

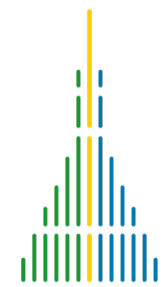
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# Exploring the impact of transfer learning on GAN-based HRTF upsampling

A. Hogg, H. Liu, M. Jenkins and L. Picinali



forum acusticum 2023

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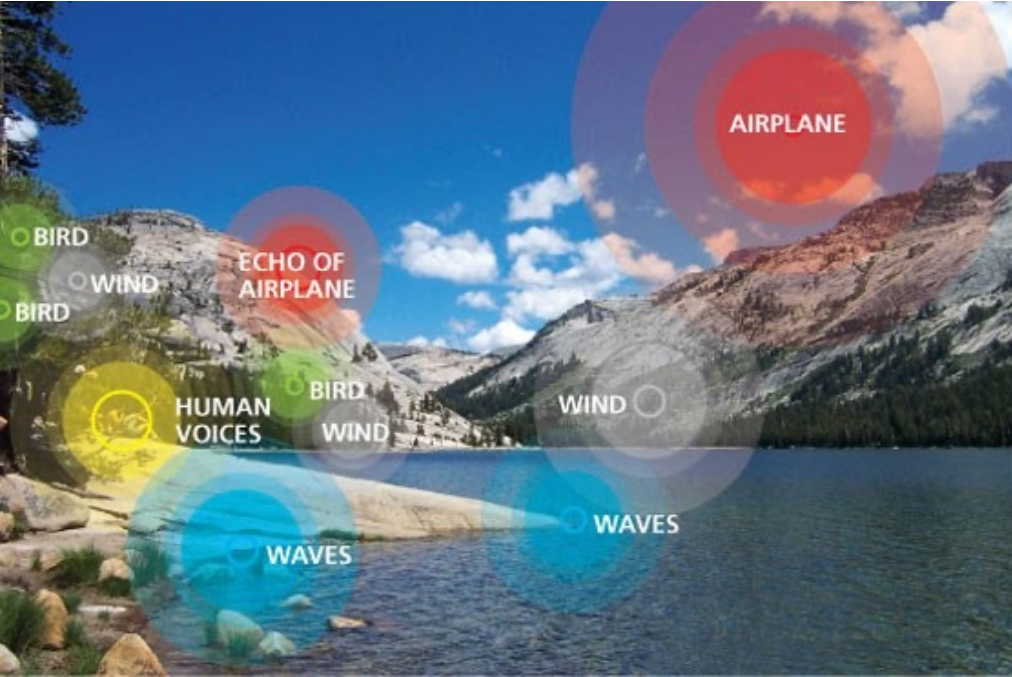


# Basics of binaural spatialization

## Head related transfer functions

# Basics of binaural spatialization

## What is 3D audio?



# Basics of binaural spatialization

How can I simulate it?

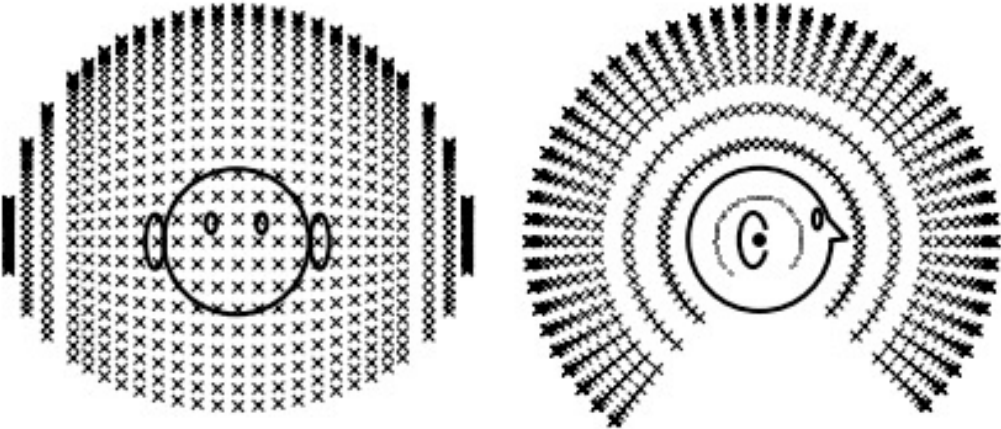


Spherical loudspeaker array

# Basics of binaural spatialization

## Do I really need so many loudspeakers?

- Head Related Transfer Function (HRTF)



# Basics of binaural spatialization

## But is measuring individual HRTFs practical?

- Controlled environment
- Expensive setup
- **Time consuming**

## One Possible solution: HRTF spatial upsampling

# Spatially upsampling low-resolution HRTFs

Super-resolution generative adversarial networks (GANs)

# Super-resolution GANs

## Motivation

- GANs have been shown to work well for the task of upsampling images

4x SRGAN



Original



C. Ledig, L. Theis, F. Huszar, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang, et al., “**Photo-realistic single image super-resolution using a generative adversarial network**,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2017. 11



# Super-resolution GANs

## Can SRGANs be used to upsample HRTF data?

- HRTF data is not uniformly spaced (like pixels in an image)
- HRTF data occupies an extra dimension (unlike images that are only 2D in space)
- The amount of HRTF data is limited (whereas there are millions of images available to train SRGANs)

## One Possible solution to HRTF data occupying an extra dimension:

- Augmenting the data so that it can be processed in the same way as 2D images
  - For example, 3D to 2D projections

## One Possible solution to the limited amount of HRTF data:

- Increase data available by generating synthetic data and use of transfer learning

# The problem of spherical data

## The cubed sphere projection

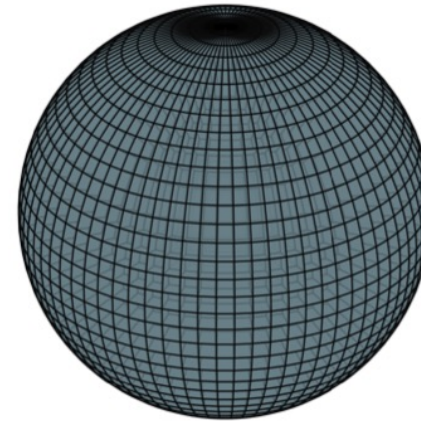
# How to fit a sphere to a grid?

## Problem

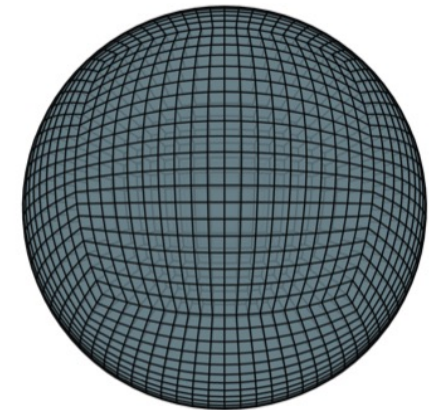
- Projections can distort the relationship between two adjacent points, complicating kernel weight sharing

## Solution

- Use six gnomonic projections onto tangent planes that form a cube around the sphere (cubed sphere)
  - The advantage is that the grid cells are more uniformly-sized

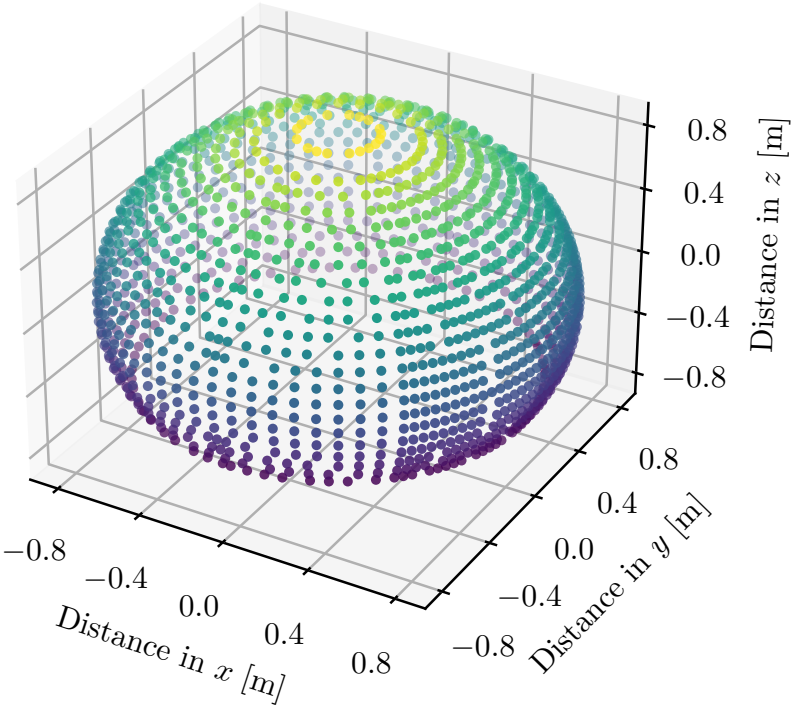


Standard polar coordinates

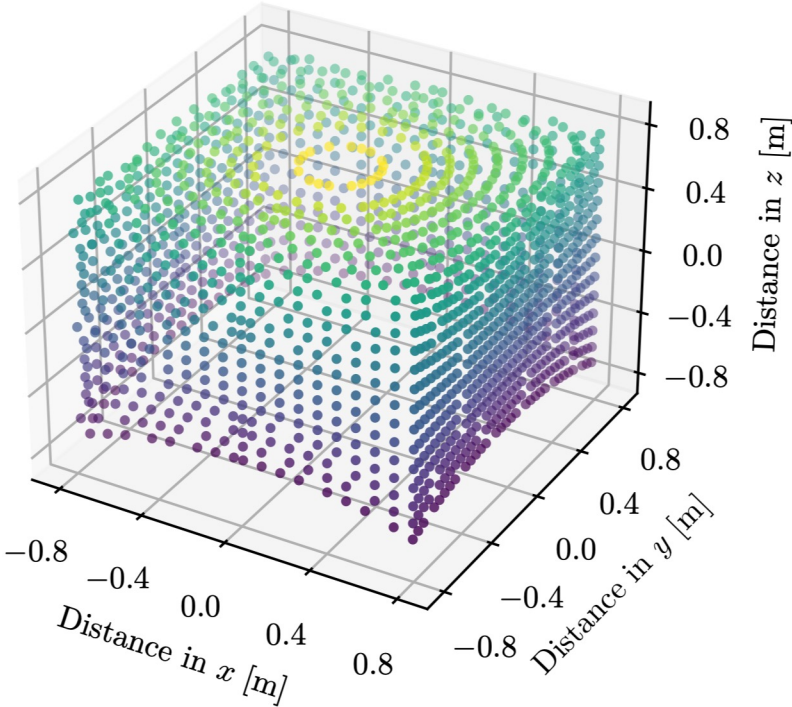


Cubed sphere

# Original data & projected data

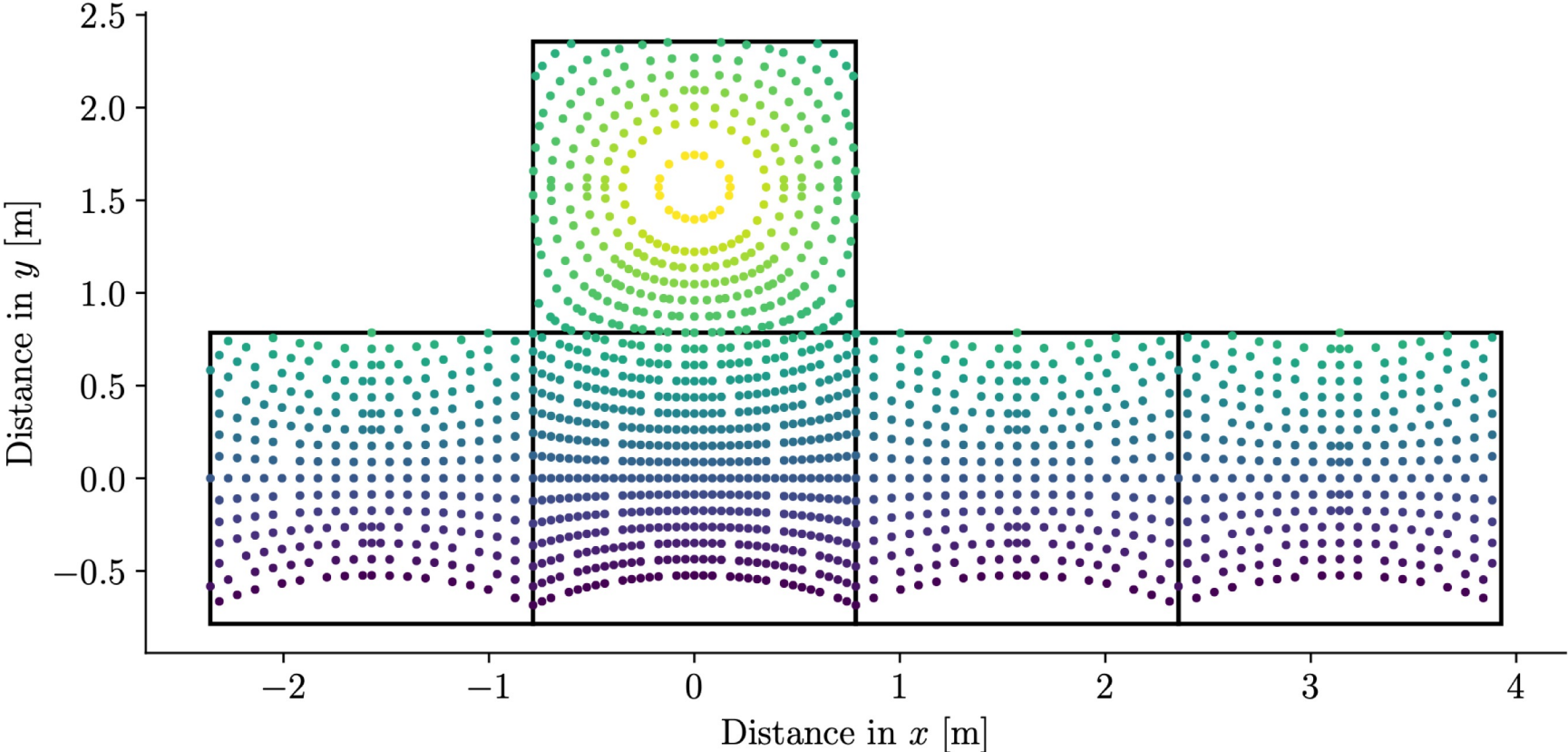


Original data



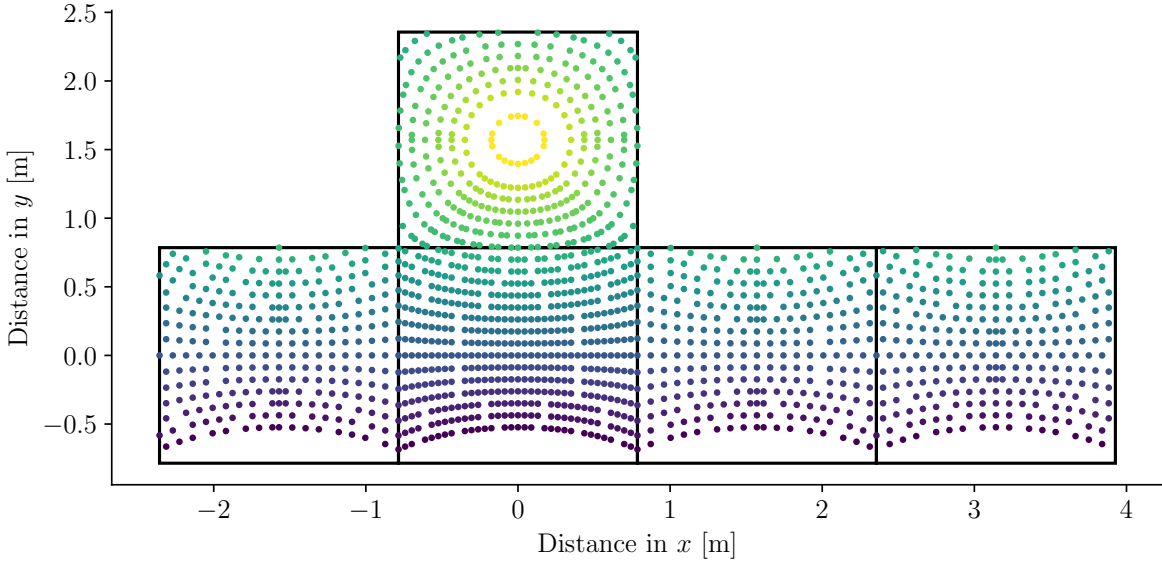
Projected data

# Flattened cube

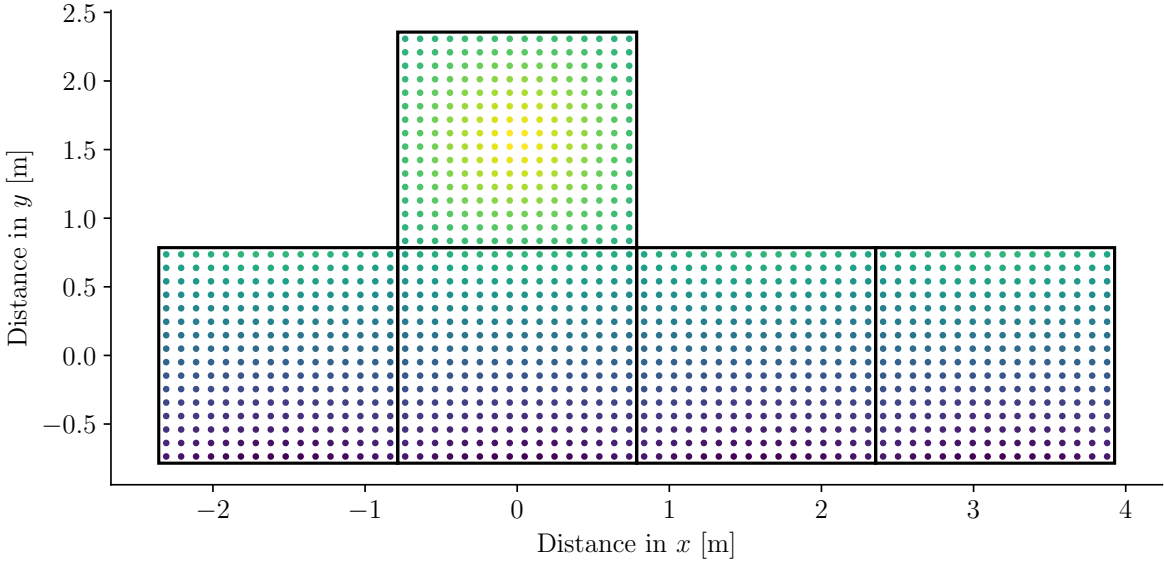


Flattened cube

# Interpolated HRIRs

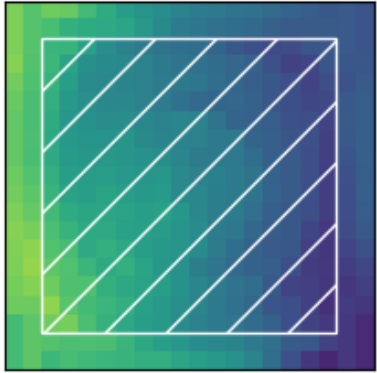
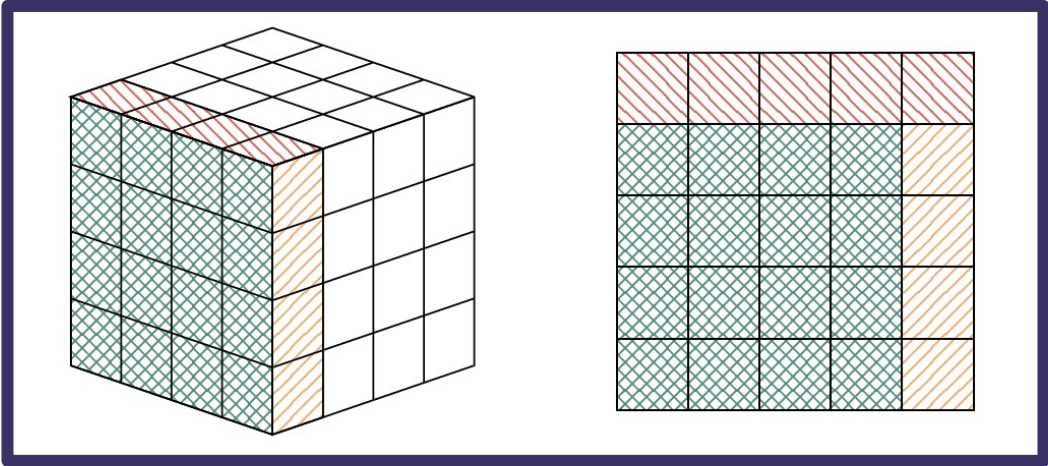


Original data

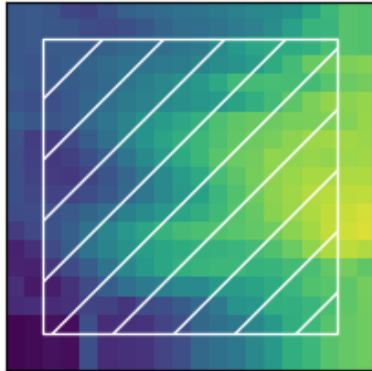
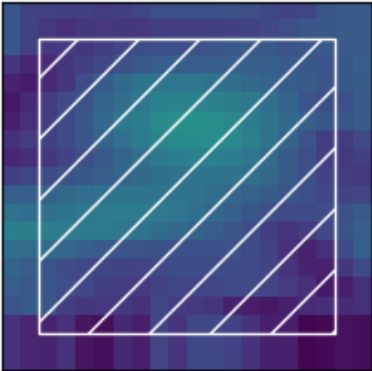
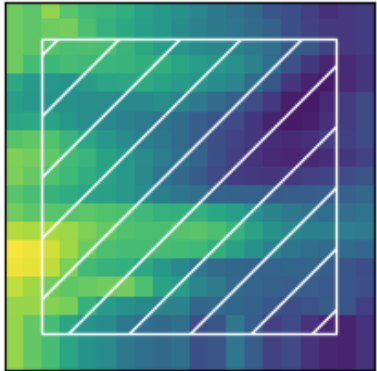
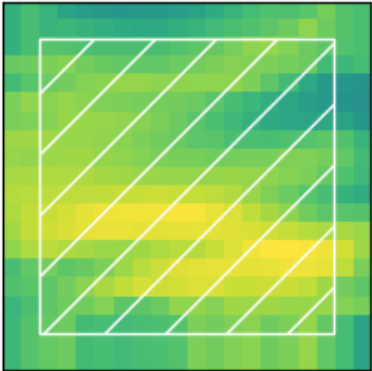


Barycentric interpolated data

# Padding based on adjacent cube faces



Each face is padded with data from the adjacent faces





# The problem of small data sets

## Transfer learning

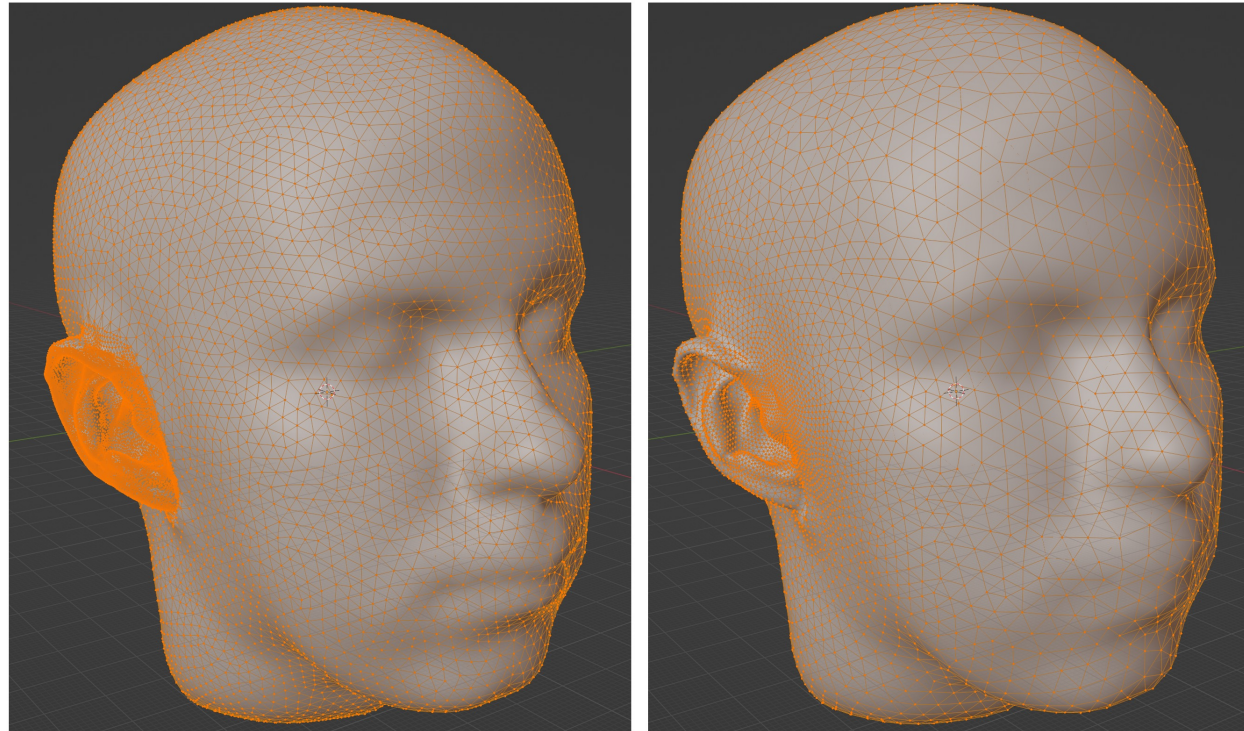
# Parametric pinna model data

The Parametric Pinna Model (PPM) is used to randomly generate meshes for synthetic HRTF data generation.



Head stitching

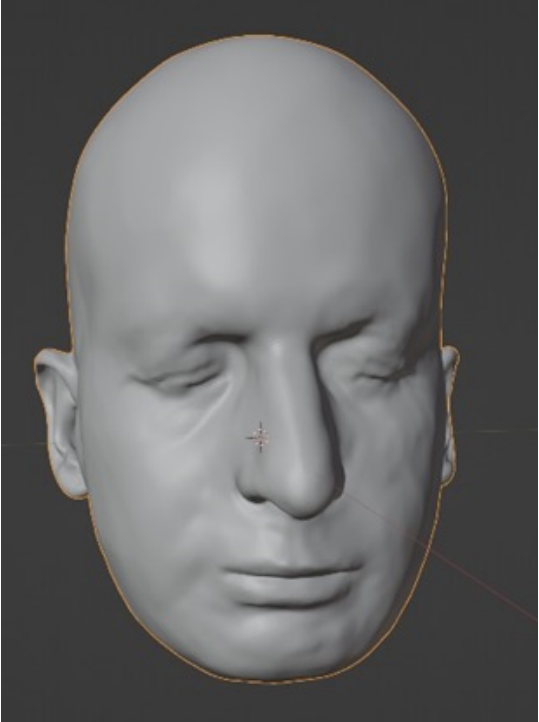
# Mesh Grading



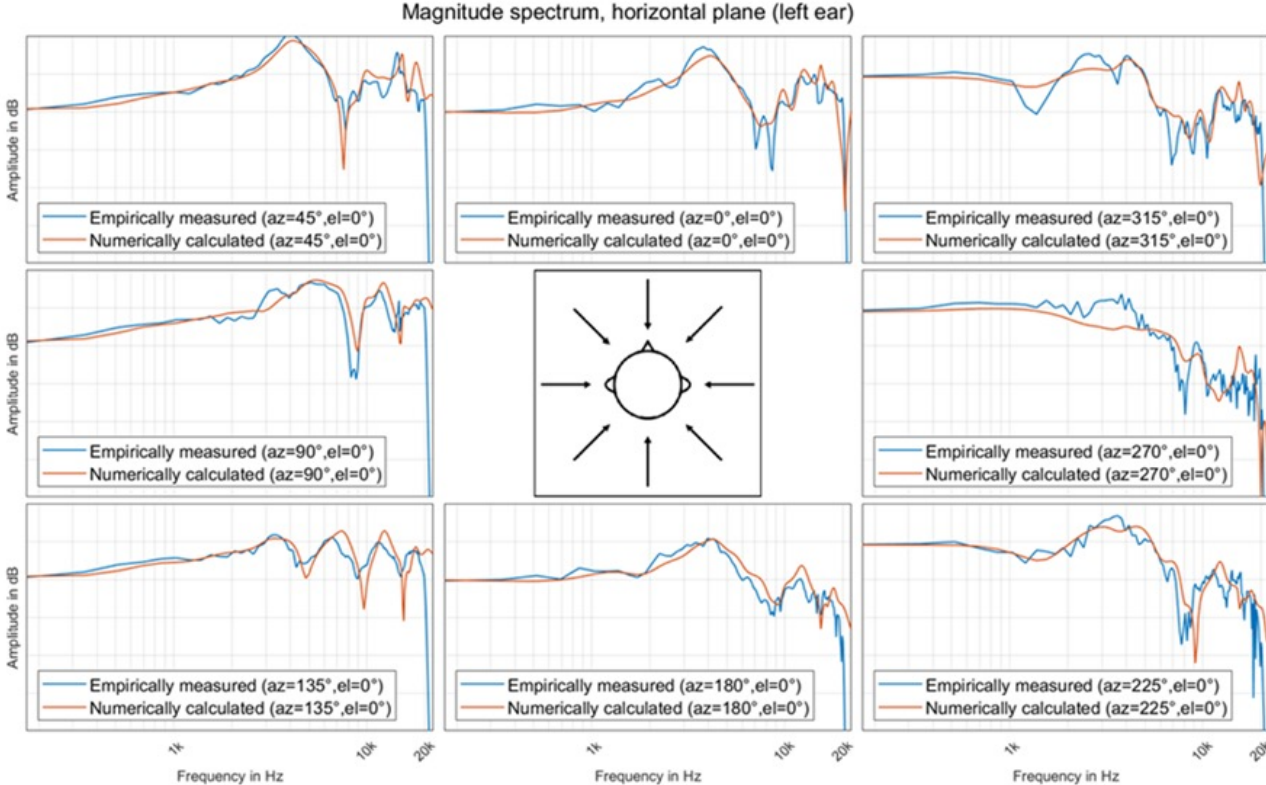
Original mesh (left, 63,472 triangles) and mesh after Mesh Grading (right, 20,362 triangles)

# BEM calculated HRTF from 3D meshes

Head model



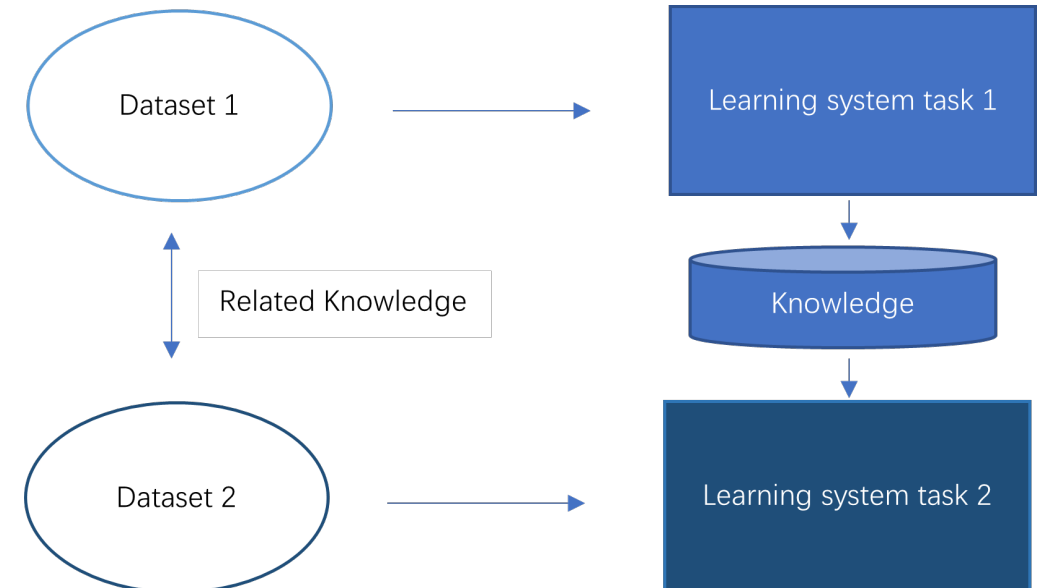
Comparison between measured and BEM data



# Transfer learning

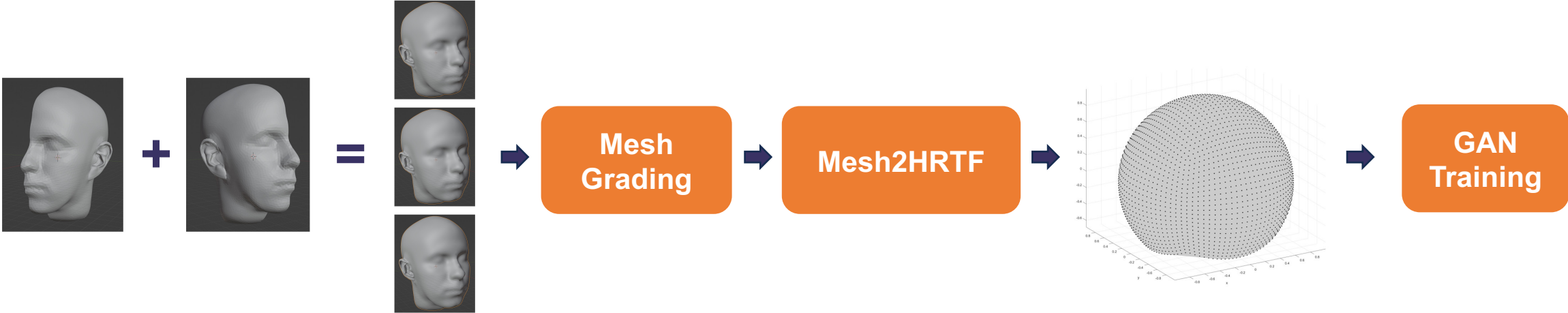
## Possible solutions

- **Train the entire network with synthetic data, keep the parameters and biases unchanged, and re-train the entire network with measured data**
- Train the entire network with synthetic data, and then freeze the parameters and biases of the lower layers of the network and only train the higher layers with measured data
- Train the entire network with synthetic data first, then only re-initialize the higher layers and train the entire network with measured data
- Train half of the network with synthetic data, then add new layers and train the entire network with measured data

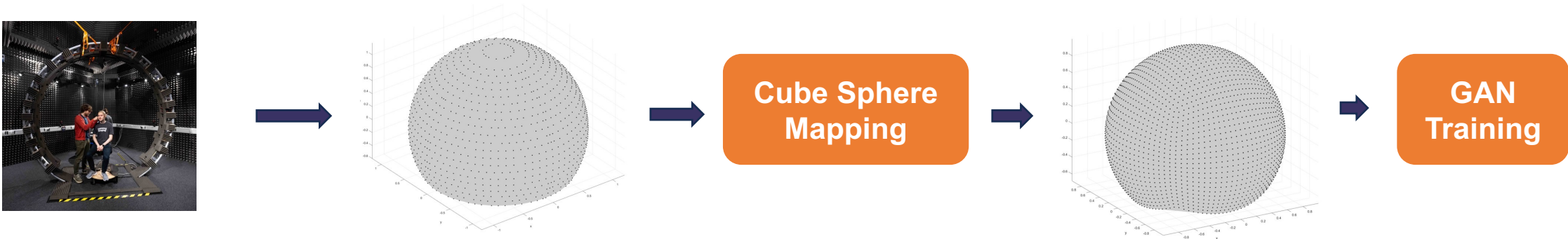


# Transfer learning from generated low-resolution parametric pinna HRTF data

## 1) Train of synthetic data



## 2) Reinitialize output layers of the Generator and Discriminator and retain all layers on real HRTF data

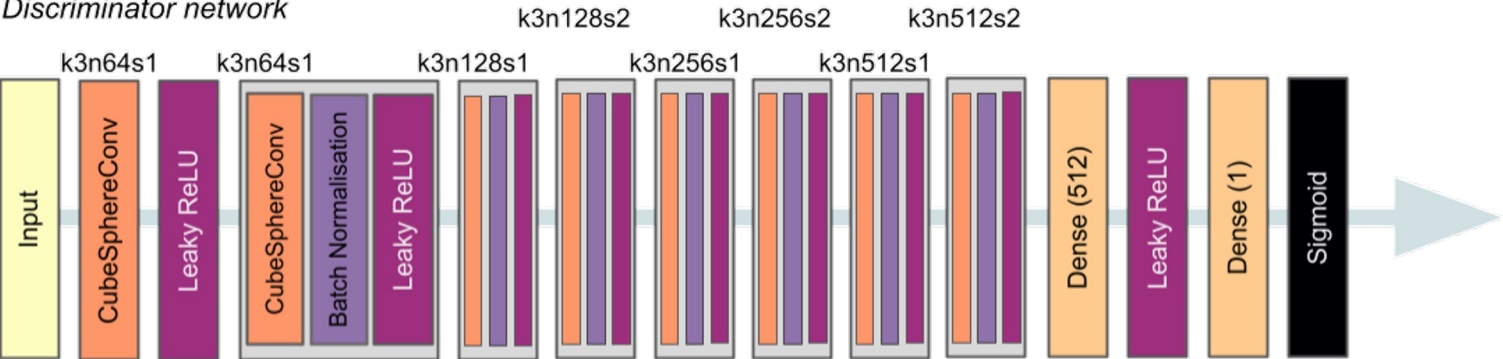


# Network architecture

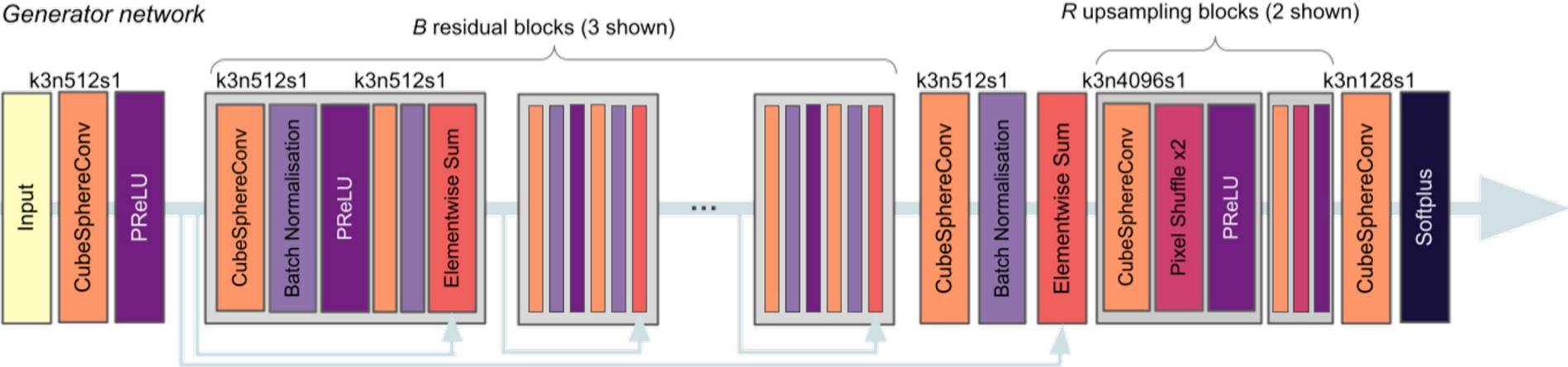
## Generative adversarial network

# Discriminator and Generator

Discriminator network



Generator network





# Results

## Statistical and perceptual

## Data used for training:

- **1,000 SONICOM synthetic HRTFs** - Transfer learning training data (Exp 1)
- **203 SONICOM HRTFs** - Transfer learning training data (Exp 2)
- **170 ARI HRTFs** - Training data
- **51 ARI HRTFs** - Evaluation data

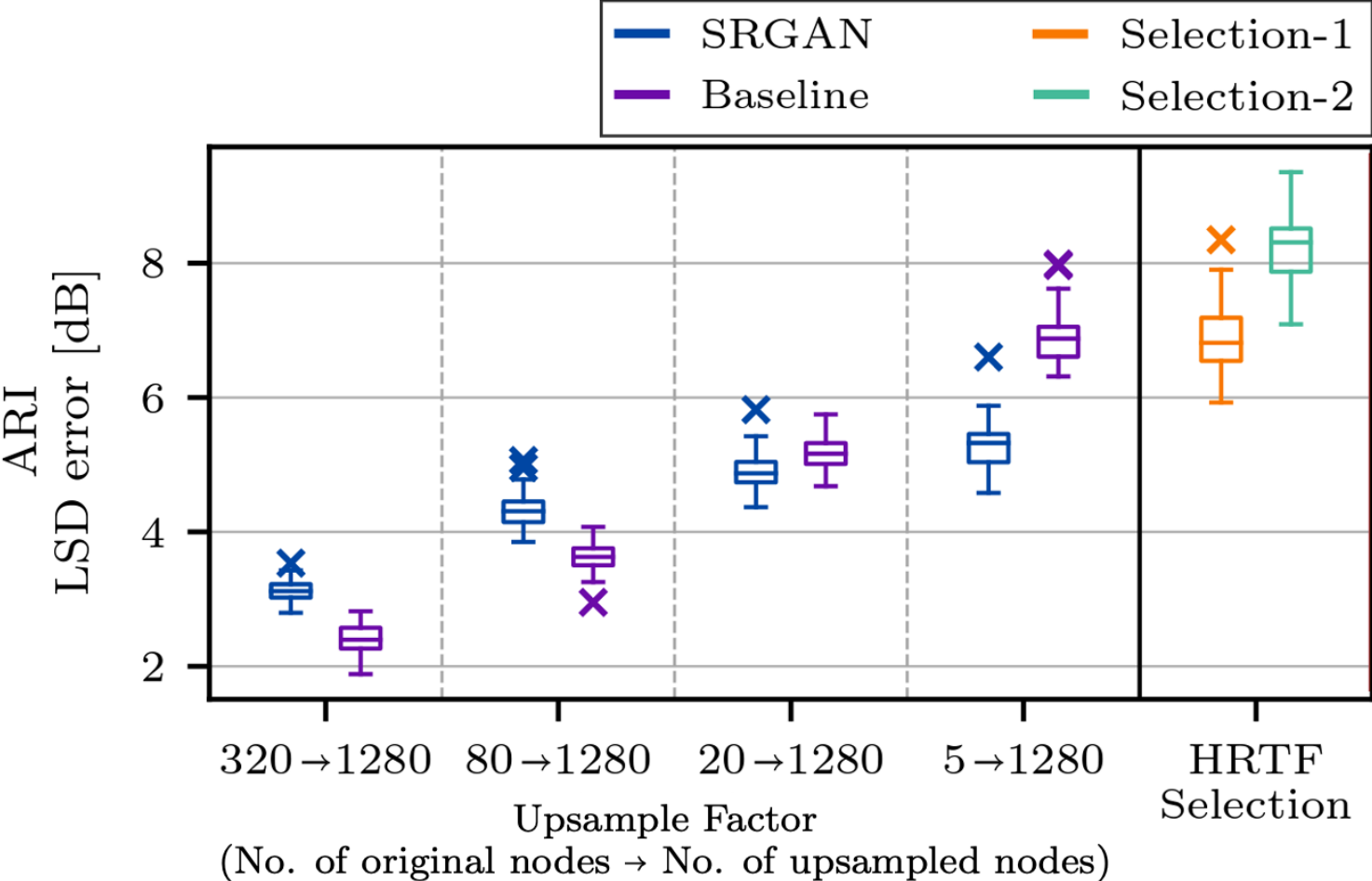
# Spectral distortion metric results

## Spectral distortion metric:

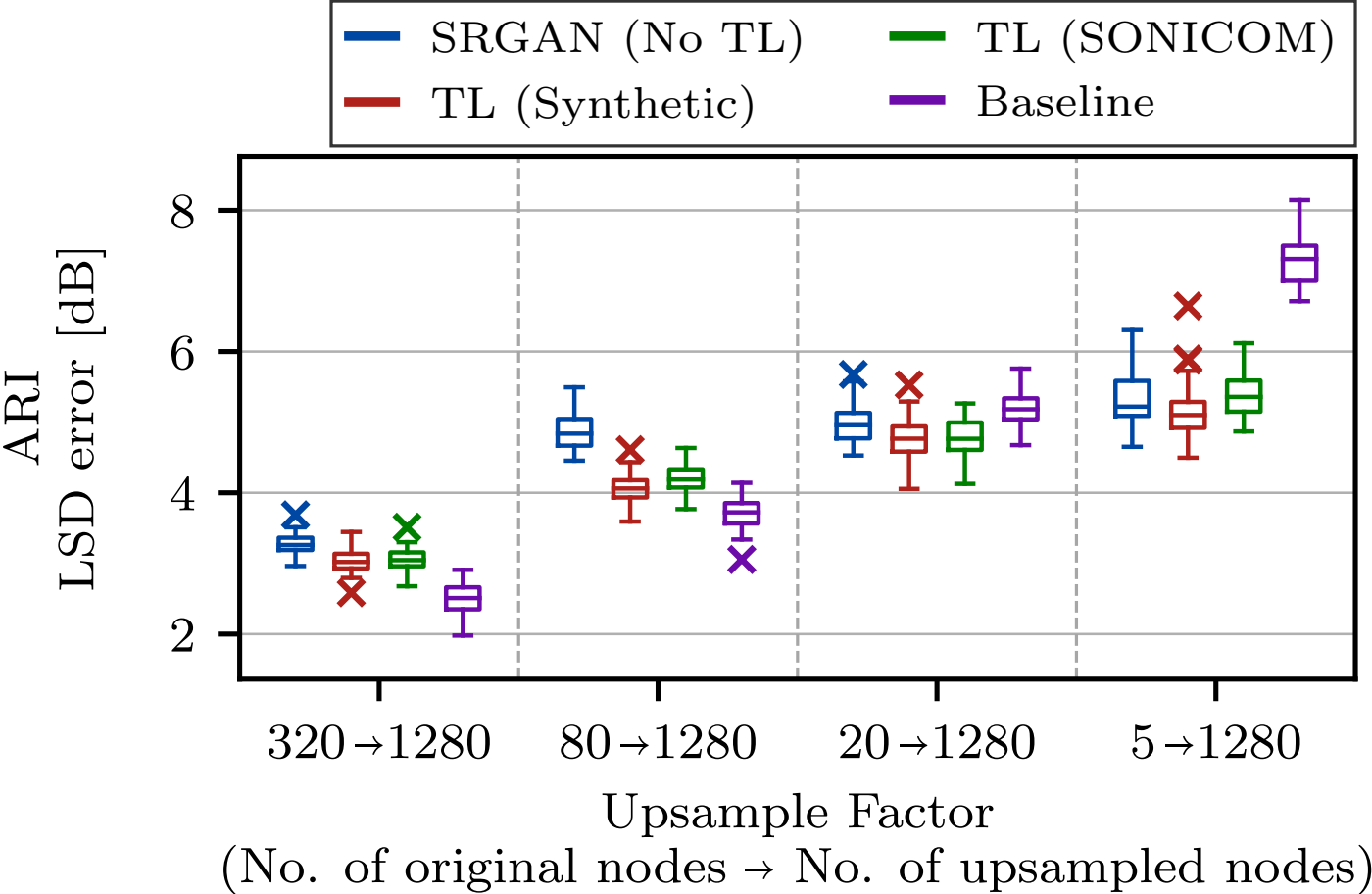
- The SD of two HRTFs are first averaged over frequency bands, then averaged over measurement nodes (impulse responses)

$$SD = \frac{1}{N} \sum_{n=1}^N \sqrt{\frac{1}{M} \sum_{k=1}^M \left( 20 \log_{10} \frac{|HRTF(f_k, \phi_n)|}{|HRTF'(f_k, \phi_n)|} \right)^2}$$

# Spectral distortion metric results



# Spectral distortion metric results

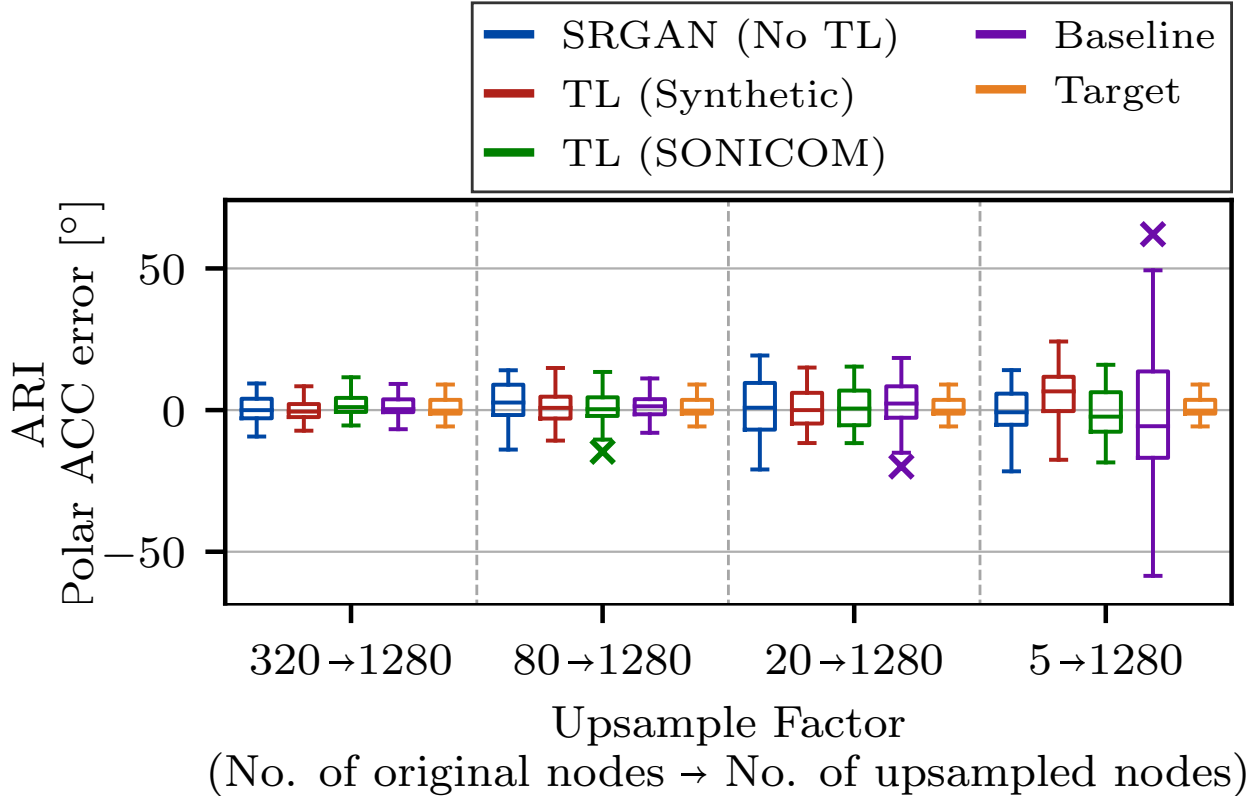


# Modelled perceptual evaluation

## Barumerli2022 model

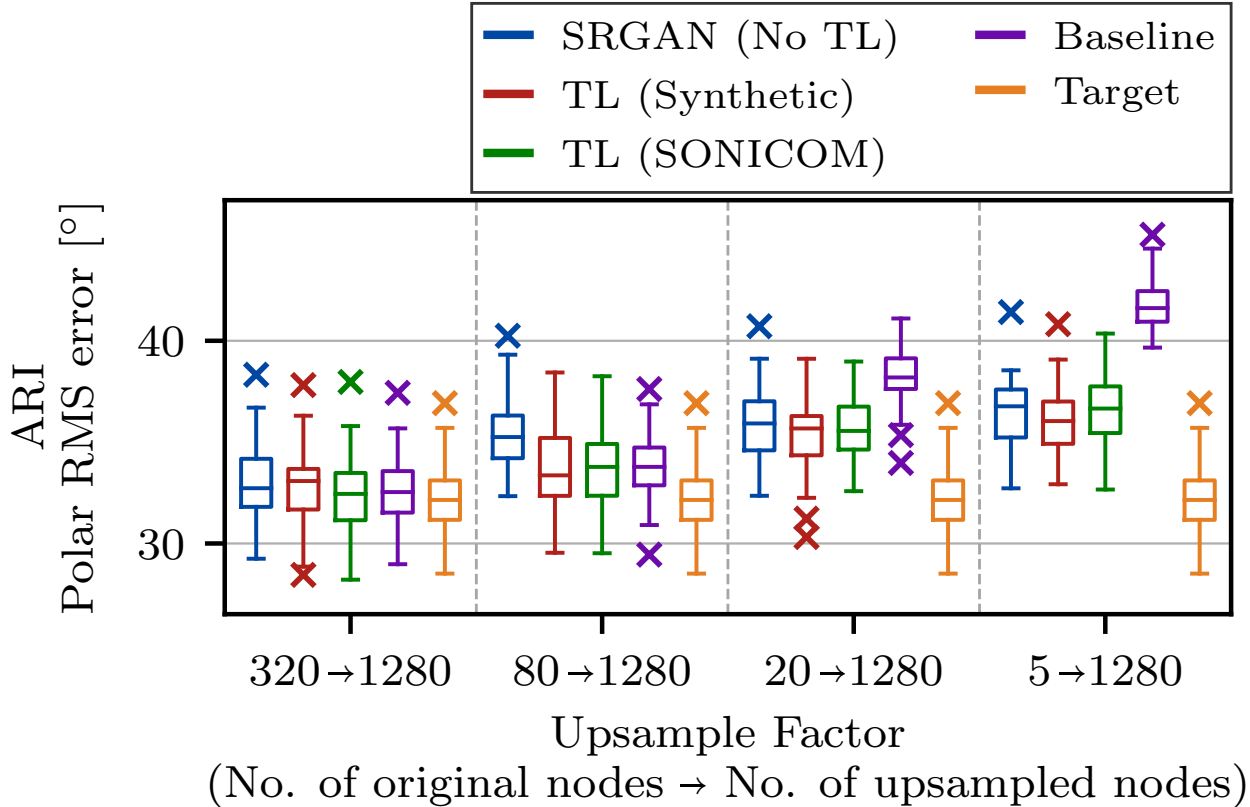
Barumerli et al. designed a Bayesian spherical sound localization model that could predict performances of individuals using different HRTFs through a mathematical model

# Modelled perceptual evaluation



Localisation evaluation - Polar Accuracy Error (Elevation Bias)

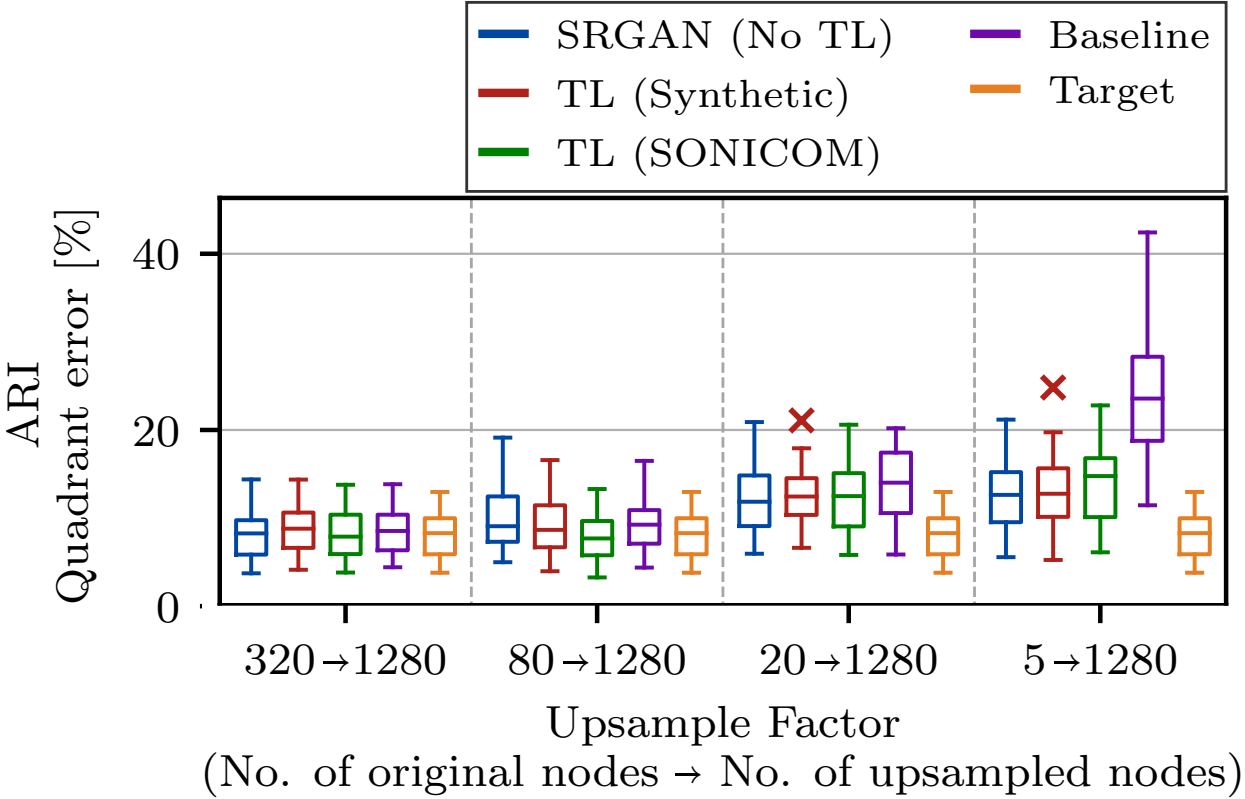
# Modelled perceptual evaluation



Localisation evaluation - Polar RMS Error



# Modelled perceptual evaluation



Localisation evaluation - Quadrant Error

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Thank You



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