Concurrent Acquisition of Word Meaning and Lexical Categories

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Introduction

- Learning the meaning of words from ambiguous and noisy context is a challenging task for language learners.
- Children draw on cross-situational statistics as well as syntactic cues to constrain potential referents of words in a complex scene.
- We model this process by integrating an LDA-based word-class learning module with a probabilistic word learning model.
- Incrementally induced word classes significantly improve word learning, comparable to manually assigned PoS categories.

Cross-situational learning

- Each sentence paired with a simulated scene representation, as a union of semantic features for words in the sentence:

Utterance: { *mommy, ate, broccoli* }
Scene: { ANIMATE, HUMAN, ..., CONSUMPTION, ACTION, ... BROCCOLI, VEGETABLE, ... PLATE, OBJECT, ... }

- Word meaning is defined as a probability distribution over semantic features
- Word meanings are acquired using an incremental probabilistic alignment algorithm

Word class induction

- Latent Dirichlet Allocation-based model: word types correspond to documents, context words correspond to words in documents
- Use an incremental version of the collapsed Gibbs sampler

for $t = 1 \to \infty$ **do**
  for $i = 1 \to I_t$ **do**
    sample $z_{t_i} \sim P(z_{t_i} | \mathbf{z}_{t_i - 1}, \mathbf{w}_{t_i}, \mathbf{d}_{t_i})$
    increment $n_t^{z_{t_i}, w_{t_i}}$ and $n_t^{z_{t_i}, d_{t_i}}$

- Only condition on previous word tokens:

$$P(z_t | \mathbf{z}_{t-1}, \mathbf{w}_t, \mathbf{d}_t) \propto \frac{(n_{t-1}^{z_t, d_t} + \alpha) \times (n_{t-1}^{z_t, w_t} + \beta)}{\sum_{j=1}^{V_{t-1}} n_{t-1}^{z_t, w_j} + \beta}.$$

Word classes accelerate learning of meaning

- Alignment between words and semantic features is split into word-based and category-based components:

$$a(w|f, U^{(t)}, S^{(t)}) = \lambda^{(t)}(w) \times a_w(w|f, U^{(t)}, S^{(t)}) + (1 - \lambda^{(t)}(w)) \times a_c(w|f, U^{(t)}, S^{(t)})$$

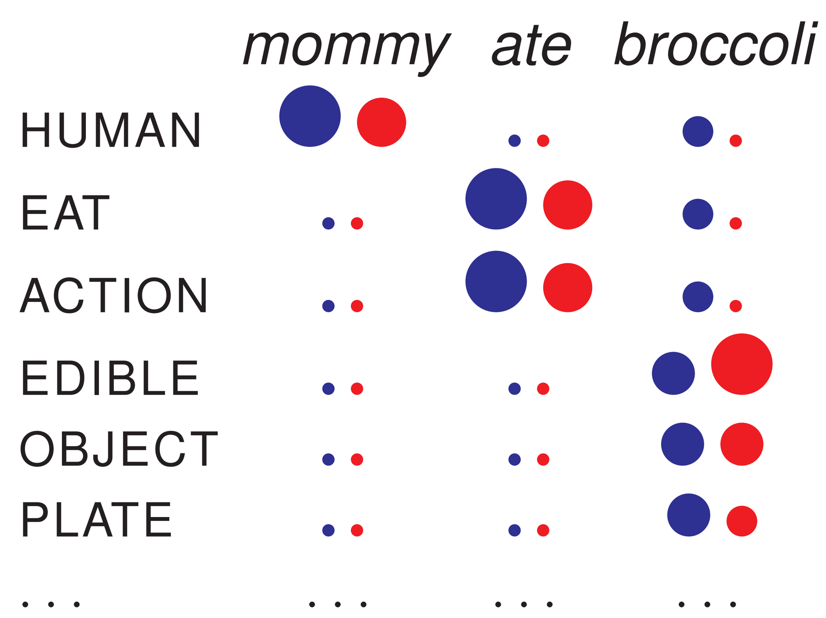
- Word-based alignment at time t:

$$a_w(w|f, U^{(t)}, S^{(t)}) = \frac{p^{(t-1)}(f|w)}{\sum_{w' \in U^{(t)}} p^{(t-1)}(f|w')}$$

- Category-based alignment at time t:

$$a_c(w|f, U^{(t)}, S^{(t)}) = \frac{p^{(t-1)}(f|\text{cat}(w))}{\sum_{w' \in U^{(t)}} p^{(t-1)}(f|\text{cat}(w'))}$$

- Interaction of cross-situational and distributional evidence:



- Computing category likelihoods from word meanings:

$$p^{(t)}(f|\text{cat}(w)) = \frac{1}{|\text{cat}(w)|} \sum_{w' \in \text{cat}(w)} p^{(t)}(f|w')$$

- The interpolation parameter depends on word frequency $n^{(t)}(w)$:

$$\lambda^{(t)}(w) = \frac{n^{(t)}(w)}{n^{(t)}(w) + 1}$$

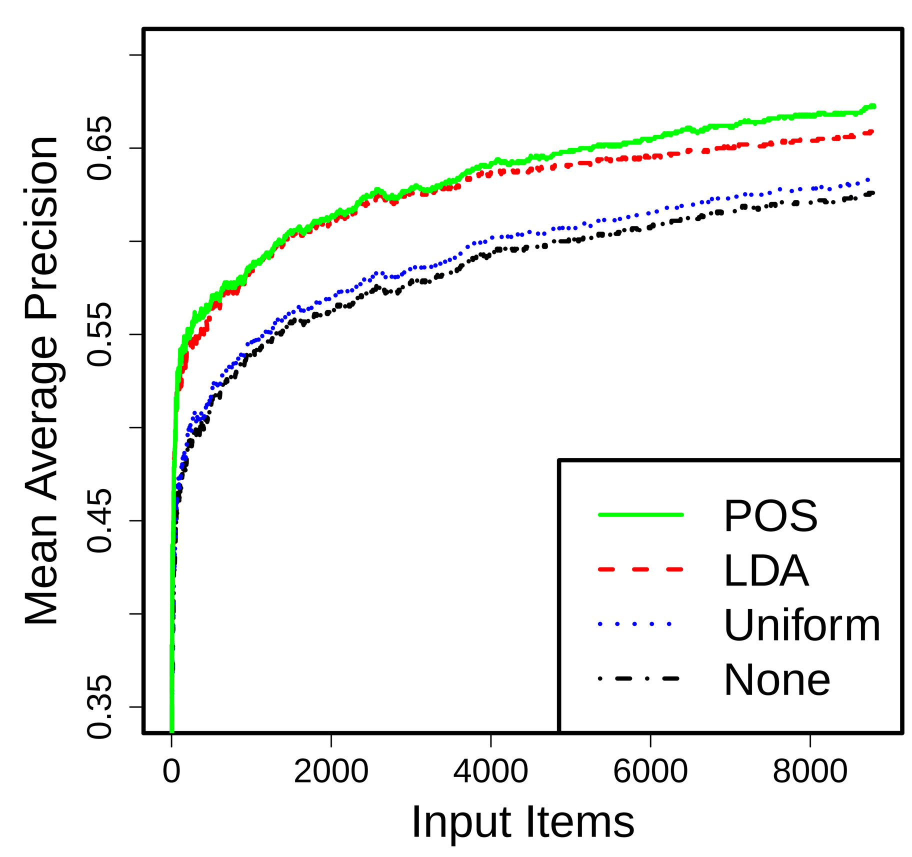
- Finally, word meanings are updated based on accumulated alignments:

$$p^{(t)}(f|w) = \frac{\sum_{i=1}^{t} a(w|f, U^{(i)}, S^{(i)})}{\sum_{f' \in F} \sum_{i=1}^{t} a(w|f', U^{(i)}, S^{(i)})}$$

Sample categories

do are have can not go put did get play
is that it what not there he was where put
you not I the we what it they your a
to you we and I will not can it on
it a that the not he this right got she
are do is have on in can want did going
one I not shall there then you are we it
is in are on oh with and of have do
the a your of that it this some not very
going want bit go have look got will at little

Learning curves



Conclusion

- Categories induced from distributional cues improve cross-situational word learning
- Contribution of our categories is comparable to gold, manually assigned PoS tags
- LDA word class induction gives **soft** categories. In future work, we plan to exploit the whole distribution over categories for each word.

References

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