

NaturalLI: Natural Logic Inference for Common Sense Reasoning

Gabor Angeli, Chris Manning

Stanford University

October 26, 2014



Natural Logic Inference for Common Sense Reasoning

Kittens play with yarn

Kittens play with computers

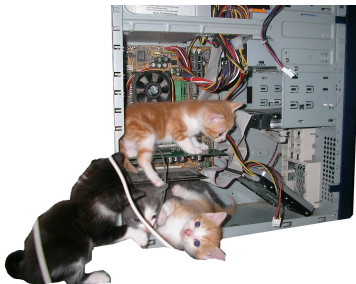


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Common Sense Reasoning for NLP

The city refused the demonstrators a permit because they feared violence.



Common Sense Reasoning for NLP

*The city refused the demonstrators a permit because they feared
violence.*

a city fears violence

demonstrators fear violence



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I ate the cake with a cherry vs. I ate the cake with a fork

cakes come with cherries

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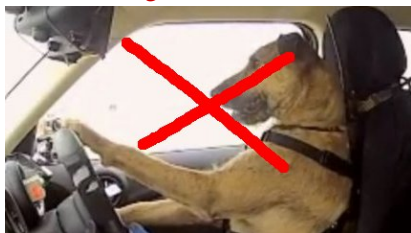
Put a sarcastic comment in your talk. That's a great idea.

Sarcasm in your talk is a great idea



Common Sense Reasoning for Vision

Dogs drive cars

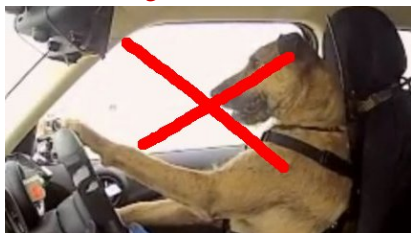


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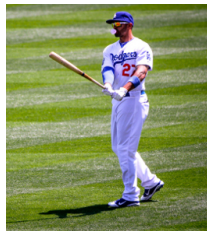
People drive cars



Baseball is played underwater



Baseball is played on grass



Prior Work on Common Sense Reasoning

Old School AI: Nuanced reasoning; tiny coverage.

- Default reasoning (Reiter 1980; McCarthy 1980).
- Theorem proving (e.g., Datalog).



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Information Extraction: Shallow inference, large data.

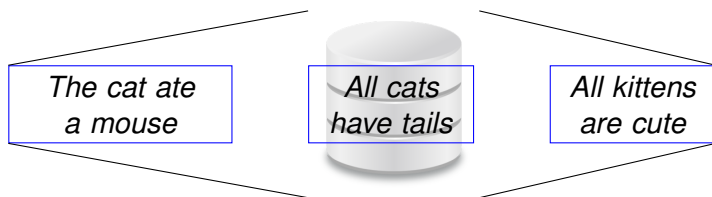
- OpenIE (Yates et al., 2007), NELL (Carlson et al., 2010).
- *Extraction* of facts from a large corpus; fuzzy lookup.



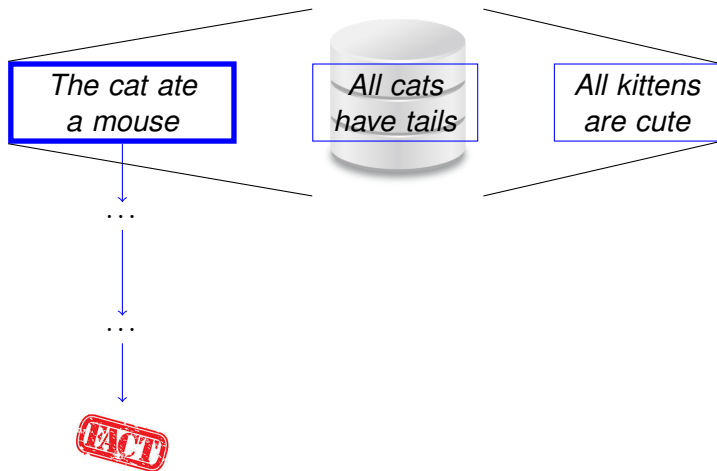
Start with a large knowledge base



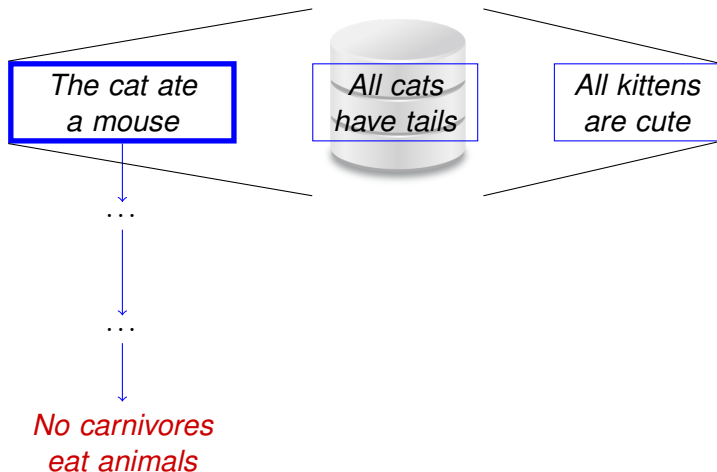
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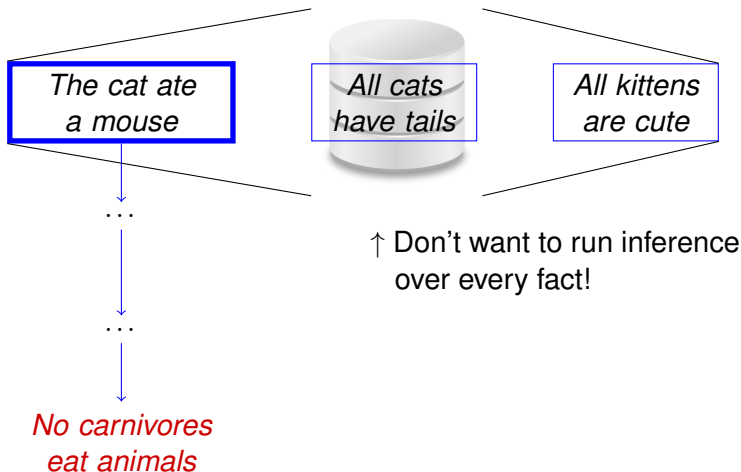
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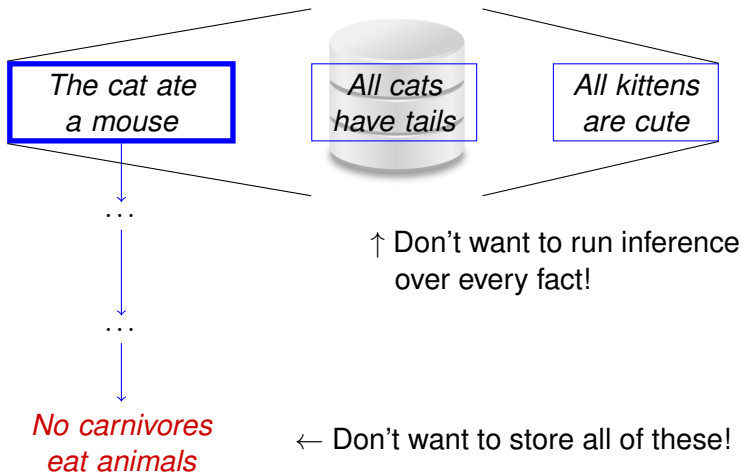
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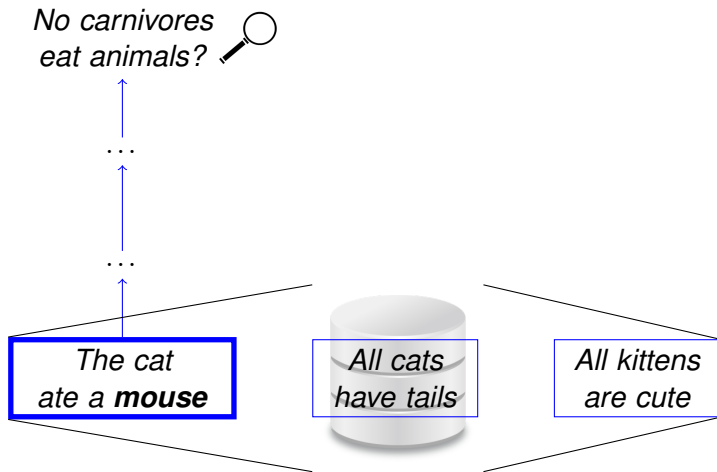
Infer new facts...



Infer new facts...



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



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

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eat animals? 🔍

The carnivores
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The **cat**
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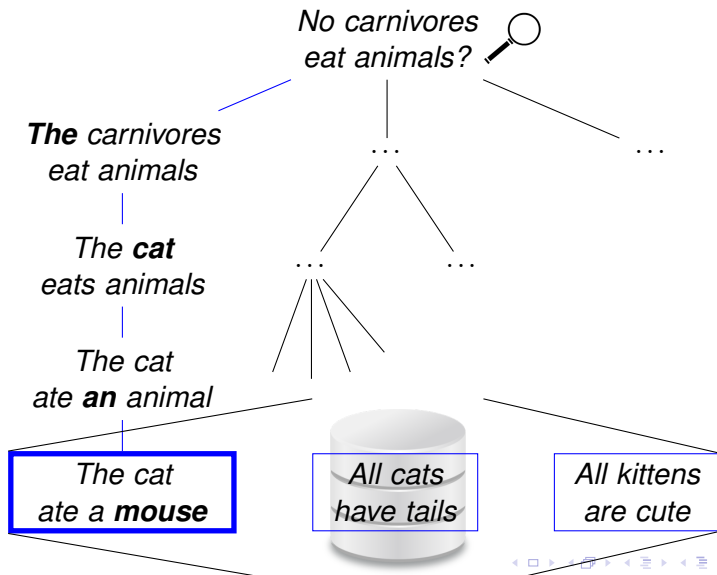
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...Without aligning to any particular premise.



A Better Knowledge Base Lookup

Lookup in 270 million entry KB...

...by lemmas 12% recall

...with NaturalLI 49% recall (91% precision)



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- Fast.
- Minimal pre-processing of query.
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Natural Logic



Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

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(*all mice are rodents*)

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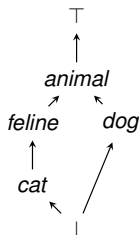
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Facts are text; inference is lexical mutation



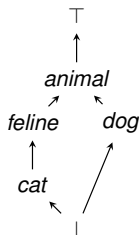
Natural Logic and Polarity

Treat hypernymy as a *partial order*.

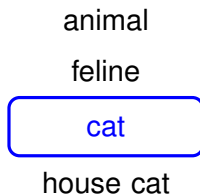


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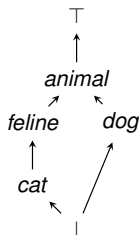


Polarity is the direction a lexical item can move in the ordering.



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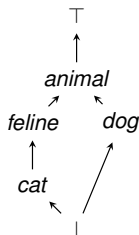


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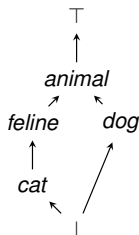


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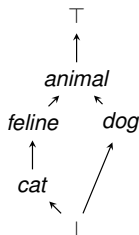


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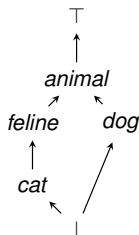


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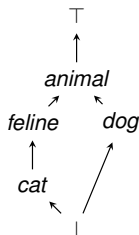


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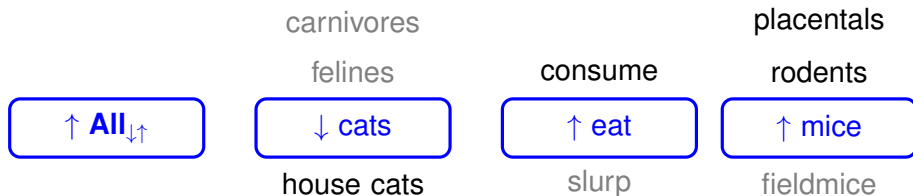


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An Example Inference

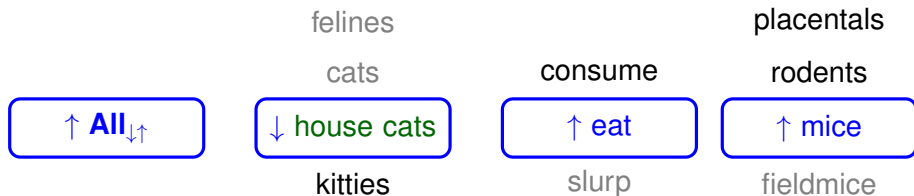
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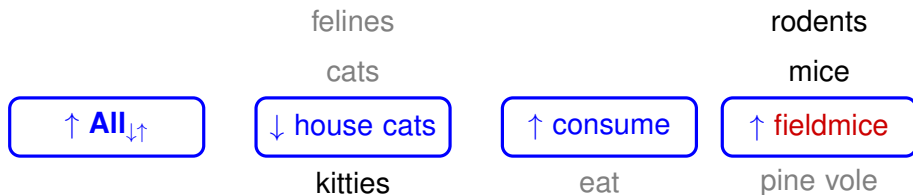
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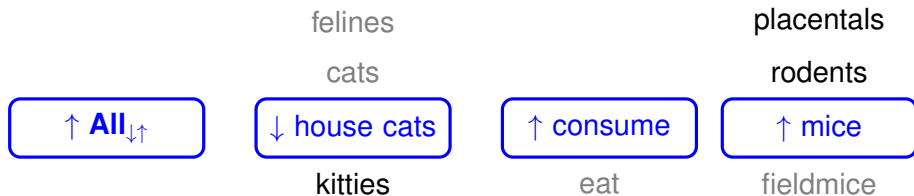
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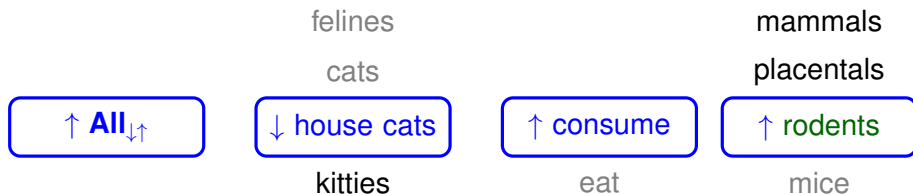
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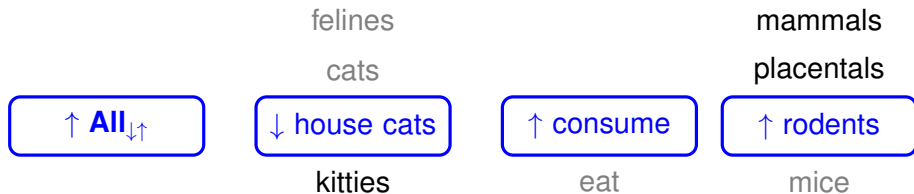


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Inference is reversible.



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- ✓ Computationally fast during inference.
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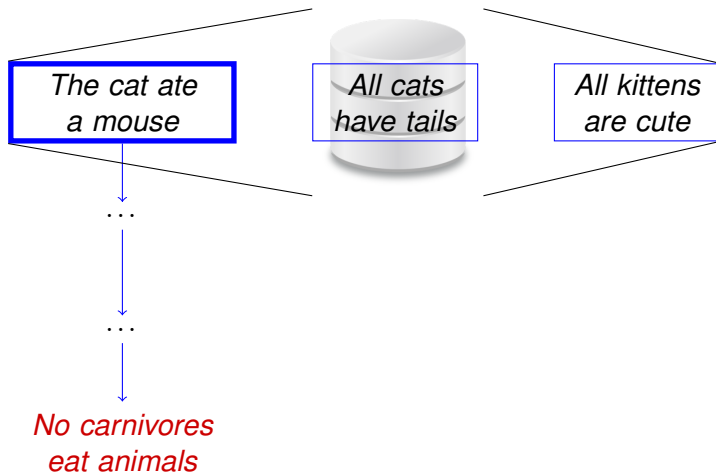


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 - We expect *readers* to make these inferences instantly.



Natural Logic Inference is Search



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eat animals? 🔍

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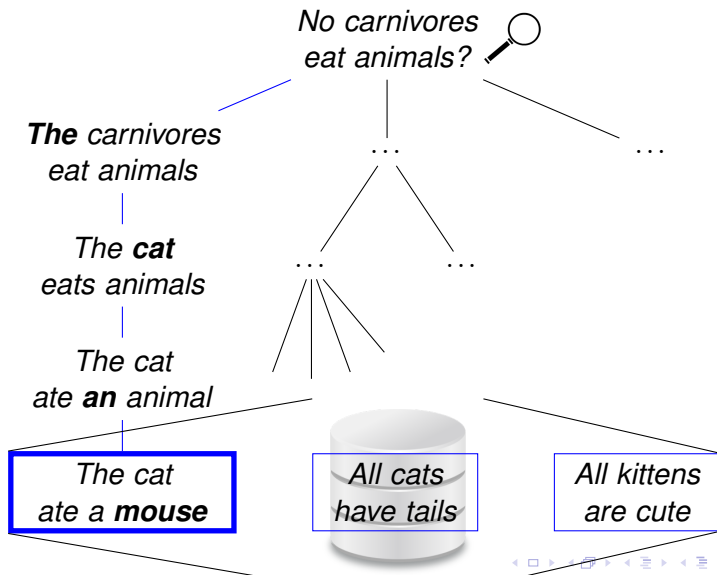
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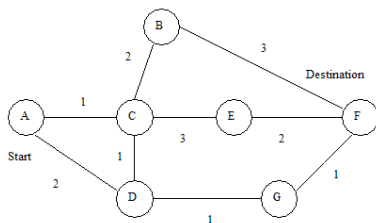
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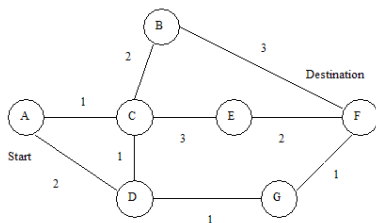
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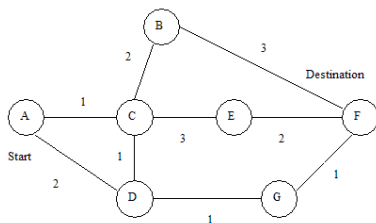
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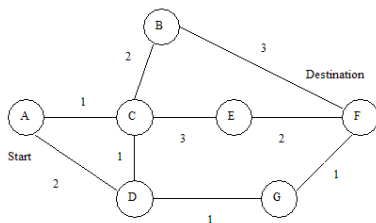
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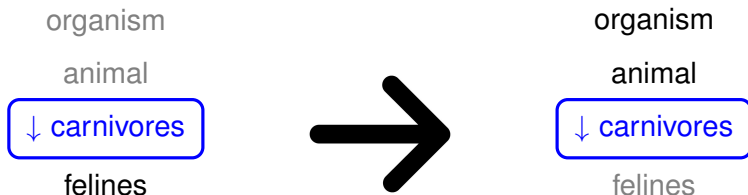
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Edge Costs How “wrong” an inference step is (learned)



An Example Search (as reverse inference)

Search mutates *opposite* to polarity



An Example Search (as reverse inference)

**Truth
maintained:**

true

**Current
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An Example Search (as reverse inference)

**Truth
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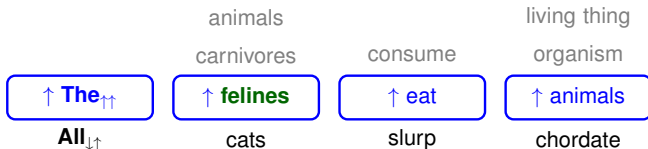


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An Example Search (as graph search)

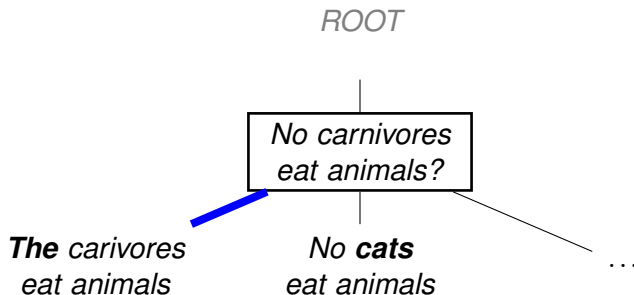
Shorthand for a node:



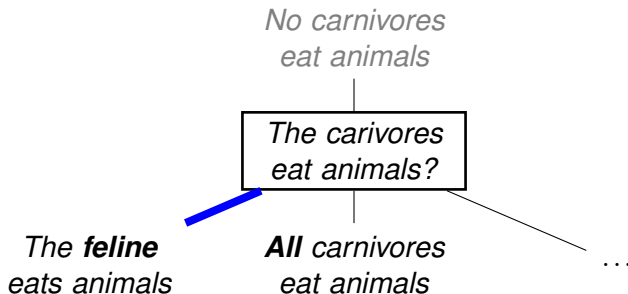
*No carnivores
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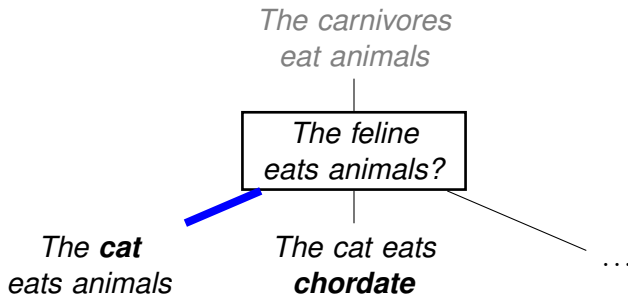
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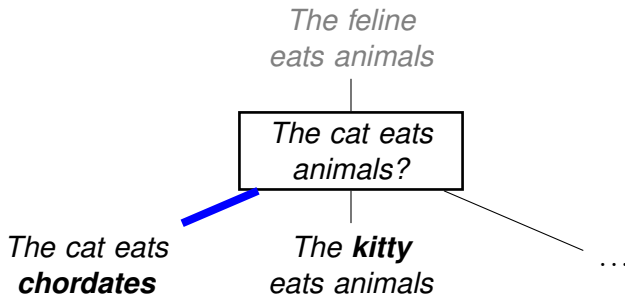
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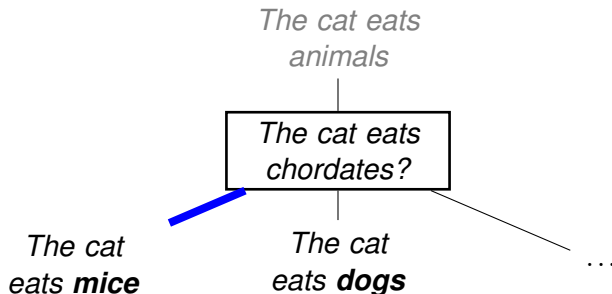
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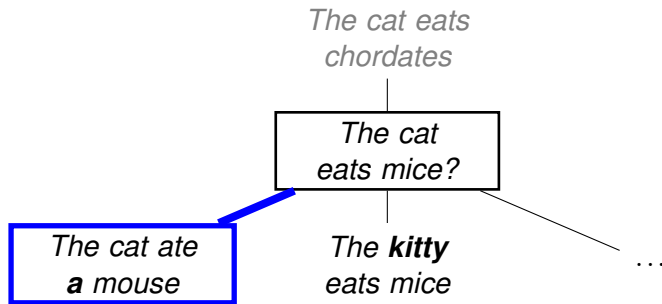
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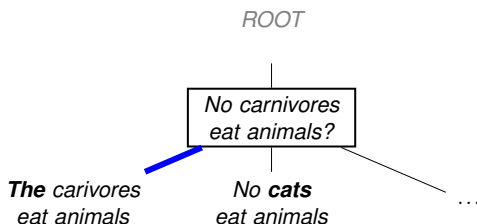
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An Example Search (with edges)



Template

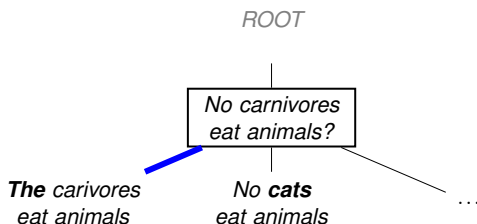
Instance

Edge

Operator Negate



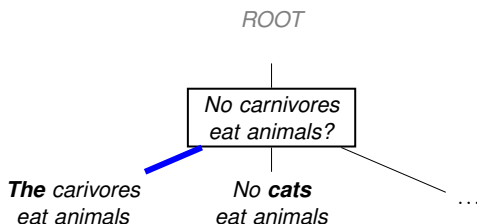
An Example Search (with edges)



Template	Instance	Edge
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An Example Search (with edges)



Template	Instance	Edge
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Edge Templates

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



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Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.



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Can learn parameters θ .



Contribution: Simple Transitivity

Taken for granted: $A \Rightarrow B$ and $B \Rightarrow C$ then $A \Rightarrow C$.



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- *nocturnal* $\xrightarrow{\downarrow}$ *diurnal*, *all* $\xrightarrow{\wedge}$ *not all*
∴ *all bats are nocturnal* $\xrightarrow{?}$ *not all bats are diurnal*



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\equiv	\equiv	\sqsubseteq	\supseteq	\uparrow	\Downarrow	\smile	#
\sqsubseteq	\sqsubseteq	\sqsubseteq	#	\Downarrow	\Downarrow	#	#
\supseteq	\supseteq	#	\supseteq	\smile	#	\smile	#
\uparrow	\uparrow	\smile	\Downarrow	\equiv	\supseteq	\sqsubseteq	#
\Downarrow	\Downarrow	#	\Downarrow	\sqsubseteq	#	\sqsubseteq	#
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#	#	#	#	#	#	#	#



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Taken for granted: $A \Rightarrow B$ and $B \Rightarrow C$ then $A \Rightarrow C$.

More complicated in (prior work on) Natural Logic:

- $\text{nocturnal} \xrightarrow{\downarrow} \text{diurnal}, \quad \text{all} \xrightarrow{\uparrow} \text{not all}$
 $\therefore \text{all bats are nocturnal} \xrightarrow{?} \text{not all bats are diurnal}$

\bowtie	\equiv	\sqsubseteq	\supseteq	\uparrow	\Downarrow	\smile	#
\equiv	\equiv	\sqsubseteq	\supseteq	\uparrow	\Downarrow	\smile	#
\sqsubseteq	\sqsubseteq	\sqsubseteq	#	\Downarrow	\Downarrow	#	#
\supseteq	\supseteq	#	\supseteq	\smile	#	\smile	#
\uparrow	\uparrow	\smile	\Downarrow	\equiv	\supseteq	\sqsubseteq	#
\Downarrow	\Downarrow	#	\Downarrow	\sqsubseteq	#	\sqsubseteq	#
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⊗	≡	⊆	⊇	人	↓	∪	#
≡	≡	⊆	⊇	人	↓	∪	#
⊆	⊆	⊆	#	↓	↓	#	#
⊇	⊇	#	⊇	#	#	∪	#
人	人	∪	↓	⊆	⊆	⊆	#
↓	↓	#	⊆	⊆	#	⊆	#
∪	∪	∪	⊆	⊇	⊇	#	#
#	#	#	#	#	#	#	#



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Natural Logic Analog of Transitivity:

State Fact

\Rightarrow *all bats are nocturnal,*

Mutation



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\Rightarrow	<i>not all bats are diurnal</i>	

- Complex *join table* can be reduced to tracking a simple binary distinction.



Experiments

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Not a blind test set!

- “Can we make deep inferences without knowing the premise *a priori*?”



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Our Knowledge Base:

- 270 million lemmatized Ollie extractions.



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- 4x improvement in recall.



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Complexity doesn't grow with knowledge base size.



Thanks!



<http://plato42.stanford.edu/naturalli>

