Robust Semantics for Semantic Parsing

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Outline

- I: Supervised and SemiSupervised Semantic Parser Induction
- II: Clustered Entailment Semantics

I: Semantic Parser Induction

- Thompson and Mooney (2003); Zettlemoyer and Collins (2005, 2007); Wong and Mooney (2007); Lu *et al.* (2008); Kwiatkowski *et al.* (2010, 2011); Börschinger *et al.* (2011) generalize the problem of inducing parsers from language-specific treebanks like WSJ to that of inducing parsers from paired sentences and unaligned language-independent logical forms.
  - The sentences can be in any language.
  - The logical forms might be database queries, dependency graphs, λ-terms, robot action primitives and PDDL state descriptions, etc.
- This is the way the child learns language, *pace* Montague 1970 (Kwiatkowski *et al.* 2012)
- However, the approach suffers from an acute shortage of suitable datasets.

Semisupervised Semantic Parser Induction

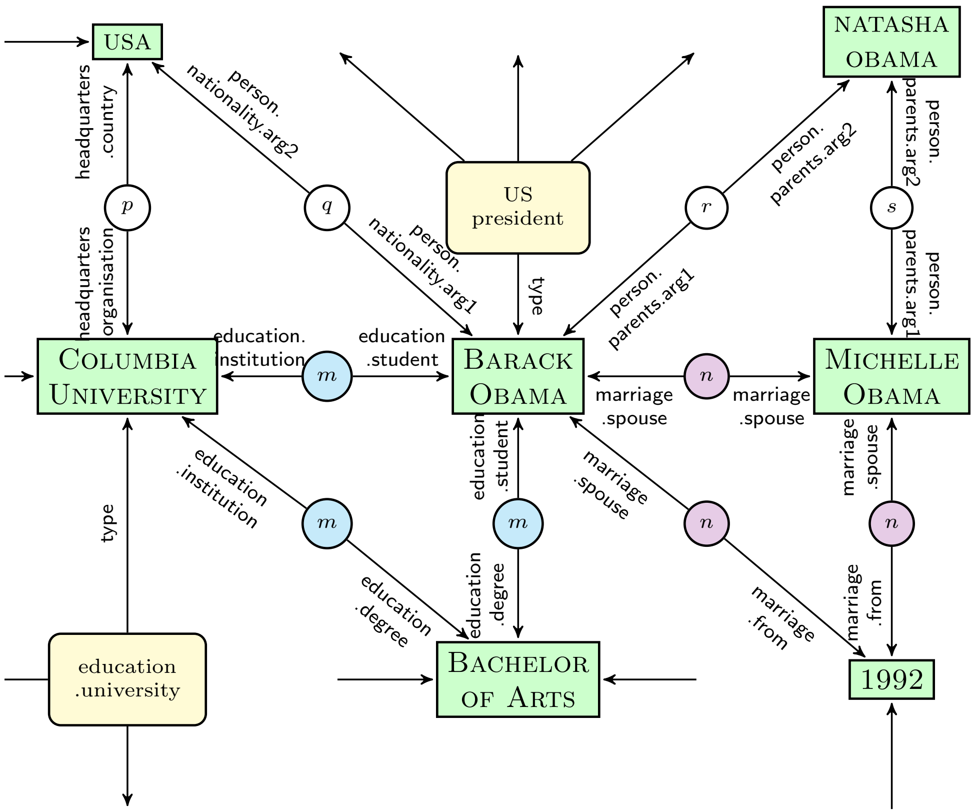
- Question-answer pairs are abundantly available for large databases. So, learn from them.
- Clarke *et al.* (2010); Liang *et al.* (2011); Cai and Yates (2013a,b); Kwiatkowski *et al.* (2013); Berant *et al.* (2013)
- "Given my dataset, to what questions is 42 the answer?"
- Not that many—very few for the same named entities

Semantic Parsing with Freebase without QA pairs

- Reddy *et al.* (2014):
  - Rather than inducing a parser from questions and answers. . .
  - Take a semantic parser that already builds ungrounded logical forms and learn the relation between those logical forms and the grounded knowledge graph,
- Specifically:
  - First turn the ungrounded logical forms into graphs of the same type as the knowledge graph;
  - Then learn the mapping between the elements of the semantic and grounded knowledge-base graphs;
  - Then redefine the semantics of the semantic parser in grounded terms that can be evaluated as knowledge-base queries.

The Knowledge Graph

- Freebase is what used to be called a Semantic Net
- Cliques represent facts.
- Clique q represents the fact that *Obama's nationality is American*
- Clique m represents the complex fact that *Obama did his BA at Columbia*

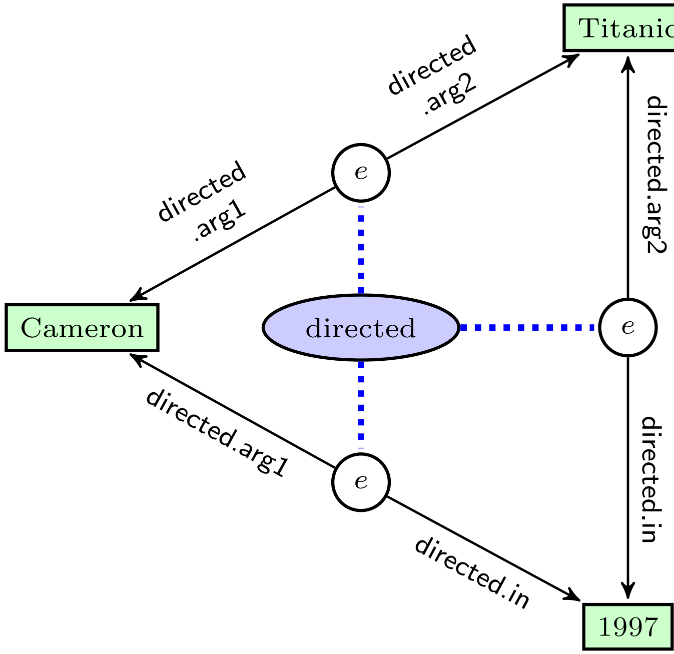


Parsing to NeoDavidsonian Logical Form using CCG

- Cameron directed *Titanic* in 1997.

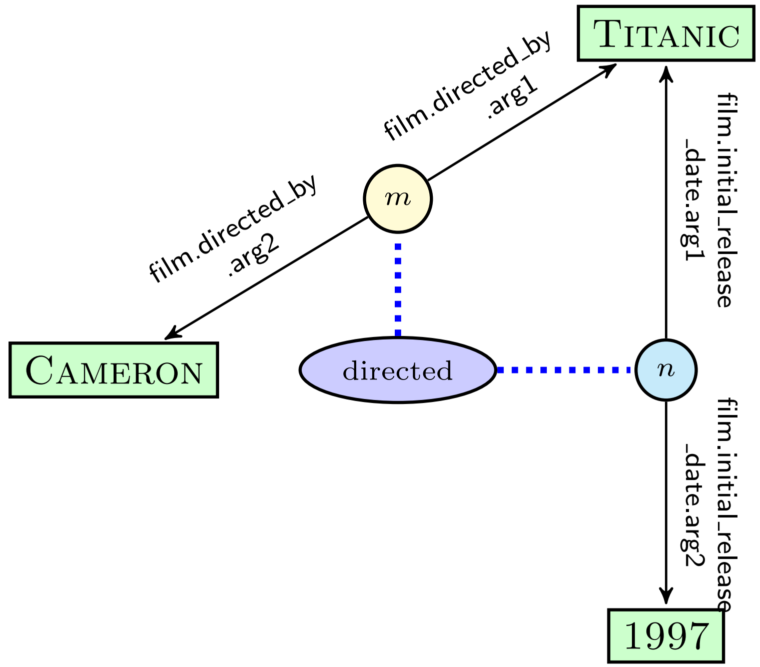
$$
\begin{array}{ccccc}
\text{Cameron} & \text{directed} & \textit{Titanic} & \text{in} & \text{1997} \\
\hline
NP & S\backslash NP/PP_{in}/NP & NP & PP_{in}/NP & NP \\
cameron & \lambda w\lambda x\lambda y.directed.arg1(e,y)\land directed.arg2(e,w)\land directed.in(e,x) & titanic & \lambda x.x & 1997 \\
\hline
 & \multicolumn{2}{c}{S\backslash NP/PP \quad >} & \multicolumn{2}{c}{>} \\
 & \multicolumn{2}{c}{\lambda x\lambda y.directed.arg1(e,y)\land directed.arg2(e,titanic)\land directed.in(e,x)} & \multicolumn{2}{c}{1997} \\
\hline
 & \multicolumn{4}{c}{S\backslash NP:\lambda y.directed.arg1(e,y)\land directed.arg2(e,titanic)\land directed.in(e,1997) \quad >} \\
\hline
\multicolumn{5}{c}{S:directed.arg1(e,cameron)\land directed.arg2(e,titanic)\land directed.in(e,1997) \quad <}
\end{array}
$$

Map Logical Form to LF graph



$$\text{directed.arg1}(e, \text{Cameron}) \land$$
$$\text{directed.arg2}(e, \text{Titanic}) \land \text{directed.in}(e, 1997)$$

Map LF graph to Knowledge graph



film.directed_by.arg2(m, CAMERON) $\wedge$
film.directed_by.arg1(m, TITANIC) $\wedge$
film.initial_release_date.arg1(n, TITANIC) $\wedge$
film.initial_release_date.arg2(n, 1997)

How do we Find the Mapping?

- In the grounded graph, we need to identify:
  - Freebase entities corresponding to semantic entities (e.g. CAMERON corresponds to *cameron*)
  - Freebase relations corresponding to semantic relations (e.g. film.directed_by.arg2 corresponds to directed.arg1)
  - FreeBase fact identifiers corresponding to various occurrences of semantic event identifier(s) (e.g. m and n correspond to different facts related to the semantic event identifier e)
- But there are $O(k+1)^n$ grounded graphs possible for each ungrounded logical form (where n is the number of edges in the ungrounded graph, k the number of candidate corresponding grounded edges per ungrounded edge, plus 1 for no corresponding edge.)

Learning from Denotations

- Learning proceeds by creating question-like logical forms by replacing named entities in logical forms mined from web text with a variable to produce property-denoting graphs, such as the one corresponding to:
  $\lambda x.directed.arg1(e, cameron) \wedge directed.arg2(e, x) \wedge directed.in(e, 1997)$
- The learner then finds the denotation of this property from other similar sentences in the mined logical forms—in this case, other films directed by Cameron.
- It then tries to find the subgraph of the knowledge graph with the the most similar denotation—in this case, the subgraph composed of relations m and n.
- The mapping of terms from logical forms to Freebase is determined by such pairings.

Choosing a Knowledge Base Subgraph

- Learning is by Averaged Perceptron (Collins, 2002).
- A number of heuristics exploit similarities between the two graphs (cf. Kwiatkowski *et al.* 2013).
- Features classes are:
  - subsumption relations between semantic graph and knowledge base subgraph;
  - Lexical similarity of edge labels in semantic graph and knowledge base subgraph;
  - Multiple knowledge base edge labels with the same stem;
  - Multiple knowledge base edges with the same mediating fact label;
- There are also a number of heuristic constraints on the answer term, such as definiteness/uniqueness.

Experiments

- Training Data: ClueWeb09, a snapshot of Web in 2009
  - 503.9 million English webpages
  - Automatically annotated with Freebase entity types (Lin *et al.*, 2012)
  - Parse sentences containing at least two entities for which FreeBase defines a relation
  - Noisy lexicon for lexical alignments initialisation

- Test Datasets: Free917 (Kwiatkowski *et al.*, 2013) and WebQuestions (Berant *et al.*, 2013)

Freebase Domains

- Target Domins: Business, Film, People
  - Largest domains of Freebase

- 5-10 million denotation queries for 10-20 iterations
  - Queries via Virtuoso RDF/SQL server
  - Slow in dealing with millions of queries
  - So we currently work with limited domains

Results

Dataset	System	P	R	F
Free917	MWG	52.6	49.1	50.8
	KCAZ13	72.6	66.1	69.2
	GRAPHPARSER	**81.9**	**76.6**	**79.2**
WebQuestions	MWG	39.4	34.0	36.5
	PARASEMPRE	37.5	37.5	37.5
	GRAPHPARSER	**41.9**	**37.0**	**39.3**

- MWG: Greedy Maximum Weighted Graph; KCAZ13: Kwiatkowski *et al.* (2013) supervised model; PARASEMPRE: Berant and Liang (2014) supervised model along with paraphrasing; GRAPHPARSER: Our model

Error Analysis on WebQuestions

- $>$15% structural mismatch between language and Freebase
  - What did Charles Darwin do? (Charles Darwin does Biologist)
  - Where did Charles Darwin come from? (UK vs The Mount)
  - Who is the grandmother of Prince William? (Freebase does not express grandmother relation directly.)

Error Analysis on WebQuestions

- Reddy adds two paraphrase rules which convert *do* $\Rightarrow$ *profession*, and *come from* $\Rightarrow$ *birthplace*.

Dataset	System	P	R	F
WebQuestions	MWG	39.4	34.0	36.5
	PARASEMPRE	37.5	37.5	37.5
	GRAPHPARSER	41.9	37.0	39.3
	GRAPHPARSER+PARA	**44.7**	**38.4**	**41.3**

Interim Summary

- Scalable Semantic Parsing without Question-Answer pairs;
- Semantic Parsing as a Graph Matching Problem:
- Denotation-based weak supervision:
- Improves over the state of the art:
- Benefits mightily from paraphrase.

☡ But it is highly language-specific

Another Approach

- Treat the knowledge graphs as a case for machine translation.

- Find the part of the knowledge graph that looks like the best translation of the question graph into knowledge graph-ese.

- To do this we need logical forms for for both that are less tied to the form of specific sentences in specific languages, embodying notions of paraphrase and entailment as a founding principle, rather than as an add-on.

- A different approach to graded semantics from vector-based approaches of Garrette *et al.* (2011); Beltagy *et al.* (2013) and Riedel *et al.* (2013)

II: Clustered Entailment Semantics (Lewis and Steedman, 2013a,b)

- The central problem of QA is that there are too many ways of asking and answering questions, and we have no idea of the semantics that relates them.
- *Did Google buy YouTube?*

  1. Google purchased YouTube.
  2. Google's purchase of YouTube
  3. Google acquired every company.
  4. YouTube may be sold to Google.
  5. Google will buy YouTube or Microsoft.
  6. Google didn't take over YouTube.
- Major motivation for PropBank/VerbNet annotation (Banarescu *et al.*, 2012)
- Can we do it automatically?

Answering questions by Parsing Text

- Question answering with traditional logical forms and theorem proving augmented with resources like WordNet, gazeteers, etc. has precision around 75%–but recall is around 4% (Bos and Markert 2005).
- This is worse than finite-state string matching
- Instead, Lewis and Steedman 2013a parse text errorfully to mine clusters of paraphrases for relations between named entities like "Shakespeare" and "Macbeth", "Google" and "YouTube" (cf. Riedel *et al.* 2013).
- Typing the relation clusters probabilistically eliminates ambiguity of the *Born in Hawai'i/born in 1961* kind.
- Logical operators such as negation and modality are handled by a (more or less) traditional Montagovian semantics (Steedman 2012)

Results: PASCAL Challenge dataset

- Examples:

Question	Answer	Sentence
What did Delta merge with?	Northwest	The 747 freighters came with Delta's acquisition of Northwest
What spoke with Hu Jintao?	Obama	Obama conveyed his respect for the Dalai Lama to China's president Hu Jintao during their first meeting
What arrived in Colorado?	Zazi	Zazi flew back to Colorado. . .
What ran for Congress?	Young	. . . Young was elected to Congress in 1972

- Full results in Lewis and Steedman (2013a)

Clustering Cross-linguistically

- We apply the method to answer questions in language A from text in language B, using standard MOSES MT as a baseline (Lewis and Steedman 2013b).
  - Find the answer to: *Who wrote Measure for Measure?*
  - From e.g. French—e.g.: *Shakespeare est l'auteur de* Mesure pour mesure.
- We also use cross-linguistic clusters to re-rank Moses n-best lists to promote translations that preserve the cluster-based meaning representation from source to target.

Example

Source:	Le Princess Elizabeth arrive à Dunkerque le 3 août 1999
SMT 1-best:	The Princess Elizabeth is to manage to Dunkirk on 3 August 1999.
Reranked 1-best:	The Princess Elizabeth arrives at Dunkirk on 3 August 1999.

Reranking Moses

-

	Percentage of Translations preferred
1-best Moses	5%
Reranked best	39%
No preference	56%

- Many cases of “no preference” were where Moses and the prefered translation were similar strings but differed in attachment decisons invisible to the human judges.

- These results are obtained without the use of parallel text.

- Full results in Lewis and Steedman (2013b).

Directional Entailments: The Hidden Language of Logical Form

- The above approach fails to distinguish paraphrase from entailment.

- X_{person} *elected to* Y_{office} entails X_{person} *ran for* Y_{office} but not *vice versa*.

- The paraphrase relation depends on more global properties of the named entity relation graph.

- Lewis (2014); Lewis and Steedman (2014) apply the entailment graphs of Berant *et al.* (2012) to generate more articulated entailment structures.

Local Entailment Probabilities

- The typed named-entity technique is applied to estimate local probabilites of entailments:

  a. $p(conquer\,x\,y \Rightarrow invade\,x\,y) = 0.9$

  b. $p(invade\,x\,y \Rightarrow attack\,x\,y) = 0.8$

  c. $p(conquer\,x\,y \Rightarrow attack\,x\,y) = 0.4$

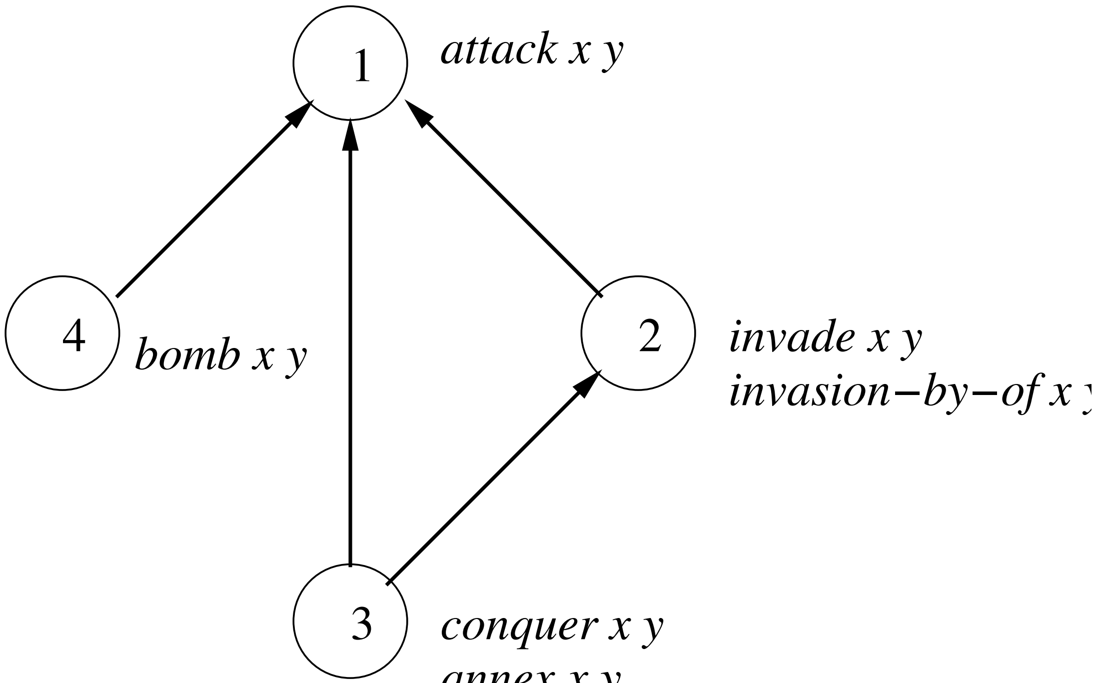
  d. $p(bomb\,x\,y \Rightarrow attack\,x\,y) = 0.7$

  (etc.)

Global Entailments

- The local entailment probabilities are used to construct an entailment graph using integer linear programming with $\pm$ weights around $p = 0.5$ with the global constraint that the graph must be closed under transitivity.
- Thus, (c) will be included despite low observed frequency.
- Cliques within the entailment graphs are collapsed to a single cluster relation identifier, as in the previous approach.

Entailment graph



- A simple entailment graph for relations between countries.

Lexicon

- The lexicon obtained from the entailment graph

  attack := $(S\backslash NP)/NP : \lambda x \lambda y \lambda e.rel_1\, x\, y\, e$
  bomb := $(S\backslash NP)/NP : \lambda x \lambda y \lambda e.rel_1\, x\, y\, e \wedge rel_4\, x\, y\, e$
  invade := $(S\backslash NP)/NP : \lambda x \lambda y \lambda e.rel_1\, x\, y\, e \wedge rel_2\, x\, y\, e$
  conquer := $(S\backslash NP)/NP : \lambda x \lambda y \lambda e.rel_1\, x\, y\, e \wedge rel_2\, x\, y\, e \wedge rel_3\, x\, y\, e$
  annex := $(S\backslash NP)/NP : \lambda x \lambda y \lambda e.rel_1\, x\, y\, e \wedge rel_2\, x\, y\, e \wedge rel_3\, x\, y\, e$

- These logical forms support correct inference under negation, such as that *conquered* entails *attacked* and *didn't invade* entails *didn't conquer*
- Primitives like rel_3 correspond to "hidden" semantic primitives that distinguish these concepts.
- If we do this cross-linguistically we may see that some of them correspond to universal elements like evidentiality that are masked in English.

Experiment

- Baselines are Majority Class (don't know) and Berant *et al.* 2011 Non Compositional direct entailment between reverb patterns.
- We also compare with Additive and Multiplicative Vector-based distributional semantics (SCS) using a logistic regression classifier.
- The Zeichner entailments, unlike RTE, rely predominantly on lexical entailment.

This dataset does not otherwise play to the syntactic and logical strengths of CCG, and includes many non-compositional idioms (eg light verb construction) quite favorable to e.g. vector composition.

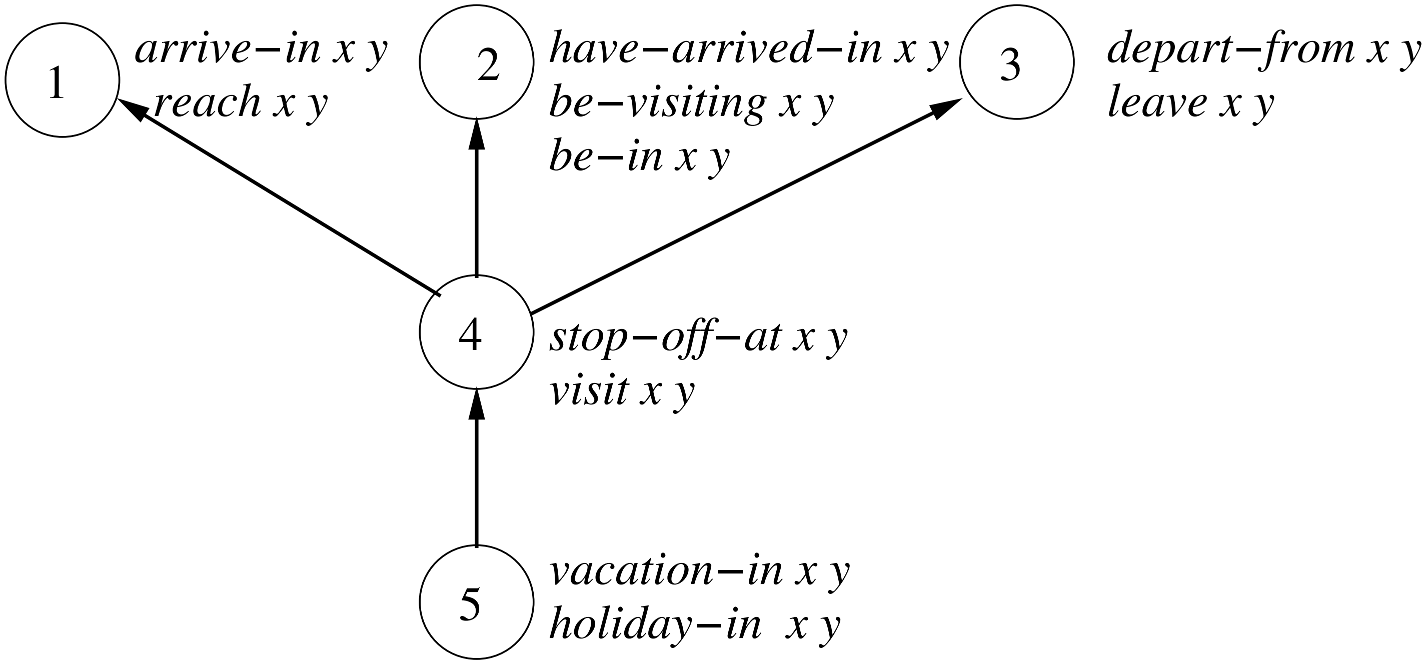
Results

System	Accuracy (all)	AUC (all)
Majority Class	56.8%	0.46
Non Compositional	57.4%	0.48
CCG Baseline	57.8%	0.46
CCG ChineseWhispers	58.0%	0.50
VectorMultiplicative	61.3%	0.51
VectorAdditive	63.5%	0.57
CCG Entailment Graphs	64.0%	0.58
CCG Entailment Graphs+ Implicative Verb Lexicon	**65.0%**	**0.59**

- Last line shows the effect of adding 50 hand-coded frequent implicative verbs where *managing to win* entails *winning*, while *failing to win* entails *not winning* (Bos, 2013).

- AUC is area under Precision-Recall curve, computed with a trapezoid approximation, as a measure of reliability of confidence estimates.

Generalizing to Temporal Semantics



- A simple entailment graph for relations over events does not capture relations of causation and temporal sequence.

Temporal Semantics

- As in the case of the semantics of content words like nouns and verbs, the semantics of tense, aspect, modality, evidentiality, and intensionality has always seemed to bog down in conflicting and overlapping ontology, and ill-defined or world-knowledge-entangled notions like "inertia worlds", "relevance", "extended now", "perfect time span", "consequent state", "preparatory activity", and the like.
  - #Einstein has visited New York (*vs.* Einstein visited New York).
  - #I have forgotten your name but I have remembered it again (*vs.* I forgot your name but I remembered it again).
- Such relations seem like A Suitable Case for Treatment as hidden relations, letting machine learning find out what the consequent states of people *visiting* places, *forgetting* and *remembering* things, etc. usually are.

Timestamped Data

- One source of information concerning these hidden relations is timestamped news, of the kind available in the University of Washington NewsSpike corpus of 0.5M newswire articles (Zhang and Weld, 2013).
- In such data, we find that statements that so-and-so *is visiting*, *is in* and the perfect *has arrived in* such and such a place, occur in stories with the same datestamp, whereas *is arriving*, *is on her way to*, occur in preceding stories, while *has left, is on her way back from, returned*, etc. occur in later ones.
- This information provides a basis for inference that *visiting* entails *being in*, that the latter is the consequent state of *arriving*, and that *arrival* and *departure* coincide with the beginning and end of the progressive state of *visiting*.
- Our event calculus is instant- and state–based (Steedman, 1982; Kowalski and Sergot, 1986), not interval-based as in Allen (1983)—see Galton (1990) .

A Neo-Reichenbachian Operator Semantics

- Some handbuilt lexical entries for auxiliary verbs:

$$\text{has} := (S\backslash NP)/(S_{en}\backslash NP) : \lambda p_E \lambda y.consequent\text{-}state\,(p_E\, y)\,\mathbf{R} \wedge \mathbf{R} = \mathbf{NOW}$$

$$\text{will} := (S\backslash NP)/(S_{b}\backslash NP) : \lambda p_E \lambda y.prior \Rightarrow imminent\text{-}state\,(p_E\, y)\,\mathbf{R}) \\ \wedge\, \mathbf{R} = \mathbf{NOW}$$

$$\text{is} := (S\backslash NP)/(S_{ing}\backslash NP) : \lambda p_E \lambda y.progressive\text{-}state\,(p_E\, y)\,\mathbf{R} \wedge \mathbf{R} = \mathbf{NOW}$$

A Neo-Reichenbachian Operator Semantics

- Some handbuilt lexical entries for implicative verbs:

$$\text{tried} := (S\backslash NP)/(S_{to}\backslash NP) : \lambda p_E \lambda y.rel_{try}\, p_E\, y\, \mathbf{R} \wedge rel_{want}\, p_E\, y\, \mathbf{R}$$
$$\wedge\, preparatory\text{-}activity\,(p_E\, y)\, y\, \mathbf{R} \wedge \mathbf{R} < \mathbf{NOW}$$

$$\text{failed} := (S\backslash NP)/(S_{to}\backslash NP) : \lambda p_E \lambda y.rel_{try}\, p_E\, y\, \mathbf{R} \wedge rel_{want}\, p_E\, y\, \mathbf{R}$$
$$\wedge\, preparatory\text{-}activity\,(p_E\, y)\, y\, \mathbf{R} \wedge \neg p_E\, y\, \mathbf{R} \wedge \mathbf{R} < \mathbf{NOW}$$

$$\text{managed} := (S\backslash NP)/(S_{to}\backslash NP) : \lambda p_E \lambda y.rel_{try}\, p_E\, y\, \mathbf{R} \wedge rel_{want}\, p_E\, y\, \mathbf{R}$$
$$\wedge\, preparatory\text{-}activity\,(p_E\, y)\, y\, \mathbf{R} \wedge p_E\, y\, \mathbf{R} \wedge \mathbf{R} < \mathbf{NOW}$$

Conclusion: Lexical Semantics as Entailment

- Learning over denotations of relations over typed named entities allows us to construct logical forms for content words as conjunctions of entailments over paraphrase clusters.
- Under more traditional semantic theories employing eliminative definitions these entailments would have been thought of as belonging to the domain of inference rather than semantics, either as meaning postulates relating logical forms or as “encyclopædic” general knowledge.
- These conjunctive terms of this logical language are very close to the language-specific grammar, and support fast inference of entailment.

Conclusion: Lexical Semantics as Entailment

- We can think of the cliques or clusters in the graph as related to the hidden primitives of the Language of Mind which the child language learner accesses.
- However, very few terms in the adult logical form correspond directly to primitives of the Language of Mind. (*red* and maybe *attack* might be exceptions.)
- Even those terms that are cognitively primitive like color terms will not be unambiguously lexicalized in all languages
- Perhaps this can be developed cross-linguistically into a full hidden interlingua for MT.
- Perhaps we can treat SPARQL as just another target language for SMT

References

Allen, James, 1983. "Maintaining Knowledge about Temporal Intervals." *Communications of the Association for Computing Machinery* 26:832–843.

Banarescu, Laura, Bonial, Claire, Cai, Shu, Georgescu, Madalina, Griffitt, Kira, Hermjakob, Ulf, Knight, Kevin, Koehn, Philipp, Palmer, Martha, and Schneider, Nathan, 2012. "Abstract Meaning Representation (AMR) 1.0 Specification."

Beltagy, Islam, Chau, Cuong, Boleda, Gemma, Garrette, Dan, Erk, Katrin, and Mooney, Raymond, 2013. "Montague Meets Markov: Deep Semantics with Probabilistic Logical Form." In *2nd Joint Conference on Lexical and*

*Computational Semantics (*SEM): Proceeding of the Main Conference and the Shared Task*. 11–21.

Berant, Jonathan, Chou, Andrew, Frostig, Roy, and Liang, Percy, 2013. “Semantic Parsing on Freebase from Question-Answer Pairs.” In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*. Seattle: ACL, 1533–1544.

Berant, Jonathan, Dagan, Ido, Adler, Meni, and Goldberger, Jacob, 2012. “Efficient Tree-Based Approximation for Entailment Graph Learning.” In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers-Volume 1*. Association for Computational Linguistics, 117–125.

Berant, Jonathan, Goldberger, Jacob, and Dagan, Ido, 2011. “Global Learning of

Typed Entailment Rules." In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics*. Portland, OR, 610–619.

Berant, Jonathan and Liang, Percy, 2014. "Semantic Parsing via Paraphrasing." In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Baltimore, MD, 1415–1425.

Börschinger, Benjamin, Jones, Bevan K., and Johnson, Mark, 2011. "Reducing Grounded Learning Tasks To Grammatical Inference." In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*. Edinburgh: ACL, 1416–1425.

Bos, Johan, 2013. "Is There a Place for Logic in Recognizing Textual Entailment?" *Linguistic Issues in Language Technology* 9.

Bos, Johan and Markert, Katja, 2005. "Combining Shallow and Deep

NLP Methods for Recognizing Textual Entailment." In *Proceedings of the First PASCAL Challenge Workshop on Recognizing Textual Entailment*. `http://www.pascal-network.org/Challenges/RTE/`: Pascal, 65–68.

Cai, Qingqing and Yates, Alexander, 2013a. "Large-scale Semantic Parsing via Schema Matching and Lexicon Extension." In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Sofia, Bulgaria: ACL, 423–433.

Cai, Qingqing and Yates, Alexander, 2013b. "Semantic Parsing Freebase: Towards Open-domain Semantic Parsing." In *Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 1: Proceedings of the Main Conference and the Shared Task: Semantic Textual Similarity*. Atlanta: ACL, 328–338.

Clarke, James, Goldwasser, Dan, Chang, Ming-Wei, and Roth, Dan, 2010.

"Driving Semantic Parsing from the World's Response." In *Proceedings of the Fourteenth Conference on Computational Natural Language Learning*. Uppsala: ACL, 18–27.

Collins, Michael, 2002. "Discriminative Training Methods for Hidden Markov Models: Theory and Experiments with Perceptron Algorithms." In *Proceedings of the 10th Conference on Empirical Methods in Natural Language Processing*. ACL, 1–8.

Galton, Anthony, 1990. "A Critical Examination of Allen's Theory of Action and Time." *Artificial Intelligence* 42:159–188.

Garrette, Dan, Erk, Katrin, and Mooney, Raymond, 2011. "Integrating Logical Representations with Probabilistic Information using Markov Logic." In *Proceedings of the Ninth International Conference on Computational Semantics*. ACL, 105–114.

Kowalski, Robert and Sergot, Maurice, 1986. "A Logic-Based Calculus of Events." *New Generation Computing* 4:67–95.

Kwiatkowski, Tom, Choi, Eunsol, Artzi, Yoav, and Zettlemoyer, Luke, 2013. "Scaling Semantic Parsers with On-the-Fly Ontology Matching." In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*. Seattle: ACL, 1545–1556.

Kwiatkowski, Tom, Goldwater, Sharon, Zettlemoyer, Luke, and Steedman, Mark, 2012. "A Probabilistic Model of Syntactic and Semantic Acquisition from Child-Directed Utterances and their Meanings." In *Proceedings of the 13th Conference of the European Chapter of the ACL (EACL 2012)*. Avignon: ACL, 234–244.

Kwiatkowski, Tom, Zettlemoyer, Luke, Goldwater, Sharon, and Steedman, Mark,

2010. "Inducing Probabilistic CCG Grammars from Logical Form with Higher-Order Unification." In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. Cambridge, MA: ACL, 1223–1233.

Kwiatkowski, Tom, Zettlemoyer, Luke, Goldwater, Sharon, and Steedman, Mark, 2011. "Lexical Generalization in CCG Grammar Induction for Semantic Parsing." In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. Edinburgh: ACL, 1512–1523.

Lewis, Mike, 2014. *Natural Semantics for Wide Coverage CCG Parsers*. Ph.D. thesis, University of Edinburgh.

Lewis, Mike and Steedman, Mark, 2013a. "Combined Distributional and Logical Semantics." *Transactions of the Association for Computational Linguistics* 1:179–192.

Lewis, Mike and Steedman, Mark, 2013b. "Unsupervised Induction of Cross-Lingual Semantic Relations." In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. ACL, 681–692.

Lewis, Mike and Steedman, Mark, 2014. "Combining Formal and Distributional Models of Temporal and Intensional Semantics." In *Proceedings of the ACL Workshop on Semantic Parsing*. Baltimore, MD: ACL, 28–32.

Liang, Percy, Jordan, Michael, and Klein, Dan, 2011. "Learning Dependency-Based Compositional Semantics." In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*. Portland, OR: ACL, 590–599.

Lin, Thomas, Mausam, and Etzioni, Oren, 2012. "Entity Linking at Web Scale." In *Proceedings of the Joint Workshop on Automatic Knowledge Base Construction and Web-scale Knowledge Extraction*. ACL, 84–88.

Lu, Wei, Ng, Hwee Tou, Lee, Wee Sun, and Zettlemoyer, Luke S., 2008. "A Generative Model for Parsing Natural Language to Meaning Representations." In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*. Honolulu, Hawaii: ACL, 783–792.

Montague, Richard, 1970. "English as a Formal Language." In Bruno Visentini (ed.), *Linguaggi nella Società e nella Technica*, Milan: Edizioni di Communità. 189–224. Reprinted as **?**:188-221.

Reddy, Siva, Lapata, Mirella, and Steedman, Mark, 2014. "Large-scale Semantic Parsing without Question-Answer Pairs." *Transactions of the Association for Computational Linguistics* 2:to appear.

Riedel, Sebastian, Yao, Limin, McCallum, Andrew, and Marlin, Benjamin, 2013. "Relation Extraction with Matrix Factorization and Universal Schemas." In

Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. Atlanta: ACL, 74–84.

Steedman, Mark, 1982. "Reference to Past Time." In Robert Jarvella and Wolfgang Klein (eds.), *Speech, Place, and Action*, New York: Wiley. 125–157.

Steedman, Mark, 2000. *The Syntactic Process*. Cambridge, MA: MIT Press.

Steedman, Mark, 2012. *Taking Scope: The Natural Semantics of Quantifiers*. Cambridge, MA: MIT Press.

Thompson, Cynthia and Mooney, Raymond, 2003. "Acquiring Word-Meaning Mappings for Natural Language Interfaces." *Journal of Artificial Intelligence Research* 18:1–44.

Wong, Yuk Wah and Mooney, Raymond, 2007. "Learning Synchronous Grammars for Semantic Parsing with Lambda Calculus." In *Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics*. ACL, 960–967.

Zettlemoyer, Luke and Collins, Michael, 2005. "Learning to Map Sentences to Logical Form: Structured Classification with Probabilistic Categorial Grammars." In *Proceedings of the 21st Conference on Uncertainty in AI (UAI)*. Edinburgh: AAAI, 658–666.

Zettlemoyer, Luke and Collins, Michael, 2007. "Online Learning of Relaxed CCG Grammars for Parsing to Logical Form." In *Proceedings of the Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP/CoNLL)*. Prague: ACL, 678–687.

Zhang, Congle and Weld, Daniel, 2013. "Harvesting Parallel News Streams to

Generate Paraphrases of Event Relations." In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. Seattle: ACL, 1776–1786.