

2023 September 26

Deep Learning for Music Analysis and Generation

Source Separation

(audio → audio)



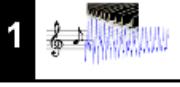
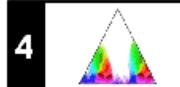
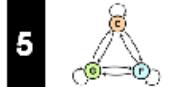
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Objectives

- To be familiar with how people **work on spectrograms**
- It's a type of *conditional* audio **generation** task (with *strong condition*)
 - “**audio (mixture) → audio (stem)**”
 - Will talk about other types of audio generation tasks in the forthcoming lectures

Reference 1: FMP Notebook

<https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8.html>

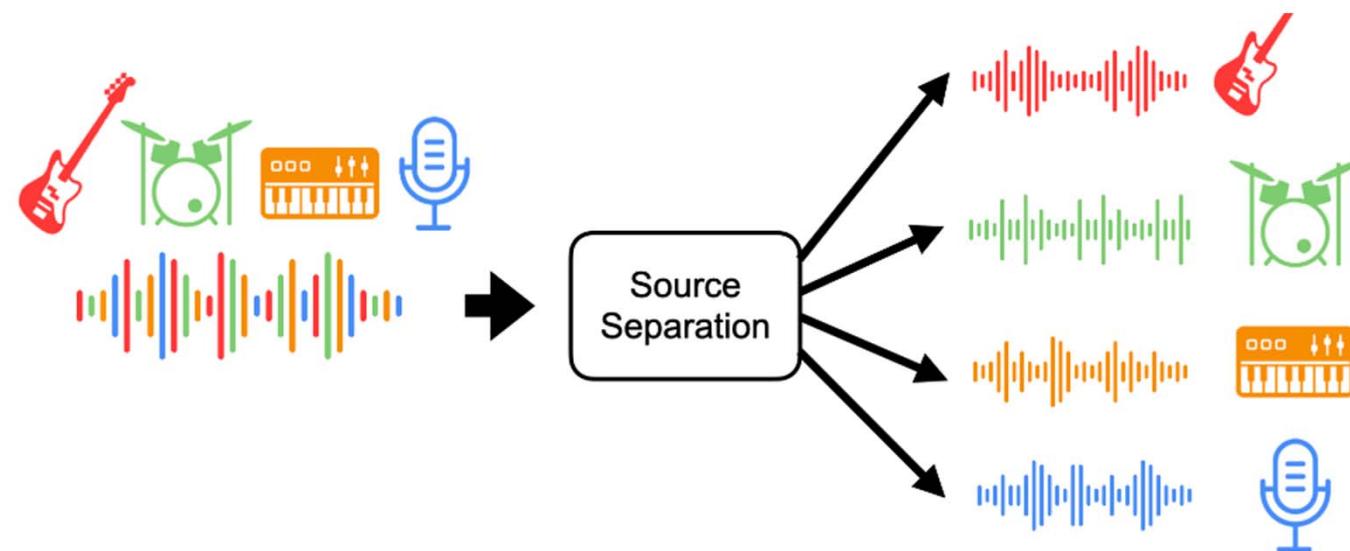
Part	Title	Notions, Techniques & Algorithms	HTML	IPYNB
B	 Basics	Basic information on Python, Jupyter notebooks, Anaconda package management system, Python environments, visualizations, and other topics	[html]	[ipynb]
0	 Overview	Overview of the notebooks (https://www.audiolabs-erlangen.de/FMP)	[html]	[ipynb]
1	 Music Representations	Music notation, MIDI, audio signal, waveform, pitch, loudness, timbre	[html]	[ipynb]
2	 Fourier Analysis of Signals	Discrete/analog signal, sinusoid, exponential, Fourier transform, Fourier representation, DFT, FFT, STFT	[html]	[ipynb]
3	 Music Synchronization	Chroma feature, dynamic programming, dynamic time warping (DTW), alignment, user interface	[html]	[ipynb]
4	 Music Structure Analysis	Similarity matrix, repetition, thumbnail, homogeneity, novelty, evaluation, precision, recall, F-measure, visualization, scape plot	[html]	[ipynb]
5	 Chord Recognition	Harmony, music theory, chords, scales, templates, hidden Markov model (HMM), evaluation	[html]	[ipynb]
6	 Tempo and Beat Tracking	Onset, novelty, tempo, tempogram, beat, periodicity, Fourier analysis, autocorrelation	[html]	[ipynb]
7	 Content-Based Audio Retrieval	Identification, fingerprint, indexing, inverted list, matching, version, cover song	[html]	[ipynb]
8	 Musically Informed Audio Decomposition	signal reconstruction, instantaneous frequency, fundamental frequency (F0), trajectory, nonnegative matrix factorization (NMF)	[html]	[ipynb]

Reference 2: ISMIR 2020 Tutorial

<https://source-separation.github.io/tutorial/landing.html>

Open Source Tools & Data for Music Source Separation

By Ethan Manilow, Prem Seetharaman, and Justin Salamon



Outline

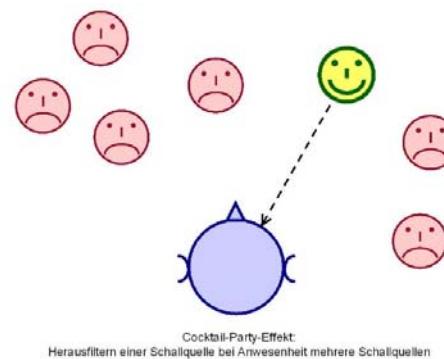
- **General idea**
- Traditional methods
- Deep learning based methods

What is Source Separation?

https://source-separation.github.io/tutorial/intro/src_sep_101.html

- The process of isolating individual sounds (*sources*) in an auditory mixture of multiple sounds
- *Underdetermined* problem
 - Fewer observations $y(t)$ (1 or 2; mono or stereo) than the required outcomes $x_i(t)$ (e.g., 4)

$$y(t) = \sum_{i=1}^N x_i(t).$$



- In speech: cocktail party effect

Demo: Source Separation

<https://www.gaudiolab.com/technology/source-separation>

♪♪ Eagles 'Hotel California'



GAUDIO

Why Source Separation?

https://source-separation.github.io/tutorial/intro/src_sep_101.html

- Benefit **downstream MIR** problems
 - automatic music transcription [PAB+02, MSP20],
 - lyric and music alignment [FGO+06],
 - musical instrument detection [HKV09],
 - lyric recognition [MV10],
 - automatic singer identification [WWollmerS11, HL15, SDL19],
 - vocal activity detection [SED18a],
 - fundamental frequency estimation [JBEW19], and
 - understanding the predictions of black-box audio models.
[HMW20a, HMW20b]

Why Source Separation?

https://source-separation.github.io/tutorial/intro/src_sep_101.html

- Benefit **music generation**
 - Re-mix of the sources
 - Up-mix: stereo to 5.1-channel
 - Replacement of some of the sources
 - Audio editing
- **Active music listening**

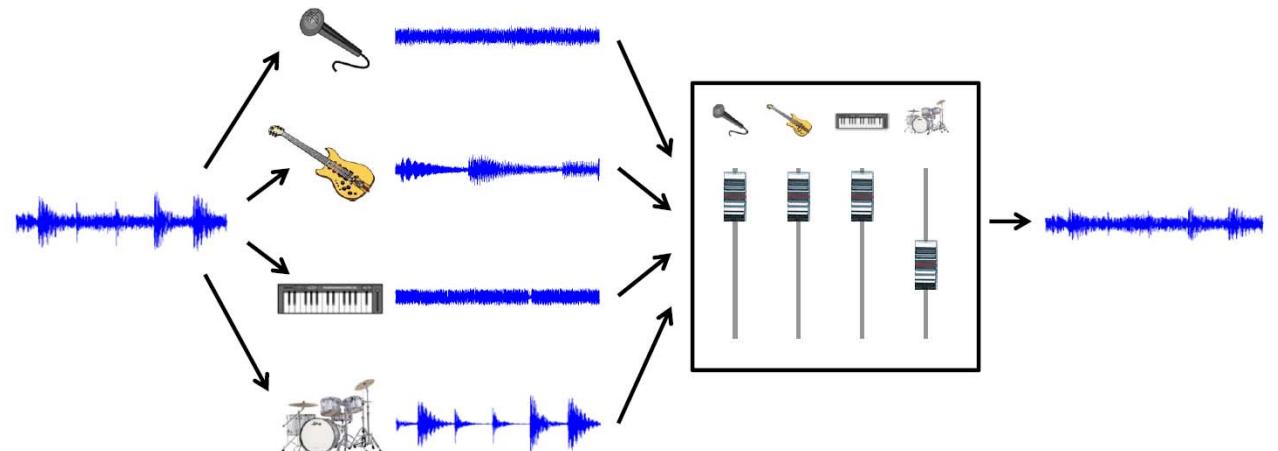
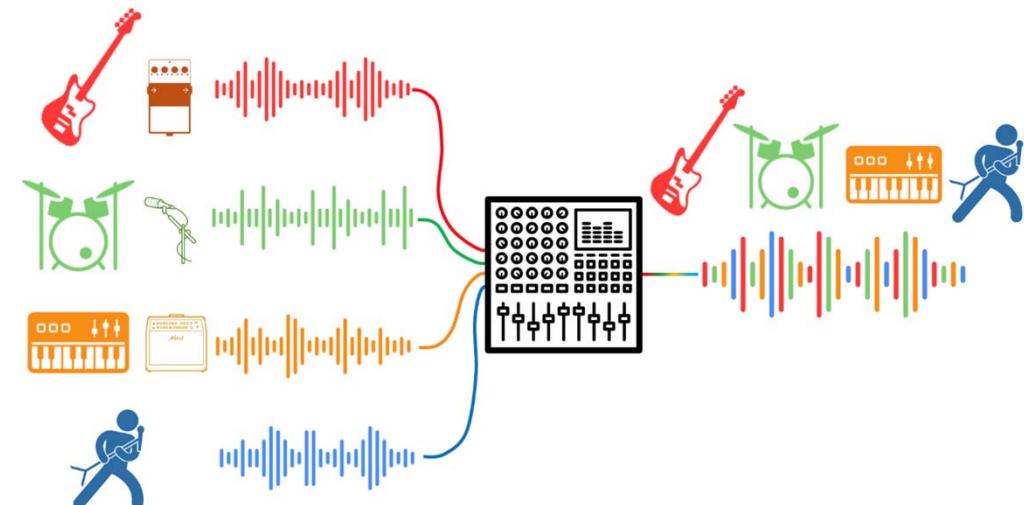


Figure from [Mueller, FPM, Chapter 8, Springer 2015]

Why Source Separation is Difficult?

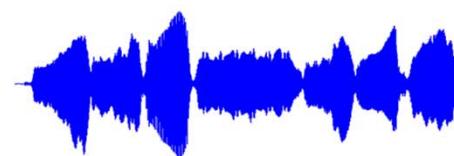
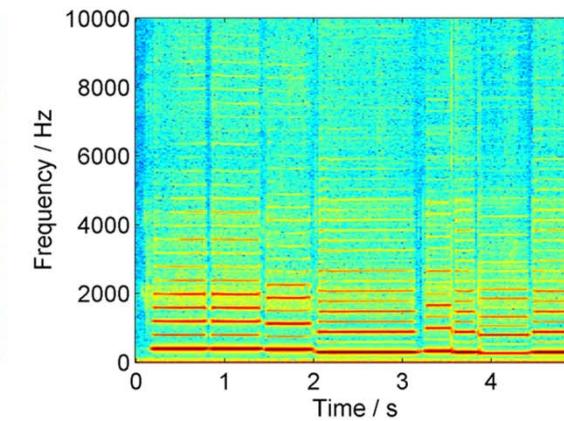
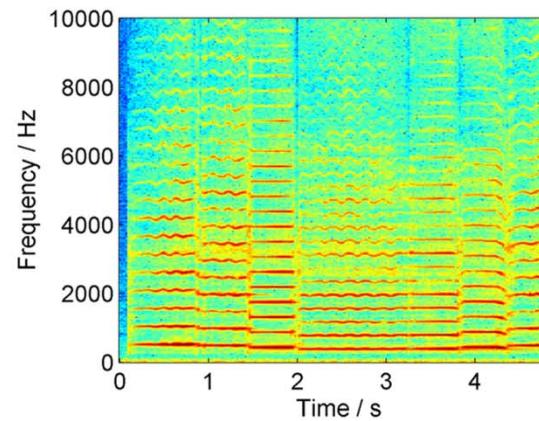
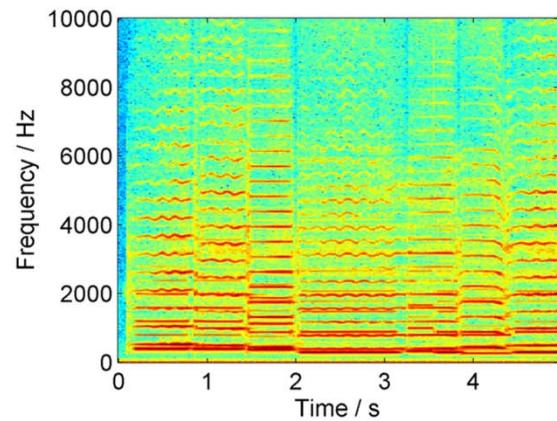
https://source-separation.github.io/tutorial/intro/src_sep_101.html

- Sources in music are **highly correlated** (harmonically and rhythmically)
- The **mixing** of music signals is **complex** and **non-linear**
 - Reverb, EQ, ...
 - Don't know how the mixing was done
- It's actually an **audio-domain music generation** problem
 - Instrument recognition (*discriminative*) vs. instrument separation (*generative*)
 - The bar for quality can be high

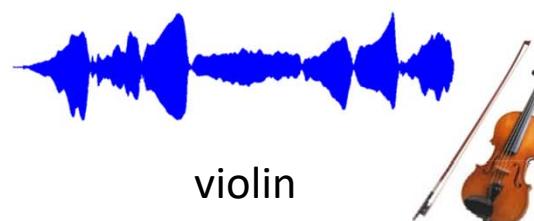


Why Source Separation is Difficult?

- Sources in music are **highly correlated** (harmonically and rhythmically)



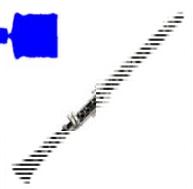
mixture



violin



clarinet



Why Source Separation is Difficult?

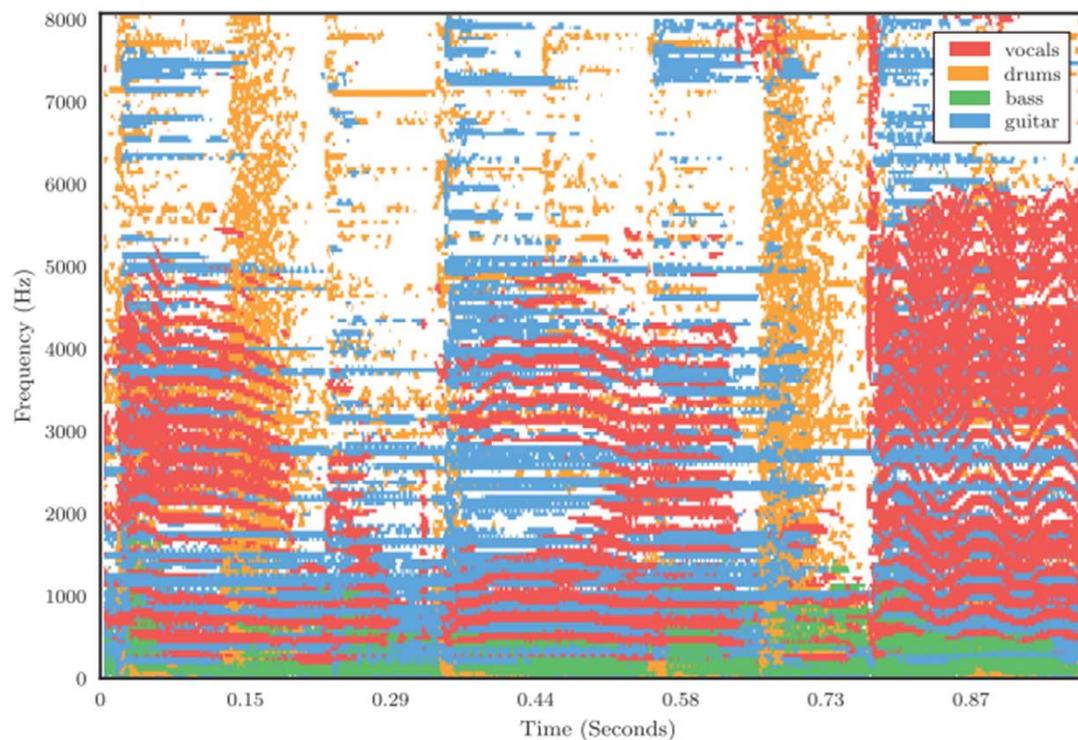
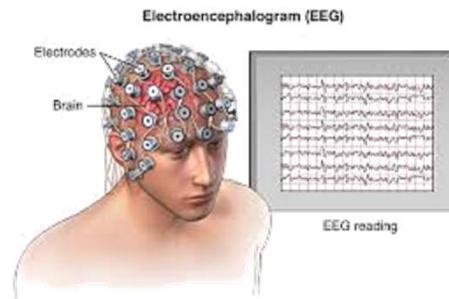


Figure 1: Representation of a music mixture in the time-frequency domain. The dominant musical source in each time-frequency bin is displayed with a different color.

Ref: Cano et al, "Musical source separation: An introduction," IEEE Signal Processing Magazine 2019

Types of Separation Problems

- #sources vs. #output channels
 - Overdetermined vs **underdetermined**
- Amount of side information
 - **Blind** source separation vs. **informed** source separation
 - *Score* informed
 - *Lyrics* informed
 - *Melody* informed
 - We mainly talk about blind, and underdetermined source separation
- Online or offline

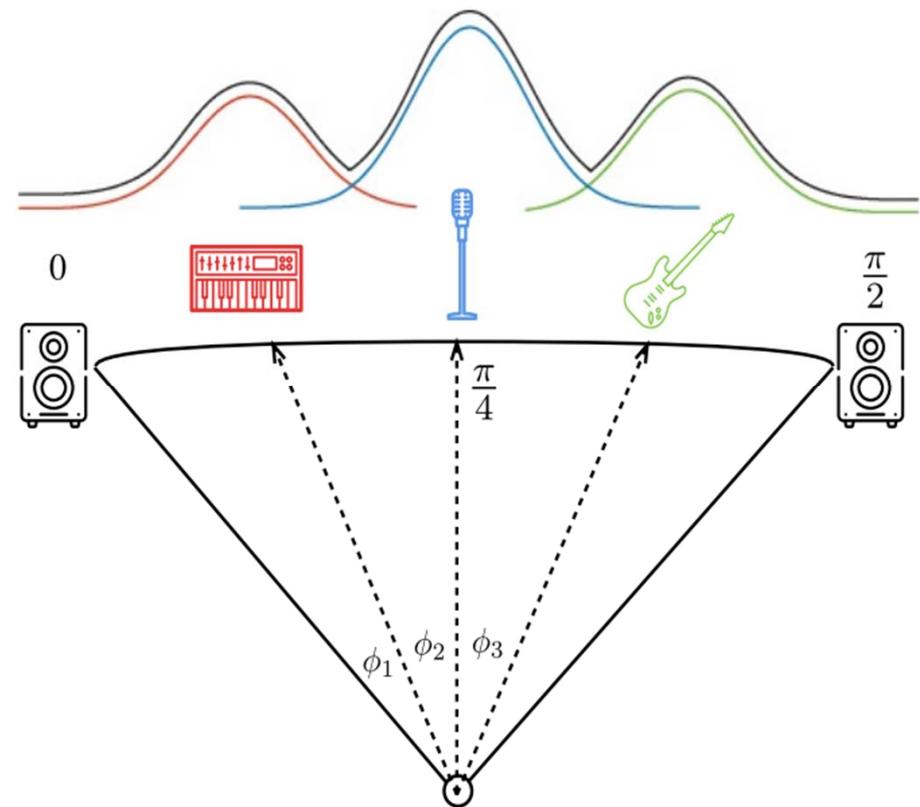


Types of Separation Problems

- What the #output channels are
 - **Two** stems: vocal vs. *non-vocal*
 - or: lead vs. *accompaniments*
 - **Four** stems: vocal, drums, bass, and *others*
 - Beyond four stems
 - Uncertain number of output channels
- Do different output channels correspond to different instruments?
 - Not always
 - Choral music separation (soprano, alto, tenor, and bass)
 - Speaker separation

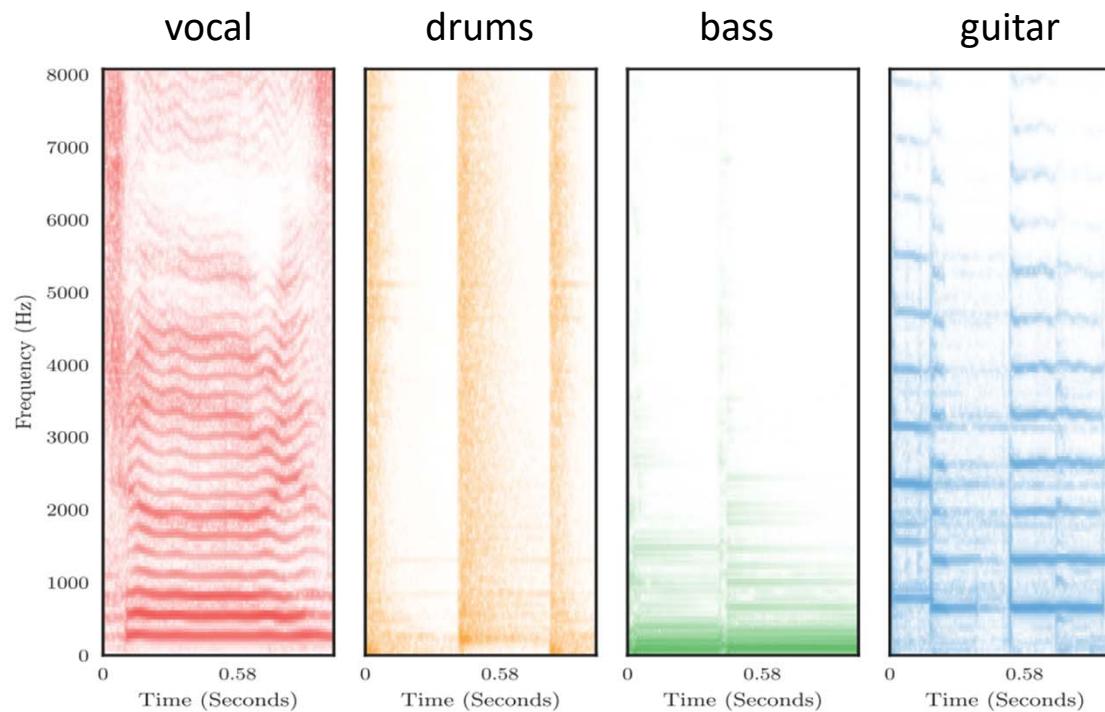
Clues for Stereo Source Separation

- Utilizing *spatial position* for separation
 - Vocal are usually in the middle



Clues for Monaural Source Separation

- Different sound sources may have different *time-frequency characteristics* (timbre, pitch range, etc)



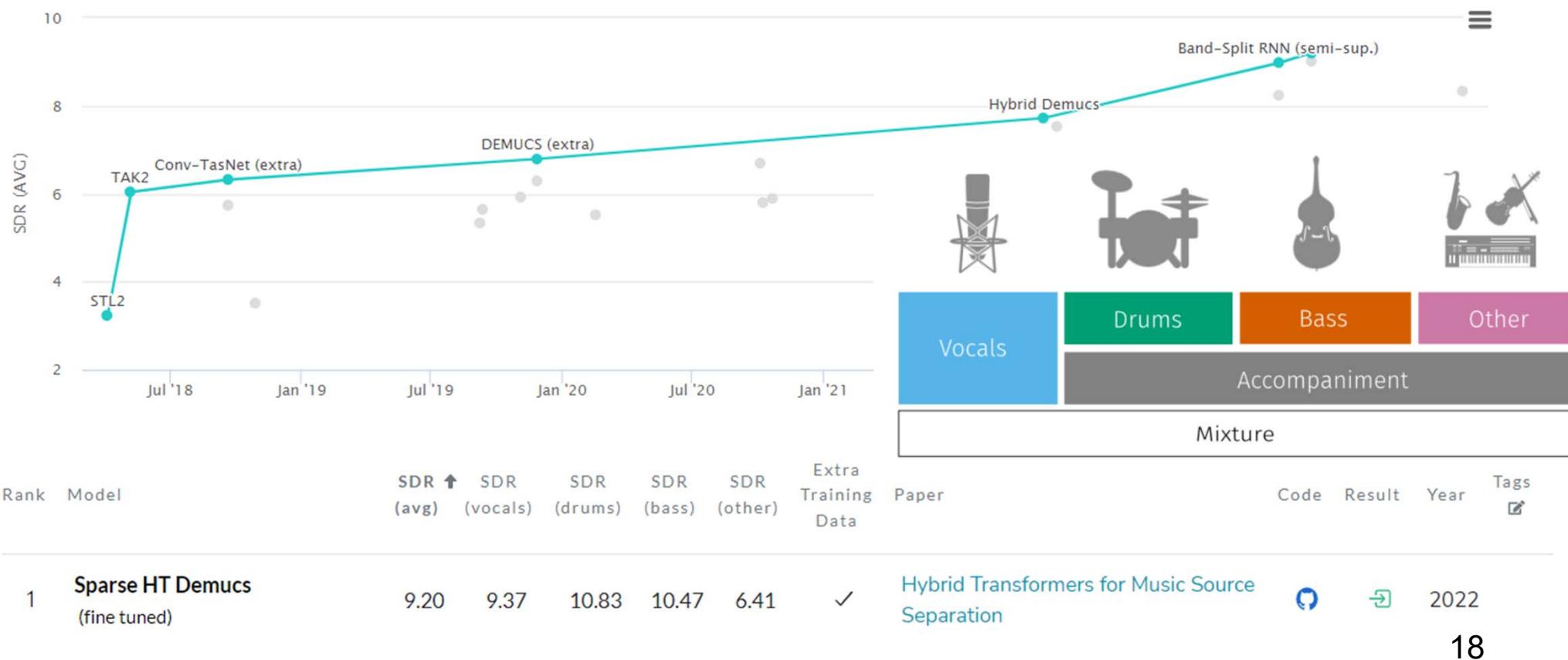
Ref: Cano et al, "Musical source separation: An introduction," IEEE Signal Processing Magazine 2019

Approach

- **Traditional** methods
 - *Unsupervised*: rule-based, model-based
 - Faster, light-weight, but limited performance
- **Deep learning** based methods
 - *Supervised*: learn from “clean sources”
 - Mixture in, clean sources out
 - Very good result to date

Benchmark 1

<https://paperswithcode.com/sota/music-source-separation-on-musdb18>



Benchmark 2

<https://www.aicrowd.com/challenges/sound-demixing-challenge-2023>

🕒 Warm-Up Round: Completed 🕒 Phase I: Completed 🕒 Phase 2: Completed

SONY moises MITSUBISHI ELECTRIC
Changes for the Better

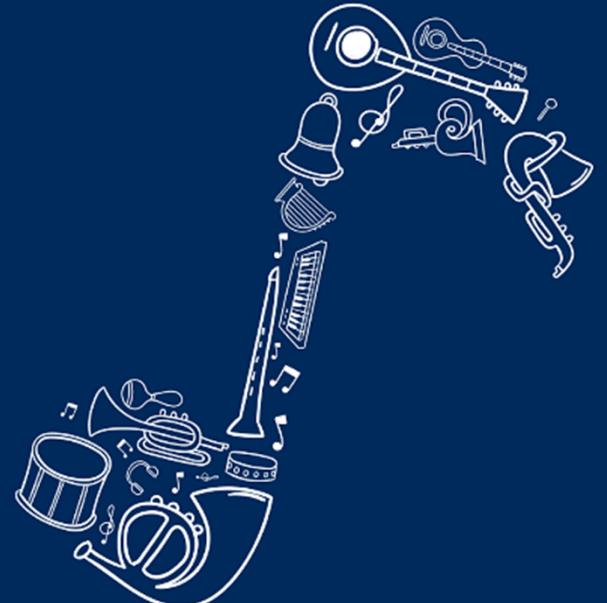
Sound Demixing Challenge 2023

Build A System To Perform Audio Source Separation

💡 \$42,000
Cash Prize Pool

Cinematic Sound Demixing Track - CDX'23
Source separation of a cinematic audio track into dialogue, sound-effects and misc.

Music Demixing Track - MDX'23
Music source separation of an audio signal into separate tracks for vocals, bass, drums, and other



7514 830

16.9k 1992

Evaluation Metrics

<https://source-separation.github.io/tutorial/basics/evaluation.html>

- **Source-to-Distortion Ratio (SDR)**
- Source-to-Interference Ratio (SIR)
- Source-to-Artifact Ratio (SAR)
 - true sources: **a, b**
 - estimated sources: **ae, be**
 - SDR(a): how **ae** is similar to **a**
 - SIR(a): how **ae** is similar to **b**
 - SAR(a): how **ae** is not similar to either **a or b**
 - we can also compute SDR(b), SIR(b), SAR(b)

Evaluation Library: mir_eval

https://github.com/craffel/mir_eval

- mir_eval can be used in most MIR tasks as well (e.g., chord recognition, onset detection, segmentation)

Examples

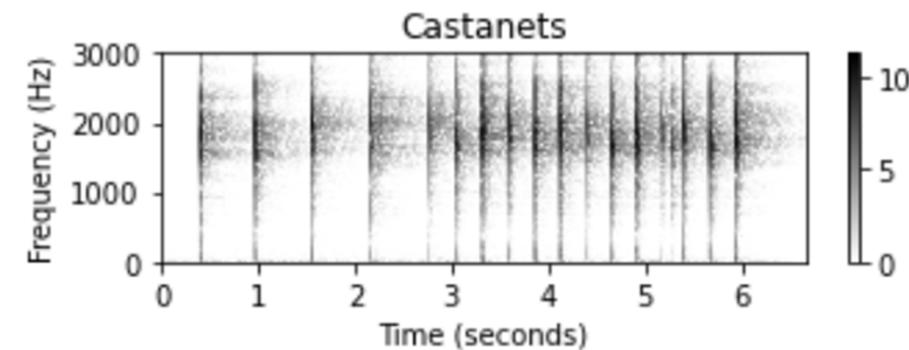
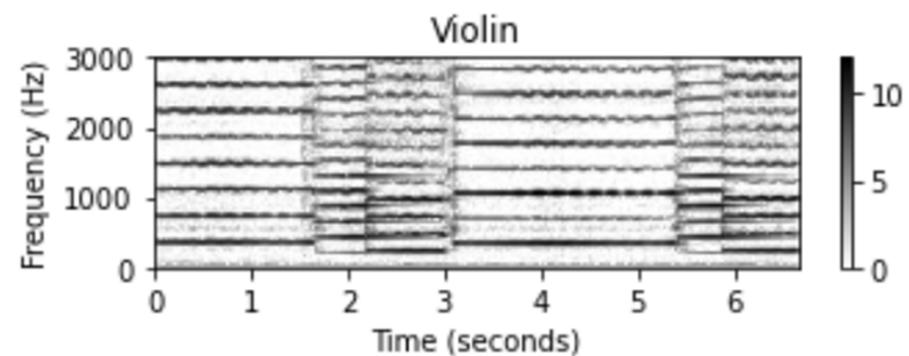
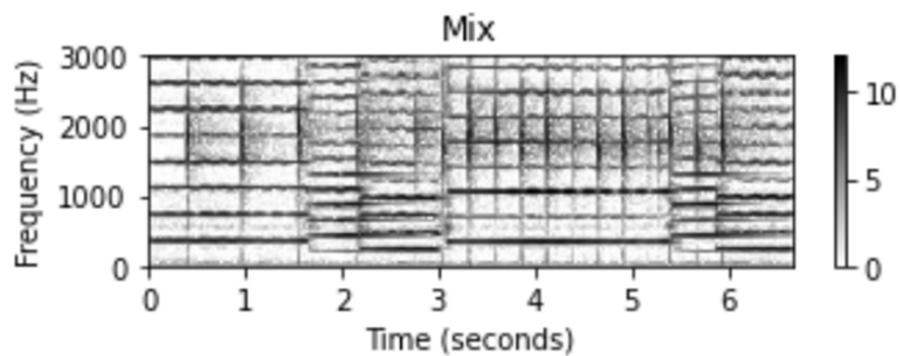
```
>>> # reference_sources[n] should be an ndarray of samples of the
>>> # n'th reference source
>>> # estimated_sources[n] should be the same for the n'th estimated
>>> # source
>>> (sdr, sir, sar,
...     perm) = mir_eval.separation.bss_eval_sources(reference_sources,
...                                                 estimated_sources)
```

Outline

- General idea
- **Traditional methods (*non-DL, unsupervised*)**
 - Median filtering
 - Nonnegative matrix factorization (NMF)
 - Robust principal component analysis (RPCA)
- Deep learning based methods

Harmonic Percussive Source Separation (HPSS)

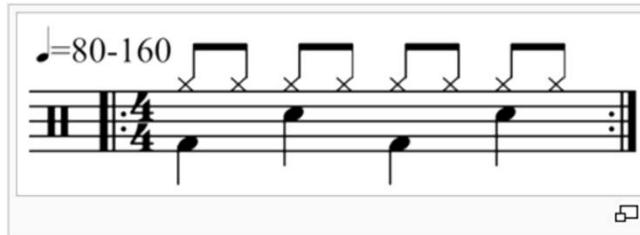
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S1_HPS.html



- Work on the **spectrogram**

Motivation: Drum Transcription

- The drum track in popular music conveys information about tempo, rhythm, style, and possibly the structure of a song



B = Bass drum HH = Hi-hat S = Snare drum

HH|x-x-x-x-x-x-x-x-||
S|-----o-----o---||
B|o-----o-----||
1 + 2 + 3 + 4 +

From Wikipedia

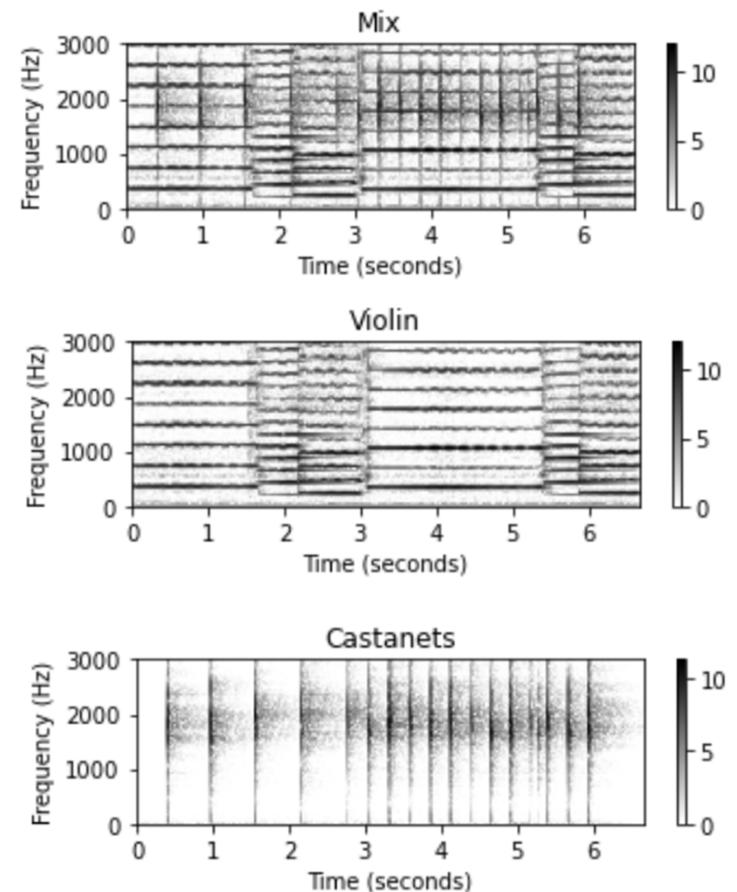


Median-Filtering Approach

- Intuition
 - stable **harmonic** or stationary components form **horizontal lines** on the spectrogram
 - **percussive** components form **vertical lines** with a broadband frequency response
- Simple DSP techniques; no ML

```
A = np.array([5.,3,2,8,2])
filter_len = 3
A_result = signal.medfilt(A, kernel_size=filter_len)
print('A      = ', A)
print('A_result = ', A_result)
```

[https://www.audiolabs-
erlangen.de/resources/MIR/FMP/C8/C8S1_HPS.html](https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S1_HPS.html)



Ref 1: Ono et al, “Separation of a monaural audio signal into harmonic/percussive components by complementary diffusion on spectrogram,” EUSIPCO 2008

Ref 2: Fitzgerald, “Harmonic/percussive separation using median filtering,” DAFX 2010

HPSS via Median Filtering & Masking

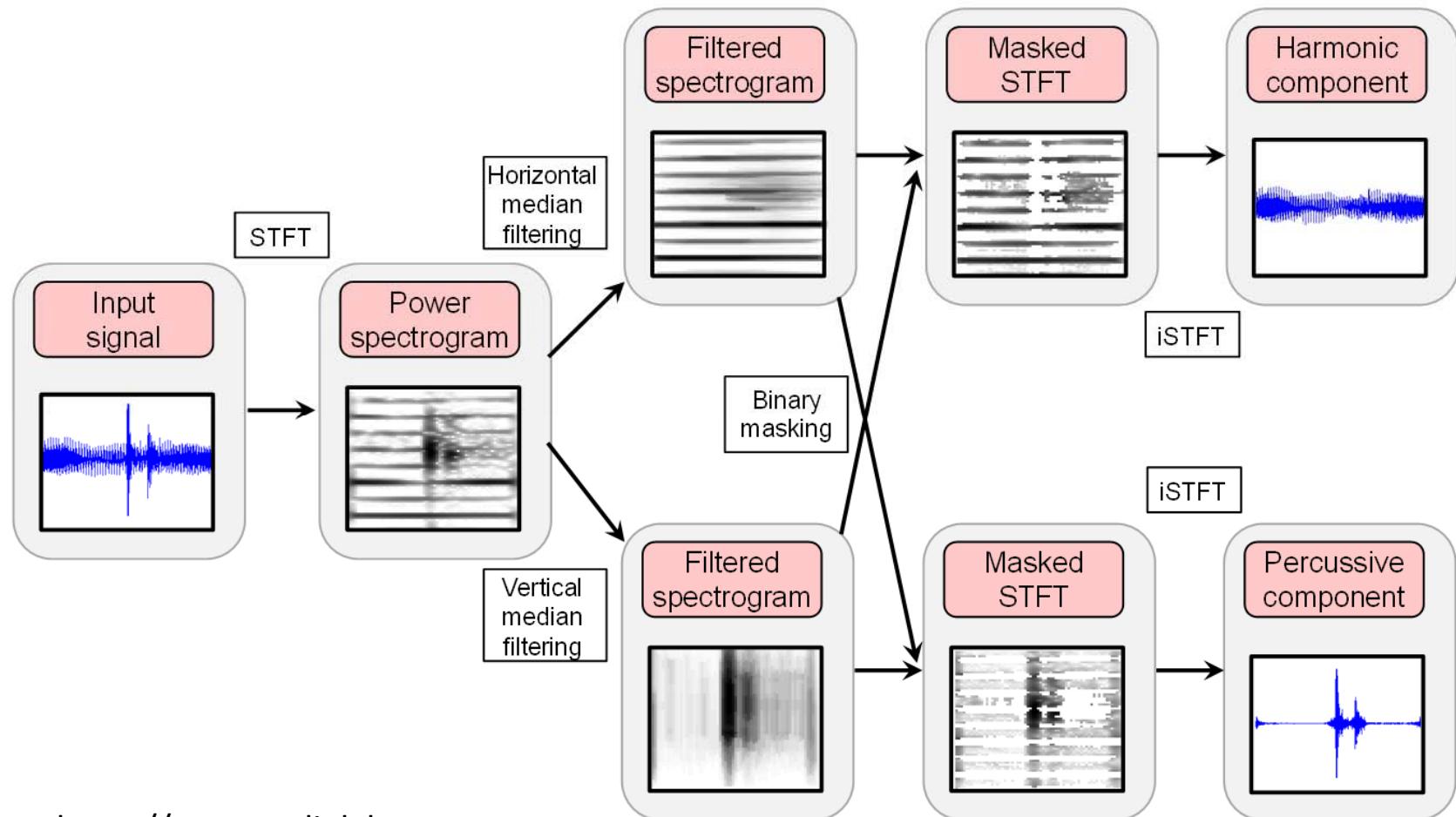
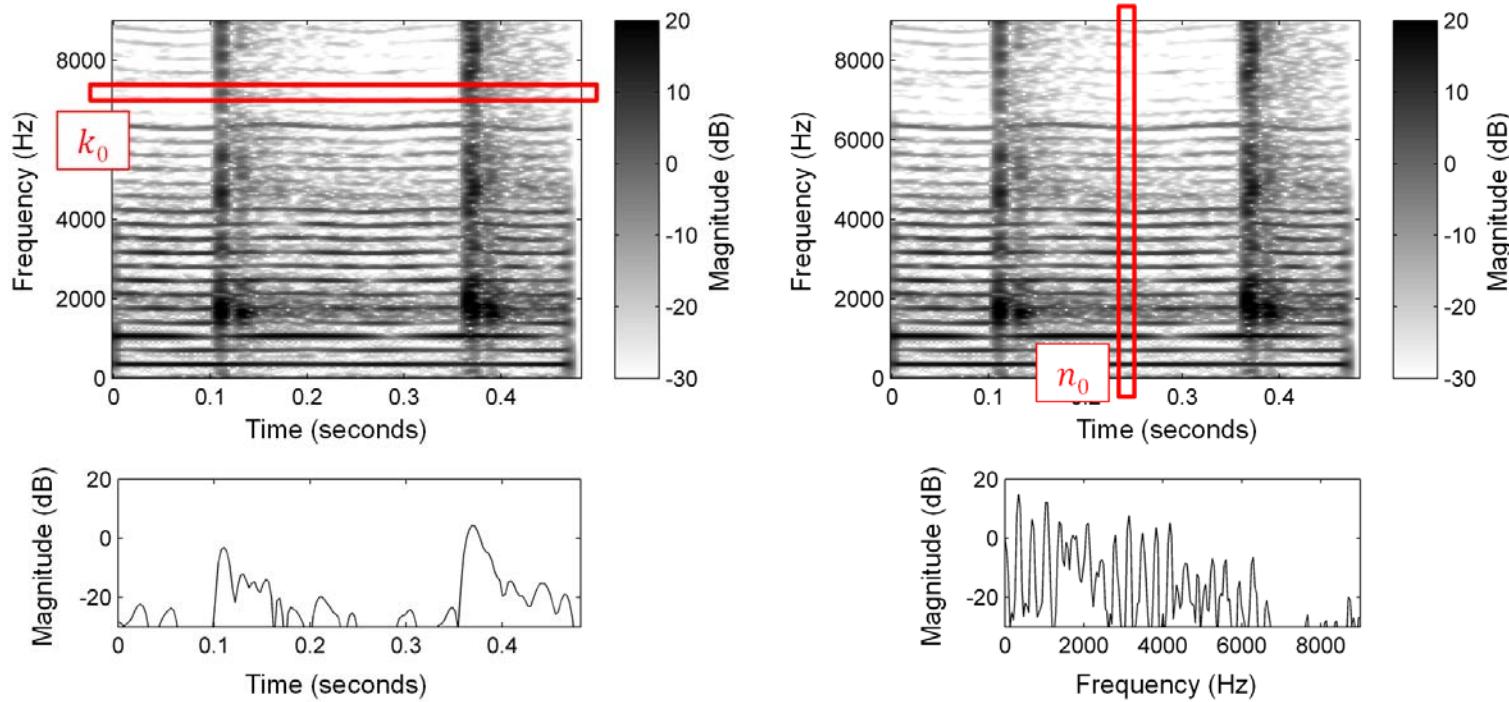


Figure source: https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S1_HPS.html

Median Filtering

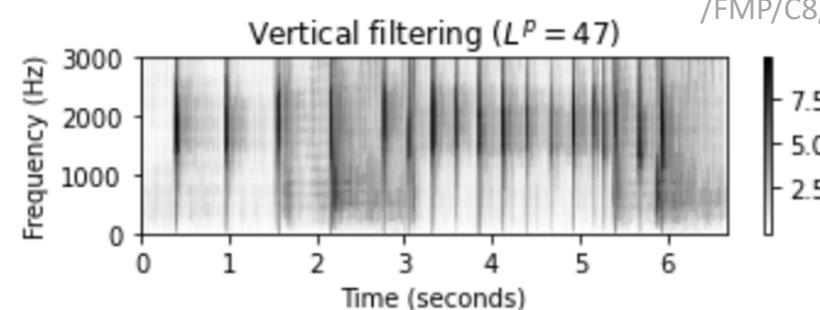
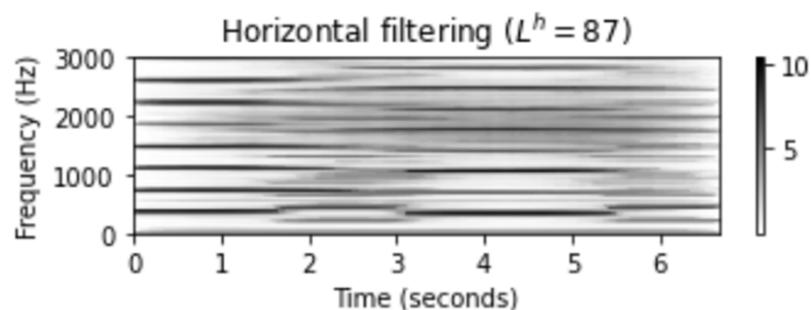
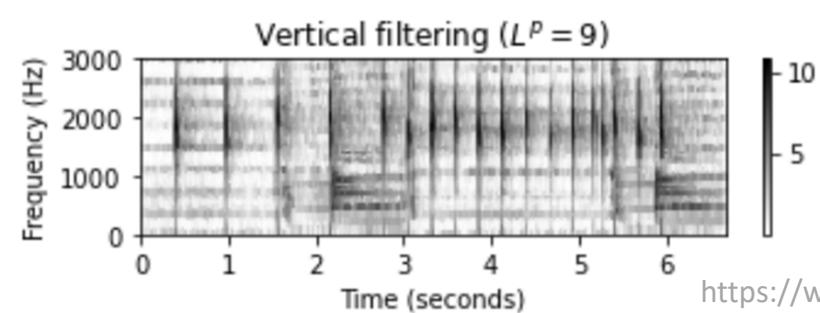
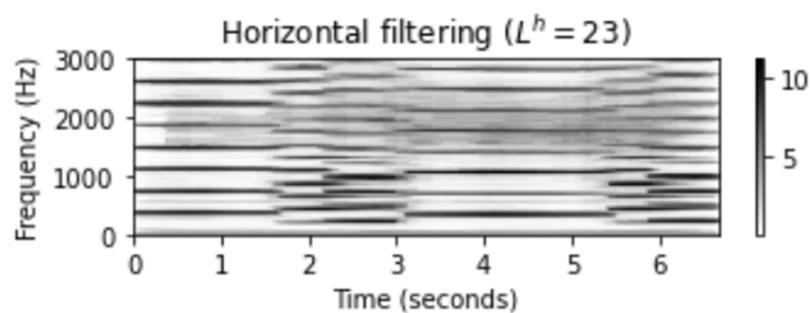
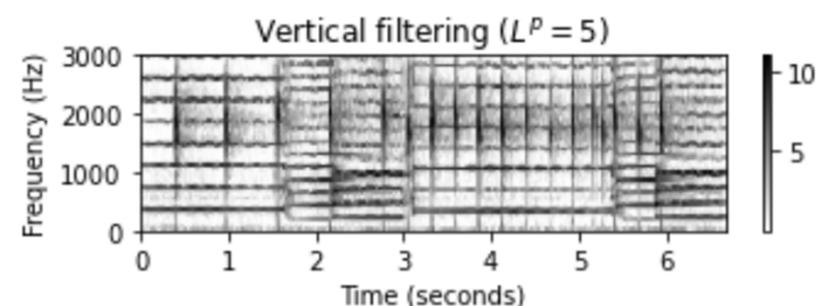
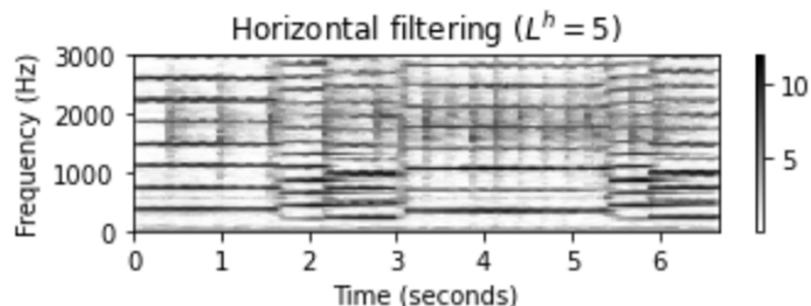


$$\tilde{Y}_h(t, k) := \text{median}(Y(t - \ell_h, k), \dots, Y(t + \ell_h, k))$$

$$\tilde{Y}_p(t, k) := \text{median}(Y(t, k - \ell_p), \dots, Y(t, k + \ell_p))$$

Figure from [Mueller, FPM, Chapter 8, Springer 2015]

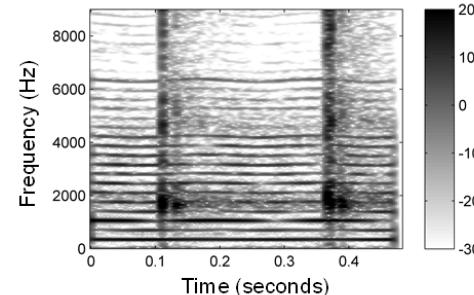
Effect of Filter Length



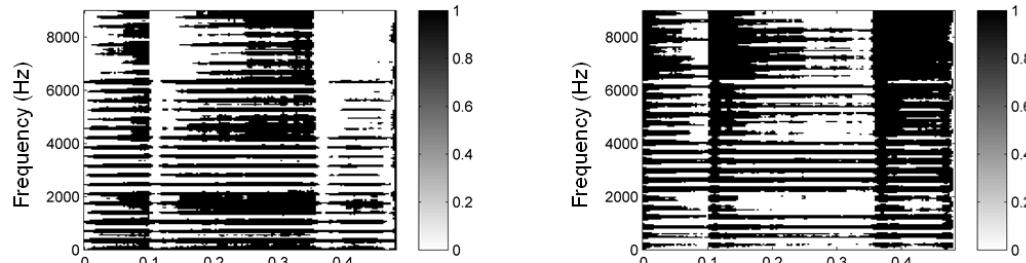
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S1_HPS.html

Masking

violin + castanets



binary
mask



soft
mask

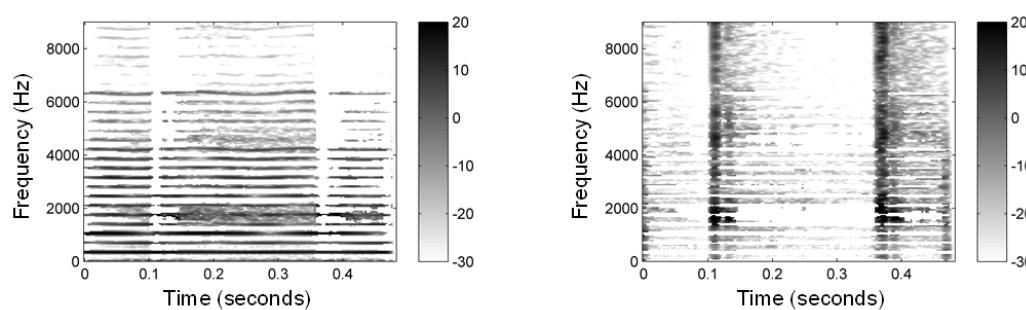


Figure from [Mueller, FPM, Chapter 8, Springer 2015]

Parameters

- Window size, hop size
- Filter length
- Masking method

Q1: Given sampling rate = 44.1 kHz, FFT window size = 4096 samples, hopsize = 1024 samples, what's the physical meaning of using a vertical (percussive) median filter length=17?

Q2: What's the physical meaning of using a horizontal (harmonic) median filter length=17?

Wait ... How about Phase?

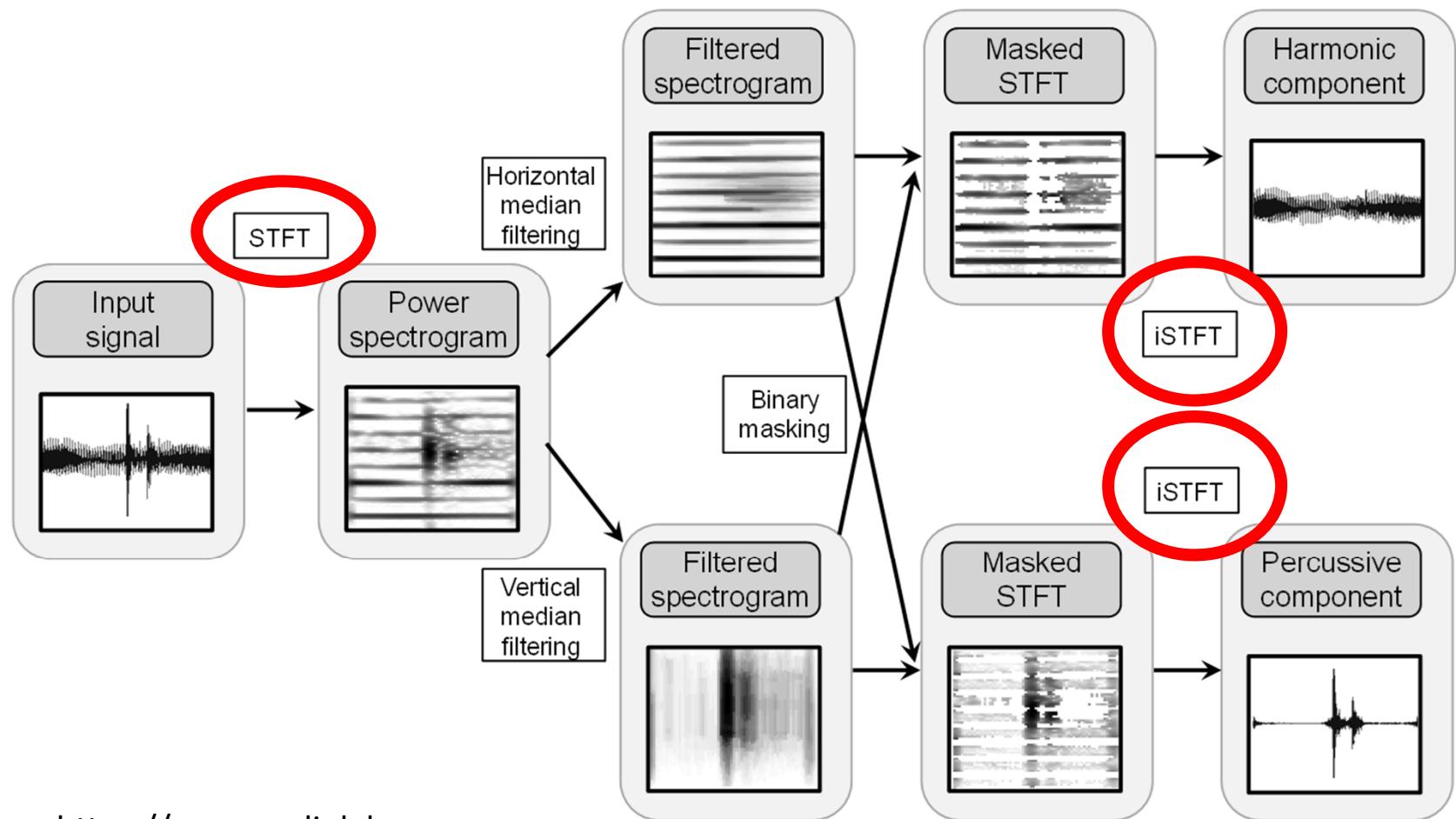
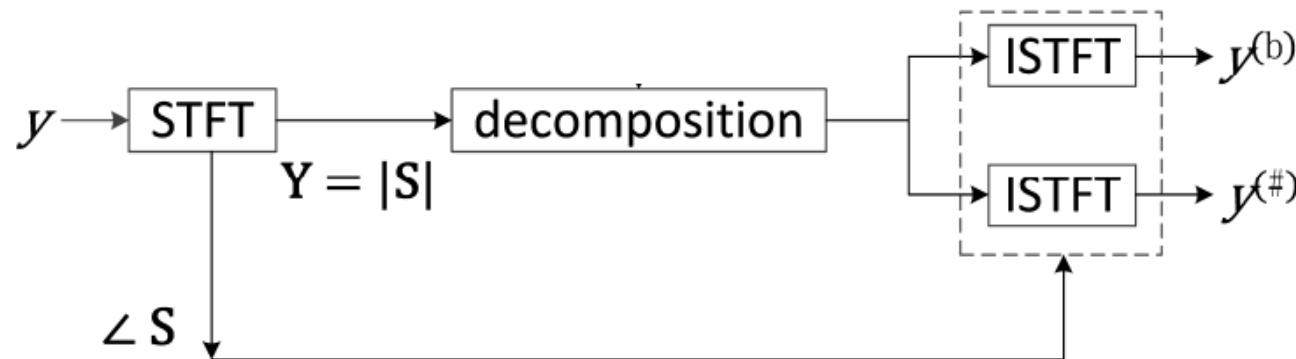


Figure source: https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S1_HPS.html

Reconstruction: Use the Phase of the Mixture

(so that we only need to care about the magnitude)

1. Given a mixture y , compute the STFT \mathbf{Y}
2. Decompose the magnitude $|\mathbf{Y}|$ into two matrices \mathbf{A} and \mathbf{B} (which are also real-valued)
3. Make \mathbf{A} and \mathbf{B} complex-valued by adding the **phase of the mixture** $\angle \mathbf{Y}$
4. Do inverse STFT (ISTFT)



Deal with Phase: Approaches

<https://source-separation.github.io/tutorial/basics/phase.html>

- **Copy the phase from the mixture**
 - Work fine for source separation (but maybe **NOT** for other audio generation problems)
- **Given the magnitude, estimate the phase** (see the lecture on “**vocoder**”)
 - General-purpose solution
- **Work on audio waveforms, not spectrograms**
 - General-purpose solution

Implementation

<https://librosa.org/doc/main/generated/librosa.effects.hpss.html>

librosa.decompose.hpss

(previous page)
Q1: 183 Hz
Q2: 0.395 second

`librosa.decompose.hpss(S, *, kernel_size=31, power=2.0, mask=False, margin=1.0)` [source]

Median-filtering harmonic percussive source separation (HPSS).

If `margin = 1.0`, decomposes an input spectrogram $S = H + P$ where H contains the harmonic components, and P contains the percussive components.

If `margin > 1.0`, decomposes an input spectrogram $S = H + P + R$ where R contains residual components not included in H or P .

This implementation is based upon the algorithm described by ¹ and ².

- [1] Fitzgerald, Derry. "Harmonic/percussive separation using median filtering." 13th International Conference on Digital Audio Effects (DAFX10), Graz, Austria, 2010.
- [2] Driedger, Müller, Disch. "Extending harmonic-percussive separation of audio." 15th International Society for Music Information Retrieval Conference (ISMIR 2014), Taipei, Taiwan, 2014.

Extension: Adding a Residual Component

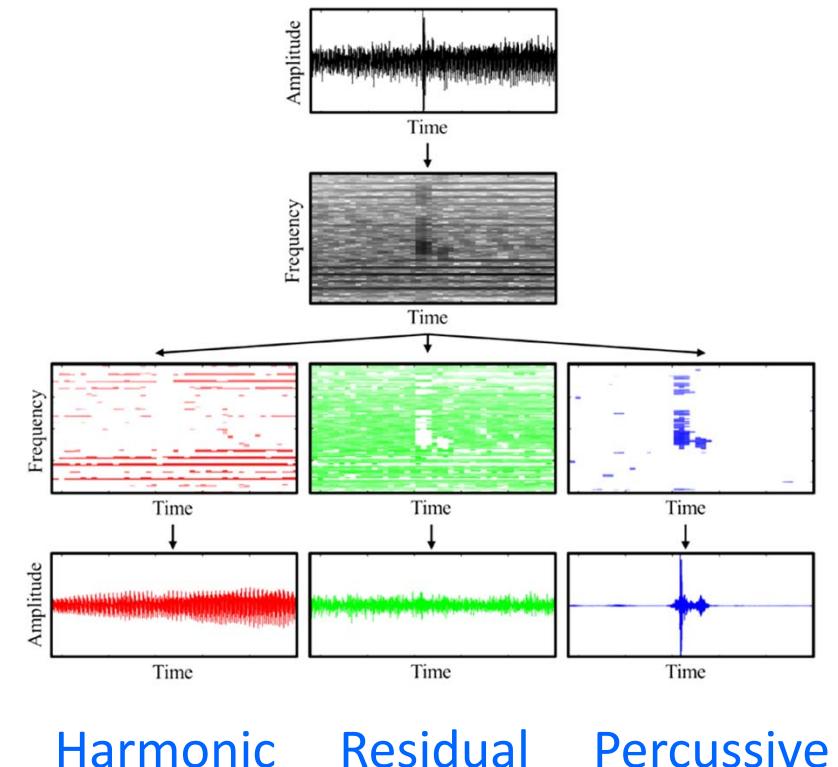
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S1_HRPS.html

$$M_h(t, k) := \left(\tilde{Y}_h(t, k) / (\tilde{Y}_p(t, k) + \epsilon) \right) > \beta$$

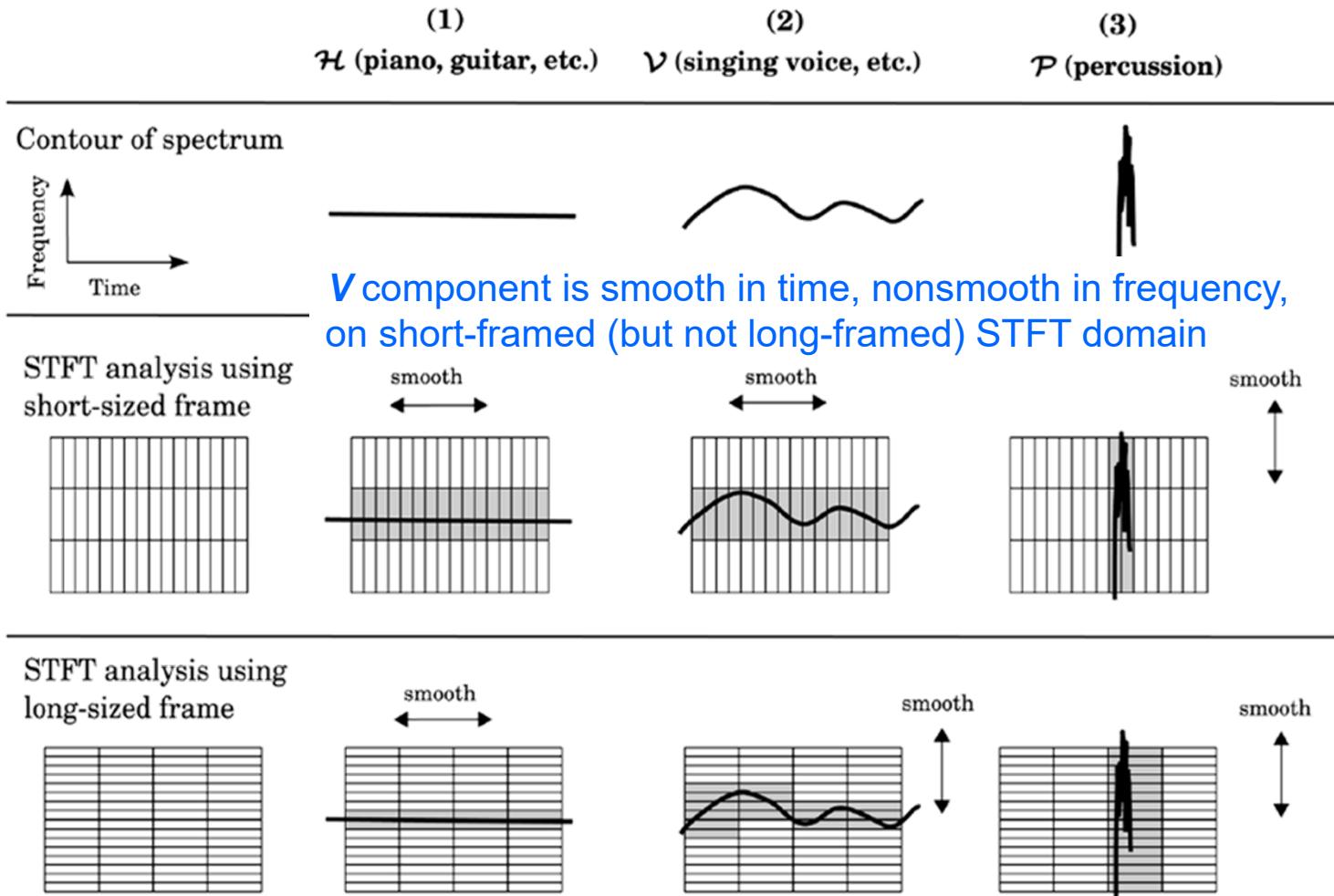
$$M_p(t, k) := \left(\tilde{Y}_p(t, k) / (\tilde{Y}_h(t, k) + \epsilon) \right) \geq \beta$$

$$M_r(t, k) := 1 - (M_h(t, k) + M_p(t, k))$$

- The *harmonic* component contains the **violin**,
the *percussive* component contains the **castanets**,
and the *residual* contains the **applause**
- More demo: <http://www.audiolabs-erlangen.de/resources/2014-ISMIR-ExtHPSep/>



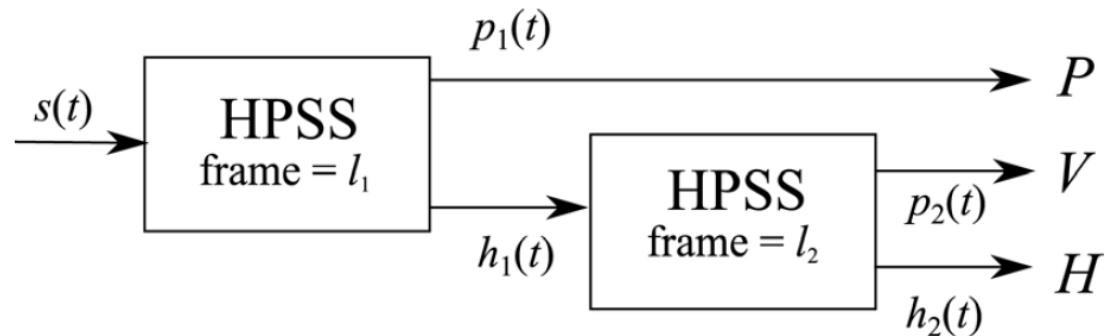
Extension: Separating the Vocals



Ref: Tachibana et al, "Singing voice enhancement in monaural music signals based on two-stage harmonic/percussive sound separation on multiple resolution spectrograms," TASLP 2014

Extension: Separating the Vocals

- Singing voice: intermediate component between ‘harmonic’ and ‘percussive’
- Perform the **two HPSS** on spectrograms with **two different time-frequency resolutions**



Ref: Tachibana et al, “Singing voice enhancement in monaural music signals based on two-stage harmonic/percussive sound separation on multiple resolution spectrograms,” TASLP 2014

Strong Assumption, OK but Limited Performance

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S1_HPS.html

Piece	x	x_h	x_p
Violin + Castanets	▶ - ⏪ ⋮	▶ - ⏪ ⋮	▶ - ⏪ ⋮
Violin + Castanets + Applause	▶ - ⏪ ⋮	▶ - ⏪ ⋮	▶ - ⏪ ⋮
Chopin, Op. 28 No. 4	▶ - ⏪ ⋮	▶ - ⏪ ⋮	▶ - ⏪ ⋮
Vibrato + Impulses + Noise	▶ - ⏪ ⋮	▶ 0:00 - ⏪	▶ 0:00 - ⏪
Bearlin, Roads	▶ 0:00 - ⏪	▶ 0:00 - ⏪	▶ 0:00 - ⏪
Bornemark, Stop Messing With Me	▶ 0:00 - ⏪	▶ 0:00 - ⏪	▶ 0:00 - ⏪

Outline

- General idea
- Traditional methods (*non-DL, unsupervised*)
 - Median filtering
 - **Nonnegative matrix factorization (NMF)**
 - Robust principal component analysis (RPCA)
- Deep learning based methods

Nonnegative Matrix Factorization (NMF)

- Factorize a non-negative matrix (e.g., the **magnitude spectrogram**) into two
 - Templates*
 - Activations*

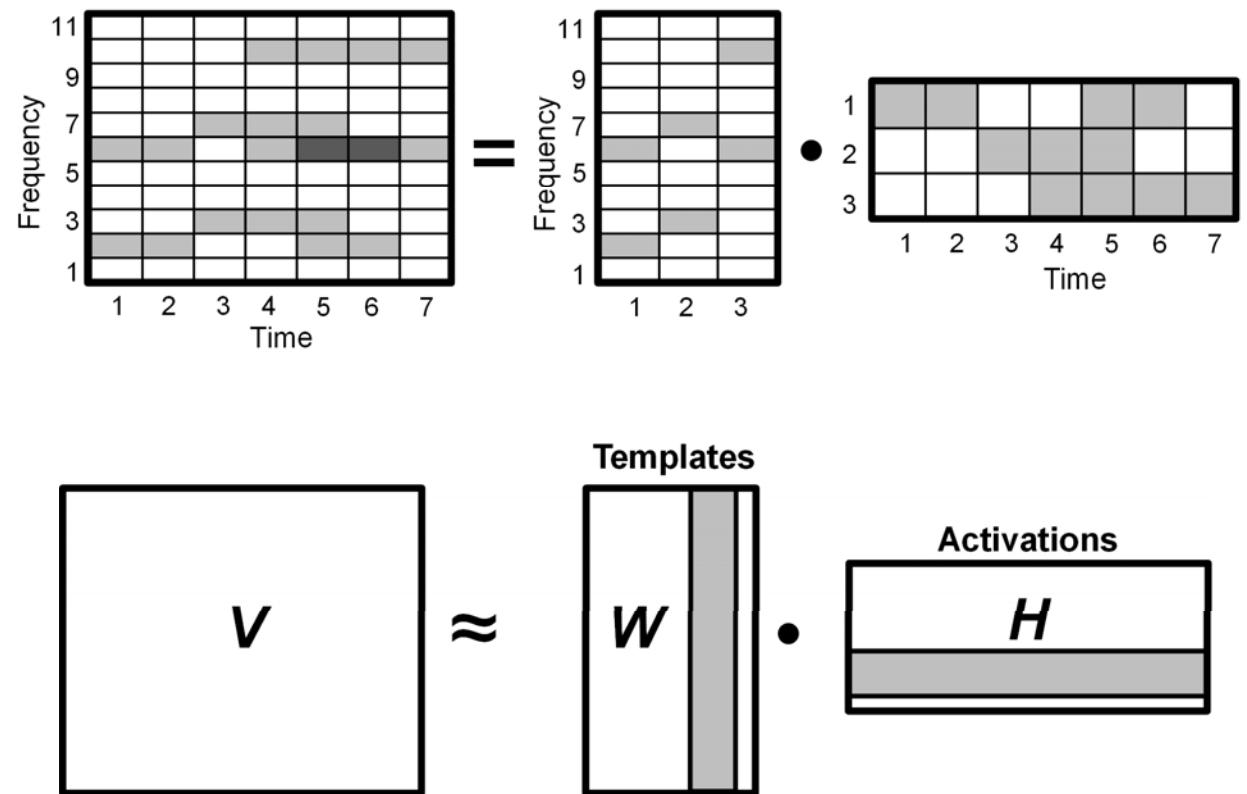


Figure from [Mueller, FPM, Chapter 8, Springer 2015]

NMF: Basic Idea

Given a *nonnegative* matrix \mathbf{V} of dimensions $F \times N$, NMF is the problem of finding a factorization

$$\mathbf{V} \approx \mathbf{W}\mathbf{H}$$

where \mathbf{W} and \mathbf{H} are *nonnegative* matrices of dimensions $F \times K$ and $K \times N$, respectively.

K is usually chosen such that $F K + K N \ll F N$, hence reducing the data dimension, but not always.

NMF: Basic Idea

Along VQ, PCA or ICA, NMF provides an **unsupervised linear representation** of data

$$\begin{array}{ccc} \mathbf{v}_n & \approx & \mathbf{W} & \mathbf{h}_n \\ \text{data vector} & & \text{"explanatory variables"} & \text{"regressors"} \\ & & \text{"basis", "dictionary"} & \text{"expansion coefficients"} \\ & & \text{"patterns"} & \text{"activation coefficients"} \end{array}$$

and \mathbf{W} is learnt from the set of data vectors $\mathbf{V} = [\mathbf{v}_1 \dots \mathbf{v}_N]$.

- ▶ **nonneg.** of \mathbf{W} ensures *interpretability* of the dictionary
(features \mathbf{w}_k and data \mathbf{v}_n belong to same space).
- ▶ **nonneg.** of \mathbf{H} tends to *produce part-based representations*
because subtractive combinations are forbidden.

NMF: Algorithm

- **Cost function:** Euclidean distance

$$\|V - WH\|^2 = \sum_{ij} (V_{ij} - WH_{ij})^2$$

- Iterative update
 - Fix W , update H
 - Fix H , update W

$$H_{a\mu} \leftarrow H_{a\mu} + \eta_{a\mu} [(W^T V)_{a\mu} - (W^T W H)_{a\mu}].$$

- **Multiplicative** update
 - easily preserve nonnegativity
 - easy to implement
 - fast ($O(FKN)$ per iteration)
 - zeros remain zeros!

$$\eta_{a\mu} = \frac{H_{a\mu}}{(W^T W H)_{a\mu}},$$

$$H_{a\mu} \leftarrow H_{a\mu} \frac{(W^T V)_{a\mu}}{(W^T W H)_{a\mu}}$$

Ref 1: Lee & Seung, “Algorithms for non-negative matrix factorization,” NIPS 2001

Ref 2: Lin, “On the convergence of multiplicative update algorithms for non-negative matrix factorization,” TNN 2007

NMF-based Music Transcription

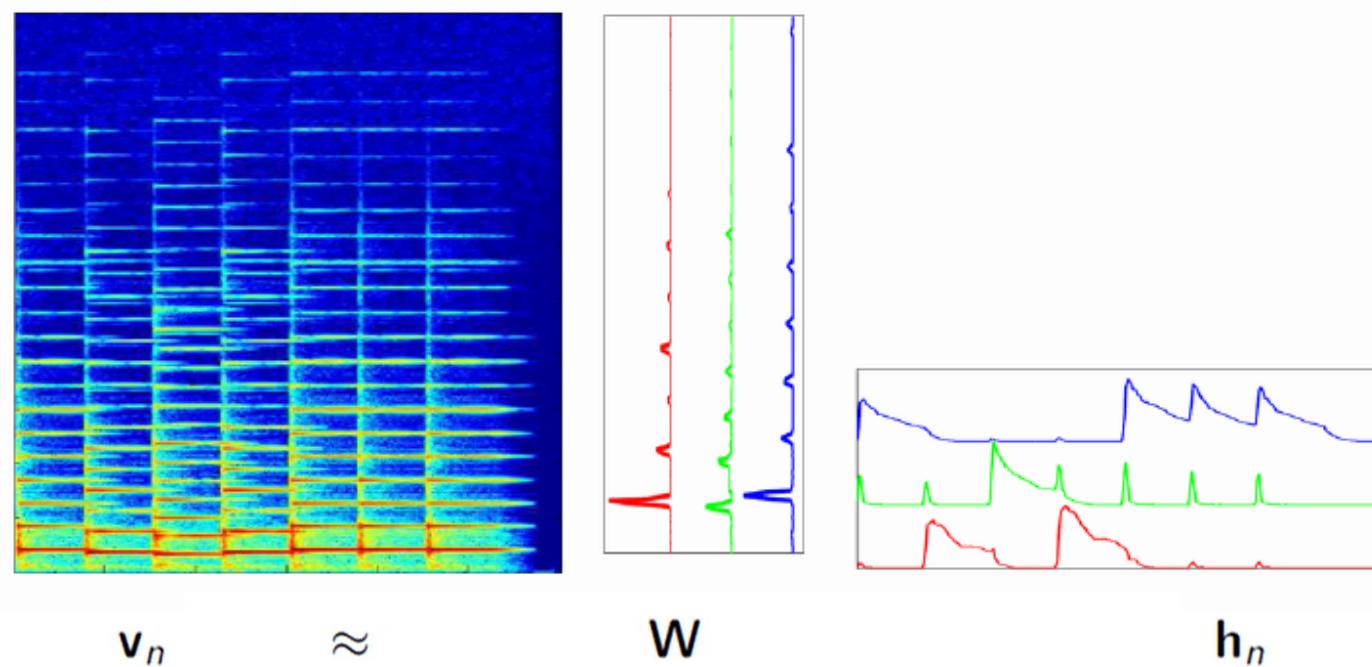
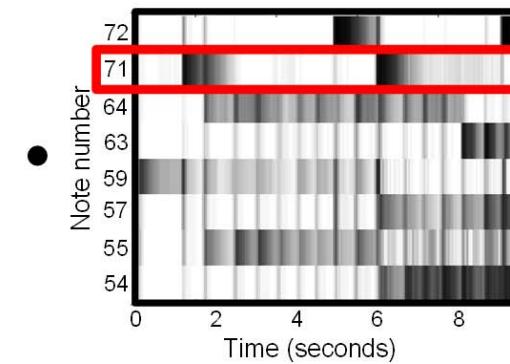
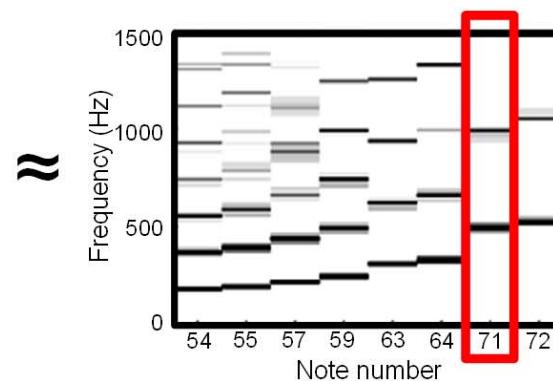
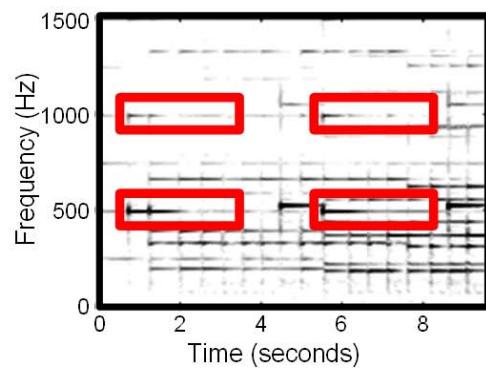
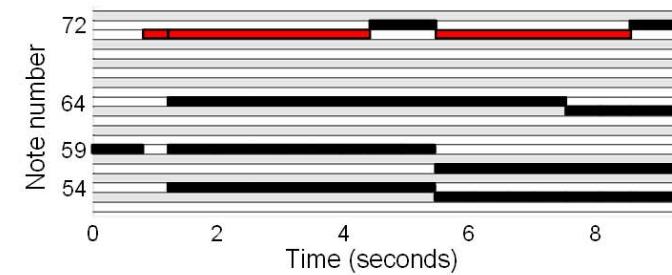
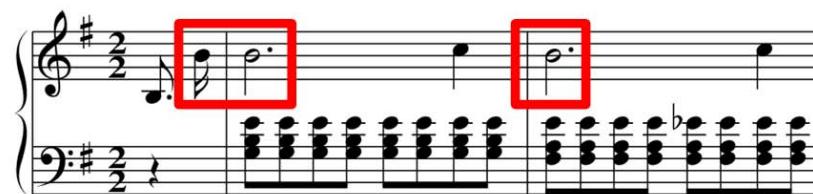


Figure from Byran & Sun's slides

Figure from Byran & Sun's slides

NMF-based Music Transcription

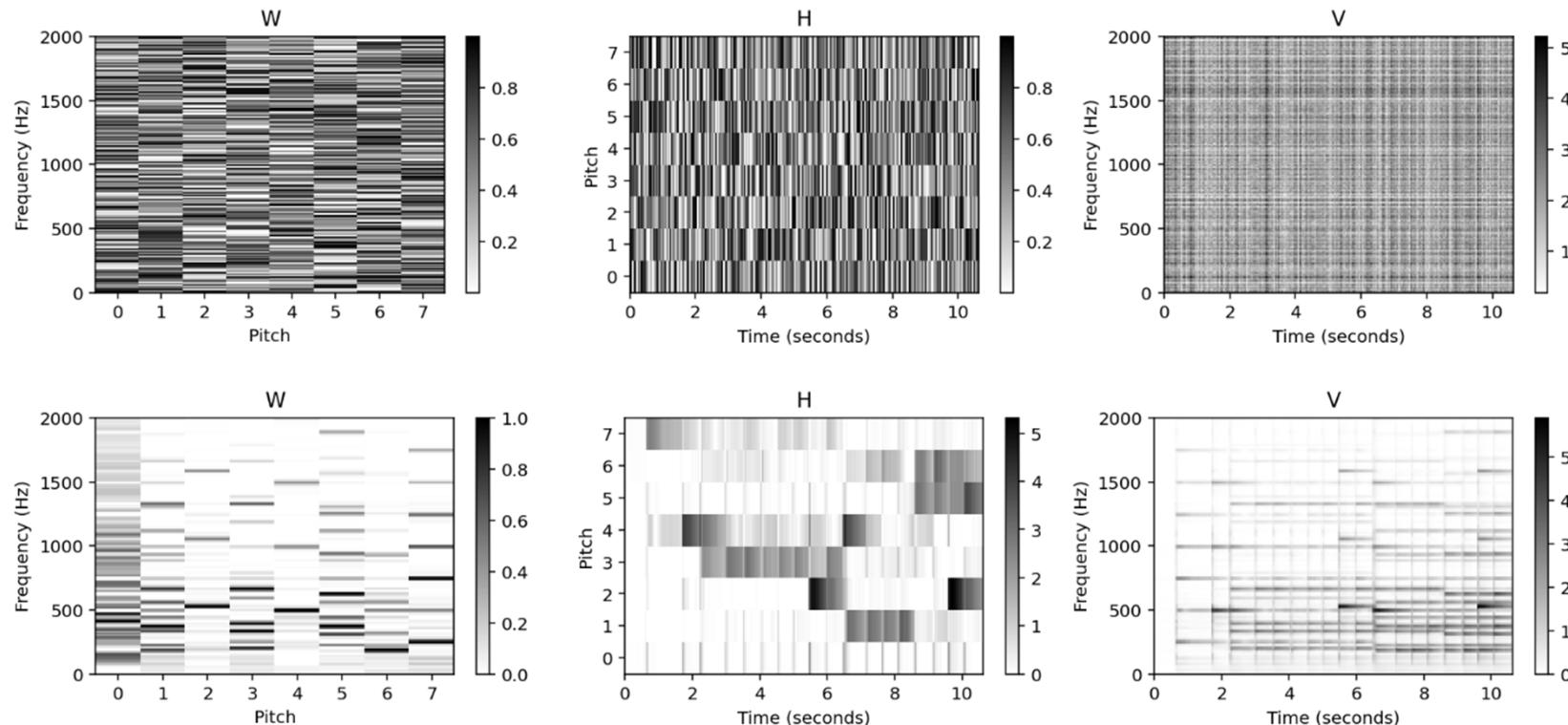
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S3_NMFbasic.html



NMF with Random Initialization

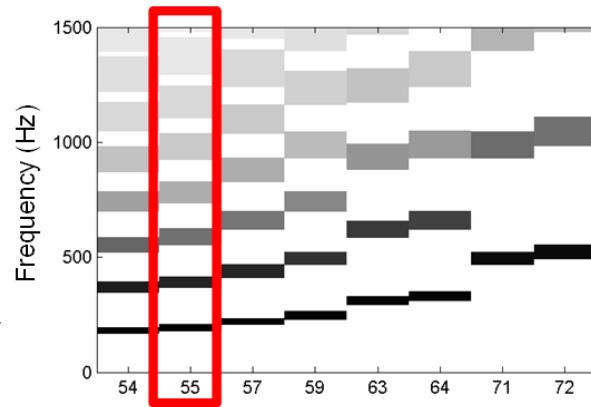
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S3_NMFbasic.html

- OK reconstruction, but lacks clear musical semantics

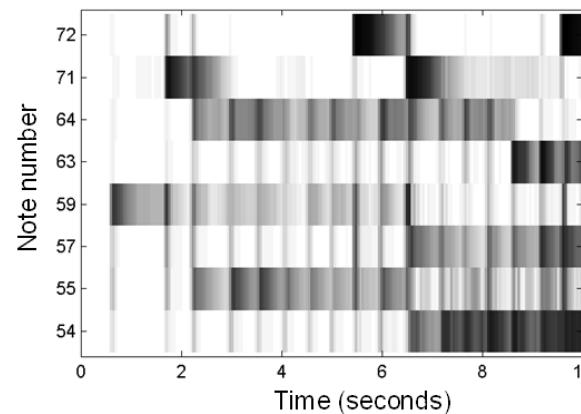
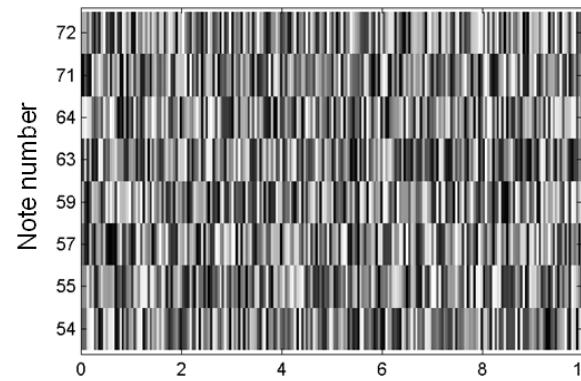
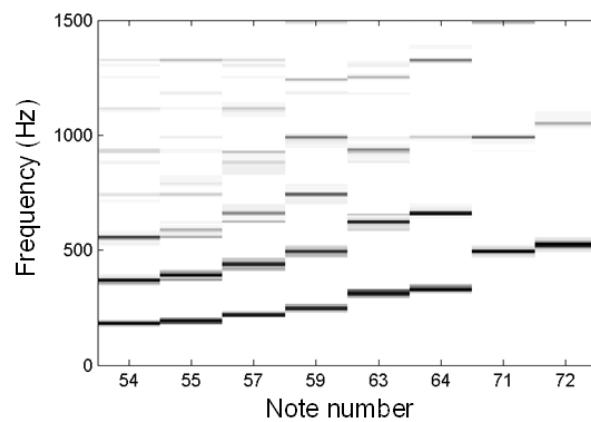


NMF with Harmonic Template Initialization (on W)

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S3_NMFbasic.html

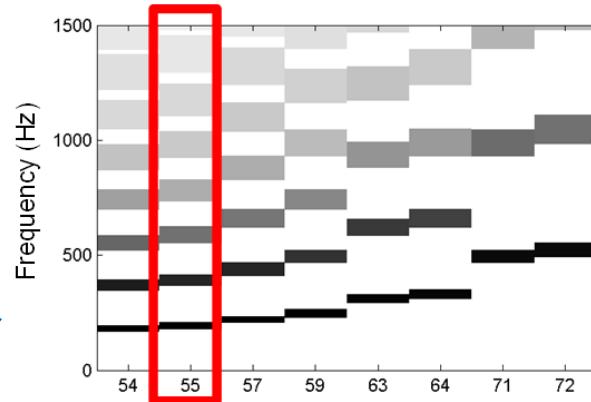


zeros remain zeros using the *multiplicative update*

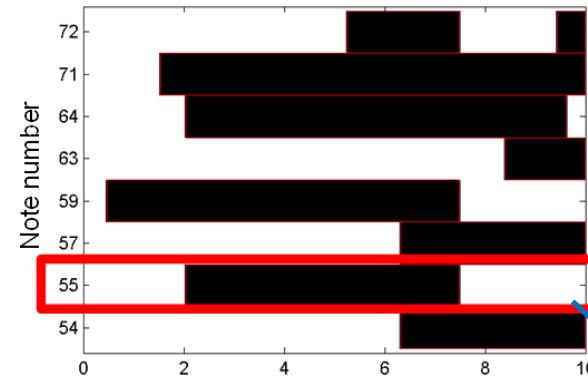
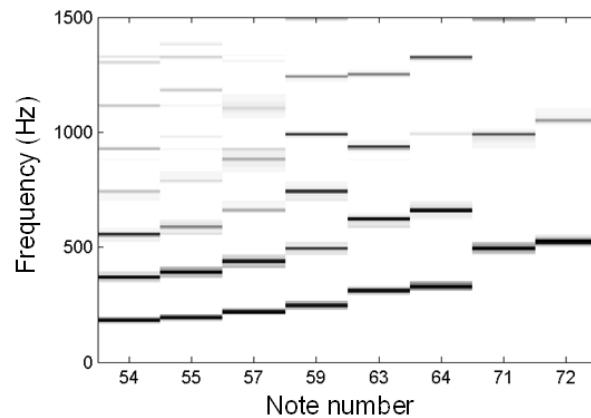


NMF with Score-Informed Initialization (on W and H)

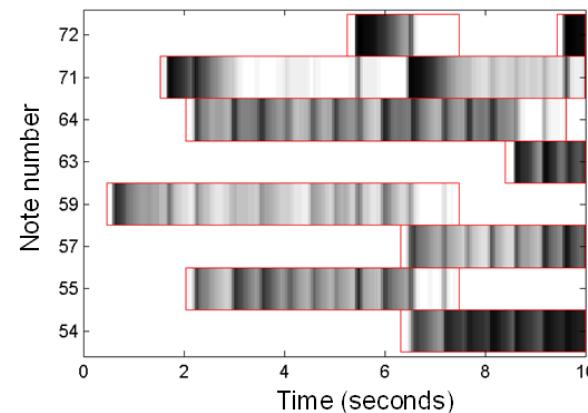
https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S3_NMFbasic.html



zeros remain zeros!

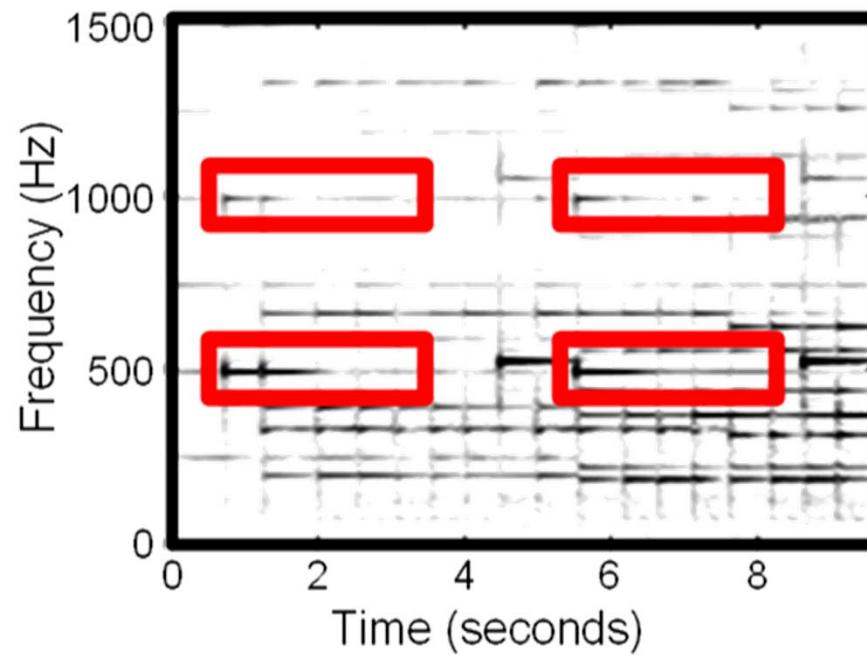
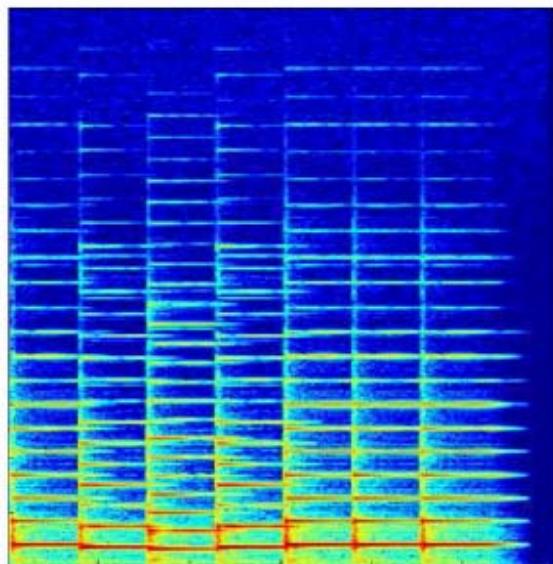


zeros remain zeros!



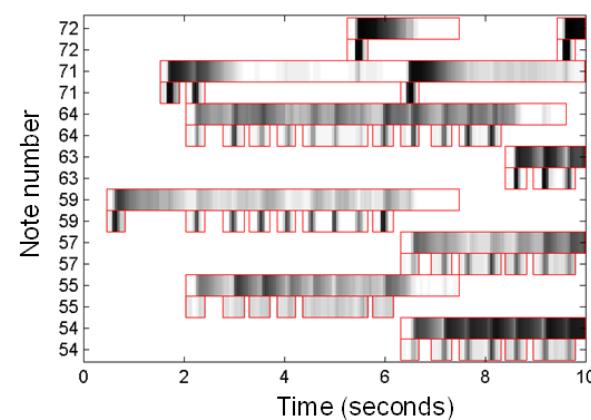
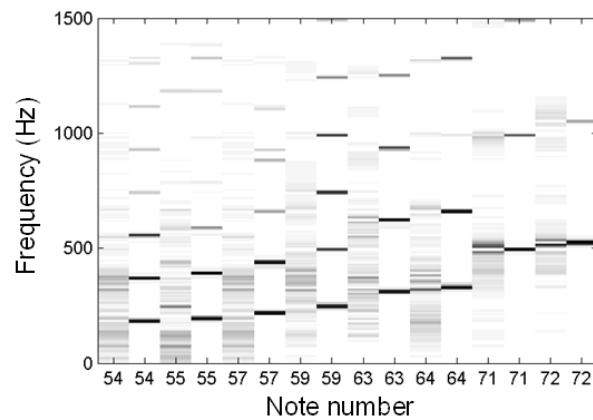
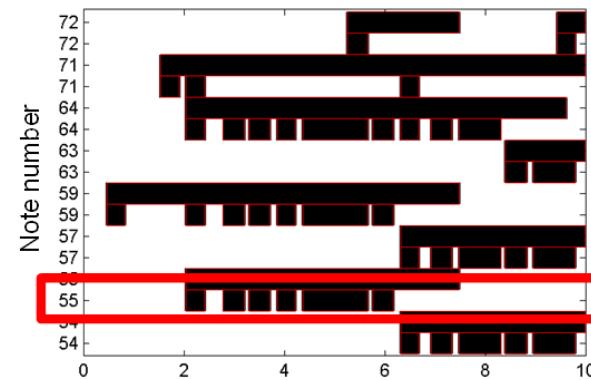
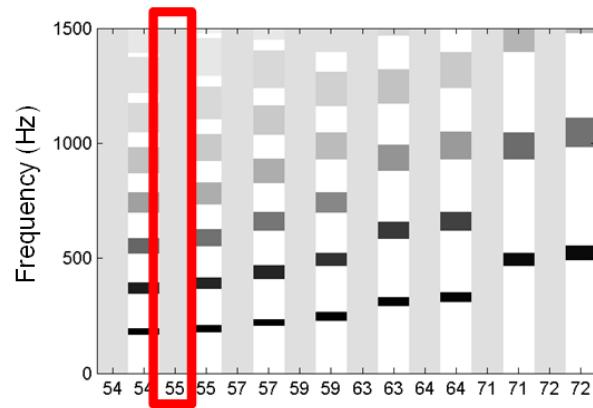
Dealing with Transients

- **Transient:** a high amplitude, short-duration sound at the beginning of a waveform that occurs in phenomena such as musical sounds



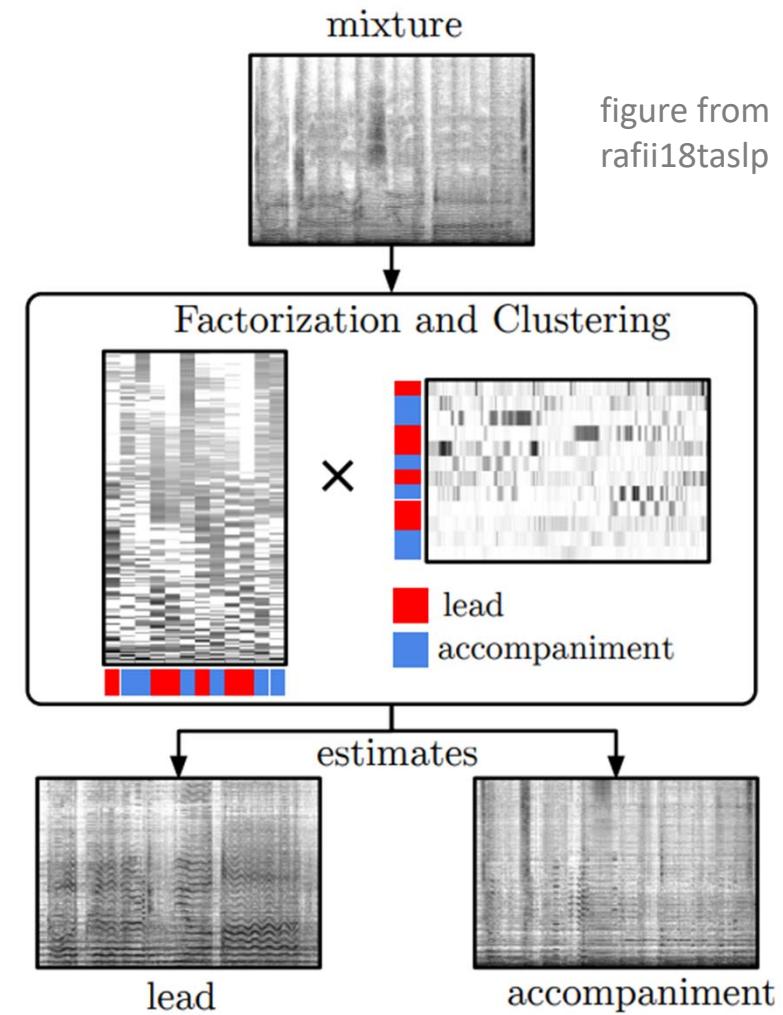
NMF with Score-Informed Initialization + Onset

https://www.audiolabs-erlangen.de/resources/MIR/FMP/C8/C8S3_NMFbasic.html



NMF-based Source Separation

- **NMF-based factorization**
- **Template clustering/classification**
 - For example, by reusing a vocal/non-vocal classifier (on the templates) with MFCC, LFPC, and PLP coefficients as features
- $\min_H \| V_{\text{mix}} - [W_A, W_B]H \|_F$
 - $\widehat{V}_A = W_A H_A$
 - $\widehat{V}_B = W_B H_B$



Ref 1: Vembu & Baumann, "Separation of vocals from polyphonic audio recordings," ISMIR 2005

Ref 2: Rafii et al, "An overview of lead and accompaniment separation in music," TASLP 2018

Outline

- General idea
- **Traditional methods (*non-DL, unsupervised*)**
 - Median filtering
 - Nonnegative matrix factorization (NMF)
 - **Robust principal component analysis (RPCA)**
- Deep learning based methods

RPCA-based Source Separation

- Decompose a matrix into a **sparse** matrix (*assumed to correspond to vocal*) and a **low-rank** matrix (*instrumental background*) and

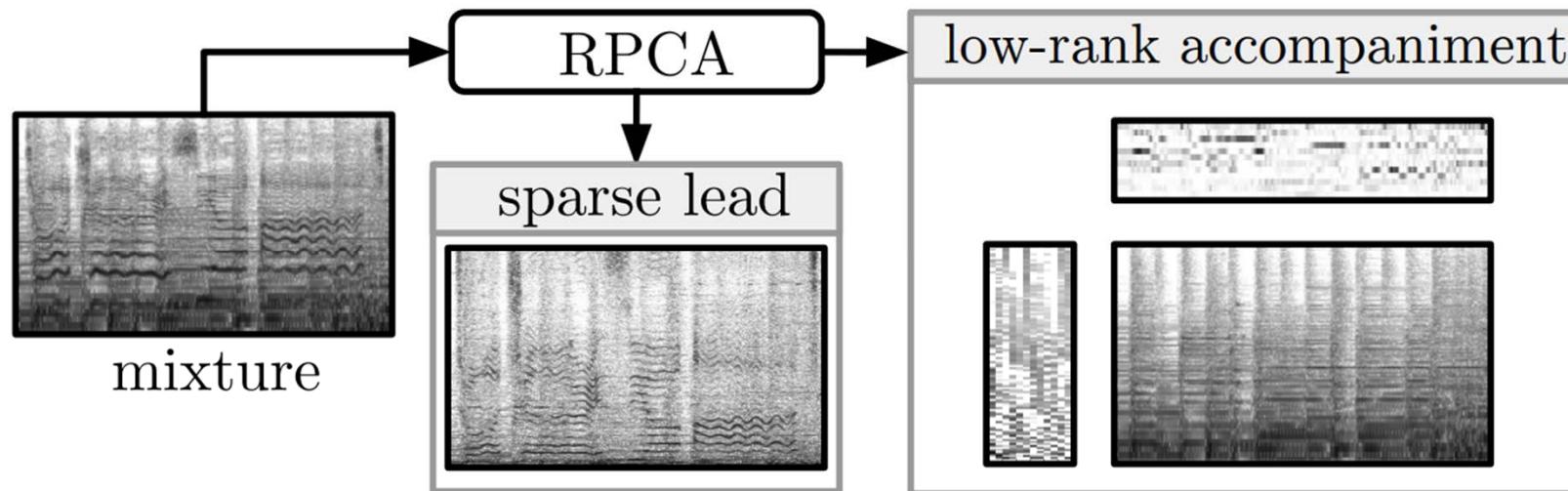


figure from
rafii18taslp

- Ref 1: Huang et al, "Singing-voice separation from monaural recordings using robust principal component analysis," ICASSP 2014
Ref 2: Rafii et al, "An overview of lead and accompaniment separation in music," TASLP 2018

Robust Principal Component Analysis (RPCA)

- Decomposes M into a **low-rank** matrix L plus a **sparse** matrix S

$$\min \|L\|_* + \lambda \|S\|_1$$

$$\text{s.t. } L + S = M$$

- **l_1 norm:** $\|S\|_1 = \sum_{ij} |S_{ij}|$ (sum of absolute values; a convex relaxation of l_0 norm)
- **Nuclear norm:** $\|L\|_* = \sum_i \sigma_i(L)$ (sum of singular values; a convex relaxation of the rank of the matrix)

Ref: Lin et al, "The augmented Lagrange multiplier method for exact recovery of corrupted low-rank matrices," 2009

Algorithm: Augmented Lagrangian Approach

$$\begin{array}{ll}\text{minimize} & \|L\|_* + \lambda\|S\|_1 + \frac{1}{2\tau}\|M - L - S\|_F^2 \\ \text{subject to} & L + S = M\end{array}$$

Lagrangian

$$\mathcal{L}(L, S; Y) = \|L\|_* + \lambda\|S\|_1 + \frac{1}{\tau}\langle Y, M - L - S \rangle + \frac{1}{2\tau}\|M - L - S\|_F^2$$

Easy to minimize over L and S separately

$$\arg \min_L \mathcal{L}(L, S, Y) = \mathcal{D}_\tau(M - S + Y)$$

$$\arg \min_S \mathcal{L}(L, S, Y) = \mathcal{S}_{\lambda\tau}(M - L + Y)$$

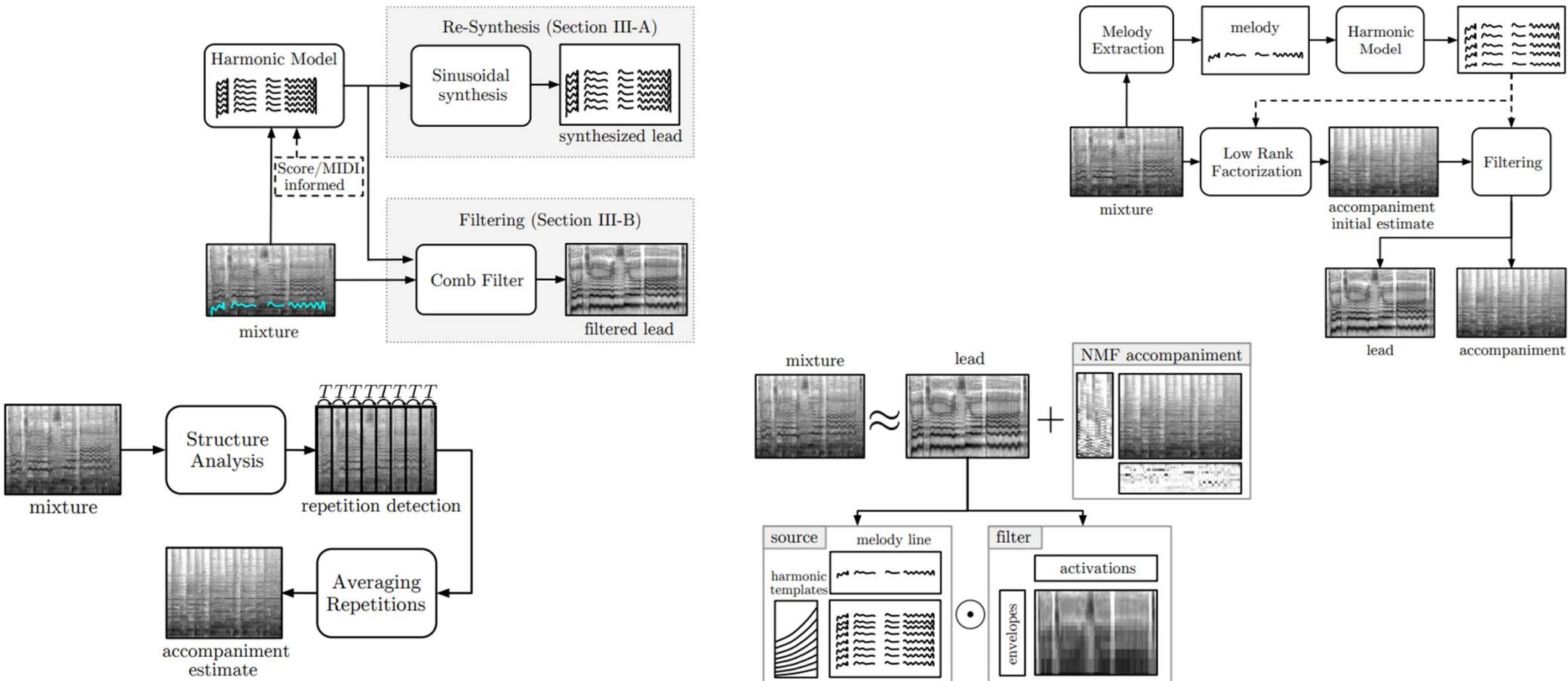
Scalar shrinkage: $\mathcal{S}_\tau[x] = \text{sgn}(x) \max(|x| - \tau, 0)$

- Componentwise thresholding $\mathcal{S}_\tau(X)$
- Singular value thresholding $\mathcal{D}_\tau(X)$

$$\mathcal{D}_\tau(X) = U\mathcal{S}_\tau(\Sigma)V^* \quad X = U\Sigma V^*$$

Ref: Lin et al, "The augmented Lagrange multiplier method for exact recovery of corrupted low-rank matrices," 2009

Many Other Unsupervised Methods



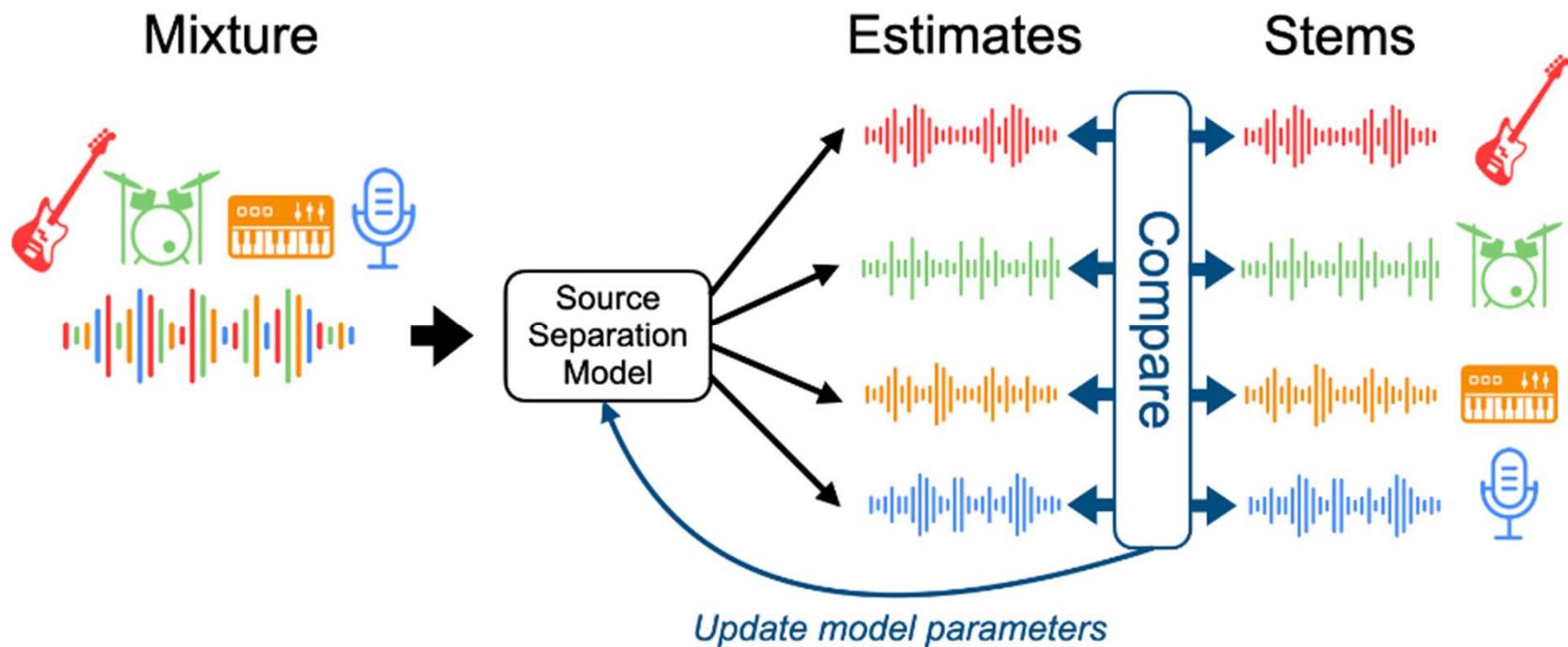
Ref: Rafii et al, “An overview of lead and accompaniment separation in music,” TASLP 2018

Outline

- General idea
- Traditional methods
- **Deep learning based methods**

Supervised Approach

- Learn from **paired data** of {mixture, stems}



Why Not Using a Supervised Approach?

- **Challenge 1:** Scarcity of paired data in the early days
- **Challenge 2:** It involves **audio-domain music generation**, which is hard

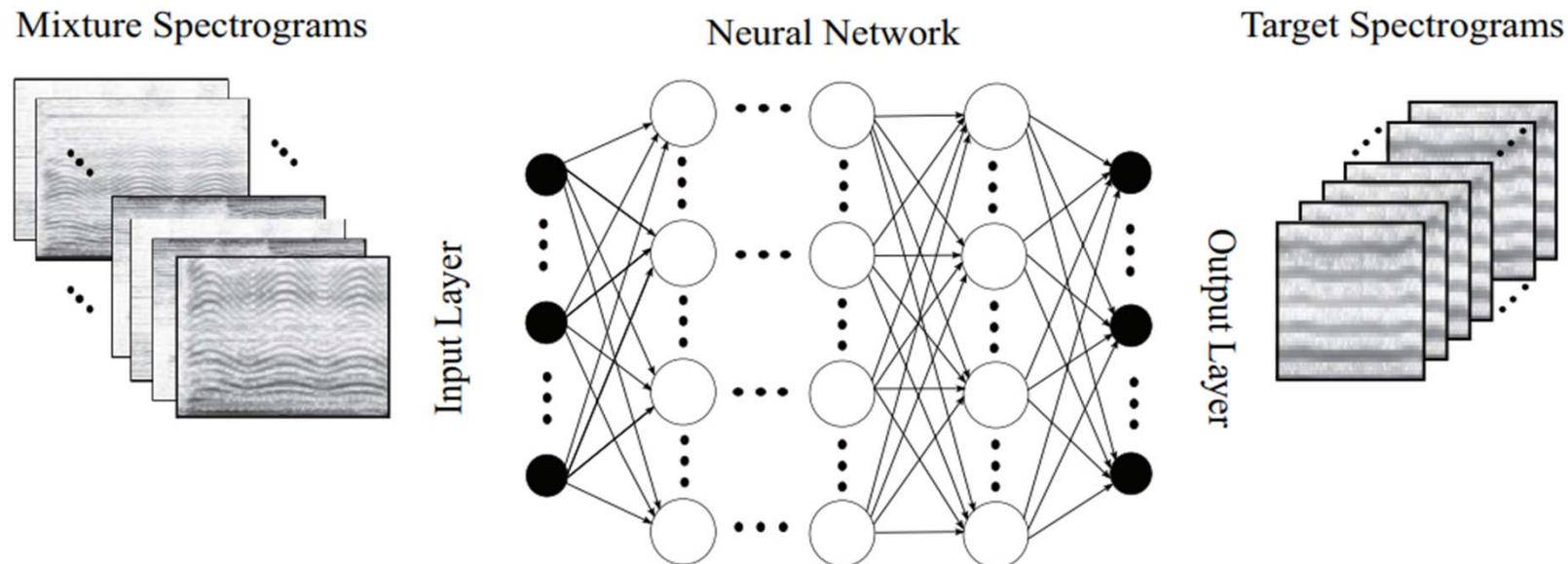


Figure source: Cano et al, "Musical source separation: An introduction," IEEE Signal Processing Magazine 2019

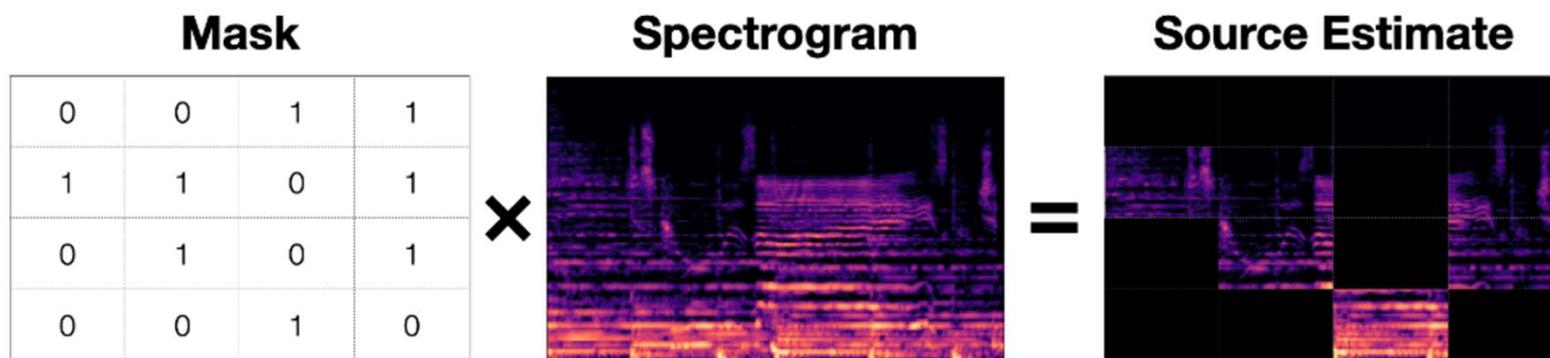
59

Solutions

- **Challenge 1:** Scarce of paired data in the early days
 - ✓ Solution
 - Creation of **new datasets** for source separation
 - **Data augmentation** techniques
- **Challenge 2:** It involves **audio-domain music generation**, which is hard
 - ✓ Solution
 - Predict “**masks**”, rather than the actual stem
 - Or, **directly predict the stem anyway**

Breakthrough 1: Predicting the “Mask”

https://source-separation.github.io/tutorial/basics/tf_and_masking.html



- Bypass the difficulty of generating the audio directly
- Can be either **binary** mask or **soft** mask
- Can be considered as **a classification problem**
 - For example: whether a **time-frequency bin** is vocal or not

RNN-based Approach

Given the input features, \mathbf{x}_t , from the mixture, we obtain the output predictions $\hat{\mathbf{y}}_{1t}$ and $\hat{\mathbf{y}}_{2t}$ through the network. The soft time-frequency mask \mathbf{m}_t is defined as follows:

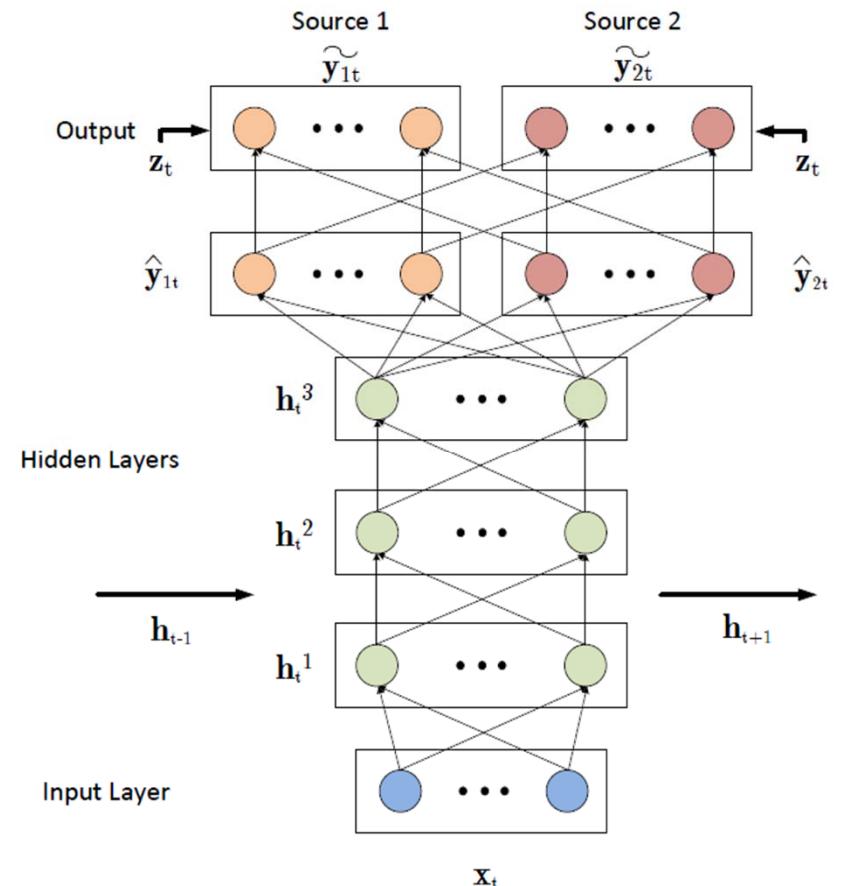
$$\mathbf{m}_t(f) = \frac{|\hat{\mathbf{y}}_{1t}(f)|}{|\hat{\mathbf{y}}_{1t}(f)| + |\hat{\mathbf{y}}_{2t}(f)|}, \quad (4)$$

where $f \in \{1, \dots, F\}$ represents different frequencies.

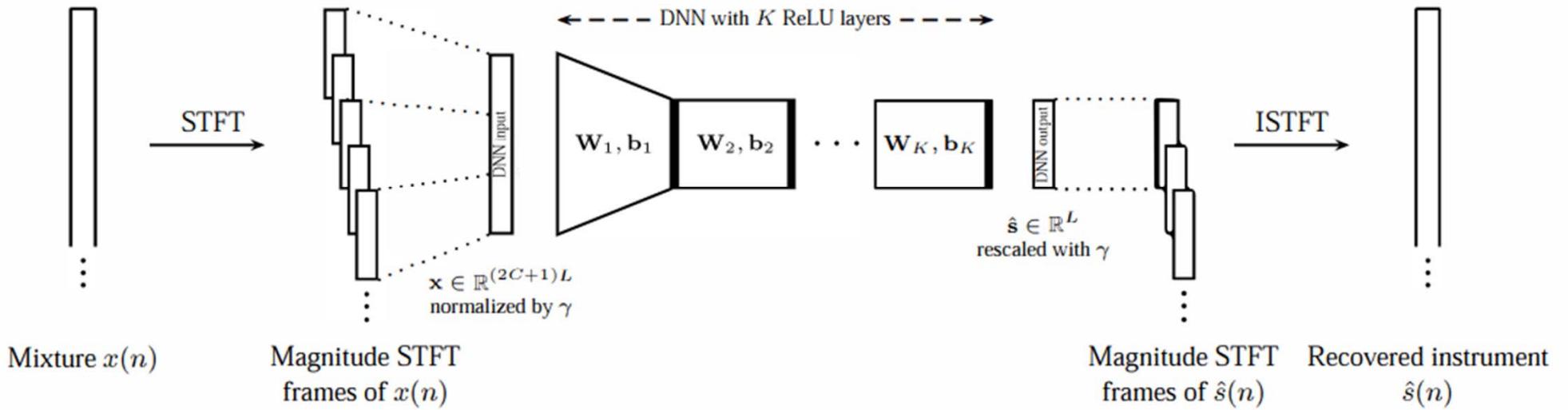
Once a time-frequency mask \mathbf{m}_t is computed, it is applied to the magnitude spectra \mathbf{z}_t of the mixture signals to obtain the estimated separation spectra $\hat{\mathbf{s}}_{1t}$ and $\hat{\mathbf{s}}_{2t}$, which correspond to sources 1 and 2, as follows:

$$\begin{aligned} \hat{\mathbf{s}}_{1t}(f) &= \mathbf{m}_t(f) \mathbf{z}_t(f) \\ \hat{\mathbf{s}}_{2t}(f) &= (1 - \mathbf{m}_t(f)) \mathbf{z}_t(f), \end{aligned} \quad (5)$$

where $f \in \{1, \dots, F\}$ represents different frequencies.



DNN-based Approach

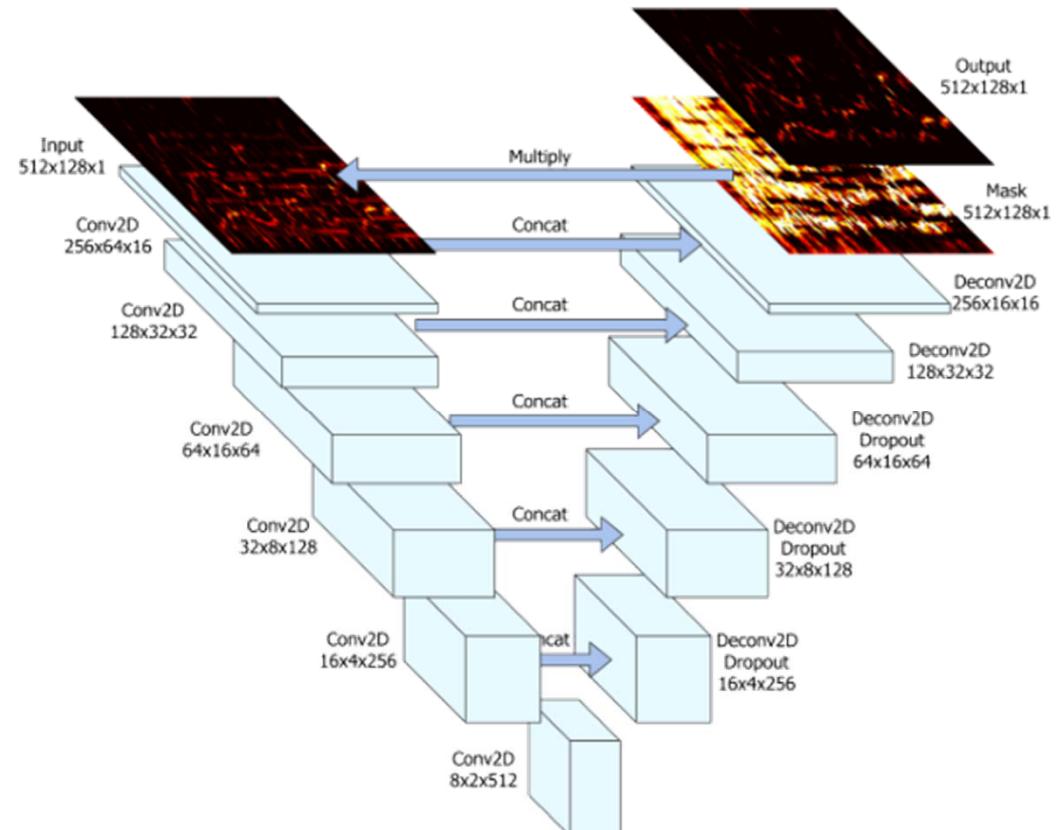


- Like the previous approach; operate *frame-by-frame*
- Connection between frames handled by recurrent layers or by stacking frames

U-Net-based Approach

<https://source-separation.github.io/tutorial/approaches/deep/architectures.html>

- Input a spectrogram (***multiple frames***), output a mask
 - Exploit 2D time-frequency patterns
 - Fixed-size input/output
 - An audio signal must be broken up into spectrograms with fixed number of time and frequency dimensions
- U-Net: **encoder/decoder** with symmetric skip connections
 - Down-sample and then up-sample



Ref: Jansson et al, "Singing voice separation with deep u-net convolutional networks," ISMIR 2017

Library: Spleeter

(It uses the U-Net approach)

<https://github.com/deezer/spleeter>

Spleeter is Deezer source separation library with pretrained models written in Python and uses Tensorflow. It makes it easy to train source separation model (assuming you have a dataset of isolated sources), and provides already trained state of the art model for performing various flavour of separation :

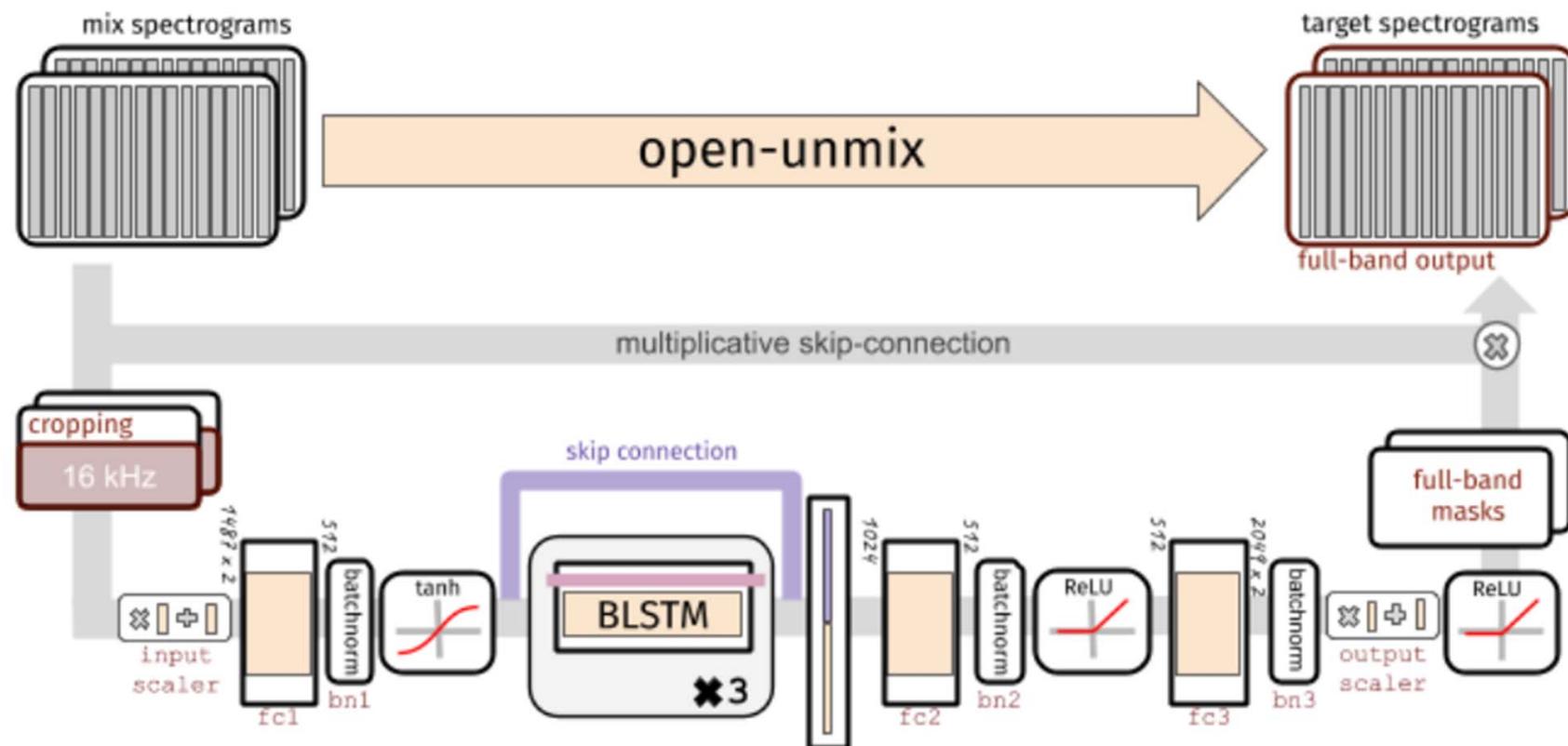
- Vocals (singing voice) / accompaniment separation (2 stems)
- Vocals / drums / bass / other separation (4 stems)
- Vocals / drums / bass / piano / other separation (5 stems)

2 stems and 4 stems models have high performances on the musdb dataset. **Spleeter** is also very fast as it can perform separation of audio files to 4 stems 100x faster than real-time when run on a GPU.

We designed **Spleeter** so you can use it straight from command line as well as directly in your own development pipeline as a Python library. It can be installed with pip or be used with Docker.

Library: Open-Unmix

<https://sigsep.github.io/open-unmix/>



Ref: Stöter et al, "Open-Unmix - A reference implementation for music source separation," J. Open Source Software 2019

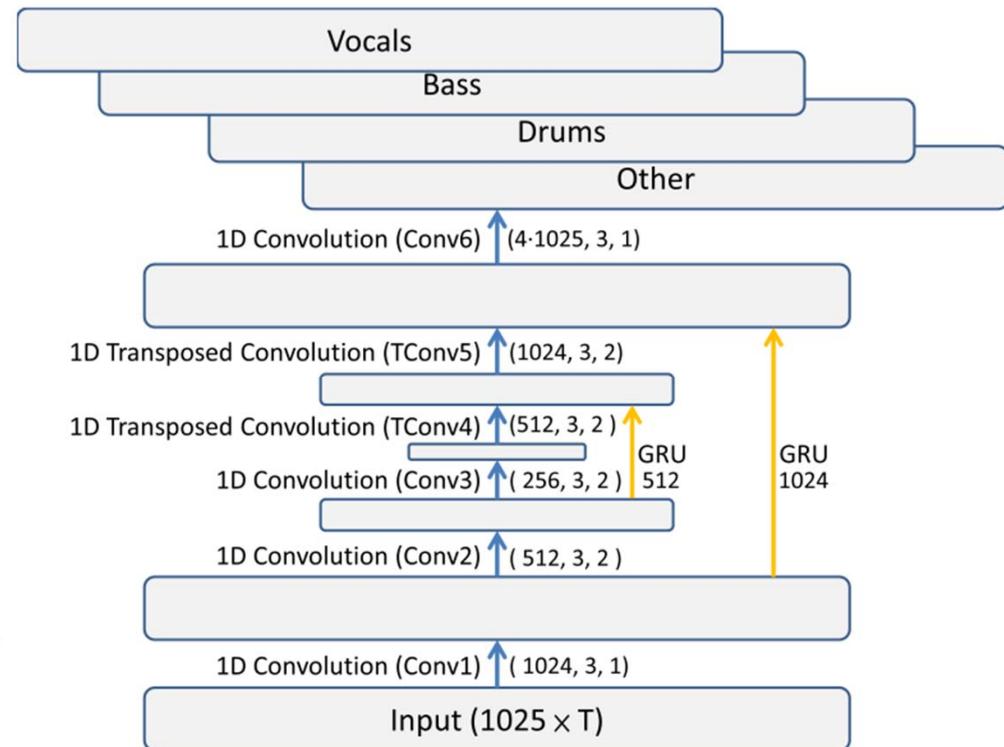
Breakthrough 2: Advance in Neural Audio Generation

- Generative models become more and more powerful, for not only images but also audio
 - More on the details of such models in the next lectures
- **Let's predict (synthesize) the stem directly**
 - *Discriminative → generative*



Let's Synthesize the Stems: the ARC Model

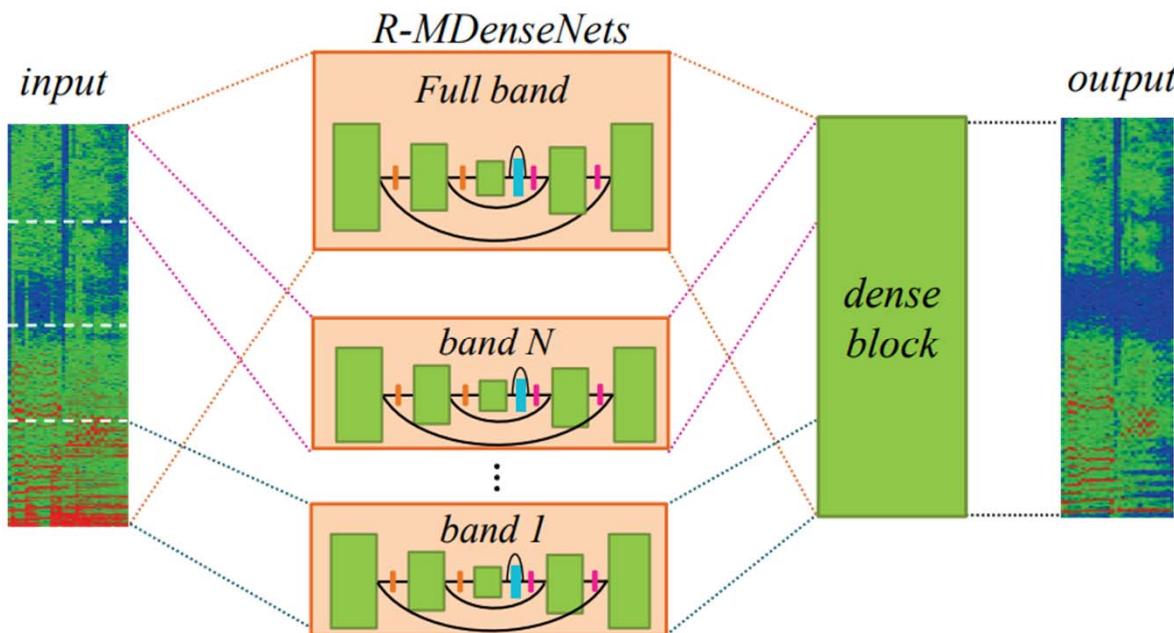
- ARC model [liu18icmla]
 - Leaky ReLU instead of softmax at output
 - “In our pilot experiments, we also tried to apply a softmax function to the output layer so that the network predicts masks for different sources and enforces the condition that the summation of the predicted source spectrograms is equal to the mixture spectrogram. We found that this setting ***largely speeds up*** the training process, but ***the result becomes much worse***. Therefore, we decided to use a leaky ReLU as the nonlinearity function to the output layer to **directly estimate the source spectrograms**”.
 - 1D convolution instead of 2D (so that we can use *recurrent* skip connections)



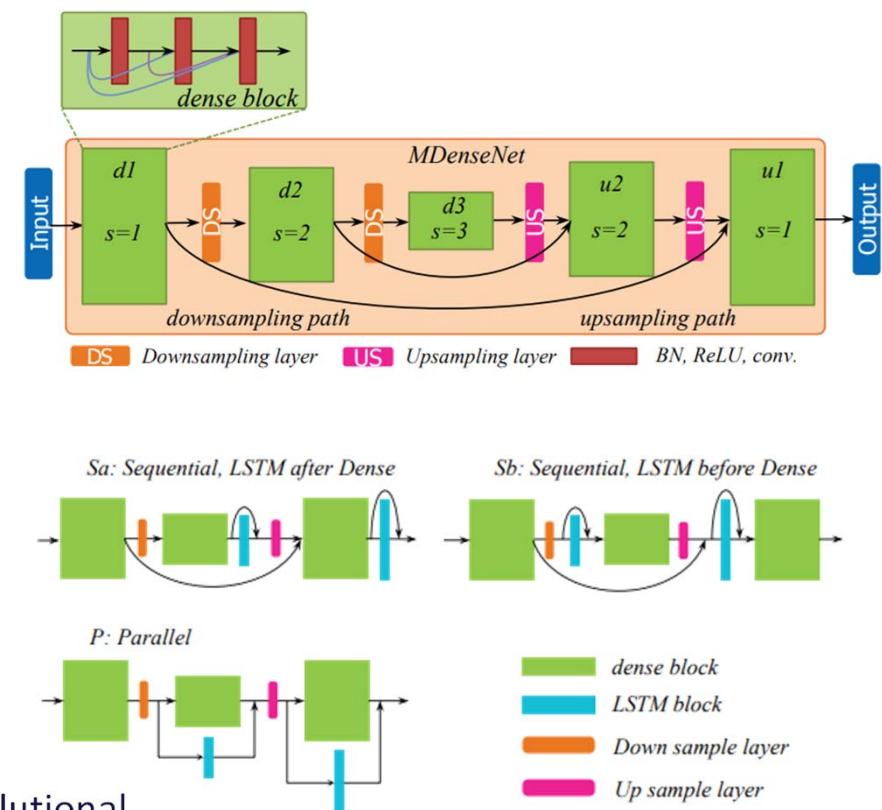
Ref: Liu and Yang, “Denoising auto-encoder with recurrent skip connections and residual regression for music source separation,” ICMLA 2018

MMDenseLSTM

- DenseNet with multi-scale and multi-band structure
- LSTM for long-term dependencies



Ref: Takahashi et al, "MMDenseLSTM: An efficient combination of convolutional and recurrent neural networks for audio source separation," IWAENC 2018



How about Phase?

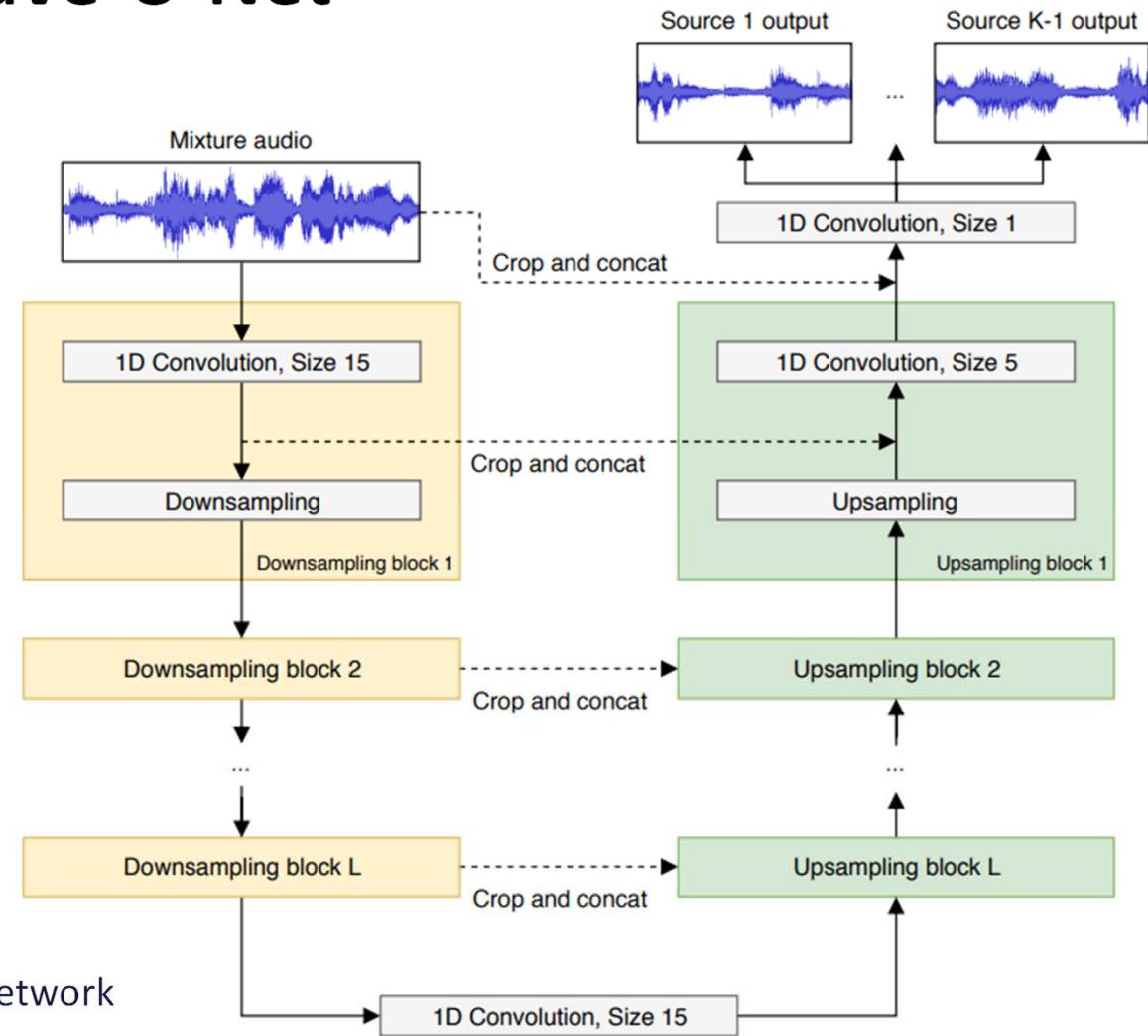
<https://source-separation.github.io/tutorial/basics/phase.html>

- Copy the phase from the mixture
 - Work fine for source separation (but maybe NOT for other audio generation problems)
- Given the magnitude, estimate the phase (see the lecture on “vocoder”)
 - General-purpose solution
- Work on audio waveforms, not spectrograms
 - General-purpose solution

Wave-U-Net

- Work on audio **waveforms**
- The “claimed” limits of the STFT approach
 - “the STFT output depends on many parameters, such as the size and overlap of audio frames, [...] which are not optimized along with the separation model]”
 - “does not estimate the source phase”
 - “the mixture phase is ignored in the estimation of sources”
- However, poor performance

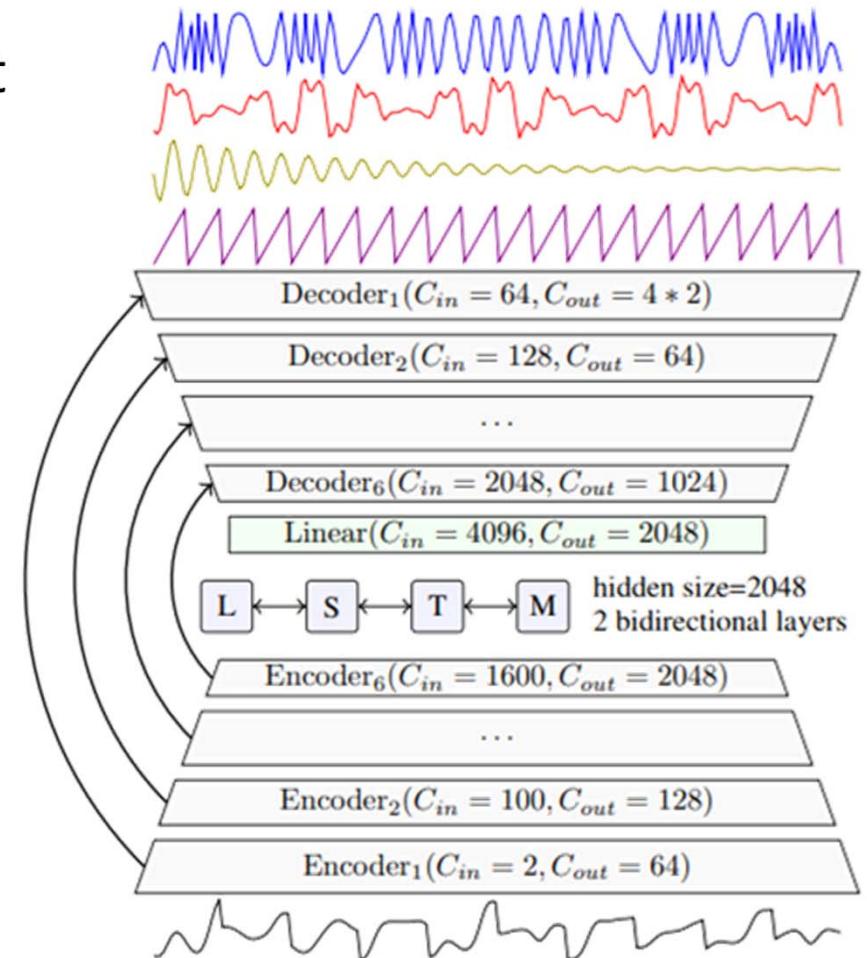
Ref: Stoller et al, “Wave-U-Net: A multi-scale neural network for end-to-end audio source separation,” ISMIR 2018



Demucs (v2)

- Several novel elements inspired by latest work on audio synthesis at that time

Difference	Valid set	Test set
	L1 loss	SDR
no BiLSTM	0.171	5.40
no pitch/tempo aug.	0.156	5.80
no initial weight rescaling	0.156	5.88
no 1x1 convolutions in encoder	0.154	5.89
ReLU instead of GLU	0.157	5.92
no BiLSTM, depth=7	0.160	5.94
MSE loss	N/A	5.99
no resampling	0.153	6.03
no shift trick	N/A	6.05
kernel size of 1 in decoder convolutions	0.153	6.11
Reference	0.150	6.28

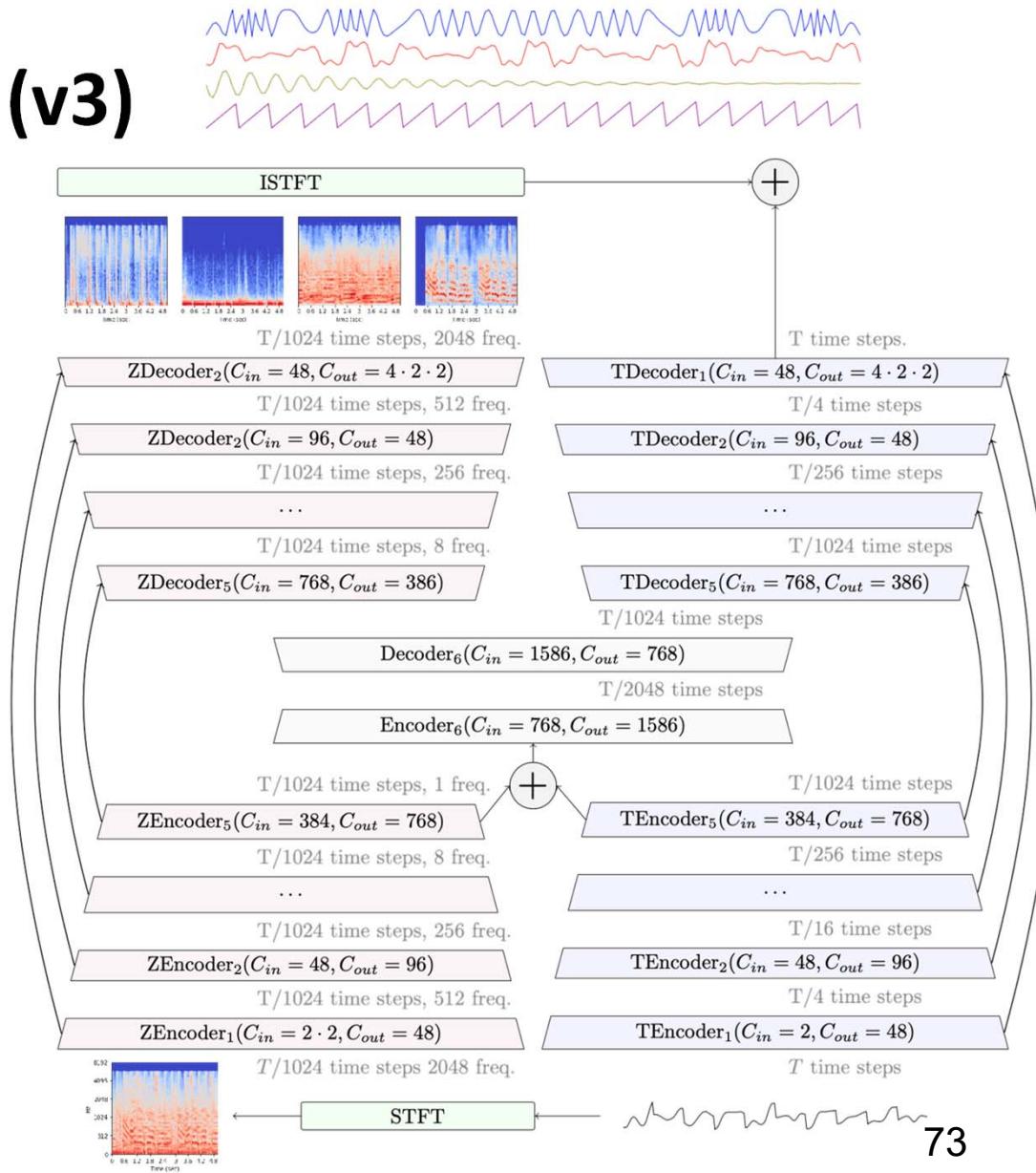


Ref: Défossez et al, "Music source separation in the waveform domain," arXiv 2019

Demucs (v3)

- “The model is composed of a temporal branch, a spectral branch, and shared layers.”
- “The output of the spectral branch is inversed with the ISTFT, and summed with the temporal branch output, giving the final model prediction.”
- “The model is free to use whichever representation is most convenient for different parts of the signal, even within one source, and can freely share information between the two representations.”

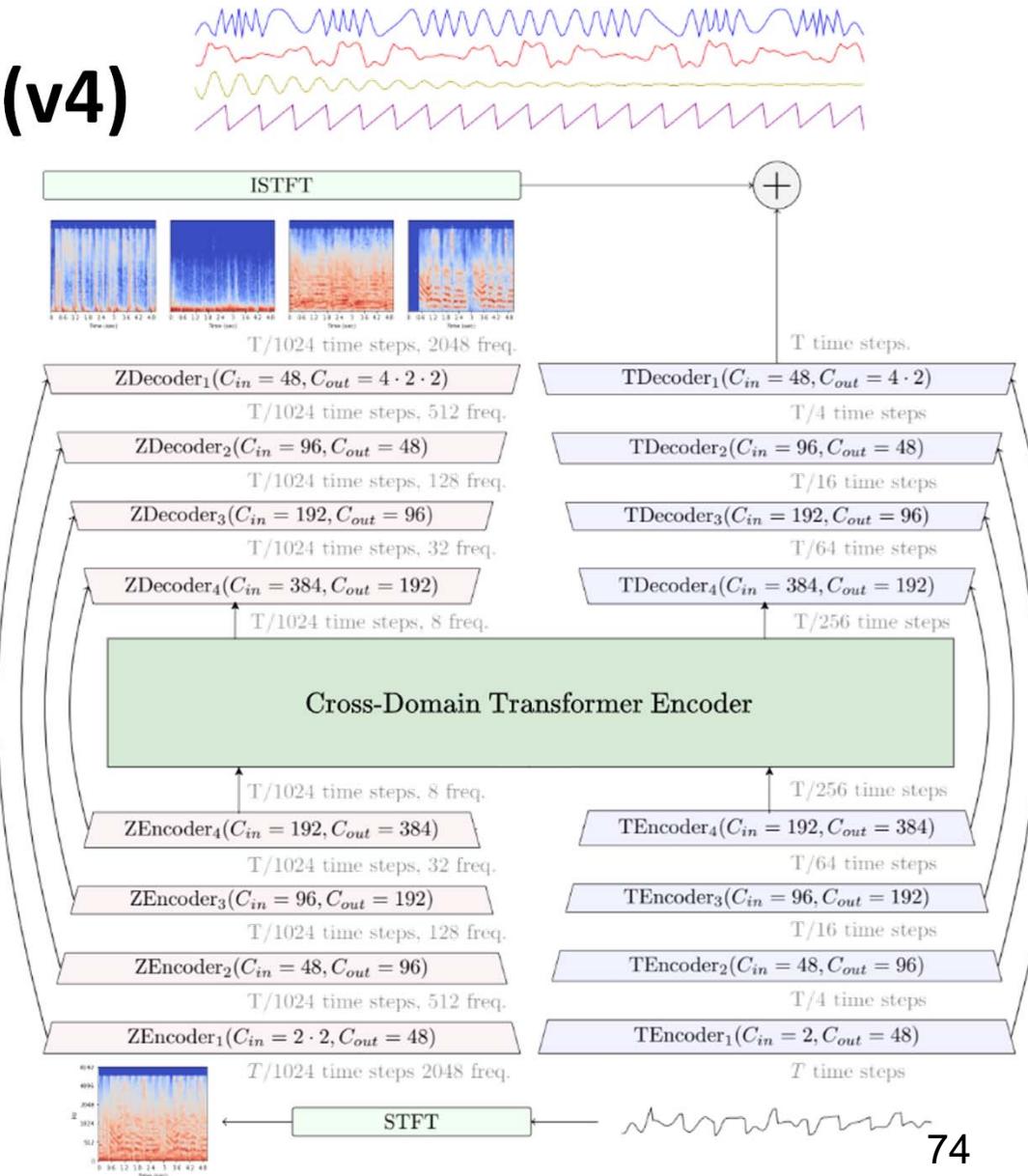
Ref: Défossez, “Hybrid spectrogram and waveform source separation,” ISMIR MDX Workshop 2021



Demucs (v4)

- Use **Transformer** to learn long range contextual information
 - “Innermost layers are replaced by a cross-domain Transformer Encoder, using self-attention within one domain, and cross-attention across domains.”
- Need larger data to benefit from the Transformer
 - “highly benefited from using extra training data”

Ref: Rouard et al, “Hybrid Transformers for music source separation,” ICASSP 2023



Library: Demucs

<https://github.com/facebookresearch/demucs>

Model	Domain	Extra data?	Overall SDR
Wave-U-Net	waveform	no	3.2
Open-Unmix	spectrogram	no	5.3
Demucs (v2)	waveform	no	6.3
Band-Split RNN	spectrogram	no	8.2
Hybrid Demucs (v3)	hybrid	no	7.7
MMDenseLSTM	spectrogram	804 songs	6.0
Spleeter	spectrogram	25k songs	5.9
HT Demucs f.t. (v4)	hybrid	800 songs	9.0

Audiostrip is providing free online separation with Demucs on their website <https://audiostrip.co.uk/>.

Neutone provides a realtime Demucs model in their free VST/AU plugin that can be used in your favorite DAW.

Other pre-trained models can be selected with the `-n` flag. The list of pre-trained models is:

- `htdemucs_6s` : 6 sources version of `htdemucs`, with `piano` and `guitar` being added as sources. Note that the `piano` source is not working great at the moment.

More and More Datasets

- **MIR-1k** (<https://zenodo.org/record/3532216>) /2010
 - 1,000 song clips which the music accompaniment and the singing voice are recorded at left and right channels (i.e., **vocal/others**)
- **MedleyDB** (<https://medleydb.weebly.com/downloads.html>) / 2014, 2016
 - 194 songs, with a diverse set of stems (piano, flute, violin, viola, bassoon, etc)
- **MUSDB** (<https://sigsep.github.io/datasets/musdb.html>) /2017, 2019
 - 150 full-length songs (~10h duration) with **drums/bass/vocals/others** stems
- **Moisesdb** (<https://github.com/moises-ai/moises-db>) / 2023
 - 240 tracks; for source separation beyond 4 stems (e.g., 6 stems including **piano/guitar**)

Extra (Private) Datasets

Rank	Model	SDR ↑ (avg)	SDR (vocals)	SDR (drums)	SDR (bass)	SDR (other)	Extra Training Data	Paper	Code	Result	Year
1	Sparse HT Demucs (fine tuned)	9.20	9.37	10.83	10.47	6.41	✓	Hybrid Transformers for Music Source Separation	🔗	🔗	2022
2	Hybrid Transformer Demucs (f.t.)	9.00	9.20	10.08	9.78	6.42	✓	Hybrid Transformers for Music Source Separation	🔗	🔗	2022
3	Band-Split RNN (semi-sup.)	8.97	10.47	10.15	8.16	7.08	✓	Music Source Separation with Band-split RNN	🔗	🔗	2022
4	TFC-TDF-UNet (v3)	8.34	9.59	8.44	8.45	6.86	✗	Sound Demixing Challenge 2023 Music Demixing Track Technical Report: TFC-TDF-UNet v3	🔗	🔗	2023
5	Band-Split RNN	8.23	10.21	8.58	7.51	6.62	✗	Music Source Separation with Band-split RNN	🔗	🔗	2022
6	Hybrid Demucs	7.72	8.04	8.58	8.67	5.59	✗	Hybrid Spectrogram and Waveform Source Separation	🔗	🔗	2021
7	KUIELab-MDX-Net	7.54	9.00	7.33	7.86	5.95	✗	KUIELab-MDX-Net: A Two-Stream Neural Network for Music Demixing	🔗	🔗	2021

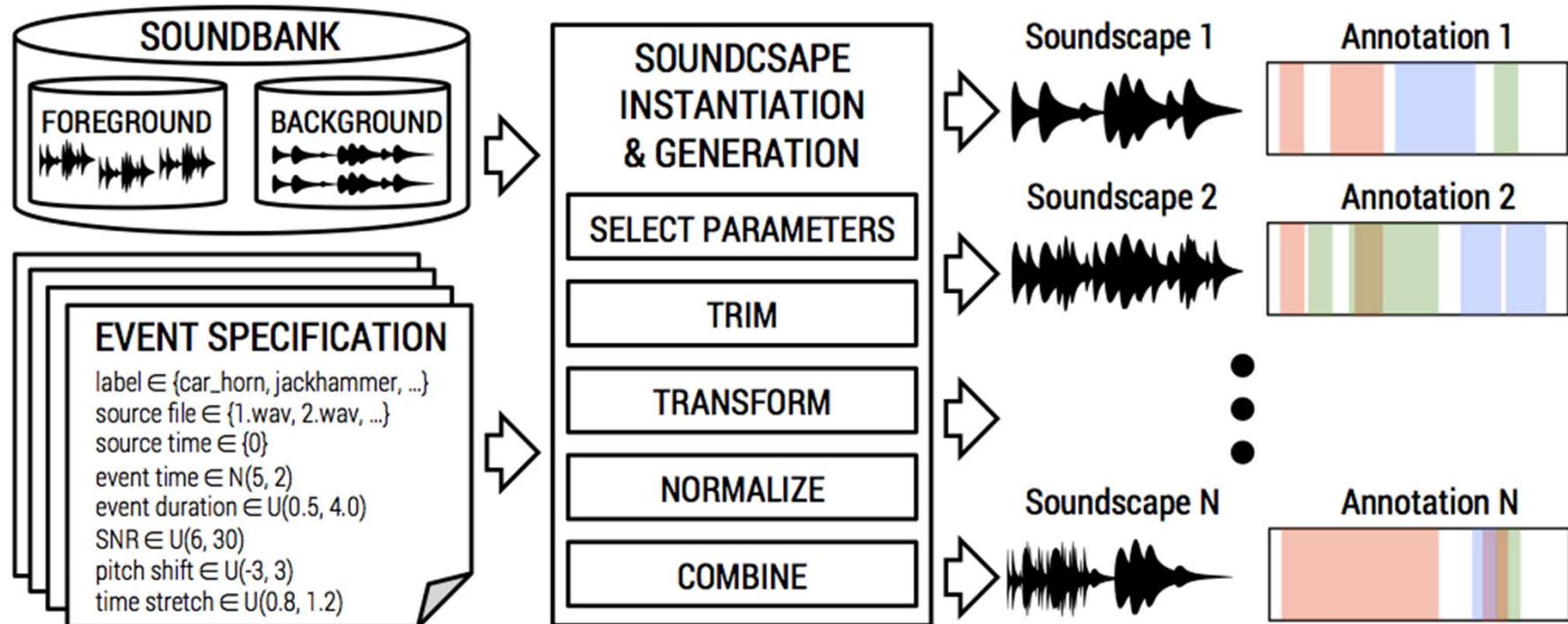
Breakthrough 3: Data Augmentation

- “We use the following data modifications on-the-fly when we construct a training mini-batch sequence”
 - Random swapping left/right channel for each instrument
 - Random scaling with uniform amplitudes from [0.25,1.25]
 - Random chunking into sequences for each instrument
 - **Random mixing of instruments from different songs**

Ref: Uhlich et al, “Improving music source separation based on deep neural networks through data augmentation and network blending,” ICASSP 2017

Library: Scaper

<https://source-separation.github.io/tutorial/data/scaper.html>

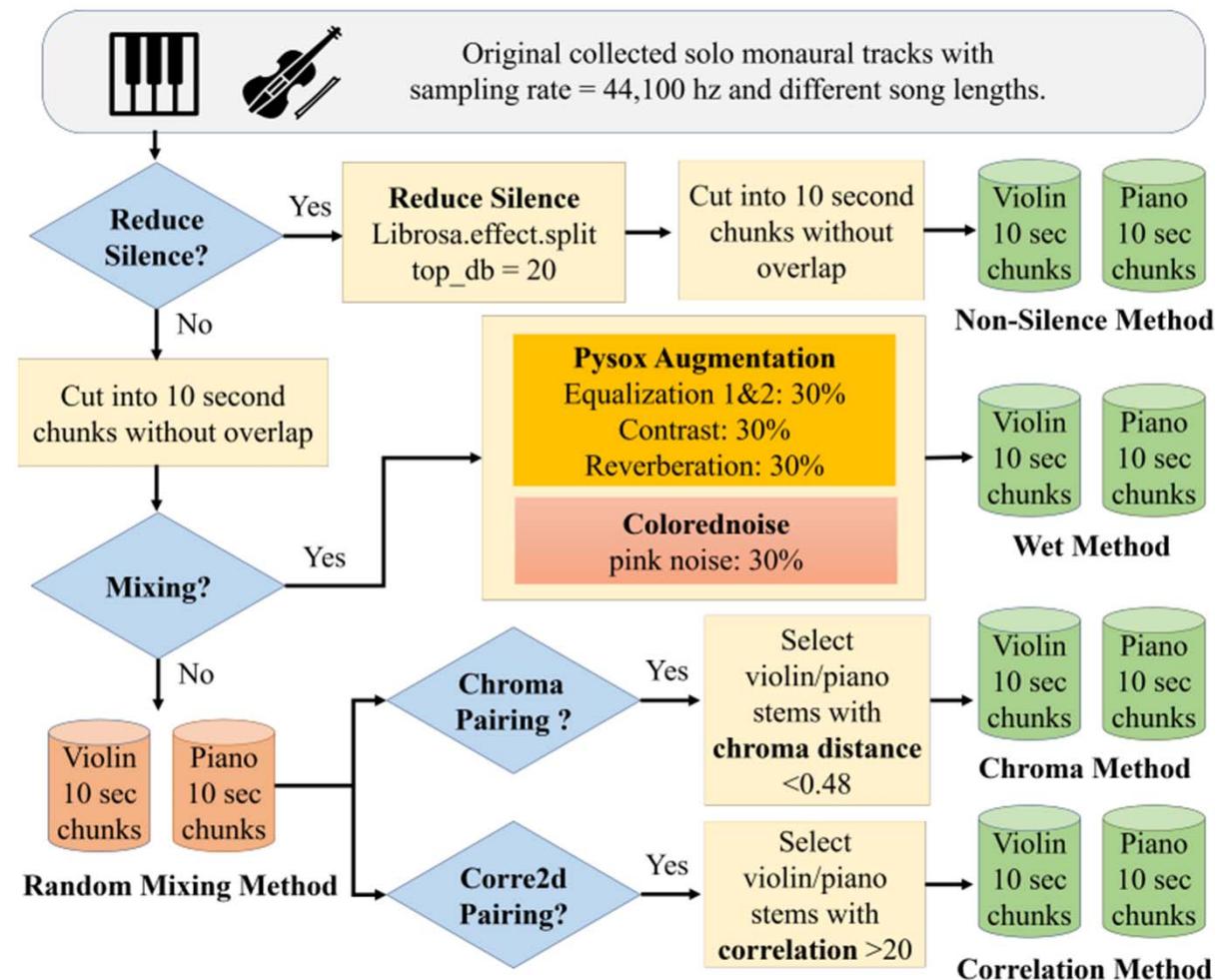


Mixing-Specific Data Augmentation

- Use `pysox` (<https://github.com/rabitt/pysox>) to simulate mixing settings employed in music production

Mixing	Description
Contrast	
Equalizer 1	
Equalizer 2	
Reverb	
Pink noise	

Ref: Chiu et al, "Mixing-specific data augmentation techniques for improved blind violin/piano source separation," MMSP 2020



Recap

- How people work on spectrograms?
 - Copy the phase of the mixture (for source separation)
 - Vocoder (see next lecture)
 - Work on waveforms instead of spectrograms (or both)
- It's a type of audio generation task (with *strong condition*)
 - “audio (mixture) → audio (stem)”
 - Earlier deep learning approaches predict mask: *discriminative* setting
 - SOTA approaches synthesize the stems from the input mixture: *generative* setting
 - But, we haven't talked about the details of the up-sampling layers (see next lecture)