Learning word meaning by inferring speakers' intentions:

An incremental approach to socially-guided statistical learning

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Many thanks to ...

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Abstract

How do children learn the meanings of words? While some accounts suggest that word learning happens in a single moment, others privilege the gradual accumulation of information across time. Previous modeling work has attempted to unify these viewpoints in a single framework that allows for both in-the-moment interpretation and gradual statistical accumulation, but at the cost of substantial computational complexity. We describe a new, incremental model of this interaction, in which statistical associations are the product of in-the-moment interpretations. This process-level model successfully captures a number of experimental findings (including some that were not captured by previous, computational-level analyses) and suggests a number of extensions.

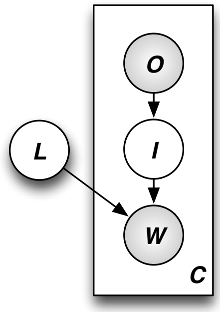

Figure 1. Caption.

Introduction

How do children learn their first words?

Model

Model Specification

By Bayes' rule:

$$P(I,L|C) \propto P(C|I,L)P(I,L). \tag{1}$$

$$P(I,L|W,O) \propto P(W,O|I,L)P(I,L). \tag{2}$$

But the objects O are observed in the context. In addition, for simplicity, we assume that there is a uniform prior over possible intentions (though we return to this issue in the Discussion). By the generative model in Figure 1, the remaining expression can be factored as follows:

$$P(I,L|W,O) \propto P(W|I,L)P(I|O)P(I)P(L). \tag{3}$$

But now we integrate over all possible L:

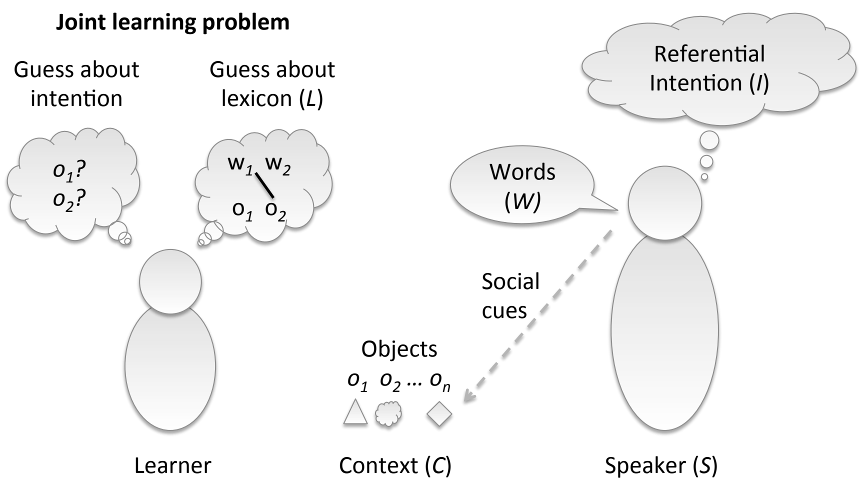

Figure 2. Caption. From Frank (in press).

$$P(I|W,O) \propto \int_L P(W|I,L)P(I|O)P(I)P(L) \tag{4}$$

In this model, the lexicon L consists of two separate parts. The referential lexicon L_R is a set of integrated Dirichlet-Multinomial distributions, one for each object in the world. This distribution represents the posterior probability of a particular word, relative to that object.

$$P(L) = \prod_{o \in W} P(L_{R_o}) + P(L_{NR}). \tag{5}$$

$p(\vec{w}|I,R,L_R,L_{NR}) = p(w|O_i) * prod_{s \in S-S_r} P(W_s|L_{NR})$

Inference

Batch inference using a gibbs sampler.

$$P_t(L|W_{1...t},O_{1...t}) \propto P_{t-1}(L|...)P(W_t,I_t,R_t|L) \tag{6}$$

Incremental inference using a particle filter.

$$P_t(L|W_{1...t},O_{1...t}) \propto P_{t-1}(L|...)P(I_t|W_t,O_t) \tag{7}$$

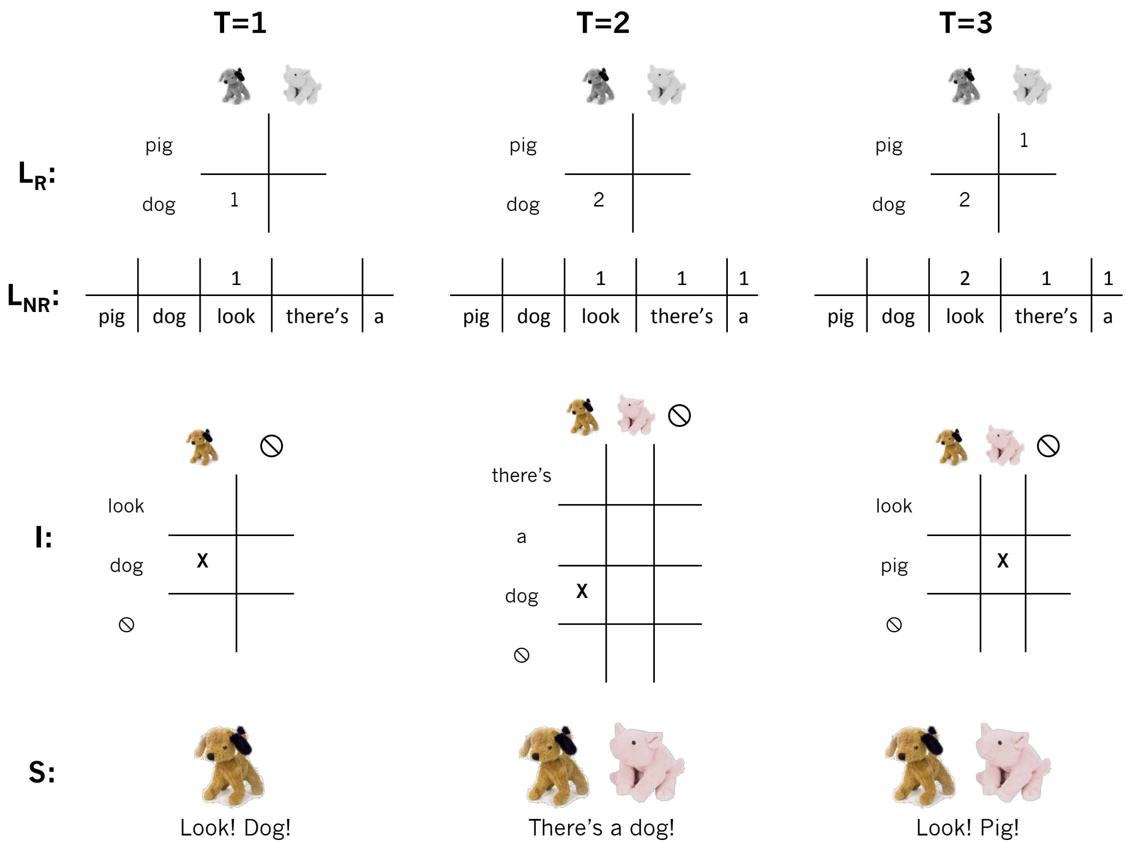

Figure 3. Caption.

Simulations

Cross-situational word learning with adults

Yu & Smith (2007).

Experiments with children

Disambiguation.

Dewar & Xu (2007).

Corpus simulations

Rollins subset (Frank, Goodman, & Tenenbaum, 2009)

Fernald & Morikawa (Johnson, Demuth, & Frank, 2012)

Discussion