

## Formal definitions of graph measures

We employed several commonly used measures that are listed below. We did not include *assortativity* because of the symmetric degree distributions we used for the small-world and Erdős-Rényi networks.

### Average degree ( $k$ )

The degree of node  $i$  is defined as the sum of the row elements  $j$  in the adjacency matrix  $A$  containing binary values that represent the network's connectivity

$$k_i = \sum_j^N A_{ij}$$

and the average degree  $k$  is the average over all nodal degrees

$$\langle k \rangle = \frac{1}{N} \sum_i k_i = \frac{1}{N} \sum_{i,j} A_{ij} .$$

### Edge density

The edge density represents the fraction of existing edges in the network out of the total number of possible edges

$$m = \frac{1}{N(N-1)} \sum_{\substack{i,j \\ i \neq j}}^N A_{ij} .$$

### Characteristic path length ( $L$ )

$L$  represents the average minimum number of edges between any two points in the network.

To account for isolated nodes, we used the so-called global efficiency

$$E = \frac{1}{N(N-1)} \sum_{\substack{i,j \\ i \neq j}}^N \frac{1}{d_{ij}} ,$$

where  $d_{ij}$  is the minimum number of edges between nodes  $i$  and  $j$ , and defined  $L$  as the harmonic mean  $L = 1/E$  .

### Average clustering coefficient ( $C$ )

The average clustering coefficient refers to the probability that neighbors of a node are also connected. It measures the occurrence of clusters in the network by means of

$$C = \frac{1}{N} \sum_i \frac{2n_i}{k_i(k_i-1)} ,$$

where  $n_i$  represents the number of existing edges between neighbors of node  $i$ .

#### *Small-world index (SW)*

The small-world index has often been used to indicate the presence of a small-world network [1-6]. It is defined as

$$SW = \frac{C/C_{\text{rand}}}{L/L_{\text{rand}}},$$

where  $C_{\text{rand}}$  and  $L_{\text{rand}}$  are the clustering coefficient and path length of random networks with the same number of nodes and edges and often also the same degree distribution. Since small-world networks are characterized by  $C \gg C_{\text{rand}}$  and  $L \approx L_{\text{rand}}$ , the ratio becomes  $SW \gg 1$ .

#### *Number of hubs (NHUBS)*

We assigned nodes as hubs when their nodal degree exceeded the average degree of the network

$$NHUBS = \sum_i^N [k_i > \langle k \rangle].$$

#### *Maximum degree (MAXD)*

The largest nodal degree defines the maximum degree of the network in terms of

$$MAXD = \max_i [k_i].$$

#### *Synchronizability (S)*

$S$  describes the network's capacity to synchronize [see, e.g., 7,8] and is calculated from the eigenvalues of the graph's Laplacian matrix  $\mathbf{A}$

$$\mathbf{A} = \mathbf{D} - \mathbf{A},$$

where  $\mathbf{D}$  represents a diagonal matrix containing the nodal degrees. The synchronizability is defined as the ratio between the first non-zero eigenvalue  $\lambda_2$  and the largest eigenvalue  $\lambda_{\text{max}}$  of  $\mathbf{A}$ , that is,

$$S = \frac{\lambda_2}{\lambda_{\text{max}}}.$$

### *Central point dominance (CPD)*

The central point dominance is a measure that describes the distribution of betweenness centrality scores of nodes  $B_i$ , i.e. the fraction of shortest paths from node  $p$  to node  $q$  that runs through node  $i$ . It was introduced by Freeman [9] and defined as follows

$$CPD = \frac{1}{N-1} \sum_i^N (B_{\max} - B_i),$$

where

$$B_i = \frac{2}{(N-1)(N-2)} \sum_{i \neq j}^N \frac{\sigma(p, i, q)}{\sigma(p, q)}.$$

The number of shortest paths between node  $p$  and node  $q$  that run through node  $i$  is indicated here by  $\sigma(p, i, q)$ , the number of total shortest paths between node  $p$  and  $q$  by  $\sigma(p, q)$ .

### **References**

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