S1 Appendix

Data analysis

Topic networks and temporal null networks were created, visualized, and analyzed in the R statistical environment [1] using the iGraph package [2]. Benchmark random networks were generated using the Brain Connectivity Toolbox in MATLAB [3], but were analyzed using the iGraph package. Community detection was carried out in MATLAB using the GenLouvain toolbox [4]. Correlation coefficients and probability values were obtained using the Hmisc package in R [5].

Network Measures

Here we provide a brief description of the more common network measures used in this study.

The **degree** of a node is the number of edges, regardless of weight, connected to the node [3]. Degree then represents one aspect of the node's importance, measured by the number of neighbors it has in the network. It is defined as follows:

$$k_i = \sum_{j \in N} a_{ij}, \tag{1}$$

where N is the set of all nodes in the network, and a_{ij} is 1 if nodes i and j are connected by an edge and 0 if not.

The **strength** of a node is the sum of the weights of all edges connected to the node [3]. This measure is similar to degree in that it sums a node's connecting edges, but strength additionally allows for edges of varying weights. It is defined as follows:

$$s_i = \sum_{j \in N} w_{ij}, \tag{2}$$

where w_{ij} is the weight of the edge between nodes i and j if they are connected and 0 if not.

The **betweenness centrality** of a node is the proportion of all shortest paths within the network that pass through the given node [6]. Betweenness centrality represents the extent to which a specific node functions as a bridge between nodes in disparate parts of the network. It is defined as follows:

$$b_i = \frac{1}{(n-1)(n-2)} \sum_{h,j \in N; h \neq j, h \neq i, j \neq i} \frac{\rho_{hj}^{(i)}}{\rho_{hj}}, \tag{3}$$

where ρ_{hj} is the number of shortest weighted paths between h and j, $\rho_{hj}^{(i)}$ is the number of shortest weighted paths between h and j that pass through node i, and n is the number of nodes in the graph.

The **participation coefficient** of a node is the extent to which it is strongly associated with nodes in modules or communities other than its own [7]. Participation falls between 0 and 1, with higher values representing more diversity within a node's connections. It is defined as follows:

$$y_i^w = 1 - \sum_{m \in M} \left(\frac{s_i(m)}{s_i} \right)^2,$$

where M is the set of modules and $s_i(m)$ is sum of edge weights from node i to other nodes in module m.

The **clustering coefficient** of a node can be defined as the probability that two of its adjacent nodes are connected to each other. A node's clustering coefficient then represents the amount of interconnectedness in a node's local neighborhood. The version used in the current study is a measure of transitivity, as given by Barrat [8]. It is defined as follows:

$$t_i^w = \frac{1}{s_i(k_i - 1)} \sum_{h,j \in N} \frac{(w_{ij} + w_{ih})}{2} a_{ij} a_{ih} a_{hj}. \tag{4}$$

The **global efficiency** of a network can be defined as the average inverse shortest path length between any two nodes [9]. Global efficiency is often thought of as representing the amount of integration within and between disparate parts of the network. It is defined as follows:

$$E^w = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N; j \neq i} d_{ij}^{-1}}{n - 1}, \tag{5}$$

where d_{ij} is the shortest weighted path length between node i and node j, defined as the minimum distance required to traverse the graph from node i to node j. The algorithm for calculating this measure is described by Newman [10].

The **path length** of a network is the average shortest path length between all node pairs [11]. In many graphs, path length is inversely correlated with global efficiency, and is therefore often interpreted as representing an alternative measure of network integration. A version of the path length for a weighted network is as follows:

$$L = \frac{1}{n(n-1)} \sum_{i \neq j} d_{ij}. \tag{6}$$

The **small-world propensity** measures the extent to which a network is characterized by high levels of local clustering and low average path length [12]. It is defined as follows:

$$\Phi = 1 - \sqrt{\frac{\Delta_T^2 + \Delta_L^2}{2}}, \tag{7}$$

where

$$\Delta_T = \frac{T_{lattice} - T_{observed}}{T_{lattice} - T_{random}}, \quad (8)$$

and

$$\Delta_L = \frac{L_{observed} - L_{random}}{L_{lattice} - L_{random}}, \quad (9)$$

with T representing the network clustering (transitivity) coefficient, defined as the average node-specific t_i^w values.

The **stochastic block model** assumes a community structure in which between- and within-group connections occur with a specific probability (in the unweighted case) or an expected edge weight (in the weighted case). Unlike modularity, which characterizes a community structure with many (strong) connections within groups and few (weak) connections between groups, the stochastic block model characterizes a community structure with consistent connection patterns within and between groups. For the unweighted case [13], it is defined as follows:

$$P_{g,B}(A) = \prod_{i \neq j} B_{g_i g_j}^{a_{ij}} \left(1 - B_{g_i g_j}\right)^{(1-a_{ij})}, \quad (10)$$

where $g \in 1, ..., K^n$ is a vector of community memberships, assuming K distinct communities, and $B \in [0,1]^{KxK}$ is a matrix of community-wise edge probabilities.

For the exponential weighted framework used in the current study [14], the model is defined as follows:

$$P_{g,\Lambda}(A) = \prod_{i \neq j} \Lambda_{g_i g_j} e^{-\Lambda_{g_i g_j} w_{ij}}, \quad (11)$$

where $\Lambda \in [0, \infty)^{KxK}$ is a matrix of community-wise rate parameters.

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