

NaturalLI: Natural Logic Inference for Common Sense Reasoning

Gabor Angeli, Chris Manning

Stanford University

November 21, 2014



Natural Logic Inference for Common Sense Reasoning

Kittens play with yarn

Kittens play with computers

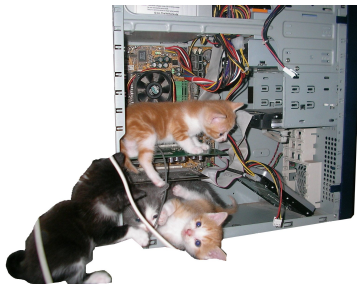


Natural Logic Inference for Common Sense Reasoning

Kittens play with yarn



Kittens play with computers



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*



Common Sense Reasoning for NLP

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

a city fears violence

demonstrators fear violence

I ate the cake with a cherry vs. I ate the cake with a fork

cakes come with cherries

cakes are eaten using cherries



Common Sense Reasoning for NLP

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

a city fears violence

demonstrators fear violence

I ate the cake with a cherry vs. I ate the cake with a fork

cakes come with cherries

cakes are eaten using cherries

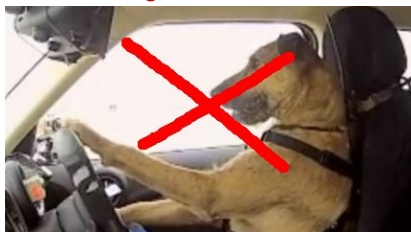
Put a sarcastic comment in your talk. That's a great idea.

Sarcasm in your talk is a great idea



Common Sense Reasoning for Vision

Dogs drive cars

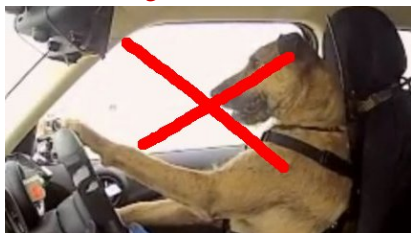


People drive cars



Common Sense Reasoning for Vision

Dogs drive cars



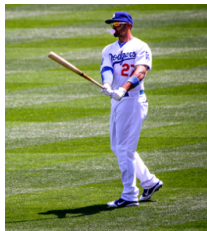
People drive cars



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).
- Theorem proving (e.g., Datalog).



Prior Work on Common Sense Reasoning

Old School AI: Nuanced reasoning; tiny coverage.

- Default reasoning (Reiter 1980; McCarthy 1980).
- Theorem proving (e.g., Datalog).

Textual Entailment: Rich inference; small data.

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



Prior Work on Common Sense Reasoning

Old School AI: Nuanced reasoning; tiny coverage.

- Default reasoning (Reiter 1980; McCarthy 1980).
- Theorem proving (e.g., Datalog).

Textual Entailment: Rich inference; small data.

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

Information Extraction: Shallow inference, large data.

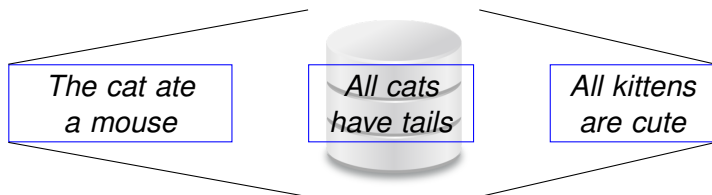
- OpenIE (Yates et al., 2007), NELL (Carlson et al., 2010).
- *Extraction* of facts from a large corpus; fuzzy lookup.



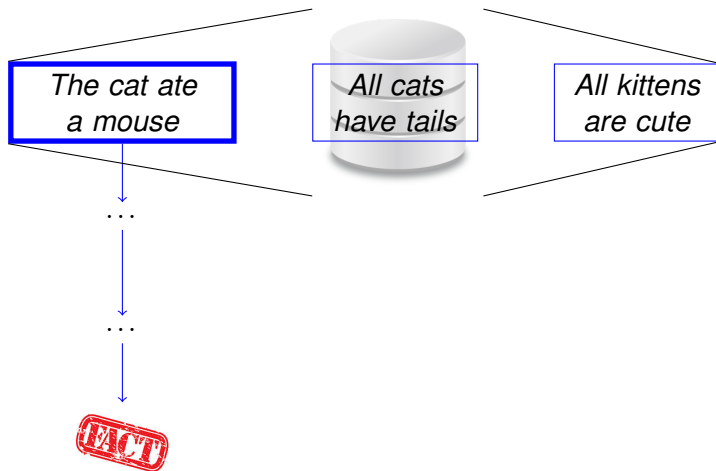
Start with a large knowledge base



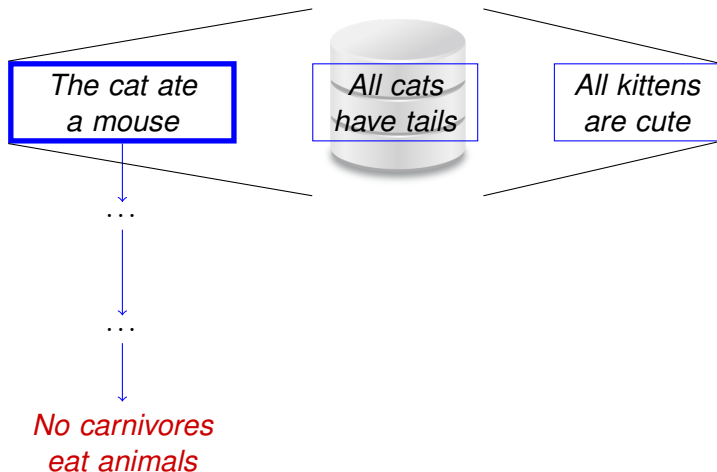
Start with a large knowledge base



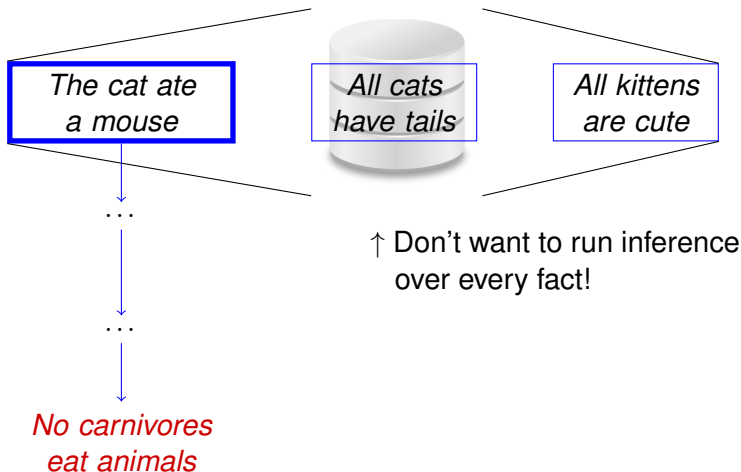
Infer new facts...



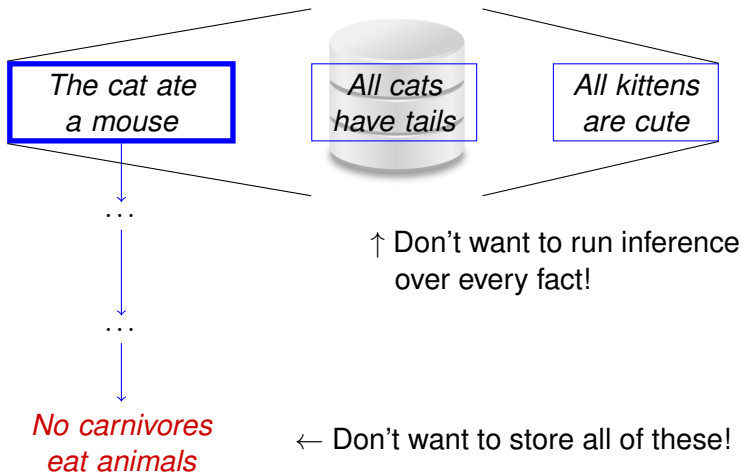
Infer new facts...



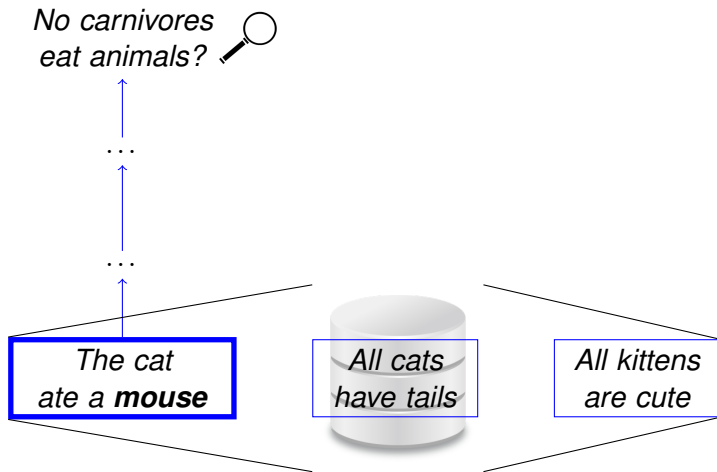
Infer new facts...



Infer new facts...



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



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

No carnivores
eat animals? 🔍

The carnivores
eat animals

The **cat**
eats animals

The cat
ate **an** animal

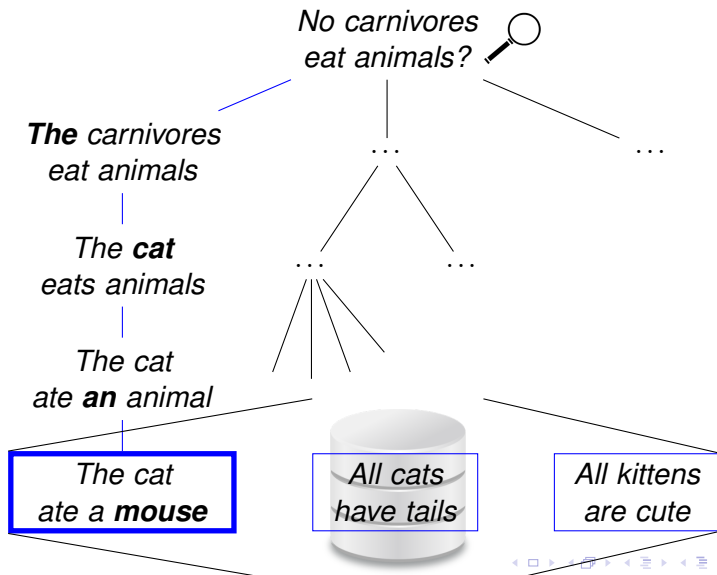
The cat
ate a **mouse**

All cats
have tails

All kittens
are cute



...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)



A Better Knowledge Base Lookup

Lookup in 270 million entry KB...

...by lemmas 12% recall

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

Formal logical entailment: Not just fuzzy lookup.



A Better Knowledge Base Lookup

Lookup in 270 million entry KB...

...by lemmas 12% recall

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

Formal logical entailment: Not just fuzzy lookup.

Maintain good properties of fuzzy lookup.

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



A Better Knowledge Base Lookup

Lookup in 270 million entry KB...

- ...by lemmas 12% recall
- ...with NaturalLI 49% recall (91% precision)

Formal logical entailment: Not just fuzzy lookup.

Maintain good properties of fuzzy lookup.

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



Natural Logic



Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

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

∴ *Some cat ate a **rodent***



Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

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

∴ *Some cat ate a **rodent***

Cognitively easy inferences are easy:

- Most cats eat mice
∴ *Most cats eat **rodents***



Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

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

∴ *Some cat ate a **rodent***

Cognitively easy inferences are easy:

- Most cats eat mice
∴ *Most cats eat **rodents***
- “*All students who know a foreign language learned it at university.*”



Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

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

∴ *Some cat ate a **rodent***

Cognitively easy inferences are easy:

- Most cats eat mice
∴ *Most cats eat **rodents***
- “All students who know a foreign language learned it at university.”
∴ *“They learned it at school.”*



Natural Logic as Syllogisms

s/Natural Logic/Syllogistic Reasoning/g

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

∴ *Some cat ate a **rodent***

Cognitively easy inferences are easy:

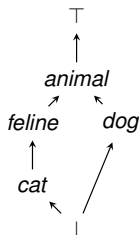
- Most cats eat mice
∴ *Most cats eat **rodents***
- “All students who know a foreign language learned it at university.”
∴ *“They learned it at school.”*

Facts are text; inference is lexical mutation



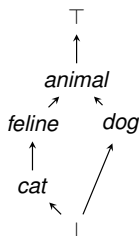
Natural Logic and Polarity

Treat hypernymy as a *partial order*.



Natural Logic and Polarity

Treat hypernymy as a *partial order*.

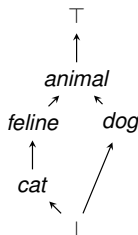


Polarity is the direction a lexical item can move in the ordering.



Natural Logic and Polarity

Treat hypernymy as a *partial order*.

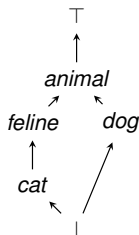


Polarity is the direction a lexical item can move in the ordering.



Natural Logic and Polarity

Treat hypernymy as a *partial order*.

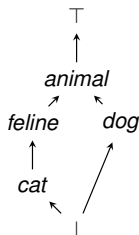


Polarity is the direction a lexical item can move in the ordering.



Natural Logic and Polarity

Treat hypernymy as a *partial order*.

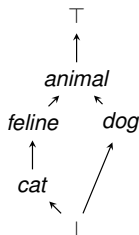


Polarity is the direction a lexical item can move in the ordering.



Natural Logic and Polarity

Treat hypernymy as a *partial order*.

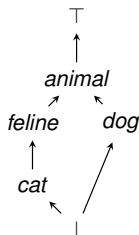


Polarity is the direction a lexical item can move in the ordering.



Natural Logic and Polarity

Treat hypernymy as a *partial order*.

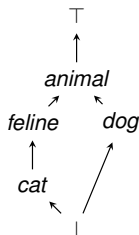


Polarity is the direction a lexical item can move in the ordering.



Natural Logic and Polarity

Treat hypernymy as a *partial order*.



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



An Example Inference

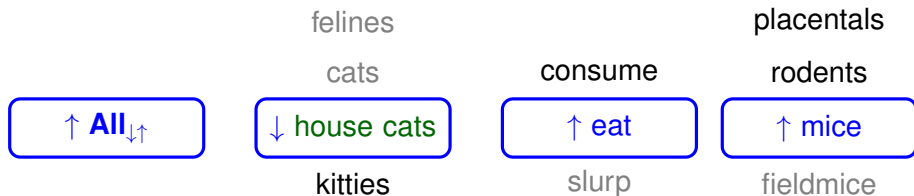
Quantifiers determines the *polarity* (\uparrow or \downarrow) of words.



An Example Inference

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

Mutations must respect *polarity*.



An Example Inference

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

Mutations must respect *polarity*.



An Example Inference

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

Mutations must respect *polarity*.



An Example Inference

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

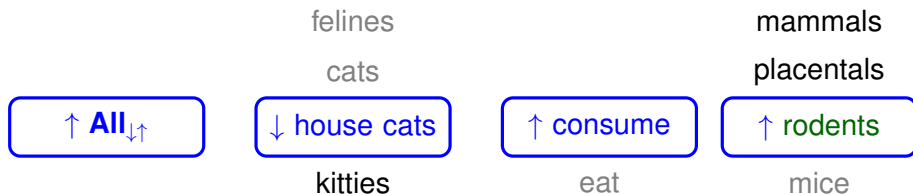
Mutations must respect *polarity*.



An Example Inference

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

Mutations must respect *polarity*.

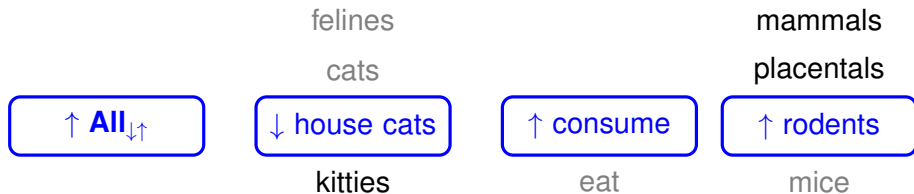


An Example Inference

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

Mutations must respect *polarity*.

Inference is reversible.



Properties of Natural Logic

- ✓ Computationally fast during inference.
 - “Semantic” parse of query is just syntactic parse.
 - Inference is lexical mutations / insertions / deletions.



Properties of Natural Logic

- ✓ Computationally fast during inference.
 - “Semantic” parse of query is just syntactic parse.
 - Inference is lexical mutations / insertions / deletions.
- ✓ Computationally fast during pre-processing.
 - Plain text!



Properties of Natural Logic

- ✓ Computationally fast during inference.
 - “Semantic” parse of query is just syntactic parse.
 - Inference is lexical mutations / insertions / deletions.
- ✓ Computationally fast during pre-processing.
 - Plain text!
- ✓ Still captures common inferences.
 - We make these types of inferences regularly and instantly.

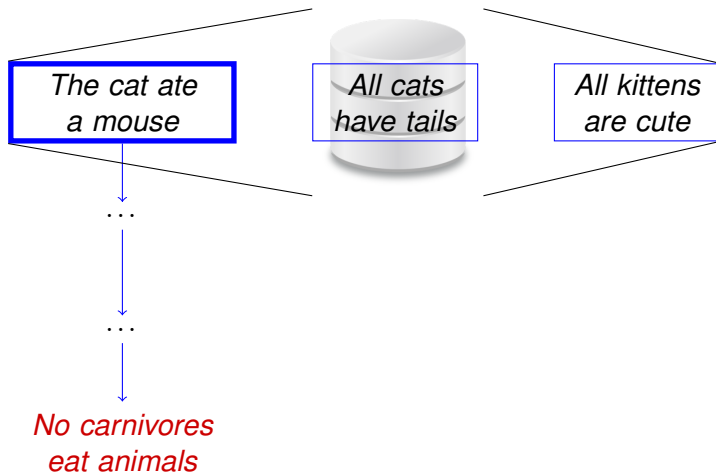


Properties of Natural Logic

- ✓ Computationally fast during inference.
 - “Semantic” parse of query is just syntactic parse.
 - Inference is lexical mutations / insertions / deletions.
- ✓ Computationally fast during pre-processing.
 - Plain text!
- ✓ 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



Natural Logic Inference is Search

No carnivores
eat animals? 🔍

The carnivores
eat animals

The **cat**
eats animals

The cat
ate **an** animal

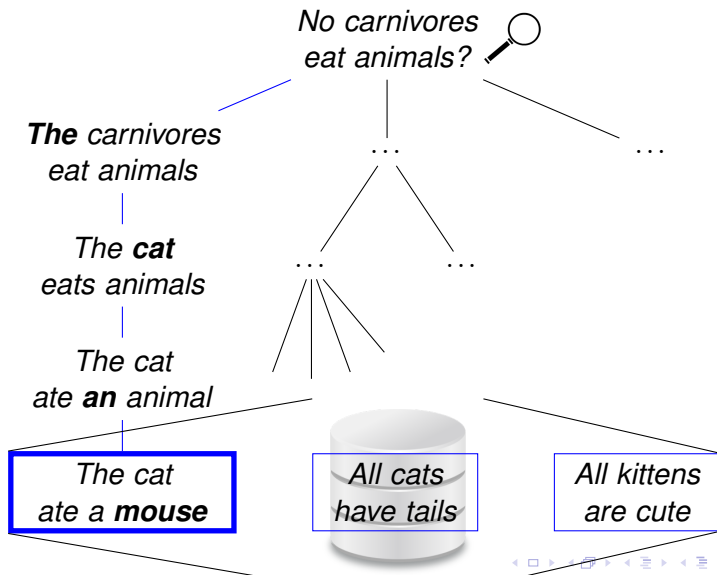
The cat
ate a **mouse**

All cats
have tails

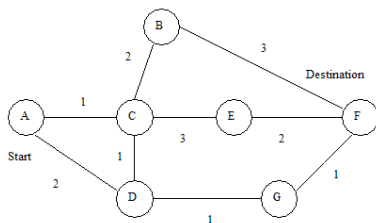
All kittens
are cute



Natural Logic Inference is Search



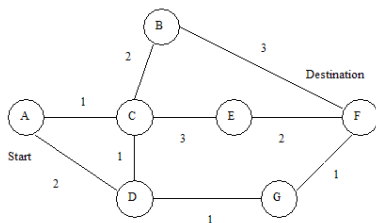
Natural Logic Inference is Search



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



Natural Logic Inference is Search



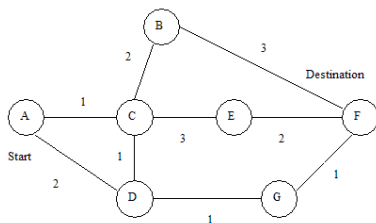
Nodes (*fact*, truth maintained $\in \{\text{true}, \text{false}\}$)

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

End Nodes *any known fact*



Natural Logic Inference is Search



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

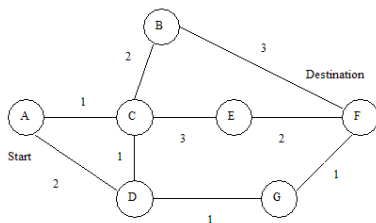
Start Node (*query fact*, *true*)

End Nodes *any known fact*

Edges Mutations of the current fact



Natural Logic Inference is Search



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

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

End Nodes *any known fact*

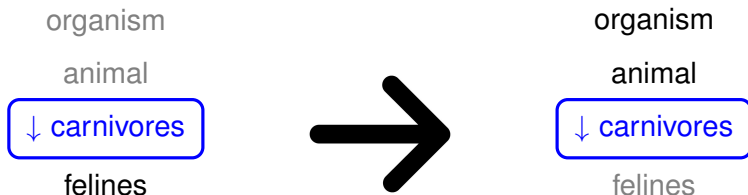
Edges Mutations of the current fact

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:



An Example Search (as reverse inference)

**Truth
maintained:**

false

**Current
Node:**

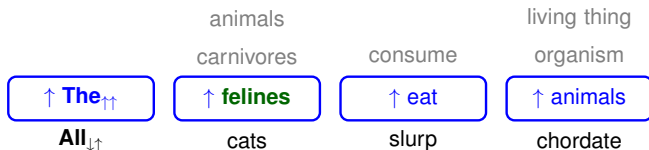


An Example Search (as reverse inference)

**Truth
maintained:**

false

**Current
Node:**



An Example Search (as reverse inference)

**Truth
maintained:**

false

**Current
Node:**



An Example Search (as reverse inference)

Truth
maintained:

false

Current
Node:



An Example Search (as reverse inference)

Truth
maintained:

false

Current
Node:



An Example Search (as reverse inference)

Truth
maintained:

false

Current
Node:



An Example Search (as graph search)

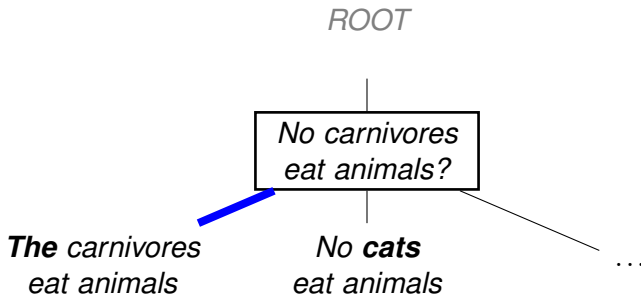
Shorthand for a node:



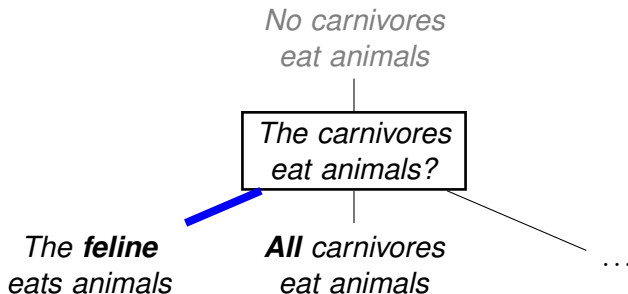
*No carnivores
eat animals?*



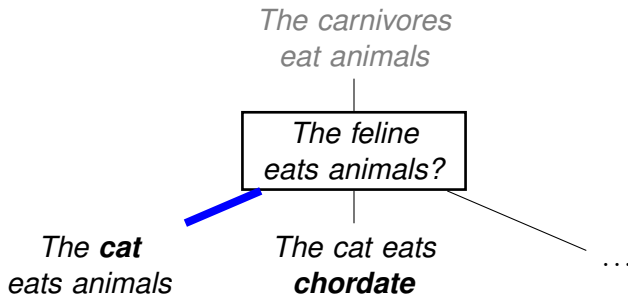
An Example Search (as graph search)



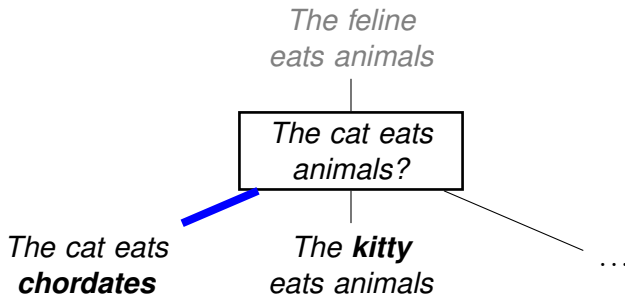
An Example Search (as graph search)



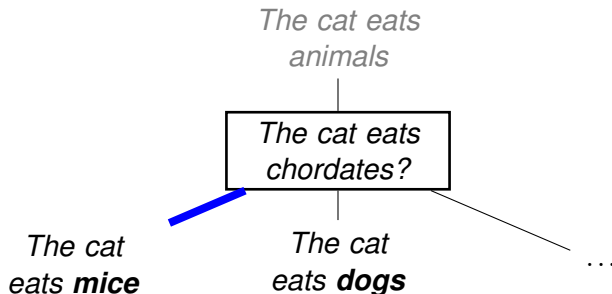
An Example Search (as graph search)



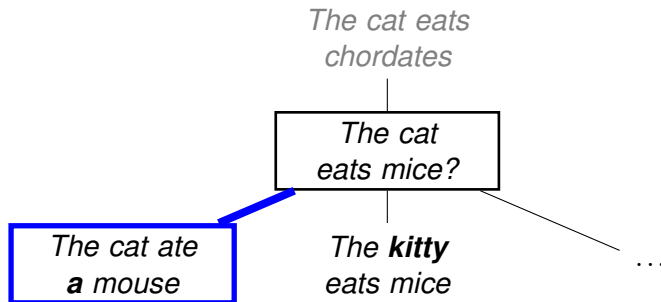
An Example Search (as graph search)



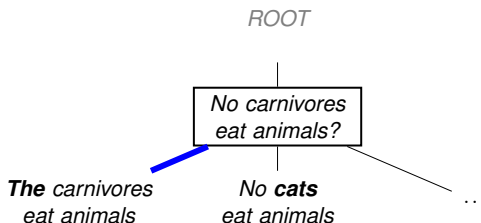
An Example Search (as graph search)



An Example Search (as graph search)



An Example Search (with edges)



Template

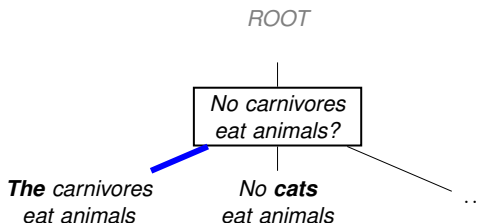
Instance

Edge

Operator Negate



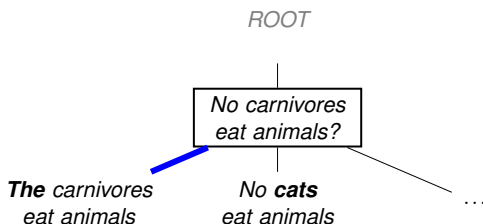
An Example Search (with edges)



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



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> \rightarrow <i>cat</i>
Hyponym	<i>cat</i> \rightarrow <i>animal</i>
Antonym	<i>good</i> \rightarrow <i>bad</i>
Synonym	<i>cat</i> \rightarrow <i>true cat</i>
Add Word	<i>cat</i> \rightarrow .
Delete Word	. \rightarrow <i>cat</i>
Operator Weaken	<i>some</i> \rightarrow <i>all</i>
Operator Strengthen	<i>all</i> \rightarrow <i>some</i>
Operator Negate	<i>all</i> \rightarrow <i>no</i>
Operator Synonym	<i>all</i> \rightarrow <i>every</i>
Nearest Neighbor	<i>cat</i> \rightarrow <i>dog</i>



“Soft” Natural Logic

Want to make likely (but not certain) inferences.

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



“Soft” Natural Logic

Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
- Each *edge template* has a cost $\theta \geq 0$.



“Soft” Natural Logic

Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
- Each *edge template* has a cost $\theta \geq 0$.

Detail: Variation among *edge instances* of a template.

- WordNet: *cat* \rightarrow *feline* **vs.** *cup* \rightarrow *container*.
- Nearest neighbors distance.
- Each *edge instance* has a distance f .



“Soft” Natural Logic

Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
- Each *edge template* has a cost $\theta \geq 0$.

Detail: Variation among *edge instances* of a template.

- WordNet: *cat* \rightarrow *feline* **vs.** *cup* \rightarrow *container*.
- Nearest neighbors distance.
- Each *edge instance* has a distance f .

Cost of an edge is $\theta_i \cdot f_i$.



“Soft” Natural Logic

Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
- Each *edge template* has a cost $\theta \geq 0$.

Detail: Variation among *edge instances* of a template.

- WordNet: *cat* \rightarrow *feline* **vs.** *cup* \rightarrow *container*.
- Nearest neighbors distance.
- Each *edge instance* has a distance f .

Cost of an edge is $\theta_i \cdot f_i$.

Cost of a path is $\theta \cdot f$.



“Soft” Natural Logic

Want to make likely (but not certain) inferences.

- Same motivation as Markov Logic, Probabilistic Soft Logic, etc.
- Each *edge template* has a cost $\theta \geq 0$.

Detail: Variation among *edge instances* of a template.

- WordNet: *cat* \rightarrow *feline* **vs.** *cup* \rightarrow *container*.
- Nearest neighbors distance.
- Each *edge instance* has a distance f .

Cost of an edge is $\theta_i \cdot f_i$.

Cost of a path is $\theta \cdot \mathbf{f}$.

Can learn parameters θ .



Contribution: Simple Transitivity

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



Contribution: Simple Transitivity

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

More complicated in (prior work on) Natural Logic:

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



Contribution: Simple Transitivity

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

More complicated in (prior work on) Natural Logic:

- \bullet *nocturnal* $\xrightarrow{\downarrow}$ *diurnal*, *all* $\xrightarrow{\uparrow}$ *not all*
 \therefore *all bats are nocturnal* $\xrightarrow{?}$ *not all bats are diurnal*

\boxtimes	\equiv	\sqsubseteq	\supseteq	\uparrow	\Downarrow	\smile	#
\equiv	\equiv	\sqsubseteq	\supseteq	\uparrow	\Downarrow	\smile	#
\sqsubseteq	\sqsubseteq	\sqsubseteq	#	\Downarrow	\Downarrow	#	#
\supseteq	\supseteq	#	\supseteq	\smile	#	\smile	#
\uparrow	\uparrow	\smile	\Downarrow	\equiv	\supseteq	\sqsubseteq	#
\Downarrow	\Downarrow	#	\Downarrow	\sqsubseteq	#	\sqsubseteq	#
\smile	\smile	\smile	#	\supseteq	\supseteq	#	#
#	#	#	#	#	#	#	#



Contribution: Simple Transitivity

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

More complicated in (prior work on) Natural Logic:

- $\text{nocturnal} \xrightarrow{\downarrow} \text{diurnal}, \quad \text{all} \xrightarrow{\uparrow} \text{not all}$
 $\therefore \text{all bats are nocturnal} \xrightarrow{?} \text{not all bats are diurnal}$

\bowtie	\equiv	\sqsubseteq	\supseteq	\uparrow	\Downarrow	\smile	#
\equiv	\equiv	\sqsubseteq	\supseteq	\uparrow	\Downarrow	\smile	#
\sqsubseteq	\sqsubseteq	\sqsubseteq	#	\Downarrow	\Downarrow	#	#
\supseteq	\supseteq	#	\supseteq	\smile	#	\smile	#
\uparrow	\uparrow	\smile	\Downarrow	\equiv	\supseteq	\sqsubseteq	#
\Downarrow	\Downarrow	#	\Downarrow	\sqsubseteq	#	\sqsubseteq	#
\smile	\smile	\smile	#	\supseteq	\supseteq	#	#
#	#	#	#	#	#	#	#



Contribution: Simple Transitivity

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

More complicated in (prior work on) Natural Logic:

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

⊗	≡	⊆	⊇	人	↓	∪	#
≡	≡	⊆	⊇	人	↓	∪	#
⊆	⊆	⊆	#	↓	↓	#	#
⊇	⊇	#	⊇	#	#	∪	#
人	人	∪	↓	⊆	⊆	⊆	#
↓	↓	#	⊆	⊆	#	⊆	#
∪	∪	∪	⊆	⊇	⊇	#	#
#	#	#	#	#	#	#	#



Contribution: Simple Transitivity

Natural Logic Analog of Transitivity:

State Fact

\Rightarrow *all bats are nocturnal,*

Mutation



Contribution: Simple Transitivity

Natural Logic Analog of Transitivity:

State Fact

\Rightarrow *all bats are nocturnal,*

Mutation

(*nocturnal* $\xrightarrow{\downarrow}$ *diurnal*)



Contribution: Simple Transitivity

Natural Logic Analog of Transitivity:

State **Fact**

\Rightarrow *all bats are nocturnal,*

$\Rightarrow \neg$ *all bats are diurnal,*

Mutation

(*nocturnal* $\xrightarrow{\downarrow}$ *diurnal*)



Contribution: Simple Transitivity

Natural Logic Analog of Transitivity:

State Fact

\Rightarrow *all bats are nocturnal,*

$\Rightarrow \neg$ *all bats are diurnal,*

Mutation

(*nocturnal* $\xrightarrow{\downarrow}$ *diurnal*)

(*all* $\xrightarrow{\uparrow}$ *not all*)



Contribution: Simple Transitivity

Natural Logic Analog of Transitivity:

State Fact

\Rightarrow *all bats are nocturnal,*

$\Rightarrow \neg$ *all bats are diurnal,*

\Rightarrow *not all bats are diurnal*

Mutation

(*nocturnal* $\xrightarrow{\downarrow}$ *diurnal*)

(*all* $\xrightarrow{\uparrow}$ *not all*)



Contribution: Simple Transitivity

Natural Logic Analog of Transitivity:

State	Fact	Mutation
\Rightarrow	<i>all bats are nocturnal,</i>	$(nocturnal \xrightarrow{\downarrow} diurnal)$
$\Rightarrow \neg$	<i>all bats are diurnal,</i>	$(all \xrightarrow{\uparrow} not\ all)$
\Rightarrow	<i>not all bats are diurnal</i>	

- 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.
H: *At most ten commissioners spend time at home.*
- 9 focused sections; 3 in scope for this work.



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.
H: *At most ten commissioners spend time at home.*
- 9 focused sections; 3 in scope for this work.

Not a blind test set!

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



FraCaS Results

Systems

M07: MacCartney and Manning (2007)

M08: MacCartney and Manning (2008)

- *Classify* entailment after aligning premise and hypothesis.

N: NaturalLI (this work)

- *Search* blindly from hypothesis for the premise.



FraCaS Results

Systems

M07: MacCartney and Manning (2007)

M08: MacCartney and Manning (2008)

- *Classify* entailment after aligning premise and hypothesis.

N: NaturalLI (this work)

- *Search* blindly from hypothesis for the premise.

§	Category	Accuracy		
		M07	M08	N
1	Quantifiers	84	97	95
5	Adjectives	60	80	73
6	Comparatives	69	81	87



FraCaS Results

Systems

M07: MacCartney and Manning (2007)

M08: MacCartney and Manning (2008)

- *Classify* entailment after aligning premise and hypothesis.

N: NaturalLI (this work)

- *Search* blindly from hypothesis for the premise.

§	Category	Accuracy		
		M07	M08	N
1	Quantifiers	84	97	95
5	Adjectives	60	80	73
6	Comparatives	69	81	87
Applicable (1,5,6)		76	90	89



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.
- Small (1378 train / 1080 test), but fairly broad coverage.



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.
- Small (1378 train / 1080 test), but fairly broad coverage.

Our Knowledge Base:

- 270 million lemmatized Ollie extractions.



ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.

NaturalLI: Our system.



ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.

NaturalLI: Our system.

NaturalLI Only: Use only inference (prohibit exact matches).



ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.

NaturalLI: Our system.

NaturalLI Only: Use only inference (prohibit exact matches).

System	P	R
Direct Lookup	100.0	12.1



ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.

NaturalLI: Our system.

NaturalLI Only: Use only inference (prohibit exact matches).

System	P	R
Direct Lookup	100.0	12.1
NaturalLI Only	88.8	40.1
NaturalLI	90.6	49.1



ConceptNet Results

Systems

Direct Lookup: Lookup by lemmas.

NaturalLI: Our system.

NaturalLI Only: Use only inference (prohibit exact matches).

System	P	R
Direct Lookup	100.0	12.1
NaturalLI Only	88.8	40.1
NaturalLI	90.6	49.1

- 4x improvement in recall.



Conclusions

Takeaways

- *Deep* inferences from a *large* knowledge base.
- Leverage arbitrarily large plain-text knowledge bases.
- “Soft” logic with probability of truth.



Conclusions

Takeaways

- *Deep* inferences from a *large* knowledge base.
- Leverage arbitrarily large plain-text knowledge bases.
- “Soft” logic with probability of truth.

Strictly better than querying a knowledge base.

- 12% recall \rightarrow 49% recall @ 91% precision.
- Checks logical entailment (not just fuzzy query).



Conclusions

Takeaways

- *Deep* inferences from a *large* knowledge base.
- Leverage arbitrarily large plain-text knowledge bases.
- “Soft” logic with probability of truth.

Strictly better than querying a knowledge base.

- 12% recall → 49% recall @ 91% precision.
- Checks logical entailment (not just fuzzy query).

Complexity doesn't grow with knowledge base size.



Thanks!

