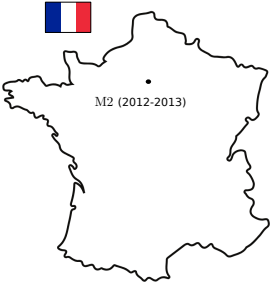
Phase recovery for audio demixing: contributions and perspectives

Talk at Neural DSP - Helsinki, August 18th, 2022

Paul Magron, Researcher - INRIA Nancy Grand Est

Background in a nutshell



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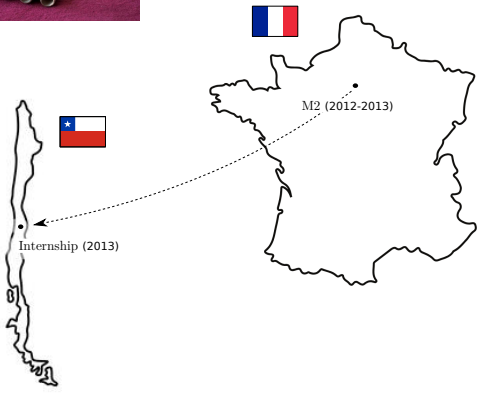

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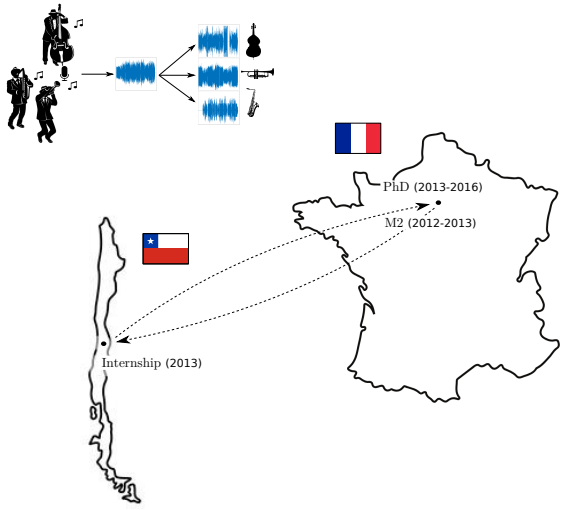

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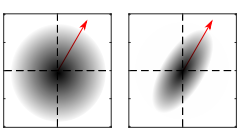

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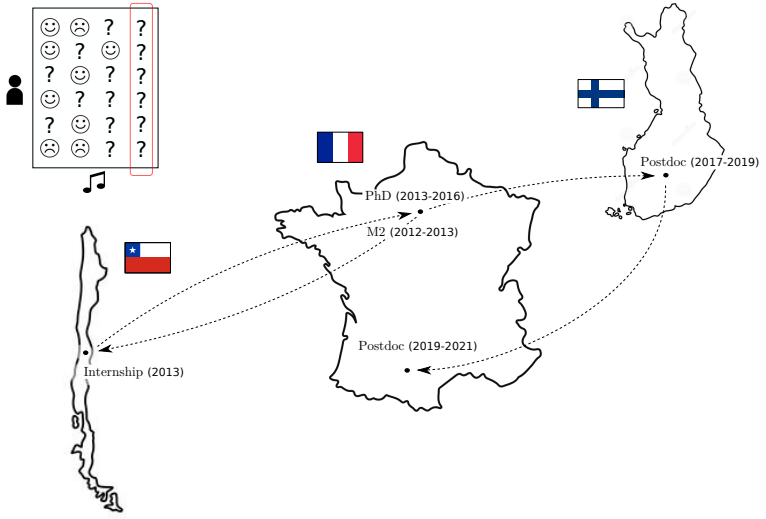

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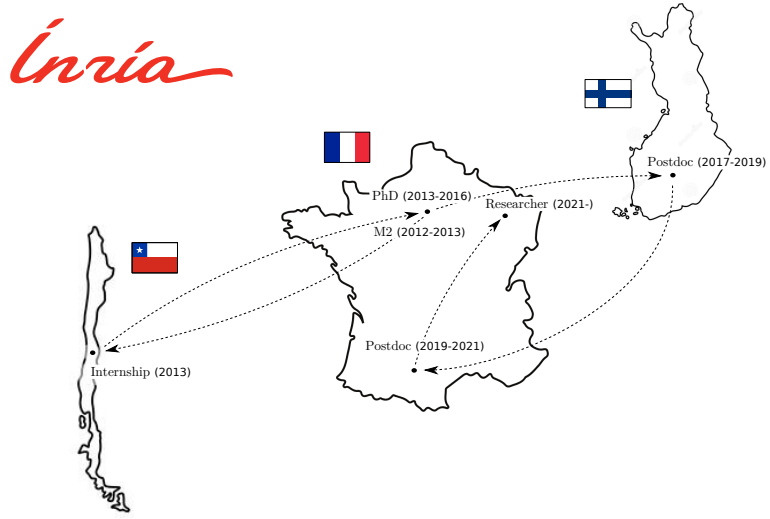

The audio realm

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Speech

Ambient sounds

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Music signals

Audio demixing

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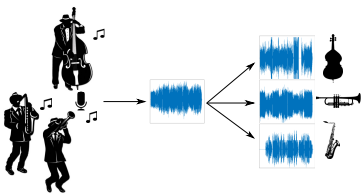

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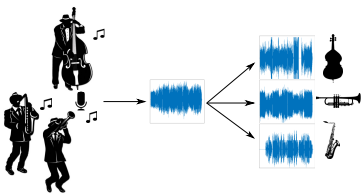
- An important preprocessing for many analysis tasks (e.g., polyphonic music transcription).



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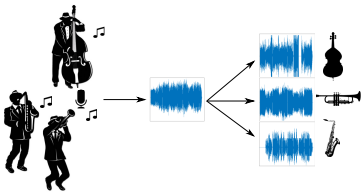

An example: Backing track generation

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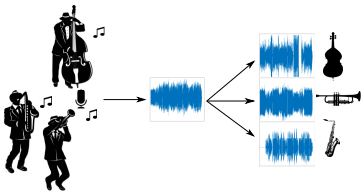
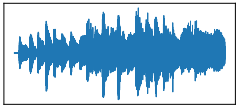


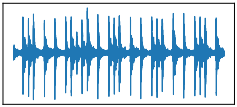
An example: Backing track generation

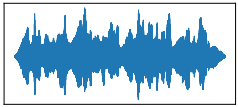
- Consider a mixture
- Demix the instruments and create a backing track

Setting the stage

- The raw material: audio signals.







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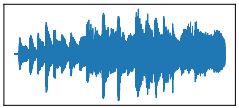

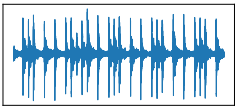

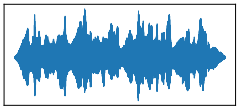

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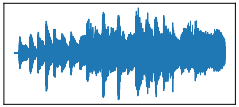
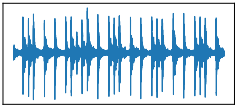
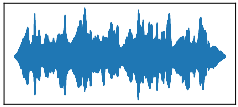
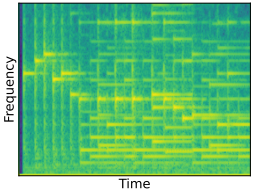
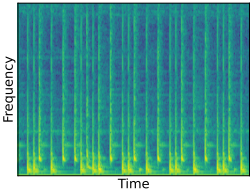


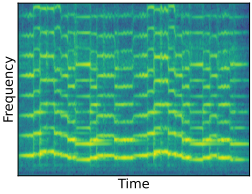




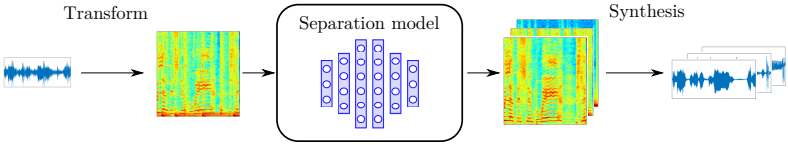
- It's hard to see structure there...
- We rather transform them into a time-frequency representation, e.g., a spectrogram.







The demixing pipeline



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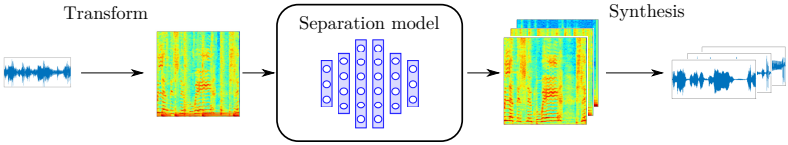

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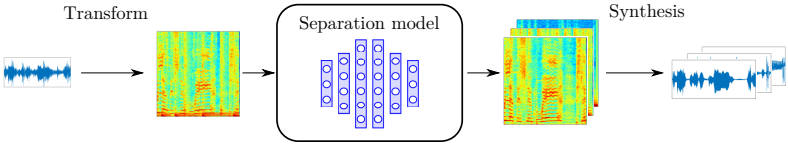

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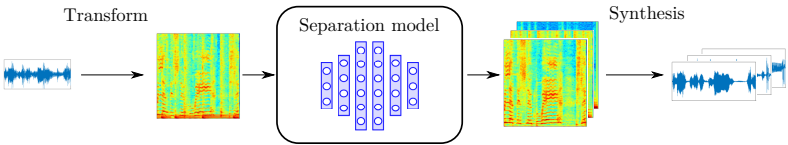

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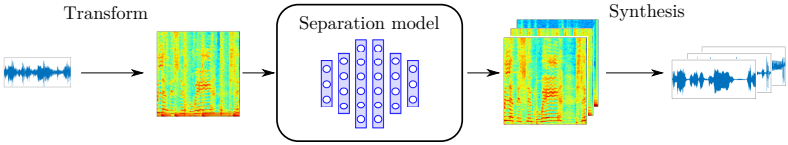

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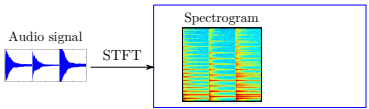
Nowadays demixing performance:

The phase catch

$$\mathbf{x} \in \mathbb{R}^N \xrightarrow{\text{STFT}} \mathbf{X} \in \mathbb{C}^{F \times T}$$

The STFT produces a spectrogram $|X|$



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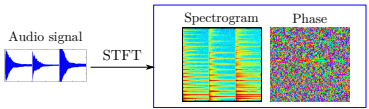
$$\mathbf{x} \in \mathbb{R}^N \xrightarrow{\text{STFT}} \mathbf{X} \in \mathbb{C}^{F \times T}$$

The STFT produces a spectrogram $|X|$
... but also a phase $\angle X$.



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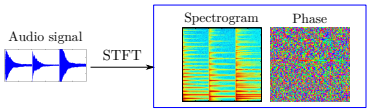
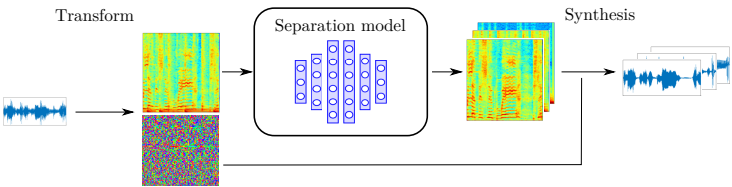


The actual demixing pipeline:



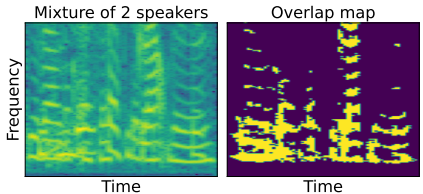
▷ The mixture's phase is assigned to each source using a Wiener-like filter.

The potential of phase recovery

✗ Wiener-like filter: Issues in sound quality when sources *overlap* in the TF domain.

When sources overlap:

$$|X| \neq |S_1| + |S_2|$$
$$\angle X \neq \angle S_1 \text{ or } \angle S_2$$



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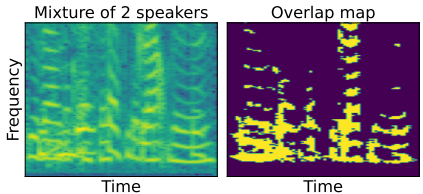
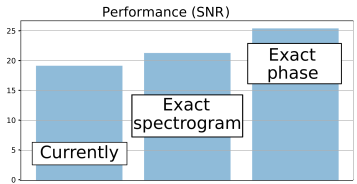


Given the current state of the art:



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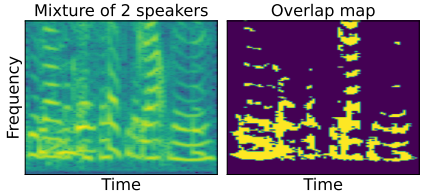

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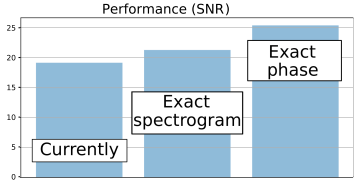
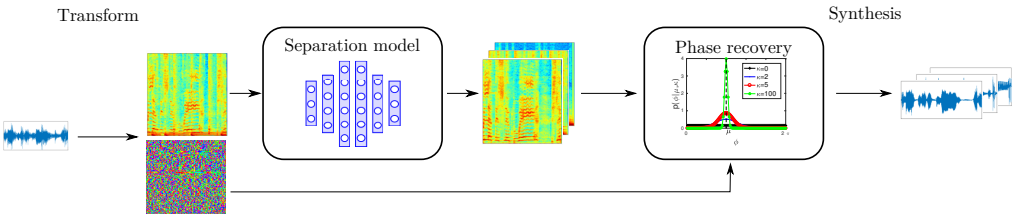


Main message

More potential gain in phase recovery than in magnitude estimation.

Phase recovery for audio demixing



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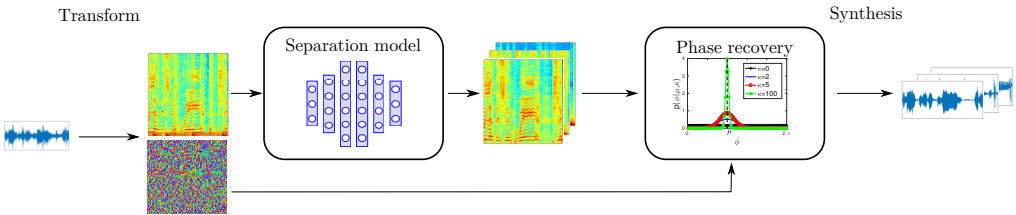
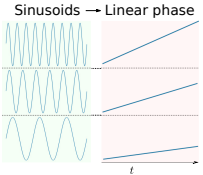
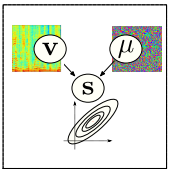


Main contributions

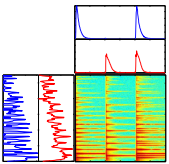
Phase models



Statistical framework



Factorization methods



Introduction

Model-based phase recovery

Probabilistic phase modeling

Factorization methods

Conclusion

Model-based phase recovery

Sinusoidal phase model

Consider a mixture of sinusoids: $x(n) = \sum_{p=1}^{P} A_p \sin(2\pi \underbrace{\nu_p}_{\text{normalized frequency}} n + \phi_{0,p})$.

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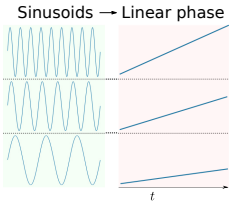

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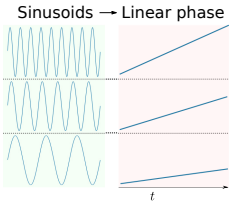

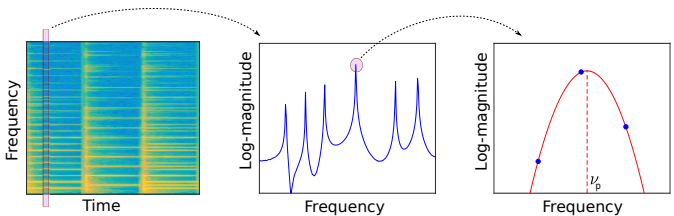

Sinusoidal phase model

Consider a mixture of sinusoids: $x(n) = \sum_{p=1}^{P} A_p \sin(2\pi \underbrace{\nu_p}_{\text{normalized frequency}} n + \phi_{0,p})$.

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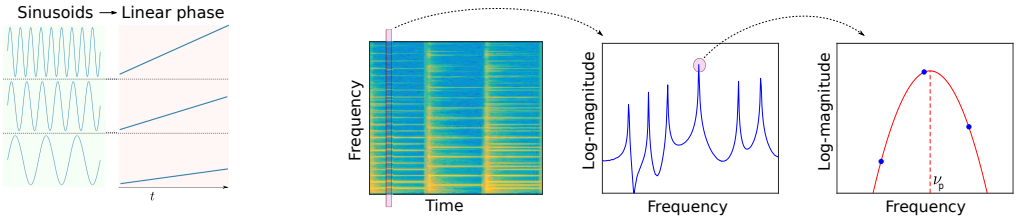


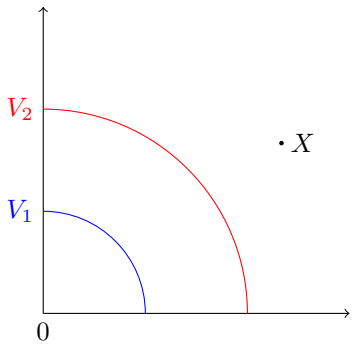
✓ Accounts for non-stationary signals, suitable for real-time processing.

✗ Bad performance for "pure" phase recovery: need to use an additional information.

An iterative source separation algorithm

Problem Given target magnitude spectrograms $\mathbf{V}_j$, solve:

$$\min_{\{\hat{\mathbf{S}}_j\}} ||\mathbf{X} - \sum_{j=1}^{J} \hat{\mathbf{S}}_j||^2 \quad \text{s.t.} \quad |\hat{\mathbf{S}}_j| = \mathbf{V}_j$$



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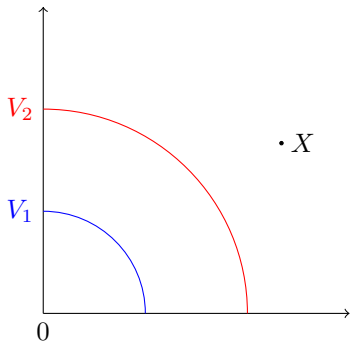

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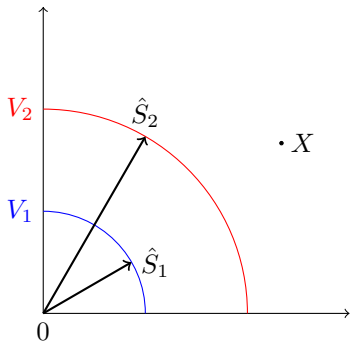

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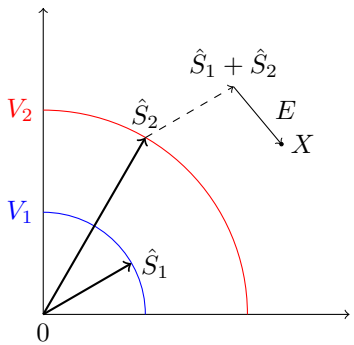

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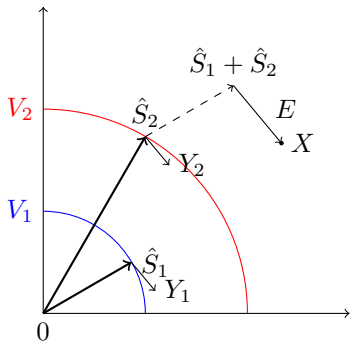

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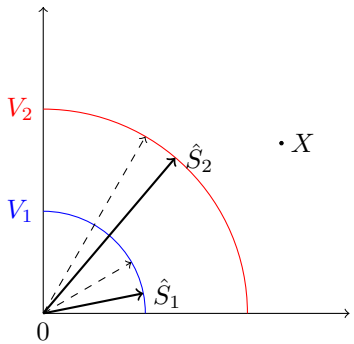

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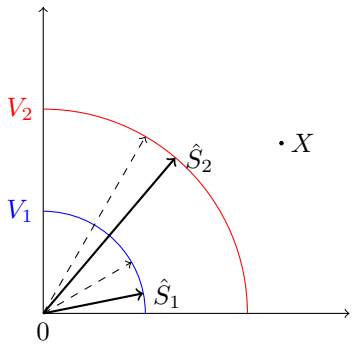

✓ Leveraging the sinusoidal phase model reduces interference between source estimates.

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Recently: Some attempts at predicting the phase using DNNs.

- ✗ Generic architectures which does not account for the particular phase structure.

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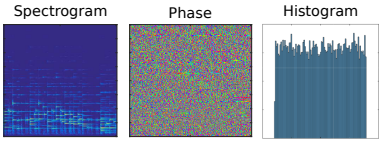
- ▷ Architectural choices (non-linearities, loss functions) adapted to the phase (periodicity).
- ▷ Identify and exploit perceptual phase invariants.

Probabilistic phase modeling

A statistical view

A simple example

- The phase appears uniformly-distributed.



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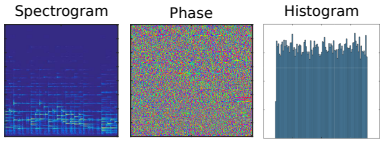
- The phase appears uniformly-distributed.
- But is that consistent with, e.g., the sinusoidal model?



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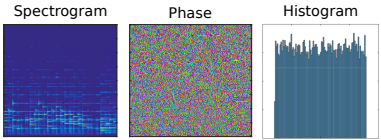

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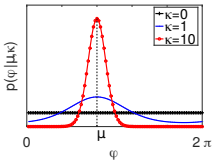
Von Mises phase $\phi_{f,t} \sim \mathcal{VM}(\mu_{f,t}, \kappa)$

- ▷ Assume some structure (e.g., sinusoidal) for the location parameter $\mu_{f,t}$.



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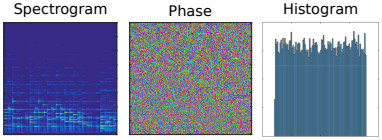

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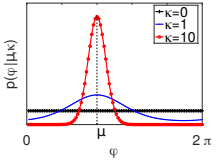
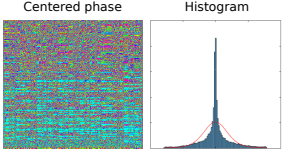




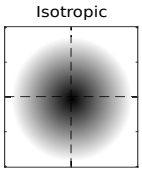
✓ Both models are statistically relevant, but convey a different information about the phase.

- ▷ Uniform → describes the *global* behavior.
- ▷ Von Mises → accounts for the *local* structure.

Modeling complex-valued coefficients

Isotropic Gaussian model

$$s \sim \mathcal{N}_{\mathbb{C}}(m, \Gamma) \text{ with } \Gamma = \begin{pmatrix} \gamma & 0 \\ 0 & \gamma \end{pmatrix}$$



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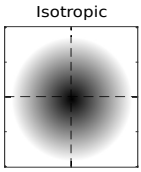

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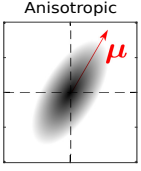

c is the *relation* term, defined as a function of the phase parameter μ.

✓ Allows to incorporate phase priors.

Application to demixing

Mixture model In each time-frequency bin: $x = \sum_j s_j$ with $s_j \sim \mathcal{N}_{\mathbb{C}}(m_j, \Gamma_j)$.

- ▷ Choose an appropriate parametrization for m_j and Γ_j (a bit technical).
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- ▷ Posterior mean of the sources: $\hat{\mathbf{S}}_j = \mathbb{E}(\mathbf{S}_j | \mathbf{X})$.
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Performance

   

✓ Including a phase prior in the filter improves the separation quality.

Perspective: anisotropic deep learning

✗ Bayesian deep learning / variational autoencoders (VAE) are limited to isotropic distributions.

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Proposal: Combine deep learning and anisotropic modeling, e.g., via anisotropic VAEs.

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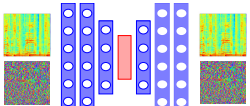

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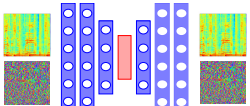

▷ A strong effort in modeling and optimization is needed for deriving appropriate estimation techniques.

Factorization methods

A leap in the past: nonnegative matrix factorization (NMF)

Given a (nonnegative) spectrogram $\mathbf{V}$, find a factorization $\mathbf{WH}$ such that the factors $\mathbf{W}$ and $\mathbf{H}$ are:

- ▷ low rank.
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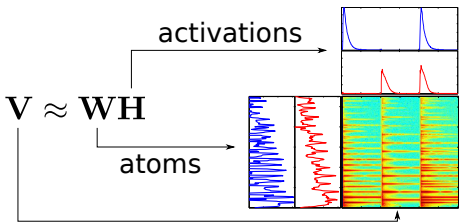

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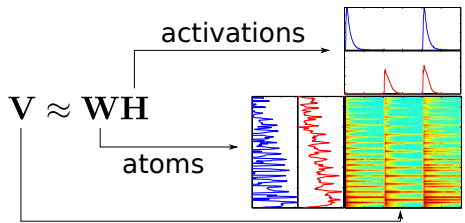

Estimation via an optimization problem:

$$\min_{\mathbf{W},\mathbf{H}} D(\mathbf{V}, \mathbf{WH})$$

NMF for audio demixing

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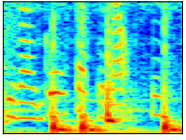

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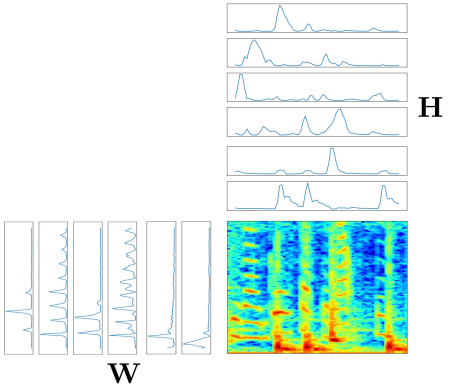

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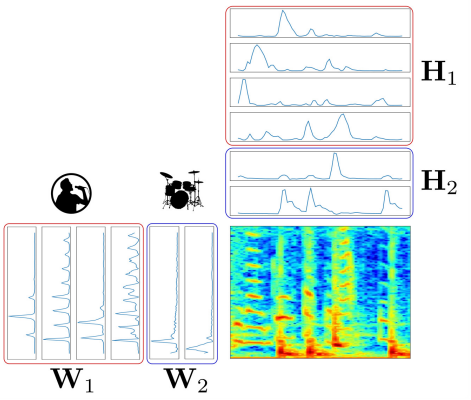

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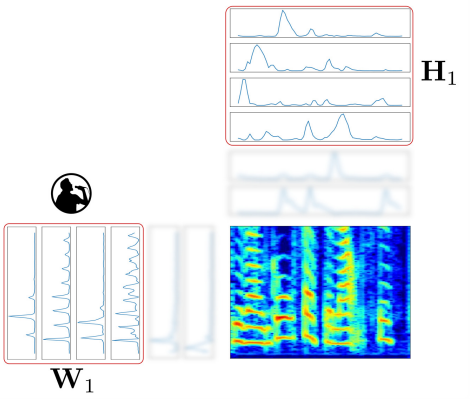

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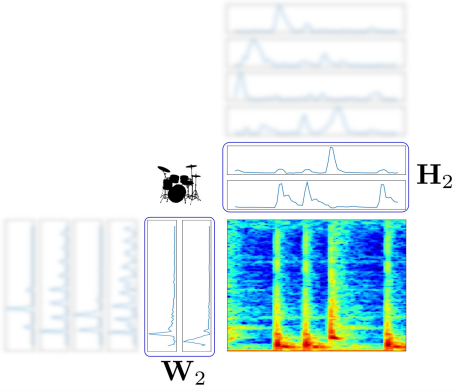

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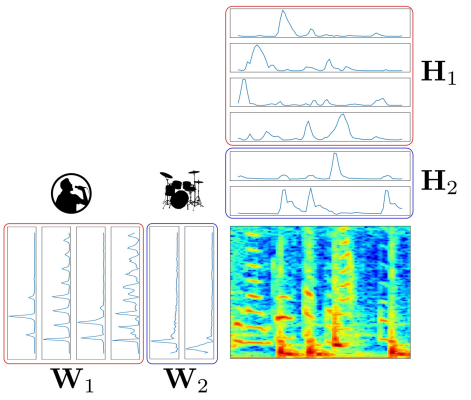

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Pretrain $\mathbf{W}_1$ and $\mathbf{W}_2$ on subsets of isolated tracks.

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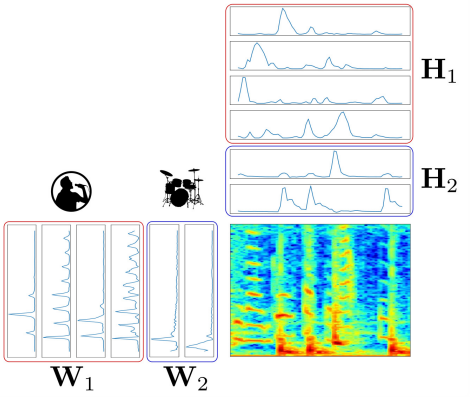

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Pretrain $\mathbf{W}_1$ and $\mathbf{W}_2$ on subsets of isolated tracks.

✗ Ignores the phase / assumes the magnitudes are additive.

✗ The low-rank assumption is not verified in practice.

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- ▷ Complex NMF $>$ NMF: the advantage of accounting for the phase.
- ▷ Complex NMF $>$ NMF + phase recovery: the advantage of a joint training approach.

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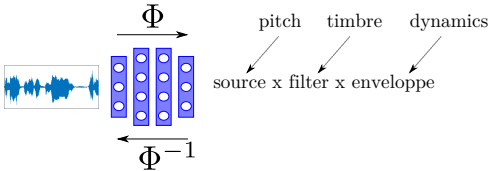

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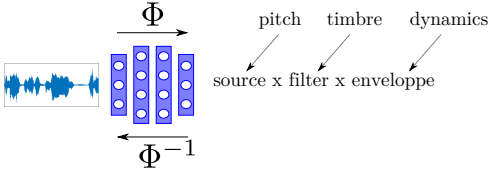
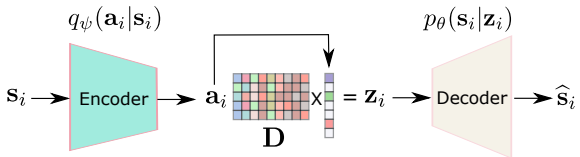


A first attempt: VAE with a sparse dictionary model.



✓ Nice performance in terms of sparsity and speech modeling / reconstruction.

✗ Fixed dictionary and no nonnegativity: non-interpretable factors.

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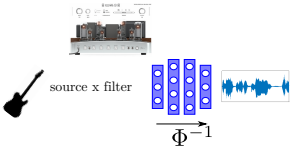

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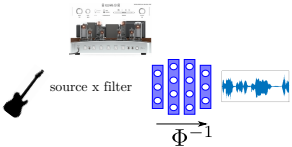
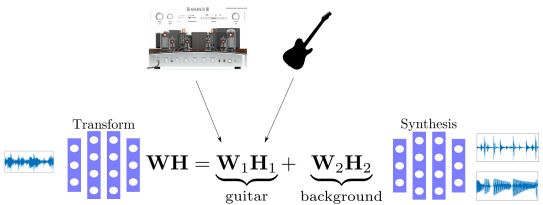


Proposal: incorporate the generative model into the demixing pipeline.



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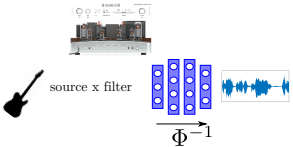

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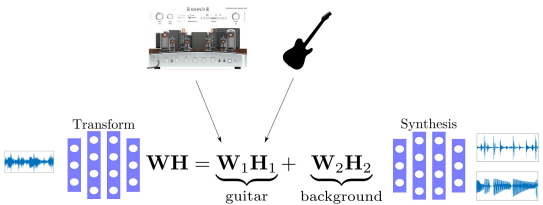

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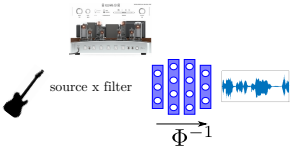

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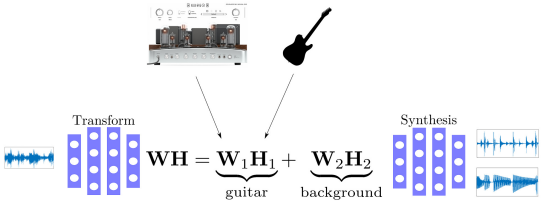

- ✓ High quality backing track generation.
- ✓ Optimal generative model parameters = a preset!

Conclusion

Where are we now?

Main messages

- The room for improvement of phase recovery: more potential gain than with magnitudes.
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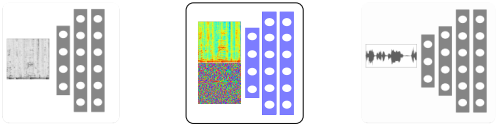
The proposed alternative

Complex-domain / phase-aware deep learning



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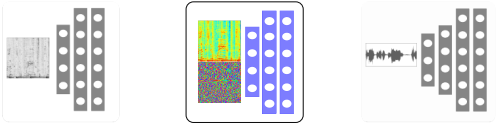

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Open questions

- ▷ How to handle phase in deep learning?
- ▷ How to exploit anisotropic probabilistic modeling?
- ▷ How to efficiently learn to factorize?

References

Magron et al., "Phase reconstruction of spectrograms with linear unwrapping: application to audio signal restoration", *Proc. EUSIPCO*, August 2015.

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Thanks!

https://magronp.github.io/

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