

Learning Open Domain Knowledge from Text

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Stanford University

November 5, 2015



Learning “Knowledge?”



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Knowledge = *True Statements*



Harder For Computers Than Humans

...for a human

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

...for a computer



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- Need to learn lexical items.
- Syntax is often non-trivial.
- Many “facts” in same sentence.

How do we Represent Knowledge?

Unstructured Text



The New York Times



Fixed-Schema Knowledge Bases

 A formal portrait of Barack Obama, the 44th President of the United States, standing in front of the American flag and the Oval Office desk.	
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



The New York Times



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



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A graduated cylinder is best to measure the volume of a liquid



This Thesis

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



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Takes as input a candidate textual statement.

Produces as output the truth of that statement.

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 - ✓ *Obama was born in Hawaii*
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- 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

Flexibility



Prior Work

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



Flexibility

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

Prior Work

Open Relation Extraction: (RABBITS; eat; ???)



→
Flexibility

[Banko et al., 2007, Fader et al., 2011, Mausam et al., 2012]



Prior Work

Entailment: If *a watch measures time*, does *it measure volume?*



PASCAL²

Pattern Analysis, Statistical Modelling and
Computational Learning

Flexibility

[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



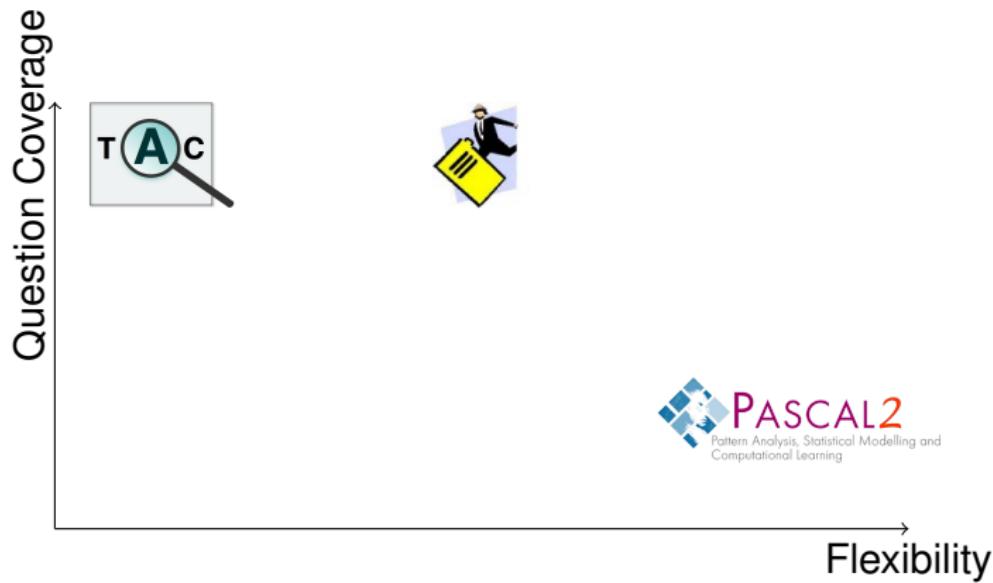
PASCAL2

Pattern Analysis, Statistical Modelling and
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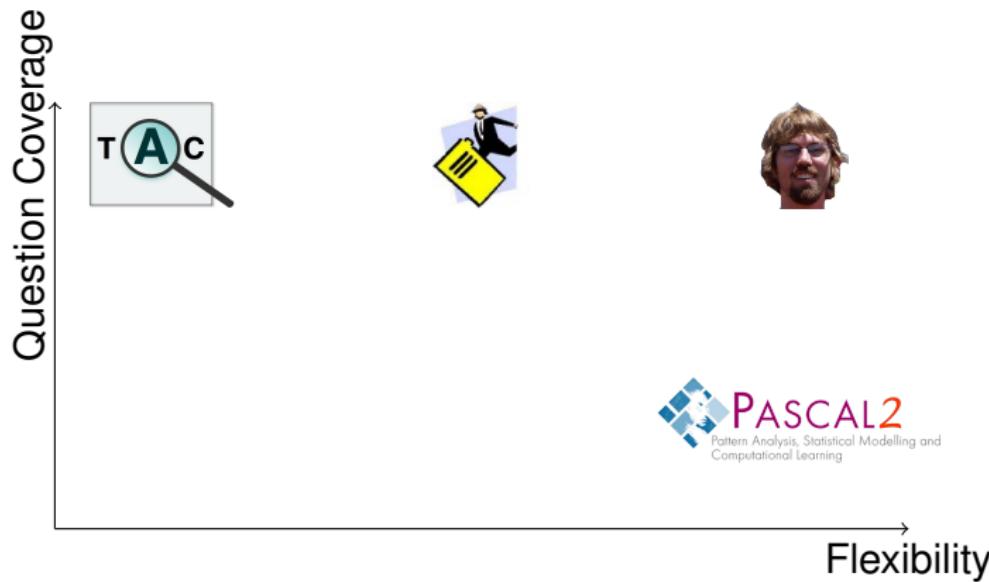


Prior Work



Prior Work

This Thesis: Formal reasoning with text over large corpora



Roadmap



Common Sense Reasoning: *Cats have tails*

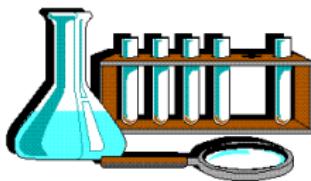
[Angeli and Manning, 2013, Angeli and Manning, 2014]



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

Roadmap



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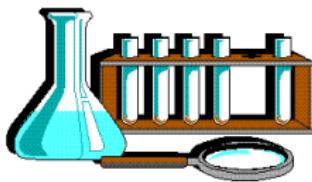
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Reasoning About Common Sense Facts

✓ Kittens play with yarn ✗ Kittens play with computers

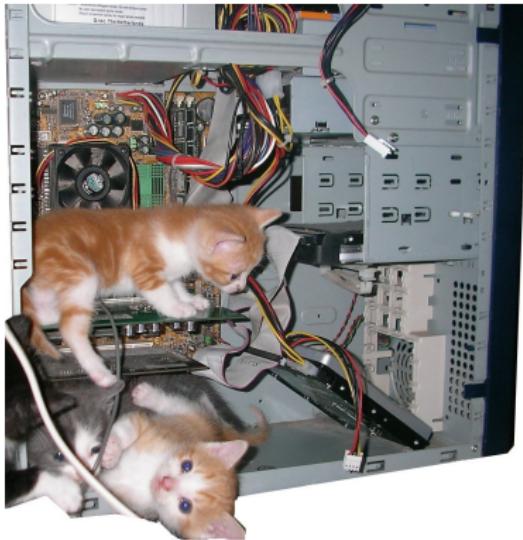


Reasoning About Common Sense Facts

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Common Sense Reasoning for NLP

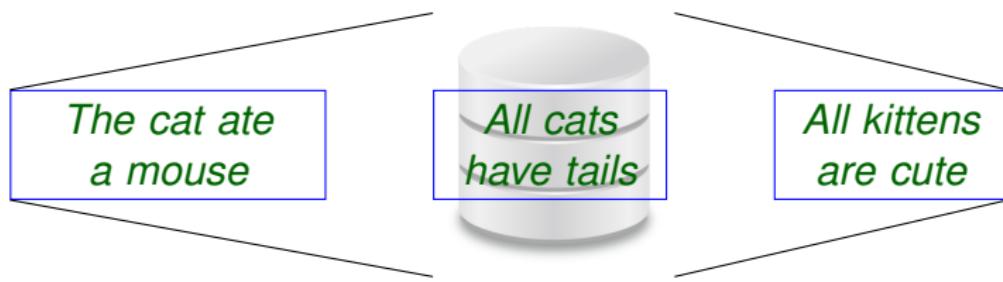
They ate the pizza with anchovies



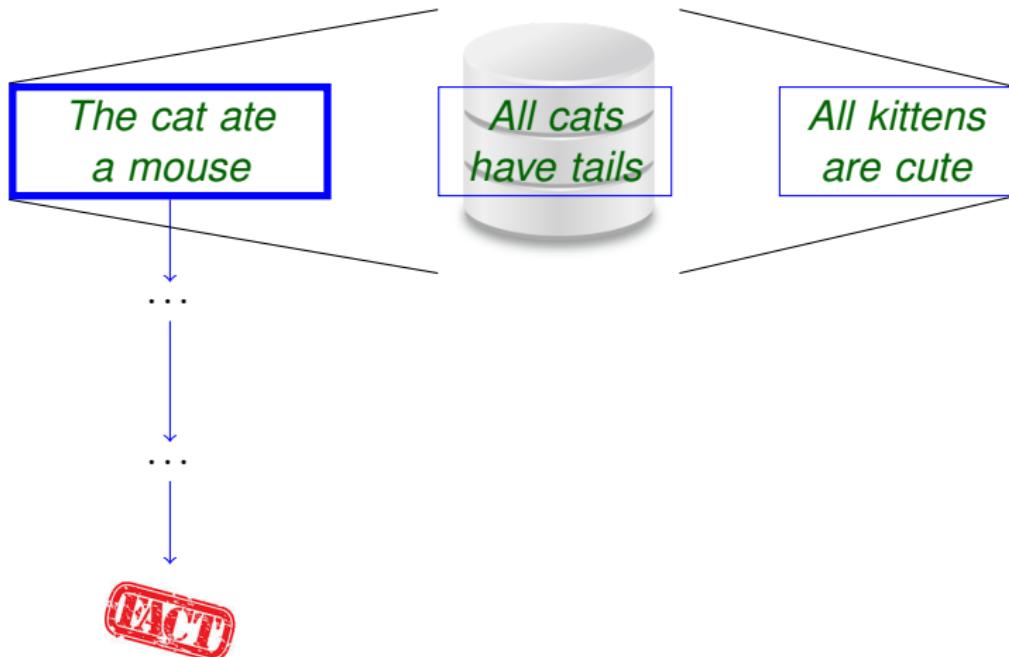
Start with a large knowledge base



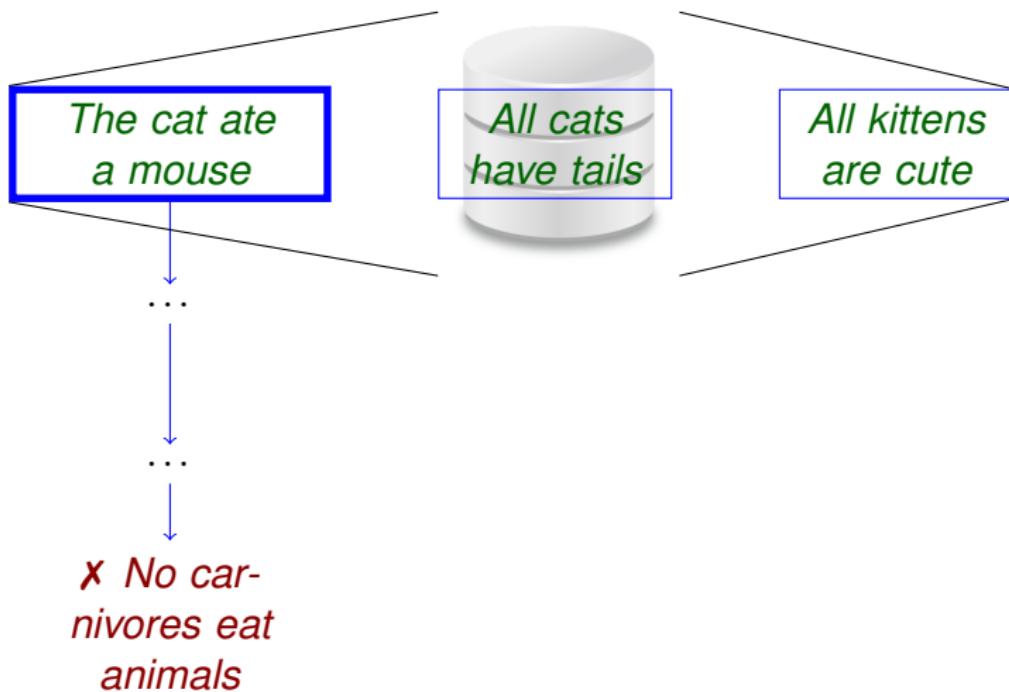
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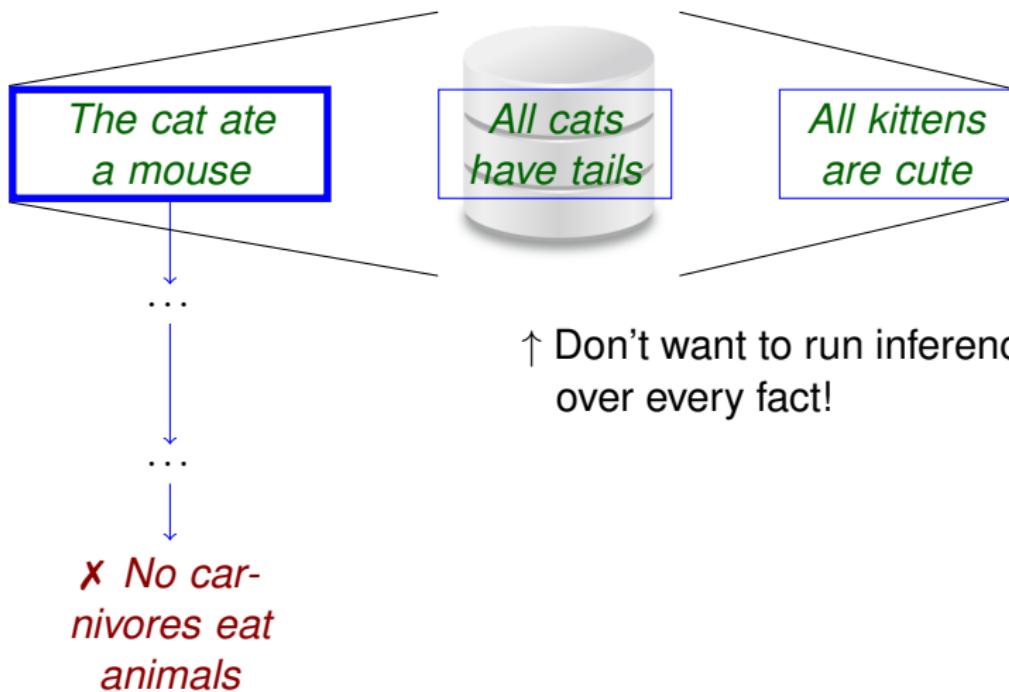
Infer new facts...



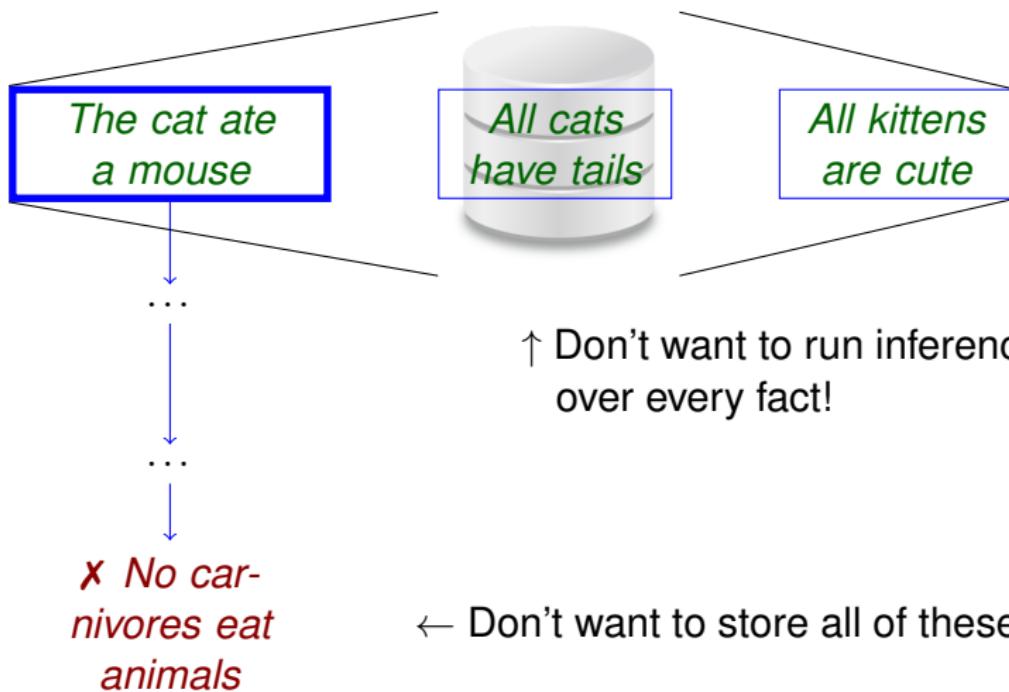
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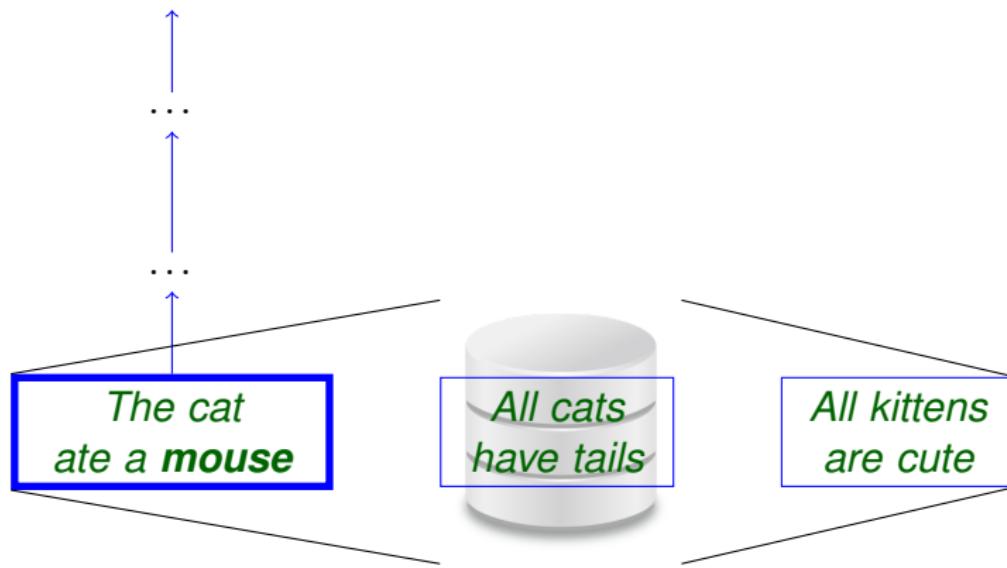


Infer new facts...



Infer new facts...on demand from a query...

*No carnivores
eat animals?*



...Using text as the meaning representation...

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The carnivores
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The cat
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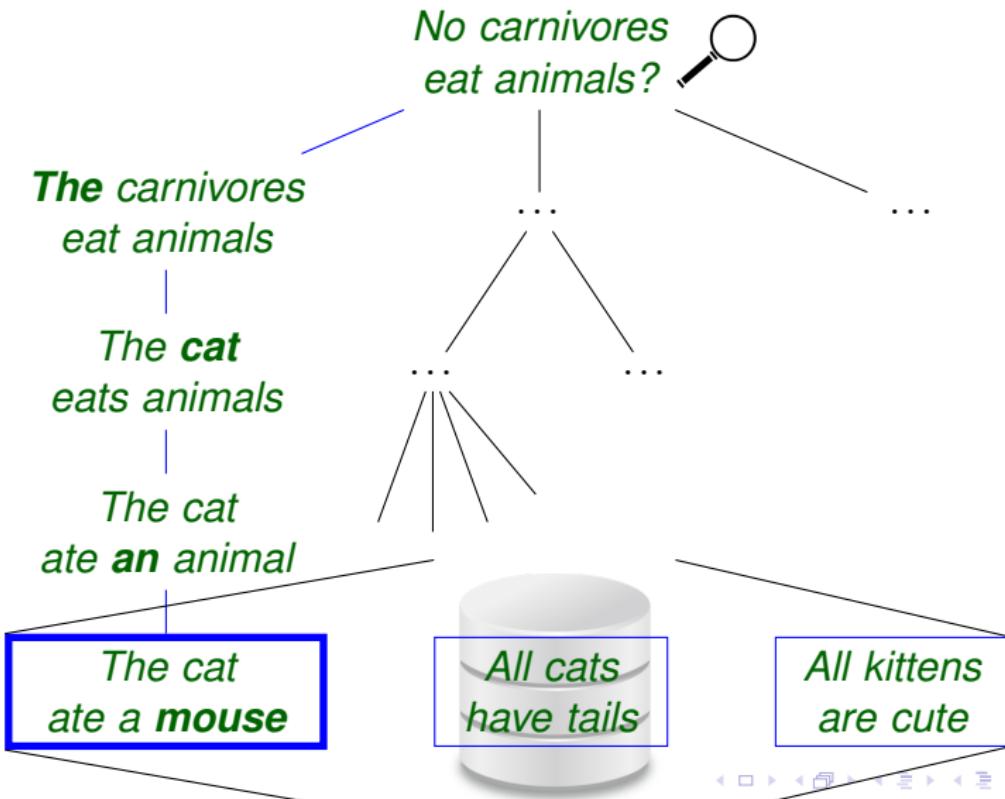
The cat
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The cat
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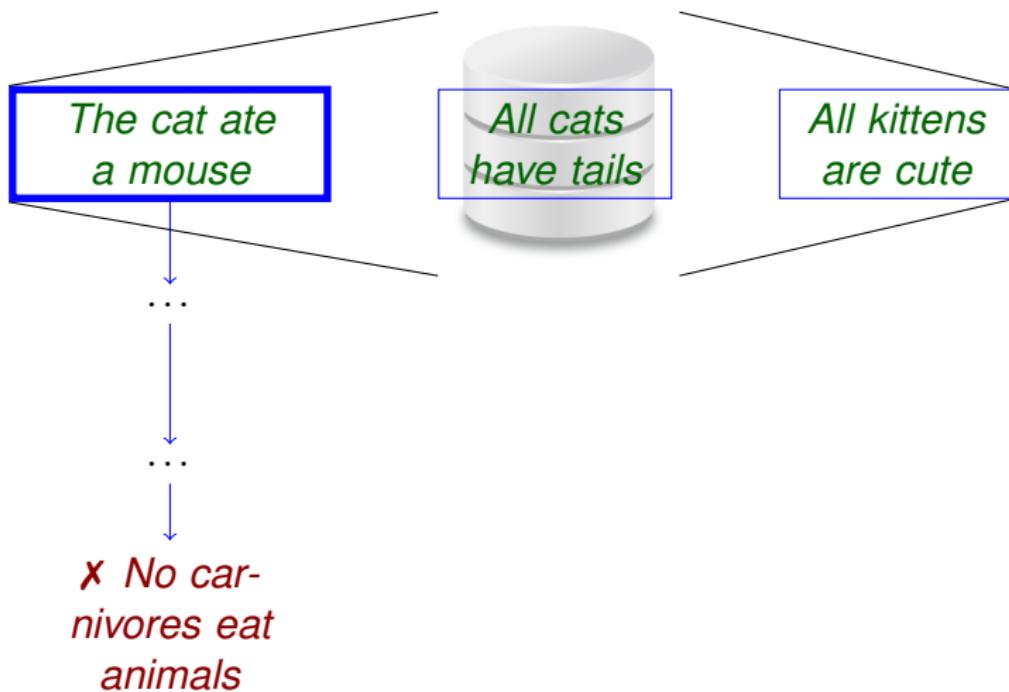
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Infer new facts...



We're Doing Logical Inference

The cat ate a mouse $\models \neg$ *No carnivores eat animals*



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Recall: Inference on every query: **speed is important!**



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Detour: Let's talk about logic!



First Order Logic is Intractable



Theorem Provers

- Propositional logic is already NP-complete!

First Order Logic is Intractable



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Markov Logic Networks

- Grounding 3,800 rules takes 7 hours (Alchemy).



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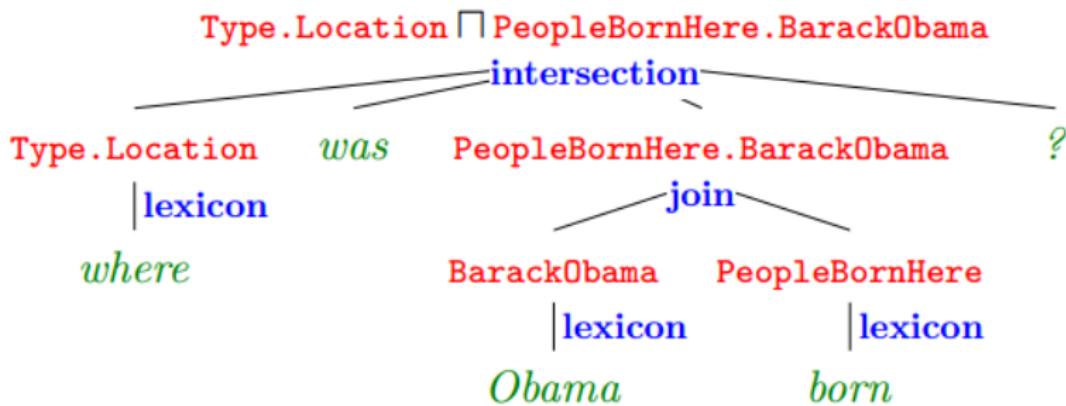
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Markov Logic Networks

- 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

$$\exists x (\text{location}(x) \wedge \text{born_in}(\text{Obama}, x))$$


[Berant et al., 2013]



First Order Logic is Inexpressive



Some people think that Obama was born in Kenya.

- Second order logic:

$$\exists x \exists P [P = \text{born} \wedge \text{think}(x, P) \wedge P(\text{Obama}, \text{Kenya})]$$

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

- *Most* is not a first-order quantifier.
- Scoping ambiguities everywhere!

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- But, can still infer: ***Most students learned it at a school.***

Natural Logic



[Sánchez Valencia, 1991, MacCartney and Manning, 2008, Icard and Moss, 2014]

Natural Logic

Does a given mutation to a sentence preserve its truth?



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Logic over natural language

- *Instantaneous* and *perfect* semantic parsing!
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Expressive (for common inferences)

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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*



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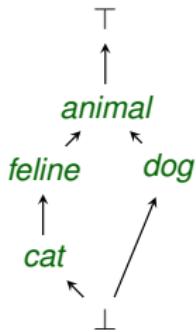
Beyond syllogisms

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



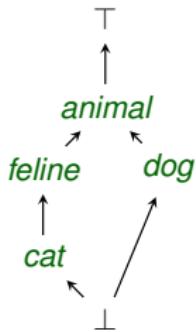
Natural Logic and Polarity

Treat hypernymy as a *partial order*.



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

animal

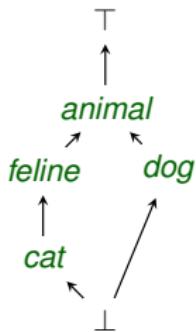
feline

cat

house cat

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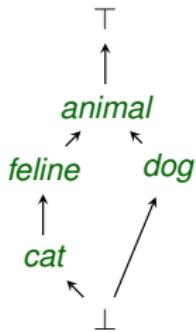
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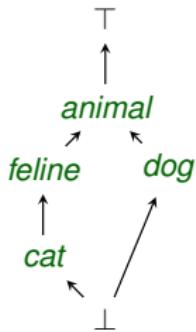
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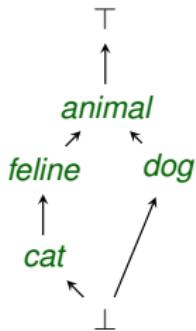
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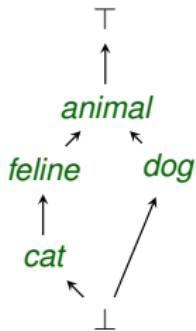
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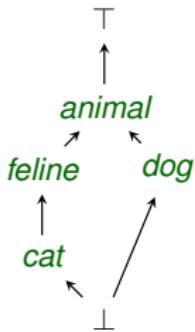
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An Example Inference

Quantifiers determines the *polarity* (\uparrow or \downarrow) of words.



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Mutations must respect *polarity*.



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\uparrow All \downarrow

\downarrow house cats

\uparrow consume

\uparrow mice

felines

cats

kitties

placentals

rodents

eat

fieldmice



An Example Inference

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Mutations must respect *polarity*.

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\uparrow consume

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cats

kitties

rodents

mice

eat

pine vole



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mammals

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mice



An Example Inference

Quantifiers determines the *polarity* (\uparrow or \downarrow) of words.

Mutations must respect *polarity*.

Inference is reversible.

felines

cats

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kitties

\uparrow consume

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mammals

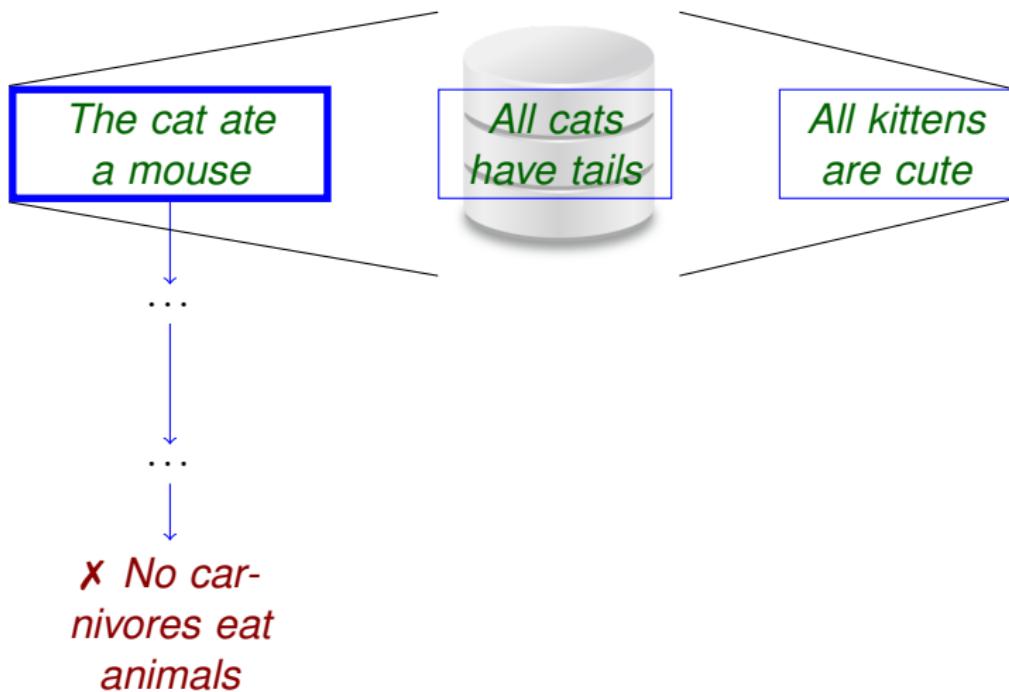
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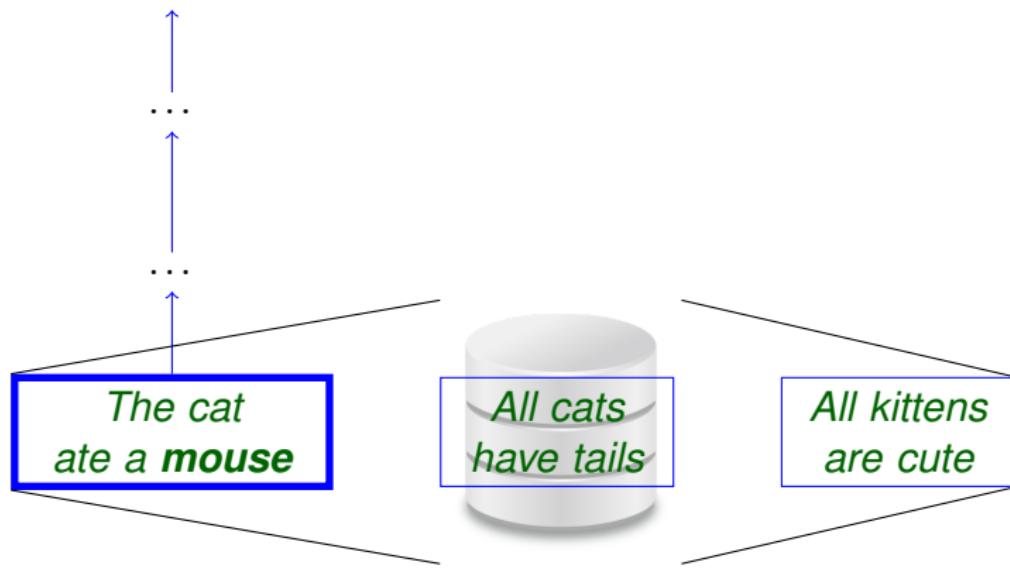


Infer new facts...



Infer new facts...on demand from a query...

*No carnivores
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...Using text as the meaning representation...

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The carnivores
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The cat
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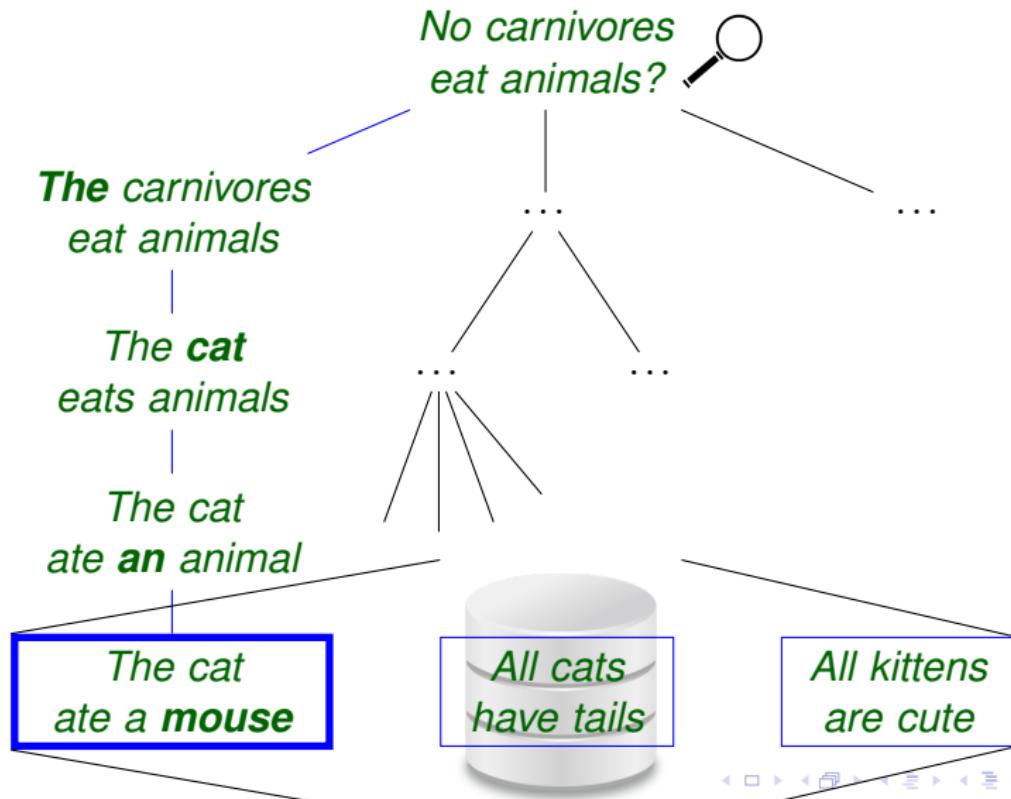
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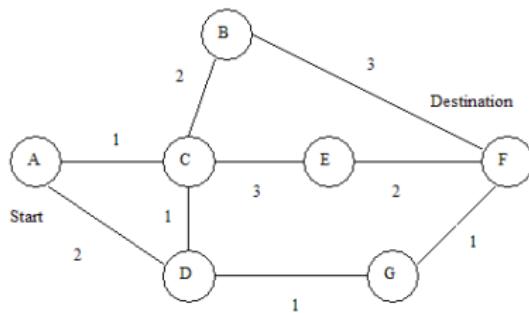
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Natural Logic Inference is Search

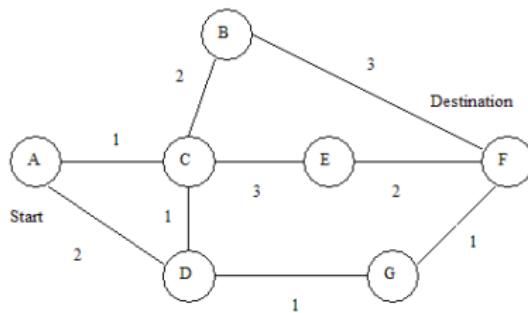


Nodes

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



Natural Logic Inference is Search



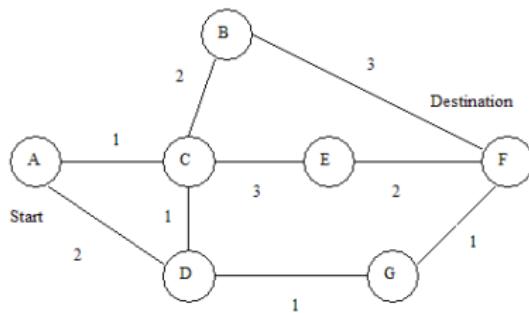
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Start Node (*query fact, ✓ true*)

End Nodes *any known fact*



Natural Logic Inference is Search



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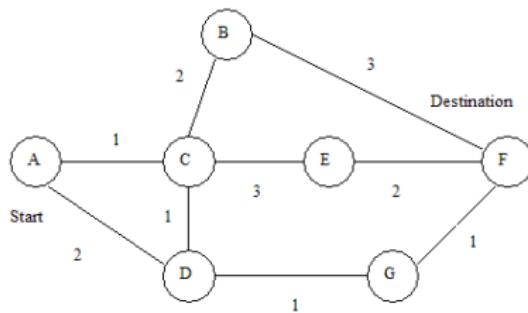
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Natural Logic Inference is Search



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

Start Node (*query fact, ✓ true*)

End Nodes *any known fact*

Edges Mutations of the current fact

Edge Costs How “wrong” an inference step is (learned)



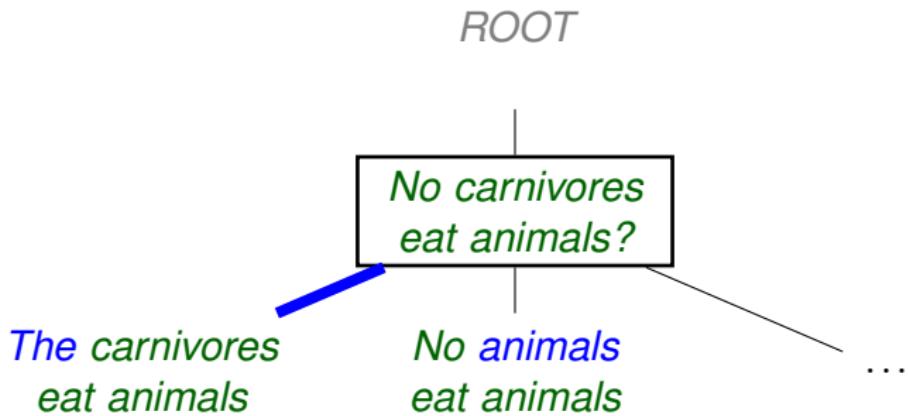
An Example Search

Shorthand for a node:

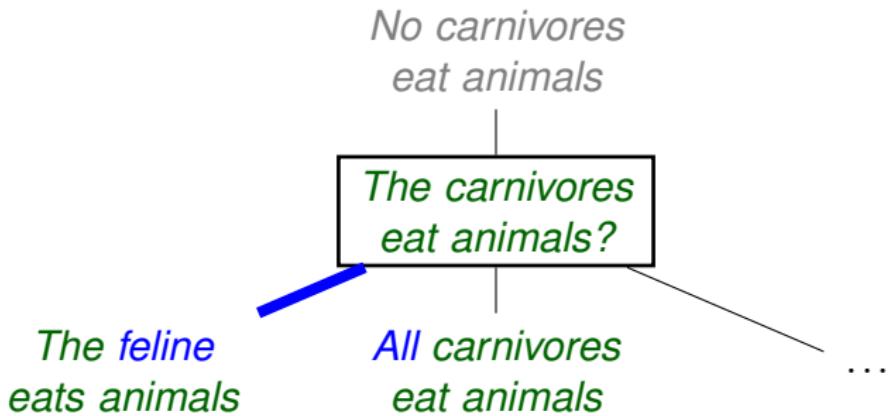


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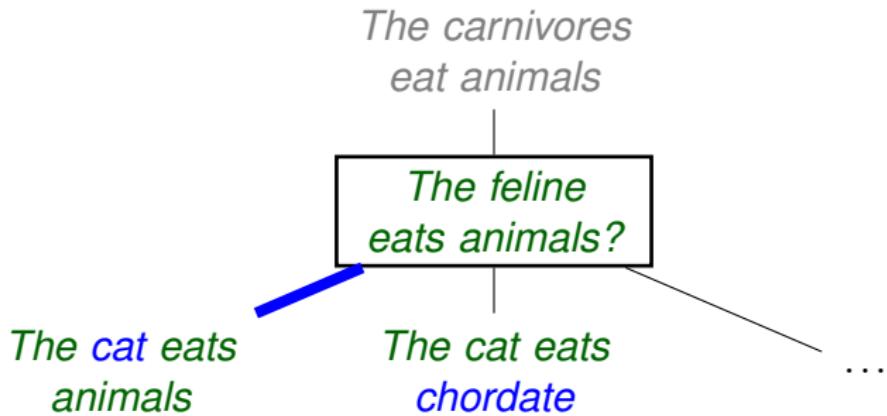
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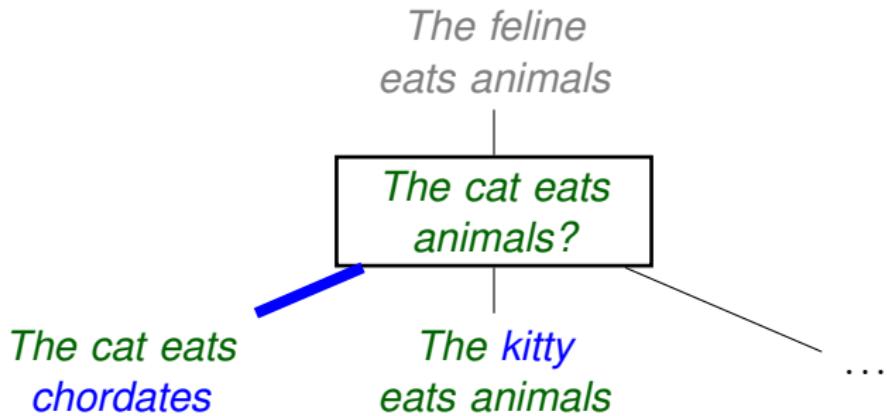
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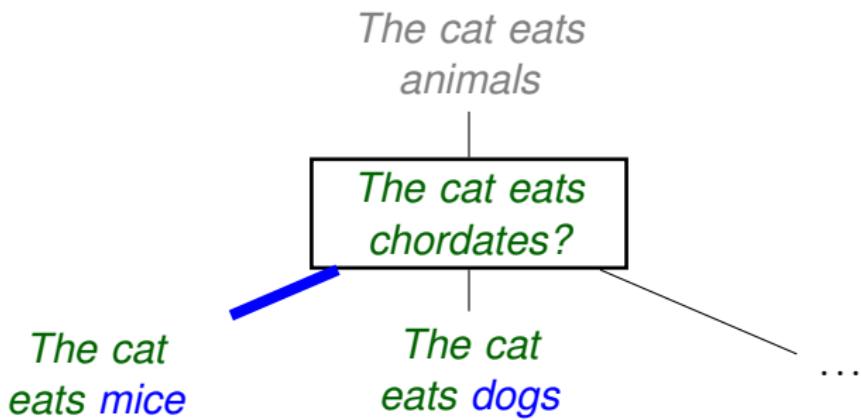
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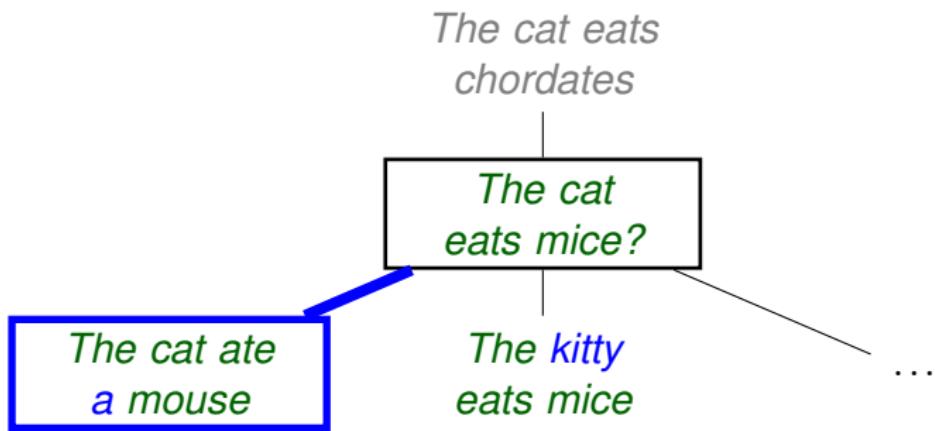
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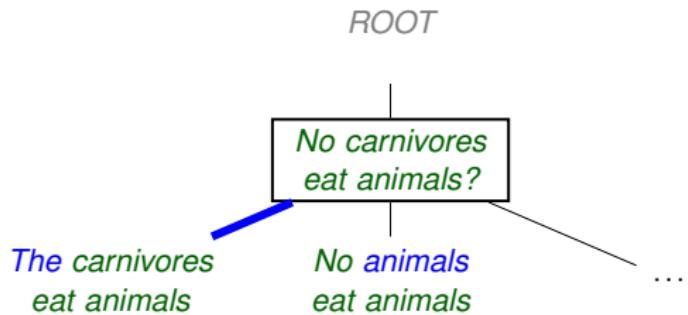
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An Example Search



An Example Search (with edges)



Template

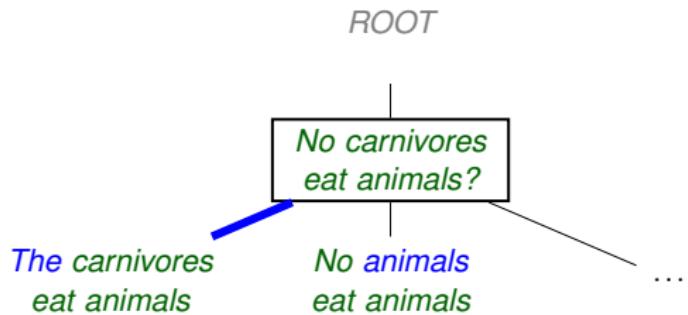
Instance

Edge

Operator Negate



An Example Search (with edges)



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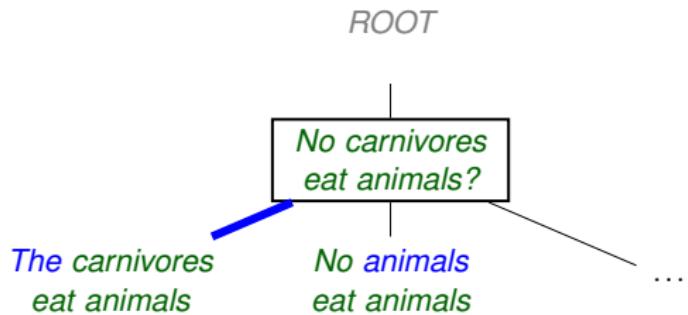
Operator Negate

Instance

No → The

Edge

An Example Search (with edges)



Template

Operator Negate

Instance

No → The

Edge

No carnivores eat animals →
The carnivores eat animals



Edge Templates

Template	Instance
Hypernym	<i>animal</i> → <i>cat</i>
Hyponym	<i>cat</i> → <i>animal</i>
Antonym	<i>good</i> → <i>bad</i>
Synonym	<i>cat</i> → <i>true cat</i>
Add Word	<i>cat</i> → .
Delete Word	. → <i>cat</i>
Operator Weaken	<i>some</i> → <i>all</i>
Operator Strengthen	<i>all</i> → <i>some</i>
Operator Negate	<i>all</i> → <i>no</i>
Operator Synonym	<i>all</i> → <i>every</i>
Nearest Neighbor	<i>cat</i> → <i>dog</i>

“Soft” Natural Logic

Want to make likely (but not certain) inferences.

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Can learn parameters θ .



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.



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Our Knowledge Base:

- 270 million lemmatized Ollie extractions.



ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.

Thesis: This thesis.



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- 4x improvement in recall.



Success?



Not Yet!



The Internet doesn't speak in atomic utterances

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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.*



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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*

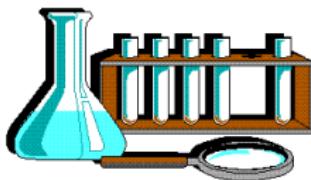
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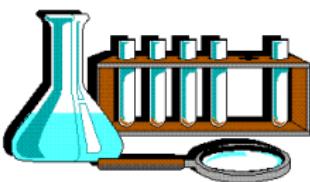
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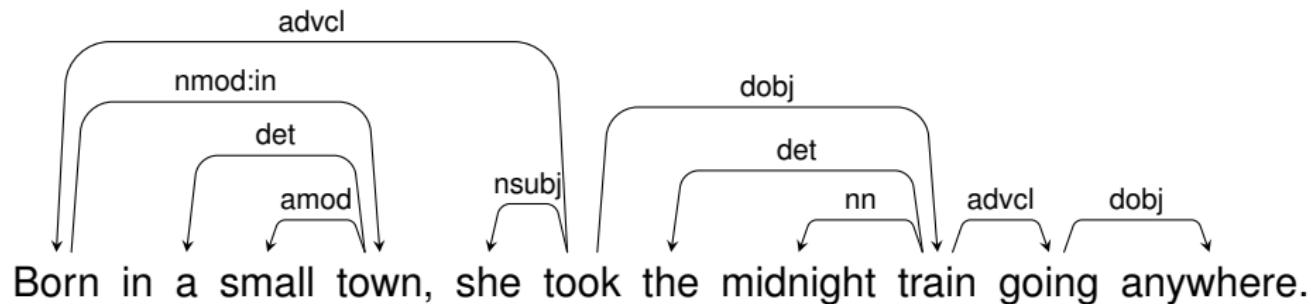
Atomic Clauses from Sentences

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.



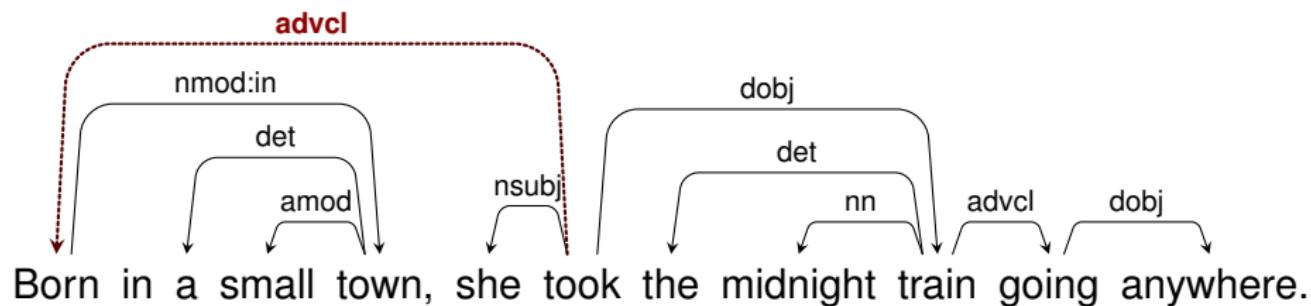
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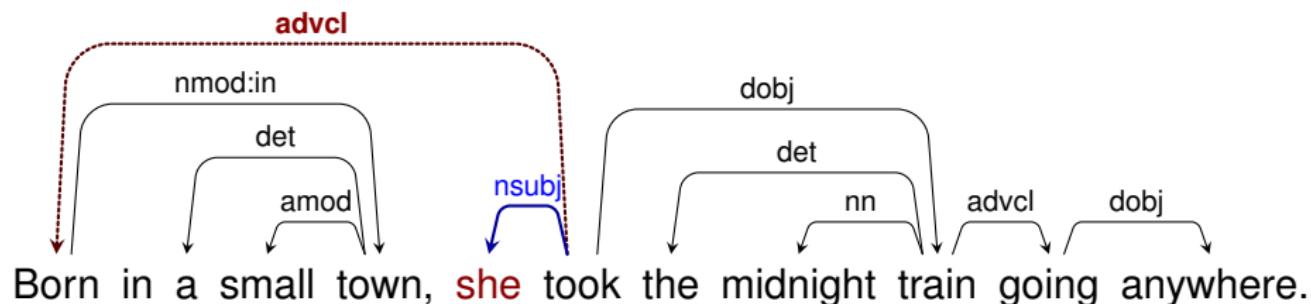
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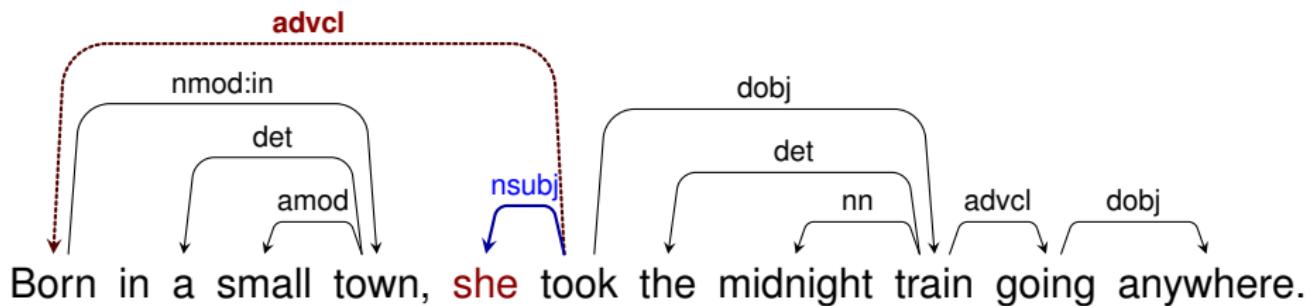
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Clause Classifier

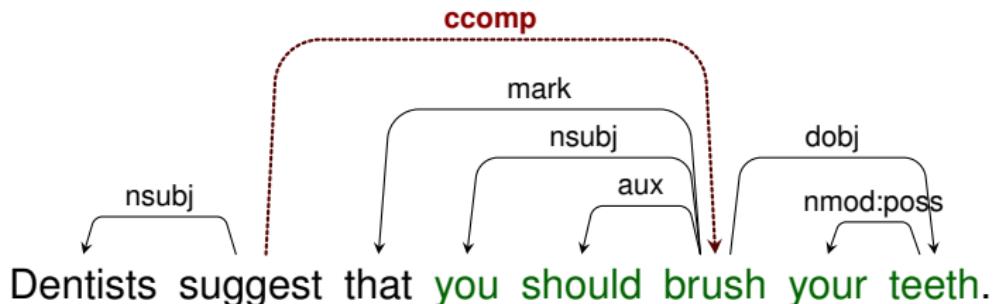


Input: Dependency arc.

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Clause Classifier



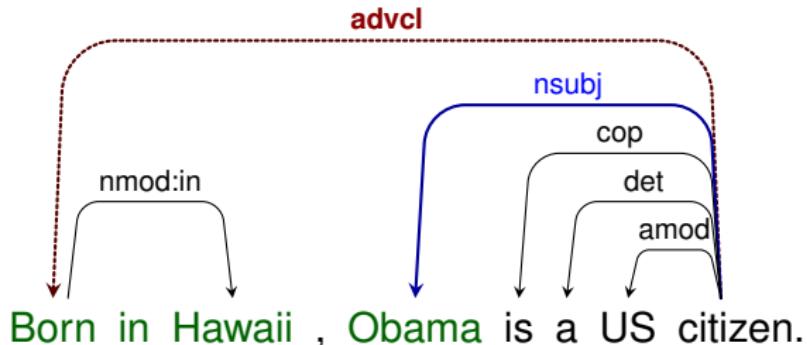
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- **Yield** (*you should brush your teeth*)



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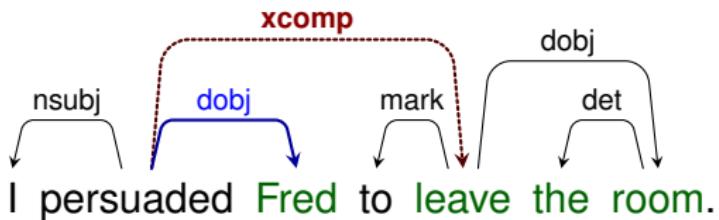
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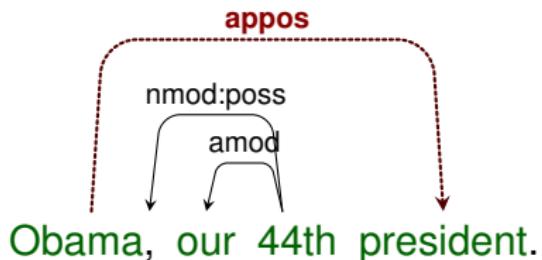
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- **Yield (Parent Subject)** (*Obama is our 44th president*)



Classifier Training

Training Data Generation

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



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1. Label the Penn Treebank with Open IE triples using traces.
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3. **Positive Labels:** A sequence of actions which yields a relation (33.5k examples).
Negative Labels: All other sequences of actions (1.1M examples).



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3. **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.

Maximally Shorten Clauses

Some strange, nuanced 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*



Maximally Shorten Clauses

An entailment function:

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⇒ ✓ *Heinz Fischer*

⇒ ✓ *Obama*

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Natural Logic For Clause Shortening

Quantifiers determines the *polarity* (\uparrow or \downarrow) of words.

Mutations must respect *polarity*.

Polarity determines valid deletions.

	mammals		something
	rabbits	consume	liquid
\uparrow Some $\uparrow\uparrow$	\uparrow young rabbits	\uparrow drink	\uparrow milk
	baby rabbits	slurp	Lucerne



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Bonus: Knowledge Base Triples

Heinz Fischer visited US \implies (HEINZ FISCHER; visited; US)



Bonus: Knowledge Base Triples

*Heinz Fischer visited US
Obama born in Hawaii*

⇒ (HEINZ FISCHER; visited; US)
⇒ (OBAMA; born in; HAWAII)



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...

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).

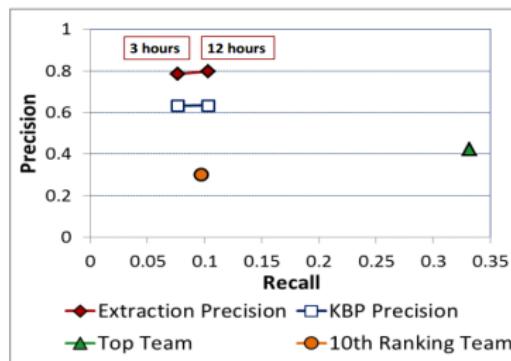


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Comparison: *Open Information Extraction to KBP Relations in 3 Hours.* [Soderland et al., 2013]



Map Triples to Structured Knowledge Base

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

System	P	R	F ₁
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Median Team			18.6
Our System +  + 	58.6	18.6	28.3
Top Team	45.7	35.8	40.2



Roadmap



Common Sense Reasoning: *Cats have tails*

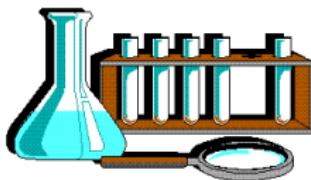
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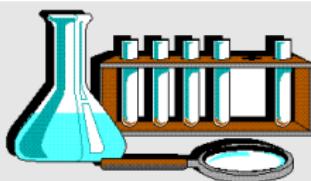
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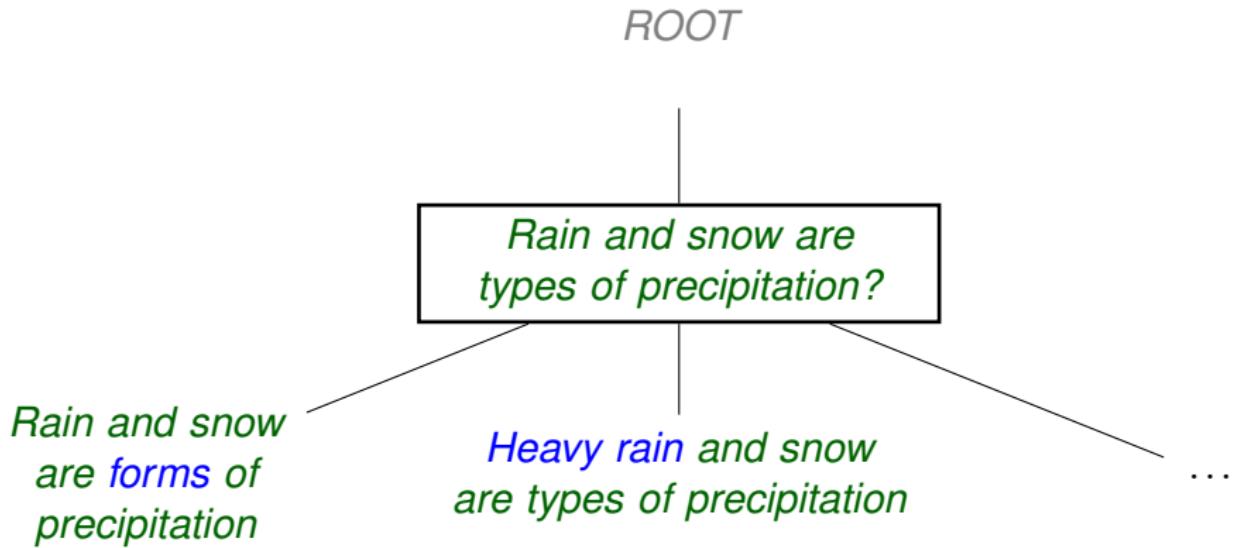


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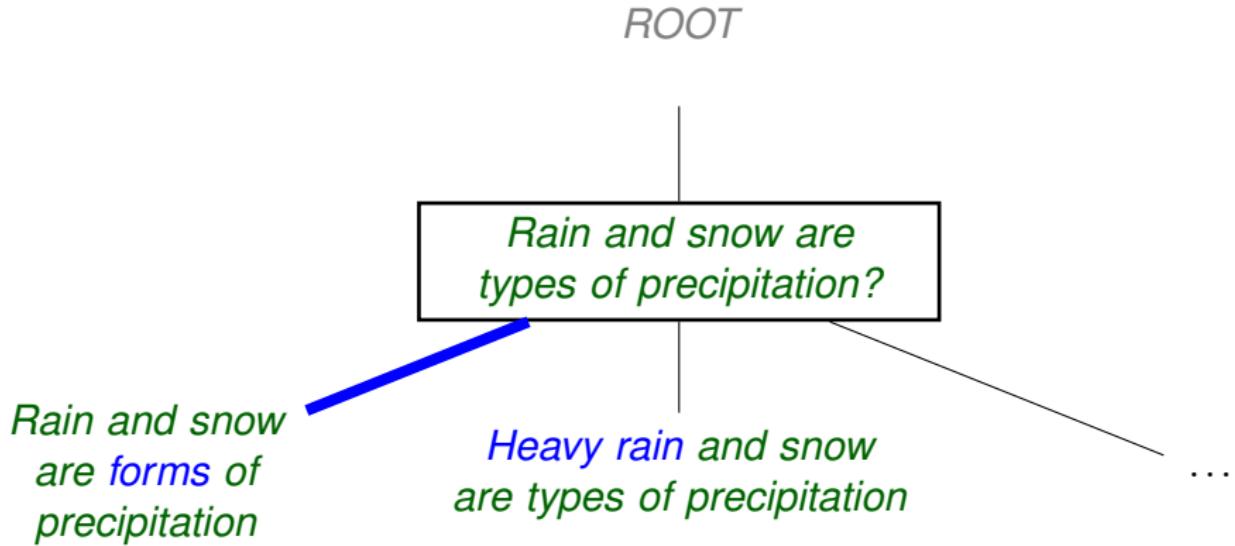
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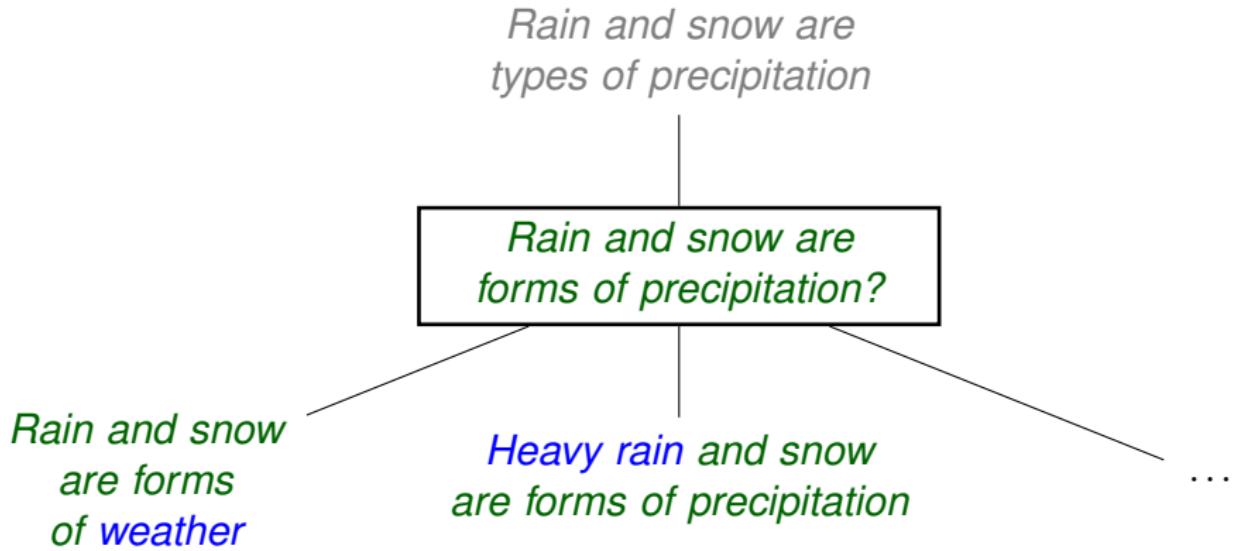
An Example Search



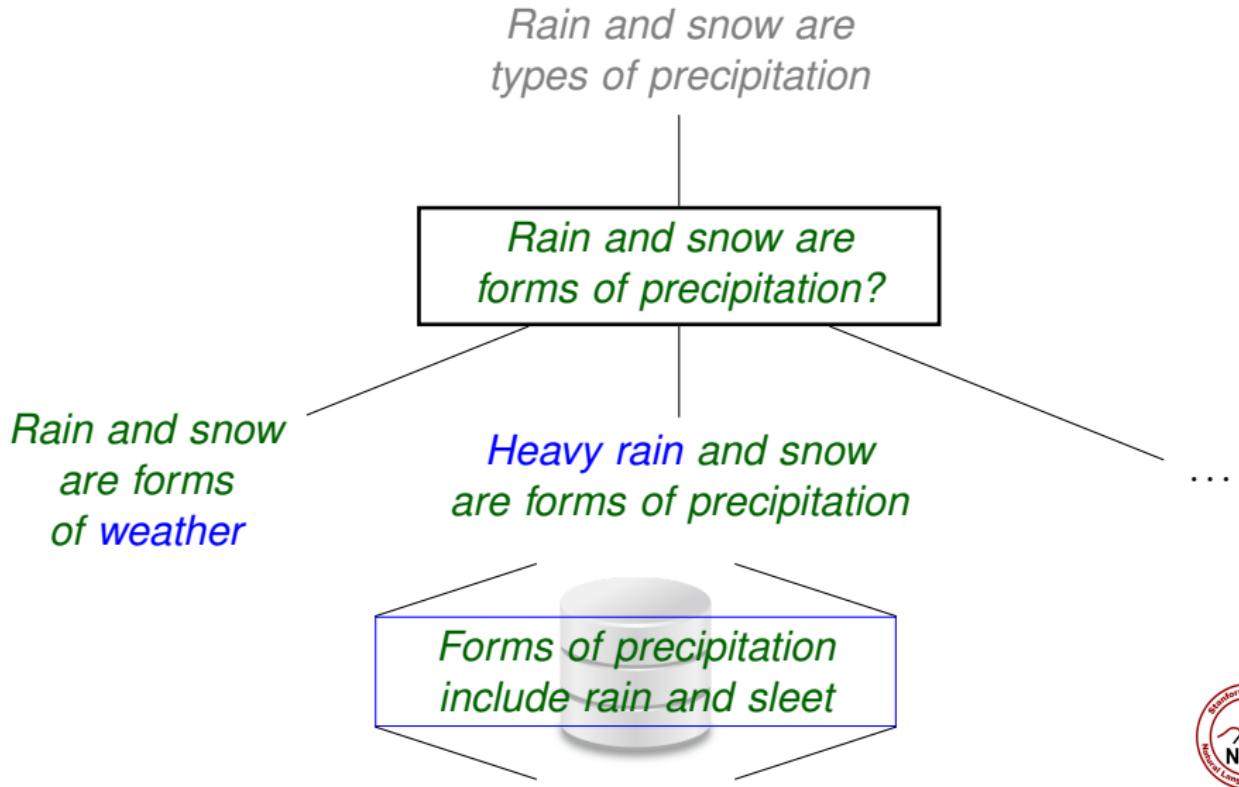
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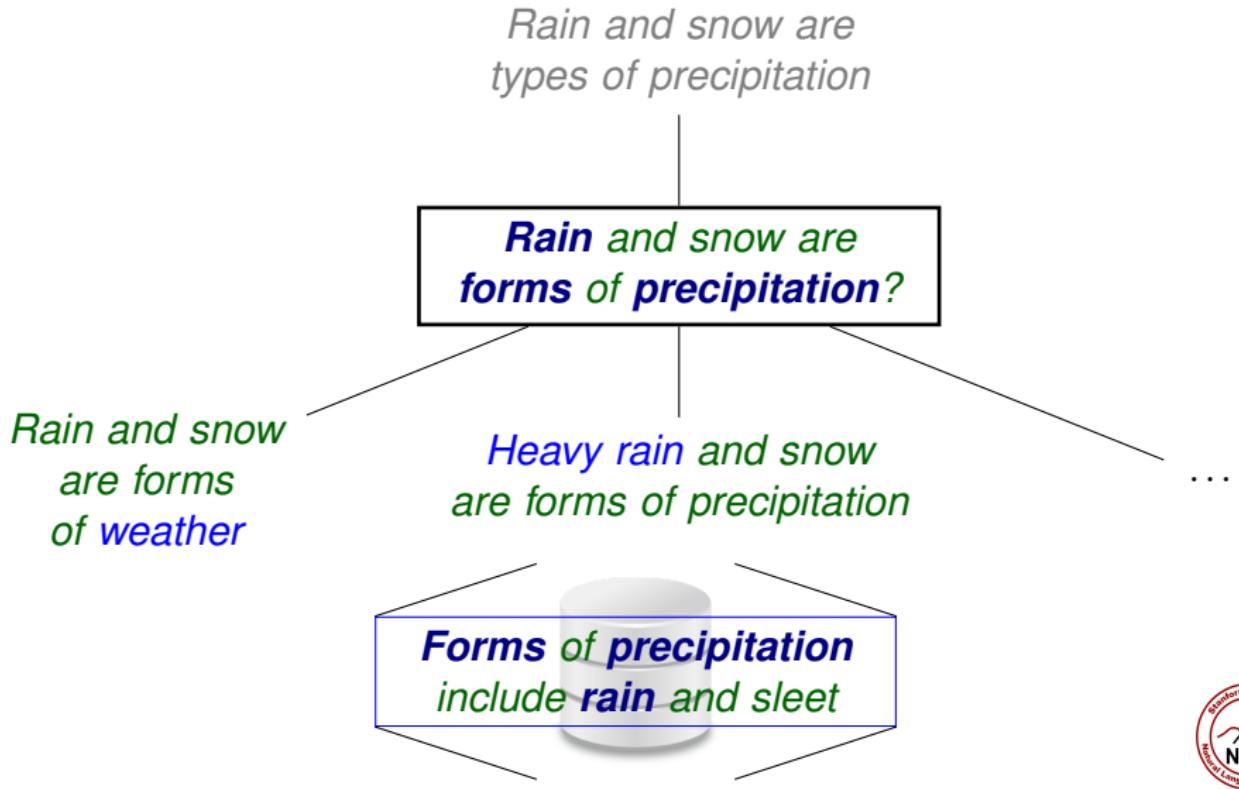
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An Example Search



An Example Search



Lexical Alignment Classifier

Forms of precipitation include rain and sleet

Rain and snow are forms of precipitation



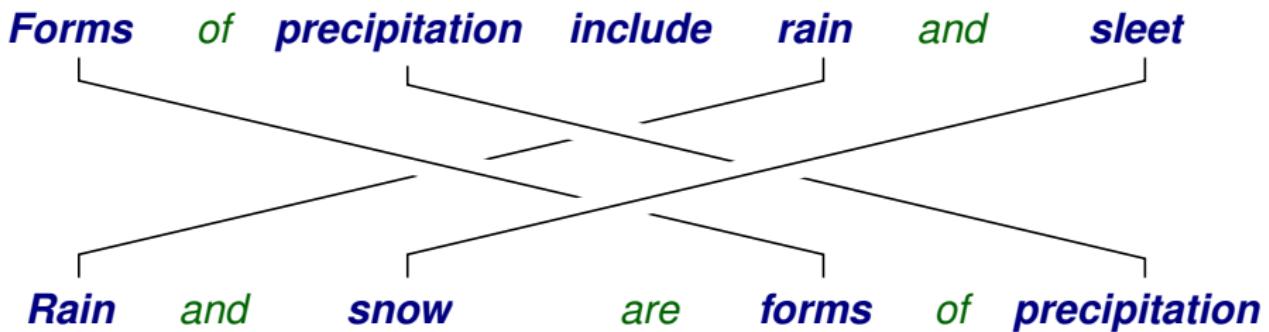
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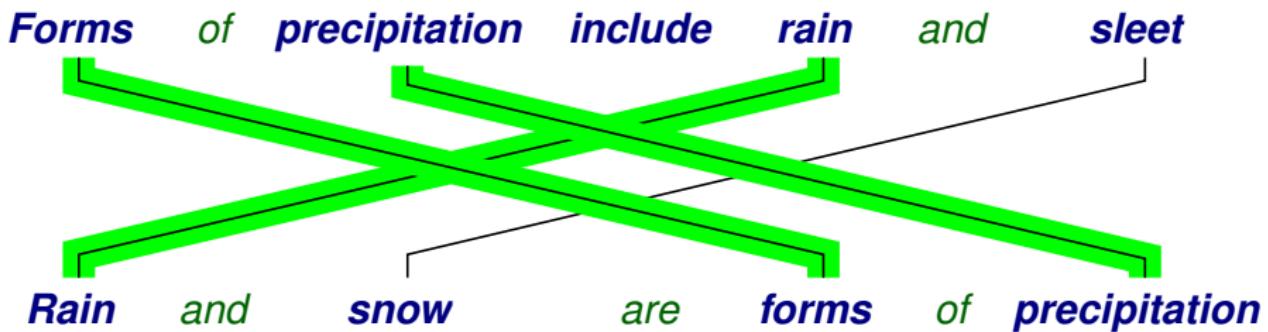
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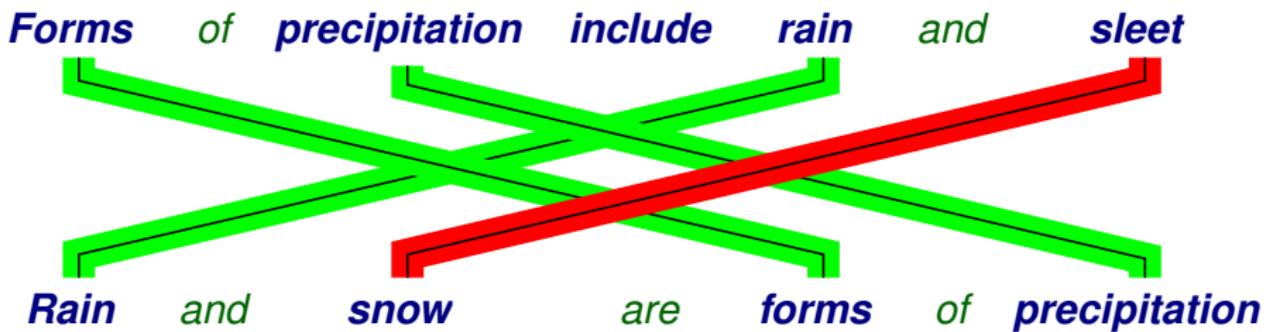


Features

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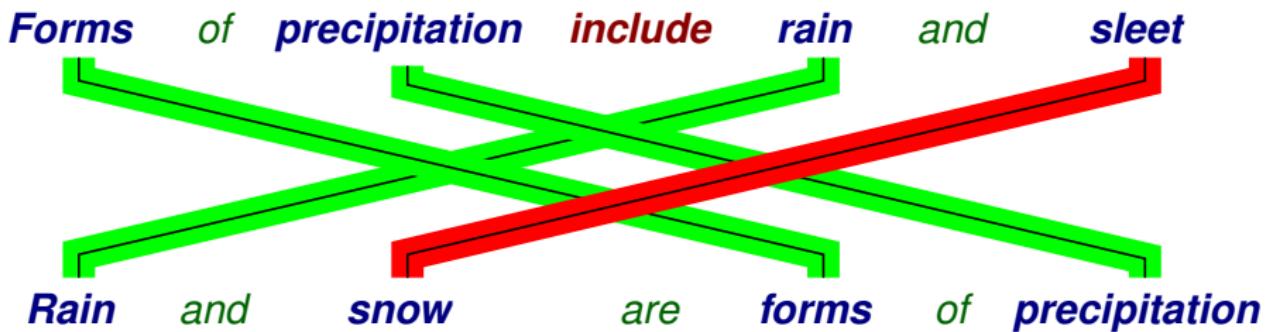


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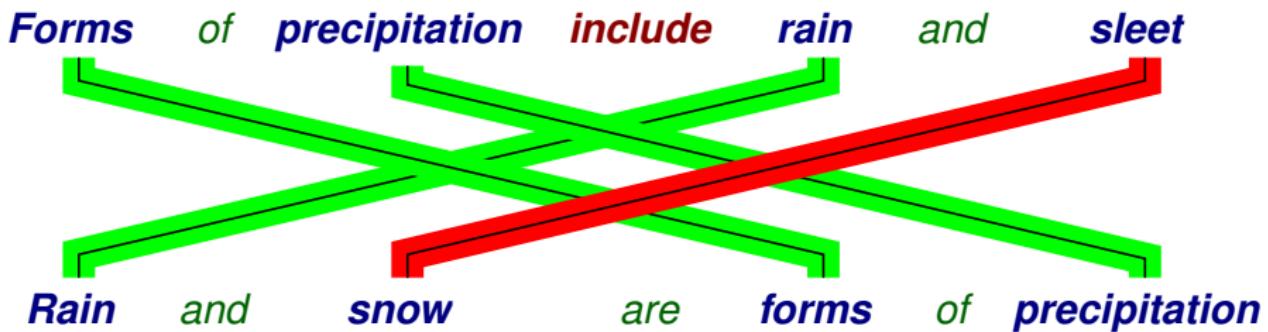


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Lexical Alignment Classifier



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Competitive with Stanford RTE system (63% on RTE3)



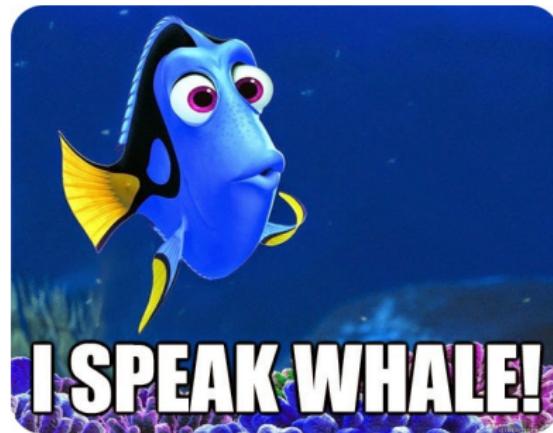
Old Problem: Logic + Lexical Classifiers

FOL and lexical classifiers don't speak the same language



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



Big Picture

Run our usual search

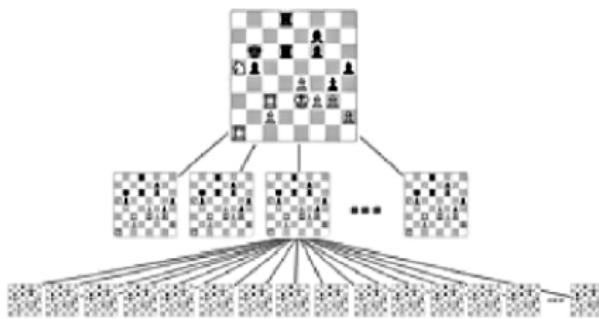
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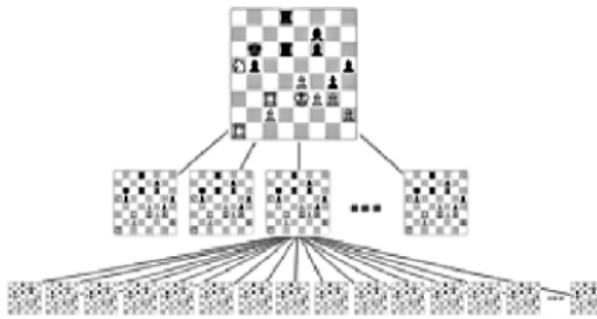
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Visit 1M nodes / second: We have to be fast!



Dissecting Our Classifier

Anatomy of a Classifier

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

$$p(\text{entail} \mid x) = \frac{1}{1 + \exp(-w^T f(x))}$$



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



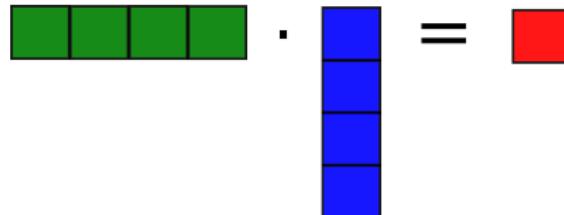
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Each step updates a small number of features

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The diagram shows a horizontal vector of four colored squares (green, yellow, green, green) multiplied by a vertical vector of three colored squares (blue, orange, blue). The result is a single red square, representing the dot product of the two vectors.



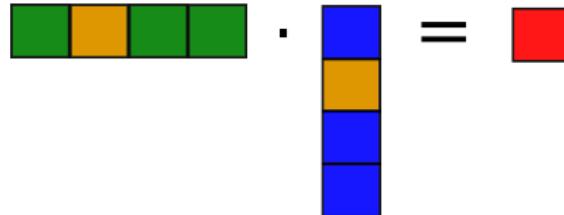
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$$v' = v - w_i \cdot f_i + w_i \cdot f_i$$



Why is this Important?



Faster Search \Rightarrow Deeper Reasoning

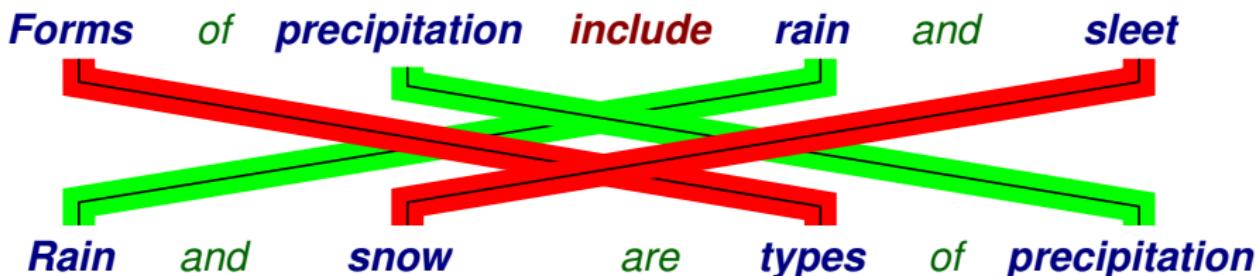
- **Speed:** Around 1M search states visited per second
- **Memory:** 32 byte search states

Speed: Don't re-featurize at every timestep.

Memory: Never store intermediate fact as String.



An Example Search

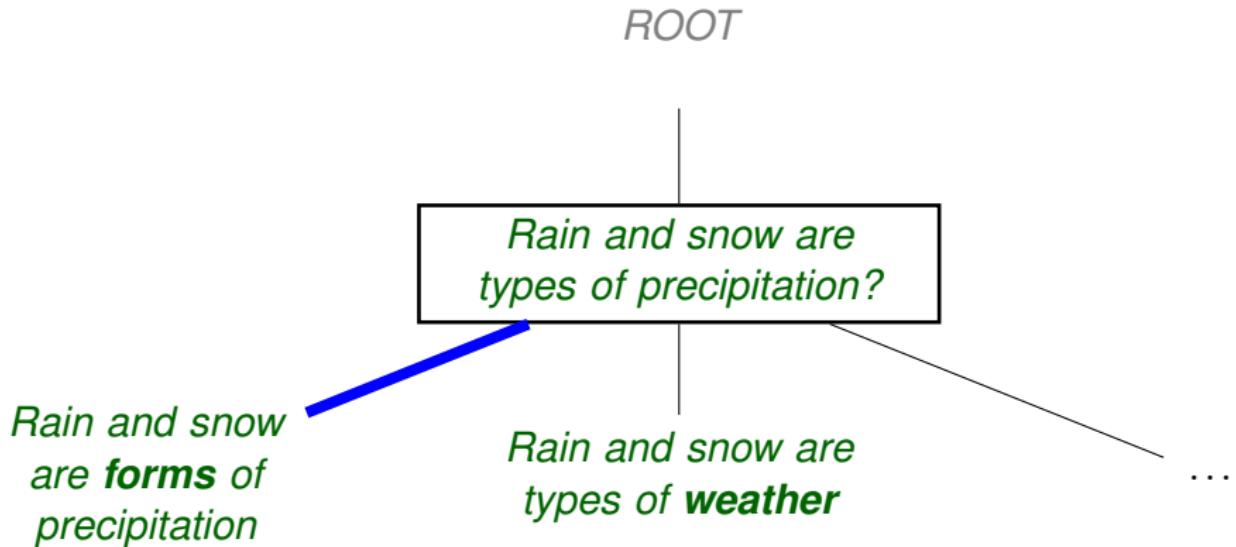


Score $w^T f(x)$: -0.5

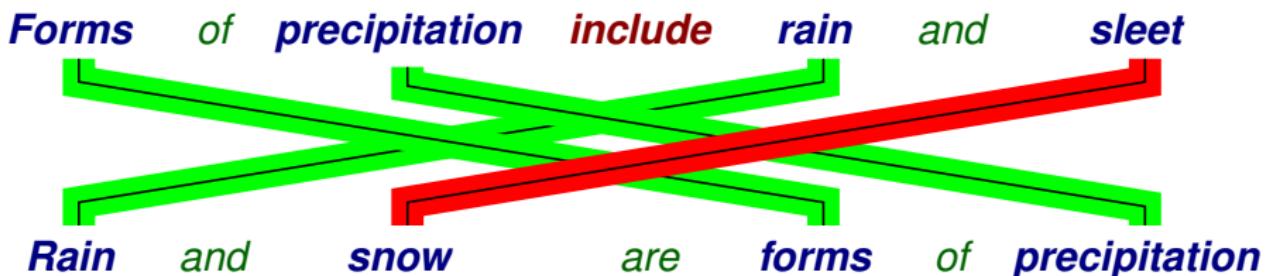
Feature	w	f(x)
Matching words	2.0	2
Mismatched words	-1.0	2
Unmatched premise	-0.5	1
Unmatched consequent	-0.75	0
Bias	-2.0	1



An Example Search



An Example Search

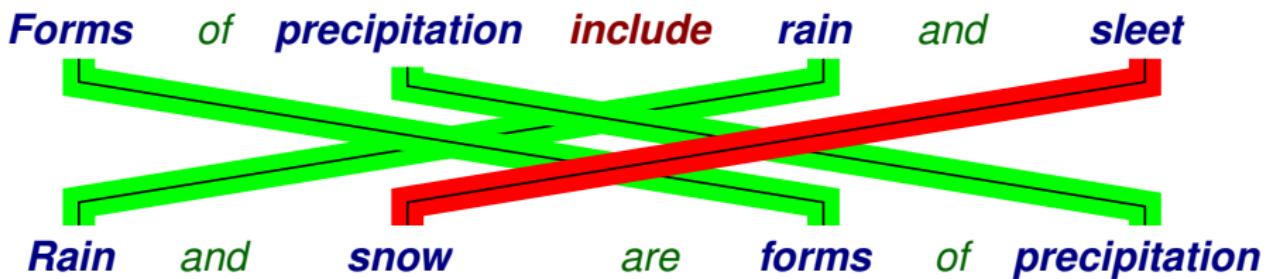


$$\text{Score } w^T f(x): -0.5 + 2 - -1$$

Feature	w	f(x)
Matching words	2.0	3
Mismatched words	-1.0	1
Unmatched premise	-0.5	1
Unmatched consequent	-0.75	0
Bias	-2.0	1



An Example Search



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

Feature	w	f(x)
Matching words	2.0	3
Mismatched words	-1.0	1
Unmatched premise	-0.5	1
Unmatched consequent	-0.75	0
Bias	-2.0	1



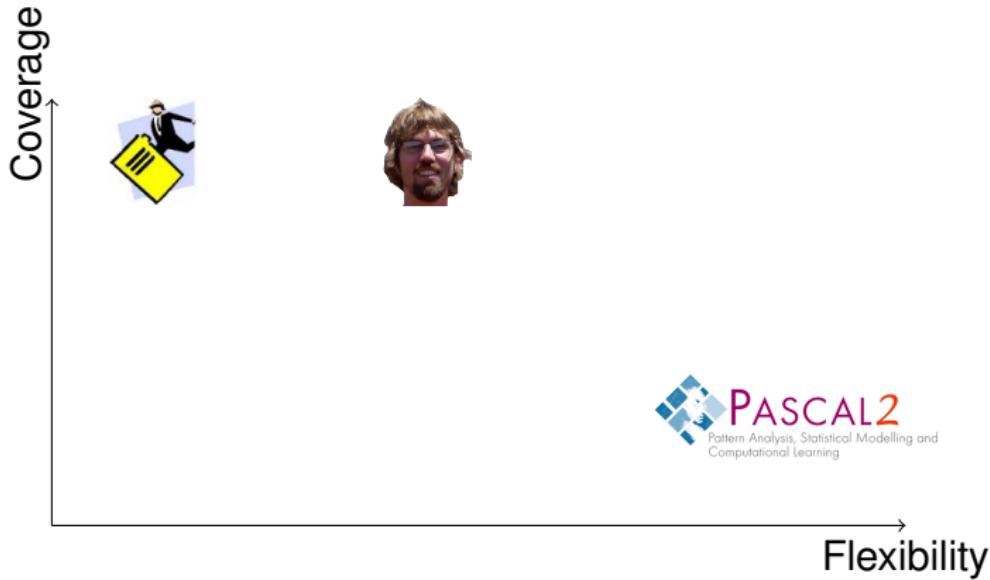
The Full System

Common Sense Reasoning



The Full System

+ Complex Premises



The Full System

+ Evaluation Function

Coverage



Flexibility



The Full System

Common Sense Facts

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



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 w/ natural logic
- 3 F₁ improvement on knowledge base population



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 w/ natural logic
- 3 F₁ improvement on knowledge base population

Evaluation Function

- Use lexical classifier as evaluation function
- Detect likely entailment / contradictions

Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams



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



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 ... great for watching TV ... 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*

Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams

System	Train	Test
KNOWBOT	45	
KNOWBOT (ORACLE)	57	

[Hixon et al., 2015]

Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams

System	Train	Test
KNOWBOT	45	
KNOWBOT (ORACLE)	57	
IR Baseline	49	
This Thesis	52	

[Hixon et al., 2015]



Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams

System	Train	Test
KNOWBOT	45	
KNOWBOT (ORACLE)	57	
IR Baseline	49	
This Thesis	52	
More Data + IR Baseline	62	
More Data + This Thesis	65	

[Hixon et al., 2015]

Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams

System	Train	Test
KNOWBOT	45	—
KNOWBOT (ORACLE)	57	—
IR Baseline	49	42
This Thesis	52	51
More Data + IR Baseline	62	58
More Data + This Thesis	65	61

[Hixon et al., 2015]

Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams

System	Train	Test
KNOWBOT	45	—
KNOWBOT (ORACLE)	57	—
IR Baseline	49	42
This Thesis	52	51
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More Data + This Thesis	65	61
This Thesis +  + 	74	67

[Hixon et al., 2015]

Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams

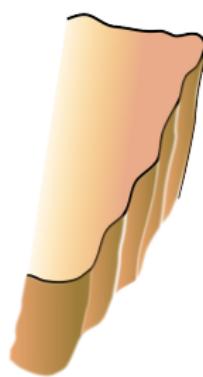
System	Train	Test
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We're able to pass 4th grade science!

[Hixon et al., 2015]

Remaining Work

First Order Logic

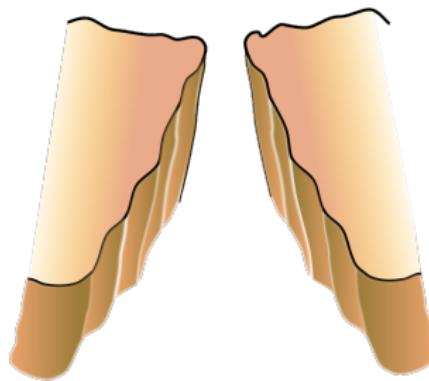


Lexical Methods



Remaining Work

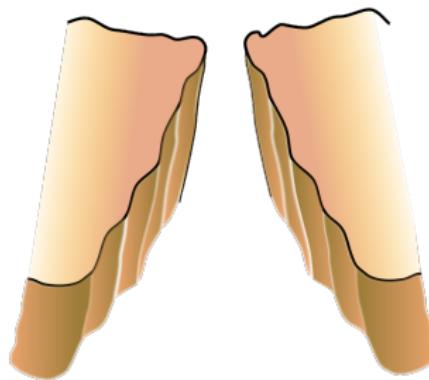
Natural Logic



Lexical Methods

Remaining Work

Natural Logic



Lexical Methods

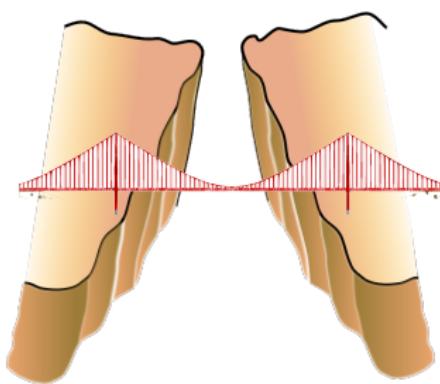
- Already useful for textual entailment
[MacCartney and Manning, 2008, MacCartney, 2009]



Remaining Work

Natural Logic

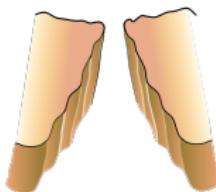
Lexical Methods



- 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



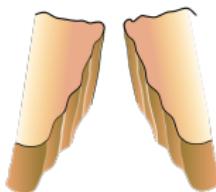
Remaining Work



1. Encode logic in traditionally lexical representations
[Bowman, 2014, Bowman et al., 2015]

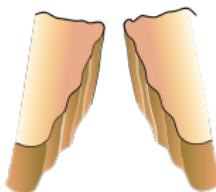


Remaining Work



1. Encode logic in traditionally lexical representations
[Bowman, 2014, Bowman et al., 2015]
2. Make natural logic more expressive

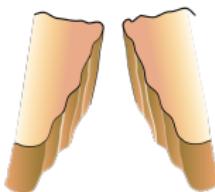
Remaining Work



1. Encode logic in traditionally lexical representations
[Bowman, 2014, Bowman et al., 2015]
2. Make natural logic more expressive
 - Propositional + Natural logics:
Apples are red \vee *Bananas are red*
Bananas are not red
 \therefore *Apples are red*



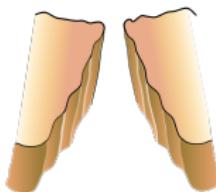
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Remaining Work



1. Encode logic in traditionally lexical representations
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2. Make natural logic more expressive
 - Propositional + Natural logics:
Apples are red \vee *Bananas are red*
Bananas are not red
 \therefore *Apples are red*
 - Syntactic and idiomatic entailment models: SNLI corpus?



Thanks!



Thanks!



Thanks!



Questions?



THE BEST THESIS DEFENSE IS A GOOD THESIS OFFENSE.



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