Depression Speaks

Automatic Discrimination Between Depressed and Non-Depressed Speakers Based on Nonverbal Speech Features

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Unita' Operative Salute Mentale (Italy)
University of Glasgow (UK)

Outline

- Introduction
- The Data
- The Approach
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Why Depression?

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- 300 million patients in 2015 (World Health Organisation)

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- Second cause of disability after ischaemia (European Commission)

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- Second cause of disability after ischaemia (European Commission)
- Most important suicide factor for elderly people (European Commission)

Why Nonverbal (Speech) Behaviour?

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- Traditional methods (HRSD and BDI-II) not fully robust to biases of both clinicians and patients

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- Traditional methods (HRSD and BDI-II) not fully robust to biases of both clinicians and patients
- Detection of nonverbal behavioural markers can limit the effect of biases while reducing the costs

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Depression

Control

Depression

20

Control

Depression

20 42

Control

Depression

20 42

Control

20

Depression

20 42

Control

20 37

Depression

20 42

DSM-based diagnosis by professional clinicians

Control

20 37

Depression

20 42

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20 37

Match based on gender, age and education

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BDI-II Questionnaire

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Match based on gender, age and education

BDI-II Questionnaire

62 Diary recordings
57 Tale recordings

Depression

20 42

DSM-based diagnosis by professional clinicians

BDI-II Questionnaire

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Match based on gender, age and education

52 Diary recordings
54 Tale recordings

Depression

20 42

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Diary is an interview about the activities of the last week end (spontaneous speech)

62 Diary recordings
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Depression:

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Control:

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Depression

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Tale is reading a short story written by Aesopus (read speech)

Depression

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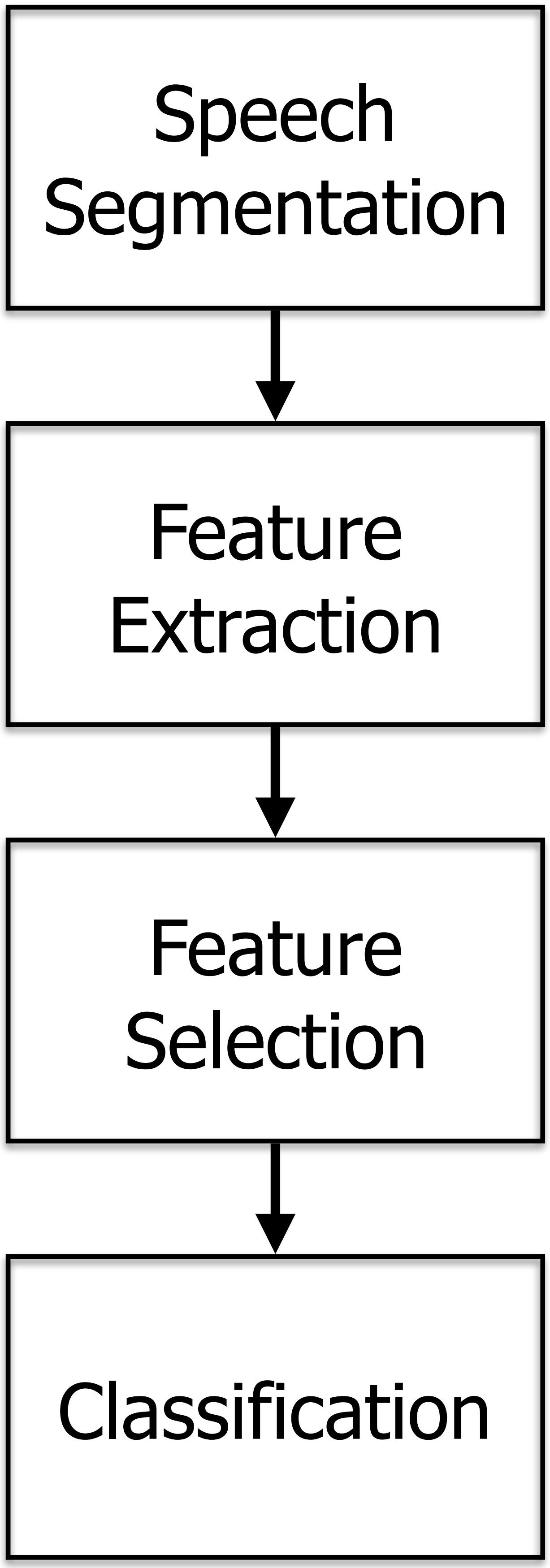
Speech Segmentation
Feature Extraction
Feature Selection
Classification

Speech Segmentation

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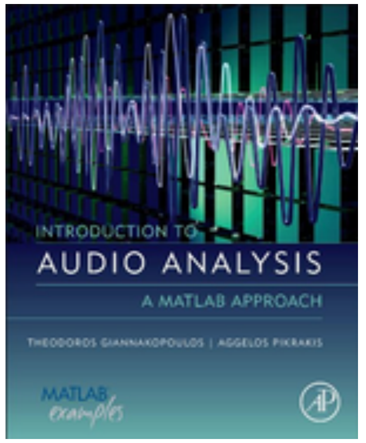
Feature Extraction

↓

Feature Selection

↓

Classification



Speech Segmentation

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Feature Extraction

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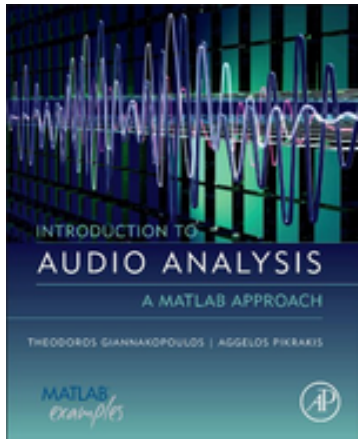
Classification



Selection of patient or control speech

Speech Segmentation

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Feature Extraction

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Feature Selection

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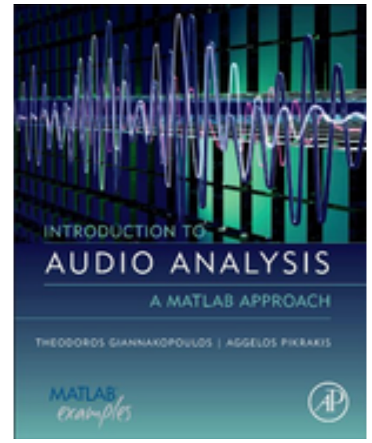
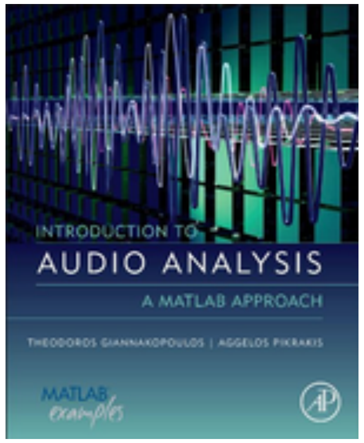
Classification



openSMILE:)
by audEERING™

Selection of patient or control speech

Speech Segmentation



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Extraction of 384 features (IS09)

Feature Selection

Classification

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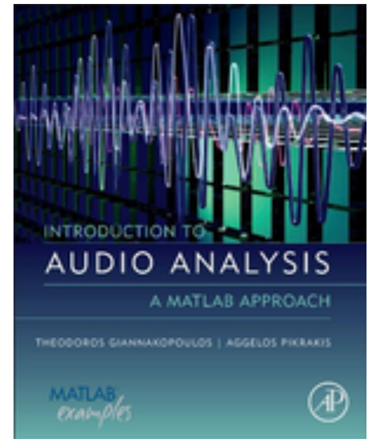

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Infinite Latent Feature Selection

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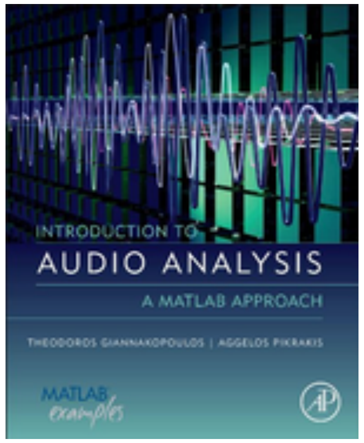

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Identification of markers

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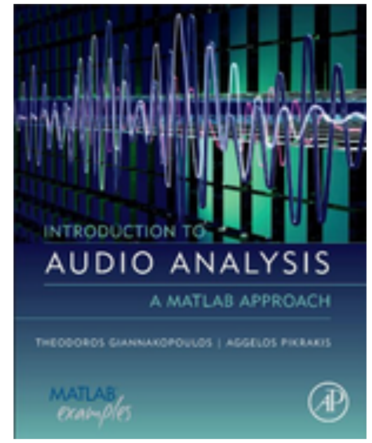
Speech Segmentation		Selection of patient or control speech
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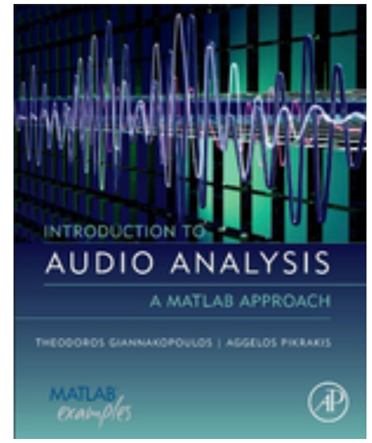
Classification	Support Vector Machines	

Speech Segmentation		Selection of patient or control speech
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Classification	Support Vector Machines	Depressed vs Control

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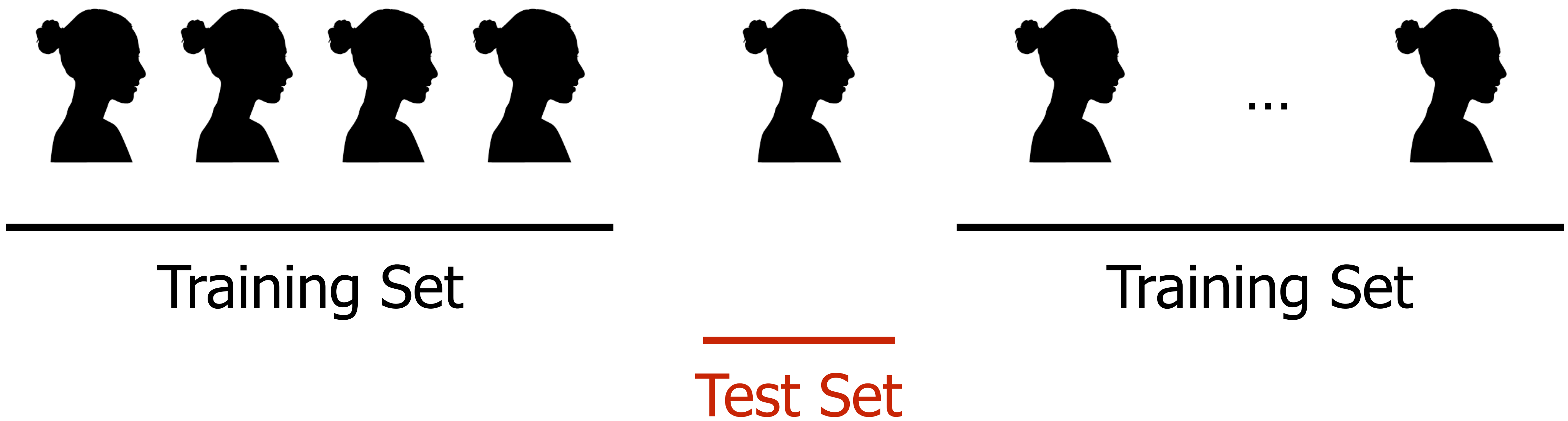
Leave One Subject Out



Leave One Subject Out approach for both Linear Kernel SVM and Infinite Latent Feature Selection

Results

Task	Precision	Recall	Accuracy
Diary	66%	60%	68%
Tale	75%	74%	76%
Diary-FS	74%	65%	74%
Tale-FS	74%	80%	77%

Diary

	D	C
D	74.2%	25.8%
C	40.4%	59.6%

Diary-FS

	D	C
D	80.62%	19.4%
C	34.6%	65.4%

Tale

	D	C
D	77.2%	22.8%
C	25.9%	74.1%

Tale-FS

	D	C
D	73.7%	26.3%
C	20.4%	79.6%

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- Unlike previous works, the approach performs better on read speech (in line with the psychiatric literature)
- Future work includes the adoption of Deep Networks and the use of the transcriptions

Thank You!

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