Informational and topological signatures of individuality and age

Giovanni Petri
IPAM MAC-2024
Higher-order signatures of individuality and age

Giovanni Petri
IPAM MAC-2024

Network Science Institute at Northeastern University
Higher-order signatures of individuality and age

Giovanni Petri
IPAM MAC-2024
What is topology?
What is topology?

THE BRIDGES OF KONIGSBERG
What is topology?
What is topology?
Why topology?

DOT = 0-simplex
EDGE = 1-simplex

Why topology?

DOT = 0-simplex

EDGE = 1-simplex

TRIANGLE = 2-simplex

\[ \neq \]

\[ = + \]

Why topology?

**Definition of k-simplex**

\[ \sigma = [p_0, p_1, p_2, \ldots, p_k] \]

Why topology?

Definition of k-simplex

\[ \sigma = [p_0, p_1, p_2, \ldots, p_k] \]

Multivariate information

\[ P(X) = P(X_0, X_1, X_2, \ldots, X_k) \]

Definition of k-simplex

$$\sigma = [p_0, p_1, p_2, \ldots, p_k]$$

Multivariate information

$$P(X) = P(X_0, X_1, X_2, \ldots, X_k)$$

Intrinsically higher-order!
Why topology?

Definition of $k$-simplex

$$\sigma = [p_0, p_1, p_2, \ldots, p_k]$$

Multivariate information

$$P(X) = P(X_0, X_1, X_2, \ldots, X_k)$$

Intrinsically higher-order!

Why topology?

Definition of $k$-simplex

$$\sigma = [p_0, p_1, p_2, \ldots, p_k]$$

Multivariate information

$$P(X) = P(X_0, X_1, X_2, \ldots, X_k)$$

Intrinsically higher-order!

Intrinsically non-local!

Topology in the wild
Topology in the wild
Topology in the wild
Simplicial Complex

From data to simplices

DOT = 0-simplex
EDGE = 1-simplex
TRIANGLE = 2-simplex

\[ R_\varepsilon \]

From data to simplices

- DOT = 0-simplex
- EDGE = 1-simplex
- TRIANGLE = 2-simplex

Connected components

Quantitative comparison

Quantitative topological comparison
Quantitative comparison

Quantitative topological comparison
Quantitative topological comparison


Quantitative comparison
Quantitative comparison

[Diagram showing quantitative comparison on the left and a scatter plot on the right.]
Quantitative comparison

- Wasserstein distance
- Quantitative topological comparison
Alteration of functional topology

rs-fMRI, 15 subjects, 2 sessions
1 recording condition

Altered functional topology

rs-fMRI, 15 subjects, 2 sessions 1 recording condition

Altered functional topology

rs-fMRI,
15 subjects,
2 sessions
1 recording condition


Altered functional topology

rs-fMRI,
15 subjects,
2 sessions
1 recording condition


Altered functional topology


Scaffolds in one slide
Scaffolds in one slide
Scaffolds in one slide
Scaffolds in one slide
Scaffolds in one slide

- Diluted FC
- Min-weight FC

Scaffold

Diluted FC

Min-weight FC
Scaffolds: local alterations

Scaffolds: local alterations

(a) [Image of brain network]

(b) [Image of brain network]

Scaffolds: local alterations

Distributed reorganisation of the hierarchy of functional circuits

Scaffold fingerprinting

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Scaffold fingerprinting

100 subjects (HCP), rs-fMRI, test+retest

Functional connectivity

Scaffolds
Scaffold fingerprinting

100 subjects (HCP), rs-fMRI, test+retest

Functional connectivity

Scaffolds
100 subjects (HCP), rs-fMRI, test+retest

<table>
<thead>
<tr>
<th>Functional Connectivity</th>
<th>Scaffolds</th>
</tr>
</thead>
</table>

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Scaffold fingerprinting

100 subjects (HCP), rs-fMRI, test+retest

**Functional Connectivity**

Effect Size = 1.832

**Scaffolds**

Effect Size = 5.077

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Scaffold fingerprinting

100 subjects (HCP), rs-fMRI, test+retest

Scaffold distances

FC distances

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Scaffold fingerprinting

Scaffold distances

Effect sizes

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Scaffold fingerprinting

Scaffold distances

Effect sizes

Incredibile fingerprinting capacity!
No idea on the origin!

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Scaffold fingerprinting

Scaffold distances

Effect sizes

Incredibile fingerprinting capacity!

QUASI idea on the origin!

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Topo+Info brain fingerprinting

Topo+Info brain fingerprinting

A Redundant Communities
B Synergistic Communities

C

D

E


Topo+Info brain fingerprinting

Synergy

Redundancy
Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Topo+Info brain fingerprinting

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Topo+Info brain fingerprinting

Poetto, Saggar, Battaglia, Vaccarino, Rabuffo, Petri in prep
Summing up
Summing up

- Topological information discriminates well across individuals
- Mesoscale markers (scaffold) incredibly powerful to discriminate
Summing up

- Topological information discriminates well across individuals
- Mesoscale markers (scaffold) incredibly powerful to discriminate
- Related to local HOI info-theory, but not sufficient to explain
Summing up

- Topological information discriminates well across individuals
- Mesoscale markers (scaffold) incredibly powerful to discriminate
- Related to local HOI info-theory, but not sufficient to explain
- “Long” timescales (at least 100TRs fMRI)
Higher-order organization of multivariate time series

Received: 18 March 2022
Accepted: 21 October 2022
Published online: 02 January 2023

Andrea Santoro, Federico Battiston, Giovanni Petri, & Enrico Amico

Time series analysis has proven to be a powerful method to characterize complex phenomena in biology, neuroscience, and economics, and to...
Temporal topology
Temporal topology

(a) Multivariate time series

(b) 1-order co-fluctuation

(c) Filtration

(d) Persistence Diagram

- Brain
- Financial
- Ecosystem
- Social
Temporal topology

(a) 2 synchronous pairwise interactions
1 synchronous group interaction

(b) Simplicial complex

$K_t$

$w_{ij}(t)$

$w_{ijk}(t)$
Temporal topology

(a) 2 synchronous pairwise interactions
1 synchronous group interaction

(b) Simplicial complex

Hyper-Coherence

List of violating triangles
Temporal topology

(a) 2 synchronous pairwise interactions
(b) 1 synchronous group interaction

(b) Simplicial complex

Hyper-Coherence
Hyper-Complexity

List of violating triangles
Homological scaffold
Temporal topology

Hypercoherence:
Fraction of violating triangles

Figure 2. Global and local higher-order indicators distinguish the dynamical regimes of coupled chaotic maps. (a) We report the temporal evolution of the hyper coherence indicator for multivariate time series with \( N = 119 \) nodes and \( T = 1200 \), obtained by concatenating five different CML regimes with fixed time length \( L = 240 \). Namely, Fully Developed Turbulence (FDT) at \( \theta = 0.05 \), Pattern Selection (PS) at \( \theta = 0.12 \), Spatiotemporal Intermittency II (STI) at \( \theta = 0.3 \), Brownian motion with Defects (BMWD) at \( \theta = 0.08 \), and Defect Turbulence (DT) at \( \theta = 0.068 \). (b) Notably, when projecting the list of violating triangles \( v \) as a weighted graph (see Methods for the definition of downward projections), the edge weight distribution \( P(w_{ij}) \) reflects the nature of the different dynamical regimes. In particular, the modular structure identified by the Louvain method \([63]\) is stable across time points for synchronized regimes, as confirmed by the ECS values \([64]\). (c) We plot the temporal evolution of the hyper complexity indicator and the (d) distribution of weights \( P(\bar{w}_{ij}) \) of the homological scaffold constructed from the persistent homology generators of \( H_1 \). For the sake of comparison, we also report in panels (a, c) the same indicators for a null model obtained when independently reshuffling the multivariate time series (grey curve). Shaded regions and error bars represent standard deviations across 100 independent realizations. To demonstrate the performance of our topological indicators, we show here that hyper coherence and hyper complexity easily distinguish different dynamical regimes generated by canonical models of spatiotemporal chaos. As a case study, we consider discretely coupled map lattices (CMLs) \([65]\), which are high-dimensional dynamical systems defined on discrete time and space, with continuous state variables. CMLs are broadly used to model complex spatiotemporal dynamics in several different fields including biology \([66]\), and finance \([67], [68]\). In particular, we consider a ring lattice with \( N \) sites, and we assume that the dynamical evolution of the system of the state \( x_i \) of each site \( i \) is the result of two different competing dynamics: an internal chaotic dynamic, and an external diffusive coupling dynamic among the first nearest-neighbour sites. Their dynamics can be expressed as

\[
x_i(t+1) = (1 - \varepsilon) f[x_i(t)] + \varepsilon \left( f[x_{i-1}(t)] + f[x_{i+1}(t)] \right)
\]

Hypercoherence: Fraction of violating triangles

Triangle projection: Project triangles on edges and count
Temporal topology

Hypercoherence: Fraction of violating triangles

Triangle projection: Project triangles on edges and count

Total persistent complexity

Temporal topology

Hypercoherence:
Fraction of violating triangles

Triangle projection:
Project triangles on edges and count

Total persistent complexity

Scaffold weight distribution

\[ x_i(t + 1) = (1 - \varepsilon) f[x_i(t)] + \frac{\varepsilon}{2} (f[x_{i-1}(t)] + f[x_j]). \]
Temporal topology

Figure 3. Higher-order indicators for real-world multivariate time series.

(a) Violin plots showing the distribution of hyper coherence for three real-world datasets, namely, resting-state fMRI data (N=119 brain regions), financial prices of 119 assets in NYSE, and the US historical data of several infectious diseases at the US state-level (N=50). The real distributions are compared against the five CML dynamical regimes, as well as the corresponding null models obtained when independently reshuffling synthetic and real-world multivariate time series. Note how the distributions of the three real-world datasets employed exhibit noticeable differences in their profile, yet always statistically distinct from the corresponding null models.

(b) Two-dimensional histogram of the different contributions associated with 1D cycles in the landscape of coherent and decoherent co-fluctuations. Here, the position of each point in the triangle is determined by the three different contributions associated with the 1D cycles. For example, a point would be at the centre of the triangle if the hyper complexity indicator splits into three equal contributions of Full Coherence (FC), Coherence Transition (CT), and Full Decoherence (FD), while a corner position is reserved for points whose mainly contributions come either from FC, CT, or FD.

angles $v$, yet aggregated at the level of industrial sectors, for the financial time series. The highest values capture the onset of the major periods of financial instability (2002, corresponding to the market downturn, and 2007–2008, corresponding to the great recession that took place as a consequence of the subprime mortgage crisis), which are characterized by an increased synchronization of stock prices, which clearly distinguishes them from the unsynchronized intervals 2002–2007 and 2013–2018, which in turn corresponds to a more stable period of the economy.

Similar analyses can be produced by focusing on the hyper complexity indicator and the nodal strength of the homological scaffold constructed from the persistent homology generators of $H_1$ (see Methods for details). In particular, Fig. 4c depicts the brain map obtained when isolating the 15% low-hyper complexity frames, which, as previously shown, are the ones associated with a more synchronized dynamical phase. Here, the highest absolute values are the ones associated with the Default Mode Network (DMN), which is known to be the most active network during wakeful rest [85, 86]. By contrast, for the financial time series in Fig. 4d, the temporal evolution of the nodal strength of the homological scaffold provides fine details on the downturns of certain economic sectors. For instance, consumer goods, basic materials, as well as oil and gas, are the main sectors affected by the great recession of 2007.

Finally, by analysing the historical data of epidemic outbreaks in the US, we show that the temporal evolution of the higher-order measures (i.e. hyper coherence, the three contributions of hyper complexity, and the average edge violations; see Methods for definition) can be used to classify different infectious diseases. In particular, a support vector machine (SVM) classifier reports a high accuracy level, i.e. around 85%, using a 10-fold cross-validation setting repeated 50 times (for a comparison between classifiers see SI Table S1). To provide a more intuitive representation of this result, we report in Fig. 4e a planar embedding of the historical data of epidemic outbreaks.
Aside: disease classification

Embedding vectors for each time-point:

\[ \bar{t} = (\text{Hyper-complexity}, \text{CC pers}, \text{CI pers}, \text{II pers}, \text{hypercoherence}) \]

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>
Aside: disease classification

Embedding vectors for each time-point:

\[ \vec{\tau} = (\text{Hyper-complexity, CC pers, CI pers, II pers, hypercoherence}) \]

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td><strong>0.85</strong></td>
<td><strong>0.85</strong></td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td><strong>0.85</strong></td>
<td><strong>0.85</strong></td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

What did Covid look like in Italy (trained on US data)
Aside: disease classification

Embedding vectors for each time-point:

$\mathcal{I}$ = (Hyper-complexity, CC pers, CI pers, II pers, hypercoherence)

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td><strong>0.85</strong></td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td><strong>0.85</strong></td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

What did Covid look like in Italy (trained on US data)
Aside: disease classification

Embedding vectors for each time-point:

\[
T = \text{(Hyper-complexity, CC pers, CI pers, II pers, hypercoherence)}
\]

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

What did Covid look like in Italy (trained on US data)

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RBF SVM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision Tree</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td></td>
<td></td>
</tr>
<tr>
<td>k-NN</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Comparison of classifier scores

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Table S1.

<table>
<thead>
<tr>
<th>Disease</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gonorrhea</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hepatitis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Influenza</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Measles</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pertussis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clamydia</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Polio</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Aside: disease classification

Embedding vectors for each time-point:

\[
T = \text{(Hyper-complexity, CC pers, CI pers, II pers, hypercoherence)}
\]

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

What did Covid look like in Italy (trained on US data)

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RBF SVM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision Tree</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Forest</td>
<td></td>
<td></td>
</tr>
<tr>
<td>k-NN</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Comparison of classifier scores

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Table S1.
Aside: disease classification

**Embedding vectors for each time-point:**

\[ I = \text{(Hyper-complexity, CC pers, CI pers, II pers, hypercoherence)} \]

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td><strong>0.85</strong></td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td><strong>0.85</strong></td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

**What did Covid look like in Italy (trained on US data)**
Aside: disease classification

Embedding vectors for each time-point:

\[ I = \text{(Hyper-complexity, CC pers, CI pers, II pers, hypercoherence)} \]

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

What did Covid look like in Italy (trained on US data)
Aside: disease classification

Embedding vectors for each time-point:

$\tilde{I} = (\text{Hyper-complexity, CC pers, CI pers, II pers, hypercoherence})$

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Avg. accuracy</th>
<th>F1 weighted score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian NB</td>
<td>0.47</td>
<td>0.43</td>
</tr>
<tr>
<td>RBF SVM</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.83</td>
<td>0.83</td>
</tr>
</tbody>
</table>

What did Covid look like in Italy (trained on US data)

Comparison of classifier scores

- Gaussian NB: 0.47, F1 weighted: 0.43
- RBF SVM: 0.85, F1 weighted: 0.85
- Decision Tree: 0.81, F1 weighted: 0.81
- Random Forest: 0.85, F1 weighted: 0.85
- k-NN: 0.83, F1 weighted: 0.83
Back to brains!
**Tasks**

**Dataset**

fMRI data

- 100 unrelated subjects of the Human Connectome Project (HCP)
- Resting-state & 7 different cognitive tasks
- 119 ROIs (100 Schaefer + 19 subcortical)

Tasks

Rest and 7 HCP tasks

Hyper-coherence

Network Science Institute at Northeastern University

NPL
Comparison with low-order

Different representations:

- Nodal level (BOLD signal & FC)
- Edge level (edge time series and eFC)
- Triangle level (Violating triangles)
- Topological level (Homological scaffold)

Time-resolved topology

BOLD Matrices

Brain Regions

Time (TRs)
Time-resolved topology

**BOLD Matrices**

**Correlation over time**

- **Brain Regions**
  - Time (TRs)
  - Subjects

- **Correlation over time**
  - Time (TRs)
  - Subjects
Time-resolved topology

BOLD Matrices

Correlation over time

Average over subjects
Time-resolved topology

BOLD Matrices

Correlation over time

Average over subjects
Time-resolved topology

Instantaneous fingerprinting

Instantaneous fingerprinting


Instantaneous fingerprinting

Instantaneous fingerprinting

Brain fingerprinting for different methods

Summing up

Conundrum:
Time-resolved topology

Summing up

- Global higher-order indicators are not able to distinguish between rest and tasks. Local markers (scaffold) incredibly powerful.
- Local higher-order information can be used to discriminate tasks.
- Hyper-coherent triangles outperform other methods for individual identification.

Conundrum:
Time-resolved topology

Summing up

• Global higher-order indicators are not able to distinguish between rest and tasks. Local markers (scaffold) incredibly powerful.

• Local higher-order information can be used to discriminate tasks.

• Hyper-coherent triangles outperform other methods for individual identification.

Conundrum:

• Global information (scaffolds) very discriminative at long timescales.
Time-resolved topology

Summing up

• Global higher-order indicators are not able to distinguish between rest and tasks. Local markers (scaffold) incredibly powerful.

• Local higher-order information can be used to discriminate tasks.

• Hyper-coherent triangles outperform other methods for individual identification.

Conundrum:

• Global information (scaffolds) very discriminative at long timescales.

• Local information (triangles) at short timescale.
Talk to me @lordgrilo Check stuff out @ lordgrilo.github.io
The physics of higher-order interactions in complex systems

Federico Battiston, Enrico Amico, Alain Barrat, Ginestra Bianconi, Guilherme Ferraz de Arruda, Benedetta Franceschiello, Iacopo Iacopini, Sonia Kéfi, Vito Latora, Yamir Moreno, Michael M. Murray, Tiago Peixoto, Francesco Vaccarino, and Giovanni Petri.

Main collaborators:
Marta Morandini  
Maxime Lucas  
Manish Sagar  
Matteo Diano  
Simone Poetto  
Francesco Vaccarino  
Demian Battaglia  
Giovanni Rabuffo  
Enrico Amico  
Federico Battiston  
Andrea Santoro

Understanding Complex Systems

Book Series
There are 141 volumes in this series
Published 2004 - 2021

Contributors: Bianconi, Krioukov, Moreno, Barrat, Scarpino, Jost, Vaccarino, Bobrowski, Arenas, Skardal, Bick, Porter, Pikowski, Lambiotte, Schaub, ....
The physics of higher-order interactions in complex systems

Federico Battiston1,2, Enrico Amico3,4, Alain Barrat4,5, Ginestra Bianconi4,6, Guilherme Ferraz de Arruda6,7, Benedetta Franceschiello8,9, Iacopo Iacopini6,8,9, Sonia Kéfi11,12, Vito Latora10,13,14, Yamir Moreno6,10,14,15, Micah M. Murray8,10,16, Tiago P. Peixoto5,10,17, Francesco Vaccarino8,16 and Giovanni Petri8,18,19

We are hiring PhDs (in London!)

Main collaborators:

Marta Morandini
Maxime Lucas
Manish Saggar
Matteo Diano

Simone Poetto
Francesco Vaccarino
Demian Battaglia
Giovanni Rabuffo

Enrico Amico
Federico Battiston
Andrea Santoro

Understanding Complex Systems

Book Series
There are 141 volumes in this series
Published 2004 - 2021

Contributors: Bianconi, Krioukov, Moreno, Barrat, Scarpino, Jost, Vaccarino, Bobrowski, Arenas, Skardal, Bick, Porter, Pikowsk, Lambiotte, Schaub, ....
MSCA Doctoral Network

Coordinator

Vrije Universiteit Amsterdam

Netherlands (NL)

Benefits

Alfréd Rényi Institute of Mathematics

Hungary (HU)

Universidade de Porto

Portugal (PT)

Technische Universität München

Germany (DE)

Universita degli Studi di Napoli Federico II

Italy (IT)

Aix Marseille Université

France (FR)

CENTAI Institute SPA

Italy (IT)

Universidad de Zaragoza

Spain (ES)

Kadir Has Universitesi

Turkey (TR)

Associated Partners

Amsterdam UMC - VUmc

Netherlands (NL)

Universiteit van Amsterdam

Netherlands (NL)

Universidade de Sao Paulo

Brazil (BR)

Rheinisch-Westfälische Technische Hochschule Aachen

Germany (DE)

University of California, Davis

United States of America

CWTs B.V.

Netherlands (NL)

BT Wireless

United Kingdom (UK)

Politecnico di Torino

Italy (IT)

Eötvös Loránd University

Hungary (HU)
The physics of higher-order interactions in complex systems

Federico Battiston, Enrico Amico, Alain Barrat, Ginestra Bianconi, Guilherme Ferraz de Arruda, Benedetta Franceschiello, Iacopo Iacopini, Sonia Kéfi, Vito Latora, Yamir Moreno, Michal M. Murray, Tiago P. Peixoto, Francesco Vaccarino, and Giovanni Petri

Understanding Complex Systems

Book Series
There are 141 volumes in this series
Published 2004 - 2021

Contributors: Bianconi, Krioukov, Moreno, Barrat, Scarpino, Jost, Vaccarino, Bobrowski, Arenas, Skardal, Bick, Porter, Pikowski, Lambiotte, Schaub, ….

Talk to me @lordgrilo Check stuff out @ lordgrilo.github.io

Network Science Institute
at Northeastern University
We are hiring Phds+postdocs (in London!)
The physics of higher-order interactions in complex systems

Federico Battiston1,2, Enrico Amico1,3, Alain Barrat4,5, Ginestra Bianconi6,7,
Guilherme Ferraz de Arruda4,8, Benedetta Franceschiello4,9, Iacopo Iacopini2,10, Sonia Kéfi11,12,
Vito Latora13,14,15, Yamir Moreno16,17, Micah M. Murray18,19, Tiago P. Peixoto20,19,
Francesco Vaccarino21,22 and Giovanni Petri21,22

Understanding Complex Systems

Book Series
There are 141 volumes in this series
Published 2004 - 2021

Contributors: Bianconi, Krioukov, Moreno, Barrat, Scarpino,
Jost, Vaccarino, Bobrowski, Arenas, Skardal, Bick, Porter, Pikovsky,
Lambiotte, Schaub, ....

Talk to me @lordgrilo Check stuff out @ lordgrilo.github.io

Network Science Institute
at Northeastern University
We are hiring Phds+postdocs (in London!)