Improving Sound Separation Using Sound Classification

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Google AI

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Prior work: End-to-end universal sound separation [1]

- **10 dB** SI-SDRi **but still behind STFT oracle binary mask result of 16 dB**
- Assuming that sound detection is easier than separation
  - What if we **could detect the sources in a mixture**?

[1] Ilya Kavalerov, Scott Wisdom, Hakan Erdogan, Brian Patton, Kevin Wilson, Jonathan Le Roux, and John R Hershey, "Universal sound separation," Proc. WASPAA, 2019, pp. 175–179.

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Potential pitfalls of end-to-end separation networks training:

- Can the neural network practically learn a good decomposition **for all sounds of interest**?
- Might not be the best way to utilize the **high-level semantics** of sounds
- A separation network might need a bit of **guidance**

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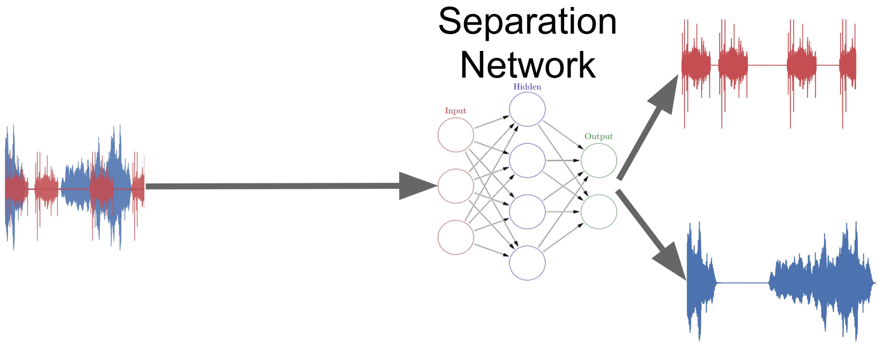
Idea: Guiding source separation using semantic representations audio sources

1. A neural network performing source separation on a mixture of signals



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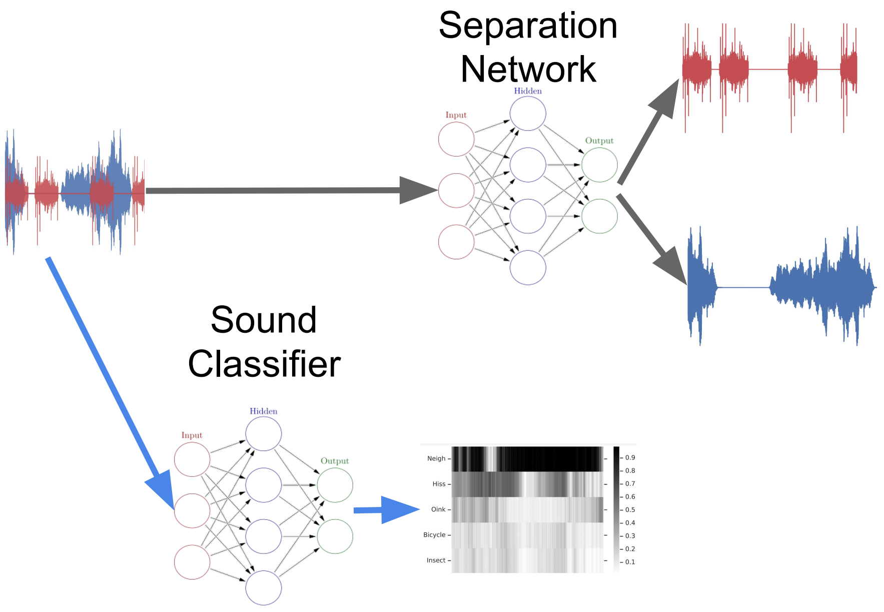
2. **Extract a high-level semantic representation** for the input audio "conditional embedding"



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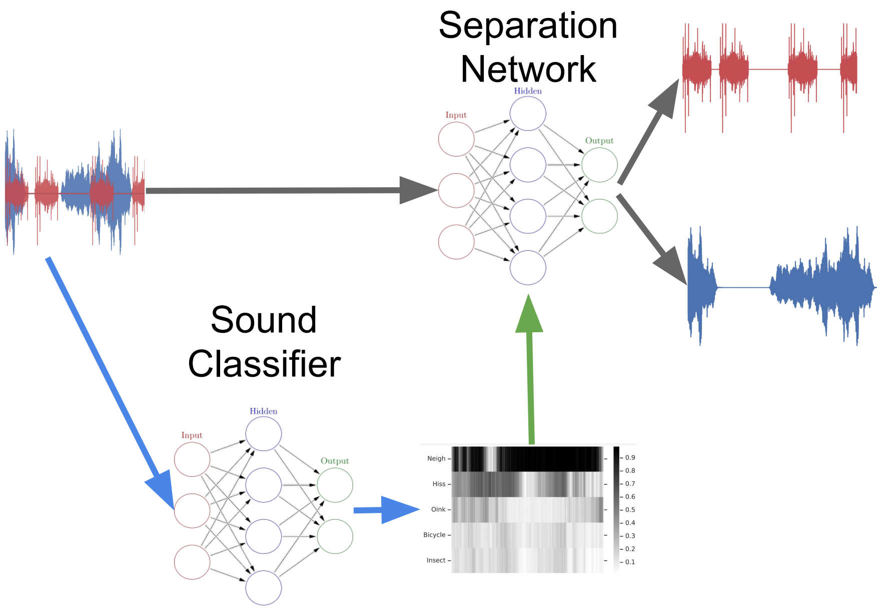
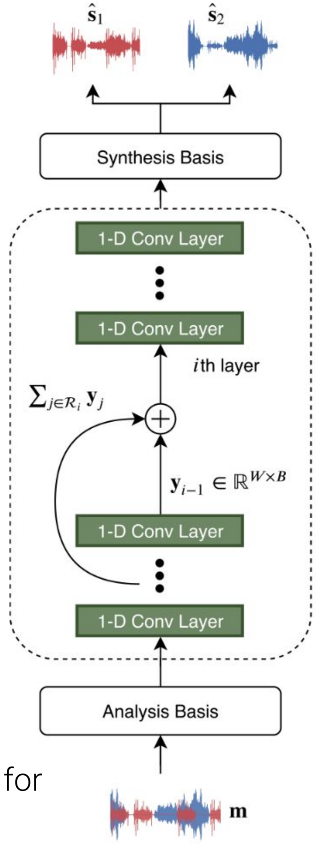
3. **Guide/condition** the separation network using this embedding in order to improve its accuracy



Separation Network:
Time-Dilated Convolution Network (TDCN++)

Baseline Separation Network: (similar to ConvTasNet [2])

- **Analysis/Synthesis Basis:**
  - **Learnable**: 1D convolution/deconvolution layers
  - **Fixed**: STFT basis



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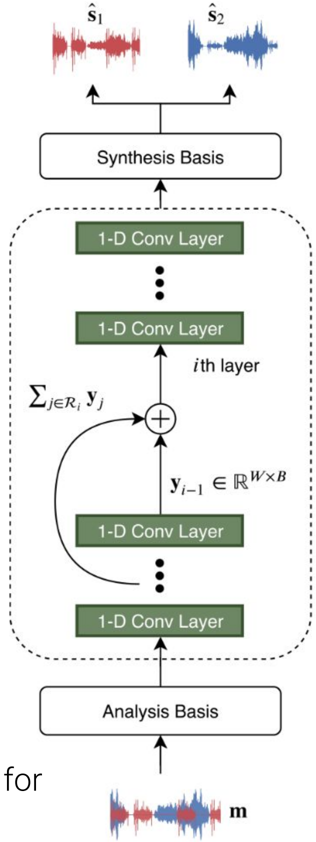
- **Separator:**
  - 32 1D Separable convolutional blocks
  - Residual connections from previous blocks



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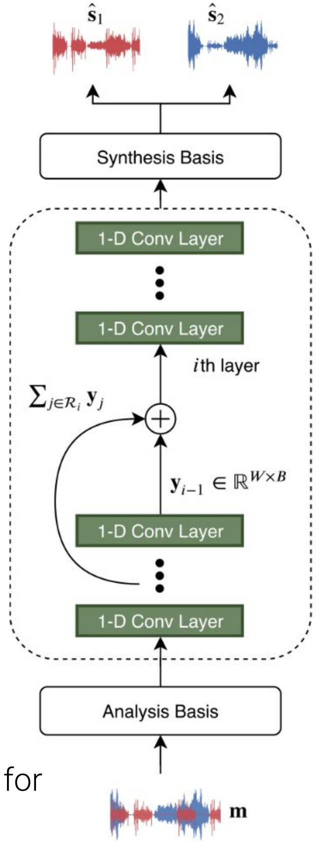
Loss:

- **Permutation Invariant Signal to Noise Ratio (SNR)**

$$\mathcal{L} = -SNR(\mathbf{s}_{p^*}, \hat{\mathbf{s}}) = -10 \log_{10} \frac{||\mathbf{s}_{p^*}||^2}{||\mathbf{s}_{p^*} - \hat{\mathbf{s}}||^2}$$



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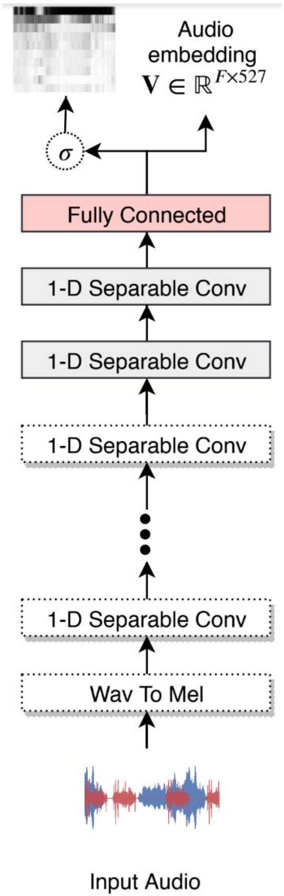
Extract audio embeddings from a pre-trained sound classifier

Sound classifier:

- Event sound classifier (**527 classes**)
- Trained on **AudioSet**
- **MobileNet for audio**

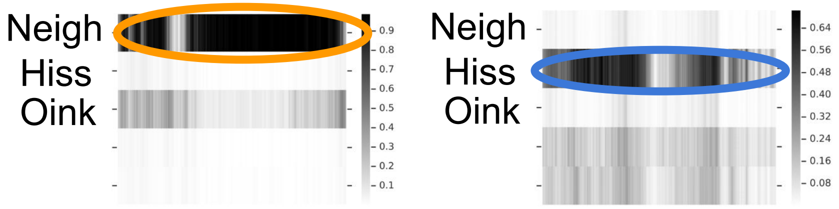
How good are these embeddings?

- The sound classifier has also been trained using **mixtures** of sounds



Type of frame-wise conditional embeddings

- Embeddings of the **source** signals
  - An angry horse
  - Insect hissing



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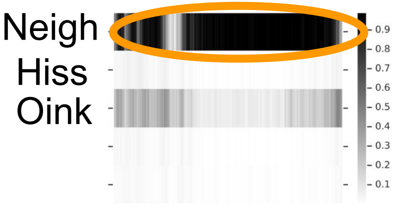
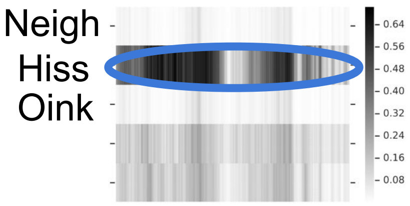
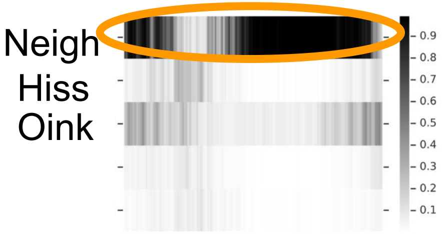




- Embedding of the **mixture** signal:
  - **Not always enclosing the semantic information of all the sources**



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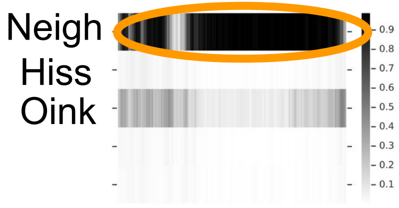

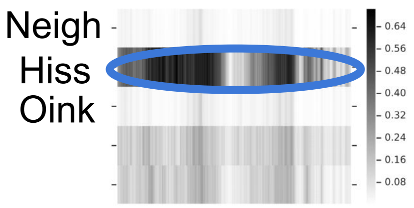

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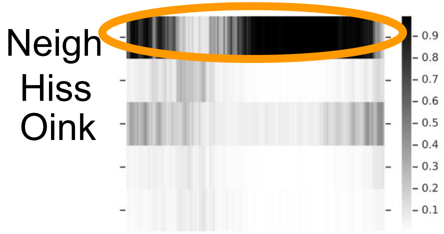

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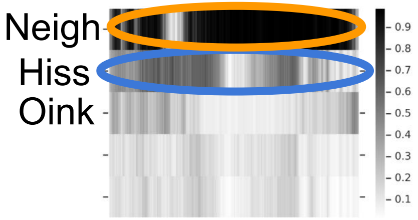
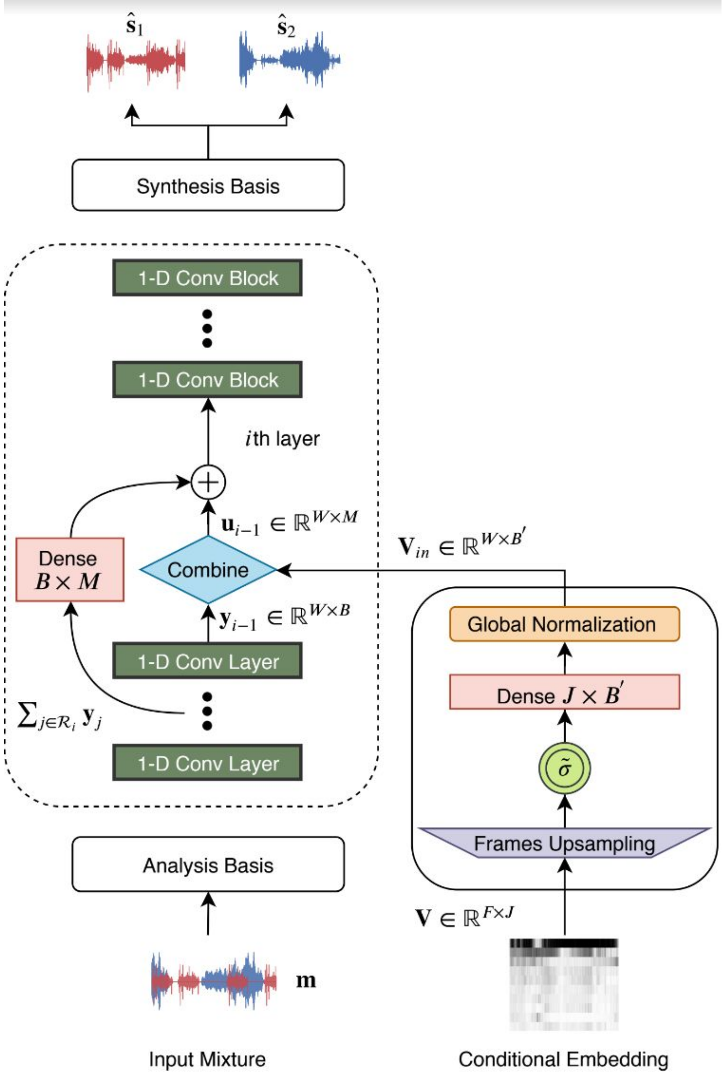
- **Soft OR** embedding:
  - The probability that one or more sources is active



Integrating semantic information in TDCN++

Integrate at i-th layer of a TDCN++ :



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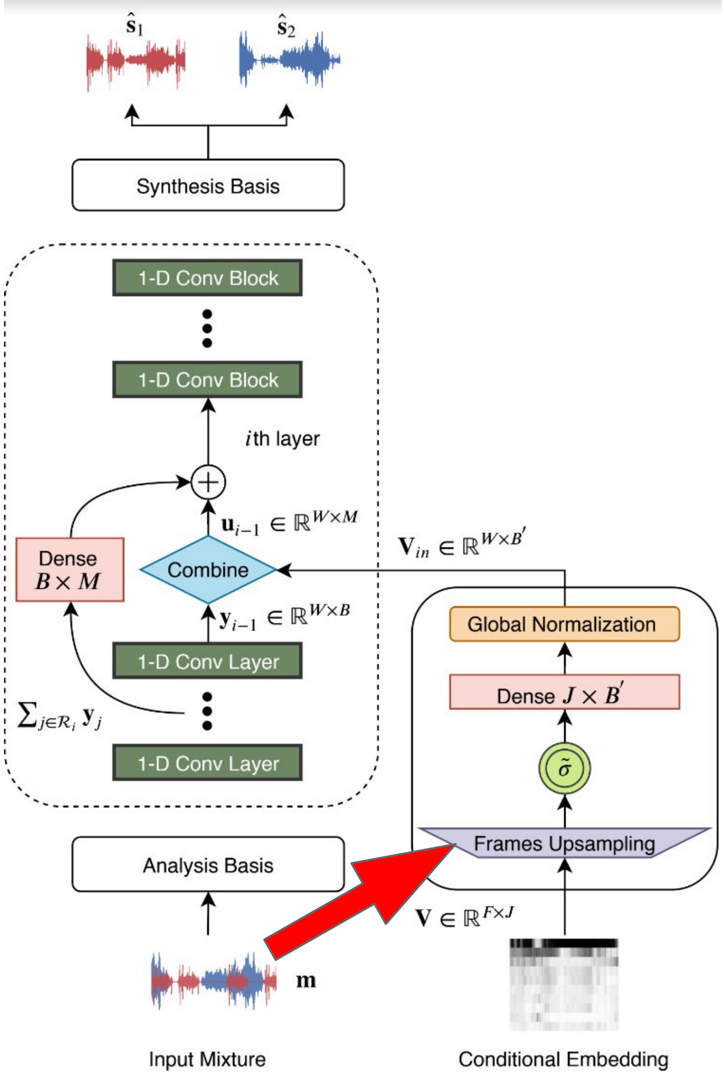
Integrate at i-th layer of a TDCN++ :

1. **Resample** the embedding in time



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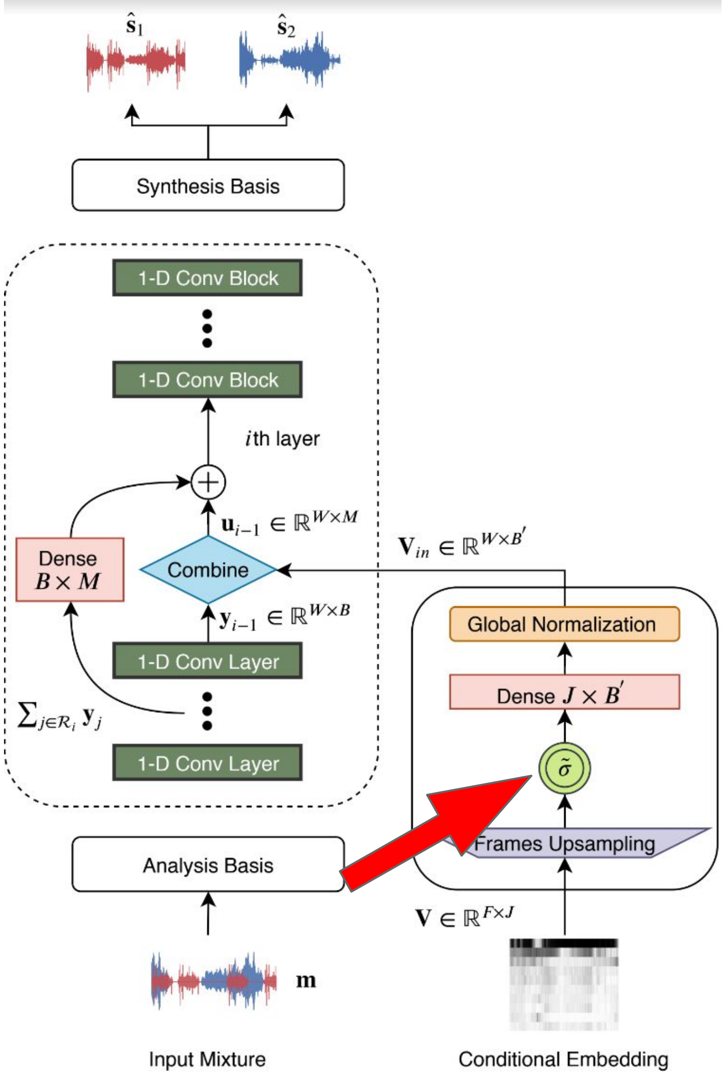
Integrate at i-th layer of a TDCN++ :

1. **Resample** the embedding in time
2. Apply a **sigmoid** on the embedding vector



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Integrate at i-th layer of a TDCN++ :

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2. Apply a **sigmoid** on the embedding vector
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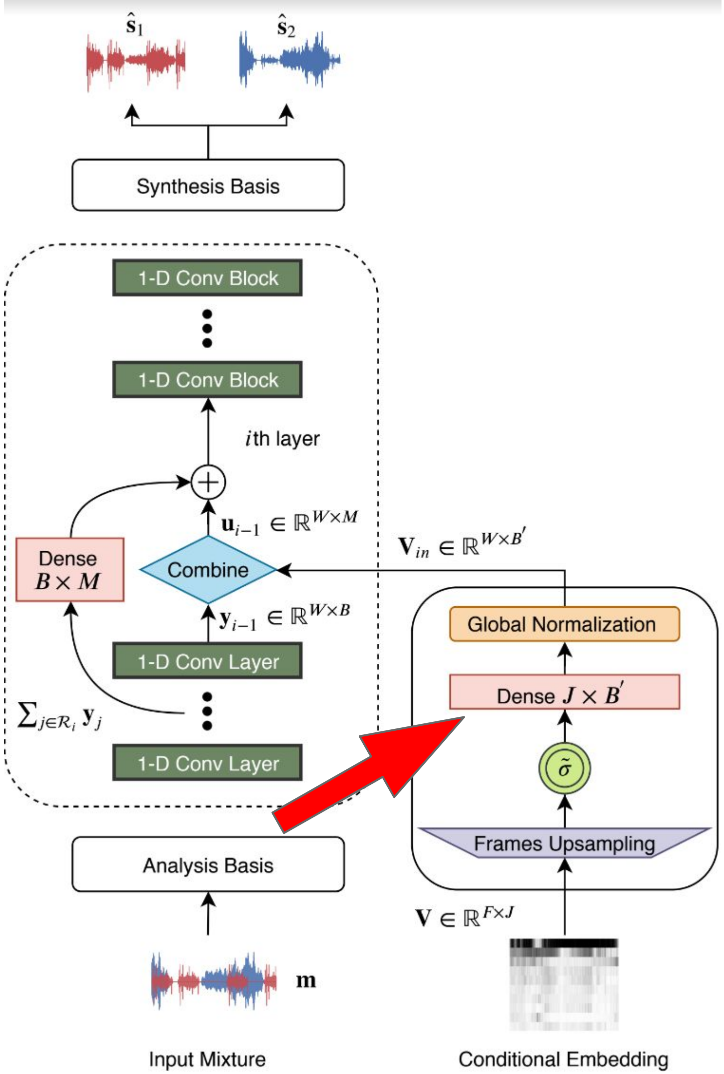

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Integrate at i-th layer of a TDCN++ :

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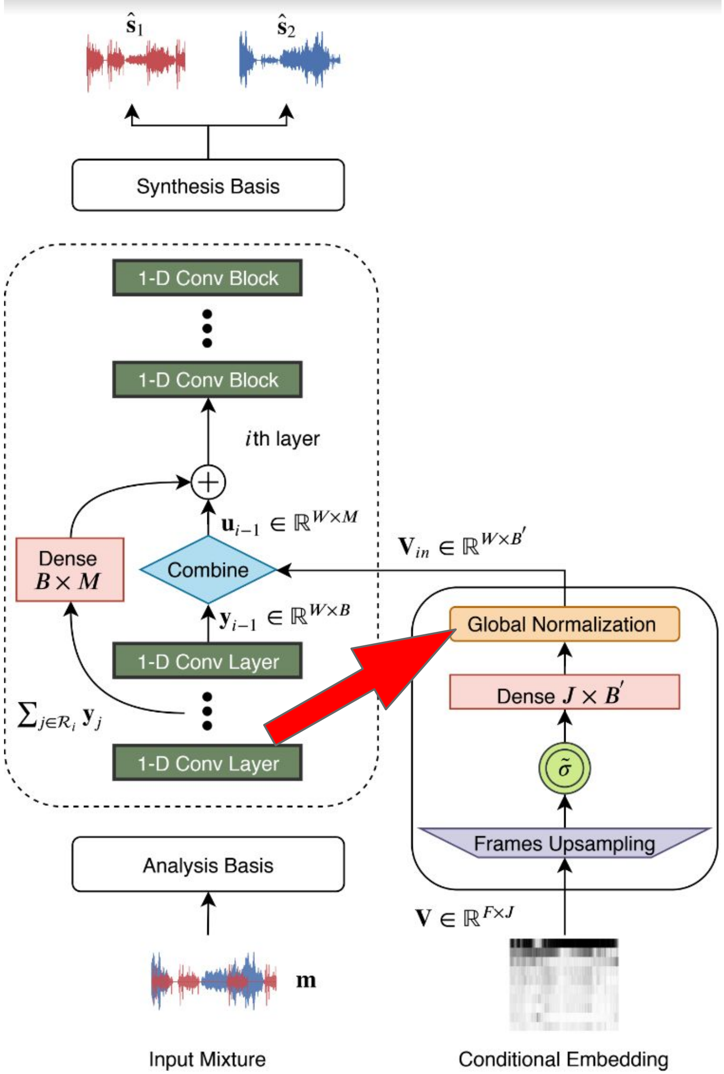
4. **Global normalization**



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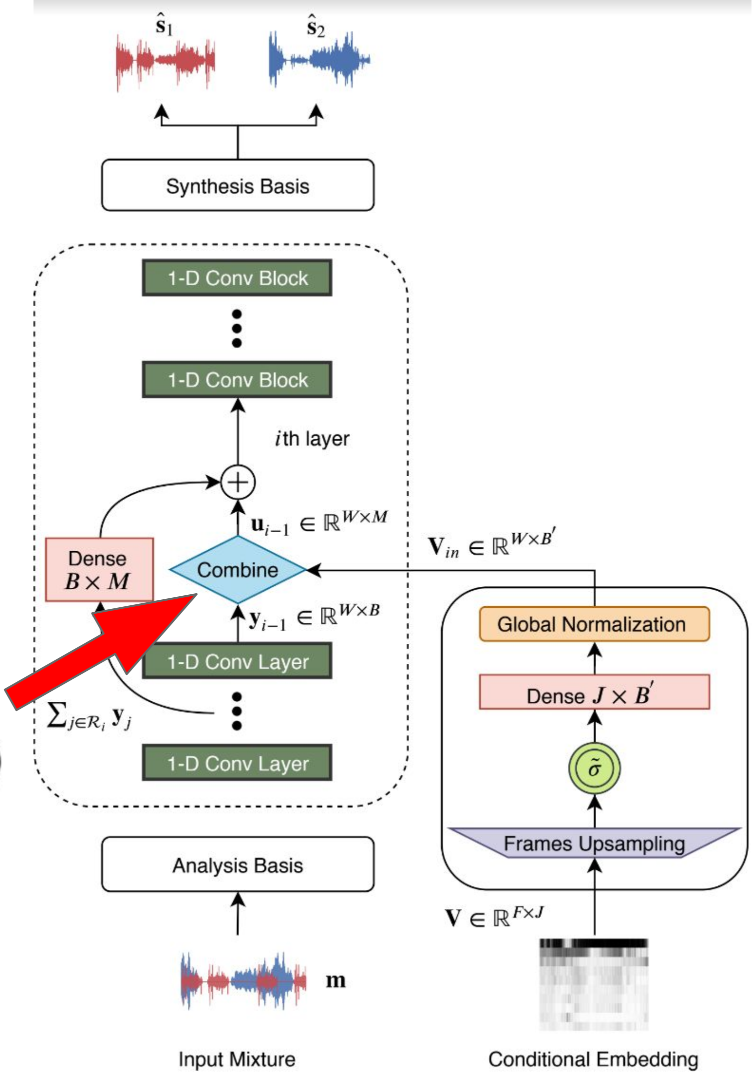
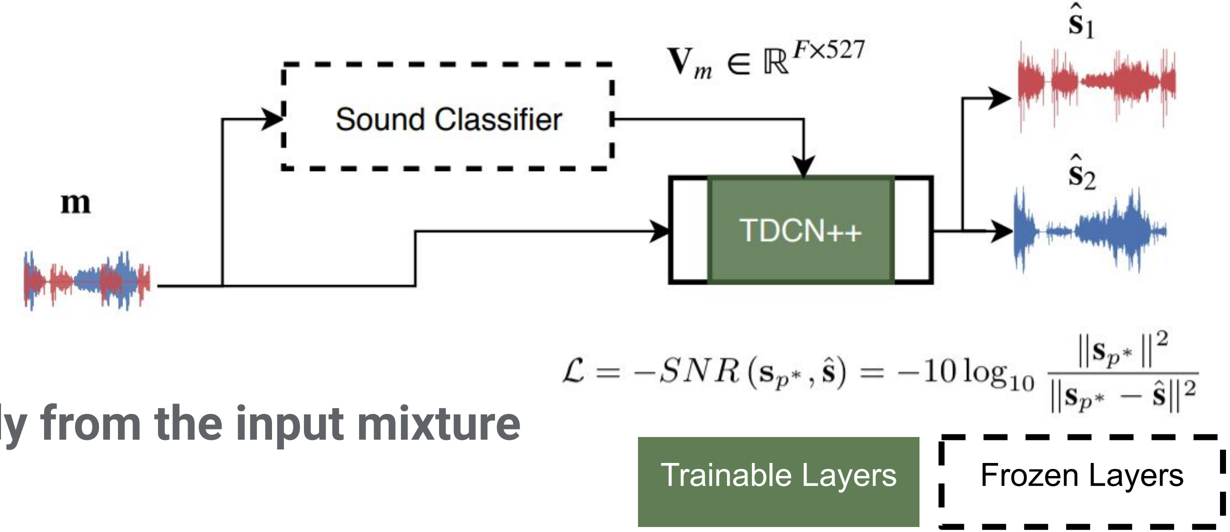
Integrate at i-th layer of a TDCN++ :

1. **Resample** the embedding in time
2. Apply a **sigmoid** on the embedding vector
3. **Reduce** channels dimensions
4. **Global normalization**
5. **Combine** with activations:
   a. Concatenate $\mathbf{u}_{i-1} = [\mathbf{V}_{\text{in}}, \mathbf{y}_{i-1}] \in \mathbb{R}^{W \times (B+B')}$
   b. Gating $\mathbf{u}_{i-1} = \mathbf{V}_{\text{in}} \odot \mathbf{y}_{i-1} \in \mathbb{R}^{W \times B}$



TDCN++ with pre-trained embeddings



Baseline experiment:

- Using the embedding **only from the input mixture**

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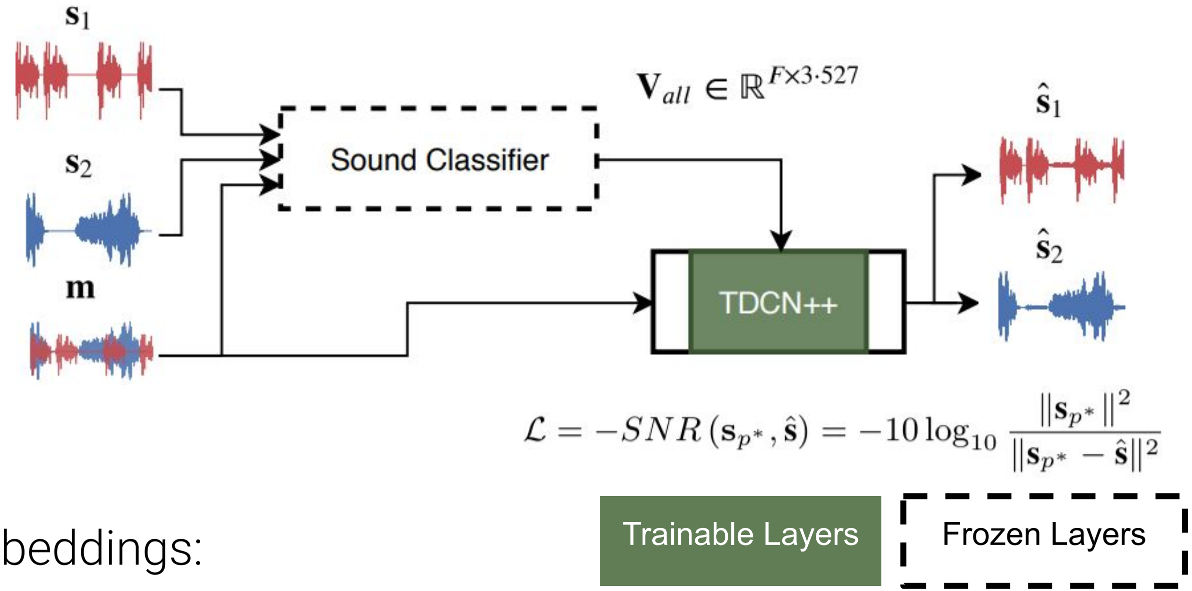

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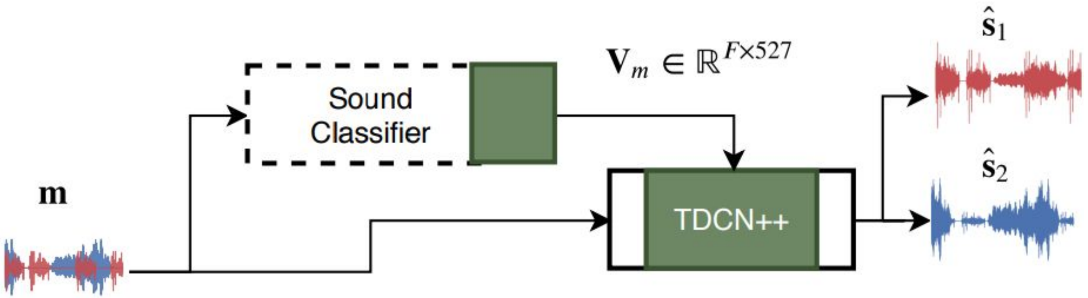
Oracle experiment with “all” embeddings:

- Concatenate the embeddings for **mixture and all the sources**
  - This is a **measure of upper bound of the performance improvement we can get from the integration of the semantic information**

Oracle experiment with soft-OR embedding

TDCN++ with fine-tuned embeddings



Problem: The pre-trained mixture embedding

- Is **not fine-tuned for the task** for separation
- Embeddings are trained on **different data and task**

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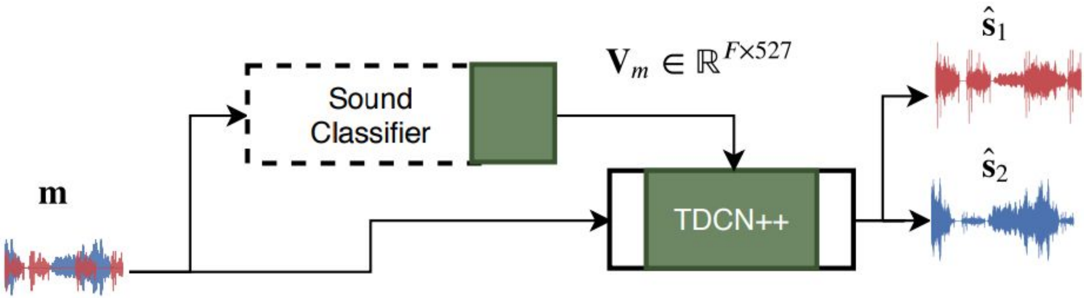
Trainable Layers

Frozen Layers

TDCN++ with fine-tuned embeddings



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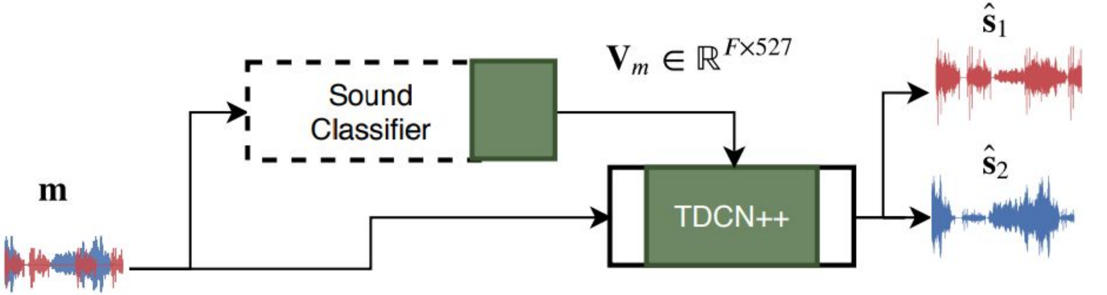
Idea: Refining the embeddings before conditioning

- **Fine-tuning** the last layers of the sound classifier

TDCN++ with fine-tuned embeddings



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Trainable Layers

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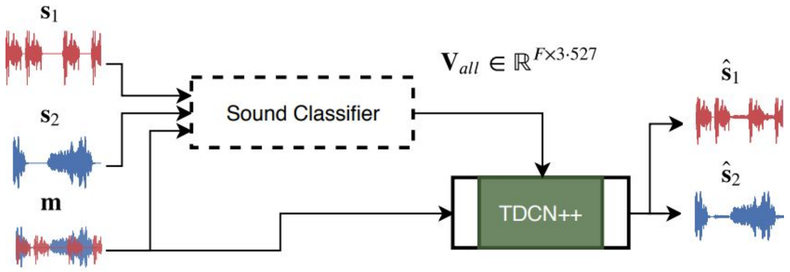
Idea: Refining the embeddings before conditioning

- **Fine-tuning** the last layers of the sound classifier
- **End-to-end source separation**:
  - The **loss remains the same as before**

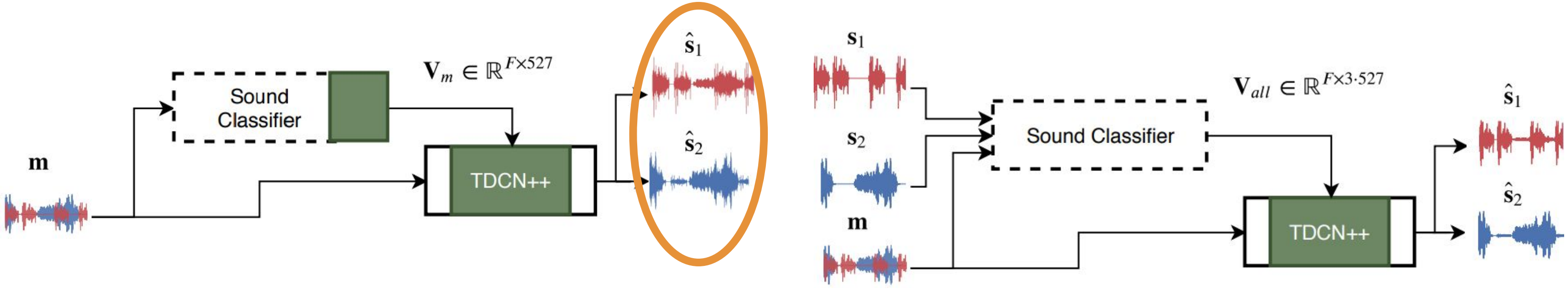
First estimate the sources and then extract the conditional embeddings



The Premise:

- **Using embeddings from clean sources** might lead to better separation performance **[SPOILER ALERT]**

First estimate the sources and then extract the conditional embeddings



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Idea: Extending end-to-end architecture for getting "all" embeddings

1. **Try to separate the sources first**

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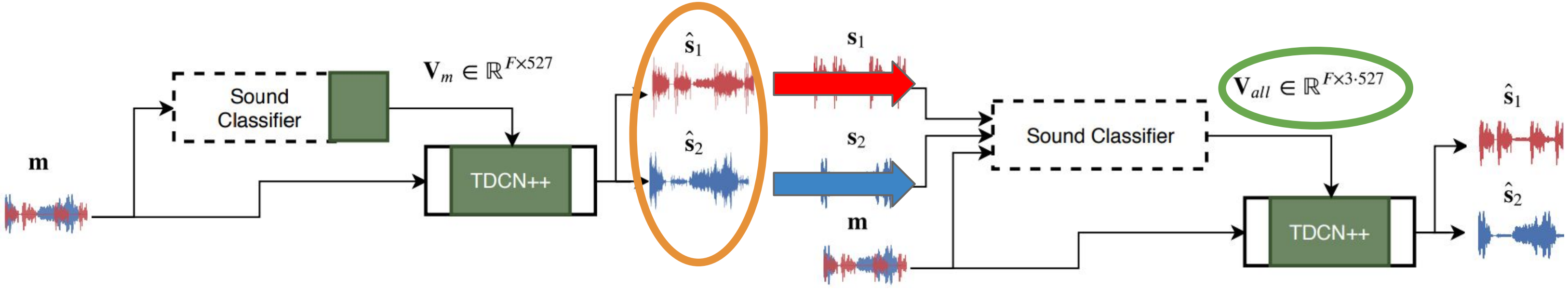

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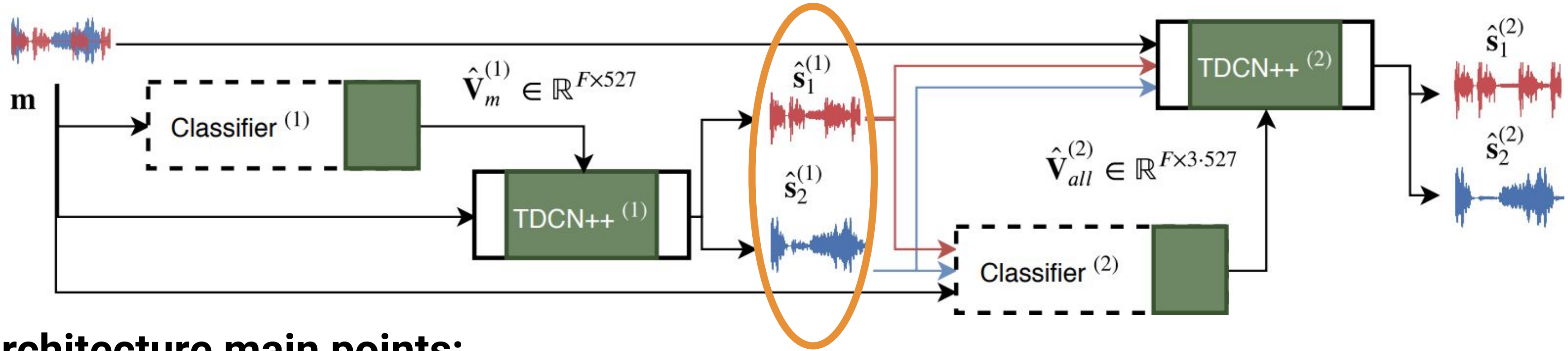
Idea: Extending end-to-end architecture for getting "all" embeddings

1. **Try to separate the sources first**
2. **Use the first estimates of the sources in order to extract embeddings corresponding to the clean sources**

Iterative separation and refinement of embeddings (iTDCN++)



Architecture main points:

1. **Estimate the separated sources** and then extract the embeddings for both the estimates and the input mixture

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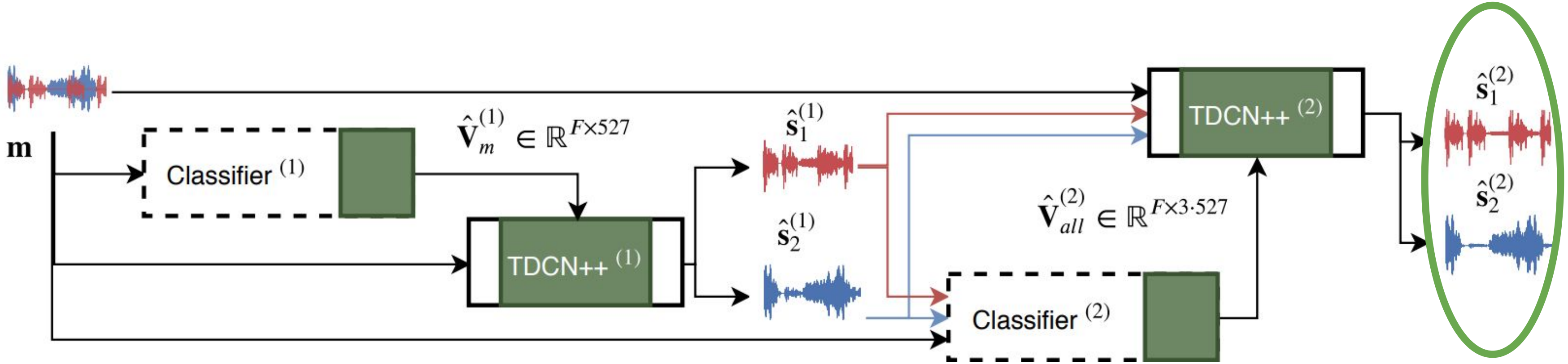

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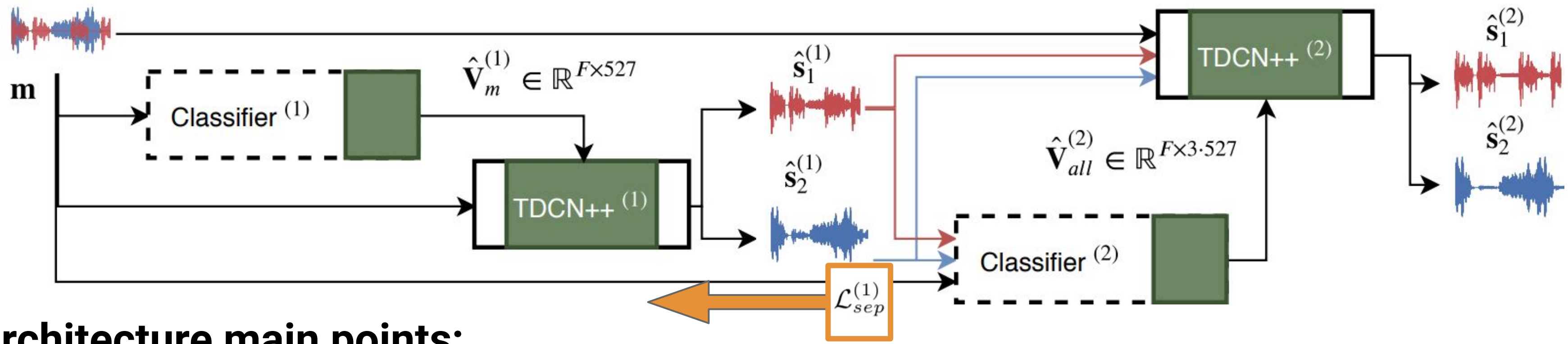

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Source separation losses:

1. First separation estimation:

$$\boxed{\mathcal{L}_{sep}^{(1)} = -SNR\left(\mathbf{s}_{p^*}, \hat{\mathbf{s}}^{(1)}\right)}$$

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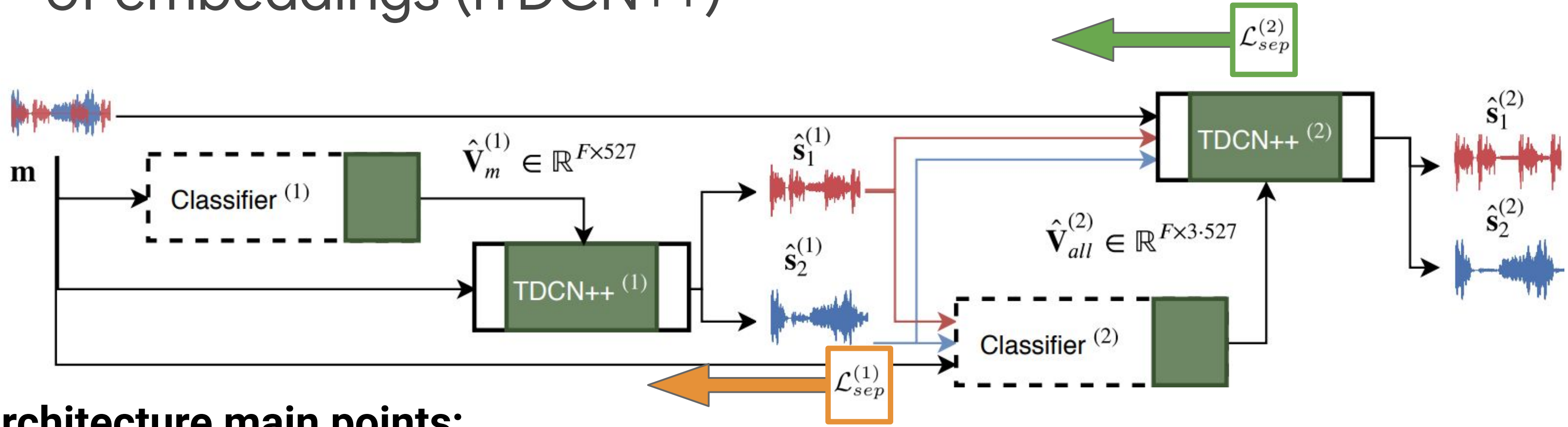

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Source separation losses:

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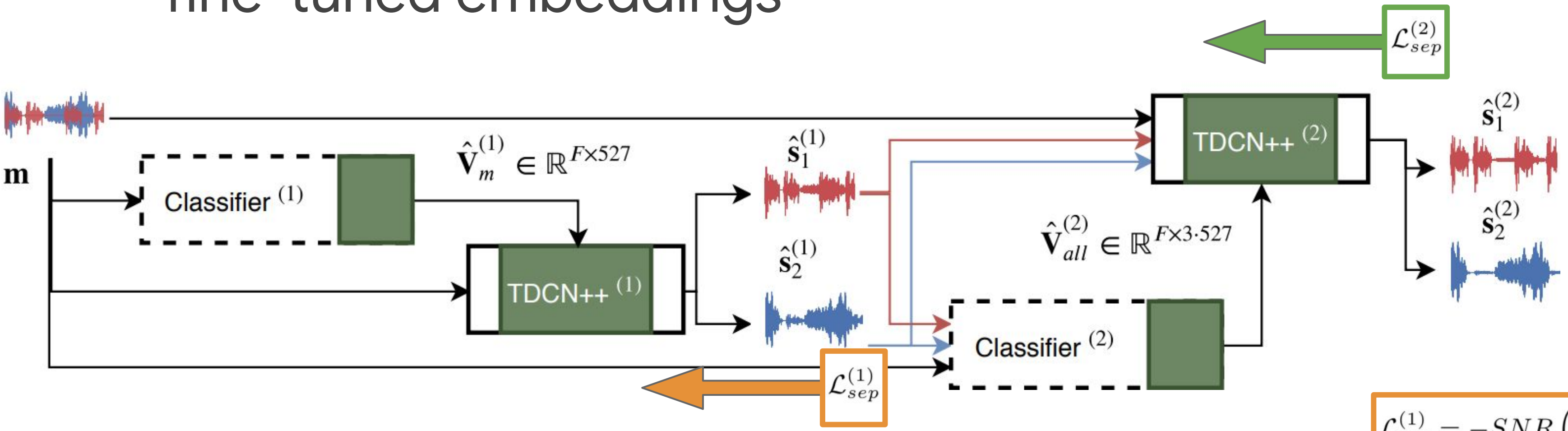
Guided Iterative separation and fine-tuned embeddings



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Idea: Use the "ideal" embeddings as targets

Embeddings Losses: sigmoid cross-entropy (SCE)

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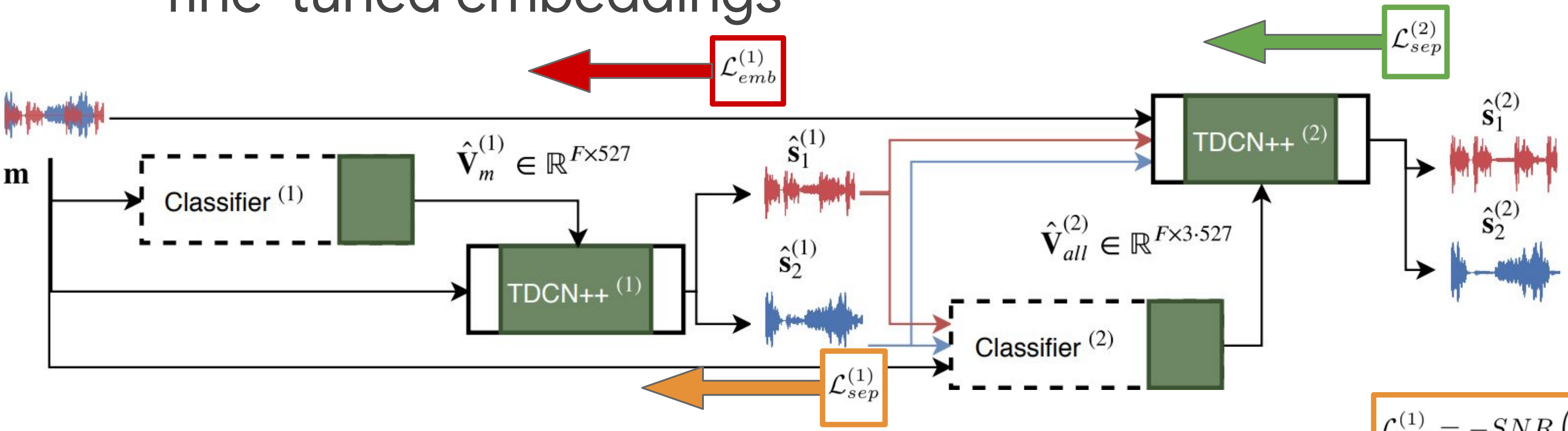

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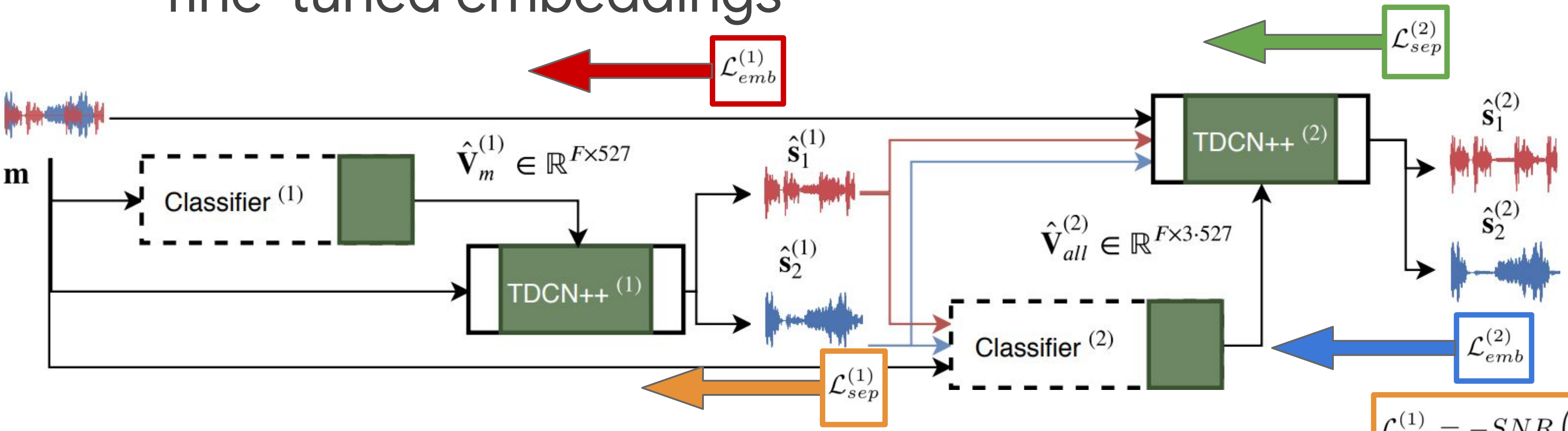
Embeddings Losses: sigmoid cross-entropy (SCE)

- Making the **mixture embedding** look like the **soft OR embedding**: $\mathcal{L}^{(1)}_{emb} = SCE\left(\mathbf{V}^{p^*}_{or}, \hat{\mathbf{V}}^{(1)}_m\right)$

Guided Iterative separation and fine-tuned embeddings



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Embeddings Losses: sigmoid cross-entropy (SCE)

- Making the **mixture embedding** look like the **soft OR embedding**: $\mathcal{L}_{emb}^{(1)} = SCE\left(\mathbf{V}_{or}^{p^*}, \hat{\mathbf{V}}_m^{(1)}\right)$
- Making the **sources embeddings** look like the **target ones**: $\mathcal{L}_{emb}^{(2)} = SCE\left(\mathbf{V}_{or}^{p^*}, \hat{\mathbf{V}}_m^{(2)}\right) + SCE\left(\mathbf{V}_{s}^{p^*}, \hat{\mathbf{V}}_s^{(2)}\right)$

Experiments on Universal Sound Separation

Task:

- 2 -source separation

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Prosound Dataset:

- Wide variety of sound classes
  - (animal calls, musical instruments, speech, artificial sounds, etc.)
  - 3 seconds clips sampled at 16kHz
- Train/Val/Test splits:
  - 11.7 hours training mixtures
  - 3.2 hours validation mixtures
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Evaluation Metric:

- Permutation-invariant scale-invariant signal-to-distortion ratio improvement (SI-SDRi)

Performance (SI-SDR improvement in dB)

	Method	Embeddings Type	Embeddings Fine-tuning	STFT Val.	STFT Test	Learned Val.	Learned Test
Baselines	TDCN++ with no embeddings [8]	-	-	9.9	9.1	9.1	8.5
	iTDCN++ with no embeddings [8]	-	-	10.6	9.8	9.3	8.7
Proposed	Pretrained embeddings & TDCN++	mixture	-	10.3	9.4	9.4	8.6
	Fine-tuned embeddings & TDCN++	mixture	✓	10.2	9.4	9.3	8.5
	Guided fine-tuned embeddings & TDCN++	mixture	✓	10.3	9.4	9.4	8.6
	Pretrained embeddings & iTDCN++	all	-	10.8	9.9	9.9	9.0
	Fine-tuned embeddings & iTDCN++	all	✓	**11.1**	10.1	**10.1**	**9.2**
	Guided fine-tuned embeddings & iTDCN++	all	✓	**11.1**	**10.2**	10.0	9.1
Oracles	Pretrained embeddings & TDCN++	all	-	11.3	10.6	11.0	10.2
		soft-OR	-	11.4	10.6	10.7	10.1
	STFT binary mask	-	-	16.8	16.2	-	-

1. **Consistent performance improvement when we use embeddings for source separation**
    a. Improvement also when simple pre-trained embeddings are used

Performance (SI-SDR improvement in dB)

	Method	Embeddings Type	Embeddings Fine-tuning	STFT Val.	STFT Test	Learned Val.	Learned Test
Baselines	TDCN++ with no embeddings [8]	-	-	9.9	$\boxed{9.1}$	9.1	$\boxed{8.5}$
	iTDCN++ with no embeddings [8]	-	-	10.6	9.8	9.3	8.7
Proposed	Pretrained embeddings & TDCN++	mixture	-	10.3	9.4	9.4	8.6
	Fine-tuned embeddings & TDCN++	mixture	✓	10.2	$\boxed{9.4}$	9.3	$\boxed{8.5}$
	Guided fine-tuned embeddings & TDCN++	mixture	✓	10.3	9.4	9.4	8.6
	Pretrained embeddings & iTDCN++	all	-	10.8	9.9	9.9	9.0
	Fine-tuned embeddings & iTDCN++	all	✓	**11.1**	10.1	**10.1**	**9.2**
	Guided fine-tuned embeddings & iTDCN++	all	✓	**11.1**	**10.2**	10.0	9.1
Oracles	Pretrained embeddings & TDCN++	all	-	11.3	10.6	11.0	10.2
		soft-OR	-	11.4	10.6	10.7	10.1
	STFT binary mask	-	-	16.8	16.2	-	-

1. **Consistent performance improvement when we use embeddings for source separation**
   a. Improvement also when simple pre-trained embeddings are used
   b. Improvement also with the simpler end-to-end approach

Performance (SI-SDR improvement in dB)

	Method	Embeddings		STFT		Learned	
		Type	Fine-tuning	Val.	Test	Val.	Test
Baselines	TDCN++ with no embeddings [8]	-	-	9.9	9.1	9.1	8.5
	iTDCN++ with no embeddings [8]	-	-	10.6	$\boxed{9.8}$	9.3	$\boxed{8.7}$
Proposed	Pretrained embeddings & TDCN++	mixture	-	10.3	9.4	9.4	8.6
	Fine-tuned embeddings & TDCN++	mixture	✓	10.2	9.4	9.3	8.5
	Guided fine-tuned embeddings & TDCN++	mixture	✓	10.3	9.4	9.4	8.6
	Pretrained embeddings & iTDCN++	all	-	10.8	9.9	9.9	9.0
	Fine-tuned embeddings & iTDCN++	all	✓	**11.1**	10.1	**10.1**	$\boxed{\textbf{9.2}}$
	Guided fine-tuned embeddings & iTDCN++	all	✓	**11.1**	$\boxed{\textbf{10.2}}$	10.0	9.1
Oracles	Pretrained embeddings & TDCN++	all	-	11.3	10.6	11.0	10.2
		soft-OR	-	11.4	10.6	10.7	10.1
	STFT binary mask	-	-	16.8	16.2	-	-

1. **Consistent performance improvement when we use embeddings for source separation**
   a. Improvement also when simple pre-trained embeddings are used
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2. Improvement over iTDCN++ **for the non-oracle case: 0.4 dB (STFT basis) & 0.5 dB (Learnable basis)**

Performance (SI-SDR improvement in dB)

	Method	Embeddings Type	Embeddings Fine-tuning	STFT Val.	STFT Test	Learned Val.	Learned Test
Baselines	TDCN++ with no embeddings [8]	-	-	9.9	9.1	9.1	8.5
	iTDCN++ with no embeddings [8]	-	-	10.6	9.8	9.3	8.7
Proposed	Pretrained embeddings & TDCN++	mixture	-	10.3	9.4	9.4	8.6
	Fine-tuned embeddings & TDCN++	mixture	✓	10.2	9.4	9.3	8.5
	Guided fine-tuned embeddings & TDCN++	mixture	✓	10.3	9.4	9.4	8.6
	Pretrained embeddings & iTDCN++	all	-	10.8	9.9	9.9	9.0
	Fine-tuned embeddings & iTDCN++	all	✓	**11.1**	10.1	**10.1**	**9.2**
	Guided fine-tuned embeddings & iTDCN++	all	✓	**11.1**	**10.2**	10.0	9.1
Oracles	Pretrained embeddings & TDCN++	all	-	11.3	10.6	11.0	10.2
		soft-OR	-	11.4	10.6	10.7	10.1
	STFT binary mask	-	-	16.8	16.2	-	-

1. **Consistent performance improvement when we use embeddings for source separation**
   a. Improvement also when simple pre-trained embeddings are used
   b. Improvement also with the simpler end-to-end approach
2. Improvement over iTDCN++ **for the non-oracle case: 0.4 dB (STFT basis)** & **0.5 dB (Learnable basis)**
3. Improvement over iTDCN++ **for the oracle case: 0.8 dB (STFT basis)** & **1.5 dB (Learnable basis)**

Conclusions & Future Work

Proposed

A **new way to integrate semantic information of audio** in order to perform higher quality universal sound separation.

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Trained and evaluated >1000 models with different parameter configurations. Variable ways of conditioning separation networks for better source separation.

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Results

Our iterative approach achieves an improvement of **0.5 dB (learnable basis)** and **0.4 dB (STFT basis)** in SI-SDR over the baseline iterative model having no embeddings.

Conclusions & Future Work

Proposed	A **new way to integrate semantic information of audio** in order to perform higher quality universal sound separation.
Explored	**Trained and evaluated >1000 models** with different parameter configurations. Variable ways of conditioning separation networks for better source separation.
Results	Our iterative approach achieves an improvement of **0.5 dB (learnable basis)** and **0.4 dB (STFT basis)** in SI-SDR over the baseline iterative model having no embeddings.
Future	Check whether separated sounds help sound classification (there is DCASE 2020 Task 4 using the new Free Universal Sound Separation (FUSS) dataset that explores this task). Source separation with an unknown number of sources.

Thank you all!

Waiting to see you at the Q&A session!

Efthymios Tzinis

Google AI