Distributional learning & lexical category acquisition:

What makes words easy to categorize?

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Introduction

Words can be categorized into lexical categories using the contexts in which they occur [Harris, 1954], but some words more easily than others.

What distributional properties of a word makes it easier to categorize?

CAVEAT

The statistical analysis has been refined since the submission. We present new results, that are sometimes different than what appears in the paper.

Differences are highlighted.

Got evidence it works

We know there is information in distributional cooccurrences that supports learning of lexical categories [Cartwright & Brent, 1997; Redington & al 1998].

Behavioral experiments have confirmed that children use co-occurrences to group words along syntactic dimensions [Frost & al, 2016; Mintz & al, 2014; Reeder & al, 2013; van Heugten & Johnson, 2010; Zhang & al, 2014].

Contrasted contexts

Frequent Frames:

[Mintz, 2003]

Flexible Frames:

$$you_X + X_the$$

[St. Clair & al, 2010]

Bigrams vs trigrams:

[Monaghan & al, 2004]

Utterance boundaries:

[Freudenthal & al, 2008]

Evaluated learning mechanisms

- Incremental Bayesian clustering [Parisien, 2008]
- Incremental Entropy-based clustering [Chrupała & Alishahi, 2010]
- MOSAI

 [Freudenthal & al, 2016]

The evaluation concerns whether good categories are learned and whether learning follows aspects of the developmental patern.

A concept of easiness

Children categorize certain words better than others.

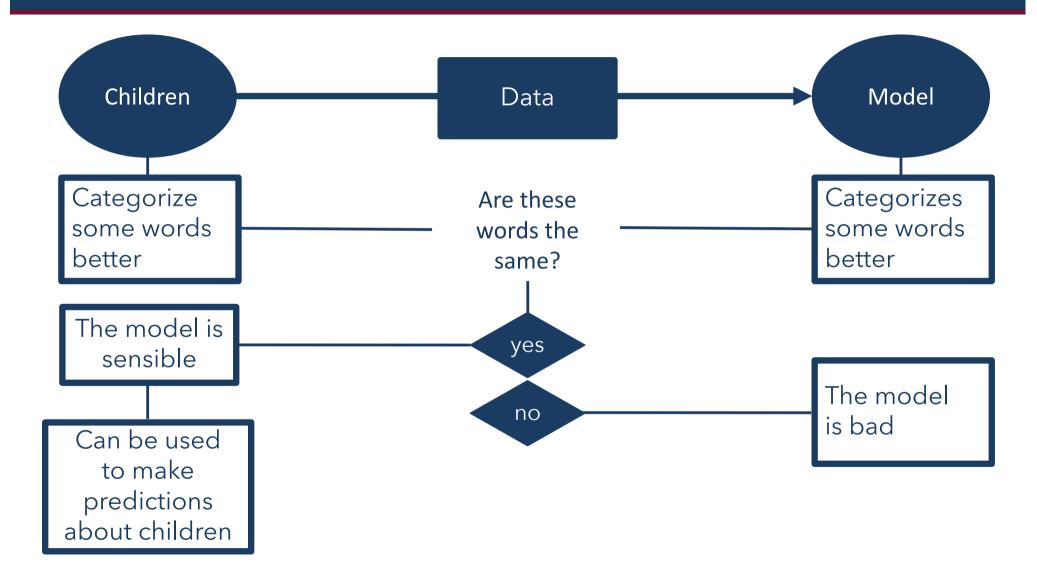
- What causes words to be categorized better?
- Are words that are easier to categorize using distributional information also those that children categorize better?

Many potential predictors

Frequency is not enough in accounting for lexical category acquisition [Matthews & Bannard, 2010].

Diversity, **predictability**, and **entropy** are other pieces of distributional information that children can track and might contribute to explain easiness.

The logic of the experiment



Experimental setting

- Unsupervised PoS tagging experiment (5 tags)
- Transcribed English Child-directed speech (13 individual corpora)
- Bigrams and trigrams (with utterance boundaries) as contexts [b_x; x_c; a_b_x; b_x_c; x_c_d]
- Exemplar-based clustering (TiMBL: IB1, cosine, 1 NN, no feature weighting)
- Incremental training (40 to 70% of the input corpus)

Statistical analysis

- Logistic mixed-effects models (with crossed-effects):
 - Random intercepts for each corpus and word + random slopes
 for both random effects
- Predictors included based on reduction in AIC
- Interactions between each predictor and time were tested and included if they improved the fit

Predictors and outcomes

- Token frequency
- Diversity
- Average conditional probability
- Entropy (normalized)*
- Time
- PoS tag of the word



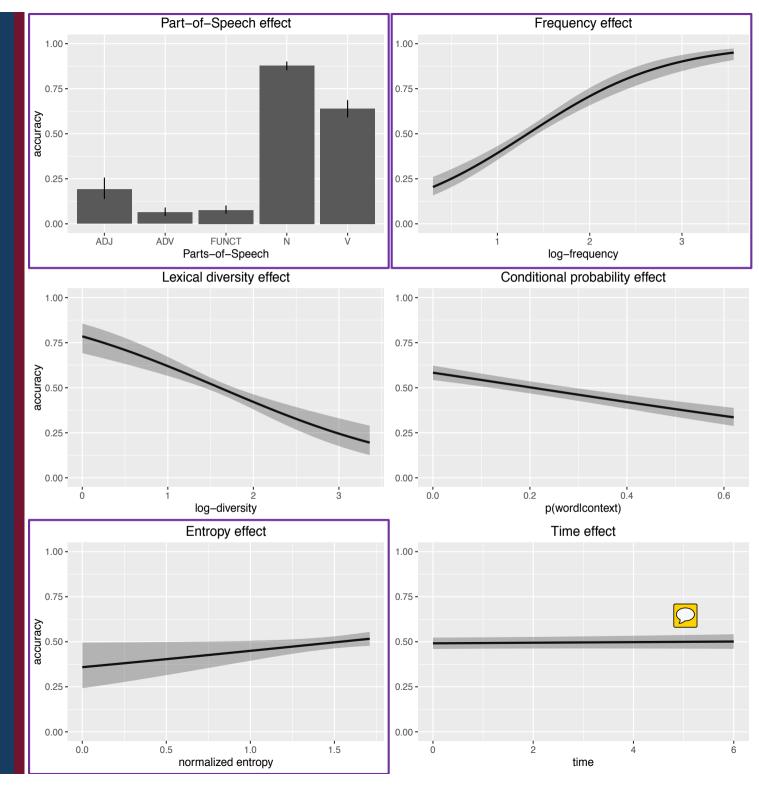
*exponentiated



Operationalization

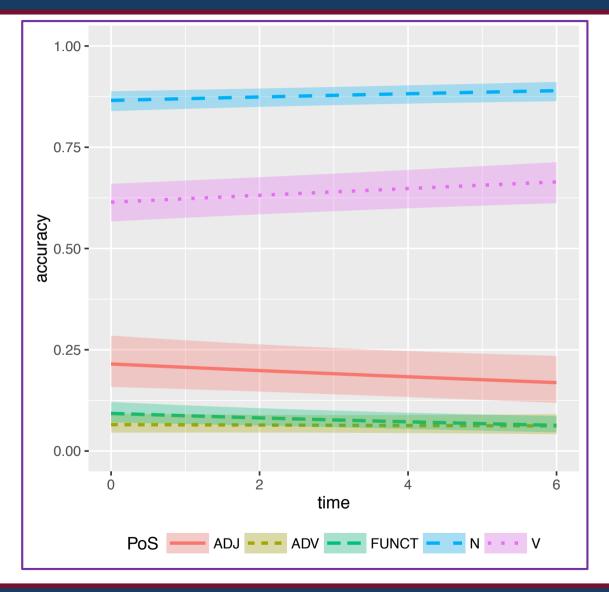
We ran the clustering experiment, finding the nearest neighbor in the training set for target words in the test set. Categorization accuracy was used as a dependent variable to assess *easiness*. Results

Main effects





Interactions



Beware of the noise

Words are easier to categorize when highly specific:

- > are frequent
- > occur with fewer contexts
- > are hard to predict given the contexts in which they occur
- > are nouns or verbs

apple; forget; table; door; ...

Quantify **how useful a context** is to categorization and assess which distributional properties affect it

Test **other learning mechanisms** than Memory Based Learning (e.g. neural nets, Bayesian inference)

Extend this approach beyond distributional properties

Thank you!

Questions?

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