Leveraging Linguistic Structure for Open Domain Information Extraction

Gabor Angeli, Melvin Johnson Premkumar, Chris Manning

Stanford University

July 27, 2015

Motivation: Question Answering

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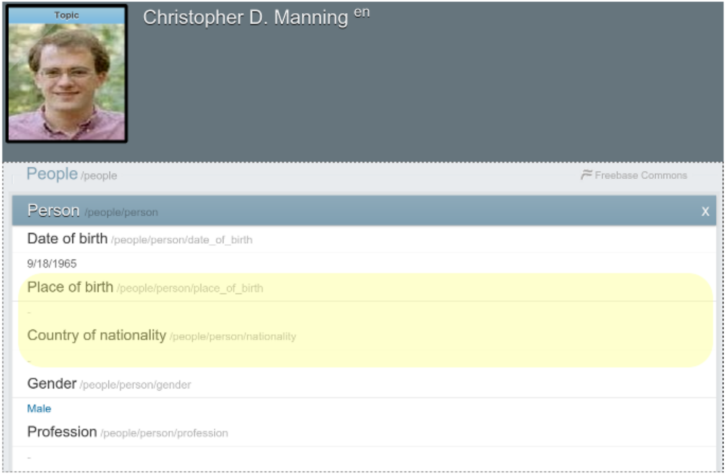

Motivation: Question Answering

Christopher Manning

Professor of Linguistics and Computer Science

Natural Language Processing Group, Stanford University

Brief Bio

- I'm Australian ("I come from a land of wide open spaces ...")
- BA (Hons) Australian National University 1989 (majors in mathematics, computer science and linguistics)
- PhD Stanford Linguistics 1995
- Asst Professor Carnegie Mellon University Computational Linguistics Program 1994-96
- Lecturer University of Sydney Dept of Linguistics 1996-99
- Asst Professor Stanford University Depts of Computer Science and Linguistics 1999-2006
- Assoc Professor Stanford University Depts of Linguistics and Computer Science 2006-2012
- Professor Stanford University Depts of Linguistics and Computer Science 2012-

Motivation: Question Answering

Australia

Christopher D. Manning, origin

Feedback

Information [Relation] Extraction

Input: Sentences containing (subject, object).
Output: Relation between subject and object.

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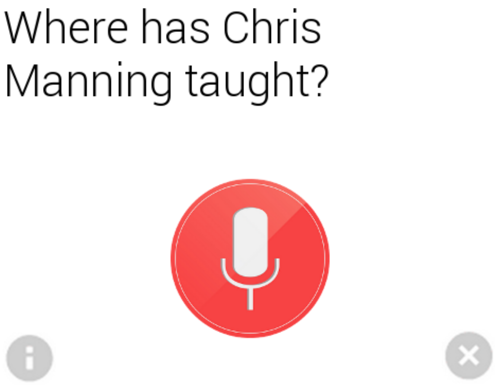

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Christopher Manning is an Associate Professor of Computer Science and Linguistics at Stanford University. Chris received a Bachelors degree and University Medal from the Australian National University and a Ph.D. from Stanford in 1994, both in Linguistics. Chris taught at Carnegie Mellon University and The University of Sydney before joining the Stanford faculty in 1999. He is a Fellow of the American Association for Artificial Intelligence and of the Association for Computational Linguistics, and is one of the most cited authors in natural language processing, for his research on a broad range of statistical natural language topics from tagging and parsing to grammar induction and text understanding.

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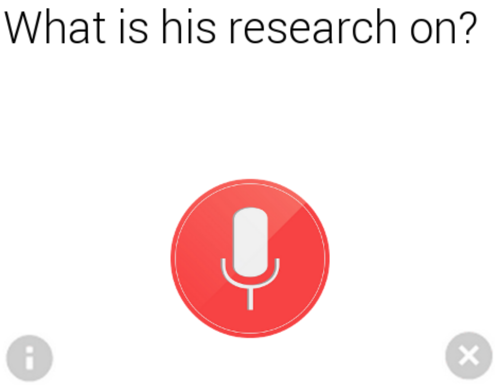

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More to life than a fixed relation schema

Open Information Extraction

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(Obama, was born in, Hawaii)
(young rabbits, drink, milk)
(Heinz Fischer, visits, United States)

Prior Work

OpenIE (UW)

- TextRunner, ReVerb, Ollie, OpenIE 4.
- Learn surface and/or dependency patterns for triples.

kill **Antibiotics** kill **your friendly bacteria** , and when these have been killed the Candida yeast can mutate into a fungus . (via ClueWeb12)
Antibiotics kill **most bacteria** , but can leave resistant individual strains free to reproduce without competition from other bacteria . (via ClueWeb12)
Antibiotics kill **beneficial bacteria** , and then the yeast can start to grow in numbers . (via ClueWeb12)

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NELL (CMU)

- Bootstrapping an ontology from a small number of seed examples.

steel_carbon_fiber_eastern is a building material	937	07-jul-2015	92.0
n06__51_pm is a dataset used within the scientific field of machine learning	934	25-jun-2015	99.8
equity_deals is an economic sector	937	07-jul-2015	90.7
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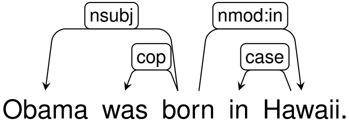
Useful for matrix factorization, MLNs, QA, etc.

Challenge: Long Sentences

Short sentences are easy:



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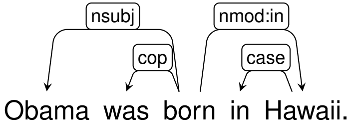
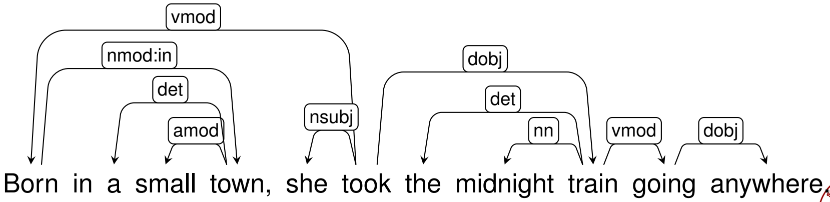


But most sentences are longer:



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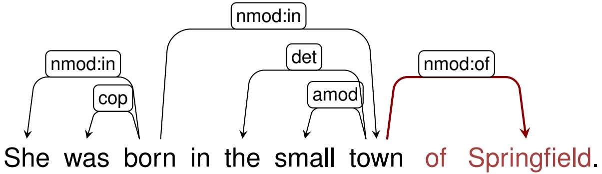

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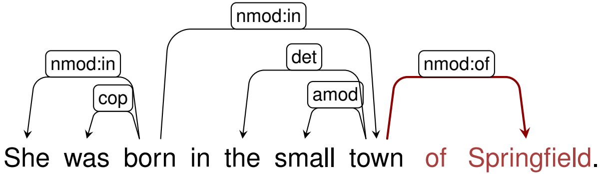
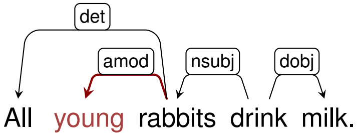


Sometimes logically invalid:



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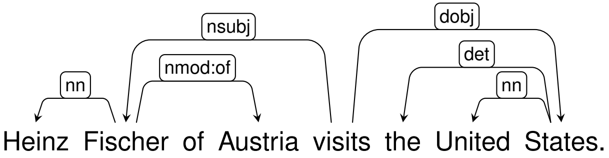

(Heinz Fischer of Austria; visits; the United States)

Is this about Heinz Fischer or Austria?

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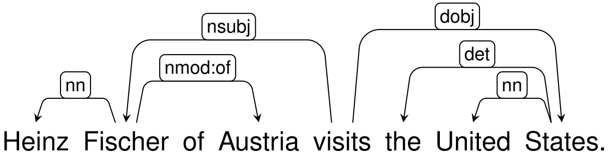

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  (United States president Obama; visits; China)

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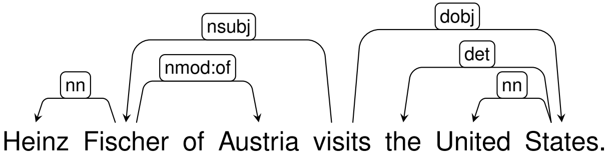

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- Is the subject a PERSON or LOCATION?
  (United States president Obama; visits; China)
- Downstream applications don't want to deal with this.
- Downstream applications have less context to figure this out.

Approach Open IE As *Entailment*

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- Yield short, entailed clauses from sentences.

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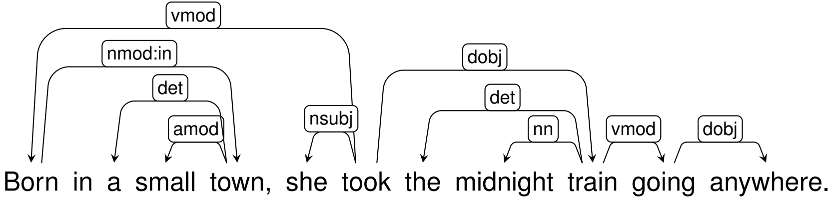
Yield clauses

Input: Long sentence.

Born in a small town, she took the midnight train going anywhere.

Output: Short clauses.

she Born in a small town.



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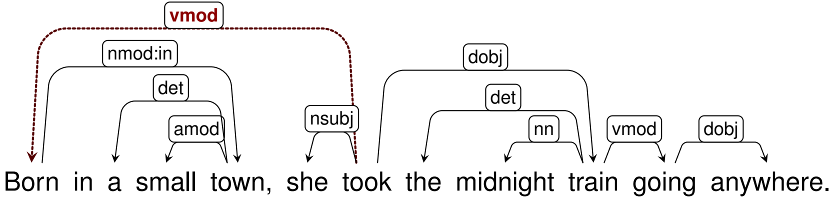

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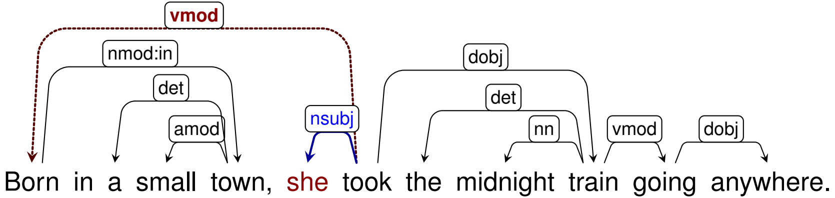
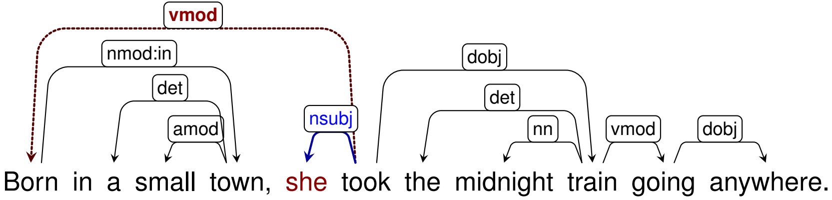


Clause Classifier



Input: Dependency arc.

Output: *Action* to take.

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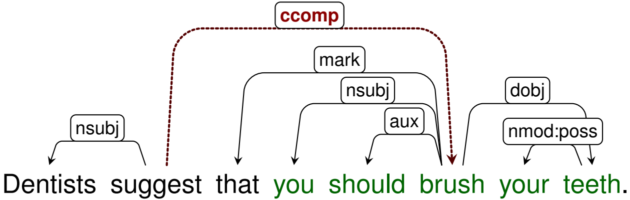

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- **Yield** (*you should brush your teeth*)

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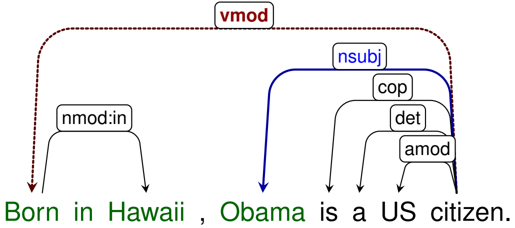

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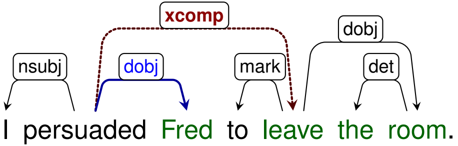

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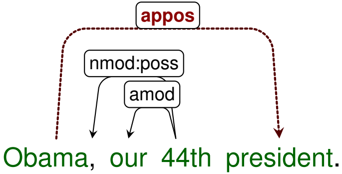

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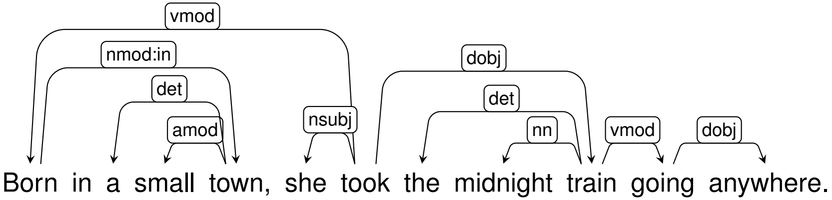
- **Yield (Parent Subject)** (*Obama is our 44th president*)

A Search Problem

Breadth First Search:



Decision:

Yielded Clauses:

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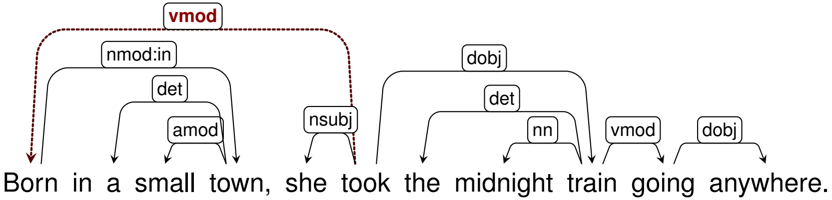

Decision: Edge: vmod **Action**: Yield (subject controller)

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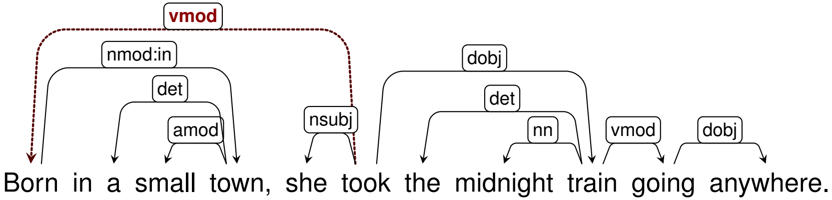

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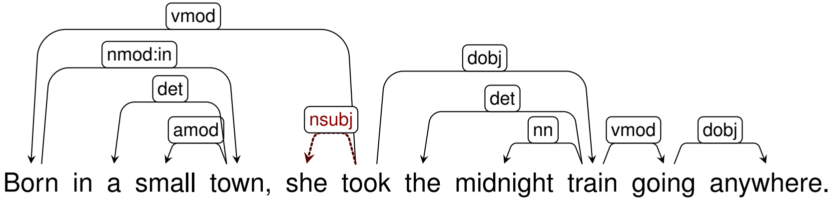

Decision: Edge: nsubj **Action**: Stop

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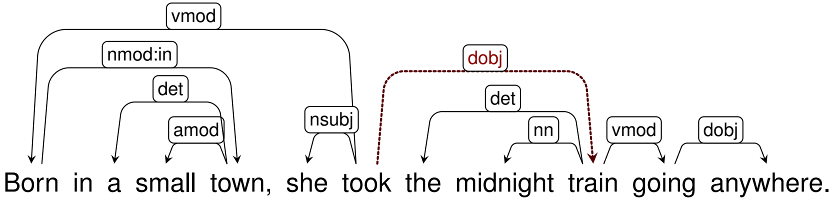

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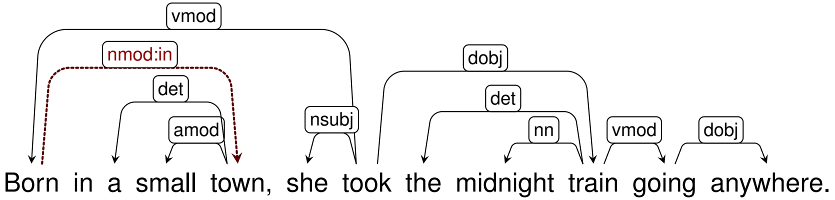

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Classifier Training

Training Data Generation

1. Take $66\,880$ sentences (newswire, newsgroups, Wikipedia).

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4. Positive Labels: A sequence of actions which yields a known relation.
   Negative Labels: All other sequences of actions.

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3. Run exhaustive search.
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   Negative Labels: All other sequences of actions.

Features:

- Edge label; incoming edge label.
- Neighbors of governor; neighbors of dependent; number of neighbors.
- Existence of subject/object edges at governor; dependent.
- POS tag of governor; dependent.

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Maximally Shorten Clauses

Some strange, nuanced function:

*Heinz Fischer **of Austria***	$\Longrightarrow$	*Heinz Fischer*
***United States president** Obama*	$\Longrightarrow$	*Obama*
*All **young** rabbits drink milk*	$\not\Longrightarrow$	*All rabbits drink milk*
*Some **young** rabbits drink milk*	$\Longrightarrow$	*Some rabbits drink milk*
*Enemies give **fake** praise*	$\not\Longrightarrow$	*Enemies give praise*
*Friends give **true** praise*	$\Longrightarrow$	*Friends give praise*

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An entailment function:

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Maximally Shorten Clauses

A natural logic entailment function:

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Braindead for humans, but not computers

- *All young rabbits drink milk* $\not\Longrightarrow$ *All rabbits drink milk*
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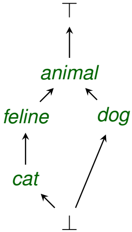
Hard even for first order logic

- *Most cats eat mice* $\Longrightarrow$ *Most cats eat rodents*
- *All students who know a foreign language learned it at university*
  $\Longrightarrow$ *They learned it at school.*

Natural Logic and Polarity

Order phrases into a *partial order*.



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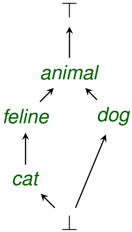

***Polarity* is the direction a lexical item can move in the ordering.**

animal

feline

$\boxed{\text{cat}}$

house cat

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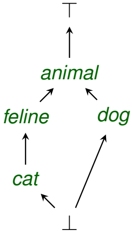

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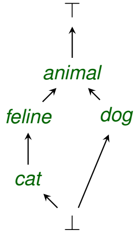

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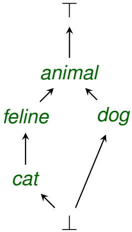

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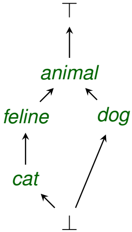

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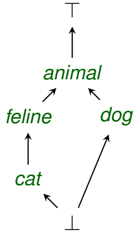

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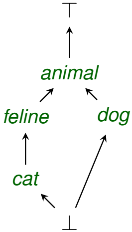

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Natural Logic For Clause Shortening

Quantifiers determines the *polarity* (↑ or ↓) of words.

Mutations must respect *polarity*.

Polarity determines valid deletions.

	mammals		something
	rabbits	consume	liquid
$\boxed{\uparrow \textbf{Some}_{\uparrow\uparrow}}$	$\boxed{\uparrow \text{young rabbits}}$	$\boxed{\uparrow \text{drink}}$	$\boxed{\uparrow \text{milk}}$
	baby rabbits	slurp	Lucerne

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	animals		something
	mammals	consume	liquid
↑ **Some**$_{\uparrow\uparrow}$	↑ rabbits	↑ drink	↑ milk
	young rabbits	slurp	Lucerne

Natural Logic For Clause Shortening

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Approach Open IE As *Entailment*

Challenge: Long Sentences

- ✓ Yield short, entailed clauses from sentences.

Challenge: Lost Context

- ✓ Shorten these clauses only when logically valid.

Challenge: Too Much Context

- ✓ Shorten these clauses as much as possible.

No Longer A Challenge

- Segment these short clauses into triples.

No Longer A Challenge

Heinz Fischer visited US $\Longrightarrow$ (Heinz Fischer; visited; US)

No Longer A Challenge

Heinz Fischer visited US	$\Longrightarrow$	(Heinz Fischer; visited; US)
Obama born in Hawaii	$\Longrightarrow$	(Obama; born in; Hawaii)

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	$\ldots$	

6 dependency patterns (+ 8 nominal patterns)

Useful Without Triples

Simple, short sentences are themselves useful

- ... for relation extraction (Miwa et al. 2010).
- ... for textual entailment (Hickl and Bensley, 2007).
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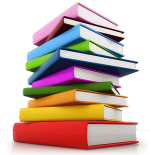
Two use-cases:

Triples for Logical Reasoning	**Text for Surface Reasoning**
	

Problem

How do you evaluate open domain triples?

Extrinsic Evaluation: Knowledge Base Population

Unstructured Text


The New York Times
WEDNESDAY, JULY 11, 2007
$25 AND UNDER
The Brisket Speaks With a Texas Accent

$\Longrightarrow$

Structured Knowledge Base

Barack Obama

44th President of the United States

Personal details

Born	Barack Hussein Obama II August 4, 1961 (age 52) Honolulu, Hawaii, U.S.
Political party	Democratic
Spouse(s)	Michelle LaVaughn Robinson (m. 1992–present)
Children	Malia Ann Obama (b. 1998) Natasha Obama (b. 2001)

Extrinsic Evaluation: Knowledge Base Population

Relation Extraction Task:

- Fixed schema of 41 relations.
- Precision: answers marked correct by humans.
- Recall: answers returned by any team (including LDC annotators).

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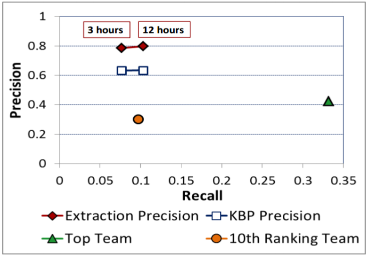
Comparison: *Open Information Extraction to KBP Relations in 3 Hours*. (Soderland et. al)



Prerequisite Task: Open IE → KBP Relations

1. Hand-coded mapping.
   (Same as UW; both over 1-2 weeks)

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   - Rank by $\text{PMI}^2(r_o, r_k \mid t_1, t_2)$:

$$\mathrm{PMI}^2(r_k, r_o \mid t_1, t_2) = \log\left(\frac{p(r_k, r_o \mid t_1, t_2)^2}{p(r_k \mid t_1, t_2) \cdot p(r_o \mid t_1, t_2)}\right).$$

Prerequisite Task: Open IE → KBP Relations

KBP Relation	Open IE Relation	PMI^2
Per:Date_Of_Birth	*be bear on*	1.83
	bear on	1.28
Per:Date_Of_Death	*die on*	0.70
	be assassinate on	0.65
Per:LOC_Of_Birth	*be bear in*	1.21
Per:LOC_Of_Death	**elect president of*	2.89
Per:Religion	*speak about*	0.67
	popular for	0.60
Per:Parents	*daughter of*	0.54
	son of	1.52
Per:LOC_Residence	*of*	1.48
	**independent from*	1.18

Results

TAC-KBP 2013 Slot Filling Challenge:

- End-to-end task – includes IR + consistency.
- **Precision:** facts LDC evaluators judged as correct.
  Recall: facts other teams (including LDC annotators) also found.

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Median Team			18.6
Our System +  + 	58.6	18.6	28.3
Top Team	45.7	35.8	40.2

Takeaways

Open IE is a sentence simplification task

Sentence simplification is an entailment task

Put burden on Open IE, not downstream tasks

Released in Stanford CoreNLP

http://nlp.stanford.edu/software/openie.shtml

```
annotators = tokenize,ssplit,pos,lemma,parse,natlog,openie
Collection<RelationTriple> triples
     = sentence.get(RelationTriplesAnnotation.class)
```