Nonnegative Autoencoders with Applications to Music Audio Decomposing

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Guest Lecture
Central Conservatory of Music (CCOM)
Beijing, March 2023

Friedrich-Alexander-Universität Erlangen-Nürnberg

Fraunhofer IIS

Meinard Müller

- Mathematics (Diplom/Master, 1997)
  Computer Science (PhD, 2001)
  Information Retrieval (Habilitation, 2007)
- Senior Researcher (2007-2012)
- Professor Semantic Audio Processing (since 2012)
- Former President of the International Society for Music Information Retrieval (MIR)
- IEEE Fellow for contributions to Music Signal Processing

universitätbonn

max planck institut informatik

FAU

ISMIR

IEEE

Meinard Müller: Research Group

Semantic Audio Processing

- Michael Krause
- Yigitcan Özer
- Simon Schwär
- Johannes Zeitler
- Peter Meier (external)





- Christof Weiß
- Sebastian Rosenzweig
- Frank Zalkow
- Christian Dittmar
- Stefan Balke
- Jonathan Driedger
- Thomas Prätzlich
- …







International Audio Laboratories Erlangen

Fraunhofer IIS

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

mp3

AUDIO LABS

FAU FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG

- 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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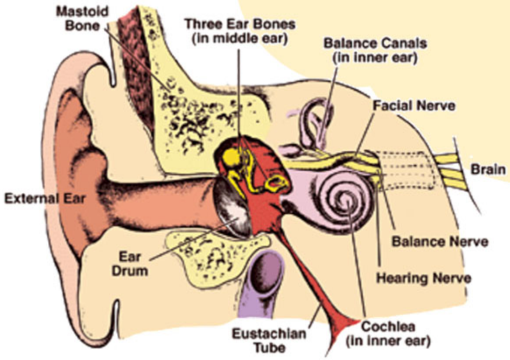
Audio Coding

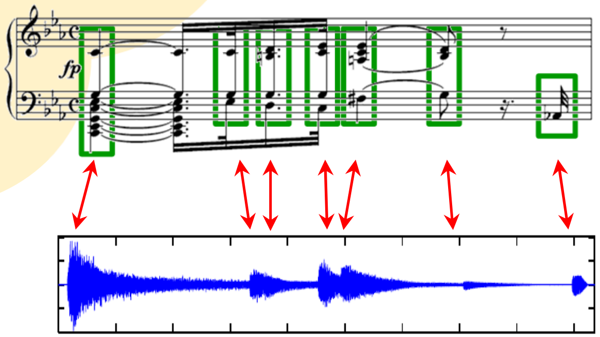
3D Audio

Audio



Psychoacoustics

Internet of Things



Music Processing

AudioLabs – FAU

- 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

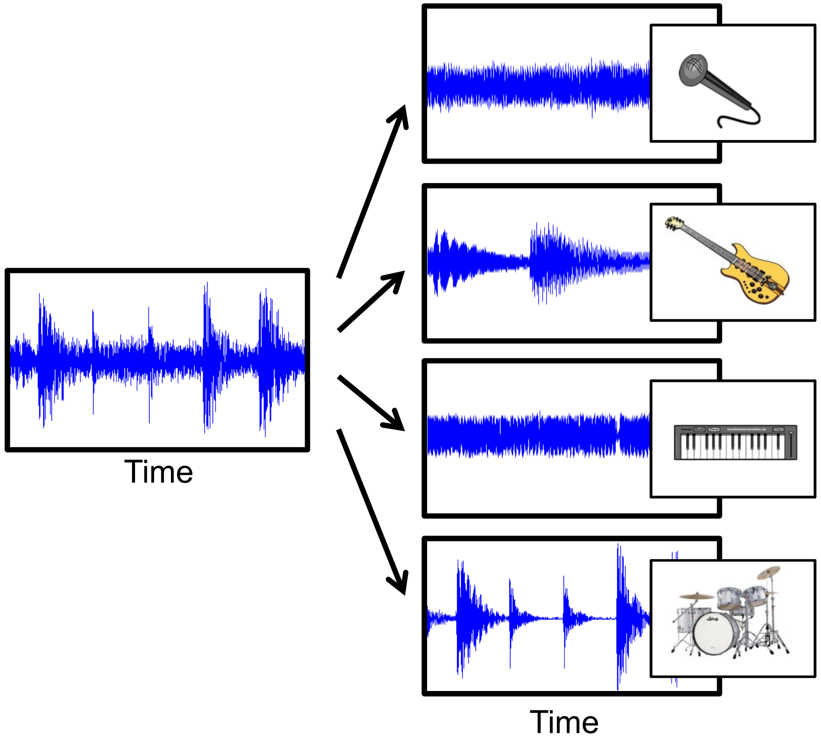
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- "Cocktail party effect"

Source Separation

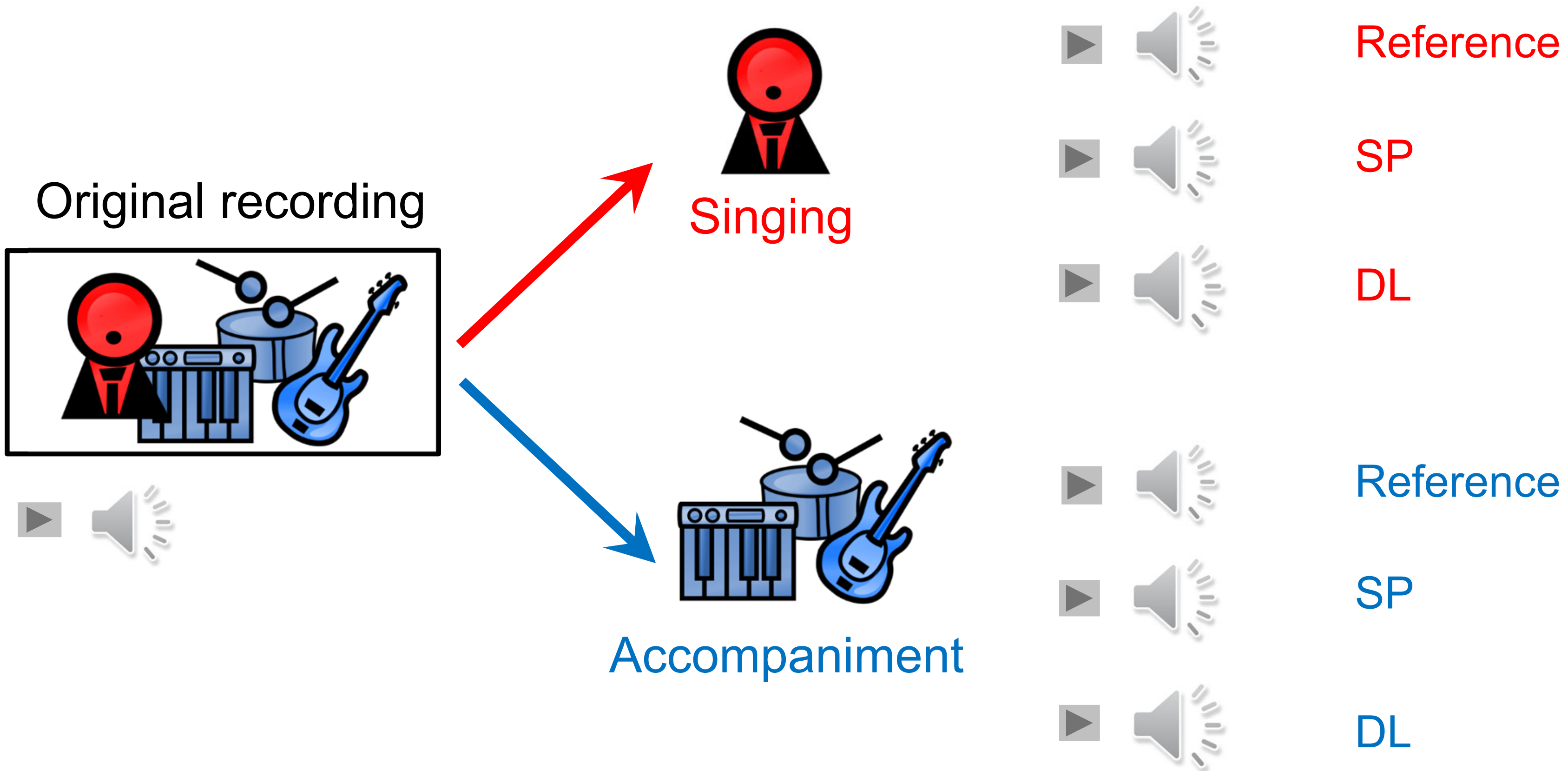
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- “Cocktail party effect”
- Several input signals
- Sources are assumed to be statistically independent

Source Separation (Music)

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



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

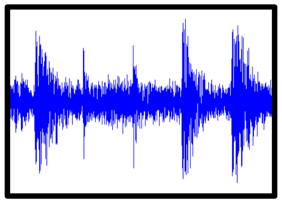
Score-Informed Source Separation

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

Musical
Information

Audio
Signal



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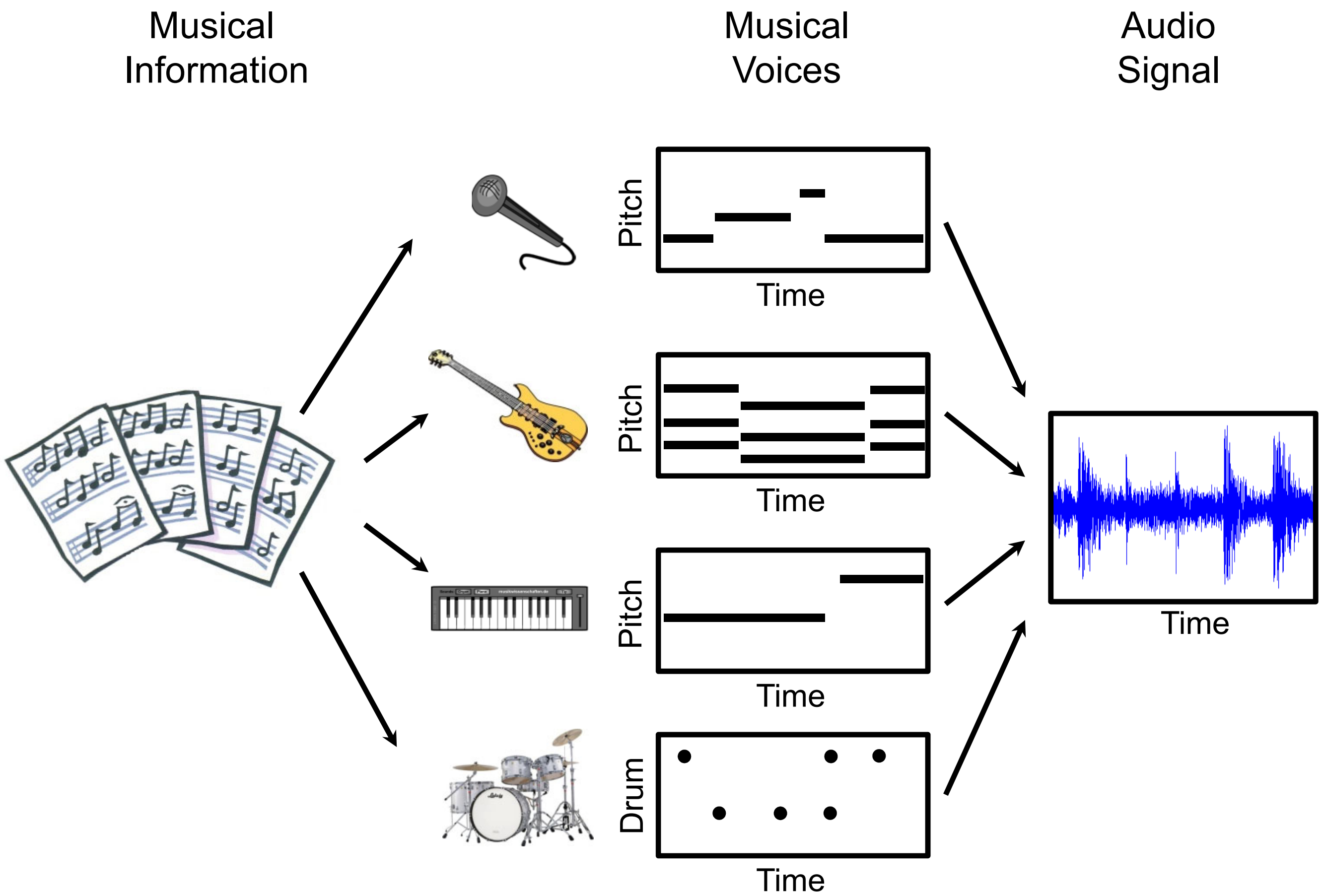

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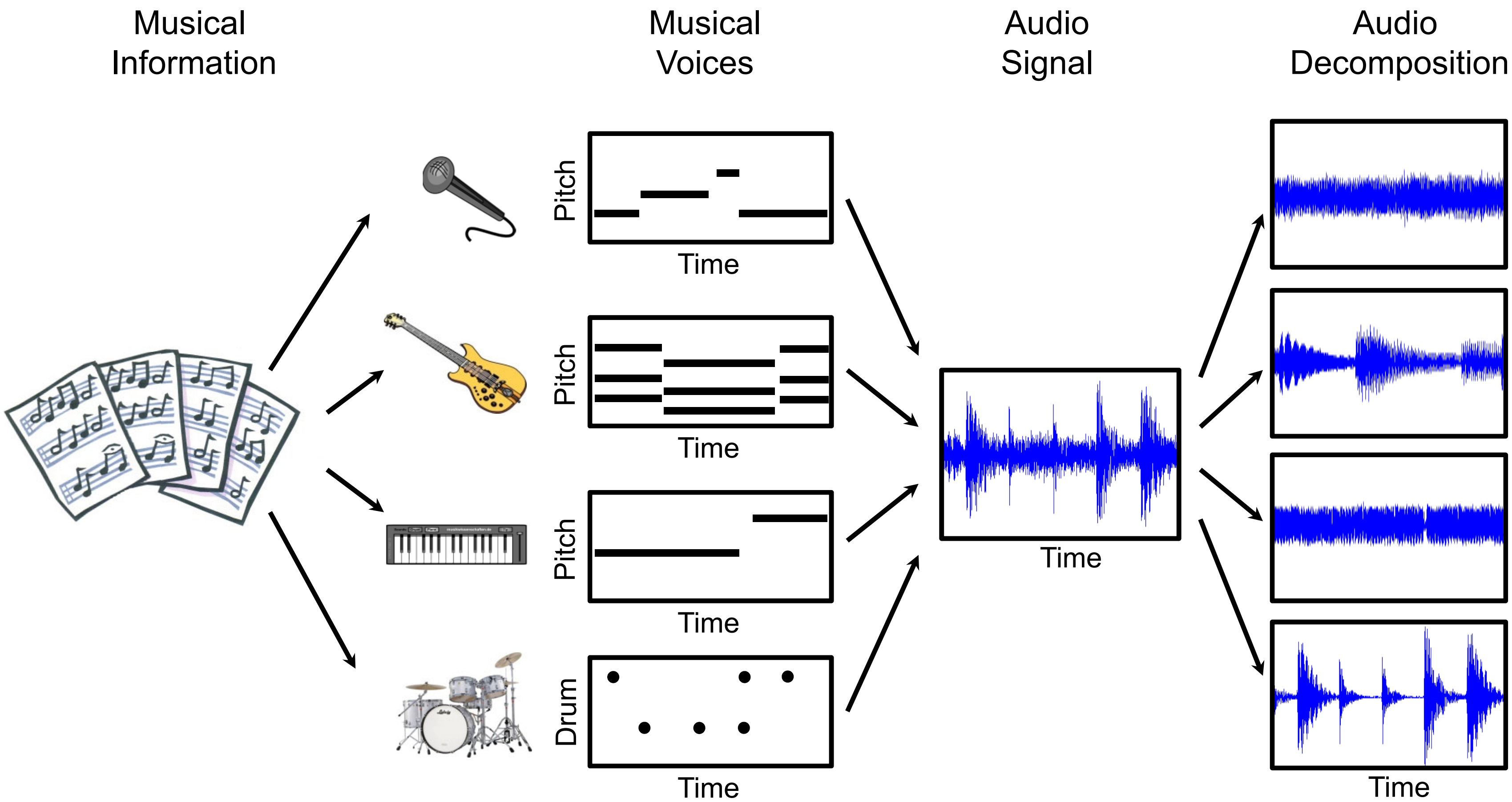
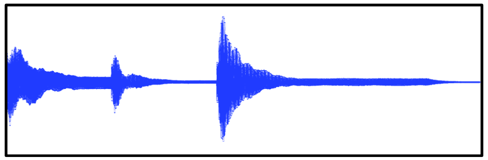


Score-Informed Audio Decomposition



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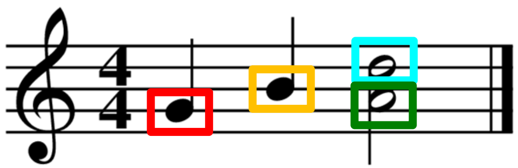

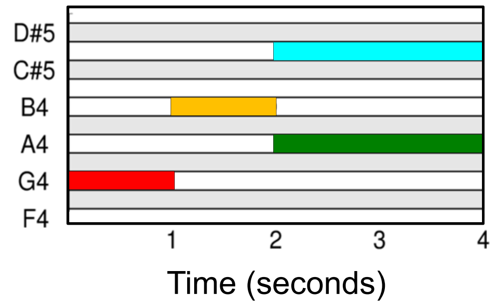

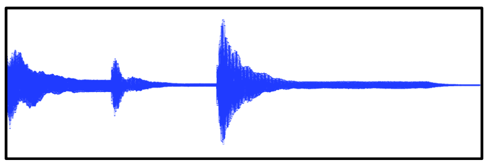

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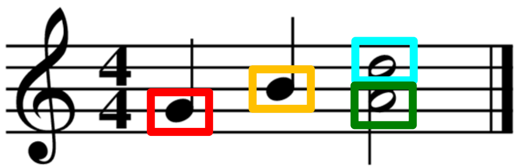
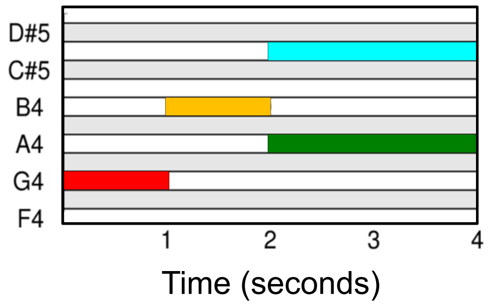
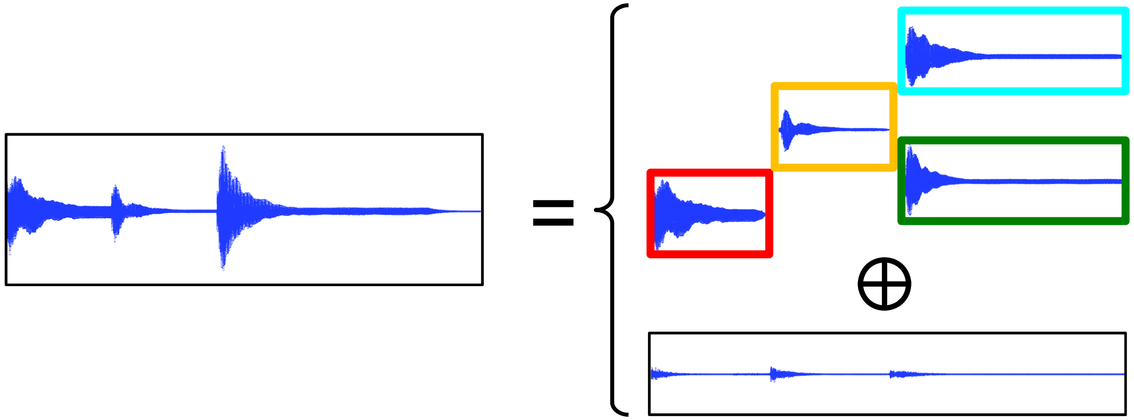
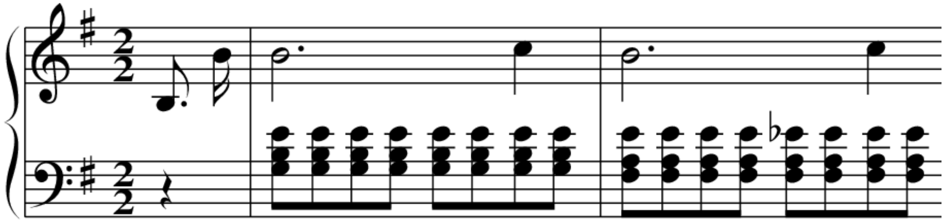




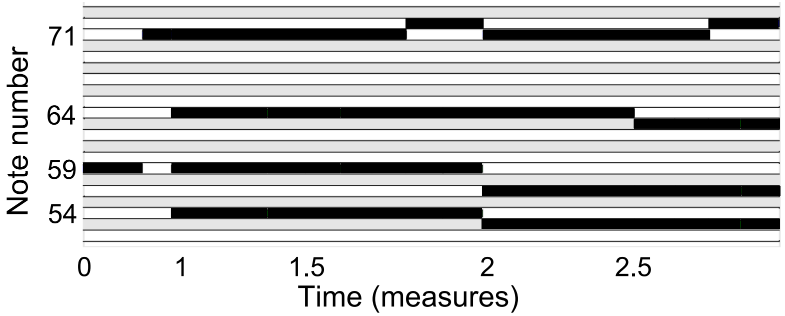


Score-Informed Audio Decomposition

Sheet music

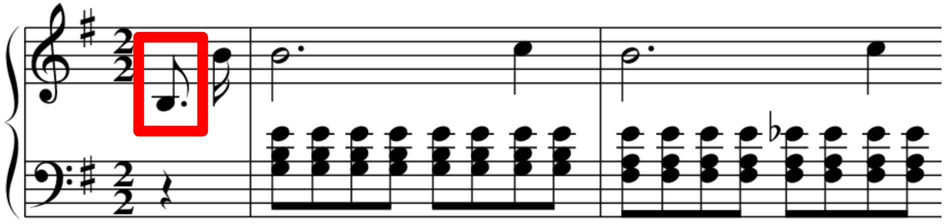


Piano roll



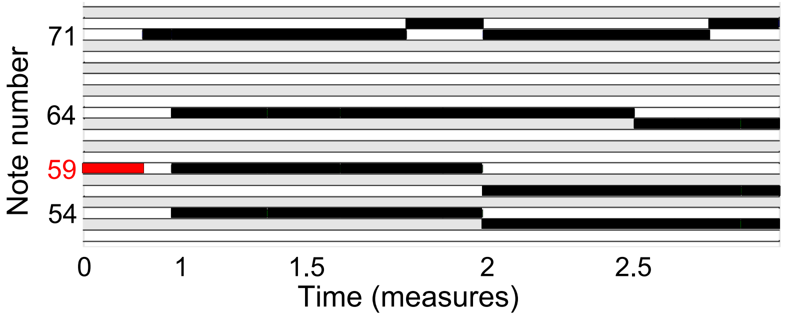
Score-Informed Audio Decomposition

Sheet music



p = 59

Piano roll

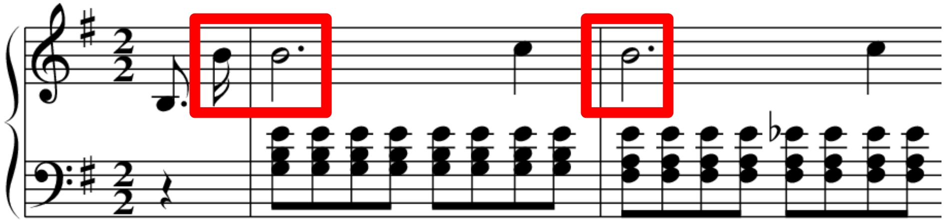


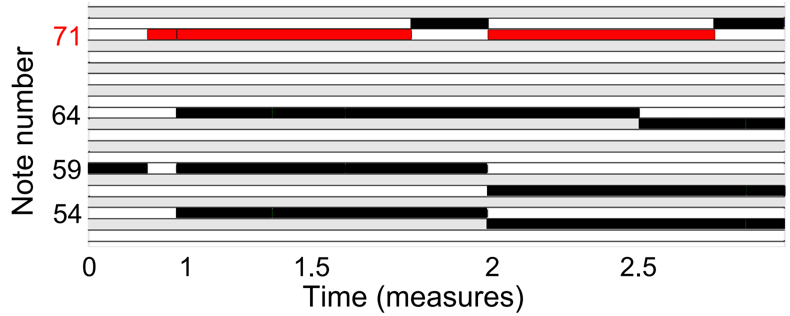
Score-Informed Audio Decomposition

Sheet music

p = 71

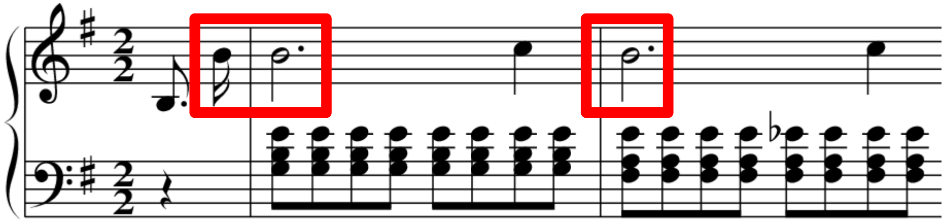
Piano roll





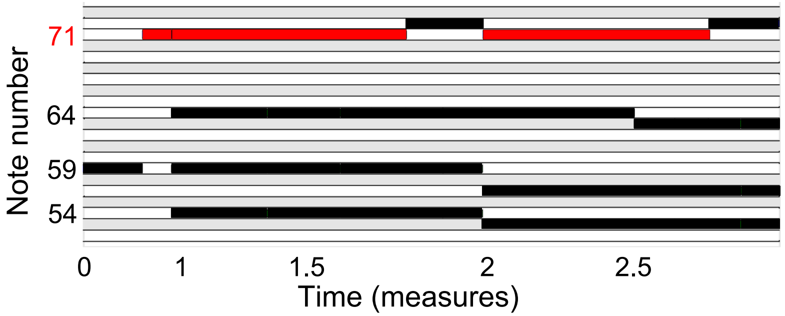
Score-Informed Audio Decomposition

Sheet music

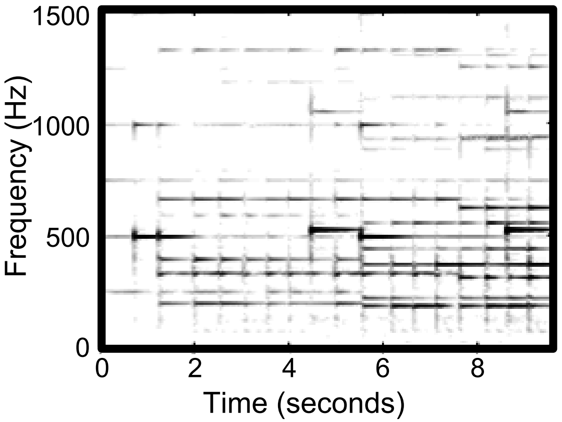


p = 71

Piano roll



Spectrogram



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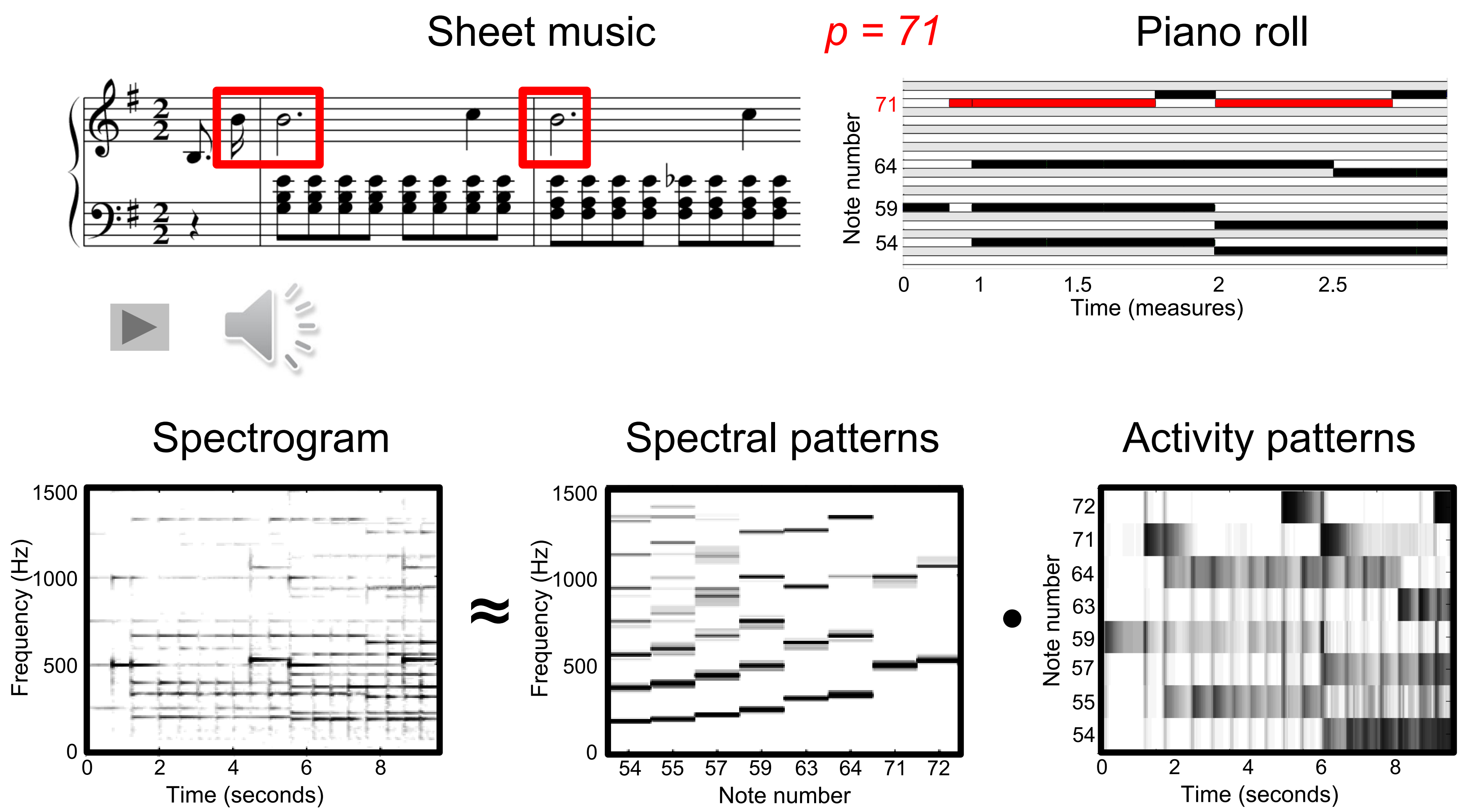

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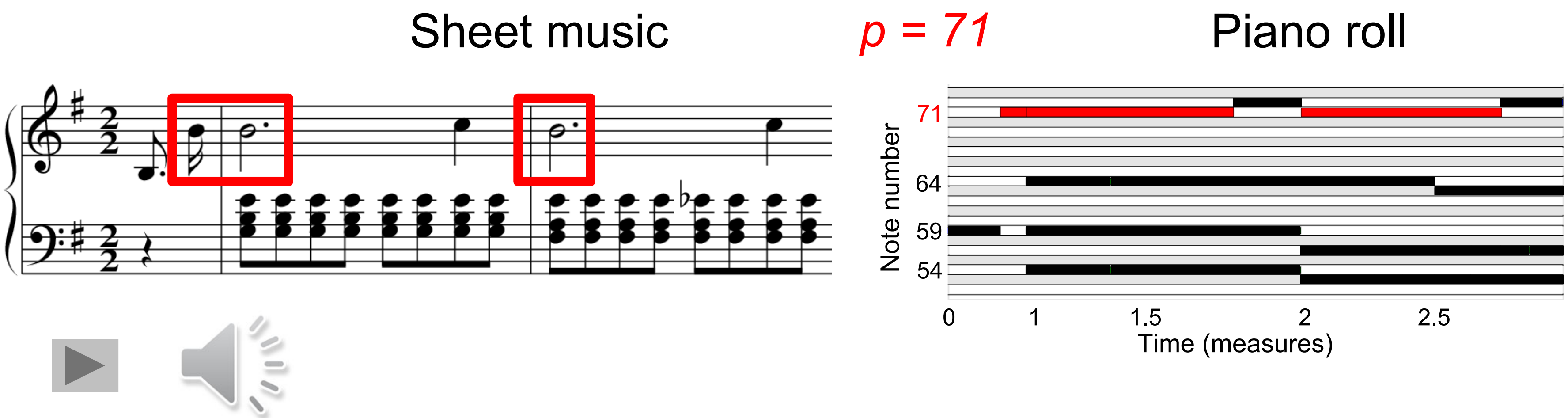

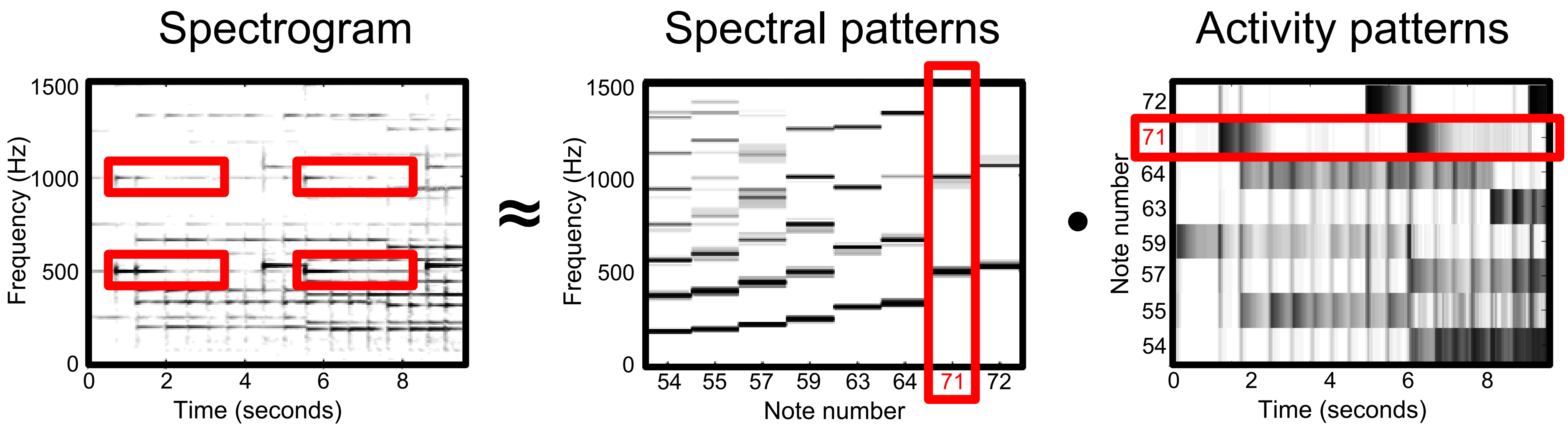

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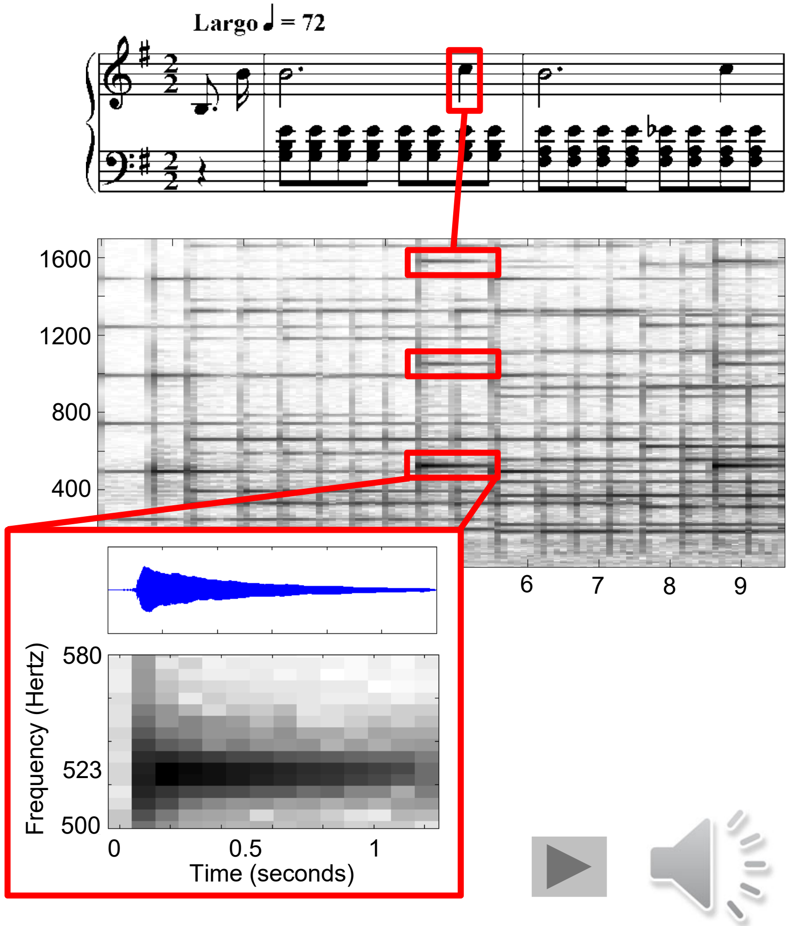
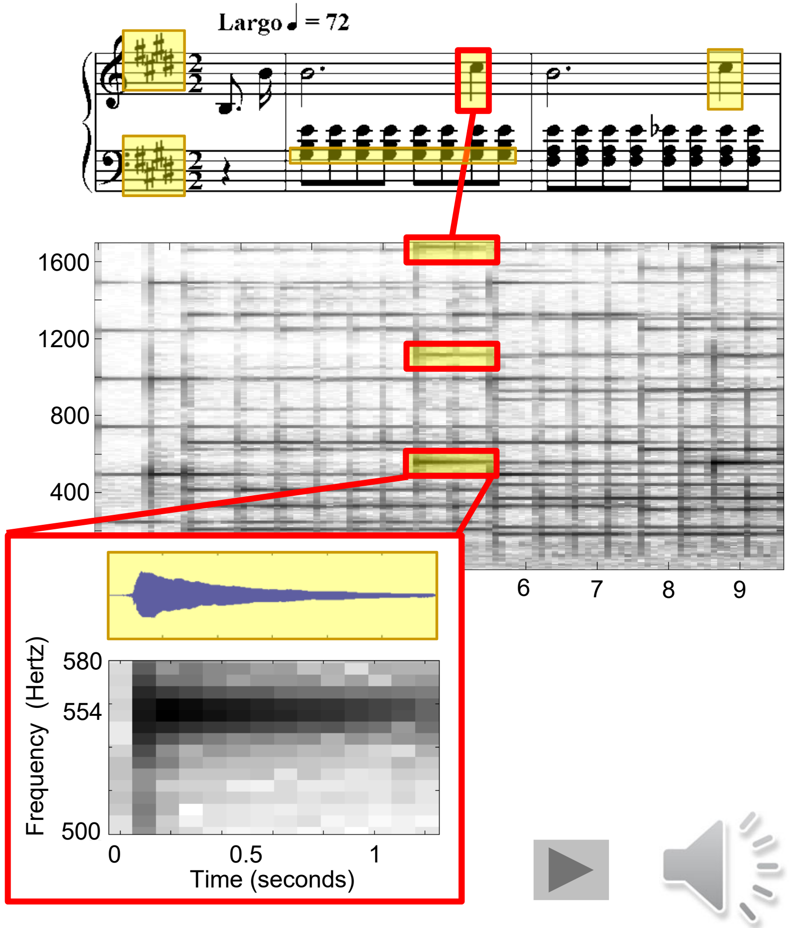
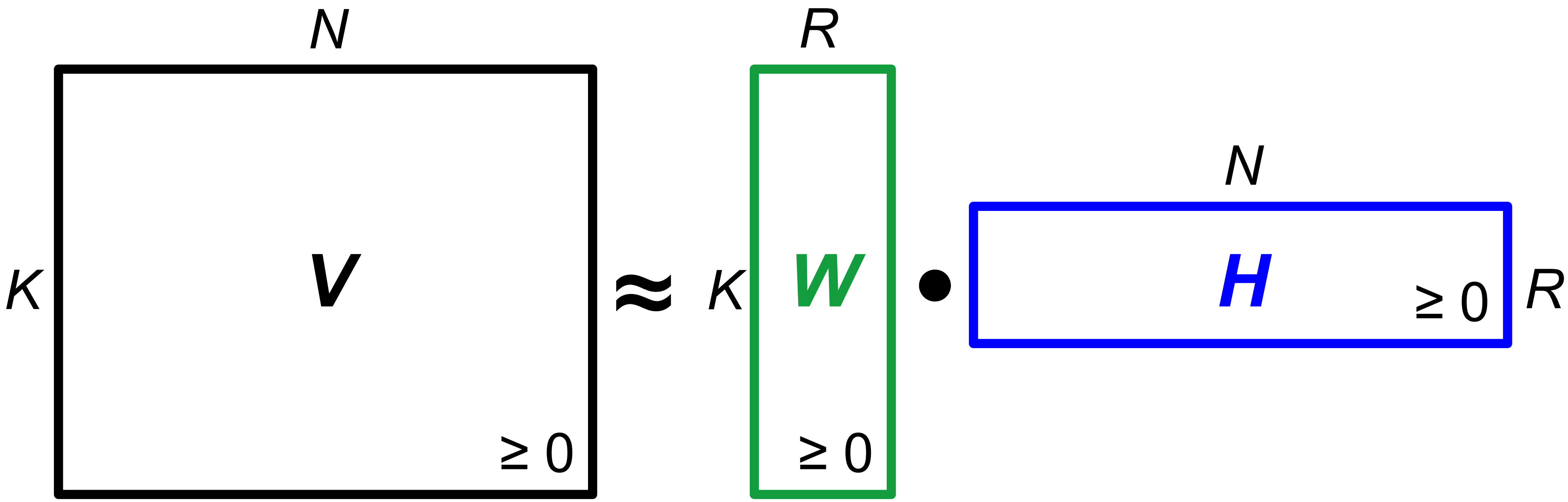


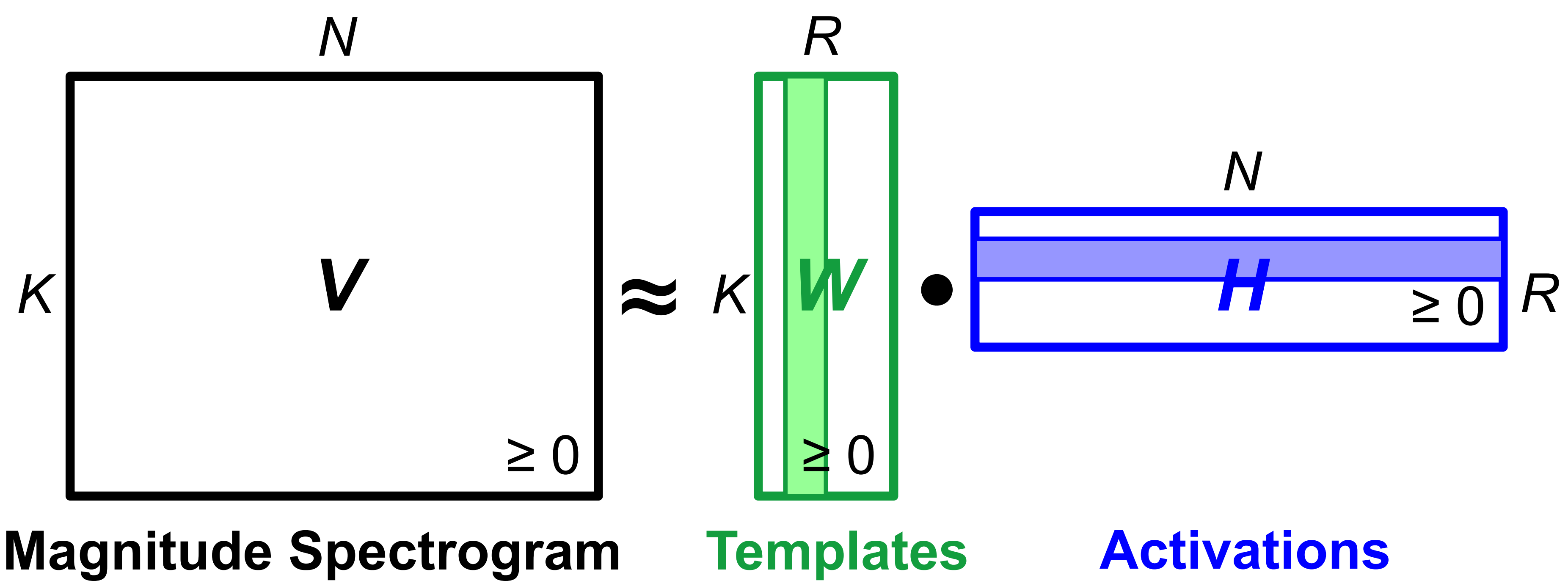


Nonnegative Matrix Factorization (NMF)



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

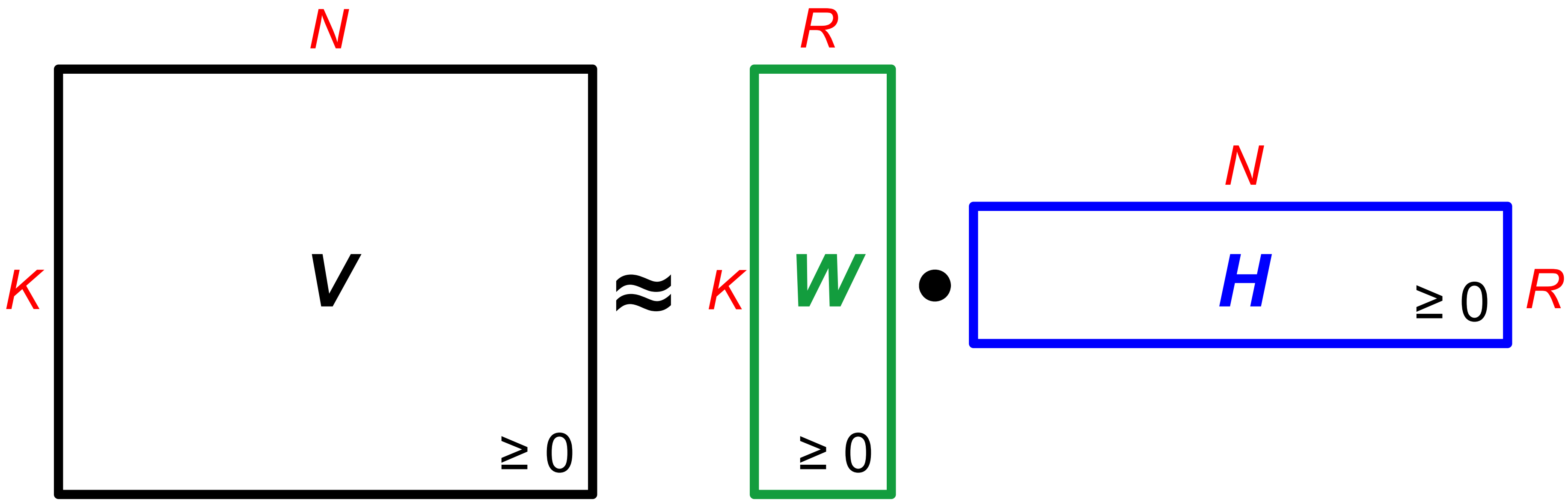
Nonnegative Matrix Factorization (NMF)



Templates: Pitch + Timbre "How does it sound"

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

Nonnegative Matrix Factorization (NMF)

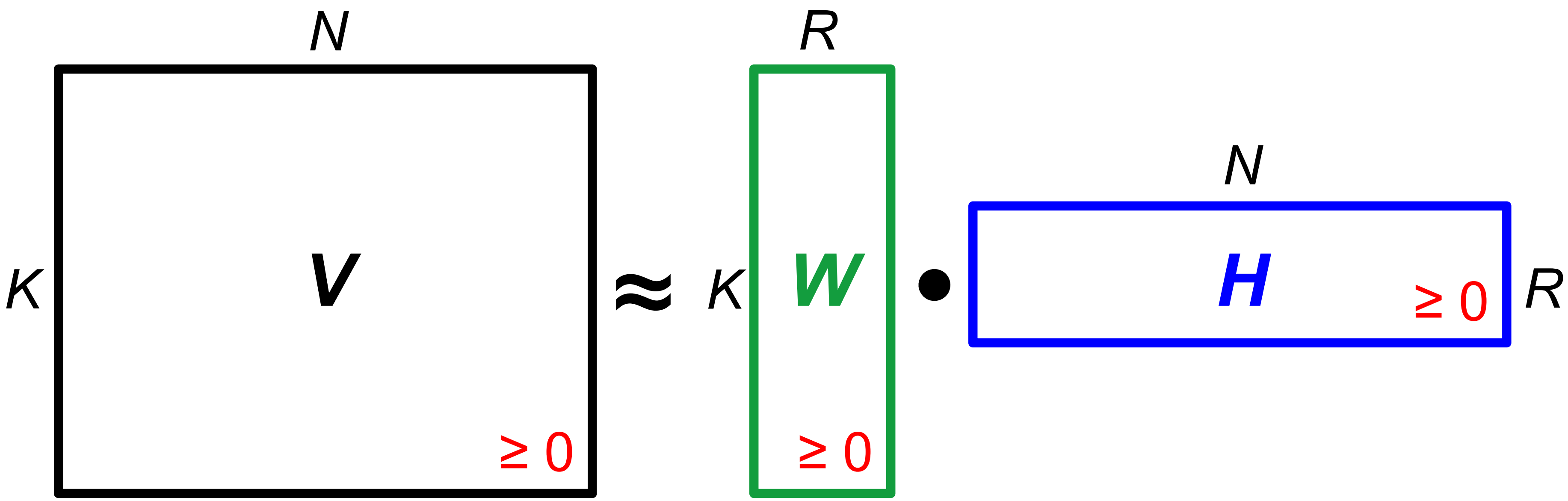


$V \in \mathbb{R}_{\geq 0}^{K \times N}$ $\quad$ $W \in \mathbb{R}_{\geq 0}^{K \times R}$ $\quad$ $H \in \mathbb{R}_{\geq 0}^{R \times N}$

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)



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

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*)

$D := RN$

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

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

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

Variables

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

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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

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

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NMF Optimization

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

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

Variables

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

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$\rho \in [1:R]$

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Apply chain rule from calculus

NMF Optimization

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

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

Rearrange summands

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NMF Optimization

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

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

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

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

Introduce transposed $W^{\top}$

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NMF Optimization

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

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$H_{\rho\nu}$

$\rho \in [1:R]$

$\nu \in [1:N]$

$$
\begin{aligned}
\frac{\partial \varphi^W}{\partial H_{\rho\nu}} &= \frac{\partial \left(\sum_{k=1}^K \sum_{n=1}^N \left(V_{kn} - \sum_{r=1}^R W_{kr} H_{rn}\right)^2 \right)}{\partial H_{\rho\nu}} \\
&= \frac{\partial \left(\sum_{k=1}^K \left(V_{k\nu} - \sum_{r=1}^R W_{kr} H_{r\nu}\right)^2 \right)}{\partial H_{\rho\nu}} \\
&= \sum_{k=1}^K 2 \left(V_{k\nu} - \sum_{r=1}^R W_{kr} H_{r\nu} \right) \cdot (-W_{k\rho}) \\
&= 2 \left(\sum_{r=1}^R \sum_{k=1}^K W_{k\rho} W_{kr} H_{r\nu} - \sum_{k=1}^K W_{k\rho} V_{k\nu} \right) \\
&= 2 \left(\sum_{r=1}^R \left(\sum_{k=1}^K W_{\rho k}^\top W_{kr} \right) H_{r\nu} - \sum_{k=1}^K W_{\rho k}^\top V_{k\nu} \right) \\
&\boxed{= 2\big((W^\top WH)_{\rho\nu} - (W^\top V)_{\rho\nu}\big).}
\end{aligned}
$$

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 $\gamma_{rn}^{(\ell)} \geq 0$

NMF Optimization

Gradient descent

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

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

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

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

Issues:

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NMF Optimization

Gradient descent

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Choose adaptive learning rate:

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

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

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

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

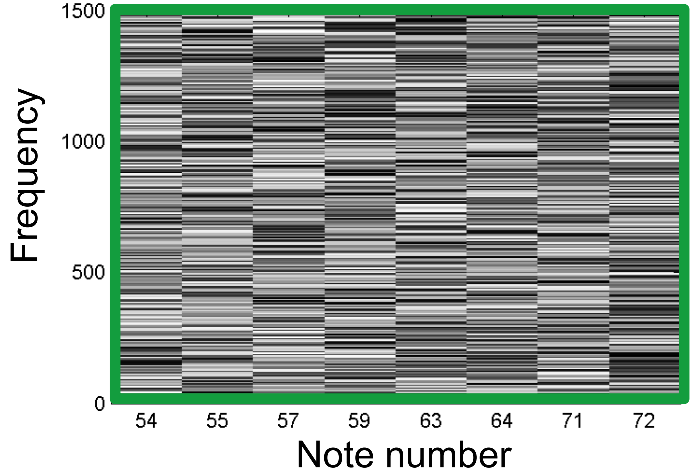
(2) $W^{(\ell+1)} = W^{(\ell)} \odot \left(\left(V (H^{(\ell+1)})^\top\right) \oslash \left(W^{(\ell)} H^{(\ell+1)} (H^{(\ell+1)})^\top\right)\right)$

(3) Increase ℓ by one.

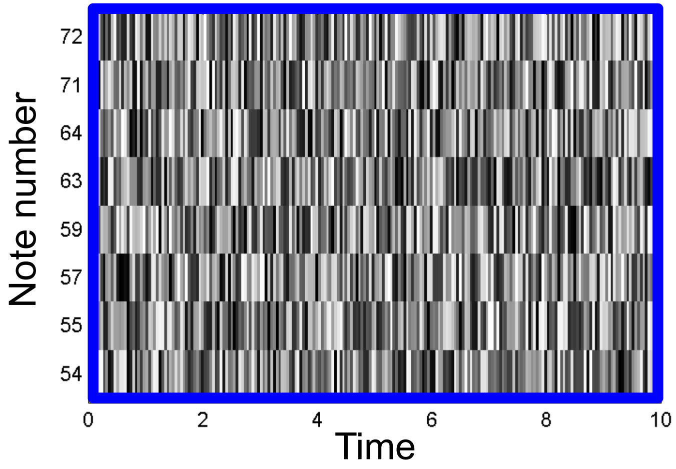
Repeat the steps (1) to (3) until $\|H^{(\ell)} - H^{(\ell-1)}\| \leq \varepsilon$ and $\|W^{(\ell)} - W^{(\ell-1)}\| \leq \varepsilon$ (or until some other stop criterion is fulfilled). Finally, set $H = H^{(\ell)}$ and $W = W^{(\ell)}$.

NMF-based Spectrogram Decomposition

Template initialization

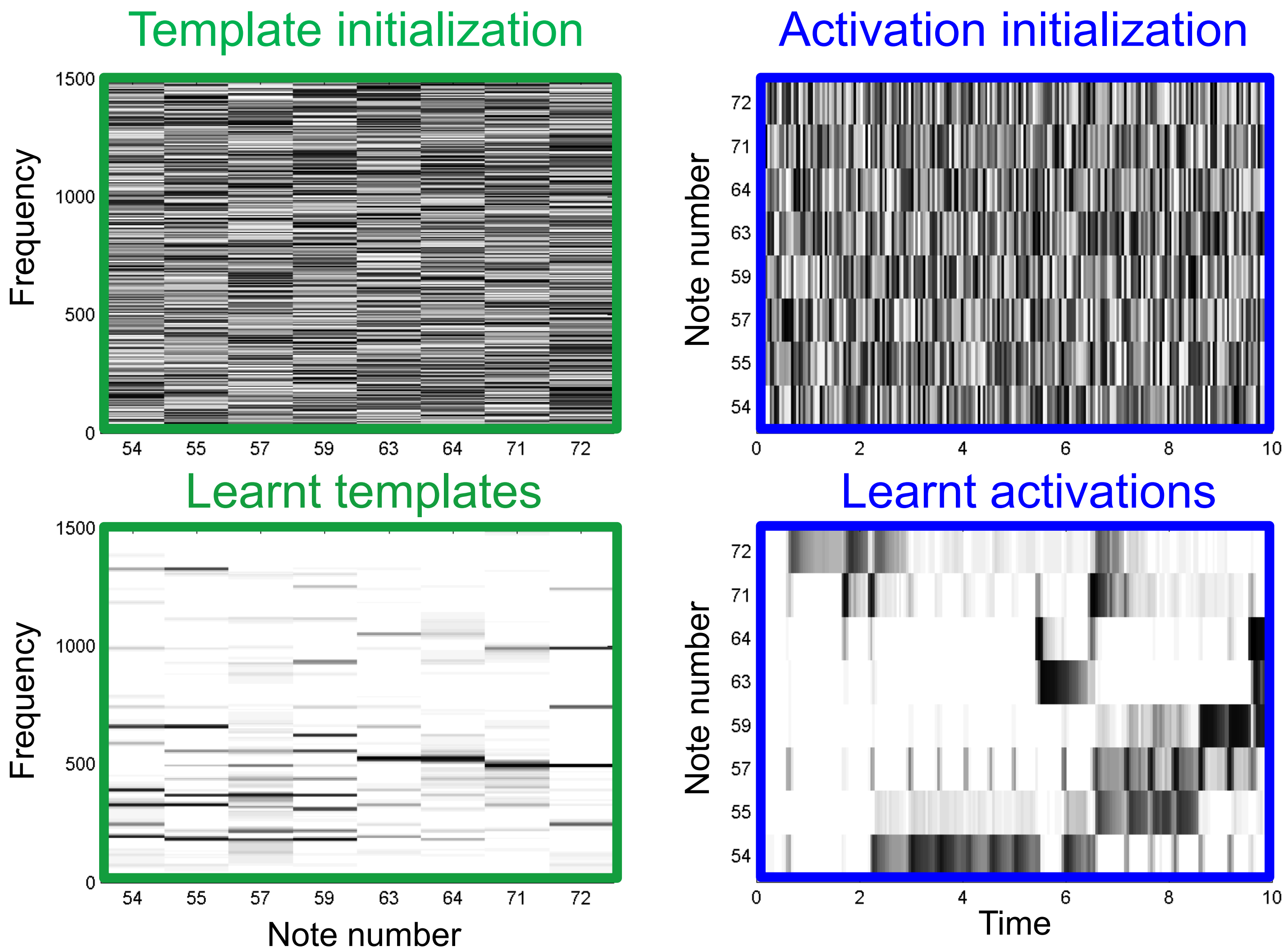


Activation initialization



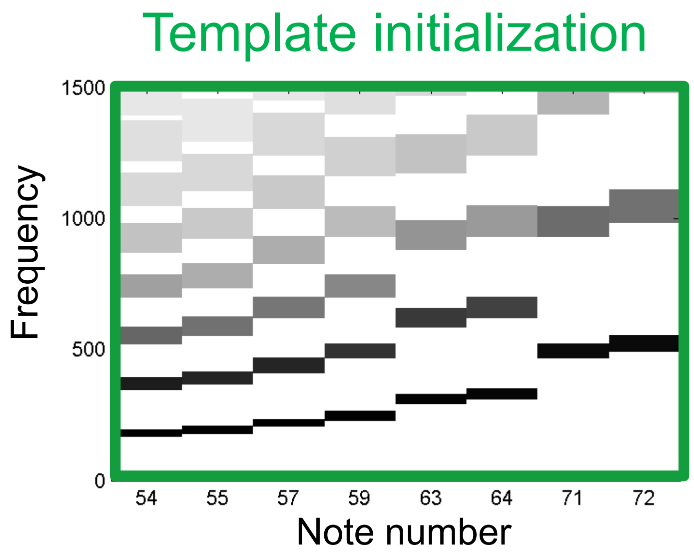
Random initialization

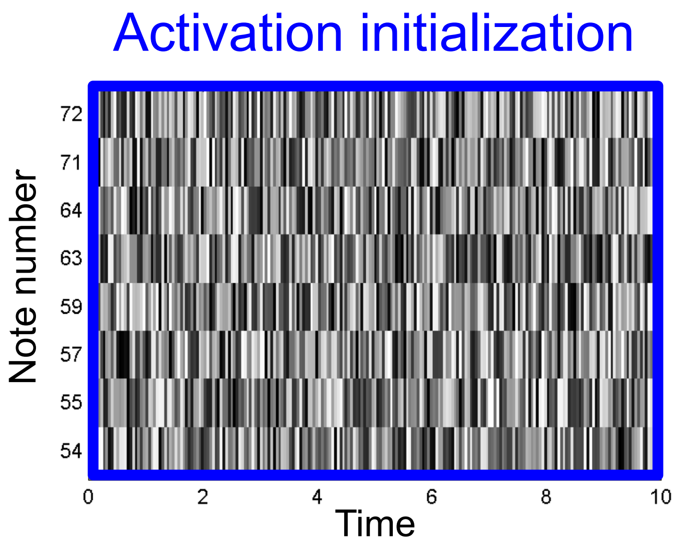
NMF-based Spectrogram Decomposition



Random initialization → No semantic meaning

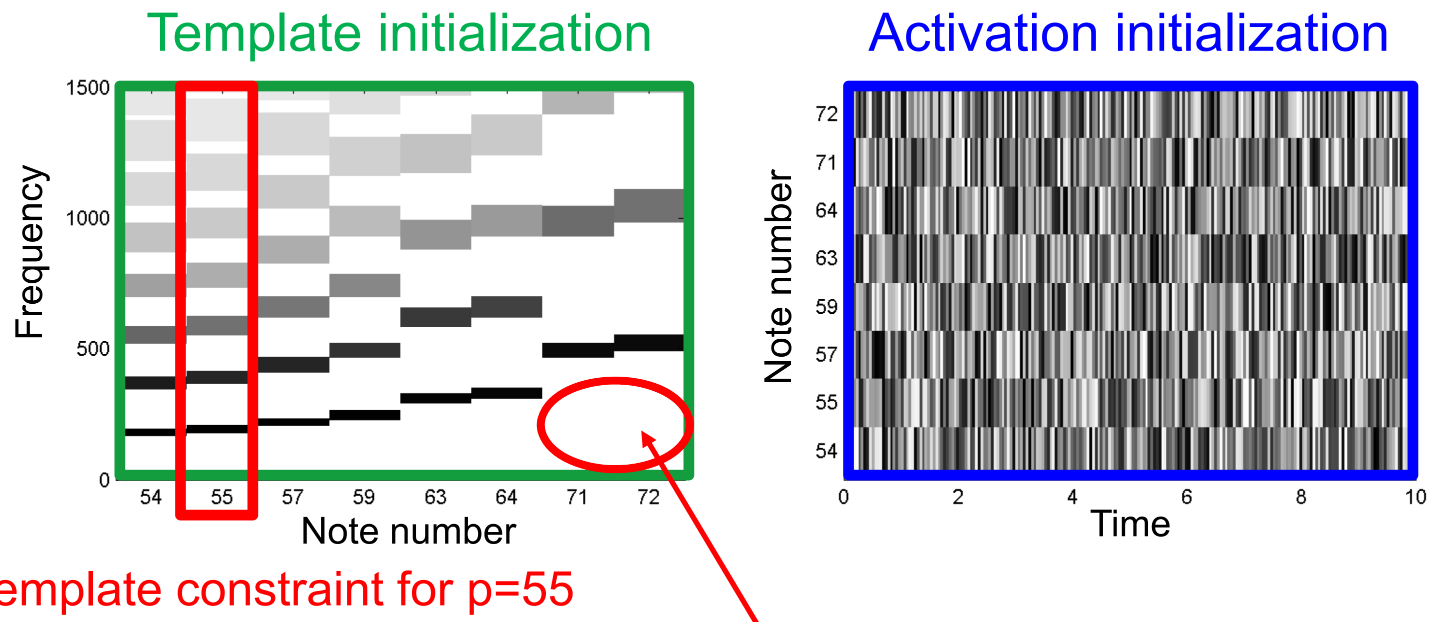
Constrained NMF: Templates





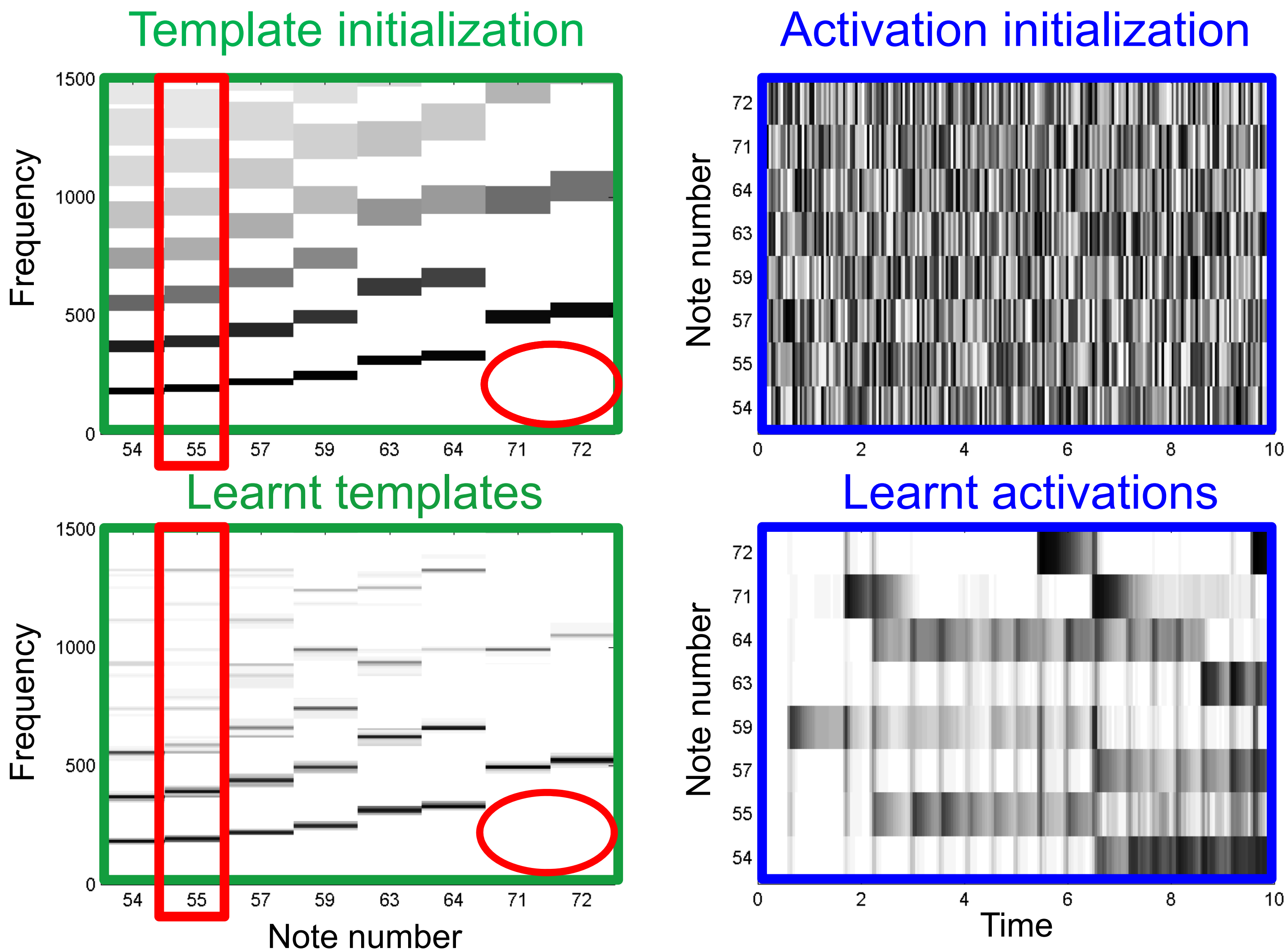
Enforce harmonic structure with zero-valued entries

Constrained NMF: Templates



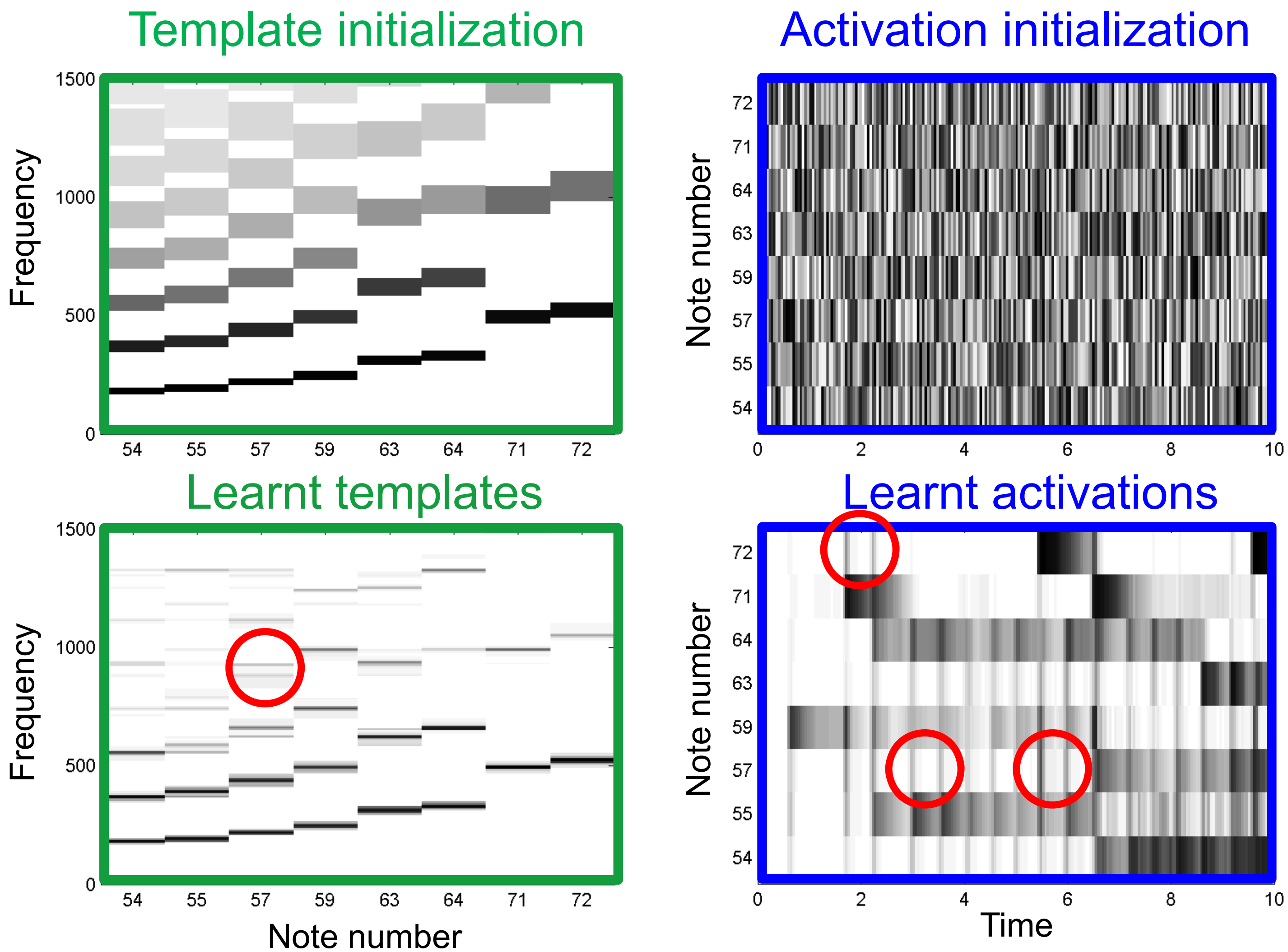
Enforce harmonic structure with zero-valued entries

Constrained NMF: Templates



Zero-valued entries remain zero-valued entries!

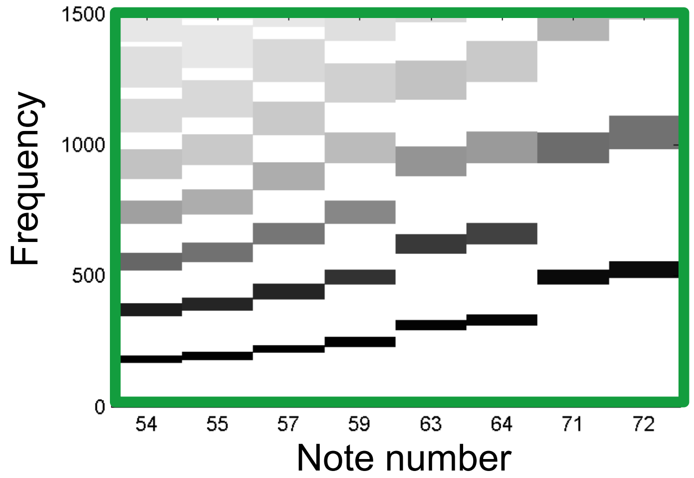
Constrained NMF: Templates



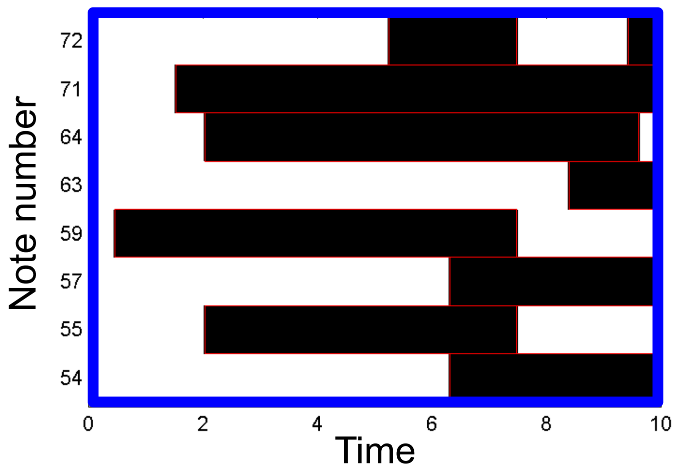
Pitch templates misused to represent onsets

Constrained NMF: Double Constraints

Template initialization

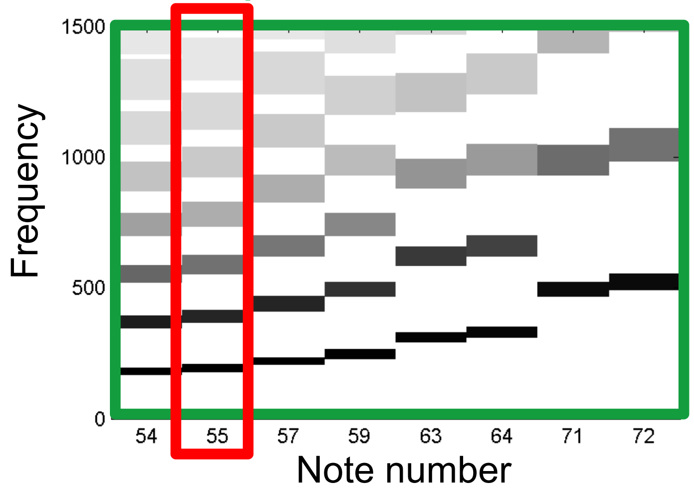


Activation initialization



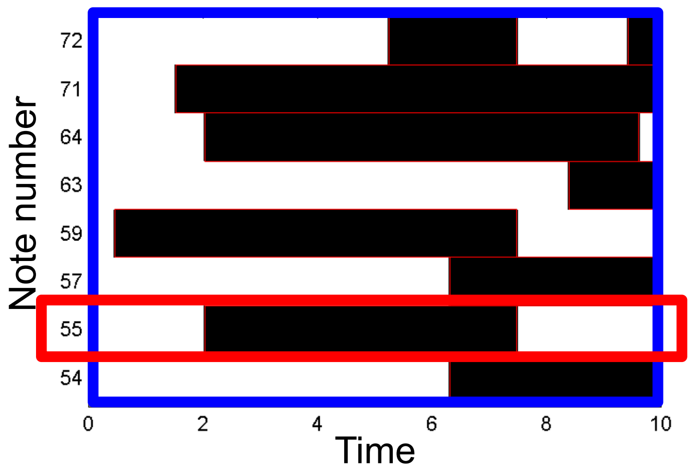
Constrained NMF: Double Constraints

Template initialization



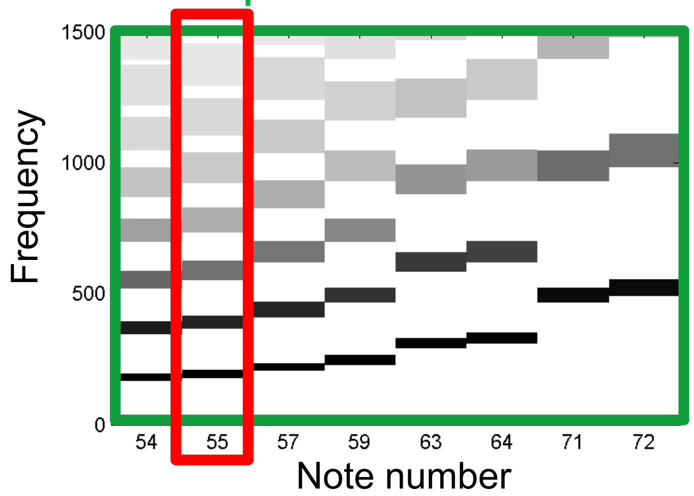
Template constraint for p=55

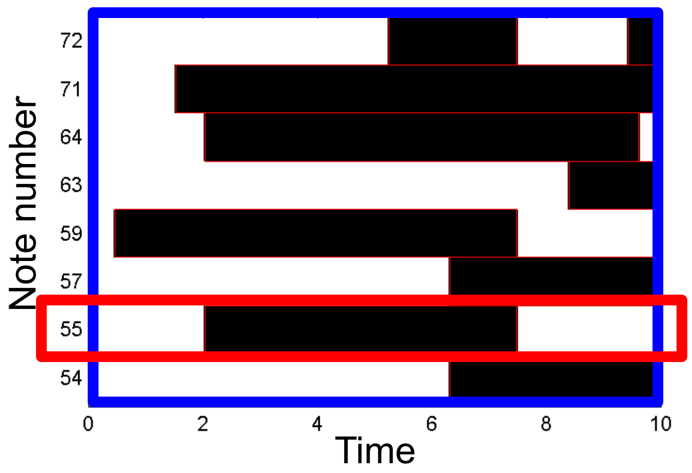
Activation initialization



Activation constraints for p=55

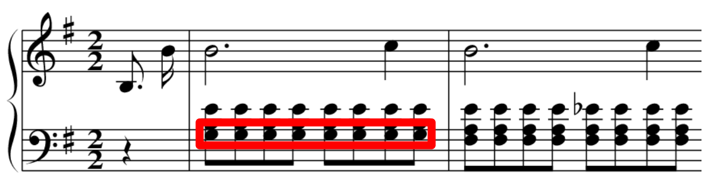
Constrained NMF: Double Constraints

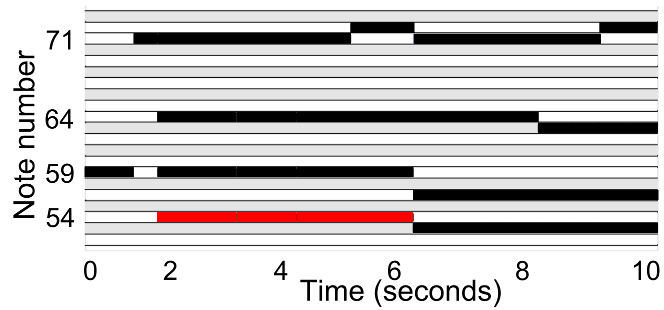




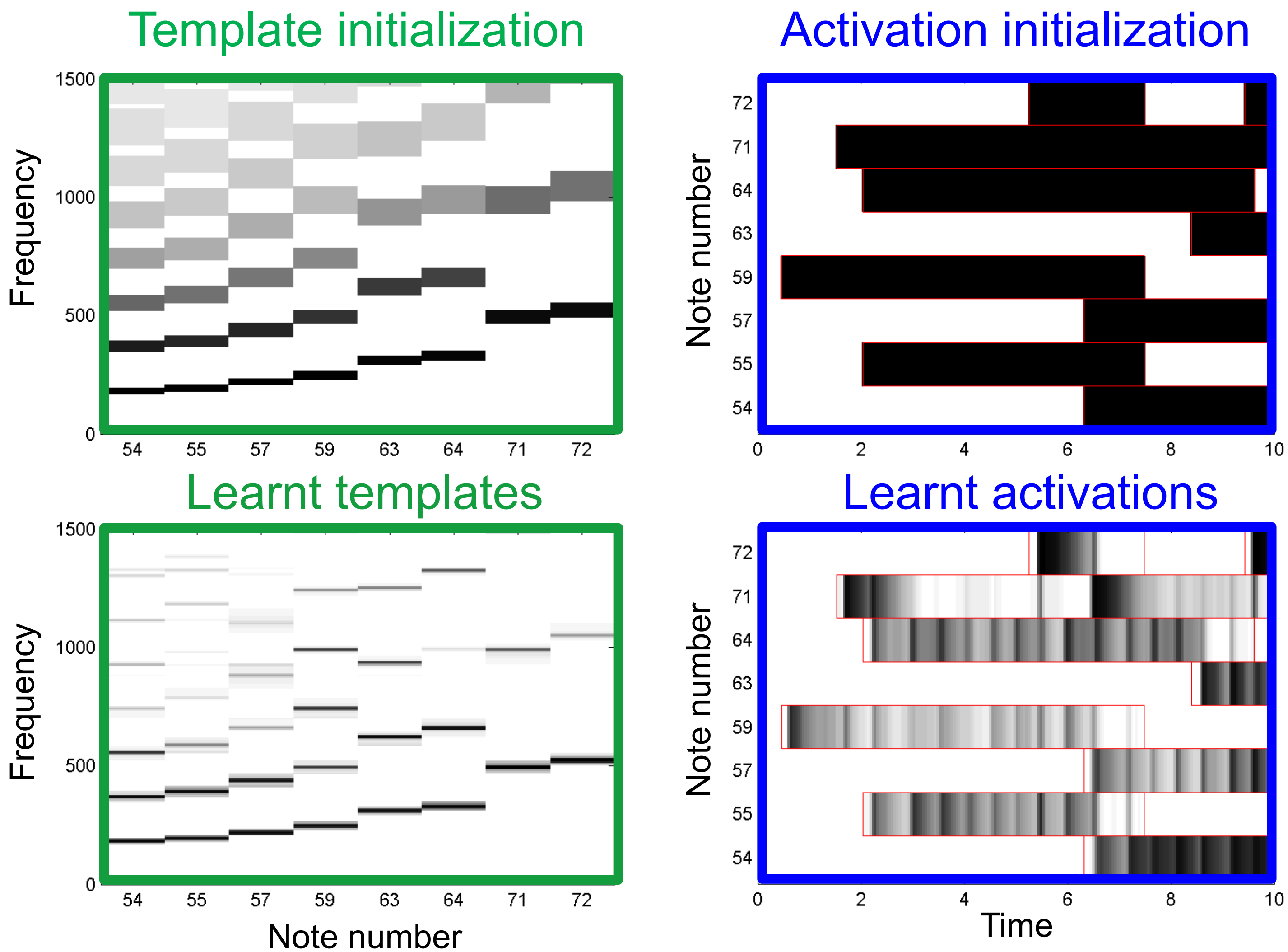
Such information may come from a synchronized score

Sheet music





Constrained NMF: Double Constraints

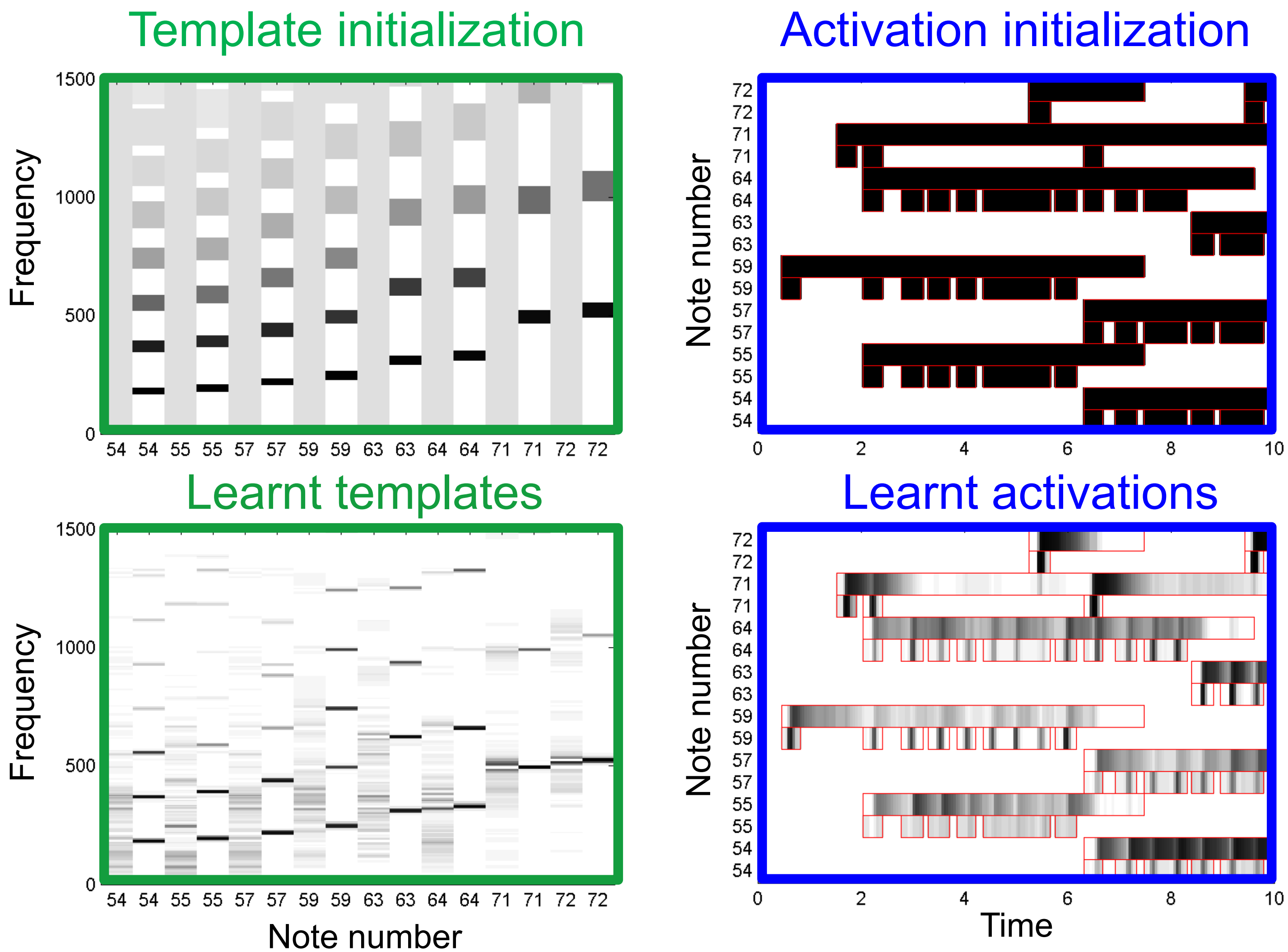


Original

Model

Significant gain in structure, but onsets are missing

Constrained NMF: Onset Templates



Original

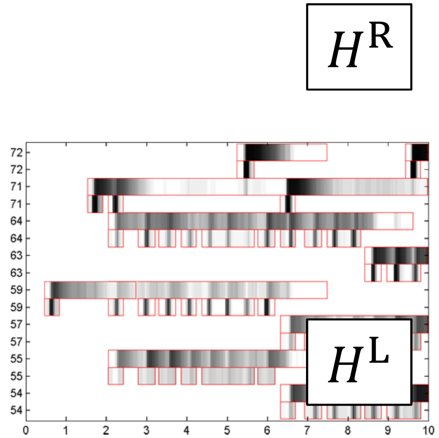
Model Onset

Meinard Müller

Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

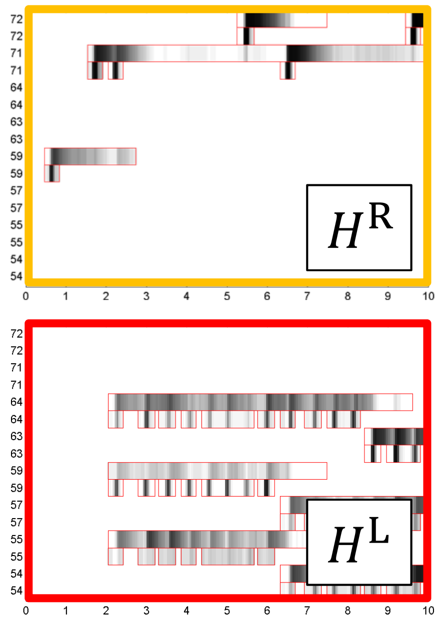
1. Split activation matrix



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

1. Split activation matrix

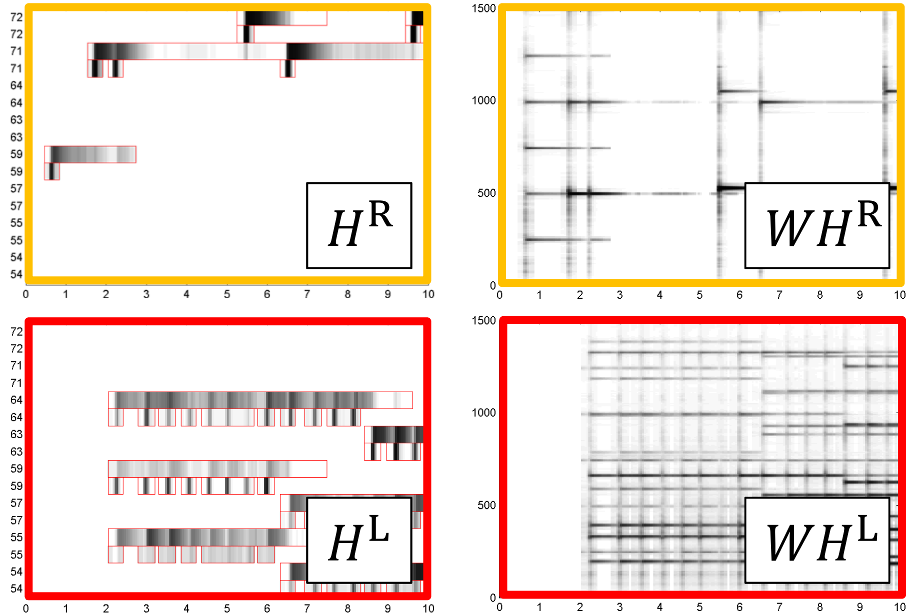


AUDIO LABS

Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

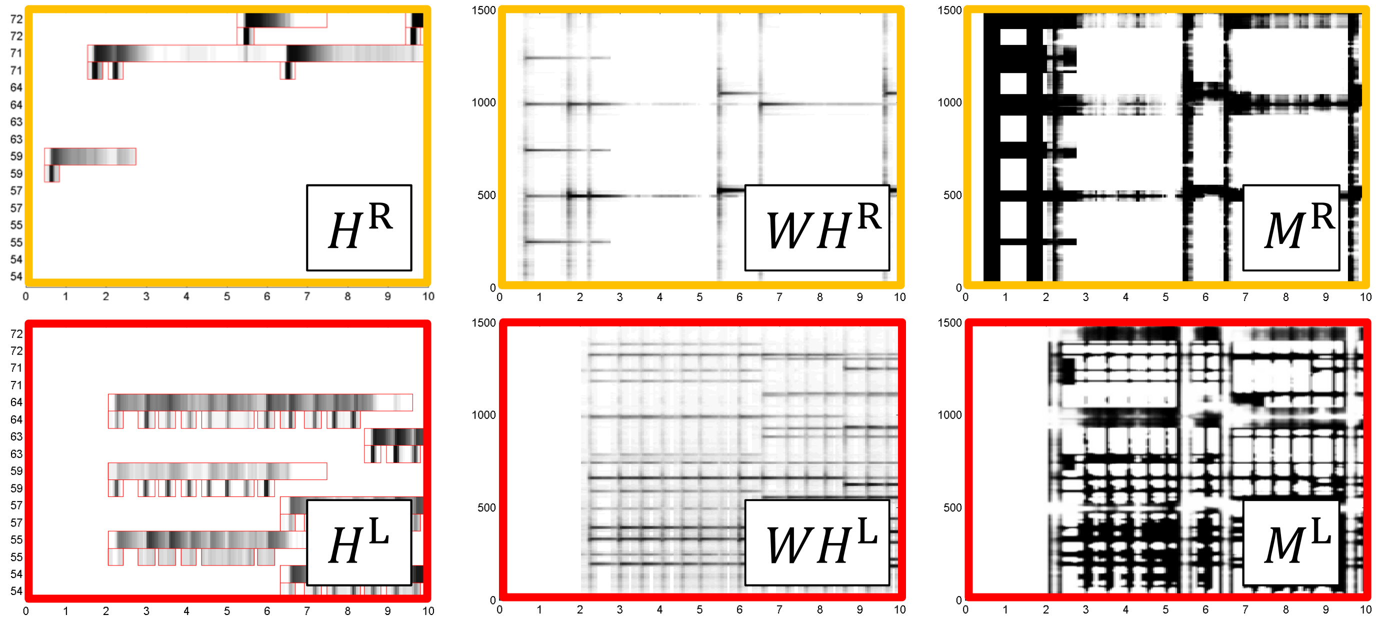
1. Split activation matrix
2. Model spectrogram for left/right



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

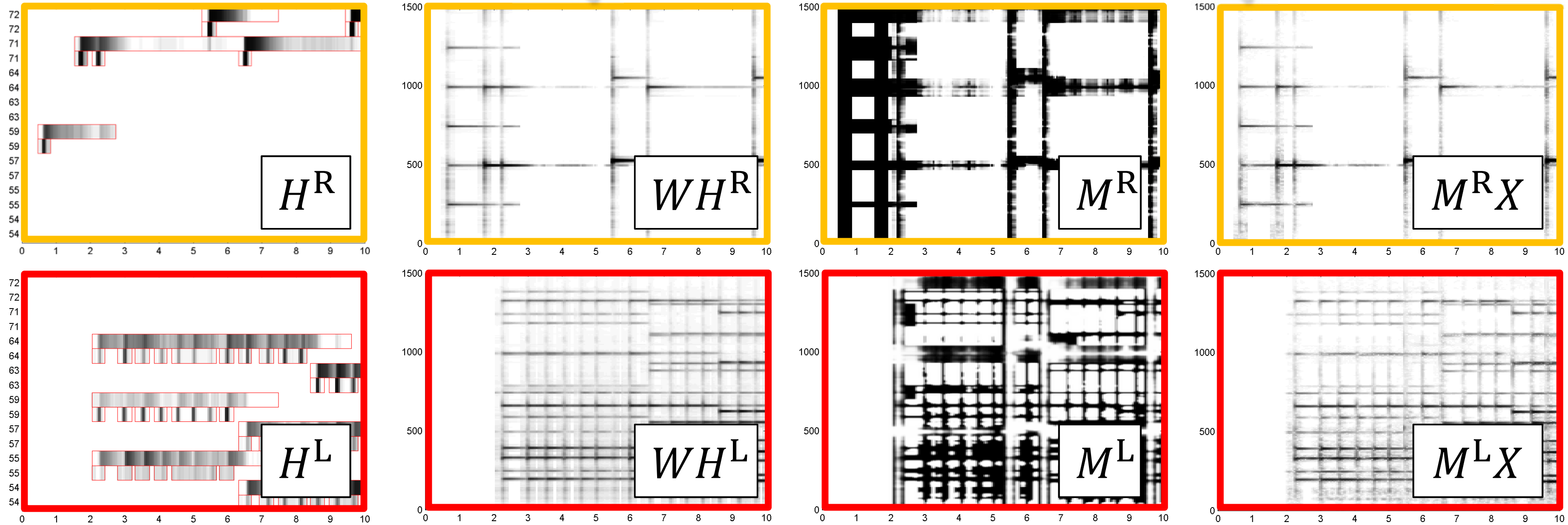
1. Split activation matrix
2. Model spectrogram for left/right
3. Separation masks for left/right



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

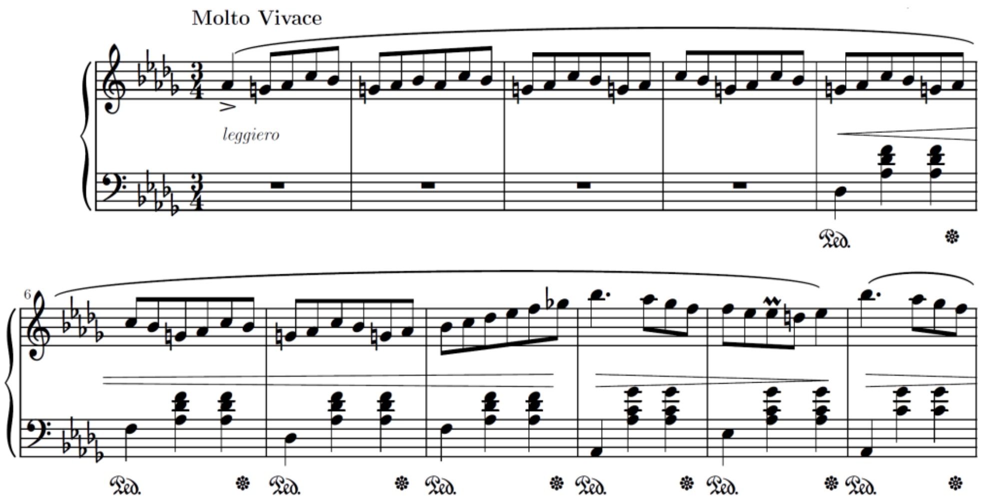
1. Split activation matrix
2. Model spectrogram for left/right
3. Separation masks for left/right
4. Estimated spectrograms for left/right



Score-Informed Audio Decompostion

Application: Separating left and right hands for piano

Chopin, Waltz Op. 64, No. 1



Original

Score-Informed Constraints

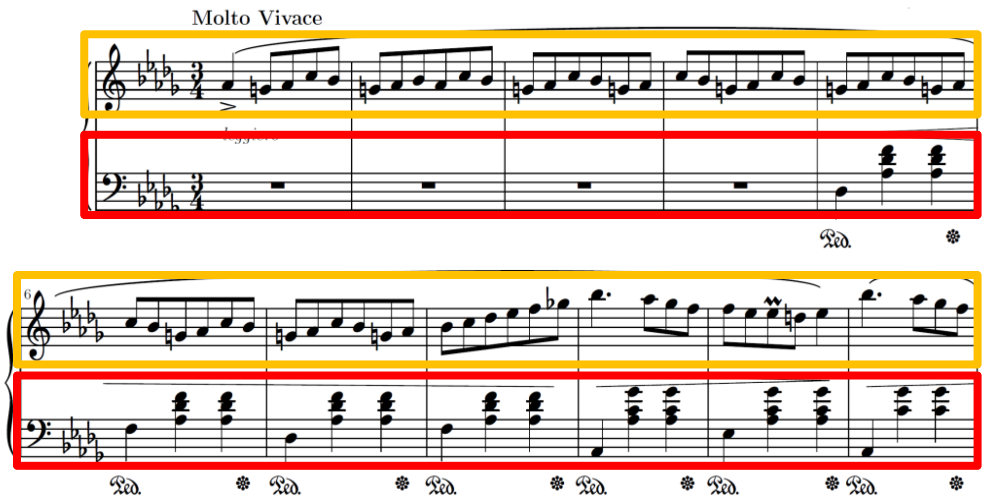
Ewert, Müller: Using Score-Informed Constraints for NMF-based Source Separation. Proc. ICASSP, 2012.

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

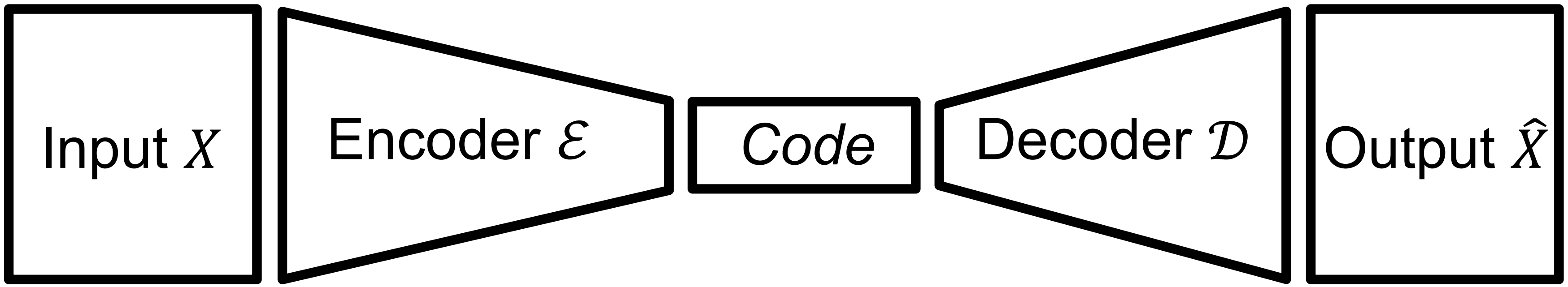
Ewert, Müller: Using Score-Informed Constraints for NMF-based Source Separation. Proc. ICASSP, 2012.

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

Conclusions (NMF)

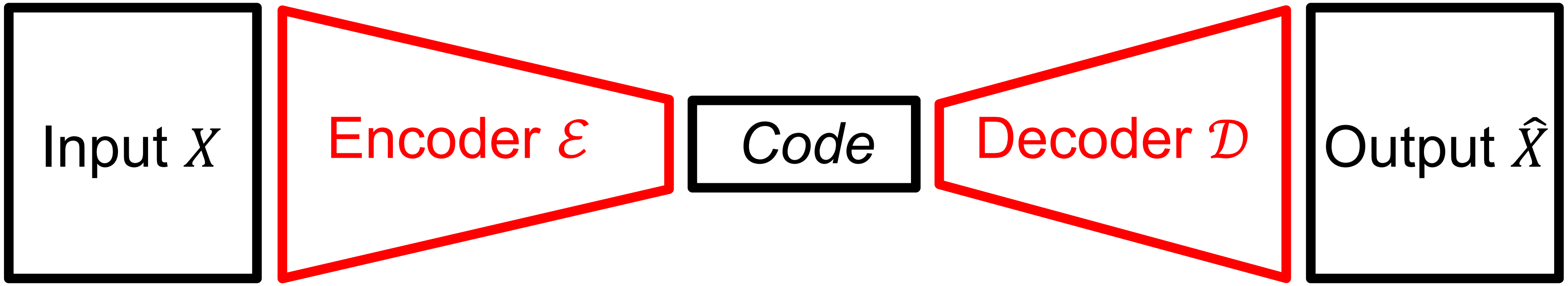
- NMF used for spectrogram decomposition
- Multiplicative update rules make it easy to constrain NMF model via zero initialization
- Exploiting score information to guide separation process (requires score–audio synchronization)
- Application: Separation of arbitrary note groups from given audio recording

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

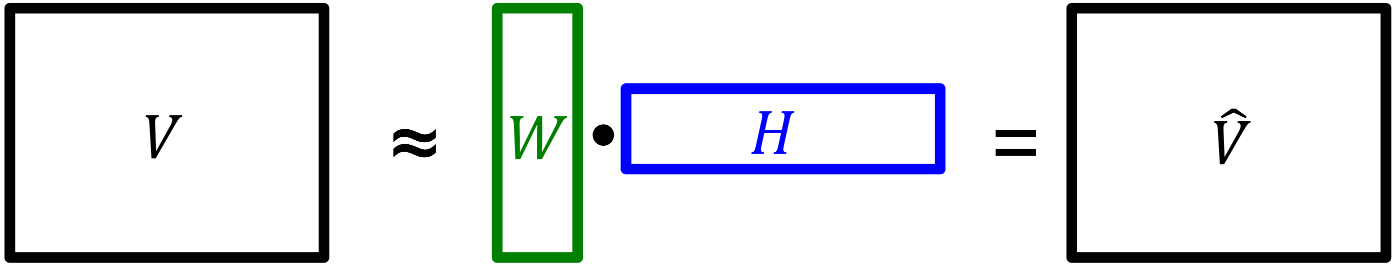
$$V \approx W \bullet H = \hat{V}$$

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

NMF and Autoencoder (AE)

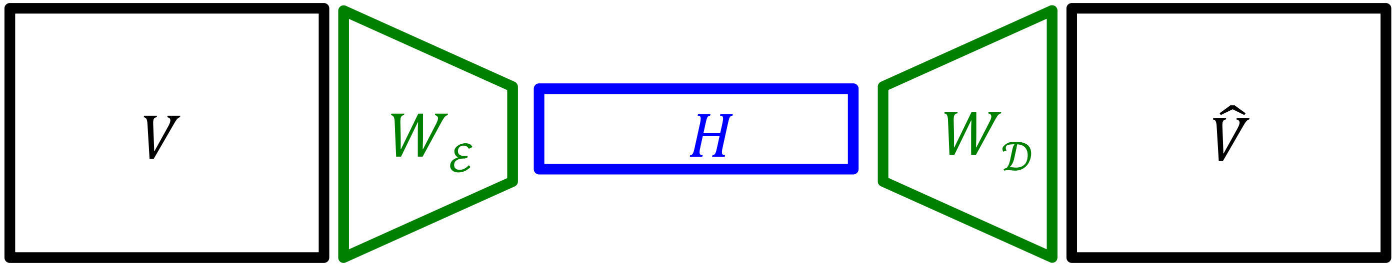
Nonnegative Autoencoder
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.

NMF



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

AE

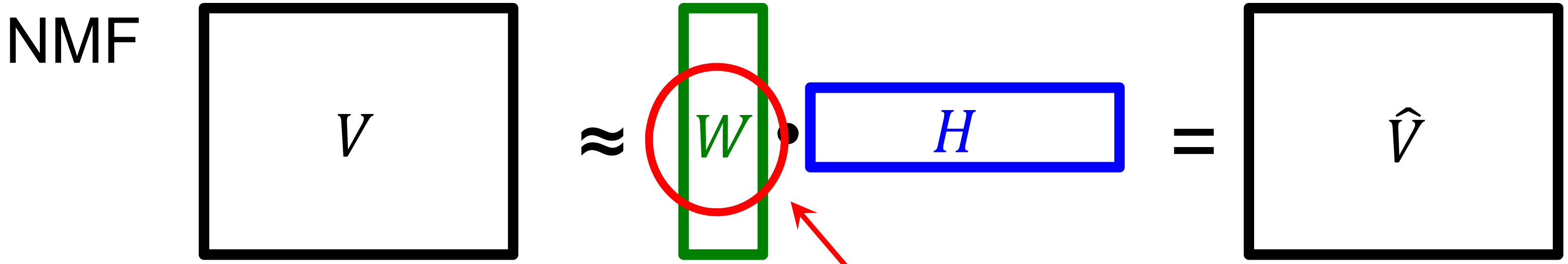


Encoder $\mathcal{E}$ Code Decoder $\mathcal{D}$

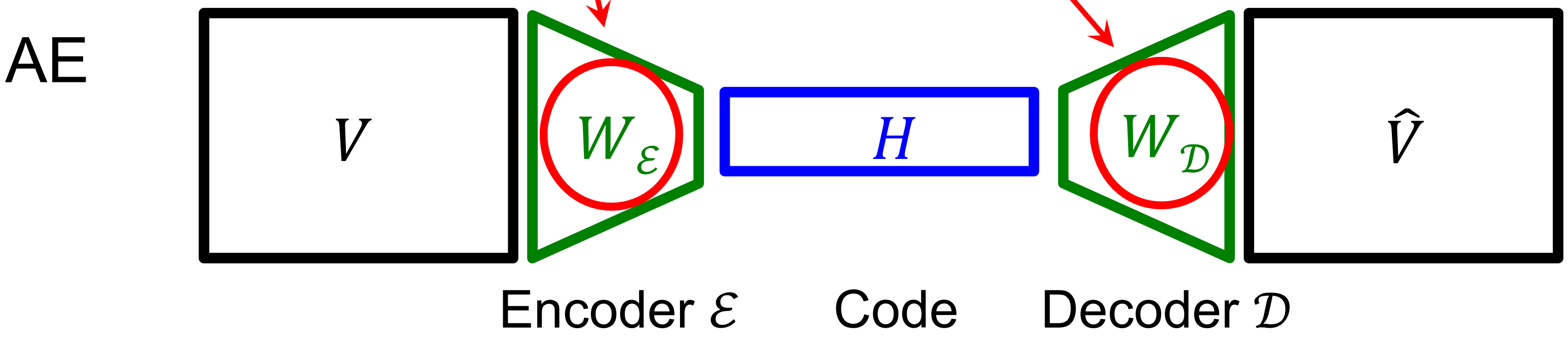
1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

NMF and Autoencoder (AE)

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



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



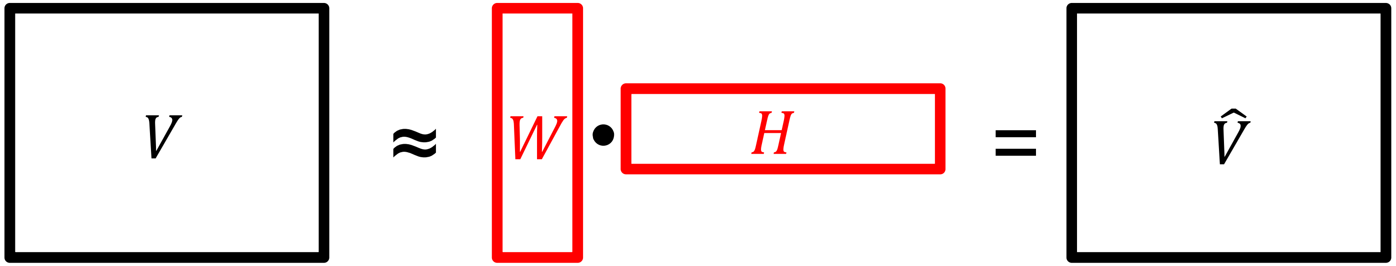
1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

Fully connected network

NMF and Autoencoder (AE)

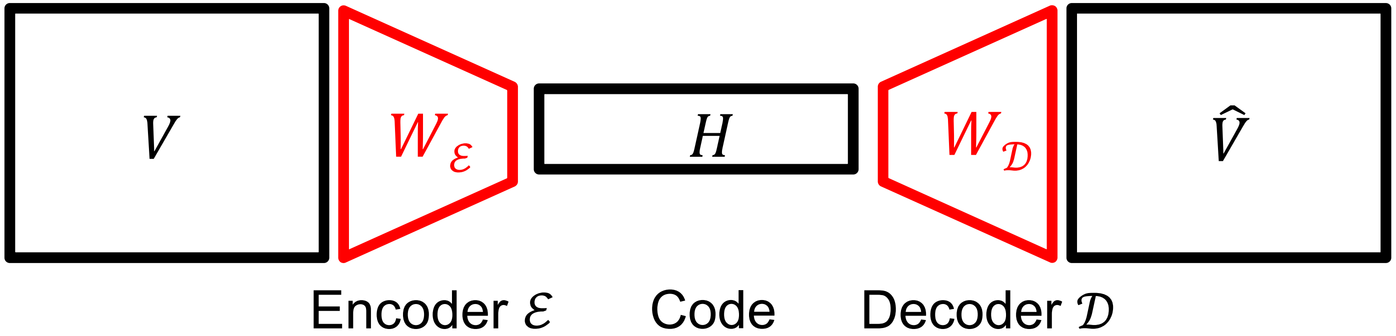
Nonnegative Autoencoder
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.

NMF



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

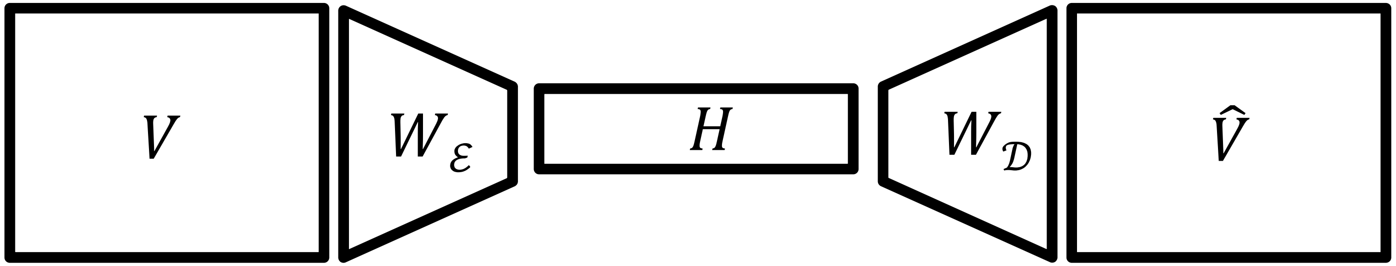
AE



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 $W_{\mathcal{D}}$

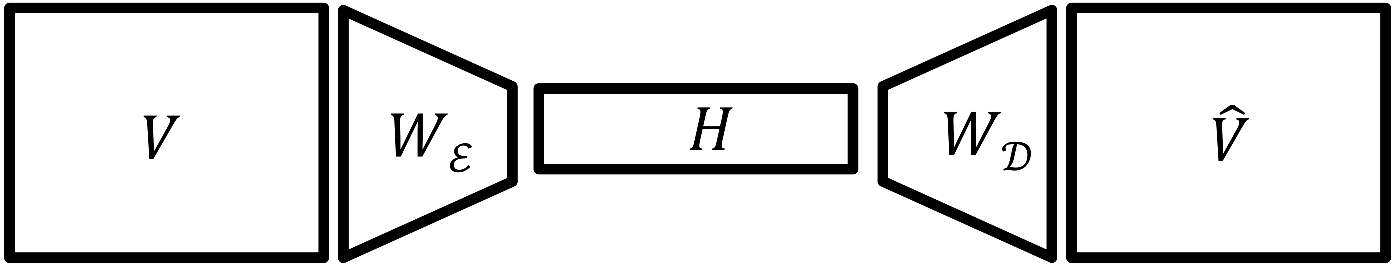
Nonnegative Autoencoder (NAE)



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)

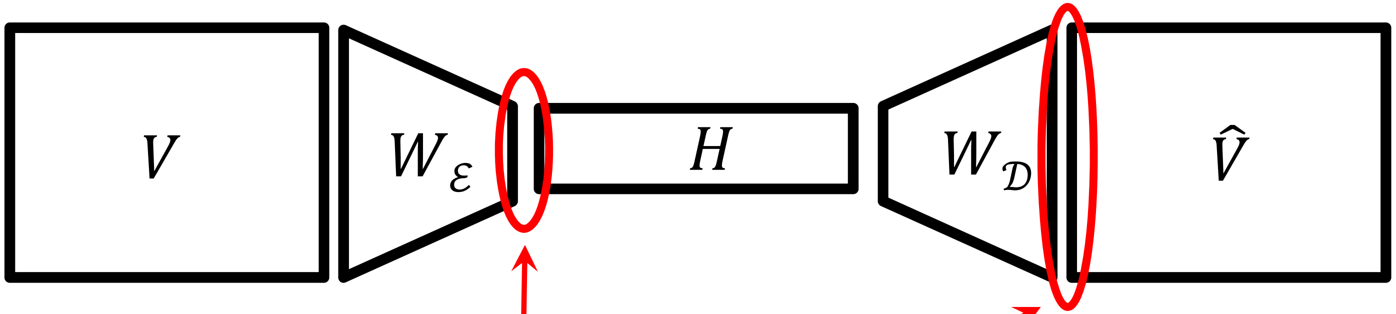


1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

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

- Loss function: same as in NMF

Nonnegative Autoencoder (NAE)

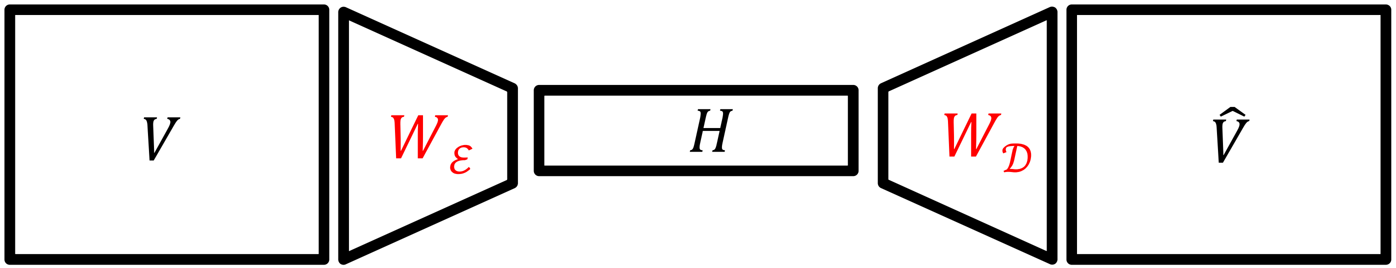


1. Layer: $H = \max(W_{\mathcal{E}}\, V, 0)$
2. Layer: $\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$

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

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

Nonnegative Autoencoder (NAE)



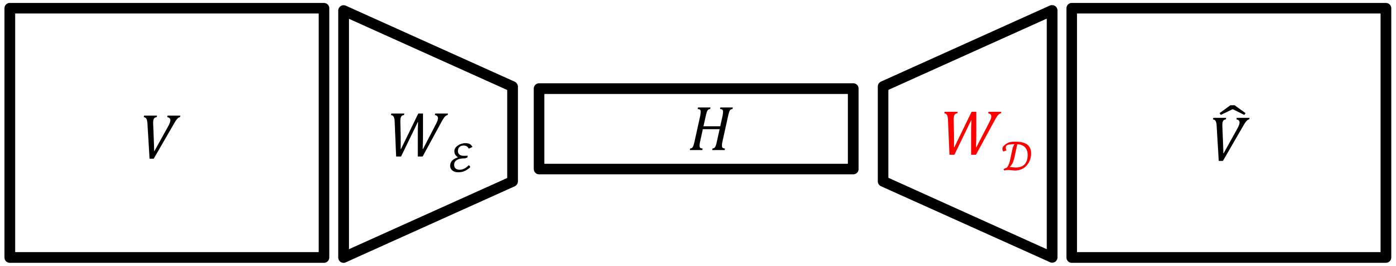
1. Layer: $H = \max(W_{\mathcal{E}}\, V, 0)$
2. Layer: $\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$

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

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

- 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

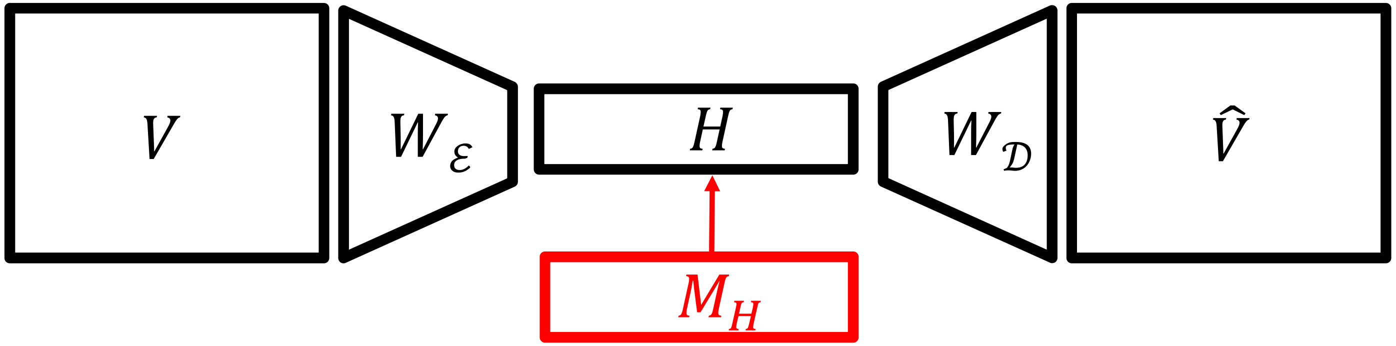


$$H = \max(W_{\mathcal{E}}\, V, 0)$$
$$\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$$

- 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:

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

NMF vs. NAE

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

NAE with Multiplicative Update Rules

- Encoder:

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

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

- Structured Dropout:

$$H' = H \odot M_H$$

- Decoder:

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

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

Similar idea and computation as for NMF.

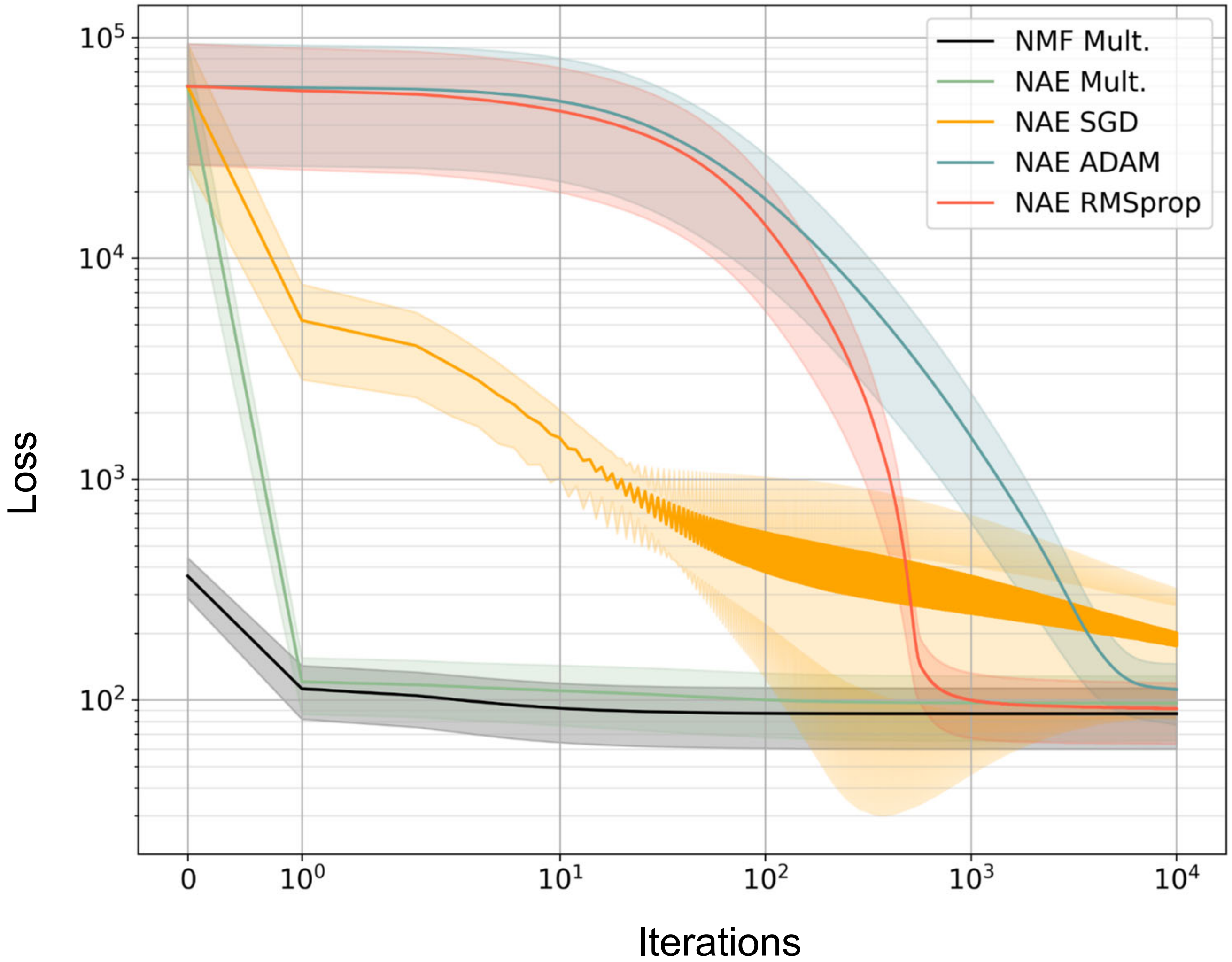
NMF vs. NAE

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

Approximation Loss

NMF vs. NAE

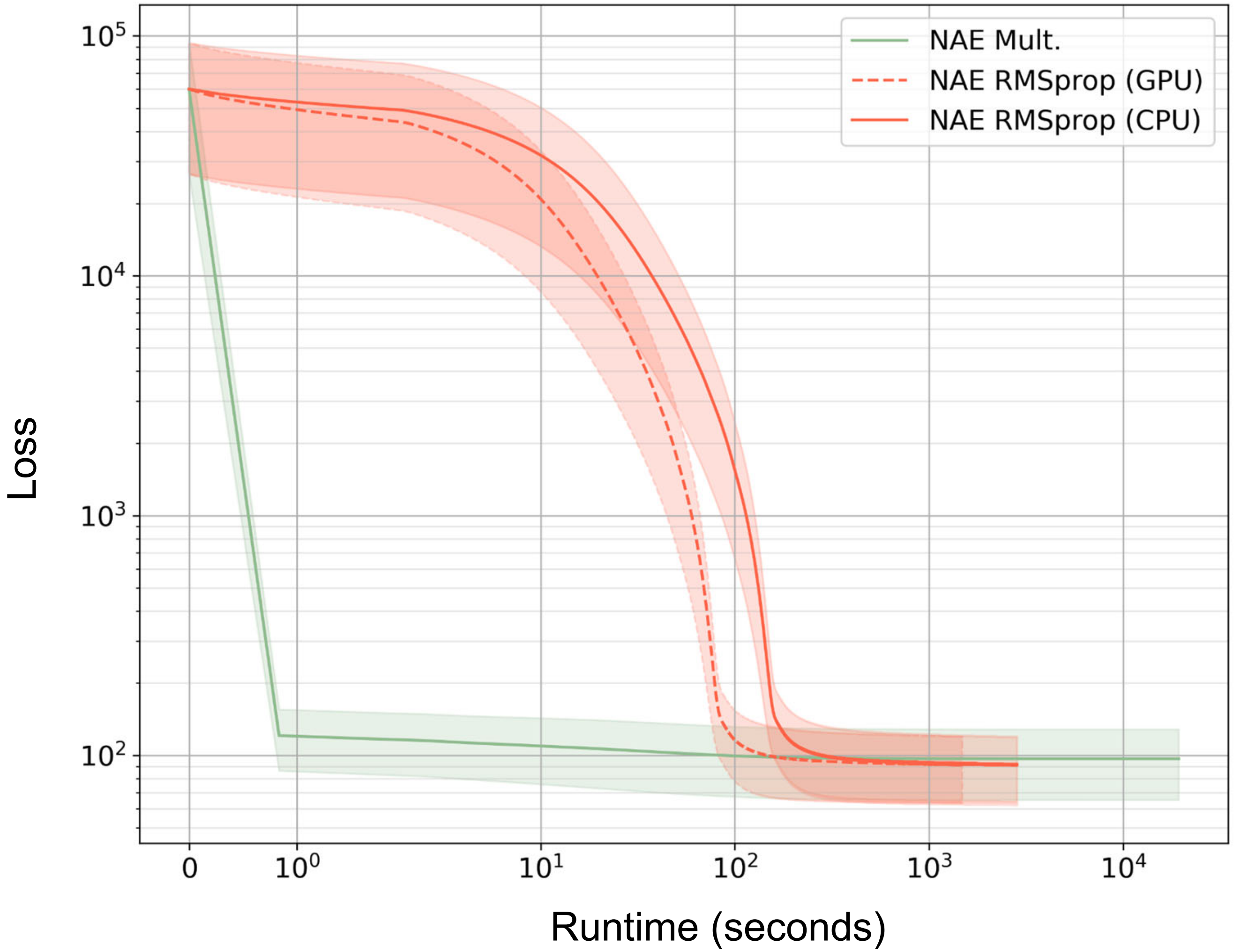
Özer, Hansen, Zunner, Müller: Investigating Nonnegative Autoencoders for Efficient Audio Decomposition. Proc. EUSIPCO, 2022.



Approximation Loss

NMF vs. NAE

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



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

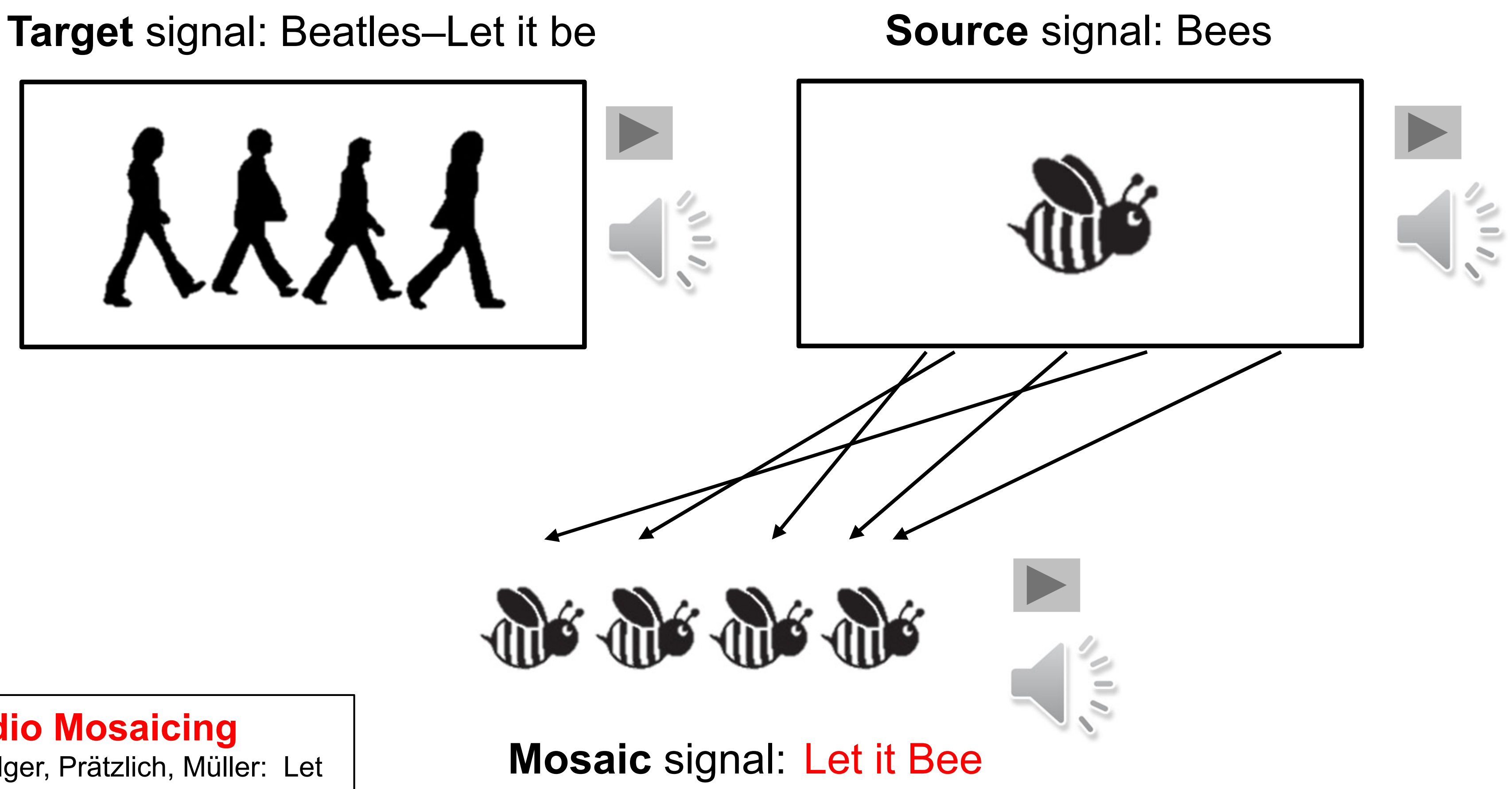
- More complex networks
  - Deeper networks (more layers)
  - Different layer types (CNN, RNN, …) and activation functions
  - Modification of loss function and regularization terms

- Understanding encoder – decoder relationship
  - Nonnegativity
  - Pseudo-inverse

- Update rules
  - Constraints and convergence issues
  - Adaptive learning rates and projected gradient descent

Score-Informed Audio Decomposition

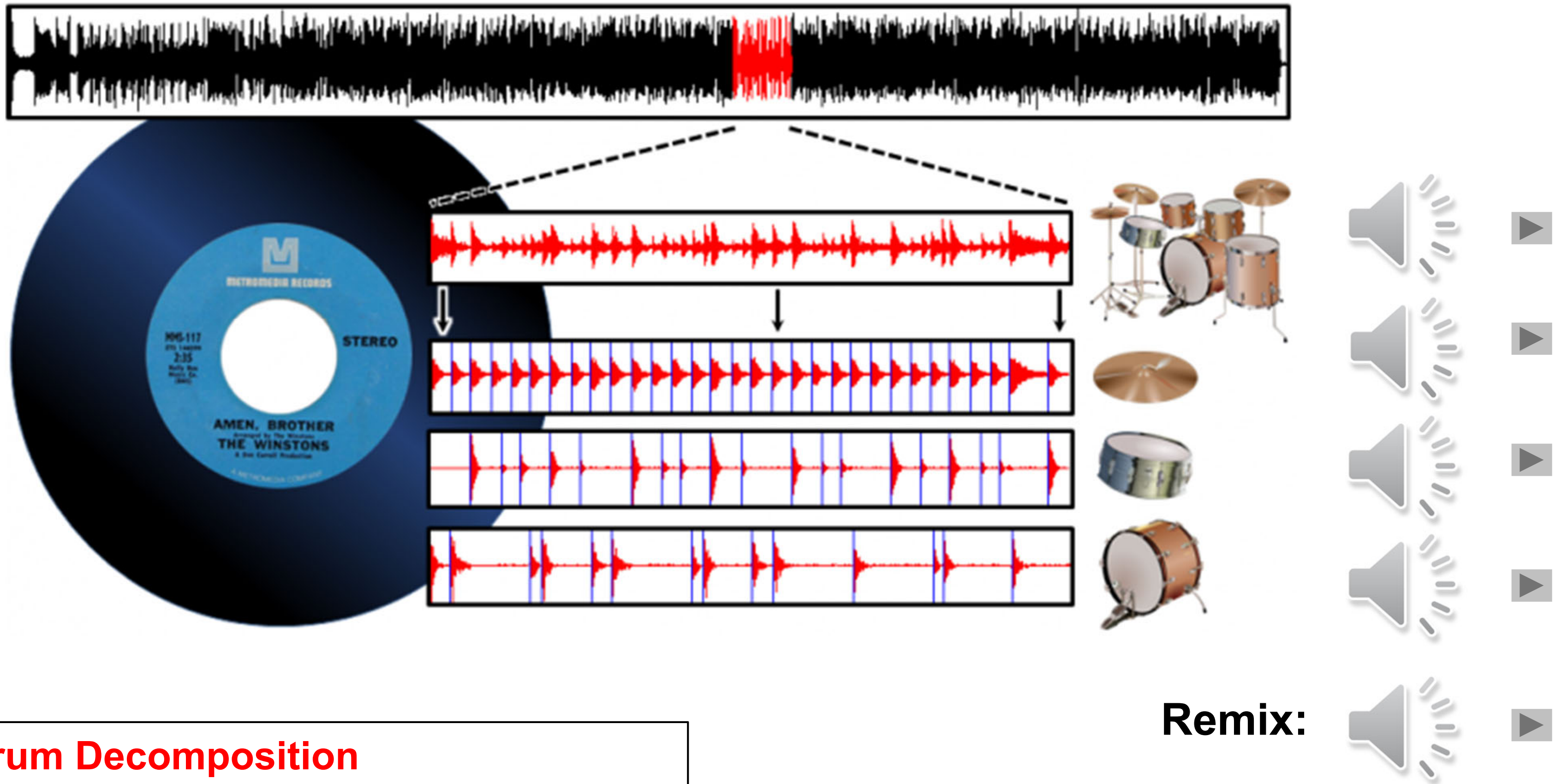
Audio mosaicing (style transfer)



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

Score-Informed Audio Decomposition

Informed Drum-Sound Decomposition



Remix:

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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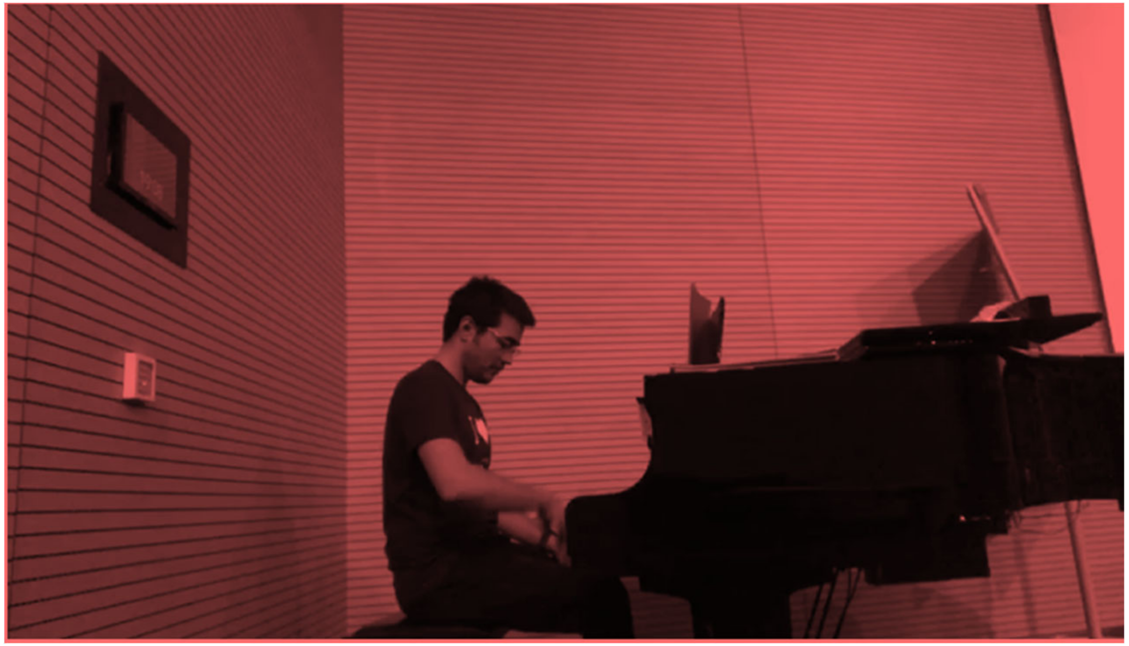
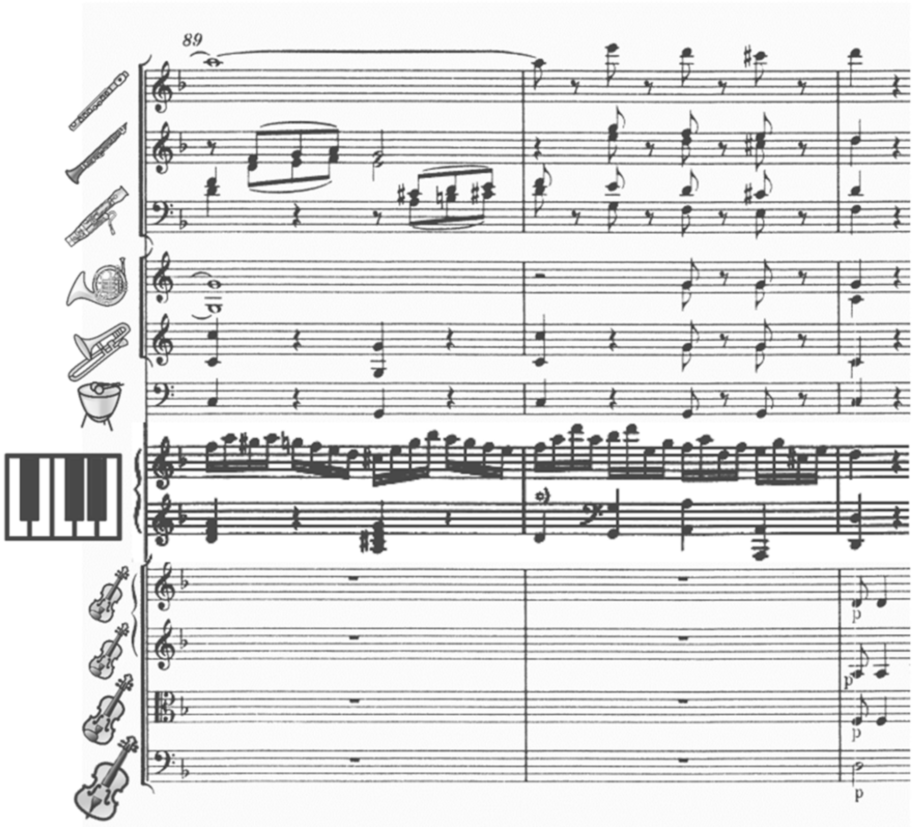


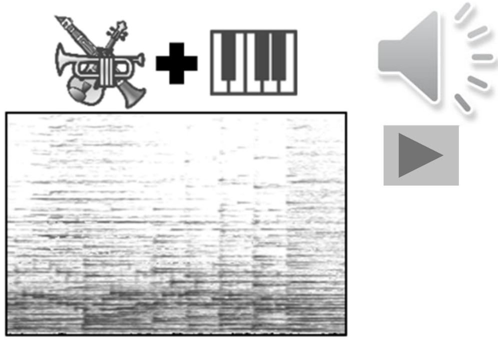
Only Piano!

Where is the orchestra?

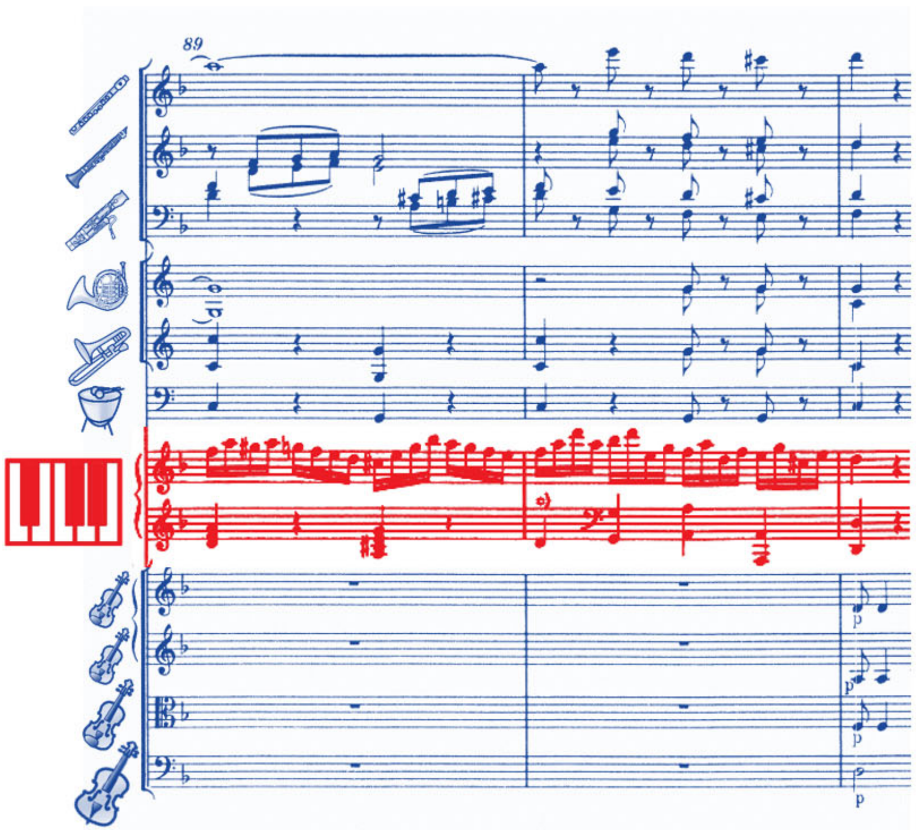
AUDIO LABS

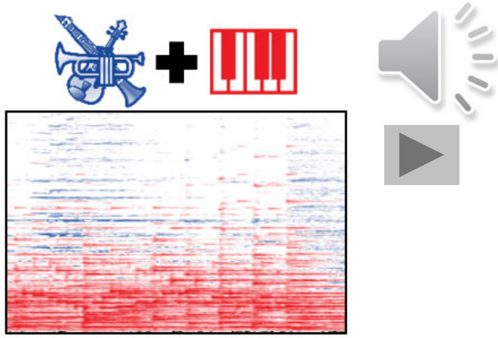
Source Separation (Piano Concerto)



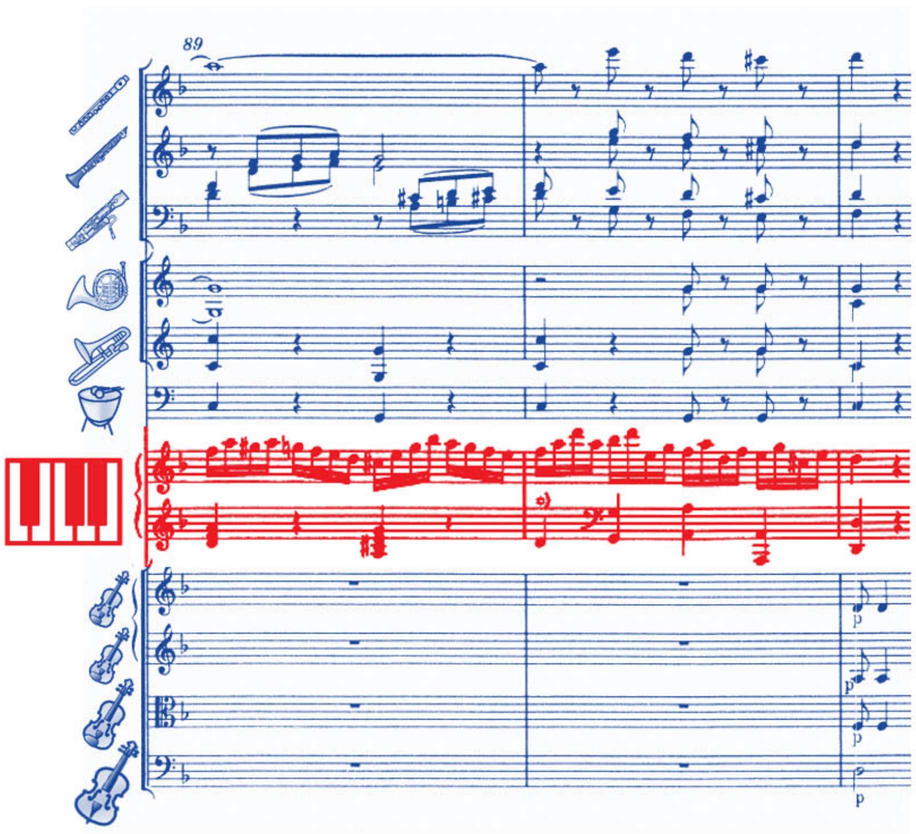


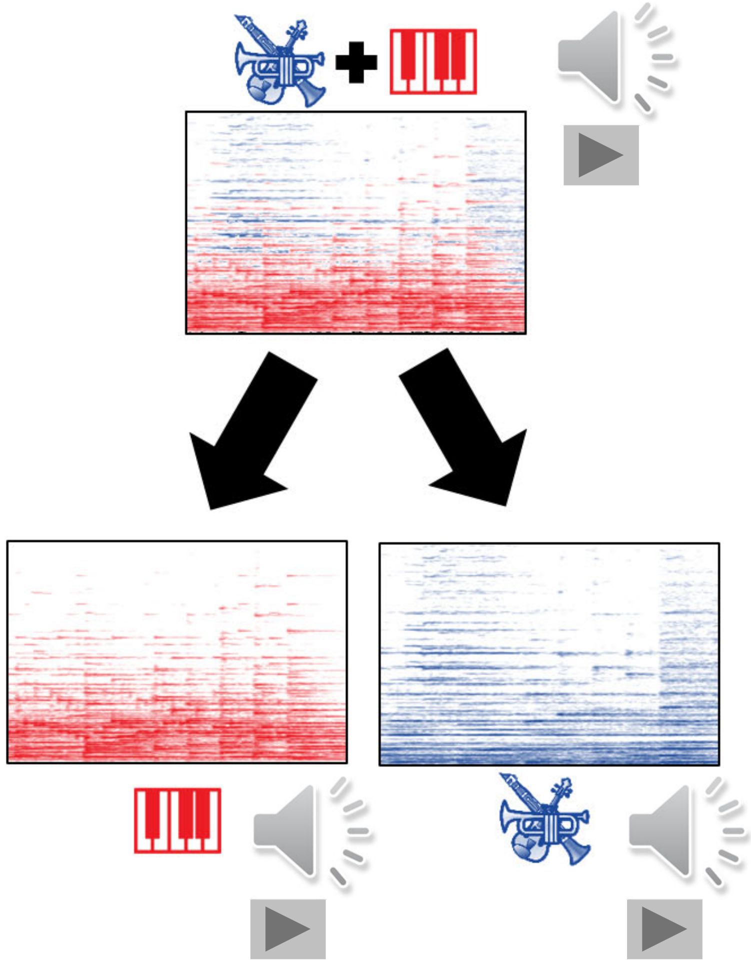
Source Separation (Piano Concerto)



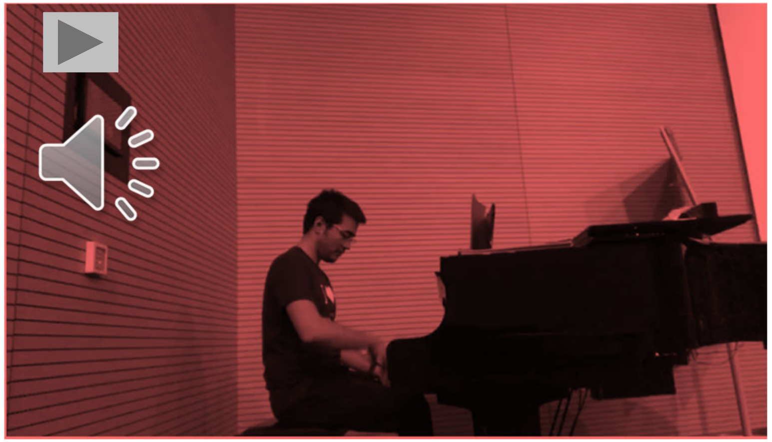


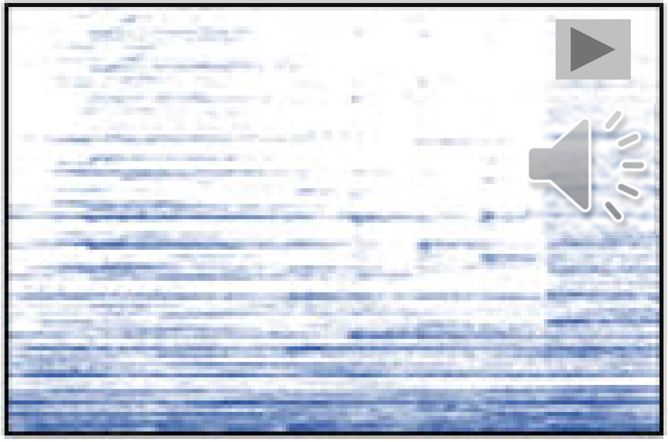
Source Separation (Piano Concerto)





Source Separation (Piano Concerto)

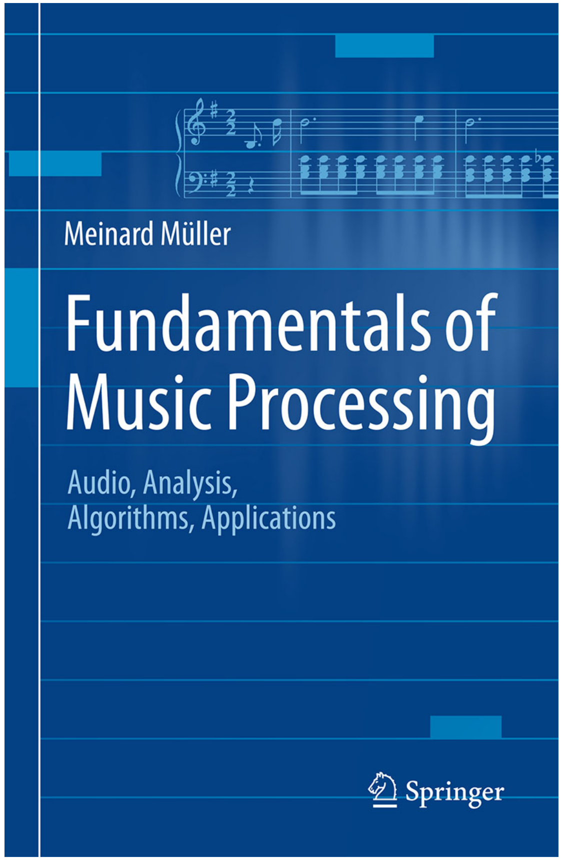




Piano Source Separation

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

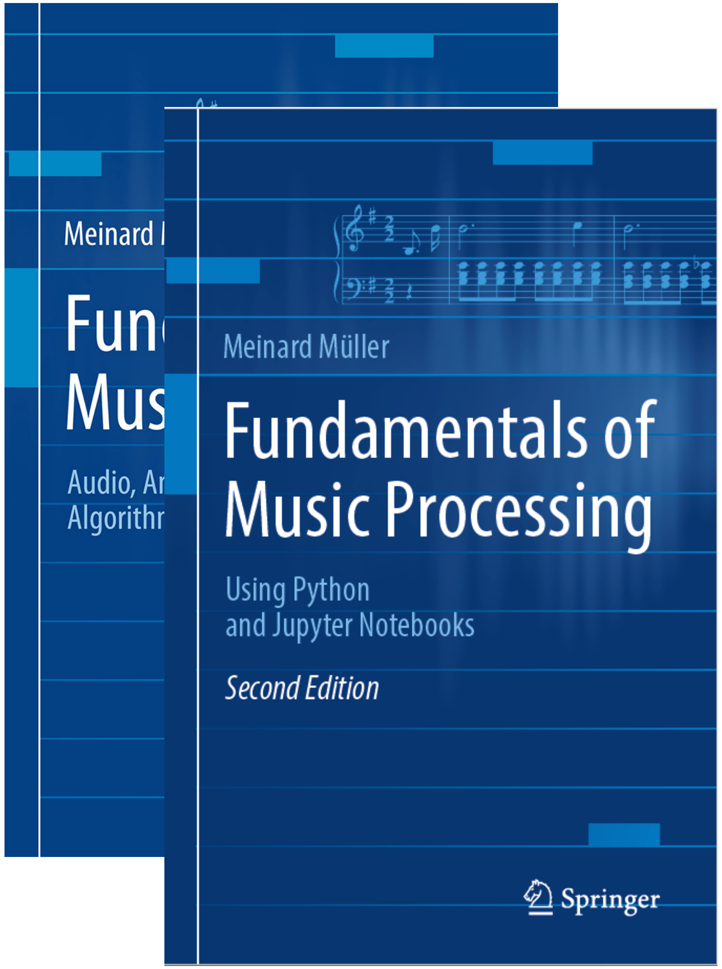
Fundamentals of Music Processing (FMP)



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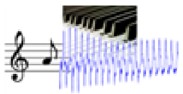
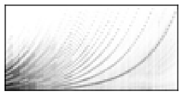
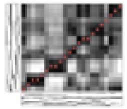
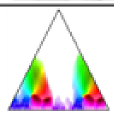
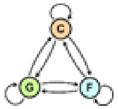
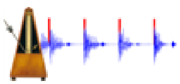
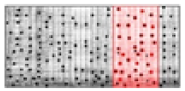
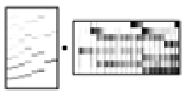
2nd edition
Meinard Müller
Fundamentals of Music Processing
Using Python and Jupyter Notebooks
Springer, 2021

Fundamentals of Music Processing (FMP)

Chapter		Music Processing Scenario
1		Music Represenations
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

Meinard Müller
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Audio, Analysis, Algorithms, Applications
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Springer, 2021

FMP Notebooks: Education & Research

Fundamentals of Music Processing

Meinard Müller

Springer

INTERNATIONAL AUDIO LABORATORIES ERLANGEN

AUDIO LABS

FMP Notebooks

Python Notebooks for Fundamentals of Music Processing

The FMP notebooks offer a collection of educational material closely following the textbook Fundamentals of Music Processing (FMP). This is the starting website, which is opened when calling https://www.audiolabs-erlangen.de/FMP. Besides giving an overview, this website provides information on the license, the main contributors, and some links.

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

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

References (FMP Textbook & 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

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.