Answer Extraction: Redundancy & Semantics

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NLP Systems and Applications
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Roadmap

- Integrating Redundancy-based Answer Extraction
  - Answer projection

- Answer reweighting

- Structure-based extraction
  - Semantic structure-based extraction
    - FrameNet (Shen et al.)
Redundancy-Based Approaches & TREC

- Redundancy-based approaches:
  - Exploit redundancy and large scale of web to
    - Identify ‘easy’ contexts for answer extraction
    - Identify statistical relations b/t answers and questions
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    - More effective using Web as collection than TREC

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  - How integrate with TREC QA model?
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- Issue:
  - How integrate with TREC QA model?
    - Requires answer string AND supporting TREC document
Answer Projection

- Idea:
  - Project Web-based answer onto some TREC doc
  - Find best supporting document in AQUAINT
Answer Projection

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- Baseline approach: (Concordia, 2007)
  - Run query on Lucene index of TREC docs
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  - Identify documents where top-ranked answer appears
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- **Baseline approach: (Concordia, 2007)**
  - Run query on Lucene index of TREC docs
  - Identify documents where top-ranked answer appears
  - Select one with highest retrieval score
Answer Projection

- Modifications:
  - Not just retrieval status value
Answer Projection

- Modifications:
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    - Tf·idf of question terms
  - No information from answer term
    - E.g. answer term frequency (baseline: binary)
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- New weighting:
  - Retrieval score x (frequency of answer + freq. of target)
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- No major improvement:
  - Selects correct document for 60% of correct answers
Answer Projection as Search

- Insight: (Mishne & De Rijk, 2005)
- Redundancy-based approach provides answer
- Why not search TREC collection after Web retrieval?
Answer Projection as Search

- Insight: (Mishne & De Rijk, 2005)
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  - Phrase-Answer: All words, Answer words as phrase
## Results

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<thead>
<tr>
<th>Model</th>
<th>MRR</th>
<th>p@1</th>
</tr>
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<tbody>
<tr>
<td>baseline</td>
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<td>0.346</td>
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<td>0.340 (-1%)</td>
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<tr>
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Results

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- Topic drift to answer away from question
- Require answer as phrase, without weighting improves
Web-Based Boosting

- Harabagiu et al 2005
- Create search engine queries from question
- Extract most redundant answers from search
  - Augment Deep NLP approach
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  - Deep QA bias to matching NE type, syntactic class
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- Intuition:
  - QA answer search too focused on query terms
  - Deep QA bias to matching NE type, syntactic class
  - Reweighting improves
- Web-boosting improves significantly: 20%
Semantic Structure-based Answer Extraction

- Shen and Lapata, 2007

- Intuition:
  - Surface forms obscure Q&A patterns
  - Q: *What year did the U.S. buy Alaska?*
  - \( S_A : \ldots \text{before Russia sold Alaska to the United States in 1867} \)
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  - Different lexical choice, different dependency structure
- Learn predicate-argument structure?
  - Different argument structure: Agent vs recipient, etc
Semantic Similarity

- Semantic relations:
  - Basic semantic domain:
    - Buying and selling
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  - Semantic roles:
    - Buyer, Goods, Seller
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- Examples of surface forms:
  - [Lee] Seller sold a textbook [to Abby] Buyer
  - [Kim] Seller sold [the sweater] Goods
Semantic Roles & QA

- Approach:
  - Perform semantic role labeling
    - FrameNet
  - Perform structural and semantic role matching
  - Use role matching to select answer
Semantic Roles & QA

- **Approach:**
  - Perform semantic role labeling
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  - Perform structural and semantic role matching
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- **Comparison:**
  - Contrast with syntax or shallow SRL approach
Frames

- Semantic roles specific to Frame
  - Frame:
    - Schematic representation of situation
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  - Evokation:
    - Predicates with similar semantics evoke same frame
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  - Frame:
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  - Evokation:
    - Predicates with similar semantics evoke same frame
  - Frame elements:
    - Semantic roles
    - Defined per frame
    - Correspond to salient entities in the evoked situation
FrameNet

- Database includes:
  - Surface syntactic realizations of semantic roles
  - Sentences (BNC) annotated with frame/role info

- Frame example: Commerce_Sell
FrameNet

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    - Non-core (peripheral) semantic roles:
      - Means, Manner
        - Not specific to frame
### Core Roles

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<td>ATTRIBUTE</td>
<td>The ATTRIBUTE is a scalar property that the ITEM possesses.</td>
</tr>
<tr>
<td>DIFFERENCE</td>
<td>The distance by which an ITEM changes its position on the scale.</td>
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<tr>
<td>FINAL_STATE</td>
<td>A description that presents the ITEM’s state after the change in the ATTRIBUTE’s value as an independent predication.</td>
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<td>FINAL_VALUE</td>
<td>The position on the scale where the ITEM ends up.</td>
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<td>INITIAL_VALUE</td>
<td>The initial position on the scale from which the ITEM moves away.</td>
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<td>ITEM</td>
<td>The entity that has a position on the scale.</td>
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<tr>
<td>VALUE_RANGE</td>
<td>A portion of the scale, typically identified by its end points, along which the values of the ATTRIBUTE fluctuate.</td>
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### Some Non-Core Roles

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<td>DURATION</td>
<td>The length of time over which the change takes place.</td>
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<tr>
<td>SPEED</td>
<td>The rate of change of the VALUE.</td>
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<td>GROUP</td>
<td>The GROUP in which an ITEM changes the value of an ATTRIBUTE in a specified way.</td>
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Bridging Surface Gaps in QA

- Semantics: WordNet
  - Query expansion
  - Extended WordNet chains for inference
  - WordNet classes for answer filtering
Bridging Surface Gaps in QA

- **Semantics:** WordNet
  - Query expansion
  - Extended WordNet chains for inference
  - WordNet classes for answer filtering

- **Syntax:**
  - Structure matching and alignment
    - Cui et al, 2005; Aktolga et al, 2011
Semantic Roles in QA

- Narayanan and Harabagiu, 2004
- Inference over predicate-argument structure
  - Derived PropBank and FrameNet
Semantic Roles in QA

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- Sun et al, 2005
  - ASSERT Shallow semantic parser based on PropBank
  - Compare pred-arg structure b/t Q & A
    - No improvement due to inadequate coverage
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- Sun et al, 2005
  - ASSERT Shallow semantic parser based on PropBank
  - Compare pred-arg structure b/t Q & A
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- Kaisser et al, 2006
  - Question paraphrasing based on FrameNet
    - Reformulations sent to Google for search
      - Coverage problems due to strict matching
Approach

- Standard processing:
- Question processing:
  - Answer type classification
Approach

- Standard processing:
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      - Similar to Li and Roth
    - Question reformulation
Approach

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    - Similar to AskMSR/Aranea
Approach (cont’d)

- Passage retrieval:
  - Top 50 sentences from Lemur
    - Add gold standard sentences from TREC
Approach (cont’d)

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  - Select sentences which match pattern
    - Also with >= 1 question key word
Approach (cont’d)

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- NE tagged:
  - If matching Answer type, keep those NPs
  - Otherwise keep all NPs
Semantic Matching

- Derive semantic structures from sentences
  - P: predicate
    - Word or phrase evoking FrameNet frame
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  - Set(SRA): set of semantic role assignments
    - <w,SR,s>:
      - w: frame element; SR: semantic role; s: score
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- Perform for questions and answer candidates
  - Expected Answer Phrases (EAPs) are Qwords
    - Who, what, where
    - Must be frame elements
  - Compare resulting semantic structures
  - Select highest ranked
Semantic Structure Generation Basis

- Exploits annotated sentences from FrameNet
  - Augmented with dependency parse output
- Key assumption:
Semantic Structure Generation Basis

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- Key assumption:
  - Sentences that share dependency relations will also share semantic roles, if evoked same frames
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- Lexical semantics argues:
  - Argument structure determined largely by word meaning
Predicate Identification

- Identify predicate candidates by lookup
- Match POS-tagged tokens to FrameNet entries
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- Lookup predicate in FrameNet:
  - Keep all matching frames: Why?
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    - Avoid hard decisions
Predicate ID Example

- Q: Who beat Floyd Patterson to take the title away?
- Candidates:
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Predicate ID Example

- Q: Who beat Floyd Patterson to take the title away?
- Candidates:
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  - Select: Beat
- Frame lookup: Cause_harm
- Require that answer predicate ‘match’ question
Semantic Role Assignment

- Assume dependency path $R=\langle r_1, r_2, ..., r_L \rangle$
- Mark each edge with direction of traversal: U/D
- $R = \langle \text{subj}_U, \text{obj}_D \rangle$
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  - Represent frame element by path
  - In FrameNet:
    - Extract all dependency paths b/t $w$ & $p$
    - Label according to annotated semantic role
Computing Path Compatibility

\[ s(w, SR) = \max_{R_{SR} \in M} [\text{sim}(R_w, R_{SR}) \cdot P(R_{SR})] \]

- M: Set of dep paths for role SR in FrameNet
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- Sim(R1,R2): Path similarity
  - Adapt string kernel
  - Weighted sum of common subsequences
    - Unigram and bigram sequences
    - Weight: tf-idf like: association b/t role and dep. relation

\[
\text{weight}_{SR}(r) = f_r \cdot \log(1 + \frac{N}{n_r})
\]
Assigning Semantic Roles

- Generate set of semantic role assignments
- Represent as complete bipartite graph
  - Connect frame element to all SRs licensed by predicate
  - Weight as above
Q: Who discovered prions?
S: 1997: Stanley B. Prusiner, United States, discovery of prions, ...

SemStruc^q

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- Represent as complete bipartite graph
  - Connect frame element to all SRs licensed by predicate
  - Weight as above
- How can we pick mapping of words to roles?
  - Pick highest scoring SR?
    - ‘Local’: could assign multiple words to the same role!
  - Need global solution:
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- Represent as complete bipartite graph
  - Connect frame element to all SRs licensed by predicate
  - Weight as above
- How can we pick mapping of words to roles?
  - Pick highest scoring SR?
    - ‘Local’: could assign multiple words to the same role!
  - Need global solution:
    - Minimum weight bipartite edge cover problem
    - Assign semantic role to each frame element
      - FE can have multiple roles (soft labeling)
Q: Who discovered prions?
S: 1997: Stanley B. Prusiner, United States, discovery of prions, ...

SemStruc_{q}:
- p: discover
- Original SR assignments:
  - EAP
  - prions
- Optimized SR assignments:
  - EAP
  - prions

SemStruc_{ac} (ac: Stanley B. Prusiner):
- p: discovery
- Original SR assignments:
  - ac
  - prions
- Optimized SR assignments:
  - ac
  - prions
Semantic Structure Matching

- Measure similarity b/t question and answers
- Two factors:
Semantic Structure Matching

- Measure similarity between question and answers
- Two factors:
  - Predicate matching
Semantic Structure Matching

- Measure similarity between question and answers
- Two factors:
  - Predicate matching:
    - Match if evoke same frame
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    • Match if evoke same frame
    • Match if evoke frames in hypernym/hyponym relation
      • Frame: inherits_from or is_inherited_by
Semantic Structure Matching

- Measure similarity b/t question and answers

- Two factors:
  - Predicate matching:
    - Match if evoke same frame
    - Match if evoke frames in hypernym/hyponym relation
      - Frame: inherits_from or is_inherited_by
  - SR assignment match (only if preds match)
    - Sum of similarities of subgraphs
      - Subgraph is FE w and all connected SRs

\[
Sim(SubG_1, SubG_2) = \sum_{\text{nd}_1^{SR} \in SubG_1, \text{nd}_2^{SR} \in SubG_2} \frac{1}{s(nd^w_1, nd_1^{SR}) - s(nd^w_1, nd_2^{SR}) + 1}
\]
Comparisons

- Syntax only baseline:
  - Identify verbs, noun phrases, and expected answers
  - Compute dependency paths b/t phrases
    - Compare key phrase to expected answer phrase to
    - Same key phrase and answer candidate
    - Based on dynamic time warping approach
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- Shallow semantics baseline:
  - Use Shalmaneser to parse questions and answer cand
    - Assigns semantic roles, trained on FrameNet
  - If frames match, check phrases with same role as EAP
    - Rank by word overlap
Evaluation

• Q1: How does incompleteness of FrameNet affect utility for QA systems?
  • Are there questions for which there is no frame or no annotated sentence data?
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- Are there questions for which there is no frame or no annotated sentence data?

Q2: Are questions amenable to FrameNet analysis?
- Do questions and their answers evoke the same frame? The same roles?
FrameNet Applicability

- Analysis:

<table>
<thead>
<tr>
<th>Data</th>
<th>Total</th>
<th>NoFrame</th>
<th>NoAnnot</th>
<th>NoMatch</th>
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<tbody>
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<td>29</td>
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<td>152</td>
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<tr>
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- NoFrame: No frame for predicate: sponsor, sink
FrameNet Applicability

- **Analysis:**
  - **NoFrame**: No frame for predicate: sponsor, sink
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FrameNet Utility

- Analysis on Q&A pairs with frames, annotation, match

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<tr>
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<td>8.92</td>
<td>17.33</td>
<td>13.16</td>
</tr>
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<td>SynMatch</td>
<td>35.53*</td>
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<td>40.00*</td>
<td>36.84*</td>
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<tr>
<td>SemMatch</td>
<td>53.29*†</td>
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<td>54.67*†</td>
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- Good results, but
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- Good results, but
  - Over-optimistic
    - SemParse still has coverage problems
FrameNet Utility (II)

- Q3: Does semantic soft matching improve?
- Approach:
  - Use FrameNet semantic match
Q3: Does semantic soft matching improve?

Approach:
- Use FrameNet semantic match
- If no answer found
FrameNet Utility (II)

- Q3: Does semantic soft matching improve?

- Approach:
  - Use FrameNet semantic match
  - If no answer found, back off to syntax based approach

- Soft match best: semantic parsing too brittle, Q

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<td>32.88*</td>
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<td>35.95*</td>
<td>34.38*</td>
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<tr>
<td>+SemParse</td>
<td>25.23</td>
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<td>28.57</td>
<td>26.70</td>
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Summary

- FrameNet and QA:
  - FrameNet still limited (coverage/annotations)
  - Bigger problem is lack of alignment b/t Q & A frames

- Even if limited,
  - Substantially improves where applicable
  - Useful in conjunction with other QA strategies
  - Soft role assignment, matching key to effectiveness
Thematic Roles

- Describe semantic roles of verbal arguments
- Capture commonality across verbs
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  - E.g. subject of break, open is AGENT
    - AGENT: volitional cause
    - THEME: things affected by action
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  - John\textsubscript{AGENT} broke the window\textsubscript{THEME}
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  - John \text{AGENT} broke the window \text{THEME}
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  - The window \text{THEME} was broken by John \text{AGENT}
Thematic Roles

- Thematic grid, θ-grid, case frame
- Set of thematic role arguments of verb
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  • Verbs allow different surface realizations of roles
    • Doris_{AGENT} gave the book_{THEME} to Cary_{GOAL}
    • Doris_{AGENT} gave Cary_{GOAL} the book_{THEME}
  • Group verbs into classes based on shared patterns
## Canonical Roles

<table>
<thead>
<tr>
<th>Thematic Role</th>
<th>Example</th>
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<tr>
<td>AGENT</td>
<td>The waiter spilled the soup.</td>
</tr>
<tr>
<td>EXPERIENCER</td>
<td>John has a headache.</td>
</tr>
<tr>
<td>FORCE</td>
<td>The wind blows debris from the mall into our yards.</td>
</tr>
<tr>
<td>THEME</td>
<td>Only after Benjamin Franklin broke the ice...</td>
</tr>
<tr>
<td>RESULT</td>
<td>The French government has built a regulation-size baseball diamond...</td>
</tr>
<tr>
<td>CONTENT</td>
<td>Mona asked “You met Mary Ann at a supermarket?”</td>
</tr>
<tr>
<td>INSTRUMENT</td>
<td>He turned to poaching catfish, stunning them with a shocking device...</td>
</tr>
<tr>
<td>BENEFICIARY</td>
<td>Whenever Ann Callahan makes hotel reservations for her boss...</td>
</tr>
<tr>
<td>SOURCE</td>
<td>I flew in from Boston.</td>
</tr>
<tr>
<td>GOAL</td>
<td>I drove to Portland.</td>
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Thematic Role Issues

- Hard to produce
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- Hard to produce
- Standard set of roles
  - Fragmentation: Often need to make more specific
    - E.g., INSTRUMENTS can be subject or not
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    - Most AGENTs: animate, volitional, sentient, causal
    - But not all....

- Strategies:
  - Generalized semantic roles: PROTO-AGENT/PROTO-PATIENT
    - Defined heuristically: PropBank
  - Define roles specific to verbs/nouns: FrameNet
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- Penn and Chinese Treebank
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- Roles specific to verb sense
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  - Arg0: PROTO-AGENT; Arg1: PROTO-PATIENT, etc
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    - Ex1: [Arg0 The group] agreed [Arg1 it wouldn’t make an offer]