

Towards an effective structure of complex networks and its contributions to epidemiology and neuroscience

Antoine Allard

Universitat de Barcelona

March 9th, 2017



UNIVERSITAT DE
BARCELONA



*Fonds de recherche
Nature et
technologies*

Québec 



Complex networks

- Structure in-between *order* and *randomness*.
- What are the fundamental properties or building blocks, if any?
 - ▶ determine higher-level structural properties;
 - ▶ predict the time-evolution/outcome of dynamical processes;
 - ▶ ex.: degree distribution, assortativity, motifs, communities.
- Incomplete answer: partial glimpse at the global picture
 - ▶ encouraging numerical results (ex.: dk -series);
 - ▶ lack of a unique, reliable and comprehensive way to compare networks;
 - ▶ limited analytical calculations.

How to effectively compress the information contained in the structure?

Learn about its fundamental properties along the way.

Outline

1. Approaches to an effective structure of complex networks

- Onion decomposition
- Metric space embedding

2. Applications

- Sexual transmission of Zika
- Structural connectomes

Outline

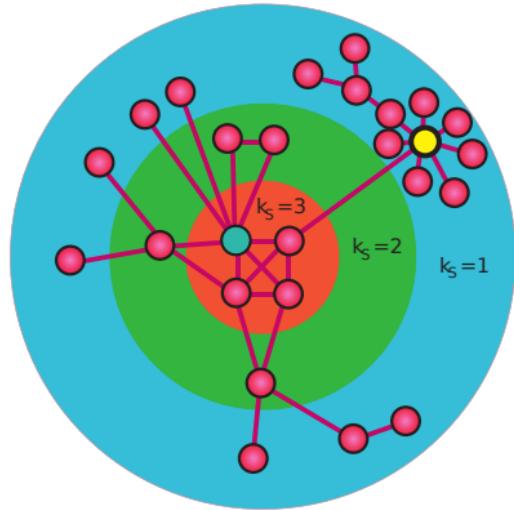
1. Approaches to an effective structure of complex networks

- Onion decomposition
- Metric space embedding

2. Applications

- Sexual transmission of Zika
- Structural connectomes

Onion decomposition



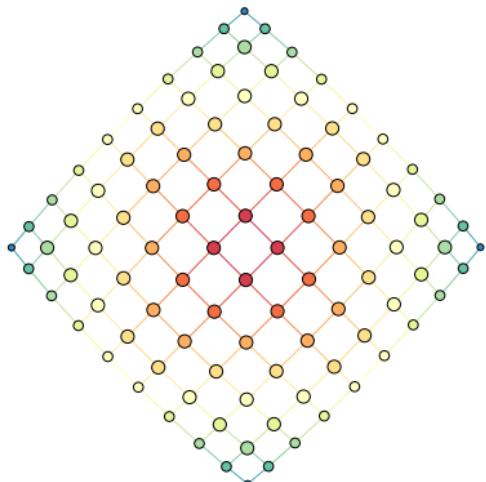
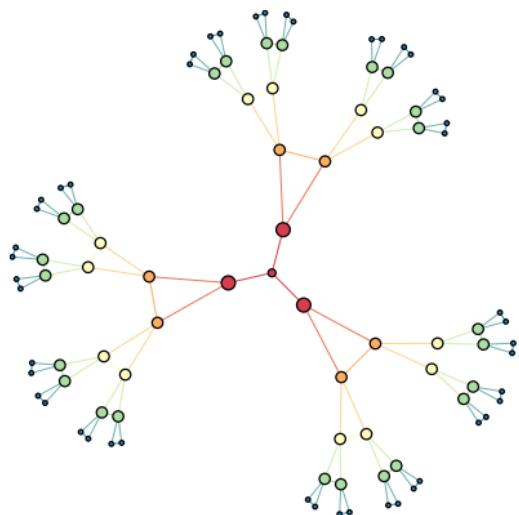
k -core: maximal subgraph such that all nodes have degree at least k .

A node is of coreness c , if in the c -th core but not in the $(c + 1)$ -th.

Measure of centrality.

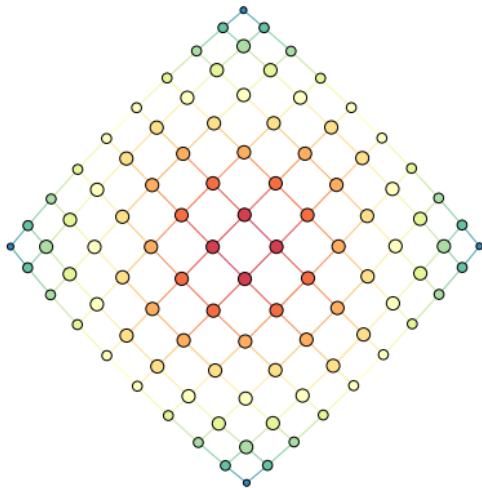
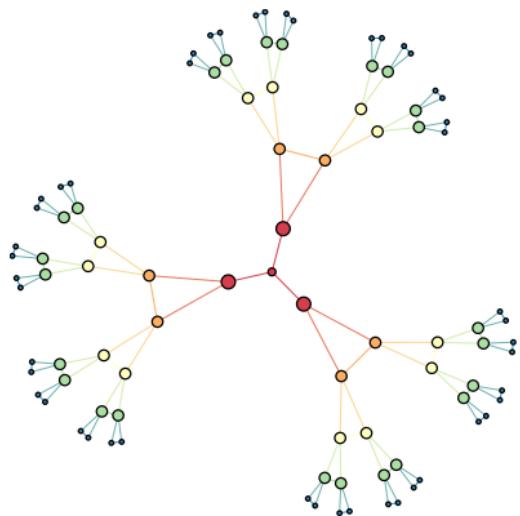
Onion decomposition

Networks may have identical k -core decompositions (ex.: all nodes in the 2-core).



Onion decomposition

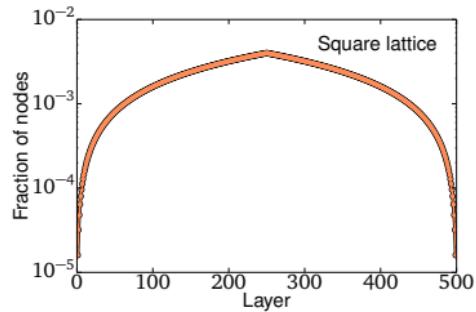
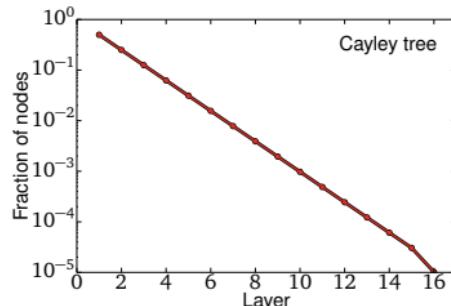
Networks may have identical k -core decompositions (ex.: all nodes in the 2-core).



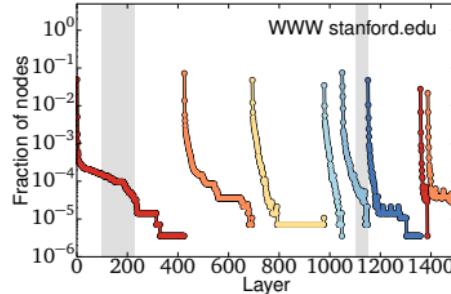
Onion decomposition: keeps track of the layer at which nodes are removed.

Onion decomposition

Fraction of the nodes removed at each layer.

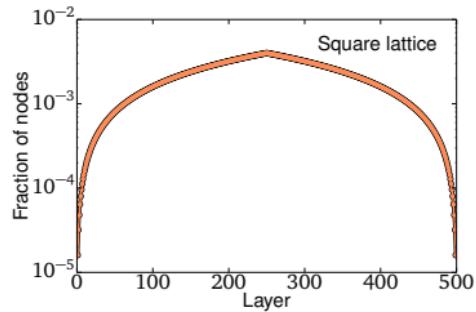
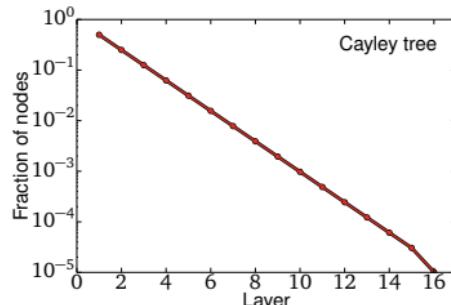


Identification of peculiar subgraphs (ex. subset of the WWW).

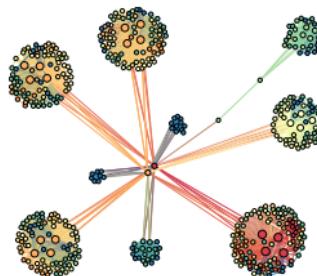
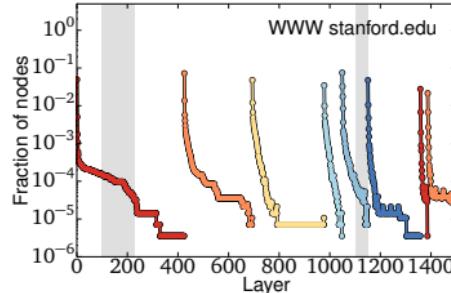


Onion decomposition

Fraction of the nodes removed at each layer.

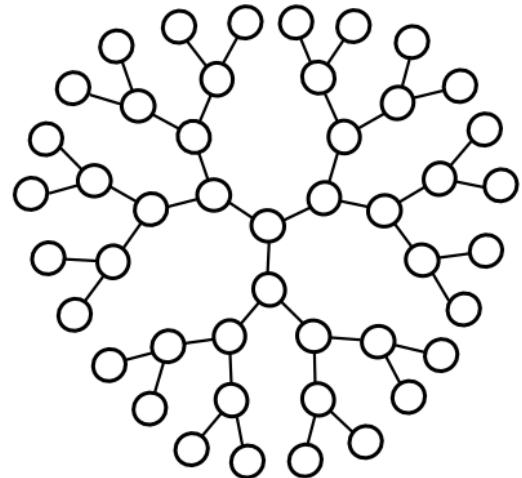


Identification of peculiar subgraphs (ex. subset of the WWW).



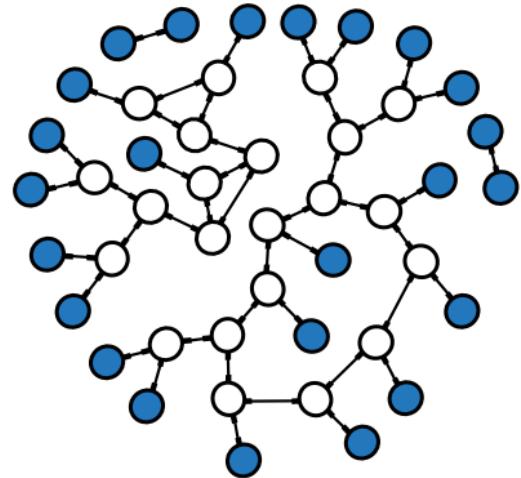
Onion decomposition

Random ensemble definition.



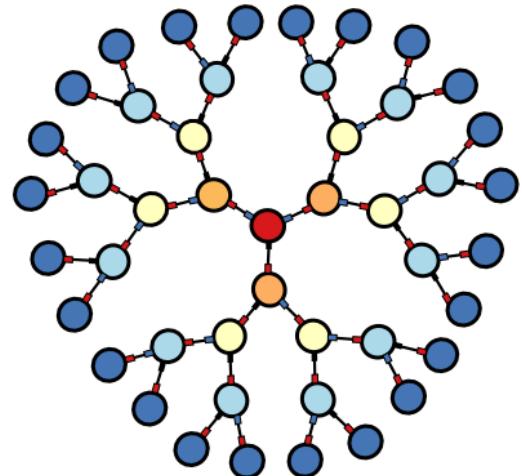
Onion decomposition

Random ensemble definition.



Onion decomposition

Random ensemble definition.

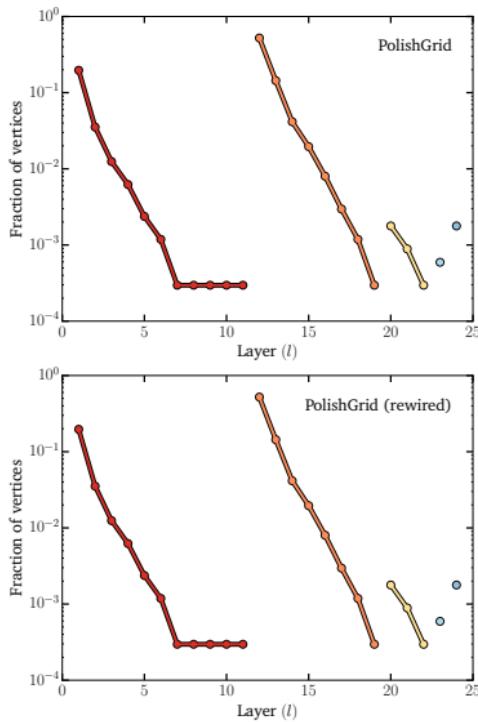


Local connection rules

- Nodes of coreness c and in layer ℓ must have
 1. *exactly* c links to layers $\ell' \geq \ell$ if in first layer of the core.
 2. *at least* $c + 1$ links to layers $\ell' \geq \ell - 1$ and *at most* c links to layers $\ell' \geq \ell$ otherwise.
- Links are randomly rewired preserving the density of links between layers on average.
- Requires less information than the CCM ($\ell_{\max} \sim k_{\max}^{1/2}$).

Onion decomposition

Random ensemble definition.

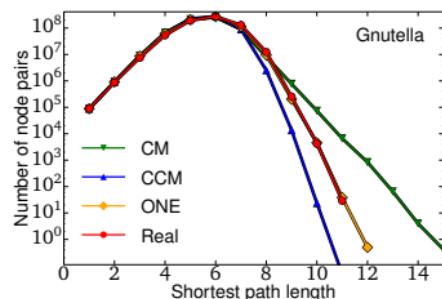
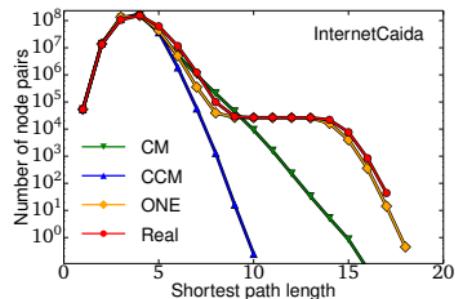


Local connection rules

- Nodes of coreness c and in layer ℓ must have
 1. *exactly* c links to layers $\ell' \geq \ell$ if in first layer of the core.
 2. *at least* $c + 1$ links to layers $\ell' \geq \ell - 1$ and *at most* c links to layers $\ell' \geq \ell$ otherwise.
- Links are randomly rewired preserving the density of links between layers on average.
- Requires less information than the CCM ($\ell_{\max} \sim k_{\max}^{1/2}$).

Onion decomposition

Random ensemble definition.

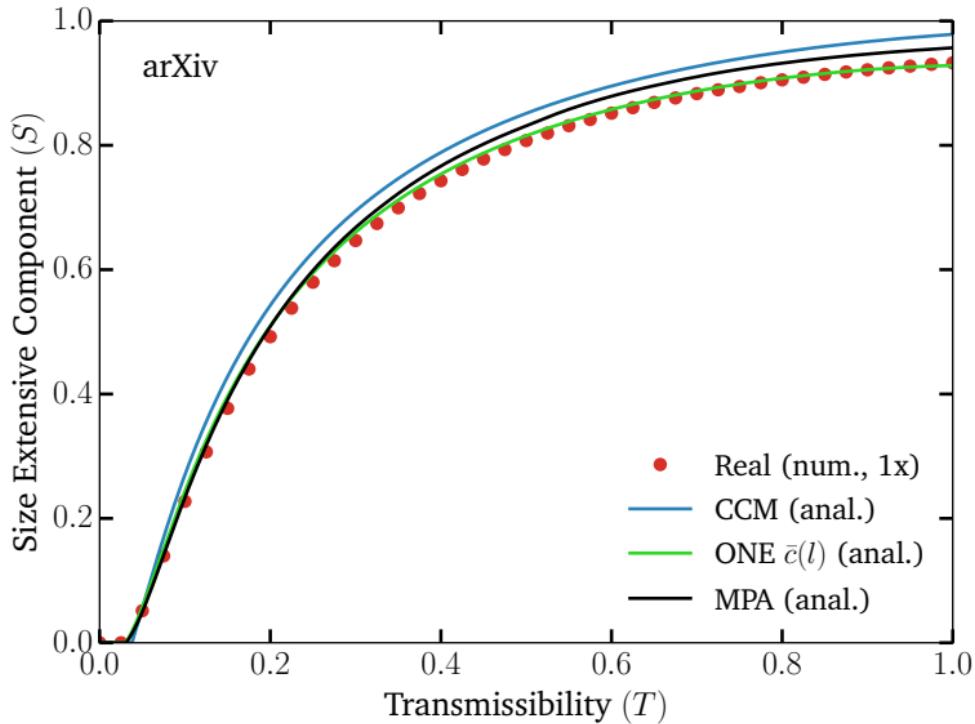


Local connection rules

- Nodes of coreness c and in layer ℓ must have
 1. *exactly* c links to layers $\ell' \geq \ell$ if in first layer of the core.
 2. *at least* $c + 1$ links to layers $\ell' \geq \ell - 1$ and *at most* c links to layers $\ell' \geq \ell$ otherwise.
- Links are randomly rewired preserving the density of links between layers on average.
- Requires less information than the CCM ($\ell_{\max} \sim k_{\max}^{1/2}$).

Onion decomposition

Analytical percolation results.



Outline

1. Approaches to an effective structure of complex networks

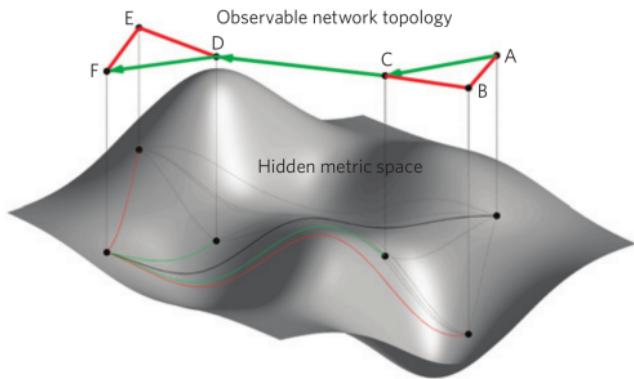
- o Onion decomposition
- o Metric space embedding

2. Applications

- o Sexual transmission of Zika
- o Structural connectomes

Metric space embedding

Hidden metric space framework: *distance* encodes the likelihood of being *connected*.



Phys. Rev. Lett. 100:078701 (2008)
Nature Phys. 5:74 (2009)

Geometric interpretation

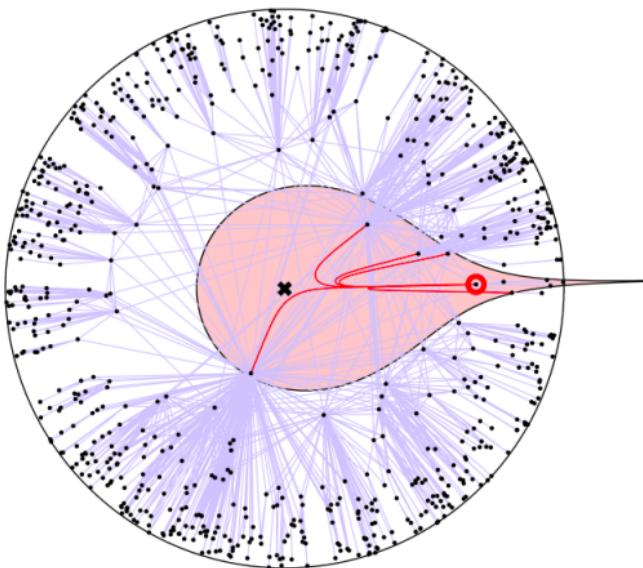
- Clustering
- Self-similarity
- Realistic models of growing networks
- Emergence of preferential attachment
- Hyperbolic geometry

Mapping topology to coordinates.

- International trade
- Identification of biochemical pathways
- Efficient routing protocol

Metric space embedding

Hidden metric space framework: *distance* encodes the likelihood of being *connected*.



Geometric interpretation

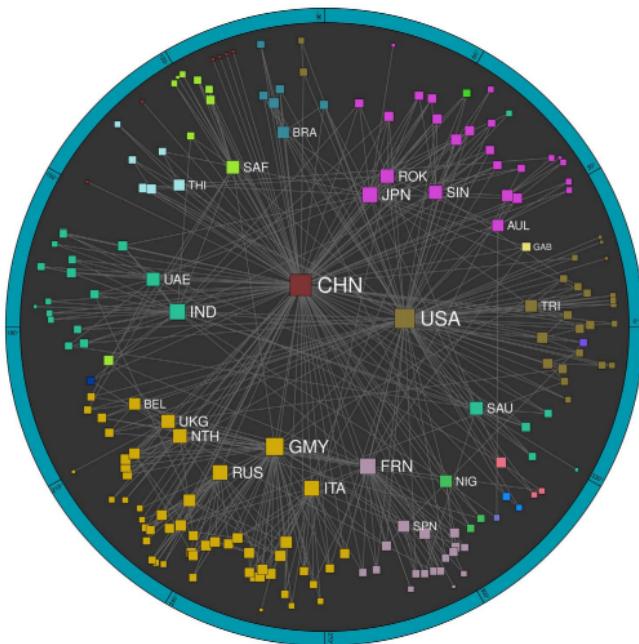
- Clustering
- Self-similarity
- Realistic models of growing networks
- Emergence of preferential attachment
- Hyperbolic geometry

Mapping topology to coordinates.

- International trade
- Identification of biochemical pathways
- Efficient routing protocol

Metric space embedding

Hidden metric space framework: *distance* encodes the likelihood of being *connected*.



Geometric interpretation

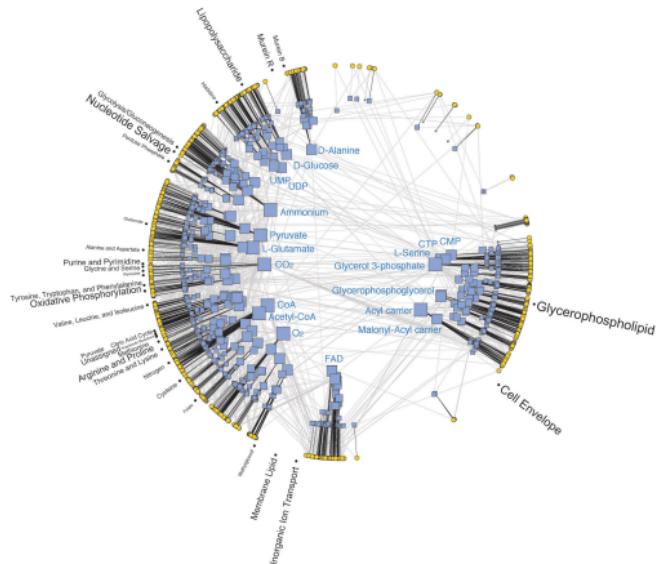
- Clustering
- Self-similarity
- Realistic models of growing networks
- Emergence of preferential attachment
- Hyperbolic geometry

Mapping topology to coordinates.

- International trade
- Identification of biochemical pathways
- Efficient routing protocol

Metric space embedding

Hidden metric space framework: *distance* encodes the likelihood of being *connected*.



Geometric interpretation

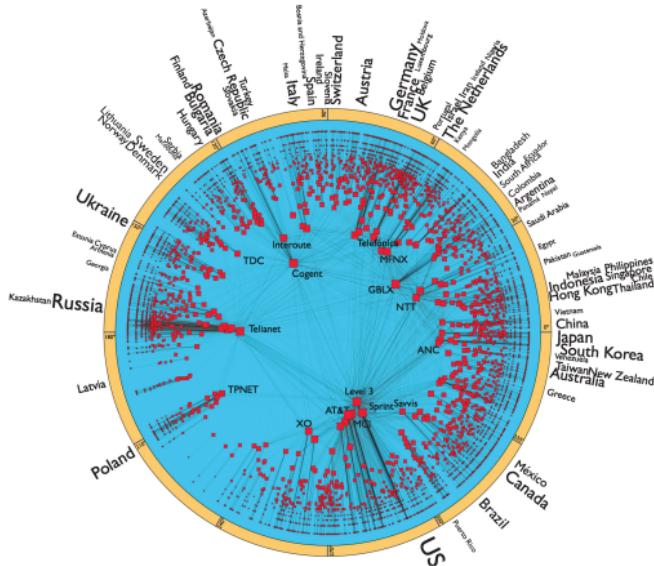
- Clustering
- Self-similarity
- Realistic models of growing networks
- Emergence of preferential attachment
- Hyperbolic geometry

Mapping topology to coordinates.

- International trade
- Identification of biochemical pathways
- Efficient routing protocol

Metric space embedding

Hidden metric space framework: *distance* encodes the likelihood of being *connected*.



Nat. Commun. 1:62 (2010)

Geometric interpretation

- Clustering
- Self-similarity
- Realistic models of growing networks
- Emergence of preferential attachment
- Hyperbolic geometry

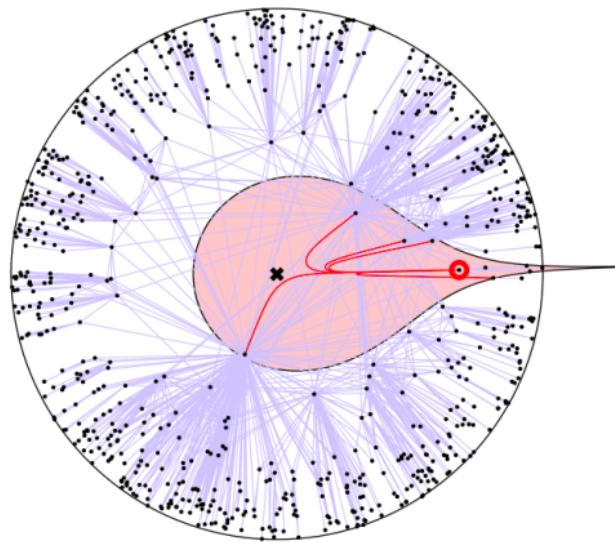
Mapping topology to coordinates.

- International trade
- Identification of biochemical pathways
- Efficient routing protocol

Metric space embedding

Weighted organization of complex networks

- Intensity of interactions (e.g., volume of trade, number of passengers)
- Non-trivially coupled with the binary network topology (i.e., $\bar{s}(k) \sim k^\eta$)
- New perspective on interactions (e.g., rich-club)

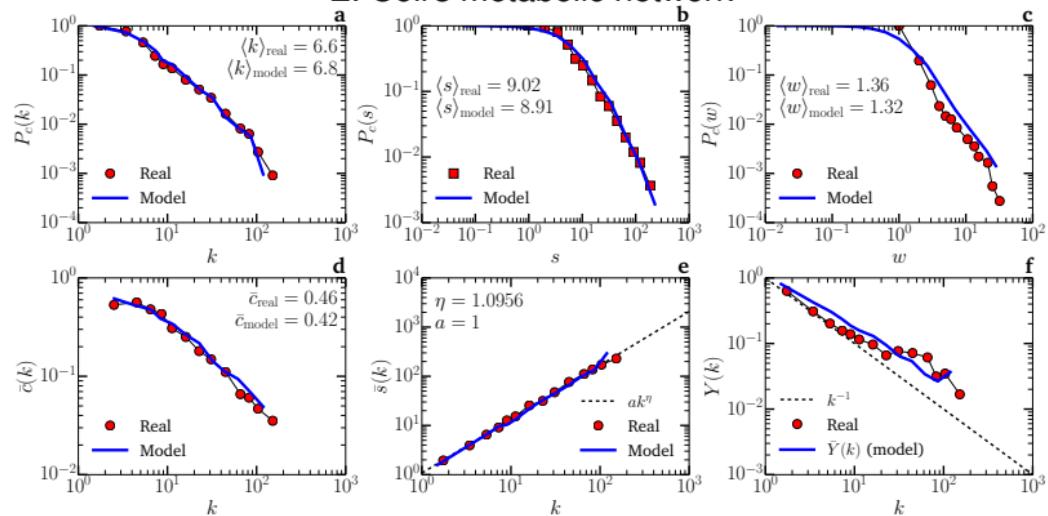


Metric space embedding

Weighted organization of complex networks

- Intensity of interactions (e.g., volume of trade, number of passengers)
- Non-trivially coupled with the binary network topology (i.e., $\bar{s}(k) \sim k^\eta$)
- New perspective on interactions (e.g., rich-club)

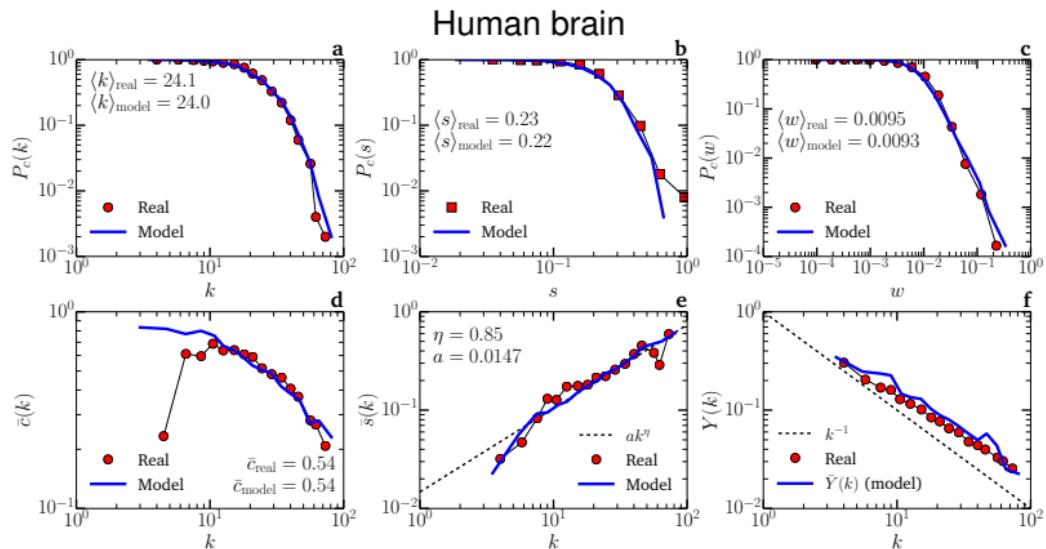
E. Coli's metabolic network



Metric space embedding

Weighted organization of complex networks

- Intensity of interactions (e.g., volume of trade, number of passengers)
- Non-trivially coupled with the binary network topology (i.e., $\bar{s}(k) \sim k^\eta$)
- New perspective on interactions (e.g., rich-club)



Outline

1. Approaches to an effective structure of complex networks

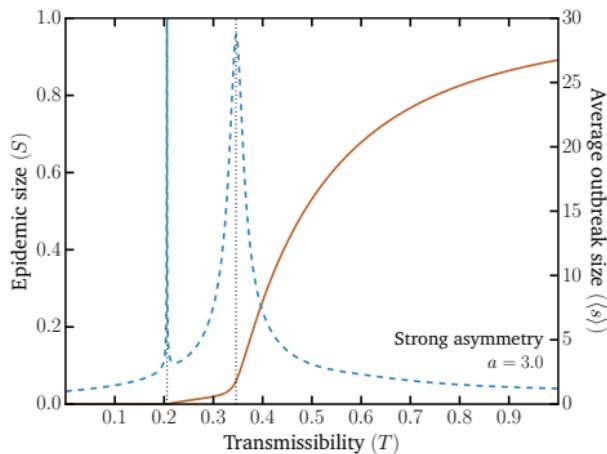
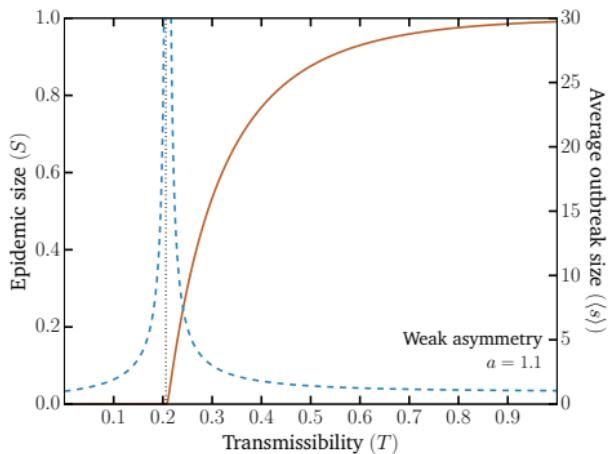
- Onion decomposition
- Metric space embedding

2. Applications

- Sexual transmission of Zika
- Structural connectomes

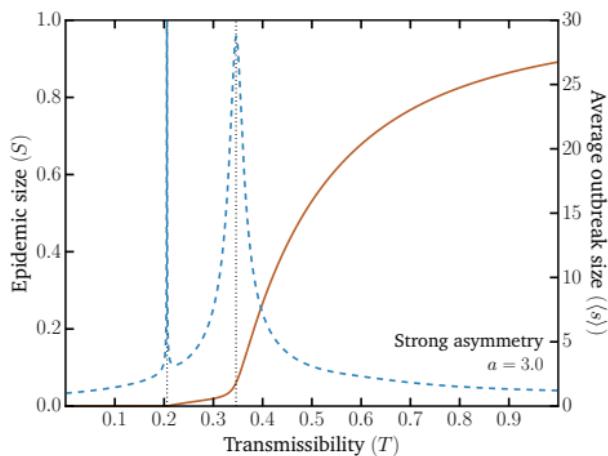
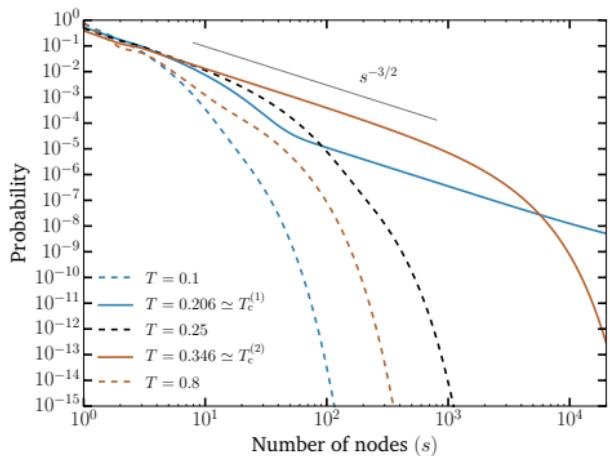
Sexual transmission of Zika

Men are approx. 10 times more likely to transmit to a partner than women.



Sexual transmission of Zika

Men are approx. 10 times more likely to transmit to a partner than women.



Outline

1. Approaches to an effective structure of complex networks

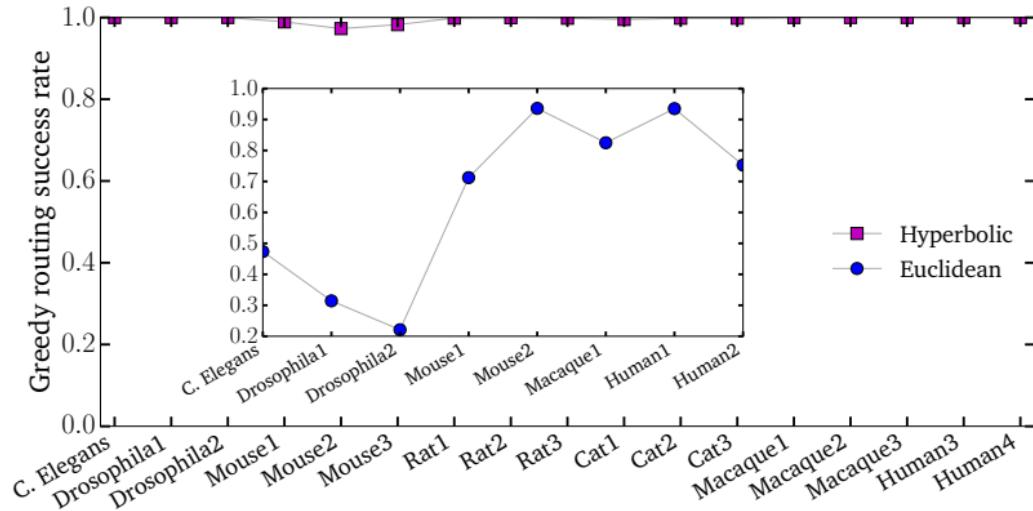
- Onion decomposition
- Metric space embedding

2. Applications

- Sexual transmission of Zika
- Structural connectomes

Connectomes

1) Universal principles shaping the structure of connectomes?



2) Inferring structure from functional connectomes via hidden metric space.

Collaborators



M. Á. Serrano
(U. Barcelona)



G. García-Pérez
(U. Barcelona)



M. Boguña
(U. Barcelona)



J. A. Grochow
(SFI, U. Colorado)



L. Hébert-Dufresne
(SFI, Institute for
Disease Modeling)



S. V. Scarpino
(U. Vermont)



B. M. Althouse
(Institute for Disease
Modeling)