1. Introduction

Distributional bootstrapping hypothesizes that children start grouping words into lexical categories using patterns of co-occurrences. In the acquisition literature, computational models have been used to test this hypothesis and assess the effectiveness of a handful of different cues, most notably:

- **frequent frames** (FF) [1]: 45 most-frequent A\_X\_B trigrams.
- **flexible frames** (ff) [2]: 45 most-frequent words, used as left and right bigrams that can be combined on the fly to provide frame-like information.

However, they both display some problems:
- **arbitrariness**: what is frequent? why only a specific type of cue?
- **poor scalability**: frequent contexts may always occur with the same word
- **category bias**: in English, FF occur with more verbs than nouns
- **low coverage**: few types occur in FF
- **biased evaluation**: train and test on the same data, with serious risk of overfitting.

2. Model

Beyond token frequency, we suggest other distributional features of words - that children track - may play a role, including type frequency (number of different words a cue occurs with) and association strength (how predictable is the cue given the context).

Let:

- \( \text{token}_F \) = \( \frac{\text{log}_2(\text{count}(c_i))}{\text{avg}(\text{log}_2(\text{count}(c)))} \) (1)
- \( \text{type}_F \) = \( \frac{\text{log}_2(\text{count}(w_i))}{\text{avg}(\text{log}_2(\text{count}(w)))} \) (2)
- \( p = \frac{1}{\text{count}(w_i)} \sum_{j=1}^{W-1} \frac{\text{log}_2(\text{count}(w_j,c_i))}{\text{log}_2(\text{count}(w_j))} \) (3)
- \( \text{score} = \text{token}_F \cdot \text{type}_F \cdot p \) (4)

A context is salient if \( \text{score} > 1 \). Raw counts are log-transformed since every new occurrence is a little less important and to emphasize the search for structure: hapaxes have log 0 and are not considered.

5. Conclusions & future work

There is a trade-off between coverage, accuracy, and scalability: evaluating on one dimension without considering interactions is likely to lead to biased inferences.

**Type frequency** seems to be better than token frequency, because it ensures that a cue is systematic and not idiosyncratic.

Currently, we are
- (i) evaluating models on more corpora from typologically different languages
- (ii) evaluating learning curves
- (iii) testing models on core vocabulary
- (iv) training models on core vocabulary, to evaluate generalization.

4. Results

<table>
<thead>
<tr>
<th>Context type</th>
<th># contexts</th>
<th>Useless</th>
<th>Missed words (%)</th>
<th>Hits</th>
<th>Acc.</th>
<th>p \cdot \text{token}_F</th>
<th>p \cdot \text{type}_F</th>
</tr>
</thead>
<tbody>
<tr>
<td>frequent frames</td>
<td>45</td>
<td>3 (6.7%)</td>
<td>83.7</td>
<td>290</td>
<td>.83</td>
<td>45 \cdot \text{token}_F</td>
<td>45 \cdot \text{type}_F</td>
</tr>
<tr>
<td>flexible frames</td>
<td>90</td>
<td>0</td>
<td>16.6</td>
<td>1405</td>
<td>.66</td>
<td>90 \cdot \text{token}_F</td>
<td>90 \cdot \text{type}_F</td>
</tr>
<tr>
<td>2grams</td>
<td>75</td>
<td>0</td>
<td>10.2</td>
<td>1559</td>
<td>.67</td>
<td>75 \cdot \text{token}_F</td>
<td>75 \cdot \text{type}_F</td>
</tr>
<tr>
<td>3grams</td>
<td>348</td>
<td>13 (3.7%)</td>
<td>37.3</td>
<td>1073</td>
<td>.68</td>
<td>348 \cdot \text{token}_F</td>
<td>348 \cdot \text{type}_F</td>
</tr>
<tr>
<td>all</td>
<td>490</td>
<td>11 (2.2%)</td>
<td>3.8</td>
<td>1669</td>
<td>.64</td>
<td>490 \cdot \text{token}_F</td>
<td>490 \cdot \text{type}_F</td>
</tr>
<tr>
<td>2grams</td>
<td>21</td>
<td>0</td>
<td>19.5</td>
<td>1377</td>
<td>.67</td>
<td>21 \cdot \text{token}_F</td>
<td>21 \cdot \text{type}_F</td>
</tr>
<tr>
<td>3grams</td>
<td>42</td>
<td>0</td>
<td>56.7</td>
<td>788</td>
<td>.76</td>
<td>42 \cdot \text{token}_F</td>
<td>42 \cdot \text{type}_F</td>
</tr>
<tr>
<td>all</td>
<td>97</td>
<td>0</td>
<td>8.7</td>
<td>161</td>
<td>.67</td>
<td>97 \cdot \text{token}_F</td>
<td>97 \cdot \text{type}_F</td>
</tr>
<tr>
<td>2grams</td>
<td>211</td>
<td>0</td>
<td>2.6</td>
<td>1624</td>
<td>.64</td>
<td>211 \cdot \text{token}_F</td>
<td>211 \cdot \text{type}_F</td>
</tr>
<tr>
<td>3grams</td>
<td>659</td>
<td>7 (1%)</td>
<td>25.5</td>
<td>1249</td>
<td>.63</td>
<td>659 \cdot \text{token}_F</td>
<td>659 \cdot \text{type}_F</td>
</tr>
<tr>
<td>all</td>
<td>964</td>
<td>8 (0.8%)</td>
<td>1.2</td>
<td>1562</td>
<td>.60</td>
<td>964 \cdot \text{token}_F</td>
<td>964 \cdot \text{type}_F</td>
</tr>
</tbody>
</table>

Table 1: Evaluation of several sets of distributional cues, with baselines at the top and our models grouped according to the included pieces of information.

Column 1 specifies the type of context used.

Column 2 shows the number of salient contexts.

Column 3 shows how many of them could not be used for categorization.

Column 4 provides the percentage of words from the training set (total = 3191) that could not be categorized by the contexts.

Column 5 gives the raw number of hits (test set = 2600 words).

Column 6 shows accuracy on supervised PoS tagging.

*The model including \( \text{Token}_F \) and \( \text{type}_F \) only is not shown since results were markedly worse than all other models, on all dimensions except for coverage.*

A. References


B. Acknowledgements

The presented research was supported by a BOF/TOP grant (ID 29072) of the Research Council of the University of Antwerp.

The poster was designed on Overleaf with the fundamental help of Chris Emmery and is based onto the template developed by Brian Amburg.