4. Robust Semantics for NLP

Mark Steedman (*with* Mike Lewis, Siva Reddy, Javad Hosseini, *and others*)

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Outline

I: Distributional Theories of Content: Collocation *vs.* Denotation

II: Entailment-based Paraphrase Cluster Semantics (Lewis and Steedman, 2013a, 2014)

III: Multilingual Entailment-based Semantics (Lewis and Steedman, 2013b)

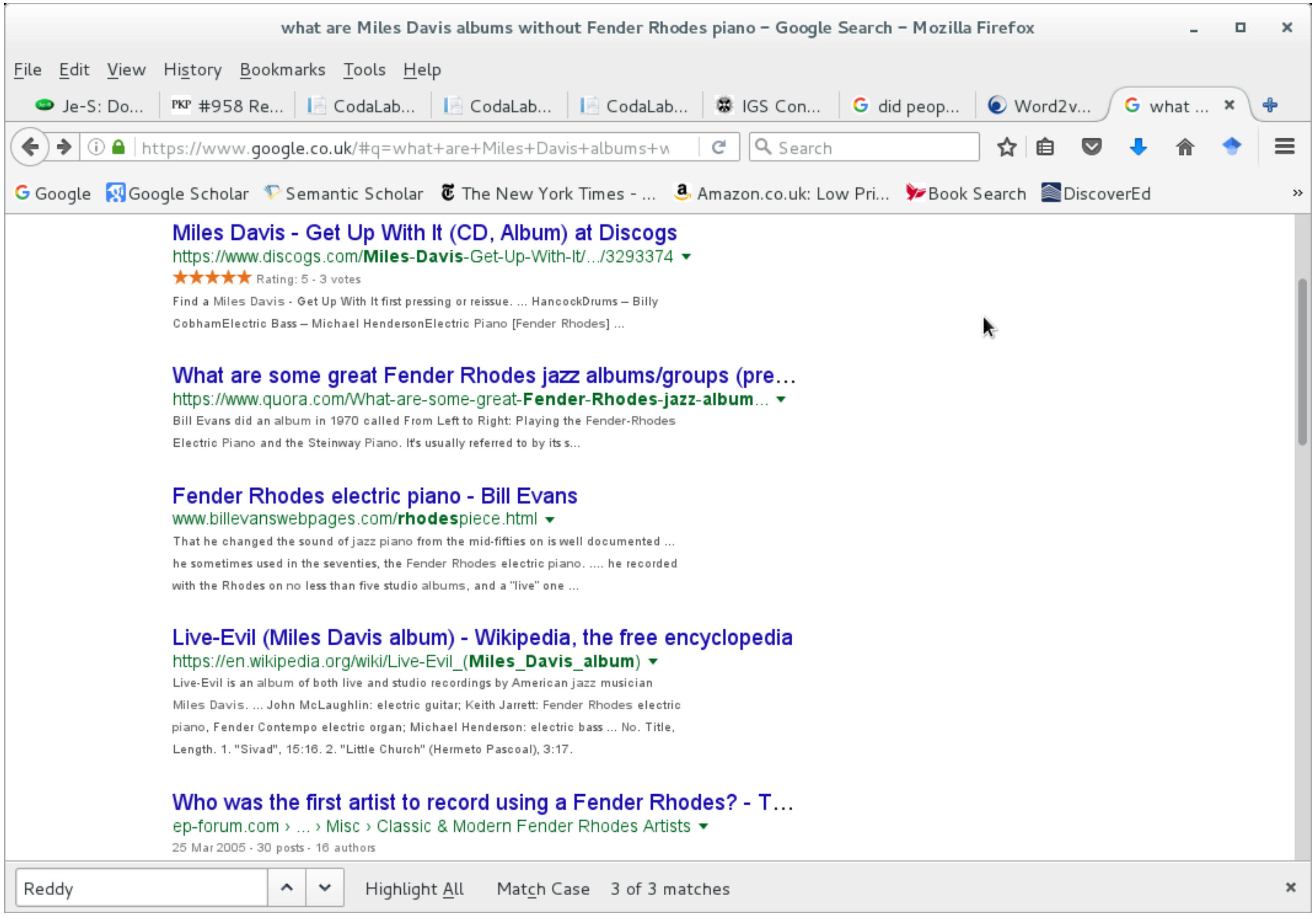
IV: Entailment-based Semantics of Temporality

V: Querying FreeBase

The Problem of Content

- We have (somewhat) robust wide coverage parsers that work on the scale of Bn of words They can read the web (and build logical forms) thousands of times faster than we can ourselves.

- So why can't we have them read the web for us, so that we can ask them questions like "What are recordings by Miles Davis without Fender Rhodes piano", and get a more helpful answer than the following?


what are Miles Davis albums without Fender Rhodes piano – Google Search – Mozilla Firefox
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https://www.google.co.uk/#q=what+are+Miles+Davis+albums+w
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Miles Davis - Get Up With It (CD, Album) at Discogs
https://www.discogs.com/Miles-Davis-Get-Up-With-It/.../3293374
Rating: 5 - 3 votes
Find a Miles Davis - Get Up With It first pressing or reissue. ... HancockDrums – Billy CobhamElectric Bass – Michael HendersonElectric Piano [Fender Rhodes] ...
What are some great Fender Rhodes jazz albums/groups (pre...
https://www.quora.com/What-are-some-great-Fender-Rhodes-jazz-album...
Bill Evans did an album in 1970 called From Left to Right: Playing the Fender-Rhodes Electric Piano and the Steinway Piano. It's usually referred to by its s...
Fender Rhodes electric piano - Bill Evans
www.billevanswebpages.com/rhodespiece.html
That he changed the sound of jazz piano from the mid-fifties on is well documented ... he sometimes used in the seventies, the Fender Rhodes electric piano. .... he recorded with the Rhodes on no less than five studio albums, and a "live" one ...
Live-Evil (Miles Davis album) - Wikipedia, the free encyclopedia
https://en.wikipedia.org/wiki/Live-Evil_(Miles_Davis_album)
Live-Evil is an album of both live and studio recordings by American jazz musician Miles Davis. ... John McLaughlin: electric guitar; Keith Jarrett: Fender Rhodes electric piano, Fender Contempo electric organ; Michael Henderson: electric bass ... No. Title, Length. 1. "Sivad", 15:16. 2. "Little Church" (Hermeto Pascoal), 3:17.
Who was the first artist to record using a Fender Rhodes? - T...
ep-forum.com › ... › Misc › Classic & Modern Fender Rhodes Artists
25 Mar 2005 - 30 posts - 16 authors
Reddy
Highlight All
Match Case
3 of 3 matches

Too Many Ways of Answering The Question

- 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.
- Your Question: *Has Verizon bought Yahoo?*
- The Text:

1. Verizon purchased Yahoo. ("Yes")
2. Verizon's purchase of Yahoo ("Yes")
3. Verizon owns Yahoo ("Yes")
4. Verizon managed to buy Yahoo. ("Yes")
5. Verizon acquired every company. ("Yes")
6. Yahoo may be sold to Verizon. ("Maybe")
7. Verizon will buy Yahoo or Yazoo. ("Maybe not")
8. Verizon didn't take over Yahoo. ("No")

The Problem

- The hard problem in semantics is not the logical operators, but the content that they apply over.

- How do we define a theory of content that is robust in the sense of generalizing across linguistic form, and compositional in the sense of:
  - being compatible with logical operator semantics and
  - supporting commonsense inference?

Previous Work

- Many have tried to build a form-independent semantics by hand:
  - both in linguistics, as in the "Generative Semantics" of the '70s and the related conceptual representations of Schank and Langacker;
  - and in computational linguistics, as in WordNet, FrameNet, Generative Lexicon, VerbNet/PropBank, BabelNet, AMR . . .
  - and in knowledge graphs such as FreeBase.

Previous Work

- Such hand-built semantic resources are extremely useful, but they are notoriously incomplete and language-specific.

- So why not let machine learning do the work instead?

- Treat semantic primitives as hidden.

- Mine them from unlabeled multilingual text, using Machine Reading.

One (Somewhat⋆) New Approach

- Clustering by Collocation
  - Meanings are vectors (etc.)
  - Composition is via Linear Algebraic Operations such as vector addition, matrix multiplication, Frobenius algebra, packed dependency trees, etc.
  - Vectors are good for underspecification and disambiguation (Analogy tasks and Jeopardy questions), and for building RNN embeddings-based "Supertagger" front-ends for CCG parsers, and related transition models for transition-based dependency parsers

⋆ Cf. the MDS "Semantic Differential" (1957), which Wordnet was developed by George Miller partly in reaction to.

For Example: Analogy via Word2Vec

- king - man + woman = [["queen",0.7118192911148071], ["monarch",0.6189674139022 ["princess",0.5902431011199951], ["crown prince",0.5499460697174072], ["prince",0.5377321243286133]]
- picnic - beer + wine = [["wine tasting",0.5751593112945557], ["picnic lunch",0.5423362255096436], ["picnics",0.5164458155632019], ["brunch",0.509375810623169], ["dinner",0.5043480396270752]]
- right - good + bad = [["wrong",0.548572838306427], ["fielder Joe Borchard",0.47464582324028015], ["left",0.46392881870269775], ["fielderJeromy Burnitz",0.45308032631874084], ["fielder Lucas Duda",0.4393044114112854]]
- Bernanke - USA + Russia = [["Ben Bernanke",0.6536909937858582], ["Kudrin",0.6301712989807129], ["Chairman Ben Bernanke",0.6148115396499634], ["Medvedev",0.6024096608161926], ["Putin",0.5873086452484131]]

Orthogonality in Vector Components

- "A is to B as C is to D" works best when the two components AB and BC are orthogonal i.e. independent, and if A and D are close anyway. Compare:
  - smaller - small + big = [["bigger",0.7836999297142029], ["larger",0.58667969703674
    ["Bigger",0.5707237720489502], ["biggest",0.5240510106086731], ["splashier",0.510
  - unhappy - happy + fortunate = [["incensed",0.4933996498584747], ["displeased",0.4742095172405243], ["unfortunate",0.4623183409690857], ["frustrated",0.4529050886631012], ["miffed",0.445096492767334]]
  - Las Meninas - Velasquez + Picasso = [["Paul Cëzanne",0.6370980739593506], ["Pablo Picasso",0.634435772895813], ["Renoir",0.6213735938072205], ["Dubuffet",0.619714617729187],["Degas",0.6172788143157959]]
  - kill - dead + alive = [["destroy",0.4605627655982971], ["exterminate",0.4236845970
    ["survive",0.3986499309539795], ["stymie",0.3975395560264587 4]]

Factorization in Vector Components

- Mitchell and Steedman (2015) show that the orthogality effect holds for a range of morpho-syntactic components, and that in general the cosine of vector differences is a strong predictor of performance on the word analogy task for CBOW, SkipGram, and GloVe.

- But this makes them look rather like old fashioned morpho-syntactic-semantic *features* male/female, active/inactive, good/bad, etc.

- It is unclear how to apply logical operators like negation to vectors.

- Beltagy *et al.* (2013) use vectors to estimate similarity between formulæ for purposes of predicing entailment in an otherwise standard hybrid logical approach.

Another (Somewhat⋆) New Approach

- Clustering by Denotation:
  - Meanings are automatically-extracted hidden relations, identified by automatic parsing and recognition of Named Entities either in text or in knowledge graphs.
  - Semantic composition is via syntactic derivation and traditional Logical Operators such as $\neg$, $\wedge$, $\vee$, etc.
  - Denotations are good for inference of *entailment* from the text to an answer to your question.
  - They are directly compatible with negation, quantifiers, modality, etc.

⋆ Cf. Lin and Pantel, 2001; Hovy *et al.*, 2001.

II: Entailment-based Paraphrase Cluster Semantics

- Instead of traditional lexical entries like the following:

(1) author $:= N/PP[of] : \lambda x \lambda y.author'xy$
write $:= (S\backslash NP)/NP : \lambda x \lambda y.write'xy$

- —we seek a lexicon capturing entailment via logical forms defined as (conjunctions of) paraphrase clusters like the following:

(2) author $:= N/PP_{of} : \lambda x_{book} \lambda y_{person}.relation37'xy$
write $:= (S\backslash NP)/NP : \lambda x_{book} \lambda y_{person}.relation37'xy$

- Such a "distributional" lexicon for content words works exactly like the naive lexicon (1) with respect to the semantics of quantification and negation.

Finding Typed Relation Expressions in Text

- We obtain the clusters by parsing (e.g.) Gigaword text with (e.g.) the CCG-based logical-form-building C&C parser, (Bos *et al.*, 2004), using the semantics from Steedman 2012, with a lexicon of the first type (1), to identify expressions relating Named Entities such as Verizon, Yahoo, Scott, *Waverley*, etc.

- Nominal compounds for the same MUC named entity type are merged.

- Entities are soft-clustered into types according to a suitable method (Topic models, WordNet clusters, FreeBase types, etc.)

- These types are used to distinguish homonyms like the two versions of the *born in* relation relating PERSONS to DATES versus LOCATIONS.

Example

- Obama was born in Hawai'i.

$$(3)\ \text{born} := (S\backslash NP)/PP[in] : \lambda x \lambda y. \left\{ \begin{array}{l} x = LOC \wedge y = PER \Rightarrow rel49 \\ x = DAT \wedge y = PER \Rightarrow rel53 \end{array} \right\} xy$$

$$\text{Obama} := \left\{ \begin{array}{c} PER = 0.9 \\ LOC = 0.1 \end{array} \right\}$$

$$\text{Hawai'i} := \left\{ \begin{array}{c} LOC = 0.7 \\ DAT = 0.1 \end{array} \right\}$$

- The "Packed" Distributional Logical Form

$$(4)\ S : \left\{ \begin{array}{c} rel49 = 0.63 \\ rel53 = 0.27 \end{array} \right\} hawaii' obama'$$

Directional Entailments

- We now search for potential entailments between such typed relations, where for multiple pairs of entities of type X and Y, if we find relation A in the text we often also find relation B stated as well.

- Entailment is a directed relation: X_{person} *elected to* Y_{office} does entail X_{person} *ran for* Y_{office} but not *vice versa*.

- Thus we use an assymetric similarity measure rather than Cosine.

- Lewis (2015); Lewis and Steedman (2014) apply the entailment graphs of Berant *et al.* (2012) to generate more articulated entailment structures.

Local Entailment Probabilities

- First, the typed named-entity technique is applied to (errorfully) estimate local probabilities of entailments:

a. $p(\mathit{conquer}\, x_{country}\, y_{country} \Rightarrow \mathit{invade}\, x_{country}\, y_{country}) = 0.9$
b. $p(\mathit{invade}\, x_{country}\, y_{country} \Rightarrow \mathit{attack}\, x_{country}\, y_{country}) = 0.8$
c. $p(\mathit{invasion}\,(\mathit{of}\ x_{country})\,(\mathit{by}\, y_{country}) \Rightarrow \mathit{attack}\, x_{country}\, y_{country}) = 0.8$
d. $p(\mathit{invade}\, x_{country}\, y_{country} \Rightarrow \mathit{invasion}\,(\mathit{of}\ x_{country})\,(\mathit{by}\, y_{country})) = 0.7$
e. $p(\mathit{invasion}\,(\mathit{of}\ x_{country})\,(\mathit{by}\, y_{country}) \Rightarrow \mathit{invade}\, x_{country}\, y_{country}) = 0.7$
f. $p(\mathit{conquer}\, x_{country}\, y_{country} \Rightarrow \mathit{attack}\, x_{country}\, y_{country}) = 0.4$
g. $p(\mathit{conquer}\, x_{country}\, y_{country} \Rightarrow \mathit{conqueror}\,(\mathit{of}\ x_{country})\, y_{country}) = 0.7$
h. $p(\mathit{conqueror}\,(\mathit{of}\ x_{country})\, y_{country} \Rightarrow \mathit{conquer}\, x_{country}\, y_{country}) = 0.7$
i. $p(\mathit{bomb}\, x_{country}\, y_{country} \Rightarrow \mathit{attack}\, x_{country}\, y_{country}) = 0.7$
(etc.)

Global Entailments

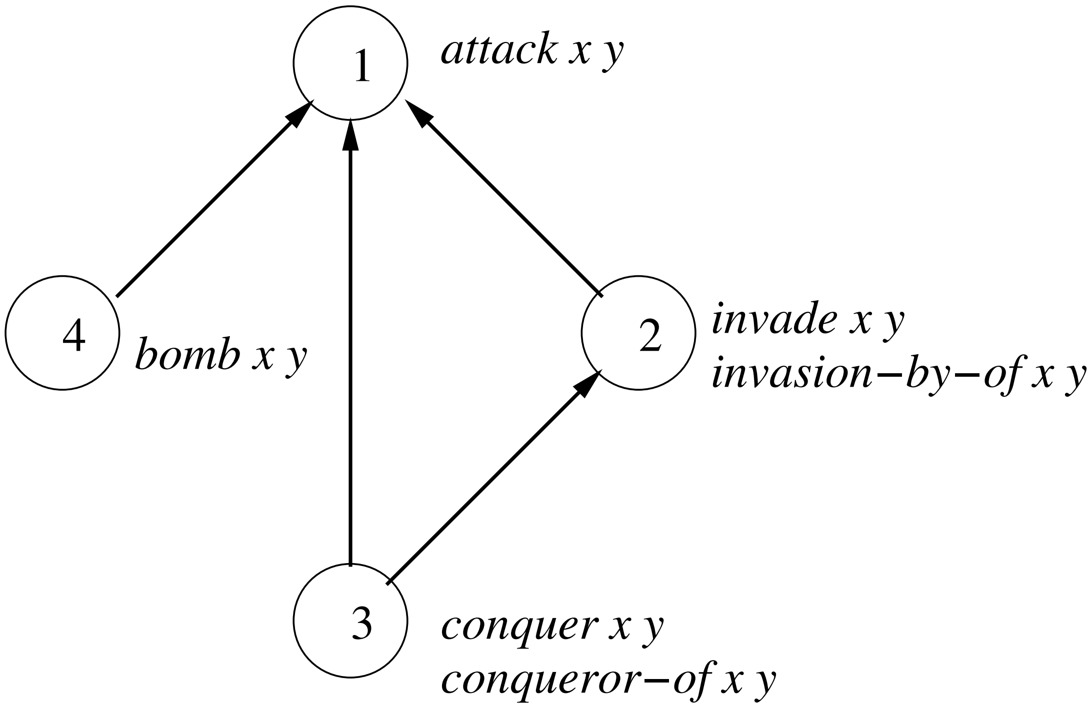
- The local entailment probabilities are then used to construct an entailment graph using integer linear programming with a prior $p = 0.25$ with the global constraint that the graph must be closed under transitivity.

- Thus, (f) will be included despite low observed frequency, while other low frequency spurious local entailments will be excluded..

- Cliques within the entailment graphs are collapsed to a single paraphase cluster relation identifier.

- The entailment graph is Boolean, rather than probabilistic.

Entailment graph



- A simple entailment graph for relations between countries.

Lexicon

- The lexicon obtained from the entailment graph

$$\text{attack} := (S\backslash NP)/NP : \lambda x \lambda y \lambda e.\mathit{rel_1}\, x\, y\, e$$
$$\text{bomb} := (S\backslash NP)/NP : \lambda x \lambda y \lambda e.\mathit{rel_1}\, x\, y\, e \wedge \mathit{rel_4}\, x\, y\, e$$
$$\text{invade} := (S\backslash NP)/NP : \lambda x \lambda y \lambda e.\mathit{rel_1}\, x\, y\, e \wedge \mathit{rel_2}\, x\, y\, e$$
$$\text{conquer} := (S\backslash NP)/NP : \lambda x \lambda y \lambda e.\mathit{rel_1}\, x\, y\, e \wedge \mathit{rel_2}\, x\, y\, e \wedge \mathit{rel_3}\, x\, y\, e$$
$$\text{conqueror} := VP_{pred}/PP_{of} : \lambda x \lambda p \lambda y \lambda e.p\, y \wedge \mathit{rel_1}\, x\, y\, e \wedge \mathit{rel_2}\, x\, y\, e \wedge \mathit{rel_3}\, x\, y\, e$$

- These logical forms support correct inference under negation, such as that *conquered* entails *attacked* and *didn't attack* entails *didn't conquer*

Entailment

- Thus, to answer a question "Did X conquer Y" we look for sentences which subsume the conjunctive logical form $rel_2 \wedge rel_1$, or satisfy its negation $\neg rel_2 \vee \neg rel_1$.

- Note that if we know that *invasion-of* is a paraphrase of $invade = rel_2$, we also know *invasion-of* entails $attack = rel_1$.

Examples from Question-Answer Test Set

- Examples:

Question	Answer	From Unseen 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) and Lewis (2015)

III: Multilingual Entailment Cluster Semantics

- If we can find entailments including paraphrases by observing local entailments between statements in English of relations over typed named entities, there is no reason we shouldn't consider statements in other languages concerning named entities of the same types as nodes in the same entailment graph.

- Thus from French *Shakespeare est l'auteur de* Mesure pour mesure, and knowledge of how French named entities map to English, we should be able to work out that *être l'auteur de* is a member of the *write* cluster.

- We use cross-linguistic paraphrase clusters to re-rank Moses n-best lists to promote translations that preserve the cluster-based meaning representation from source to target.

Experiment: Reranking SMT Translations

- For a source (French) sentence that can be dependency-parsed to deliver a cluster-semantic logical form:
- We Moses-translate (to English) taking the 50-best list and parsing (with C&C) to produce cluster-semantic logical forms.
- If the logical form of the top ranked translation is different from that of the source, we choose whatever translation from the remainder of the n-best list has the logical form that most closely resembles the source cluster semantics.

Reranking SMT

- 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.

- Fluent bilingual human annotators are then asked to choose between the one-best Moses translation and the cluster-based alternative.

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

Reranking SMT

- Many cases of "no preference" were where Moses and the preferred translation were similar strings differing only in attachment decisons visible only in the logical form.

- No parallel text was used in these experiments.

- This is good, because SMT has already used up all of the available parallel text (Och, 2007)

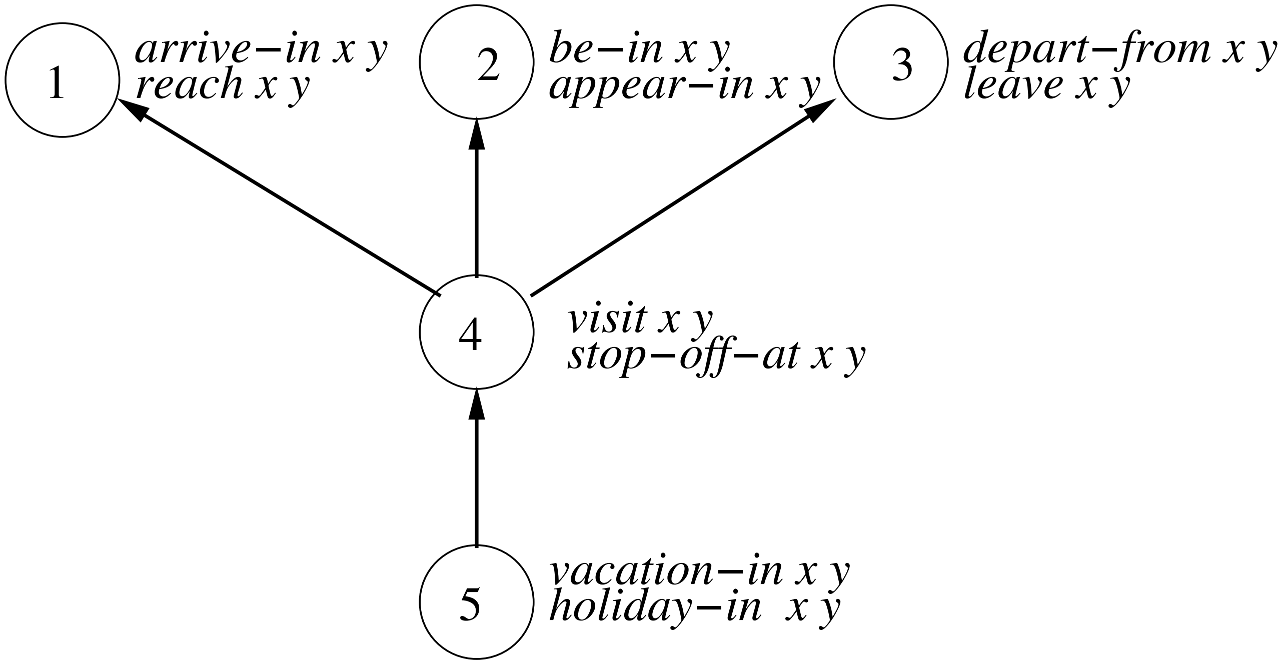
- The undoubted improvements in Google translate since then are due to better (neural) machine learning from the existing data and *bigger (parallel) computers*.

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

IV: 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.

Entailment Semantics for Temporality



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

Temporal Semantics from Timestamped Data

{"arg1":"OBAMA","arg2":"MINNEAPOLIS","sentences":
[{"relationphrase":"be in","tokens":
["Obama","is","in","Minneapolis","to","push","for","tougher","gun","laws","and","highlight","some","of","the","things","the
"a1":[0,1],"a2":[3,4],"v":[1,3],"fromArticleId":371037},
{"relationphrase":"head to","tokens":
["Obama","heads","to","Minneapolis","to","sell","gun","plan","."],
"a1":[0,1],"a2":[3,4],"v":[1,3],"fromArticleId":369952},
{"relationphrase":"be visit","tokens":
["Monday",",","Obama","is","visiting","Minneapolis","to","discuss","his","plan","to","battle","gun","violence","."],
"a1":[2,3],"a2":[5,6],"v":[3,5],"fromArticleId":433846}], ... }
{"arg1":"DAVID BECKHAM","arg2":"PARIS","sentences":
[{"relationphrase":"have arrive in","tokens":
["David","Beckham","has","arrived","in","Paris","to","complete","a","dramatic","deadline","day","move","to","Paris","St-Ger
"a1":[0,2],"a2":[5,6],"v":[2,5],"fromArticleId":456691},
{"relationphrase":"go to","tokens":
["David","Beckham","Goes","to","Paris",",","Kate","Middleton","Shops","Incognito",",","and","Dolce","\u0026","Gabbana","\u0
"a1":[0,2],"a2":[4,5],"v":[2,4],"fromArticleId":452413}], ... }

Timestamped Data

- We have begun pilot experiments with timestamped news, using 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*.
- We can use it as the input to a neo-Reichenbachian semantics of temporality

Reconnecting with Logical Operator Semantics

- Some handbuilt lexical entries for auxiliary verbs (closed-class words):

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

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

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

- Cf. Steedman, 1977; Webber, 1978; Steedman, 1982; Moens and Steedman, 1988; White, 1994; Steedman, 1997; Pustejovsky, 1998; Filip, 2008, *passim*.

Reconnecting with Logical Operator Semantics

- Some potentially learnable lexical entries for implicative verbs:

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

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

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

- Needs negation as failure to find positive entailing text.

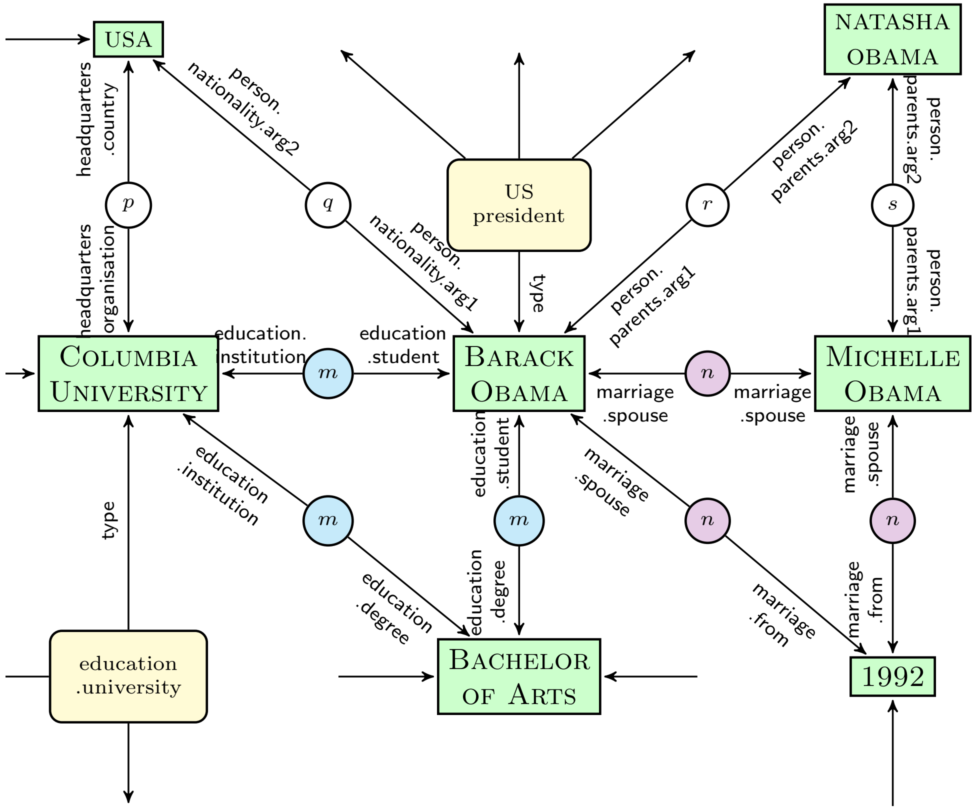
V: Querying Freebase

- Reddy *et al.* (2014):
  - Rather than inducing a semantic parser from Freebase questions and answers,for which there is no training data . . .
  - Take a parser that already builds logical forms and learn the relation between those logical forms and the relations in the already denotational knowledge graph.

- Specifically:
  - First automatically map the linguistic logical forms into graphs of the same type as the knowledge graph;
  - Then learn the mapping between the elements of the semantic and knowledge-base graphs.

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 fact that *Obama did his BA at Columbia*



Parsing to Logical Form using CCG

- Cameron directed *Titanic* in 1997.

$$
\begin{array}{ccccc}
\text{Cameron} & \text{directed} & \textit{Titanic} & \text{in} & \text{1997} \\
\overline{NP} & \overline{S\backslash NP/PP_{in}/NP} & \overline{NP} & \overline{PP_{in}/NP} & \overline{NP} \\
cameron & \lambda w\lambda x\lambda y.directed.arg1(E,y)\wedge directed.arg2(F,w)\wedge directed.in(G,x) & titanic & \lambda x.x & 1997
\end{array}
$$

$$
\xrightarrow{\quad\quad >\quad\quad}
$$

$$
S\backslash NP/PP
$$

$$
\lambda x\lambda y.directed.arg1(E,y)\wedge directed.arg2(F,titanic)\wedge directed.in(G,x) \qquad 1997
$$

$$
\xrightarrow{\quad\quad >\quad\quad}
$$

$$
S\backslash NP : \lambda y.directed.arg1(E,y)\wedge directed.arg2(F,titanic)\wedge directed.in(G,1997)
$$

$$
\xleftarrow{\quad\quad <\quad\quad}
$$

$$
S : directed.arg1(E,cameron)\wedge directed.arg2(F,titanic)\wedge directed.in(G,1997)
$$

- The logical form language is preprocessed to be homorphic to the freebase language.

Mapping from logical forms To FreeBase paths

- Cameron directed *Titanic* in 1997.

$$\begin{array}{lcl}
\mathit{directed.arg1}(E,\mathit{cameron}) & & \mathit{film.directed\text{-}by.arg2}(m, y_{person}) \\
\wedge\mathit{directed.arg2}(F,\mathit{titanic}) & \Rightarrow & \wedge\mathit{film.directed\text{-}by.arg1}(m, x_{film}) \\
\wedge\mathit{directed.in}(G,\mathit{1997}) & & \wedge\mathit{film.initial\text{-}release\text{-}date.arg1}(n, x_{film}) \\
 & & \wedge\mathit{film.initial\text{-}release\text{-}date.arg2}(n, w_{year})
\end{array}$$

The Nature of the Mapping

- In the parser logical form, we need to replace
  - Entity variables with Freebase entities (e.g. *Cameron* with CAMERON)
  - Edge labels with Freebase relations (e.g. directed.arg1 with film.directed_by.arg2)
  - Event variables with factual variables (e.g. E becomes m and F becomes n)
- But there are $O(k+1)^n$ grounded graphs possible for each logical form (including missing edges)
- Reddy *et al.* (2014, 2016) use heuristics whose success depends on English-specific stem similarity between the primitives of the ungrounded and grounded logical forms.

A Better Way to Query Knowledge Graphs

- Treat the paths relating named entities in the graph itself as logical forms of a rather stilted natural language, collecting local entailment probabilities, e.g:

  (5) $p(directed\, w_{year}\, x_{film}\, y_{person} \Rightarrow film.directed\text{-}by.arg2(m, y_{person}) \wedge film.directed\text{-}by.arg1(m, x_{film}) \wedge film.initial\text{-}release\text{-}date.arg1(n, x_{film}) \wedge film.initial\text{-}release\text{-}date.arg2(n, w_{year})) = 0.9$

- Then include such typed relations in the global entailment graph using ILP, where they will end up in the same paraphrase cluster as *directed/3*

- Finally, redefine the semantics of the original parser yet again, so that every occurence of cluster identifiers like *directed/3* in the entailment semantic conjunctions is replaced by the corresponding path expression.

A Better Way to Query Knowledge Graphs

- This can be done for any language for which the entailment semantics has been trained.
- The parsers can now be used to query the knowledge graph directly.
- Because they are entailment-supporting on the basis of exposure to a much wider range of text than just the knowledge graph, they will be able to give entailed answers that are not there in the graph, such as that Obama ran for office on the basis of facts that are, such as that he was elected.
- This also provides a way of dealing with the notorious incompleteness of the knowledge graph. (Lincoln's son Tad lacks a nationality in Freebase,)

An Even Better Way to Query Knowledge Graphs

- Building the knowledge graph directly from the parser, in the multilingual entailment cluster-based semantics, by machine reading.

- Harrington and Clark (2009); Harrington (2010) show that such Semantic Nets can be queried and updated efficiently at the scale we can now build them using the spreading activation of Collins and Loftus (1975).

- In the old days, the received wisdom was that SA didn't work: either the decay rate was too high, so too few nodes were activated, or it was too low, so the whole network woke up.

- From Harrington and Clark (2009):

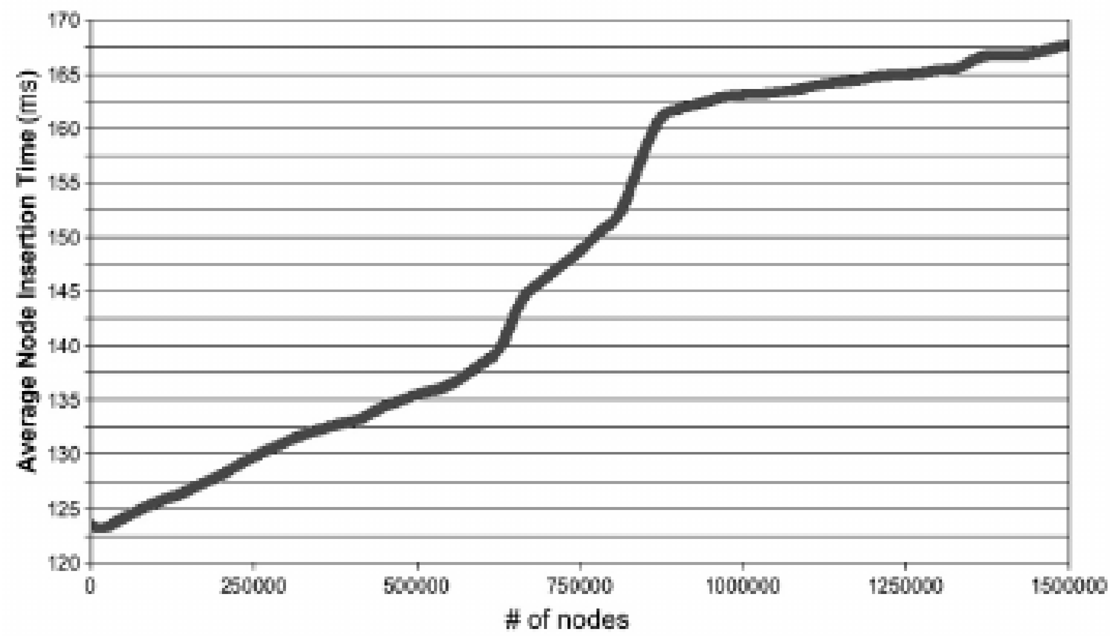


Figure 5. Average time to add a new node to the network vs. total number of nodes

Building Entailment-Semantic Nets Using SA

- The above proposal promises to solve two separate problems of classical semantic nets, namely: query form mismatch; and complexity of search and update.

Conclusion I: Denotation-based

- Learning over denotations, defined as relations over typed named entities, allows us to build entailment into lexical logical forms for content words via conjunctions of paraphrase clusters.

- The individual conjuncts are potentially language-independent.

- Mining them by machine reading remains a hard task, for which we have no more than proof-of-concept!

- The lexical conjunctions are projected onto sentential logical forms including traditional logical operators by the function words and CCG syntax.

- The sentential logical forms support fast inference of common-sense entailment.

Conclusion II: Collocation-based

- Learning over Collocations, represented as a vector space with reduced dimensionality, also represents meanings in terms of hidden components
- Projection by vector addition remains a hard baseline to beat!
- By superimposing a number of distinct collocations, they remain the most powerful mechanism known for resolving ambiguity, as in the use of embeddings and LSTM in parsing models (Lewis *et al.*, 2016; Dyer *et al.*, 2016).

When Firth (1957/1968):179 made his oft-cited remark about knowing a word by the company it keeps, he was actually talking about word sense-disambiguation.

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Conclusions: For Philosophy of Language

- 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.
- Carnap (1952) introduced meaning postulates in support of Inductive Logic, including a model of Probability, basically to keep the model small and consistent.
- Like Katz and Fodor (1963); Katz and Postal (1964); Katz (1971), we are in effect packing meaning postulates into the lexicon.
- This suggests that our semantic representation expresses an a pragmatic empiricist view of analytic meaning of the kind advocated by Quine (1951).

Conclusions: For Psychology

- Do children acquire the meaning of words like "invade" and "conquer" by building entailment graphs?
- I suggest they do, and that this is the mechanism for what Gleitman (1990) called syntactic bootstrapping of the lexicon—that is:
  - Once children have acquired core competence (by semantic bootstrapping of the kind modeled computationally by Kwiatkowski *et al.* 2012 and Abend *et al.*, 2017), they can detect that "annex" is a transitive verb meaning some kind of attack without knowing exactly what it means.
  - They can then acquire the full meaning by piecemeal observation of its entailments and paraphrases in use.

  This is a major mechanism of cultural inheritance of concepts that would otherwise in many cases take more than an individual lifetime to develop.

Conclusions: For Cognitive Science

- These terms compile into a (still) language-specific Language of Thought (Fodor 1975, *passim*), which is roughly what adult speakers do their thinking in.
- To the extent that the cliques or clusters in the graph are constructed from multilingual text, this meaning representation will approximate the hidden language-independent "private" Language of Mind which the child language learner accesses.
- However, very few terms in any adult logical form correspond directly to the hidden primitives of that Language of Mind. (*red* and maybe *attack* might be exceptions.)
- Even those terms that are cognitively primitive (such as color terms) will not be unambiguously lexicalized in all languages.

Conclusions V: For Artificial Intelligence

- Some conceptual primitives, such as that things can only be in one place at a time, probably predate human cognition, and are unlikely to be discoverable at all by machine reading of the kind advocated here.
- These properties are hard-wired into our minds by 600M years of vertebrate evolution.
- These are exactly the properties that Artificial Intelligence planning builds in to the representation via the "Closed World Assumption" and the STRIPS dynamic logic of change.
- Computational Lingustics should learn from AI in defining a Linear Dynamic Logic for distributional clustered entailment semantics.

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