Phonological bootstrapping with Naïve Discriminative Learning



Giovanni Cassani, Robert Grimm, Steven Gillis, Walter Daelemans name.surname@uantwerpen.be

1. Phonological bootstrapping

The hypothesis is that phonetics provide reliable cues to group words into coarse lexical categories, such as nouns and verbs. Thus, the sound of words is not entirely arbitrary but there are regularities that provide category level information to bootstrap the acquisition of syntax.

We used Naïve Discriminative Learning to run computational simulations of lexical category acquisition based on phonological cues, evaluating how effective category learning was.

2. Discriminative learning

Naïve Discriminative Learning (NDL) implements a very simple form of error driven learning through a flat neural network that learns cue-outcome associations using the Rescorla-Wagner equations:

$$\Delta V_{ij} = \begin{cases} \alpha_i \beta_1 (\lambda - \sum_{c \in t} V_c) & \text{if } c_i \in t \text{ and } o_j \in t \\ \alpha_i \beta_2 (0 - \sum_{c \in t} V_c) & \text{if } c_i \in t \text{ and } o_j \notin t \\ 0 & \text{if } c_i \notin t \end{cases}$$

Cue-outcome associations are:

- strengthened if cue and outcome are present
- weakened if the cue is present and the outcome isn't
- left unchanged when the cue is not present

The change in association depends on the number of cues in a learning trial and on the amount of error in predicting each outcome given the present cues. Associations are updated independently for every outcome.

4. Conclusions & future work

Under certain conditions, tagging words based on localist phonological features using the NDL model is feasible. The grid search shows that:

- > unambiguous words are easier
- > known words are easier
- > Training on **single words** is easier than on full utterances
- > Syllables perform better, but may not scale to non-words
- > Summing activation values is better
- > Comparing to baseline only helps when training on utterances and considering frequencies
- > reduced/full vowels and stress/no stress don't make a difference

NEXT: Correlate model's decisions and confidence with behavioral results from children and adults to see whether the model is sensitive to the same information and uses it like humans do.

3. Experimental design & results

A grid search over parameters was carried out, using **four different test sets**, obtained crossing **ambiguousness** (ambiguous, unambiguous) and **novelty** (known, new), resulting in four test sets. The other parameters that were investigated are:

Training regime: words or utterances
Vowels: full or reduced (unstressed) vowels
Activation values: sum or frequencies
K top active words: 20, 50, 100, 200

Cue type: triphones or syllables
Stress: sensitive to stress or not
Evaluation: count or compare to baseline
Words to flush at baseline: 0, 20, 50, 100

	unambiguous utterances words			ambiguous utterances words				
	sum red full	freq red full	sum red full	freq red full	sum red full	freq red full	sum red full	freq red full
у		0000 0000 0000 0000 0000 0000		0000 0000 0000 0000 0000 0000				
d i s t r n		0000 0000 0000 0000 0000 0000		0000 0000 0000 0000 0000 0000				
s y I I <u>y</u>	0000 0000 0000 0000 0000 0000		0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000				
a c b o l u e n s t n	0000 0000		0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000				
У		0000 0000 0000 0000 0000 0000		0000 0000 0000 0000 0000 0000				
d i s t r n		0000 0000 0000 0000 0000		0000 0000				
t r	_		0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000				
p h c o o n n u e e n				0000 0000 0000 0000 0000 0000				
w s t n								
у		0000 0000 0000 0000 0000 0000		0000 0000 0000 0000				
d i s t r n		0000 0000 0000 0000 0000 0000		0000 0000 0000 0000 0000 0000				
s y I I <u>y</u>	0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000			0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000
a c b o l u e n s t n	0000 0000 0000 0000 0000 0000		0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000			0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000
уу		0000 0000 0000 0000						
d i s t r n		0000 0000 0000 0000 0000		0000 0000 0000 0000 0000 0000				0000 0000
t r i p	_		0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000			••••• •••• •••• ••••	
k h c n o o o n u w e n n s t n			0000 0000 0000 0000 0000 0000	0000 0000 0000 0000 0000 0000				0000 0000 0000 0000 0000 0000

Entropy 0.0 • 0.2 • 0.4 • 0.6 • 0.8 Accuracy • 0.0 • 0.2 • 0.4 • 0.6 Most.frequent • • A • B • C • N • O • V

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