Which distributional cues help the most?

Unsupervised context selection for lexical category acquisition

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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 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 word).

$$token\_F = \frac{log_2(count(c_i))}{avg(log_2(count(c)))} \quad (1)$$

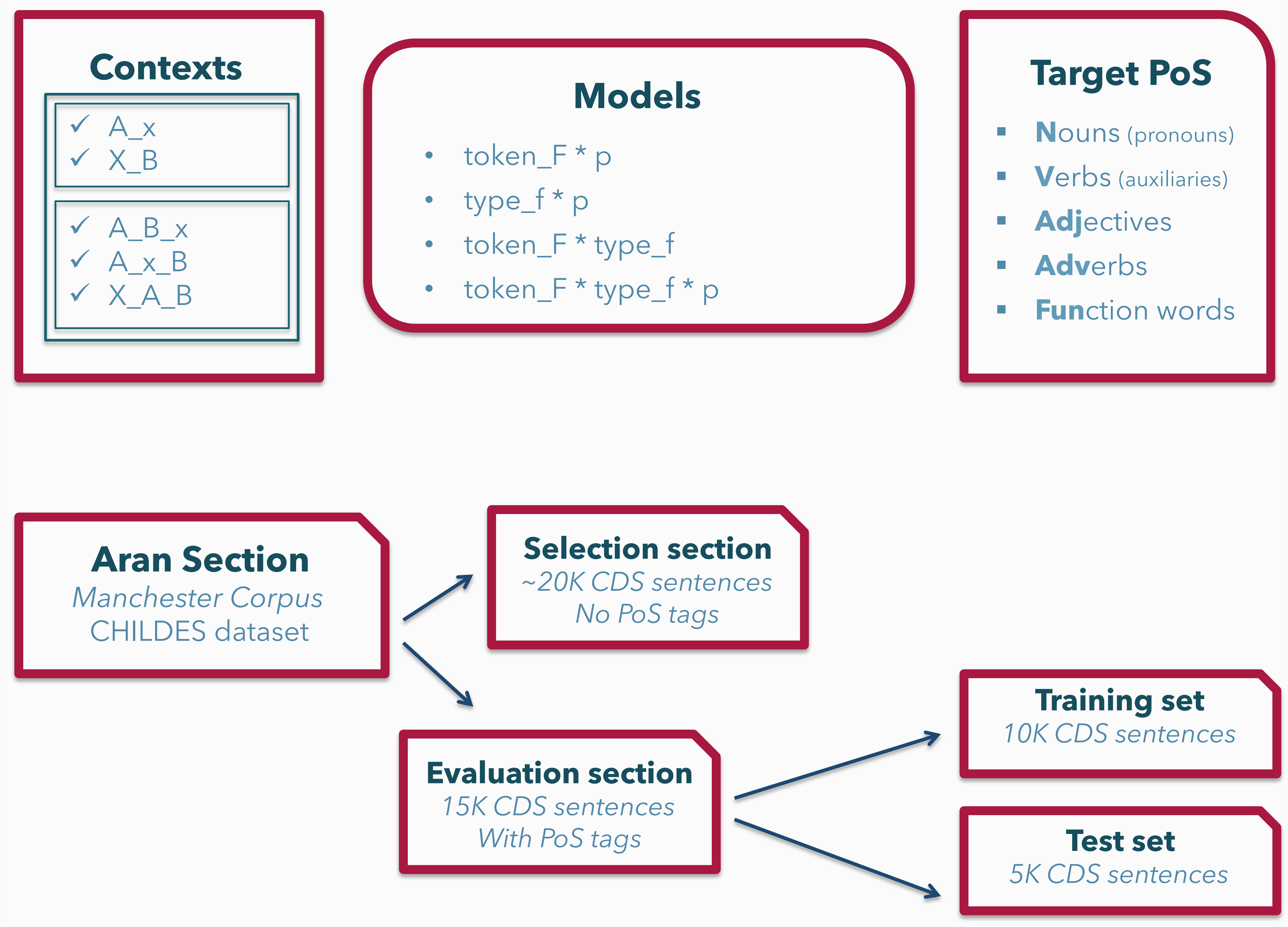
$$type\_f = \frac{log_2(\|W_{ci}\|)}{avg(log_2(\|W_c\|))} \quad (2)$$

$$p = \frac{1}{\|W_{ci}\|} \sum_{j=1}^{\|W_{ci}\|} \frac{log_2(count(w_j, c_i))}{log_2(count(w_j))} \quad (3)$$

$$score = token\_F \cdot type\_f \cdot p \quad (4)$$

A context is salient if $score > 1$.
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.

3. Experimental setting



We evaluate performance on **5 dimensions**:
*__number of selected contexts__: more parsimonious sets make search faster
*__number of useless contexts__: how many of the selected contexts don't appear or only occur with one word in the training set
*__coverage__: how many types from the training set occur with the selected contexts
*__number of hits__: number of correctly categorized types in the test set
*__accuracy__: micro-F1 score of a supervised PoS experiment

4. Results

Context type	*# contexts*	*Useless*	*Missed words (%)*	*Hits*	*Acc.*
frequent frames	45	3 (6.7%)	83.7	290	**.83**
flexible frames	90	0	16.6	1405	.66
		$p \cdot token\_F$			
2grams	75	0	10.2	1559	.671
3grams	348	13 (3.7%)	37.3	1073	.681
all	490	11 (2.2%)	3.8	**1669**	.664
		$p \cdot type\_f$			
2grams	21	0	19.5	1377	.674
3grams	42	0	56.7	788	.756
all	97	0	8.7	1611	.679
		$p \cdot token\_F \cdot type\_f$			
2grams	211	0	2.6	1624	.641
3grams	659	7 (1%)	25.5	1249	.653
all	964	8 (0.8%)	**1.2**	1562	.609

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 *Token_F* and *type_f* only is not shown since results were markedly worse than all other models, on all dimensions except for coverage.

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**
(ii) testing models on **core vocabulary**
(iv) training models on core vocabulary, to evaluate **generalization**

A. References

[1] Toben H. Mintz. Frequent frames as a cue for grammatical categories in child-directed speech. *Cognition*, 90(1):91–117, 2003.

[2] Michelle C St Clair, Padraic Monaghan, and Morten H Christiansen. Learning grammatical categories from distributional cues: Flexible frames for language acquisition. *Cognition*, 116(3):341–360, 2010.

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