Supplementary materials 1

*Centrality Indices*

Since a graph had been abstracted and formatted from data, we constructed graphs at voxel level. Then we calculated the temporal Pearson’s correlation ($r\_{ij}$) of times series between the *i-* and *j-*th voxels and constructed a correlation matrix R = ($r\_{ij}$), 1≤*i*, *j*≤N (N is the number of voxels). Next, we used *P* = 0.0001 (uncorrected) as a statistical significance threshold of correlation $r\_{0}$. Finally, we set up an adjacency matrix $A = (a\_{ij})\_{1\leq i\leq N,1\leq j\leq N}$ of a binary graph (1a) or a weighted graph (1b) as following:

$a\_{ij}= \left\{\begin{array}{c}0,r\_{ij}<r\_{0}\\1,r\_{ij}\geq r\_{0}\end{array}\right.$ (1a)

$a\_{ij}= \left\{\begin{array}{c}0,r\_{ij}<r\_{0}\\r\_{ij},r\_{ij}\geq r\_{0}\end{array}\right.$ (1b)

1. *Degree Centrality (DC)*

DC, the most local centrality measure, is computed as in the following equation:

$$DC\left(i\right)=\sum\_{j=1}^{N}a\_{ij}$$

1. *Subgraph Centrality (SC)*

A network comprises of subgraphs and SC is used to measure the participation of a node in all subgraphs (Estrada & Rodríguez-Velázquez, 2005). $μ\_{j}(i)$ is the *i*-th of the *j*-th eigenvector and $λ\_{j}$ is the eigenvalue corresponding to the *j-*th eigenvector. SC is categorized into mesoscale centrality.

$$SC\left(i\right)=\sum\_{j=1}^{N}[μ\_{j}(i)]^{2}sinh⁡(λ\_{j})$$

1. *Eigenvector Centrality (EC)*

The first eigenvector of the adjacency matrix is the one that corresponds to the largest eigenvalue and what we called EC. EC is a global centrality which captures the global features.

$$EC\left(i\right)=μ\_{1}\left(i\right)=\frac{1}{λ\_{1}}Aμ\_{1}=\frac{1}{λ\_{1}}\sum\_{j=1}^{N}a\_{ij}μ\_{1}(j)$$

1. *Page-rank Centrality (PC)*

PC is a variant of EC and thus a global centrality as well. It introduces a small probability (1-d=0.15) for random damping to handle walking traps on a graph (Boldi, Santini, & Vigna, 2009).

$$PC\left(i\right)=r\left(i\right)=1-d+d\sum\_{j=1}^{N}\frac{a\_{ij}r(j)}{\sum\_{i=1}^{N}a\_{ij}}$$