Learning Open Domain Knowledge from Text

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Want: General Purpose AI

Have: “Idiot Savants”

- Relation extractors can’t predict sentiment.
- Sentiment analyzers can’t produce parse trees.

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- Sentiment analyzers can't produce parse trees.
- Movie sentiment analyzers perform poorly on product reviews.

Towards Intelligence

Glue systems together $\Rightarrow$ **CoreNLP:** Great, but not "intelligence"

Towards Intelligence

Glue systems together ⇒ CoreNLP: Great, but not “intelligence”

Joint Models: Difficult to scale

How Are Humans Intelligent?

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We leverage an immense amount of background knowledge.

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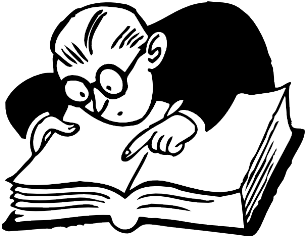
"The Good Dinosaur was Pixar 's second best movie in 2015"

My Ph.D. Work: A Key First Step

Knowledge = *Justified true beliefs*



Harder for Computers than Humans

...for a human

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

...for a computer

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

How do we Represent Knowledge?

Unstructured Text

$\Rightarrow$

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)**

$$\Longrightarrow \quad (\textsf{SUBJECT};\ \text{relation};\ \textsf{OBJECT})$$

How do we Represent Knowledge?

Unstructured Text


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

$\Rightarrow$

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**

$\Longrightarrow$

cats have tails
rabbits eat carrots
Obama enjoys playing basketball

How do we Represent Knowledge?

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1. **Fixed-Schema Knowledge Bases**
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A graduated cylinder is best to measure the volume of a liquid

Text is Knowledge

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

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We need a system that:

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

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

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Takes as input a candidate textual statement.
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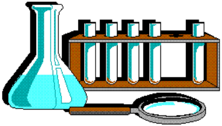
- Generalizes Fixed-Schema KBs
  ✓ *Obama was born in Hawaii*
  ✗ *Obama was born in Kenya*
- Generalizes Open IE
  ✓ *Rabbits eat carrots*
- More precise than web search
  ✗ *A stopwatch is best to measure the volume of a liquid.*

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

Reasoning About Common Sense Facts

✓ *Kittens play with yarn* ✗ *Kittens play with computers*

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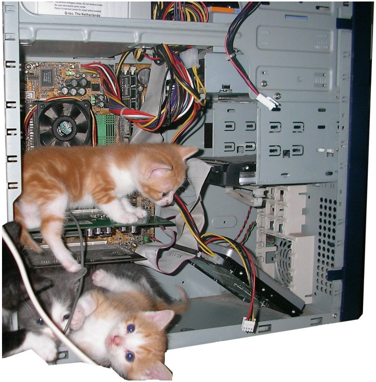

Common Sense Reasoning for NLP

They ate the pizza with anchovies

Start with a large knowledge base (270M facts)

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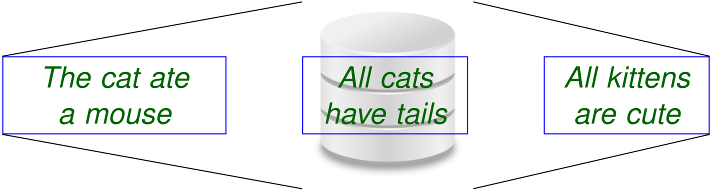
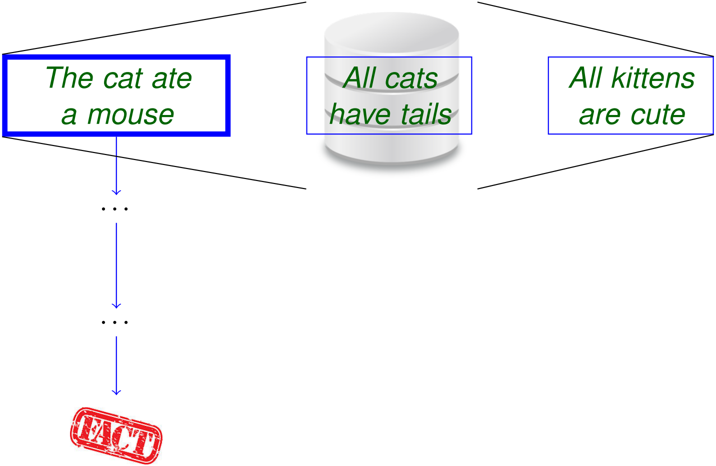


Infer new facts...



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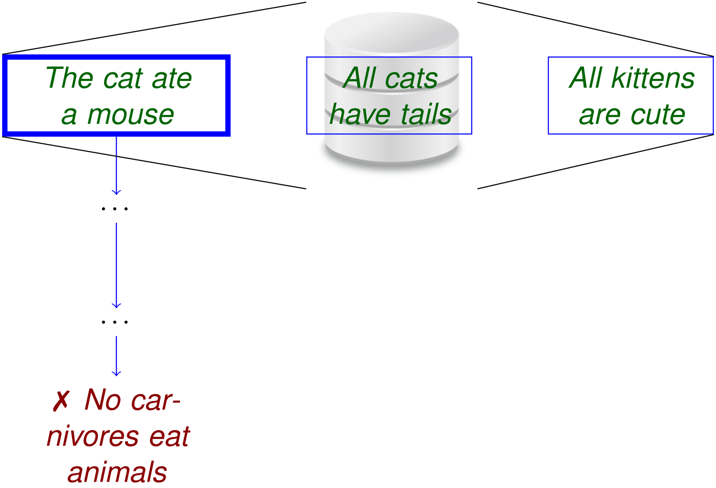


Infer new facts...

The cat ate a mouse

All cats have tails

All kittens are cute

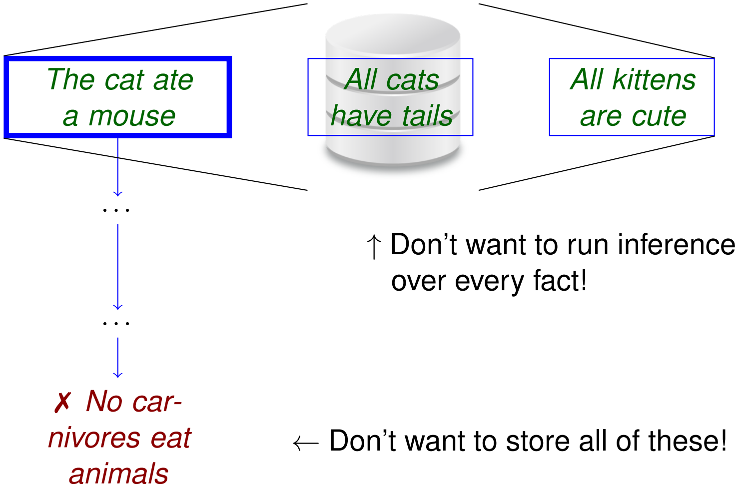
. . .

. . .

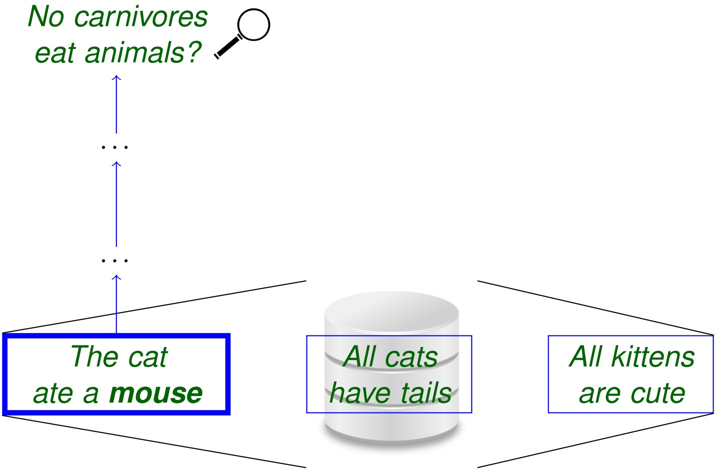
✗ *No carnivores eat animals*

↑ Don't want to run inference over every fact!

Infer new facts...



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



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

No carnivores eat animals?

***The** carnivores eat animals*

*The **cat** eats animals*

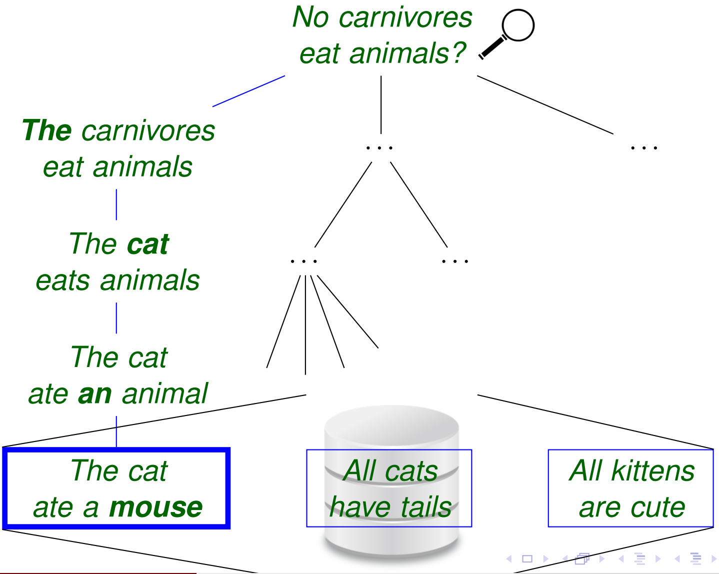
*The cat ate **an** animal*

*The cat ate a **mouse***

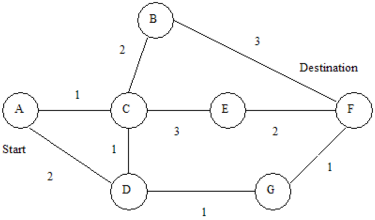
All cats have tails

All kittens are cute

...Without aligning to any particular premise.

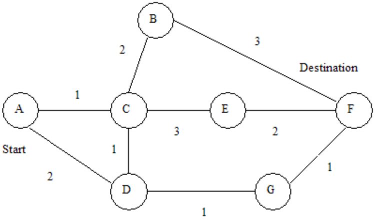


A Search Problem



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

A Search Problem



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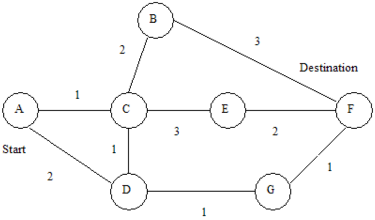

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Start Node (*query fact*, ✓ *true*)
End Nodes *any known fact*

Edges Mutations of the current fact
Edge Costs How "wrong" an inference step is (learned)

A Search Problem Over Valid Inferences

Transitions (mutations) have to be precise:

The *carnivores eat animals*	$\models \neg$	***No*** *carnivores eat animals*
The *carnivores eat animals*	$\models$	***Some*** *carnivores eat animals*

A Search Problem Over Valid Inferences

Transitions (mutations) have to be precise:

The *carnivores eat animals*	$\vDash \neg$	***No*** *carnivores eat animals*
The *carnivores eat animals*	$\vDash$	***Some*** *carnivores eat animals*

Transitions have to respect logical entailment

- Logic should be fast (visit 1M nodes / sec).
- Logic should operate over text.

Natural Logics

A class of proof-theoretic logics over the syntax of natural language.

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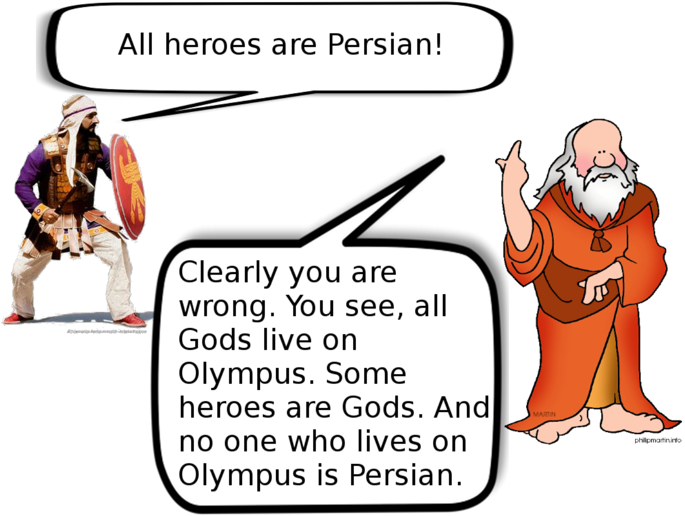
A class of proof-theoretic logics over the syntax of natural language.

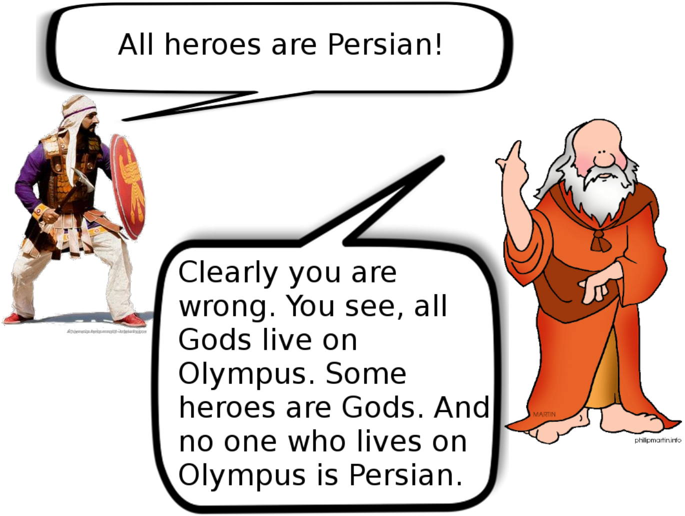
Perfect tool for large-scale logical inference

- *Instantaneous* and *perfect* semantic parsing
- Fast inference
- Plays nice with lexical methods
- Handles common non-first-order phenomena

The Persians are Invading Greece



How Did You Solve This?



Show of Hands: First Order Logic?

1		$\forall x\ \text{God}(x) \supset \text{LivesOnOlympus}(x)$	
2		$\exists x\ \text{Hero}(x) \wedge \text{God}(x)$	
3		$\neg\exists x\ \text{LivesOnOlympus}(x) \wedge \text{Persian}(x)$	
4		$\quad \forall x\ \text{Hero(x)} \supset \text{Persian}(x)$	
5	a	$\quad\quad \text{Hero}(a) \wedge \text{God}(a)$	$\exists$E, 2
6		$\quad\quad \text{Hero}(a)$	$\wedge$E, 5
7		$\quad\quad \text{Hero(a)} \supset \text{Persian}(a)$	$\forall$E, 4
8		$\quad\quad \text{Persian}(a)$	$\Rightarrow$E, 6, 7
9		$\quad\quad \text{God}(a)$	$\wedge$E, 5
10		$\quad\quad \text{God}(a) \supset \text{LivesOnOlympus}(a)$	$\forall$E, 1
11		$\quad\quad \text{LivesOnOlympus}(a)$	$\Rightarrow$E, 9, 10
12		$\quad\quad \text{LivesOnOlympus}(a) \wedge \text{Persian}(a)$	$\wedge$I, 8, 11
13		$\quad\quad \exists x\ \text{LivesOnOlympus}(x) \wedge \text{Persian}(x)$	$\exists$I, 12
14		$\quad \exists x\ \text{LivesOnOlympus}(x) \wedge \text{Persian}(x)$	R, 12
15		$\quad \perp$	$\perp$ I, 3, 14
16		$\neg\ \forall x\ \text{Hero(x)} \supset \text{Persian}(x)$	$\neg$ I, 4—15

Syllogisms: The First Natural Logic

1	*All Gods live on Mount Olympus*	
2	*Some heroes are Gods*	
3	*Nobody who lives on Mount Olympus is Persian*	
4	*Some heroes live on Mount Olympus*	AII (Darii), 1, 2
5	*Some heroes are not Persian*	EIO (Ferio), 4, 3
6	$\neg$ *All heroes are Persian*	SaP $\perp$ SoP, 5

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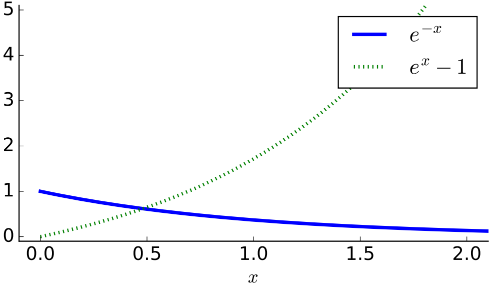
5	*Some heroes are not Persian*	EIO (Ferio), 4, 3
6	¬ *All heroes are Persian*	SaP $\perp$ SoP, 5

...But syllogisms are cripplingly unexpressive

$f : X \rightarrow Y$ is *monotone* w.r.t. partial orders $\leq_X, \leq_Y$ iff
$$\forall x_0 \forall x_1 \geq_X x_0;\ \ f(x_1) \geq_Y f(x_0).$$



[Sánchez Valencia, 1991, Icard and Moss, 2014]

Monotonicity Calculus

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$\leq_Y$ for truth values:

P	**Q**	**P $\leq_Y$ Q**
true	true	true
true	false	false
false	true	true
false	false	true

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$\leq_Y$ for truth values:

P	**Q**	**P $\leq_Y$ Q**	**P $\supset$ Q**
true	true	true	true
true	false	false	false
false	true	true	true
false	false	true	true

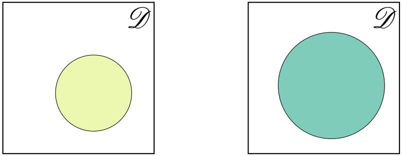
$\leq_Y$ denotes entailment

Monotonicity in Language

$f : X \to Y$ is *monotone* w.r.t. partial orders $\leq_X, \leq_Y$ iff
$\forall x_0 \forall x_1 \geq_X x_0;\ \ f(x_1) \geq_Y f(x_0)$.

f : **denotations** $\to$ **truth values**

$\leq_X$ **for denotations**: subset.



$[\![cat]\!] \subseteq [\![feline]\!]$

Proofs in Natural Logic

Quantifiers are functions with monotonicity.

Words are in either upward, downward, or non-monotone contexts.

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***Polarity* is the direction a lexical item can "move."**

animal

feline

$\boxed{\text{cat}}$

house cat

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living thing

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house cat

An Example Inference

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

	carnivores		placentals
	felines	consume	rodents
↑ **All**$_{\downarrow\uparrow}$	↓ cats	↑ eat	↑ mice
	house cats	slurp	fieldmice

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Mutations must respect *polarity*.

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	kitties	eat	pine vole

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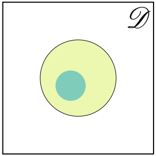
Mutations must respect *polarity*.

What about negation?

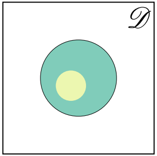
	felines		mammals
	cats		placentals
↑ **All**$_{\downarrow\uparrow}$	↓ house cats	↑ consume	↑ rodents
	kitties	eat	mice

Reasoning with Negation (Exclusion)



$\varphi \sqsubseteq \psi$

(*forward entail.*)



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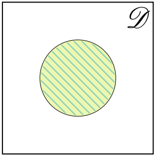
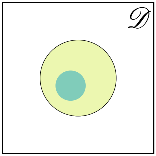


$\varphi \equiv \psi$

(*equivalence*)

[MacCartney and Manning, 2008]

Reasoning with Negation (Exclusion)



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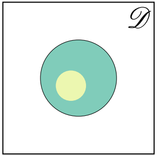

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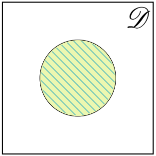
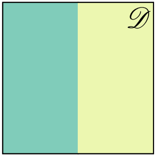


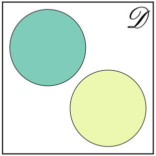
$\varphi \equiv \psi$

(*equivalence*)



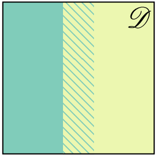
$\varphi \curlywedge \psi$

(*negation*)



$\varphi \mid \psi$

(*alternation*)



$\varphi \smile \psi$

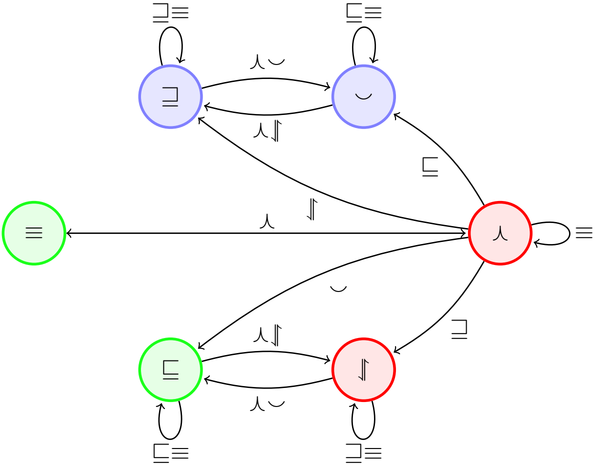
(*cover*)

[MacCartney and Manning, 2008]

“Join Table”

$\bowtie$	$\equiv$	$\sqsubseteq$	$\sqsupseteq$	$\curlywedge$	$\mid$	$\smile$	$\#$
$\equiv$	$\equiv$	$\sqsubseteq$	$\sqsupseteq$	$\curlywedge$	$\mid$	$\smile$	$\#$
$\sqsubseteq$	$\sqsubseteq$	$\sqsubseteq$	$\#$	$\mid$	$\mid$	$\#$	$\#$
$\sqsupseteq$	$\sqsupseteq$	$\#$	$\sqsupseteq$	$\smile$	$\#$	$\smile$	$\#$
$\curlywedge$	$\curlywedge$	$\smile$	$\mid$	$\equiv$	$\sqsupseteq$	$\sqsubseteq$	$\#$
$\mid$	$\mid$	$\#$	$\mid$	$\sqsubseteq$	$\#$	$\sqsubseteq$	$\#$
$\smile$	$\smile$	$\smile$	$\#$	$\sqsupseteq$	$\sqsupseteq$	$\#$	$\#$
$\#$	$\#$	$\#$	$\#$	$\#$	$\#$	$\#$	$\#$

Contribution: Don't Need Join Table



[Angeli and Manning, 2014]

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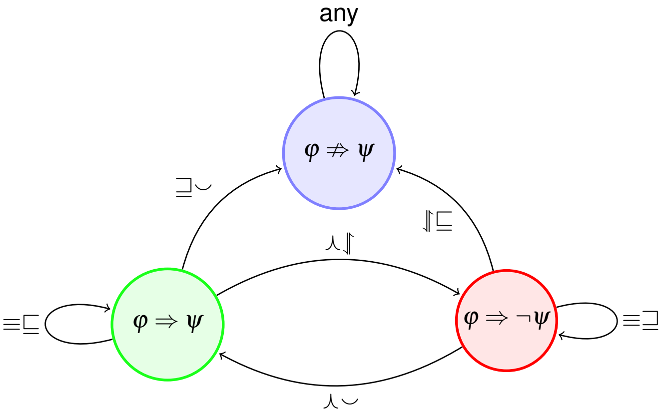


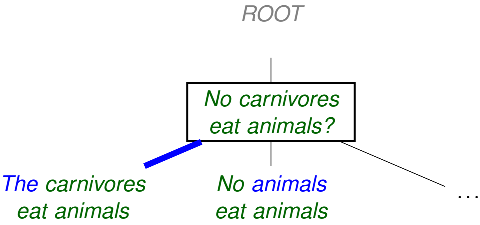
[Angeli and Manning, 2014]

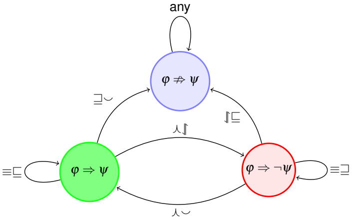
Shorthand for a node:

	organism		living thing
	animal	consume	organism
$\uparrow$ **No**$_{\downarrow\downarrow}$	$\downarrow$ carnivores	$\downarrow$ eat	$\downarrow$ animals
	felines	slurp	chordate

No carnivores eat animals?

An Example Search





An Example Search

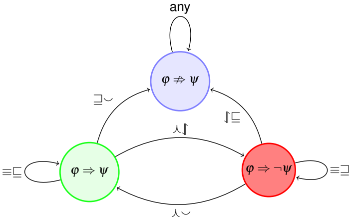
No carnivores eat animals

The carnivores eat animals?

The feline eats animals

All carnivores eat animals

. . .



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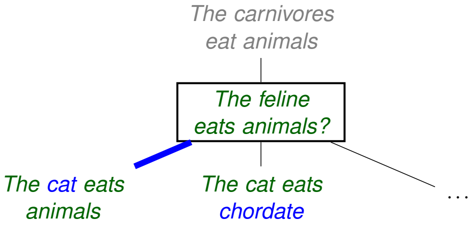

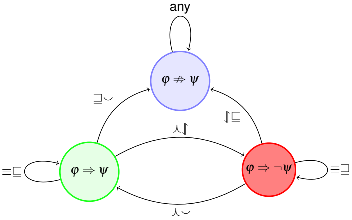

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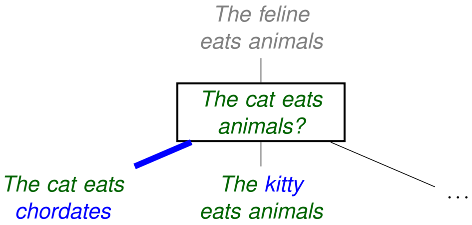

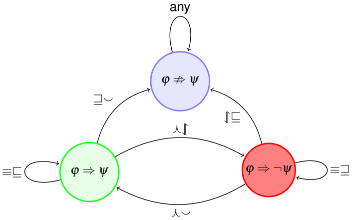

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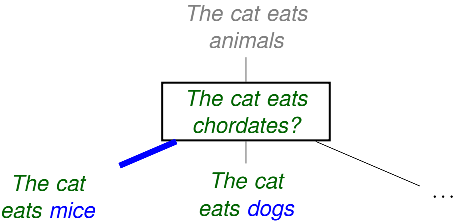
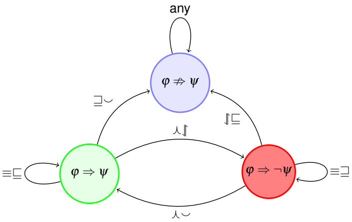




An Example Search

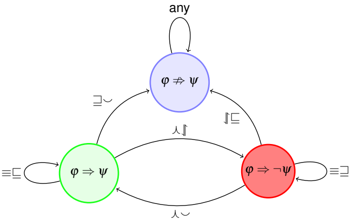
The cat eats chordates

The cat eats mice?

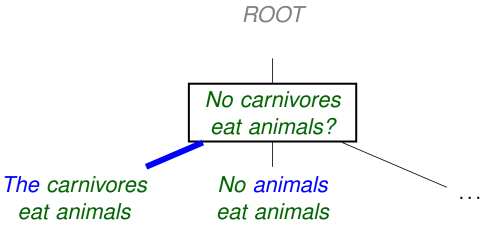
The cat ate a mouse

The kitty eats mice

. . .



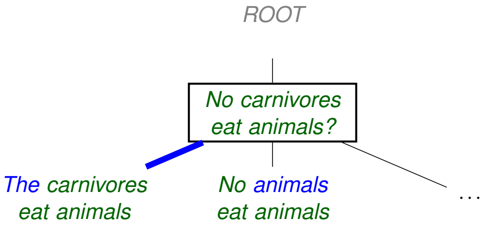
An Example Search (with edges)



Edge | **Instance** | **Template**

No carnivores eat animals $\rightarrow$
The carnivores eat animals

An Example Search (with edges)



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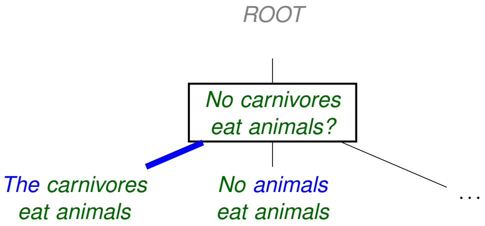

Edge	**Instance**	**Template**
No carnivores eat animals → *The carnivores eat animals*	*No* → *The*	Operator Negate

Edge Templates

Template	Instance
Hypernym	*animal* $\rightarrow$ *cat*
Hyponym	*cat* $\rightarrow$ *animal*
Antonym	*good* $\rightarrow$ *bad*
Synonym	*cat* $\rightarrow$ *true cat*
Add Word	*cat* $\rightarrow \cdot$
Delete Word	$\cdot \rightarrow$ *cat*
Operator Weaken	*some* $\rightarrow$ *all*
Operator Strengthen	*all* $\rightarrow$ *some*
Operator Negate	*all* $\rightarrow$ *no*
Operator Synonym	*all* $\rightarrow$ *every*
Nearest Neighbor	*cat* $\rightarrow$ *dog*

“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*
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Our Knowledge Base:

- 270 million lemmatized Ollie extractions.

ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.

This Work.

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- 4x improvement in recall.

New Solutions to Old Problems

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Cycorp® ConceptNet 5

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Cycorp® ConceptNet 5

New Solution: Treat unstructured text as your ontology!

Success?

Not Yet!

The Internet doesn't speak in atomic utterances

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

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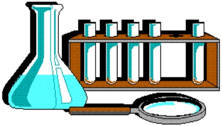
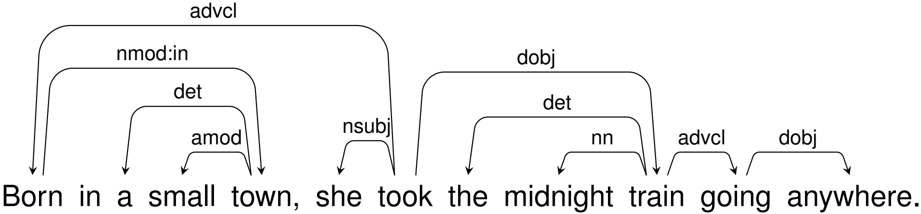


Lexical + Logical Reasoning:
A graduated cylinder would be best to measure the volume of a liquid

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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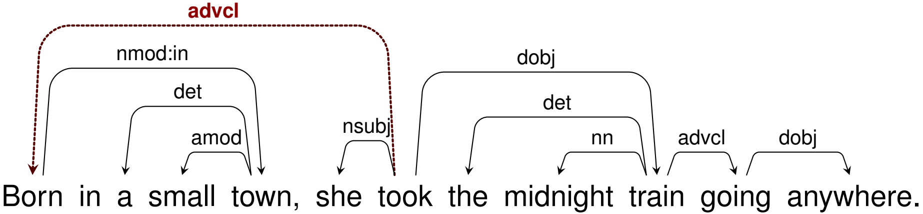

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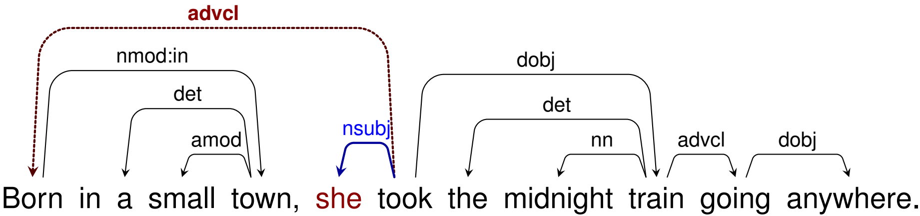
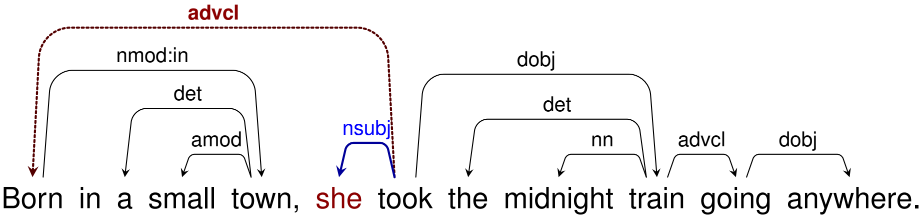


Clause Classifier



Input: Dependency arc.
Output: *Action* to take.

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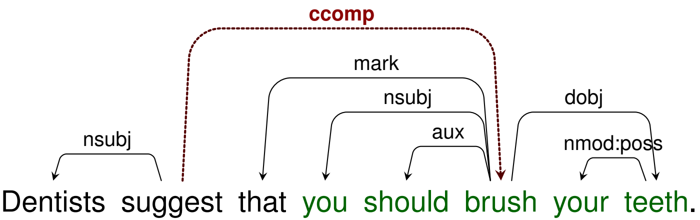

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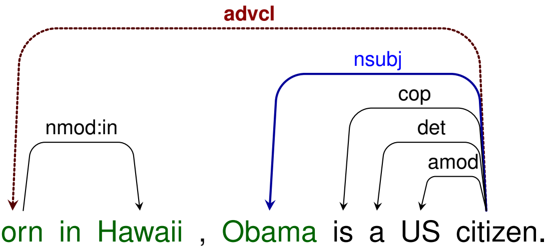

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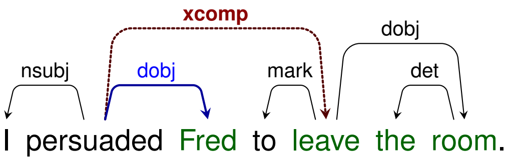

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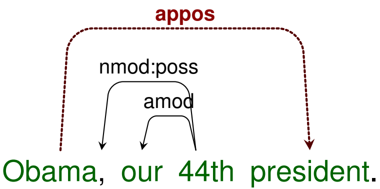

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Classifier Training

Training Data Generation

1. Label a constituency treebank with relation triples.
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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***	$\Longrightarrow$	✓ *Heinz Fischer*
***United States president** Obama*	$\Longrightarrow$	✓ *Obama*
*All **young** rabbits drink milk*	$\not\Longrightarrow$	✗ *All rabbits drink milk*
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Natural Logic For Clause Shortening

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

Mutations must respect *polarity*.

Polarity determines valid deletions.

	mammals		something
	rabbits	consume	liquid
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	...	

5 dependency tree patterns (+ 8 nominal patterns)

Extrinsic Evaluation: Knowledge Base Population

Unstructured Text

$\Longrightarrow$

Structured Knowledge Base

Barack Obama

44th President of the United States

Personal details

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

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- Precision: answers marked correct by humans.
- Recall: answers returned by any team (including LDC annotators).

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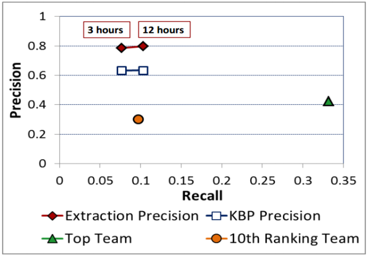
Comparison: *Open Information Extraction to KBP Relations in 3 Hours*. [Soderland et al., 2013]



Map Triples to Structured Knowledge Base

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

Results

TAC-KBP 2013 Slot Filling Challenge:

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

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

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

Complex premises:
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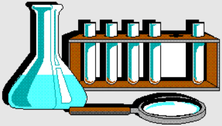


Lexical + Logical Reasoning:
A graduated cylinder would be best to measure the volume of a liquid

An Example Search

ROOT

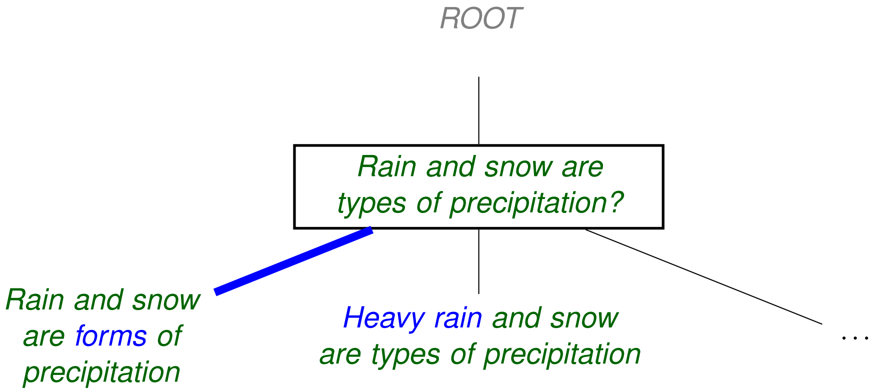
Rain and snow are types of precipitation?

Rain and snow are forms of precipitation

Heavy rain and snow are types of precipitation

. . .

An Example Search



An Example Search

Rain and snow are types of precipitation

Rain and snow are forms of precipitation?

Rain and snow are forms of weather

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An Example Search

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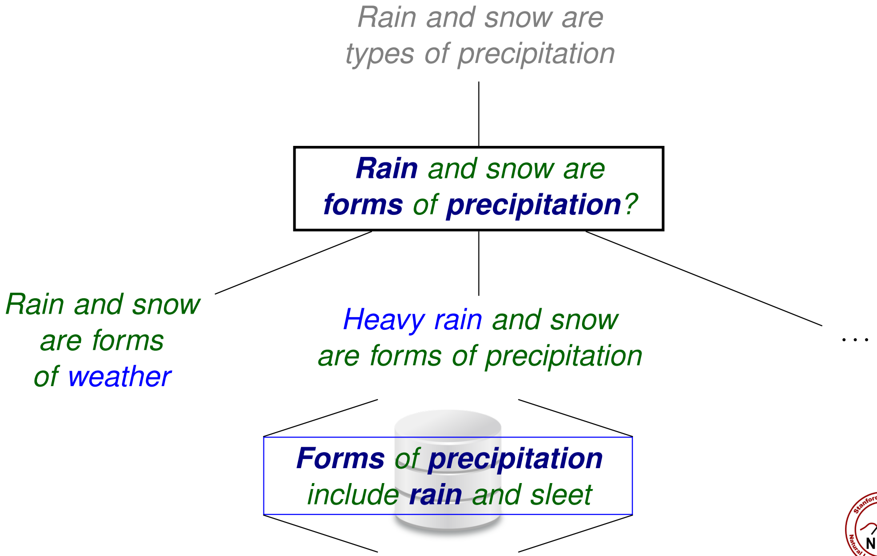
Heavy rain and snow are forms of precipitation

. . .

Forms of precipitation include rain and sleet

An Example Search



Lexical Alignment Classifier

Forms of precipitation include rain and sleet

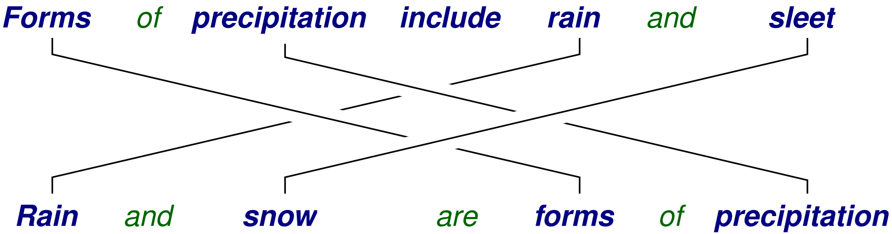
Rain and snow are forms of precipitation

Lexical Alignment Classifier

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

Rain *and* ***snow*** *are* ***forms*** *of* ***precipitation***

Lexical Alignment Classifier



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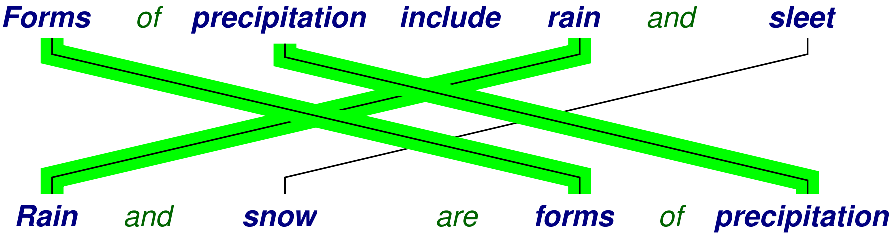
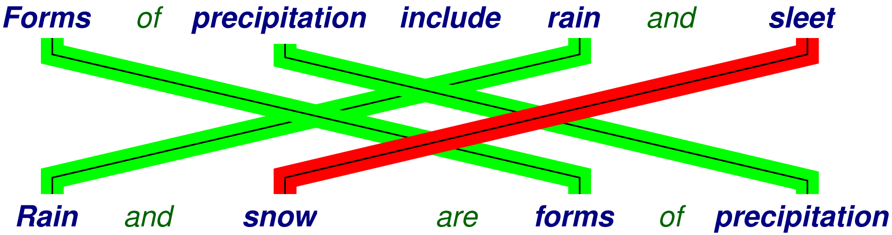


Features

1. Matching words

Lexical Alignment Classifier



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1. Matching words
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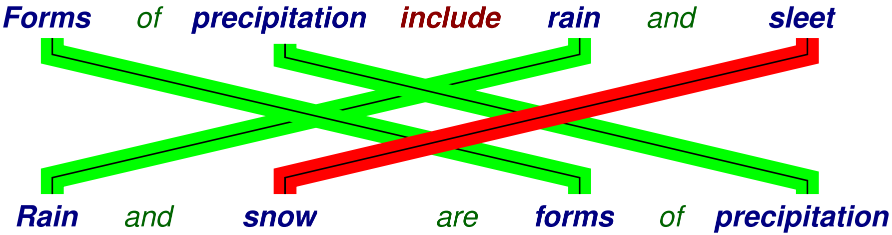

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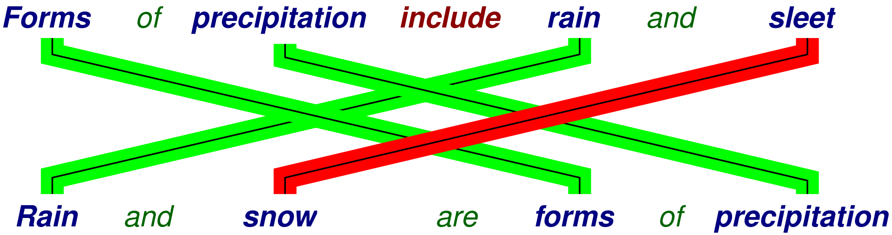

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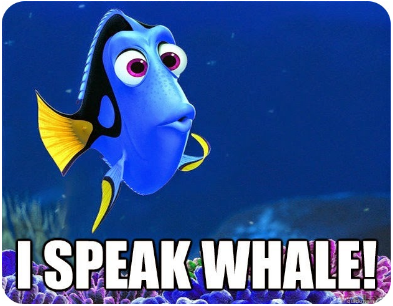
Competitive with Stanford RTE system (63% on RTE3)

Old Problem: Logic + Lexical Classifiers

FOL and lexical classifiers don't speak the same language

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!

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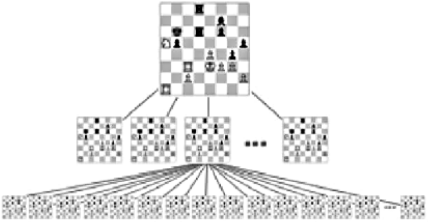

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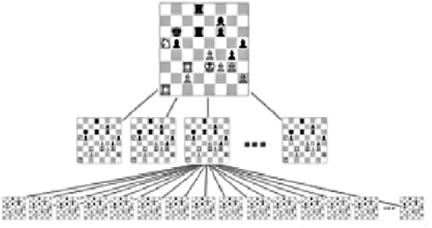

Visit 1M nodes / second: We have to be fast!

Dissecting Our Classifier

Anatomy of a Classifier

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

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

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$$p(\text{entail} \mid x) \text{ monotone w.r.t. } \left(w^{\mathrm{T}} f(x)\right)$$

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

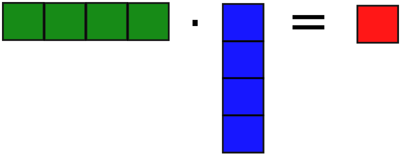
Incorporating our Evaluation Function

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

$$w^{\mathrm{T}} f(x) = v$$



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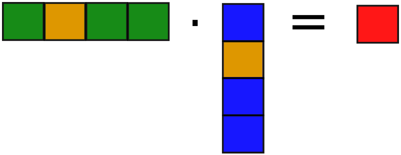

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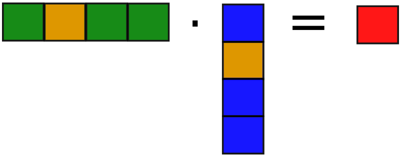
$$v' = v - w_i \cdot f_i + w_i \cdot f_i$$



Why is this Important?

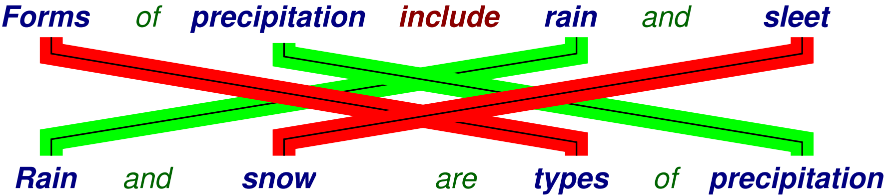
Faster Search $\Rightarrow$ Deeper Reasoning

- **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.

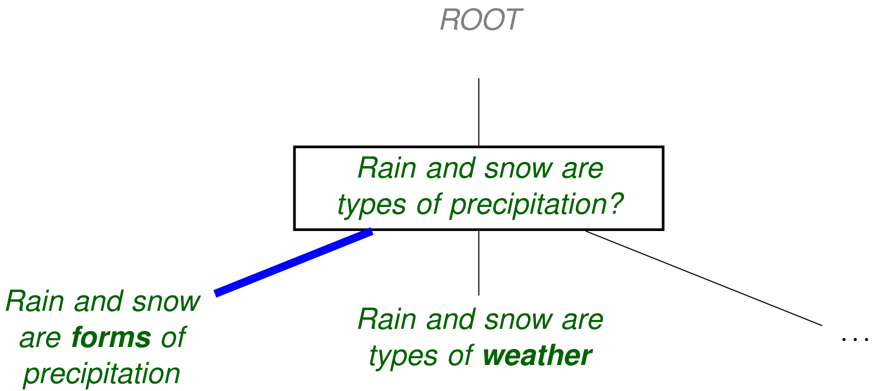
An Example Search



Score $w^{\mathrm{T}} f(x)$**:** -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



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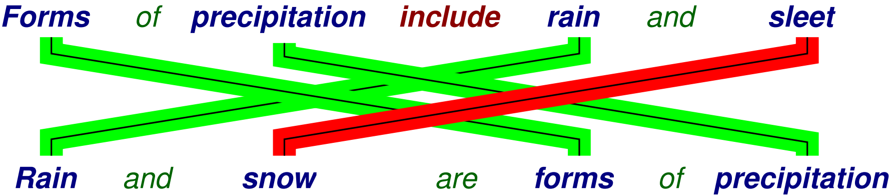

Score $w^{\mathrm{T}} f(x)$: -0.5 + 2 − -1

Feature	w	$f(x)$
Matching words	2.0	**3**
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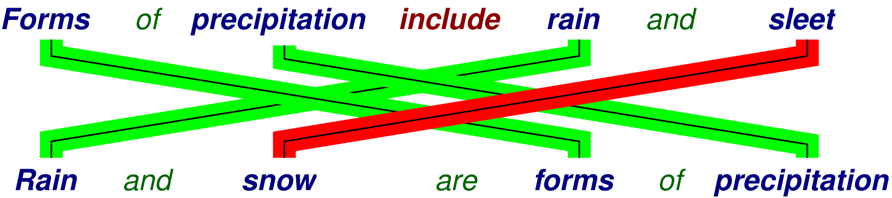

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Solving 4^{th} Grade Science

Multiple choice questions from real 4^{th} grade science exams

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Which activity is an example of a good health habit?

(A) Watching television
(B) Smoking cigarettes
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Solving 4^{th} Grade Science

Multiple choice questions from real 4^{th} grade science exams

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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 diner is an example of a poor health habit.*
- *Healthy is exercising*

Solving 4^{th} Grade Science

Multiple choice questions from real 4^{th} grade science exams

System	Train	Test
KNOWBOT	45	
KNOWBOT (ORACLE)	57	

[Hixon et al., 2015]

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Multiple choice questions from real 4^{th} grade science exams

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[Hixon et al., 2015]

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KNOWBOT (ORACLE)	57	
IR Baseline	49	
This Work	52	
More Data + IR Baseline	62	
More Data + This Work	**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 Work	52	51
More Data + IR Baseline	62	58
More Data + This Work	**65**	**61**

[Hixon et al., 2015]

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KNOWBOT (ORACLE)	57	–
IR Baseline	49	42
This Work	52	51
More Data + IR Baseline	62	58
More Data + This Work	65	61
This Work +  + 	**74**	**67**

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We're able to pass 4^{th} grade science!

[Hixon et al., 2015]

The Full System

Common Sense Facts

- Text is knowledge
- Soft natural logic inference as search
- 4x improvement in recall

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Evaluation Function

- Use lexical classifier as evaluation function
- Detect likely entailment / contradictions
- 3% improvement on science exam questions

Going Forward

Before 1990's: Knowledge was a big deal

- Pitiful compute
- Pitiful quantities of data (e.g., no internet)

$\Rightarrow$ Cyc (2.1M facts)

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Future: Open-domain non-factoid knowledge

- Tackle hard science questions
- Dialog systems for knowledge acquisition
- Reinforcement / "never ending" language learning

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