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## Topological analysis of the brain functional networks

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## Research Background

- Internet as a social infrastructure**
  - A lot of systems essential for our life are provided on the Internet
  - It is desired to make the Internet into higher quality to handle rapidly increasing traffic demand and the number of devices
- Internet as a large-scale and complex network**
  - It consist of interconnections of many Autonomous Systems (ASes)
  - Since ASes construct connections to other ASes selfishly, it has been pointed out that a lot of traffic will concentrate on some ASes<sup>[13]</sup>

The Internet is now on the way to fragileness

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We focus on  
**Brain Functional Networks (BFNs)**  
as clues to construct the high-quality Internet



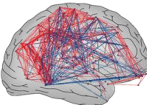
AS-level Topology

[13] M. Faloutsos et al., The internet as a complex network, *Journal of Information Science*, 2000, 26(1), 1-23.

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## Brain Functional Networks (BFNs)

- Networks reflecting brain functional interaction**
  - Divide a brain into tens of thousands of voxels (measuring points)
  - Construct a link between voxels where brain activity transition is similar
- Properties of BFNs**
  - High efficiency communication
  - Robustness and Adaptability against environmental change
  - Very small energy consumption



The Internet also need these properties

We expect that the Internet can be **high quality** by incorporating some of BFNs' topological characteristic

"High quality" means 1) High communication performance  
2) Robustness against node and link failures and traffic changes  
3) High energy efficiency

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## Comparison of Topological Characteristic

- There are many researches analyzing a topology with graph theory<sup>[5,7,9,12]</sup>

	BFNs	Internet
# of nodes	Very large	Very large
Degree distribution	Power-law	Power-law
Small-world-ness	✓	✓
Modularity	High	High
<b>Fractality</b>	✓	X

Significant Difference

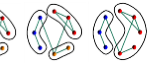
[5] E. Bullmore and O. Sporns, Complex brain networks: graph theoretical analysis of structural and functional systems, *Nature Reviews Neuroscience*, 12(9):148-158, Mar. 2009.  
[7] V. M. Eguíluz et al., Scale-free brain functional networks, *Physical Review Letters*, 28(1):1-4, Jan. 2005.  
[9] S. K. Ghoshal et al., A small world of mind: topological control of global integration of self-organizing models in functional brain networks, *PLoS ONE*, 10(10):2022-2030, Feb. 2015.  
[12] D. Montuori et al., Hierarchical modularity in human brain functional networks, *Frontiers in Human Brain Research*, 3(20):1-12, Oct. 2009.

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## Fractality<sup>[14]</sup>

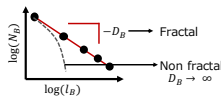
[14] C. Song, S. Havlin, and H. Makse, Self-similarity of complex networks, *Nature*, 433(7025), Jan. 2005.

- A property of repeating structures at every scale**
  - A topology has fractality when  $D_B$  is finite, calculated by  $N_B(I_B) \sim I_B^{-D_B}$

BOX → 

$I_B$ : Box size  
 $N_B$ : # of boxes

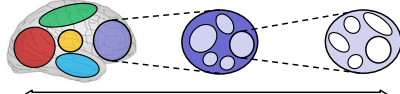
$I_B = 1, N_B = 4$     $I_B = 2, N_B = 3$     $I_B = 3, N_B = 2$



log( $N_B$ ) vs log( $I_B$ )

- $D_B$  → Fractal  
Non fractal  $D_B \rightarrow \infty$

- Strong relations with hierarchical module structure**
  - Regard box as module with different box size



LARGE ← Box size → SMALL

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## Research Objective

- Our Research Goal**
  - Produce the Internet with BFNs' fractality for making it higher quality

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For attaining this goal, **in this research...**

1. Reveal the topological structure of BFNs
2. Reveal the quality of BFNs from a information network perspective

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### Topology Data

- Brain activity measurement with fMRI**
  - One male subject under resting-state conditions
  - 80130 voxels, 2000 time steps
- Processing measurement data**
  - Apply motion correction (Realignment) and slice timing correction by using SPM8
- Obtaining topology**
  - Calculate correlation coefficient between two voxels by Piasson's method
  - Add links between voxels where correlation coefficient is 0.95 or more

Obtain topology with **11420 nodes and 44040 links**  
Voxel-level topology

Calculate correlation coefficient

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### Topology Decomposition

- Two types of topology by hierarchical modules**
  - Module-level topology
  - Inner-module topology

\* We use "Louvain method"<sup>[3]</sup> for extracting modules.  
\* We call the level of hierarchy as "Path".

Decompose whole topological structure into (1) module-level, (2) inner-module, and (3) inter-module

Aim to reveal these three topological structure

Path	# of nodes	# of links
0	11420	44049
1	1989	3007
2	432	654
3	179	288
4	146	236

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### Summary of Analysis of Topological Structure

Sharing similar structure over all Paths

Path (Hierarchy)

#### Module-level Topology

- Fractality
- Power-law degree distribution
- Hub-hub repulsion (low degree-correlation)

#### Inner-module Topology

- Power-law degree distribution
- High degree-correlation

#### Inter-module Link

- A large module constructs many links to various modules
- A small module constructs a few links to a small variety of modules
- A node with average degree of inner-module constructs lots of links

#### Module-level Topology (1/2)

- Fractality**
  - Module-level topologies at all Paths have fractality
- Degree distribution**
  - Module-level topologies at all Paths follow power-law

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- Fractality**
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- Degree distribution**
  - Module-level topologies at all Paths follow power-law

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### Module-level Topology (2/2) [results of topology at Path2]

- Degree-Correlation**
  - Method**

$$R(k_1, k_2) = P(k_1, k_2) / P_p(k_1, k_2)$$
    - $P(k_1, k_2)$ : probability of finding a node with  $k_1$  links connected to a node with  $k_2$  links
    - $P_p(k_1, k_2)$ : random uncorrelated counterpart of  $P(k_1, k_2)$
  - When  $R(k_1, k_2)$  takes high values, a topology has more links than random topology between nodes with degree  $(k_1, k_2)$
  - Result**
    - Hub-Hub repulsion
      - Only a few links exist between nodes with high-degree

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### Inner-module Topology (1/2)

- Degree distribution**
  - Inner-module topologies at all Paths follow power-law

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### Inner-module Topology (2/2) [results of topology at Path2]

- Degree-Correlation**
  - The method of  $R(k_1, k_2)$  is not applicable because it is difficult to calculate  $R(k_1, k_2)$  for small-scale topology
  - Method**

$$I = (L - L_{min}) / (L_{max} - L_{min})$$
    - $L = \sum_{(i,j) \in E} k_i \cdot k_j$ , where  $E$  is a set of links and  $k_i$  is a degree of node  $i$
    - $L_{max} (L_{min})$ : max (min) value of  $L$  among topology with same degree sequence
  - When  $I$  takes high value, high(low)-degree nodes tend to be connected with high(low)-degree nodes
  - Result**
    - Higher degree-correlation
      - $I = 0.726$  (average value of topologies with more than 100 nodes)

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### Inter-module Links [results of topology at Path2]

- Correlation between node degree and the number of inter-module links**
  - Inter-module links tend to exist between nodes whose degree is average degree of each inner-module topology
- Correlation between module size and the number of inter-module links**
  - Large module
    - constructs many links to various modules
  - Medium or small module
    - constructs a few links to a small variety of modules

