NaturalLI: Natural Logic Inference for Common Sense Reasoning

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Natural Logic Inference for Common Sense Reasoning

Kittens play with yarn

Kittens play with computers





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The city refused the demonstrators a permit because they feared 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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I ate the cake with a cherry vs. I ate the cake with a fork cakes come with cherries cakes are eaten using cherries

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



People drive cars



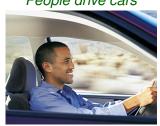


Common Sense Reasoning for Vision

Dogs drive cars



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Baseball is played underwater



Baseball is played on grass





Prior Work on Common Sense Reasoning

Old School Al: Nuanced reasoning; tiny coverage.

- Default reasoning (Reiter 1980; McCarthy 1980).
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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.

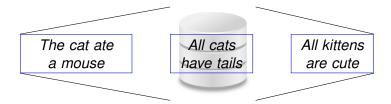


Start with a large knowledge base

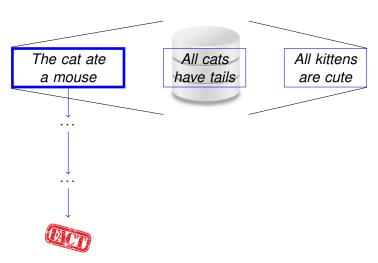




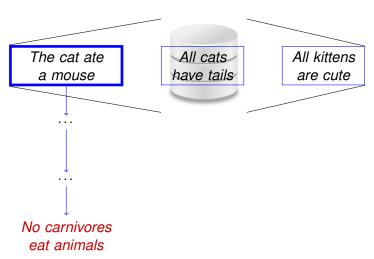
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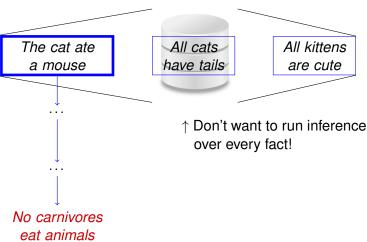




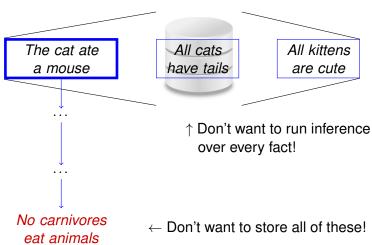






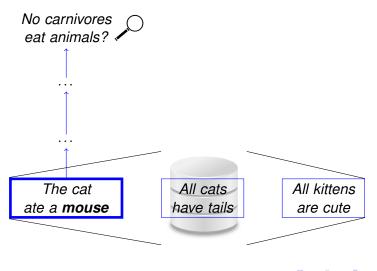






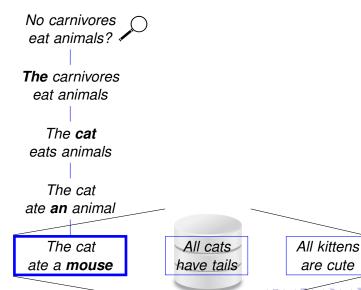


Infer new facts...on demand from a query...



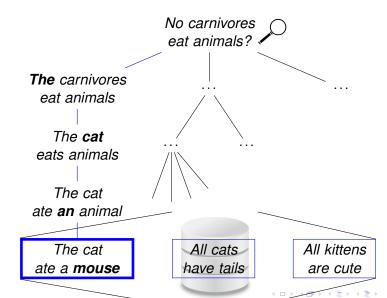


... Using text as the meaning representation...





...Without aligning to any particular premise.





Lookup in 270 million entry KB...

...by lemmas 12% recall

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



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Natural Logic



s/Natural Logic/Syllogistic Reasoning/g

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



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Cognitively easy inferences are easy:

- Most cats eat mice
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Facts are text; inference is lexical mutation



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

animal
feline
cat
house cat



8 / 22

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



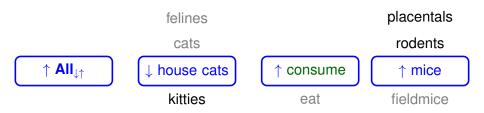


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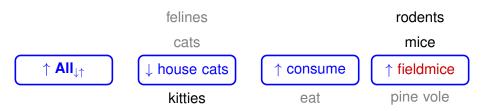


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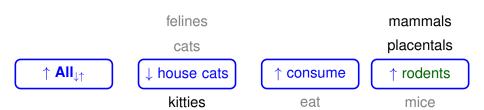


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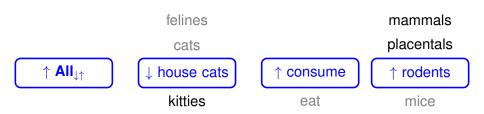




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Mutations must respect polarity.

Inference is reversible.





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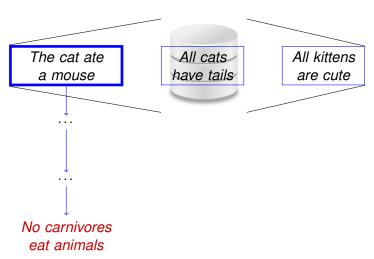
10 / 22

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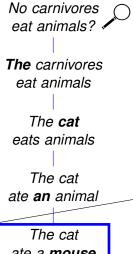
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 - We expect readers to make these inferences instantly.







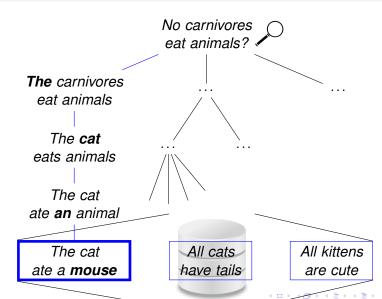




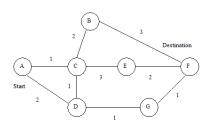
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All cats have tails All kittens are cute





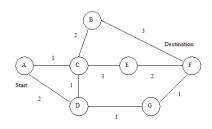




Nodes

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

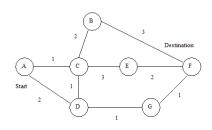




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Start Node (query fact, true) any known fact **End Nodes**





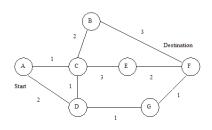
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Search mutates *opposite* to polarity





Truth true maintained:





Truth false maintained:





Truth false maintained:





Truth false maintained:





Truth false maintained:





Truth false maintained:





Truth false maintained:





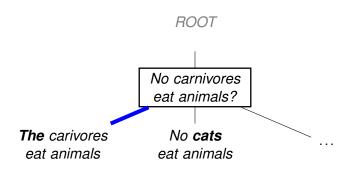
Shorthand for a node:



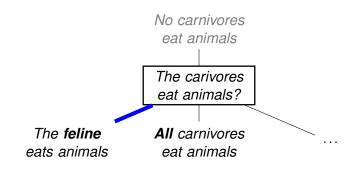


No carnivores eat animals?



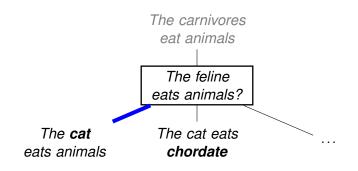




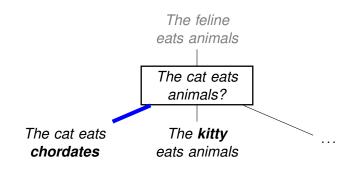




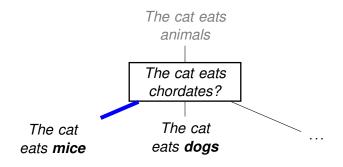






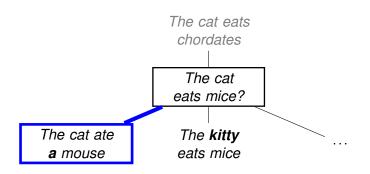






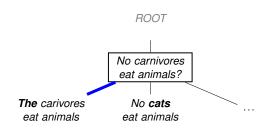








An Example Search (with edges)

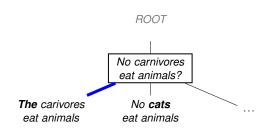


Template Instance Edge

Operator Negate



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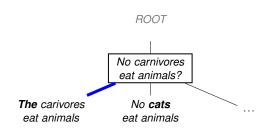


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An Example Search (with edges)



Template Instance Edge No carnivores eat animals \rightarrow Operator Negate $No \rightarrow The$ The carnivores eat animals



Edge Templates

Template Instance Hypernym animal \rightarrow cat Hyponym $cat \rightarrow animal$ $good \rightarrow bad$ Antonym 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

 $cat \rightarrow dog$



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



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October 26, 2014

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Natural Logic Analog of Transitivity:

State **Fact** 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.
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Not a blind test set!

 "Can we make deep inferences without knowing the premise a priori?"



FraCaS Results

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M07: MacCartney and Manning (2007)

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Classify entailment after aligning premise and hypothesis.

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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:

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• 4x improvement in recall.



Conclusions

Takeaways

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Complexity doesn't grow with knowledge base size.



Thanks!



http://plato42.stanford.edu/naturalli



