Audio data analysis

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Credits

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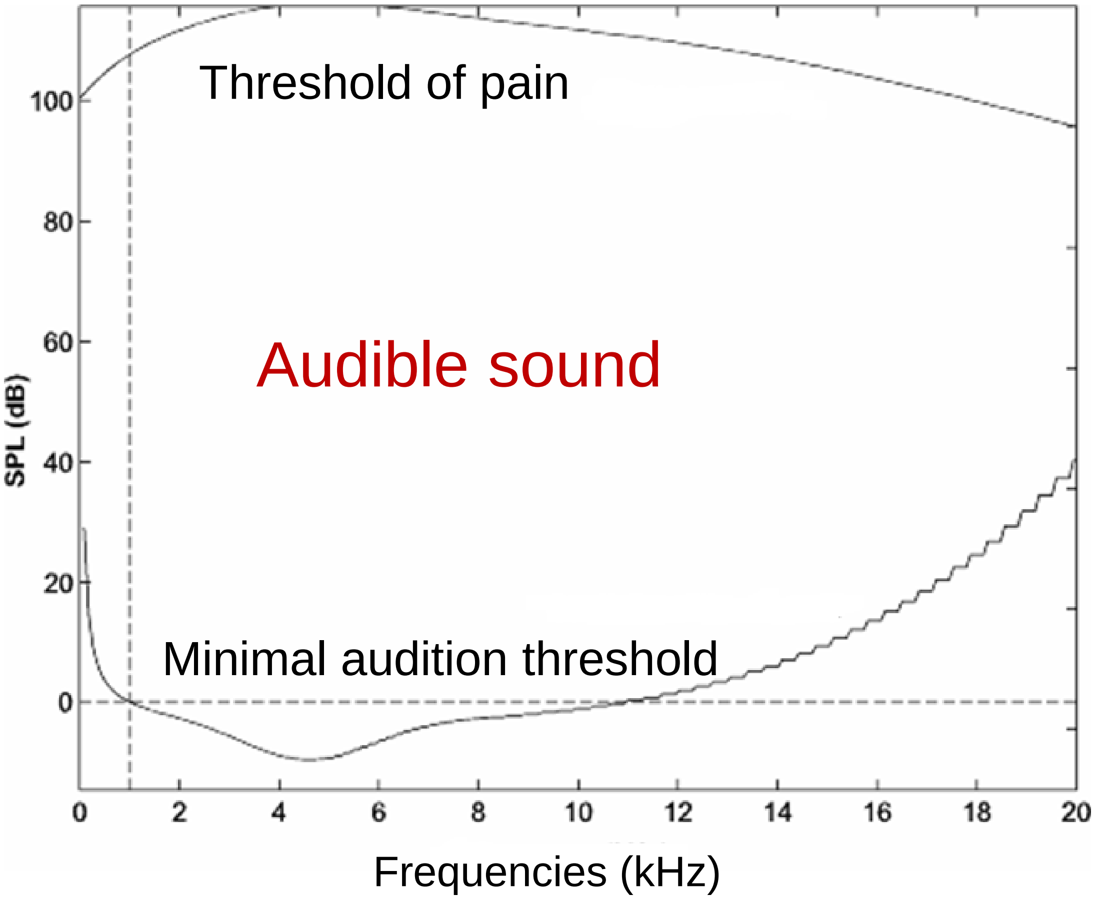
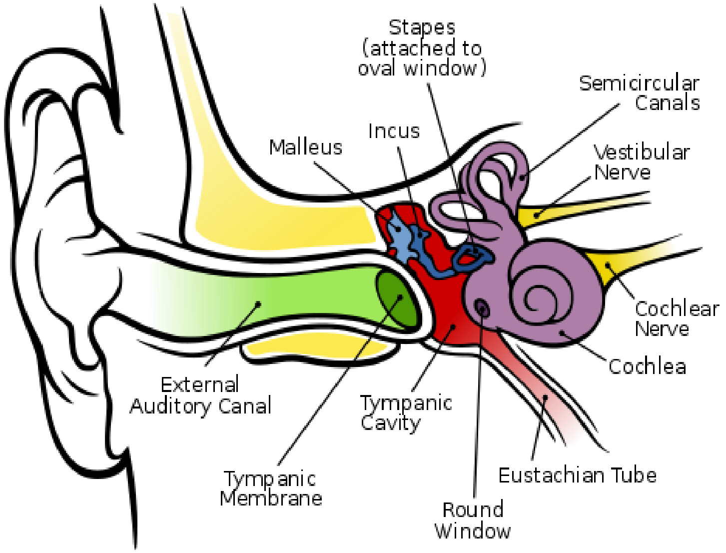
About "audio"…

► Audio frequency:

the range of audible frequencies (20 to 20,000 Hz)

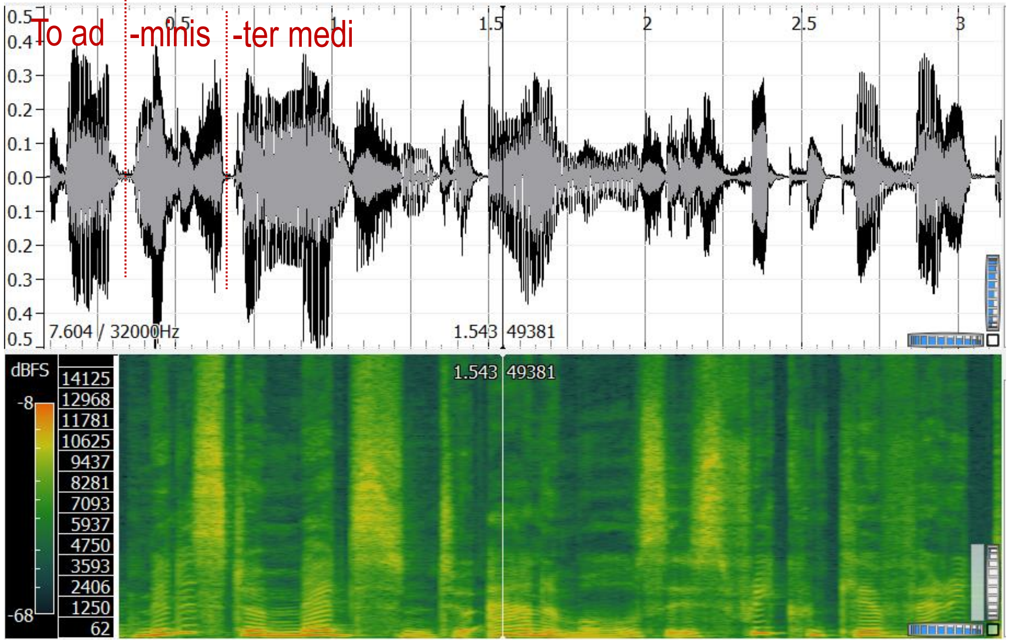




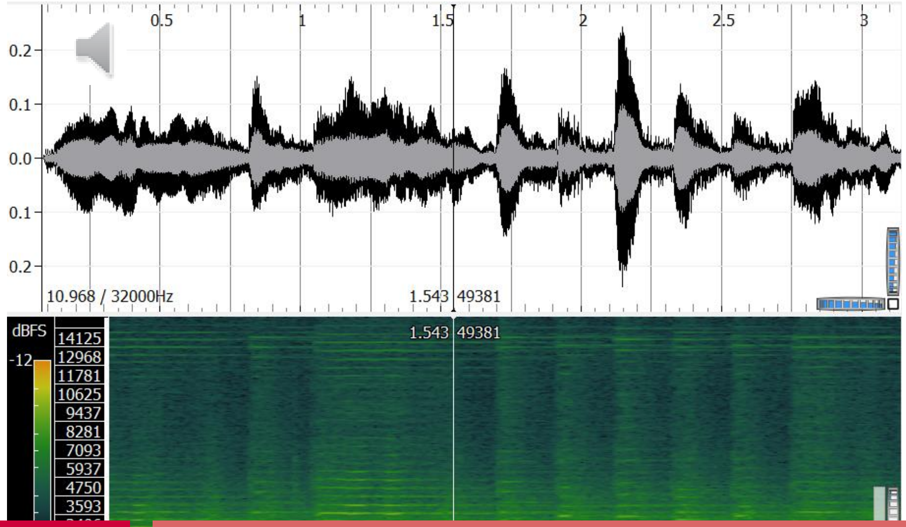
About "audio"…

► Audio content categories

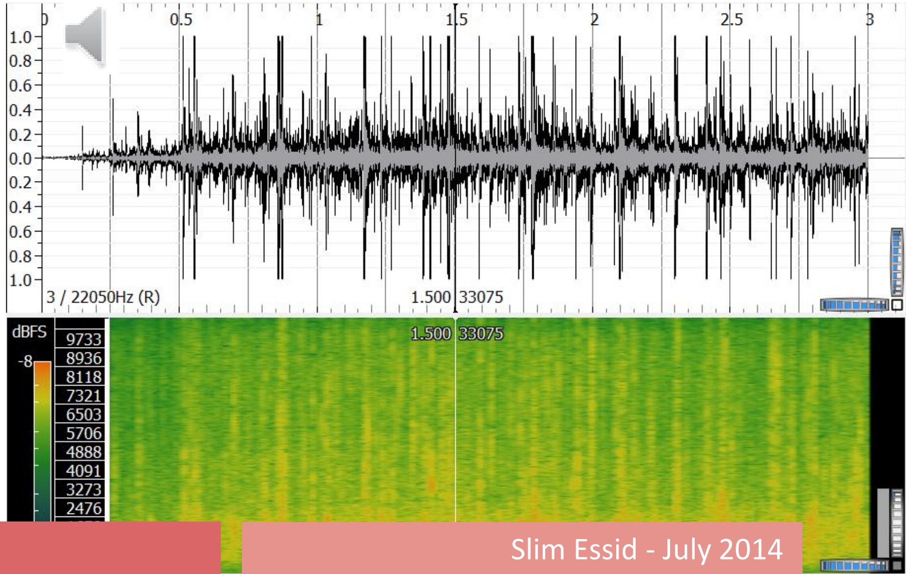
Speech



Music



Environmental

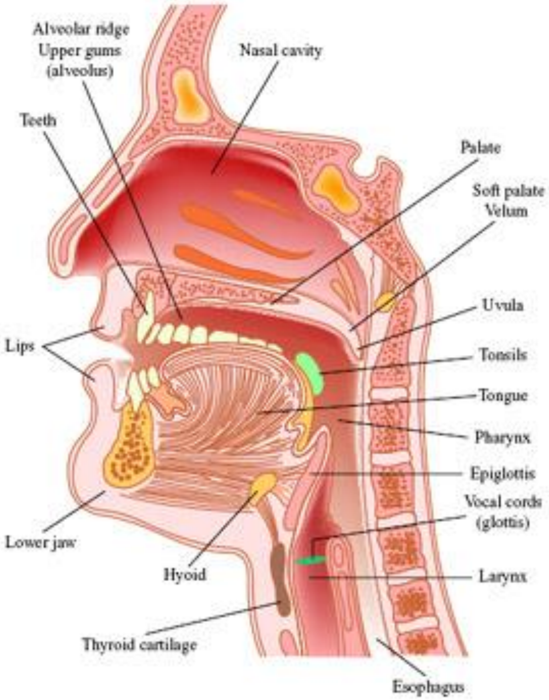


About “audio”…

► An important distinction: speech vs non-speech

Speech signals

“Simple” production model:
the source-filter model



Music & non-speech (environmental)

No generic production model:
“timbre”, “pitch”, “loudness”, …

Image: Edward Flemming, course materials for 24.910 Topics in Linguistic Theory: Laboratory Phonology, Spring 2007. MIT OpenCourseWare (http://ocw.mit.edu/), Massachusetts Institute of Technology. Downloaded on 05 May 2012

About "audio"…

▶ Different research communities

Music Information Research		Speech
Music classification (genre, mood, …)	Signal representations	Speech recognition
Transcription	Audio coding	Speaker recognition
Rhythm analysis	Source separation	Speech enhancement
…	Sound synthesis	…
	…	

Computer audition

About "audio"…

► Research fields

Acoustics

Linguistics

Psychology

Psychoacoustics

Audio content analysis

Musicology

Signal processing

Knowledge engineering

Machine learning

Databases

Statistics

About "audio"…

▶ Research fields

Acoustics

Linguistics

Psychology

Psychoacoustics

Audio content analysis

Musicology

Signal processing

Knowledge engineering

Machine learning

Databases

Statistics

Why analyse audio data?

- **For archive management, indexing**
  - » Broadcast content segmentation and classification: speech/music/jingles…, speakers
  - » Music **autotagging**: genre (classical, jazz, rock,…), mood, usage…
  - » Search engines

- **For broadcasters**
  - » Music/effects/speech excerpt search
  - » Playlist generation, Djing

Why analyse audio data?

- **For designers and producers**
  - » Audio sample search
  - » Music transcription (beat, rhythm, chords, notes)
  - » Broadcast content monitoring, plagiarism detection, *hit prediction*

- **For end-users**
  - » Content-based search (shazam++)
  - » Non-linear and interactive content consuming (“skip intro”, “replay the chorus”, Karaoke: “remove the vocals”…)
  - » Recommendation
  - » Personalised playlist generation

Audio-driven multimedia analysis

- **Motivation** for audio-driven content analysis
  - » critical information is conveyed by the audio content
  - » audio and visual information play complementary roles for the detection of key concepts/events

- Video examples

Audio-driven multimedia analysis

▶ Video examples

→ Use audio-based laughter detection

- Applause detection
- Cheering detection

- Keyword spotting: “Goal!”
- Sound loudness
- Applause/cheering detection

Audio-driven multimedia analysis

► Key audio-based components

- Speech activity detection
- Jingle detection
- Emotion recognition
- Speech/Music/ Applause/Laughter/ … detection
- Speaker identification
- Social signal processing: roles, interactions,…
- Speaker diarization: "Who spoke when?"
- Speech-to-text transcription
- Music classification genre, mood, …
- Natural language processing

→ At the heart of all components: a classification task (supervised or unsupervised)

Audio-driven multimedia analysis

Speech activity detection

Jingle detection

Emotion recognition

Speech/Music/
Applause/Laughter/
…
detection

Speaker identification

Social signal processing:
roles, interactions,…

Speaker diarization:
"Who spoke when?"

Speech-to-text transcription

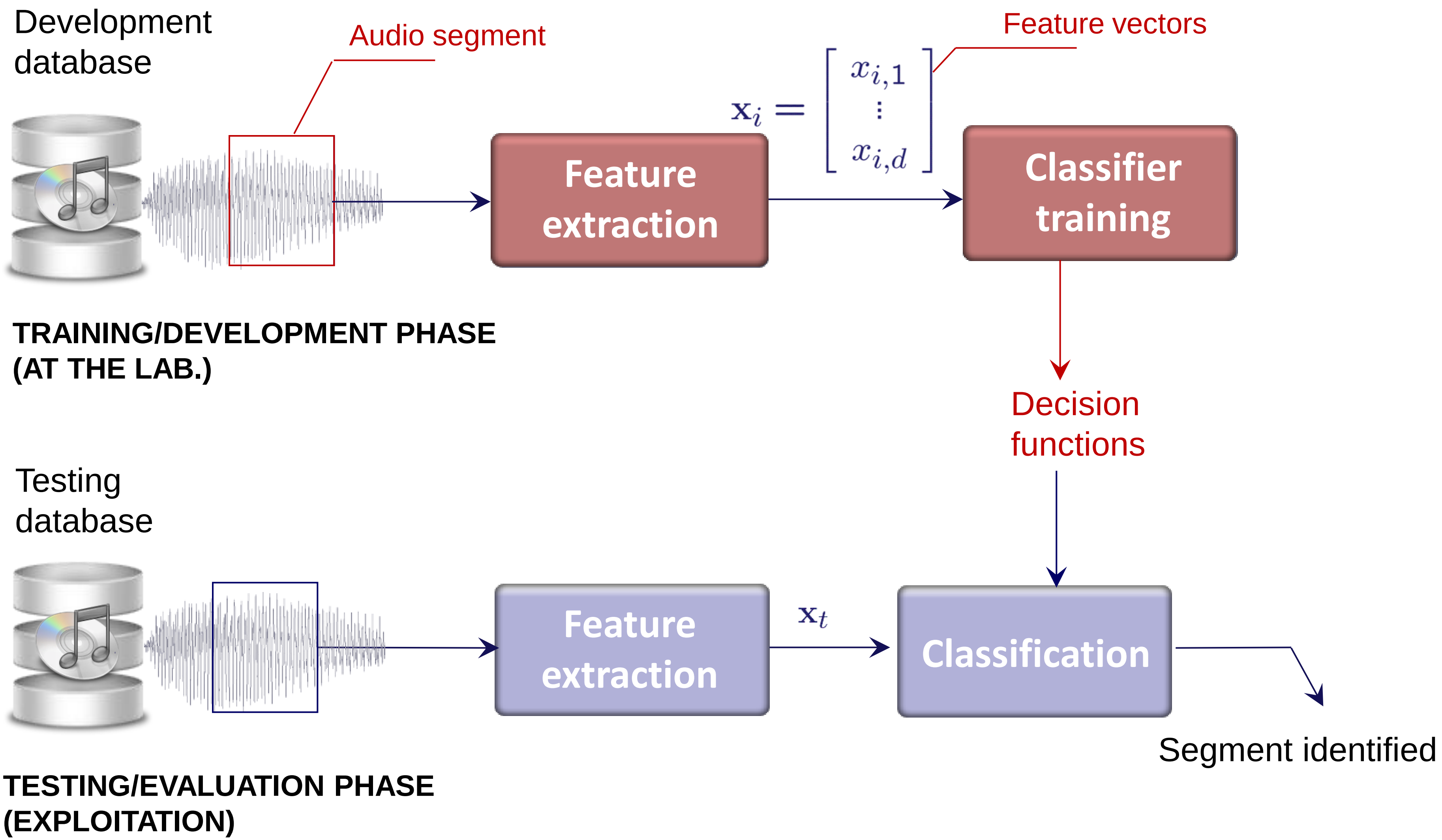
Music classification
genre, mood, …

Natural language processing

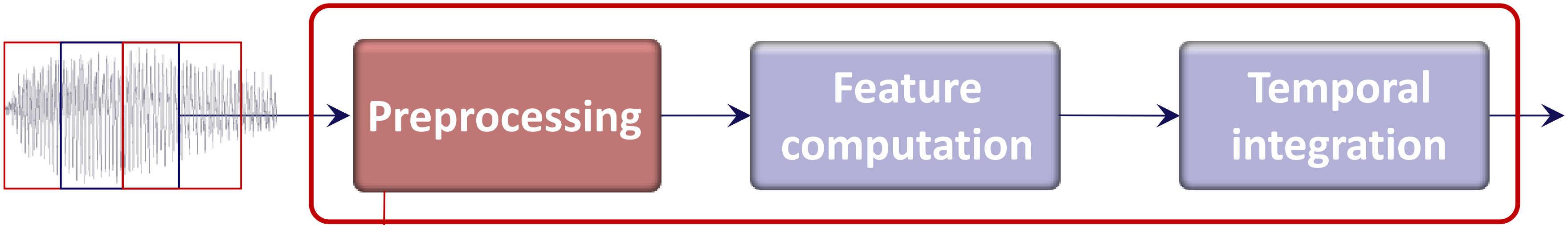
→ At the heart of all components: a classification task (supervised or unsupervised)

General classification architecture

▶ Overview



▶ Feature extraction process



Motivation:

- signal denoising/enhancement
- information rate reduction, eg. subsampling
- normalisation, eg.:

$$\tilde{s}(n) = s(n) - \bar{s}, \ \bar{s} = \frac{1}{L}\sum_{n=0}^{L-1} s(n)$$

$$\hat{s}(n) = \frac{\tilde{s}(n)}{\max_n |\tilde{s}(n)|}$$

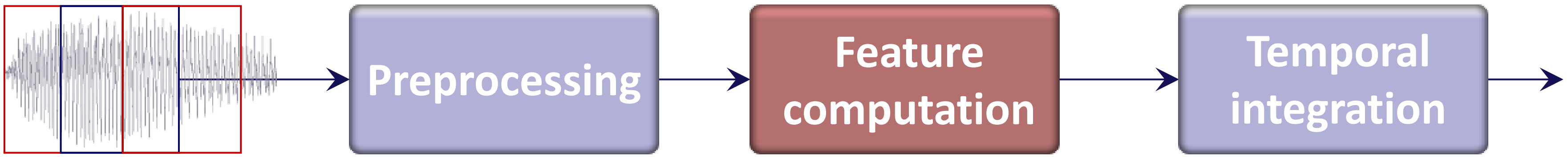
Exercise

In Python:

- load an audio file;
- normalise it;
- visualise it.

Use scipy.io.wavfile

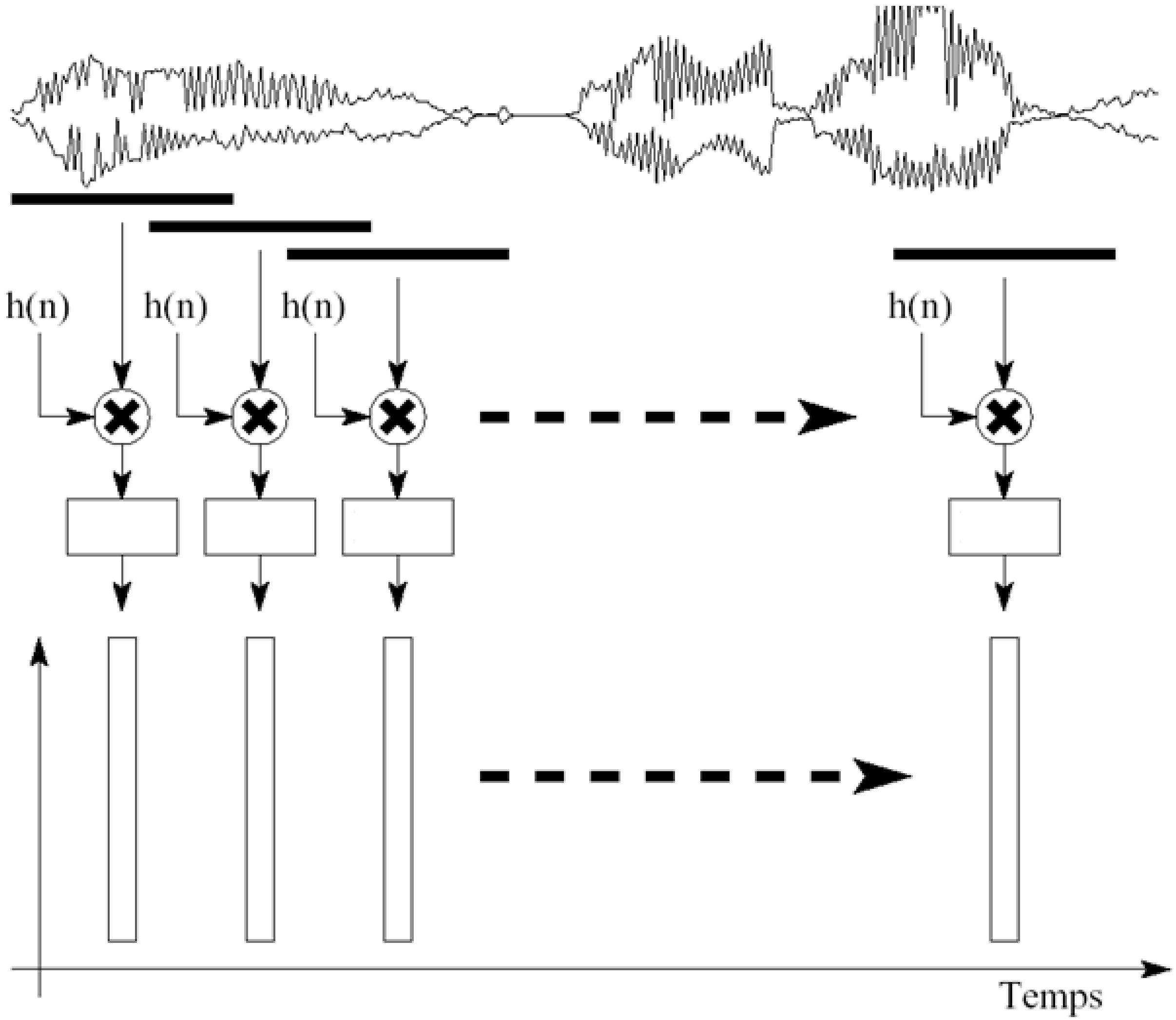
- Feature extraction process



→ Relies on audio signal processing techniques

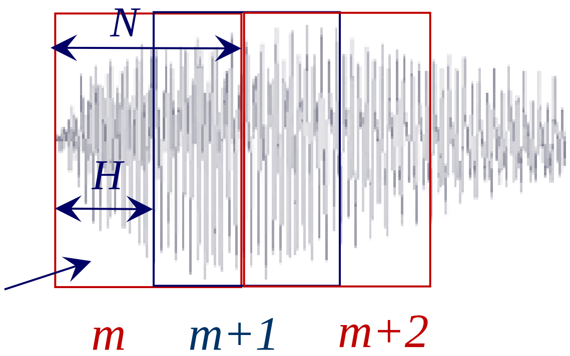
Audio signal analysis

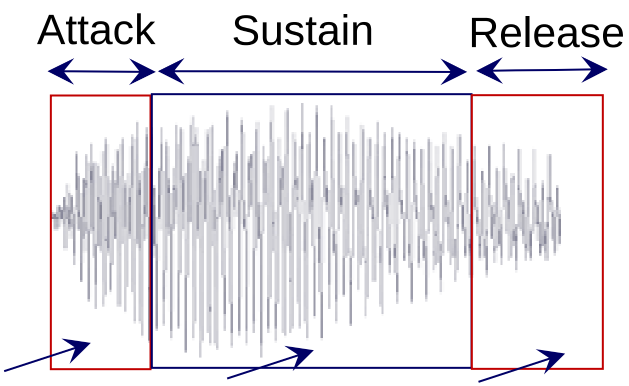
► Short-Term analysis windows



Drawing by J. Laroche, modified

Signal framing





» Static temporal segmentation

» Dynamic temporal segmentation

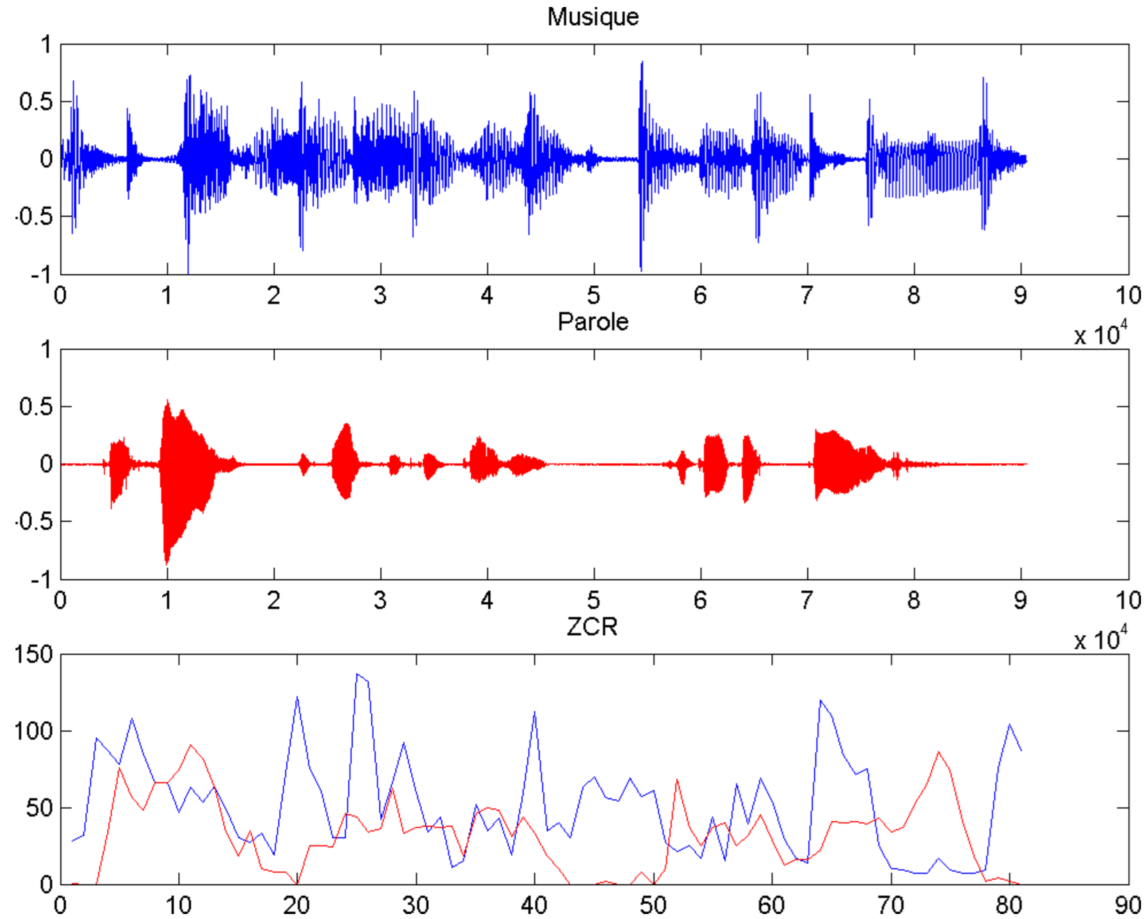
Feature types

- **Temporal features**: extracted directly from the waveform samples
- **Spectral features:** extracted from a frequential representation of the signal
- **Perceptual features**: extracted using a perceptual representation based on **psychoacoustic** considerations

Zero Crossing Rates

$$\frac{1}{2}\sum_{n=2}^{N}|sign(x_n) - sign(x_{n-1})|$$

Characterises noisy and transient sections

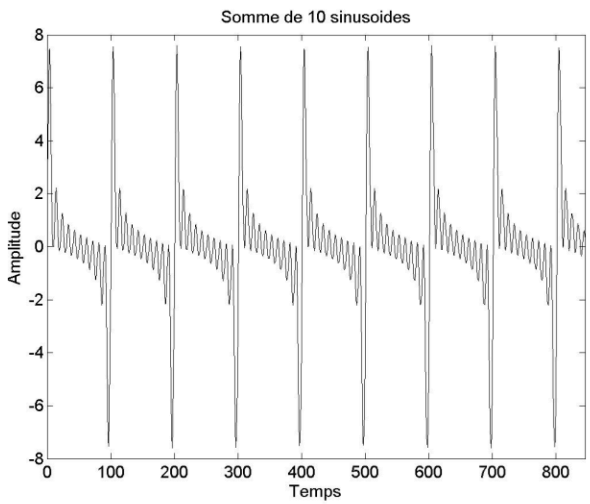


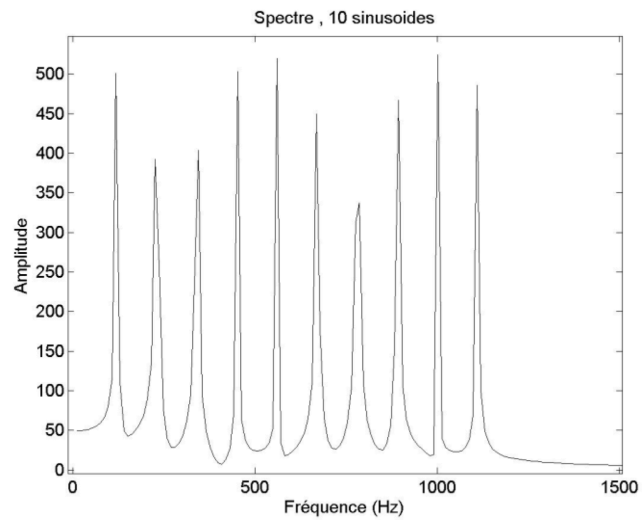
▶ Discrete Fourier Transform

$$X_k = \sum_{n=0}^{N-1} x_n \exp(-j2\pi \frac{k}{N} n),$$

$$x_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k \exp\left(j2\pi \frac{k}{N} n\right)$$

$$|X_k|$$





In practice: computed using the **Fast Fourier Transform (FFT)**

Discrete Fourier Transform (DFT)

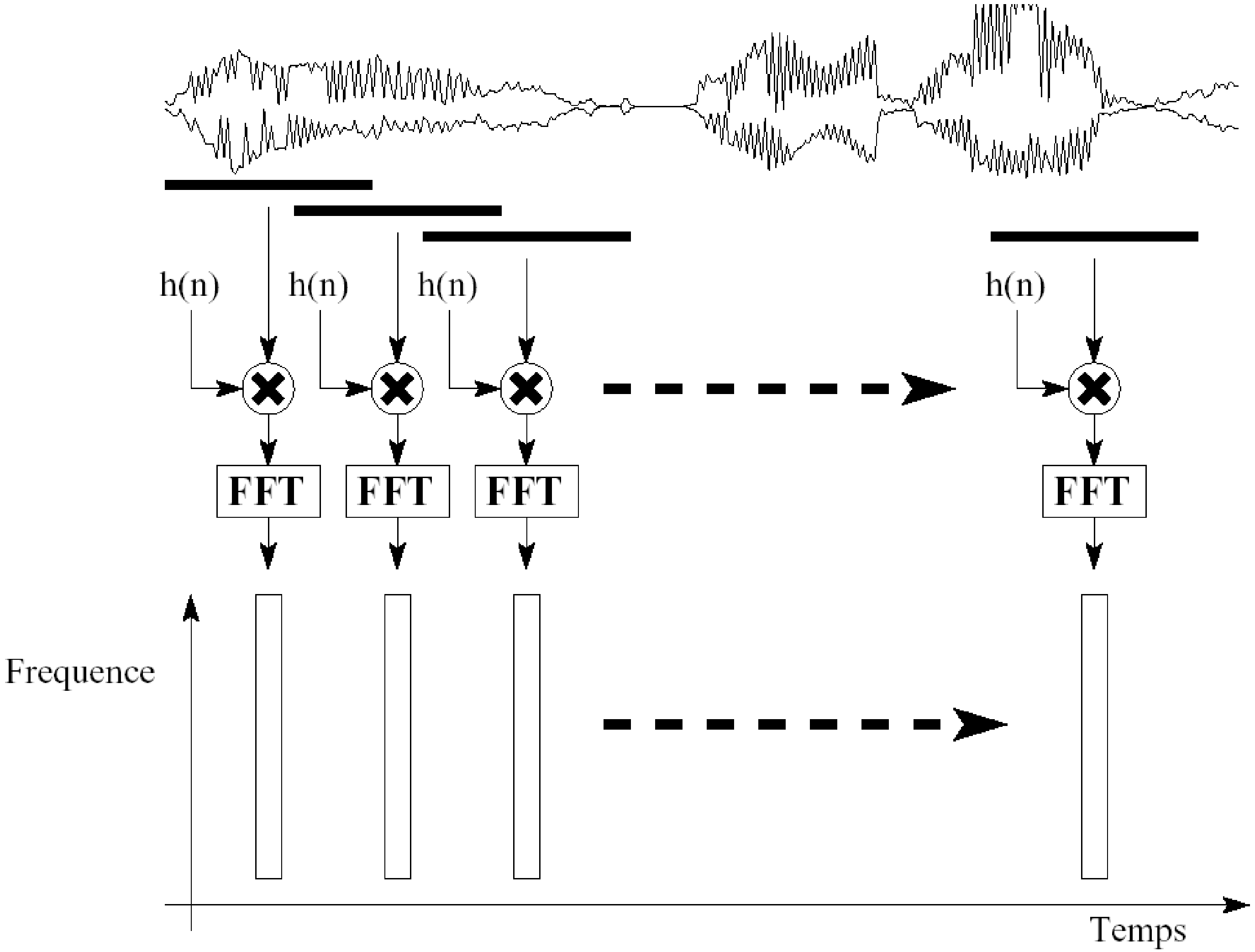
▶ Important properties

- Being a **discrete time** Fourier Transform, the DFT is **periodic**, with period 1 (in reduced frequency $f = \frac{f}{f_s}$; f_s : sampling frequency)
- For signals $x(n)$ and $y(n)$; $n \in \{0, \dots, N-1\}$

Property	**Numerical series**	**DFT**
Linearity	$\{ax(n) + by(n)\}$	$\{aX(k) + bY(k)\}$
Hermitian symmetry	$x(n)$ **real**	$X(k) = X^*(-k)$
Time translation	$x(n - n_0)$	$X(k)e^{-\frac{2j\pi k}{N}n_0}$
Convolution	$x(n) \star y(n)$ $\triangleq \sum_k x(k)y(n-k)$	$X(k)Y(k)$
Conjugation	$\{x^*(n)\}$	$\{X^*(-k)\}$

Spectral analysis

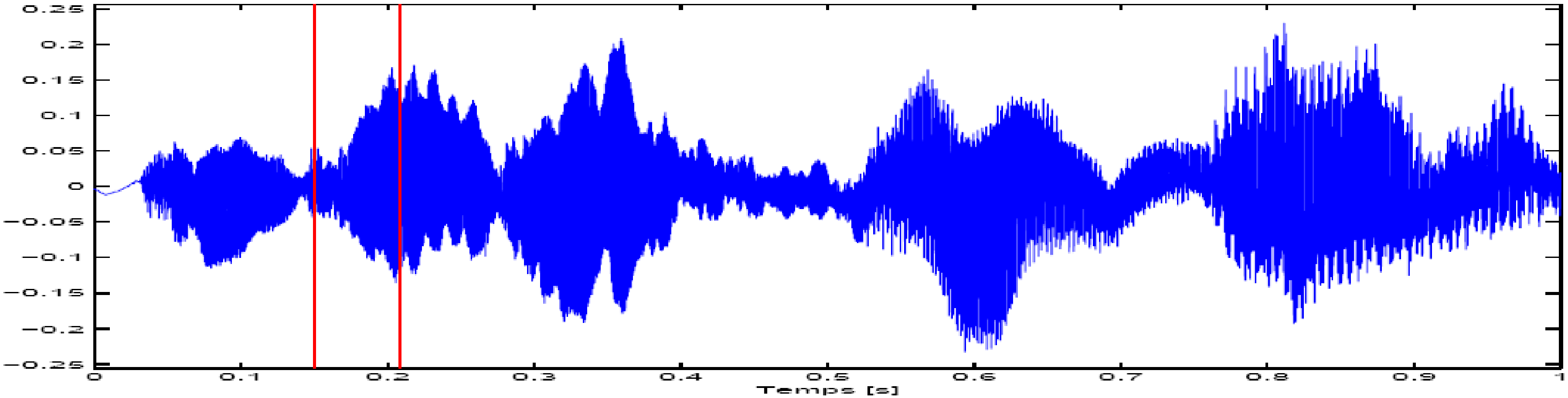
► Spectral analysis by Short-Term Fourier Transform (STFT)

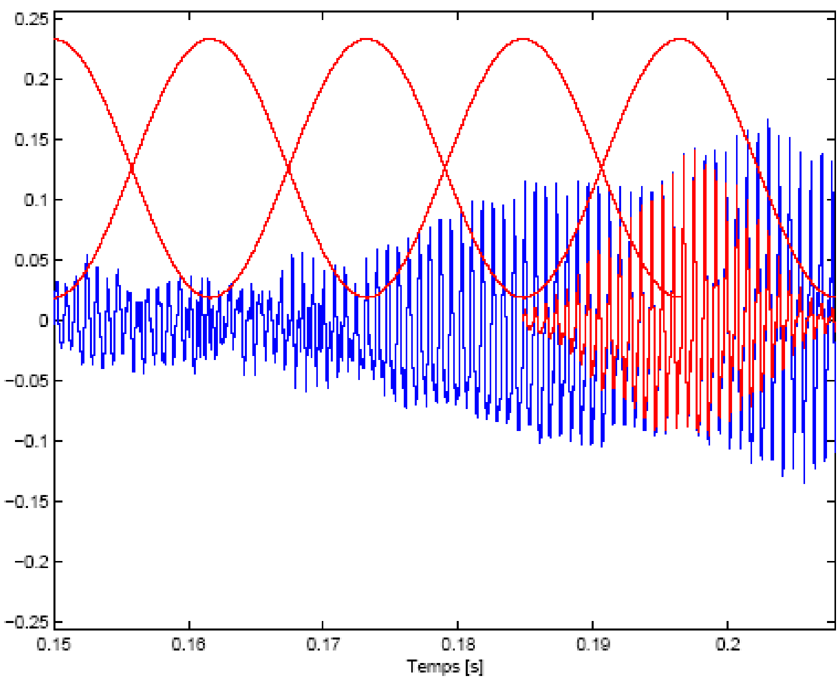


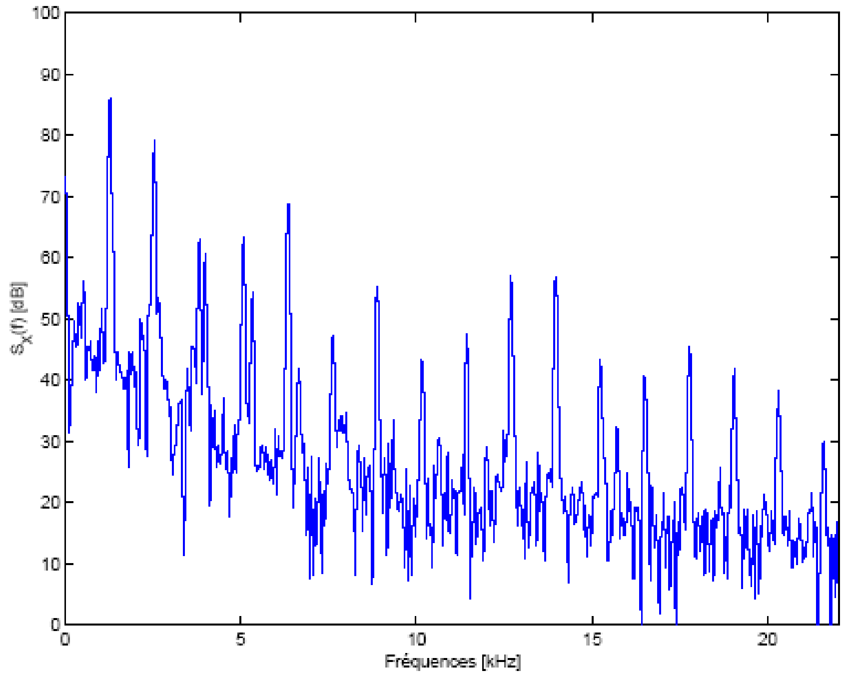
Drawing by J. Laroche

Spectral analysis

- ► Violin excerpt: 20-ms overlapping windows (s_r = 44.1kHz ; N = 882 samples)



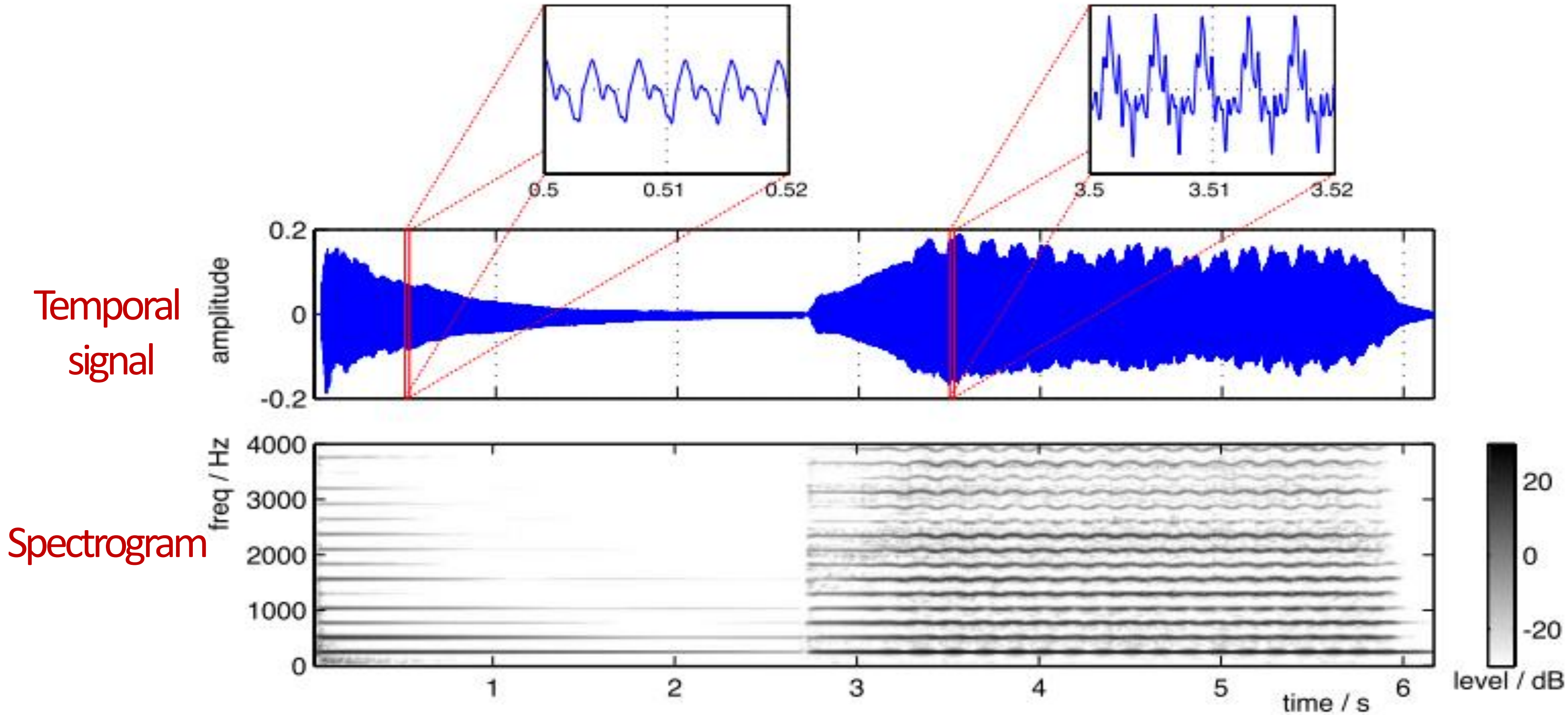




Spectral analysis

▶ Spectrogram

C note (262 Hz) produced by a piano and a violin



From M. Mueller & al. « Signal Processing for Music Analysis, IEEE Trans. On Selected topics in Signal Processing », October 2011.

Spectral analysis

► Exercise

In Python:

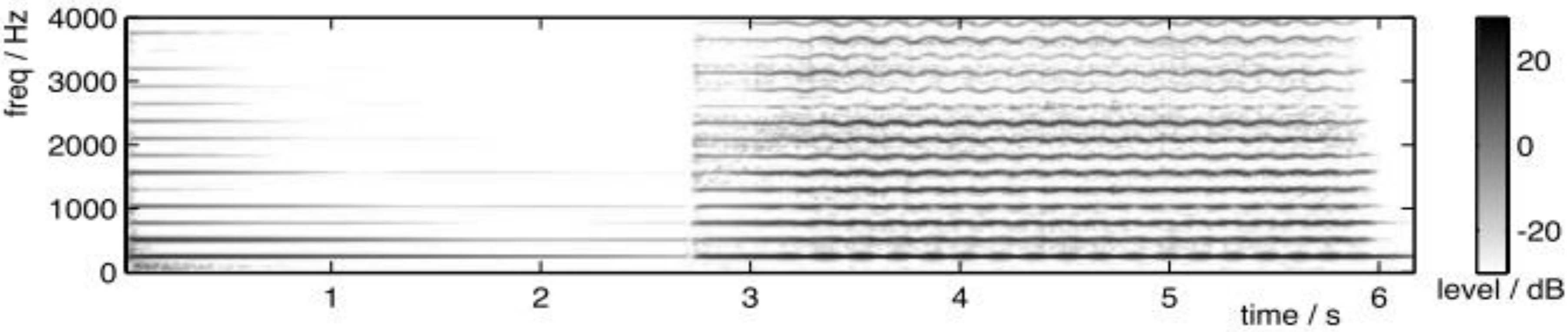
- Compute short-term spectra of an audio signal using FTT
- At home: compute and display spectrogram

- Use
  - » **scipy.io.wavfile**
  - » **pylab.specgram**
- Compare to hand crafted spectrogram obtained with:
  - » **scipy.fftpack** and **pylab.imshow**

▶ Limitations of the spectrogram representation

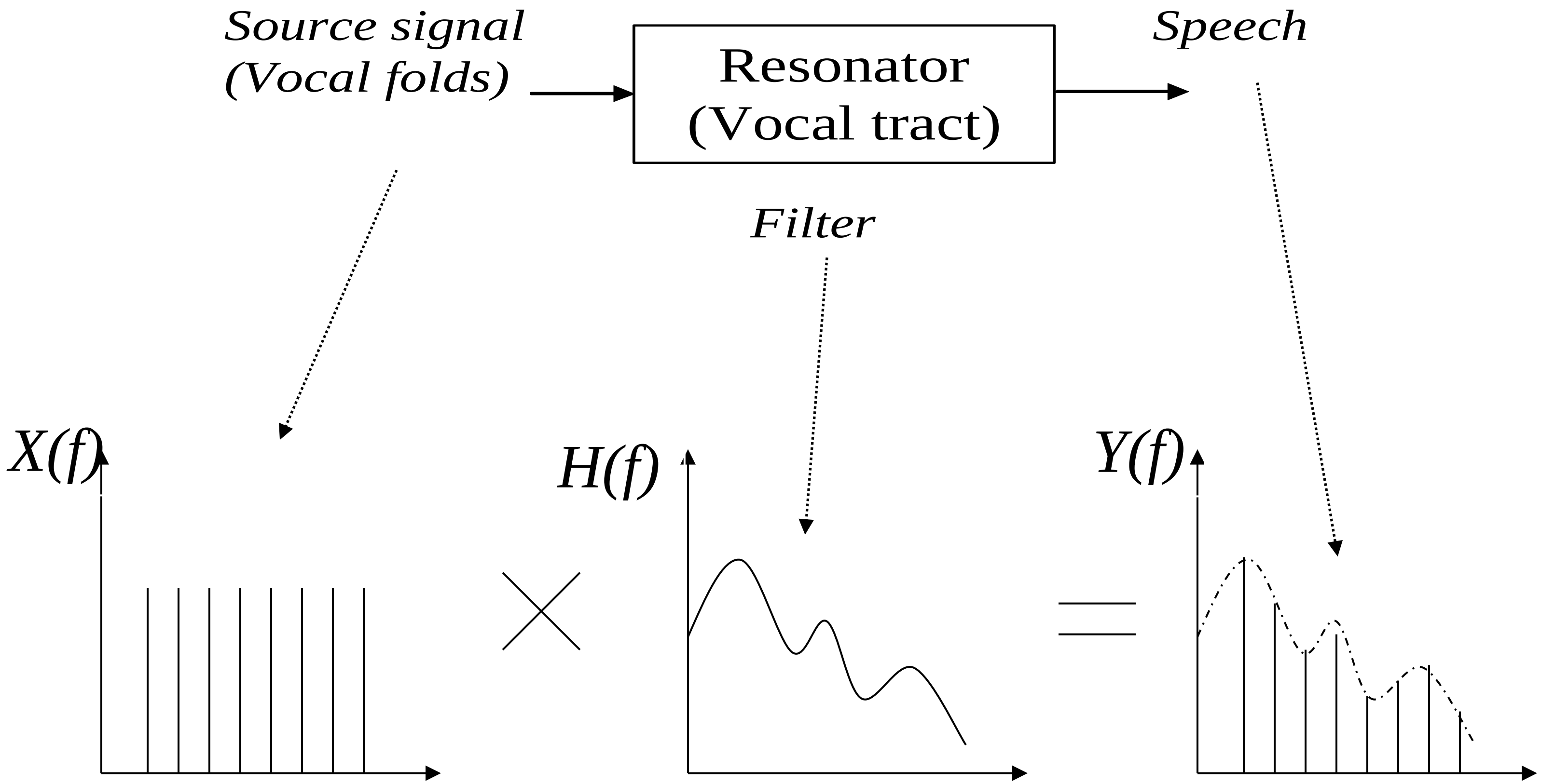
- Large representation
  - » Typically 512 coefs every 10 ms
  - » High dimensionality
- Much detail
  - » Redundant representation
  - » High-level features (pitch, vibrato, timbre) are not highlighted

→ Still a low-level representation, not yet a model



The source-filter model

- Distinction between:
  - » source: excitation → fine spectral structure
  - » filter: resonator → coarse structure



Cepstrum

▶ Principle

- Source-filter model:
- In the frequency domain:

$$\begin{aligned} y(n) &= x(n) * h(n) \\ Y(f) &= X(f)H(f) \\ \log|Y(f)| &= \log|X(f)| + \log|H(f)| \end{aligned}$$

- By inverse DFT: $$c_y(q) = c_x(q) + c_h(q)$$

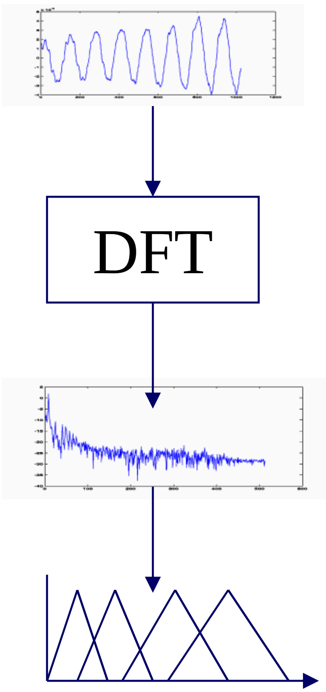
where $c_y(q) = \mathrm{iDFT}[\log|Y(f)|]$: real cepstrum definition

→ deconvolution is thus achieved: filter is separated from excitation

- First few cepstral coefficients
  - » low quefrency: “slow iDFT waves”
  - » represent the filter → spectral envelope
- Next coefficients represent the source → fine spectral structure

Cepstral representations

► MFCC: Mel Frequency Cepstral Coefficients

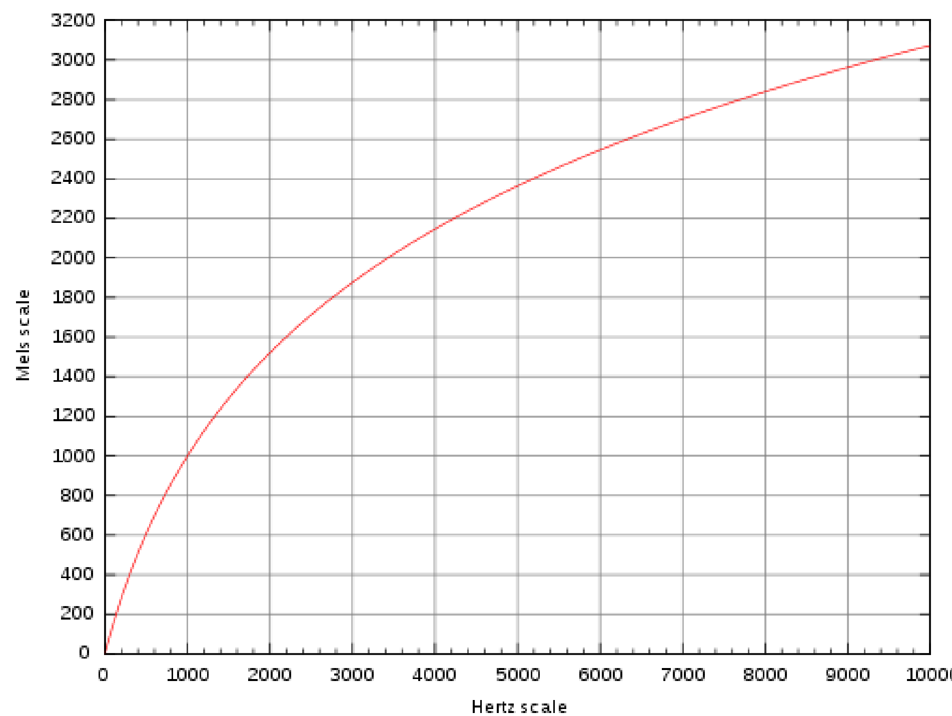


Audio frame

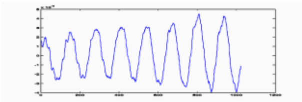
Magnitude spectrum

Triangular filter banc
in Mel scale

Mel scale

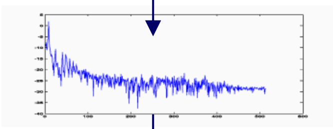


► MFCC: Mel Frequency Cepstral Coefficients

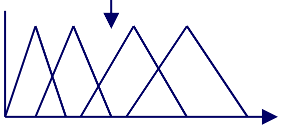


Audio frame

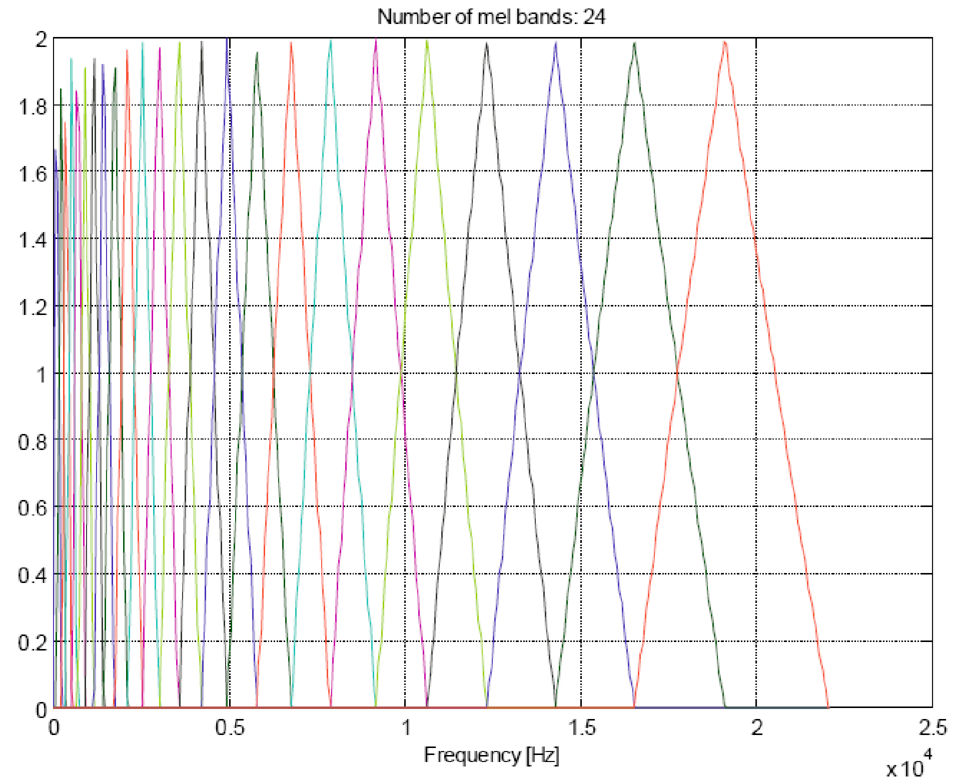
DFT



Magnitude spectrum

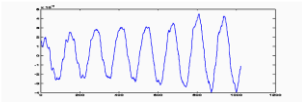


Triangular filter banc
in Mel scale



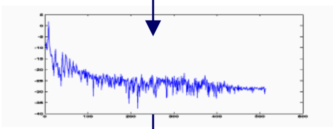
Cepstral representations

► MFCC: Mel Frequency Cepstral Coefficients

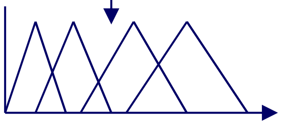


Audio frame

DFT



Magnitude spectrum



Triangular filter banc
in Mel scale

Log → DCT

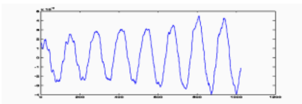
13 first coefs
(in general)

Discrete Cosine Transform:

- nice decorrelation properties (like PCA)
- yields diagonal covariance matrices

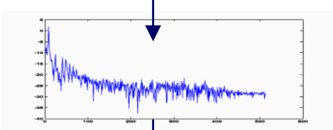
Cepstral representations

► MFCC: Mel Frequency Cepstral Coefficients

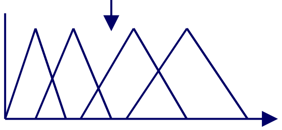


Audio frame

DFT



Magnitude spectrum



Triangular filter banc
in Mel scale

Log

DCT

13 first coefs
(in general)

dt

dt²

39-coefficient
feature vector

First and second derivatives:
speed and acceleration

→ Coarse temporal modelling

About MFCCs

► … very popular!

- In speech applications:
  - » Well justified: source-filter model makes sense
  - » Nice properties from a statistical modelling viewpoint: decorrelation
  - » Effective: state-of-the-art features for speaker and speech tasks
- In general audio classification:
  - » "Source-filter" model does not always hold
  - » Still, MFCCs work well in practice! they are the default choice

Other spectral features: **spectral moments**

- Ordre 1: Centre de Gravité Spectral (centroïde spectral)

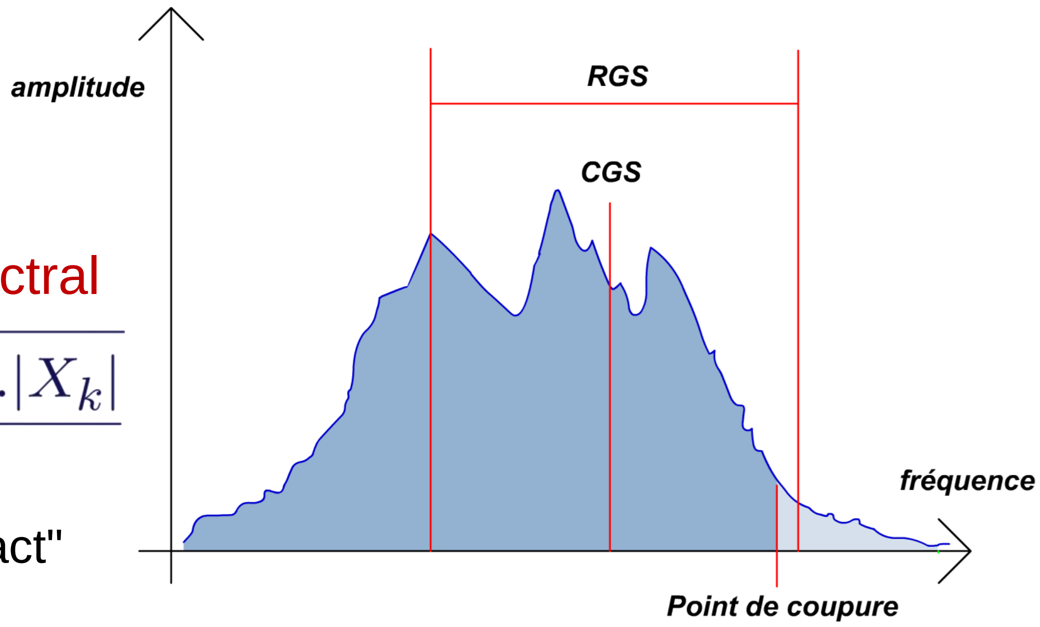
$$CGS = \frac{\sum_{k=1}^{N} k.|X_k|}{\sum_{k=1}^{N} |X_k|}$$

  - CGS élevé: son brillant
  - CGS faible: son chaud, rond

- Ordre 2 : Rayon de Giration Spectral

$$RGS = \sqrt{\frac{\sum_{k=1}^{N} (k - CGS)^2.|X_k|}{\sum_{k=1}^{N} |X_k|}}$$

  - RGS faible, le timbre est "compact"

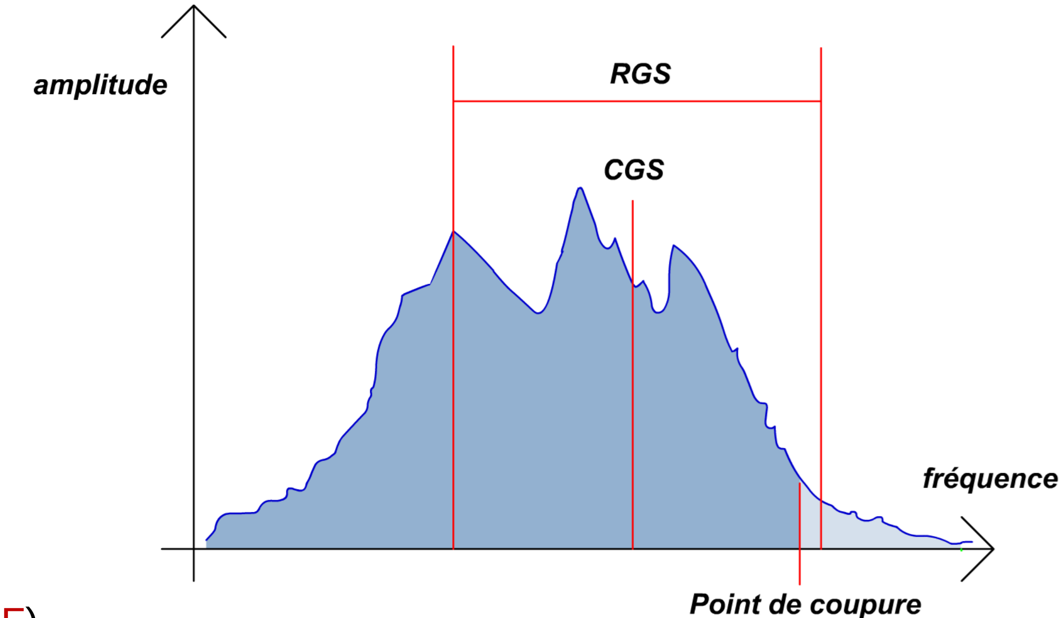


- Ordres 3,4 également utilisés…

Fréquence de coupure

fréquence Fc au dessous de laquelle 85% de la distribution spectrale est concentrée

$$\sum_{k=1}^{Fc} |X_k| = 0.85 \times \sum_{k=1}^{N} |X_k|$$



Platitude spectrale

mesurée par sous-bandes sb (MPEG7 ASF)

$$ASF(sb) = \frac{\left(\prod_{k \in sb} X_k\right)^{\frac{1}{K_{sb}}}}{\frac{1}{K_{sb}} \sum_{k \in sb} X_k}$$

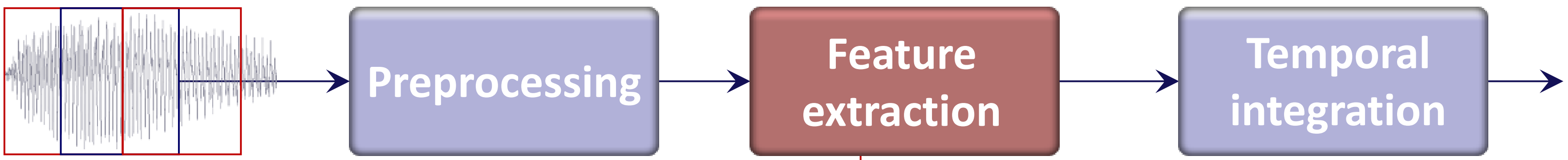
Spectre plat : ASF ↗ , 0 < ASF < 1

Flux spectral (variation temporelle du contenu spectral)

$$Flux = \sum_{k=1}^{N} \left(|X_k(m)| - |X_k(m-1)|\right)^2$$

Classification architecture

▶ Feature extraction process

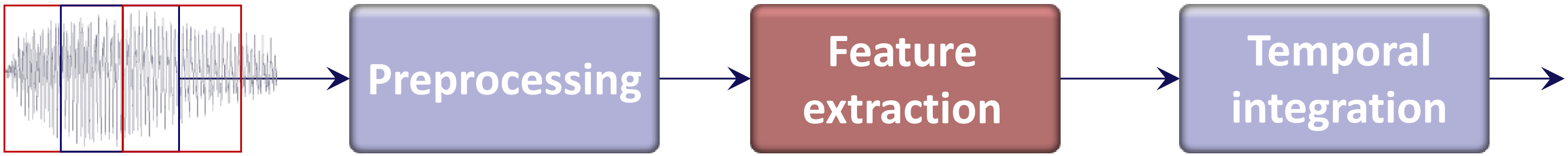


- Cepstral: MFCC, …
- Spectral
- Temporal
- Perceptual

Which features to use?

Classification architecture

▶ Feature extraction process



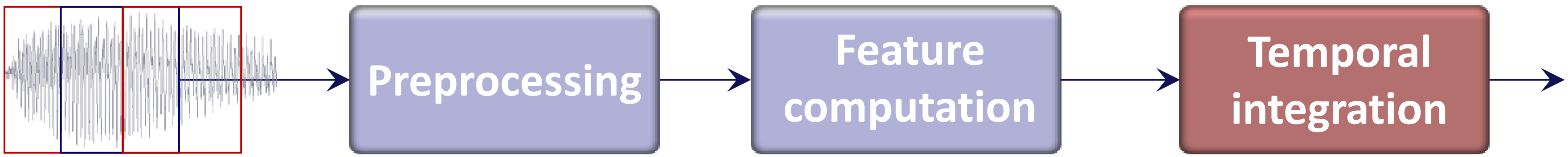
Which features to use for a given task?

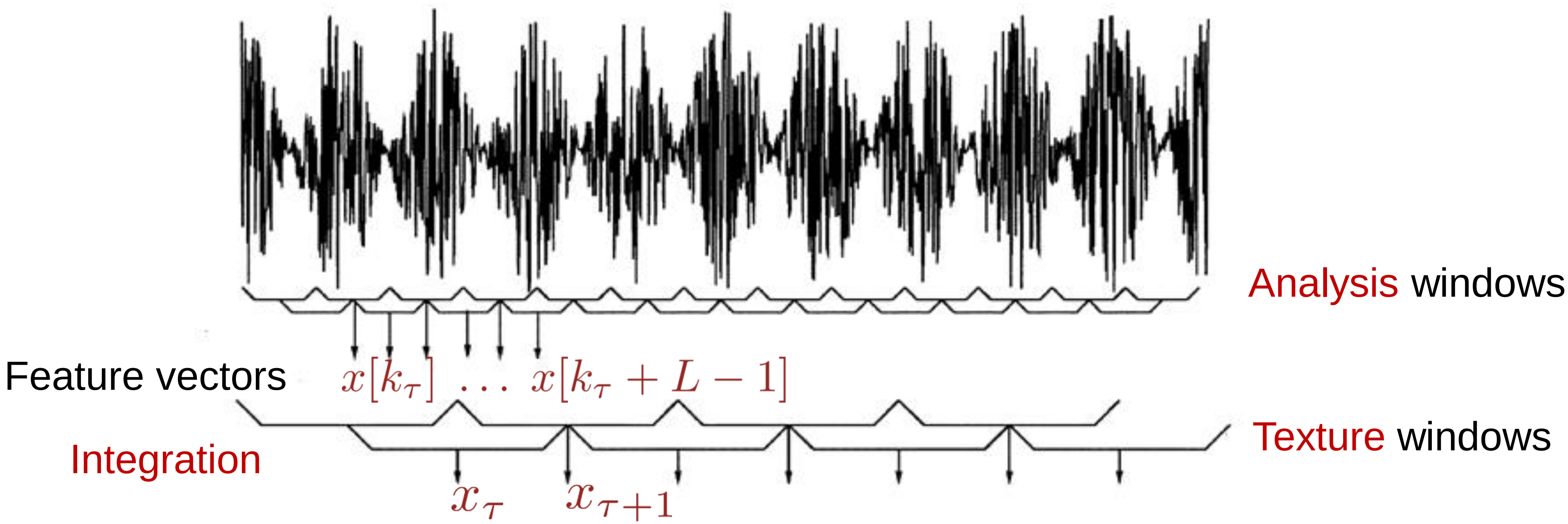
- Use intuition/expert knowledge
- Use automatic **feature selection** algorithms

- Alternatively, use **feature learning**

Classification architecture

► Feature extraction process



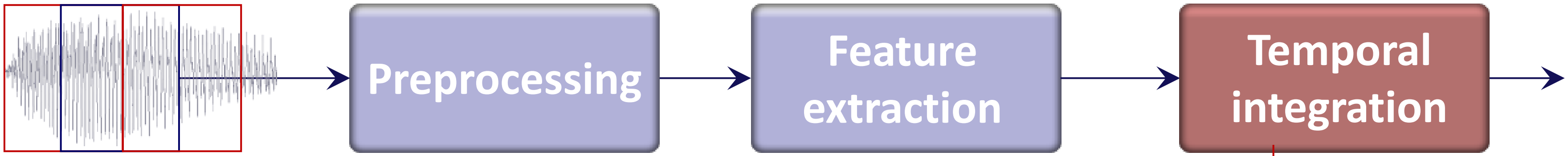


$$x_\tau = g\{x[k_\tau], \ldots, x[k_\tau + L - 1]\}$$

eg. $x_\tau = \mathrm{mean}\{x[k_\tau], \ldots, x[k_\tau + L - 1]\}$

Temporal integration

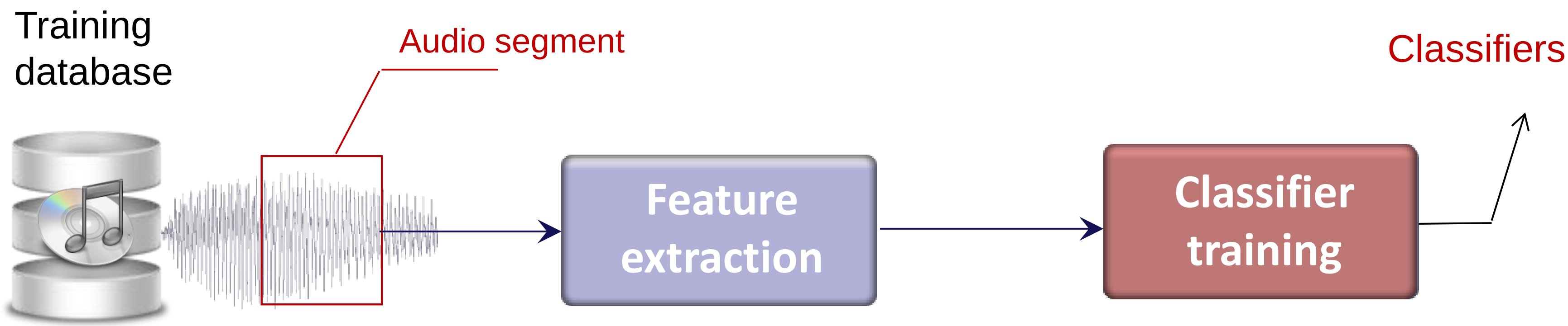
► At the feature level



- smoothing to improve robustness
- synchronise features extracted from different temporal horizons
- capture temporal evolution of features

Classification architecture

▶ Classifier training



Training data: assembled from all available audio instances

$$\boldsymbol{X} = \begin{pmatrix} \mathbf{x}_1^T \\ \vdots \\ \mathbf{x}_i^T \\ \vdots \\ \mathbf{x}_l^T \end{pmatrix} = \begin{pmatrix} x_{1,1} & \dots & x_{1,j} & \dots & x_{1,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i,1} & \dots & x_{i,j} & \dots & x_{i,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{l,1} & \dots & x_{l,j} & \dots & x_{l,d} \end{pmatrix}, \quad \boldsymbol{y} = \begin{pmatrix} y_1 \\ \vdots \\ y_i \\ \vdots \\ y_l \end{pmatrix}$$

Training examples

Class labels

Unknown in non-supervised problems

References

- ***Books***

  - (Rabiner, 93) L. R. Rabiner, *Fundamentals of Speech Processing*. PTR Prentice-Hall, Inc., 1993.
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