Old Problem: Logic + ML often at odds

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ML gives us practical, generalizable systems:

P: *Ovaries are the female part of the flower, which produces eggs that are needed for making seeds.*

H: *A flower produces the seeds.*

...But struggles with logical subtleties

P: *Eating candy for dinner is an example of a poor health habit.*

H: *Eating candy is an example of a good health habit.*

Make ML more first-order-logic-like

Markov Logic Networks

- [Richardson and Domingos, 2006]
- [Niu et al., 2011]

Probabilistic Soft Logic

- [Kimmig et al., 2012]
- [Beltagy et al., 2014]

Deep Learning + Logic

- [Rocktäschel et al., 2014]

Find logics that are better for ML

Natural Logic!

[Sánchez Valencia, 1991, MacCartney and Manning, 2008, Icard III and Moss, 2014]

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Logic over natural language

- *Instantaneous* and *perfect* semantic parsing!
- Plays nice with lexical methods

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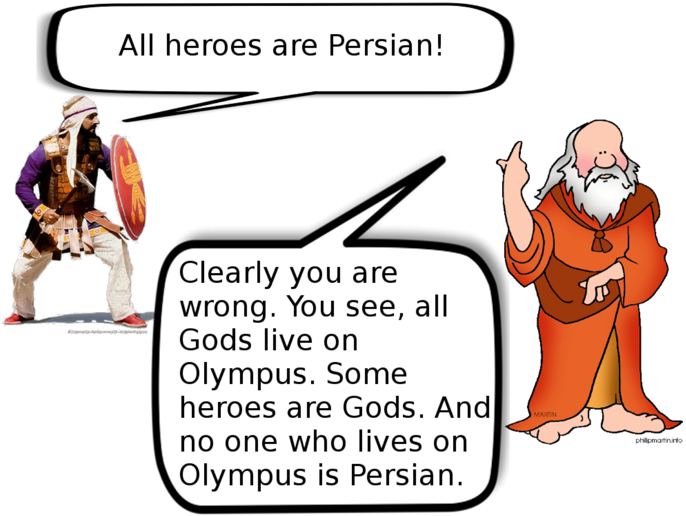
Expressive (for common inferences)

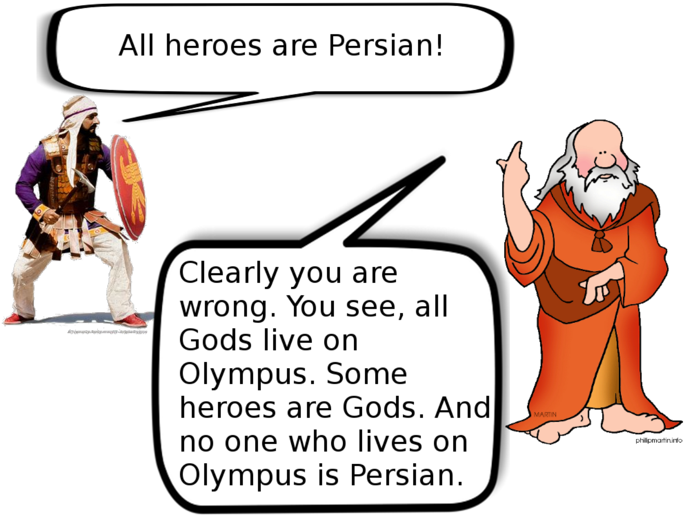
- Second-order phenomena; *most*; quantifier scoping
- No free lunch: shallow quantification; single-premise only

[Sánchez Valencia, 1991, MacCartney and Manning, 2008, Icard III and Moss, 2014]

The Persians are Invading Greece



How Did You Solve This?



Show of Hands: First Order Logic?

1	$\forall x\ \text{God}(x) \supset \text{LivesOnOlympus}(x)$	
2	$\exists x\ \text{Hero}(x) \wedge \text{God}(x)$	
3	$\neg\exists x\ \text{LivesOnOlympus}(x) \wedge \text{Persian}(x)$	
4	$\quad \forall x\ \text{Hero(x)} \supset \text{Persian}(x)$	
5	$\quad a \quad \text{Hero}(a) \wedge \text{God}(a)$	$\exists$E, 2
6	$\quad\quad \text{Hero}(a)$	$\wedge$E, 5
7	$\quad\quad \text{Hero(a)} \supset \text{Persian}(a)$	$\forall$E, 4
8	$\quad\quad \text{Persian}(a)$	$\Rightarrow$E, 6, 7
9	$\quad\quad \text{God}(a)$	$\wedge$E, 5
10	$\quad\quad \text{God}(a) \supset \text{LivesOnOlympus}(a)$	$\forall$E, 1
11	$\quad\quad \text{LivesOnOlympus}(a)$	$\Rightarrow$E, 9, 10
12	$\quad\quad \text{LivesOnOlympus}(a) \wedge \text{Persian}(a)$	$\wedge$I, 8, 11
13	$\quad\quad \exists x\ \text{LivesOnOlympus}(x) \wedge \text{Persian}(x)$	$\exists$I, 12
14	$\quad \exists x\ \text{LivesOnOlympus}(x) \wedge \text{Persian}(x)$	R, 12
15	$\quad \bot$	$\bot$ I, 3, 14
16	$\neg\ \forall x\ \text{Hero(x)} \supset \text{Persian}(x)$	$\neg$ I, 4—15

Syllogisms: The First Natural Logic

1	*All Gods live on Mount Olympus*	
2	*Some heroes are Gods*	
3	*Nobody who lives on Mount Olympus is Persian*	
4	*Some heroes live on Mount Olympus*	AII (Darii), 1, 2
5	*Some heroes are not Persian*	EIO (Ferio), 4, 3
6	$\neg$ *All heroes are Persian*	SaP $\perp$ SoP, 5

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6	¬ *All heroes are Persian*	SaP $\perp$ SoP, 5

...But syllogisms are cripplingly unexpressive

Modern Natural Logic

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

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

Modern Natural Logic

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Mutations must respect *polarity*.

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Mutations must respect *polarity*.

Not pictured: also handles negation

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

Natural Logic Inference as Search

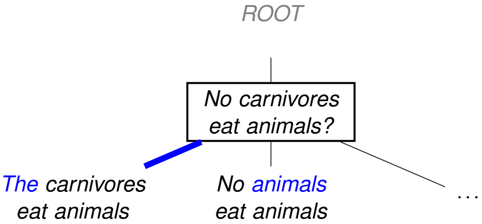
Shorthand for a node:

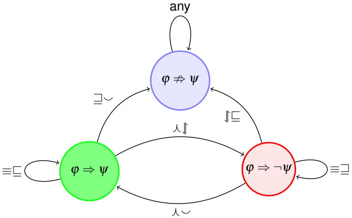
	organism		living thing
	animal	consume	organism
$\uparrow$ **No**$_{\downarrow\downarrow}$	$\downarrow$ carnivores	$\downarrow$ eat	$\downarrow$ animals
	felines	slurp	chordate

$\Downarrow$

No carnivores eat animals?

Natural Logic Inference as Search





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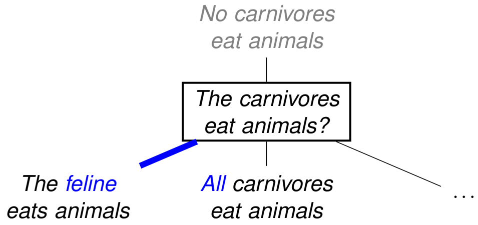

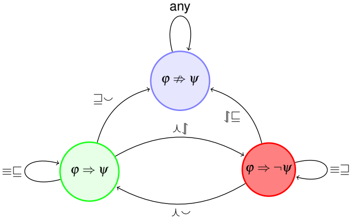

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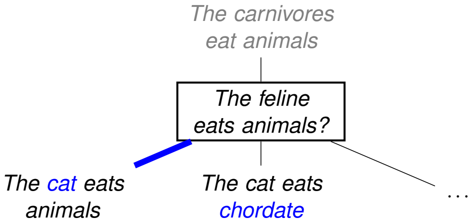

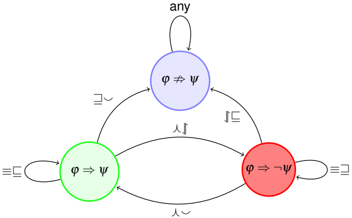

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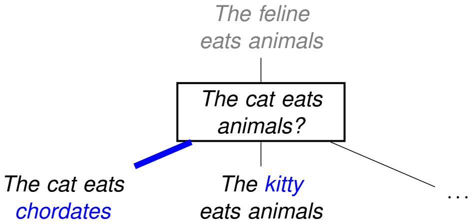

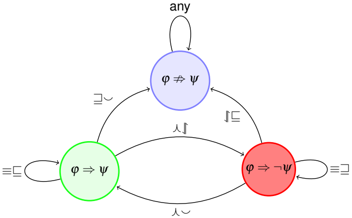

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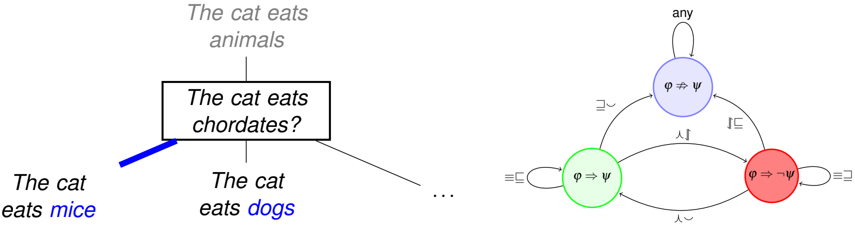

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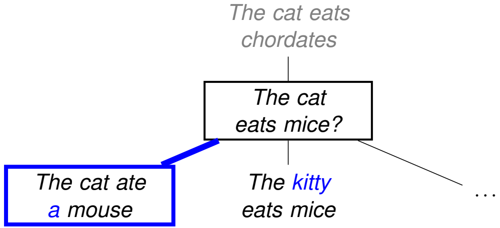

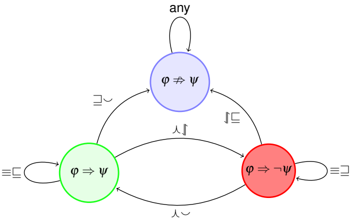

Three Contributions for Generalizable Inference

1. **Partial order over meronymy + relations**

Earth

EU | have

$\uparrow$ Germany | $\uparrow$ own

Berlin | sell

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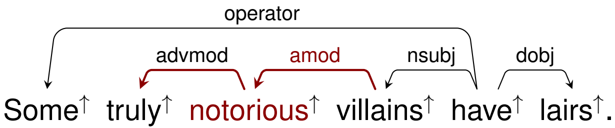
2. **Natural Logic over dependency trees**



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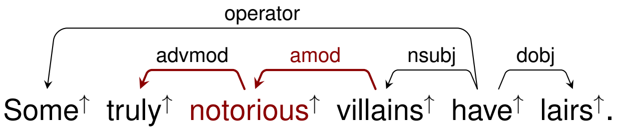

3. **Hybrid statistical / logical solver**

An Example Search

ROOT

Rain and snow are types of precipitation?

Rain and snow are forms of precipitation

Heavy rain and snow are types of precipitation

. . .

An Example Search

ROOT

Rain and snow are types of precipitation?

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An Example Search

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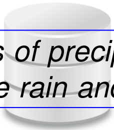

Forms of precipitation include rain and sleet

An Example Search

Rain and snow are types of precipitation

Rain *and snow are* ***forms*** *of* ***precipitation****?*

Rain and snow are forms of weather

Heavy rain and snow are forms of precipitation

. . .

Forms *of* ***precipitation*** *include* ***rain*** *and sleet*

Lexical Alignment Classifier

Forms *of* ***precipitation*** ***include*** ***rain*** *and* ***sleet***

Rain *and* ***snow*** *are* ***forms*** *of* ***precipitation***

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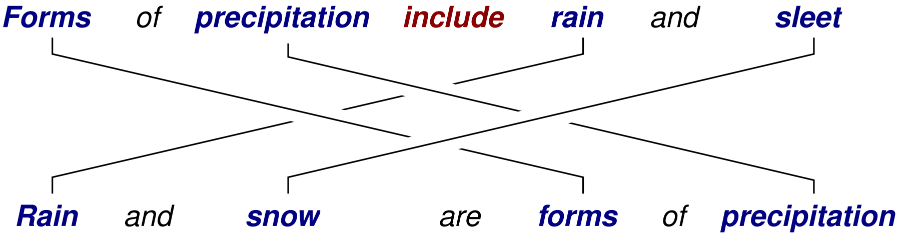

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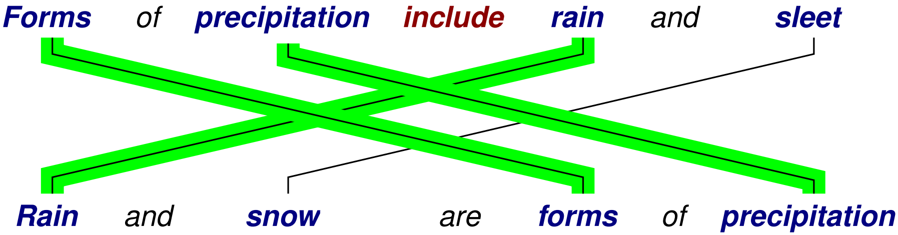
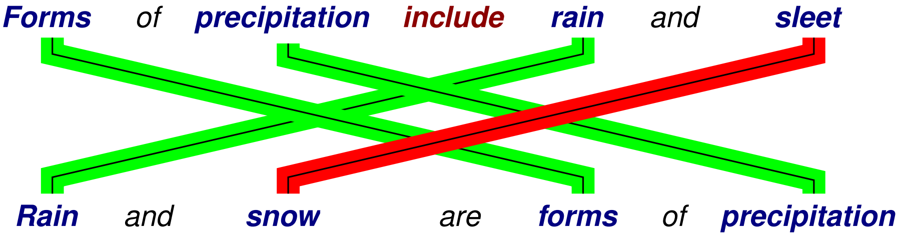


Features

1. Matching words

Lexical Alignment Classifier



Features

1. Matching words
2. Mismatched words

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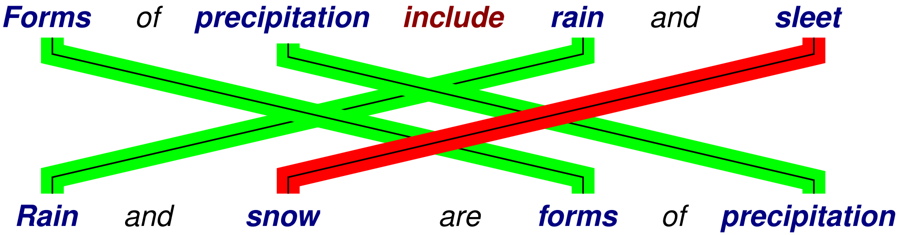

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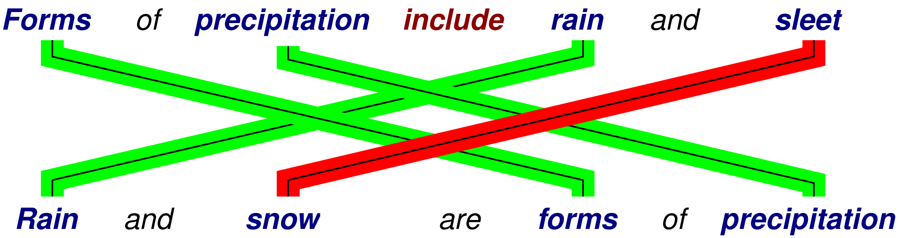

Features

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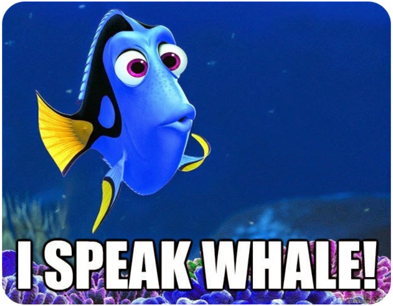
Competitive with Stanford RTE system (63% on RTE3)

Old Problem: Logic + Lexical Classifiers

FOL and lexical classifiers don't speak the same language

Old Problem: Logic + Lexical Classifiers

FOL and lexical classifiers don't speak the same language
...but natural logic does!



Big Picture

Run our usual search

1. If we find a premise, great!

Big Picture

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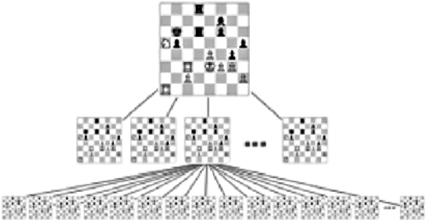

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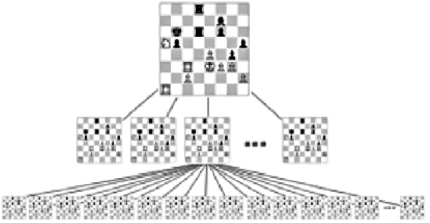

Visit 1M nodes / second: We have to be fast!

Dissecting Our Classifier

Anatomy of a Classifier

- Features f (matching / mismatched / unmatched words)
- Weights w
- Entailment pair x

$$p(\text{entail} \mid x) = \frac{1}{1+\exp(-w^{T} f(x))}$$

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$$p(\text{entail} \mid x) \text{ monotone w.r.t. } \left(w^{\mathrm{T}} f(x)\right)$$

- Only need $w^{\mathrm{T}} f(x)$ during search to compute $\max p(\text{entail} \mid x)$
- $w^{\mathrm{T}} f(x)$ is our evaluation function

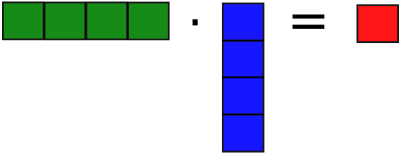
Incorporating our Evaluation Function

Anatomy of a Search Step

1. Mutate a word, or
2. Delete a word, or
3. Insert a word.

Each step updates a small number of features

$$w^{\mathrm{T}} f(x) = v$$



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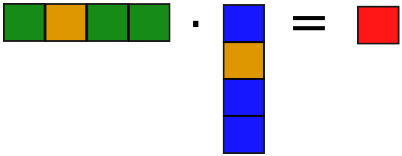

Incorporating our Evaluation Function

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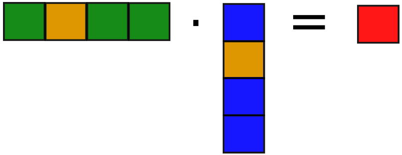
$$v' = v - w_i \cdot f_i + w_i \cdot f_i$$



Why is this Important?

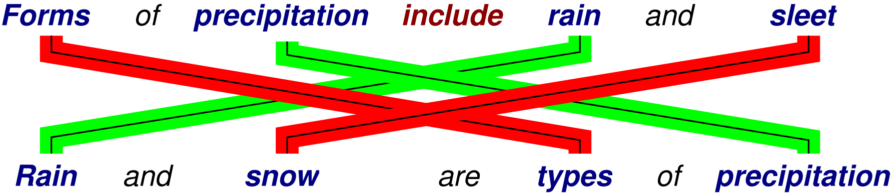
Faster Search ⇒ Deeper Reasoning

- **Speed:** Around 1M search states visited per second
- **Memory:** 32 byte search states

Speed: Don't re-featurize at every timestep.

Memory: Never store intermediate fact as String.

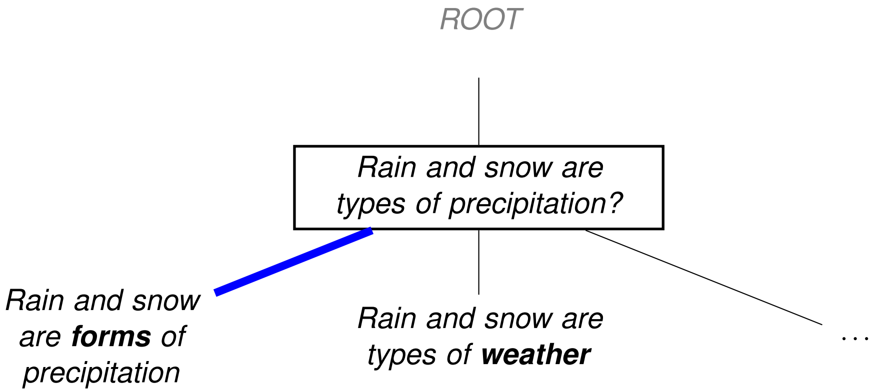
Another Example Search



Score $w^{\mathrm{T}} f(x)$**:** -0.5

Feature	w	$f(x)$
Matching words	2.0	2
Mismatched words	-1.0	2
Unmatched premise	-0.5	1
Unmatched consequent	-0.75	0
Bias	-2.0	1

Another Example Search



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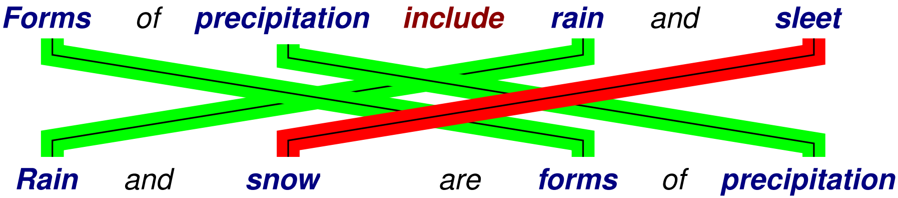

Score $w^{\mathrm{T}} f(x)$**:** -0.5 + 2 − -1

Feature	w	$f(x)$
Matching words	2.0	**3**
Mismatched words	-1.0	**1**
Unmatched premise	-0.5	1
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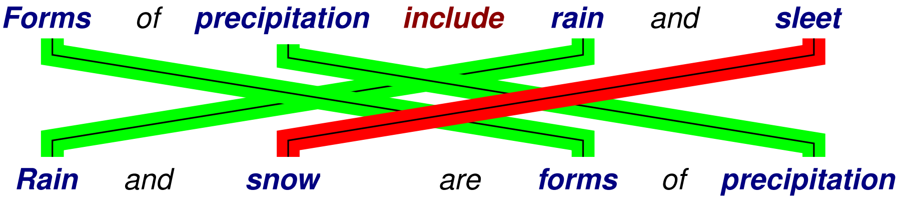

Score $w^{\mathrm{T}} f(x)$**:** 2.5

Feature	w	$f(x)$
Matching words	2.0	**3**
Mismatched words	-1.0	**1**
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Solving 4^{th} Grade Science

Multiple choice questions from real 4^{th} grade science exams

Solving 4^{th} Grade Science

Multiple choice questions from real 4^{th} grade science exams

Which activity is an example of a good health habit?

(A) Watching television
(B) Smoking cigarettes
(C) Eating candy
(D) Exercising every day

Solving 4^{th} Grade Science

Multiple choice questions from real 4^{th} grade science exams

Which activity is an example of a good health habit?

(A) Watching television
(B) Smoking cigarettes
(C) Eating candy
(D) Exercising every day

In our corpus:

- *Plasma TV's can display up to 16 million colors ... great for watching TV ... also make a good screen.*
- *Not smoking or drinking alcohol is good for health, regardless of whether clothing is worn or not.*
- *Eating candy for diner is an example of a poor health habit.*
- *Healthy is exercising*

Solving 4^{th} Grade Science

Multiple choice questions from real 4^{th} grade science exams

System	Train	Test
KNOWBOT	45	
KNOWBOT (ORACLE)	57	

[Hixon et al., 2015]

Solving 4^{th} Grade Science

Multiple choice questions from real 4^{th} grade science exams

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KNOWBOT	45	
KNOWBOT (ORACLE)	57	
IR Baseline	49	
This Work	52	

[Hixon et al., 2015]

Solving 4^{th} Grade Science

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IR Baseline	49	
This Work	52	
More Data + IR Baseline	62	
More Data + This Work	**65**	

[Hixon et al., 2015]

Solving 4th Grade Science

Multiple choice questions from real 4th grade science exams

System	**Train**	**Test**
KNOWBOT	45	–
KNOWBOT (ORACLE)	57	–
IR Baseline	49	42
This Work	52	51
More Data + IR Baseline	62	58
More Data + This Work	**65**	**61**

[Hixon et al., 2015]

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More Data + This Work	65	61
This Work +  + 	**74**	**67**

[Hixon et al., 2015]

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This Work +  + 	**74**	**67**

We're able to pass 4th grade science!

[Hixon et al., 2015]

Conclusions

Natural Logic

- A logic over the syntax of natural language
- Expressive but efficient

Natural Logic "plays nice" with statistical (/deep?) methods

- Both operate directly over text
- Use lexical classifier as evaluation function

NaturalLI + Evaluation Function

- Also detects *likely* entailment / contradictions
- 3% improvement on science exam questions

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