

# Computational Neuroscience Workshop

## Brain States Recognition from EEG Recordings with Machine Learning

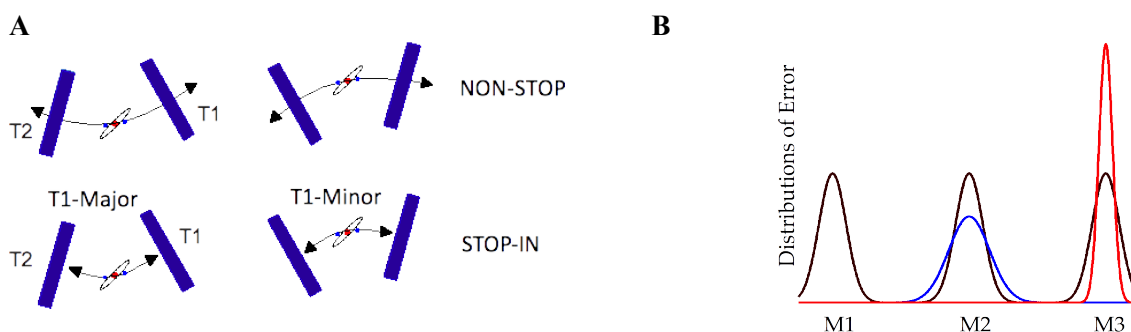
The goal of this workshop is to have a first hands on contact with some algorithms of Computational Neuroscience and with some classification algorithms, which are commonly used in Machine Learning. We will use a set of EEG data recorded during a psychophysical experiment aimed at testing a hypothesis of the influence of motivation onto movement.

### Experimental Description

We will use a dataset from an experiment for the study on decision-making between movements of opposite motor cost (FIG 1A). We asked our participants to perform this task under several conditions of different social pressure (FIG 1B). This manipulation was aimed at inducing different motivated states, which we will use to measure by means of electro-encephalographic recordings.

A single participant takes part in each session. Each session is composed of several trials, to gather the neural and behavioural data we will analyse next. Each trial follows the same timeline: it first starts with the presentation of a geometrical distribution (blue rectangles) from an origin cue (a small red circle) presented at the centre of the computer screen (FIG 1A). Once the stimuli have been presented, the volunteer must choose a target and make a planar reaching movement, while trying to touch the rectangle of his/her choice which was synchronized as a function of the finger position. At each trial, we recorded the index finger trajectories as a response of the presentation of the stimuli by means of a 3D tracking device, as well as electro-encephalographic signals, which provide us with a metric of the brain state at the beginning of the trial.

It is well known that the cost of each movement exerts an influence on each trajectory and choice between trajectories. Our hypothesis is that our motivated state also influences our decisions between movements and/or the specifics of each movement we perform. To assess that, we measured how often the volunteer chose the right/left rectangle and analysed the speed, movement and error rate.



**Figure 1. A.** Presentation of geometrical schemas for decision-making. At each schema, there is two goals (T1 on the right or T2 on the left), a red origin cue. All trajectories depart from that origin cue. To assess cost difference we designed two T1-Major schemas (the movement towards the right implies a lesser cost, than the one towards the left), and T1-Minor (reversed costs with respect to the T1-Major arrangement). **B.** Manipulation of the internal motivation of the participant. Distributions of error of the participant (black) and of their partners (blue --- lesser skill, and red – higher skill).

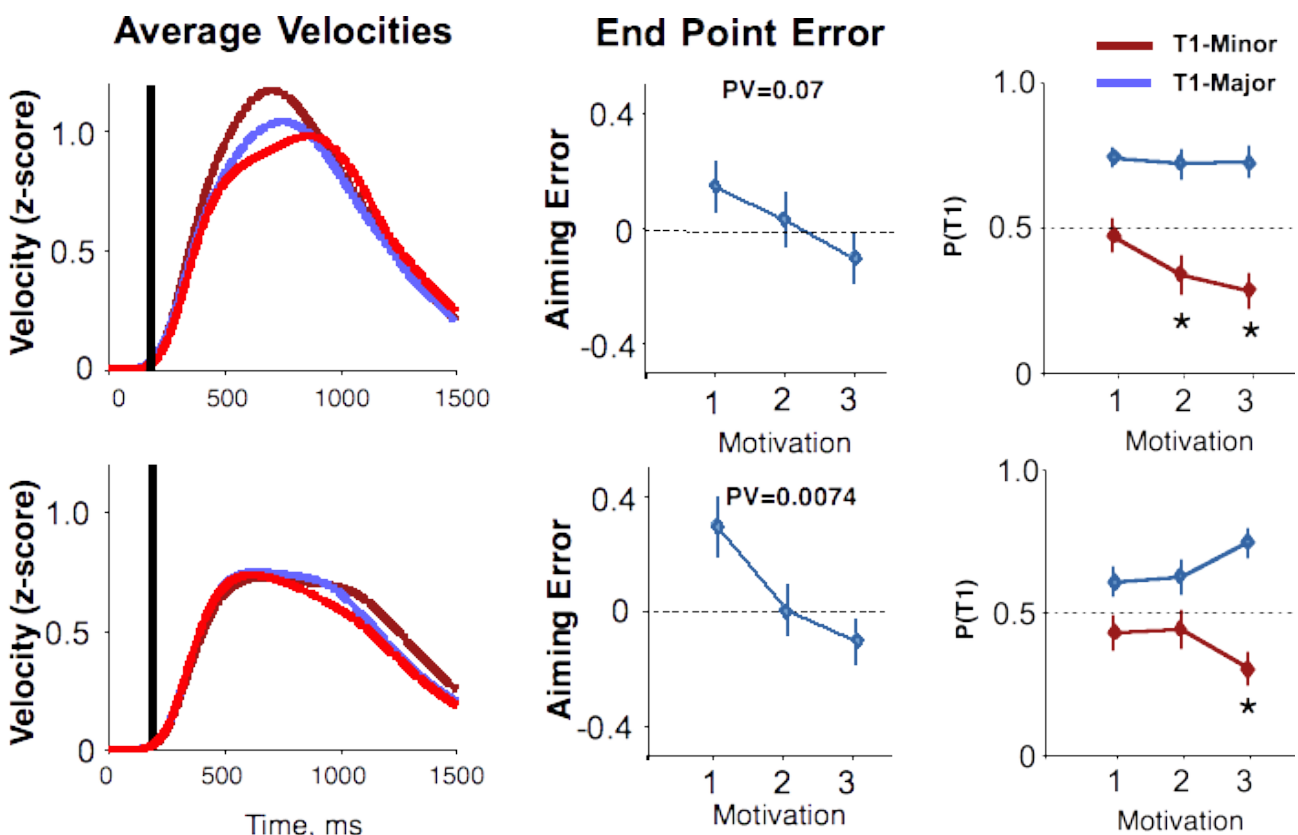
Although the goal choice (rectangle) is free, the goal of each movement is that of winning points as by being more precise by arriving at the centre of the rectangle long side. The more central is our arrival, the more points we will win, the further

off is our trajectory, the lower is the outcome. Furthermore, upon movement completion, we showed the subject a green error bar [0-100%], indicating the amount of points earned in that trial.

**We used social pressure to manipulate the participant's motivated state.** In this context, the manipulation of the motivational state consists of simulating the presence of a partner player with a skill different from that of the participant. In summary, we create avatars to induce three potential motivated states:

- *State 0 (Motivation 0)*, play alone (most relax).
- *State 1 (Motivation 1)*, Play with a player of a lesser skill.
- *State 2 (Motivation 2)*, Play with a player of a higher skill level.

Furthermore, every time our participant finishes a trial by movement execution, we show him/her the amount of points he/she won, contingent on the precision upon target arrival. We also show the points of the partner on that specific trial (when playing with a partner). To prevent that the subject starts a competition against the partner, we instructed him/her that the purpose of the partner's presence is not competition, but rather keeping company to the participant during task performance.



**Figure 2.** A. Velocity profiles as a function of the motivated stat. B. Arrival Error as a function of the motivated state. C. Frequency of choice of the rectangle on the right for both geometrical target configurations (T1-Major/T1-Minor).

### Data Recordings

In addition to trajectories, which report the decision and assess movement precision, we also record electroencephalograms, which allow us to extract a metric of brain activity during decision-making for each motivated state.

## DATA ANALYSIS

The part related to movement analyses is provided (no need to care about that). FIG 2 (left) shows three typical trajectories in each of the three motivated states, in the centre it shows the precision error of our participant in each of the three motivated states. In the centre, it shows the precision error of our subject in each of the three motivated states (1,2,3), and the graph in the centre shows the frequency with which it selected the right target as a function of the motivated state.

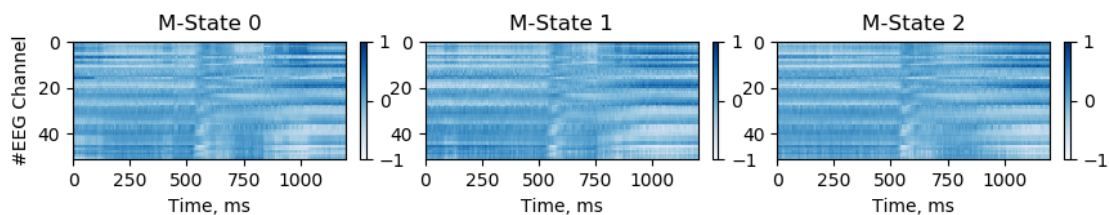
PLEASE, DOWNLOAD THE NECESSARY SOFTWARE FROM THE FOLLOWING LINK:

[https://ubarcelona-my.sharepoint.com/:f/g/personal/ignasi\\_cos\\_ub\\_edu/EpKJUjB68ChCnJGOPYvgx9QBcnweW8xpZ1TdZDtITmVKQg?e=VRKldp](https://ubarcelona-my.sharepoint.com/:f/g/personal/ignasi_cos_ub_edu/EpKJUjB68ChCnJGOPYvgx9QBcnweW8xpZ1TdZDtITmVKQg?e=VRKldp)

It contains a compressed set of files with the scripts to run.

## BRAIN DATA ANALYSES

The analysis of cerebral data will be performed by means of a program written in Python (a programming language developed for numerical calculus), which is written and made available to you.



**Figure 3.** Colour maps showing the average recording for each motivated state (Motivation 0 – Alone, Motivation 1 – Partner of lesser skill, Motivation 2 – Partner of higher skill). The y axis indicates the #electrode, and the x-axis time in ms. These are 1200ms data fragments.

Figure 3 shows a data EEG segment for each motivated state (which we know yield diverse motor responses). Our question is whether, by means of computer science algorithms, we would be able to distinguish these states. To this end, we will follow the next steps:

- **Open a terminal and execute the following command:**

- `python3 mostra_EEGs.py`

1. Band-pass signal within three frequency bands. The EEG signals are a combination of different frequencies, because they are created by very many neurons that communicate across themselves, the combination of which we may record via EEG electrodes.
  - a. Because of this, historically, EEG signals are studied by frequency band: Alpha ( $\alpha$ : 8 -15 Hz), Beta ( $\beta$ : 15-32 Hz), Gamma ( $\gamma \geq 32$  Hz). Since we do not know how the brain does to code the level of motivation induced experimentally, it is convenient to decompose the signal into its frequency components to identify whether there is a relationship between frequency and the motivated state:

- **Open a terminal and execute the following command:**

- `python3 separa_EEG_frequencies.py`

This should show us the EEG signal for each band in three different colours: blue (alpha-band), green (beta band), orange (gamma band).

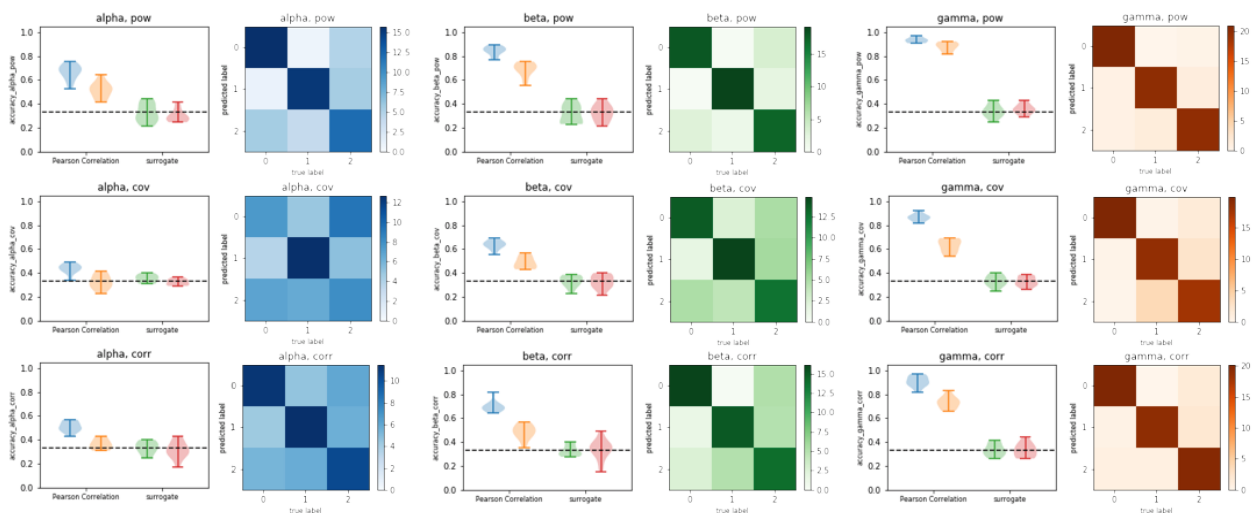
- b. The decomposition within bands of frequency is performed by means of band-pass filters, which return the components corresponding to each frequency band.
2. The classification of different motivated states is made by means of two classic classifiers: a logistic regressor and a k-means. The algorithm works in two steps, a training step to calculate the parameters characterizing each state, and an exploitation one, to assess the new data we wish to classify. If you execute your program in python, you will see an example of classification. In our case, we have use three metrics to classify our states:
    - a. Local electrode activity.
    - b. Correlation between electrodes.
    - c. Covariance between electrodes.

We will attempt a classification with each of the three metrics:

- **Open a terminal and execute the following command:**
  - `python3 classifica_EEG_Motivacio.py`

The results shown next should eventually show up and be stored as graphic files in .png format. In general, there are two effects worth noticing (FIG 4):

- The logistic regressor classifies better than the k-means; see Success Rate (%) in light blue) --- K-means in orange.
- The frequency band that most contributes to the classification is the gamma band (red).



**Figure 4.** This group of graphs shows the classification rates of the three motivated states, expressed as a percentage for both classifiers (logistic – light blue; k-means in orange). On the right of each classification rate we find its related confusion matrix, which shows the degree of classification obtained across the three states considered (in the ideal case, it should be a diagonal matrix). Present 9 cases, as a function of two factors: frequency band (alpha, beta, gamma) and a metric of classification (three metrics: electrode power, statistical covariance, and electrode correlation). The graphs are distributed by frequency from left to right and by metric from top to bottom. The next figure shows the activity, correlations between electrodes and covariances that contribute the most to the reported classifications.

3. The fact that the classification is possible ( $SR > \text{chance level}$ ), shows that these algorithms can identify cerebral states related to the three motivational states with a certain degree of reliability. However, this classification does not tell us much about which electrodes, and therefore, which are the brain areas responsible for these state differences. To identify where lays the difference, we can measure the contribution of each electrode individually to the consecution of this classification, by means of the recursive elimination algorithm. In brief, we eliminate the contribution of each electrode in an controlled fashion, and we assess how our classification degrades. To test this, run the next script:

- **Open a terminal and execute the following command:**
  - `python3 classificaContribucio_EEG_Motivacio.py`

This should generate the images shown in FIG 5 as .png graphic files. Your task would be to order them. Which conclusion can you draw?

