Slot Filling through Statistical Processing and Inference Rules

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Overview

- System descriptions
- Results
- Follow-up experiments
System

Preprocessing

Documents

Information Extraction System

Cross-doc Coreference System

Lucene

Run-time

TAC-KBP KB

Doc Index

TAC-KBP KB

Redundancy Removal

Single-doc Filler Extraction

Document Retrieval

Answers

Document, Entity Pairs

Query

No external knowledge source is used.
Preprocessing

Documents → Information Extraction System → Cross-doc Coreference System → Lucene

Run-time


TAC 2010 Workshop

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Wu Shu-chen, the former first wife, visited her husband Chen Shui-bian in detention in the morning.

She was accompanied by their son Chen Chih-chung and Lawrence Gao, a Democratic Progressive Party lawmaker.
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Information Extraction System

- Trained on data annotated based on KLUE2 ontology
  - 52 entity types: PERSON, ORG, EVENT_MEETING etc
  - 47 relation types: locatedAt, employeeOf, partOfMany etc

- Targeted annotations for low-count relations (< 100 instances)
  - 22 relation types
  - 846 additional documents (short self-sufficient paragraphs): 16.9k mentions and 8.3k relations

- Total: 1367 documents
  - 85.8k mentions and 33.4k relations
Improvements On Mention Detection/Coreference

- **Mention Detection**
  - Using revised annotation ontology KLUE2
  - Improved from last year: $F = 78.57 \rightarrow 82.95$

- **Coreference Resolution**
  - Used hard constraints induced by parse-tree paths
  - Improved from last year: $F = 68.48 \rightarrow 69.31$ (on system mentions)
  - While reducing run-time by 50%
Improvements on Relation Detection

- **Sequential Decoding of Relations**
  - Modeling the dependency between relations
  - Are both *locatedAt* relations valid?
    - A 23-year-old [man](green) will appear in [court](gray) Thursday in connection with the failed [bombings](gray) in [London](green).

- **Decode using a stack decoder**
  - Order mention pairs within each sentence, from left to right
  - For each mention pair, run the existence detector and the type classifier (both are MaxEnt-based)
Relation Detection

- Cascaded Model (TAC-KBP 2009)
- Sequential Model

(on true mentions/entities)
Documents → Information Extraction System → Cross-doc Coreference System

Doc Index → TAC-KBP KB

Answers → Redundancy Removal → Single-doc Filler Extraction

Query → Document, Entity Pairs

Preprocessing

Run-time
Cross-Document Coreference

- **Via Entity Linking** *(TAC-KBP 2009)*
  - (Entity, Document) → KB ID or null
  - Built a reverse document index
    - Keys are KB ID, values are documents containing the KB ID
Preprocessing

Documents

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Document Retrieval

Document, Entity Pairs

Query
Document Retrieval

Query

Query Document

YES

Query has KB ID?

NO

Consult Reversed Document Index

Get documents from Lucene Search

KB ID | Doc IDs
--- | ---
kbe0109446 | Doc_1234 Doc_5678 ...
...
...

Query Expansion for Acronyms

Query Match 1 Document 1

Query Match 2 Document 2
Documents Indexing with Lucene

- **Indexing only mention strings**
  - If we miss mentions, we miss documents

- **Improving mention detection**
  - Added query mentions to dictionaries of applicable types
    - “CC” is added to the ORGANIZATION dictionary
    - Nudge the system to treat them like the other dictionary entries
  - Improved document recall: 77.79 → 84.62 (LDC training queries)
Acronym Query: “CC”

- Comedy Central? Circuit City?
  - Query Document: Following an investigation, the Competition Commission (CC) said it was seeking ...

- If a query is an acronym
  - Find full names in the query document
  - Retrieve documents using both the acronym and the full names

- Significant improvement: doc recall 0 → 100 while reducing # of docs retrieved from 1.3k to 180.
Example: per:children

Query: Chen Shui-bian

Wu Shu-chen, the former first wife, visited her husband Chen Shui-bian in detention in the morning.

She was accompanied by their son Chen Chih-chung and Lawrence Gao, a Democratic Progressive Party lawmaker.
Example: per:children

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Query: Chen Shui-bian

Per:children: Chen Chih-chung

Wu Shu-chen, the former first wife, visited her husband Chen Shui-bian in detention in the morning. She was accompanied by their son Chen Chih-chung and Lawrence Gao, a Democratic Progressive Party lawmaker.
Example: per:children

Query: Chen Shui-bian

Per:children: Chen Chuh-chung

Wu Shu-chen, the former first wife, visited her husband Chen Shui-bian in detention in the morning. She was accompanied by their son Chen Chih-chung and Lawrence Gao, a Democratic Progressive Party lawmaker.
Single-Document Slot Filler Extraction

Find all relevant entities:

- Chen Shui-bian
- Document
- Wu Shuchen, her, she
- their
  - per:children
  - Chen Chih-chung
- per:spouse
  - their
  - Wu Shuchen, her, she
- Chen Shui-bian, her, she
- partOfMany

Relation Inference:

- Chen Shui-bian, husband
- son, Chen Chih-chung
- per:children

Collect non-duplicate fillers:

- Chen Shui-bian
  - Per:children: Chen Chih-chung.
Relation Inference

- **Level 0**: no inference (just use the original relations)
- **Level 1**: use basic relation properties
  - Equivalence, transitivity, symmetry.
- **Level 2**: use simple implications
  - *Palmisano* managerOf *IBM* implies *Palmisano* employeeOf *IBM*.
- **Level 3**: relation chaining
  - If *Ben* colleague *Vittorio* and *Vittorio* employeeOf *IBM* then *Ben* employeeOf *IBM*.
- **Level 4**: recursive reasoning (using extracted slots in inference)
  - If *Chen Shui-bian* per:spouse *Wu* and *Wu* per:children *Chen Chih-chung*, then *Chen Shui-bian* per:children *Chen Chih-chung*. 
Example Rules

per:date_of_birth(X,Y) :- bornOn(X,Y).
per:age(X,Y) :- ageOf(X,Y).
per:employee_of(X,Y) :- employedBy(X,Y).

per:religion(X,Y) :- partOfMany(X,Y), religious(Y).
per:religion(X,Y) :- located(X,Z), religiousFacility(Z,Y).

per:origin(X,Y) :- isOrigin(Y), coref(X,Y).
per:origin(X,Y) :- partOfMany(X,Y), isGPE(Y).
per:origin(X,Y) :- per:sibling(X,Z), per:origin(Z,Y).
per:origin(X,Y) :- partOfMany(X,Z), per:origin(Z,Y).

per:siblings(X,Y) :- isSibling(Y), relativeOf(X,Y).
per:siblings(X,Y) :- per:parents(Z,X), per:parents(Z,Y), X!=Y.
per:siblings(X,Y) :- partOfMany(X,Z), per:siblings(Z,Y), X!=Y.
Redundancy Removal

- Accumulate instance counts for fillers.

- **Group fillers into equivalence classes**
  - Fillers linked to the same KB entity are grouped.
  - Group fillers based on string similarity.
  - Heuristics for person/organization names.

- **Pick the highest \( n \) classes based on counts:** representatives (longest) are answers.
Results & Conclusions
Internal Results on LDC Training Queries

- Baseline: r/p/f=17.21/24.05/20.06
- Submission: r/p/f=36.85/33.02/34.83
- Relation filtering (threshold = 0.85)
- Relation filtering (threshold = 0.58)
- Give up dbpedia
- Eq-classing fillers
- Corpus v3
- max 800 docs
- Query expansion for acronyms
- Deal with wrong GPE mentions in ORG queries
- Lucene docs vetting
Official Results

- **IBM1**: max 5k docs for extraction, and 2 slot types filtered (per:employee_of and per:charges)
- **IBM2**: Same as IBM1 but no slot type was filtered
- **IBM3**: Same as IBM1 but with max 800 docs for extraction

<table>
<thead>
<tr>
<th>System</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
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<tr>
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<td>27.5</td>
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<tr>
<td>IBM2</td>
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<td>27.0</td>
</tr>
<tr>
<td>IBM3</td>
<td>31.0</td>
<td>25.9</td>
<td>28.2</td>
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<td>TopSystem</td>
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<td>Top2System</td>
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<td>18.7</td>
<td>29.2</td>
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</tbody>
</table>
Effect of Inference on Performance

Level 0: no inference
Level 1: basic relation properties
Level 2: simple relation implications
Level 3: relation chaining
Level 4: recursive reasoning
Post-filtering

- Reject a filler based on its inference traces
  - Potential gain in precision

- Trained a MaxEnt model to reject a filler
  - Training data: system output without redundancy checks
  - Features: inference traces with no lexical info
  - 3.7k/ 4.5k positive/negative examples

“Sam Palmisano, the current chief executive officer of IBM, ...”
## Post-filtering (10-fold cross-validation)

<table>
<thead>
<tr>
<th>T</th>
<th>Accuracy</th>
<th>True Positive %</th>
<th>False Negative %</th>
<th>False Positive %</th>
<th>True Negative %</th>
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<td>19.4</td>
<td>12.7</td>
<td>14.0</td>
<td>53.9</td>
</tr>
</tbody>
</table>

Reject a filler only if classifier predicts WRONG with confidence > T
Conclusions

- Demonstrated an effective combination of statistical IE and rule-based reasoning
- Observed significant benefits from recursive reasoning
- Established a direction towards a fully statistical system