Natural Language Inference for Question Answering

Gabor Angeli

Stanford University

April 14, 2015

My View on Question Answering

Two parts to question answering:

- Understanding the question
- Understanding the corpus (IE)

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    [Angeli et al., 2014a, Angeli et al., 2014b]
  - What facts are entailed by the corpus?
    [ACL OpenIE Submission]
  - How do we find if a fact is entailed by the corpus?
    [Angeli and Manning, 2013, Angeli and Manning, 2014]

Challenges that Inference Will Solve

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Questions don't always talk about named entities

- ✓ *Where was Barack Obama born?*
- ? *What treatments are there for diabetes?*
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Answers aren't always literally justified in text

- ✓ *Born in Hawaii, Barack Obama ...*
- ? *Doctors prescribe Insulin for Diabetes.*
- ✗ *All animals have tails.*

No entailment: What facts are in the corpus?

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Relation Extraction + TAC-KBP

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- Done: KBP 2013 – 2014
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Does it address the challenges?

- Fixed relation schema
- Very named-entity-centric
- Zero entailments from text

Mini-Entailment: List facts entailed by corpus

Extract maximally informative, correct things

Natural Logic + OpenIE (ACL submission)

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Does it address the challenges?

- Open relation schema
- Named entity agnostic
- Only limited entailment from text

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- Open relation schema
- Named entity agnostic
- Large class of entailments from corpus

Main Idea of Thesis

Natural language inference allows us to leverage latent information in plain text to find support for enough types of questions to be useful for open-domain QA.

KBP: Directly find facts in text

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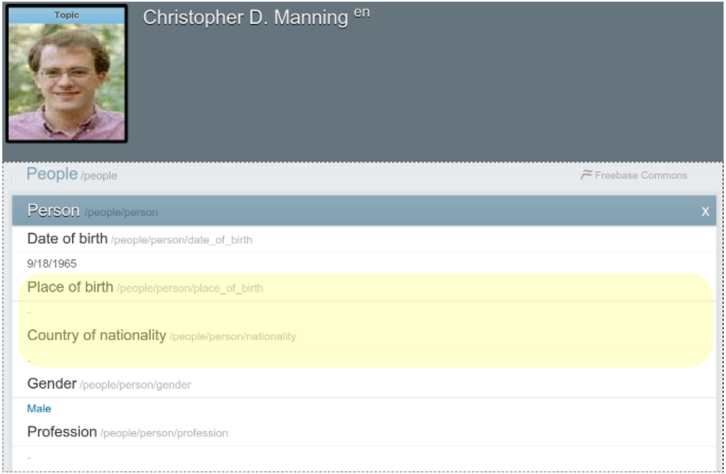

KBP: Directly find facts in text

Christopher Manning

Professor of Linguistics and Computer Science

Natural Language Processing Group, Stanford University

Brief Bio

- I'm Australian ("I come from a land of wide open spaces ...")
- BA (Hons) Australian National University 1989 (majors in mathematics, computer science and linguistics)
- PhD Stanford Linguistics 1995
- Asst Professor Carnegie Mellon University Computational Linguistics Program 1994-96
- Lecturer University of Sydney Dept of Linguistics 1996-99
- Asst Professor Stanford University Depts of Computer Science and Linguistics 1999-2006
- Assoc Professor Stanford University Depts of Linguistics and Computer Science 2006-2012
- Professor Stanford University Depts of Linguistics and Computer Science 2012-

KBP: Directly find facts in text

Active Learning for Relation Extraction

Input: Sentences containing (entity, slot value).
Output: Relation between entity and slot value.

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  But. . .

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- **Distantly Supervised:** Artificially produce "supervised" data.
  Training data: $\{$(entity, relation, slot value)$\}$.
  But...

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- **Supervised:** Trivial as a supervised classifier.
  Training data: {(sentence, relation)}.
  But… this training data is expensive to produce.

- **Distantly Supervised:** Artificially produce "supervised" data.
  Training data: {(entity, relation, slot value)}.
  But… this training data is much more noisy.

Active Learning: Combine Benefits of Both

Adding carefully selected supervision improves distantly supervised relation extraction.

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Old problem: Supervision is expensive, but very useful.

Old solution: Active learning!

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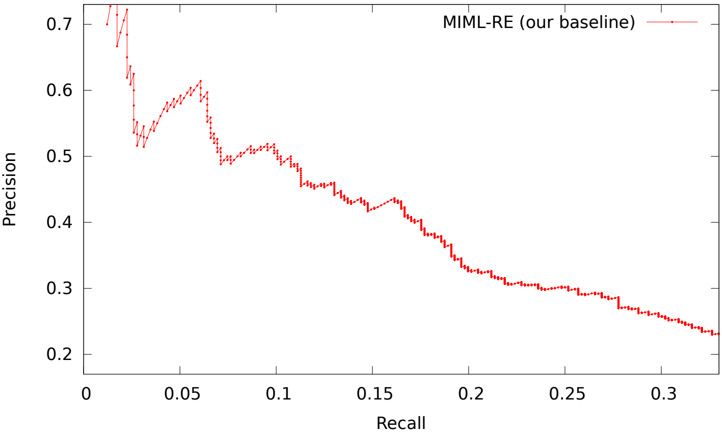
- Select a subset of sentences to annotate.
- Fix these labels during training.

State-of-the-art results

Slot filling evaluation of Surdeanu et al. (2012).



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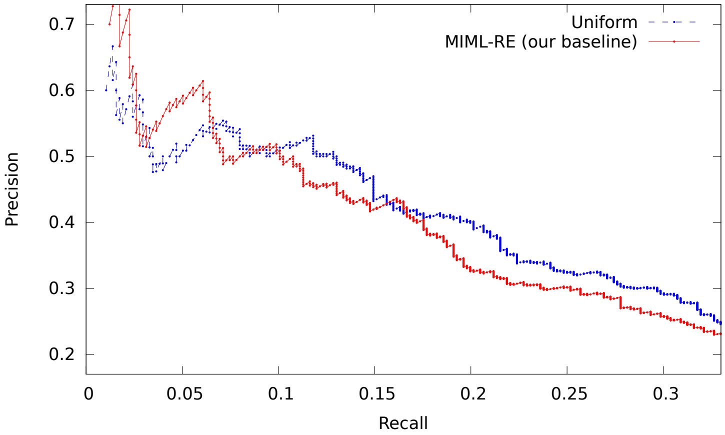

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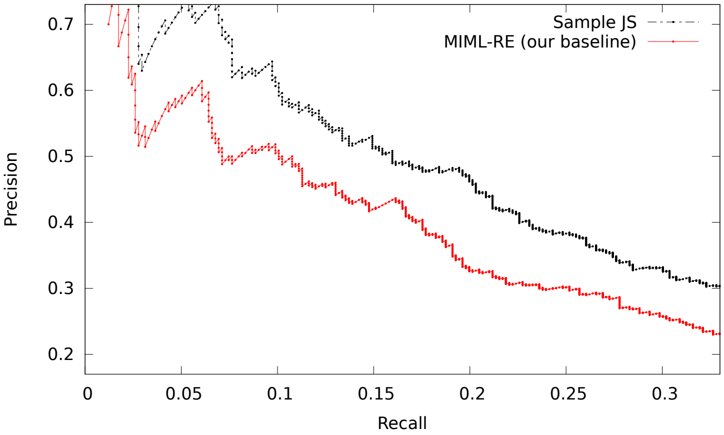

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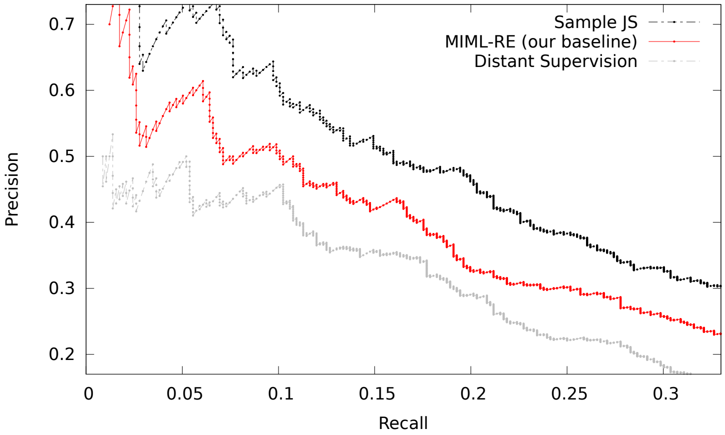

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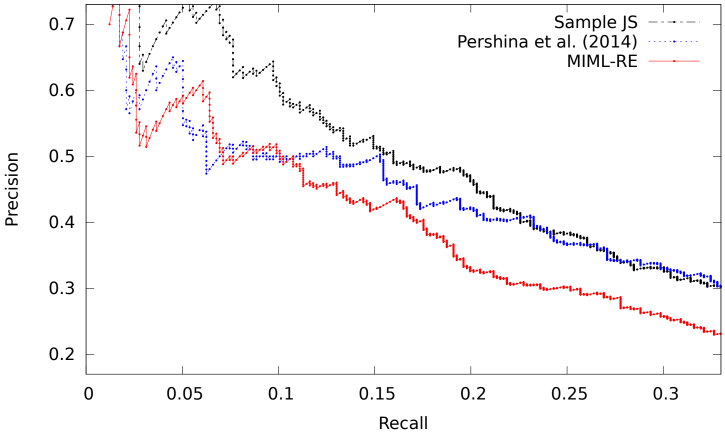

KBP is already "entailment"

Chris, a tenured professor at Stanford, is friends with Fei-Fei

$\Rightarrow$ *Chris is a tenured professor at Stanford*

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$\Rightarrow$ *Chris is employed by Stanford*

$\Rightarrow$ (*Chris*; *employee_of*; *Stanford*)

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Born in a small town, she took the midnight train going anywhere

$\Rightarrow$ *She took the midnight train going anywhere*

$\Rightarrow$ *She took the midnight train*

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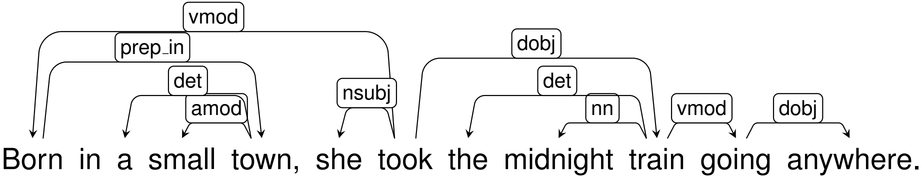
$\Rightarrow$ (*She*; *took*; *midnight train*)

Treat As Entailment



(input)

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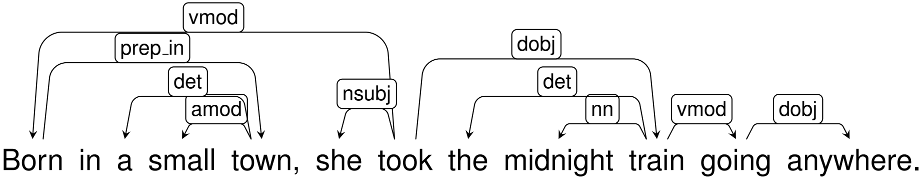

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↓

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she took the midnight train
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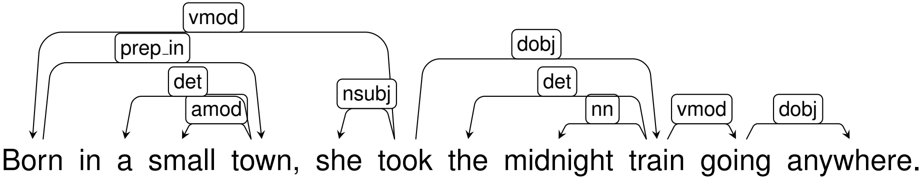

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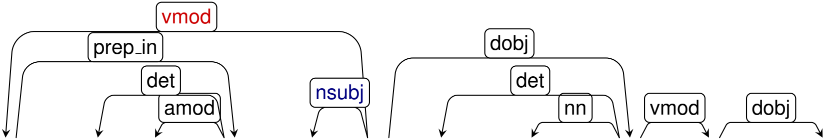

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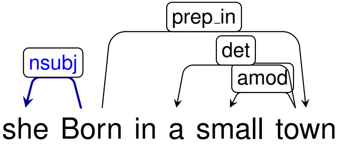

(extracted clause)

↓

she Born in small town

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she Born in town

↓

(she; born in; small town)

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Chris, a tenured professor at Stanford, is friends with Fei-Fei
$\Rightarrow$ (*Chris*; *is friends with*; *Fei-Fei*)

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3. Optionally segment into triples

State-of-the-art OpenIE

KBP 2013 end-to-end evaluation:

System	P	R	F_1
UW Official	**69.8**	11.4	19.6
Ollie	57.4	4.8	8.9
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Facts are text; inference is lexical mutation

Natural Logic and Polarity

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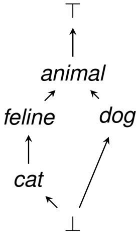

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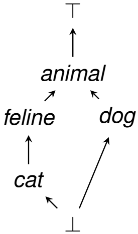

Polarity **is the direction a lexical item can move in the ordering.**

animal

feline

$\boxed{\text{cat}}$

house cat

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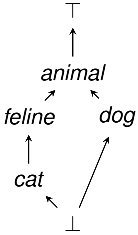

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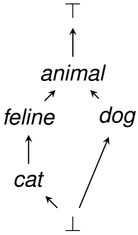

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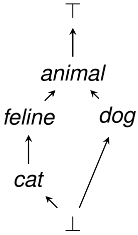

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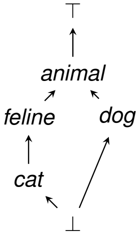

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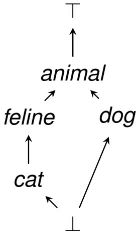

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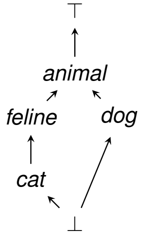

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An Example Inference

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

Mutations must respect *polarity*.

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	kitties	eat	pine vole

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Inference is reversible.

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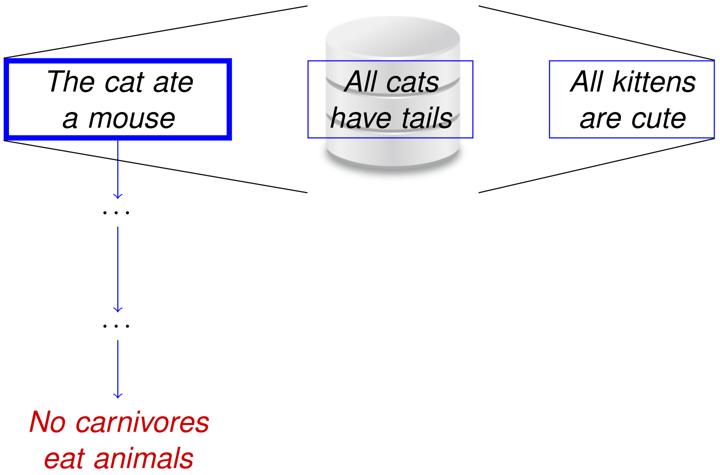
Natural Logic Inference is Search



Natural Logic Inference is Search

No carnivores eat animals?

__The__ carnivores eat animals

The __cat__ eats animals

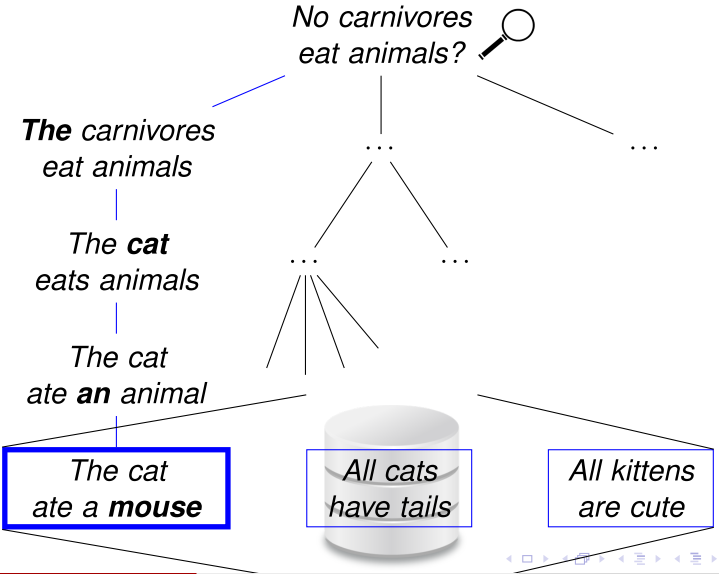
The cat ate __an__ animal

The cat ate a __mouse__

All cats have tails

All kittens are cute

Natural Logic Inference is Search



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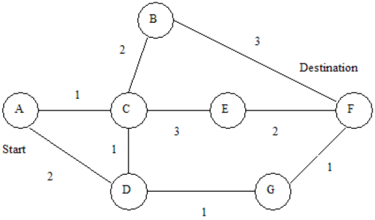

Nodes (*fact*, truth maintained $\in \{\text{true}, \text{false}\}$)

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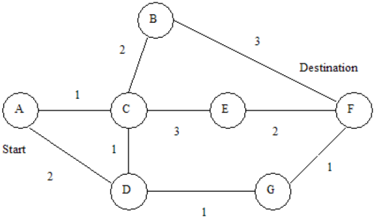

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Start Node (*query fact*, *true*)

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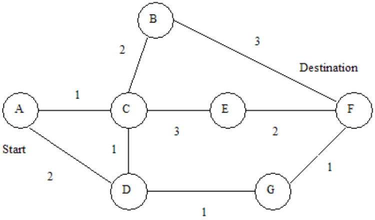
Natural Logic Inference is Search



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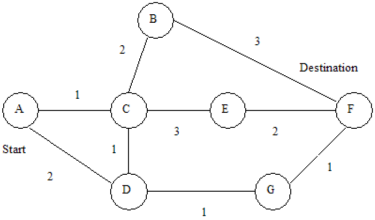

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Edges Mutations of the current fact
Edge Costs How "wrong" an inference step is (learned)

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:	↑ **The**$_{\uparrow\uparrow}$	↑ carnivores	↑ eat	↑ animals
	All$_{\downarrow\uparrow}$	felines	slurp	chordate

An Example Search (as reverse inference)

Truth maintained: *false*

Current Node:

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

An Example Search (as reverse inference)

Truth maintained: *false*

Current Node:

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

An Example Search (as reverse inference)

Truth maintained: *false*

Current Node:

	carnivores		organisms
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$\uparrow$ **The**$_{\uparrow\uparrow}$	$\uparrow$ cats	$\uparrow$ eat	$\uparrow$ **chordates**
All$_{\downarrow\uparrow}$	kitties	slurp	mice

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Truth maintained: *false*

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

An Example Search (as reverse inference)

Truth maintained: *false*

	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

Current Node:

An Example Search (as graph search)

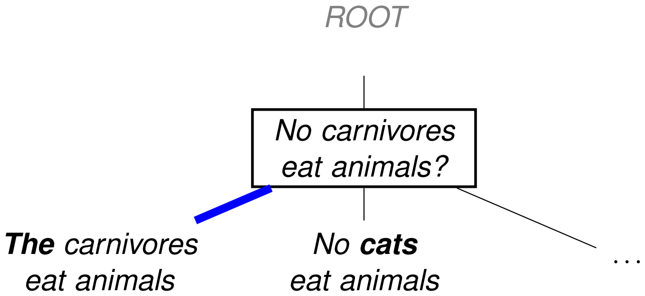
Shorthand for a node:

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

$\Downarrow$

No carnivores eat animals?

An Example Search (as graph search)



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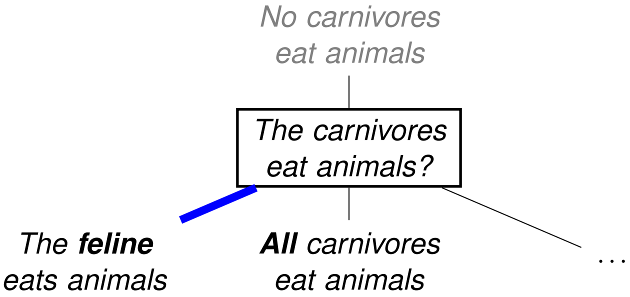

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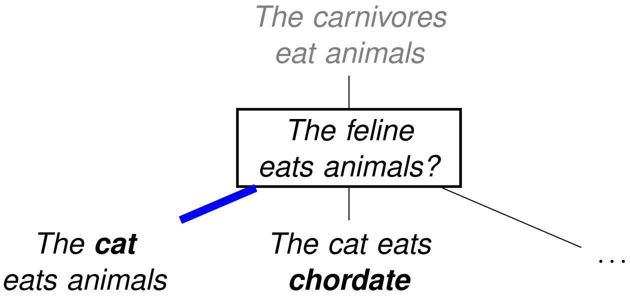

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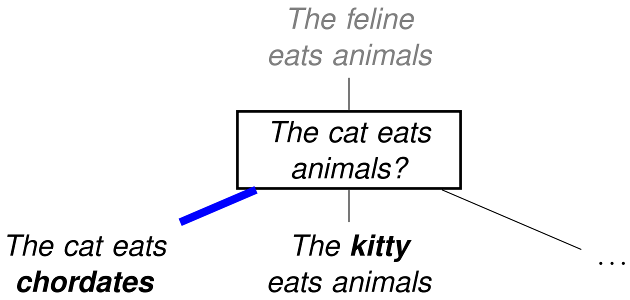


An Example Search (as graph search)

The cat eats animals

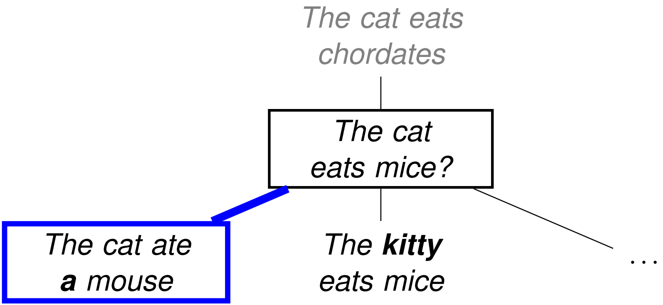
The cat eats chordates?

*The cat eats **mice***

*The cat eats **dogs***

. . .

An Example Search (as graph search)



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Complexity doesn’t grow with knowledge base size.

The "Proposal" Part

Possible Projects

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  What if the entailment rules aren't in WordNet?

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Evaluate on:

- AI2 Biology tests
- WebQuestions
- TREC QA

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Probabilistic logic of "some:" *some cats have tails*; *some cats are male* $\Rightarrow$ *some males have tails* (with some probability)

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Implementation 2: Learn hyperplane between true and false facts.

- Positives from the internet.
- Negatives from mutating *each* positive, + unrelated facts.

Thanks!

References I

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