

# Complex systems and complex networks: a talk for *palaeo* and *neoecologists*

Alessio Cardillo (@a\_cardillo)

Pyrenean Institute of Ecology (IPE) – CSIC, Zaragoza (Spain)

IPE's talks — Thursday, October 3<sup>rd</sup> 2024



Instituto  
Pirenaico  
de Ecología  
**CSIC**

# ¿Que demonios hace un físico de sistemas complejos entre nosotros?

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de Ecología  
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# Who is Alessio Cardillo?



UNIVERSITÀ  
degli STUDI  
di CATANIA

- BSc and MSc (2010) in Physics.
- Studying urban street networks.



**Universidad**  
Zaragoza



1542 Instituto Universitario de Investigación  
**Biocomputación y Física**  
**de Sistemas Complejos**  
**Universidad Zaragoza**

- PhD in Physics (2011 – 2014).
- Switch from structure to dynamics on networks.

# Who is Alessio Cardillo?



- High mobility.
- Very broad range of research topics: linguistics, archaeology, mobility, humanities, collective behaviors (vaccination, cooperation, synchronization), etc..
- Working in highly multidisciplinary teams.



UNIVERSITÀ  
degli STUDI  
di CATANIA



Instituto Universitario de Investigación en  
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de Sistemas Complejos  
Universidad Zaragoza



Universidad  
Zaragoza

EPFL



University of  
BRISTOL



UNIVERSITAT ROVIRA I VIRGILI



Universitat Oberta  
de Catalunya



# Who is Alessio Cardillo?



... Not a dog. Not a wolf. All he knows is what he's not. ...

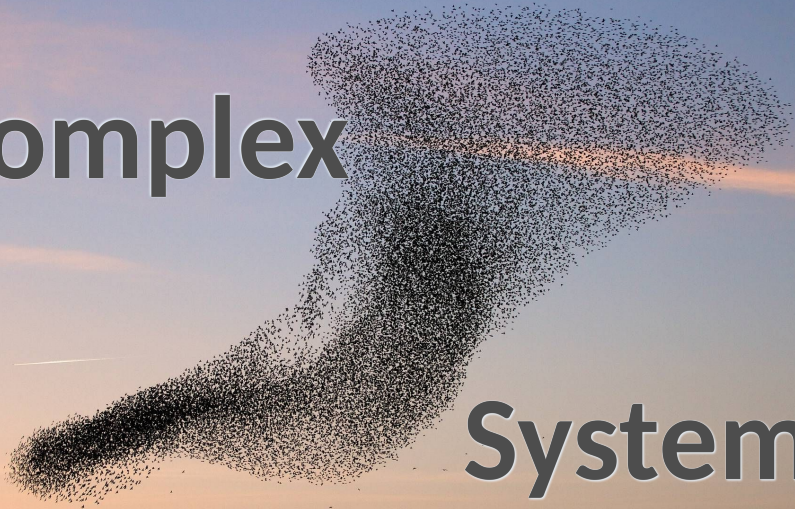
• <https://en.wikiquote.org/wiki/Balto>

## Outline

- Short self presentation.
- Complex systems.
- Graph theory/network science in a nutshell.
- Networks and neo-ecology (nestedness).
- Networks and palaeoecology (time-varying networks).

**Complex**

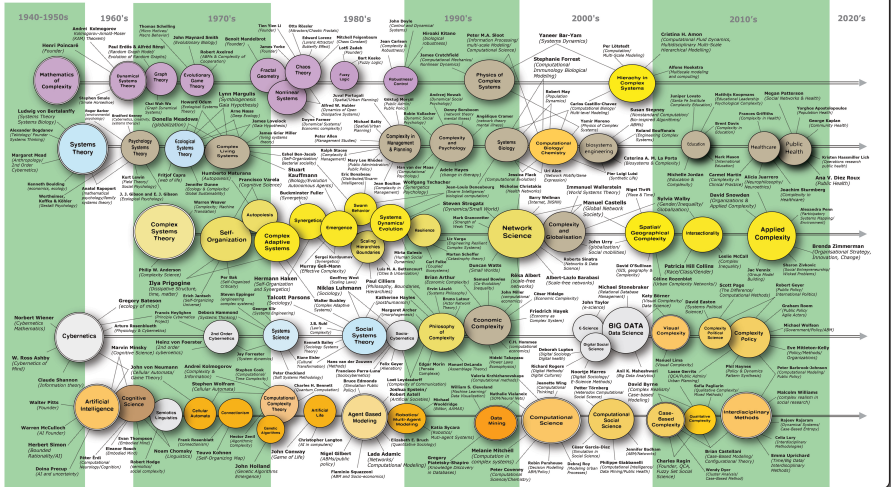
**Systems**



# Complex systems

## 2021 Map of the Complexity Sciences

Brian Castellani & Lasse Gerrits



[https://www.art-sciencefactory.com/complexity-map\\_feb09.html](https://www.art-sciencefactory.com/complexity-map_feb09.html)



The Nobel Prize in Physics 2021

Syukuro Manabe  
Klaus Hasselmann  
Giorgio Parisi

## Giorgio Parisi Facts

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© Nobel Prize Outreach.  
Photo: Stefan Bladh

Giorgio Parisi  
The Nobel Prize in Physics 2021

Born: 4 August 1948, Rome, Italy

Affiliation at the time of the award: Sapienza University of Rome, Rome, Italy

Prize motivation: “for the discovery of the interplay of disorder and fluctuations in physical systems from atomic to planetary scales”

Prize share: 1/2

<https://www.nobelprize.org/prizes/physics/2021/parisi/facts/>



**What *is* a complex system?**

















# Complex systems

## Journal of Physics: Complexity

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EDITORIAL • OPEN ACCESS

### Complex systems in the spotlight: next steps after the 2021 Nobel Prize in Physics

Ginestra Bianconi<sup>30,1,2</sup> , Alex Arenas<sup>3</sup> , Jacob Biamonte<sup>4</sup> , Lincoln D Carr<sup>5,6,7</sup> ,  
Byungnam Kahng<sup>8</sup> , Janos Kertesz<sup>9,10,11</sup> , Jürgen Kurths<sup>12,13</sup> , Linyuan Lü<sup>14</sup> ,  
Cristina Masoller<sup>15</sup> , Adilson E Motter<sup>16,17</sup> , Matjaž Perc<sup>10,18,19,20</sup> , Filippo Radicchi<sup>21</sup> ,  
Ramakrishna Ramaswamy<sup>22</sup> , Francisco A Rodrigues<sup>23</sup> , Marta Sales-Pardo<sup>24</sup> ,  
Maxi San Miguel<sup>25</sup> , Stefan Thurner<sup>10,26,27</sup>  and Taha Yasseri<sup>28,29</sup>  – [Hide full author list](#)

Published 16 January 2023 • © 2023 The Author(s). Published by IOP Publishing Ltd

[Journal of Physics: Complexity, Volume 4, Number 1](#)

[Celebrating Complex Systems in honour of the 2021 Nobel Prize in Physics](#)

**Citation** Ginestra Bianconi *et al* 2023 *J. Phys. Complex.* **4** 010201

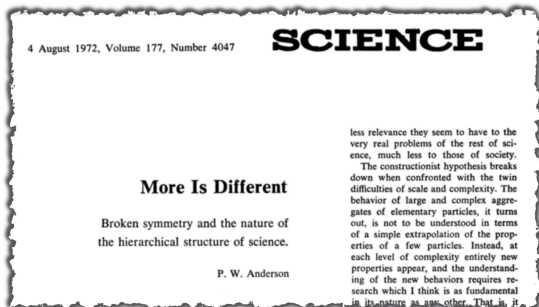
**DOI** [10.1088/2632-072X/ac7f75](https://doi.org/10.1088/2632-072X/ac7f75)

## Complex systems

*“... any system consisting of many interconnected parts which, as a whole, display properties that are not trivial aggregates of those of its constituents”*

# Complex systems

*“... any system consisting of many interconnected parts which, as a whole, display properties that are not trivial aggregates of those of its constituents”*

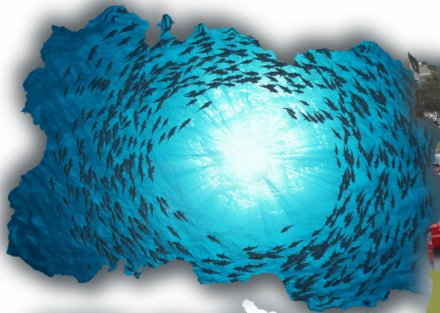


P.W. Anderson. Science **177**(4047), 393-396 (1972). DOI: 10.1126/science.177.4047.393

## Complex systems

“any system consisting of many **interconnected parts** which, as a whole, display **properties that are not trivial aggregates of those of its constituents**”

# Complex systems





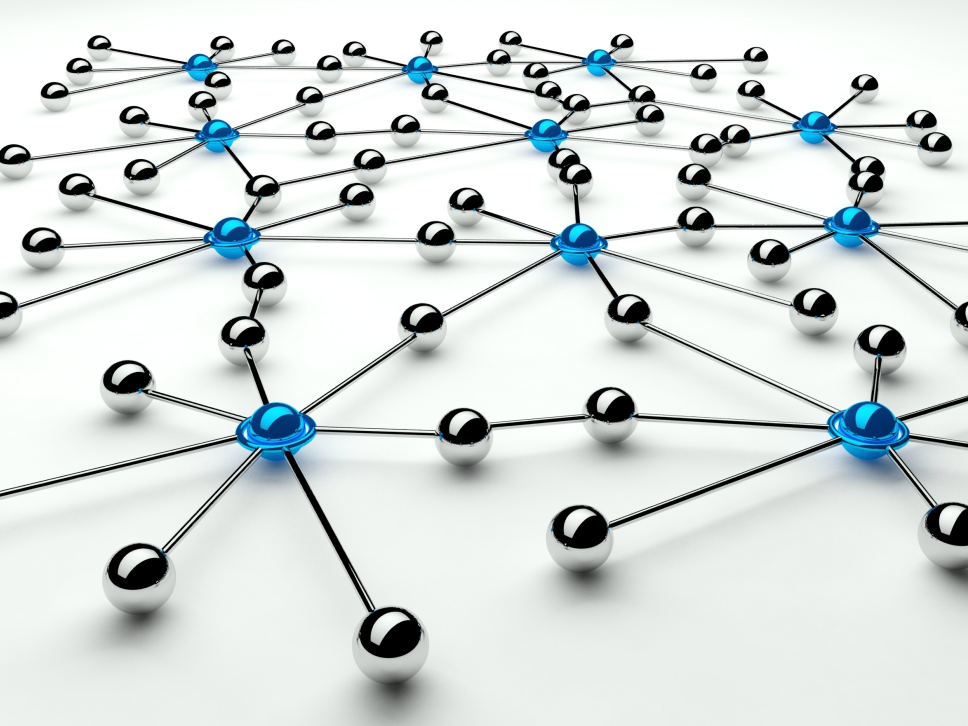
## Complex systems

“any system consisting of many **interconnected parts** which, as a whole, display **properties that are not trivial aggregates of those of its constituents**”

## Complex systems



Using networks to study complex systems is like paleontology ...



# Graph theory/network science in a nutshell

## Once upon a time ...

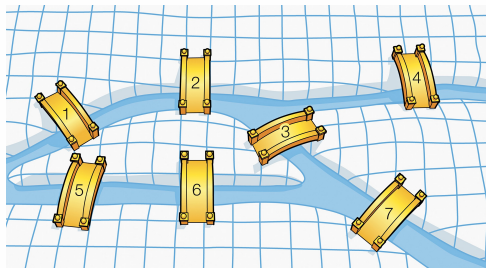
In 173x a mathematical puzzle based on the city of Königsberg was posed.



# Graph theory/network science in a nutshell

## Once upon a time ...

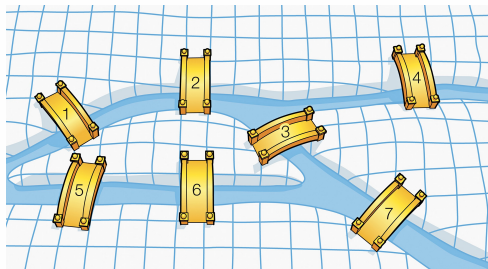
In 173x a mathematical puzzle based on the city of Königsberg was posed.



# Graph theory/network science in a nutshell

## The puzzle

Can we find a path that makes us explore the city passing from each bridge just once?

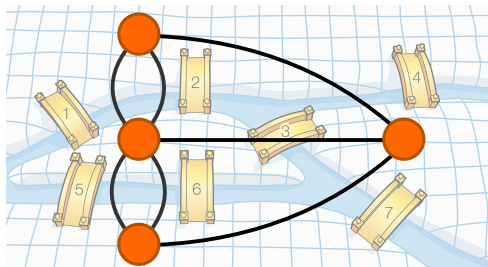


[https://en.wikipedia.org/wiki/Seven\\_Bridges\\_of\\_K%C3%B6nigsberg](https://en.wikipedia.org/wiki/Seven_Bridges_of_K%C3%B6nigsberg)

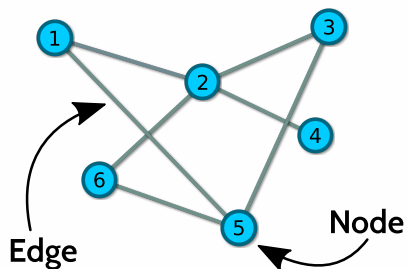
# Graph theory/network science in a nutshell

## The solution

In 1736 Leonard Euler found the answer and gave birth to [graph theory](#).



# Graph theory/network science in a nutshell



$N \times N$  Adjacency matrix

$$\mathcal{A} = \begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \end{pmatrix}$$

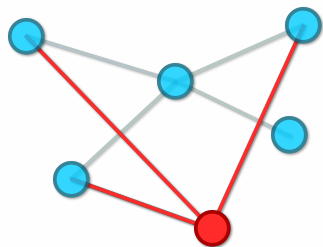


# Graph theory/network science in a nutshell

## Advantages

- Easy mathematical formalism.
- Ability to go beyond visual inspection.
- Possibility to adopt many techniques from statistical physics/nonlinear dynamics.

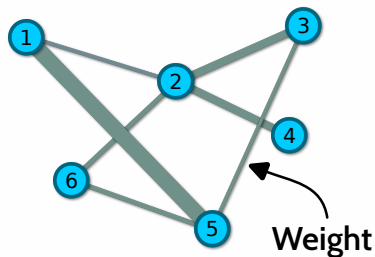
# Graph theory/network science in a nutshell



**Degree**

$$k_i = \sum_j a_{ij} .$$

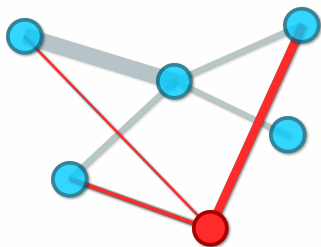
# Graph theory/network science in a nutshell



$N \times N$  Weight matrix

$$W = \begin{pmatrix} 0 & 2 & 0 & 0 & 7 & 0 \\ 2 & 0 & 3 & 1 & 0 & 1 \\ 0 & 3 & 0 & 0 & 5 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 7 & 0 & 5 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \end{pmatrix}$$

# Graph theory/network science in a nutshell

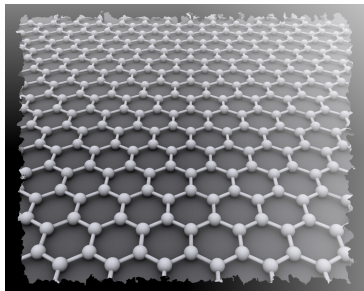


**Strength**

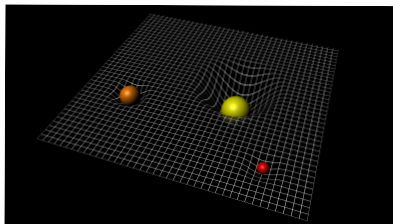
$$S_i = \sum_j W_{ij} .$$

# Graph theory/network science in a nutshell

**lattice / random**



**continuum**

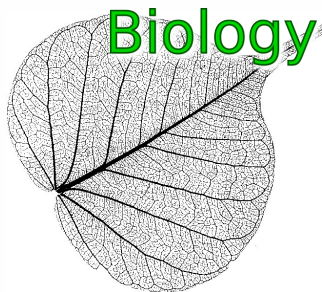


**Complex  
systems**

# Graph theory/network science in a nutshell



Social  
Science



Neuroscience

Transportation



# Graph theory/network science in a nutshell

## Network science's flavors

- Spatial networks
- Networks of networks
- Time-varying networks
- Multiple interactions (multilayer/multiplex)
- High-order networks
- ...

**So what?**



## So what?

- 1 Which structural features/indicators of the network capture relevant aspects (e.g., stability) of the ecosystem?

## So what?

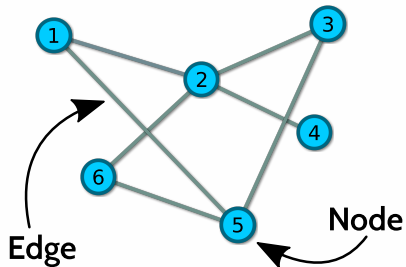
- 1 Which structural features/indicators of the network capture relevant aspects (e.g., stability) of the ecosystem?
- 2 Can we use network/complexity science to see *underneath the underneath* and extract information/get insight **invisible** to “*traditional*” methods?

# Networks and *neo-ecology*



# Mesoscopic structures

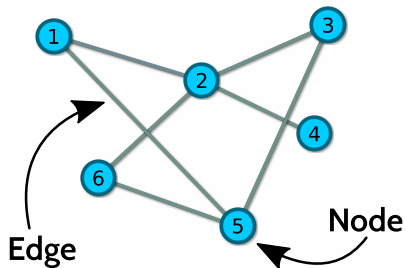
## Mesoscopic structures



$N \times N$  Adjacency matrix

$$\mathcal{A} = \begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \end{pmatrix}$$

# Mesoscopic structures

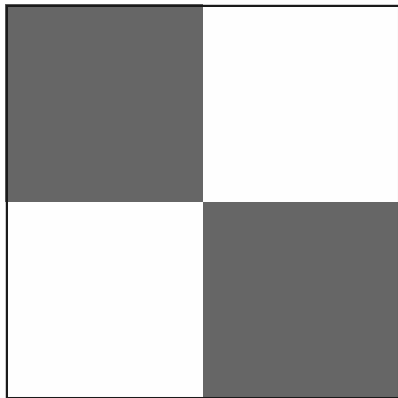
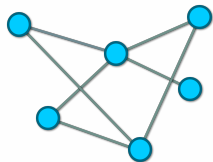


$N \times N$  Adjacency matrix

$$\mathcal{A} = \begin{pmatrix} \square & \blacksquare & \square & \square & \blacksquare & \square \\ \blacksquare & \square & \blacksquare & \blacksquare & \square & \blacksquare \\ \square & \blacksquare & \square & \square & \blacksquare & \square \\ \square & \blacksquare & \square & \square & \square & \square \\ \blacksquare & \square & \blacksquare & \square & \square & \blacksquare \\ \square & \blacksquare & \square & \square & \blacksquare & \square \end{pmatrix}$$

# Mesoscopic structures

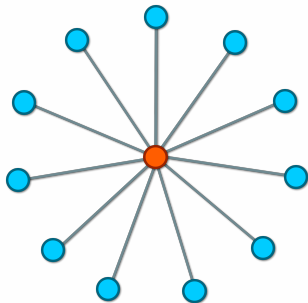
## Communities



•S. Fortunato, & M. E. J. Newman, *Nature Physics*, **18**, 848 (2022). DOI: [10.1038/s41567-022-01716-7](https://doi.org/10.1038/s41567-022-01716-7)

# Mesoscopic structures

Core-periphery

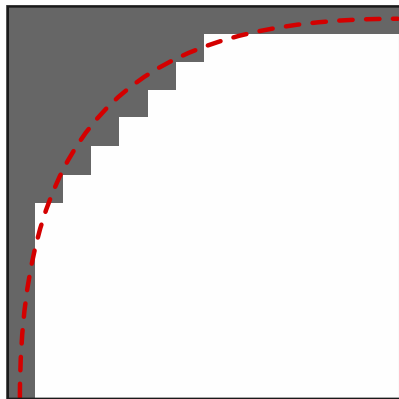
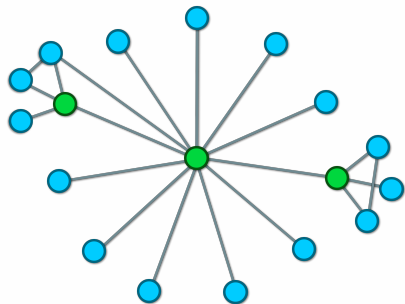


• S. P. Borgatti, & M. G. Everett, *Soc. Net.*, **21** 375 (2000). DOI: [10.1016/S0378-8733\(99\)00019-2](https://doi.org/10.1016/S0378-8733(99)00019-2)



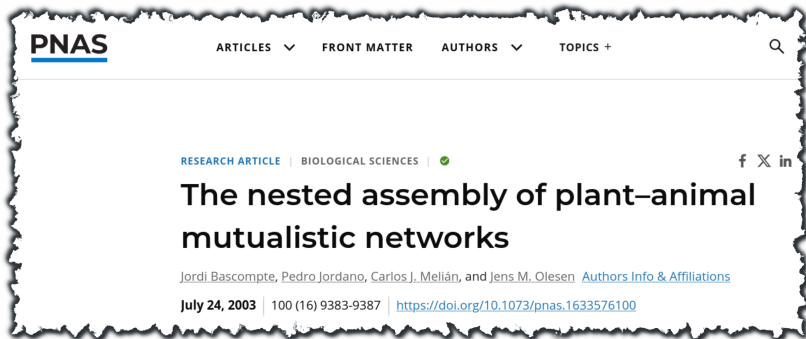
# Mesoscopic structures

## Nested structures



- M. S. Mariani, *et al.* Phys. Rep., **813**, 1 (2019). DOI: [10.1016/j.physrep.2019.04.001](https://doi.org/10.1016/j.physrep.2019.04.001)

# Mesososcopic structures



PNAS

ARTICLES ▾ FRONT MATTER AUTHORS ▾ TOPICS +

RESEARCH ARTICLE | BIOLOGICAL SCIENCES | ✓

f X in

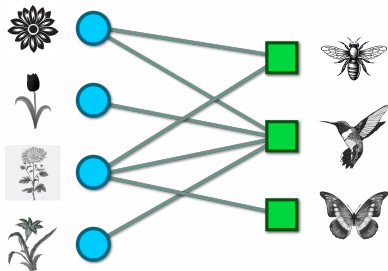
## The nested assembly of plant–animal mutualistic networks

Jordi Bascompte, Pedro Jordano, Carlos J. Melián, and Jens M. Olesen [Authors Info & Affiliations](#)

July 24, 2003 | 100 (16) 9383-9387 | <https://doi.org/10.1073/pnas.1633576100>

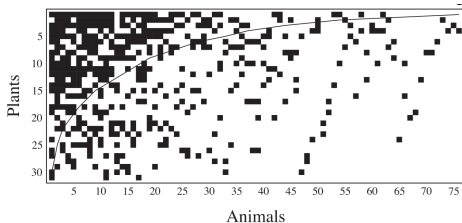
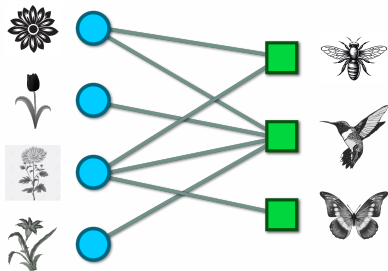
- J. Bascompte, *et al.* Proc. Nat. Acad. Sci. USA, **100**, 9383, (2003). DOI: 10.1073/pnas.1633576100

# Mesoscopic structures



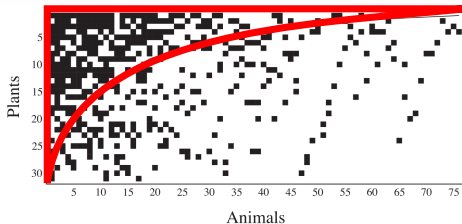
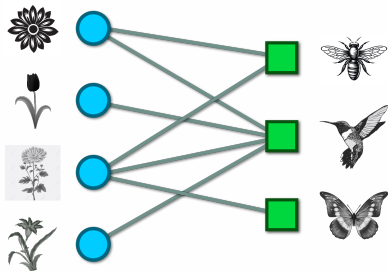
• J. Bascompte, *et al.* Proc. Nat. Acad. Sci. USA, **100**, 9383, (2003). DOI: [10.1073/pnas.1633576100](https://doi.org/10.1073/pnas.1633576100)

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• J. Bascompte, *et al.* Proc. Nat. Acad. Sci. USA, **100**, 9383, (2003). DOI: [10.1073/pnas.1633576100](https://doi.org/10.1073/pnas.1633576100)

# Networks and *palaeo-ecology*



## Estabilidad y resiliencia de **CO**munidades vegetales en escalas tempo**RA**les largas: evaluación de **RE**DES de co-**O**currencia a partir de **R**egistros paleo**A**mbientales



**IPE**  
**CSIC**



PID2022-141558NB-I00

## Objectives

- Tracing (Pyrenean) ecosystem's stability over (long) time.
- Determine how ecological communities re-organize after (external) disturbance (*e.g.*, introduction of agriculture).
- Studying networks of taxa over long time.



# Project CORREDORAS



## Data

**Source** Basa de la Mora (1913m asl).

# Project CORREDORAS

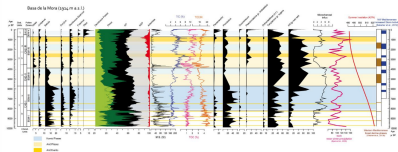


## Data

**Source** Basa de la Mora (1913m asl).

**Type-A** Plant and fungi taxa derived from fossil spores and pollen grains.

# Project CORREDORAS



## Data

**Source** Basa de la Mora (1913m asl).

**Type-A** Plant and fungi taxa derived from fossil spores and pollen grains.

**Type-B** Abiotic conditions as erosion rates, lake level fluctuations or temperature reconstructions (chironomid-based).

# Project CORREDORAS



## Data

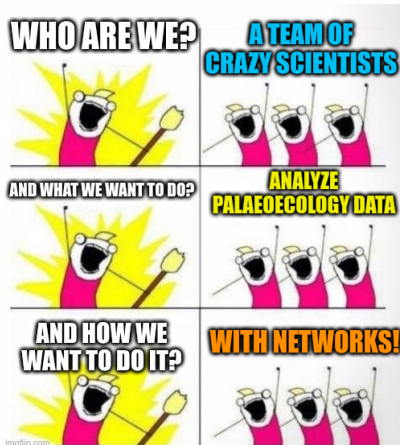
**Source** Basa de la Mora (1913m asl).

**Type-A** Plant and fungi taxa derived from fossil spores and pollen grains.

**Type-B** Abiotic conditions as erosion rates, lake level fluctuations or temperature reconstructions (chironomid-based).

**How-1** Depth-age model recording the last 10k years with a 10yr/cm resolution.

# Project CORREDORAS



## Data

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**Type-A** Plant and fungi taxa derived from fossil spores and pollen grains.

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**How-1** Depth-age model recording the last 10k years with a 10yr/cm resolution.

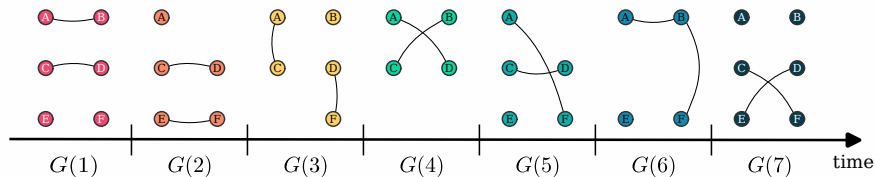
**How-2** Analyzing networks of taxa's **co-occurrence**.

## Networks and time: time-varying networks

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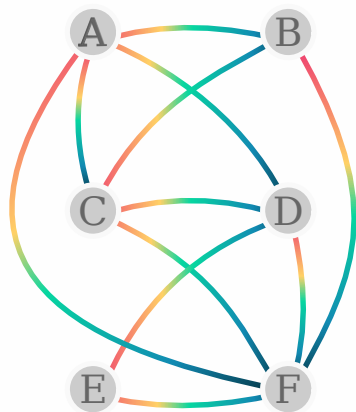
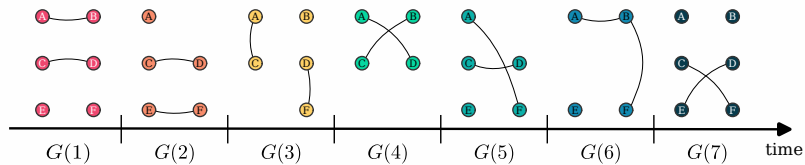
- Interactions
- Constituents

# Networks and time: time-varying networks





# Networks and time: time-varying networks



The Simpsons S19E09 Eternal Moonshine of the Simpson Mind - Carly Comando - Everyday



<https://www.youtube.com/watch?v=faWaqRyR8nY>







Hamer S.

1 ✓  
1 ✓  
4 ✓

5 ✓  
6 ✓  
5 ✓

**F**





















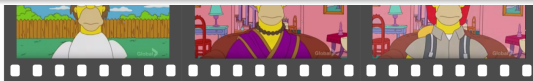






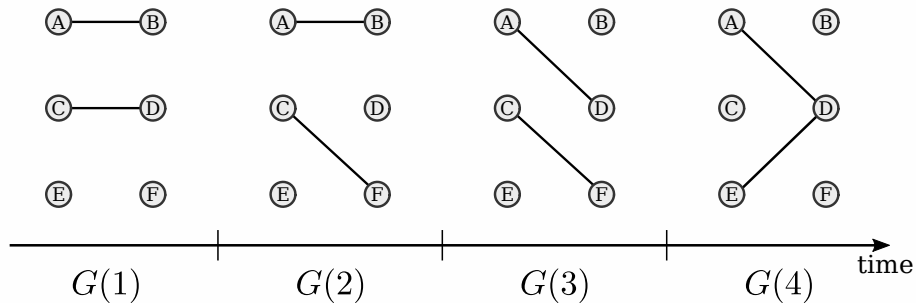


**How can we (and why we should) measure the interactions' persistence in time-varying networks?**

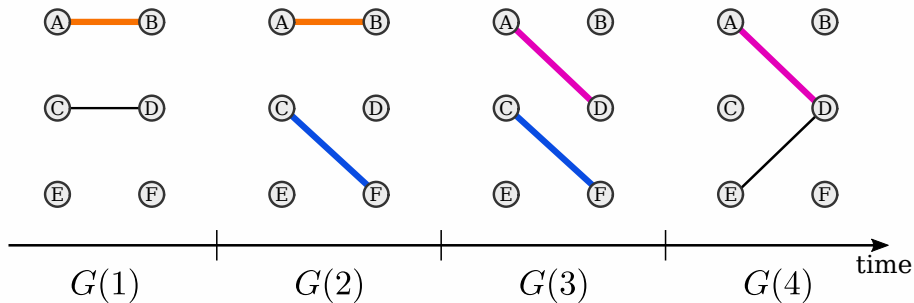


# Temporality

# Temporality



# Temporality



# Temporality

## Definition of temporality, $\mathcal{T}$

$$\mathcal{T}_{m,n} = \frac{U_{m,n} - \cap_{m,n}}{U_{m,n}} = 1 - \frac{\cap_{m,n}}{U_{m,n}},$$

$U_{m,n}$  → Size of the union of the edges' sets of snapshots  $G(m)$  and  $G(n)$ .

$\cap_{m,n}$  → Size of the intersection of the same sets.

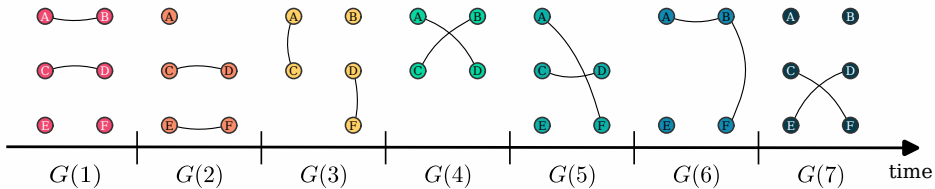
- A. Li, *et al.* Nature Comms., **11**, 2259, (2020). DOI: [10.1038/s41467-020-16088-w](https://doi.org/10.1038/s41467-020-16088-w)
- F. Bauzá Minguenza, *et al.* Sci. Rep., **13**, 765 (2023). DOI: [10.1038/s41598-022-25907-7](https://doi.org/10.1038/s41598-022-25907-7)

## Temporality

$$\mathcal{T}_{m,n} = \begin{cases} 1 & \text{if } \cap_{m,n} = 0 \\ 0 & \text{if } \cap_{m,n} = \cup_{m,n} \end{cases}$$

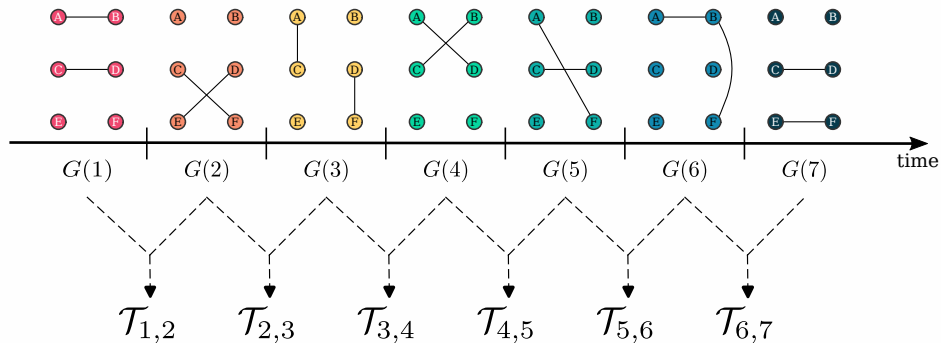
# Temporality

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# Temporality



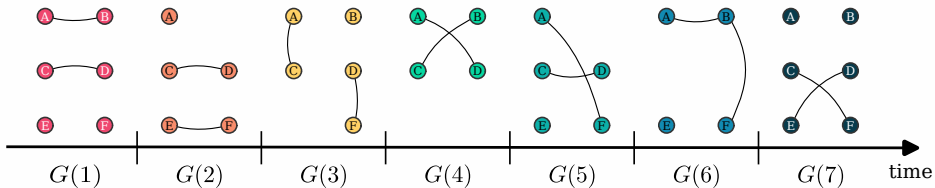
# Temporality

## Average temporality

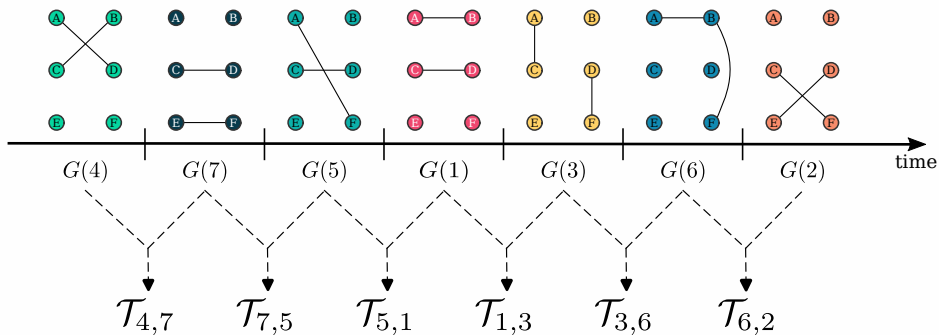
$$\overline{\mathcal{T}} = \frac{1}{N_s - 1} \sum_{m=1}^{N_s-1} \mathcal{T}_{m,m+1}$$

## How *special* your network is: Null model

## How *special* your network is: Null model

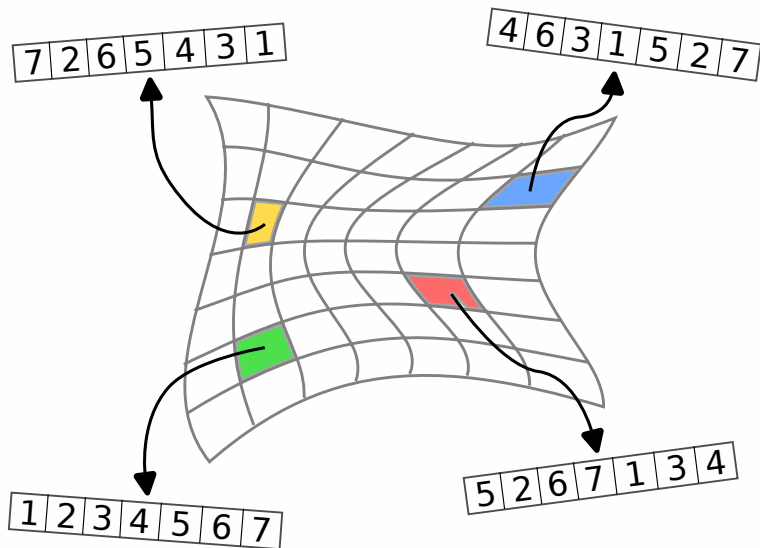


## How special your network is: Null model



• L. Gauvin, *et al.* SIAM Review, **64**, 763–830, (2022). DOI: [10.1137/19M1242252](https://doi.org/10.1137/19M1242252)

## How special your network is: Null model



## How *special* your network is: Null model

### Caveats

- The space of configurations can become quite big (*i.e.*, long computation time).

## How *special* your network is: Null model

### Caveats

- The space of configurations can become quite big (*i.e.*, long computation time).
- The concept of persistence should be extended to weighted edges.



Summing up ...

## Take home messages

- A *quick overview* on complex systems (and networks).

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- How network science can be used in ecological systems.

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- How network science can be used in ecological systems.
- Why a complex system scientist can (and *should*) sit among ecologists.
- (real) Multidisciplinary collaborations can trigger **interesting questions** stemming **from both sides** of the collaboration.



GOBIERNO  
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acardillo@ipe.csic.es



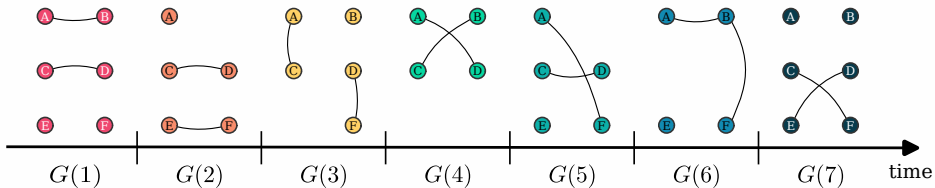
<https://cardillo.web.bifi.es/>



@a\_cardillo

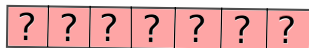
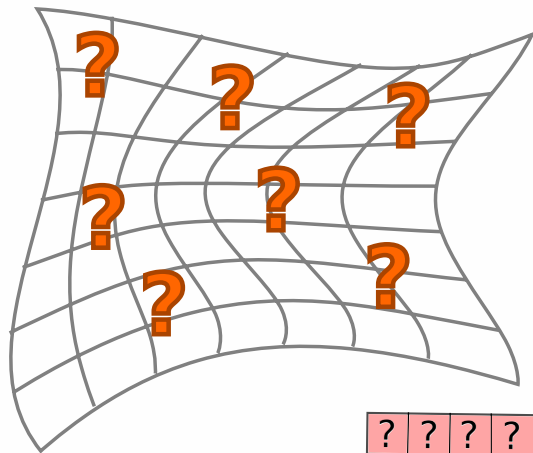
Extra contents

## Finding the optimal order

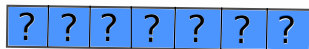




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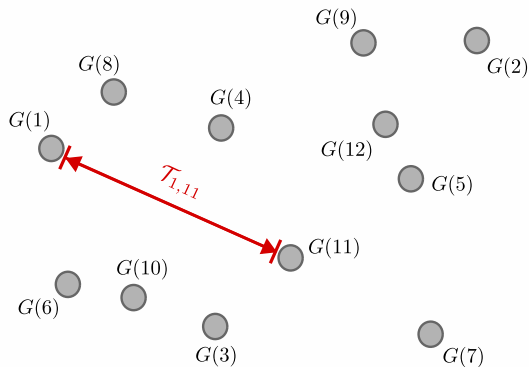
$\bar{T}_{\max}$



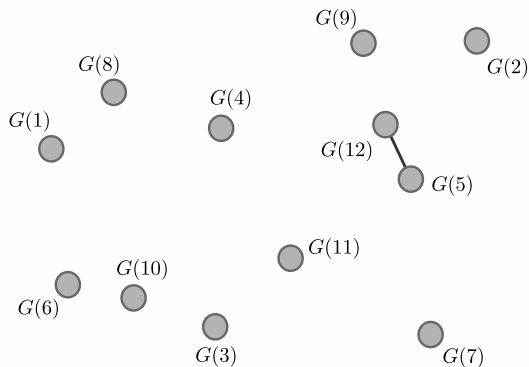
$\bar{T}_{\min}$

## Finding the optimal order

- 1 Embed snapshots in a metric space with  $d_{m,n} = \mathcal{T}_{m,n}$

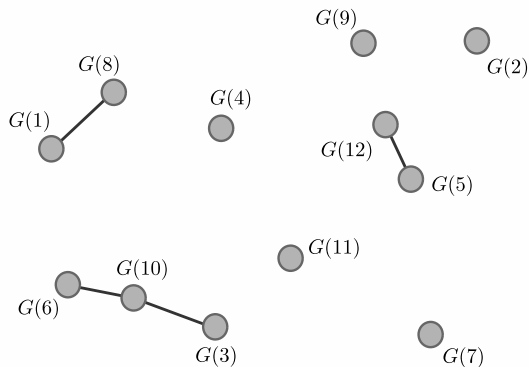


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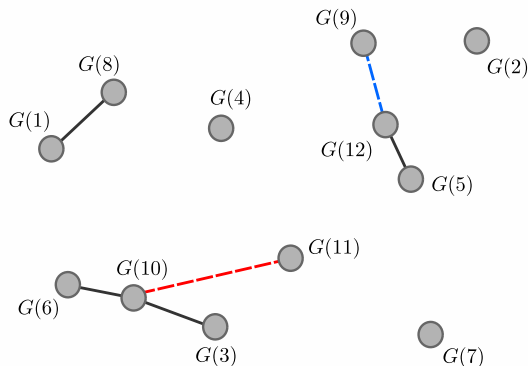
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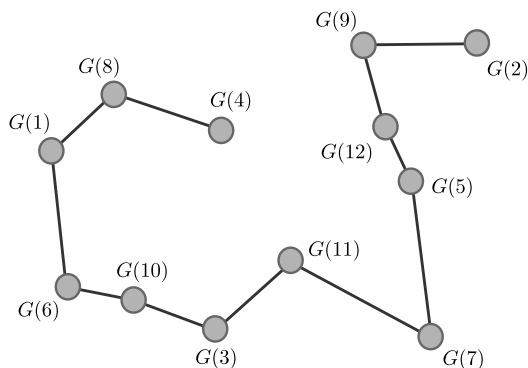
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- 5 Repeat steps 3 and 4 until getting an open chain.