A Joint Model of Language and Perception for Grounded Attribute Learning

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Pervasive Computing

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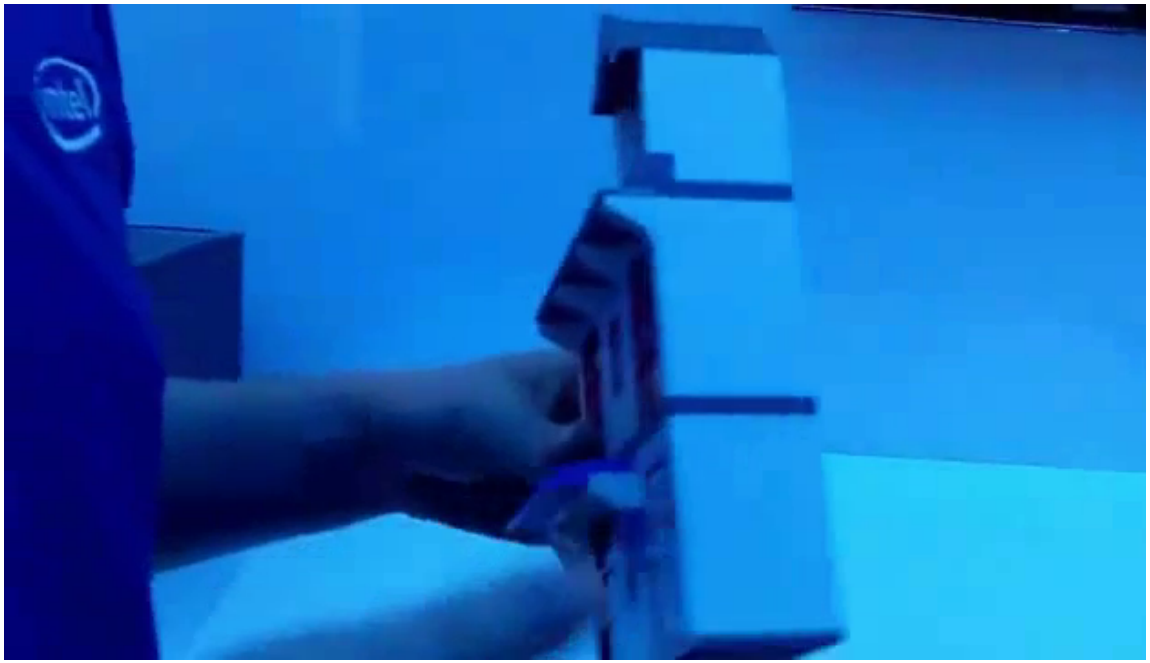
Learning Attributes

- Physically grounded systems → opportunities for learning
- **Motivation**: robots learning from **interaction**
  - With people
  - With environment
- Need a model to learn from real-world input
  - Language and sensory data about novel, physical things



- **Goal: learn new ideas from interacting with the world.**

Some Related Work

- Vision
  - Object recognition (Felzenszwalb et al., TPAMI 2009; *et al.*, CVPR 2009)
  - Visual attributes of objects (CVPR Farhadi et al., 2009; Parikh & Grauman, ICCV 2011)
  - Kernel descriptors (Bo et al., NIPS 2010; IROS 2011)
- Semantic Parsing
  - Inducing semantic parsers (Liang et al., ACL 2011; Wong & Mooney, ACL 2007; ...)
  - CCG parsers (Zettlemoyer & Collins, ACL 2009; Kwiatkowski et al., EMNLP 2011; ...)
- Grounded Language Acquisition and Parsing for Robotics
  - Parsing NL in known world and action models (Matuszek et al., ISER 2012; Tellex et al. AAAI 2011; Kollar et al., HRI 2010; ...)
  - Parsing NL for RoboCup and navigation (Mooney et al, Chen & Mooney, AAAI 2011)
  - Language grounding for semantic mapping (Kruijff & Zender, HRI 2006)
- And many more!

Outline

- Introduction & Motivation
- Related Work
- **Task Description**
- Background
- Joint Model & Model Learning
- Experimental Results
- Discussion and Future Work

Task Description

- Learning to select objects described by attribute
- Learn **previously unknown attributes**
  - Yellow: new word describing new idea
- NLP-style semantic parsing: mapping NL to formal representation
- Grounded in real-world perception

Task Description

Language

"yellow"

Formal Expression

`color-NEW-1(x)`

Classifier

$C_{color\text{-}new\text{-}1}(x) = \{0,1\}$

Ground Truth

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  - Semantic parsing model; perceptual model
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[Steedman (book) 2000, Kwiatkowski *et al* EMNLP 2010, 2011]

Categorial Combinatory Grammars

- Capture **syntax** and **semantics** of language
- Parse sentences to expressions in λ-calculus
- Space of possible parses defined by:

lexical entries

$$\text{red} \vdash N : \lambda x \,.\, \text{color-red}(x)$$
$$\text{block} \vdash N \backslash N : \lambda x \,.\, x$$

along with combinatory rules.

- Probabilistic CCGs define a log-linear model over:

sentence x
parse y
logical form z

$$p(y, z \mid x; \theta, \Lambda) = \frac{e^{\theta \cdot \phi(x,y,z)}}{\sum_{y',z'} e^{\theta \cdot \phi(x,y',z')}}$$

[Bo et al IROS 2011, CVPR 2011]

Perceptual Model

- Visual model is a set of binary classifiers, one/attribute
  - Each perceptual classifier is applied independently

$c_{color\text{-}yellow}(x)$

- Kernel descriptors
  - Trained using linear SVM

$$P(w_{o,c} = 1 | o; \Theta^P) = \frac{e^{\Theta_c^P \cdot \phi(o)}}{1 + e^{\Theta_c^P \cdot \phi(o)}}$$

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Joint Model

- Goal: compute the probability of an indicated set

$$P(G \mid x, O) = \sum_z \sum_w P(G, z, w \mid x, O)$$

- World model (product of possible classifier assignments to all objects o in O):

$$P(w \mid O) = \prod_{o \in O} \prod_{c \in C} P(w_{o,c} | o)$$

- Joint Model:

$$\underbrace{P(G, z, w \mid x, O)}_{\text{Joint Probability}} = \underbrace{P(z \mid x)}_{\text{Parsing Model}} \underbrace{P(w \mid O)}_{\text{World Model}} \underbrace{P(G \mid z, w)}_{\text{Grounding Query}}$$

Joint Model

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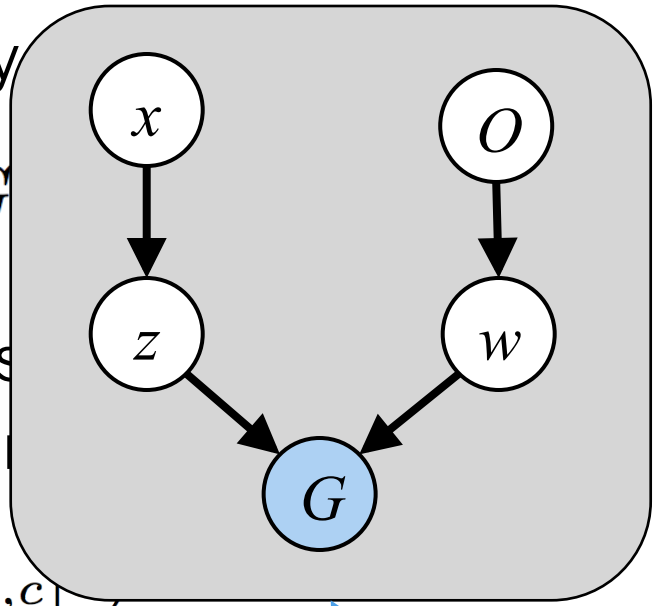

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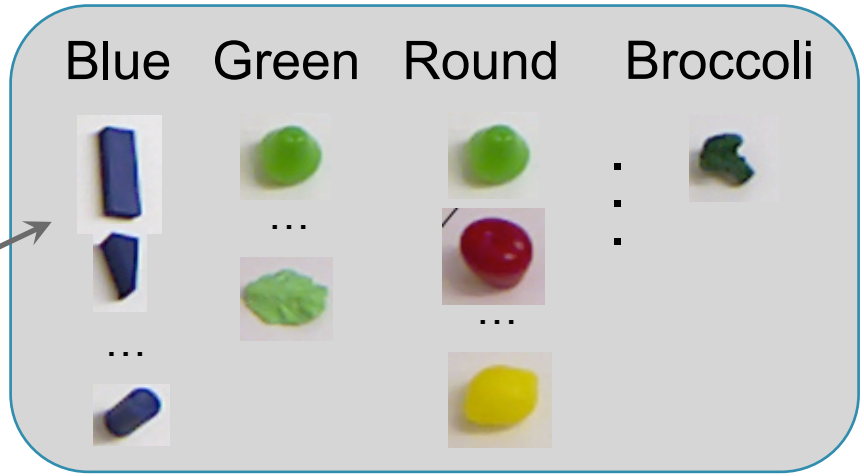
Inference

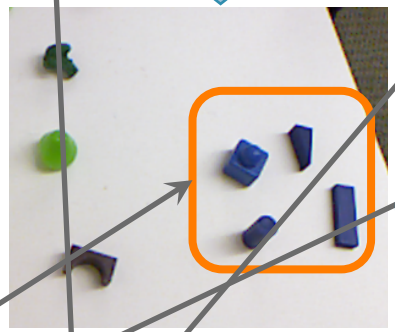
"These are the ones that are blue"

Semantic Parsing

$\lambda x.\text{color-blue}(x)$

Binary Attribute Classifiers





Grounded Query

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

Joint Probability

Parsing Model

Vision Model

Grounding Query

Why Joint Learning?

- Language helps determine attribute relations
- New language can be ambiguous: "This is <*new word*>."
  - New color attribute?

    "This is red."
  - New shape attribute?

    "This is square."
  - Synonym?

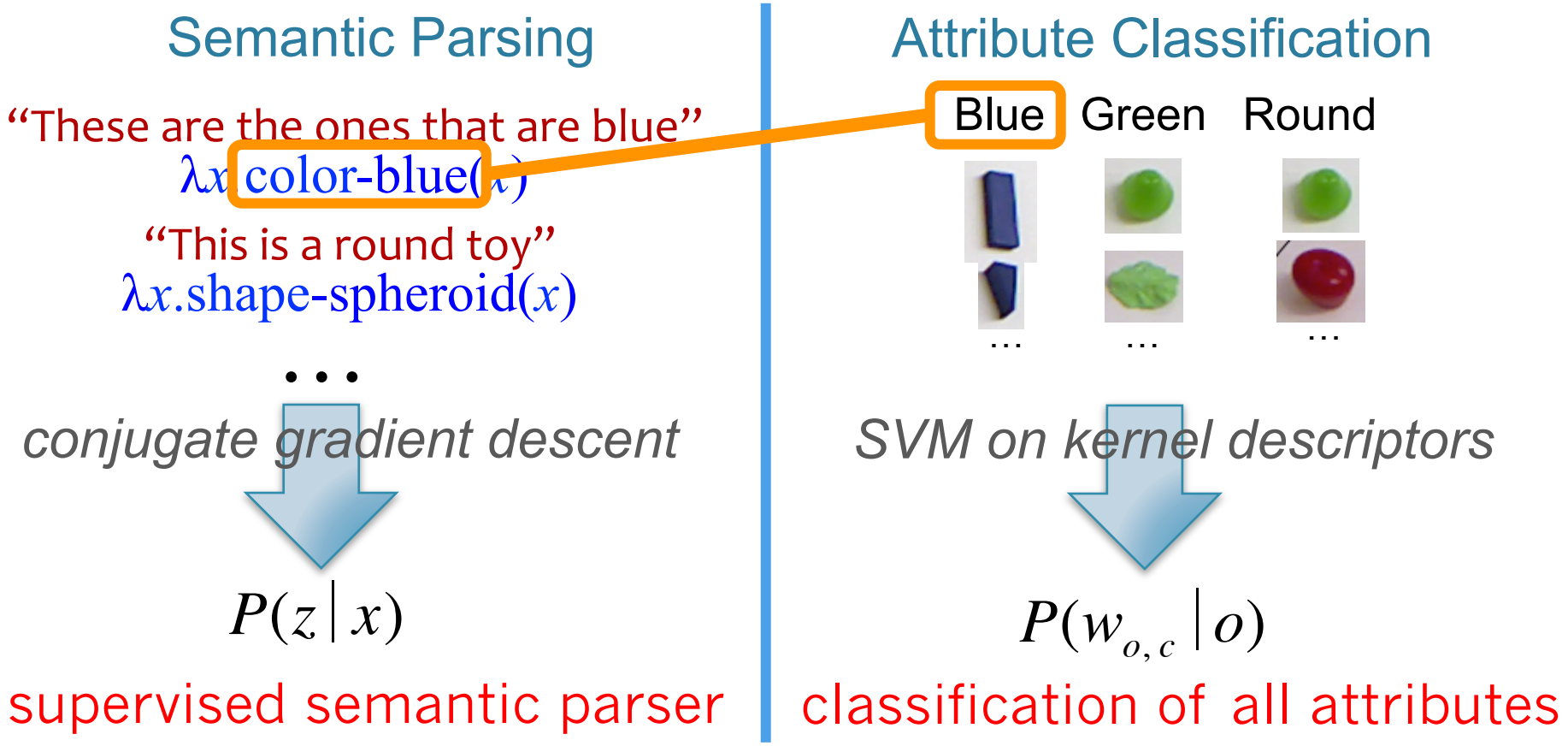
    "This is saffron."
  - No attribute at all

    "This is toy."

- Vision helps decide among these possible classifiers

Supervised Learning

- With labeled sentence meaning, object groups, alignment
  - Decomposes into two independent learning problems:



Unsupervised Learning

- Labeling is expensive – can it be avoided?

("It's the blue one" ,  , ) . . .

- Initialization
  - Train an initial supervised model from labeled scenes (sentence/logic and object/attributes)
- Add *N* new, unknown attribute classifiers
  - Initialize to a small, near-uniform distribution
  - Pair with every unknown word/phrase
- Objective: $LL(D;\Theta^L,\Theta^P) = \sum_{i=1\ldots n} \ln P(G_i|x_i,O_i;\Theta^L,\Theta^P)$

Unsupervised Learning

- Using an EM-style algorithm:
  1. Compute latent $P(z \mid x)$ and $P(w_{c,o} \mid o)$

$$P(z, w \mid x_i, O_i, G_i; \Theta^L, \Theta^P) = \frac{P(z \mid x_i; \Theta^L) P(w \mid O_i; \Theta^P) P(G_i \mid z, w)}{\sum_{z'} \sum_{w'} P(z' \mid x_i; \Theta^L) P(w' \mid O_i; \Theta^P) P(G_i \mid z', w')}$$

  2. Re-estimate parameters of parsing and vision models

$$\Delta^L = \sum_{z'} \sum_{w'} P(z', w' \mid x_i, O_i, G_i; \Theta^L, \Theta^P) * (E_{P(y \mid x_i, z'; \Theta^L)} \left[\phi_j^L(x_i, y, z') \right] - E_{P(y, z \mid x_i; \Theta^L)} \left[\phi_j^L(x_i, y, z) \right])$$

$$\Delta_c^P = \sum_{z'} \sum_{w'} P(z', w' \mid x_i, O_i, G_i; \Theta^L, \Theta^P) * \sum_{o \in O_i} \left[w'_{o,c} - P(w'_{o,c} = 1 \mid \phi(o); \Theta^P) \right] \phi(o)$$

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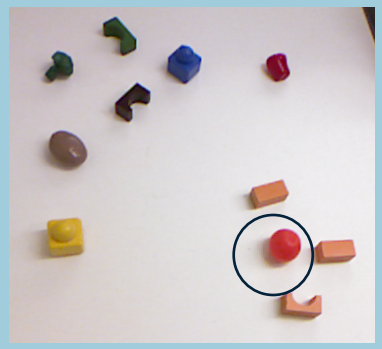
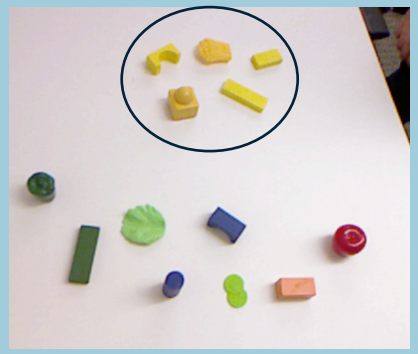


1: Initialization

"This is an orange ball."

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



2: Training

"All of these toys are yellow."

color-blue(x) ?

shape-rect(x) ?

shape-cyl.(x) ?

3: Testing

"It's the yellow block."

color-blue(x)

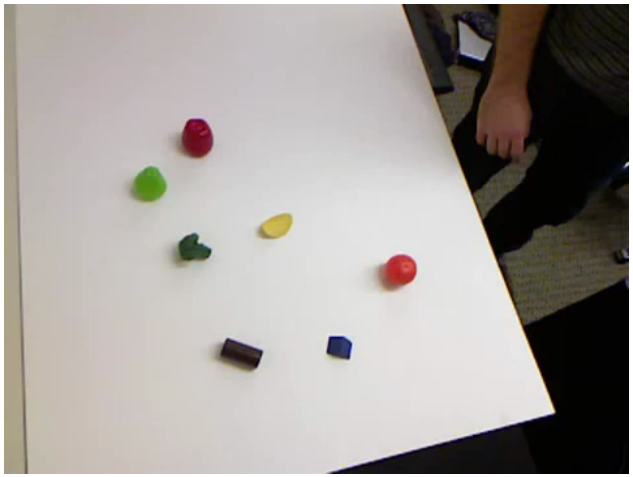
shape-rect(x)

shape-cyl.(x)

color-NEW(x)

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

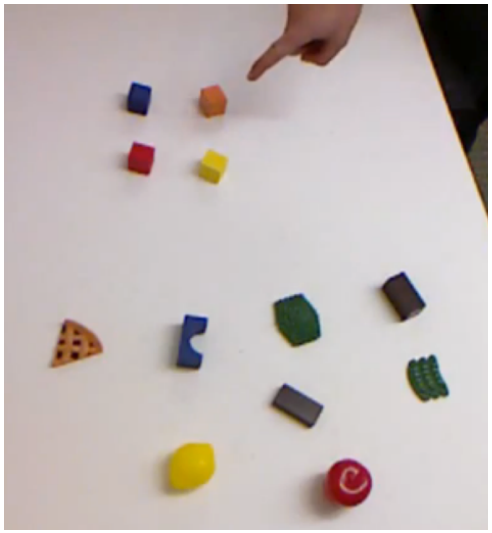
"This one's an orange ball."

Showing HIT 1 of 3 Next HIT

$$\lambda x \,.\, \text{orange}(x) \wedge \text{spheroid}(x)$$

Experimental Evaluation

- 142 scenes, 6 color and 6 shape attributes
- ~1,000 NL sentences from Mechanical Turk
- Ground truth formulas and classifier assignments



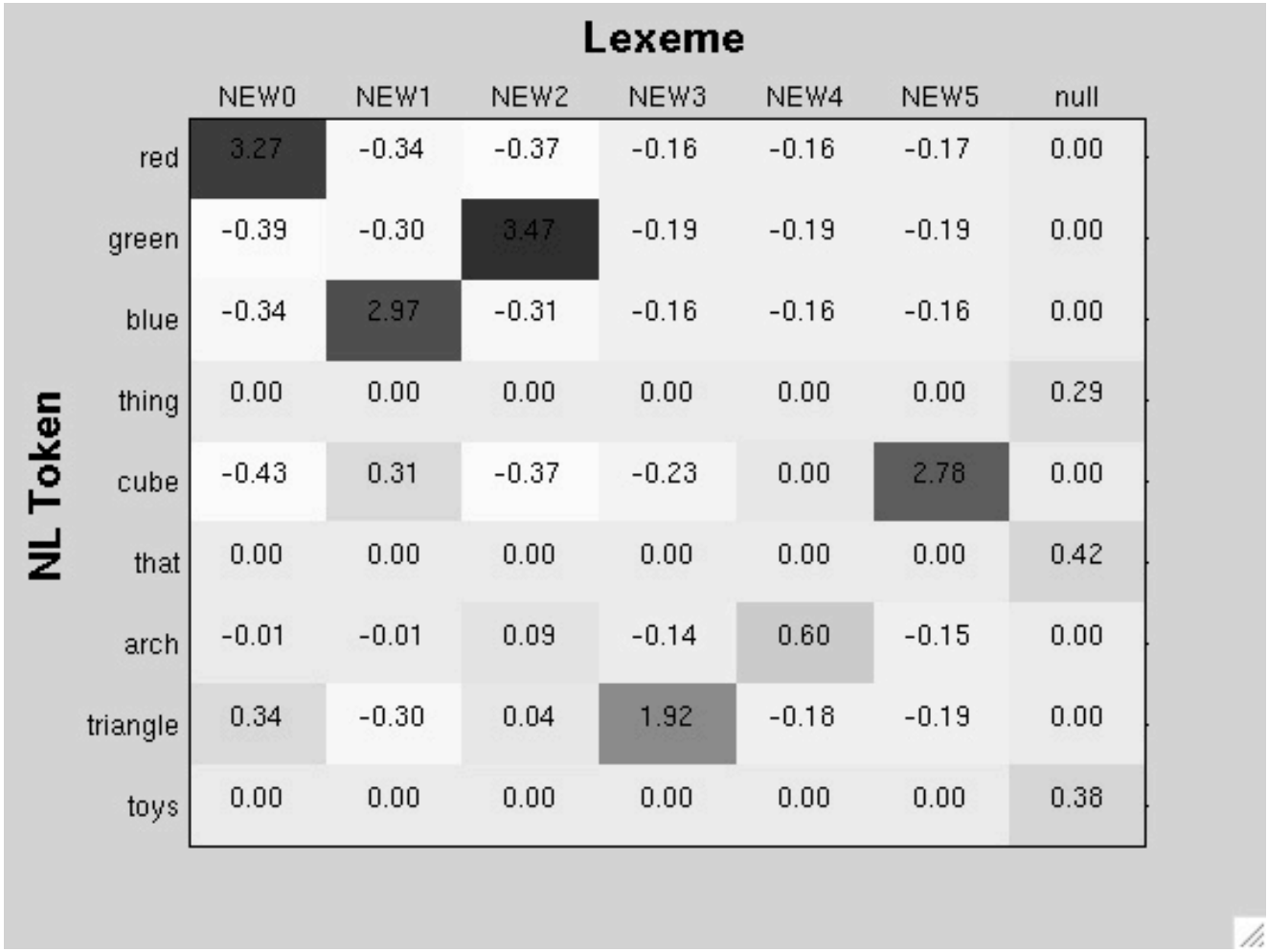
- 20 splits into
  - 30% training items for initialization (3 colors, 3 shapes)
  - 55% training items for training (3 new colors, 3 new shapes)
  - 10% test cases with new colors+shapes

Precision = 82%, Recall = 71%, F1 = 76%

Object Classifier Results

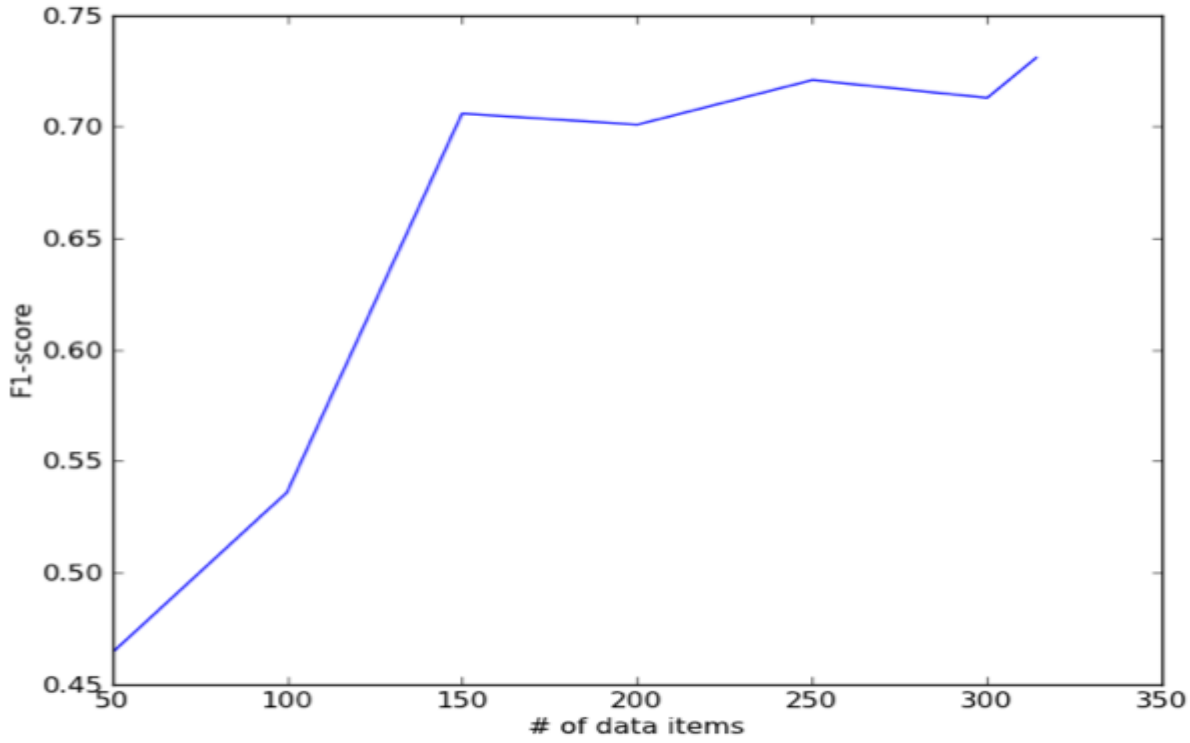
x-axis:
Novel
NL words

y-axis:
Selected
classifiers
(including
null)



Initialization Data

- Primarily initializing language model
- Training focused on learning new attributes/words



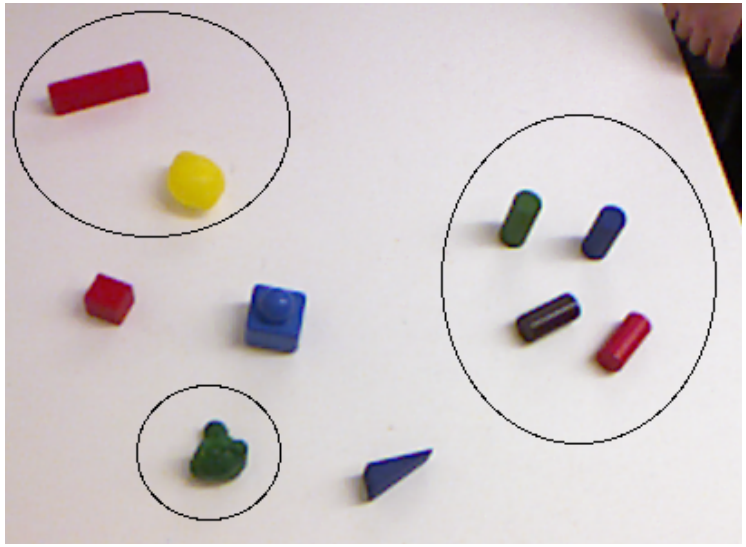
Failure cases

- Bad parses:

"This is a red, toy rectangle."

$\lambda x.\text{rect}(x) \wedge \text{triangle}(x)$

- Bad classification:



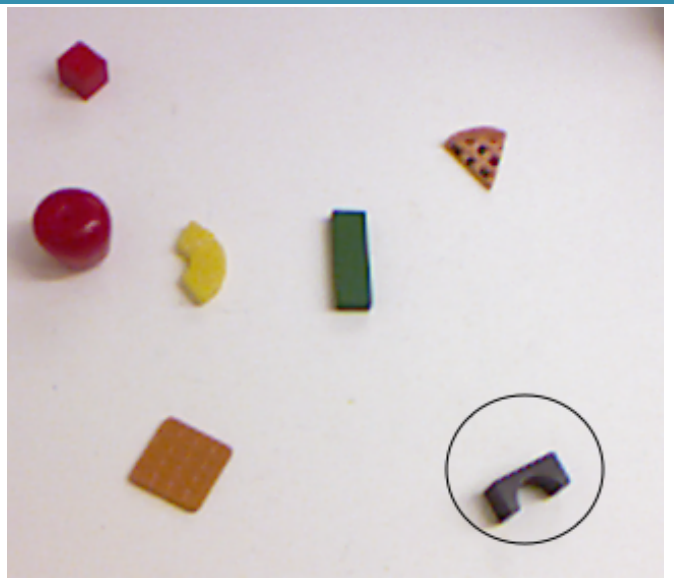
Cylinders (lengthwise) look like rectangular solids

Humans made the same errors – data is noisy!

Failure cases

- Incorrect human input
  - Typos
  - Visual errors

"This is a blue toy shaped like a half-pipe."



It's brown, with blue specular highlights. (This confused the classifiers, too)

- Unexpected human input

"This object is a fake piece of green lettuce. Do not try to eat!"

Discussion

- Accurate language and attribute models can be learned **from data**:
  - Language, raw percepts, and target objects
- Language and vision combine to learn previously-**unrepresented** ideas
  - extending the world model by *interaction*, not programming.
- **Future Work**
  - Scale complexity of language, sensory streams
  - Extend to learning tasks, goals, and more attributes
  - Implement in interactive setting

Thanks!

- Questions?