias objective using Wikipedia distribution
- LP1=relaxing collective integer program
Loose ends

• Learn not only $w$ but embedding $g(\gamma)$ and similarity between entity pairs
  – Applying the model should remain fast
• CPU cost of spotting + disambiguation compared to basic indexing
  – Use coarse page/site features to prune candidates?
• Training and evaluation at Web scale
  – Active learning framework
  – Exploit social tagging?
Pieces to the puzzle

Catalog of types and entities

Query API provider

Query processor

Compo-site index

Indexer

Entity annotations

Disambiguator

Spotter

Raw corpus
InContext subqueries

- Scientist who studied whales
  - $?s \in \text{Category:Scientist}$
  - $?s \in \text{Category:MarineBiologist}$
  - InContext(?c, ?s, study studied whale whales)

- Query expansion
  - Did Einstein, Bohr, Rutherford...study whales?
  - WordNet knows 650 scientistest, 860 cities
  - Wikipedia?
  - Impractical query times
Indexing for InContext queries

- Index expansion
  - Costeau → scientist → person → organism → living_thing → … → entity
  - Pretend all these tokens appear wherever Cousteau does, and index these

- Works ok for small type sets (5—10 broad types), but
  - WordNet: 15k internal, 80k total noun types
  - Wikipedia: 250k categories

- Index size explosion unacceptable
Pre-generalize

- Index a subset $R \subset A$
- Query type $a \notin R$
- Want $k$ answers
- Probe index with $g$, ask for $k' > k$ answers

Post-filter

- Fetch $k'$ high-scoring (mentions of) entities $w \in ^+ g$
- Check if $w \in ^+ a$ as well (using forward and reachability index); if not, discard
- If $< k$ survive, restart with larger $k$ (expensive!)
Cost-benefit considerations

• How much space saved by indexing $R$ instead of the whole of $A$?
  – Cannot afford to try out many $Rs$, need quick estimate

• What is the average query slowdown owing to $a \rightarrow g$ pre-generalize and post-filter?
  – Depends on query workload
  – Cannot afford to test on too many queries

• [CPD2006]
Index size vs. query slowdown

- Annotated TREC corpus
- Space = 520MB < inverted index = 910MB
- Query slowdown ≈ 1.8
- From TREC to Web?

<table>
<thead>
<tr>
<th>Corpus/Index</th>
<th>Gbytes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original corpus</td>
<td>5.72</td>
</tr>
<tr>
<td>Gzipped corpus</td>
<td>1.33</td>
</tr>
<tr>
<td>Stem index</td>
<td>0.91</td>
</tr>
<tr>
<td>Full type index</td>
<td>4.30</td>
</tr>
<tr>
<td>Reachability index</td>
<td>0.01</td>
</tr>
<tr>
<td>Forward index</td>
<td>1.16</td>
</tr>
<tr>
<td>Atype subset index</td>
<td>0.52</td>
</tr>
</tbody>
</table>
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Query API provider
How to score and aggregate

- Literals in query match tokens in context
- Context is a candidate because it mentions an entity of the target type
- What is the score of a context?
- How should context scores be aggregated into entity evidence?
Scoring a context

- Rarity of matches
- Distance from candidate position to matches
- Many occurrences of one match
  - Closest is good
- Combining scores from many selectors
  - Sum is good

InContext(?c, ?p, +invent* +television), ?p ∈ + Person, Aggregate(?c)
Laplacian scoring

- Represent snippet using feature vector $z_i$
- **Local score** of snippet is $w^T z_i$
- Affinity $a_{ij}$ between (mentions in) snippets
  - “Andrew McCallum” vs. “A. K. McCallum”
  - “18 feet”, “19 ft”, “3—4 meters”
- Global score $f_i$

$$
\min_{\{f_i\}} \sum_i \left( f_i - w^T z_i \right)^2 + C \sum_{i,j} a_{ij} \left( f_i - f_j \right)^2
$$

- During training fit $w$ using partial order on $f$
Local scores unreliable

- Confounding candidates with correct units/type
- Can aggregation over snippets help
- Avoid deep NLP?
- Here we focus on quantity answers
Snippet score-quantity scatter

- Both axes scaled to [0, 1] for clarity
- Relevant/good snippets = +, irrelevant/bad = ◦
- Ideal $w \Rightarrow$ horizontal line separating + from ◦
- No such $w$ for any query in our experiments
- **Rectangles** densely packed with many +, few ◦
  - Possibly > 1 rectangles for some queries
Consensus rectangles

- Relevant rectangle/s in sea of irrelevant snippets
- Many low-scoring relevant snippets
- How to detect and rank consensus rectangles?
- Position and shape varies across queries
  - Cannot use standard nonlinear discriminants
Interval-hunting

- RankSVM: Independent snippet comparison
- IntervalMerit
  - Scan for all interval narrower than $1:(1+\text{tolerance}/100)$
  - Compare snippets inside interval to those outside
- IntervalRank: Exploit collective features
Summary

• How to open up new info pathways across docs and semistructured knowledge bases
• Propose new access methods into this richer info network
• Evolve into a practical search API?
  – Panel at WWW 2009
  – Prototype with .5B pages, 40x8 CPUs
• What will end-users adopt today? Vs.
• How can they take advantage of the new type-entity-snippet composite data model?
References

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