Why it's hard for robots to learn word meanings

Paul Cohen
Department of Computer Science

How Children Learn Word Meanings

"Here is how they do it: Young children can parse adult speech (or sign) into distinct words. They think of the world as containing entities, properties, events, and processes; most important, they see the world as containing objects. They know enough about the minds of others to figure out what they are intending to refer to when they use words. They can generalize…They can also make sense of pronouns and proper names, which refer to distinct individuals, not to categories…Months after their first words, [children exploit]… the syntactic and semantic properties of the utterances that new words belong to. This enables the learning of many more words, including those that could only be acquired through this sort of linguistic scaffolding." – Paul Bloom

The Environment of Child Language Acquisition

Child and adult are embedded in a *scene* the child can parse and understand

Most dialog with kids is *about* something, usually present or immediately inferable things

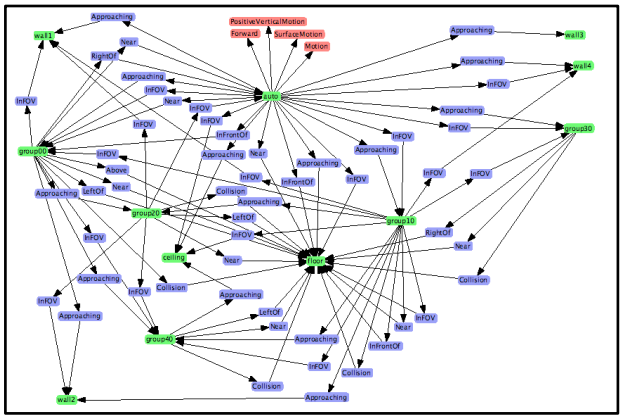
Mental state is perhaps the most interesting inferable thing

Not like corpus-based language learning

“ Don’t you want your cookie? ”
“ No”
“ You are so stubborn!”
<< kid learns some of what stubborn means >>

Associative learning of word meanings

“stubborn” =



“ Don’t you want your cookie? ”
“ No”
“ You are so stubborn!”

Referential ambiguity:
An objection to an empiricist account

"Poor thing!" (the dog)

"Do you think it's full?" (the cup)

"Isn't it hot?" (the coffee)

"OMG look at that!" (the whole scene)

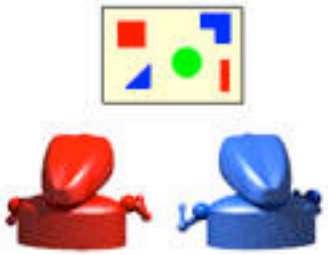
"Quick, take a picture!" (someone outside of the scene)

"Do you suppose it hurts?" (???)

Heuristics (e.g., whole object assumption), parents work hard, kids are good mind readers, and above all the empirical fact that we can figure out the referents in each sentence given the scene.

Robots learn word meanings: Early attempts

the talking heads



The agents look at the scene on the whiteboard in front of them.

One agent says a word which distinguishes one object in the scene from all the others.

If the other agent doesn't know the meaning of the word, the game fails.

If one agent doesn't know the meaning of a word used by another, it can't pick out the object that the other agent is talking about. But it can try to work out a property - such as a color or size - that identifies one object in the scene, and learn that as the meaning of the unknown word.

Luc Steels
http://talking-heads.csl.sony.fr

the talking heads

One agent says a word which distinguishes one object in the scene from all the others.

The hearer checks the word against its own vocabulary.

The hearer understands the word 'wabaku' to mean 'red'.

As the agents learn each other's words, they begin to be able to communicate. In this example, the hearer has successfully recognised that the word 'wabaku' denotes a particular shade of red, and has been able to identify the object that the speaker has in mind.

Luc Steels
http://talking-heads.csl.sony.fr

Associative learning issues

What should this representation be? The scene is often dynamic

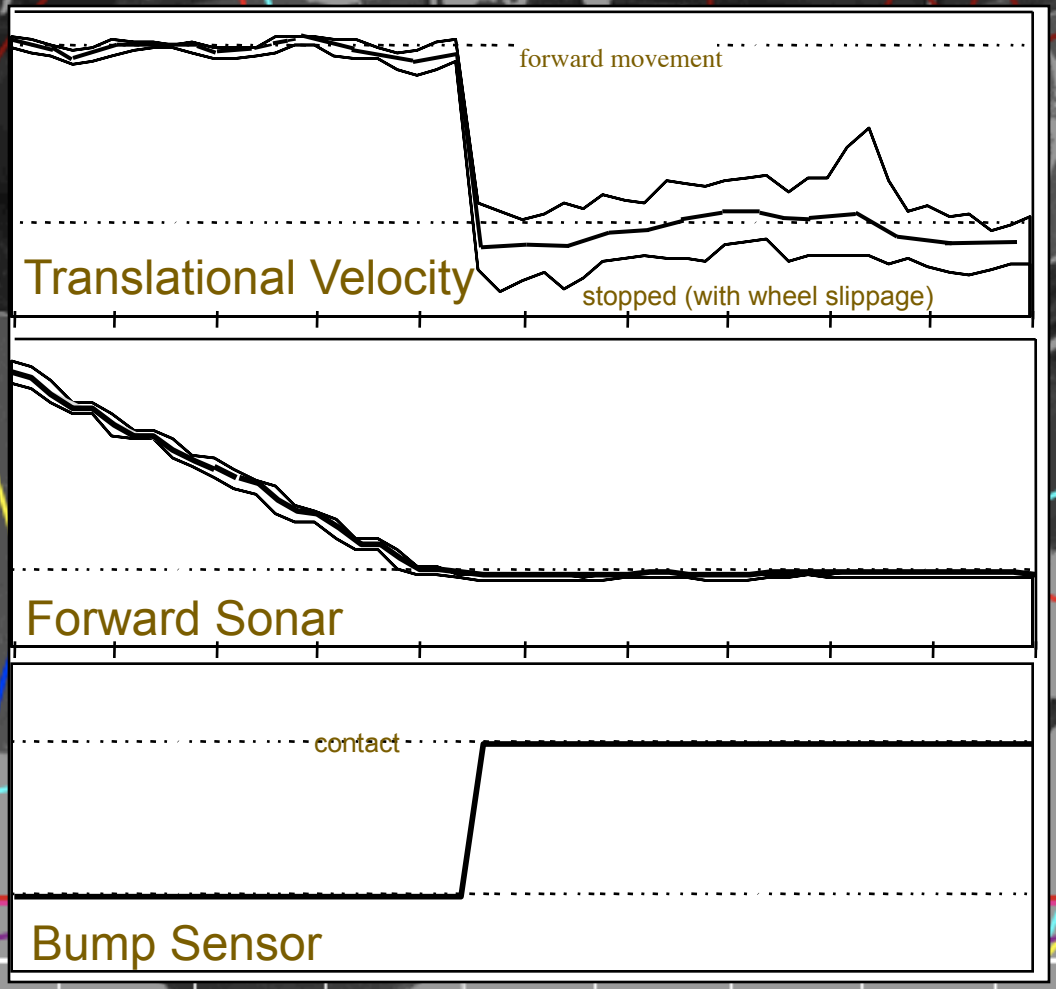
How to represent unobservables like speaker's intentions?

How best to collect the data

How to associate words with aspects of scenes

Formal representations of scenes	Sentences
	“ Don’t you want your cookie? ” “ No” “ You are so stubborn!”

Robot Baby
Associating Words with Sensory Patterns
(with Tim Oates, 1998 - 2001)



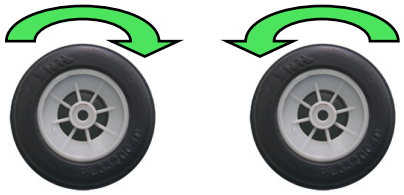
Assessment of Robot Baby word learning

Good

- Making sensory experience part of word meaning – what it "feels like" to bump something
- Associating sensory prototypes with classes of words, as classes of words have meanings, too
- Ability to represent temporal "story" is good for verb meanings

Not So Good

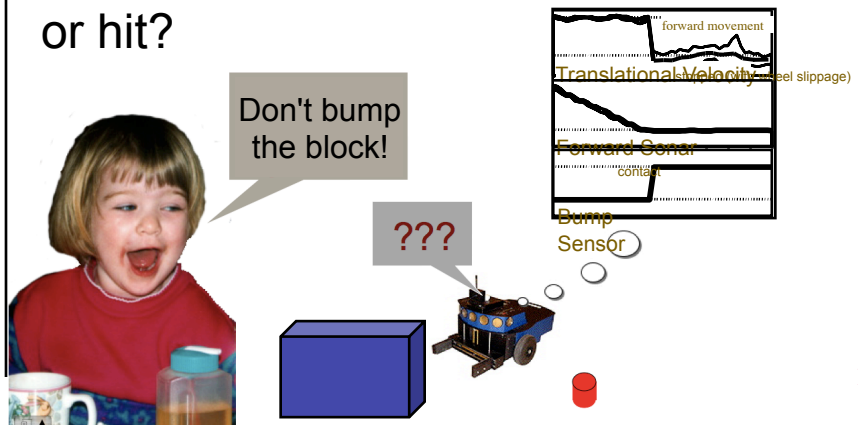
- There's more to the meaning of a word than the sensory experience associated with it



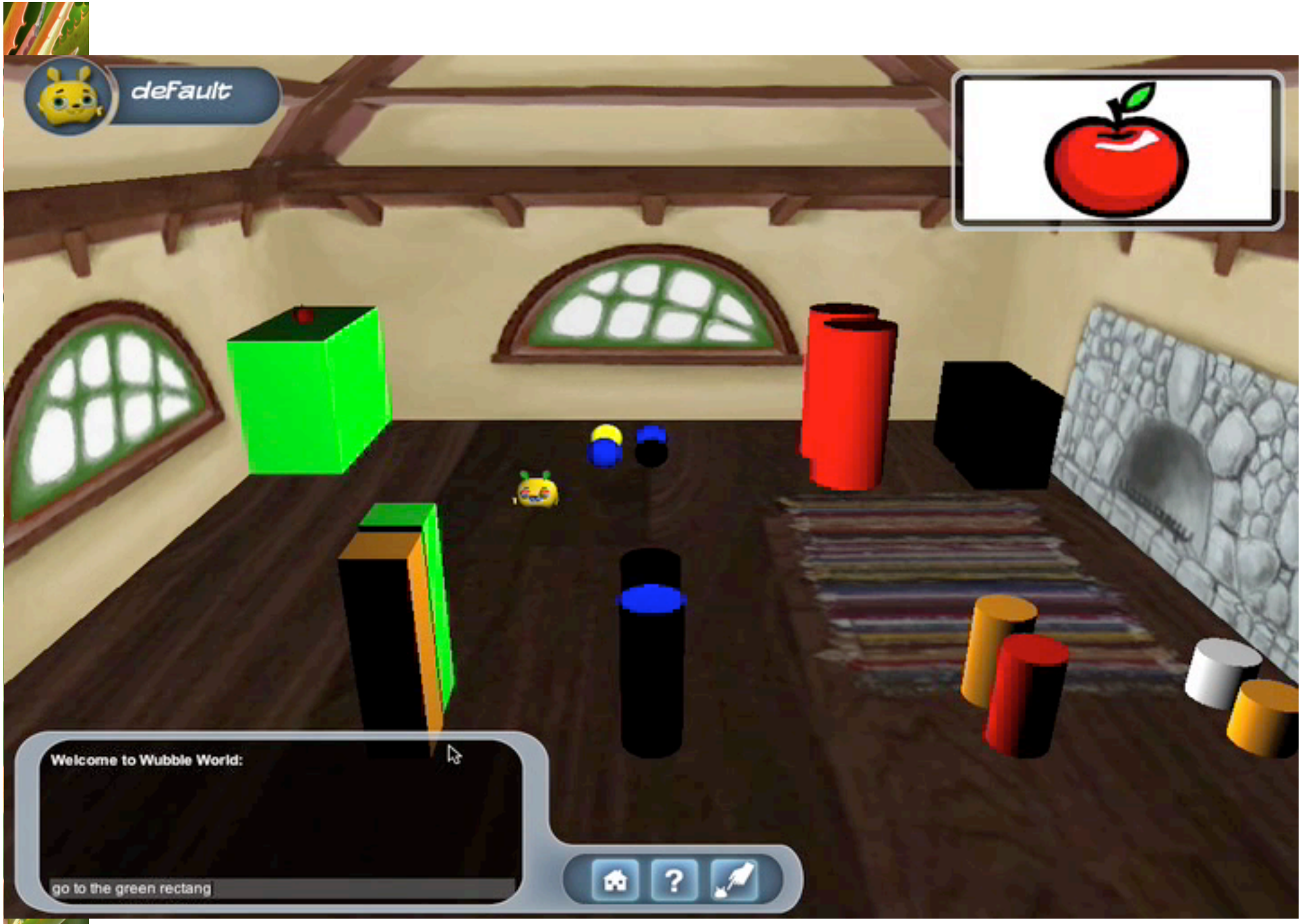
"Forward" "Backward"

But can't learn that forward and backward are *antonyms*

- Sensory prototypes don't individuate and denote things and relations. Where's the *object of the verb*, the thing the robot bumped or hit?



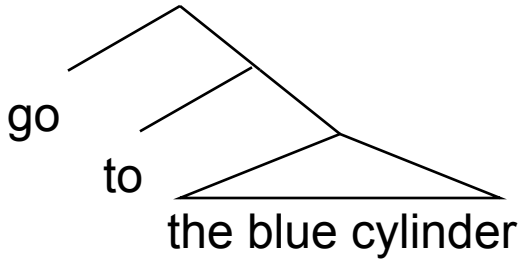
Getting a Sentence-Scene Corpus Quickly


deFault
Welcome to Wubbie World:
go to the green rectang

How Wubbles Learn the Meanings of Words

"Go to the blue cylinder"

1. parse



3. score correspondences between retrieved representation and scene

2. retrieve a semantic representation of a word or phrase

4. act or ask

5. given positive feedback, update semantic representation

Assessment of Wubble World word learning

Good

Simple, gradual learning method based on positive instances only. Learns multiple word meanings simultaneously. Converges fast to correct meaning.

Demonstrates that kids can teach wubbles word meanings in an enjoyable web-based game

Syntactic bootstrapping - parse first, guess at part of speech, create new feature vector for it

Not So Good

Unclear whether it will work for richer semantic representations

Even these smart, geeky kids were bored after two hours (NB: all agreed that wubbles that learn and respond are better than usual fare)

Very poor semantics, very few parts of speech, what about syntactically ambiguous words?

What about verbs?

What about the speaker's mental state? “I want the red one…No, the other one.”

Checkpoint

- Most learning of word meanings in AI is superficial in the sense of associating sensory features with words
- You can't *do* much with those learned meanings: antonymy, synonymy, comparing word senses, metaphor, etc.
- Some of those learned meanings don't even function as representations; don't individuate or denote, aren't composable, etc.

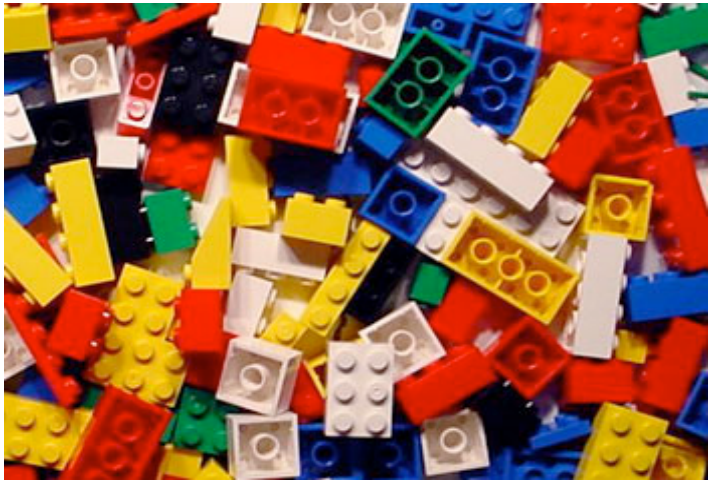
- Games are probably a good data collection method
- Association isn't a bad way to learn
- If we had better features we could learn deeper word meanings

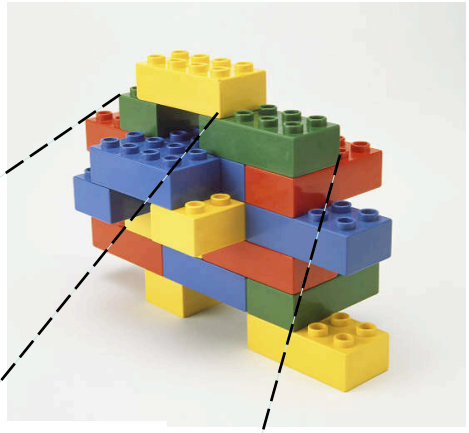
- If words are just names for concepts then word learning is largely concept learning: deeper meaning = associations w/ more concepts
- Word meanings are acquired gradually and deepen over time
- Deep understanding doesn't require a big, fancy vocabulary

Desiderata for concept representations

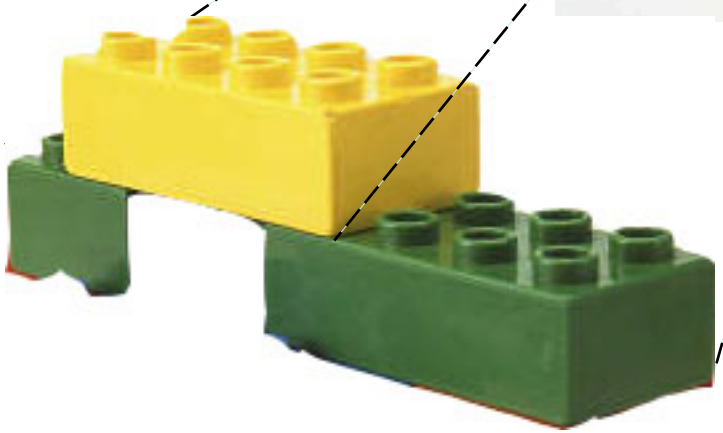
"you are so stubborn!"

Long Term Memory Concepts





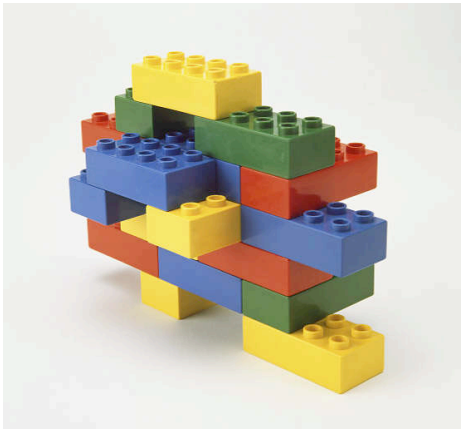
"stubborn"



Short Term Memory Scene Representation

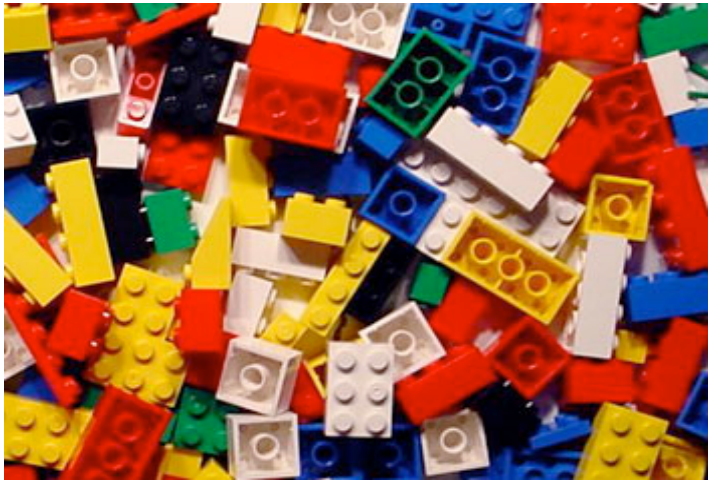
These probably aren't arbitrary arrangements, they have a syntax, e.g., type constraints.

They do work, e.g., comparing concepts, finding similar concepts, inference – prediction and explanation -- and QA, analogy, metaphor



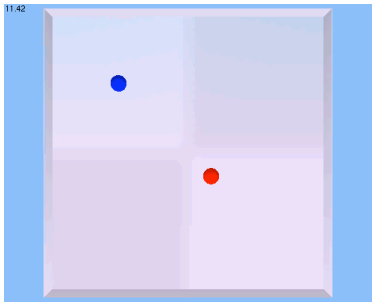
Short Term Memory Scene Representation

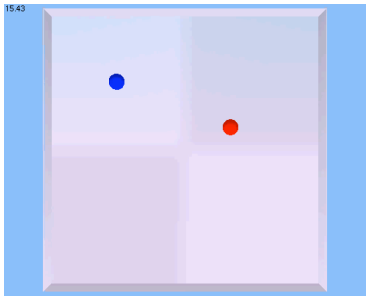
Long Term Memory Concepts

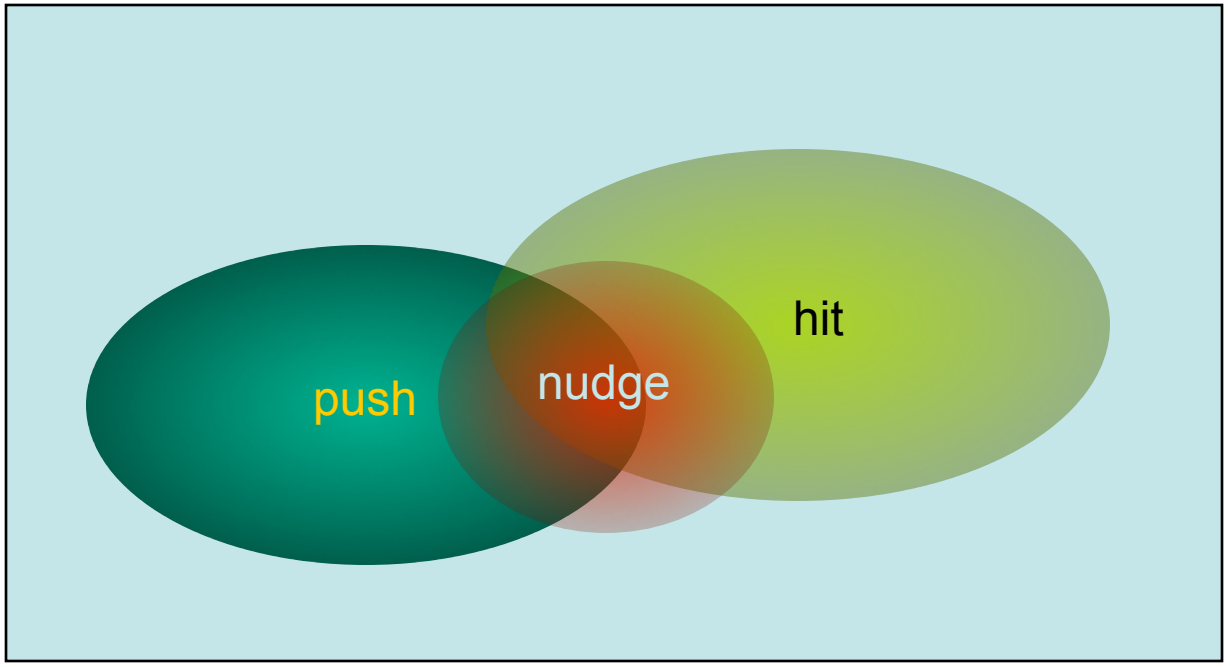


We haven't found an off-the-shelf source of these concepts or semantic primitives

Pr(utter word | semantic features) is gradual function of the features







Clustering experiences in metric space and associating words with joint probability distributions Pr(utter word | dimensions) seem to work

Representations of verbs should “tell the story”

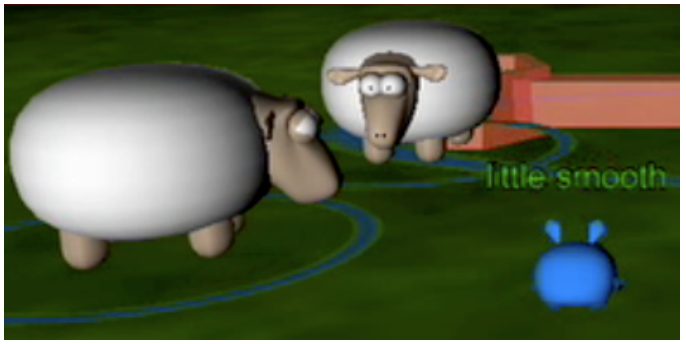
jump over	
InBackOf(W,D)	----------11111111
NegativeVerticalMotion(W)	----------1111-----
Away(W,ceiling)	---------11111-----
Towards(W,floor)	---------11111-----
Away(W,D)	------11----1111111
Below(D,W)	------11111--------
Above(W,D)	------11111--------
PositiveVerticalMotion(W)	----111-------11---
Away(W,floor)	----1111-------11--
Towards(W,ceiling)	----1111------111--
Jump(W)	---11-------------
Towards(W,D)	--1111---111-------
SurfaceMotion(W)	--1111111111111111
Motion(W)	--1111111111111111
Forward(W)	-1111111111111111
Collision(W,floor)	11111--------111--1
On(W,floor)	11111--------111--1
InFrontOf(W,D)	111111------------

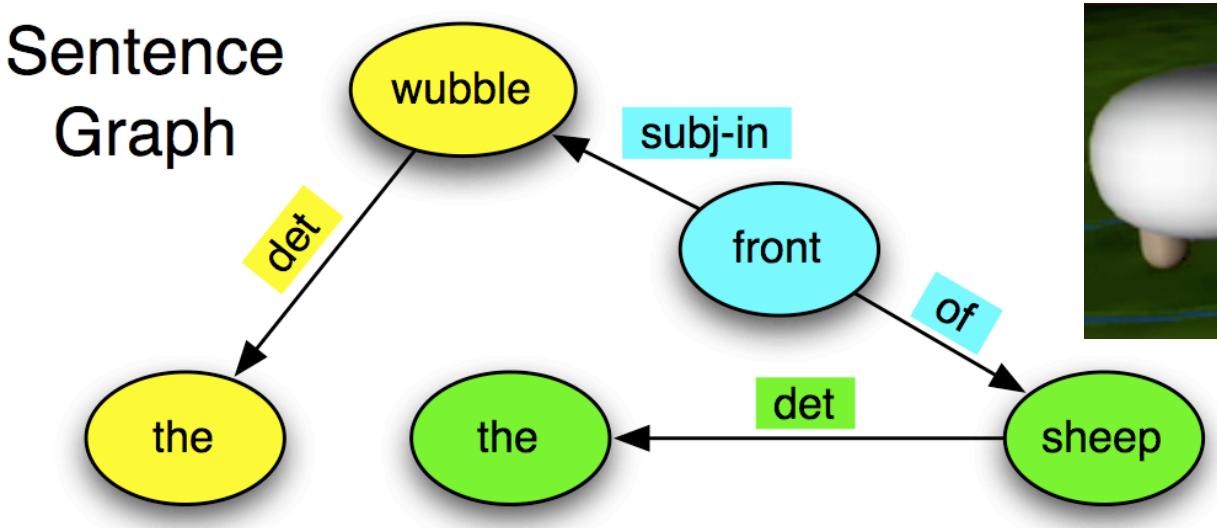
But they also should be denoting and afford propositional reasoning

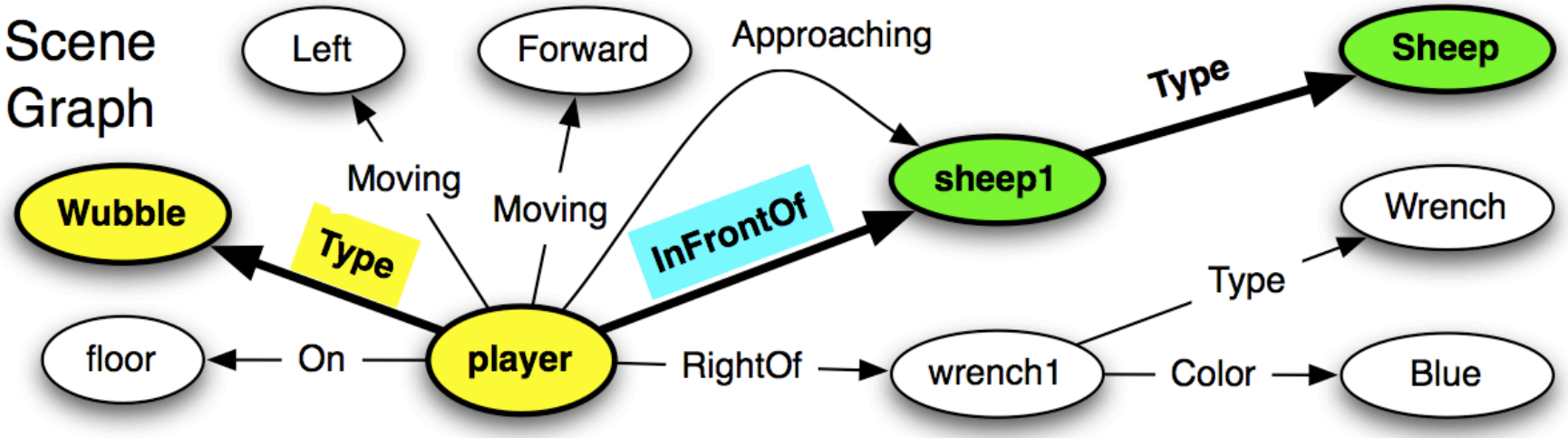
Softbots learn word meanings: Current work

Unsupervised Learning of Associations Between Sentence and Static Scene Graphs

Daniel Hewlett







Verb models for Wubble World

Wesley Kerr

Time

249 propositions

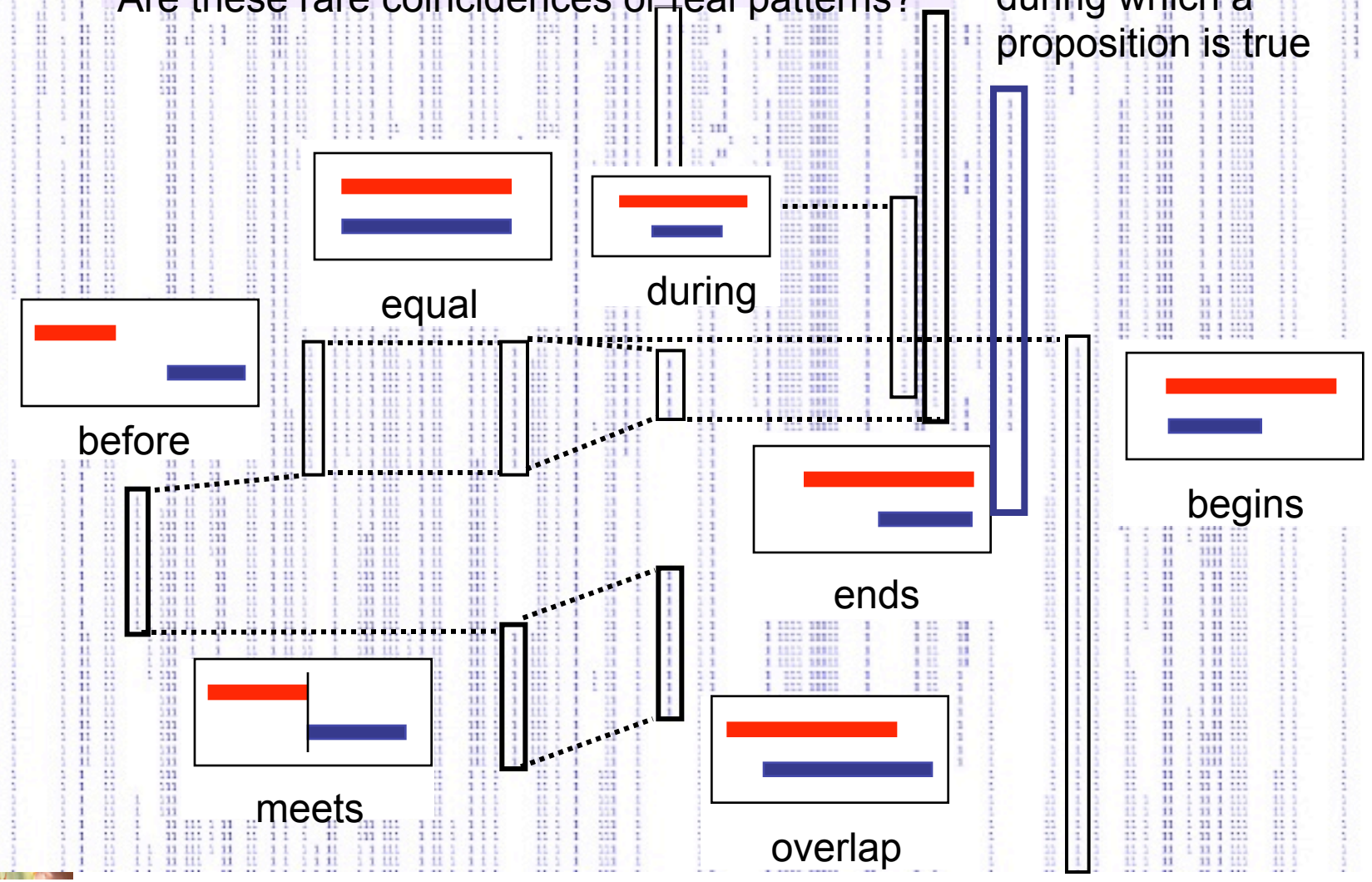
Verb models for Wubble World

These are the seven Allen Relations

Coincidence without cause is rare

Are these rare coincidences or real patterns?

A *fluent* is an interval during which a proposition is true

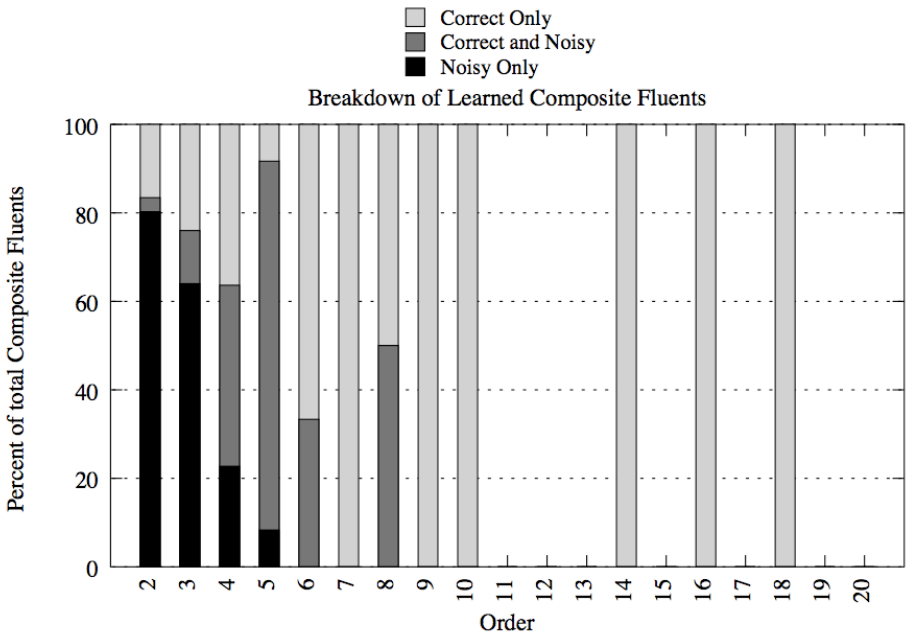


Illustrative results

jump over

InBackOf(W,D)	----------11111111
NegativeVerticalMotion(W)	----------1111-----
Away(W,ceiling)	---------11111-----
Towards(W,floor)	---------11111-----
Away(W,D)	------11----1111111
Below(D,W)	------11111--------
Above(W,D)	------11111--------
PositiveVerticalMotion(W)	----111-------11---
Away(W,floor)	----1111-------11--
Towards(W,ceiling)	----1111------111--
Jump(W)	---11-------------
Towards(W,D)	--1111---111-------
SurfaceMotion(W)	--1111111111111111
Motion(W)	--1111111111111111
Forward(W)	-1111111111111111
Collision(W,floor)	11111--------111--1
On(W,floor)	11111--------111--1
InFrontOf(W,D)	111111------------

The algorithm learned an 18-fluent pattern correspoding to jump-over with no intrusions from the other 221 noise fluents

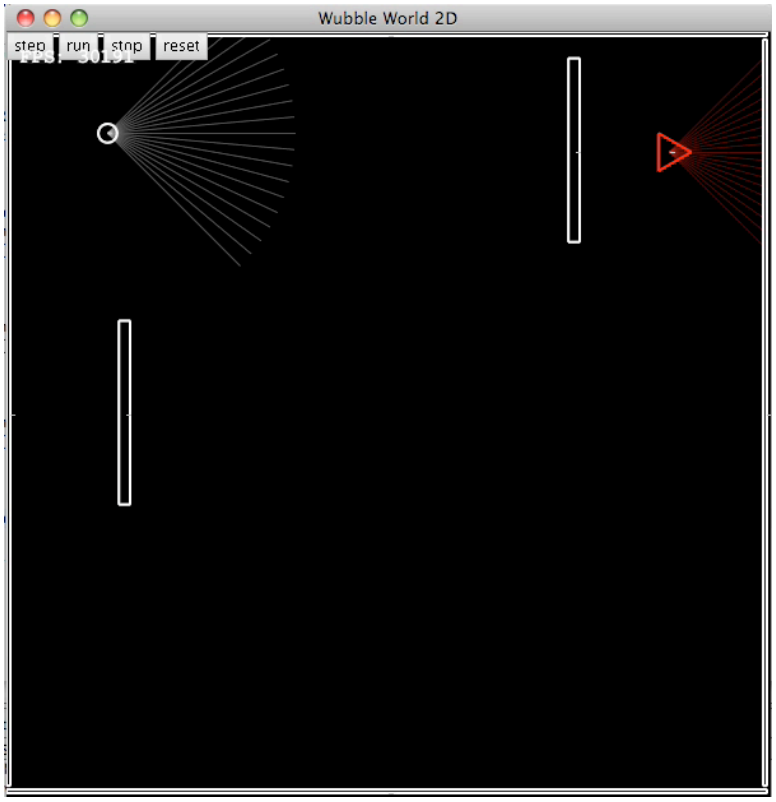


Omniscient Word Learning

Heider and Simmel, 1944
(e.g., http://www.youtube.com/watch?v=sZBKer6PMtM)

Omniscient Word Learning

Wes Kerr, Jim O'Donnell



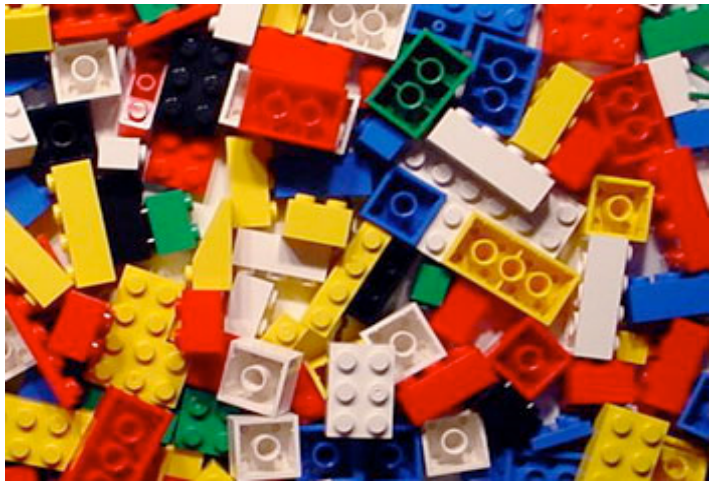
Each agent is controlled by a Soar-based BDI system so we have access to

- position and velocity
- dynamics
- perceptions of each agent
- which controllers were "on"
- which goals were "on"
- affective state
- inferences given state

Protocol

1) Run the agents in social interactions, recording all of the above (the "semantic trace")
2) Make movies and show them to humans, who annotate them
3) Bring the annotations into correspondence with the semantic trace to figure out the meanings of words

Why it is hard for robots to learn word meanings



Not sensing and perception, learning methods, lack of data, lack of humans to interact with, or lack of interesting environments

It's the lack of conceptual foundations for word meanings that connect to sensing and perception, are learnable from data, and that support all the kinds of reasoning one does with linguistically-expressed concepts