Separake
Source Separation with a Little Help from Echoes

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Echoes Help Indoor Processing

- beamforming
- source localization
- self-localization

What about speech separation ?

1. Is speech separation easier with echoes than without ?
2. Full RIR vs a few early reflections ?

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2. Full RIR vs a few early reflections ?

1. Assume knowledge of a few (1-6) early echoes
2. Plug in multichannel NMF [1]
3. Three baseline scenarios
   - *Anechoic* conditions
   - *Learn* transfer functions
   - Ignore reverberation (i.e. consider 0 echoes)
4. Numerical Experiments

[1] Ozerov & Févotte, 2010

Outline

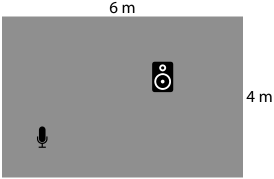
1. Approximate Propagation Model

2. NMF Algorithms

3. Results from Numerical Experiments

Full Image Microphone Model

$$h_{jm}(t) = \sum_{k=0}^{K} \alpha_{jm}^{k}\delta(t - t_{jm}^{k}) + \epsilon_{jm}(t)$$



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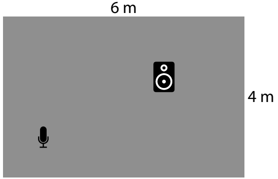

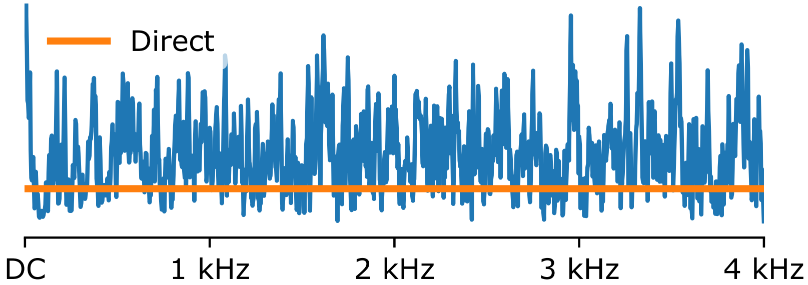

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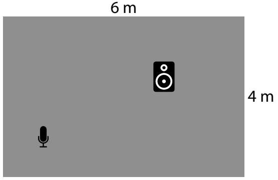

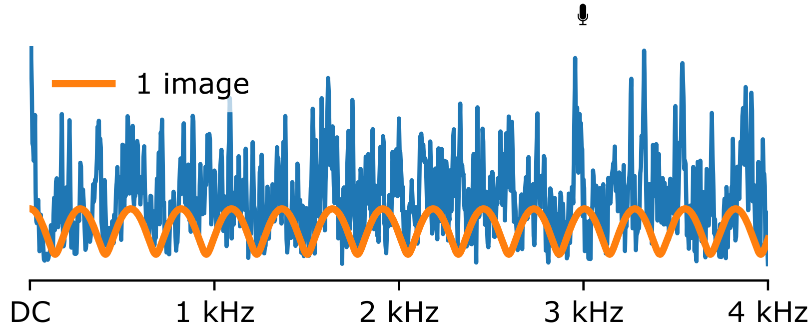

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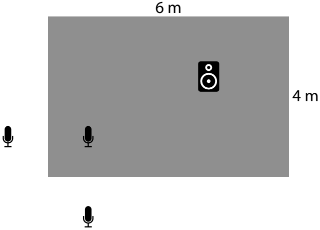

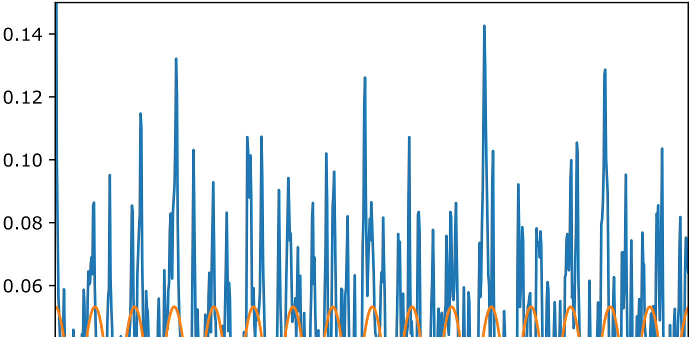

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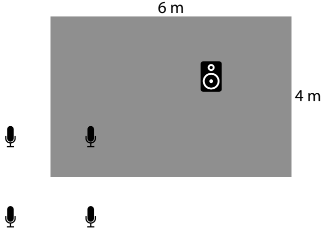
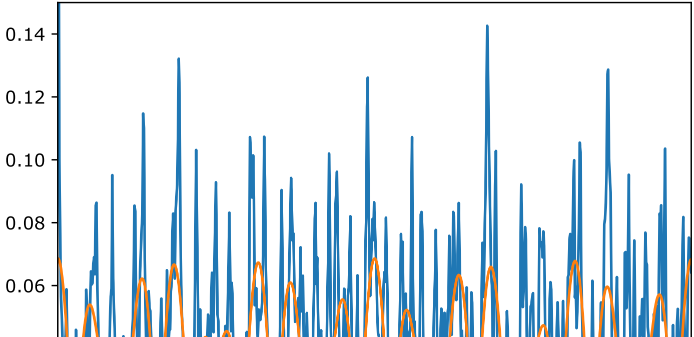
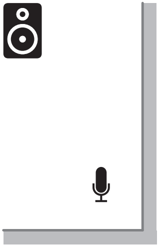
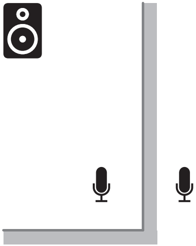
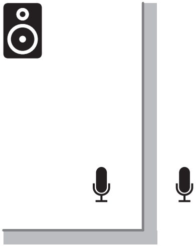


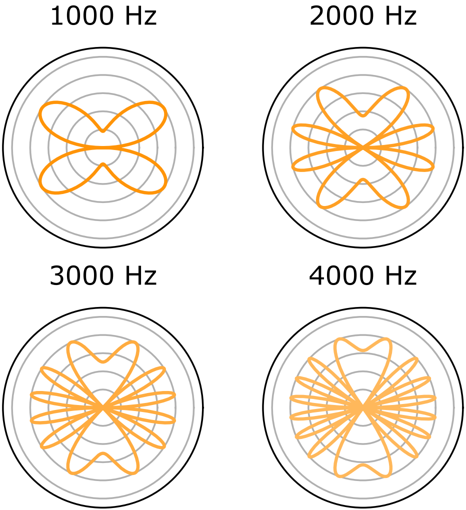


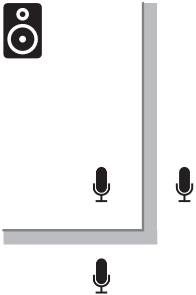


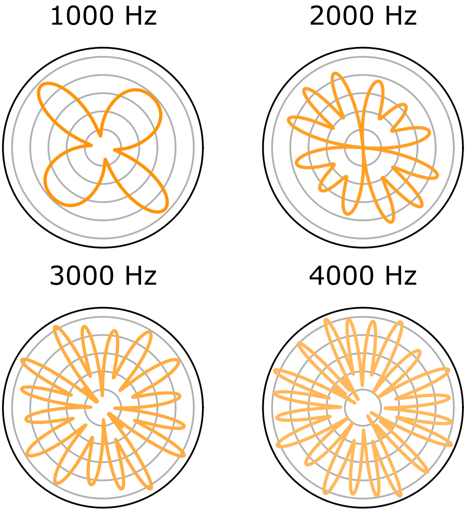
Why should that help ?






1000 Hz
2000 Hz
3000 Hz
4000 Hz

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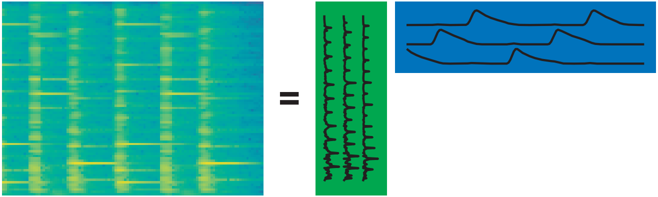


Multiplicative Updates View (Lee & Seung 2001)

Source signal's magnitude spectrogram decomposes non-negatively

$$|\mathbf{X}_j| = \mathbf{D}_j \mathbf{Z}_j$$

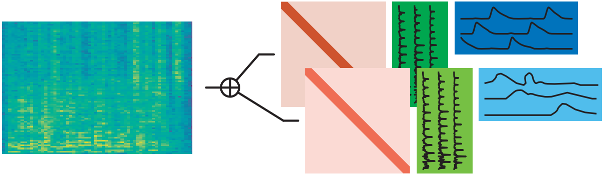
Expectation Minimization View (Ozerov & Févote 2010)

Source signal's variance spectrogram decomposes non-negatively

$$X_j[f, n] \sim \mathcal{CN}(0, (\mathbf{D}_j \mathbf{Z}_j)_{fn})$$

Microphone magnitude spectrogram model

$$\widehat{\mathbf{V}}_m = \sum_j \mathrm{diag}(|H_{mj}|)\mathbf{D}_j\mathbf{Z}_j$$



Minimize *Itakura-Saito* divergence

$$C_{\mathsf{MU}}(\mathbf{Z}_j) = \sum_{mfn} d_{\mathsf{IS}}(V_m[f,n] \,|\, \widehat{V}_m[f,n]) + \gamma \sum_j \|\mathbf{Z}_j\|_1,$$

- Efficient multiplicative update rules (Ozerov & Févotte 2010)
- Regularization needed for large number of latent variables

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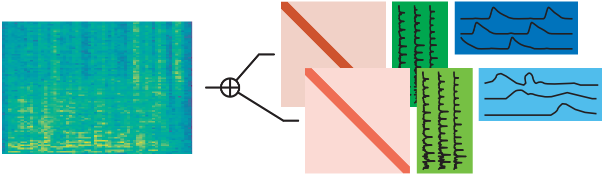

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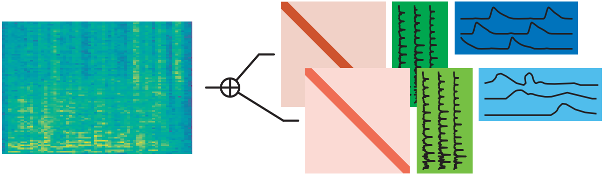

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Probabilistic Model

Source are complex Gaussian with low-rank spectrogram

$$X_j[f,n] \sim \mathcal{CN}(0, (\mathbf{D}_j \mathbf{Z}_j)_{fn})$$

Microphone signals have variance

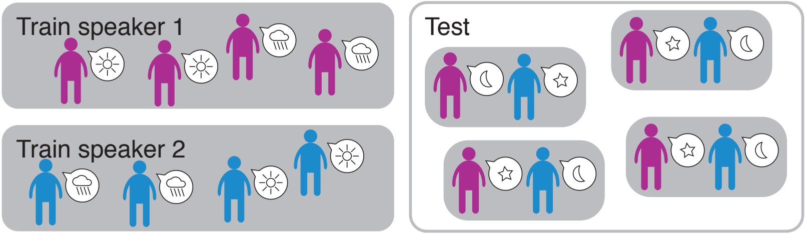
$$\boldsymbol{\Sigma}_{\mathbf{y}}[f,n] = \widehat{\mathbf{H}}[f]\, \boldsymbol{\Sigma}_{\mathbf{x}}[f,n]\, \widehat{\mathbf{H}}^H[f] + \boldsymbol{\Sigma}_{\mathbf{b}}[f,n],$$

Minimize Negative Log-likelihood

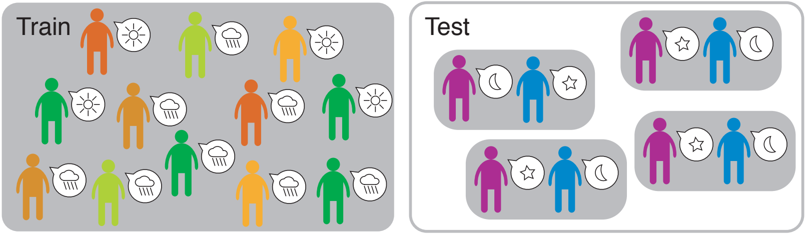
$$C_{\mathsf{EM}}(\mathbf{Z}_j) = \sum_{fn} \operatorname{trace}\left(\mathbf{y}[f,n]\mathbf{y}[f,n]^H \boldsymbol{\Sigma}_{\mathbf{y}}^{-1}[f,n]\right) + \log\det \boldsymbol{\Sigma}_{\mathbf{y}}[f,n]$$

Efficiently minimized by Expectation-Minimization algorithm (Ozerov & Févotte 2010)

Speaker Dependent



Universal



Remarks on Using a Universal Dictionary

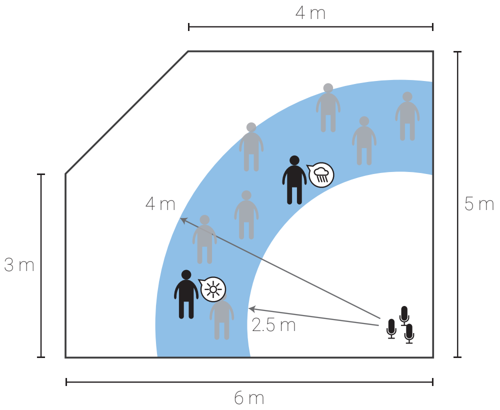
Remark 1: Anechoic separation with MU-NMF

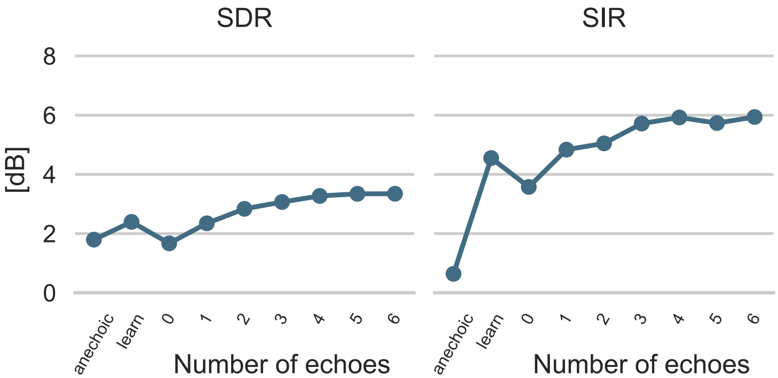
Anechoic separation cannot work!

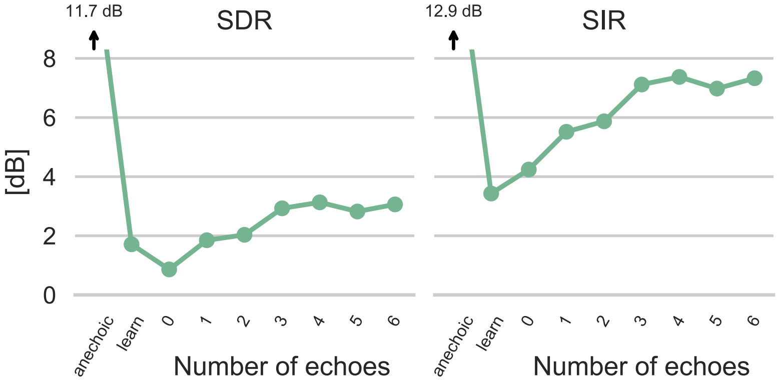
$$\mathbf{V}_m = \sum_j \mathbf{D}_j \mathbf{Z}_j \quad \rightarrow \quad \mathbf{V}_m = \sum_j \mathbf{D} \mathbf{Z}_j = \mathbf{D} \sum \mathbf{Z}_j$$

Remark 2: EM-NMF with Universal Dictionary

- Unclear how to enforce sparsity in EM (to us)
- Left for future work


4 m
5 m
4 m
3 m
2.5 m
6 m


SDR
SIR
[dB]
8
6
4
2
0
anechoic
learn
0
1
2
3
4
5
6
Number of echoes
anechoic
learn
0
1
2
3
4
5
6
Number of echoes


11.7 dB
SDR
12.9 dB
SIR
[dB]
8
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learn
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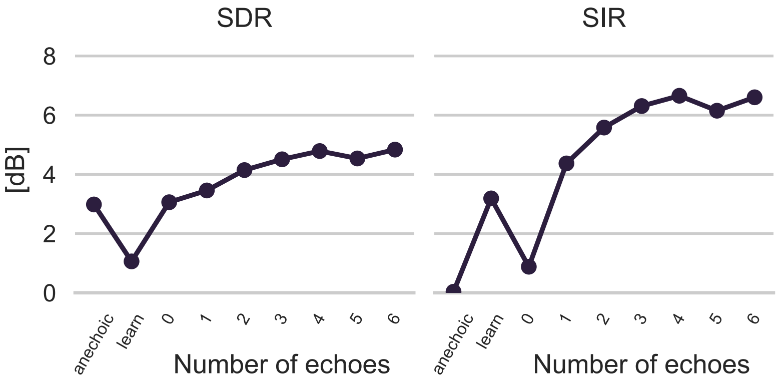
Number of echoes
Number of echoes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Number of echoes
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Conclusion

- Single echo improves performance
- Enables universal dictionary
- First few echoes most important

Future Work

- Compare to BSS
- Include (deeply) learnt models
- Underdetermined case

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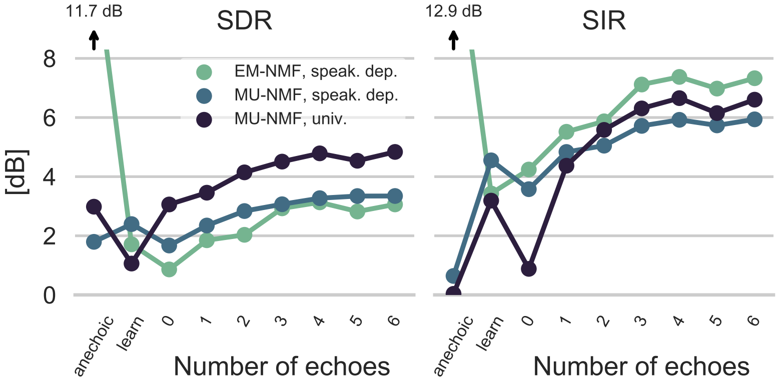
Thank you! Questions ?



11.7 dB
SDR
12.9 dB
SIR
EM-NMF, speak. dep.
MU-NMF, speak. dep.
MU-NMF, univ.
[dB]
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0
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learn
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