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

AUDIO LABS

Tutorial T3, EUROGRAPHICS

Saarbrücken, May 8, 2023

# Learning with Music Signals: Technology Meets Education

## Audio Decomposition


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Fraunhofer IIS

# Source Separation

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

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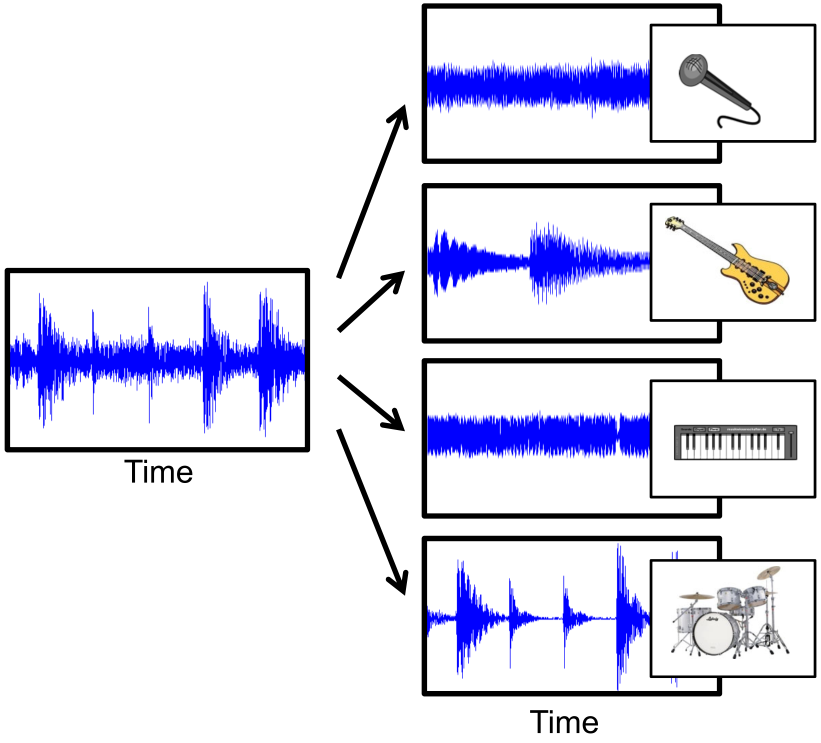
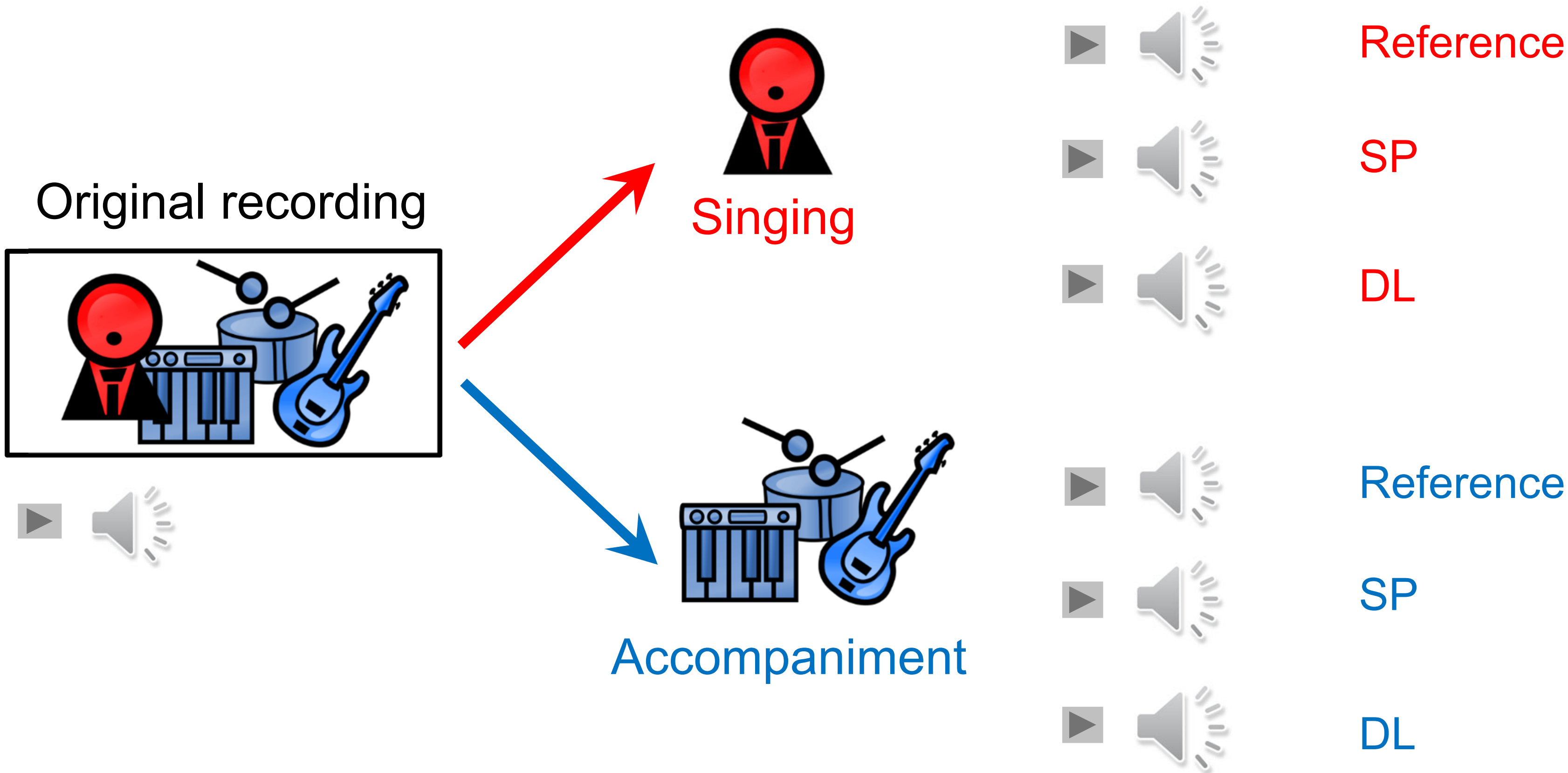
- Decomposition of audio stream into different sound sources
- Central task in digital signal processing
- “Cocktail party effect”
- Several input signals
- Sources are assumed to be statistically independent

# 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

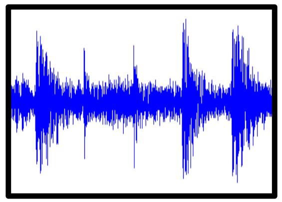
# Score-Informed Source Separation

**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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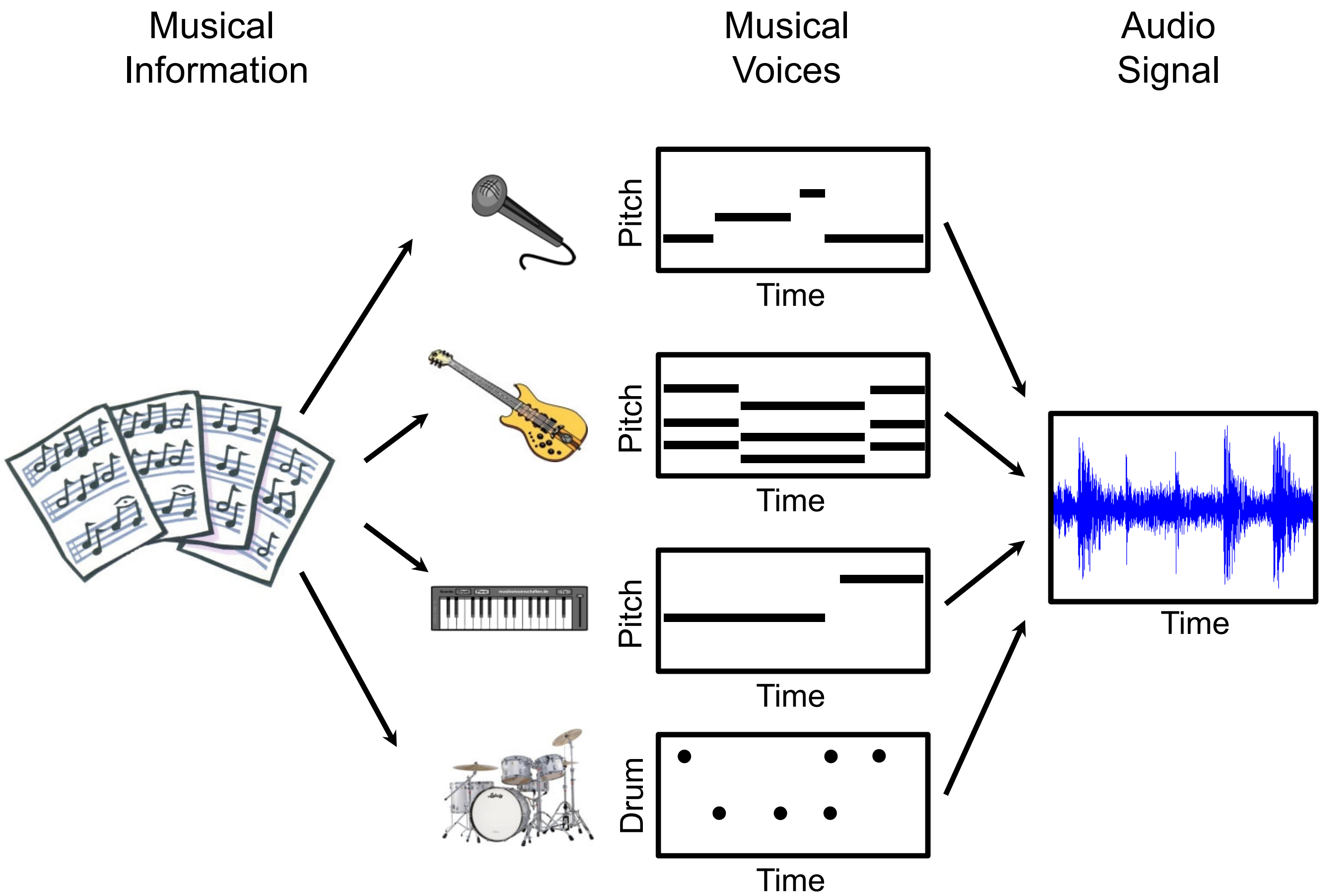

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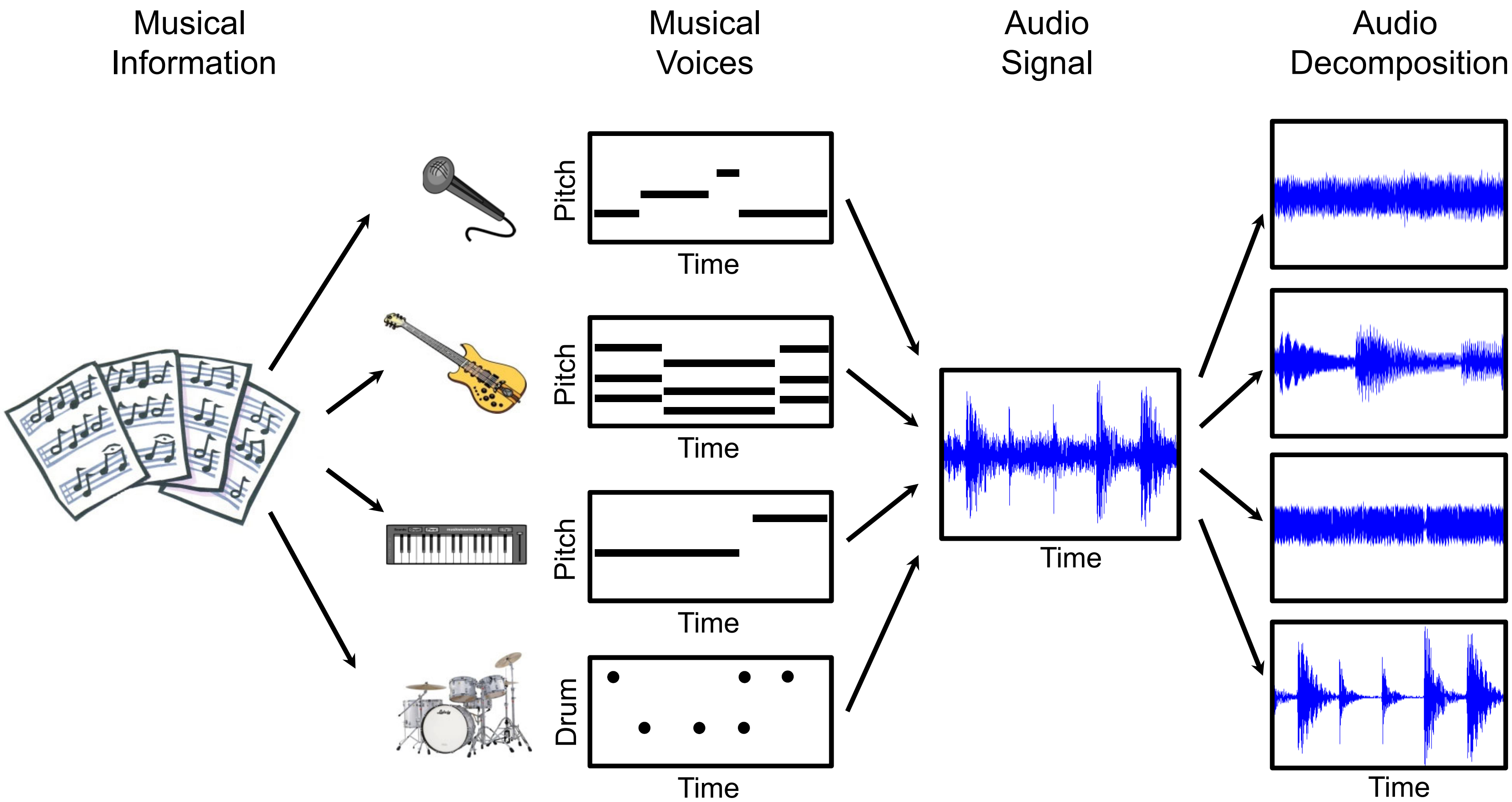

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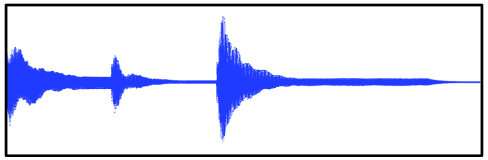

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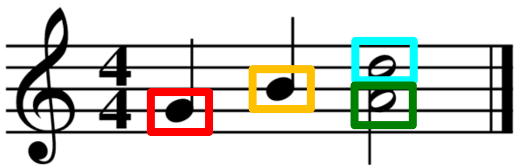

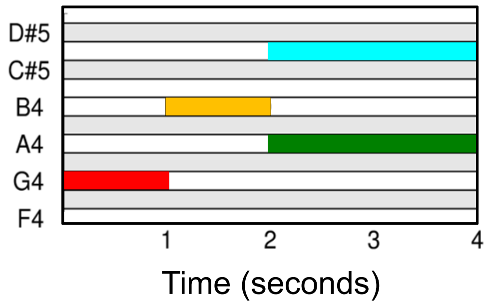


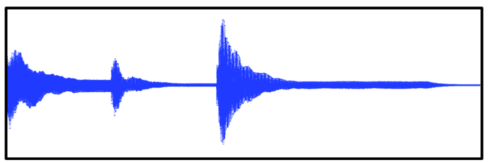

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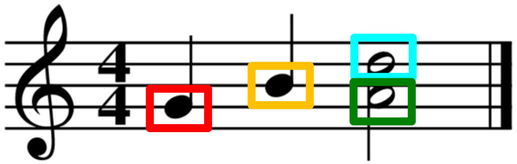
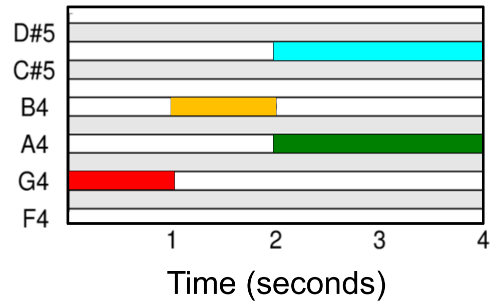
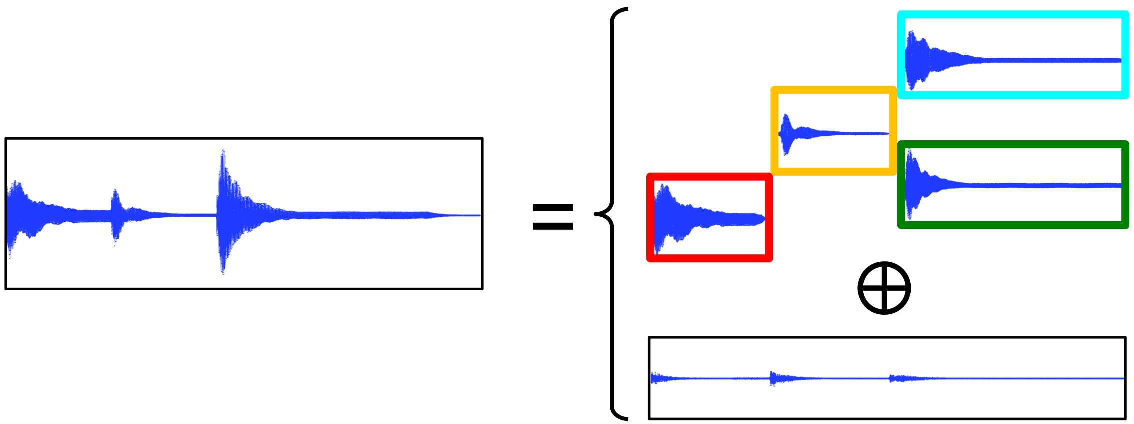
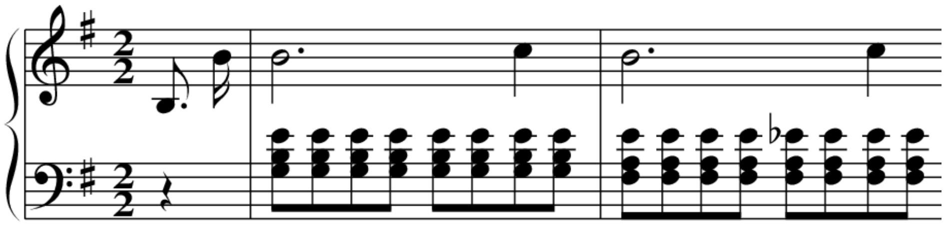




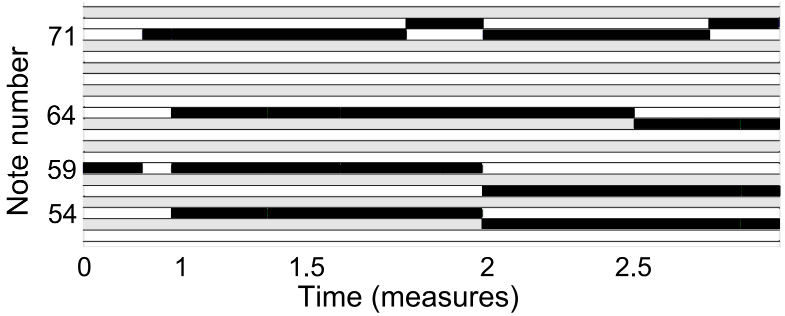



# Score-Informed Audio Decomposition

Sheet music



Piano roll



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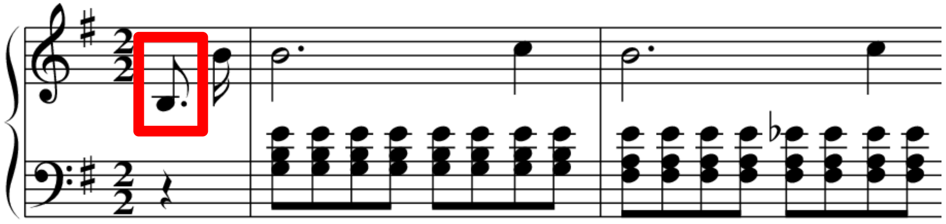
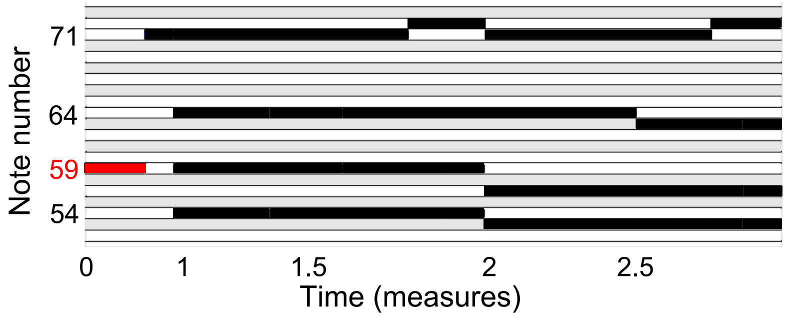


$p = 59$

Piano roll



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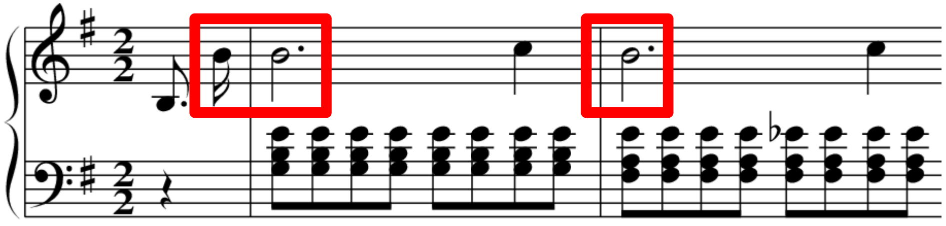
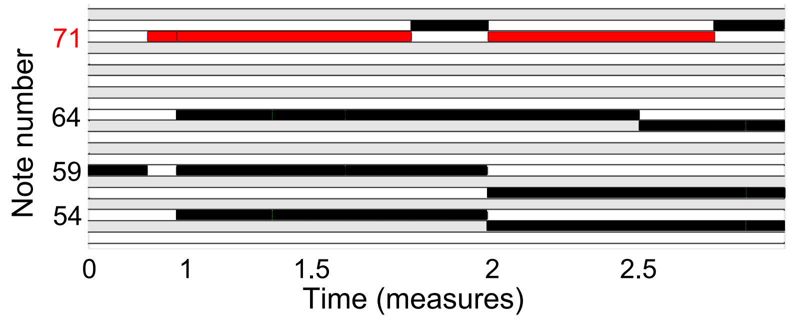
Sheet music



$p = 71$

Piano roll



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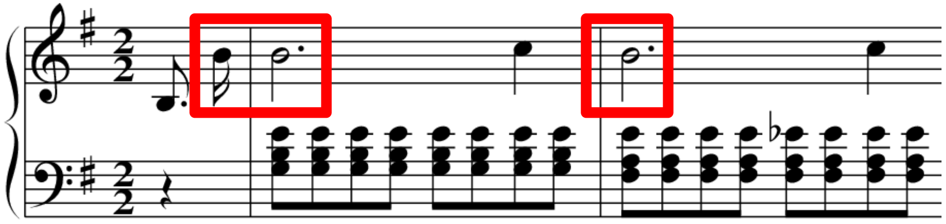
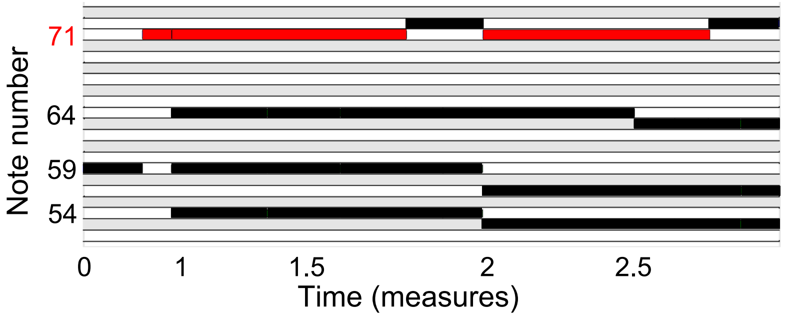
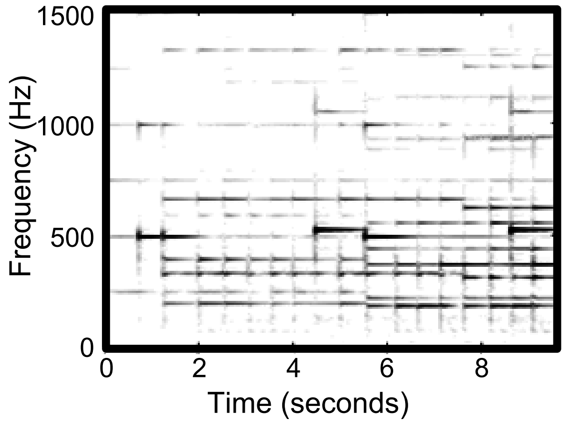
Sheet music



*p* = 71 Piano roll




Spectrogram

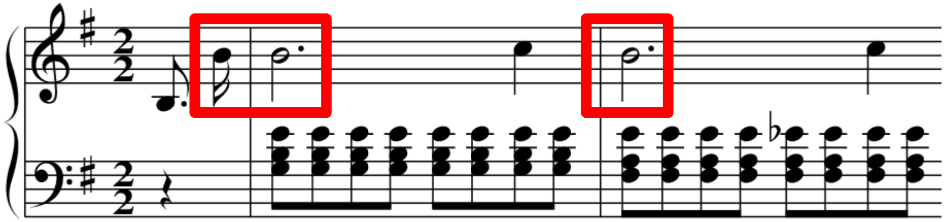


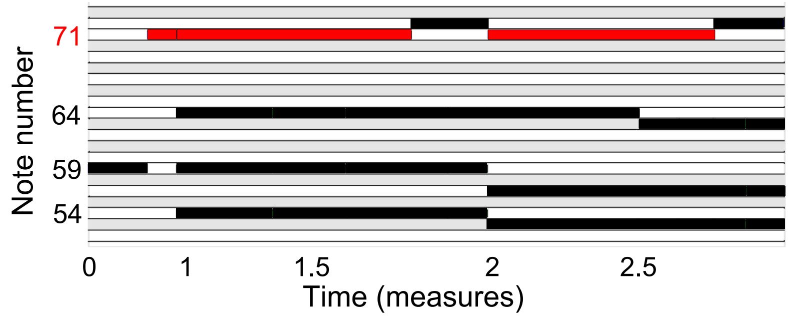
# Score-Informed Audio Decomposition

Sheet music

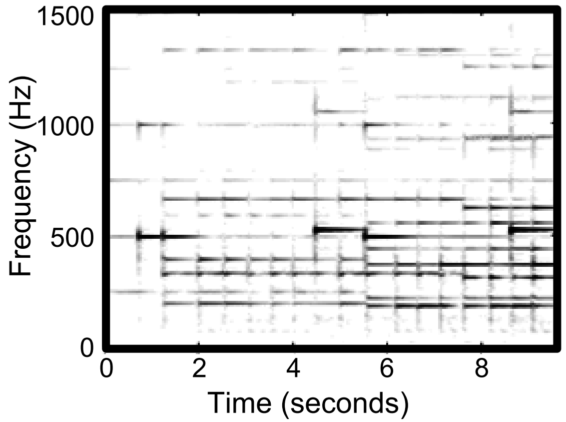
*p = 71*

Piano roll






Spectrogram

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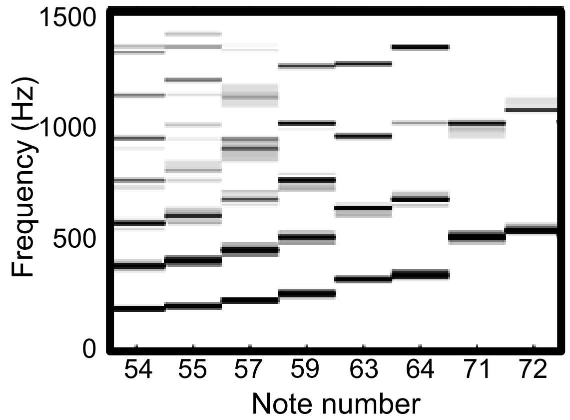
Spectral patterns

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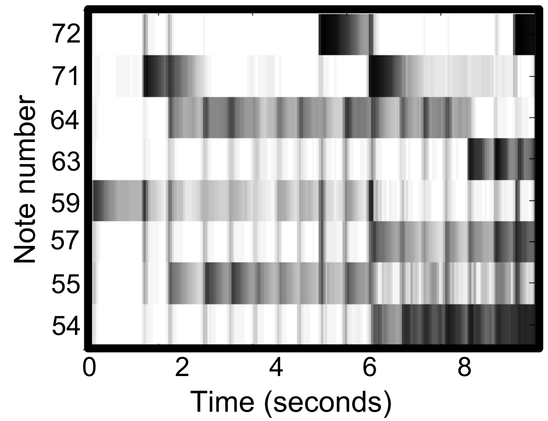
Activity patterns



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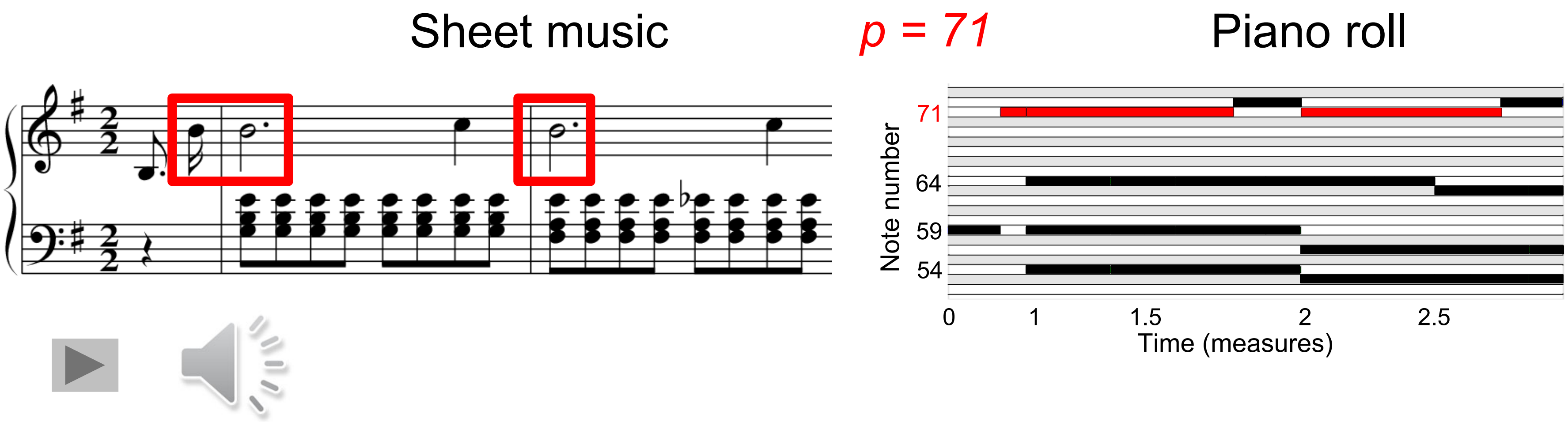


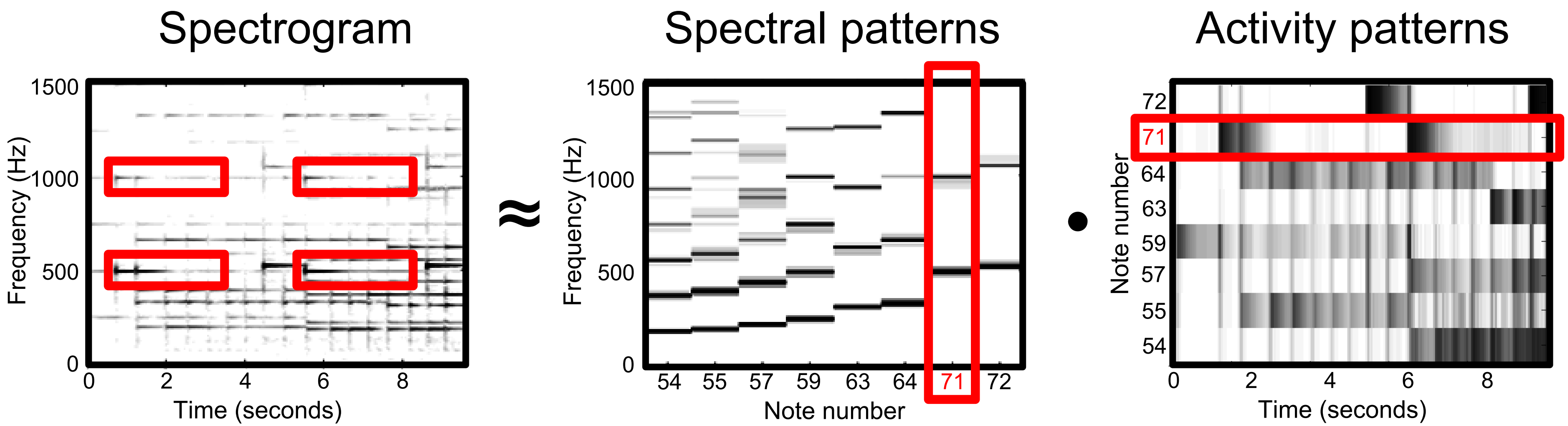

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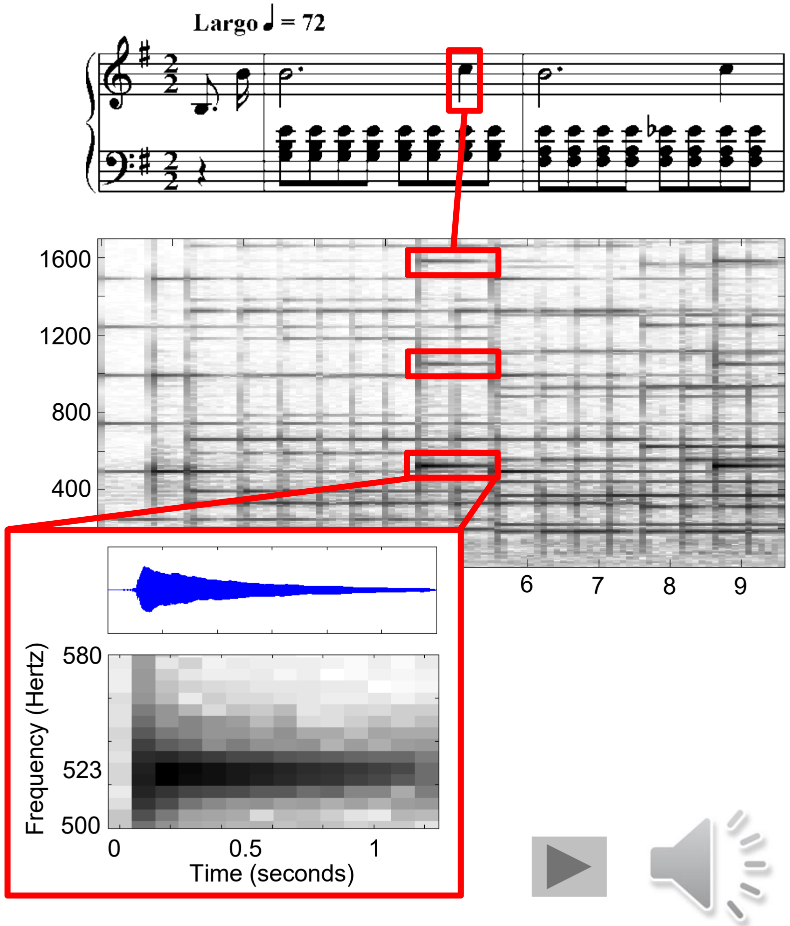
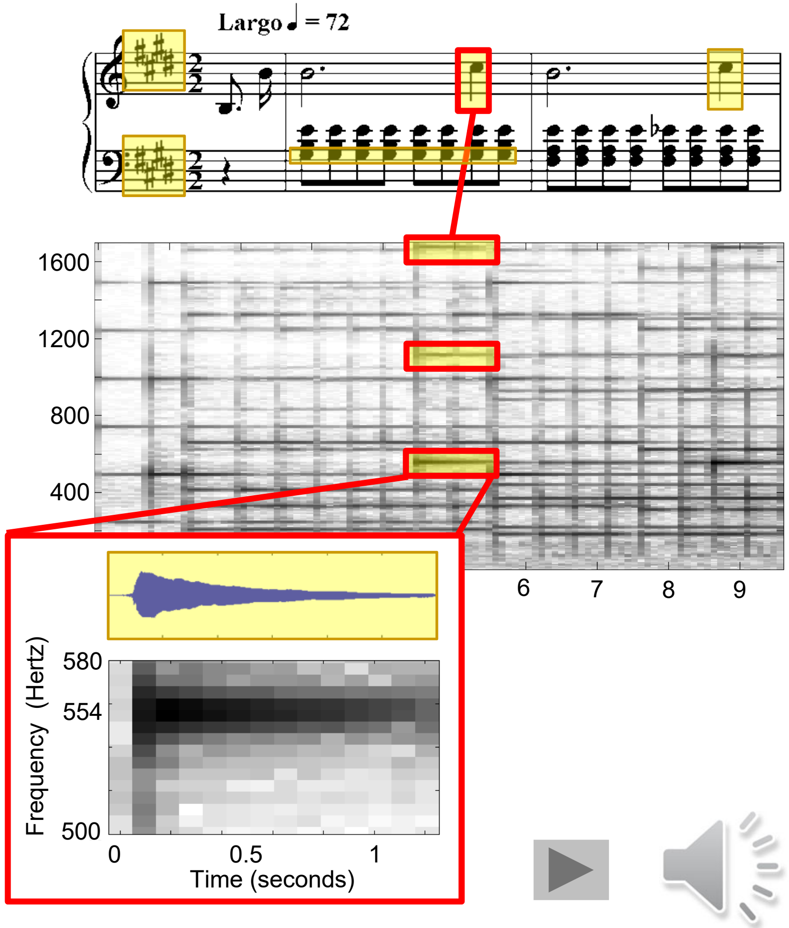
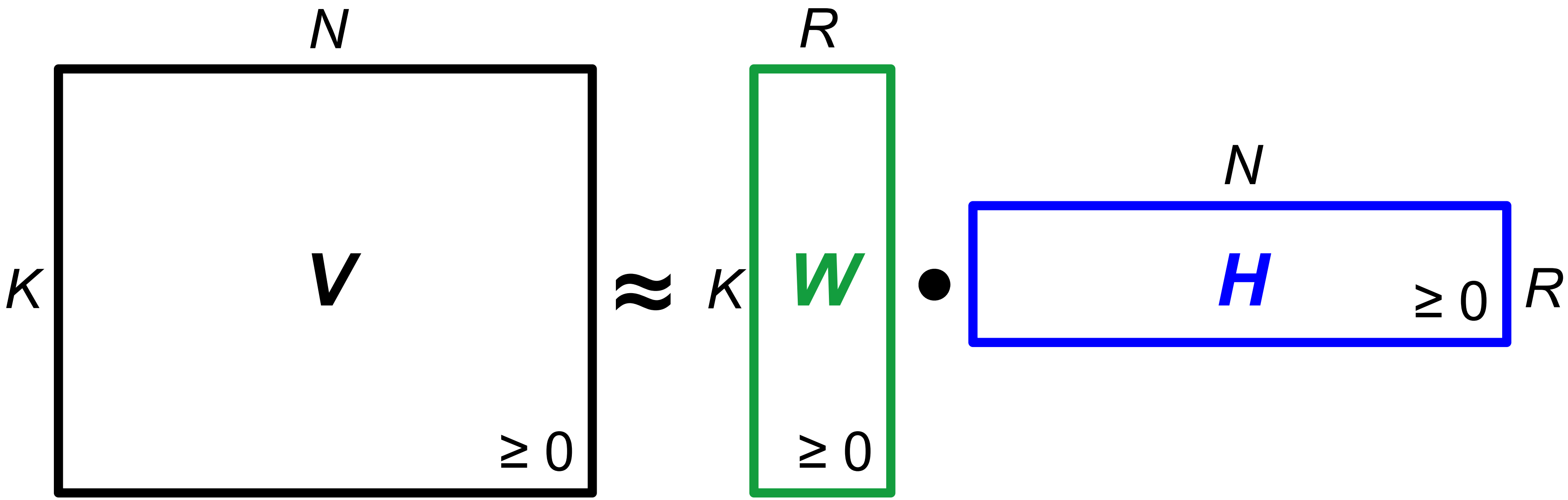


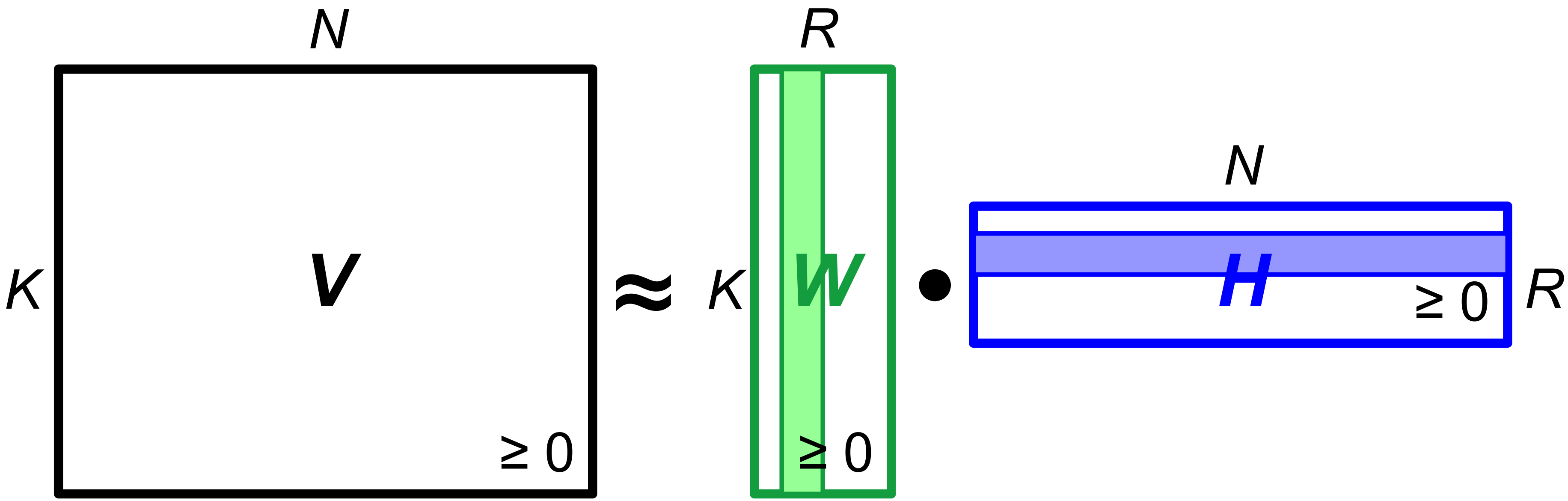



# Nonnegative Matrix Factorization (NMF)




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

# Nonnegative Matrix Factorization (NMF)

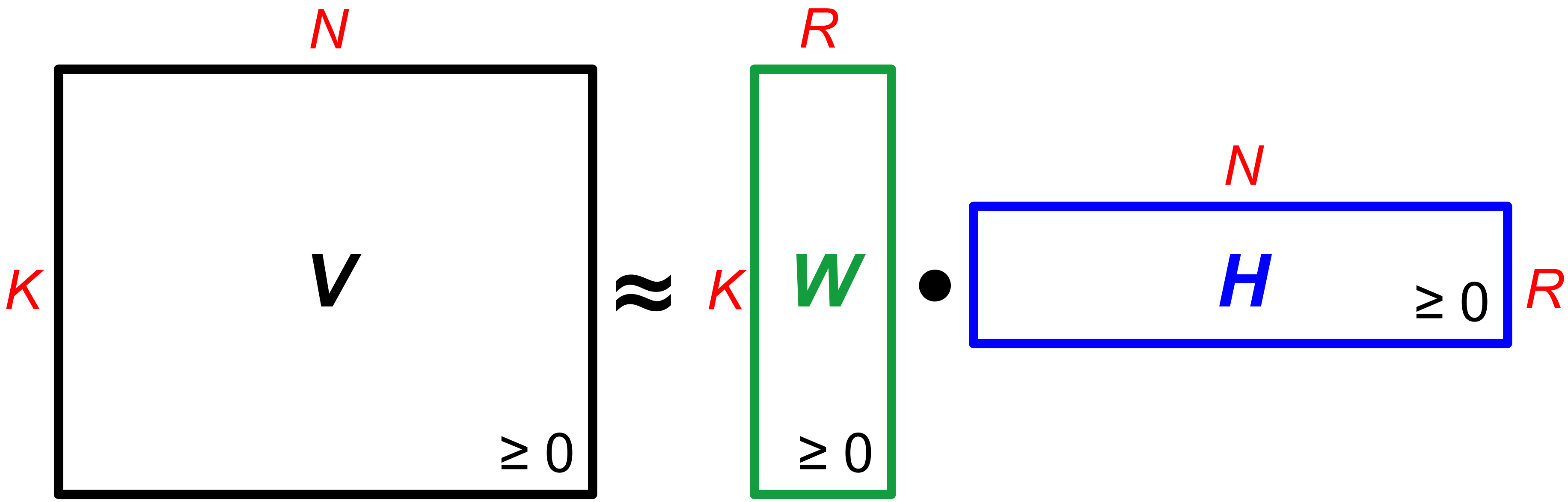



**Magnitude Spectrogram** **Templates** **Activations**

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

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

# Nonnegative Matrix Factorization (NMF)

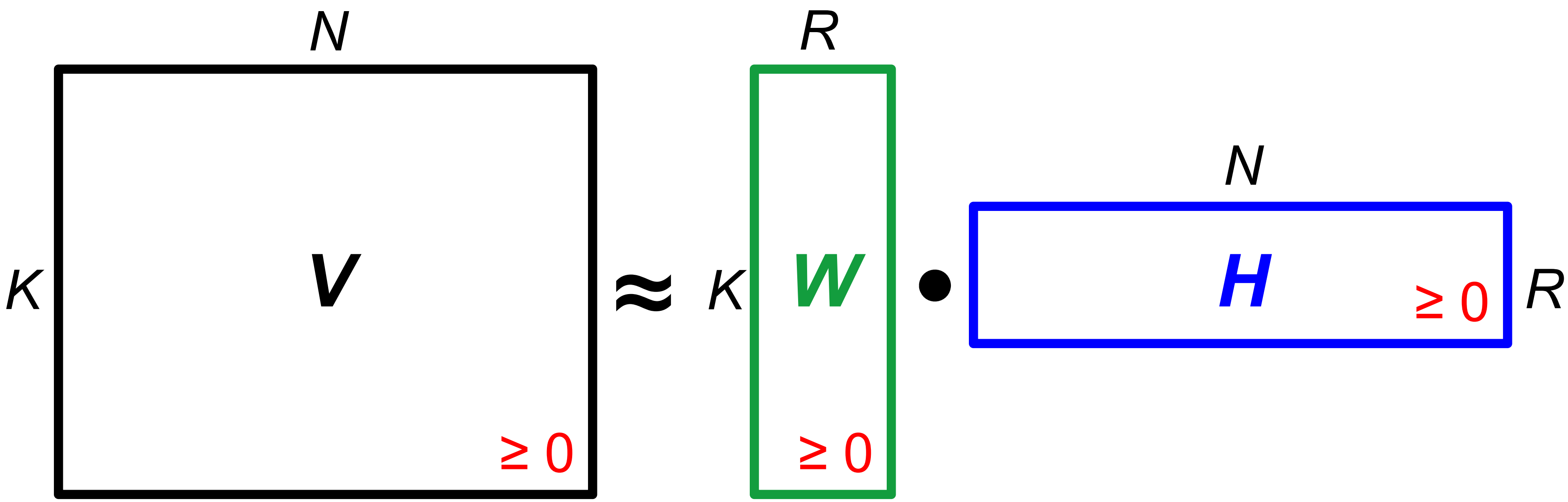



$V \in \mathbb{R}_{\geq 0}^{K \times N}$ $\quad W \in \mathbb{R}_{\geq 0}^{K \times R}$ $\quad H \in \mathbb{R}_{\geq 0}^{R \times N}$

## 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)




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

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

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

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

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

Apply chain rule from calculus

Variables

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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

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

Introduce transposed $W^\top$

# NMF Optimization

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

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

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





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

# NMF Optimization

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

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

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

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# NMF Optimization

## Gradient descent

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

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

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

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

Choose adaptive learning rate:

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

Issues:

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

- Update rule become multiplicative
- Nonnegative values stay nonnegative





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

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

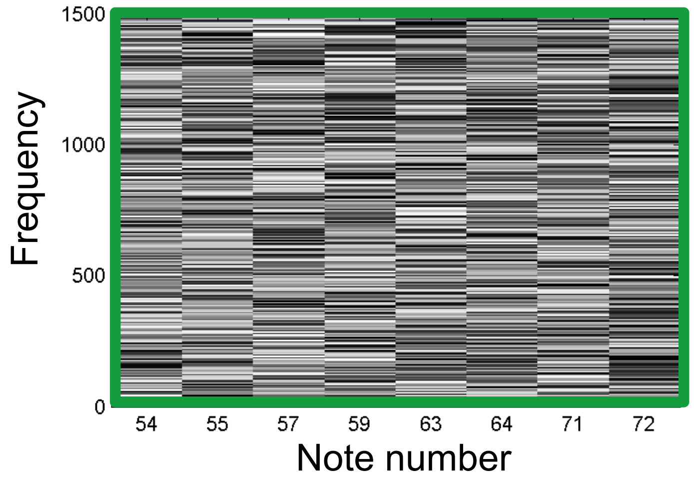
(3) Increase $\ell$ by one.

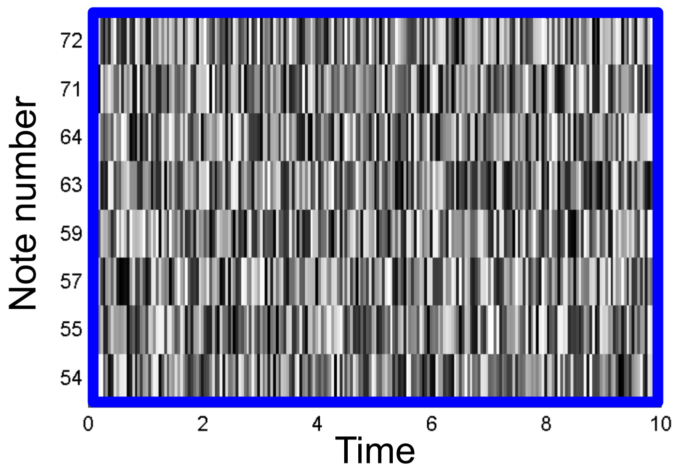
Repeat the steps (1) to (3) until $\|H^{(\ell)} - H^{(\ell-1)}\| \leq \varepsilon$ and $\|W^{(\ell)} - W^{(\ell-1)}\| \leq \varepsilon$ (or until some other stop criterion is fulfilled). Finally, set $H = H^{(\ell)}$ and $W = W^{(\ell)}$.

# NMF-based Spectrogram Decomposition

Template initialization

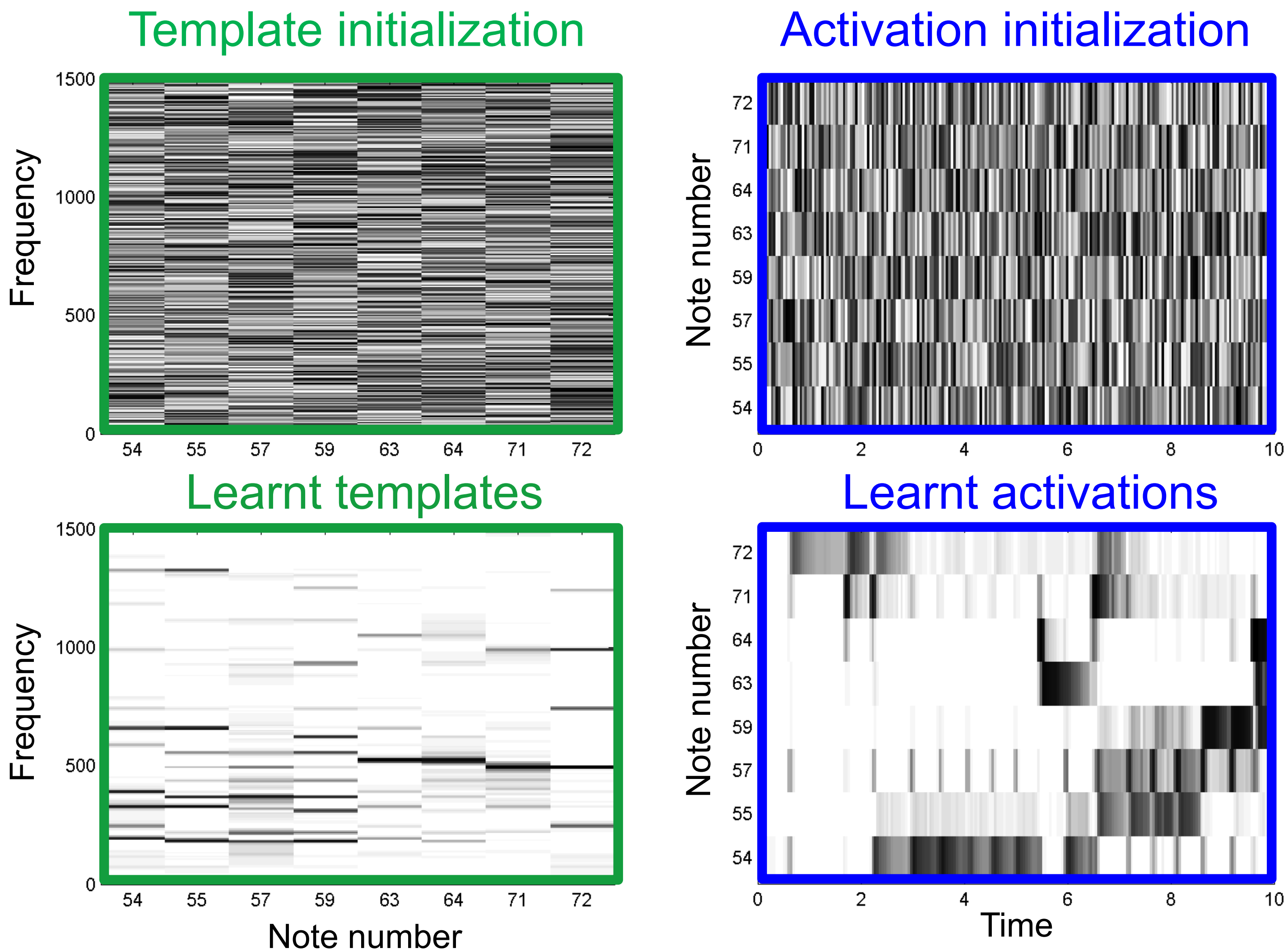
Activation initialization




Random initialization

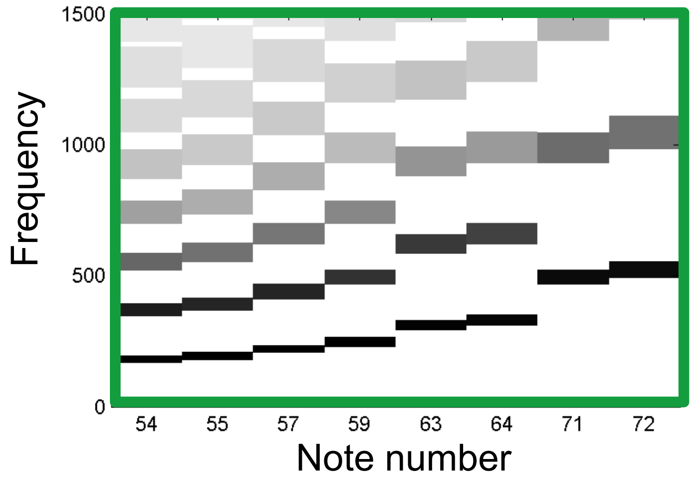
# NMF-based Spectrogram Decomposition



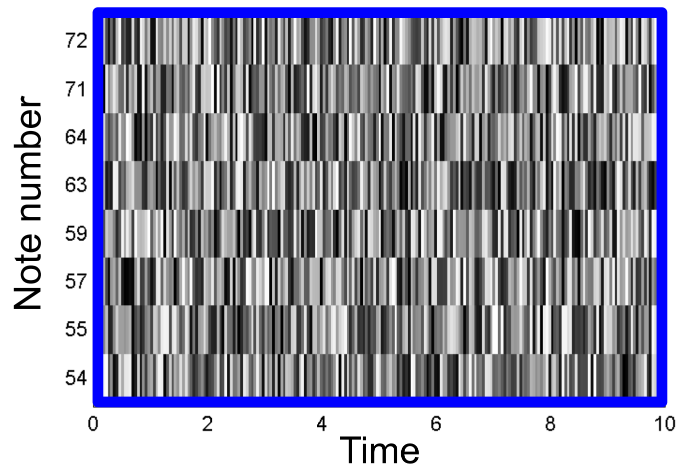

Random initialization → No semantic meaning

# Constrained NMF: Templates

Template initialization

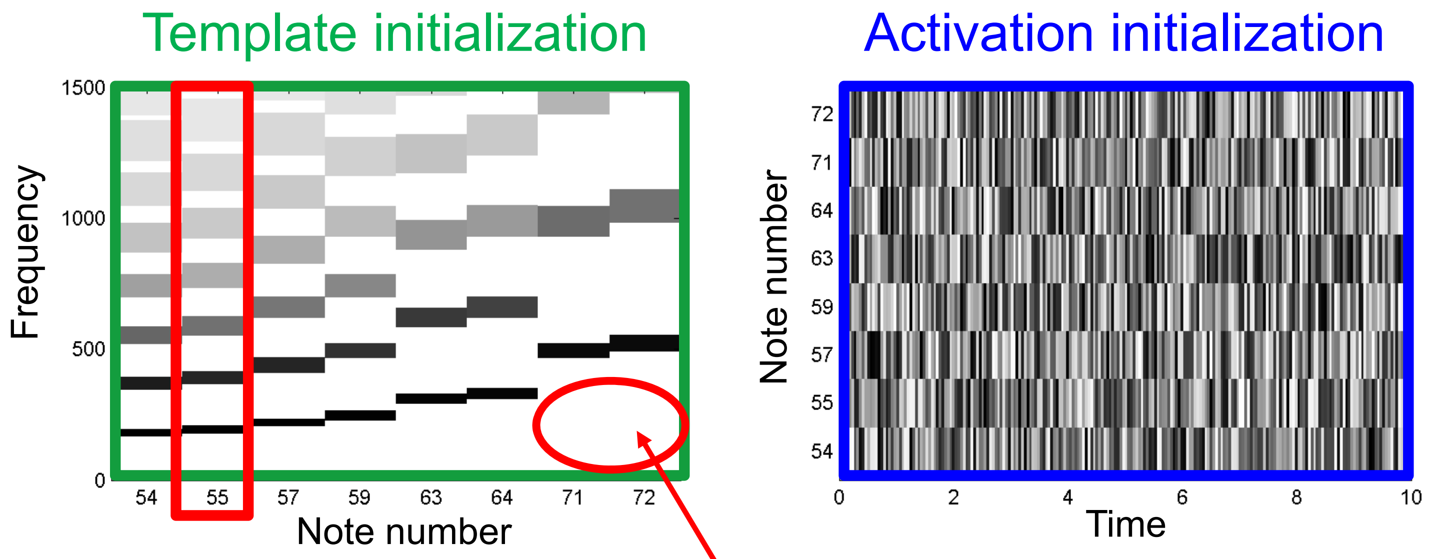



Activation initialization




Enforce harmonic structure with zero-valued entries

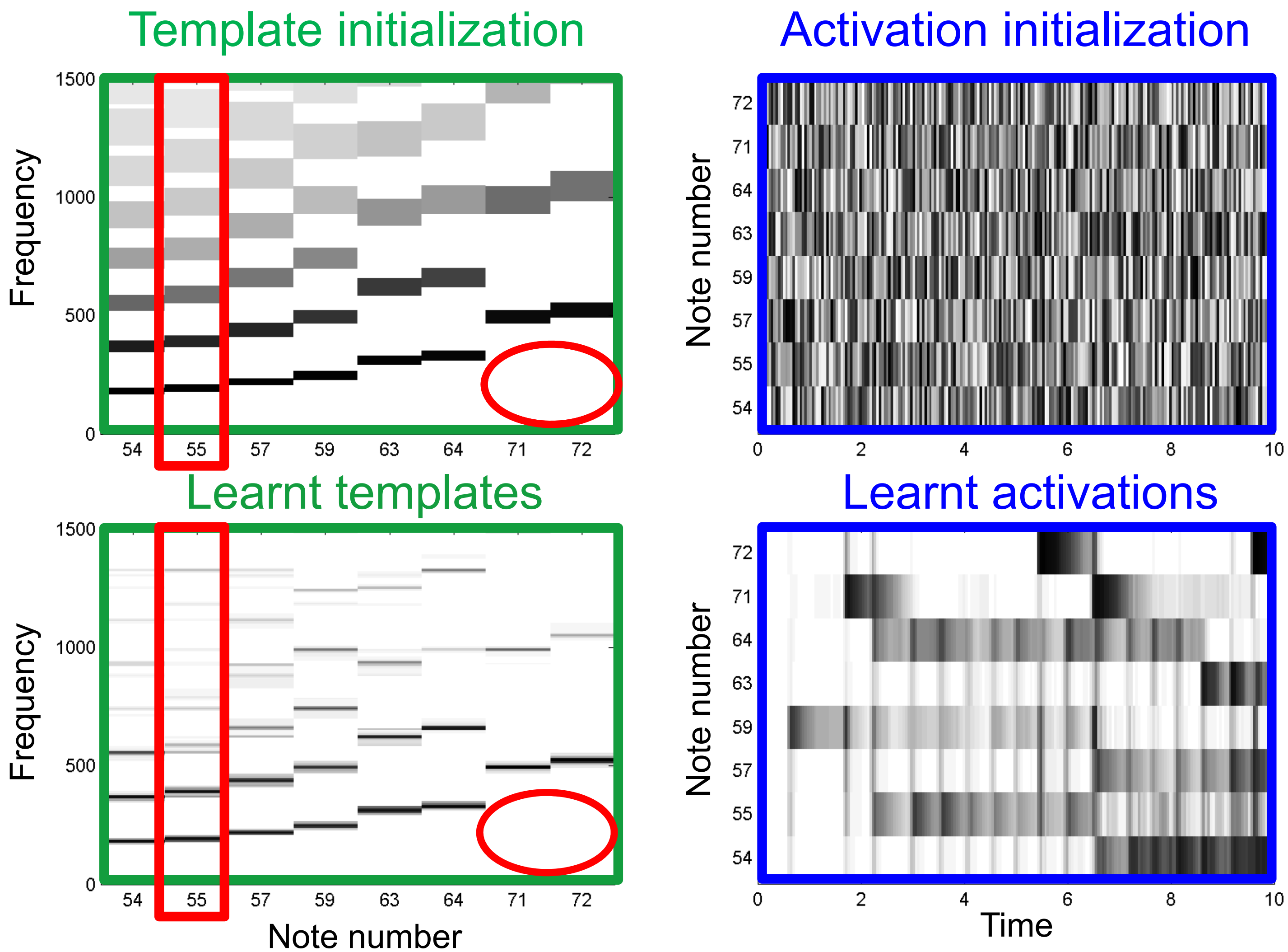
# Constrained NMF: Templates




Template constraint for p=55

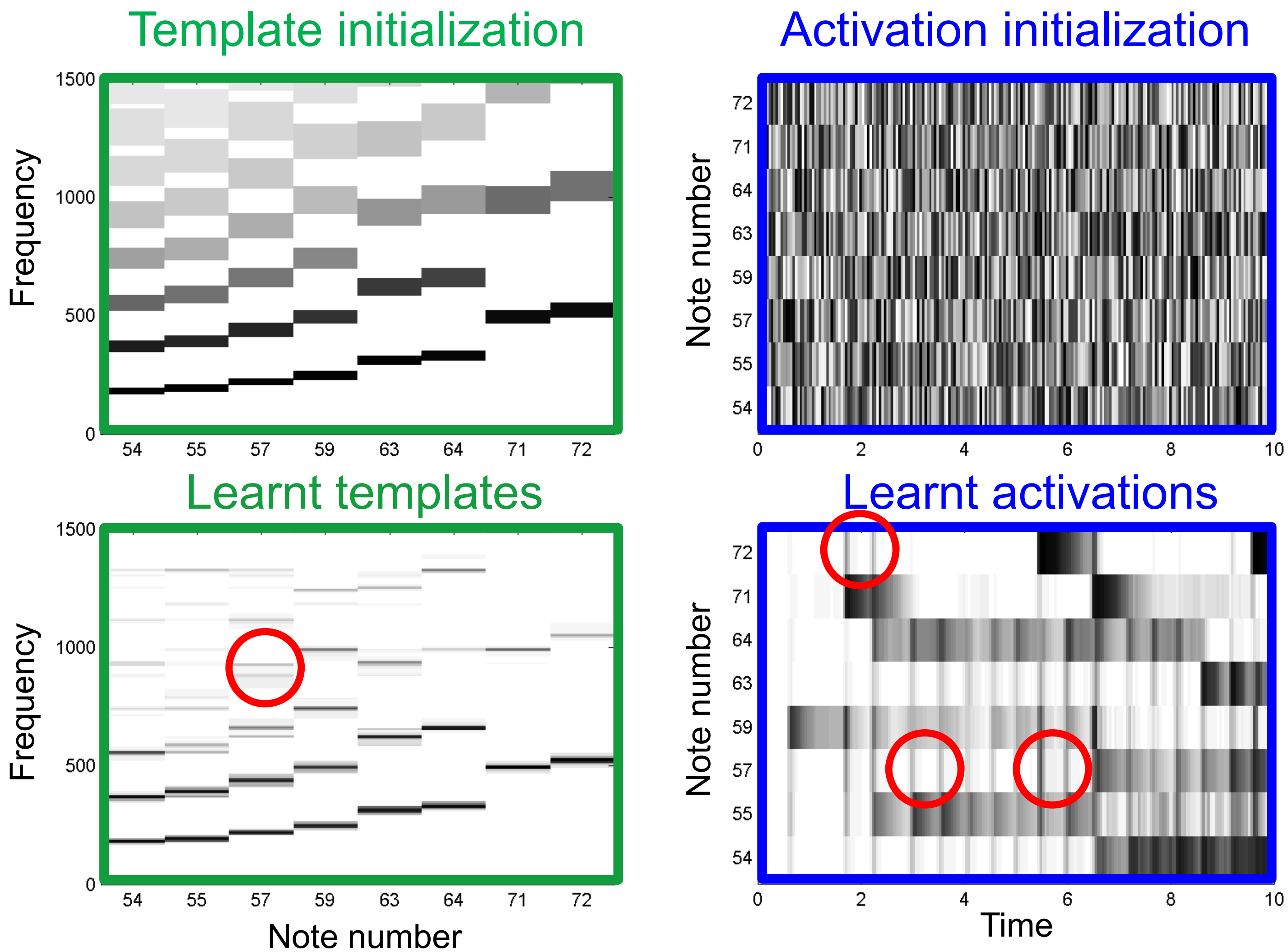
Enforce harmonic structure with zero-valued entries

# Constrained NMF: Templates



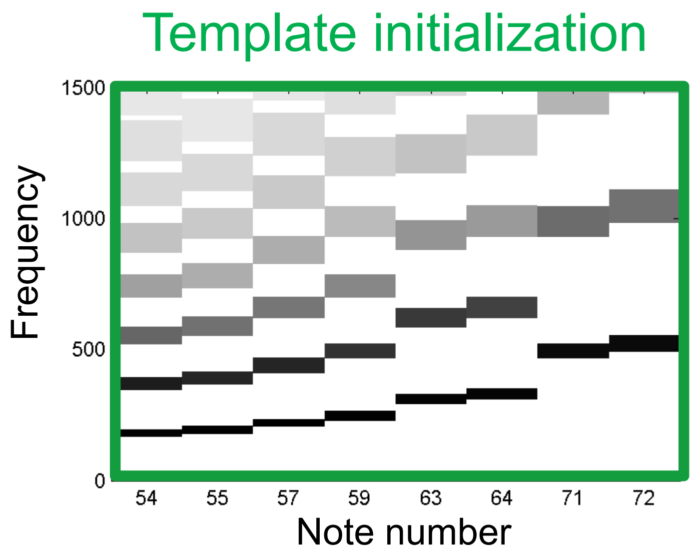

Zero-valued entries remain zero-valued entries!

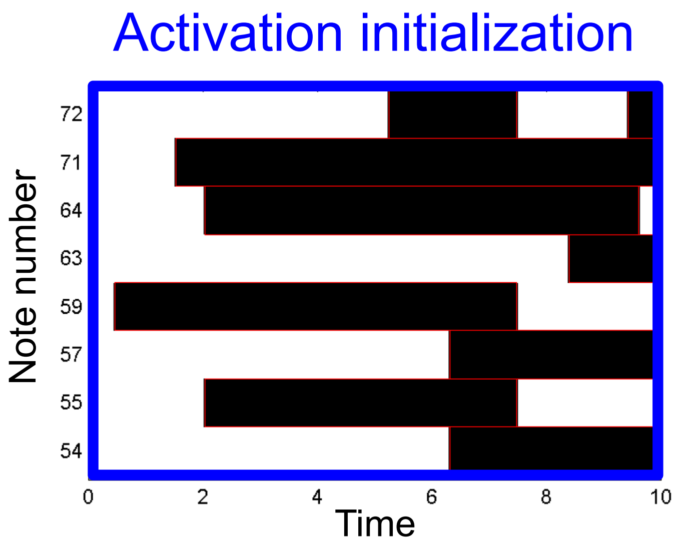
# Constrained NMF: Templates




Pitch templates misused to represent onsets

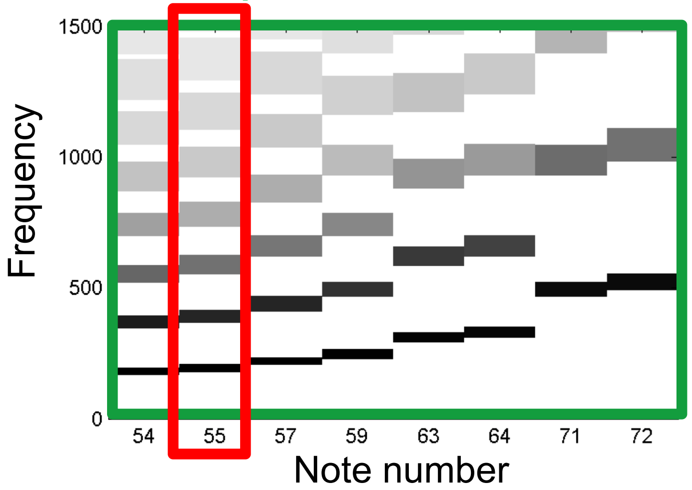
# Constrained NMF: Double Constraints



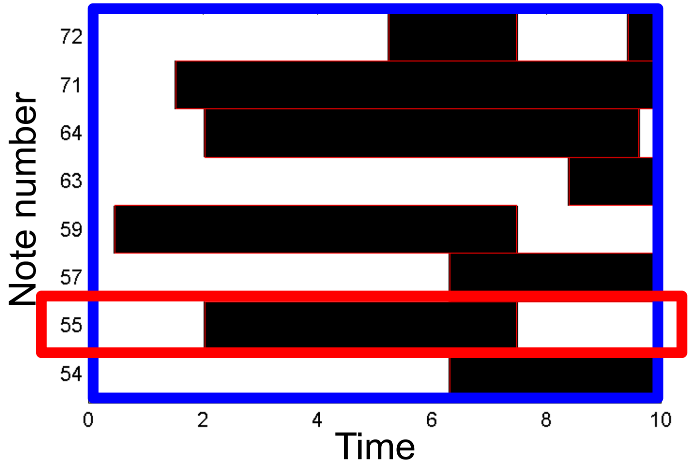
# Constrained NMF: Double Constraints

Template initialization




Template constraint for p=55

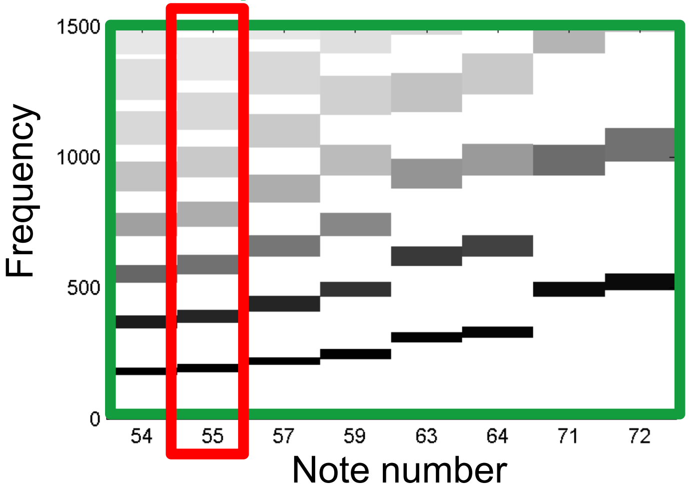
Activation initialization




Activation constraints for p=55

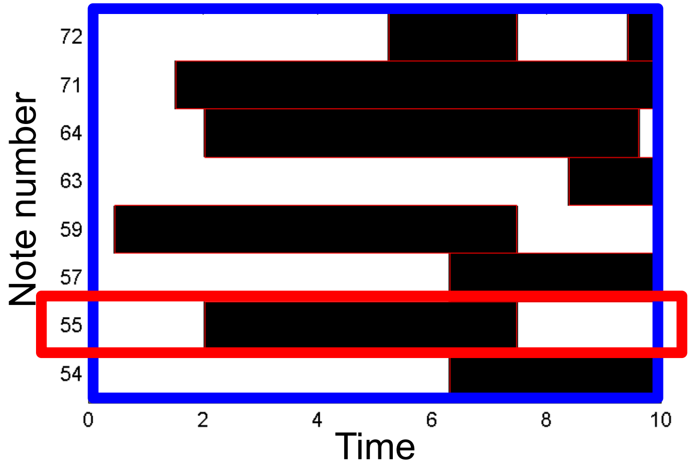
# Constrained NMF: Double Constraints

Template initialization




Template constraint for p=55

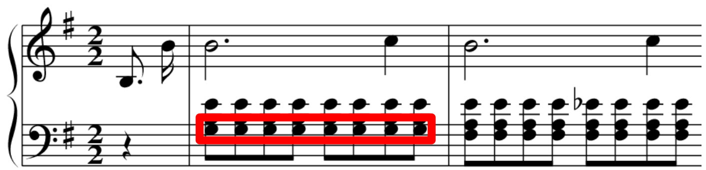
Activation initialization

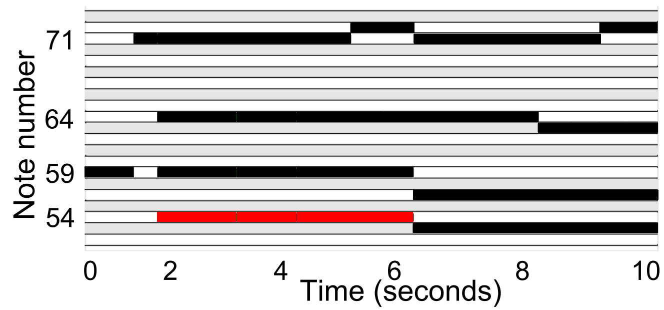



Activation constraints for p=55

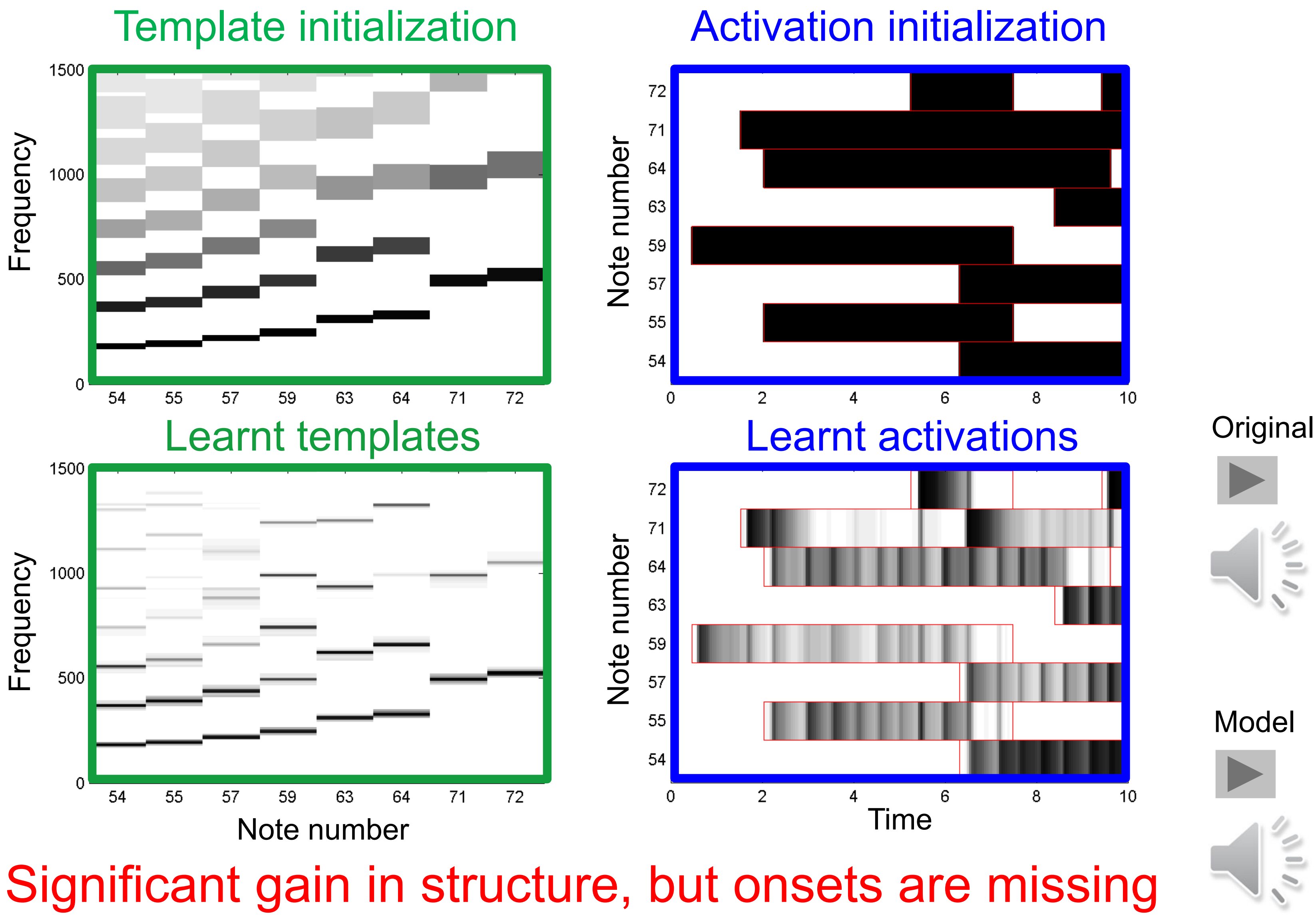
Such information may come from a synchronized score

Sheet music



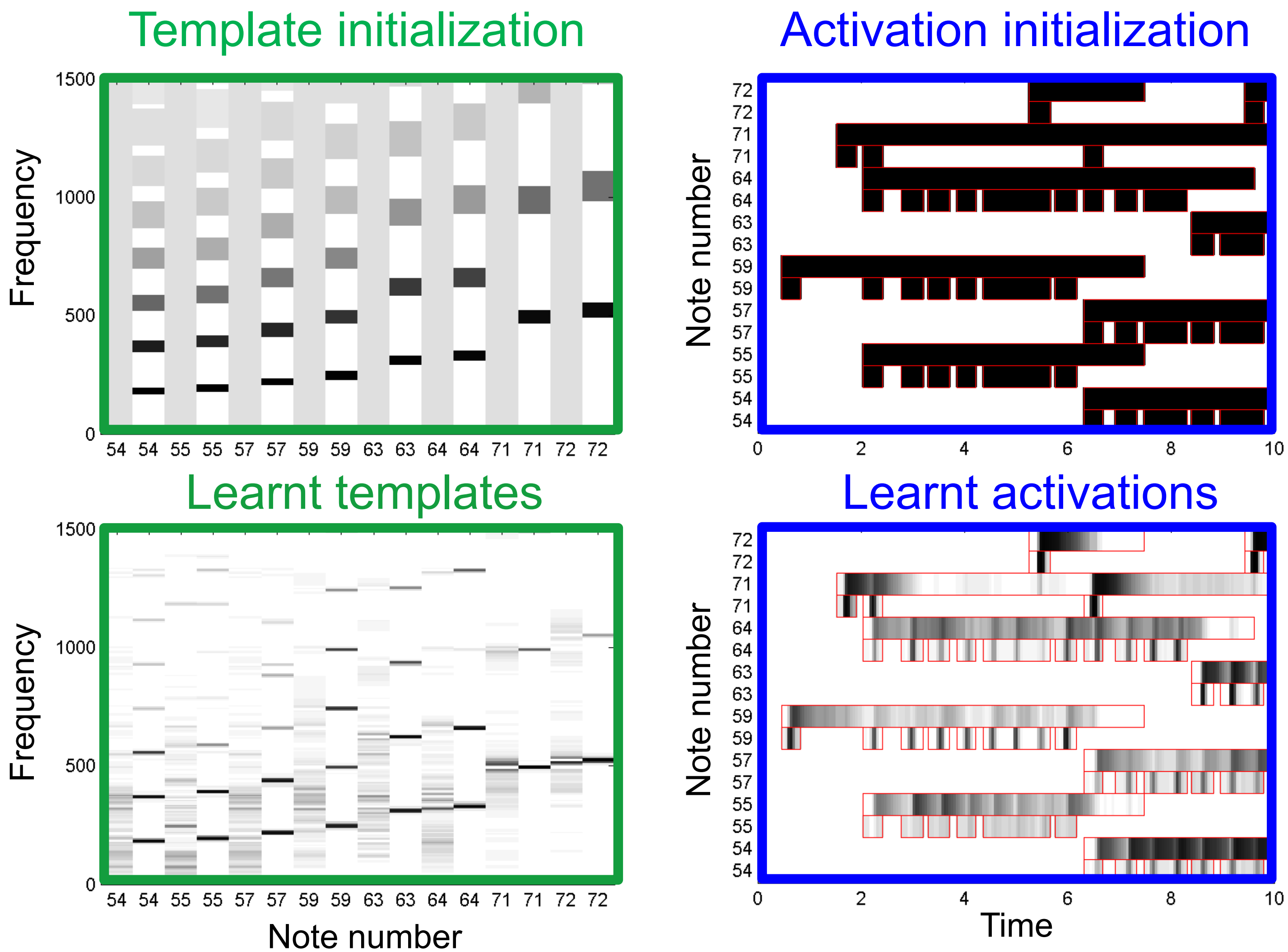


# Constrained NMF: Double Constraints




Significant gain in structure, but onsets are missing

# Constrained NMF: Onset Templates



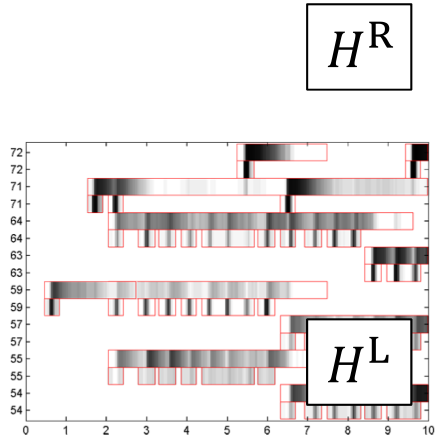

Original

Model Onset

# Score-Informed Audio Decompostion

## Application: Separating left and right hands for piano

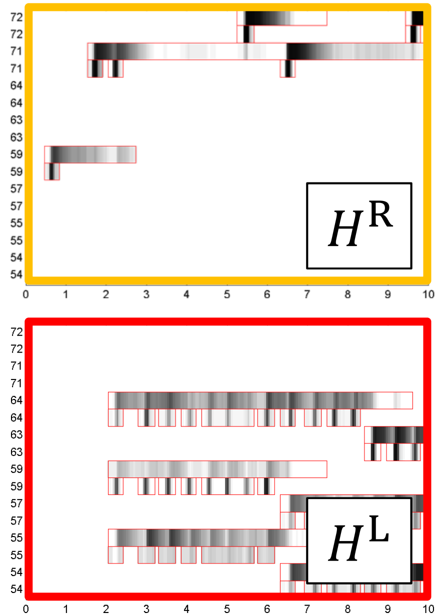

1. Split activation matrix



# Score-Informed Audio Decompostion

## Application: Separating left and right hands for piano

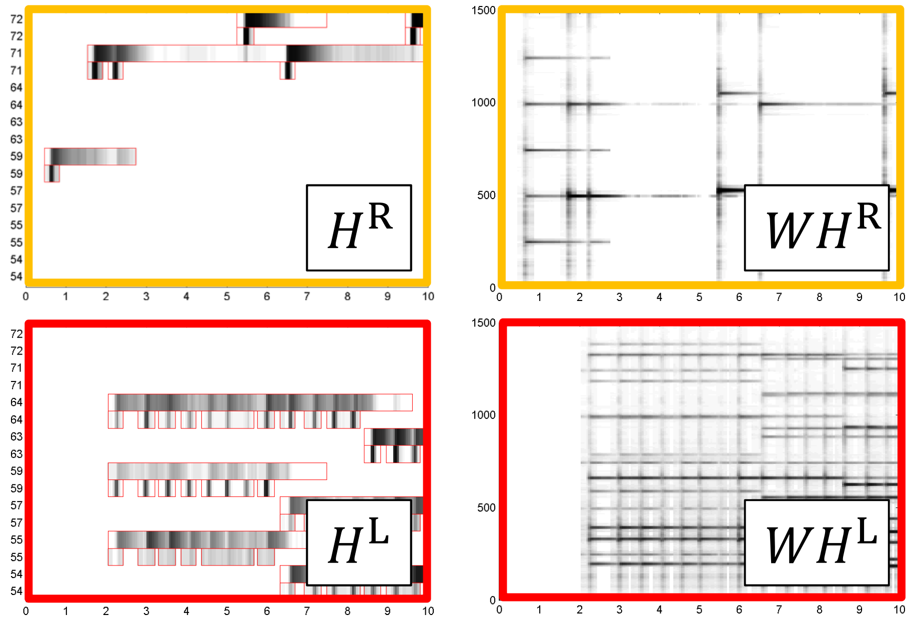

1. Split activation matrix



# Score-Informed Audio Decompostion

## Application: Separating left and right hands for piano

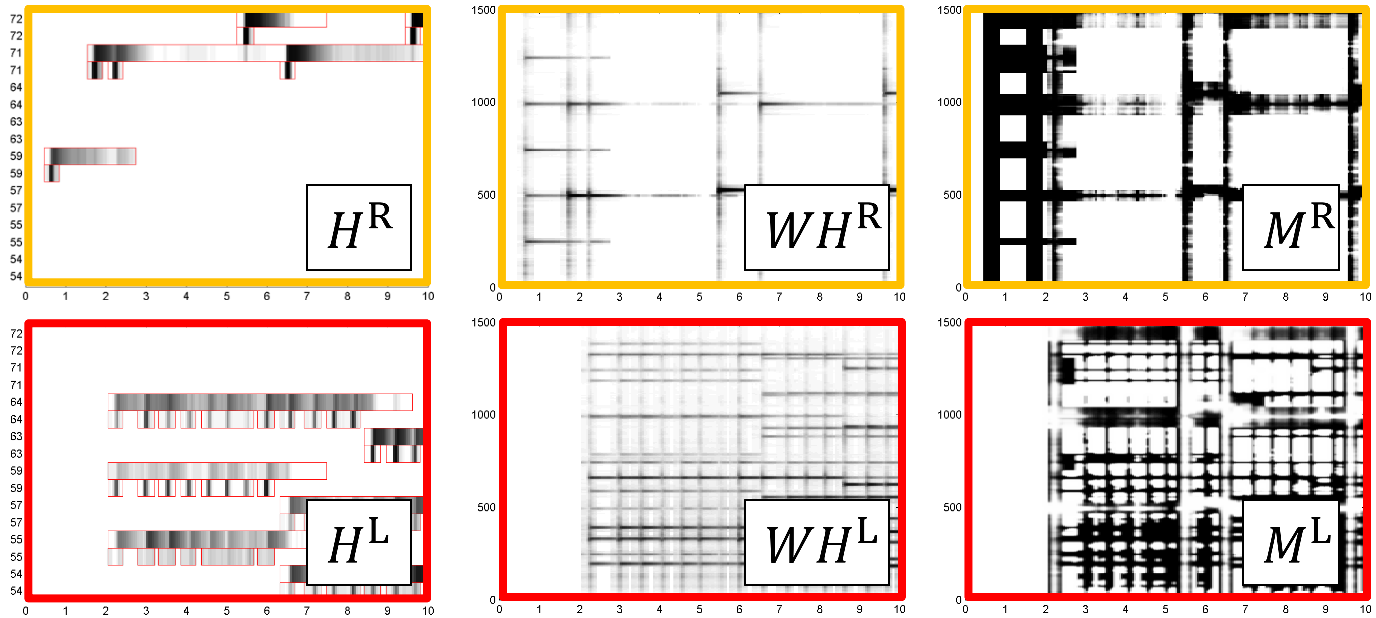

1. Split activation matrix
2. Model spectrogram for left/right



# 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





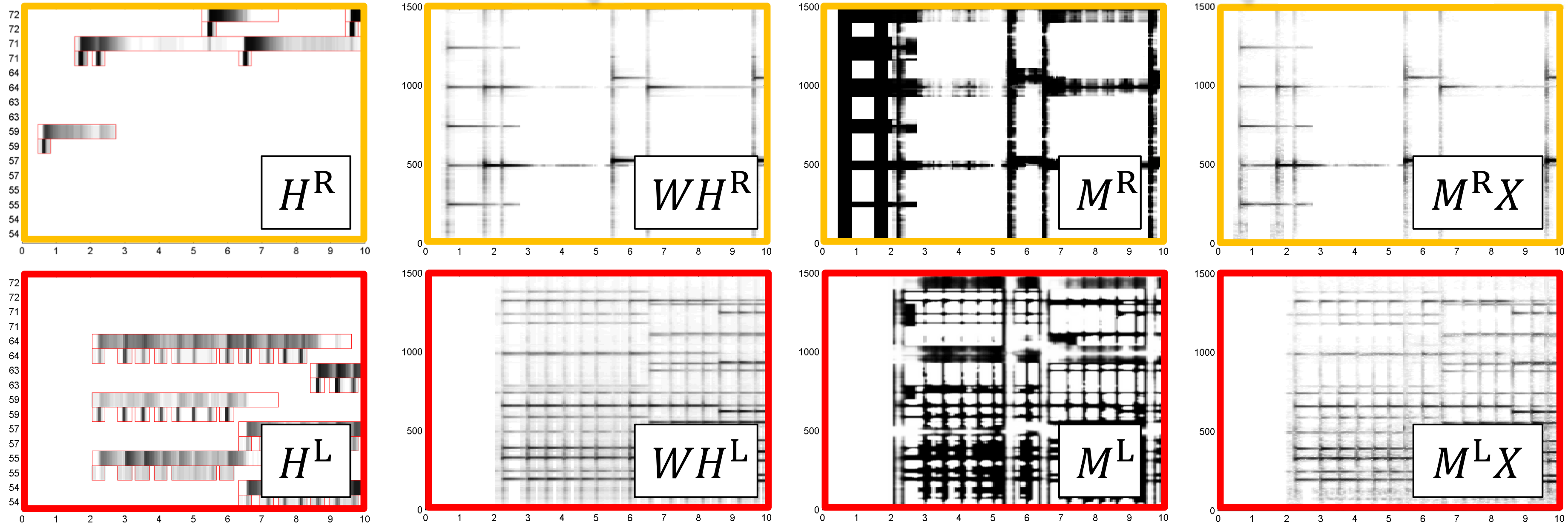



AUDIO LABS

# Score-Informed Audio Decompostion

## Application: Separating left and right hands for piano

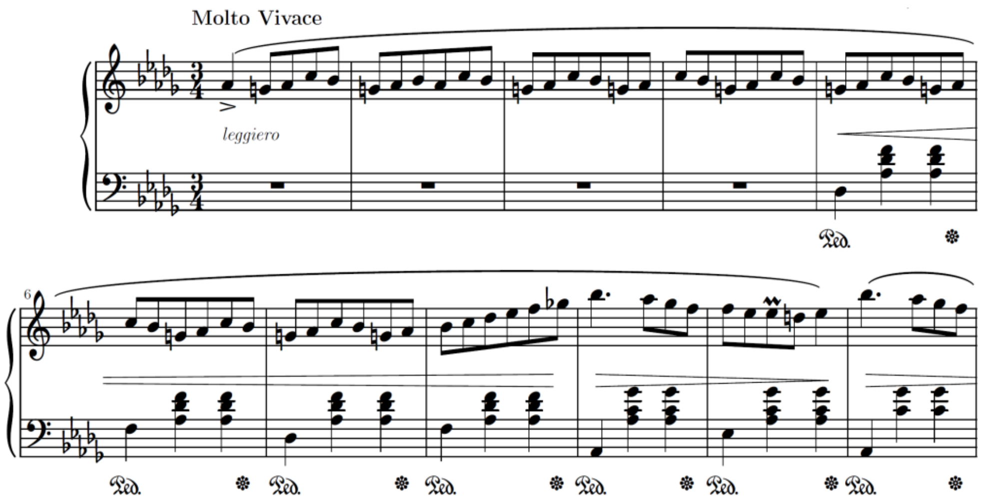

1. Split activation matrix
2. Model spectrogram for left/right
3. Separation masks for left/right
4. Estimated spectrograms for left/right



# Score-Informed Audio Decompostion

## Application: Separating left and right hands for piano

Chopin, Waltz Op. 64, No. 1




Original

**Score-Informed Constraints**

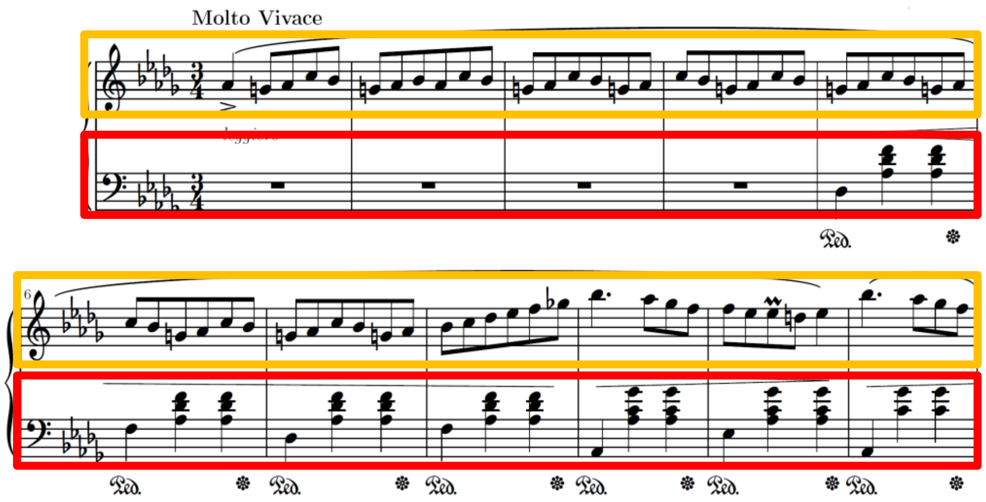
Ewert, Müller: Using Score-Informed Constraints for NMF-based Source Separation. Proc. ICASSP, 2012.

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**

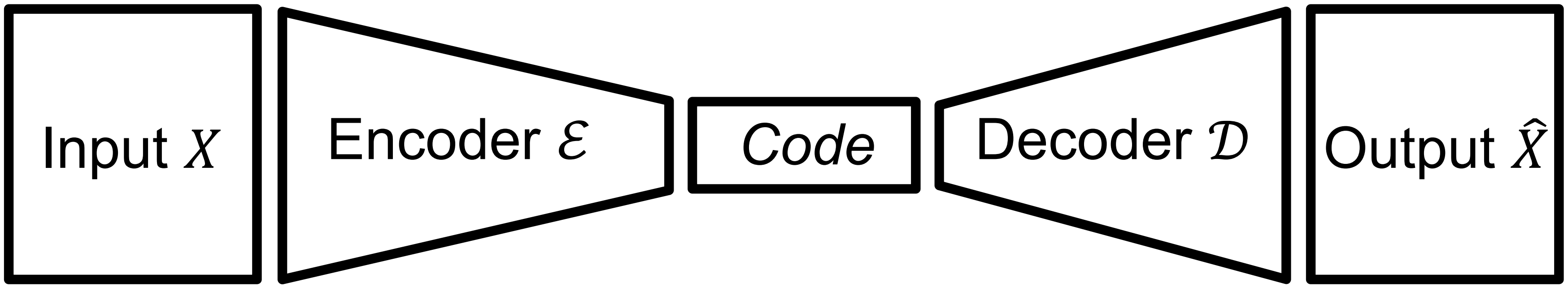
Ewert, Müller: Using Score-Informed Constraints for NMF-based Source Separation. Proc. ICASSP, 2012.

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

# Conclusions (NMF)

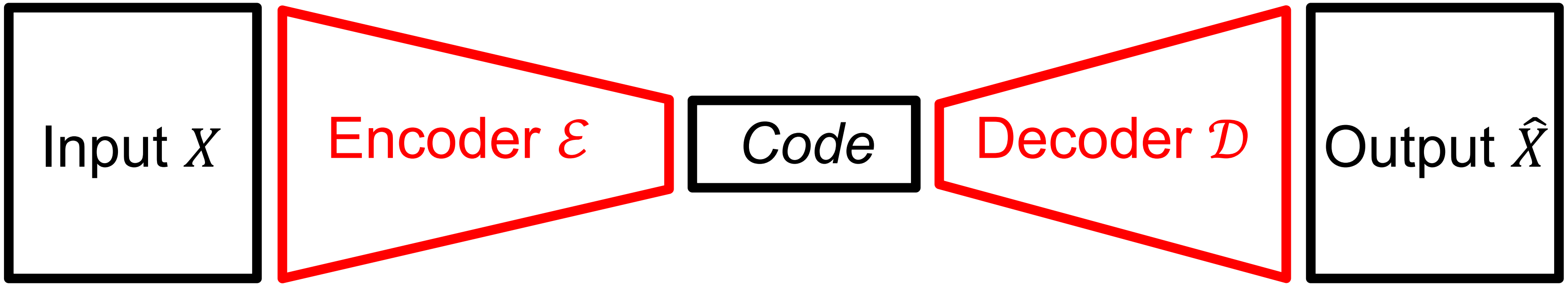
- NMF used for spectrogram decomposition
- Multiplicative update rules make it easy to constrain NMF model via zero initialization
- Exploiting score information to guide separation process (requires score–audio synchronization)
- Application: Separation of arbitrary note groups from given audio recording

# Autoencoder




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

# Autoencoder



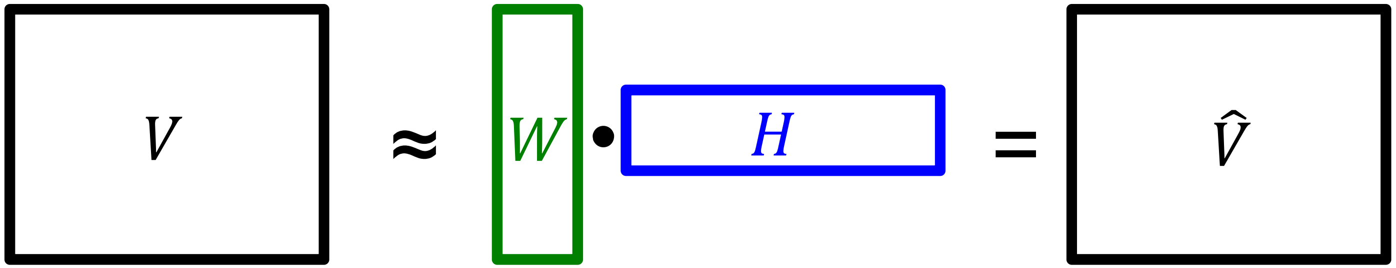

- Specific type of neural network
- Encoder: Compress input $X$ into a low-dimensional code
- Decoder: Reconstruct output $\hat{X}$ from code
- Goal: Learn parameters for encoder and decoder such that output is close to input with respect to some loss function:

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

# NMF and Autoencoder (AE)

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

NMF

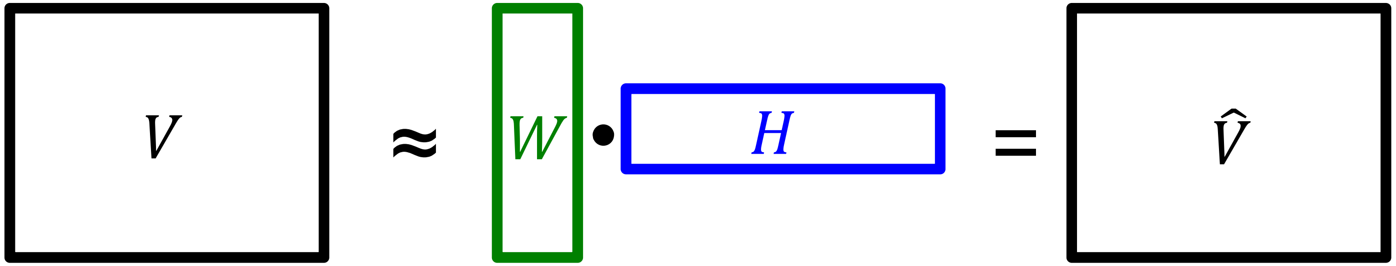



$V \approx WH$ implies $W^{+}V \approx H$ with pseudoinverse $W^{+}$

# NMF and Autoencoder (AE)

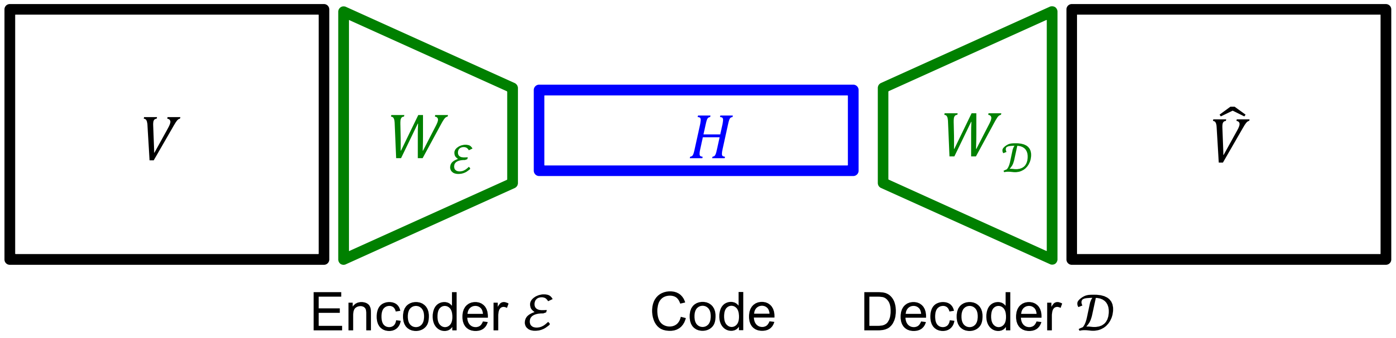
**Nonnegative Autoencoder**
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.

NMF




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

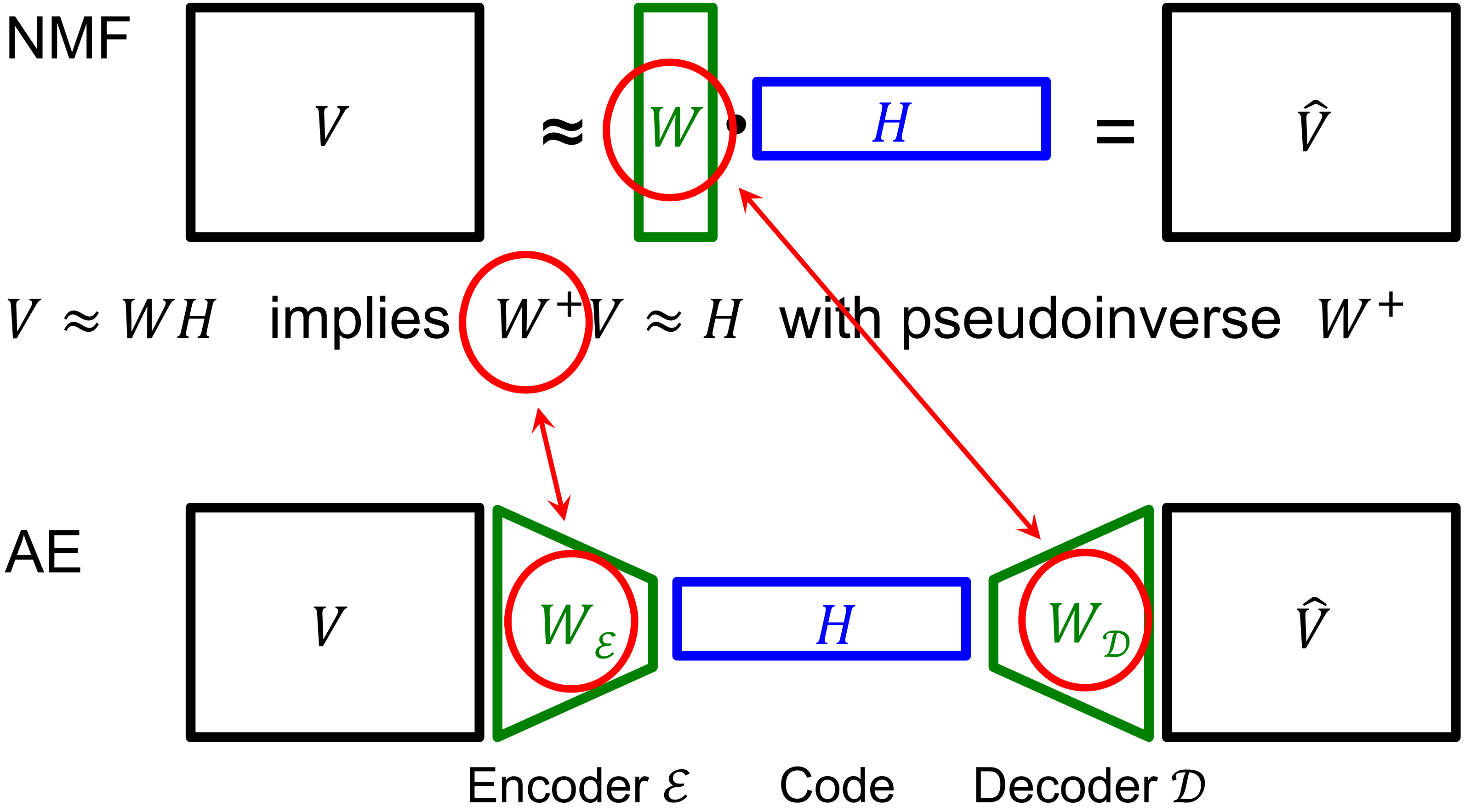
AE




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

# NMF and Autoencoder (AE)

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



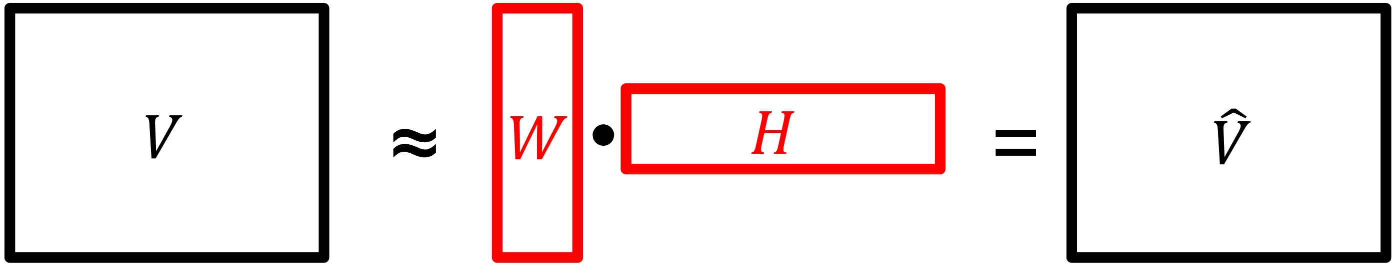

1. Layer: $H = W_{\mathcal{E}} V$
2. Layer: $\hat{V} = W_{\mathcal{D}} H$

Fully connected network

# NMF and Autoencoder (AE)

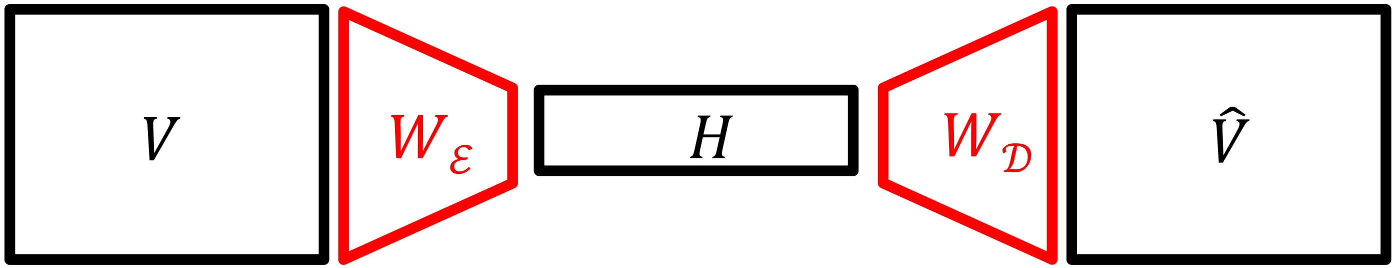
**Nonnegative Autoencoder**
Smaragdis, Venkataramani: A Neural Network Alternative to Non-Negative Audio Models, Proc. ICASSP 2017.

NMF




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

AE

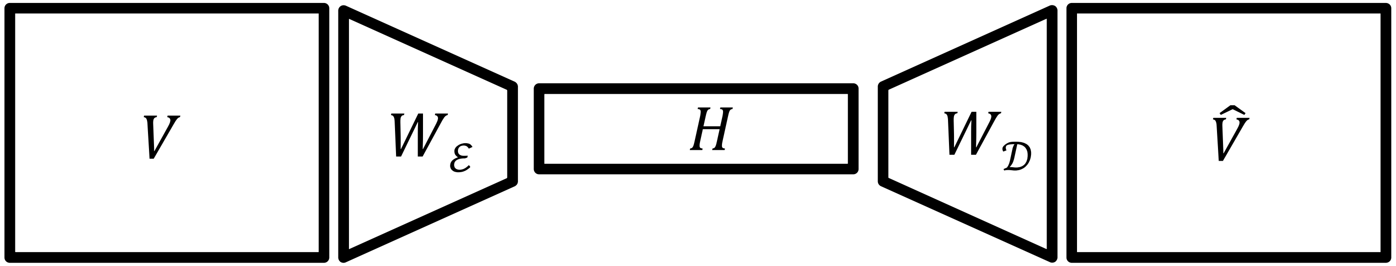



Encoder $\mathcal{E}$ Code Decoder $\mathcal{D}$

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 $W_{\mathcal{D}}$

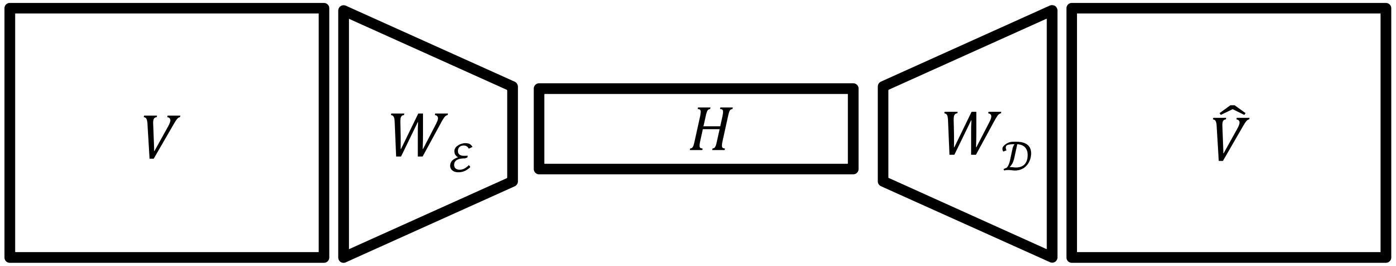
# Nonnegative Autoencoder (NAE)




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)

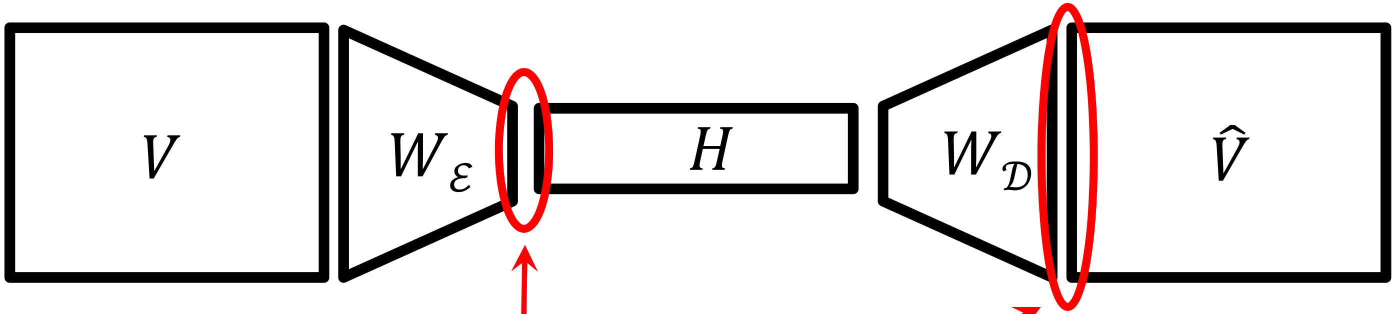



1. Layer: $H = W_{\mathcal{E}}\, V$
2. Layer: $\hat{V} = W_{\mathcal{D}}\, H$

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

- Loss function: same as in NMF

# Nonnegative Autoencoder (NAE)

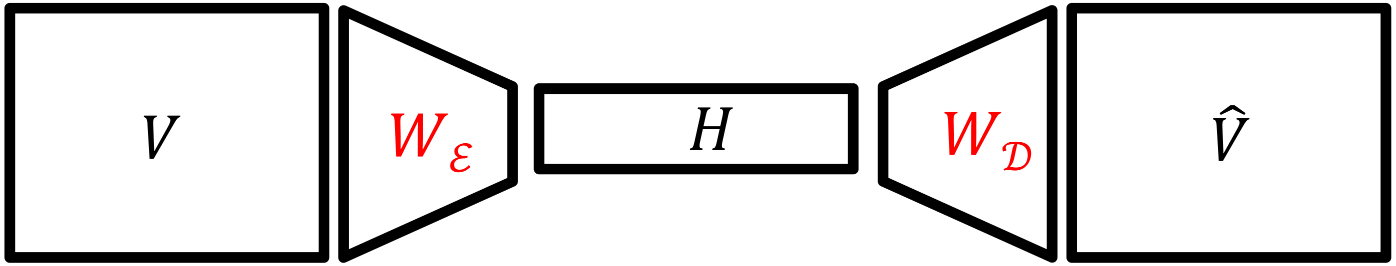



1. Layer: $H = \max(W_\mathcal{E}\, V, 0)$
2. Layer: $\hat{V} = \max(W_\mathcal{D}\, H, 0)$

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

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

# Nonnegative Autoencoder (NAE)



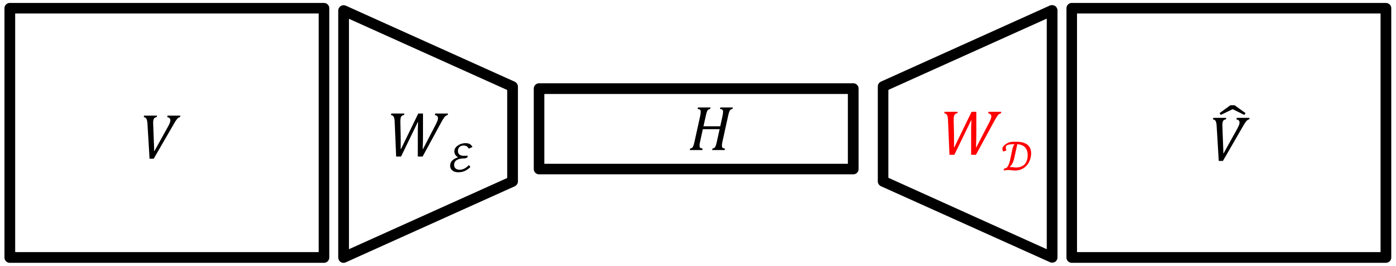

1. Layer: $H = \max(W_\mathcal{E}\, V, 0)$
2. Layer: $\hat{V} = \max(W_\mathcal{D}\, H, 0)$

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

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

- 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

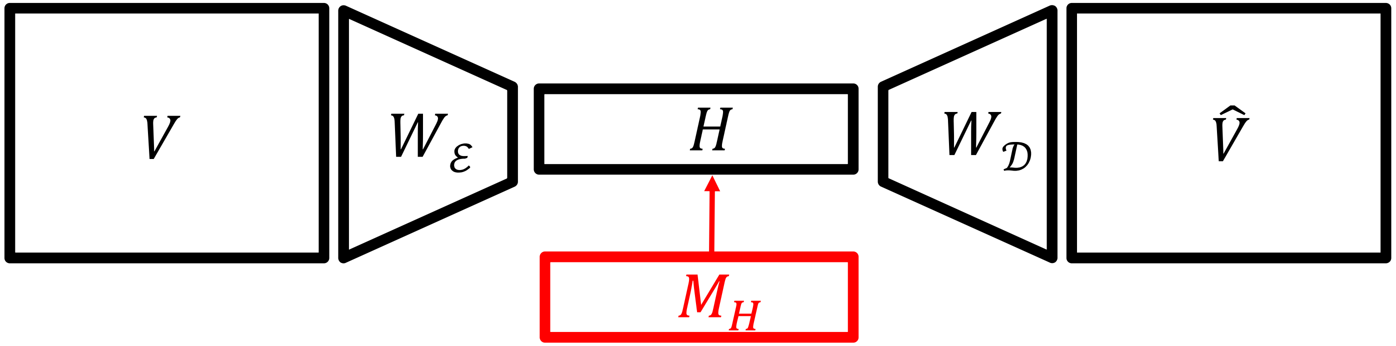



$$H = \max(W_{\mathcal{E}}\, V, 0)$$
$$\hat{V} = \max(W_{\mathcal{D}}\, H, 0)$$

- 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 $\gamma$.

# 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:

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

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

Similar idea and computation as for NMF.

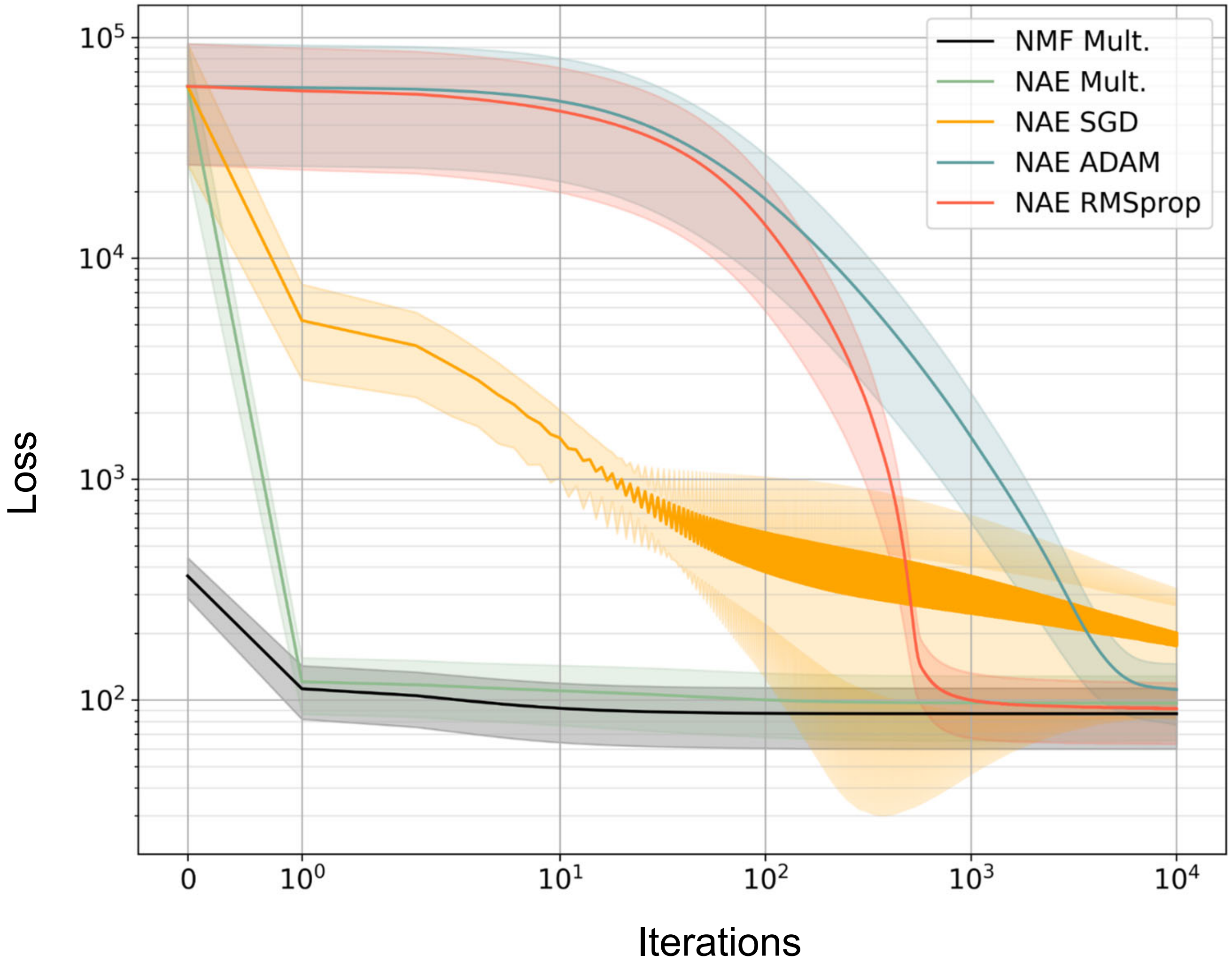
**NMF vs. NAE**

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

# Approximation Loss

**NMF vs. NAE**

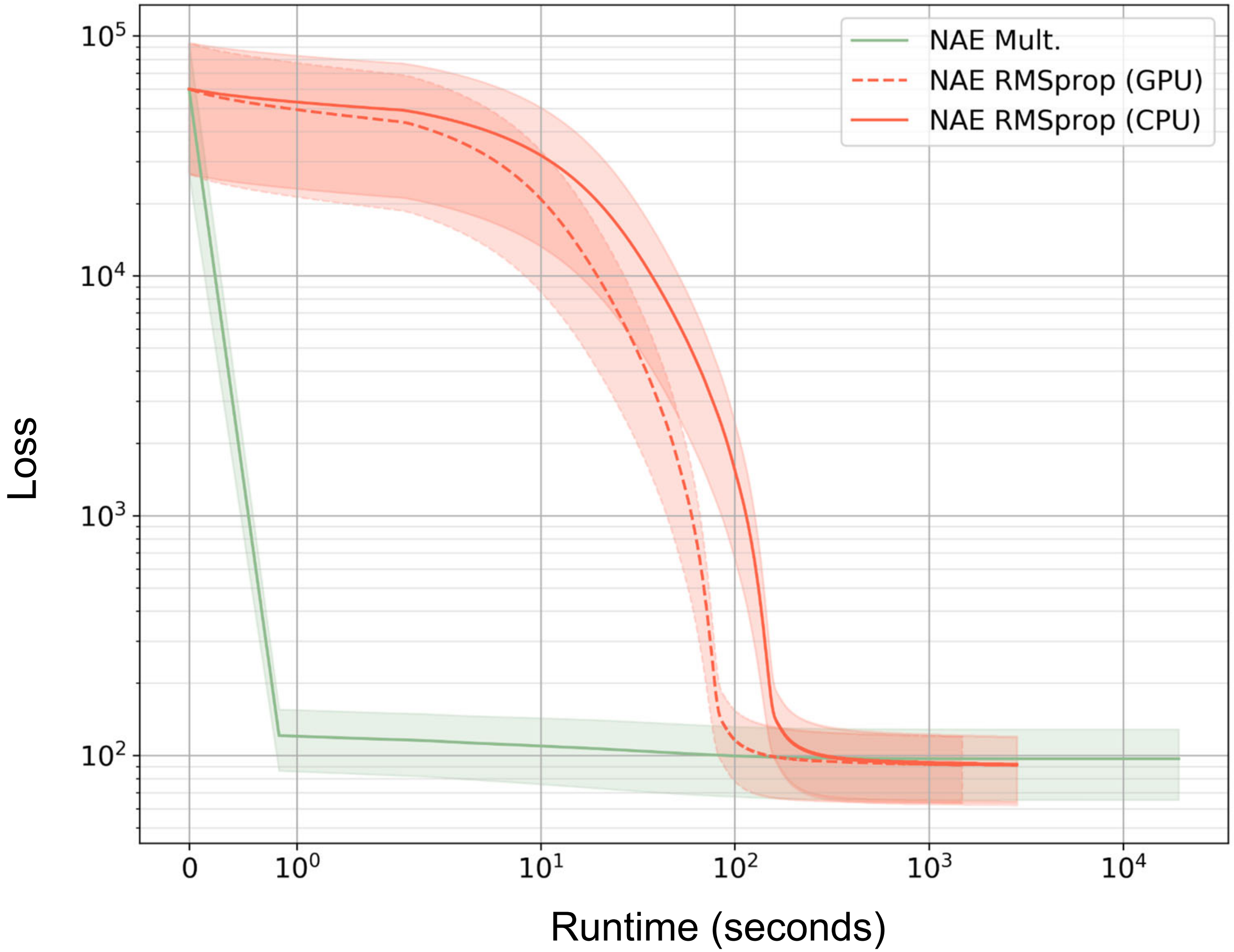
Özer, Hansen, Zunner, Müller: Investigating Nonnegative Autoencoders for Efficient Audio Decomposition. Proc. EUSIPCO, 2022.



# 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





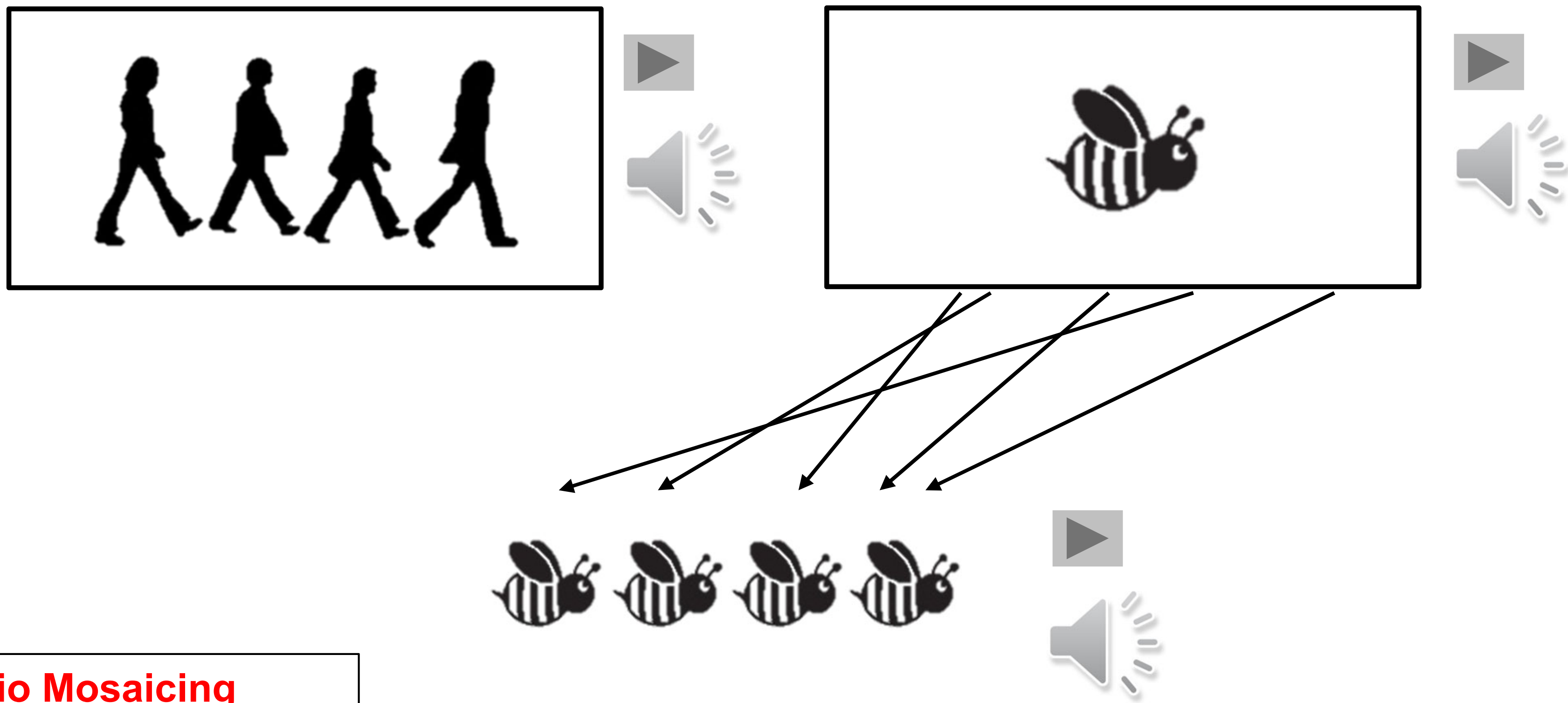
AUDIO LABS

# Score-Informed Audio Decomposition

Audio mosaicing (style transfer)

**Target** signal: Beatles–Let it be

**Source** signal: Bees

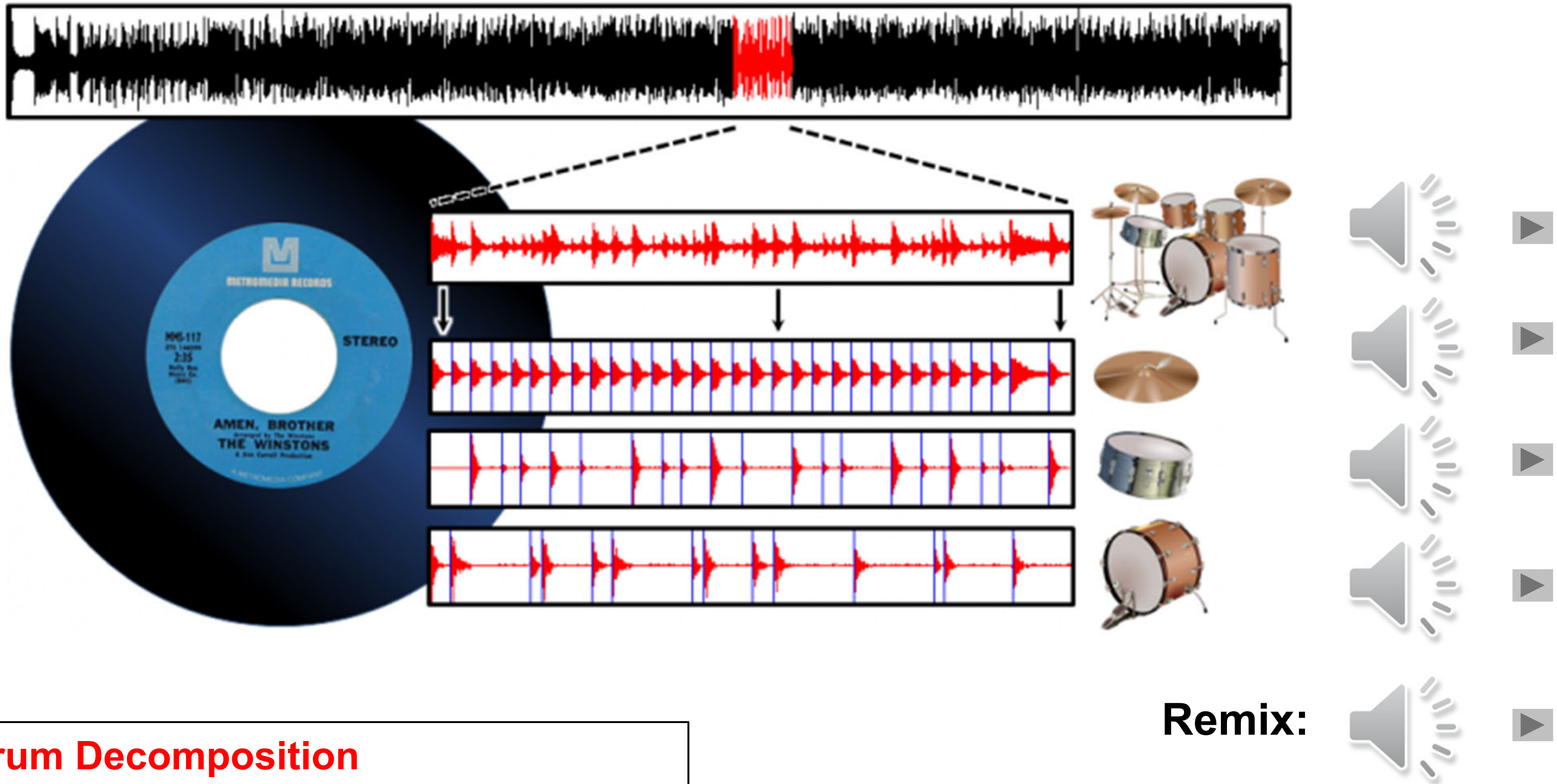


**Mosaic** signal: Let it Bee

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

# 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

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- Yigitcan Özer
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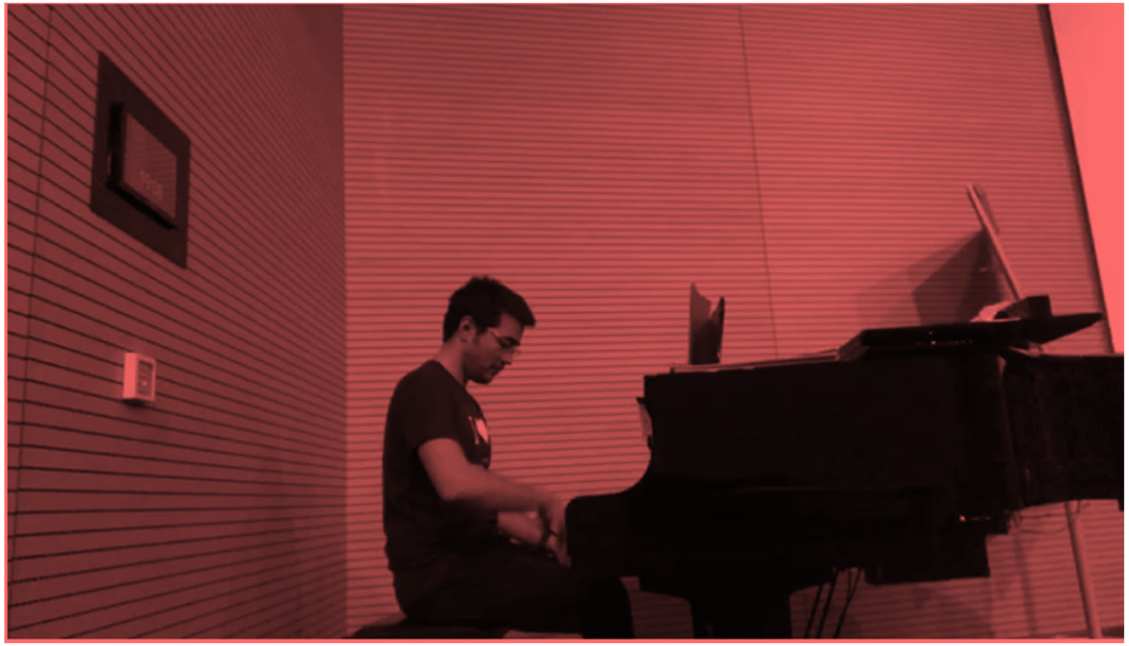
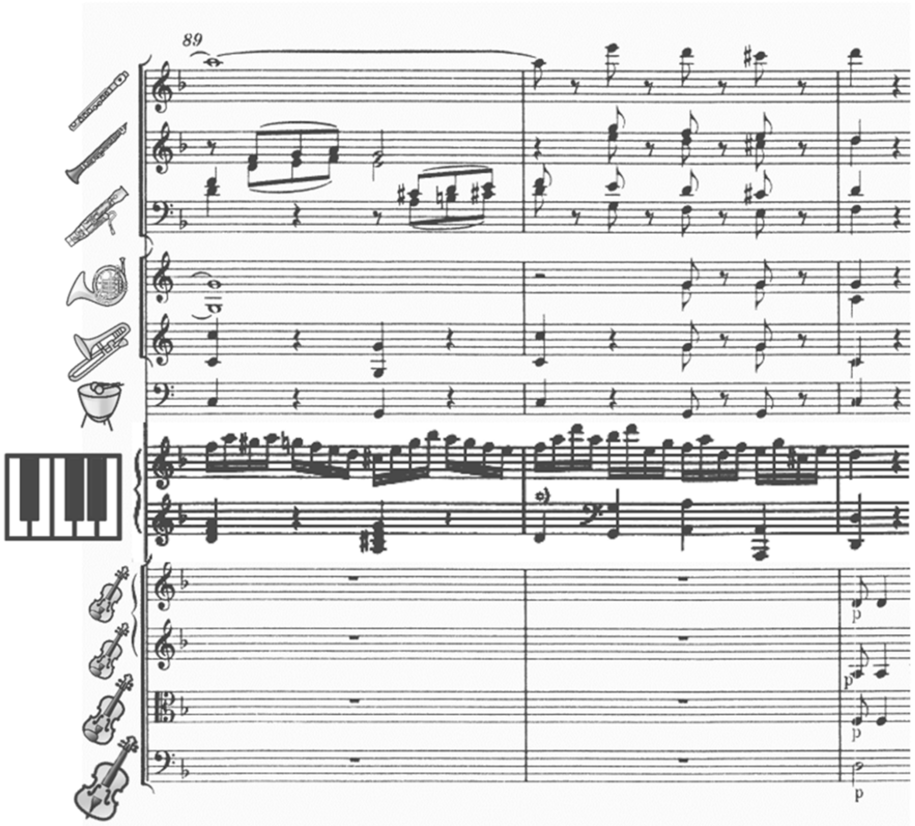
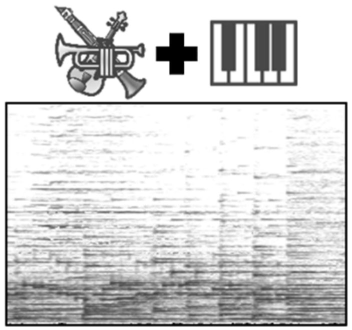


**Only Piano!**

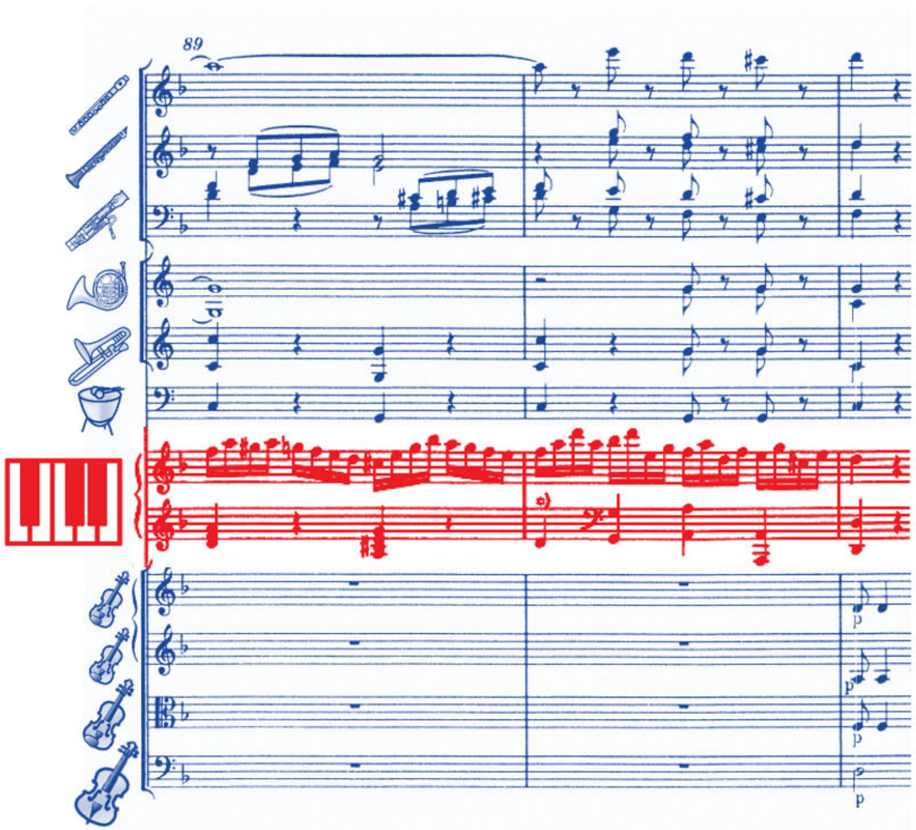
**Where is the orchestra?**

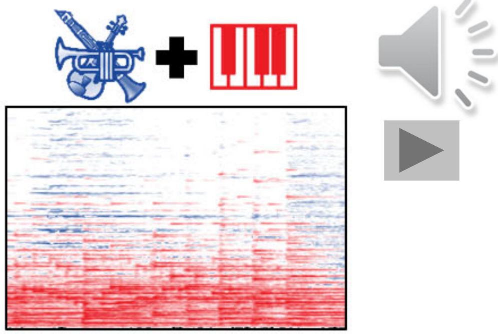
# Source Separation (Piano Concerto)



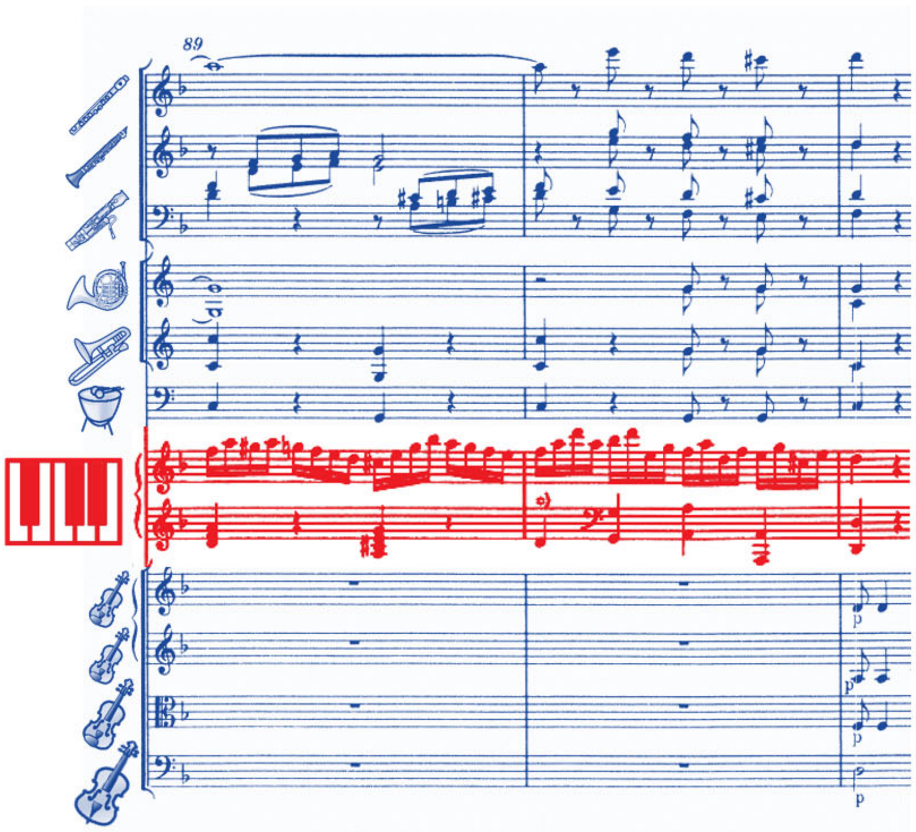


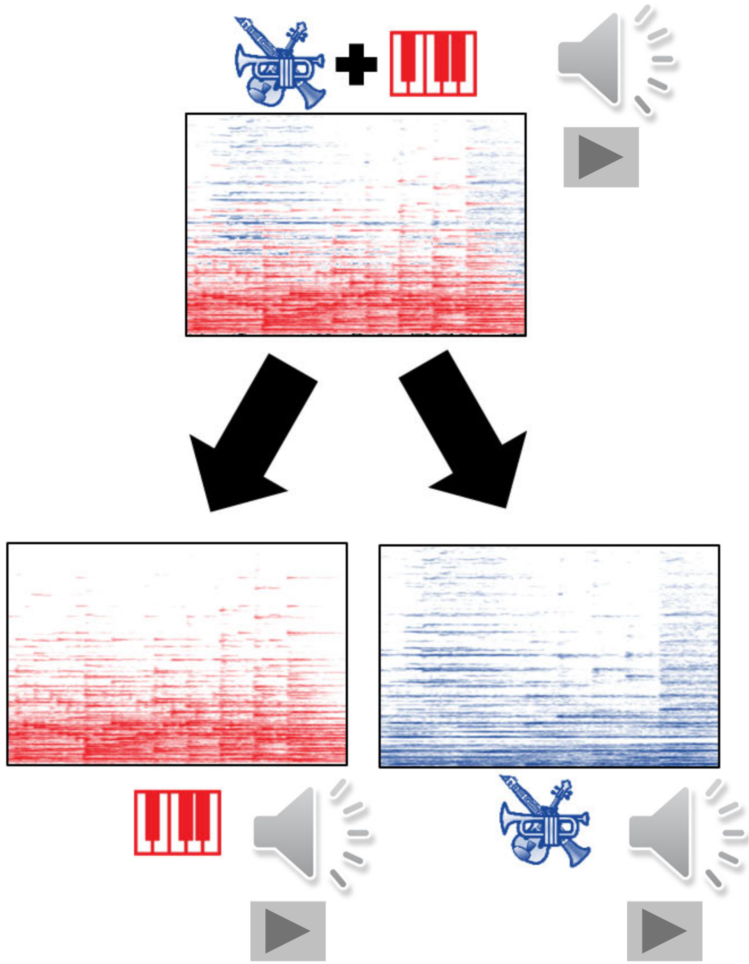
# Source Separation (Piano Concerto)



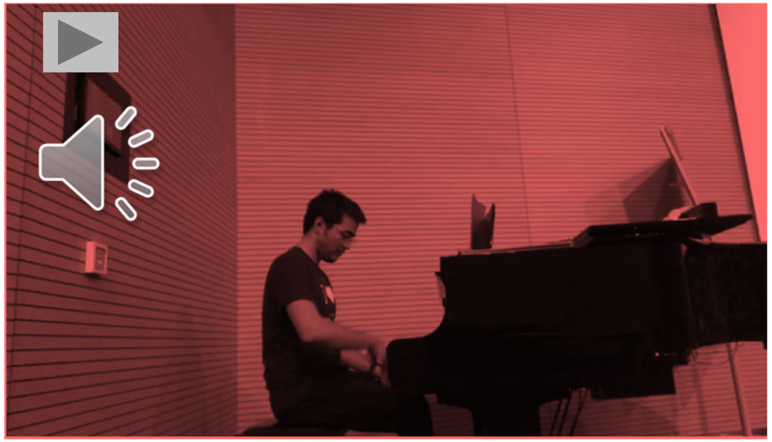



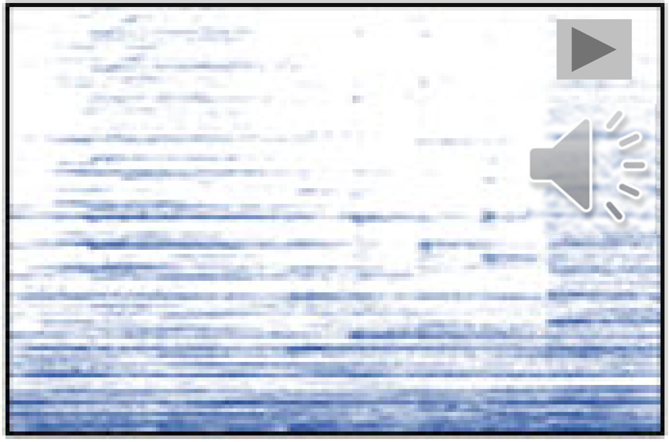
# Source Separation (Piano Concerto)





# Source Separation (Piano Concerto)





**Piano Source Separation**

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

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