# Community structure detection for the functional connectivity networks of the brain

Rodica loana Lung $^1$  Mihai Suciu $^1$  Regina Meszlényi $^{2-3}$  Krisztian Buza $^3$  Noémi Gaskó  $^1$ 

<sup>1</sup>Babeş-Bolyai University, Cluj-Napoca, Romania <sup>2</sup>Department of Cognitive Science, Budapest University of Technology and Economics, Budapest, Hungary <sup>3</sup>Brain Imaging Center, Research Center for Natural Sciences, Hungarian Academy of Sciences, Budapest, Hungary

#### Introduction

- small datasets such as functional connectivity networks of the brain present a challenging structure which can reveal important information;
- **Goal:** use a new game theoretic tool that combines the concept of Nash equilibria with an extremal optimization algorithm to identify network community structure.

## The community structure detection game

Weighted graph: 
$$G = (V, E)$$
,  $V$  the set of nodes,  $V = \{i\}_{i=\overline{1,n}}$ ,  $E$  the

## Functional connectivity networks of the brain

- public resting-state fMRI database from the 1000 Functional Connectomes Project, Addiction Connectome Preprocessed Initiative
- the dataset contains 126 subjects' resting-state data, based on which, and an atlas of 90 functional regions of interest (ROI), we calculated the Pearson correlation between the activities of the ROIs.
- "averaged" networks, in which nodes correspond to ROIs, with the weight of each connection as the average of the correlations over all subjects, as well as subjects divided in categories: (A) healthy subjects, (B) cannabis users without ADHD, (C) subjects with childhood diagnoses of ADHD who does not use cannabis, (D) subjects with childhood diagnoses of ADHD who regularly use cannabis. Only positive correlations with values above 0.35 were considered. performing multiple runs led to different results for each run and each algorithm, with Oslom, Infomap and Louvain finding structures with maximum 3 communities. ► W-NEO approach: after performing 30 independent runs for each network, the resulting community structures were aggregated: each node was placed in the same community with the node with which it was placed in the same community most of the times in the 30 runs. a further step consisted in uniting the communities having the smallest fitness values with those with which they have the strongest connection.

set of edges,  $W = \{w_{ij}\}_{i,j \in V}$  the set of weights  $w_{ij}$  associated to each edge  $e_{ij} = (i, j)$  from E. Let game  $\Gamma = (N, S, U)$  be composed of:

players: network nodes;

**strategies:** players choose among available communities;

 $S = S_1 \times S_2 \times \ldots \times S_n$  is the set of strategy profiles, where  $\times$  represents the cartesian product,  $S_i$  is the set of strategies of player i.

**payoff functions**  $u_i: S \to \mathbb{R}$  - the contribution of a node to its community:

$$u_i(s_1, s_2, \ldots, s_n) = f(C_{s_i}) - f(C_{s_i} \setminus \{i\}),$$

where

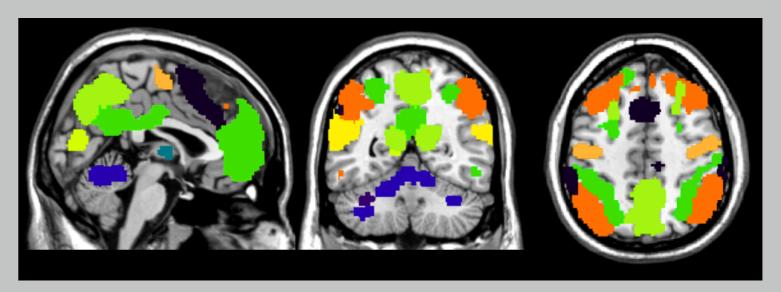
$$oldsymbol{f}(oldsymbol{C}) = rac{\sum_{i,j\in C} w_{ij}}{\sum_{i\in C,j\in V} w_{ij}}$$

is the fitness of community C.

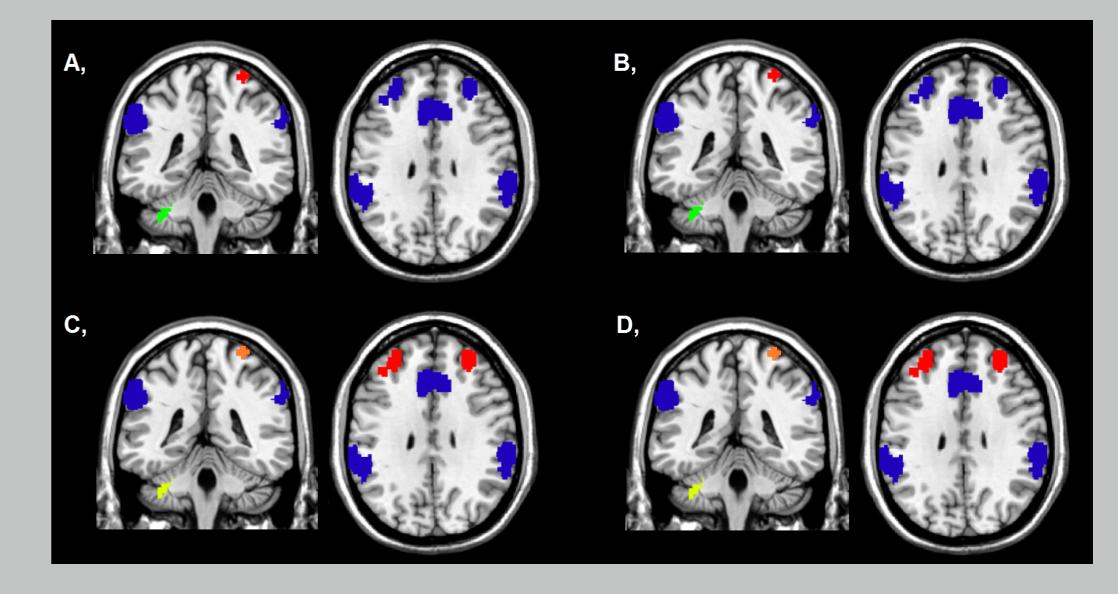
A Nash equilibrium (NE) of game  $\Gamma$  is a partition over the set of nodes (players) such that no node can increase its payoff by unilateral deviation. We can consider this also as an alternate definition for the community structure of a network!

# Weighted Nash Extremal Optimization (W-NEO)

W-NEO extends EO by evolving a population of pairs of individuals  $(s, s_{best})$ that search independently for the Nash equilibria of game  $\Gamma$ .



Community structure of the brain functional connectivity network averaged over all the Figure 3: subjects.



Algorithm 1: Weighted Nash Extremal Optimization

Randomly initialize and evaluate popsize pairs of configurations  $(s, s_{best})$ . Compute  $k_{Nash}$  as the average number of players that improve their payoffs when unilaterally switching from s to  $s_{best}$ ;

Set  $k_1 = k_{Nash}$ ;

#### repeat

Update  $\boldsymbol{k} = \min\{\boldsymbol{k_{Nash}}, [\boldsymbol{k}_1 + 2\frac{\boldsymbol{nr.it}}{\boldsymbol{MaxGen}}(1 - \boldsymbol{k}_1)]\};^1$ Apply the W-NEO step (Algorithm 2) on each pair  $(s, s_{best})$ ; Update  $k_{Nash}$ ;

**until** the maximum number of generation is reached; Return  $s_{best}$  with highest fitness.

Algorithm 2: W-NEO step (s, s<sub>best</sub>)

Evaluate payoffs  $u_i(s)$ ; Find the k worst components in s and replace them with a random community value; if (s Nash ascends<sup>2</sup>  $s_{best}$ ) then

Set  $s_{best} := s$ .

end if

 $^{\perp}$  nr.it is the iteration number, and  $[\cdot]$  represents the integer part. <sup>2</sup> there are less players that can improve their payoffs by unilaterally switching their Figure 4: Community structure of the anterior and posterior salience network in case of (A) healthy subjects, (B) cannabis users without ADHD, (C) subjects with childhood diagnoses of ADHD who does not use cannabis, (D) subjects with childhood diagnoses of ADHD who regularly use cannabis.

**Results:** we examined the structure of two large communities of brain regions, the so called default mode network (DMN): DMN is more intact (more ROIs are in the same community) in non-addicted subjects. The salience network has a critical role in attention, therefore it is expected to be related to ADHD. In healthy subjects and cannabis addicts without ADHD, the salience networks were found to be intact, in particular 11 and 12 ROIs were observed within the same community. However, in subjects diagnosed with ADHD, the salience network's largest community has only 7 ROIs, see Fig.4.

# communities from s to $s_{best}$ than vice-versa

### Numerical results - synthetic networks

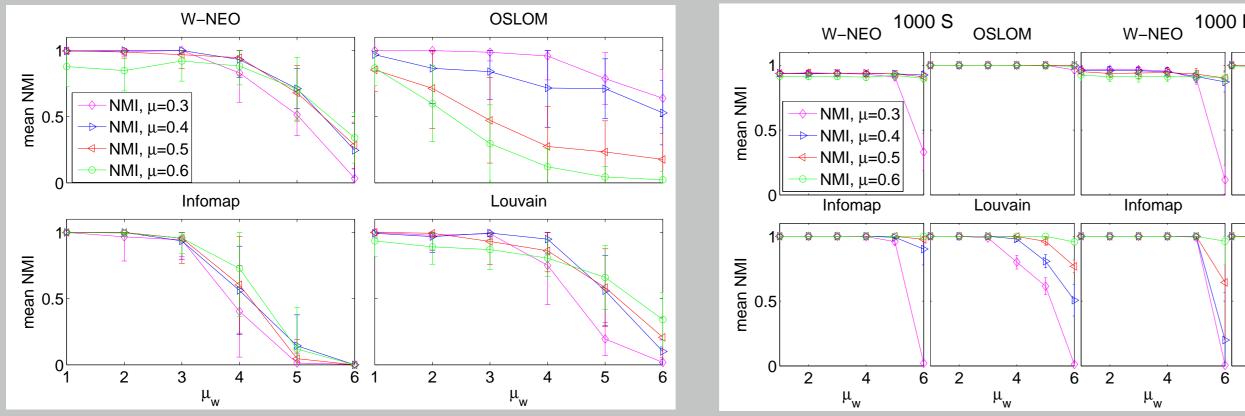


Figure 1: LFR, 128 nodes, average NMIs

Louvain

OSLOM

Figure 2: LFR, 1000 nodes, average NMIs.

#### Conclusion

The brain networks are small, with very unclear structure, difficult to identify; a game theoretic approach capable to identify strong connections in these networks and construct community structures that can offer relevant knowledge about the functioning of the brain.

# Acknowledgments

K. Buza was supported by the grant of the National Research, Development and Innovation Office - NKFIH PD 111710 and the János Bolyai Research Scholarship of the Hungarian Academy of Sciences. This work was also supported by a grant of the Romanian National Authority for Scientific Research and Innovation, CNCS - UEFISCDI, project number PN-II-RU-TE-2014-4-2332.