

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

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DOI: [10.21105/joss.03842](https://doi.org/10.21105/joss.03842)

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Submitted: 21 September 2021

Published: 01 December 2021

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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 brain data to experimental variables, such as sensory stimuli or behavioral responses.

Information-based measures, such as information theoretic quantities, machine-learning models or measures of distances, currently provide ideal tools for quantifying the coupling between brain signals, and the link between brain network's activity and task variables. Nevertheless, progress is limited by the lack of neuroinformatics tools that combine methods for the estimate of information-based measures from neural data and the assessment of their statistical relevance at the population level. *Frites* provides such an integrated framework and it is optimally developed for the discovery of cognitive brain networks from multi-channel neurophysiological datasets.

Statement of need

Frites (*Framework for Information Theoretical analysis of Electrophysiological data and Statistics*) is a pure Python package for cognitive (task-related) brain network inference, which combines in a single framework information-based analyses of neurophysiological data and group-level statistical inference.

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. More precisely, this package can be used to study the relation between local brain activity, cross-frequency coupling ([Combrisson et al., 2020](#)) and inter-areal functional connectivity (FC) with experimental variables (i.e., cognitive tasks). For what concerns FC, the toolbox allows the estimate of dynamic (i.e., time-resolve), undirected (e.g., mutual information) and directed (e.g., Granger causality) functional connectivity (FC) on a single-trial basis ([Brovelli et al., 2015](#)). The core functions for information measures exploit a NumPy tensor-based implementation of the Gaussian Copula Mutual-Information ([Ince et al., 2017](#)). Nevertheless, the definition

of custom estimators, such as kernel methods (Wollstadt et al., 2019) and `scikit-learn` cross-validated classifiers (Pedregosa et al., 2011), is also supported.

The package integrates a non-parametric permutation-based statistical framework 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 supports both fixed- and random-effect models to adapt to inter-individuals and inter-sessions variability (Combrisson et al., 2021).

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

In order to facilitate automated and efficient usage, Frites provides a set of high-level workflows that integrate several analysis steps from information-based estimation to network-level statistical inference.

Since several computations implemented in the workflows, such as permutation tests, are computationally demanding, Frites natively supports parallel processing using the `Joblib` package. In addition, some functions can further be accelerated using the `Numba` compiler (Lam et al., 2015) as an optional dependency. Programming optimizations and external dependencies allow to investigate large-scale datasets in a reasonable time.

Acknowledgements

EC and AB were supported by the PRC project “Causal” (ANR-18-CE28-0016). This project/research has received funding from the European Union’s Horizon 2020 Framework Programme for Research and Innovation under the Specific Grant Agreement No. 945539 (Human Brain Project SGA3). RB acknowledges support through a PhD Scholarship awarded by the Neuroschool. This work has received support from the French government under the Programme Investissements d’Avenir, Initiative d’Excellence d’Aix-Marseille Université via A*Midex (AMX-19-IET-004) and ANR (ANR-17-EURE-0029) funding. RAAI was supported by the Wellcome Trust [214120/Z/18/Z]. VLC is supported by a scholarship from the European Union’s Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 859937.

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