A psychologically motivated model of word learning

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Overview

- Recent experiments suggest an inability for word learners to track multiple possible meanings for a word in realistic learning environments.
- We present a model based on testing single hypotheses.
  - Reinforcement Learning
- Taken together with independently motivated external cues, our model learns well from real child-directed data.
- Full cross-situational knowledge is not necessary to learn meanings from context.
Background
How cross-situational is word learning?

- “smick”
- Instance 1:

- Instance 2:

- Will the learner remember the consistent presence of the duck?
Two hypotheses

- Hypothesis A:
  - The learner remembers all she has seen
  - “Full cross-situational knowledge”
  - Assumed by many computational models (e.g. Siskind 2000; Frank, Goodman & Tenenbaum 2009; Fazly, Alishahi & Stevenson 2010)

- Hypothesis B:
  - The learner remembers the duck only if the duck was chosen as a hypothesized meaning.
  - “Partial cross-situational knowledge”
  - Current model adopts this hypothesis
Full cross-situational knowledge

- Words and objects are assigned alignment probabilities.
- “Look it’s a bear with a bottle!”

Alignment between a word and concept becomes less likely when other words in the utterance align with that concept with high probability.

The sum of alignment probabilities across situations is used to calculate meaning probabilities for each word.
Experimental work

- Smith, Smith & Blythe (2010): In more realistic learning tasks, subjects remember less
- Is memory of the duck inherent to the learning mechanism?
  - One series of experiments suggests not
    - Medina, Trueswell, Snedeker & Gleitman (2011)
    - Trueswell, Medina, Hafri & Gleitman (submitted), and as presented tomorrow at LSA (see: Stevens, Yang, Trueswell & Gleitman talk).
  - These experiments track the time course of learning.
  - Subjects behave as if they only remember one hypothesis.
Approach

- We want to know if partial cross-situational knowledge is good enough to learn words in the real world.
- We assume that learners only consider a single hypothesis per instance of a word.
- Predicts experimental results of Medina et al. (2011) & Trueswell et al. (submitted)
- By building in cues à la Yu and Ballard (2007), this model can successfully learn words from CHILDES data.
The Model
Reinforcement Learning

- The learner selects some hypothesized word meaning $H$.
  - Techniques defined by how $H$ is chosen
- If $H$ is consistent with the current scene, then it receives a positive reward; else, reward $= 0$
- Estimated Value $= \text{average reward for all instances}$
- Hypotheses with high EVs are taken to be correct.
- This class of algorithms has been successfully applied to morphological and syntactic learning (e.g. Yang 2002).
Pursuit Learning

- The learner maintains a vector of probabilities for each word; choices are made according to these probabilities.
- For new words, all co-occurring objects are equiprobable.
- As learning progresses, the hypothesis with the highest EV becomes a more probable choice.
- The learner’s choices “pursue” the most successful meanings.
- Reward-Inaction scheme: probs only manipulated when a reward has taken place
Available cues

- Yu & Ballard (2007): external cues like gesture and prosody incorporated into a statistical model with positive effect.

- Independently motivated:
  - We know babies are sensitive to cues like gesture and eye gaze (Baldwin 1991, see Bloom 2000 for further references).
  - Prosodic information is available (Soderstrom et al. 2003; Thiessen, Hill & Saffran 2005).

- Stressed words usually map to gesturally indicated meanings, so these mappings should receive a higher weight.

- Lexicon size is also useful to the learner (Frank et al. 2009).

- RL implementation: cues determine the size of the reward.
Psychological plausibility

- We use Fazly et al.’s (2010) model as a point of comparison.
- These models have the advantage of running in real time with minimal computational complexity.
- Some powerful models, e.g. the Bayesian model of Frank et al. (2009), are not cognitively realistic given the complexity (see Beal & Roberts 2009).
  - $O(2^N)$
  - Computational vs. algorithmic
- Ours is the only model that shows the plausibility of a single-hypothesis learner.
Modeling Experimental Results
Subjects asked to click on pictures corresponding to what they think various nonsense words refer to

- High informative = two objects (chance = 50%)
- Low informative = five objects (chance = 20%)
- Groups: HI first, HI middle, HI last, HI absent
- If “smick” is supposed to mean ‘ball’, there is always a ball present during the utterance of “smick”.
- Yet, when given the choice between ‘ball’ and some other meaning, HI last subjects are almost as likely to pick the other meaning on the last instance.
Trueswell et al. (submitted)
Our model (single-hypothesis)

Simulated Word Learning, Clicking Experiment

Proportion Correct

Condition
- HI absent
- HI first
- HI last
- HI middle
Full cross-situational (Fazly et al. 2010)
Medina et al. (2011)

- Real instances of child-caregiver interaction
- HI = 50% or more correct guesses in norming study (subjects asked to guess meanings for isolated videos)
- LI = everything else
- In addition to five instances for each word, subjects gave a final conjecture
- Those who get it right initially have an advantage.
- Others waste time disconfirming false hypotheses.
Medina et al. (2011)
Our model (single-hypothesis)
Full cross-situational
Quality over Quantity

• With less information available, how can a single-hypothesis model learn successfully?
• With the right cues built in, performance actually exceeds that of a comparable full cross-situational model.
• Gestural and prosodic cues (Yu & Ballard 2007) emphasize quality instances, de-emphasize noisy ones.
• Reward amount is higher for mappings between stressed words and indicated meanings
• Larger lexicons decrease reward amount
  • Implements the conservative learner of Frank et al. (2009)
CHILDES Performance
Methodology

- 496 utterance-situation pairs from the Rollins corpus (CHILDES)
  - See Yu & Ballard (2007), Frank et al. (2009)
- Hand-coded from videos of mother-child interaction
- For single-hypothesis model, performance varies slightly, so average of 20 trials is taken
- A word is considered “learned” when its probability or EV exceeds a given threshold value.
- Compare partial and full cross-situational models
  - Precision
  - Recall
  - F-score (F1)
## Results

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<th>Precision</th>
<th>Recall</th>
<th>F-score</th>
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<td>FAS (2010), no cues</td>
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<td>0.13</td>
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Conclusion

• Learners cannot always track multiple co-occurrences.
• Reinforcement Learning provides a good class of algorithms for modeling a single-hypothesis testing mechanism.
• Our Pursuit Learning model learns well with the right (independently motivated) cues.
• Full cross-situational knowledge is not necessary to learn meanings from context.
References


