Explorations in Bootstrapping Guided Search

8th Language and Computation Day

Deirdre Lungley
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October 8, 2009
Explorations in Bootstrapping Guided Search

Research Contribution

1. Automatically acquire a domain model for a document collection
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2. Allow for user adaptation through the incorporation of log data
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1. Automatically acquire a domain model for a document collection
2. Allow for user adaptation through the incorporation of log data
3. Provide an insight into the different nature of general search, e.g., WWW search versus intranet search
Explorations in Bootstrapping Guided Search

Methodology

- Formal Concept Analysis (FCA) lattice based domain model
  - Navigational qualities
  - Coatoms provide initial query refinement suggestions
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  - Use combination of NLP and mining of query logs
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    - Also extract terms which co-occur with query term(s)
  - Query log mining:
    - Machine learning through relative relevance
    - Learn the URLs relevant to a query term(s)
    - Attach query term(s) to these URLs
Explorations in Bootstrapping Guided Search

Early Interactive Intranet Experiment\(^1\)

- Simulate log data transactions for some frequent queries

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**Early Interactive Intranet Experiment**¹

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Early Interactive Intranet Experiment

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- Results:

<table>
<thead>
<tr>
<th>% suggestions judged relevant</th>
<th>Adapted Lattice</th>
<th>B1: Unadapted Lattice</th>
<th>B2: Frequent Terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>73%</td>
<td></td>
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**Explorations in Bootstrapping Guided Search**

**Early Interactive Intranet Experiment**¹

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Results confirm our assumption that users would prefer query refinement suggestions learnt from user queries over content generated terms

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World Wide Web Bootstrapping Experiment

- MSN Search Asset Data Collection
- 15 million queries and related clicks
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- Results of Mechanical Turk evaluation:

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Observations

- Can we say deriving suggestions from logs works better on intranet data?
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- Suggests evaluation of query-only adaptation
  - Intranet experiment
  - Adapt relative relevance learning
  - Highly dependant on good precision (P@1/P@2/P@5)
  - Nutch (VSM) to Lucene (BM25F)
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Deriving query suggestions from Intranet Query Logs using MLE

Research Questions:
- Usefulness of dialogue log component
- Suitability of Web derived suggestions for domain-specific search
- General Web user perception of "usefulness" of extracted suggestions
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- Experimental setup:
  - Suggestions generated for top 25 most frequently submitted queries
  - 67 participants for both evaluations
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<th>Relevant – MT</th>
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<tr>
<td>MLE-Session</td>
<td>71.0%</td>
<td>63.6%</td>
</tr>
<tr>
<td>MLE-Discourse</td>
<td>75.7%</td>
<td>68.9%</td>
</tr>
<tr>
<td>MLE-Discourse-Add</td>
<td>72.1%</td>
<td>63.6%</td>
</tr>
<tr>
<td>MLE-Discourse-Replace</td>
<td>75.2%</td>
<td>73.1%</td>
</tr>
<tr>
<td>Baseline-Snippets</td>
<td>54.9%</td>
<td>51.3%</td>
</tr>
<tr>
<td>Baseline-Google</td>
<td>35.6%</td>
<td>58.3%</td>
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Going Forward

- Revisit lattice document descriptors
  - Move from "Related searches" to "concepts"
  - Conceptual representation to map a specific URL into some space
  - Latent Semantic Analysis (LSA) kernel
Questions?
Automade: Automatically Maintained Domain Knowledge

Calendar of the University of Essex
- Driving and Parking of Vehicles within...http://www.essex.ac.uk/academic/docs/vehicles.html
- Rules Governing the Driving and Parking of Vehicles within...http://www.essex.ac.uk/academic/docs/vehicles.html
- Academic Regulations, Rules Governing the Driving and Parking of Vehicles within...http://www.essex.ac.uk/academic/docs/vehicles.html
- Communications Office at the University of Essex - Organizing an event...http://www.essex.ac.uk/communications/events.html
- Information on Car Parking...http://www.essex.ac.uk/personnel/news/default.htm
- Travel Information - Getting around once you've arrived...http://www.essex.ac.uk/students/travel/gettingaround.html
- Parking on campus...http://www.essex.ac.uk/academics/docs/campus.html
- Car Parking Information...http://www.essex.ac.uk/personnel/news/default.htm
- Car Parking Information...http://www.essex.ac.uk/personnel/news/default.htm
- University of Essex, University Campus...http://www.essex.ac.uk/academics/docs/campus.html
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Figure: Automade - UoE Intranet