Revealing functional organization by modeling fMRI responses to natural stimuli

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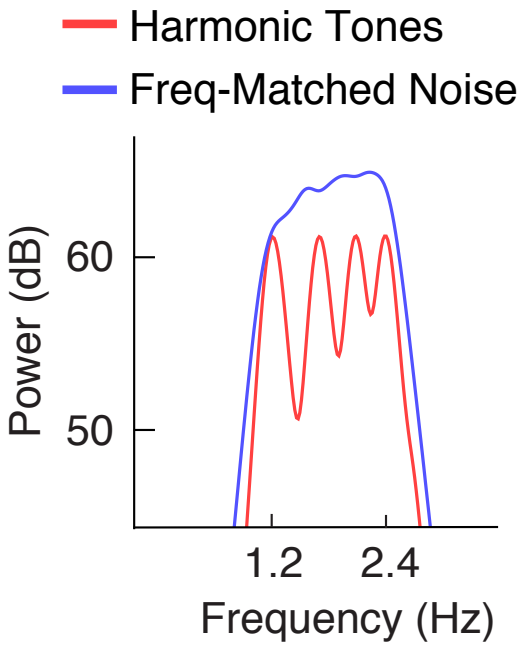
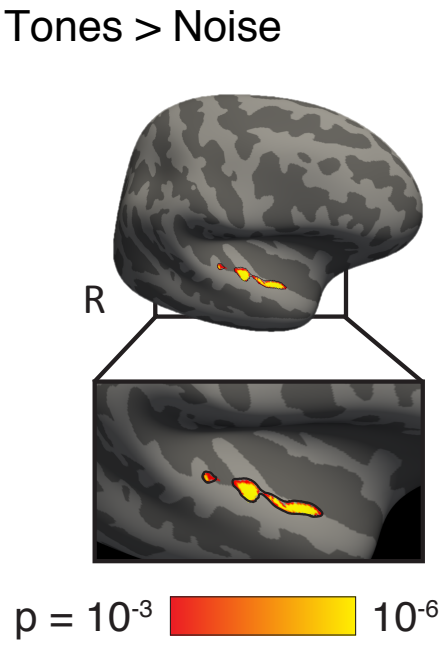
Standard Approach

Example of standard approach: “Pitch-responsive” regions

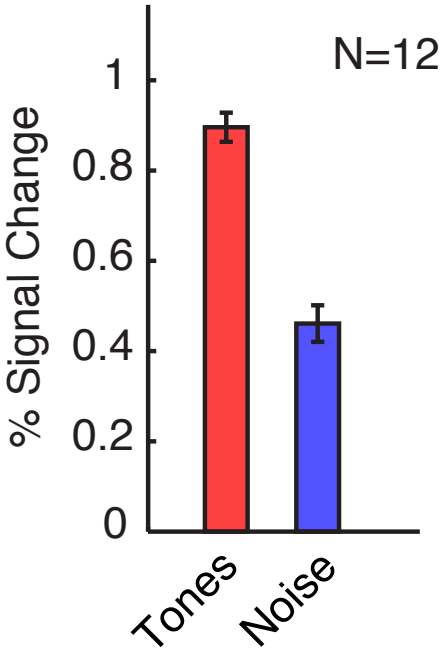
Simulated Excitation Pattern



fMRI Pitch Responses in Example Human Subject



Average fMRI Response of Human Pitch Region



Norman-Haignere et al., 2013, J Neurosci

Limitations of Standard Approach

Only test small number of human-intuitive hypotheses (e.g. pitch)

$\Rightarrow$ Many possible ways cortex could be organized

$\Rightarrow$ Organization could be counter-intuitive

Alternative Data-Driven Approach

1. Measure responses to large set of 165 natural sounds

   $\Rightarrow$ Vary on many ecologically relevant dimensions

2. Use statistical criteria to search large space of possible response patterns

   $\Rightarrow$ Not dependent on prior functional hypotheses

Norman-Haignere et al., 2015, *Neuron*

50 of the 165 Sounds in Experiment (each 2-seconds)

1. Man speaking
2. Flushing toilet
3. Pouring liquid
4. Tooth-brushing
5. Woman speaking
6. Car accelerating
7. Biting and chewing
8. Laughing
9. Typing
10. Car engine starting
11. Running water
12. Breathing
13. Keys jangling
14. Dishes clanking
20. Zipper
21. Cellphone vibrating
22. Water dripping
23. Scratching
24. Car windows
25. Telephone ringing
26. Chopping food
27. Telephone dialing
28. Girl speaking
29. Car horn
30. Writing
31. Computer startup sound
32. Background speech
33. Songbird
39. Crumpling paper
40. Siren
41. Splashing water
42. Computer speech
43. Alarm clock
44. Walking with heels
45. Vacuum
46. Wind
47. Boy speaking
48. Chair rolling
49. Rock song
50. Door knocking

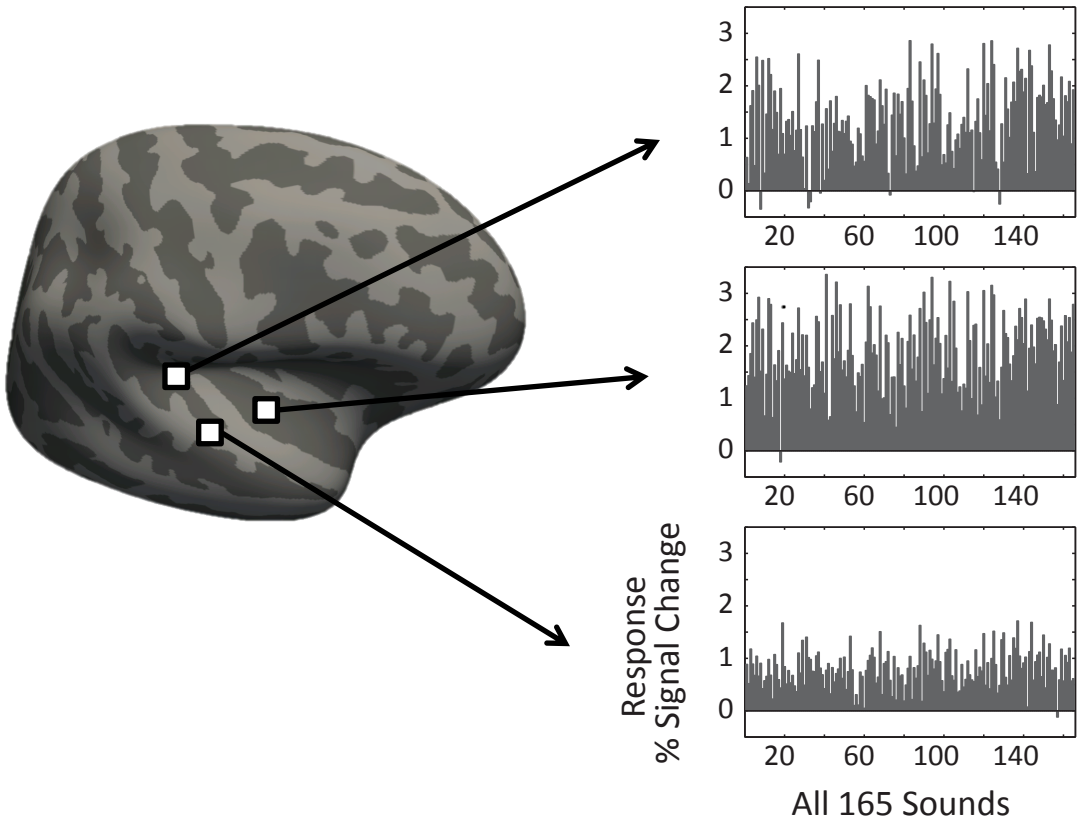
Scanned 10 human subjects

All native English speakers and not active musicians

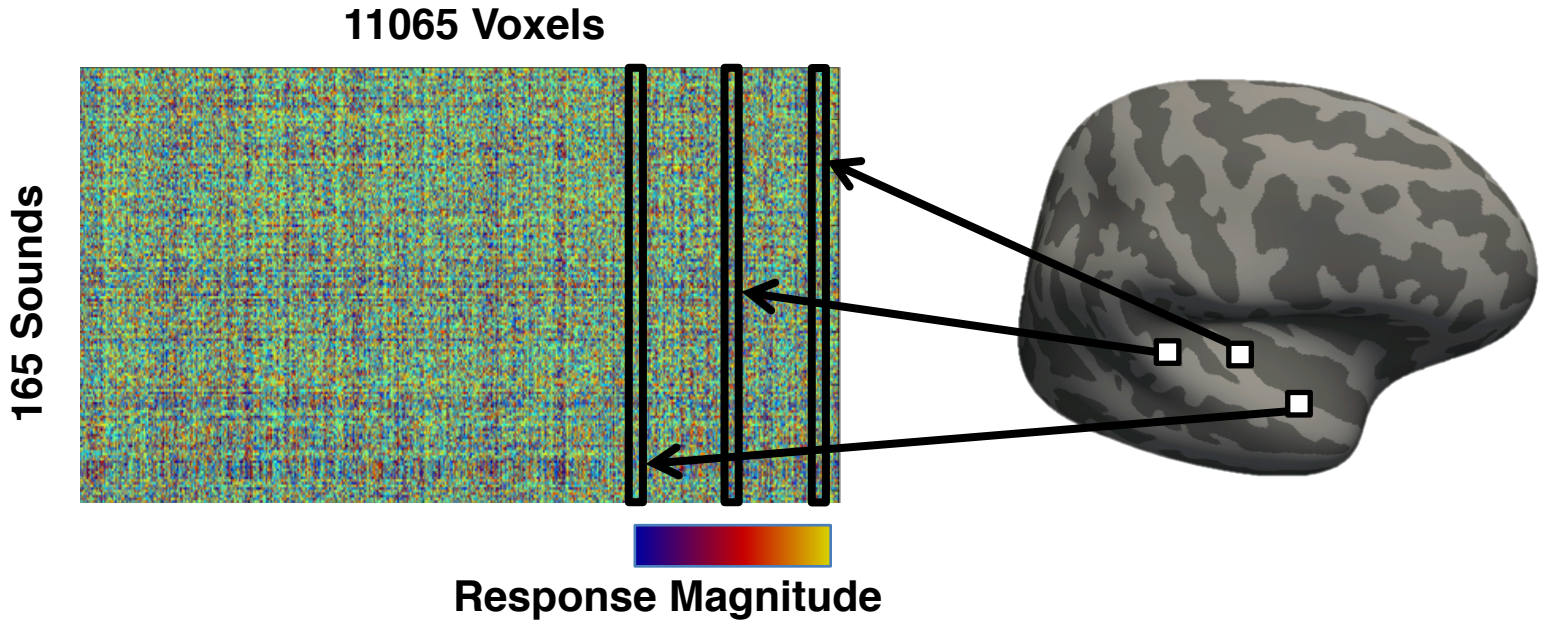
18. Walking (hard surface)
37. Guitar

Voxel Responses

- For each voxel, we measure it's average response to each sound

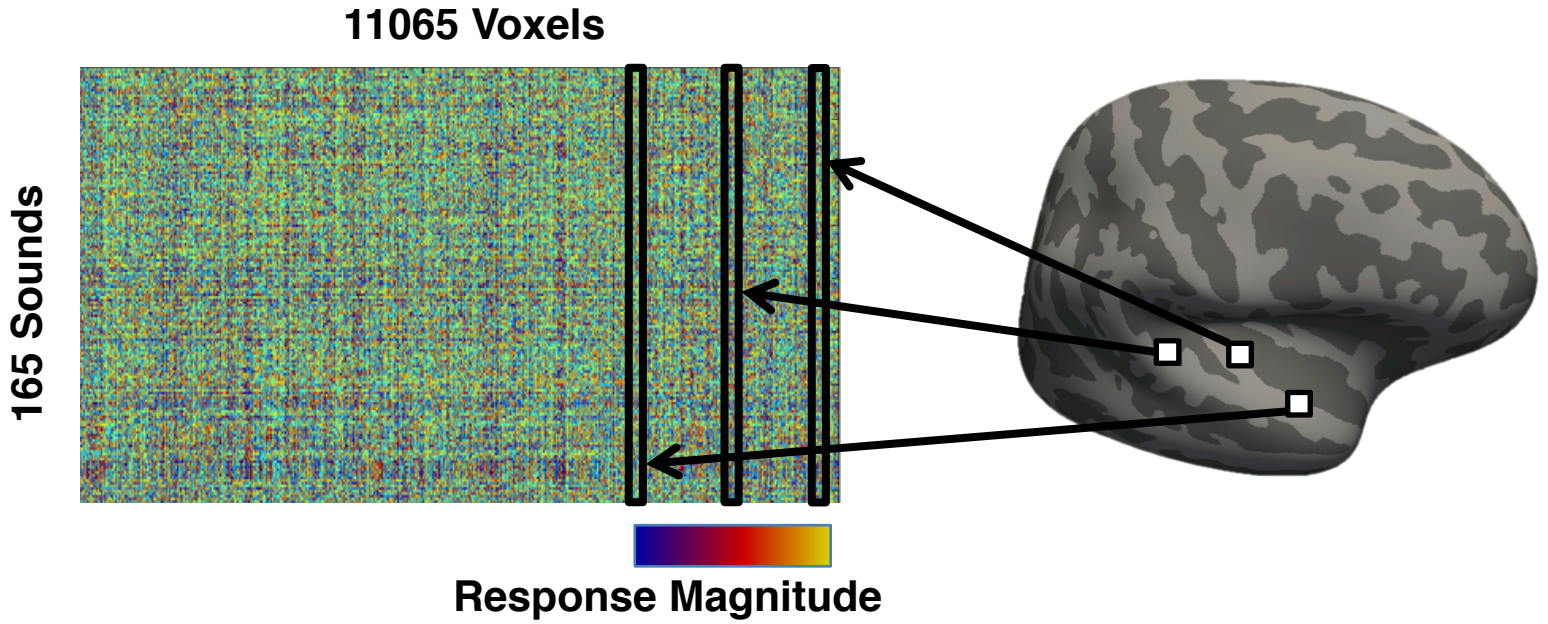


Data Matrix



How can we discover structure from this matrix?

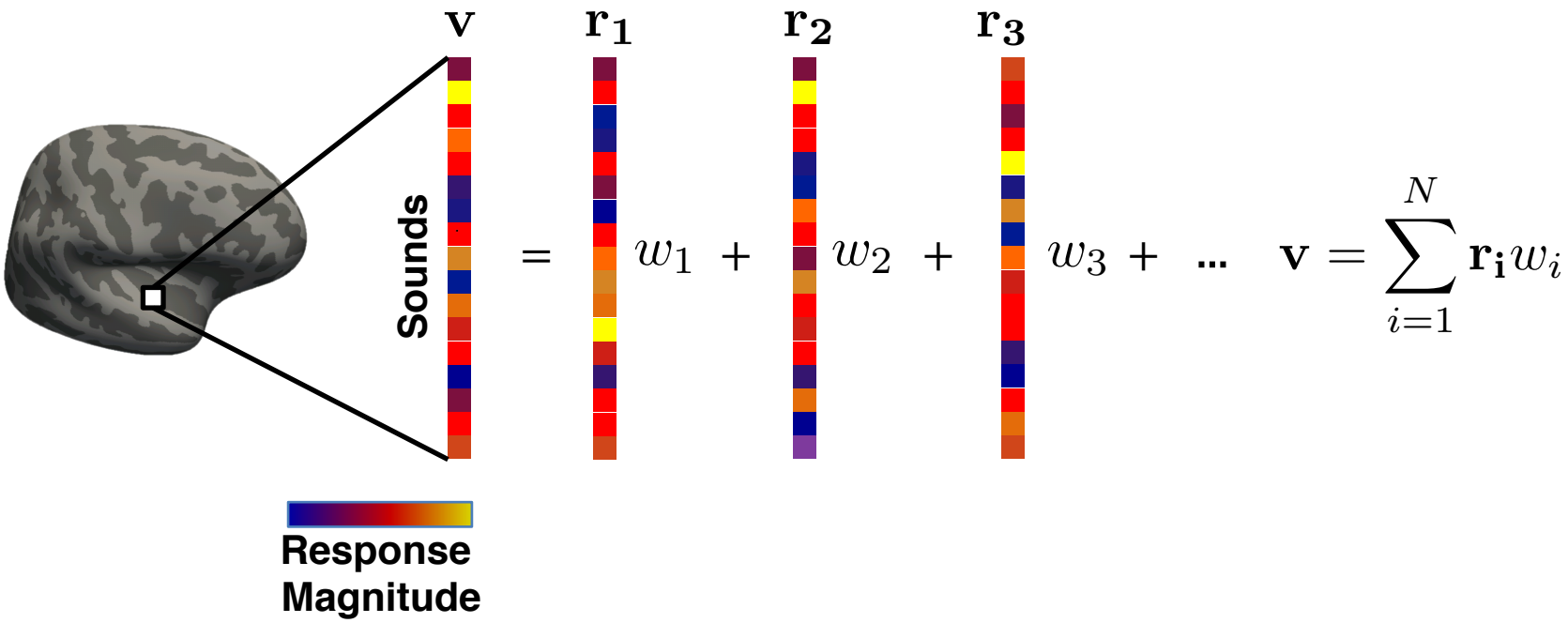
Data Matrix



Two assumptions motivating a simple linear model:

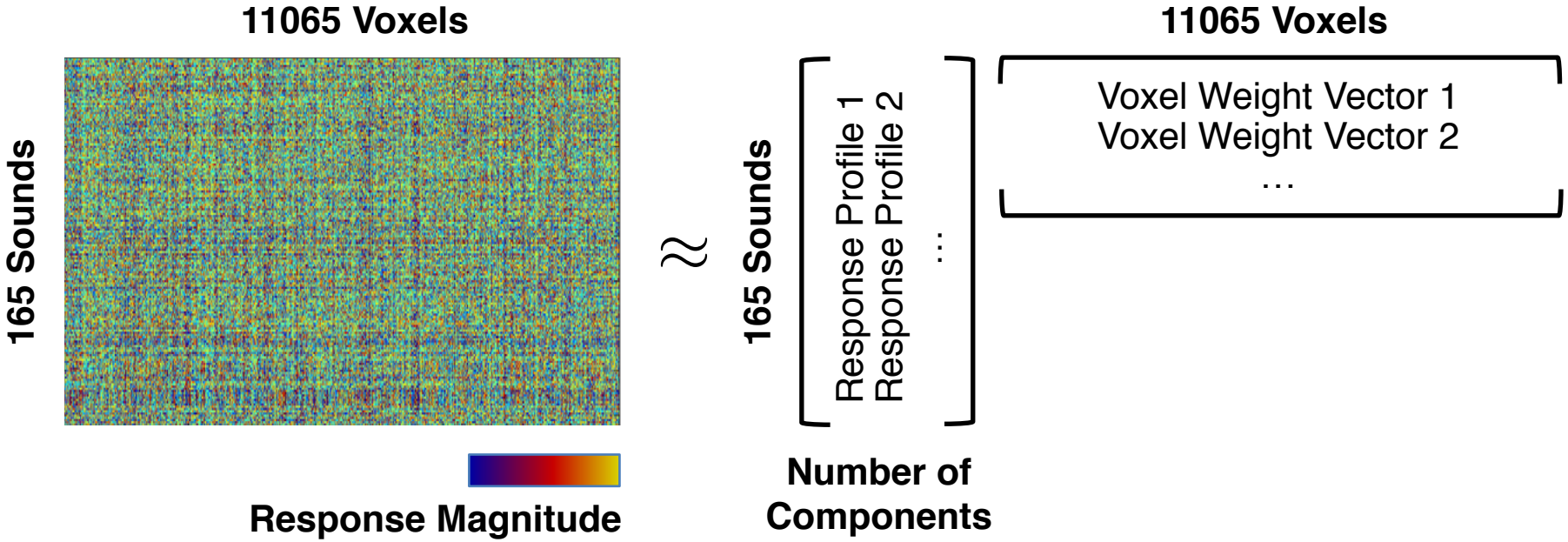
1. Neuronal populations with distinct responses to the sound set
2. fMRI signal reflects summed response of neuronal populations in each voxel

Linear Model of Voxel Responses



Voxel responses modeled as weighted sum of response profiles

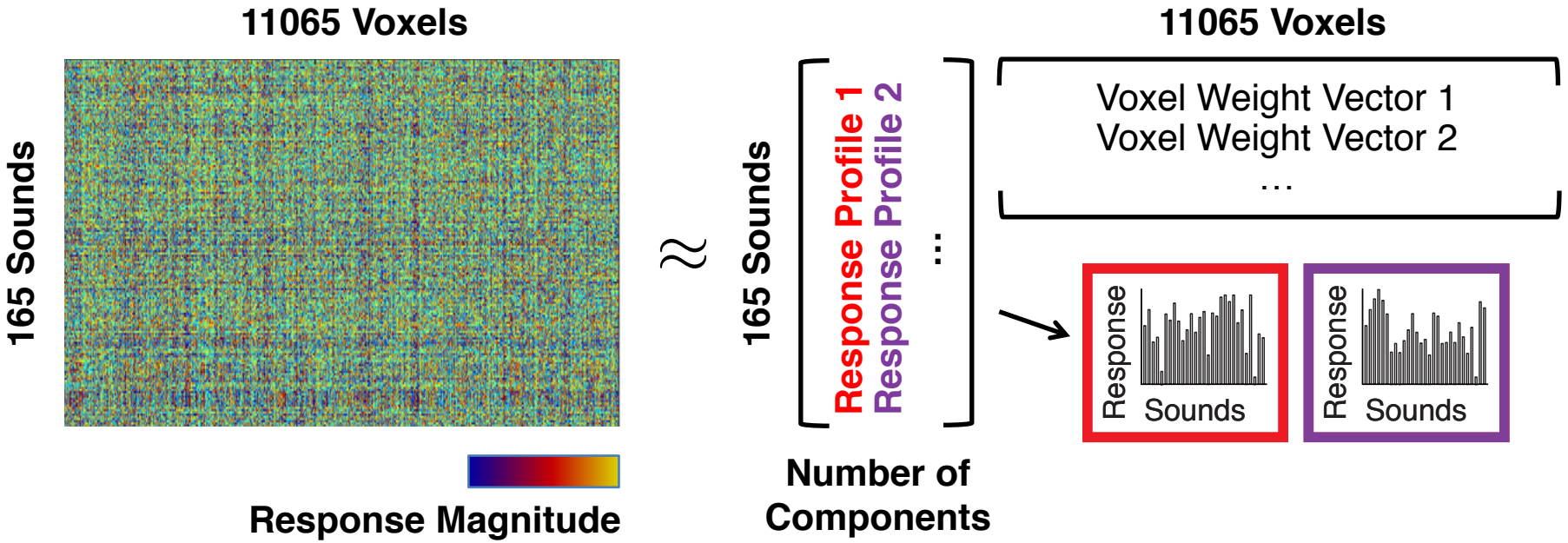
Matrix Factorization



Factor response matrix into set of components, each with:

1. Response profile to all 165 sounds
2. Voxel weights specifying contribution of each component to each voxel

Matrix Factorization



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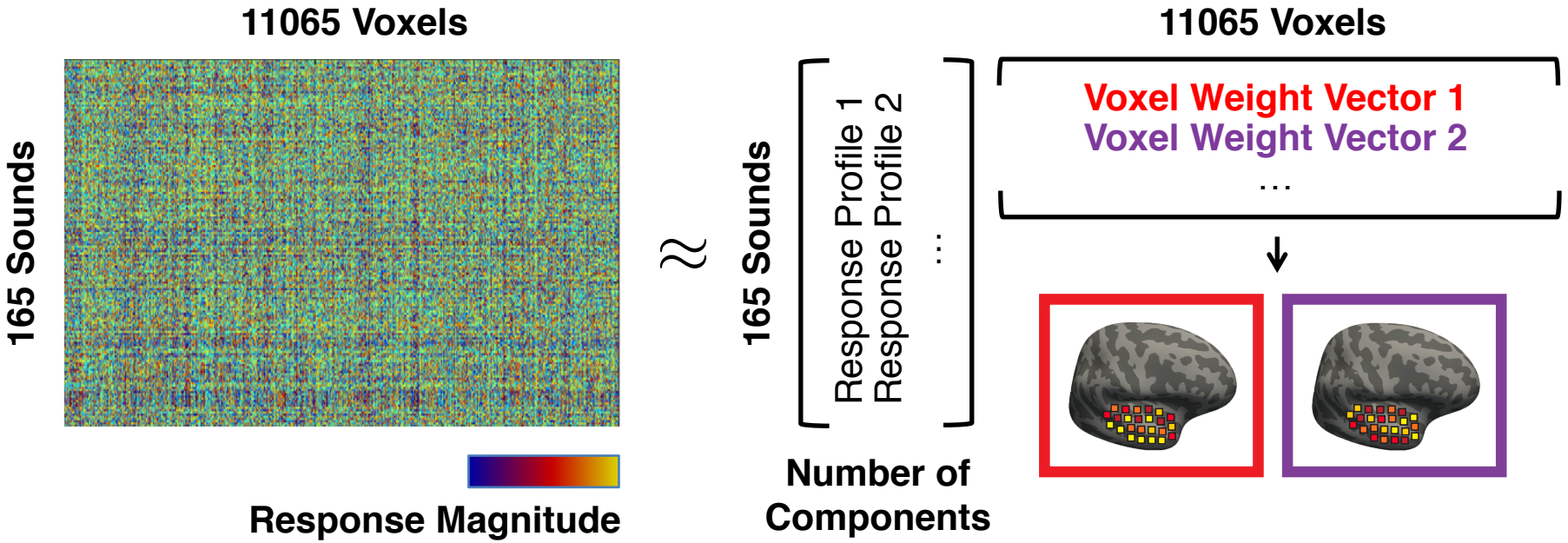
1. Response profile to all 165 sounds
2. Voxel weights specifying contribution of each component to each voxel

Matrix Factorization



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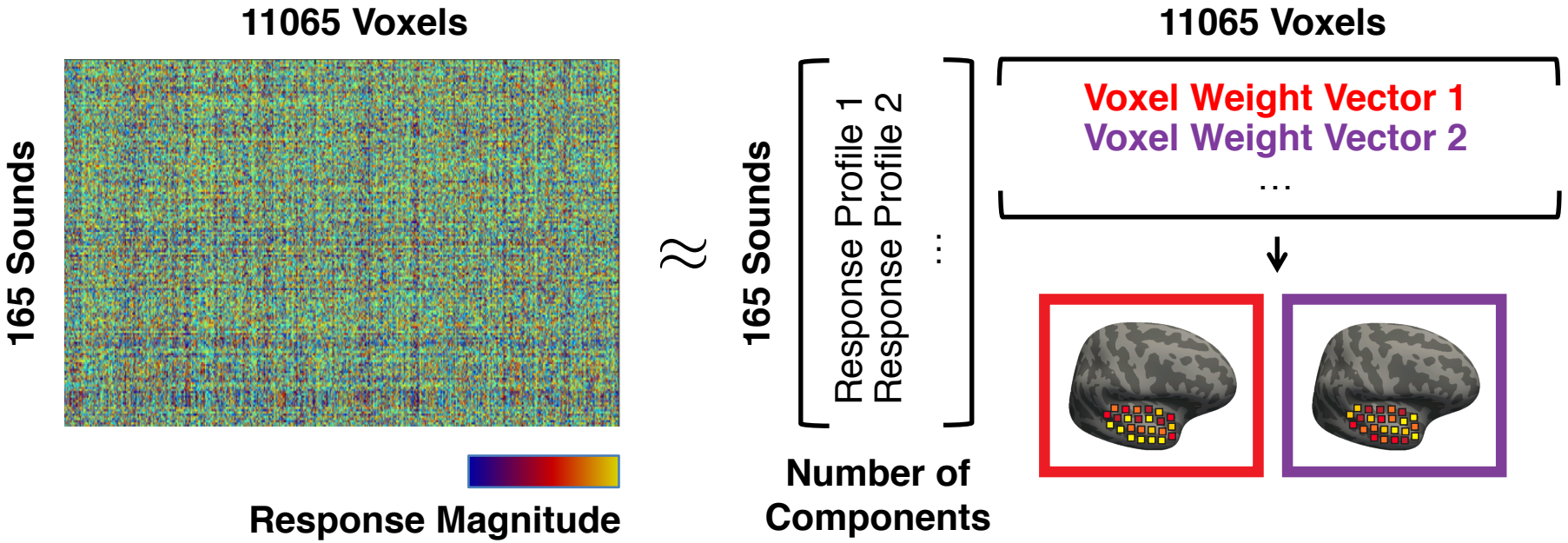
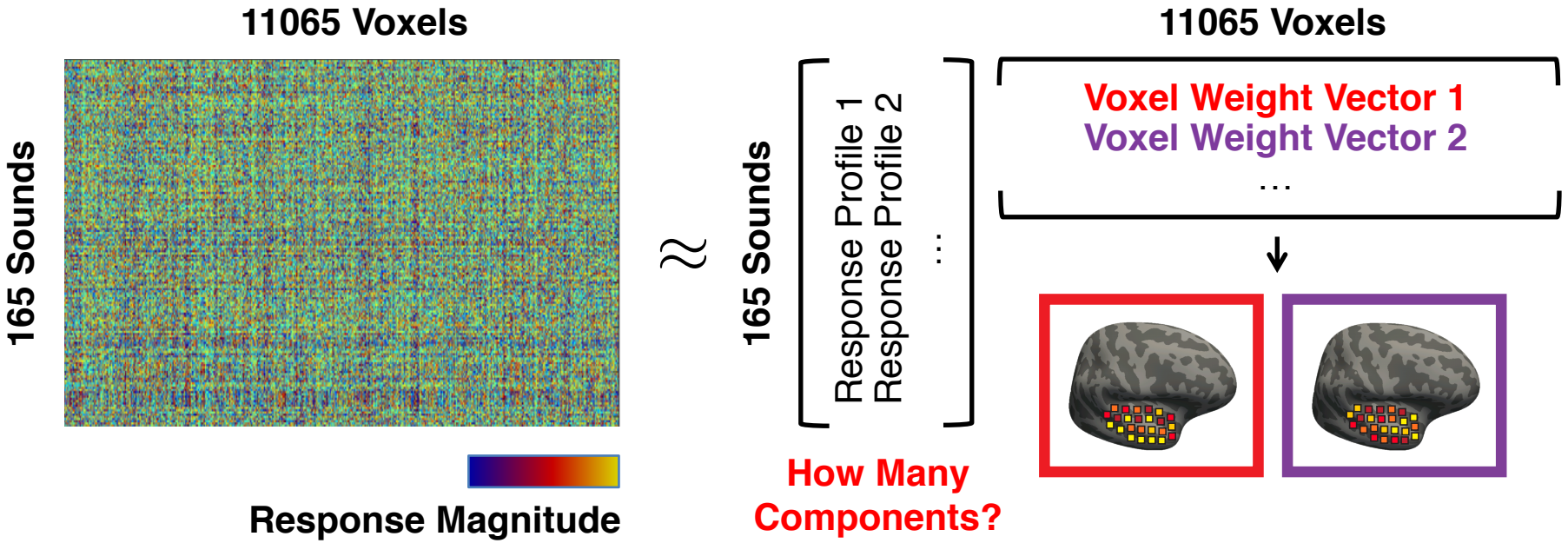
2. Voxel weights specifying contribution of each component to each voxel

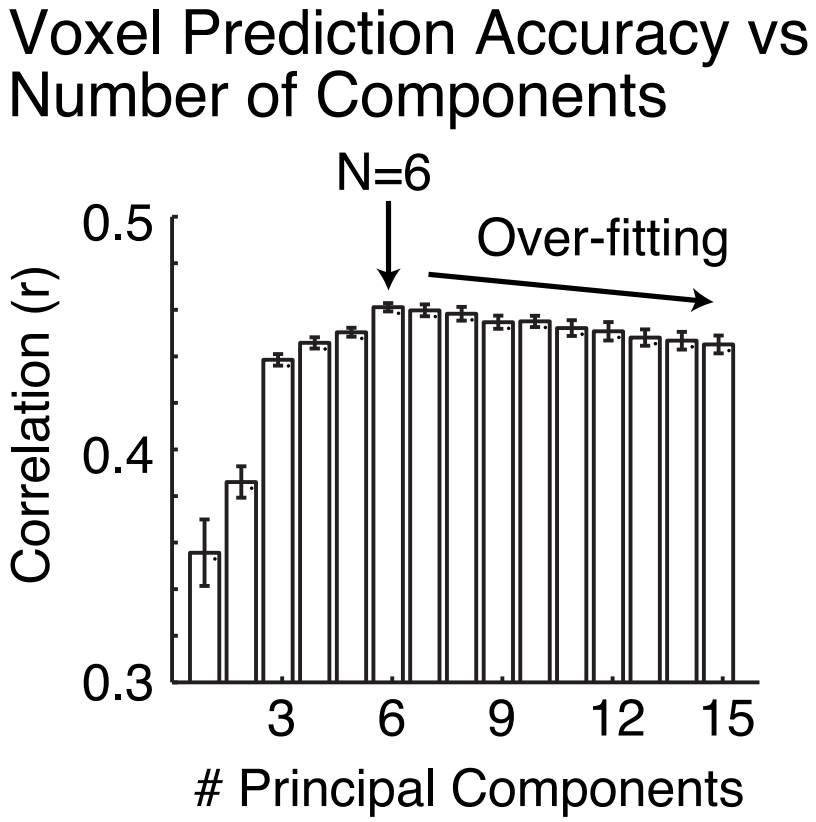
Matrix Factorization



1. No information about sounds or anatomy used
2. Consistent functional or anatomical structure must reflect structure in data

Matrix Factorization





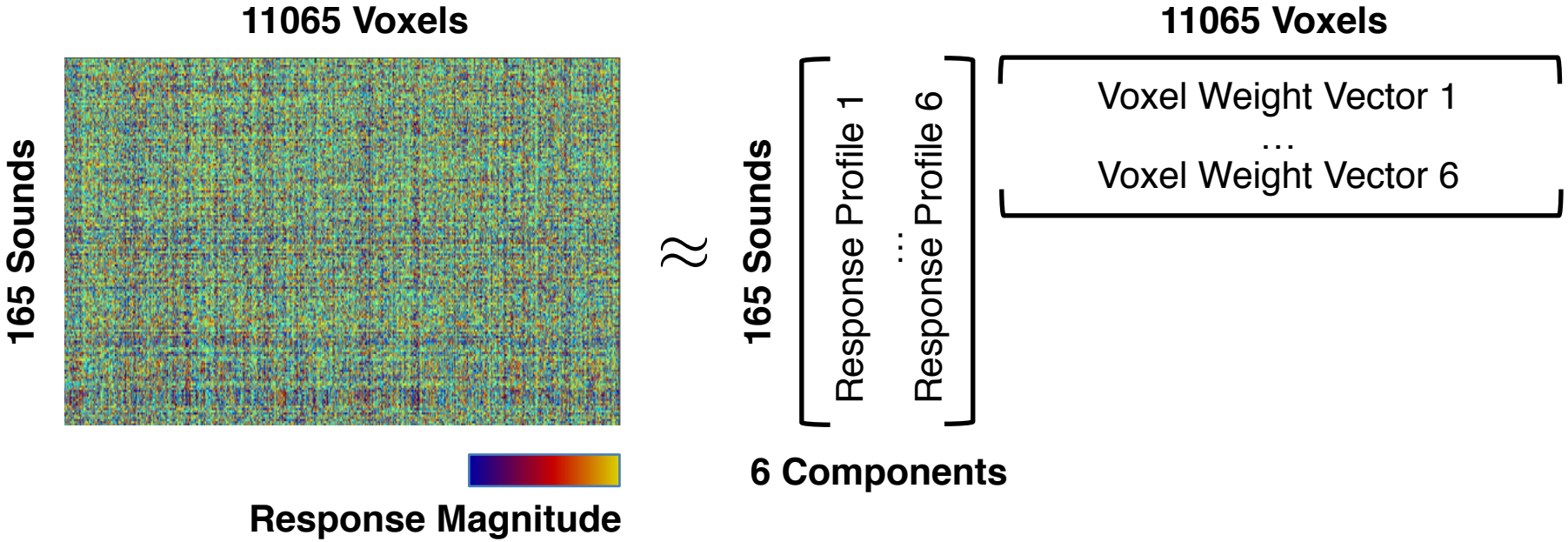
Prediction accuracy best with top 6 principal components

$\Rightarrow$ Higher-order components driven by noise

$\Rightarrow$ Explain >80% of replicable response variance across natural sounds

$\Rightarrow$ **Stimulus set high-dimensional but fMRI responses low-dimensional**

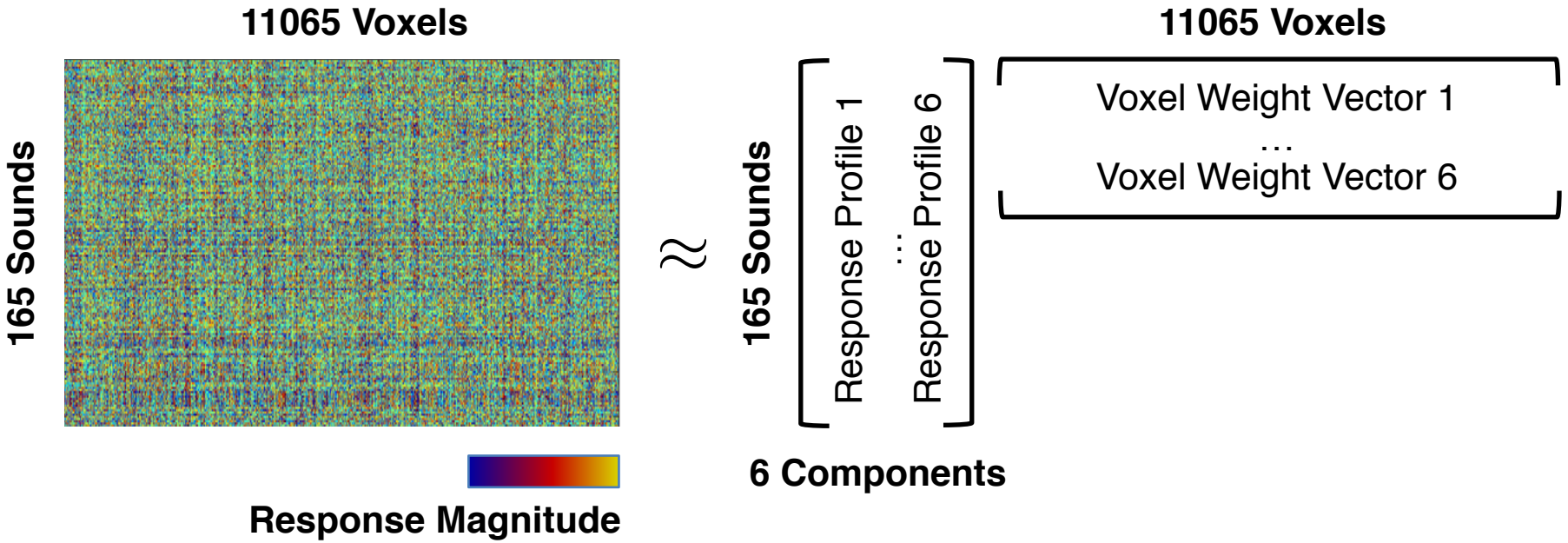
Matrix Factorization



Matrix approximation still ill-posed (many equally good solutions)

$\Rightarrow$ Used two methods to constrain the solution via statistics of the voxel weights

Matrix Factorization



Method 1: Non-parametric algorithm

Search for components with maximally non-Gaussian weights, quantified using a non-parametric estimate of entropy

(Hyvarinen, 2000)

Method 2: Probabilistic model

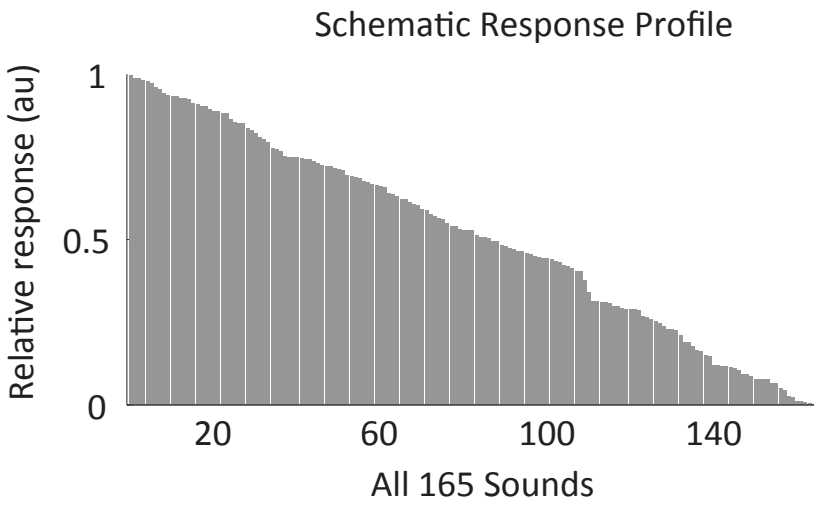
Find components which maximize likelihood of the data given a parametric prior (Gamma distr.) on voxel weights

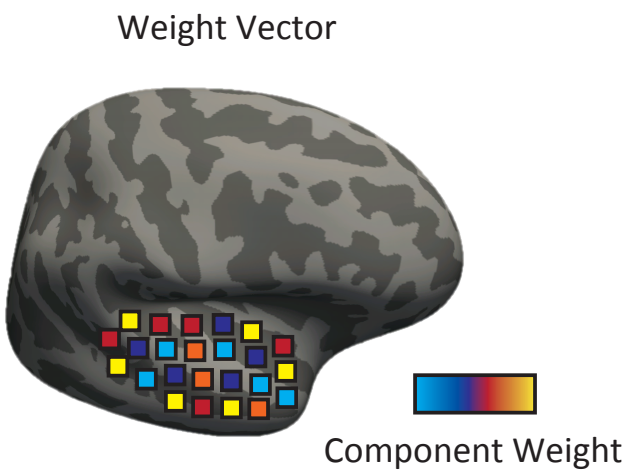
(Liang, Hoffman, Mysore, 2014)

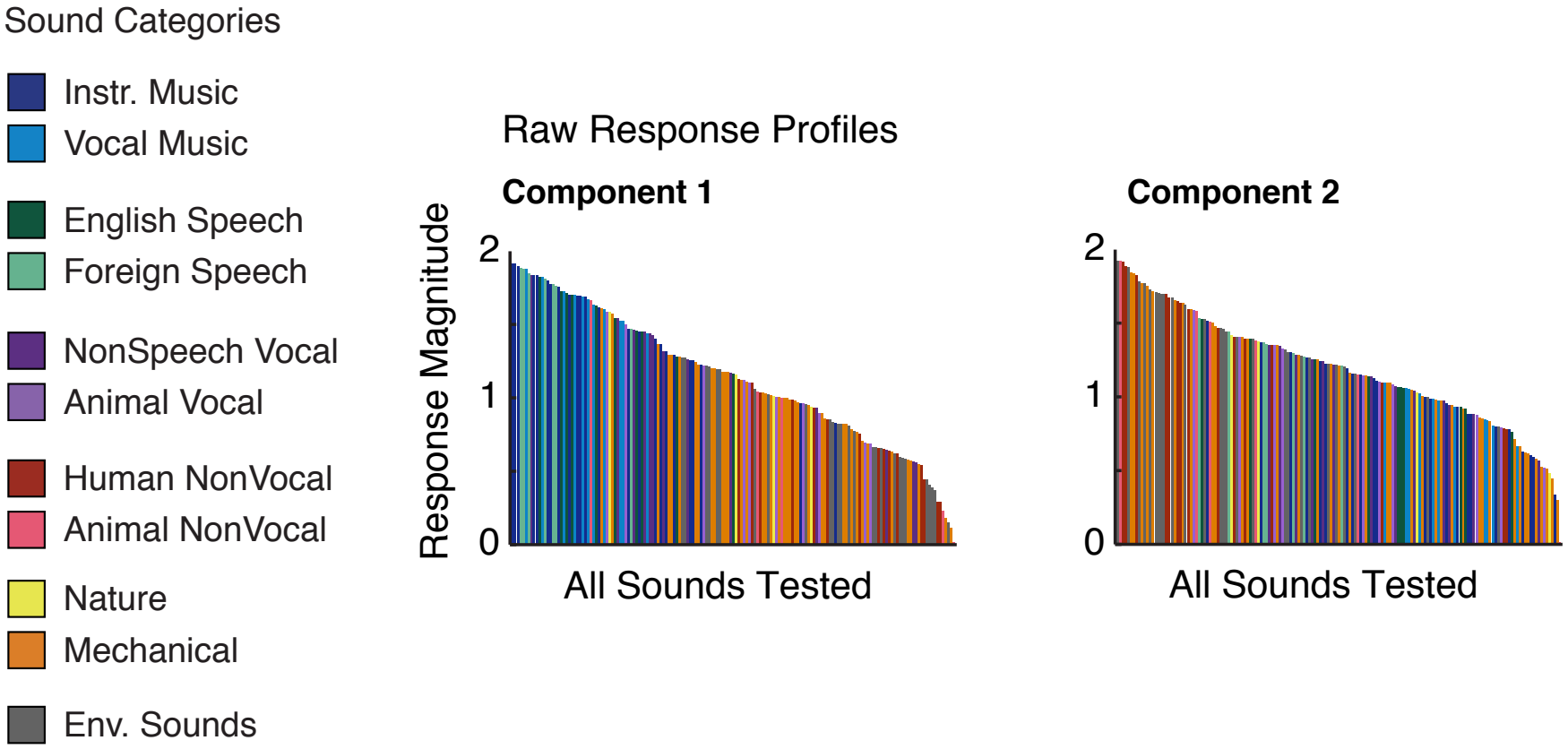
Probing the Discovered Components

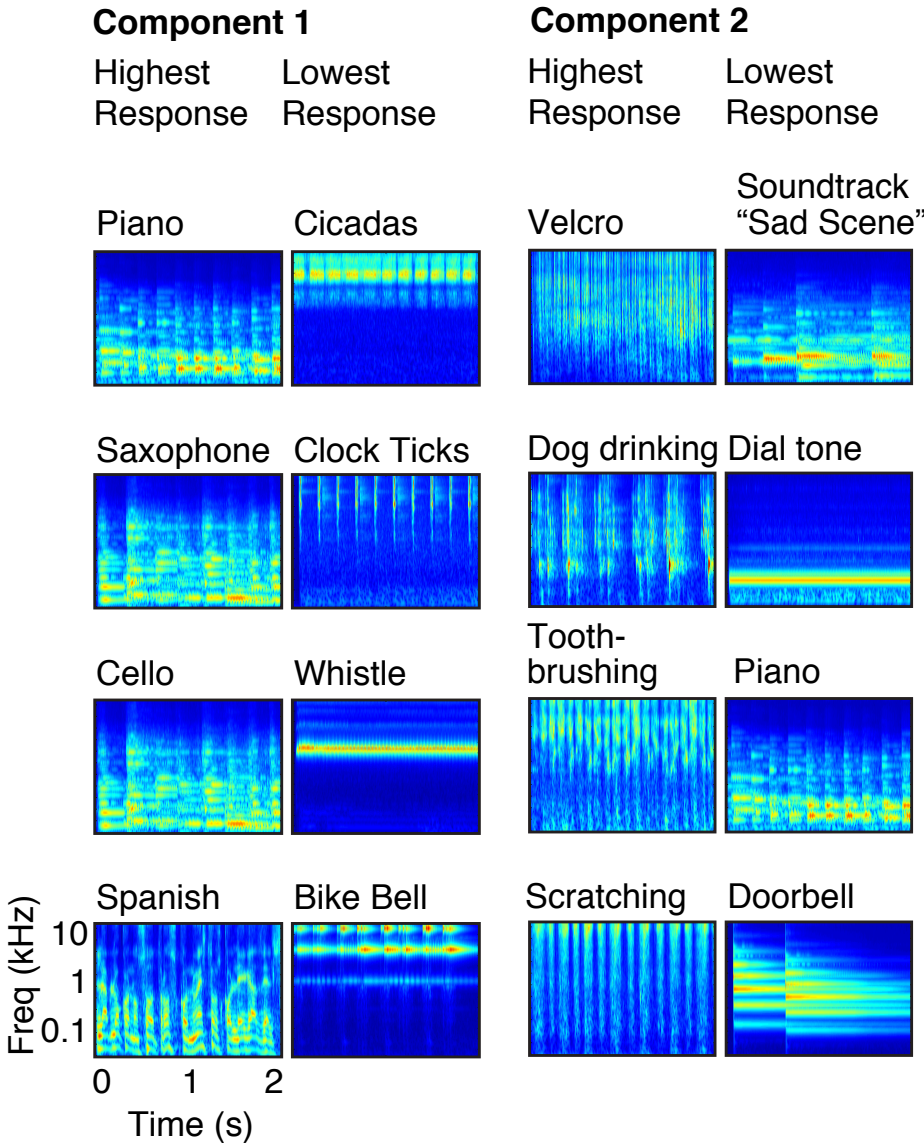
We now have 6 dimensions, each with:

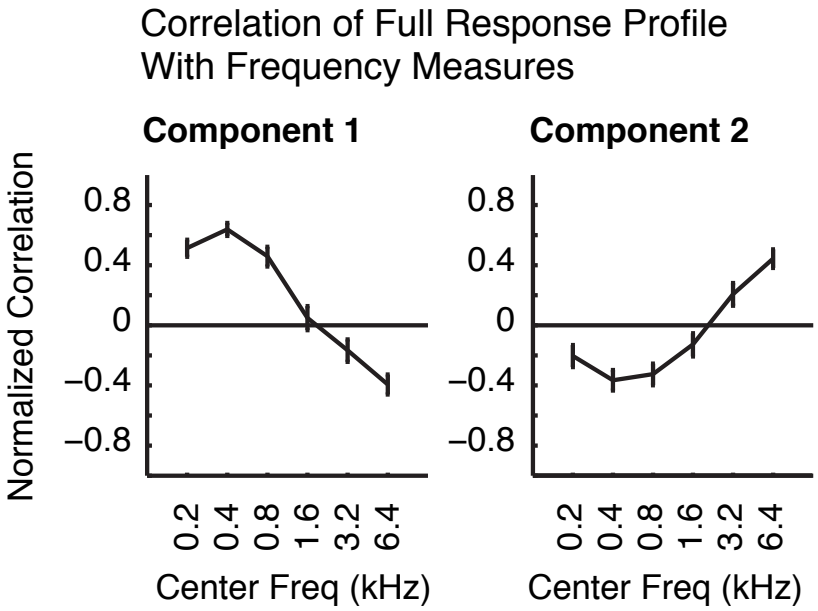
1. A response profile (165-dimensional vector)
2. A weight vector, specifying its contribution to each voxel

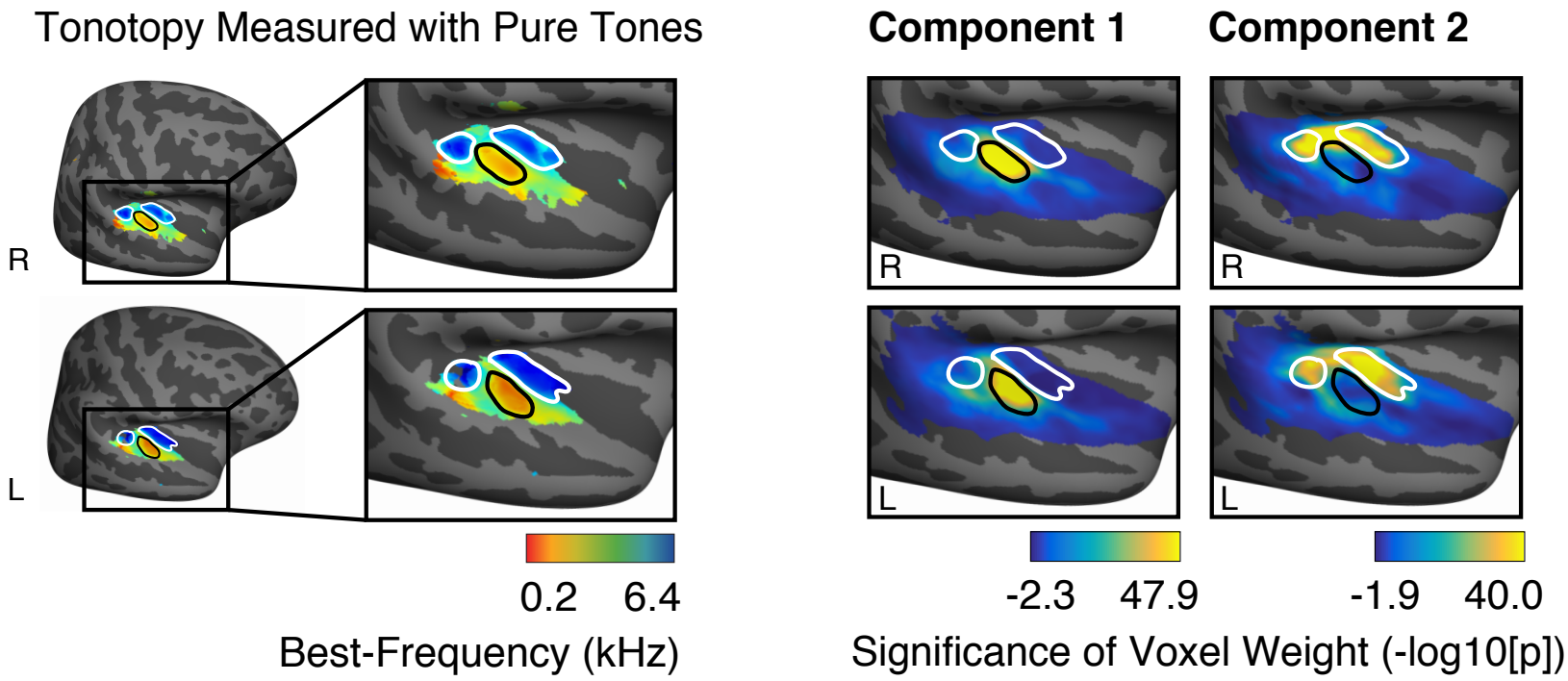





Sound Categories
Instr. Music
Vocal Music
English Speech
Foreign Speech
NonSpeech Vocal
Animal Vocal
Human NonVocal
Animal NonVocal
Nature
Mechanical
Env. Sounds
Raw Response Profiles
Component 1
Component 2
Response Magnitude
2
1
0
All Sounds Tested
2
1
0
All Sounds Tested


Component 1
Highest Response
Lowest Response
Component 2
Highest Response
Lowest Response
Piano
Cicadas
Velcro
Soundtrack "Sad Scene"
Saxophone
Clock Ticks
Dog drinking
Dial tone
Cello
Whistle
Tooth-brushing
Piano
Spanish
Bike Bell
Scratching
Doorbell
Freq (kHz)
10
1
0.1
0
1
2
Time (s)

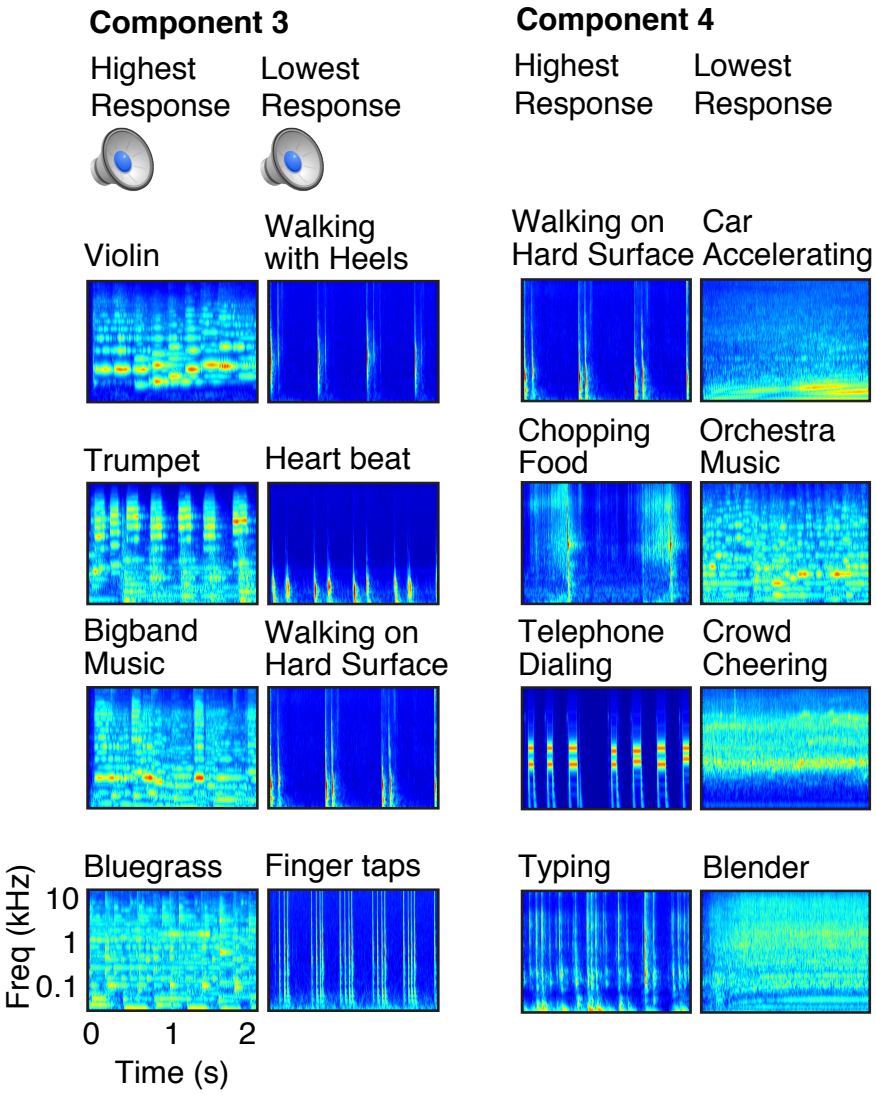

Correlation of Full Response Profile With Frequency Measures
Component 1
Component 2
Normalized Correlation
0.8
0.4
0
−0.4
−0.8
0.2
0.4
0.8
1.6
3.2
6.4
Center Freq (kHz)

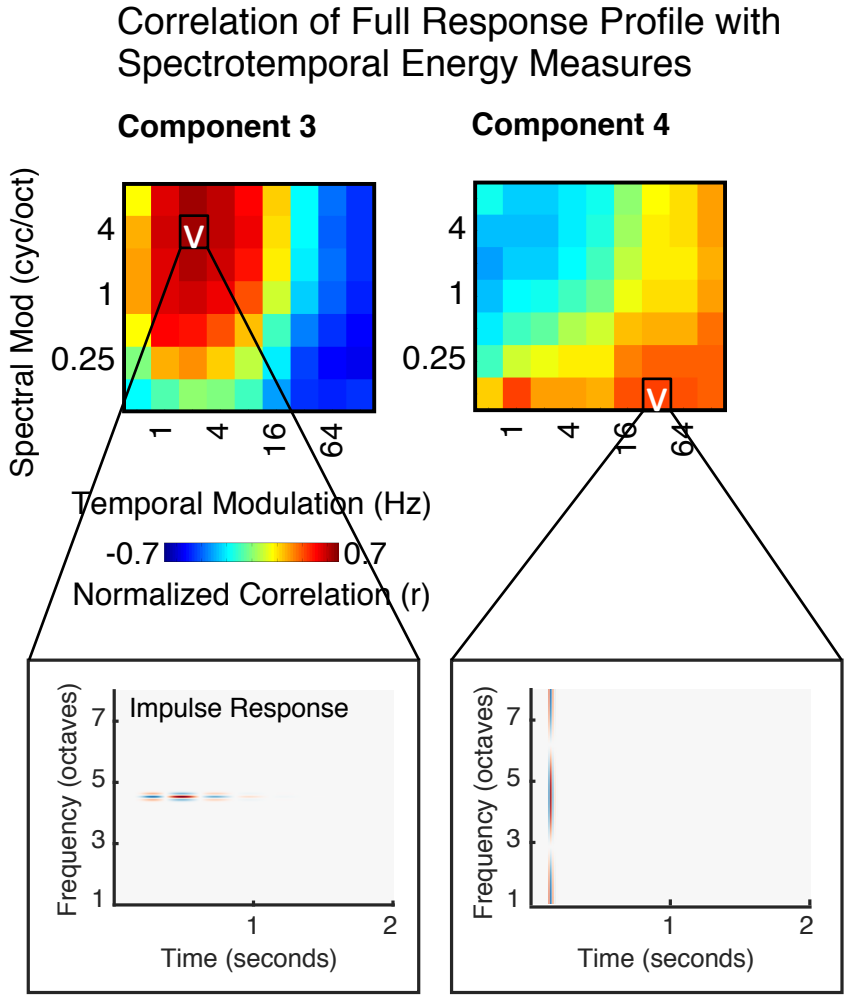


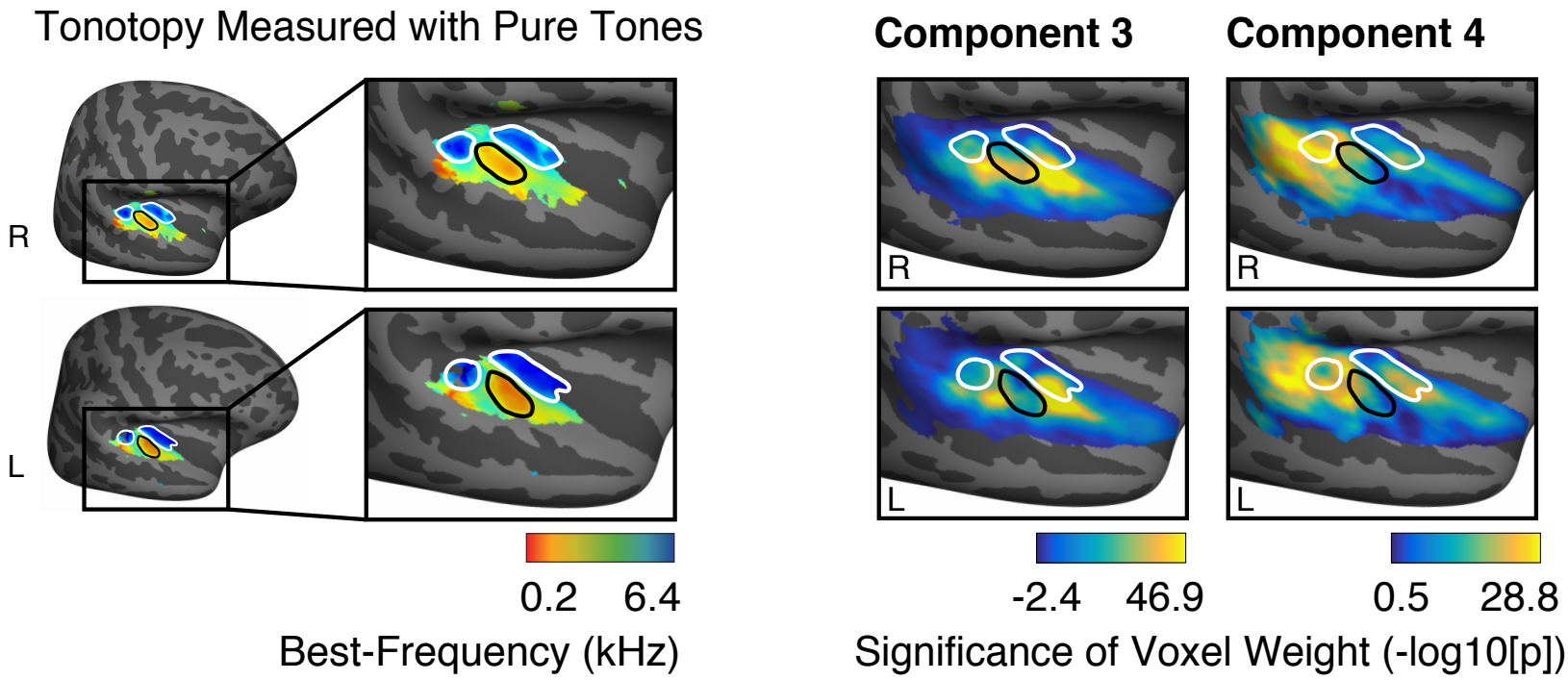
Voxel decomposition discovers tonotopy without prior functional hypotheses

$\Rightarrow$ Tonotopy most widely accepted organizing dimension

$\Rightarrow$ **Helps validate approach**

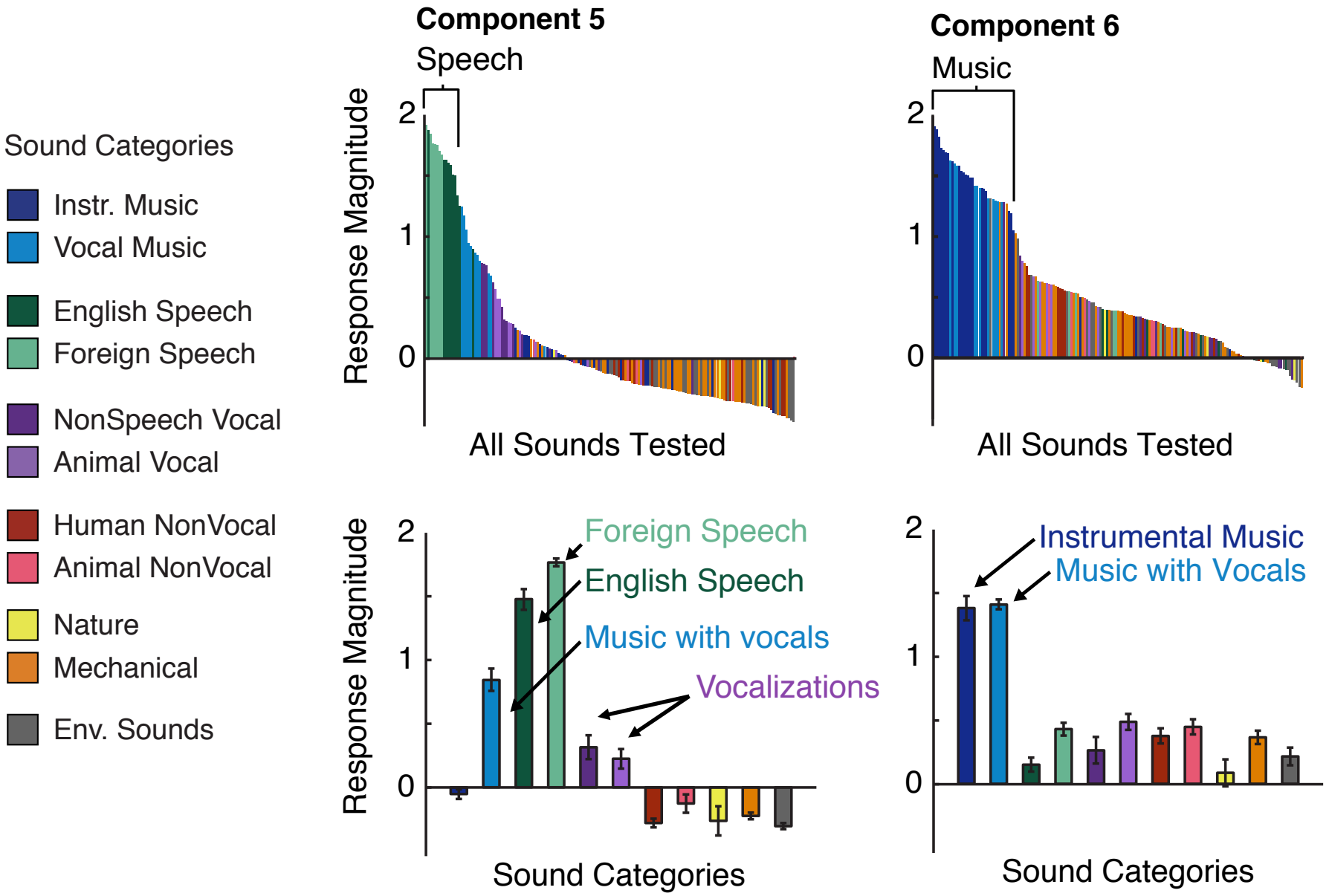

Component 3
Highest Response
Lowest Response
Violin
Walking with Heels
Trumpet
Heart beat
Bigband Music
Walking on Hard Surface
Bluegrass
Finger taps
Freq (kHz)
10
1
0.1
0
1
2
Time (s)
Component 4
Highest Response
Lowest Response
Walking on Hard Surface
Car Accelerating
Chopping Food
Orchestra Music
Telephone Dialing
Crowd Cheering
Typing
Blender

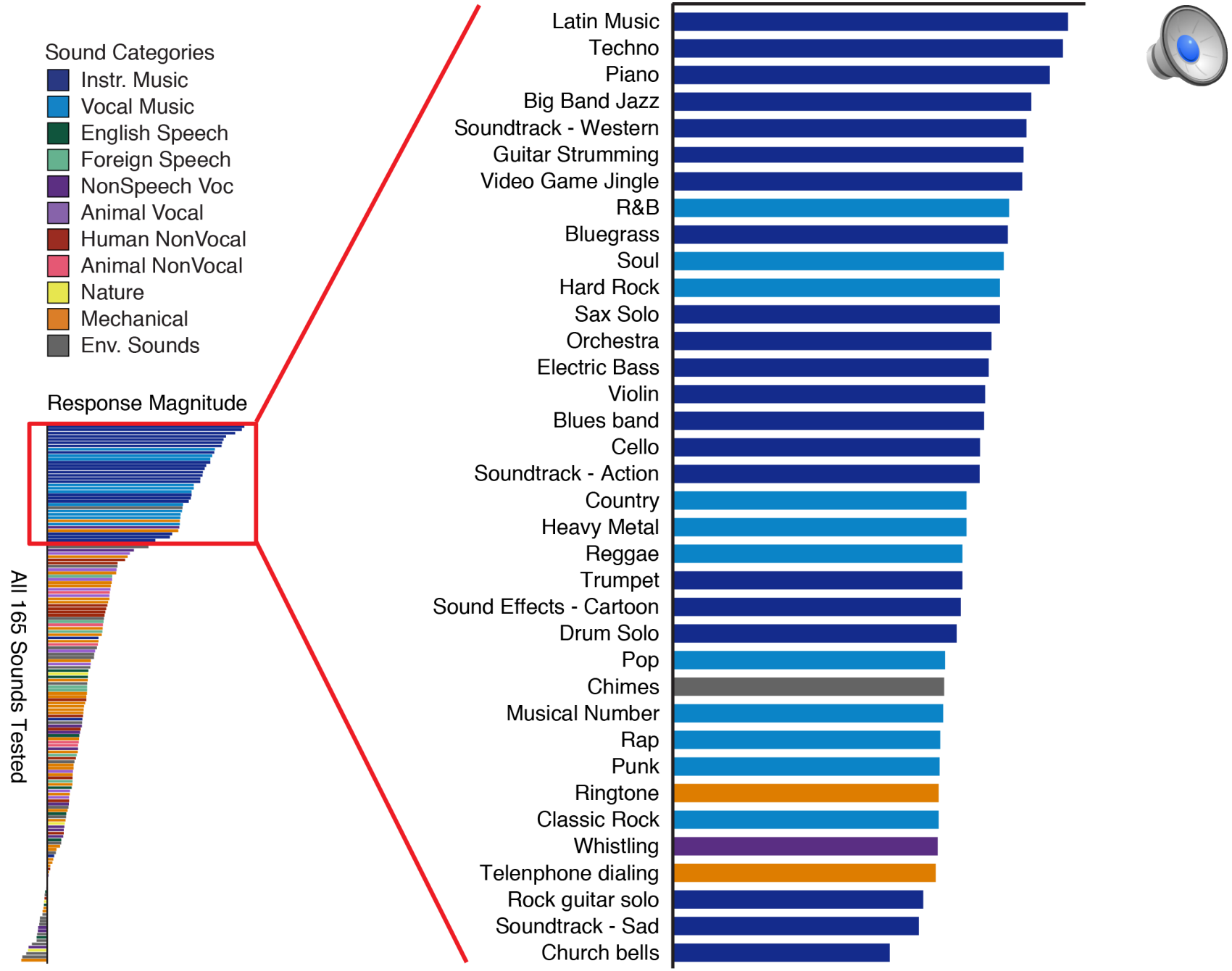

Correlation of Full Response Profile with Spectrotemporal Energy Measures
Component 3
Component 4
Spectral Mod (cyc/oct)
4
1
0.25
1
4
16
64
Temporal Modulation (Hz)
-0.7
0.7
Normalized Correlation (r)
Impulse Response
Frequency (octaves)
7
5
3
1
1
2
Time (seconds)

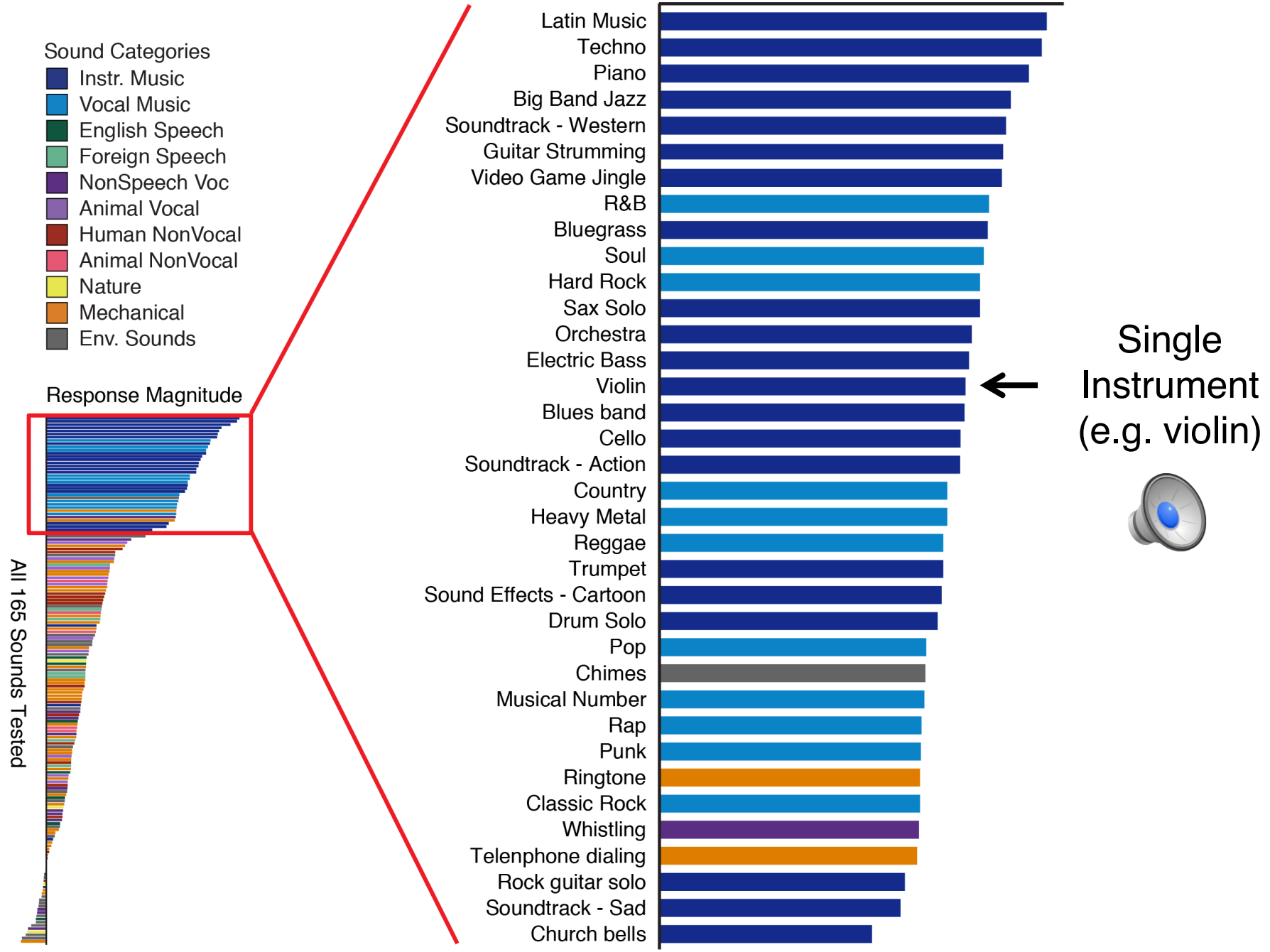


Fine spectral modulations / pitch (Comp 3) mapped more anteriorly

Rapid temporal modulations (Comp 4) mapped more posteriorly


Sound Categories
Instr. Music
Vocal Music
English Speech
Foreign Speech
NonSpeech Vocal
Animal Vocal
Human NonVocal
Animal NonVocal
Nature
Mechanical
Env. Sounds
Component 5
Speech
Response Magnitude
2
1
0
All Sounds Tested
Component 6
Music
2
1
0
All Sounds Tested
Response Magnitude
2
1
0
Foreign Speech
English Speech
Music with vocals
Vocalizations
Sound Categories
2
1
0
Instrumental Music
Music with Vocals
Sound Categories


Sound Categories
Instr. Music
Vocal Music
English Speech
Foreign Speech
NonSpeech Voc
Animal Vocal
Human NonVocal
Animal NonVocal
Nature
Mechanical
Env. Sounds
Response Magnitude
All 165 Sounds Tested
Latin Music
Techno
Piano
Big Band Jazz
Soundtrack - Western
Guitar Strumming
Video Game Jingle
R&B
Bluegrass
Soul
Hard Rock
Sax Solo
Orchestra
Electric Bass
Violin
Blues band
Cello
Soundtrack - Action
Country
Heavy Metal
Reggae
Trumpet
Sound Effects - Cartoon
Drum Solo
Pop
Chimes
Musical Number
Rap
Punk
Ringtone
Classic Rock
Whistling
Telenphone dialing
Rock guitar solo
Soundtrack - Sad
Church bells


Sound Categories
Instr. Music
Vocal Music
English Speech
Foreign Speech
NonSpeech Voc
Animal Vocal
Human NonVocal
Animal NonVocal
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Env. Sounds
Response Magnitude
All 165 Sounds Tested
Latin Music
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Blues band
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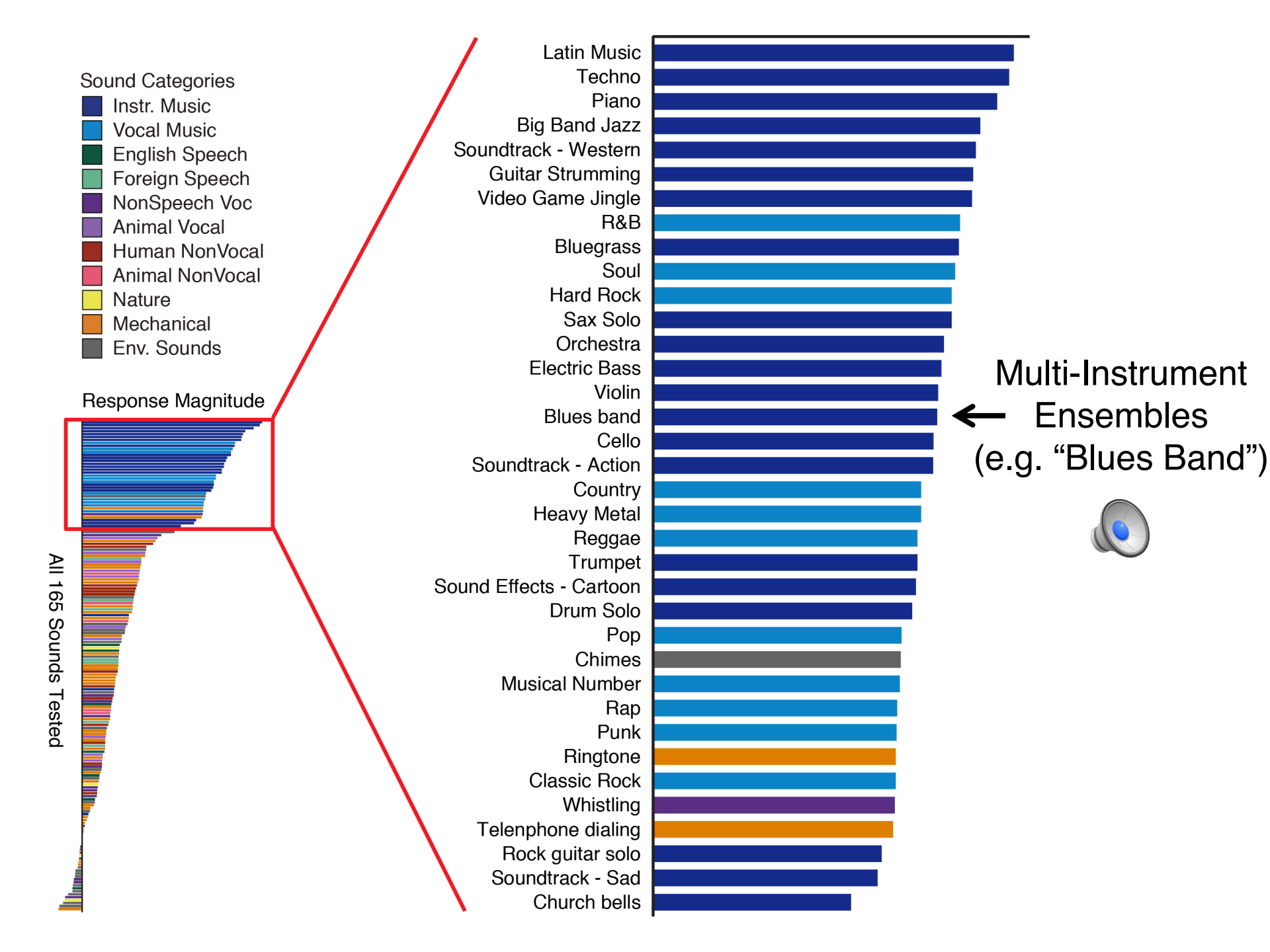
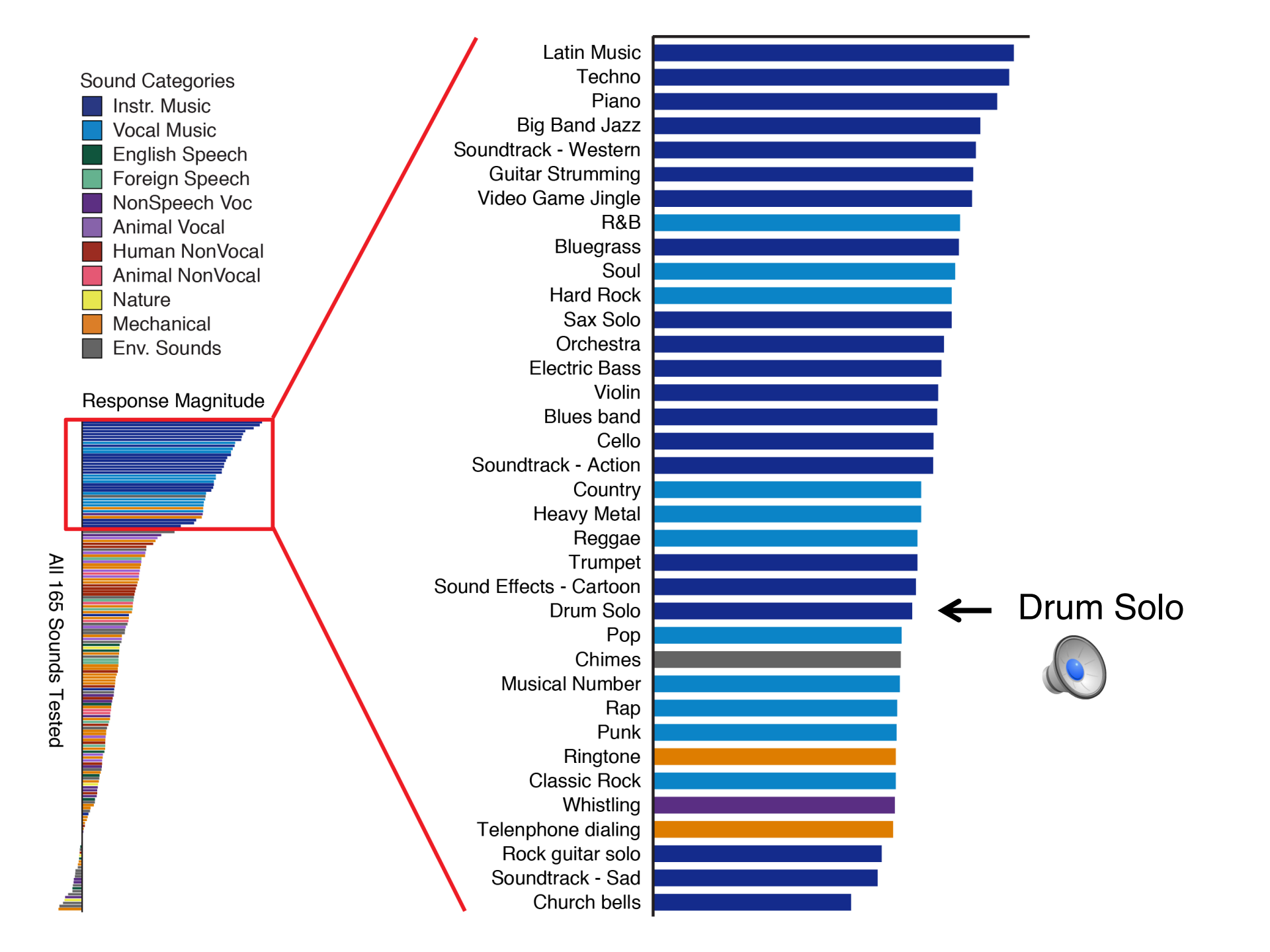
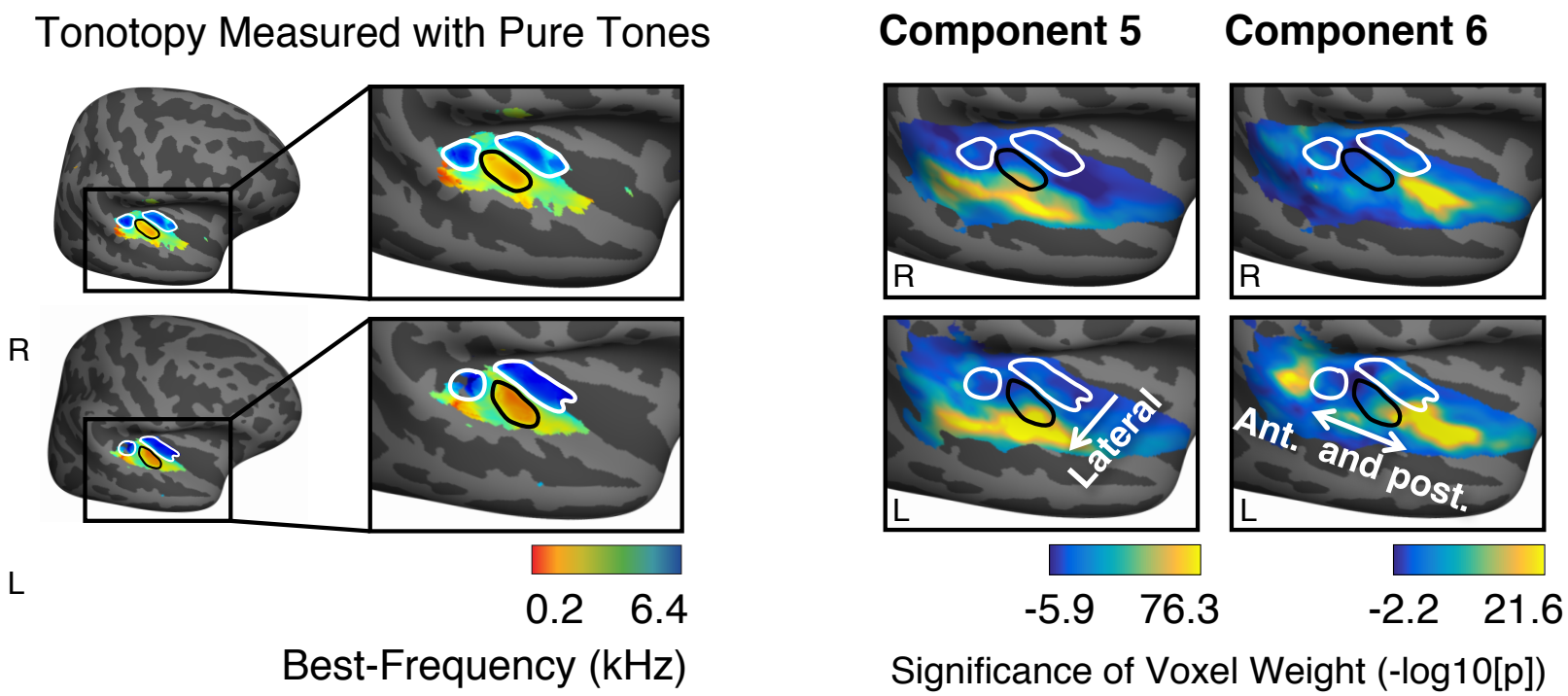
Soundtrack - Action
Country
Heavy Metal
Reggae
Trumpet
Sound Effects - Cartoon
Drum Solo
Pop
Chimes
Musical Number
Rap
Punk
Ringtone
Classic Rock
Whistling
Telenphone dialing
Rock guitar solo
Soundtrack - Sad
Church bells
Single Instrument (e.g. violin)


Sound Categories
Instr. Music
Vocal Music
English Speech
Foreign Speech
NonSpeech Voc
Animal Vocal
Human NonVocal
Animal NonVocal
Nature
Mechanical
Env. Sounds
Response Magnitude
All 165 Sounds Tested
Latin Music
Techno
Piano
Big Band Jazz
Soundtrack - Western
Guitar Strumming
Video Game Jingle
R&B
Bluegrass
Soul
Hard Rock
Sax Solo
Orchestra
Electric Bass
Violin
Blues band
Cello
Soundtrack - Action
Country
Heavy Metal
Reggae
Trumpet
Sound Effects - Cartoon
Drum Solo
Pop
Chimes
Musical Number
Rap
Punk
Ringtone
Classic Rock
Whistling
Telenphone dialing
Rock guitar solo
Soundtrack - Sad
Church bells
Multi-Instrument
Ensembles
(e.g. “Blues Band”)


Sound Categories
Instr. Music
Vocal Music
English Speech
Foreign Speech
NonSpeech Voc
Animal Vocal
Human NonVocal
Animal NonVocal
Nature
Mechanical
Env. Sounds
Response Magnitude
All 165 Sounds Tested
Latin Music
Techno
Piano
Big Band Jazz
Soundtrack - Western
Guitar Strumming
Video Game Jingle
R&B
Bluegrass
Soul
Hard Rock
Sax Solo
Orchestra
Electric Bass
Violin
Blues band
Cello
Soundtrack - Action
Country
Heavy Metal
Reggae
Trumpet
Sound Effects - Cartoon
Drum Solo
Pop
Chimes
Musical Number
Rap
Punk
Ringtone
Classic Rock
Whistling
Telenphone dialing
Rock guitar solo
Soundtrack - Sad
Church bells
Drum Solo

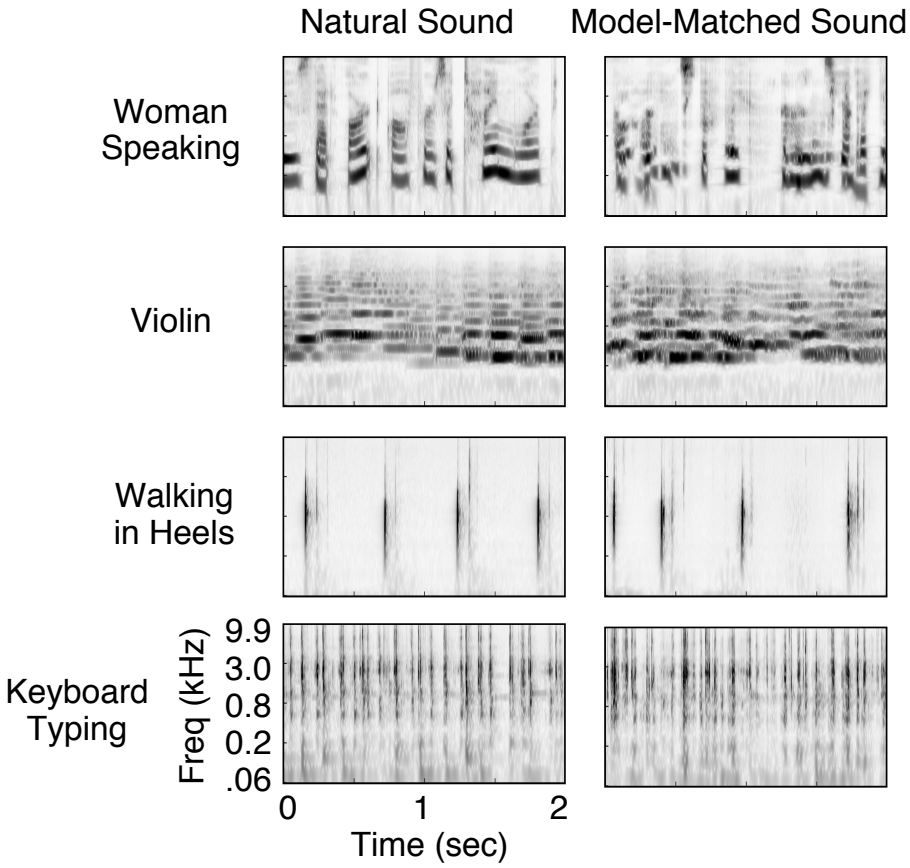


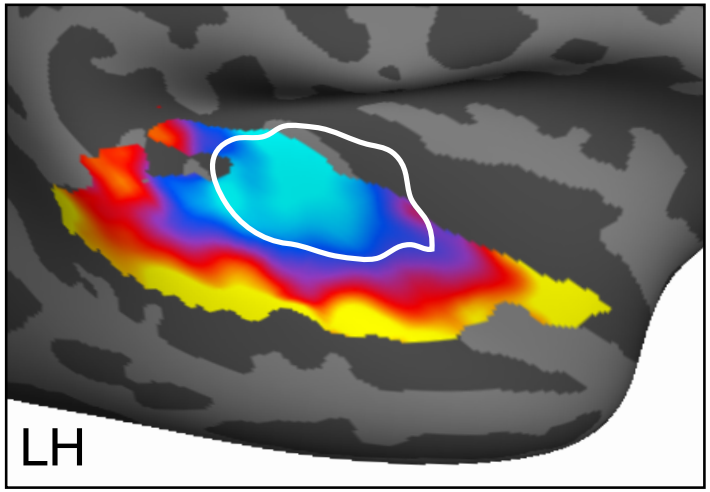
Speech-selectivity lateral to primary auditory cortex

Music-selectivity anterior and posterior to primary auditory cortex

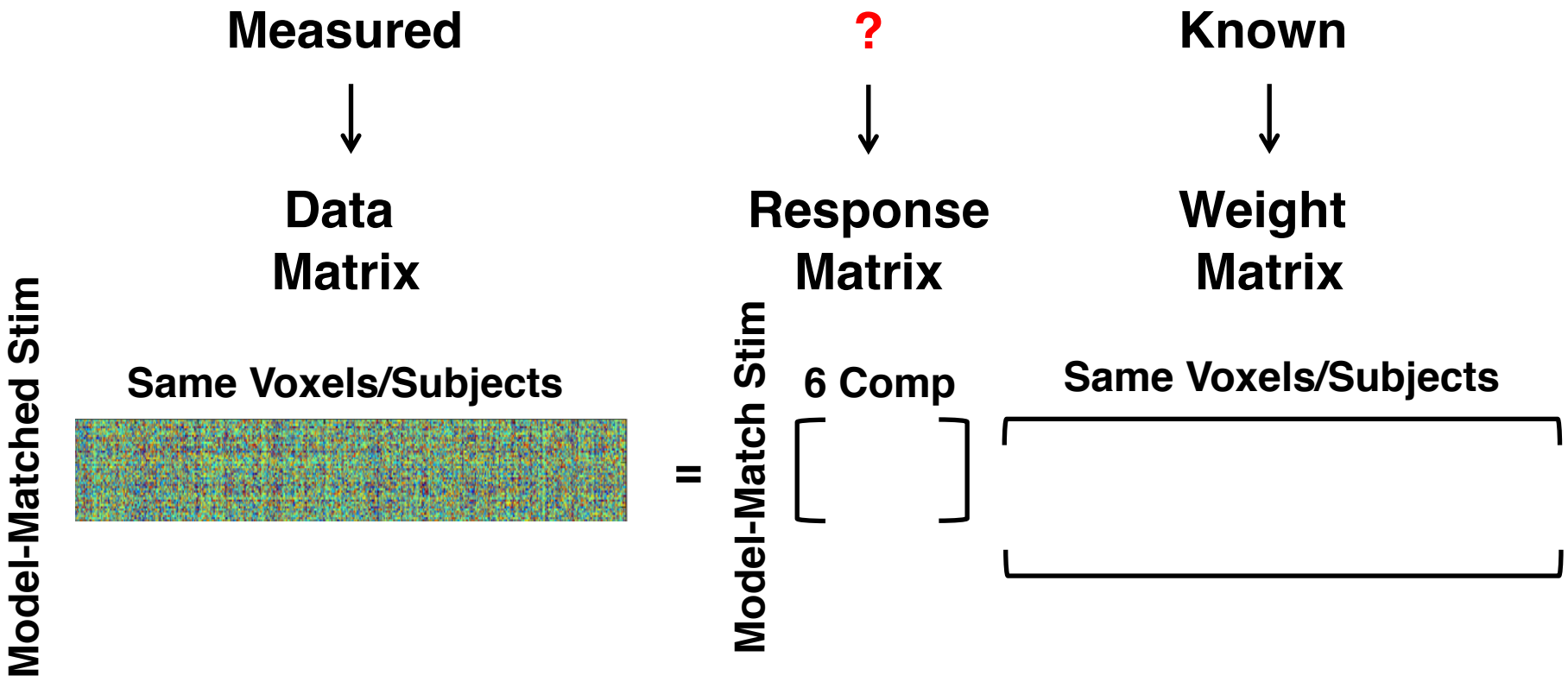
⇒ **Suggests distinct non-primary pathways for speech and music**

Can speech and music-selectivity be explained by tuning for modulation?





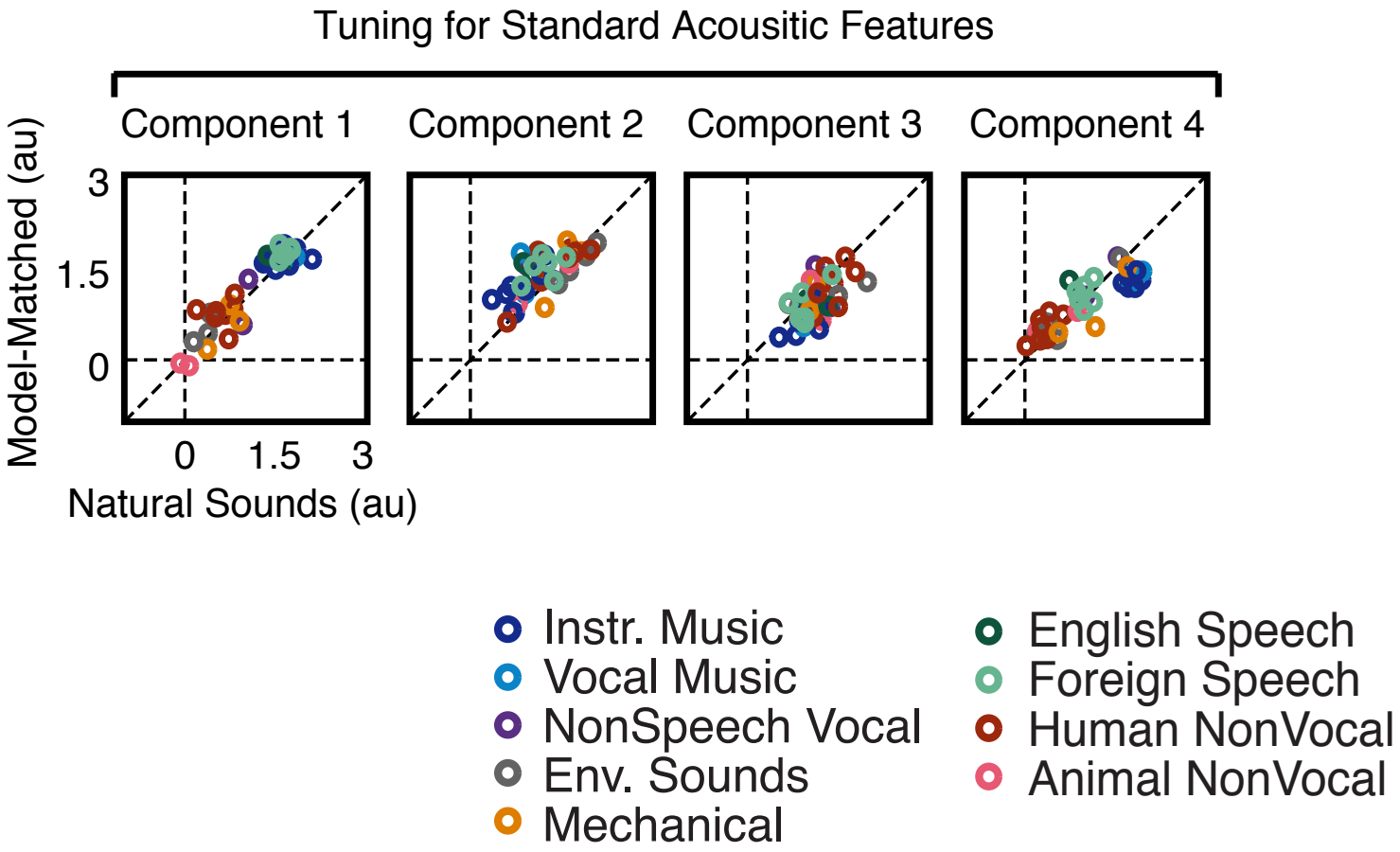
Model-Matched Stimuli



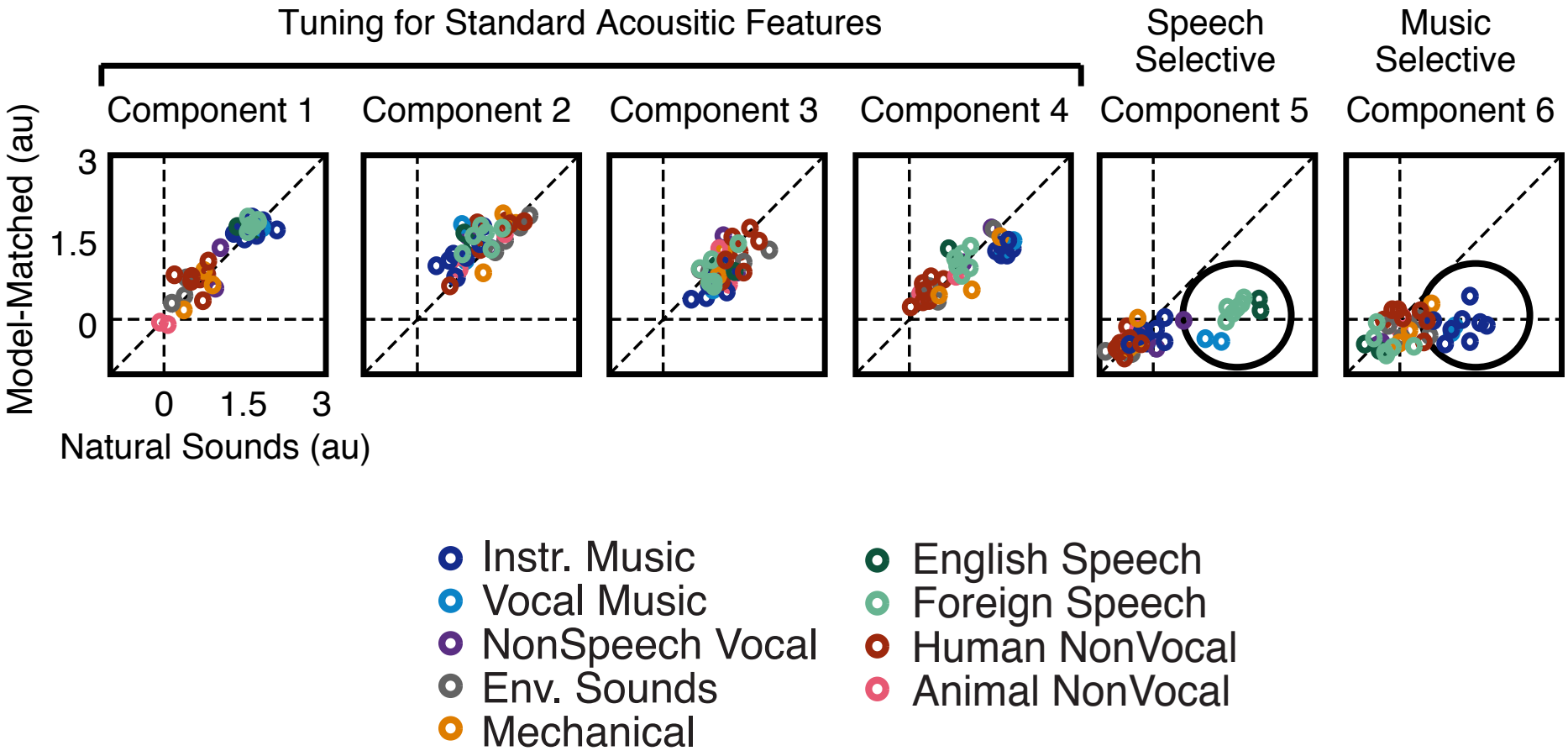
$$D = RW$$

$$DW^T(WW^T)^{-1} = R$$

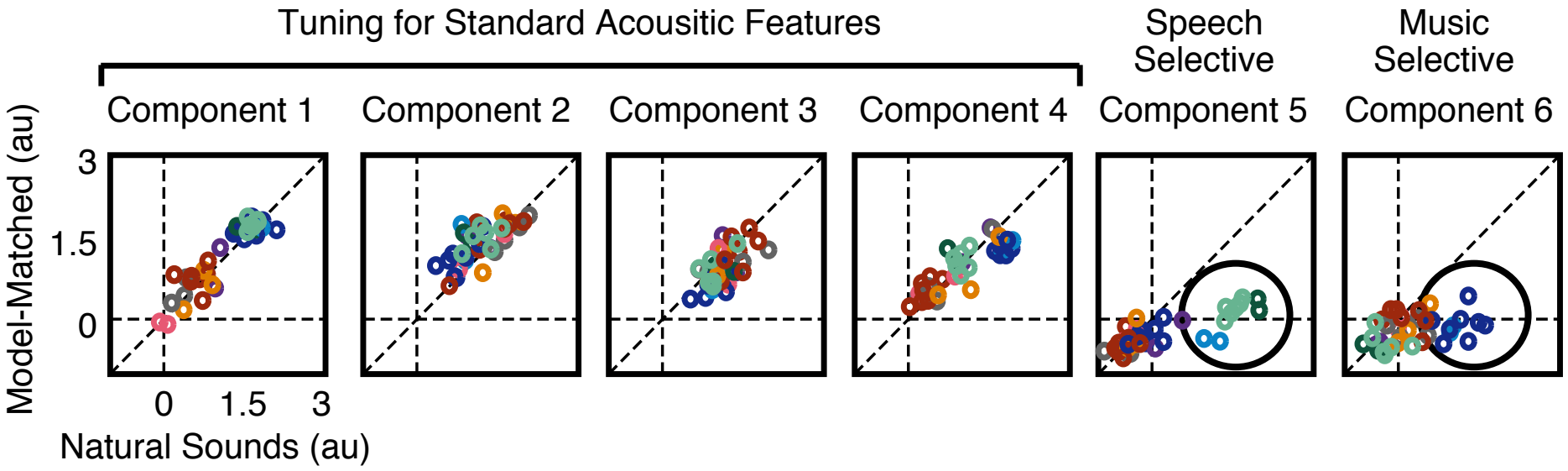
Model-Matched Stimuli



Model-Matched Stimuli

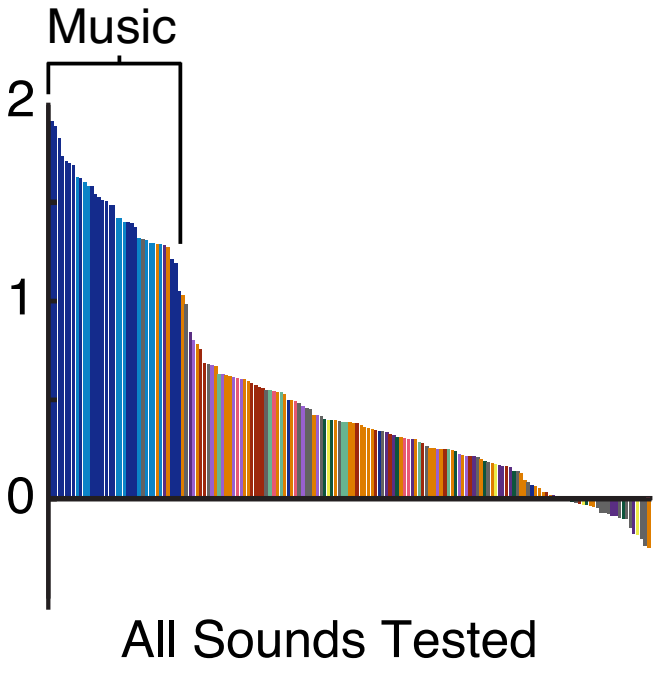


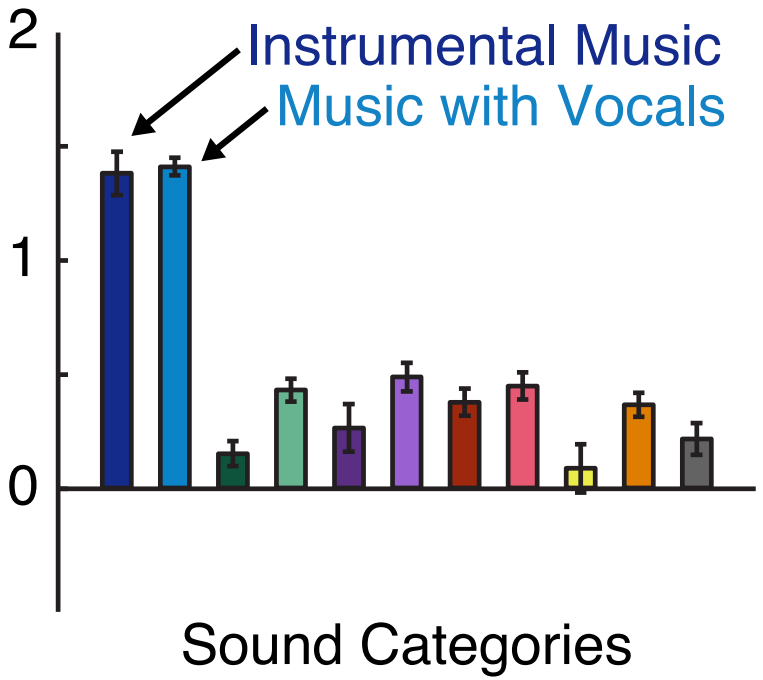
Model-Matched Stimuli



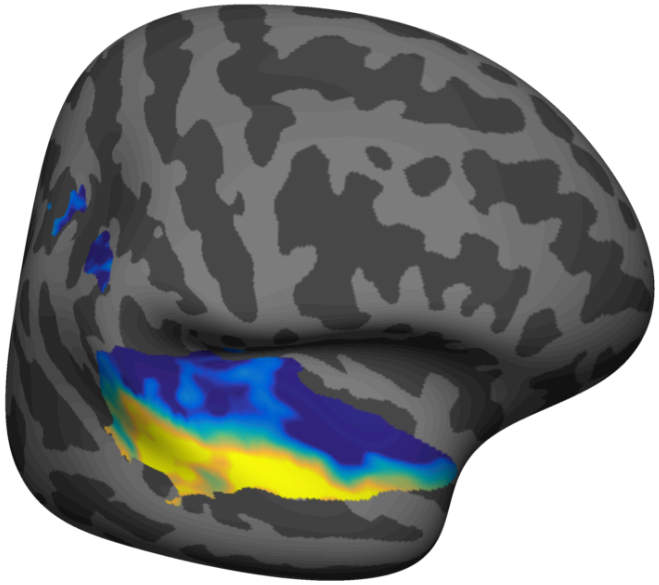
Speech and music selectivity not explained by modulation model

Why has music selectivity not been clearly observed before?





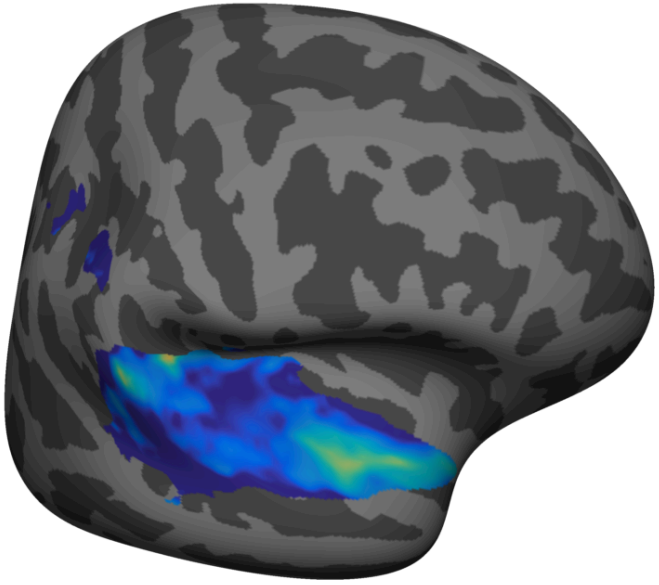
Speech-Selective
Component 5



0 0.6

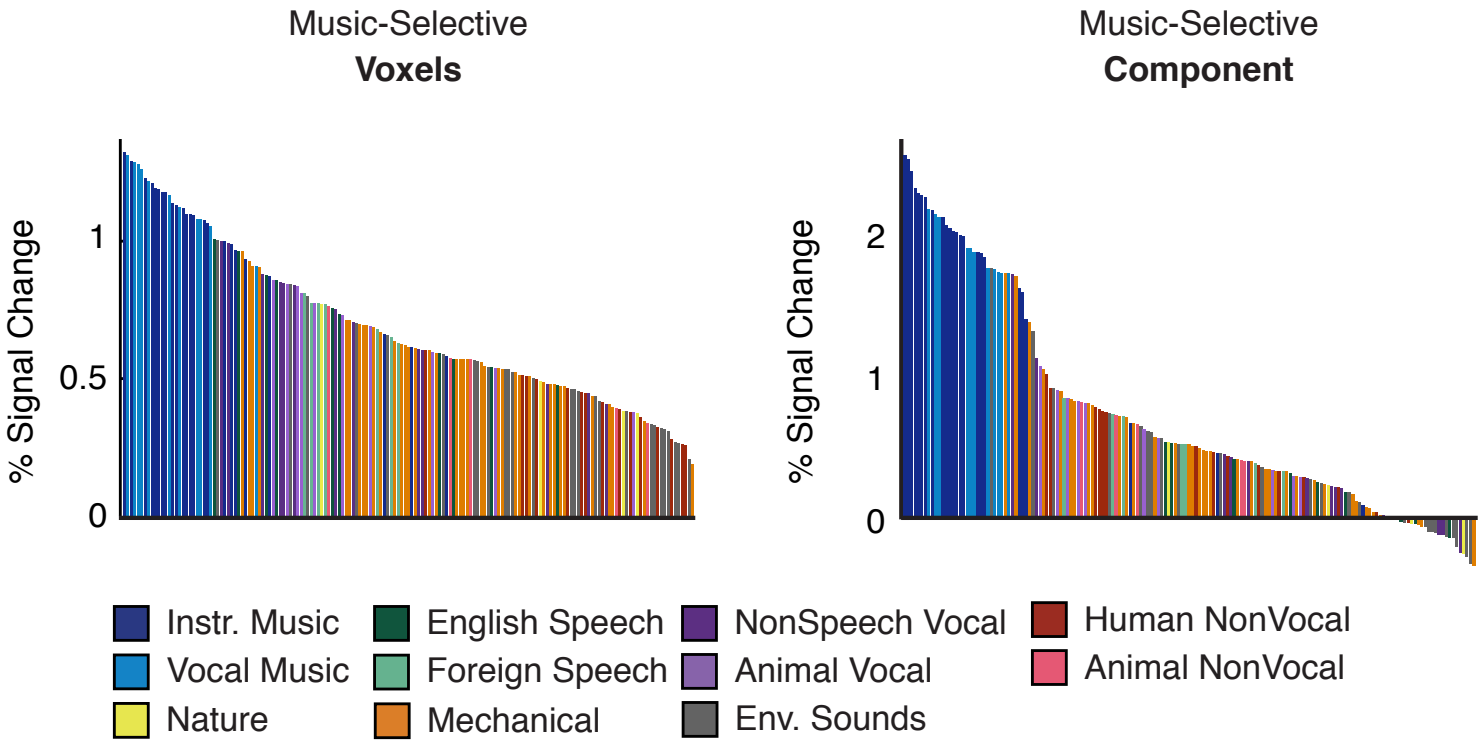
Voxel Weight
Selectivity/Purity $\left(\frac{w_i}{\sum_j^6 |w_j|}\right)$

Music-Selective
Component 6



0 0.6

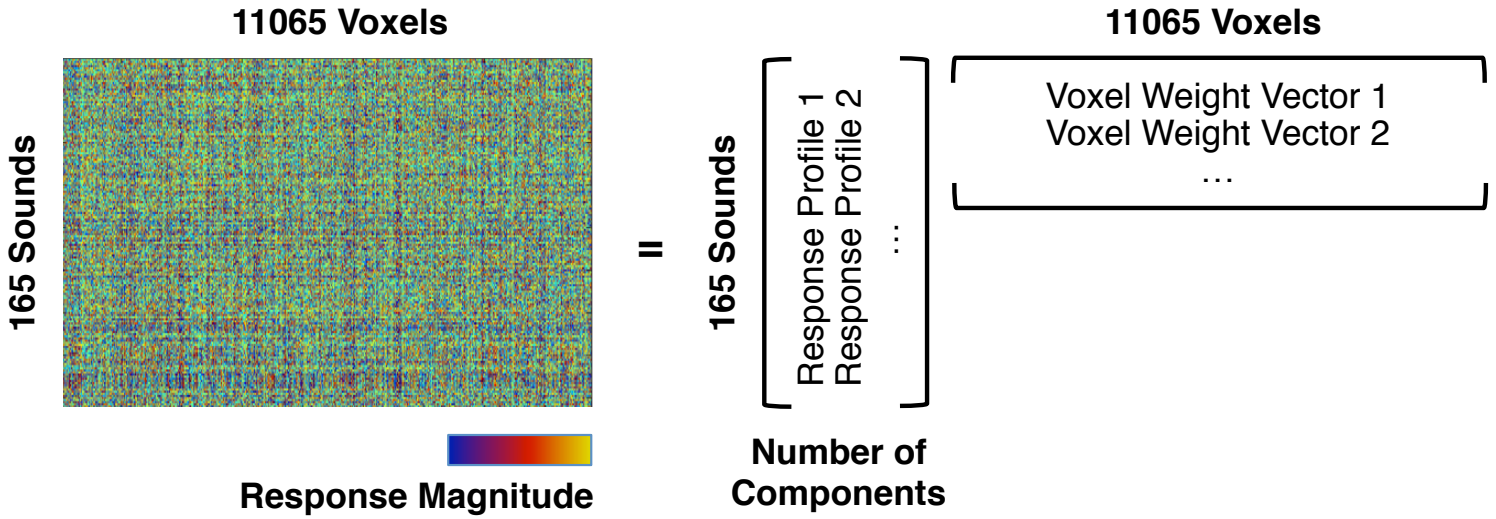
Voxel Weight
Selectivity/Purity $\left(\frac{w_i}{\sum_j^6 |w_j|}\right)$


Music-Selective
Voxels
% Signal Change
1
0.5
0
Music-Selective
Component
% Signal Change
2
1
0
Instr. Music
Vocal Music
Nature
English Speech
Foreign Speech
Mechanical
NonSpeech Vocal
Animal Vocal
Env. Sounds
Human NonVocal
Animal NonVocal

Conclusions from Part 2

1. Novel approach for discovering functional organization

   $\Rightarrow$ Voxel decomposition of responses to natural sounds



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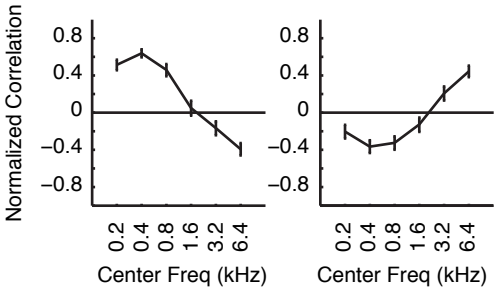
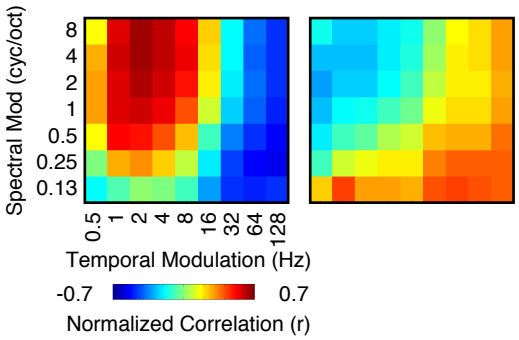
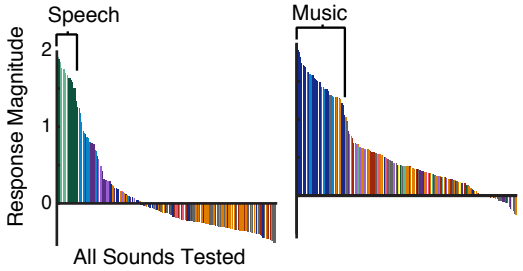
2. Six components explain responses throughout auditory cortex

   $\Rightarrow$ Each with interpretable response selectivity, despite lack of constraints







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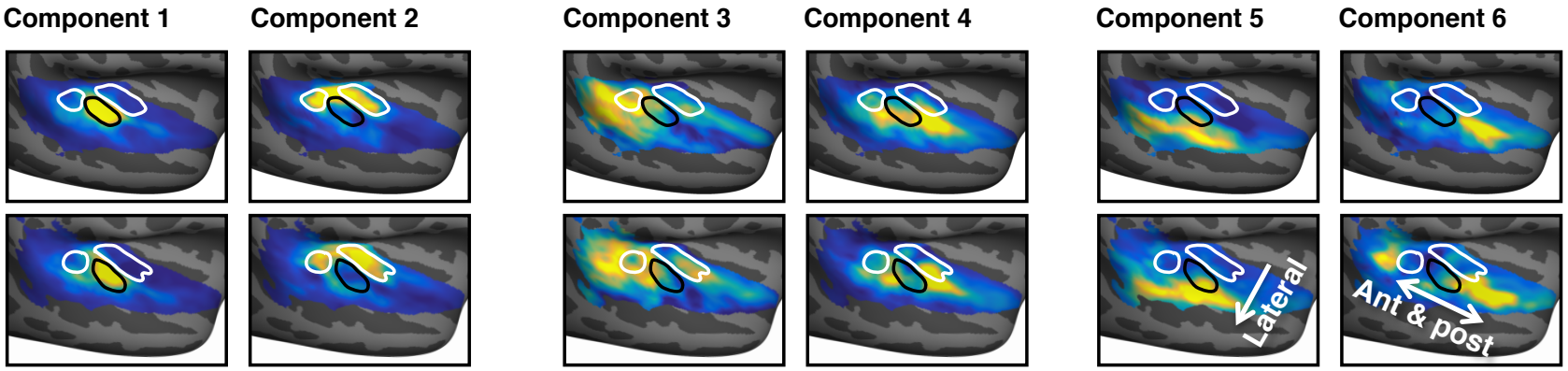

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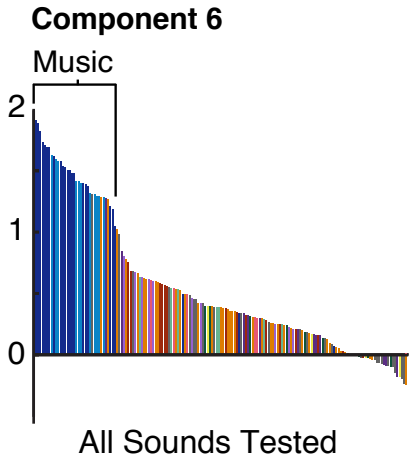

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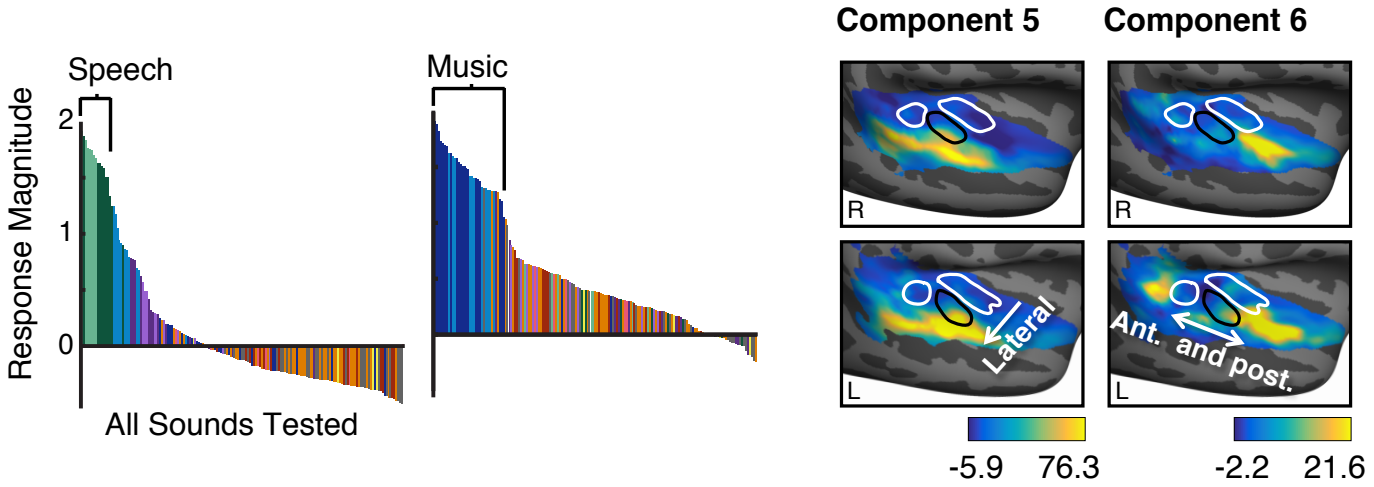
4. And distinct non-primary pathways for music and speech



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Thanks!