Analyse, transformation et reconnaissance des signaux sonores

« Analysis, transformation and recognition of audio signals »

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A research done in collaboration….

- **An immense thanks to all ….**

Analysis, transformation, recognition ... of audio signals

An audio signal

$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots \mathbf{x}_N]$$

ANALYSIS → **Signal representations**

Models

TRANSFORMATION → **Denoise, Separate, Time-shift,...**

RECOGNITION → **Classify, Identify,…**

« Hello, .. »

Text or symbols

« Hello, .. »

SYNTHESIS →

Audio signal

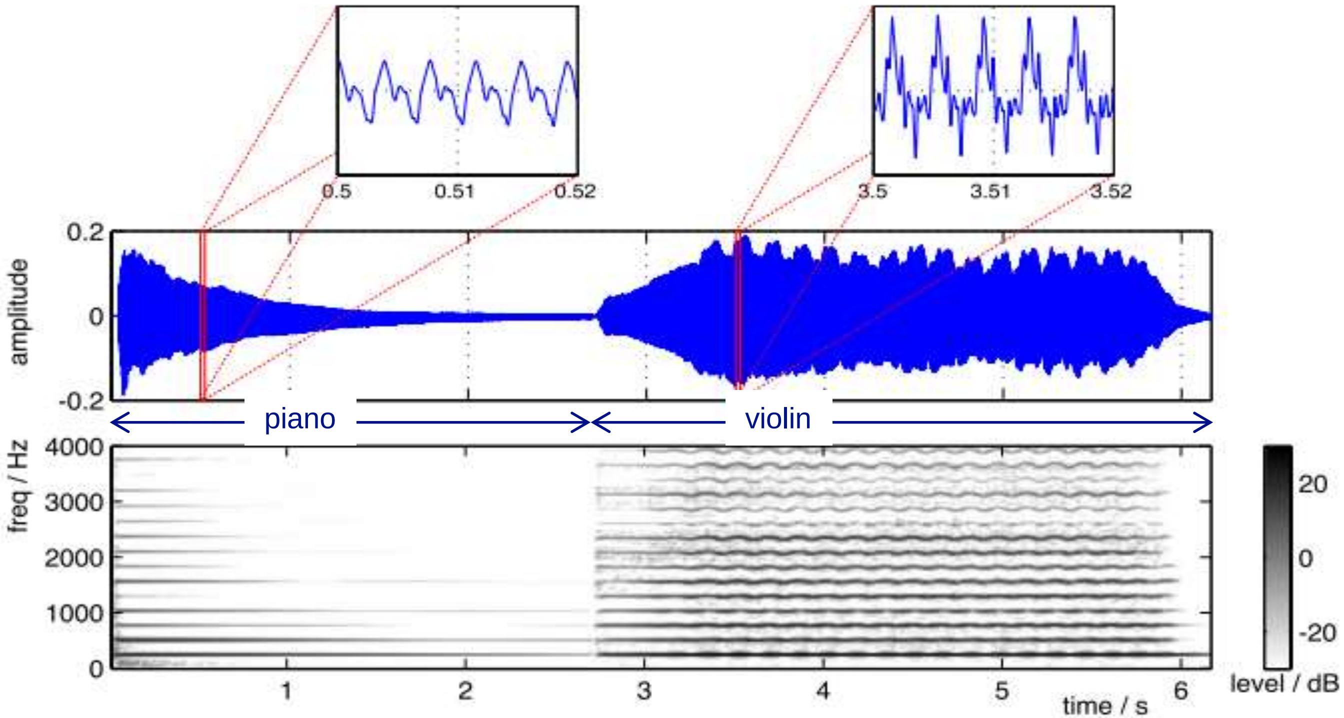
Analysis: Time-frequency representations

- **Example with a music signal :** note C (Do), with fundamental frequency of 262 Hz, played on a piano and then on a violin.

Time-domain signal

Spectrogram

(Short-term Fourier Transform)



Images from M. Mueller, D. Ellis, A. Klapuri, G. Richard « Signal Processing for Music Analysis, IEEE Trans. On Selected topics of Signal Processing, oct. 2011

Some generic signal models

- **Sum of sinusoïds + noise**

$$x(n) = \sum_{i=1}^{I} A_i.sin(2\pi\nu_i n + \phi_i) + b(n)$$

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$$x(n) = \sum_{i=1}^{I} A_i(n).sin(2\pi\nu_i n + \phi_i) + m(n).b(n)$$

- Modulated noise models for speech synthesis and modification [2]
- Damped sinusoids models for parametric audio coding [3]

[2] G. Richard, C. d'Alessandro, "Analysis/synthesis and modification of the speech aperiodic component", Speech Communication, Vol. 19, Issue 3, September 1996, Pages 221–244

[3] O.Derrien, R. Badeau, G. Richard, "A Parametric Audio Coding with Exponentially Damped Sinusoids, IEEE Trans. on Audio, Speech and Language Processing, Vol 21, N° 7, July 2013.

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  - Modulated noise models for speech synthesis and modification [2]
  - Damped sinusoids models for parametric audio coding [3]
  - Adaptive Signal subspace tracking [4]
  - Frequency estimation in Amplitude/Frequency modulated models [5]

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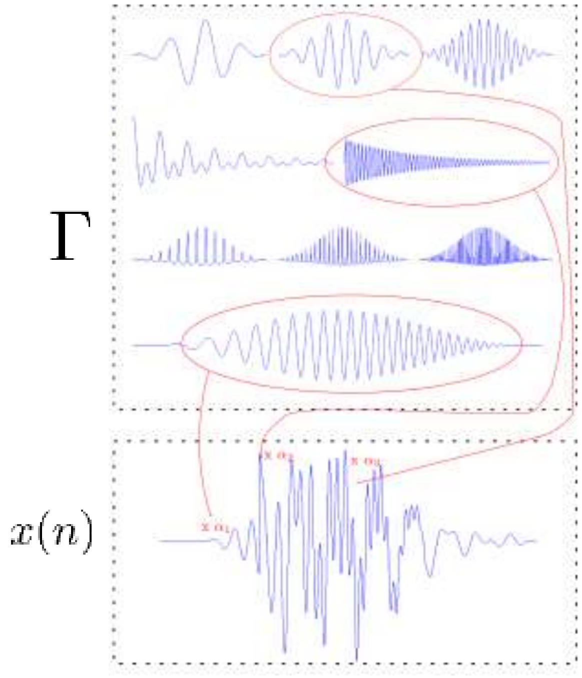
[4] R. Badeau, B. David and G. Richard, “Fast Approximated Power Iteration Subspace Tracking”, IEEE Trans. on Signal Processing, Vol. 53, Issue 8, Part 1, Aug. 2005 Page(s):2931 – 2941
[5] M. Betser, P. Collen, G. Richard and B. David « Estimation of frequency for AM/FM models using the phase vocoder framework», IEEE Trans. on Signal Processing, Vol. 56, N°. 2, February 2008., Page(s):505 - 517.

More specific models …

- **Signal « decomposition » methods**

$$x(n) = \sum_{\lambda \in \Gamma} \alpha_\lambda h_\lambda(n)$$

➡ The signal is a linear combination of atoms $h_\lambda(n)$ taken in a dictionary Γ



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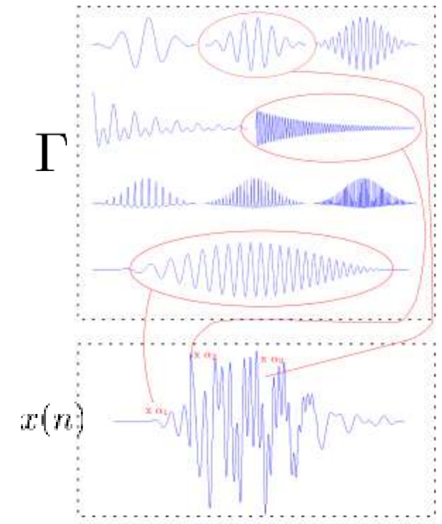
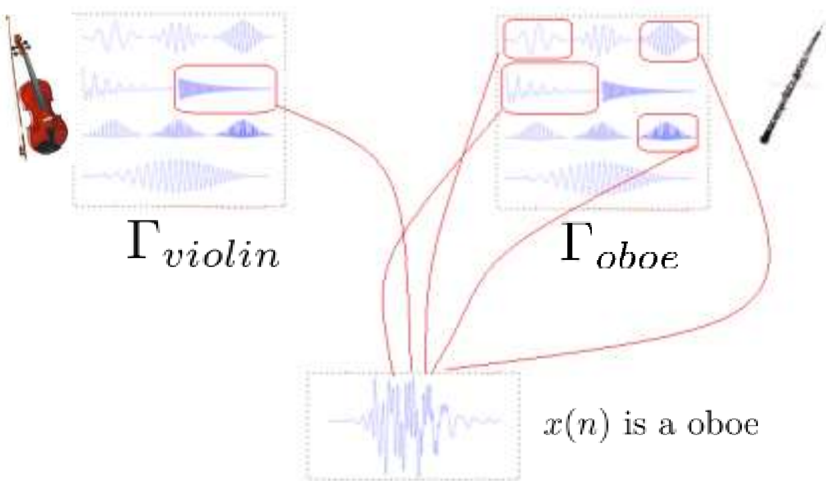


➡ With « informed » atoms :

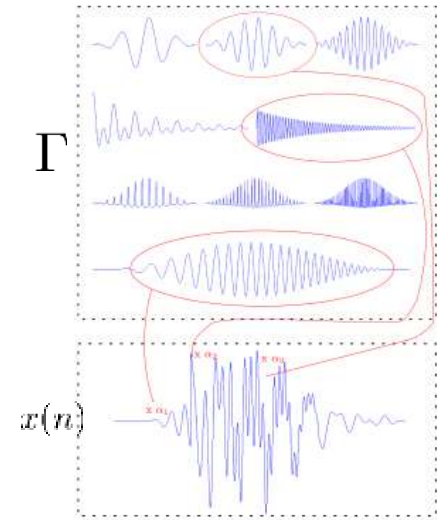
– *Source identification and separation* [6]



[6] P. Leveau, E. Vincent, G. Richard and L. Daudet, « Instrument-Specific Harmonic Atoms for Mid-Level Musical Audio Representation » IEEE Trans. on ASLP, Volume 16, N°1 Jan. 2008 Page(s):116 – 128

More specific models …

■ Signal « decomposition » methods



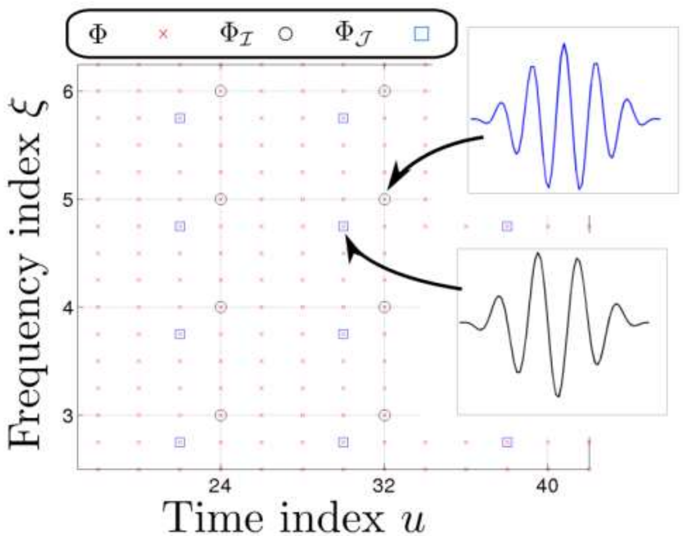
$$x(n) = \sum_{\lambda \in \Gamma} \alpha_\lambda h_\lambda(n)$$

➡ With multi-resolution time-frequency atoms :

– *Music signal compression* [7]

With sequence of random dictionaries :

– *Efficiency, denoising (audio, EEG signals)* [8]



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[7] E. Ravelli, G. Richard, L. Daudet, Union of MDCT bases for audio coding, IEEE Trans. on Audio, Speech and Language Processing, Vol. 16, Issue 8, pp 1361-1372, Nov. 2008.

[8] M. Moussallam, L. Daudet, G. Richard, "Matching pursuits with random sequential subdictionaries", Signal Processing, 2012.

More specific models …

- **Non-negative Matrix factorization (NMF)[9]**

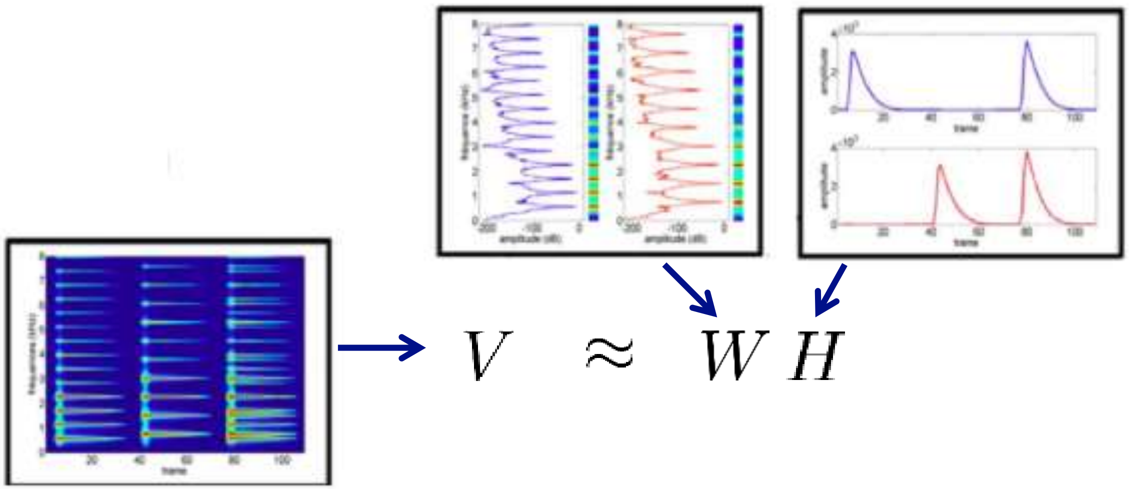
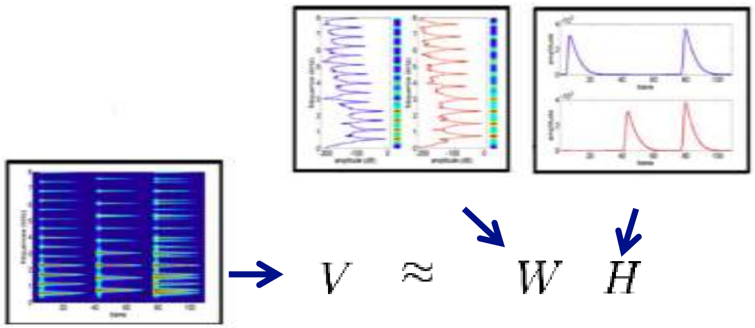


Figure from R. Hennequin

[9] D. Lee, H., Seung, Learning the parts of objects by non-negative matrix factorization. *Nature* **401,** 788–791 (1999).

More specific models …

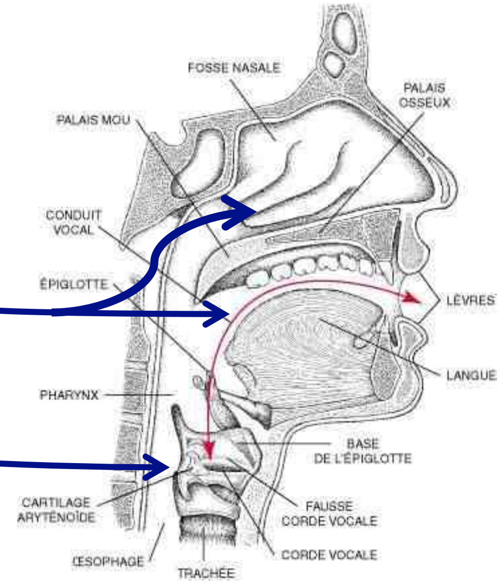
- **Non-negative Matrix factorization (NMF)[9]**
  - Underdetermined source separation



  - Un example on singing voice separation

$$\underbrace{\mathbf{X}}_{\text{Recording}} = \underbrace{\mathbf{V}}_{\text{Voice}} + \underbrace{(\mathbf{W}^M\mathbf{H}^M)}_{\text{music}},$$

$$\underbrace{\mathbf{V}}_{\text{Voice}} = \underbrace{\mathbf{S}}_{\text{source}} \bullet \underbrace{\mathbf{F}}_{\text{filter}}$$



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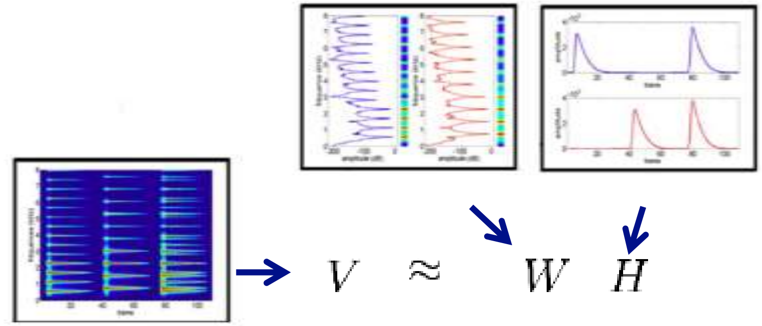

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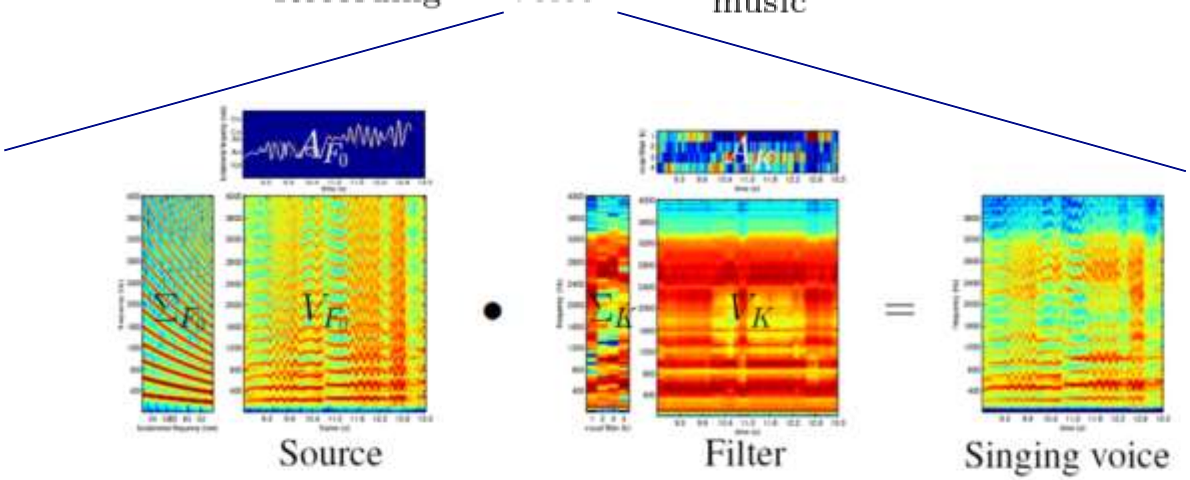

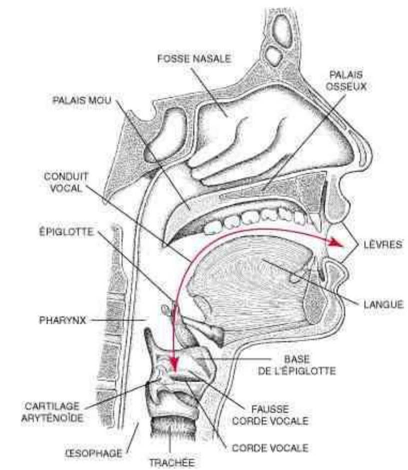

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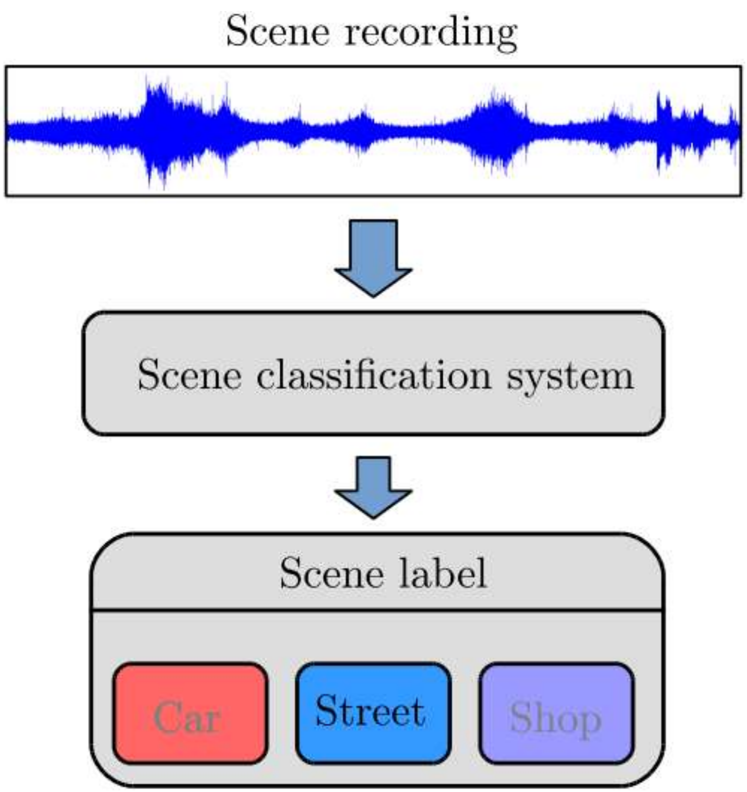
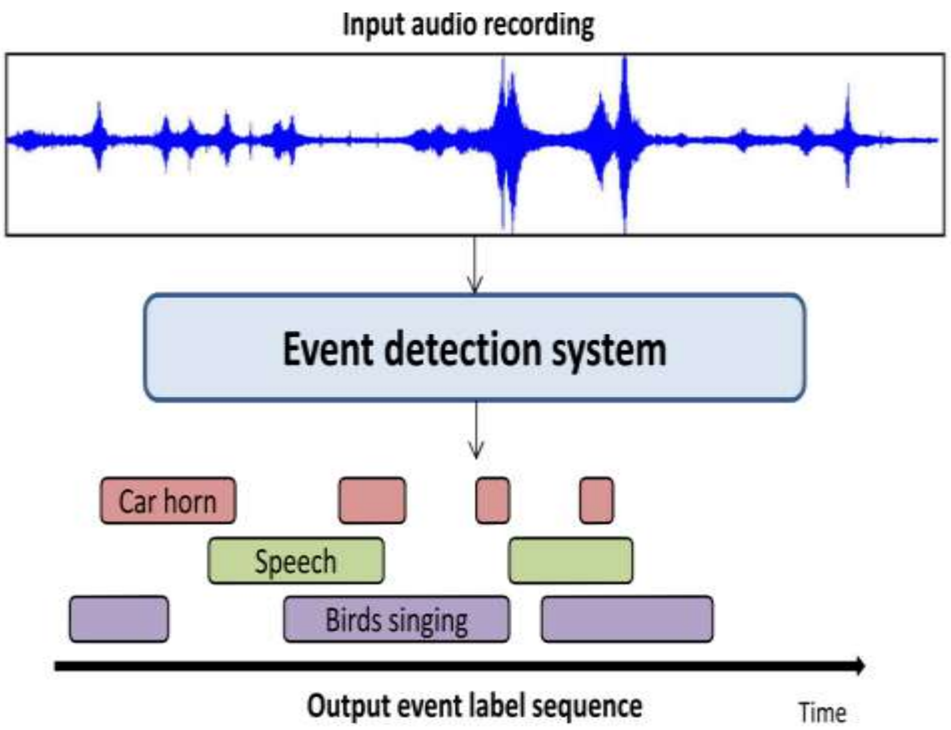
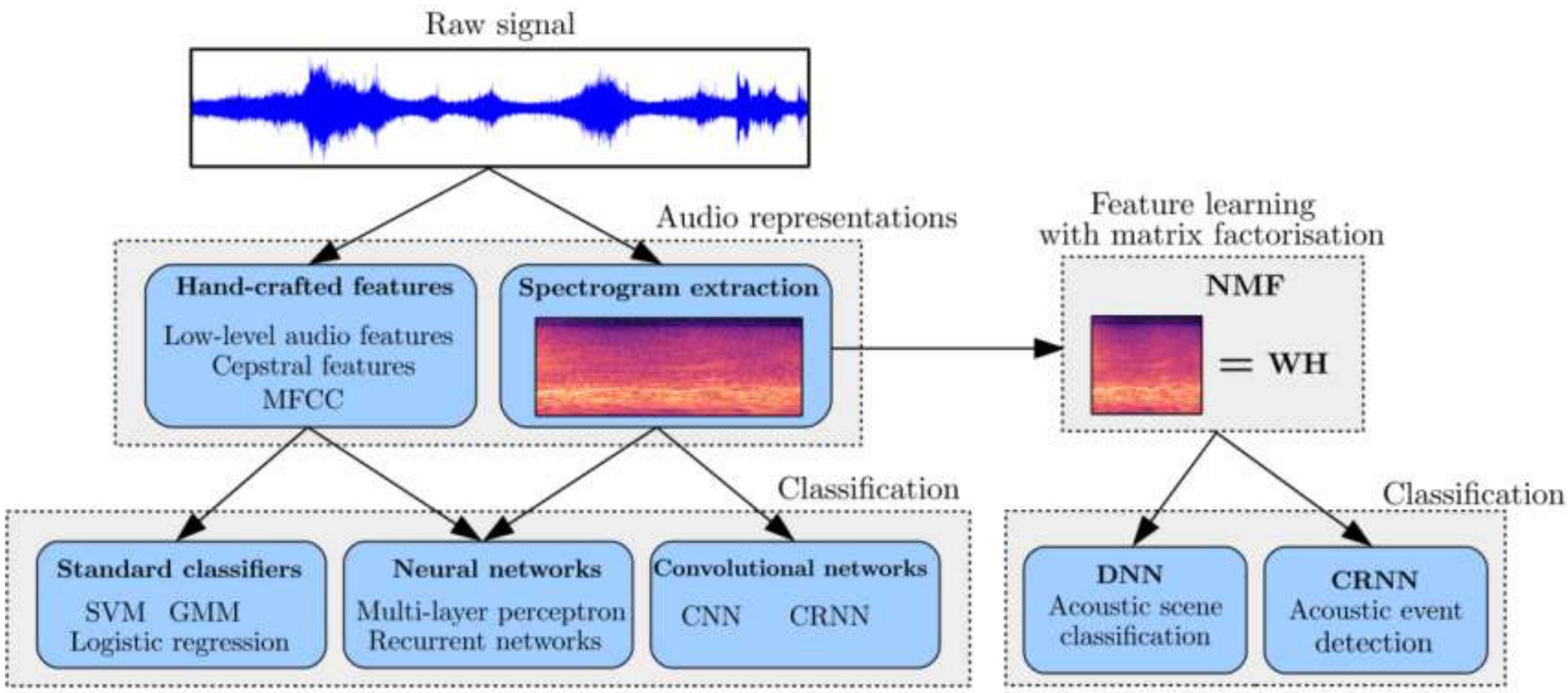
To recognize

Sound events and acoustic scene recognition





Associating signal models and deep learning



[11] V. Bisot, R. Serizel, S. Essid, G. Richard, "Feature Learning with Matrix Factorization Applied to Acoustic Scene Classification", IEEE/ACM Transactions on Audio, Speech, and Language Processing, (2017), Special Issue on Sound Scene and Event Analysis.

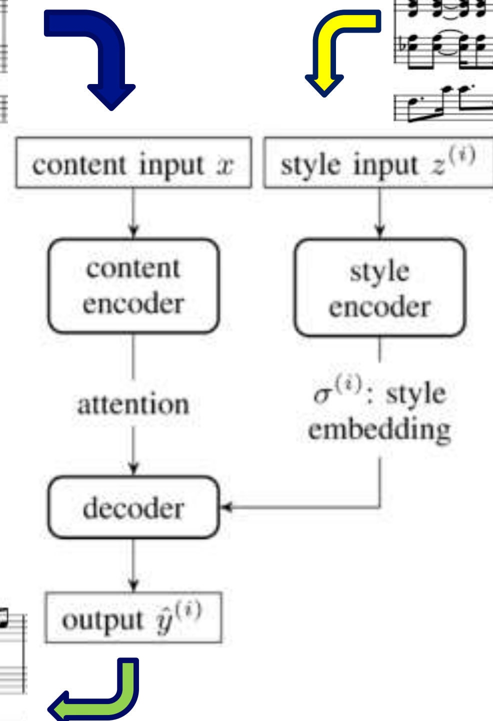
Recognize, Transform, Synthetize …

Symbolic music style transfer

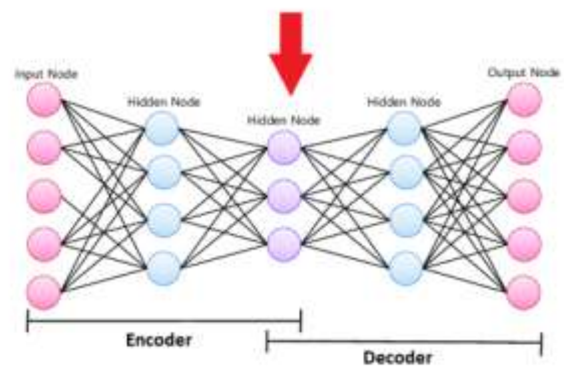
- … Or playing a given music file in the style of another music excerpt.

Swing jazz

Samba



Signal representation



[13] Ondrej Cifka, Umut Simsekli, Gaël Richard, "Groove2Groove: One-Shot Music Style Transfer with Supervision from Synthetic Data", IEEE/ACM Transactions on Audio, Speech, and Language Processing, (preprint) accepted for publication, 2020

Sound examples at : *https://groove2groove.telecom-paris.fr*

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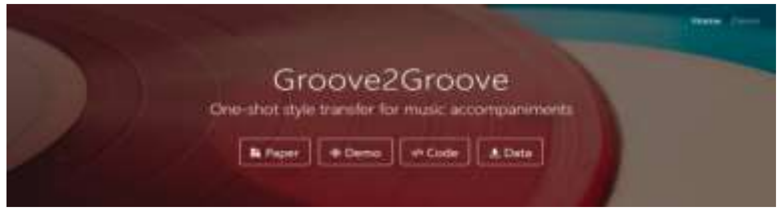
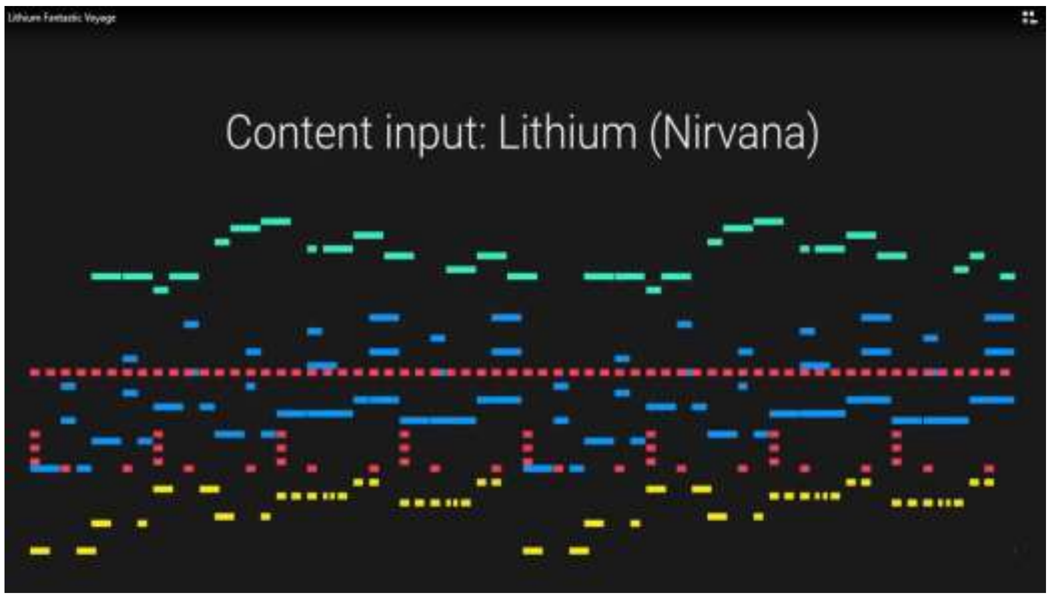
- … Or playing a given music file in the style of another music excerpt.

A short demo





[13] Ondrej Cifka, Umut Simsekli, Gaël Richard, "Groove2Groove: One-Shot Music Style Transfer with Supervision from Synthetic Data", IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 28, 2020

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Conclusion

- **… towards hybrid models**

  - Models are **parameter efficient** and **interpretable**,
  - Deep Neural networks are **very powerful** but needs **huge amount of data** and **computing power**, and are not always easily interpretable.

  - Hybrid models: promise for more explanability, frugality and efficiency