Leveraging Linguistic Structure for Open Domain Information Extraction

Gabor Angeli, Melvin Johnson Premkumar, Chris Manning

Stanford University

July 27, 2015
Motivation: Question Answering

Where is Chris Manning from?
Motivation: Question Answering
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.*
**Input**: Sentences containing `(subject, object)`.

**Output**: Relation between subject and object.

\[ I \ 'm \ Australian \implies per:origin \]
Information [Relation] Extraction

**Input**: Sentences containing (subject, object).

**Output**: Relation between subject and object.

I'm Australian $\implies$ per:origin
Information [Relation] Extraction

**Input**: Sentences containing *(subject, object)*.

**Output**: Relation between *subject* and *object*.

*I'm Australian* $\implies$ *per:origin*
What about...

Where has Chris Manning taught?
What about...

Christopher Manning
Associate Professor
Stanford University

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.
What about...

What is his research on?
What about...  

Christopher Manning  
Associate Professor  
Stanford University  

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.
More to life than a fixed relation schema
More to life than a fixed relation schema

(Chris, taught at, Carnegie Mellon)
(Chris, taught at, University of Sydney)
(his research, is on, A broad range of statistical natural language topics)
More to life than a fixed relation schema

(Chris, taught at, Carnegie Mellon)
(Chris, taught at, University of Sydney)
(his research, is on, A broad range of statistical natural language topics)
(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)
```
Prior Work

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

NELL (CMU)
- Bootstrapping an ontology from a small number of seed examples.

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)
Prior Work

OpenIE (UW)

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

NELL (CMU)

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

Useful for matrix factorization, MLNs, QA, etc.
Challenge: Long Sentences

Short sentences are easy:

Obama was born in Hawaii.

But most sentences are longer:

Born in a small town, she took the midnight train going anywhere.
Challenge: Long Sentences

Short sentences are easy:

Obama was born in Hawaii.

But most sentences are longer:

Born in a small town, she took the midnight train going anywhere.
Challenge: Lost Context

Sometimes annoying:

She was born in the small town of Springfield.
Challenge: Lost Context

Sometimes annoying:

She was born in the small town of Springfield.

Sometimes logically invalid:

All young rabbits drink milk.
Challenge: Too Much Context

Is this about Heinz Fischer or Austria?
Challenge: Too Much Context

Is this about Heinz Fischer or Austria?

- Is the subject a PERSON or LOCATION?
  - (United States president Obama; visits; China)
Challenge: Too Much Context

Is this about Heinz Fischer or Austria?
- Is the subject a PERSON or LOCATION?
  \[(\text{United States president Obama}; \text{visits}; \text{China})\]
- Downstream applications don’t want to deal with this.
- Downstream applications have less context to figure this out.
Approach Open IE As *Entailment*

**Challenge: Long Sentences**
- Yield short, entailed clauses from sentences.
Approach Open IE As *Entailment*

**Challenge: Long Sentences**
- Yield short, entailed clauses from sentences.

**Challenge: Lost Context**
- Shorten these clauses only when logically valid.
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.
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.
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.*
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._

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

**Input:** Dependency arc.

**Output:** *Action* to take.
Dentists suggest that you should brush your teeth.

**Input:** Dependency arc.

**Output:** *Action* to take.

- **Yield** *(you should brush your teeth)*
Born in Hawaii, Obama is a US citizen.

**Input:** Dependency arc.

**Output:** *Action* to take.

- **Yield** (*you should brush your teeth*)
- **Yield (Subject Controller)** (*Obama Born in Hawaii*)
I persuaded Fred to leave the room.

**Input:** Dependency arc.

**Output:** Action to take.

- Yield *(you should brush your teeth)*
- Yield (Subject Controller) *(Obama Born in Hawaii)*
- Yield (Object Controller) *(Fred leave the room)*
Clause Classifier

Obama, our 44th president.

Input: Dependency arc.
Output: Action to take.

- **Yield** *(you should brush your teeth)*
- **Yield (Subject Controller)** *(Obama Born in Hawaii)*
- **Yield (Object Controller)** *(Fred leave the room)*
- **Yield (Parent Subject)** *(Obama is our 44th president)*
A Search Problem

Breadth First Search:

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

Decision:

Yielded Clauses:

```
Born in a small town, she took the midnight train going anywhere.
```
Breadth First Search:

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

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

Yielded Clauses:

*Born in a small town, she took the midnight train going anywhere*
A Search Problem

Breadth First Search:

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

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

Yielded Clauses:

Born in a small town, she took the midnight train going anywhere
she Born in a small town
A Search Problem

Breadth First Search:

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

Decision: Edge: nsubj  Action: Stop

Yielded Clauses:

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

she Born in a small town
A Search Problem

Breadth First Search:

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

Decision: **Edge**: dobj  **Action**: Stop

Yielded Clauses:

* Born in a small town, she took the midnight train going anywhere
* she Born in a small town
A Search Problem

Breadth First Search:

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

Decision: Edge: nmod:in  Action: Stop

Yielded Clauses:

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

she Born in a small town
Classifier Training

Training Data Generation


2. Apply distant supervision to label relations in sentence.

3. Run exhaustive search.

Positive Labels: A sequence of actions which yields a known relation.

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.
Training Data Generation

2. Apply distant supervision to label relations in sentence.
Classifier Training

Training Data Generation

2. Apply *distant supervision* to label relations in sentence.
3. Run exhaustive search.

Positive Labels: A sequence of actions which yields a known relation.

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.
Classifier Training

Training Data Generation

2. Apply *distant supervision* to label relations in sentence.
3. Run exhaustive search.
4. Positive Labels: A sequence of actions which yields a known relation.
   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.
Classifer Training

Training Data Generation

2. Apply distant supervision to label relations in sentence.
3. Run exhaustive search.
4. Positive Labels: A sequence of actions which yields a known relation.
   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.
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.
Maximally Shorten Clauses

Some strange, nuanced function:

Heinz Fischer of Austria  $\implies$  Heinz Fischer
United States president Obama  $\implies$  Obama
All young rabbits drink milk  $\nRightarrow$  All rabbits drink milk
Some young rabbits drink milk  $\implies$  Some rabbits drink milk
Enemies give fake praise  $\nRightarrow$  Enemies give praise
Friends give true praise  $\implies$  Friends give praise
Maximally Shorten Clauses

An entailment function:

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

A natural logic entailment function:

- Heinz Fischer of Austria
  - Heinz Fischer

- United States president Obama
  - Obama

- All young rabbits drink milk
  - All rabbits drink milk

- Some young rabbits drink milk
  - Some rabbits drink milk

- Enemies give fake praise
  - Enemies give praise

- Friends give true praise
  - Friends give praise
If I mutate a sentence in this way, do I preserve its truth?
Natural Logic

If I mutate a sentence in this way, do I preserve its truth?

Braindead for humans, but not computers

- All young rabbits drink milk $\iff$ All rabbits drink milk
- Some young rabbits drink milk $\implies$ Some rabbits drink milk

$\neg$ Most cats eat mice $\implies$ Most cats eat rodents

All students who know a foreign language learned it at university $\implies$ They learned it at school.
If I mutate a sentence in this way, do I preserve its truth?

Braindead for humans, but not computers

- All young rabbits drink milk $\nRightarrow$ All rabbits drink milk
- Some young rabbits drink milk $\nRightarrow$ Some rabbits drink milk

Hard even for first order logic

- Most cats eat mice $\nRightarrow$ Most cats eat rodents
- All students who know a foreign language learned it at university $\nRightarrow$ They learned it at school.
Order phrases into a *partial order.*

\[
\begin{align*}
\top & \quad \downarrow \\
\downarrow & \quad \downarrow & \quad \downarrow \\
animal & \quad feline & \quad dog \\
\downarrow & \quad \downarrow \\
cat & \\
\downarrow & \\
\bot
\end{align*}
\]
Natural Logic and Polarity

Order phrases into a *partial order*.

```
⊤
  ↘
  animal
  ↘
feline  dog
  ↘
  cat
  ↘
⊥
```

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

animal

feline

cat

house cat
Natural Logic and Polarity

Order phrases into a partial order.

Polarity is the direction a lexical item can move in the ordering.
Natural Logic and Polarity

Order phrases into a *partial order*.

\[
\begin{array}{c}
\top \\
\downarrow \\
\text{animal} \\
\downarrow \\
\text{feline} & \text{dog} \\
\downarrow \\
\text{cat} \\
\downarrow \\
\bot
\end{array}
\]

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

\[
\begin{array}{c}
\text{living thing} \\
\text{animal} \\
\boxed{\uparrow \text{feline}} \\
\text{cat}
\end{array}
\]
Natural Logic and Polarity

Order phrases into a *partial order*.

\[
\begin{array}{c}
\bot \\
\uparrow \\
\text{animal} \\
\downarrow \\
\text{feline} \\
\uparrow \\
\text{cat} \\
\downarrow \\
\text{dog} \\
\end{array}
\]

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

Order phrases into a *partial order*.

\[ \top \quad \downarrow \quad \text{animal} \quad \downarrow \quad \text{feline} \quad \downarrow \quad \text{dog} \quad \downarrow \quad \text{cat} \quad \downarrow \quad \bot \]

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

\[ \text{thing} \quad \downarrow \quad \text{living thing} \quad \downarrow \quad \text{animal} \quad \downarrow \quad \text{feline} \]
Natural Logic and Polarity

Order phrases into a *partial order*.

```
\[
\begin{array}{c}
\top \\
\downarrow \\
\text{animal} \\
\downarrow \\
\text{feline} \\
\downarrow \\
\text{cat} \\
\downarrow \\
\bot \\
\end{array}
\]
```

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

```
\[
\begin{array}{c}
\text{living thing} \\
\downarrow \\
\text{animal} \\
\downarrow \boxed{\text{feline}} \\
\downarrow \\
\text{cat} \\
\end{array}
\]
```
Order phrases into a *partial order*. 

\[ \top \]
\[ \Downarrow \]
\[ \text{animal} \]
\[ \Downarrow \]
\[ \text{feline} \]
\[ \Downarrow \]
\[ \text{dog} \]
\[ \Downarrow \]
\[ \text{cat} \]
\[ \Downarrow \]
\[ \bot \]

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

\[ \text{animal} \]
\[ \Downarrow \]
\[ \text{feline} \]
\[ \Downarrow \]
\[ \text{cat} \]
\[ \Downarrow \]
\[ \text{house cat} \]
Quantifiers determines the *polarity* (↑ or ↓) of words.

Mutations must respect *polarity*.

Polarity determines valid deletions.

- Some
- young rabbits
- mamals
- rabbits
- consume
- drink
- liquid
- milk
- Lucerne
Quantifiers determine the *polarity* (↑ or ↓) of words.

Mutations must respect *polarity*.

Polarity determines valid deletions.

- Some rabbits consume milk and Lucerne by slurping something liquid.
- Some young rabbits consume milk and Lucerne by slurping something liquid.
- Some young rabbits consume milk and Lucerne by slurping something liquid.
Quantifiers determine the *polarity* (↑ or ↓) of words.

Mutations must respect *polarity*.

Polarity determines valid deletions.

`mammals` `rabbits` `contribute` `drank` `something liquid`

`↑ All ↓↑` `↑ young rabbits` `↑ drink` `↑ milk` `Lucerne`
Quantifiers determine the *polarity* (↑ or ↓) of words.

Mutations must respect *polarity*.

Polarity determines valid deletions.
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 \implies (Heinz Fischer; visited; US)
Heinz Fischer visited US
Obama born in Hawaii

⇒

(Heinz Fischer; visited; US)
(Obama; born in; Hawaii)
Heinz Fischer visited US  \[\implies\]  (Heinz Fischer; visited; US)

Obama born in Hawaii  \[\implies\]  (Obama; born in; Hawaii)

Cats are cute  \[\implies\]  (Cats; are; cute)
Heinz Fischer visited US  $\iff$ (Heinz Fischer; visited; US)
Obama born in Hawaii  $\iff$ (Obama; born in; Hawaii)
Cats are cute  $\iff$ (Cats; are; cute)
Cats are sitting next to dogs  $\iff$ (Cats; are sitting next to; dogs)
No Longer A Challenge

Heinz Fischer visited US $\implies$ (Heinz Fischer; visited; US)
Obama born in Hawaii $\implies$ (Obama; born in; Hawaii)
Cats are cute $\implies$ (Cats; are; cute)
Cats are sitting next to dogs $\implies$ (Cats; are sitting next to; dogs)

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).
- ... for summarization (Siddharthan et al. 2004).
Simple, short sentences are themselves useful

- ... for relation extraction (Miwa et al. 2010).
- ... for textual entailment (Hickl and Bensley, 2007).
- ... for summarization (Siddharthan et al. 2004).

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

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)
Natalia 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).
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).

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)
Prerequisite Task: Open IE → KBP Relations

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

2. Learned relation mapping.
   - For each type signature $t_1, t_2$;
   - For an open IE relation $r_o$ and KBP relation $r_k$;

$\text{PMI}^2(r_k, r_o | t_1, t_2) = \log \frac{p(r_k, r_o | t_1, t_2)^2}{p(r_k | t_1, t_2) \cdot p(r_o | t_1, t_2)}$. 

Angeli, Premkumar, Manning (Stanford)
Prerequisite Task: Open IE → KBP Relations

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

2. Learned relation mapping.
   - For each type signature $t_1, t_2$;
   - For an open IE relation $r_o$ and KBP relation $r_k$;
   - Compute:
     \[
     p(r_k, r_o \mid t_1, t_2) = \frac{\text{count}(r_k, r_o, t_1, t_2)}{\sum_{r_k', r_o'} \text{count}(r_k', r_o', t_1, t_2)}.
     \]
Prerequisite Task: Open IE → KBP Relations

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

2 Learned relation mapping.
   - For each type signature \( t_1, t_2 \);
   - For an open IE relation \( r_o \) and KBP relation \( r_k \);
   - Compute:
     \[
     p(r_k, r_o \mid t_1, t_2) = \frac{\text{count}(r_k, r_o, t_1, t_2)}{\sum_{r'_k, r'_o} \text{count}(r'_k, r'_o, t_1, t_2)}.
     \]
   - Rank by PMI\(^2\)(\( r_o, r_k \mid t_1, t_2 \)):
     \[
     \text{PMI}^2(r_k, r_o \mid t_1, t_2) = \log \left( \frac{p(r_k, r_o \mid t_1, t_2)^2}{p(r_k \mid t_1, t_2) \cdot p(r_o \mid t_1, t_2)} \right).
     \]
### Prerequisite Task: Open IE → KBP Relations

<table>
<thead>
<tr>
<th>KBP Relation</th>
<th>Open IE Relation</th>
<th>PMI²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per:Date_Of_Birth</td>
<td><em>be bear on</em></td>
<td>1.83</td>
</tr>
<tr>
<td></td>
<td><em>bear on</em></td>
<td>1.28</td>
</tr>
<tr>
<td>Per:Date_Of_Death</td>
<td><em>die on</em></td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td><em>be assassinate on</em></td>
<td>0.65</td>
</tr>
<tr>
<td>Per:LOC_Of_Birth</td>
<td><em>be bear in</em></td>
<td>1.21</td>
</tr>
<tr>
<td>Per:LOC_Of_Death</td>
<td><em>elect president of</em></td>
<td>2.89</td>
</tr>
<tr>
<td>Per:Religion</td>
<td><em>speak about</em></td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td><em>popular for</em></td>
<td>0.60</td>
</tr>
<tr>
<td>Per:Parents</td>
<td><em>daughter of</em></td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td><em>son of</em></td>
<td>1.52</td>
</tr>
<tr>
<td>Per:LOC_Residence</td>
<td><em>of</em></td>
<td>1.48</td>
</tr>
<tr>
<td></td>
<td><em>independent from</em></td>
<td>1.18</td>
</tr>
</tbody>
</table>
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.

<table>
<thead>
<tr>
<th>System</th>
<th>P</th>
<th>R</th>
<th>F₁</th>
</tr>
</thead>
<tbody>
<tr>
<td>UW Submission</td>
<td>69.8</td>
<td>11.4</td>
<td>19.6</td>
</tr>
<tr>
<td>Ollie</td>
<td>57.7</td>
<td>11.8</td>
<td>19.6</td>
</tr>
</tbody>
</table>
## 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.

<table>
<thead>
<tr>
<th>System</th>
<th>P</th>
<th>R</th>
<th>F₁</th>
</tr>
</thead>
<tbody>
<tr>
<td>UW Submission</td>
<td>69.8</td>
<td>11.4</td>
<td>19.6</td>
</tr>
<tr>
<td>Ollie</td>
<td>57.7</td>
<td>11.8</td>
<td>19.6</td>
</tr>
<tr>
<td><strong>Our System</strong></td>
<td><strong>61.9</strong></td>
<td><strong>13.9</strong></td>
<td><strong>22.7</strong></td>
</tr>
</tbody>
</table>

### Median Team

Median Team: 18.6

### Our System +

Our System +: 58.6 18.6 28.3

### Top Team

Top Team: 45.7 35.8 40.2

*Angeli, Premkumar, Manning (Stanford)*

*Linguistics for Open IE*
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.

<table>
<thead>
<tr>
<th>System</th>
<th>P</th>
<th>R</th>
<th>F₁</th>
</tr>
</thead>
<tbody>
<tr>
<td>UW Submission</td>
<td>69.8</td>
<td>11.4</td>
<td>19.6</td>
</tr>
<tr>
<td>Ollie</td>
<td>57.7</td>
<td>11.8</td>
<td>19.6</td>
</tr>
<tr>
<td><strong>Our System</strong></td>
<td>61.9</td>
<td>13.9</td>
<td>22.7</td>
</tr>
<tr>
<td>Median Team</td>
<td></td>
<td></td>
<td>18.6</td>
</tr>
<tr>
<td><strong>Our System + 🔔 + 🔫</strong></td>
<td>58.6</td>
<td>18.6</td>
<td>28.3</td>
</tr>
<tr>
<td>Top Team</td>
<td>45.7</td>
<td>35.8</td>
<td>40.2</td>
</tr>
</tbody>
</table>
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


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