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

Loss Functions Matter

Three Case Studies in Informed Loss Design

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

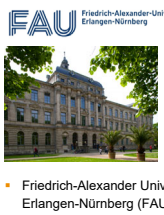
ADASP Workshop
Telecom Paris, France, June 12, 2025

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

International Audio Laboratories Erlangen

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



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

International Audio Laboratories Erlangen

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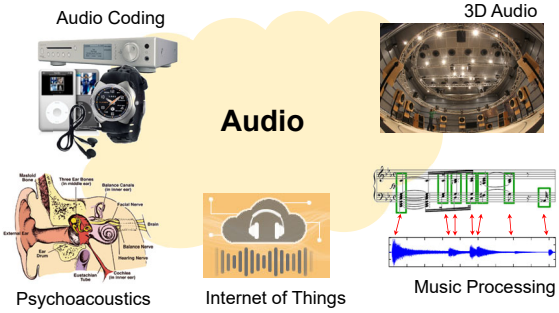

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- Simon Schwär
- Johannes Zeitler
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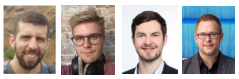
- Stefan Balke



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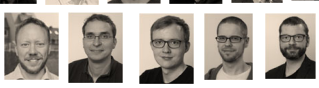

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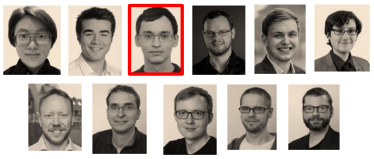

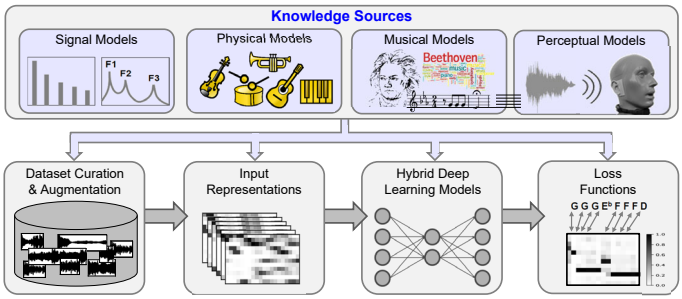

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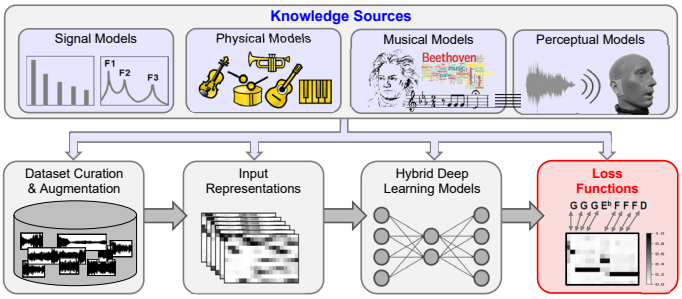

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Overview

- Multi-Scale Spectral Loss
  Knowledge Source: Signal Representations
- Hierarchical Classification Loss
  Knowledge Source: Musical Hierarchies
- Differentiable Alignment Loss
  Knowledge Source: Temporal Coherence


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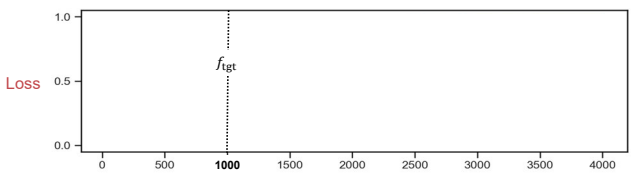
Literature
- Turian, Henry: I'm sorry for your loss: Spectrally-based audio distances are bad at pitch. Proc. Adv. Neural Inf. Process. Syst., 2020.
- Hayes, Saitis, Fazekas: Sinusoidal frequency estimation by gradient descent. Proc. ICASSP, 2023.
- Torres, Peeters, Richard: Unsupervised Harmonic Parameter Estimation Using DDSP and Spectral Optimal Transport. Proc. ICASSP, 2024
- **Schwär**, Müller: Multi-Scale Spectral Loss Revisited. IEEE Signal Processing Letters, 30: 1712–1716, 2023.

Example Scenario: Sinusoidal Frequency Estimation

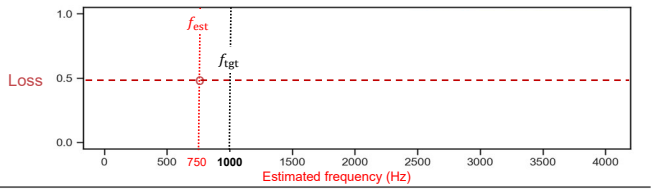
Sinusoid with target frequency: $f_{\text{tgt}} = 1000$ Hz



Example Scenario: Sinusoidal Frequency Estimation

Sinusoid with target frequency: $f_{\text{tgt}} = 1000$ Hz

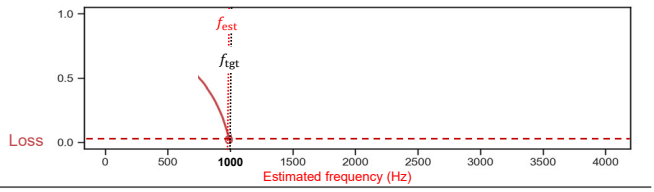
Sinusoid with estimated frequency: $f_{\text{est}} = 750$ Hz



Example Scenario: Sinusoidal Frequency Estimation

Sinusoid with target frequency: $f_{\text{tgt}} = 1000$ Hz

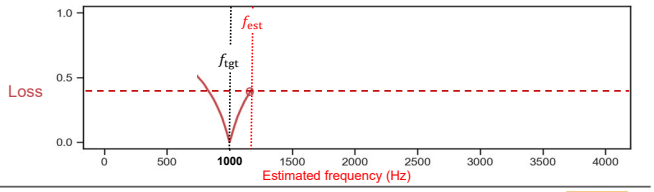
Sinusoid with estimated frequency: $f_{\text{est}} = 972$ Hz



Example Scenario: Sinusoidal Frequency Estimation

Sinusoid with target frequency: $f_{\text{tgt}} = 1000$ Hz

Sinusoid with estimated frequency: $f_{\text{est}} = 1100$ Hz

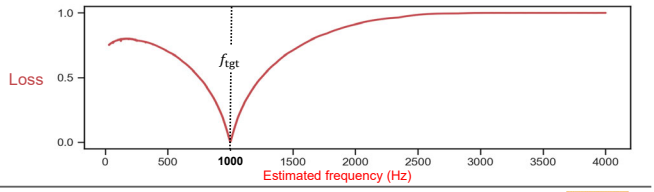


Example Scenario: Sinusoidal Frequency Estimation

Sinusoid with target frequency: $f_{\text{tgt}} = 1000$ Hz

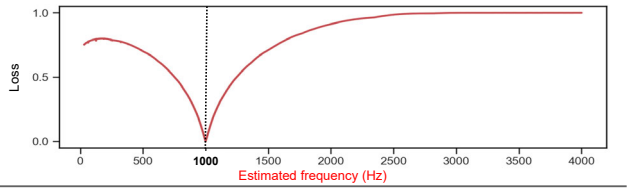
Sinusoidal sweep of estimated frequencies f_{est}

Loss landscape over **estimates** for a given **target**



Example Scenario: Sinusoidal Frequency Estimation

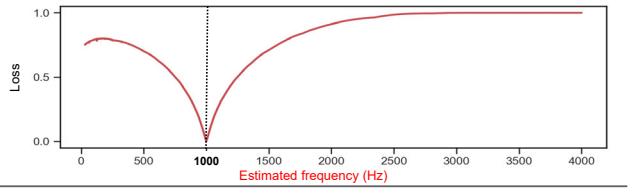
Loss landscape depends a lot on the chosen loss function to compare **estimated** and **target** signal



Example Scenario: Sinusoidal Frequency Estimation

Loss landscape depends a lot on the chosen loss function to compare **estimated** and **target** signal

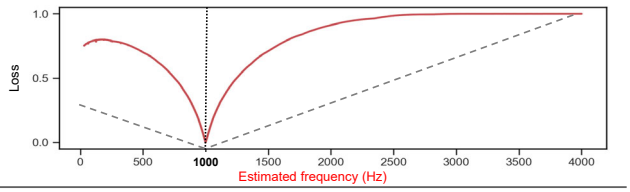
- Loss function discussed later



Example Scenario: Sinusoidal Frequency Estimation

Loss landscape depends a lot on the chosen loss function to compare **estimated** and **target** signal

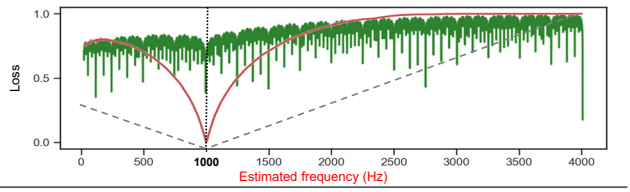
- Loss function discussed later
- Ideal convex loss



Example Scenario: Sinusoidal Frequency Estimation

Loss landscape depends a lot on the chosen loss function to compare **estimated** and **target** signal

- Loss function discussed later
- Ideal convex loss
- Multi-Scale Spectral (MSS) loss with standard settings



Example Scenario: Sinusoidal Frequency Estimation

Loss landscape depends a lot on the chosen loss function to compare **estimated** and **target** signal

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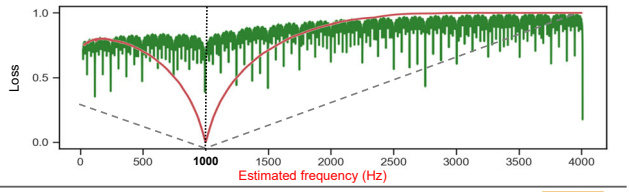
The MSS loss is what we widely use in audio processing (e.g., DDSP)



Multi-Scale Spectral Loss

- x input signal
- N window size
- H hop size
- w window function
- p compression function
- d distance function
- $\mathcal{N}$ set of window sizes
- $\mathcal{P}$ set of compression function

Configuration	Value	Description
Window Type	WR	Rectangular window
	WH	Hann window
	WF	Flat Top window
Window Size(s)	S1	$\mathcal{N} = \{64\}$
	S2	$\mathcal{N} = \{512\}$
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Magnitude Compression	C0	$\mathcal{P} = \{x\}$
	C1	$\mathcal{P} = \{\log(x + \varepsilon)\},\ \varepsilon = 10^{-7}$
	C2	$\mathcal{P} = \{\log(1 + \gamma x)\},\ \gamma = 1$
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Matrix Distance	D1	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_1$
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Spectrum $\mathcal{Y}_{w,N,p}(m,k) = p\left(\left|\sum_{n=0}^{N-1} x[n+mH]w[n]\exp\left(\frac{-i2\pi kn}{N}\right)\right|\right)$

MSS loss $\mathcal{L}_{\mathrm{MSS}}(x,\hat{x}) := \sum_{N\in\mathcal{N}}\sum_{p\in\mathcal{P}} d(\mathcal{Y}_{w,N,p}, \hat{\mathcal{Y}}_{w,N,p})$

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Spectrum $$\mathcal{Y}_{w,N,p}(m,k) = p\left(\left|\sum_{n=0}^{N-1} x[n+mH]w[n]\exp\left(\frac{-i2\pi kn}{N}\right)\right|\right)$$

MSS loss $$\mathcal{L}_{\text{MSS}}(x,\hat{x}) := \sum_{N\in\mathcal{N}}\sum_{p\in\mathcal{P}} d(\mathcal{Y}_{w,N,p}, \hat{\mathcal{Y}}_{w,N,p})$$

Multi-Scale Spectral Loss

- x input signal
- N window size
- H hop size
- w window function
- p compression function
- d distance function
- $\mathcal{N}$ set of window sizes
- $\mathcal{P}$ set of compression function

MSS loss with standard settings: (WH, S4, C4, D1)

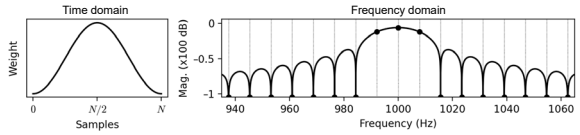
Configuration	Value	Description
Window Type	WR	Rectangular window
	WH	Hann window
	WF	Flat Top window
Window Size(s)	S1	$\mathcal{N} = \{64\}$
	S2	$\mathcal{N} = \{512\}$
	S3	$\mathcal{N} = \{2048\}$
	S4	$\mathcal{N} = \{64, 128, 256, 512, 1024, 2048\}$
	S5	$\mathcal{N} = \{67, 127, 257, 509, 1021, 2053\}$
Magnitude Compression	C0	$\mathcal{P} = \{x\}$
	C1	$\mathcal{P} = \{\log(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
	C2	$\mathcal{P} = \{\log(1+\gamma x)\},\ \gamma = 1$
	C3	$\mathcal{P} = \{20\log_{10}(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
	C4	$\mathcal{P} = \{x,\ \log(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
Matrix Distance	D1	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_1$
	D2	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_2^2$

Spectrum $$\mathcal{Y}_{w,N,p}(m,k) = p\left(\left|\sum_{n=0}^{N-1} x[n+mH]w[n]\exp\left(\frac{-i2\pi kn}{N}\right)\right|\right)$$

MSS loss $$\mathcal{L}_{\text{MSS}}(x,\hat{x}) := \sum_{N\in\mathcal{N}}\sum_{p\in\mathcal{P}} d(\mathcal{Y}_{w,N,p}, \hat{\mathcal{Y}}_{w,N,p})$$

Spectrum-Based Distance

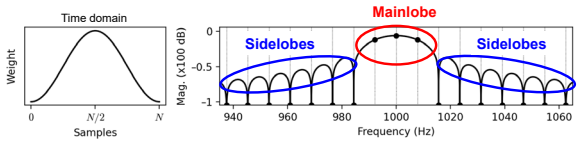
Hann window



- Input signal: Sinusoid with frequency $f = 1000$ Hz

Spectrum-Based Distance

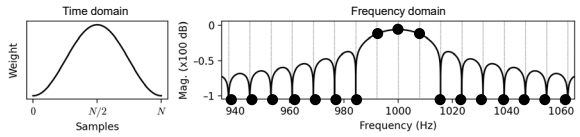
Hann window



- Input signal: Sinusoid with frequency $f = 1000$ Hz
- STFT → Spectral leakage due to windowing

Spectrum-Based Distance

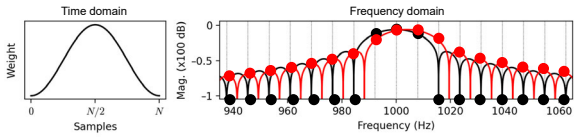
Hann window



- Input signal: Sinusoid with frequency $f = 1000$ Hz
- STFT → Spectral leakage due to windowing
- Discrete STFT → **Frequency grid**

Spectrum-Based Distance

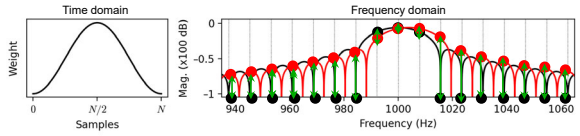
Hann window



- Input signal: Sinusoid with frequency $f = 1000$ Hz
- STFT → Spectral leakage due to windowing
- Discrete STFT → **Frequency grid**
- Second signal: Sinusoid with frequency $f = 1003.9$ Hz

Spectrum-Based Distance

Hann window

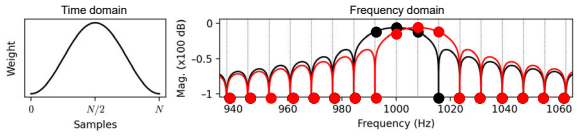


- Input signal: Sinusoid with frequency $f = 1000$ Hz
- STFT → Spectral leakage due to windowing
- Discrete STFT → **Frequency grid**
- Second signal: Sinusoid with frequency $f = 1003.9$ Hz

Distance depends on
- Grid sampling
- Mainlobe & sidelobes
- Window type
- STFT parameters

Spectrum-Based Distance

Hann window

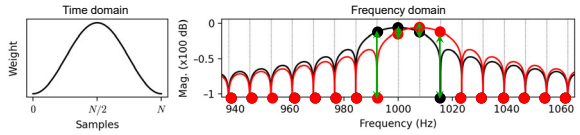


- Input signal: Sinusoid with frequency $f = 1000$ Hz
- STFT → Spectral leakage due to windowing
- Discrete STFT → **Frequency grid**
- Second signal: Sinusoid with frequency $f = 1007.8$ Hz

Distance depends on
- Grid sampling
- Mainlobe & sidelobes
- Window type
- STFT parameters

Spectrum-Based Distance

Hann window

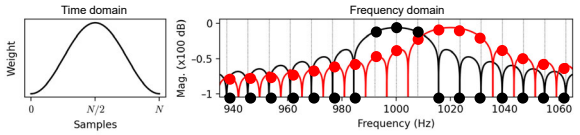


- Input signal: Sinusoid with frequency $f = 1000$ Hz
- STFT → Spectral leakage due to windowing
- Discrete STFT → **Frequency grid**
- Second signal: Sinusoid with frequency $f = 1007.8$ Hz

Distance depends on
- Grid sampling
- Mainlobe & sidelobes
- Window type
- STFT parameters

Spectrum-Based Distance

Hann window

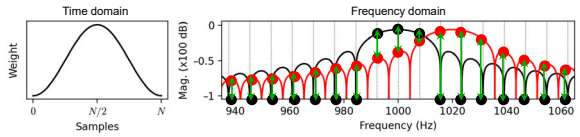


- Input signal: Sinusoid with frequency $f = 1000$ Hz
- STFT → Spectral leakage due to windowing
- Discrete STFT → **Frequency grid**
- Second signal: Sinusoid with frequency $f = 1020$ Hz

Distance depends on
- Grid sampling
- Mainlobe & sidelobes
- Window type
- STFT parameters

Spectrum-Based Distance

Hann window

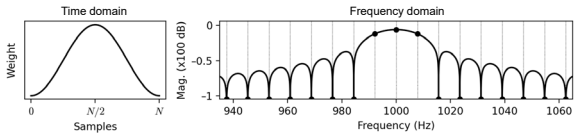


- Input signal: Sinusoid with frequency $f = 1000$ Hz
- STFT → Spectral leakage due to windowing
- Discrete STFT → **Frequency grid**
- Second signal: Sinusoid with frequency $f = 1020$ Hz

Distance depends on
- Grid sampling
- Mainlobe & sidelobes
- Window type
- STFT parameters

Dependency: Window Type

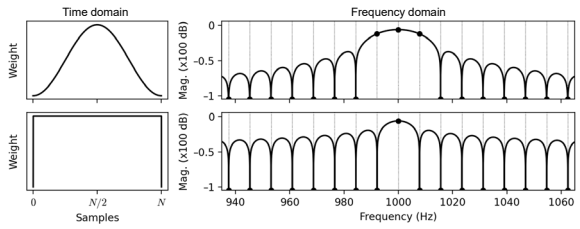
Hann window



Dependency: Window Type

Hann window

Rectangular window

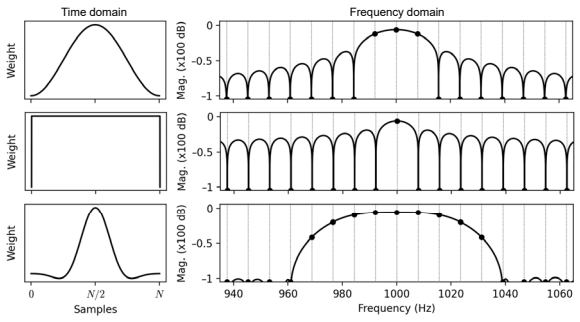


Dependency: Window Type

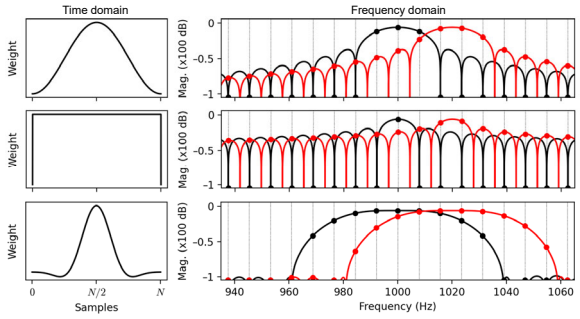
Hann window

Rectangular window

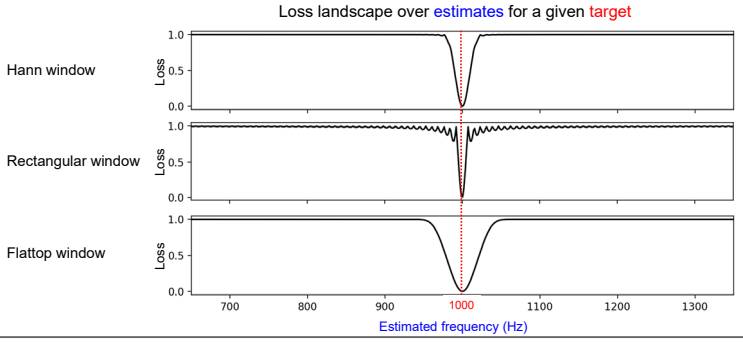
Flattop window



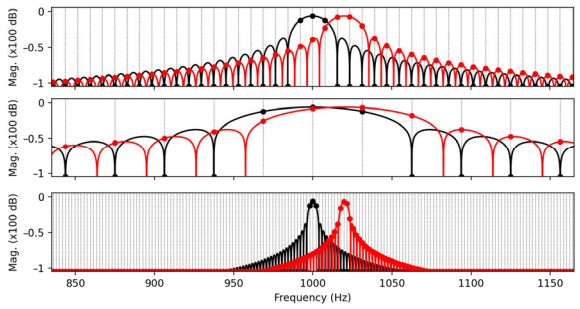
Dependency: Window Type



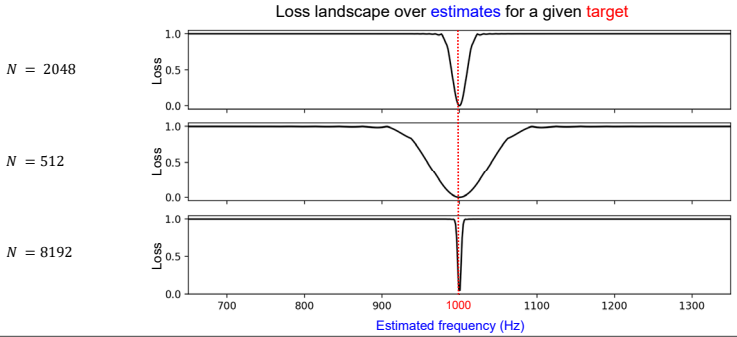
Dependency: Window Type



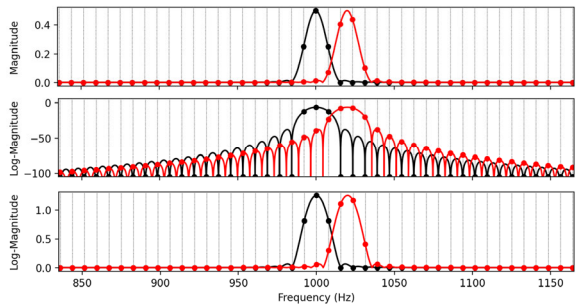
Dependency: Window Size



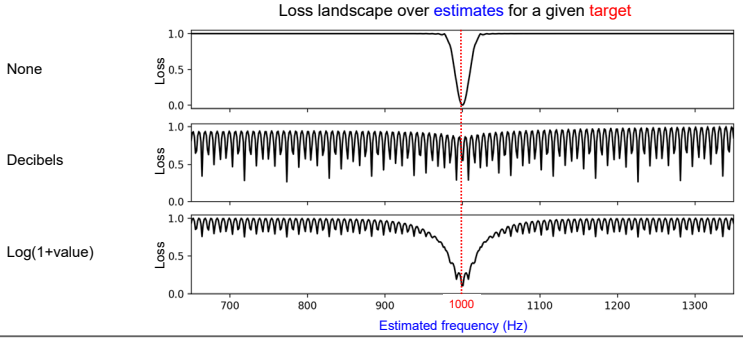
Dependency: Window Size



Dependency: Magnitude Compression



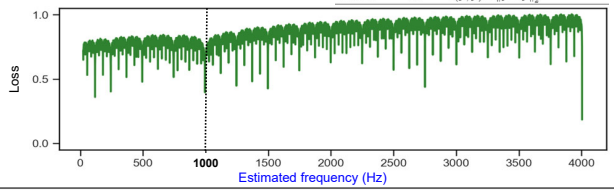
Dependency: Magnitude Compression



Experiments

- MSS loss with standard settings (WH, S4, C4, D1)

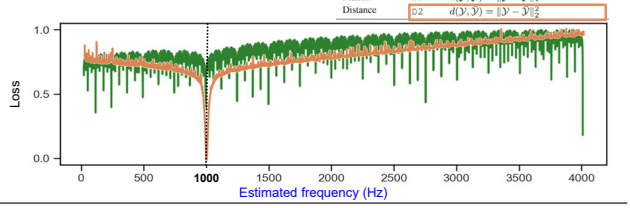
Configuration	Value	Description
Window Type	WR	Rectangular window
	WH	Hann window
	WF	Flat Top window
Window Size(s)	S1	$\mathcal{N} = \{64\}$
	S2	$\mathcal{N} = \{512\}$
	S3	$\mathcal{N} = \{2048\}$
	S4	$\mathcal{N} = \{64, 128, 256, 512, 1024, 2048\}$
	S5	$\mathcal{N} = \{67, 127, 257, 509, 1021, 2053\}$
Magnitude Compression	C0	$\mathcal{P} = \{x\}$
	C1	$\mathcal{P} = \{\log(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
	C2	$\mathcal{P} = \{\log(1+\gamma x)\},\ \gamma = 1$
	C3	$\mathcal{P} = \{20\log_{10}(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
	C4	$\mathcal{P} = \{x,\ \log(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
Matrix Distance	D1	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_1$
	D2	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_2^2$



Experiments

- MSS loss with standard settings (WH, S4, C4, D1)
- Modified Hann MSS (WH, S5, C4, D2)

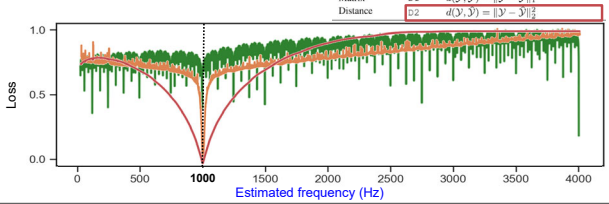
Configuration	Value	Description
Window Type	WR	Rectangular window
	WH	Hann window
	WF	Flat Top window
Window Size(s)	S1	$\mathcal{N} = \{64\}$
	S2	$\mathcal{N} = \{512\}$
	S3	$\mathcal{N} = \{2048\}$
	S4	$\mathcal{N} = \{64, 128, 256, 512, 1024, 2048\}$
	S5	$\mathcal{N} = \{67, 127, 257, 509, 1021, 2053\}$
Magnitude Compression	C0	$\mathcal{P} = \{x\}$
	C1	$\mathcal{P} = \{\log(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
	C2	$\mathcal{P} = \{\log(1+\gamma x)\},\ \gamma = 1$
	C3	$\mathcal{P} = \{20\log_{10}(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
	C4	$\mathcal{P} = \{x,\ \log(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
Matrix Distance	D1	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_1$
	D2	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_2^2$



Experiments

- MSS loss with standard settings (WH, S4, C4, D1)
- Modified Hann MSS (WH, S5, C4, D2)
- Smooth MSS (WF, S5, C2, D2)

Configuration	Value	Description
Window Type	WR	Rectangular window
	WH	Hann window
	WF	Flat Top window
Window Size(s)	S1	$\mathcal{N} = \{64\}$
	S2	$\mathcal{N} = \{512\}$
	S3	$\mathcal{N} = \{2048\}$
	S4	$\mathcal{N} = \{64, 128, 256, 512, 1024, 2048\}$
	S5	$\mathcal{N} = \{67, 127, 257, 509, 1021, 2053\}$
Magnitude Compression	C0	$\mathcal{P} = \{x\}$
	C1	$\mathcal{P} = \{\log(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
	C2	$\mathcal{P} = \{\log(1+\gamma x)\},\ \gamma = 1$
	C3	$\mathcal{P} = \{20\log_{10}(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
	C4	$\mathcal{P} = \{x,\ \log(x+\varepsilon)\},\ \varepsilon = 10^{-7}$
Matrix Distance	D1	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_1$
	D2	$d(\mathcal{Y}, \hat{\mathcal{Y}}) = \|\mathcal{Y} - \hat{\mathcal{Y}}\|_2^2$

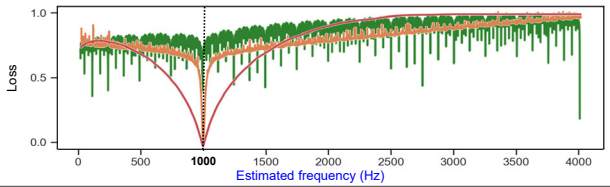


Experiments

GRA (Gradient-Sign Ranking Accuracy)

- Measures how often the loss gradient points in the correct direction.
- **Step size** distinguishes local gradient behavior from global trend.

Configuration	GRA			
Step Size	0.3 ct.	3 ct.	30 ct.	300 ct.
Standard MSS	0.523	0.529	0.573	0.775
Modified Hann MSS	0.613	0.635	0.708	0.923
Smooth MSS	0.999	0.993	0.952	0.860



Overview

- Multi-Scale Spectral Loss
  Knowledge Source: Signal Representations
- Hierarchical Classification Loss
  Knowledge Source: Musical Hierarchies
- Differentiable Alignment Loss
  Knowledge Source: Temporal Coherence


Simon Schwär


Michael Krause


Johannes Zeitler

Literature
- Silla, Freitas: A survey of hierarchical classification across different application domains. Data Mining and Knowledge Discovery, 22(1-29: 31–72, 2011.
- Wehrmann, Cerri, Barros: Hierarchical multi-label classification networks. Proc. ICML, 2018.
- **Krause**, Müller: Hierarchical Classification for Singing Activity, Gender, and Type in Complex Music Recordings. Proc. ICASSP, 2022.
- **Krause**, Müller: Hierarchical Classification for Instrument Activity Detection in Orchestral Music Recordings. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 31: 2567–2578, 2023.
- Weiß, Arifi-Müller, **Krause**, Zalkow, Klauk, Kleinertz, Müller: Wagner Ring Dataset: A Complex Opera Scenario for Music Processing and Computational Musicology. Transaction of the International Society for Music Information Retrieval (TISMIR), 6(1): 135–149, 2023.

Wagner Ring Dataset

- Tetralogy (four operas)

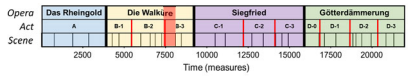
Opera	Das Rheingold	Die Walküre	Siegfried	Götterdämmerung

Wagner Ring Dataset

- Tetralogy (four operas)
- 11 Acts

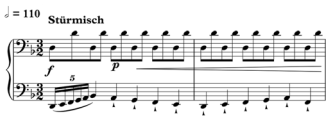
Wagner Ring Dataset

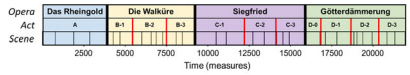
- Tetralogy (four operas)
- 11 Acts
- 21,939 measures



Wagner Ring Dataset
Raw Data

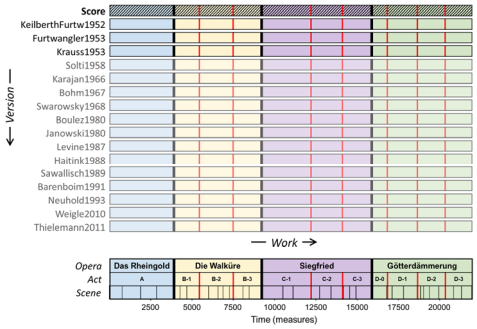
- Symbolic score:
  - Piano reduction
  - 822 pages





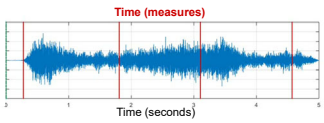
Wagner Ring Dataset
Raw Data

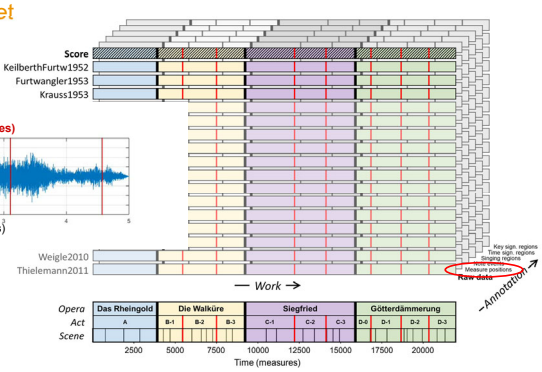
- Symbolic score:
  - Piano reduction
  - 822 pages
- Audio recordings:
  - 16 performances
  - 232 hours
  - 3 performances in Public Domain (EU)



Wagner Ring Dataset
Annotations

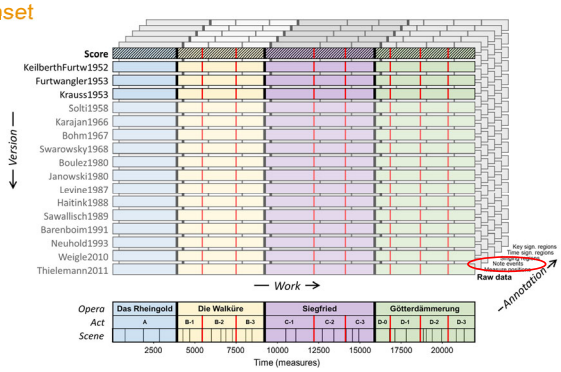
- Measure positions





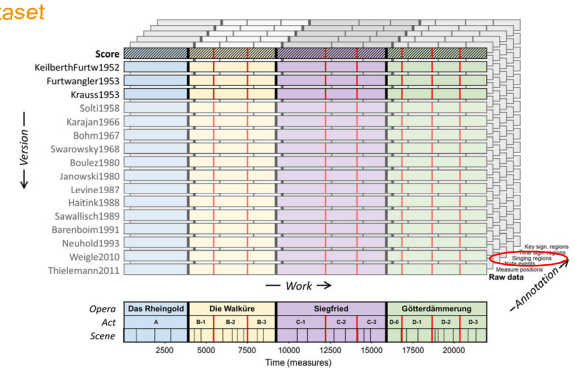
Wagner Ring Dataset
Annotations

- Measure positions
- Note events



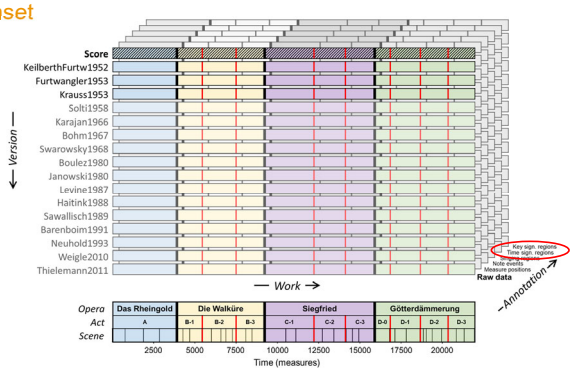
Wagner Ring Dataset
Annotations

- Measure positions
- Note events
- Singing regions



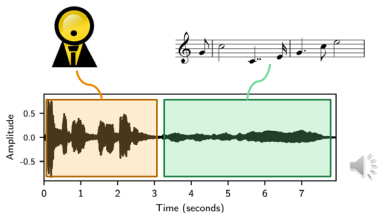
Wagner Ring Dataset
Annotations

- Measure positions
- Note events
- Singing regions
- Time signatures
- Key signatures



PhD Thesis by Michael Krause (2023)
Activity Detection for Sound Events in Orchestral Music Recordings

Singing Voice Detection | Leitmotif Detection | Instrument Detection



Hierarchical Classification
Singing Voice Detection

	Levels
Singing activity	Activity

Hierarchical Classification
Singing Voice Detection

	Levels
Singing activity	Activity
Male / Female	Gender

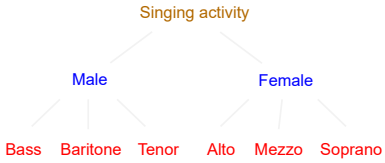
Hierarchical Classification
Singing Voice Detection

	Levels
Singing activity	Activity
Male / Female	Gender
Bass / Baritone / Tenor / Alto / Mezzo / Soprano	Voice type

Hierarchical Strategies for Activity Detection

- Strategy A: Independent Decisions
- Strategy B: Bottom-Up Aggregation
- Strategy C: Top-Down Divide-and-Conquer
- Strategy D: Joint Classification
- Strategy $D^{\alpha,\beta}$: Joint Classification with Consistency Losses

Hierarchical Strategies for Activity Detection
Strategy A: Independent Decisions

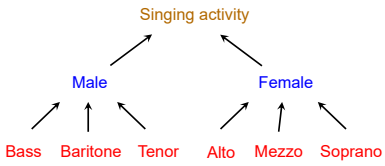


- Train and evaluate separate models for each hierarchy level
  - Activity classifier
  - Gender classifier
  - Voice type classifier

Hierarchical Strategies for Activity Detection
Strategy A: Independent Decisions

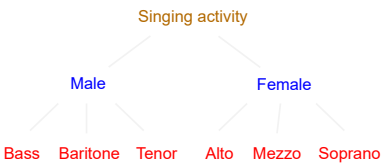
- Train and evaluate separate models for each hierarchy level
  - Activity classifier
  - Gender classifier
  - Voice type classifier
- Outputs may be inconsistent

Hierarchical Strategies for Activity Detection
Strategy B: Bottom-Up Aggregation



- Train and evaluate a single model for the lowest hierarchy level
  - Voice type classifier
- Aggregate results from lower levels
- Consistency is trivially fulfilled
- May cause poor predictions on upper levels due to error propagation

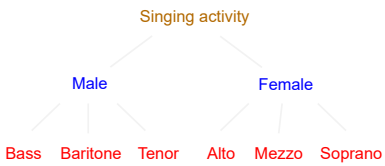
Hierarchical Strategies for Activity Detection
Strategy D: Joint Classification



- Train and evaluate a single model for all classes

  → **Multi-task model**
- Need additional loss terms to promote consistent predictions

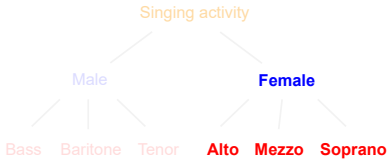
Hierarchical Strategies for Activity Detection
Strategy $D^{\alpha,\beta}$: Joint Classification with Consistency Losses



Hierarchical Strategies for Activity Detection
Strategy $D^{\alpha,\beta}$: Joint Classification with Consistency Losses

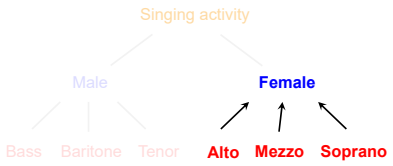
- Notation:
  - c: a class
  - p_c: probability of c

Hierarchical Strategies for Activity Detection
Strategy $D^{\alpha,\beta}$: Joint Classification with Consistency Losses



- Notation:
  - c: a class
  - p_c: probability of c
  - $c\downarrow$: child classes of c

Hierarchical Strategies for Activity Detection
Strategy $D^{\alpha,\beta}$: Joint Classification with Consistency Losses



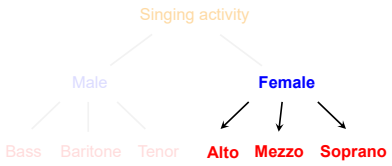
- Notation:
  - c: a class
  - p_c: probability of c
  - $c\downarrow$: child classes of c
- For **bottom-up** consistency, minimize

$$\sum_{c' \in c\downarrow} \max\{0, p_{c'} - p_c\}^2$$

p_c should be at least as high as any $p_{c'}$

→ penalty for every $p_{c'} > p_c$

Hierarchical Strategies for Activity Detection
Strategy $D^{\alpha,\beta}$: Joint Classification with Consistency Losses



- Notation:
  - c: a class
  - p_c: probability of c
  - $c\downarrow$: child classes of c
- For **top-down** consistency, minimize

$$\max\{0, p_c - \max_{c' \in c\downarrow} p_{c'}\}^2$$

p_c should not be above largest $p_{c'}$

Hierarchical Strategies for Activity Detection
Strategy $D^{\alpha,\beta}$: Joint Classification with Consistency Losses

Bottom-up loss term:

$$\mathcal{L}_{\uparrow} = \frac{1}{|\mathbf{C} \setminus \mathbf{C}^H|} \sum_{h=2}^{H} \sum_{c \in \mathbf{C}^h} \sum_{c' \in c\downarrow} \max\{0, p_{c'} - p_c\}^2$$

Top-down loss term:

$$\mathcal{L}_{\downarrow} = \frac{1}{|\mathbf{C} \setminus \mathbf{C}^1|} \sum_{h=2}^{H} \sum_{c \in \mathbf{C}^h} \max\{0, p_c - \max_{c' \in c\downarrow} p_{c'}\}^2$$

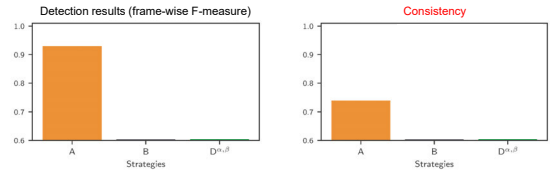
Joint loss term:

$$\mathcal{L} = \mathcal{L}_{\text{BCE}} + \alpha\mathcal{L}_{\downarrow} + \beta\mathcal{L}_{\uparrow}$$

Notation

$\mathbf{C}$	All classes
$\mathbf{C}^h$	Classes at level h
H	Number of levels
$c\downarrow$	Children of c
p_c	Probability for c

Results: Female Singing



Consistency

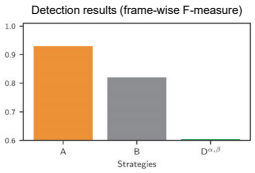
$\mathcal{I}_c^{\text{Est}}$ Frames predicted as c

$\mathcal{I}_{c\downarrow}^{\text{Est}}$ Frames predicted as child of c

$$\gamma_c = \frac{|\mathcal{I}_c^{\text{Est}} \cap \mathcal{I}_{c\downarrow}^{\text{Est}}|}{|\mathcal{I}_c^{\text{Est}} \cup \mathcal{I}_{c\downarrow}^{\text{Est}}|}$$

- Strategy A (Independent Decisions) yields good but inconsistent results

Results: Female Singing



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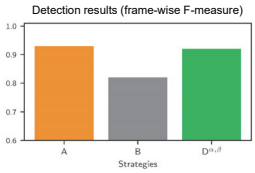
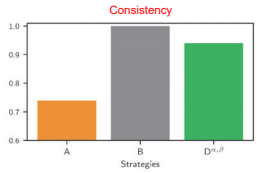
- Strategy A (Independent Decisions) yields good but inconsistent results
- Strategy B (Bottom-Up Aggregation) gives worse but consistent results

Results: Female Singing





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$\mathcal{I}_c^{\mathrm{Est}}$ Frames predicted as c

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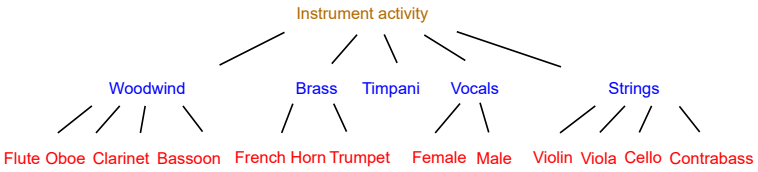
- Strategy A (Independent Decisions) yields good but inconsistent results
- Strategy B (Bottom-Up Aggregation) gives worse but consistent results
- Strategy $D^{\alpha,\beta}$ (Joint with Consistency Losses) provides good trade-off

Scenario: Hierarchical Instrument Classification

- Musical instruments can naturally be arranged into hierarchies



- Instrument-level annotations hard to obtain

Overview

- Multi-Scale Spectral Loss
  Knowledge Source: Signal Representations
- Hierarchical Classification Loss
  Knowledge Source: Musical Hierarchies
- Differentiable Alignment Loss
  Knowledge Source: Temporal Coherence


Simon Schwär


Michael Krause

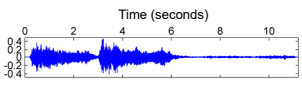

Johannes Zeitler

Literature

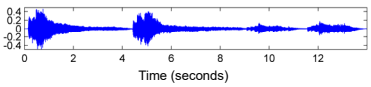
- Cuturi, Blondel: Soft-DTW: A Differentiable Loss Function for Time-Series. ICML, 2017.
- Blondel, Mensch, Vert: Differentiable Divergences Between Time Series. AISTATS, 2021.
- **Krause**, Weiß, Müller: Soft Dynamic Time Warping For Multi Pitch Estimation And Beyond. Proc. ICASSP, 2023.
- **Zeitler**, Deniffel, **Krause**, Müller: Stabilizing Training with Soft Dynamic Time Warping: A Case Study for Pitch Class Estimation with Weakly Aligned Targets. Proc. ISMIR, 2023.
- **Zeitler**, **Krause**, Müller: Soft Dynamic Time Warping with Variable Step Weights. Proc. ICASSP, 2024.

Motivation: Audio-Audio Alignment
Beethoven's Fifth

Karajan (Orchester)



Gould (Piano)



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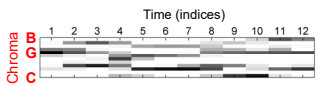
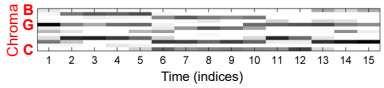


Time–chroma representations

Gould (Piano)



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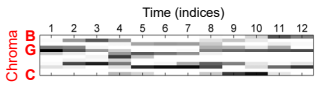

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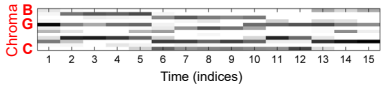

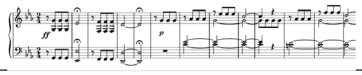

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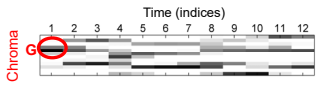

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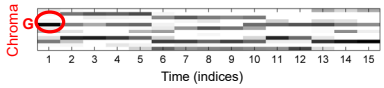

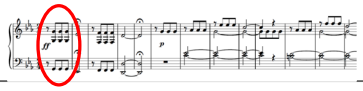

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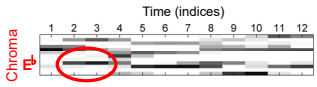

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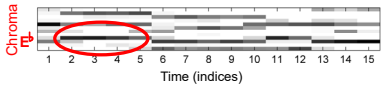

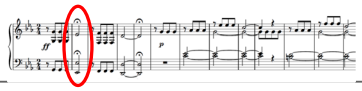

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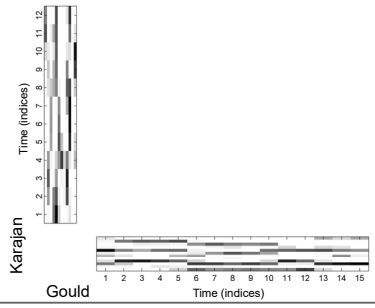

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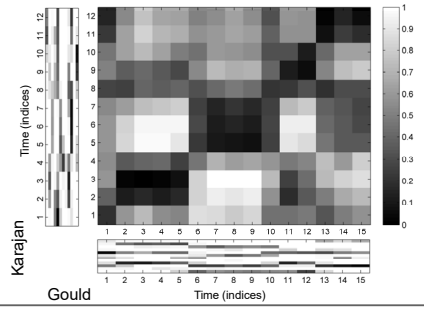
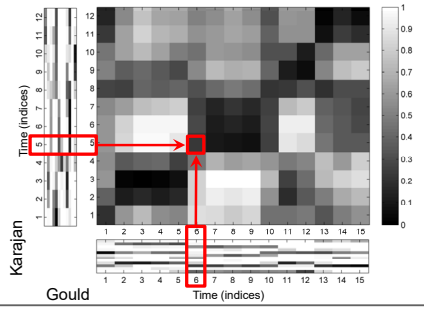


Cost matrix

Motivation: Audio-Audio Alignment
Beethoven's Fifth



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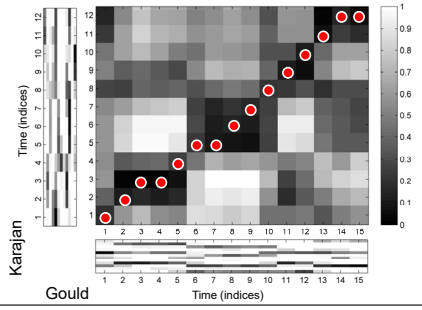
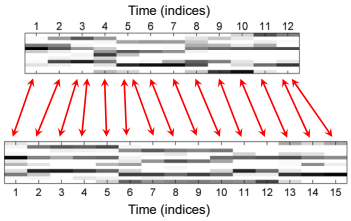


Cost-minimizing warping path

Motivation: Audio-Audio Alignment
Beethoven's Fifth

Karajan (Orchester)

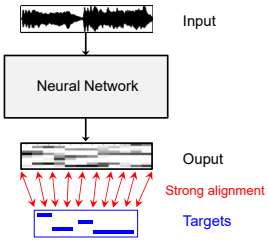
Gould (Piano)



Cost-minimizing warping path

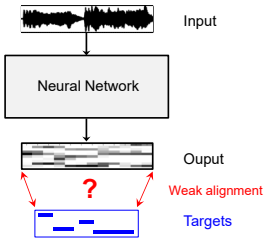
→ Strong alignment

Feature Learning



- Task: Learn audio features using a neural network
- Loss: Binary cross-entropy
  - framewise loss
  - requires strongly aligned targets
  - hard to obtain

Feature Learning



- Task: Learn audio features using a neural network
- Loss: Binary cross-entropy
  - framewise loss
  - requires strongly aligned targets
  - hard to obtain
- Alignment as part of loss function
  - requires only weakly aligned targets
  - needs to be differentiable
- Problem: DTW is not differentiable
  → Soft DTW

Dynamic Time Warping (DTW)

$X := (x_1, x_2, \ldots, x_N)$

$Y := (y_1, y_2, \ldots, y_M)$

$x_n, y_m \in \mathcal{F},\ n \in [1:N],\ m \in [1:M]$

$\mathcal{F}$ = Feature space

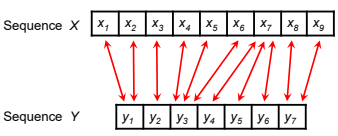
Alignment matrix

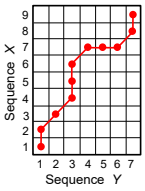
$A \in \{0,1\}^{N \times M}$

Set of all possible alignment matrices

$\mathcal{A}_{N,M} \subset \{0,1\}^{N \times M}$

Alignment





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Alignment matrix

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Set of all possible alignment matrices

$\mathcal{A}_{N,M} \subset \{0,1\}^{N \times M}$

Cost measure: $c : \mathcal{F} \times \mathcal{F} \to \mathbb{R}_{\geq 0}$

Cost matrix: $C \in \mathbb{R}^{N \times M}$ with $C(n,m) := c(x_n, y_m)$

Cost of alignment: $\langle A, C \rangle$

DTW cost: $\mathrm{DTW}(C) = \min(\{\langle A, C \rangle \mid A \in \mathcal{A}_{N,M}\})$

Optimal alignment: $A^* = \operatorname{argmin}(\{\langle A, C \rangle \mid A \in \mathcal{A}_{N,M}\})$

Dynamic Time Warping (DTW)

DTW cost: $\mathrm{DTW}(C) = \min\left(\{\langle A, C\rangle \mid A \in \mathcal{A}_{N,M}\}\right)$

- Efficient computation via Bellman's recursion in O(*NM*)

  $D(n,m) = \min\{D(n-1,m), D(n,m-1), D(n,m)\} + C(n,m)$

  for *n>1* and *m>1* and suitable initialization.

  $\mathrm{DTW}(C) = D(N,M)$

- Problem: DTW(C) is not differentiable with regard to *C*
- Idea: Replace min-function by a smooth version

$$\min^{\gamma}(\mathcal{S}) = -\gamma \log \sum\nolimits_{s\in\mathcal{S}} \exp(-s/\gamma)$$

for set $\mathcal{S} \subset \mathbb{R}$ and temperature parameter $\gamma \in \mathbb{R}$

Soft Dynamic Time Warping (SDTW)

SDTW cost: $\mathrm{SDTW}^{\gamma}(C) = \min^{\gamma}\left(\{\langle A, C\rangle \mid A \in \mathcal{A}_{N,M}\}\right)$

- Efficient computation via Bellman's recursion in O(*NM*) still works:

  $D^{\gamma}(n,m) = \min^{\gamma}\{D^{\gamma}(n-1,m), D^{\gamma}(n,m-1), D^{\gamma}(n,m)\} + C(n,m)$

  for *n>1* and *m>1* and suitable initialization.

  $\mathrm{SDTW}^{\gamma}(C) = D^{\gamma}(N,M)$

- Limit case: $\mathrm{SDTW}^{\gamma}(C) \xrightarrow{\gamma\to 0} \mathrm{DTW}(C)$
- SDTW(C) is differentiable with regard to *C*
- Questions:
  - How does the gradient look like?
  - Can it be computed efficiently?
  - How does SDTW generalize the alignment concept?

Soft Dynamic Time Warping (SDTW)

Soft-DTW
Cuturi, Blondel: Soft-DTW: A Differentiable Loss Function for Time-Series. ICML, 2017

SDTW cost: $\mathrm{SDTW}^{\gamma}(C) = \min^{\gamma}\left(\{\langle A, C\rangle \mid A \in \mathcal{A}_{N,M}\}\right)$

- Define $p^{\gamma}(C)$ as the following "probability" distribution over $\mathcal{A}_{N,M}$:

$$p^{\gamma}(C)_A = \frac{\exp(-\langle A, C\rangle/\gamma)}{\sum_{A'\in\mathcal{A}_{N,M}} \exp(-\langle A', C\rangle/\gamma)} \quad \text{for } A \in \mathcal{A}_{N,M}$$

- The expected alignment with respect to $p^{\gamma}(C)$ is given by:

$$E^{\gamma}(C) = \sum\nolimits_{A\in\mathcal{A}_{N,M}} p^{\gamma}(C)_A A \quad \in \mathbb{R}^{N\times M}$$

- The gradient is given by:

$$\nabla_C \mathrm{SDTW}^{\gamma}(C) = E^{\gamma}(C)$$

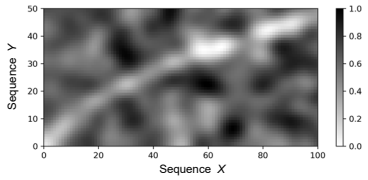
- The gradient can be computed efficiently in O(*NM*) via a recursive algorithm.

Soft Dynamic Time Warping (SDTW)

Expected alignment : $E^{\gamma}(C) = \sum_{A\in\mathcal{A}_{N,M}} p^{\gamma}(C)_A A \quad \in \mathbb{R}^{N\times M}$

- Can be interpreted as a smoothed version of an alignment
- Degree of smoothing depends on temperature parameter γ

Cost matrix C



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Expected alignment : $E^{\gamma}(C) = \sum_{A\in\mathcal{A}_{N,M}} p^{\gamma}(C)_A A \quad \in \mathbb{R}^{N\times M}$

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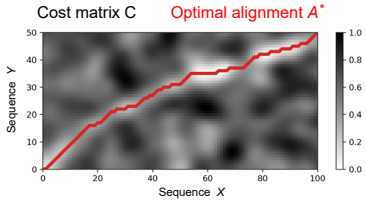
Cost matrix C Optimal alignment A^*

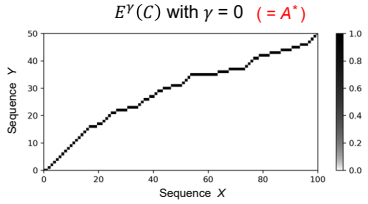


Soft Dynamic Time Warping (SDTW)

Expected alignment : $E^{\gamma}(C) = \sum_{A\in\mathcal{A}_{N,M}} p^{\gamma}(C)_A A \quad \in \mathbb{R}^{N\times M}$

- Can be interpreted as a smoothed version of an alignment
- Degree of smoothing depends on temperature parameter γ

$E^{\gamma}(C)$ with $\gamma = 0$ ($= A^*$)



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Expected alignment : $E^{\gamma}(C) = \sum_{A \in \mathcal{A}_{N,M}} p^{\gamma}(C)_A A \quad \in \mathbb{R}^{N \times M}$

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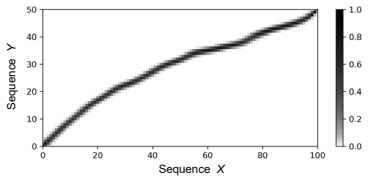
$E^{\gamma}(C)$ with γ = 0.1

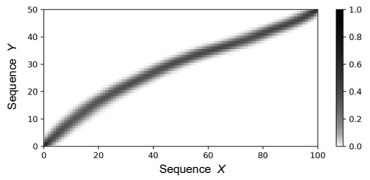


Soft Dynamic Time Warping (SDTW)

Expected alignment : $E^{\gamma}(C) = \sum_{A \in \mathcal{A}_{N,M}} p^{\gamma}(C)_A A \quad \in \mathbb{R}^{N \times M}$

- Can be interpreted as a smoothed version of an alignment
- Degree of smoothing depends on temperature parameter γ

$E^{\gamma}(C)$ with γ = 1



Soft Dynamic Time Warping (SDTW)

Expected alignment : $E^{\gamma}(C) = \sum_{A \in \mathcal{A}_{N,M}} p^{\gamma}(C)_A A \quad \in \mathbb{R}^{N \times M}$

- Can be interpreted as a smoothed version of an alignment
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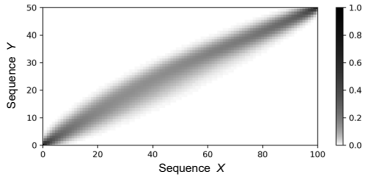
$E^{\gamma}(C)$ with γ = 10

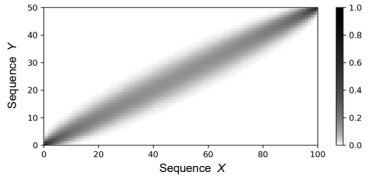


Soft Dynamic Time Warping (SDTW)

Expected alignment : $E^{\gamma}(C) = \sum_{A \in \mathcal{A}_{N,M}} p^{\gamma}(C)_A A \quad \in \mathbb{R}^{N \times M}$

- Can be interpreted as a smoothed version of an alignment
- Degree of smoothing depends on temperature parameter γ

$E^{\gamma}(C)$ with γ = 100

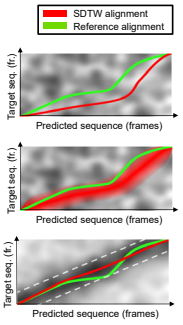


Soft Dynamic Time Warping (SDTW)
Conclusions

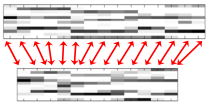
- Direct generalization of DTW (replacing min by smooth variant)
- Gradient is given by expected alignment
- Fast forward algorithm: O(*NM*)
- Fast gradient computation: O(*NM*)
- SDTW yields a (typically) poor lower bound for DTW
- Can be used as loss function to learn from weakly aligned sequences

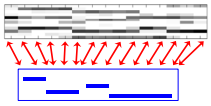
Soft Dynamic Time Warping (SDTW)
Stabilizing Training

- Standard SDTW often unstable
  - Unstable training in early stages
  - Degenerate output alignment
- Hyperparameter adjustment
  - High temperature to smooth alignments
  - Temperature annealing
- Diagonal prior
- Modified step size condition



Soft Dynamic Time Warping (SDTW)
Representation Learning





- Symmetric application
  - Learn representation of both sequences
  - Needs a contrastive loss term
- Assymmetric application
  - Use fixed (e.g., binary) encoding of target
  - Learn representation of only one sequences
  - No contrastive loss term need
- Simulation of CTC-loss using SDTW possible
- Many DTW variants also possible for SDTW

Conclusions

- Multi-Scale Spectral Loss
  Knowledge Source: Signal Representations
- Hierarchical Classification Loss
  Knowledge Source: Musical Hierarchies
- Differentiable Alignment Loss
  Knowledge Source: Temporal Coherence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Conclusions

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Müller, Zeitler: **2025 ISMIR Tutorial**
Differentiable Alignment Techniques for Music Processing: Techniques and Applications