

Mining Audiograms to Improve the Interpretability of Automated Audiometry Measurements

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Carleton
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clearwater

June 13th, 2018
IEEE Medical Measurements and Applications 2018

Background

*“Nowhere is the **irony** of global inequality more striking than in hearing health care, with more than **80% of people with hearing loss residing [...] where services are either totally absent or very limited.**”*

Swanepoel et al. 2010

Background

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The consequences of hearing loss are multifaceted (World Health Organization 2018)

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The consequences of hearing loss are multifaceted (World Health Organization 2018)



Functional

- Delayed language acquisition
- Poor academic performance
- Dependence

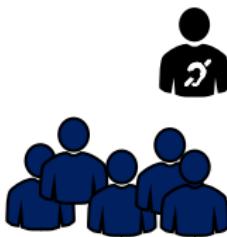
Background

The consequences of hearing loss are multifaceted (World Health Organization 2018)



Functional

- Delayed language acquisition
- Poor academic performance
- Dependence



Social

- Isolation
- Feelings of shame and frustration

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Functional

- Delayed language acquisition
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Social

- Isolation
- Feelings of shame and frustration



Economic

- US\$750B annual global cost
- Unemployment
- Accidents in the workplace

Background

SHOEBOX Audiometry

What?

- Portable iPad-based audiometer

Why?

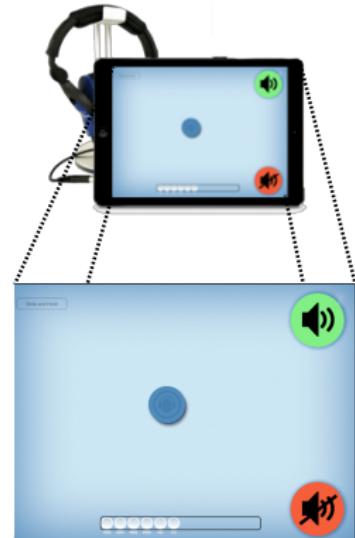
- Democratize access to hearing healthcare for underserved communities

How?

- iPad, calibrated headphones and app
- Automated or manual testing outside the sound booth

For whom?

- For specialists and non-specialists



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Background

Audiogram: what does it mean?



Background

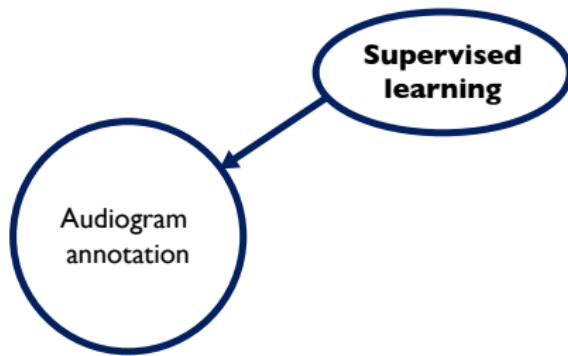
Audiometry in the era of AI and machine learning

**Supervised
learning**

Background

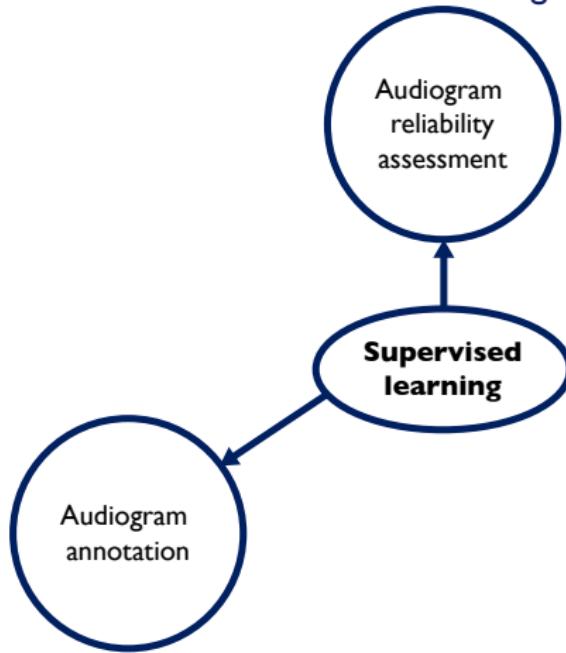
Audiometry in the era of AI and machine learning

Example: "Mild precipitously sloping to severe symmetrically, consistent with age-related hearing loss."



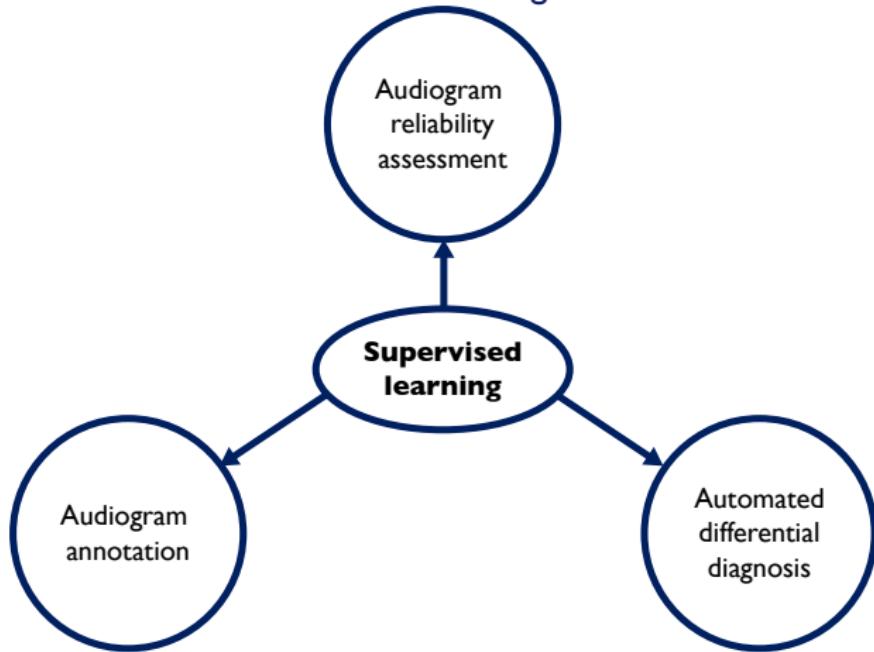
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Audiometry in the era of AI and machine learning



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Audiometry in the era of AI and machine learning



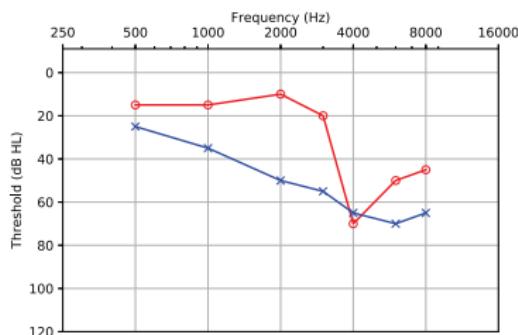
Assembling a training set

Assembling a training set

The NHANES dataset



National Health and Nutrition Examination Survey

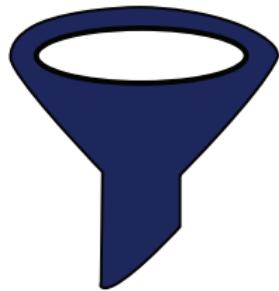


- U.S.-wide health survey on the general population
- 15k+ audiograms collected between 1999-2012
- Air conduction thresholds (500 Hz - 8000 Hz) without masking
- Standard audiology procedure by technicians

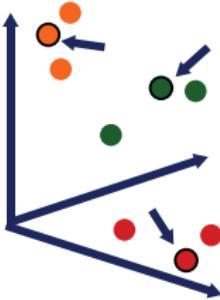
Assembling a training set

Pipeline

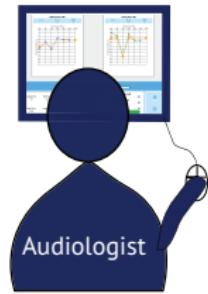
I. Cleaning & Filtering



II. Clustering & Sampling



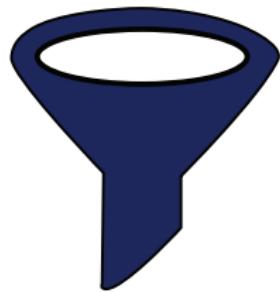
III. Annotation



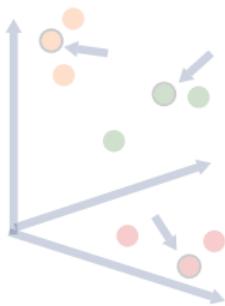
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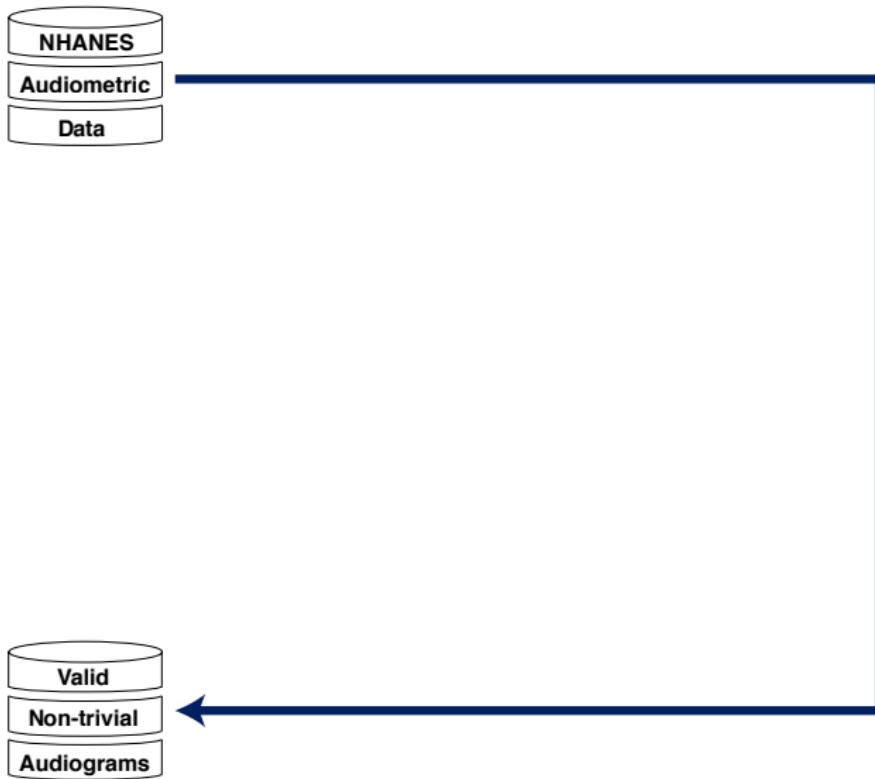


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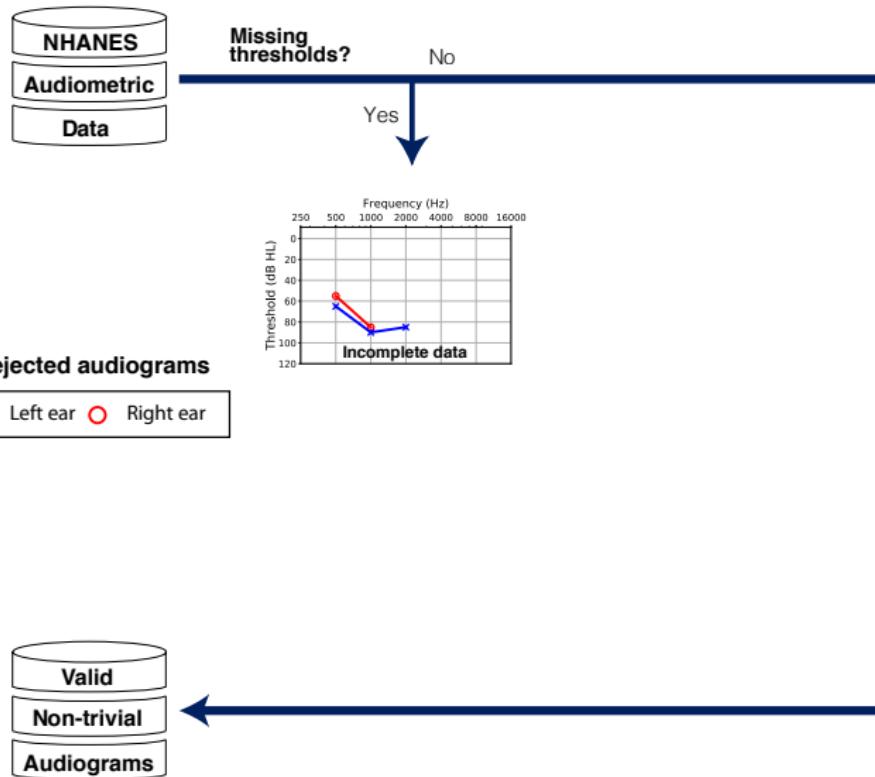
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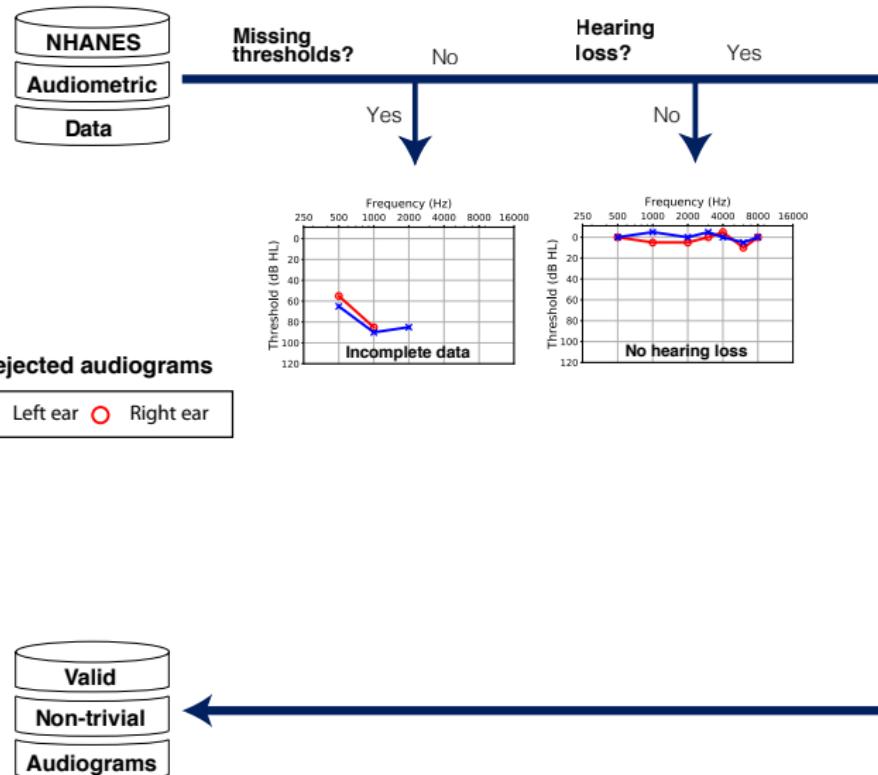
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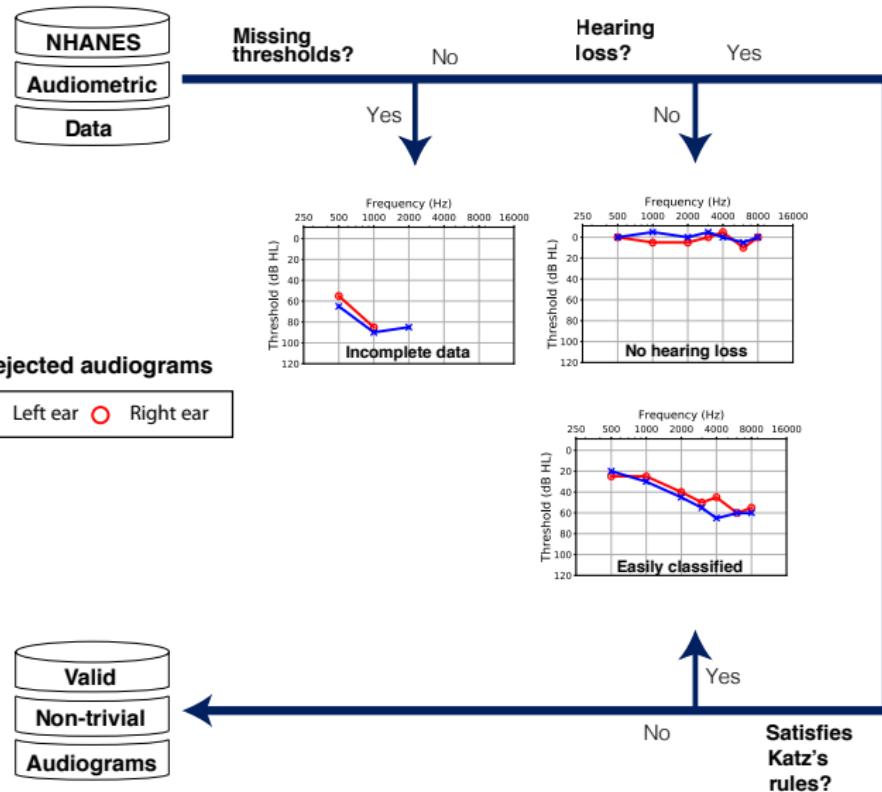
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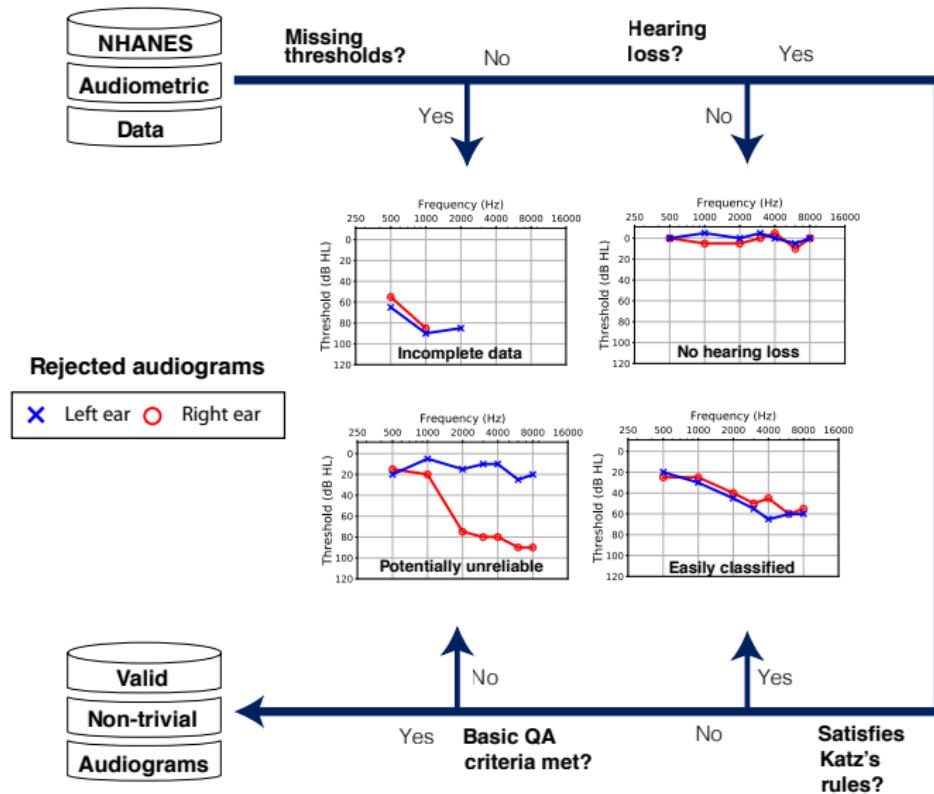
Assembling a training set

I. Cleaning and filtering



Assembling a training set

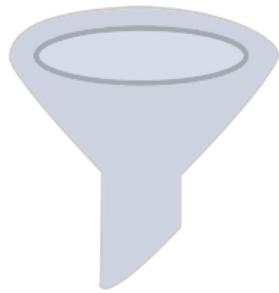
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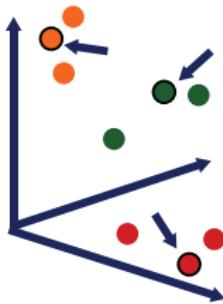
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II. Clustering & Sampling

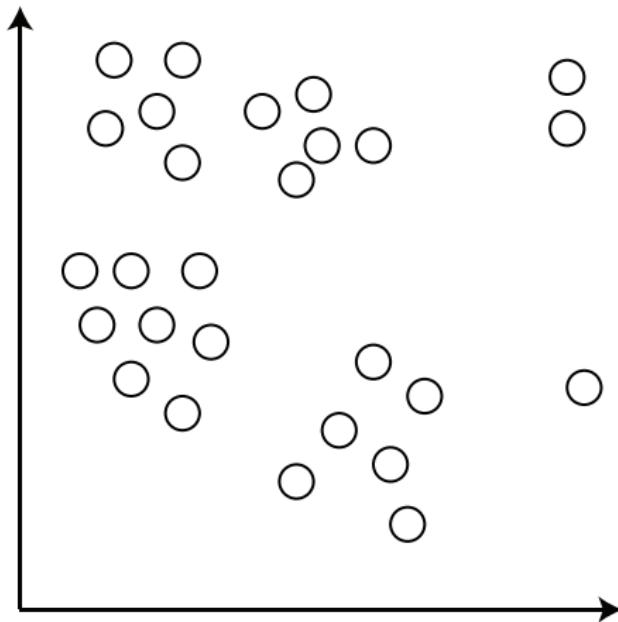


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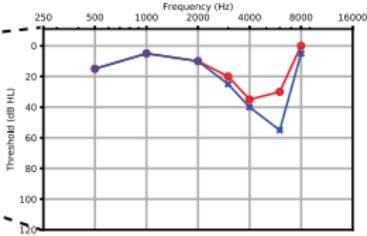
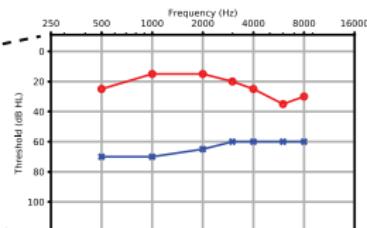
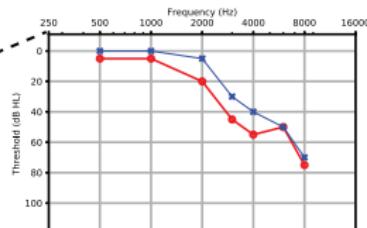
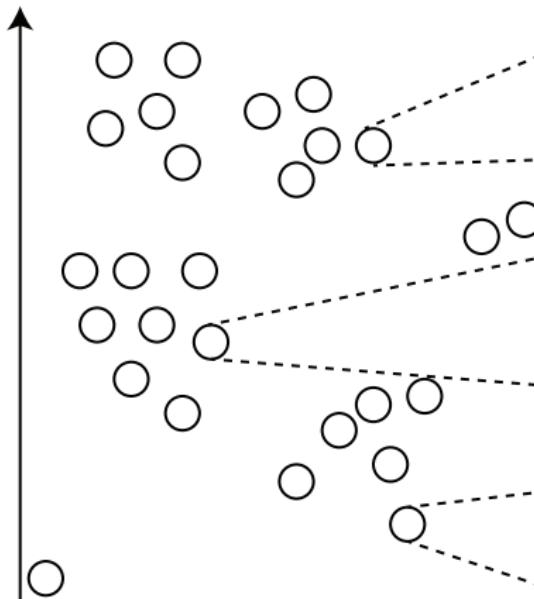
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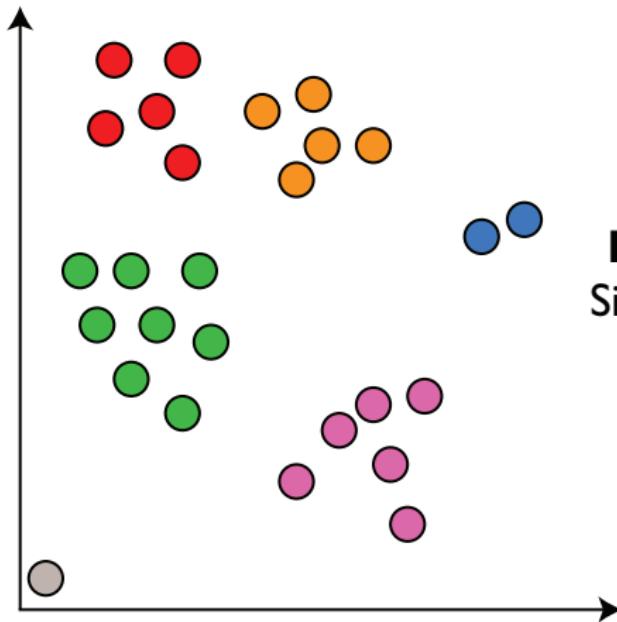
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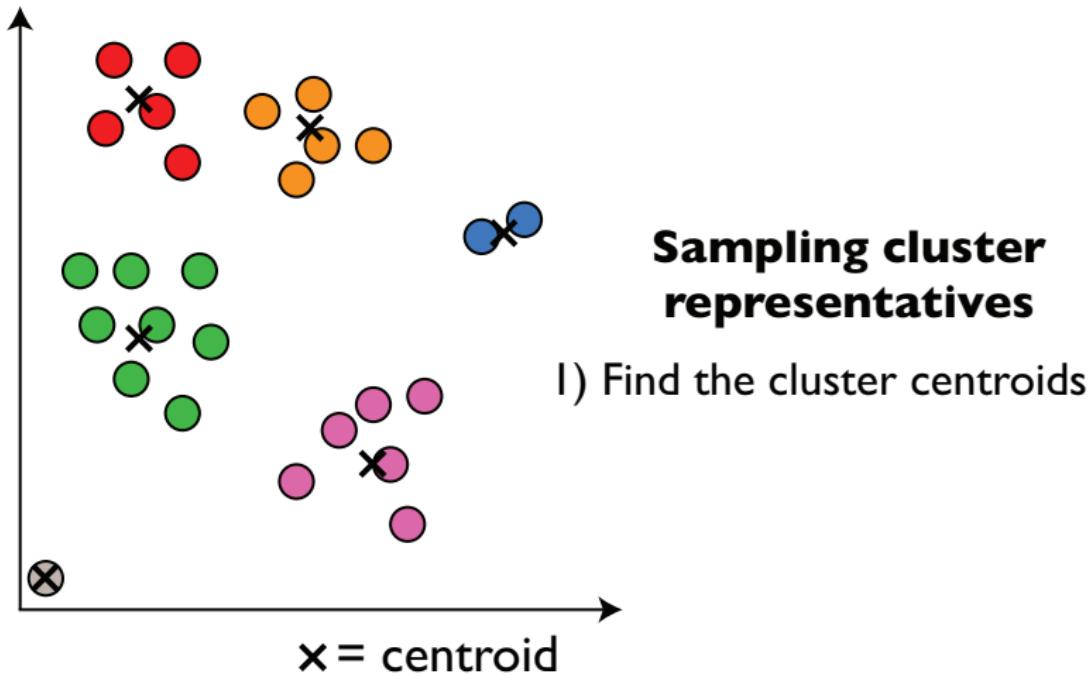


Hierarchical clustering
Silhouette index maximization

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

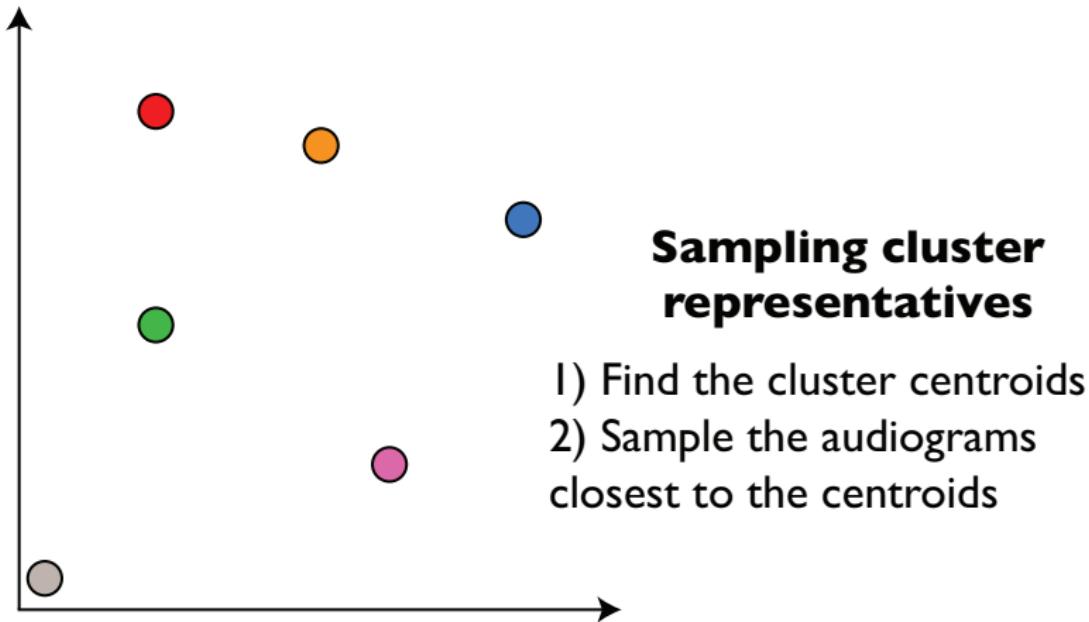
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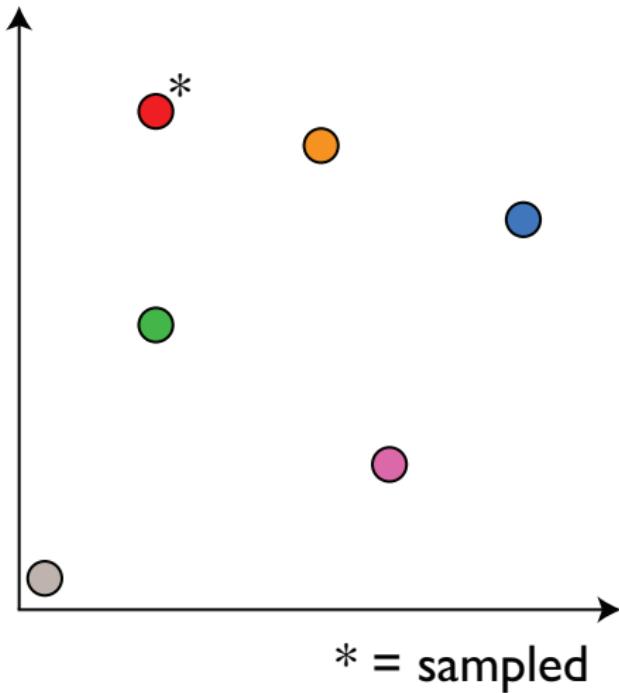
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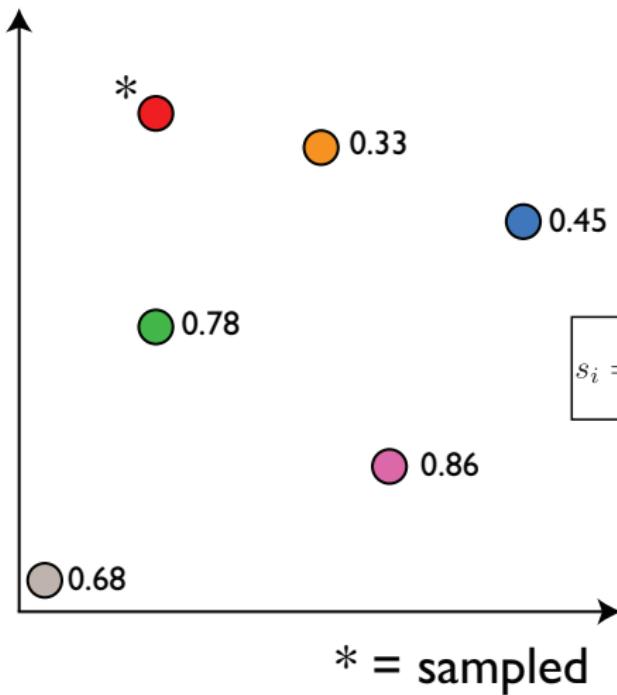


Iterative greedy forward search

- I) Initialize the sample at random

Assembling a training set

II. Clustering and sampling



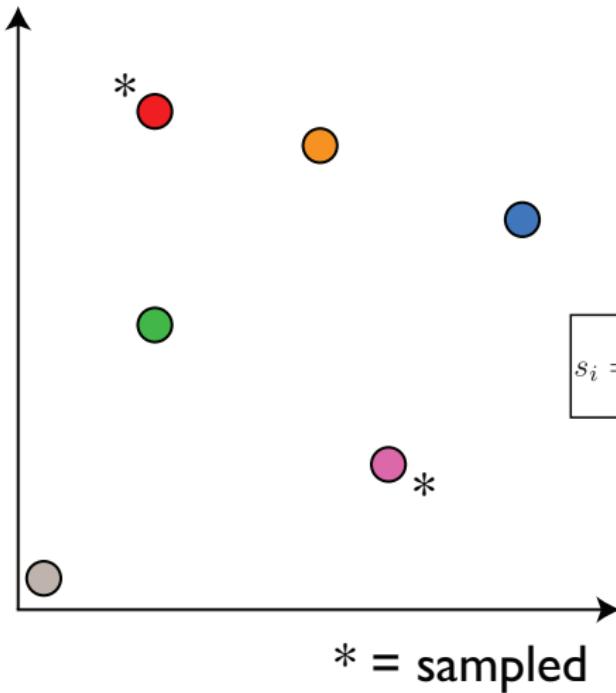
Iterative greedy forward search

- I) Initialize the sample at random
- 2) Assign a score to all unsampled audiograms:

$$s_i = \alpha \frac{d_i - d_{min}}{d_{max} - d_{min}} + (1 - \alpha) \frac{c_i - c_{min}}{c_{max} - c_{min}}$$

Assembling a training set

II. Clustering and sampling



Iterative greedy forward search

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- 3) Iterate until desired sample size

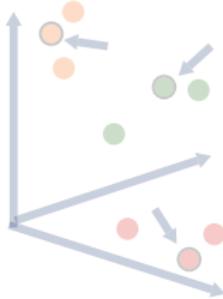
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III. Annotation



Assembling a training set

III. Annotation



Annotation:

- Configuration (shape)
- Severity
- Symmetry
- Reliability
- Notches

Powered by modern web technologies:



React



amazon
webservices

Assembling a training set

III. Annotation

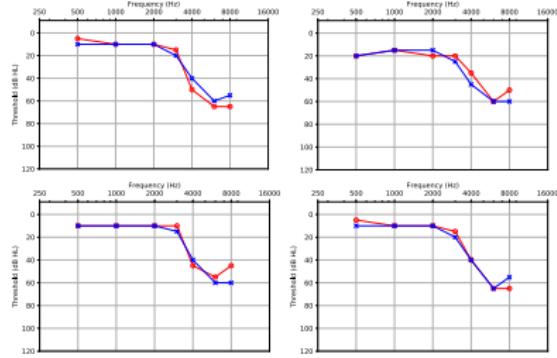
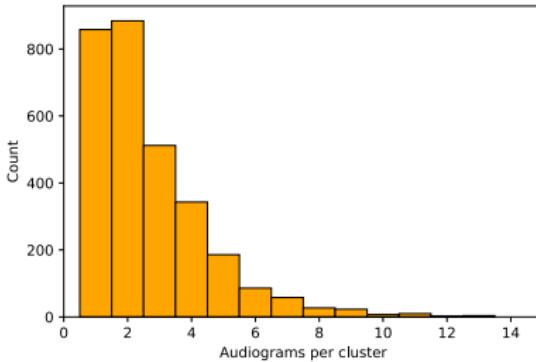
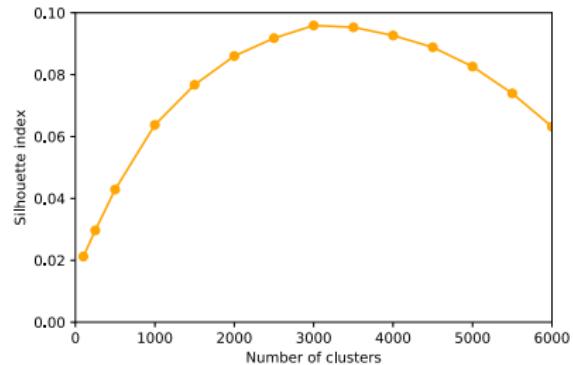
Experimental settings:

- 3 licensed professional audiologists
 - Trained at different institutions
- 325 audiograms
 - Heterogeneous sample
 - 48 duplicates for intra-rater reliability estimation
- Basic instructions regarding annotation format
- Annotations completed independently

Preliminary results

Preliminary results

Clustering



Preliminary results

Intra-rater reliability

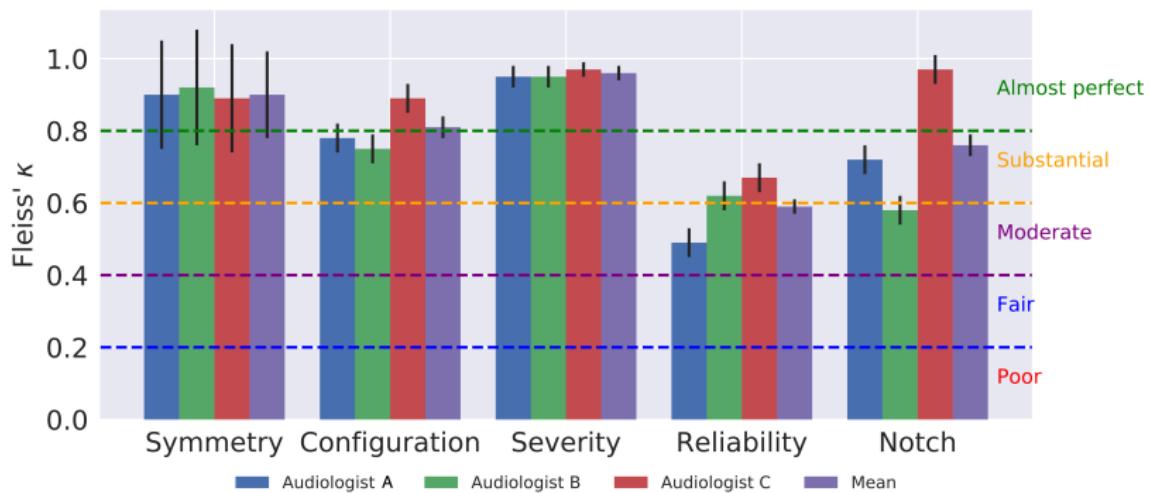


Figure: Intra-rater reliability (Fleiss' κ)

Preliminary results

Inter-rater reliability

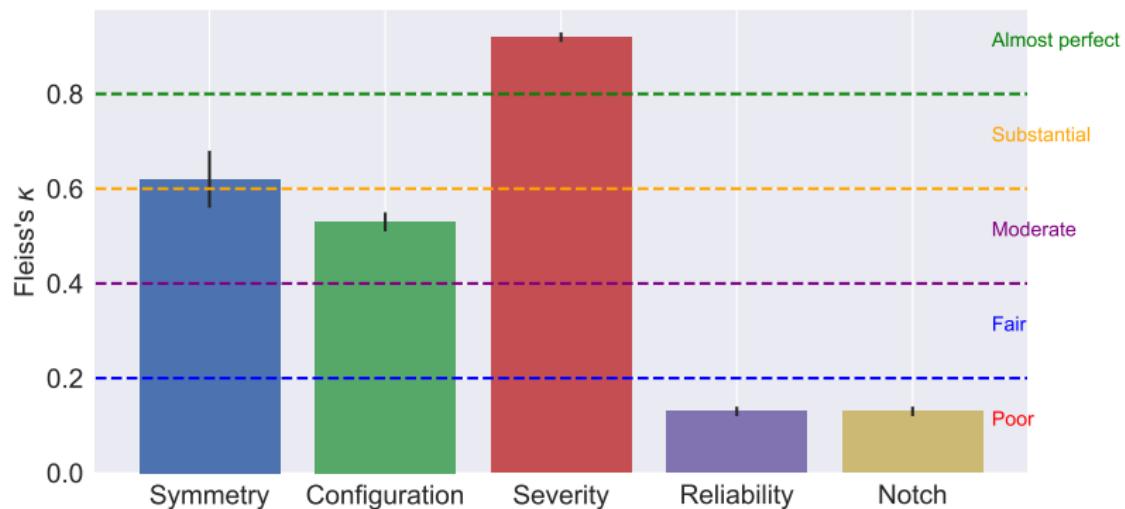


Figure: Inter-rater reliability (Fleiss' κ)

Preliminary results

Agreement with existing rules

Table: Agreement between audiologists and traditional rules (Schlauch and Nelson 2015)

Configuration	Annotator
Flat	-0.29 (0.09)
Sloping	-0.01 (0.09)
Precipitous	-0.54 (0.14)
Rising	1.00 (N/A)

Closing remarks

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Contributions

- A strategy for sampling a heterogeneous set of audiograms
- A web-based annotation environment to quickly annotate hundreds of audiograms
- Measured *intra-* and *inter-rater* reliability on audiogram annotation tasks
- Demonstration that annotators rarely produce the annotation that existing rules yield (configuration)

Closing remarks

What we're up to

- Developing and validating a machine learning model to automate audiogram annotation
- Collaborating with audiologists to compare our model with rule-based approaches
- Working on adding ICD10 diagnosis as a target variable

Acknowledgments

Funding agencies

This work would not be possible without the support of the following funding agencies:



Thank you for listening.

We will gladly take your questions.



References I

-  Schlauch, Robert S. and Peggy Nelson (2015). 'Puretone Evaluation'. In: *Handbook of Clinical Audiology*. Ed. by Jack Katz et al. Seventh. Wolters Kluwer. Chap. 4, pp. 29–47.
-  Swanepoel, De Wet et al. (2010). 'Telehealth in audiology: The need and potential to reach underserved communities'. In: *International Journal of Audiology* 49.3, pp. 195–202. ISSN: 14992027. DOI: 10.3109/14992020903470783.
-  World Health Organization (2018). *Deafness and hearing loss*. URL: <http://www.who.int/en/news-room/fact-sheets/detail/deafness-and-hearing-loss> (visited on 05/14/2018).