Learning Open Domain Knowledge from Text

Gabor Angeli

Stanford University

November 5, 2015
Learning “Knowledge?”
Knowledge = *True Statements*
...for a human

Born in Honolulu, Hawaii, Obama is a graduate of Columbia University and Harvard Law School.

...for a computer
Harder For Computers Than Humans

...for a human

Born in Honolulu, Hawaii, Obama is a graduate of Columbia University and Harvard Law School.

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Rattled for Austin, Alaska, Jesus is the mouse in Microsoft Google but Facebook Twitter Snapchat.
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- Need to learn lexical items.
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- Need to learn lexical items.
- Syntax is often non-trivial.
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...for a human

**Born** in Honolulu, Hawaii, Obama is a **graduate** of Columbia University and Harvard Law School.

...for a computer

Rattled for Austin, Alaska, Jesus is the mouse in Microsoft Google but Facebook Twitter Snapchat.

- Need to learn lexical items.
- Syntax is often non-trivial.
- Many “facts” in same sentence.
How do we Represent Knowledge?

Unstructured Text

Fixed-Schema Knowledge Bases

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)
How do we Represent Knowledge?

Unstructured Text

Fixed-Schema Knowledge Bases

(Obama; born_in; Honolulu)
(Obama; born_in; Hawaii)
(Obama; born_on; 1961-8-4)
(Obama; spouse; Michelle)
(Obama; children; Malia)
(Obama; children; Natasha)
How do we Represent Knowledge?

Active area of research:

- Supervised relation extractors
  [Doddington et al., 2004, Surdeanu and Ciaramita, 2007].

- Distantly supervised extractors
  [Wu and Weld, 2007, Mintz et al., 2009].

- Weakly+distantly supervised extractors
  [Hoffmann et al., 2011, Surdeanu et al., 2012].

- Partially+weakly+distantly supervised extractors
  [Angeli et al., 2014a, Angeli et al., 2014b].
More to Life Than Fixed Relation Schema
How do we Represent Knowledge?

Unstructured Text

1. Fixed-Schema Knowledge Bases
2. Open-Domain KBs (Open IE)

⇒

(SUBJECT; relation; OBJECT)
How do we Represent Knowledge?

Unstructured Text

1. Fixed-Schema Knowledge Bases
2. Open-Domain KBs (Open IE)

⇒

(CATS; have; TAILS)
(RABBITS; eat; CARROTS)
(ObAMA; enjoys playing; BASKETBALL)
How do we Represent Knowledge?

Unstructured Text

1. Fixed-Schema Knowledge Bases
2. Open-Domain KBs (Open IE)
3. Unstructured Text

- cats have tails
- rabbits eat carrots
- Obama enjoys playing basketball
How do we Represent Knowledge?

1. Fixed-Schema Knowledge Bases
2. Open-Domain KBs (Open IE)
3. Unstructured Text

Unstructured Text

cats have tails
rabbits eat carrots
Obama enjoys playing basketball
A graduated cylinder is best to measure the volume of a liquid
This Thesis

Store Information as Text (easier)
Query Information as Text (hard!)

Build a system that:
- Takes as input a candidate textual statement.
- Produces as output the truth of that statement.

Generalizes Fixed-Schema KBs
- Obama was born in Hawaii
- Obama was born in Kenya

Generalizes Open IE
- Rabbits eat carrots

More precise than web search
- A stopwatch is best to measure the volume of a liquid.
This Thesis

Store Information as Text (easier)
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- Generalizes Fixed-Schema KBs
  - ✓ Obama was born in Hawaii
  - ✗ Obama was born in Kenya

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This Thesis

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  Takes as input a candidate textual statement.
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- Generalizes Fixed-Schema KBs
  - Obama was born in Hawaii
  - Obama was born in Kenya

- Generalizes Open IE
  - Rabbits eat carrots
Store Information as Text (easier)
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Build a system that:

- Takes as input a candidate textual statement.
- Produces as output the truth of that statement.

- Generalizes Fixed-Schema KBs
  - ✔ Obama was born in Hawaii
  - ✗ Obama was born in Kenya

- Generalizes Open IE
  - ✔ Rabbits eat carrots

- More precise than web search
  - ✗ A stopwatch is best to measure the volume of a liquid.
Prior Work
Prior Work

Relation Extraction: (BARACK OBAMA; born_in; ???)

[Hoffmann et al., 2011, Surdeanu et al., 2012, Angeli et al., 2014b]
Prior Work

Open Relation Extraction: \((\text{RABBITS}; \text{eat}; ???)\)

[Banko et al., 2007, Fader et al., 2011, Mausam et al., 2012]
Entailment: If *a watch measures time*, does *it measure volume*?

[Glickman et al., 2006, MacCartney, 2009]
Textual Entailment

Single Premise:

*Mitsubishi Motors Corp.'s new vehicle sales in the US fell 46 percent in June.*

Single Hypothesis:

*Mitsubishi sales rose 46 percent.*

Classification Task: If you accept the premise, would you accept the hypothesis?
Prior Work

Flexibility

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Prior Work

Flexibility

Question Coverage

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Prior Work

This Thesis: Formal reasoning with text over large corpora

- Flexibility
- Question Coverage

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Common Sense Reasoning: *Cats have tails*  
[Angeli and Manning, 2013, Angeli and Manning, 2014]

Complex premises: *Born in Hawaii, Obama is a graduate of Columbia*  
[Angeli et al., 2015]

Lexical + Logical Reasoning: *A graduated cylinder would be best to measure the volume of a liquid*
Common Sense Reasoning:
Cats have tails
[Angeli and Manning, 2013, Angeli and Manning, 2014]

Complex premises:
Born in Hawaii, Obama is a graduate of Columbia
[Angeli et al., 2015]

Lexical + Logical Reasoning:
A graduated cylinder would be best to measure the volume of a liquid
'Kittens play with yarn' ✔ 'Kittens play with computers' ✗
Reasoning About Common Sense Facts

✔ Kittens play with yarn

✗ Kittens play with computers
Common Sense Reasoning for NLP

They ate the pizza with anchovies

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James Constable, 2010
Start with a large knowledge base
Start with a large knowledge base

The cat ate a mouse

All cats have tails

All kittens are cute
Infer new facts...

- The cat ate a mouse
- All cats have tails
- All kittens are cute
Infer new facts...

- The cat ate a mouse
- All cats have tails
- All kittens are cute
- No carnivores eat animals
Infer new facts...

- The cat ate a mouse
- All cats have tails
- All kittens are cute

Don’t want to run inference over every fact!

✗ No carnivores eat animals
Infer new facts...

- The cat ate a mouse
- All cats have tails
- All kittens are cute

Don’t want to run inference over every fact!

Don’t want to store all of these!

* No carnivores eat animals
Infer new facts...on demand from a query...

No carnivores eat animals?

The cat ate a *mouse*

All cats have *tails*

All kittens are *cute*
No carnivores eat animals?

The carnivores eat animals

The cat eats animals

The cat ate an animal

The cat ate a mouse

All cats have tails

All kittens are cute
...Without aligning to any particular premise.

- No carnivores eat animals?
- The carnivores eat animals
  - The cat eats animals
    - The cat ate an animal
      - The cat ate a mouse
  - All cats have tails
  - All kittens are cute
Infer new facts...

The cat ate a mouse

All cats have tails

All kittens are cute

✗ No carnivores eat animals
The cat ate a mouse \[\vdash \neg \text{No carnivores eat animals}\]
We’re Doing Logical Inference

The cat ate a mouse \( \models \neg \text{No carnivores eat animals} \)

**Recall:** Inference on every query: **speed is important!**
We’re Doing Logical Inference

\[ \text{The cat ate a mouse} \vdash \neg \text{No carnivores eat animals} \]

Recall: Inference on every query: speed is important!

Recall: Both premise and query are sentences.
We’re Doing Logical Inference

\[\text{The cat ate a mouse} \models \neg \text{No carnivores eat animals}\]

**Recall:** Inference on every query: \textit{speed is important}!

**Recall:** Both premise and query are sentences.

**Detour:** Let’s talk about logic!
First Order Logic is **Intractable**

Theorem Provers
- Propositional logic is already NP-complete!

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First Order Logic is **Intractable**

**Theorem Provers**
- Propositional logic is already NP-complete!

**Markov Logic Networks**
- Grounding 3,800 rules takes 7 hours (Alchemy).
First Order Logic is **Intractable**

---

**Theorem Provers**
- Propositional logic is already NP-complete!

**Markov Logic Networks**
- Grounding 3,800 rules takes 7 hours (Alchemy).
- Add Chris Ré + decades of DB research: 106 seconds.
- ... but still slow for open-domain inference.
First order logic is an unnatural language

\[ \exists x \ (\text{location}(x) \land \text{born\_in}(\text{Obama}, x)) \]

[Berant et al., 2013]
First Order Logic is **Inexpressive**

Some people think that Obama was born in Kenya.

- Second order logic:
  $\exists x \exists P [P = \text{born} \land \text{think}(x, P) \land P(\text{Obama, Kenya})]$

- But, can still infer: Some people think that Obama is from Kenya.
- Most students who learned a foreign language learned it at a university.
- Most is not a first-order quantifier.
- Scoping ambiguities everywhere!
- But, can still infer: Most students learned it at a school.
First Order Logic is **Inexpressive**

Some people think that Obama was born in Kenya.

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- But, can still infer: *Some people think that Obama is from Kenya.*
Some people think that Obama was born in Kenya.

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First Order Logic is **Inexpressive**

Some people think that Obama was born in Kenya.

- Second order logic:
  \[ \exists x \exists P \left[ P = \text{born} \land \text{think}(x, P) \land P(\text{Obama, Kenya}) \right] \]
- But, can still infer: *Some people think that Obama is from Kenya.*

Most students who learned a foreign language learned it at a university.

- *Most* is not a first-order quantifier.
- Scoping ambiguities everywhere!
- But, can still infer: *Most students learned it at a school.*
Does a given mutation to a sentence preserve its truth?
Natural Logic

Does a given mutation to a sentence preserve its truth?

Logic over natural language

- *Instantaneous* and *perfect* semantic parsing!
- Plays nice with lexical methods
Does a given mutation to a sentence preserve its truth?

Logic over natural language

- *Instantaneous* and *perfect* semantic parsing!
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Tractable

- Polynomial time entailment checking
  [MacCartney and Manning, 2008].
Does a given mutation to a sentence preserve its truth?

Logic over natural language
- *Instantaneous* and *perfect* semantic parsing!
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Tractable
- Polynomial time entailment checking [MacCartney and Manning, 2008].

Expressive (for common inferences)
- Second-order phenomena; *most*; quantifier scoping
Natural Logic

Does a given mutation to a sentence preserve its truth?

Logic over natural language
- *Instantaneous* and *perfect* semantic parsing!
- Plays nice with lexical methods

Tractable
- Polynomial time entailment checking
  [MacCartney and Manning, 2008].

Expressive (for common inferences)
- Second-order phenomena; *most*; quantifier scoping
- No free lunch: shallow quantification; single-premise only
Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

Some cat ate a mouse
(all mice are rodents)

∴ Some cat ate a rodent
Natural Logic as Syllogisms

Some cat ate a mouse
(all mice are rodents)
∴ Some cat ate a rodent

Beyond syllogisms

- General-purpose logic
  - Compositional grammar
  - Arbitrary quantifiers
- Model-theoretic soundness + completeness proof
  [Icard and Moss, 2014]
Natural Logic and Polarity

Treat hypernymy as a *partial order*.

\[
\top \\
\downarrow \\
\text{animal} \\
\downarrow \\
\text{feline} \quad \downarrow \\
\text{cat} \quad \text{dog} \\
\downarrow \\
\bot
\]
Treat hypernymy as a *partial order*. 

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

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

Treat hypernymy as a *partial order*.

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

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

animal

feline

\[\uparrow \text{cat} \]

house cat
Natural Logic and Polarity

Treat hypernymy as a \textit{partial order}.

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

\textit{Polarity} is the direction a lexical item can move in the ordering.

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

Treat hypernymy as a *partial order*.

```
⊤

animal

↑

feline

dog

↑

cat

⊥
```

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

```
thing

↑ animal

living thing

feline
```
Natural Logic and Polarity

Treat hypernymy as a *partial order*.

\[
\begin{align*}
\top & \quad \downarrow \quad \text{animal} \\
\downarrow & \quad \text{feline} & \quad \text{dog} \\
\downarrow & \quad \text{cat} & \quad \downarrow \\
\bot 
\end{align*}
\]

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

\[
\begin{align*}
\text{thing} \\
\downarrow & \quad \text{living thing} \\
\downarrow & \quad \text{animal} \\
\downarrow & \quad \text{feline}
\end{align*}
\]
Natural Logic and Polarity

Treat hypernymy as a *partial order*.

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

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

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

Treat hypernymy as a *partial order*.

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

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

```
animal
feline
\downarrow cat
house cat
```

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An Example Inference

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

- ↑ All↓↓
- ↓ cats
  - house cats
- ↑ eat
  - slurp
- ↑ mice
  - fieldmice
- carnivores
- felines
- consume
- placentals
- rodents
An Example Inference

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

Mutations must respect *polarity*.
An Example Inference

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

Mutations must respect *polarity*.

- **↑ All**
- **↓ house cats**
- **↑ consume**
- **↑ mice**

- **felines**
- **cats**
- **kitties**
- **placentals**
- **rodents**
- **fieldmice**
An Example Inference

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

<table>
<thead>
<tr>
<th>Quantifier</th>
<th>Word 1</th>
<th>Word 2</th>
<th>Word 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>↑ All ↓↑</td>
<td>felines</td>
<td>cats</td>
<td>rodents</td>
</tr>
<tr>
<td>↓ house cats</td>
<td></td>
<td>kittens</td>
<td>mice</td>
</tr>
<tr>
<td>↑ consume</td>
<td></td>
<td>eat</td>
<td>fieldmice</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>pine vole</td>
</tr>
</tbody>
</table>
An Example Inference

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

Mutations must respect *polarity*.

- **↑** *All* ↓↑
- **↓** *house cats* ↓
- **↑** *consume* ↑
- **↑** *mice* ↑

- **↑** *felines* ↓
- **↑** *cats* ↓
- **↑** *kitties* ↓
- **↑** *placentals* ↓
- **↑** *rodents* ↓
- **↑** *fieldmice* ↓
Quantifiers determine the *polarity* (↑ or ↓) of words. Mutations must respect *polarity*.
Quantifiers determine the *polarity* (↑ or ↓) of words.

Mutations must respect *polarity*.

Inference is reversible.
Infer new facts...

- The cat ate a mouse
- All cats have tails
- All kittens are cute

✗ No carnivores eat animals
Infer new facts...on demand from a query...

No carnivores eat animals?

The cat ate a mouse

All cats have tails

All kittens are cute
...Using text as the meaning representation...

No carnivores eat animals?

The carnivores eat animals

The cat eats animals

The cat ate an animal

The cat ate a mouse

All cats have tails

All kittens are cute
...Without aligning to any particular premise.

No carnivores eat animals?

The carnivores eat animals

The cat eats animals

The cat ate an animal

The cat ate a mouse

All cats have tails

All kittens are cute
Natural Logic Inference is Search

Nodes

( fact, truth maintained ∈ {true, false} )
Natural Logic Inference is Search

Nodes  
( $fact$, truth maintained $\in \{\text{true}, \text{false}\}$ )

Start Node  
( query $fact$, ✔ true )

End Nodes  
any known fact
Natural Logic Inference is Search

Nodes

(\textit{fact}, \text{truth maintained} \in \{\text{true}, \text{false}\})

Start Node

(\textit{query fact}, \checkmark \text{true})

End Nodes

\textit{any known fact}

Edges

Mutations of the current fact
**Natural Logic Inference is Search**

Nodes: \((\text{fact}, \text{truth maintained} \in \{\text{true, false}\})\)

Start Node: \((\text{query fact, } \checkmark \text{ true})\)

End Nodes: any known fact

Edges: Mutations of the current fact

Edge Costs: How “wrong” an inference step is (learned)
An Example Search

Shorthand for a node:

organism
  ↓
animal
carnivores
  ↓
consume
eat
  ↓
living thing
organism
animals
  ↓
felines
slurp
chordate

No carnivores eat animals?
An Example Search

ROOT

No carnivores eat animals?

The carnivores eat animals

No animals eat animals

...
An Example Search

No carnivores eat animals

The carnivores eat animals?

The feline eats animals

All carnivores eat animals

...
An Example Search

The carnivores eat animals

The feline eats animals?

The cat eats animals

The cat eats chordate

...
An Example Search

The feline eats animals

The cat eats animals?

The cat eats chordates

The kitty eats animals

...
An Example Search

The cat eats animals

The cat eats chordates?

The cat eats mice

The cat eats dogs
The cat eats chordates

The cat eats mice?

The cat ate a mouse

The kitty eats mice

...
An Example Search (with edges)

ROOT

No carnivores eat animals?

The carnivores eat animals

No animals eat animals

Template
Operator Negate

Instance

Edge
An Example Search (with edges)

ROOT

No carnivores eat animals?

Instance:
- The carnivores eat animals
- No animals eat animals

Template:
Operator Negate

Edge:
No → The
An Example Search (with edges)

ROOT

No carnivores eat animals?

The carnivores eat animals

No animals eat animals

Template
Operator Negate

Instance
No \rightarrow The

Edge
No carnivores eat animals \rightarrow The carnivores eat animals
## Edge Templates

<table>
<thead>
<tr>
<th>Template</th>
<th>Instance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypernym</td>
<td>animal → cat</td>
</tr>
<tr>
<td>Hyponym</td>
<td>cat → animal</td>
</tr>
<tr>
<td>Antonym</td>
<td>good → bad</td>
</tr>
<tr>
<td>Synonym</td>
<td>cat → true cat</td>
</tr>
<tr>
<td>Add Word</td>
<td>cat → ·</td>
</tr>
<tr>
<td>Delete Word</td>
<td>· → cat</td>
</tr>
<tr>
<td>Operator Weaken</td>
<td>some → all</td>
</tr>
<tr>
<td>Operator Strengthen</td>
<td>all → some</td>
</tr>
<tr>
<td>Operator Negate</td>
<td>all → no</td>
</tr>
<tr>
<td>Operator Synonym</td>
<td>all → every</td>
</tr>
<tr>
<td>Nearest Neighbor</td>
<td>cat → dog</td>
</tr>
</tbody>
</table>
“Soft” Natural Logic

Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
“Soft” Natural Logic

Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
- Each edge template has a cost $\theta \geq 0$. 

### WordNet:
- cat → feline
- cup → container

### Nearest neighbors distance.

Each edge instance has a distance $f$.

Cost of an edge is $\theta \cdot f$.

Cost of a path is $\theta \cdot f$.

Can learn parameters $\theta$. 

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“Soft” Natural Logic

Want to make likely (but not certain) inferences.
- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
- Each edge template has a cost $\theta \geq 0$.

Detail: Variation among edge instances of a template.
- WordNet: *cat* $\rightarrow$ *feline* vs. *cup* $\rightarrow$ *container*.
- Nearest neighbors distance.
- Each edge instance has a distance $f$. 
“Soft” Natural Logic

Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
- Each edge template has a cost $\theta \geq 0$.

Detail: Variation among edge instances of a template.

- WordNet: $cat \rightarrow feline$ vs. $cup \rightarrow container$.
- Nearest neighbors distance.
- Each edge instance has a distance $f$.

Cost of an edge is $\theta_i \cdot f_i$. 
“Soft” Natural Logic

Want to make likely (but not certain) inferences.
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Detail: Variation among edge instances of a template.
- WordNet: $\text{cat} \rightarrow \text{feline vs. cup} \rightarrow \text{container}$.
- Nearest neighbors distance.
- Each edge instance has a distance $f$.

Cost of an edge is $\theta_i \cdot f_i$.
Cost of a path is $\theta \cdot f$. 
“Soft” Natural Logic

Want to make likely (but not certain) inferences.
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- Nearest neighbors distance.
- Each edge instance has a distance $f$.

Cost of an edge is $\theta_i \cdot f_i$.
Cost of a path is $\theta \cdot f$.
Can learn parameters $\theta$. 
Experiments

ConceptNet:

- A semi-curated collection of common-sense facts.
  - not all birds can fly
  - noses are used to smell
  - nobody wants to die
  - music is used for pleasure

- Negatives: ReVerb extractions marked false by Turkers.
- Small (1378 train / 1080 test), but fairly broad coverage.
Experiments

ConceptNet:

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  - *nobody wants to die*
  - *music is used for pleasure*

- Negatives: ReVerb extractions marked false by Turkers.
- Small (1378 train / 1080 test), but fairly broad coverage.

Our Knowledge Base:

- 270 million lemmatized Ollie extractions.
ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.
Thesis: This thesis.
ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.
Thesis: This thesis.
Thesis - Lookup: Remove query facts from KB.
ConceptNet Results

Systems

**Direct Lookup**: Lookup by lemmas.

**Thesis**: This thesis.

**Thesis - Lookup**: Remove query facts from KB.

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## ConceptNet Results

### Systems

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- 4x improvement in recall.
Success?
The Internet doesn’t speak in atomic utterances
The Internet doesn’t speak in atomic utterances

- Where was Obama born?
  - *Born in Hawaii, Obama is a graduate of Columbia University and Harvard Law School.*
The Internet doesn’t speak in atomic utterances

- Where was Obama born?
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  - ⇒ *Obama was born in Hawaii.*
The Internet doesn’t speak in atomic utterances

- Where was Obama born?
  - *Born in Hawaii, Obama is a graduate of Columbia University and Harvard Law School.*
  - ⇒ *Obama was born in Hawaii.*

- Let’s store the inferred fact instead
Roadmap

Common Sense Reasoning:
*Cats have tails*
[Angeli and Manning, 2013, Angeli and Manning, 2014]

Complex premises:
*Born in Hawaii, Obama is a graduate of Columbia*
[Angeli et al., 2015]

Lexical + Logical Reasoning:
*A graduated cylinder would be best to measure the volume of a liquid*
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Atomic Clauses from Sentences

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

Output: Short clauses.
She was born in a small town.

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

**Output:** Short clauses.

*She was 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)*
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

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)*
Classifier Training

Training Data Generation

1. Label the Penn Treebank with Open IE triples using traces.
2. Run exhaustive search over possible clause splits.

Positive Labels: A sequence of actions which yields a relation (33.5k examples).
Negative Labels: All other sequences of actions (1.1M examples).

Features:
- Edge label; incoming edge label.
- Neighbors of governor + 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
United States president Obama
All young rabbits drink milk
Some young rabbits drink milk
Enemies give fake praise
Friends give true praise

\[ \Rightarrow \] ✓ Heinz Fischer
\[ \Rightarrow \] ✓ Obama
\[ \not\Rightarrow \] ✗ All rabbits drink milk
\[ \Rightarrow \] ✓ Some rabbits drink milk
\[ \not\Rightarrow \] ✗ Enemies give praise
\[ \Rightarrow \] ✓ 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
A natural logic entailment 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
Natural Logic For Clause Shortening

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

Mutations must respect polarity.

Polarity determines valid deletions.

Some mammals rabbits consume something liquid

↑ Some↑↑

↑ young rabbits

↑ drink

↑ milk

↑ baby rabbits

↑ slurp

Lucerne
Quantifiers determine the *polarity* (↑ or ↓) of words.
Mutations must respect *polarity*.
Polarity determines valid deletions.
Quantifiers determine the *polarity* (↑ or ↓) of words.

Mutations must respect *polarity*.

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

Mutations must respect *polarity*.

Polarity determines valid deletions.
Heinz Fischer visited US \implies (HEINZ FISCHER; visited; US)
Heinz Fischer visited US  \implies  (HEINZ FISCHER; visited; US)
Obama born in Hawaii  \implies  (OBAMA; born in; HAWAII)
Heinz Fischer visited US
Obama born in Hawaii
Cats are cute

⇒ (HEINZ FISCHER; visited; US)
⇒ (OBAMA; born in; HAWAII)
⇒ (CATS; are; CUTE)
Bonus: Knowledge Base Triples

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)
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)

5 dependency tree patterns (+ 8 nominal patterns)
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)
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).

Comparison:

Open Information Extraction to KBP Relations in 3 Hours. [Soderland et al., 2013]
Extrinsic Evaluation: Knowledge Base Population

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Comparison: *Open Information Extraction to KBP Relations in 3 Hours*. [Soderland et al., 2013]
### Map Triples to Structured Knowledge Base

<table>
<thead>
<tr>
<th>KBP Relation</th>
<th>Text</th>
<th>PMI^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per:Date_Of_Birth</td>
<td>be bear on</td>
<td>1.83</td>
</tr>
<tr>
<td></td>
<td>bear on</td>
<td>1.28</td>
</tr>
<tr>
<td>Per:Date_Of_Death</td>
<td>die on</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>be assassinate on</td>
<td>0.65</td>
</tr>
<tr>
<td>Per:LOC_Of_Birth</td>
<td>be bear in</td>
<td>1.21</td>
</tr>
<tr>
<td>Per:LOC_Of_Death</td>
<td>*elect president of</td>
<td>2.89</td>
</tr>
<tr>
<td>Per:Religion</td>
<td>speak about</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>popular for</td>
<td>0.60</td>
</tr>
<tr>
<td>Per:Parents</td>
<td>daughter of</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>son of</td>
<td>1.52</td>
</tr>
<tr>
<td>Per:LOC_Residence</td>
<td>of</td>
<td>1.48</td>
</tr>
<tr>
<td></td>
<td>*independent from</td>
<td>1.18</td>
</tr>
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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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<td><strong>Our System</strong></td>
<td>61.9</td>
<td>13.9</td>
<td>22.7</td>
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<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>
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<tr>
<td>Top Team</td>
<td>45.7</td>
<td>35.8</td>
<td>40.2</td>
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**Roadmap**

**Common Sense Reasoning:**
*Cats have tails*
[Angeli and Manning, 2013, Angeli and Manning, 2014]

**Complex premises:**
*Born in Hawaii, Obama is a graduate of Columbia*
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*A graduated cylinder would be best to measure the volume of a liquid*
Rain and snow are types of precipitation?

Rain and snow are forms of precipitation

Heavy rain and snow are types of precipitation

...
Rain and snow are types of precipitation?

Rain and snow are forms of precipitation.

Heavy rain and snow are types of precipitation.
Rain and snow are forms of precipitation?

- Rain and snow are forms of precipitation.
- Heavy rain and snow are forms of precipitation.
Rain and snow are types of precipitation.

Rain and snow are forms of precipitation?

Heavy rain and snow are forms of precipitation.

Forms of precipitation include rain and sleet.
Rain and snow are types of precipitation

Rain and snow are forms of precipitation?

Rain and snow are forms of weather

Heavy rain and snow are forms of precipitation

Forms of precipitation include rain and sleet
Forms of precipitation include rain and sleet

Rain and snow are forms of precipitation
Forms of precipitation include rain and sleet.

Rain and snow are forms of precipitation.
Forms of precipitation include rain and sleet.

Rain and snow are forms of precipitation.
Forms of precipitation include rain and sleet.

Rain and snow are forms of precipitation.

Features

1. Matching words
Forms of precipitation include rain and sleet. Rain and snow are forms of precipitation.

Features

1. Matching words
2. Mismatched words
Forms of precipitation include rain and sleet.

Rain and snow are forms of precipitation.

Features

1. Matching words
2. Mismatched words
3. Unmatched words in premise/consequent
Lexical Alignment Classifier

**Forms of precipitation include rain and sleet**

**Rain and snow are forms of precipitation**

**Features**

1. Matching words
2. Mismatched words
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**Competitive with Stanford RTE system (63% on RTE3)**
FOL and lexical classifiers don’t speak the same language
Old Problem: Logic + Lexical Classifiers

FOL and lexical classifiers don’t speak the same language
...but natural logic does!
Big Picture

Run our usual search

1. If we find a premise, great!
Run our usual search

1. If we find a premise, great!
2. If not, use lexical classifier as an *evaluation function*
Run our usual search

1. If we find a premise, great!
2. If not, use lexical classifier as an evaluation function

Visit 1M nodes / second: We have to be fast!
Anatomy of a Classifier

- Features $f$ (matching / mismatched / unmatched words)
- Weights $w$
- Entailment pair $x$

\[ p(\text{entail} \mid x) = \frac{1}{1+\exp(-w^Tf(x))} \]
Dissecting Our Classifier

Anatomy of a Classifier

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$p(\text{entail} \mid x)$ monotone w.r.t. $(w^T f(x))$
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\[
p(\text{entail} \mid x) = \frac{1}{1+\exp(-w^Tf(x))}
\]

$p(\text{entail} \mid x)$ monotone w.r.t. $(w^Tf(x))$

- Only need $w^Tf(x)$ during search to compute $\max p(\text{entail} \mid x)$
- $w^Tf(x)$ is our evaluation function
Incorporating our Evaluation Function

Anatomy of a Search Step

1. Mutate a word, or
2. Delete a word, or
3. Insert a word.

Each step updates a small number of features

\[ w^T f(x) = v \]
Incorporating our Evaluation Function

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Incorporating our Evaluation Function

Anatomy of a Search Step

1. Mutate a word, or
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Each step updates a small number of features

\[ v' = v - w_i \cdot f_i + w_i \cdot f_i \]
Faster Search $\Rightarrow$ Deeper Reasoning

- **Speed:** Around 1M search states visited per second
- **Memory:** 32 byte search states

**Speed:** Don’t re-featurize at every timestep.

**Memory:** Never store intermediate fact as String.
An Example Search

**Forms of precipitation include** rain and sleet.

Rain and snow are types of precipitation.

**Score** $w^T f(x)$: -0.5

<table>
<thead>
<tr>
<th>Feature</th>
<th>$w$</th>
<th>$f(x)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matching words</td>
<td>2.0</td>
<td>2</td>
</tr>
<tr>
<td>Mismatched words</td>
<td>-1.0</td>
<td>2</td>
</tr>
<tr>
<td>Unmatched premise</td>
<td>-0.5</td>
<td>1</td>
</tr>
<tr>
<td>Unmatched consequent</td>
<td>-0.75</td>
<td>0</td>
</tr>
<tr>
<td>Bias</td>
<td>-2.0</td>
<td>1</td>
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</table>
Rain and snow are types of precipitation?

Rain and snow are forms of precipitation

Rain and snow are types of weather
An Example Search

**Forms of precipitation include rain and sleet.**

Rain and snow are forms of precipitation.

**Score** $w^T f(x)$: $-0.5 + 2 - 1$

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Score $w^T f(x): 2.5$

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The Full System

Common Sense Reasoning

Flexibility vs. Coverage

PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

Gabor Angeli (Stanford)
The Full System

\[ \text{Coverage} \rightarrow \text{Flexibility} \]

+ Complex Premises

Gabor Angeli (Stanford)
The Full System

Evaluation Function

+ Coverage

Flexibility

Gabor Angeli (Stanford)
Learning Knowledge From Text
November 5, 2015
The Full System

Common Sense Facts

- Natural logic inference as search
- Soft relaxation of “strict” inference
- 4x improvement in recall

Complex Premises

- Split the premise into atomic clauses
- Shorten each clause with natural logic

Evaluation Function

- Use lexical classifier as evaluation function
- Detect likely entailment / contradictions
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- 3 F₁ improvement on knowledge base population
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Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams

Which activity is an example of a good health habit?

(A) Watching television
(B) Smoking cigarettes
(C) Eating candy
(D) Exercising every day

In our corpus:

Plasma TV’s can display up to 16 million colors. . .

also make a good screen.

Not smoking or drinking alcohol is good for health, regardless of
whether clothing is worn or not.

Eating candy for dinner is an example of a poor health habit.

Healthy is exercising.
Multiple choice questions from real 4\textsuperscript{th} grade science exams

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- Healthy is exercising
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<table>
<thead>
<tr>
<th>System</th>
<th>Train</th>
<th>Test</th>
</tr>
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<tbody>
<tr>
<td>KNOWBOT</td>
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[More Data + IR Baseline]

[More Data + This Thesis]

We're able to pass 4<sup>th</sup> grade science!

[Hixon et al., 2015]
Solving 4<sup>th</sup> Grade Science

Multiple choice questions from real 4<sup>th</sup> grade science exams

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[1] Hixon et al., 2015

Gabor Angeli (Stanford)
Solving 4\textsuperscript{th} Grade Science

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[Hixon et al., 2015]
Remaining Work

First Order Logic

Lexical Methods

Already useful for textual entailment [MacCartney and Manning, 2008, MacCartney, 2009]

This thesis:
Useful for question answering

We can bridge the two methods
Remaining Work

Natural Logic  Lexical Methods

This thesis: Already useful for textual entailment (MacCartney and Manning, 2008, MacCartney, 2009)

This thesis: Useful for question answering

We can bridge the two methods
Remaining Work

Natural Logic  Lexical Methods

- Already useful for textual entailment
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Remaining Work

Natural Logic  Lexical Methods

- Already useful for textual entailment
  [MacCartney and Manning, 2008, MacCartney, 2009]

- **This thesis**: Useful for question answering
  **This thesis**: We can bridge the two methods
1. Encode logic in traditionally lexical representations [Bowman, 2014, Bowman et al., 2015]

\[
\text{Apples are red} \lor \text{Bananas are red} \\
\text{Bananas are not red} \\
\therefore \text{Apples are red}
\]
Remaining Work

1. Encode logic in traditionally lexical representations [Bowman, 2014, Bowman et al., 2015]
2. Make natural logic more expressive
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   - Propositional + Natural logics:
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     \]
   - Syntactic and idiomatic entailment models: SNLI corpus?
Thanks!
Thanks!
Questions?

The Best Thesis Defense is a Good Thesis Offense.
References I


Fader, A., Soderland, S., and Etzioni, O. (2011). Identifying relations for open information extraction. In *EMNLP.*


Recent progress on monotonicity.
_Linguistic Issues in Language Technology._

_Natural Language Inference._

Modeling semantic containment and exclusion in natural language inference.
In _Coling._

Open language learning for information extraction.
In _EMNLP._


Soderland, S., Gilmer, J., Bart, R., Etzioni, O., and Weld, D. S. (2013). Open information extraction to KBP relations in 3 hours. In *Text Analysis Conference*.


In *EMNLP*.


Autonomously semantifying wikipedia.

In *Proceedings of the sixteenth ACM conference on information and knowledge management*. ACM.