INTERNATIONAL AUDIO LABORATORIES ERLANGEN

Guest Lecture
Sound and Music Computing (CS4347)
National University of Singapore

Nonnegative Autoencoders with Applications to Music Audio Decomposing

Meinard Müller
International Audio Laboratories Erlangen
meinard.mueller@audiolabs-erlangen.de

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Meinard Müller

- Mathematics (Diplom/Master)
  Computer Science (PhD)
  Information Retrieval (Habilitation)
- Since 2012: Professor
  Semantic Audio Processing
- Former President of the International Society for Music Information Retrieval (MIR)
- IEEE Fellow for contributions to Music Signal Processing

Meinard Müller: Research Group
Semantic Audio Processing

- Sebastian Rosenzweig
- Michael Krause
- Yigitcan Özer
- Peter Meier (external)
- Christof Weiß

- Frank Zalkow
- Christian Dittmar
- Stefan Balke
- Jonathan Driedger
- Thomas Prätzlich
- …

International Audio Laboratories Erlangen

- Fraunhofer Institute for Integrated Circuits IIS
- Largest Fraunhofer institute with ≈ 1000 members
- Applied research for sensor, audio, and media technology

- Friedrich-Alexander Universität Erlangen-Nürnberg (FAU)
- One of Germany's largest universities with ≈ 40,000 students
- Strong Technical Faculty

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Audio

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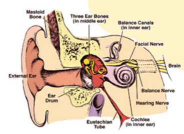
Audio Coding

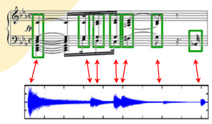
3D Audio

Audio



Psychoacoustics

Internet of Things



Music Processing

International Audio Laboratories Erlangen

- Prof. Dr. Jürgen Herre
  Audio Coding
- Prof. Dr. Bernd Edler
  Audio Signal Analysis
- Prof. Dr. Meinard Müller
  Semantic Audio Processing
- Prof. Dr. Emanuël Habets
  Spatial Audio Signal Processing
- Prof. Dr. Nils Peters
  Audio Signal Processing
- Dr. Stefan Turowski
  Coordinator AudioLabs-FAU

Source Separation

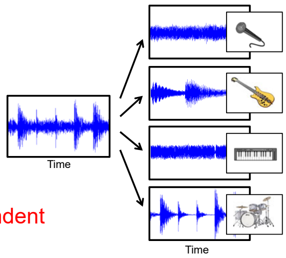
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- "Cocktail party effect"

Source Separation

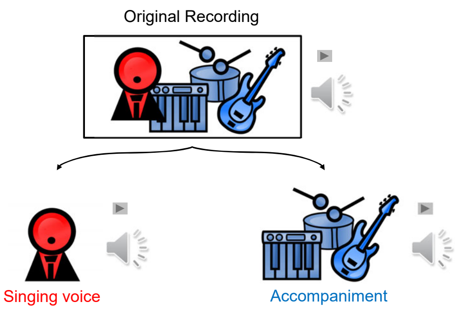
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- "Cocktail party effect"
- Several input signals
- Sources are assumed to be statistically independent

Source Separation (Music)

- Main melody, accompaniment, drum track
- Instrumental voices
- Individual note events
- Only mono or stereo
- Sources are often highly dependent

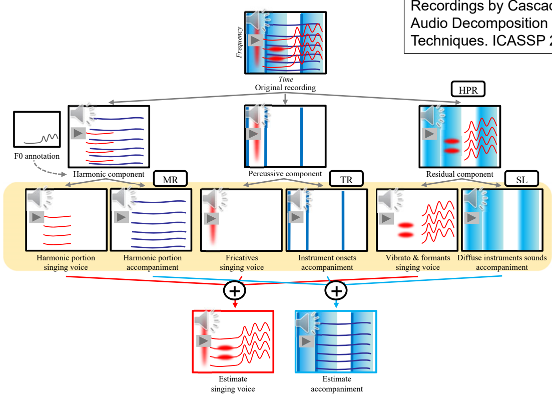


Singing Voice Extraction



Singing Voice Extraction

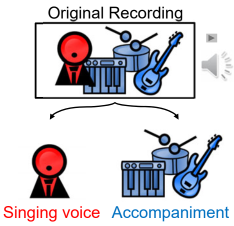
Traditional Approach
Driedger, Müller: Extracting Singing Voice from Music Recordings by Cascading Audio Decomposition Techniques. ICASSP 2015.



Singing Voice Extraction

Deep learning has lead to breakthrough

DL-Based Approach
Stöter, Uhlich Luitkus, Mitsufuji: Open-Unmix – A Reference Implementation for Music Source Separation. JOSS 2019.



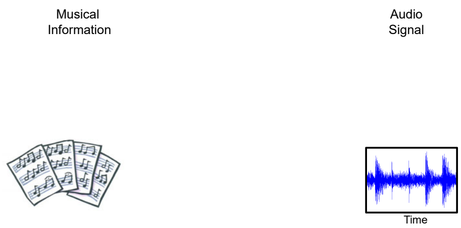
Reference voices:

Engineering approach:

Deep learning approach:

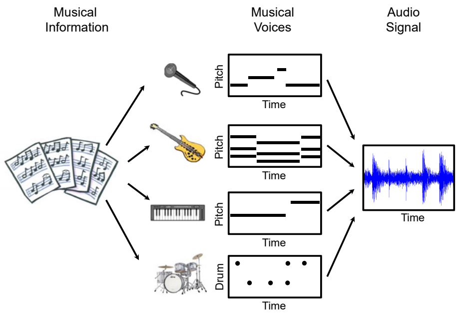
Score-Informed Source Separation

Exploit musical score to support decomposition process



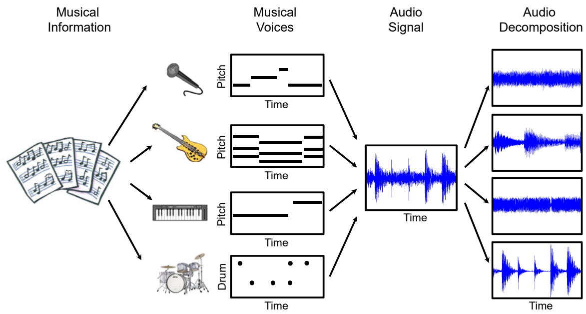
Score-Informed Source Separation

Exploit musical score to support decomposition process



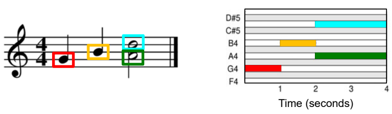
Score-Informed Source Separation

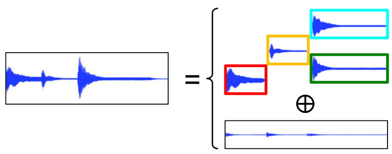
Exploit musical score to support decomposition process



Score-Informed Audio Decomposition

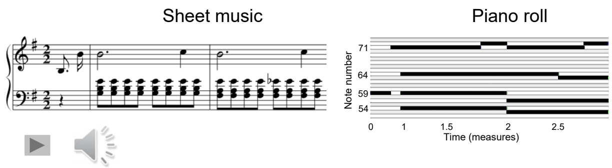
Notewise decomposition



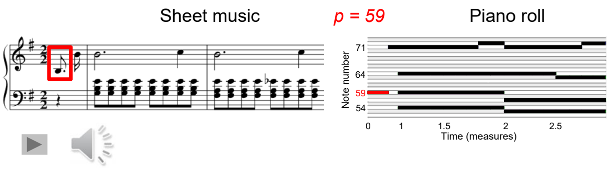


Prior Knowledge
Ewert, Pardo, Müller, Plumbley: Score-Informed Source Separation for Musical Audio Recordings. IEEE SPM, 2014.

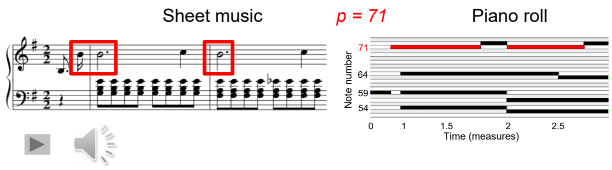
Score-Informed Audio Decomposition



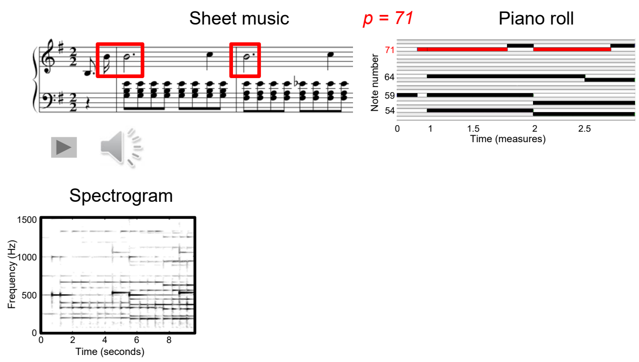
Score-Informed Audio Decomposition



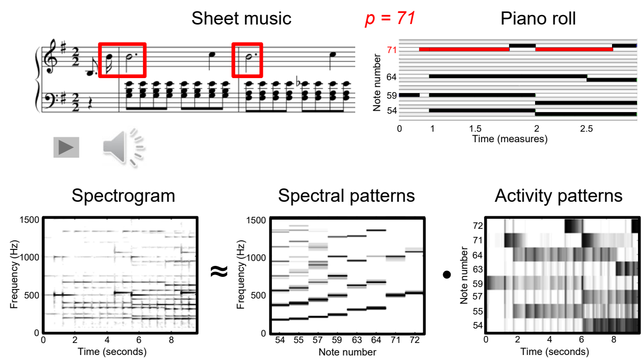
Score-Informed Audio Decomposition



Score-Informed Audio Decomposition



Score-Informed Audio Decomposition



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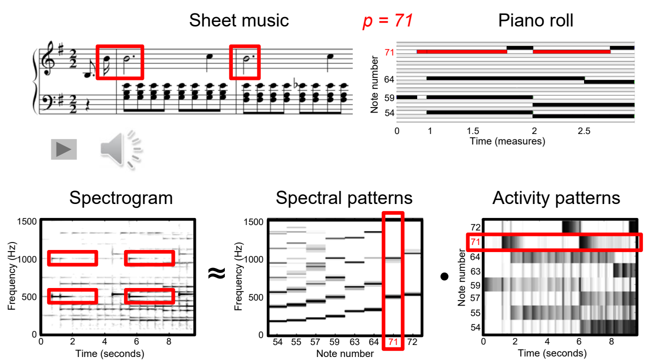
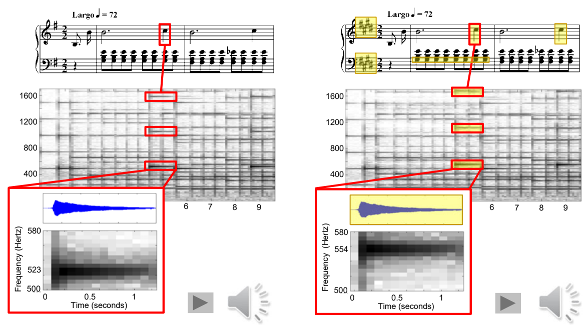
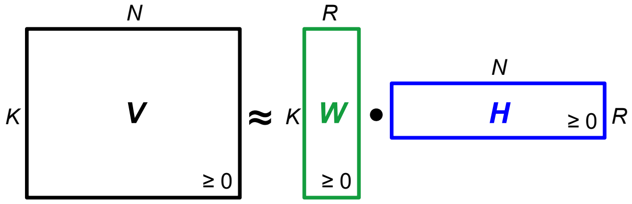


Score-Informed Audio Decomposition

Application: Audio editing

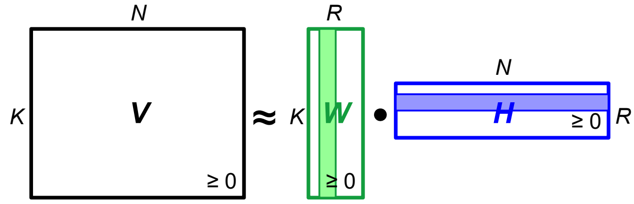


Nonnegative Matrix Factorization (NMF)



$V \in \mathbb{R}_{\geq 0}^{K \times N}$ $W \in \mathbb{R}_{\geq 0}^{K \times R}$ $H \in \mathbb{R}_{\geq 0}^{R \times N}$

Nonnegative Matrix Factorization (NMF)

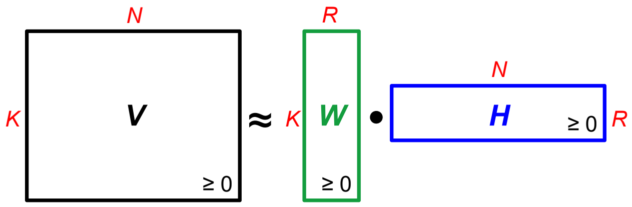


Magnitude Spectrogram **Templates** **Activations**

Templates: **Pitch + Timbre** **“How does it sound”**

Activations: **Onset time + Duration** **“When does it sound”**

Nonnegative Matrix Factorization (NMF)

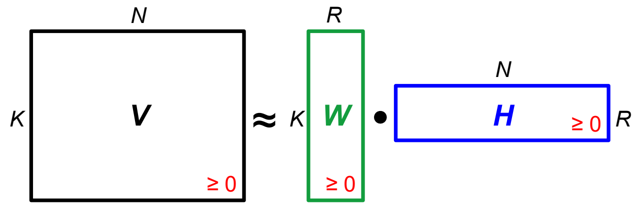


$V \in \mathbb{R}_{\geq 0}^{K \times N}$ $W \in \mathbb{R}_{\geq 0}^{K \times R}$ $H \in \mathbb{R}_{\geq 0}^{R \times N}$

Dimensionality reduction

- *K*, *N* typically much larger than *R* (maximal rank)
- Example: *N = 1000, K = 500, R = 20*
  K x N = 500,000, *K x R = 10,000,* *R x N = 20,000*

Nonnegative Matrix Factorization (NMF)



$V \in \mathbb{R}_{\geq 0}^{K \times N}$ $W \in \mathbb{R}_{\geq 0}^{K \times R}$ $H \in \mathbb{R}_{\geq 0}^{R \times N}$

Nonnegativity:

- Prevents mutual cancellation of template vectors
- Encourages semantically meaningful decomposition

NMF Optimization

Optimization problem:

Given $V \in \mathbb{R}_{\geq 0}^{K \times N}$ and rank parameter R minimize

$$\|V - WH\|^2$$

with respect to $W \in \mathbb{R}_{\geq 0}^{K \times R}$ and $H \in \mathbb{R}_{\geq 0}^{R \times N}$.

Optimization not easy:

- Nonnegativity constraints
- Nonconvexity when jointly optimizing *W* and *H*

Strategy: Iteratively optimize *W* and *H* via gradient descent

NMF Optimization

Computation of gradient with respect to *H* (fixed *W*)

$D := RN$

$\varphi^W : \mathbb{R}^D \to \mathbb{R}$

$\varphi^W(H) := \|V - WH\|^2$

Variables

$H \in \mathbb{R}^{R \times N}$

$H_{\rho\nu}$

$\rho \in [1:R]$

$\nu \in [1:N]$

NMF Optimization

Computation of gradient with respect to *H* (fixed *W*)

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$\varphi^W(H) := \|V - WH\|^2$

$$\frac{\partial \varphi^W}{\partial H_{\rho\nu}} = \frac{\partial\left(\sum_{k=1}^K\sum_{n=1}^N\left(V_{kn}-\sum_{r=1}^R W_{kr}H_{rn}\right)^2\right)}{\partial H_{\rho\nu}}$$

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$$= \frac{\partial\left(\sum_{k=1}^K\left(V_{k\nu}-\sum_{r=1}^R W_{kr}H_{r\nu}\right)^2\right)}{\partial H_{\rho\nu}}$$

Summand that does not depend on $H_{\rho\nu}$ must be zero

Variables

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$$= \sum_{k=1}^K 2\left(V_{k\nu}-\sum_{r=1}^R W_{kr}H_{r\nu}\right)\cdot(-W_{k\rho})$$

Apply chain rule from calculus

Variables

$H \in \mathbb{R}^{R\times N}$

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NMF Optimization

Computation of gradient with respect to *H* (fixed *W*)

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$$= \sum_{k=1}^K 2\left(V_{k\nu}-\sum_{r=1}^R W_{kr}H_{r\nu}\right)\cdot(-W_{k\rho})$$

$$= 2\left(\sum_{r=1}^R\sum_{k=1}^K W_{k\rho}W_{kr}H_{r\nu} - \sum_{k=1}^K W_{k\rho}V_{k\nu}\right)$$

Rearrange summands

Variables

$H \in \mathbb{R}^{R\times N}$

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NMF Optimization

Computation of gradient with respect to *H* (fixed *W*)

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Introduce transposed $W^\top$

Variables

$H \in \mathbb{R}^{R\times N}$

$H_{\rho\nu}$

$\rho \in [1:R]$

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NMF Optimization

Computation of gradient with respect to *H* (fixed *W*)

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$$\boxed{= 2\left((W^\top WH)_{\rho\nu} - (W^\top V)_{\rho\nu}\right).}$$

Variables

$H \in \mathbb{R}^{R\times N}$

$H_{\rho\nu}$

$\rho \in [1:R]$

$\nu \in [1:N]$

NMF Optimization

Gradient descent

Initialization $H^{(0)} \in \mathbb{R}^{R \times N}$

Iteration for $\ell = 0, 1, 2, \ldots$

$$H_{rn}^{(\ell+1)} = H_{rn}^{(\ell)} - \gamma_{rn}^{(\ell)} \cdot \left(\left(W^\top W H^{(\ell)}\right)_{rn} - \left(W^\top V\right)_{rn} \right)$$

with suitable learning rate $\gamma_{rn}^{(\ell)} \geq 0$

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with suitable learning rate $\gamma_{rn}^{(\ell)} \geq 0$

Issues:

- How to do the initialization?
- How to choose the learning rate?
- How to ensure nonnegativity?

NMF Optimization

Gradient descent

Choose adaptive learning rate:

$$\gamma_{rn}^{(\ell)} := \frac{H_{rn}^{(\ell)}}{\left(W^\top W H^{(\ell)}\right)_{rn}}$$

Initialization $H^{(0)} \in \mathbb{R}^{R \times N}$

Iteration for $\ell = 0, 1, 2, \ldots$

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Issues:

- How to do the initialization?
- How to choose the learning rate?
- How to ensure nonnegativity?

- Update rule become multiplicative
- Nonnegative values stay nonnegative

NMF Optimization

Algorithm: NMF ($V \approx WH$)

Input: Nonnegative matrix V of size $K \times N$
Rank parameter $R \in \mathbb{N}$
Threshold ε used as stop criterion

Output: Nonnegative template matrix W of size $K \times R$
Nonnegative activation matrix H of size $R \times N$

Procedure: Define nonnegative matrices $W^{(0)}$ and $H^{(0)}$ by some random or informed initialization. Furthermore set $\ell = 0$. Apply the following update rules (written in matrix notation):

(1) $H^{(\ell+1)} = H^{(\ell)} \odot \left(\left((W^{(\ell)})^\top V \right) \oslash \left((W^{(\ell)})^\top W^{(\ell)} H^{(\ell)} \right) \right)$

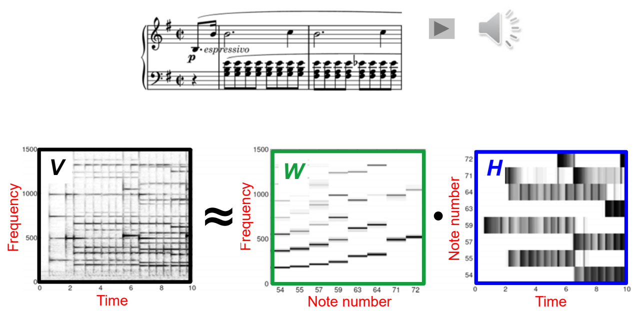
(2) $W^{(\ell+1)} = W^{(\ell)} \odot \left(\left(V (H^{(\ell+1)})^\top \right) \oslash \left(W^{(\ell)} H^{(\ell+1)} (H^{(\ell+1)})^\top \right) \right)$

(3) Increase ℓ by one.

Repeat the steps (1) to (3) until $\|H^{(\ell)} - H^{(\ell-1)}\| \leq \varepsilon$ and $\|W^{(\ell)} - W^{(\ell-1)}\| \leq \varepsilon$ (or until some other stop criterion is fulfilled). Finally, set $H = H^{(\ell)}$ and $W = W^{(\ell)}$.

Lee, Seung: Algorithms for Non-Negative Matrix Factorization. Proc. NIPS, 2000.

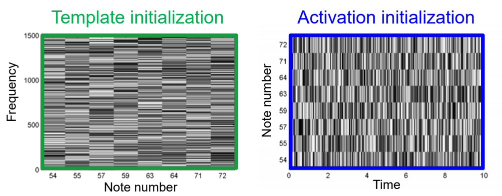
NMF-based Spectrogram Decomposition



Templates: Pitch + Timbre **"How does it sound"**

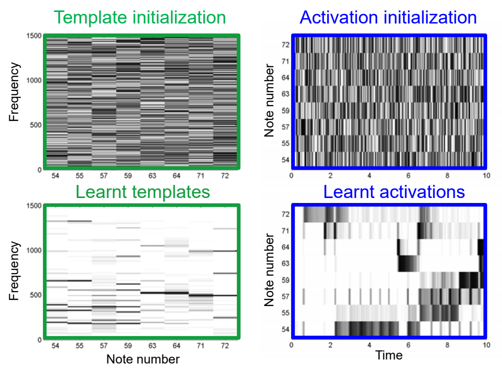
Activations: Onset time + Duration **"When does it sound"**

NMF-based Spectrogram Decomposition



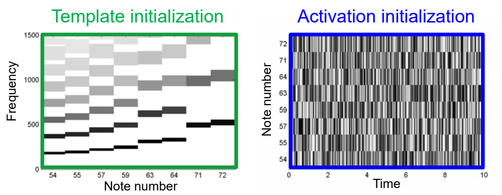
Random initialization

NMF-based Spectrogram Decomposition



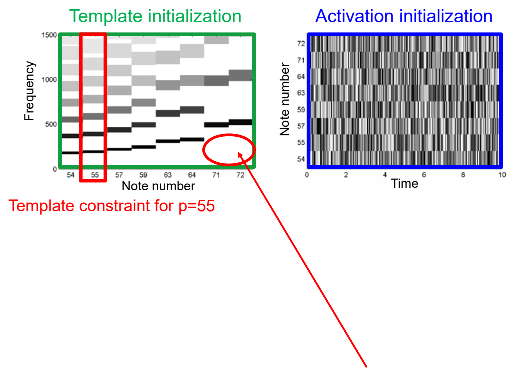
Random initialization → No semantic meaning

Constrained NMF: Templates



Enforce harmonic structure with zero-valued entries

Constrained NMF: Templates



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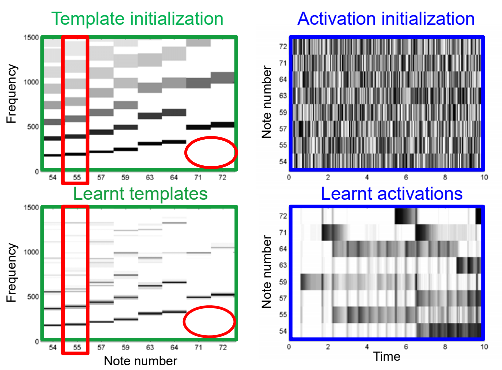
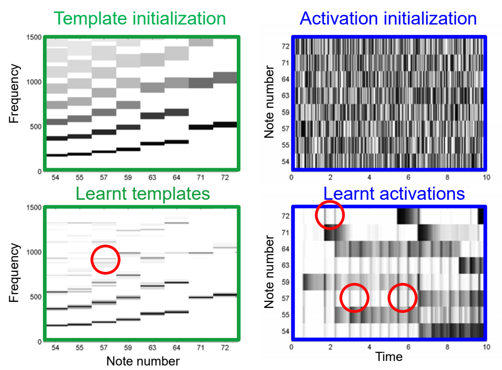


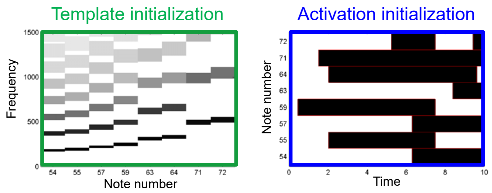
Zero-valued entries remain zero-valued entries!

Constrained NMF: Templates

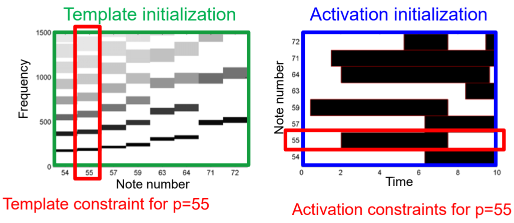


Pitch templates misused to represent onsets

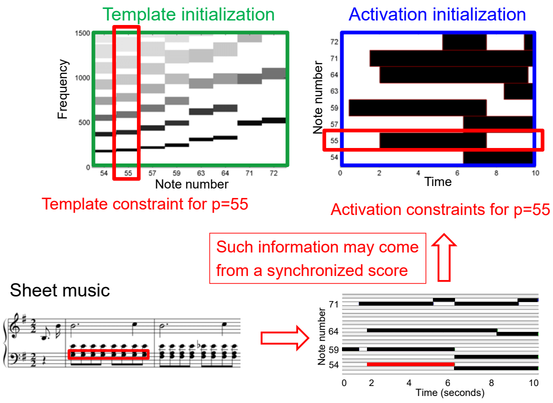
Constrained NMF: Double Constraints



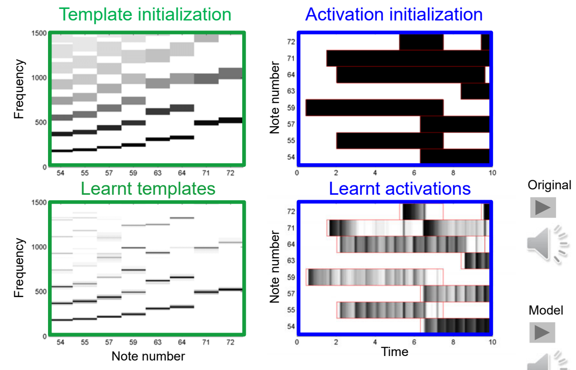
Constrained NMF: Double Constraints



Constrained NMF: Double Constraints

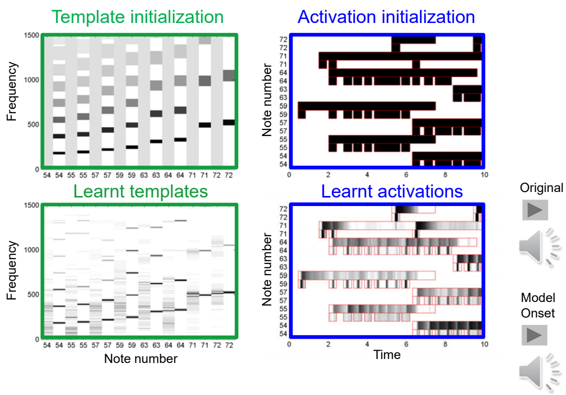


Constrained NMF: Double Constraints



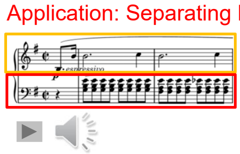
Significant gain in structure, but onsets are missing

Constrained NMF: Onset Templates

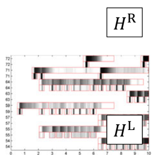


Score-Informed Audio Decompostion

Application: Separating left and right hands for piano



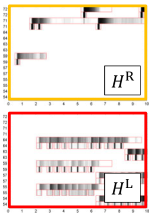
1. Split activation matrix



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

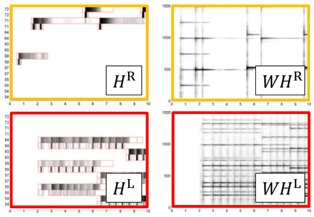
1. Split activation matrix



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

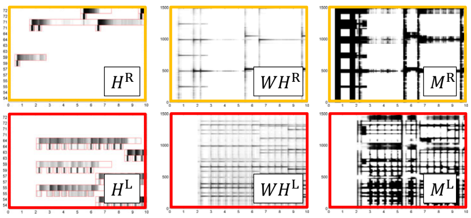
1. Split activation matrix
2. Model spectrogram for left/right



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

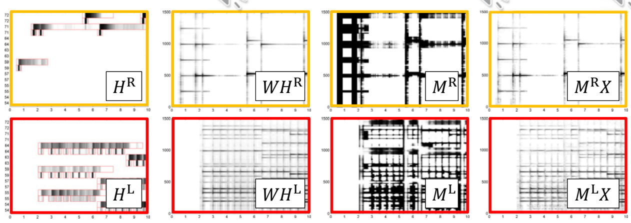
1. Split activation matrix
2. Model spectrogram for left/right
3. Separation masks for left/right



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

1. Split activation matrix
2. Model spectrogram for left/right
3. Separation masks for left/right
4. Estimated spectrograms for left/right



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

Chopin, Waltz Op. 64, No. 1

Original

Ewert, Müller: Using Score-Informed Constraints for NMF-based Source Separation. Proc. ICASSP, 2012.

Further results available at
http://www.mpi-inf.mpg.de/resources/MIR/ICASSP2012-ScoreInformedNMF/

Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

Chopin, Waltz Op. 64, No. 1

Original

Left/right hand

Right hand

Left hand

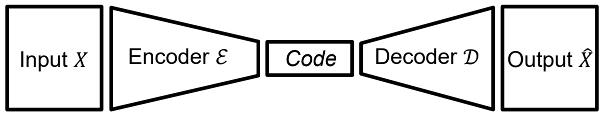
Ewert, Müller: Using Score-Informed Constraints for NMF-based Source Separation. Proc. ICASSP, 2012.

Further results available at
http://www.mpi-inf.mpg.de/resources/MIR/ICASSP2012-ScoreInformedNMF/

Conclusions (NMF)

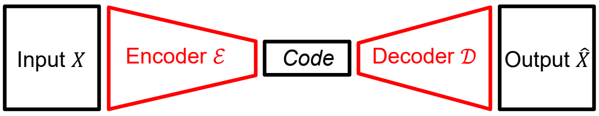
- NMF used for spectrogram decomposition
- Multiplicative update rules make it easy to constrain NMF model via zero initialization
- Exploiting score information to guide separation process (requires score–audio synchronization)
- Application: Separation of arbitrary note groups from given audio recording

Autoencoder



- Specific type of neural network
- Encoder: Compress input X into a low-dimensional code
- Decoder: Reconstruct output $\hat{X}$ from code

Autoencoder

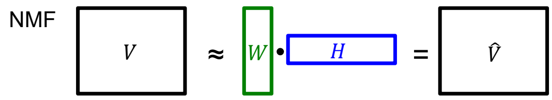


- Specific type of neural network
- Encoder: Compress input X into a low-dimensional code
- Decoder: Reconstruct output $\hat{X}$ from code
- Goal: Learn parameters for encoder and decoder such that output is close to input with respect to some loss function:

$$\mathcal{L}(X, \hat{X}) \approx 0$$

NMF and Autoencoder (AE)

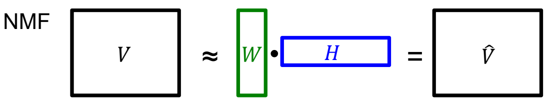
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.



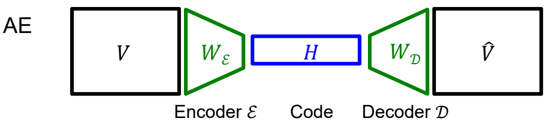
$V \approx WH$ implies $W^+V \approx H$ with pseudoinverse W^+

NMF and Autoencoder (AE)

Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.



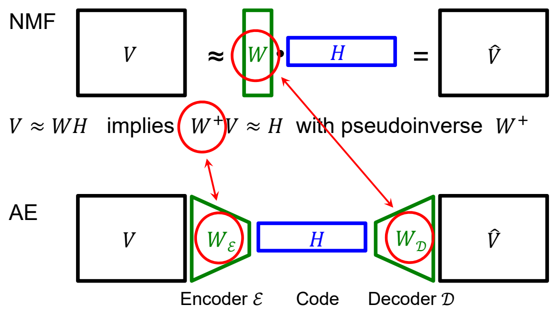
$V \approx WH$ implies $W^+V \approx H$ with pseudoinverse W^+



1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

NMF and Autoencoder (AE)

Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.



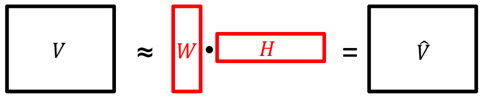
1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

Fully connected network

NMF and Autoencoder (AE)

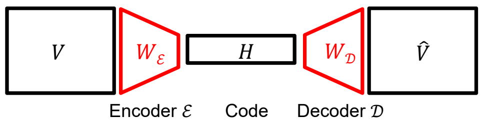
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.

NMF



$V \approx WH$ implies $W^{+}V \approx H$ with pseudoinverse W^{+}

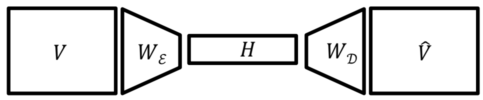
AE



1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

NMF: Learn H and W
AE: Learn $W_{\mathcal{E}}$ and $W_{\mathcal{D}}$

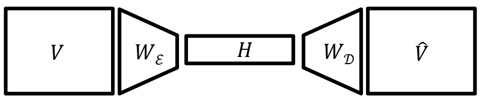
Nonnegative Autoencoder (NAE)



1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

- How can one adjust the AE to simulate NMF?
- How can one achieve nonnegativity?
- How can one incorporate musical knowledge?
- …

Nonnegative Autoencoder (NAE)

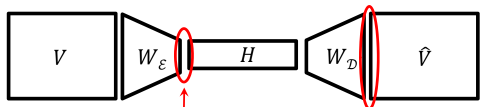


1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

$\mathcal{L}(V,\hat{V}) = \|V - \hat{V}\|^2$

- Loss function: same as in NMF

Nonnegative Autoencoder (NAE)

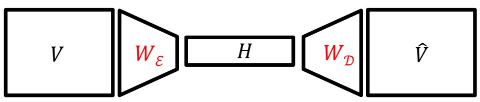


1. Layer: $H = \max(W_{\mathcal{E}}\, V, 0)$
2. Layer: $\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$

$\mathcal{L}(V,\hat{V}) = \|V - \hat{V}\|^2$

- Loss function: same as in NMF
- Activation function (ReLU) makes H and $\hat{V}$ nonnegative

Nonnegative Autoencoder (NAE)



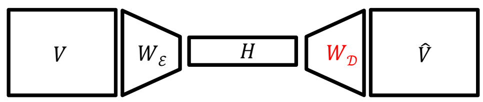
1. Layer: $H = \max(W_{\mathcal{E}}\, V, 0)$
2. Layer: $\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$

$\mathcal{L}(V,\hat{V}) = \|V - \hat{V}\|^2$

$$W_{\mathcal{D}} \leftarrow \max\left(W_{\mathcal{D}} - \gamma \frac{\partial \mathcal{L}}{\partial W_{\mathcal{D}}}, 0\right)$$

- Loss function: same as in NMF
- Activation function (ReLU) makes H and $\hat{V}$ nonnegative
- Projected gradient descent can be used to keep $W_{\mathcal{D}}$ (and $W_{\mathcal{E}}$) nonnegative

Musical Constraints

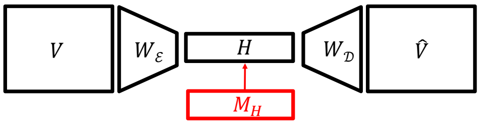


$H = \max(W_{\mathcal{E}}\, V, 0)$
$\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$

- Template constraints: Project certain entries in $W_{\mathcal{D}}$ to zero values (using projected gradient decent)

Musical Constraints

Ewert, Sandler: Structured Dropout for Weak Label and Multi-Instance Learning and Its Application to Score-Informed Source Separation. Proc. ICASSP, 2017.



$$H' = H \odot M_H$$
$$\hat{V} = \max(W_{\mathcal{D}} H', 0)$$

- Template constraints: Project certain entries in $W_{\mathcal{D}}$ to zero values (using projected gradient decent)
- Activation constraints: Use structured dropout by applying pointwise multiplication with binary mask M_H

NAE with Multiplicative Update Rules

- Multiplicative update rules in NMF:
  - Preserve nonnegativity
  - Lead to fast convergence
- Question: Can one introduce multiplicative update rules to train network weights for NAE?
- Use in additive gradient descent

$$W^{(\ell+1)} = W^{(\ell)} - \gamma \cdot \frac{\partial \mathcal{L}}{\partial W}$$

a suitable (adaptive) learning rate γ .

NAE with Multiplicative Update Rules

- Encoder:

$$H = W_{\mathcal{E}} V$$

- Structured Dropout:

$$H' = H \odot M_H$$

- Decoder:

$$\hat{V} = W_{\mathcal{D}} H'$$

Zunner: Neural Networks with Nonnegativity Constraints for Decomposing Music Recordings. Master Thesis, FAU, 2021.

NAE with Multiplicative Update Rules

- Encoder:

$$H = W_{\mathcal{E}} V$$

$$W_{\mathcal{E},rk}^{(\ell+1)} = W_{\mathcal{E},rk}^{(\ell)} \cdot \frac{\left(\left(\left(W_{\mathcal{D}}^{\top} V\right) \odot M_H\right) V^{\top}\right)_{rk}}{\left(\left(\left(W_{\mathcal{D}}^{\top} W_{\mathcal{D}} H'^{(\ell)}\right) \odot M_H\right) V^{\top}\right)_{rk}}$$

- Structured Dropout:

$$H' = H \odot M_H$$

- Decoder:

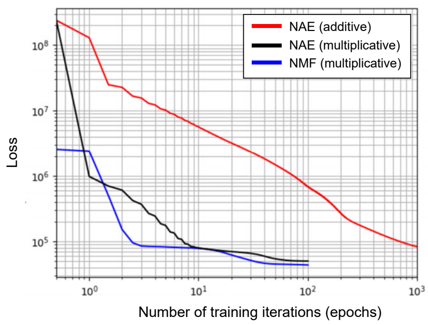
$$\hat{V} = W_{\mathcal{D}} H'$$

$$W_{\mathcal{D},kr}^{(\ell+1)} = W_{\mathcal{D},kr}^{(\ell)} \cdot \frac{\left(V H'^{\top}\right)_{kr}}{\left(W_{\mathcal{D}}^{(\ell)} H' H'^{\top}\right)_{kr}}$$

Similar idea and computation as for NMF.

Zunner: Neural Networks with Nonnegativity Constraints for Decomposing Music Recordings. Master Thesis, FAU, 2021.

Approximation Loss



Zunner: Neural Networks with Nonnegativity Constraints for Decomposing Music Recordings. Master Thesis, FAU, 2021.

Conclusions (NAE)

- Simulation of NMF:
  - Decoder corresponds to NMF templates
  - Encoder learns a kind of pseudo-inverse
  - Code corresponds to NMF activations
- Nonnegativity can be achieved via
  - activation function (ReLU)
  - projected gradient descent
  - multiplicative update rules
- Musical knowledge can be integrated via
  - removing network weights (template constraints)
  - structured dropout (activation constraints)

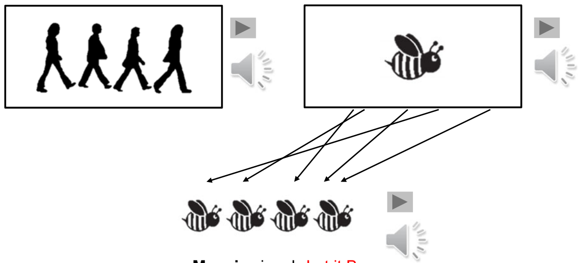
Outlook

- More complex networks
  - Deeper networks (more layers)
  - Different layer types (CNN, RNN, …) and activation functions
  - Modification of loss function and regularization terms
- Understanding encoder – decoder relationship
  - Nonnegativity
  - Pseudo-inverse
- Update rules
  - Constraints and conversion issues
  - Adaptive learning rates and projected gradient descent

Audio Mosaicing (Style Transfer)

Target signal: Beatles–Let it be

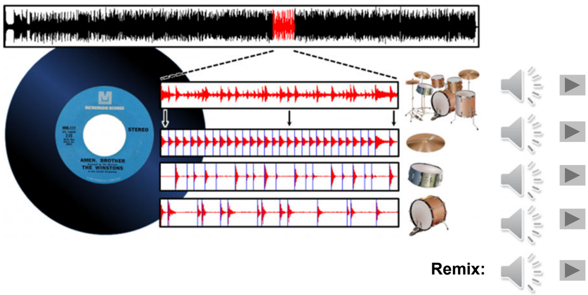
Source signal: Bees



Mosaic signal: Let it Bee

Driedger, Prätzlich, Müller: Let It Bee – Towards NMF-Inspired Audio Mosaicing, ISMIR 2015..

Informed Drum-Sound Decomposition



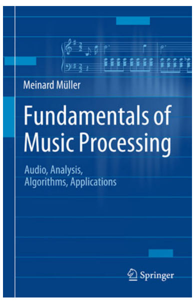
Dittmar, Müller: Reverse Engineering the Amen Break – Score-Informed Separation and Restoration Applied to Drum Recordings, IEEE/ACM TASLP, 2016.

Suárez: DNN-Based Matrix Factorization with Applications to Drum Sound Decomposition. Master Thesis, FAU, 2020.

Reconstruction of Sound Events

- Reconstruction via spectral masking (Wiener filtering)
- Alternative: Resynthesis approach
- Differentiable Digital Signal Processing (DDSP) combines classical DSP and deep learning
- Generative adversarial networks may help to reduce the artifacts

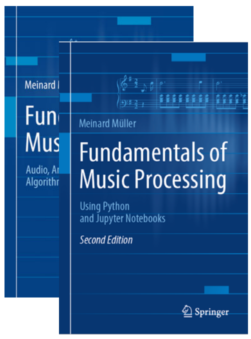
Fundamentals of Music Processing (FMP)



Meinard Müller
Fundamentals of Music Processing
Audio, Analysis, Algorithms, Applications
Springer, 2015

Accompanying website:
www.music-processing.de

Fundamentals of Music Processing (FMP)



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Fundamentals of Music Processing
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Springer, 2015

Accompanying website:
www.music-processing.de

2nd edition
Meinard Müller
Fundamentals of Music Processing
Using Python and Jupyter Notebooks
Springer, 2021

Fundamentals of Music Processing (FMP)

Chapter	Music Processing Scenario
1	Music Representations
2	Fourier Analysis of Signals
3	Music Synchronization
4	Music Structure Analysis
5	Chord Recognition
6	Tempo and Beat Tracking
7	Content-Based Audio Retrieval
8	Musically Informed Audio Decomposition

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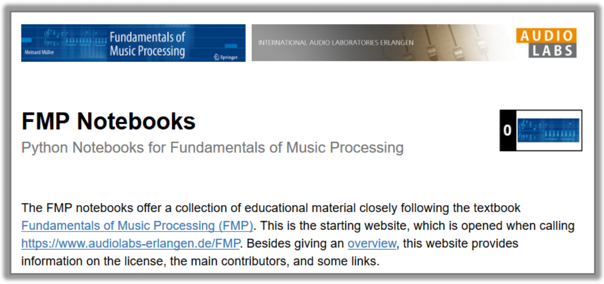
Springer, 2021

FMP Notebooks: Education & Research



https://www.audiolabs-erlangen.de/FMP

References (FMP Notebooks)

- Meinard Müller: Fundamentals of Music Processing – Using Python and Jupyter Notebooks. 2nd Edition, Springer, 2021.
  https://www.springer.com/gp/book/9783030698072
- Meinard Müller and Frank Zalkow: libfmp: A Python Package for Fundamentals of Music Processing. Journal of Open Source Software (JOSS), 6(63): 1–5, 2021.
  https://joss.theoj.org/papers/10.21105/joss.03326
- Meinard Müller: An Educational Guide Through the FMP Notebooks for Teaching and Learning Fundamentals of Music Processing. Signals, 2(2): 245–285, 2021.
  https://www.mdpi.com/2624-6120/2/2/18
- Meinard Müller and Frank Zalkow: FMP Notebooks: Educational Material for Teaching and Learning Fundamentals of Music Processing. Proc. International Society for Music Information Retrieval Conference (ISMIR): 573–580, 2019.
  https://zenodo.org/record/3527872#.YOhEQOgzaUk
- Meinard Müller, Brian McFee, and Katherine Kinnaird: Interactive Learning of Signal Processing Through Music: Making Fourier Analysis Concrete for Students. IEEE Signal Processing Magazine, 38(3): 73–84, 2021.
  https://ieeexplore.ieee.org/document/9418542

Resources (Group Meinard Müller)

- FMP Notebooks:
  https://www.audiolabs-erlangen.de/FMP
- libfmp:
  https://github.com/meinardmueller/libfmp
- synctoolbox:
  https://github.com/meinardmueller/synctoolbox
- libtsm:
  https://github.com/meinardmueller/libtsm
- Preparation Course Python (PCP) Notebooks:
  https://www.audiolabs-erlangen.de/resources/MIR/PCP/PCP.html
  https://github.com/meinardmueller/PCP

Resources

- librosa:
  https://librosa.org/
- madmom:
  https://github.com/CPJKU/madmom
- Essentia Python tutorial:
  https://essentia.upf.edu/essentia_python_tutorial.html
- mirdata:
  https://github.com/mir-dataset-loaders/mirdata
- open-unmix:
  https://github.com/sigsep/open-unmix-pytorch
- Open Source Tools & Data for Music Source Separation:
  https://source-separation.github.io/tutorial/landing.html

Thanks

- Yigitcan Özer (PhD student)
- Michael Krause (PhD student)
- Tim Zunner (Master Thesis 2021)
- Edgar Suárez Guarnizo (Master Thesis 2020)
- Christian Dittmar (PhD 2018, Fraunhofer IIS)

References (NMF, NAE)

- Daniel Lee and Sebastian Seung: **Algorithms for Non-Negative Matrix Factorization.** Proc. NIPS, 2000.

- Sebastian Ewert and Meinard Müller: **Using Score-Informed Constraints for NMF-Based Source Separation.** Proc. ICASSP, 2012.

- Paris Smaragdis and Shrikant Venkataramani: **A Neural Network Alternative to Non-Negative Audio Models.** Proc. ICASSP, 2017.

- Sebastian Ewert and Mark B. Sandler: **Structured Dropout for Weak Label and Multi-Instance Learning and Its Application to Score-Informed Source Separation.** Proc. ICASSP, 2017.

- Tim Zunner: **Neural Networks with Nonnegativity Constraints for Decomposing Music Recordings.** Master Thesis, FAU, 2021.

- Edgar Andrés Suárez Guarnizo: **DNN-Based Matrix Factorization with Applications to Drum Sound Decomposition.** Master Thesis, FAU, 2020.