Brain Connectivity Toolbox

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Frequently asked questions

What is the Brain Connectivity Toolbox?

The Brain Connectivity Toolbox is a Matlab toolbox for analysis of complex brain networks. The toolbox contains network analysis functions and complex brain network datasets.

What do I need to use the Brain Connectivity Toolbox?

- A recent (preferably >2010) version of Matlab. Many functions should also work in Octave, an open-source alternative to Matlab (details).
- Basic familiarity with manipulating data and running functions in Matlab (details). Familiarity with the Matlab programming language is useful but not essential.
- Network matrices. The Brain Connectivity Toolbox is primarily a network analysis toolbox and provides only limited support for network construction.

Which network matrices can I use with the Brain Connectivity Toolbox?

- The network matrices should be square; rows and columns in these matrices should represent network nodes, matrix entries should represent network links.
- The network matrices should not be too small. As a general rule of thumb, the toolbox is designed to be used with networks of 20 to 20,000 nodes.
- The network matrices should preferably be in double-precision and non-sparse formats. Sparse, single-precision or logical formats may sometimes cause errors.
- Network matrices may be binary or weighted, directed or undirected. Each function specifies the network type for which it is suitable.
- In general, network matrices should not contain negative weights. However, several functions are specifically designed for matrices with positive and negative weights.
- In general, randomization functions are designed for non-dense matrices; many randomization functions will be too slow and/or ineffective in dense matrices.
- The Brain Connectivity Toolbox contains several network matrices; these may be used as examples or to get started.

How do I install and run the Brain Connectivity Toolbox?

Download and extract the contents of BCT.zip, navigate to these contents in Matlab (or add the contents directory to the Matlab path), and run individual functions from the Matlab command window.

Where can I find more help?

1. On this website. The following pages,

   Network construction
   Network measures
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   contain additional information about using the toolbox and about individual functions.

2. Inside individual function headers. Each function contains a header with detailed information about its use and relevant journal papers. Individual function headers may be accessed by entering `doc function_name` in the Matlab command window.

3. In relevant journal papers. You could start by reading Complex network measures of brain connectivity: Uses and interpretations and references therein.

4. From authors of the toolbox; see the [illegible] page for further information.

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List of measures

For each measure, we provide a brief description and include the type of compatible associated networks (see Network construction for more information).

BU, binary undirected networks; BD, binary directed networks;
WU, weighted undirected networks; WD, weighted directed networks.

More detailed information about each measure (including relevant journal references) is included inside individual function headers. Individual function headers may be accessed by typing doc `function_name` in the Matlab command window.

Notes: 1. Measures for binary and undirected networks will often be faster to compute than measures for weighted and directed networks. 2. Most network measures should be compared with measures computed on corresponding reference (null model) networks.

Contents

Degree and Similarity

- ***Degree***: Node degree is the number of links connected to the node. In directed networks, the in-degree is the number of inward links and the out-degree is the number of outward links. Connection weights are ignored in calculations.

  degrees_und.m (BU, WU networks); degrees_dir.m (BD, WD networks).
  Contributor: OS.

- ***Strength***: Node strength is the sum of weights of links connected to the node. In directed networks, the in-strength is the sum of inward link weights and the out-strength is the sum of outward link weights.

  strengths_und.m (WU Traduire networks); strengths_dir.m (WD networks).
  Contributor: OS.

- ***Joint degree***: This function returns a matrix in which the value of each element (u,v) corresponds to the number of nodes that have u outgoing connections and v incoming connections. Connection weights are ignored.

  jdegree.m (BD, WD networks).
  Contributor: OS.

- ***Topological overlap***: The m-th step generalized topological overlap measure quantifies the extent to which a pair of nodes have similar m-th step neighbors (nodes that are reachable by a path of at most length m).

  gtom.m (BU networks).
  Contributor: JG.

- ***Neighborhood overlap***: These functions compute the overlap between the neighborhoods of pairs of nodes linked by edges.

edge_nei_overlap_bu.m (BU networks); edge_nei_overlap_bd.m (BD networks).
Contributor: OS.

- ***Matching index:*** The matching index computes for any two nodes u and v, the amount of overlap in the connection patterns of u and v. Self-connections and u-v connections are ignored. The matching index is a symmetric quantity, similar to a correlation or a dot product.

  matching_ind_und.m (BU networks); matching_ind.m (BD networks).
  Contributor: OS, RB.

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Density and Rentian Scaling

- ***Density:*** Density is the fraction of present connections to possible connections. Connection weights are ignored in calculations.

  density_und.m (BU, WU networks); density_dir.m (BD, WD networks).
  Contributor: OS.

- ***Rentian scaling:*** Physical Rentian scaling is a property of systems that are cost-efficiently embedded into physical space. It is what is called a "topo-physical" property because it combines information regarding the topological organization of the network with information about the physical placement of connections.

  rentian_scaling.m (BU networks).
  Contributor: DB.

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Clustering and Community Structure

- ***Clustering coefficient:*** The clustering coefficient is the fraction of triangles around a node and is equivalent to the fraction of node's neighbors that are neighbors of each other.

  clustering_coef_bu.m (BU networks); clustering_coef_bd.m (BD networks);
  clustering_coef_wu.m (WU networks); clustering_coef_wd.m (WD networks).
  Contributor: MR.

- ***Transitivity:*** The transitivity is the ratio of triangles to triplets in the network and is an alternative to the clustering coefficient.

  transitivity_bu.m (BU networks); transitivity_bd.m (BD networks);
  transitivity_wu.m (WU networks); transitivity_wd.m (WD networks).
  Contributors: AG, MR.

- ***Local efficiency:*** The local efficiency is the global efficiency (see below) computed on node neighborhoods, and is related to the clustering coefficient.

  efficiency_bin.m (BU, BD networks); efficiency_wei.m (WU, WD networks).
  Contributor: MR.

- ***Connected components:*** Connected components are subnetworks in which all pairs of nodes are connected by paths.

  get_components.m (BU networks).
  Contributor: JG.

- ***Community structure and modularity:*** The optimal community structure is a subdivision of the network into nonoverlapping groups of nodes in a way that maximizes the number of within-group edges, and minimizes the number of between-group edges. The modularity is a statistic that quantifies the degree to which the network may be subdivided into such clearly delineated groups.

  modularity_und.m (BU, WU networks): Newman's spectral algorithm.
  modularity_dir.m (BD, WD networks): Newman's algorithm for directed networks.

modularity_louvain_und.m (BU, WU networks): Louvain algorithm.
modularity_louvain_dir.m (BD, WD networks): Louvain algorithm for directed networks.

modularity_finetune_und.m (BU, WU networks): fine-tuning algorithm.
modularity_finetune_dir.m (BD, WD networks): fine-tuning algorithm for directed networks.

Contributors: MR, JP, AG, DB.

Note: For similarity of community partitions see Network Comparison.

- ***Modularity degeneracy and consensus partitioning:*** Modularity degeneracy is the existence of multiple distinct high-modularity partitions of the same network. Consensus partitioning aims to provide a single consensus partition of these degenerate partitions.

  agreement.m, agreement_weighted.m (BU, BD, WU, WD networks)
  consensus_und.m (BU, BD, WU, WD networks)

  Note: the inputs to these functions are not networks but some partitions of these networks (or derivatives of these partitions).

  Contributor: RB.

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Assortativity and Core Structure

- ***Assortativity:*** The assortativity coefficient is a correlation coefficient between the degrees of all nodes on two opposite ends of a link. A positive assortativity coefficient indicates that nodes tend to link to other nodes with the same or similar degree.

  assortativity_bin.m (BU, BD networks).
  assortativity_wei.m (WU, WD networks).

  Contributors: OS, VT, MS, MR.

- ***Rich club coefficient:*** The rich club coefficient at level k is the fraction of edges that connect nodes of degree k or higher out of the maximum number of edges that such nodes might share.

  rich_club_bu.m (BU networks); rich_club_bd.m (BD networks).
  rich_club_wu.m (WU networks); rich_club_wd.m (WD networks).

  Contributors: MH, OS.

- ***K-core:*** The k-core is the largest subnetwork comprising nodes of degree at least k. The k-core is computed by recursively peeling off nodes with degree lower than k, until no such nodes remain in the subnetwork.

  kcore_bu.m (BU networks); kcore_bd.m (BD networks).
  Contributor: OS.

- ***S-core:*** The s-core is the largest subnetwork comprising nodes of strength at least s. The s-core is computed analogously to the more widely used k-core, but is based on node strengths instead of node degrees.

  score_wu.m (WU networks).
  Contributor: OS.

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Paths and Distances

- ***Paths and walks:*** Paths are sequences of linked nodes that never visit a single node more than once. Walks are sequences of linked nodes that may visit a single node more than once.

  findpaths.m (BU, BD networks); findwalks.m (BU, BD networks).

  Contributor: OS.

- ***Distance and characteristic path length:*** The reachability matrix describes whether pairs of nodes are connected by paths (reachable). The distance matrix contains lengths of shortest paths between all pairs of nodes. The characteristic path length is the average shortest path length in the network.

  distance_bin.m (BU, BD networks): distance matrix (algebraic algorithm).
  reachdist.m (BU, BD networks): reachability and distance matrices
  (alternative algebraic algorithm -- returns nonzeros on the main diagonal, unlike distance_bin).
  breadthdist.m (BD, BU networks): reachability and distance matrices (breadth-first search). This algorithm is slower but less memory-intensive compared to the above. This function requires an auxiliary function breadth.m.

  distance_wei.m (WU, WD networks): distance matrix (Dijkstra's algorithm). The input matrix must be a mapping from weight to distance (usually weight inversion).

  Contributors: OS, MR, RB, AA.

- ***Global efficiency:*** The global efficiency is the average inverse shortest path length in the network, and is inversely related to the characteristic path length.

  efficiency_bin.m (BU, BD networks); efficiency_wei (WU networks).
  Contributor: MR.

- ***Characteristic path length, global efficiency, eccentricity, radius, diameter:*** The characteristic path length is the average shortest path length in the network. The global efficiency is the average inverse shortest path length in the network. The node eccentricity is the maximal shortest path length between a node and any other node. The radius is the minimum eccentricity and the diameter is the maximum eccentricity.

  charpath.m (BU, BD, WU, WD networks).
  Contributor: OS.

- ***Cycle probability:*** Cycles are paths which begin and end at the same node. Cycle probability for path length d, is the fraction of all paths of length d-1 that may be extended to form cycles of length d.

  cycprob.m (BU, BD networks)
  Contributor: OS.

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Centrality

Some centrality are listed in previous sections: degree functions allow to determine nodes with a large number of connections ("degree centrality"), while distance functions allow to determine nodes which are close to other nodes ("closeness centrality").

- ***Betweenness centrality:*** Node betweenness centrality is the fraction of all shortest paths

  in the network that contain a given node. Nodes with high values of betweenness centrality participate in a large number of shortest paths.

  betweenness_bin.m (BU, BD networks): Kintali's algorithm.
  betweenness_wei.m (WU, WD networks): Brandes's algorithm.
  Contributor: MR.

- ***Edge betweenness centrality:*** Edge betweenness centrality is the fraction of all shortest paths in the network that contain a given edge. Edges with high values of betweenness centrality participate in a large number of shortest paths.

  edge_betweenness_bin.m (BU, BD networks);
  edge_betweenness_wei.m (WU, WD networks).
  Contributor: MR.

- ***Within-module degree z-score:*** The within-module degree z-score is a within-module version of degree centrality. This measure requires a previously determined community structure (see above).

module_degree_zscore.m; (BU, BD, WU, WD networks).
Contributor: MR.

- ***Participation coefficient:*** Participation coefficient is a measure of diversity of intermodular connections of individual nodes. This measure requires a previously determined community structure (see above).

  participation_coef.m (BU, BD, WU, WD networks).
  Contributor: MR.

- ***Eigenvector centrality:*** Eigenector centrality is a self-referential measure of centrality -- nodes have high eigenvector centrality if they connect to other nodes that have high eigenvector centrality.

  eigenvector_centrality_und.m (BU, WU networks).
  Contributors: XZ, RB.

- ***PageRank centrality:*** The PageRank centrality is a variant of eigenvector centrality.

  pagerank_centrality.m (BU, WU networks).
  Contributors: XZ, RB.

- ***Subgraph centrality:*** The subgraph centrality of a node is a weighted sum of closed walks of different lengths in the network starting and ending at the node.

  subgraph_centrality.m (BU networks).
  Contributors: XZ, RB.

- ***K-coreness centrality:*** The k-core is the largest subgraph comprising nodes of degree at least k. The coreness of a node is k if the node belongs to the k-core but not to the (k+1)-core.

  kcoreness_centrality_bu.m (BU networks);
  kcoreness_centrality_bd.m (BD networks).
  Contributor: OS.

- ***Flow coefficient:*** The flow coefficient is similar to betweenness centrality, but computes centrality based on on local neighborhoods. The flow coefficient is inversely related to the clustering coefficient.

  flow_coef_bd.m (BU, BD networks).
  Contributor: OS.

- ***Shortcuts:*** Shorcuts are central edges which significantly reduce the characteristic path length in the network.

  erange.m (BD networks).
  Contributor: OS.

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Motifs

- ***Structural motifs:*** Structural motifs (or simply motifs) are small (e.g. 3 or 4 node) patterns of local connectivity that occur in the network with a statistically surprising frequency. In weighted networks, the motif frequency may be supplemented by its weighted generalizations, the motif intensity and the motif coherence.

  motif3struct_bin.m; motif4struct_bin.m (BD networks).
  motif3struct_wei.m; motif4struct_wei.m (WD networks).
  All functions require the library motif34lib.mat generated with make_motif34lib.m.

  Motif legend: find_motif34.m (BD networks): This function returns all motif isomorphs for a given motif id and size. The function may also return the motif id for a given motif connection matrix. In addition, motif-3 legend is in Figure 1 of Sporns and Kötter (2004).

  Contributor: MR.

- ***Functional motifs:*** Functional motifs are subsets of connection patterns embedded within structural motifs. Functional motif frequency is the frequency of functional motif occurence around a node. In weighted networks, the motif frequency may be supplemented by its weighted generalizations, the motif intensity and the motif coherence.

  motif3funct_bin.m; motif4funct_bin.m (BD networks).
  motif3funct_wei.m; motif4funct_wei.m (WD networks).
  All functions require the library motif34lib.mat generated with make_motif34lib.m.

  Motif legend: find_motif34.m (BD networks): This function returns all motif isomorphs for a given motif id and size. The function may also return the motif id for a given motif connection matrix. In addition, motif-3 legend is in Figure 1 of Sporns and Kötter (2004).

  Contributor: MR.

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Characterization of networks with negative weights

These functions compute measures of modularity, degeneracy and centrality, and construct a degree-, weight- and strength- conserving null model in fully connected, undirected networks with positive and negative weights.

The functions are supplementary information to the paper
Weight-conserving characterization of complex functional brain networks
Rubinov M, Sporns O (2011) NeuroImage, 56:2068-2079.

- ***Network modularity:***
  modularity_louvain_und_sign.m (WU networks): Louvain modularity algorithm.
  Contributor: MR.

- ***Probabilistic fine-tuning and high-modularity degeneracy***
  modularity_finetune_und_sign.m (WU networks): fine-tuning modularity algorithm.
  modularity_probtune_und_sign.m (WU networks): probabilistic fine-tuning modularity algorithm.
  partition_distance.m (BU, BD, WU, WD networks): distance between modularity partitions.
  Contributor: MR.

- ***Nodal centrality:***
  strengths_und_sign.m (WU networks): nodal strength.
  diversity_coef_sign.m (WU networks): nodal diversity coefficient.
  participation_coef_sign.m (WU networks): nodal participation coefficient.
  Contributor: MR.

- ***Degree-, weight- and strength-distribution preserving null model:***
  null_model_und_sign.m (WU networks), null_model_dir_sign.m (WD networks); degree-, weight- and strength- preserving null model.
  randmio_und.m (WU networks): auxiliary function for null_model_und_sign.m.
  randmio_dir.m (WU networks): auxiliary function for null_model_dir_sign.m.
  Contributor: MR.

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Network construction

A network is defined by a collection of nodes (vertices) and links (edges) between pairs of nodes. Nodes in large-scale brain networks usually represent brain regions, while links represent anatomical, functional, or effective connections, depending on the dataset.

Networks may be represented by their connectivity (adjacency) matrices. Rows and columns in these matrices denote nodes, while matrix entries denote links. In addition to the type of connectivity (anatomical, functional or effective), links are also differentiated on the basis of their weight and directionality.

- ***Thresholding:*** These functions threshold connectivity matrices by absolute weight, or by proportion of strongest weights. All remaining weights (if present) are retained.

  threshold_absolute.m, threshold_proportional.m (BU, BD, WU, WD networks).
  Contributor: MR.

- ***Weight conversion:*** This function may either binarize a weighted connection matrix, normalize an input weighted connection matrix or convert an input weighted connection matrix to a weighted connection-length matrix.

  weight_conversion.m (WU, WD networks).
  Contributor: MR.

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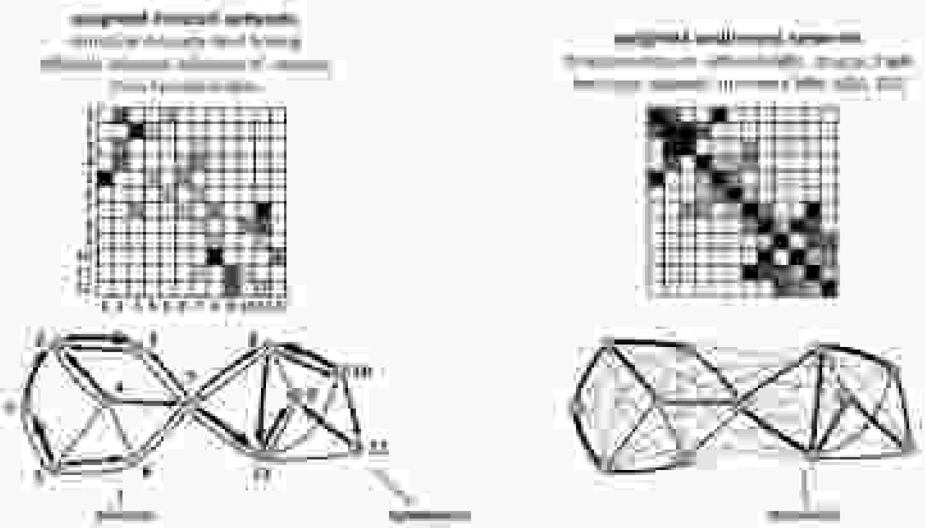

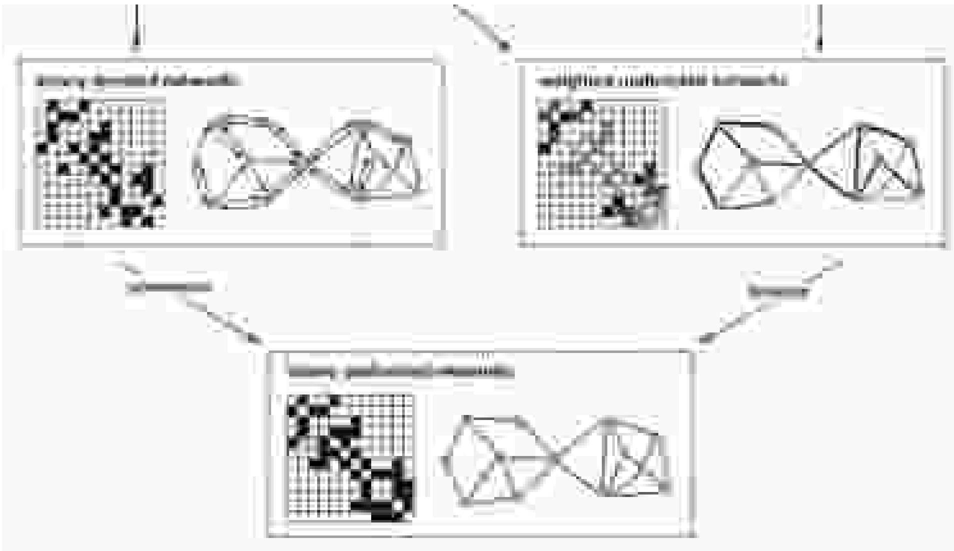

Figure from: Rubinov M, Sporns O (2010) NeuroImage 52:1059-69.

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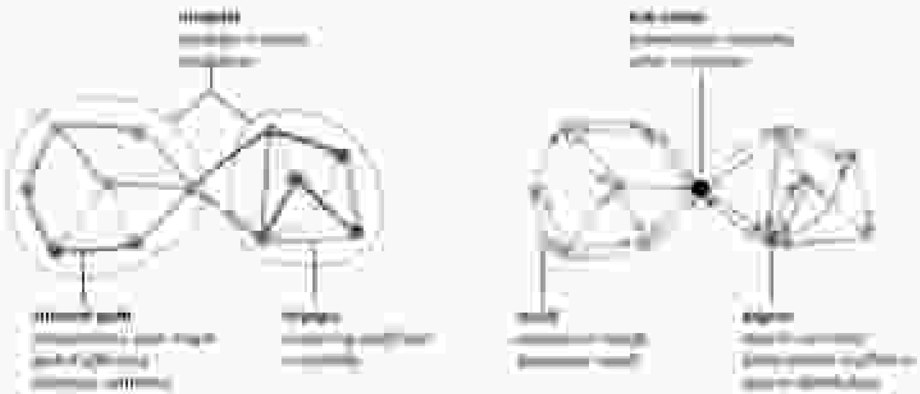
Network measures

An individual network measure may characterize one or several aspects of global and local brain connectivity. The Brain Connectivity Toolbox contains measures that variously detect aspects of functional integration and segregation, quantify importance of individual brain regions, characterize patterns of local anatomical circuitry, and test resilience of networks to insult. The figure below illustrates some basic network measures, while the table below contains mathematical definitions of many measures.

Network measures are often represented in multiple ways. Thus, measures of individual network elements (such as nodes or links) typically quantify connectivity profiles associated with these elements and hence reflect the way in which these elements are embedded in the network. Measurement values of all individual elements comprise a distribution, which provides a more global description of the network. This distribution is most commonly characterized by its mean, although other features, such as distribution shape, may be more important if the distribution is inhomogeneous. In addition to these different representations, network measures also have binary and weighted, directed and undirected variants. Weighted and directed variants of measures are typically generalizations of binary undirected variants and therefore reduce to the latter when computed on binary undirected networks.

An illustration of some toolbox measures (full list of measures).



Definitions of most toolbox measures (download table).

Text, figure and table from: Rubinov M, Sporns O (2010) NeuroImage 52:1059-69.

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Network comparison

Complex network measures may be used to study connectivity relationships in individual subjects or between subject groups. Comparisons of within-subject or within-group structural and functional connectivity aim to provide insights into structural-functional connectivity relationships. Comparison of between-subject or between-group connectivity aim to detect changes of network connectivity associated with distinct subject populations or functional paradigms.

- ***Comparison of network community partitions:*** This function quantifies the similarity of (the distance between) a pair of community-structure partitions with two information-theoretic measures, the variation of information and the mutual information. This function takes community affiliation vectors, computed with community detection algorithms, as input (for details see Network Measures).

  partition_distance.m (BU, BD, WU, WD networks);
  Contributor: MR.

Network Based Statistic Toolbox

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