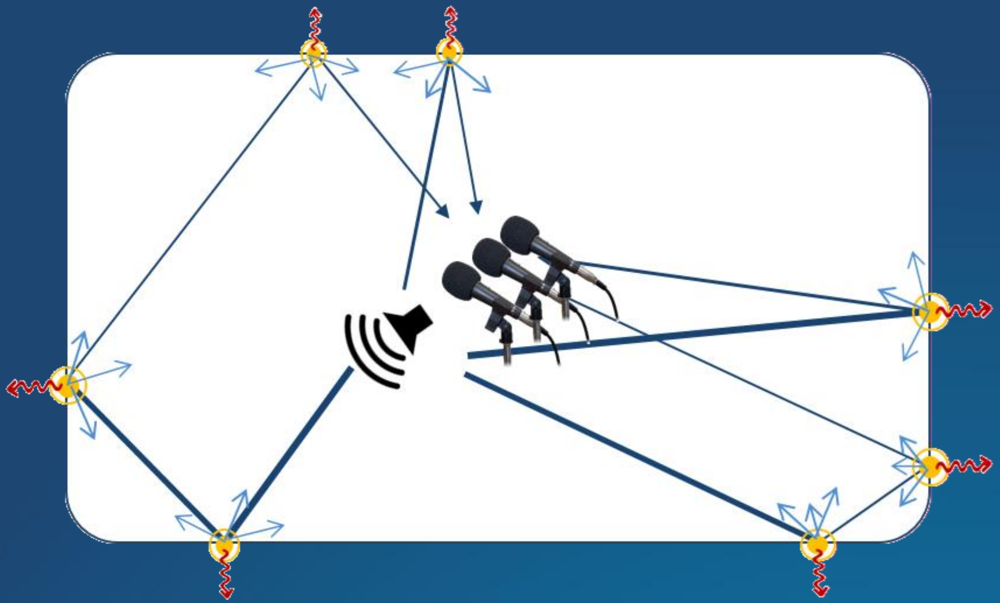
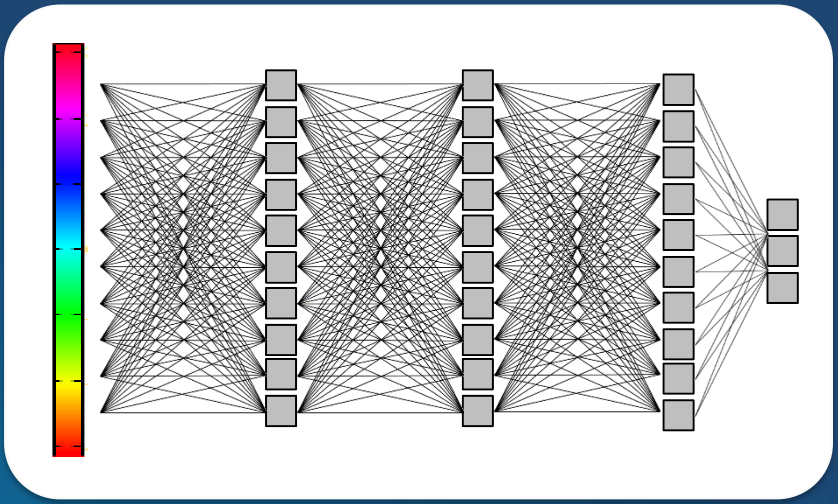
# Machine Learning for Indoor Acoustics

Antoine Deleforge
Inria (Nancy - Grand Est)





👏

*« What is the shape of the room? »*

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*« Is the floor made of tiles or carpet? »*

# OUTLINE

1) Intro & Background
2) Virtually-Supervised Learning
3) Examples and Results
4) Conclusions and Outlook

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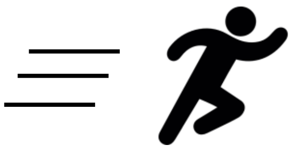
- Sound has a **speed:** $c \approx 343$ m/sec



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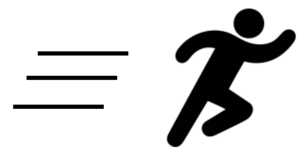
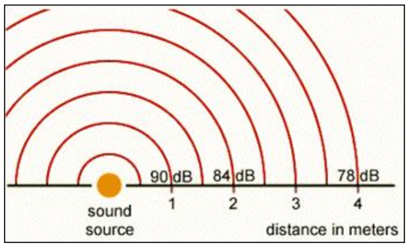


- Sound **dissipates:** ≈ -6 dB every doubling of distance



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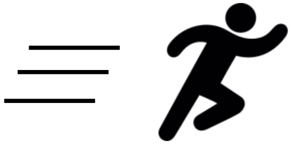

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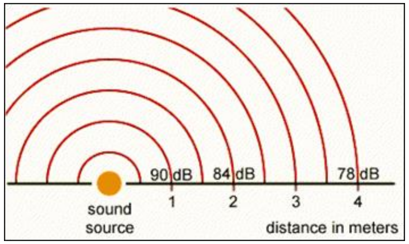


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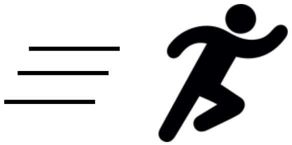

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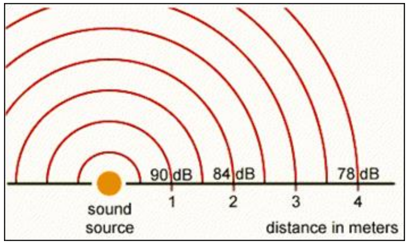


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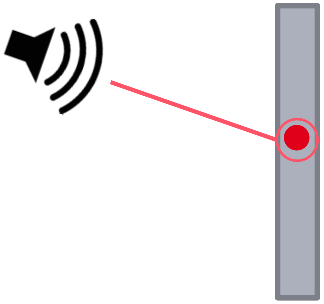

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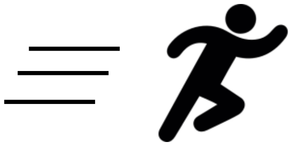

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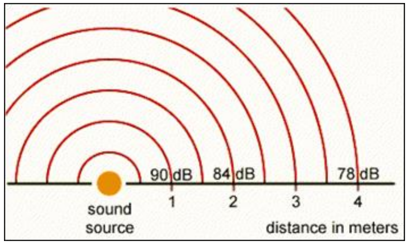


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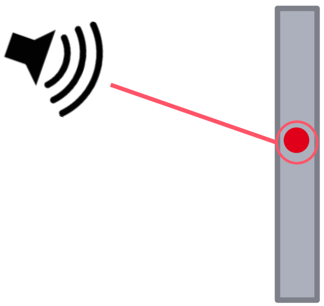

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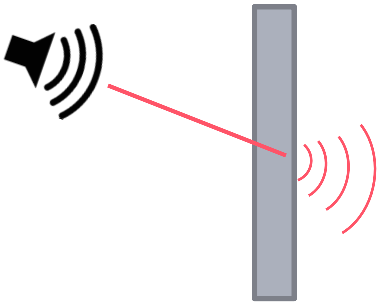

Transmission

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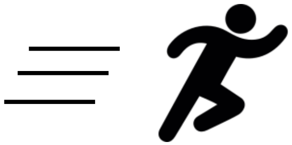

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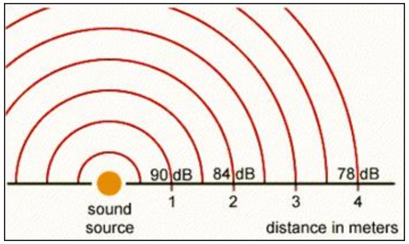


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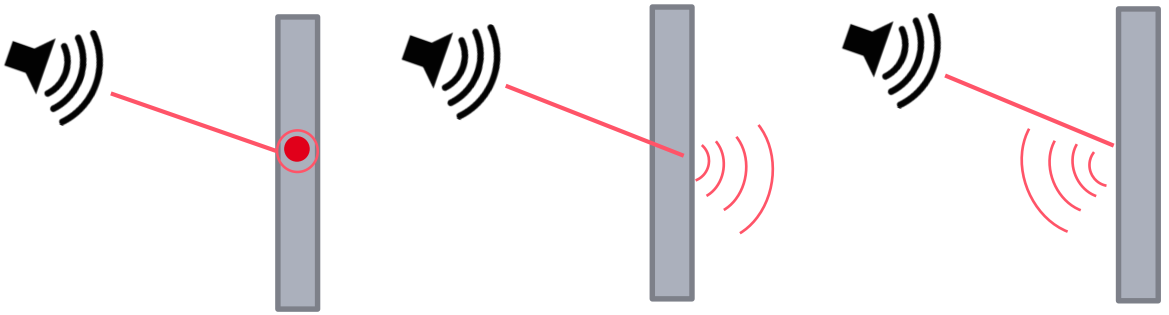

Absorption Transmission Reflexion

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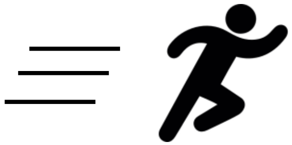

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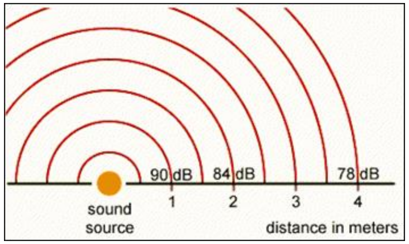


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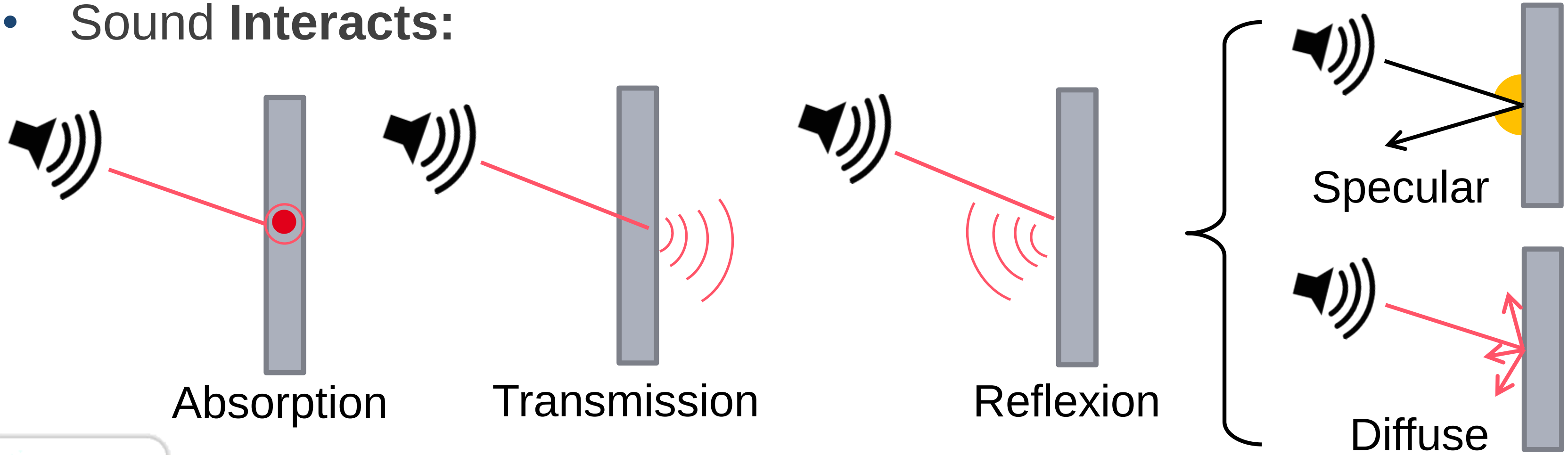

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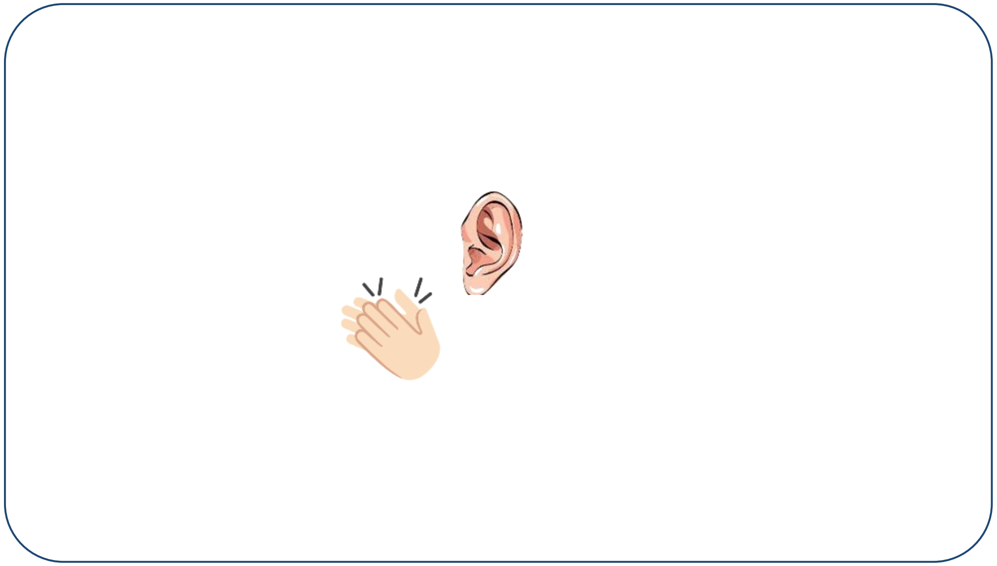

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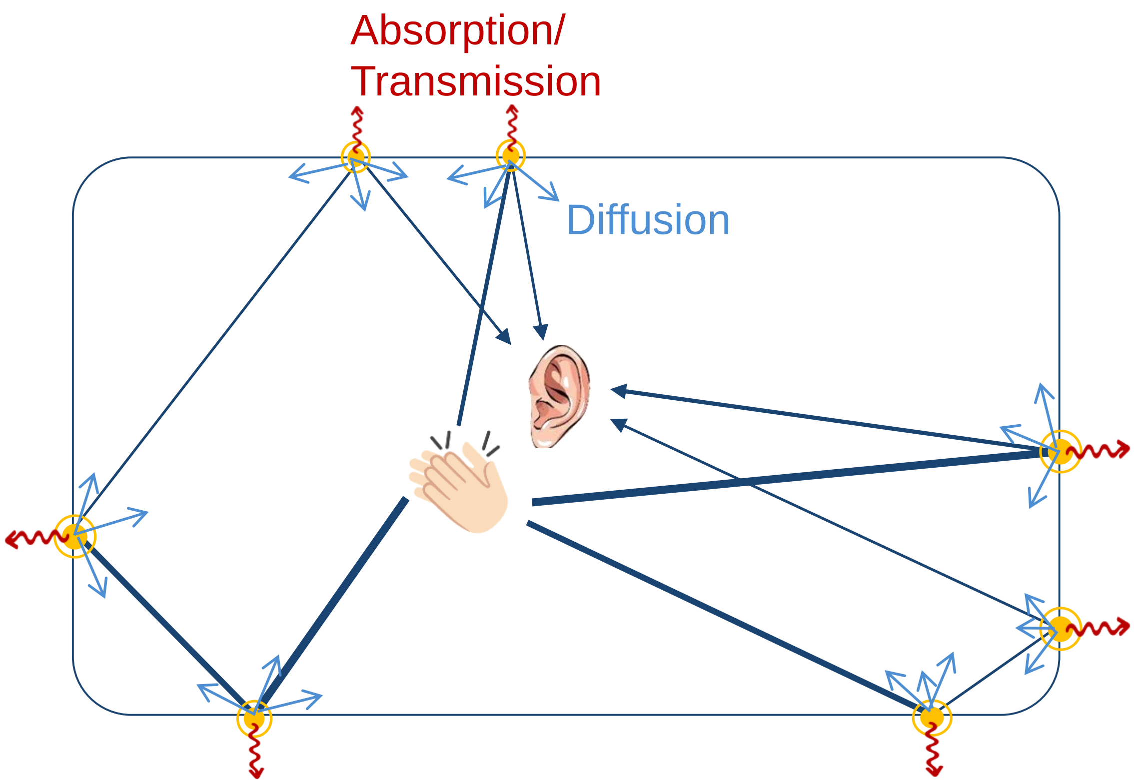

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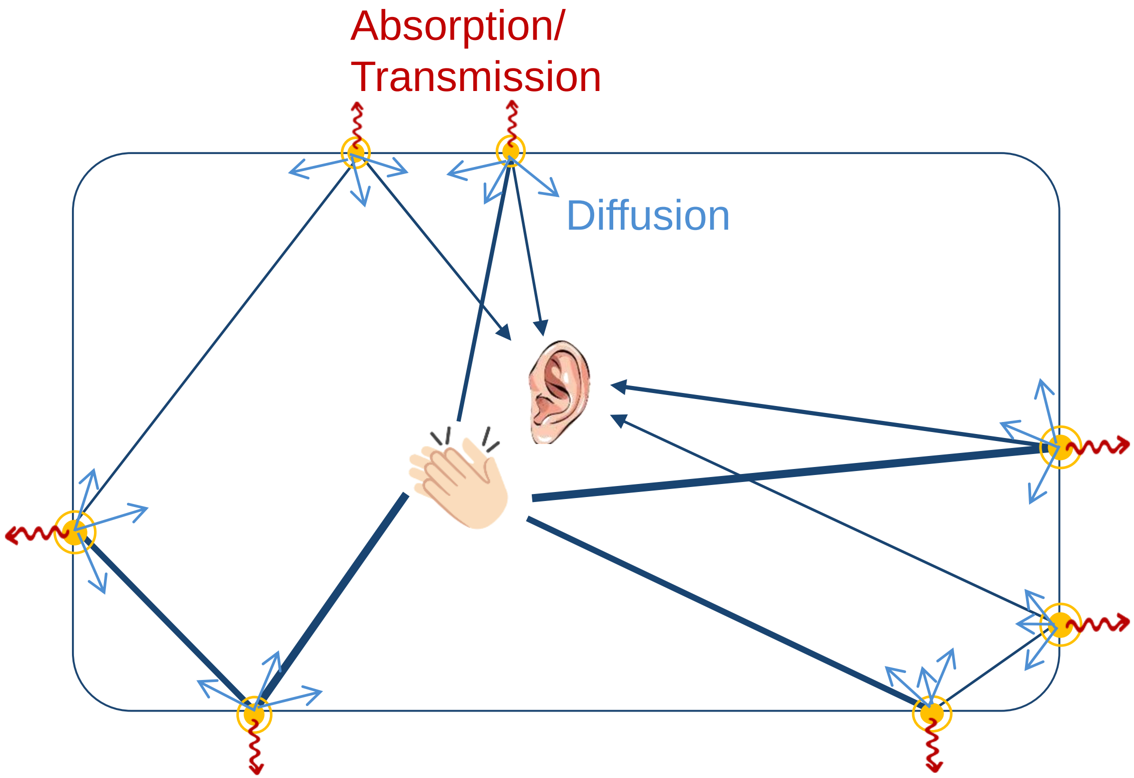
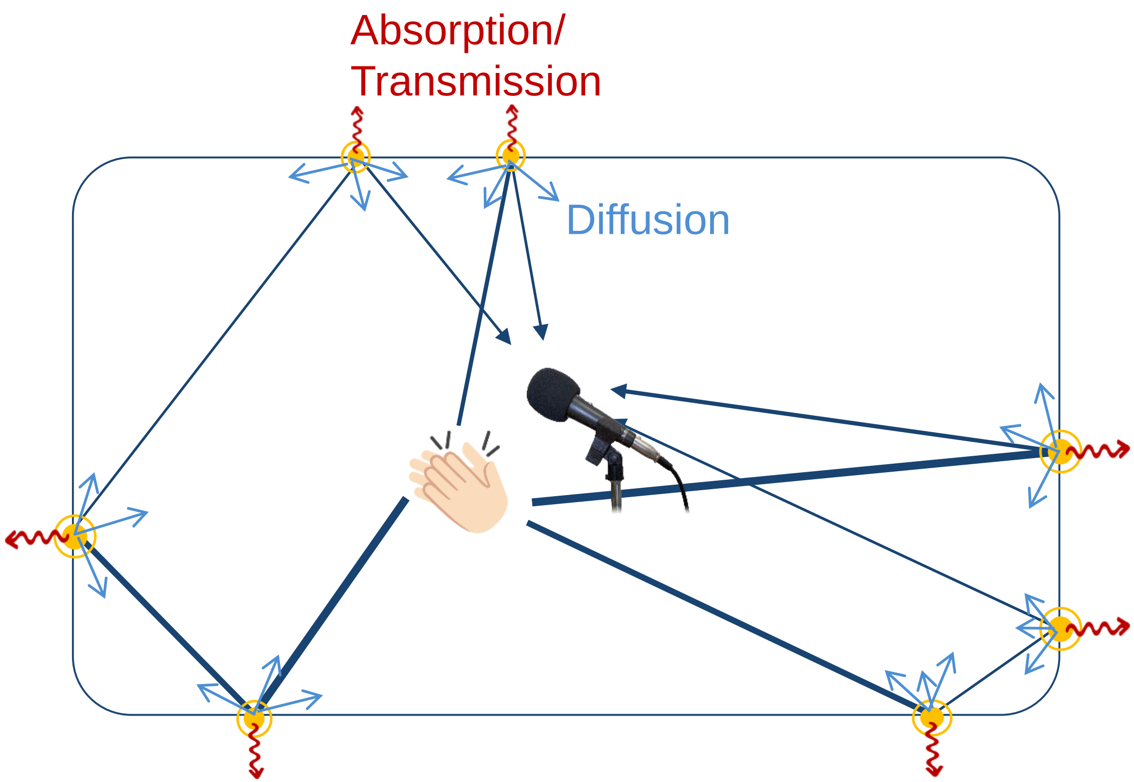



« Reverberation »




« Reverberation »

A signal model of reverberation?

# The Room Impulse Response

- **Impulse response:** The response of an LTI system to a perfect impulse (*Dirac*).
- **Room Impulse response (RIR):** Captures the linear filtering effect due to the propagation of sound from a **point source** to a **microphone** inside a room

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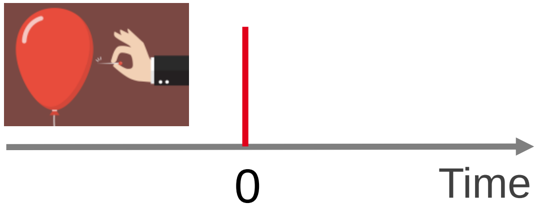

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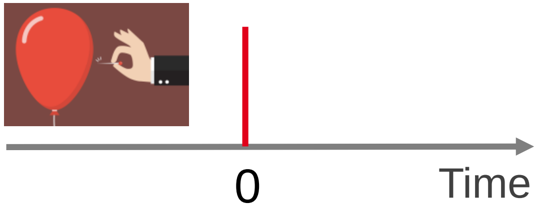


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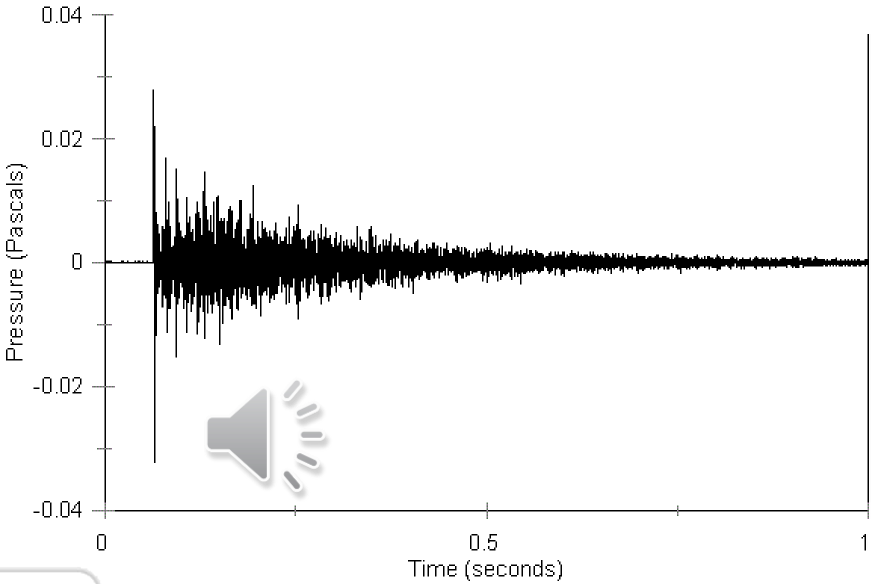


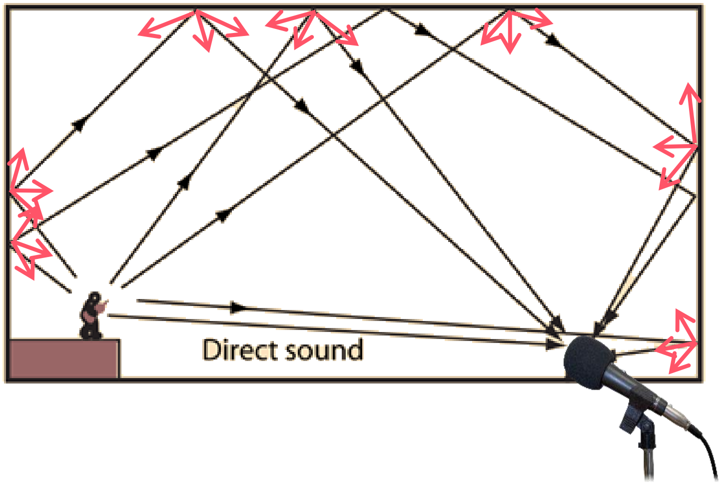

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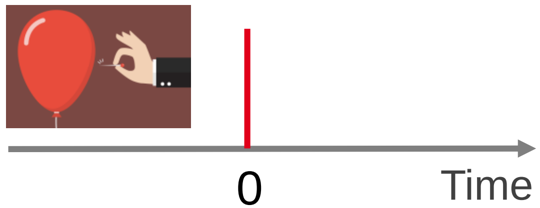


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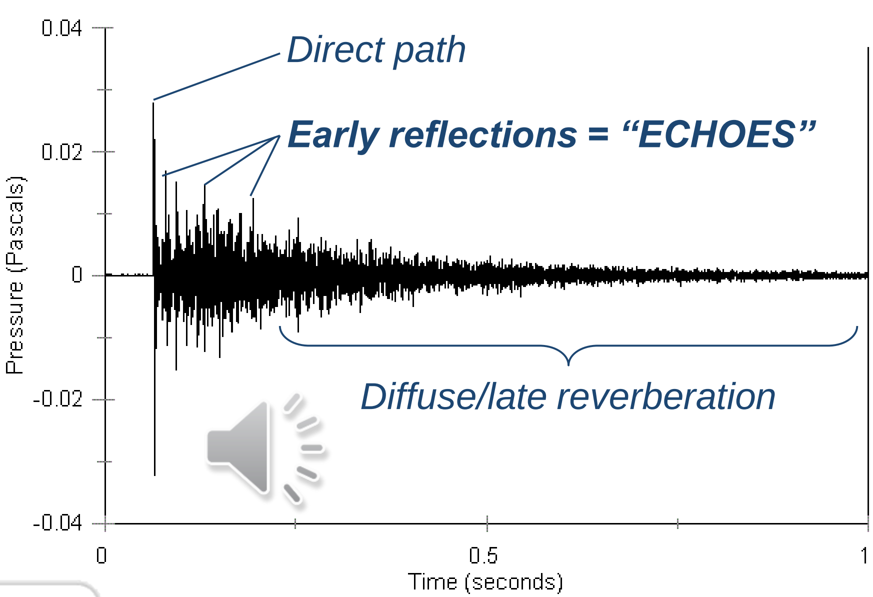


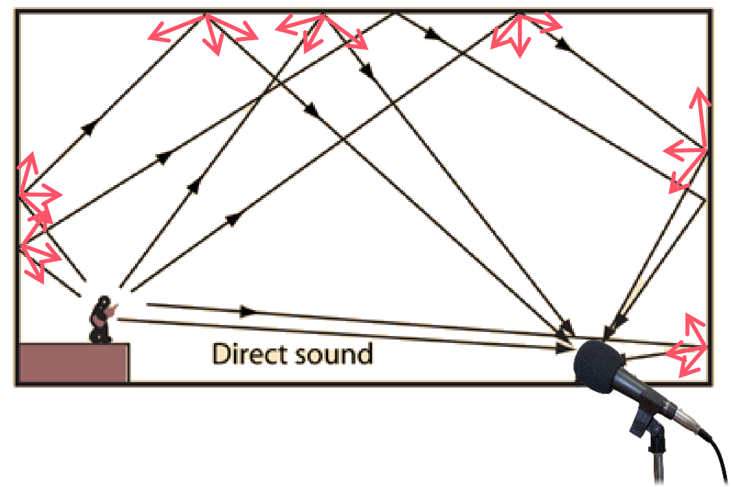

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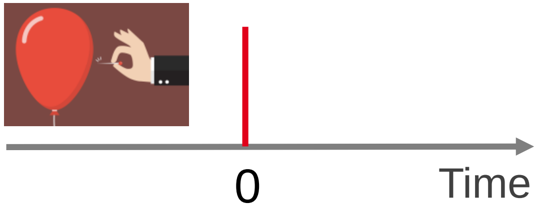


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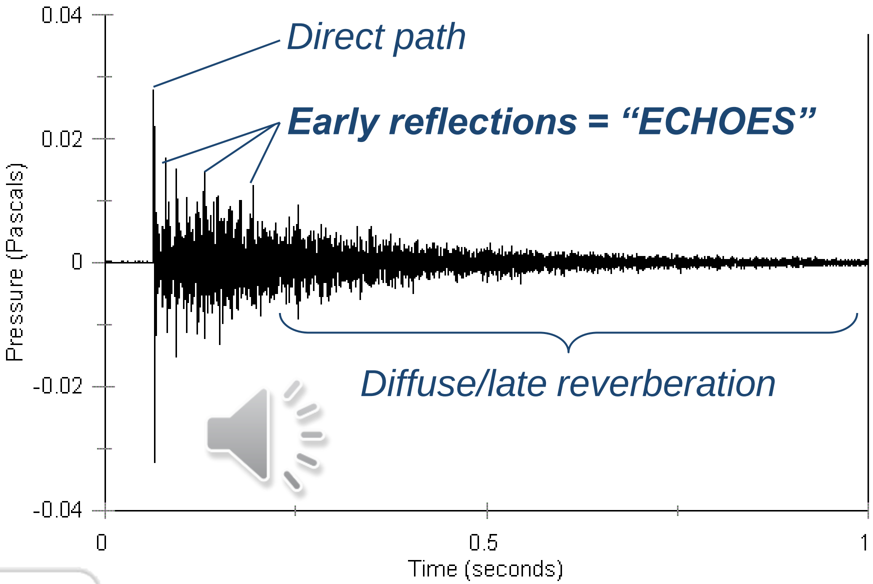


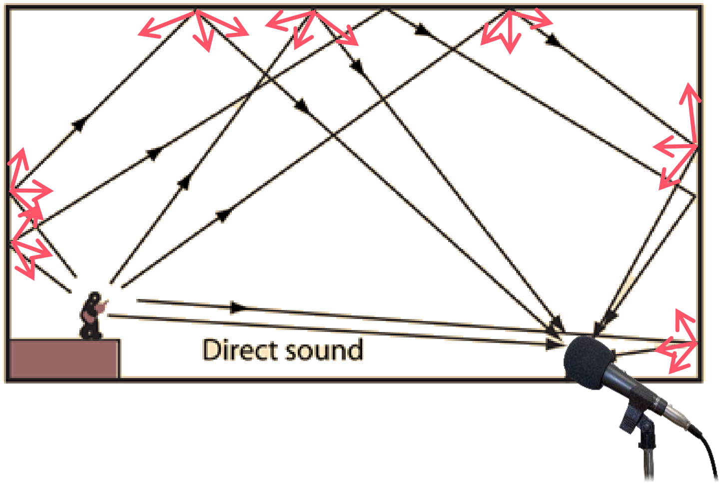


The Fourier transform $\widetilde{h}(\omega)$ of a RIR is called ***Room Transfer Function***

It captures the effect of the room in different ***frequency bands***.

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# The Room Impulse Response

- Can be used to « reverberate » any dry sound source signal $s(t)$ :

$$x(t) = (h * s)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{+\infty} h(u)s(t-u)du \quad \overset{\text{Fourier}}{\longleftrightarrow} \quad \widetilde{x}(\omega) = \widetilde{h}(\omega)\widetilde{s}(\omega)$$

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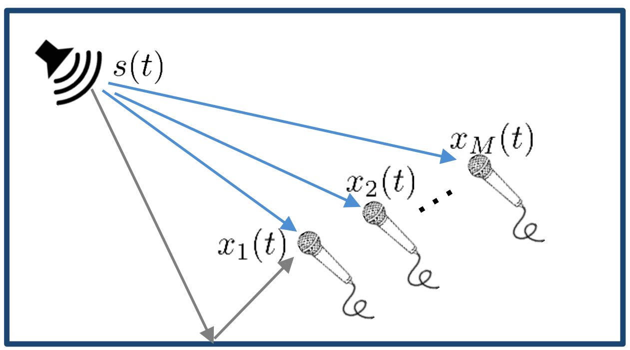
- Generalization to multiple microphones:



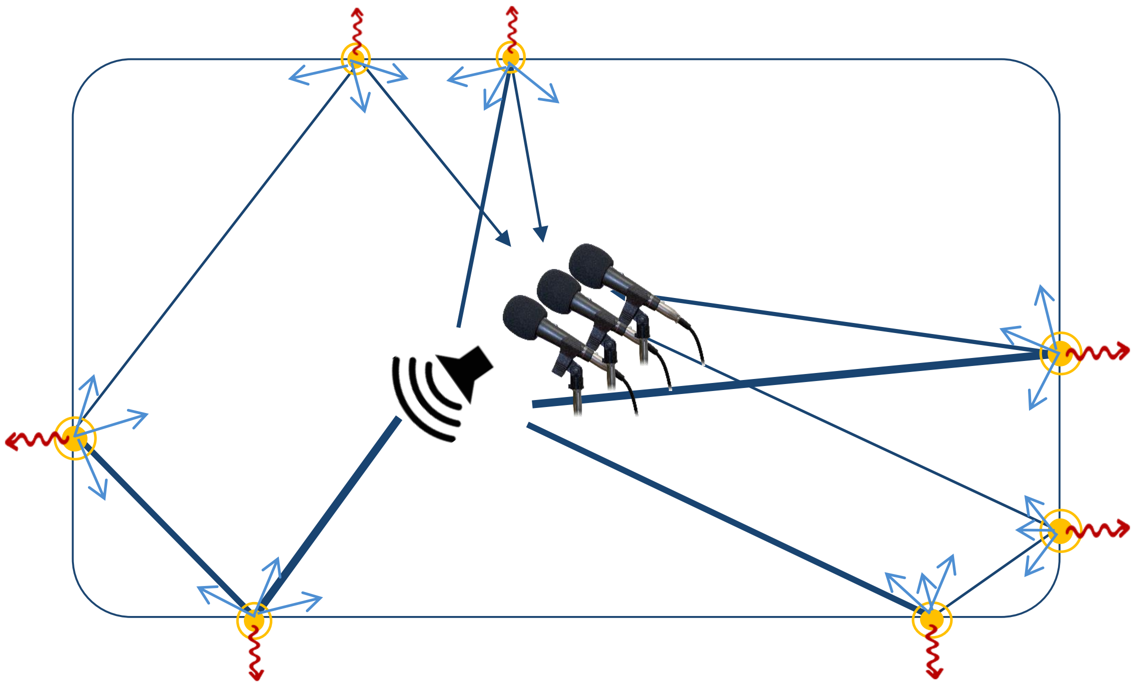

$$\begin{cases} x_1(t) = (h_1 * s)(t) + n_2(t) \\ x_2(t) = (h_2 * s)(t) + n_2(t) \\ \quad\vdots \qquad\qquad \vdots \\ x_M(t) = (h_M * s)(t) + n_M(t) \end{cases}$$


Linear


Circular

Spherical

# 1) Intro & Background



- Source & receivers positions & properties
- Room geometry
- Surface properties

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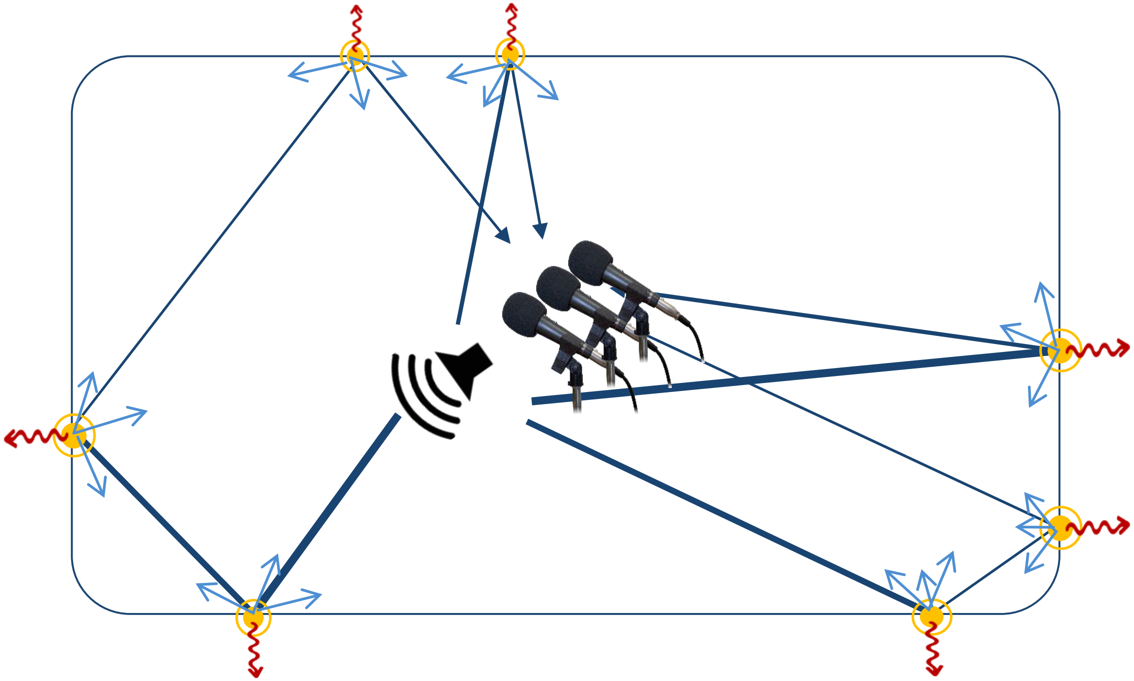

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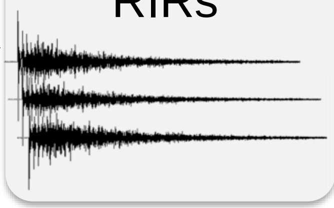

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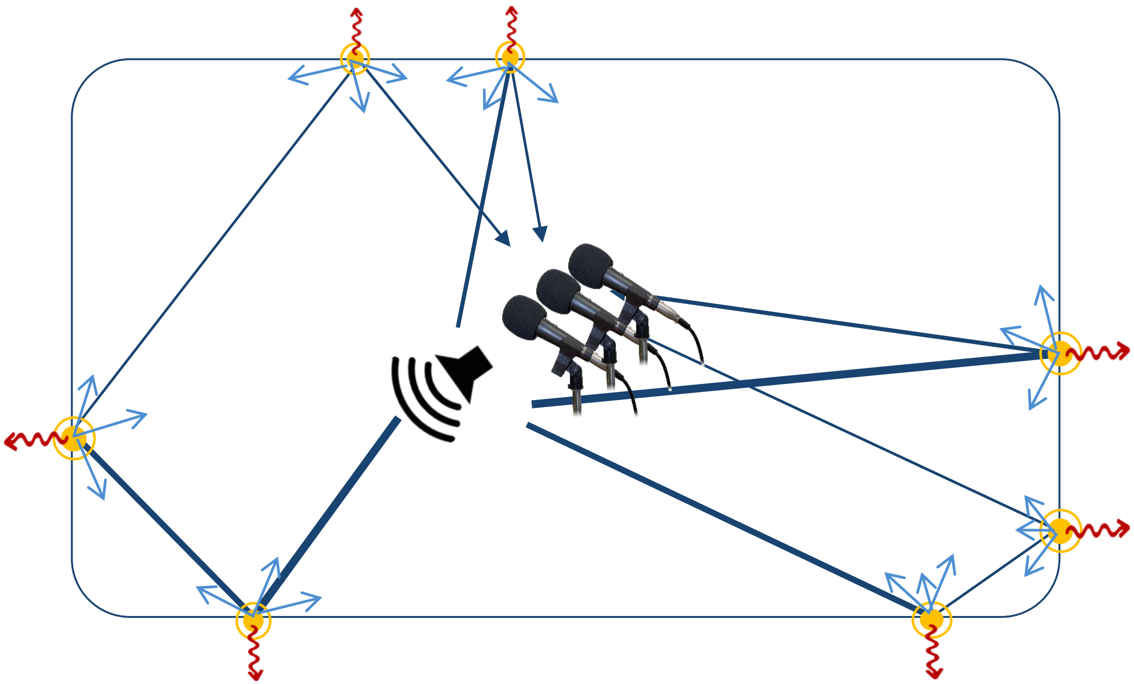

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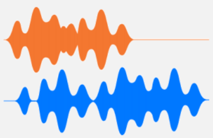
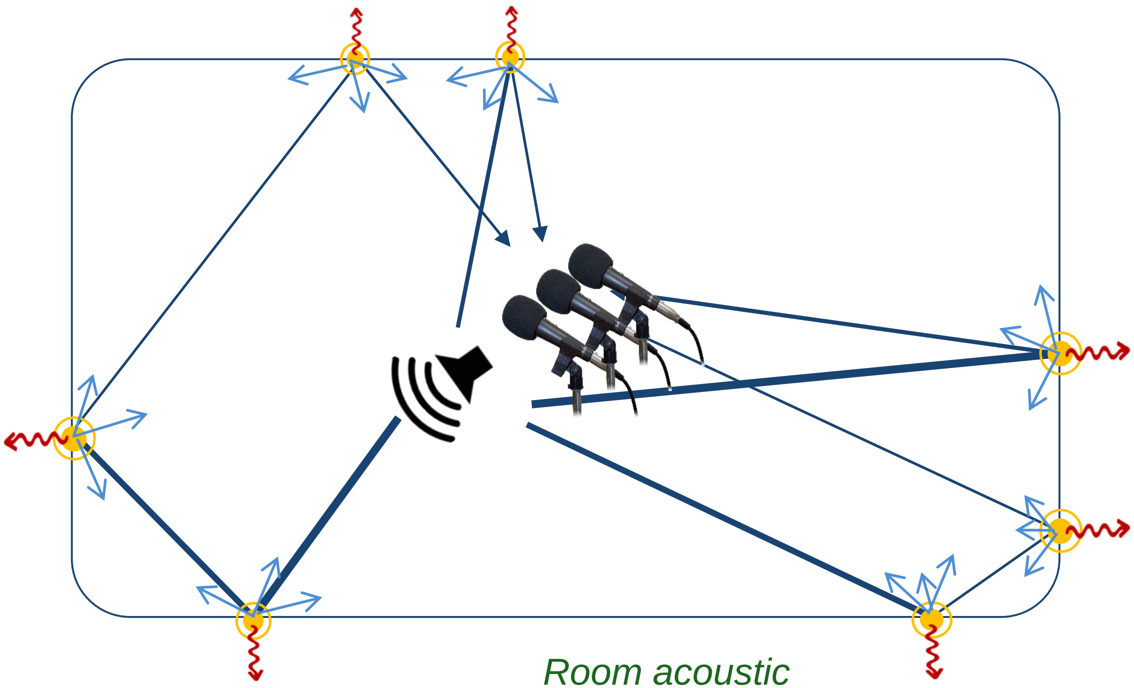
RIRs

Revereberated audio signals





*Room acoustic simulators ☑*

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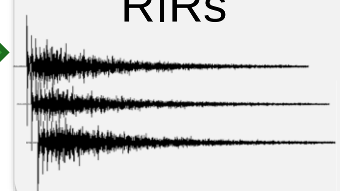

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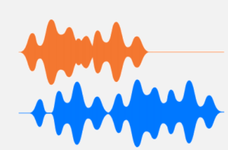

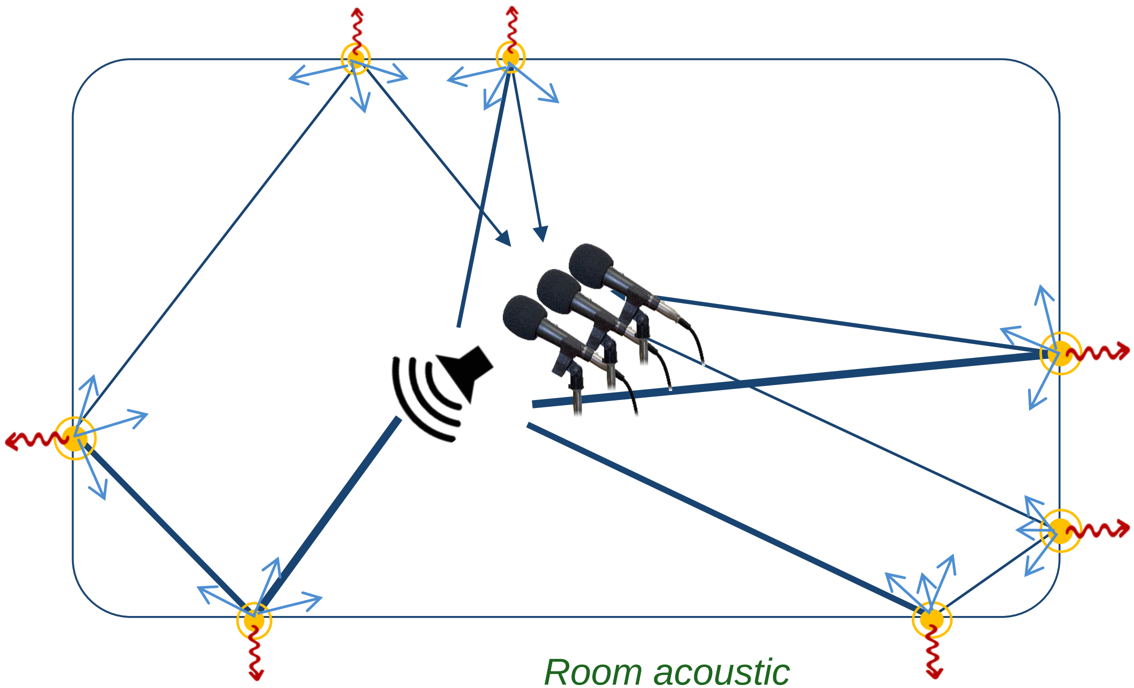

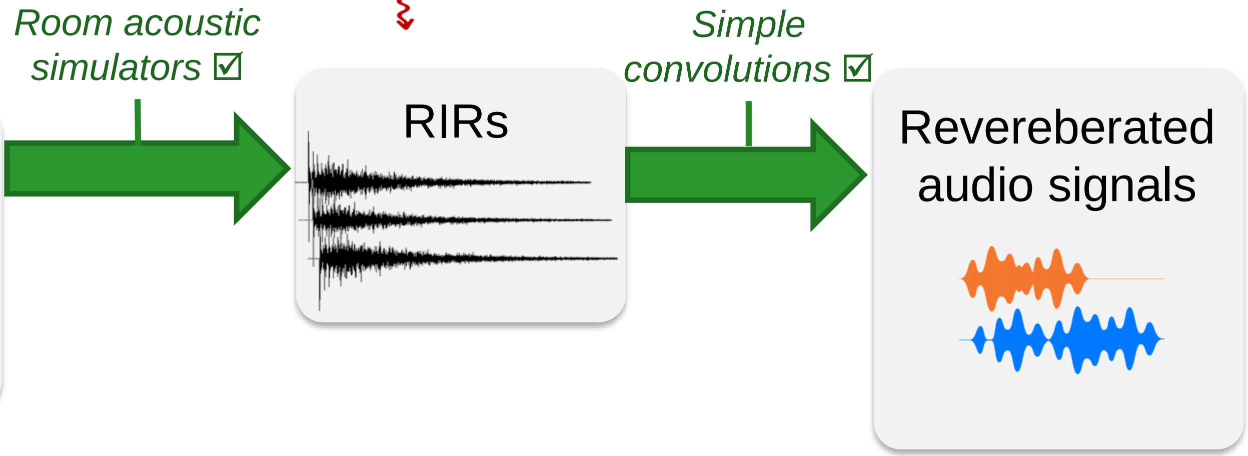


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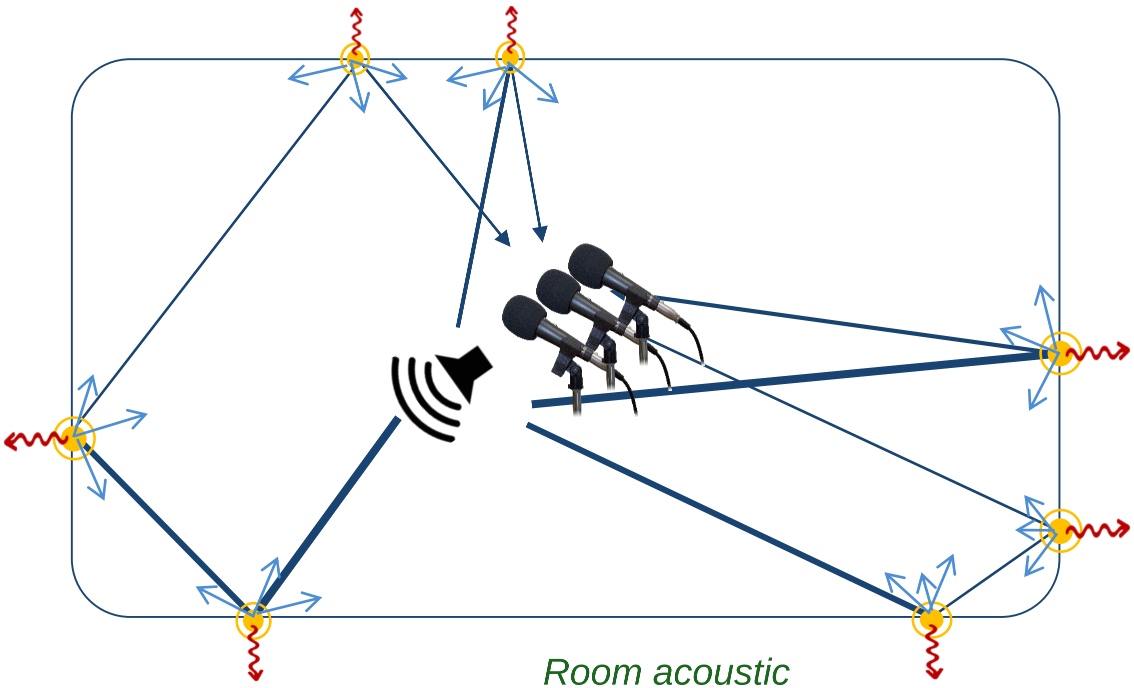

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?

*Simple convolutions ☑*

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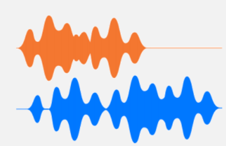

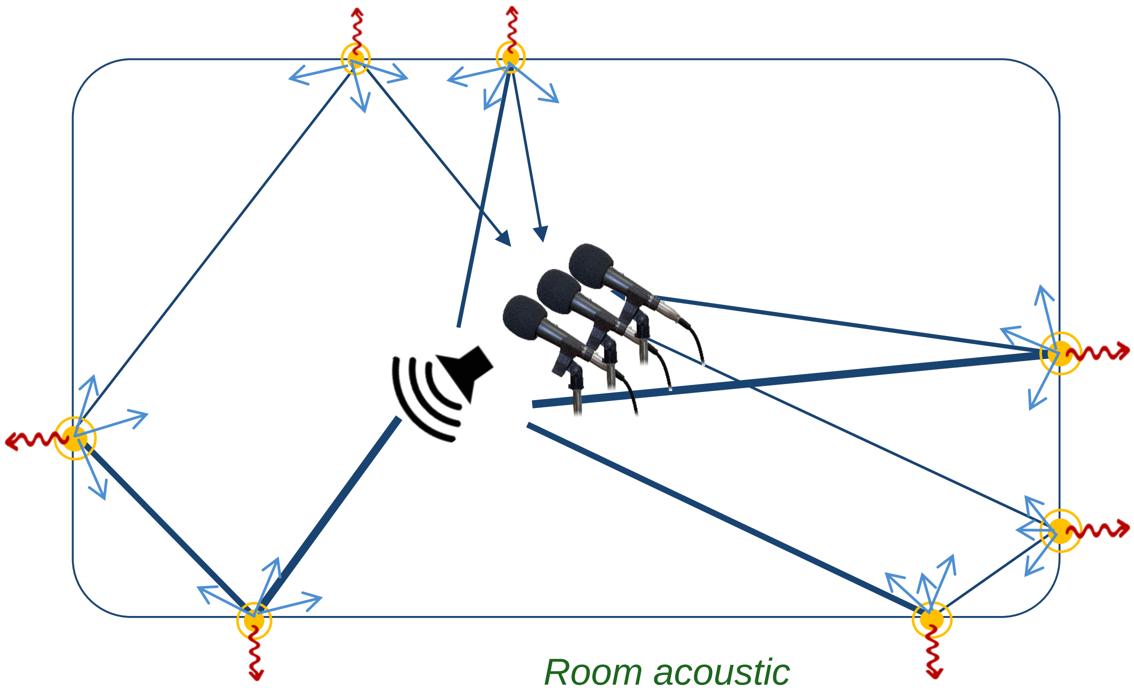

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*(Blind)*

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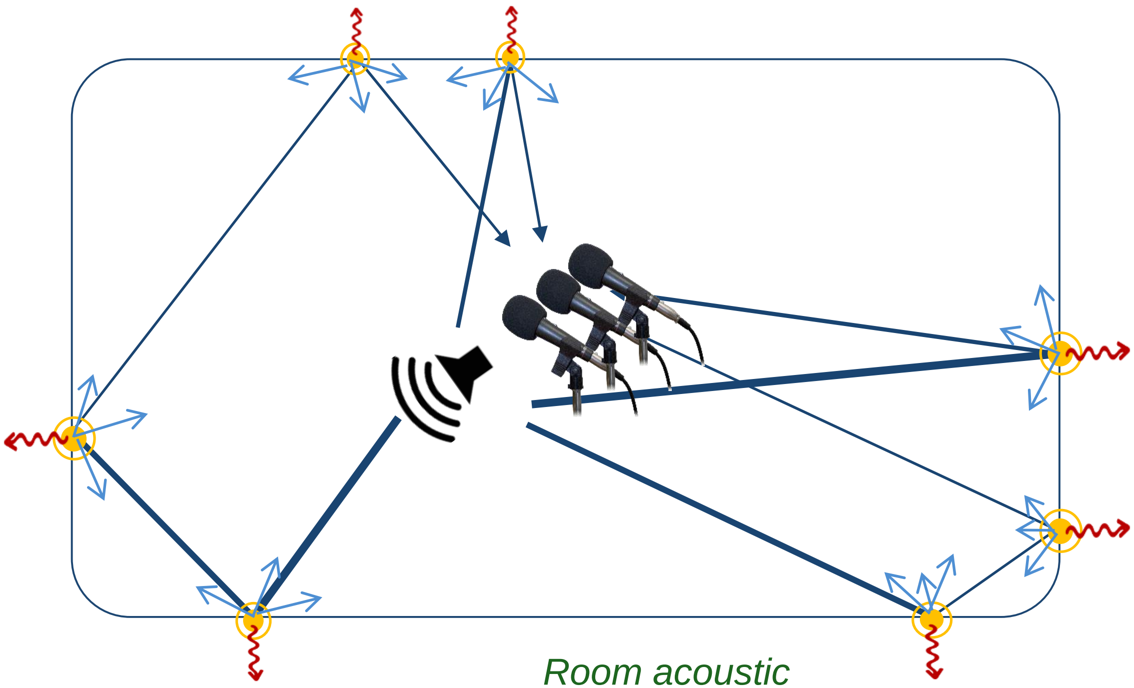

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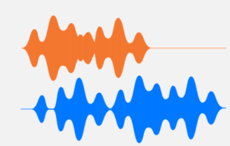

*(Blind)*

?

Difficult (interesting) inverse problems!

# Why do we care?

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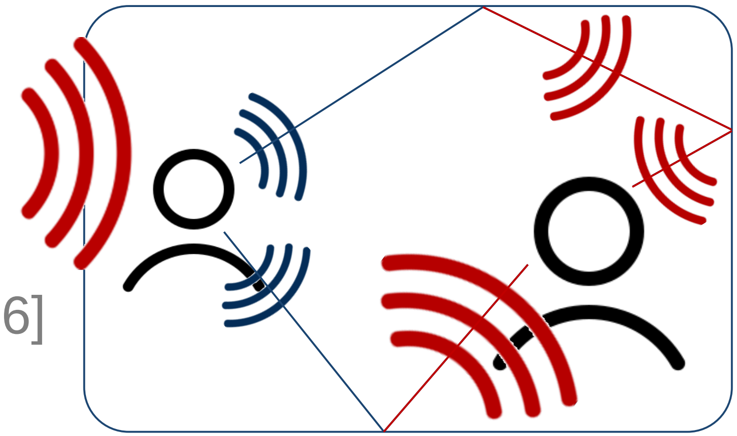
1) Indoor noise disturbance

➡ Make acoustic diagnosis faster / better [16]



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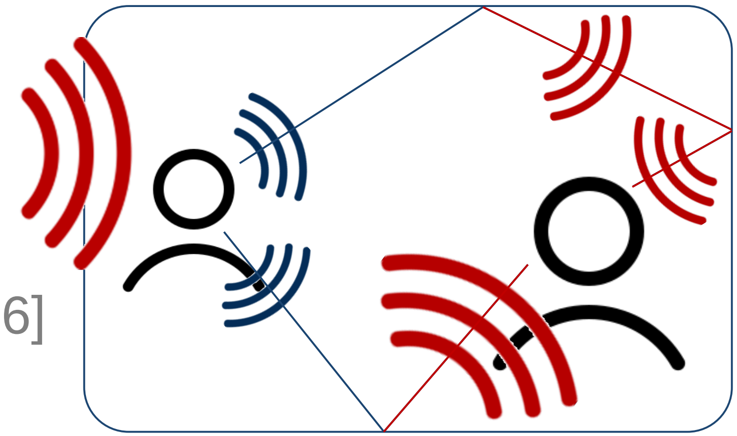

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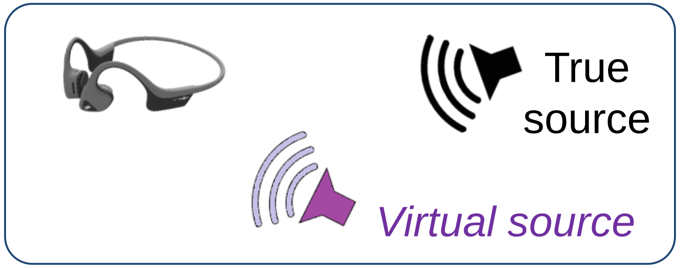
2) Audio Augmented Reality [6, 17]



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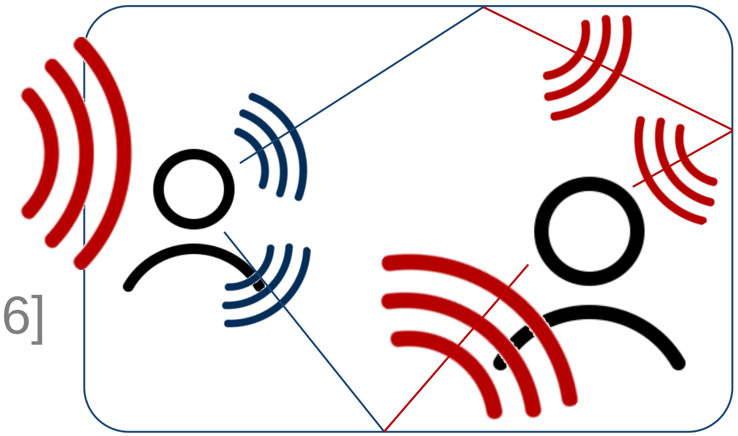
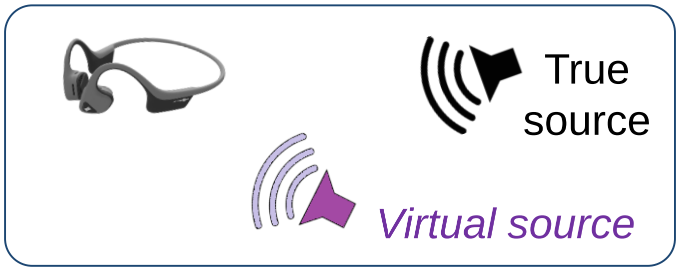
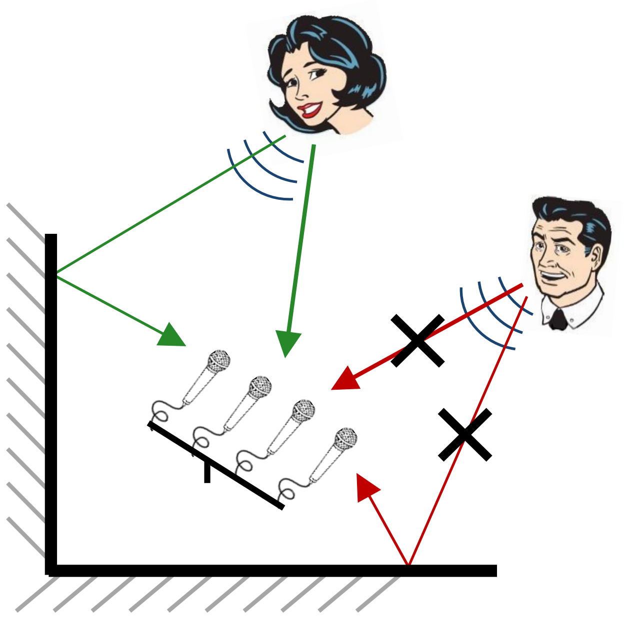


1) Indoor noise disturbance

➡ Make acoustic diagnosis faster / better [16]

2) Audio Augmented Reality [6, 17]



3) « *Echo-Aware* » Audio Signal Processing [7, 8]

- Hearing aids
- Vocal assistant devices
- …

# OUTLINE

**1) Intro & Background**

2) Virtually-Supervised Learning

3) Examples and Results

4) Conclusions and Outlook

# OUTLINE

1) Intro & Background

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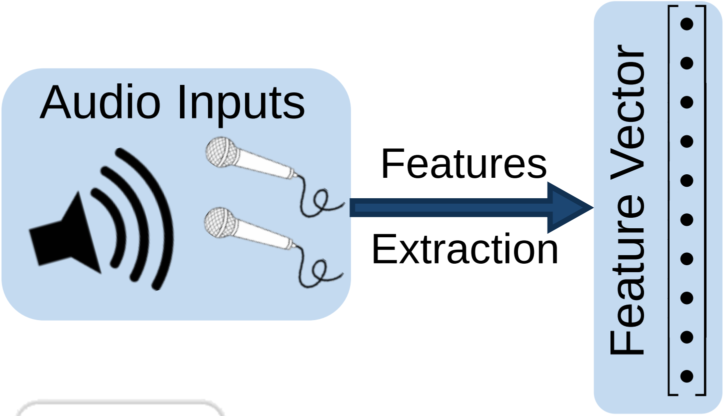
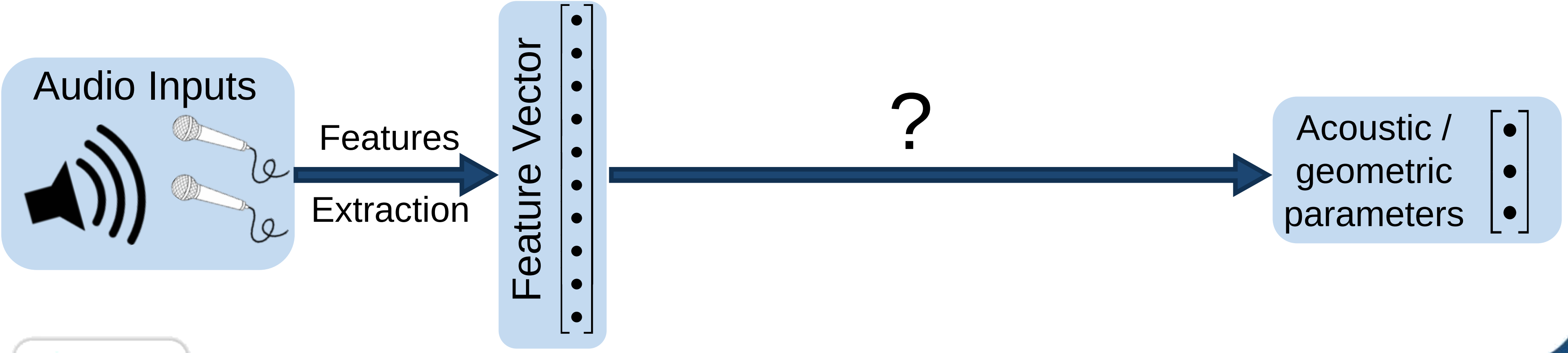
# 2) Virtually Supervised Learning

# 2) Virtually Supervised Learning




Audio Inputs
Features
Extraction
Feature Vector
?
Acoustic /
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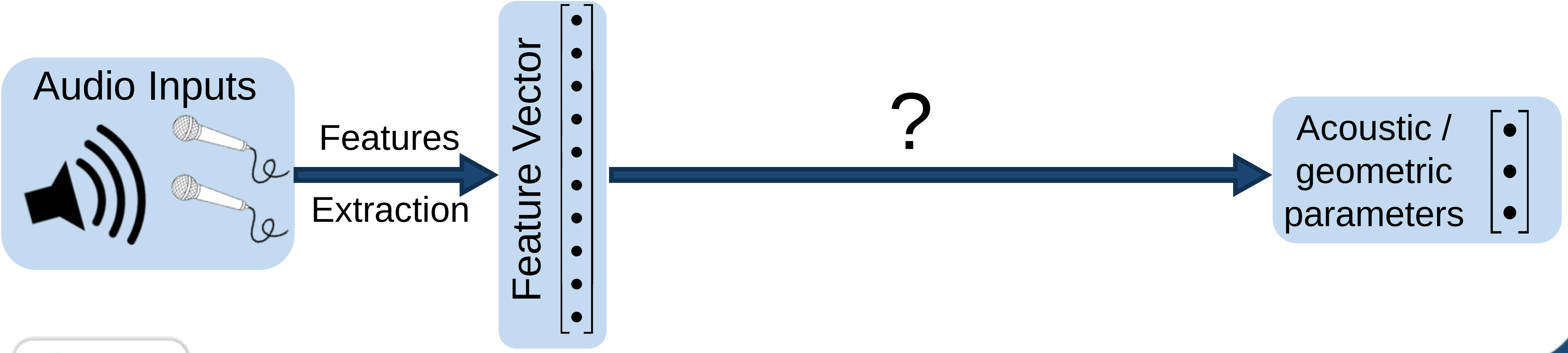
parameters

## a) Physics-Driven Approaches



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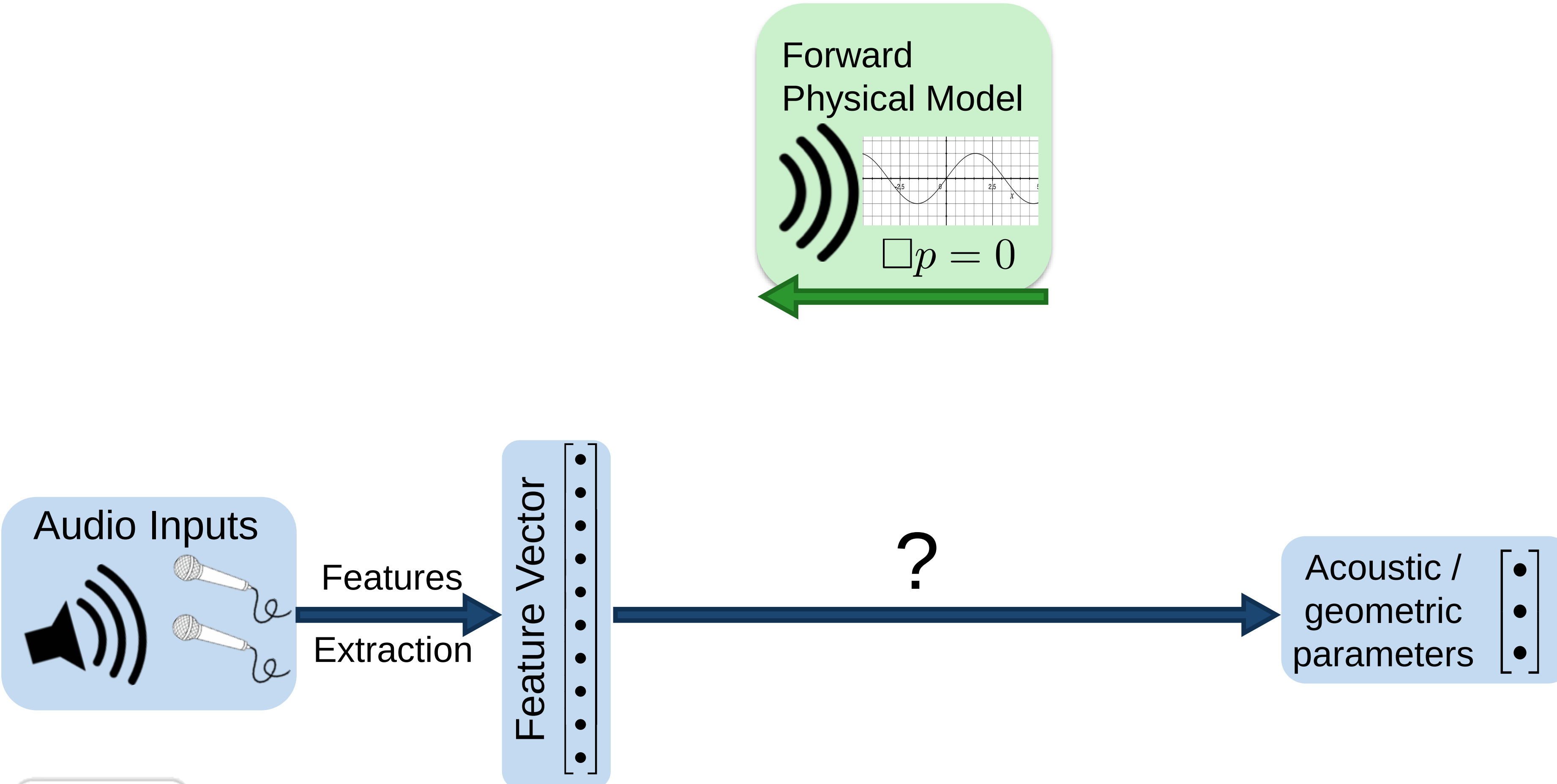

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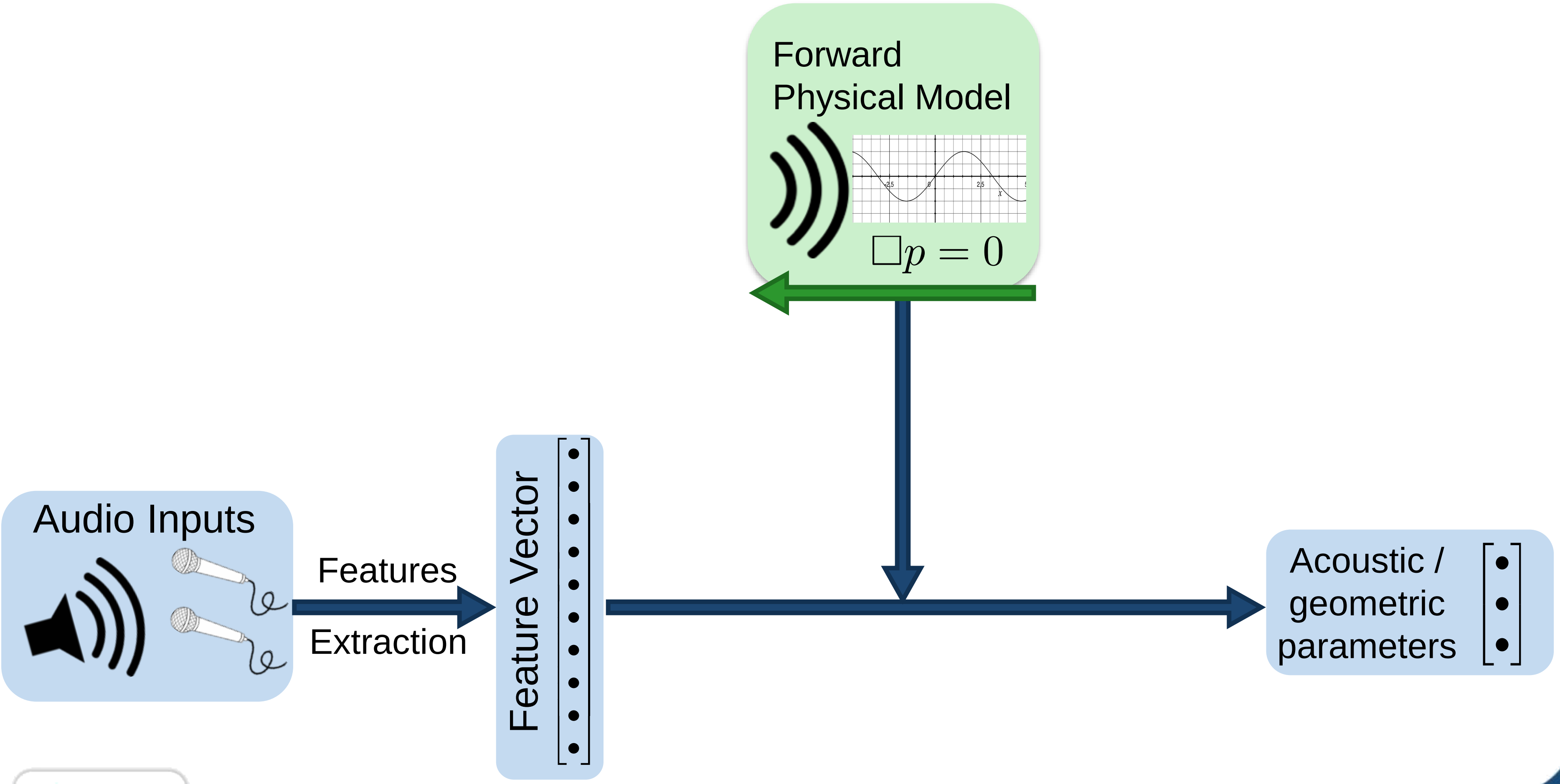

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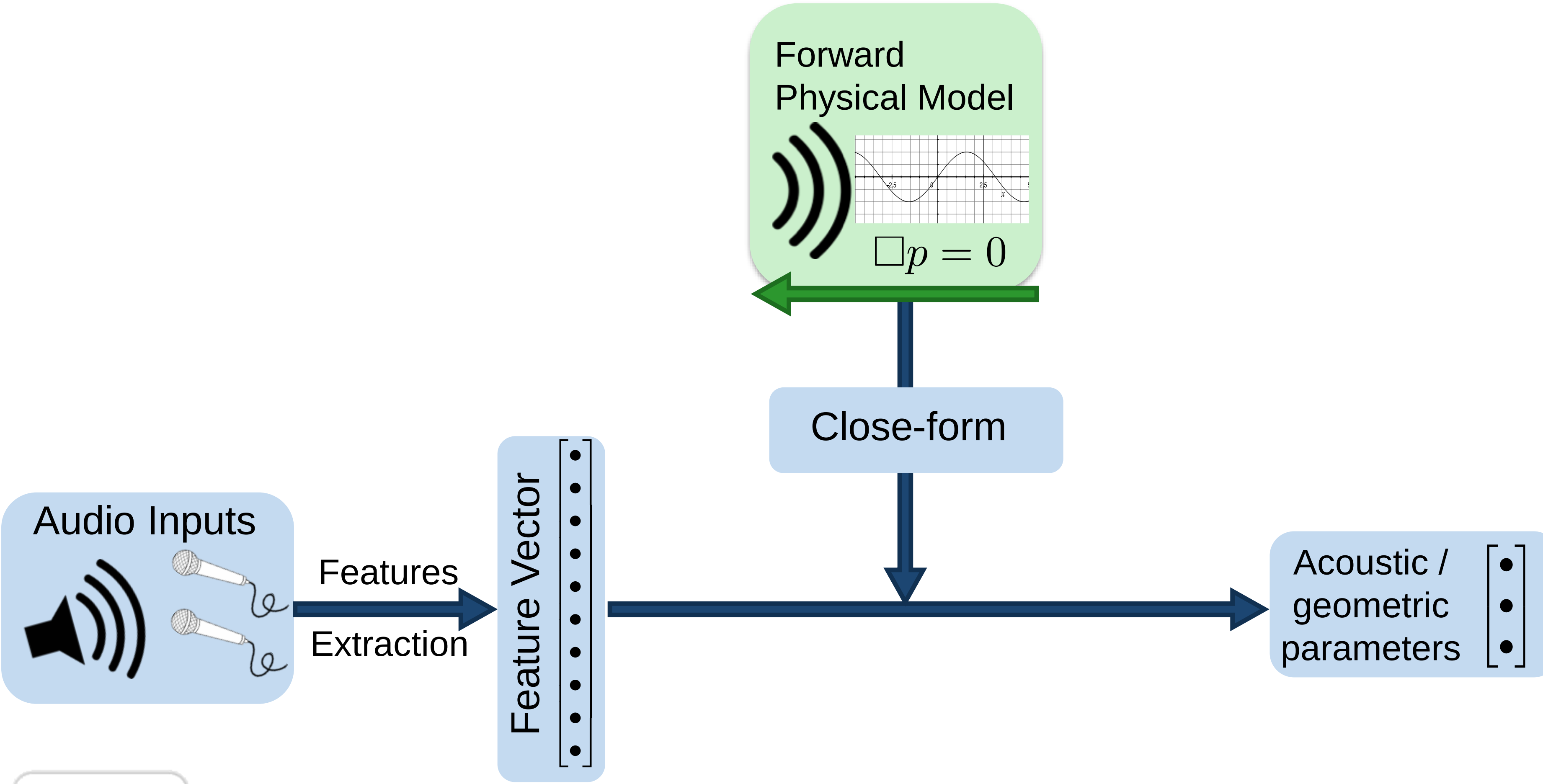

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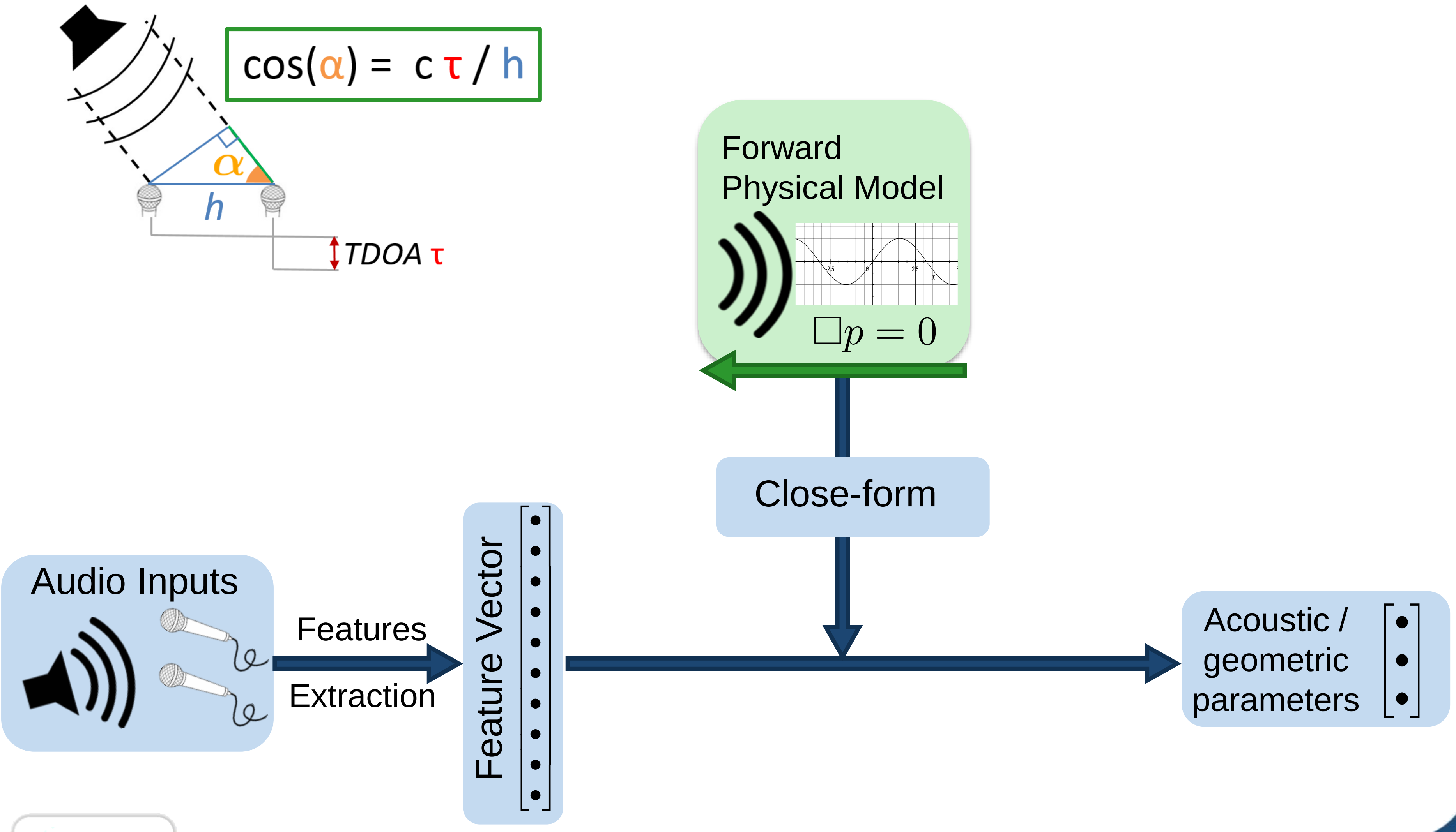

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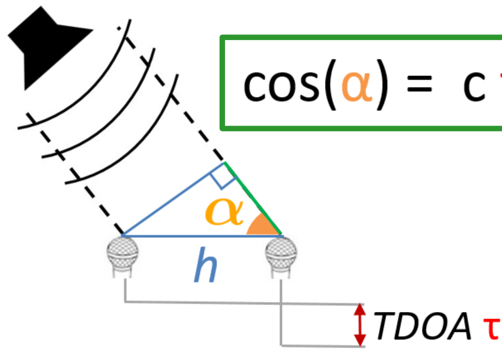
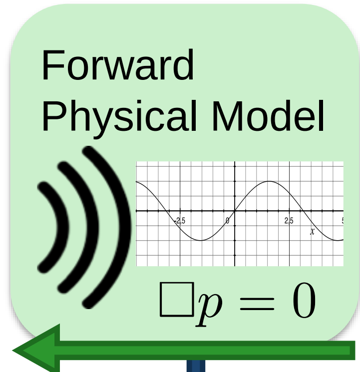
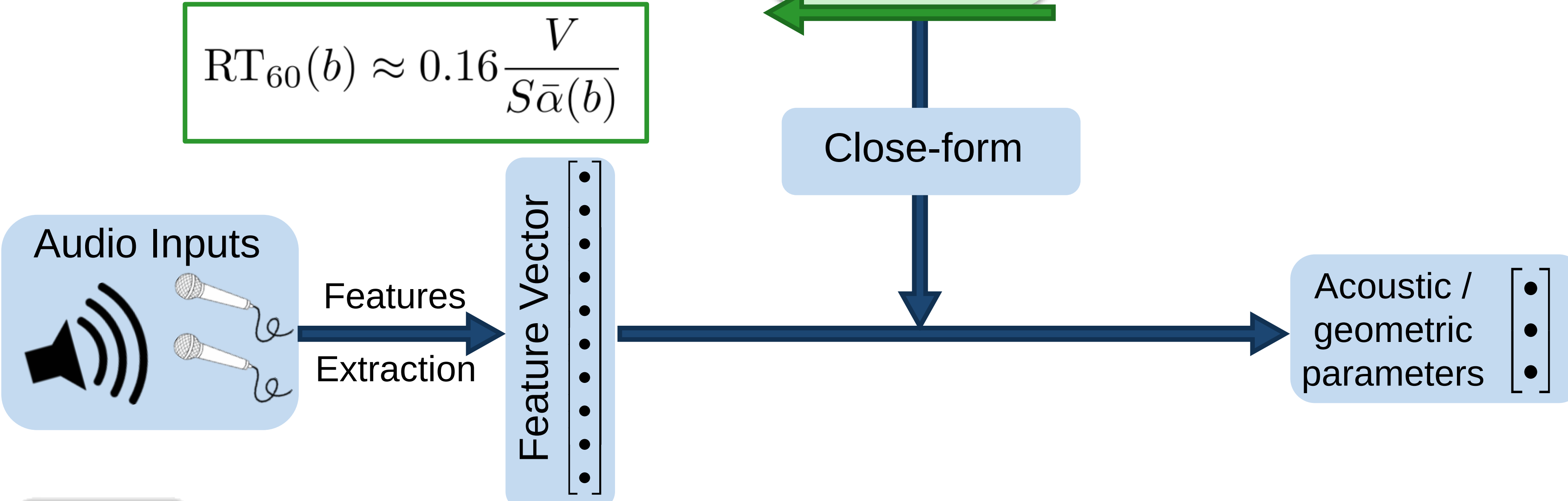



$$\cos(\alpha) = c\,\tau / h$$

*Sabine's law:*

$$\mathrm{RT}_{60}(b) \approx 0.16 \frac{V}{S\bar{\alpha}(b)}$$



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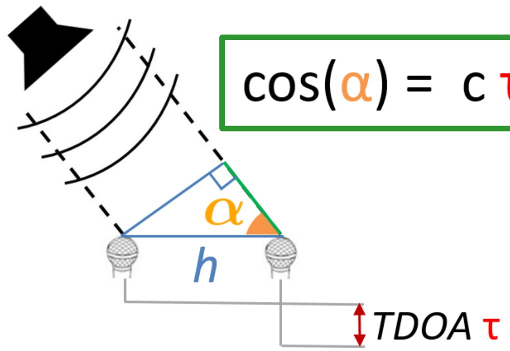


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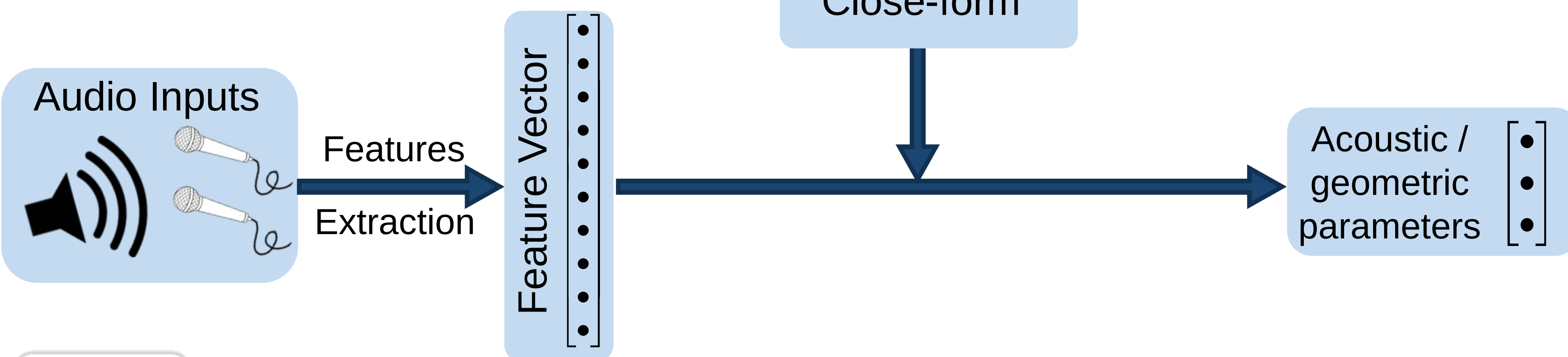


✓ No training data needed

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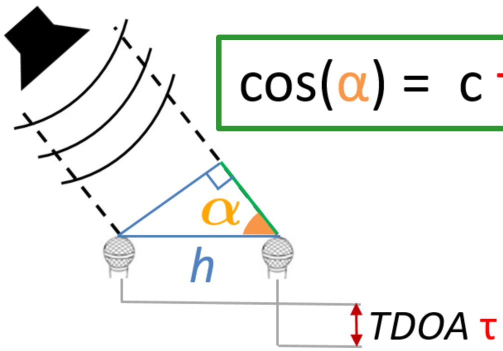


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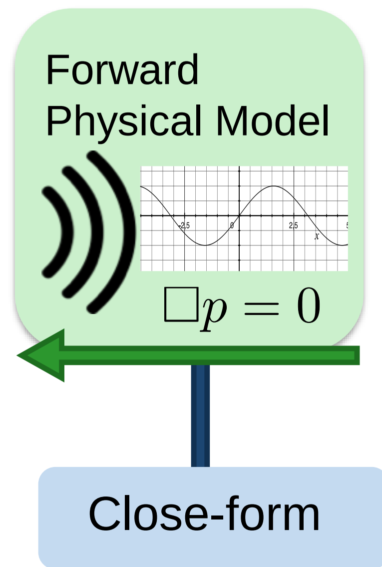
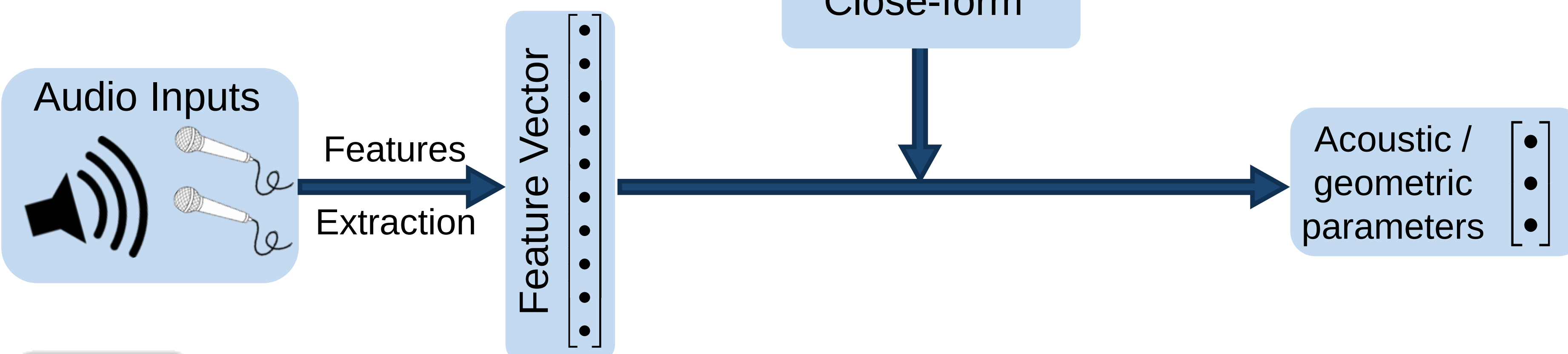
- ✓ No training data needed
- ✓ Computationally efficient



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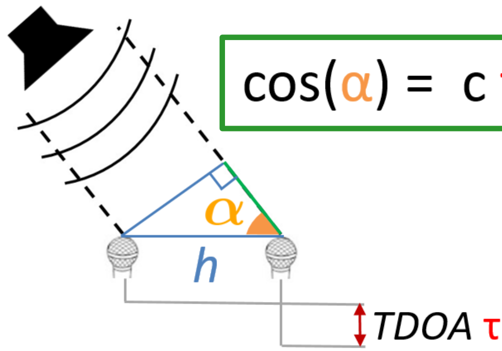


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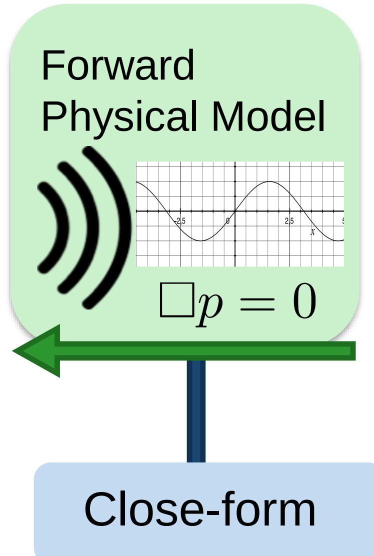
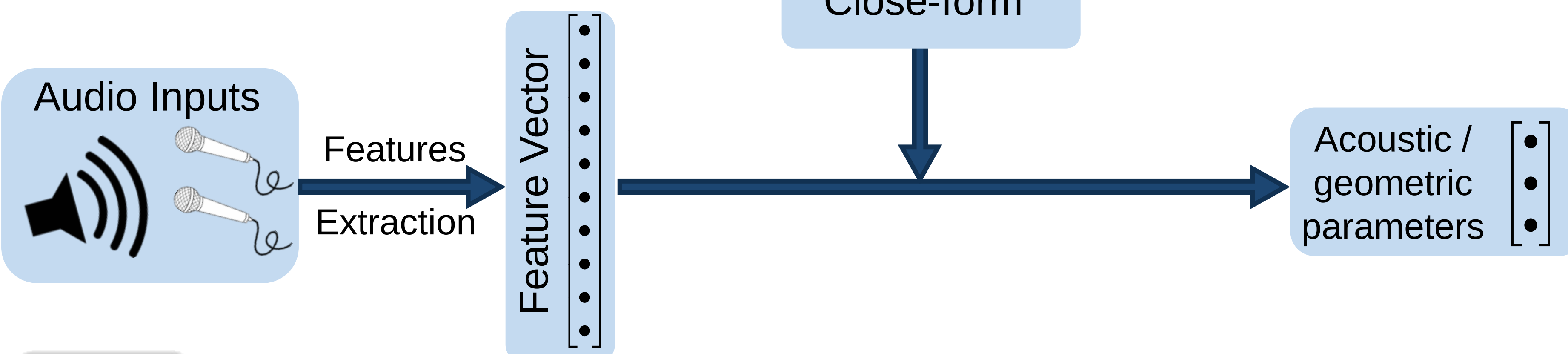



- ✓ No training data needed
- ✓ Computationally efficient
- ☒ Suffers in complex conditions



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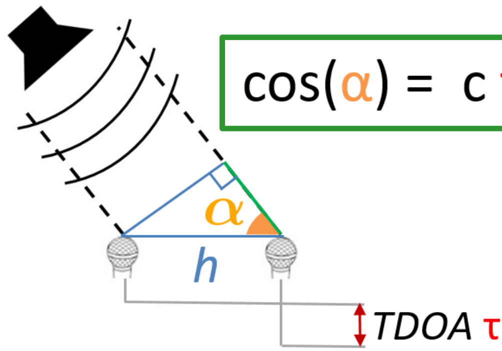


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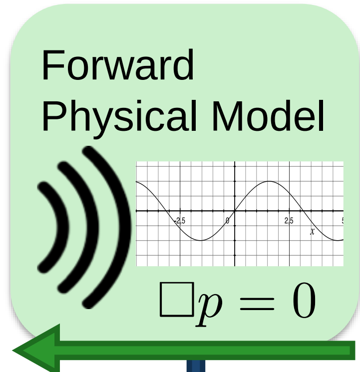



- ✓ No training data needed
- ✓ Computationally efficient
- ☒ Suffers in complex conditions
- ☒ Limited

Close-form

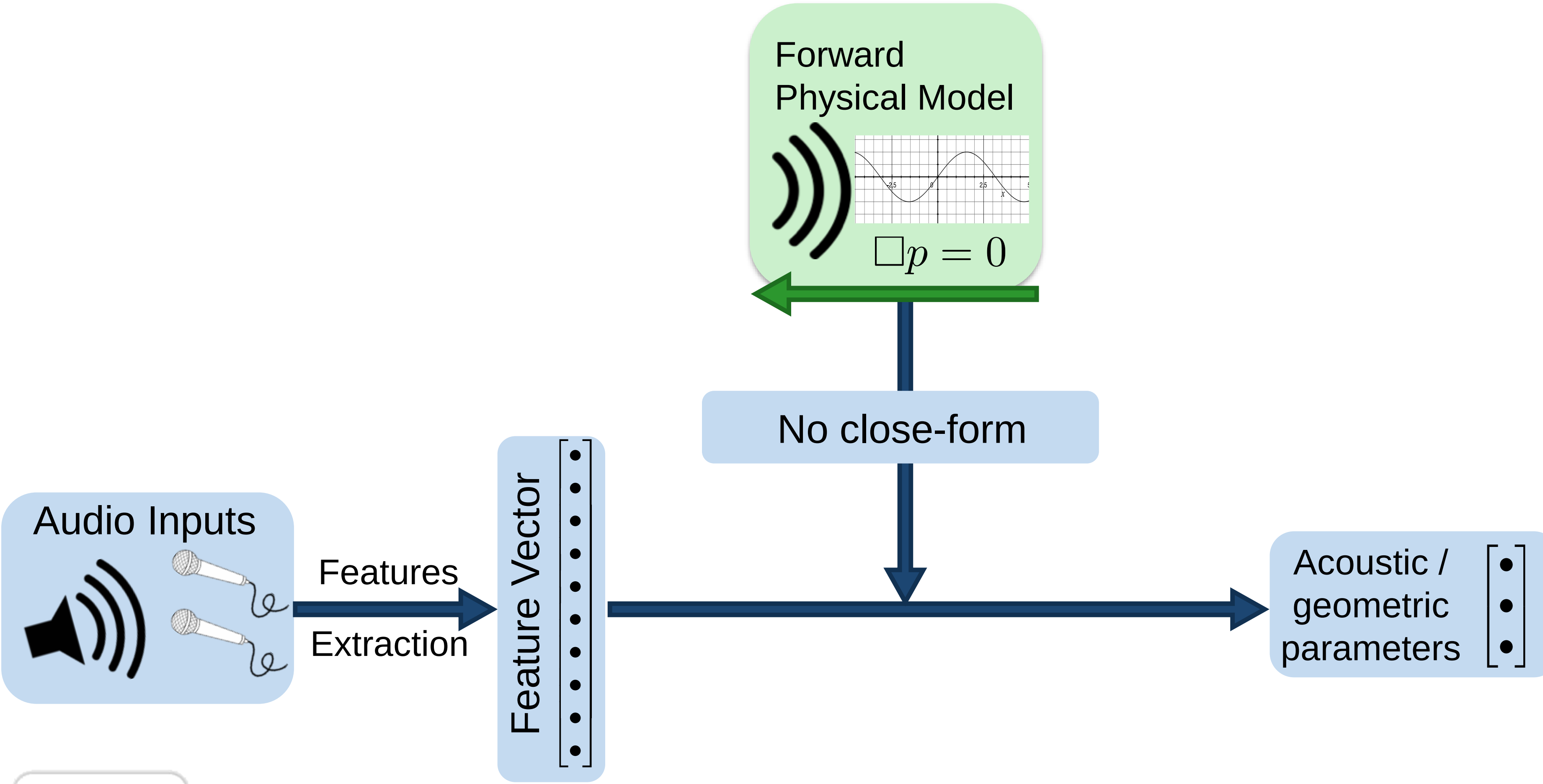
Audio Inputs

Features Extraction

Feature Vector

Acoustic / geometric parameters

## a) Physics-Driven Approaches

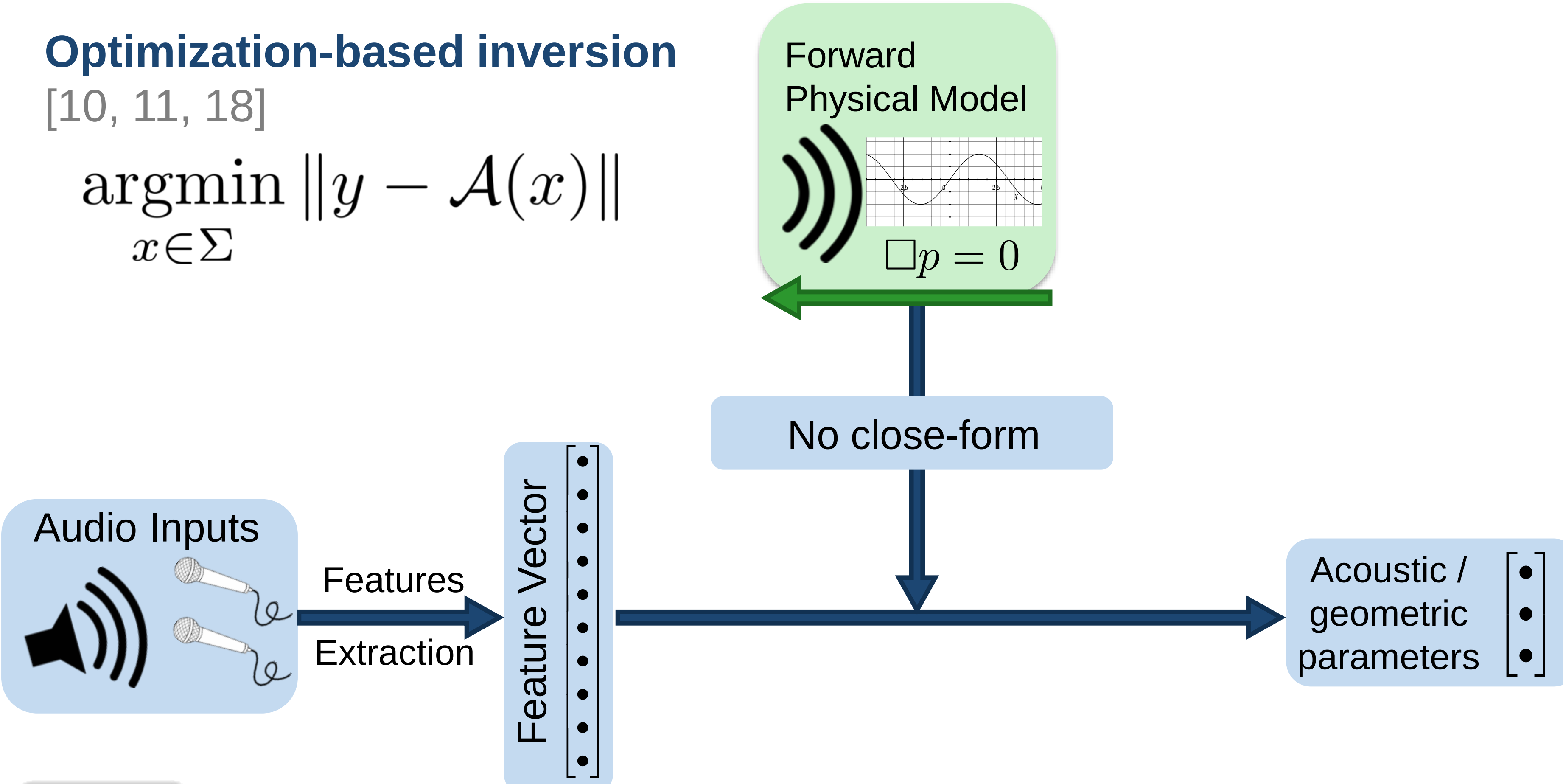


# a) Physics-Driven Approaches

**Optimization-based inversion**

[10, 11, 18]

$$\underset{x\in\Sigma}{\operatorname{argmin}} \|y - \mathcal{A}(x)\|$$



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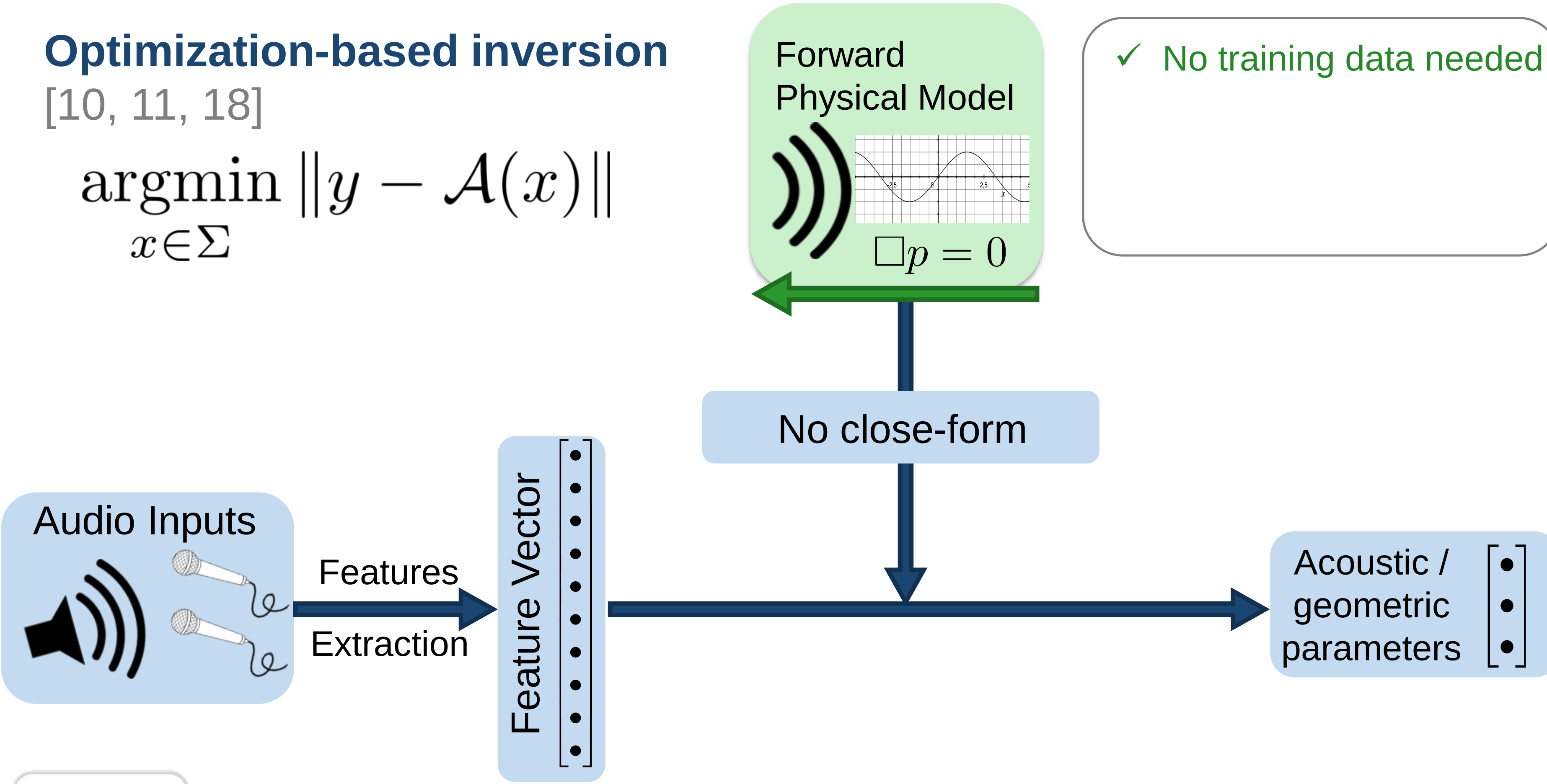

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**Optimization-based inversion**
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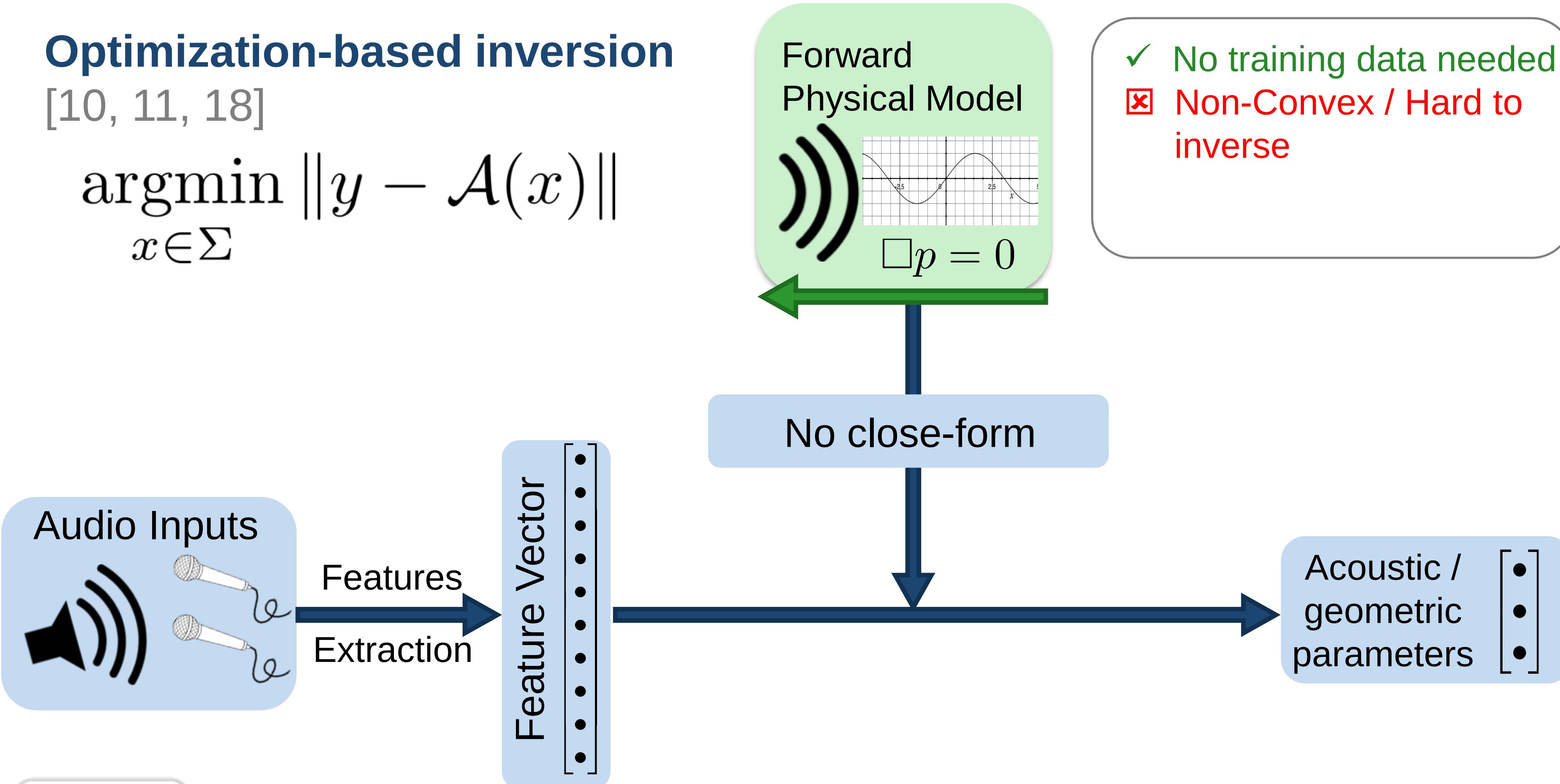
- ✓ No training data needed
- ☒ Non-Convex / Hard to inverse



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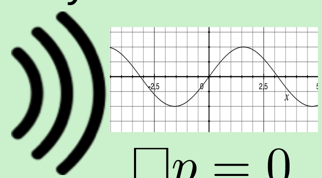
Forward Physical Model



$\Box p = 0$

- ✓ No training data needed
- ☒ Non-Convex / Hard to inverse
- ☒ Sensitive to model mismatch

No close-form

Audio Inputs

Features Extraction

Feature Vector

Acoustic / geometric parameters

## b) Real-Data-Driven Approaches [1, 2, 3, 6]

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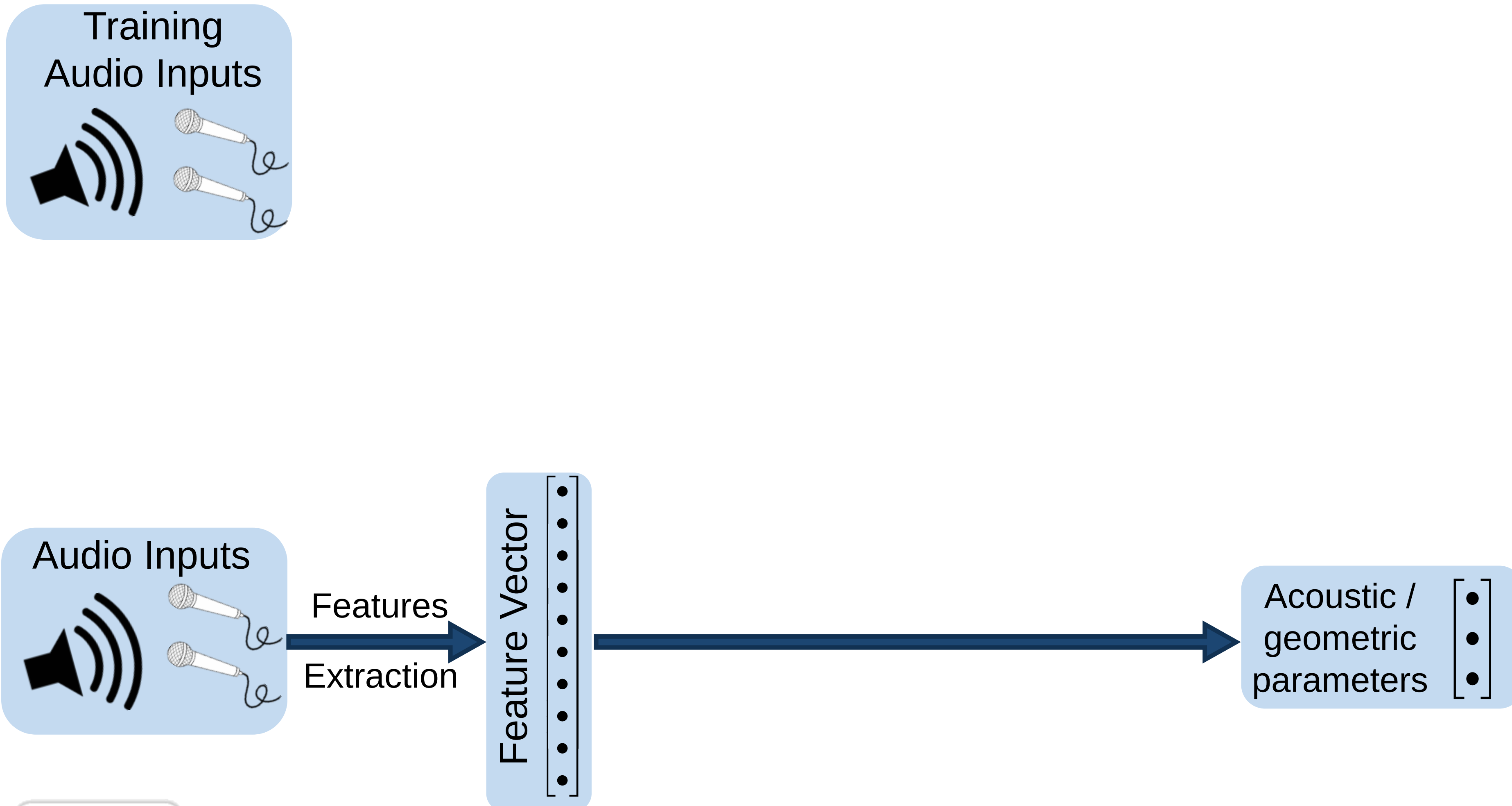

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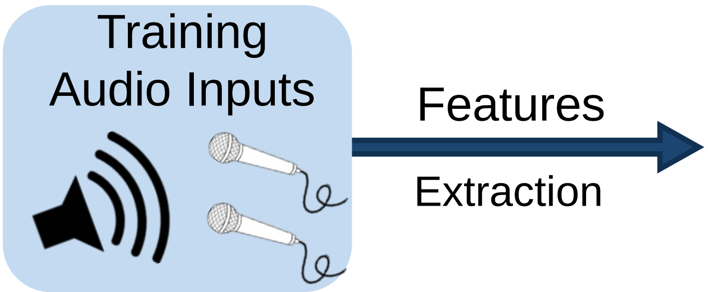


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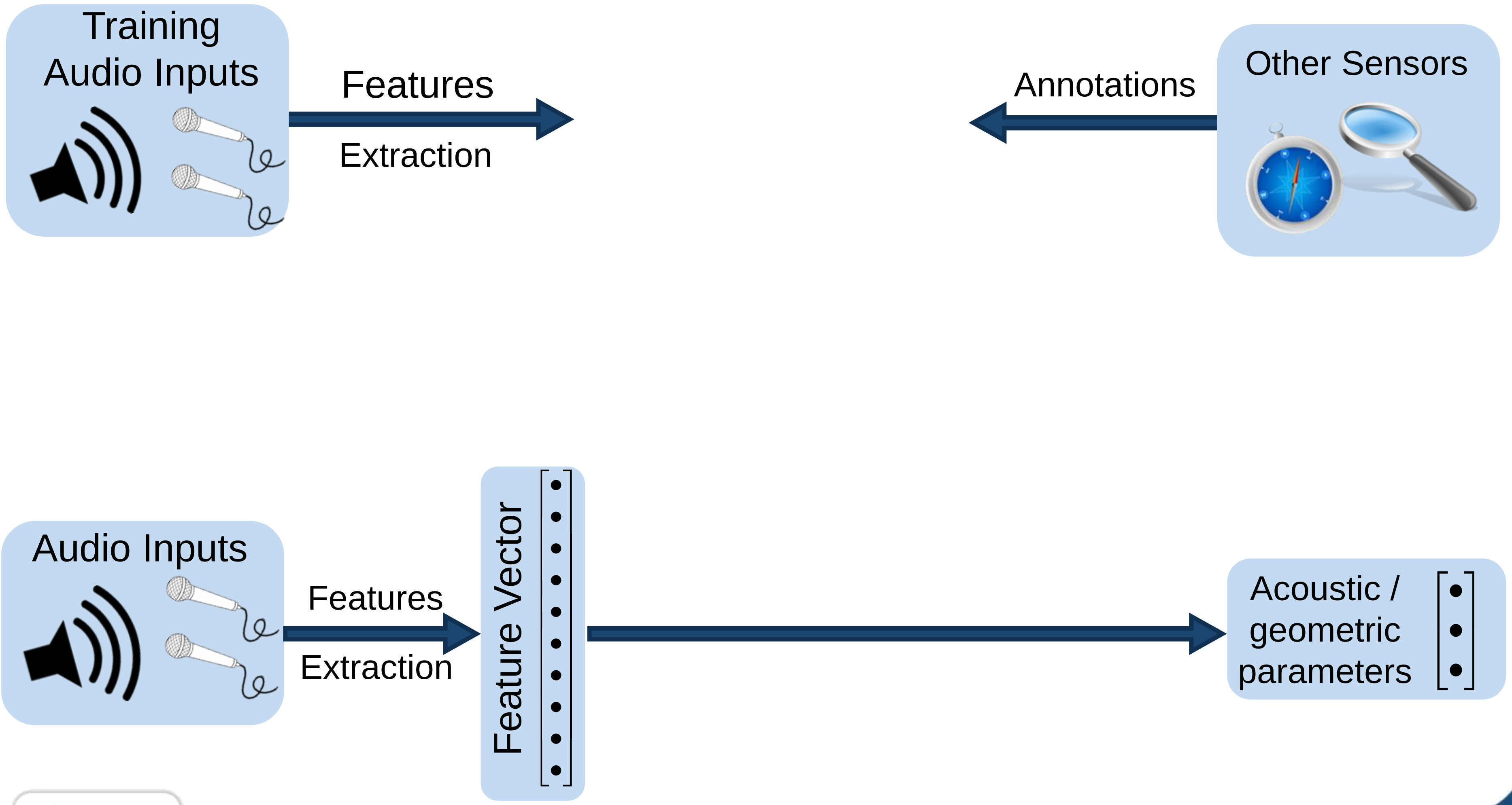

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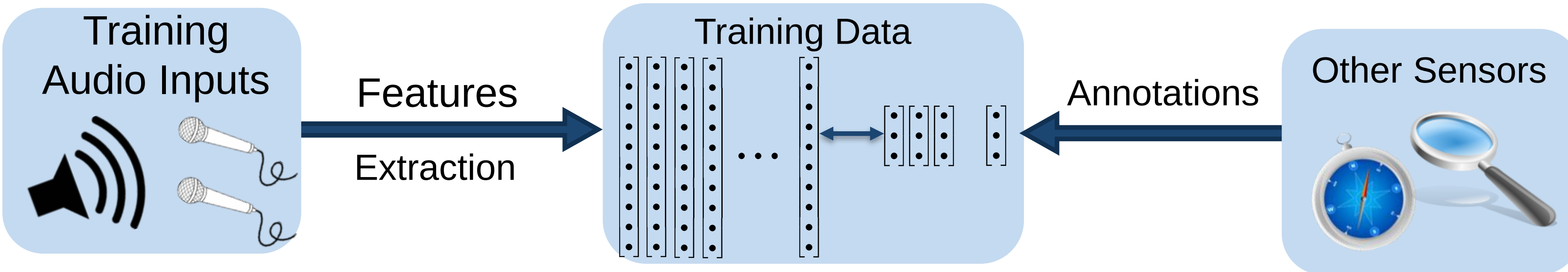


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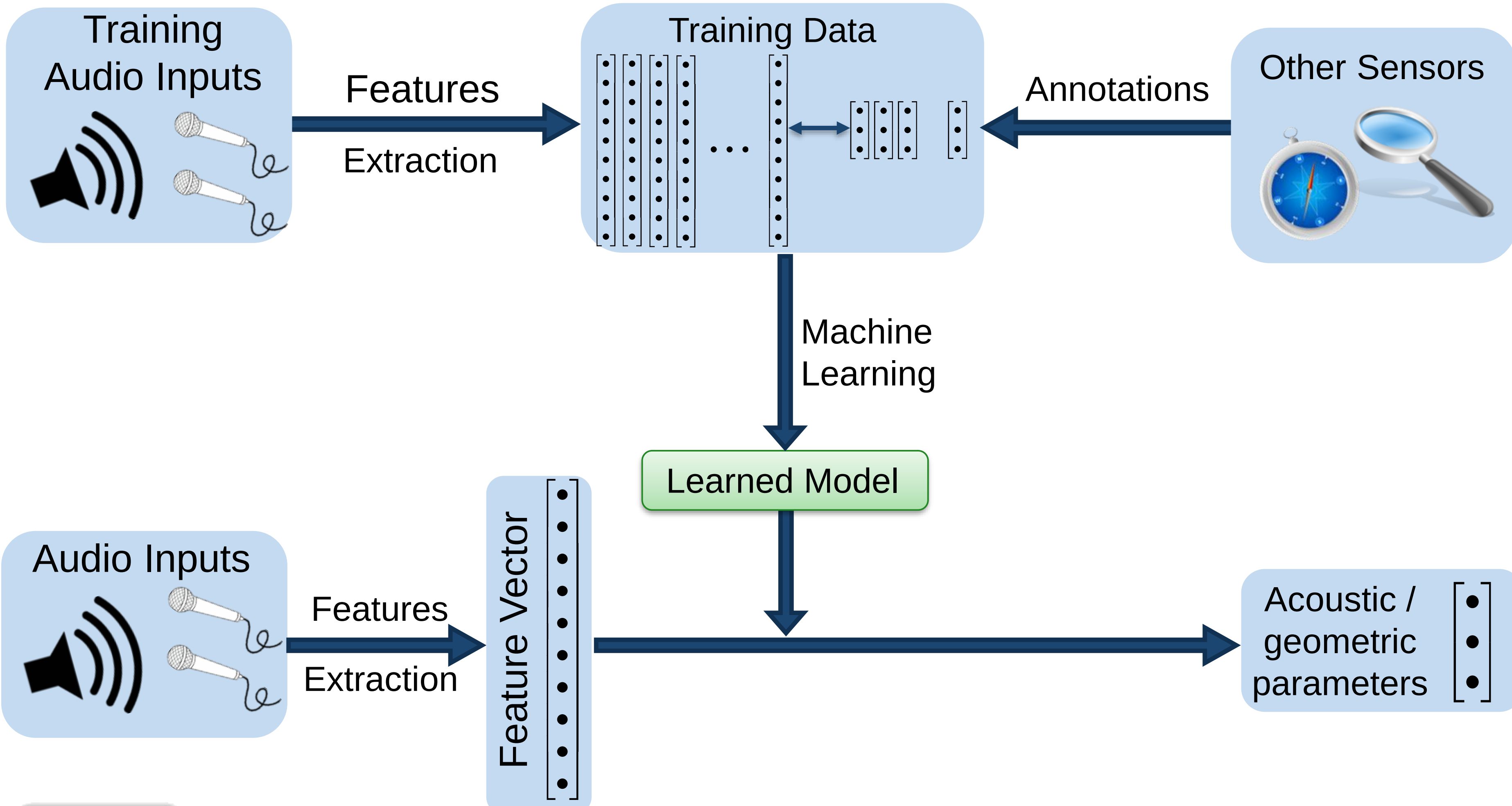

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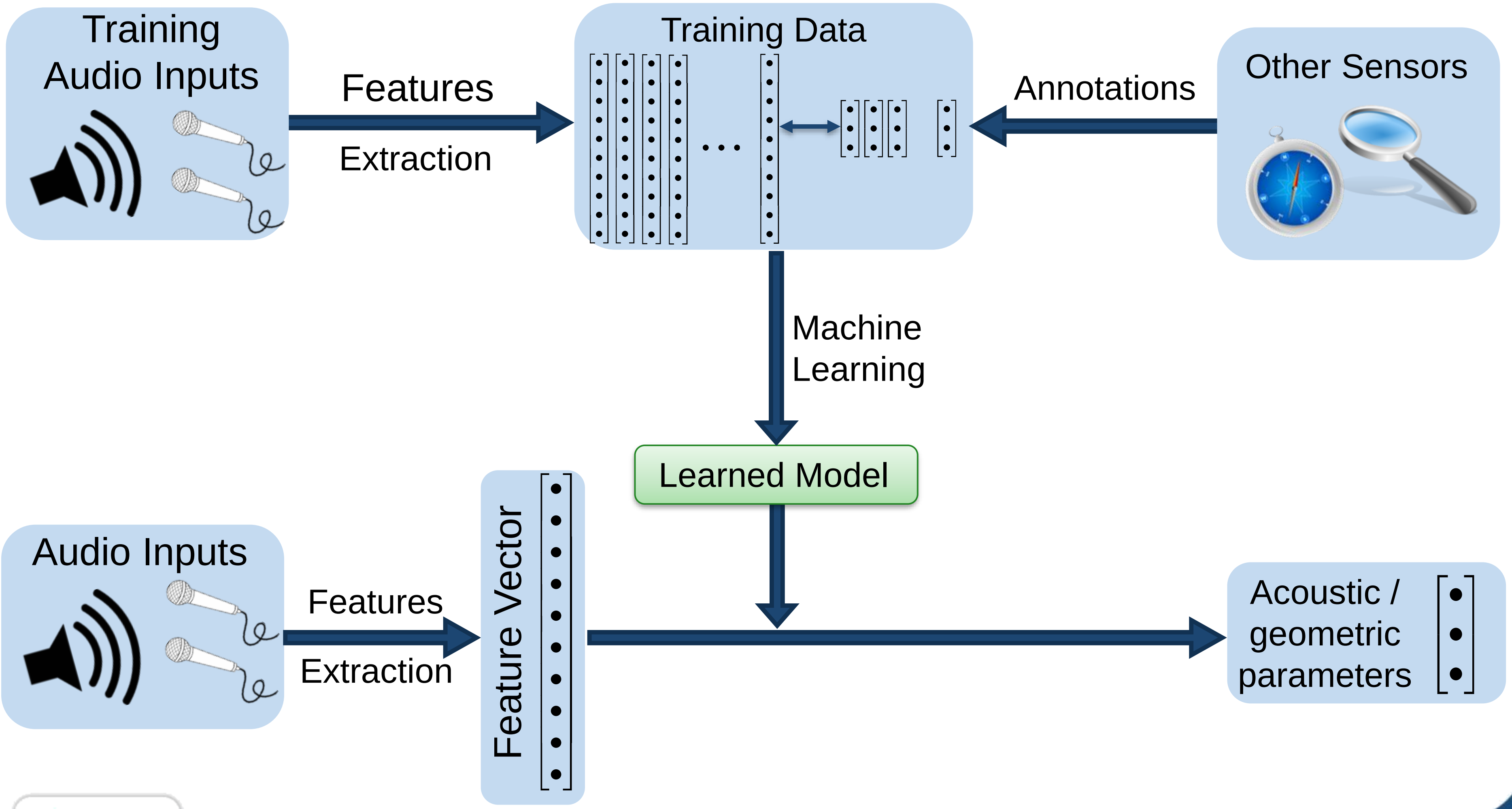

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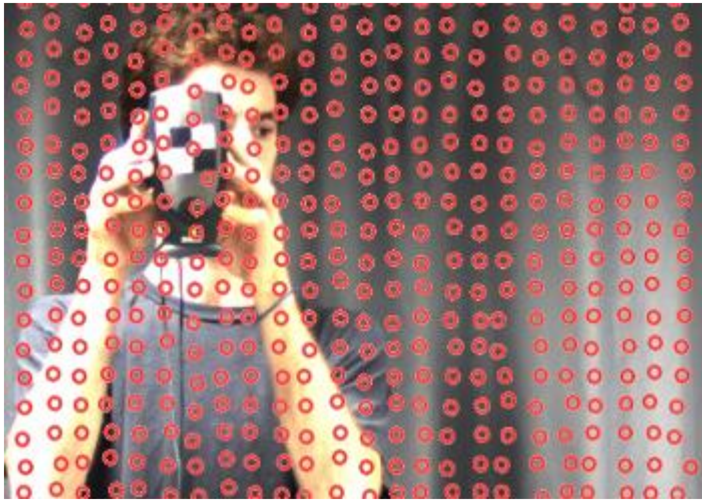
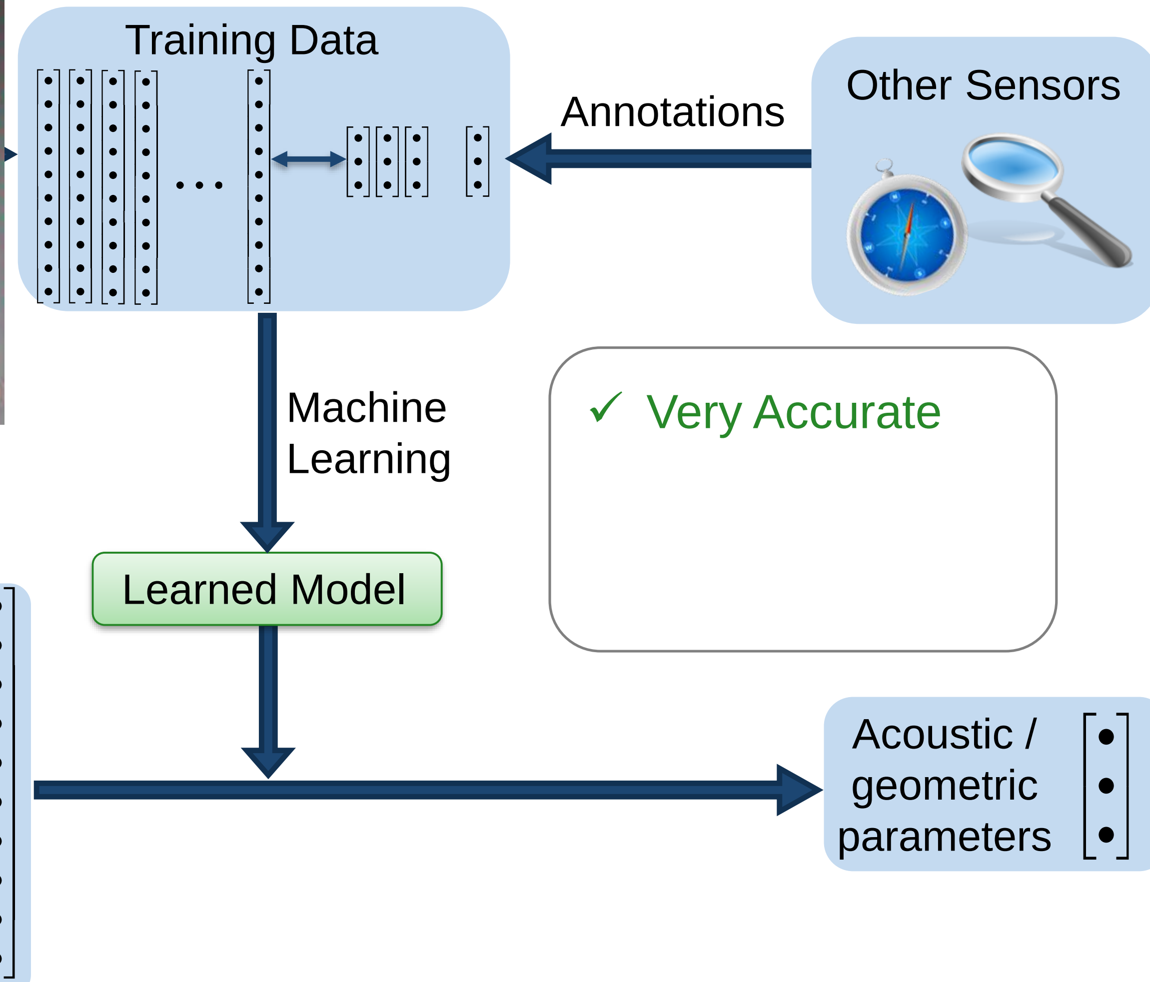
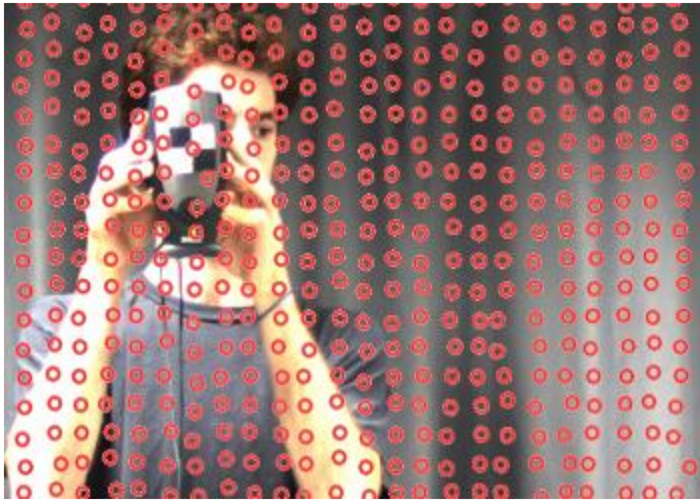


Check on Youtube:
https://youtu.be/mhOlcVpY7iA




✓ Very Accurate

# b) Real-Data-Driven Approaches [1, 2, 3, 6]



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Training Data

Annotations

Other Sensors

Machine Learning

Learned Model

- ✓ Very Accurate
- ✓ Noise-Robust

Audio Inputs

Features Extraction

Feature Vector

Acoustic / geometric parameters

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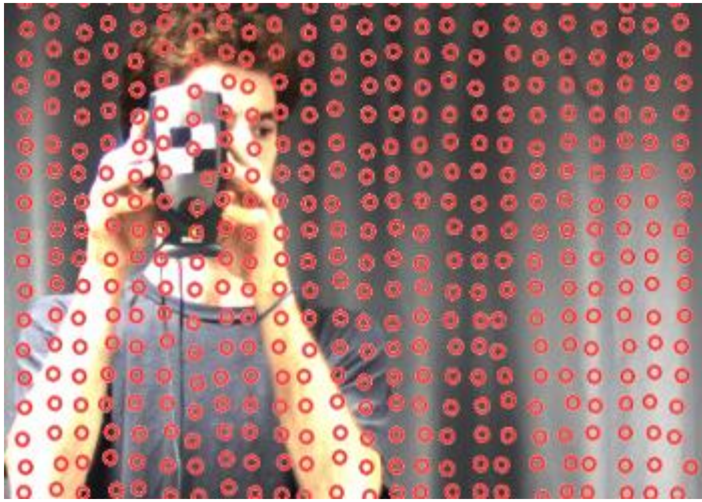

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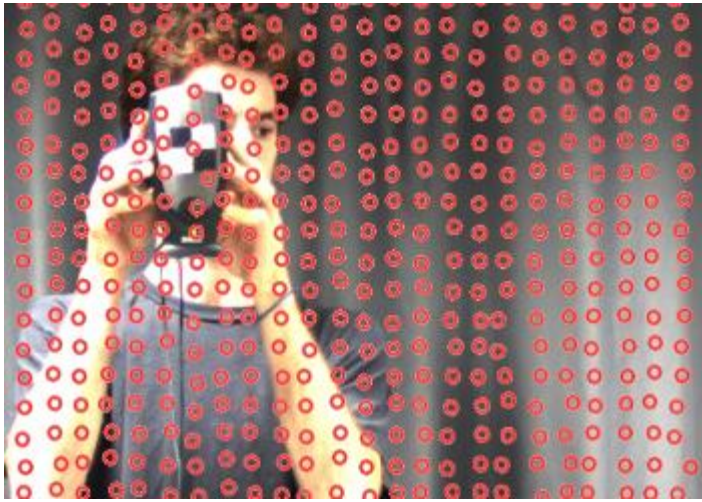

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Training Data

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- ✓ Very Accurate
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- ☒ Room-specific
- ☒ Costly to aquire

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## c) *Virtually-Supervised Learning*

[4, 5, 9, 16, 17]

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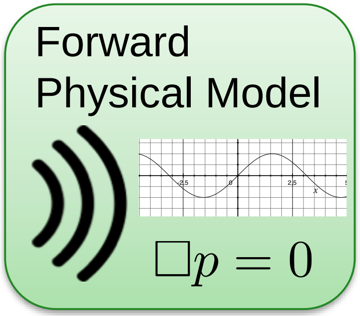


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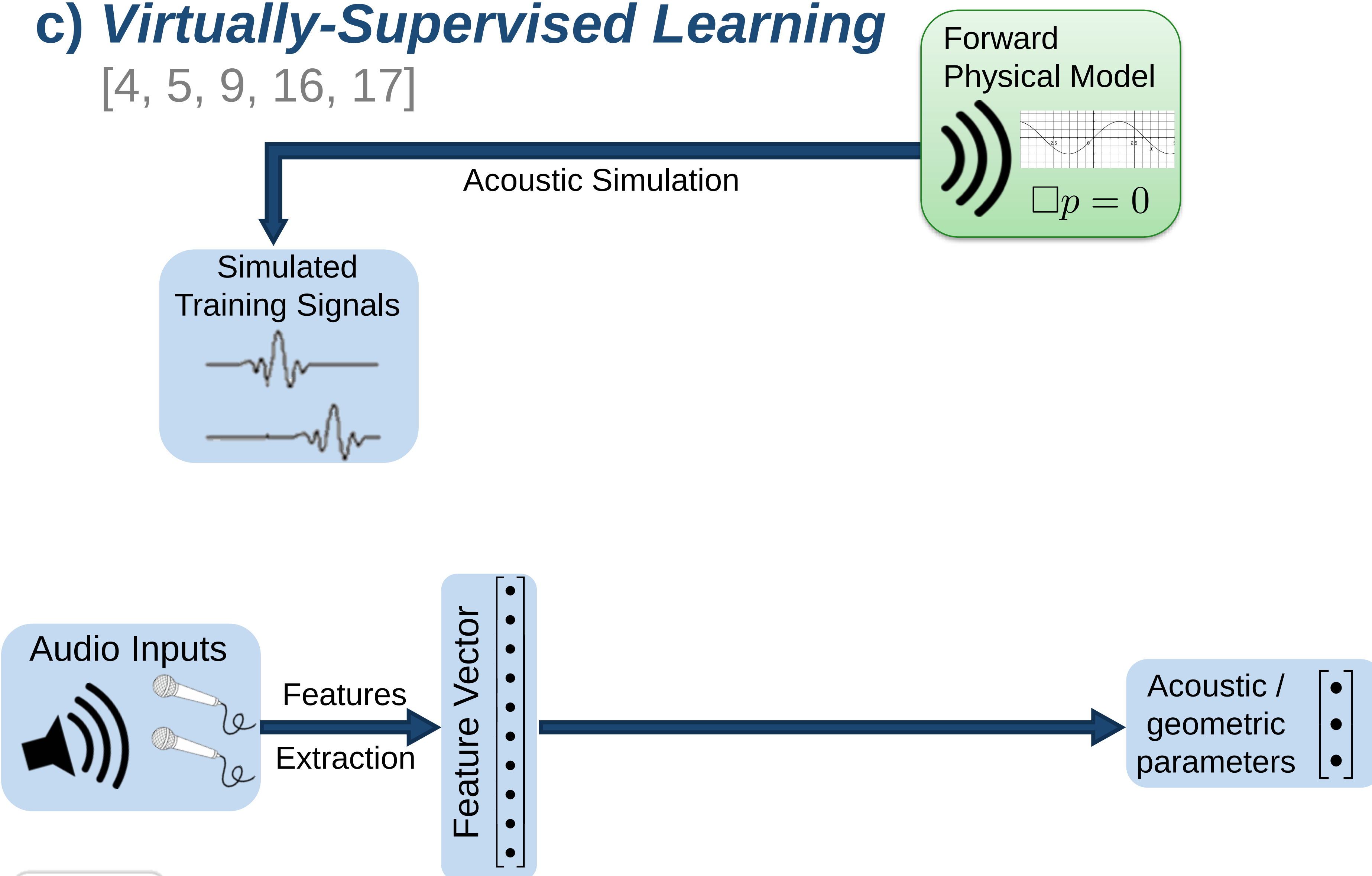

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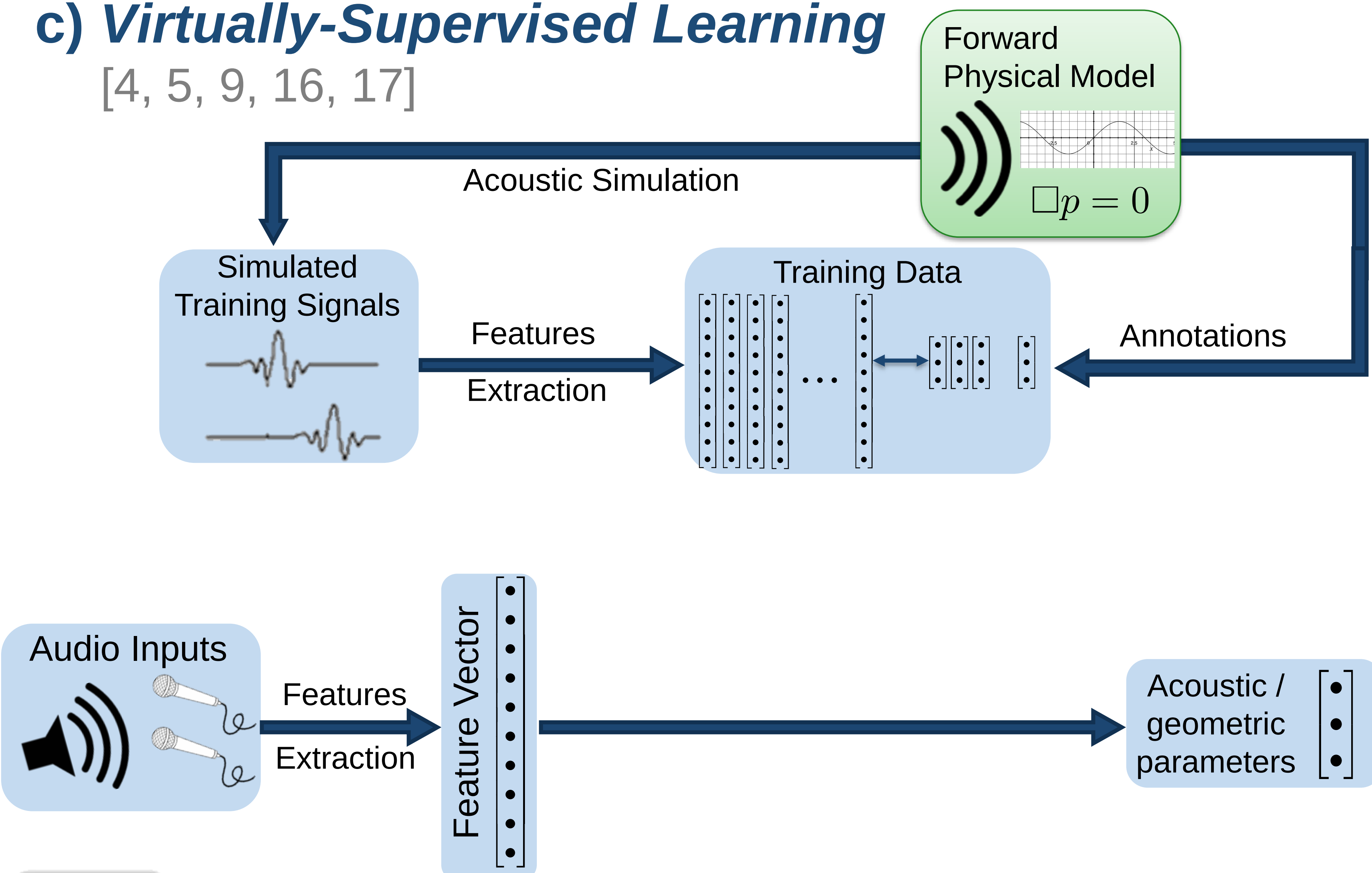

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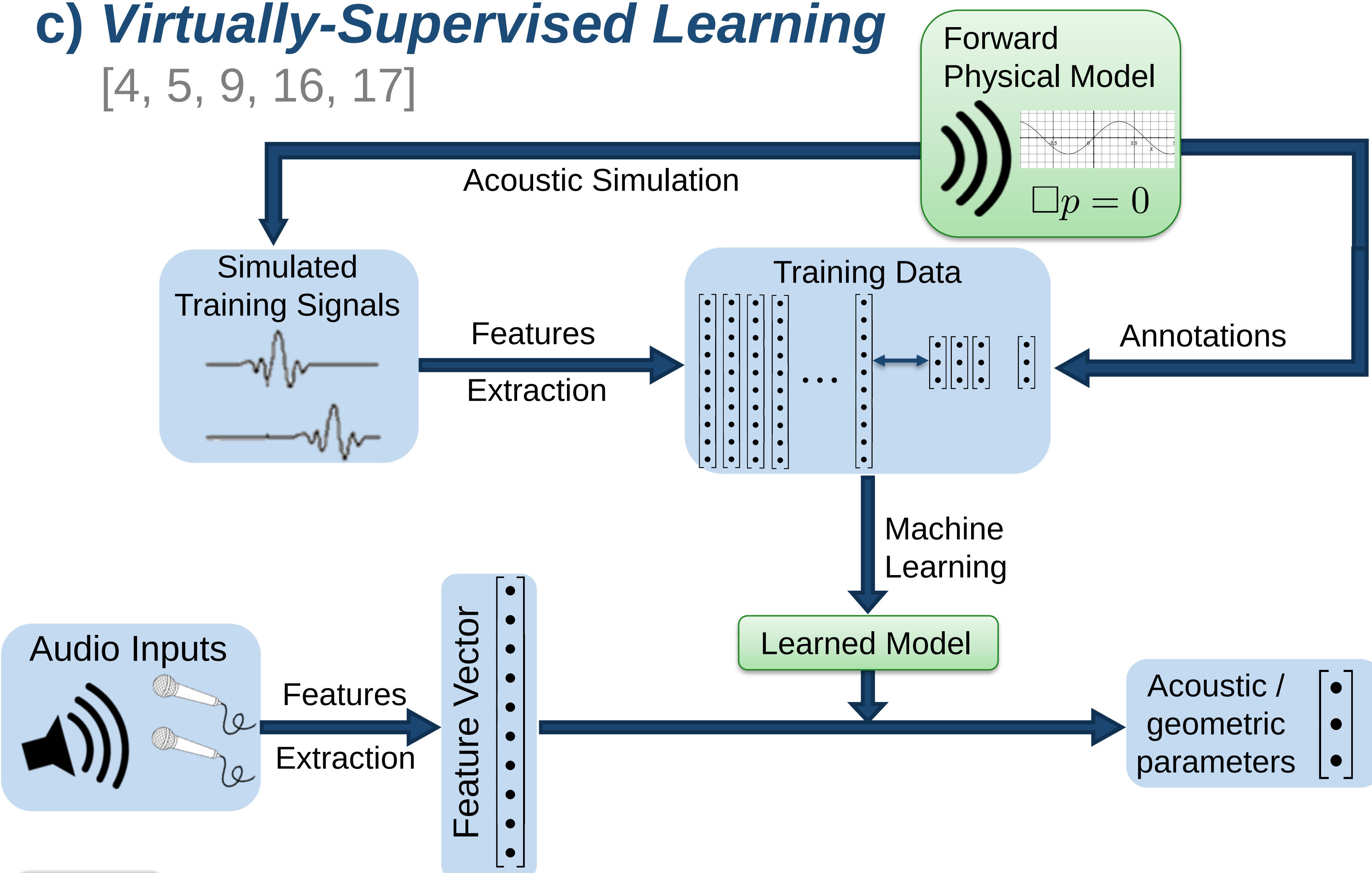

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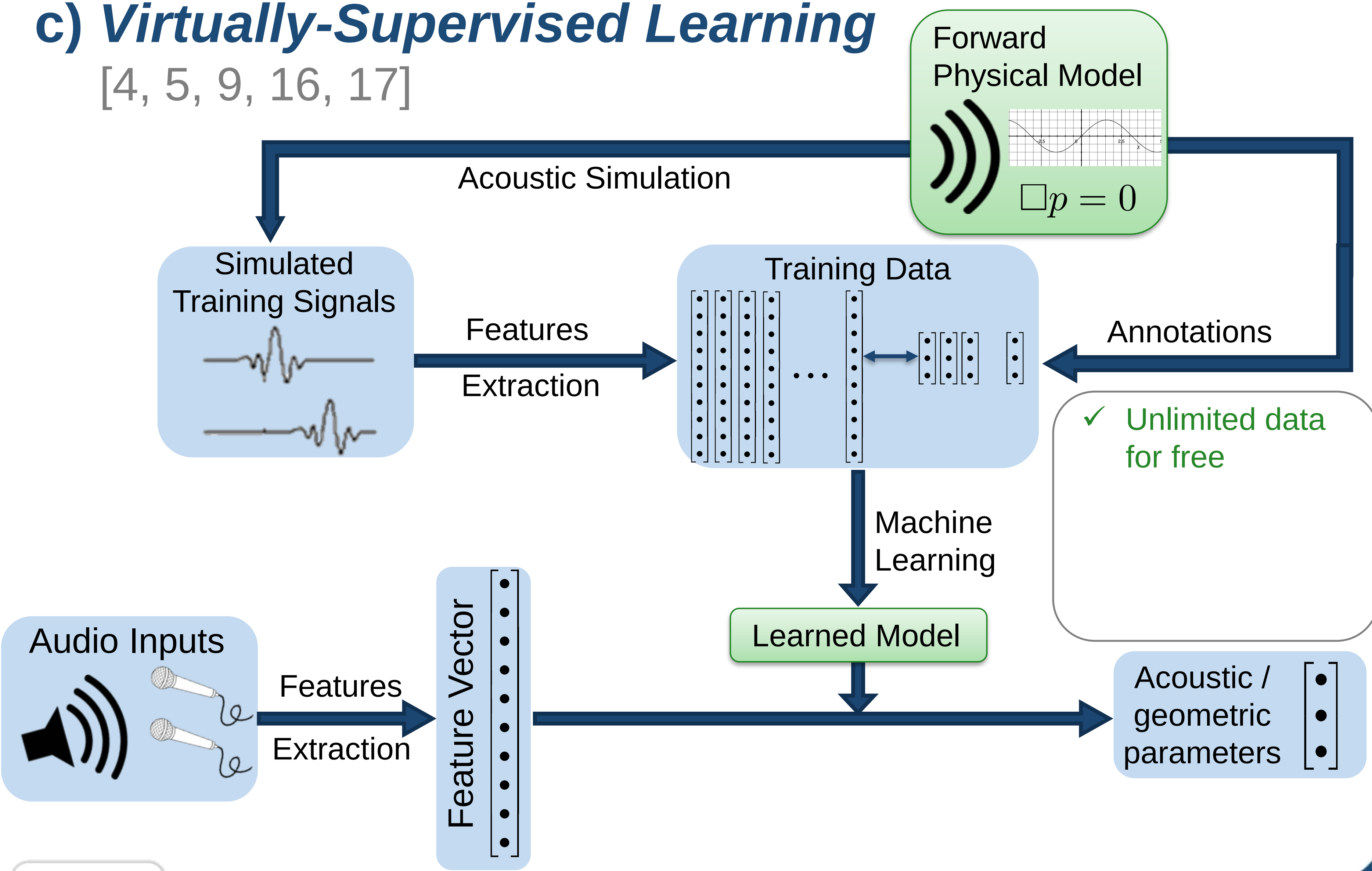

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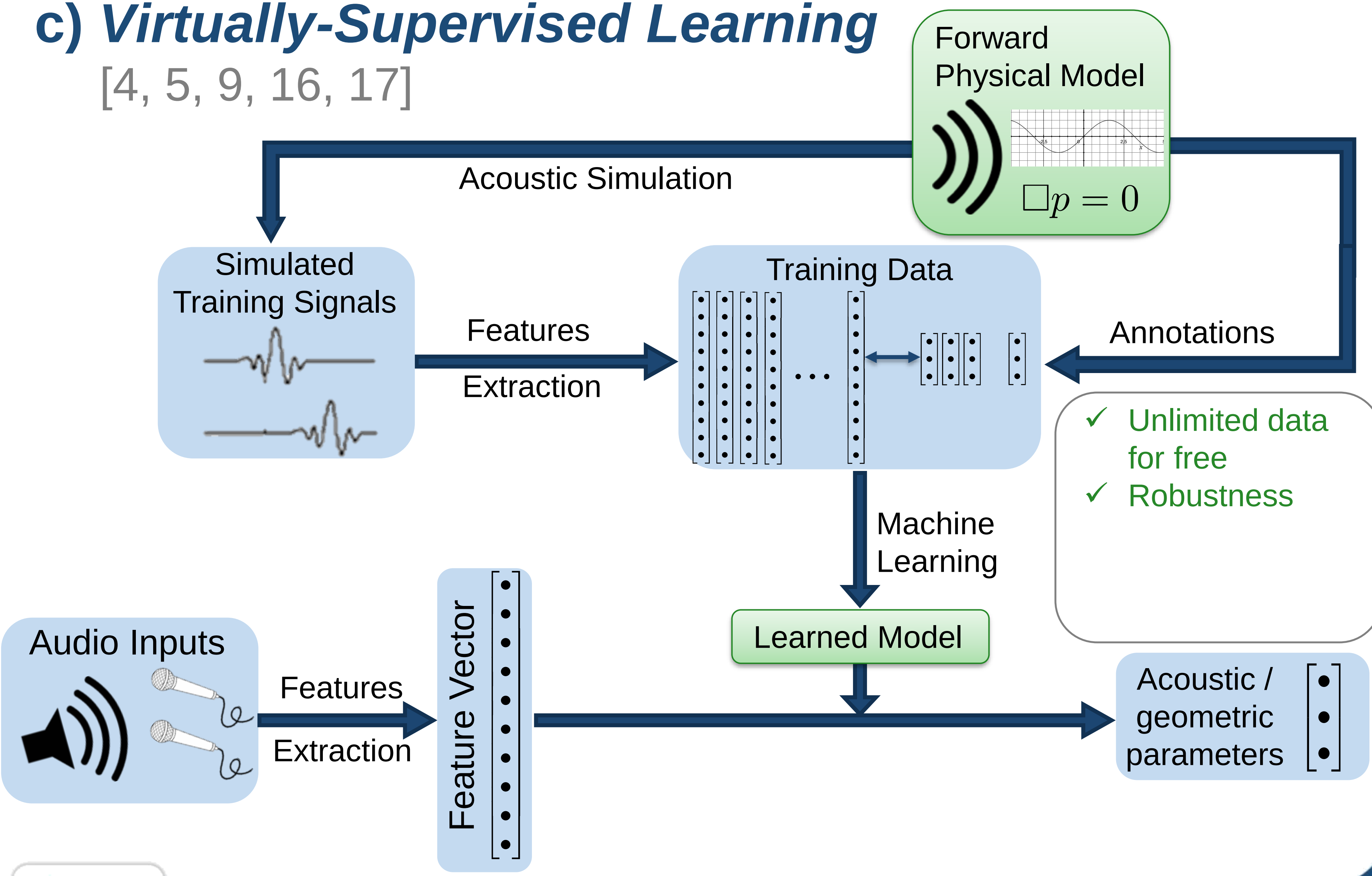


✓ Unlimited data for free
✓ Robustness

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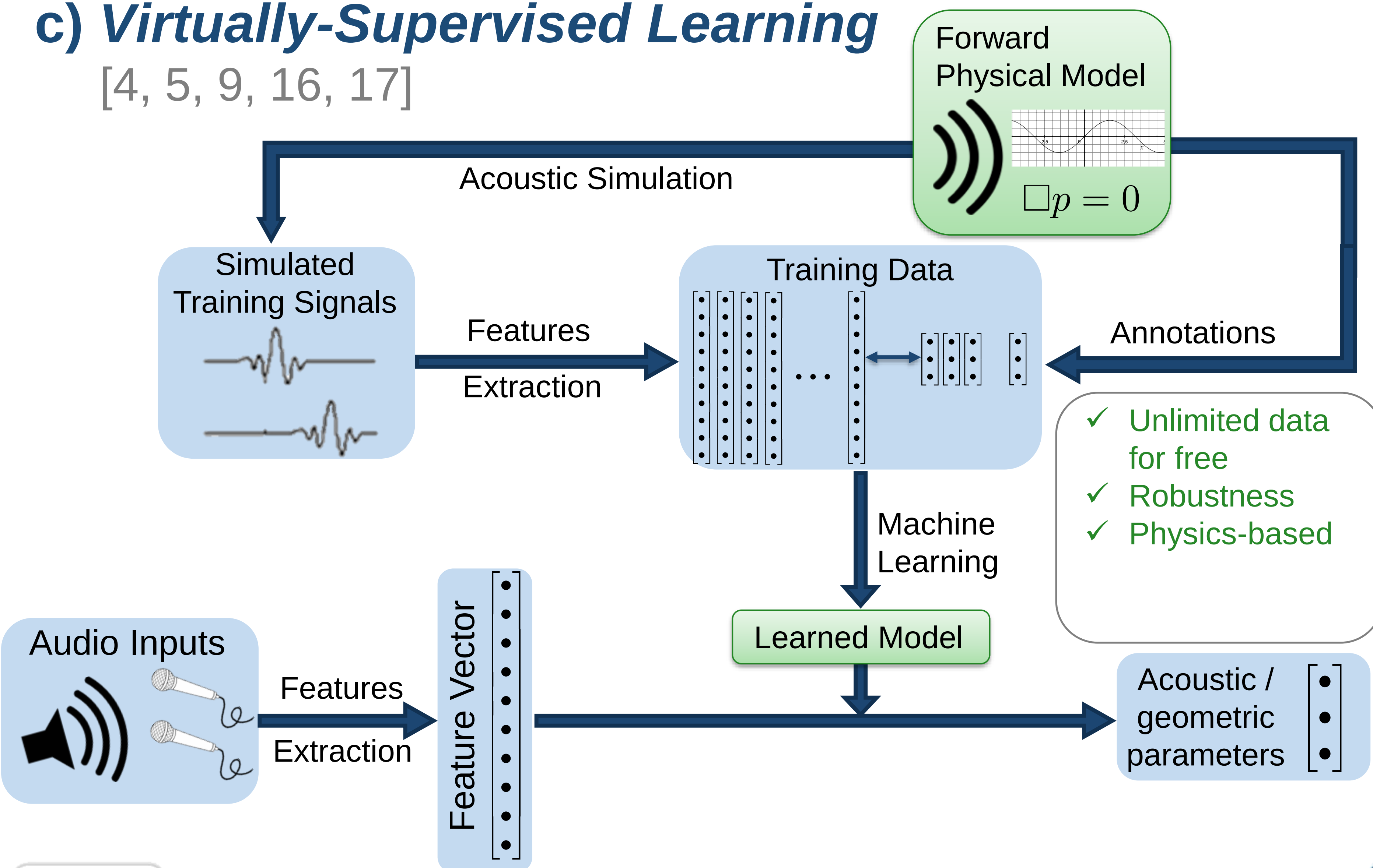

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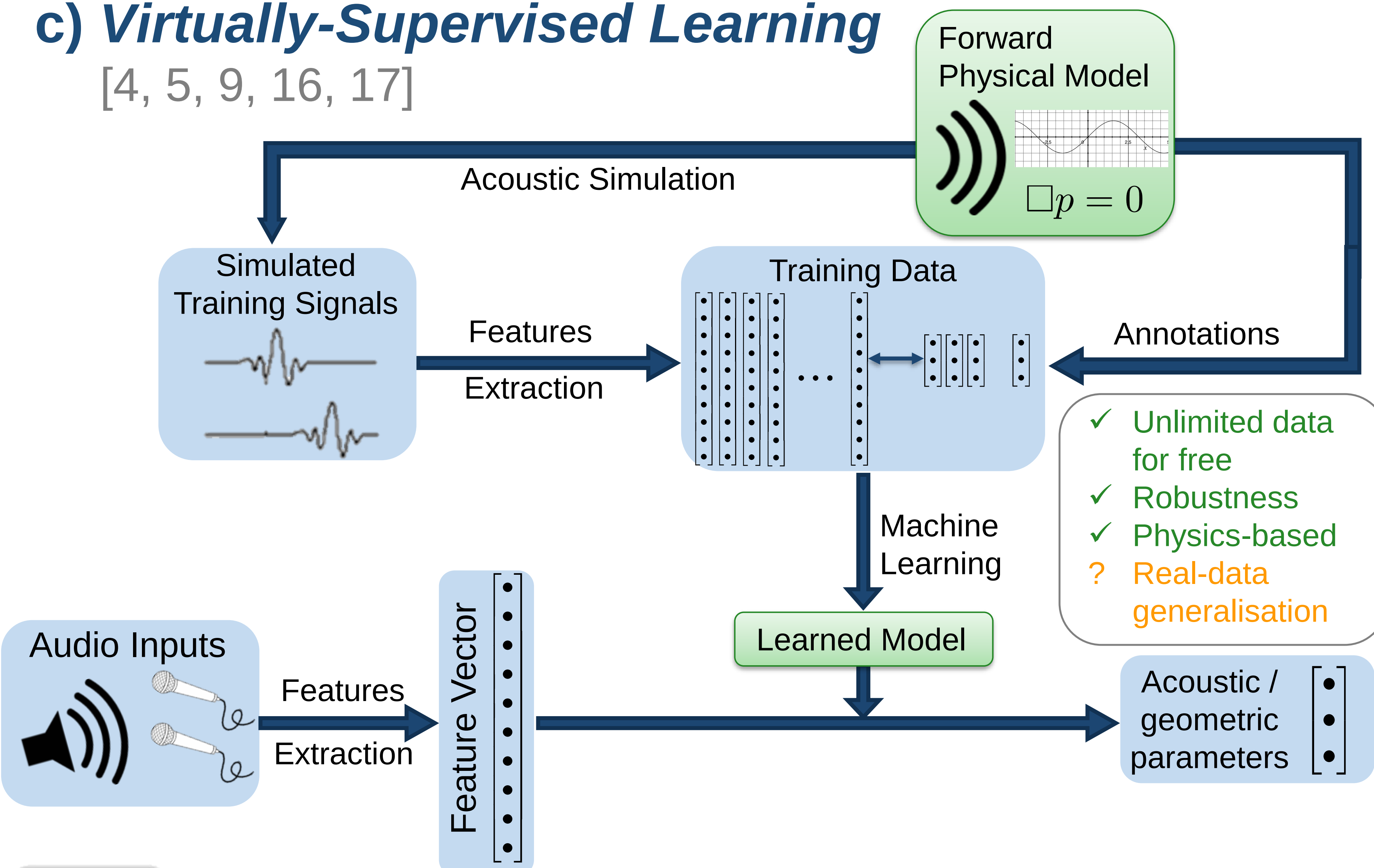


- ✓ Unlimited data for free
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- ✓ Physics-based
- ? Real-data generalisation

# RIR Simulation Trade-offs

| Realism vs. Computational complexity | Diversity vs. Training set size |
| --- | --- |

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| • Discretized wave equation solvers (e.g. FDTD) $$\frac{1}{c^2}\frac{\partial^2 p}{\partial t^2} - \nabla^2 p = 0$$ | |

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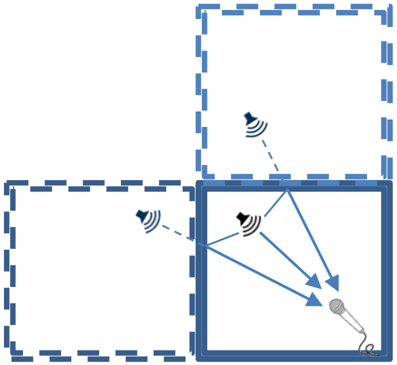
• Image source method [13]



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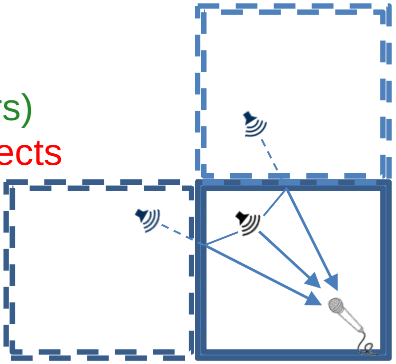
- Image source method [13]

✓ Fast (for low reflection orders)
☒ Doesn't capture low-freq effects
☒ Specular reflections only



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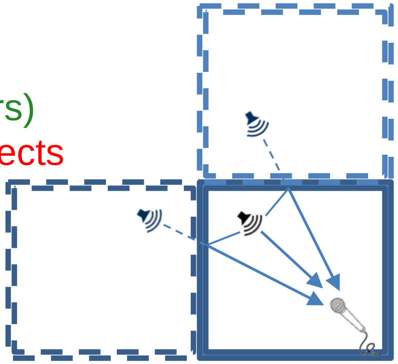
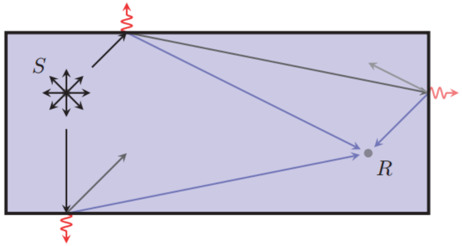


- Energy-based / Ray-based / Particle-based methods



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### Realism vs. Computational complexity

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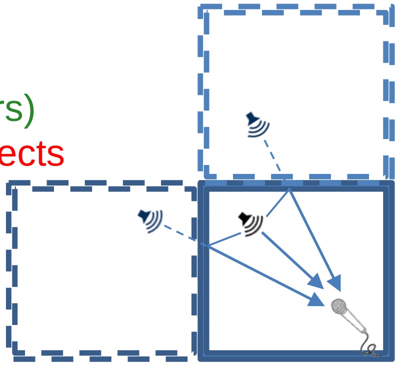

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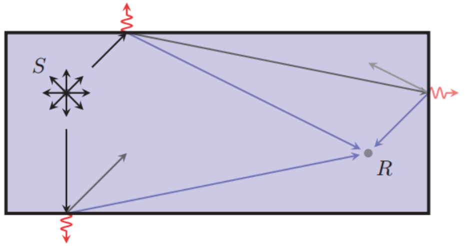


✓ Versatile
☒ Doesn’t capture low-freq effects
☒ Approx. TOAs

### Diversity vs. Training set size

# RIR Simulation Trade-offs

| Realism vs. Computational complexity | Diversity vs. Training set size |
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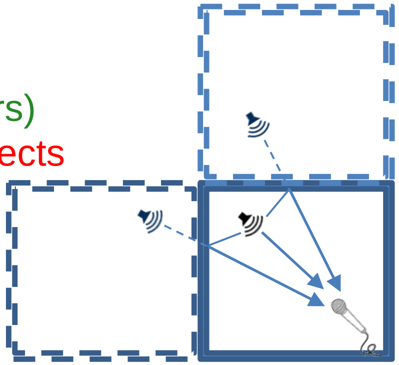

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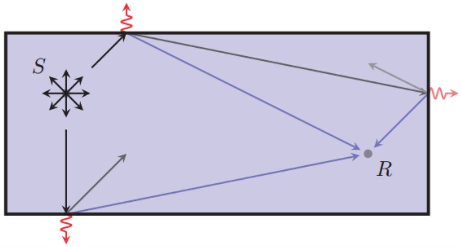


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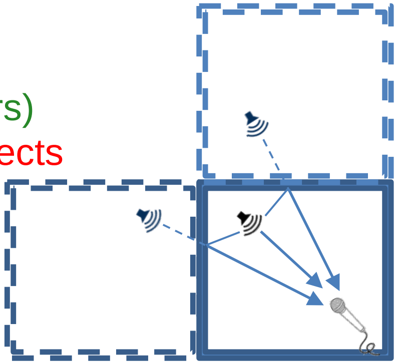

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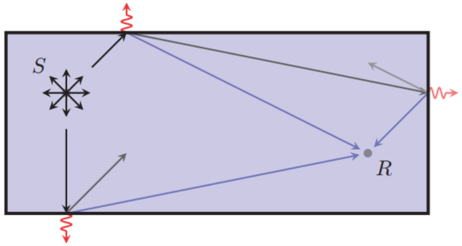


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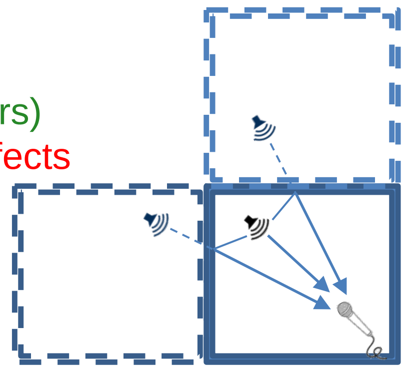

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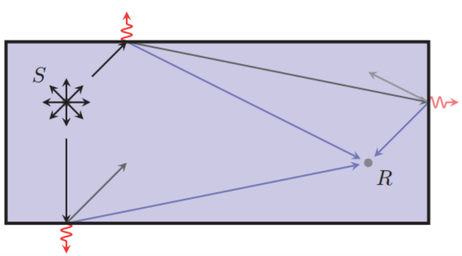


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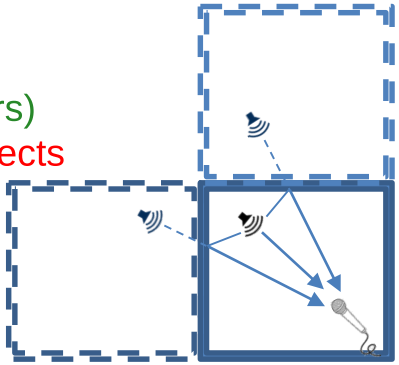

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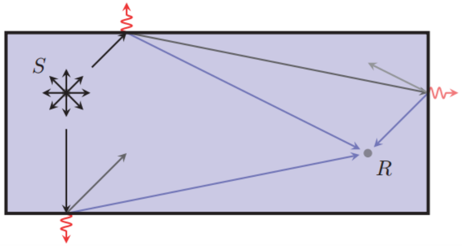


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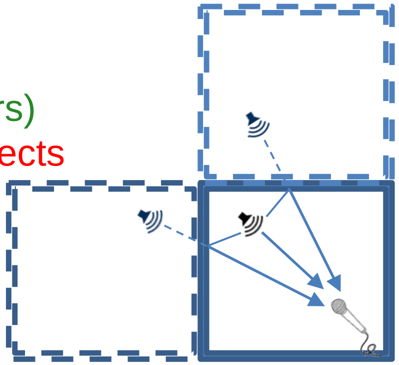

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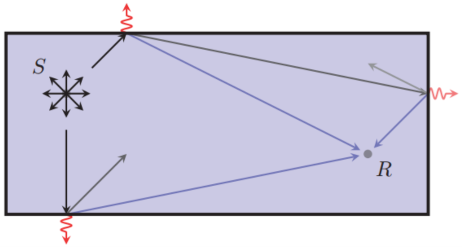


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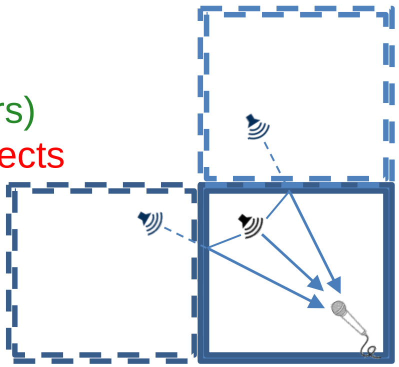

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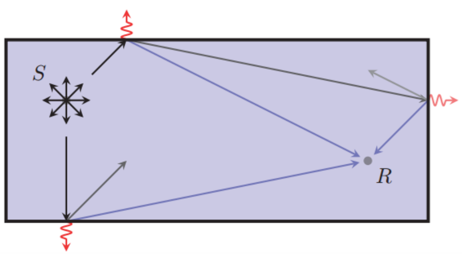


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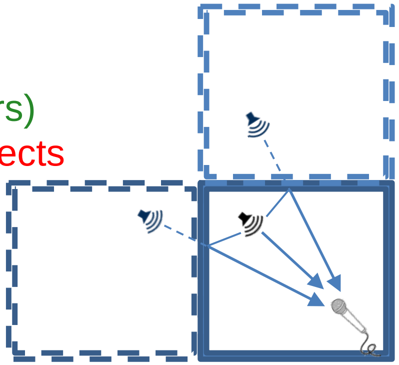

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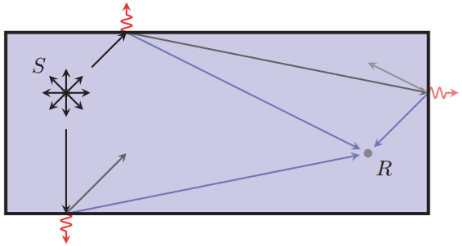


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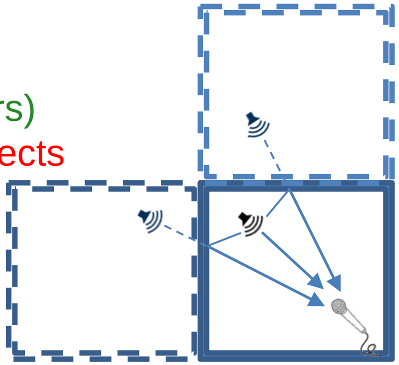

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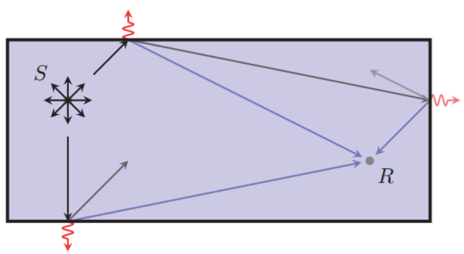


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A **« reflectivity-biased »** acoustic sampling strategy [16]

For each surface type (wall, ceiling, floor) toss a coin:

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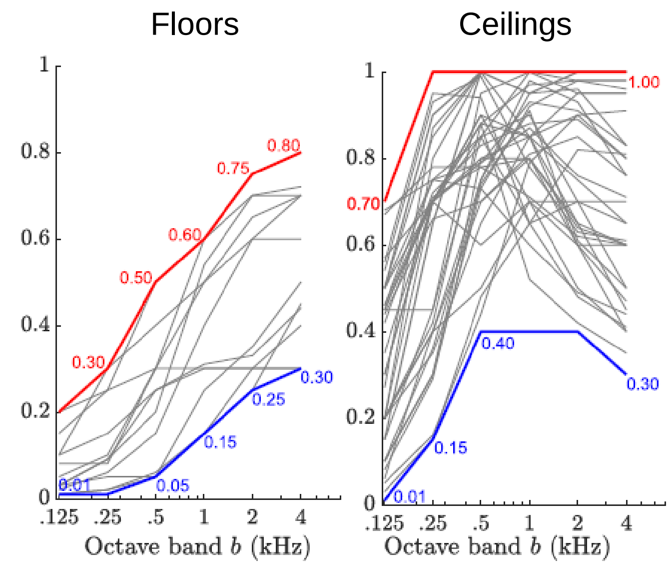

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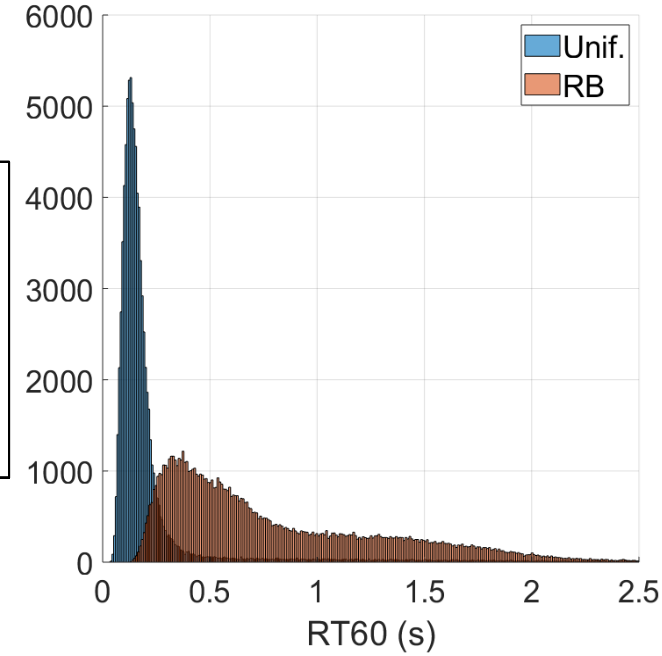

# OUTLINE

1) Intro & Background

**2) Virtually-Supervised Learning**

3) Examples and Results

4) Conclusions and Outlook

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Absorption
coefficient in [0,1]

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Area in m²

Antoine.Deleforge@inria.fr

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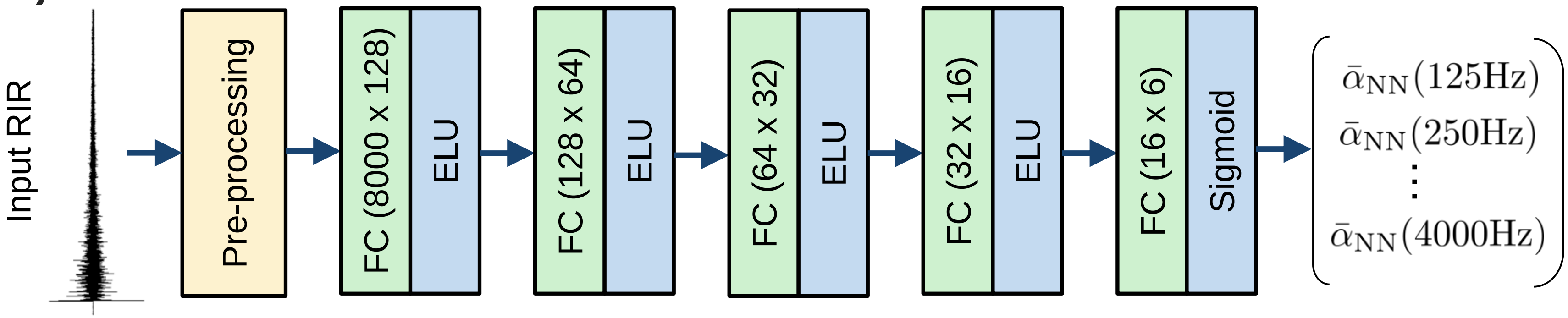

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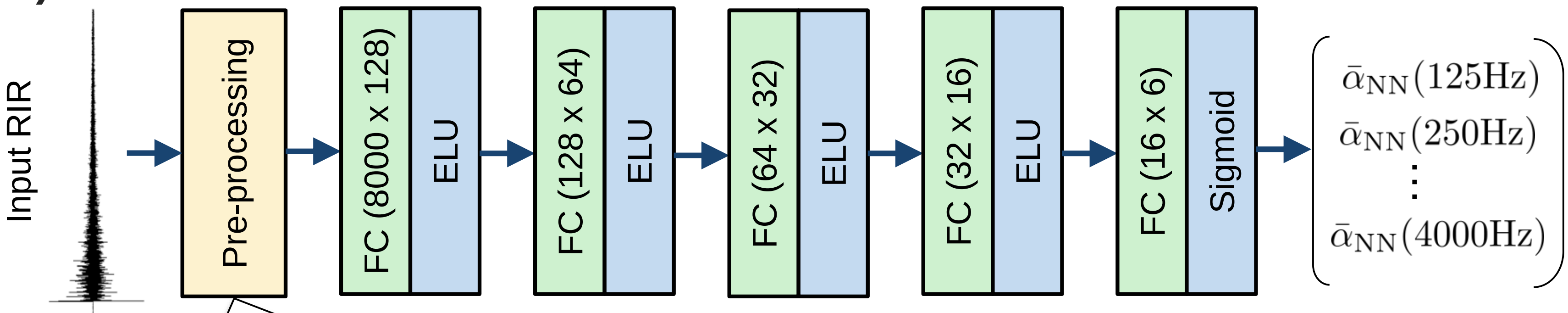


- Resample to 16 kHz
- Crop to 0.5 sec
- Normalize to max = 1
- Additive white Gaussian noise (SNR= 30 dB)

$\rightarrow$ Input vector in $\mathbb{R}^{8000}$

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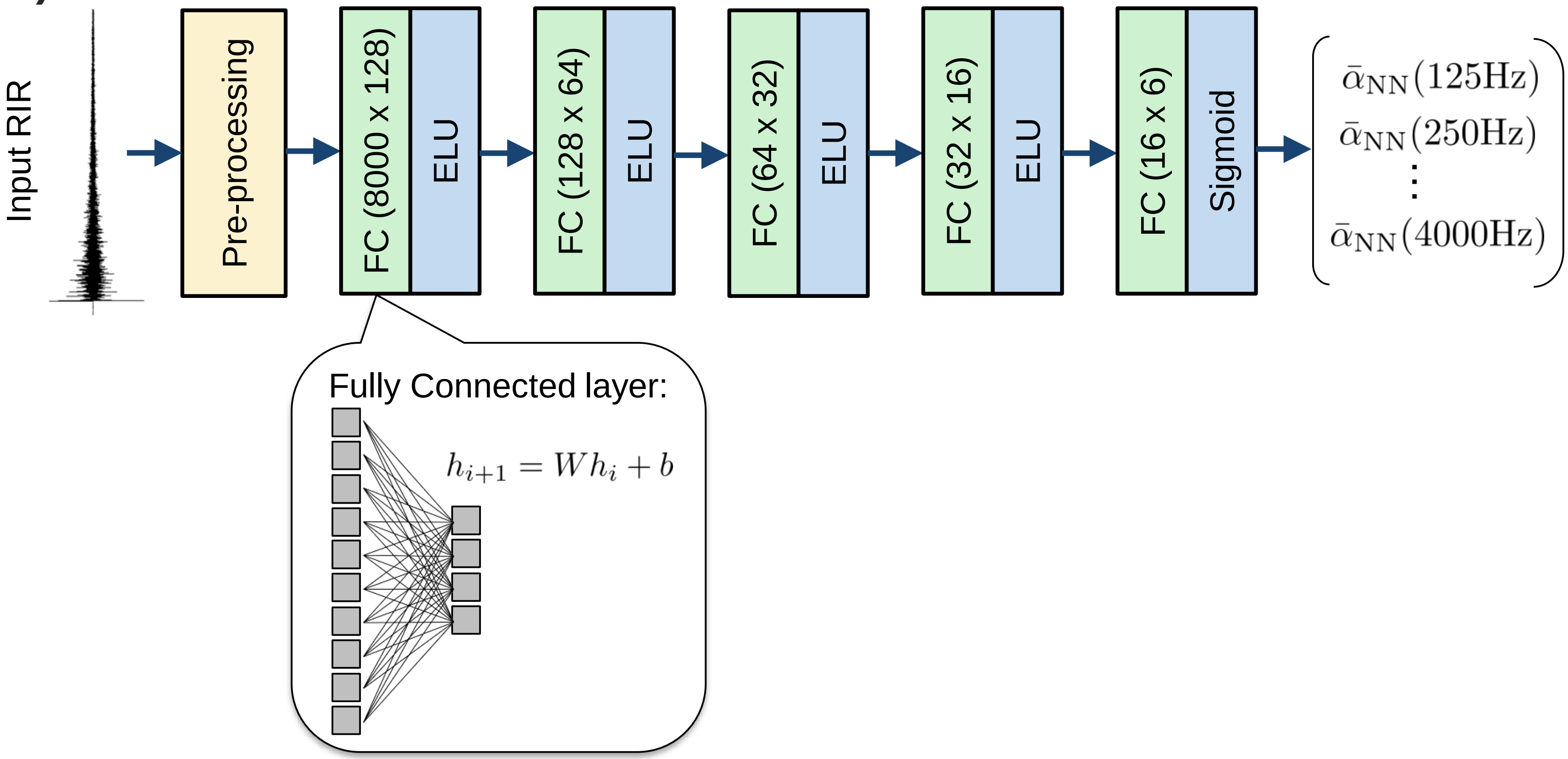

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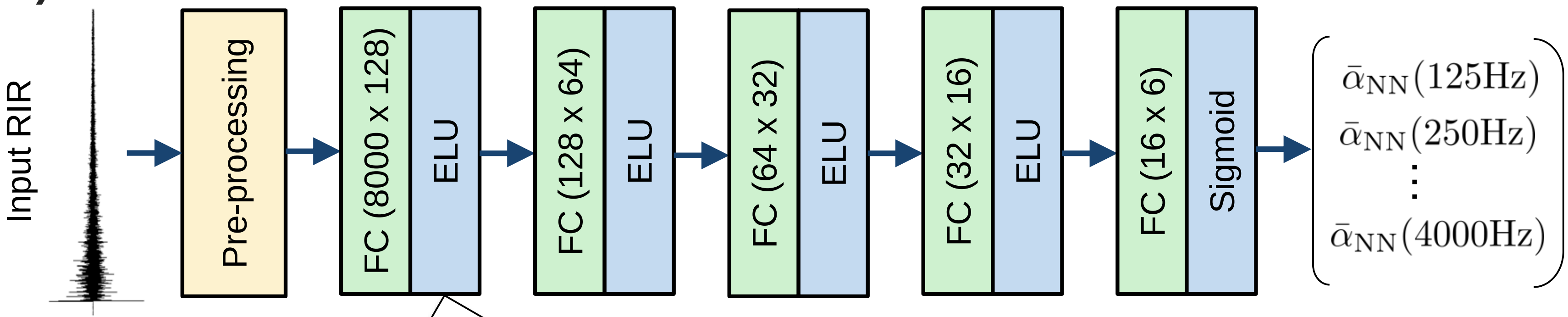
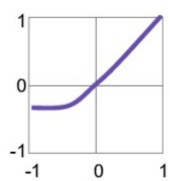



Exponential Linear Unit:




$$y = \begin{cases} x, & x \geq 0 \\ \alpha(e^x - 1), & x < 0 \end{cases}$$

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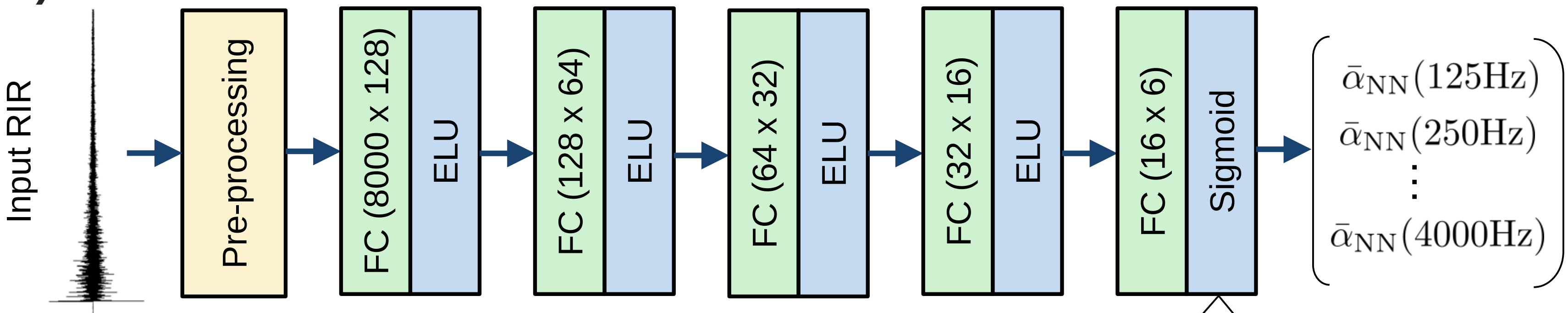


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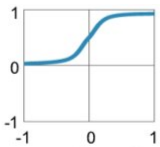


$y = 1/(1+e^{-x})$

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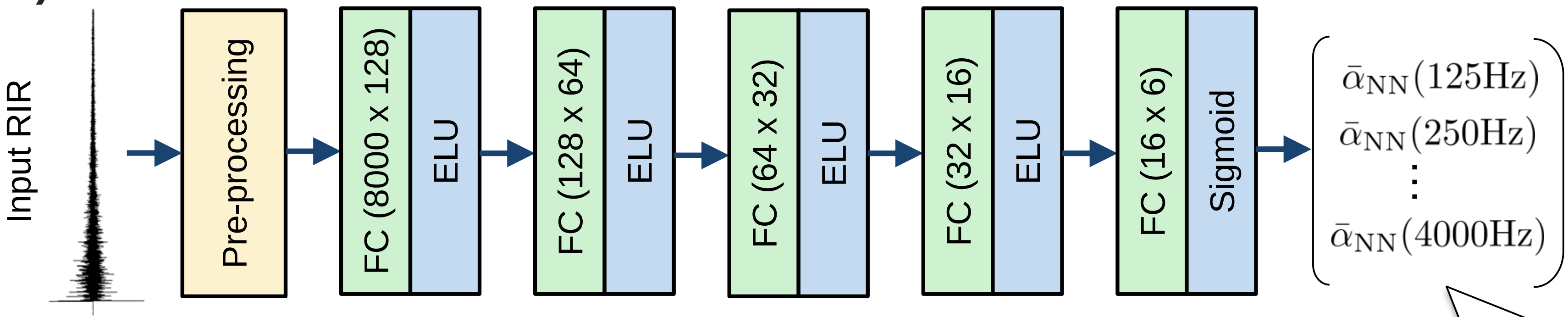


- Output vector in $[0, 1]^6$
- Loss Function = Mean Squared Error
- Optimal parameters on dev. set over 200 epochs

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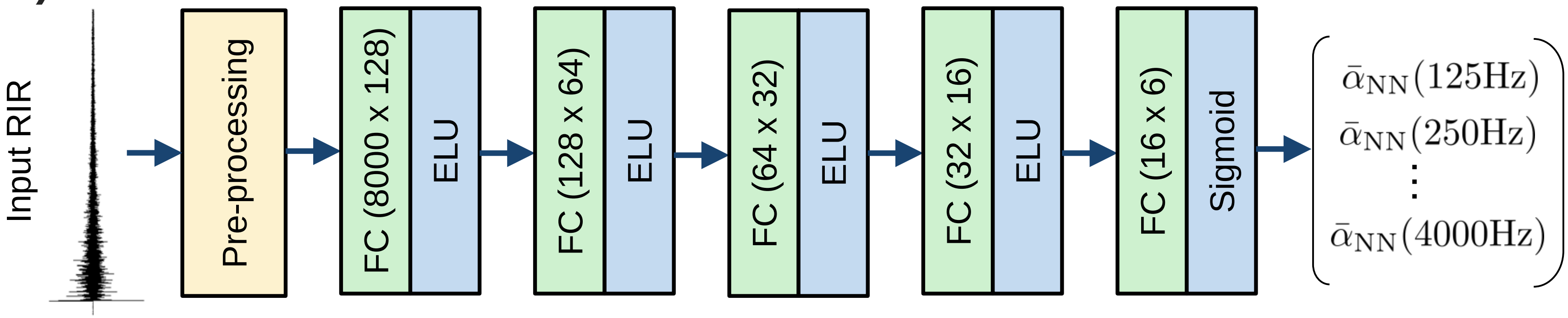


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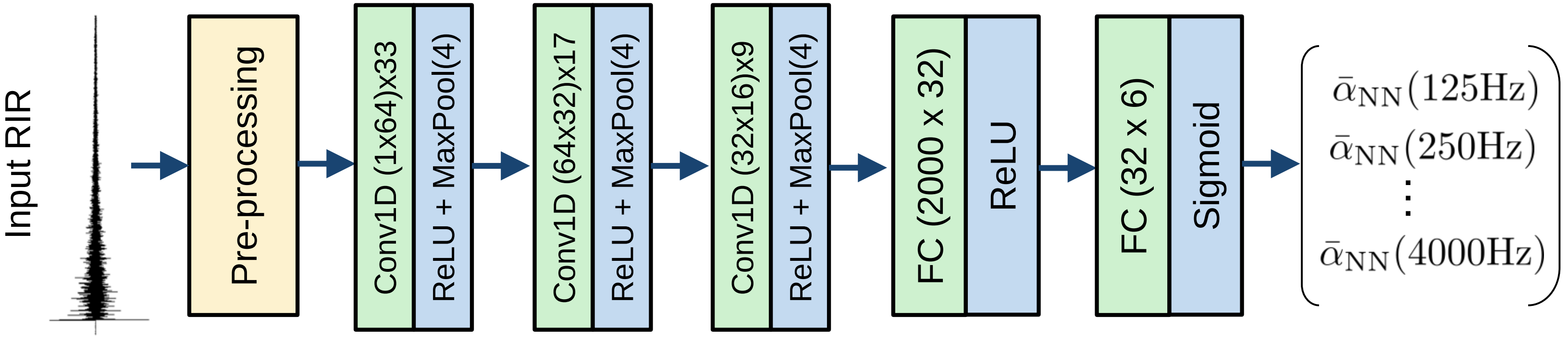

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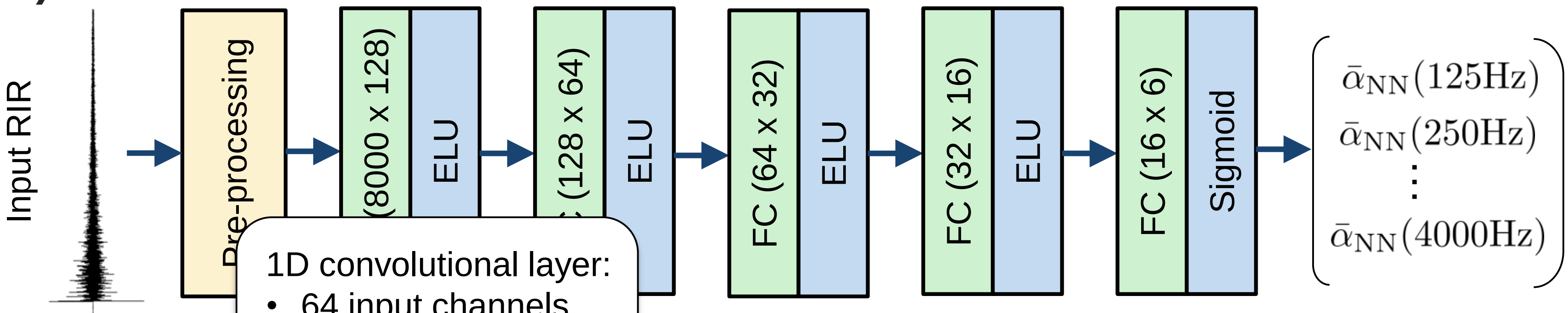


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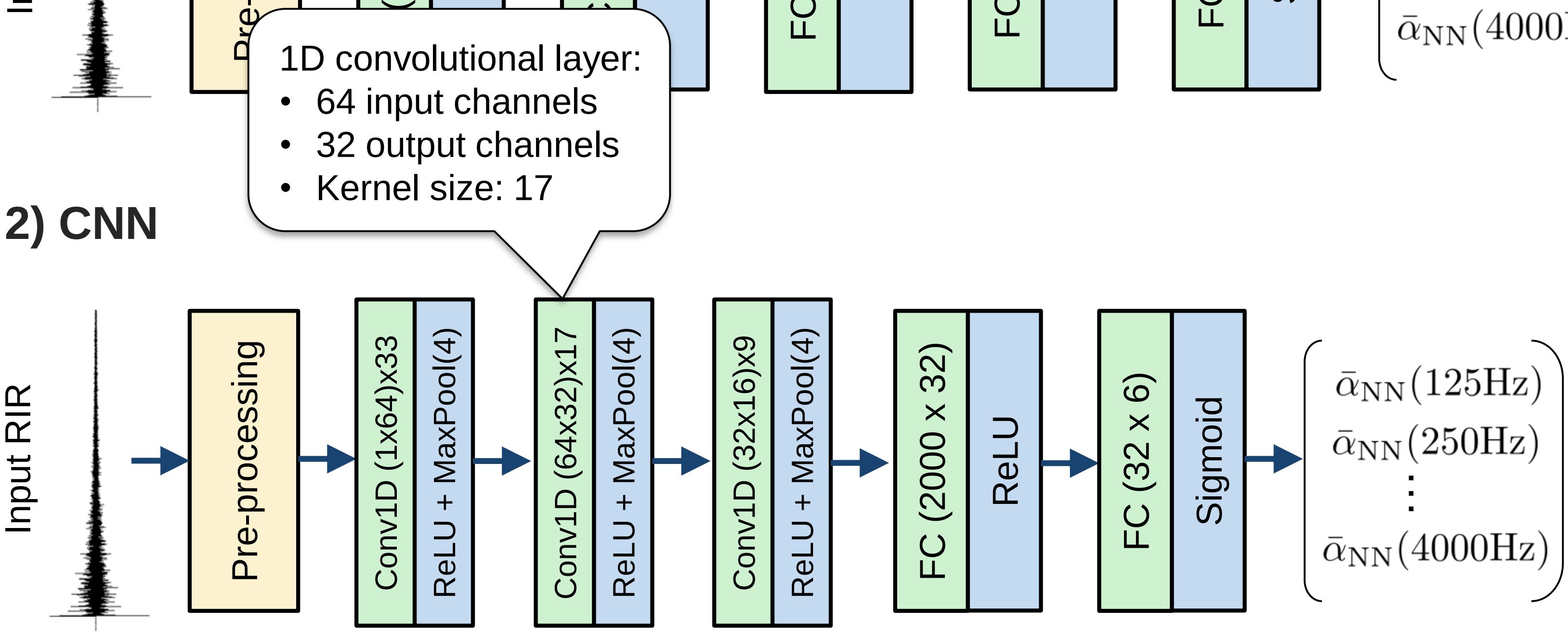

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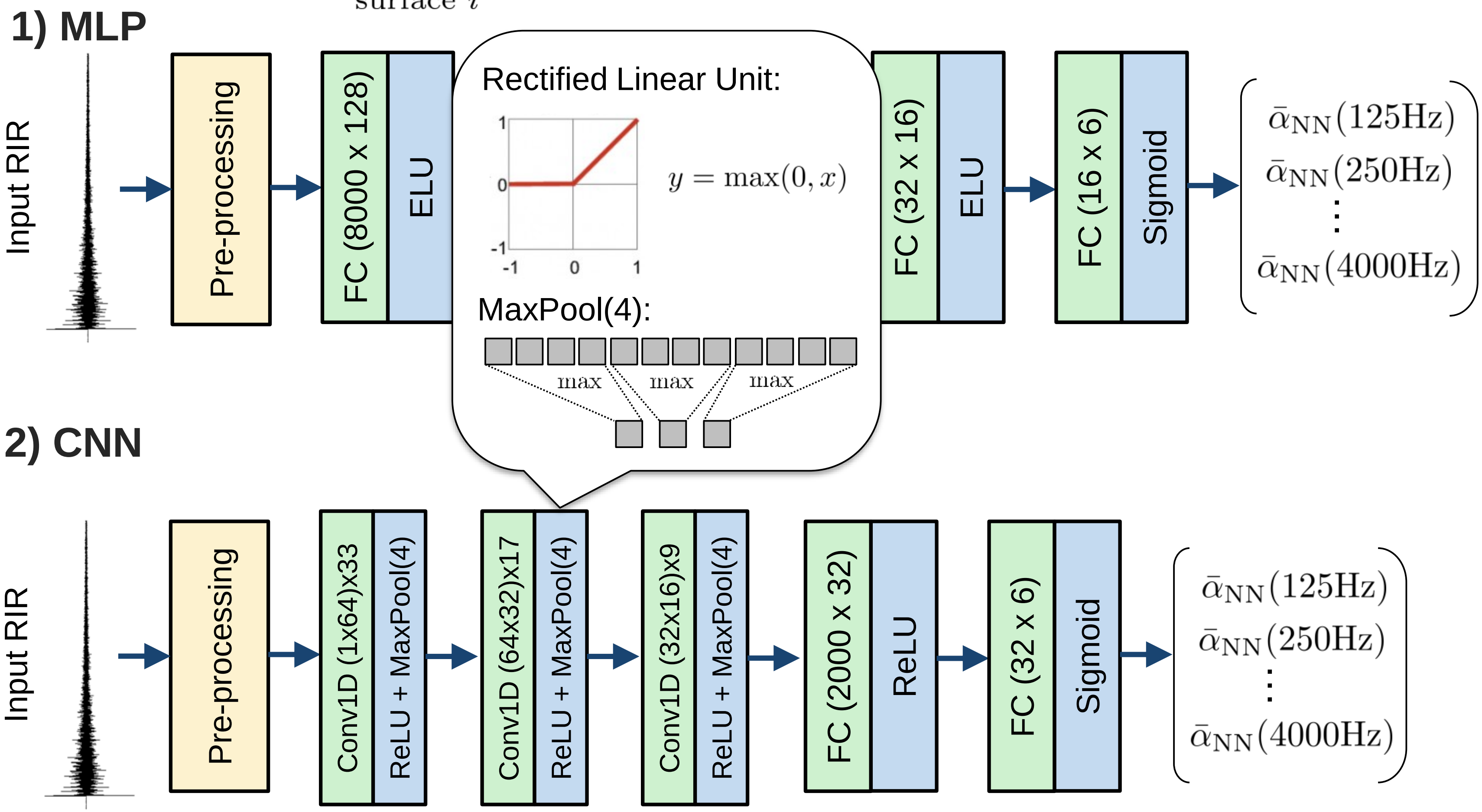

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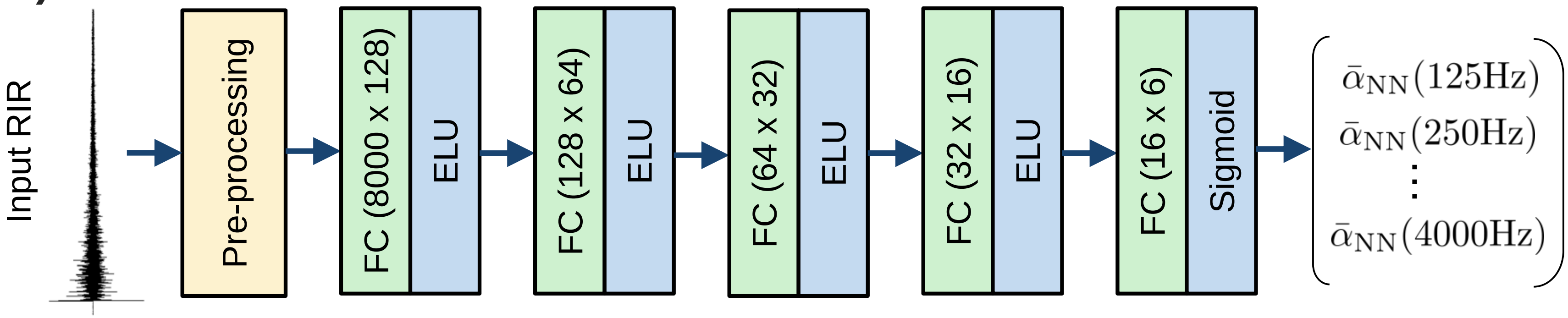
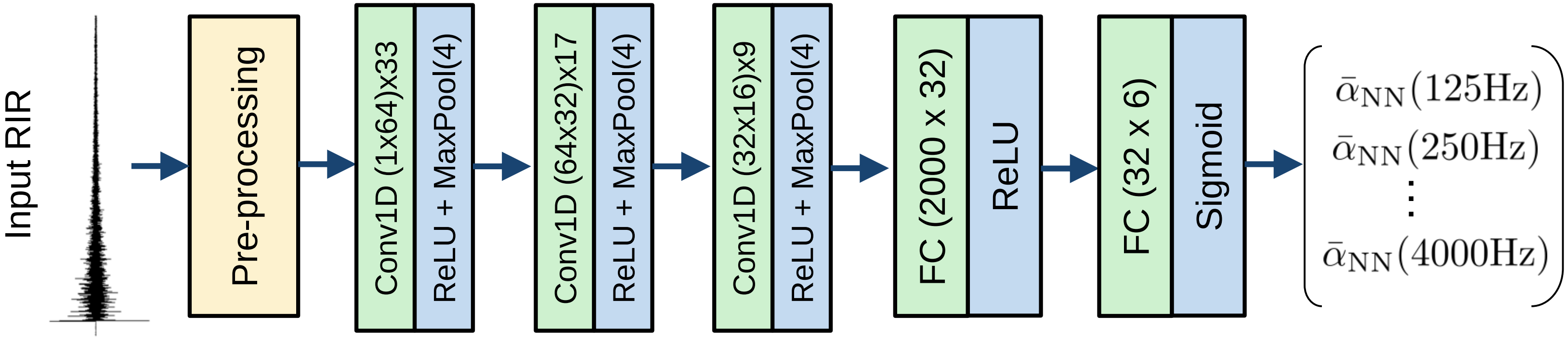



**2) CNN**



## Example 1: RIR -> Mean absorption profile of surfaces [16]

- **Simulated test results:** RoomSim, real absorption profiles, 5 room geometries, 500 RIRs
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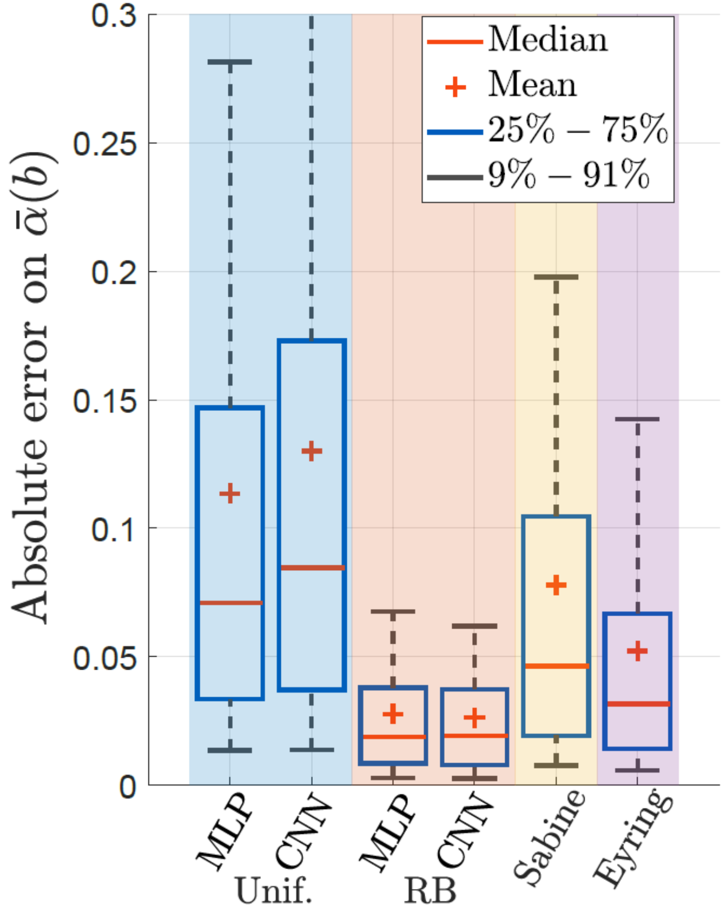

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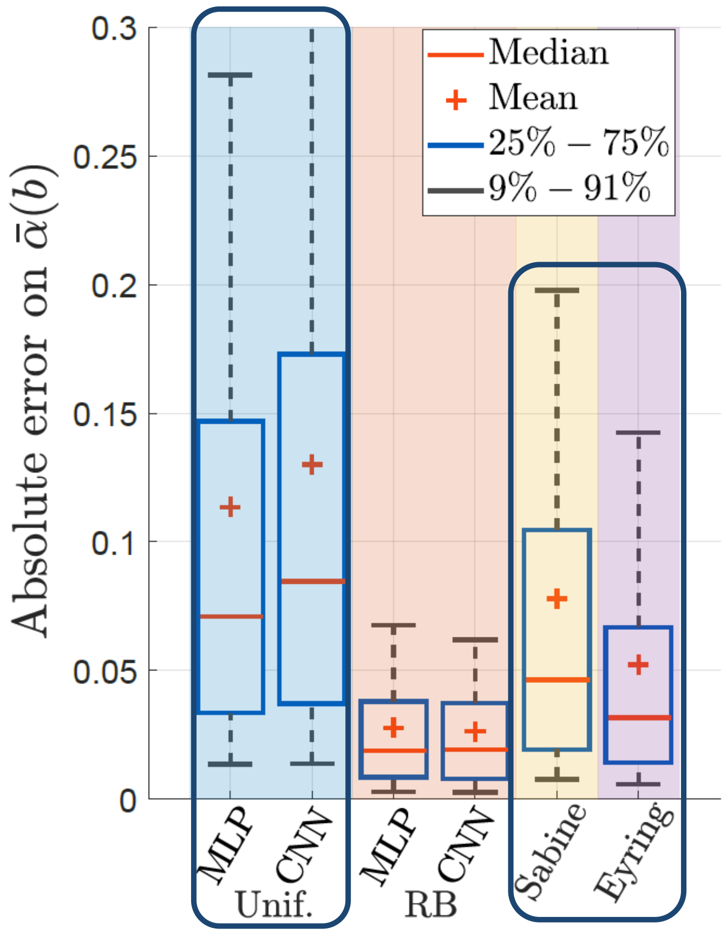

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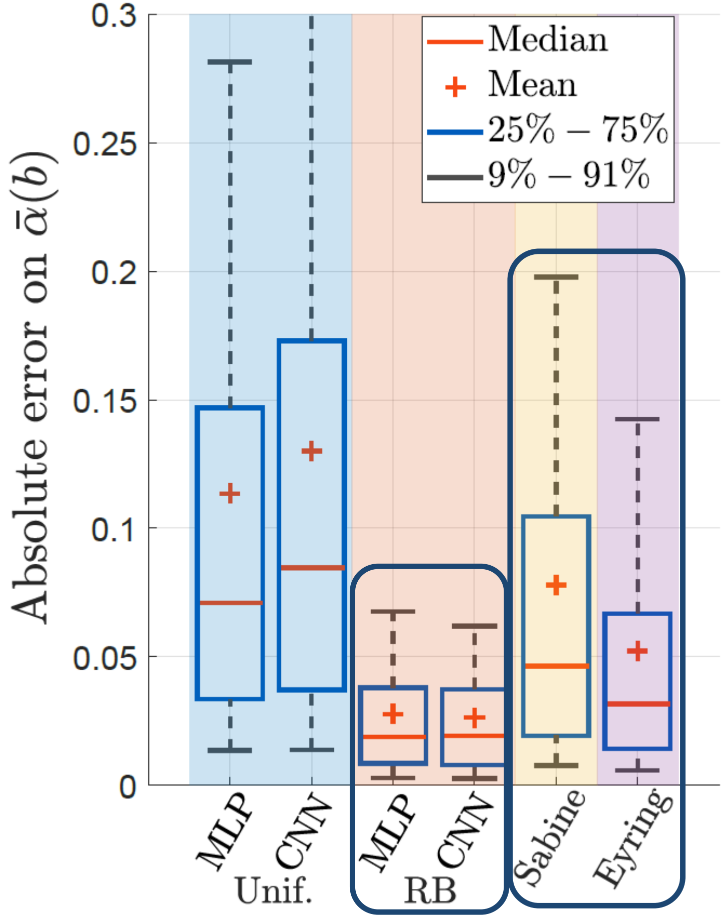

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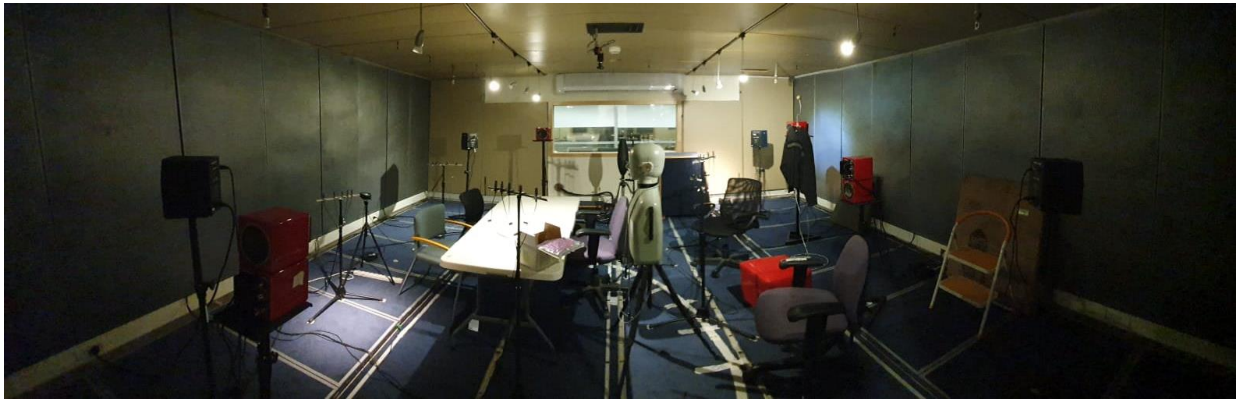
- Encouraging generalizability to **real data** (900 RIRs, 10 room configurations [12])



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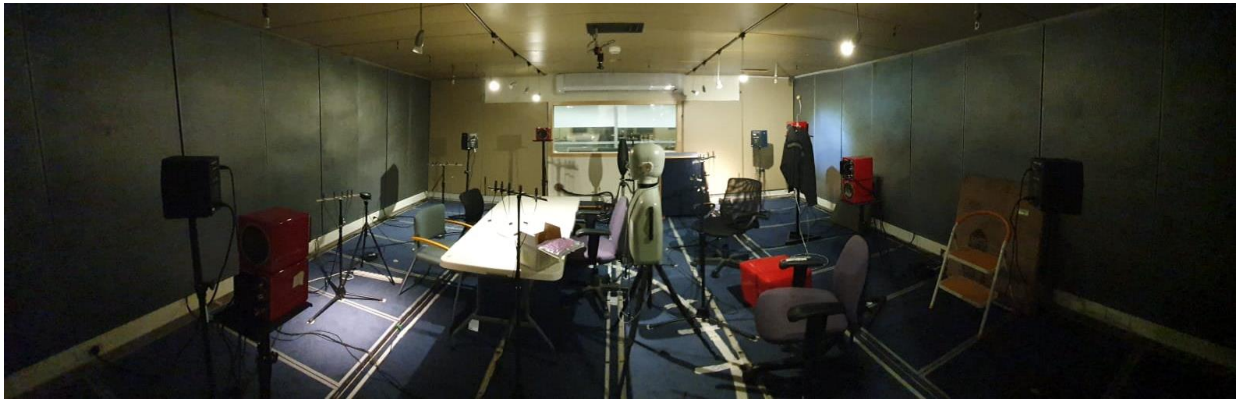

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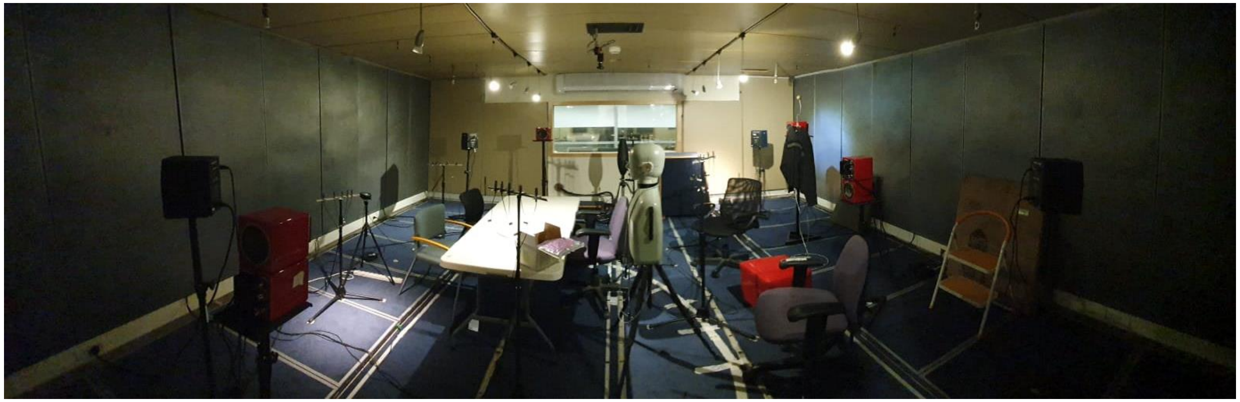

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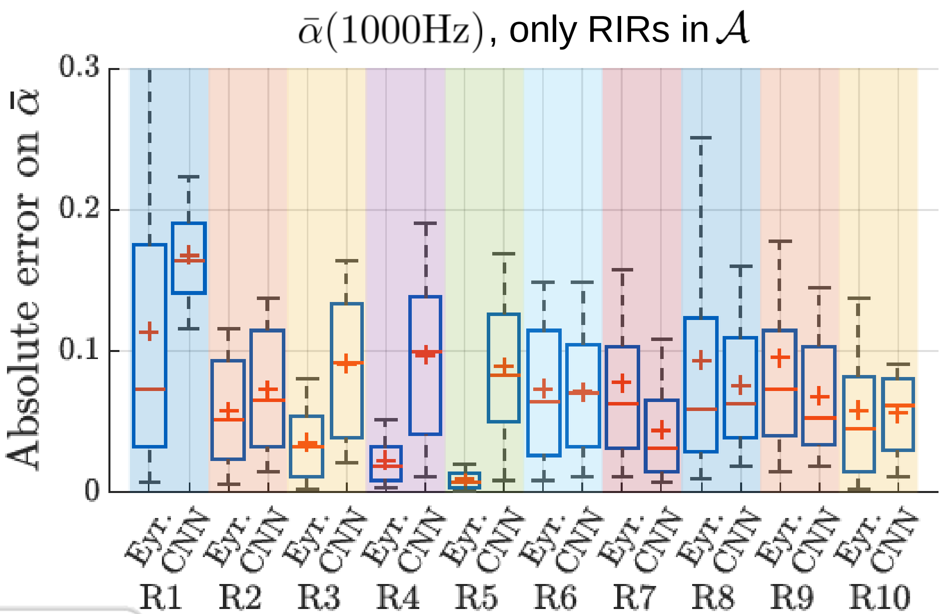

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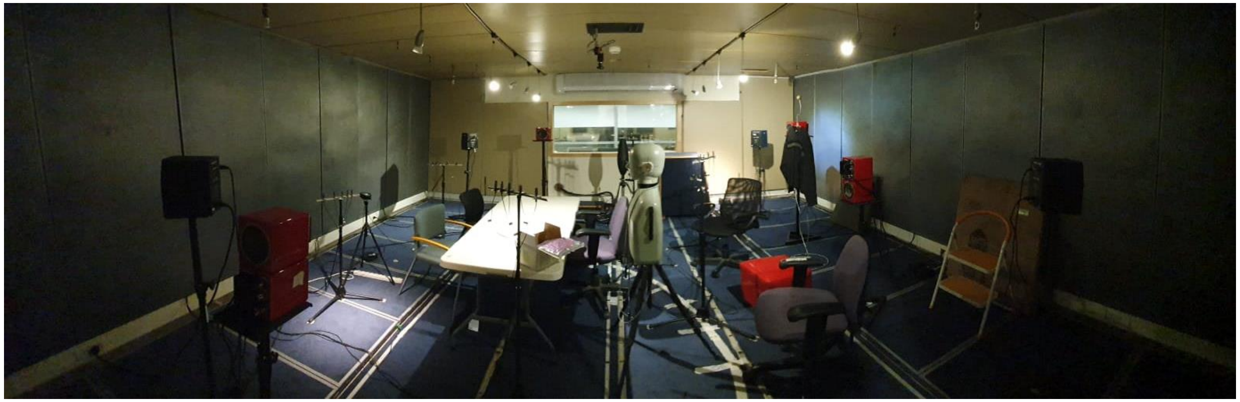

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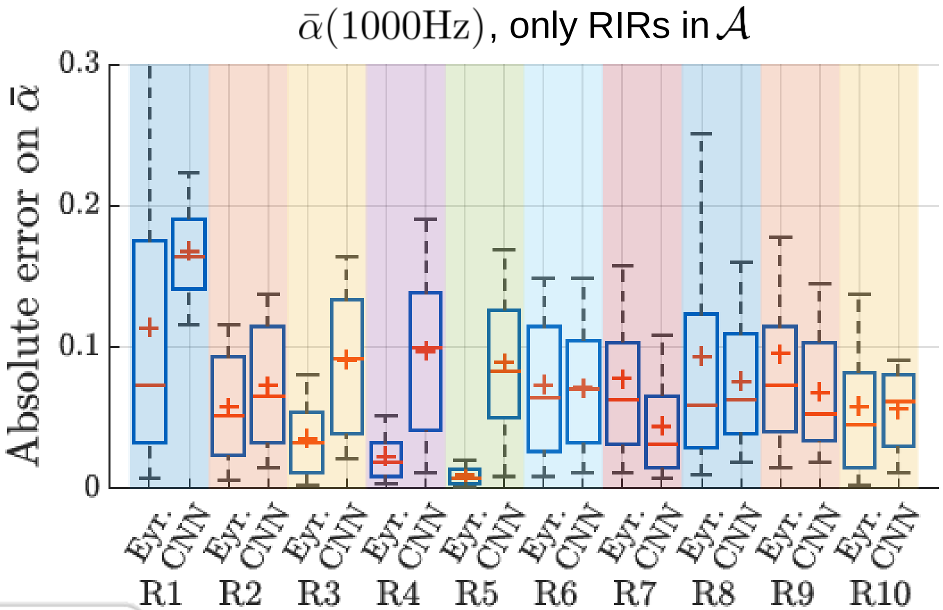


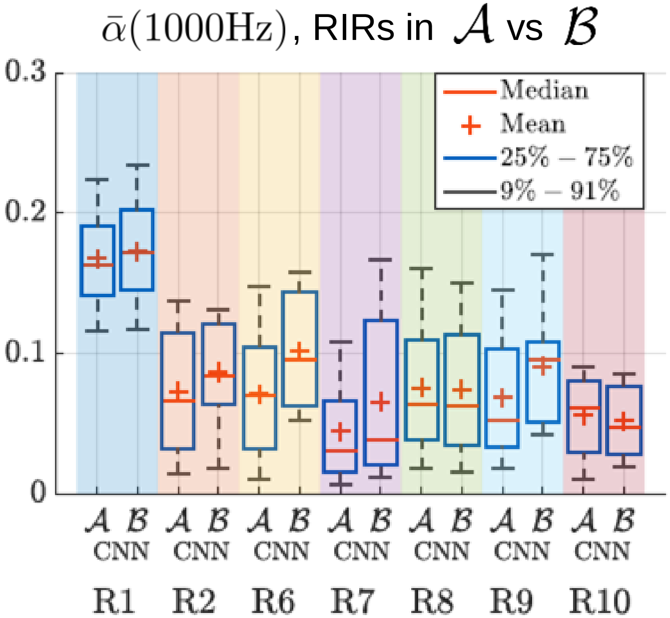

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- Two microphones
- Nearest surface is most reflective
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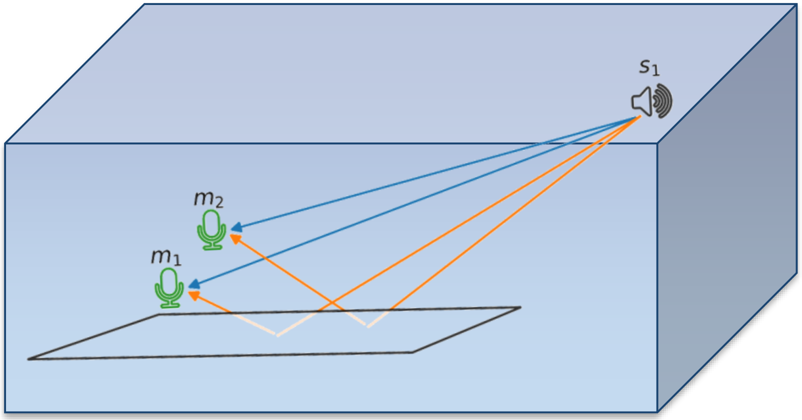

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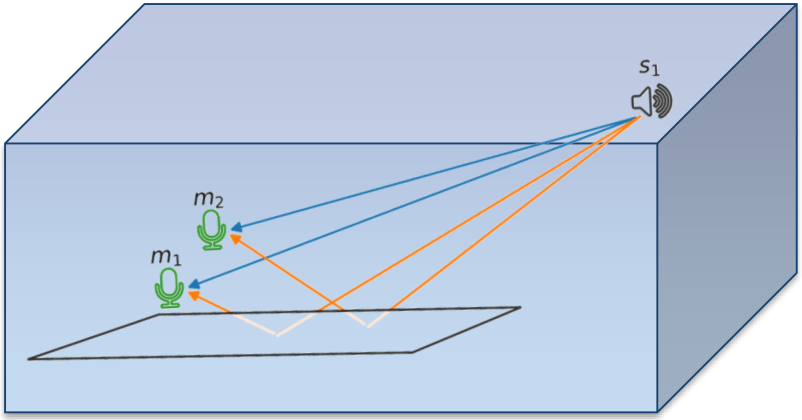


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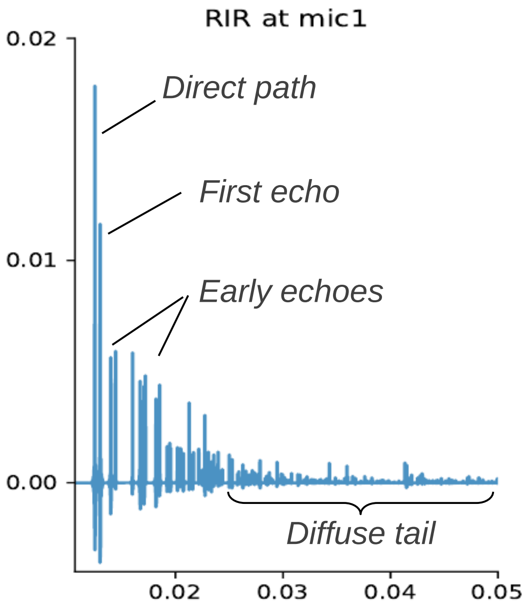

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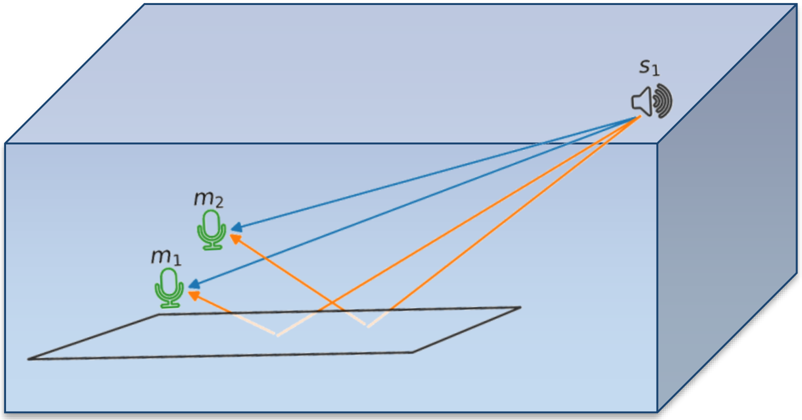


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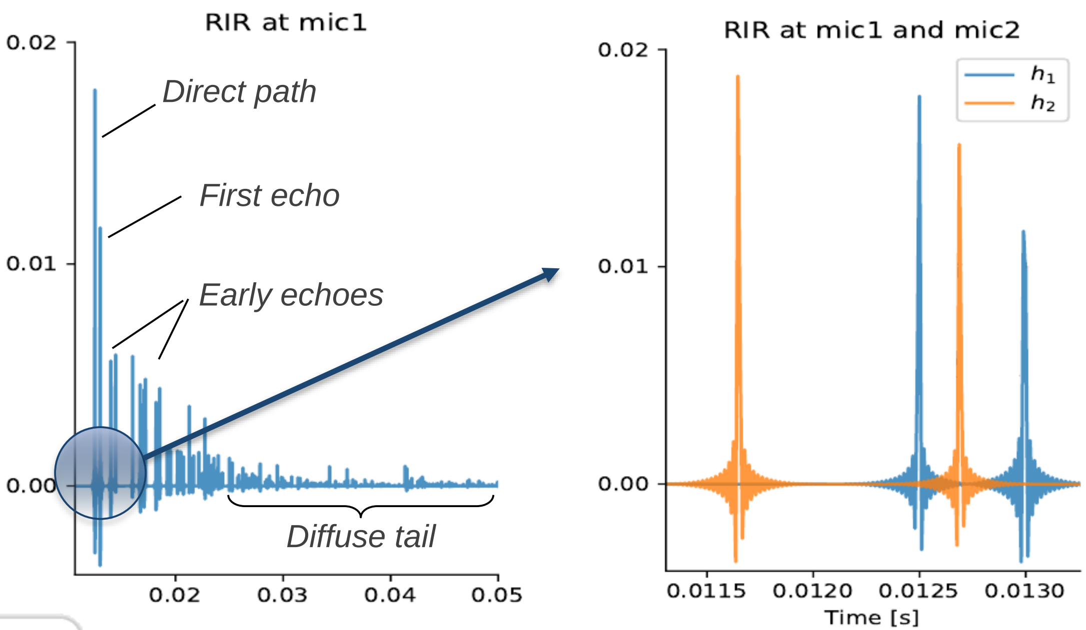


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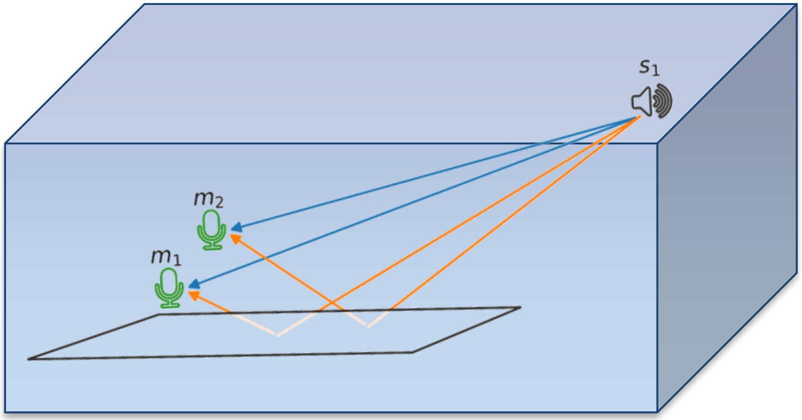


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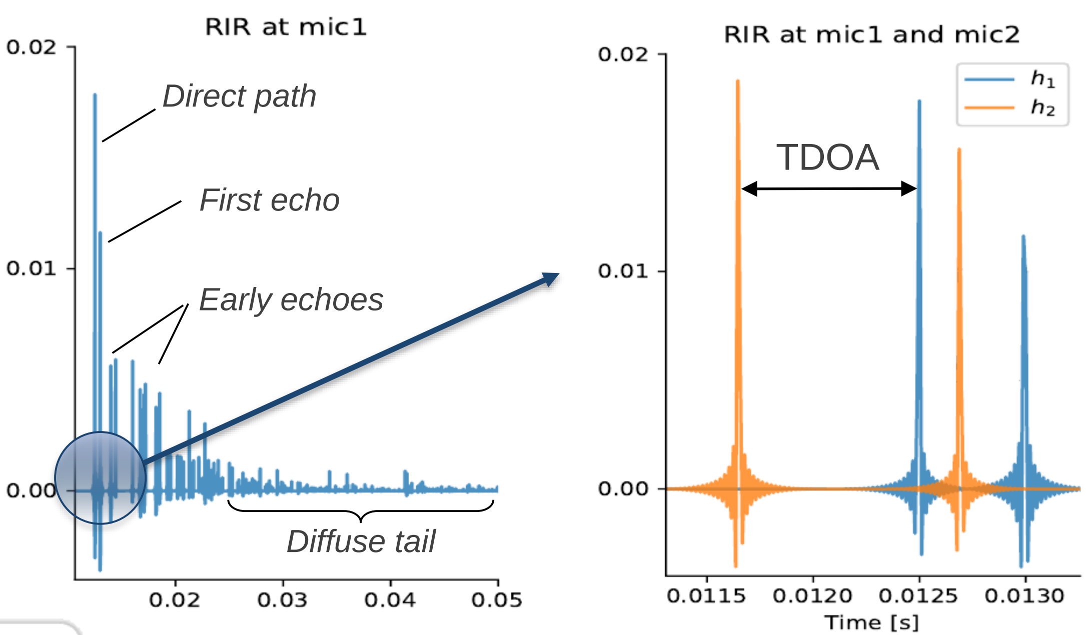

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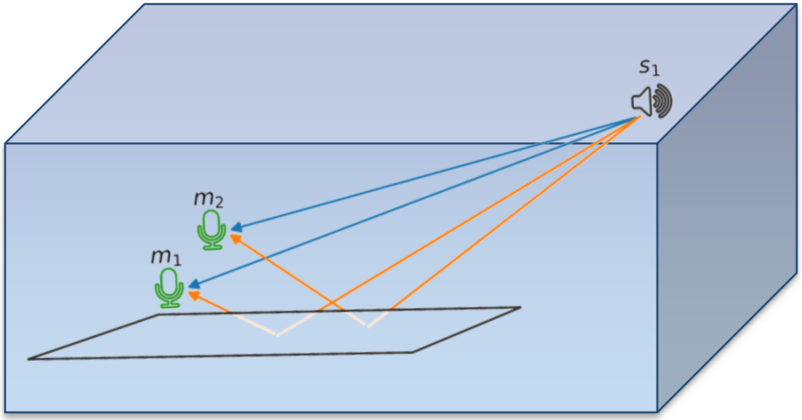


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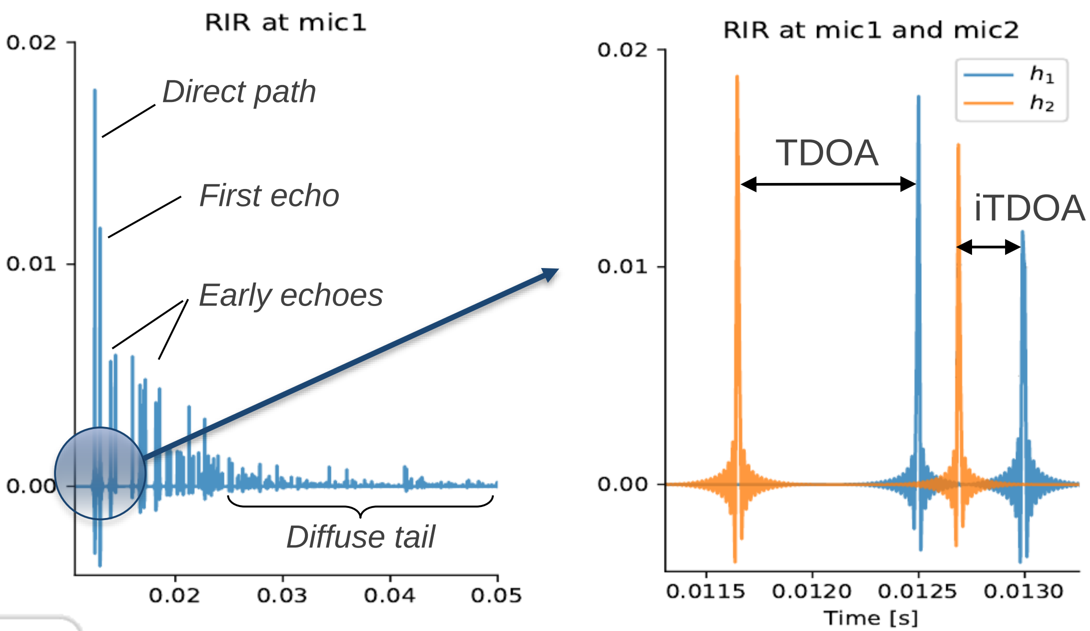

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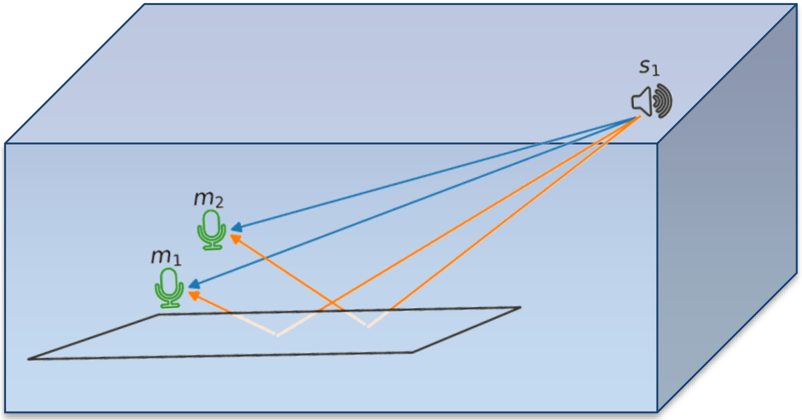


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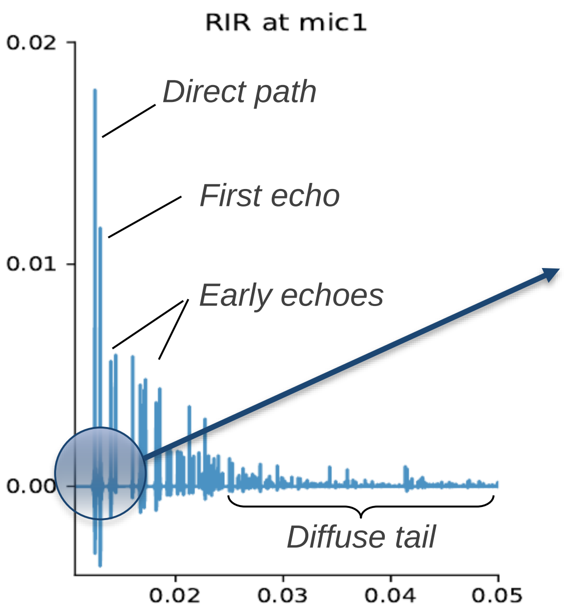


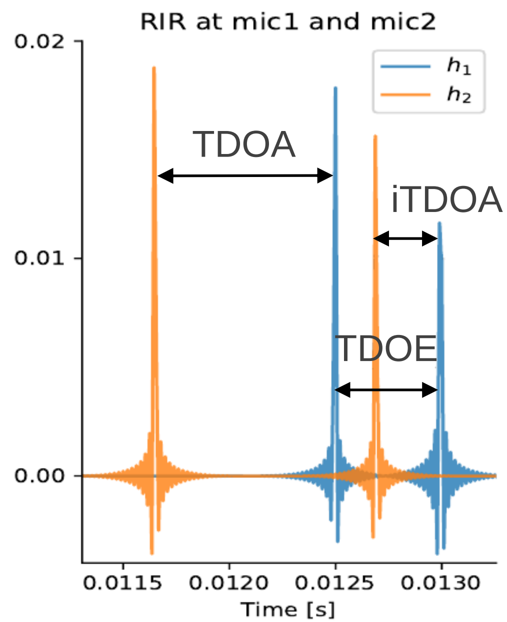

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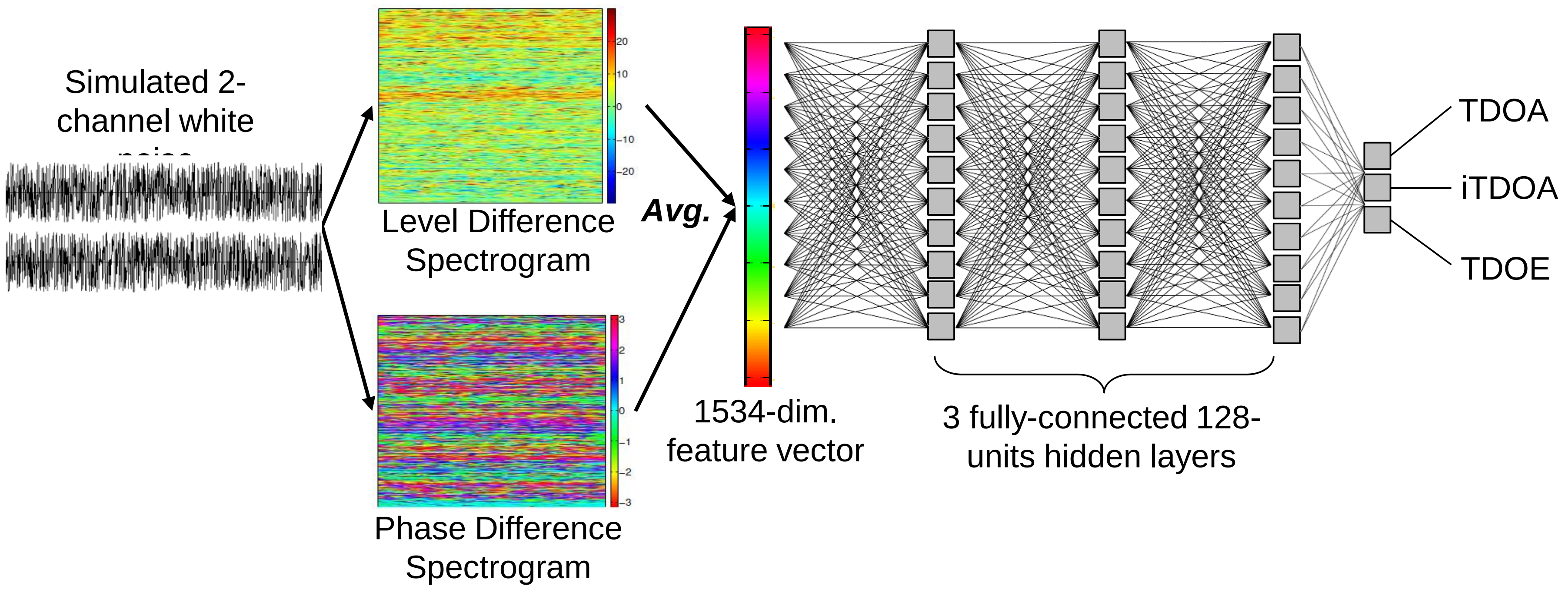

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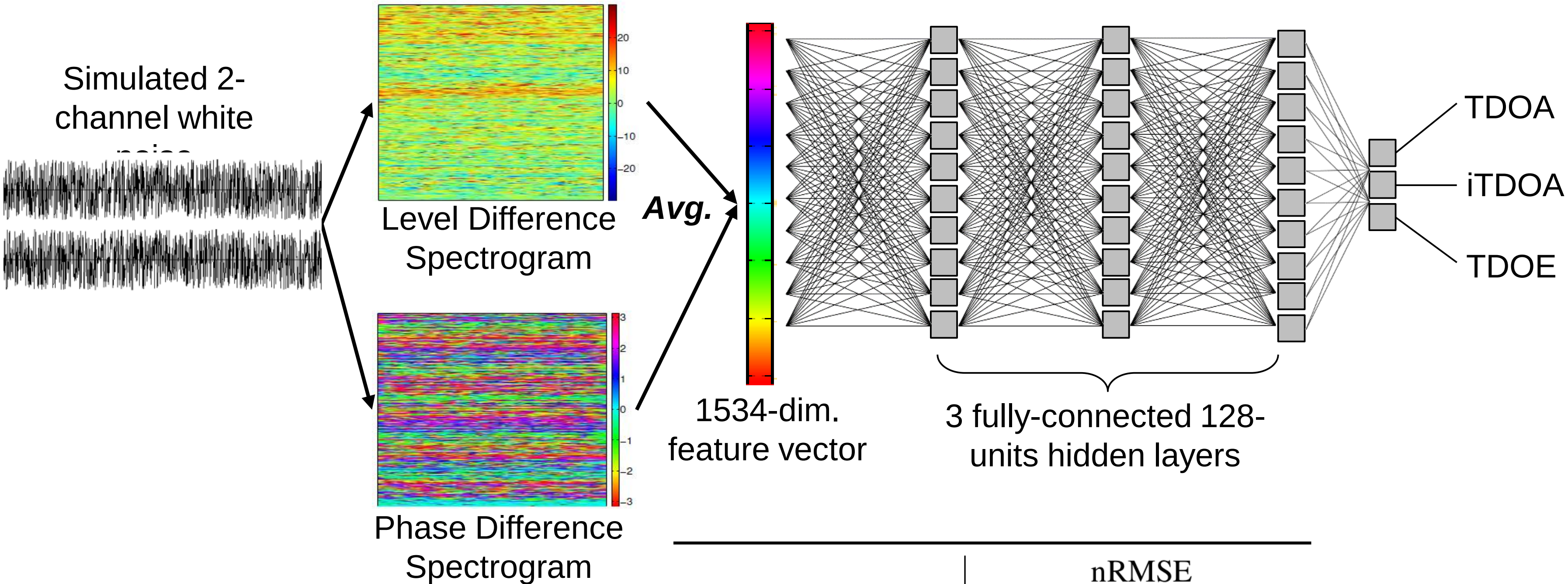


## Results on test set

| | Input | nRMSE TDOA | nRMSE iTDOA | nRMSE TDOE |
|---|---|---|---|---|
| MIRAGE | wn | 0.18 | 0.28 | 0.25 |
| MIRAGE | wn+n | 0.68 | 0.69 | 0.89 |
| MIRAGE | sp | 0.31 | 0.34 | 0.56 |
| MIRAGE | sp+n | 0.99 | 0.98 | 1.48 |
| GCC-PHAT | wn | 0.21 | - | - |
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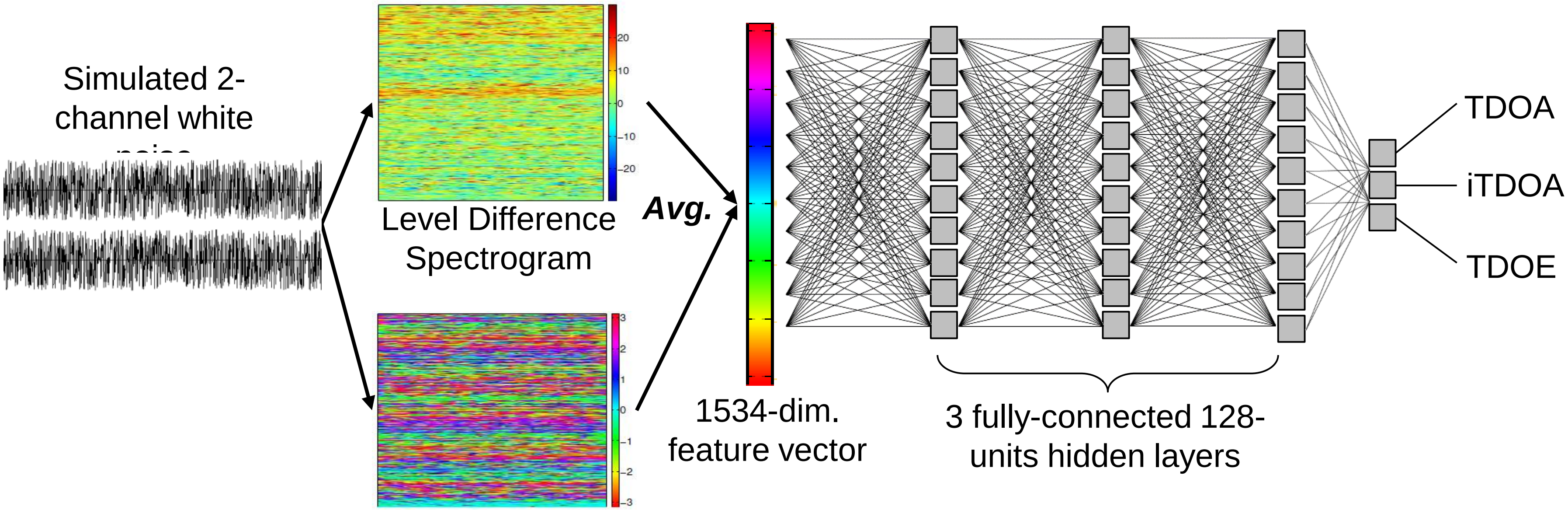


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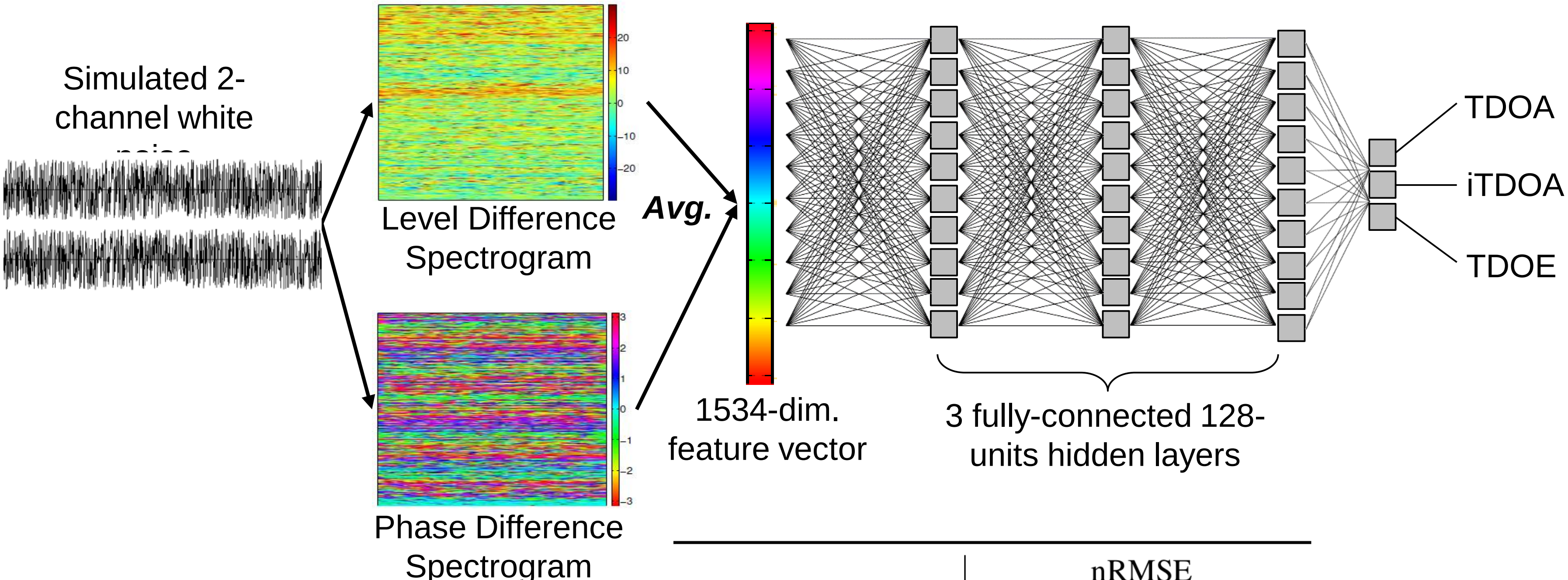


# Results on test set

- ✓ Good results with white noise
- ☒ Poor generalization to noisy speech and real data

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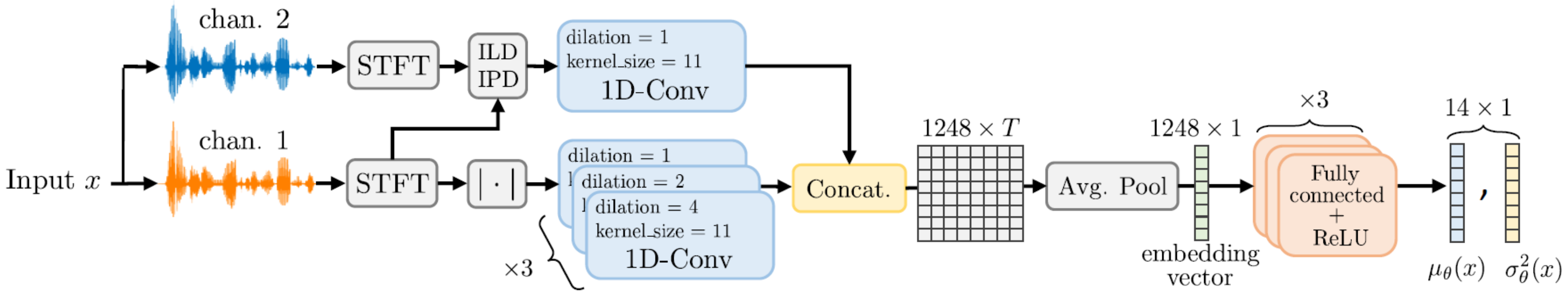

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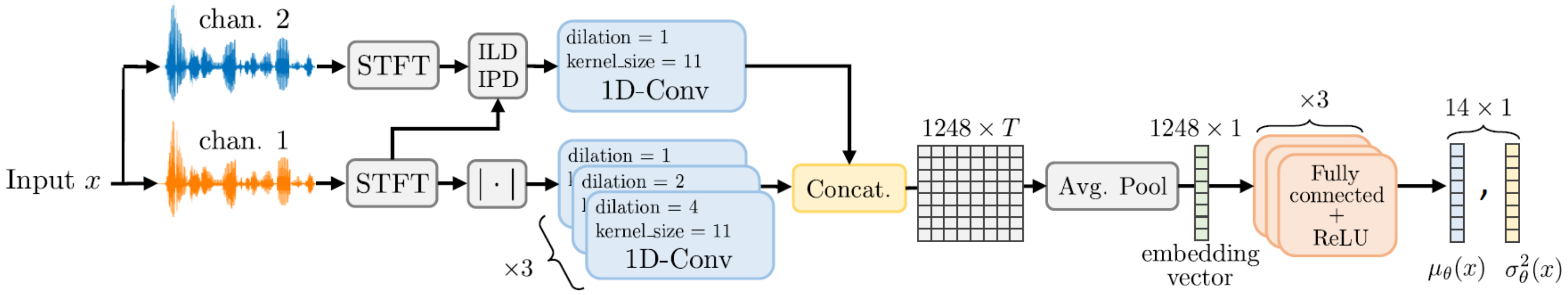


- A maximum-likelihood cost-function: $\mathcal{L}_\theta(\boldsymbol{x},\boldsymbol{y}) = -\log p_\theta(\boldsymbol{y}|\boldsymbol{x}) = -\log \mathcal{N}(\boldsymbol{y};\boldsymbol{\mu}_\theta(\boldsymbol{x}),\boldsymbol{\sigma}^2_\theta(\boldsymbol{x}))$

$$\stackrel{c}{=} \frac{1}{2}\sum_{d=1}^{D} \log \sigma^2_{d,\theta}(\boldsymbol{x}) + \frac{(y_d - \mu_{d,\theta}(\boldsymbol{x}))^2}{\sigma^2_{d,\theta}(\boldsymbol{x})}$$

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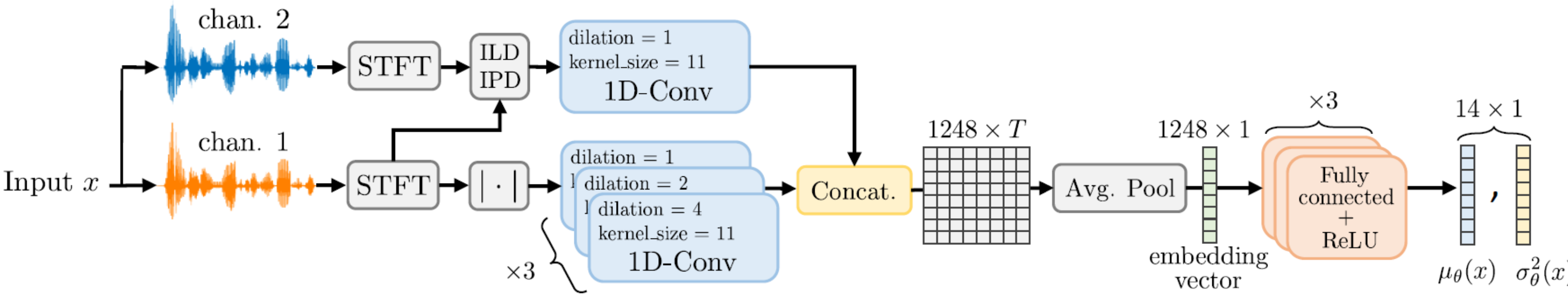


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- Allows aggreting multiple source-receiver recordings via Bayes' theorem:

$$\boxed{p_\theta(y_d|\bar{\boldsymbol{x}} = [\boldsymbol{x}_1,\dots,\boldsymbol{x}_J]) = \mathcal{N}(y_d;\bar{\mu}_{d,\theta}(\bar{\boldsymbol{x}}), 1/\bar{\gamma}^2_{d,\theta}(\bar{\boldsymbol{x}}))} \quad \bar{\mu}_{d,\theta}(\bar{\boldsymbol{x}}) = \sum_{j=1}^{J} \frac{\gamma^2_{d,\theta}(\boldsymbol{x}_j)}{\bar{\gamma}^2_{d,\theta}(\bar{\boldsymbol{x}})}\mu_{d,\theta}(\boldsymbol{x}_j),\ \bar{\gamma}^2_{d,\theta}(\bar{\boldsymbol{x}}) = \sum_{j=1}^{J}\gamma^2_{d,\theta}(\boldsymbol{x}_j)$$

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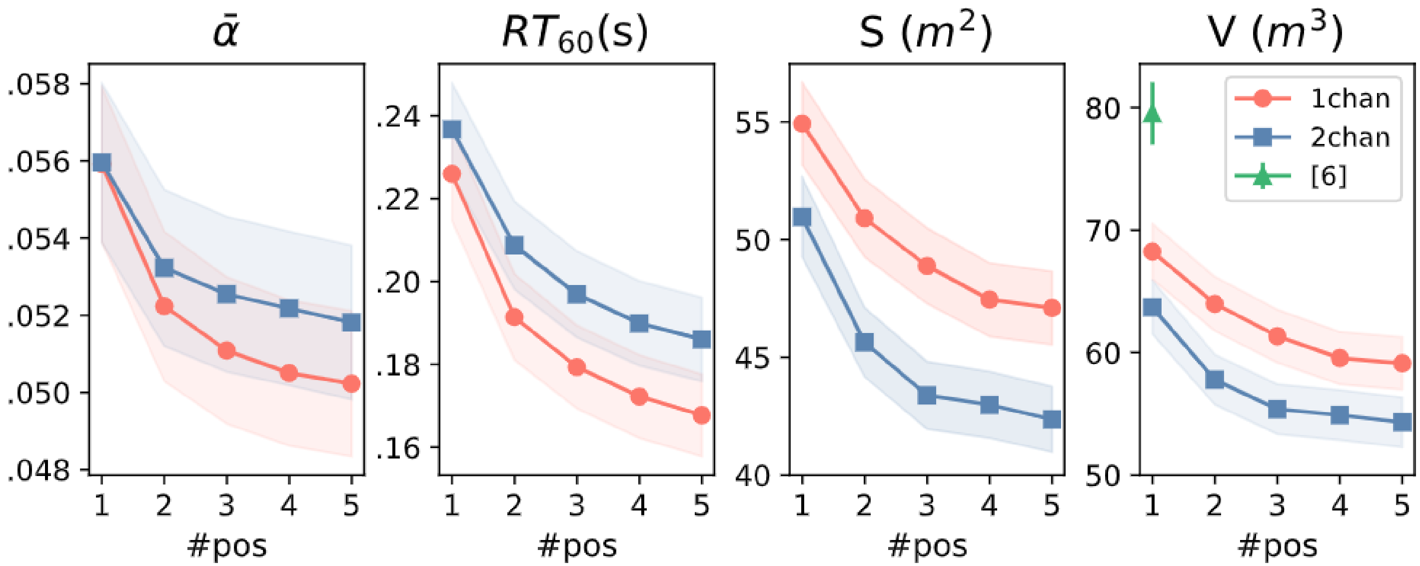


| Method | Features | # pos | $\bar{\alpha}$ | $RT_{60}$ | $S$ | $V$ |
|---|---|---|---|---|---|---|
| [6] | SC | 1 | - | - | - | 137.8 |
| Ours | SC | 1 | **0.061** | 0.134 | 129.6 | 154.5 |
| Ours | SC | 5 | **0.060** | 0.097 | 125.8 | 149.1 |
| Ours | SC+IC | 1 | 0.084 | 0.101 | 89.4 | 107.6 |
| Ours | SC+IC | 5 | 0.094 | **0.062** | **50.2** | **68.8** |

Mean results on 3 real rooms [12] (30 rec. per room)

- ✓ 2-channels help V and S
- ✓ Multiple observati ons help
- ☒ Poor results for mean absorption below 1000 Hz

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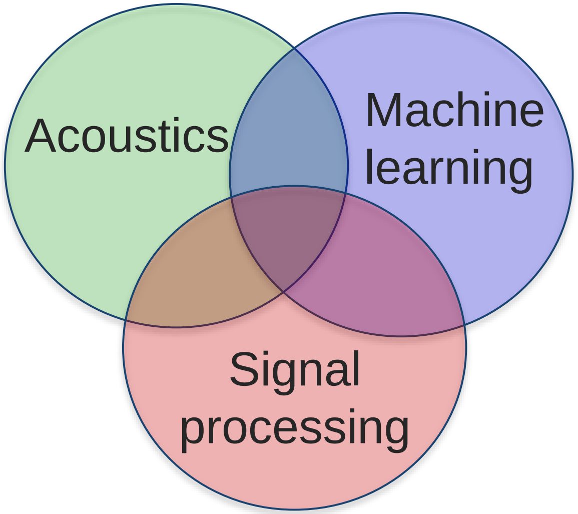

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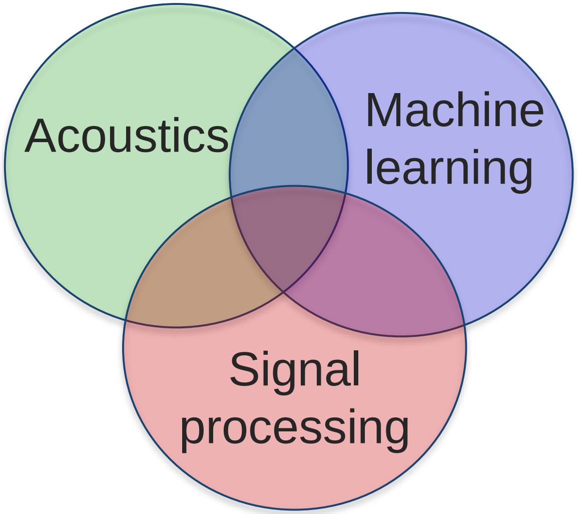

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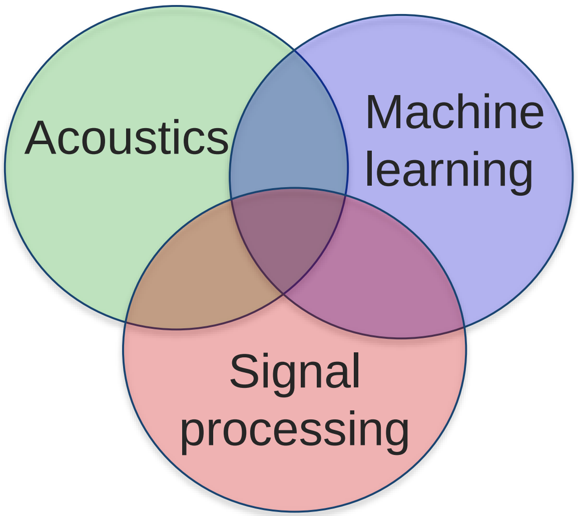

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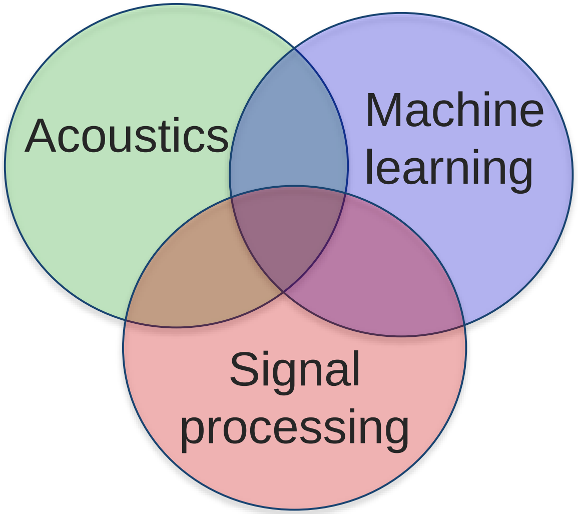


***Thank You ! Questions?***

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