Combined Distributional and Logical Semantics

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Obama's birthplace is not Kenya



• Induce the meanings of words from corpora

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X was born in Y

(Obama, Hawaii)

(Shakespeare, Stratford)

(Obama, 1961)

X's birthplace is Y

(Obama, Hawaii)

(Shakespeare, Stratford)

. . .

(Jesus, Bethlehem)

(e.g. Lin & Pantel, 2001)

. . .

sim(X was born in Y, X's birthplace is Y) > t

Obama was born in Hawaii

⇒ Obama's birthplace is Hawaii





Obama's birthplace is not Kenya







Obama NP obama

was (S\NP)/(S\NP)

born in (S\NP)/NP $\lambda p \lambda x . p(x)$ $\lambda y \lambda x . born_in'(x, y)$

Hawaii NP hawaii

S\NP λx . born_in'(x, hawaii)

S\NP λx . born_in'(x, hawaii)

S born_in'(obama, hawaii)

Obama NP obama



born in Kenya (S\NP)/NP NP λyλx . born_in'(x, y) kenya

> **S\NP** λx . born_in'(x, kenya)

S\NP λx . ¬born_in'(x, kenya)

S ¬born_in'(obama, kenya)

Obama wasn't born in Kenya

 \Rightarrow

Obama was born in Kenya

Every US president was born in the United States

\Rightarrow

Obama wasn't born in Kenya

Nicole Kidman and Barack Obama were born in Hawaii

\Leftrightarrow

Nicole Kidman was born in Hawaii and Barack Obama was born in Hawaii





Obama's birthplace is not Kenya



¬birthplace'(obama, kenya) ⇒? born_in'(obama, kenya)

- + Models semantic operators ("not", "every", etc.)
- + Abstracts away from syntax (conjunctions, passive voice, relative clauses, etc)

- Doesn't model meaning of content words

- Existing approaches:
- Compositional vector space models
 - (e.g. Coecke et al., 2011, Baroni et al., 2012, Grefenstette 2013)
- Learn inference rules as logical axioms
 (e.g. Garrette et al., 2011, Beltagy et at., 2013)

Obama was born in Hawaii

born_in'(obama, hawaii)

Hawaii is Obama's birthplace

Obama was born in Hawaii relation53(obama, hawaii)

Hawaii is Obama's birthplace relation53(obama, hawaii)

Learn lexical entries such that:

born \vdash (S\NP)/PP[in] : $\lambda x \lambda y$. relation53(x,y) birthplace \vdash N/PP[of] : $\lambda x \lambda y$. relation53(x,y)



relation53(obama, hawaii)

Gather statistics on predicates in large corpus:

born_in'(X, Y)

(Obama, Hawaii)

(Shakespeare, Stratford)

. . .

(Obama, 1961)

birthplace_of'(X, Y)

(Obama, Hawaii)

(Shakespeare, Stratford)

. . .

(Jesus, Bethlehem)

employeeOf'(X, Y) workFor'(X, Y)

buy'(X, Y) purchase'(X, Y) acquisitionOf'(X, Y)

write'(X, Y) authorOf'(X,Y)

born_in'(X, Y)

birth_place(X,Y)

born_in'(X, Y) birth_place(X,Y) buy'(X, Y) purchase'(X, Y) acquisitionOf'(X, Y)







Cluster using Chinese Whispers (Biemann, 2006)





Obama's birthplace is not Kenya





Obama was born in Hawaii Obama was born in 1961



Ambiguity

Create multiple <u>typed</u> lexical entries:

born \vdash (S\NP)/PP[in] : $\lambda y_{\text{LOC}} \lambda x_{\text{PER}}$. birthPlace(x,y) born \vdash (S\NP)/PP[in] : $\lambda y_{\text{DAT}} \lambda x_{\text{PER}}$. birthDate(x,y)

(similar to: Schoenmackers et al., 2010; Berant et al., 2011)

Clustering Typed Predicates

Only cluster predicates with the same type

born_in(X:PER, Y:DAT) birth_date(X:PER,Y:DAT) relation53(X, Y)



Topic Model

One 'document' per predicate One 'word' per argument

lives in X
Hawaii
London
France

year of X	
-----------	--

1564

2001

1945

born in X
Hawaii
2001
London
1564

Topic Model

One 'document' per predicate One 'word' per argument



(see also: Melamud et al., 2013)

Example Types

. . .

suspect, assailant, fugitive, accomplice, ...

author, singer, actress, actor, dad, ...

city, area, country, region, town, capital, ...

subsidiary, automaker, airline, Co., GM, ...

musical, thriller, sequel, special, ...









Compositional Semantics

born ⊢ **(S\NP)/PP[in]** born ⊢ **(S\NP)/PP[in]**

- born \vdash (S\NP)/PP[in] : $\lambda y_{LOC} \lambda x_{PER}$. birthPlace(x,y)
- born \vdash (S\NP)/PP[in] : $\lambda y_{DAT} \lambda x_{PER}$. birthDate(x,y)

Compositional Semantics

- born \vdash (S\NP)/PP[in] : $\lambda y_{LOC} \lambda x_{PER}$. birthPlace(x,y)
- born \vdash (S\NP)/PP[in] : $\lambda y_{\text{DAT}} \lambda x_{\text{PFR}}$. birthDate(x,y)

born \vdash (S\NP)/PP[in]: $\lambda y \lambda x$. $\begin{cases} (x:LOC, y:PER) \Rightarrow birthPlace(x, y) \\ (x:DAT, y:PER) \Rightarrow birthDate(x, y) \end{cases}$

Compositional Semantics

Output packed logical form capturing joint distribution:

Obama was born in Hawaii in 1961

 $\begin{cases} birthPlace \sim 0.9 \\ birthDate \sim 0.1 \end{cases}$ (Obama, Hawaii)

 $\Lambda \left\{ \begin{array}{c} birthPlace \sim 0.1 \\ birthDate \sim 0.9 \end{array} \right\} (Obama, 1961)$

Training Details

- Train on English Gigaword
- Use C&C parser for syntax (Clark and Curran 2004)
- 15 entity types
- Lexicon includes manual entries for some function words ("every", "not", etc.)

Evaluation

Automatically generate question set from corpus

Google bought YouTube Who bought YouTube? What did Google buy?

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Automatically generate question set from corpus

Google bought YouTube Who bought YouTube? What did Google buy?

Generate 1000 questions Manual evaluation

Comparison Systems

- Reverb (Fader et al., 2011)
- Relational LDA (Yao et al., 2011)
- CCG Baseline
- CCG + WordNet
- CCG using Distributional Clusters

QA Results



Accuracy

Examples

Question: What did Delta merge with?

Sentence: The 747 freighters came with Delta's acquisition of Northwest

Answer: Northwest

Evaluating Formal Semantics

Problems involving inference using quantifiers from the FraCaS Suite (Section 1):

Premises:

Every European has the right to live in Europe. Every European is a person. Every person who has the right to live in Europe can travel freely within Europe.

Hypothesis: Every European can travel freely within Europe

Evaluating Formal Semantics

	Single Premise Sentence	Multiple Premise Sentences
Natural Logic 2007	84%	-
Natural Logic 2008	98%	-
CCG-Dist (parser)	70%	50%
CCG-Dist (gold syntax)	89%	80%

Conclusions

- Formal and distributional semantics complement each other
- Modelling content words using cluster identifiers gives the benefits of both

Thanks!

Any questions?