Semi-Supervised Adversarial Audio Source Separation applied to Singing Voice Extraction

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MLSP-L8: Deep Learning III
ICASSP
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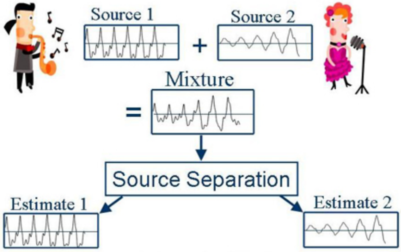
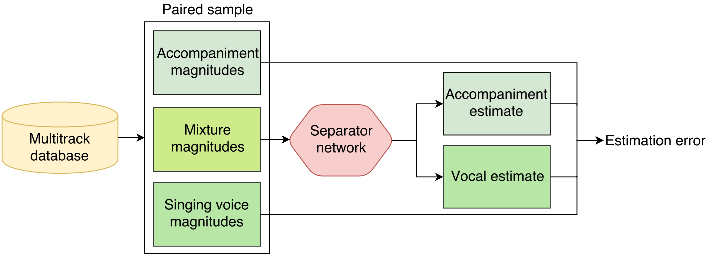
Audio source separation

- Task: Recover sources from mixtures
- Example: Music instrument separation:



Current state of the art [5, 3, 1]



- Training on multitrack datasets
- Neural network
- Discriminative, MSE loss

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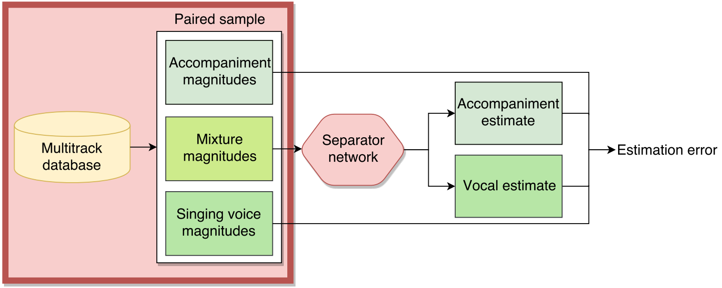
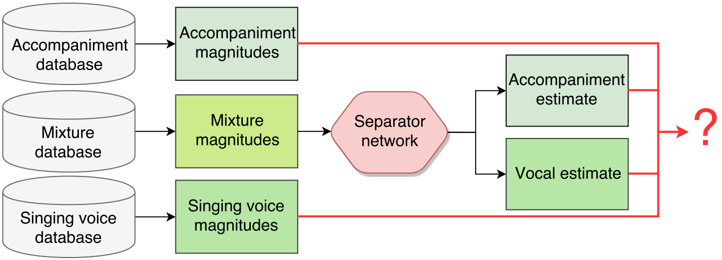


- **Training on multitrack datasets (small $\Rightarrow$ overfitting!)**
- Neural network
- Discriminative, MSE loss

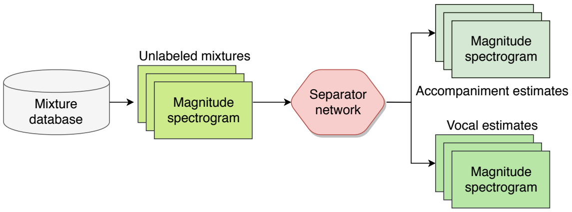
Our goal



$\Rightarrow$ How to also learn from unpaired mixtures and sources?

- Random mixing ignores source correlations [4, 2]

Intuition


Mixture database
Unlabeled mixtures
Magnitude spectrogram
Separator network
Magnitude spectrogram
Accompaniment estimates
Vocal estimates
Magnitude spectrogram

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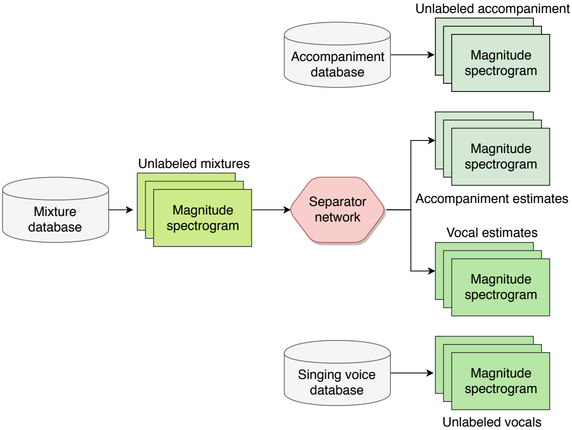
Unlabeled accompaniment
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Singing voice database
Magnitude spectrogram
Unlabeled vocals

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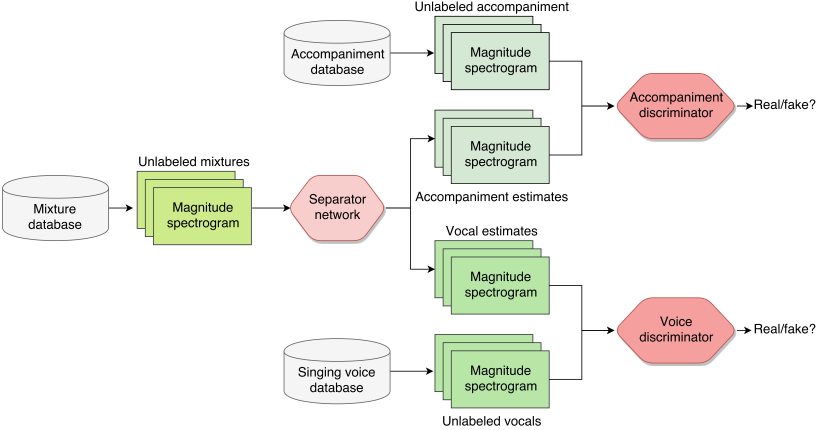
Unlabeled accompaniment
Accompaniment database
Magnitude spectrogram
Accompaniment discriminator
Real/fake?
Magnitude spectrogram
Accompaniment estimates
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$$\begin{array}{rcl} E_{m\sim p_{\text{data}}}\ q_\phi(s^k|m) & = & E_{m\sim p_{\text{data}}}\ p(s^k|m) \\ \text{Overall separator output} & = & \text{Source distribution} \end{array}$$

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- Necessary condition for optimal separator
- Loss: Minimise divergence between source outputs: $L_{\text{u}} = \sum_{k=1}^{K} D[{}^{\text{out}}q_\phi^k || p_{\text{s}}^k]$

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- Supervised loss: MSE between estimate and ground truth
- Unsupervised loss:
  - $L_{\mathrm{u}} = \sum_{k=1}^{K} D[{}^{\mathrm{out}}q_{\phi}^{k} || p_{\mathrm{s}}^{k}]$
  - L_{add}: MSE between sum of source estimates and mixture
- Total loss:
  $L = L_{\mathrm{s}} + \alpha L_{\mathrm{u}} + \beta L_{\mathrm{add}}$

Divergence minimization with GANs

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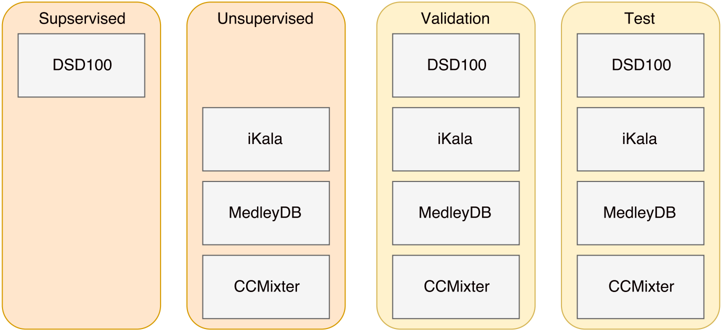
- **Our separator is a conditional generator**

$\Rightarrow$ We use one discriminator per source to estimate the Wasserstein distance $W[{}^{\text{out}}q_{\phi}^{k}||p_{s}^{k}]$

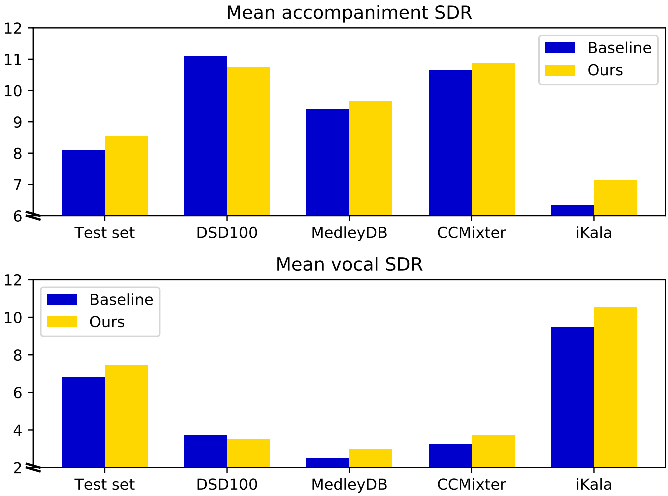
Experimental setup



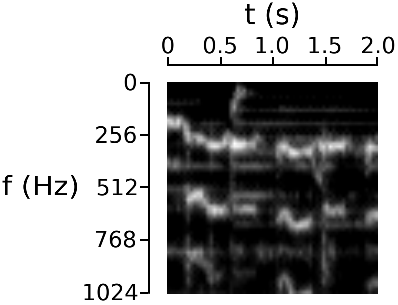
- Avoids dataset bias
- Supervised and semi-supervised training with early stopping
- U-Net as separator, DCGAN as discriminator

Results

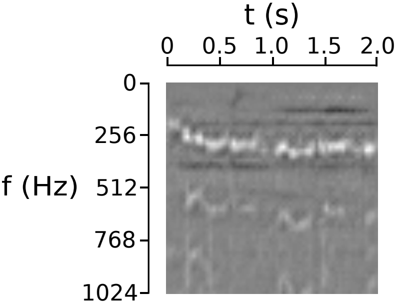
Performance



Results
Qualitative

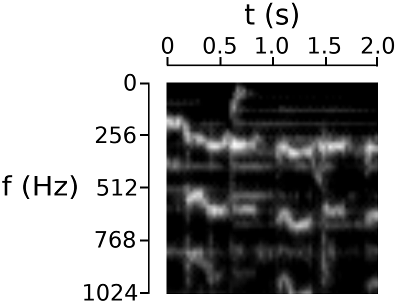


(a) Separator estimate x



(b) $\nabla_x D(x)$

Results
Qualitative



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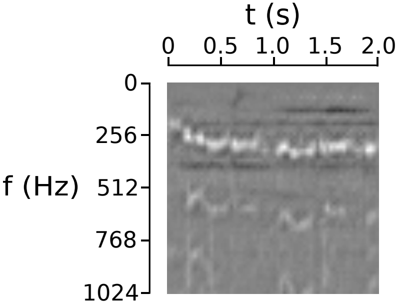

(b) $\nabla_x D(x)$

$\Rightarrow$ Discriminator appears to work

- More perceptual loss function?

Summary

- Current SotA methods only use multi-track data
- Our approach also uses solo source recordings
- Performance improvement in singing voice separation experiment
- More perceptual loss? (seeks posterior modes, not means)

End

Code available at
`https://github.com/f90/AdversarialAudioSeparation`

Thank you for your attention!

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