Applications of Machine Learning in Retrospective Studies on Hearing

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CU BIC CARLETON UNIVERSITY BIOMEDICAL INFORMATICS COLABORATORY
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clearwater

Background

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Studies on the prevalence of hearing loss are important

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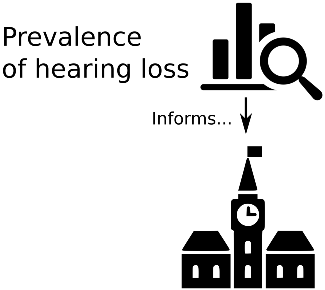

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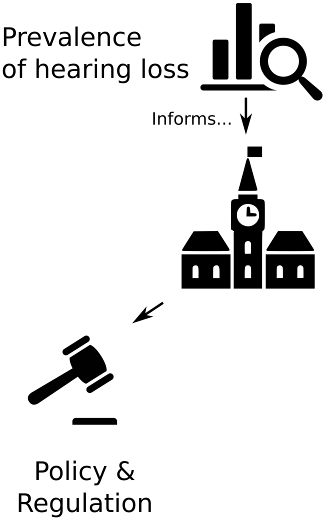

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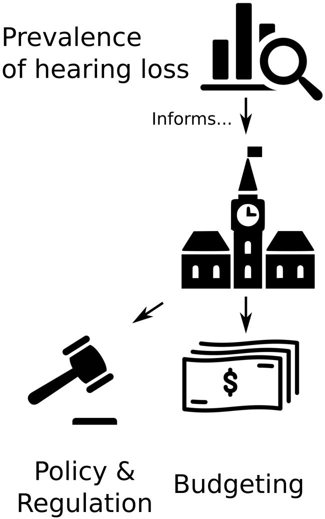

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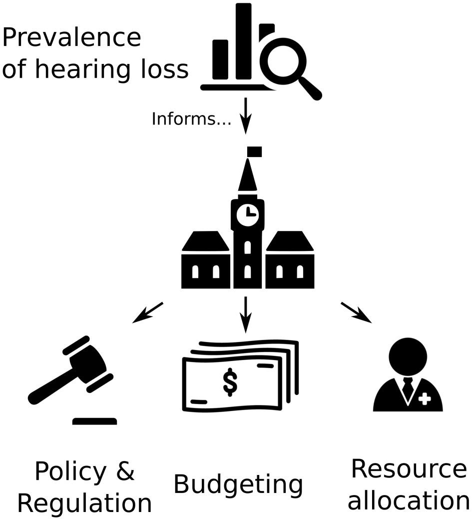

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The audiogram

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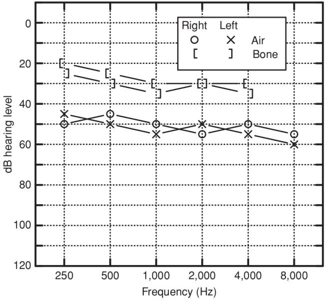

Figure: A typical pure tone audiogram

The Problem

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Problem 1: Datasets can be polluted with poor quality audiograms

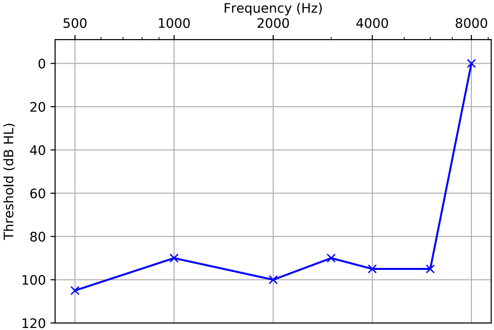

Figure: An audiogram of questionable quality

The Problem

Problem 2: Interpolation-based imputation sometimes fails

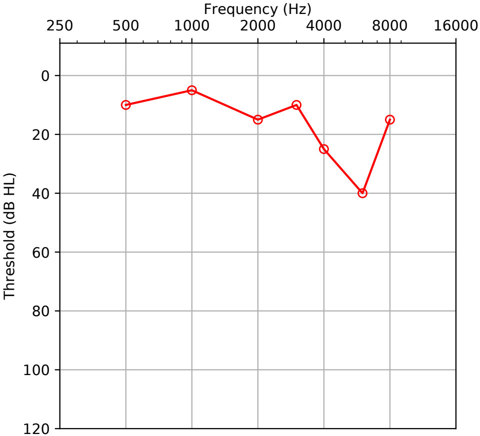

Figure: A case where interpolation fails

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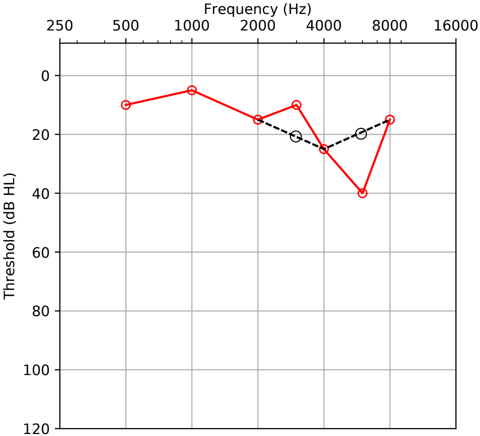

Figure: A case where interpolation fails

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Research Questions

In our paper, we explore the following questions:

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1. Can we automatically **identify potential quality issues** in large audiograms datasets collected as part of studies on the prevalence of hearing loss?

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In our paper, we explore the following questions:

1. Can we automatically **identify potential quality issues** in large audiograms datasets collected as part of studies on the prevalence of hearing loss?
2. Can a **data-driven approach** leveraging similarity between audiograms **improve the imputation accuracy** in incomplete audiograms?

Part I: Investigating Unsupervised Learning for Quality Assurance

Part I: Unsupervised Learning for QA

Assumptions

Let us make the following assumptions:

Part I: Unsupervised Learning for QA

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Part I: Unsupervised Learning for QA

Assumptions

Let us make the following assumptions:

1. The anatomy & physiology of the ear limits the possible audiograms
2. The audiograms are manifestations of some fixed, but unknown number of natural processes (diseases of the ear)
3. We have access to a large quantity of audiograms from a representative sample of the population

Part I: Unsupervised Learning for QA

Leveraging existing data

In this study, we had access to a large database of 15k+ unlabeled audiograms.

National Health and Nutrition Examination Survey

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nhanes

National Health and Nutrition Examination Survey

How do we leverage this dataset to flag potential quality issues?

Part I: Unsupervised Learning for QA

Modeling the prior probability landscape

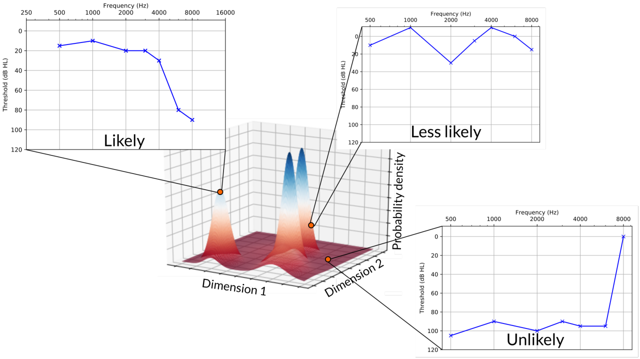

Figure: Conceptual representation of the density estimation problem

Part I: Unsupervised Learning for QA

Modeling the prior probability landscape

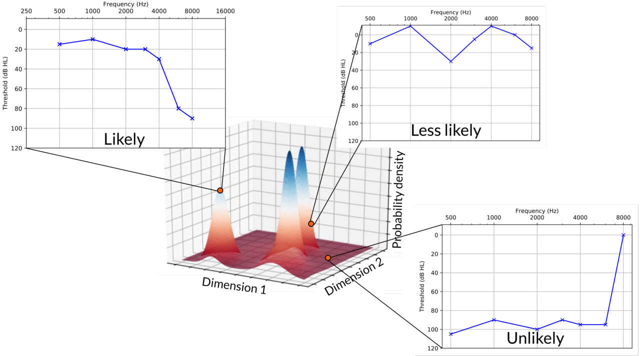

Figure: Conceptual representation of the density estimation problem

That's fine and dandy, but how do we do that?

Part I: Unsupervised Learning for QA

Gaussian Mixture Models

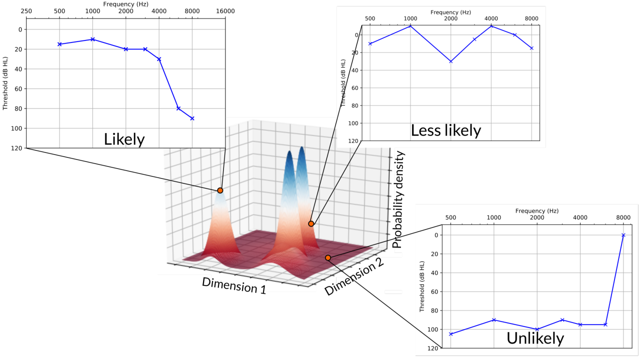

Figure: Conceptual representation of the density estimation problem

$$P(\mathbf{x}) = \sum_{c=1}^{C} \pi_c \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_c, \mathbf{S}_c)$$

Methodology

Optimizing model complexity

Minimize the Bayesian information criterion (BIC)

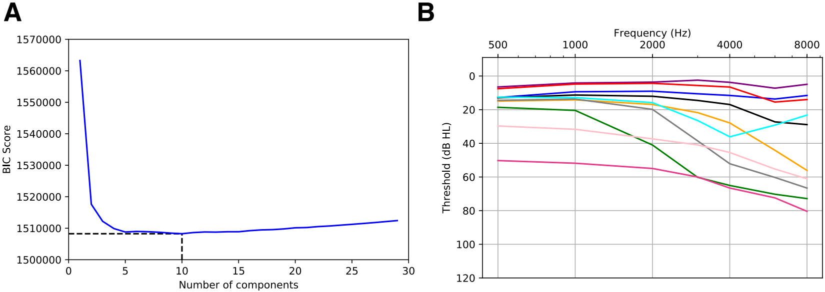

Figure: GMM complexity tuning and resulting components

Part I: Unsupervised Learning for QA

Results

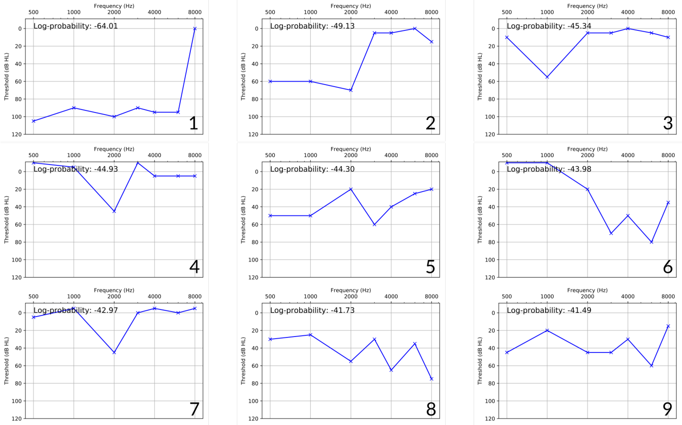

Figure: Audiograms in the NHANES dataset with the lowest log-probability

Part II: Imputing Missing Values

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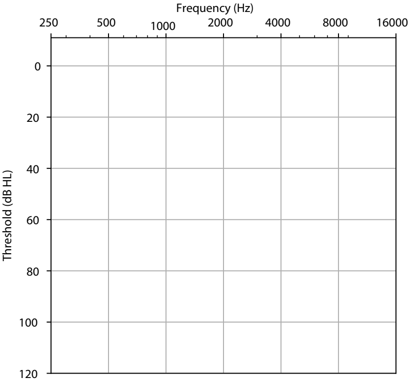
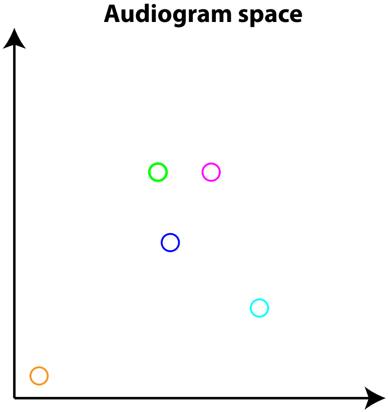
How our k-NN imputation method works





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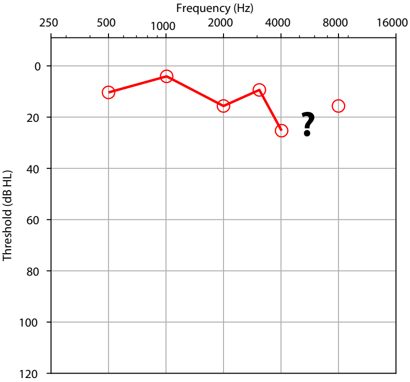

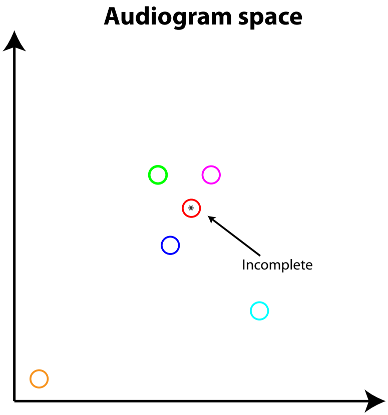

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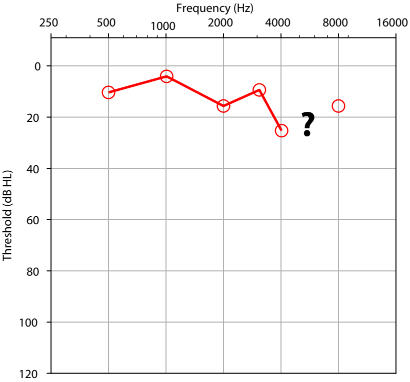

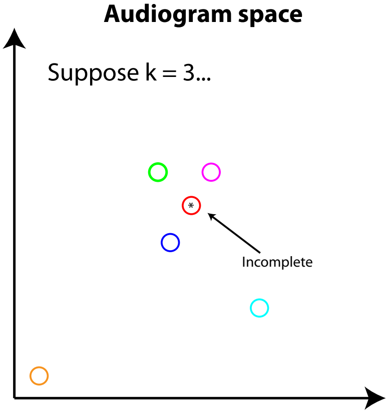

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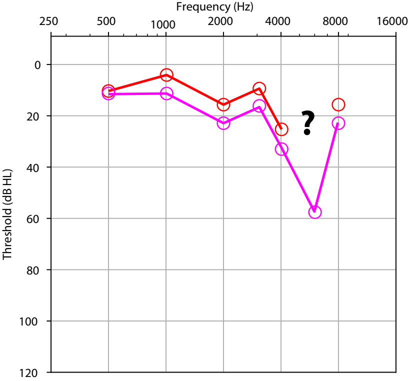

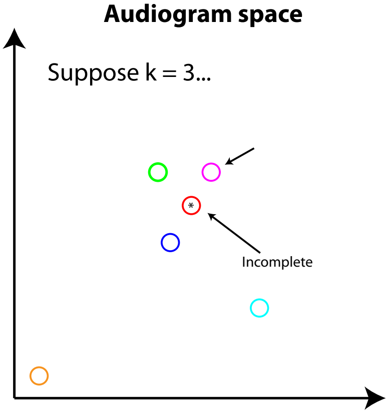

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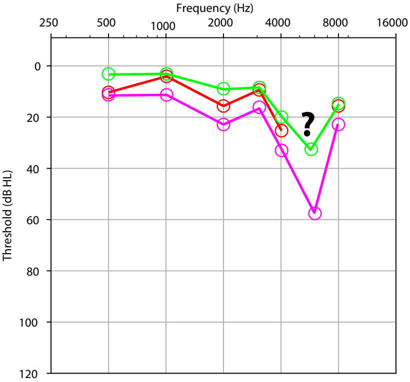

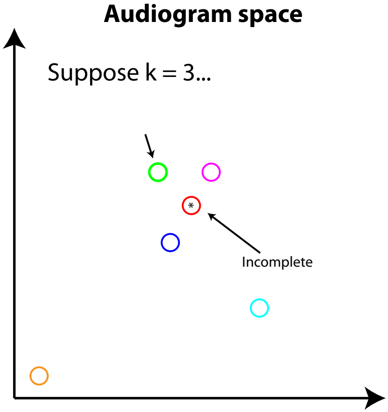

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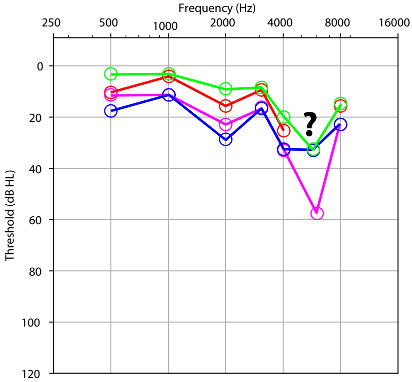

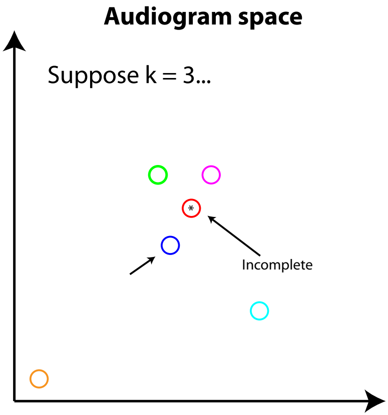

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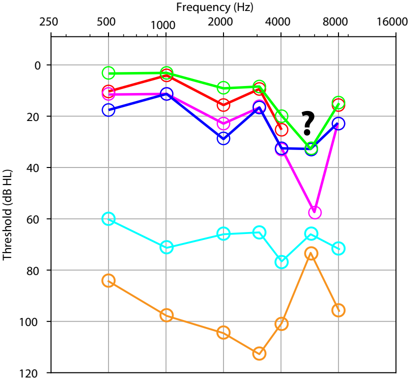

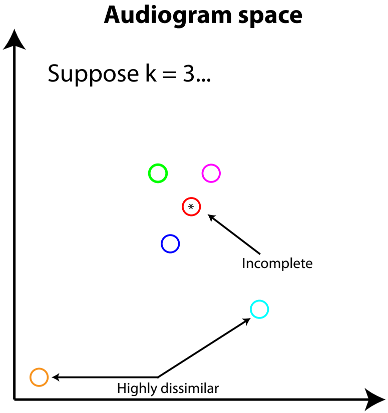

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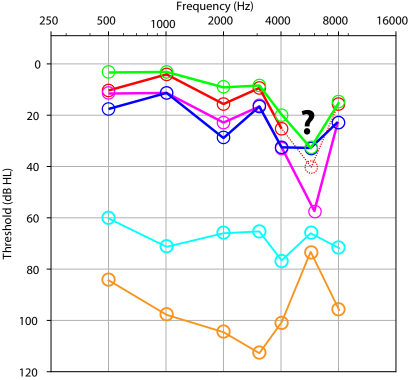

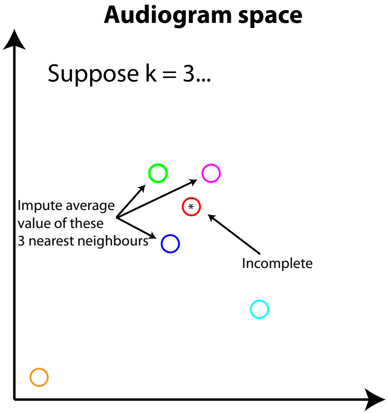

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Our experiment

Adult audiograms

Pediatric audiograms

Training (90% data) **Test (10% data)**

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nhanes
National Health and Nutrition Examination Survey

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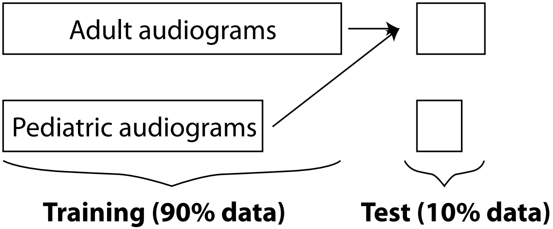

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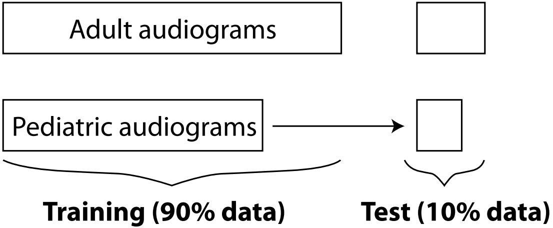

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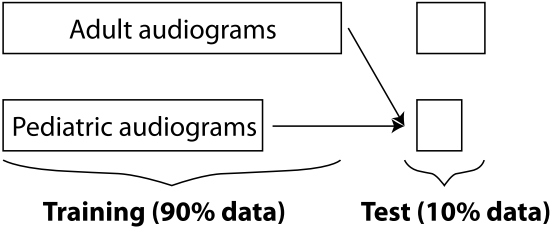

Part II: Imputing Missing Values

Results

Table: Mean absolute error of threshold imputation on a hold-out test set of **pædiatric audiograms**

Training Set	3,000 Hz		6,000 Hz	
	Averaging	k-NN	Averaging	k-NN
All Children	4.68 ± 3.84	4.39 ± 3.54 4.40 ± 3.50	7.66 ± 6.34	6.53 ± 5.19 6.50 ± 5.31

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Table: Mean absolute error of threshold imputation on a hold-out test set of **adult audiograms**

Training Set	3,000 Hz		6,000 Hz	
	Averaging	k-NN	Averaging	k-NN
All	5.49 ± 4.95	5.38 ± 4.75	7.36 ± 6.19	6.92 ± 5.74
Adults		5.39 ± 4.76		6.96 ± 5.74

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- Quantitative evaluation of our QA method with trained audiologist(s)

Comments? Questions?