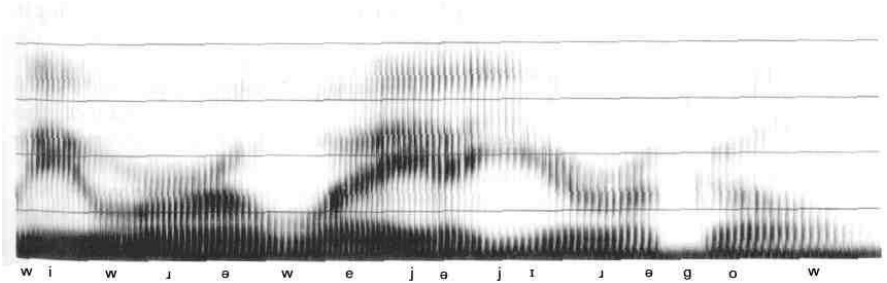
Towards Responsible Speech Processing

Isabel Trancoso

inesc id lisboa

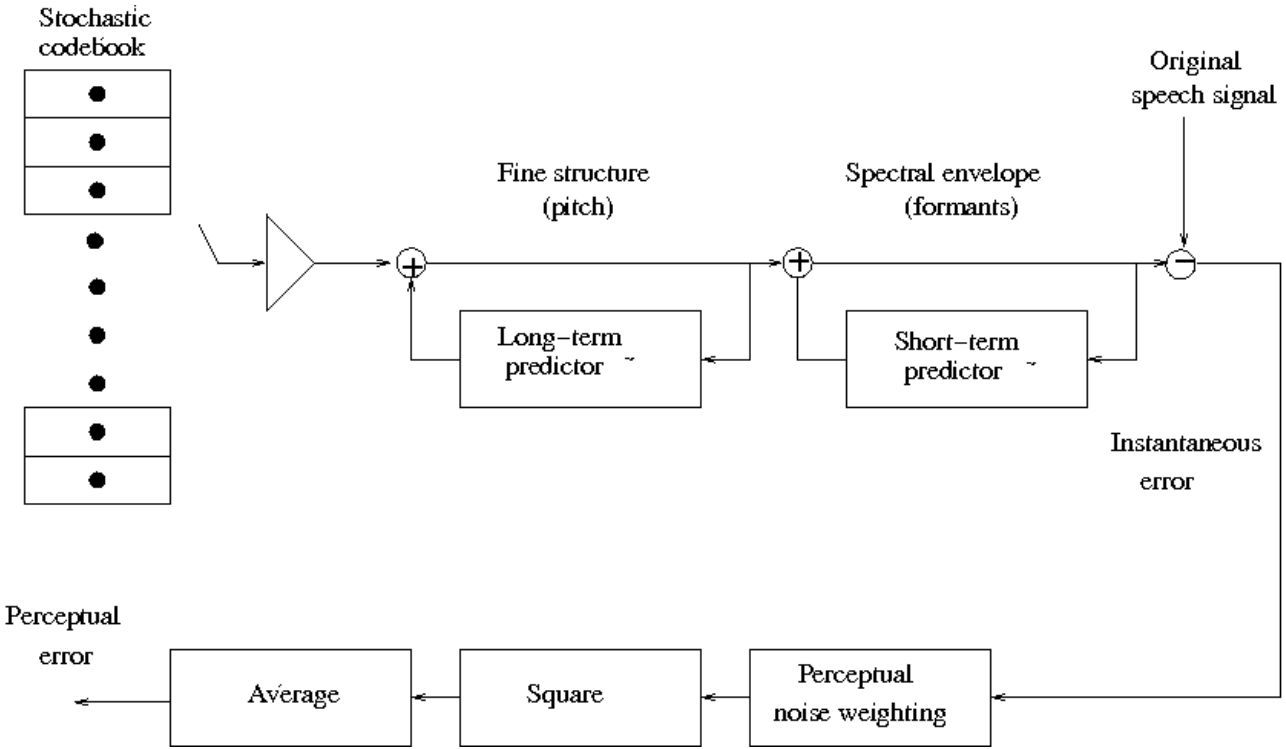
TÉCNICO LISBOA

From the old HP2116C@IST…
… to a CRAY supercomputer @AT&T Bell Labs



http://home.cc.umanitoba.ca/%7Ekrussll/13/sec4/specgram.htm

CELP Coder


Stochastic codebook
Original speech signal
Fine structure (pitch)
Spectral envelope (formants)
Long−term predictor
Short−term predictor
Instantaneous error
Perceptual error
Average
Square
Perceptual noise weighting

In the 1980s


determination
technology
aspects
understanding
synthesiser
experimental
computer
intonation
knowledge-based
experiments
Voice recognition
conversion
simulation
acoustic-phonetic
warping
dialogue
spectral
German
clustering
communication
Speaker-independent
representation
syllables
control
output
segmentation
study
signal
English
without
issues
isolated word recognition
Chinese
recognition
telephone
feature
adaptive
technique
prosodic
quality
residual
analysis
model
rule
LPC
phoneme
New
human
Real-time
digit
service
auditory
voice
hindi
phonetic
base
linguistic
performance
ASR
DTW
synthesis
TES
use
measure
data
vowel
speech
text-to-speech system
tract
French
formant
information
speech recognition
acoustic
coder
Word
aid
dynamic
method
Time
pitch
coding
network
automatic
text
effects
estimation
system
Italian
sounds
application
design
Markov
speech synthesis
word recognition
vector quantization
research
linear
simple
parameters
language
approach
Automatic speech recognition
patterns
algorithm
input
modelling
text-to-speech
result
comparison
written
recognition system
implementation
prediction
dutch
large vocabulary
Spoken
robust
second
independent
extraction
isolated
hidden
Japanese
vocoder
coarticulation
predictive
grapheme-to-phoneme

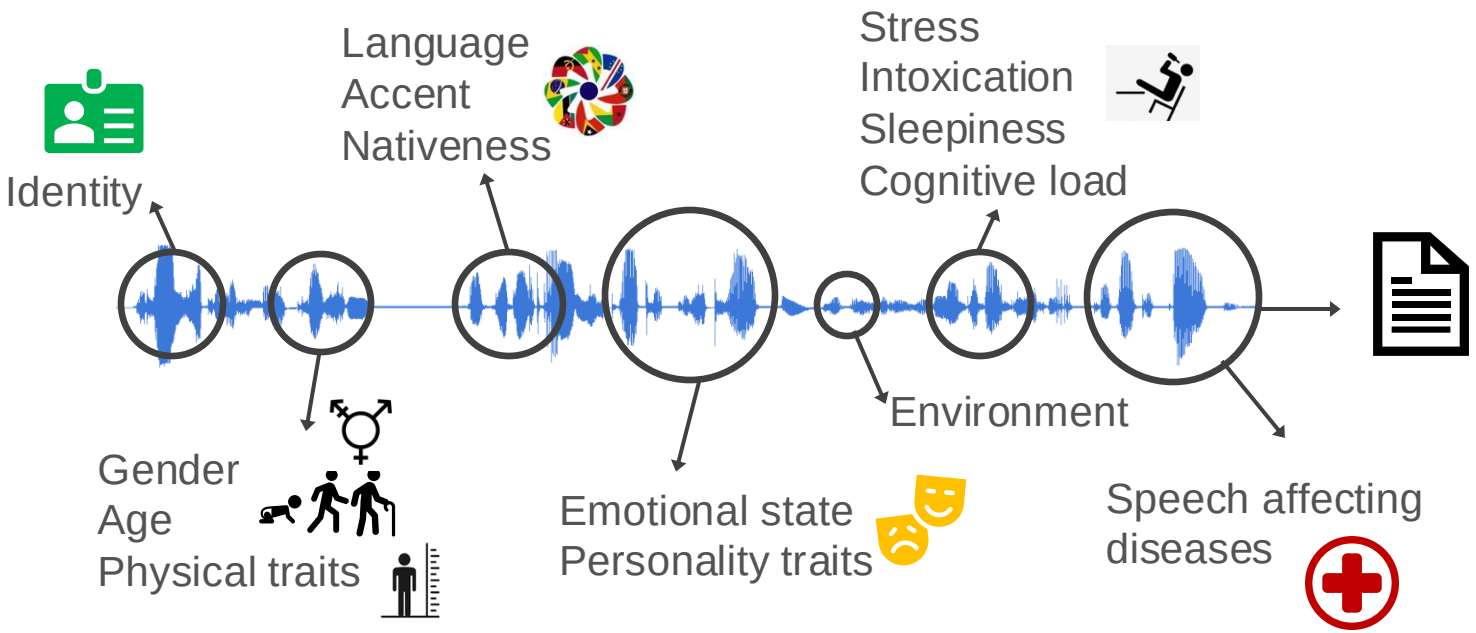
In the 2020s


speech
recognition
learning
dialogue
models
self-supervised
evaluation
automatic
language
large
transformers
representations
data
model
speaker
chatgpt
classification
detection
asr
robust
machine
open-domain
benchmark
towards
generation
based
diarization
conversational
benchmarking
leveraging
pre-training
memorizing
adapters
datasets
generative
subjective
empathetic
prosody
features
synthetic
children's
representation
systems
utility
publicly
analysis
tasks
deep
via
approach
truth
selection
available
annotating
exploring
human
chatbots
timing
text
using
era

Pillars of Responsible AI

- Robustness & Safety
- Fairness & Inclusion
- Explainability
- Privacy & Security
- Sustainability
- Accountability & Governance
- User Agency, Trust & Wellbeing

Info in speech



Pillars of Responsible Speech Processing

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Fairness & Inclusion

- Models tend to reflect stereotypes present in their training data; Internet-trained models have internet-scale biases
- Bias along the dimensions of accent, race, gender, age, ...
  - M. Adda-Decker and L. Lamel. Do speech recognizers prefer female speakers? Interspeech 2005.
  - R. Tatman. Gender and Dialect Bias in YouTube's Automatic Captions. EthNLP@EACL 2017.
  - D. Harwell. The accent gap. Washington Post, 2018.
  - L. Lima. Empirical analysis of bias in voice-based personal assistants. Companion of The WWW Conference, 2019.
  - A.Koenecke, Racial disparities in speech recognition, Proc. National Academy of Sciences, 2020
  - A. Kulkarni et al., Unveiling Biases while Embracing Sustainability, Interspeech 2024
  - S. Feng et al., Towards inclusive automatic speech recognition, Computer Speech and Language, 2024

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  - Child speech was recognized worst

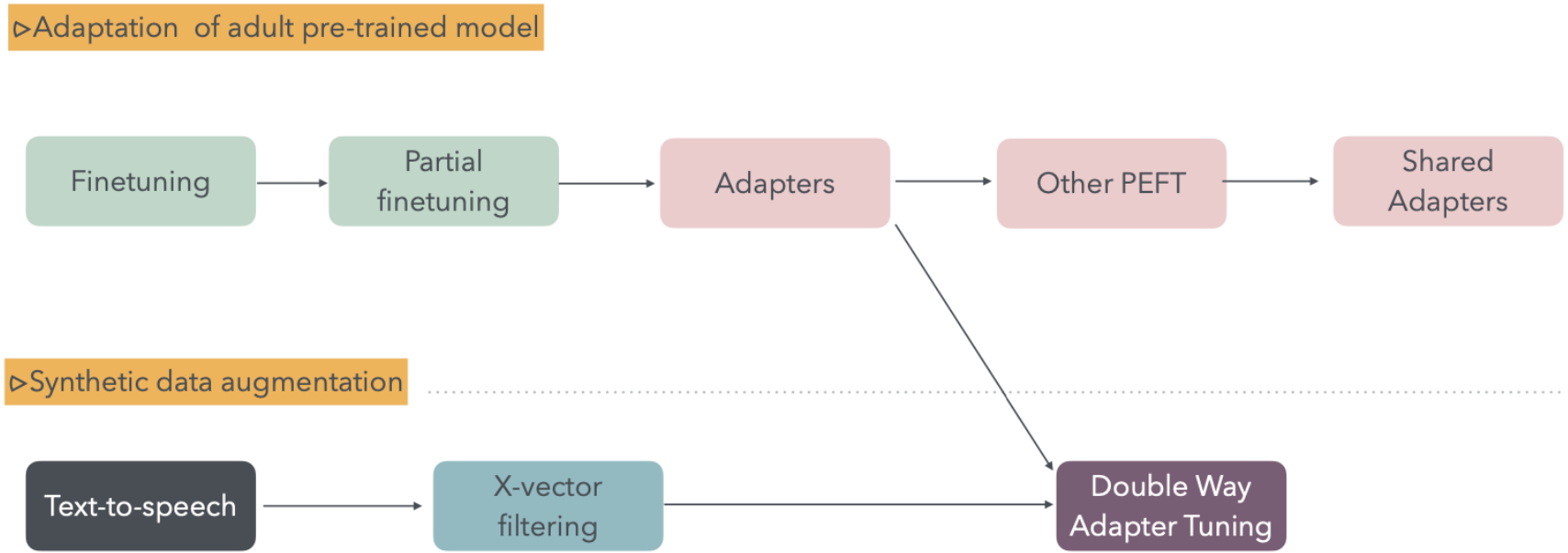
Towards improved ASR for children

PhD Thesis of Thomas Rolland, supervised by Alberto Abad

- Introduction to Partial fine-tuning: A comprehensive evaluation of end-to-end children's automatic speech recognition adaptation (IS 2024, Thursday, SS-8)
- Exploring adapters with conformers for children's automatic speech recognition (ICASSP 2024)
- Shared-Adapters: A novel Transformer-based parameter efficient transfer learning approach for children's automatic speech recognition (IS 2024, Tuesday, A8-O4)
- Improved children's automatic speech recognition combining adapters and synthetic data augmentation (ICASSP 2024)

TAPAS PRR Plano de Recuperação e Resiliência REPÚBLICA PORTUGUESA Financiado pela União Europeia NextGenerationEU

Roadmap towards improving ASR for children

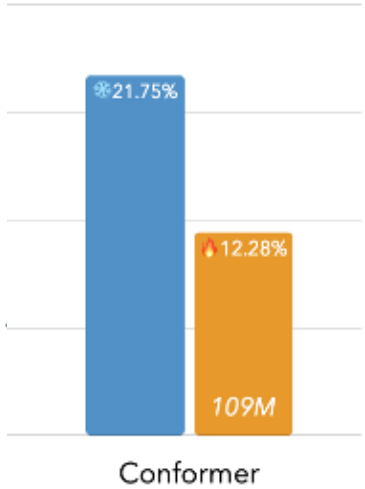


Finetuning

Children's speech

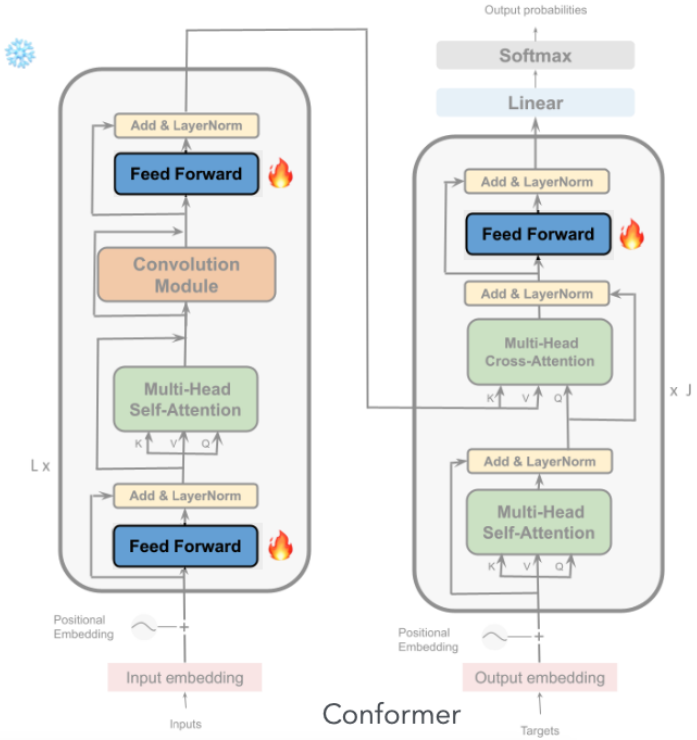
My Science Tutor
MyST
(Ward et al. 2013)

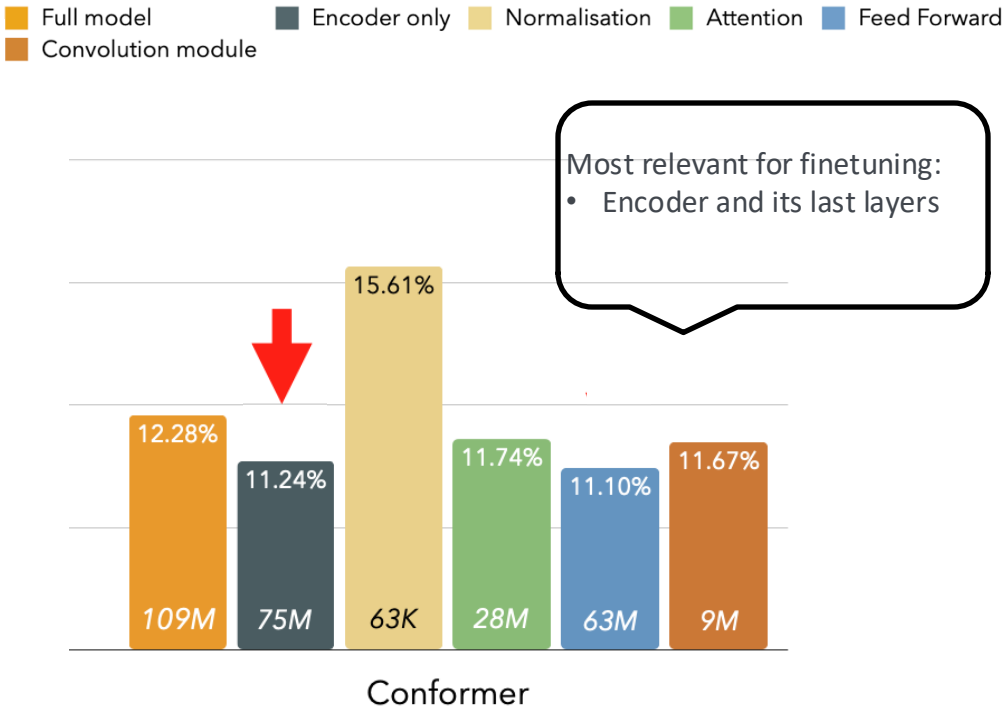
🔥 Adult ASR model



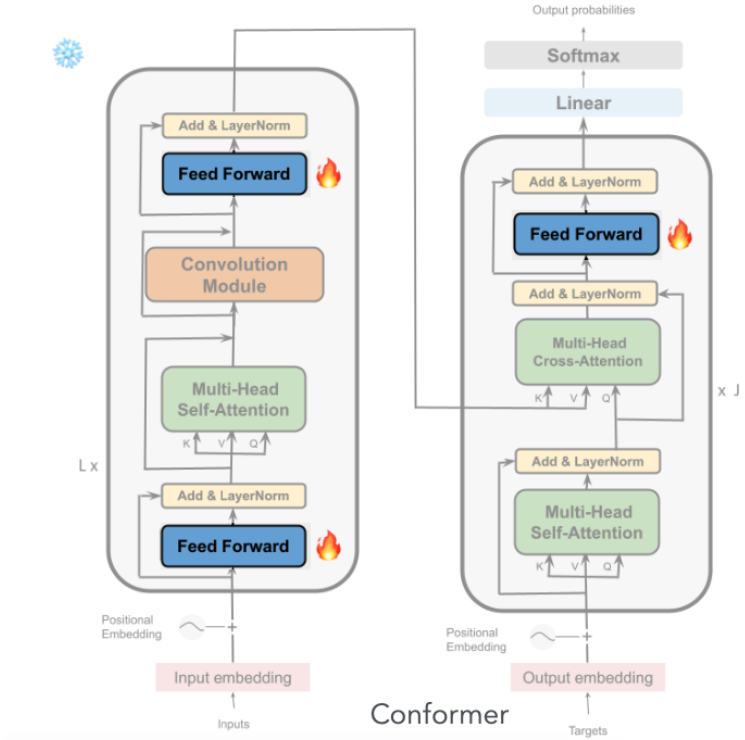
(Gulati et al. 2020)
https://huggingface.co/speechbrain/asr-conformer-transformerlm-librispeech

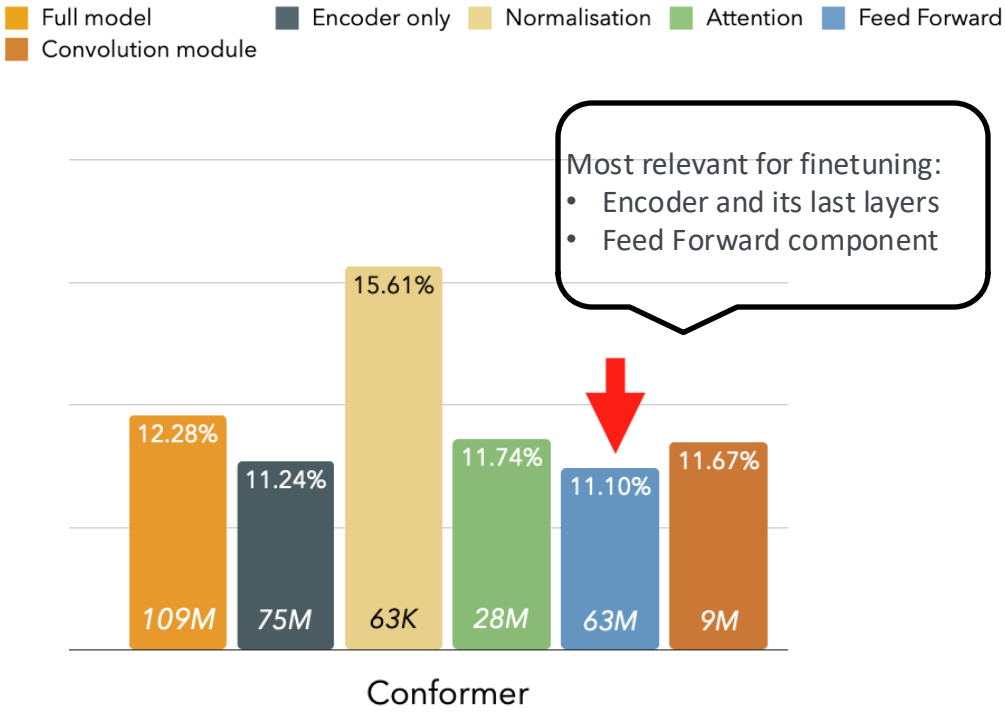
Partial finetuning





Partial finetuning





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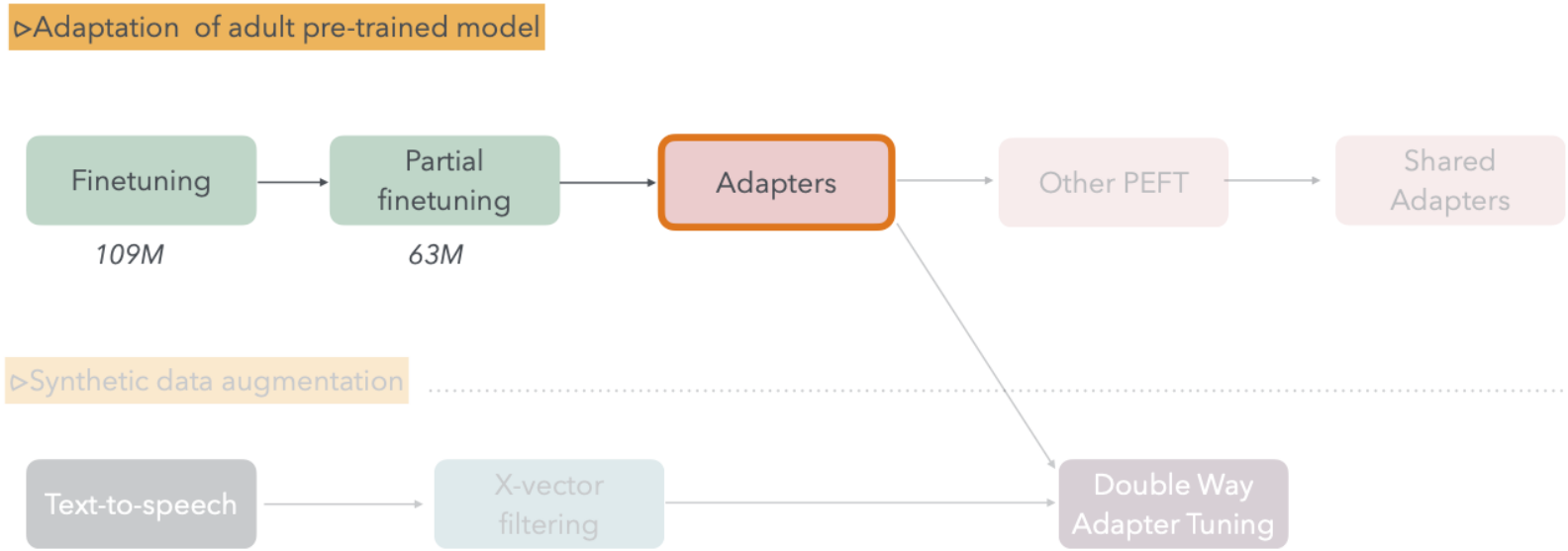


Roadmap towards improving ASR for children

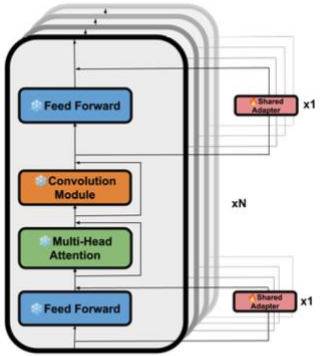
▹Adaptation of adult pre-trained model

Finetuning → Partial finetuning → Adapters → Other PEFT → Shared Adapters

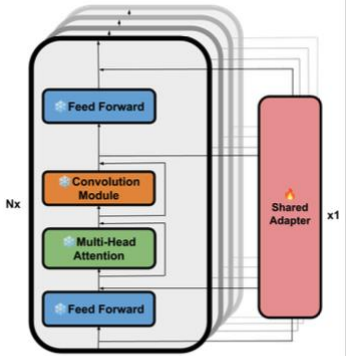
109M 63M 12M 6M 1M

▹Synthetic data augmentation

Text-to-speech → X-vector filtering

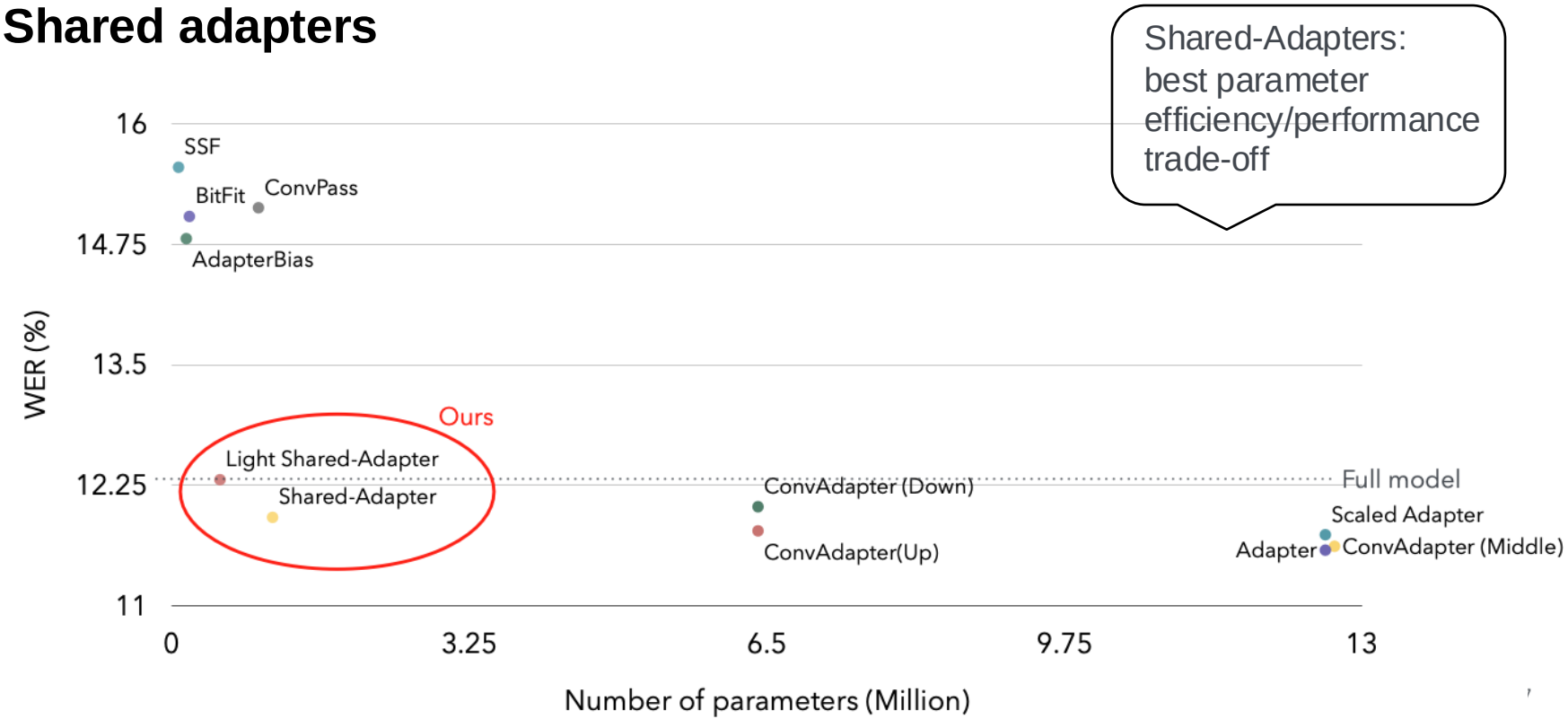


Shared-Adapter



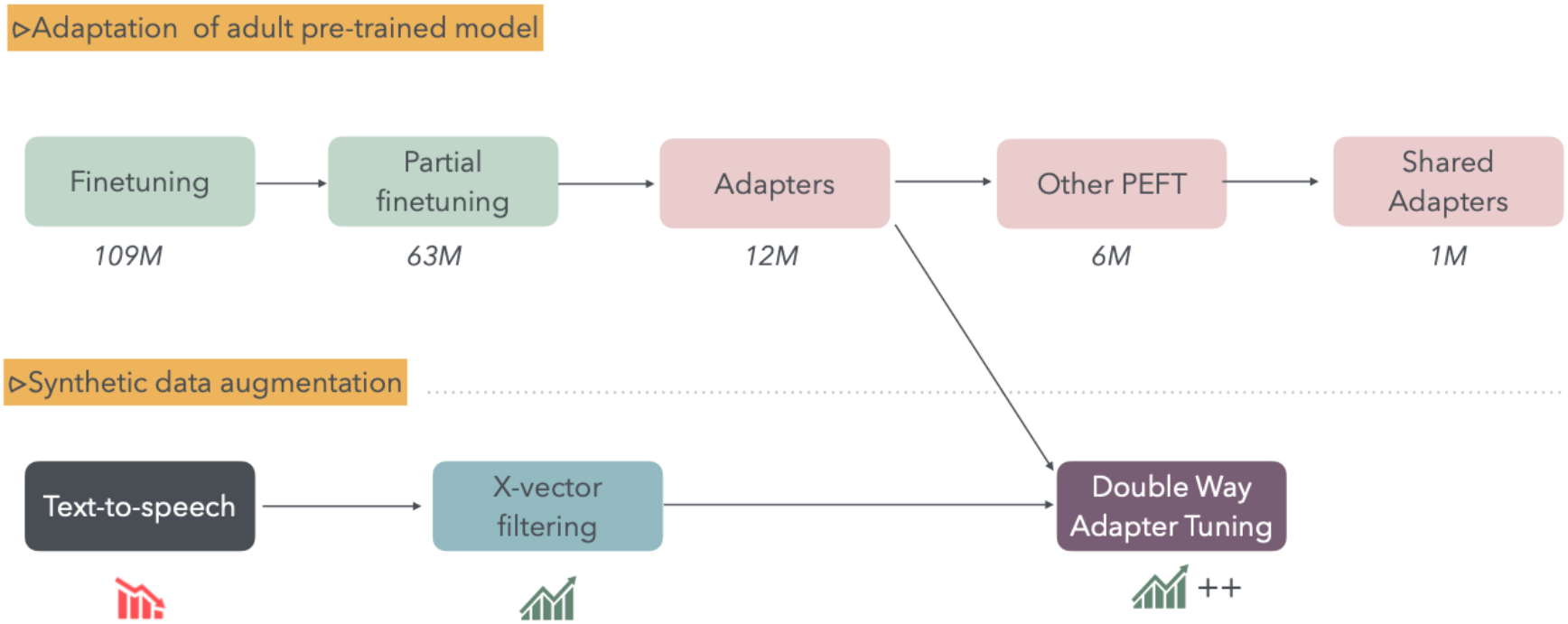
Light Shared-Adapter

Shared adapters

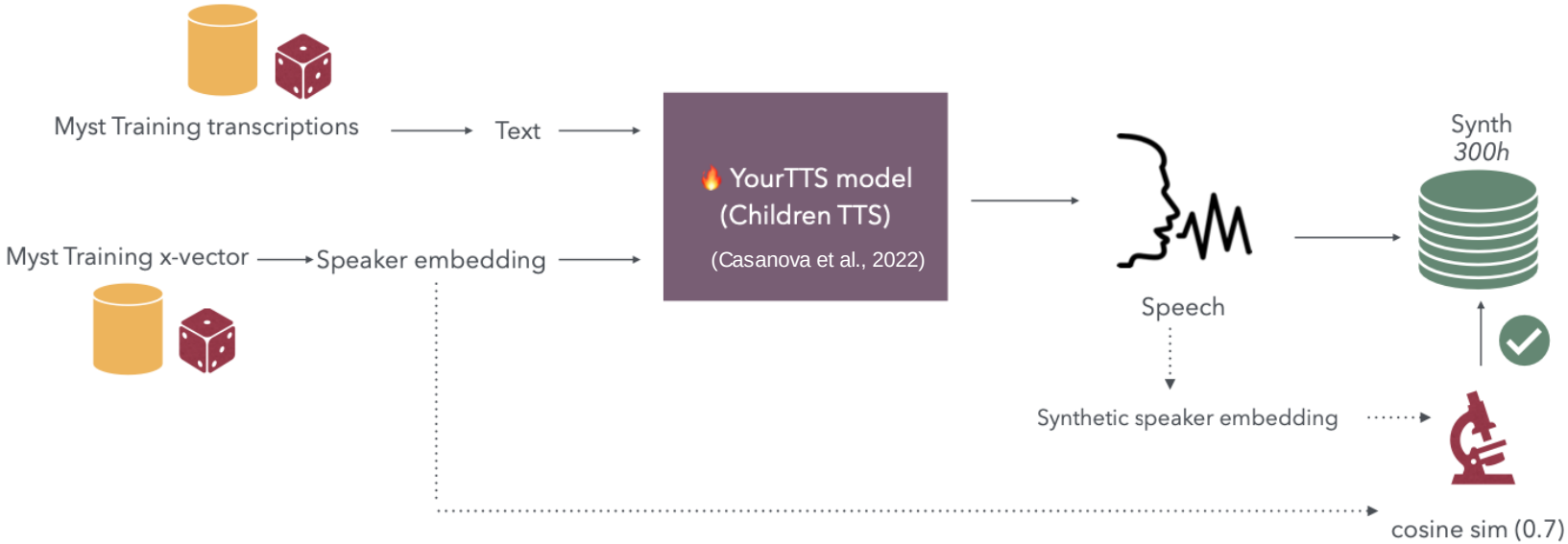


SSF (Lian et al., 2022) ; BifFit (Zaken et al., 2022); ConvPass (Li et al., 2023); AdapterBias (Fu et al., 2022); ConvAdapter (Yang et al., 2023); Scaled Adapter (He et al., 2022).

Roadmap towards improving ASR for children



Synthetic data augmentation



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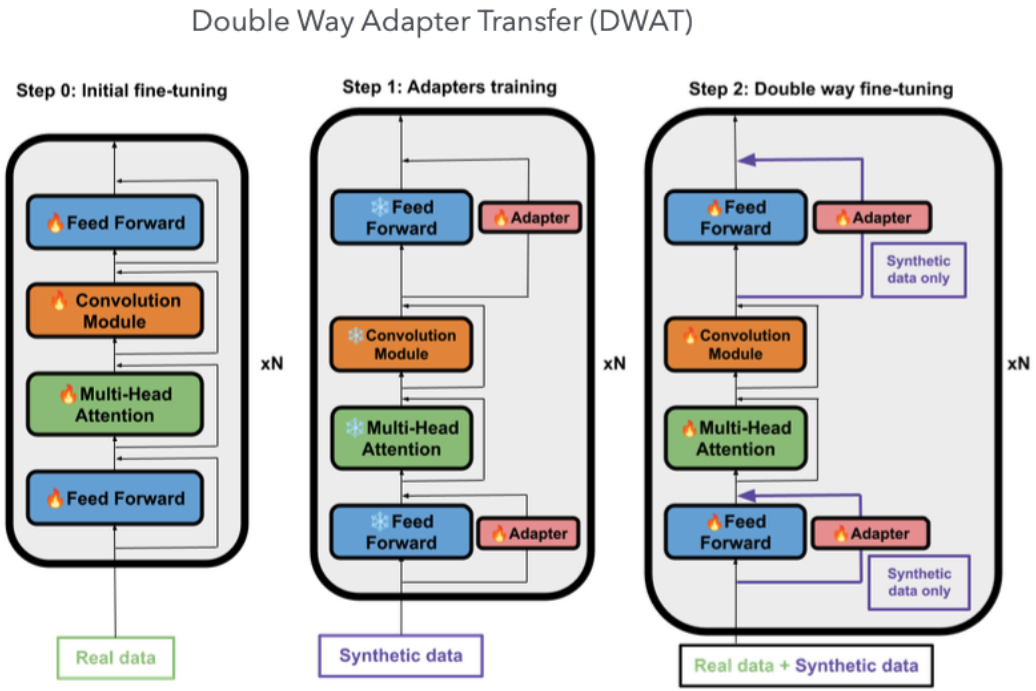

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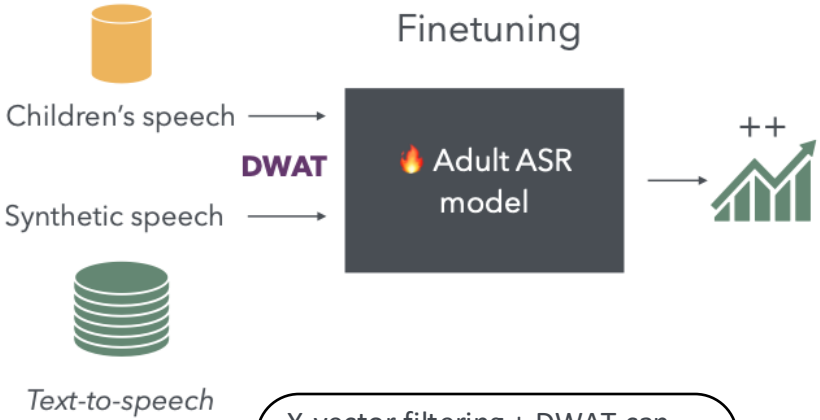
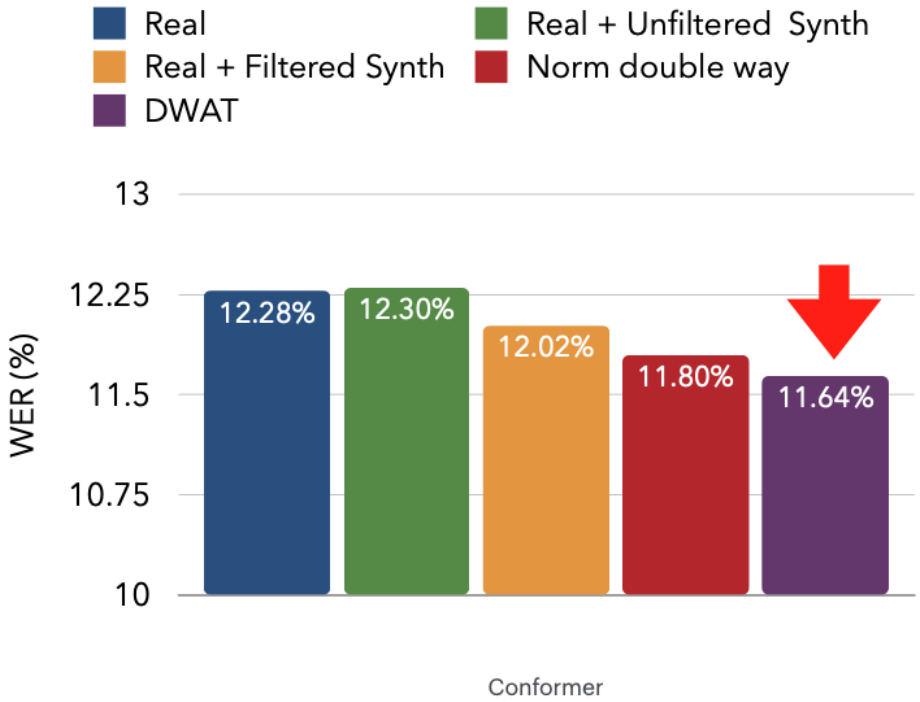


X-vector filtering + DWAT can reduce the mismatch between real and synthetic data, and control the quality and speakers' variability of the synthetic utterances.



Towards improved ASR for children

Fine-tuning:
- Essential for good children's ASR performance

Selective fine-tuning:
- Encoder and its last layers
- Feed Forward component

Can such bias mitigation strategies be adopted to other biases?

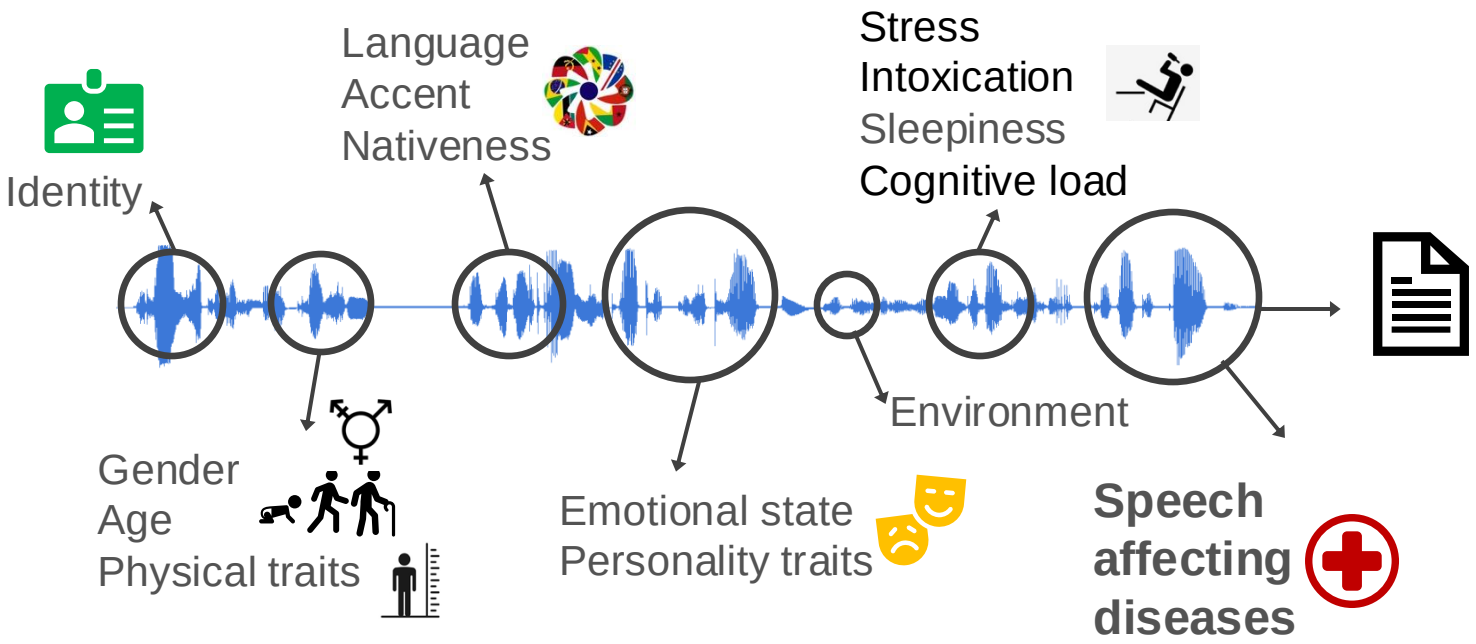
Additive fine-tuning:
- Shared-Adapters, the best parameter efficiency / performance trade-off

Synthetic data augmentation:
- Can enhance fine-tuning
- Must address domain mismatches between real and synthetic speech data

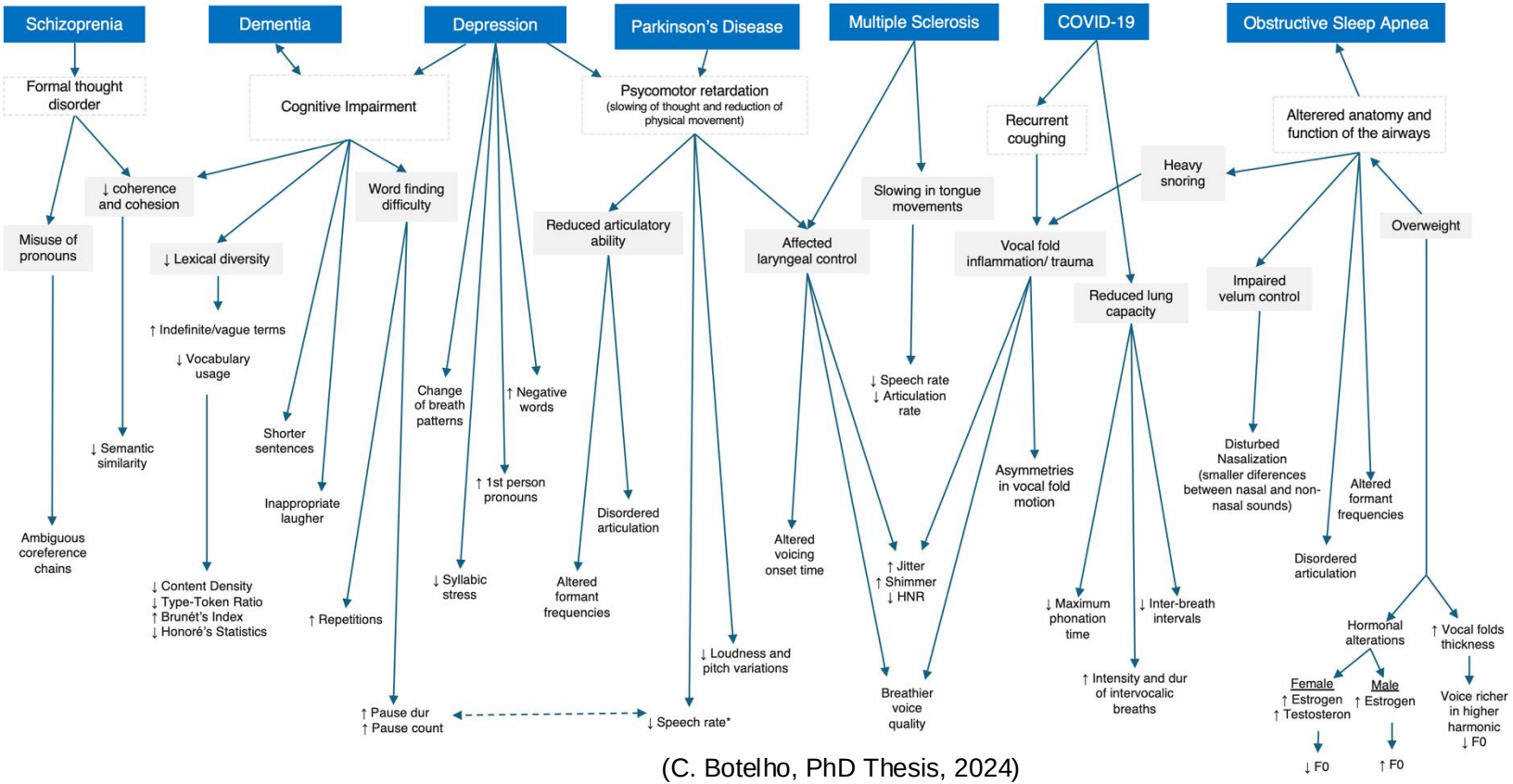
Explainability

- Choosing the most accurate and explainable model
  - The Great AI Debate@NIPS 2017
- Interpretable Machine Learning (Molnar et al., 2020)
- Local, global & mixed explanations
- Particularly relevant for domains such as criminal justice or healthcare

Info in speech



Speech affecting diseases



(C. Botelho, PhD Thesis, 2024)

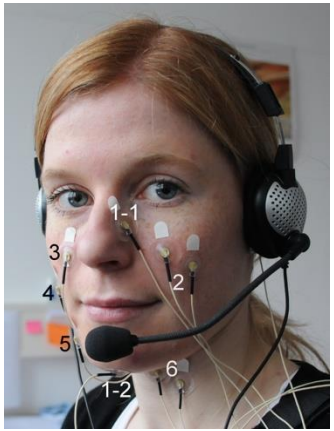
Data scarcity

- Collection in clinical facilities, lack of longitudinal studies, different conditions
- Crowdsourced collection (e.g. COVID-19, CLAC)
- In-the-wild collection (e.g. WSM) → VLOGs
  - PhD of Joana Correia

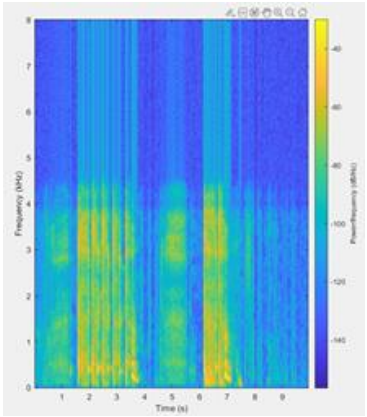
Beyond Speech

- Other non-invasive and invasive modalities
- Other body sounds (respiratory sounds, snoring, coughing)

(Botelho et al., 2021)



(Botelho et al, 2020; Diener et al. 2020)



(Solera et al., 2021)

Explainability

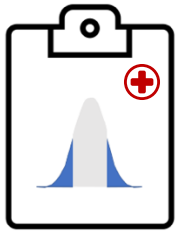
- PhD thesis of Catarina Botelho, supervised by I. Trancoso, A. Abad, T. Schultz
  - Macro-descriptors for Alzheimer's disease detection using large language models (IS 2024, Tuesday, SS-5B)
  - Towards reference speech characterization for health applications (IS 2023)
  - Challenges on studies of pathological speech in longitudinal and cross-domain corpora (IS 2022)

Definition of reference speech

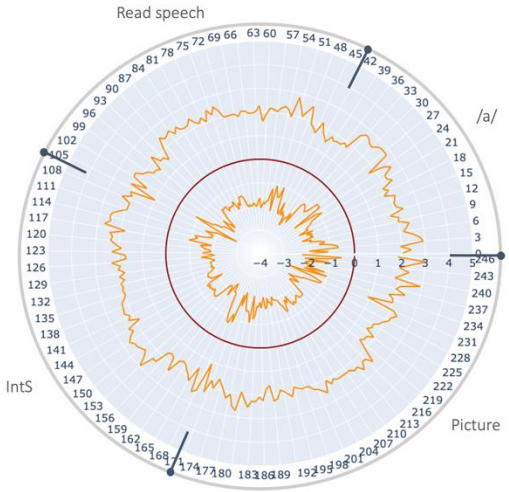
Extract features

Remove outliers

Partition reference data



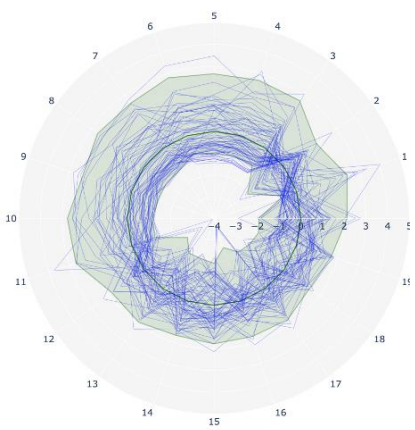
Reference Intervals

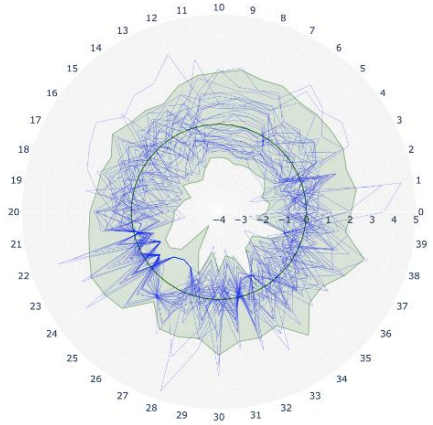


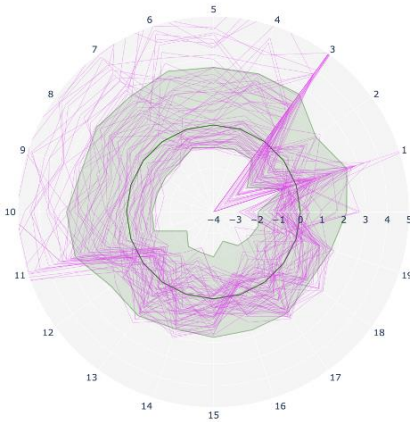
Features

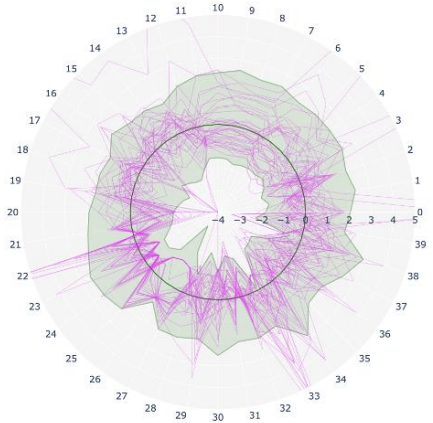
Category	Feature Name	Functional	Method
Content	Content density	–	BlaBla
	Idea density	–	BlaBla
	Honoré statistic	–	BlaBla
	Brunet's Index	–	BlaBla
	TTR	–	BlaBla
	Discourse marker rate	–	BlaBla
	Polarity	–	TextBlob
	Repetition ratio	–	manual
	First person pronouns	–	manual
	Coherence	mean, variability	cosine similarity
	Coreference chain ratio	–	wl-coref
	Ambiguous coreference chain	–	wl-coref
Vocal tract	F1	mean, median	praat
	F2	mean, median	praat
	F3	mean, median	praat
	F4	mean, median	praat
Rhythm	Speech rate	–	praat
	Articulation rate	–	praat
	Average syllable duration	–	praat
	Mean pause duration	–	praat
	Mean speech duration	–	praat
	Silence rate	–	praat
	Silence-to-speech ratio	–	praat
	Mean silence count	–	praat
Voice quality	F0	mean, std	praat
	HNR	–	praat
	local Jitter	–	praat
	local absolute Jitter	–	praat
	RAP Jitter	–	praat
	ppq5 Jitter	–	praat
	local Shimmer	–	praat
	local db Shimmer	–	praat
	apq3 Shimmer	–	praat
	aqpq5 Shimmer	–	praat
	apq11 Shimmer	–	praat

Radar plots









Sustained vowels (Female)

Picture description (Female)

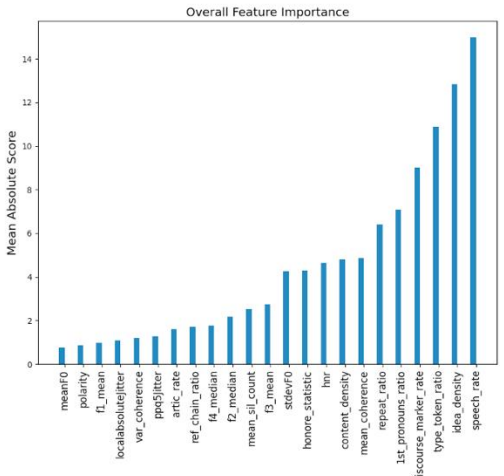
Datasets:

- CLAC (RIs)
  (Haulcy and Glass, 2021)
- PC-GITA (PD)
  (Orozco-Arroyave et al., 2014)
- ADReSS (AD)
  (Luz et al., 2020)

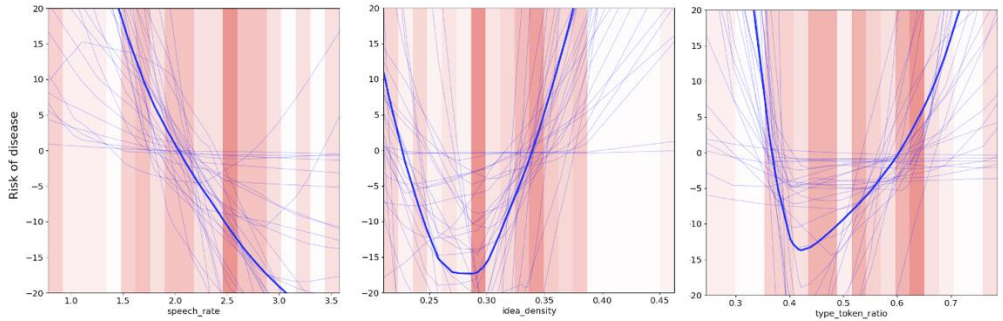
Neural Additive Model (NAMs)

- Linear combination of neural networks, each attending to a single feature, that are trained jointly using backpropagation (Agarwal et al., 2021)

Male subjects



Accuracy on test male recordings: 77.3%



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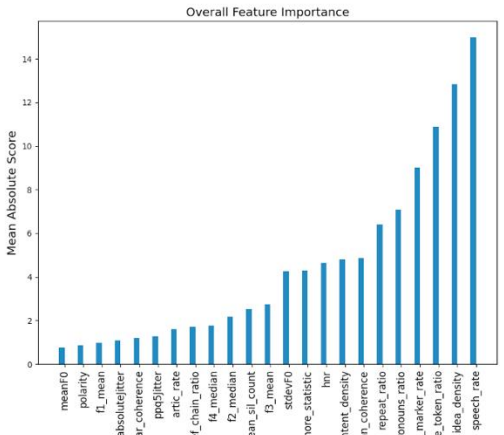

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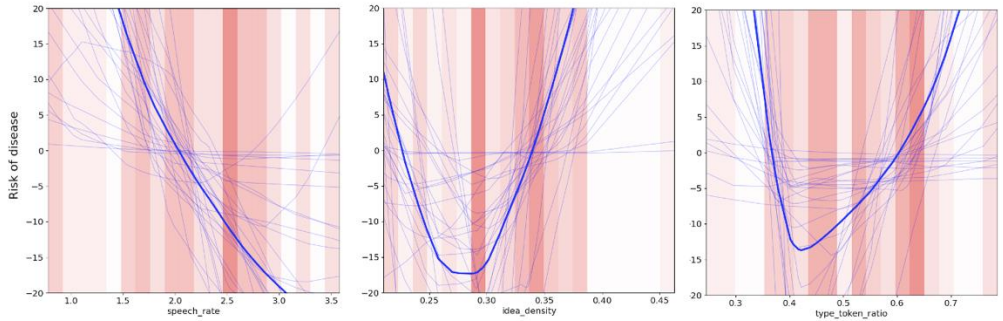
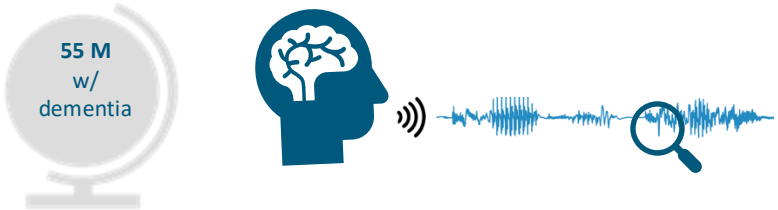


Not a posteriori explanations

Macro-descriptors for AD detection using LLMs



- ↓ Coherence
- ↓ Lexical diversity
- ↑ Word finding difficulties
- ↓ Sentence Length

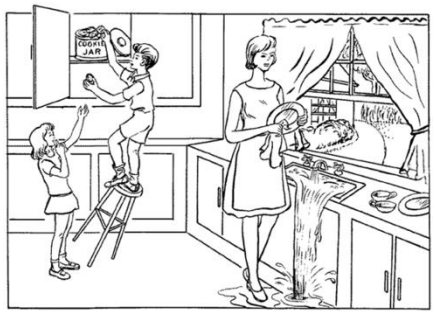
- Are LLMs already able to perform AD detection from speech transcriptions?
- Can we leverage the potential of LLMs to capture **macro-descriptors** that describe and help differentiate between the speech of healthy/AD subjects?

LLMs

- Mistral-7BInstruct-v0.2 (Jiang et al., 2023)
- Mixtral-8x7B-Instruct-v0.1 (Jiang et al., 2024)
- GPT-3.5-Turbo (Ouyang et al.,2022)

Data

- ADReSS
  - 78 AD + 78 Control



Transcriptions

- Manual
- Automatic (best of 5 ASR models):
  - whisper-large (Radford et a., 2023)
    - WER: 26.9 %
  - wav2vec2-large-robust-ft-swbd-300h (Hsu et al, 2021)
    - WER: 37.9%
    - wav2vec failed to output a transcription for 6 files
- Example:
  - manual: “uh well this here”
  - whisper: this here
  - wav2vec: uhe this yeur

Prompting strategies

P1.1

Diagnosis query

P1.2

Info on AD speech
+
Diagnosis query

P1.3 Info on AD speech

7 concepts of the "Cookie Theft" + Diagnosis query

P1.4 Info on AD speech + 7 concepts of the "Cookie Theft"

2 examples + Diagnosis query

P1.5 Info on "fluent speech" + 7 concepts of the "Cookie Theft"

Fluency evaluation query

P2.1 Fluency evaluator

7 concepts of the "Cookie Theft" + Query for macro-descriptors

P2.2 Fluency evaluator + 7 concepts of the "Cookie Theft"

Query for macro-descriptors + Diagnosis query

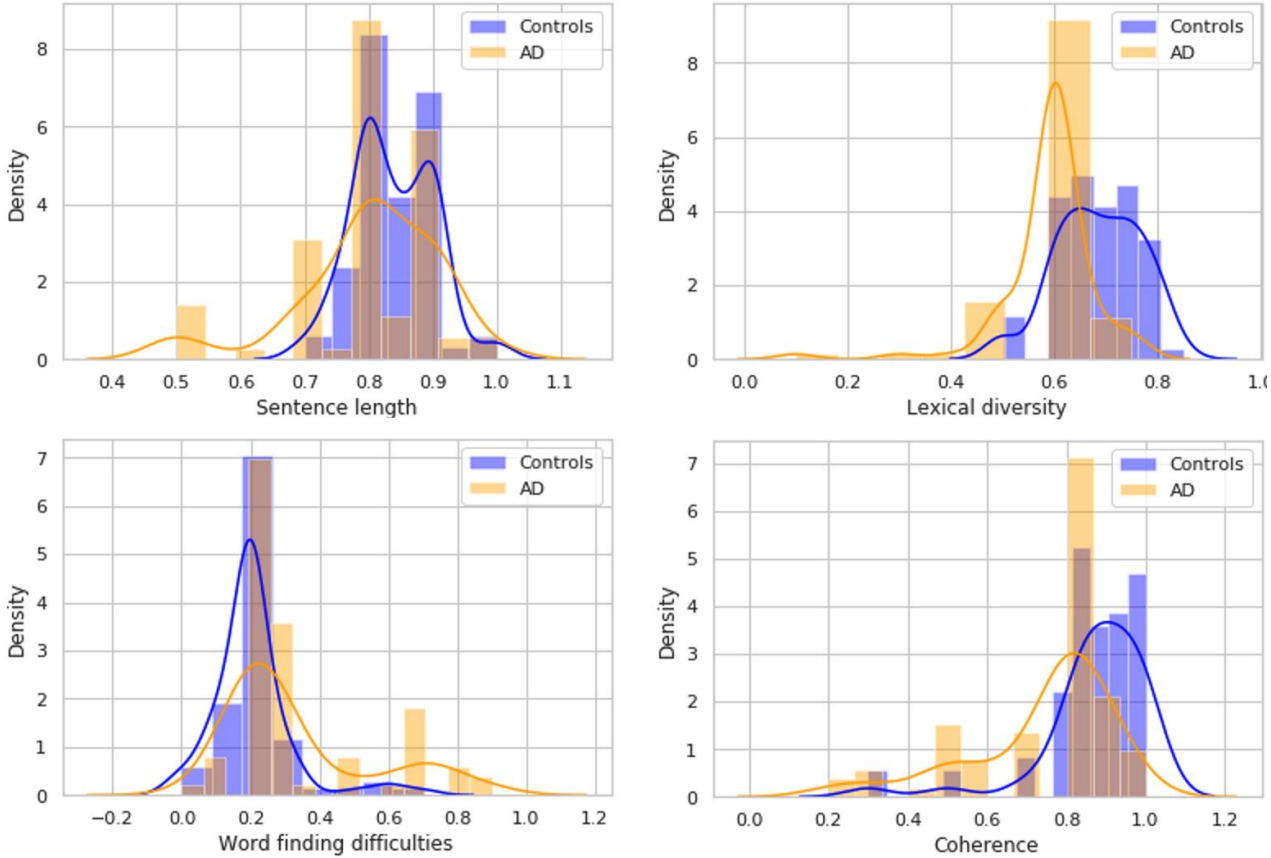
Distributions of the macro-descriptors

Annotations by Mistral
Transcriptions by Whisper
Prompt P2.2

Transcription

I don't see nothing but some roots. It's like somebody took some pencils or something and went up and down those things. Oh, I see a girl standing there or something. Some little knots or something on there. Oh, a lot of it around here. Some kind of little flower. And a sun. And a sun. And a girl is there. And there's something else over there. There's another girl. Look like... Look like some old girl is in there. I don't see nothing but some marks and things. Look to me about the same, except them things up there…

Coherence 0.3
Word Finding Difficulties 0.8
Lexical Diversity 0.5
Sentence Length 0.6
AD Prediction: YES
Confidence: HIGH



Potential of LLMs for AD detection

- Support Vector Machine
- Linear Discriminant Analysis
- 1-Nearest Neighbour
- Decision Tree
- Random Forest

Best classification results:

ASR	LLM	Prompt	Classifier	10F CV Accuracy	Test Accuracy
Whisper	Mistral 7B	P2.2	RF	78.7 %	79.2 %
Whisper	Mistral 7B	P2.2	SVM	73.1%	81.3%

Potential of LLMs for AD detection

- Support Vector Machine
- Linear Discriminant Analysis
- 1-Nearest Neighbour
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Employing LLMs as extractors of macro-descriptors for AD compares favourably with the direct prediction of AD by the LLM:

- ↑ performance
- ↓ failed predictions
- ↑ **interpretability**

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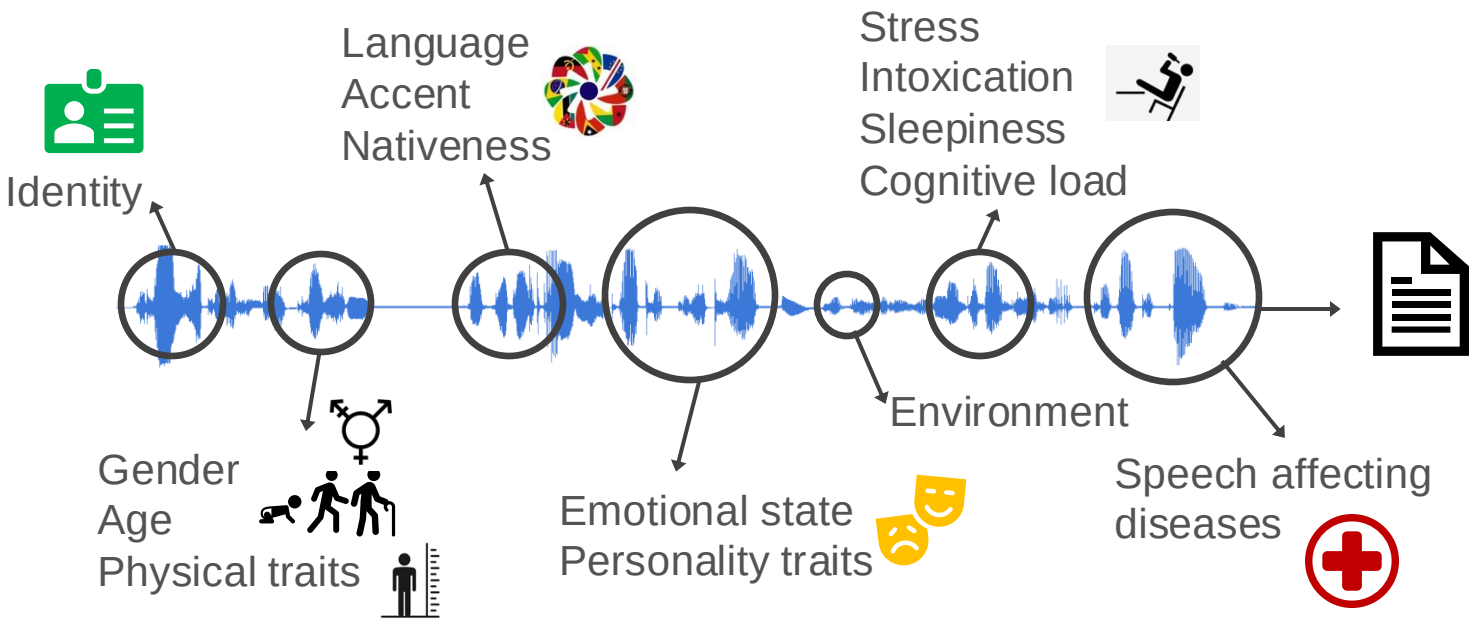
Privacy and Security



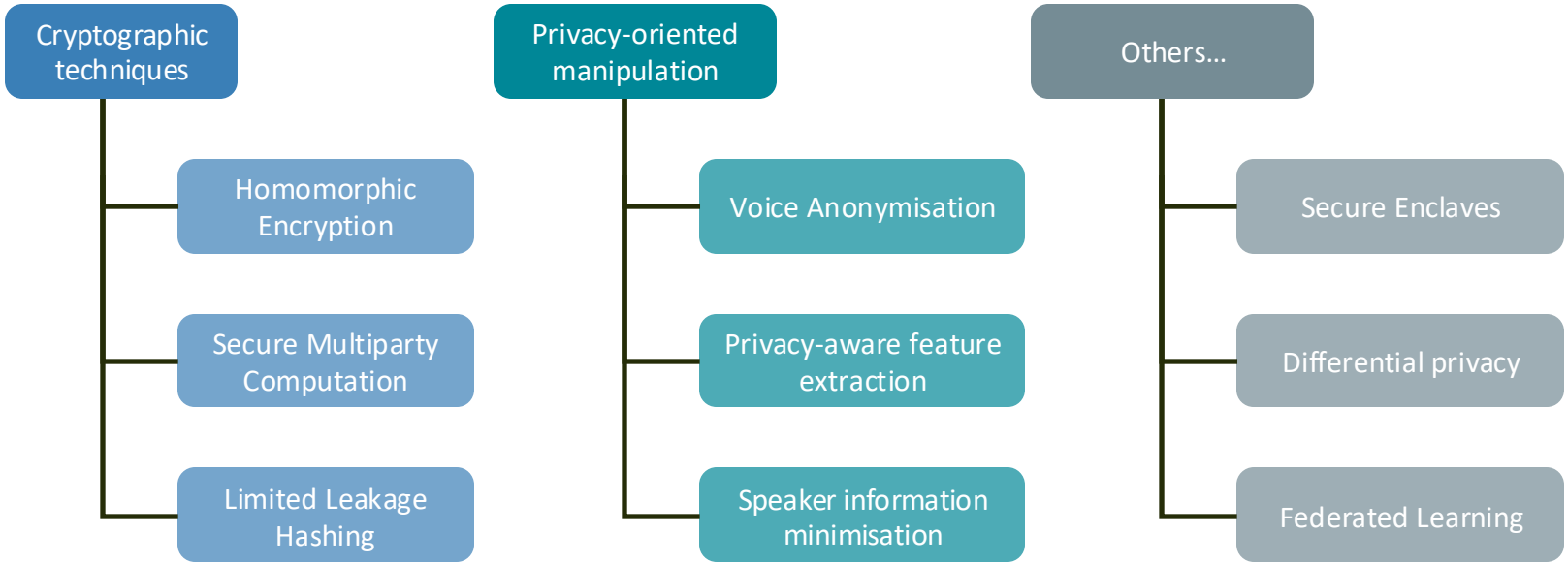
Vulnerabilities: Profiling & Impersonation

ISCA SIG Security and Privacy in Speech Communication

Privacy-preserving ML for remote speech processing

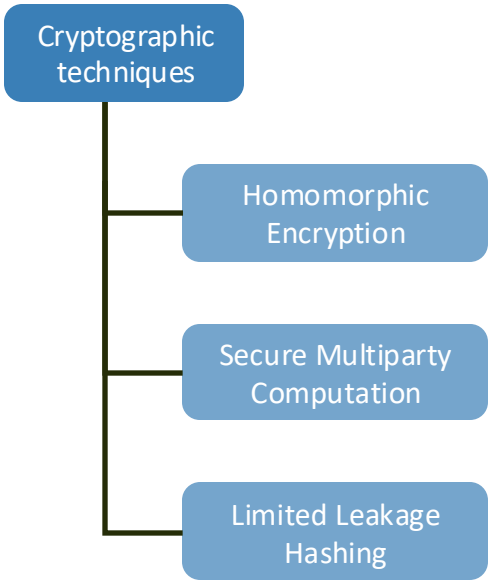
- PhD thesis of Francisco Teixeira, supervised by I. Trancoso, A. Abad & B. Raj
  - Privacy-oriented Manipulation of Speaker Representations (IEEE Access, 2024)
  - Privacy-preserving Automatic Speaker Diarization (ICASSP 2023)
  - Towards end-to-end private Automatic Speaker Recognition (IS 2022)

Privacy in Remote Speech Processing



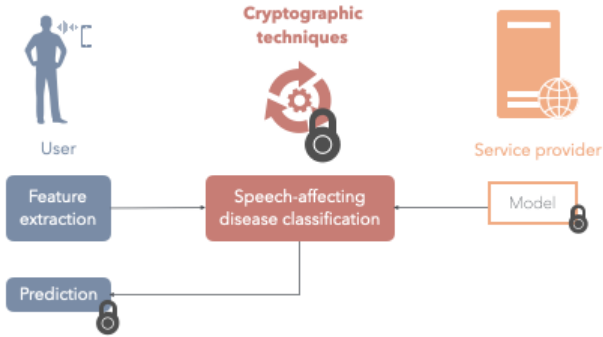
Cryptographic techniques

- Suited to tasks where it is difficult to disentangle speaker and task-related information
- Require the collaboration of the user and the service provider
- Provide confidentiality and formal privacy guarantees
- High computational and communication costs



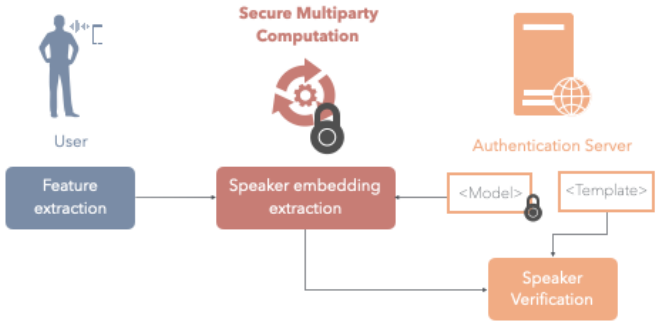
Cryptographic techniques

- Privacy-preserving Support Vector Machine w/ Radial Basis Function kernel:
  - Relied on Homomorphic Encryption, Secure Multiparty Computation and Secure Modular Hashing
  - Application to Disease detection (PD, OSA)
  - No performance degradation compared to baseline
  - 2000x slower than a non-encrypted classifier



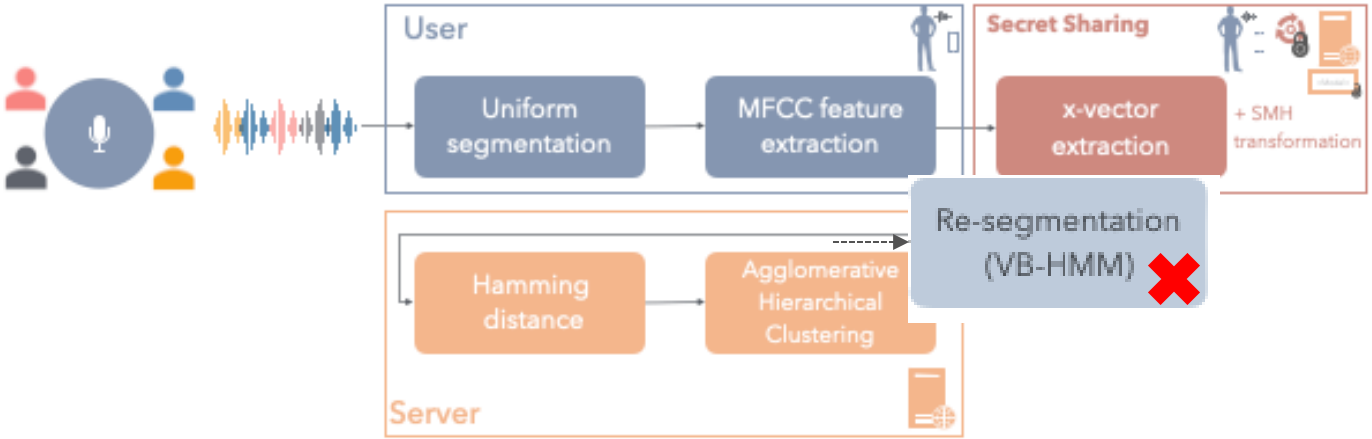
Cryptographic techniques

- Privacy-preserving speaker embedding extraction (x-vectors)
  - Relied only on Secret Sharing protocols, involving 2, 3 & 4 parties
  - Applied to speaker verification (using using cosine similarity scores)
  - No performance degradation compared to baseline
  - Only computationally feasible if involving at least a trusted 3rd party



Cryptographic techniques

- Application to Automatic Speaker Diarization (ASD) (N. Rayant et al., 2021)
- Degradation of around 10% in DER from original baseline
- PP-Diarization of 4 minutes takes 5-7 minutes using 3-party protocol.



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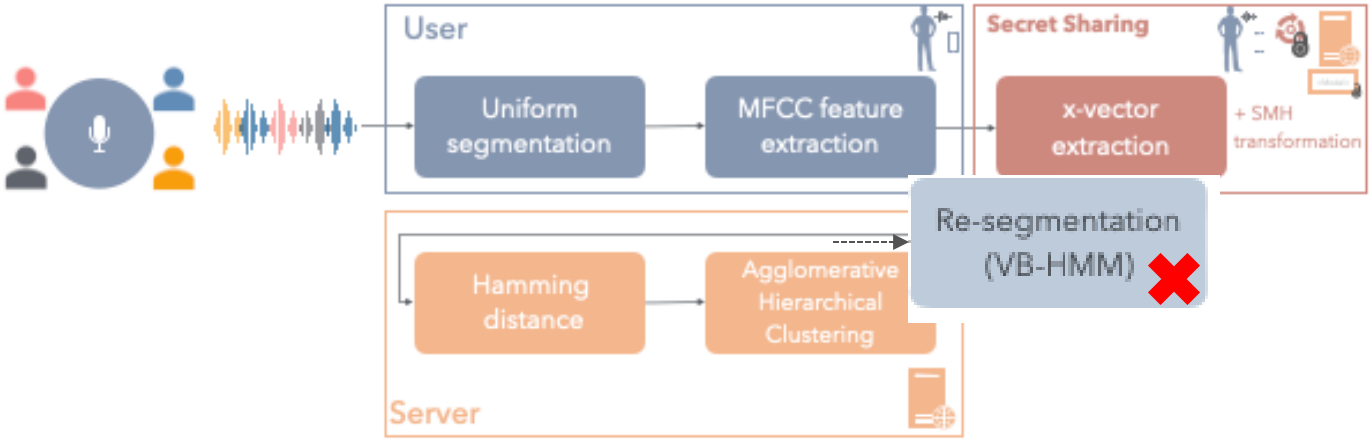
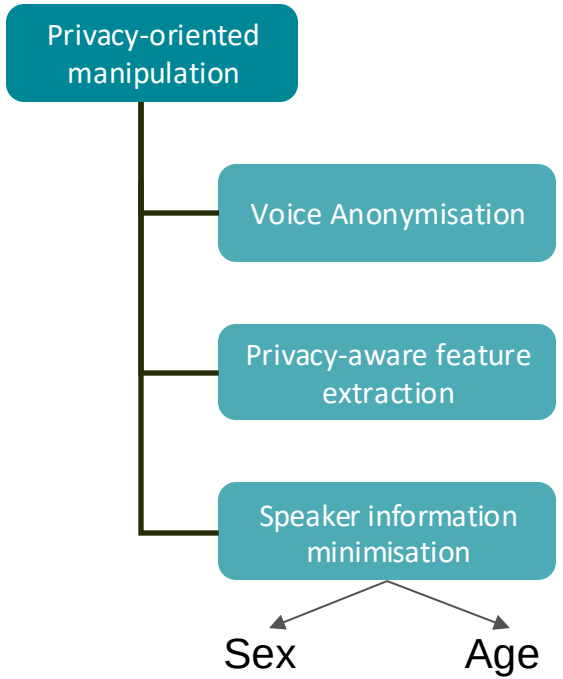
Usable for low-complexity tasks, but still impractical for high-complexity applications



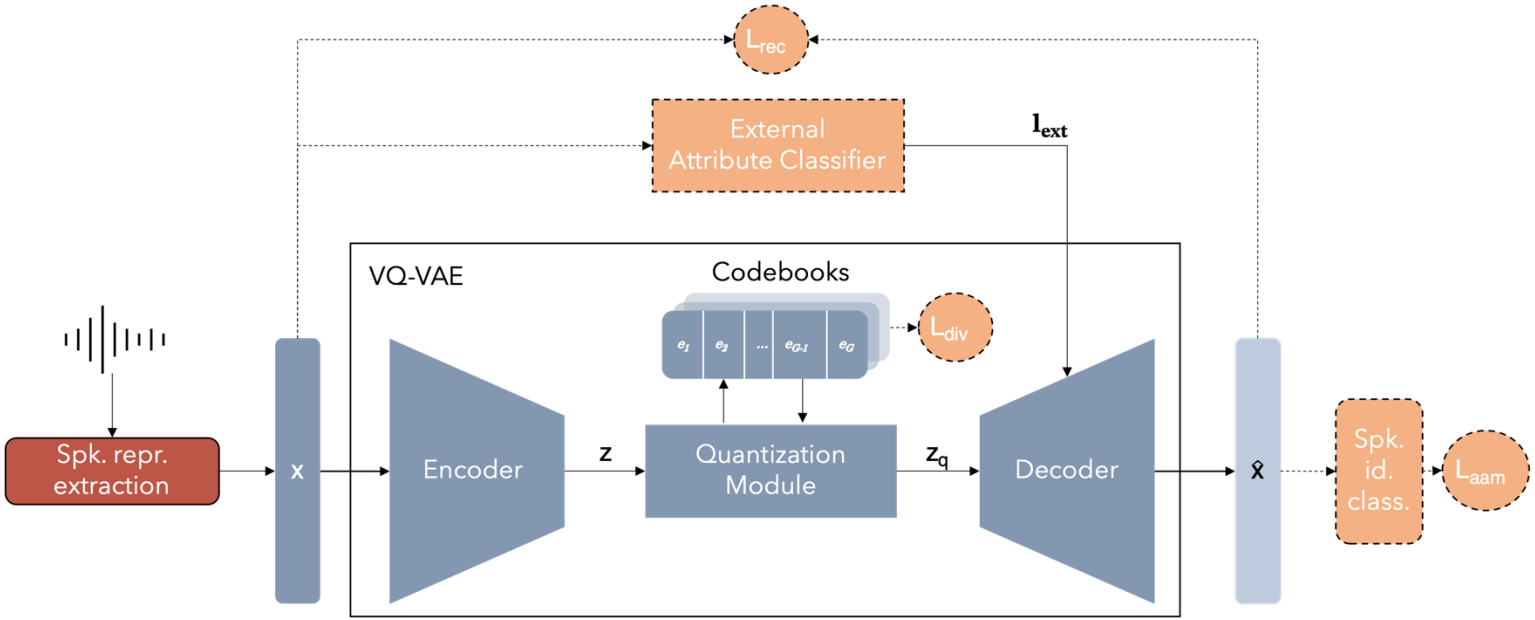
Privacy-oriented manipulation

Speaker information minimisation

- Remove or obfuscate task-unrelated information
- User-centred: can be performed directly on the user's device
- Empirical guarantees of privacy
- Low computational costs

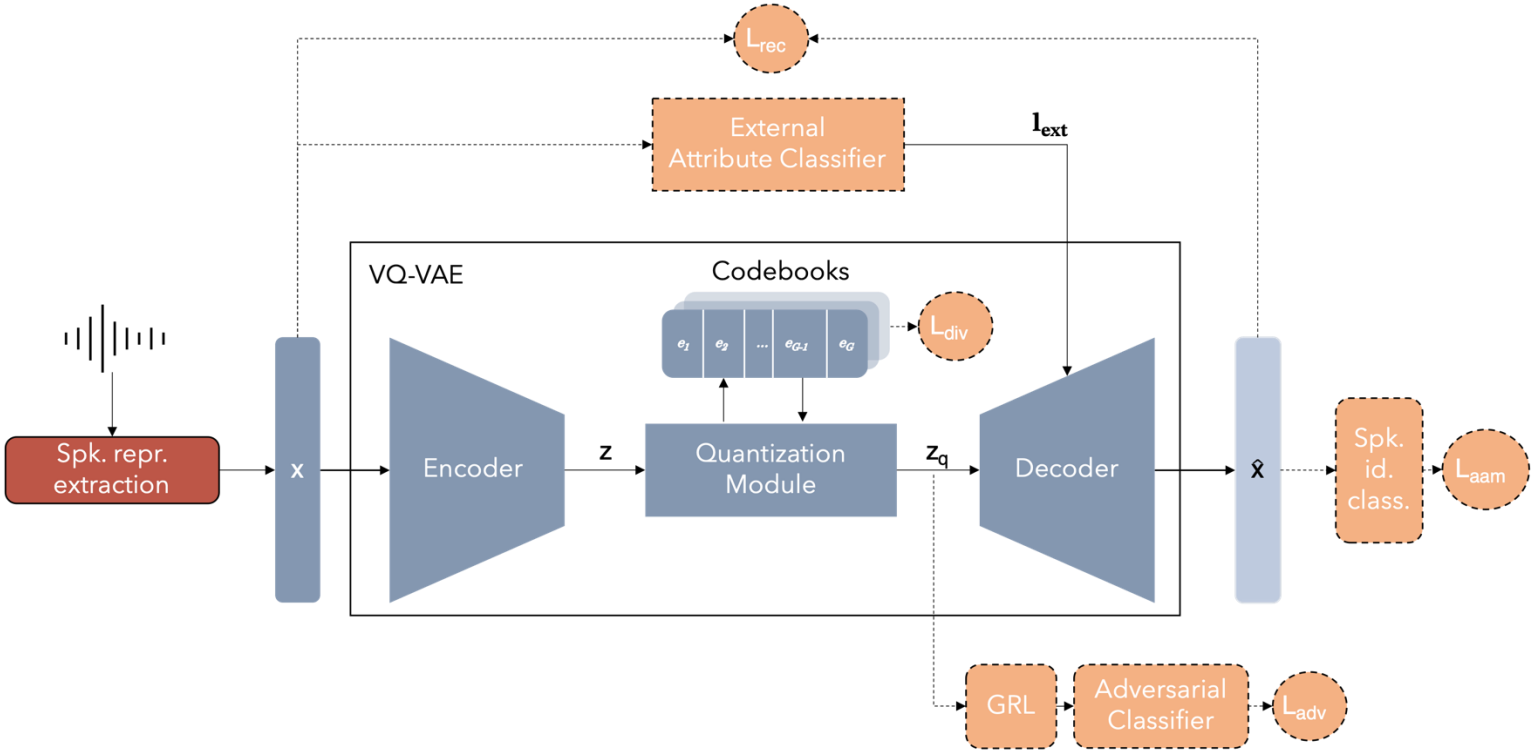


Privacy-oriented manipulation of speaker representations

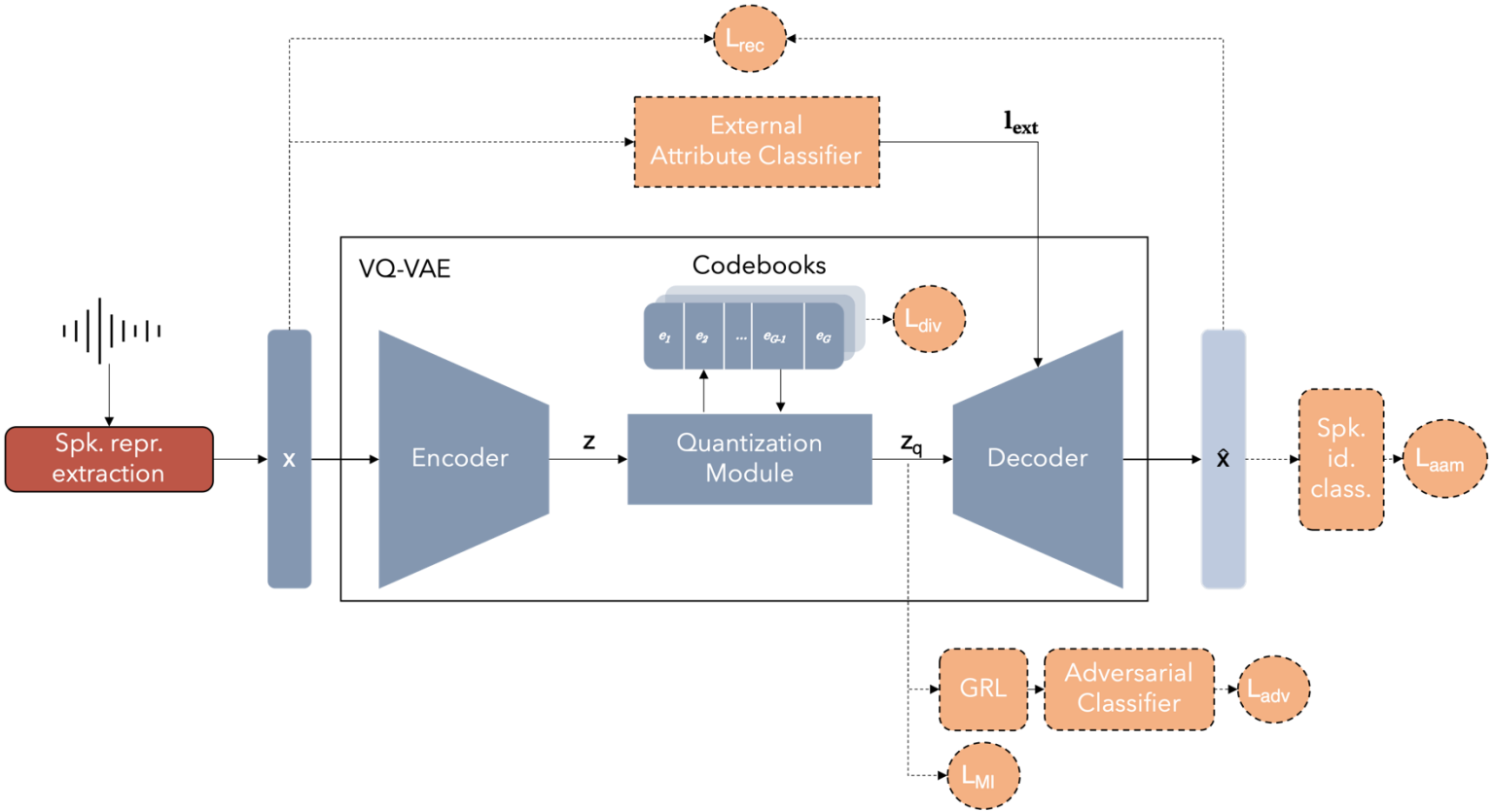


(Van Den Oord et al., 2017; P.-G. Noé et al., 2021)

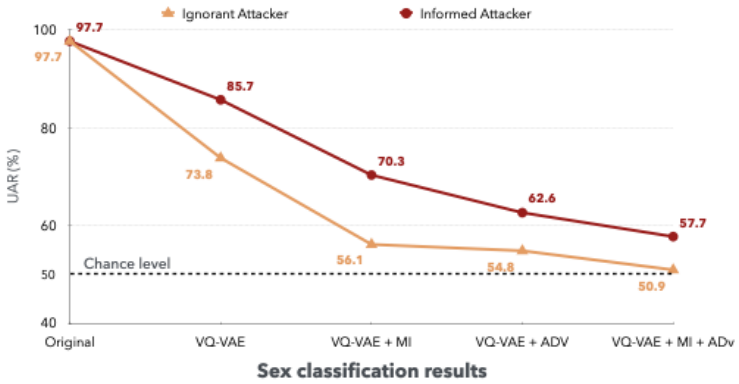
Privacy-oriented manipulation of speaker representations



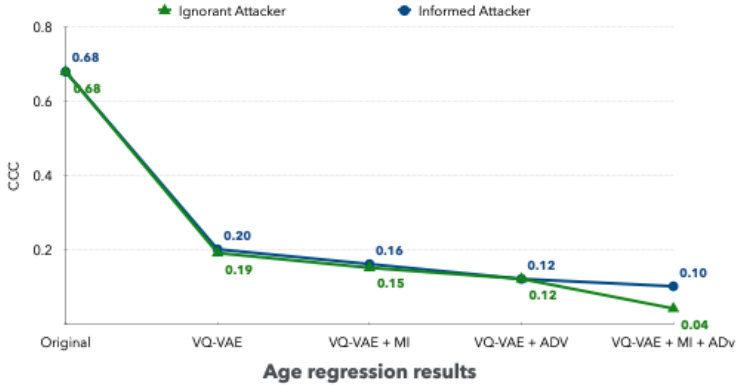
Privacy-oriented manipulation of speaker representations



Privacy-oriented manipulation of speaker representations

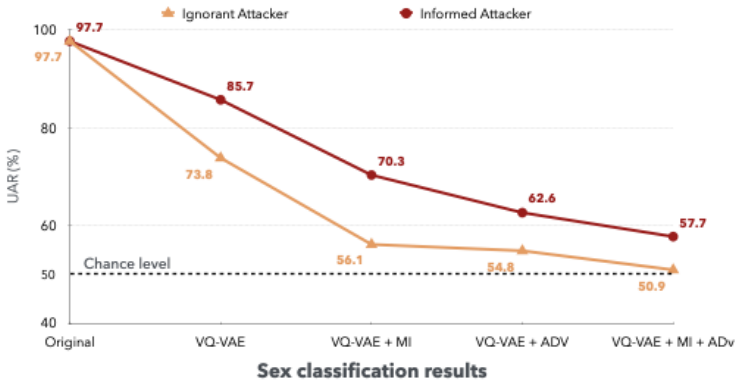


Sex classification results

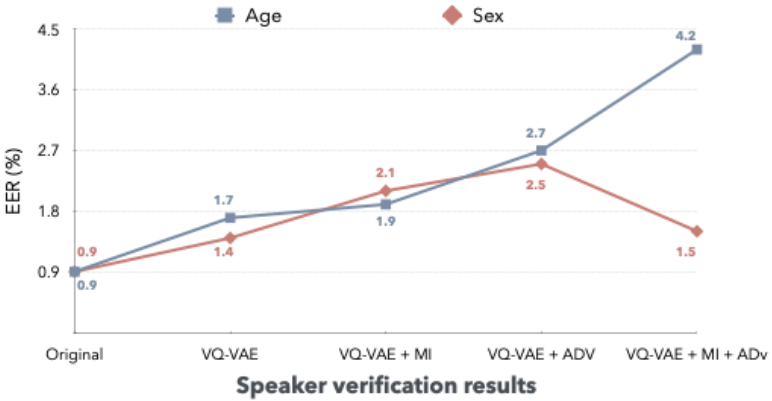


Age regression results

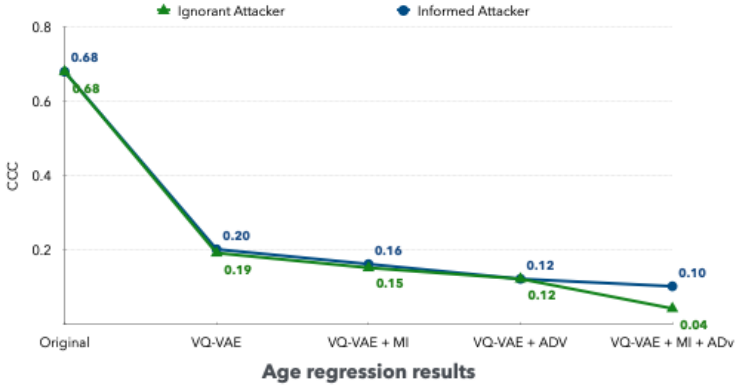
Privacy-oriented manipulation of speaker representations



Sex classification results



Speaker verification results



Age regression results

Trade-off between privacy and task performance (although approach only tested for ASV).

Can this type of manipulation be explored for voice anonymization?

VQ-VAE — Sex information manipulation

Original (Male)

Male2Female

“Genderless”

Original (Female)

Female2Male

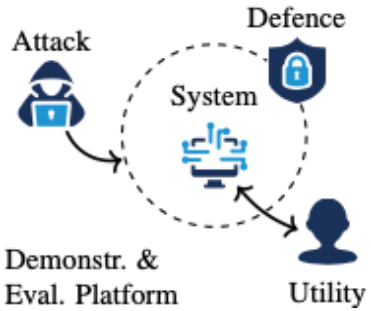
“Genderless”

VQ-VAE — Age information manipulation

Original (adult M)	7	12	14	20	40	80
Original (adult F)	7	12	14	20	40	80

Challenges - Privacy for Smart Speech Technology (PSST)

- Marie Skodowska-Curie Action - Doctoral Networks (DN-JD)
- PSST is recruiting 12 PhD students. Contact us at: info@psst-doctoralnetwork.eu
  - Protection against deepfakes in speech
  - Speech anonymisation for privacy-preserving emotion recognition
  - Disentangled representations for selective attribute suppression
  - Transparent Exchange of Speaker Attributes
  - Revealing social relationships in conversations
  - Robust attack models and tools for the credible evaluation of anonymisation and attribute suppression
  - Privacy impact assessment for comprehensive attacks exploiting audio, speech, and metadata
  - Attacking information bottlenecks – Theoretical metrics and bounds of privacy
  - Robust privacy-preserving industrial voice interfaces
  - Detection of speech-affecting diseases in anonymized speech
  - Utility of Speech Samples as Privacy-Preserving, Transparent and Reusable Model-Updates for Distributed Learning
  - Methods for subjective and objective evaluation of privacy



Sustainability

- The size of SOTA NLP language models has doubled every 3-4 months
- Reporting is usually limited to compute resources used strictly for training
  - Thousands of petaFLOP/s-day range
- Forecasting the carbon footprint of inference is harder:
  - 3 billion tokens would have to be generated for inference costs to catch up with training costs (Lakim et al., 2022)
  - At some point during its beta, GPT-3 was reported to generate 4.5 billion words per day

    https://openai.com/index/gpt-3-apps/

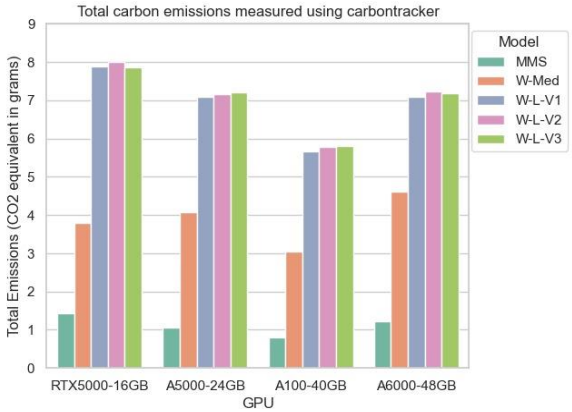
Sustainability

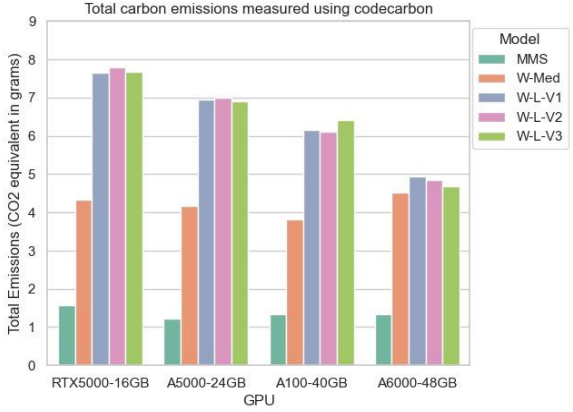
- Collaboration with Ajinkya Kulkarni and Miguel Couceiro
  - Unveiling Biases while Embracing Sustainability: Assessing the Dual Challenges of Automatic Speech Recognition Systems (IS 2024, Thursday, SS-7)

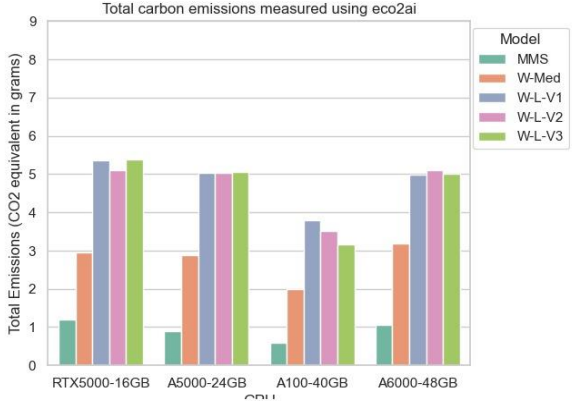
Sustainability study

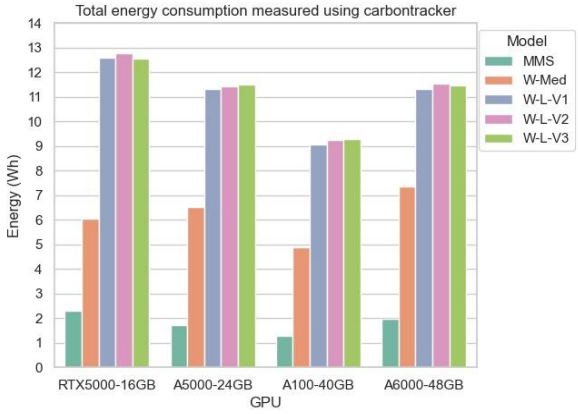
- 5 ASR systems
  - Massive Multilingual Speech Model by Meta AI, 2023 (Pratap et al., 2024)
    - MMS (~1 B)
  - Whisper by Open AI, 2022 (Radford et al., 2022)
    - Medium (0.769 B), Large-v1 (1.550 B), Large-v2 (1.550 B) and Large-v3 (1.550 B)
- 3 different platforms to measure the carbon emission intensity and energy consumption
  - Codecarbon (https://codecarbon.io/), Carbontracker (https://carbontracker.org/), Eco2ai (S. Budennyy et al., 2022)
- Inference of ASR on 20 mins of speech utterances across 4 NVIDIA GPUs, x 3 times
  - RTX-5000-16GB, RTX-A5000-24GB, A100-40GB, A6000-48GB
- Cloud service provider
  - Choice of region, time of day, preference for data centers with lower PUE (Dodge et al., 2022)
  - Based in Tamil, Nadu, India, 32GB of RAM, 7 CPU cores

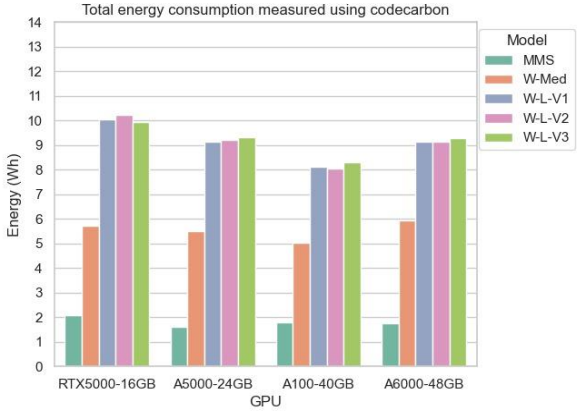
Sustainability study - Results

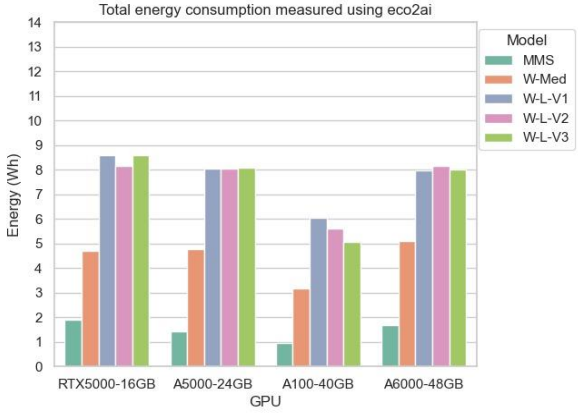












Sustainability study - Discussion

- Clear advantage of MMS over Whisper variants
  - MMS features multiple Transformer blocks, each enhanced with a language-specific adapter, that can be dynamically loaded and swapped during inference.
- Whisper Medium > Whisper Large variants
  - Whisper large variants have 2 x number of parameters
  - Similar behaviour of the 3 Whisper Large variants

Language-specific adapters can help save carbon emissions. Mixture of Experts are energy efficient architectures (Lakim et al., 2022)

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- Slight advantage of NVIDIA GPU A100-40GB over other NVIDIA GPUs
- All platforms show similar trends for the 5 ASR
  - Slightly optimistic view provided by eco2ai

Language-specific adapters can help save carbon emissions. Mixture of Experts are energy efficient architectures (Lakim et al., 2022)

Wide GPU bandwidth seems to have a positive impact in both carbon emissions and energy consumption.

Need for a comprehensive sustainability analysis of ASR systems that considers diversity:
- ✓ performance metrics
- ✓ implementations
- ✓ evaluation methodologies

Towards 1-bit LLMs

- Post-Training Quantization (PTQ) vs. Quantization-Aware Training (QAT) (Hutson, 2024)
- BitNet 1.58b (Wang et al., 2023)
  - QAT: 1, 0, -1
  - Binarized 3B LLaMa model
  -
- BiLLM (Huang et al., 2024)
  - QAT: 1-bit for most weights, 2-bit for salient weights
  - Binarized 13B LLaMa model
  -
- OneBit (Xu et al., 2024)
  - QAT + PTQ
  - Binarized 13B LLaMa model

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Potential advantages of custom hardware

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Potential advantages of custom hardware

Potential advantages in terms of privacy-preserving ML ?

Pillars of Responsible Speech Processing

- Robustness & Safety
- **Fairness & Inclusion**
- **Explainability**
- **Privacy & Security**
- **Sustainability**
- Accountability & Governance
- User Agency, Trust & Wellbeing

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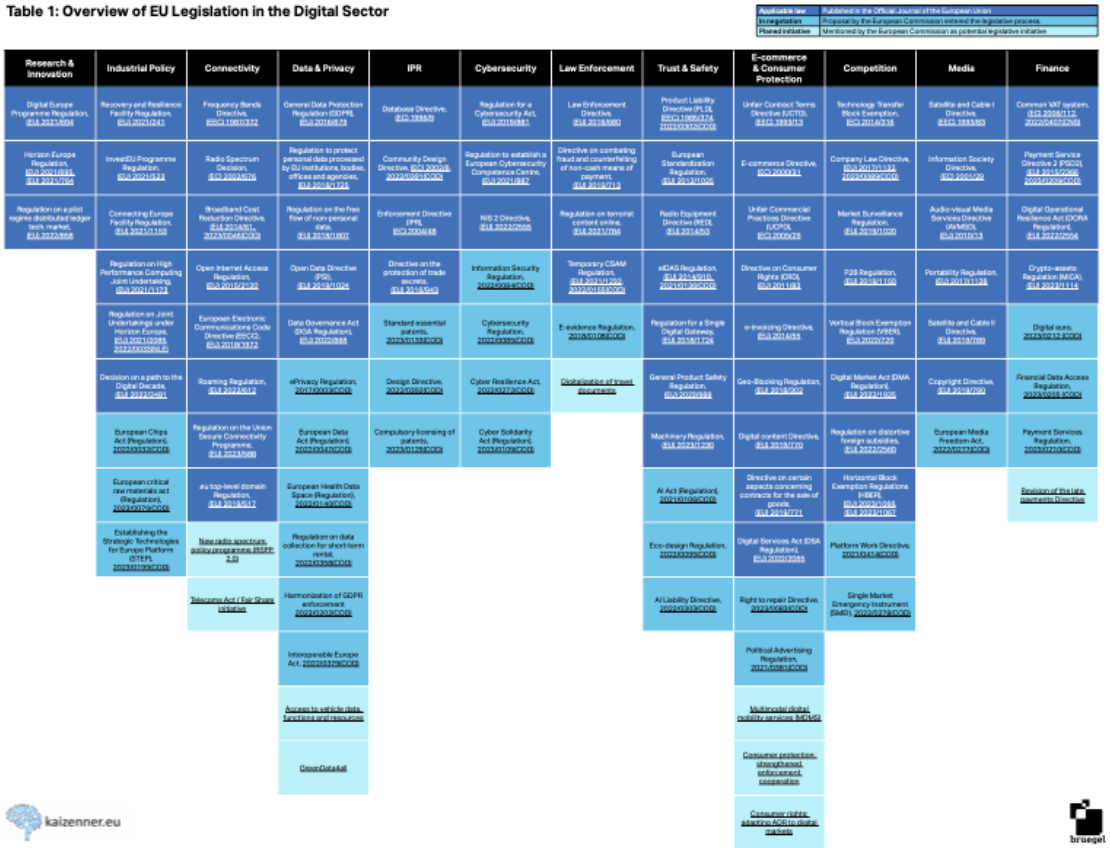
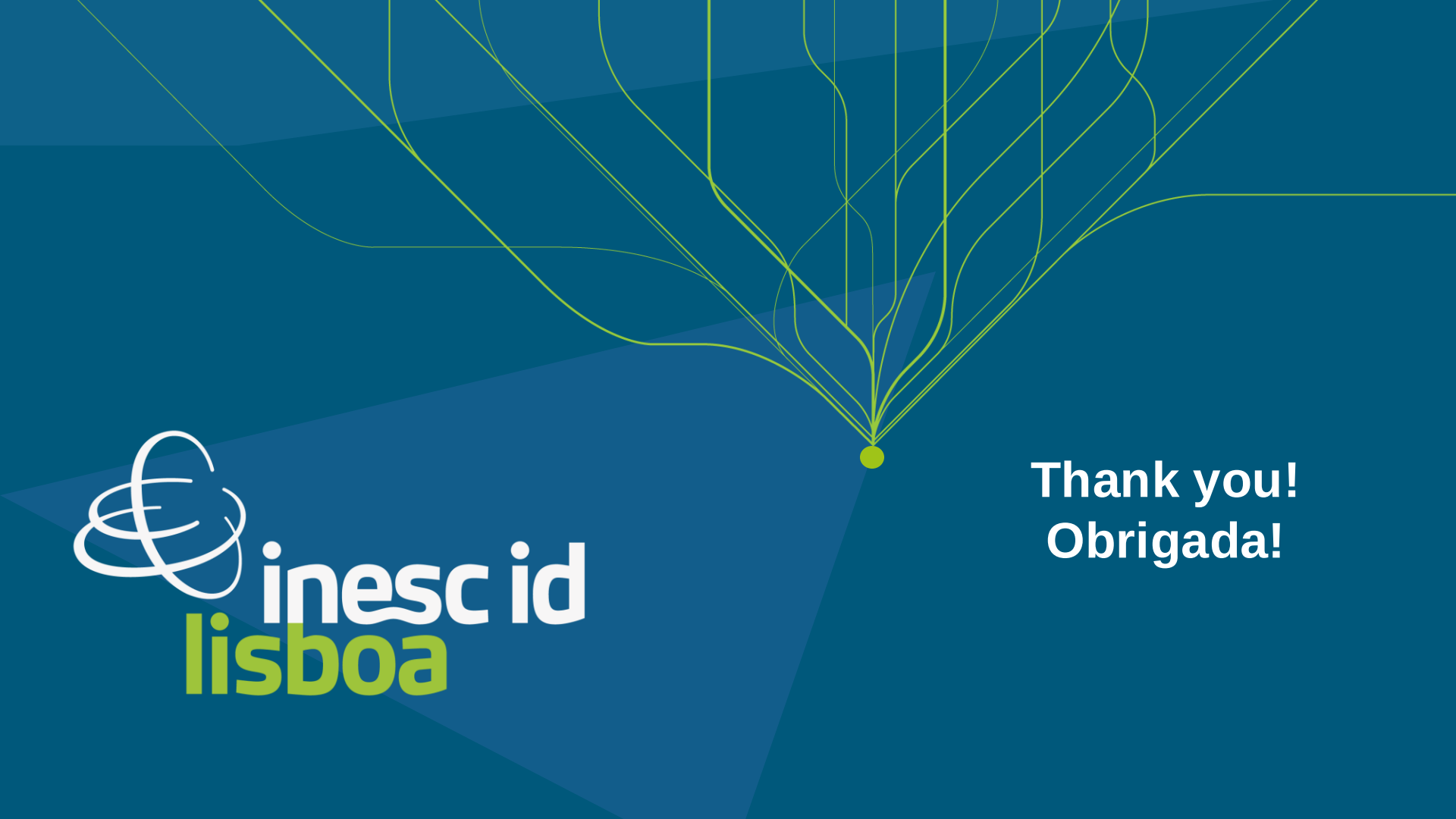
AI Act

The Regulation on Artificial Intelligence is dense (Nautch et al., 2019) and very complex

- 180 recitals
- 113 articles
- 13 annexes
- 459 pages

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Thank you!
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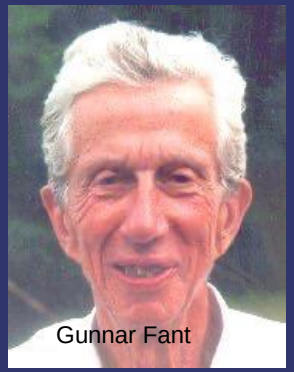
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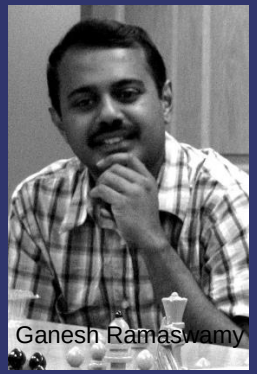
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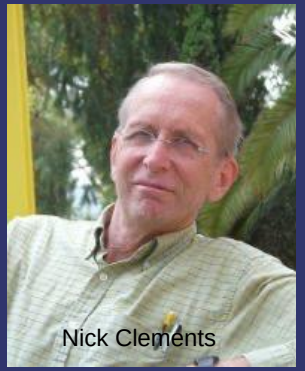
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Philip Jackson
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Thank you all!

Thank you!
Obrigada!

to my family...

Thank you!

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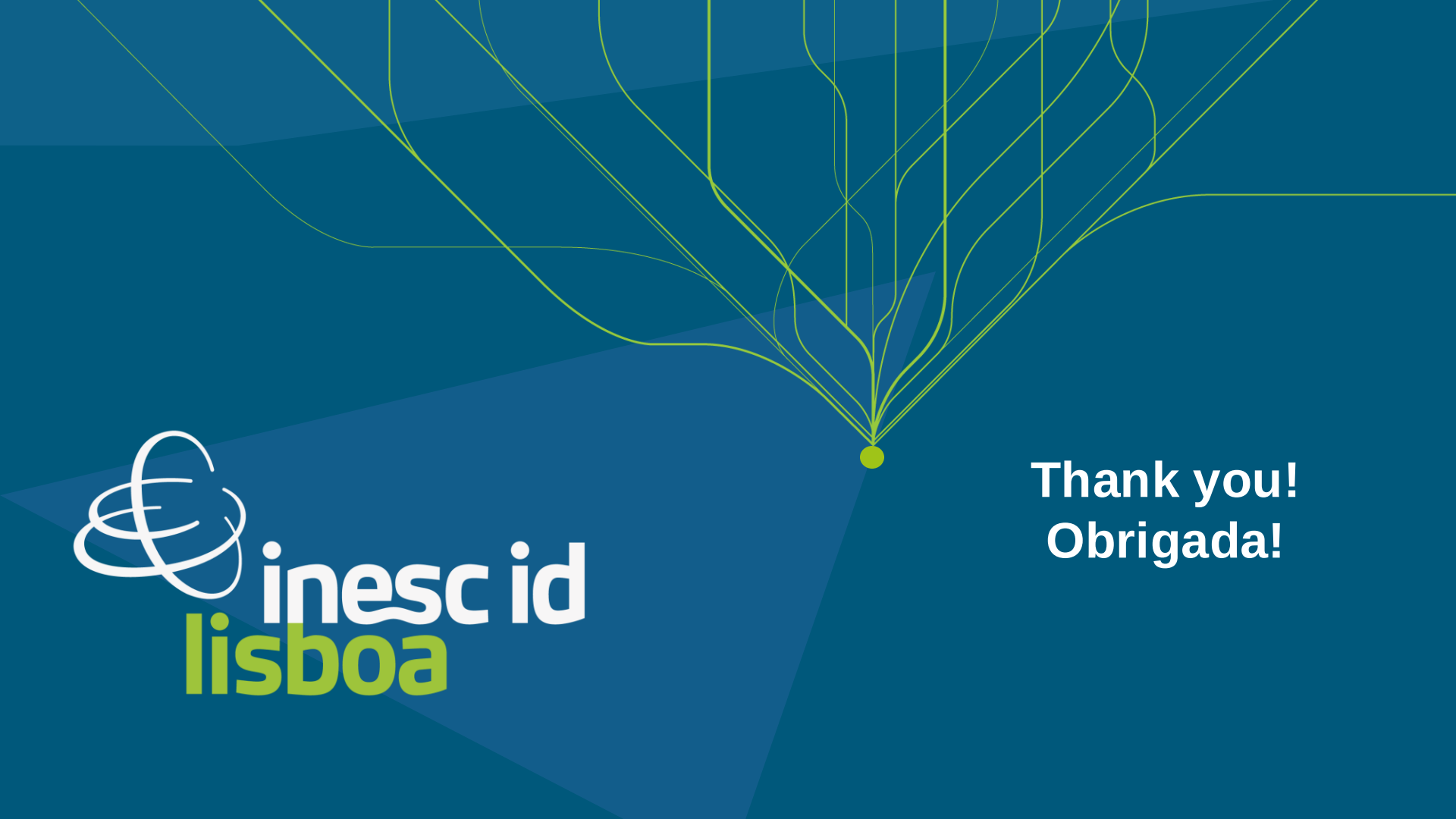
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