Complex-valued and hybrid models for audio processing

MULTISPEECH team seminar - INRIA Nancy Grand-Est

Paul Magron

IRIT, Université de Toulouse, CNRS - Signal & Communications team

Academic background

- PhD – *Télécom ParisTech* (R. Badeau, B. David) 2013 - 2016
  Phase recovery based on signal modeling: application to audio source separation.
- Postdoc – *Tampere University* (T. Virtanen) 2017 - 2019
  Probabilistic phase modelling and real-time sound source separation.
- Postdoc – *IRIT* (C. Févotte) 2019 -
  Content-aware music recommendation.

Publications since 2015:

- 4 journal articles.
  - 2 *IEEE Transactions on Audio, Speech, and Language Processing*
  - 1 *IEEE Signal Processing Letters*
  - 1 *IEEE Journal of Selected Topics in Signal Processing*
- 19 conference articles.
  - 1 best paper award (iWAENC 2018)
- 13 co-authors from 7 institutions.

Research field

Audio signal processing

- Telecommunications: speech coding and synthesis.
- Medical devices: hearing aids.
- Educational softwares: language/music learning.
- Music information retrieval, music streaming.

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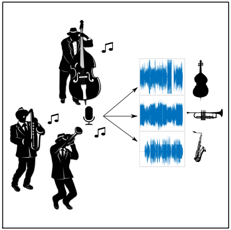

Source separation

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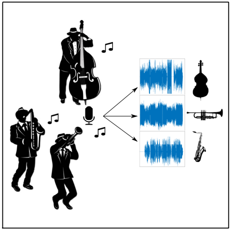

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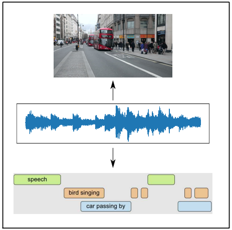

Acoustic scene analysis

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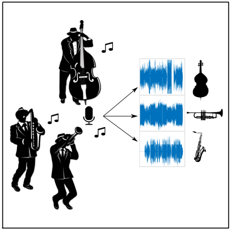

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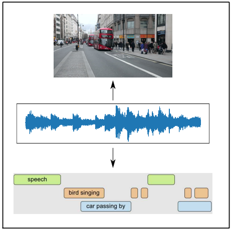

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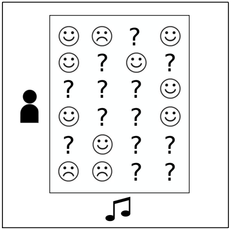


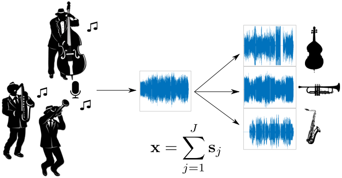
Music recommendation

Audio source separation

Audio source separation

Audio content is usually composed of several constitutive sounds:

- ▷ One or several speakers + noise.
- ▷ Environmental / domestic sounds.
- ▷ Musical instruments.



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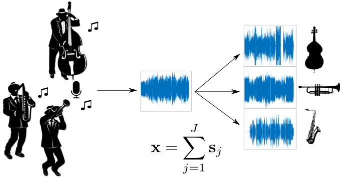

$$\mathbf{x} = \sum_{j=1}^{J} \mathbf{s}_j$$

Source separation = recovering the sources from the mixture.

- ▷ Automatic speech recognition → clean speech vs. noise.
- ▷ Rhythm analysis → drums vs. harmonic instruments.
- ▷ Stationary / transient decomposition → time-stretching.

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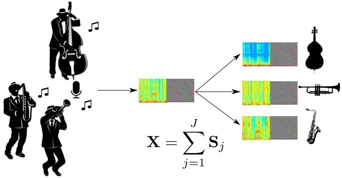

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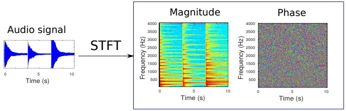
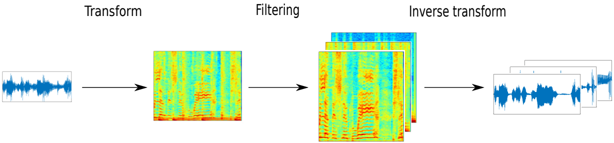
Time-frequency separation = acts on the short-time Fourier transform (STFT).



Source separation general framework



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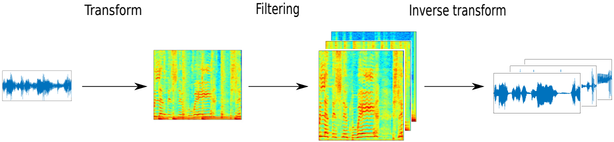

1. Nonnegative representation: $V = |STFT(x)|^2$.

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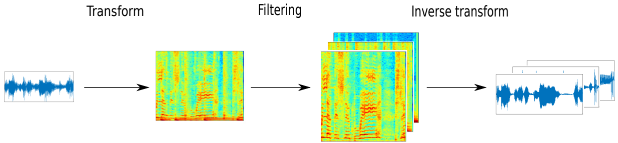

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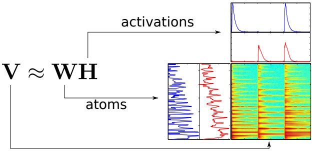

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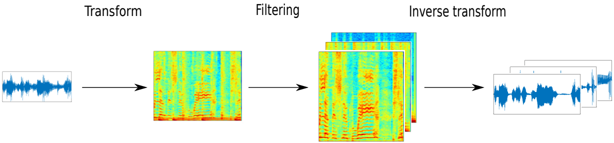

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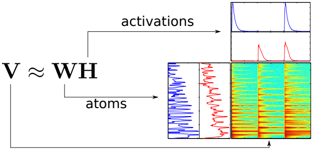

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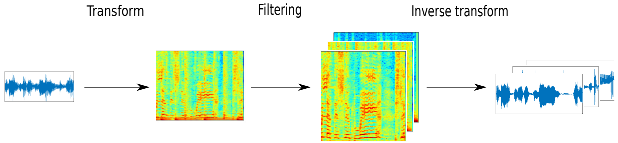

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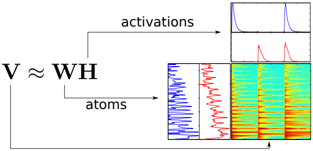

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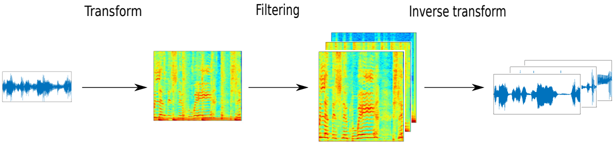

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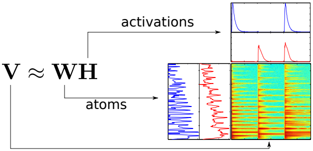

The phase problem

Wiener filter

$$\underbrace{\boxed{\hat{\mathsf{S}}_j}}_{\text{Source STFT (Estimated)}} = \underbrace{\boxed{\frac{\hat{\mathsf{V}}_j}{\sum_{k=1}^{J} \hat{\mathsf{V}}_k}}}_{\text{Mask}} \odot \underbrace{\boxed{\mathsf{X}}}_{\text{Mixture STFT}}$$

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Inconsistency

$$\mathcal{I}(\mathsf{Y}) = ||\mathsf{Y} - \mathcal{G}(\mathsf{Y})||^2$$
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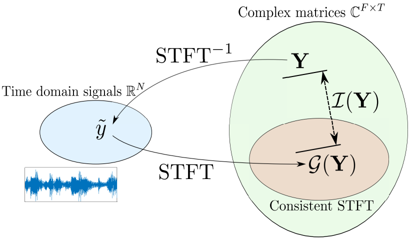

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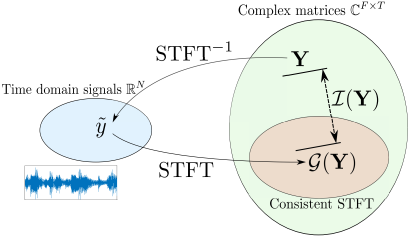
- ▷ Griffin-Lim (GL): minimization of $\mathcal{I}$.
- ▷ Extension to source separation.
- ▷ Combination with Wiener filtering.



The phase problem

Comparative study [ICASSP 15]

- Room for improvement for phase recovery.
- Test alternative separation methods accounting for the phase:
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  - Signal model-based.
- The most promising uses a signal model for structuring the phase / STFT.

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My approach

- Leveraging model-based phase properties in source separation.
- A phase-aware probabilistic framework.
- Joint estimation of magnitude and phase.

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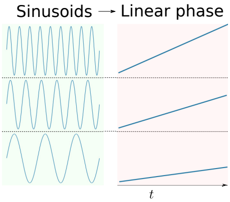
Model-based phase recovery

Sinusoidal phase model

For a mixture of sinusoids, the phase is:

$$\mu_{f,t} = \mu_{f,t-1} + 2\pi \underbrace{\nu_{f,t}}_{\text{normalized frequency}}$$



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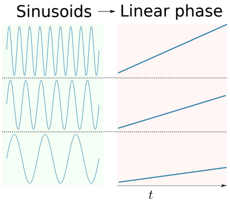

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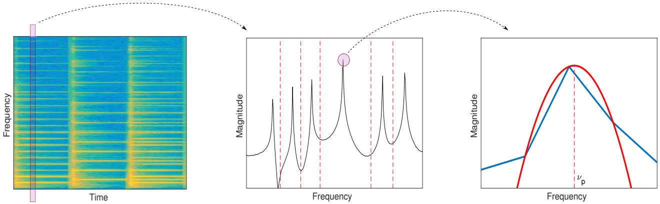
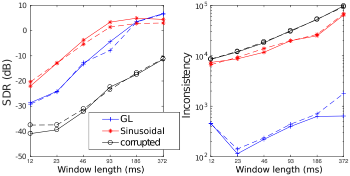
Recursive estimation in each time frame:



Sinusoidal phase model

Restoration of piano pieces:



- ▷ Better performance than the consistency-based GL algorithm.
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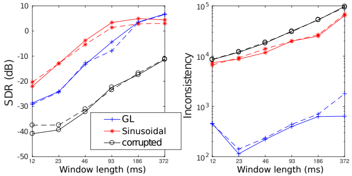

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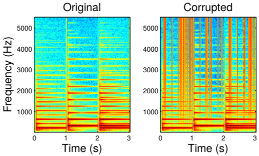
Applications

- ▷ Click removal [EUSIPCO 15].
- ▷ Source separation.



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Repeating attacks

Why treating attacks?

- ▷ Perceptive quality of the sound.
- ▷ Initialize the sinusoidal model.

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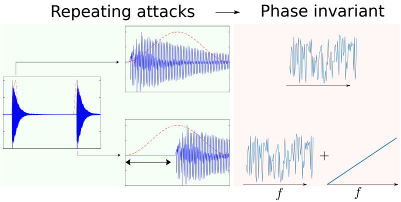
Model within onset frames:

$$\mu_{f,t} = \underbrace{\psi_f}_{\text{invariant}} + \underbrace{\eta_t}_{\text{offset}} f$$



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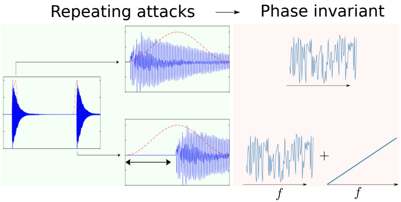

Incorporation in a mixture model

- ▷ Estimation with coordinate descente.
- ▷ Slight improvement over using the mixture's phase [WASPAA 15].

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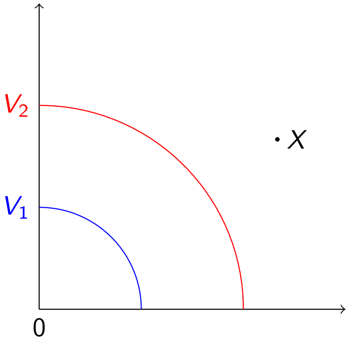
Source separation iterative algorithm

Problem

$$\min_{\boldsymbol{\mu}} ||\mathsf{X} - \sum_{j=1}^{J} \mathsf{V}_j e^{\mathrm{i}\boldsymbol{\mu}_j}||^2$$



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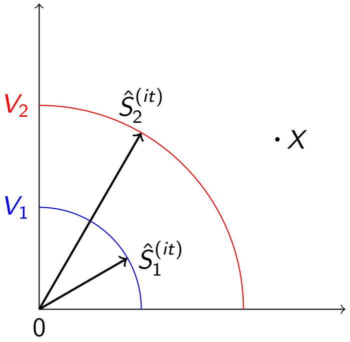

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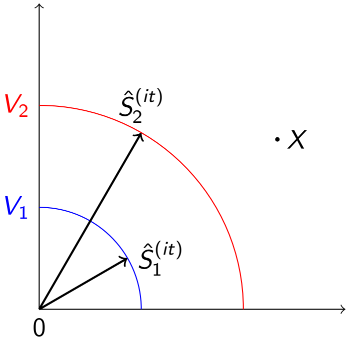

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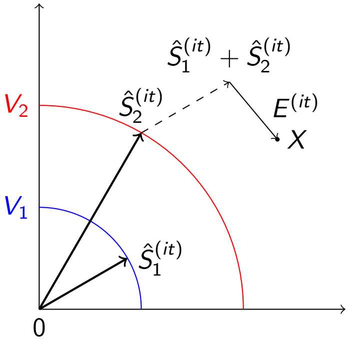

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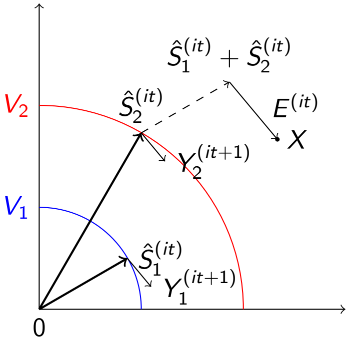

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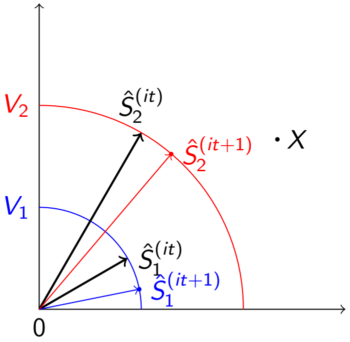
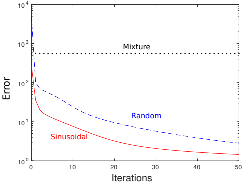


Source separation iterative algorithm

Initialization impact (DSD100 dataset):

	SDR	SIR	SAR
Mixture	7.5	13.7	8.9
Random	9.5	22.8	9.7
Sinusoidal	13.6	31.0	13.7



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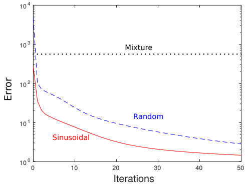
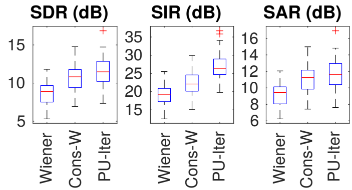


Comparison with Wiener filters:



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How to re-introduce consistency?

Time-domain formulation

$$\min_{\{\tilde{s}_j\}} \sum_j |||\text{STFT}(\tilde{s}_j)| - V_j||^2 \text{ s. t. } \sum_j \tilde{s}_j = \tilde{x}$$

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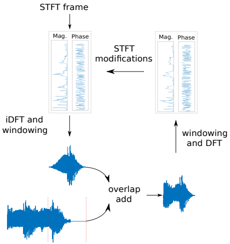
- Auxiliary function method: the (well-known) MISI algorithm, but convergence-guaranteed.

Online implementation

- Useful for real-time applications (hearing aids): for a latency of 16 ms, same results as the offline counterpart.
- Allows initialization with the sinusoidal phase: better results in some cases.



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Alternative divergences

- Euclidean distance: not the most appropriate in audio.
- Popular alternative: the beta-divergences.

$\beta = 2$	$\beta = 1$	$\beta = 0$
Euclidean	Kullback-Leibler (KL)	Itakura-Saito (IS)
Emphasis on high-energy components	$\leftarrow$ In between $\rightarrow$	Scale invariance

P. Magron, P.-H. Vial, T. Oberlin, C. Févotte, "Phase recovery with Bregman divergences for audio source separation", *Proc. IEEE International Conference on Audio, Speech and Signal Processing (ICASSP)*, June 2021.
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Alternative divergences

- Euclidean distance: not the most appropriate in audio.
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Phase retrieval with beta-divergences

$$\min_{\{\tilde{s}_j\}} \sum_j D_\beta(|\mathrm{STFT}(\tilde{s}_j)|^d, V_j) \text{ s. t. } \sum_j \tilde{s}_j = \tilde{x}$$

- Optimization with accelerated gradient descent or ADMM.
- Experimentally: alternative divergences (e.g., KL or $\beta = 0.5$) $>$ Euclidean.

P. Magron, P.-H. Vial, T. Oberlin, C. Févotte, "Phase recovery with Bregman divergences for audio source separation", *Proc. IEEE International Conference on Audio, Speech and Signal Processing (ICASSP)*, June 2021.

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Probabilistic phase modelling

Probabilistic framework

Why?

- Modeling uncertainty.
- Incorporating prior information.
- Obtaining estimators with nice statistical properties.
- Deriving inference schemes with convergence guarantees.

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$\Rightarrow$ Phase-unaware estimators.

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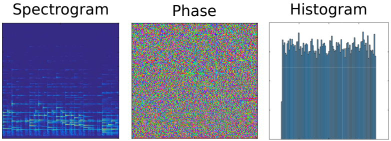
My approach

A phase-aware probabilistic framework for source separation.

Is the phase really uniform?

A simple example (piano piece), where the phase appears uniformly-distributed.



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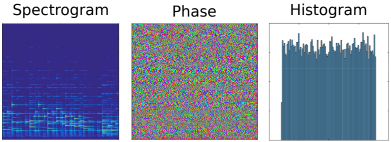

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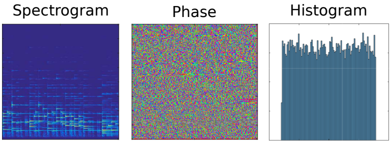

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Interpretation

- ▷ The histogram validates an iid assumption on $\{\phi_{f,t}\}$:

$$\phi_{f,t} \sim \mathcal{D} \text{ and independent } \rightarrow \mathcal{D} = \mathcal{U}_{[0,2\pi[}$$

- ▷ This model only conveys a **global** information.

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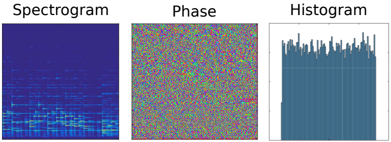

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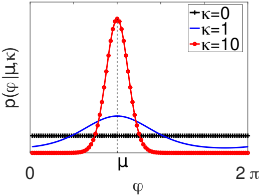
What about the **local structure** of the phase?

Von Mises phase model

Von Mises distribution

$$\phi_{ft} \sim \mathcal{VM}(\mu_{ft}, \kappa)$$

- $\mu_{f,t}$ = phase location.
- κ = concentration (quantifies non-uniformity).



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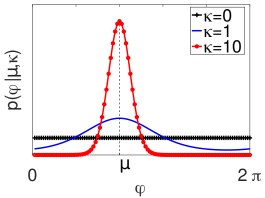


Model

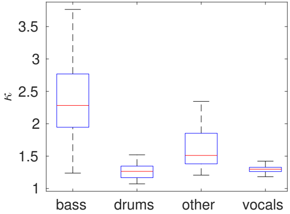
- ▷ $\mu_{f,t}$ = sinusoidal phase.
- ▷ Center the phases: $\psi_{f,t} = \phi_{f,t} - \mu_{f,t}$

Distribution	Uniform	VM	Centered VM
	$\phi_{f,t} \sim \mathcal{U}_{[0,2\pi[}$	$\phi_{ft} \sim \mathcal{VM}(\mu_{f,t}, \kappa)$	$\psi_{f,t} \sim \mathcal{VM}(0, \kappa)$
iid	✓	✗	✓
Local structure	✗	✓	✓

Von Mises phase model [iWAENC 18]

Estimation of κ (maximum likelihood):

$$\frac{I_1(\kappa)}{I_0(\kappa)} = \frac{1}{FT} \sum_{f,t} \cos(\psi_{ft})$$



- ▷ Solved with fast numerical schemes.
- ▷ κ quantifies the "sinusoidality" of the sources.

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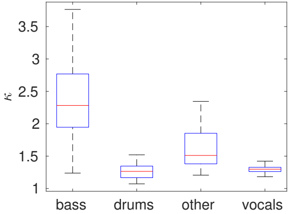
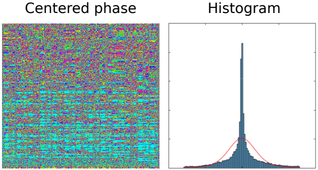


Validation

- ▷ Both uniform and VM models are statistically relevant.
- ▷ They convey different information about the phase (global vs. local).



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Multiple sources model

In each TF bin, $x = \sum_{j=1}^{J} s_j$.

Isotropic gaussian model: $s_j \sim \mathcal{N}_{\mathbb{C}}(m_j, \Gamma_j)$ with $\Gamma_j = \begin{pmatrix} \gamma_j & c_j \\ \bar{c}_j & \gamma_j \end{pmatrix}$.

- m_j: mean (location) / γ_j: variance (energy).
- c_j: relation term, usually 0.

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Polar coordinate equivalent model: $s_j = r_j e^{\mathrm{i}\phi_j}$ where:

- $r_j \sim \mathcal{R}(v_j)$ (Rayleigh magnitude).
- $\phi_j \sim \mathcal{U}_{[0,2\pi[}$ (uniform phase).

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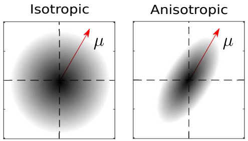
Naive idea

Consider a VM phase instead $\rightarrow$ Phase-aware... but not tractable.

Anisotropic Gaussian model



	Phase-aware	Tractable
Isotropic Gaussian	✗	✓
Rayleigh + von Mises	✓	✗
Anisotropic Gaussian	✓	✓

Source model: $s_j \sim \mathcal{N}_{\mathbb{C}}(m_j, \Gamma_j)$ with $\Gamma_j = \begin{pmatrix} \gamma_j & c_j \\ \bar{c}_j & \gamma_j \end{pmatrix}$.

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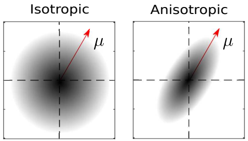

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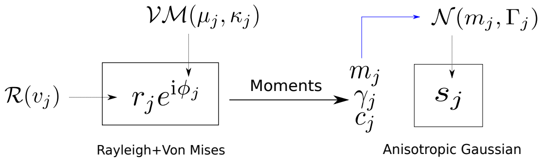

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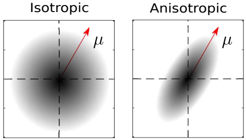

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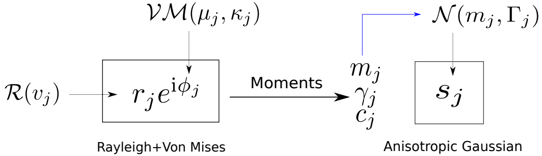

- ▷ Parameters: v_j (energy), μ_j (phase location), κ (non-uniformity).

Anisotropic Wiener filter

- ▷ Posterior mean of the sources: anisotropic Wiener filter [ICASSP 17].
- ▷ Performance (oracle separation results):

	SDR	SIR	SAR
Wiener	8.5	19.1	9.1
Anisotropic Wiener	**9.7**	**21.9**	**10.1**

Main message

- ▷ Including phase information in the filter improves the separation quality.
- ▷ Potential of a phase-aware statistical framework.

P. Magron, R. Badeau, B. David, "Phase-dependent anisotropic Gaussian model for audio source separation", *Proc. IEEE International Conference on Audio, Speech and Signal Processing (ICASSP)*, March 2017.

Again... consistency?

Problem

- ▷ The (anisotropic) Wiener filter produces inconsistent matrices.

P. Magron, J. Le Roux, T. Virtanen, "Consistent anisotropic Wiener filtering for audio source separation", *Proc. IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA)*, October 2017.

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Consistent anisotropic Wiener [WASPAA 17]

- Consider the loss function:

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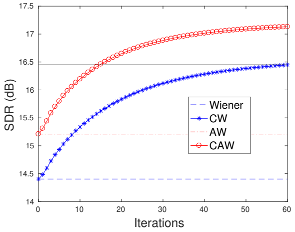
	Sinusoidal model	Consistent
Wiener	✗	✗
CW	✗	✓
AW	✓	✗
CAW	✓	✓



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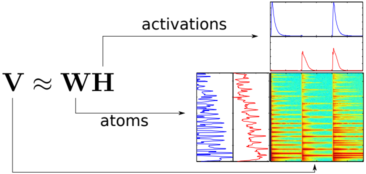
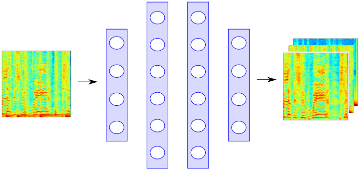
Joint estimation of magnitude and phase

Realistic source separation

Goal: estimate the magnitude **and** the phase of the sources.

- ▷ Needs an additional spectrogram-like model and estimation technique.





Approaches

- ▷ Two-stage: first estimate the magnitude, and then recover the phase.
- ▷ One-stage: jointly estimate the magnitude and the phase.

Two-stage approaches

NMF + phase recovery

- ▷ Phase recovery induces a slight improvement (interference reduction).

P. Magron, K. Drossos, S. I. Mimilakis, T. Virtanen, "Reducing interference with phase recovery in DNN-based monaural singing voice separation", *Proc. Interspeech*. September 2018.
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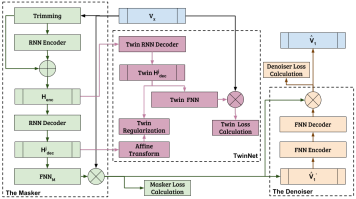
DNN + phase recovery [Interspeech 18, iWAENC 18]



- ▷ More significant results (DNNs > NMF).
- ▷ Phase recovery makes sense on top of good magnitude estimates.

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Complex NMF

Baseline NMF $|X| \approx \hat{V} = WH$

- ▷ Assumes the additivity of the sources' magnitudes $\rightarrow$ phase?

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Complex NMF $\mathsf{X} \approx \hat{\mathsf{X}} = \sum_j \underbrace{[\mathsf{W}_j \mathsf{H}_j]}_{\text{NMF}} e^{i\boldsymbol{\mu}_j}$

▷ Regularize the phases with model-based properties [ICASSP 16]:

$$\min ||\mathsf{X} - \hat{\mathsf{X}}||^2 + \underbrace{\lambda_{\text{sp}} \mathcal{C}_{\text{sp}}(\mathsf{H})}_{\text{sparsity}} + \underbrace{\lambda_{\text{sin}} \mathcal{C}_{\text{sin}}(\boldsymbol{\mu})}_{\text{sinusoidal phase}} + \underbrace{\lambda_{\text{rep}} \mathcal{C}_{\text{rep}}(\boldsymbol{\mu}, \boldsymbol{\psi}, \boldsymbol{\eta})}_{\text{repeating attacks}}$$

▷ Optimization: coordinate descent or auxiliary function method.

▷ Tuning λ_{sin} and λ_{rep}: trade-off between interference and artifact reduction.

P. Magron, R. Badeau, B. David, "Complex NMF under phase constraints based on signal modeling: application to audio source separation", *Proc. IEEE International Conference on Audio, Speech and Signal Processing (ICASSP)*, March 2016.

Complex ISNMF

Hard to extend complex NMF to non-Euclidean metrics (e.g., beta-divergences).

P. Magron, T. Virtanen, "Complex ISNMF: a phase-aware model for monaural audio source separation", *IEEE/ACM Transactions on Audio, Speech and Language*, vol. 27, no. 1, pp. 20–31, January 2019.

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Probabilistic view

(Real) Gaussian	$r \sim \mathcal{N}(m, \sigma^2)$	$m = wh$	Euclidean NMF
Poisson	$r \sim \mathcal{P}(v)$	$v = wh$	KLNMF
Isotropic Gaussian	$x \sim \mathcal{N}_{\mathbb{C}}(0, v^2 I)$	$v^2 = wh$	ISNMF
Isotropic Gaussian	$x \sim \mathcal{N}_{\mathbb{C}}(m, \sigma^2 I)$	$m = whe^{\mathrm{i}\mu}$	Complex NMF

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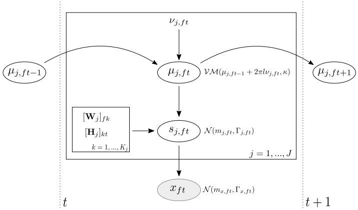
Complex ISNMF [TASLP 19]

- Anisotropic Gaussian model (NMF variance).
- Markov chain prior on the phase parameter.
- Estimation: EM algorithm.
- Better results than Complex NMF and ISNMF.



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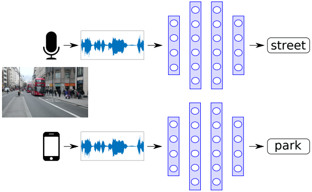
Acoustic scene classification

Domain adaptation for acoustic scene classification

Problem

- ▷ Classify an audio segment into classes.
- ▷ Mismatch between recording conditions.



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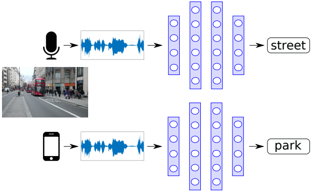

Domain adaptation [WASPAA 19]

- ▷ *Source* and *target* domain data $\rightarrow$ same latent distribution.
- ▷ Wasserstein GAN: minimize scene classification error / maximize domain classification error.

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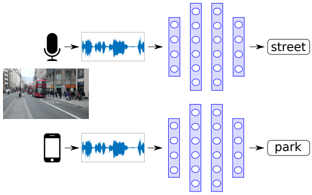

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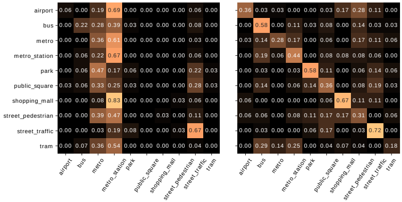

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Music recommendation

Content-aware music recommendation

Collaborative filtering with matrix factorization: $Y \approx WH$.

- $\triangleright$ Y / W / H = interactions / users preferences / songs attributes.
- $\triangleright$ Cannot recommend novel items: cold-start problem.

P. Magron, C. Févotte, "Leveraging the structure of musical preference in content-aware music recommendation", *Proc. IEEE International Conference on Audio, Speech and Signal Processing (ICASSP)*, June 2021.

P. Magron, C. Févotte, "Neural content-aware collaborative filtering for cold-start music recommendation", to be submitted in the *ACM Transactions on Information Systems*.

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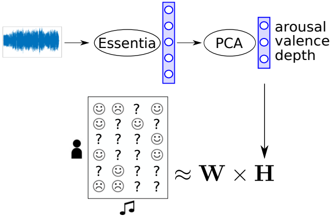

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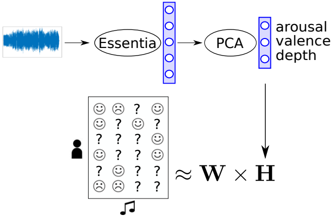
P. Magron, C. Févotte, "Neural content-aware collaborative filtering for cold-start music recommendation", to be submitted in the *ACM Transactions on Information Systems*.

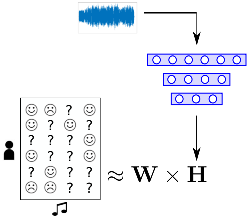
Content-aware music recommendation

Collaborative filtering with matrix factorization: $Y \approx WH$.

- ▷ Y / W / H = interactions / users preferences / songs attributes.
- ▷ Cannot recommend novel items: cold-start problem.

Content-aware recommendation





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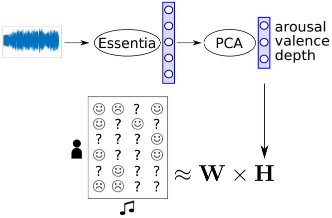

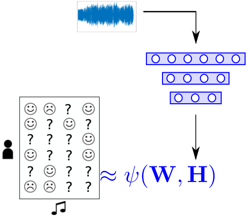

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Thanks!

- Webpage: `https://magronp.github.io/`
- Code: `https://github.com/magronp`