

Complex-valued and hybrid models for audio processing

PERCEPTION team seminar - INRIA Grenoble - Rhône-Alpes

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*
- ▷ 21 conference articles.
 - ▷ 1 best paper award (iWAENC 2018)
- ▷ 13 co-authors from 7 institutions.

Research field

Audio signal processing

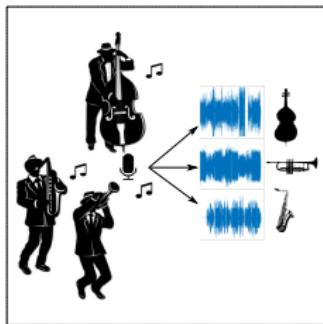
- ▷ Telecommunications: speech coding and synthesis.
- ▷ Medical devices: hearing aids.
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Main applications (of my work)



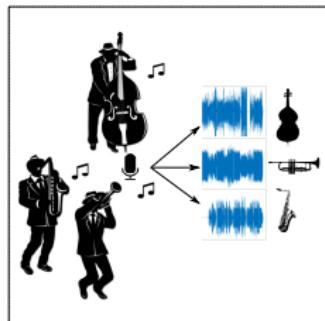
Source separation

Research field

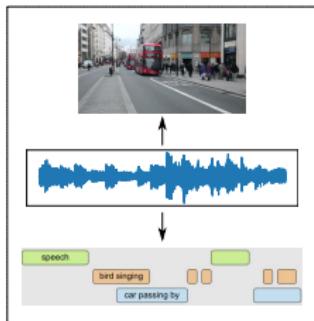
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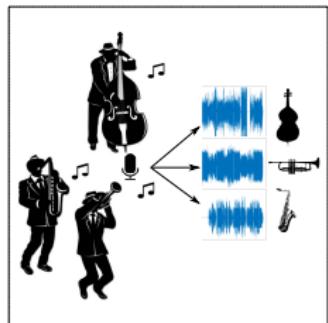
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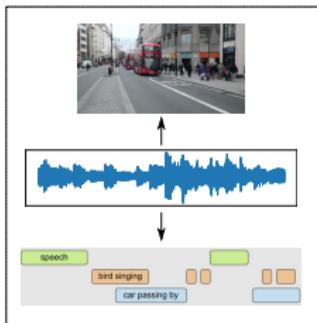
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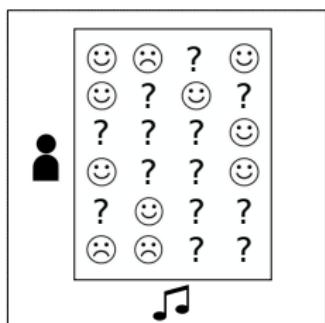
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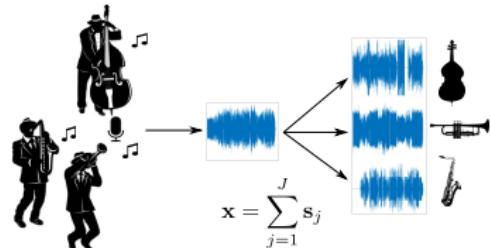
Music recommendation

Audio source separation

Audio source separation

Audio content is usually composed of several constitutive sounds:

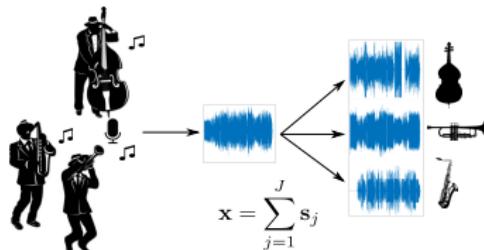
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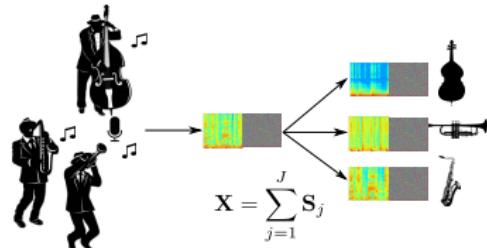
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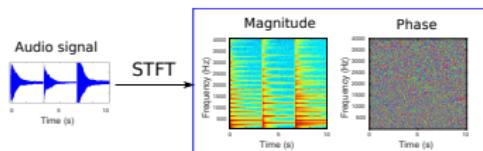
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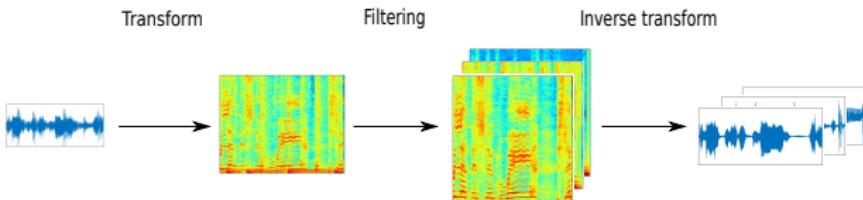
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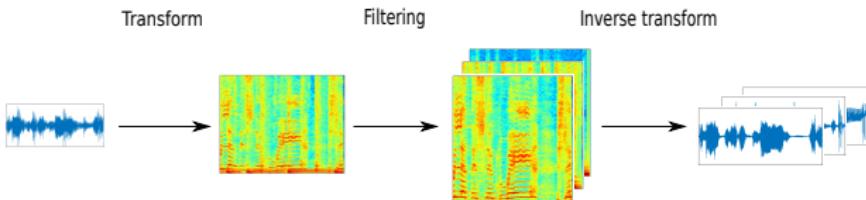
Time-frequency separation = acts on the short-time Fourier transform (STFT).



Source separation general framework

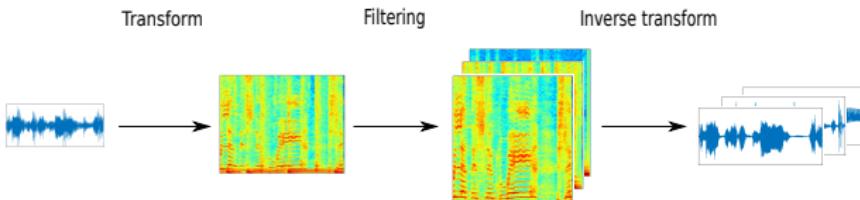


Source separation general framework



1. Nonnegative representation: $V = |\text{STFT}(x)|^2$.

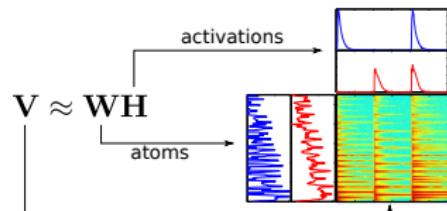
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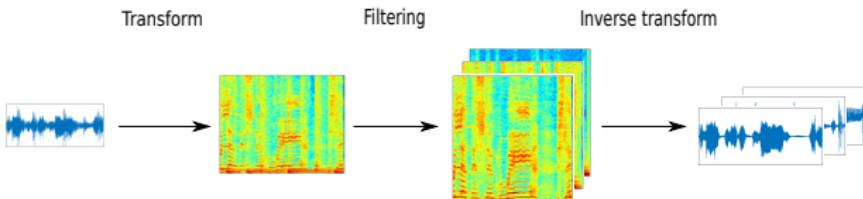
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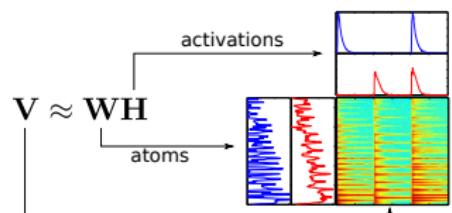
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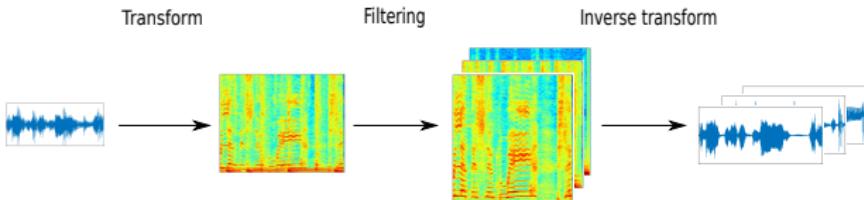
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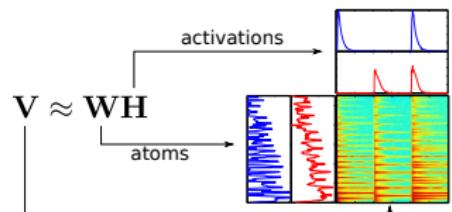
- ▷ $\min_{W,H} \mathcal{D}(V, WH)$
- ▷ $\min_{\theta} \mathcal{L}(\{V_j\}, \phi_{\theta}(V))$



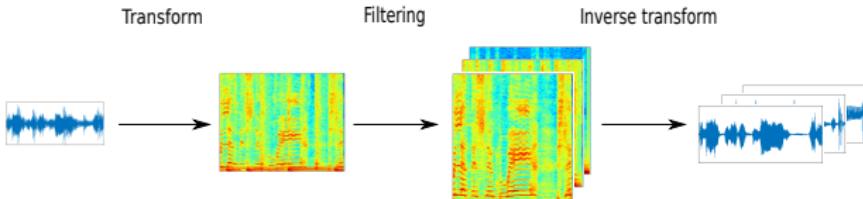
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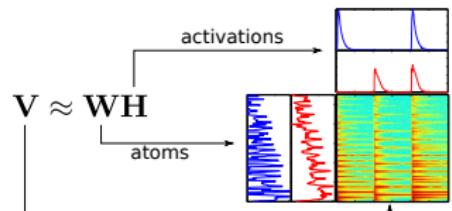
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5. Synthesis: $\tilde{s}_j = \text{STFT}^{-1}(M_j \odot X)$.



The phase problem

Wiener filter

$$\hat{S}_j = \frac{\hat{V}_j}{\sum_{k=1}^J \hat{V}_k} \odot X$$

Source STFT (Estimated) Mask Mixture STFT

$\angle S_j = \angle X \rightarrow$ Issues in sound quality when sources overlap in the TF domain.

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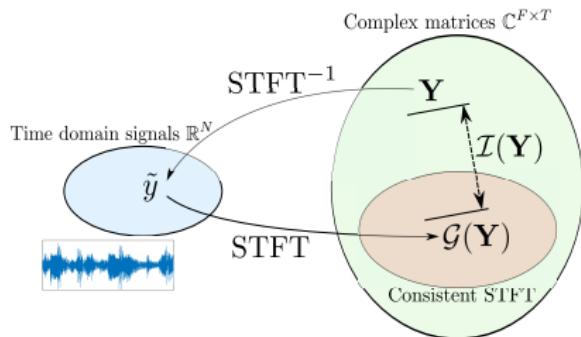
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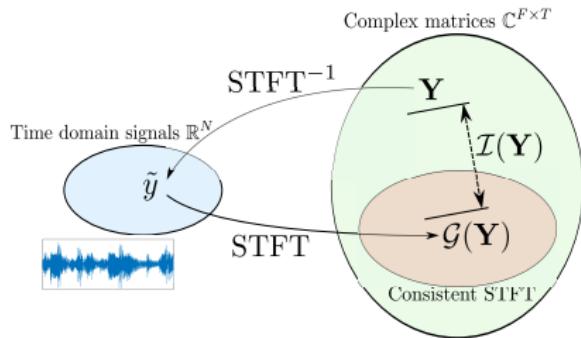
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- ▷ Griffin-Lim (GL): minimization of \mathcal{I} .
- ▷ Extension to source separation.
- ▷ Combination with Wiener filtering.



The phase problem

Comparative study [ICASSP 15]

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

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My approach

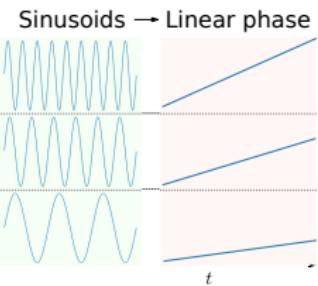
- ▷ Leveraging model-based phase properties in source separation.
- ▷ A phase-aware probabilistic framework.
- ▷ Joint estimation of magnitude and phase.

Model-based phase recovery

Sinusoidal phase model

For a mixture of sinusoids, the phase is:

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



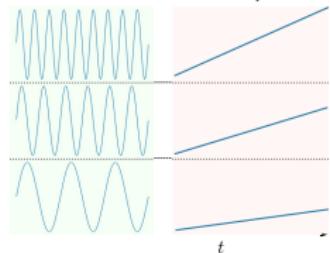
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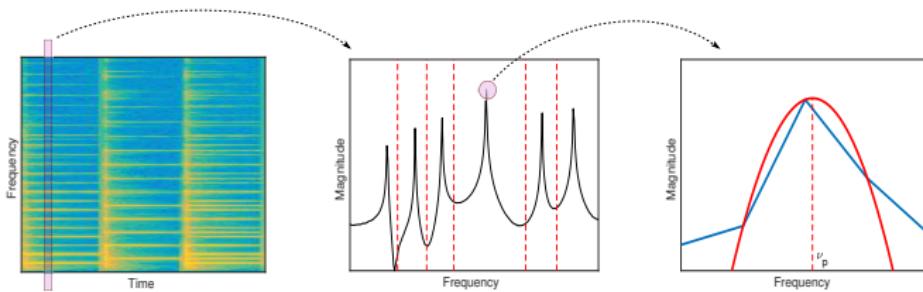
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Sinusoids \rightarrow Linear phase

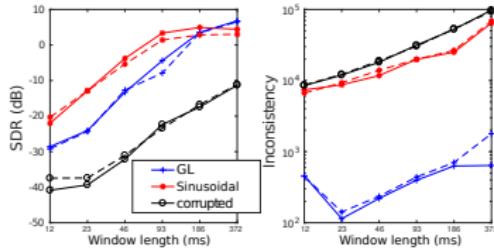


Recursive estimation in each time frame:



Sinusoidal phase model

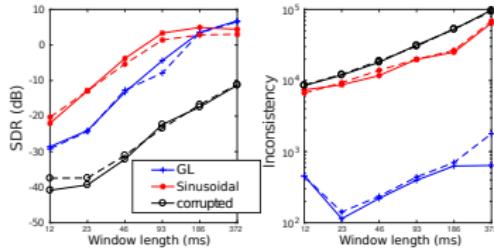
Restoration of piano pieces:



- ▷ Better performance than the consistency-based GL algorithm.
- ▷ But overall low SDR: error propagates over time frames.

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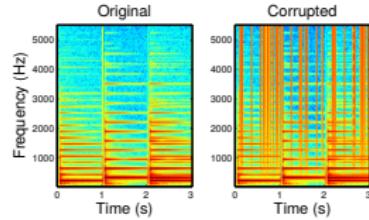
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Applications

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



Repeating attacks

Why treating attacks?

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

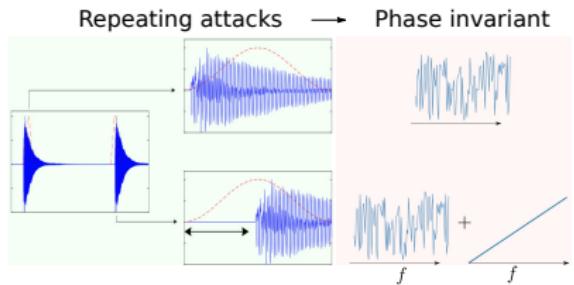
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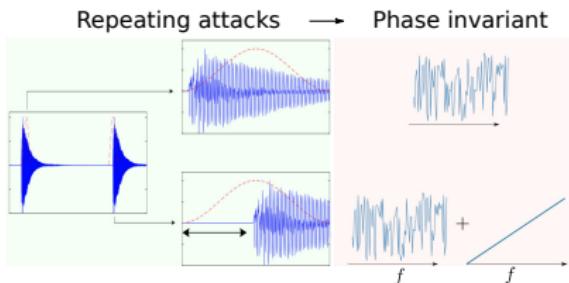
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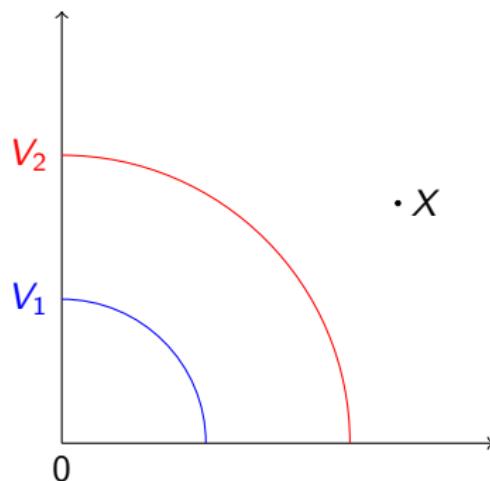
Incorporation in a mixture model

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

Source separation iterative algorithm

Problem

$$\min_{\mu} \left| \left| \mathbf{X} - \sum_{j=1}^J V_j e^{i\mu_j} \right| \right|^2$$



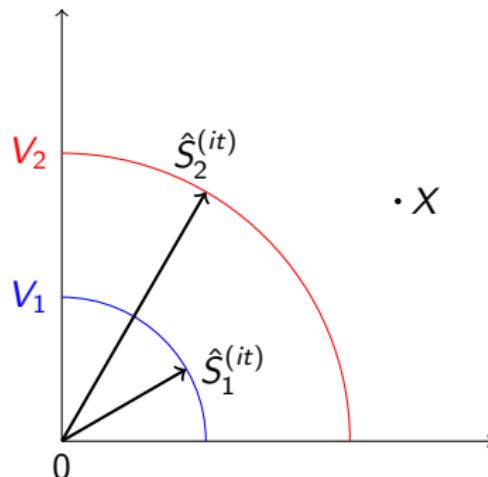
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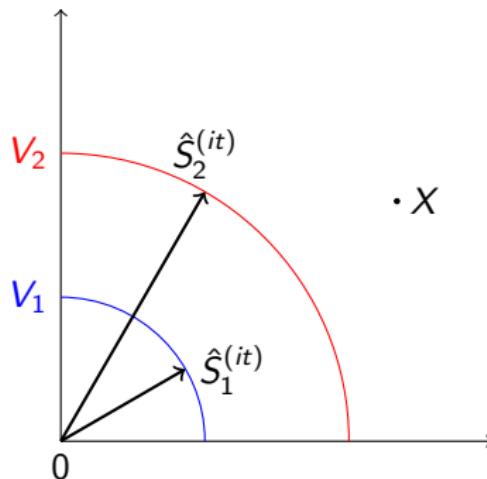
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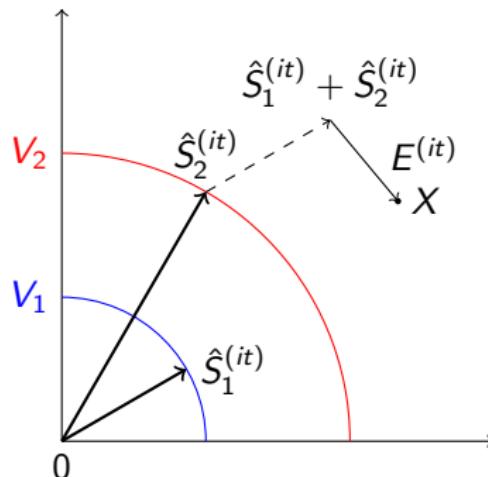
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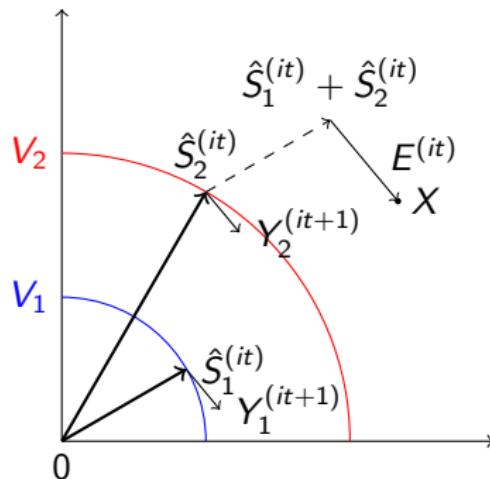
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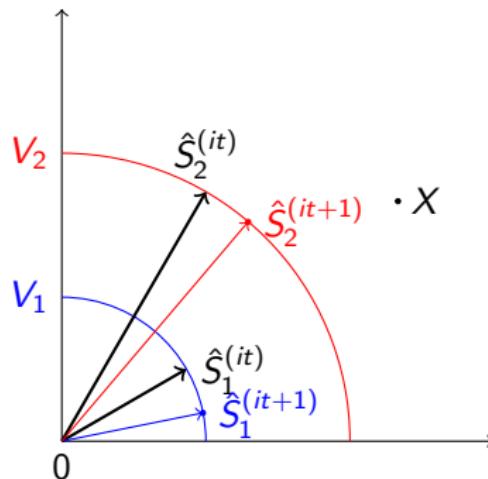
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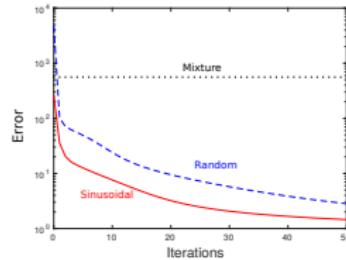
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Source separation iterative algorithm

Initialization impact (DSD100 dataset):

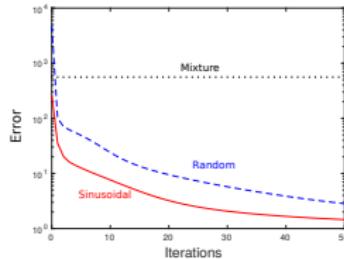
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Mixture	7.5	13.7	8.9
Random	9.5	22.8	9.7
Sinusoidal	13.6	31.0	13.7



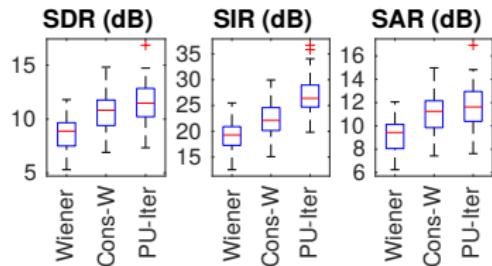
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Comparison with Wiener filters:



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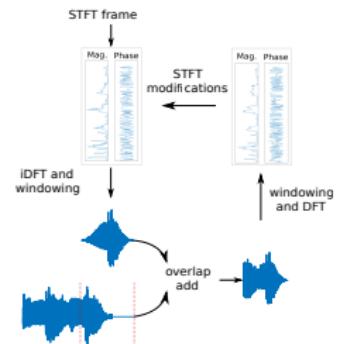
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- ▷ Auxiliary function method: the (well-known) MISI algorithm, but convergence-guaranteed.

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.



Alternative divergences

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

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

P.-H. Vial, P. Magron, T. Oberlin, C. Févotte, "Phase retrieval with Bregman divergences and application to audio signal recovery", *IEEE Journal of Selected Topics in Signal Processing*, January 2021.

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Phase retrieval with beta-divergences

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

- ▷ 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?

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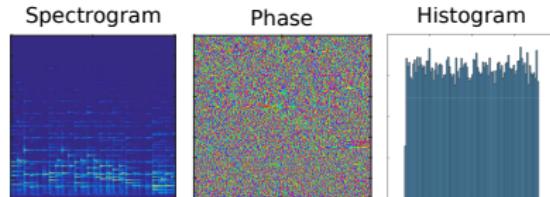
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My approach

A phase-aware probabilistic framework for source separation.

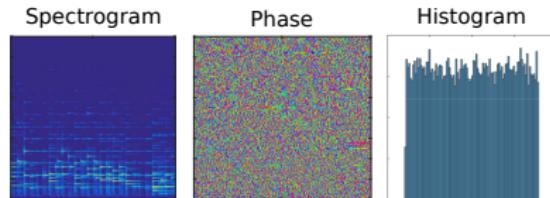
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A simple example (piano piece), where the phase appears uniformly-distributed.



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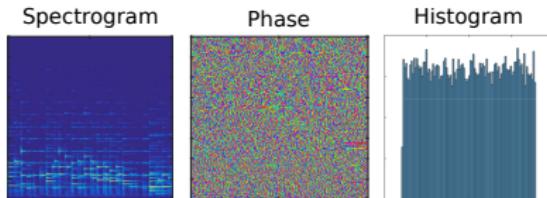
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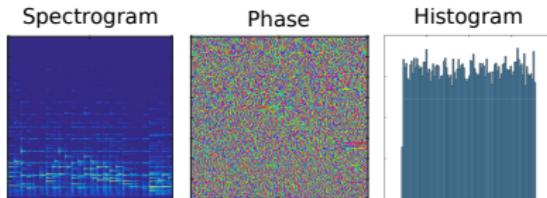
- ▷ The histogram validates an iid assumption on $\{\phi_{f,t}\}$:

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

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

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- ▷ 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.

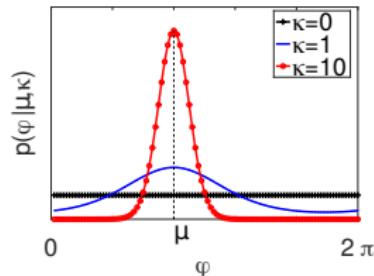
What about the **local structure** of the phase?

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).

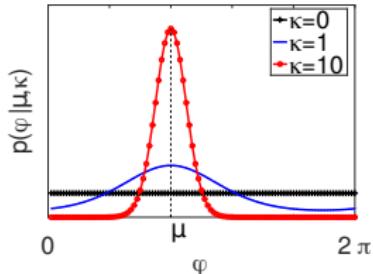


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Model

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

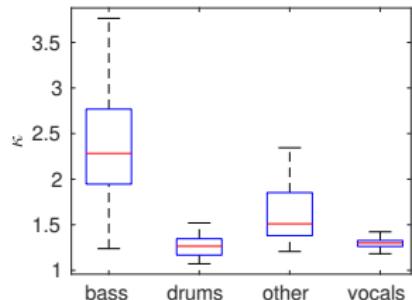
Distribution	Uniform	VM	Centered VM
iid	$\phi_{f,t} \sim \mathcal{U}_{[0,2\pi]}$	$\phi_{ft} \sim \mathcal{VM}(\mu_{f,t}, \kappa)$	$\psi_{f,t} \sim \mathcal{VM}(0, \kappa)$
Local structure	✗	✓	✓

Von Mises phase model [iWAENC 18]

Estimation of κ (maximum likelihood):

$$\frac{l_1(\kappa)}{l_0(\kappa)} = \frac{1}{FT} \sum_{f,t} \cos(\psi_{ft})$$

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

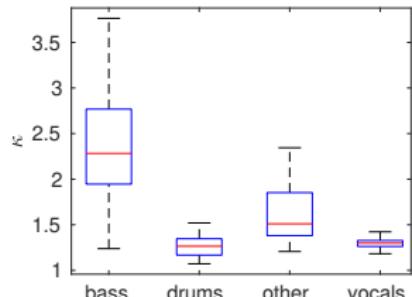


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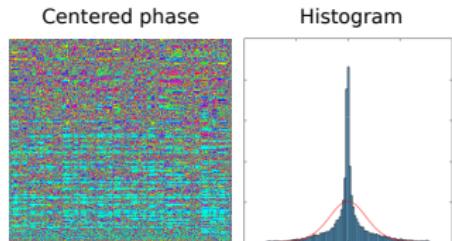
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- ▷ Solved with fast numerical schemes.
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Validation

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



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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Naive idea

Consider a VM phase instead → Phase-aware

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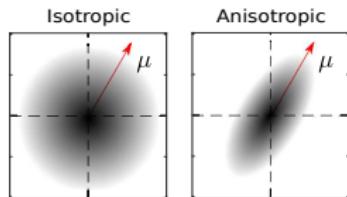
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Naive idea

Consider a VM phase instead → Phase-aware... but not tractable.

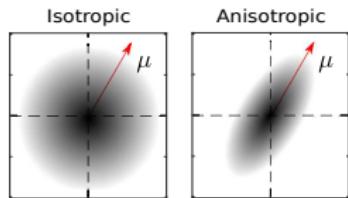
Anisotropic Gaussian model



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

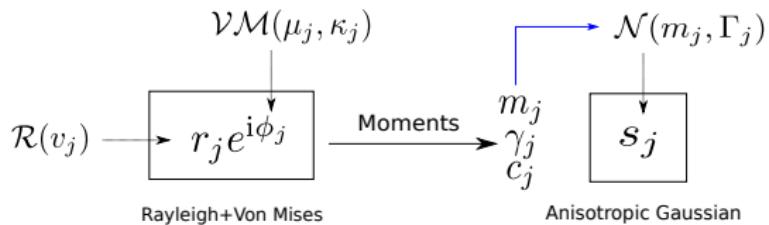
Source model: $s_j \sim \mathcal{N}_{\mathbb{C}}(m_j, \Gamma_j)$ with $\Gamma_j = \begin{pmatrix} \gamma_j & c_j \\ \bar{c}_j & \gamma_j \end{pmatrix}$.

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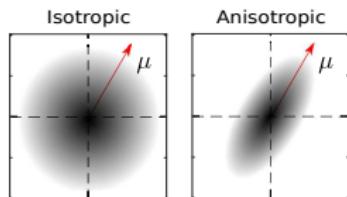


	Phase-aware	Tractable
Isotropic Gaussian	✗	✓
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Anisotropic Gaussian	✓	✓

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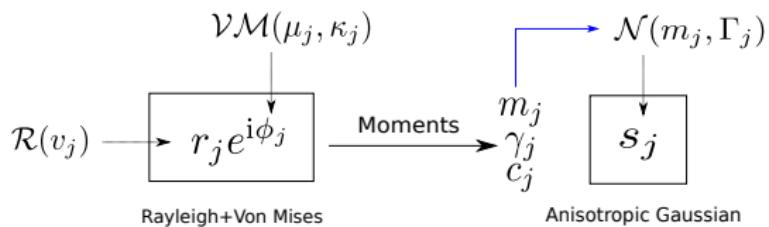


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Isotropic Gaussian	✗	✓
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- Parameters: v_j (energy), μ_j (phase location), κ (non-uniformity).

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.

Again... consistency?

Problem

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

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Consistent anisotropic Wiener [WASPAA 17]

- ▷ Consider the loss function:
 $\{\text{posterior distribution of the (anisotropic) sources}\} + \{\text{consistency constraint}\}$
- ▷ Minimization with preconditioned conjugate gradient descent.

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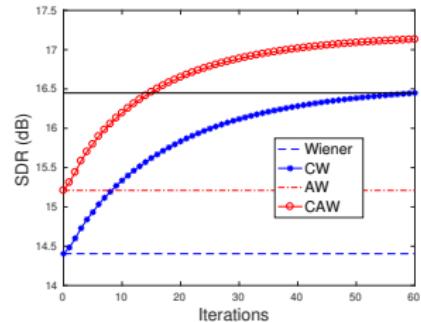
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	Sinusoidal model	Consistent
Wiener	✗	✗
CW	✗	✓
AW	✓	✗
CAW	✓	✓

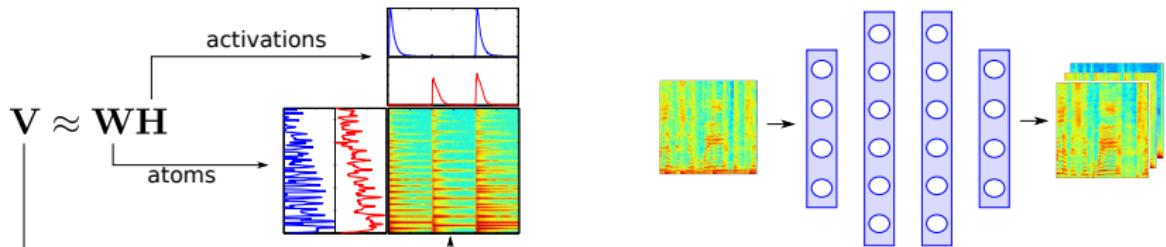


Joint estimation of magnitude and phase

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. Mimalakis, T. Virtanen, "Reducing interference with phase recovery in DNN-based monaural singing voice separation", *Proc. Interspeech*. September 2018.

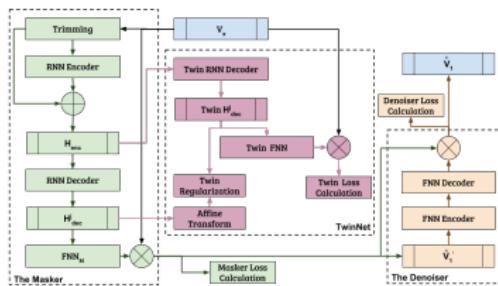
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Two-stage approaches

NMF + phase recovery

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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.

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

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Complex NMF

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

- ▷ Assumes the additivity of the sources' magnitudes → phase?

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

Complex NMF $X \approx \hat{X} = \sum_j [\underbrace{W_j H_j}_{\text{NMF}}] e^{i\mu_j}$

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

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

- ▷ Optimization: coordinate descent or auxiliary function method.
- ▷ Tuning λ_{sin} and λ_{rep} : trade-off between interference and artifact reduction.

Complex ISNMF

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

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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	$x \sim \mathcal{N}_{\mathbb{C}}(m, \sigma^2 I)$	$m = whe^{i\mu}$	Complex NMF

Complex ISNMF

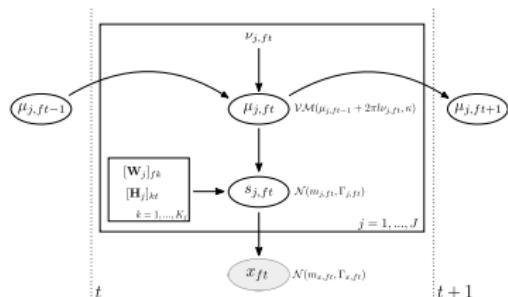
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Complex ISNMF [TASLP 19]

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

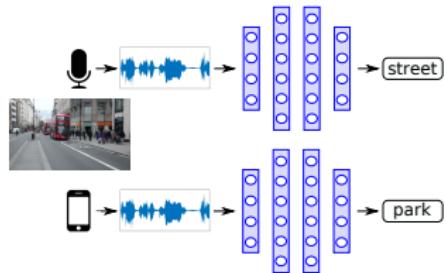


Acoustic scene classification

Domain adaptation for acoustic scene classification

Problem

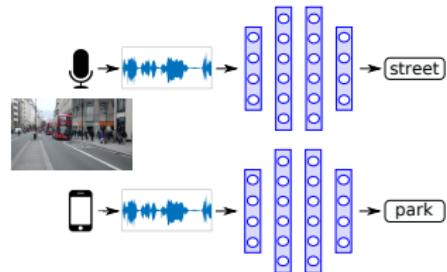
- ▷ Classify an audio segment into classes.
- ▷ Mismatch between recording conditions.



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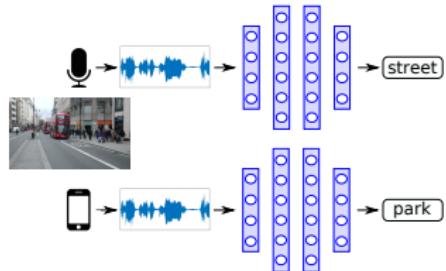
Domain adaptation [WASPAA 19]

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

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	airport	bus	metro	park	public_square	shopping_mall	street_pedestrian	street_traffic	train	airport	bus	metro	park	public_square	shopping_mall	street_pedestrian	street_traffic	train	
airport	0.06 0.00	0.19	0.61	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	-0.36	0.03	0.00	0.00	0.03	0.17	0.28	0.11	0.08	
bus	0.00 0.22	0.28	0.39	0.03 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	-0.00	0.58	0.00	0.11	0.03	0.08	0.20	0.14	0.03	0.03
metro	0.00 0.00	0.36	0.61	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	-0.03	0.14	0.28	0.17	0.00	0.06	0.00	0.17	0.11	0.06
park	0.00 0.06	0.22	0.61	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	-0.00	0.18	0.06	0.41	0.00	0.08	0.08	0.06	0.00	0.00
public_square	0.03 0.00	0.33	0.25	0.02 0.00	0.00 0.00	0.00 0.00	0.28	0.03	0.00 0.00	-0.00	0.14	0.00	0.06	0.14	0.36	0.00	0.08	0.19	0.03
shopping_mall	0.00 0.00	0.08	0.81	0.00 0.00	0.00 0.00	0.00 0.03	0.00 0.00	0.00 0.00	0.00 0.00	-0.06	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.11	0.00
street_pedestrian	0.00 0.00	0.39	0.61	0.00 0.00	0.03 0.00	0.00 0.00	0.11	0.00	0.00 0.00	-0.06	0.06	0.00	0.08	0.11	0.17	0.31	0.00	0.06	
street_traffic	0.00 0.00	0.03	0.10	0.08 0.00	0.00 0.00	0.00 0.03	0.07	0.00	0.00 0.00	-0.00	0.02	0.00	0.00	0.06	0.07	0.17	0.00	0.72	0.00
train	0.00 0.07	0.36	0.54	0.00 0.00	0.08 0.00	0.00 0.04	0.00 0.00	0.00 0.00	0.00 0.00	-0.00	0.28	0.14	0.25	0.09	0.04	0.07	0.04	0.00	0.18

K. Drossos, P. Magron, T. Virtanen, "Unsupervised adversarial domain adaptation based on the Wasserstein distance for acoustic scene classification", Proc. IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA), October 2019.

Music recommendation

Content-aware music recommendation

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

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

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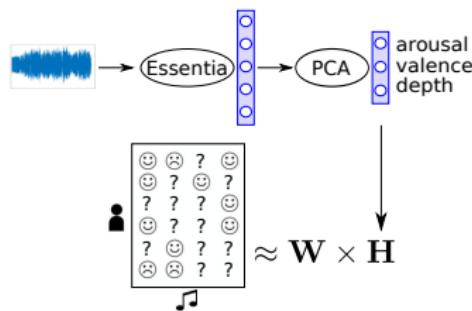
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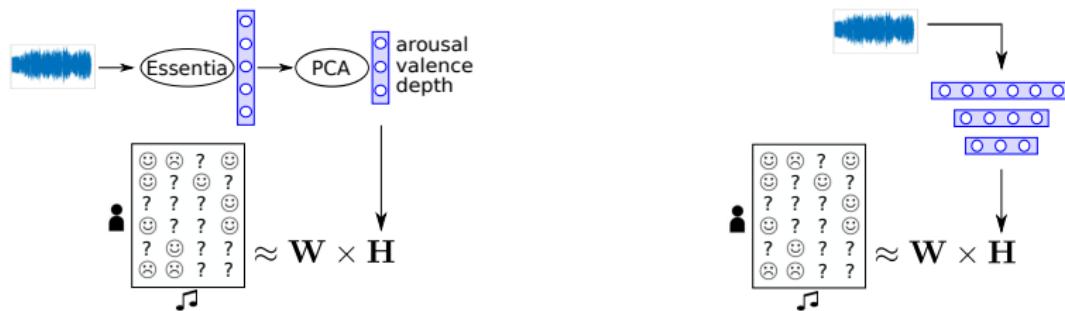
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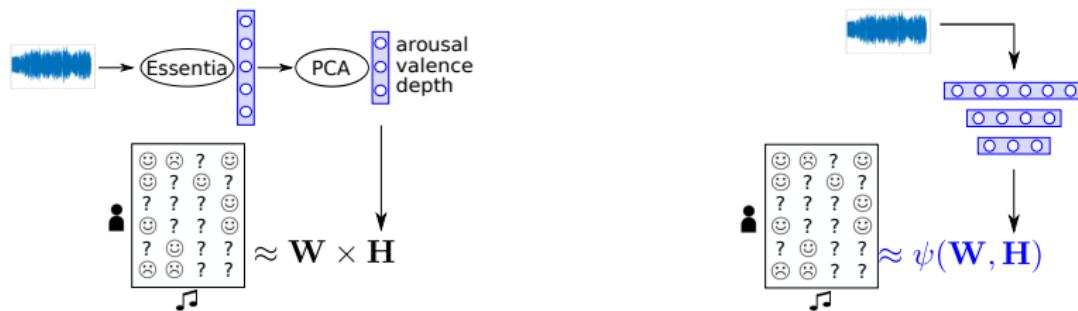
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Thanks!

- ▷ Webpage: <https://magronp.github.io/>
- ▷ Code: <https://github.com/magronp>