WTh124 Modular structure of high-order interactions in the human brain

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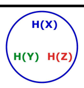
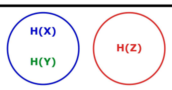
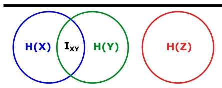
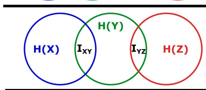
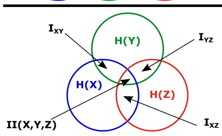
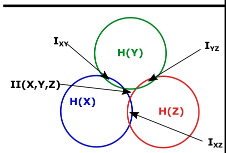
Summary

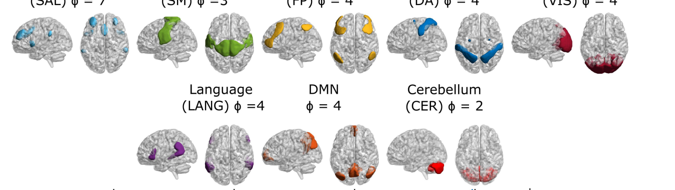
A network is highly modular when different communities of nodes have high intra-connectivity within them and low inter-connectivity between them. Different methods and strategies have been used to maximize modularity in brain networks. Most of these methods start from a connectivity matrix that defines pairwise interactions between network nodes. Following previous work [1]-[5], we built here connectivity matrices defining high-order interactions in triplets. This is defined by calculating the O-information in triplets of regions,[6],[7], represented by (X, Y, Z). If the value of the O-information is greater than 0, the interaction is redundant, while for lower values than 0, it is synergetic. When fixing Z, we built squared connectivity matrices of synergetic and redundant interaction from Z within the pair (X,Y). Finally, considering each region Z as one possible node in a network, we maximize modularity and the different resulting communites are discused.

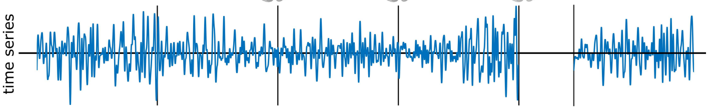
Methods

Examples of triplet interactions

Assuming $H(X)=H(Y)=H(Z)=H(i)$ and $I=I_{XY}=I_{XZ}=I_{YZ}$ we

Interacting regions **X** **Y** **Z**	$\sum_i H(i)$	$H(X,Y)$	$H(X,Z)$	$H(Y,Z)$	$H(X,Y,Z)$	$O(X,Y,Z)$
	3H(X)	H(X)	H(X)	H(X)	H(X)	H(X) > 0
	3H(X)	H(X)	2H(X)	2H(X)	2H(X)	0
	3H(X)	2H(X)-I	2H(X)	2H(X)	3H(X)-I	0
	3H(X)	2H(X)-I	2H(X)	2H(X)-I	3H(X)-I	0
	3H(X)	2H(X)-I	2H(X)-I	2H(X)-I	3H(X)-3I-II	II > 0
	3H(X)	2H(X)-I	2H(X)-I	2H(X)-I	3H(X)-3I+II	-II >0





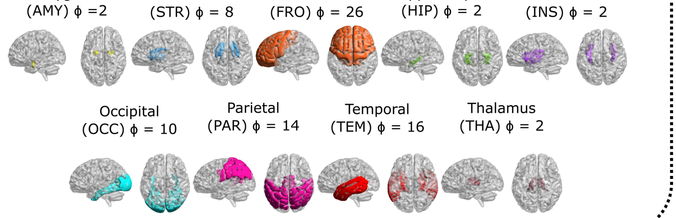
$$O(X,Y,Z) = H(X) + H(Y) + H(Z) + H(X,Y,Z) - H(X,Y) - H(X,Z) - H(Y,Z)$$

$$O(X,Y,Z) > 0 \Rightarrow R \longrightarrow R_Z(X,Y) = \frac{1}{\Phi(Z)} \sum_{m \in Z} R(X,Y,m)$$

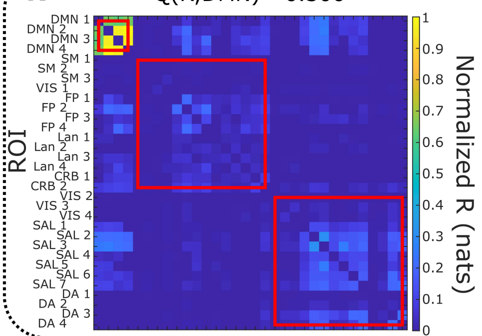
$$\Phi(Z) = \#ROIs\ in\ Z$$

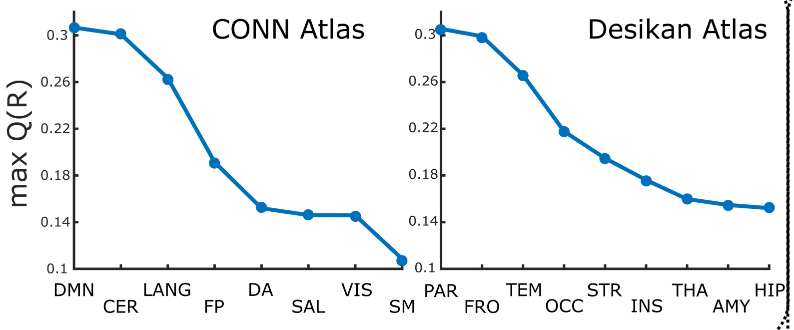
$$O(X,Y,Z) < 0 \Rightarrow S \longrightarrow S_Z(X,Y) = \frac{1}{\Phi(Z)} \sum_{m \in Z} S(X,Y,m)$$

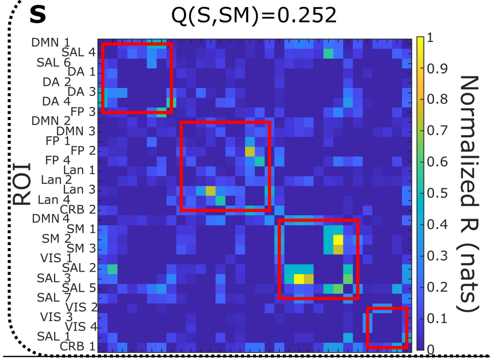
Modularity Maximization

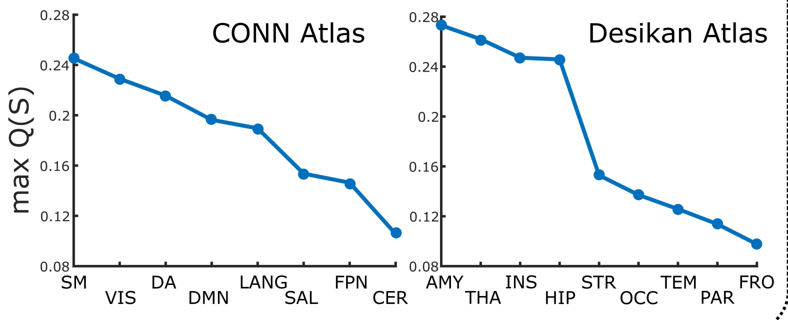


Results









Conclusions

1. When fixing a region Z, the matrix R(X,Y) -- or S(X,Y) -- is highly modular if there are several clusters whose pairs (X,Y) interact with Z redundantly -- or synergistically. In addition, the interaction within the clusters is more similar than between them. In other words, the higher the modularity of the triple interaction with Z, the more distinct functional sets of triplet interactions exists.

2. When considering Z each of the different RSNs, we find the highest modularity in redundant interactions with the Cerebellar and Default Mode Networks, and the lowest modularity for the Visual and Sensorimotor Networks. For synergy, the highest values of modularity occurred for the Visual and Sensorimotor Networks, and the lowest values for the Cerebellar and Frontoparietal Networks. Therefore, the Default Mode Network simultaneously opearates with high modularity in R and S.

3. Similarly, but considering Z an anatomical macroregion, the parietal and frontal lobes have higher modularity in R, and the amygdala and hippocampus the lowest values. For S, the highest values ocurred for the amygdala and thalamus, and the lowest for the parietal and frontal lobules. Somehow, there is more modularity for R in cortical regions, and there is more modularity in S for subcortical regions.

4. The modular structure of R and S shed new light into the organization of the high-order interactions in the human brain

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Acknowledgements

BCP was supported by a predoctoral grant from the Basque Government [PRE-20202-1-0187]. JMC was funded by Ikerbasque and the Department of Economical Development and Infrastructure of the Basque country, Elkartek Program (grant No. KK-2021/00009/BCB)