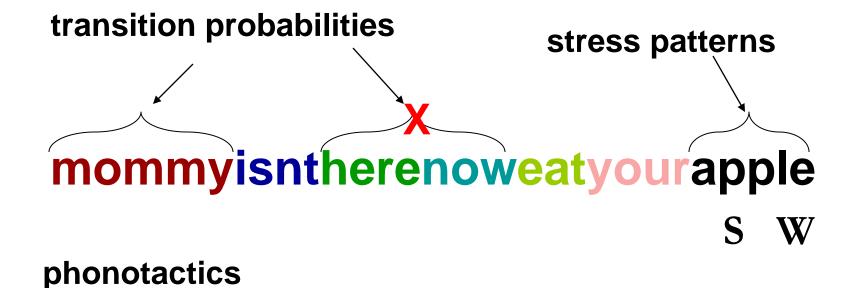
A log-linear model of language acquisition with multiple cues

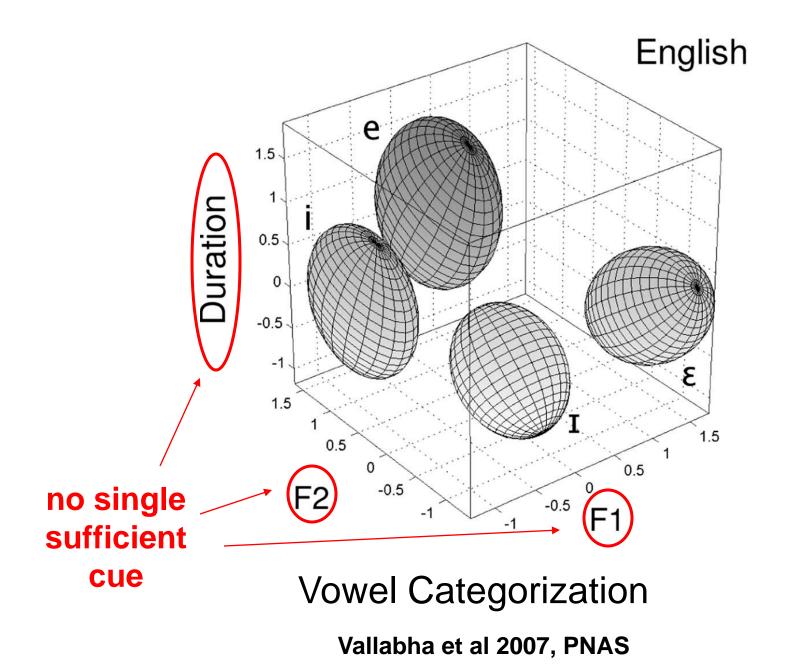
Gabriel Doyle Roger Levy
UC San Diego Linguistics
LSA 2011

mommyisntherenoweatyourapple



allophonic variation

coarticulation



Learning from Multiple Cues

- Linguistic problems can have multiple partially informative cues
- Need for models that learn to use cues jointly

The log-linear multi-cue model

 General computational model for learning structures from multiple cues

 Specific implementation in word segmentation using transition probabilities and stress patterns

Outline

- The Multiple-Cue Problem
- Case study: Word Segmentation
- Log-linear multiple-cue model
- Experimental testing

Case Study: Word Segmentation

Transition probabilities

 – p(B|A): probability that, having seen A, you'll see B next

Point to the monkey with the hat $p(\text{key}|\text{mon}) = 1 \qquad p(\text{hat}|\text{the}) = 1/2$

- Lower TP suggests separate words
- 8 month old infants use TPs to segment artificial languages (Saffran et al 1996, a.o.)

Case Study: Word Segmentation

Stress patterns

English has trochaic (Strong-Weak) bias

Double, double, toil and trouble; Fire burn and cauldron bubble

- 90% of content words start strong (Cutler & Carter 1987)
- 7.5 month old English learners segment trochaic but not iambic words (Jusczyk et al 1999)

Existing segmentation models

- Single cue-type (phonemes)
 - Bayesian MDL models (Goldwater et al 2009)
 - PUDDLE (Monaghan & Christiansen 2010)
- Multi cue-type (phonemes & stress)
 - Connectionist (Christiansen et al 1998)
 - Algorithmic (Gambell & Yang 2006)

Why a log-linear model?

- Ideal learner model; other multi-cue models aren't
- Effective in other linguistic tasks (Hayes & Wilson 2008, Poon et al 2009)
- More flexible than other models
 - new cues become new features
 - overlapping cues are easy to incorporate

Log-linear modelling

Model learns a probability distribution

$$p(W,S) = \frac{1}{Z} e^{\sum_{j} \lambda_{j} f_{j}(W,S)}$$
 Weighted sum of feature fns

- Feature functions f_j map (W,S) pairs to real numbers
- "Learning" means finding good real number weights λ for features

Feature functions

- Transition probabilities
 - Bigram counts within words
- Stress templates
 - Stress "word" counts
- Lexical
 - Word counts
- MDL Prior
 - Lexicon length

mommy ate it

mmy mo:1

SW:1, S:2

mommy:1, ate:1, it:1

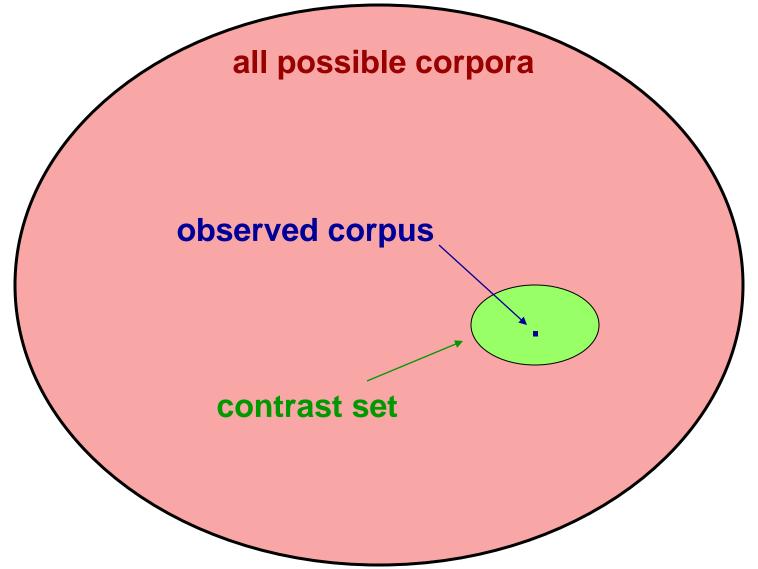
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"Normalizing" the probability

$$p(W,S) = \underbrace{\frac{1}{Z}}_{\text{Normalization constant}} \sum_{j=1}^{N} \lambda_{j} f_{j}(W,S)$$

- Probabilities need to be normalized
- Usually divide by sum
- But this sum is intractable

Contrastive estimation



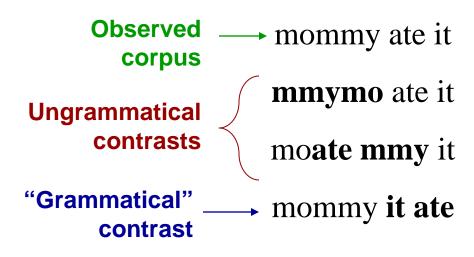
Contrastive estimation

(Smith & Eisner 2005)

- Contrast set as focused negatives
 - Want to put probability mass on grammatical outcomes
 - AND remove mass from ungrammaticals
- Good contrast sets can cause quicker convergence

Our contrast set

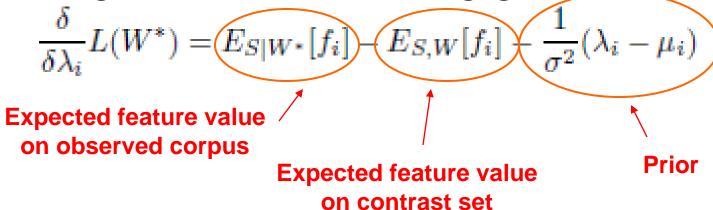
 Set of all corpora from transposing two syllables in observed corpus



Note: not the only possible contrast set

Learning the weights λ

Weights estimated using gradient ascent



- Weight increases when feature appears in observed, decreases when it appears in contrast
- Prior pulls weight toward initial bias μ_i

Experimental Questions

 Verification: Does it learn the stress biases that children exhibit? Training on childdirected English

 Application: Can these biases explain age effects in word segmentation?

Testing on artificial language

Thiessen & Saffran 2003

- Synthesized bisyllabic language, either all SW or all WS
- 7 & 9 month olds, learning English
- Preferential looking after exposure
- Words & part words in opposition

Thiessen & Saffran 2003

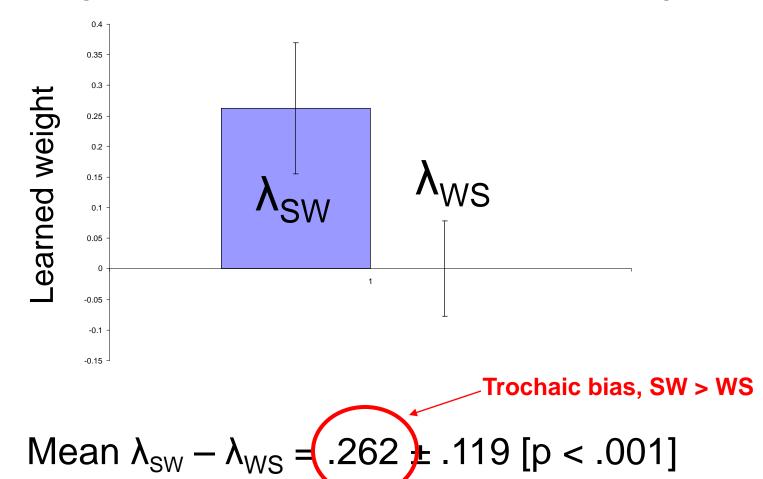
```
SW Lang
   DApuDObiBUgoDApuBUgo
   7 mos: dobi > bibu -
                            Both ages segment
                            by TPs & stress bias
   9 mos: dobi > bibu
WS Lang
   daPUdoBlbuGOdaPUbuGO
   7 mos: dobi > bibu ← 7 mos seg by TPs
   9 mos: dobi(<)bibu — 9 mos seg against TPs
```

& with stress bias

Experimental Design

- Train on English child-directed speech
 - 1638 words of Pearl-Brent database
 - 266 SW, 35 WS; 80% monosyllabic
 - Stress determined by CMU Pron Dict
 - Utterance & syllable boundaries included, non-utterance word boundaries not given
 - no prior knowledge given

Weights learned from child-directed English

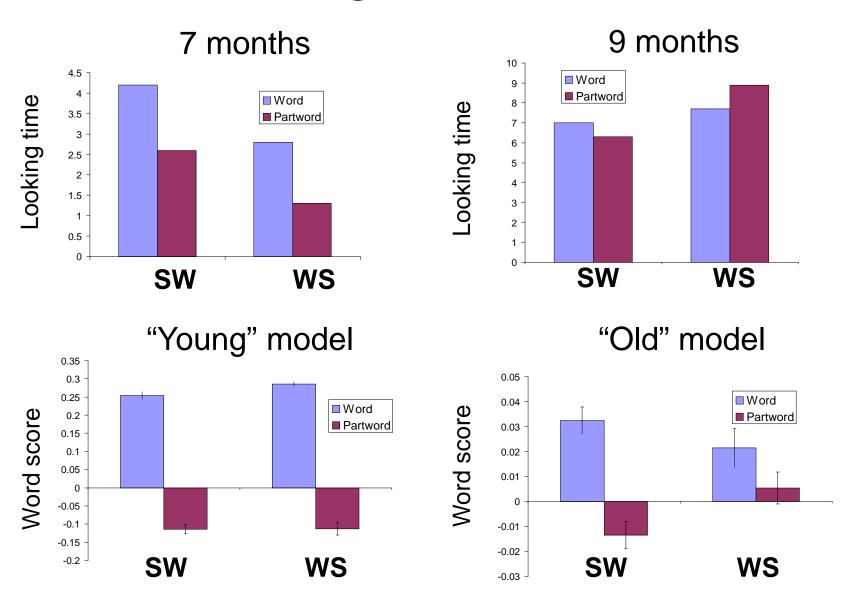


Age effects

- Idea: older infants have stronger confidence in language parameters
- Strength of learned priors increases to simulate increased linguistic experience

$$\frac{\delta}{\delta \lambda_i} L(W^*) = E_{S|W^*}[f_i] - E_{S,W}[f_i] - \underbrace{\frac{1}{\sigma^2}}_{} (\lambda_i + \underbrace{\mu_i}_{})$$
 prior strength prior value

Age effects



Conclusions

- Model learns stress bias from unsegmented data
- Model shows similar behavioral change to infants learning a language
- Behavioral change can result strictly from exposure, not a change in the segmentation method

Future Extensions

- Expand set of cues (e.g., phonotactics)
- Additional experimental applications
- Move into other linguistic problems

Thank you!

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