

## Blind Audio Source Separation with min.vol. $\beta$ -divergence NMF

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- ▶ Joint work with Valentin Leplat (UMONS  $\rightarrow$  UCLouvain) and Nicolas Gillis (UMONS)
- ▶ [1] Leplat, V, Gillis, N., Ang, M.S., “*Blind audio source separation with minimum-volume betadivergence NMF*”, IEEE Trans. Signal Processing 68, pp.3400-3410, May, 2020. DOI: 10.1109/TSP.2020.2991801
  - ▶ arxiv: 1907.02404
  - ▶ MATLAB: <https://sites.google.com/site/nicolasgillis/publications>
  - ▶ Youtube - Decomposition of El Doudou song: <https://www.youtube.com/watch?v=1BrpxvpghKQ>

# What

- Single-channel

# What

- Single-channel blind

# What

- Single-channel blind source separation

# What

- ▶ Single-channel blind source separation on audio data
  
- ▶ How

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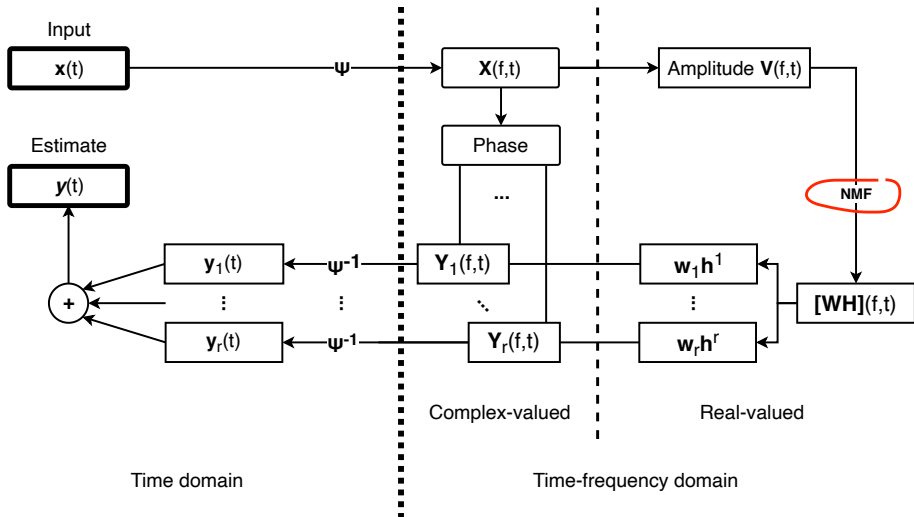
# What

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- ▶ The model actually also works for other applications.

# What

- ▶ Given  $x(t) = \sum_{k=1}^K s^{(k)}(t)$  : observed recording in  $\mathbb{R}^T$
- ▶  $s^{(k)}(t), k = 1, 2, \dots, K$  : source signals
- ▶ Goal: find  $s^{(k)}$  from  $x(t)$
- ▶  $x(t) \xrightarrow{STFT} X \in \mathbb{C}^{F \times T}$
- ▶ Amplitude spectrogram  $V = |X| \in \mathbb{R}^{F \times T}$
- ▶ BSS: perform NMF on  $V$ , assuming
  - ▶ Each source  $\iff$  each rank-1 component
  - ▶ No sound cancellation: NMF

# The BSS pipeline



# Minvol $\beta$ -divergence NMF

$$\min_{W,H} D_{\beta}(V|WH) + \lambda \log \det(W^T W + \delta I_r)$$

$$\text{s.t. } H \geq 0$$

$$W \geq 0$$

$$W(:, j) \in \Delta^r \text{ for all } j$$

# Minvol $\beta$ -divergence NMF

$\beta$ -divergence  $d_{\beta=1}(x|y) = x \log \frac{x}{y} - x + y$

constant  $\geq 0$ ,  
for lower bound

$\min_{W,H} D_{\beta}(V|WH) + \lambda \log \det (W^T W + \delta I_r)$

logdet volume

s.t.  $H \geq 0$  Activation  $\geq 0$

$W \geq 0$  Basis profile  $\geq 0$

$W(:, j) \in \Delta^K$  for all  $j$  Basis normalization



# Identifiability Theorem

- ▶ **Theorem 1** Assume  $V = W^* H^*$  where  $\text{rank}(V) = K$ ,  $W^* \geq 0$ , and  $H^*$  satisfies the *sufficiently scattered condition*, then the optimal sol. of

$$\min_{W \geq 0, H \geq 0} \det(W^T W) \quad \text{s.t.} \quad V = WH, \quad W^T e = e,$$

recovers  $(W^*, H^*)$  up to permutation and scaling.

- ▶ It is the first result of this type in the audio source separation literature.
- ▶ For the DEF of sufficiently scattered condition and the proof of theorem 1, see [1].

## Algorithm to solve minvol $\beta$ -NMF

- ▶ Propose an algo. to solve the minvol  $\beta$ -NMF.

$$\begin{aligned} \min_{W \geq 0, H \geq 0} \quad & D_\beta(V|WH) + \lambda \log \det(W^\top W + \delta I_r) \\ \text{s.t.} \quad & H \geq 0, W \geq 0, W(:, j) \in \Delta^K \end{aligned}$$

- ▶ Idea: majorization-minimization (MM)

$$f(x) \leq g(x; \theta),$$

where  $f$  are the  $\beta$ -divergence and  $\log \det(W^\top W + \delta I)$ ; see [1].

- ▶ Objective function monotonically decrease  $\rightarrow$  theoretical convergence.

# Mary had a little lamb

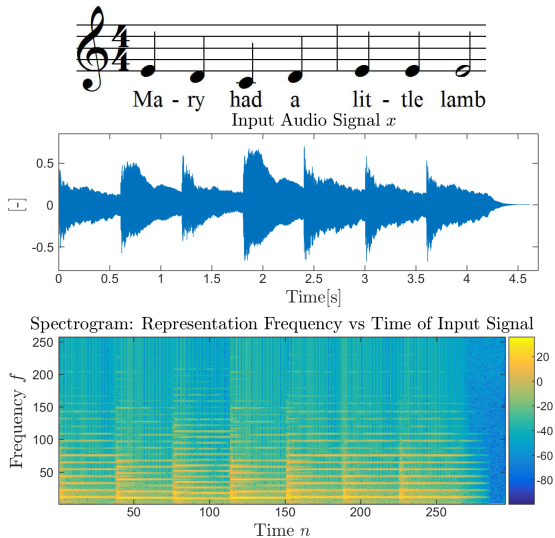


Figure: Three representations of the sample "Mary had a little lamb": (top) music score, (middle) time-domain signal  $x$ , and (bottom) log amplitude spectrogram (in dB).

# Decomposing Mary had a little lamb

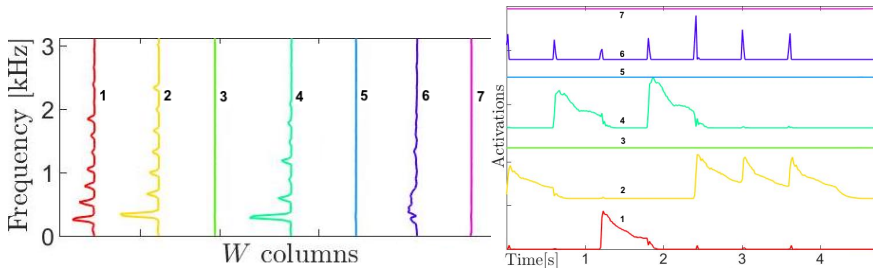


Figure: Minvol  $\beta$ -NMF applied to “Mary had a little lamb” amplitude spectrogram with  $K = 7 > 3$ . The sources 1,2,4 corresponds to the three notes, and source 6 corresponds to mechanical vibration of the piano.

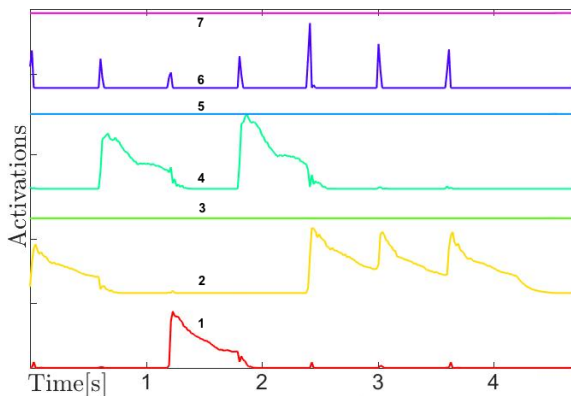
## Validating the source estimates

The frequency peaks correspond to the theoretical values.

Notes / Octaves		1-lined	2-lined	3-lined
C	Theoretical	262	523	1046.5
	By NMF	250	531.3	1031
D	Theoretical	294	587	1175
	By NMF	281.3	593.8	1188
E	Theoretical	330	659	1318.5
	By NMF	343.8	656.3	1313

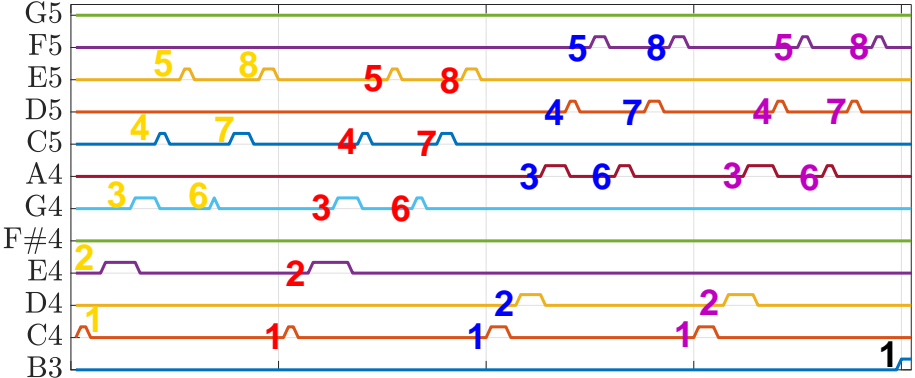
Table: Comparing frequency peaks (Hz) of the octaves obtained by minvol  $\beta$ -NMF

## Automatic model order selection



- ▶ Note that factorization rank =  $7 > 3$  = number of sources.
- ▶ Two source estimates are zero.
- ▶ 6: Hammer noise (of piano)

# More complicated example: Prelude by J.S. Bach



\* Rows of *H* here are threshold-ed to make it clear to view.

## Last page - summary

[1] Leplat, V, Gillis, N., Ang, M.S., “*Blind audio source separation with minimum-volume betadivergence NMF*”, IEEE Trans. Signal Processing 68, 2020.

- ▶ Minvol  $\beta$ -NMF
- ▶ Single-channel audio BSS
- ▶ Identifiability theorem
- ▶ MM algorithm with convergence guarantee
- ▶ Capacity of automatic model order selection

Slide, paper, code available: [angms.science](http://angms.science)

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