# Higher-order networks An introduction to simplicial complexes Lesson I 

LTCC Course
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## Outline of the course

1. Higher order networks structure and maximum entropy models
2. Higher-order non-equilibrium network models and emergent geometry
3. Simplicial topology an introduction
4. Dynamics of higher-order topological signals
5. The Dirac operator and its applications

## Lesson I: Higher order networks structure

- Higher-order networks

1. Definitions
2. Introduction to the higher-order combinatorial properties

- Background on networks and maximum entropy models
- Maximum Entropy models of simplicial complexes


## Higher-order networks

Higher-order networks are characterising the interactions between two or more nodes


Hypergraph


Simplicial complex


Network with triadic interactions

## Higher-order network data



Face-to-face interactions


Collaboration networks

## Ecosystems



Protein interactions


## Higher-order networks



## New book by Cambridge University Press!!

Providing a general view of the interplay between topology and dynamics


## The physics of higher-order interactions in complex systems

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Guilherme Ferraz de Arruda $\oplus^{8}$, Benedetta Franceschiello $\odot^{9,10}$, lacopo lacopini ${ }^{\text {© }}$, Sonia Kéfi ${ }^{11,12}$ Vito Latora $\odot^{6,13,14,15}$, Yamir Moreno $\odot^{8,15,16,17}$, Micah M. Murray $\odot^{9,10,18}$, Tiago P. Peixoto ${ }^{1,19}$,
Francesco Vaccarino ${ }^{()^{20}}$ and Giovanni Petri $\odot^{8,21 ■}$
Complex networks have become the main paradigm for modelling the dynamics of interacting systems. However, networks are intrinsically limited to describing pairwise interactions, whereas real-world systems are often characterized by higher-order interactions involving groups of three or more units. Higher-order structures, such as hypergraphs and simplicial complexes, are therefore a better tool to map the real organization of many social, blological and man-made systems. Here, we highligh recent evidence of collective behaviours induced by higher-order interactions, and we outline three key challenges for the physIcs of higher-order systems


Downward projection

b


Reconstruction


## Generalized network structures



Going beyond the framework of simple networks is of fundamental importance
for understanding the relation between structure and dynamics in complex systems

## Collaboration Networks



Each paper includes higher-order interac $\downarrow$ among the corresponding team
Jacovacci, Wu, Bianconi (2015)

## Higher-order interactions in the brain



Cho, Barcelon and Lee (2016)


Giusti et al (2016)

Petri et al. (2014)

## Multilayer brain networks



Bullmore and Sporns (2009)

## Ecosystems


a


Bairey et al. (2017)

## Explosive Epidemic Spreading on co-location hypergraphs



## Simplicial social contagions and social contagion on hypergraphs


lacopini et al. (2019)


De arruda et al. (2021)

## Triadic interactions



Sun, Radicchi, Kurths GB (2022)

## Background on network science

## Networks


the interactions between the elements of large complex systems.

# Randomness and order Complex networks 

## LATTICES

COMPLEX NETWORKS
RANDOM GRAPHS


Regular networks Symmetric


Scale free networks Small world With communities
ENCODING INFORMATION IN THEIR STRUCTURE

Totally random Binomial degree distribution

## Universalities

- Small-world: $d_{H}=\infty$
[Watts \& Strogatz 1998]
- Scale-free: $P(k) \sim k^{-\gamma}$ for $k \gg 1$ [Barabasi \& Albert 1999] with $\gamma \in(2,3]$

$$
\begin{gathered}
\langle k\rangle \rightarrow \text { const }\left\langle k^{2}\right\rangle \rightarrow \infty \\
\text { for } N \rightarrow \infty
\end{gathered}
$$

- Modularity: Local communities of nodes [Fortunato 2010]




## Interplay between network structure and dynamics



## Critical phenomena on scale-free networks

Scale free networks:

- Percolation:

Percolation threshold

$$
p_{c} \frac{\langle k(k-1)\rangle}{\langle k\rangle}=1
$$

Scale free networks are robust to random damage

- Epidemic spreading:

Epidemic threshold

$$
\lambda_{c} \frac{\langle k(k-1)\rangle}{\langle k\rangle}=1
$$

The epidemic threshold is zero on scale-free networks

## Higher-order network structure and dynamics



## Higher order networks Structure



## Hyperedges



2-hyperedge
3-hyperedge
4-hyperedge
An m-hyperedge is set nodes

$$
\alpha=\left[i_{1}, i_{2}, i_{3}, \ldots i_{m}\right]
$$

-it indicates the interactions between the m-nodes

## Hypergraphs

Hypergraph
A hypergraph $\mathcal{G}=\left(V, E_{H}\right)$ is defined by a set $V$ of $N$ nodes and a set $E_{H}$ of hyperedges, where a $(m+1)$-hyperedge indicates a set of $m+1$ nodes

$$
e=\left[v_{0}, v_{1}, v_{2}, \ldots, v_{m}\right]
$$

with generic value of $1 \leq m<N$.
An hyperdge describes the many-body interaction between the nodes.


## Simplices



2-simplex
3-simplex
0-simplex
1-simplex


## Simplices

A $d$-dimensional simplex $\alpha$ (also indicated as a $d$-simplex $\alpha$ ) is formed by a set of $(d+1)$ interacting nodes

$$
\alpha=\left[v_{0}, v_{1}, v_{2} \ldots, v_{d}\right] .
$$

It describes a many body interaction between the nodes. It allows for a topological and a geometrical interpretation of the simplex.

## Faces of a simplex

## FACES

A face of a $d$-dimensional simplex $\alpha$ is a simplex $\alpha^{\prime}$ formed by a proper subset of nodes of the simplex, i.e. $\alpha^{\prime} \subset \alpha$.


3-simplex

Faces

40 -simplices
6 1-simplices
4 2-simplices

## Simplicial complex

## SIMPLICIAL COMPLEX

A simplicial complex $\mathcal{K}$ is formed by a set of simplices that is closed under the inclusion of the faces of each simplex.
The dimension $d$ of a simplicial complex is the largest dimension of its simplices.


$$
\begin{aligned}
\mathscr{K}= & \{[1],[2],[3],[4],[5],[6], \\
& {[1,2],[1,3],[1,4],[1,5],[2,3], } \\
& {[3,4],[3,5],[3,6],[5,6], } \\
& {[1,2,3],[1,3,4],[1,3,5],[3,5,6]\} }
\end{aligned}
$$

## Dimension of a simplicial complex

The dimension of a simplicial complex $\mathscr{K}$ is the largest dimension of its simplices


This simplicial complex has dimension 2

$$
\begin{aligned}
\mathscr{K}= & \{[1],[2],[3],[4],[5],[6], \\
& {[1,2],[1,3],[1,4],[1,5],[2,3], } \\
& {[3,4],[3,5],[3,6],[5,6], } \\
& {[1,2,3],[1,3,4],[1,3,5],[3,5,6]\} }
\end{aligned}
$$

## Facets of a simplicial complex

## FACET

A facet is a simplex of a simplicial complex that is not a face of any other simplex. Therefore a simplicial complex is fully determined by the sequence of its facets.


## The facets of this simplicial complex are

$$
\mathscr{K}=\{[1,2,3],[1,3,4],[1,3,5],[3,5,6]\}
$$

## Pure simplicial complex

## PURE SIMPLICIAL COMPLEXES

A pure d-dimensional simplicial complex is formed by a set of $d$ dimensional simplices and their faces.
Therefore pure $d$-dimensional simplicial complexes admit as facets only $d$-dimensional simplices.


A pure d-dimensional simplicial complex is fully determined by an adjacency matrix tensor with ( $\mathrm{d}+1$ ) indices.
For instance this simplicial complex is determined by the tensor

$$
a_{r s p}=\left\{\begin{array}{l}
1 \text { if }(r, s, p) \in \mathscr{K} \\
0 \text { otherwise }
\end{array}\right.
$$

## Example

A simplicial complex $\mathscr{K}$ is pure
if it is formed by d-dimensional simplices and their faces


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PURE SIMPLICIAL COMPLEX


SIMPLICIAL COMPLEX THAT IS NOT PURE

## Simplicial complex skeleton



From a simplicial complex is possible to generate a network salled the simplicial complex skeleton by considering only the nodes and the links of the simplicial complex

## Clique complex



From a network is possible to generate a simplicial complex by Assuming that each clique is a simplex

## Note:

Poisson networks have a clique number that is 3 and actually on a finite expected number of triangles in the infinite network limit

However
Scale-free networks have a diverging clique number, therefore the clique complex of a scale-free network has diverging dimension. (Bianconi,Marsili 2006)

## Concatenation of the operations



Attention!
By concatenating the operations you are not guaranteed to return to the initial simplicial complex

## Generalized degrees

The generalized degree $\mathrm{k}_{\mathrm{d}, \mathrm{m}}(\alpha)$ of a m -face $\alpha$
in a d-dimensional simplicial complex is given by the number of d -dimensional simplices incident to the m -face $\alpha$.

$k_{2,0}(\alpha)$ Number of triangles incident to the node $\alpha$
$k_{2,1}(\alpha)$ Number of triangles incident to the link $\alpha$
[Bianconi \& Rahmede (2016)]

## Generalized degree

The generalized degree $\mathrm{k}_{\mathrm{d}, \mathrm{m}}(\alpha)$ of a m -face $\alpha$ in a d-dimensional simplicial complex is given by the number of d -dimensional simplices incident to the m -face $\alpha$.


## Pure simplicial complex

A simplicial complex $\mathscr{K}$ is pure
if it is formed by d-dimensional simplices and their faces


A pure d-dimensional simplicial complex is fully determined by an adjacency matrix tensor with ( $\mathrm{d}+1$ ) indices.
For instance this simplicial complex is determined by the tensor
$a_{r s p}=\left\{\begin{array}{l}1 \text { if }(r, s, p) \in \mathscr{K} \\ 0 \text { otherwise }\end{array}\right.$

## Combinatorial properties of the generalised degrees

The generalized degrees $k_{d, m}(\alpha)$ of a pure d-dimensional simplicial complex can be defined in terms of the adjacency tensor $\mathbf{a}$ as

$$
k_{d, m}(\alpha)=\sum_{\alpha^{\prime} \in \mathbb{Q}_{d}(N) \mid \alpha^{\prime} \supseteq \alpha} a_{\alpha^{\prime}}
$$

The generalized degrees obey a nice combinatorial relation as they are not independent of each other.

In fact for $m$ ' $>m$ we have

$$
k_{d, m}(\alpha)=\frac{1}{\binom{d-m}{m^{\prime}-m}} \sum_{\alpha^{\prime} \in \mathbb{Q}_{d}(N) \mid \alpha^{\prime} \supseteq \alpha} k_{d, m^{\prime}}\left(\alpha^{\prime}\right)
$$

## Simplicial complex models of arbitrary dimension

Emergent Hyperbolic Geometry Network Geometry with Flavor (NGF)<br>[Bianconi Rahmede ,2016 \& 2017]

Maximum entropy model<br>Configuration model<br>of simplicial complexes<br>[Courtney Bianconi 2016]



CODES AVAILABLE AT GITHUB $?$
ginestrab

## Information theory of ensembles of simplicial complexes

## Entropy of ensembles of simplicial complexes

To every simplicial complex $\mathscr{K}$ of $N$ nodes we associate a probability

$$
P(\mathscr{K})
$$

The entropy of the ensemble of simplicial complexes is given by

$$
S=-\sum_{\mathscr{K}} P(\mathscr{K}) \ln P(\mathscr{K})
$$

## Constraints

We might consider simplicial complex ensemble with given
Expected generalized degrees of the nodes
or
Given generalized degrees of the nodes

Soft constraints

$$
\sum_{\mathscr{K}} P(\mathscr{K})\left[\sum_{\alpha \supset i} a_{\alpha}\right]=\bar{k}_{d, 0}(i)
$$

Hard constraints

$$
\sum_{\alpha \supset i} a_{\alpha}=k_{d, 0}(i)
$$

## Maximum entropy ensembles

The maximum entropy ensembles
of simplicial complexes are caracterized by a probability measure given by

Soft constraints

$$
P(\mathscr{K})=\frac{1}{Z} e^{-\sum_{i} \lambda_{i} \Sigma_{a i} a_{\alpha}} \quad P(\mathscr{K})=\frac{1}{\mathscr{N}} \delta\left(k_{d, 0}(i), \sum_{\alpha \supset i} a_{\alpha}\right)
$$

[Courtney \& Bianconi (2015)]

## Marginal probability

The marginal probability of a d-dimensional simplex $\mu$ is given by

$$
p_{\alpha}=\frac{e^{-\sum_{r \subset \alpha} \lambda_{r}}}{1+e^{-\sum_{r \subset \alpha} \lambda_{r}}}
$$

In presence of a maximum degree K (the structural cutoff) the marginal can be written as

$$
p_{\alpha}=d!\frac{\prod_{r \subset \alpha} k_{d, 0}(r)}{\left(\left\langle k_{d, 0}(r)\right\rangle N\right)^{d}} \quad \text { where } \quad K=\left[\frac{\left(\left\langle k_{d, 0}(r)\right\rangle N\right)^{d}}{d!}\right]^{1 /(d+1)}
$$

[Courtney \& Bianconi (2015)]

## Case d=1

The marginal probability of a 1-dimensional simplex $\mu$ is given by

$$
p_{i j}=\frac{e^{-\lambda_{i}-\lambda_{j}}}{1+e^{-\lambda_{i}-\lambda_{j}}}
$$

In presence of a maximum degree K (the structural cutoff) the marginal can be written as

$$
p_{i j}=\frac{k_{d, 0}(i) k_{d, 0}(j)}{\left(\left\langle k_{d, 0}(r)\right\rangle N\right)} \quad \text { where } \quad K=\left[\left(\left\langle k_{d, 0}(r)\right\rangle N\right)\right]^{1 / 2}
$$

[Courtney \& Bianconi (2015)]

## Case d=2

The marginal probability of a 2-dimensional simplex $\mu$ is given by

$$
p_{i j r}=\frac{e^{-\lambda_{i}-\lambda_{j}-\lambda_{r}}}{1+e^{-\lambda_{i}-\lambda_{j}-\lambda_{r}}}
$$

In presence of a maximum degree $K$ (the structural cutoff) the marginal can be written as

$$
p_{i j r}=2 \frac{k_{d, 0}(i) k_{d, 0}(j) k_{d, 0}(r)}{\left(\left\langle k_{d, 0}(r)\right\rangle N\right)^{2}} \quad \text { where } \quad K=\frac{\left(\left\langle k_{d, 0}(r)\right\rangle N\right)^{2 / 3}}{2^{1 / 3}}
$$

[Courtney \& Bianconi (2015)]

## Entropy of simplicial complex ensembles

Canonical ensemble
Microcanonical ensemble

$$
S=-\sum_{\alpha \in S_{\alpha}(N)}\left[p_{\alpha} \ln p_{\alpha}+\left(1-p_{\alpha}\right) \ln \left(1-p_{\alpha}\right)\right] \quad \Sigma=\ln \mathcal{N}
$$

Non-equivalence of the ensembles

$$
\Sigma=S-\Omega
$$

[Courtney \& Bianconi (2015)] generalizing [Anand \& Bianconi (2009)-(2010)] for simple networks

## Non-equivalence of ensembles

In the uncorrelated simplicial complex limit we have

$$
\Sigma=\ln \mathcal{N}=S-\Omega
$$

Where $\Omega$ is extensive and given by

$$
\Omega=-\sum_{r=1}^{N} \ln \frac{1}{k_{d, 0}(r)!}\left(k_{d, 0}(r)\right)^{k_{d, 0}(r)} e^{-k_{d, 0}(r)}
$$

[Courtney \& Bianconi (2015)]

Asymptotic expression
for the number of simplicial complexes

## with given

 generalized degree of the nodes$$
\mathcal{N} \sim \frac{[(\langle k\rangle N)!]^{d(d+1)}}{\prod_{r=0}^{N} k_{d, 0}(r)!} \frac{1}{(d!)^{\langle k\rangle N /(d+1)}} \exp \left(-\frac{d!}{2(d+1)(\langle k\rangle N)^{d-1}}\left(\frac{\left\langle k^{2}\right\rangle}{\langle k\rangle}\right)^{d+1}\right)
$$

## Configuration model of simplicial complexes



## Construction of a random simplicial complex



## From models of pure simplicial complexes to models of hypergraphs

Pure 1-dimensional simplicial complex<br>Pure 2-dimensional simplicial complex<br>=<br>HYPERGRAPH



## Conclusions

- Simplicial complexes capture the many-body interactions of complex systems and reveal the hidden geometry and topology of data
- Pure simplicial complexes can be represented by tensors
- The generalised degrees allow to capture important combinatorial properties of simplicial complexes
- Maximum entropy models of simplicial complexes are unbiased models with given (expected) generalised degrees

Maximum entropy models for complex networks

London Taught Course (PhD Level) on You Tube at https://www.youtube.com/channel/ UCsHAVdCU5XLaBYDXoINYZvg

