INTERNATIONAL AUDIO LABORATORIES ERLANGEN
A joint institution of Fraunhofer IIS and Universität Erlangen-Nürnberg

Tutorial T3, EUROGRAPHICS
Saarbrücken, May 8, 2023

Learning with Music Signals: Technology Meets Education

Audio Decomposition

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

Friedrich-Alexander-Universität Erlangen-Nürnberg

Fraunhofer IIS

Source Separation

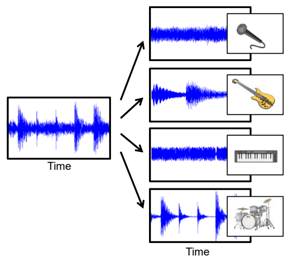
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- "Cocktail party effect"

Source Separation

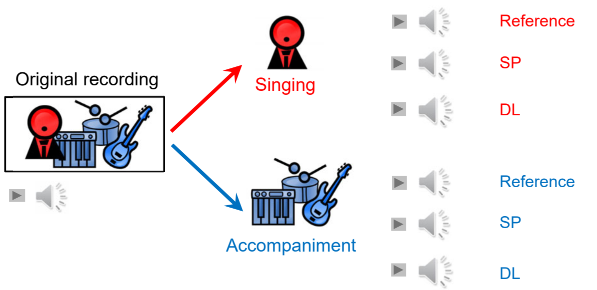
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- "Cocktail party effect"
- Several input signals
- Sources are assumed to be statistically independent

Source Separation (Music)

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



Source Separation (Singing Voice)



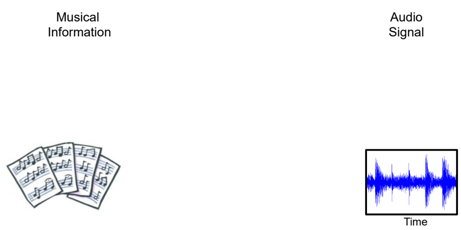
DL-Based Source Separation
Stöter, Uhlich Luitkus, Mitsufuji: Open-Unmix – A Reference Implementation for Music Source Separation. JOSS, 2019.

- Reference: Best possible result
- SP: Traditional signal processing
- DL: Deep Learning

Score-Informed Source Separation

Prior Knowledge
Ewert, Pardo, Müller, Plumbley: Score-Informed Source Separation for Musical Audio Recordings. IEEE SPM 31(3), 2014.

Exploit musical score to support decomposition process



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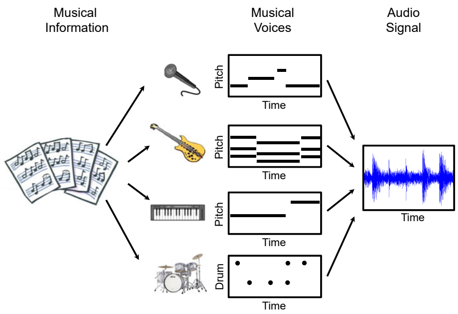

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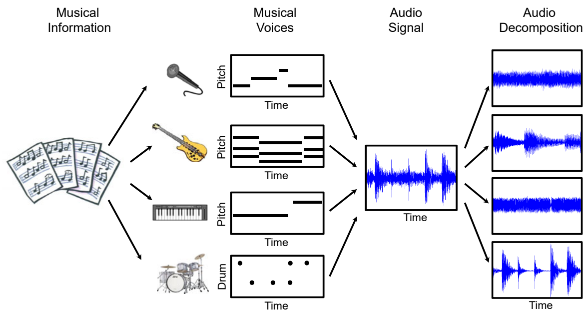

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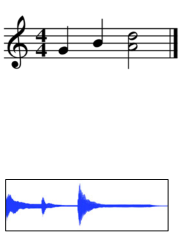

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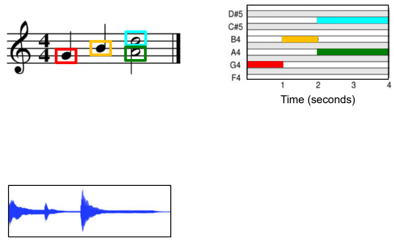

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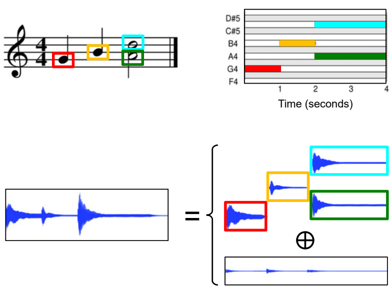

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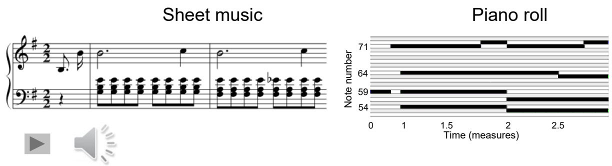

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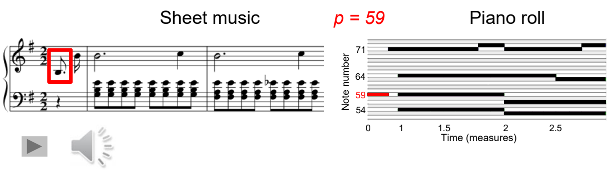

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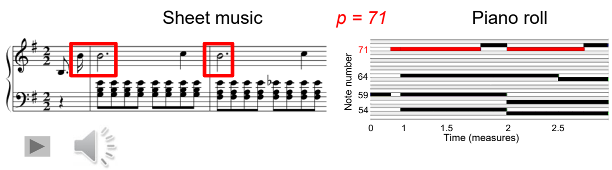

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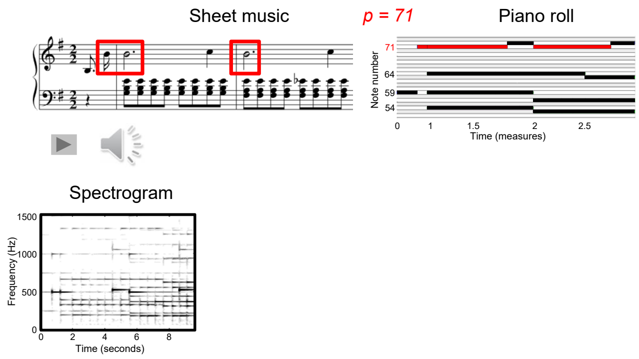

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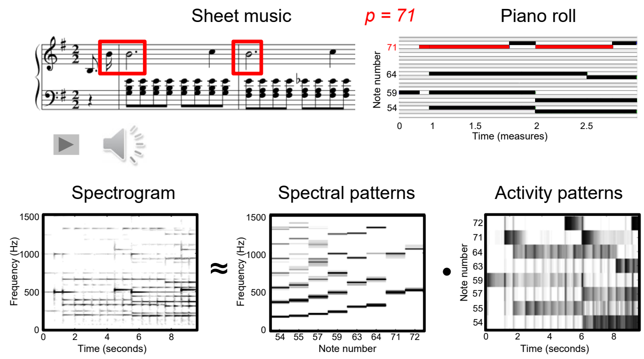

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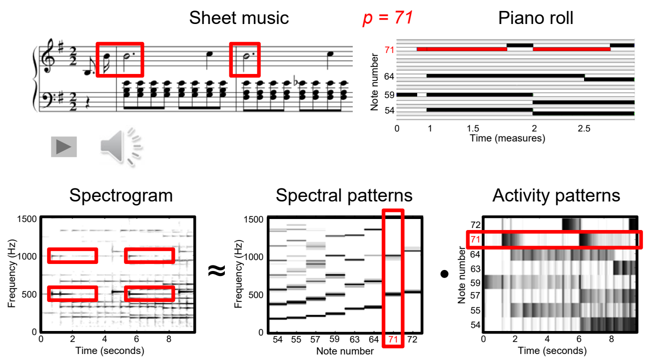

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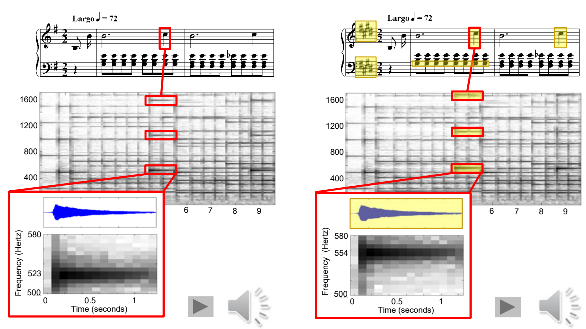
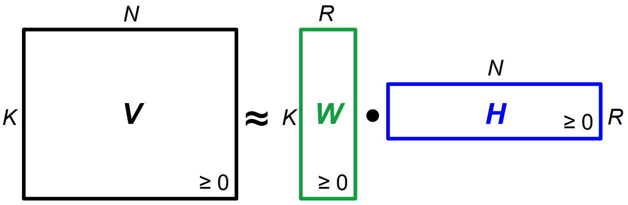
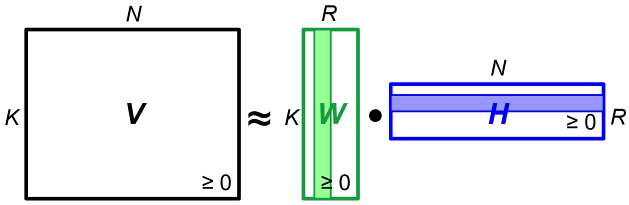


Nonnegative Matrix Factorization (NMF)



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

Nonnegative Matrix Factorization (NMF)

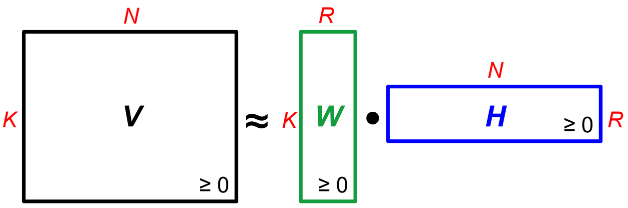


Magnitude Spectrogram **Templates** **Activations**

Templates: Pitch + Timbre "How does it sound"

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

Nonnegative Matrix Factorization (NMF)

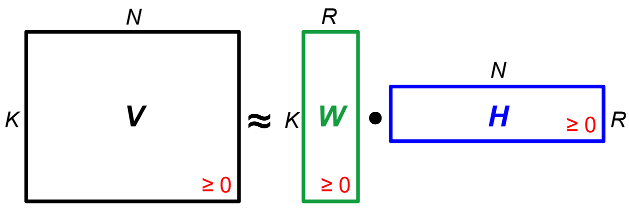


$V \in \mathbb{R}_{\geq 0}^{K \times N}$ $W \in \mathbb{R}_{\geq 0}^{K \times R}$ $H \in \mathbb{R}_{\geq 0}^{R \times N}$

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

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

$H_{\rho v}$

$\rho \in [1:R]$

$v \in [1:N]$

NMF Optimization

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

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

Variables

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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

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

Rearrange summands

Variables

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

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Introduce transposed $W^\top$

Variables

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

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

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

Variables

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

$H_{\rho\nu}$

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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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Issues:

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

NMF Optimization

Gradient descent

Choose adaptive learning rate:

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

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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

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

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

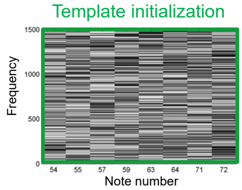
(2) $W^{(\ell+1)} = W^{(\ell)} \odot \left(\left(V (H^{(\ell+1)})^\top \right) \oslash \left(W^{(\ell)} H^{(\ell+1)} (H^{(\ell+1)})^\top \right) \right)$

(3) Increase ℓ by one.

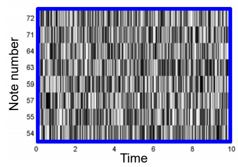
Repeat the steps (1) to (3) until $\|H^{(\ell)} - H^{(\ell-1)}\| \leq \varepsilon$ and $\|W^{(\ell)} - W^{(\ell-1)}\| \leq \varepsilon$ (or until some other stop criterion is fulfilled). Finally, set $H = H^{(\ell)}$ and $W = W^{(\ell)}$.

NMF-based Spectrogram Decomposition

Template initialization

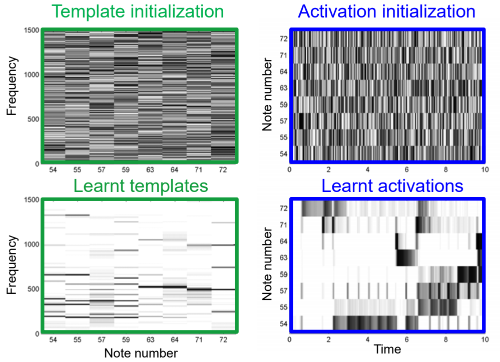


Activation initialization



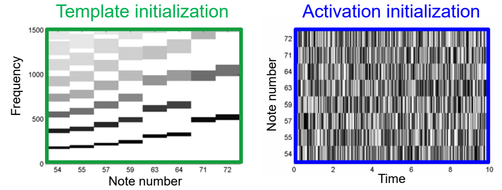
Random initialization

NMF-based Spectrogram Decomposition



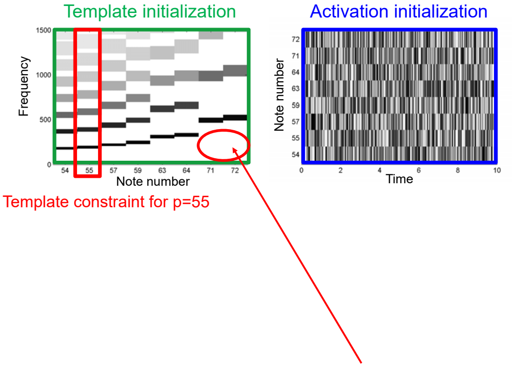
Random initialization → No semantic meaning

Constrained NMF: Templates



Enforce harmonic structure with zero-valued entries

Constrained NMF: Templates



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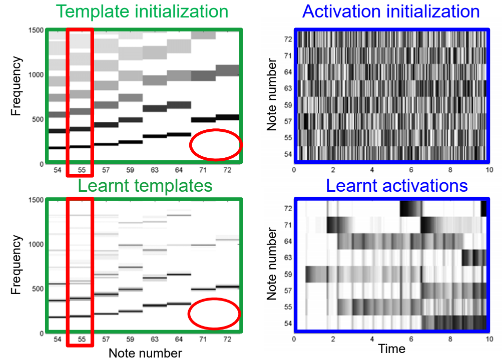
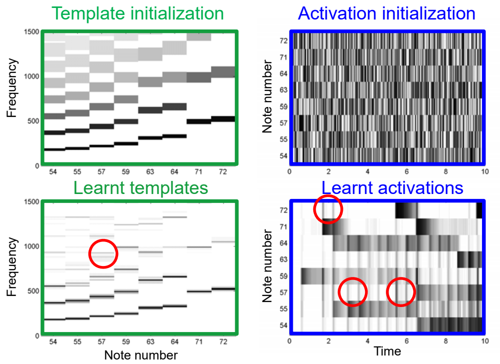


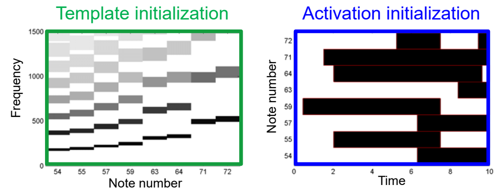
Zero-valued entries remain zero-valued entries!

Constrained NMF: Templates



Pitch templates misused to represent onsets

Constrained NMF: Double Constraints



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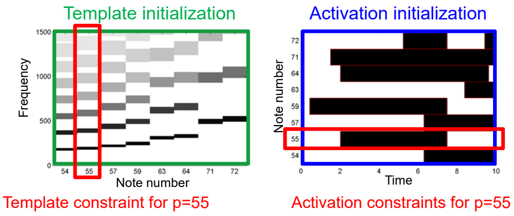

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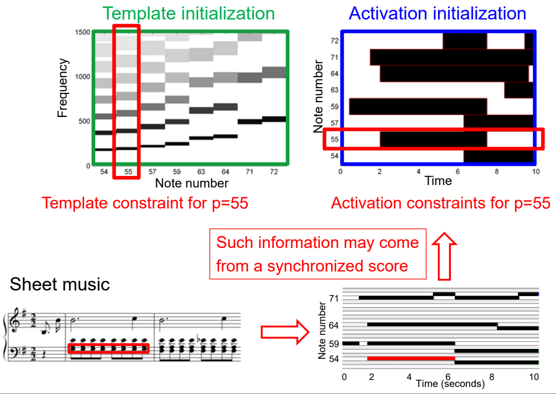
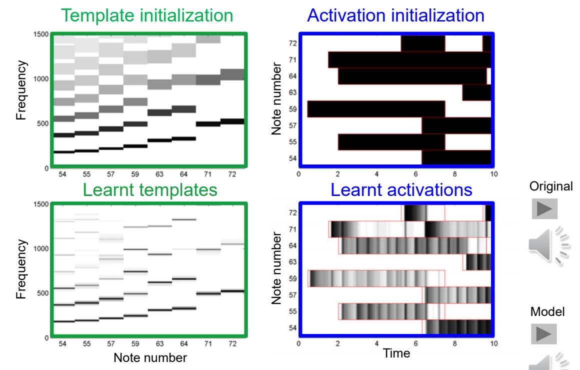
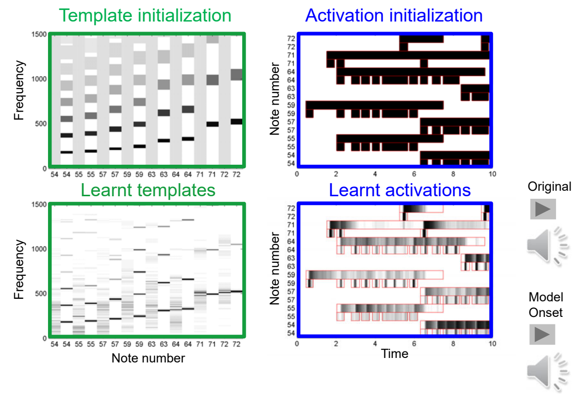


Constrained NMF: Double Constraints



Significant gain in structure, but onsets are missing

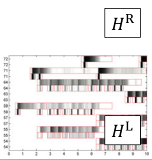
Constrained NMF: Onset Templates



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

1. Split activation matrix



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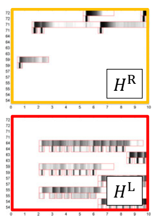
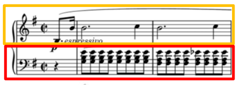
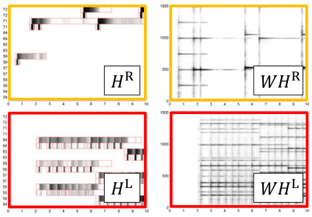


Score-Informed Audio Decompostion

Application: Separating left and right hands for piano



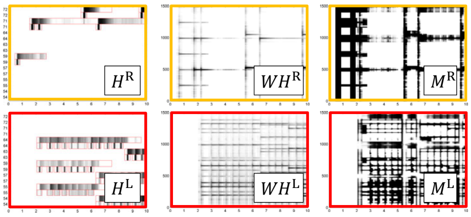
1. Split activation matrix
2. Model spectrogram for left/right



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

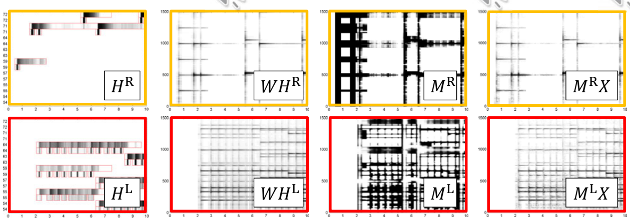
1. Split activation matrix
2. Model spectrogram for left/right
3. Separation masks for left/right



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

Score-Informed Constraints
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

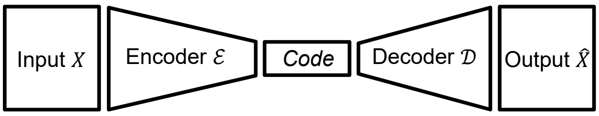
Score-Informed Constraints
Ewert, Müller: Using Score-Informed Constraints for NMF-based Source Separation. Proc. ICASSP, 2012.

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

Conclusions (NMF)

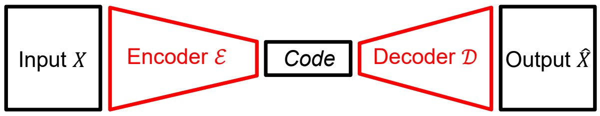
- NMF used for spectrogram decomposition
- Multiplicative update rules make it easy to constrain NMF model via zero initialization
- Exploiting score information to guide separation process (requires score–audio synchronization)
- Application: Separation of arbitrary note groups from given audio recording

Autoencoder



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

Autoencoder



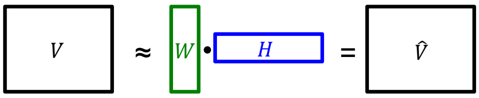
- Specific type of neural network
- Encoder: Compress input X into a low-dimensional code
- Decoder: Reconstruct output $\hat{X}$ from code
- Goal: Learn parameters for encoder and decoder such that output is close to input with respect to some loss function:

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

NMF and Autoencoder (AE)

Nonnegative Autoencoder
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^+

NMF and Autoencoder (AE)

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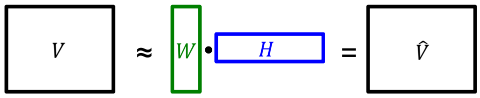
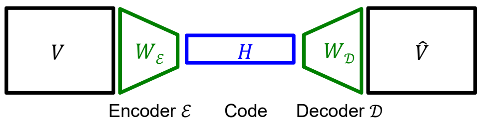
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.

NMF



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

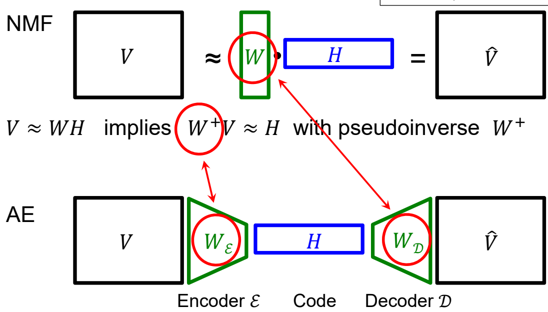
AE



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

NMF and Autoencoder (AE)

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



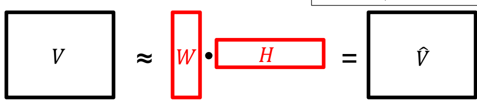
1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

Fully connected network

NMF and Autoencoder (AE)

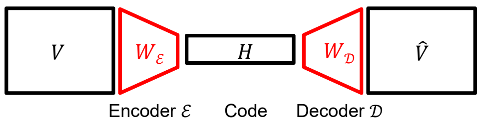
Nonnegative Autoencoder
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.

NMF



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

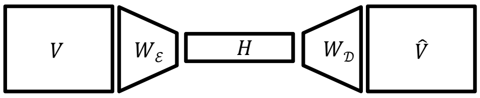
AE



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 $W_{\mathcal{D}}$

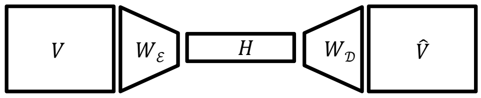
Nonnegative Autoencoder (NAE)



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)

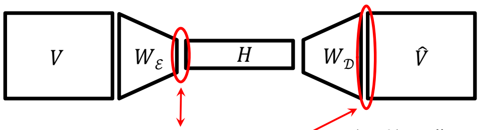


1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

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

- Loss function: same as in NMF

Nonnegative Autoencoder (NAE)

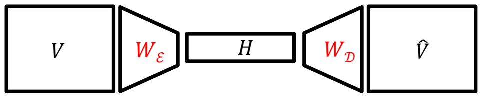


1. Layer: $H = \max(W_{\mathcal{E}}\, V, 0)$
2. Layer: $\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$

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

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

Nonnegative Autoencoder (NAE)



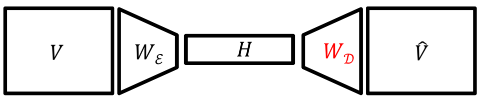
1. Layer: $H = \max(W_{\mathcal{E}}\, V, 0)$
2. Layer: $\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$

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

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

- 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

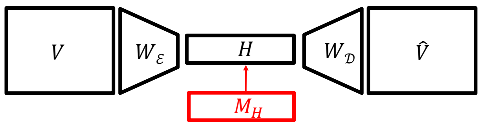


$H = \max(W_{\mathcal{E}}\, V, 0)$
$\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$

- 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:

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

NMF vs. NAE
Özer, Hansen, Zunner, Müller: Investigating Nonnegative Autoencoders for Efficient Audio Decomposition. Proc. EUSIPCO, 2022.

NAE with Multiplicative Update Rules

- Encoder:

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

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

- Structured Dropout:

$$H' = H \odot M_H$$

- Decoder:

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

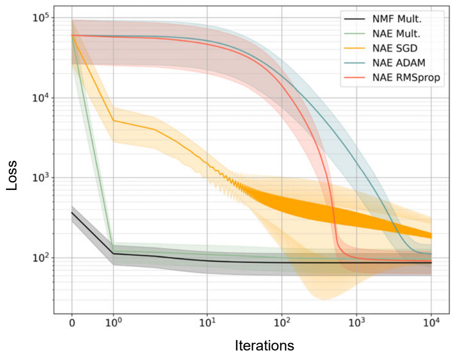
$$W^{(\ell+1)}_{\mathcal{D},kr} = W^{(\ell)}_{\mathcal{D},kr} \cdot \frac{(V H'^\top)_{kr}}{(W_{\mathcal{D}}^{(\ell)} H' H'^\top)_{kr}}$$

Similar idea and computation as for NMF.

NMF vs. NAE
Özer, Hansen, Zunner, Müller: Investigating Nonnegative Autoencoders for Efficient Audio Decomposition. Proc. EUSIPCO, 2022.

Approximation Loss

NMF vs. NAE
Özer, Hansen, Zunner, Müller: Investigating Nonnegative Autoencoders for Efficient Audio Decomposition. Proc. EUSIPCO, 2022.



Approximation Loss

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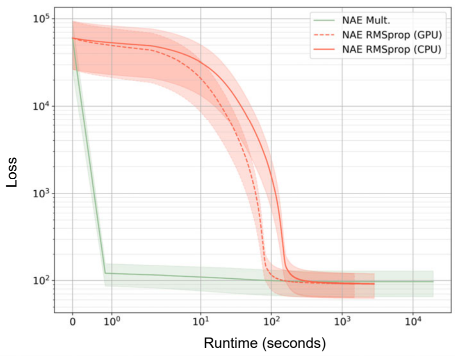


Conclusions (NAE)

- 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)

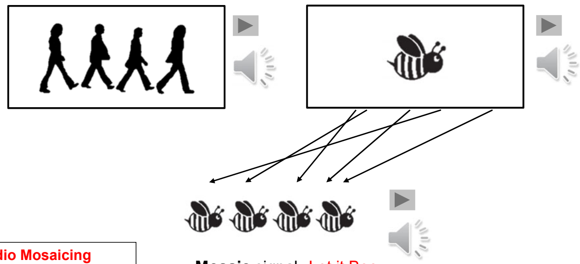
Outlook

- 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 convergence issues
  - Adaptive learning rates and projected gradient descent

Score-Informed Audio Decomposition

Audio mosaicing (style transfer)

Target signal: Beatles–Let it be **Source** signal: Bees

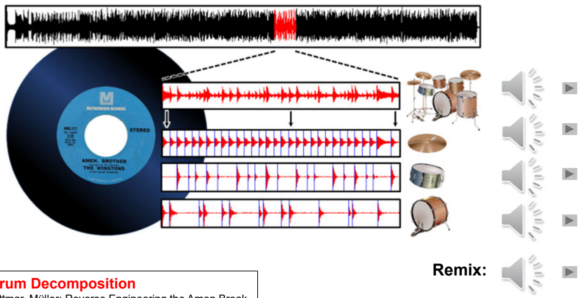


Audio Mosaicing
Driedger, Prätzlich, Müller: Let It Bee – Towards NMF-Inspired Audio Mosaicing. ISMIR, 2015.

Mosaic signal: Let it Bee

Score-Informed Audio Decomposition

Informed Drum-Sound Decomposition



Drum Decomposition
Dittmar, Müller: Reverse Engineering the Amen Break – Score-Informed Separation and Restoration Applied to Drum Recordings. IEEE/ACM TASLP 24(9), 2016.

Score-Informed Audio Decomposition

Major challenge: Reconstructed sound events often have artifacts

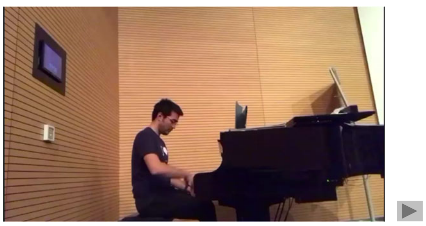
Approaches:

- Resynthesize certain sound components
- Differentiable Digital Signal Processing (DDSP) combines classical DSP and deep learning
- Generative adversarial networks may help to reduce the artifacts

DDSP
Engel et al.: DDSP: Differentiable Digital Signal Processing. ICLR, 2020.

Source Separation (Piano Concerto)

- Yigitcan Özer
- PhD student in engineering
- Pianist



Source Separation (Piano Concerto)

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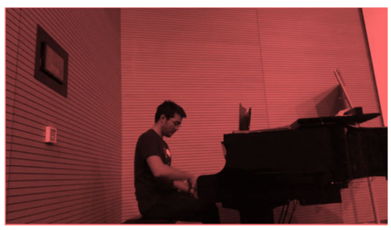
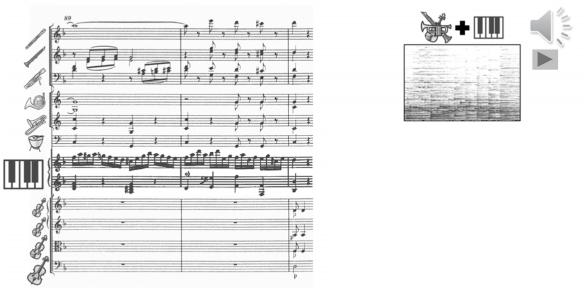


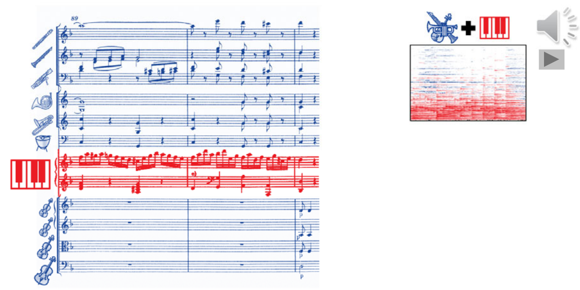
Only Piano!

Where is the orchestra?

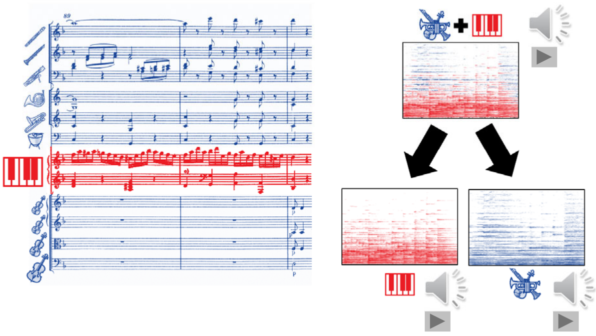
Source Separation (Piano Concerto)



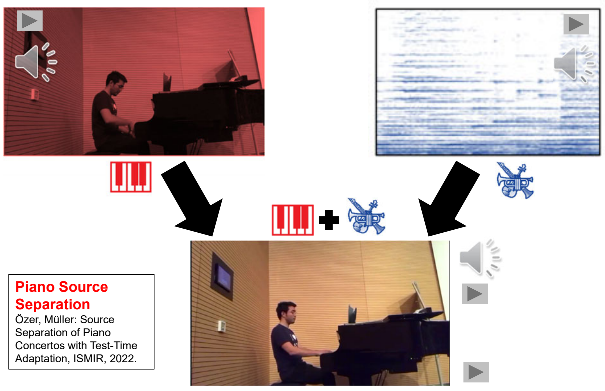
Source Separation (Piano Concerto)



Source Separation (Piano Concerto)



Source Separation (Piano Concerto)



Piano Source Separation
Özer, Müller: Source Separation of Piano Concertos with Test-Time Adaptation, ISMIR, 2022.

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.
- Yigitcan Özer, Jonathan Hansen, Tim Zunner, and Meinard Müller: Investigating Nonnegative Autoencoders for Efficient Audio Decomposition. Proc. EUSIPCO, 2022.