



Problem

- Children learn syntactic categories very early and use them well (Valian 1986, Yang 2013)
- Whether categories are innate (Chomsky) 1965) or emergent (Chomsky 1955), they must be acquired from language specific distributional information.
- Popular methods in cognitive modeling (e.g., Redington et al. 1996) and unsupervised NLP (e.g., Haghighi & Klein 2006) are computationally expensive yet still perform poorly
- Simple and empirically motivated methods (Mintz 2000) do not scale well (Chemla et al. 2009)
- Need an effective model with better connections to language development.

Bootstrapping for Categories

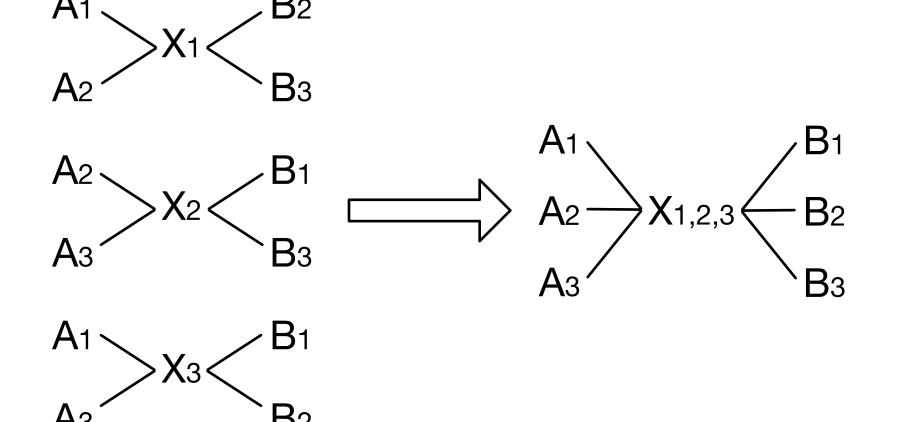
- Semantic bootstrapping: prototypical exemplars for syntactic categories (Grimshaw 1979, Pinker 1984)
- Strongly supported by analysis of childdirected input (Rondal & Cession 1990)
- **Distributional learning**: young children can use distributional regularities, including word order and morphology, to identify the categories of novel words (Brown 1957, Naigels 1990, Mintz 2002, Shi & Melacon 2010)
- **Proposal**: starting from a small set of labeled words, iteratively construct classifiers on the basis of **distributional distance** with the seeds
- Seed set increases and classifiers go from concrete to abstract

Bootstrapping for Syntactic Categories

Jordan Kodner Mitch Marcus John Hewitt Charles Yang Department of Linguistics and Computer and Information Science, University of Pennsylvania

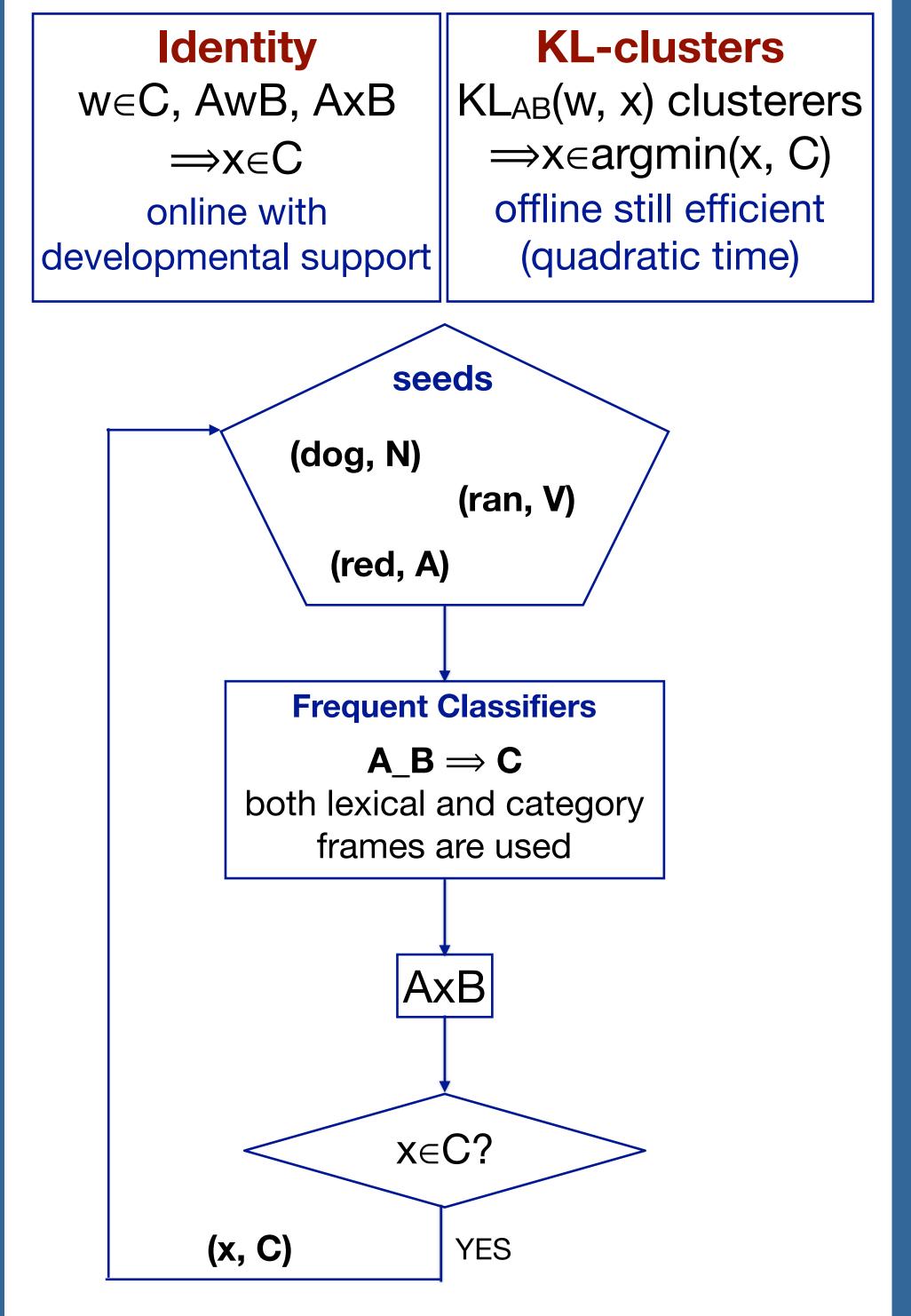
Method

From word frames to category frames (Reeder et al. 2013, Schuler et al. in press)



lexical and category frames the_N_is: (the_is, D_is, the_V, D_V) \Rightarrow N

Two frame-based distance metrics



Results

All results measured by 1-to-1 accuracy compared with baseline (initial seeds only) **Exp 1: Child-directed English**

 86 salient seed words from the Chicago early language corpus (e.g., selected this, not **the**, as a determiner seed)

- 220,000 words mapped to 7 categories
- 25-fold cross-validation
- Accuracy 62.44% (baseline: 20.5%)

Exp 2: WSJ/Chinese Treebanks

- Haghighi & Klein (2006): large word vectors
- Top 3 words per category (WSJ 45, Chinese 33): current model uses only text

	HK2006	Current	CRF
WSJ	68.8 %	55.6%	41.3%
СТВ	39.0%	46.7 %	34.4%

Exp 3: KL-clusters

- A range of languages (top 1000 words only)
- Hierarchical clustering (Parkes et al. 1998)
- Scoring by types

	# seeds	Baseline	Accuracy
CHILDES	100	10.0%	70.4%
WSJ	89	8.9%	76.2%
СТВ	85	8.5%	73.1%
German	35	3.5%	52.9%
Indonesian	34	3.4%	71.8%
Spanish	34	3.4%	62.8%

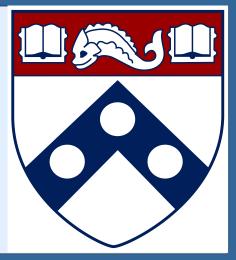
Conclusion

- frames)
- allowed)

Selected References

Chemla et al. (2009) Developmental Science. Haghighi & Klein (2006) EMNLP. Lederer et al. (1999) Cognition. Mintz (2002) Cognition. Naigels (1990) Language Acquisition. Parkes, Malek, & Marcus (1998) ACL. Redington, Chater, & Finch (1996) Cognitive Science. Reeder, Newport, & Aslin (2013) Cognitive Psychology. Rondal & Cession (1990) J. Child Language. Schuler et al. (in press) Language Learning and Development Shi & Melacon (2010) Infancy. Stevens et al. (2016) Cognitive Science. Valian (1986) Cognitive Psychology. Yang (2013) PNAS.

Acknowledgements Partially funded by the DARPA LORELEI program under Agreement No. HR0011-15-2-0023.



 Cognitive and perceptual cues (a la semantic bootstrapping) can be effectively combined with distributional linguistic cues (a la lexical and category

Robustness of results with respect to seed selection (few seeds, ambiguity

The online learning algorithm leads to developmental predictions and can incorporate other mechanisms of word learning (e.g., Lederer et al. 1999, Stevens et al. 2016)

• Future work: incorporation of structural information (e.g., morphology, non-local contexts, abstract syntax)