

### nmf\_audio\_benchmark: Benchmarking NMF algorithms on audio tasks

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#### ▶ To cite this version:

Axel Marmoret. nmf\_audio\_benchmark: Benchmarking NMF algorithms on audio tasks. Journée "Synthèse en traitement du signal audionumérique", GDR IASIS, Nov 2024, Paris, France. hal-04753826

#### HAL Id: hal-04753826 https://hal.science/hal-04753826v1

Submitted on 25 Oct 2024

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## nmf\_audio\_benchmark

# Benchmarking NMF algorithms on audio tasks



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#### Take home message

Introducing nmf\_audio\_benchmark [1], an open-source toolbox for benchmarking NMF algorithms and variants on audio tasks.

github.com/ax-le/nmf\_audio\_benchmark/

#### NMF - Nonnegative Matrix Factorization

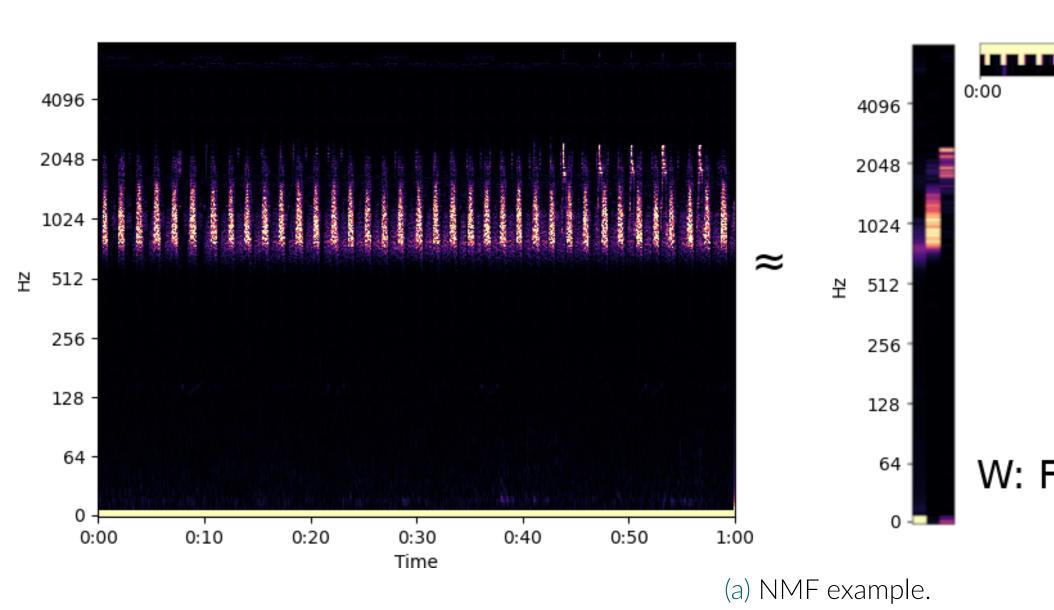
NMF is an unsupervised learning technique that factorizes a matrix V into two nonnegative matrices W and H, such that [2]:

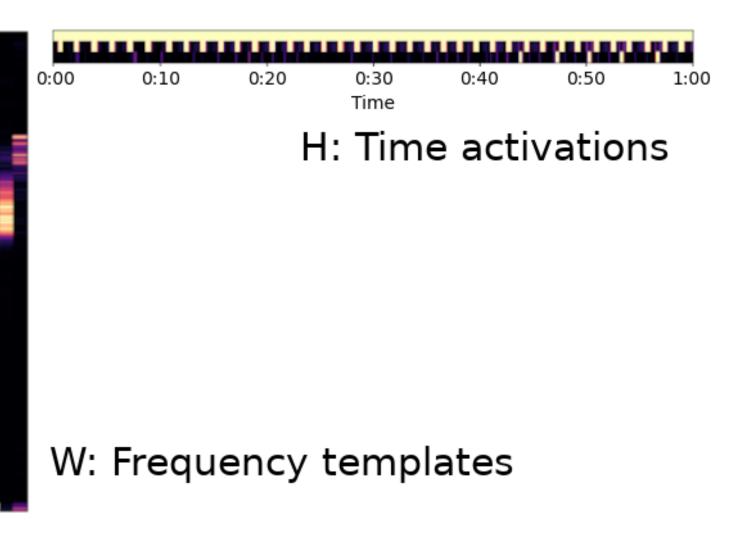
$$V \approx WH$$

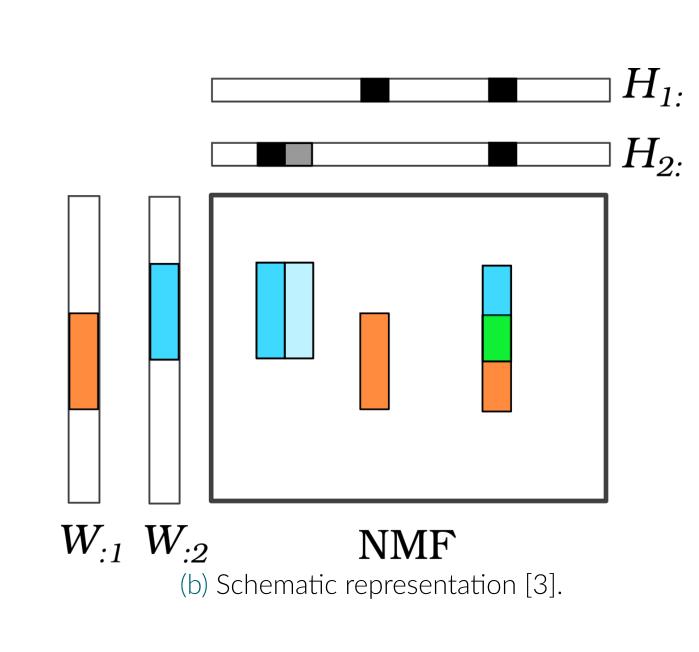
This is obtained by minimizing some distance function d() between V and WH:

$$\underset{W,H \ge 0}{\operatorname{arg\,min}} \, d(V,WH)$$

For instance, using the Euclidean distance, the optimization problem becomes:  $\underset{i,j}{\arg\min} \sum_{i,j} (V_{ij} - (WH)_{ij})^2$  $W,H \ge 0$ 







#### Why this toolbox?

**TL;DR**: help researchers in MIR to easily use NMF / help researchers in numerical optimization to test their new NMF models on audio.

#### 1. NMF models still constitute an active research domain

Goal: easy and consistent tool to evaluate a new the model. In particular, avoid having to re-implement the evaluation process for a standard task.

#### 2. Bridge (again) Audio and Low-Rank Factorization communities.

Goal: reinvigorate the use of NMF in audio processing (long-standing method [4, 5, 6], still used recently [3, 7, 8])

#### 3. In some contexts, NMF is still relevant

It may help when dealing with a limited set of data (common in Ecoacoustics), or "Out-of-distribution" data (NMF is unsupervised). In addition, NMF is a frugal and interpretable method!

#### What is the state of the toolbox now?

As of now, some tasks are already implemented in the toolbox:

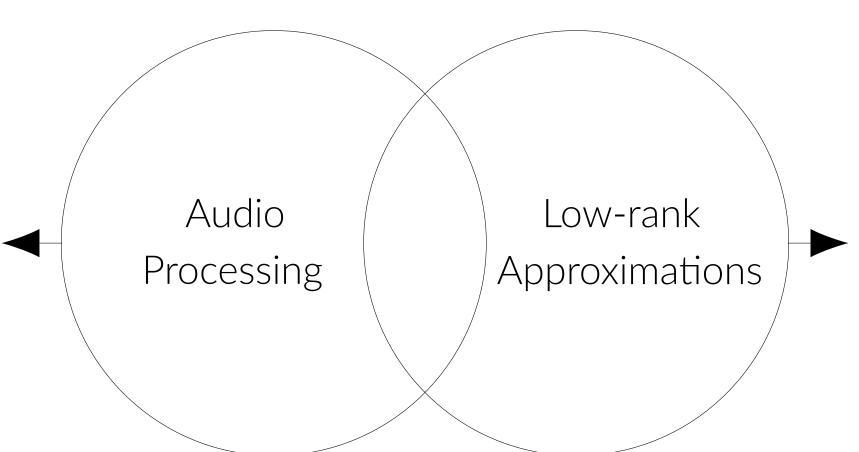
MIR:

Ecoacoustics:

- Music Transcription
- Blind Source Separation
- Blind Source Separation
- Source Count
- Music Structure Analysis
  ... and more to come!

For now, datasets include MAPS, MusDB18, SALAMI, and RWC

Pop for MIR, and AnuraSet for Ecoacoustics.



For now, several NMF are implemented:

- $\arg\min \|X WH\|_2^2$ (Euclidean-NMF) W,H>0
- $arg min d_{KL}(X, WH)$ (KL-NMF)
- W,H>0•  $\arg\min d_{IS}(X,WH)$ (IS-NMF)
- W,H>0

Details about KL- and IS-NMF in audio processing: [9].

Sometimes (soon!), Sparse-NMF [10] and minimum-volume NMF [11].

#### **Toolbox details**

The toolbox is fragmented in algorithms, where NMF models are defined, tasks, defining how to post-process W and H and defining metrics, and datasets, defining the dataloaders. The toolbox relies on the *doce* [12] package to run experiments. It is developed in Python.

#### **Future work**

## Audio Processing:

- Enhanced tasks (in particular, the Transcription task). Adding new tasks (ex: sound event detection).
- Expand datasets.

#### Low-Rank Factorizations:

- Constrained models (minimum-volume, simplex-structured, sparse, orthogonal, · · · )
- Coupled NMF & tensor models (ex: CP decomposition for multichannel processing).
- Computing NMF on GPUs instead of CPUs.

#### Off-topic, for ATIAM students: Internship proposal

I propose an internship directly based on this toolbox for the ATIAM students that may be in this room. The idea will be to use coupled NMF models in a multi-channel context, with different features (ex: factorizing simultaneously STFT, CQT, Mel, · · · ).

#### Come talk to me or reach me at axel.marmoret@imt-atlantique.fr if interested! References

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