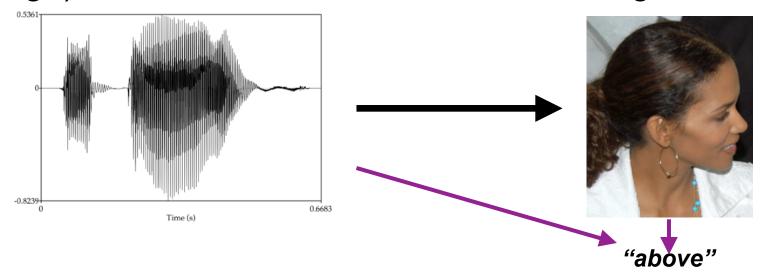
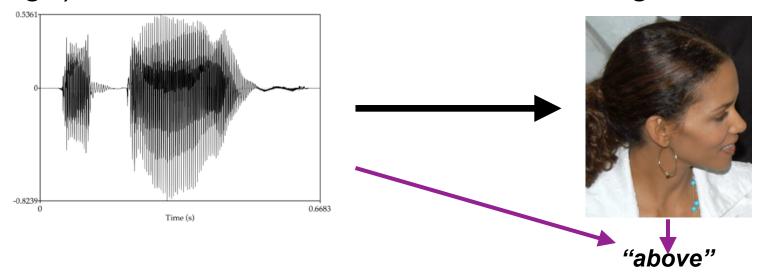


 Recognizing meaningful word sequences from sound (or sign) is a remarkable feat of human intelligence

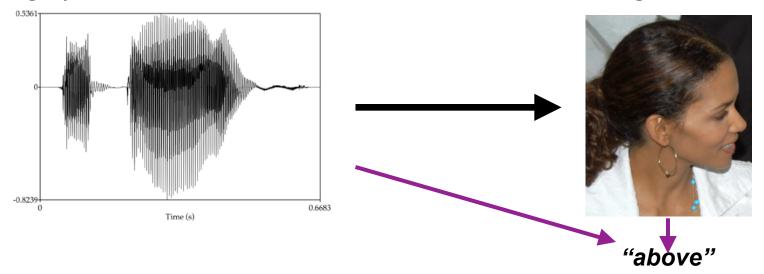


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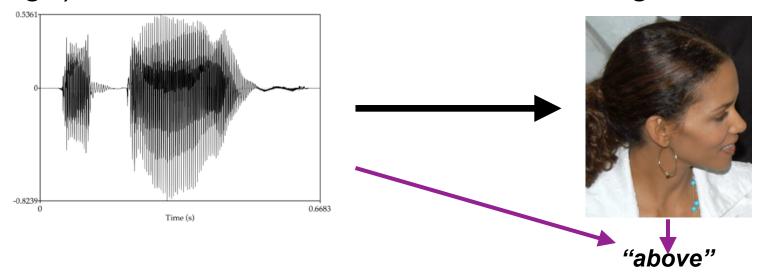
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Laurel

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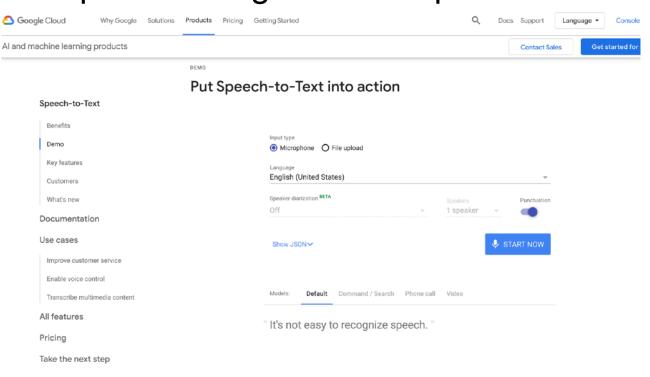
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Computer speech recognition is impressive but still fragile

Laurel



- We'll break down this hard & complex problem into something much simpler, and then scale up
- How to discriminate two minimally different sounds?

Label each one

When do you hear the transition?

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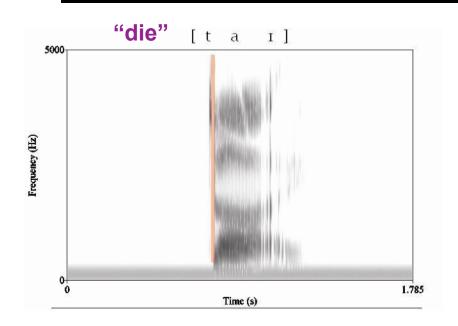
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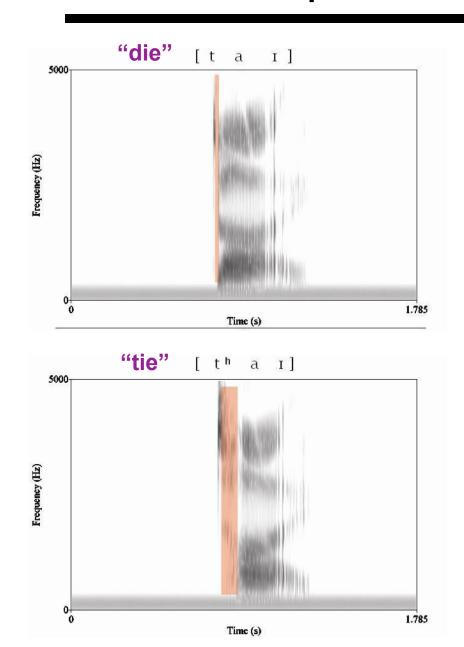
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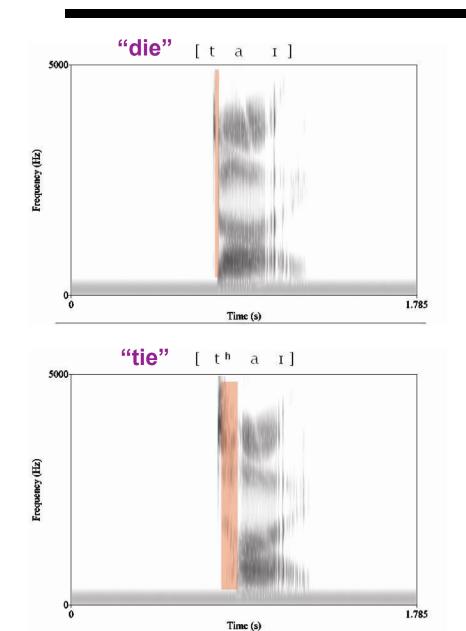
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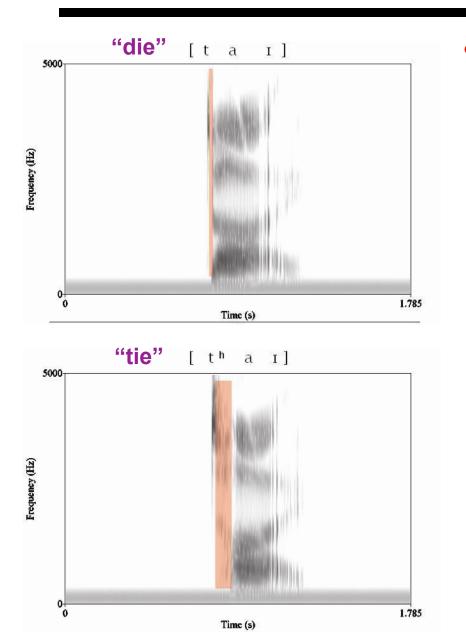
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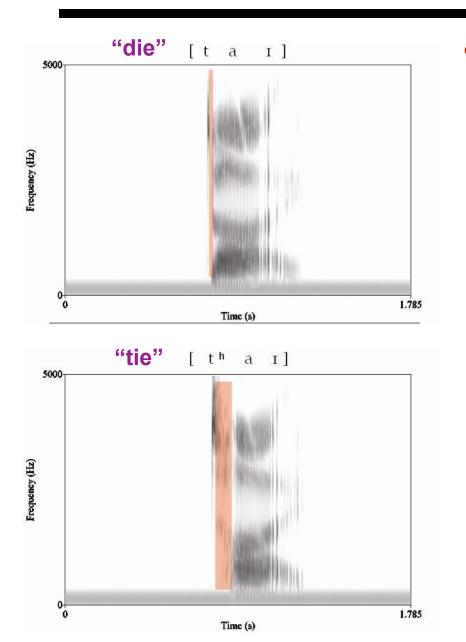




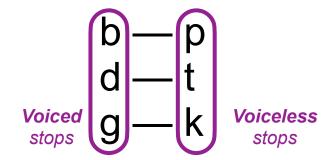
This distinction involves a single "phonetic dimension", Voice Onset Time (VOT)



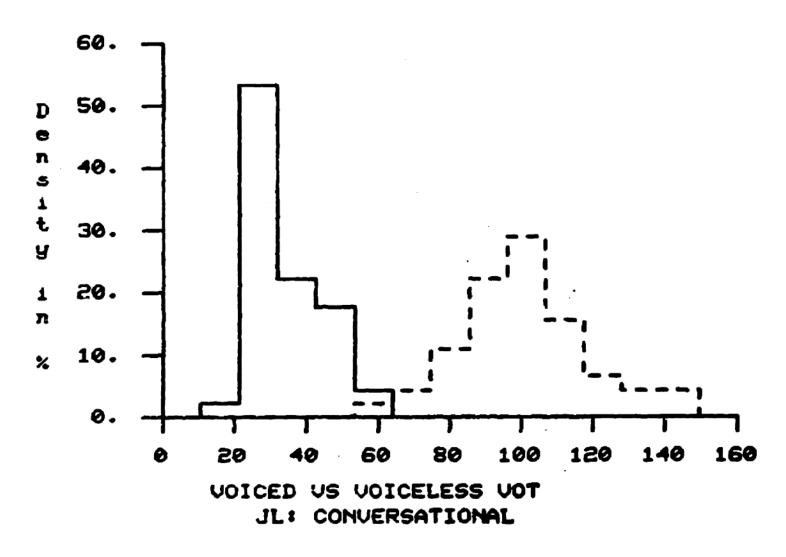
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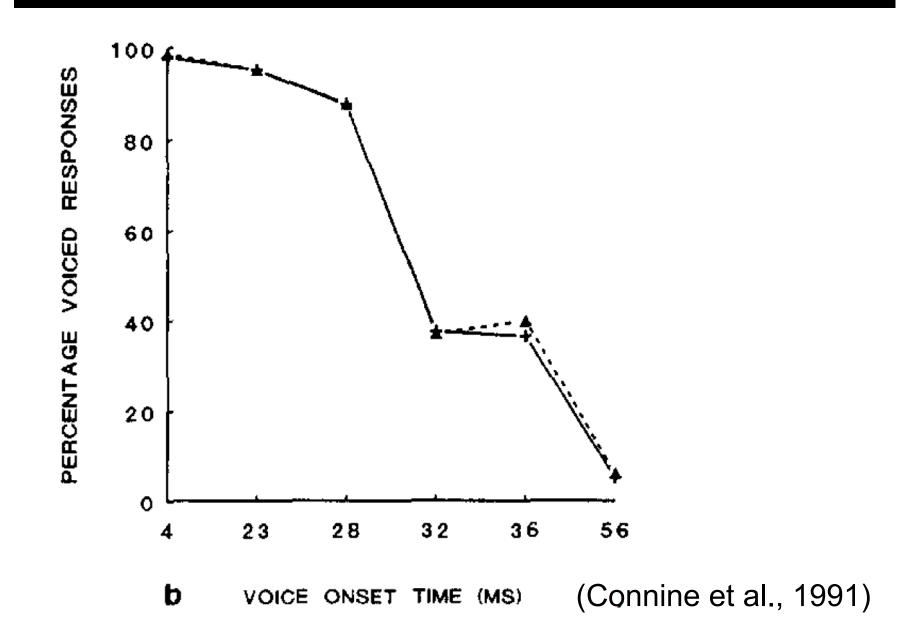
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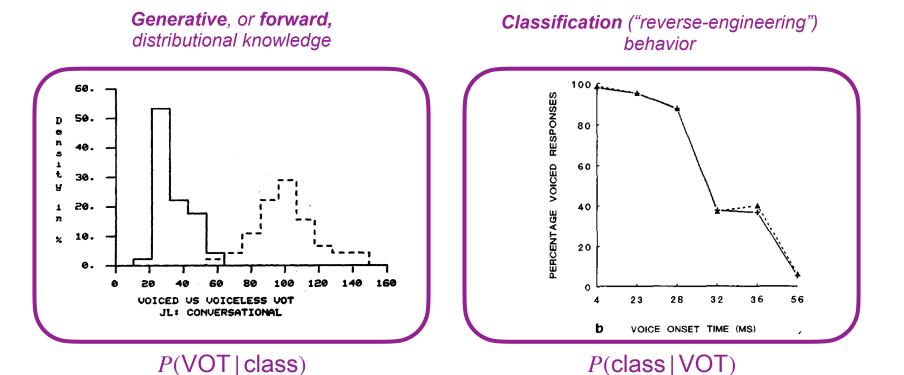


Distribution of VOTs



Human Categorization Curve





P(VOT | class)

How can we reconcile these two distributions?

 Background assumption: cognitive agent is optimized via evolution and learning to solve everyday tasks effectively

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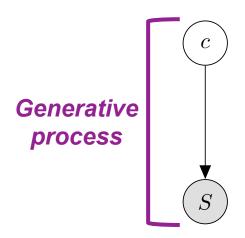
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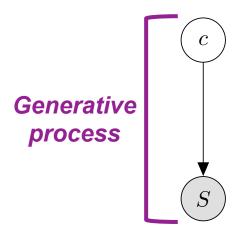
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- 5. Compare predictions with empirical data
- 6. If necessary, iterate 1–5

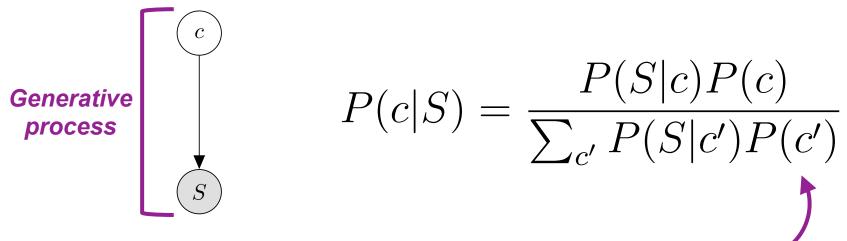


Assume sound category c manifests as speech signal S

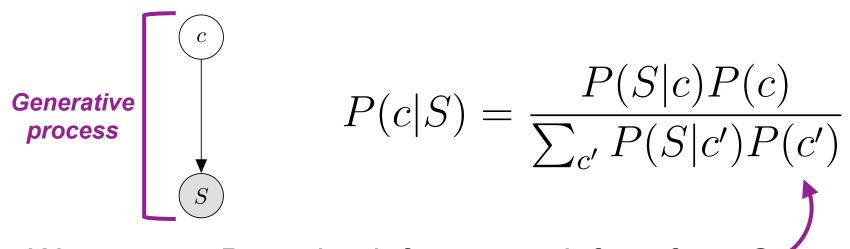


We can use Bayesian inference to infer c from S

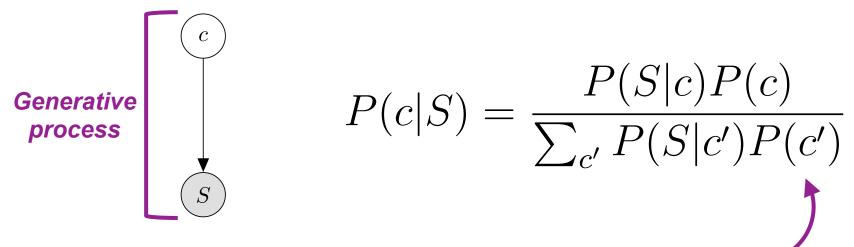
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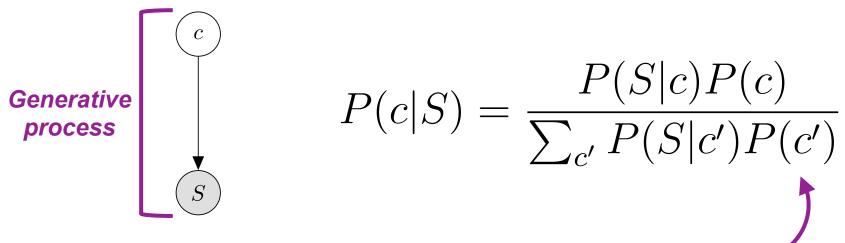
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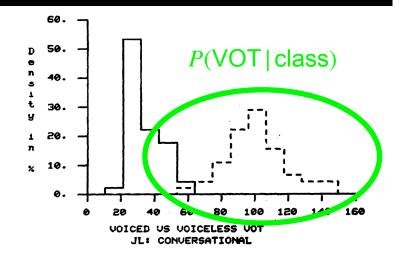


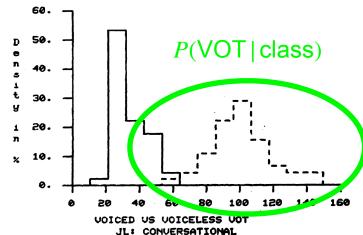
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- To make this work, we need to choose:
 - a *prior* P(c); and
 - a *likelihood* P(S|c)

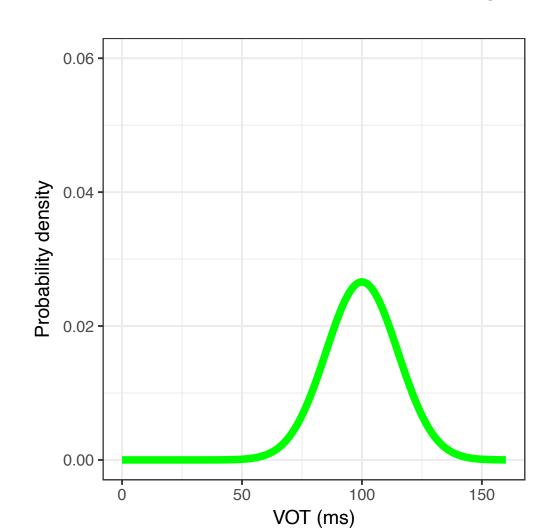


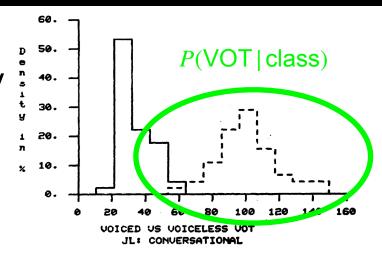
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- Out of context, the prior might be uniform

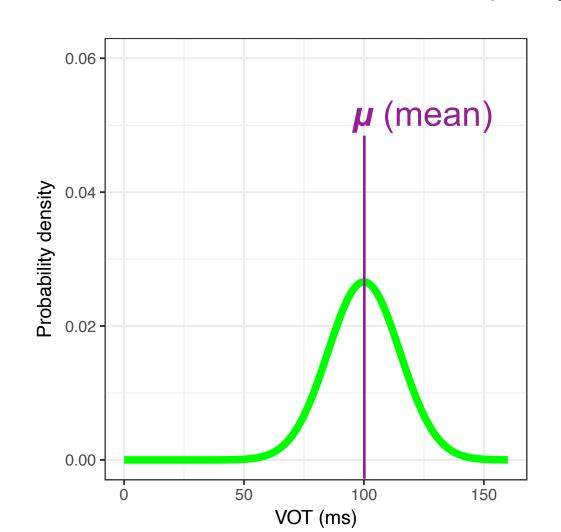
$$P(c = /b/) = P(c = /p/) = \frac{1}{2}$$

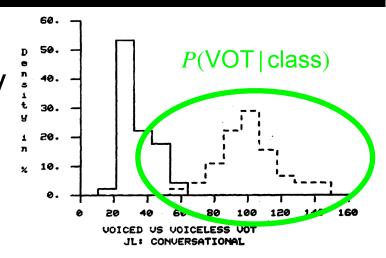


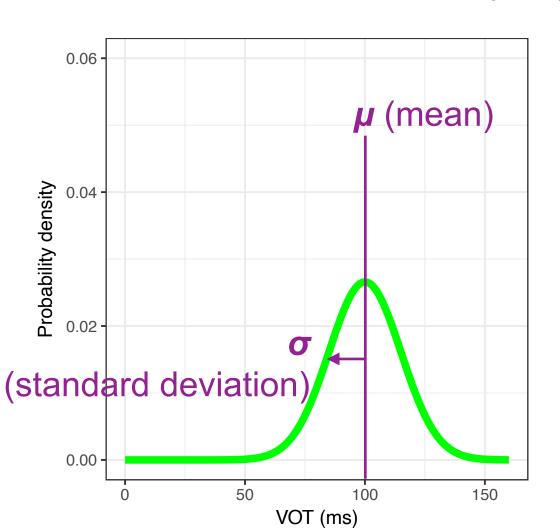


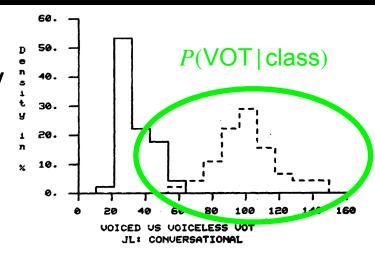


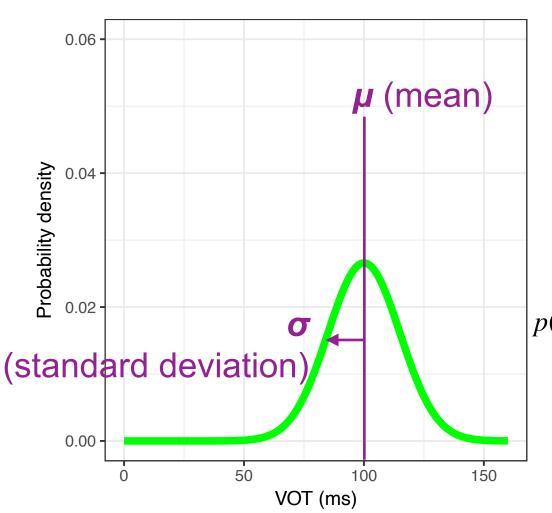


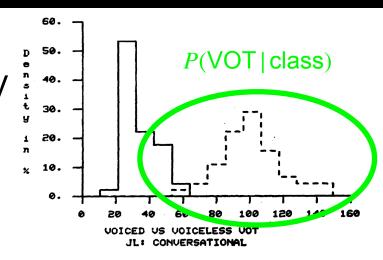






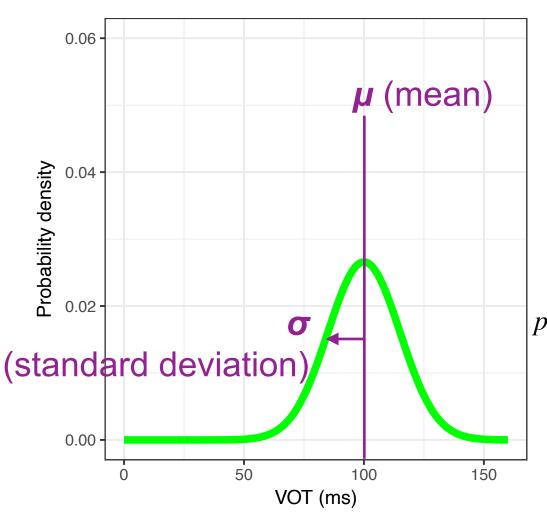


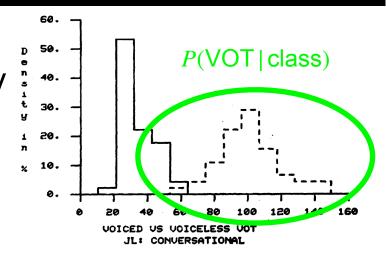




$$p(x | \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(x - \mu)^2}{2\sigma^2} \right]$$

The normal (a.k.a. Gaussian)
 distribution is a reasonable proxy

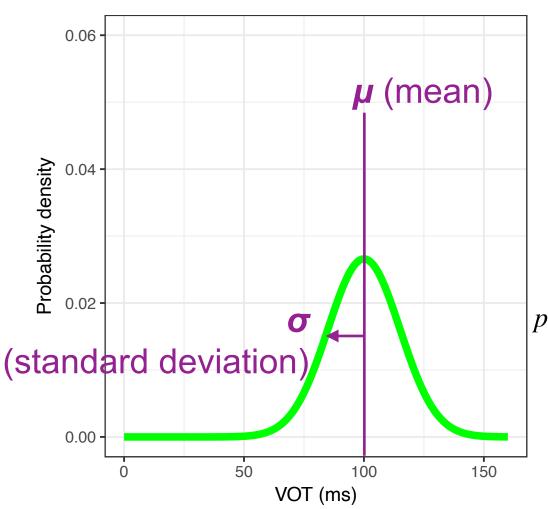


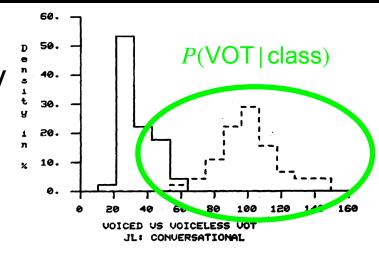


Squared deviation from mean

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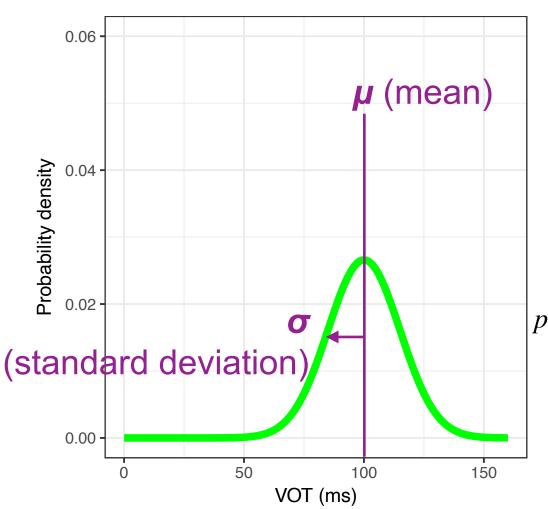


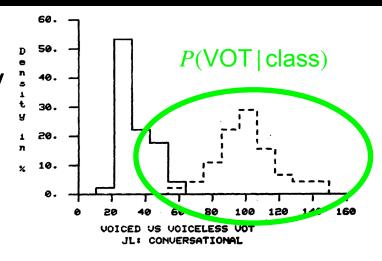
Squared deviation from mean

$$p(x \mid \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[\frac{-(x - \mu)^2}{2\sigma^2} \right]$$

Scaled by variance

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Squared deviation from mean

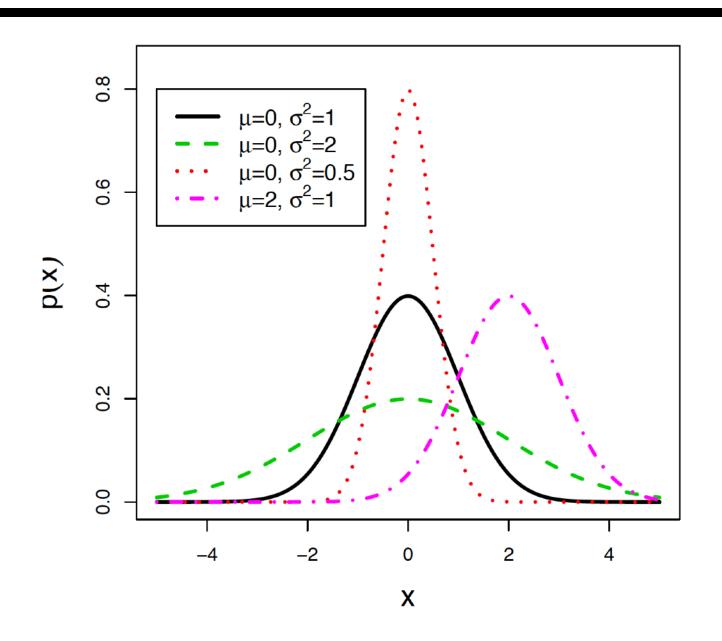
$$p(x \mid \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp$$
(normalizing constant)

Scaled by

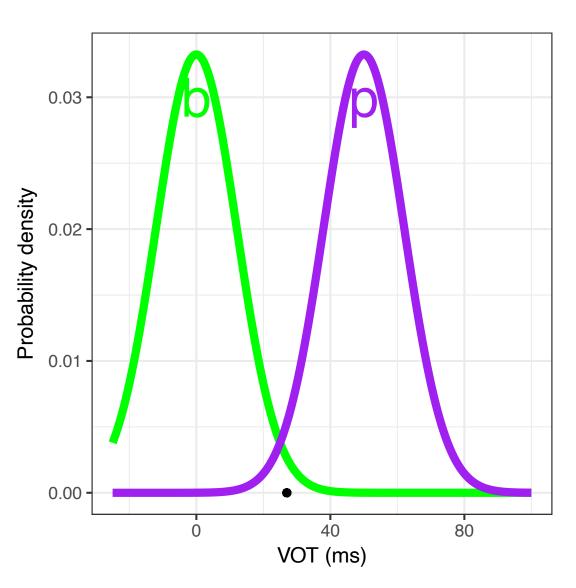
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variance

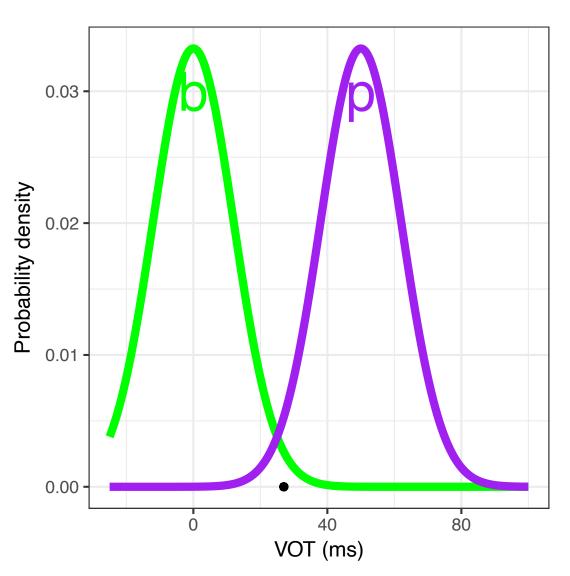
Gaussian parameters

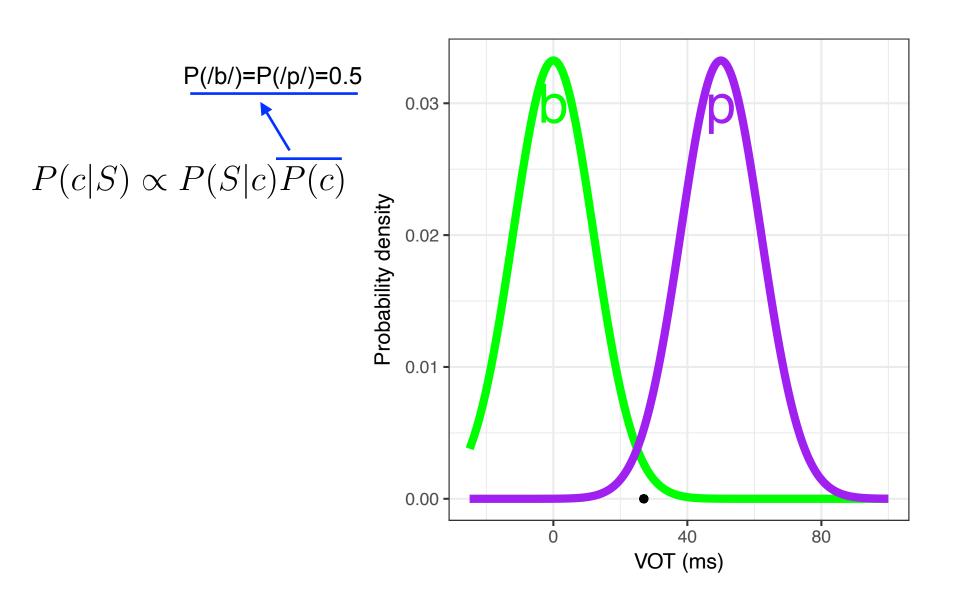


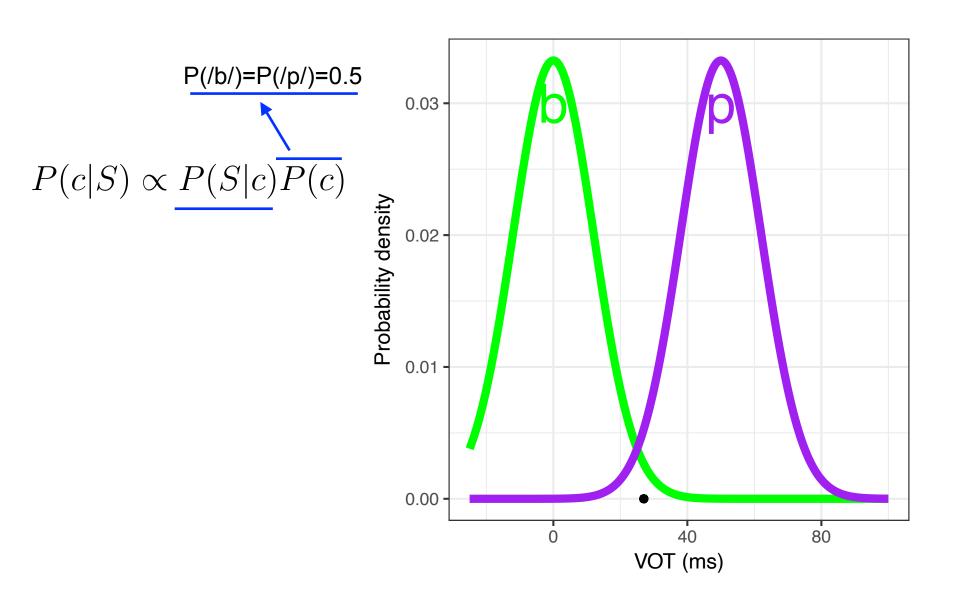


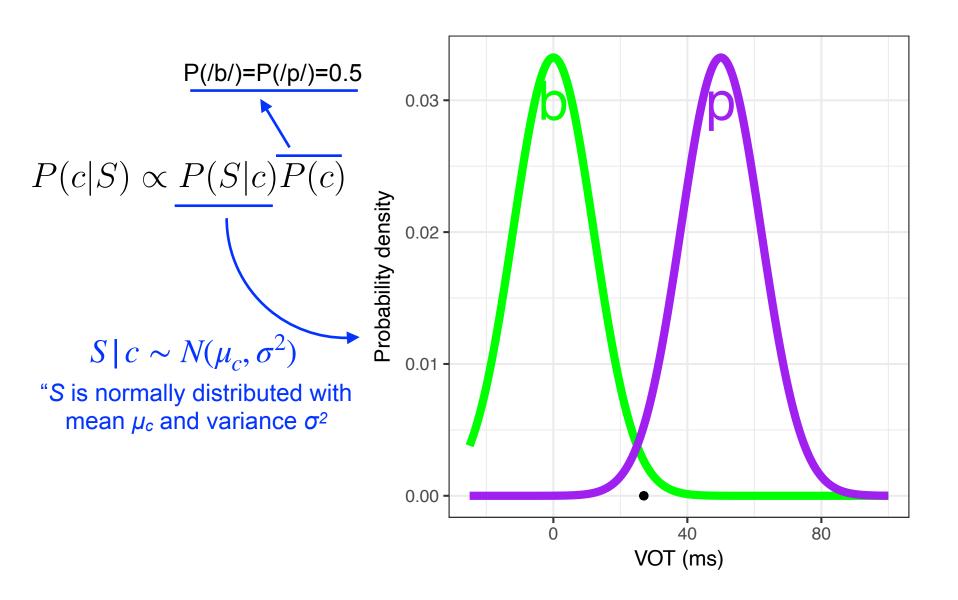


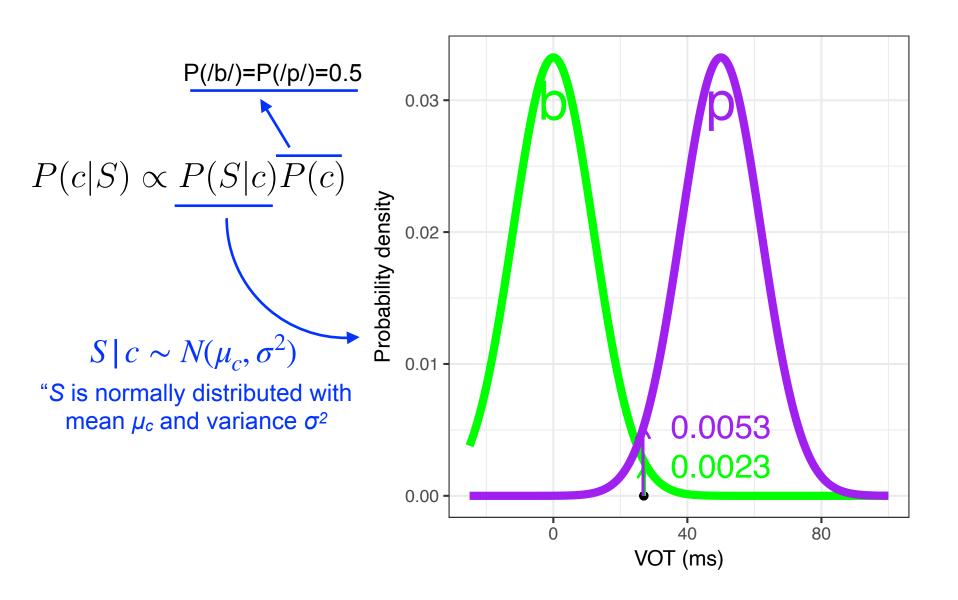


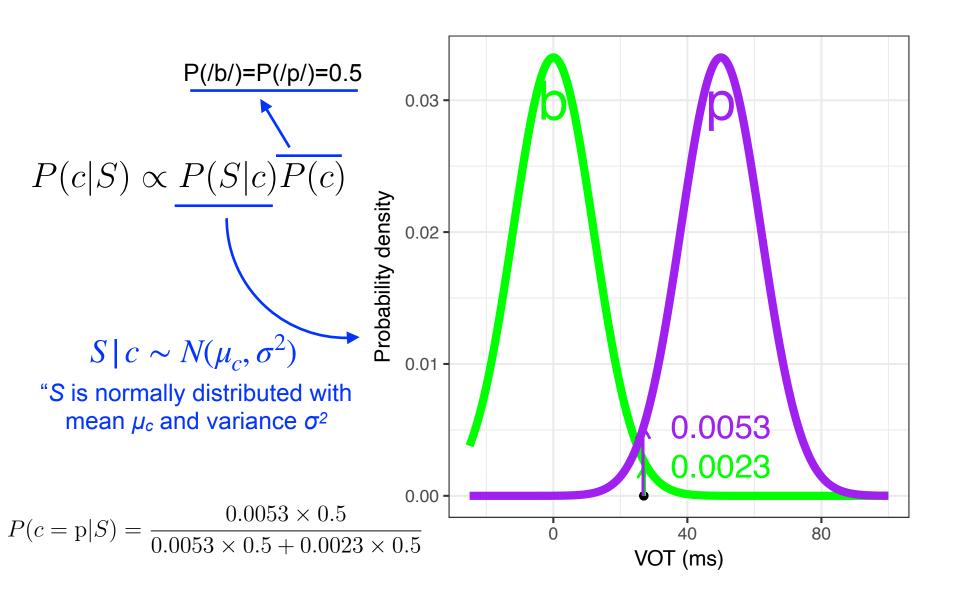


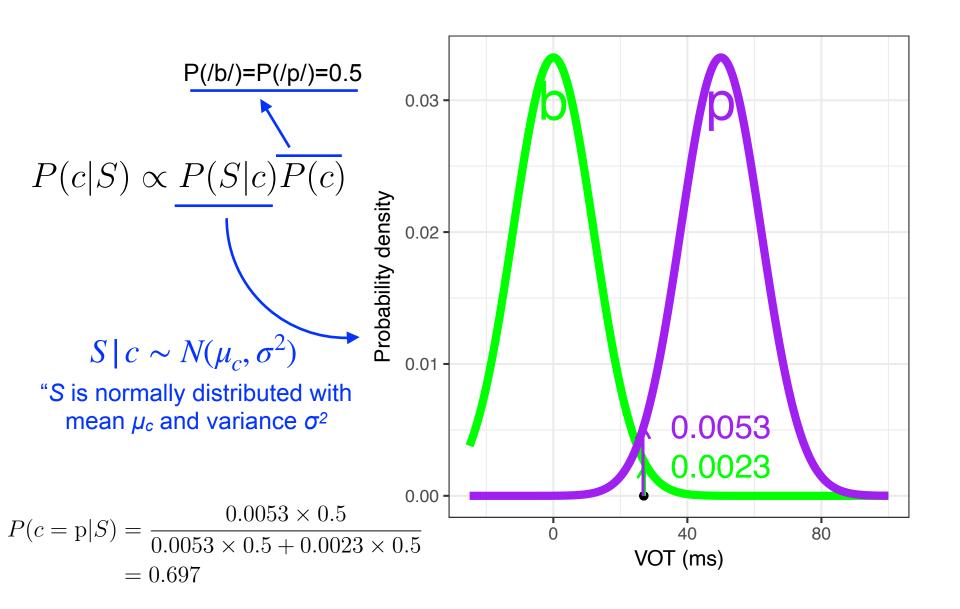




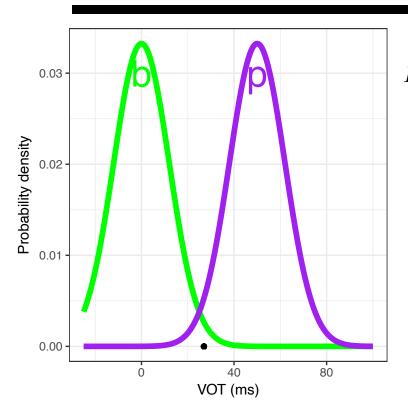






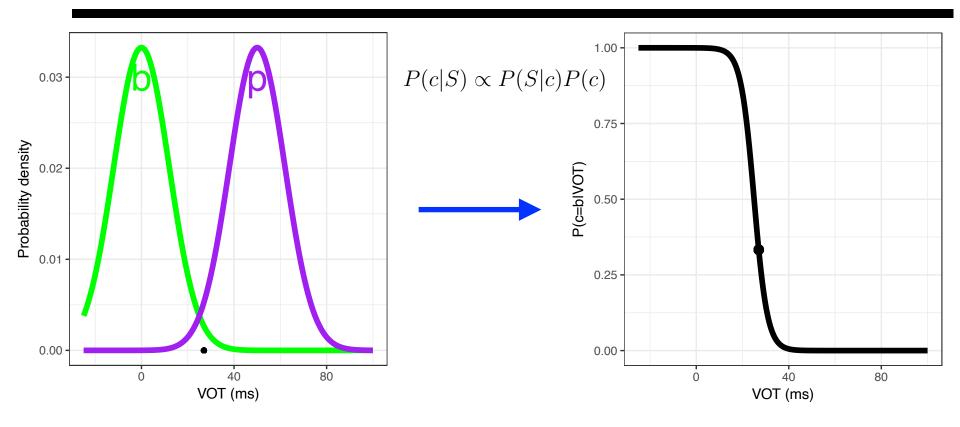


Bayesian categorization curve

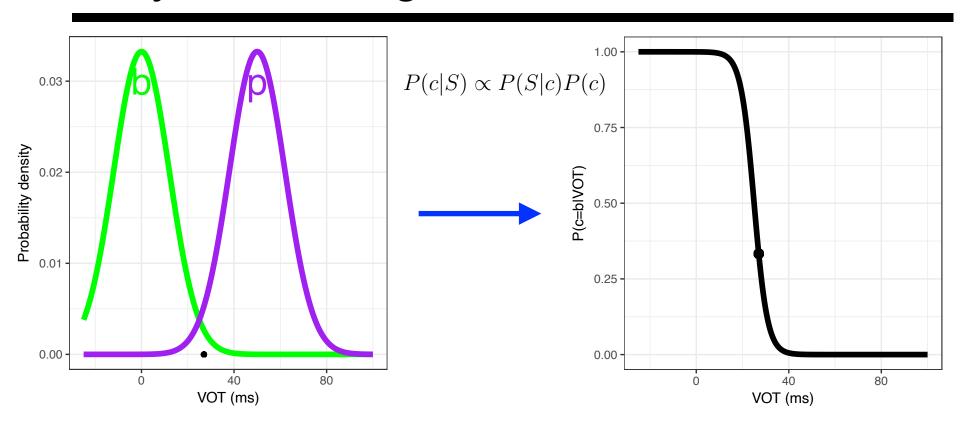


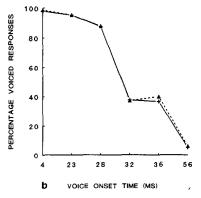
$$P(c|S) \propto P(S|c)P(c)$$

Bayesian categorization curve

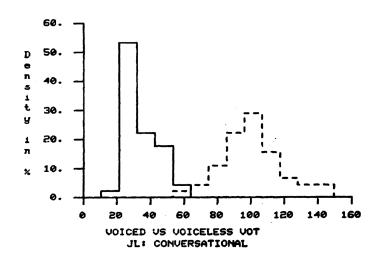


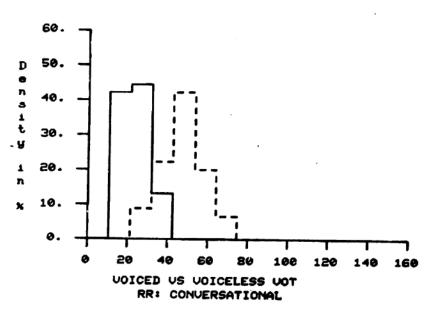
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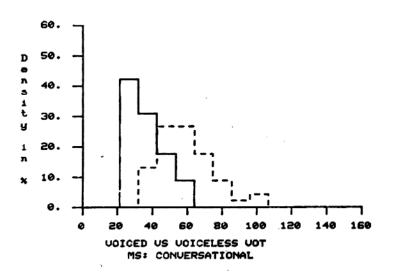


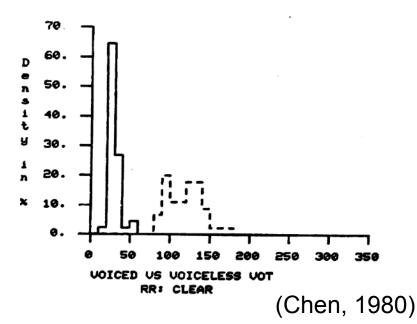


Inter-speaker variability



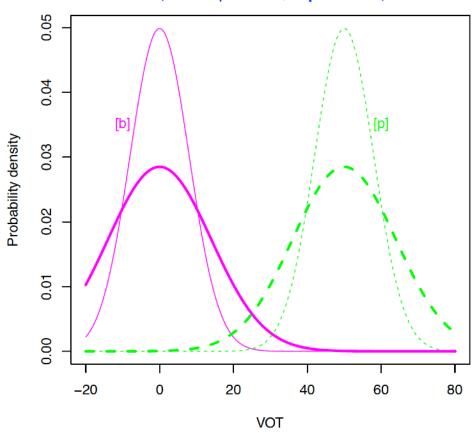




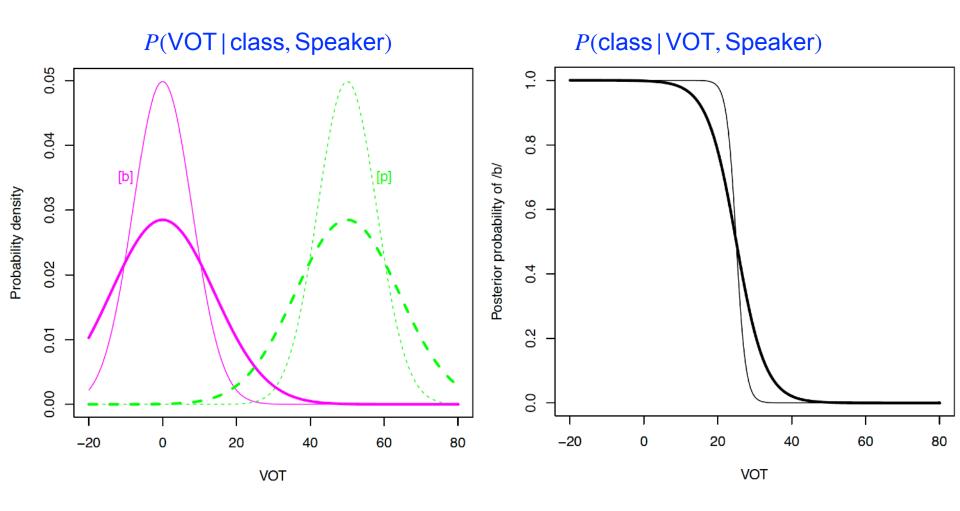


Ideal observer predictions





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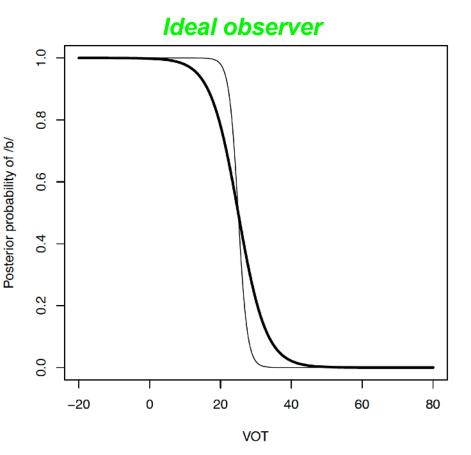


Testing effects of environment variability

- Clayards et al. (2008) tested this prediction
 - trained participants with different-variance Gaussians
 - then tested categorization

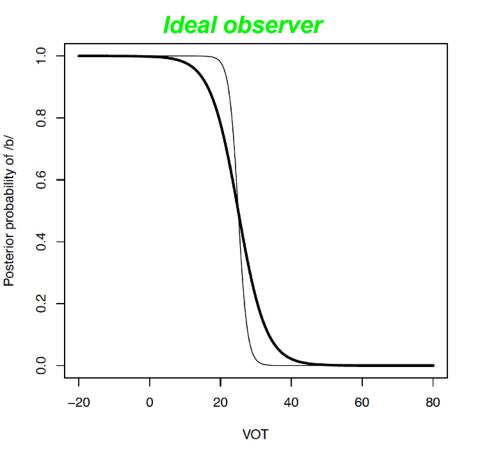
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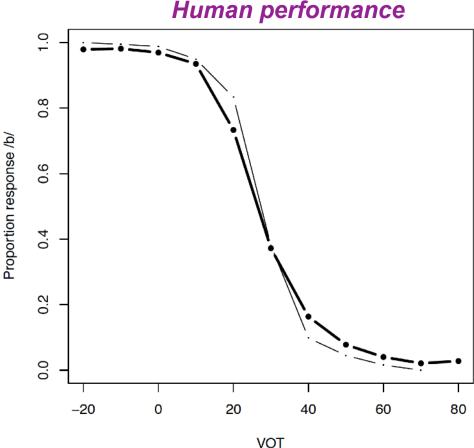
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- We explored a theoretical prediction of the implemented model and saw that experimental data confirmed the prediction