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Frites: A Python package for functional connectivity analysis and group-level statistics of neurophysiological data

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Summary

The field of cognitive computational neuroscience addresses open questions regarding the complex relation between cognitive functions and the dynamic coordination of neural activity over large-scale and hierarchical brain networks. State-of-the-art approaches involve the characterization of brain regions and inter-areal interactions that participate in cognitive processes (Battaglia & Brovelli, 2020). More precisely, the study of cognitive brain networks underlies linking local neural activity or interactions between brain regions to experimental variables, such as sensory stimuli or behavioral responses. The relation between the brain data and external variables might take complex forms (e.g. non-linear relationships) with strong variations across brain regions and participants. Therefore, powerful measures of information are required to detect complex relations and the statistical relevance at the population level should be able to adapt to the inter subject variability.

Statement of need

`Frites` (*Framework for Information Theoretical analysis of Electrophysiological data and Statistics*) is an open-source Python package, designed for researchers and students with little programming knowledge and working on the discovery of cognitive brain networks using neurophysiological data. It combines in a single framework information-based analyses of neurophysiological recordings and group-level statistical inference that can adapt to the inherent variability across participants. The measures of information and the group-level statistics functionalities are wrapped into high-level workflows. In addition, `Frites` also includes several measures of functional connectivity (FC) for measuring pairwise interactions between brain regions. To the best of our knowledge, `Frites` is the only Python software combining information-theoretical approaches with flexible group-level analyses for the discovery of cognitive brain networks.

Supported neurophysiological recordings and link with other softwares

`Frites` is suitable for the analysis of continuous and multi-channel neurophysiological data, encompassing non-invasive recordings with uniform spatial sampling (e.g., M/EEG data) such as invasive and spatially sparse recordings, such as intracranial EEG or Local Field Potentials (LFPs). The package supports standard `NumPy` array inputs (Harris et al., 2020), neuro-oriented objects from the `MNE-Python` software (Gramfort et al., 2013), but also multi-dimensional labelled `Xarray` objects (Hoyer & Hamman, 2017).

Measures of information and group-level statistics

Frites is equipped with a set of information theoretic tools for the analysis of interactions between brain signals and their relation with experimental task-related variables. By default, Frites is using the Gaussian Copula Mutual-Information (Ince et al., 2017) to study the relation between either local brain activity, cross-frequency coupling (Combrisson et al., 2020) or inter-areal FC with experimental variables (i.e., cognitive tasks). For what concerns FC, the toolbox allows the estimate of dynamic (i.e., time-resolve) (Brovelli et al., 2017), undirected (e.g., mutual information) and directed (e.g., Granger causality) FC on a single-trial basis (Brovelli et al., 2015). The networks built from the FC can then be further analyzed using graph-theoretical approaches from the Brain Connectivity Toolbox (Rubinov & Sporns, 2010). Nevertheless, Frites is not limited to the included estimators as the definition of custom ones is also supported, such as IDTxl kernel methods (Wollstadt et al., 2019), infotheory information decomposition (Candadai & Izquierdo, 2019) or scikit-learn cross-validated classifiers (Pedregosa et al., 2011). The estimated information can then be combined with the group-level statistics for the identification of feature-specific networks. While Frites is strongly oriented toward neuroscience applications, the estimators of information are agnostic to data types and can therefore be applied to different fields.

For statistical inferences, the package integrates a non-parametric permutation-based statistical framework (Maris & Oostenveld, 2007) to perform group-level inferences on non-negative measures of information. The toolbox includes different methods that cope with multiple-comparison correction problems, such as test- and cluster-wise p-value corrections. The implemented framework also supports both fixed- and random-effect models to adapt to inter-individuals and inter-sessions variability (Combrisson et al., 2022).

Workflows

Frites provides a set of workflows that integrate several analysis steps. Those workflows take as inputs the neural data coming from single or multi-participants (or single / multi sessions), estimate the amount of information shared between the brain data and the external variable, at each brain region and time bins, and finally perform network-level statistical inference, corrected for multiple comparisons. Those high-level workflows are particularly useful for users with no or little programming knowledge as all of those steps can be performed in a very few lines of code, with standard inputs like MNE-Python epochs.

Performance

Several computations implemented in the workflows, such as permutation tests, are computationally demanding. To decrease computing time, the core functions for information measures exploit a NumPy tensor-based implementation or can be accelerated using the Numba compiler (Lam et al., 2015). Then, Frites natively supports parallel processing using the Joblib package.

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