Zero-Shot Duet Singing Voices Separation with Diffusion Models

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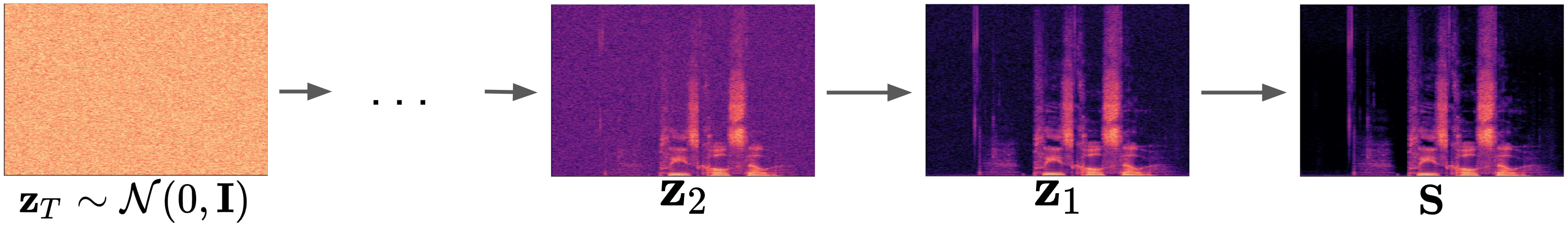
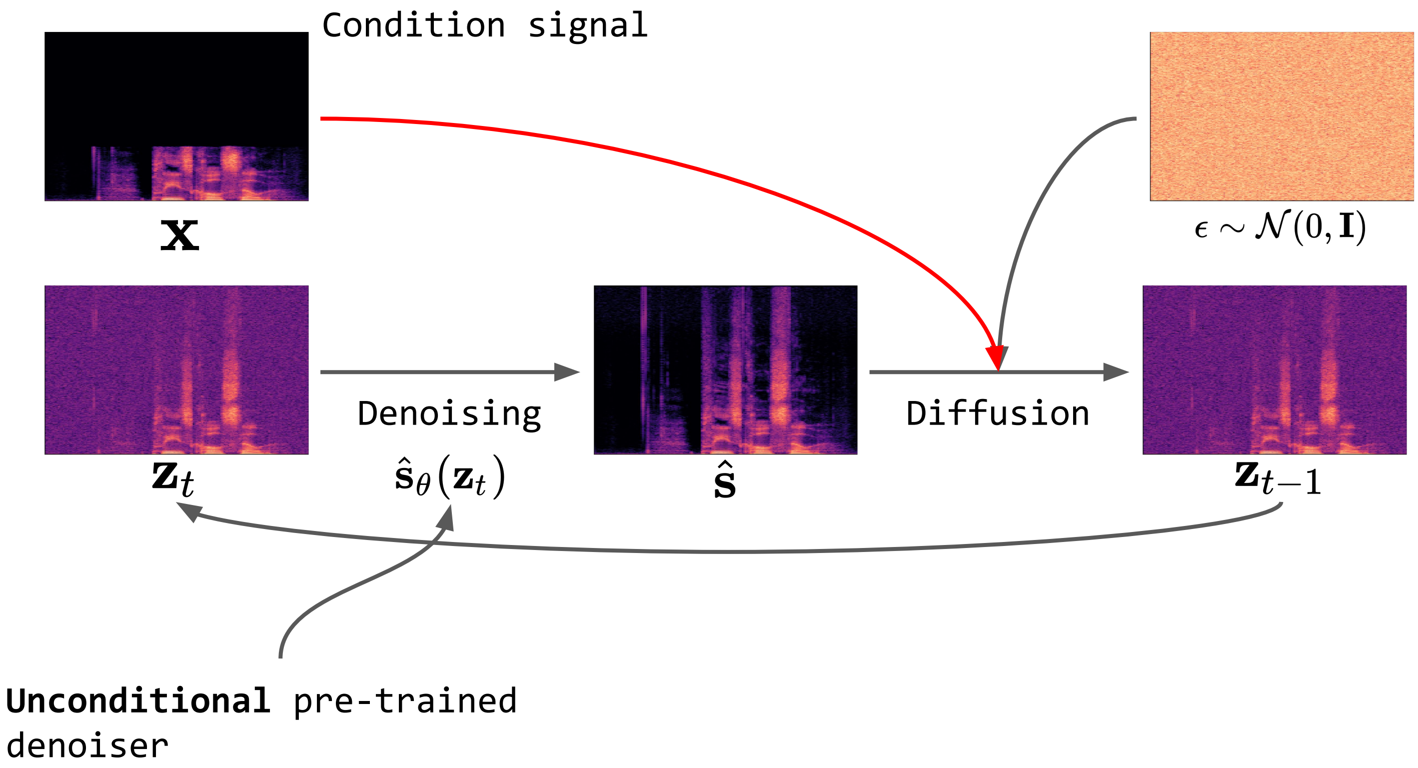
Unconditional Diffusion Generation



Ho, Jonathan, Ajay Jain, and Pieter Abbeel. "Denoising diffusion probabilistic models." Advances in Neural Information Processing Systems 33 (2020): 6840-6851.

Kingma, Diederik, et al. "Variational diffusion models." Advances in neural information processing systems 34 (2021): 21696-21707.

Posterior Sampling in Diffusion Models



General Source Separation Problem

Transfer Function

M-channel mixture

$$\mathbf{x}(n,f) = \mathbf{H}(n,f) \begin{bmatrix} s_1(n,f) \\ s_2(n,f) \\ \vdots \\ s_N(n,f) \end{bmatrix} + \epsilon$$

$$\epsilon \sim \mathcal{N}(0, \sigma_x^2)$$

Measurement Noise

N sources

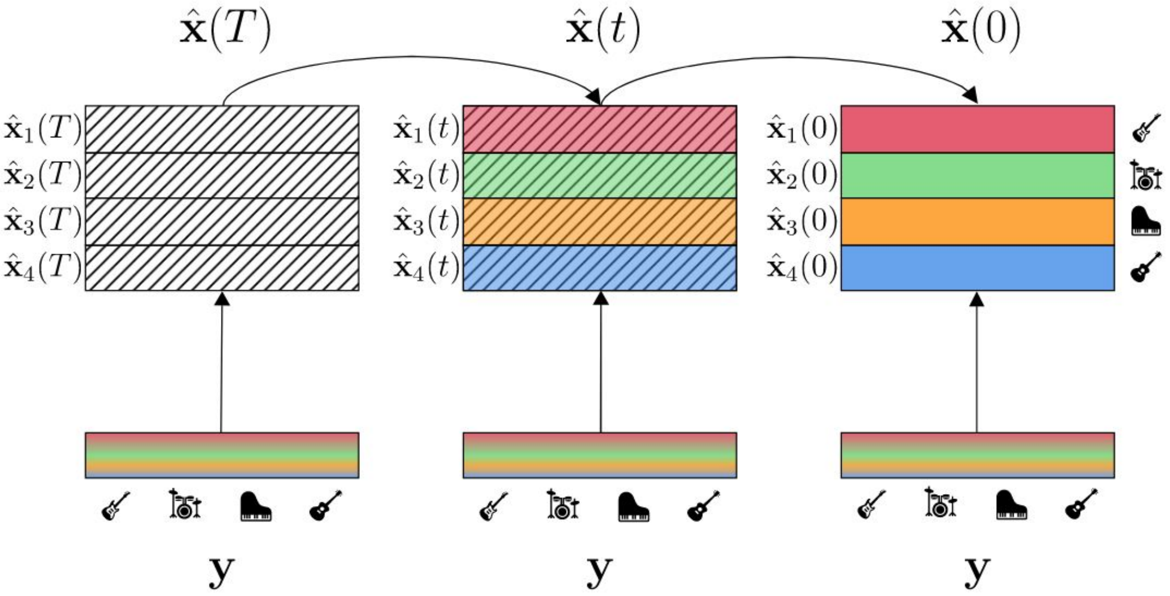
Audio Inverse Problems (N = 1)

- Bandwidth Extension (**H** is known)
  - VRDMG (Hernandez-Olivan et al., 2023)
  - CQTDiff (Moliner et al., ICASSP 2023)
  - UDM (Yu et al., ICASSP 2023)
- Dereverberation (**H** is unknown)
  - GibbsDDRM (Murata et al., 2023)
  - Saito et al., ICASSP 2023

$$p(s_1|\mathbf{x}, \mathbf{H})$$

$$p(s_1, \mathbf{H}|\mathbf{x})$$

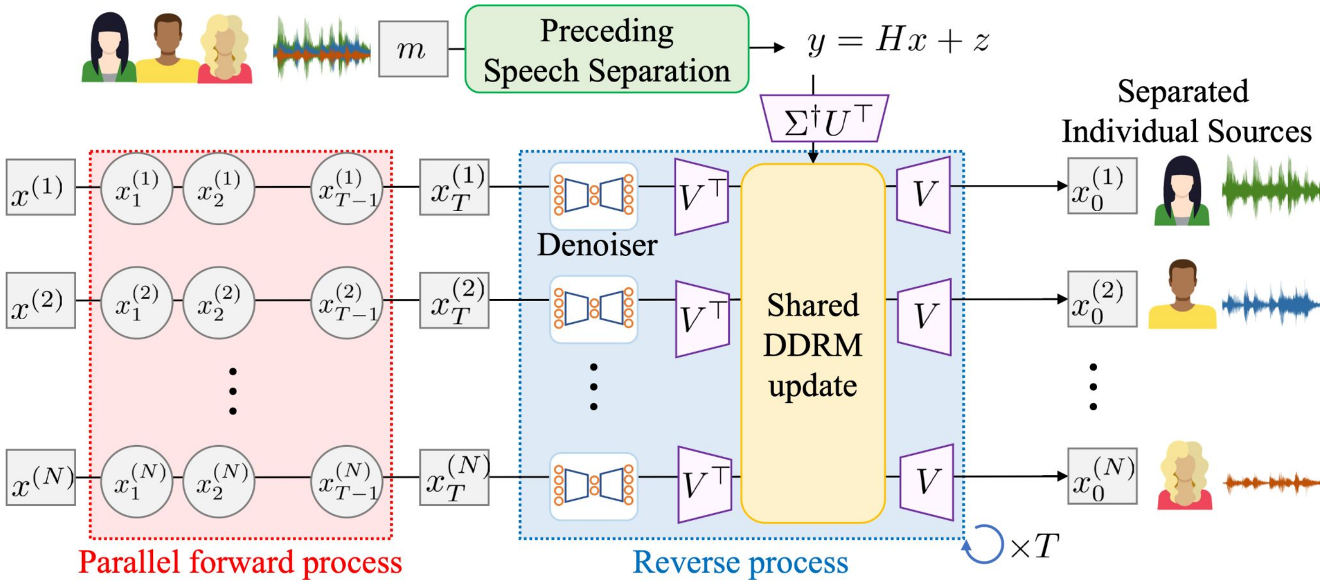
Music Source Separation (N = 4)



Source separation

Mariani, Giorgio, et al. "Multi-source diffusion models for simultaneous music generation and separation." arXiv preprint arXiv:2302.02257 (2023).

Multi Speaker ~~Separation~~ Refinement (N > 1)



Hirano, Masato, et al. "Diffusion-based Signal Refiner for Speech Enhancement." arXiv preprint arXiv:2305.05857 (2023).

Problem with Monotimbral Source Separation

- Definition
  - s_1, s_2,..., s_N have very **similar timbre**
  - All sources are drawn from the **same diffusion model**
- Problem
  - The learned prior is not enough to maintain **temporal coherency** (i.e., singer identity)

Source 1

Predict 1

Mix

Source 2

Predict 2

Proposed Methodology

Dirac Score Posterior Function (Mariani et al.)

Conditional score

$$\nabla_{\mathbf{s}_i(t)} \log p(\mathbf{s}_i(t)|\mathbf{x})$$

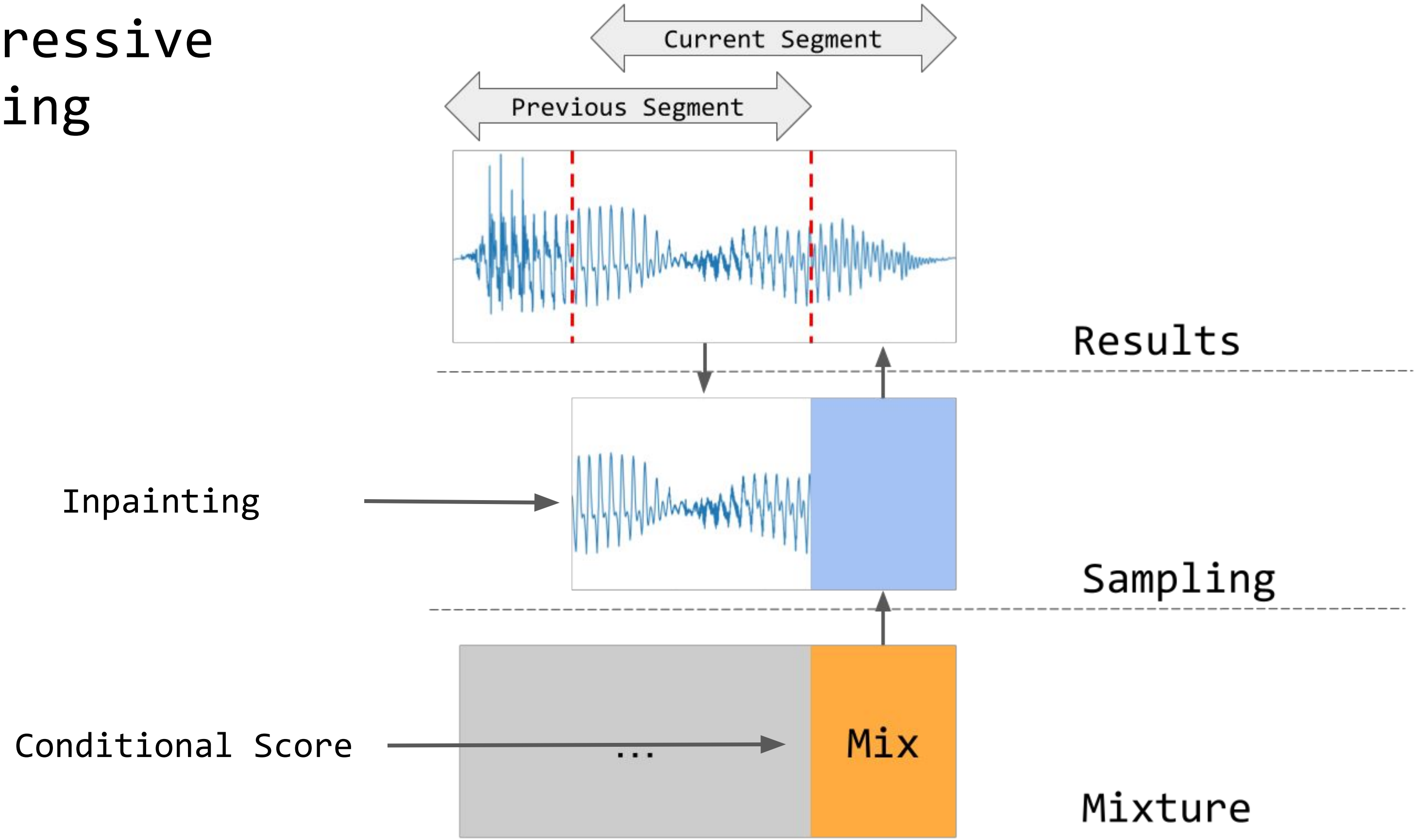
$$\approx \nabla_{\mathbf{s}_i(t)} \log p(\mathbf{s}_i(t)) - \underline{\nabla_{\mathbf{s}_i(t)} \log p(\mathbf{x} - \textstyle\sum_{i=2}^{N} \mathbf{s}_i(t))}$$

Unconditional score

$$\hat{\mathbf{s}}_1(t) = \mathbf{x} - \textstyle\sum_{i=2}^{N} \mathbf{s}_i(t)$$

Mariani, Giorgio, et al. "Multi-source diffusion models for simultaneous music generation and separation." arXiv preprint arXiv:2302.02257 (2023).

Autoregressive Inpainting



Experiment

- Score prediction model: 1D Unet Model from Mousai
  - batch size 32, 1M steps
- Training data: 8 singing datasets combined (>104 hours)
  - 24 kHz
  - 131072 samples per segment (~= 5.46 seconds)
- Test data: MedleyVox duet subset (N = 2)
- Metrics
  - SDRi
  - SI-SDRi

Sampling methods

1. **Naive**: conditional score w/o AR inpainting
2. **AR**: conditional score w/ AR inpainting
3. **Segmented:** non-overlapping chunks + conditional score
4. **AR w/ TF:** ground truth as inpainting context (not from the previous generation)
    a. Similar to teacher forcing

Note: <u>we generated three variations in each step and pick the lowest loss one</u>

Results

Methods	SI-SDRi	SDRi
iSRNet (Jeon et al., 2023)	15.10	14.20
NMF	5.12	5.97
Naive	6.61 ± 0.25	7.60 ± 0.21
Segmented	11.14 ± 0.48	11.77 ± 0.47
AR (proposed)	$\mathbf{11.24} \pm 0.40$	$\mathbf{11.89} \pm 0.34$
AR w/ TF	11.75 ± 0.38	12.34 ± 0.39

Source 1

Predict 1

Mix

Source 2

Predict 2

Source code & model weights:
https://github.com/yoyololicon/duet-svs-diffusion

The Holy Grail

A general sampling method for ***Arbitrary H*** *using* ***diffusion models on individual sources***

Potential problems:

1. On the sources
    a. Temporal coherency with monotimbral sources
2. On the transfer function
    a. Unknown multi-channel **H**
    b. Evaluation datasets?