Question-Answering: Systems & Resources

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NLP Systems & Applications
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Roadmap

- Two extremes in QA systems:
  - LCC's PowerAnswer-2
  - Insight's Patterns…
- Question classification (Li & Roth)
- Resources

PowerAnswer2

- Language Computer Corp.
  - Lots of UT Dallas affiliates
- Tasks: factoid questions
- Major novel components:
  - Web-boosting of results
  - COGEX logic prover
  - Temporal event processing
  - Extended semantic chains
- Results: “Above median”: 53.4% main

Challenges: Co-reference

- Single, basic referent:

Target 27 - *Jennifer Capriati*	
Q27.2	Who is her coach?
Q27.3	Where does she live?

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Q27.2	Who is her coach?
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- Multiple possible antecedents:
  - Depends on previous correct answers

Target 136 - *Shiite*	
Q136.1	Who was the first Imam of the Shiite sect of Islam?
Q136.2	Where is his tomb?
Q136.3	What was this person's relationship to the Prophet Mohammad?
Q136.4	Who was the third Imam of Shiite Muslims?
Q136.5	When did he die?

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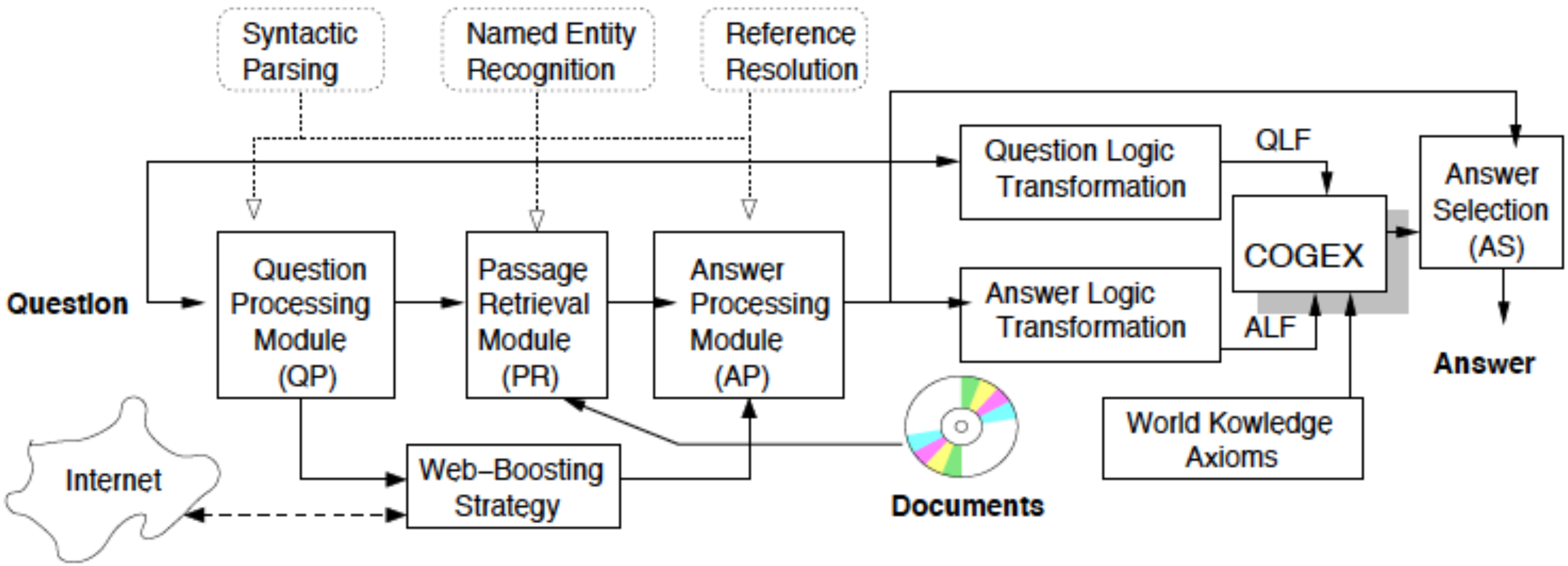
  - Establish question context, constraints

PowerAnswer-2

- Factoid QA system:



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- Complex components:
  - COGEX abductive prover
  - Word knowledge, semantics:
    - Extended WordNet, etc
  - Temporal processing

Web-Based Boosting

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

Deep Processing: Query/Answer Formulation

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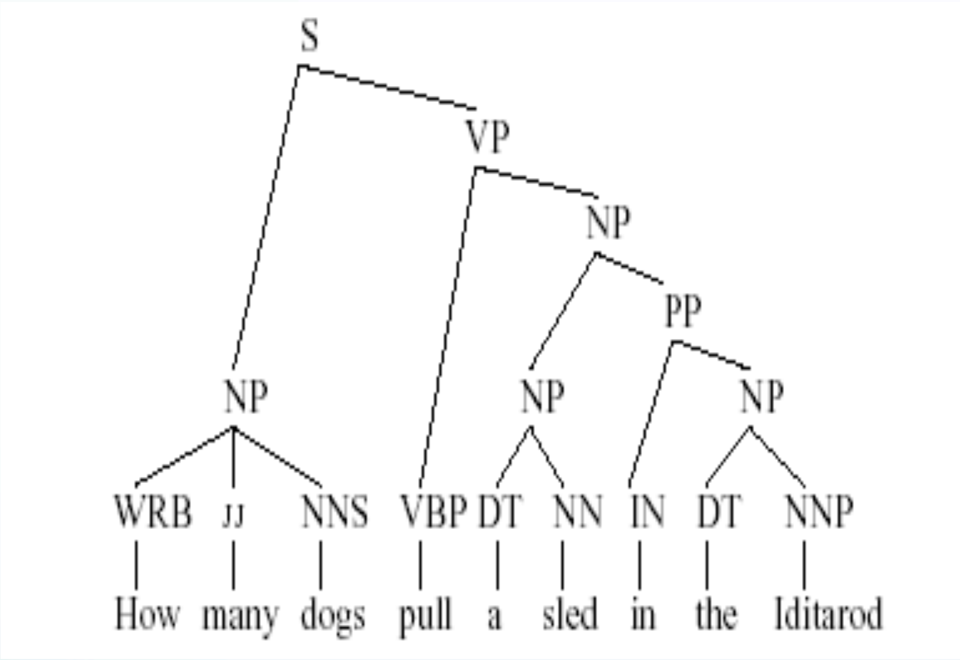
- Coreference resolution links entity references
- Translate to full logical form
  - As close as possible to syntax

Syntax to Logical Form



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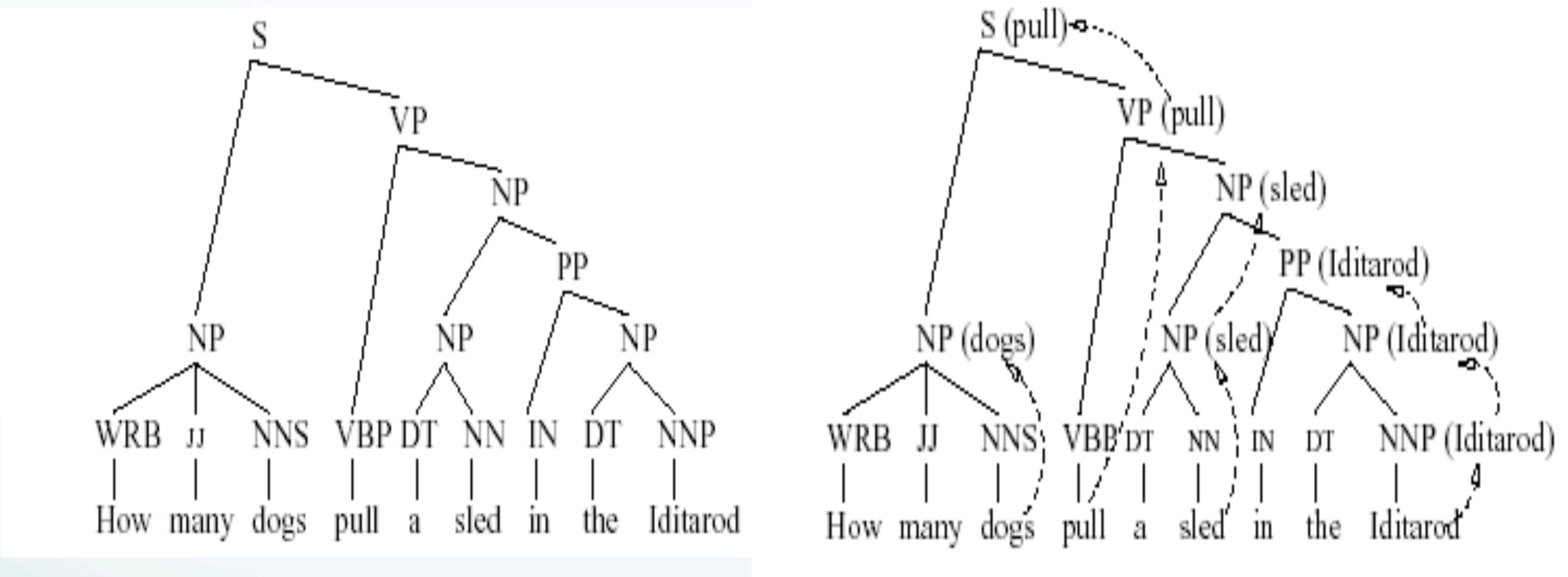

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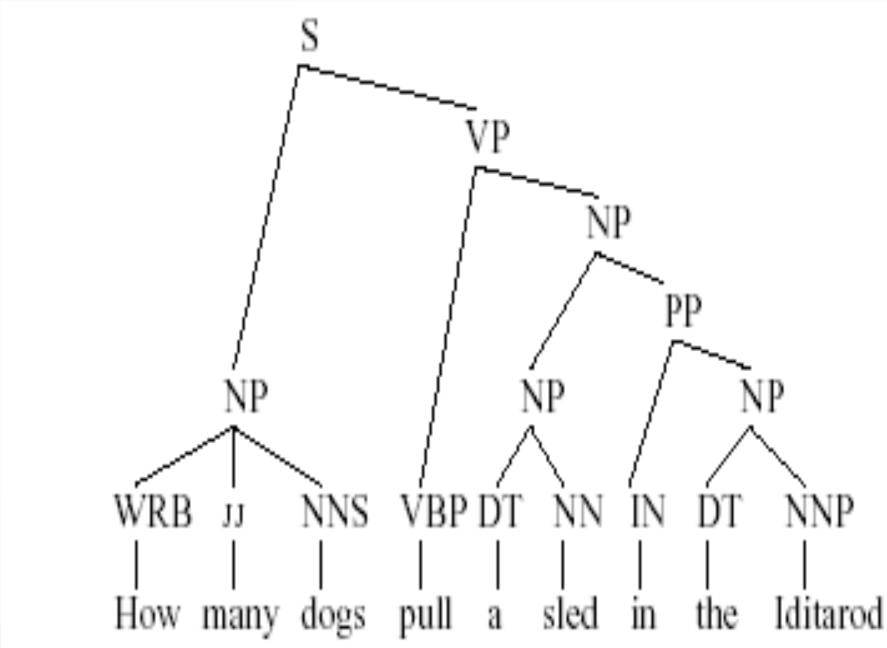

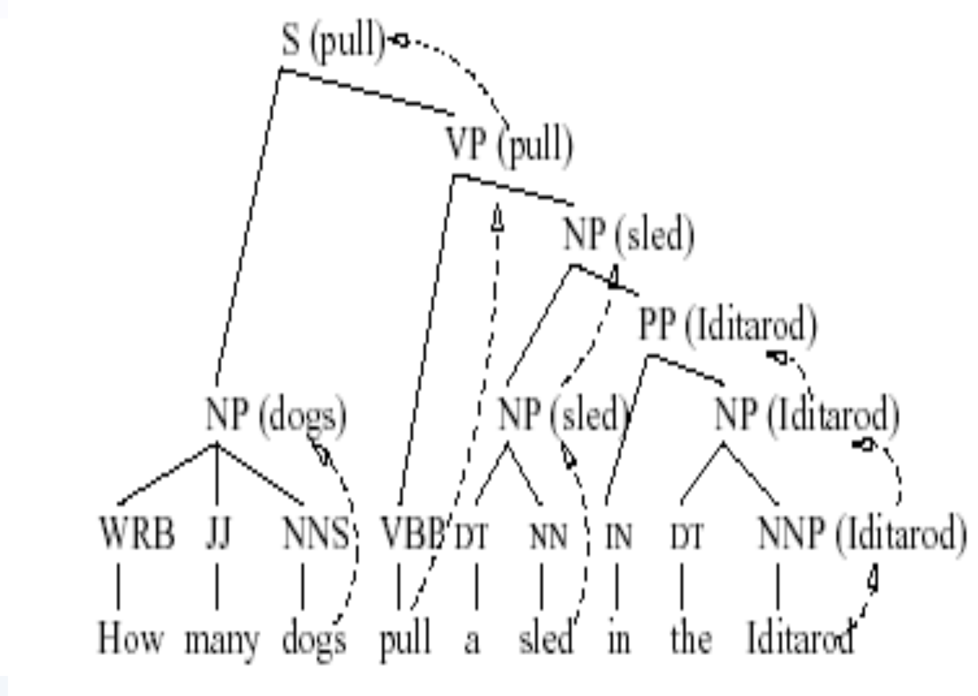

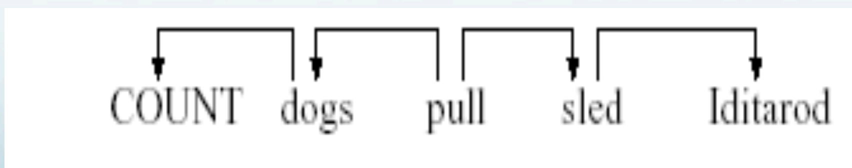

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  - Yields 10% improvement in accuracy!

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- Improves only by 2%
  - Mostly captured by surface forms

Results

	PowerAnswer-2
Factoid	0.713
List	0.468
Other	0.228
Overall	0.534

Table 2: Results in the main task.

Overview

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  - Shallow processing:
    - Web-boosting: +20%
  - Deep processing:
    - COGEX logic prover + semantics: 10%
    - Temporal processing: 2%
  - Relation queries:
    - All relatively shallow:
      - Biggest contributors: Keyword extraction, Topic signatures

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  - Contrasts with deep processing techniques
- Intuition:
  - Some surface patterns highly correlated to information
    - E.g. Mozart (1756-1791)
    - Person – birthdate, death date
      - Pattern: Capitalized word; paren, 4 digits; dash; 4 digits; paren
      - Attested 850 times in a corpus

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    - Ordered or unordered
  - More complex patterns are typically more indicative

Other Examples

- Post questions: Who is the Queen of the Netherlands?

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- Post questions: Who is the Queen of the Netherlands?
- Beatrix, Queen of the Netherlands
- Pattern elements:
  - Country name
  - Post name
  - Person name
  - Title (optional)
    - In some order

Basic Approach

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- Passage retrieval
  - Collect large number of retrieval snippets
    - Possibly with query expansion
- Answer processing:
  - Find matching patterns in candidates
    - 10s of patterns/answer type

Results

- Best result in TREC-10
- MRR (strict) 0.676:
  - Correct: 289; 120 unanswered
- Retrieval based on shallow patterns
  - Bag of patterns, and sequences
  - Still highly effective

Question Classification: Li&Roth

Roadmap

- Motivation:

Why Question Classification?

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    Q: What Canadian city has the largest population?
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    Q: What Canadian city has the largest population?
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  - Provides information for type-specific answer selection
    - *Q: What is a prism?*
    - Type? -> Definition
      - Answer patterns include: 'A prism is…'

Challenges

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- Variability:
  - What tourist attractions are there in Reims?
  - What are the names of the tourist attractions in Reims?
  - What is worth seeing in Reims?
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- Solution?
  - Machine learning – rich feature set

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  - Hierarchical classifier on semantic hierarchy of types
    - Coarse vs fine-grained
      - Up to 50 classes

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  - Differs from text categorization?
    - Shorter (much!)
    - Less information, but
    - Deep analysis more tractable

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- Results:
  - Coarse: 92.5%; Fine: 89.3%
  - Semantic features reduce error by 28%

Question Hierarchy

Class	#	Class	#
ABBREVIATION	18	term	19
abbreviation	2	vehicle	7
expression	16	word	0
DESCRIPTION	153	**HUMAN**	171
definition	126	group	24
description	13	individual	140
manner	7	title	4
reason	7	description	3
ENTITY	174	**LOCATION**	195
animal	27	city	44
body	5	country	21
color	12	mountain	5
creative	14	other	114
currency	8	state	11
disease/medicine	3	**NUMERIC**	289
event	6	code	1
food	7	count	22
instrument	1	date	146
lang	3	distance	38
letter	0	money	9
other	19	order	0
plant	7	other	24
product	9	period	18
religion	1	percent	7
sport	3	speed	9
substance	20	temp	7
symbol	2	vol.size	4
technique	1	weight	4

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    - First classifier produces (a set of) coarse labels
    - Second classifier selects from fine-grained children of coarse tags generated by the previous stage
    - Select highest density classes above threshold

Features for Question Classification

- Primitive lexical, syntactic, lexical-semantic features
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- Syntactic features:
  - Part-of-speech tags
  - Chunks
  - Head chunks : 1^{st} N, V chunks after Q-word

Syntactic Feature Example

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- Head noun chunk: ‘the first woman’

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  - Named Entities
  - WordNet Senses
  - Manual word lists
  - Distributional sense clusters

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- Augment each word with semantic category

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- What about ambiguity?
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    - Keep all alternatives
    - Let the learning algorithm sort it out
    - Why?

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- Class-specific words
  - Manually derived from 5500 questions
    - E.g. Class: Food
      - {alcoholic, apple, beer, berry, breakfast brew butter candy cereal champagne cook delicious eat fat ..}
      - Class is semantic tag for word in the list

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- Test:
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- Measures: Accuracy and class-specific precision

Results

- Syntactic features only:

Classifier	Word	POS	Chunk	Head(SYN)
Coarse	85.10	91.80	91.80	**92.50**
Fine	82.60	84.90	84.00	**85.00**

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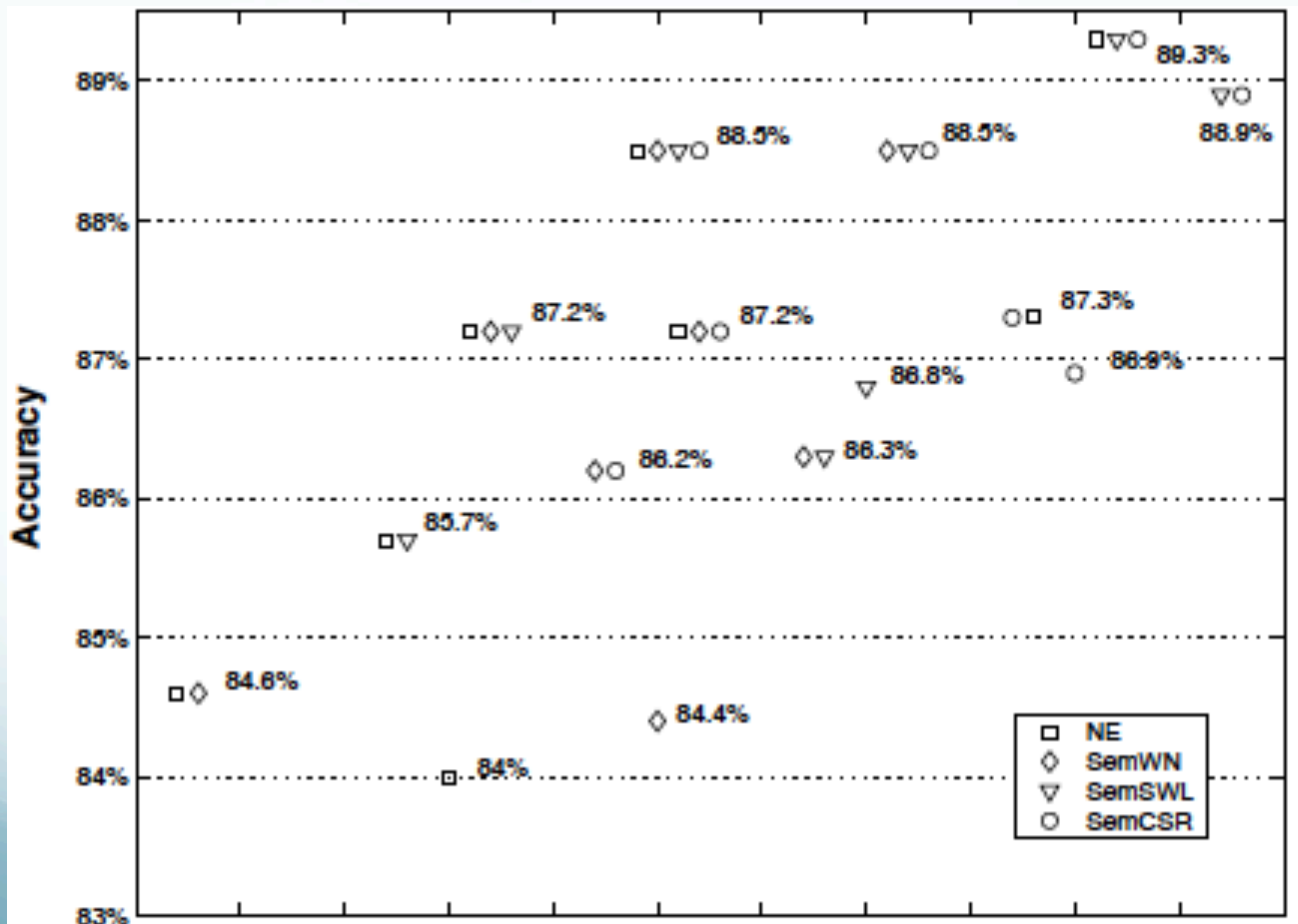
- Wh-word most common class: 41%



Accuracy
89%
88%
87%
86%
85%
84%
83%
89.3%
88.9%
88.5%
88.5%
87.2%
87.2%
87.3%
86.8%
86.9%
86.2%
86.3%
85.7%
84.6%
84.4%
84%
NE
SemWN
SemSWL
SemCSR

Class	#	Precision[c]	Class	#	Precision[c]
abb	2	100%	desc	25	36%
exp	17	94.11%	manner	8	87.5%
animal	27	85.18%	reason	7	85.71%
body	4	100%	gr	19	89.47%
color	12	100%	ind	154	90.25%
cremat	13	76.92%	title	4	100%
currency	6	100%	desc	3	100%
dismed	4	50%	city	41	97.56%
event	4	75%	country	21	95.23%
food	6	100%	mount	2	100%
instru	1	100%	LOC:other	116	89.65%
lang	3	100%	state	14	78.57%
ENTY:other	24	37.5%	count	24	91.66%
plant	3	100%	date	145	100%
product	6	66.66%	dist	37	97.29%
religion	1	100%	money	6	100%
sport	4	75%	NUM:other	15	93.33%
substance	21	80.95%	period	20	85%
symbol	2	100%	perc	9	77.77%
termeq	22	63.63%	speed	8	100%
veh	7	71.42%	temp	4	100%
def	125	97.6%	weight	4	100%
TOTAL	**1000**	**89.3%**			

Observations

- Effective coarse and fine-grained categorization
  - Mix of information sources and learning
  - Shallow syntactic features effective for coarse
  - Semantic features improve fine-grained
    - Most feature types help
      - WordNet features appear noisy
      - Use of distributional sense clusters dramatically increases feature dimensionality

NE	0.23
SemWN	16
SemCSR	23
SemSWL	557

Software Resources

- Build on existing tools
  - Focus on QA specific tasks
- General: Machine learning tools

Software Resources

- General: Machine learning tools
  - Mallet: http://mallet.cs.umass.edu
  - Weka toolkit: *www.cs.waikato.ac.nz/ml/weka/*

Software Resources

- General: Machine learning tools
  - Mallet: http://mallet.cs.umass.edu
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- NLP toolkits, collections:
  - GATE: http://gate.ac.uk
  - NLTK: http://www.nltk.org
  - LingPipe: *alias-i.com/lingpipe/*
  - Stanford NLP tools: http://nlp.stanford.edu/software/

Software Resources: Specific

- Information retrieval:
  - Lucene: http://lucene.apache.org (on patas)
    - Standard system, tutorials
  - Indri/Lemur: http://www.lemurproject.org/indri/
    - High quality research system
  - Managing Gigabytes: http://ww2.cs.mu.oz.au/mg//
    - Linked to textbook on IR

Software Resources: Cont'd

- POS taggers:
  - Stanford POS tagger
  - Treetagger
  - Maxent POS tagger
  - Brill tagger
- Stemmers: http://snowball.tartarus.org
  - Implementations of Porter stemmer in many langs
- Sentence splitters
  - NIST

Software Resources

- Parsers:
  - Constituency parser
    - Stanford parser
    - Collins/Bikel parser
    - Charniak parser
  - Dependency parsers
    - Minipar
- WSD packages:
  - WordNet::Similarity

Software Resources

- Semantic analyzer:
  - Shalmaneser
- Databases, ontologies:
  - WordNet
  - FrameNet
  - PropBank

Information Resources

- Proxies for world knowledge:
  - WordNet: Synonymy; IS-A hierarchy

Information Resources

- Proxies for world knowledge:
  - WordNet: Synonymy; IS-A hierarchy
  - Wikipedia

Information Resources

- Proxies for world knowledge:
  - WordNet: Synonymy; IS-A hierarchy
  - Wikipedia
  - Web itself
  - ....
- Training resources:
  - Question classification sets (UIUC)
  - Other TREC QA data (Questions, Answers)