Methods for Big data in Audiology

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Introduction

In recent years, there is the **growing trend in leveraging Artificial Intelligence (AI) and Machine Learning (ML)** to enhance the assessment and management of several **decision making processes.**

What is Machine Learning?

Machine Learning (ML) is the field focusing on the development of algorithms, able to achieve a certain task (such as recognition, prediction, etc.). If one considers a **regression framework** then

Output/ target variable / Label $\boldsymbol{y} \xleftarrow{?} \boldsymbol{x}$ **Input/ predictor variables/ features**

The **goal** is to find a relationship between $\boldsymbol{x}$ and $\boldsymbol{y}$. To achieve that, one needs to define a function f such that

$$\boldsymbol{y} \approx f(\boldsymbol{x})$$

and it is **data-driven**, i.e. there is no assumption about the data generating function.

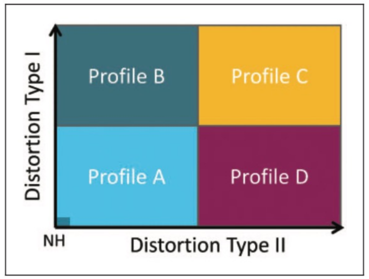
ML in Audiology

Auditory Profiling

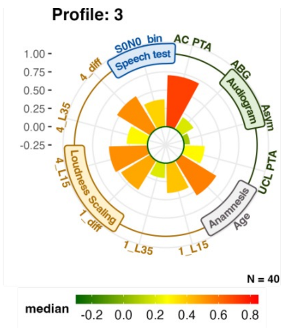
Audiogram | Speech-in-quiet | Speech-in-Noise | ...

AI/ML Model

Individual/Population Audiological Profile



Sanchez-Lopez et al., (2018)



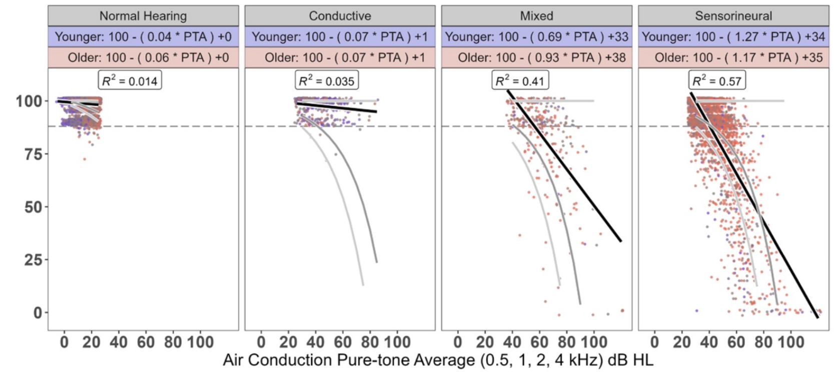
Saak et al., (2024)

Models for Understanding Audiological Tests Relationship

Audiogram ← ? → Speech-in-quiet / Speech-in-Noise / ...

AI/ML Model

Insights into Tests Predictive/Correlation relationship



Smith et al., (2024)

Motivation

Main Challenges

Auditory Profiling

- Data Heterogeneity
- Data Integration Method.

Models for Understanding Audiological Tests Relationship

- Complex Interactions
- Lack of Inference Settings

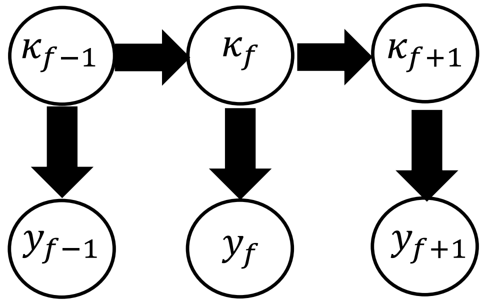
Common Challenge: focus on direct test results, offering only a momentary snapshot of hearing function, **without capturing the underlying progression or true auditory state.**

We propose **an auditory profiling solution** relying on a **state-space-model** with the following properties:

- It estimates the underlying **hearing loss trend** inferring **the true auditory state over the frequency domain**
- It handles **data heterogeneity**
- It models **audiological tests Interactions by incorporating knowledge of the speech tests**
- It provides an **inference and testing framework**

Model Formulation

We formulate a **state-space model** over the **frequency domain** of the audiogram and across **age groups**.



$$\begin{bmatrix} y_f^{a_1} \\ y_f^{a_2} \\ \cdots \\ y_f^{a_P} \end{bmatrix}_{Px1}$$

P age groups

Baseline Model :

$$\boldsymbol{y}_f = \boldsymbol{\alpha} + \boldsymbol{\beta}\,\kappa_f + \boldsymbol{\epsilon}_f$$
$$\kappa_f = \theta + \phi_1 \kappa_{f-1} + \omega_f$$
$$f = f_1, .., f_{11}$$

Extended Model :

$$\boldsymbol{y}_f = \boldsymbol{\alpha} + \boldsymbol{\beta}\,\kappa_f + \gamma_Q\,\boldsymbol{x}_Q + \gamma_N \boldsymbol{x}_N + \boldsymbol{\epsilon}_f$$
$$\kappa_f = \theta + \phi_1 \kappa_{f-1} + \omega_f$$
$$f = f_1, .., f_{11}$$

Observations:

- $\boldsymbol{y}_f$ Audiogram frequency
- $\boldsymbol{x}_Q$ Speech-in-quiet
- $\boldsymbol{x}_N$ Speech-in-noise

Estimated Parameters:

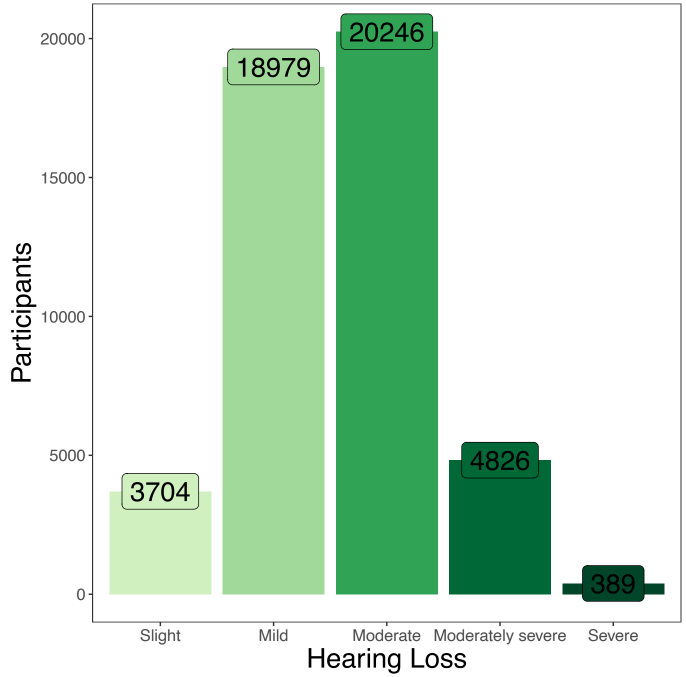
- κ_f Trend of hearing loss over frequency for all age groups
- $\boldsymbol{\alpha}$ Baseline hearing loss level across age
- $\boldsymbol{\beta}$ Quantifies the influence of κ_f on y_f

Dataset

Data: 48,144 adults, with symmetric hearing loss, age range between 40 to 90 (French Amplifon Database) for which we have**: Audiogram, Speech-in-quiet, Speech-in-noise**.

We run the model over different **population segments,** i.e. **overall**, by **degree of hearing loss**.

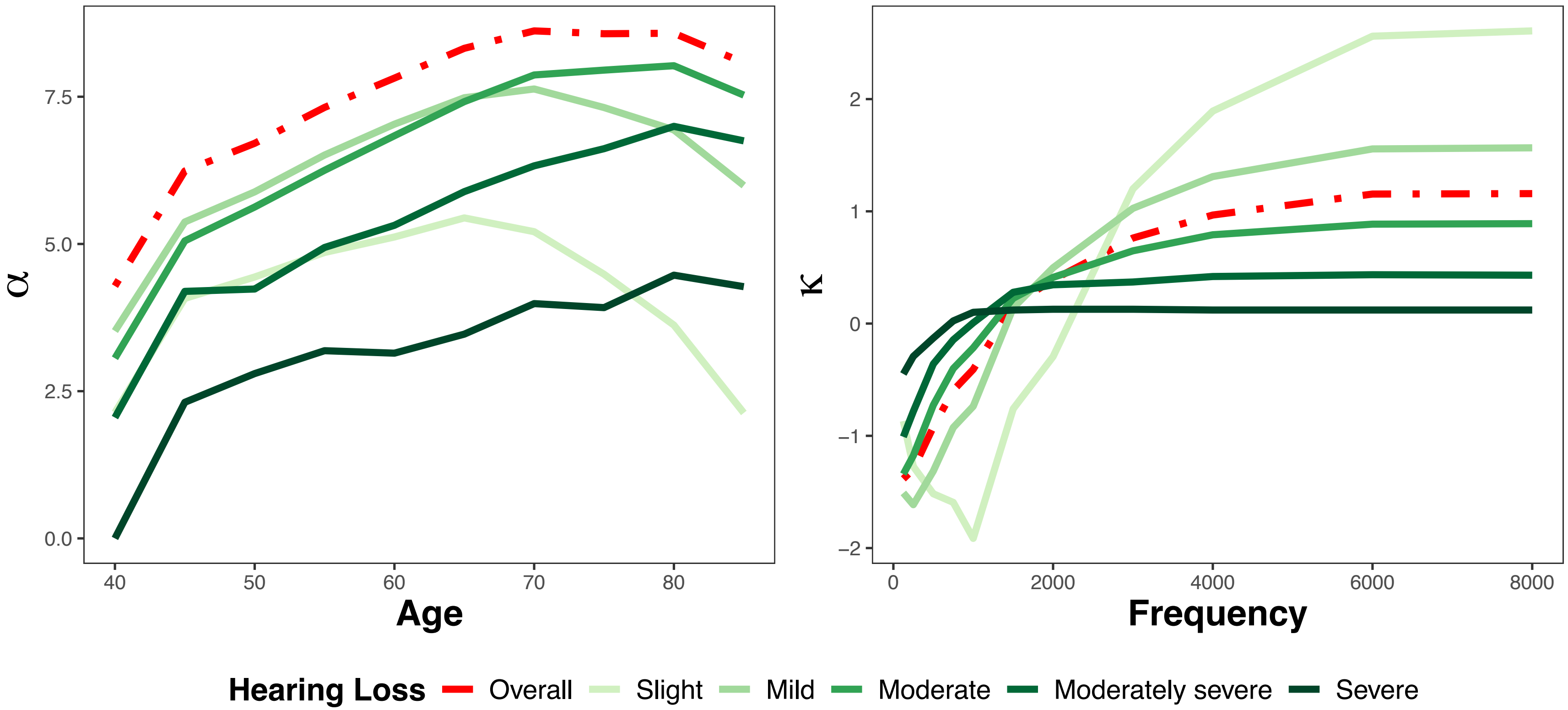
PTA Categories	
Degree of HL	**PTA Range (dB)**
Normal	-10 to 15
Slight	16 to 25
Mild	26 to 40
Moderate	41 to 55
Moderately severe	56 to 70
Severe	71 to 90



Profiles

Baseline hearing loss across age

Trend of hearing loss over frequency



Inference

Heatmaps of Speech-in-quiet and speech-in-noise coefficient Estimates

Slight

$\gamma_Q^{h_1}$

Probabilistic Level	125	250	500	750	1000	1500	2000	3000	4000	6000	8000
90%	0.66	0.48	0.71	1.57	0.57	0.61	2.49	1.58	3.34	2.96	3.54
80%	1.21	2.46	−0.2	0.11	−0.28	−0.6	−1.05	0.37	0.65	2.59	4.64
60%	0.04	0.43	0.09	−0.37	0.11	0.52	−0.41	−0.4	−0.24	0.15	0.24
40%	0.23	0.1	0.5	−0.06	0.15	0.5	−0.06	0.01	0.25	−0.06	0.6
20%	0.18	−0.23	−0.06	−0.02	0.13	0.6	−0.07	0.08	−0.16	0.03	−0.12

Frequencies

$\gamma_N^{h_1}$

Probabilistic Level	125	250	500	750	1000	1500	2000	3000	4000	6000	8000
90%	−0.16	−0.76	0.27	−0.48	0.64	0.56	−1.77	−3.67	1.27	1.17	4.77
80%	−0.07	−0.47	0.44	0.86	0.57	1.65	1.62	1.66	3.25	1.95	−0.99
60%	0.29	0.07	0.45	0.66	0.51	0.46	0.67	0.94	1.64	1.27	1.66
40%	0	0.1	−0.09	0.32	0.28	0.37	0.34	0.38	0.51	0.8	0.54
20%	0.25	0.42	0.33	0.43	0.12	0.13	0.49	0.29	0.65	0.55	0.99

Frequencies

Estimate Significance: Non−Significant | Significant at 0.05

Severe

$\gamma_Q^{h_5}$

Probabilistic Level	125	250	500	750	1000	1500	2000	3000	4000	6000	8000
90%	0.2	0.73	−0.76	0.45	−0.04	0.75	−0.92	0.07	0.21	0.45	−0.04
80%	0.19	0.17	0.86	0.48	−0.25	0.09	0.86	0.36	−0.27	0.72	0.87
60%	−0.2	−0.2	0.09	−0.26	−0.21	0.04	−0.06	−0.11	−0.11	−0.05	−0.07
40%	−0.02	0.74	0.32	0.38	0.64	0.3	0.27	0.36	0.57	0.34	0.49
20%	−0.24	0.43	0.98	−0.11	0.29	0.31	0.31	0.31	0.27	0.31	0.34

Frequencies

$\gamma_N^{h_5}$

Probabilistic Level	125	250	500	750	1000	1500	2000	3000	4000	6000	8000
90%	0.04	−0.62	0.37	−0.1	−0.26	−0.26	0.34	−0.06	−0.06	0	0.16
80%	0.34	−0.08	−0.13	−0.32	0.93	0.48	−0.5	0.22	0.77	−0.28	−0.51
60%	1	1	0.98	1	1.01	0.99	1	1	1	1	0.99
40%	0.98	0.24	0.71	0.63	0.38	0.68	0.72	0.64	0.41	0.66	0.51
20%	1.23	0.57	0.04	1.12	0.72	0.69	0.69	0.69	0.73	0.69	0.66

Frequencies

Estimate Significance: Non−Significant | Significant at 0.05

$$\boldsymbol{y}_f = \boldsymbol{\alpha} + \boldsymbol{\beta}\,\kappa_f + \gamma_Q\,\boldsymbol{x}_Q + \gamma_N \boldsymbol{x}_N + \ \boldsymbol{\epsilon}_f$$

t-Test for Regression Coefficients

$$H_0\colon \gamma_Q^{h_i} = 0 \qquad H_0\colon \gamma_Q^{h_i} \neq 0 \qquad i = 1,..,5$$

$$H_0\colon \gamma_N^{h_i} = 0 \qquad H_0\colon \gamma_N^{h_i} \neq 0 \qquad i = 1,..,5$$

Conclusions & Future Research

- We introduced a **state-space model** acting on **frequency** and **age** domains
- The **parameters** of the model acts as **auditory profiles** describing population dynamics across these 2 domains
- The models provide a framework for **inference procedures** testing differences between profiles incorporating (or not) knowledge of speech tests
- The model offers flexibility of **adding other audiological tests**
- The parameters can be used for **sharing knowledge** across databases in a **federated learning** framework
- **Future work** foresees the definition of hearing loss rates derived from the obtained parameters serving as monitoring tools in clinical decision support system (over time and frequency domains).

Thank You !

References

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