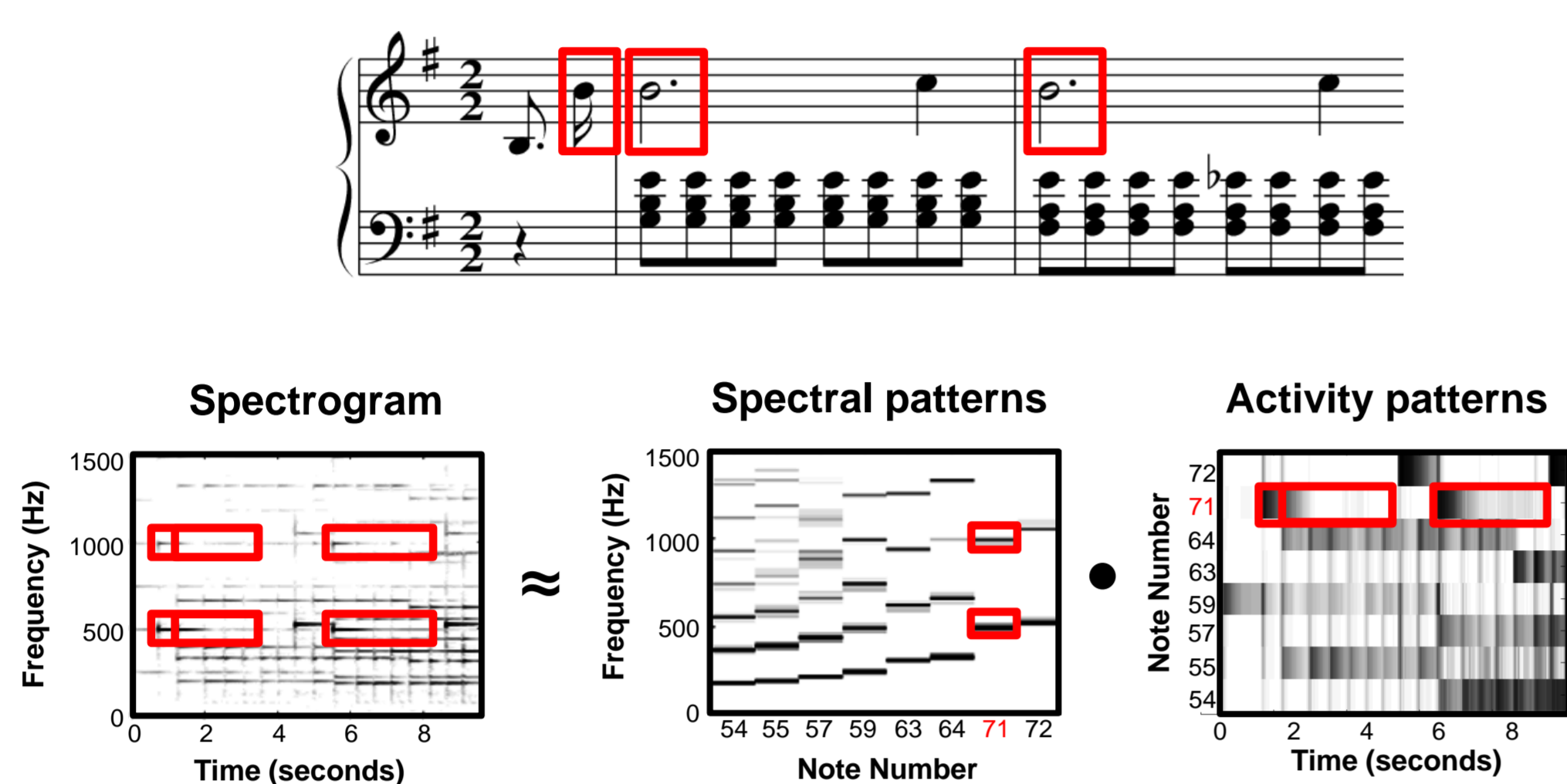


# INVESTIGATING NONNEGATIVE AUTOENCODERS FOR EFFICIENT AUDIO DECOMPOSITION

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## Introduction

- Task: Score-Informed Audio Decomposition
- Given the magnitude spectrogram of a music recording, encode
  - Spectral patterns, *templates*
  - Occurrences in time, *activations*



## NMF and NAE

- Multiplicative Nonnegative Matrix Factorization (NMF Mult.)

$$H \leftarrow H \odot (W^T V) \oslash (W^T W H + \epsilon)$$

$$W \leftarrow W \odot (V H^T) \oslash (W H H^T + \epsilon)$$

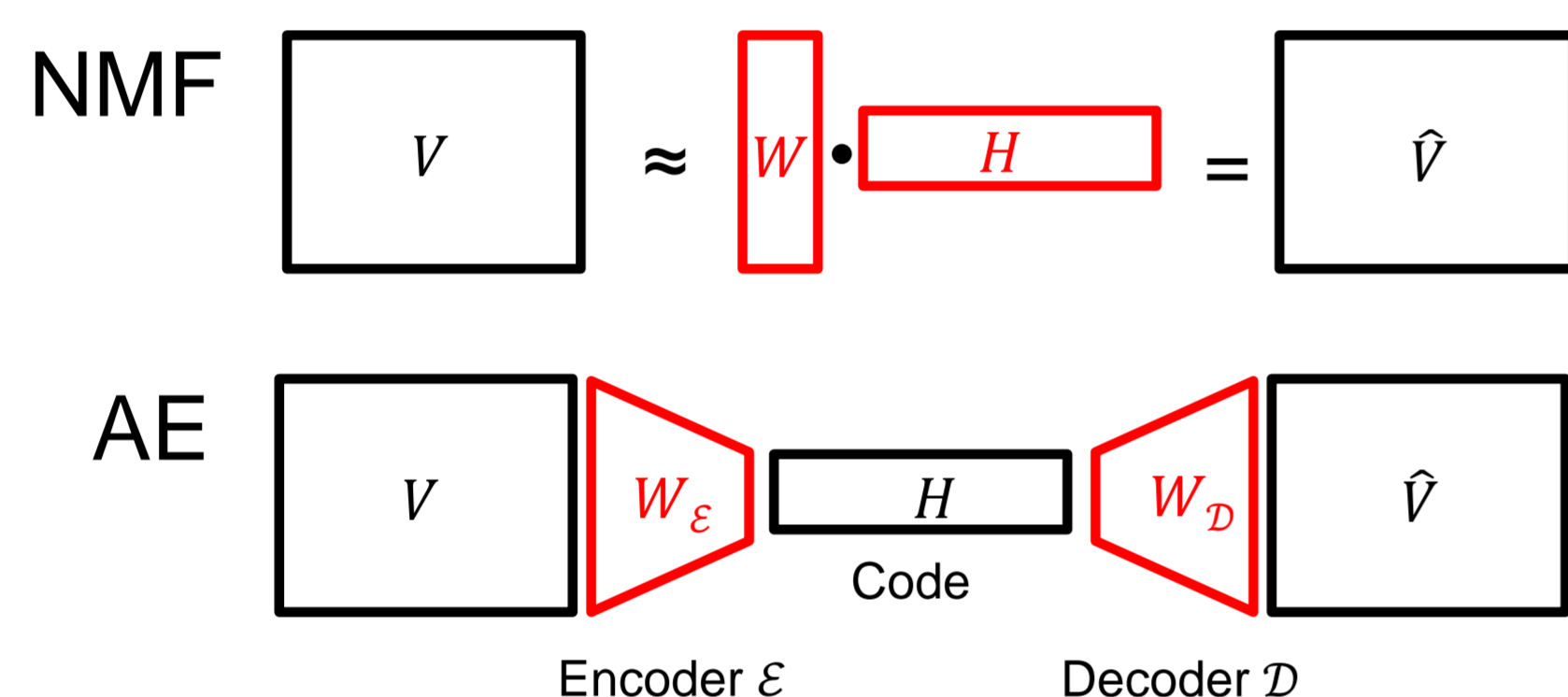
- This work: **Multiplicative NAE (NAE Mult.)**

$$W_\epsilon \leftarrow W_\epsilon \odot \left( \left( (W_D^T V) \odot H^C \right) V^T \right) \oslash \left( \left( (W_D^T W_D H') \odot H^C \right) V^T + \epsilon \right)$$

$$W_D \leftarrow W_D \odot \left( (V H'^T) \right) \oslash (W_D H' H'^T + \epsilon)$$

- Additive NAE
  - NAE SGD
  - NAE ADAM
  - NAE RMSprop

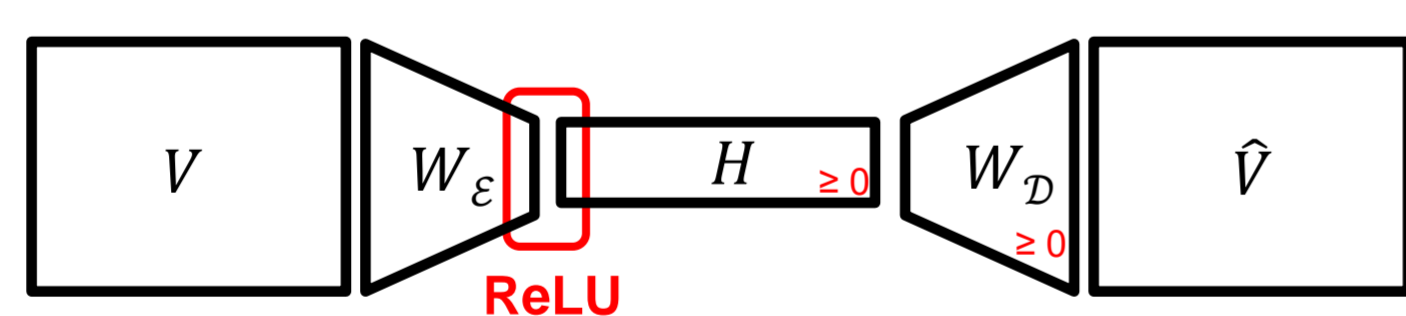
## Nonnegative Autoencoders (NAE)



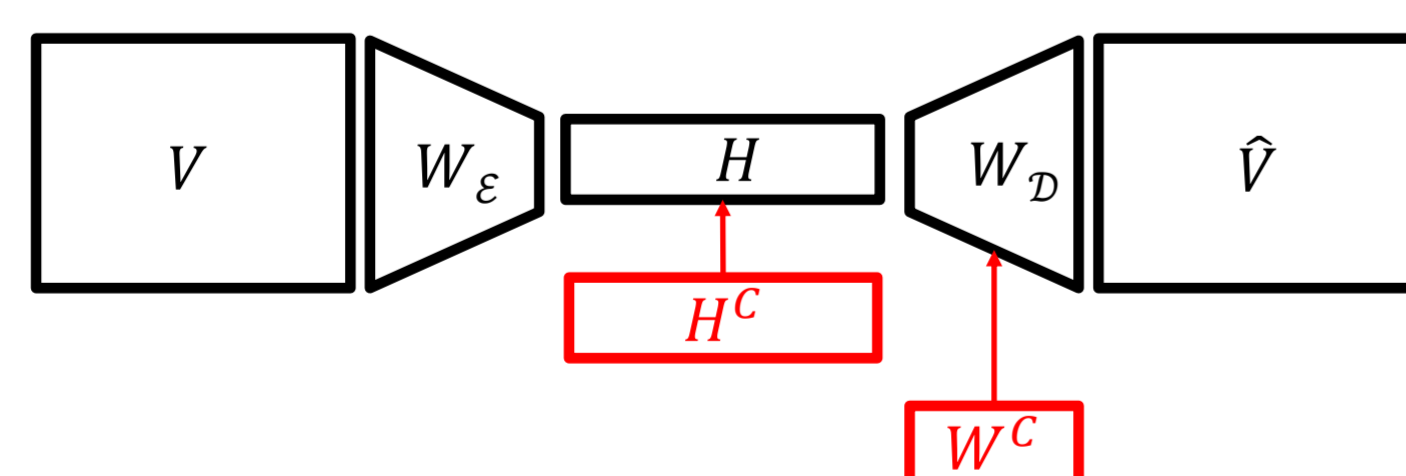
- Layer:  $H = W_\epsilon V$
- Layer:  $\hat{V} = W_D H$

NMF: Learn  $H$  and  $W$   
AE: Learn  $W_\epsilon$  and  $W_D$

- Nonnegativity constraints
  - Code  $H \rightarrow \text{ReLU}$
  - Decoder  $\mathcal{D} \rightarrow \text{Projected gradient}$



- Musical constraints
  - Activity constraints  $\rightarrow$  Structured Dropout
  - Template constraints  $\rightarrow$  Binary masking

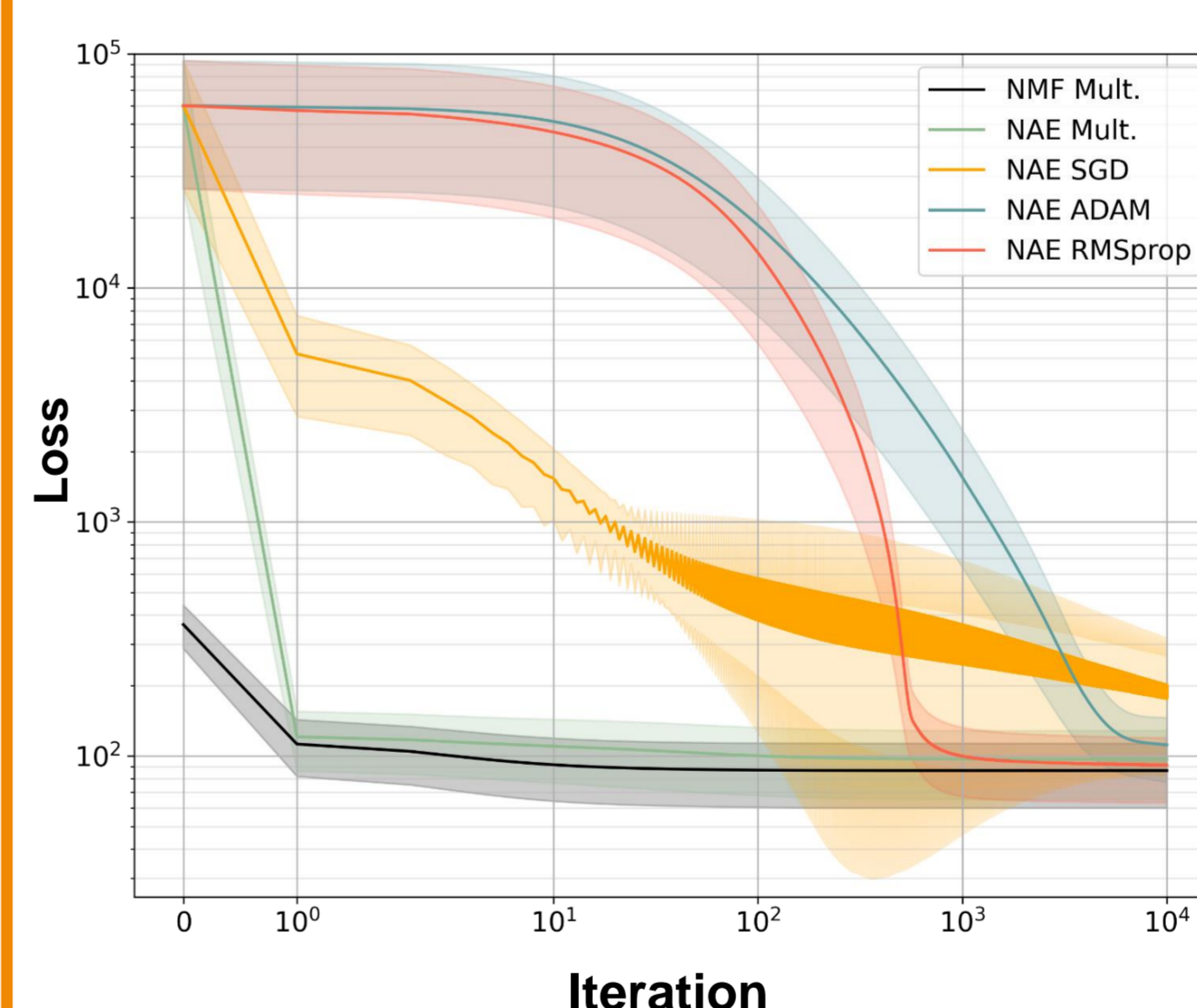


## Results

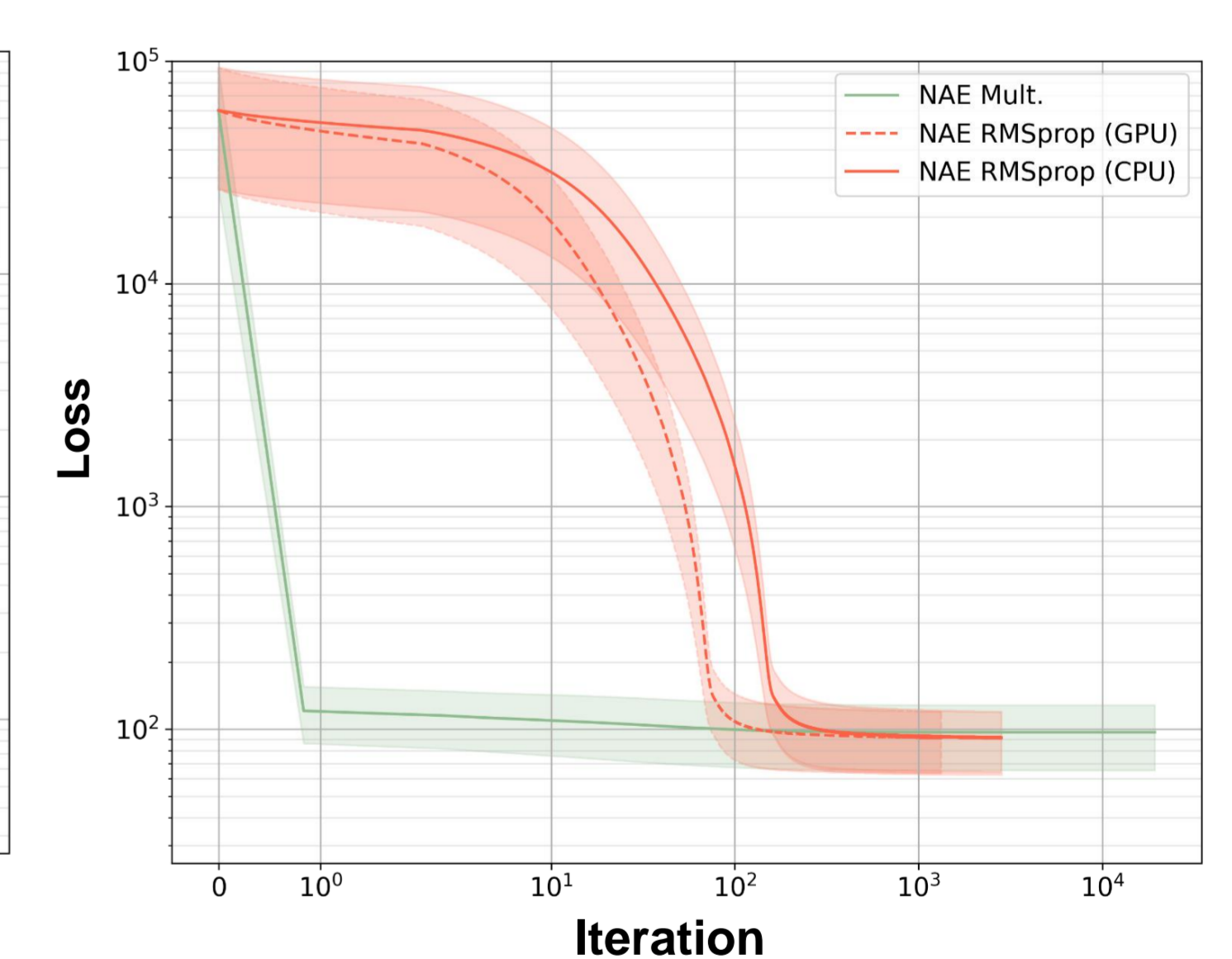
Approximation Error between  $V$  and  $\hat{V}$

File ID	Model				
	NMF Mult.	NAE Mult.	NAE SGD	NAE ADAM	NAE RMSprop
Chopin_Op028-04_SMD	46.4	49.0	62.4	57.6	48.1
Chopin_Op028-15_SMD	48.5	53.2	67.3	66.2	50.9
Chopin_Op066_SMD	79.5	87.2	139.0	101.1	85.7
Beethoven_Op031No2-01_SMD	90.7	99.2	105.1	104.4	94.9
Chopin_Op028-01_SMD	94.8	103.6	299.9	122.8	97.4
Bach_BWV875-01_SMD	97.5	107.3	219.9	129.2	104.3
Beethoven_Op111-01_EA	103.7	129.4	328.5	148.4	113.0
Chopin_Op064No1_EA	131.9	145.9	383.6	161.6	137.2

Average Approximation Error



Runtime Comparison



**RMSprop** outperforms other NAE variants in terms of the approximation quality and efficiency.

<https://resources.mpi-inf.mpg.de/MIR/ICASSP2012-ScoreInformedNMF/>

## References

- [1] Lee and Seung: Algorithms for Non-Negative Matrix Factorization. Proc. NIPS, 2000.
- [2] Ewert and Müller: Using Score-Informed Constraints for NMF-based Source Separation. ICASSP, 2012.
- [3] Smaragdis and Venkataramani: A Neural Network Alternative to Non-negative Audio Models. ICASSP, 2017.
- [4] Ewert and Sandler: Structured Dropout for Weak Label and Multi-instance Learning and its Application for Score-Informed Source Separation. ICASSP, 2017.

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