



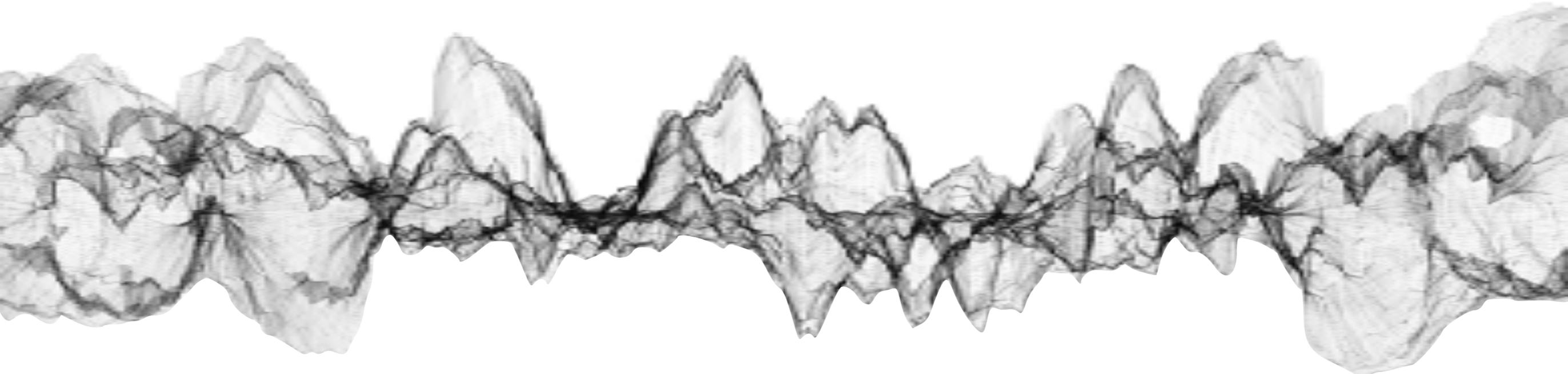
Stanford
University

GLySN
Gwilliams
Laboratory
of Speech
Neuroscience

Neural Algorithms of Human Language

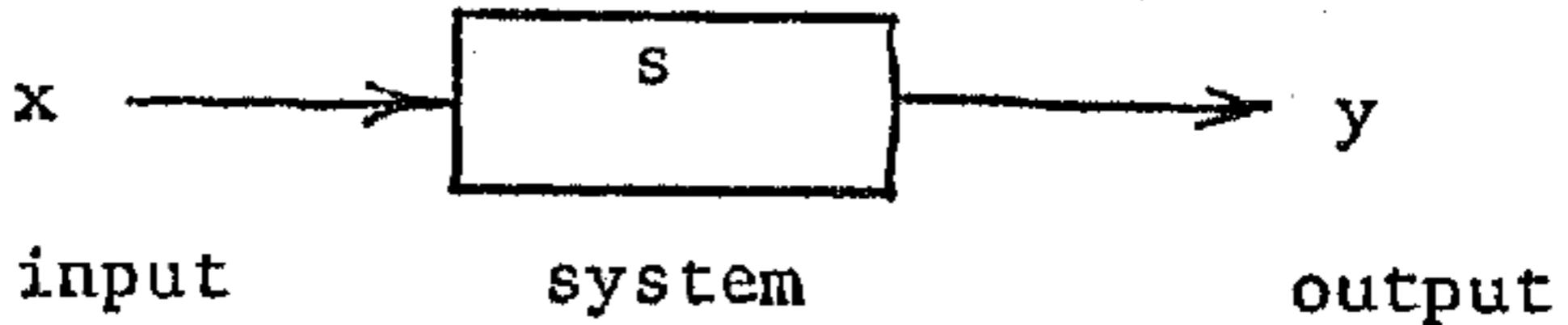
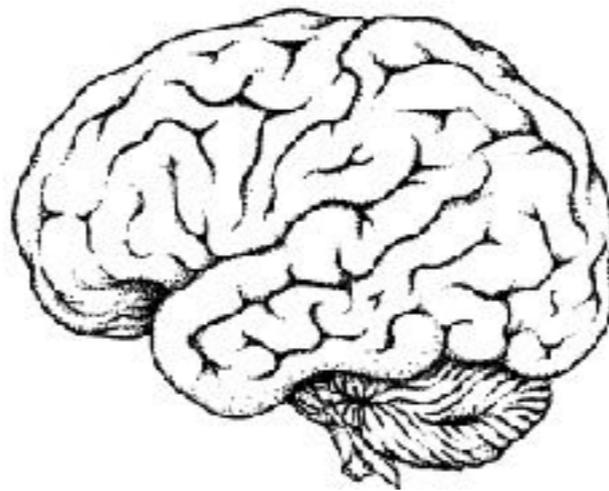
Laura Gwilliams

Gwilliams Lab of Speech Neuroscience



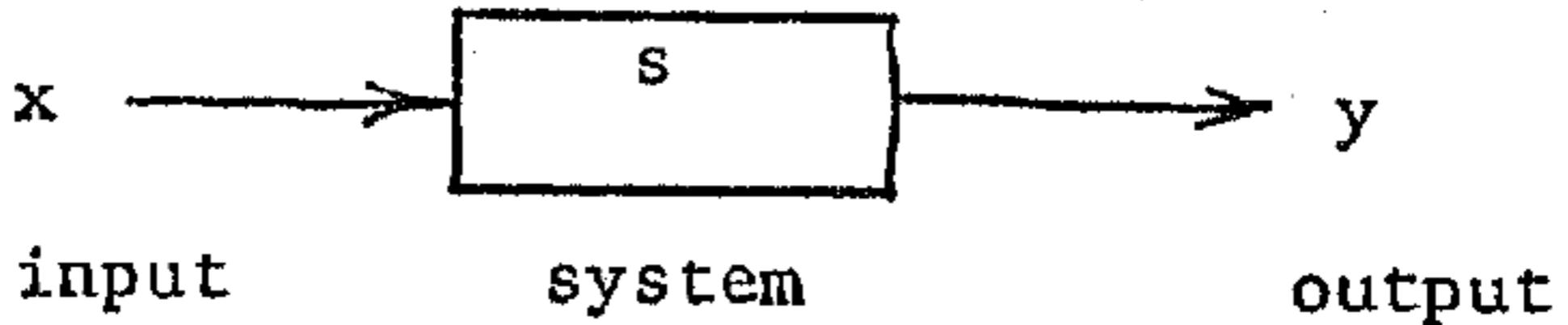
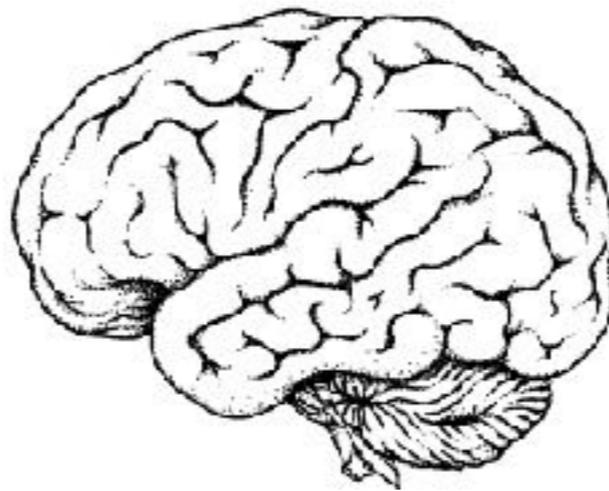
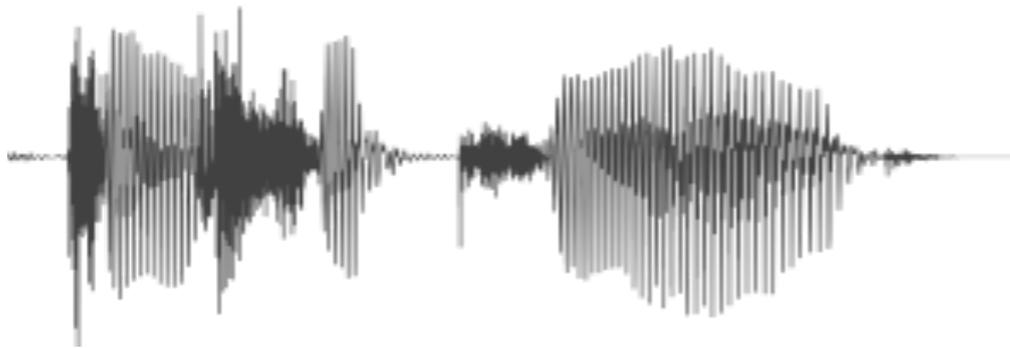
How does the brain translate between the sensory and the symbolic?

"the fat cat disappeared"



How does the brain translate between the sensory and the symbolic?

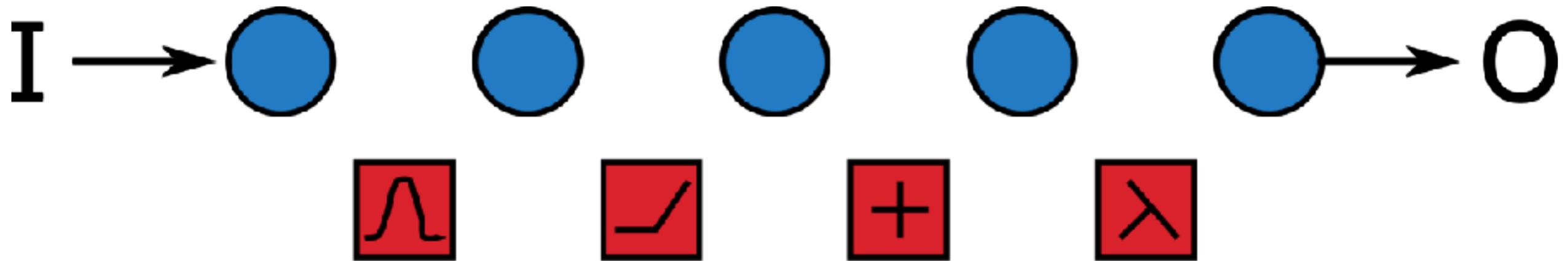
"the fat cat disappeared"



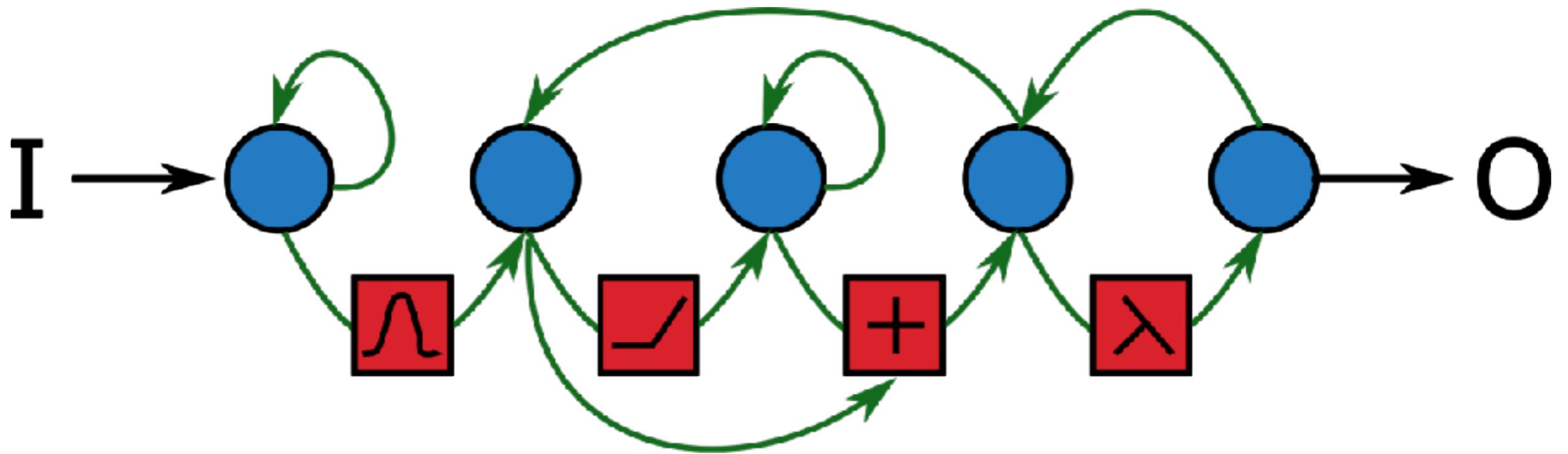
representations



representations
operations

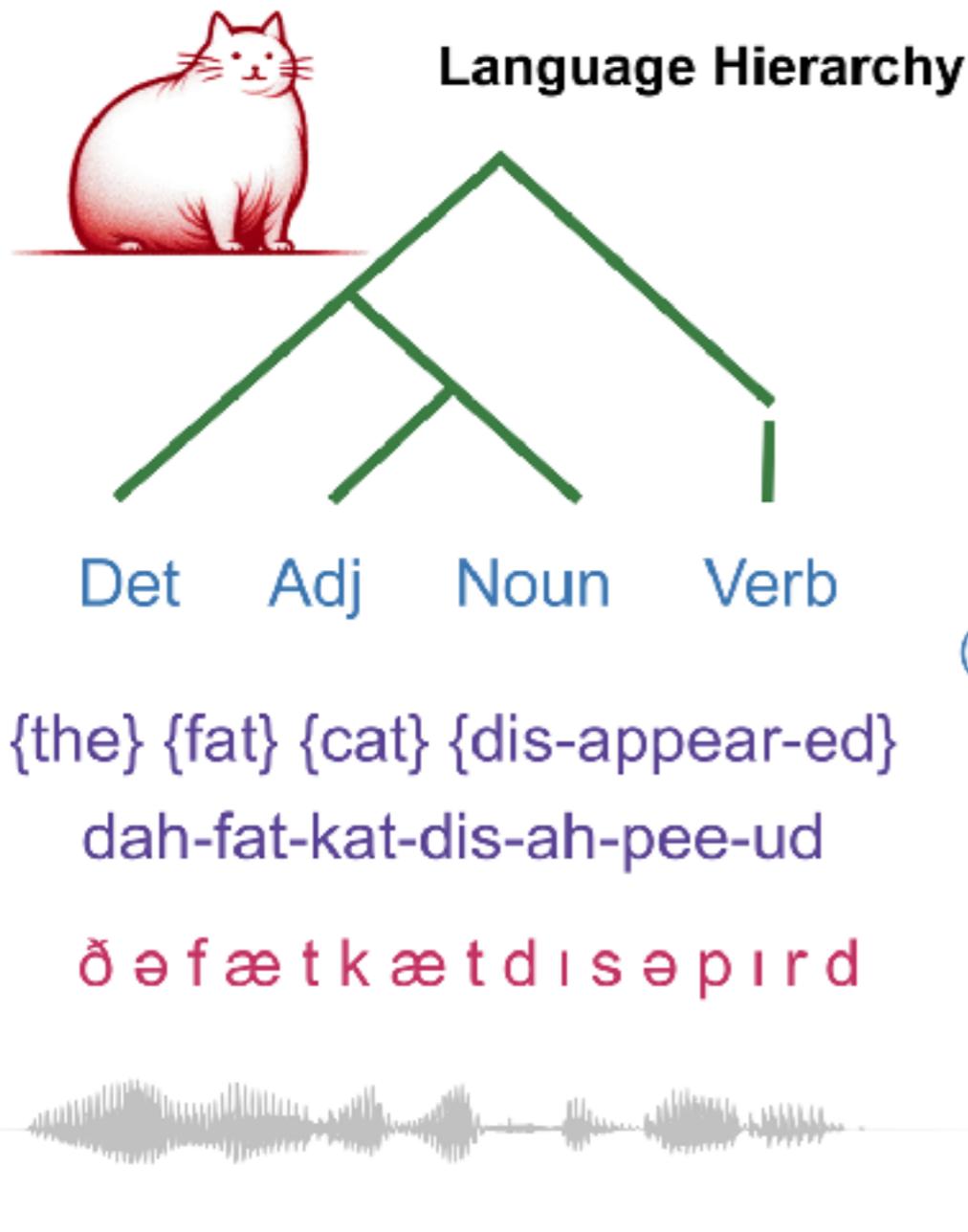


representations
operations
information flow

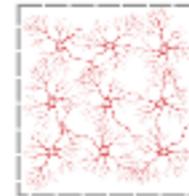


**right NOW is the most
exciting time for
language neuroscience!**

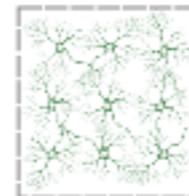
Understanding Symbolic Processing



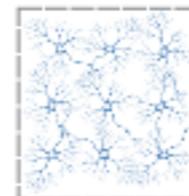
Semantic



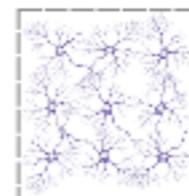
Syntactic



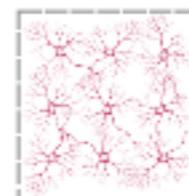
Lexical
(Word Class)



(Sub)lexical



Phonemic



Neural
Ensembles



- No animal models(?)
- How to represent numerically?
- Response variability

- Animal models
- Measurable input signal
- Response consistency
- Focal coding

Understanding Symbolic Processing

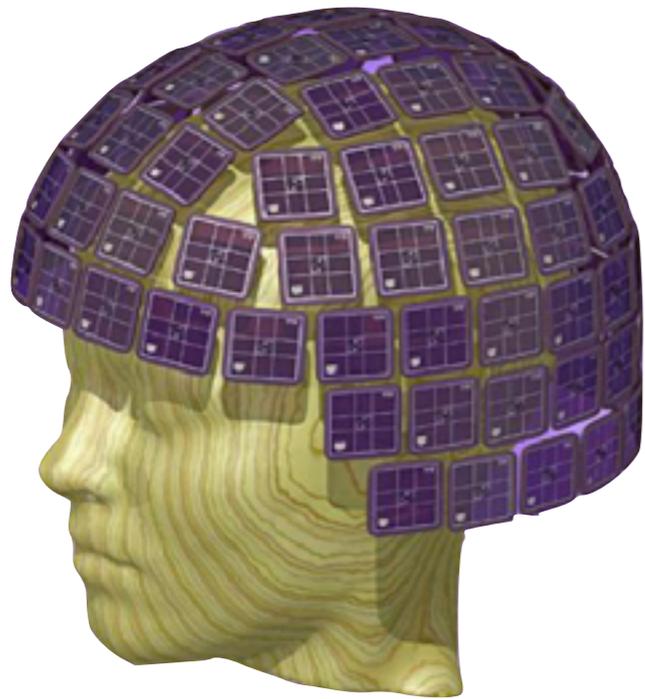
- No animal models(?)

- How to represent numerically?

**LLMs as
cognitive models**

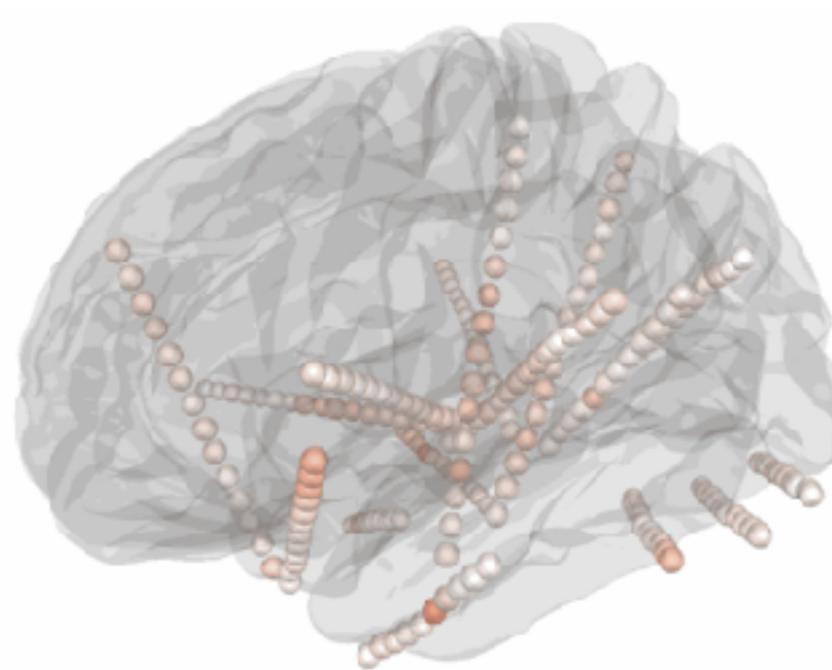
**LLMs as feature
generators**

Human Neuroscience Technology



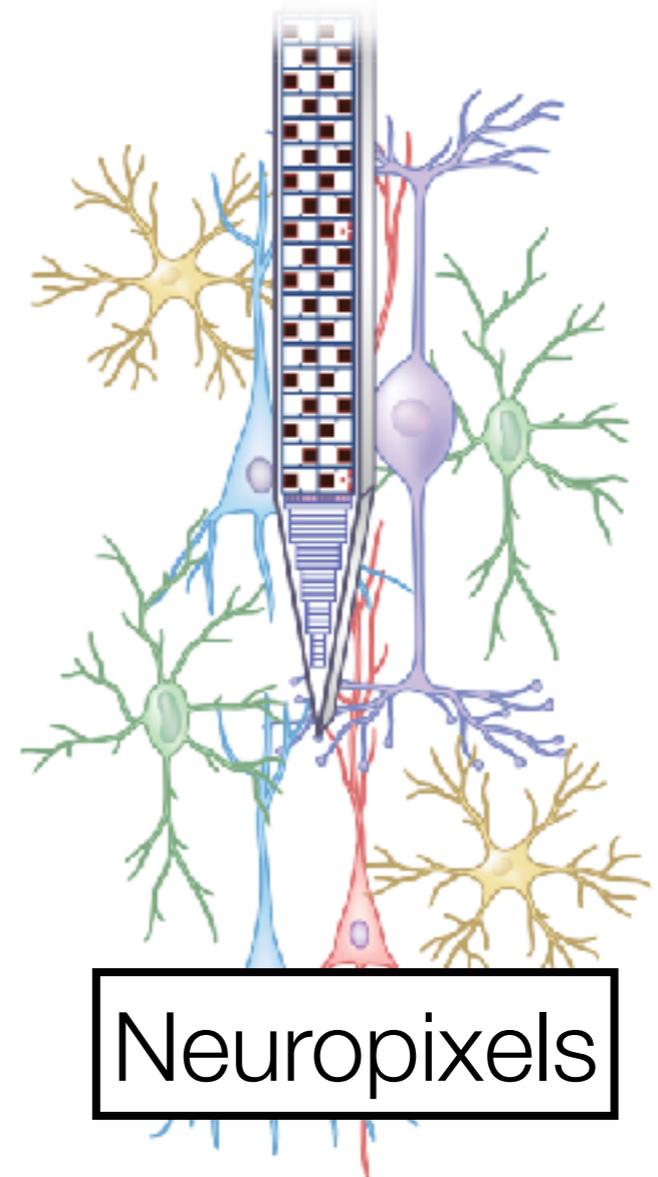
MEG / EEG

~100,000 neurons



iEEG

~10,000 neurons



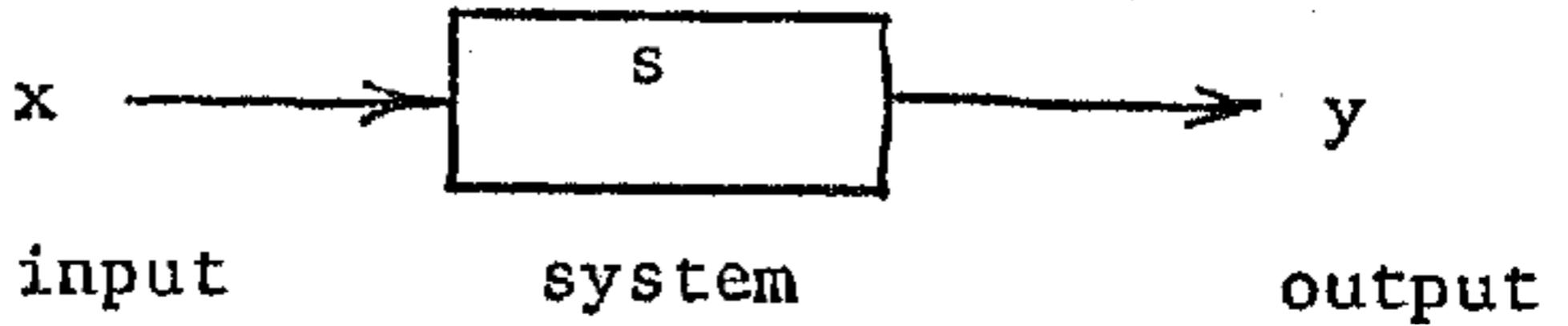
Neuropixels

~1 neurons

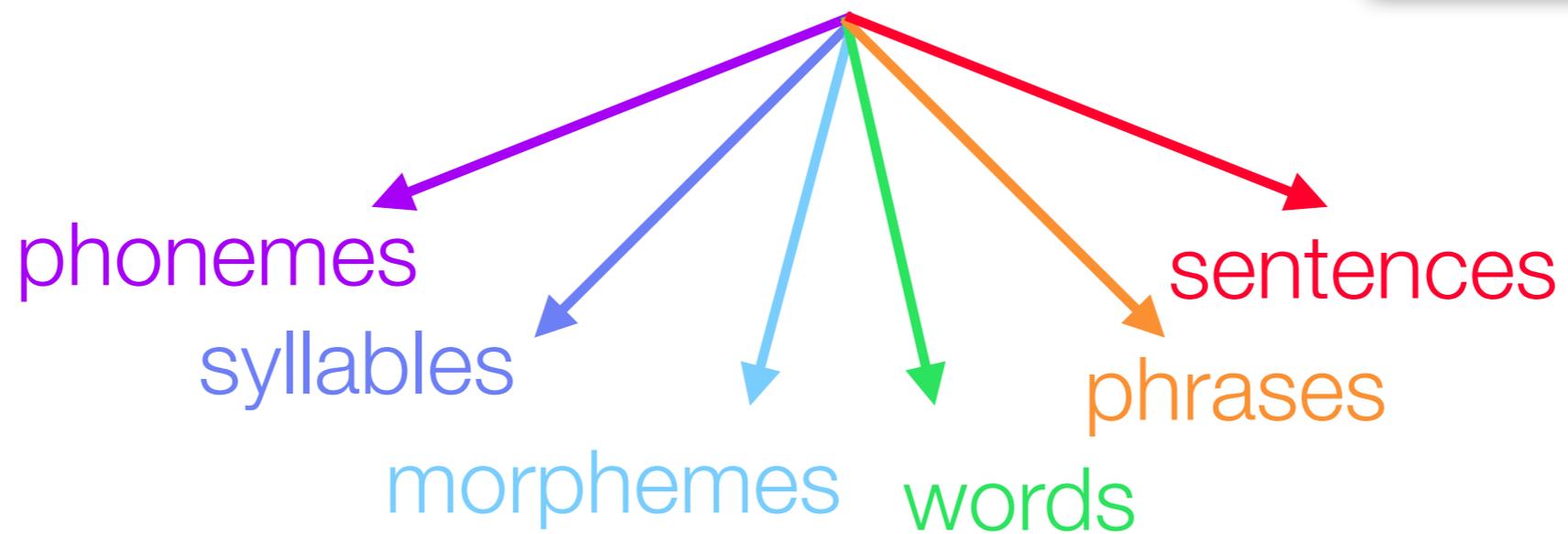
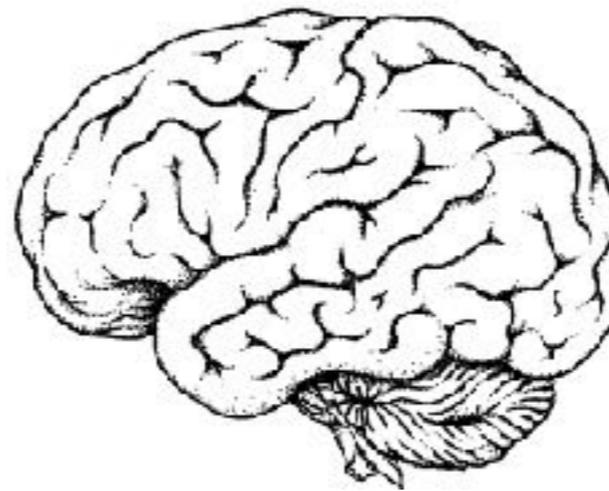
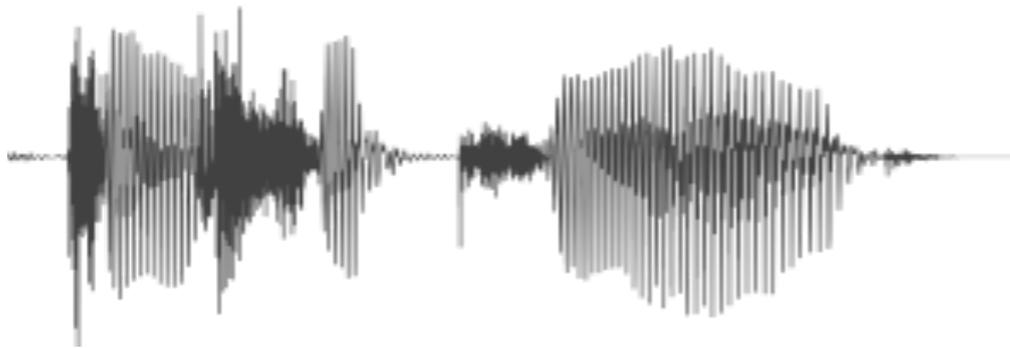
Menu

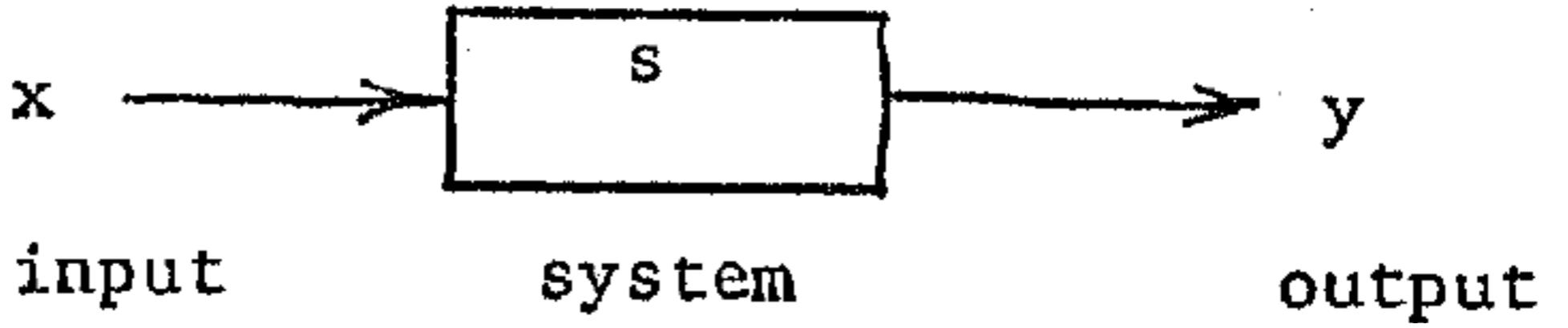
- **Neural representation:** From sensory to symbolic
- **Neural computation:** Sequencing sensory inputs
- **Neural implementation** at the level of single neurons in humans

sensory to symbolic

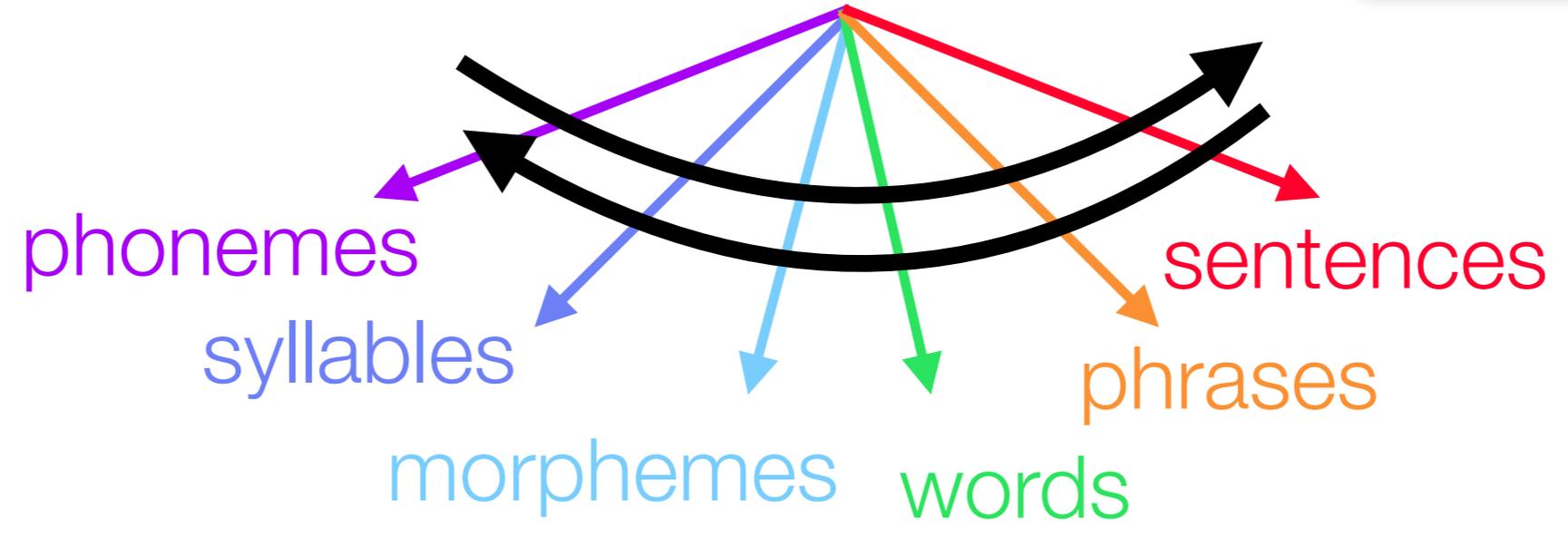
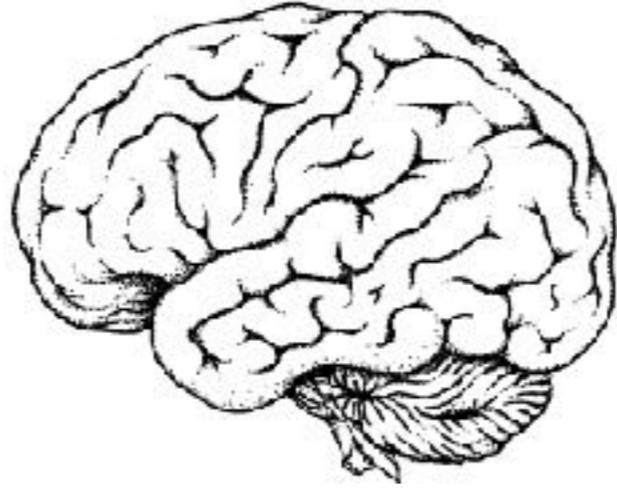


"the fat cat disappeared"





"the fat cat disappeared"



Setup

scientific data

 Check for updates

OPEN

DATA DESCRIPTOR

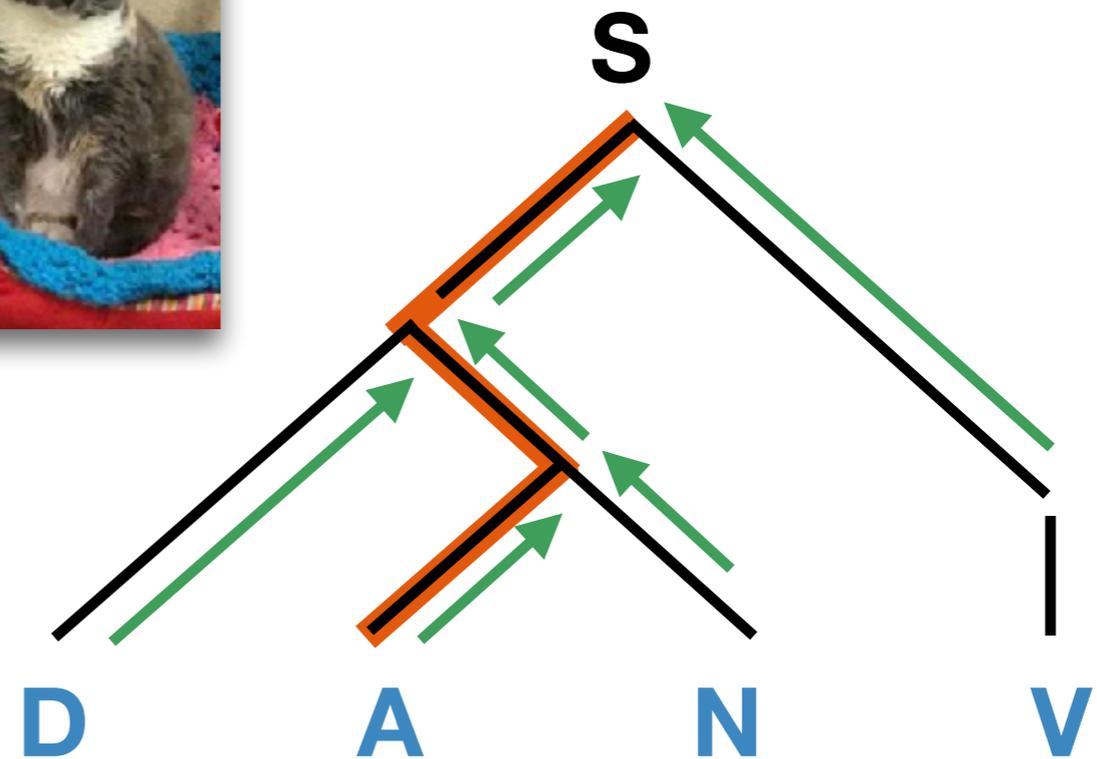
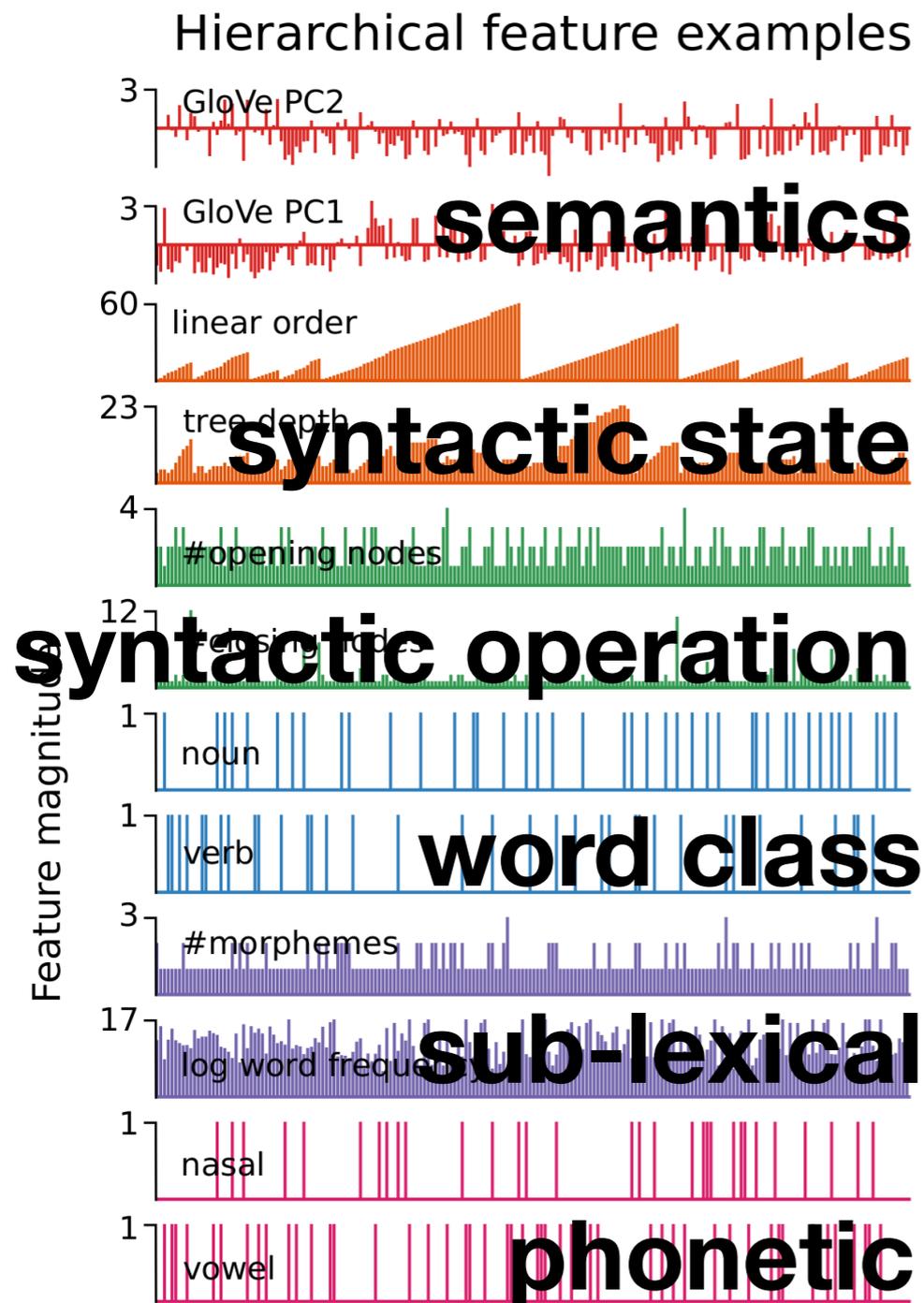
Introducing MEG-MASC a high-quality magneto-encephalography dataset for evaluating natural speech processing

Laura Gwilliams ^{1,2,3}✉, Graham Flick^{2,3,4,5}, Alec Marantz^{2,3,4}, Liina Pykkänen^{2,3,4}, David Poeppel ^{2,6} & Jean-Rémi King ^{2,7}

- ~16,000 words per participant

Setup

in what **order** are representations generated?



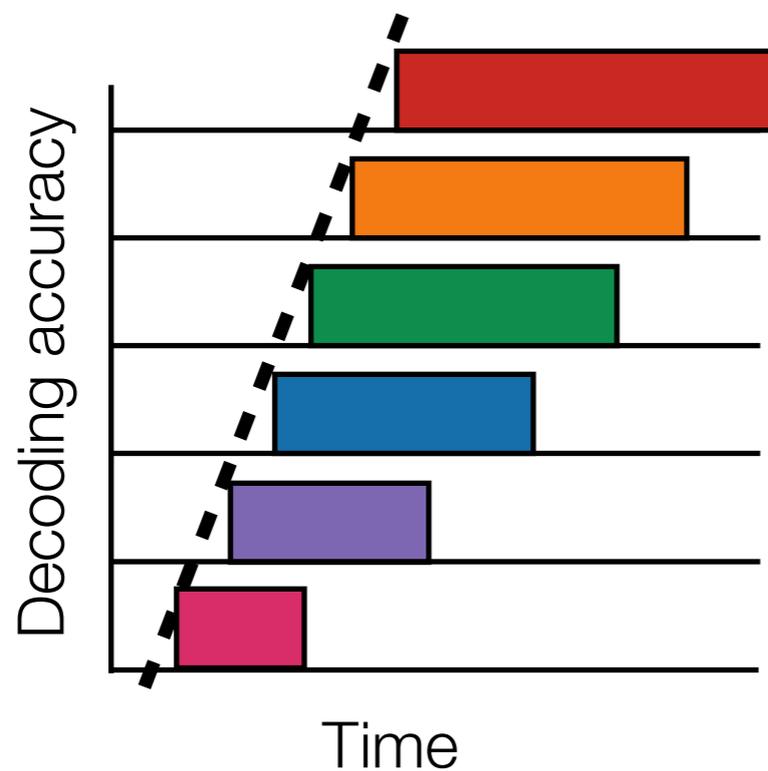
{the} {fat} {cat} {dis-appear-ed}
dah-fat-kat-dis-ah-pee-ud

-	+	-	+	-	-	+	+	-
-	-	+	-	-	+	-	-	+
+	+	+	+	+	+	+	+	+
-	-	-	-	+	-	-	+	+

Hypotheses

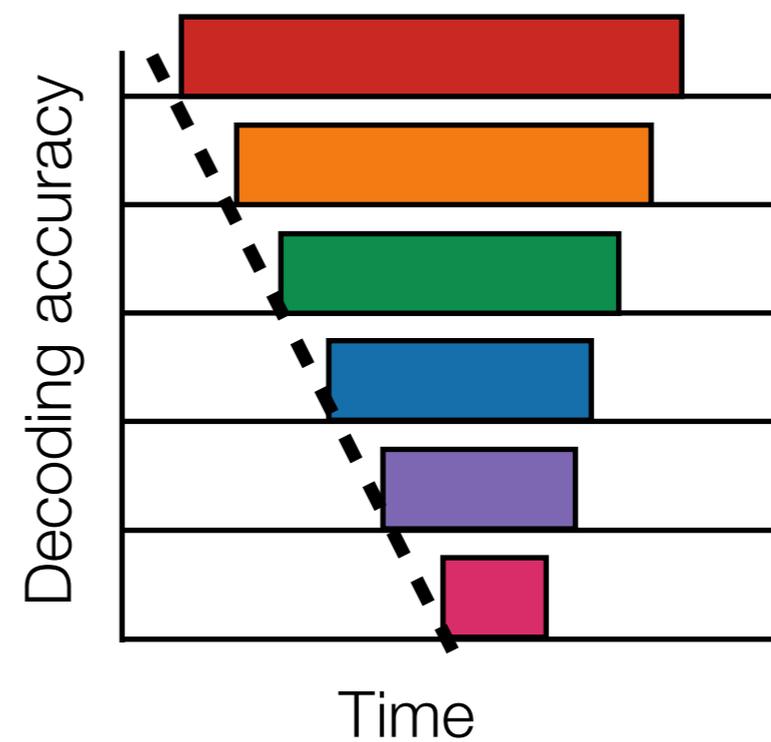
in what **order** are representations generated?

Hierarchical cascade Compositional Approach

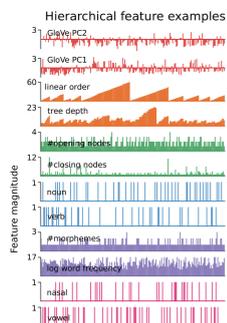


(e.g. Gaskell & Marslen-Wilson, 1997)

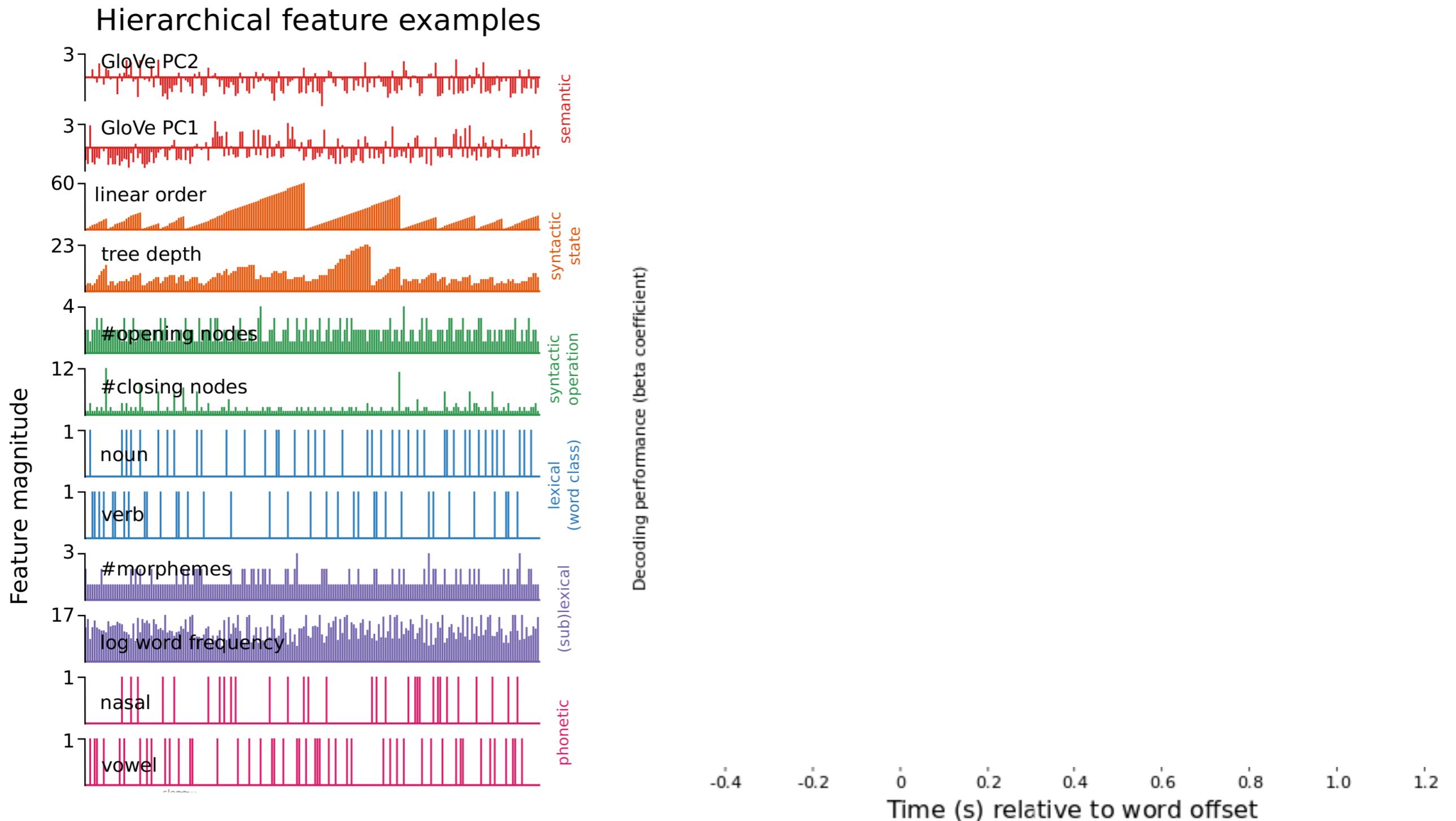
Reverse hierarchy Visual Processing



(e.g. Ahissar & Hochstein, 2004)



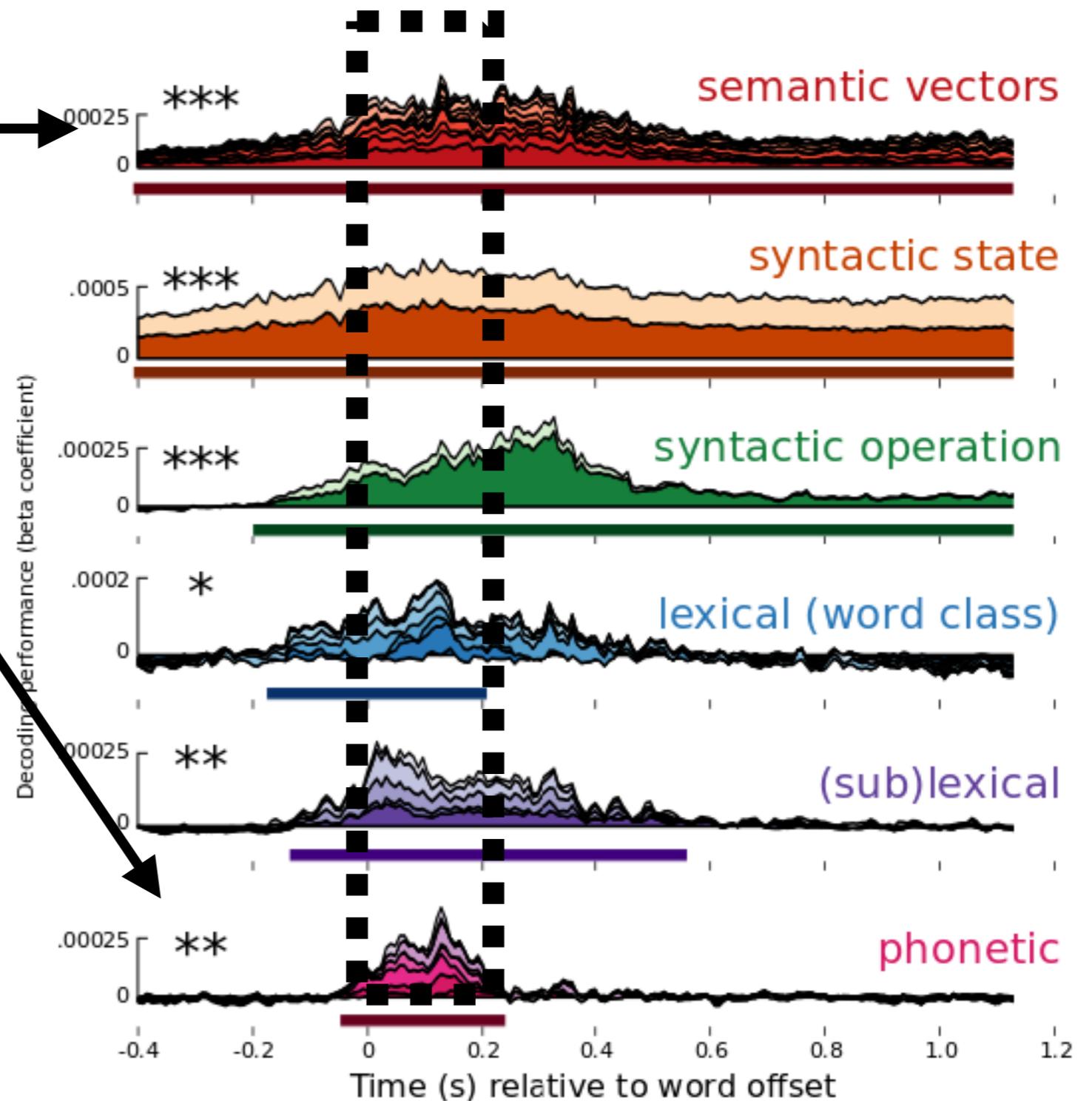
Hierarchical processing



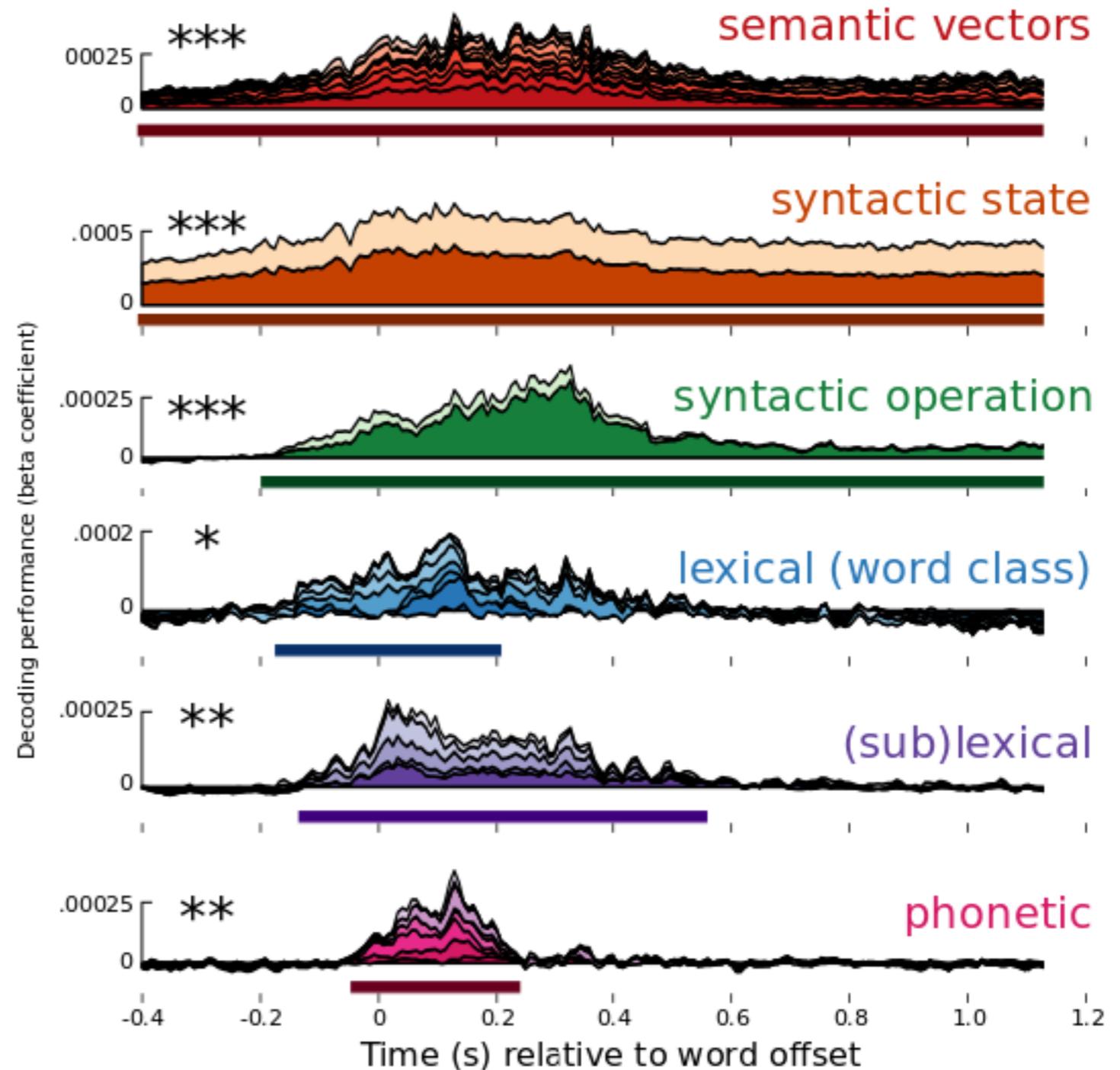
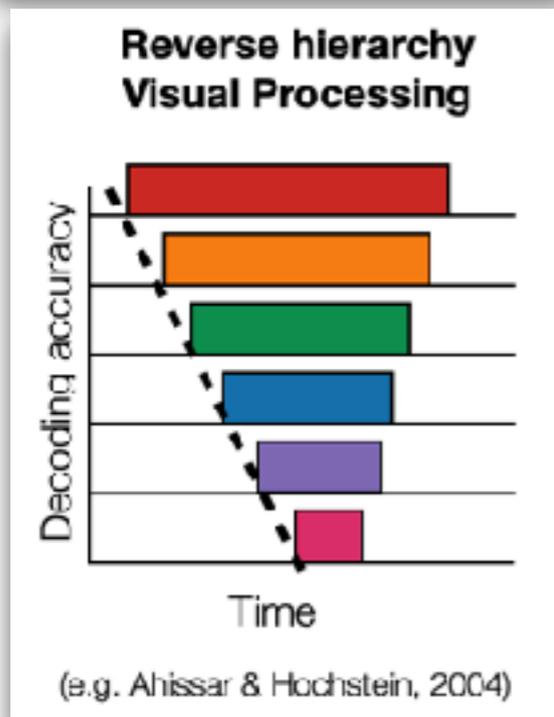
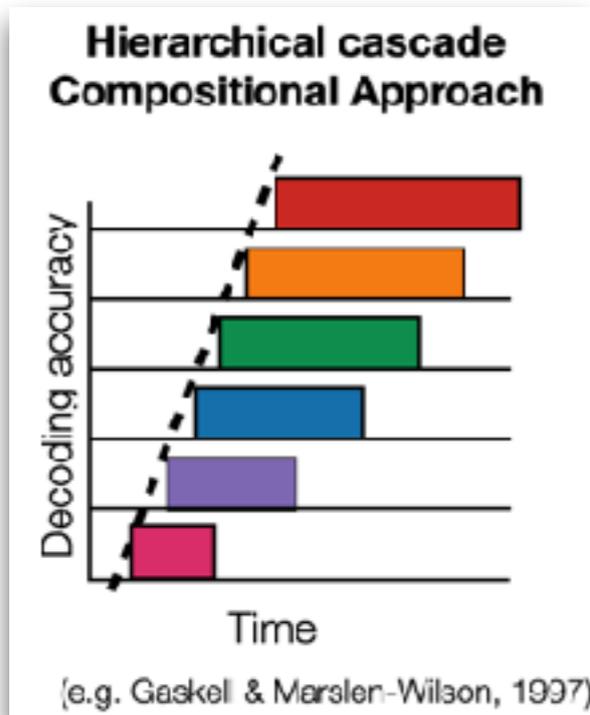
Feature Dynamics

high-level representations are activated first, and maintained the longest

local details of the input are encoded later, and for much less time



Interpretation

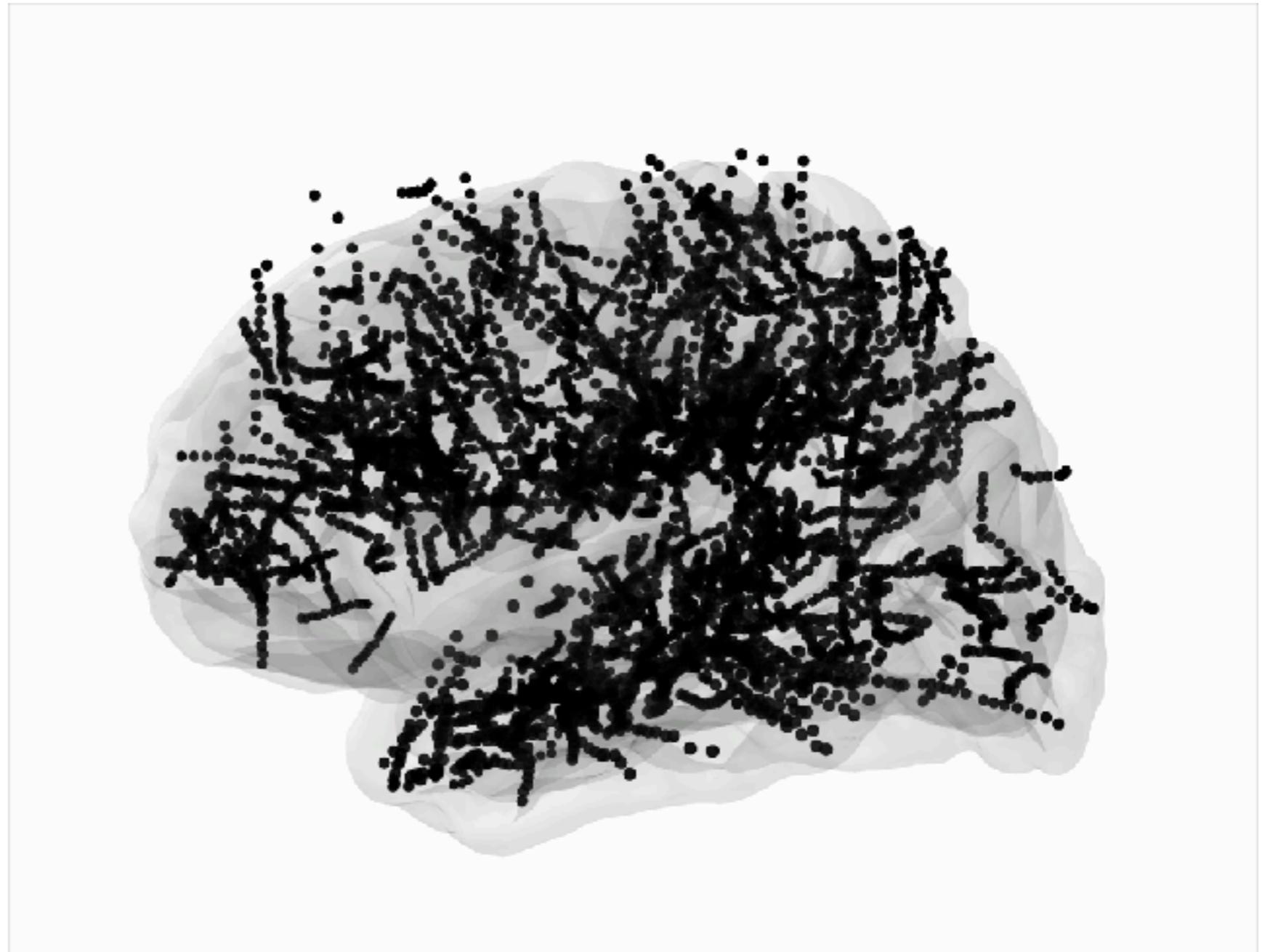


Spatial Localization Across Development

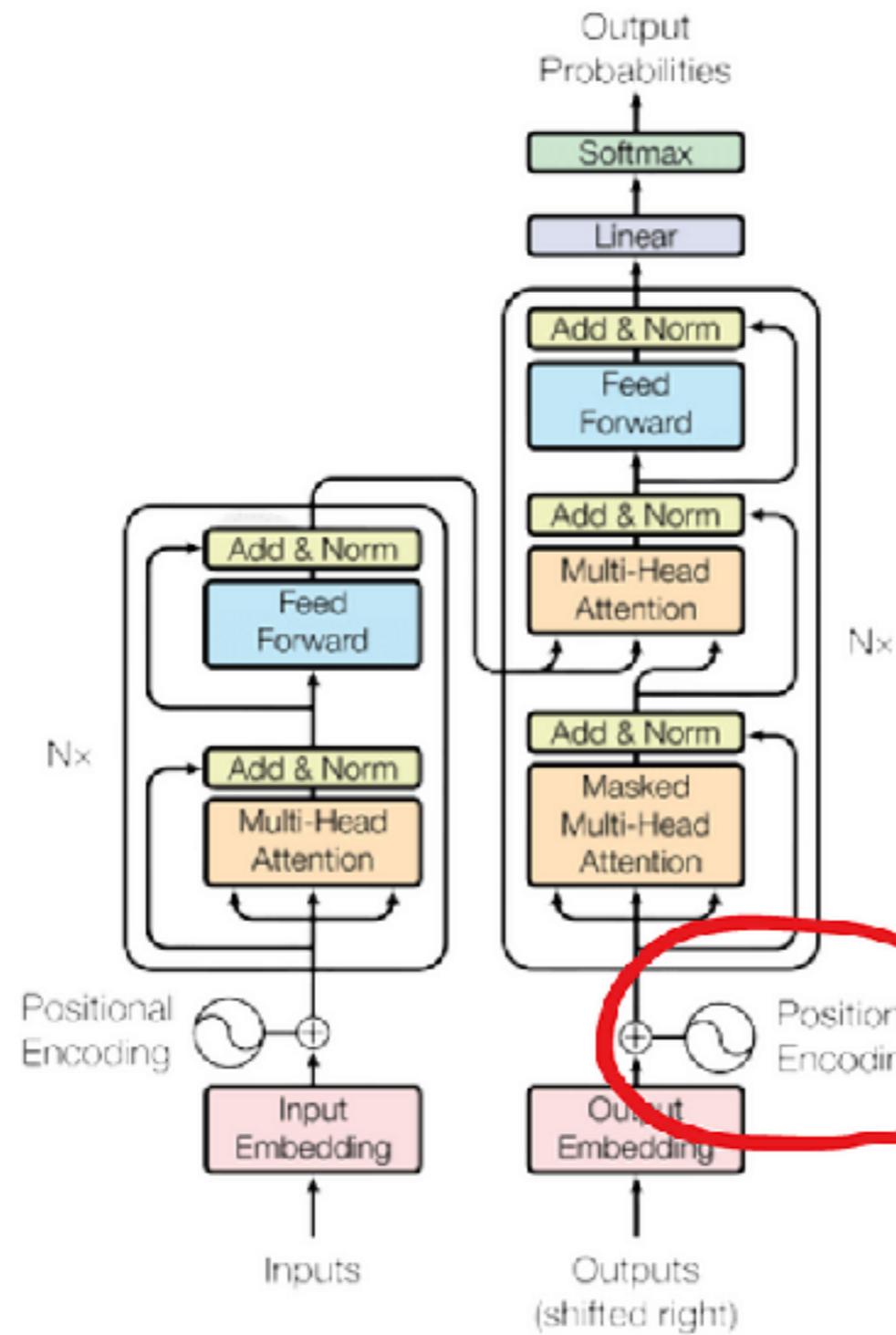


Jill Kries
Postdoc

44 children
From ages 4-17

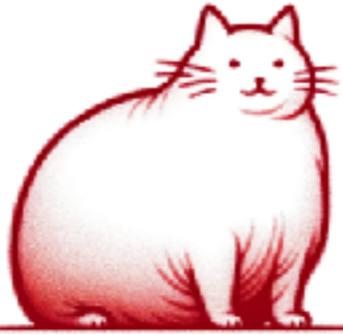


sequencing continuous speech input

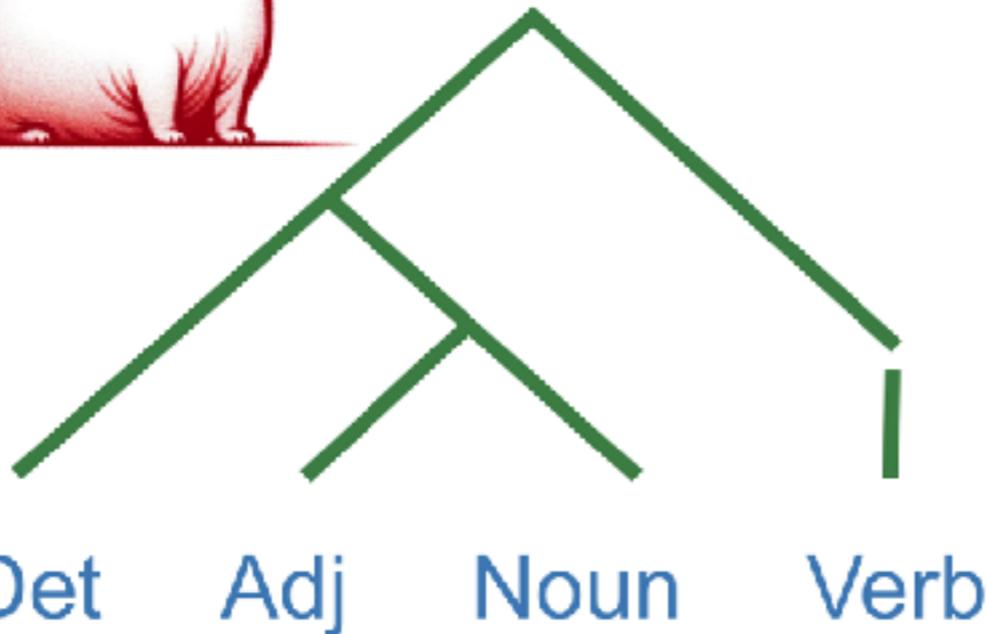


RoPE

A



Language Hierarchy

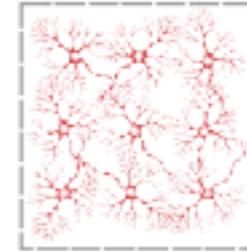


{the} {fat} {cat} {dis-appear-ed}
 dah-fat-kat-dis-ah-pee-ud

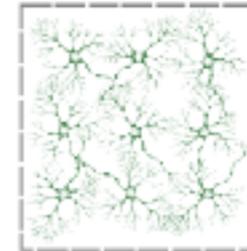
ð ə f æ t k æ t d ɪ s ə p ɪ r d



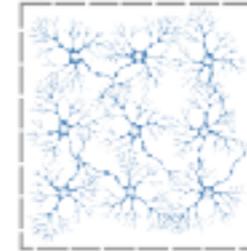
Semantic



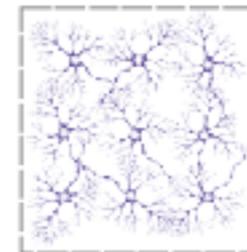
Syntactic



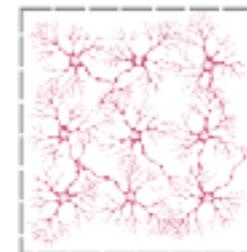
Lexical
(Word Class)



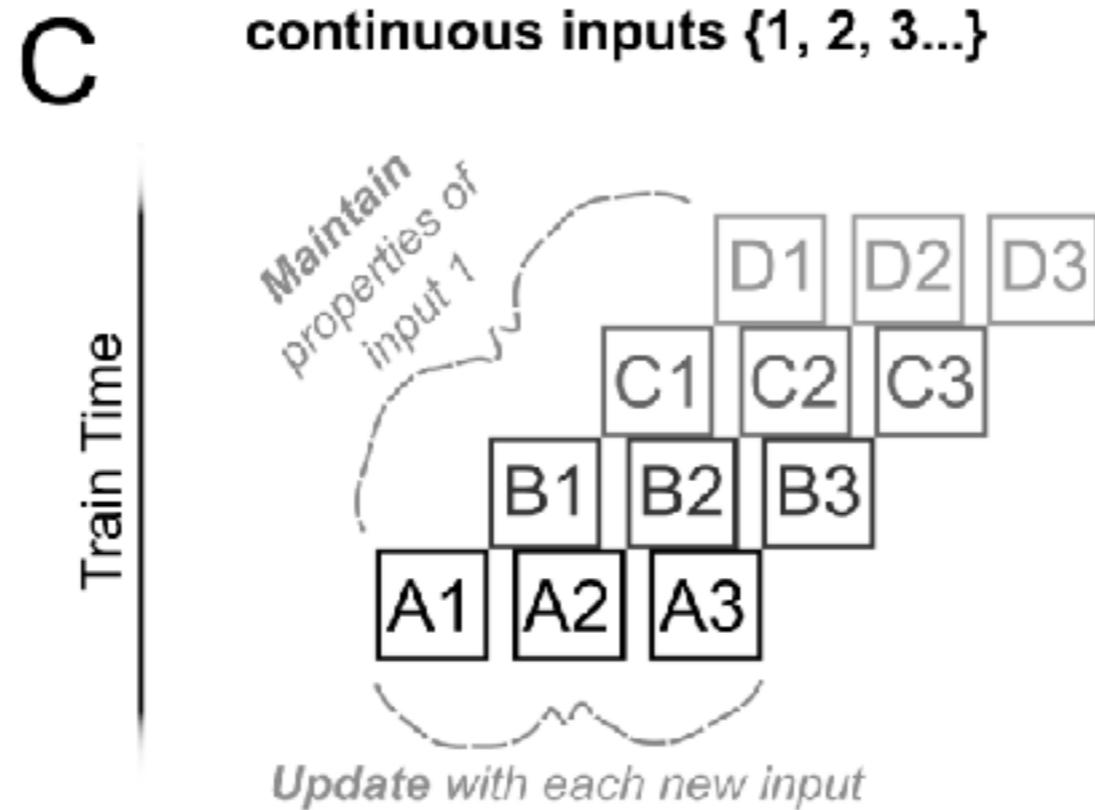
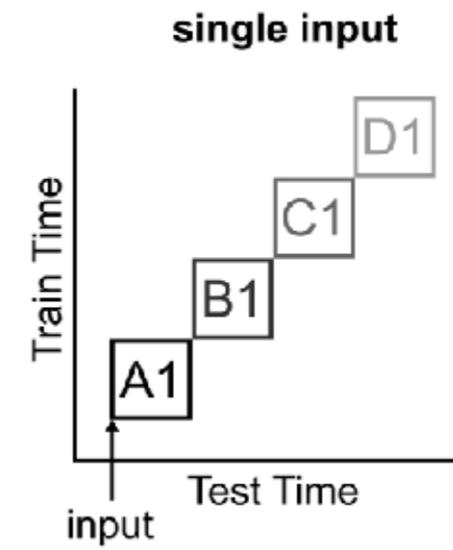
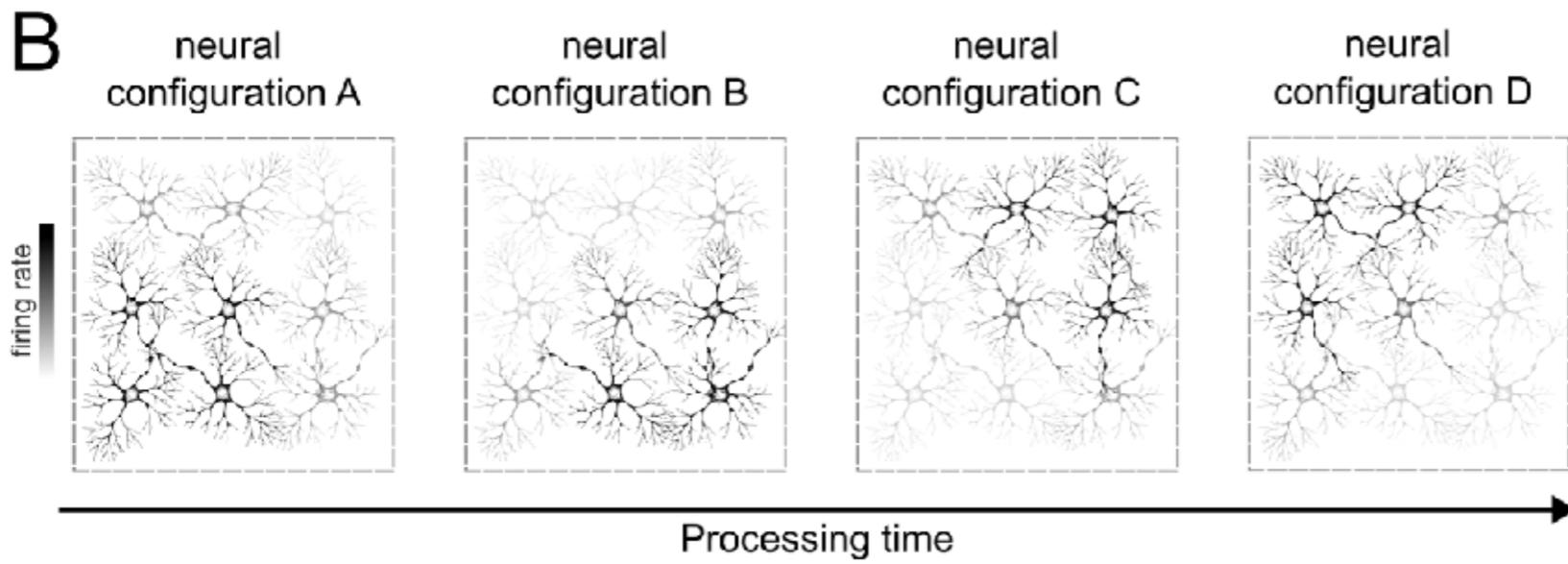
(Sub)lexical



Phonemic



Neural
Ensembles



Setup

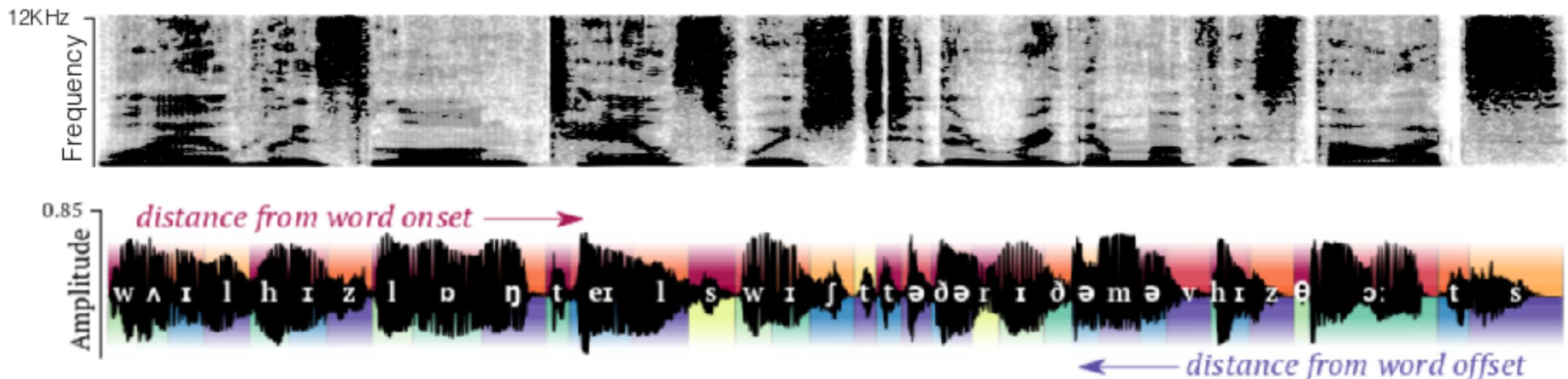
- 21 participants
- Listening to four narrative stories (twice)
- Synthesised voice (MacOS)
 - semi-controlled acoustic input
- 2 x one hour recordings
- KIT 208 channel MEG system
- Engagement task

- ~40,000 phonemes per participant
- ~16,000 words per participant



Analysis

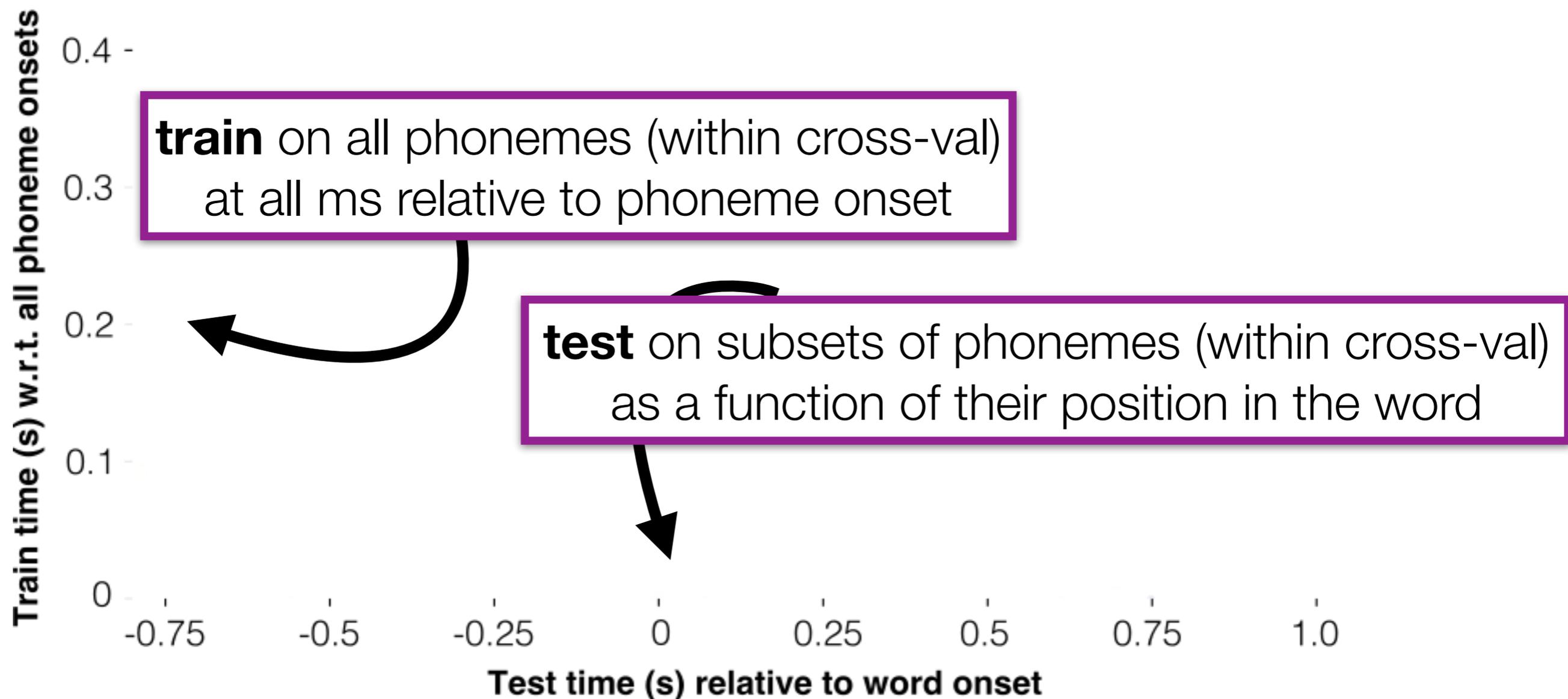
“... while his long tail swished to the rhythm of his thoughts...”



- Decode phonetic features (voicing, manner, place of articulation) as a function of the phoneme’s position in the word

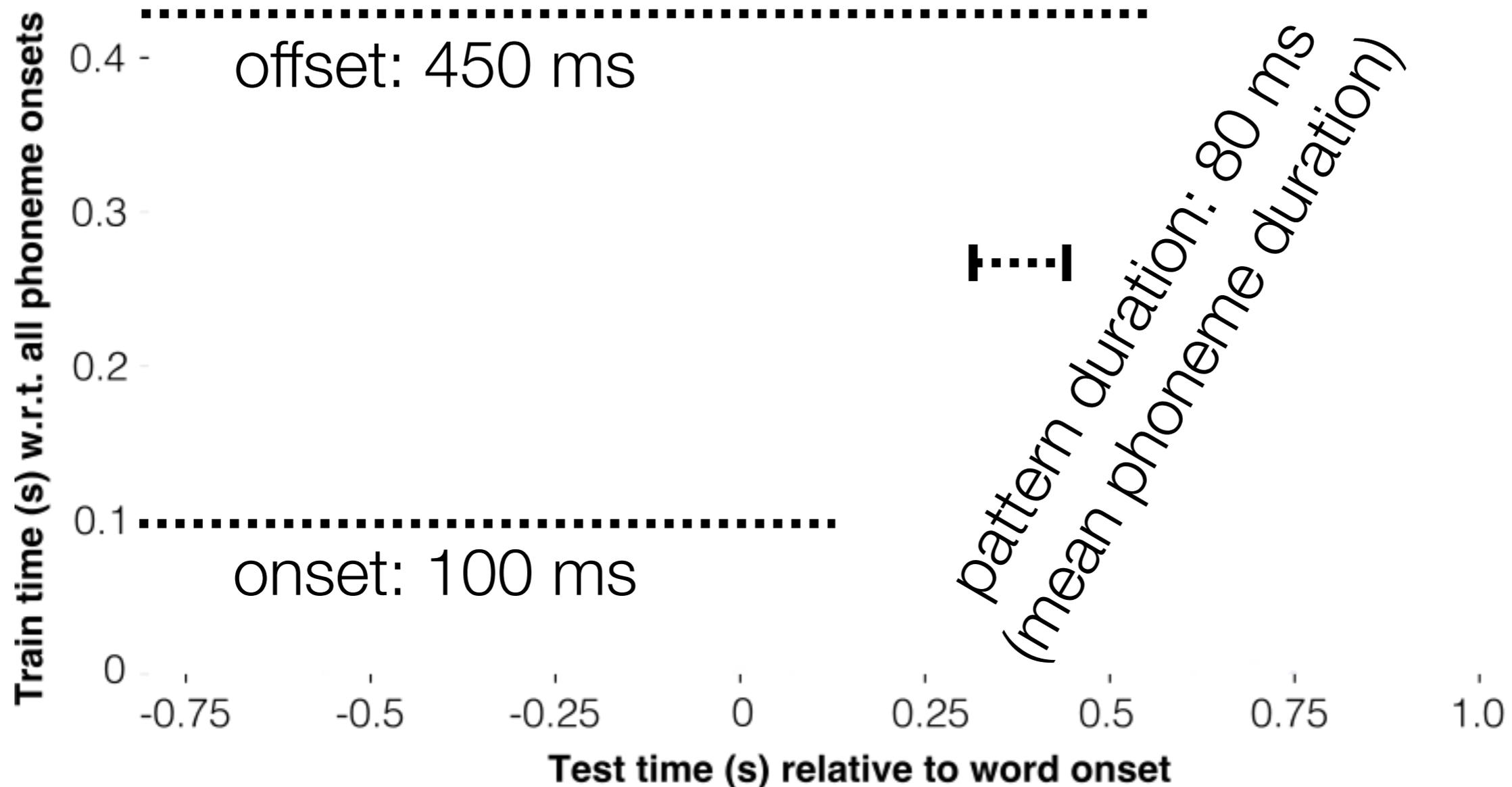
Transformation of acoustic signal

- Apply temporal generalisation to assess processing dynamics

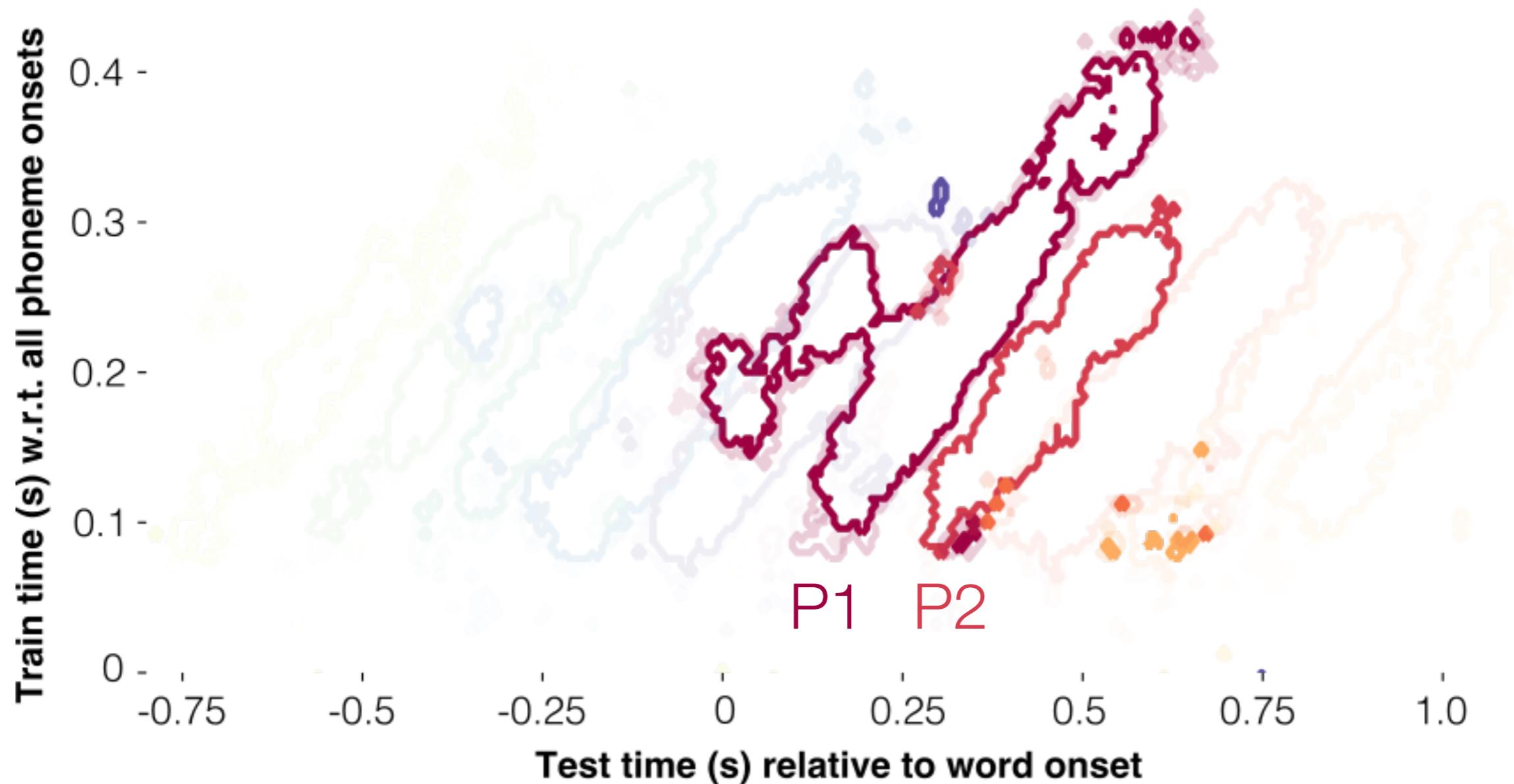


Transformation of acoustic signal

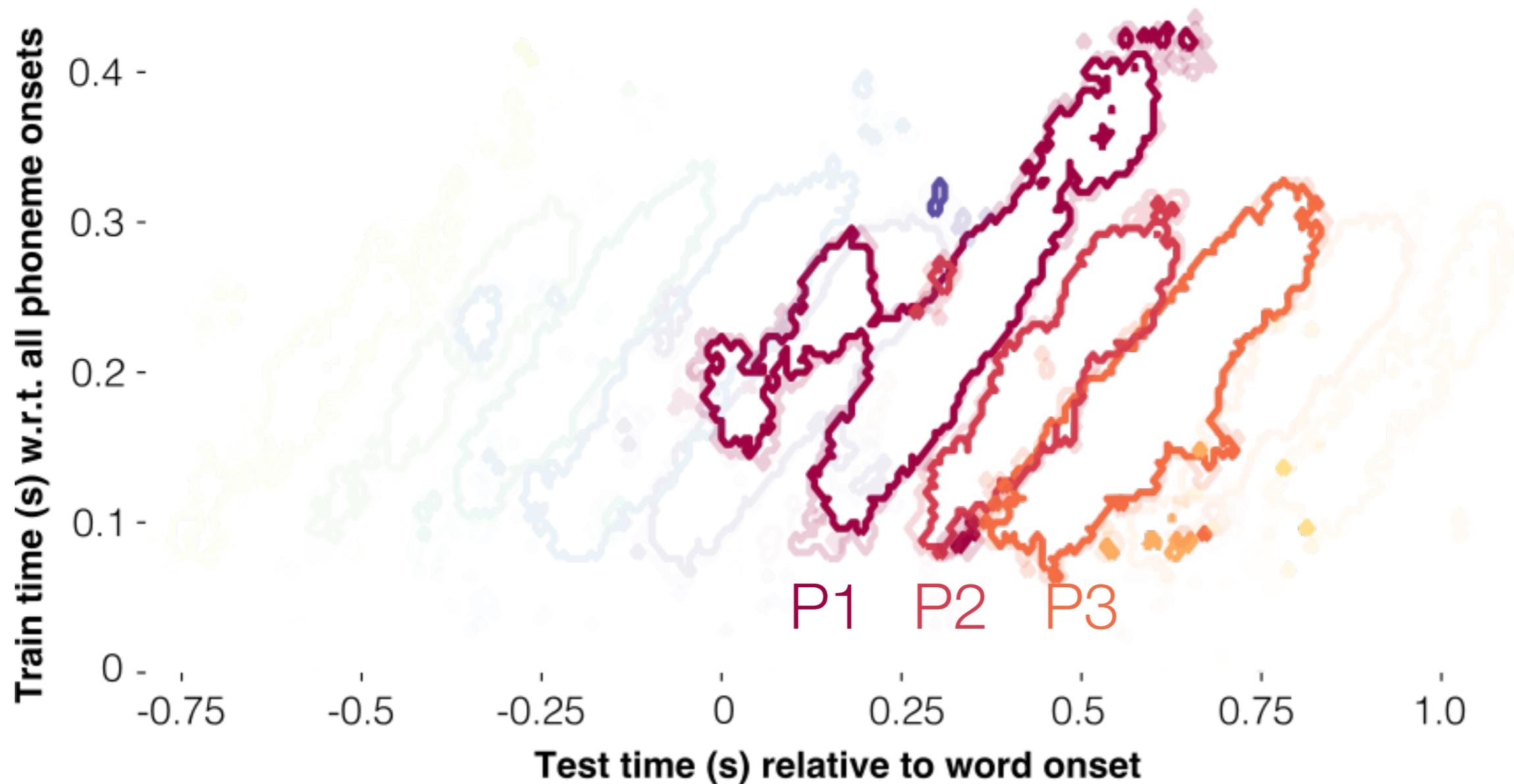
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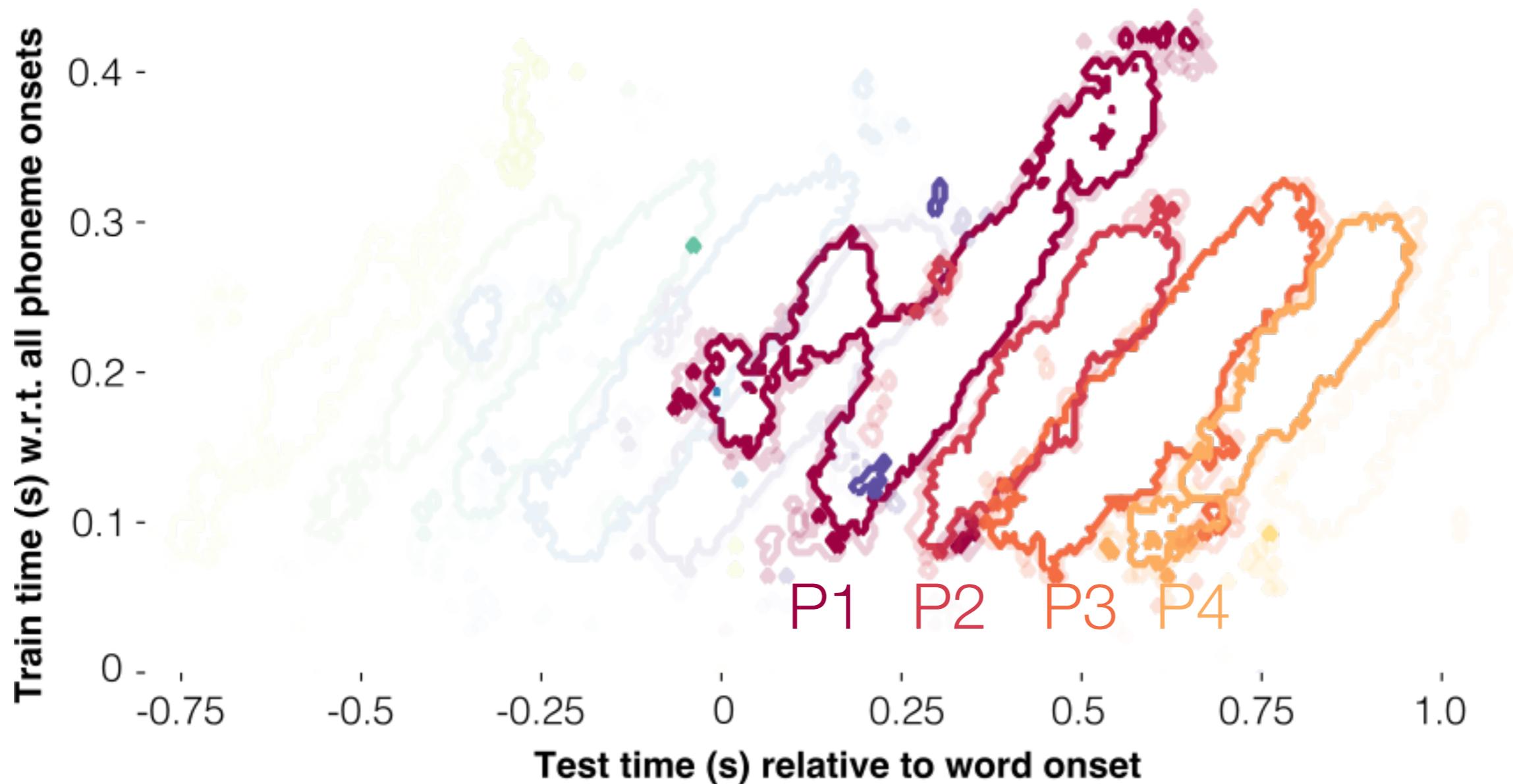
Transformation of acoustic signal



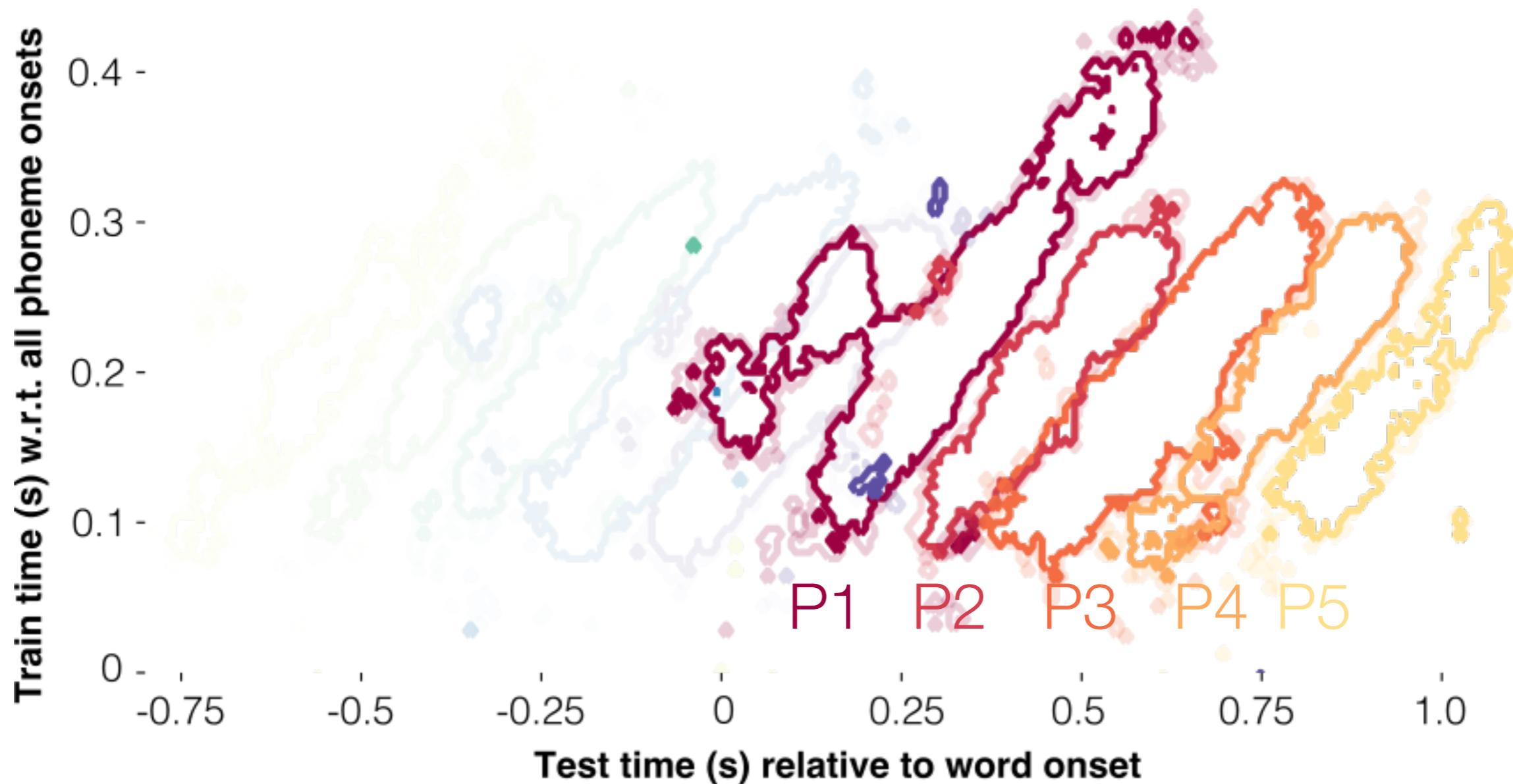
Transformation of acoustic signal



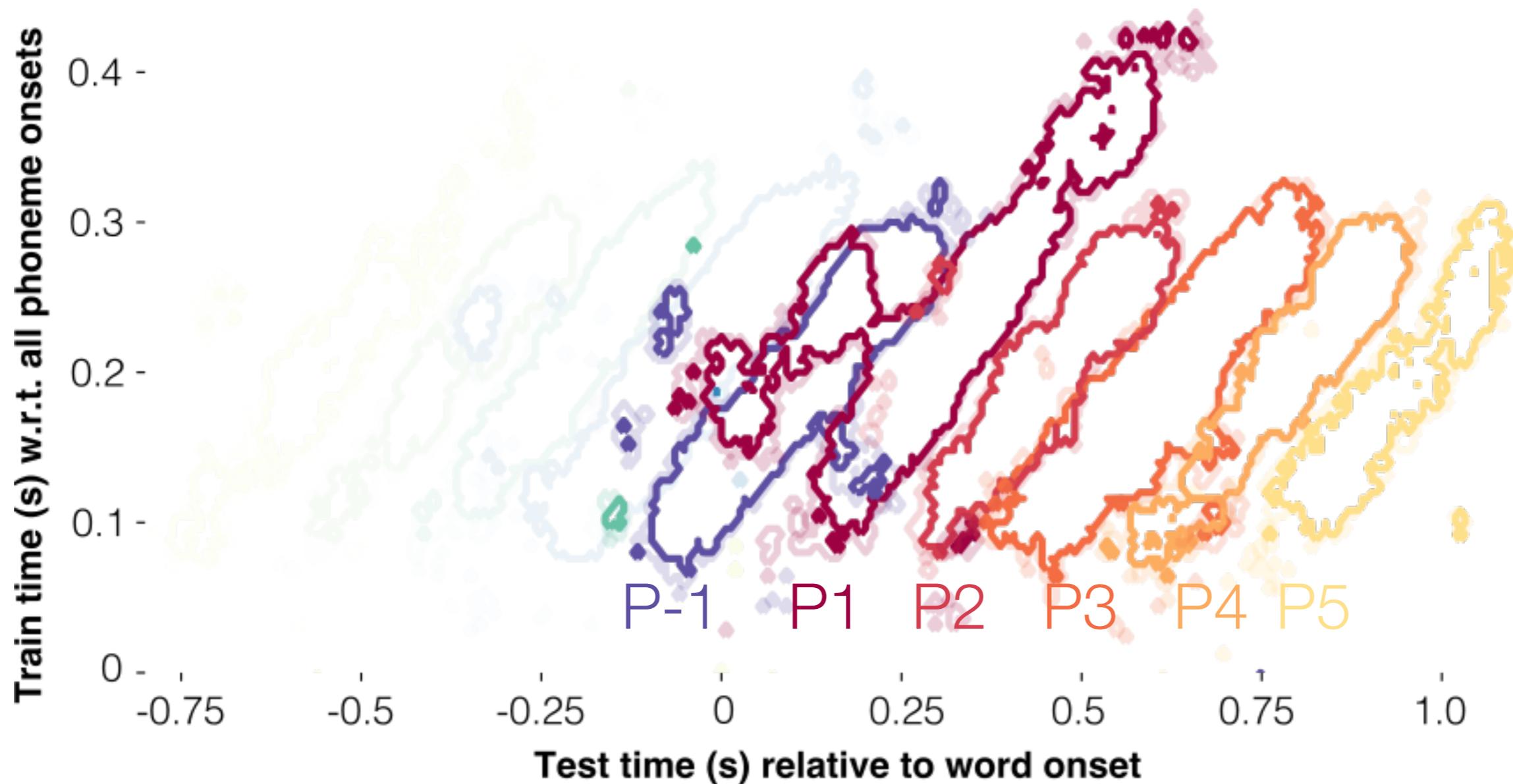
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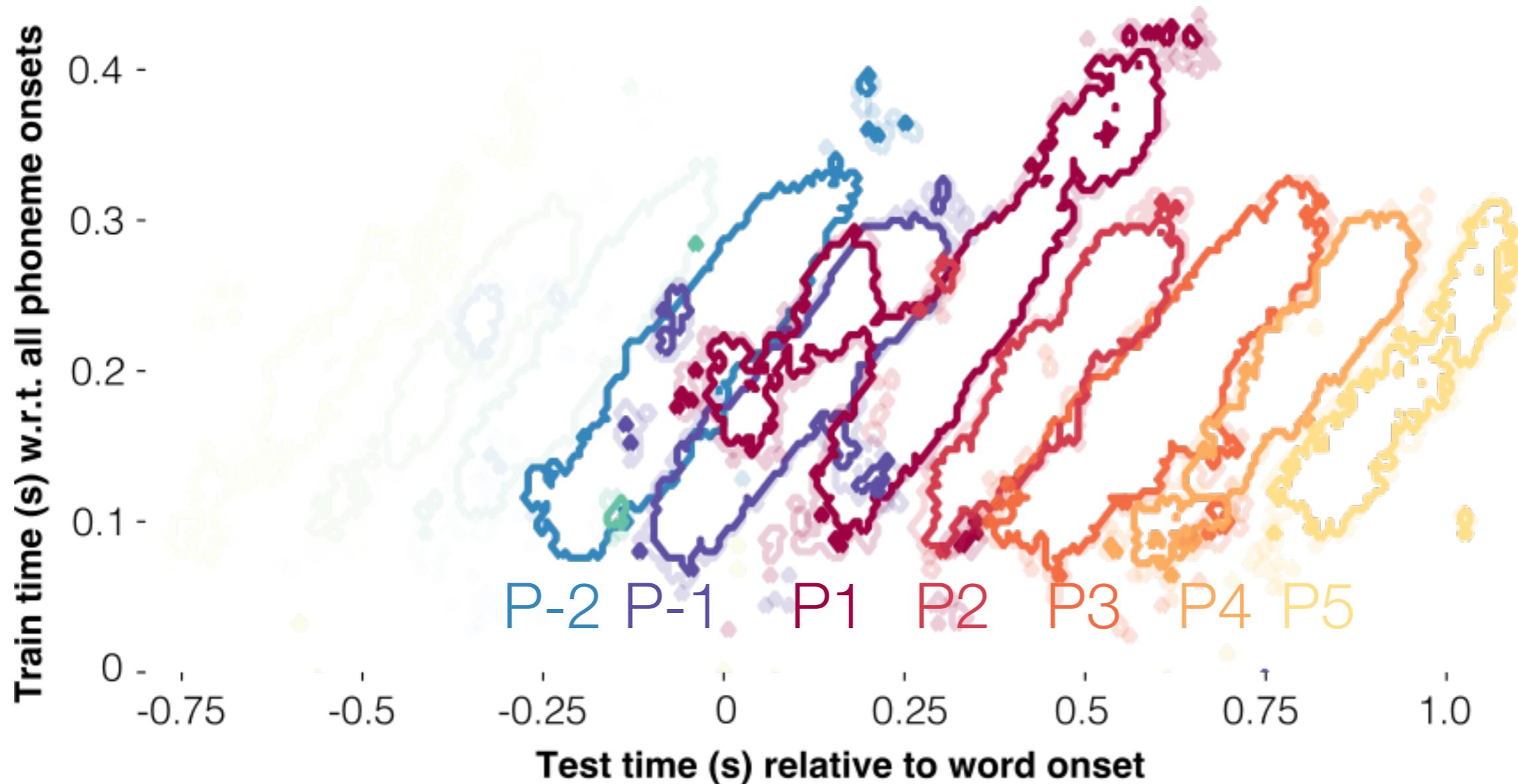
Transformation of acoustic signal



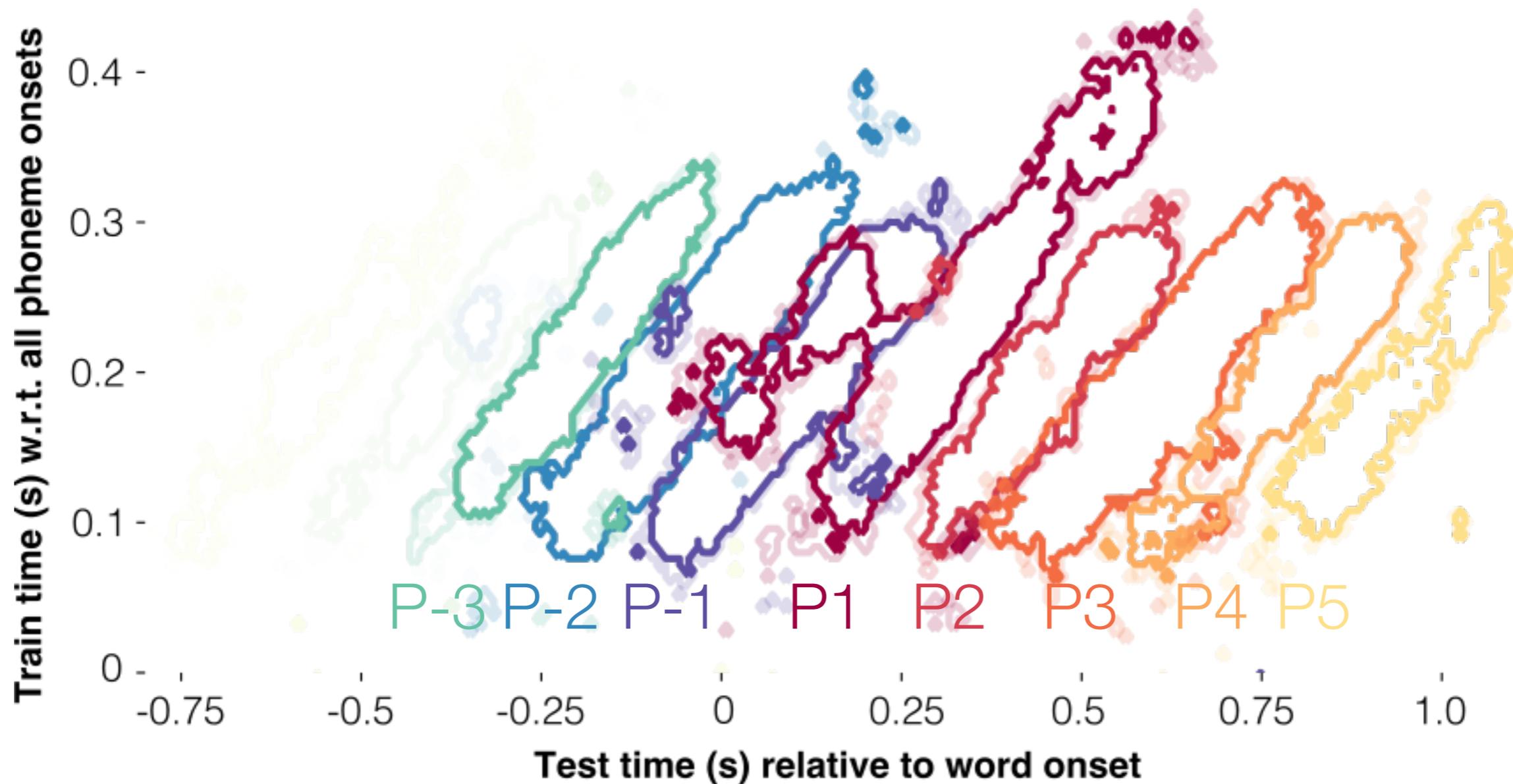
Transformation of acoustic signal



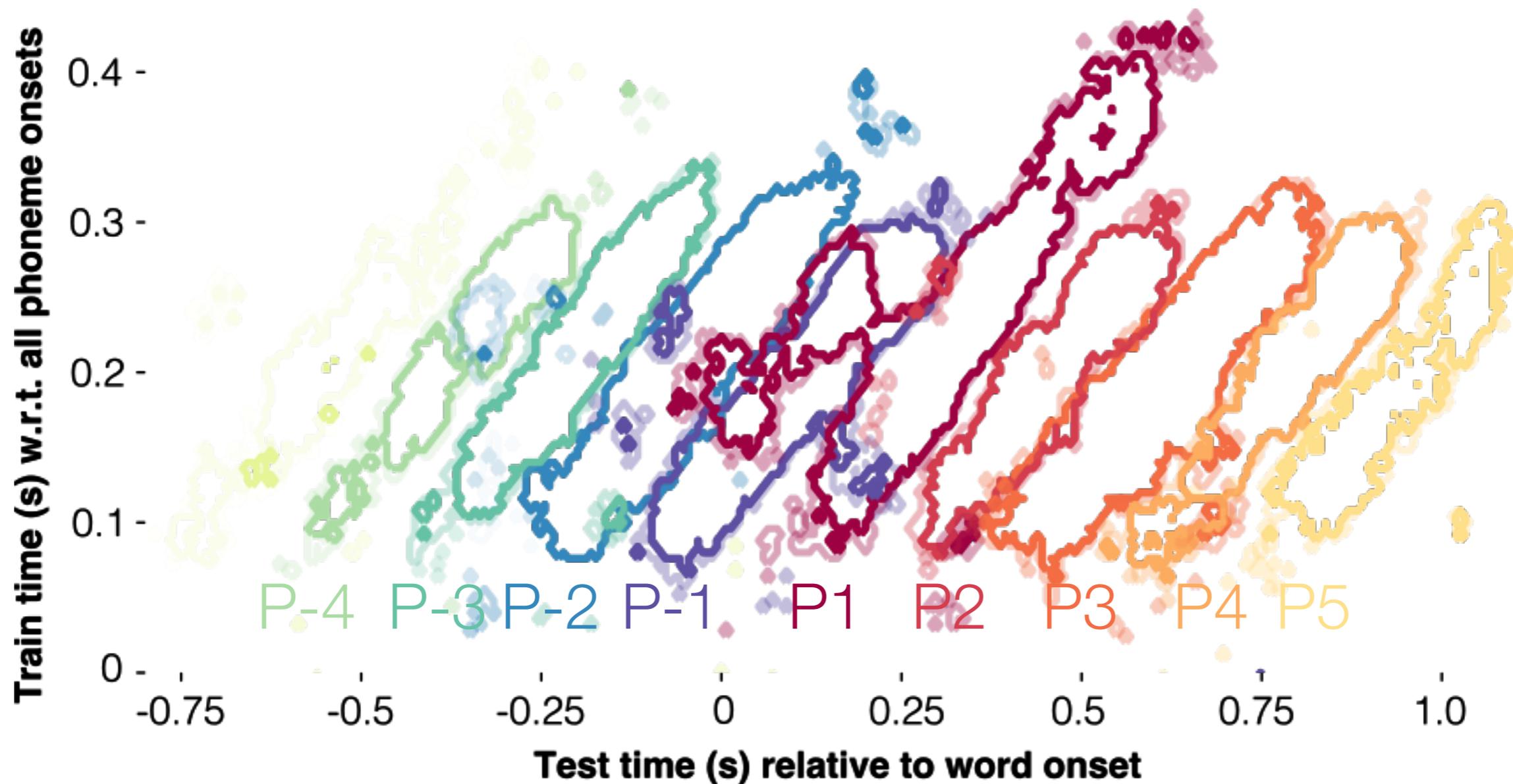
Transformation of acoustic signal



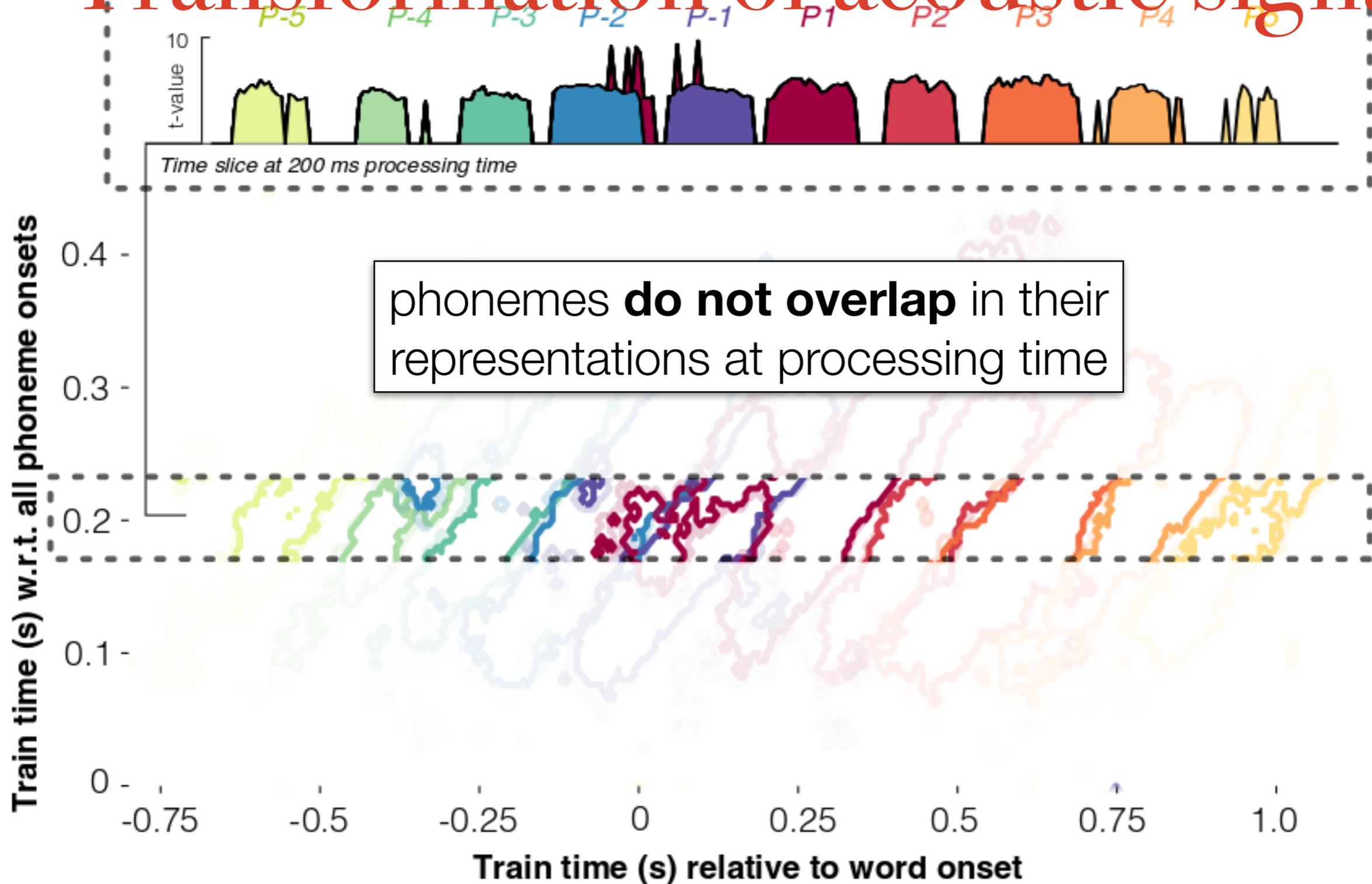
Transformation of acoustic signal

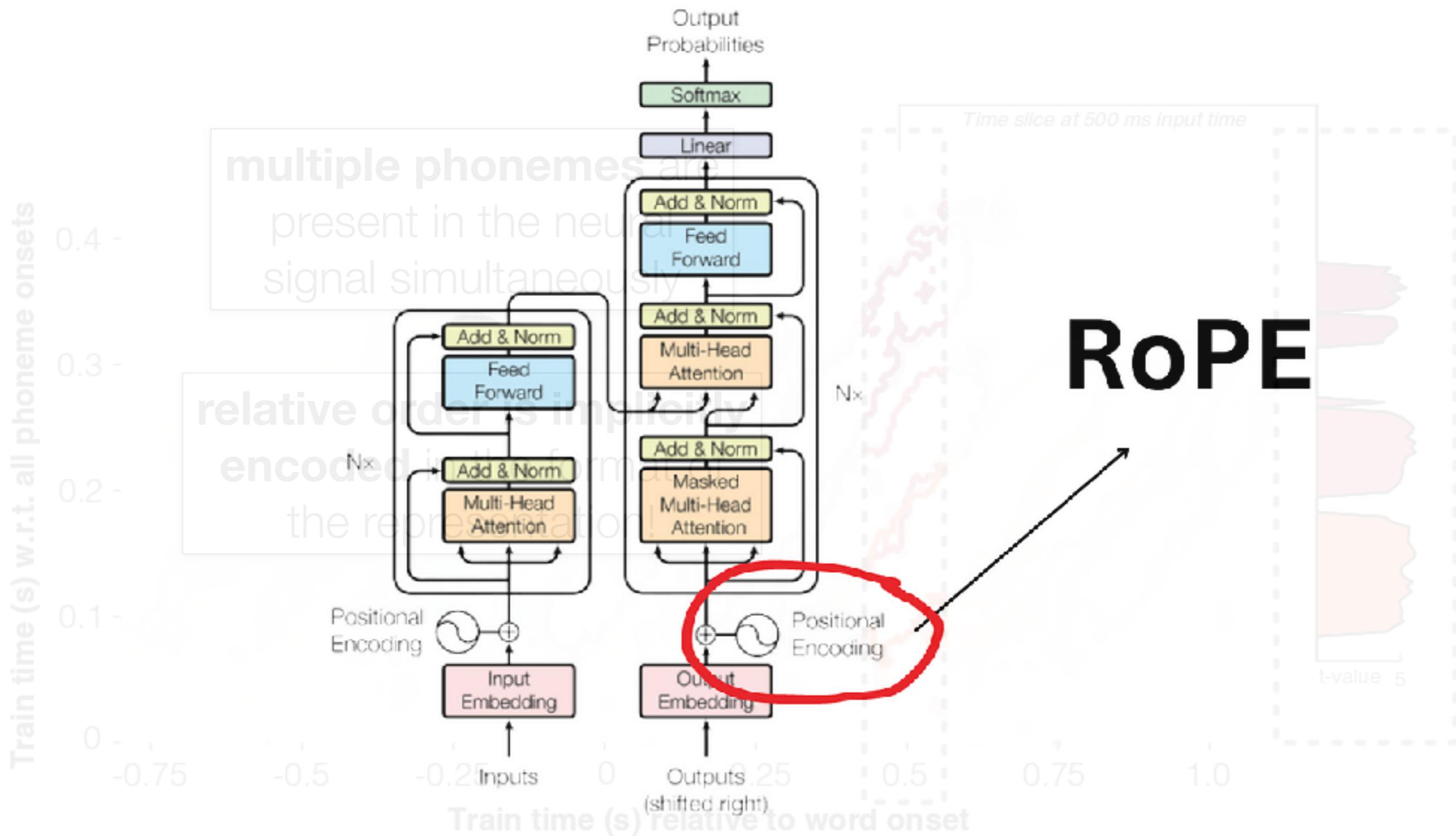


Transformation of acoustic signal



Transformation of acoustic signal

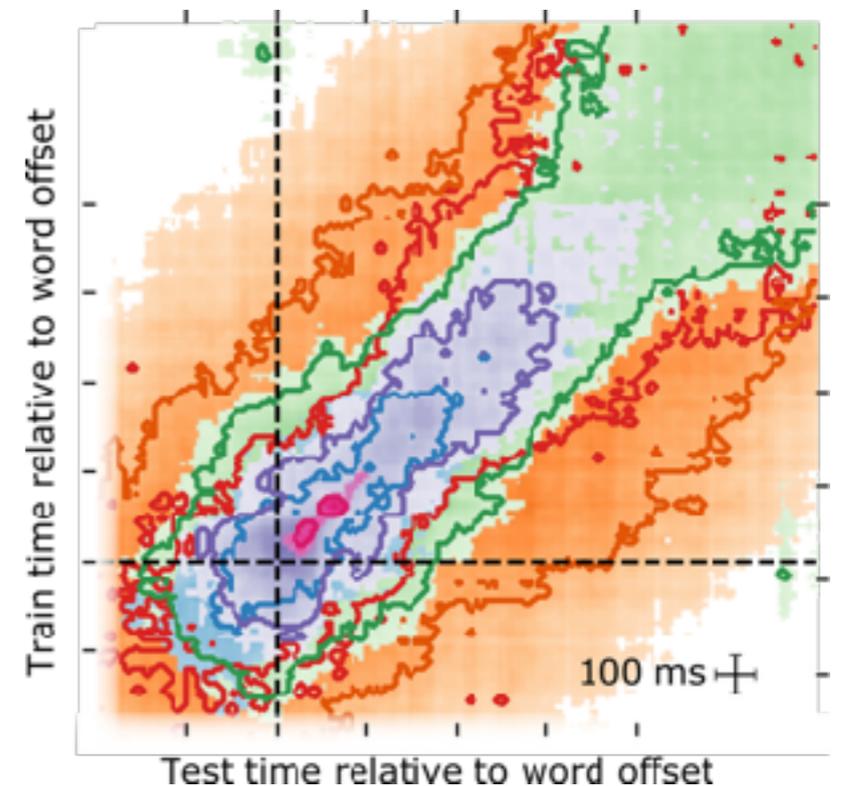




Nested hierarchy

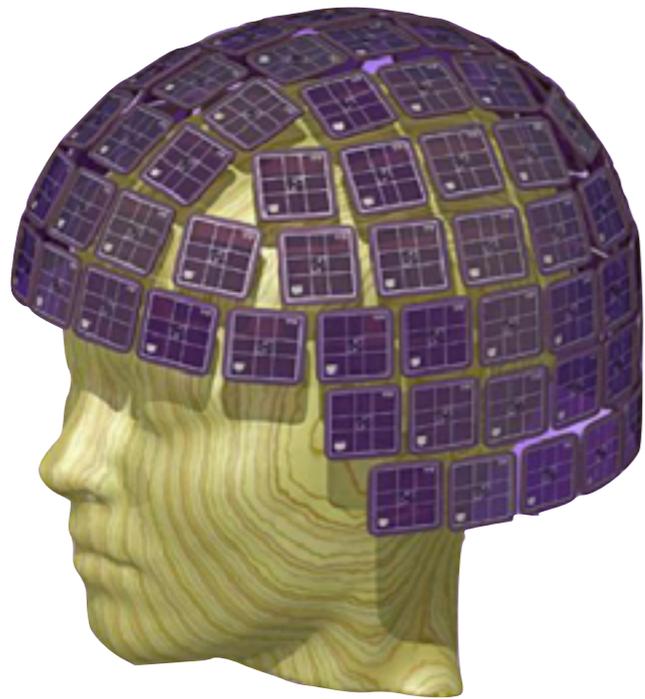


- Dynamic trajectory for all representational levels
- Speed of evolution scales with unit size



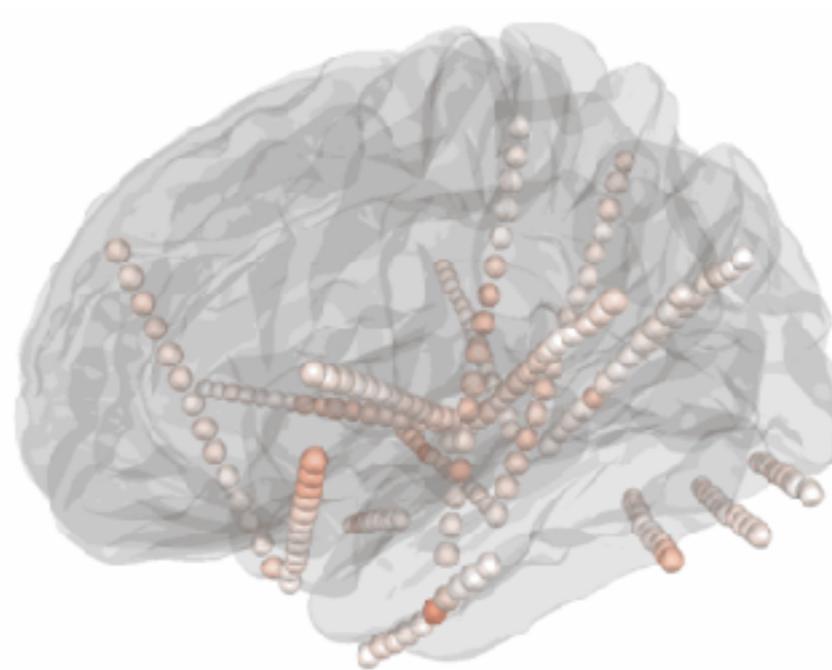
implementation in single neurons

Across neuronal scales



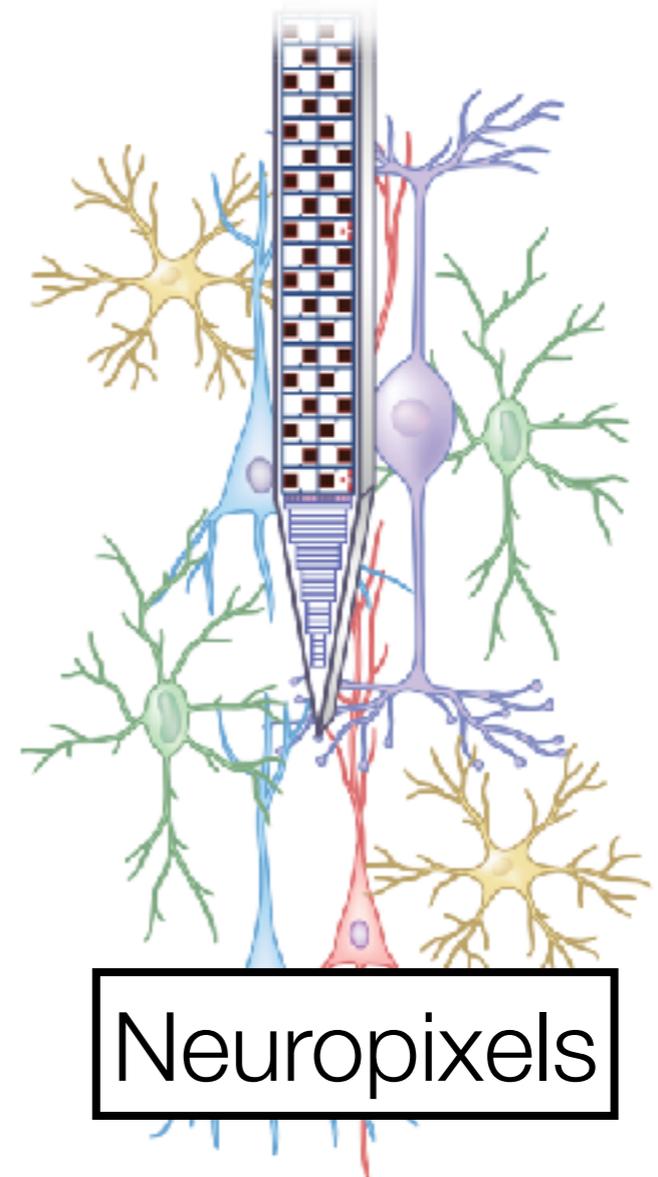
MEG / EEG

~100,000 neurons



iEEG

~10,000 neurons



Neuropixels

~1 neurons

Posterior, Middle, and Anterior STG

- Acoustic-phonetic feature tuning:
e.g., Plosive (+), fricative (x), vowel (●), nasal (■), ...



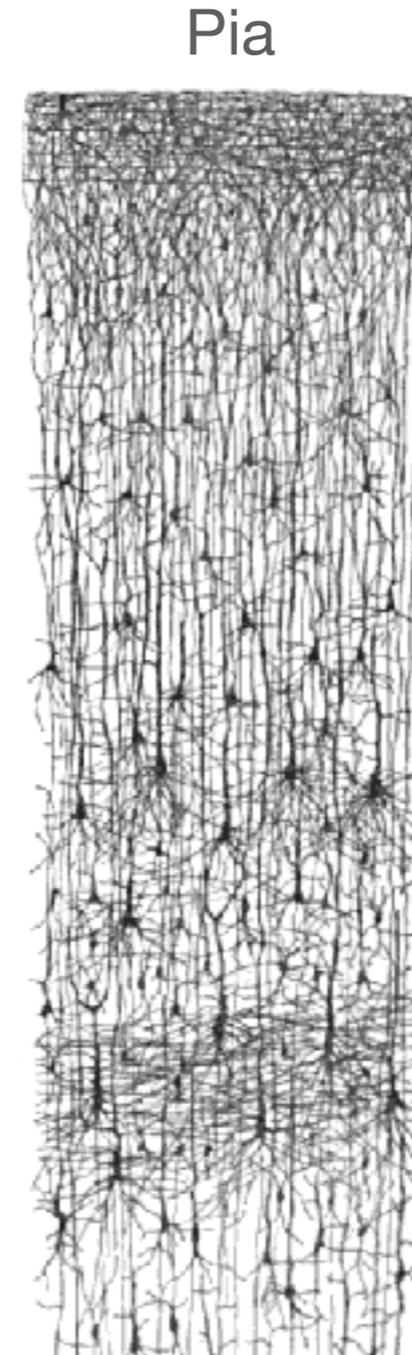
Superior temporal gyrus (STG) is a core area for speech perception in the human brain

STG neural populations encode **acoustic-phonetic features**

Broader spatial organization for **prosodic features** (onset, envelope, pitch)

Posterior, Middle, and Anterior STG

- Acoustic-phonetic feature tuning:
e.g., Plosive (+), fricative (x), vowel (●), nasal (■), ...



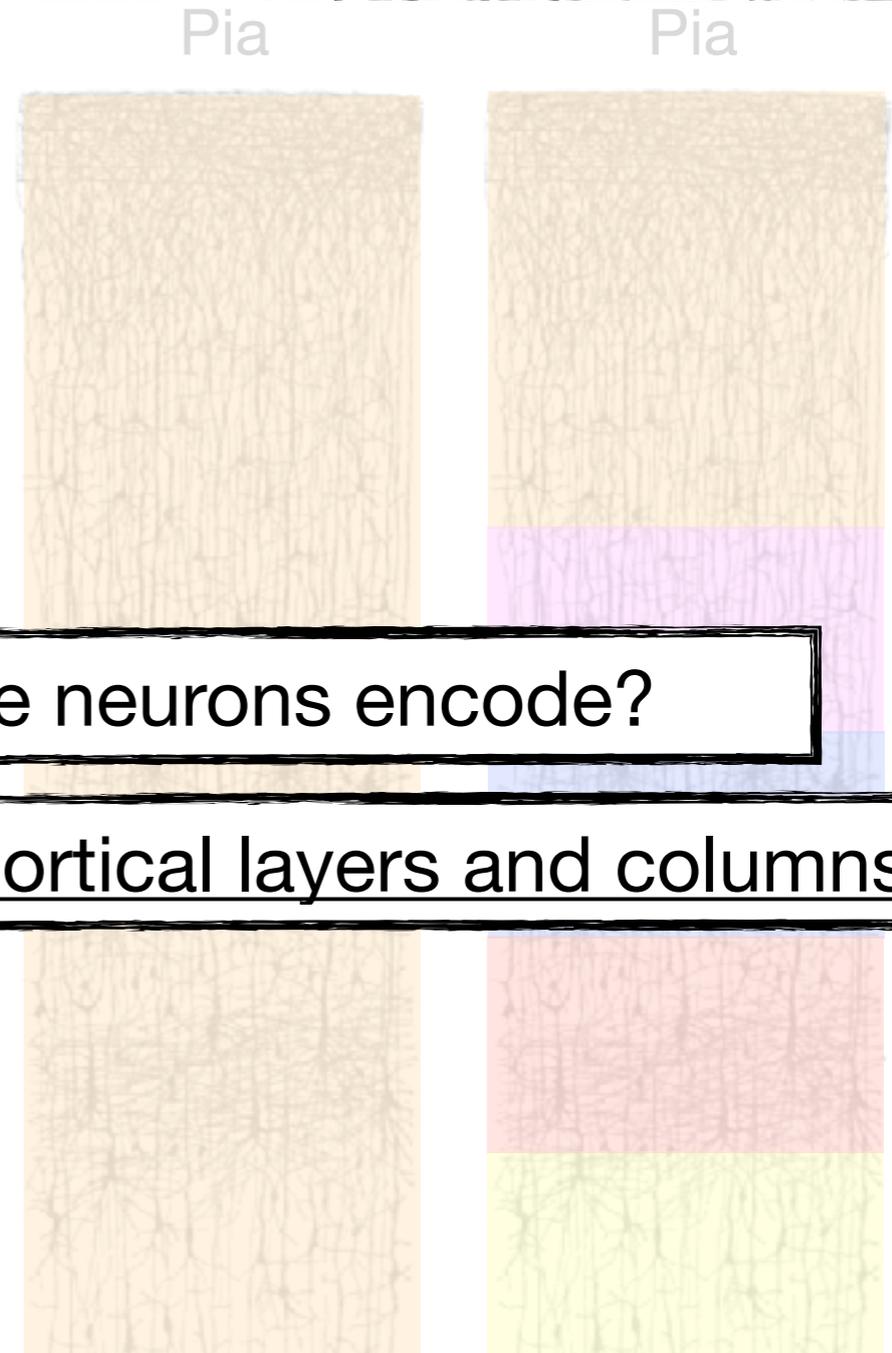
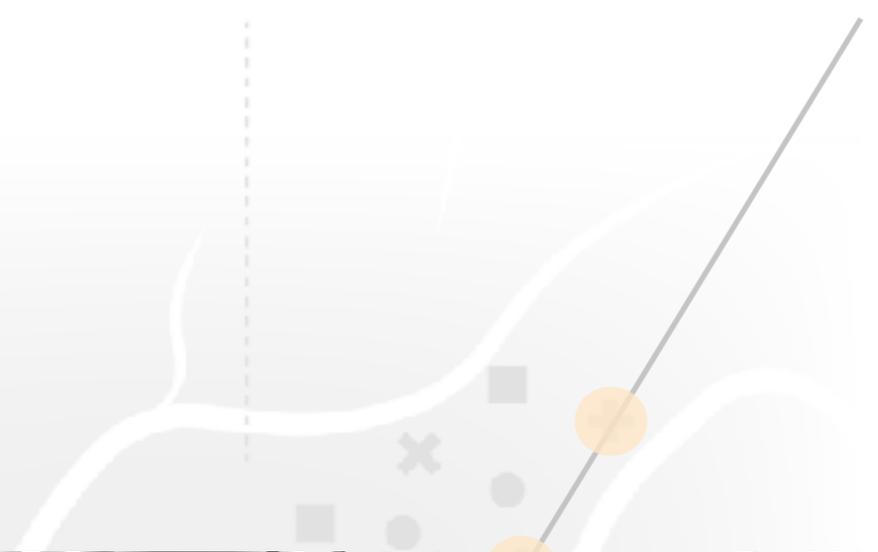
neuronal
architecture of
the cortex

(0) ... how do you record single neurons across the depth?

Posterior, Middle, and Anterior STG

• Acoustic-phonetic feature tuning:

e.g., Plosive (+), fricative (x), vowel (•), nasal (■), ...



(1) what speech features do single neurons encode?

(2) how is information organised across cortical layers and columns?



White Matter

White Matter

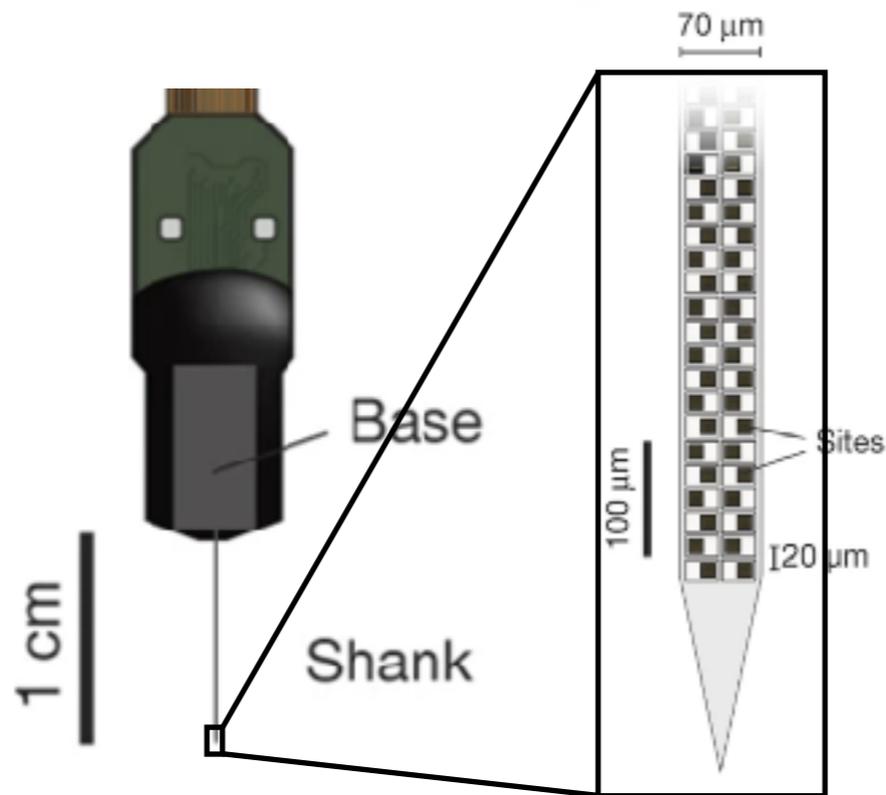
Neuropixels

960 electrodes

(384 simultaneous recording)

(0) ... how do you record single neurons across the depth?

Revolutionary leap in recording capability for animal models

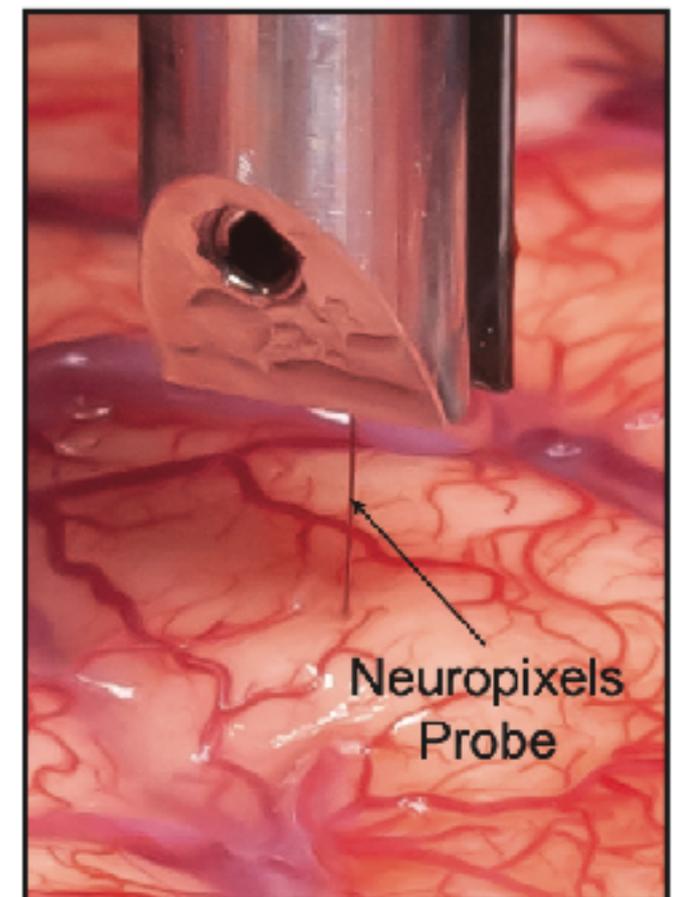


Jun *et al.*, 2017, *Nature*

Recently translated into humans

Chung*, Sellers*, Gwilliams *et al.*, 2022, *Neuron*

Paulk *et al.*, 2022, *Nature Neuroscience*

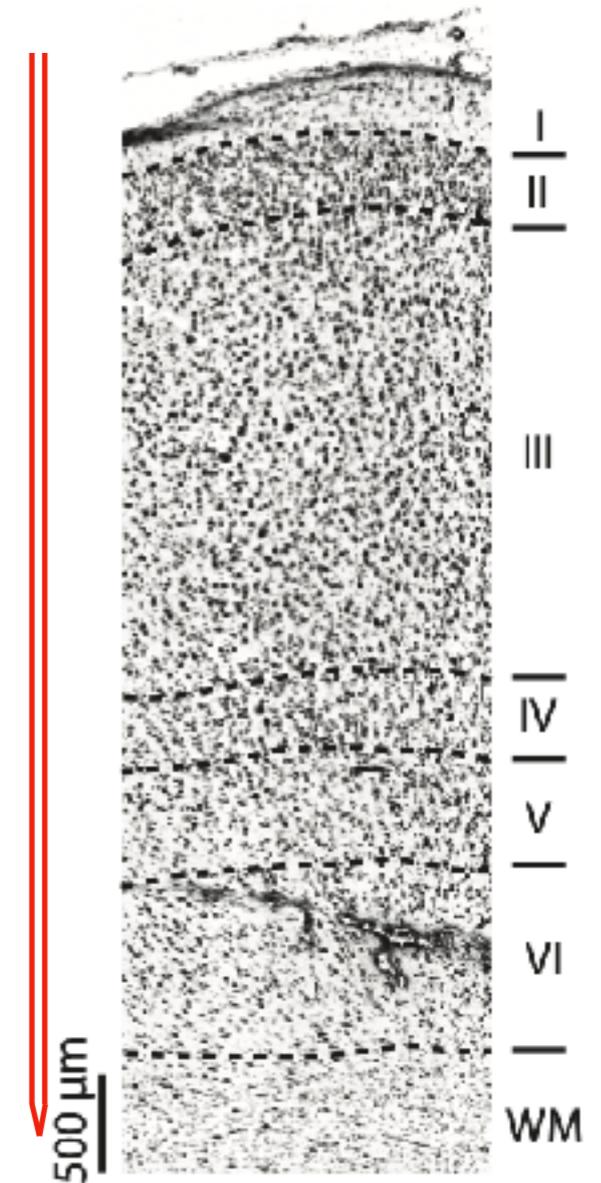
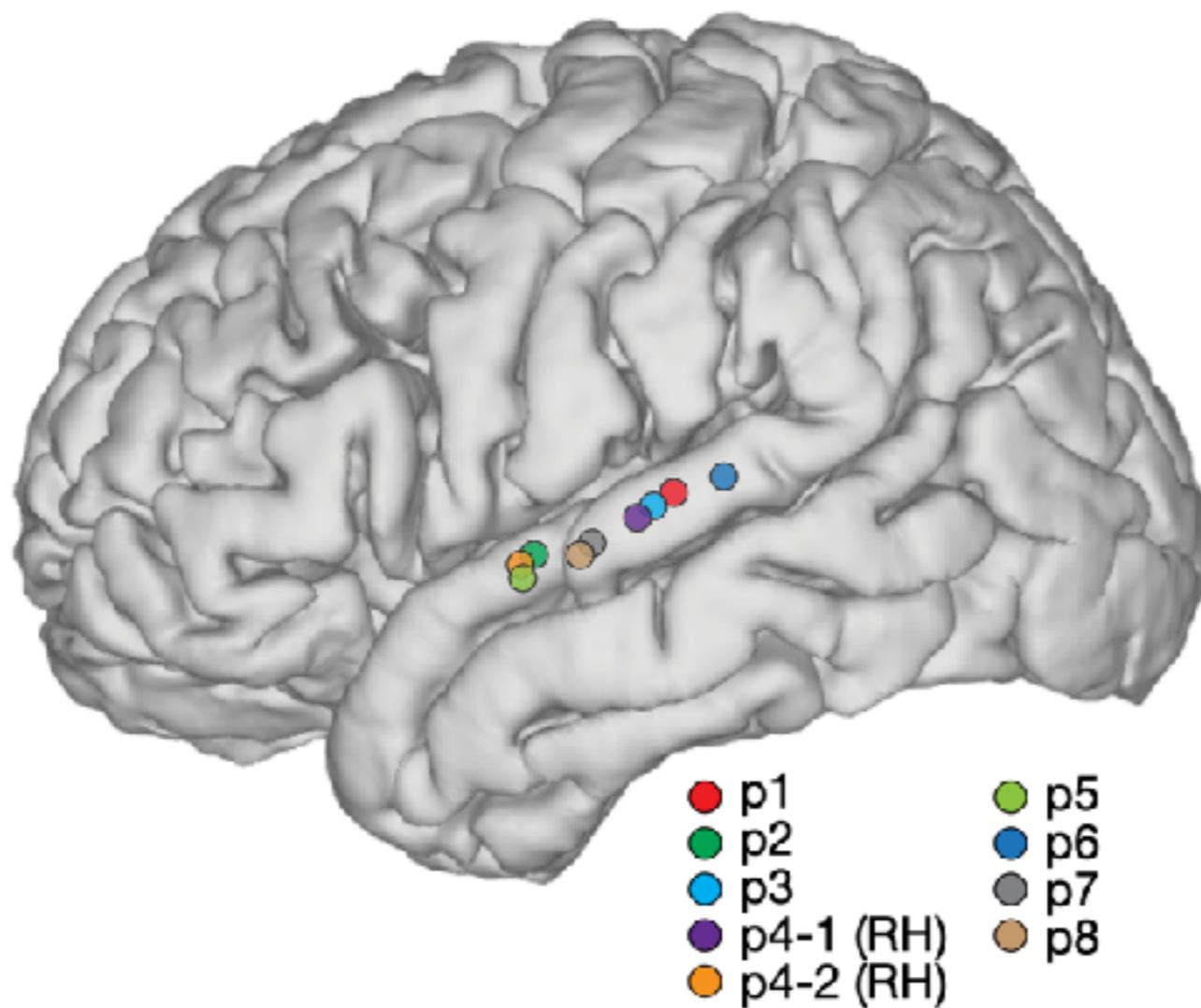


Gwilliams*, Leonard*, *et al.*, 2023, *Nature*

Simultaneous recording of 100-1000s of neurons

~3 years of work to do this safely and efficiently in humans

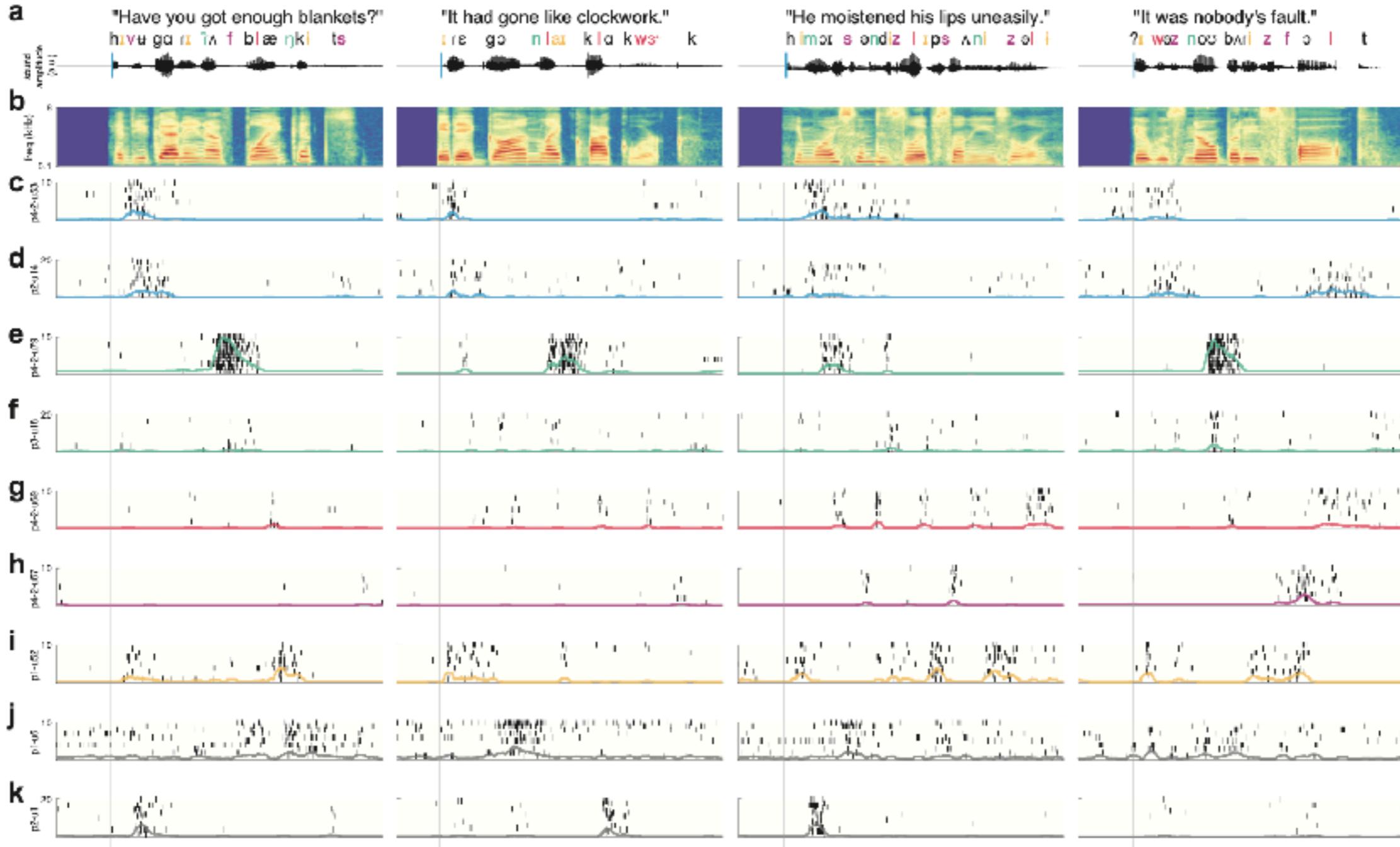
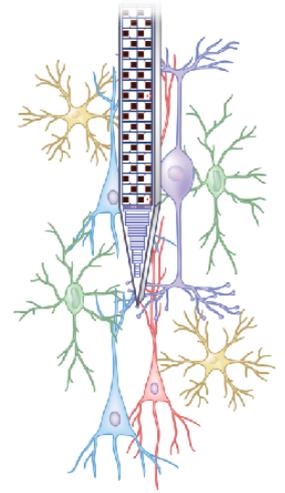
Simultaneous recording from all cortical layers



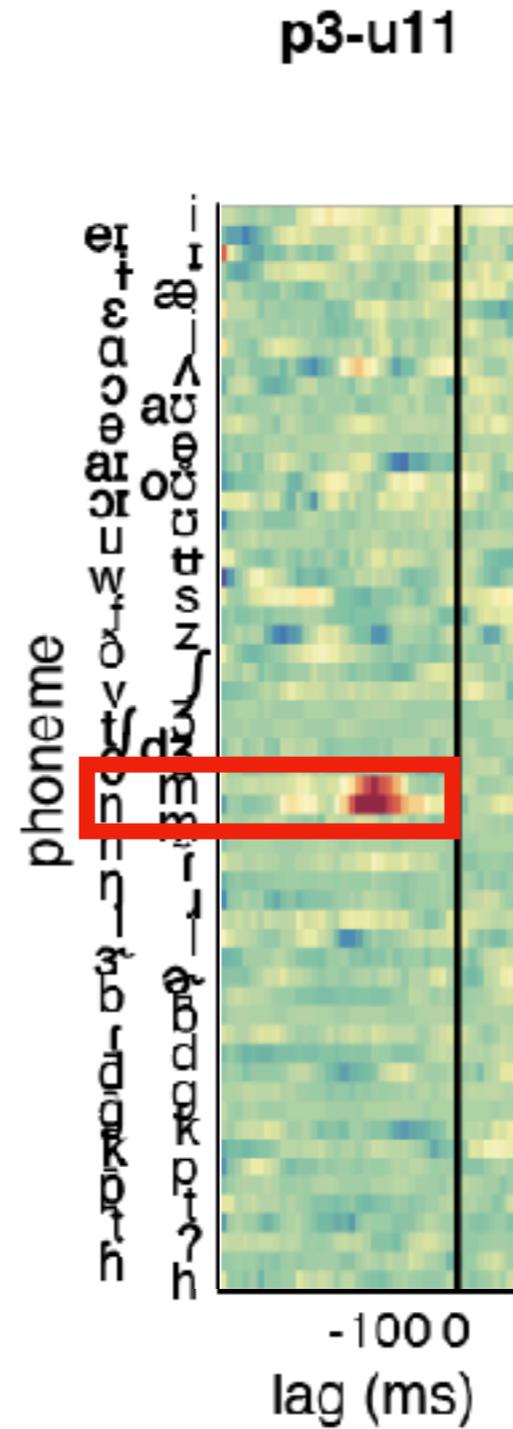
it was nobody's fault

junior what on earth's thematter with you

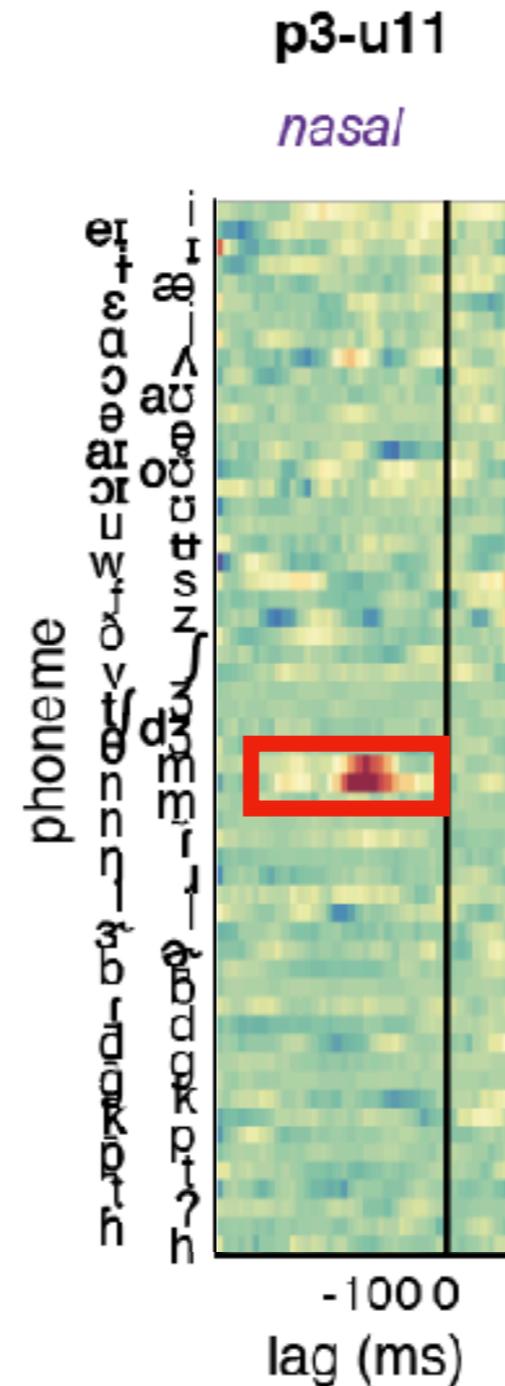
Large-scale single neuron encoding of speech sounds across the depth of human cortex



(1) what speech features do single neurons encode?



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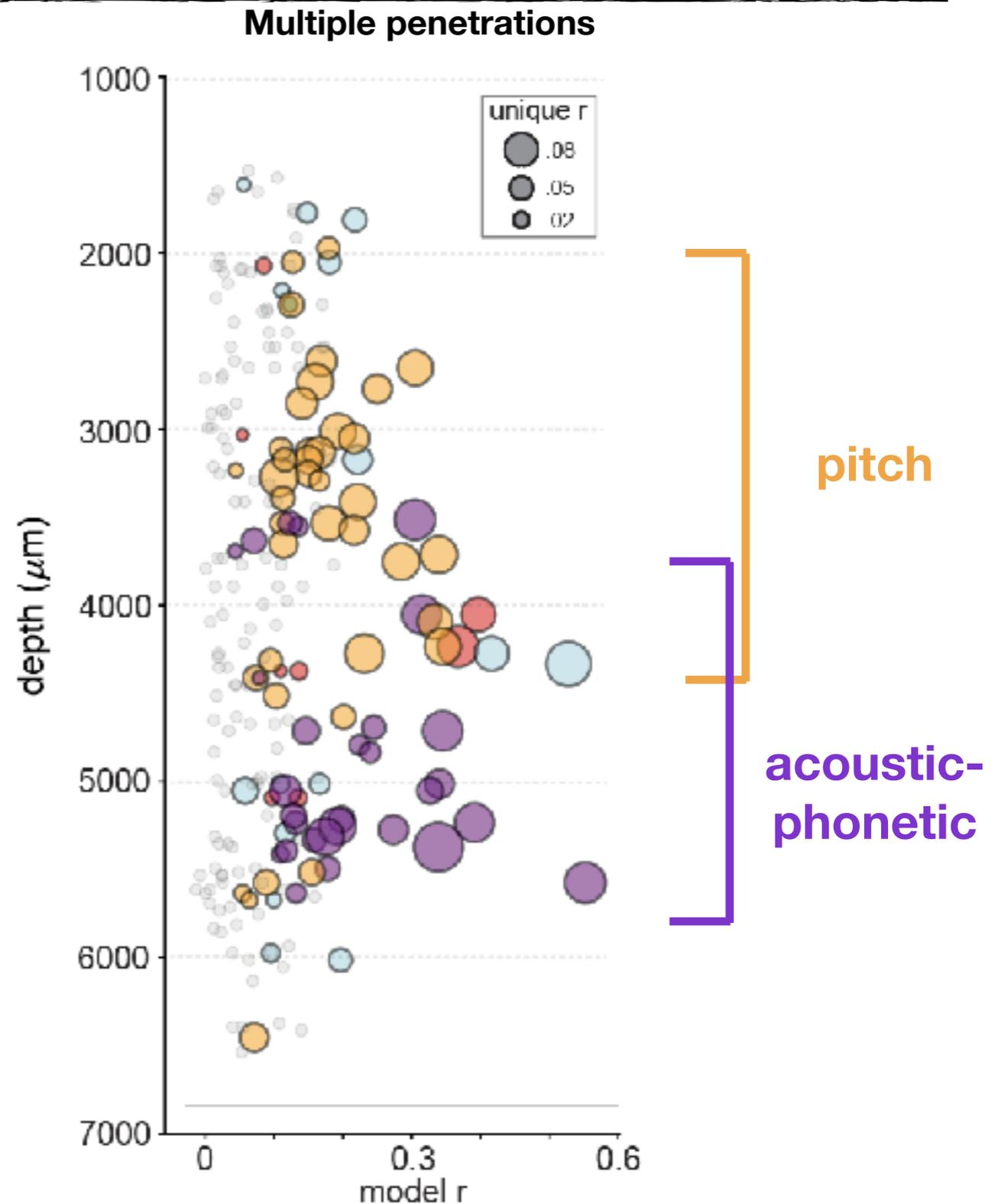
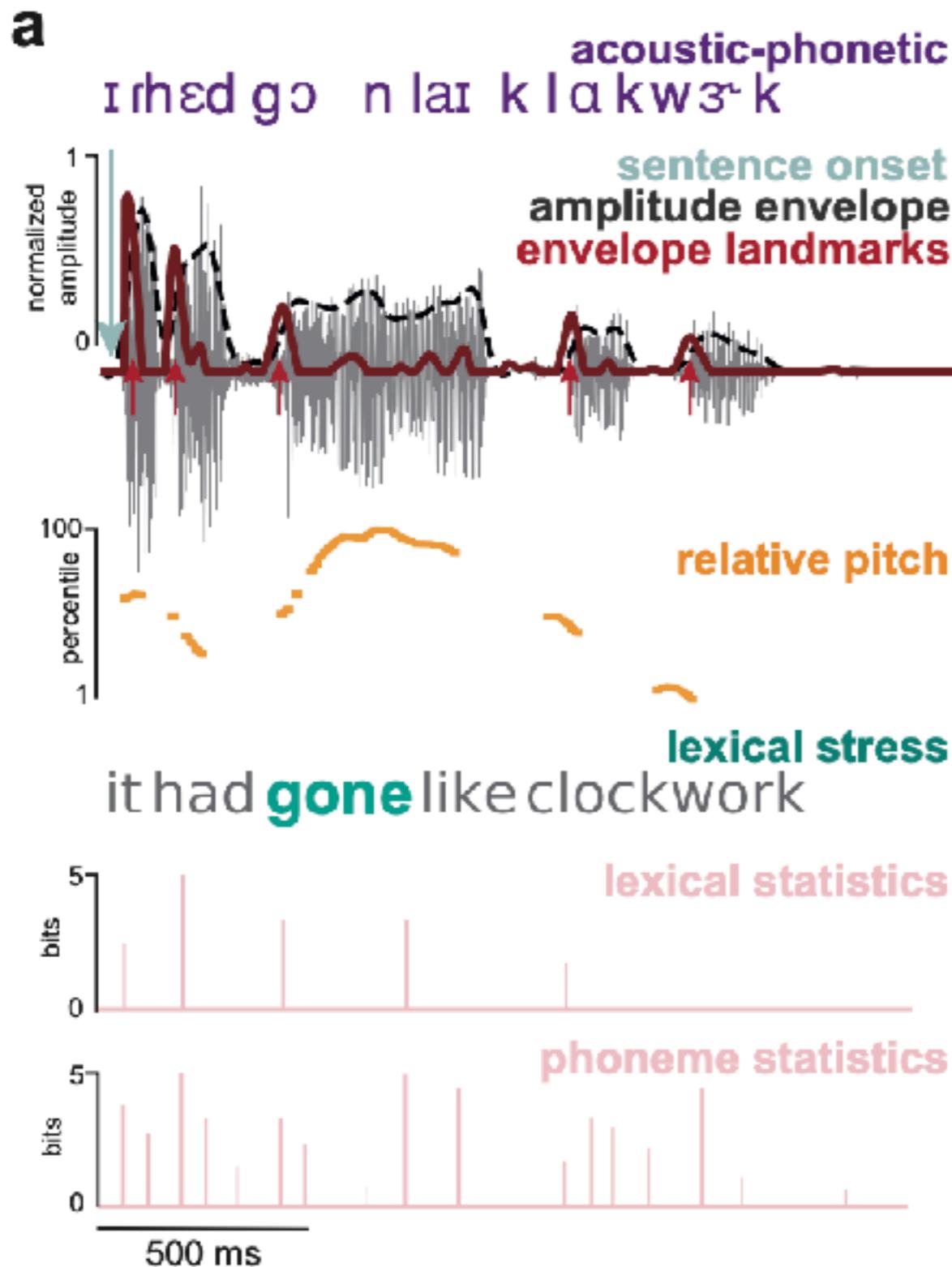


Tuning to phonetic features

No tuning to individual phonemes

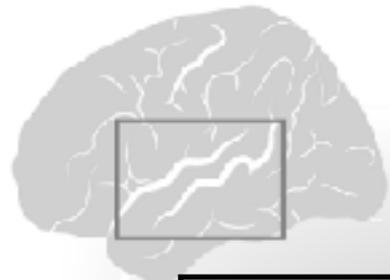
(1) what speech features do single neurons encode?

(2) how is information organised across cortical layers?

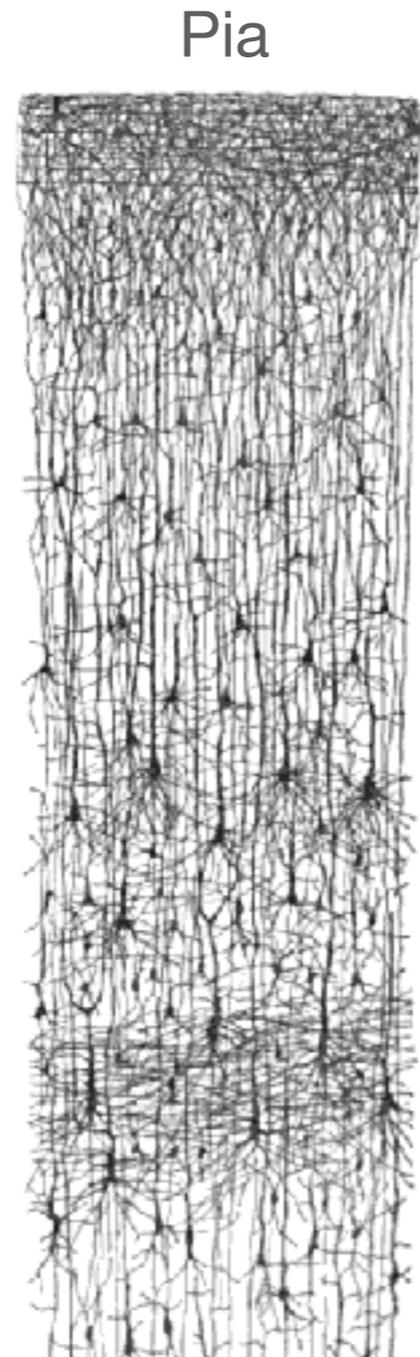


Posterior, Middle, and Anterior STG

- Acoustic-phonetic feature tuning:
e.g., Plosive (+), fricative (x), vowel (•), nasal (■), ...



The ability to record large numbers of neurons across the cortical depth opens up new possibilities for understanding **circuit-level computations** in human cortex



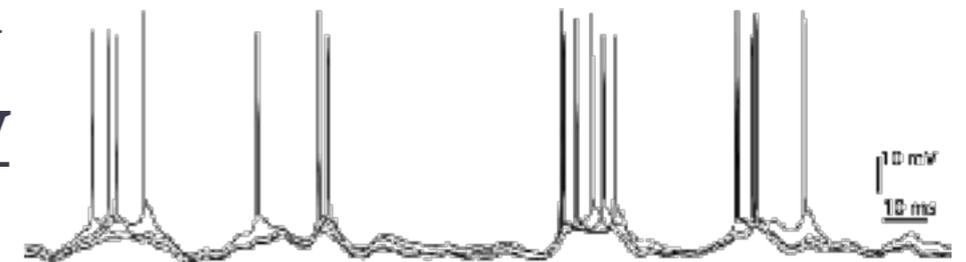
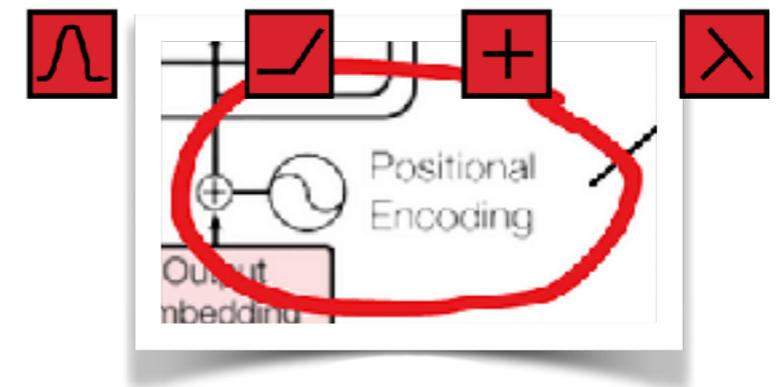
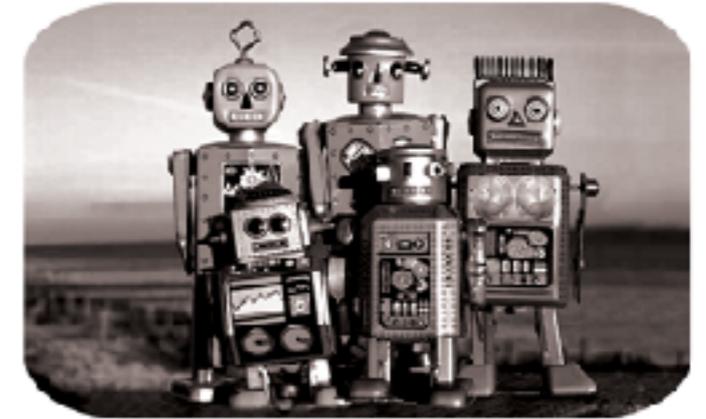
heterogenous tuning

depth-wise organisation

White Matter

Ongoing Work

- Isolate and **interpret** symbolic representations across models
- Leverage LLMs to better understand underlying **computations**
- Use empirical spiking properties and receptive fields to build **biologically inspired speech models**

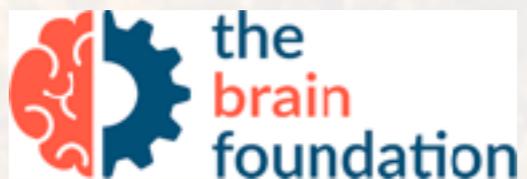


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🐦 [@GwilliamsL](https://twitter.com/GwilliamsL)



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Thank you!