Natural Language Inference for Question Answering

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Stanford University

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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]

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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?

We can do QA from Freebase ... so let’s make Freebase bigger

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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Does it address the challenges?

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

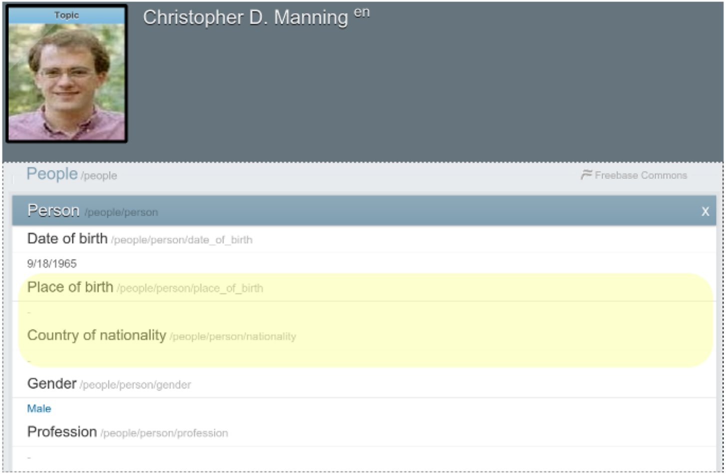
Main Idea of Thesis

Natural language inference allows us to leverage latent information in plain text to find support for more types of questions than prior approaches.

KBP: Directly find facts in text

Where is Chris Manning from?

KBP: Directly find facts in text



Christopher D. Manning en

People /people

Freebase Commons

Person /people/person

x

Date of birth /people/person/date_of_birth

9/18/1965

Place of birth /people/person/place_of_birth

-

Country of nationality /people/person/nationality

-

Gender /people/person/gender

Male

Profession /people/person/profession

-

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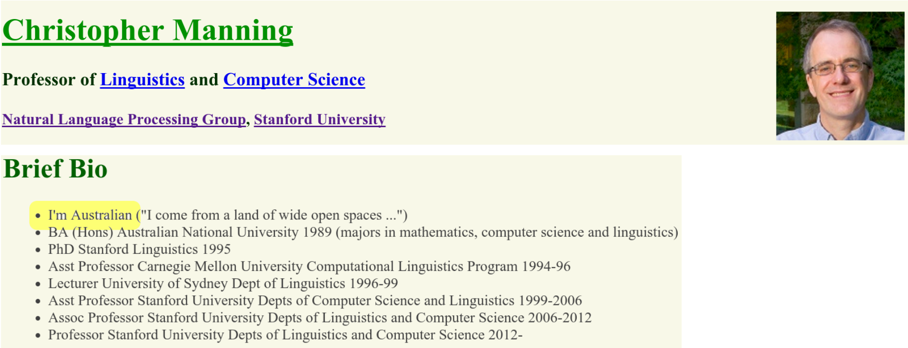

Christopher Manning

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

Australia

Christopher D. Manning, origin

Active Learning for Relation Extraction

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

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

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  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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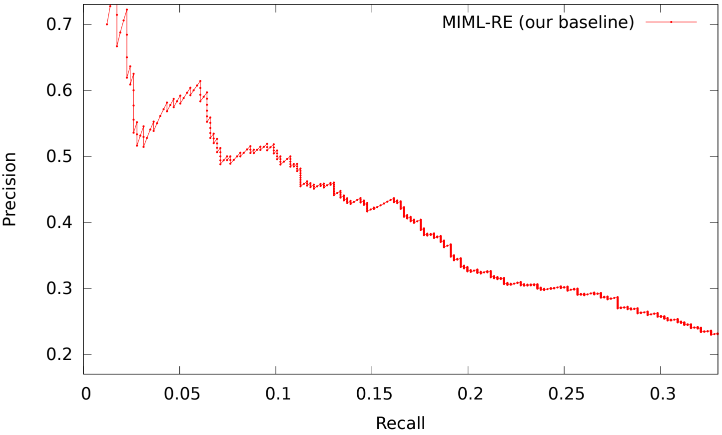
Old solution: Active learning!

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

State-of-the-art results

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



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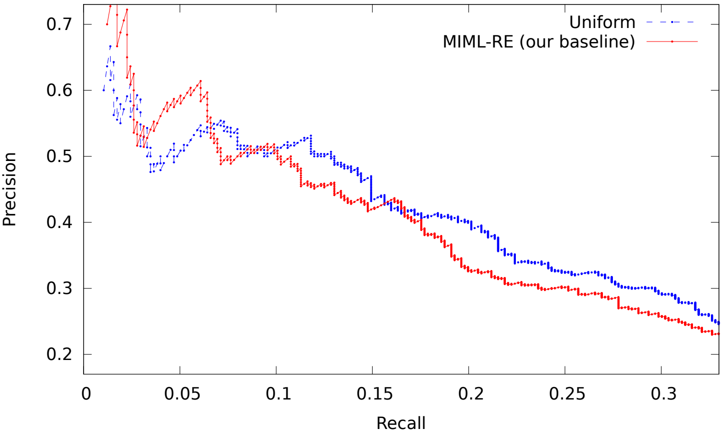

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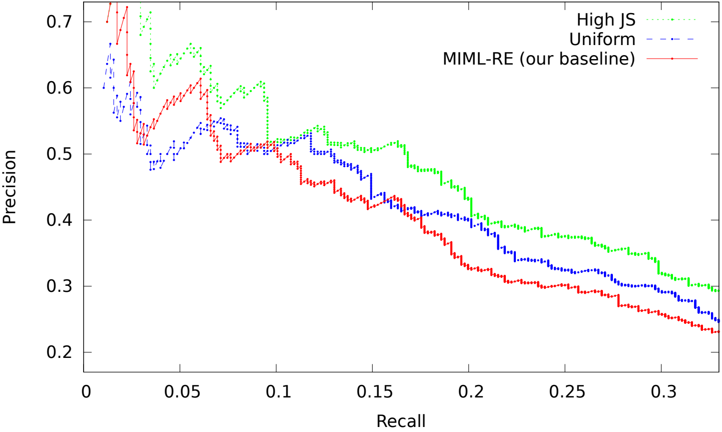

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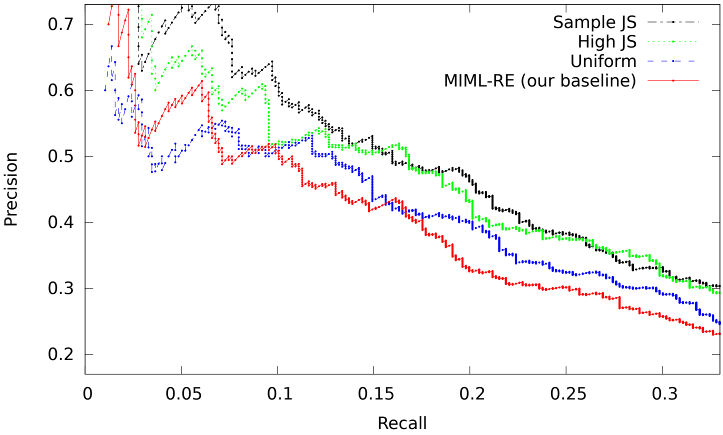

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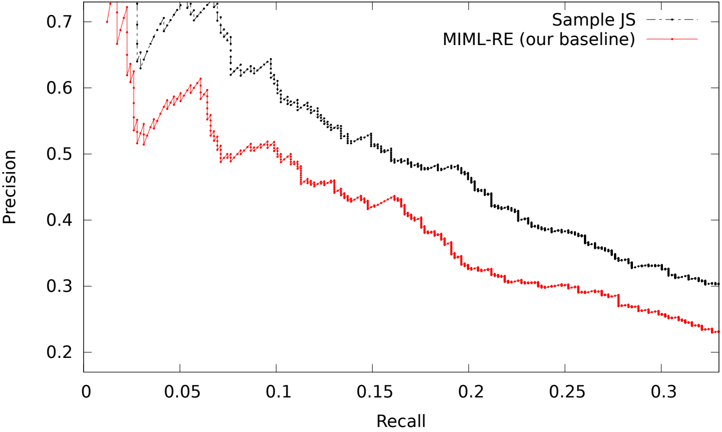

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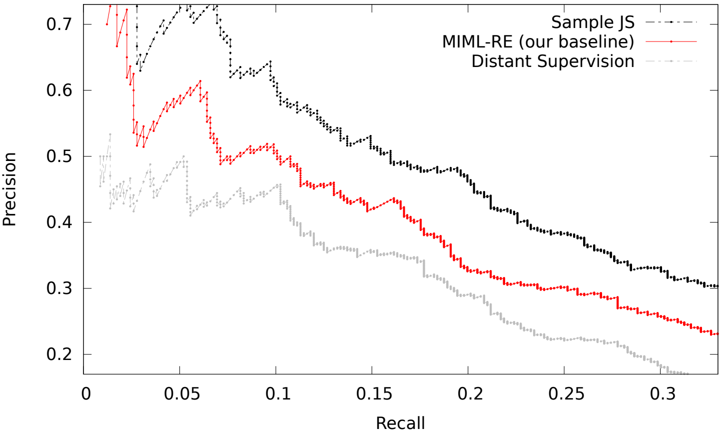

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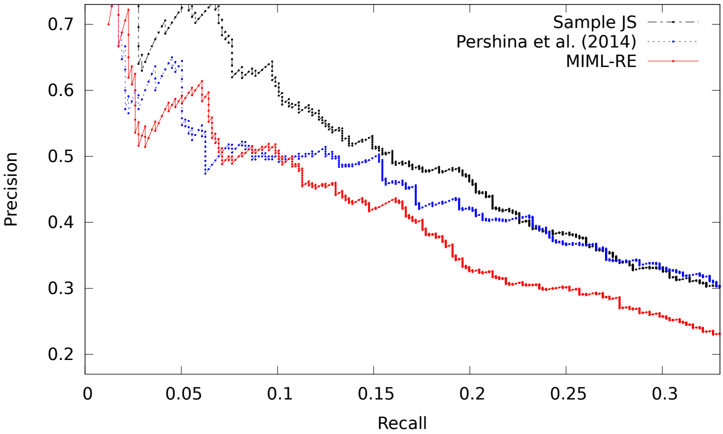

KBP is already "entailment"

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

⇒ *Chris is a tenured professor at Stanford*

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⇒ *Chris is employed by Stanford*

⇒ (*Chris*; *employee_of*; *Stanford*)

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

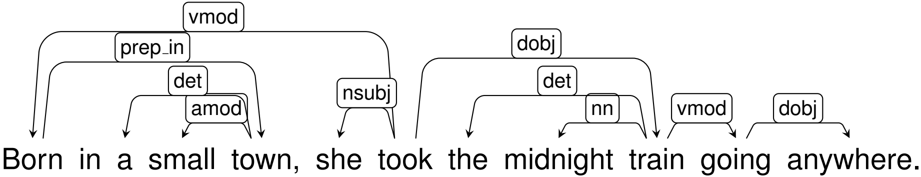
⇒ *She took the midnight train going anywhere*

⇒ *She took the midnight train*

⇒ *She took midnight train*

⇒ (*She*; *took*; *midnight train*)

Treat As Entailment



(input)

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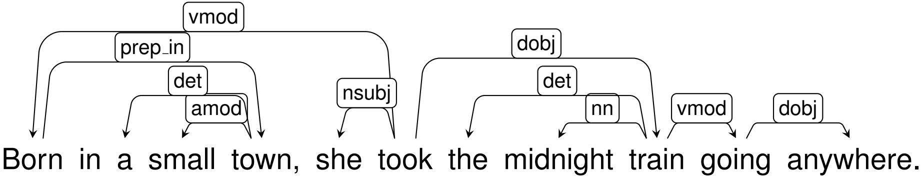

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↓

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she took midnight train
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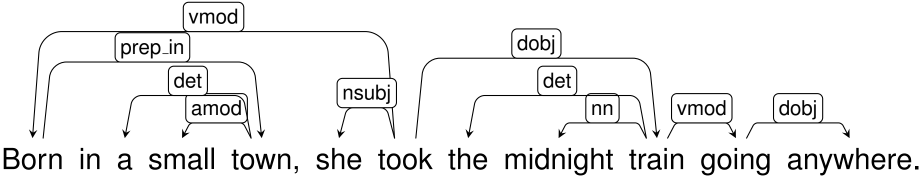

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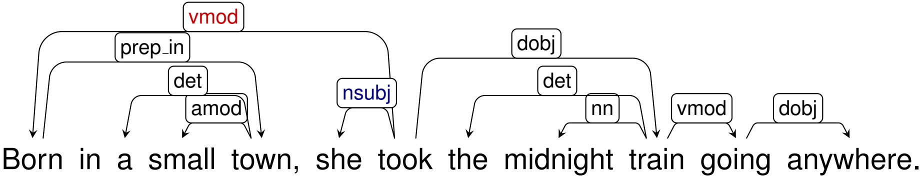

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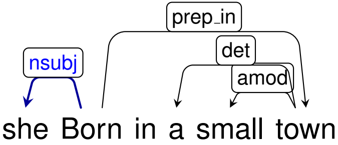

(extracted clause)

↓

she Born in small town

she Born in a town

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↓

(she; born in; small town)
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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
NaturalLI − Nominals	66.7	7.7	13.8
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- MIML-RE: 36.2 F_1; Top system: 40.2 F_1

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Natural Logic subsumes Syllogisms

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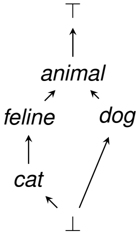
Facts are text; inference is lexical mutation

Natural Logic and Polarity

Treat hypernymy as a *partial order*.



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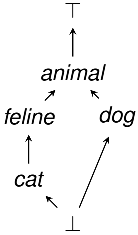

Polarity **is the direction a lexical item can move in the ordering.**

animal

feline

cat

house cat

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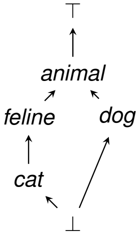

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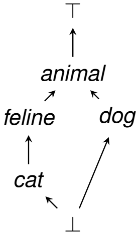

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living thing

animal

↑ feline

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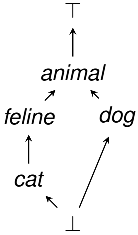

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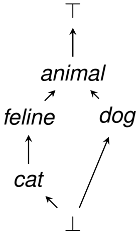

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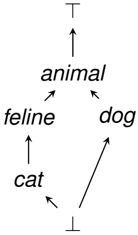

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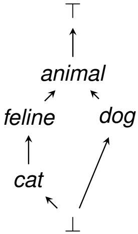

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house cat

An Example Inference

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

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

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Mutations must respect *polarity*.

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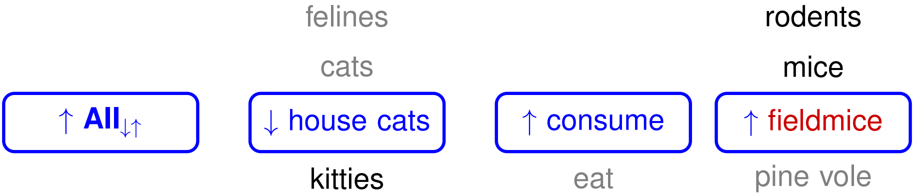

felines rodents

cats mice

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kitties eat pine vole

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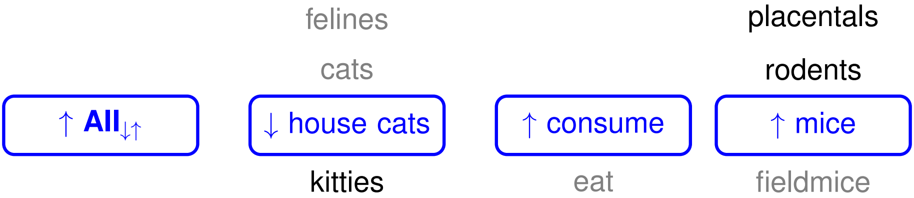

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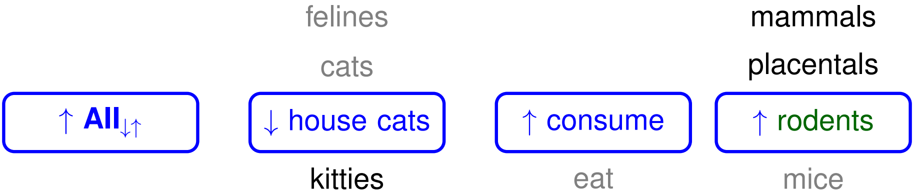

↑ **All**$_{\downarrow\uparrow}$

felines
cats
↓ house cats
kitties

↑ consume
eat

mammals
placentals
↑ rodents
mice

An Example Inference

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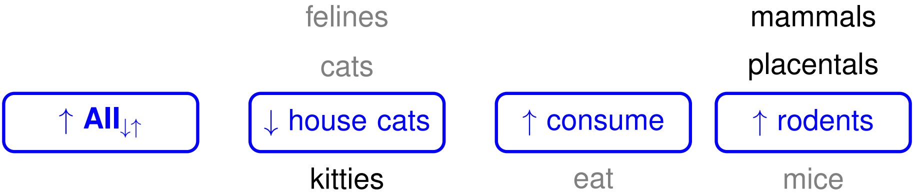
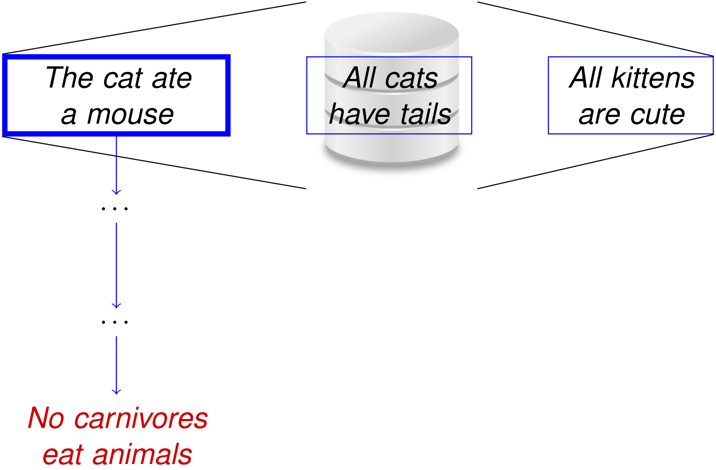
Mutations must respect *polarity*.

Inference is reversible.



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

Natural Logic Inference is Search



The cat ate a mouse

All cats have tails

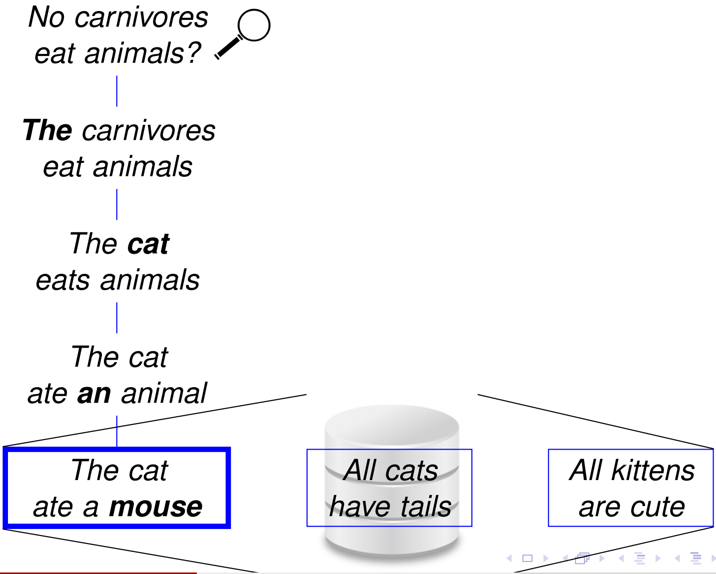
All kittens are cute

…

…

No carnivores eat animals

Natural Logic Inference is Search



No carnivores eat animals?

***The** carnivores eat animals*

*The **cat** eats animals*

*The cat ate **an** animal*

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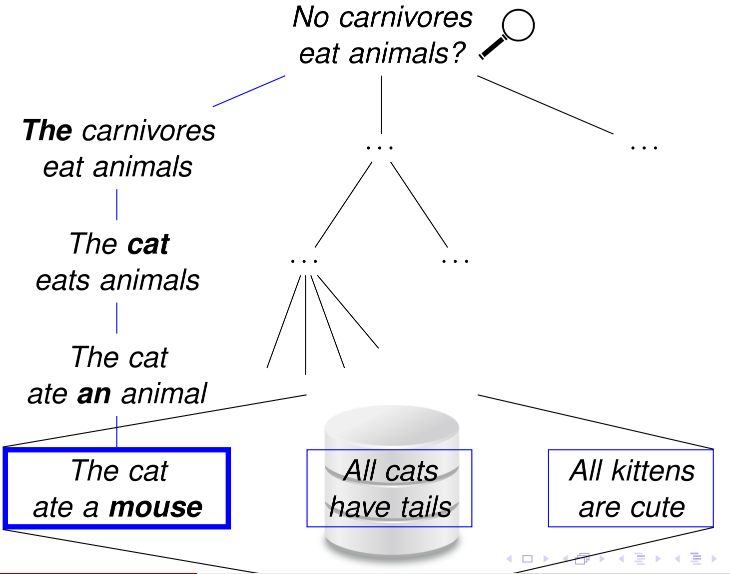

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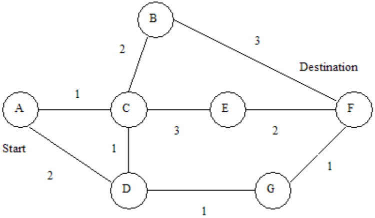

Nodes (*fact*, truth maintained $\in \{\text{true}, \text{false}\}$)

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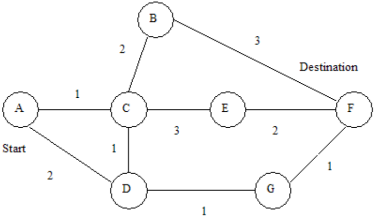

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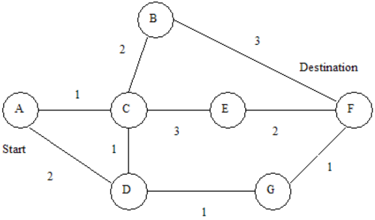

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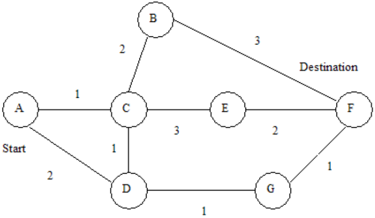

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Start Node	(*query fact*, *true*)
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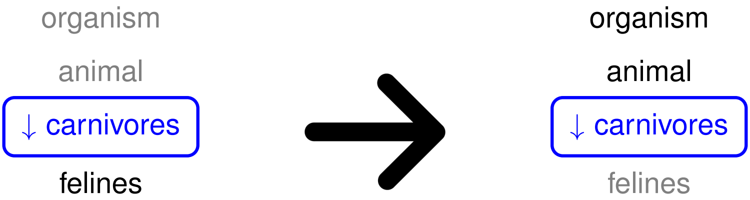
Edges	Mutations of the current fact
Edge Costs	How “wrong” an inference step is (learned)

An Example Search (as reverse inference)

Search mutates *opposite* to polarity



An Example Search (as reverse inference)

Truth maintained: *true*

Current Node:

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

An Example Search (as reverse inference)

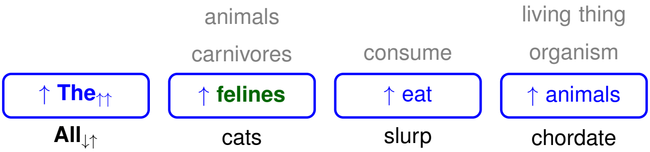
Truth maintained: *false*

Current Node:

An Example Search (as reverse inference)

Truth maintained: *false*

Current Node:



↑ **The**$_{\uparrow\uparrow}$

All$_{\downarrow\uparrow}$

animals

carnivores

↑ **felines**

cats

consume

↑ eat

slurp

living thing

organism

↑ animals

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

An Example Search (as reverse inference)

Truth maintained: *false*

Current Node:

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

An Example Search (as reverse inference)

Truth maintained: *false*

Current Node:

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

An Example Search (as graph search)

Shorthand for a node:

↑ **No**$_{\downarrow\downarrow}$

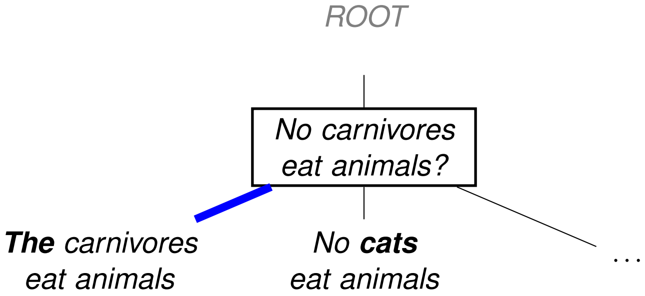
organism
animal
↑ carnivores
felines

consume
↓ eat
slurp

living thing
organism
↑ animals
chordate

No carnivores eat animals?

An Example Search (as graph search)



ROOT

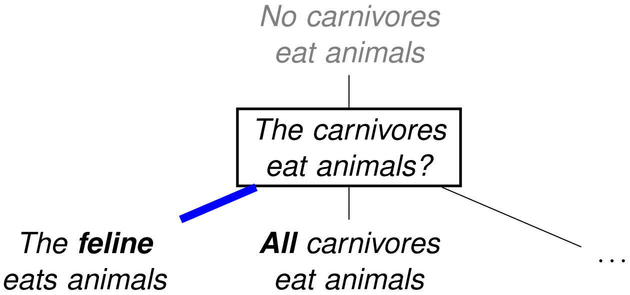
No carnivores eat animals?

***The** carnivores eat animals*

*No **cats** eat animals*

. . .

An Example Search (as graph search)



No carnivores eat animals

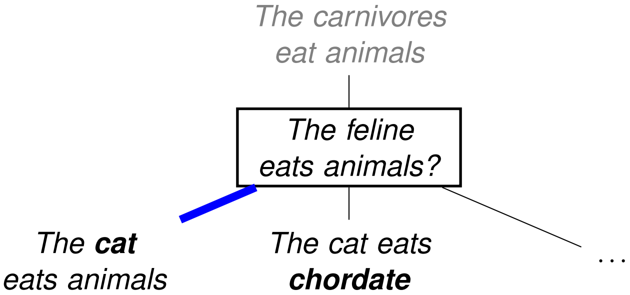
The carnivores eat animals?

The ***feline*** *eats animals*

All *carnivores eat animals*

…

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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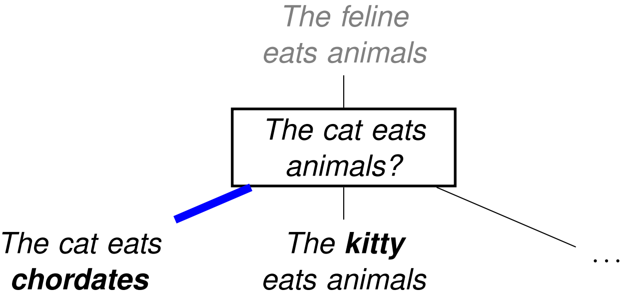

The feline eats animals

The cat eats animals?

*The cat eats **chordates***

*The **kitty** eats animals*

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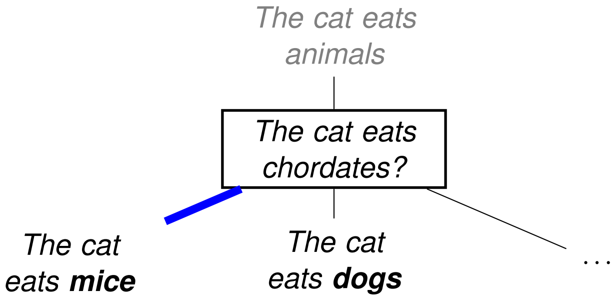

The cat eats animals

The cat eats chordates?

The cat eats ***mice***

The cat eats ***dogs***

. . .

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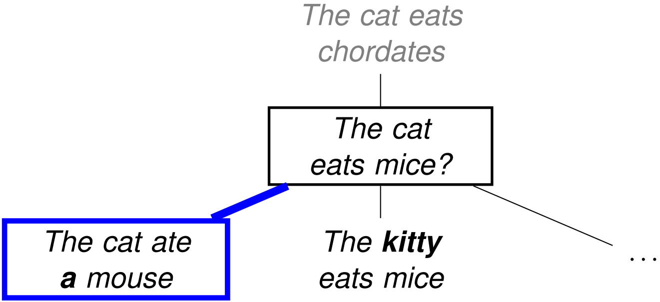

The cat eats chordates

The cat eats mice?

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Can learn parameters θ.

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High-Level Takeaways

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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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Goal: Make NaturalLI useful, not just cute.

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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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