# MODELING THE PERCEPTION OF VOWEL NASALIZATION

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# **Bayesian Perception**

### **Perception Models:**

- Bayesian models that employ step-conditioned distributions for two categories of vowels -- phonologically nasalized vowels and oral vowels.
- Bayes' Theorem

$$P(A \mid B) = \frac{P(B \mid A) \times P(A)}{P(B)}$$

$$P(Category_i \ | Acoustics) = rac{P(Acoustics | Category_i) imes P(Category_i)}{\sum_{i=1}^{n} P(Category_i) imes P(Acoustics | Category_i)}$$

### **Acoustic models:**

- Acoustic models were trained for two vowel categories: oral (V-oral) and nasalized (V-nasalized).
- Mel-frequency cepstral coefficients (MFCCs) were used to represent acoustic information (Davis and Mermelstein, 1980).
- Likelihood distributions were generated for each category.
- The models were tested with the same nonce words as presented to actual listeners.

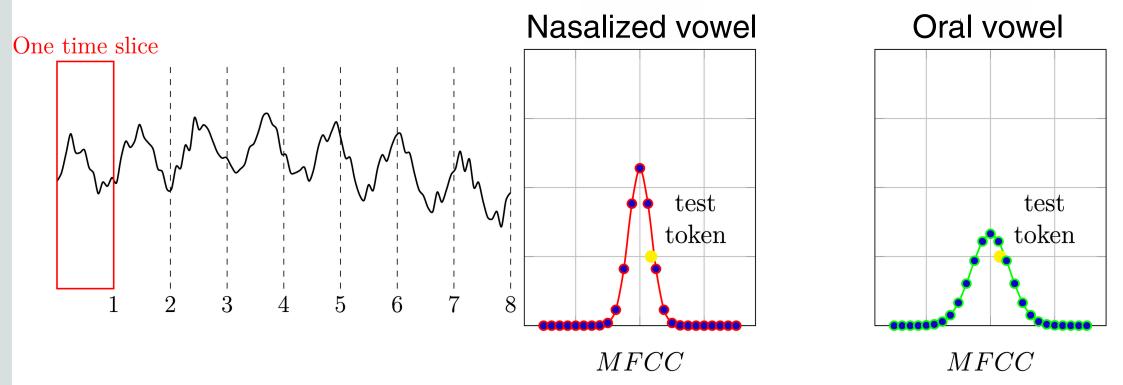


Fig. 1 Dividing a vowel into eight discrete time slices and measuring 12 MFCCs from each

time slice

Fig. 2 Simulated probability distributions for two vowel categories at each time point for a single MFCC value

# Introduction

Some debates around speech perception:

- Whether listeners access stored exemplars with fine-grained phonetic details (Pierrehumbert et al., 2002; Pierrehumbert, 2001, 2016).
   or are attuned to subtle variations such as different levels of coarticulation (Fowler, 1981, 1984).
- Whether listeners perceive speech through underspecified URs or SRs (Marslen-Wilson 1980, 1984, 1991; Ohala and Ohala, 1995; Kotzor et al. 2022).
- What is the mechanism of speech perception
   (Liberman et al. 1967; McClelland and Elman, 1986; Cutler and Norris 1979;
   McClelland and Elman 1986; Norris and McQueen 2008 etc.).

Fig. 3a Percentage of nasal

# Questions

Do listeners rely on ...

- Incremental inference updates or immediate acoustics?
- Nuanced temporal information or abstract categories?
- Underspecified representations?

Fig. 3b-c Bayesian Perception Model with Nonupdating Prior

### Take-aways

- 1. Categorical, underspecified representations are sufficient to account for the patterns in listeners' perception of vowel nasalization.
- 2. Listeners engage in Bayesian inference where their decisions are continuously updated based on previous information.

# Methodology

- Participants: 43 native American English speakers.
- Production Task:
- Wordlist of CVC (oral) and CVN (nasalized)
   words + fillers.
- Multiple repetitions of each word.

Fig. 3d-e Bayesian Perception Model with Updating Prior

- Data used to train acoustic models.
- Perception Task:
- Forced-choice segment identification task on end-truncated CVC and CVN nonce words.
- Audio stimuli presented in 8 gated time steps (gates).

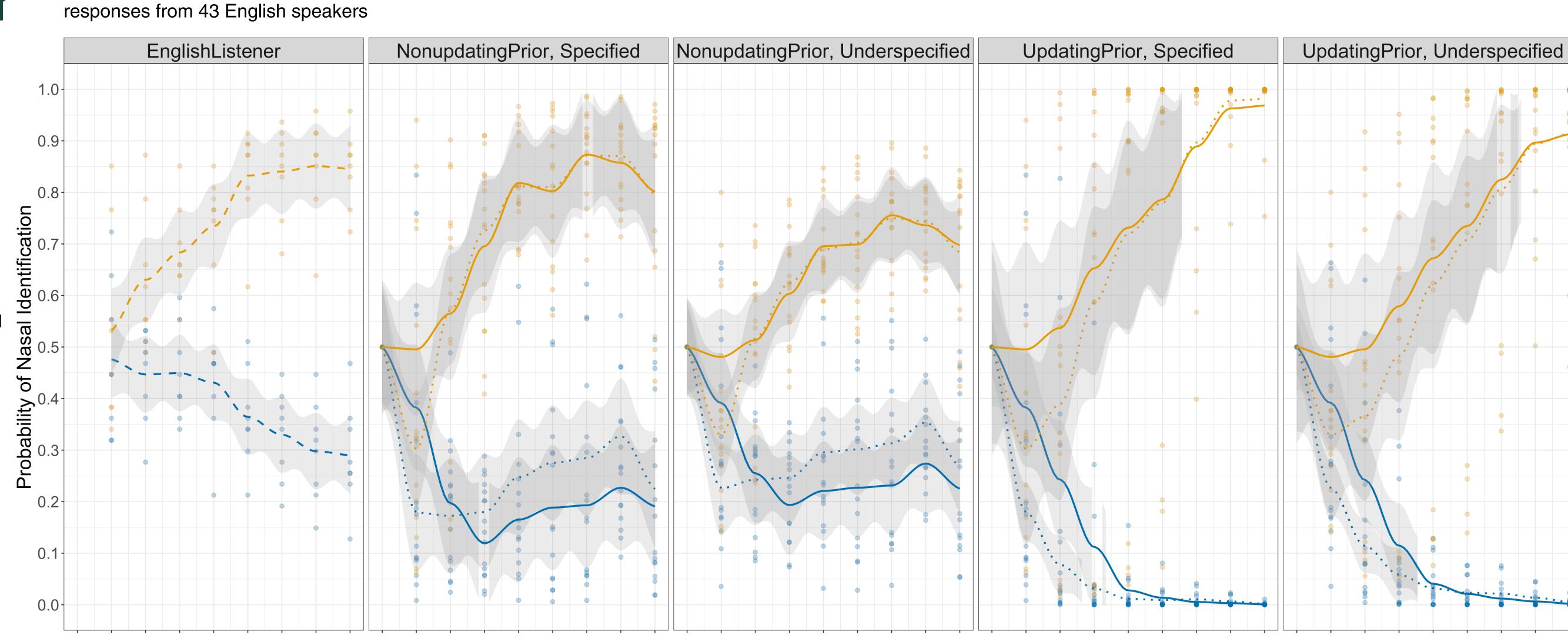
# Listener and Model Results

### Performance

humantime-insensitive modeltime-sensitive model

### Test Vowel

Oral VowelNasalized Vowel



### **Listener and Model:**

### (comparing 3a and 3b-e)

- Listeners could differentiate between V-oral and V-nasalized from the outset.
- Listener accuracy is monotonically increasing.
- Some models perform better than listeners.

# Time Sensitivity: (comparing linetypes)

- Yes: Each vowel category is represented with eight time-normalized multidimensional distributions.
- No: One distribution across the entire vowel

Time-insensitive models perform well.

→ Listeners do not need fine temporal details for perceptual accuracy.

### **Underspecification:**

### (comparing 3b and 3c; 3d and 3e)

 Yes: V-oral was trained with general data from all words (CVC+CVN), V-nasalized was trained with CVN words only.

Gates

• No: V-oral and V-nasalized were trained with context-specific data from CVC and CVN words respectively.

Models using underspecified representations match the performance from specified acoustic models.

→ Listeners do not need fully specified representations.

### **Updating Inference:**

# (comparing 3b-c and 3d-e)Yes: The posterior at each time step/gate

- becomes the prior for the next time step/gate.
- No: Unchanging, equiprobable priors.

Models with dynamically updating priors, better reflected the monotonic increasing trend in the actual listener behavior than the non-updating ones.

→ Listeners' decisions are continuously influenced by an evolving prior that incorporates newly accumulated probabilistic information .

### What's Next?

- Modeling perception in languages with different vowel nasalization patterns: nasal vowels (e.g. Hindi); phonetic nasalization (e.g. Peninsular Spanish).
- Quantitatively compare model performance.
- Evaluating the assumptions and predictions of perception theories.

## Selected References

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