CARNATIC SINGING VOICE SEPARATION USING COLD DIFFUSION ON TRAINING DATA WITH BLEEDING

CODE AND MODELS

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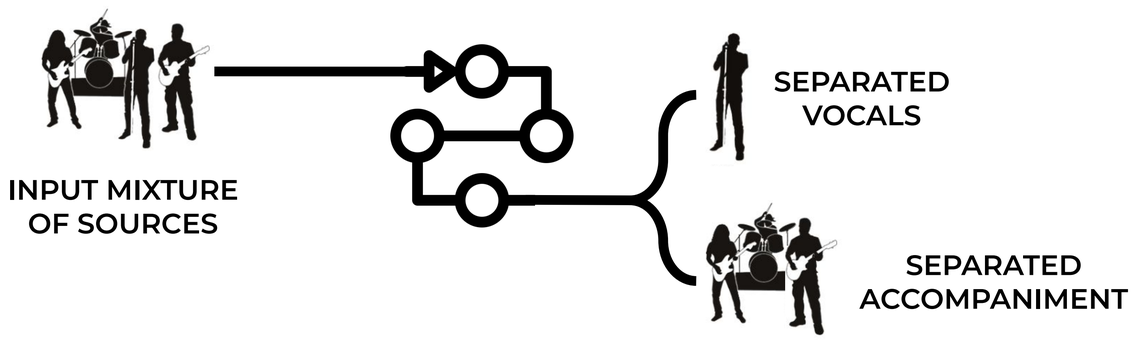
CONTEXT

SINGING VOICE EXTRACTION



The SOTA on the singing voice extraction task is lead by deep learning models

PROBLEM: what happens if...

- 🪘 Our instrument line-up is out of domain?
- 📁 No open and fully-isolated multi track data is available for our use case.

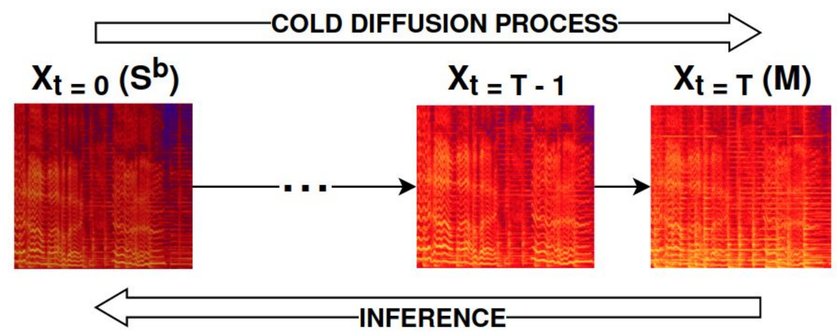
PROPOSED APPROACH

SEPARATION DATA W/ LEAKAGE

- Bleeding or leakage: the sound of the rest of the instruments being present in the background in the stem of a given source
- Can be recorded easily, e.g. in live shows
- The Saraga Dataset [1]: +34h of multi track audio data with leakage of Carnatic Music concerts

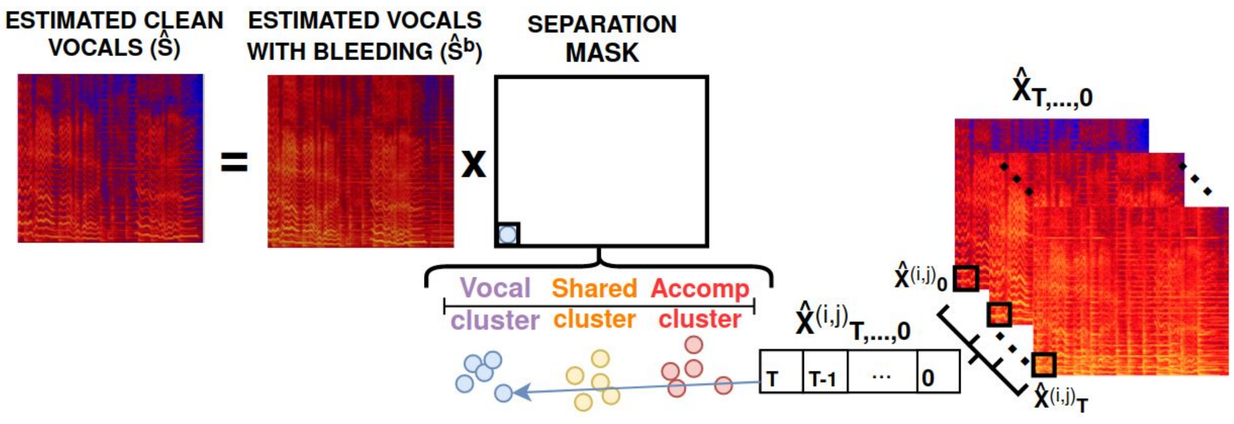
🎯GOAL: use these data to develop a singing voice extraction model
🤷‍♀️WHY: to take advantage of domain knowledge in the data for improved performance
🛠️CHALLENGE: leakage in the vocal stem

COLD SPECTROGRAM DIFFUSION (inspired by [2]



- We iteratively transform, in T steps, a mixture spectrogram to the corresponding vocals
- We train a convolutional U-Net network with skip connections, conditioned on T, following [3]
- In inference, we stack the intermediate steps in a feature matrix.

SEPARATION MASK ESTIMATION



- Given feature matrix, we cluster the frequency bins to build the separation mask
- **Vocal bins: +** energy overall, **-** energy change
- **Accomp bins: -** energy overall, **+** energy change
- **Shared bins:** middle range (we can select and remove more for more restrictive separation)

EVALUATION

- We record a clean testing set with two different singers and recording and mixing settings
- We run a controlled MUSHRA test on 25 subjects
- We select 6 tracks from the private Dunya database [4] with artist and audio quality diversity

	Mean Opinion Scores (MOS)	
	Vocal quality	Vocal isolation
Ours (*C*=5, *F*=4)	2.80 ± 0.29	**3.72** ± 0.31
Spleeter	**3.73** ± 0.17	1.97 ± 0.19

Our most *restrictive* model

Comparison of our system with *T*=8					
Config		vs. No clustering		vs. Spleeter	
C	*F*	SIRd	SARd	SIRd	SARd
2	1	+4.70	**-3.43**	+0.14	**-4.09**
3	1	+4.31	-3.56	+0.52	-4.22
3	2	+5.46	-4.49	+0.64	-5.16
4	2	+5.55	-4.71	+0.72	-5.38
4	3	+6.41	-5.53	+1.60	-6.20
5	2	+5.61	-4.69	+0.78	-5.35
5	3	+6.45	-5.59	+1.63	-6.26
5	4	**+7.14**	-6.25	**+2.32**	-6.91

The model is *adaptable*!

NOTE: By using and removing more clusters, we obtain a more restrictive separation, at the expense of source quality.

[1] A. Srinivasamurthy, S. Gulati, R. Caro, X. Serra, **"Saraga: Open Datasets for Research on Indian Art Music"**. Empirical Musicology Review, vol. 16, no. 1, pp. 85-98, 2021.
[2] A. Bansal, Em Borgnia, H. Chu, Jie S. Li, H. Kazemi, F. Huang, M. Goldblum, J. Geiping, and T. Goldstein, **"Cold Diffusion: Inverting Arbitrary Image Transforms Without Noise"**. Pre-print [under review], 2022.
[3] J. Ho, A. Jain, and P. Abbeel, **"Denoising Diffusion Probabilistic Models"**. In Proc. of the 33th Advances in Neural Information Processing Systems (NeurIPS), Online, pp. 6840–6851, 2020.
[4] A. Porter, M. Sordo and X. Serra, **"Dunya: A System to Browse Audio Music Collections Exploiting Cultural Context"**. In Proc. of the International Society for Music Information Retrieval Conference (ISMIR), 2013.

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