Interactive Learning
and its role in
Pervasive Robotics

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Motivation

- Teachable Robotics
  - Systems that learn tasks from end users
- Robots becoming more ubiquitous
  - Cooking, toys, homes…
- Move away from "mainframe model"
  - Defined tasks
  - Fixed environment
  - Expert interaction

- An HRI model for low-cost, widely deployed robots.

Goals

- Make robots capable of natural learning
  - Interpret and execute upon human input
  - Interactively learn about physically-grounded objects, attributes, and skills
  - Many components: language, LBD, active learning…
- Make ubiquitous robots useful
  - Robots operating alongside people
  - Don't try to pre-conceive all possible needs
- "Grounded Language Acquisition"
  - Learn language from interacting with people and the world

Case Studies in Teachable Robotics

1. Semantic Mapping and Direction Following
   - Following human instructions
   - Real-time world model discovery

ISER 2012 – Matuszek, Herbst, Zettlemoyer, Fox

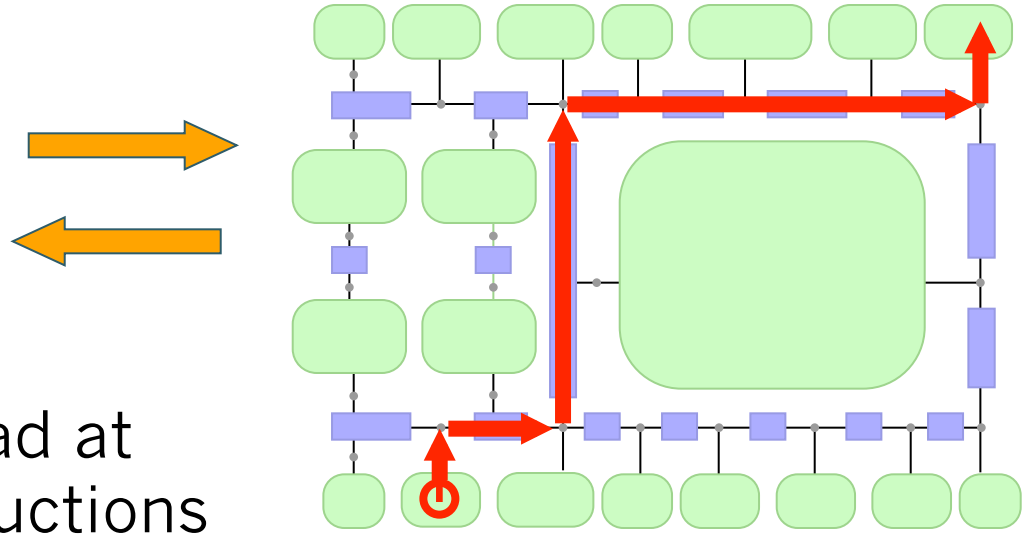
2. Learning Object Attributes
   - What colors and shapes exist in the world
   - How people refer to them

ICML 2012 – Matuszek, FitzGerald, Bo, Zettlemoyer, Fox

- Lessons learned
- Challenges and next steps

Route Instruction Following

"Leave the room and turn right, take the first left, go past the big room and go right, then go to the end of the hall and turn left."



- Humans are pretty bad at giving/following instructions
  - Missed turns, left/right errors, ...
  - *Humans* can only follow human instructions ~70% of time*
- Many sources of uncertainty
  - Map labeling errors, parse errors,
  - This is a well-studied task, but not an easy one.

* Reisbeck et al, 1985; MacMahon et al, 2006; Matuszek et al, 2010

Approach: Semantic Parsing

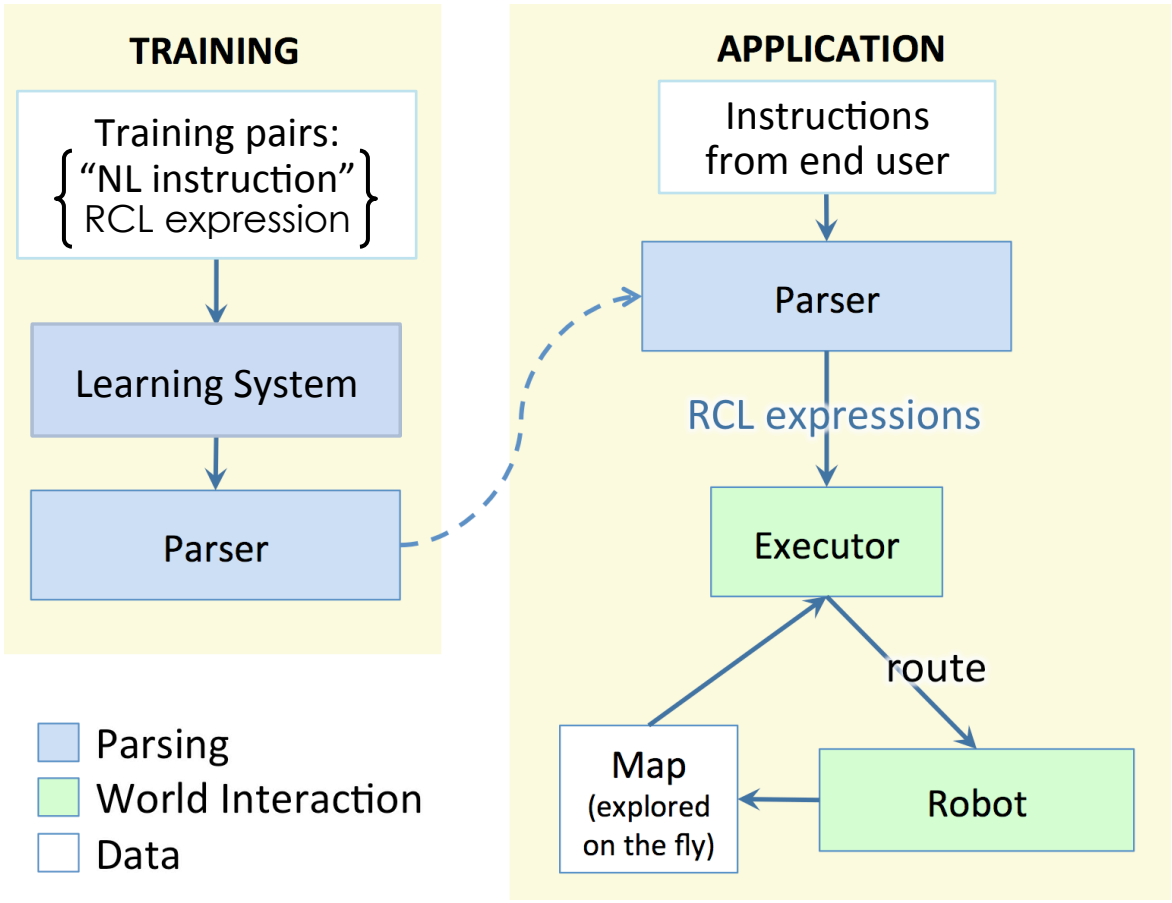
- Traditionally: NL ⟷ NL
  - Use sentence pairs to learn translation model
    "Ich bin müde" ⟷ "I'm tired"
- Our approach: NL ⟷ Robot Control Language
  - Source: natural language directions
  - Target: Robot Control Language grounded in map
- Learned parser based on many sentence pairs:

"Go down the hall to the intersection, then take a left."

```
(do-sequentially
  (do-until
    (junction current-loc)
    (move-to forward-loc))
  (turn-left)))
```

Robot Control Language

- Formal robot control language (lambda-calculus)



Example Commands

"Go left to the end of the hall."

```
(do-sequentially
   (turn-left current-loc)
   (do-until
      (or
         (not (exists forward-loc))
         (room forward-loc))
      (move-to forward-loc)))
```

"Go to the third junction and take a right."

```
(do-sequentially
   (do-n-times 3
      (do-sequentially
         (move-to forward-loc)
         (do-until
            (junction current-loc)
            (move-to forward-loc))))
   (turn-right current-loc))
```

- Humans generate English; our system generates RCL
- Assumptions: robot can execute actions, recognize objects, and determine conditionals
- Primitives can encode complex activities

Application to Route Instructions

- Training corpus
  - ~1000 paired route instruction sets
- Testing: instructions on novel maps
- How often does the robot reach the goal by the intended path (of human gold standard)?

Successes:

Short	924/1000	**66%**
Long	125/200	**49%**

- No error correction, so longer paths are strictly harder

Teaching with Language: Successes and Challenges

- Lessons and Successes
  - ✓ Robots can learn about tasks from end users
  - ✓ Language is intuitive and natural for giving directions
  - ✓ Language grounding ties in NLP community
- Challenges
  - x Formal annotations still expensive
  - x Need lots of NL training data
  - x Still bound to a pre-defined grammar
    - x Can't teach tasks that can't be expressed in existing RCL
- Local error recovery is crucial

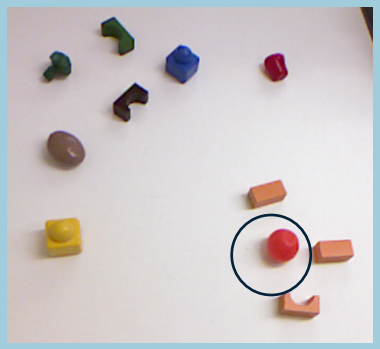
Case Study: Learning Attributes

- Learn to handle sentences about novel concepts
  - "These are limes"
  - No longer assuming underlying concepts already exist in RCL
    - What if 'green' is totally new?

- Requires:
  - Perception models
    - **green**; **round**
  - Language model
    - How words relate to these detectors

$$\lambda x \,.\, [\text{green}(x) \wedge \text{round}(x)]$$

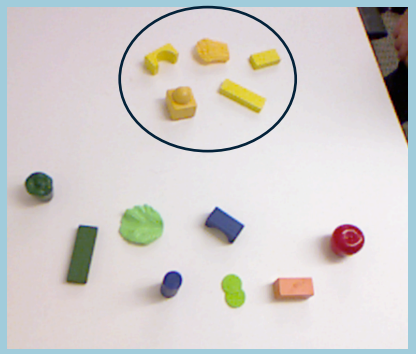
- Need a joint model for learning these together!



1: Initialization

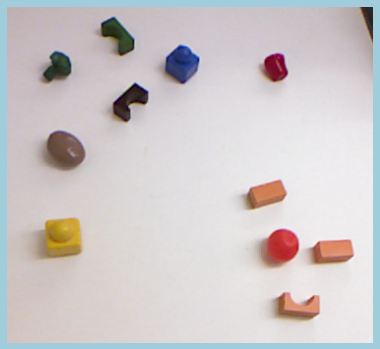
"This is an orange ball."

obj-color(x, color-orange) $\wedge$
obj-shape(x, shape-round)



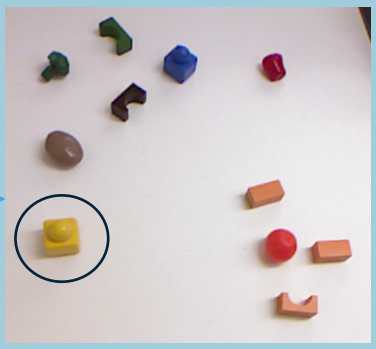
2: Training

"All of these toys are yellow."



3: Testing

"It's the yellow one."



obj-color(x, color-NEW)

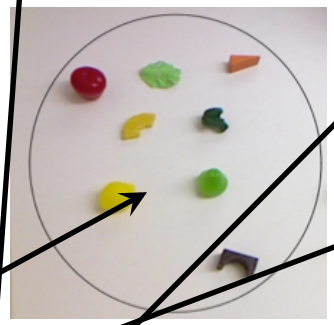
Joint Language / Perception Model

These are the ones that are not blue

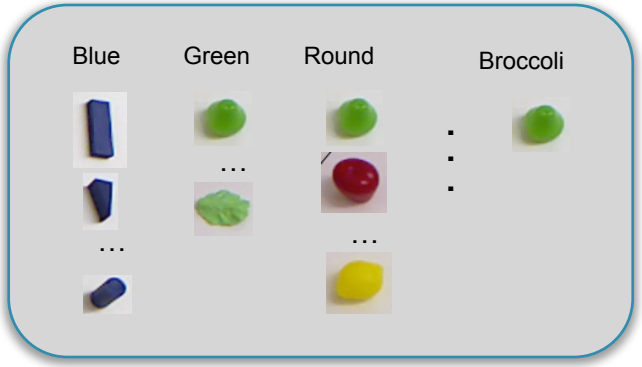
Semantic Parsing

$\lambda x.\neg color(x,blue)$

Attribute Classification



Grounded Query



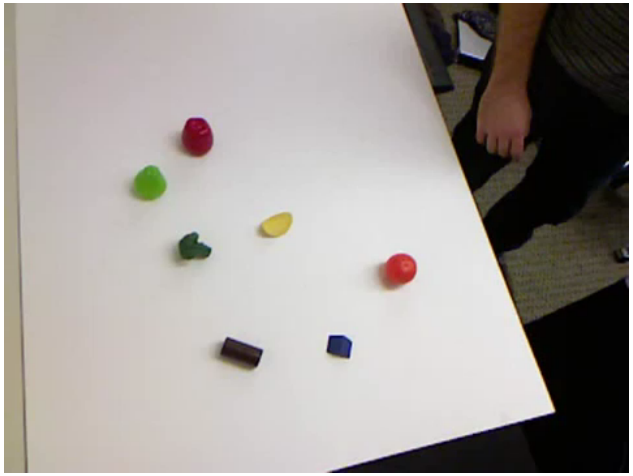
$$P(G,z,w \mid x,O) = P(z \mid x) \prod_{o \in O} \prod_{c \in C} P(c = w_{o,c} \mid o)\ \delta(G = z(w))$$

Joint Probability | Parsing Model | Vision Model | Grounding Query

NL Data from Crowdsourcing

What is the Parent Saying?

Watch the video, then **describe what the parent is saying to the child**, in complete sentences.



- Pretend you are a parent teaching a child about something.
- The question is:

How does the parent describe this group of objects?

Your answer should be the sentence(s) the parent said while pointing to these things.

Submit

"This one's an orange ball."

Showing HIT 1 of 3 Next HIT

λx. obj-color(x, color-orange) $\wedge$ obj-shape(x, spheroid)

Percepts Reduce Uncertainty

- New language can be ambiguous. Maintain hypotheses:
  - "This is <*new-word*>":
  - New attribute (color)?

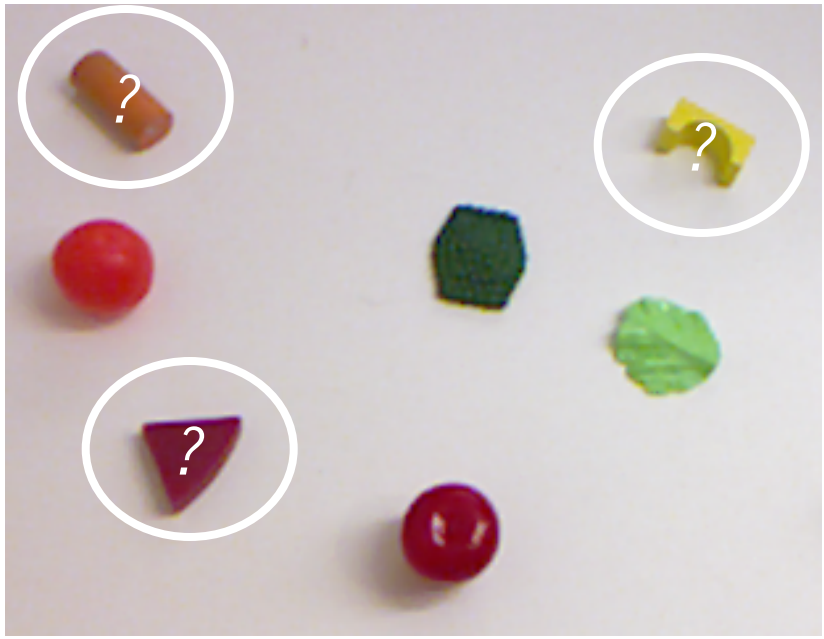
"This is red."
λx.obj-color(x, color-NEWCOL6)

  - New attribute (shape)?

"This is arched."
λx.obj-shape(x, color-NEWSHP1)

  - Synonymy?

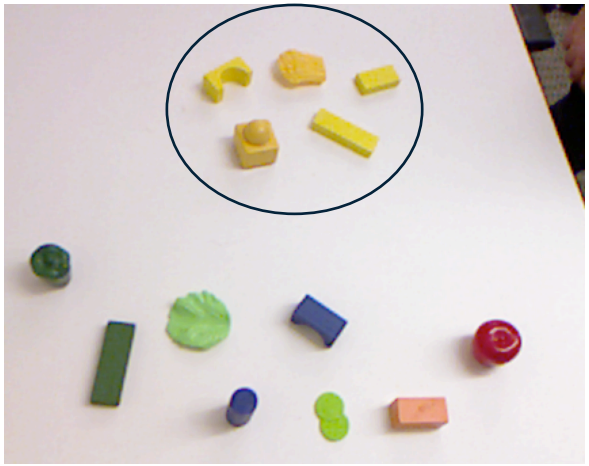
"This is peach."
λx.obj-color(x, color-orange)



After a few scenes, one hypothesis will have best predictive power.

Experimental Evaluation

- Fully Supervised Training: NL sentences from Mechanical Turk
  - 1,003 sentence/annotation pairs:
    - "These are yellow" / λx.obj-color(x, color-yellow)
  - 142 scenes (image, with a circle showing positive data)



- Training
  - 3 colors, 3 shapes used for bootstrapping
  - Train on previously unseen 3 colors and 3 shapes
- Testing: novel English, trained attributes, and novel scenes

Experimental Evaluation

- 18 trials
- Of dataset:
  - Average:
    - 502 supervised training triplets
    - 401 weakly supervised training pairs (NL/annotation)
    - 100 test NL/annotation pairs

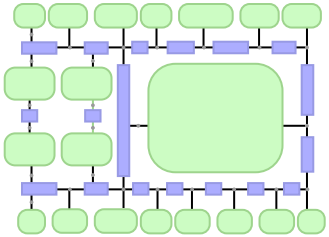
P = 0.82; R = 0.71; F = 0.76

Teaching with Language plus Vision: Successes and Challenges

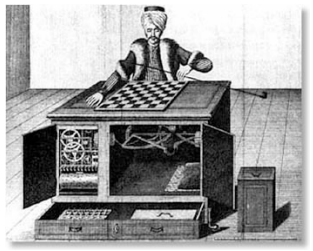
- Lessons and Successes
  - ✓ Language + vision = better interaction
    - ✓ Robot must be aware of human workspace
  - ✓ Experts providing just initializations is easier
  - ✓ Crowdsourcing for collecting non-expert data
  - ✓ Completely new concepts can be learned from users
- Challenges
  - x Some (expensive) annotation still needed
  - x Still providing some domain-specific seeding
  - x Need to learn more efficiently
    - x Still need too much training data to learn in one session

Case Study Discussion & Ideas

- Learn to understand human instructions, descriptions
  - Learn to follow instructions
  - To identify novel world attributes



- Challenges / suggestions
  - Crowdsourcing helps with (inevitable?) data needs
  - Minimize expert involvement
  - Avoid pre-defining uses
  - **Language grounding is powerful and applicable**



$\lambda x.\text{green}(x) \wedge \text{round}(x)$

- Future directions
  - Beyond language: gesture, gaze, body language
  - (Inter)active teaching / grounding

Summary: Teachable Robotics

- Users already know how they want to interact.
- We won't always know what tasks will be.
- Grounded Knowledge Acquisition lets us learn:
  - *What* humans need
  - *How* they want to convey it
- Instead of designing interaction, design teaching scenarios.