

# "MACHINE LISTENING: AI FOR SOUNDS AND MUSIC"

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### A well established domain for speech ...



### Goal: to extract « information » from the audio signal

Audio Sound capture: Localisation, Dereverberation, Denoising, ...

Audio Scene recognition: sound recorded in streets, in subway station, in office, ....)

Audio Event recognition: Speech, Music, Car noises, birds, ...

Bioacoustics: Wildlife monitoring, biodiversity, species id...

Audio Source separation

Demixing music, Singing voice extraction, source localisation,

Music recognition (or Audio ID): identifying the music recording

Music Information retrieval

Music transcription, Music similarity, Music genre recognition, Musical instrument recognition, Music recommendation, Autotagging,



Music Emotion recognition: Sad vs happy vs dance music, ....

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Music streaming, music recommendation Vocal separation, music separation

**Bioacoustics** 



Music education



Music Identification, Audio Fringerprint



Karaoke, speech to rap conversion



Sound recognition,

smarthomes, smart hearables



Stratégie de marque musicale, Supervision musicale (pub.; films)



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#### SOURCE SEPARATION







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#### SOURCE SEPARATION FOR REMIXING

Use case of the ANR project

**3DISON** 

EDISON 3D

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- Time-domain mixture representation:  $x_i(t) = \sum_{j=1}^{J} [a_{ij} \star s_j](t)$
- Time-frequency source representation:  $s_j(t) = \mathcal{T}^{-1}(\{s_{j,fn}\}_{f,n})$







### **Non Negative Matrix factorization**







# **SOURCE SEPARATION -** S. LEGLAIVE (EXAMPLE REMIXED BY RADIO FRANCE)

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S. Leglaive, R. Badeau, G. Richard, "Multichannel Audio Source Separation with Probabilistic Reverberation Priors", IEEE/ACM Transactions on Audio, Speech, and Language Processing, Vol. 24, no. 12, December 2016 Simon Leglaive, Roland Badeau, Gaël Richard, Separating Time-Frequency Sources from Time-Domain Convolutive Mixtures Using Non-negative Matrix Factorization. WASPAA, Oct. 2017 New Paltz, US.



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# Audio ID = find high-level metadata from a music recording



### **Challenges:**

Efficiency in adverse conditions (distorsion, noises,..) Scale to "Big data" (bases > millions of titles) Rapidity / Real time

### **Product example :**







# **REAL-TIME AUDIO IDENTIFICATION** *(FENET & AL.)*



## **Audio recordings recognition**

- Identical
- Approximate (live vs studio)
- Real time demonstrator
- For music recommendation, second screen applications, ...



Sébastien Fenet, Yves Grenier, Gaël Richard: An Extended Audio Fingerprint Method with Capabilities for Similar Music Detection. ISMIR 2013: 569-574

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#### SOUND EVENTS AND ACOUSTIC SCENE RECOGNITION







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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. MIN: Telecom



From time-frequency representations to dictionary learning



Data matrix  $\mathbf{V} \in \mathbb{R}^{F \times ML}$ 





Nonnegative matrix factorization

 $\min_{\mathbf{W},\mathbf{H}\geq 0} D(\mathbf{V}|\mathbf{W}\mathbf{H}) \text{ with } \mathbf{W} \in \mathbb{R}_{+}^{F imes K} \text{ and } \mathbf{H} \in \mathbb{R}_{+}^{K imes N}$ 

# Dictionary learning with NMF







### Nonnegative matrix factorization

$$\min_{\mathbf{W},\mathbf{H}\geq 0} D(\mathbf{V}|\mathbf{W}\mathbf{H}) \text{ with } \mathbf{W} \in \mathbb{R}_{+}^{F imes K} \text{ and } \mathbf{H} \in \mathbb{R}_{+}^{K imes N}$$

## Feature extraction $\rightarrow$ project on learned dictionary







#### **EXAMPLE WITH DNN: ACOUSTIC SCENE RECOGNITION**



V. Bisot & al., "Feature Learning with Matrix Factorization Applied to Acoustic Scene Classification", IEEE/ACM Transactions on Audio, Speech, and Language Processing, (2017),

V. Bisot & al., Leveraging deep neural networks with nonnegative representations for improved environmental sound classification IEEE International Workshop on Machine Learning for Signal Processing MLSP, Sep 2017, Tol Institut Mines-Télécom

# TYPICAL PERFORMANCES OF ACOUSTIC SCENE RECOGNITION (CHALLENGE DCASE 2016)



A Mesaros & al. Detection and Classification of Acoustic Scenes and Events: Outcome of the DCASE 2016 challenge IEEE/ACM Transactions on Audio, Speech, and Language Processing 26 (2), 379-393

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#### **MUSIC INFORMATION RETRIEVAL**



### **Major topics:**

- Music transcription (Multiple F0 estimation, Beat/Downbeat detection, instrument classification, ...),
- Music recommendation
- Source separation,
- Multimodal music processing





Cue	Examples	Input
Harmony	Chord change, Cadence	
Melody	Melodic pattern, pivot notes	
Timbre	Section change, new instrument	
Rhythm	Bar-length rhythm patterns	Mututu Mututu
Bass content	Bass, Double bass and kick drum highlight downbeats	



# MIR: AN EXAMPLE WITH DOWNBEAT ESTIMATION (DURAND & AL. 2017)



S Durand & al., "Robust Downbeat Tracking Using an Ensemble of Convolutional Networks", IEEE/ACM Transactions on Audio, Speech, and Language Processing, Vol 25, N°1, 2017

## **Examples at the output of each network**

https://simondurand.github.io/dnn\_audio.html

## Other audio example











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