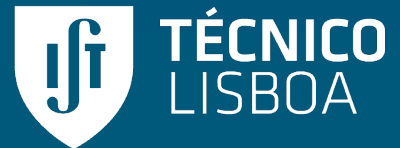


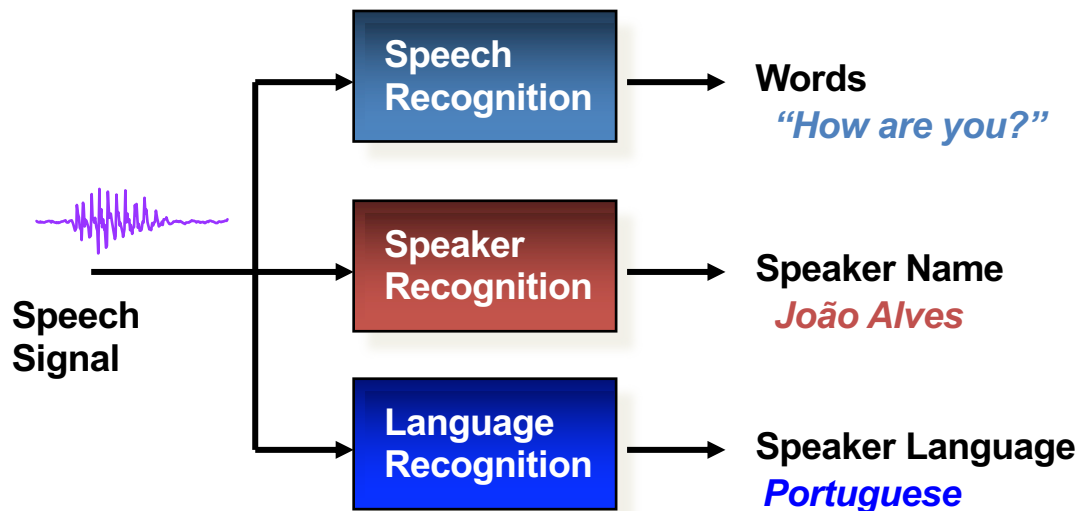
Towards the use of speech as a health biomarker

PhD Advanced Course
Molecular Biomarkers and Technologies
18 September, 2020

Alberto Abad
alberto.abad@inesc-id.pt

With contributions from: Anna Pompili, Catarina Botelho, Francisco Oliveira, Rubén Solera-Ureña, Isabel Trancoso

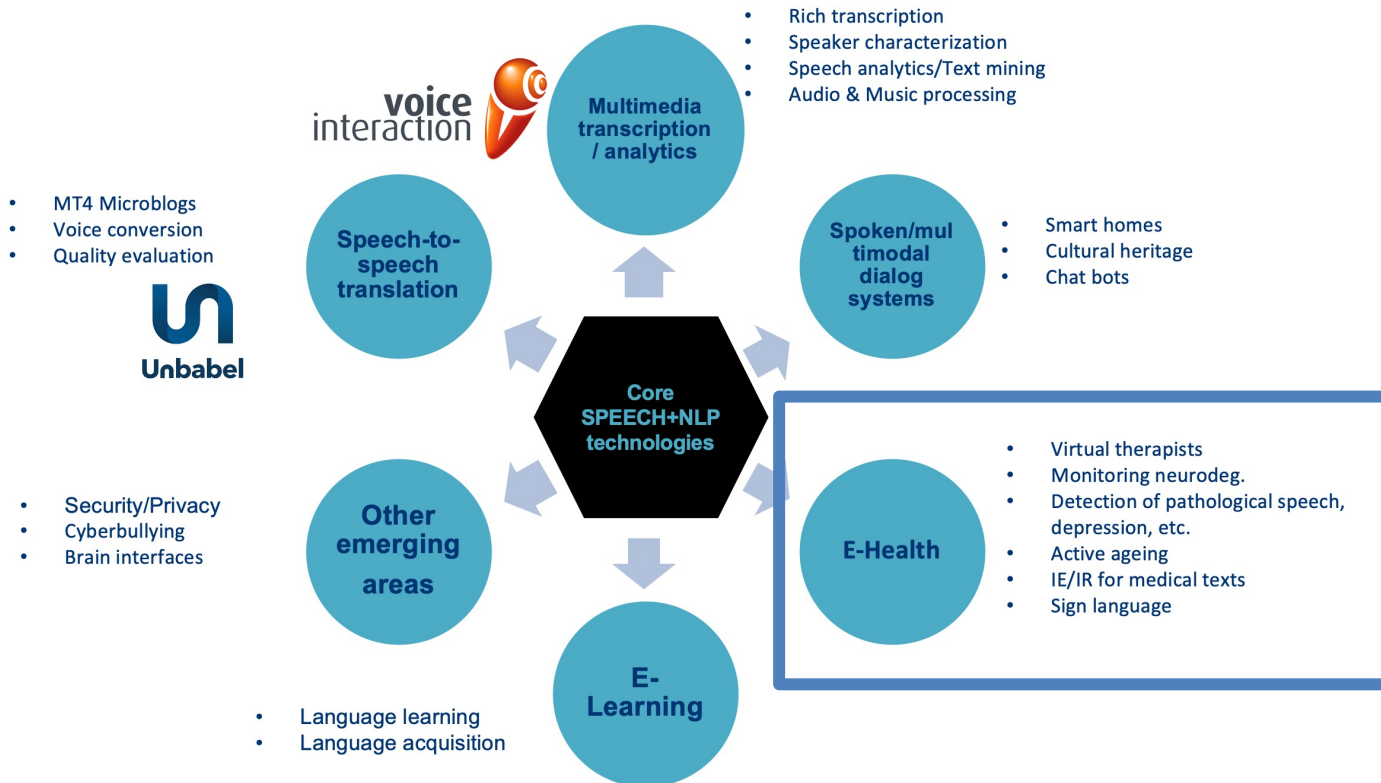




Speech processing: Speech coding, Speech enhancement, Audio segmentation, Text-to-speech synthesis, Automatic speech recognition, Speaker and language identification; Other speech pattern classification tasks

Text processing: Morphological analysis, Syntactic analysis, Semantic analysis, Discourse analysis, Named entity extraction, NL Generation, Information retrieval, Summarization, Question answering, Machine translation, Text analytics, Recommendation

Core research & application areas @ INESC-ID



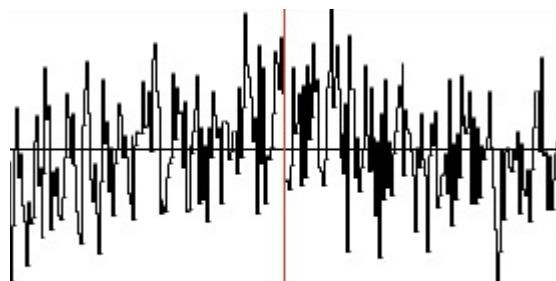
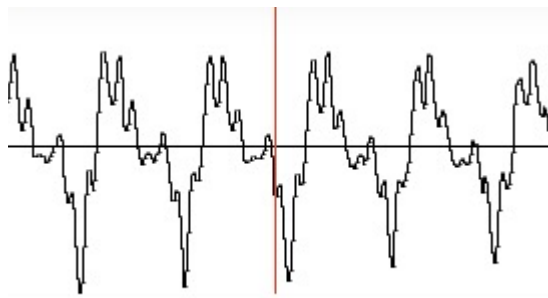
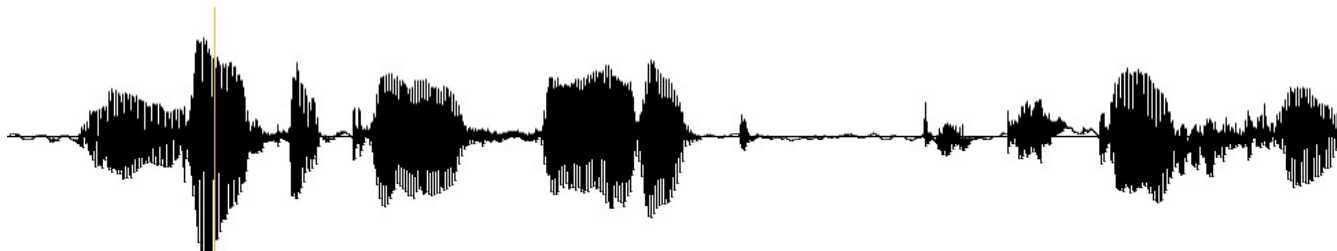
Outline

- Introduction to speech processing
- Three generations of HLT applications in e-health @INESC-ID:
 - 1G: Augmentative communication, assistive technologies and e-inclusion
 - 2G: Diagnosis and treatment of speech and language disorders
 - 3G: Speech as a health biomarker for speech-affecting diseases
- Challenges and open questions

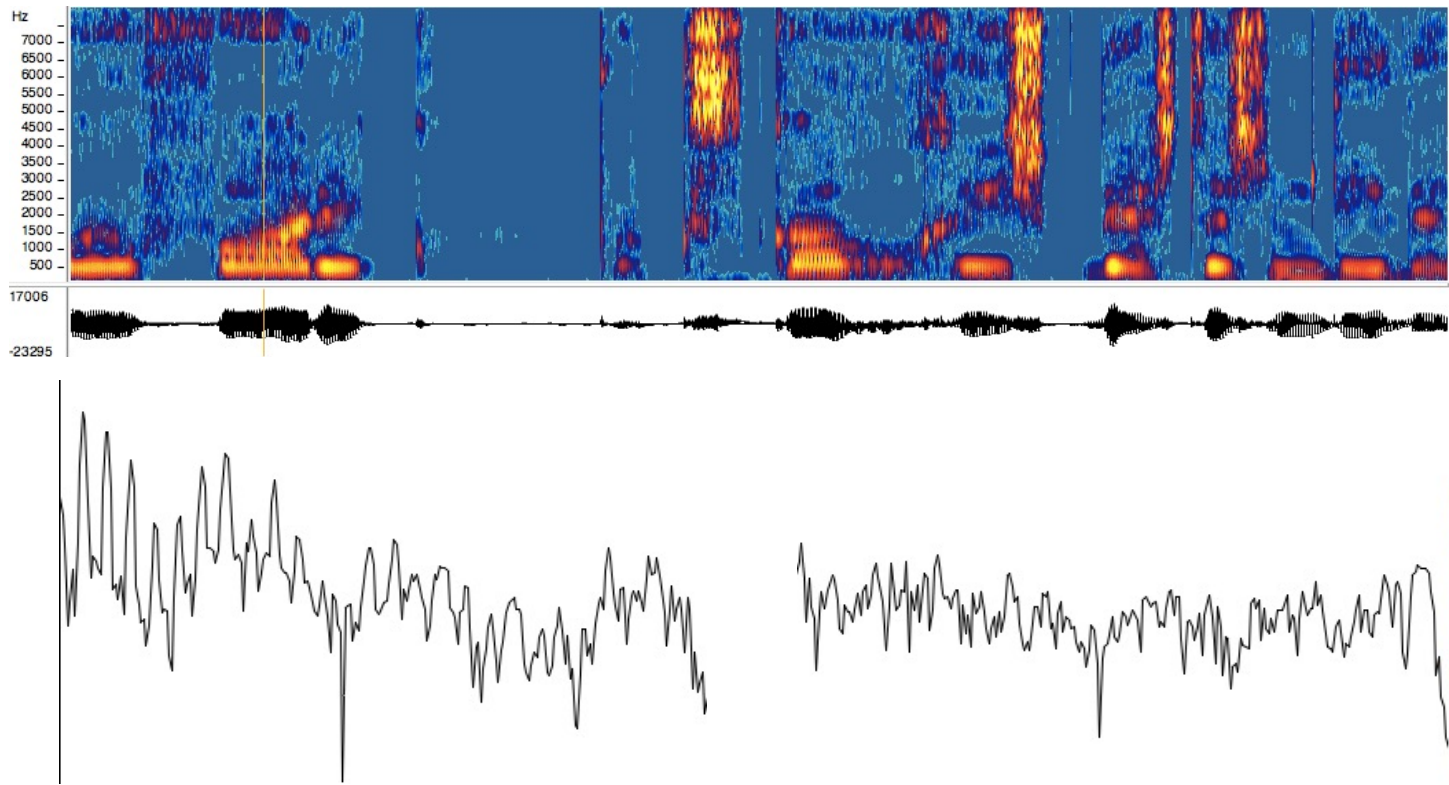
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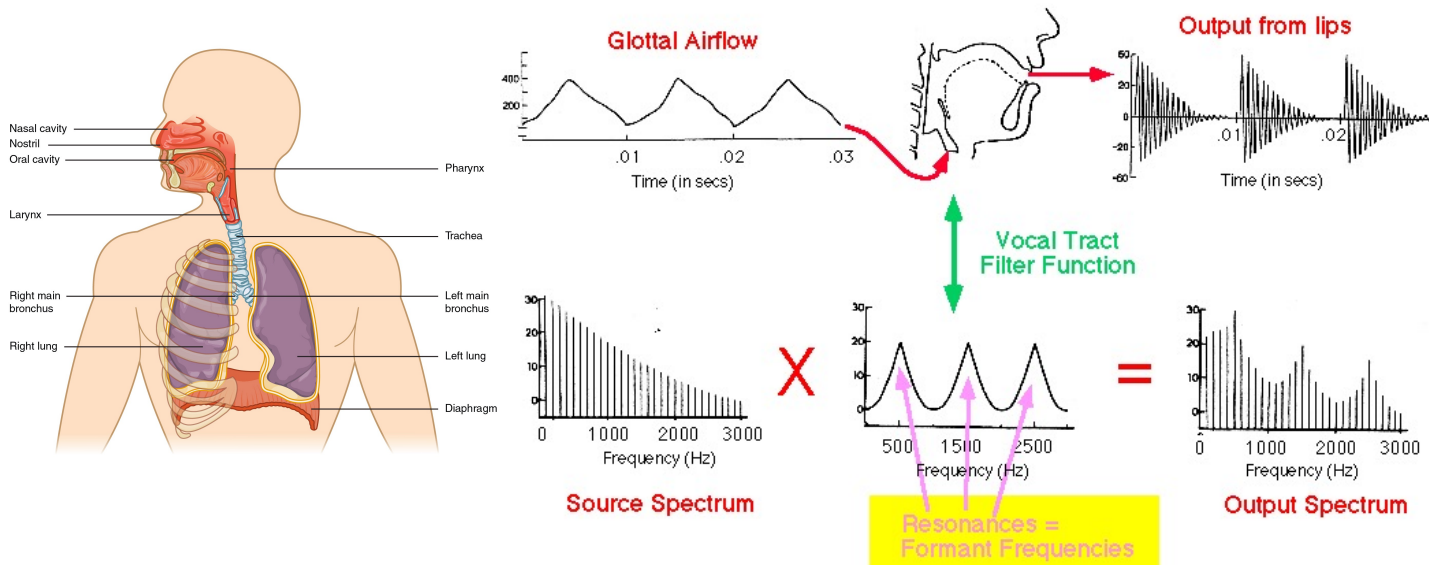
The speech signal in the time domain



Speech signal time / frequency representation

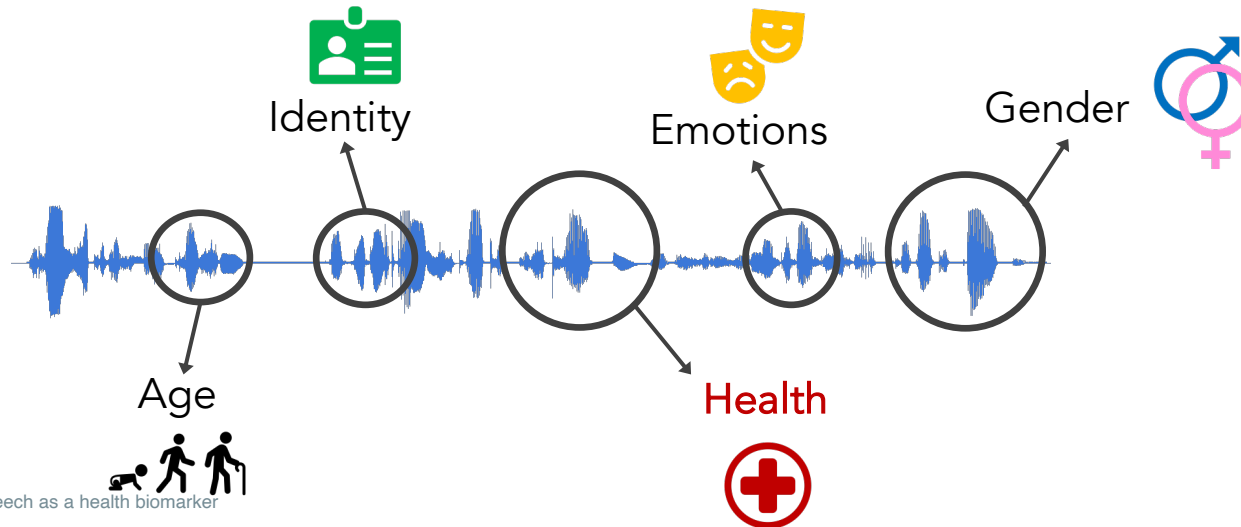


Speech signal: Physiology & Source/filter model



Speech as a carrier of information

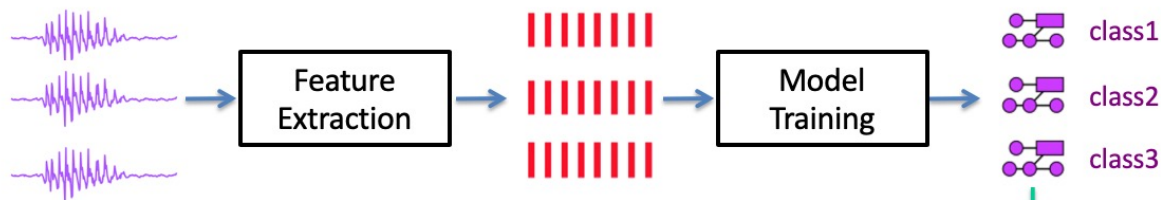
- Speech carries a lot of information:
 - Of course information related to the message (LINGUISTIC?)...
 - ... but also, speaker traits (NON-LINGUISTIC/PARA-LINGUISTIC?):
 - Gender; Age; Language/accents; ID; Personality; Education; Intoxication; Sleepiness; Friendliness; Mood; Physical Stress; Cognitive Load; Emotion; Pathologies?



Speech classification (a.k.a. machine learning, IA, etc.)

- **Objective:** To convert a speech input sequence into a class label (or sequence of labels):
- The common blocks of any ML classification task are the front-end/feature extraction and the back-end/classification:
 - The classifier module is “learnt” using **data** during the training phase and used to classify new unseen data during test

Learning/Training phase

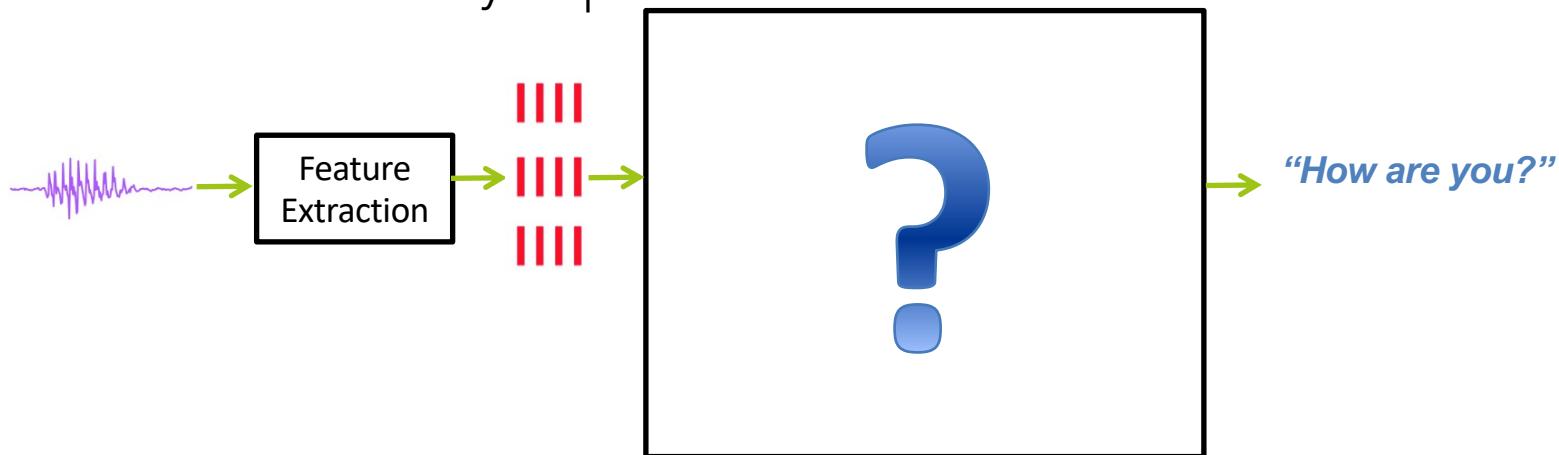


Classification phase



A special case: Automatic Speech Recognition (ASR)

- **Goal** Given a sequence of observations determine which is the most likely sequence of words



- Already decades of research on ASR (and other SLT related topics) → **Very challenging!!!**
- **Related sub-tasks:** Isolated ASR, Continuous ASR, KWS, LVCSR, STD/Search on Speech, etc.

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SLT applications in e-health @ INESC-ID

1G: Augmentative, assistive and e-inclusion applications

- Hearing impairment
 - Subtitling, meta-information, segmentation, events, etc.

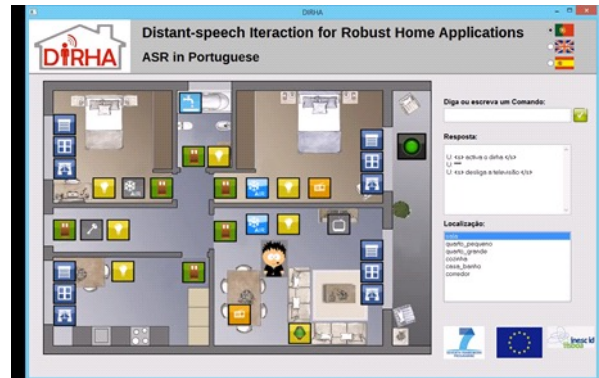
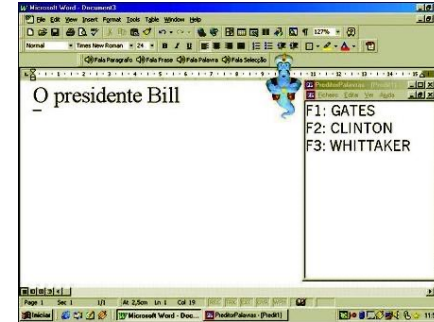
- Visual impairment
 - Text-to-speech for content access, spoken books



SLT applications in e-health @ INESC-ID

1G: Augmentative, assistive and e-inclusion applications

- Cerebral palsy
 - Text-to-speech with virtual keyboards and word prediction (Eugenio)
- Physical impairments
 - Control, home-automation, etc.



SLT applications in e-health @ INESC-ID

2G: Diagnosis and treatment of speech and language disorders

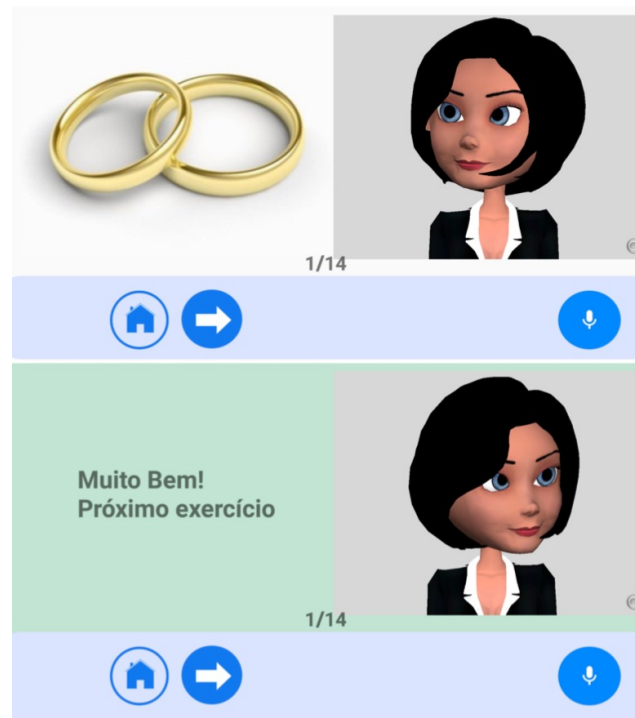
- Improved ASR and intelligibility objective measures useful in:
 - Diagnosis
 - Global and individual characteristics
 - Second opinion
 - Screening of populations
 - Therapy
 - Therapy control
 - Comparison of therapy methods
 - Computer-assisted and virtual/on-line therapy

Virtual Therapist for Aphasia Treatment

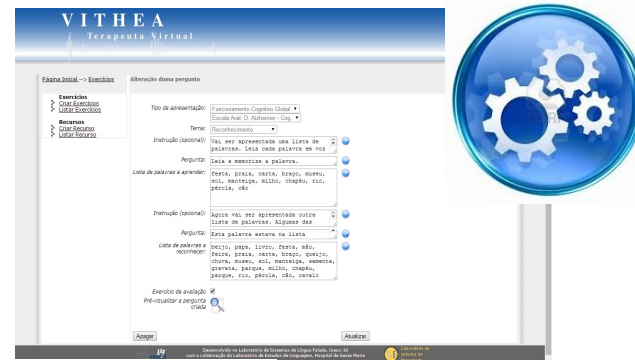
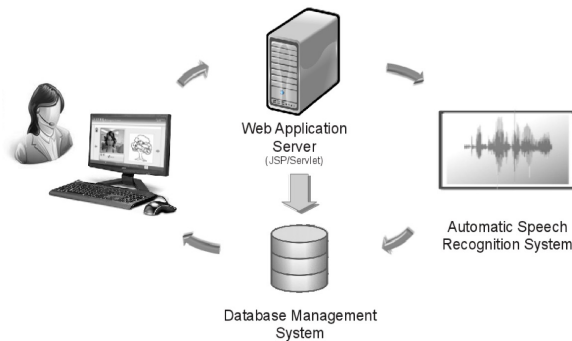


FCT

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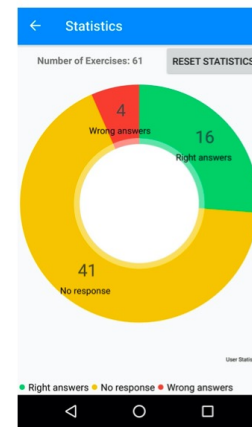
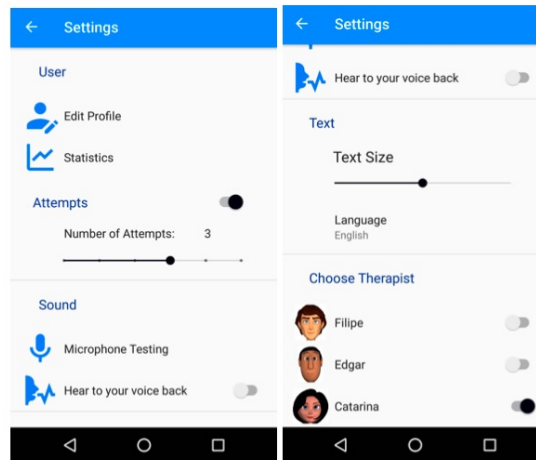
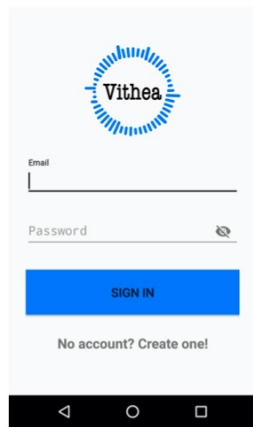


Virtual Therapist for Aphasia Treatment



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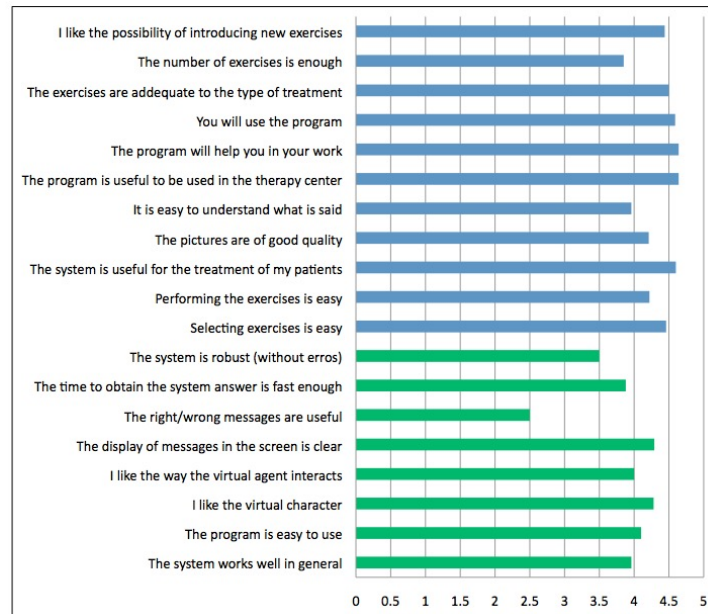
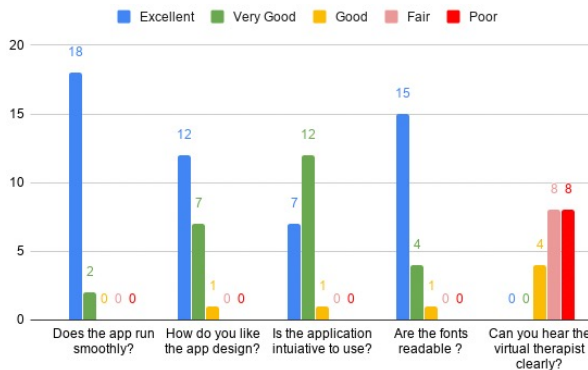
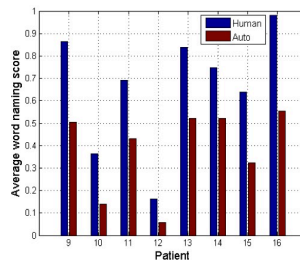
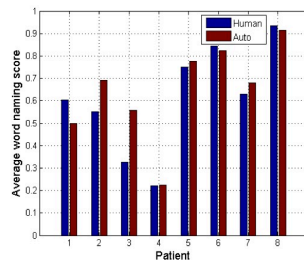


Virtual Therapist for Aphasia Treatment



FCT

Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR



Virtual Therapist for Aphasia Treatment



FCT

Fundação para a Ciência e a Tecnologia
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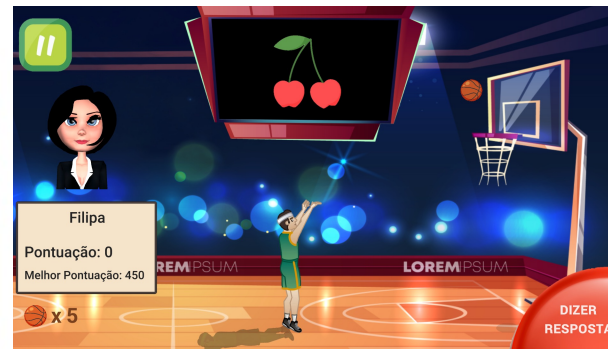
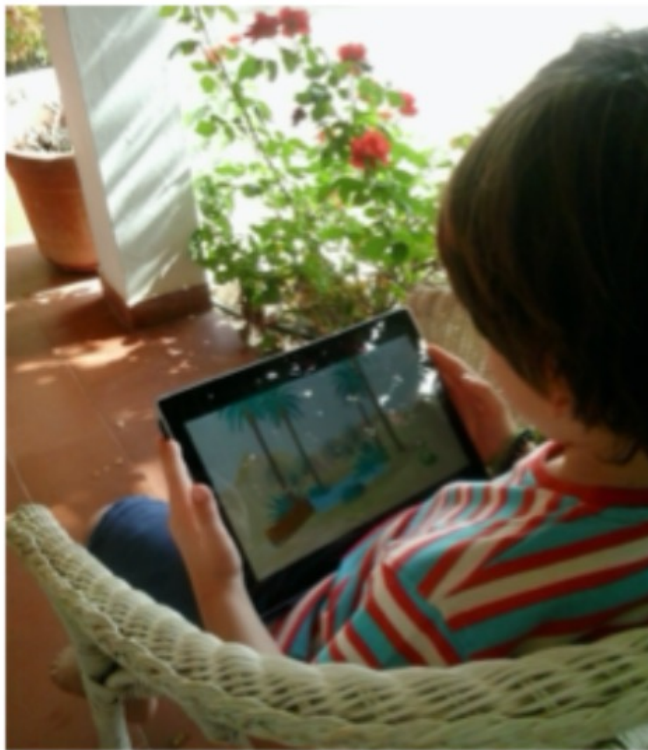
Serious digital games for speech and language therapy for children

BioVisualSpeech

Information and Communication Technologies Institute

Carnegie Mellon | PORTUGAL

AN INTERNATIONAL PARTNERSHIP



Serious digital games for speech and language therapy for children



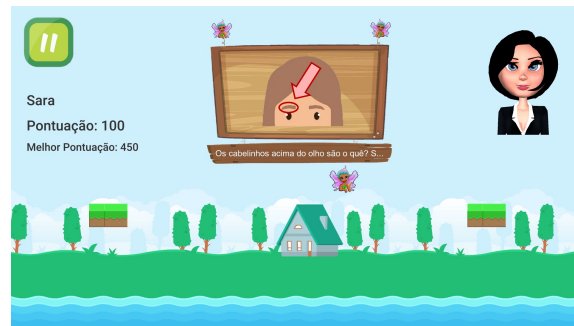
Figure 3. Stimulus used to suggest the word *mochila*

Table 3. Words with sibilants – number of children

Age	Girl	Boy	Total
5	20	19	39
6	35	35	70
7	51	33	84
8	39	50	89
9	37	37	74
Total	182	174	356

Table 4. Word samples

Phoneme	Incorrect phoneme occurrences	Total phoneme productions	Words with incorrect sibilants	Total number of words
ʃ	434	11202	422	11455
ʒ	240	2880	240	3333
s	354	6627	322	7024
z	154	2260	154	2616
Total	1182	22969	1138	22830



BioVisualSpeech

Information and Communication Technologies Institute

CarnegieMellon | PORTUGAL

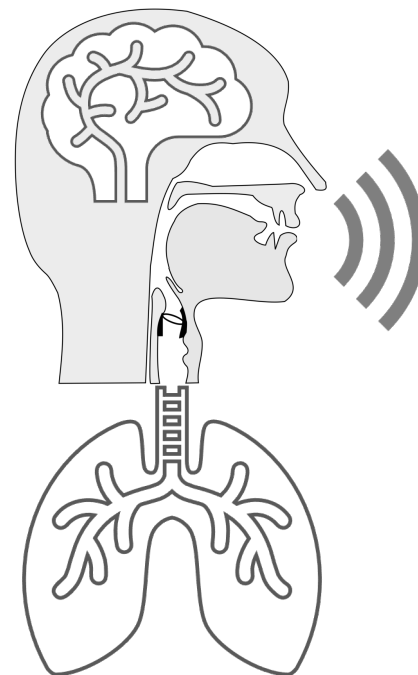
AN INTERNATIONAL PARTNERSHIP



SLT applications in e-health @ INESC-ID

3G: Speech as a health biomarker

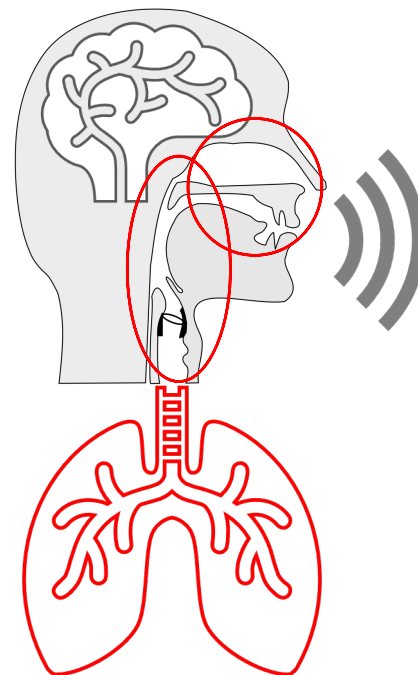
- Besides speech and language disorders, many other diseases affect speech in different ways:
 - Diseases that concern respiratory organs;
 - Neurodegenerative diseases;
 - Mood disorders;



SLT applications in e-health @ INESC-ID

3G: Speech as a health biomarker

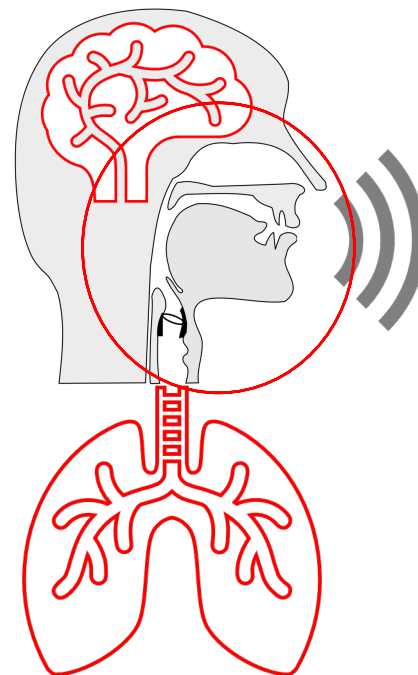
- Diseases that concern respiratory organs, e.g.:
 - Obstructive Sleep Apnea (OSA);
 - Common Cold;
 - COVID-19.



SLT applications in e-health @ INESC-ID

3G: Speech as a health biomarker

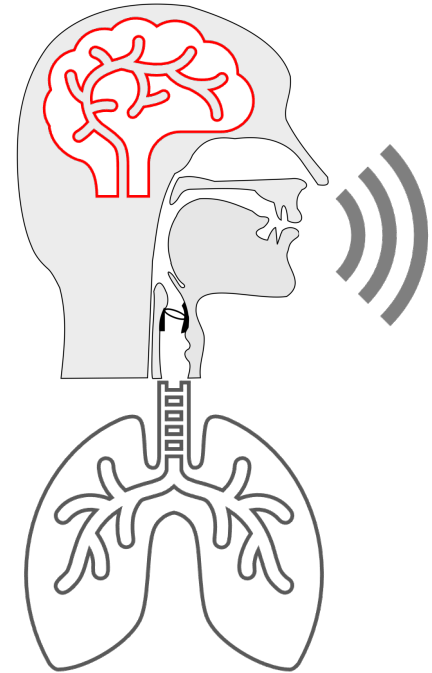
- Diseases that concern respiratory organs;
- **Neurodegenerative diseases, e.g.:**
 - Alzheimer's disease (AD);
 - Parkinson's disease (PD);
 - Huntington's disease (HD);
 - Amyotrophic lateral sclerosis (ALS).



SLT applications in e-health @ INESC-ID

3G: Speech as a health biomarker

- Diseases that concern respiratory organs;
- Neurodegenerative diseases;
- **Mood disorders, e.g.:**
 - Anxiety;
 - Depression;
 - Bipolar Disorder;
 - Post-traumatic stress disorder (PTSD).



SLT applications in e-health @ INESC-ID

3G: Speech as a health biomarker

- The potential of speech to act as a biomarker has bolstered several studies on the automatic detection of diseases, based on powerful **machine learning** classifiers, that either operate on features extracted from the speech signal, or directly on the signal itself.
- The fact that speech is **ubiquitous** and can be acquired **non-intrusively** makes it an inexpensive modality that may be used to identify high likelihoods of the presence of diseases, and the results of such early screening tests may act as alerts for users to seek medical assistance.
- Moreover, speech may be used in clinical facilities or at the patients' homes. It may also allow to remotely monitor the progress of a disease in order to adapt medication and support.

Speech as a health biomarker

Obstructive Speech Apnea (OSA)

By 2020, 230000 – 345000 people are expected to be killed in traffic accidents due to fatigue^[1]

1/3 adults suffers of inadequate sleep^[2]

9% - 38% of the adult population suffers from OSA^[3]

46% of OSA couples sleep in separate rooms^[5]

OSA speech anomalies: articulatory (slurred speech); phonation (larynx inflammation); resonance (vocal/nasal coupling)

Polysomnography (PSG) is the gold standard diagnosis: patients spend a night connected to electrodes

Speech as a health biomarker

Obstructive Sleep Apnea (OSA)

Table 4. Best performing classifiers and feature sets for OSA detection, using PSD and WOSA corpus.

	RF features; SVM			OFS features; SVM			OFS features; SVM+LDA+kNN		
	TPR (%)	TNR (%)	WA (%)	TPR (%)	TNR (%)	WA (%)	TPR (%)	TNR (%)	WA (%)
PSD	92.0	65.0	80.0	88.0	75.0	82.2	88.0	80.0	84.0
PSD-b	85.0	68.2	76.2	70.0	77.3	73.8	80.0	72.7	76.2
WOSA	12.2	37.5	25.0	75.0	87.5	81.3	75.0	87.5	81.2
PSD+WOSA	50.0	25.0	37.5	75.0	62.5	68.8	75.0	62.5	68.8

Table 5. Comparison of the performance achieved per task and the relative frequency of nasal phonemes and diphthongs.

Task	Performance			Nasal Phonemes (%)	Diphthongs (%)
	TPR (%)	TNR (%)	WA (%)		
1	84.0	70.0	78.8	12.6	6.4
3.1	84.0	65.0	75.6	13.5	5.7
3.2	92.0	75.0	84.4	25.0	10.0
3.3	72.0	65.0	68.9	18.8	6.3
3.4	84.0	70.0	77.8	6.5	6.5
3.5	92.0	65.0	80.0	12.1	5.1
3.6	80.0	85.0	82.0	8.9	4.4
3.7	84.0	75.0	80.0	14.0	7.0
3.8	84.0	75.0	80.0	14.3	7.1
3.9	92.0	65.0	80.0	11.5	1.9
3.10	88.0	60.0	75.6	16.0	4.0
4	92.0	55.0	75.6	-	-

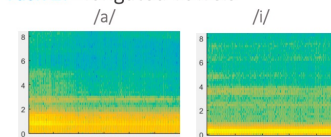
Portuguese Sleep Disorders (PSD) Corpus

Task 1: "The North Wind and the Sun"



Source: https://en.wikipedia.org/wiki/The_North_Wind_and_the_Sun

Task 2: Elongated vowels



Task 3: Reading span task

Eu disse à turma que eles teriam uma surpresa se se portassem branco.

(logical or illogical?)

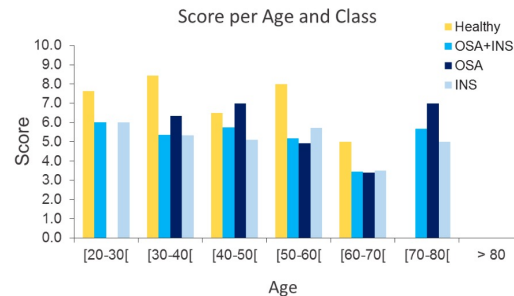
M

B F H J L
 M Q R X

Task 4: Describing the image



Source: <http://time.com/4551131/vincent-van-gogh-bedroom-bed-boxmeer/>



Speech as a health biomarker

Alzheimer's Disease

Alzheimer's Disease (AD) is the most common form of Dementia

Between 2000 and 2050, the proportion of the world's population over 60 will double from 11% to 22%

Besides alterations of memory and of spatial-temporal orientation, language impairments are also an important factor

Prevalence increases with age: U.S. census reported that 3% of people aged 65-74, 17% of people aged 75-84, and 32% of people aged 85 and older have AD

Pharmacological treatments may temporarily improve the symptoms of the disease, but they can not stop or reverse its progression

Language impairments in AD speech: naming, word-finding difficulties, repetitions, overuse of indefinite and vague terms, inappropriate use of pronouns

Speech as a health biomarker

Alzheimer's Disease: Topic coherence



...
 / Now, there is a boy
 climbing up a stool /
 ...
 / Aaaaand then it's in the
 sink the lady is washing
 the dishes /
 / cleaning a dish /
 / ahhh and but she left
 the tap open and the
 water is coming out of
 the sink /
 / she is wearing an apron
 you can see the garden
 outside /
 ...

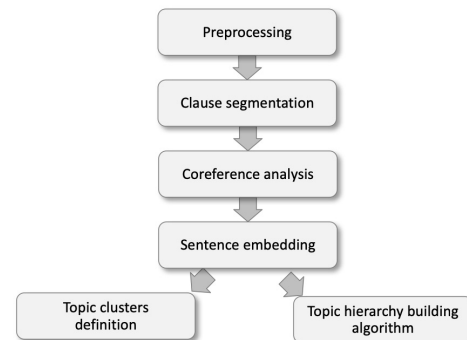
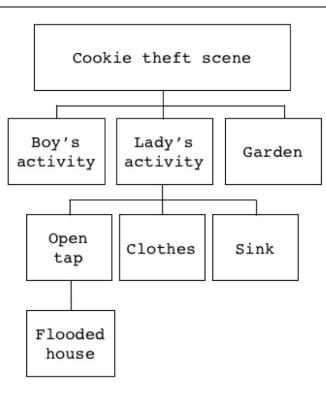
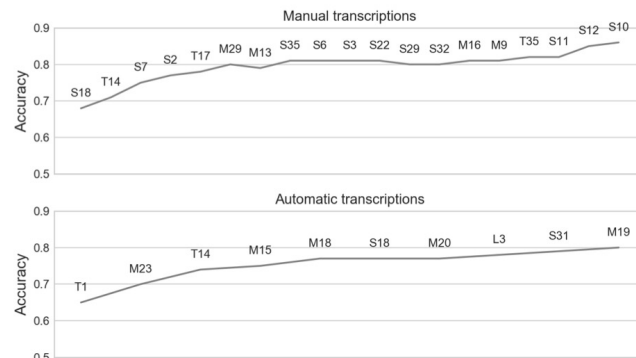


TABLE III
 SUMMARY OF AD CLASSIFICATION RESULTS (AVG. AND RANGE
 ACCURACY %)

	Manual transcriptions			Automatic transcriptions
	Topic coherence	Linguistic	Fusion	Fusion
Accuracy	79.0±4.8	82.6±5.1	85.5±2.9	79.7±3.5



Speech as a health biomarker

Alzheimer's Disease: Challenge

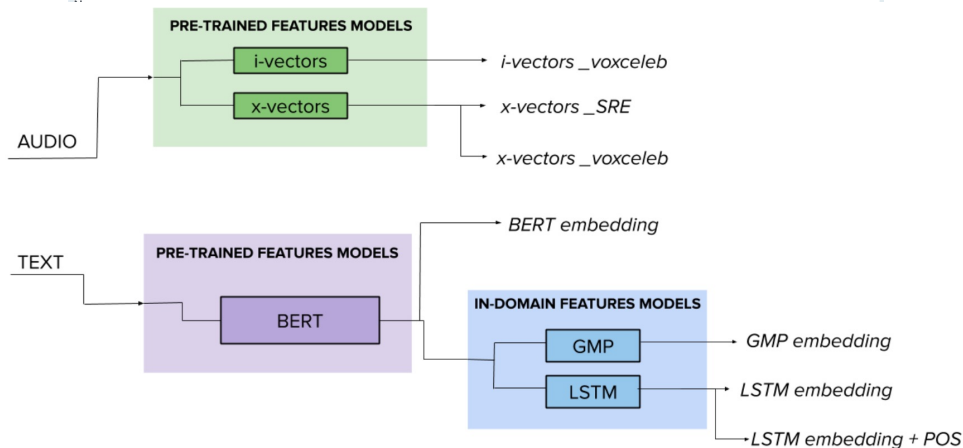


Table 2: Results of different acoustic approaches on the development set

	Accuracy	Precision	Recall	F1 Score
<i>x-vectors_Vox</i>	0.6818	0.6834	0.6919	0.6812
<i>x-vectors_SRE</i>	0.7273	0.7273	0.7273	0.7273
<i>i-vectors_Vox</i>	0.6818	0.7292	0.6818	0.6645
<i>i-vectors_Vox x-vectors_Vox</i>	0.7273	0.7273	0.7273	0.7273
<i>i-vectors_Vox x-vectors_SRE</i>	0.7273	0.7351	0.7273	0.7250

Table 3: Results of different linguistic approaches on the development set

	Accuracy	Precision	Recall	F1 Score
<i>Global Max Pool.</i>	0.7727	0.7947	0.7728	0.7684
<i>LSTM-RNNs</i>	0.8182	0.8182	0.8182	0.8182
<i>LSTM-RNNs Pos</i>	0.8636	0.8667	0.8637	0.8634
<i>GMax/LSTM-RNNs/LSTM-RNNs-Pos</i>	0.9091	0.9091	0.9091	0.9091
<i>Sentence emb. - maj. vote</i>	0.7727	0.7947	0.7728	0.7684

Table 4: Results of different acoustic and linguistic approaches on the test set

	Class	Accuracy	Precision	Recall	F1 Score
<i>Fusion of system</i>	AD	0.8125	0.9412	0.6667	0.7805
	non-AD		0.7419	0.9583	0.8364
<i>Sentence embedding</i>	AD	0.7292	0.8235	0.5833	0.6829
	non-AD		0.6774	0.8750	0.7636
<i>x-vectors_SRE</i>	AD	0.5417	0.5417	0.5417	0.5417
	non-AD		0.5417	0.5417	0.5417

Speech as a health biomarker

Parkinson's Disease

Parkinson's disease (PD) is a progressive degenerative disorder characterized by motor and non-motor symptoms.

Motor signs of PD include resting tremor, rigidity, bradykinesia, while non-motor symptoms include cognitive disorders, and sleep and sensory abnormalities.

Motor symptoms of PD influence also the speech production of language.

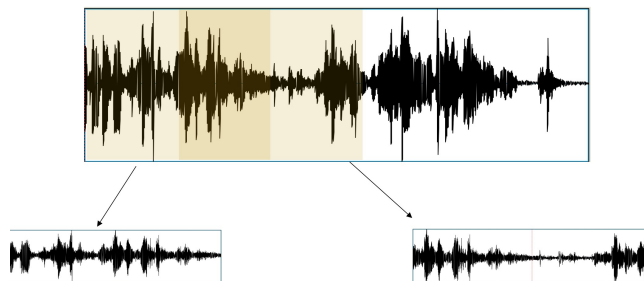
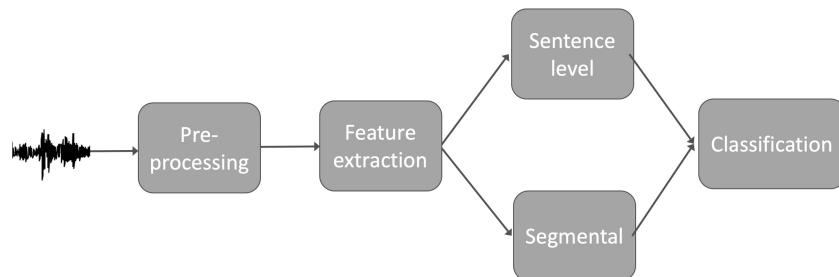
Dysarthria, which is characterized by a weakness, paralysis, or lack of coordination in the motor-speech system, is typically observed in PD patients and affects respiration, phonation, articulation and prosody.

As the disease progresses, patient alternate periods in which motor symptoms are mitigated due to medication intake (ON state), and periods with motor complications (OFF state).

The time that patients spend in the OFF condition is currently the main parameter used to assess pharmacological interventions.

Speech as a health biomarker

Parkinson's Disease: Study of production tasks



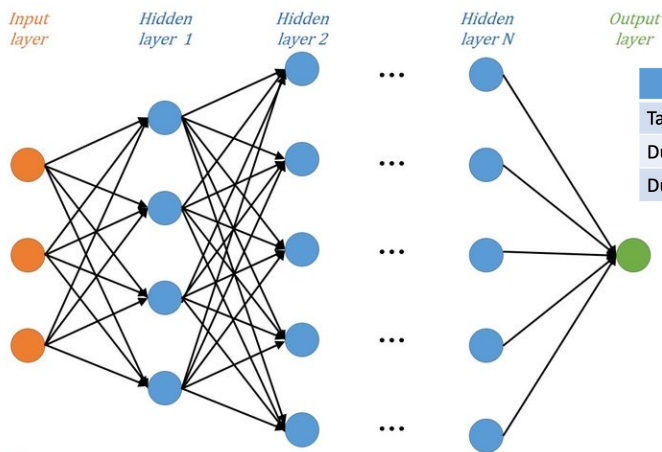
	PD patients	Healthy Control
N. of subjects:	75	65
Duration:	~7h 30m	~6h 31m

Task-dependent results on the classification task (PD vs. control)

Task	Accuracy (%)	
	Sentence Level	Segmental
Sustained vowel phonation (/a/)	55.00	58.14
Maximum phonation time (/a/)	60.00	75.65
Oral diadochokinesia	60.71	73.28
Reading of word	54.29	76.35
Reading of sentences	62.14	81.74
Reading of text	65.00	79.86
Storytelling guided by visual stimuli	66.43	82.32
Reading of prosodic sentences	70.71	85.10

Speech as a health biomarker

Parkinson's Disease: Monitoring medication state



	Training set (avg. duration x speaker)	Test set (avg. duration x speaker)
Task:	Ddk, mpt, word, sent, pros, conv	/a/, text, frog
Duration ON:	12h 55m (10m)	2h 54m (2m)
Duration OFF:	13h 24m (10m)	3h 06m (2m)

Table 3: Test results (utterance-level Acc - %) for speaker-dependent medication state assessment by task.

Feature set	/a/	Reading text	Story telling
MFCC	86.49	87.16	92.57
MFCC+ Δ s	85.14	91.22	93.24
eGeMAPS	89.19	87.16	95.27
MFCC+PCA	86.49	89.19	94.59
MFCC+ Δ s+PCA	85.14	89.19	93.92
eGeMAPS+PCA	83.78	86.49	93.24

Table 2: Optimal model configurations and results (utterance-level Acc - %) for speaker-dependent medication state assessment.

Feature set	#Coefficients	Context	Input dim.	Architecture	α	Acc devel.	Acc test
MFCC	13	15	195	256, 128, 32, 1	0.01	93.92	88.74
MFCC+ Δ s	26	11	286	256, 128, 1	0.01	93.24	89.86
eGeMAPS	23	15	345	512, 128, 1	0.001	95.95	90.54
MFCC+PCA	13	15	95	512, 128, 1	0.03	91.89	90.09
MFCC+ Δ s+PCA	26	11	85	128, 64, 1	0.03	91.89	89.41
eGeMAPS+PCA	23	15	70	128, 64, 1	0.03	96.62	87.84

Outline

- Introduction to speech processing
- Three generations of HLT applications in e-health @INESC-ID:
 - 1G: Augmentative communication, assistive technologies and e-inclusion
 - 2G: Diagnosis and treatment of speech and language disorders
 - 3G: Speech as a health biomarker for speech-affecting diseases
- **Challenges and open questions**

Challenges and open questions

- There is a significant amount of research showing that speech has the potential to be a useful bio-marker for diagnosis and monitoring of several diseases.
- However, there are still significant limitations that prevent from broad application in real clinical settings:
 1. Data limitations:
 - Small data sets; unbalanced data; In-the-wild data; cross-domain, cross-lingual; privacy concerns
 2. Not realistic (or really valuable) tasks:
 - Binary classification of HC vs disease; labels not related with speech/language issues; cold vs COVID-19?
- Possible directions for future work:
 1. Mining on-line repositories; development of privacy-preserving protocols
 2. Towards “speech tests” equivalent to blood tests to help medical diagnosis



DEFINING TECHNOLOGY

Thank you!

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