

Jointly Detecting and Separating Singing Voice: A Multi-Task Approach

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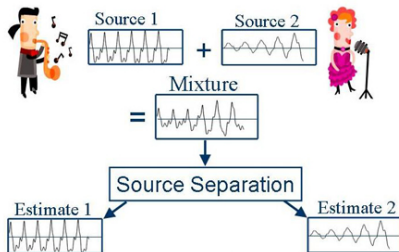
LVA ICA
05.07.2018

*Work was conducted at Queen Mary University of London

Vocal separation

Introduction

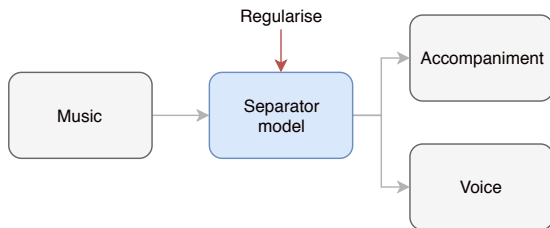
- Main task: Separate vocals from music pieces
- Applications: Karaoke generation, singer identification, voice analysis...



Vocal separation

Challenges

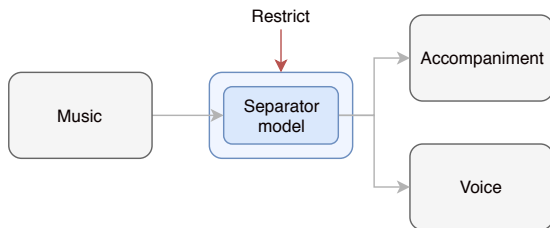
- Difficult task, small multi-track datasets \Rightarrow Overfitting
- Give model more knowledge:
 - Regularization (e.g. weight decay)



Vocal separation

Challenges

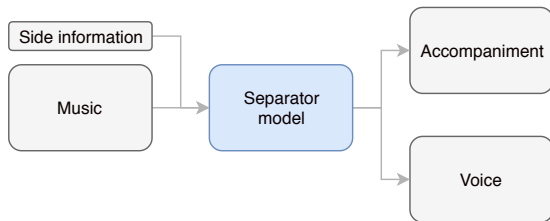
- Difficult task, small multi-track datasets \Rightarrow Overfitting
- Give model more knowledge:
 - Knowledge-driven (e.g. KAM [4])



Vocal separation

Challenges

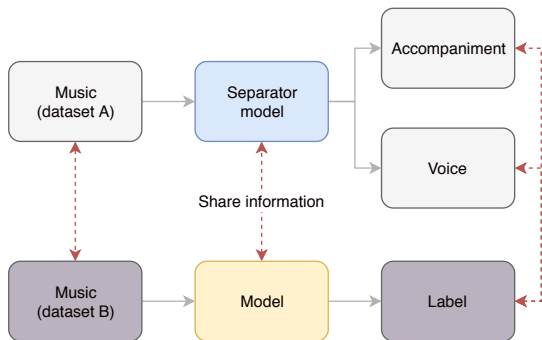
- Difficult task, small multi-track datasets \Rightarrow Overfitting
- Give model more knowledge:
 - Informed source separation [2]



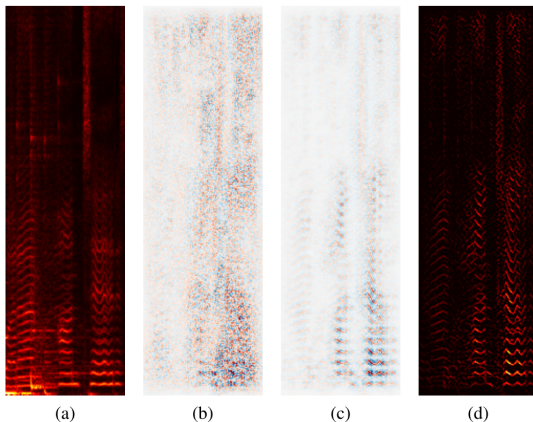
Vocal separation

Challenges

- Difficult task, small multi-track datasets \Rightarrow Overfitting
- Give model more knowledge:
 - **Integrate information from related tasks/datasets**



- Which other tasks could help?
- Vocal activity detection is promising:
 - Knowing vocal activity improves vocal separation [1]
 - Vocal detection networks learn a form of separation: [5]



Initial approach

Using additional non-vocal sections

- U-Net adaptation [3] as separator, MSE loss
 - **Sample instrumental sections also from SVD databases**
- ⇒ Diversifies instrumental training data



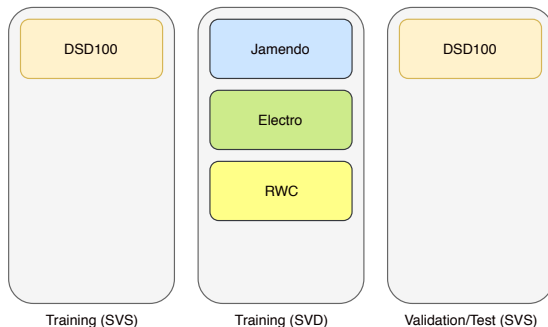
Song A
SVS Database



Song B
SVD Database

Initial approach

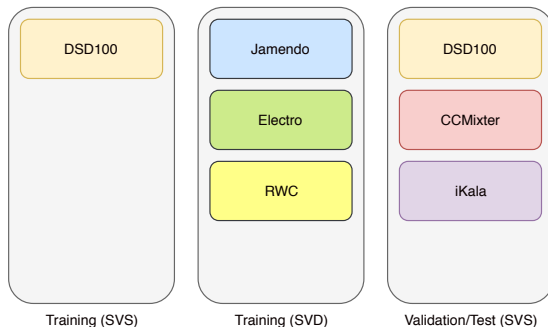
Results



Performance **decrease**

Initial approach

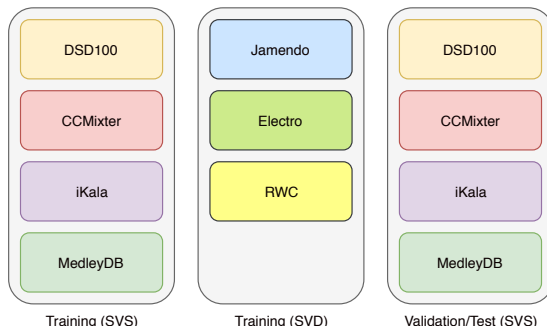
Results



Performance **increase**

Initial approach

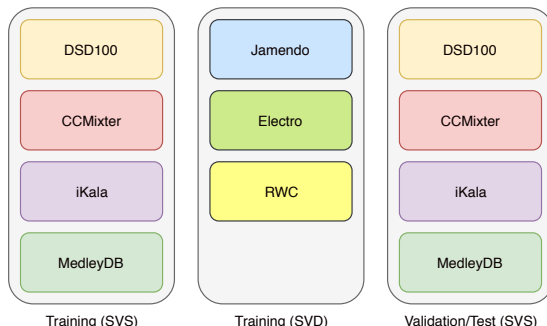
Results



Performance **decrease**

Initial approach

Results

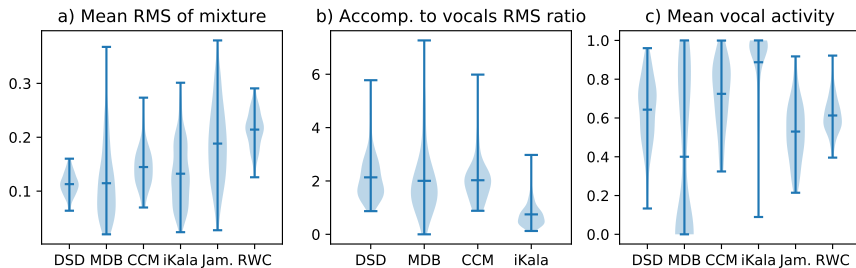


Performance **decrease**

Dataset bias?

Dataset bias

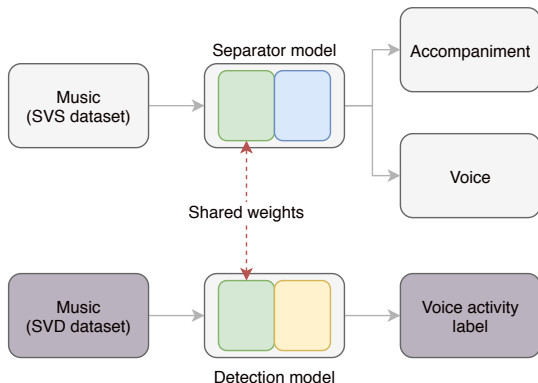
Analysis



Multi-task approach

Introduction and motivation

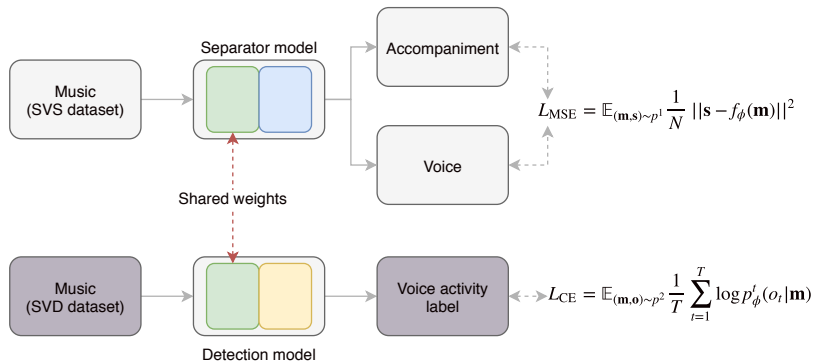
Key idea: Predict both audio and label



Multi-task approach

Introduction and motivation

Key idea: Predict both audio and label

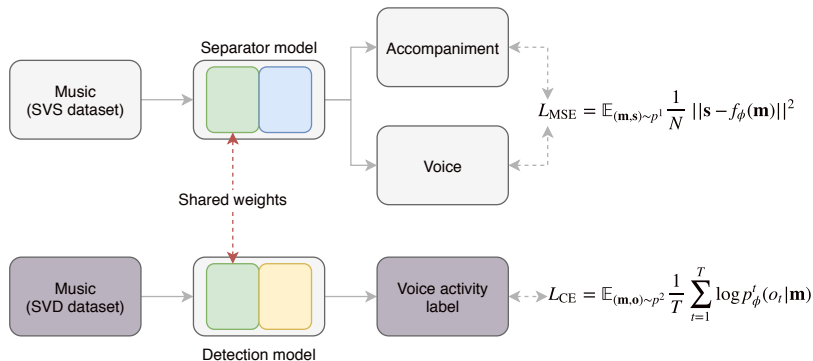


$$L_{\text{MTL}} = \alpha L_{\text{MSE}} + (1 - \alpha) L_{\text{CE}}$$

Multi-task approach

Introduction and motivation

Key idea: Predict both audio and label



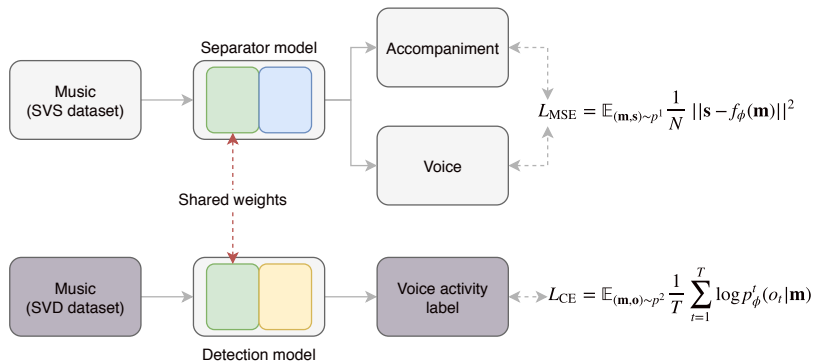
$$L_{\text{MTL}} = \alpha L_{\text{MSE}} + (1 - \alpha) L_{\text{CE}}$$

Robust to dataset bias and label accuracy

Multi-task approach

Introduction and motivation

Key idea: Predict both audio and label



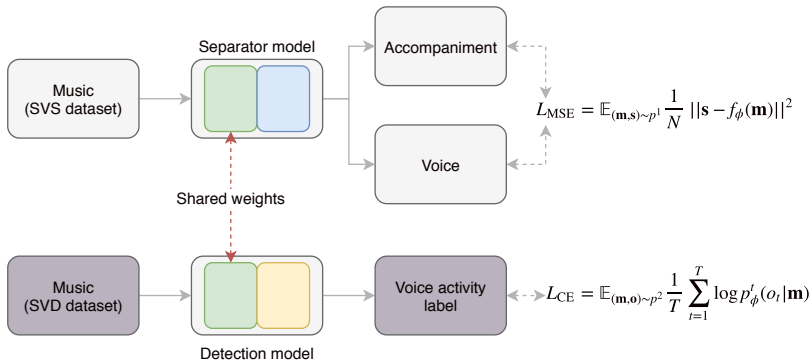
$$L_{\text{MTL}} = \alpha L_{\text{MSE}} + (1 - \alpha) L_{\text{CE}}$$

Can train with vocal sections from SVD data

Multi-task approach

Introduction and motivation

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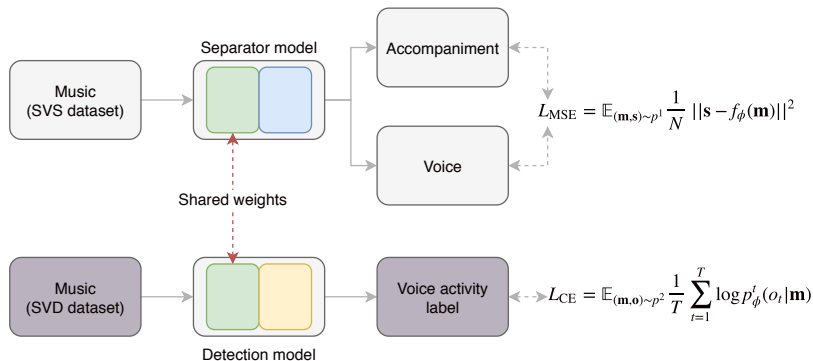
$$L_{\text{MTL}} = \alpha L_{\text{MSE}} + (1 - \alpha) L_{\text{CE}}$$

Needs only mixture at test time

Multi-task approach

Introduction and motivation

Key idea: Predict both audio and label

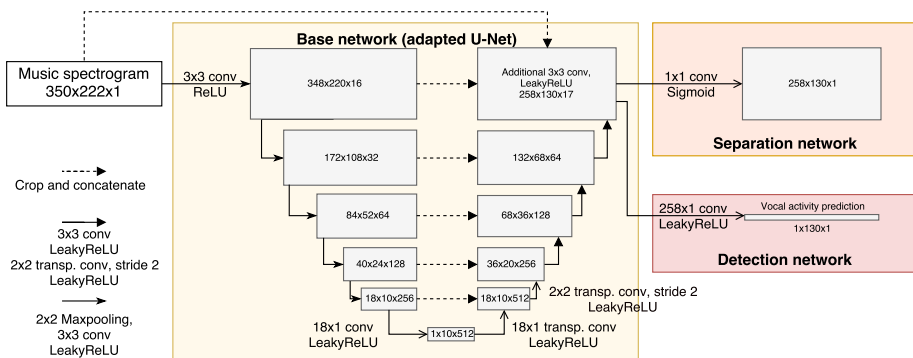


$$L_{\text{MTL}} = \alpha L_{\text{MSE}} + (1 - \alpha) L_{\text{CE}}$$

Solves two tasks at once

Experimental setup

Model architecture and dataset



- DSD100 as SVS, Jamendo as SVD training data

Experimental setup

Evaluation metrics: AU-ROC, MSE, SDR

- AU-ROC for SVD
- MSE and SDR/SIR/SAR for separation
 - SDR gives $\log(0)$ for non-vocal sections ($\approx 10\%$)
⇒ Also measure RMS of vocal estimates for non-vocal sections

Results

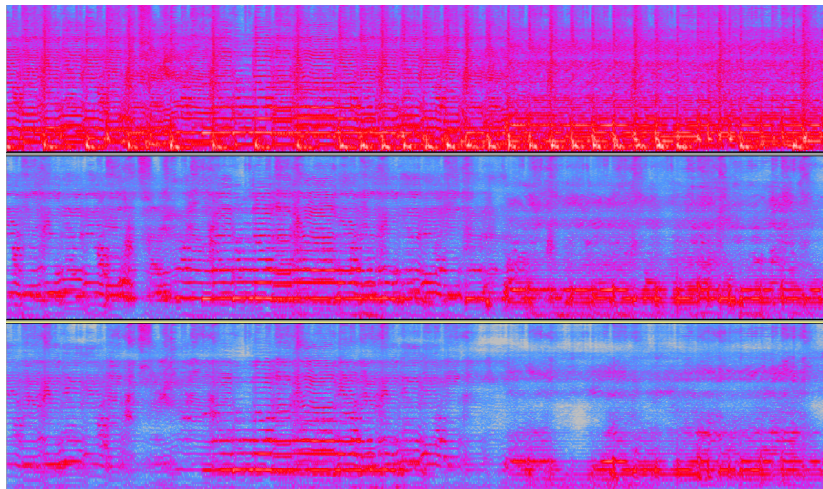
Single-task vs. multi-task model

		Metric									
		AU-ROC	MSE	Non-voc. RMS	Vocals			Accompaniment			
					SDR	SIR	SAR	SDR	SIR	SAR	
Model		SVD	0.9239	-	-	-	-	-	-	-	
		SVS	-	0.01865	0.0194	2.83	5.27	6.88	6.71	14.75	13.25
		Ours	0.9250	0.01755	0.0155	2.86	5.56	6.23	6.69	13.24	14.11

Table: Comparing SVS and SVD baseline with our approach

Results

Qualitative comparison



- Current SotA methods only use multi-track data
- Our approach also uses SVD databases
- Improved separation and detection performance
- Future work: Larger datasets, more related tasks



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