

## 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).

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

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

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

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

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.

## 5. Conclusions & future work

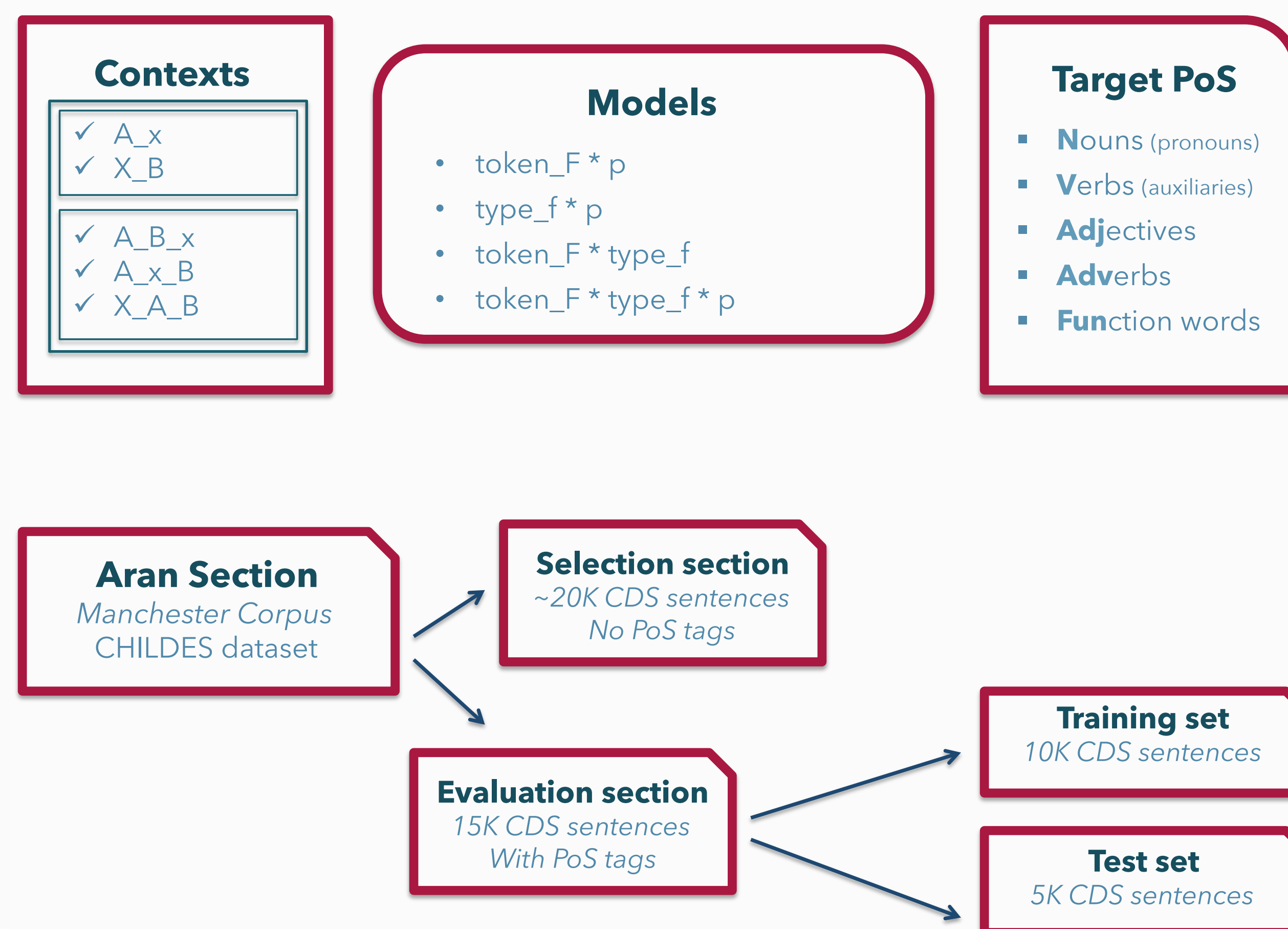
There is a **trade-off** between coverage, accuracy, and scalability: evaluating on one dimension without considering interactions is likely to lead to biased inferences.

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

Currently, we are

- evaluating models on more corpora from **typologically different languages**
- evaluating **learning curves**
- testing models on **core vocabulary**
- training models on core vocabulary, to evaluate **generalization**

## 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	<b>.83</b>
flexible frames	90	<b>0</b>	16.6	1405	.66
$p \cdot token\_F$					
2grams	75	<b>0</b>	10.2	1559	.671
3grams	348	13 (3.7%)	37.3	1073	.681
all	490	11 (2.2%)	3.8	<b>1669</b>	.664
$p \cdot type\_f$					
2grams	21	<b>0</b>	19.5	1377	.674
3grams	42	<b>0</b>	56.7	788	.756
all	97	<b>0</b>	8.7	1611	.679
$p \cdot token\_F \cdot type\_f$					
2grams	211	<b>0</b>	2.6	1624	.641
3grams	659	7 (1%)	25.5	1249	.653
all	964	8 (0.8%)	<b>1.2</b>	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.

## 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.

## B. Acknowledgements

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