



Ecole doctorale  
Terre Univers  
Environnement



Data Institute  
Univ. Grenoble Alpes



# Automatic classification of natural signals for environmental monitoring

PhD Defense, by Marielle Malfante

- Supervision -

Jérôme Mars, Mauro Dalla Mura

- Funding -

50% DGA - 50% OSUG@2020

# Volcanoes Monitoring

WHY?

- 1500 active volcanoes, 29.000.000 people < 10km of volcanoes, 50 to 60 eruptions / year,
- Societal / Economical impact,
- Scientific research.

HOW?

- Deformation, visual indicators, chemical composition, **seismicity**, etc,
- **Multimodal** problem,
- **Big Data.**



Flow of seismic  
data to be  
analyzed  
 $f_s = 50\text{Hz}$

# Seas & Oceans Monitoring

WHY?

- 70% of Earth covered by seas, >90% of Earth biomass underwater,
- Scientific research (Earth's **big unknown**),
- Focus on coastal areas (depth < 300m) : resources (energy, fishery), submarines, etc.

HOW?

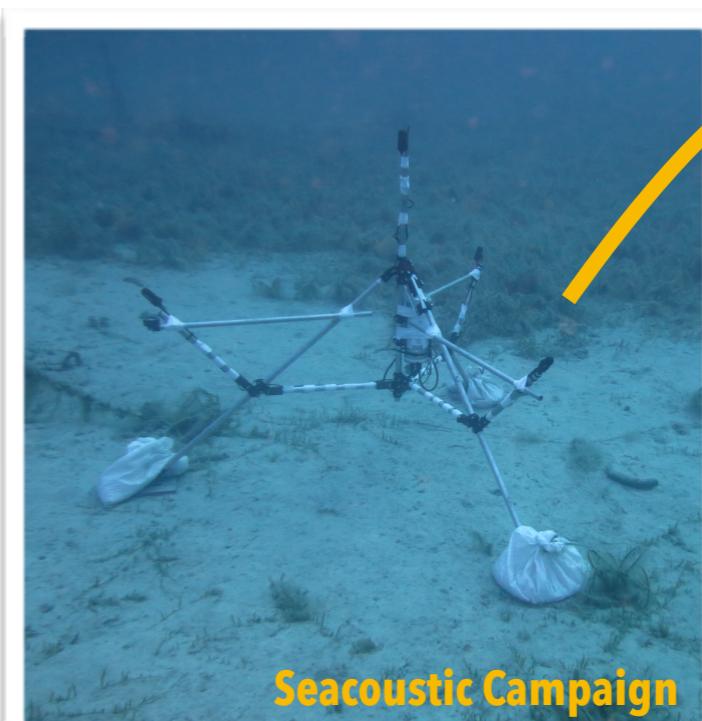
- **Data gathering campaigns**: drifting gliders, boats, specific sensors, etc,
- Multimodal problem: pressure, temperature, salinity, **acoustic (passive or active)** etc.



Flip boat



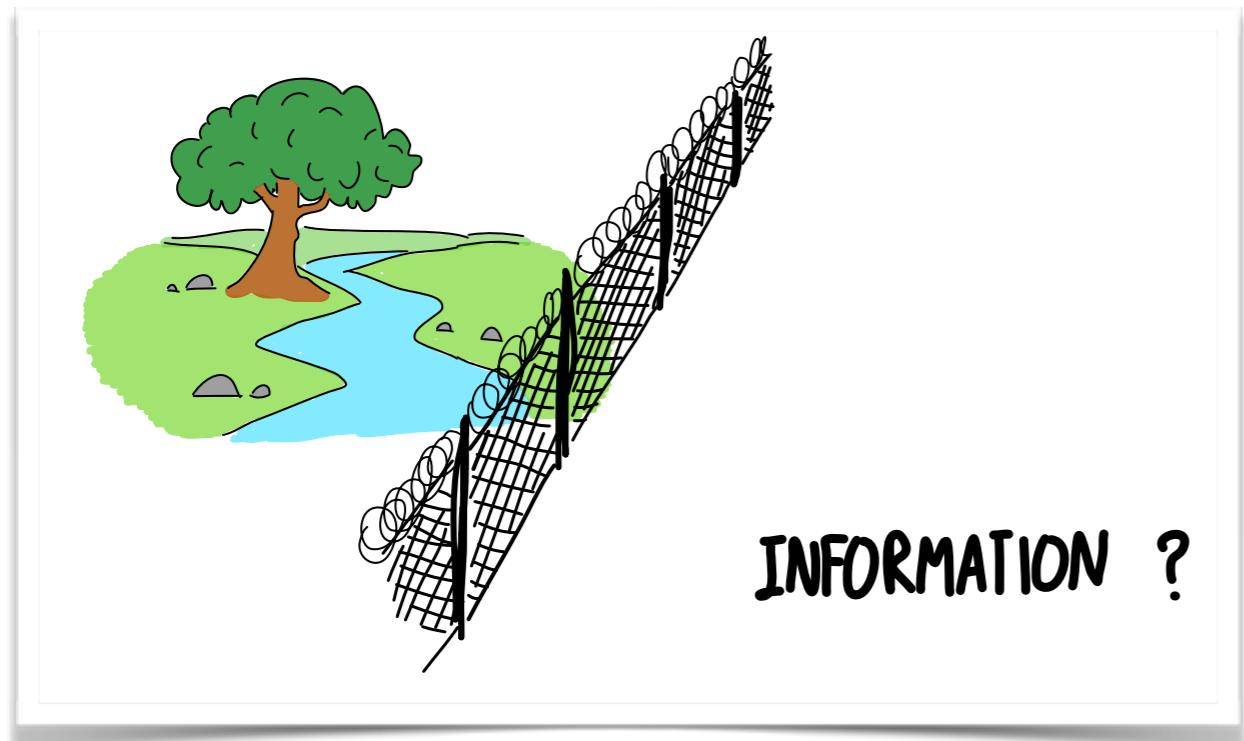
Fastwave seaglider



Seacoustic Campaign

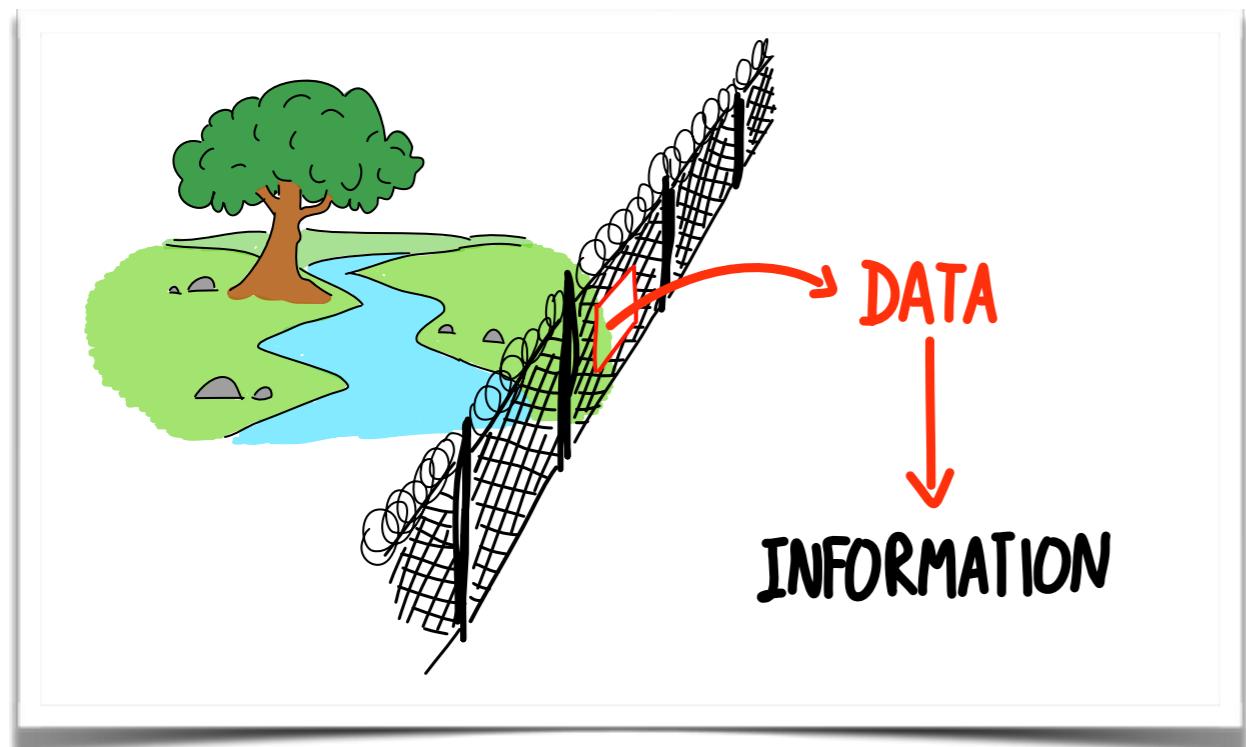
Days of acoustic signals to be analyzed  
 $f_s = 156\text{kHz}$

# 2 topics, 1 modelization

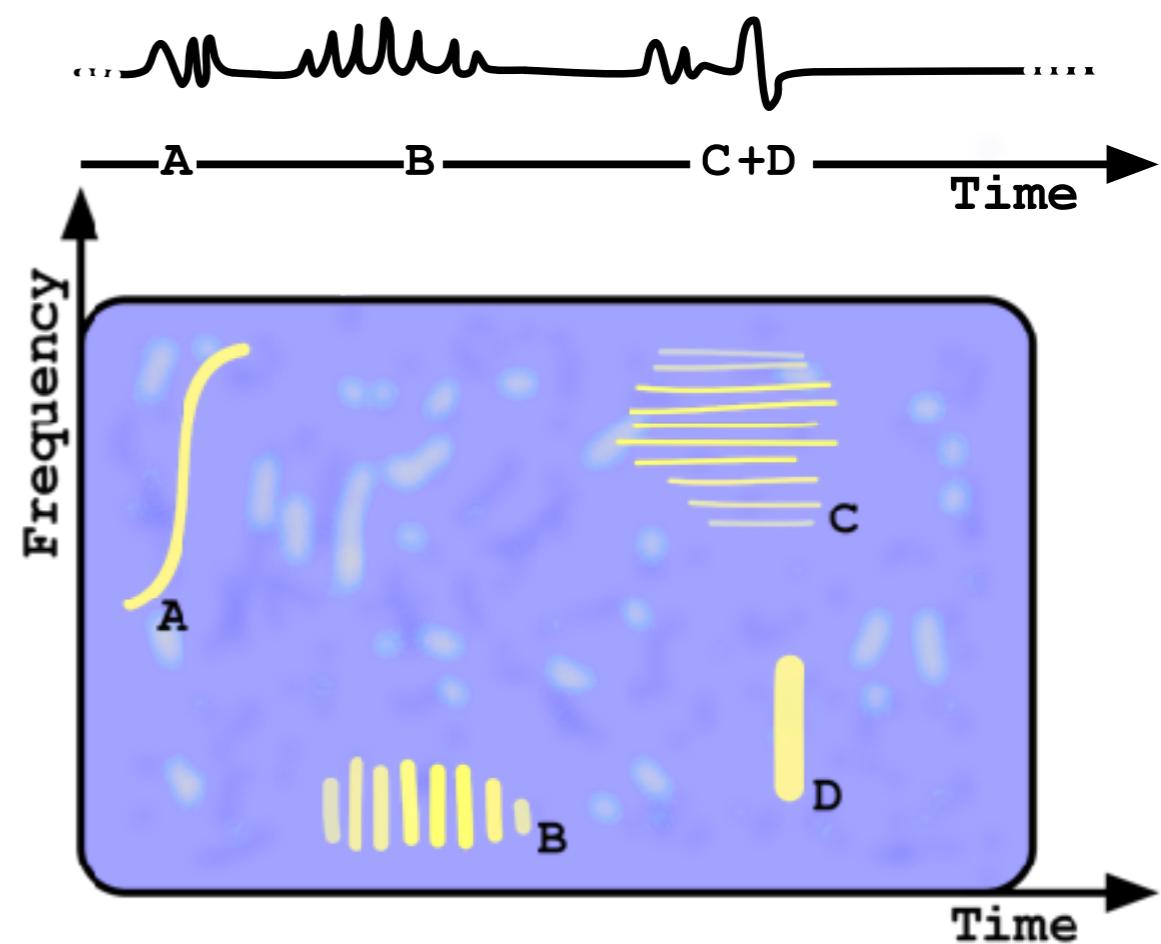


# 2 topics, 1 modelization

DATA?

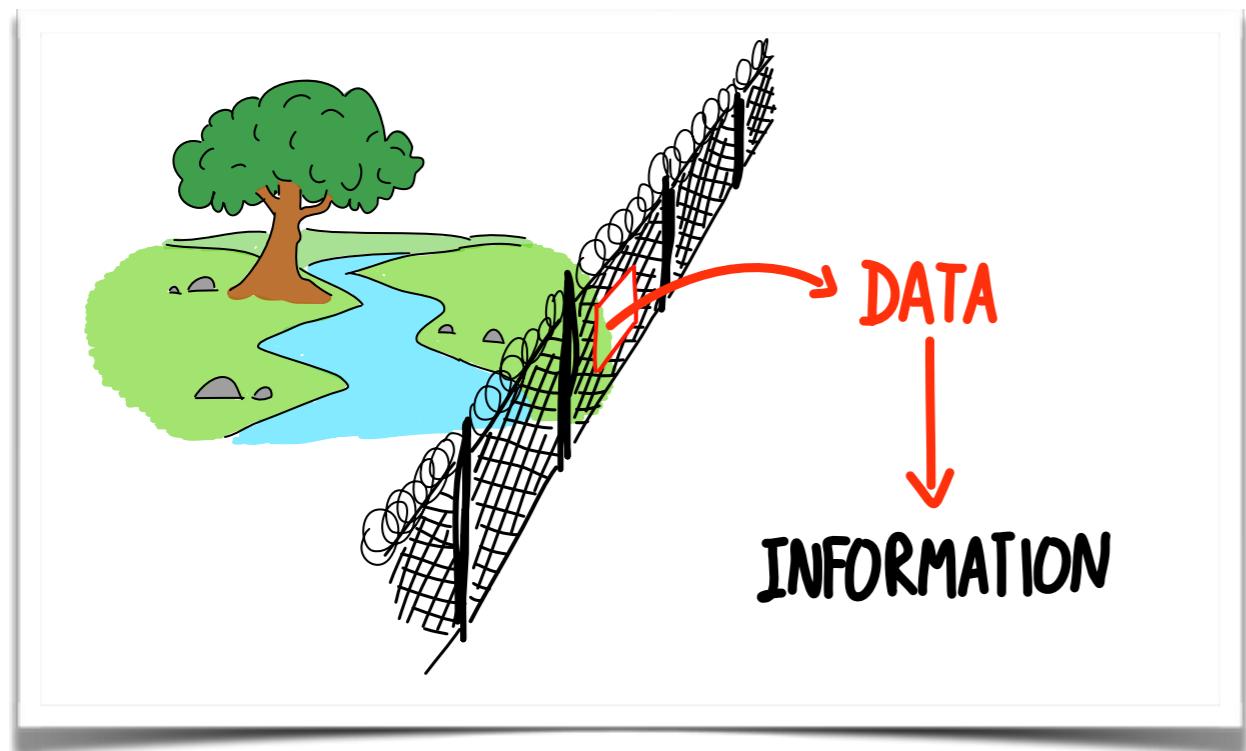


- Recording = 'Continuous' signal  $[w_k]_{k=0}^{n_t}$



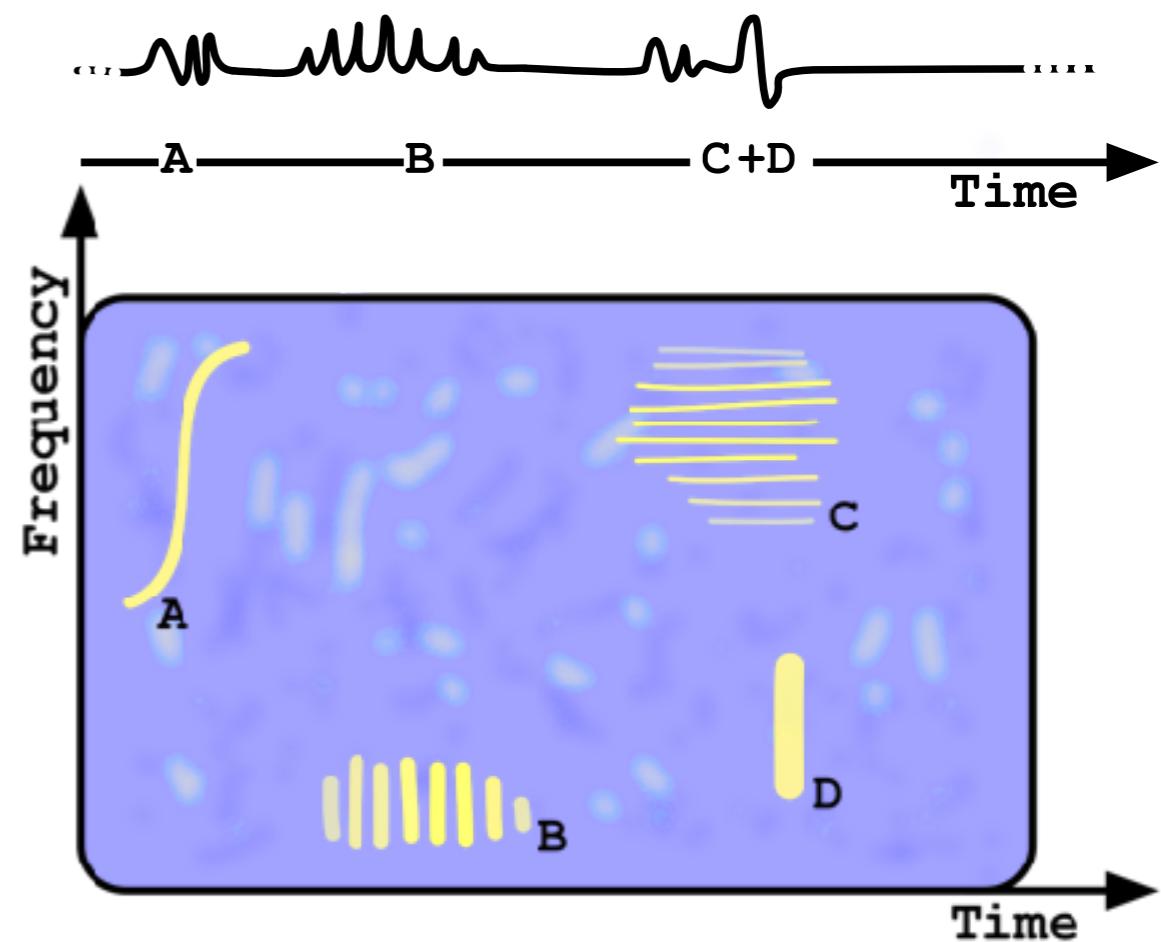
- Amount of data → Automatic methods

# 2 topics, 1 modelization



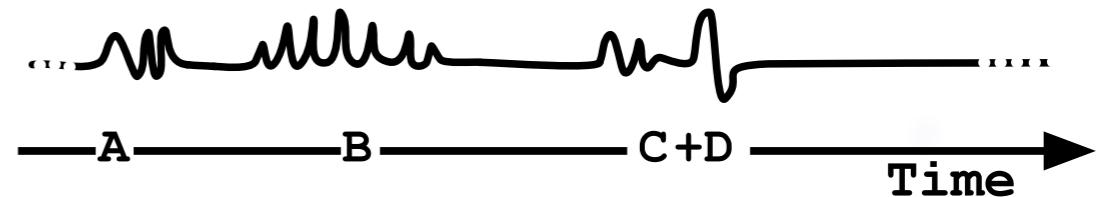
Environment	Volcanoes	Underwater areas
Wave	Seismic	Acoustic
$f_s$	50Hz	156kHz
Time scale	From seconds to weeks	From milliseconds to a few seconds

- Recording = 'Continuous' signal  $[w_k]_{k=0}^{n_t}$



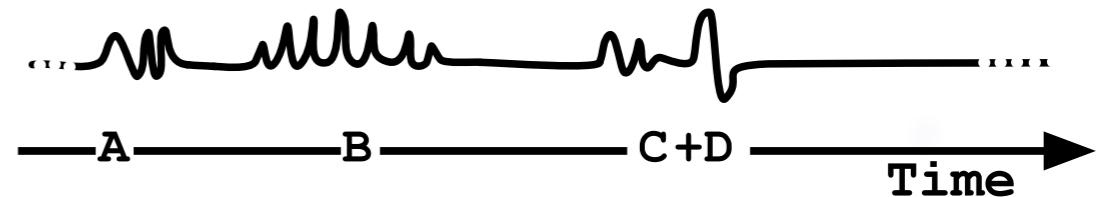
- Amount of data → Automatic methods

# Issue & Contributions



## HOW TO AUTOMATICALLY ANALYZE ENVIRONMENTAL SIGNALS?

# Issue & Contributions



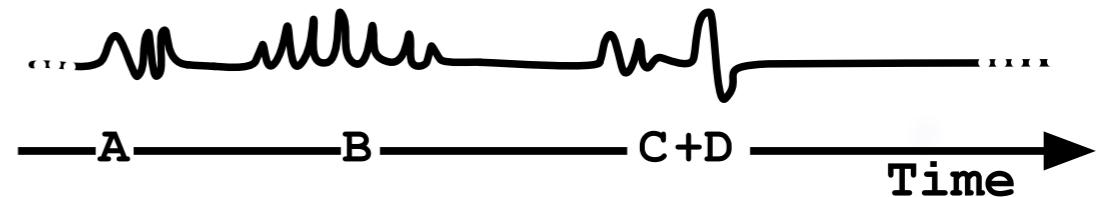
## HOW TO AUTOMATICALLY ANALYZE ENVIRONMENTAL SIGNALS?

1

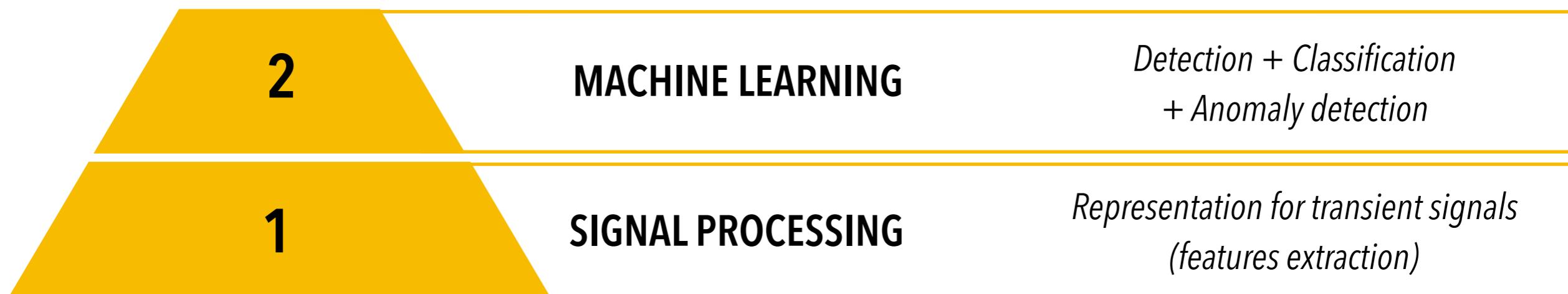
SIGNAL PROCESSING

*Representation for transient signals  
(features extraction)*

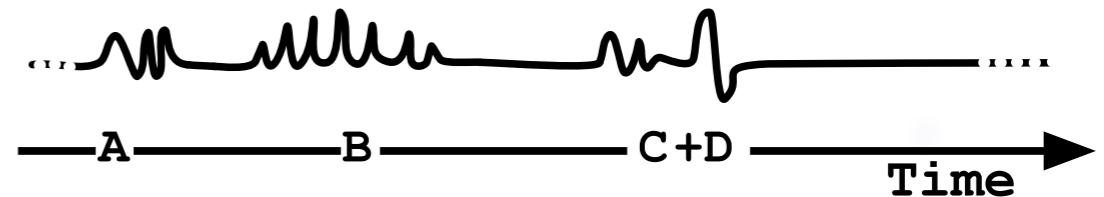
# Issue & Contributions



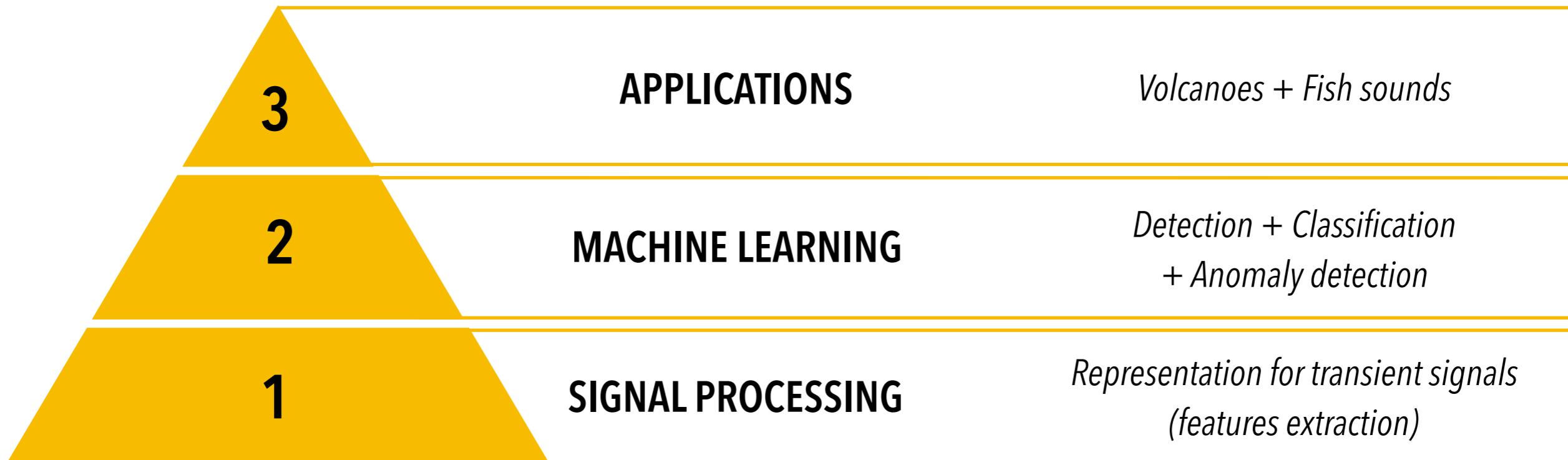
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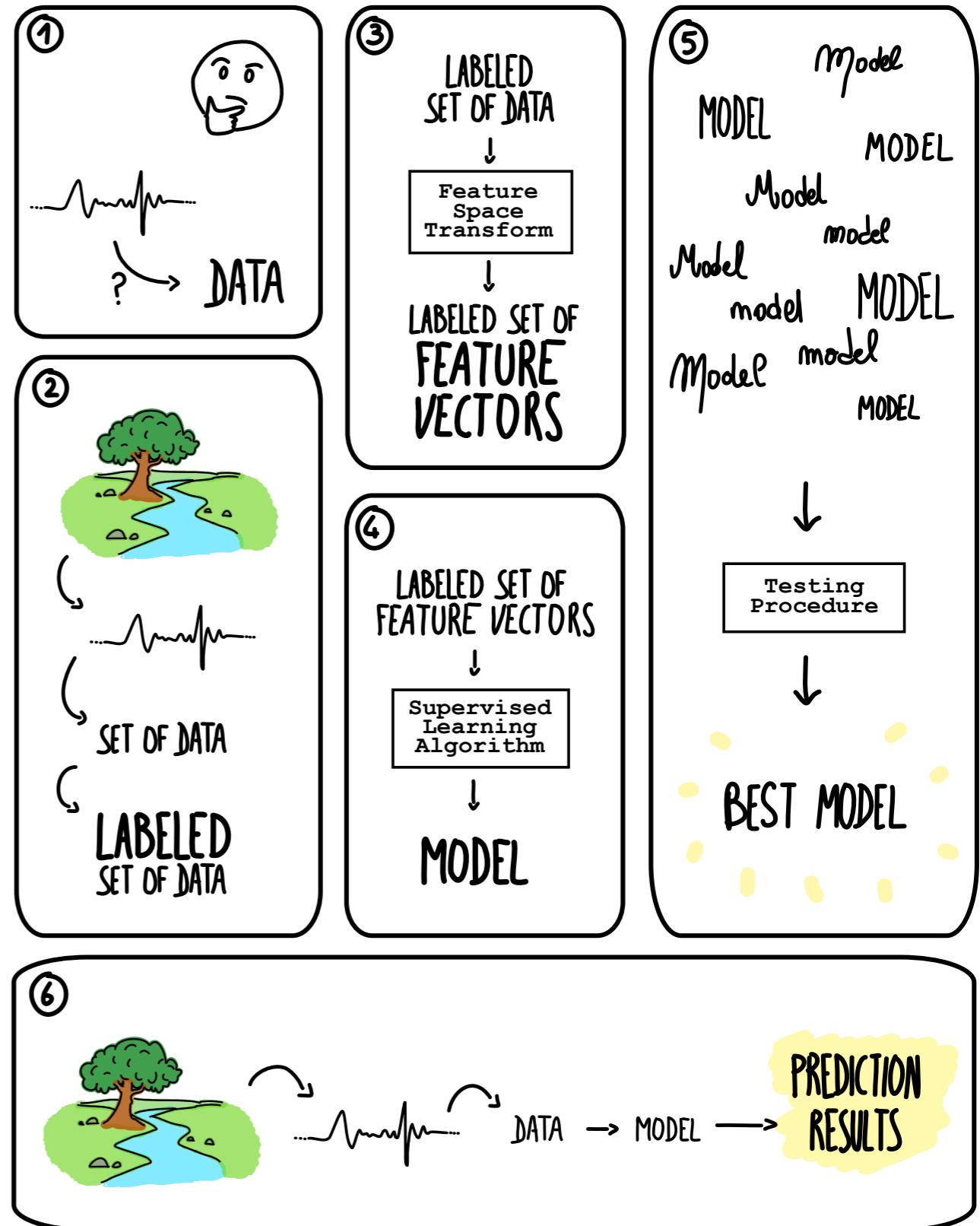
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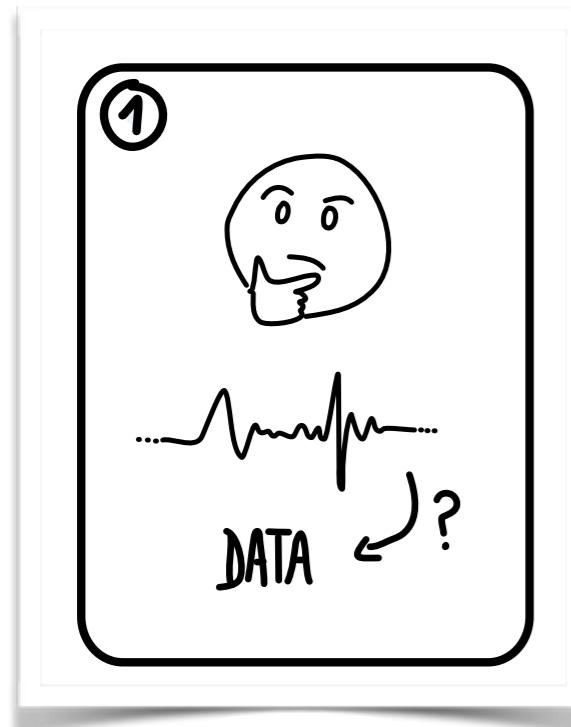
# I - CONTRIBUTIONS & CONTEXT

- Presentation of the proposed architecture (detection + classification + anomaly detection),
- Machine Learning background,
- Presentation of the proposed feature extraction scheme.

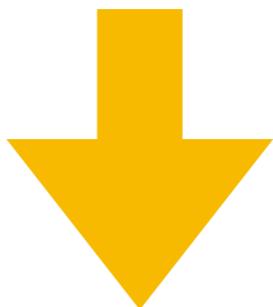
# 1 General architecture



# Data definition



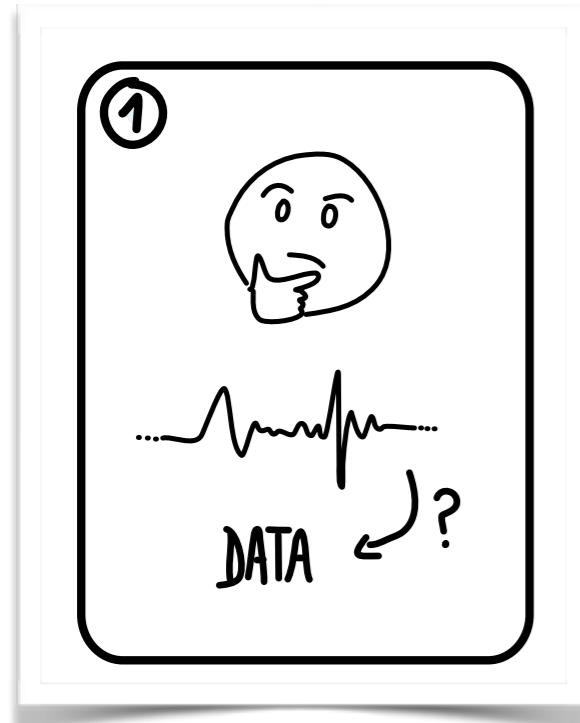
Original **recording** (continuous signal):  $[w_k]_{k=0}^{n_t}$



**Data, Observations** (bloc based, filtered signals):

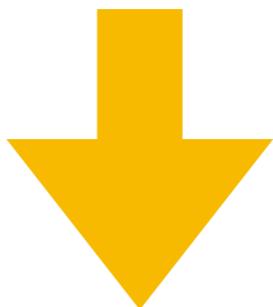
$$[s_k]_{k=1}^n = h([w_k]_{k=n_1}^{n_1+n})$$

# Data definition



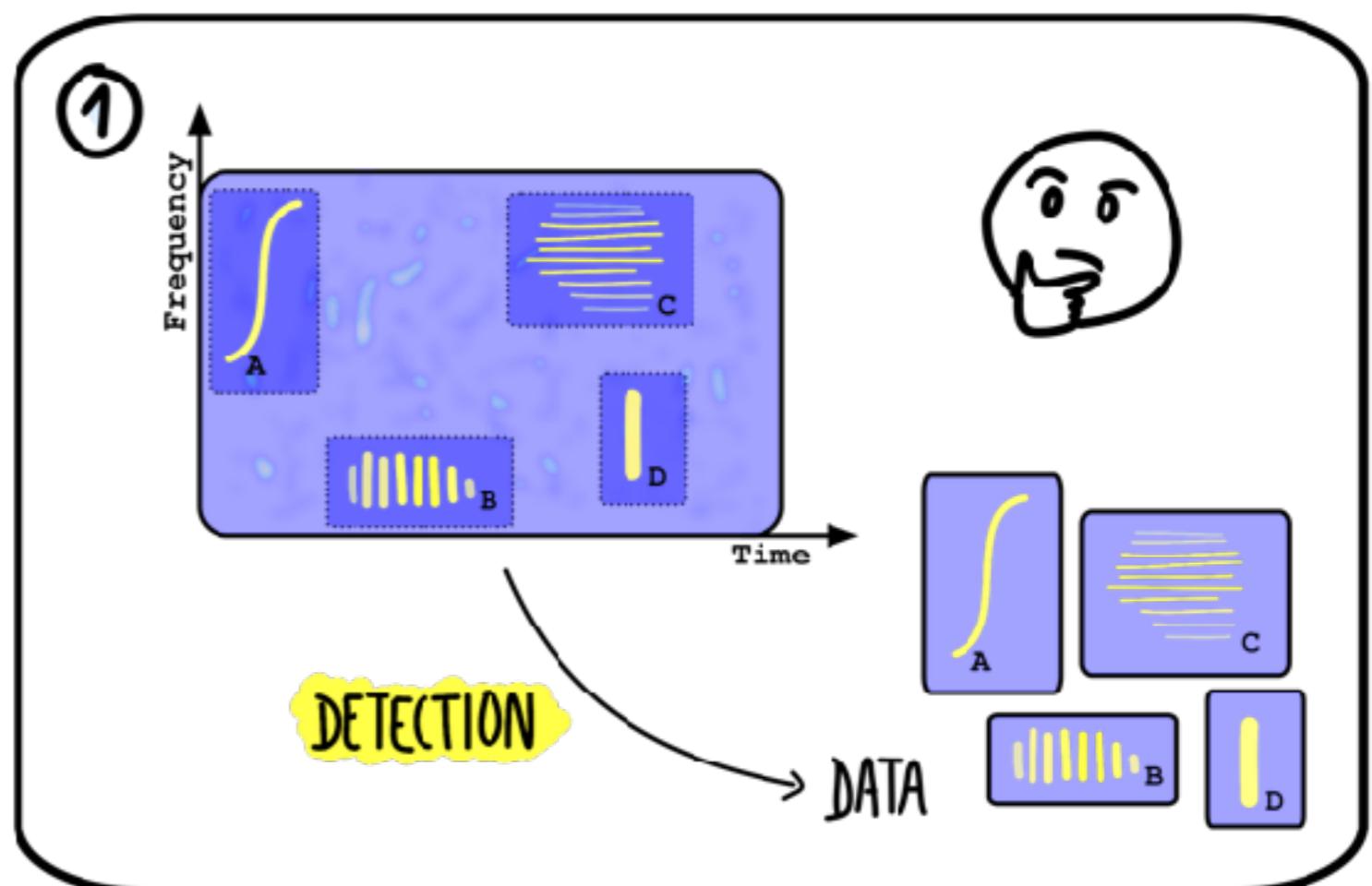
1 - Classification

Original **recording** (continuous signal):  $[w_k]_{k=0}^{n_t}$

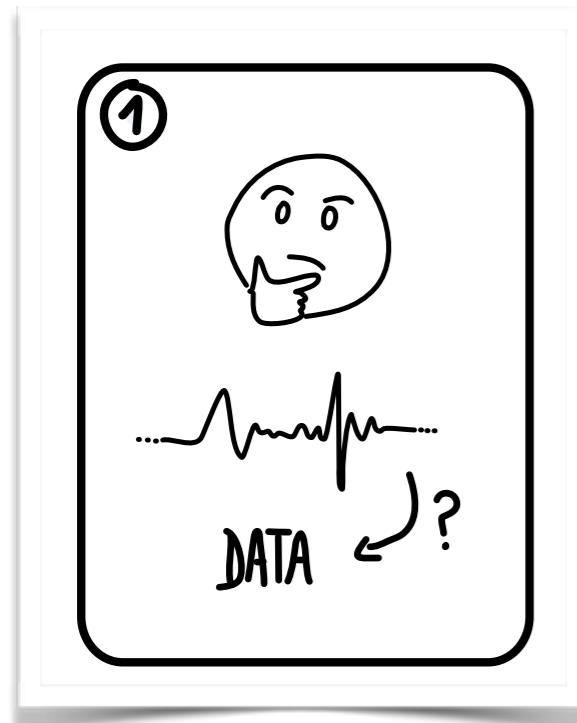


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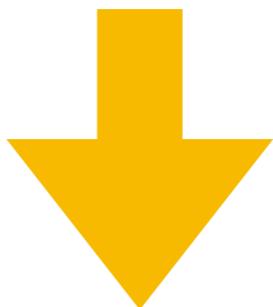


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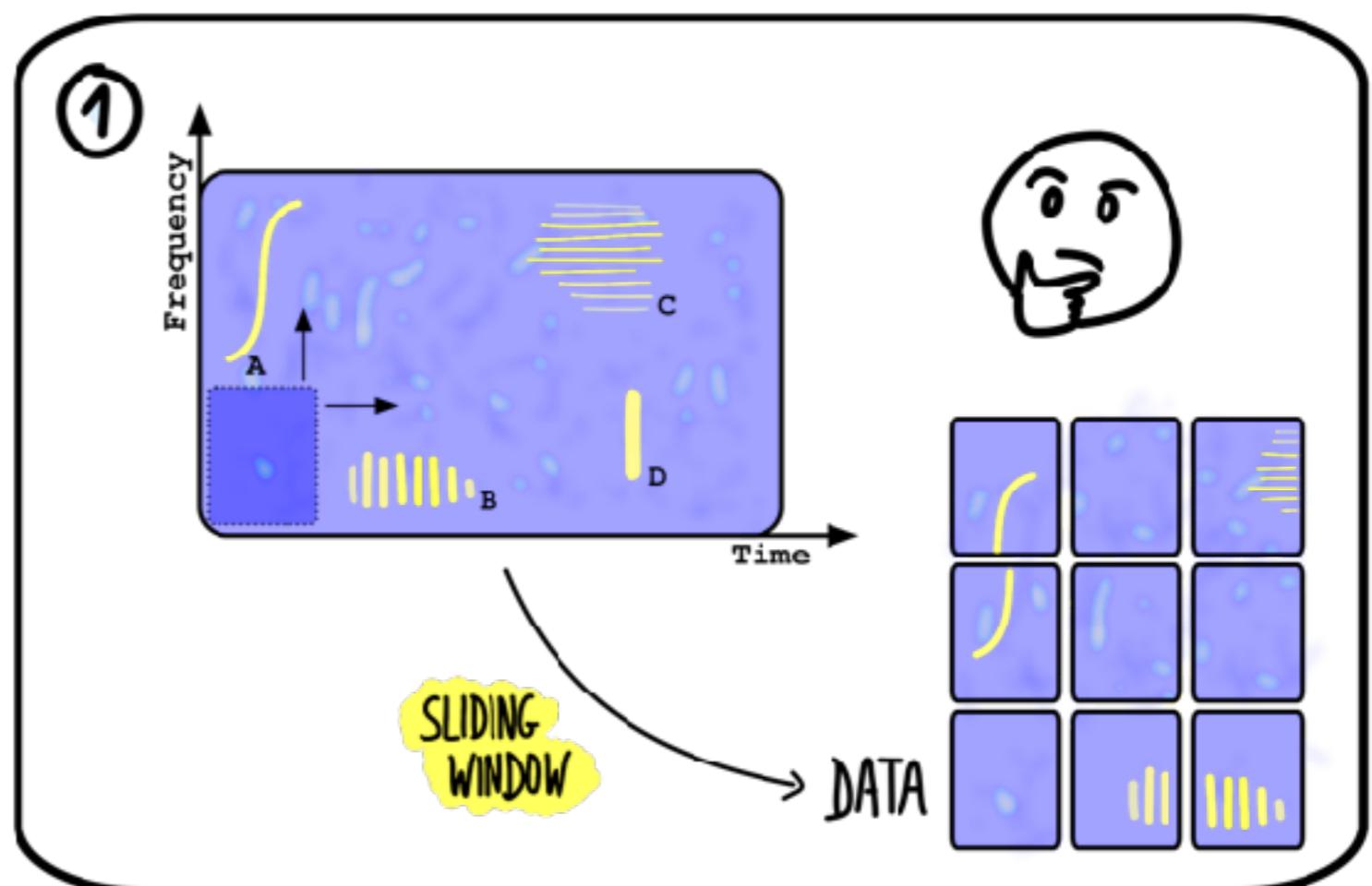
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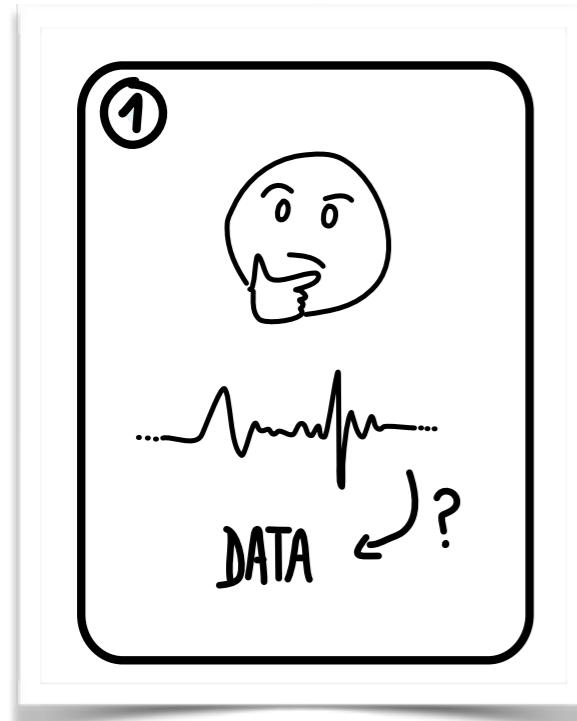


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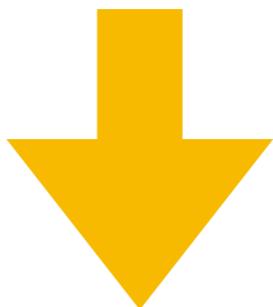
# Data definition



**Observations**  
are not images!

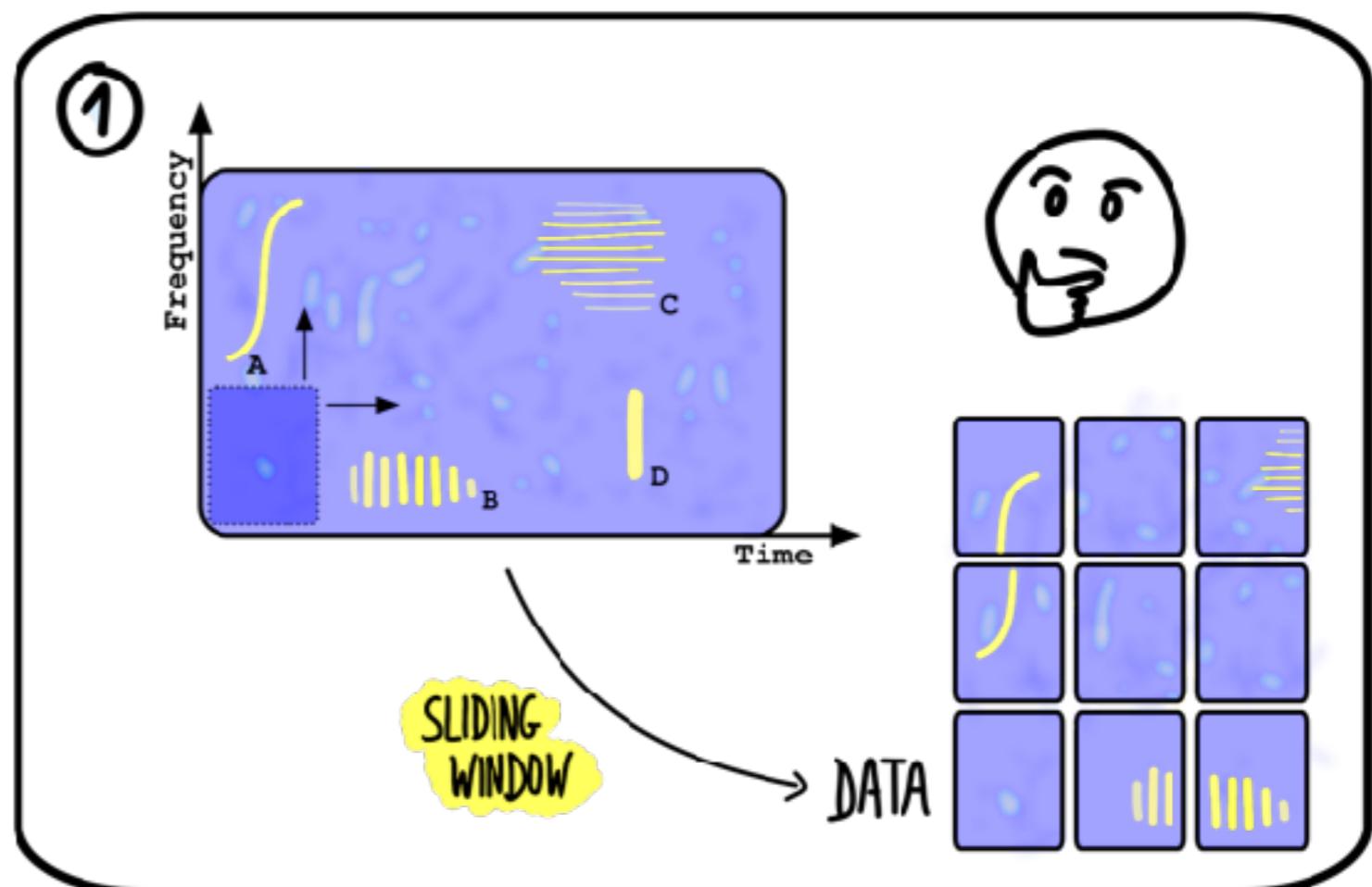
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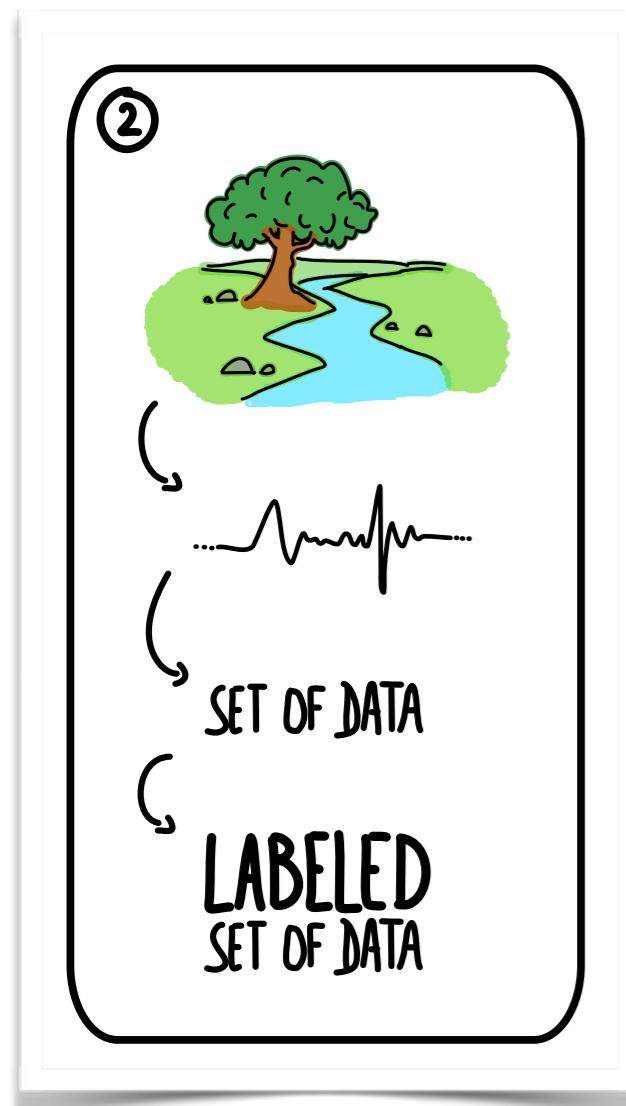


**Data, Observations** (block based, filtered signals):

$$[s_k]_{k=1}^n = h([w_k]_{k=n_1}^{n_1+n})$$



# Labeled dataset constitution



WHAT?

- Automatic classification = Automatic classification of observations into categories (**classes**),
- Set of { **observations + labels** },
- **Label**: Category of the observation.

$$\{\mathbf{S}, \mathbf{Y}\} = \{\mathbf{s}_i, y_i\}_{i=1}^N$$

with  $y_i \in \{0, \dots, C - 1\}$  and  $C$  the number of classes.

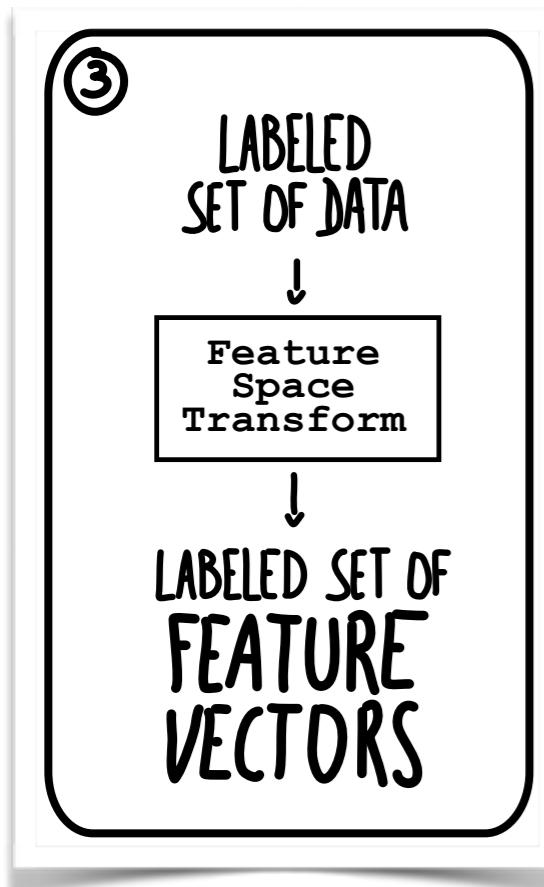
WHY?

- Supervised Machine Learning.

HOW?

- Manually,
- Collaboration with the experts,
- Transfer of human knowledge (expertise).

# Features extractions



WHAT?

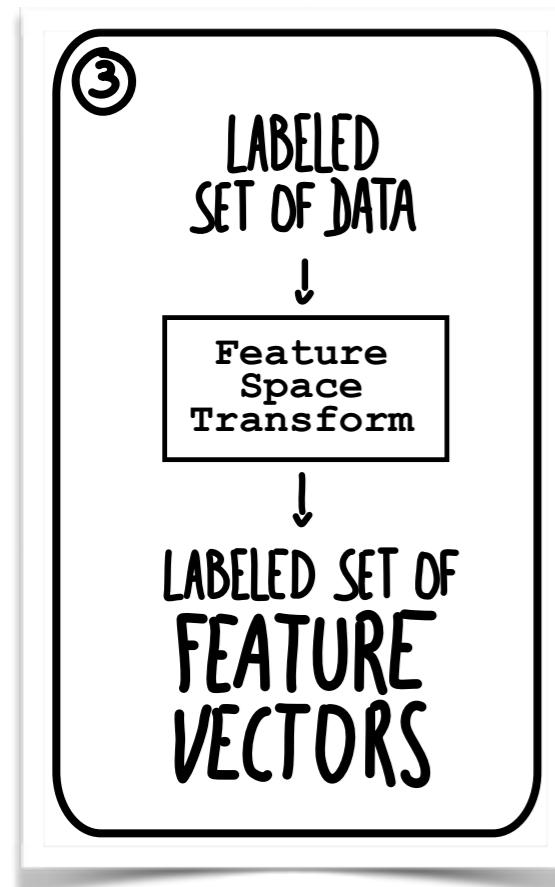
Labeled set of **observations**

$$\{\mathbf{S}, \mathbf{Y}\} = \{\mathbf{s}_i, y_i\}_{i=1}^N$$

Labeled set of **feature vectors**

$$\{\mathbf{X}, \mathbf{Y}\} = \{\mathbf{x}_i, y_i\}_{i=1}^N$$

# Features extractions



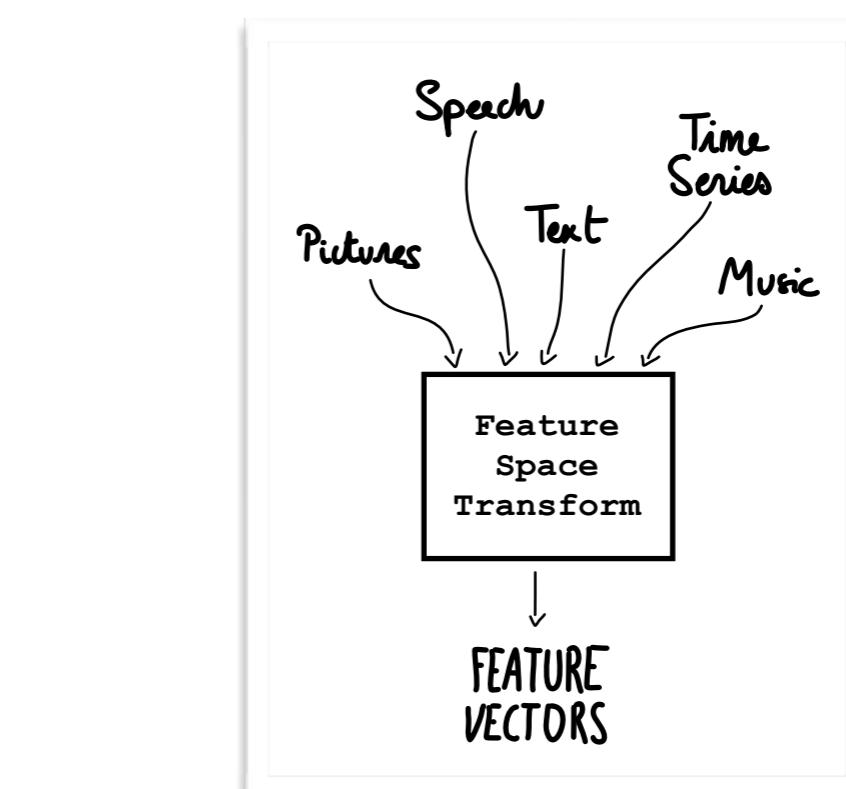
WHAT?

Labeled set of **feature vectors**.

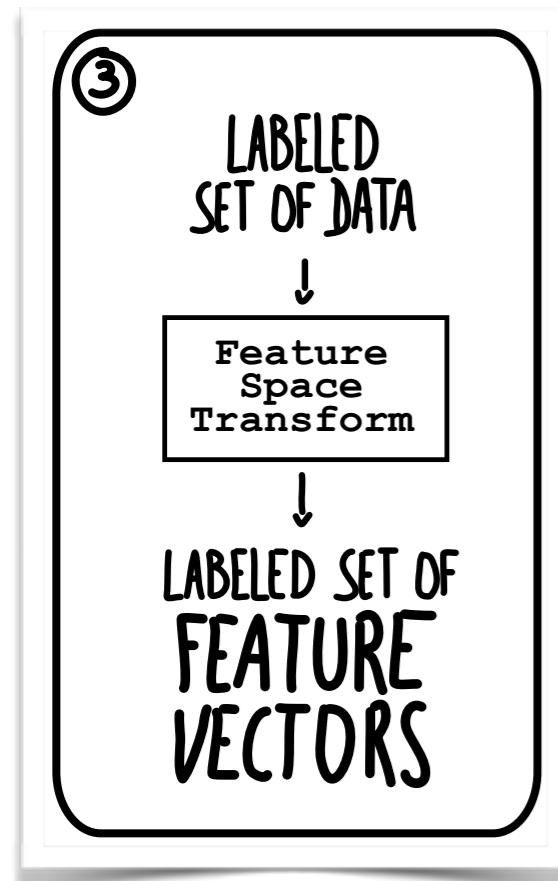
$$\{\mathbf{X}, \mathbf{Y}\} = \{\mathbf{x}_i, y_i\}_{i=1}^N$$

WHY?

- Reduced dimension [Bellman1956],
- **Separability** of the data depending on the classes,
- **Ordered invariant representations** [Duda&al2001].



# Features extractions



WHAT?

Labeled set of **feature vectors**.

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WHY?

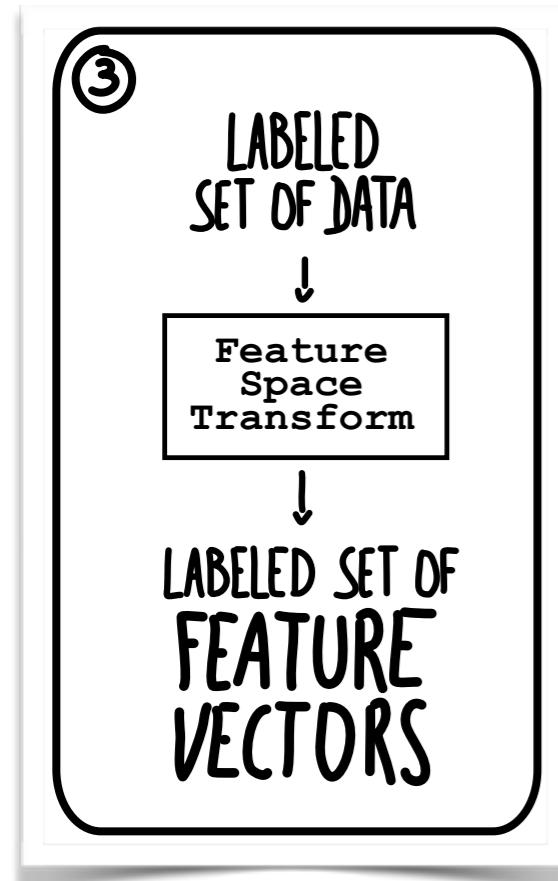
- Reduced dimension [Bellman1956],
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HOW?

- **State of the art - representation for transients**

- A. Learning features: convolutional neural networks [LeCun&al1998], non negative matrix factorization [Lawton1971], etc.
- B. Handcrafted features
  - **Input of physical meaning in the model**,
  - Mechanical transients [Tucker&al2005], bioacoustics signals [Noda&al2016], Speech [Zheng2001], Environmental Sounds [Dennis&al2011], Music [Eronen&al2000],
  - Not always **ordered invariant**.

# Features extractions



## PROPOSED APPROACH

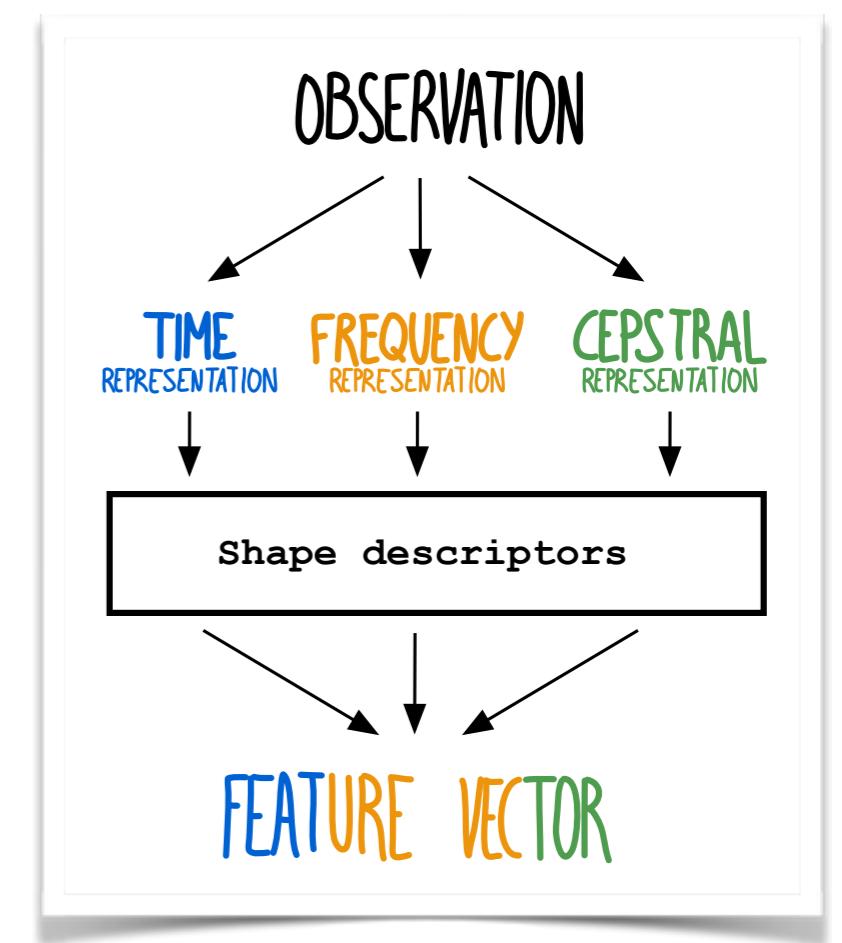
- Several **low level** (not permutable) representations:

1. Waveform,  $s_k = [s_k]_{k=1}^n$
2. Spectrum,  $S_f = |\mathcal{F}\{s_k\}|$
3. Cepstrum.  $\mathcal{S}_q = |\mathcal{F}\{S_f\}|$

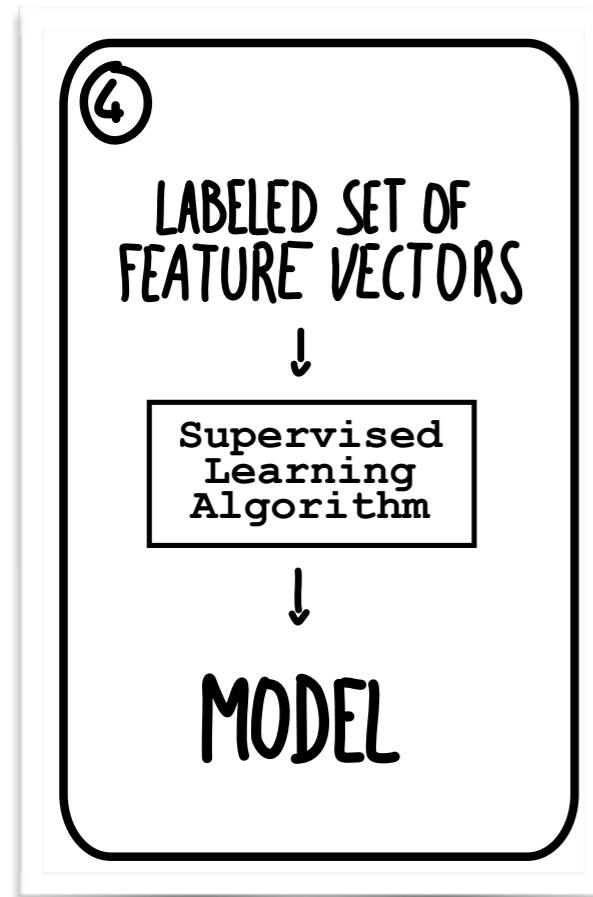
- Generic **shape descriptors** (~40):

Mean, standard deviation, Skewness, Kurtosis, centroid, RMS bandwidth, Shannon entropy, Rényi 'entropy', length, rate of attack, rate of decay, threshold crossing rate, etc.

See manuscript page 57



# Model training



## WHAT?

- Train a **model**,
- Use of **supervised learning** algorithms,
- **Learn a separation** between the different classes from the **labeled set of observations**:

$$\begin{aligned} f : \mathbf{X} &\rightarrow Y \\ \mathbf{X} &\rightarrow y \end{aligned}$$

## HOW?

### **Support Vector Machine** [Cortes&Vapnik95]

- Hyperplan **maximizing** the **margin**,
- **Kernel trick**: 'transformation' to a space of higher dimension,
- **Soft margin**.

### **Random Forest** [Breiman2001]

- Ensemble of decision trees [Quinlan86],
- At each split, minimize the impunity in the regions,
- Subset of features / data for each split / tree.

# Model selection

WHY?

- Influence of the **observations**,
- Influence of the chosen **features**,
- Influence of the **learning algorithm**,
- Influence of the **hyperparameters**.

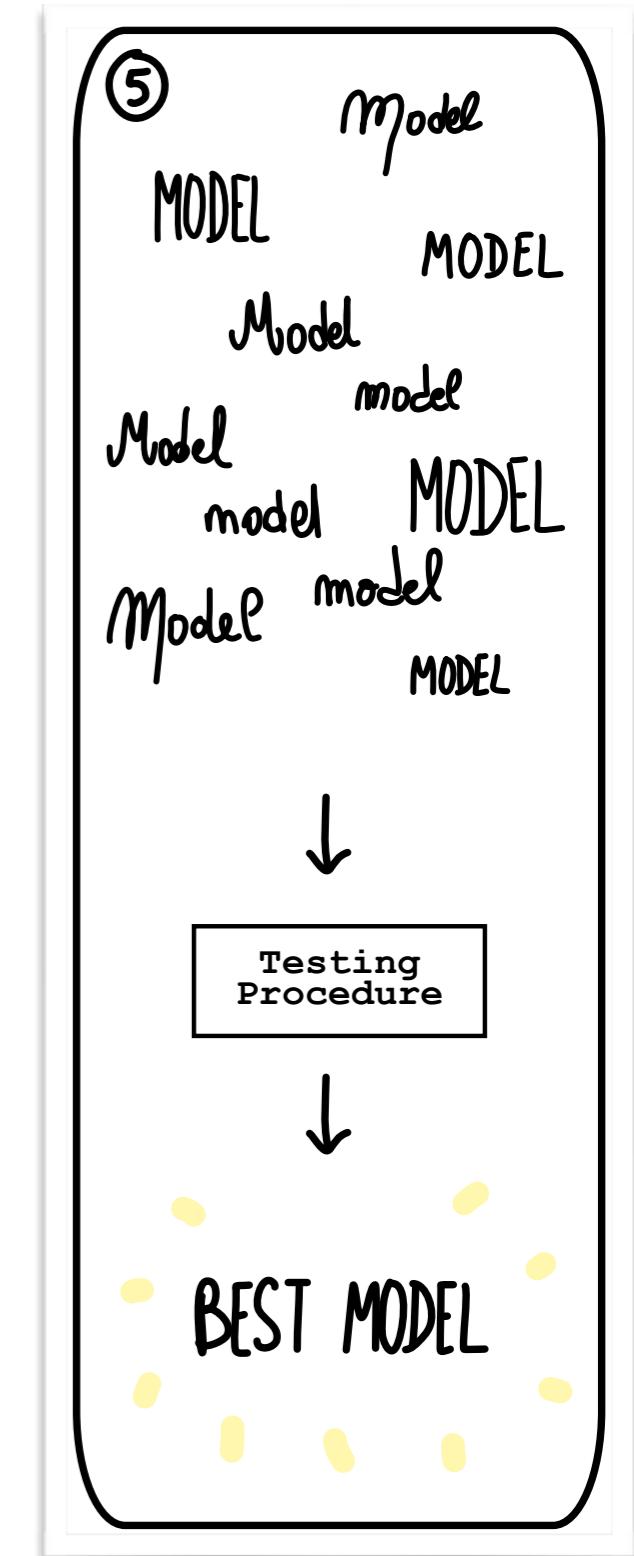
HOW?

## Estimation of the model performances

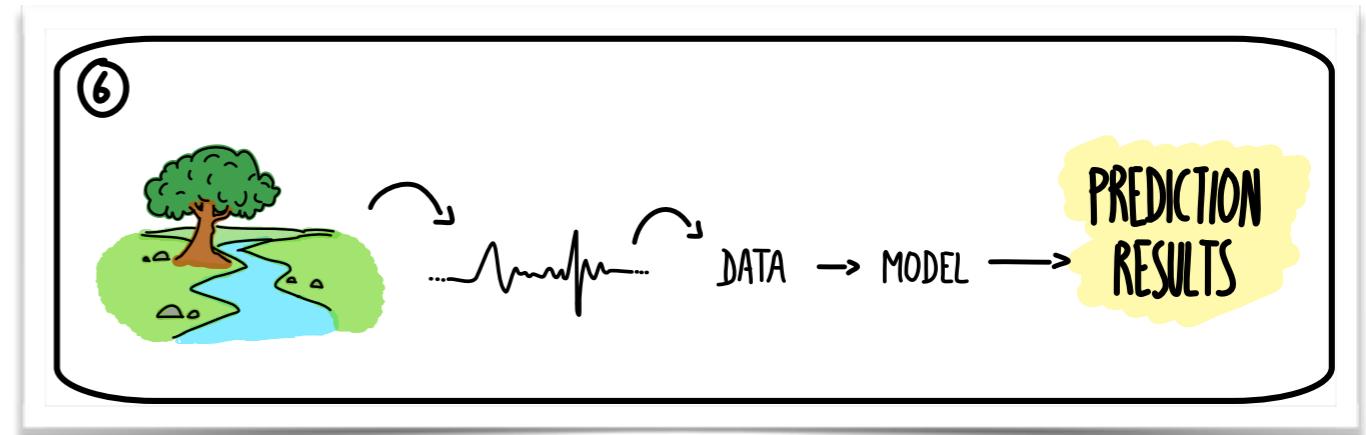
- Choice of the metric (depending on the application)

$$\text{Accuracy} = \frac{\#\text{(correct predictions)}}{\#\text{(total predictions)}}$$

- If possible [Duda&al2001]: learning - validation - test sets (Overfitting...)
- Else: **Cross-validation**
  - Learning - Testing sets (i.e., 70% - 30%)
  - Random trials of the sets (i.e., 10, 50, 200...)
  - Mean  $\pm$  std results considered



# Use of the model



## USAGES

- **Continuous analysis**

1. **Periodic** training with the new recorded observations,
2. Analysis of the **continuous flow** of recordings.

- **A posteriori analysis**

1. Training on a given period of time,
2. Analysis of **another** period of time (evolution of the observations).

## POSTPROCESSING & ANOMALY DETECTION

- **Model output**

$$p(s_i \in c) \text{ for } c \in \{0, \dots, C-1\}$$

- **Anomaly detection**

$$c_{considered}(s_i) = \operatorname{argmax}_{c \in \{0, \dots, C-1\}} p(s_i \in c)$$

**if**  $p(s_i \in c_{considered}(s_i)) > t_c$  :

$$c_{predicted}(s_i) = c_{considered}$$

**else** :

$$c_{predicted}(s_i) = \text{Unknown}$$

## II - PRACTICAL STUDIES

### 1 - Volcanoes

#### COLLABORATIONS

- Jean-Philippe Métaxian (IPGP)
- Adolfo Inza & Orlando Macedo (Arequipa observatory) - **UBINAS (Peru)**
- François Beauducel & Budi Dantoso (BPPTKG) - **MERAPI (Indonesia)**

#### FUNDING

- 2 missions in Indonesia
- Doctoral school - TUE , Idex, Data Institute

## II - PRACTICAL STUDIES

### 1 - Volcanoes

#### OUTLINE

- **Classification** task
- Ubinas & Merapi volcanoes, seismo-volcanic signals
- EXPERIMENT 1: Evaluation of the **model performances**
- EXPERIMENT 2: **Features** influence & selection
- EXPERIMENT 3: **A posteriori analysis of a 6 years dataset**
- EXPERIMENT 4: Continuous analysis & **operative monitoring**

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- ~~EXPERIMENT 4: Continuous analysis & operative monitoring~~

# Volcano-seismic signals

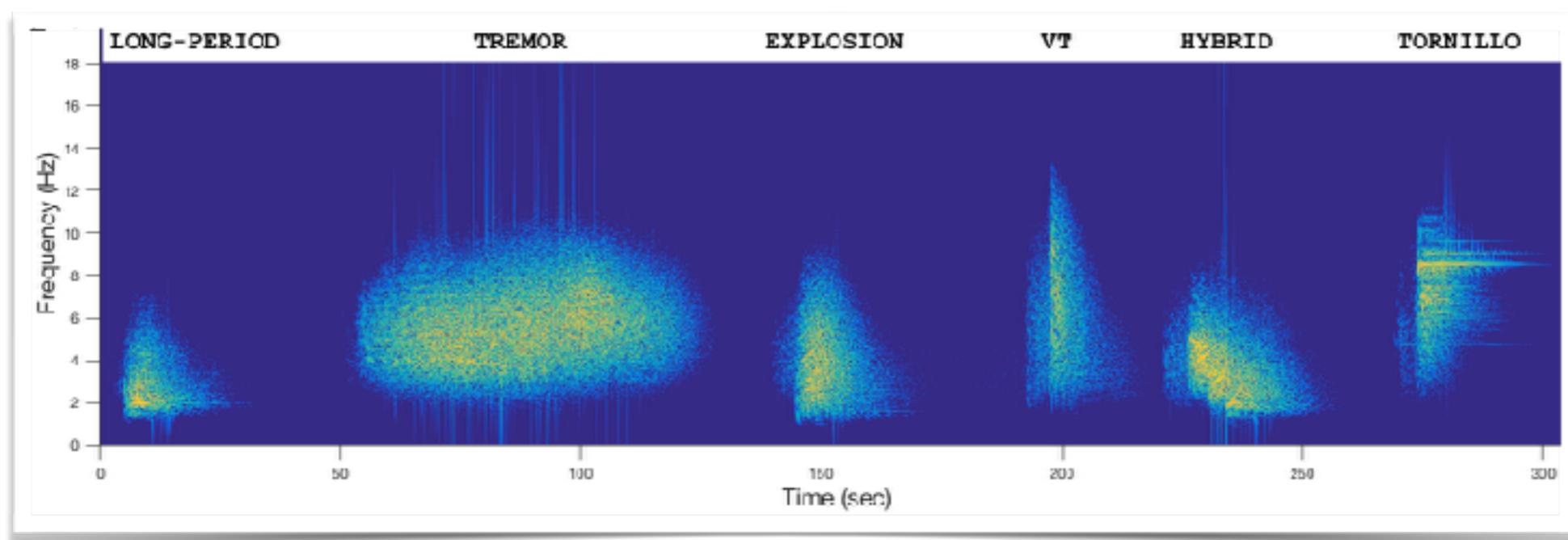
## UBINAS

- Peruvian volcano,
- Monitored since 2006,
- **3 eruptions** since 2006.

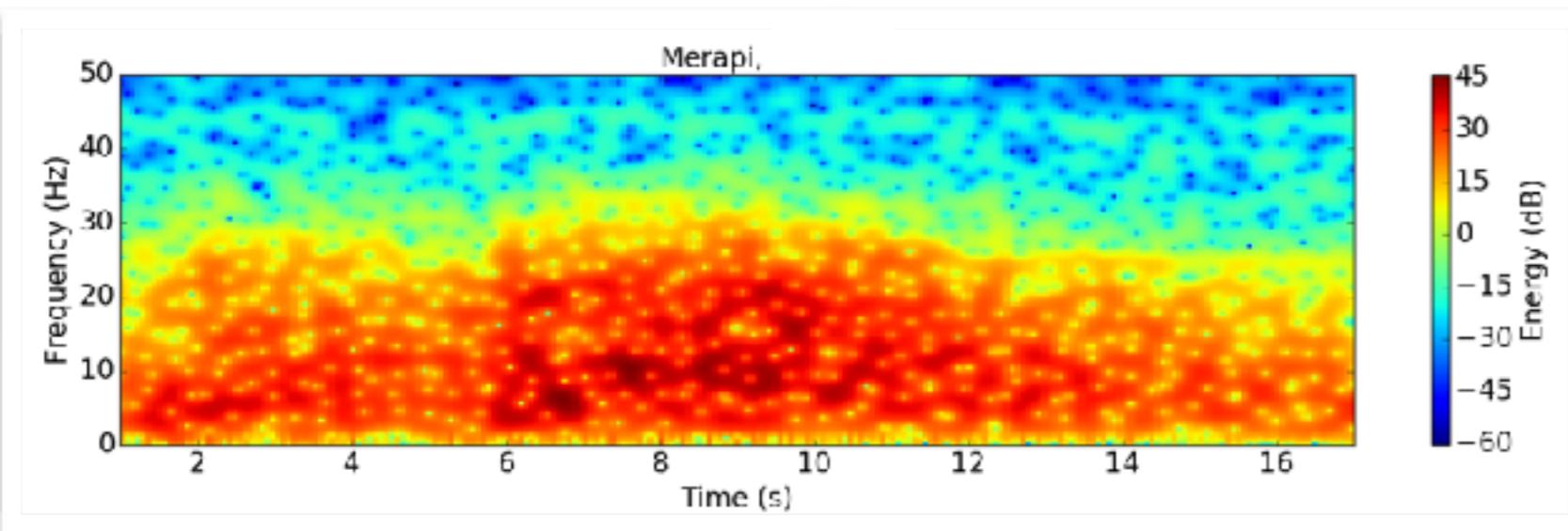


## DATASET

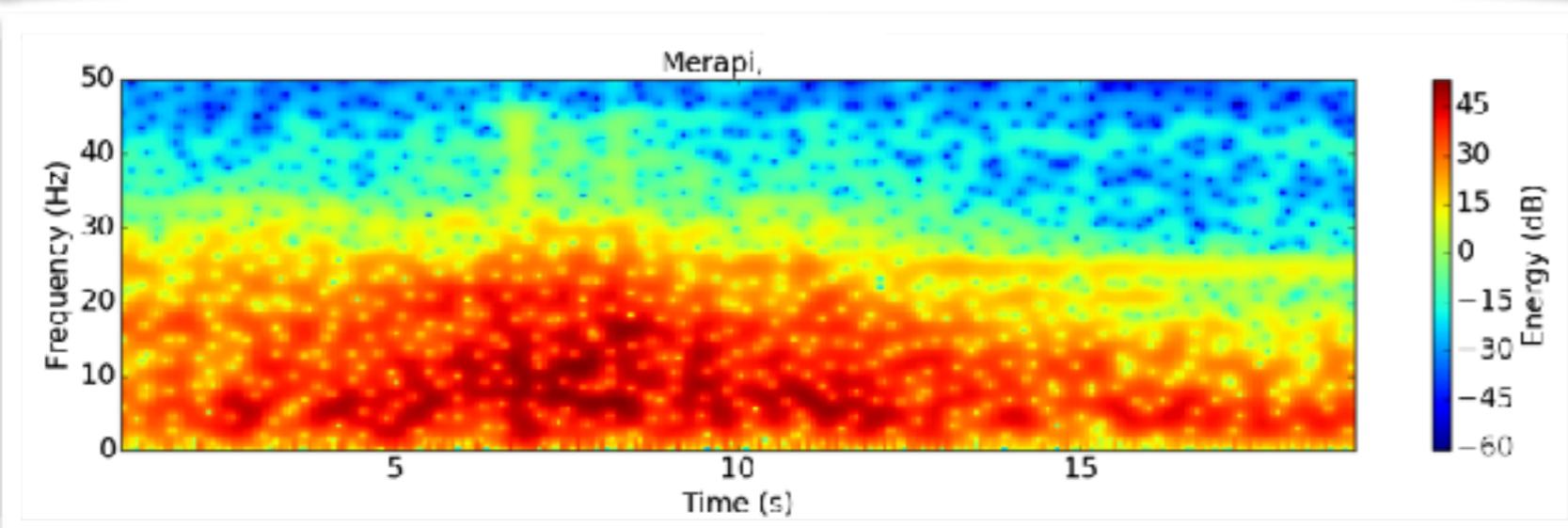
- 109,609 labeled **observations** over **6 years** of continuous volcano-seismic recordings,
- **6 classes (unbalanced)** dataset from **109** to **95,243** observations).



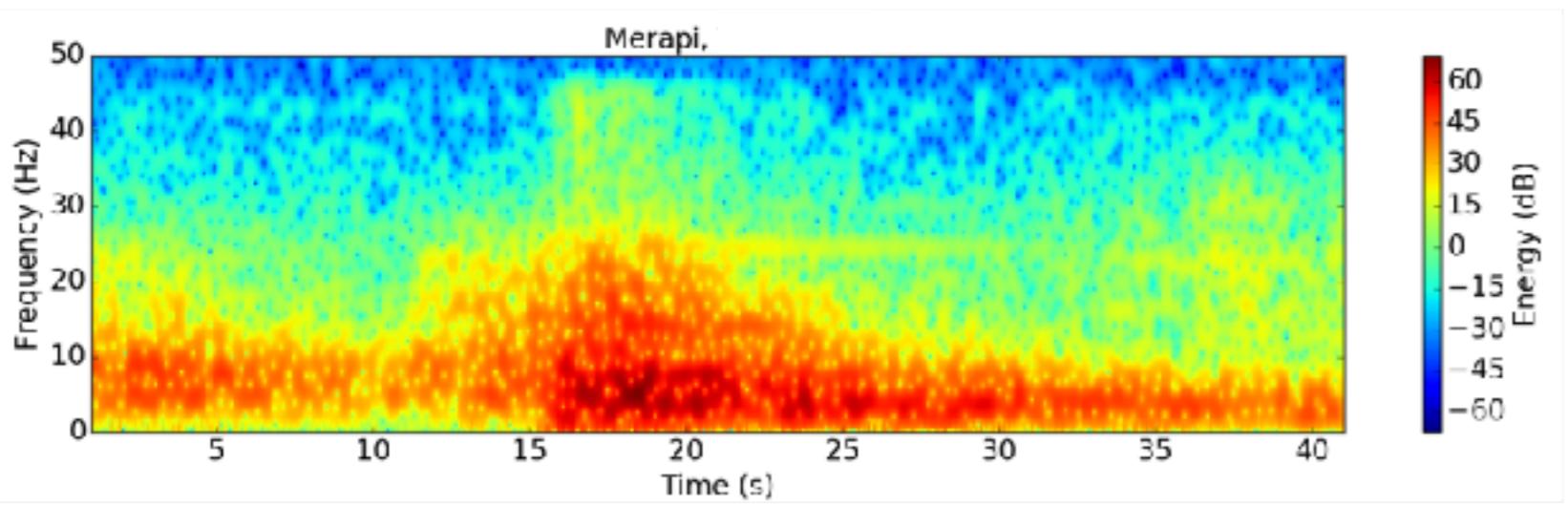
# Is it difficult to classify volcano-seismic observations?



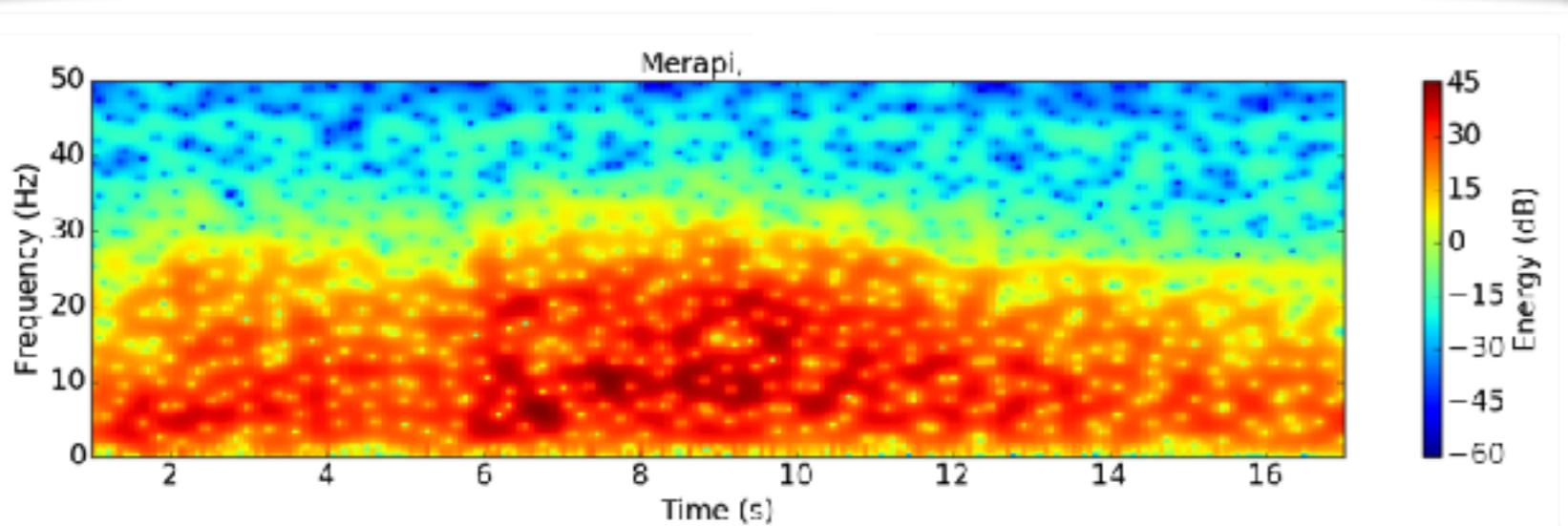
The experts  
said:  
**'Same class!'**



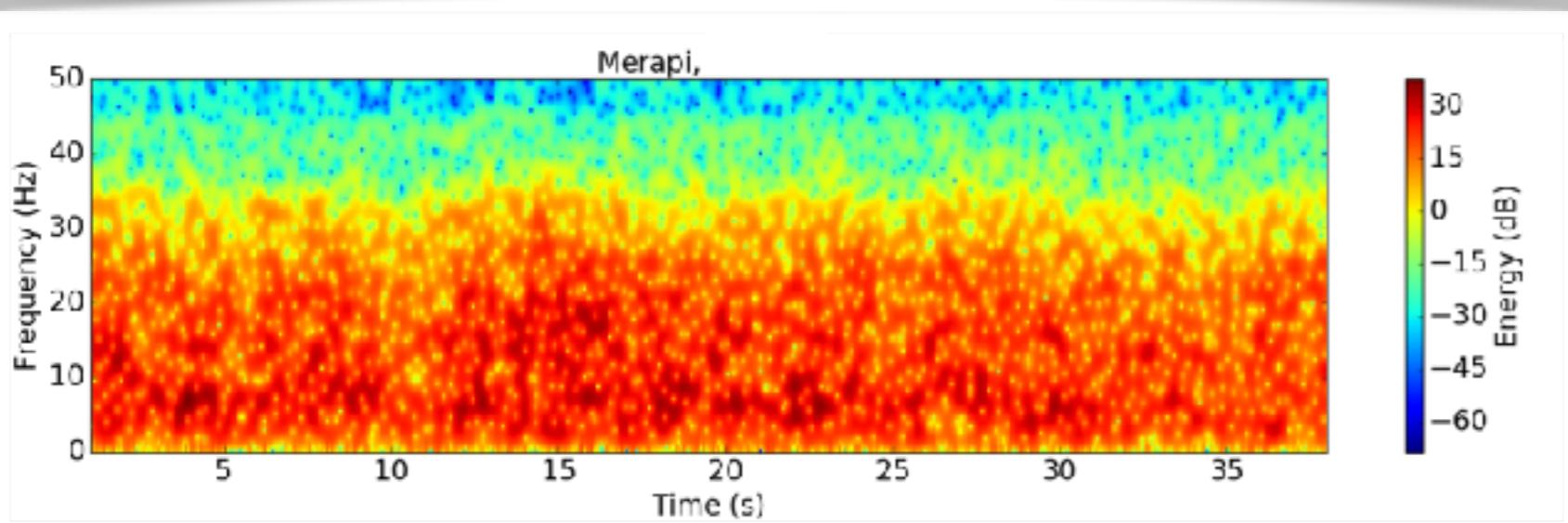
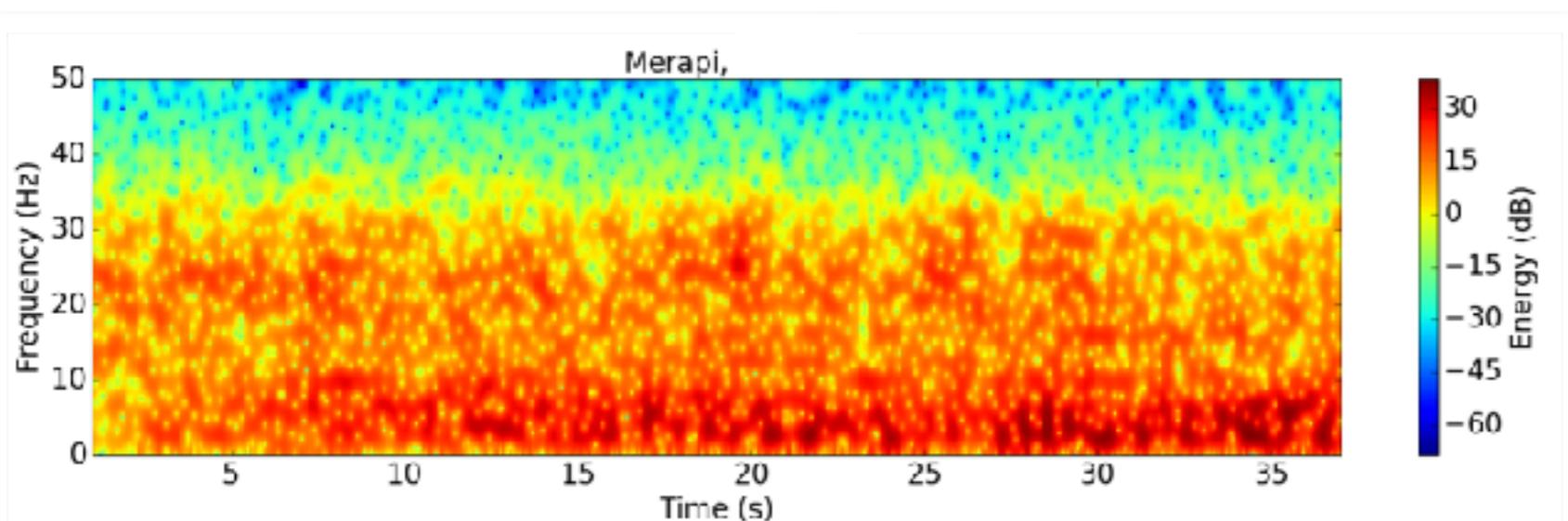
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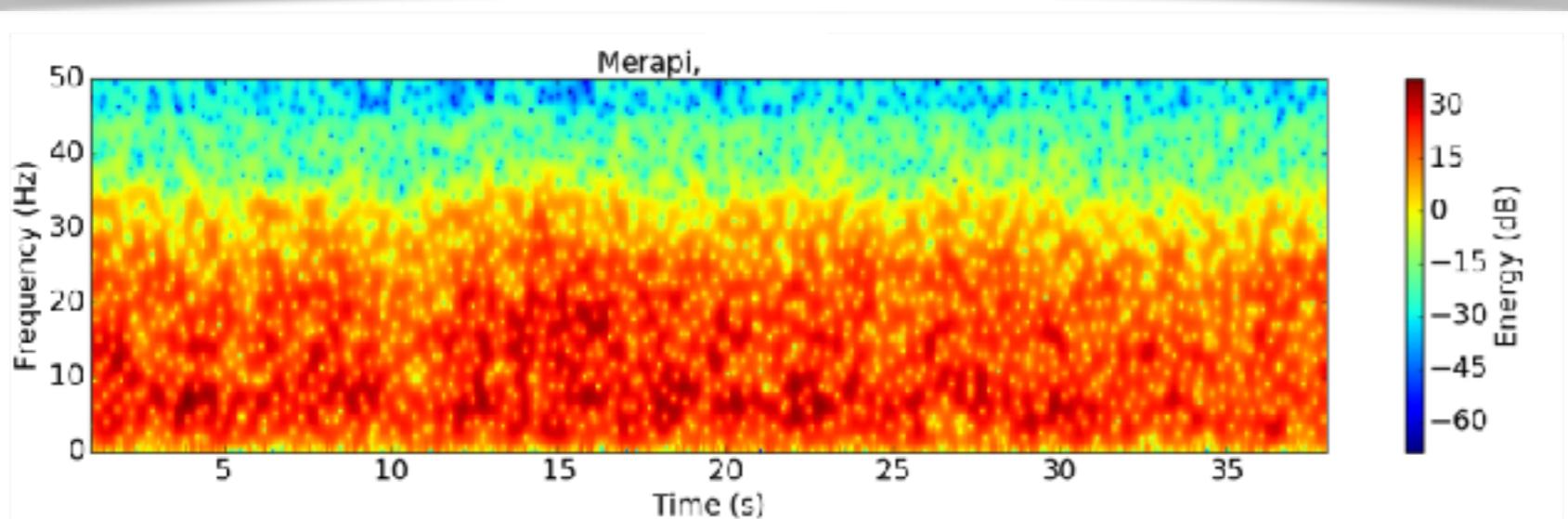
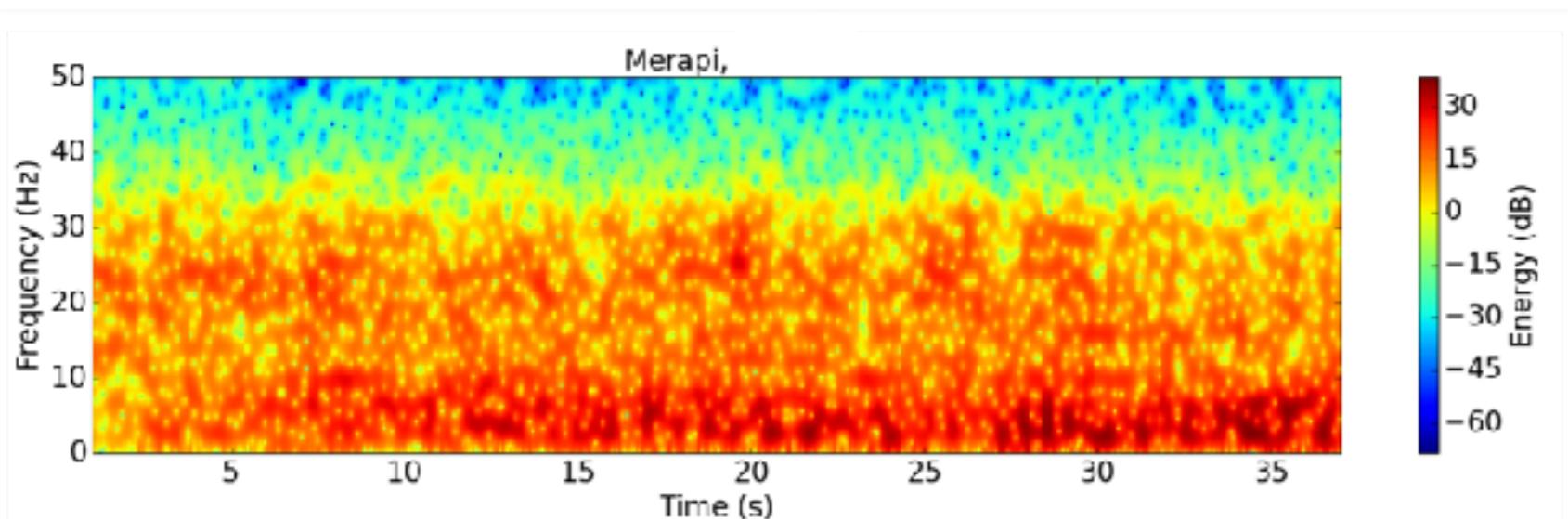
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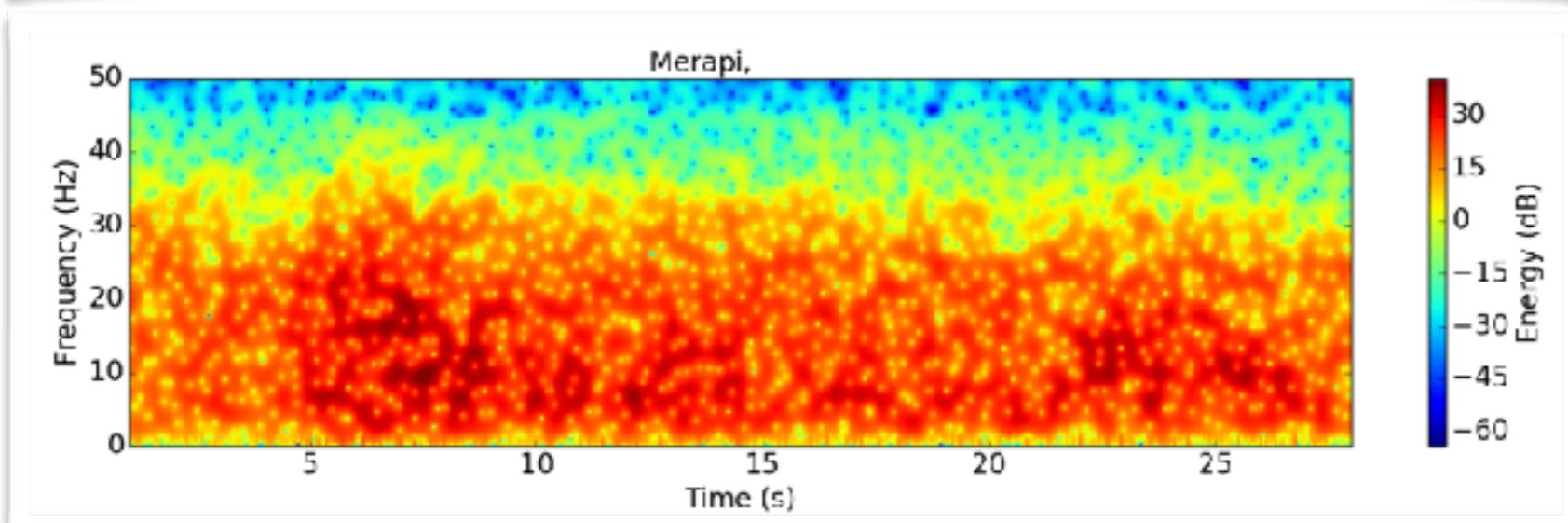
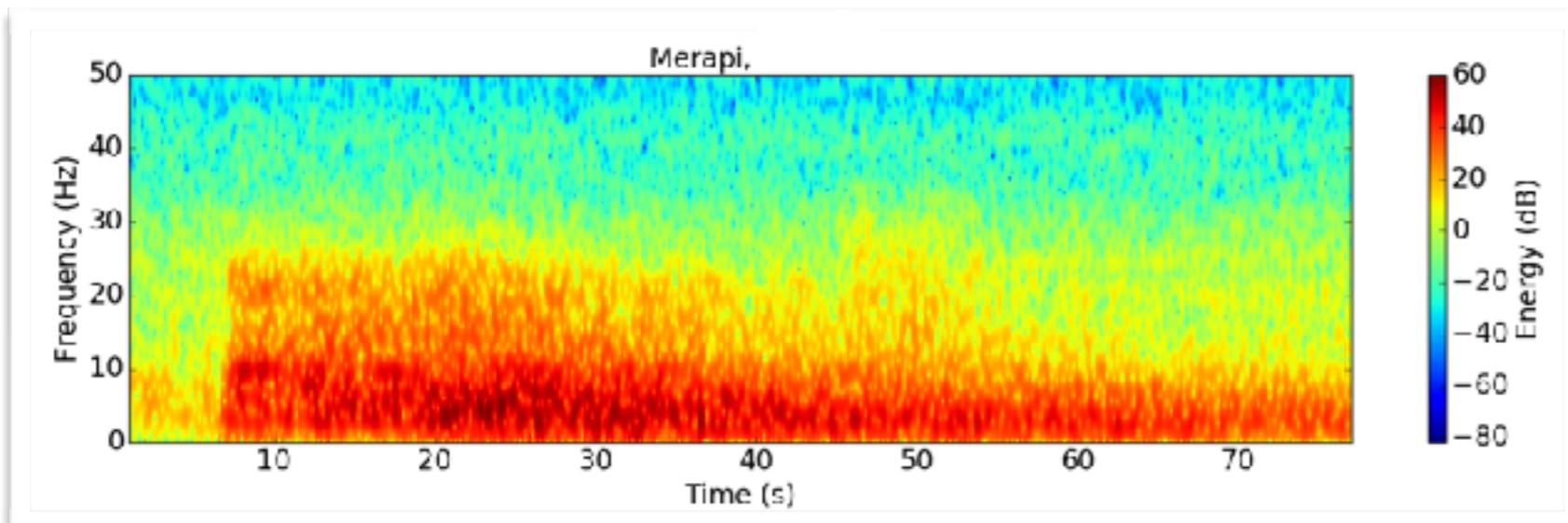


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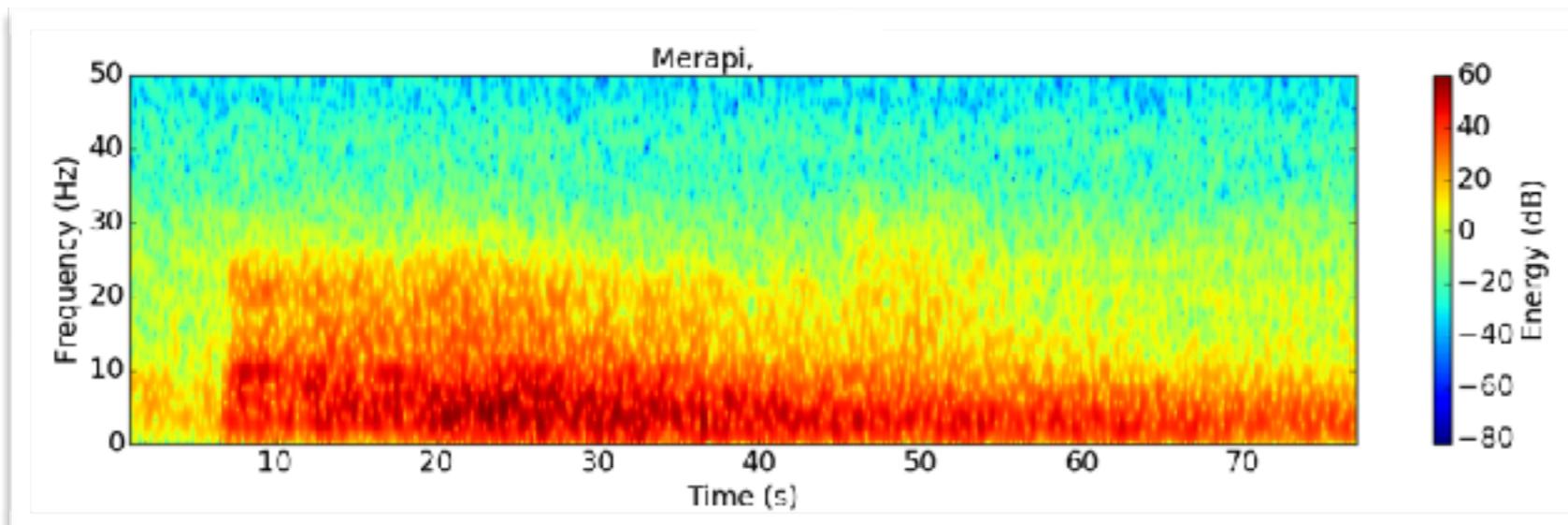
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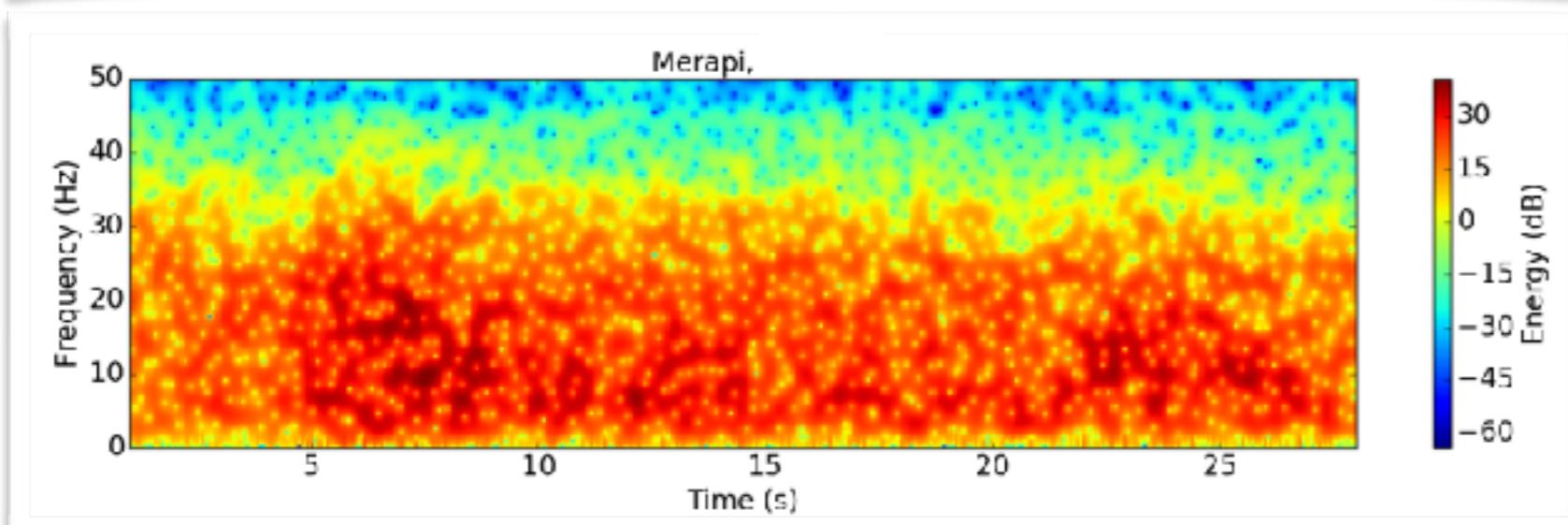
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# Evaluation of the model performances

ACCURACY  
for two learning algorithms

*Cross-validation, 70,856 observations, hyperparameters optimized, all features*

Support Vector Machine

$92.1 \pm 0.54\%$

Random Forest

$92.5 \pm 0.45\%$

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ACCURACY  
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CONFUSION MATRIX  
for the selected model

- Mixed classes have **similar causes**,
- Interest in the **accuracy** (but depends on the context).

*Cross-validation, 70,856 observations, hyperparameters optimized - RF model - all features*

Predicted Class	Expert class					
	LP	TR	VT	EXP	HYB	TOR
LP	57504	457	4	1	8	-
TR	3911	4764	-	1	3	1
VT	372	10	487	5	12	3
EXP	112	8	6	41	-	-
HYB	128	6	14	1	119	-
TOR	2	0	3	0	0	28
Accuracy	92.7%	90.8%	94.6%	84.8%	83.6%	87.6%

# A posteriori analysis of 6 years of volcano-seismic recordings

HOW?

Training on the  **$N_{\max} = 800$**  first  
**observations of each class**

- 2 weeks for LP,
- Not reached for rare classes.

WHY?

Study the **evolution** of  
the observations.

# A posteriori analysis of 6 years of volcano-seismic recordings

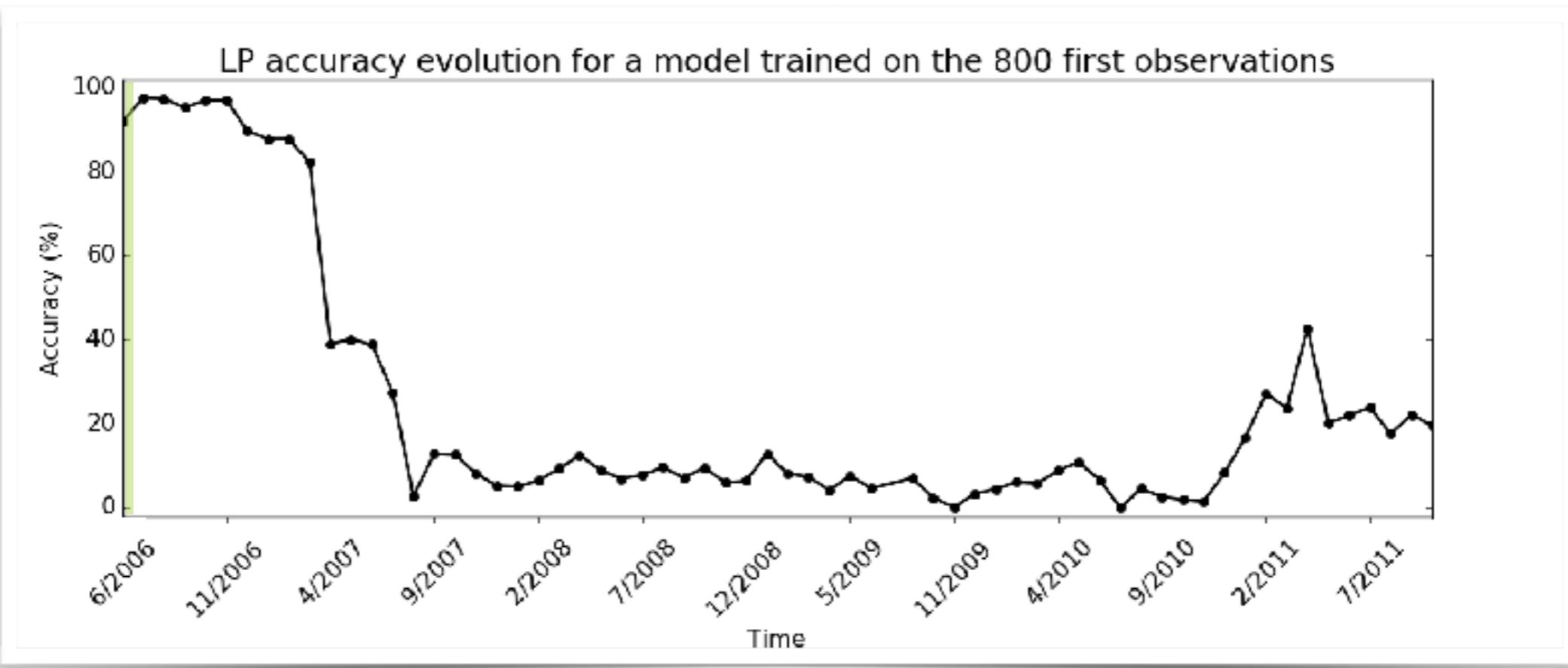
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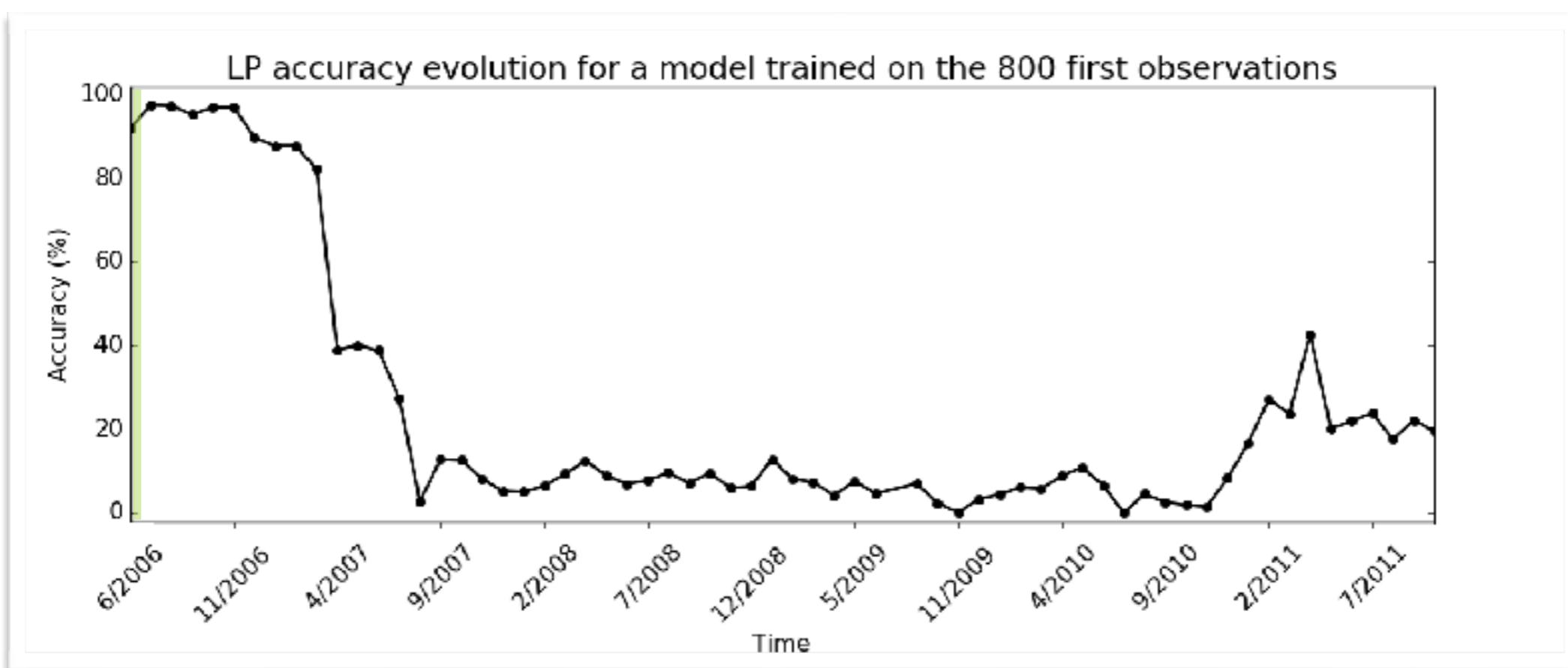
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# A posteriori analysis of 6 years of volcano-seismic recordings

## INTERPRETATION

- Evolution of the signals,
- Errors of classification in the dataset.



## II - PRACTICAL STUDIES

### 2 - Underwater acoustics

#### COLLABORATION

- Cédric Gervaise (Chair CHORUS, Fondation Grenoble INP)

#### OUTLINE

- **Detection, classification + anomaly detection**
- Focus on fish sounds - SEACOUSTIC data
- EXPERIMENT 1: Evaluation of the model performances
- EXPERIMENT 2: **Features influence & selection**
- EXPERIMENT 3: **Full analysis** of continuous recordings

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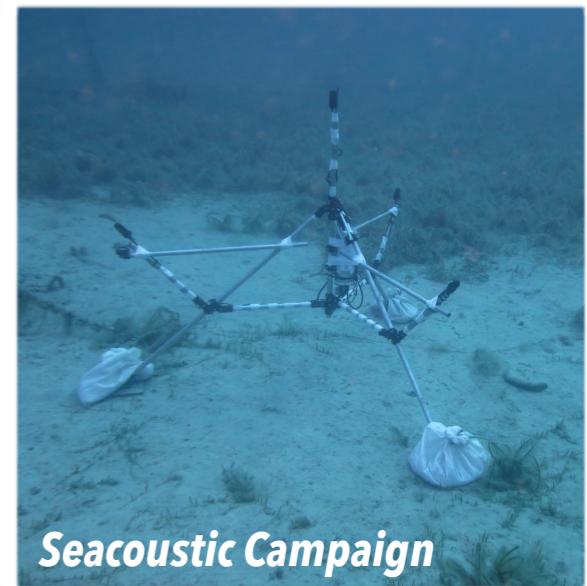
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# Underwater acoustic data

## SEACOUSTIC

- Data gathering campaign, **Passive Acoustic Monitoring**  
[Lassent&al2015],
- Objectives:
  - (i) **Determine the vitality of underwater areas,**
  - (ii) Evaluate the anthropogenic stress of a given area,
  - (iii) Link the vitality of an area with the anthropogenic stress it faces.
- **5 areas**, several days of recording,
- STARSEO station, Pointe de la Revelatta, Corsica.



Ref.	Area	Depth	Duration
1	Healthy sea-grass meadow	-20m	3.5 days
2	Healthy sea-grass meadow	-12m	1 day
3	Lower sea-grass meadow / sand border	-38m	1 day
4	Damaged meadow + Rocks	-12m	1 day
5	Rock	-12m	1 day



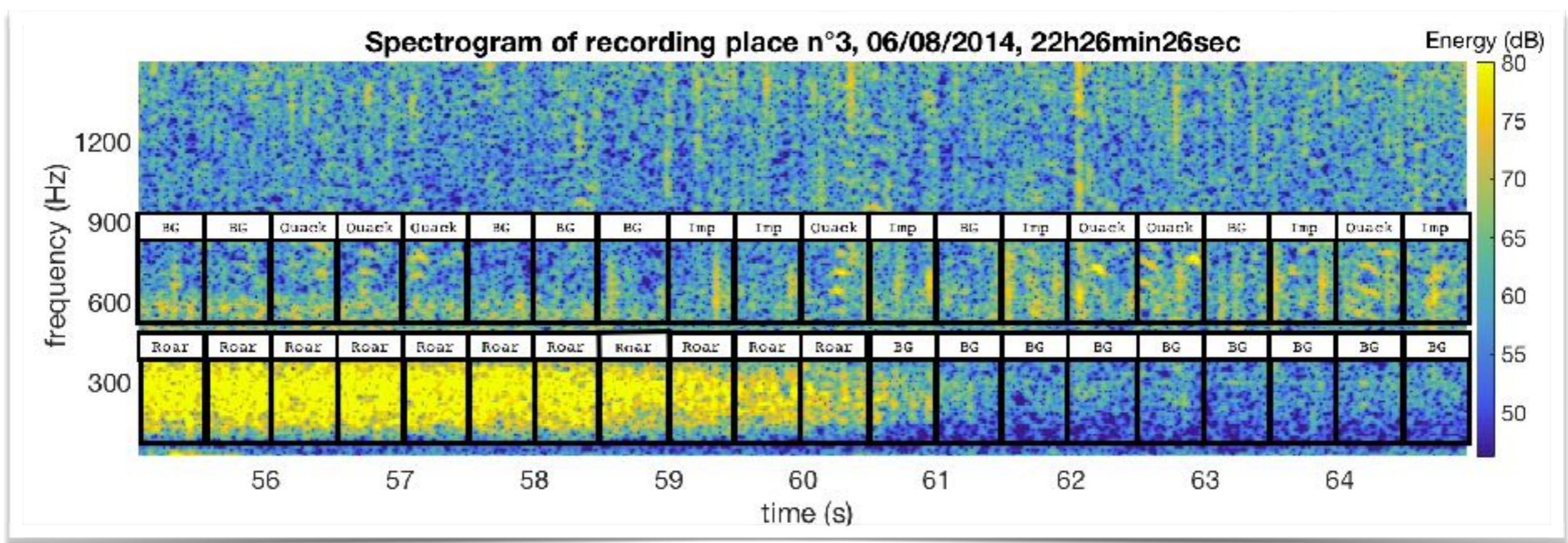
# Underwater acoustic data

## OBSERVATION

$$\Delta_t = 0.5s \quad \Delta_f = 400Hz$$

## DATASET

- **913** observations (manually extracted),
- 4 `positive' classes (fish sounds): Quacks, Drums, Impulse, Roar.
- 1 `negative' class: Background.



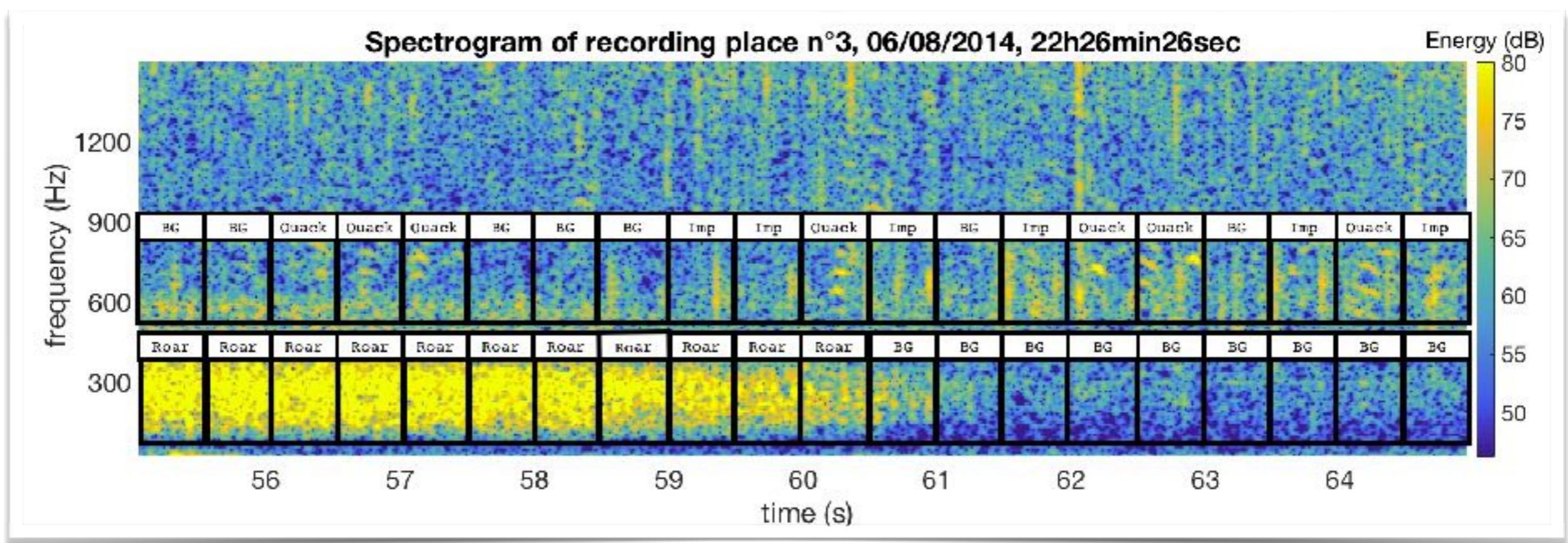
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*Cross-validation (30% - 70%) - RF - 200 trees - entropy*

## Accuracy

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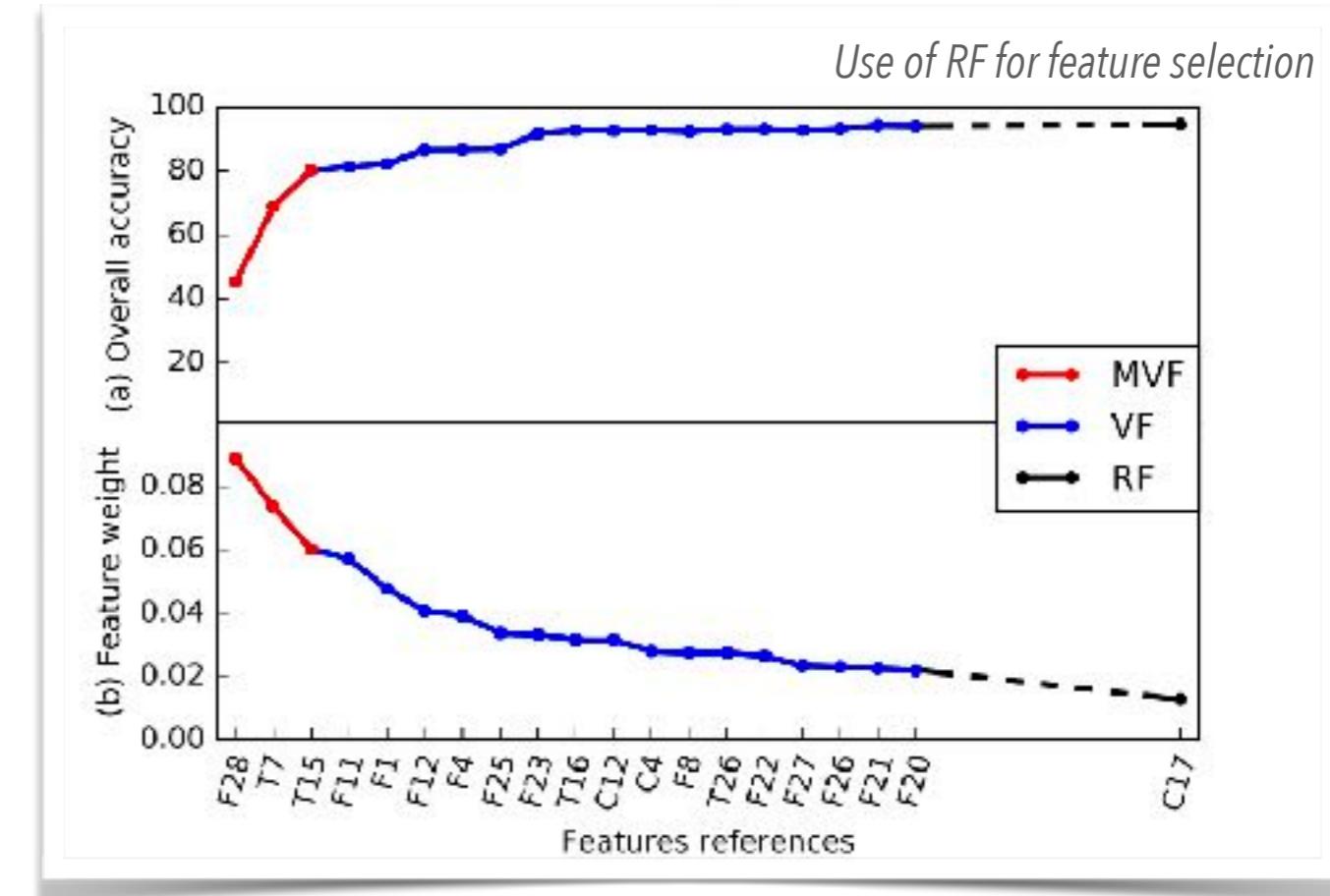
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Valuable Features (19)	$95.6 \pm 0.79\%$



## Three Most Valuable Features

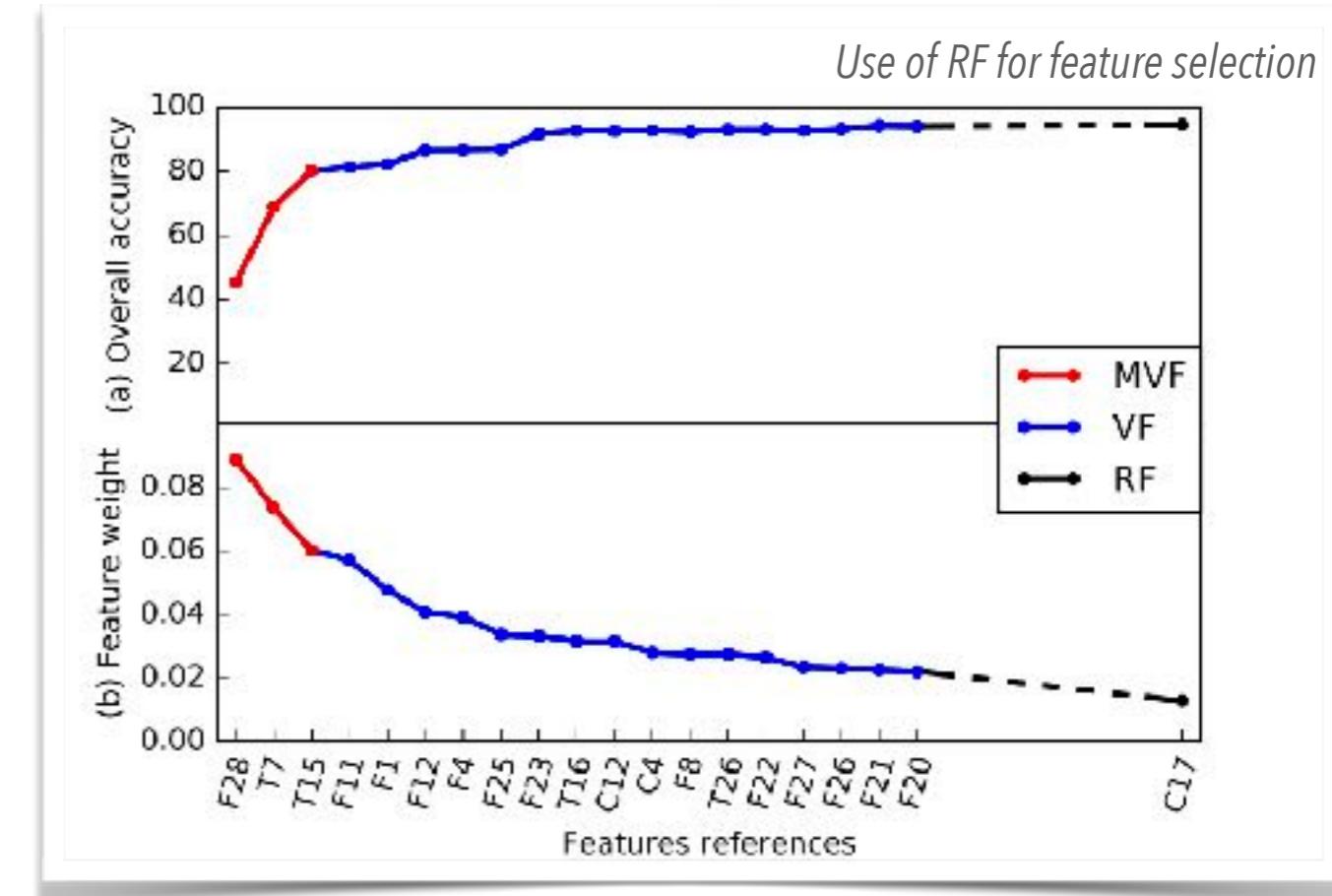
1. Energy kurtosis (from spectrum)
2. Mean kurtosis (from waveform)
3. Threshold crossing rate (from waveform)

$$\frac{1}{n} \cdot \sum_t \left( \frac{E_t - \mu_E}{\sigma_E} \right)^4$$

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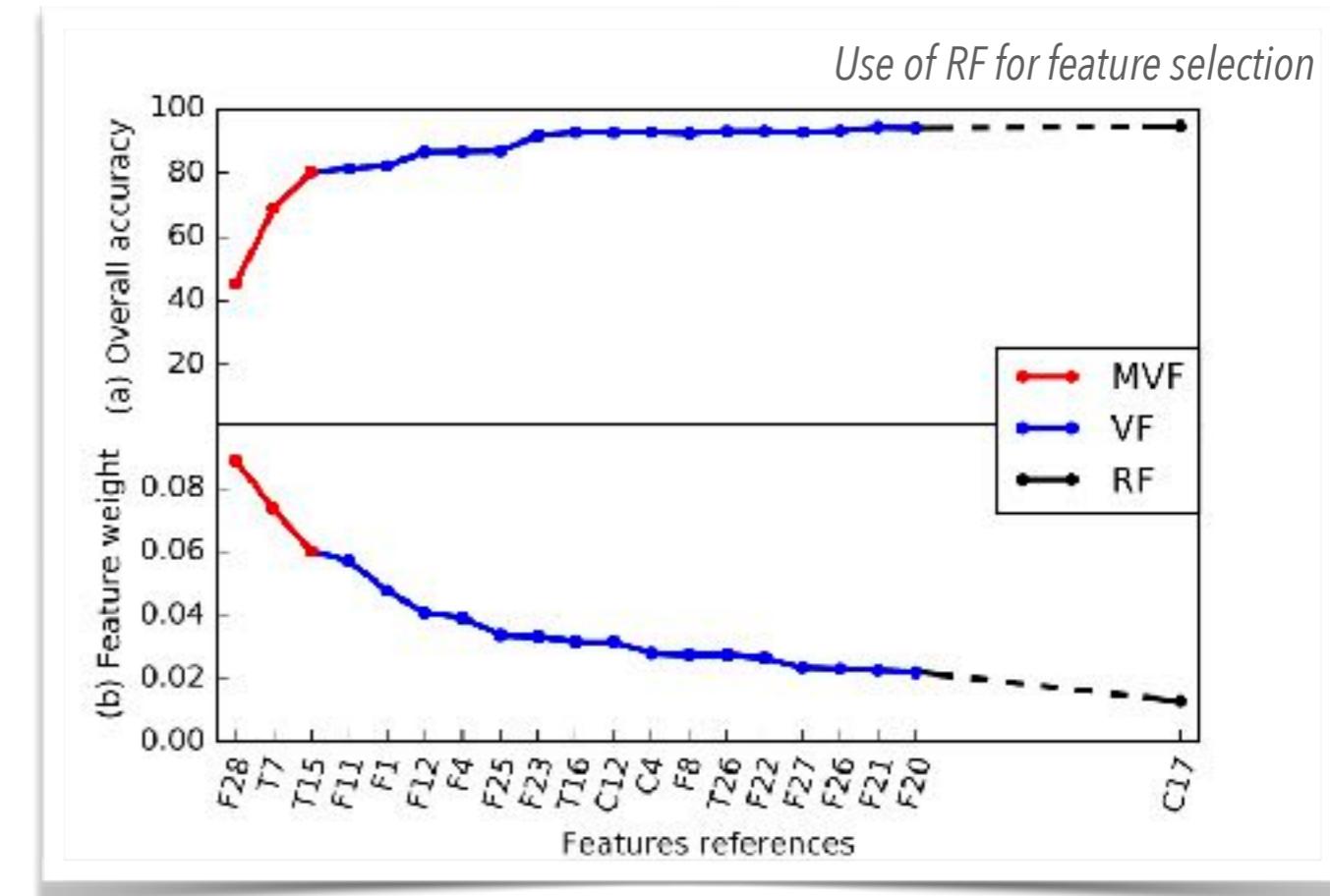
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$$\sqrt{\frac{\sum_i (i - \bar{i})^4 \cdot E_i}{E \cdot RMS_i^4}}$$

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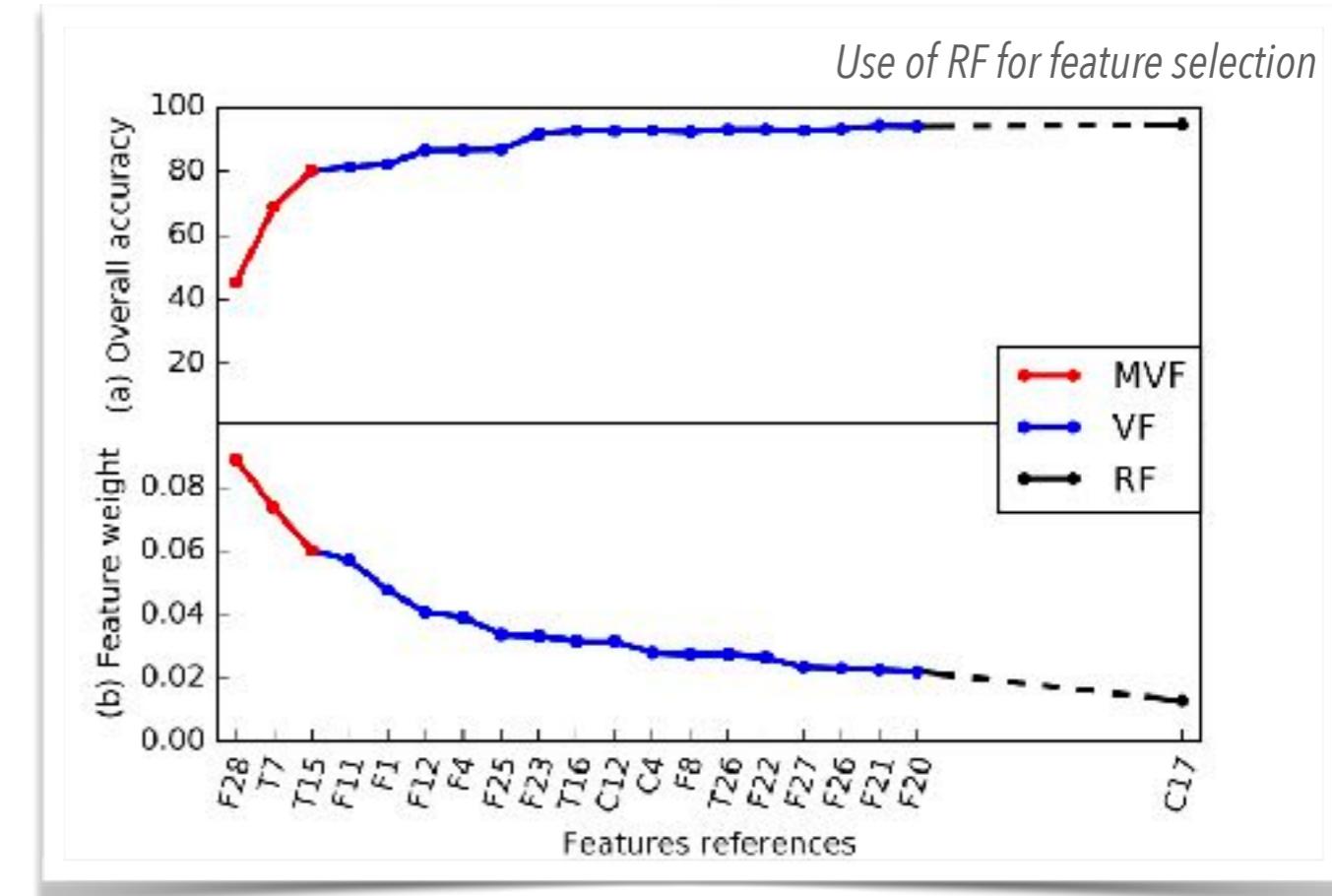
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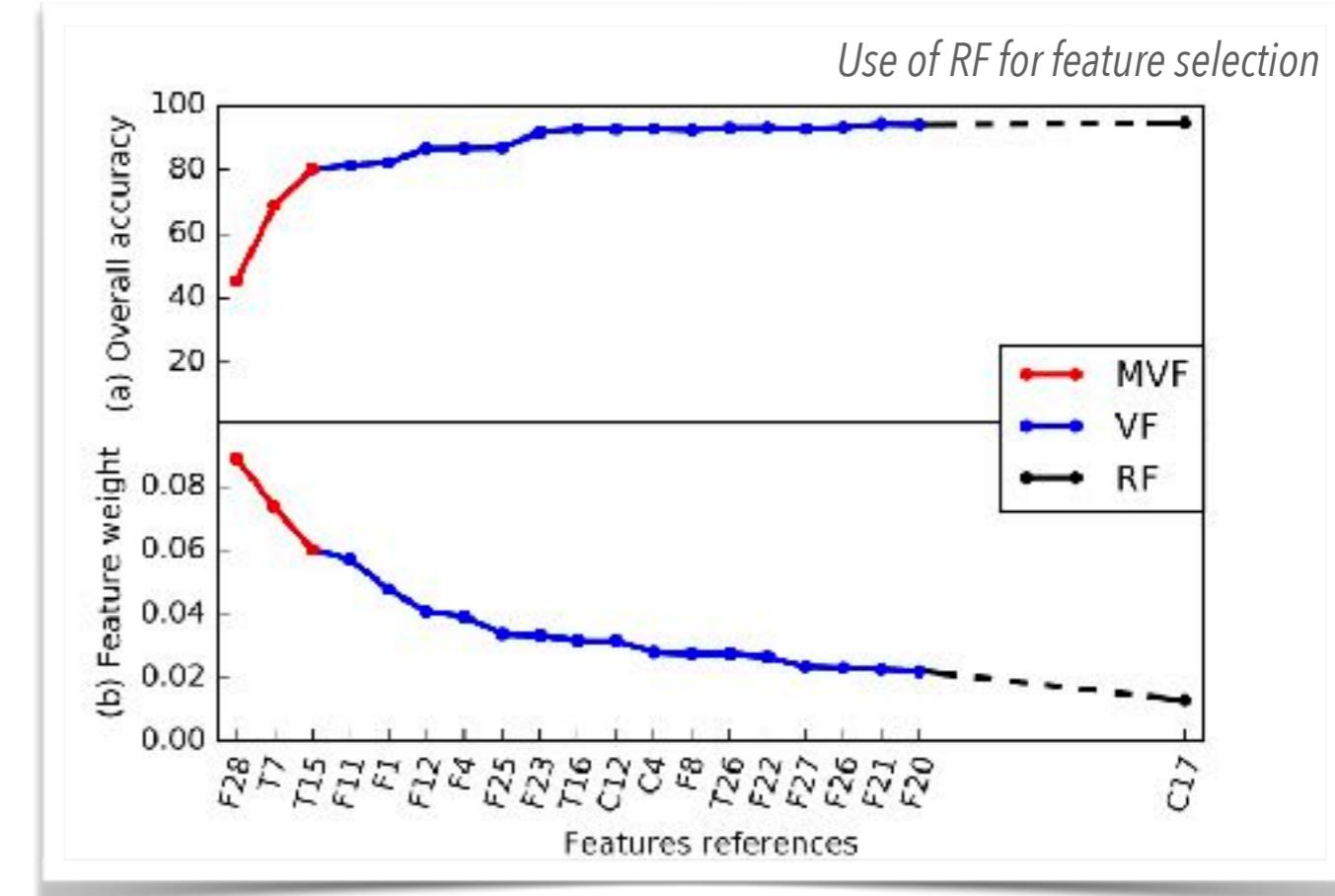
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MFCC (26)	$72.5 \pm 3.3\%$
	$75.0 \pm 1.99\%$
Deep features	to $89.5 \pm 1.15\%$

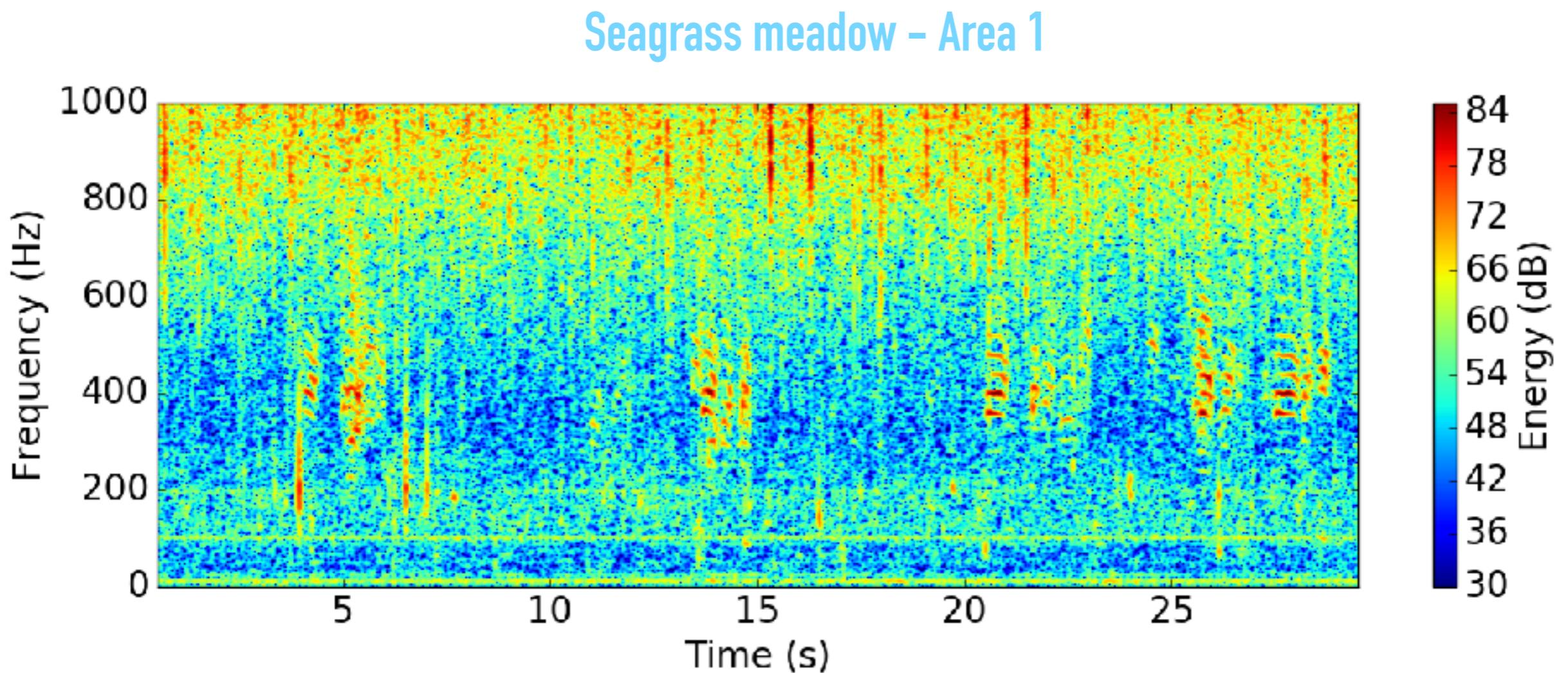


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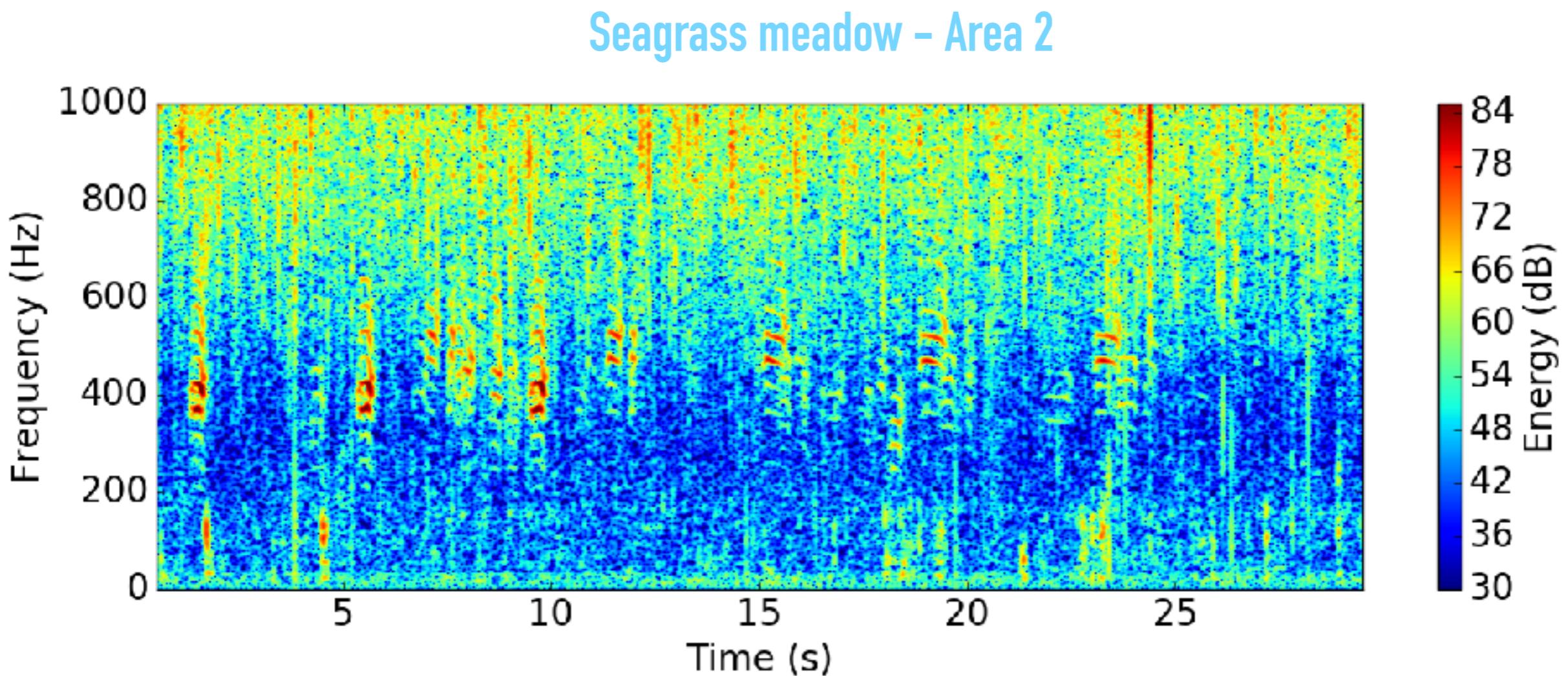
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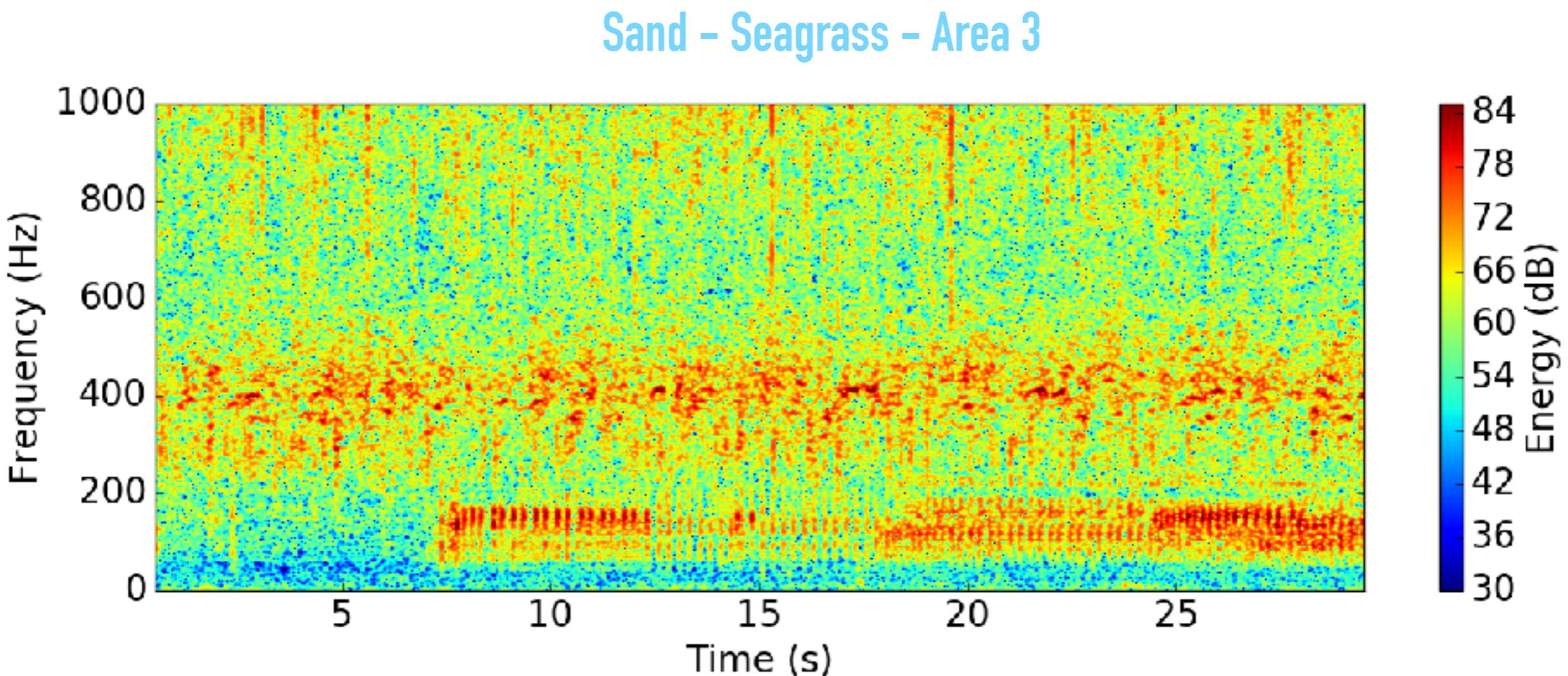
# Full analysis of continuous recordings



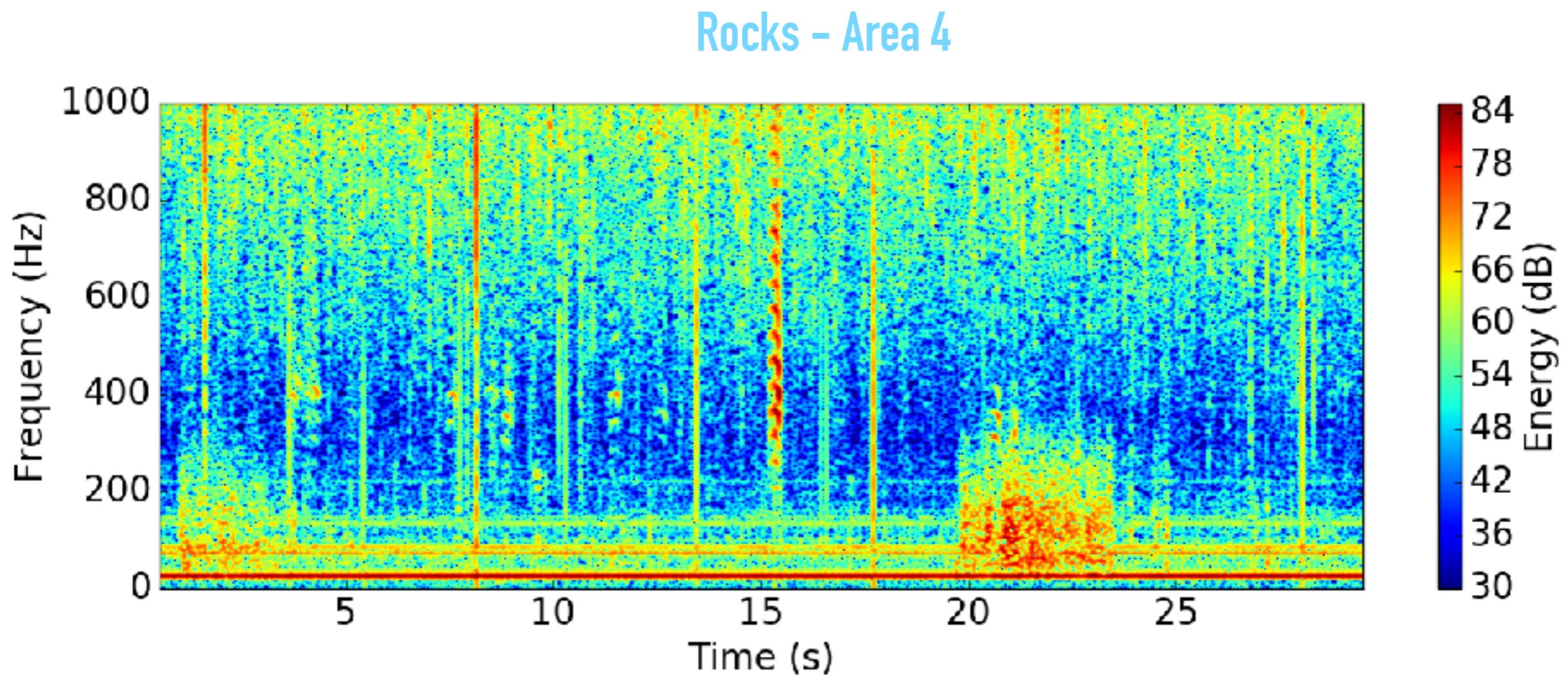
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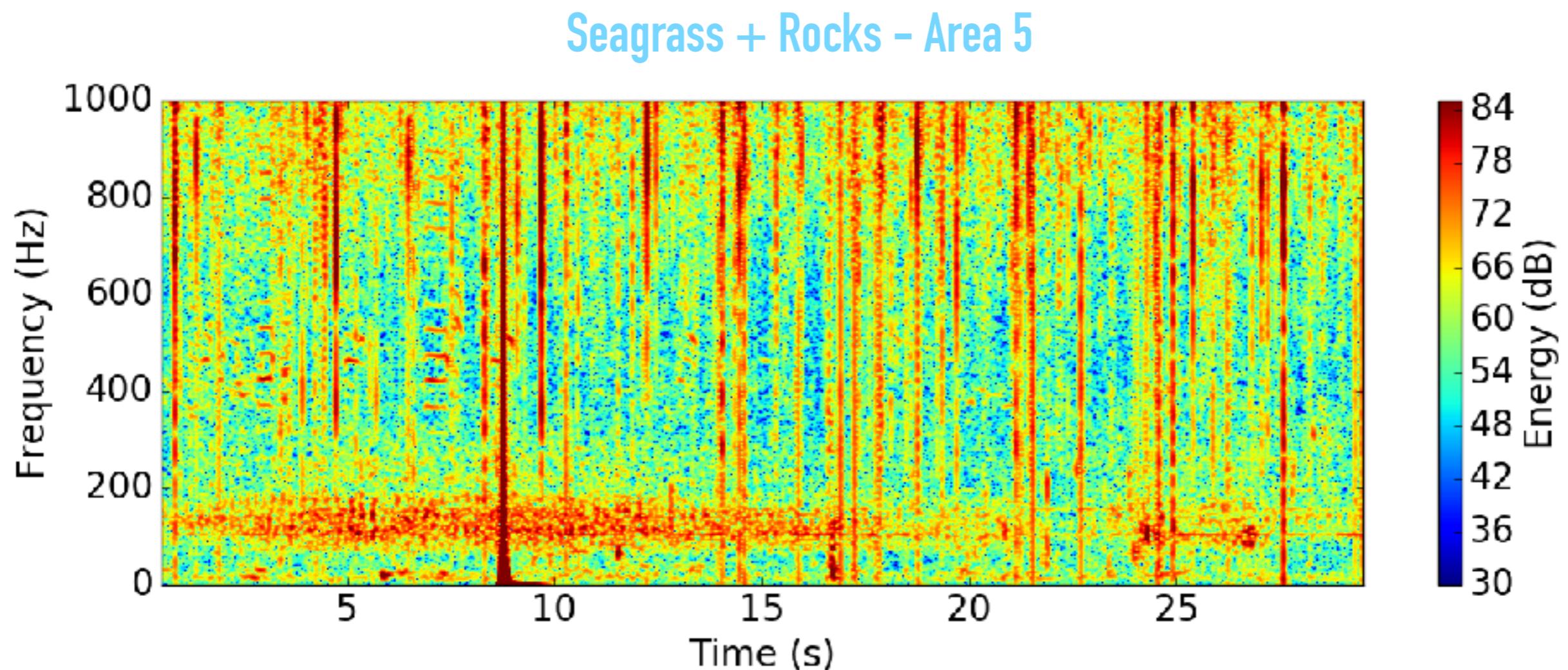
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# Full analysis of continuous recordings

1

Check the model performances under **various using conditions**

Learning

Area#3 - given time

Testing 1 - Area#3 - **Different time**

Overall accuracy = 93.4 %

		True Class (ground truth)					
		B	D	I	Q	R	U
Predicted Class	B	969	2	2	-	2	23
	D	-	133	1	-	-	2
	I	-	-	208	-	-	-
	Q	5	-	-	245	-	2
	R	-	-	-	-	58	1
	U	39	16	11	40	13	624

SVM model, all features

		True Class (ground truth)					
		B	D	I	Q	R	U
Predicted Class	B	885	6	4	-	-	21
	D	3	40	-	-	-	8
	I	16	-	21	-	-	-
	Q	6	-	-	256	-	-
	R	-	-	-	-	-	-
	U	207	24	15	127	-	651

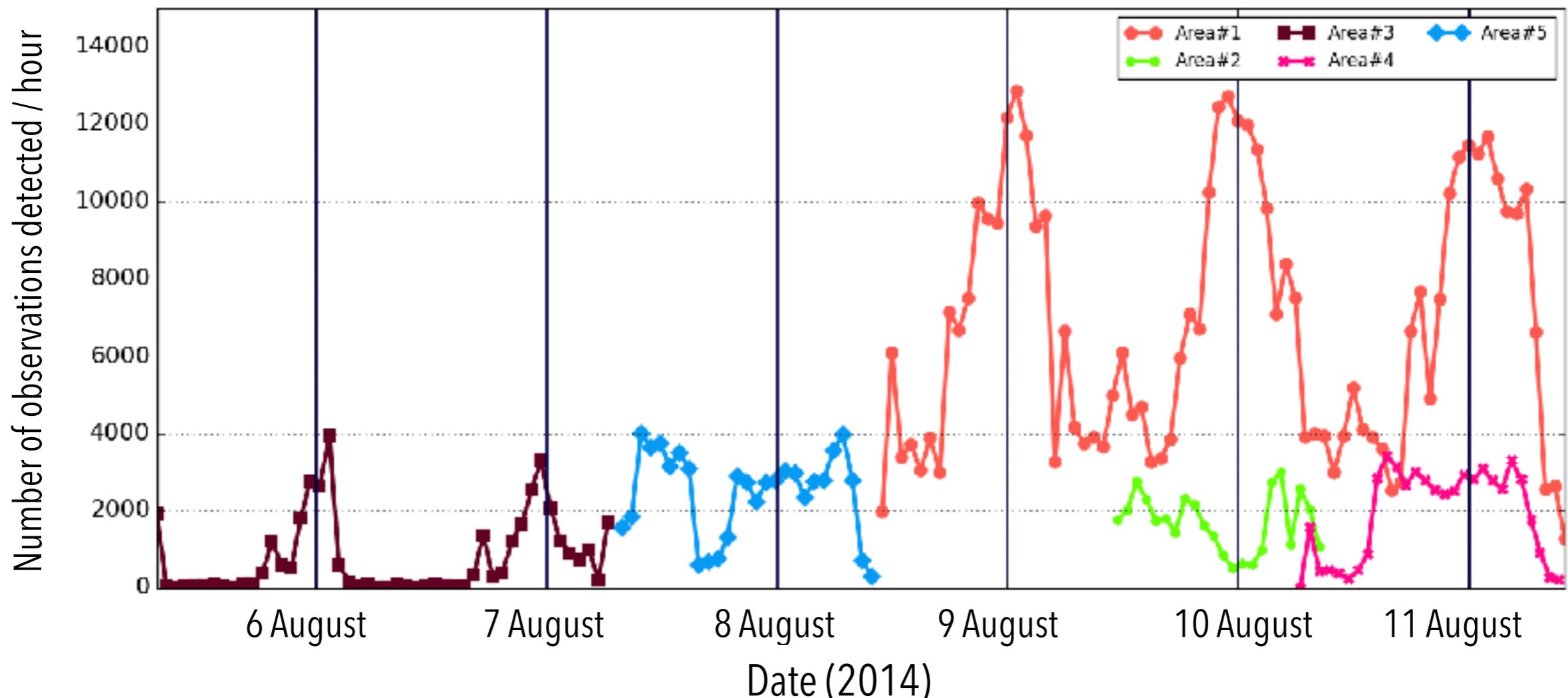
SVM model, all features

# Full analysis of continuous recordings

2

Analysis of the 5 different areas

**Hourly number of observations detected as 'Drums' (various recording areas)**



# Conclusion

# Summary

About machine learning & applications

- Scientifically mature tools?
- Usually for the same data: images, text, speech
- **What can we do for 'unusual' data?**

**Focus on the automatic processing of environmental signals.**

- Different applications, different constraints, but some **common points**:
  1. **Keep things as general as possible,**
  2. **Formalize some aspects,**
  3. **Propose operational tools (real world data),**
  4. **Knowledge on the environment,**
- 5. **Transfer of human knowledge (expertise), input of physics in the models.**

# Prospects

1

VOLCANOES

Test **detection** & classification. Issue of the validation process.

2

FEATURES

More tests. **Dictionary learning** methods. **Image processing** features.

3

POST-PROCESSING

Apply **time regularization** methods (temporal coherence).

4

MULTI-\* ANALYSIS

Multi **time scales**, **Multisource**, **Modality**, **Label**.  
**Hierarchical** models.

5

LABELING CONSTRAINT

To be reduced. **Semi-supervised** analysis.

# Prospects

**6**

MORE MODELS

Interest for other types of analysis:

1. Unsupervised analysis (less biased by human knowledge),
2. Mapping (for online visual monitoring).

Idea of hybrids architectures, running several types of analysis in parallel.

**7**

MORE DATA

Comparison of volcanoes.

Comparison of underwater areas.

Exploration of unknown environment in general.

# PhD, coding but also

International journal publications

Signal Processing Magazine,  
Journal of Acoustical Society of America,  
Journal of Geophysical Research.

Conferences

ASA 2016, Salt Lake City (USA) + Best student paper award + Lay language paper

EGU 2017, Vienna (Austria)

EUSIPCO 2017, Kos (Greece)

GRETSI 2017, Juan-les-pins (France)

OCEANS 2018, Kobe (Japan)

# PhD, coding but also

## Seminars

- Automatic Classification of Underwater Acoustics Data (poster), Machine Learning Summer School 2016, Cadiz (Spain)
- Automatic Classification and Detection of Fish Sounds (poster), *Deep Learning Summer School 2016*, Montreal (Canada)
- Machine Learning & Bioacoustics, *Serenade 2016*, Brest (France)
- Bandung (Indonesia),
- BPPTKG Yogyakarta (Indonesia),
- IPGP Paris (France)

## Teaching

- Label RES (Recherche Enseignement Supérieur) - 128h of teaching + 80h of training (signal processing, digital signal processing, C, java)
- Supervised Machine Learning & Applications to the Automatic Classification of Fish Sounds, *Chorus Workshop 2016*, Grenoble (France)
- Machine Learning: Introduction on general concepts & focus on supervised algorithms, training for BEST european student association, Grenoble (France)

# Thank you

Questions, interrogations, inquiries, comments, arguments, debate, discussions, dialogue, observations, opinions, reflections, statements, analysis, exchange, thoughts, remarks, ...

**go for it!**

