

# Classifying EEG data driven by rhythmic stimuli using a projective test

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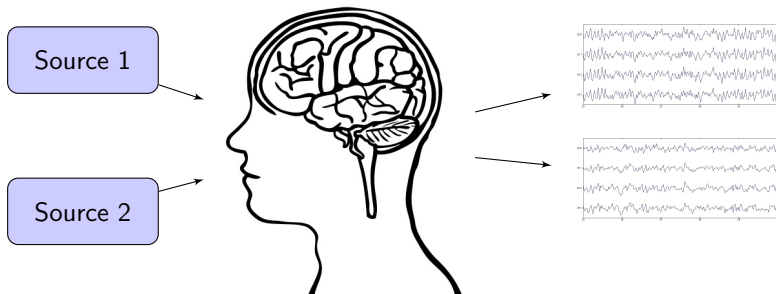
Work in progress

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# Neurobiological problem

Do stimuli of different sources produce distinct brain processes?



Can we classify them?

- The stimuli consist of **independent** samples produced by different stochastic rhythmic sources.
- Each sample is a sequence of **strong** and **weak** beats, and **silent** units generated by a probabilistic source
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# More Precisely

- Each stochastic source is characterized by a probabilistic context tree.
- **Statistical fact**: each of them can be estimated **consistently**.
- **Question**: Can we **distinguish** samples produced by different sources?

# Goal

- Our **goal** is to classify EEG signals driven by rhythmic stimuli.
- This is a problem of functional random data classification.
- Model selection in Electroencephalographic (EEG) data is a challenging task.

- First rhythm: **Waltz** (Ternary).



- Symbols:

- 2 - strong beat.
- 1 - weak beat.
- 0 - silence unit.

- Stochastic rhythm generation:

- start with a deterministic sequence

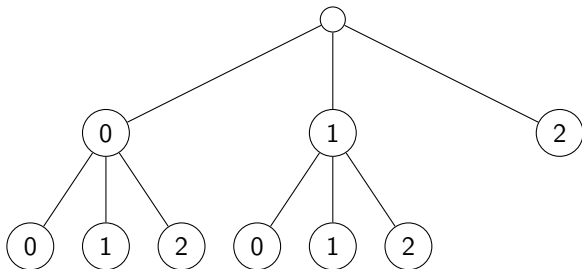
... **2 1 1 2 1 1 2 1 1 2** ...

- replace in a iid way each symbol 1 by 0 with a probability (say 20%).

A typical sample would be

...2 1 1 2 1 1 2 1 2...  
...2 1 1 2 1 0 2 0 1 2...

The correspondent context tree is



- Second rhythm: simplified **Samba** (Quaternary).



- Symbols:

- 2 - strong beat.
- 1 - weak beat.
- 0 - **constitutive** silence unit or **omitted** weak beat.

- Stochastic rhythm generation:

- start with a deterministic sequence

... 2 1 0 1 2 1 0 1 2 1 0 1 2 ...

- replace in a iid way each symbol 1 by 0 with a probability

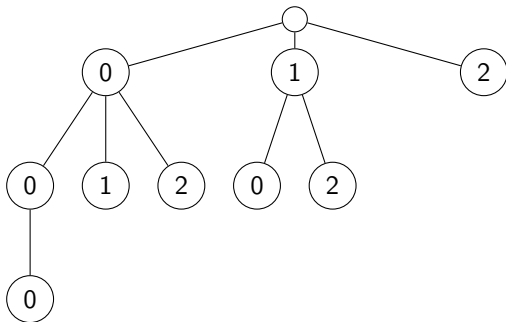


A typical sample would be

...2 1 0 1 2 1 0 1 2 1 0 1 2...

...2 1 0 0 2 1 0 1 2 0 0 0 2...

The correspondent context tree is



- Third rhythm: **Independent** rhythmic units.



- Symbols:

- 2 - strong beat.
- 1 - weak beat.
- 0 - silence unit.

- Chain generation:

- choose any symbol in a iid way with probability 1/3.

A typical sample would be

...2 1 0 1 1 2 2 0 1 0 2...

The correspondent context tree is reduced to the root. Why?

# Acquisition



- Each volunteer was exposed to two rhythmic blocks of 12 min each.
- Each rhythmic block is a concatenation of three rhythms:
  - $B_{WIS} = \{\text{Waltz}, \text{Independent}, \text{Samba}\}$
  - $B_{SIW} = \{\text{Samba}, \text{Independent}, \text{Waltz}\}$
- Each sample corresponding to a given rhythm lasts for 3 min and is preceded by a one minute interval of silence.

We mark each stimulus onset:

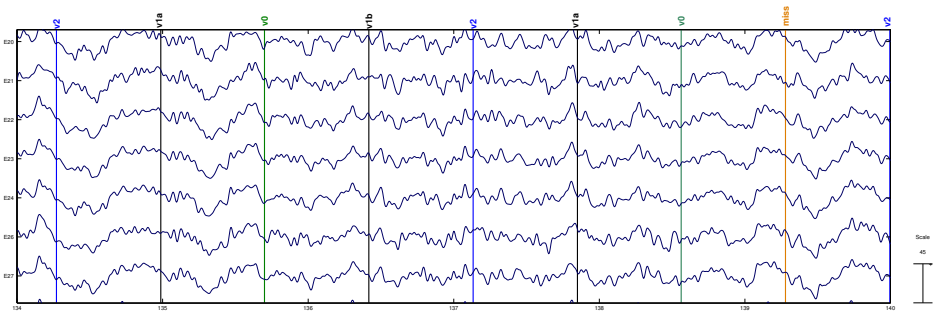
**Constitutive** silence unit  $\rightarrow V_0$

Weak beat  $\rightarrow V_1$

Strong beat  $\rightarrow V_2$

**Omitted** weak beat  $\rightarrow$  **Miss**

# EEG data



# Summarizing

- Stochastic Sources modeled by Probabilistic Context Trees.
- Each source can be statistically retrieved from a sample.
- EEG samples associated to each context tree rhythmic source.

Are the EEG samples statistically different?

How to tackle this question?

# Projective Method

- Given two random samples of functional data, we want to test if these two samples came from the same source.
- Projective method: choose a randomly **direction** and perform a one dimensional statistical test for the **projected data**.
- This method was introduced in Cuesta-Albertos, Fraiman and Ransford (2006).
- This approach was successfully employed in the classification of linguistic sonority data in Cuesta-Albertos, Fraiman, Galves, Garcia and Svarc (2007).



# Projective Method: groundwork

- If the laws of two random mechanisms are such that:
  - one of them is not “heavy-tailed” .
  - the set of the directions in which the laws are the same has positive probability.
- Then: the laws are equals!

## How to apply it?

- Consider each EEG signals collected from each electrode as an outcome of suitable random mechanisms.
- Given the *Samba* and *Waltz* EEG signals, we want to test
  - $H_0 = \{P_{Samba} = P_{Waltz}\}$  (**null** hypothesis)
  - $H_1 = \{P_{Samba} \neq P_{Waltz}\}$  (**alternative** hypothesis)

Under  $H_0 = \{P_{Samba} = P_{Waltz}\}$ , for each direction the laws are **different**.

## Algorithm:

- Choose  $N$  independent directions  $W_i, i = 1, \dots, N$ . (Brownian motions)
- For each  $i$ :
  - Test the null at level  $\eta$  by projecting *Samba* and *Waltz* on  $W_i$ , using Kolmogorov-Smirnov test.
  - Define

$$Z_i = \begin{cases} 1, & \text{if we rejected } H_0 \\ 0, & \text{if we do not rejected } H_0. \end{cases}$$

- Define the average value

$$\bar{Z} = \frac{1}{N} \sum_{i=1}^N Z_i$$

and reject  $H_0$  if  $\bar{Z} \geq c_\alpha$ .

- **Question:** what should be the value of  $c_\alpha$  to have a test of level  $\alpha$ ?
- To answer this question we use a bootstrap procedure.

## Planning:

- To use the projective method to classify EEG samples driven by Samba, Waltz and IID stimuli.
- This has not been done yet: our data sample is not big enough.

Data is being collected!

**But** something can be done immediately with the small data set of the pilot study.

## Preliminary question: for the EEG data driven by Samba

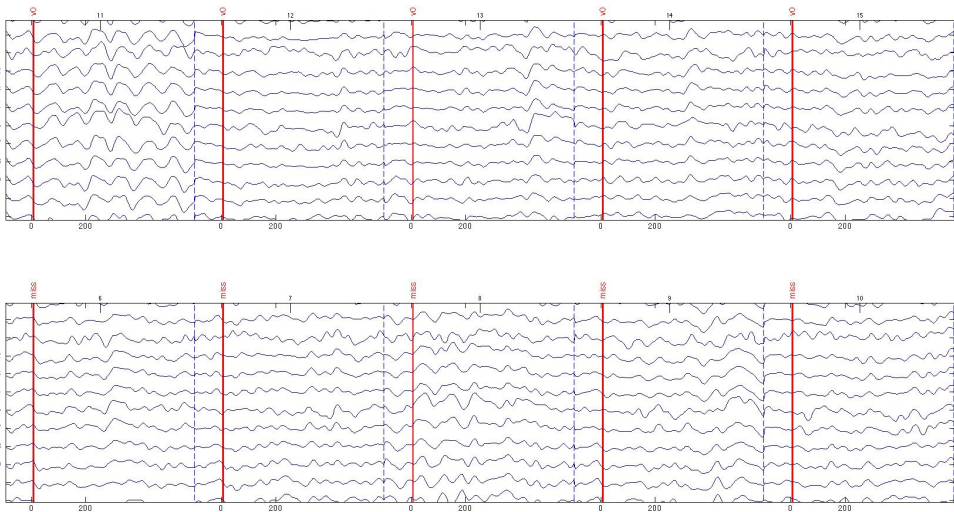
- Both Miss and  $V_0$  time intervals correspond to silence units.
- **However**, from a structural point of view Miss and  $V_0$  are entirely different.

Remember:

- Miss is an omitted weak beat.
- $V_0$  is a constitutive silence unit.

- From a structural point of view Miss and  $V_0$  are entirely different.
- Is the brain “aware” of this distinction?
- *More pragmatically: is our statistical tool able to catch this difference in the EEG signal?*

# V0 and Miss samples





# Results

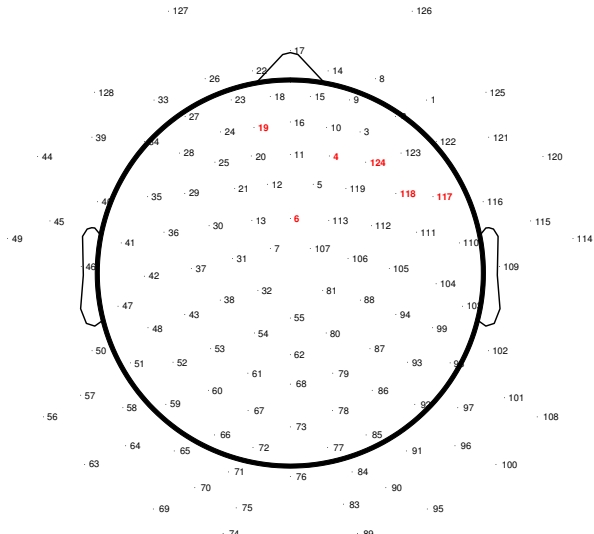
- The number of elements in  $\mathcal{M}$  and  $\mathcal{V}$  are 54 and 126 respectively.
- We applied the test with  $N = 1000$ ,  $B = 100$ ,  $\eta = \alpha = 0.1$ .
- Pilot 6:

Elect	p-value
4	0.04
6	0.01
19	0.01
117	0.02
118	0.03
124	0.04

## Pilot 6

Reject H0

Do not reject H0



To be continued....