NaturalLI: Natural Logic Inference for Common Sense Reasoning

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Stanford University

October 26, 2014

Natural Logic Inference for **Common Sense Reasoning**

Kittens play with yarn

Kittens play with computers

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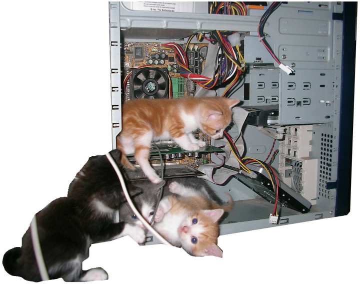

Common Sense Reasoning for NLP

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

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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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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

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).
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- RTE Challenges.
- Episodic Logic (Schubert, 2002).

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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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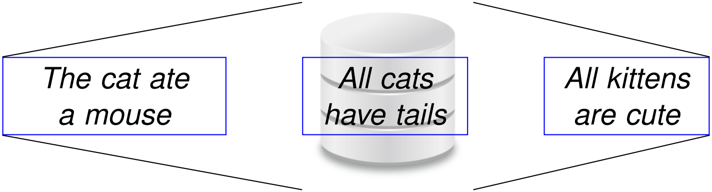

Infer new facts...

The cat ate a mouse

All cats have tails

All kittens are cute

...

...

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No carnivores eat animals

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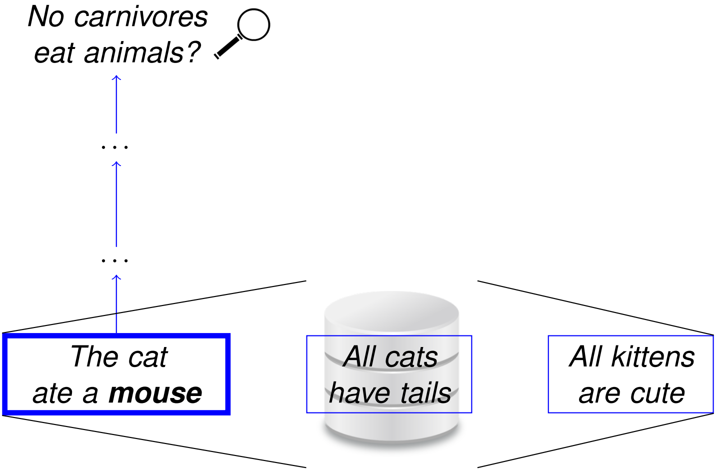
← Don't want to store all of these!

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



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

No carnivores eat animals?

__The__ carnivores eat animals

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The cat ate __an__ animal

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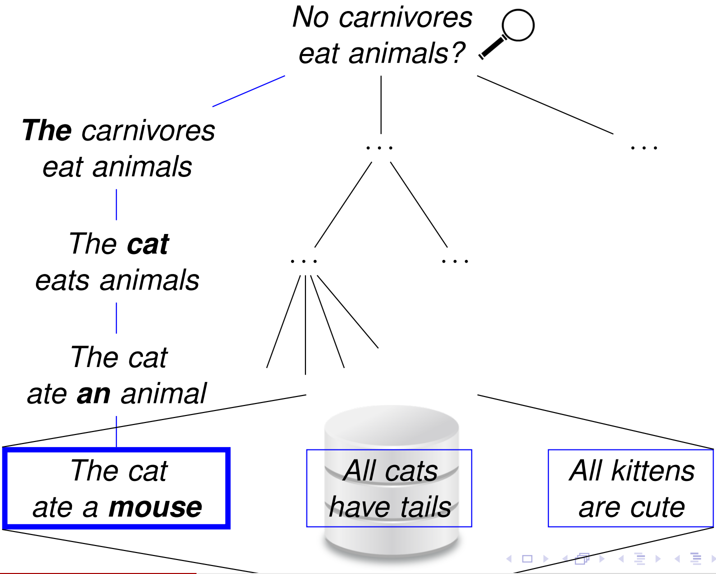
...Without aligning to any particular premise.



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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Maintain good properties of fuzzy lookup.

- Fast.
- Minimal pre-processing of query.
- Minimal pre-processing of knowledge base.

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Natural Logic

Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

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

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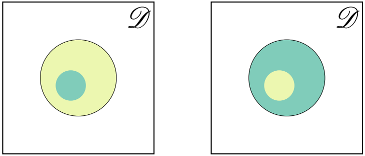
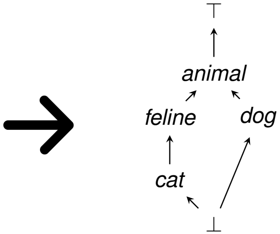
Facts are text; inference is lexical mutation

Natural Logic and Polarity

Hypernymy is a *bounded distributive lattice*.



cat $\subseteq$ *feline* *feline* $\subseteq$ *animal*



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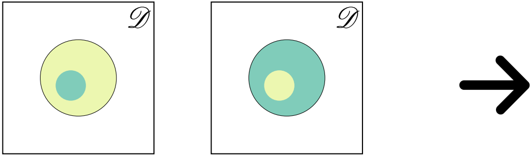

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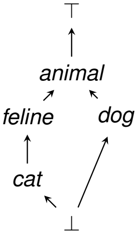

***Polarity* is the direction a lexical item can move along the lattice.**

animal

feline

cat

house cat

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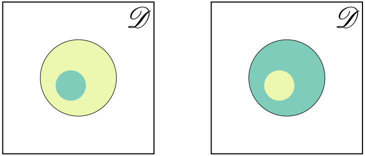

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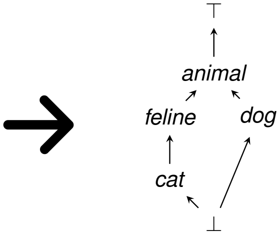

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animal

feline

$\boxed{\uparrow \text{cat}}$

house cat

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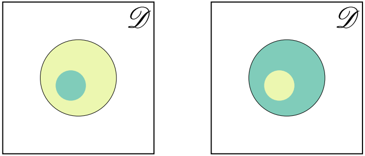

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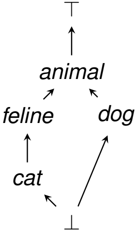

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living thing

animal

$\boxed{\uparrow \text{feline}}$

cat

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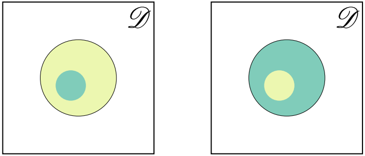

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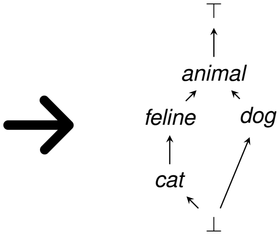

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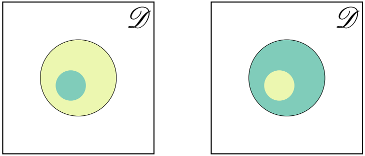

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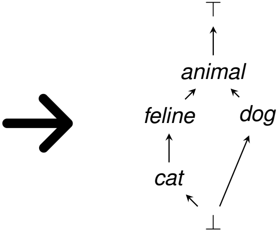

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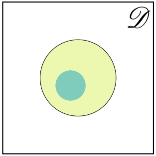

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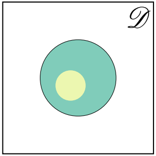

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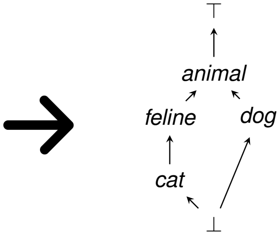

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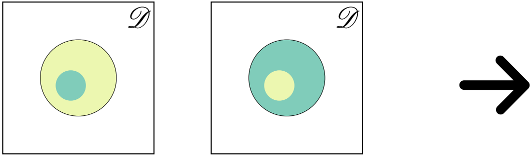

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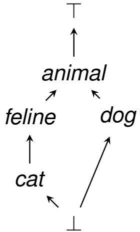

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house cat

An Example Inference

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

↑ **All**$_{\downarrow\uparrow}$	↓ cats	↑ eat	↑ mice

carnivores

felines

house cats

consume

slurp

placentals

rodents

fieldmice

An Example Inference

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

Mutations must respect *polarity*.

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

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An Example Inference

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Mutations must respect *polarity*.

Inference is reversible

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

Properties of Natural Logic

✓ Computationally fast during inference.

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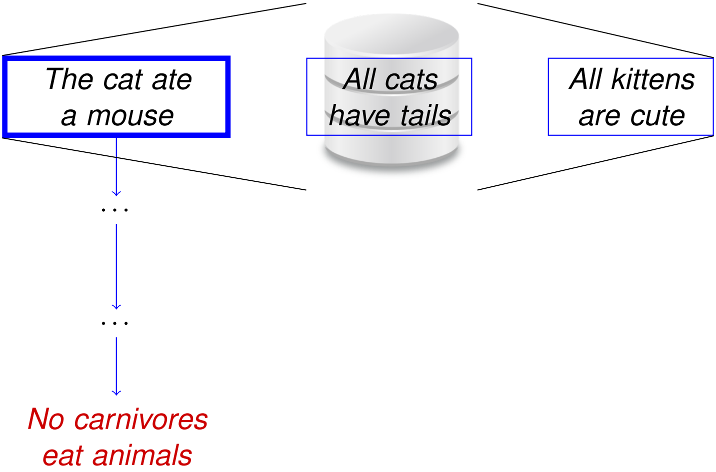
✓ Still captures common inferences.

- We make these types of inferences regularly and instantly.
- We expect *readers* to make these inferences instantly.

Natural Logic Inference is Search



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No carnivores eat animals?

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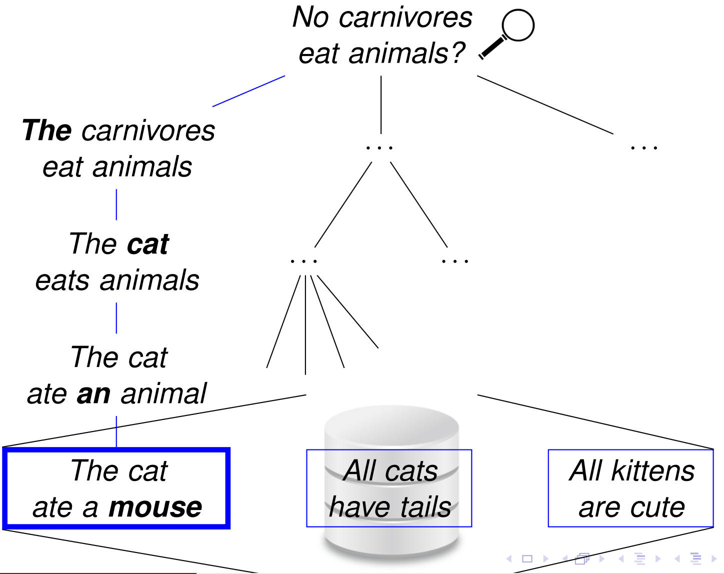

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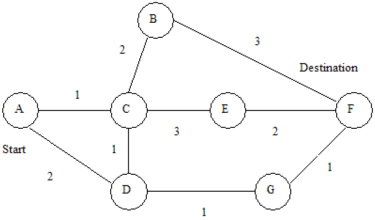

Nodes (*fact*, truth maintained $\in \{\text{true}, \text{false}\}$)

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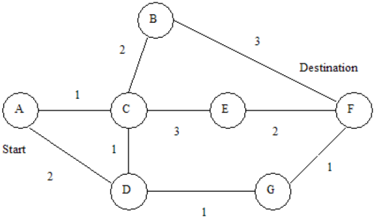

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End Nodes *any known fact*

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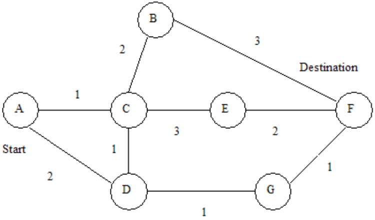

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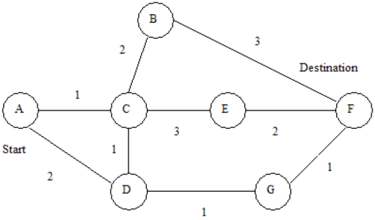

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Edges Mutations of the current fact
Edge Costs How "wrong" an inference step is (learned)

An Example Search (as reverse inference)

Search mutates *opposite* to polarity

organism		organism
animal	→	animal
↓ carnivores		↓ carnivores
felines		felines

An Example Search (as reverse inference)

Truth maintained: *true*

		organism		living thing
		animal	consume	organism
Current Node:	↑ **No**$_{\downarrow\downarrow}$	↓ carnivores	↓ eat	↓ animals
		felines	slurp	chordate

An Example Search (as reverse inference)

Truth maintained: *false*

		organism		living thing
		animal	consume	organism
Current Node:	$\uparrow$ **The**$_{\uparrow\uparrow}$	$\uparrow$ carnivores	$\uparrow$ eat	$\uparrow$ animals
	All$_{\downarrow\uparrow}$	felines	slurp	chordate

An Example Search (as reverse inference)

Truth maintained: *false*

		animals		living thing
		carnivores	consume	organism
Current Node:	$\uparrow$ **The**$_{\uparrow\uparrow}$	$\uparrow$ **felines**	$\uparrow$ eat	$\uparrow$ animals
	All$_{\downarrow\uparrow}$	cats	slurp	chordate

An Example Search (as reverse inference)

Truth maintained: *false*

		carnivores		living thing
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Truth maintained: *false*

		carnivores		organisms
		felines	consume	animals
Current Node:	$\uparrow$ **The**$_{\uparrow\uparrow}$	$\uparrow$ cats	$\uparrow$ eat	$\uparrow$ **chordates**
	All$_{\downarrow\uparrow}$	kitties	slurp	mice

An Example Search (as reverse inference)

Truth maintained: *false*

		carnivores		animals
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Current Node:	$\uparrow$ **The**$_{\uparrow\uparrow}$	$\uparrow$ cats	$\uparrow$ eat	$\uparrow$ **mice**
	All$_{\downarrow\uparrow}$	kitties	slurp	fieldmice

An Example Search (as reverse inference)

Truth maintained: *false*

Current Node:

	carnivore			animal
	feline	consumed		chordate
$\uparrow$ **The**$_{\uparrow\uparrow}$	$\uparrow$ cat	$\uparrow$ ate	$\uparrow$ **a**$_{\uparrow\uparrow}$	$\uparrow$ mouse
All$_{\downarrow\uparrow}$	kitty	slurped	**All**$_{\downarrow\uparrow}$	fieldmouse

An Example Search (as graph search)

Shorthand for a node:

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

No carnivores eat animals?

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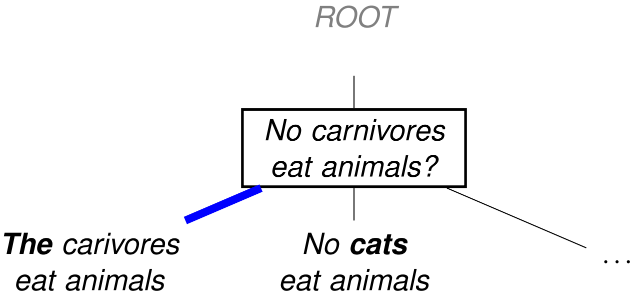

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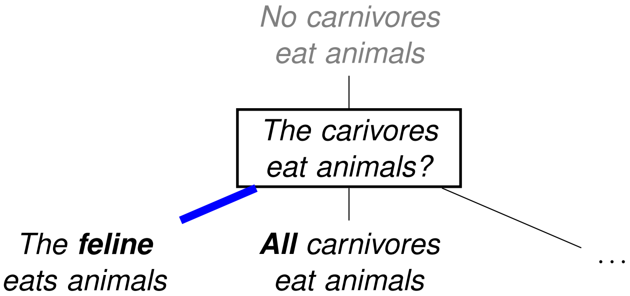

An Example Search (as graph search)

The carnivores eat animals

The feline eats animals?

*The **cat** eats animals*

*The cat eats **chordate***

...

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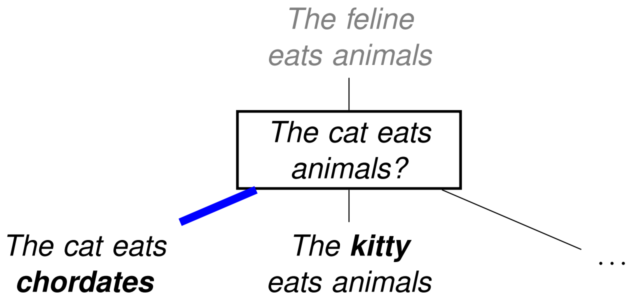

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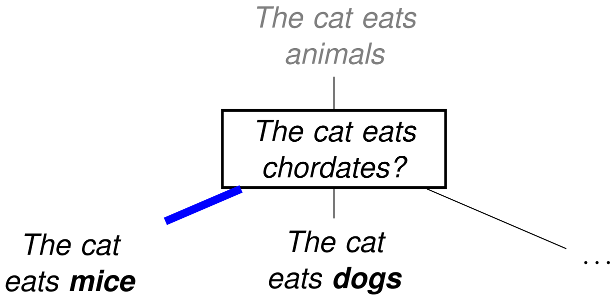

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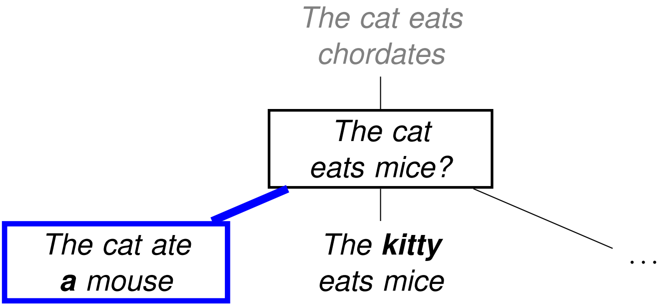

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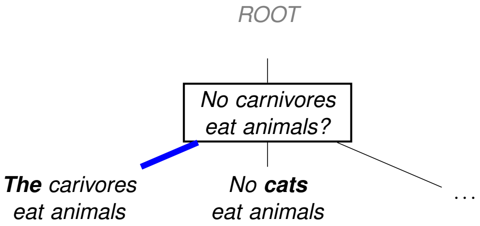

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Operator Negate		

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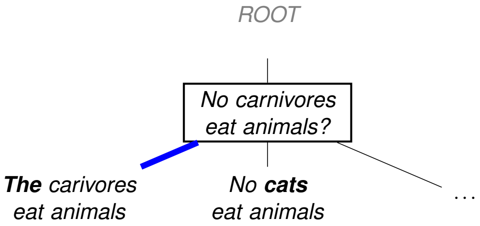
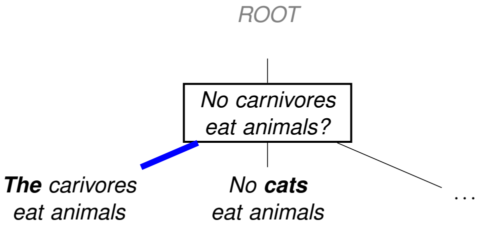


Template	Instance	Edge
Operator Negate	*No* → *The*	

An Example Search (with edges)



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

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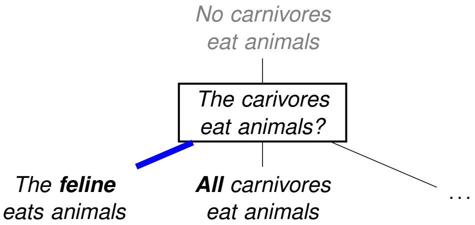

Template	**Instance**	**Edge**
Hypernym	*carnivore* $\rightarrow$ *feline*	*The carnivores eat animals* $\rightarrow$ *The feline eats animals*

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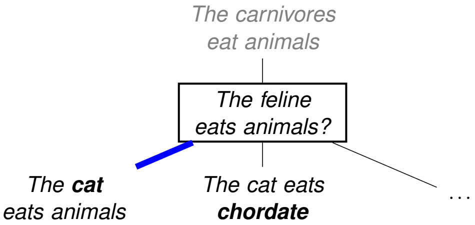

Template	**Instance**	**Edge**
Hypernym	*feline* $\rightarrow$ *cat*	*The feline eats animals* $\rightarrow$ *The cat eats animals*

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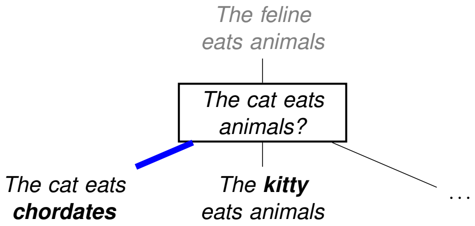

Template	**Instance**	**Edge**
Hypernym	*animal* $\rightarrow$ *chordate*	*The cat eats animals* $\rightarrow$ *The cat eats chordates*

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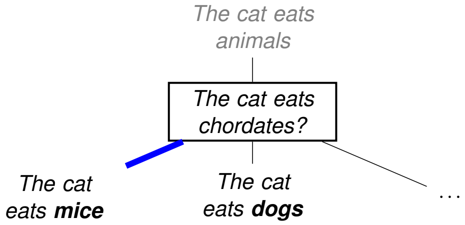

Template	**Instance**	**Edge**
Hypernym	*chordate* $\rightarrow$ *mice*	*The cat eats chordates* $\rightarrow$ *The cat eats mice*

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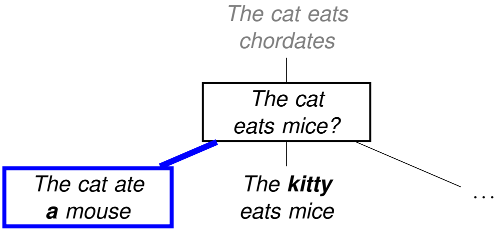

Template	**Instance**	**Edge**
Delete Existential	$\cdot \rightarrow a$	*The cat eats mice* $\rightarrow$ *The cat ate a mouse*

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$\bowtie$	$\equiv$	$\sqsubseteq$	$\sqsupseteq$	$\curlywedge$	$\mid$	$\smile$	$\#$
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$\sqsubseteq$	$\sqsubseteq$	$\sqsubseteq$	$\#$	$\mid$	$\mid$	$\#$	$\#$
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$\mid$	$\mid$	$\#$	$\mid$	$\sqsubseteq$	$\#$	$\sqsubseteq$	$\#$
$\smile$	$\smile$	$\smile$	$\#$	$\sqsupseteq$	$\sqsupseteq$	$\#$	$\#$
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$\sqsubseteq$	$\sqsubseteq$	$\sqsubseteq$	$\#$	$\upharpoonleft\downharpoonright$	$\upharpoonleft\downharpoonright$	$\#$	$\#$
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$\curlywedge$	$\curlywedge$	$\smile$	$\upharpoonleft\downharpoonright$	$\equiv$	$\sqsupseteq$	$\sqsubseteq$	$\#$
$\upharpoonleft\downharpoonright$	$\upharpoonleft\downharpoonright$	$\#$	$\upharpoonleft\downharpoonright$	$\sqsubseteq$	$\#$	$\sqsubseteq$	$\#$
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- Maintain correct Natural Logic inference tracking only *valid* and *invalid* at each state.

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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.

ConceptNet Results

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- 4x improvement in recall.

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Takeaways

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Strictly better fuzzy queries

- Checks logical entailment, not just *fuzziness*
- Support doesn’t have to be lexically similar

Thanks!

http://plato42.stanford.edu/naturalli