

NaturalLI: Natural Logic Inference for Common Sense Reasoning

Gabor Angeli, Chris Manning

Stanford University

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Natural Logic Inference for Common Sense Reasoning

Kittens play with yarn

Kittens play with computers

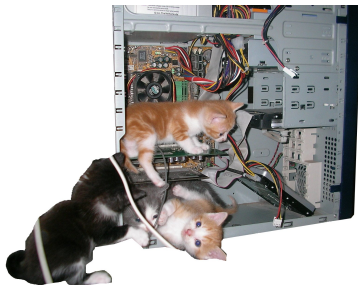


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Common Sense Reasoning for NLP

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

cakes are eaten using cherries



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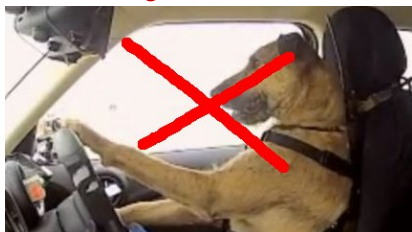
Put a sarcastic comment in your talk. That's a great idea.

Sarcasm in your talk is a great idea



Common Sense Reasoning for Vision

Dogs drive cars

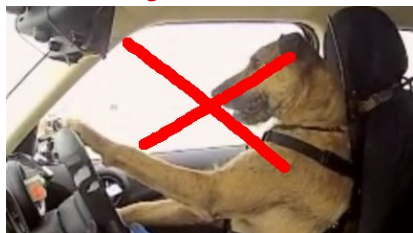


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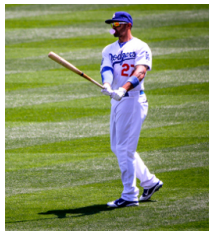
People drive cars



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.

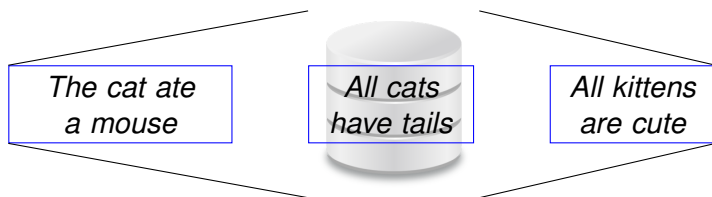
- OpenIE (Yates et al., 2007), NELL (Carlson et al., 2010).
- *Extraction* of facts from a large corpus; fuzzy lookup.



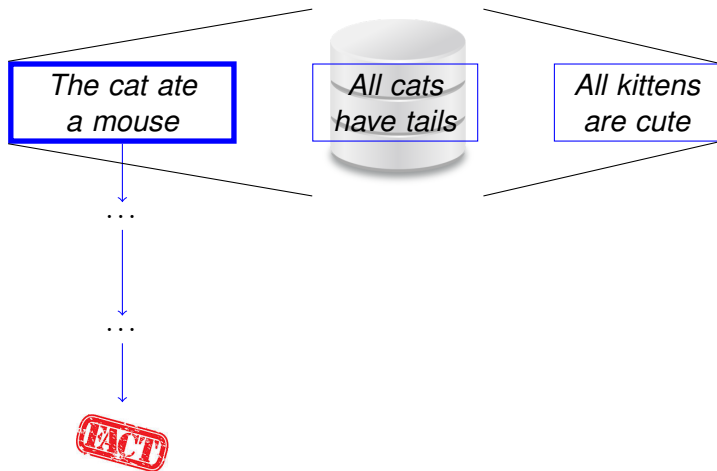
Start with a large knowledge base



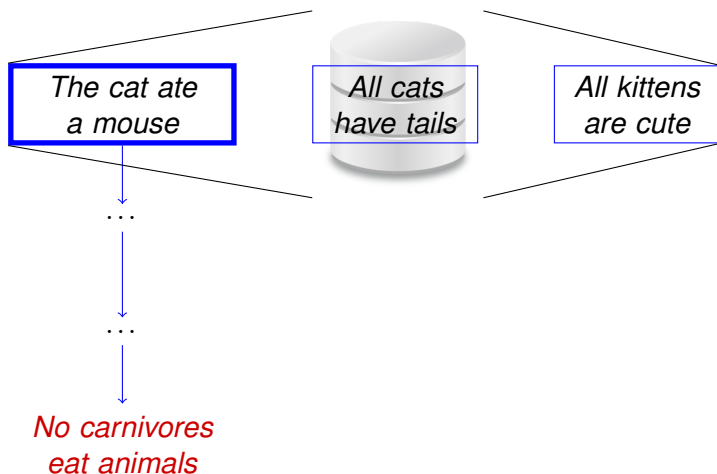
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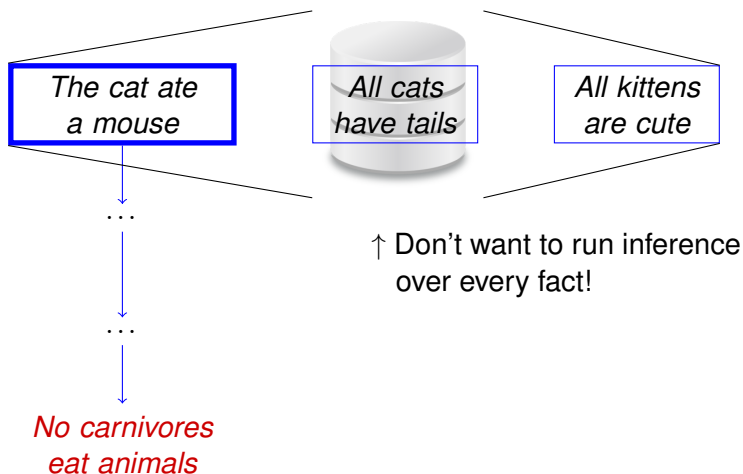
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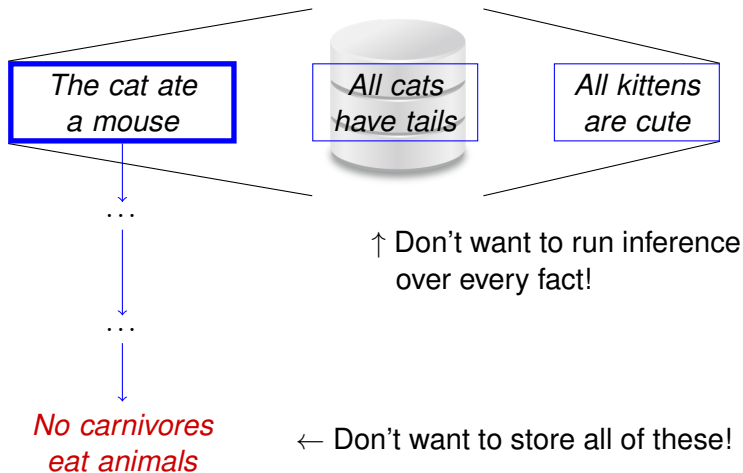
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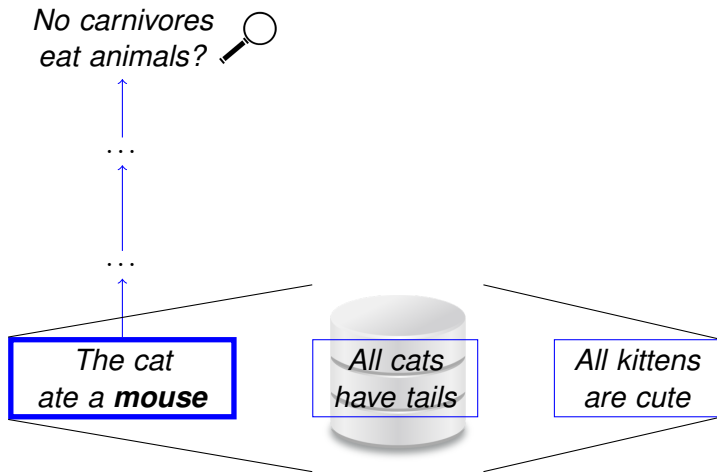
Infer new facts...



Infer new facts...



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



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

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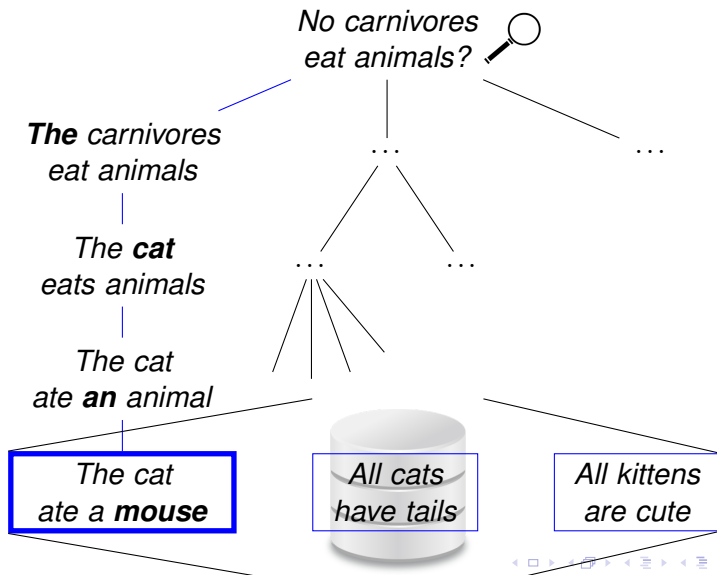
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All cats
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...Without aligning to any particular premise.



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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Natural Logic



Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

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(*all mice are rodents*)

∴ *Some cat ate a **rodent***



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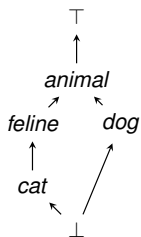
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Facts are text; inference is lexical mutation



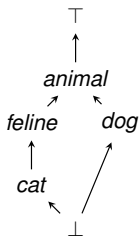
Natural Logic and Polarity

Treat hypernymy as a *partial order*.

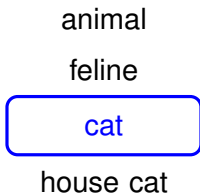


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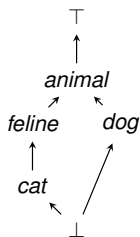


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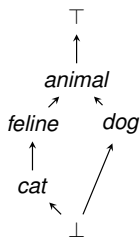


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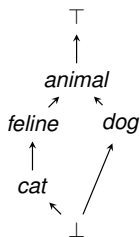


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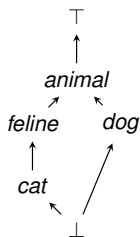


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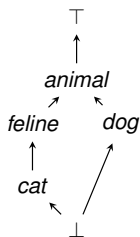


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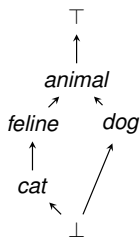


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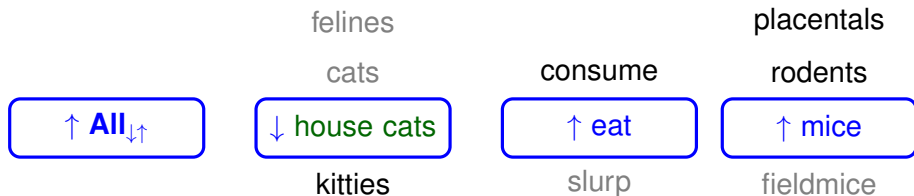
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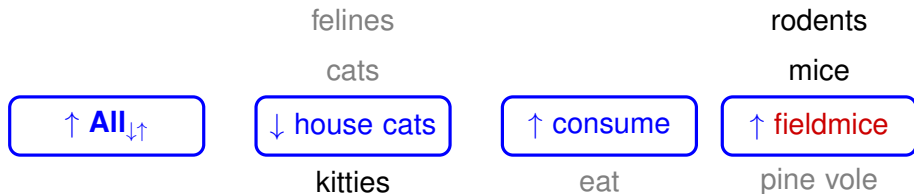
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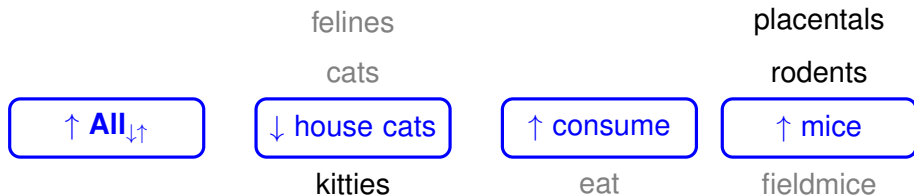
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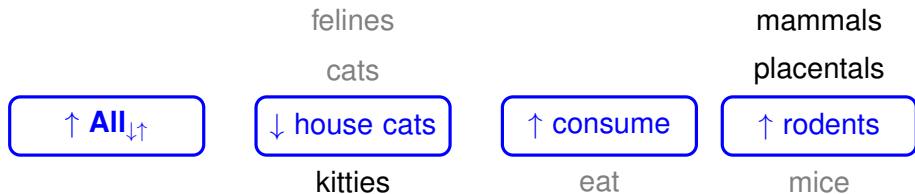


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Inference is reversible.



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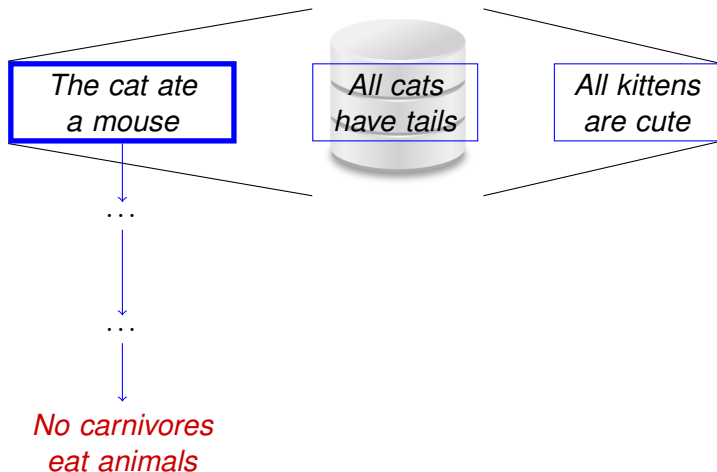


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 - We expect *readers* to make these inferences instantly.



Natural Logic Inference is Search



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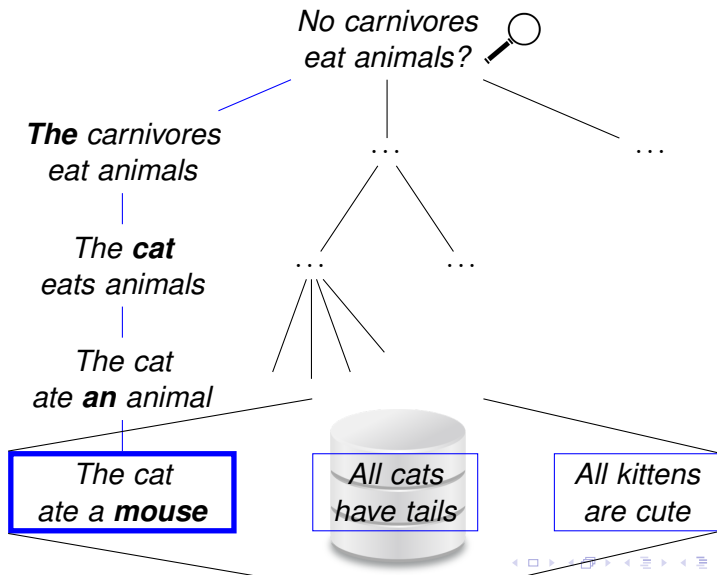
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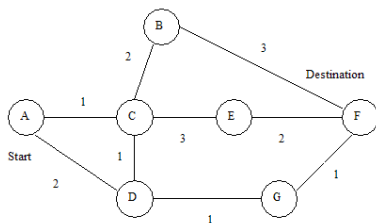
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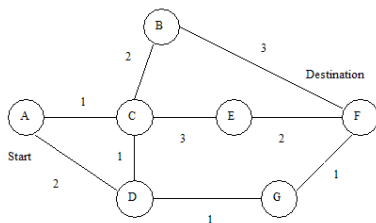
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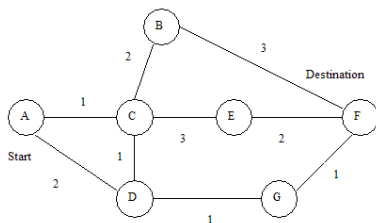
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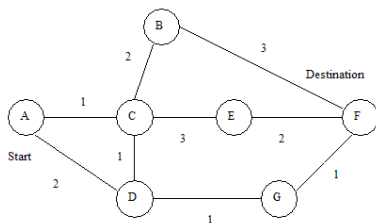
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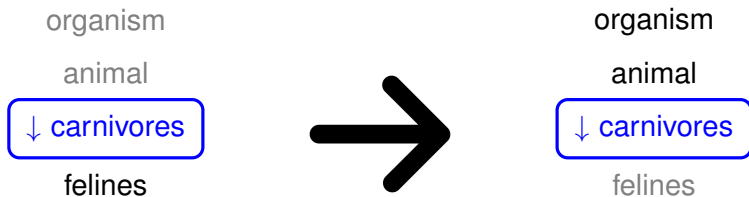
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Edge Costs How “wrong” an inference step is (learned)



An Example Search (as reverse inference)

Search mutates *opposite* to polarity



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Truth
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true

Current
Node:



An Example Search (as reverse inference)

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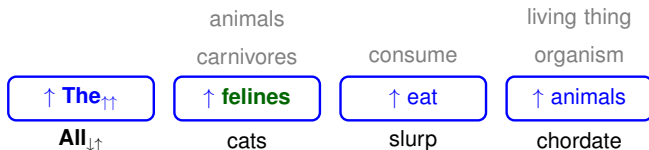


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An Example Search (as graph search)

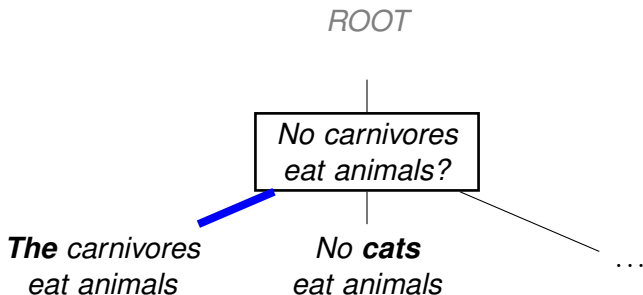
Shorthand for a node:



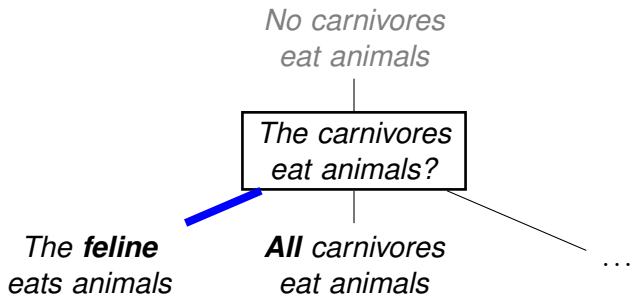
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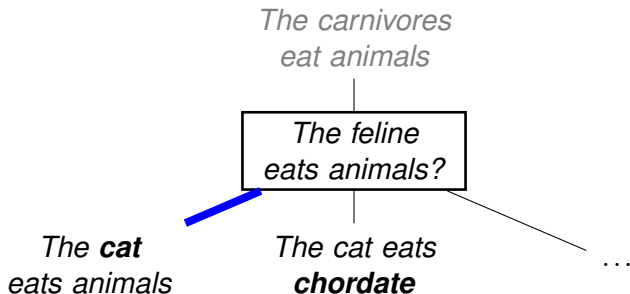
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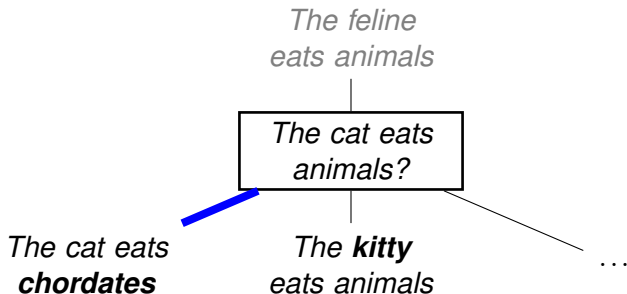
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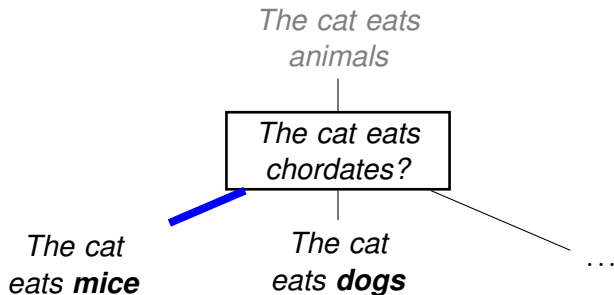
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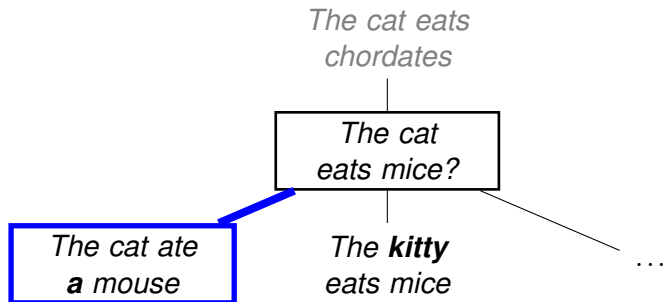
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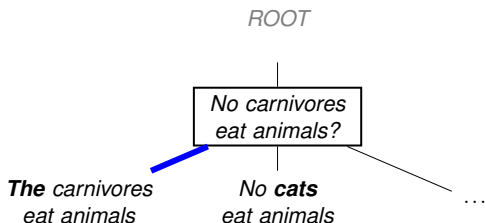
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An Example Search (with edges)



Template

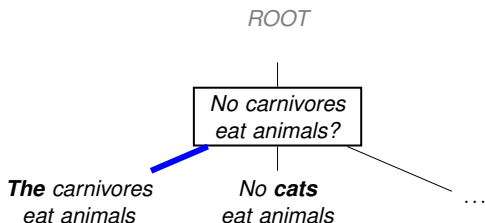
Instance

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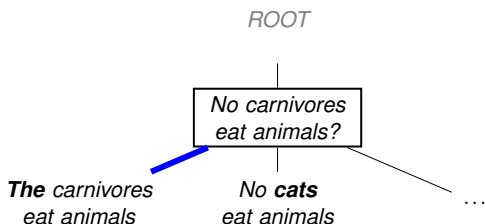
Edge

Operator Negate

No → The



An Example Search (with edges)



Template	Instance	Edge
Operator Negate	<i>No</i> → <i>The</i>	<i>No carnivores eat animals</i> → <i>The carnivores eat animals</i>



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>



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Can learn parameters θ .



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



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More complicated in (prior work on) Natural Logic:

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∴ *all bats are nocturnal* $\stackrel{?}{\rightarrow}$ *not all bats are diurnal*



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≡	≡	⊆	⊇	人	↓	∪	#
⊆	⊆	⊆	#	↓	↓	#	#
⊇	⊇	#	⊇	∪	#	∪	#
人	人	∪	↓	≡	⊇	⊆	#
↓	↓	#	↓	⊆	#	⊆	#
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⊃	⊃	#	⊃	∪	#	∪	#
人	人	∪	↓	≡	⊃	⊆	#
↓	↓	#	↓	⊆	#	⊆	#
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More complicated in (prior work on) Natural Logic:

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

⊗	≡	⊆	⊇	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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- Complex *join table* can be reduced to tracking a simple binary distinction.



Experiments

FraCaS Textual Entailment Suite:

- Used in MacCartney and Manning (2007; 2008).
- RTE-style problems: is the hypothesis entailed from the premise?
P: At least three commissioners spend a lot of time at home.
H: *At least three commissioners spend time at home.*
P: At most ten commissioners spend a lot of time at home.
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Not a blind test set!

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



FraCaS Results

Systems

M07: MacCartney and Manning (2007)

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- *Classify* entailment after aligning premise and hypothesis.

N: NaturalLI (this work)

- *Search* blindly from hypothesis for the premise.



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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.
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Our Knowledge Base:

- 270 million lemmatized Ollie extractions.



ConceptNet Results

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- 4x improvement in recall.



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Takeaways

- *Deep* inferences from a *large* knowledge base.
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Complexity doesn't grow with knowledge base size.



Thanks!

