Learning spectro-temporal representation of complex sounds with parameterized neural networks

Rachid Riad, Julien Karadayi, Anne-Catherine Bachoud-Levi and Emmanuel Dupoux

https://arxiv.org/abs/2103.07125

Examples of auditory inputs

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1. People chatting inside 
2. Car alarm 
3. Bird 

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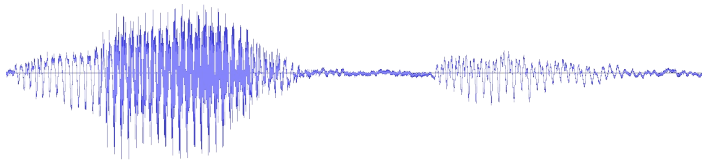
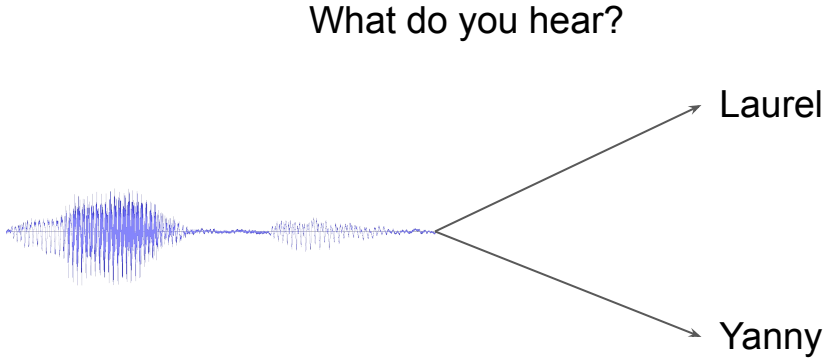


Audition

How do we obtain meaningful information from sounds?

Psychology



Audition

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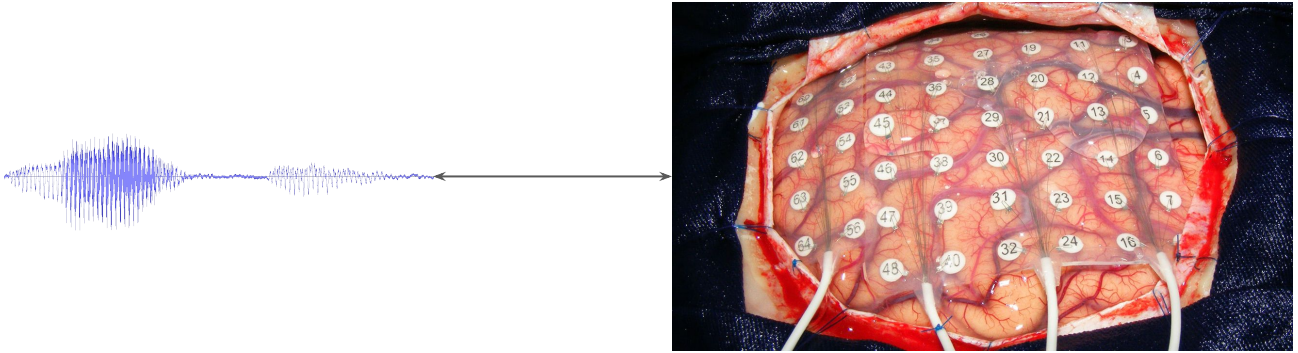
Auditory Neuroscience

How sounds are represented in the brain?

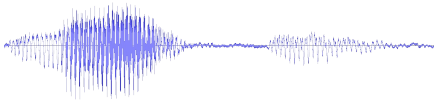


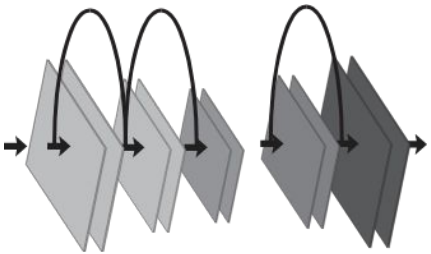
Audition

How do we obtain meaningful information from sounds?

Machine Listening

Can we design an algorithm to deal with sounds?





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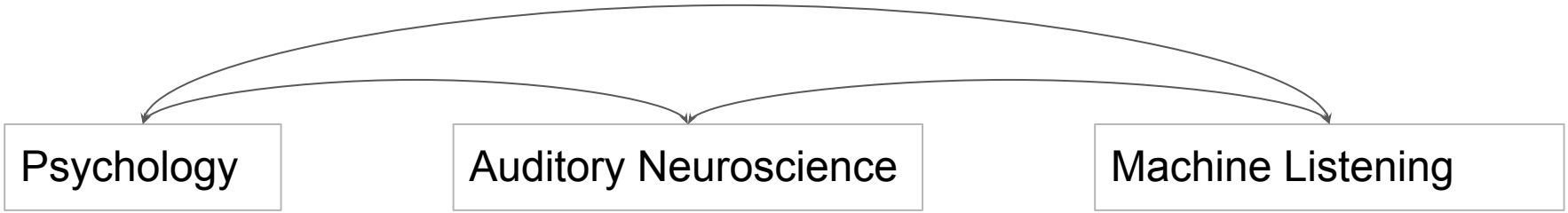

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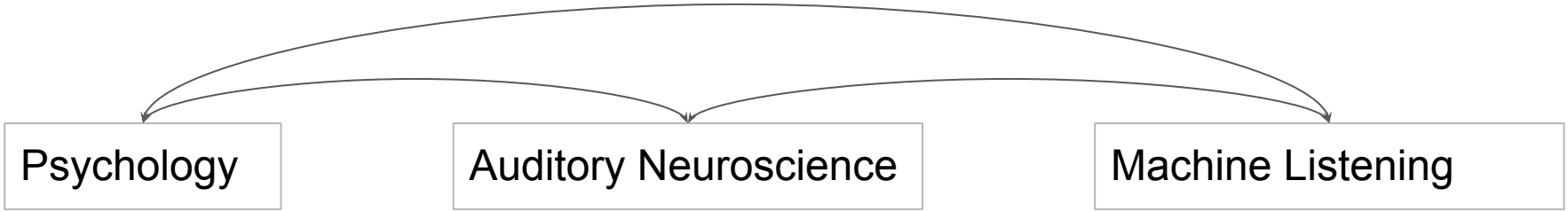
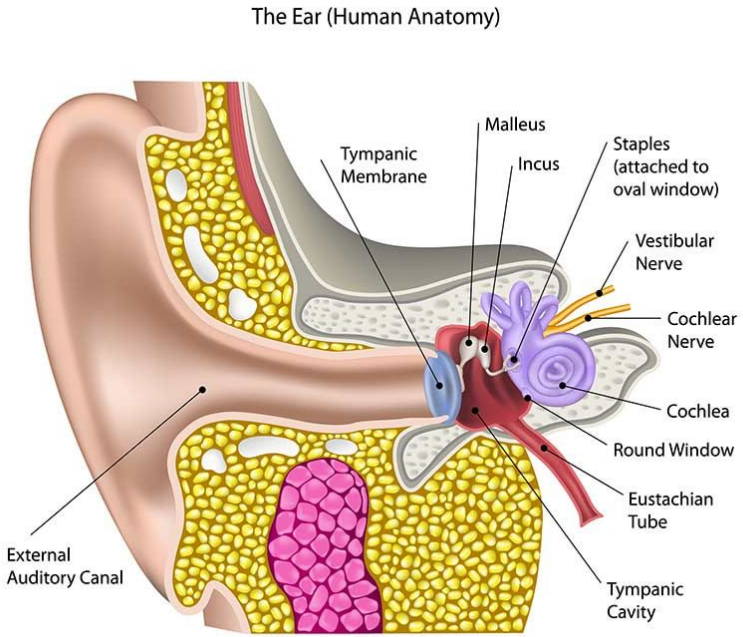


Not so much in practice!!

Classic auditory models



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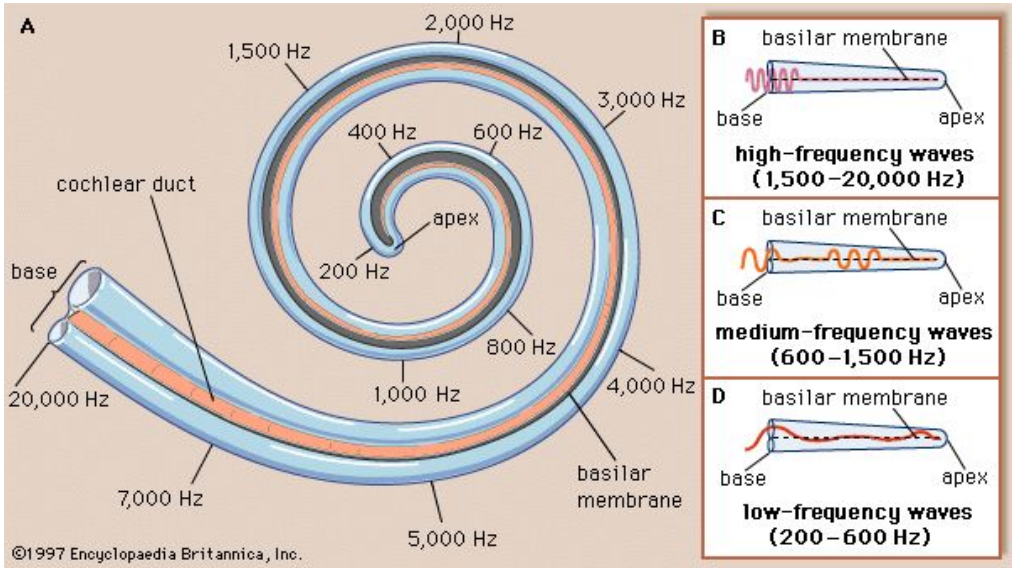

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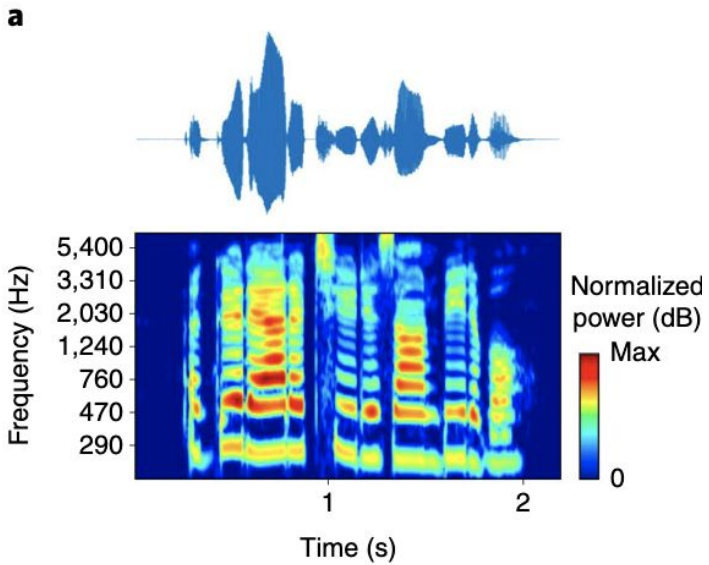
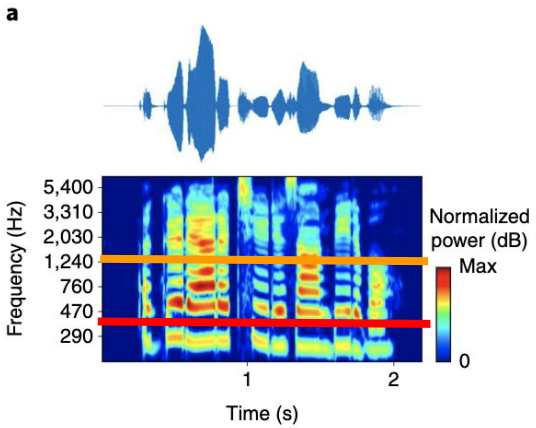
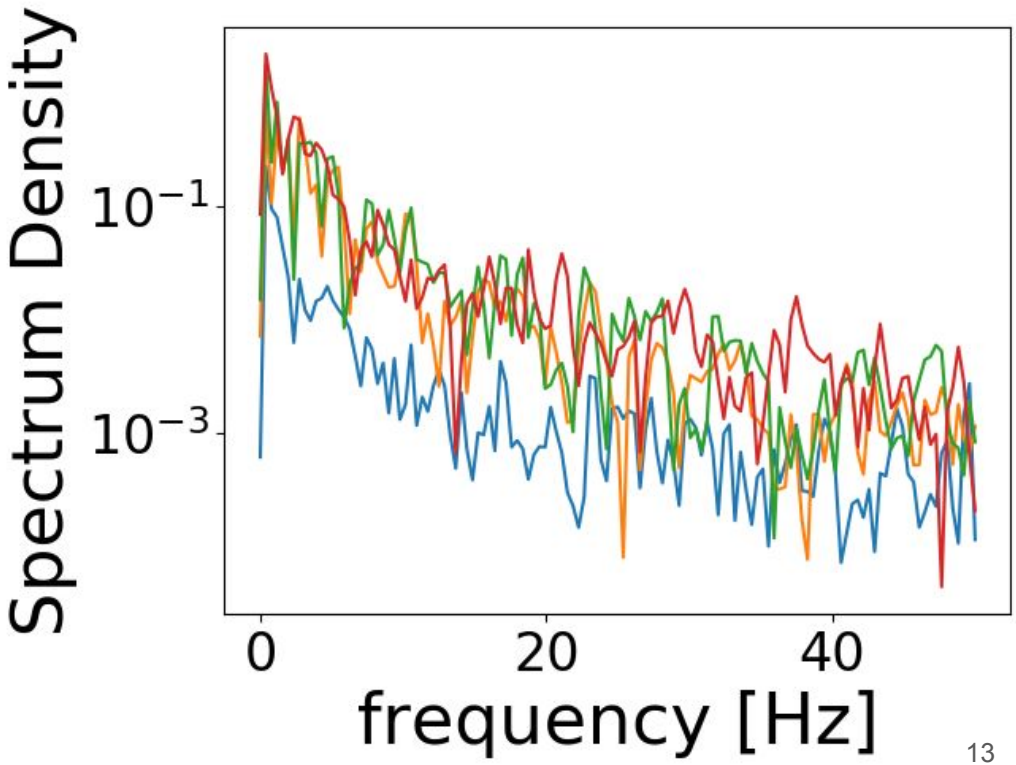


Modulations of the spectrogram





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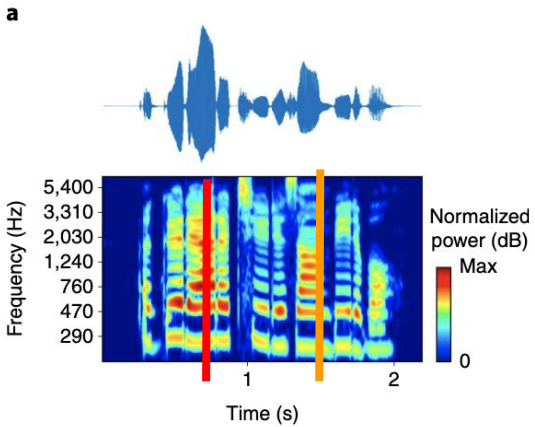

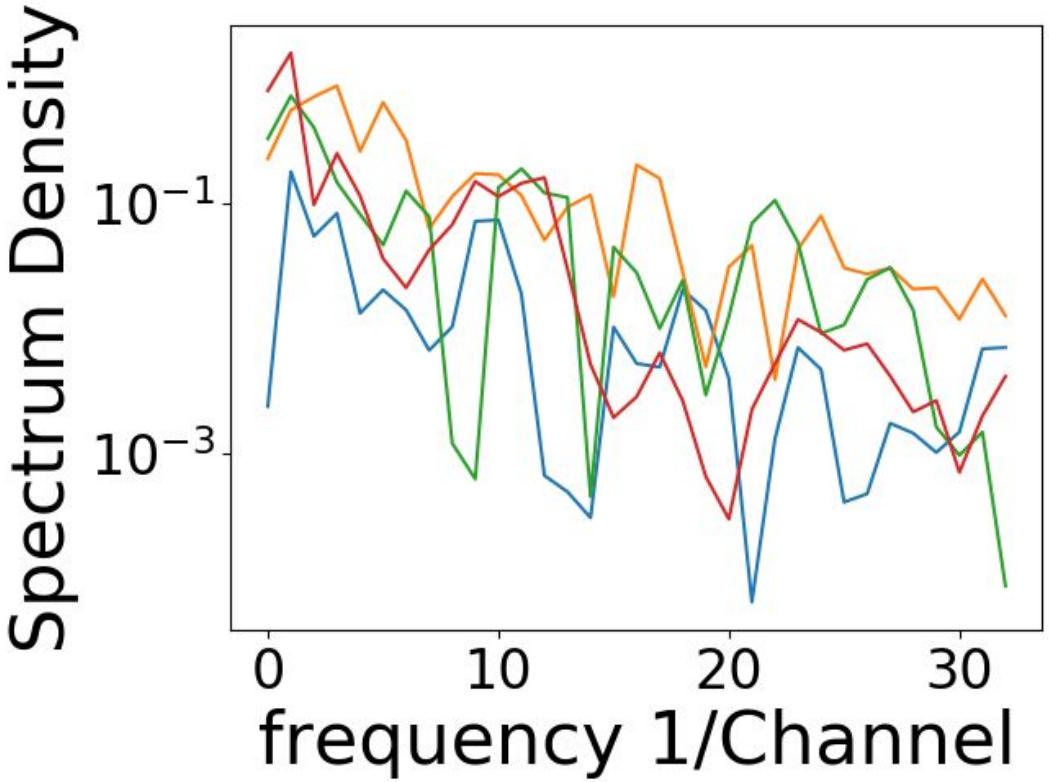

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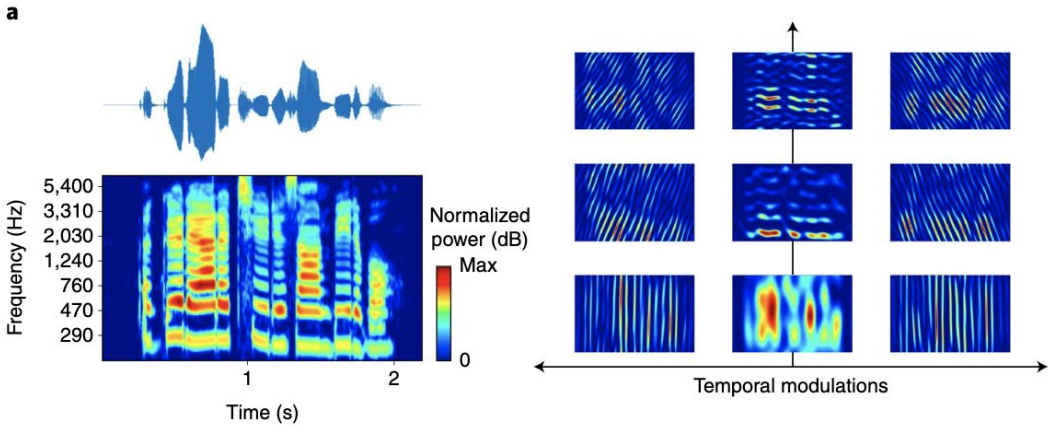

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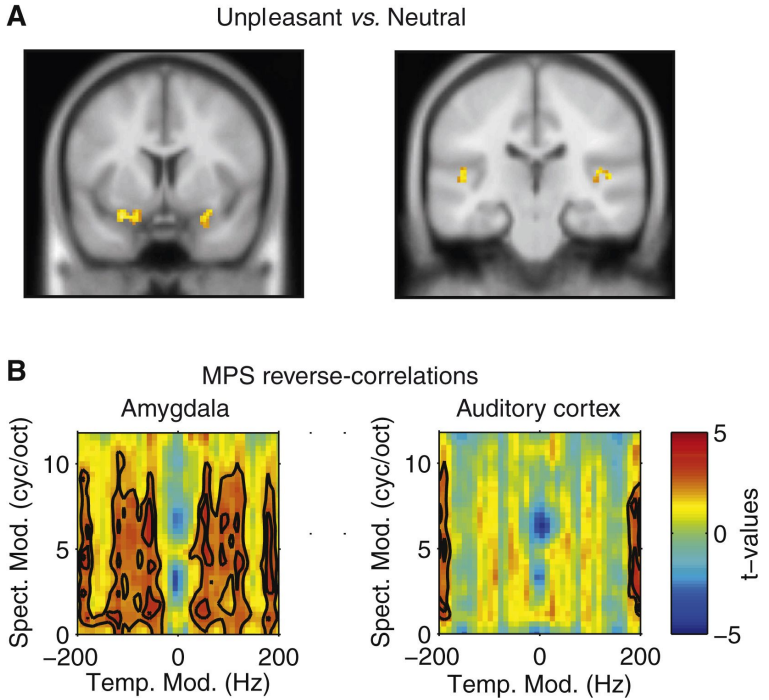
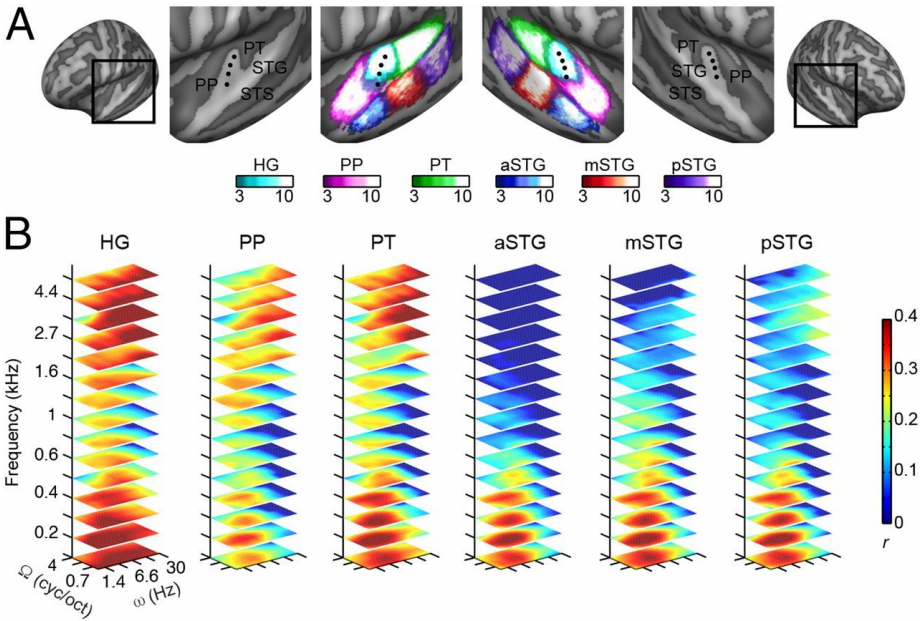


Arnal et al. 2015



Santoro et al. 2017

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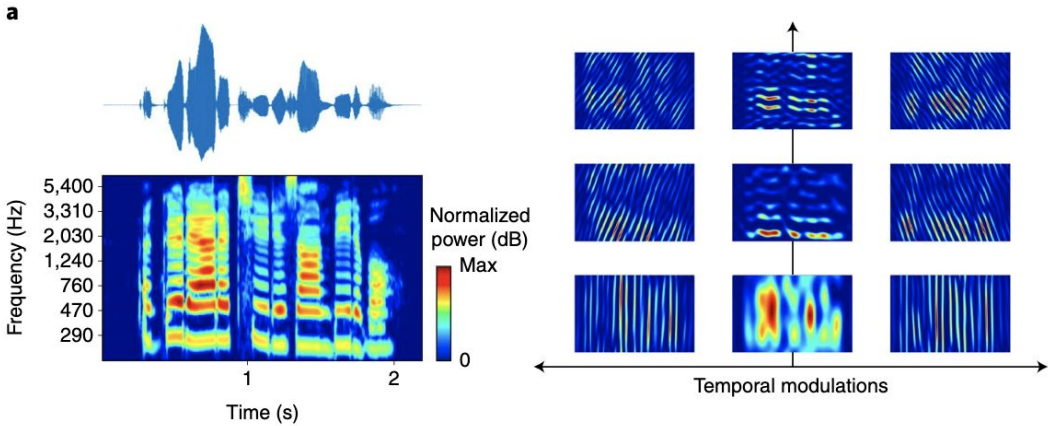
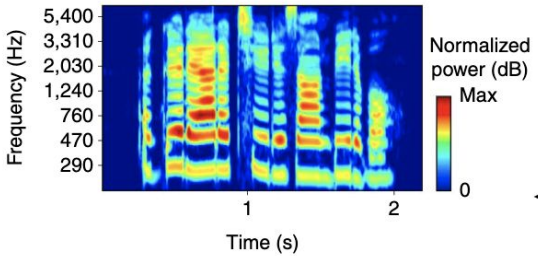
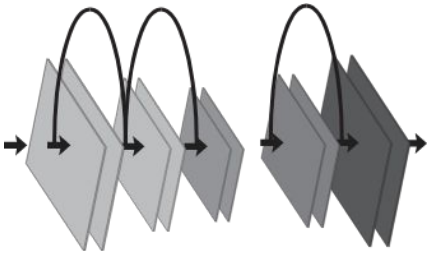


- Does not account for **behaviour**
- Does not correlate much with the **brain**

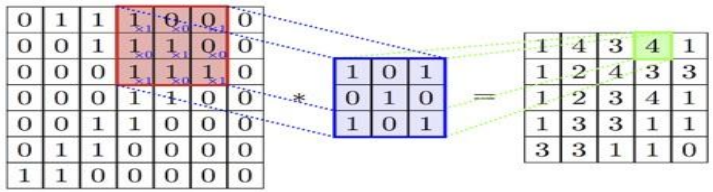
Deep Learning models as models of audition

Human level performance reached by Deep Neural Networks based on the spectrogram

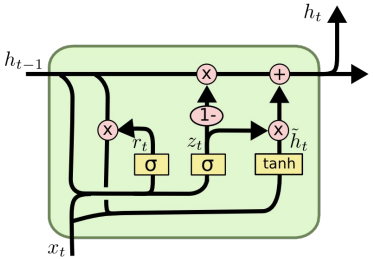




Convolution layers



Recurrent layers



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

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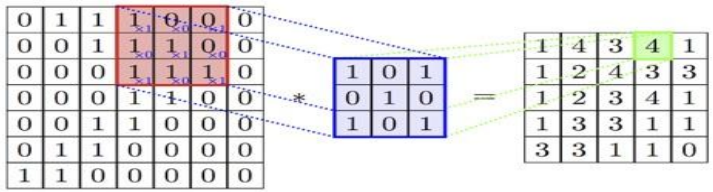
Human level performance reached by Deep Neural Networks based on the spectrogram

Not **interpretable** for neuroscientists and psychologists

Convolution layers



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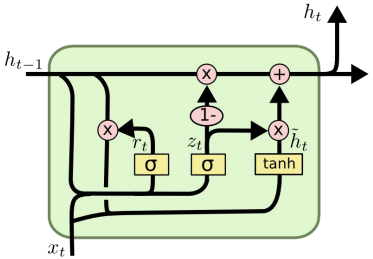

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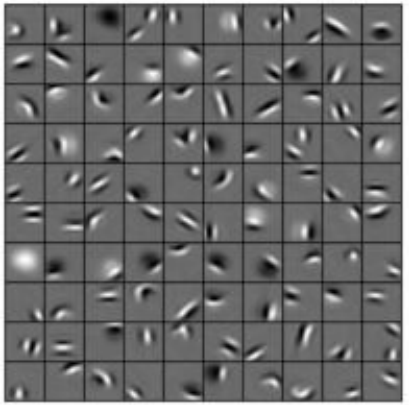

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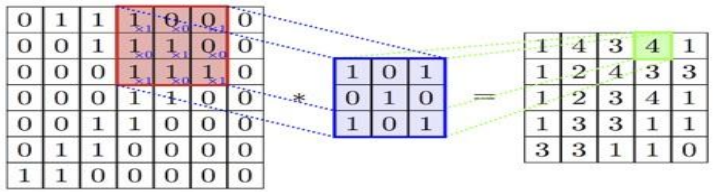

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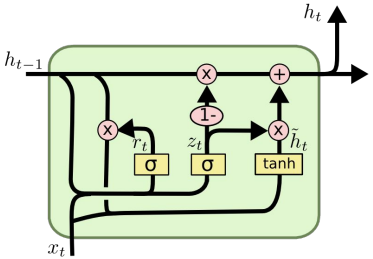

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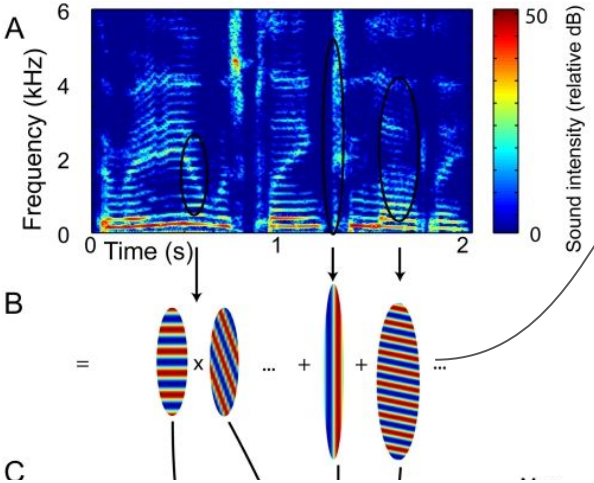
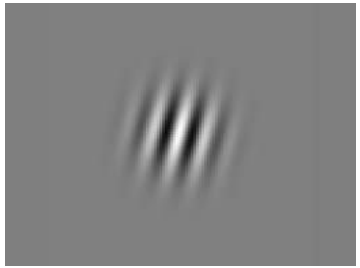
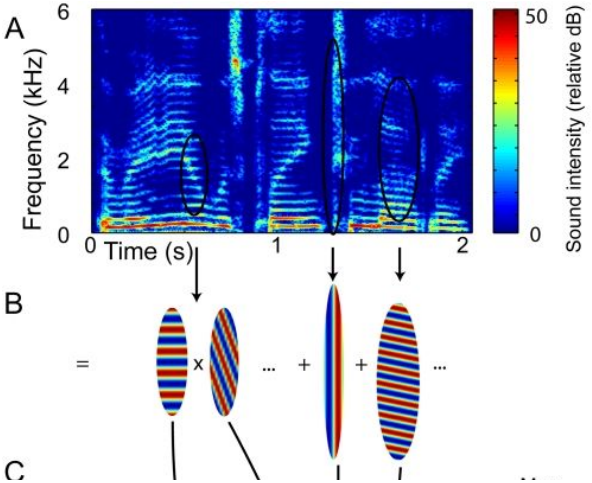
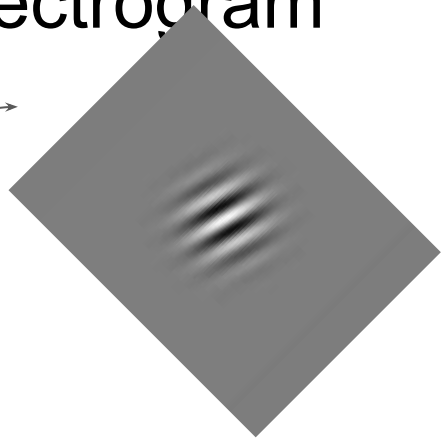




Like the Gabor patterns found in Vision processing like in V1

Modulations of the spectrogram





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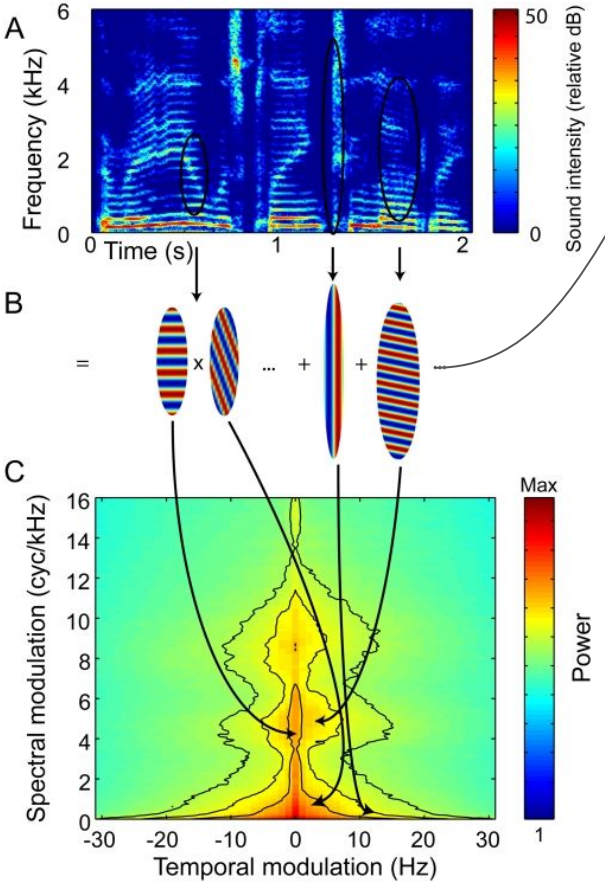
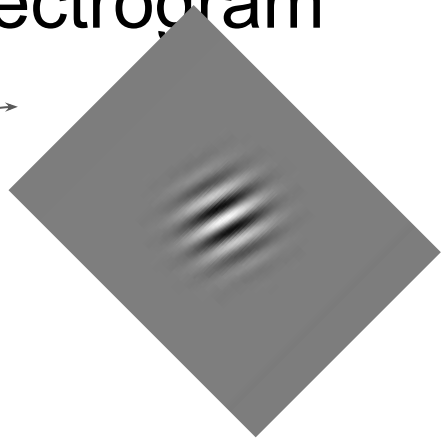


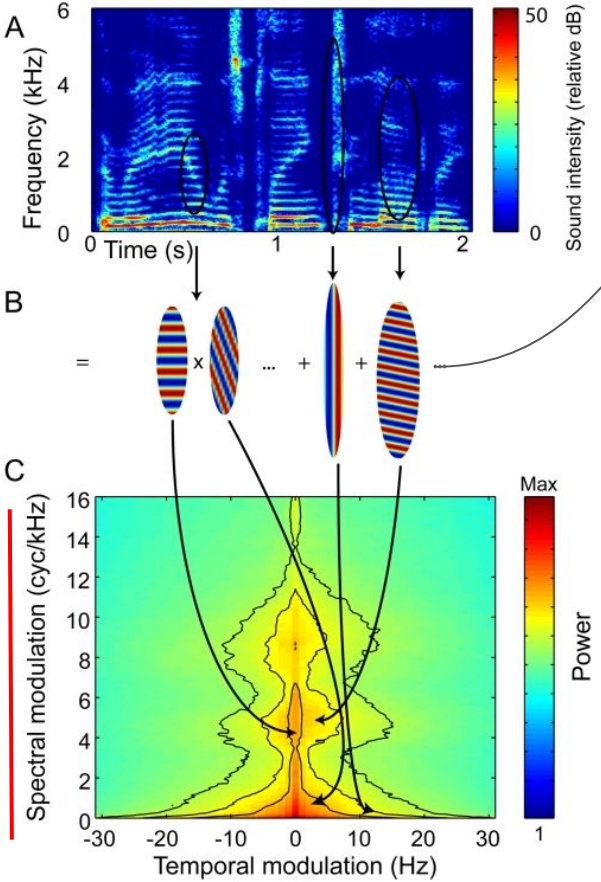


Like the Gabor patterns found in Vision processing like in V1

≠

Distribution is different in auditory domain

Modulations of the spectrogram



$$g_k(t,f) = s_k(t,f)w_k(t,f)$$

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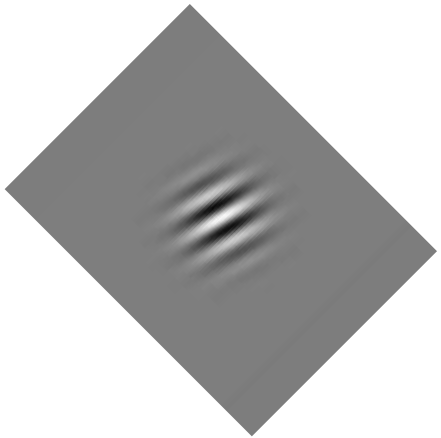
$$w_k(t,f) = e^{j(2\pi(\omega_k t+\Omega_k f))}$$

$$w_k(t,f) = e^{j(2\pi(F_k R_{\gamma_k}))}$$

$$R_{\gamma_k} = t\cos(\gamma_k) + f\sin(\gamma_k)$$

How to incorporate modulations in deep models?



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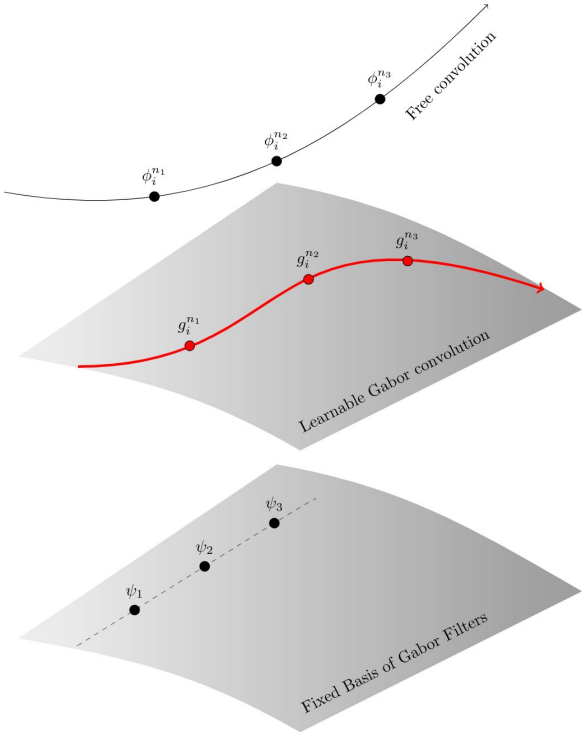
How to incorporate modulation in deep models?

The idea: Stay in the gabor Domain for the convolution, but find the relevant ones



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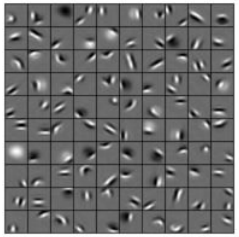
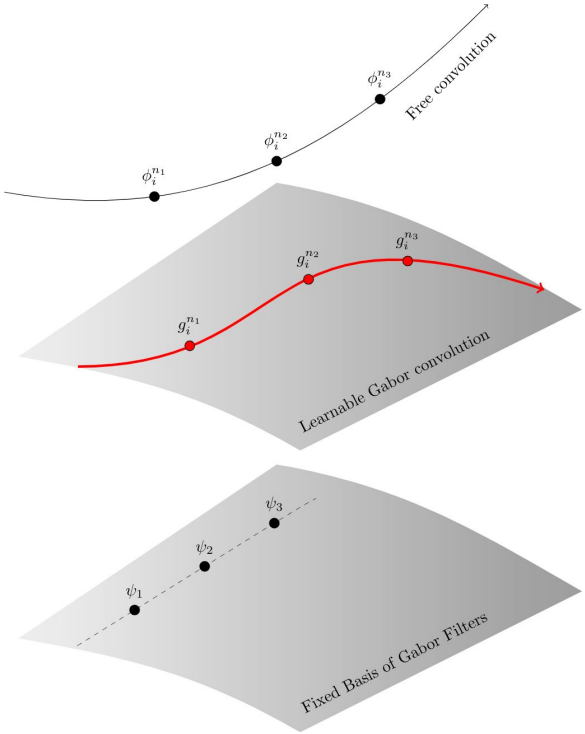
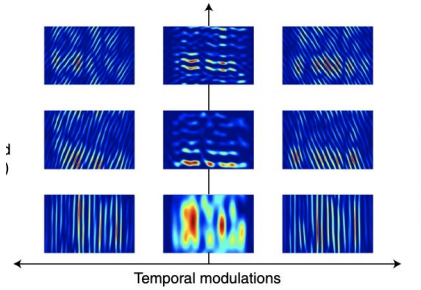
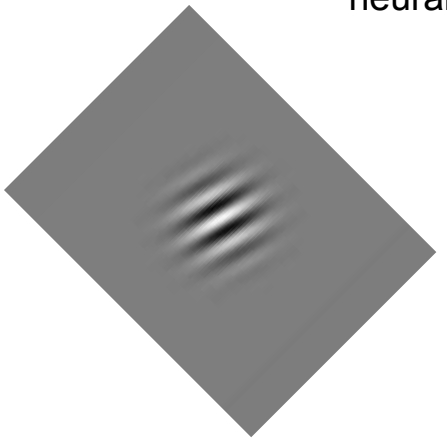






How to incorporate modulation in deep models?

How to implement the idea: Integrate convolutions into a neural network and backprop only a subset of parameters



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Learn only $(\sigma_t, \sigma_f, R_{\gamma_k}, F_k)$

4 params instead of 111*9

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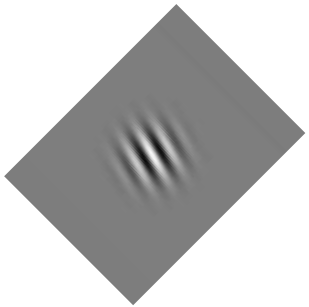
How to implement the idea: Integrate convolutions into a neural network and backprop only a subset of parameters



$$
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s_k(t,f) &= \frac{1}{2\pi\sigma_t\sigma_f} e^{-\frac{1}{2}\left(\frac{t^2}{\sigma_t^2}+\frac{f^2}{\sigma_f^2}\right)} \\
w_k(t,f) &= e^{j(2\pi(\omega_k t+\Omega_k f))} \\
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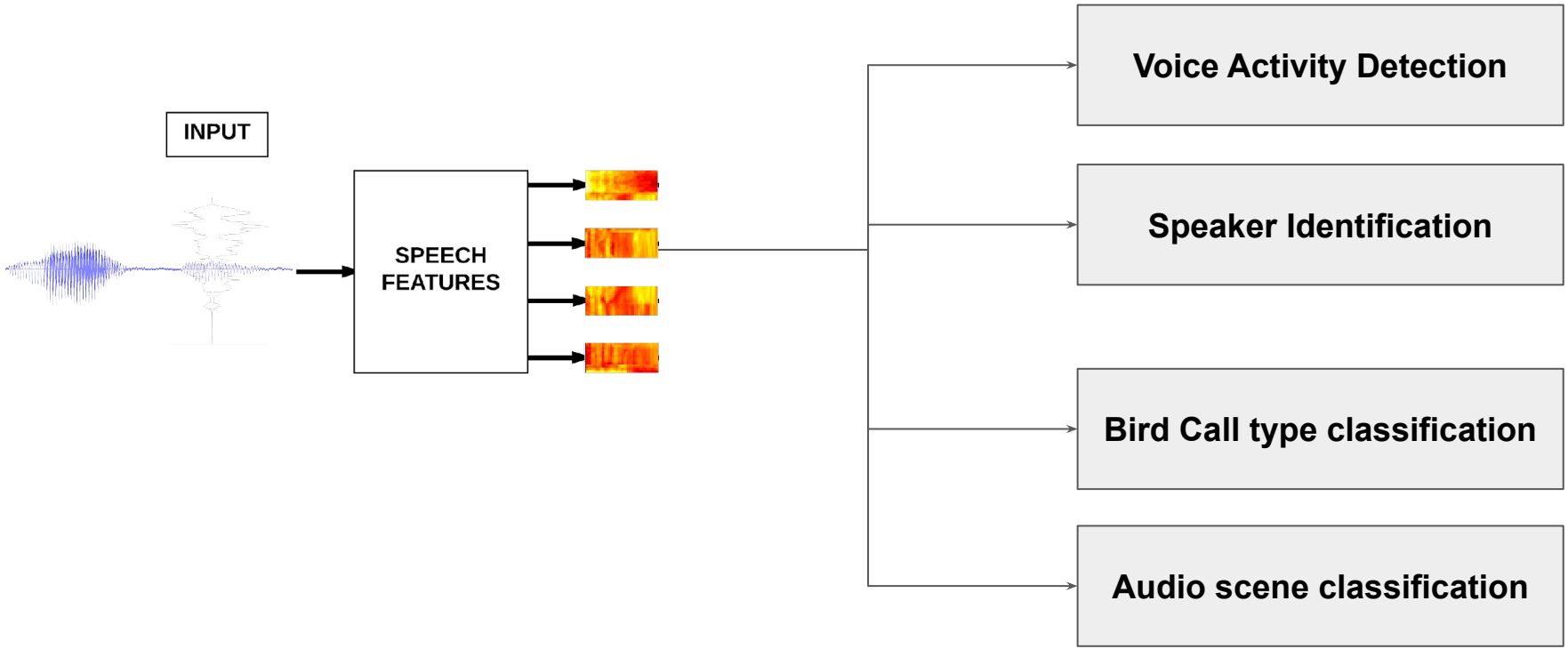
Our pipeline for audio processing



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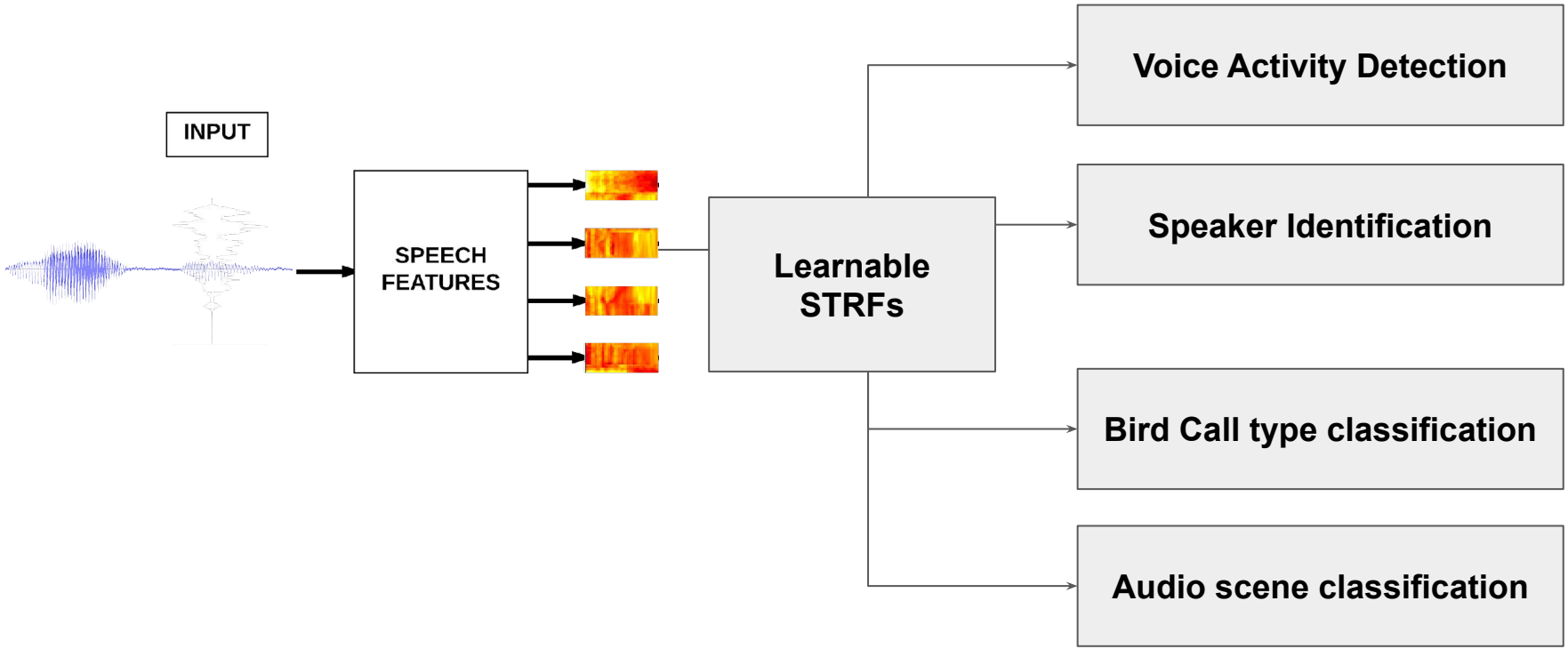
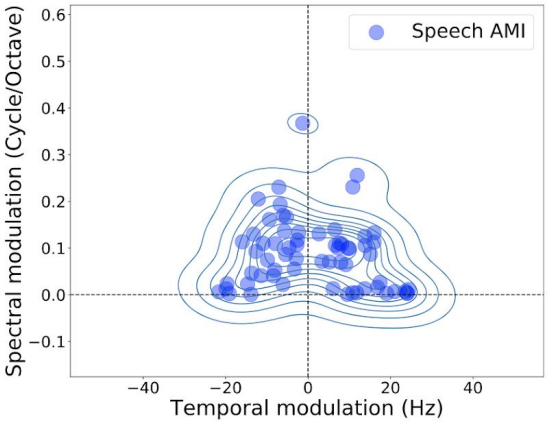
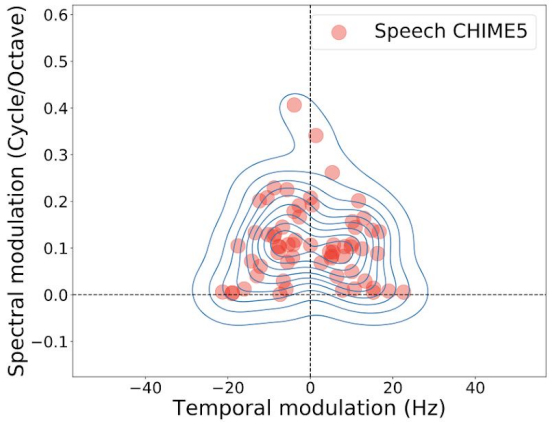


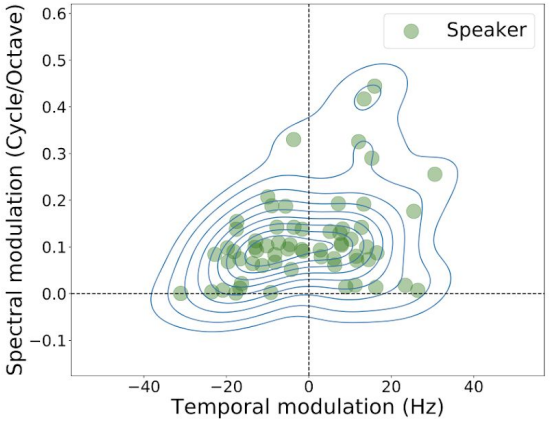
Engineering results

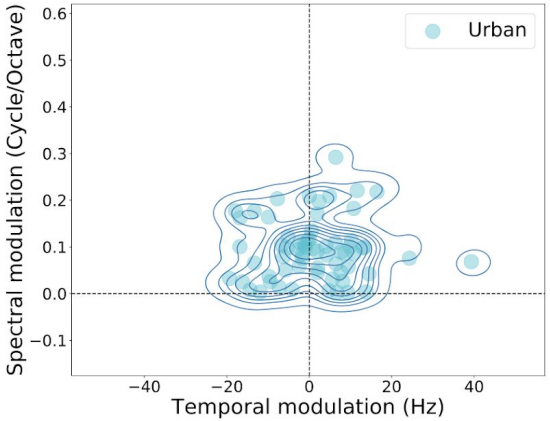
Voice Activity Detection	State-of-the-art on two datasets
Speaker Identification	Behind topline, above baseline
Bird Call type classification	Behind topline, above baseline
Audio scene classification	Close to topline

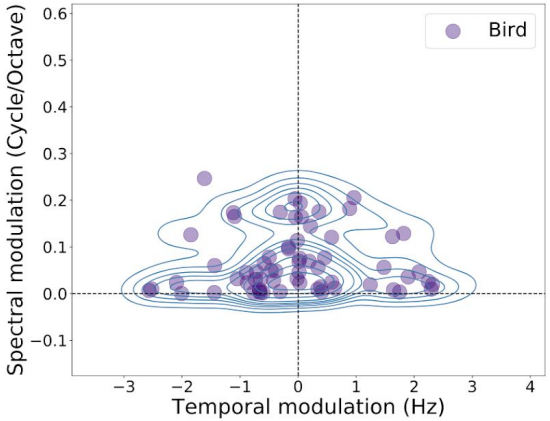
Qualitative analysis of filters



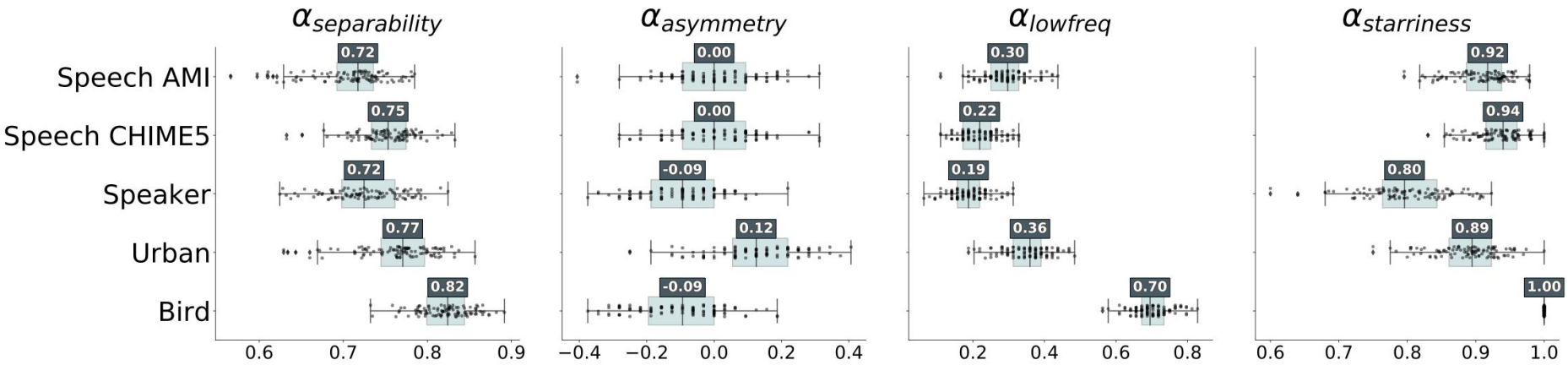






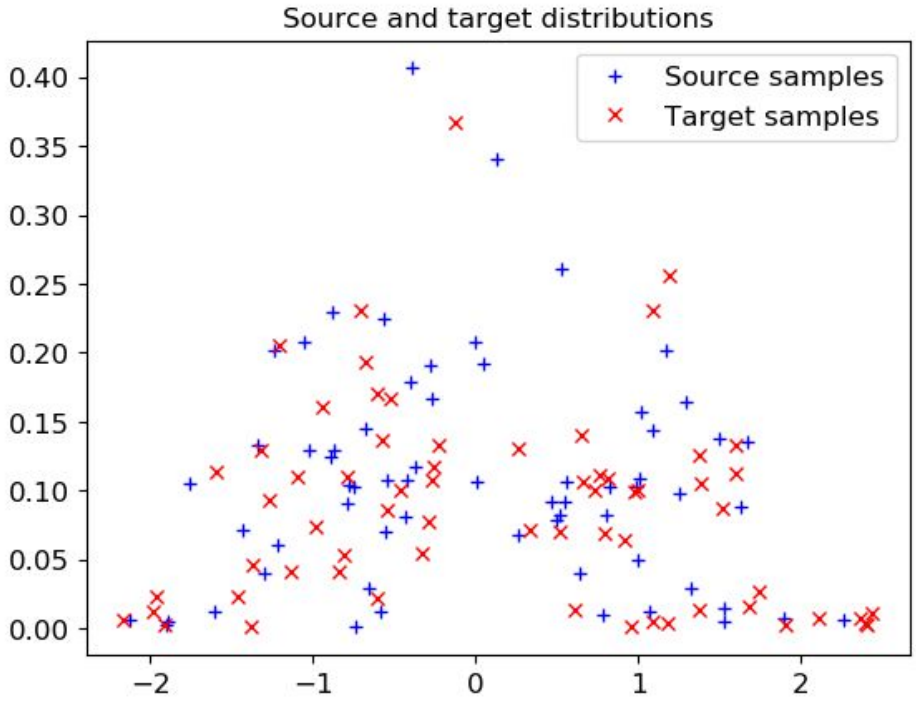


Quantitative analysis of filters



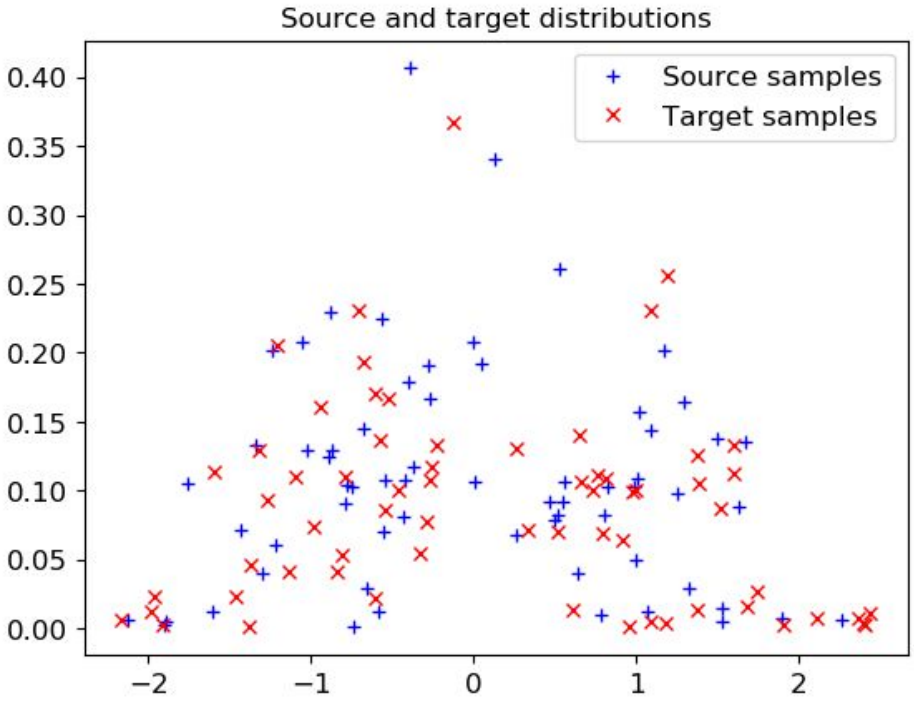
Quantitative Analysis of spectro-temporal

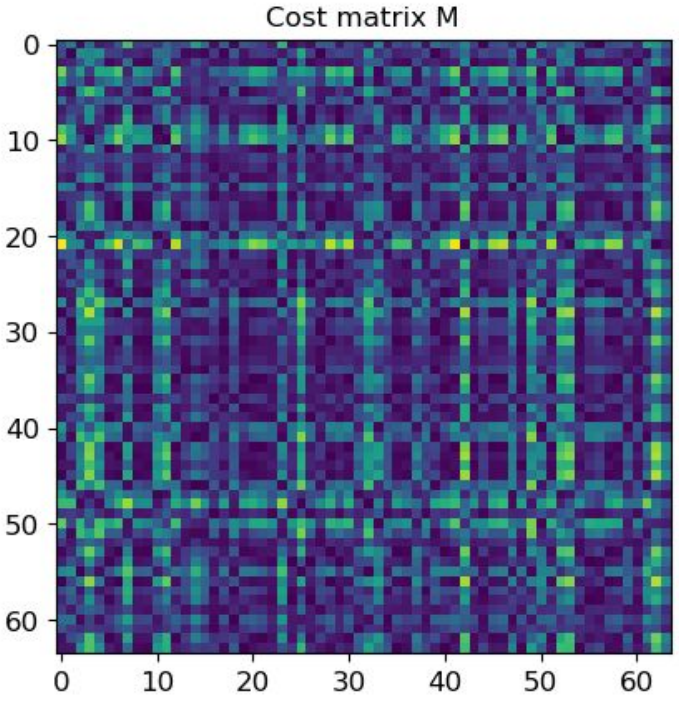
Distance between Learned STRFs with Optimal Transport



Quantitative Analysis of spectro-temporal

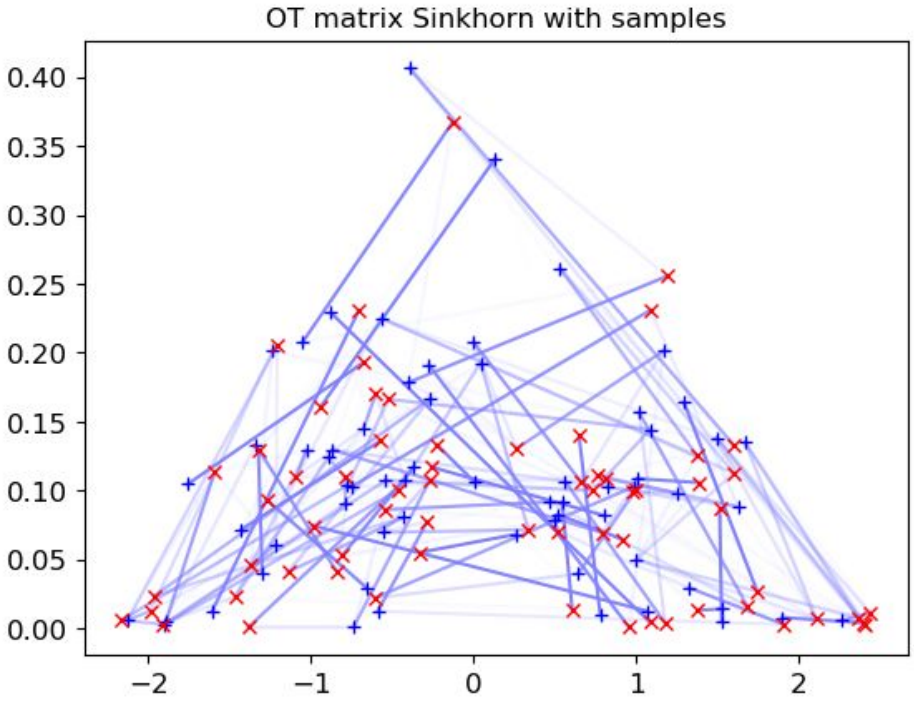
Distance between Learned STRFs with Optimal Transport

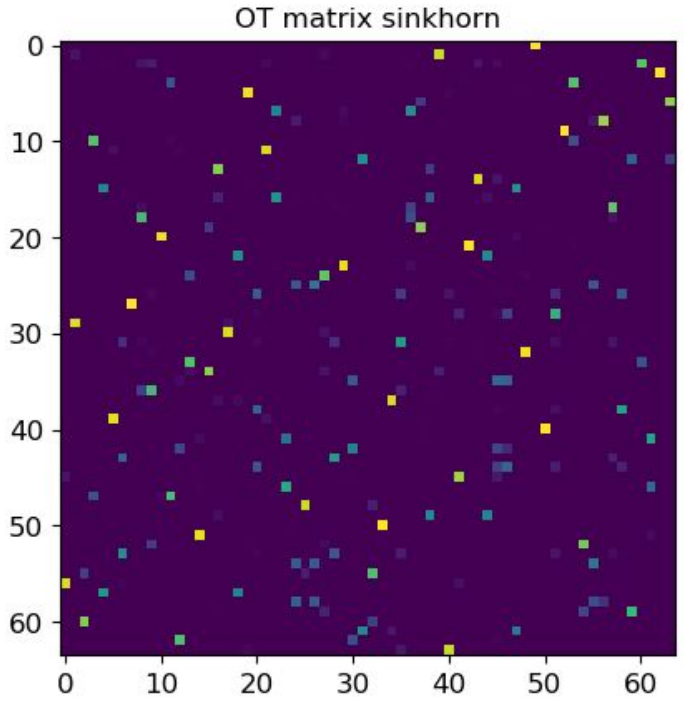




Quantitative Analysis of spectro-temporal

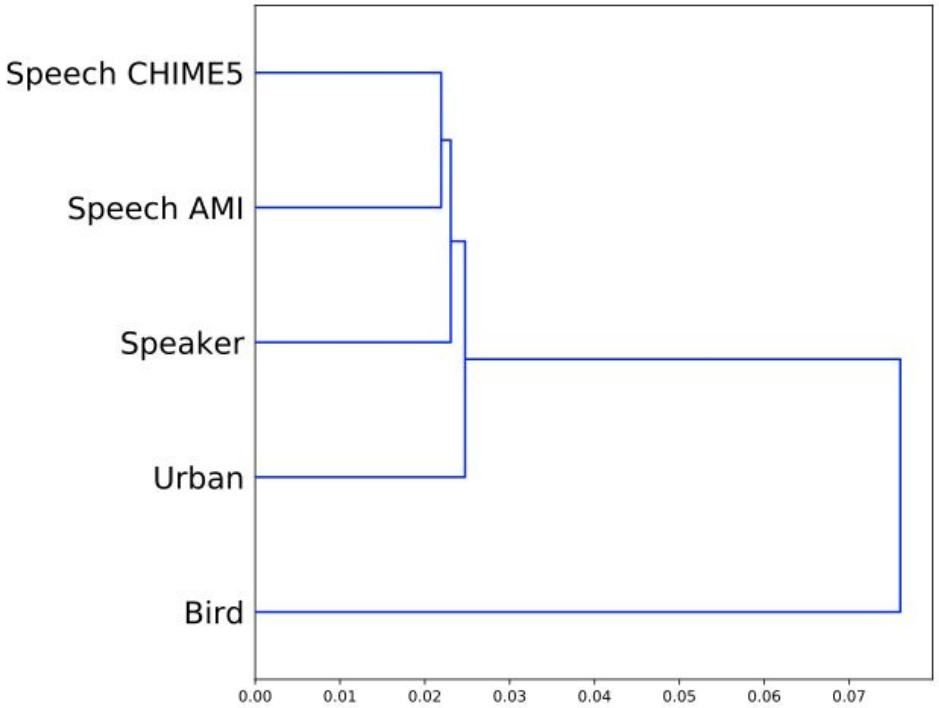
Distance between Learned STRFs with Optimal Transport





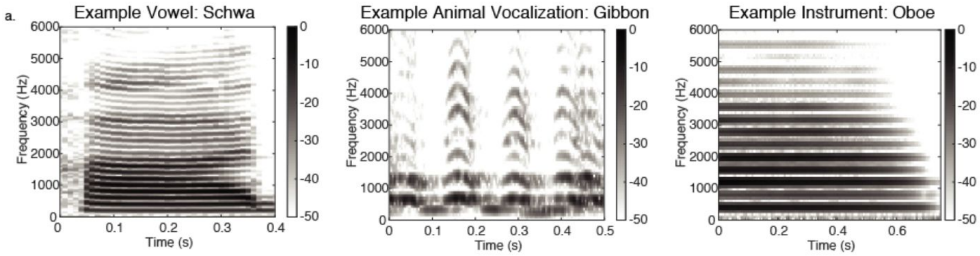
Quantitative analysis of filters

Distance between Learned STRFs with Optimal Transport



What is next?

1. Harmonicity



What is next?

1. Harmonicity

2. Tonotopic Organization for the Modulation

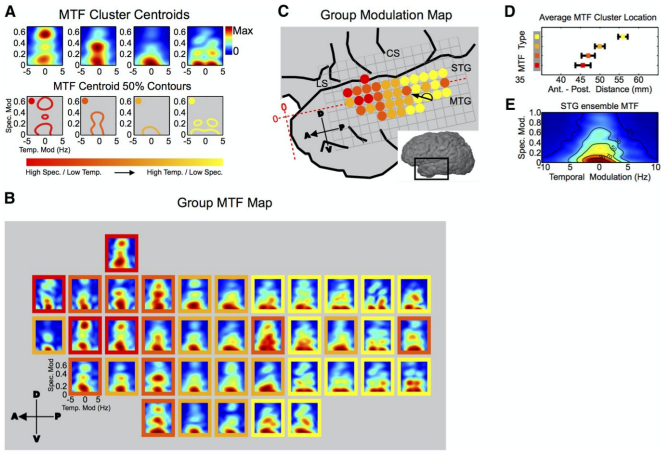


Figure 5. Organization of MTFs in STG. ***A***, K-means cluster centroids generated from all MTFs across all participants. Their respective 50% contours are shown below. The overall tuning within an individual MTF centroid is fairly well localized. The collection of MTF centroid types span modulation space from high spectral/low temporal regions (red, left) to high temporal/low spectral regions (yellow, right) as shown by the 50% contours. ***B***, Group MTF map. The map represents the average MTF across participants at each STG position. Only locations with ≥2 MTFs contributing to the average are included. Each MTF within the map is color-coded by its cluster membership. ***C***, MTF cluster identity map. MTF cluster identities from ***B*** are plotted. The cluster identity map shows a transition from high spectral/low temporal MTFs anteriorly (red) to high temporal/low spectral MTFs posteriorly (yellow) and a significant degree of local organization ($p < 1.0 \times 10^{-5}$, neighborhood similarity permutation test). ***D***, Average MTF cluster distance along the anterior–posterior extent of STG. Distances are measured from the anterior temporal pole illustrated in ***C*** (red horizontal axis). High spectral/low temporal MTFs are located anteriorly (red). High temporal/low spectral MTFs are located posteriorly (yellow, error bars represent SEM). ***E***, Ensemble MTF (population average) for STG. Contour lines represent percentage maximum. LS, lateral sulcus; STG, superior temporal gyrus; MTG, medial temporal gyrus; CS, central sulcus.