

HyperIT: A Python toolbox for an information-theoretic social neuroscience

Edoardo Chidichimo ¹

¹ Department of Psychology, University of Cambridge, UK

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: [Open Journals](#) 

Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

License

Authors of papers retain copyright,
and release the work under a
Creative Commons Attribution 4.0
International License ([CC BY 4.0](#)).

Summary

HyperIT is an open-source, class-based Python toolbox designed for an information-theoretic social neuroscience. Specifically designed for hyperscanning paradigms (simultaneous neuroimaging and neurophysiological recordings of social interactions), HyperIT is equipped to compute Shannon information theory measures including mutual information, transfer entropy, and integrated information decomposition for continuous time-series signals (fMRI, EEG, MEG, fNIRS, etc.) at different frequency bands and spatial scales of organisation. The toolbox allows flexible customisation of parameters for up to five different empirical estimators (including histogram, box kernel, kNN, Gaussian, and symbolic methods), statistical significance testing, and matrix visualisations. HyperIT integrates, depends upon, and provides an interface for the Java Information Dynamics Toolkit ([Lizier, 2014](#)) and phyid library ([Luppi et al., 2022](#); [Mediano et al., 2021](#)). To the best of the author's knowledge, there are no Python toolboxes or libraries specifically designed for hyperscanning analyses that are equipped with information-theoretic analyses whilst dealing with epochality, frequency resolution, and spatial scales of organisation.

Statement of need

For the past two decades, social neuroscience has addressed the interpersonal neural dynamics of interacting persons through the hyperscanning paradigm ([Dumas et al., 2010](#)). Synchrony and other statistical properties have been prioritised in these analyses, although most measures remain of the parametric type despite neural activity and coordination dynamics often being distinctly nonlinear. HyperIT presents the first principled and unified analysis framework for hyperscanning data using nonparametric measures.

Between interacting persons, we observe coordination and communication on various scales of organisation whose unit of transfer we can loosely describe as *information*. Whilst the idea of interpersonal information transfer may appear intuitive *prima facie*, it is not exactly clear how to define information, let alone measure its content, distribution, transfer, storage, modification, and other informational dynamics. Thus, an elegant definition and quantification of information that is *mathematically precise and consistent* is essential, particularly one that is *content-invariant* and *model-free*; i.e., making no assumptions on the information content itself nor the statistical distributions or relationship model between random variables.

Information theory, lauded as *the* mathematical theory of communication ([Shannon, 1948](#)), lends itself well to this cause, proffering domain-generalty and information as its common currency. Originally birthed for the development of communications engineering, various information-theoretic measures have found vast applicability in computer science (e.g., Kolmogorov complexity), economics (e.g., portfolio theory and Kelly gambling), statistics (e.g., Fisher information and hypothesis testing), and probability theory (e.g., limit theorems and

large derivations; Cover & Thomas (2006)). Information theory has recently earned a notable place in neuroscience, too (Timme & Lapish, 2018).

Of relevance for neuroscientific endeavours, information theory provides measures that can detect linear *and* nonlinear dependencies between continuous time-series signals, allowing researchers to analyse both the correlation and causation between two or more random variables. In all, whilst standard measures of correlation and prediction are only sensitive to linear dependencies and only describe the variable's overall relationship, information-theoretic analyses and measures can quantify and more comprehensively describe the dynamics of complex systems that may demonstrate nonlinear dependencies whilst maintaining a particular robustness to noise. HyperIT computes well-recognised and validated information-theoretic measures that, for the first time, can be simultaneously applied to both hyperscanning and intra-brain analyses for various neural recordings. Usefully, and unlike other libraries, HyperIT is equipped to handle epoched and event-based data as well as specifying both frequency bands and the level of organisation by comparing channels pairwise or by regions of interest. These measures include (I) *mutual information*, (II) *transfer entropy*, and (III) *integrated information decomposition*, described below.

Measures

Mutual information ($I(X; Y)$) is a positively-biased, symmetric measure indicating how much (Shannon) information is shared between two random variables X and Y (Equation 1). One may also interpret MI as quantifying the “distance” between the joint probability distribution (p_{XY}) and the product of marginal probability distributions ($p_X \otimes p_Y$), such that $I(X; Y) = 0$ iff $p_{XY} = p_X \otimes p_Y$. Thus, it is understood as a special instance of the Kullback-Leibler divergence measure.

$$I(X; Y) = \sum_x \sum_y p_{XY}(x, y) \log_2 \frac{p_{XY}(x, y)}{p_X(x)p_Y(y)}. \quad (1)$$

Transfer entropy ($TE_{Y \rightarrow X}$) is a measure that non-parametrically measures the statistical connectivity and time-directed transfer of information between random variables or processes. It is often taken as the non-linear equivalent of Granger causality and, indeed, equivalence has been demonstrated under Gaussianity (Barnett et al., 2009). Specifically, this measure uses conditional mutual information to quantify the reduction in uncertainty about the future of one process given knowledge about another variable and its own history (Equation 2).

$$\begin{aligned} TE_{Y \rightarrow X}^{(k, l, u, \tau)} &= I(\mathbf{Y}_{t-u}^{(l, \tau_Y)}; X_t | \mathbf{X}_{t-1}^{(k, \tau_X)}) \\ &= \sum_{\substack{x_t, \mathbf{x}_{t-1}^{(k, \tau_X)} \in \mathcal{X}, \\ \mathbf{y}_{t-u}^{(l, \tau_Y)} \in \mathcal{Y}}} p(x_t, \mathbf{x}_{t-1}^{(k, \tau_X)}, \mathbf{y}_{t-u}^{(l, \tau_Y)}) \log_2 \left(\frac{p(\mathbf{y}_{t-u}^{(l, \tau_Y)}, x_t | \mathbf{x}_{t-1}^{(k, \tau_X)})}{p(x_t | \mathbf{x}_{t-1}^{(k, \tau_X)})} \right), \quad (2) \end{aligned}$$

with parameters including embedding history length for source (l) and target (k), embedding delay for source (τ_Y) and target (τ_X), and some causal delay or interaction lag u .

More recently, approaches to exhaustively decompose a multivariate system's informational structure has described three modes; namely, information about a target variable may be redundant (Rdn): information that is shared between variables; unique (Unq): information that is specific to a single variable; or synergistic (Syn): information that is only learnt from the conjunction of multiple sources and not individually, with the exclusive-OR function being a canonical example (Williams & Beer, 2010). These so-called “partial information atoms” are

78 non-overlapping and form an additive set, exhaustively describing the informational composition
79 of a multivariate system (Equation 3).

$$I(Y; X_1, X_2) = \text{Syn}(Y; X_1, X_2) + \text{Unq}(Y; X_1) + \text{Unq}(Y; X_2) + \text{Rdn}(Y; X_1, X_2). \quad (3)$$

80 A recent development, termed *integrated information decomposition*, extends this decomposi-
81 tion to multi-source and multi-target continuous time-series random variables to decompose
82 information dynamics into various qualitative modes including information storage, copy, trans-
83 fer, erasure, downward causation, causal decoupling, and upward causation (Mediano et al.,
84 2019, 2021). This measure specifically decomposes the time-delayed mutual information
85 ($t' > t$) between two multivariate processes (Equation 4).

$$I(\mathbf{X}_t; \mathbf{X}_{t'}) = \text{Syn}(X_t^1, X_t^2; \mathbf{X}_{t'}) + \text{Unq}(X_t^1; \mathbf{X}_{t'} | X_t^2) + \text{Unq}(X_t^2; \mathbf{X}_{t'} | X_t^1) + \text{Rdn}(X_t^1, X_t^2; \mathbf{X}_{t'}). \quad (4)$$

86 Functionality

87 HyperIT, then, addresses these approaches and offers a user-friendly, class-based toolbox where
88 users can create a HyperIT object passing two multivariate sets of continuous time-series
89 signals (dimensions including epochality and multiple channels). As mentioned, users can
90 choose to bandpass filter their signals at specified frequency bands as well as specify the scale
91 of organisation by setting the “regions of interest” property; namely, specifying whether (and
92 which) channels are computed pairwise or as clusters with one another for all measures, making
93 micro-, meso-, and macro-scale analysis readily available. From here, users can call mutual
94 information and transfer entropy functions specifying estimation type and estimation-specific
95 parameters (outlined in documentation). Estimators include (a) histogram/binning, (b) box
96 kernel, (c) Gaussian, (d) k-nearest neighbour, and (e) symbolic approaches. Users may also
97 choose to conduct statistical significance testing via permutation testing for each calculation
98 and optionally visualise the measure matrices. Importantly, the toolbox relies upon the Java
99 Information Dynamics Toolkit for computing mutual information and transfer entropy with
100 various estimators (Lizier, 2014), although HyperIT makes this Java-oriented toolbox accessible
101 and compatible for Python coders who may in turn enjoy a diverse ecosystem of other scientific
102 libraries, most notably MNE and HyPyP (Ayrolles et al., 2021). Users will need to store
103 the infodynamics.jar file locally in their working directory as well as ensuring the jpye
104 dependency is installed. Finally, HyperIT employs the phyid package to compute integrated
105 information atoms (Luppi et al., 2022; Mediano et al., 2021). Thus, HyperIT offers a distinct
106 interoperability and compatibility with other Python libraries whilst providing unique features
107 of handling hyperscanning data, and versatility with epochality and scales of organisation.

108 In all, social neuroscience researchers working with continuous time-series signals (including
109 fMRI, EEG, MEG, and fNIRS), particularly in the context of hyperscanning, will be, for the
110 first time, able to comfortably compute common and powerful information-theoretic measures
111 using our HyperIT toolbox.

Acknowledgements

Thanks to Pedro A. M. Mediano, Eric C. Dominguez, Andrea I. Luppi, Richard Bethlehem, and Guillaume Dumas during the genesis of this project.

References

- Ayrolles, A., Brun, F., Chen, P., Djalovski, A., Beauxis, Y., Delorme, R., Bourgeron, T., Dikker, S., & Dumas, G. (2021). HyPyP: A Hyperscanning Python Pipeline for inter-brain connectivity analysis. *Social Cognitive and Affective Neuroscience*, 16(1-2), 72–83. <https://doi.org/10.1093/scan/nsaa141>
- Barnett, L., Barrett, A. B., & Seth, A. K. (2009). Granger causality and transfer entropy are equivalent for Gaussian variables. *Physical Review Letters*, 103(23), 238701. <https://doi.org/10.1103/PhysRevLett.103.238701>
- Cover, T. M., & Thomas, J. A. (2006). *Elements of information theory* (2nd ed). Wiley-Interscience. ISBN: 978-0-471-24195-9
- Dumas, G., Nadel, J., Soussignan, R., Martinerie, J., & Garnero, L. (2010). Inter-brain synchronization during social interaction. *PLoS ONE*, 5(8), e12166. <https://doi.org/10.1371/journal.pone.0012166>
- Lizier, J. T. (2014). JIDT: An information-theoretic toolkit for studying the dynamics of complex systems. *Frontiers in Robotics and AI*, 1. <https://doi.org/10.3389/frobt.2014.00011>
- Luppi, A. I., Mediano, P. A. M., Rosas, F. E., Holland, N., Fryer, T. D., O'Brien, J. T., Rowe, J. B., Menon, D. K., Bor, D., & Stamatakis, E. A. (2022). A synergistic core for human brain evolution and cognition. *Nature Neuroscience*, 25(6), 771–782. <https://doi.org/10.1038/s41593-022-01070-0>
- Mediano, P. A. M., Rosas, F. E., Luppi, A. I., Carhart-Harris, R. L., Bor, D., Seth, A. K., & Barrett, A. B. (2021). *Towards an extended taxonomy of information dynamics via Integrated Information Decomposition*. <https://doi.org/10.48550/ARXIV.2109.13186>
- Mediano, P. A. M., Rosas, F., Carhart-Harris, R. L., Seth, A. K., & Barrett, A. B. (2019). *Beyond integrated information: A taxonomy of information dynamics phenomena*. <https://doi.org/10.48550/ARXIV.1909.02297>
- Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, 27(3), 379–423. <https://doi.org/10.1002/j.1538-7305.1948.tb01338.x>
- Timme, N. M., & Lapish, C. (2018). A tutorial for information theory in neuroscience. *Eneuro*, 5(3), ENEURO.0052–18.2018. <https://doi.org/10.1523/ENEURO.0052-18.2018>
- Williams, P. L., & Beer, R. D. (2010). *Nonnegative decomposition of multivariate information*. <https://doi.org/10.48550/ARXIV.1004.2515>