Answer Extraction: Redundancy & Semantics

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NLP Systems and Applications
May 24, 2011

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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    - Requires answer string **AND** supporting TREC document

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      - E.g. answer term frequency (baseline: binary)
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- New weighting:
  - Retrieval score x (frequency of answer + freq. of target)
- No major improvement:
  - Selects correct document for 60% of correct answers

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  - Phrase-Answer: All words, Answer words as phrase

Results

Model	MRR	p@1
baseline	0.477	0.346
boost-answer-2	0.464 (-3%)	0.340 (-1%)
boost-answer-5	0.408 (-14%)	0.287 (-17%)
boost-answer-20	0.329 (-31%)	0.225 (-35%)
phrases	0.471 (-1%)	0.347 (0%)
boolean-answer	0.502 (+5%)	0.374 (+8%)
phrase-answer	0.525 (+10%)	0.398 (+15%)
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- Boost-Answer-N hurts!
  - Topic drift to answer away from question
- Require answer as phrase, without weighting improves

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  - Reweighting improves
- Web-boosting improves significantly: 20%

Semantic Structure-based Answer Extraction

- Shen and Lapata, 2007

- Intuition:
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  - *Q: What year did the U.S. buy Alaska?*
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    - Different argument structure: Agent vs recipient, etc

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  - Examples of surface forms:
    - **[Lee]**Seller **sold a textbook [to Abby]**Buyer
    - **[Kim]**Seller **sold [the sweater]**Goods
    - **[Abby]**Seller **sold [the car]**Goods **[for cash]**Means**.**

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  - Perform semantic role labeling
    - FrameNet
  - 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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  - Frame elements:
    - Semantic roles
    - Defined per frame
    - Correspond to salient entities in the evoked situation

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- Database includes:
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  - Sentences (BNC) annotated with frame/role info
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    - Non-core (peripheral) semantic roles:
      - Means, Manner
        - Not specific to frame

Core Roles	
ATTRIBUTE	The ATTRIBUTE is a scalar property that the ITEM possesses.
DIFFERENCE	The distance by which an ITEM changes its position on the scale.
FINAL_STATE	A description that presents the ITEM's state after the change in the ATTRIBUTE's value as an independent predication.
FINAL_VALUE	The position on the scale where the ITEM ends up.
INITIAL_STATE	A description that presents the ITEM's state before the change in the ATTRIBUTE's value as an independent predication.
INITIAL_VALUE	The initial position on the scale from which the ITEM moves away.
ITEM	The entity that has a position on the scale.
VALUE_RANGE	A portion of the scale, typically identified by its end points, along which the values of the ATTRIBUTE fluctuate.
Some Non-Core Roles	
DURATION	The length of time over which the change takes place.
SPEED	The rate of change of the VALUE.
GROUP	The GROUP in which an ITEM changes the value of an ATTRIBUTE in a specified way.

Bridging Surface Gaps in QA

- Semantics: WordNet
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- Syntax:
  - Structure matching and alignment
    - Cui et al, 2005; Aktolga et al, 2011

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

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  - Set(SRA): set of semantic role assignments
    - <w,SR,s>:
      - w: frame element; SR: semantic role; s: score
- 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

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  - Lexical semantics argues:
    - Argument structure determined largely by word meaning

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  - Select: Beat
- Frame lookup: Cause_harm
- Require that answer predicate ‘match’ question

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  - Mark each edge with direction of traversal: U/D
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  - In FrameNet:
    - Extract all dependency paths b/t *w* & *p*
    - Label according to annotated semantic role

Computing Path Compatibility

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    - Unigram and bigram sequences
  - Weight: tf-idf like: association b/t role and dep. relation

$$weight_{SR}(r) = f_r \bullet \log(1 + \frac{N}{n_r})$$

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

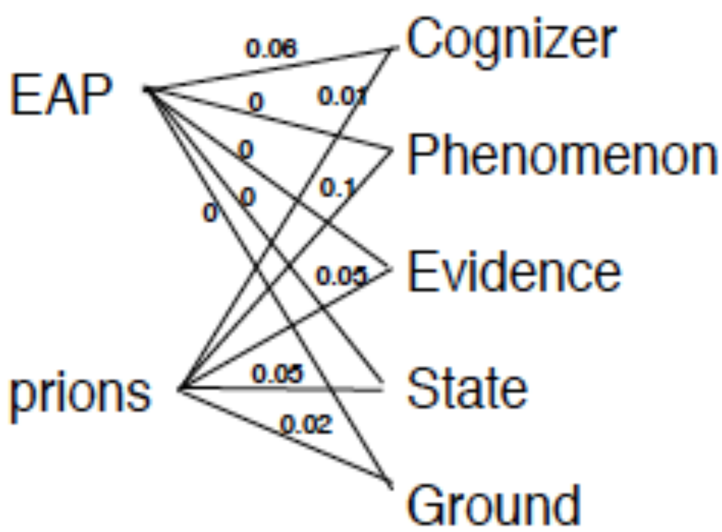
Q: Who discovered prions?

S: 1997: Stanley B. Prusiner, United States, discovery of prions, ...

SemStruc ^{q}

p: discover

Original SR assignments:



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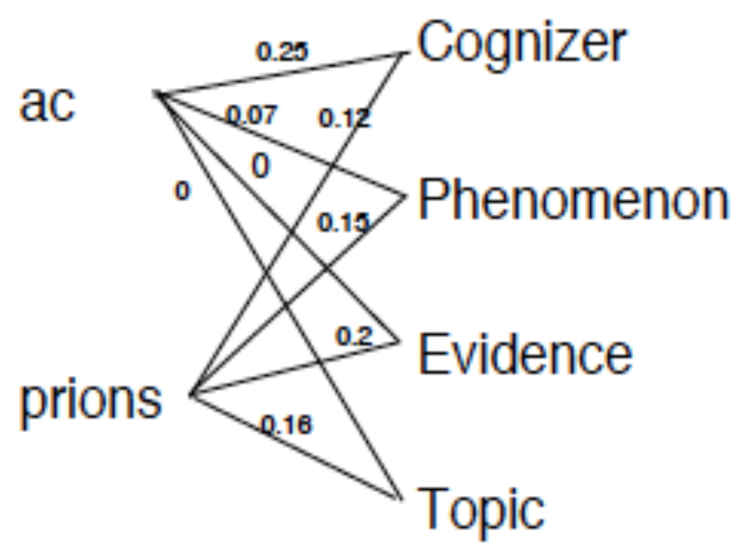

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  - Need global solution:
    - Minimum weight bipartite edge cover problem
    - Assign semantic role to each frame element
      - FE can have multiple roles (soft labeling)

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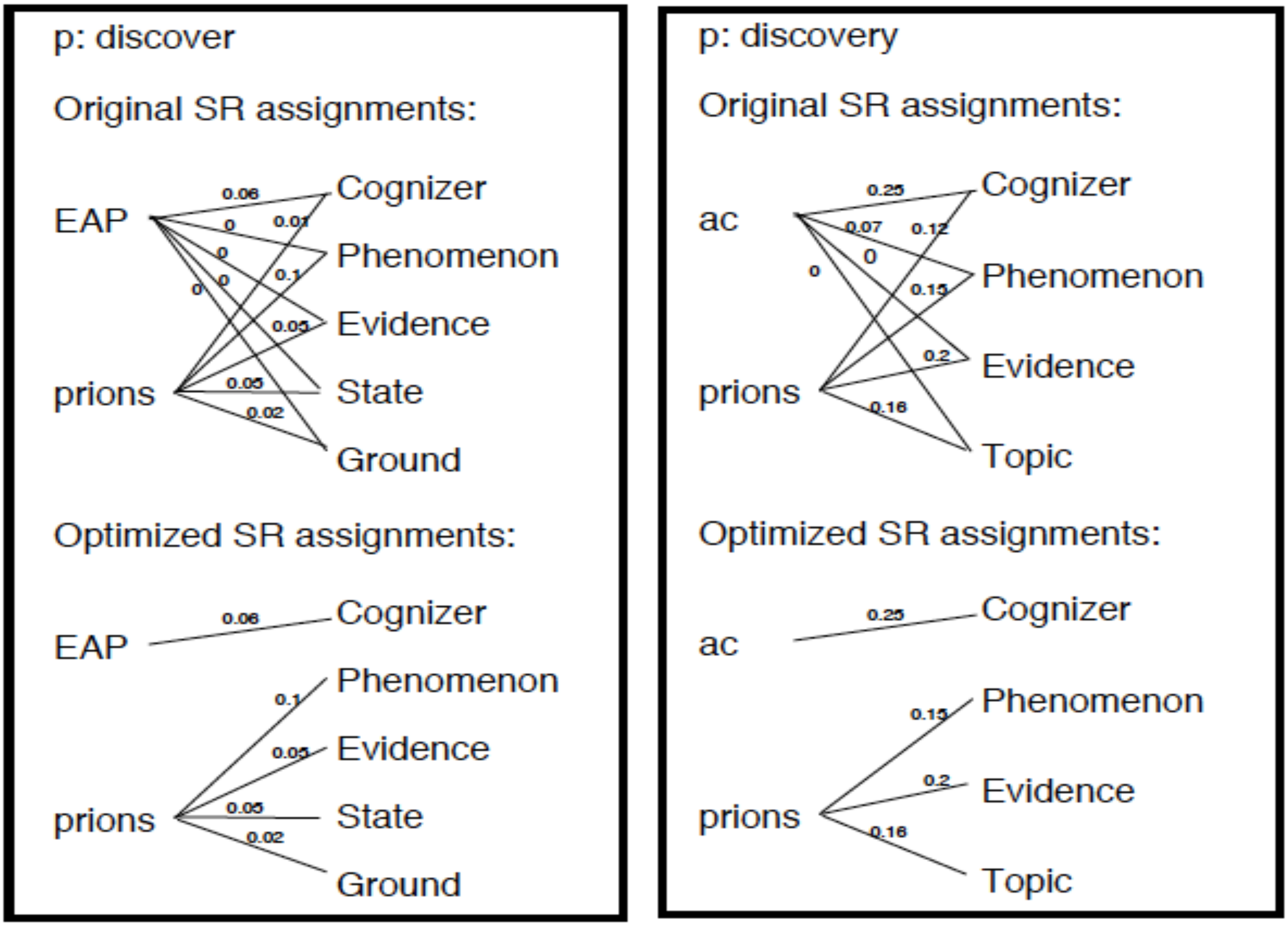

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      - Frame: inherits_from or is_inherited_by
  - SR assignment match (only if preds match)
    - Sum of similarities of subgraphs
      - Subgraph is FE w and all connected SRs

$$Sim(SubG_1, SubG_2) = \sum_{\substack{nd_1^{SR} \in SubG_1 \\ nd_2^{SR} \in SubG_2 \\ nd_1^{SR} = nd_2^{SR}}} \frac{1}{\left| s(nd^w, nd_1^{SR}) - s(nd^w, nd_2^{SR}) \right| + 1}$$

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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  - 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
- 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

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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:

Data	Total	NoFrame		NoAnnot		NoMatch		Rest	
TREC02	444	87	(19.6)	29	(6.5)	176	(39.6)	152	(34.2)
TREC03	380	55	(14.5)	30	(7.9)	183	(48.2)	112	(29.5)
TREC04	203	47	(23.1)	14	(6.9)	67	(33.0)	75	(36.9)
TREC05	352	70	(19.9)	23	(6.5)	145	(41.2)	114	(32.4)

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- NoMatch: Frame mismatch b/t Q & A

FrameNet Utility

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

Model	TREC02	TREC03	TREC04	TREC05
SemParse	13.16	8.92	17.33	13.16
SynMatch	35.53*	33.04*	40.00*	36.84*
SemMatch	53.29*†	49.11*†	54.67*†	59.65*†

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  - Over-optimistic
    - SemParse still has coverage problems

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  - If no answer found, back off to syntax based approach
- Soft match best: semantic parsing too brittle, Q

Model	TREC02	TREC03	TREC04	TREC05
SynMatch	32.88*	30.70*	35.95*	34.38*
+SemParse	25.23	23.68	28.57	26.70
+SemMatch	38.96*†	35.53*†	42.36*†	41.76*†

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

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  - Group verbs into classes based on shared patterns

Canonical Roles

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

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    - Ex1: [$_{\text{Arg0}}$The group] agreed [$_{\text{Arg1}}$it wouldn't make an offer]