Useful contexts & easy words: Effects of distributional factors on lexical category acquisition

Giovanni Cassani

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Introduction

Patterns of distributional co-occurrences are informative about lexical categories [Redington & al, 1998] but some more than others. What distributional properties of a context make it more useful?

Words can be syntactically categorized using the contexts in which they occur [Harris, 1954] but some more easily than others. What distributional properties of a word makes it easier to categorize?

- Distributional bootstrapping
 - What have we done?
 - What do we miss?
- Computational simulation
- Results
 - Easy words
 - Useful contexts
- Conclusion

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Got evidence it works

Since Cartwright & Brent [1997] and Redington & al [1998], we know there is information in distributional co-occurrences that supports learning of lexical categories.

Behavioral experiments have confirmed that children are sensitive to this information and use it 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:

you_X_the

[Mintz, 2003]

Flexible Frames:

 $you_X + X_the$

[St. Clair & al, 2010]

Bigrams vs trigrams:

you_X vs you_X_the

[Monaghan & al, 2004]

Utterance boundaries:

the x vs the x #end

[Freudenthal & al, 2008]

Evaluated learning mechanisms

- Incremental Bayesian clustering [Parisien, 2008]
- Incremental Entropy-based clustering [Chrupała & Alishahi, 2010]
- MOSAIC [Freudenthal & al, 2016]

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

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A concept of *usefulness*

Not all contexts are equally informative:

- What does it mean for a context to be useful?
- How can a child determine this?
- Using what information?

Models work on too many starting assumptions that are not yet well motivated and grounded in experimental evidence.

A concept of easiness

Not all words are equally important: children are better at categorizing certain words than others.

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

Many potential predictors

While definitely important, frequency is not enough in accounting for lexical category acquisition [Matthews & Bannard, 2010].

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

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Experimental setting

- Unsupervised PoS tagging experiment (5 tags)
- Transcribed English Child-directed speech
- 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)
- Mixed-effects models

Predictors and outcomes

- Context type (left, right, non-adj)
- # constituents (bigrams vs trigrams)
- Token frequency
- Diversity
- Average conditional probability
- Entropy (normalized)
- Time

- ☐ Gain ratio (contexts)
- ☐ Hits (words)

Operationalization

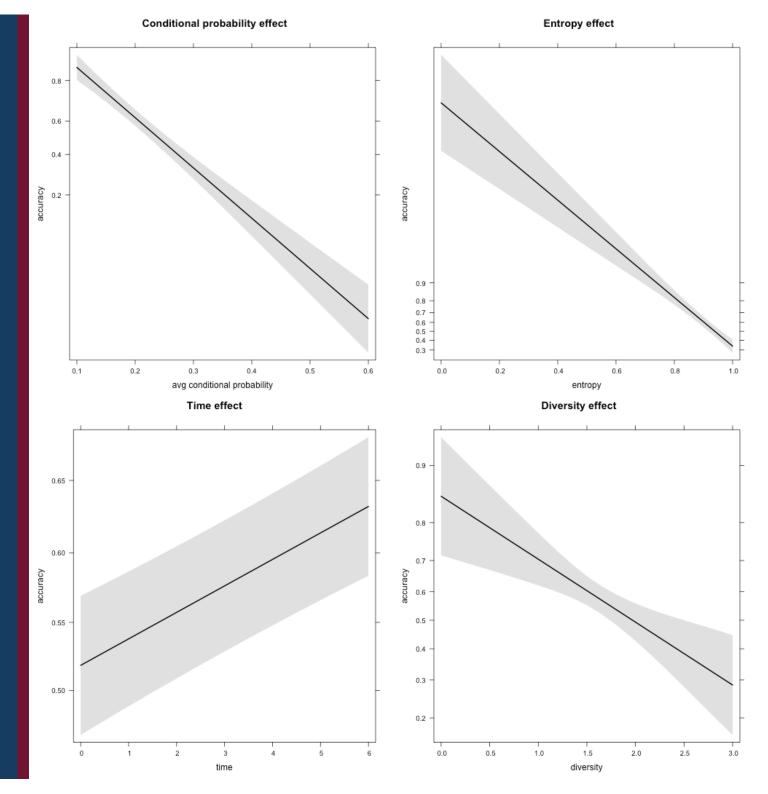
First, we ran the clustering experiment, finding the nearest neighbor in the training set for target words in the test set. Categorization accuracy was used as a dependent variable to assess *easiness*.

Then, we computed Gain Ratio from co-occurrence statistics in the training. GR values were used as dependent variables to assess *usefulness*.

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Results - Easy words

Main effects

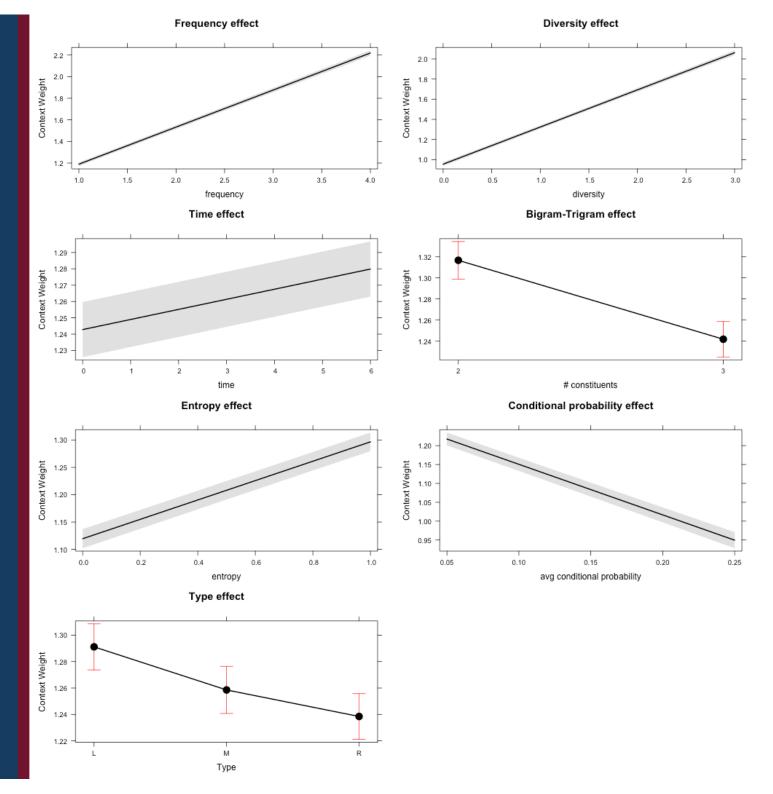




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Results - Useful contexts

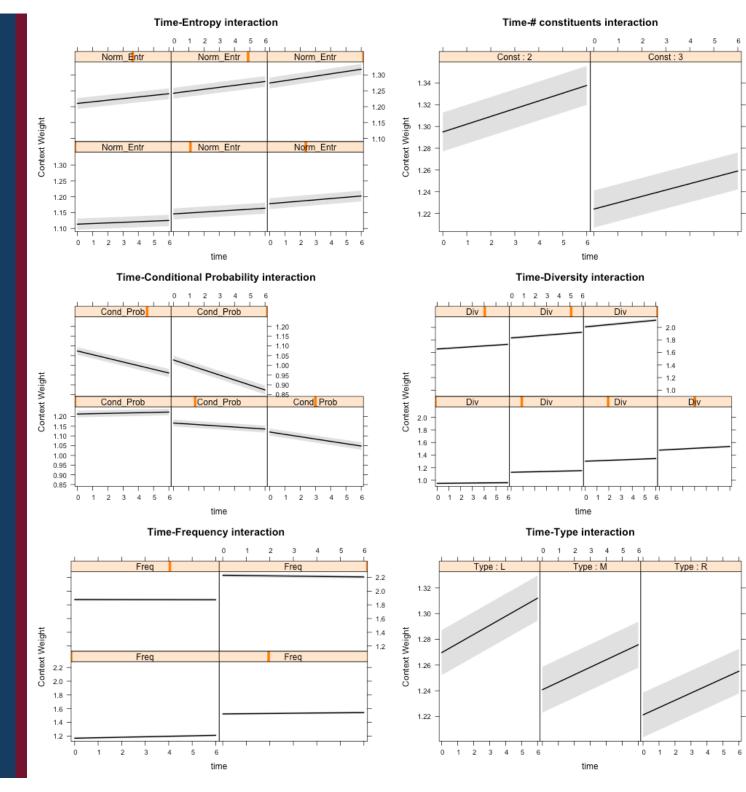
Main effects





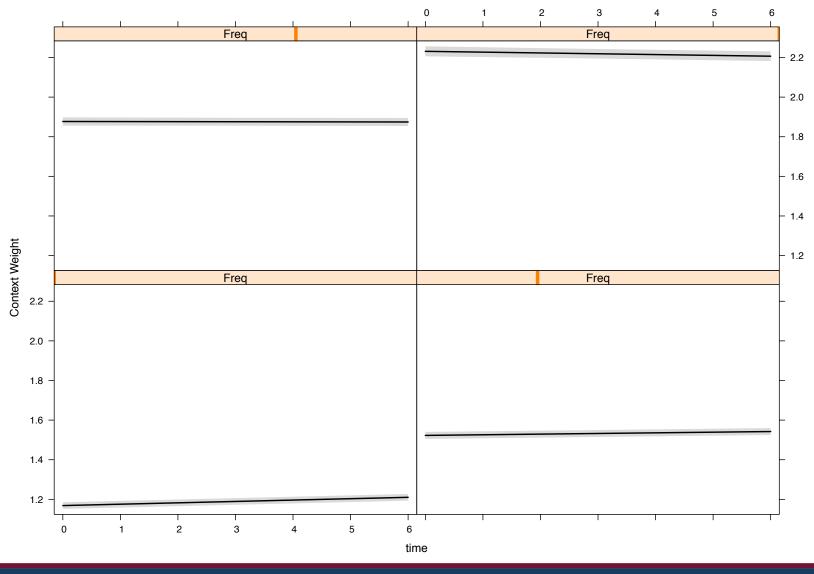
Results - Useful contexts

Interac tions

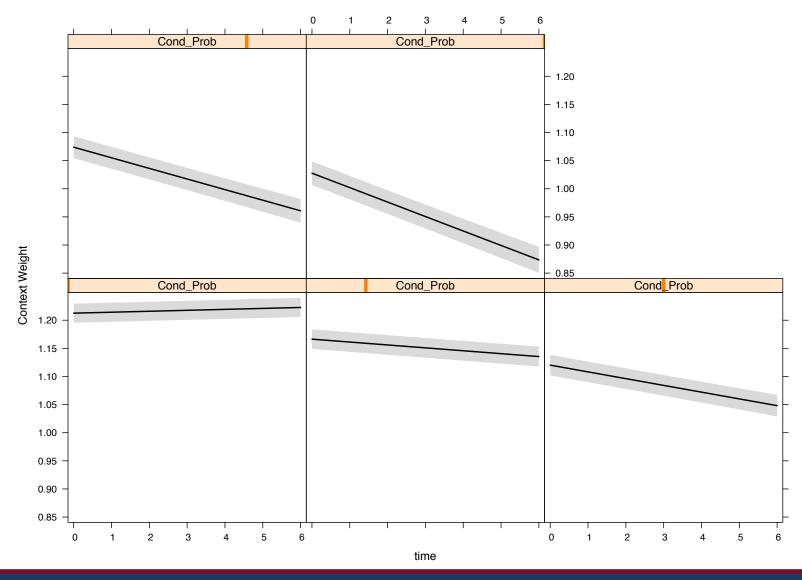




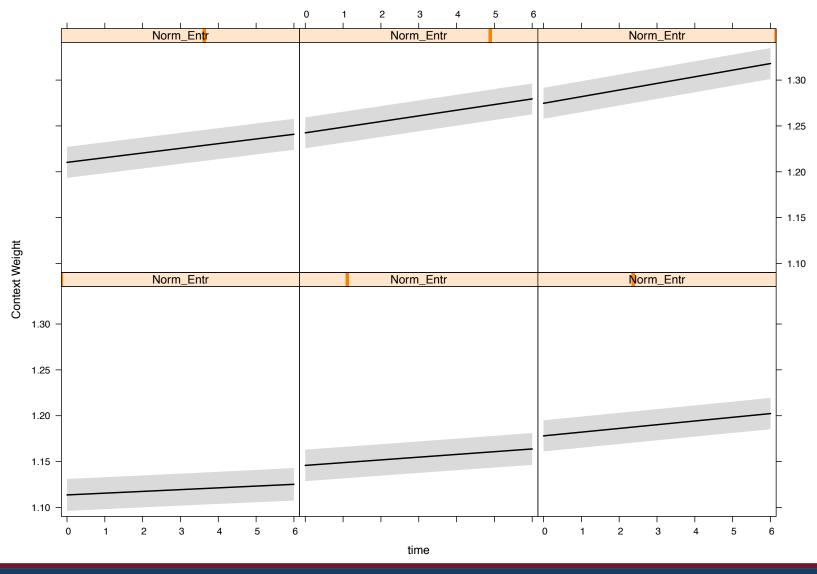
Time-frequency interaction



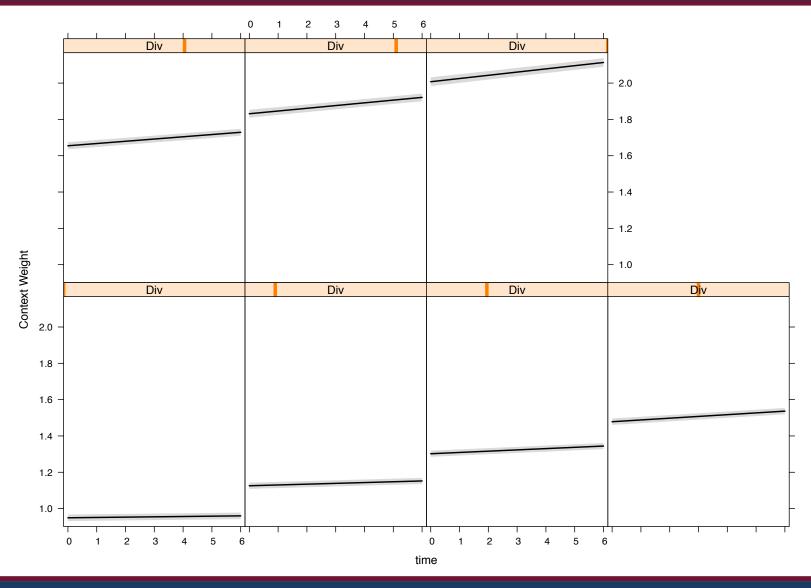
Time-probability interaction



Time-entropy interaction



Time-diversity interaction



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Systematicity > frequency

Useful contexts need to be **highly systematic**, and the more so with more exposure to the input:

- > occur frequently
- > with many different words
- > occur a comparable amount of time with all the words they co-occur with
- > **but** be hard to predict given the words they occur with

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it_X_#end; X_the; you_X; ...
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Beware of the noise

Words are easier to categorize when **highly specific**:

- > occur with fewer contexts
- > have low entropy distributions over contexts
- > are hard to predict given the contexts in which they occur (cf. positive effect of diversity of usefulness)

apple; forget; table; door; ...

Complementarity

Words that make good contexts are harder to categorize, while poor contexts consist of words that are categorized more effectively \Leftrightarrow Children categorize content words better and earlier, and use function words to do this.

A full distributional learning account can effectively explain lexical category acquisition

Thank you!

Questions?

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