

graynet: single-subject morphometric networks for neuroscience connectivity applications

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Software

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Summary

Connectivity, and network-level features in general, have proven to be valuable tools in several aspects of neuroscience research. Although network analysis is rooted in analysis of functional MRI data, it has recently gained traction in the analyses of morphometric features such as cortical thickness (Evans, 2013). Such networks of anatomical covariance (derived based on distributions of features across a group of subjects) provided insight into changes caused by various brain disorders. When we individualize this approach to enable extraction of single-subject network features, they further enriched insights into abnormalities due to disease (Tijms, Seriès, Willshaw, & Lawrie, 2012, Raamana et al. (2015), Palaniyappan, Park, Balain, Dangi, & Liddle (2015), Xu et al. (2017)). Moreover, these network-level features demonstrated potential for prognostic applications (Raamana et al., 2015, Raamana et al. (2014)), in addition to being robust to changes in scale and edge weight metrics (Raamana & Strother, 2017a).

However, deriving these network-level features from input T1w-MRI data is non-trivial. With this fully-open-source and pure-python library **graynet**, we attempt to make this task easier and extend it to support all currently available morphometric features. Currently, it interfaces directly with the outputs produced by Freesurfer (Fischl, 2012) and supports vertex-wise data. We plan to extend this to support volumetric atlases and voxel-wise features such as gray matter density. Together with many convenience scripts (e.g. to launch jobs on the high-performance cluster and assemble the outputs produced), we believe **graynet** makes an useful addition to the neuroimaging in python open source ecosystem.

graynet is dependent on the following libraries: **nibabel** (Brett et al., 2016), **networkx** (Hagberg, Schult, & Swart, 2005), **numpy** (Oliphant, 2007, Walt, Colbert, & Varoquaux (2011)) and **hiwenet** (Raamana & Strother, 2017b).

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