Acoustic Voxels:
Computational Optimization of Modular Acoustic Filters

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David I.W. Levin — Disney Research
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COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK

Massachusetts Institute of Technology

Disney Research

What are acoustic filters?

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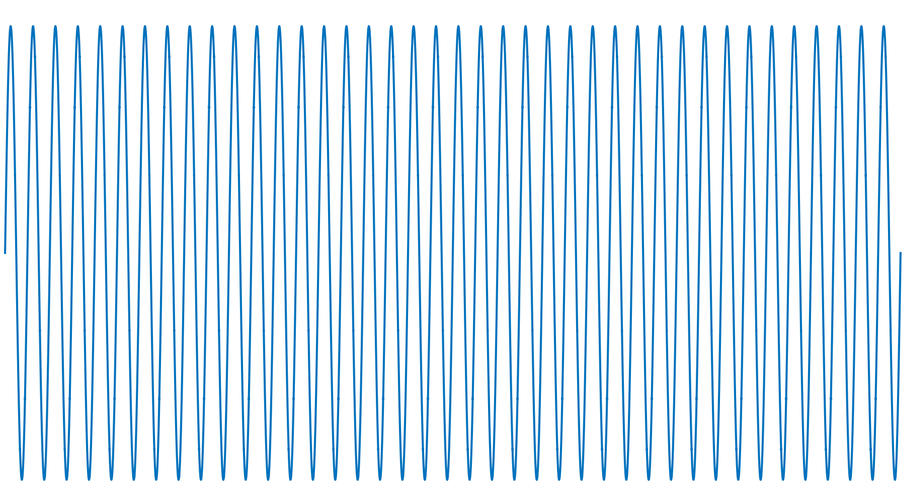

What are acoustic filters?

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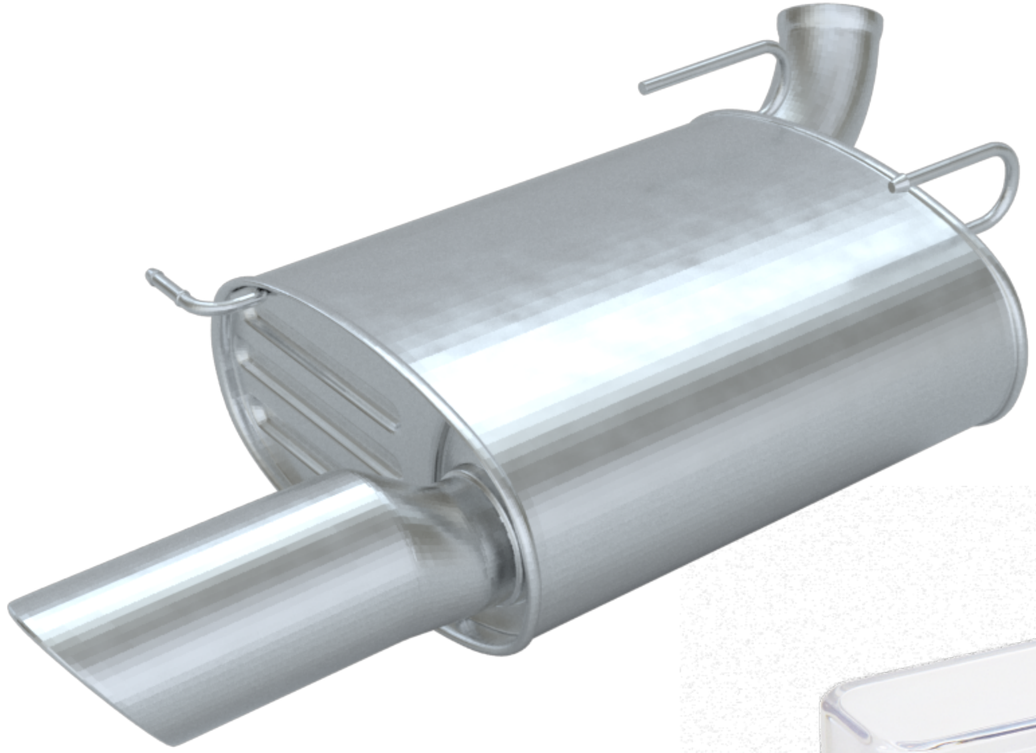

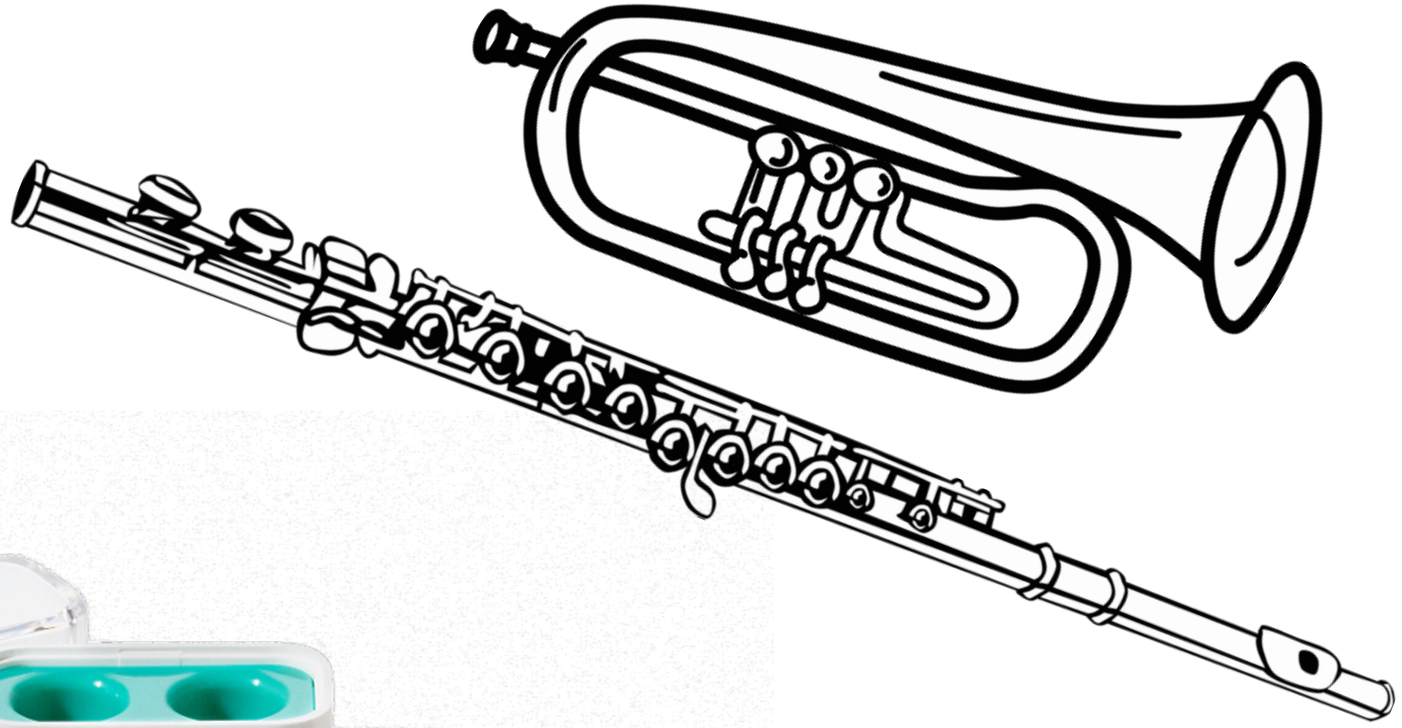

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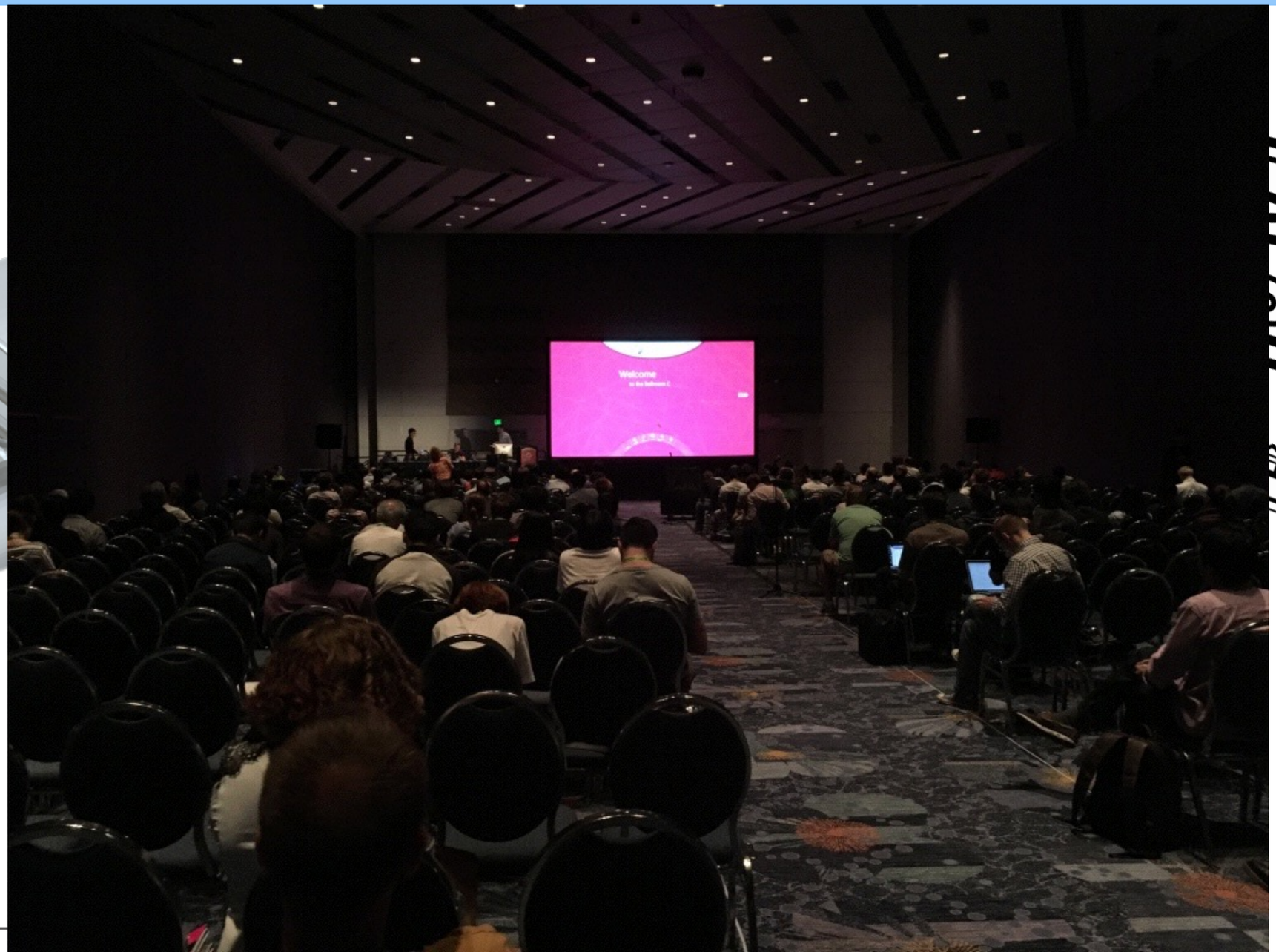
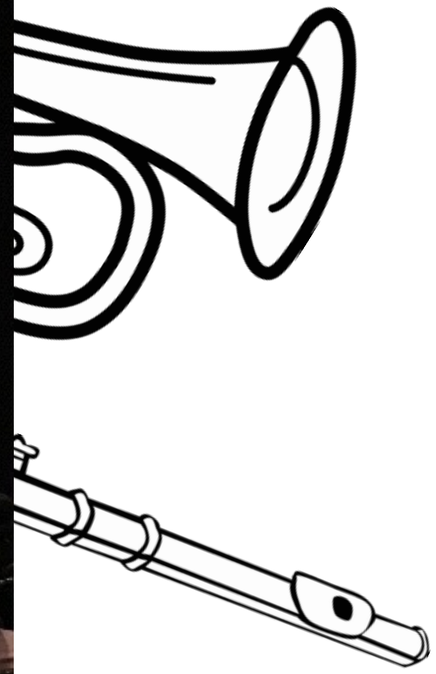
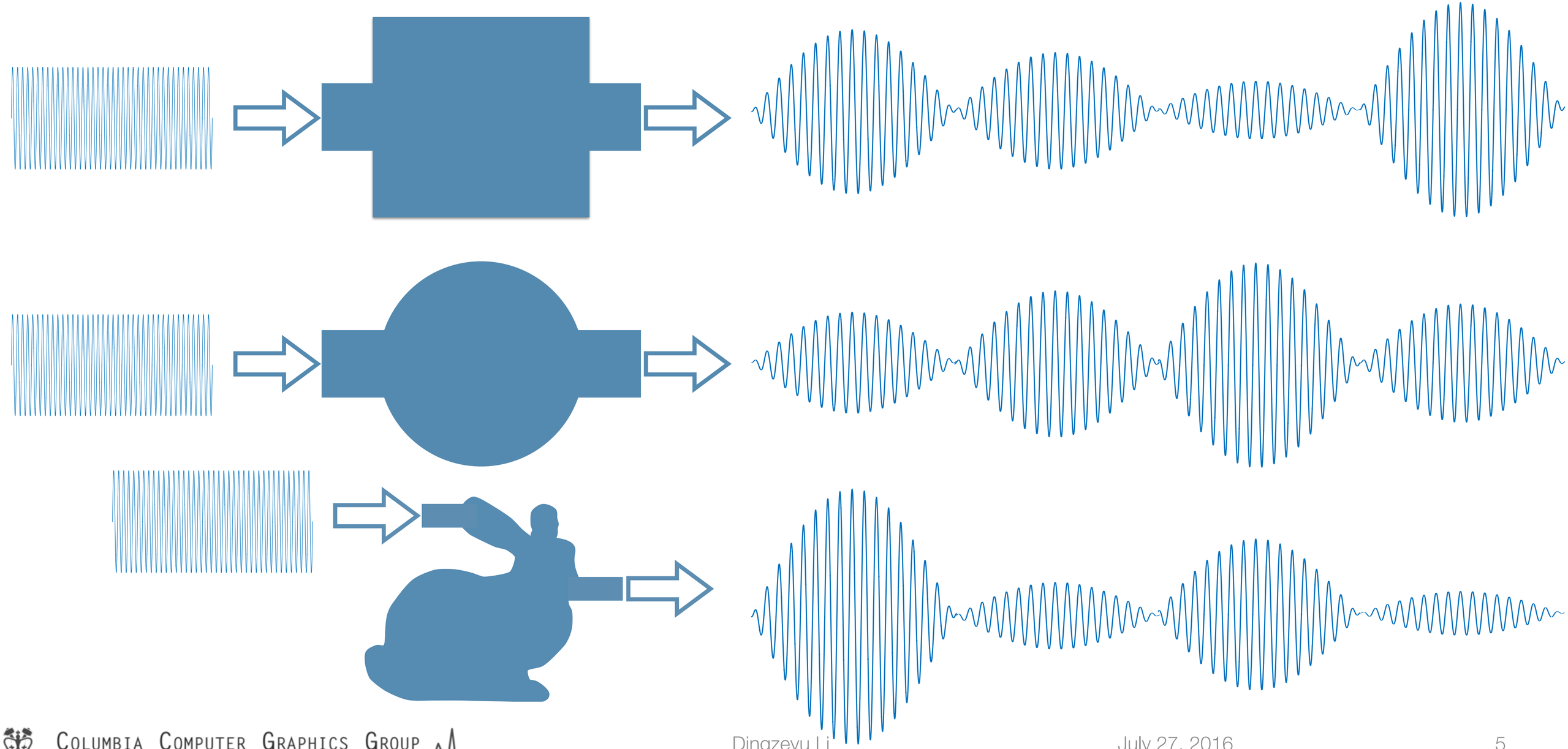
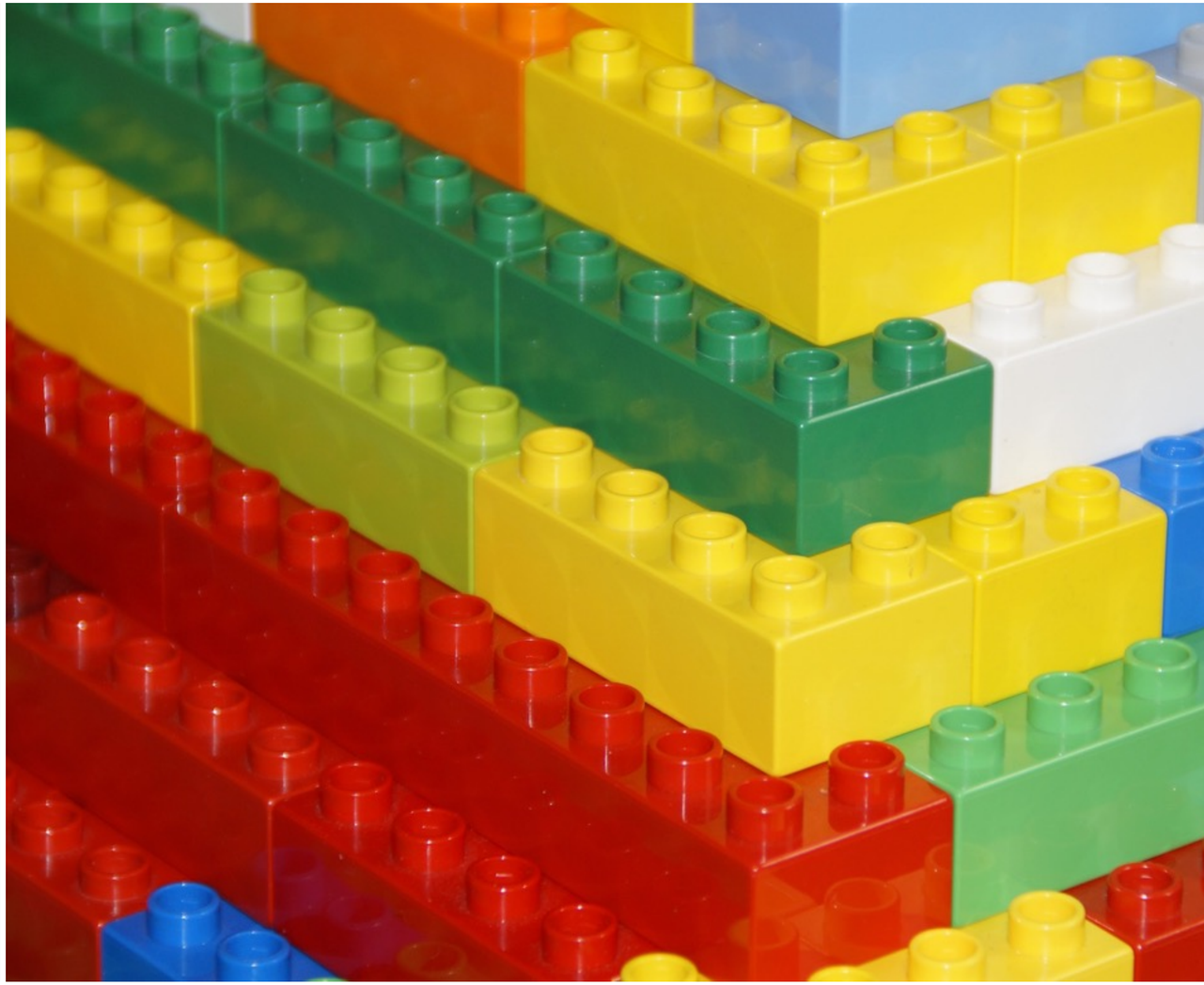




Unintuitive Acoustic Performance

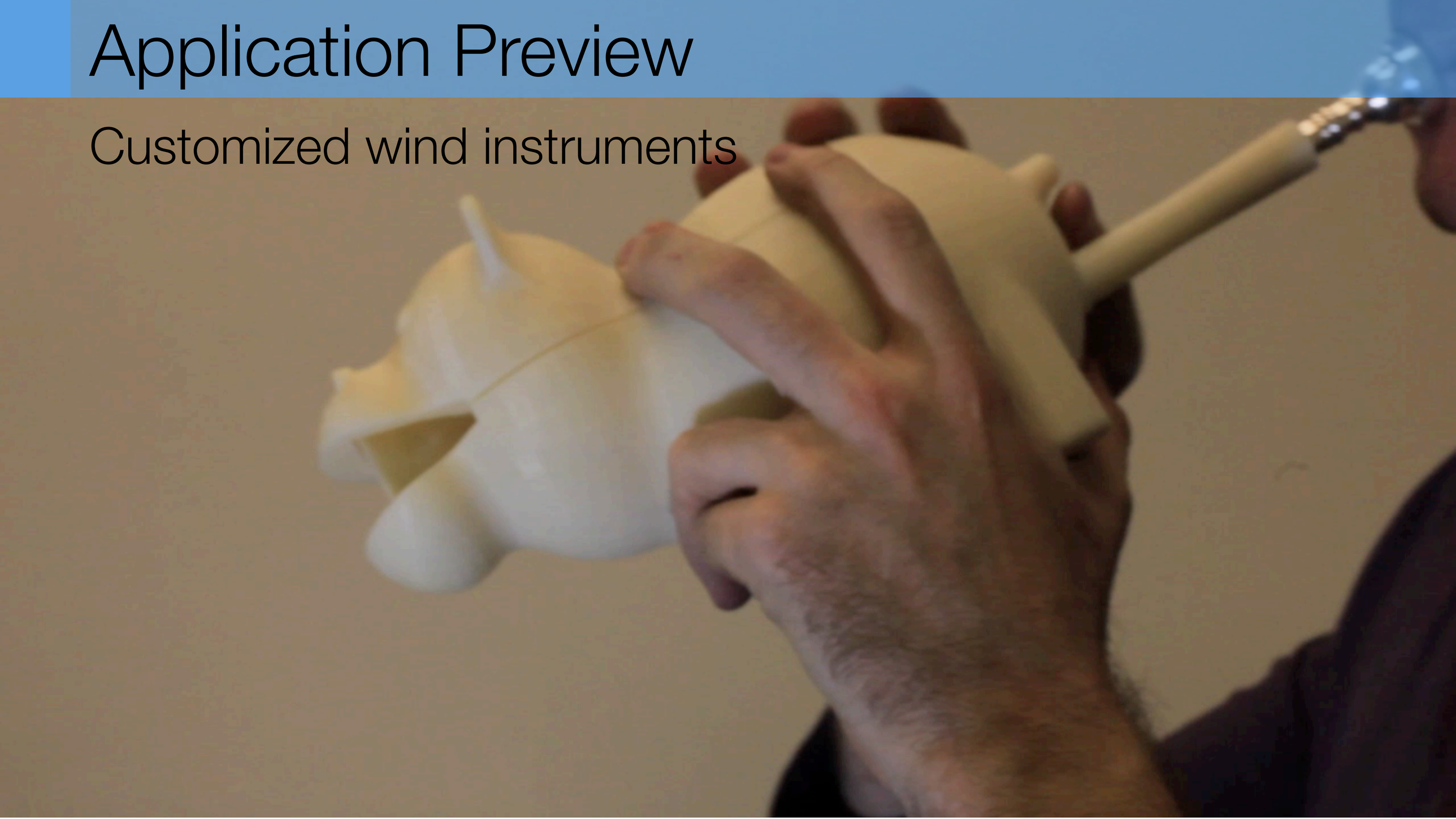


Our Approach: Modular Assembly



Application Preview

Customized wind instruments



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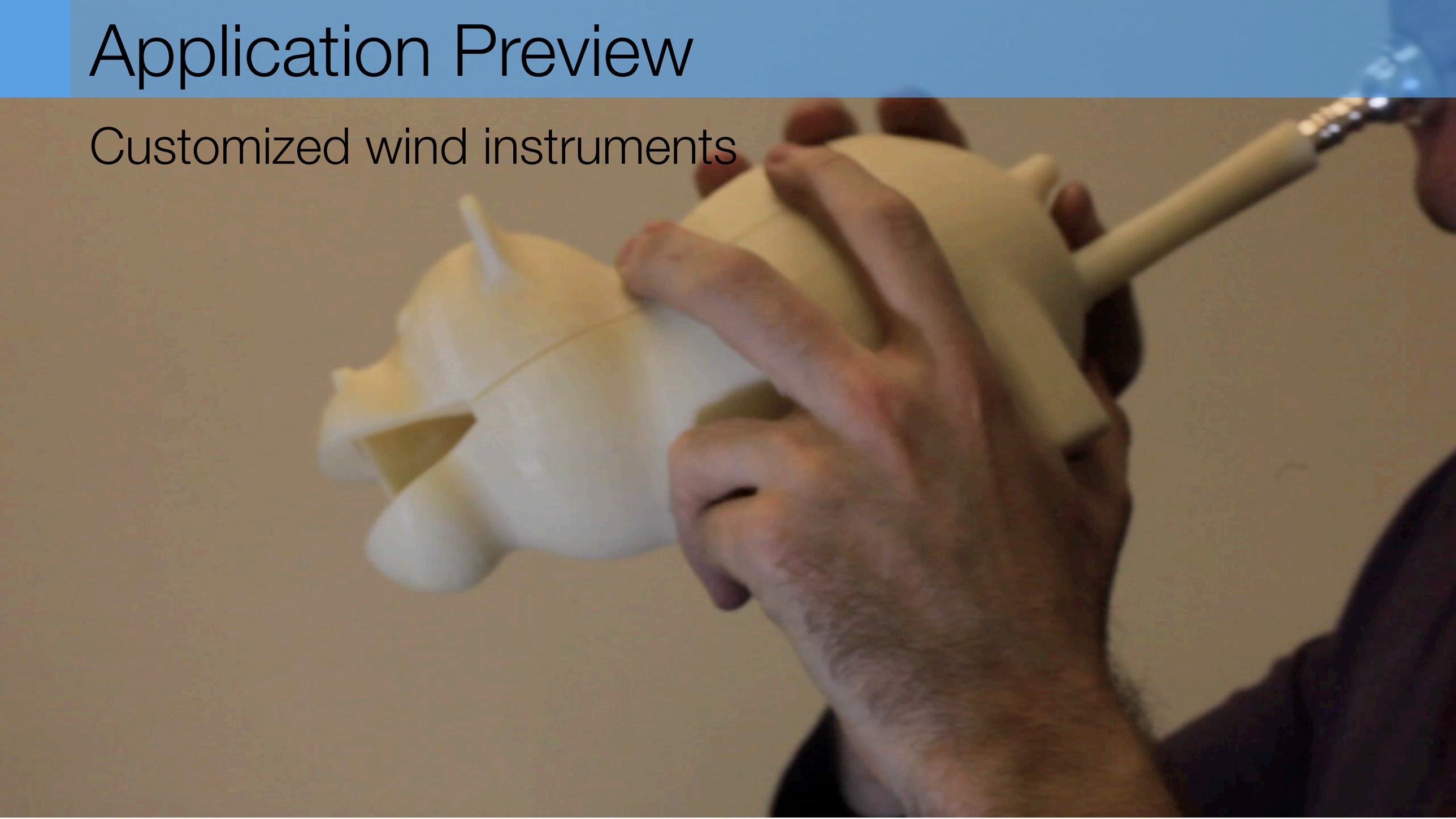
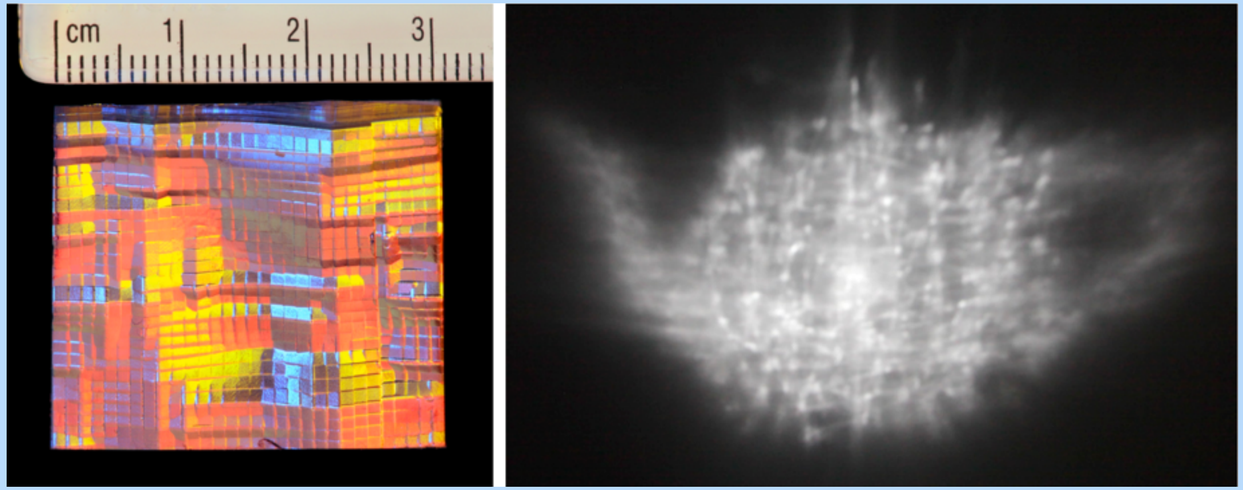


New HCI Application

Related Work - Microstructure Fabrication



[Weyrich et al. 2009]

[Hašan et al. 2010]

[Yan et al. 2015]

[Bickle et al. 2010]

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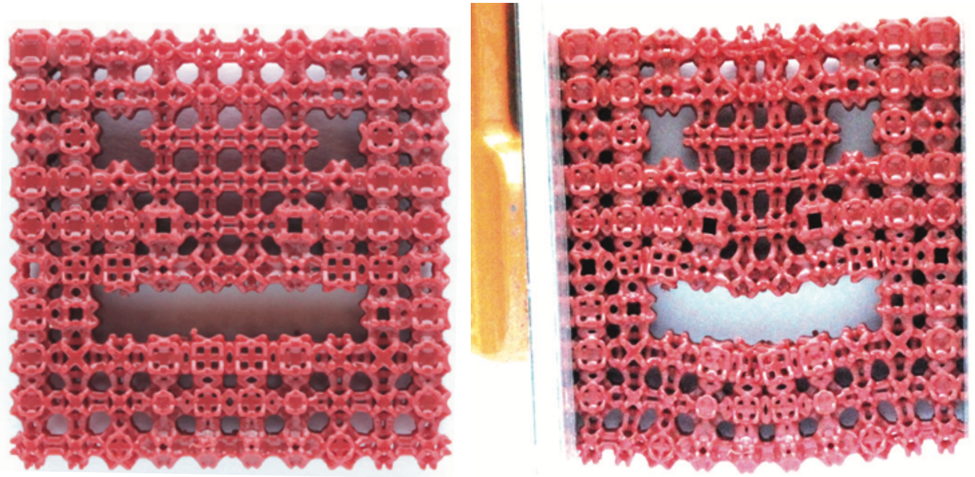

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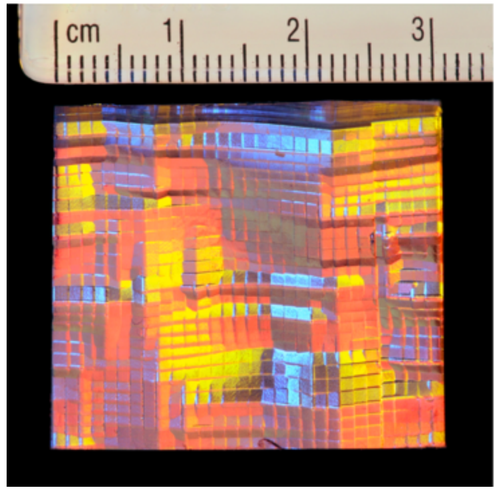

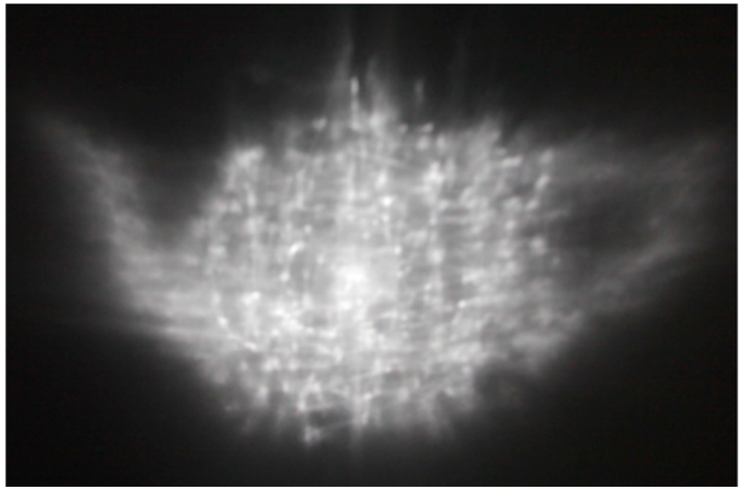

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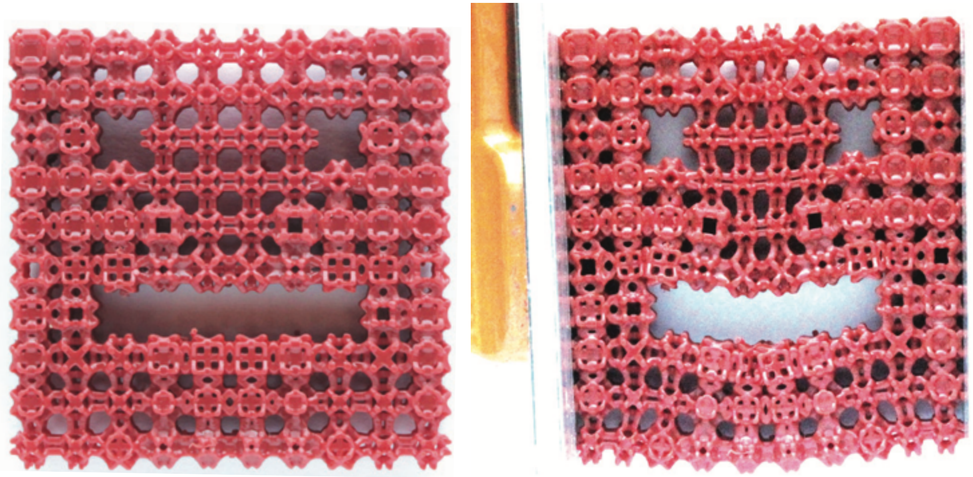

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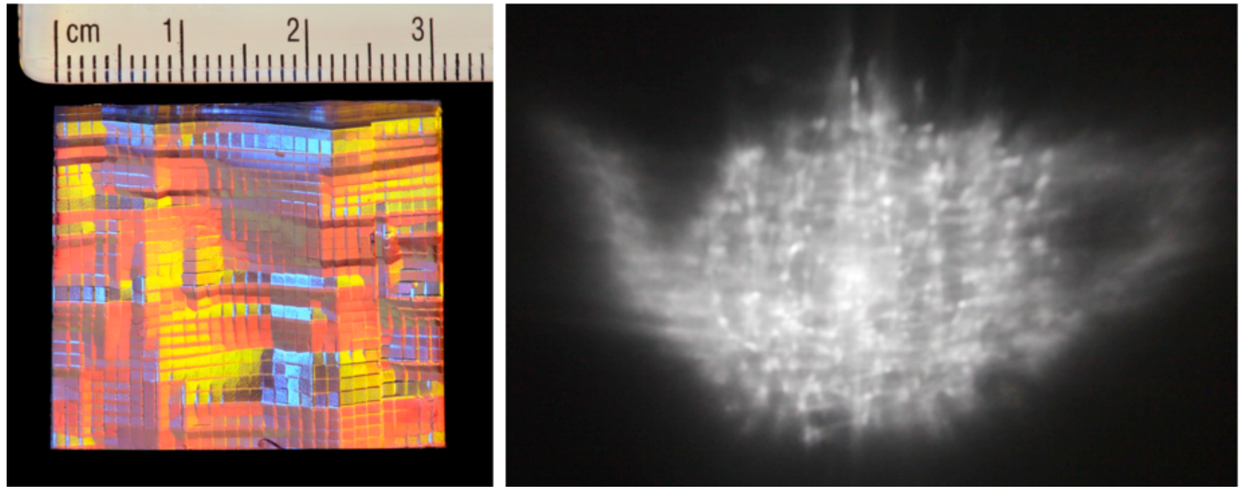

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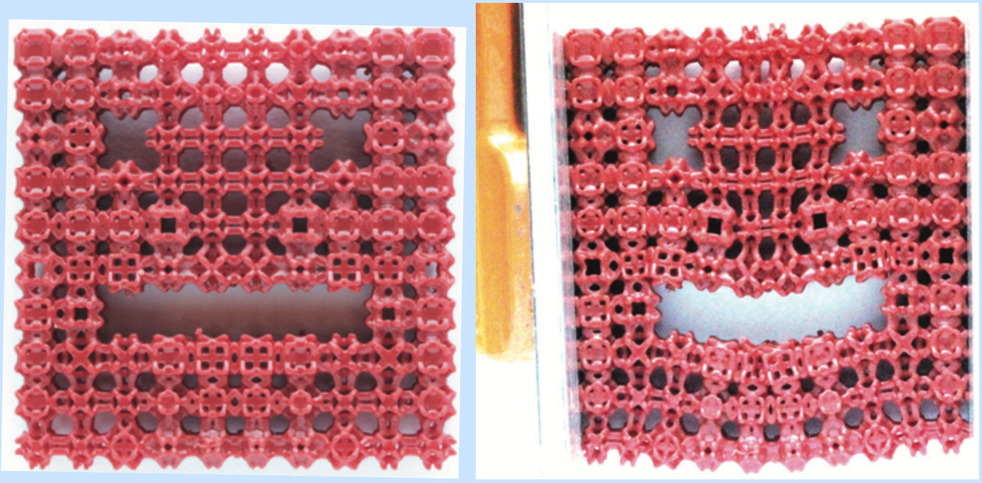

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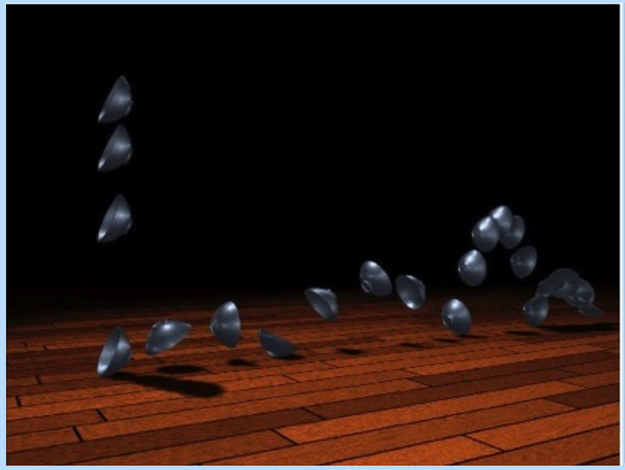

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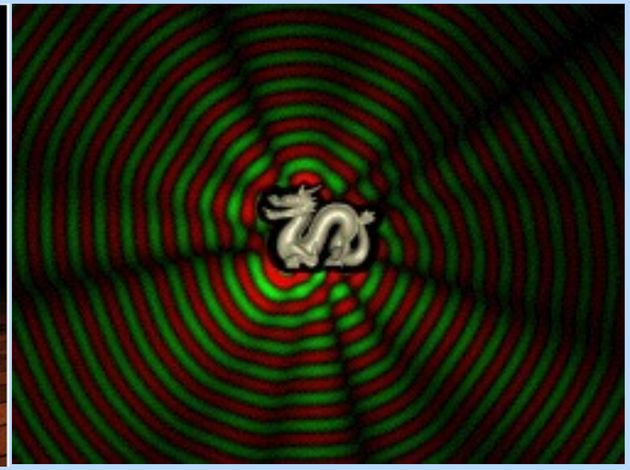

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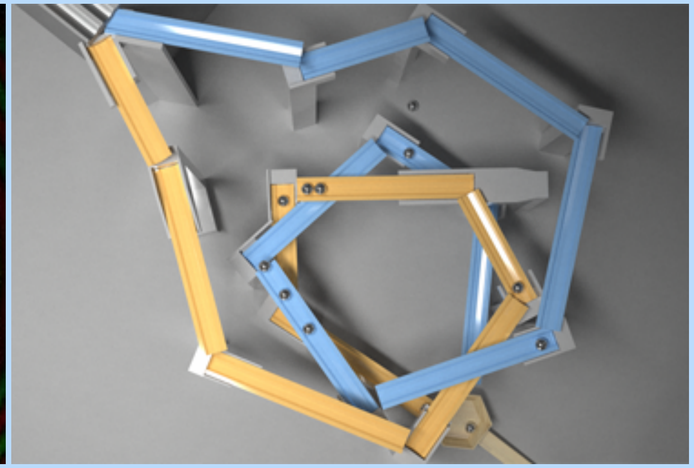

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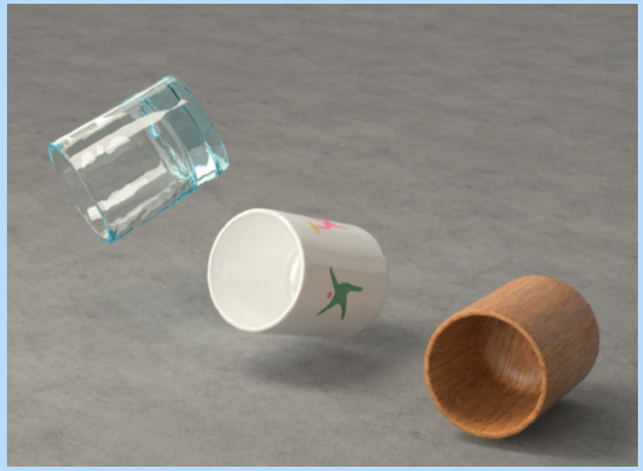

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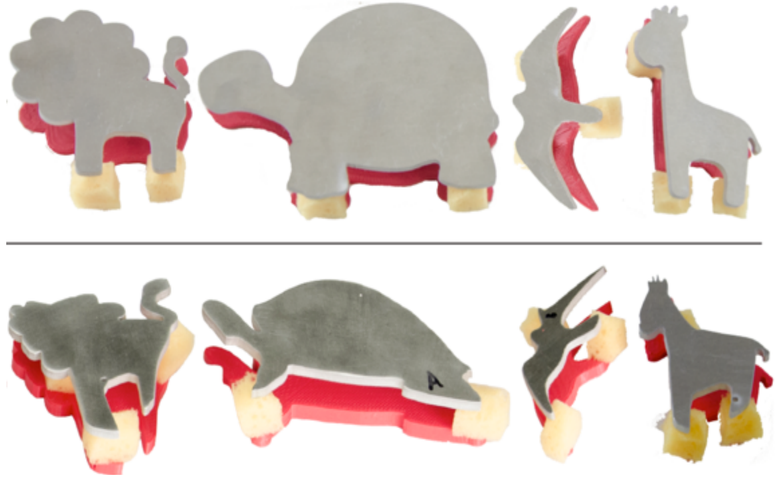

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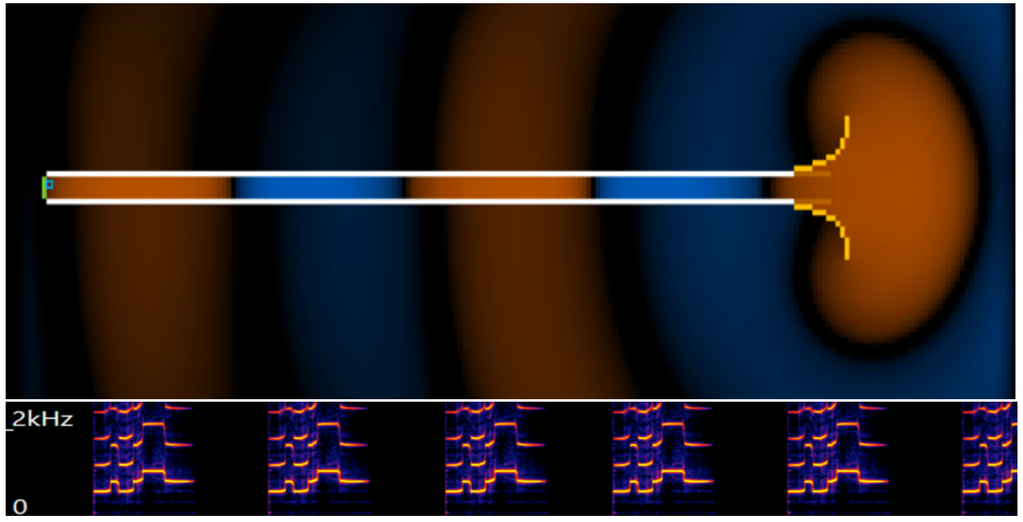

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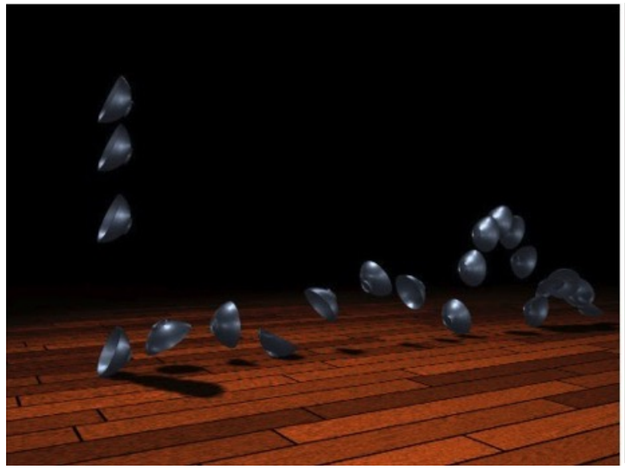

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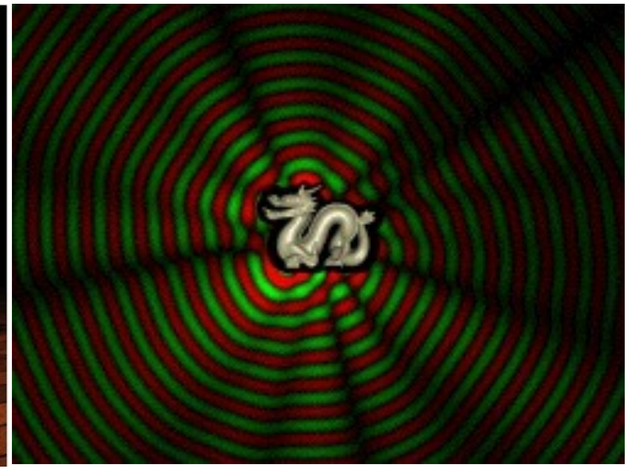

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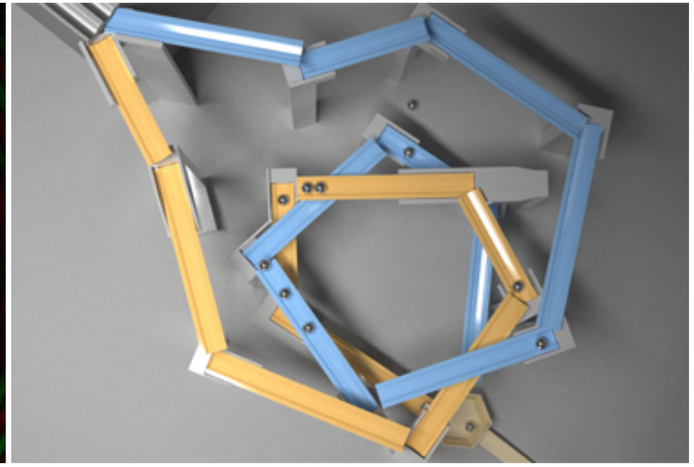

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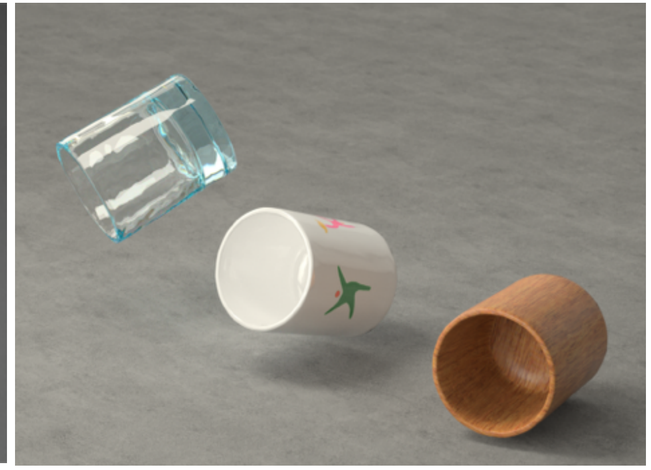

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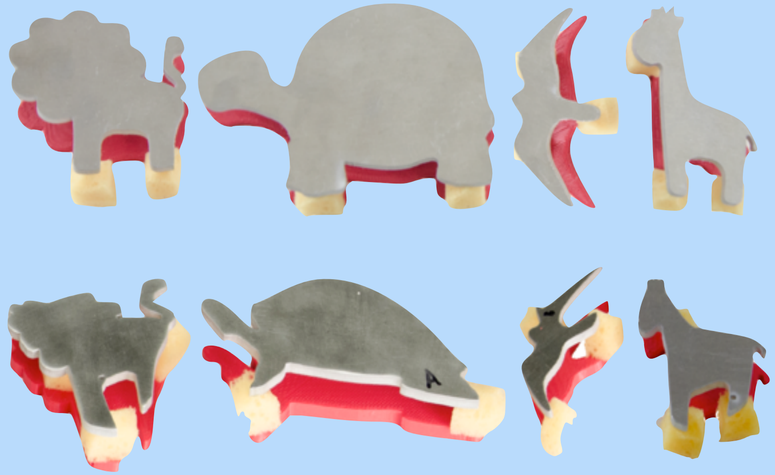

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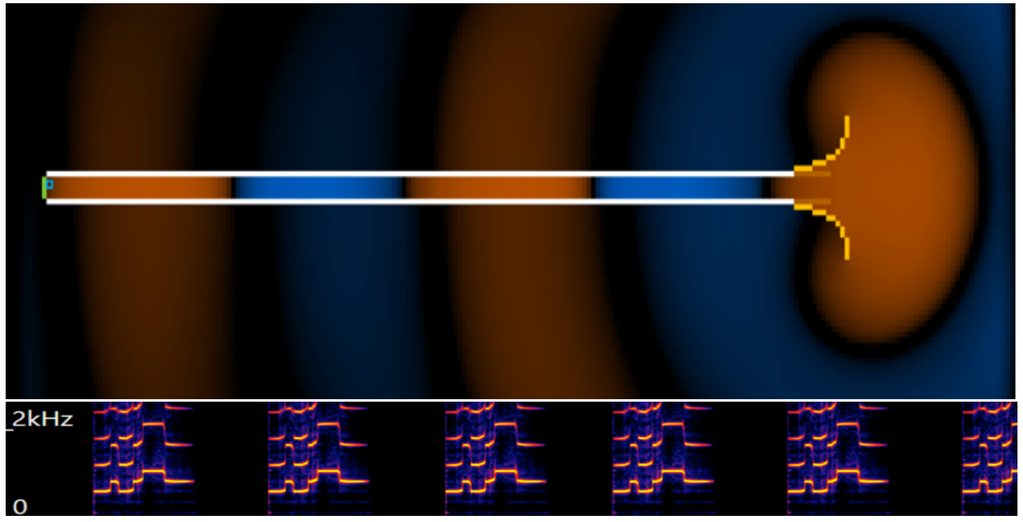

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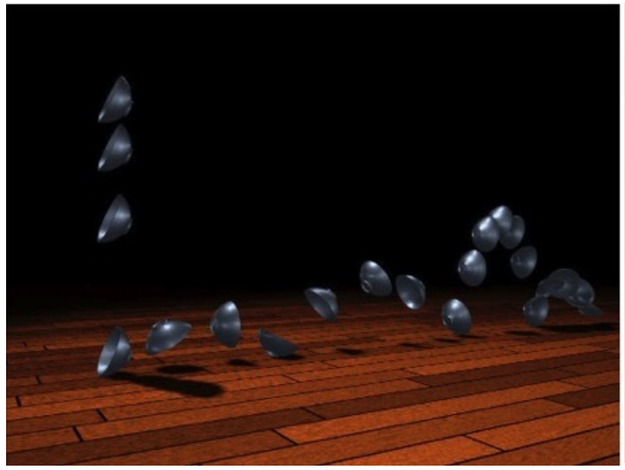

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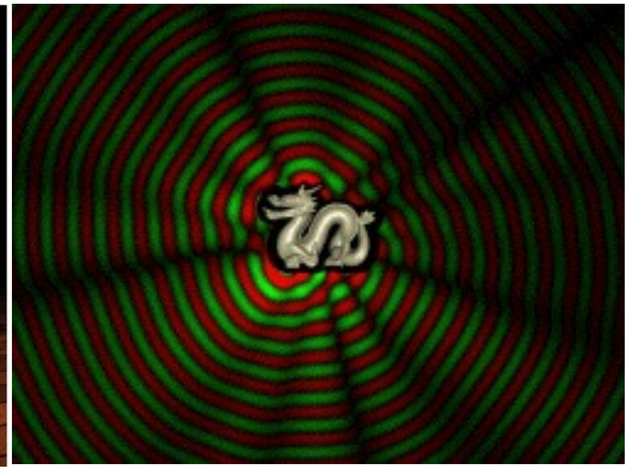

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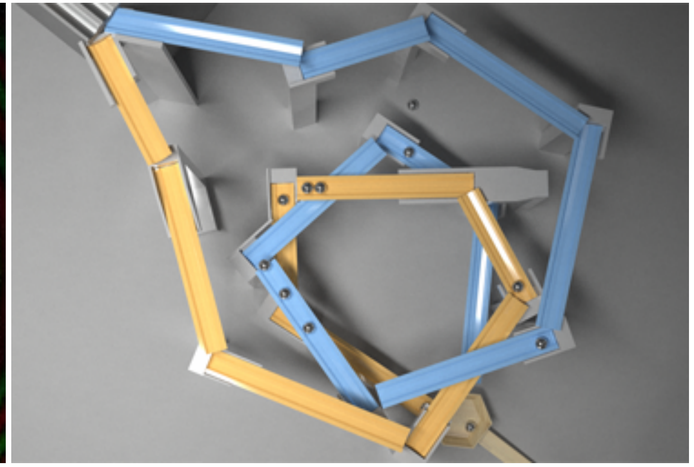

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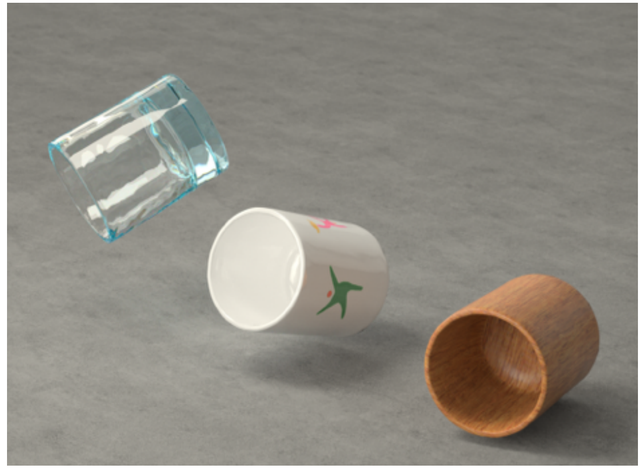

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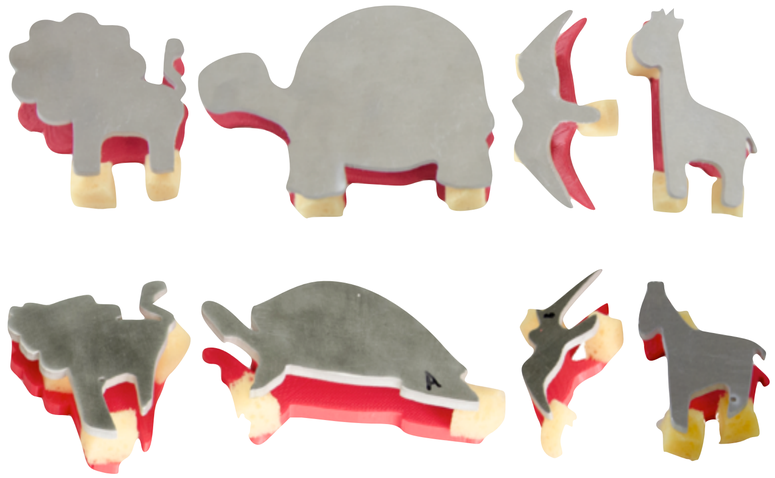

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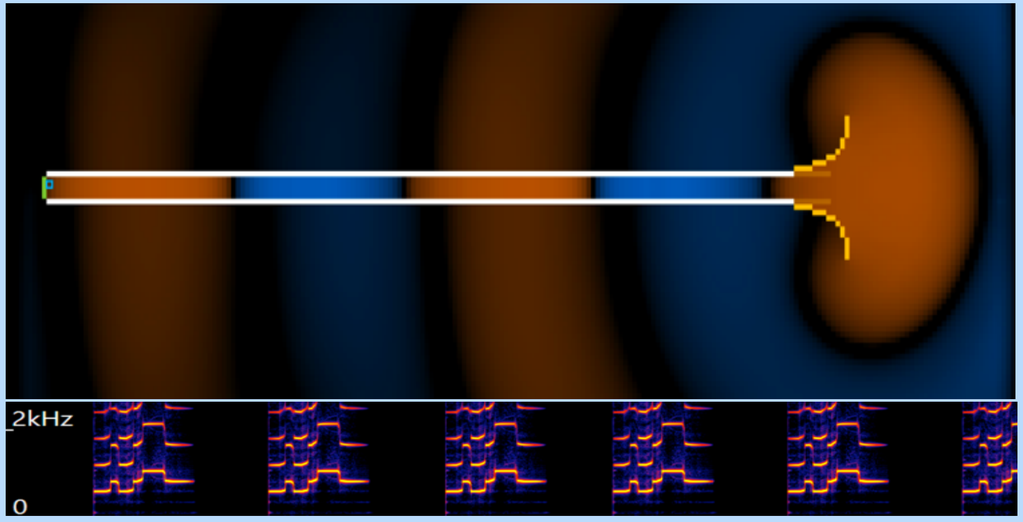

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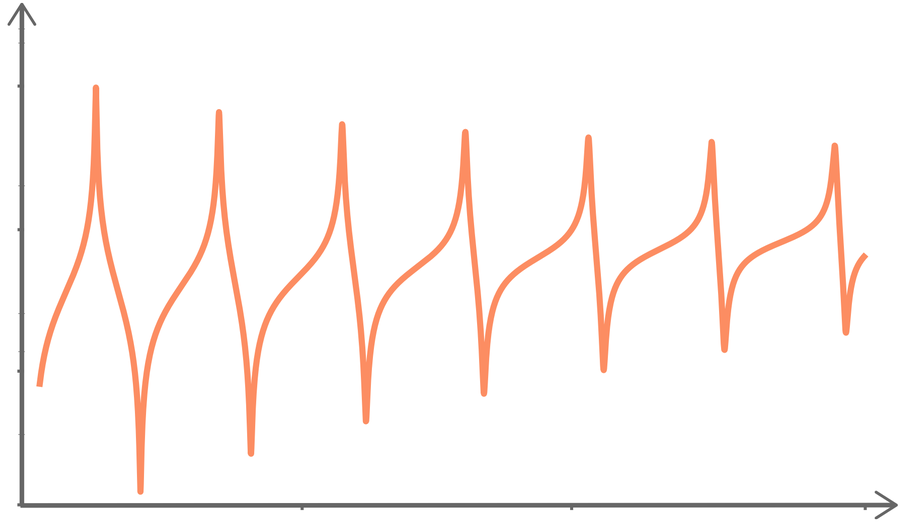
Problem Definition

Geometry

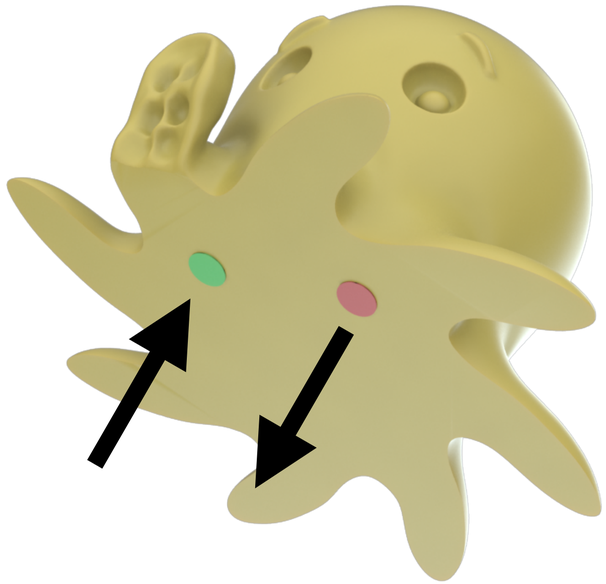
Inlet / Outlet



Target Acoustic Property

Problem Definition

Geometry



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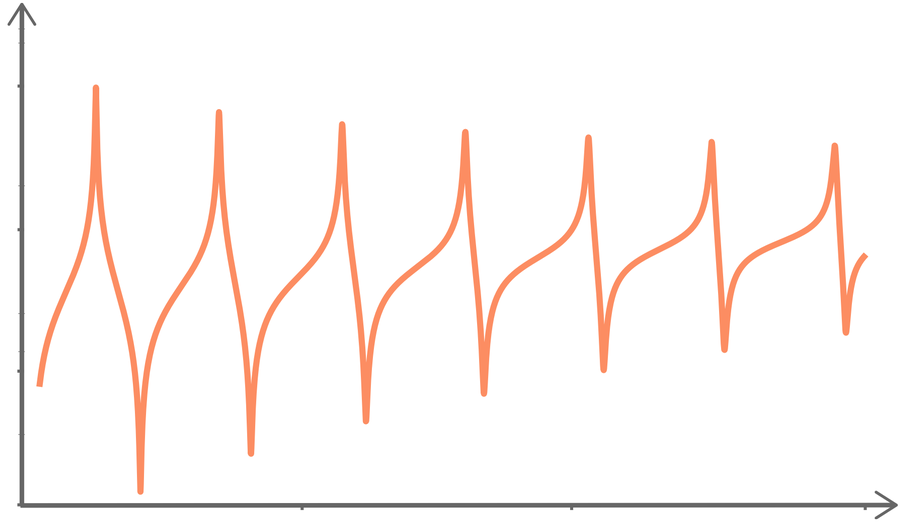

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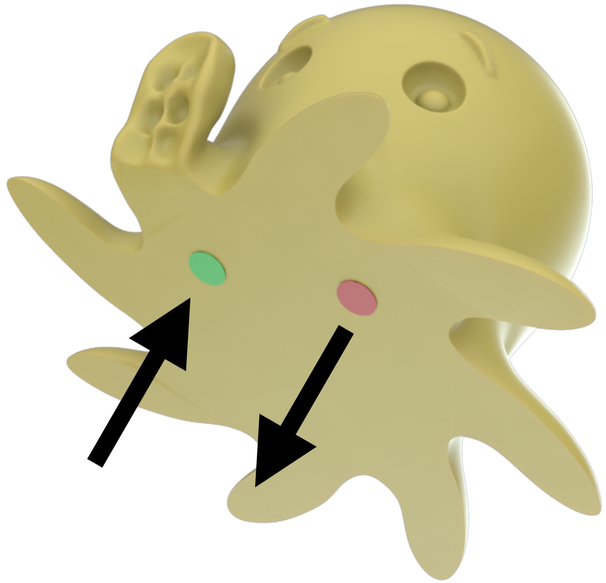

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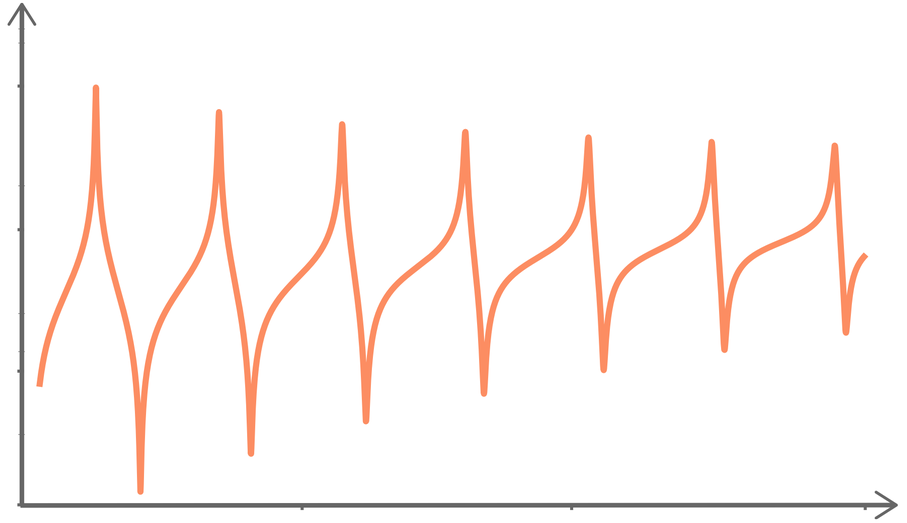


Target Acoustic Property

3D printable mesh with an internal chamber

Acoustic Metrics

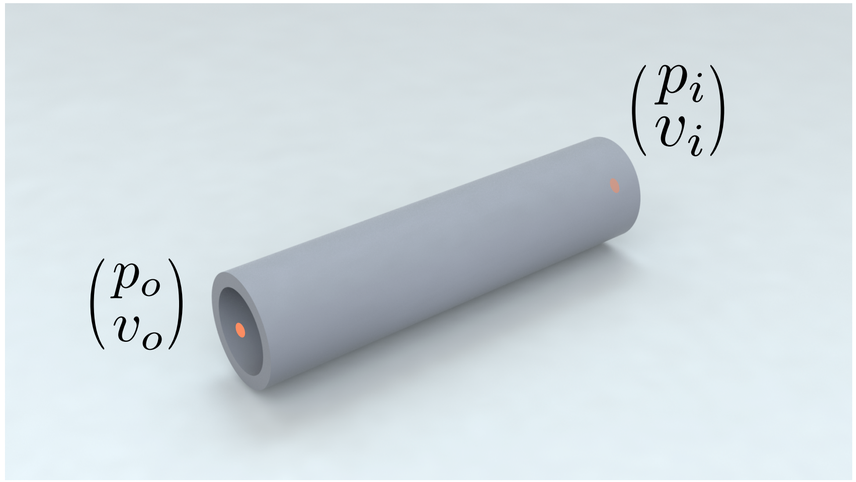
Impedance

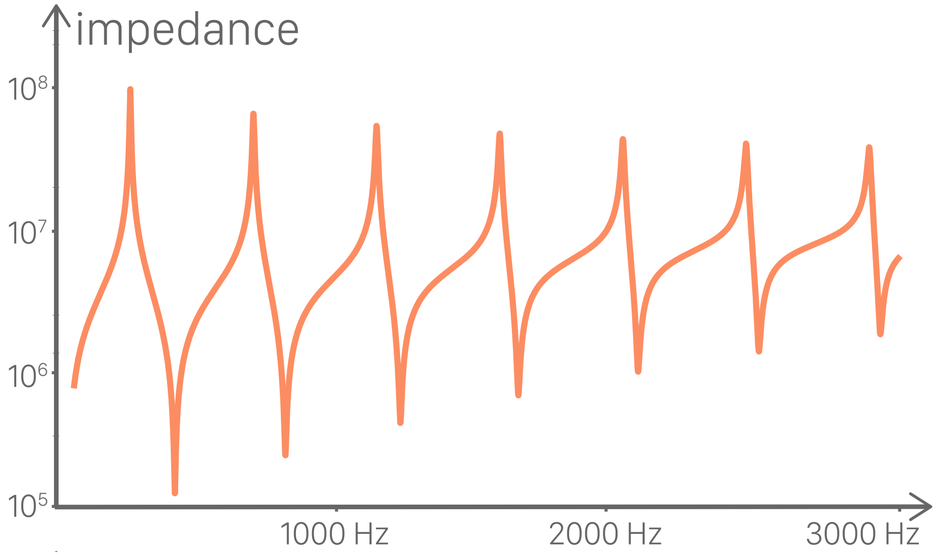
Transmission Loss

Acoustic Metrics

Impedance

$$Z(\boldsymbol{x}, \omega) = \frac{p(\boldsymbol{x}, \omega)}{v(\boldsymbol{x}, \omega)}$$





Transmission Loss

Acoustic Metrics

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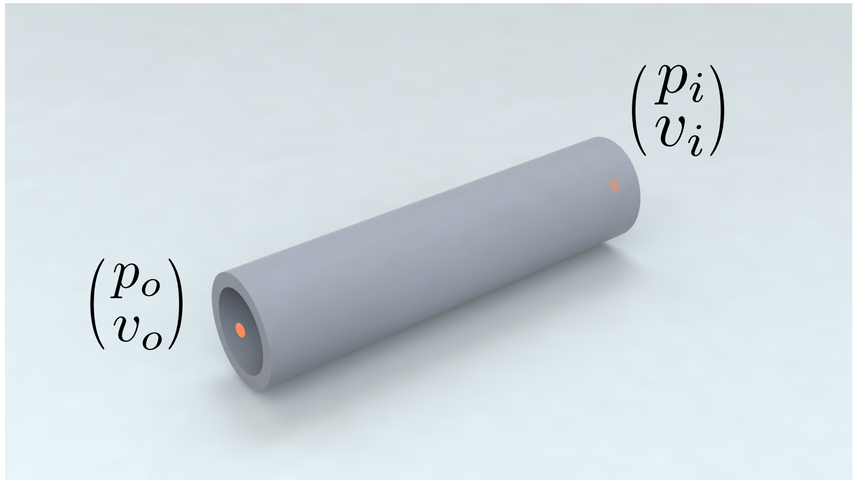

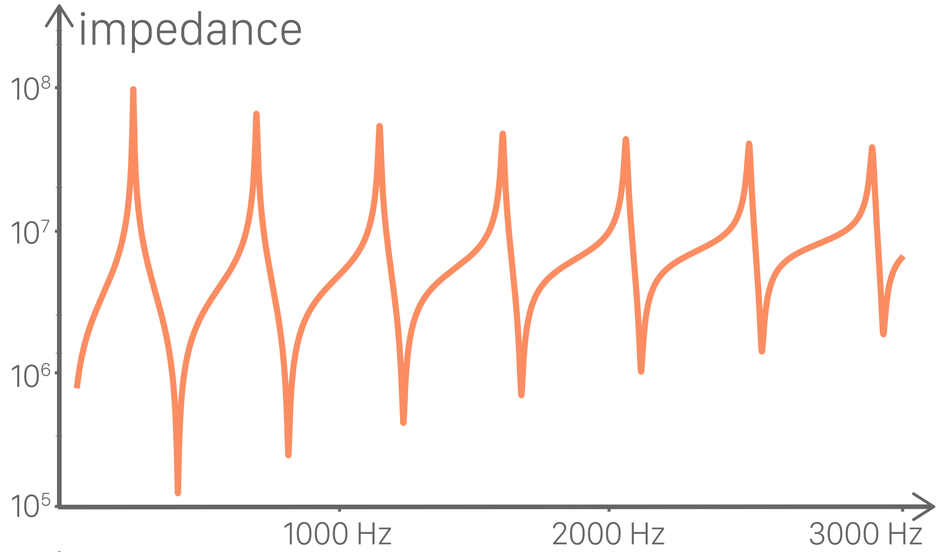

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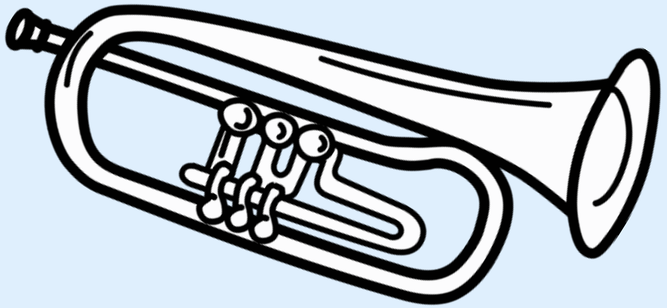

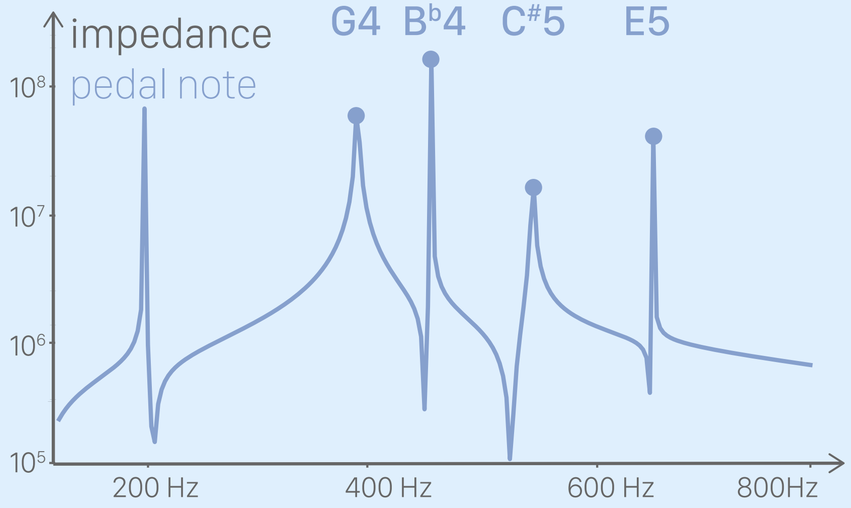

Acoustic Metrics

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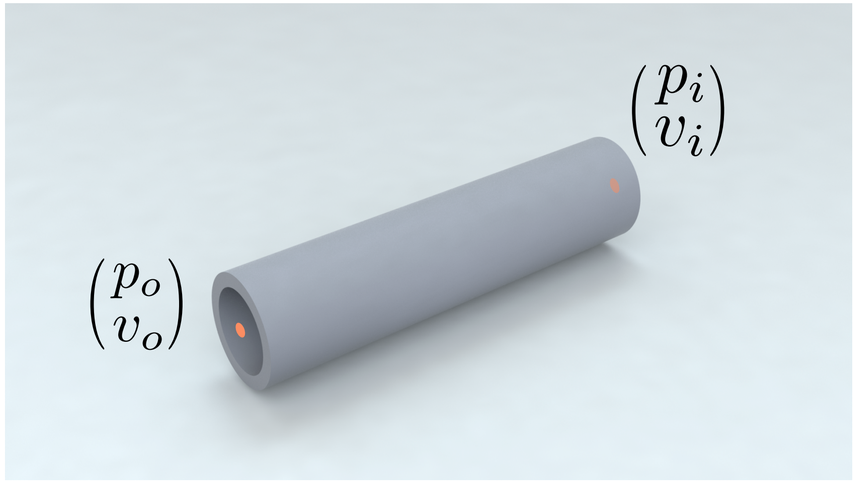

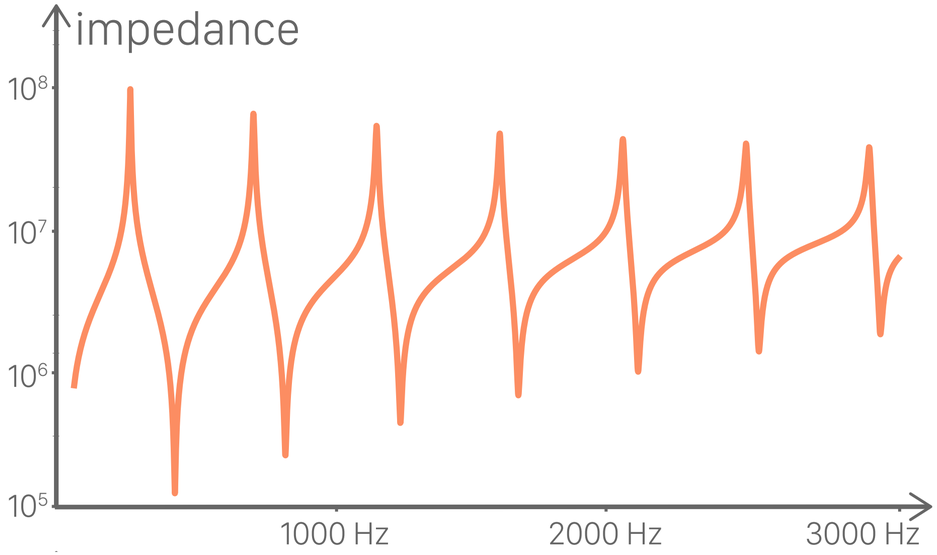

Transmission Loss

Acoustic Metrics

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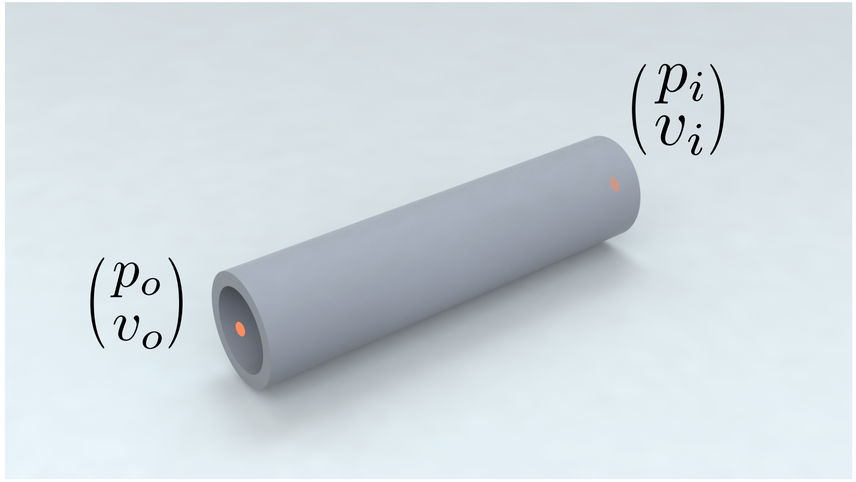
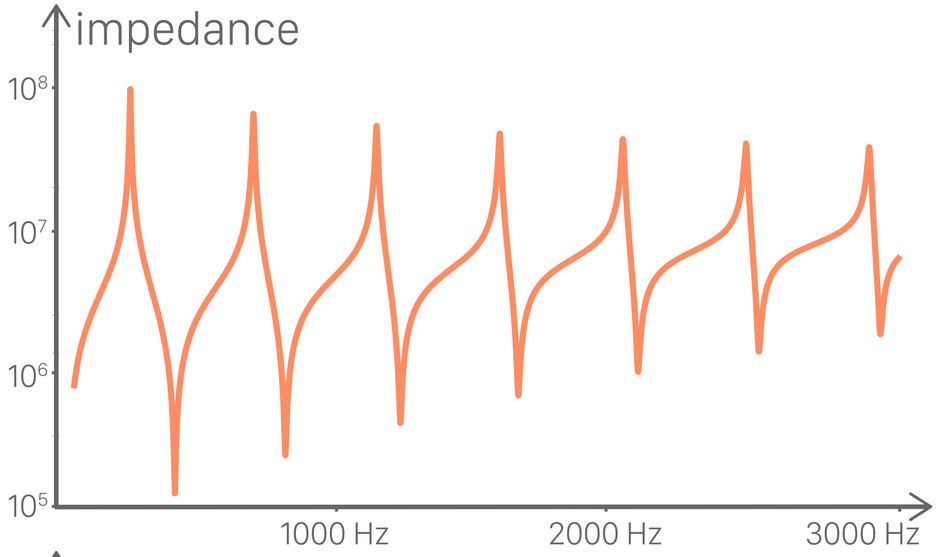
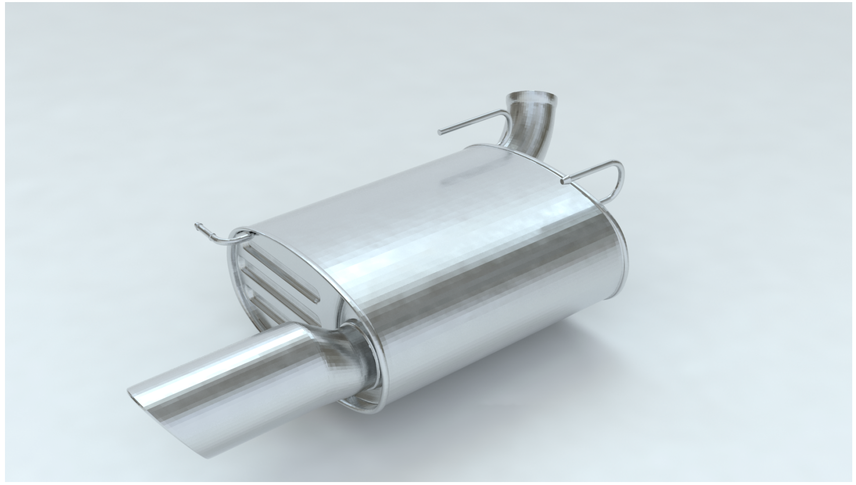
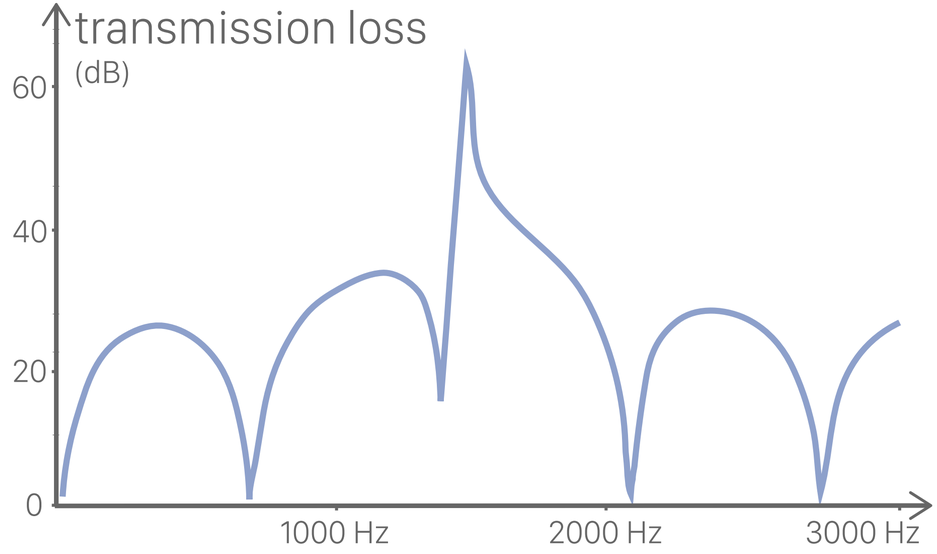




Transmission Loss

$$L_{\mathrm{TL}}(\phi) = 10 \log_{10} \left| \frac{S_{\mathrm{i}} p_{\mathrm{i}+}^2(\phi)}{S_{\mathrm{o}} p_{\mathrm{o}}^2(\phi)} \right|$$





Transmission Matrix

$$\begin{pmatrix} p_{\mathrm{o}}(\omega) \\ p_{\mathrm{i}}(\omega) \end{pmatrix} = \begin{pmatrix} T_{11}^{\omega} & T_{12}^{\omega} \\ T_{21}^{\omega} & T_{22}^{\omega} \end{pmatrix} \begin{pmatrix} v_{\mathrm{o}}(\omega) \\ v_{\mathrm{i}}(\omega) \end{pmatrix}$$

Challenges

$$\begin{pmatrix} p_{\mathrm{o}}(\omega) \\ p_{\mathrm{i}}(\omega) \end{pmatrix} = \begin{pmatrix} T_{11}^{\omega} & T_{12}^{\omega} \\ T_{21}^{\omega} & T_{22}^{\omega} \end{pmatrix} \begin{pmatrix} v_{\mathrm{o}}(\omega) \\ v_{\mathrm{i}}(\omega) \end{pmatrix}$$

Helmholtz Equation

$$\nabla^2 p(\omega) + k^2 p(\omega) = 0$$

Challenges

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Helmholtz Equation

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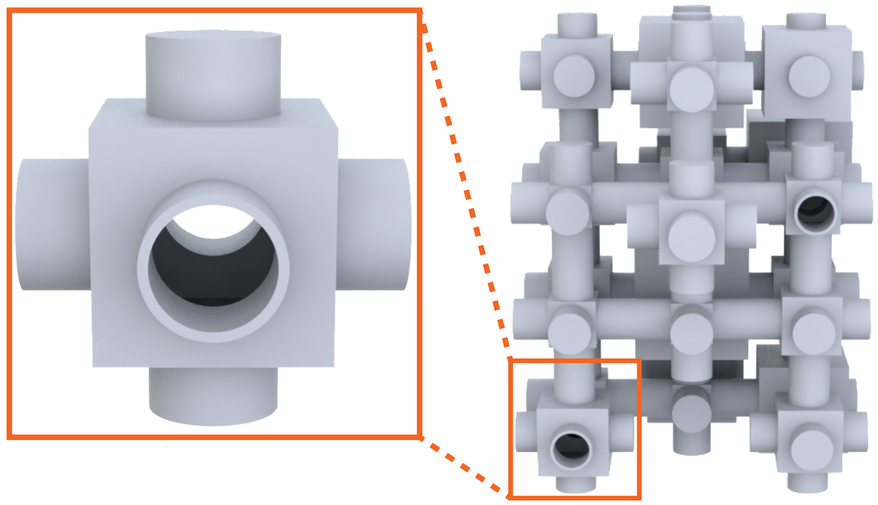
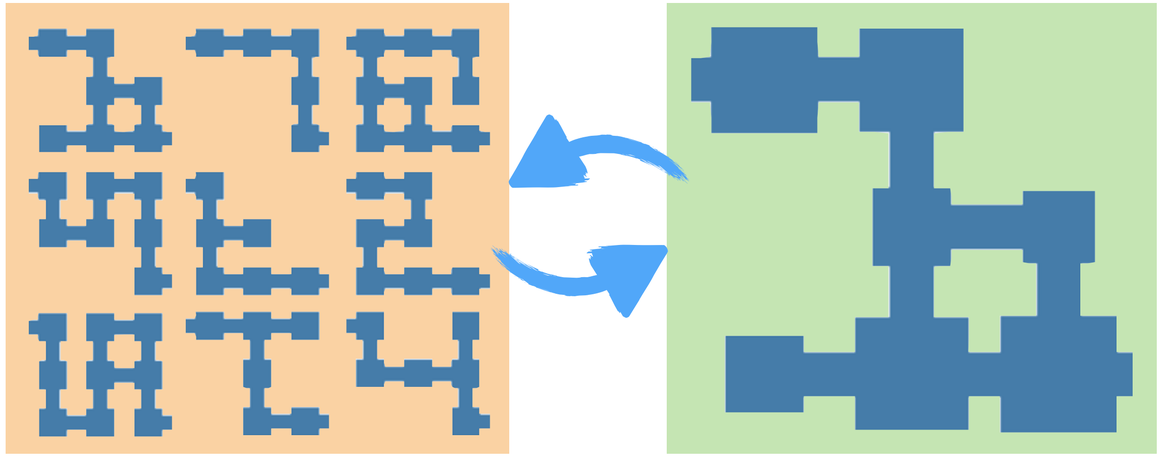
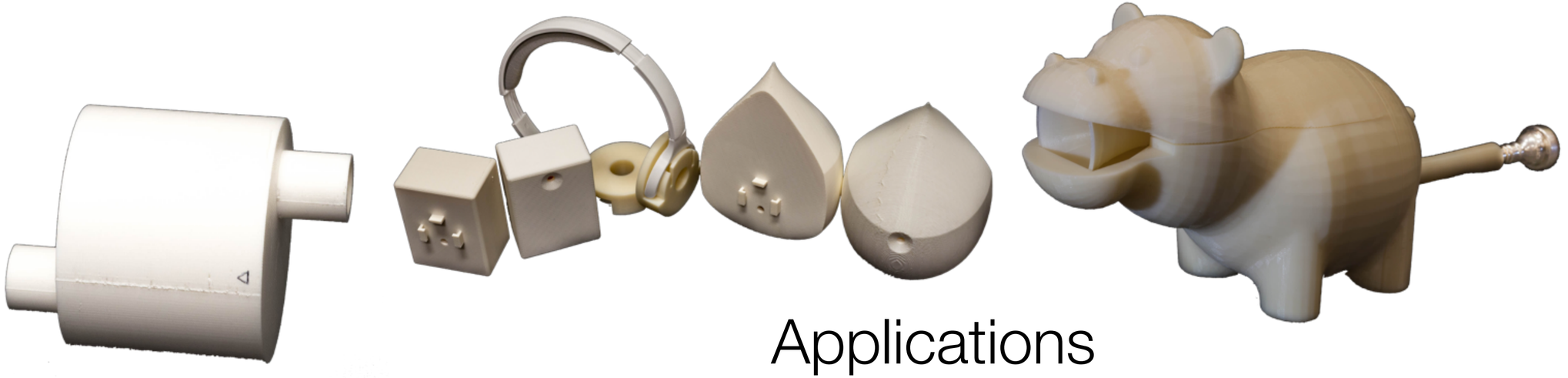
Overview



Primitive Resonators



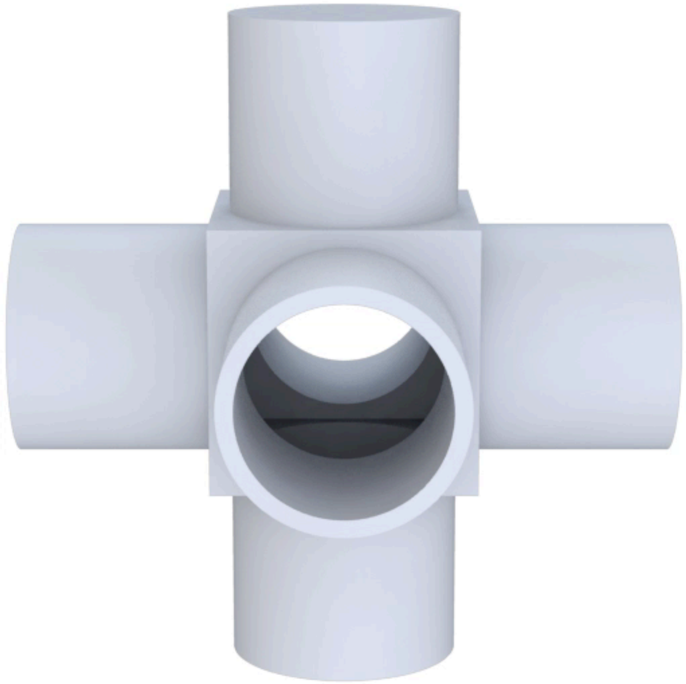
Optimization



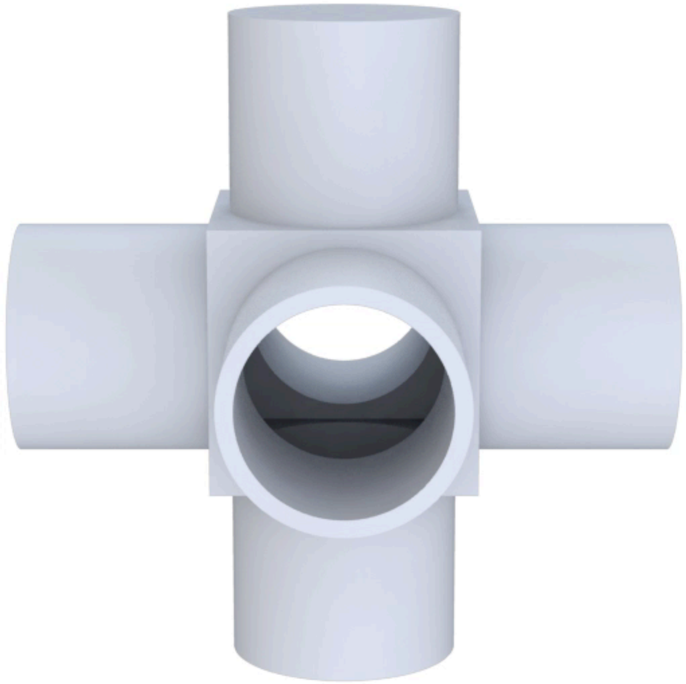
Applications

Primitive Resonators

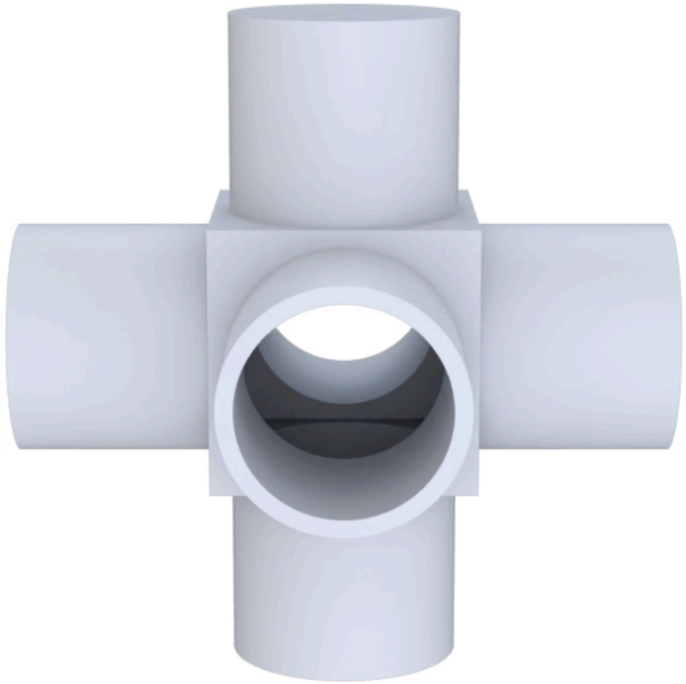
Primitive Resonators: Acoustic Voxels



Primitive Resonators: Acoustic Voxels

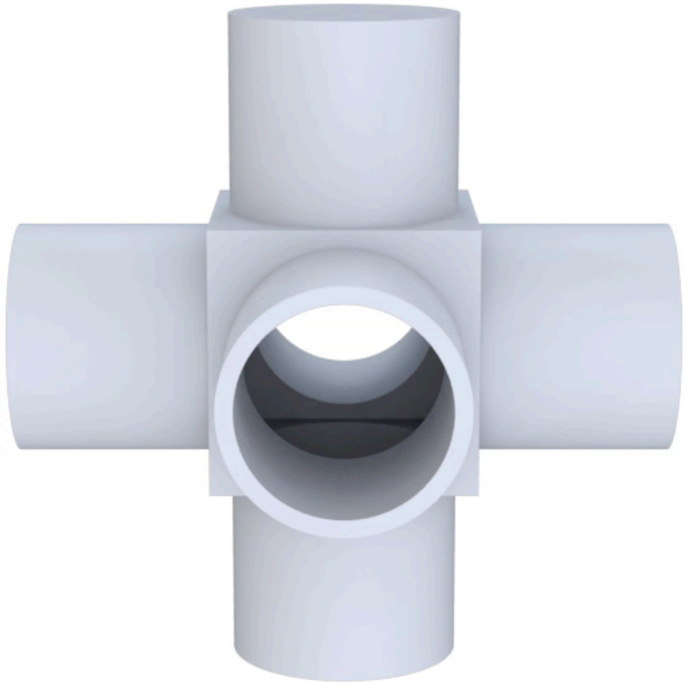


Primitive Resonators: Acoustic Voxels



Fast to precompute transmission matrix

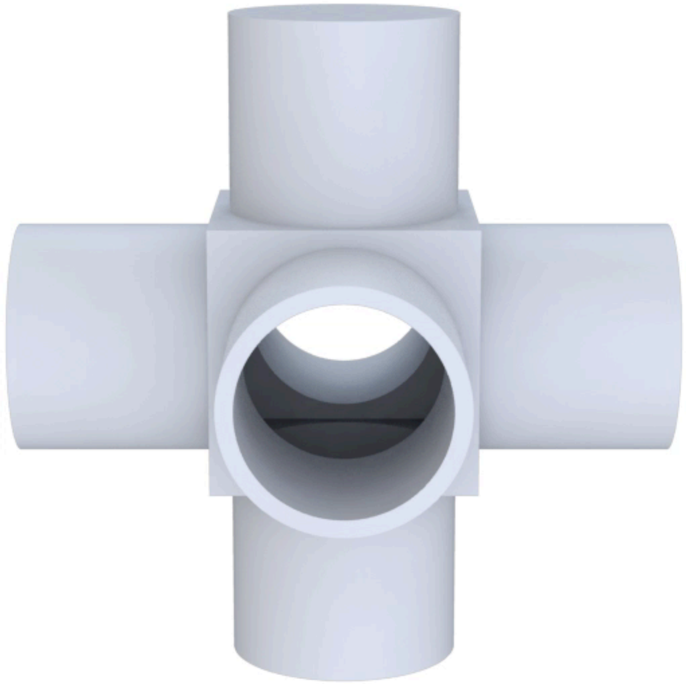
Primitive Resonators: Acoustic Voxels



Fast to precompute transmission matrix

Straightforward assembly

Primitive Resonators: Acoustic Voxels

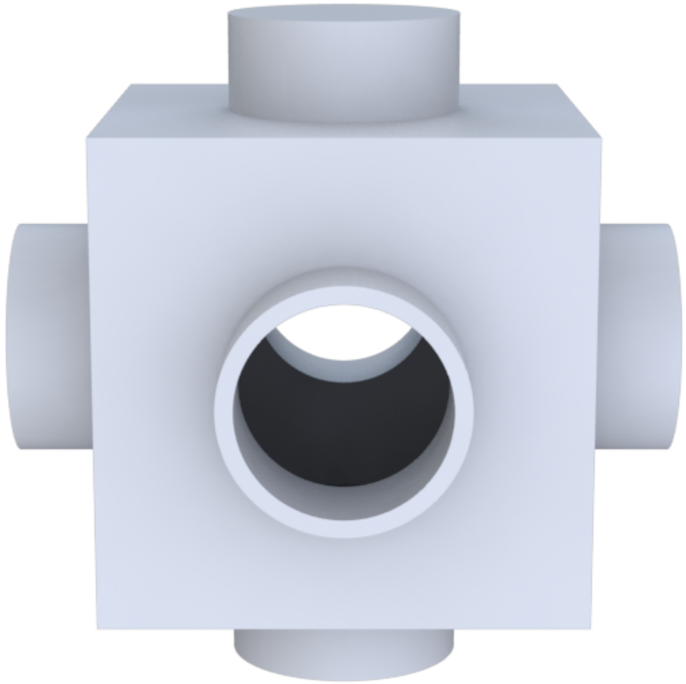


Fast to precompute transmission matrix

Straightforward assembly

Easy to evaluate & optimize

Multi-port Transmission Matrix

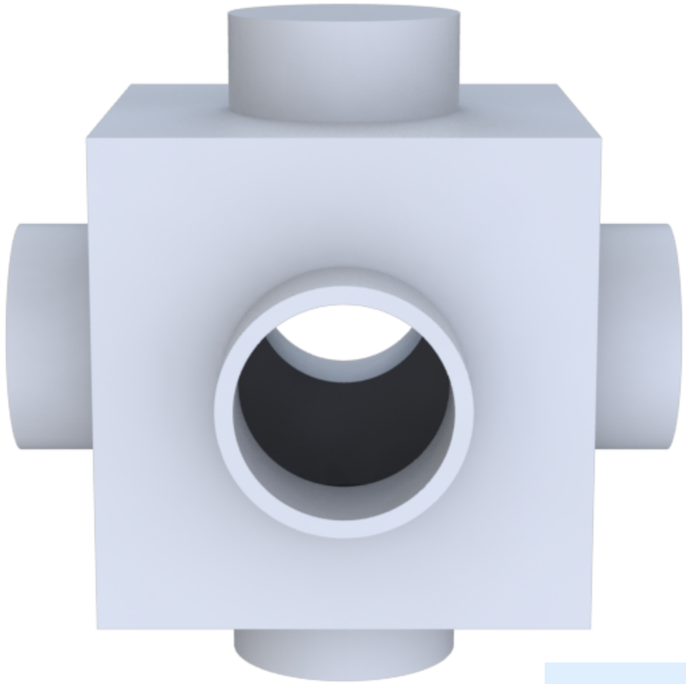


$$\begin{pmatrix} p_1(\omega) \\ \vdots \\ p_6(\omega) \end{pmatrix} = \begin{pmatrix} T^{\omega}_{11} & \cdots & T^{\omega}_{16} \\ \vdots & \ddots & \vdots \\ T^{\omega}_{61} & \cdots & T^{\omega}_{66} \end{pmatrix} \begin{pmatrix} v_1(\omega) \\ \vdots \\ v_6(\omega) \end{pmatrix}$$

Helmholtz Equation

$$\nabla^2 p(\omega) + k^2 p(\omega) = 0$$

Multi-port Transmission Matrix



$$\begin{pmatrix} p_1(\omega) \\ \vdots \\ p_6(\omega) \end{pmatrix} = \begin{pmatrix} T^{\omega}_{11} & \cdots & T^{\omega}_{16} \\ \vdots & \ddots & \vdots \\ T^{\omega}_{61} & \cdots & T^{\omega}_{66} \end{pmatrix} \begin{pmatrix} v_1(\omega) \\ \vdots \\ v_6(\omega) \end{pmatrix}$$

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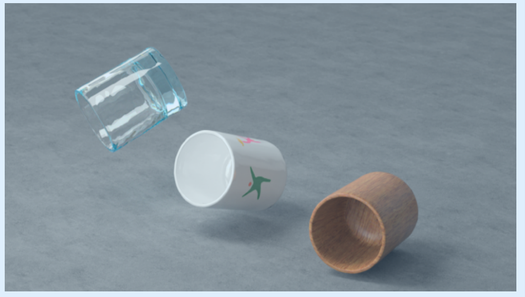
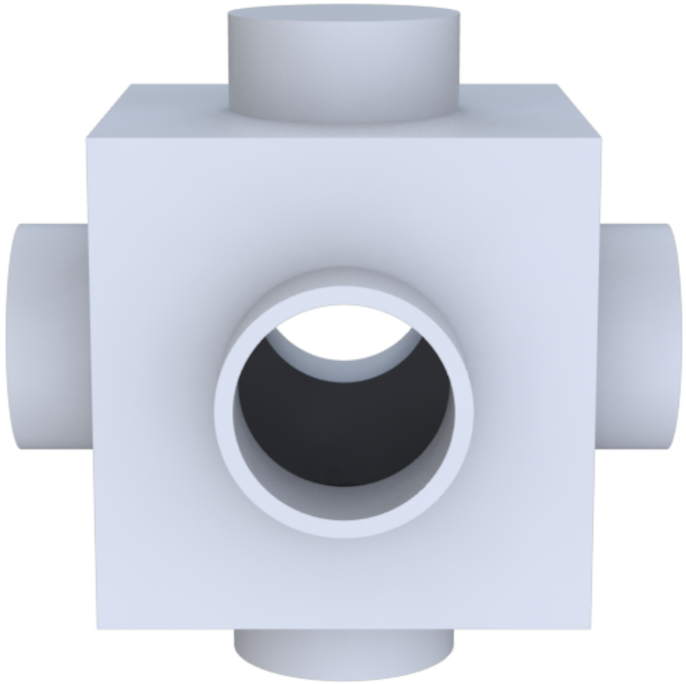
10:30am, Sound & Fluids Session, Ballroom D

Interactive Acoustic Transfer (SIGGRAPH 2016)

Li, Fei, Zheng



Multi-port Transmission Matrix



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Helmholtz Equation

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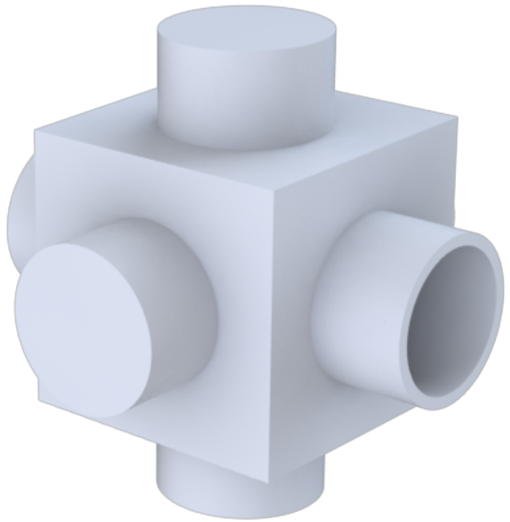
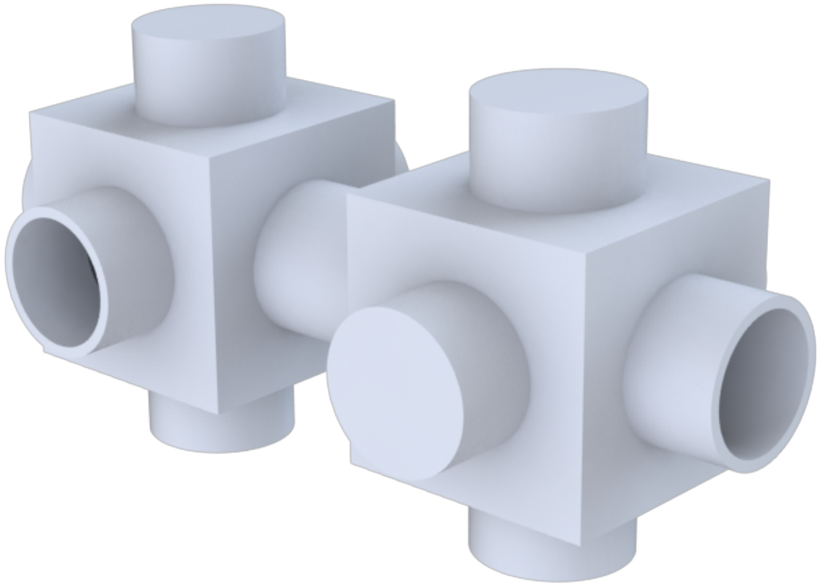
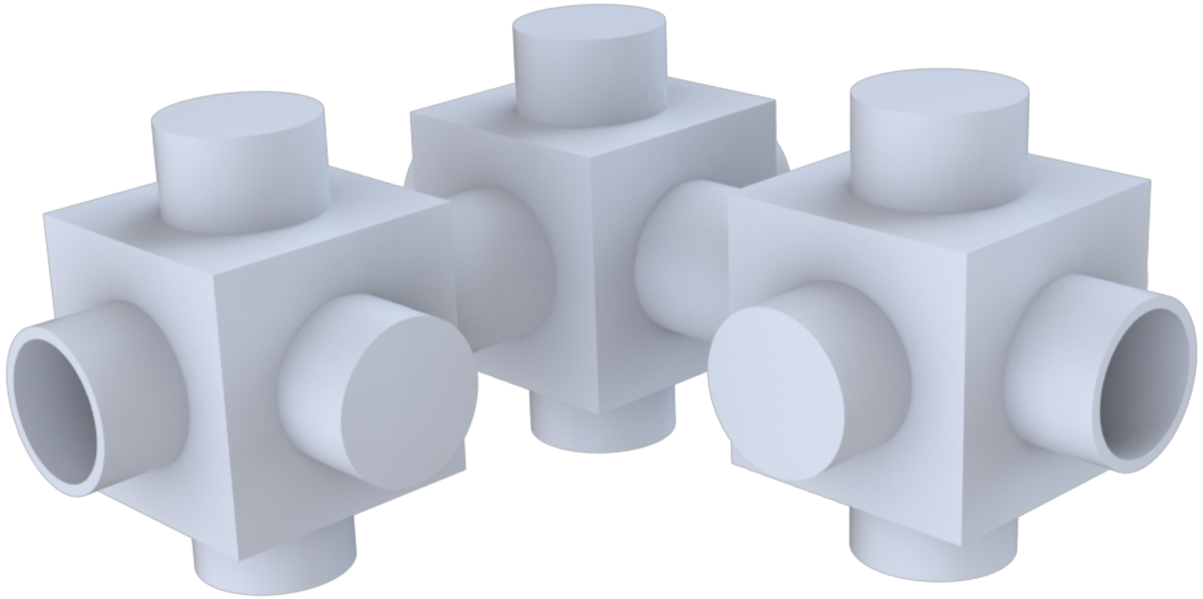
Assembly Construction



Assembly Construction



Assembly Construction



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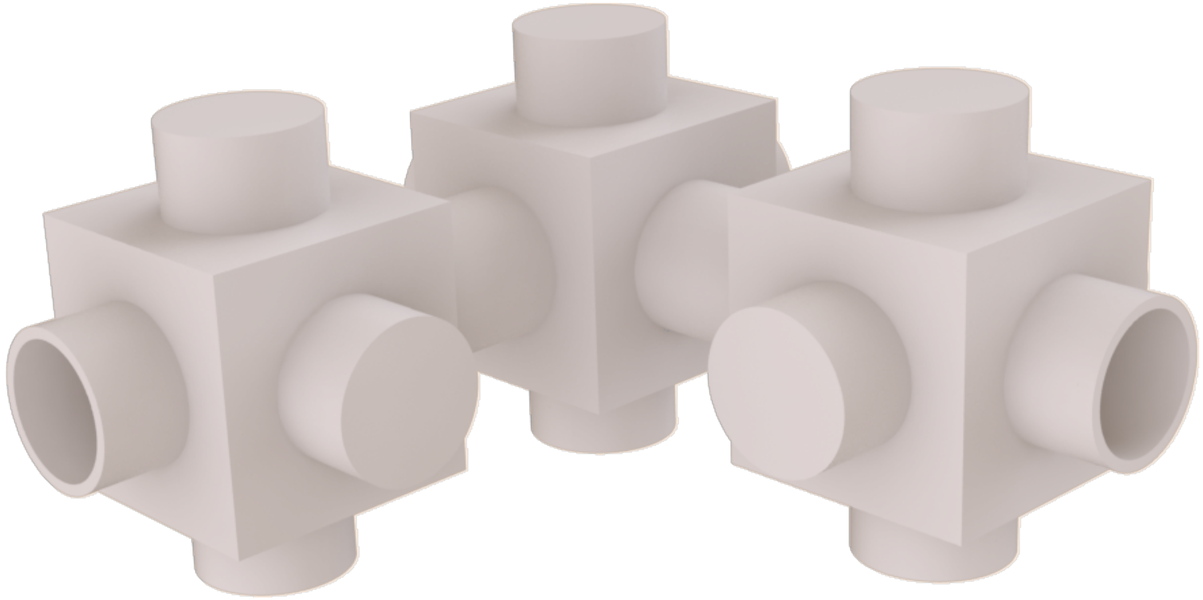
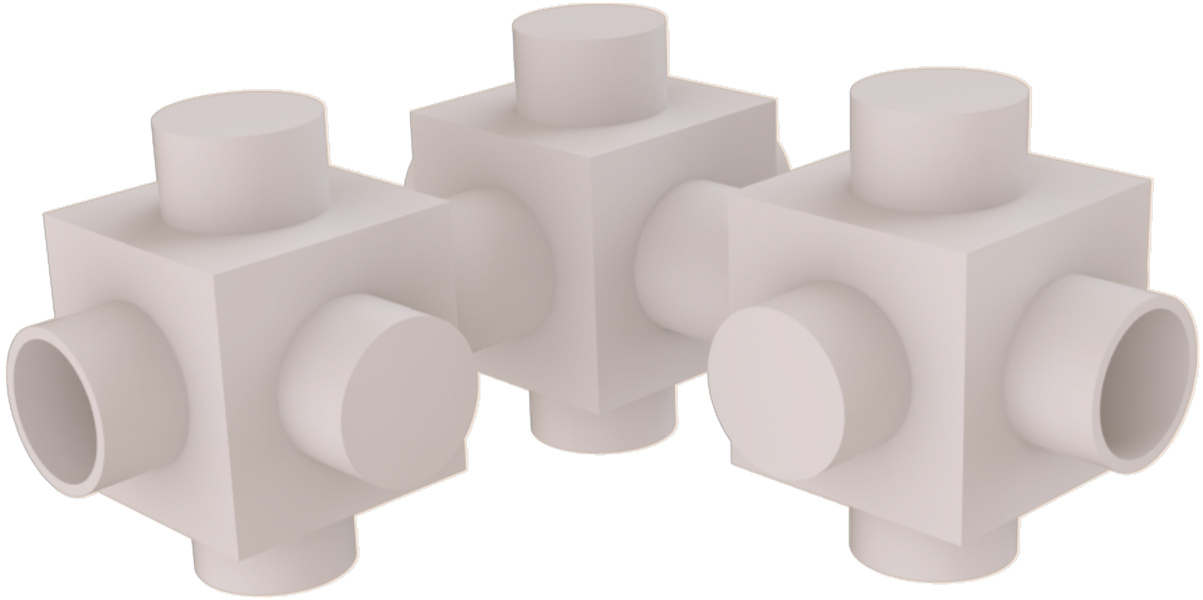


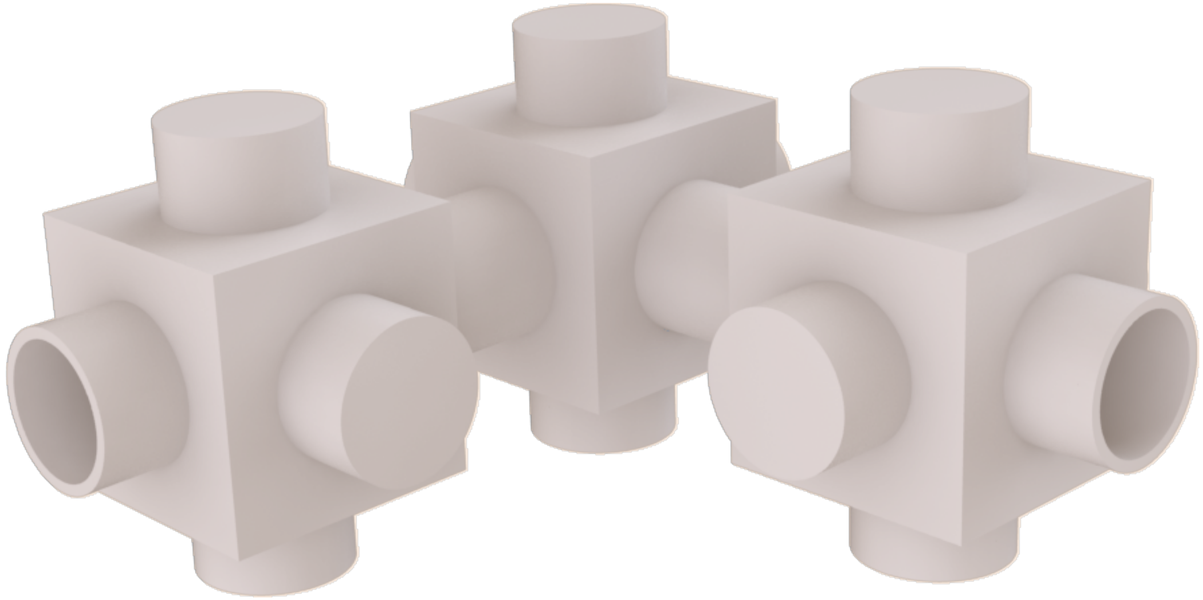
Assembly Construction



transmission matrices:
18 equations

Assembly Construction

$$\begin{pmatrix} p_1(\omega) \\ \vdots \\ p_6(\omega) \end{pmatrix} = \begin{pmatrix} T_{11}^{\omega} & \cdots & T_{16}^{\omega} \\ \vdots & \ddots & \vdots \\ T_{61}^{\omega} & \cdots & T_{66}^{\omega} \end{pmatrix} \begin{pmatrix} v_1(\omega) \\ \vdots \\ v_6(\omega) \end{pmatrix}$$



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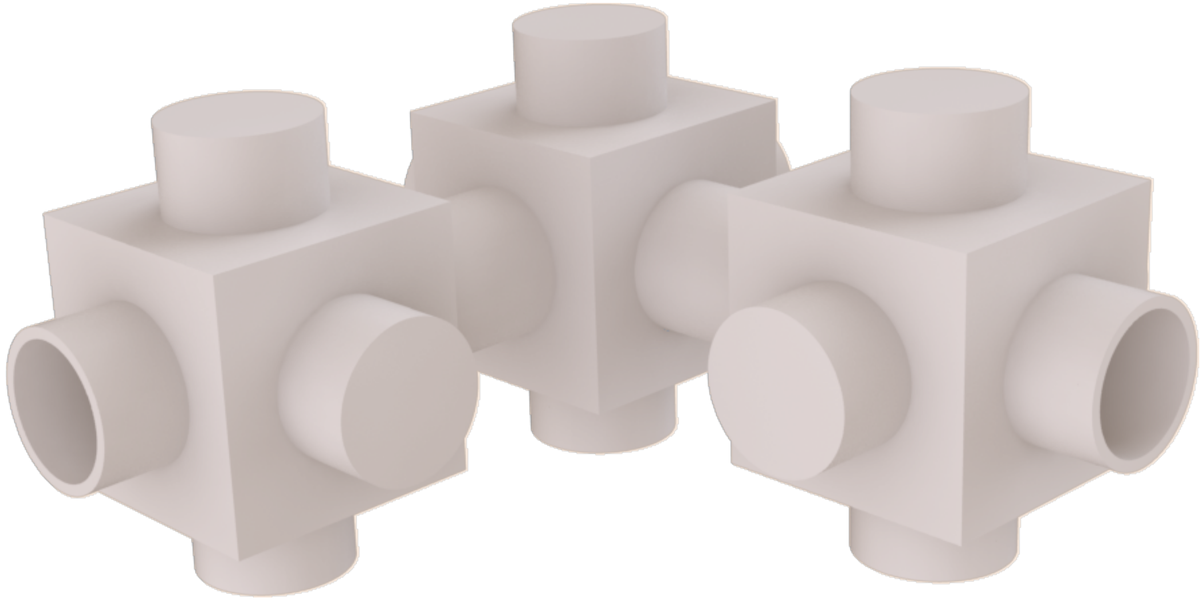

transmission matrices:
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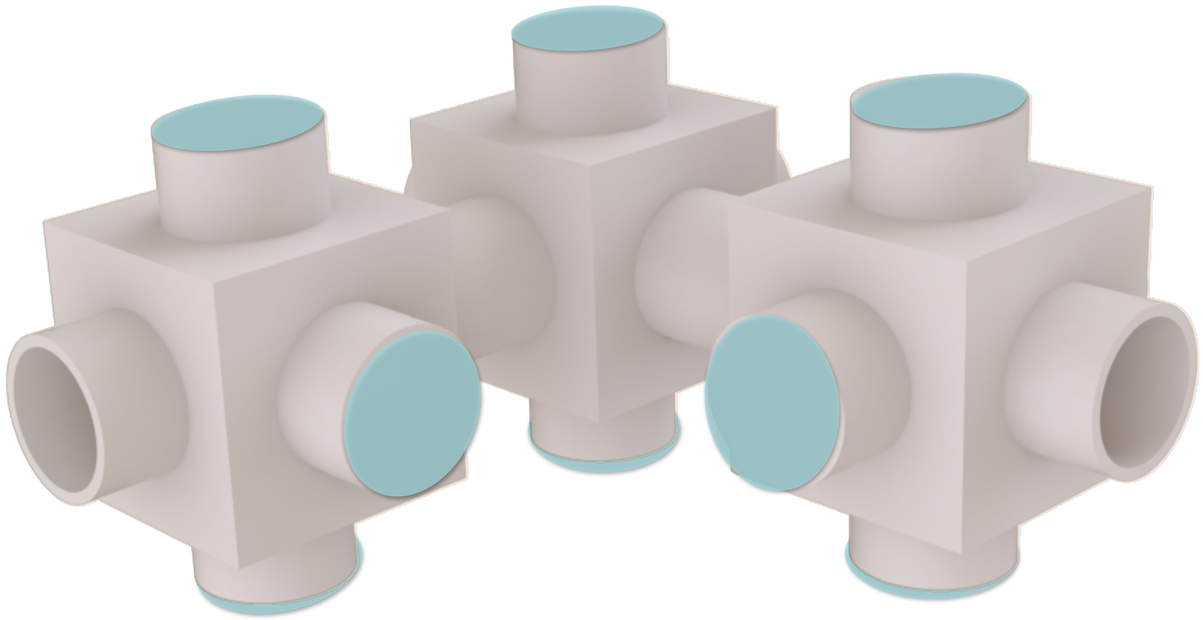
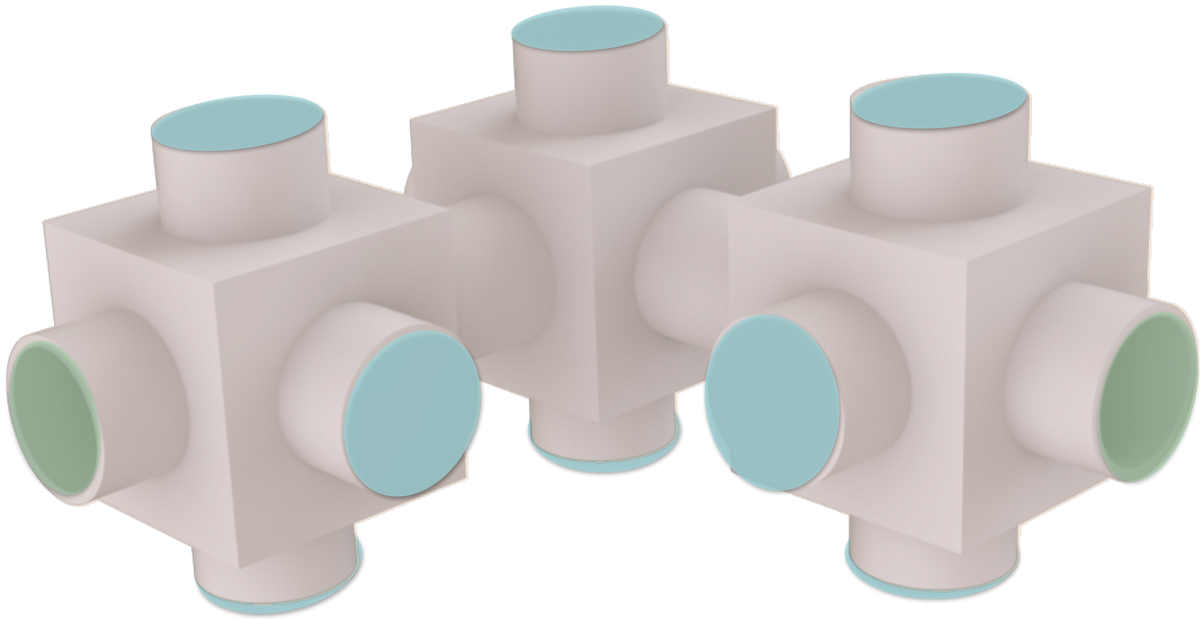
Assembly Construction



transmission matrices:
18 equations

connecting/closed faces:
16 equations

Assembly Construction

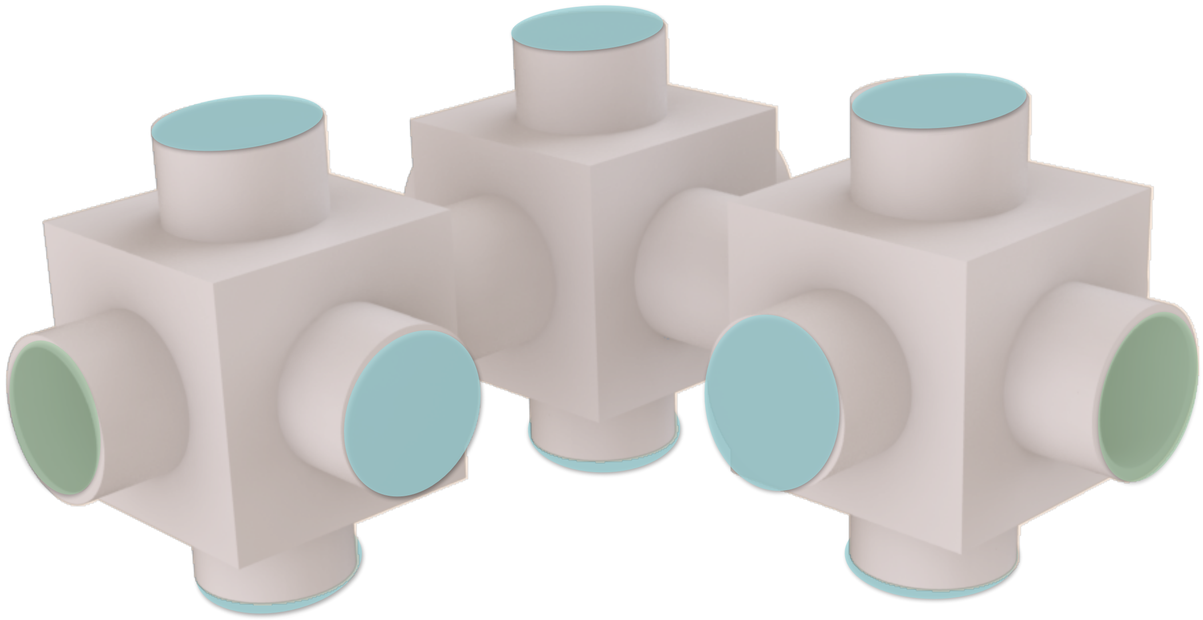


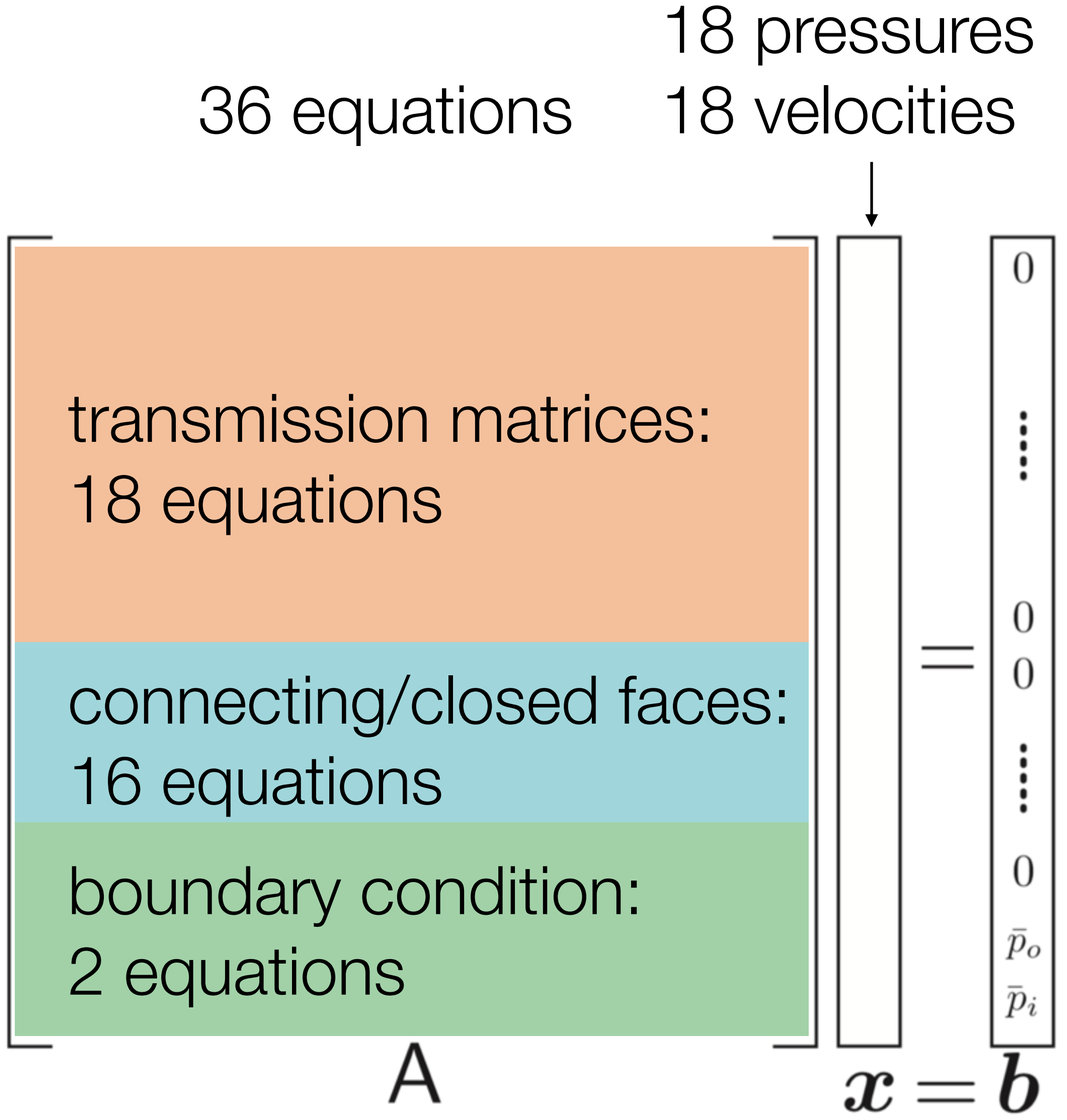
transmission matrices:
18 equations

connecting/closed faces:
16 equations

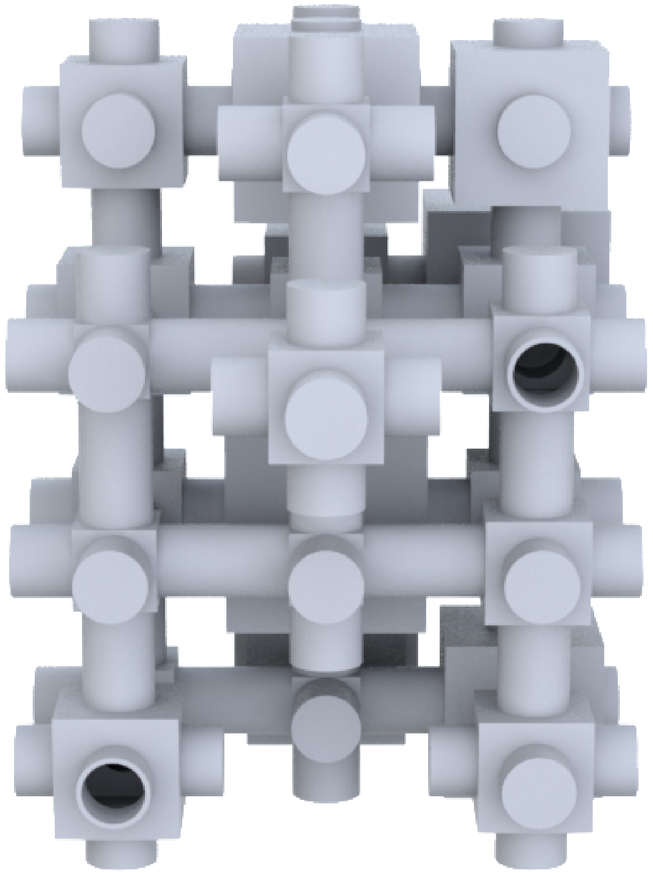
boundary condition:
2 equations

Assembly Construction





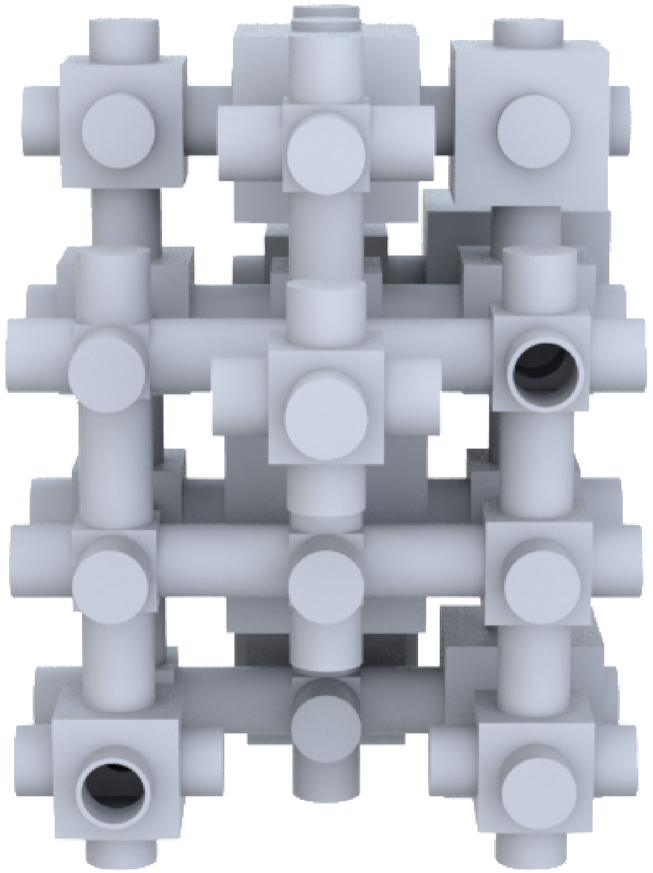
Complex Assembly Construction



$$\begin{bmatrix} I_{6\times6} & -T_1 & & & 0 \\ & I_{6\times6} & -T_2 & & \\ & & \ddots & & \\ 0 & & & I_{6\times6} & -T_N \\ 0 \cdots 0\,0\,1 \cdots 0\,0\,1 \cdots & & & & \\ 0 \cdots 0\,1\,0 \cdots 0\,-1\,0 \cdots & & & & \\ \vdots & & & & \\ 0 \cdots\cdots 0\,1\,0 \cdots 0\,-1\,0 & & & & \\ 0 \cdots 0\,1\,0 \cdots\cdots 0 & & & & \\ 0 \cdots\cdots 0\,1\,0 \cdots 0 & & & & \end{bmatrix} \begin{bmatrix} \\ \\ \\ \\ \\ \\ \\ \\ \\ \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \\ \vdots \\ 0 \\ \bar{p}_o \\ \bar{p}_i \end{bmatrix}$$

$$A \qquad \boldsymbol{x} = \boldsymbol{b}$$

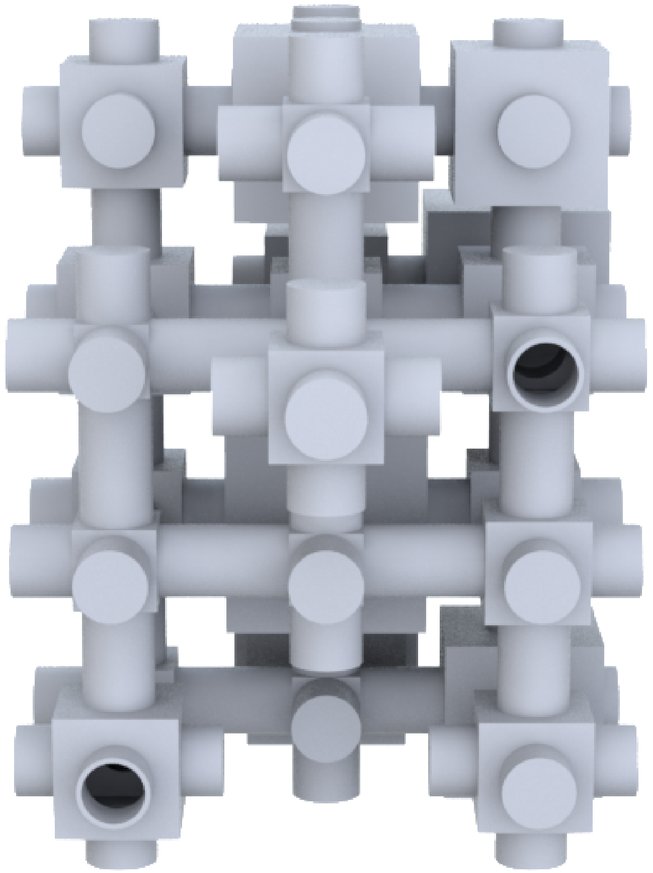
Complex Assembly Construction



$$\begin{pmatrix} p_1(\omega) \\ \vdots \\ p_6(\omega) \end{pmatrix} = \begin{pmatrix} T^{\omega}_{11} & \cdots & T^{\omega}_{16} \\ \vdots & \ddots & \vdots \\ T^{\omega}_{61} & \cdots & T^{\omega}_{66} \end{pmatrix} \begin{pmatrix} v_1(\omega) \\ \vdots \\ v_6(\omega) \end{pmatrix}$$

$$\underbrace{\begin{bmatrix} \mathsf{I}_{6\times6} & -\mathsf{T}_1 & & & 0 \\ & \mathsf{I}_{6\times6} & -\mathsf{T}_2 & & \\ & & \ddots & \ddots & \\ 0 & & & \mathsf{I}_{6\times6} & -\mathsf{T}_N \\ 0 \cdots 0\,0\,1 \cdots 0\,0\,1 \cdots & & & & \\ 0 \cdots 0\,1\,0 \cdots 0\,-1\,0 \cdots & & & & \\ \vdots & & & & \\ 0 \cdots\cdots 0\,1\,0 \cdots 0\,-1\,0 & & & & \\ 0 \cdots 0\,1\,0 \cdots\cdots 0 & & & & \\ 0 \cdots\cdots 0\,1\,0 \cdots 0 & & & & \end{bmatrix}}_{\mathsf{A}} \underbrace{\begin{bmatrix} \\ \\ \\ \\ \\ \\ \\ \\ \\ \end{bmatrix}}_{\boldsymbol{x}} = \underbrace{\begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \\ \vdots \\ 0 \\ \bar{p}_o \\ \bar{p}_i \end{bmatrix}}_{\boldsymbol{b}}$$

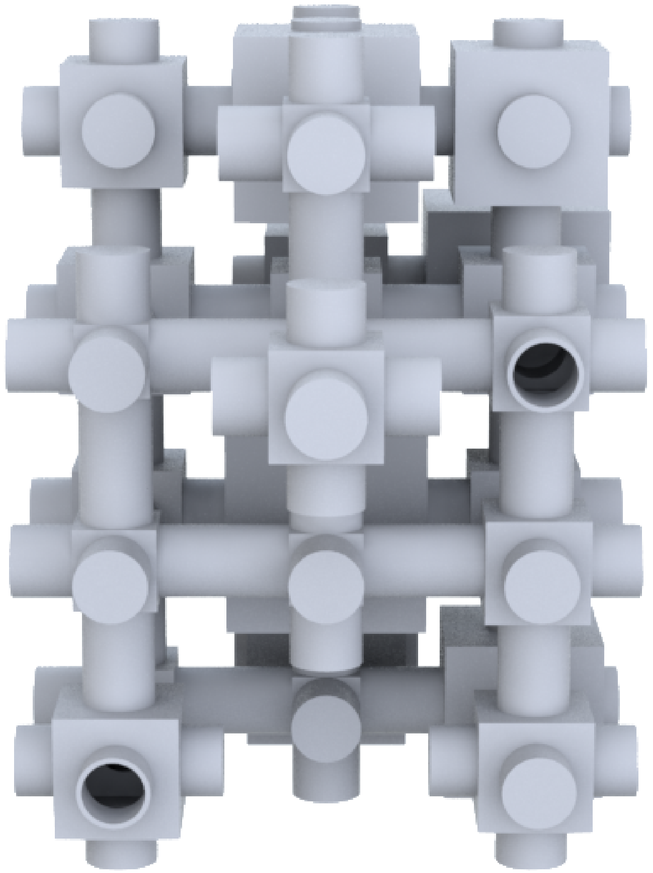
Complex Assembly Construction



$$\begin{bmatrix} I_{6\times6} & -T_1 & & & 0 \\ & I_{6\times6} & -T_2 & & \\ & & \ddots & & \\ 0 & & & I_{6\times6} & -T_N \\ 0 \cdots 0\,0\,1 \cdots 0\,0\,1 \cdots & & & & \\ 0 \cdots 0\,1\,0 \cdots 0\,-1\,0 \cdots & & & & \\ \vdots & & & & \\ 0 \cdots\cdots 0\,1\,0 \cdots 0\,-1\,0 & & & & \\ 0 \cdots 0\,1\,0 \cdots\cdots 0 & & & & \\ 0 \cdots\cdots 0\,1\,0 \cdots 0 & & & & \end{bmatrix} \begin{bmatrix} \\ \\ \\ \\ \\ \\ \\ \\ \\ \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \\ \vdots \\ 0 \\ \bar{p}_o \\ \bar{p}_i \end{bmatrix}$$

$$A \qquad \boldsymbol{x} = \boldsymbol{b}$$

Complex Assembly Construction



SPARSE

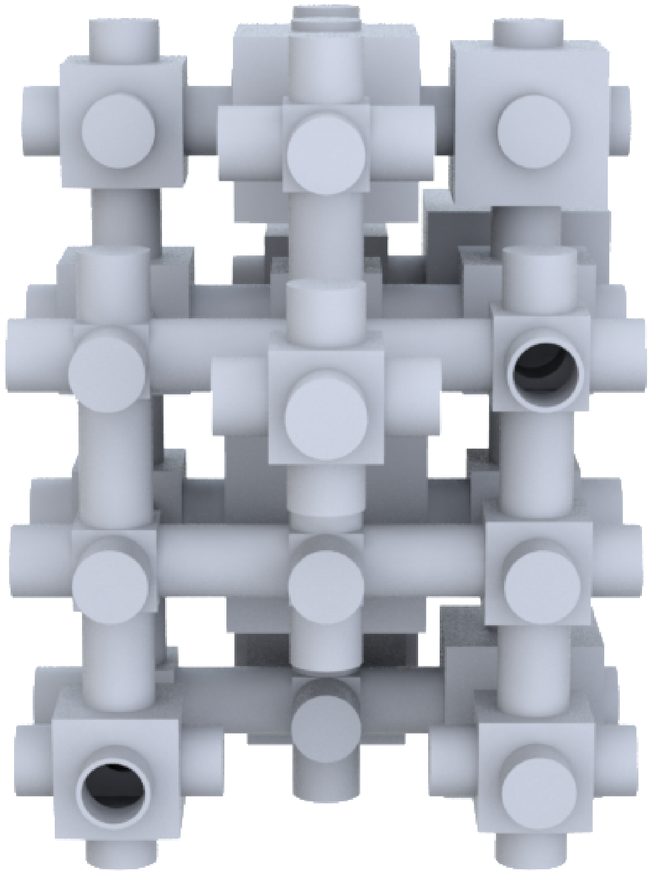
$$\begin{bmatrix} 0 & \cdots & 0\,0\,1 & \cdots & 0\,0\,1 & \cdots \\ 0 & \cdots & 0\,1\,0 & \cdots & 0\,-1\,0 & \cdots \\ \vdots & & & & & \\ 0 & \cdots\cdots & 0\,1\,0 & \cdots & 0\,-1\,0 & \\ 0 & \cdots & 0\,1\,0 & \cdots\cdots & 0 & \\ 0 & \cdots\cdots & 0\,1\,0 & \cdots & 0 & \end{bmatrix} \begin{bmatrix} \\ \\ \\ \\ \\ \\ \\ \\ \\ \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \\ \vdots \\ 0 \\ \bar{p}_o \\ \bar{p}_i \end{bmatrix}$$

$\mathsf{I}_{6\times 6} \mid -\mathsf{T}_N$

A

$\boldsymbol{x} = \boldsymbol{b}$

Complex Assembly Construction

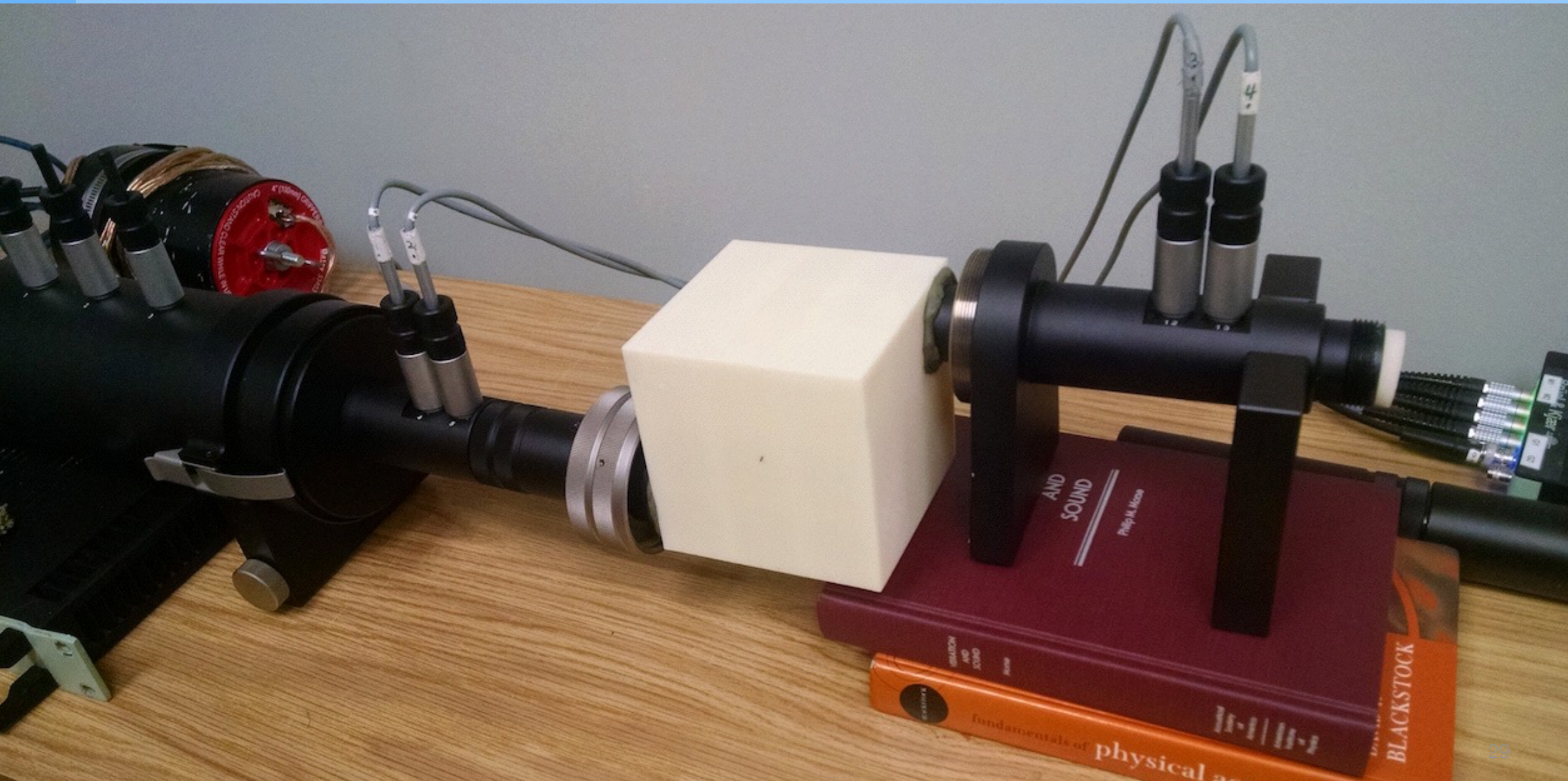


SPARSE

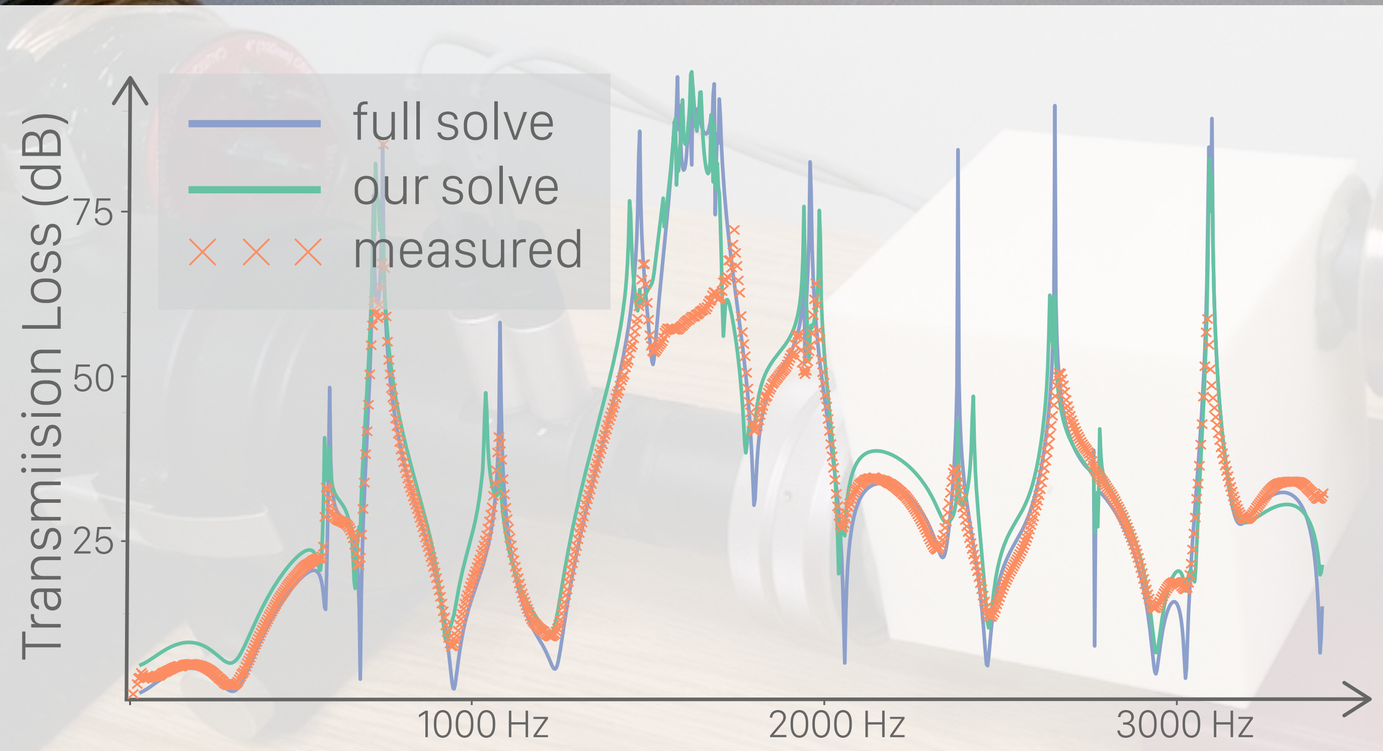
FIXED SPARSITY

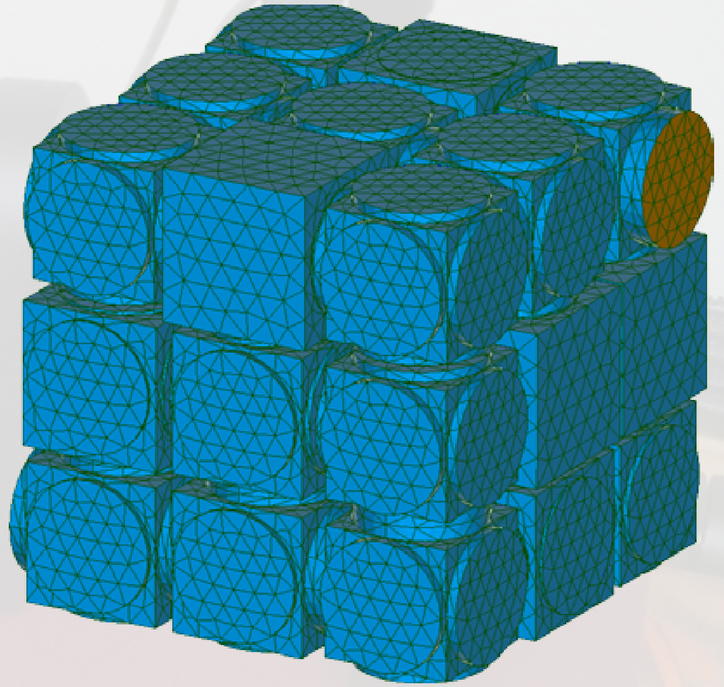
$$\mathbf{A}\,\boldsymbol{x} = \boldsymbol{b}$$

Laboratory Validation



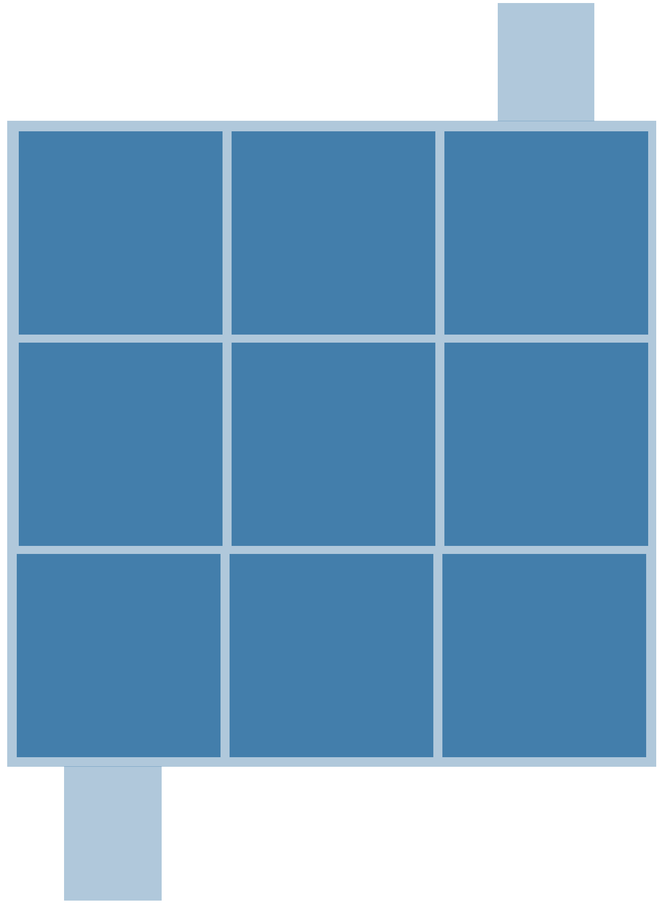
Laboratory Validation



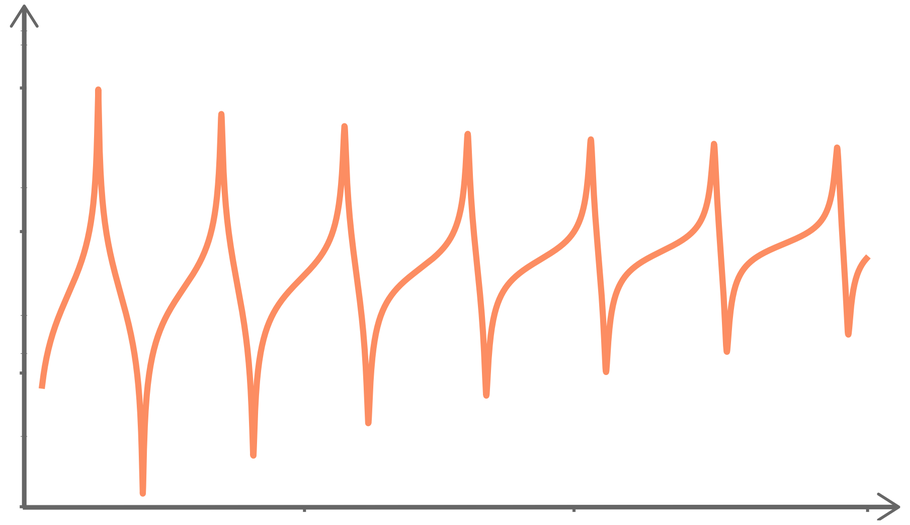


Optimization

Optimization



voxels

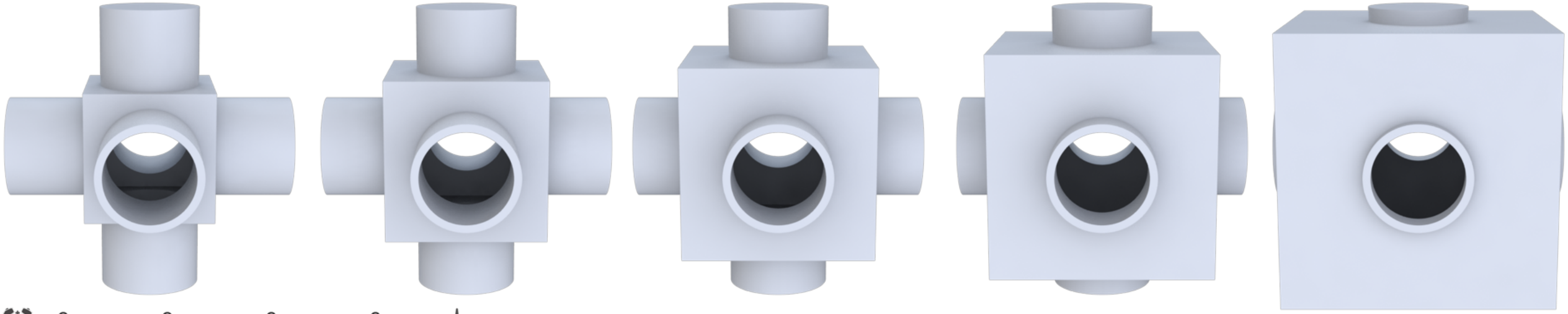


target filtering behavior

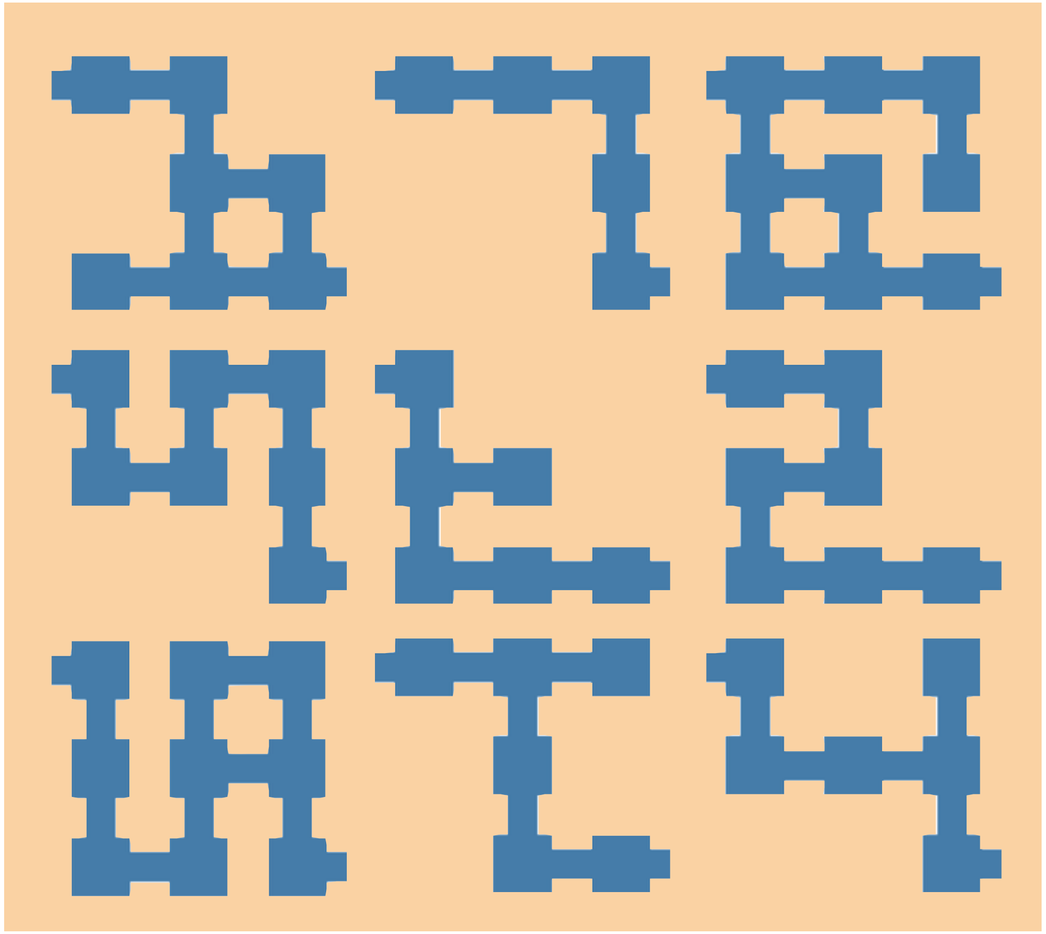
Objective Function

$$J = \sum_{i=1}^{N} \left(g_{\omega_i}(c, \mathbf{u}) - g^*_{\omega_i} \right)^2$$

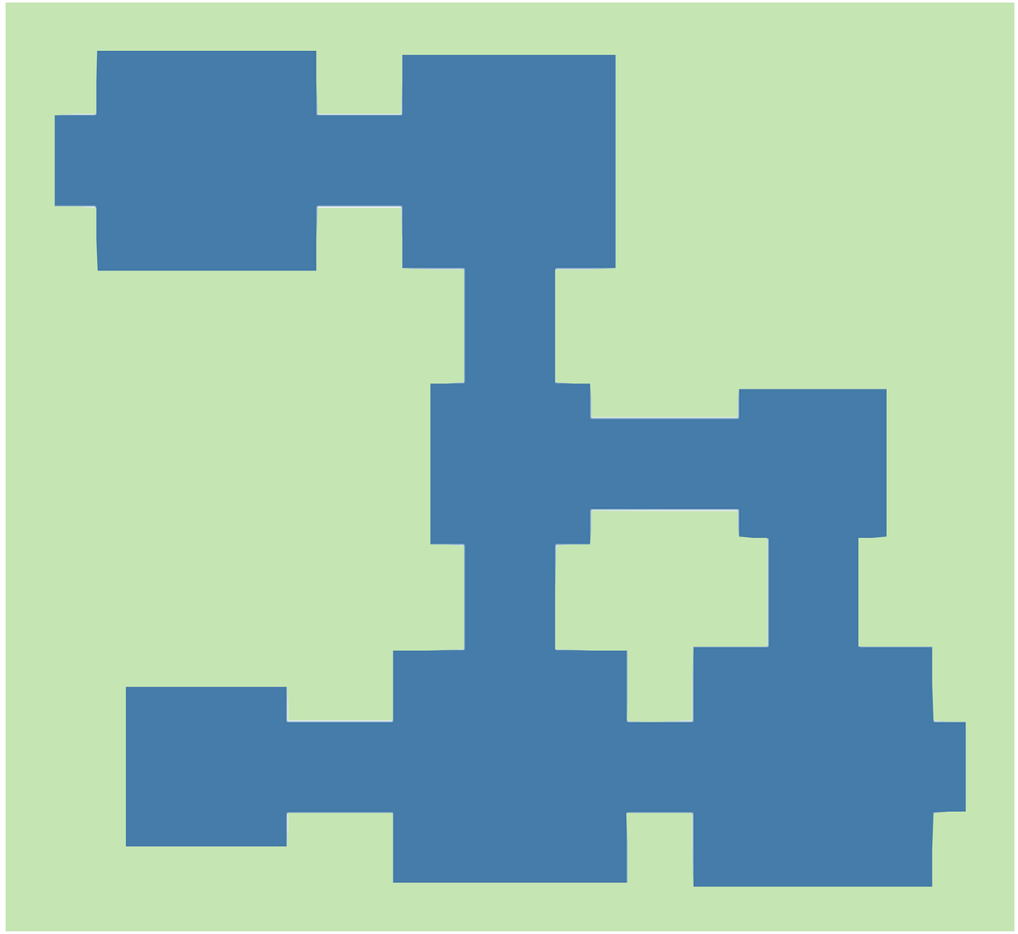
Optimization Variables: $c, \mathbf{u}$



Two-Stage Optimization

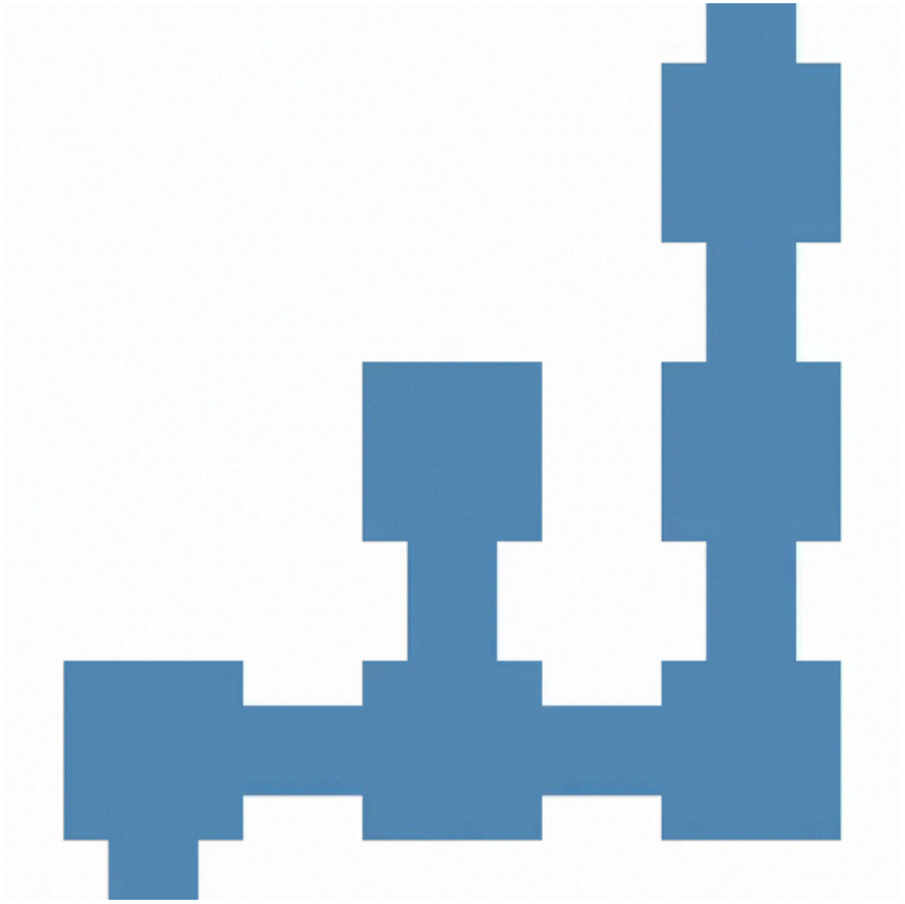


Connectivity Optimization



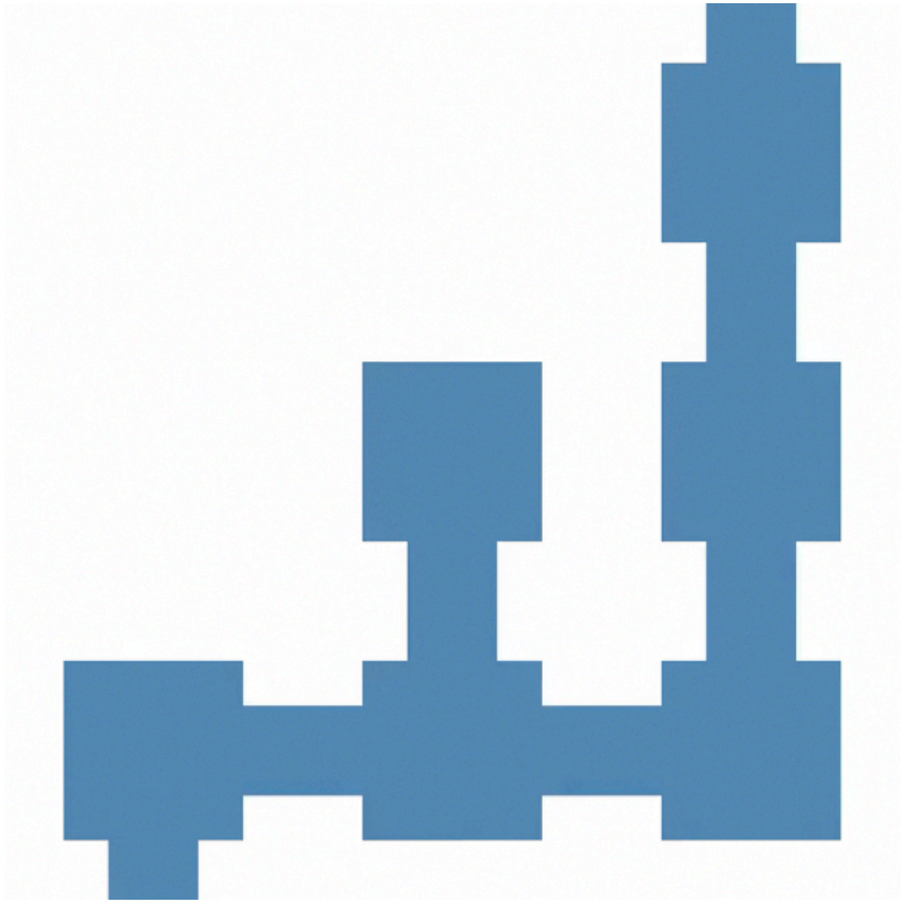
Fine-grain Optimization

Connectivity Optimization



pool of candidates

Connectivity Optimization



pool of candidates

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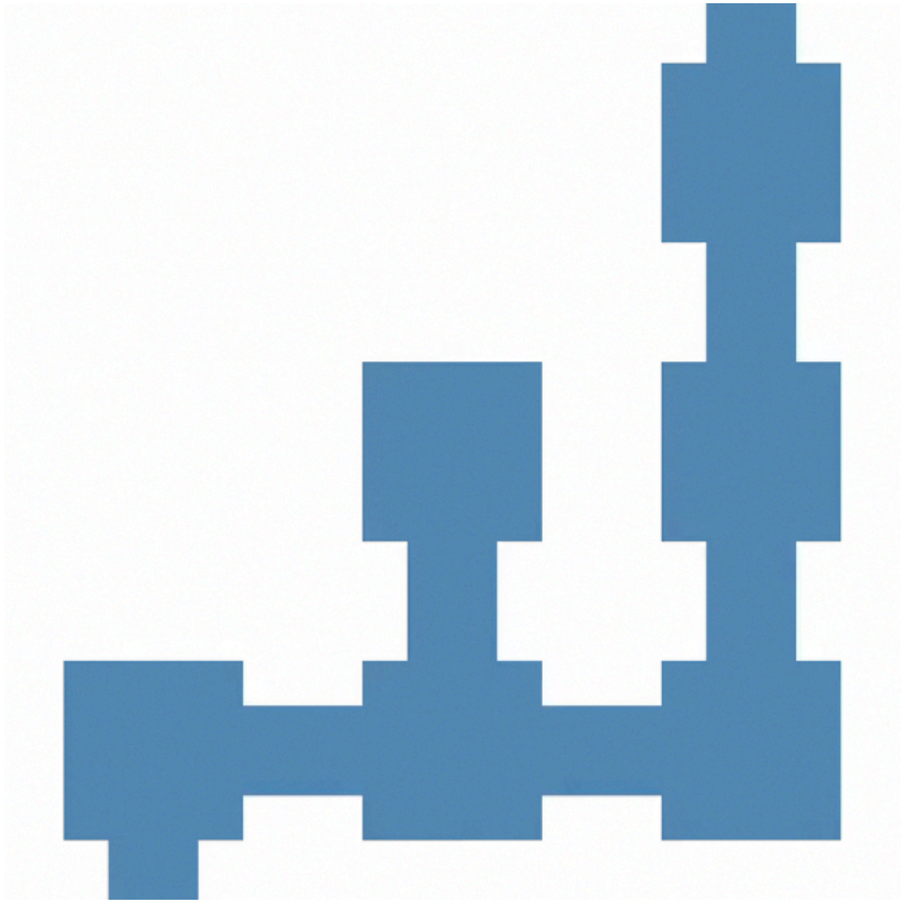
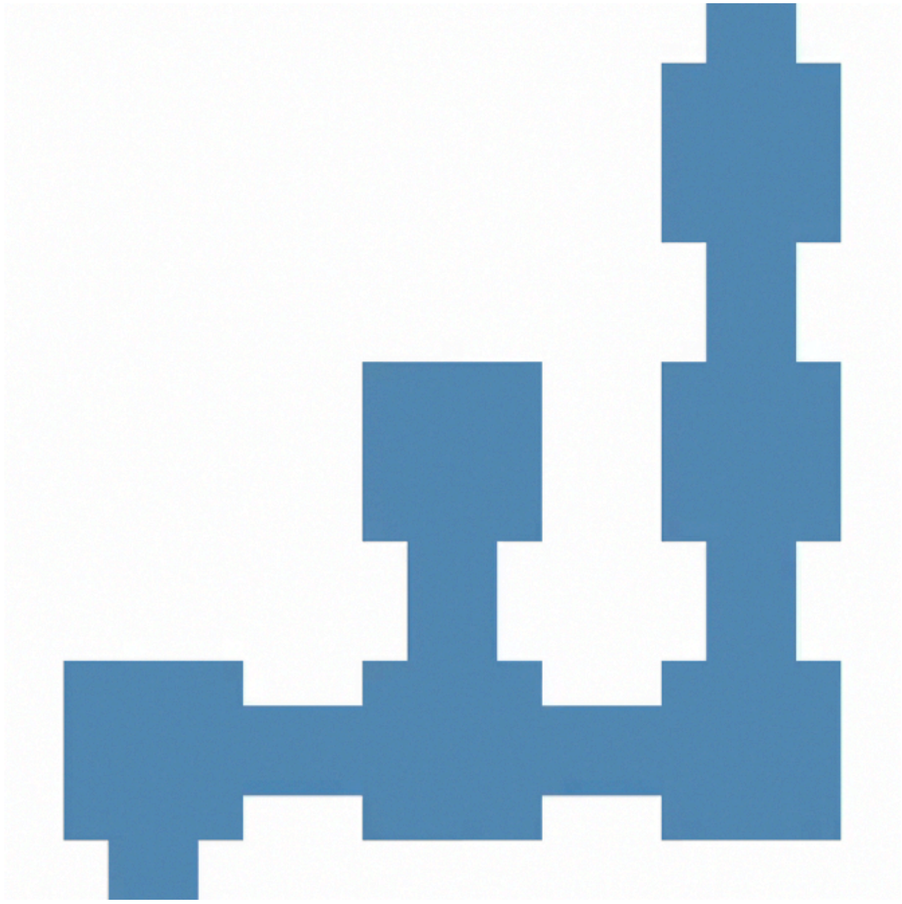


pool of candidates

evaluate the objective function

Connectivity Optimization



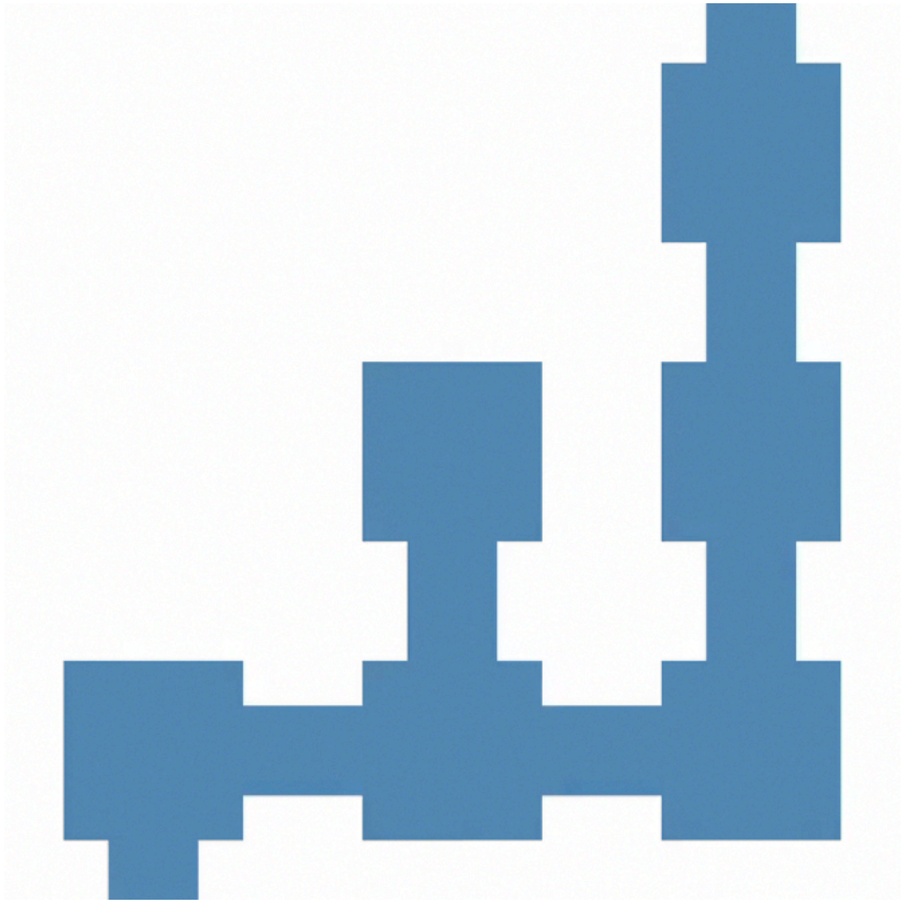
pool of candidates

evaluate the objective function

↓

weighted selection

Connectivity Optimization

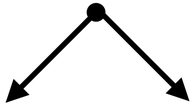


pool of candidates

evaluate the objective function

↓

weighted selection

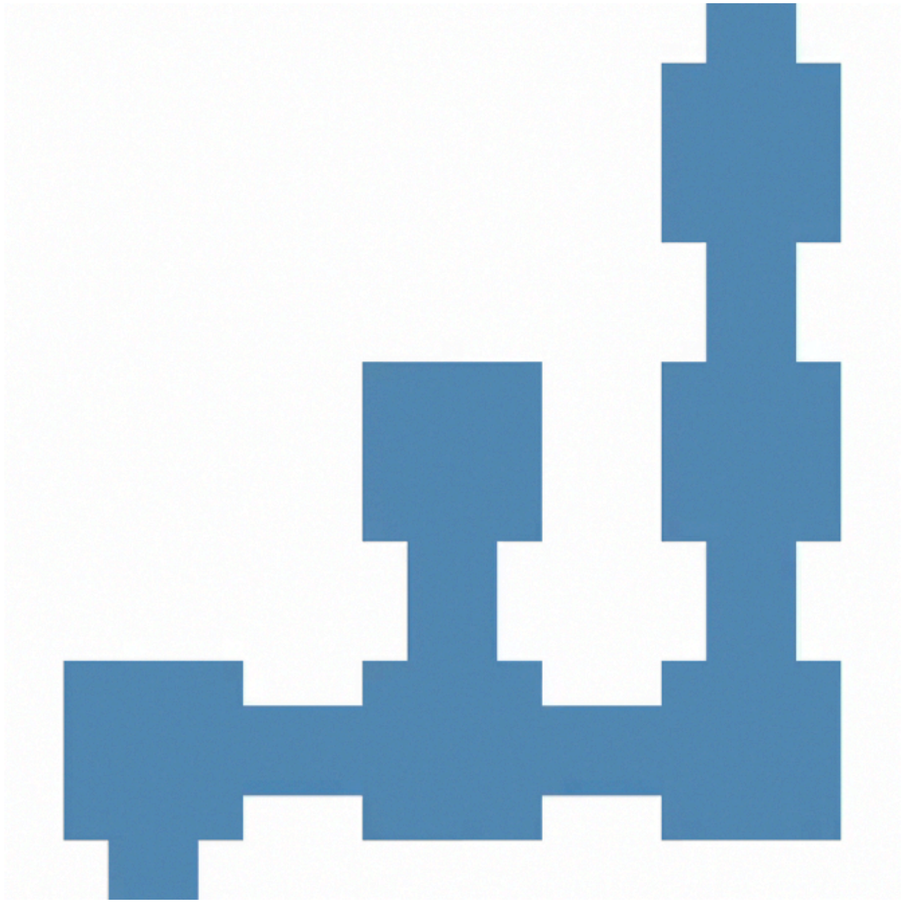


selected

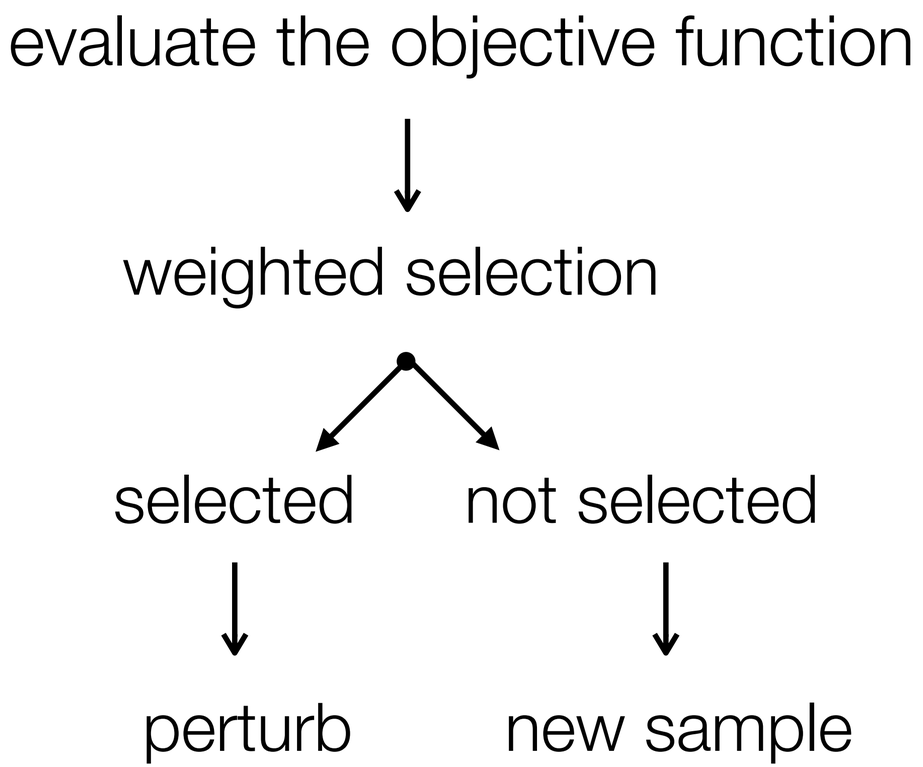
↓

perturb

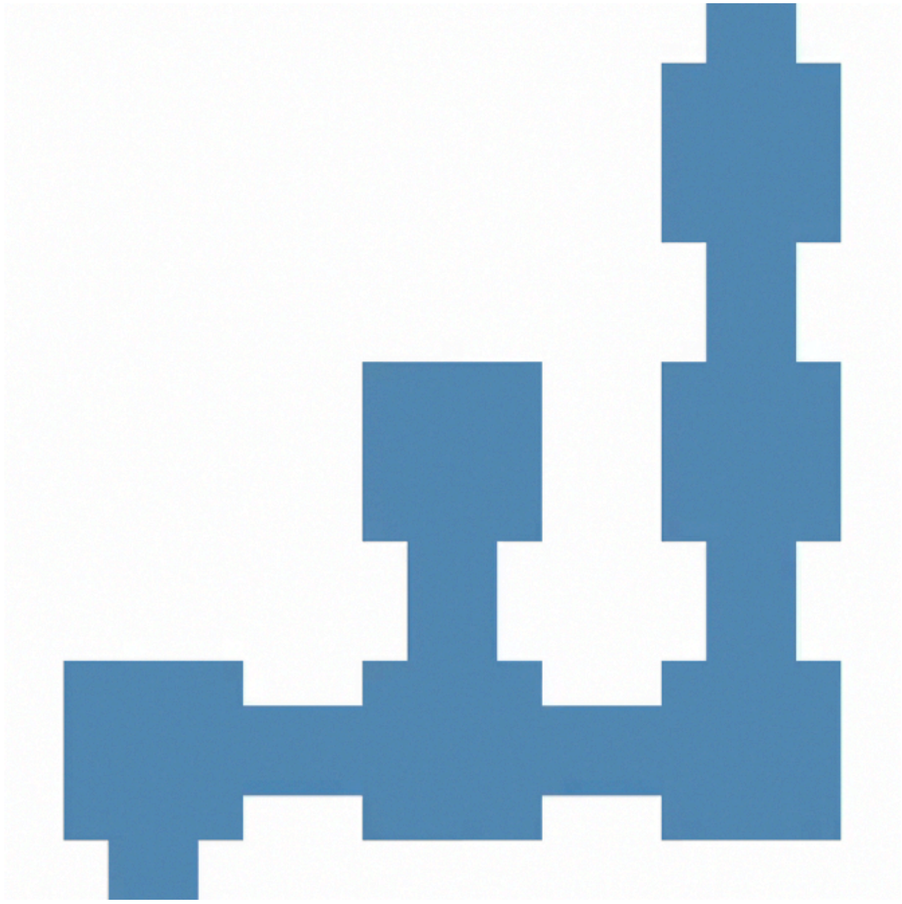
Connectivity Optimization



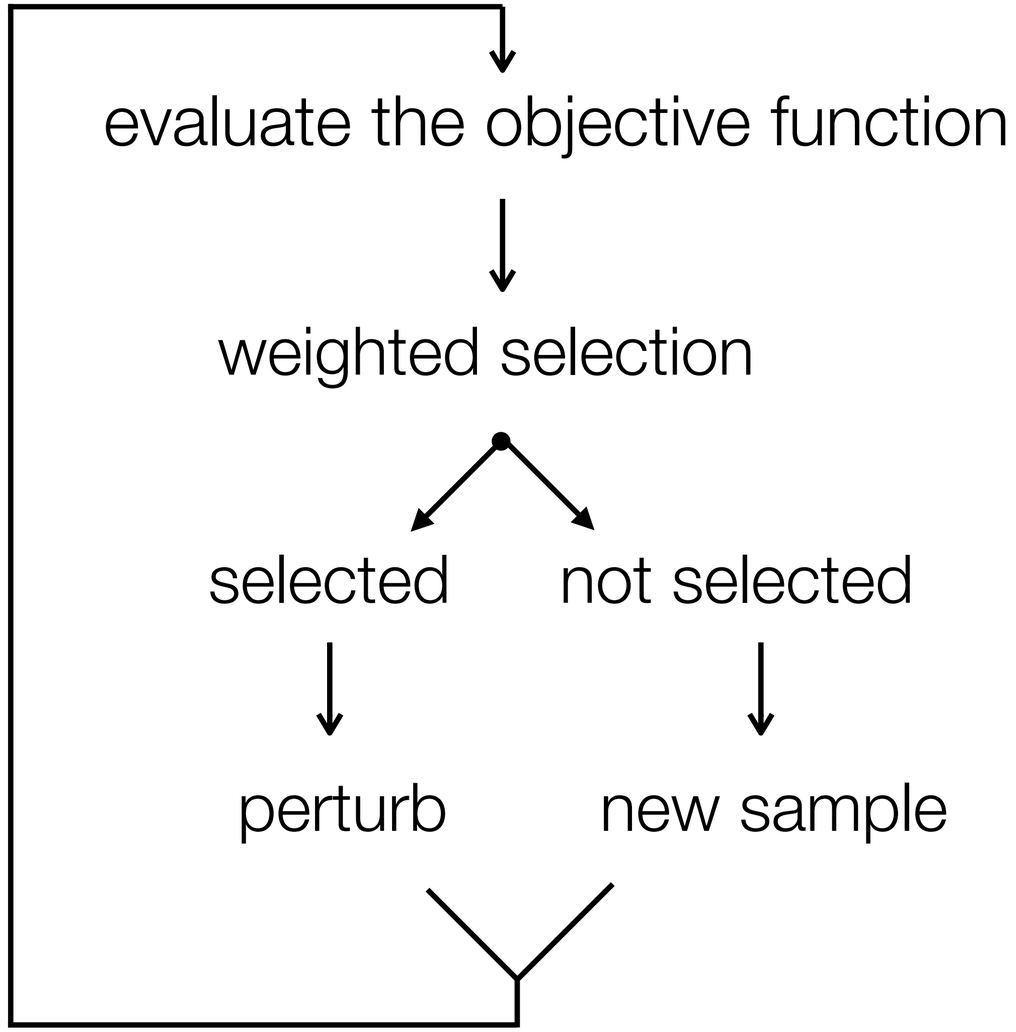
pool of candidates



Connectivity Optimization



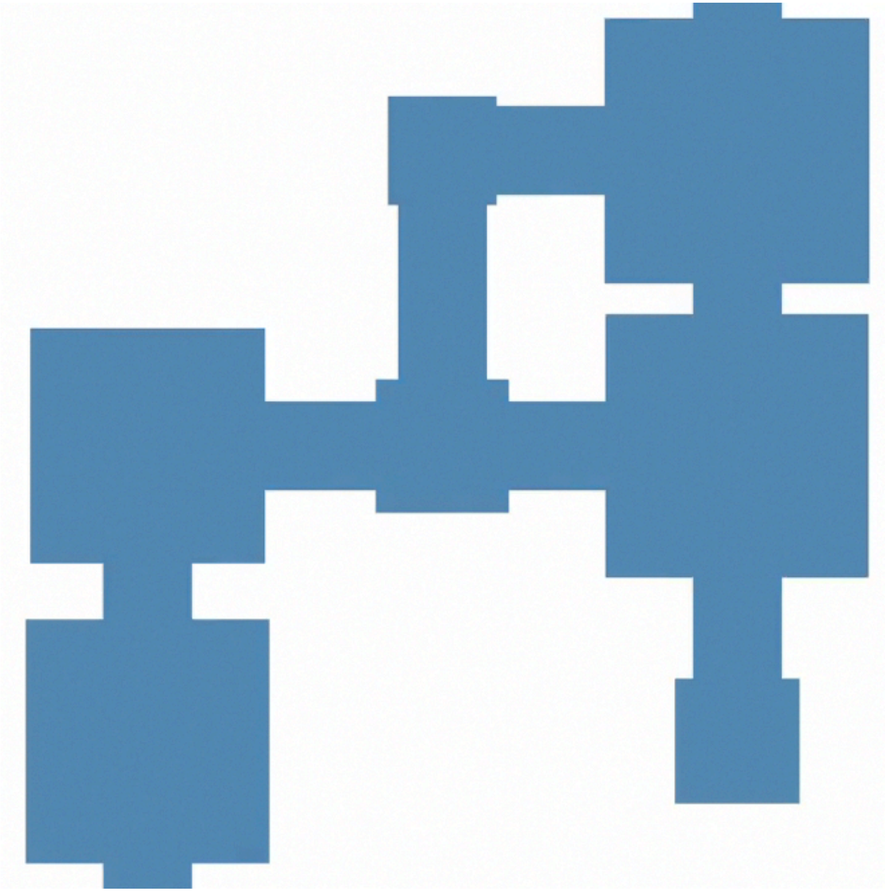
pool of candidates



Fine-grain Optimization

Gradient-based optimization (L-BFGS)

$$\frac{\partial J}{\partial \mathbf{u}}$$

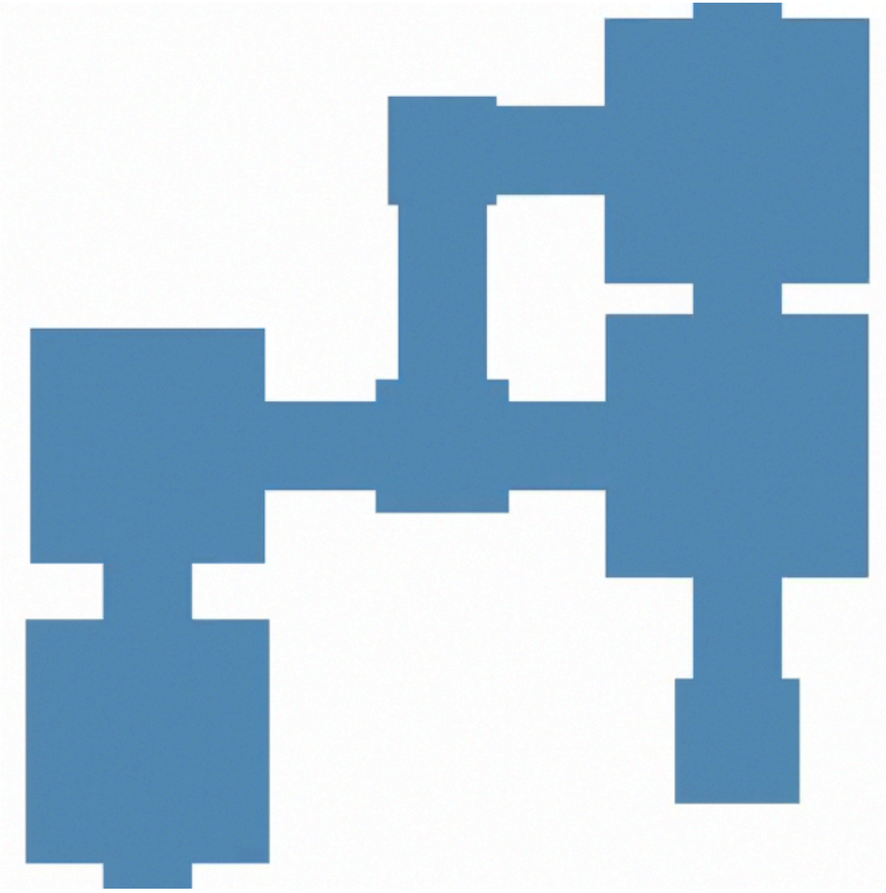


local continuous optimization

Fine-grain Optimization

Gradient-based optimization (L-BFGS)

$$\frac{\partial J}{\partial \mathbf{u}}$$



local continuous optimization

Gradient Computation

$$J = \sum_{i=1}^{N} \left(g_{\omega_i}(c, \mathbf{u}) - g^*_{\omega_i} \right)^2$$

$$\frac{\partial J}{\partial \mathbf{u}}$$

Gradient Computation

$$J = \sum_{i=1}^{N} \left(g_{\omega_i}(c, \mathbf{u}) - g^*_{\omega_i} \right)^2$$

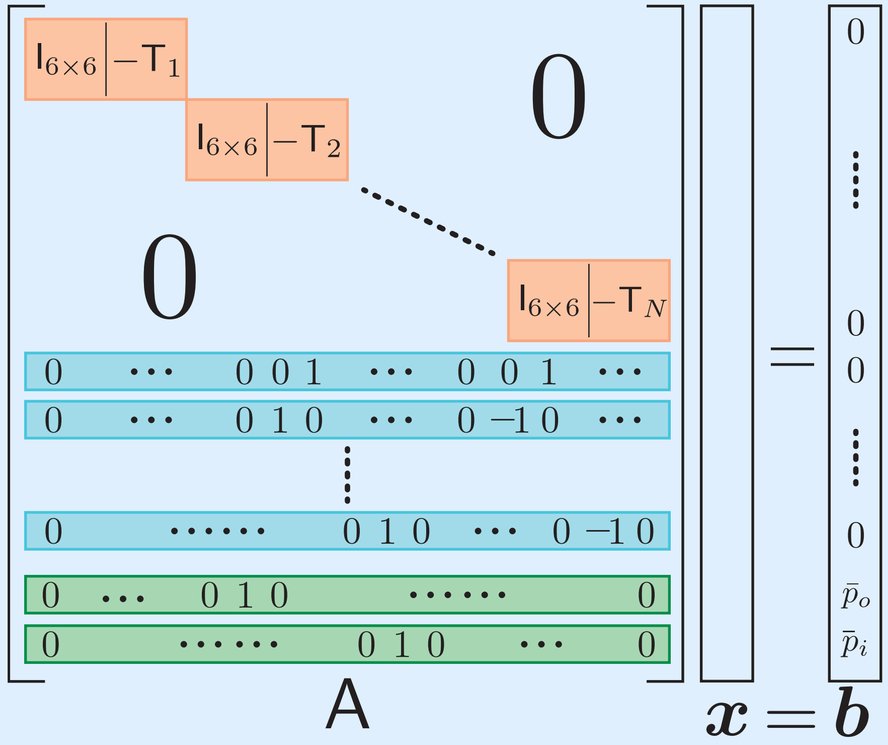
$$\frac{\partial J}{\partial \mathbf{u}} \longleftarrow \frac{\partial g}{\partial \mathbf{u}}$$

Gradient Computation

$$J = \sum_{i=1}^{N} \left(g_{\omega_i}(c, \mathbf{u}) - g^*_{\omega_i} \right)^2$$

$$\frac{\partial J}{\partial \mathbf{u}} \longleftarrow \frac{\partial g}{\partial \mathbf{u}} = \frac{\partial g}{\partial x} \frac{\partial x}{\partial \mathbf{u}}$$

1 x 12N | 12N x N



Gradient Computation

$$J = \sum_{i=1}^{N} \left(g_{\omega_i}(c, \mathbf{u}) - g^*_{\omega_i} \right)^2$$

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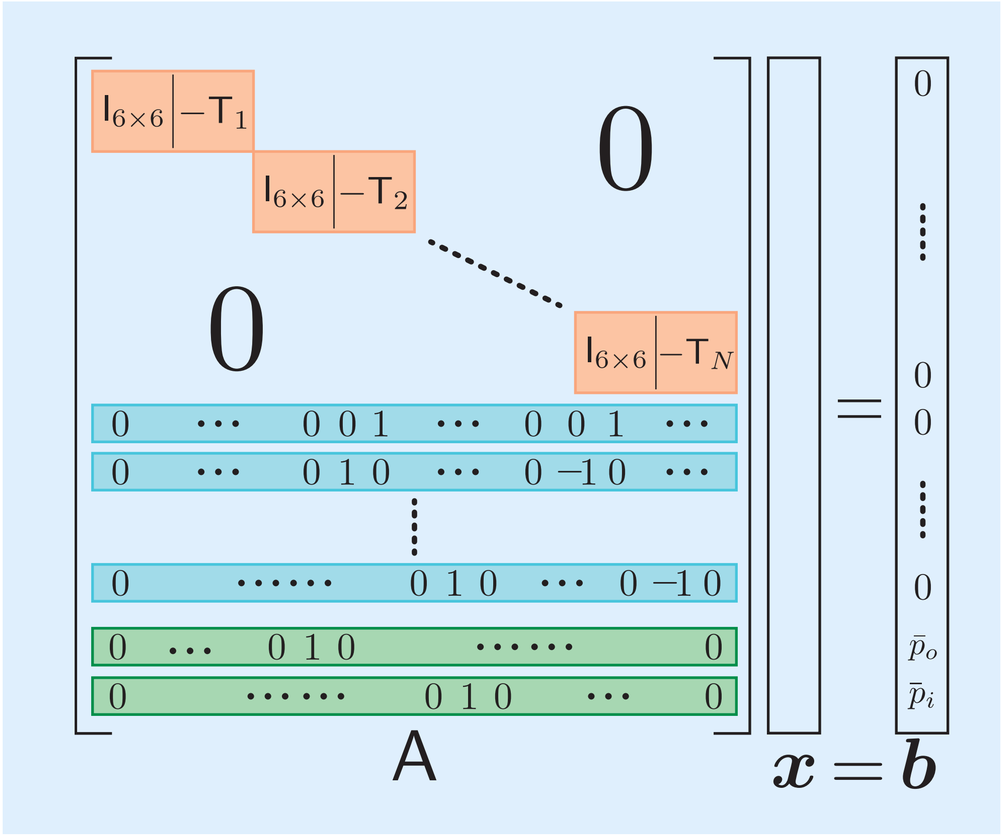

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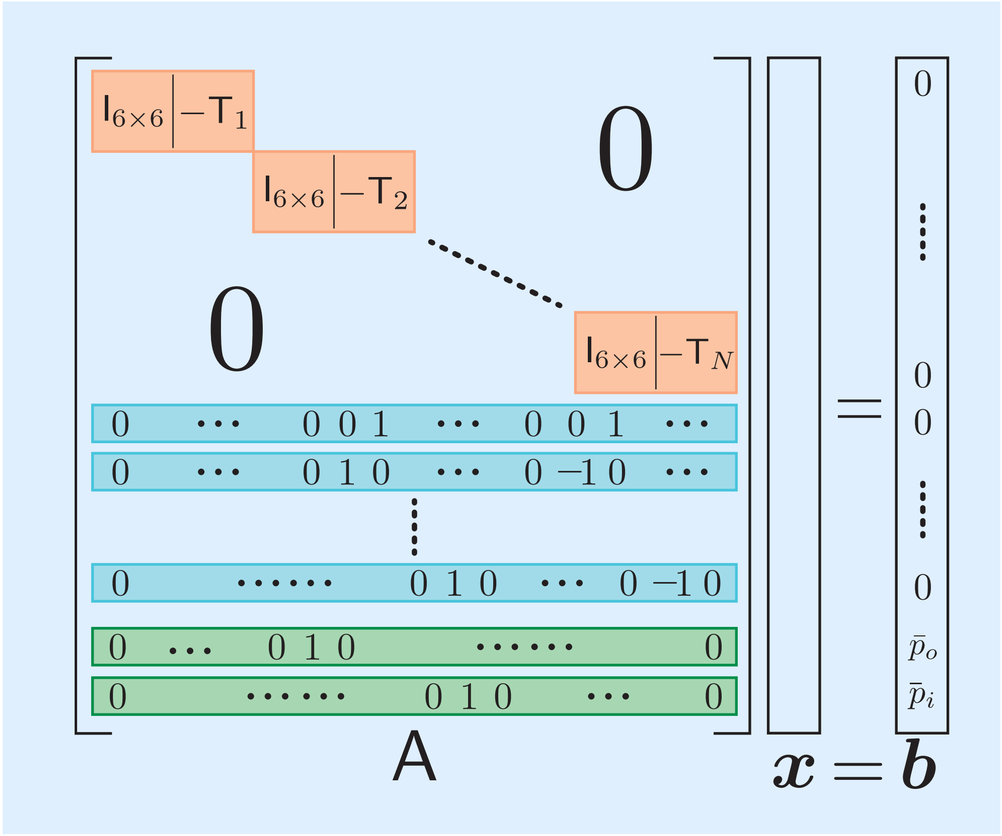

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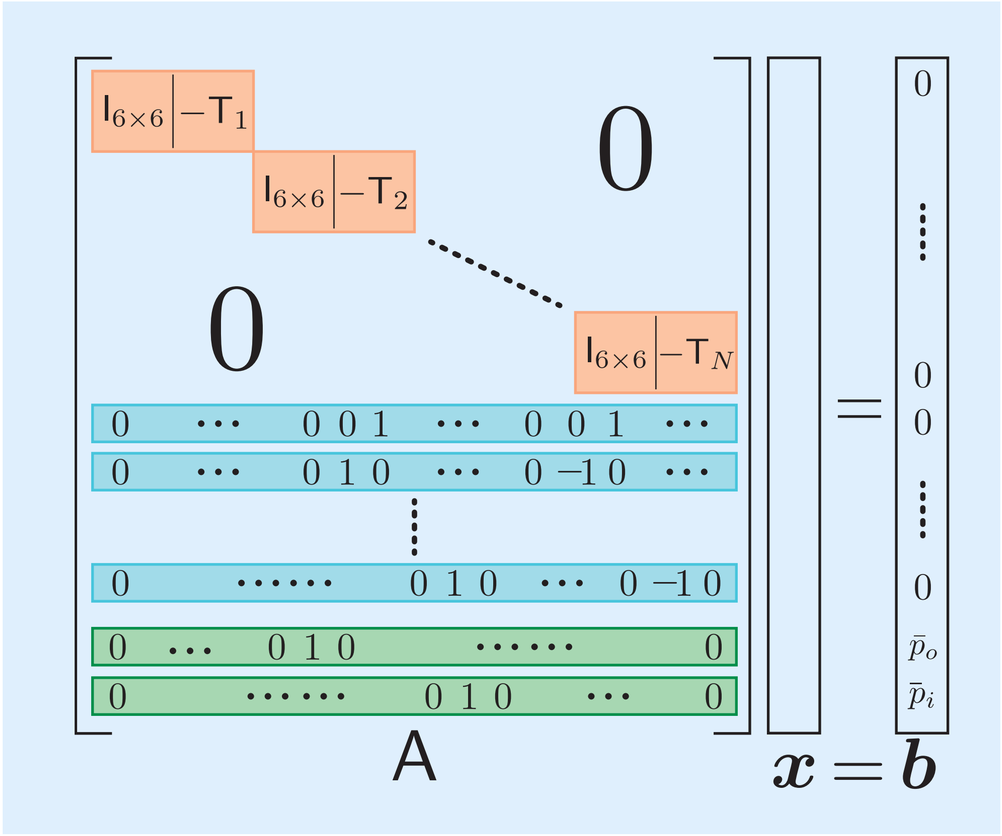
$$\mathrm{A} \frac{\partial x}{\partial \mathbf{u}} = -\frac{\partial \mathrm{A}}{\partial \mathbf{u}}$$



Adjoint Method

$$\frac{\partial g}{\partial \mathbf{u}} = \frac{\partial g}{\partial x}\,\frac{\partial x}{\partial \mathbf{u}} \quad \text{subject to} \quad \mathrm{A}\frac{\partial x}{\partial \mathbf{u}} = -\frac{\partial \mathrm{A}}{\partial \mathbf{u}}$$

12N x N

Adjoint Method

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12N x N

⇕ Adjoint Method

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12N x N

$\Updownarrow$ Adjoint Method

$$\frac{\partial g}{\partial \mathbf{u}} = \mathbf{t}^T\frac{\partial \mathrm{A}}{\partial \mathbf{u}} \quad \text{subject to} \quad \mathrm{A}\mathbf{t} = \frac{\partial g}{\partial \mathrm{T}}\frac{\partial \mathrm{T}}{\partial \mathbf{x}}$$

Adjoint Method

$$\frac{\partial g}{\partial \mathbf{u}} = \frac{\partial g}{\partial x}\frac{\partial x}{\partial \mathbf{u}} \quad \text{subject to} \quad \mathrm{A}\frac{\partial x}{\partial \mathbf{u}} = -\frac{\partial \mathrm{A}}{\partial \mathbf{u}}$$

12N x N

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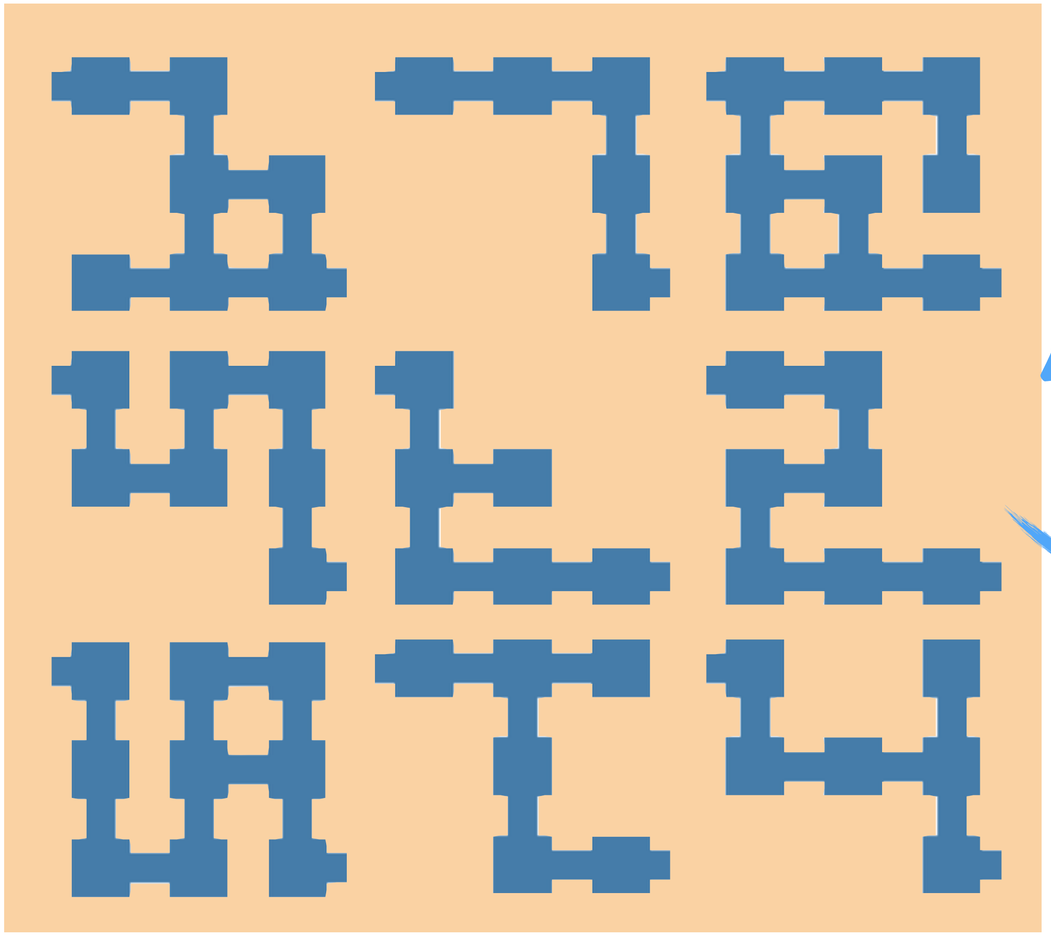
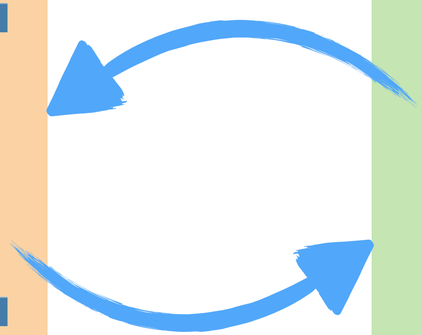
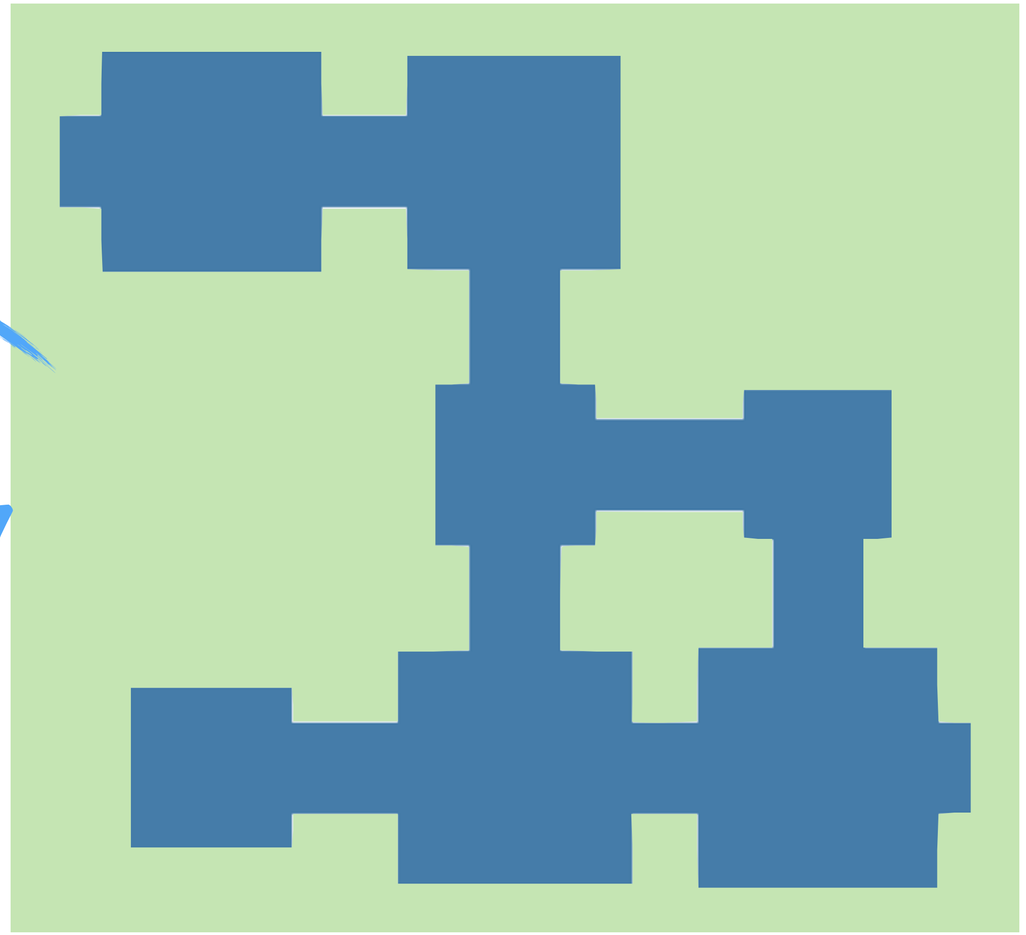
12N x 1

Iterative Two-stage Optimization



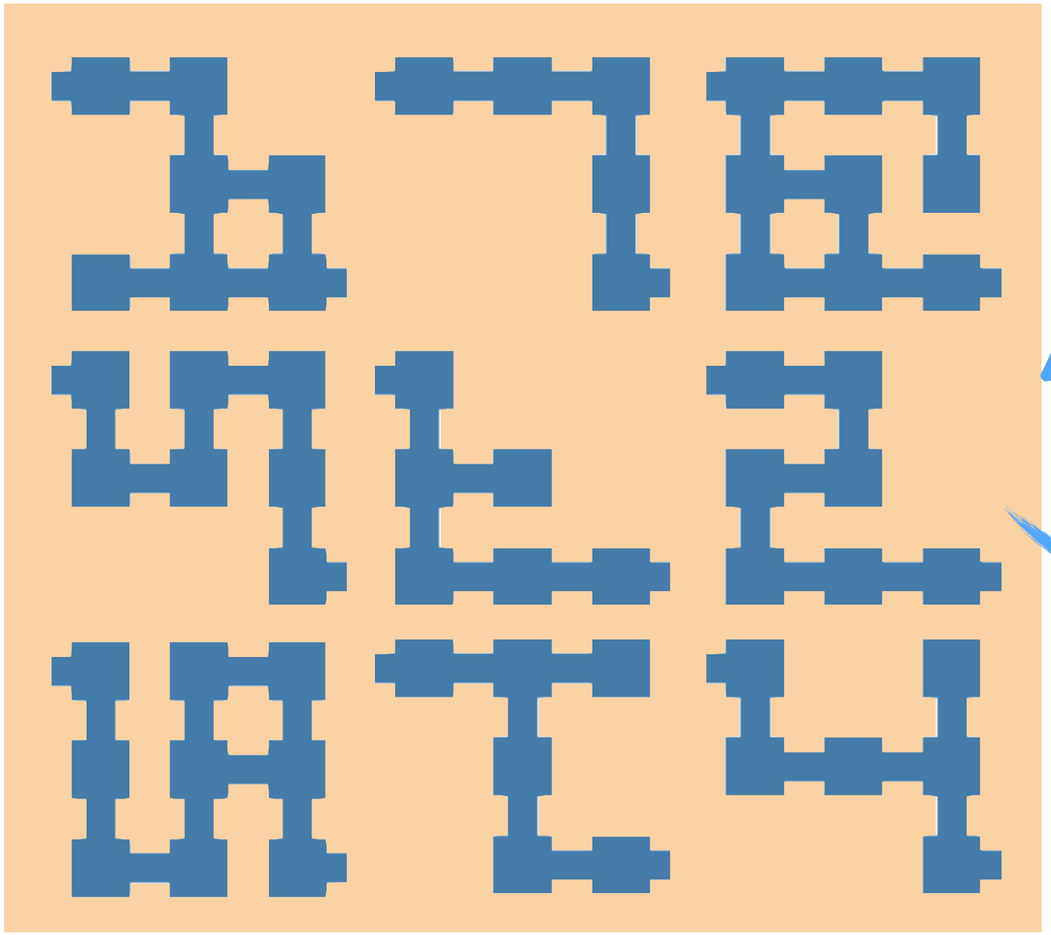


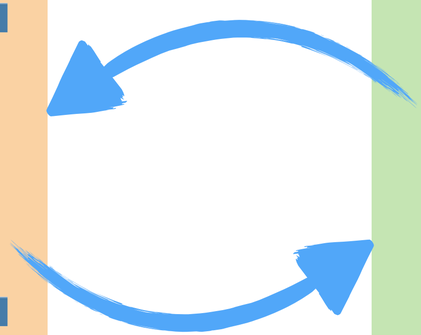


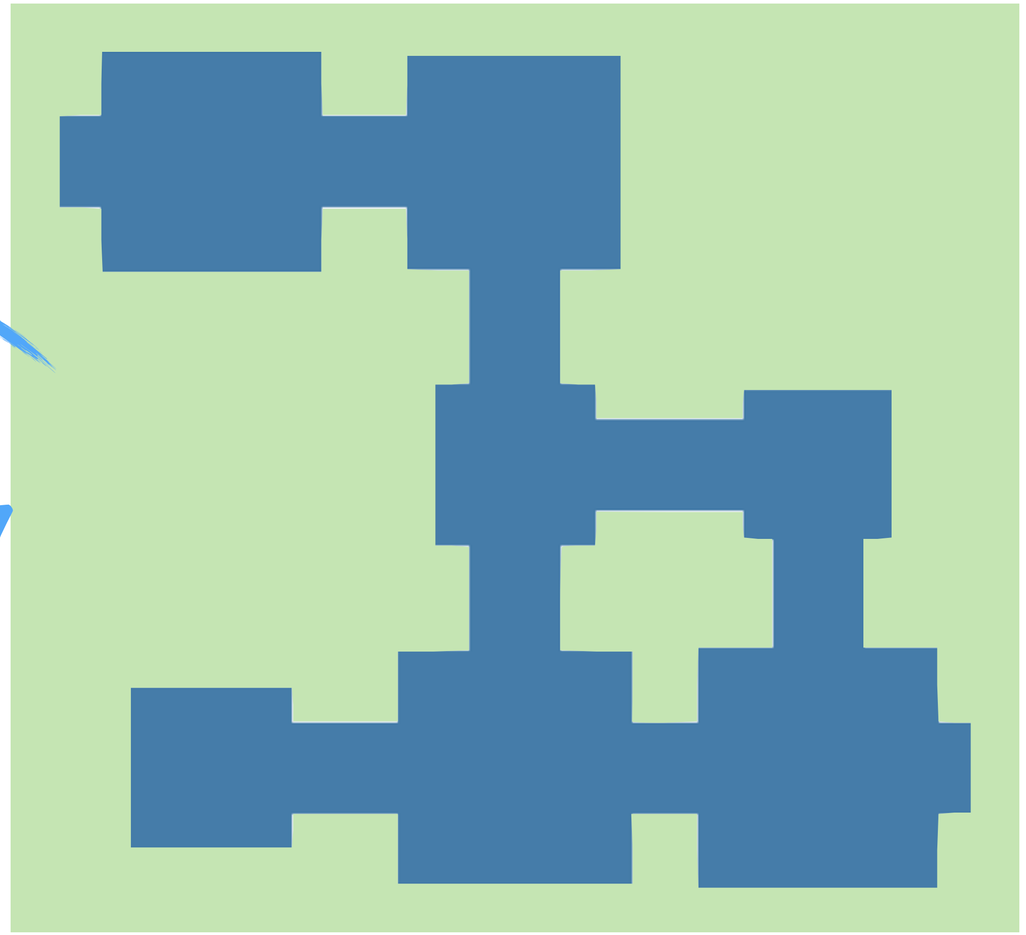
Connectivity Optimization

Fine-grain Optimization

Iterative Two-stage Optimization



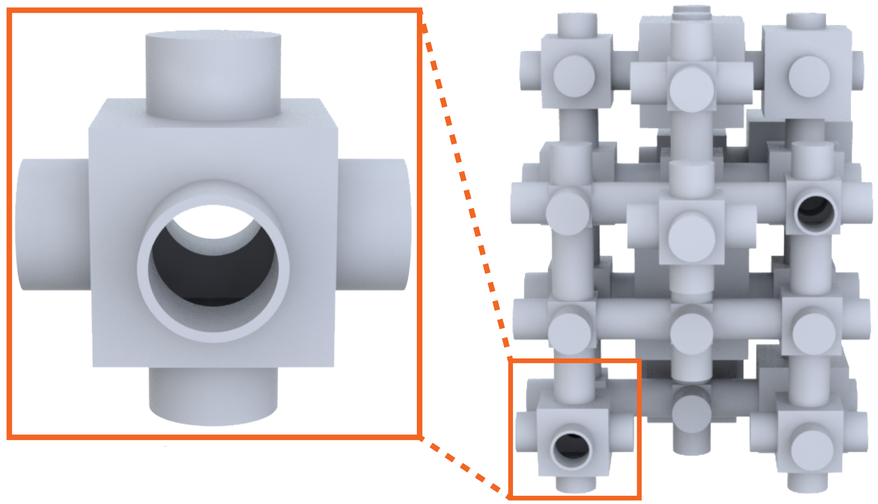




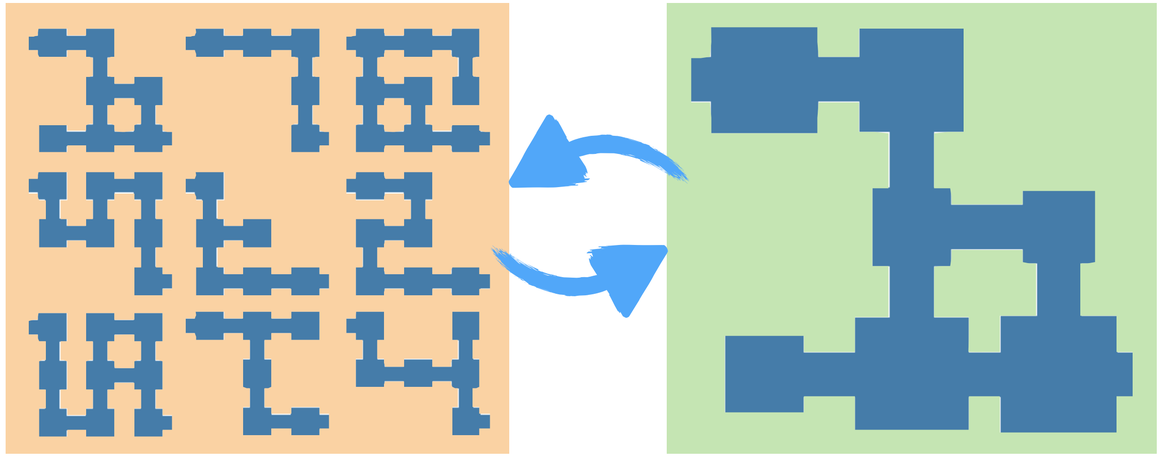
Connectivity Optimization

Fine-grain Optimization

Recap



Primitive Resonators



Optimization

Applications

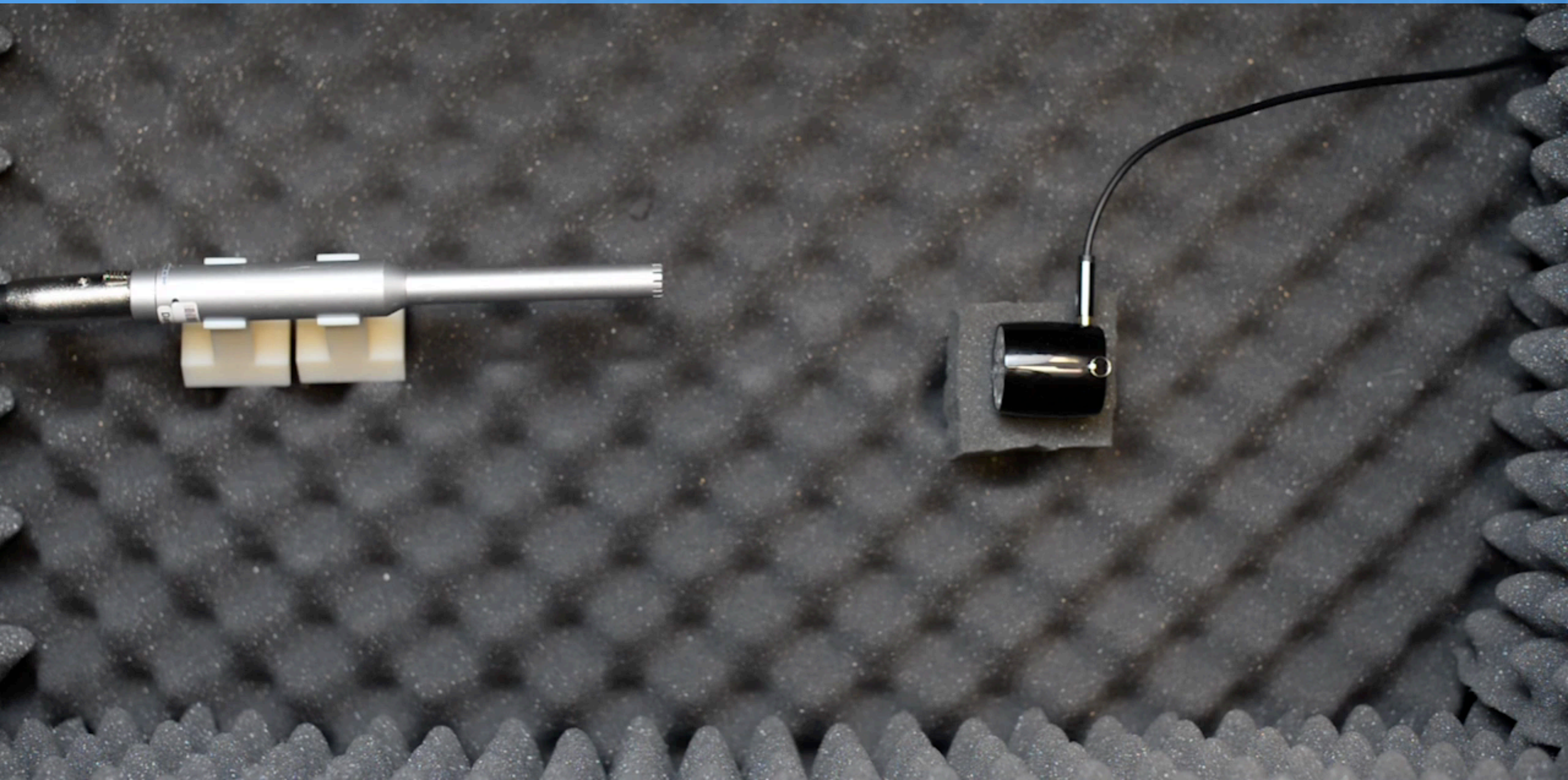
Applications

Mufflers

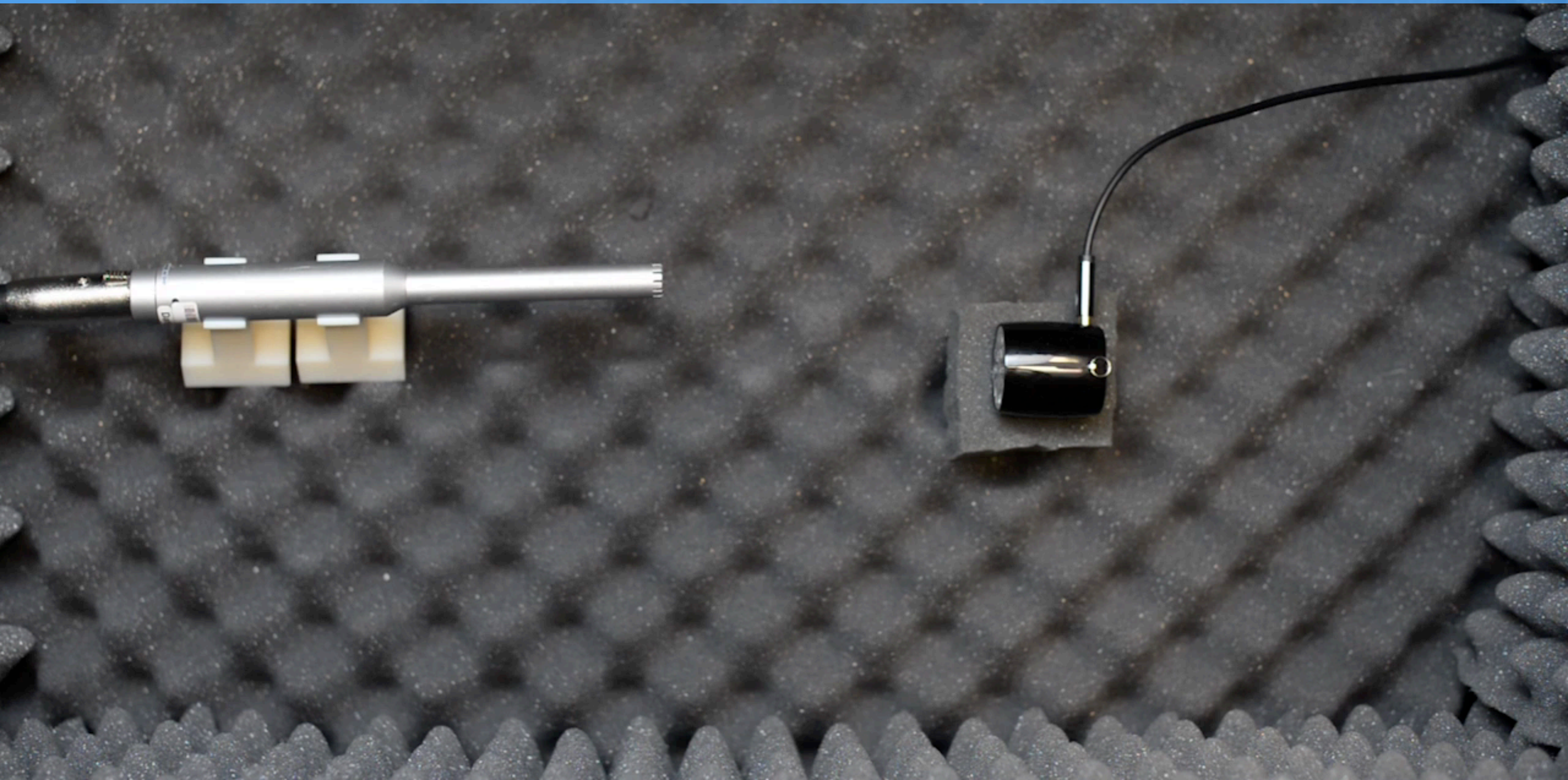
Wind Instruments

Acoustic Encoding

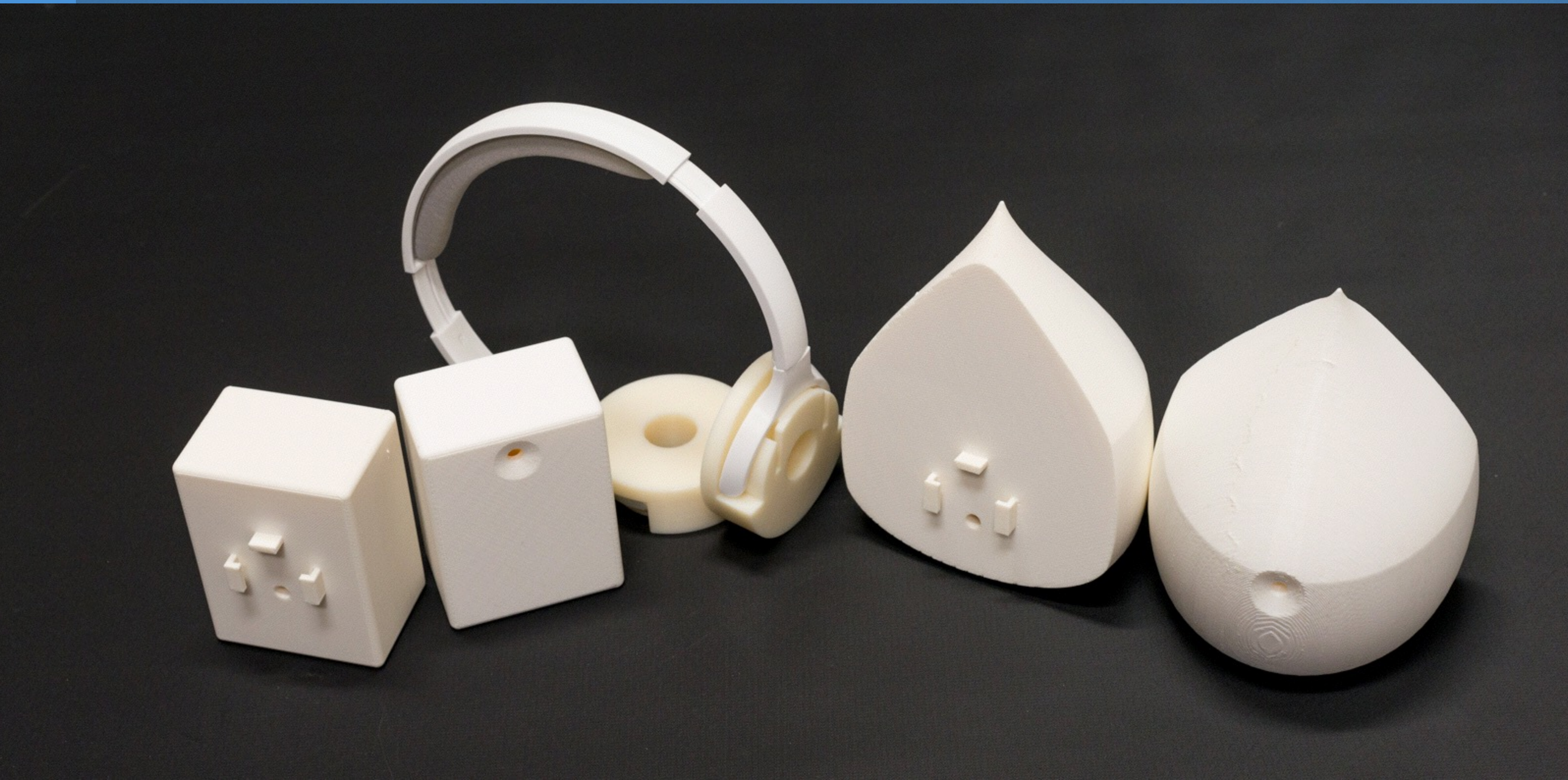
Muffler Demonstration



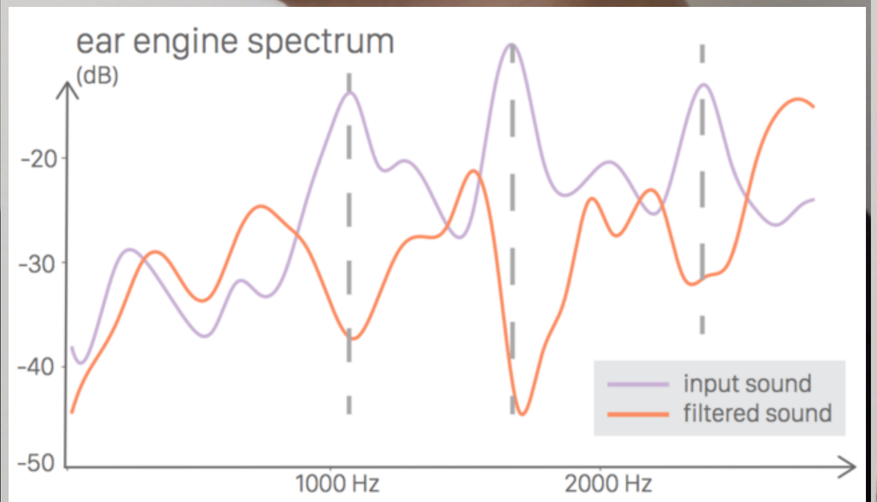
Muffler Demonstration

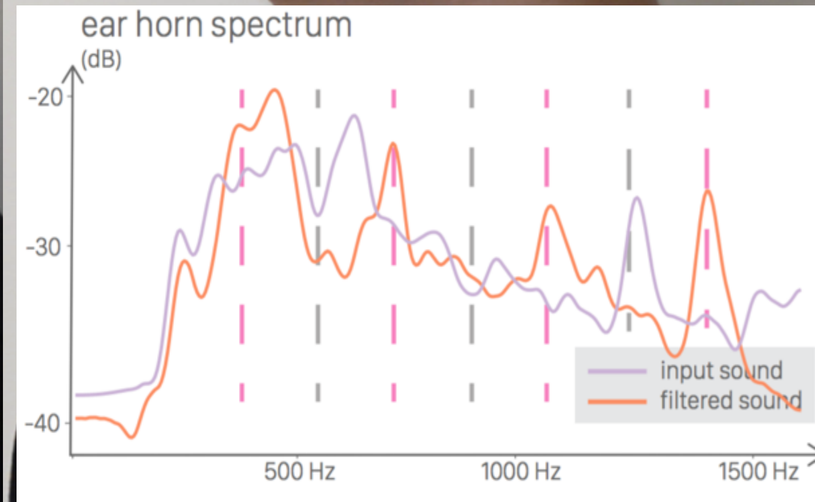


Adaptive Earmuff Application

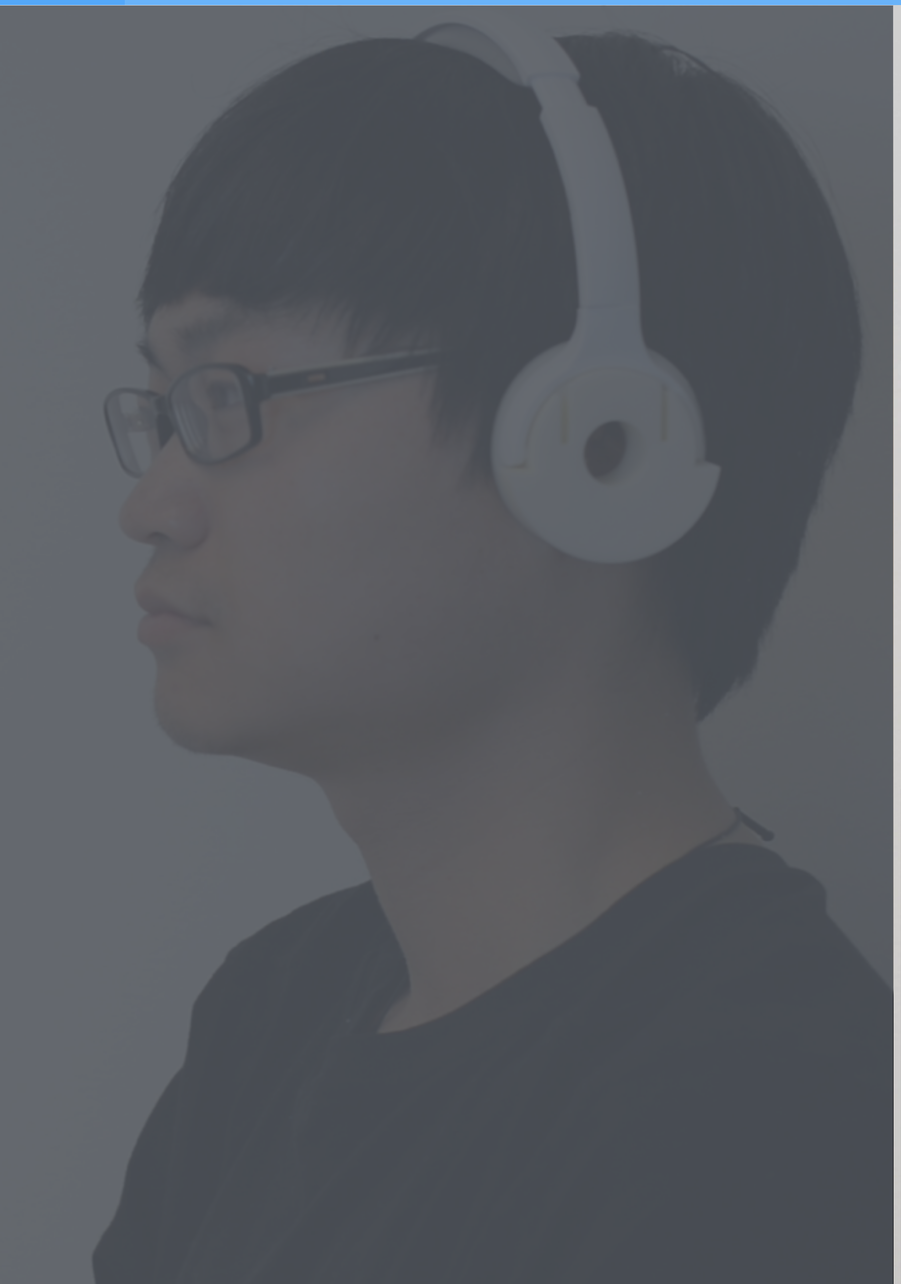


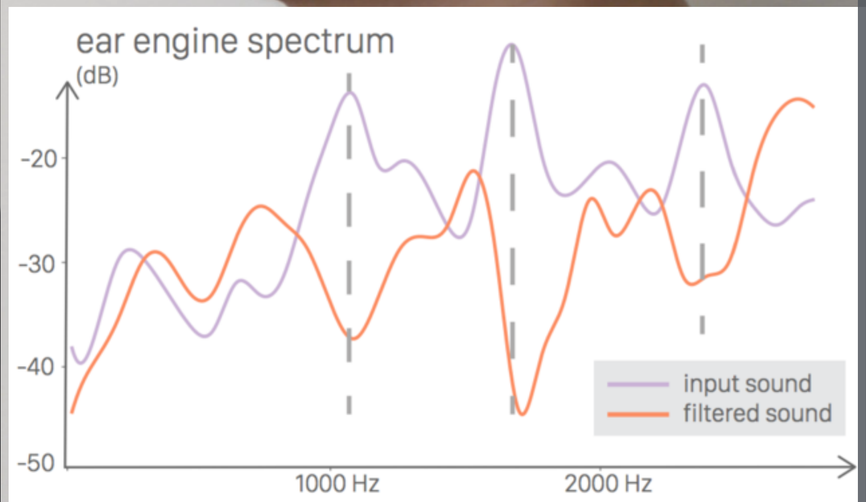
Adaptive Earmuff Application

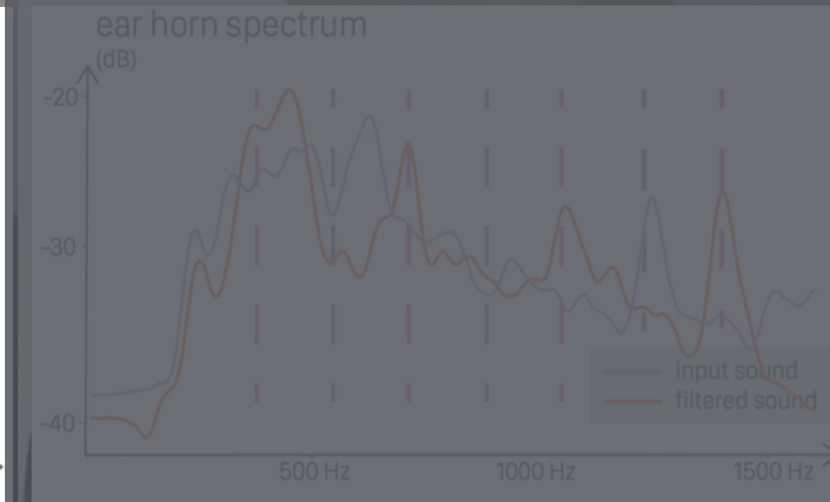




Adaptive Earmuff Application







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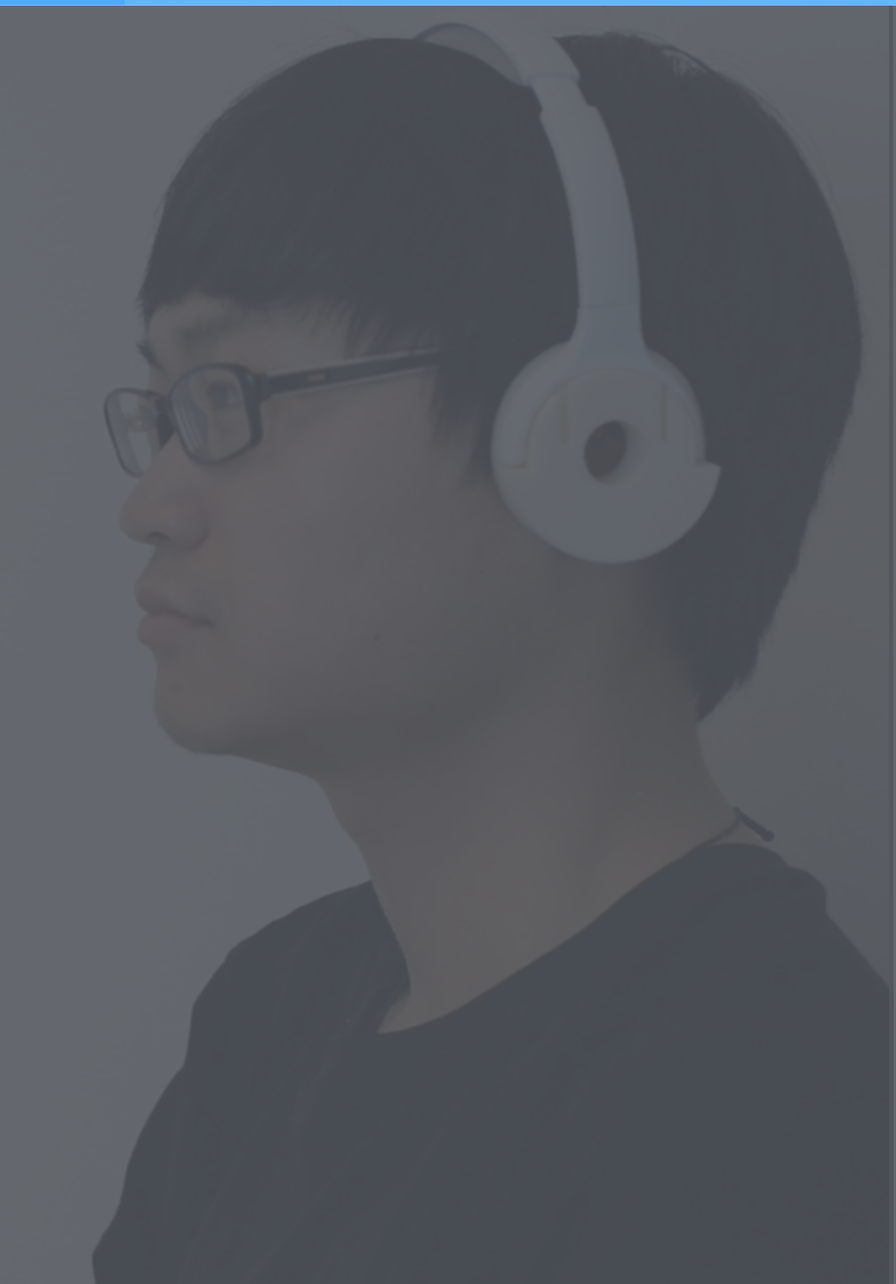

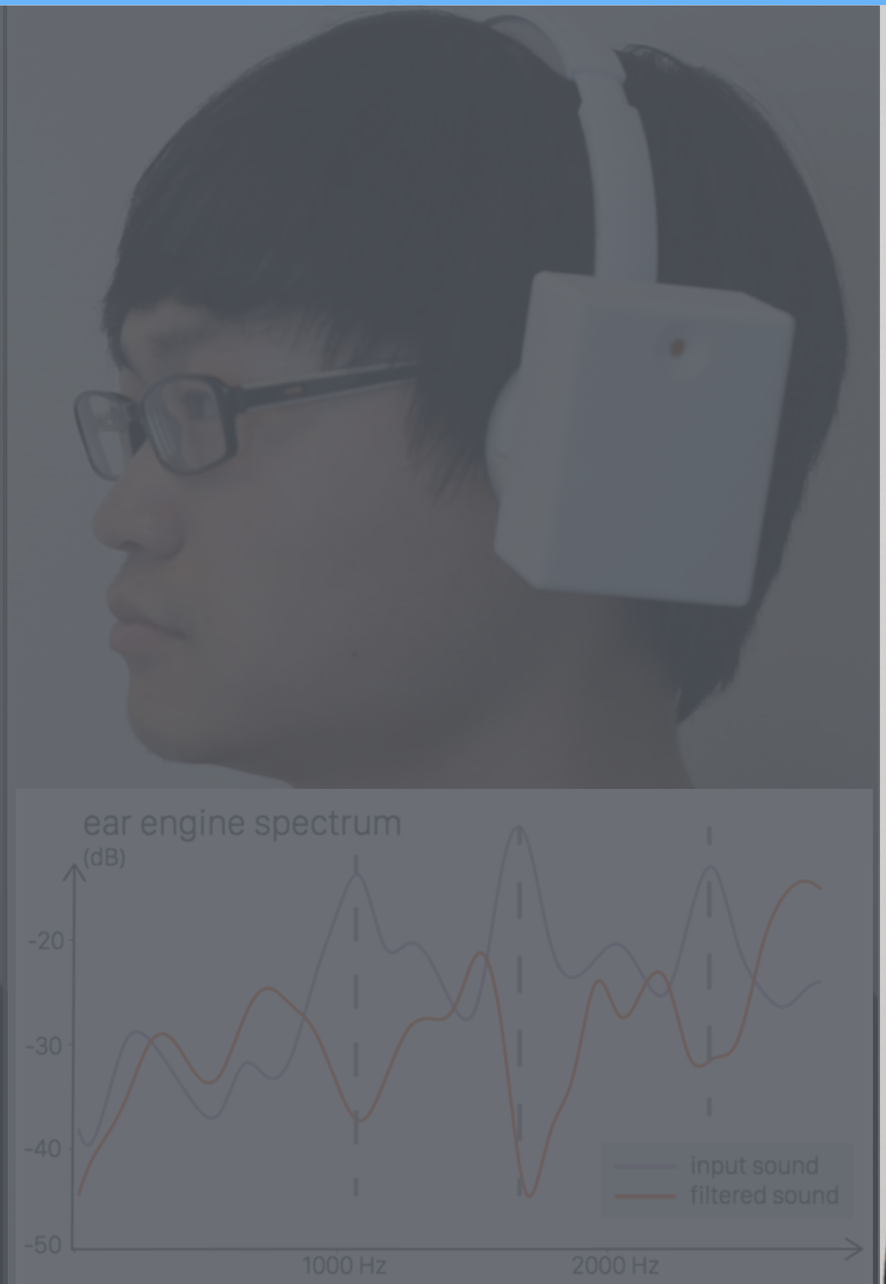

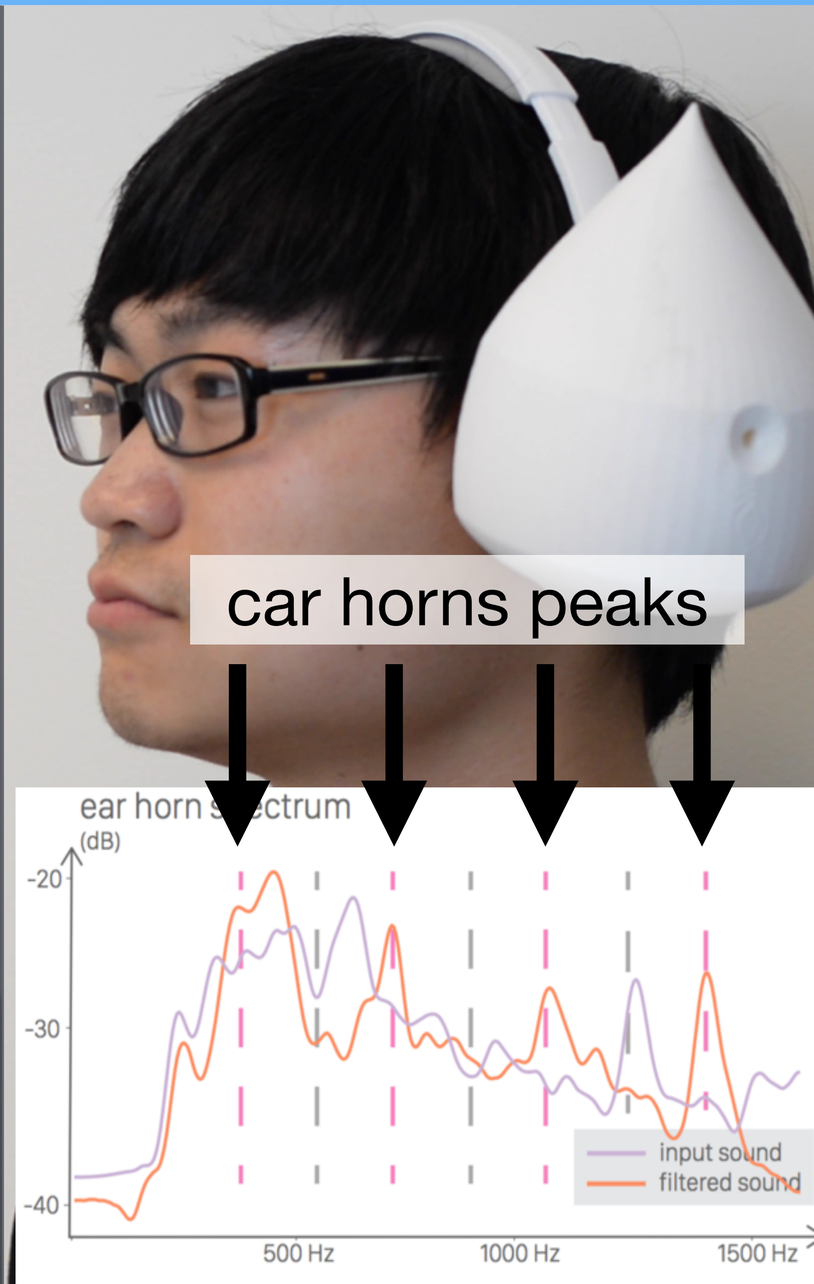

Wind Instrument Prototyping

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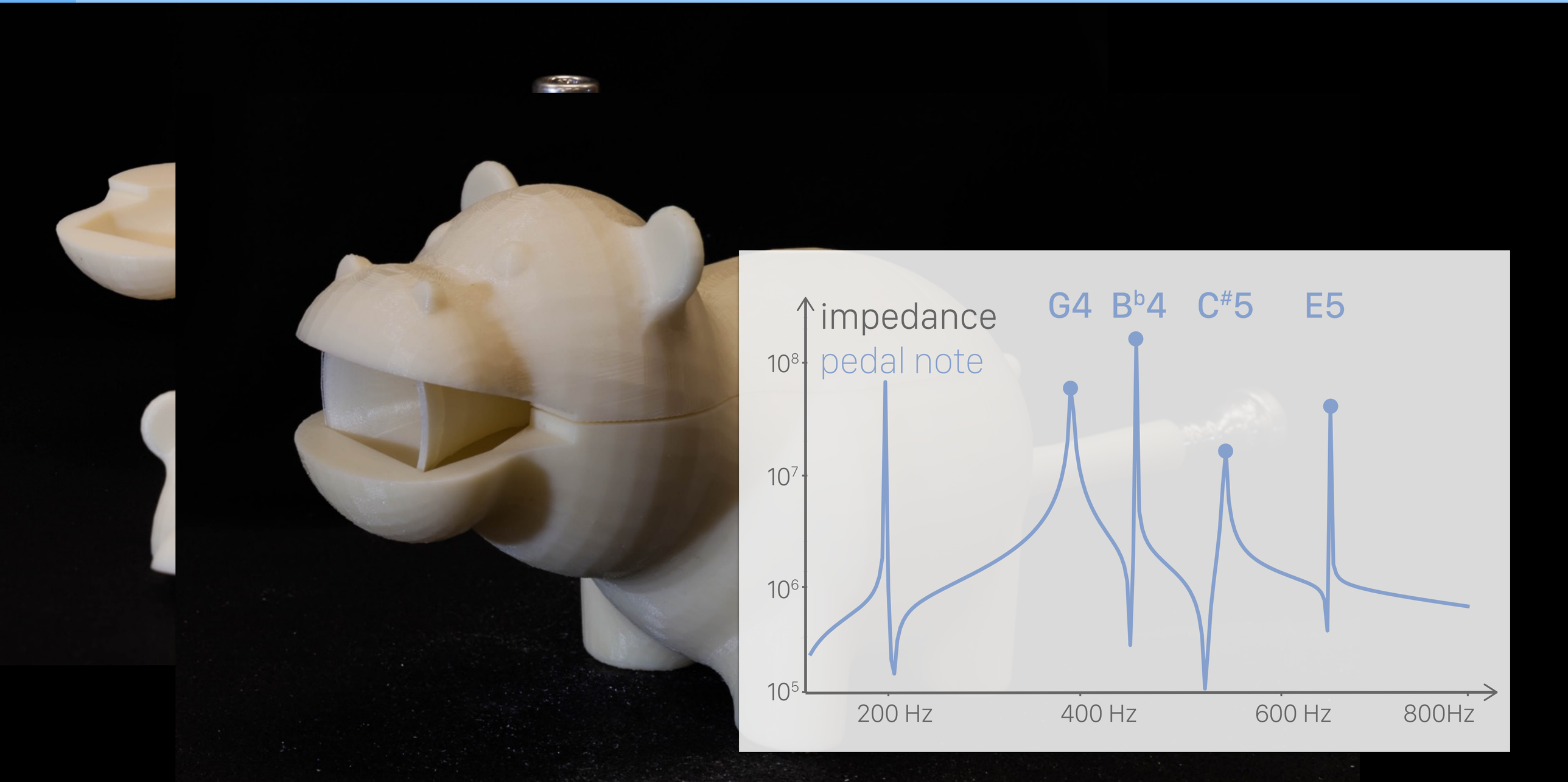
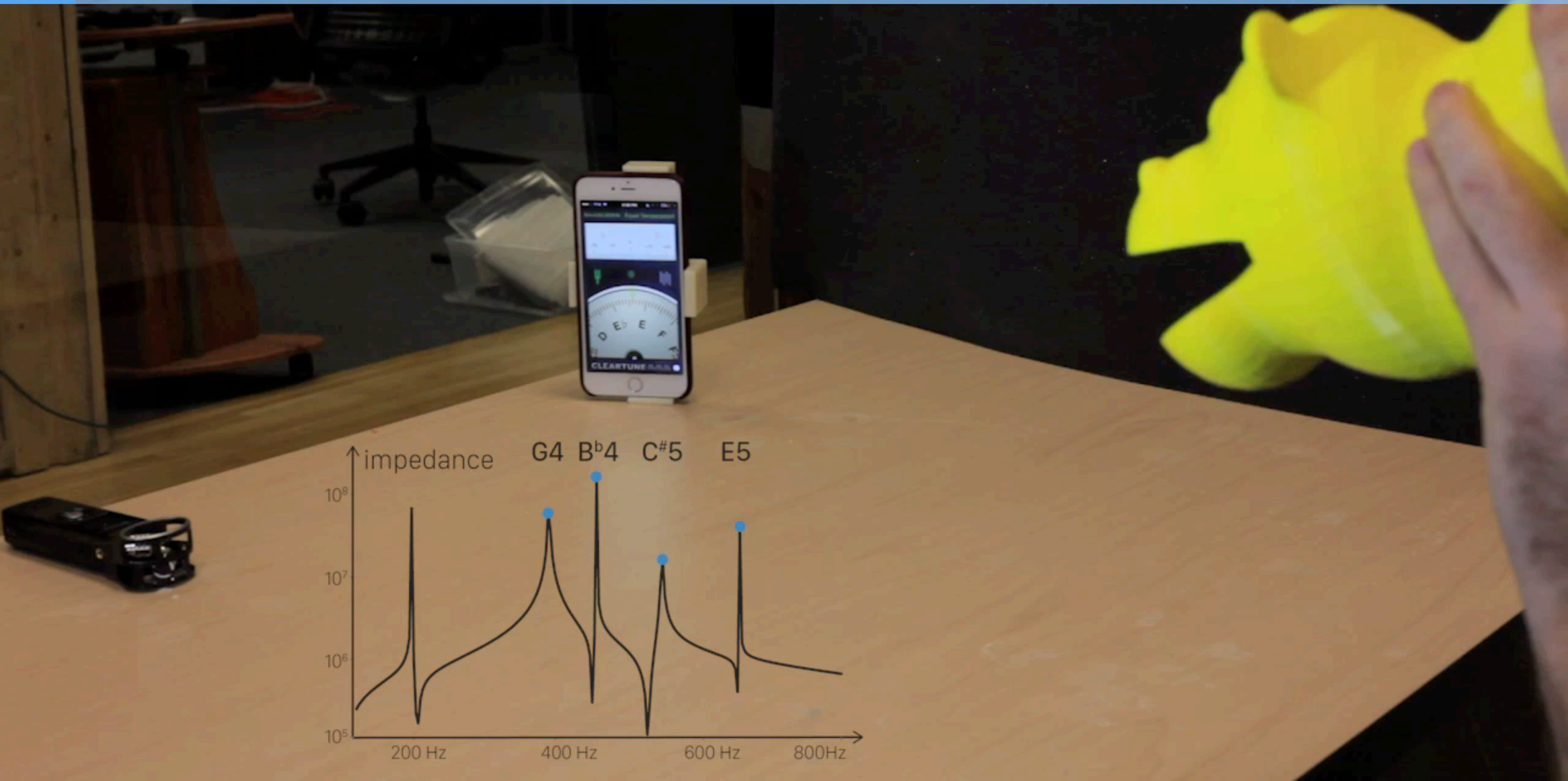
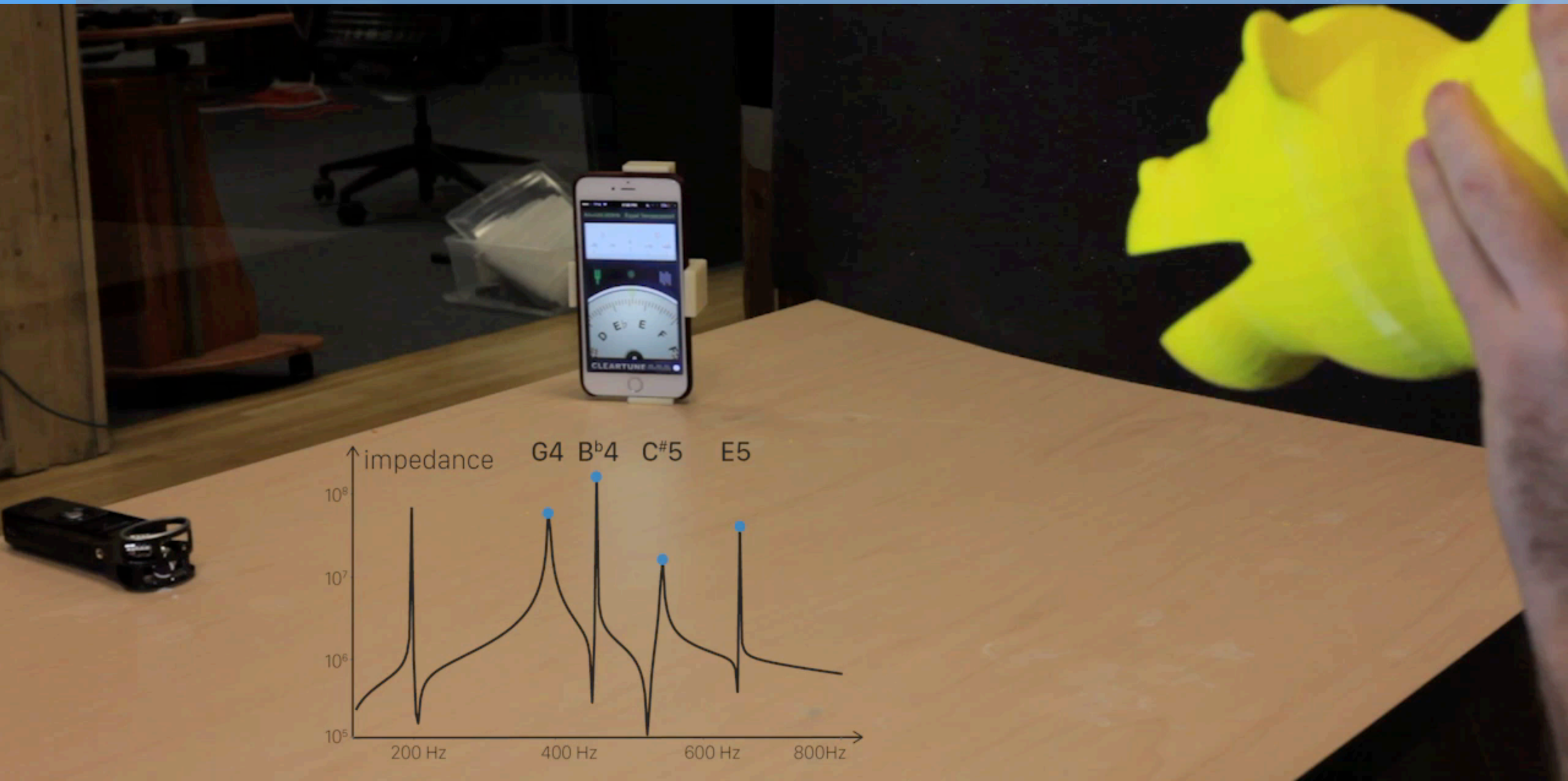


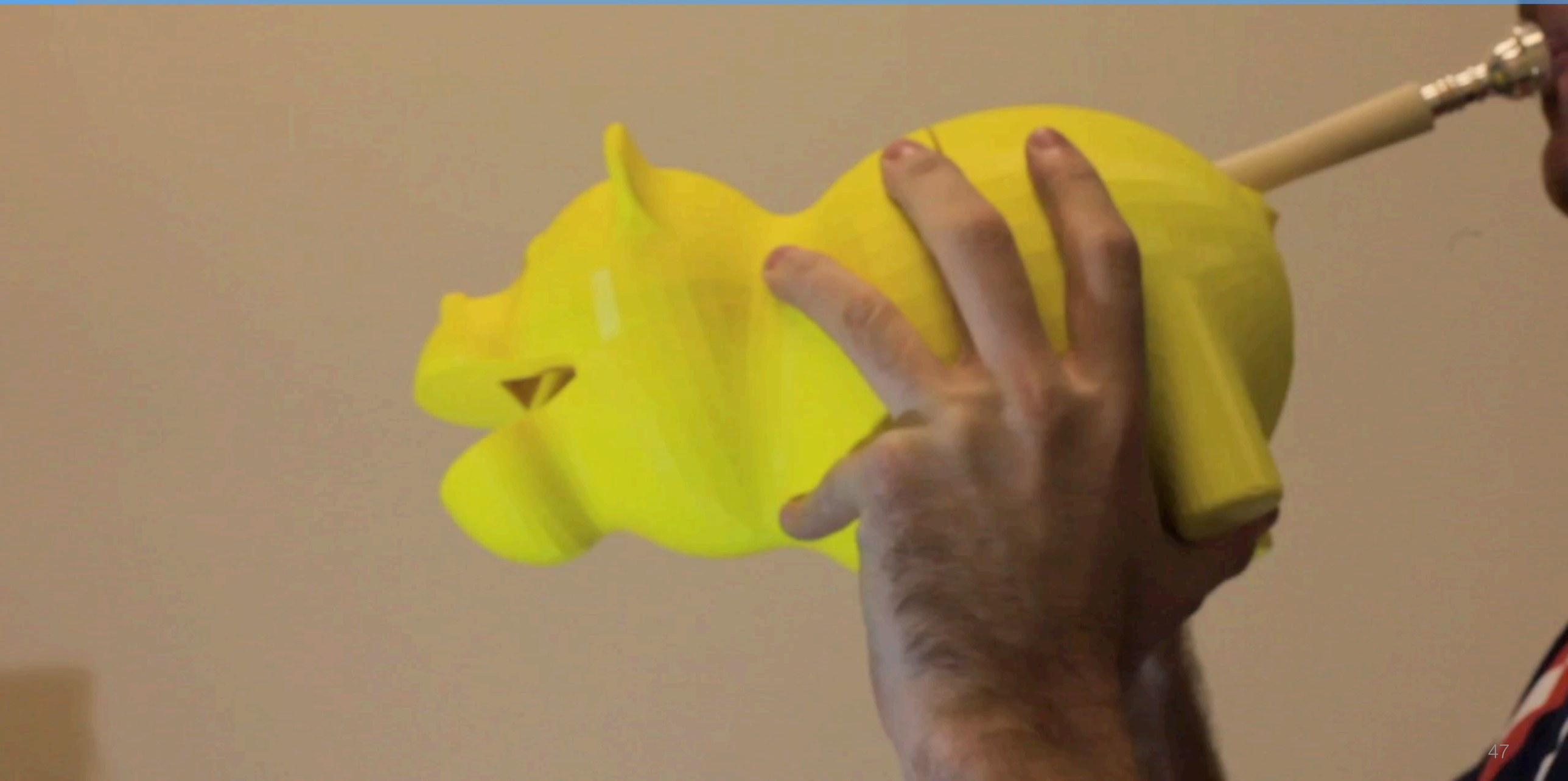
Music Notes



Music Notes



Simple Melody



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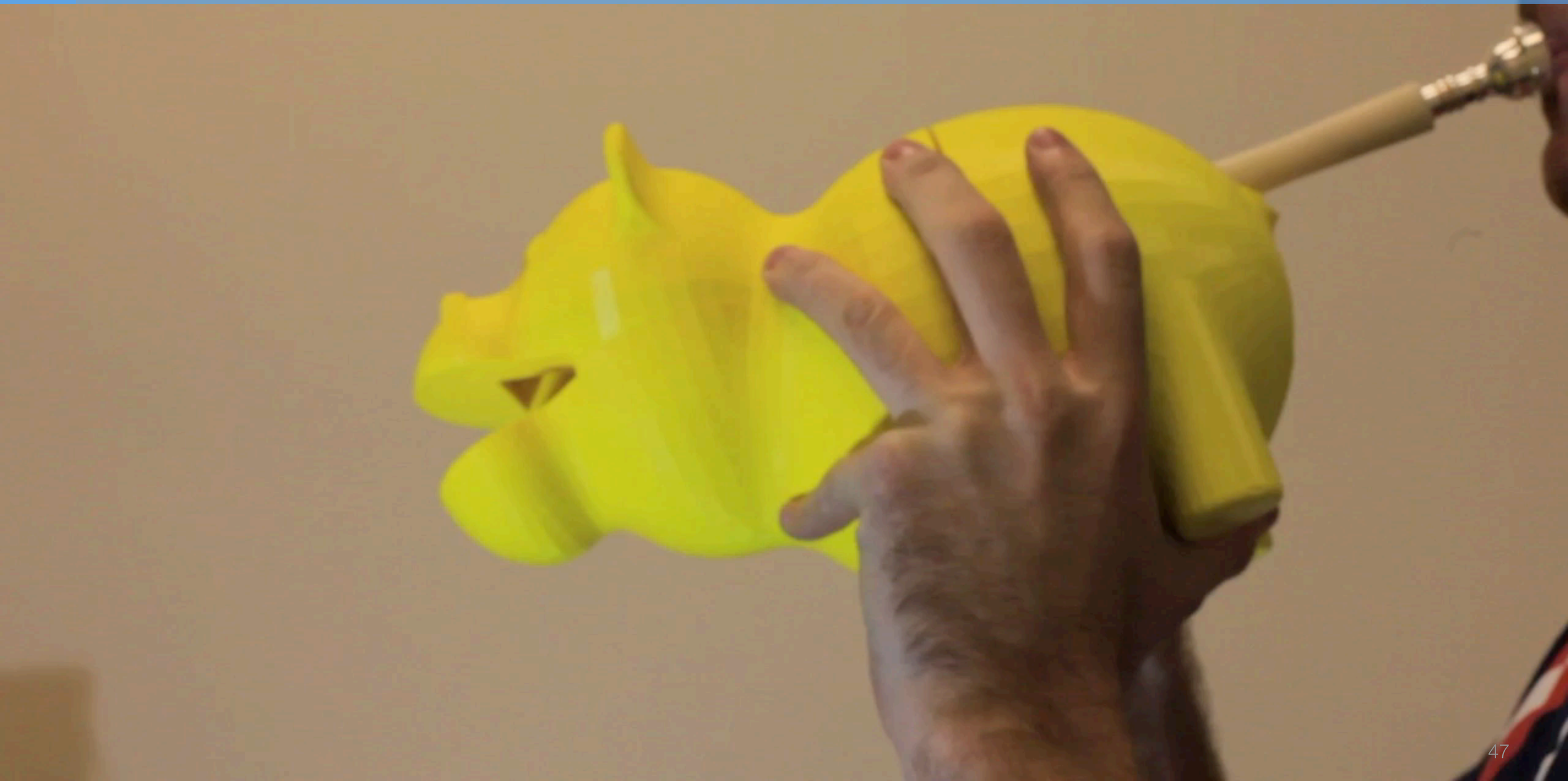

Information Encoding with Objects

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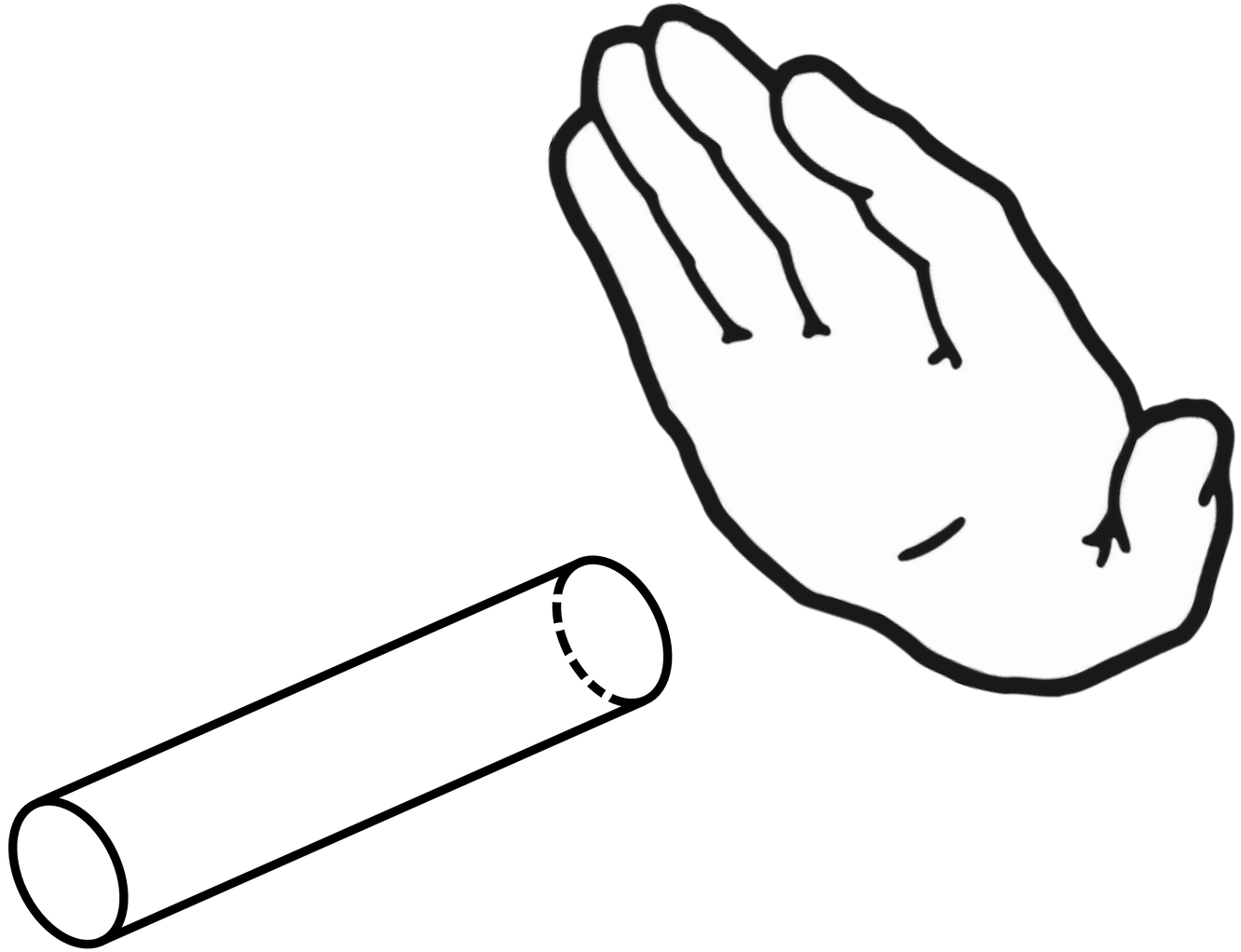
RFID [Spielberg et al. 2015]

Acoustic Tagging



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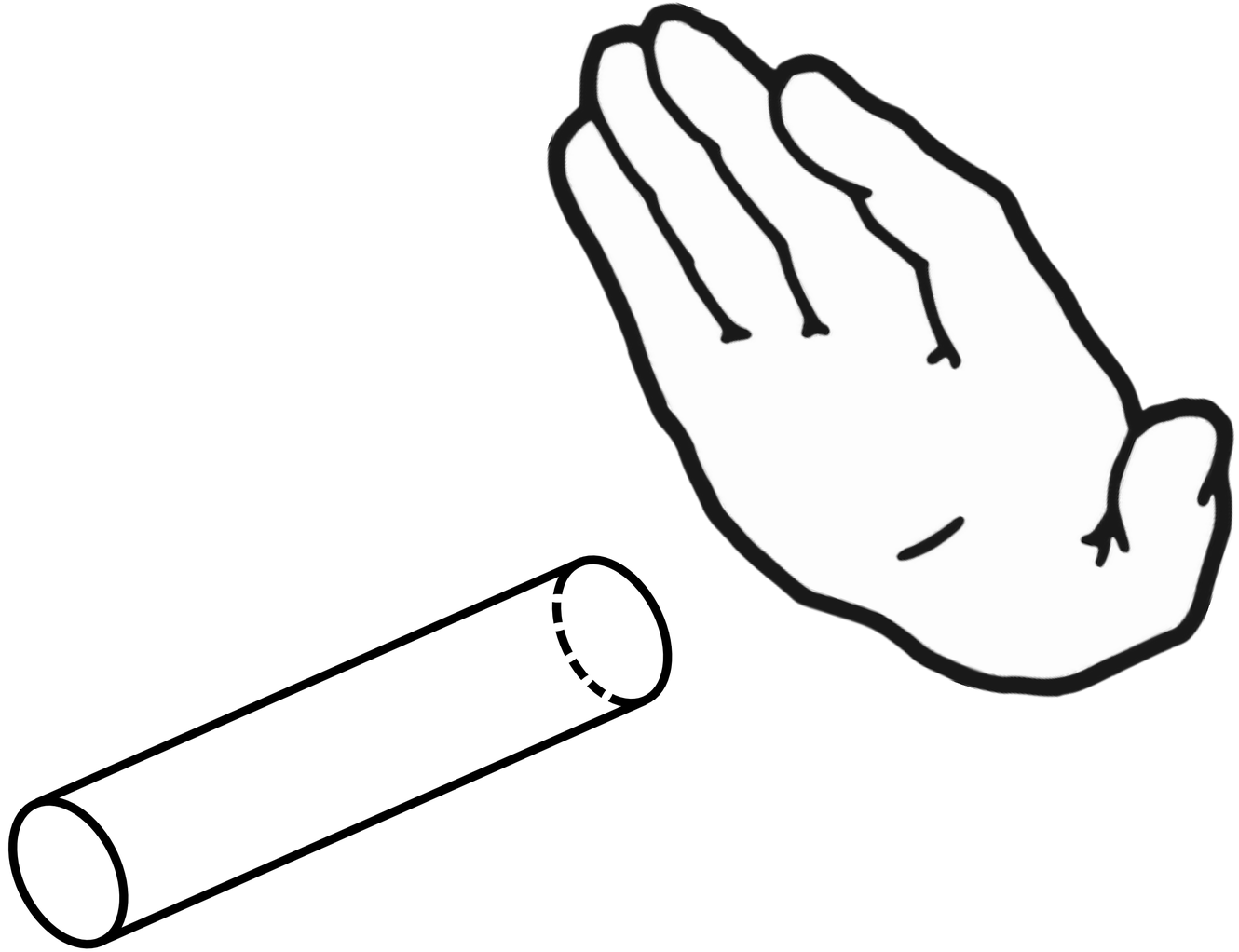
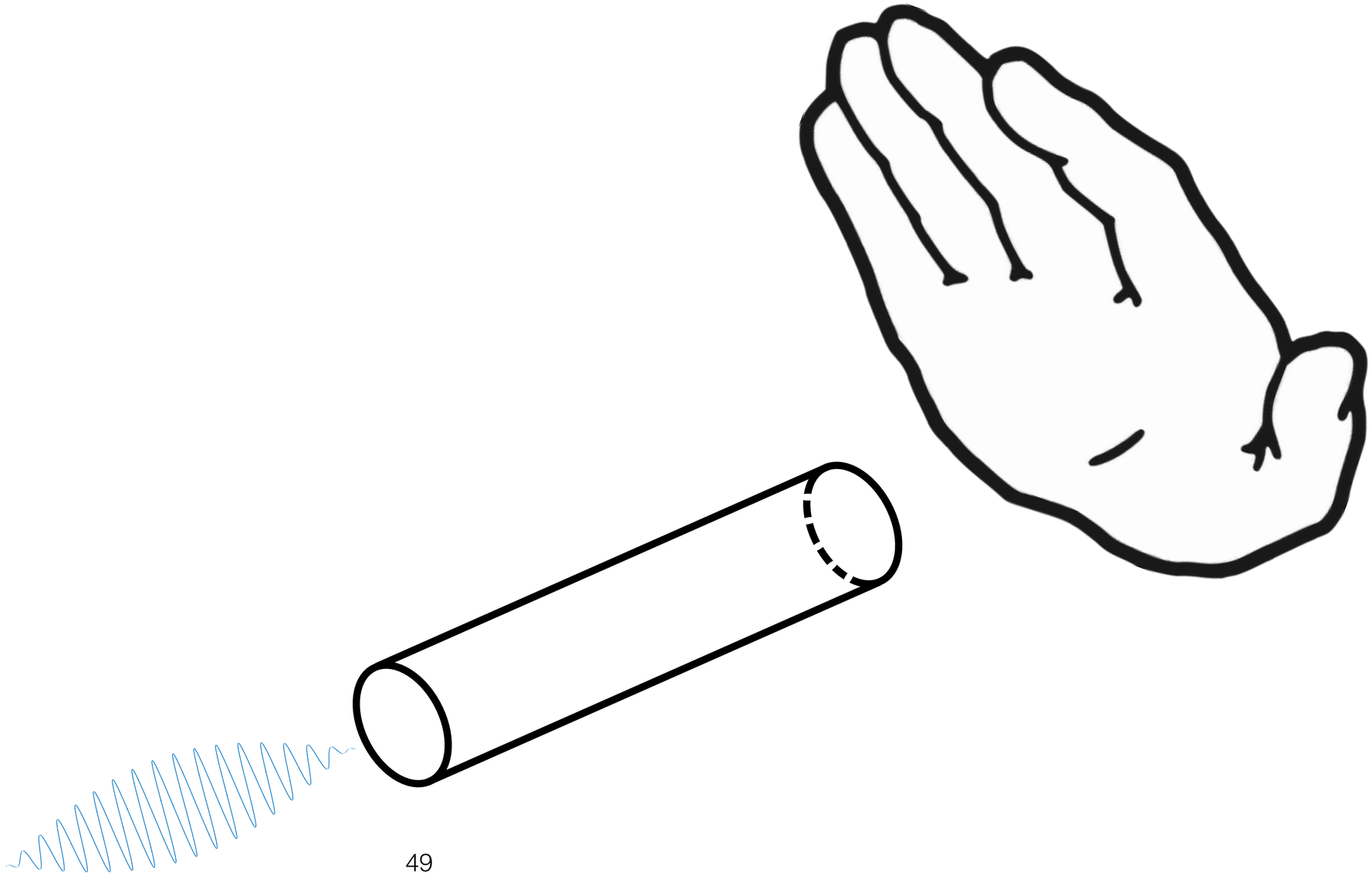


Acoustic Tagging



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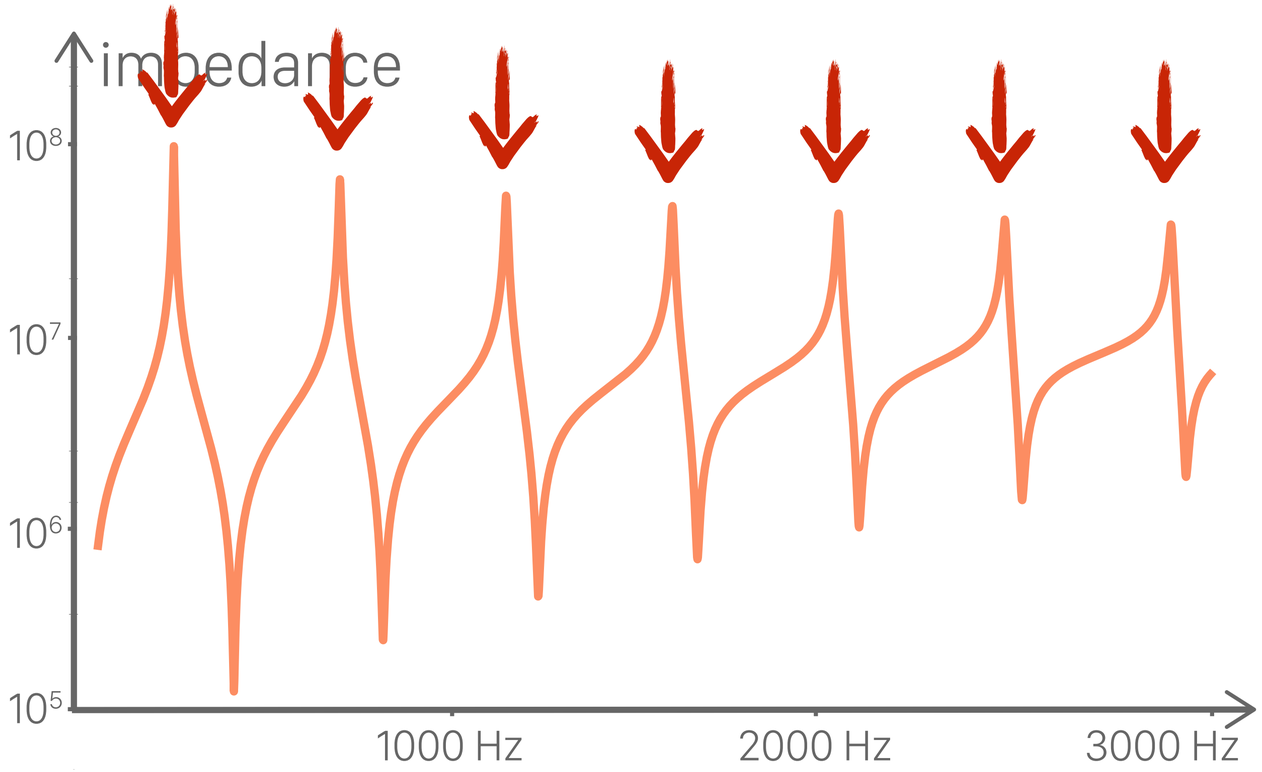
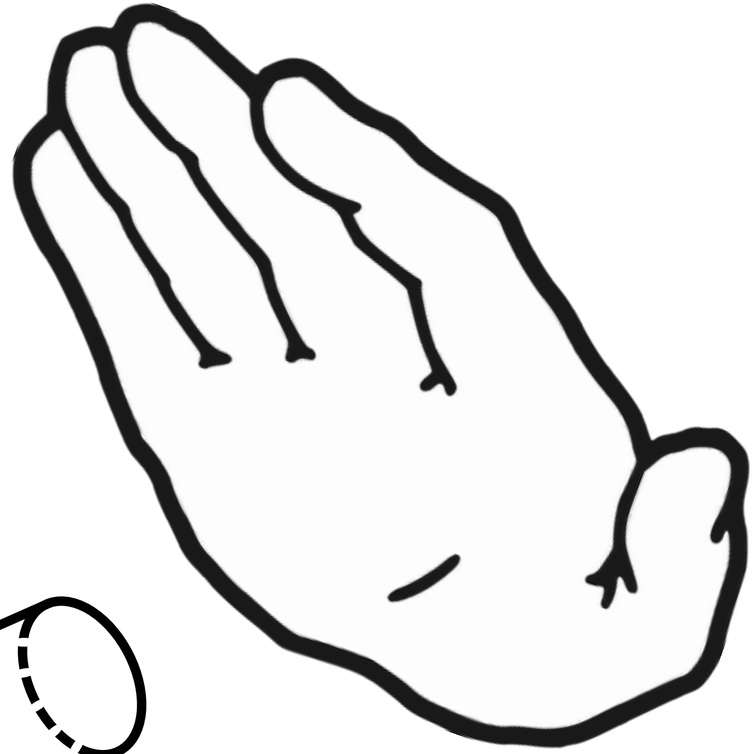
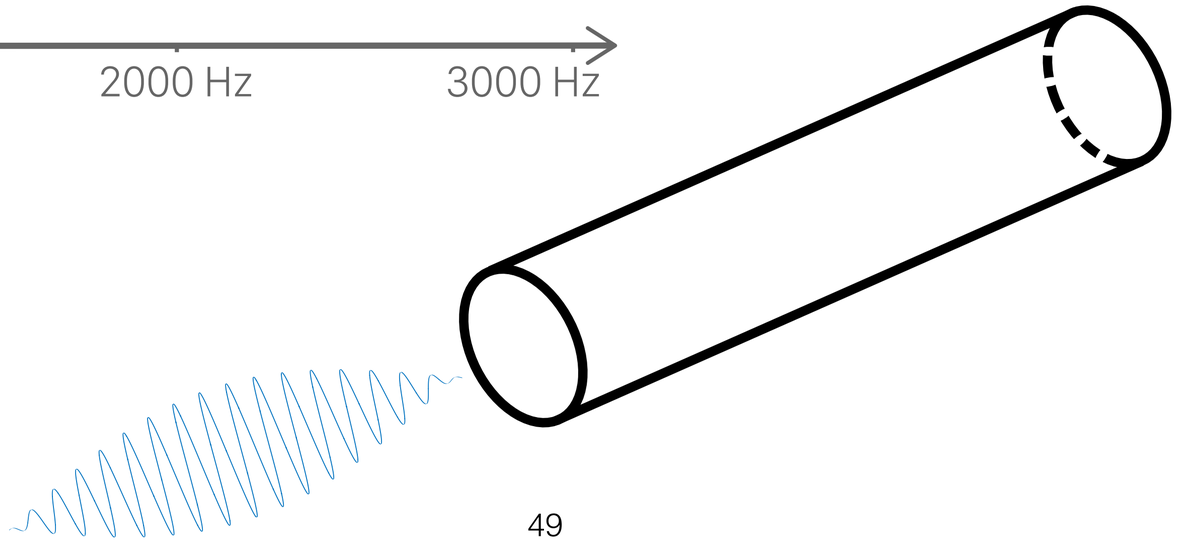


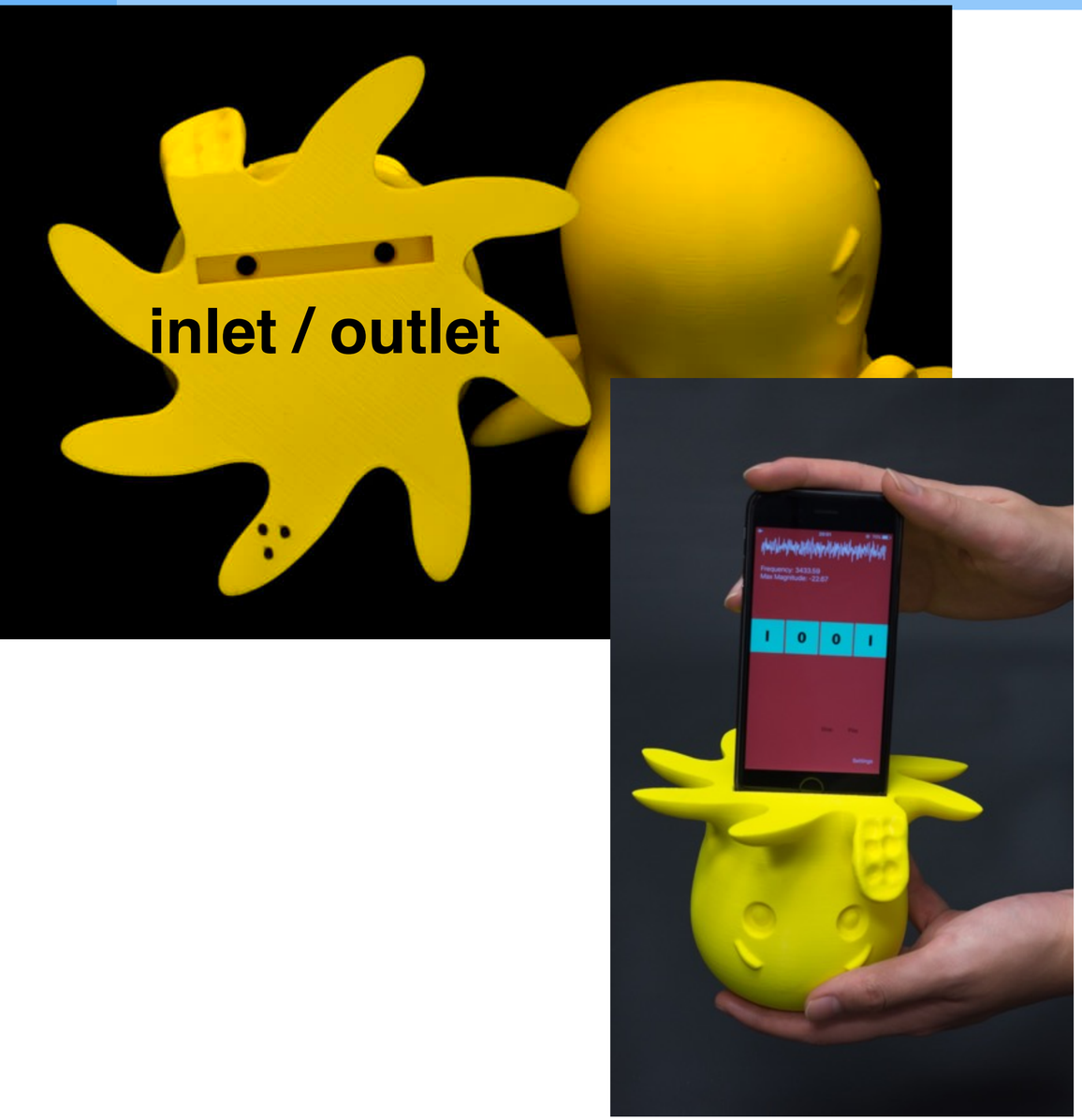


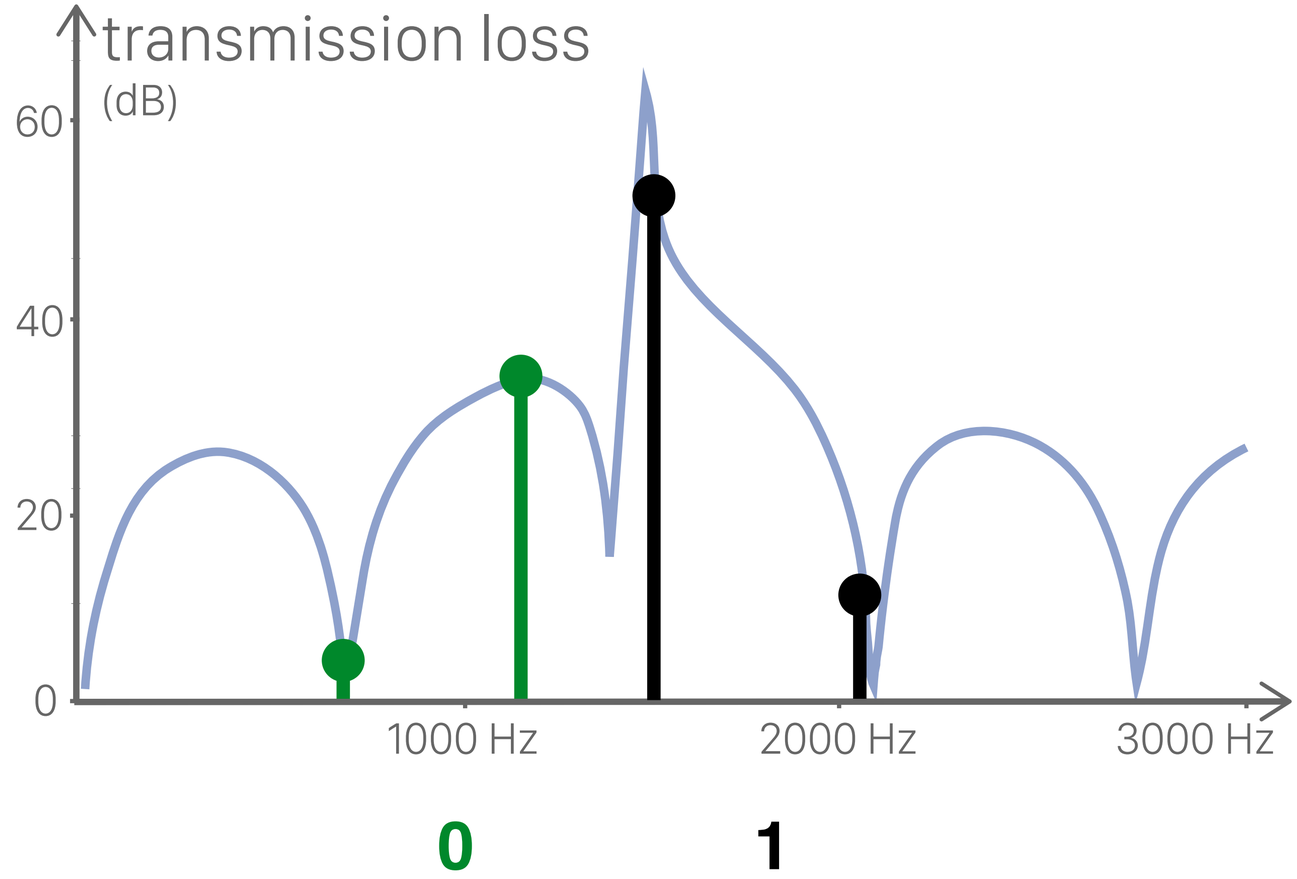


Acoustic Tagging

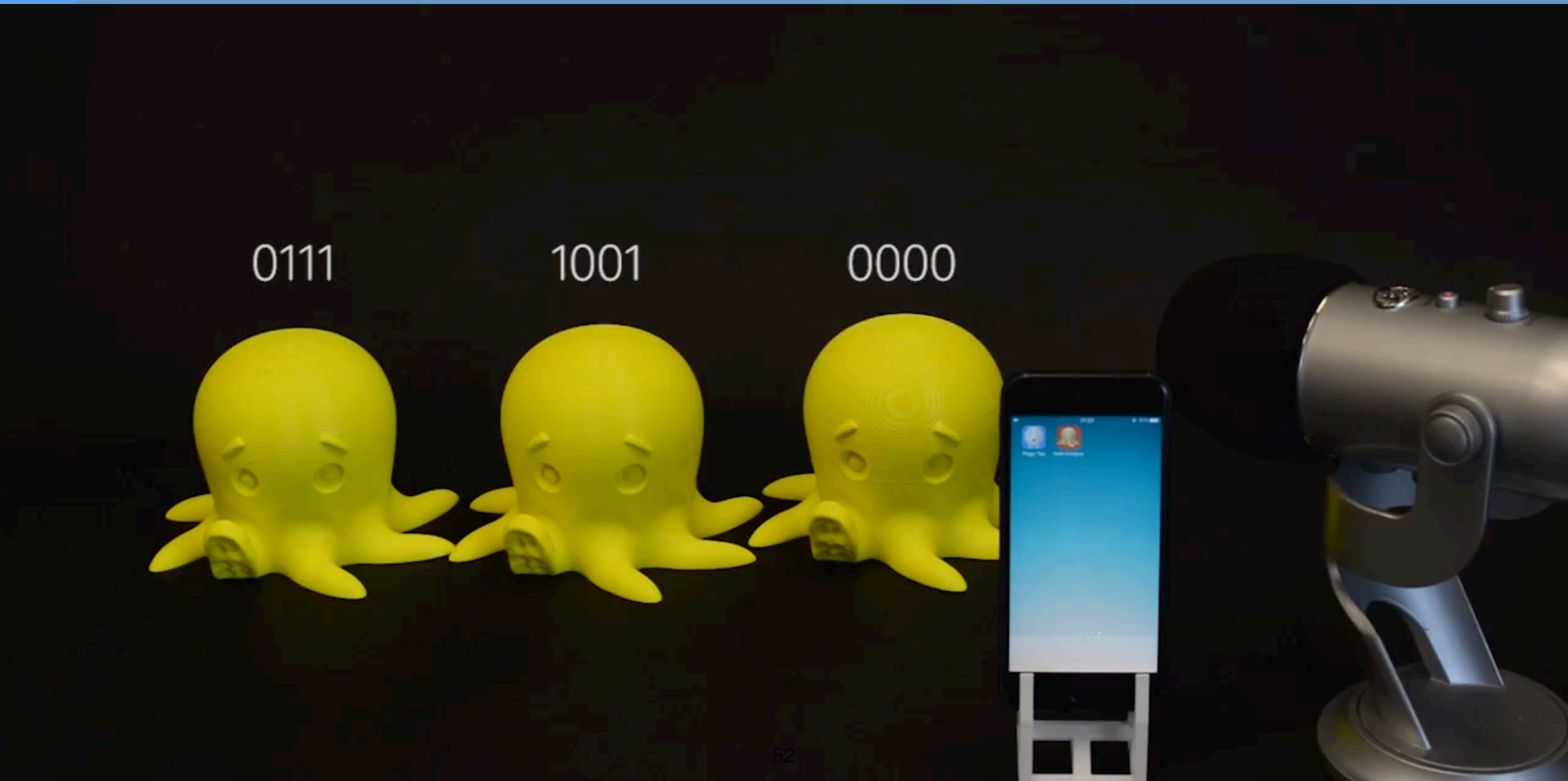
Acoustic Tagging

Basic Encoding Schemes





Acoustic Encoding



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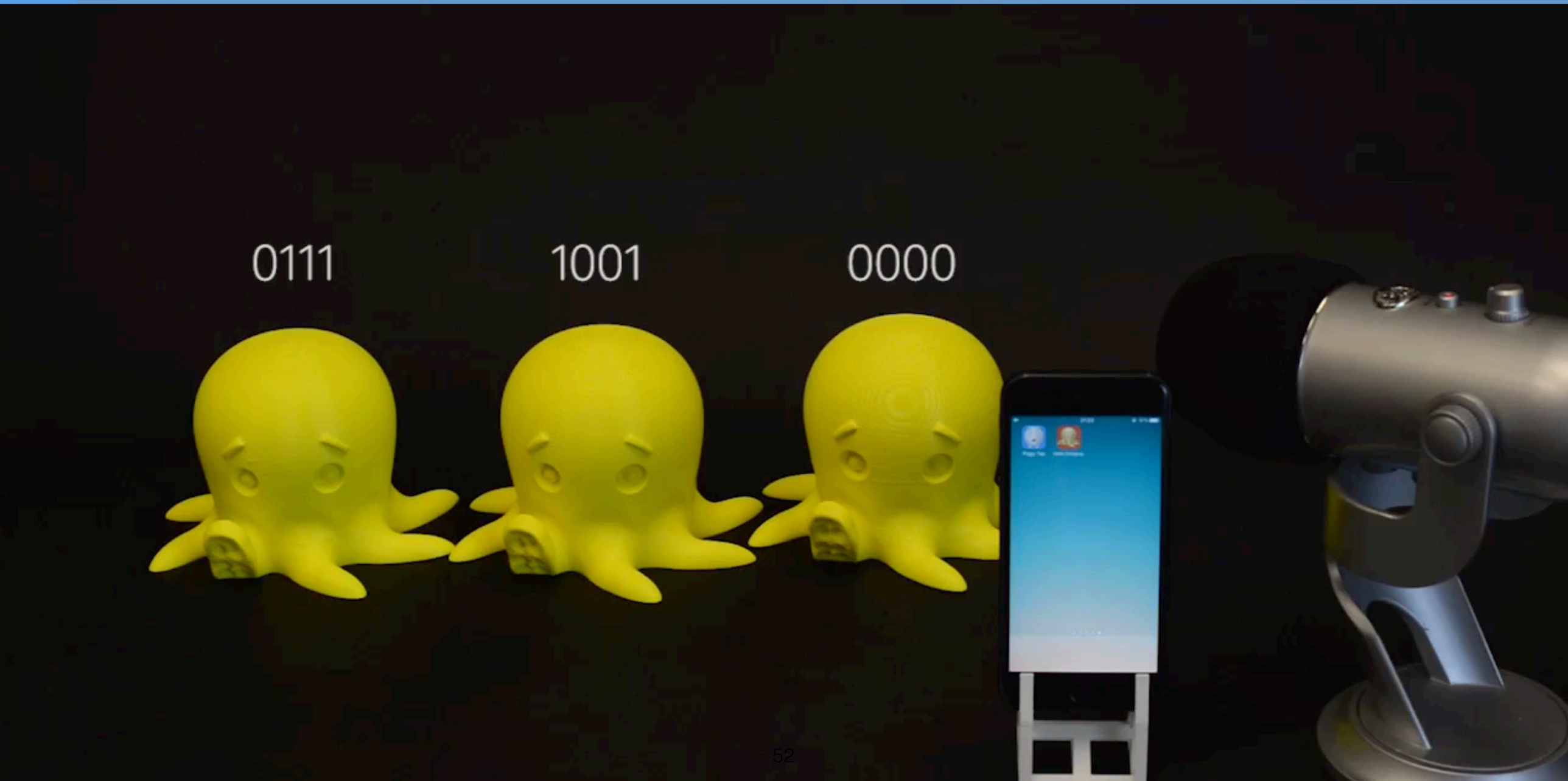

Conclusion

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A General Computational Framework for Acoustic Filter Optimization

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- efficient forward simulation
- iterative two-stage optimization

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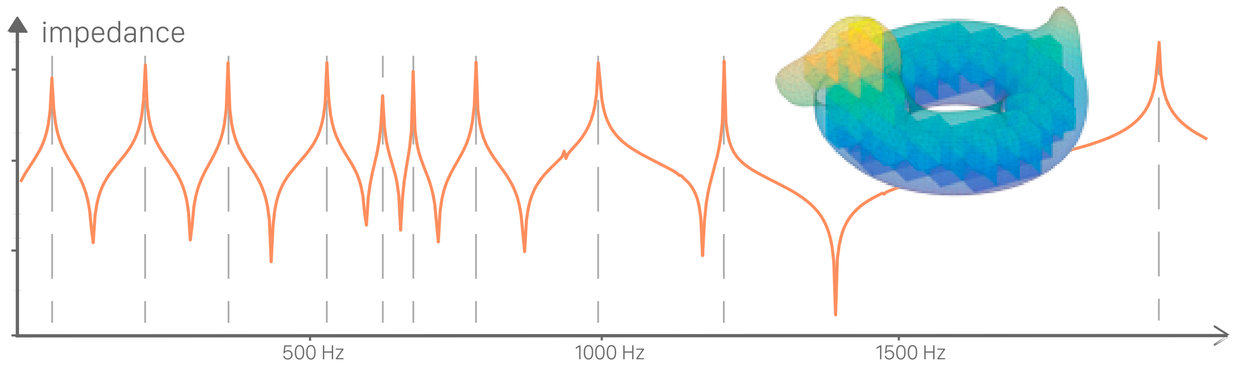

Future Work

- accelerate two-stage optimization

Conclusion

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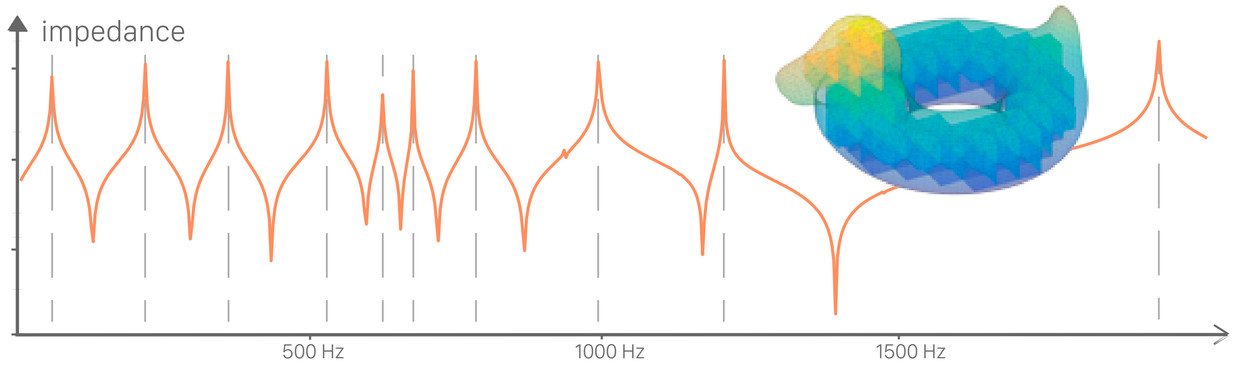

Future Work

- accelerate two-stage optimization
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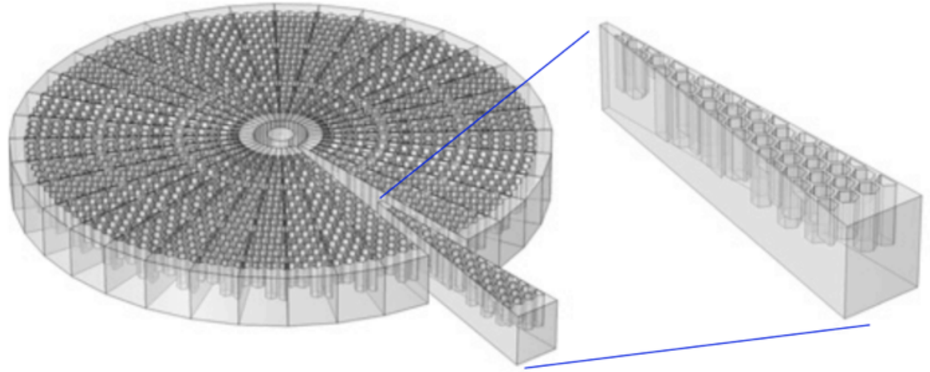

[Xie et al. 2015]

Conclusion

A General Computational Framework for Acoustic Filter Optimization

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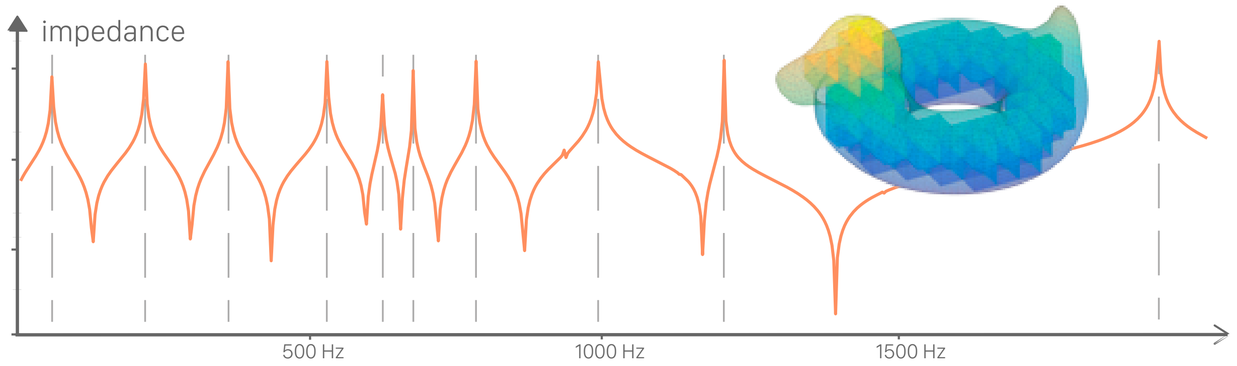

Future Work

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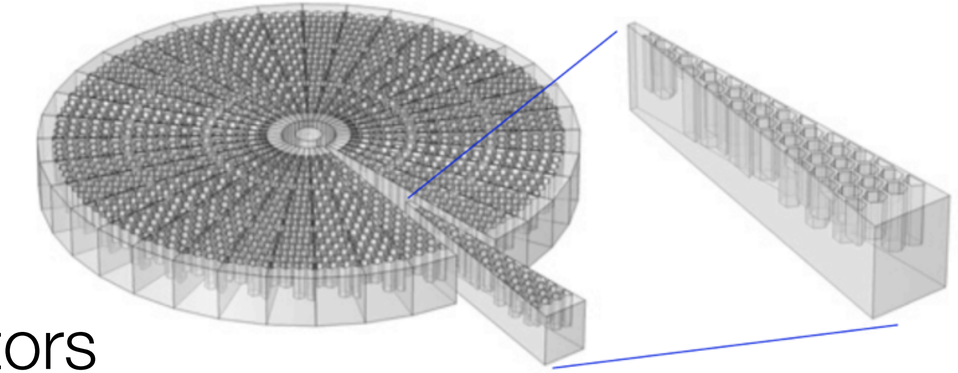
- explore different types of primitive resonators



[Xie et al. 2015]

Acknowledgement

Jui-Hsien Wang, Ioannis Kymissis, Andrei Shylo, Chang Xiao, Yonghao Yue, Yun Fei, Timothy Sun, Henrique Maia, Alec Jacobson, Keenan Crane, Syed Haris Ali

National Science Foundation (CAREER-1453101)
Adobe

Acoustic Voxels: Computational Optimization of Modular Acoustic Filters

http://www.cs.columbia.edu/cg/lego/ (or Google “acoustic voxels”)

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