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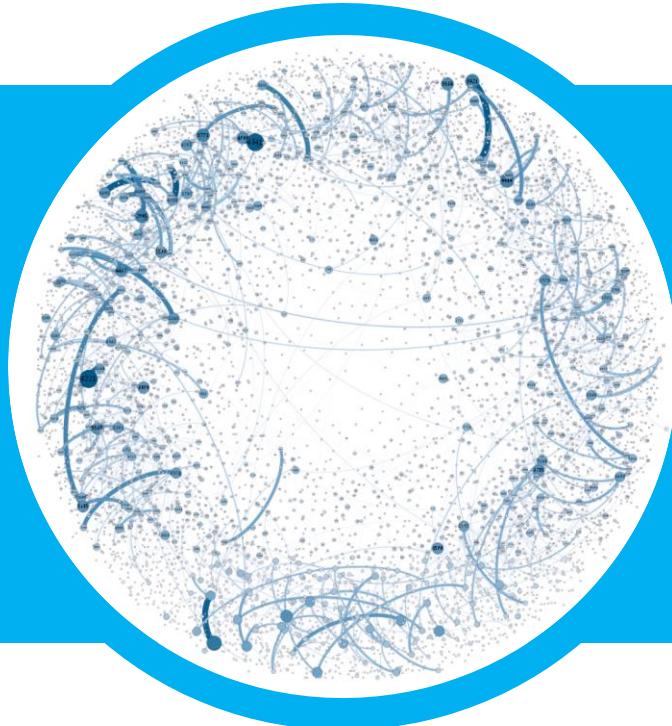


Network GPS – Navigating network dynamics

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אוניברסיטת בר-אילן

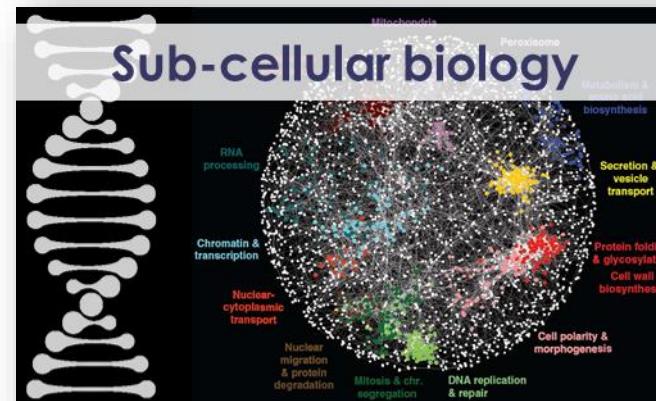
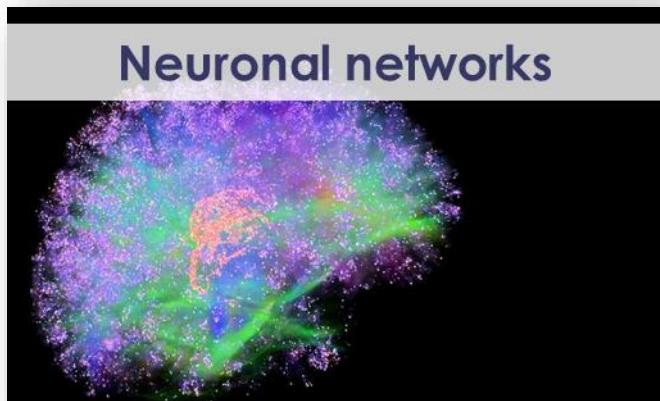




2003 NORTHEAST BLACKOUT

5.5×10^7 People affected
 10^2 Fatalities
 6×10^9 USD in damages

Crucial role of networks



Going beyond mapping

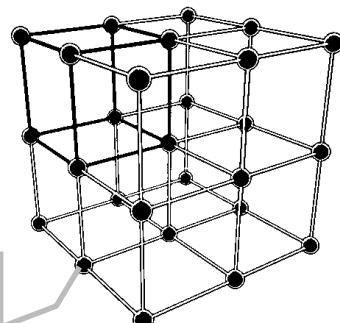


Going beyond mapping



The challenge of networks

Statistical physics comfort zone:



Each node has
 $k = 6$ nearest
neighbors

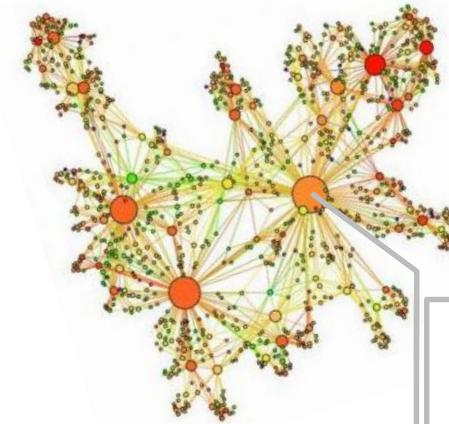
- Low dimensional
- Symmetric structures (lattice or lattice-like)

Finite dimension: $\langle d \rangle \sim \sqrt[\text{Dim}]{N}$

Degree distribution: bounded $P(k) \sim e^{-k}$

Hamiltonian dynamics

Where real networks are:



k spans
orders of
magnitude

- Disordered and weighted (for now: positive)
- Heterogeneous – Hubs and small nodes

Small world (infinite dimension): $\langle d \rangle \sim \log N$

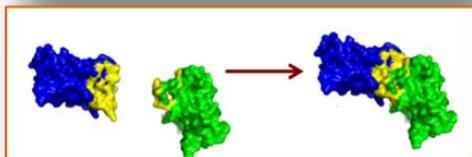
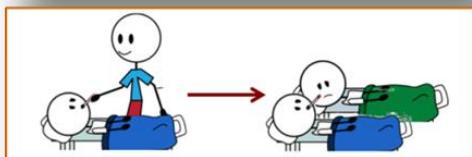
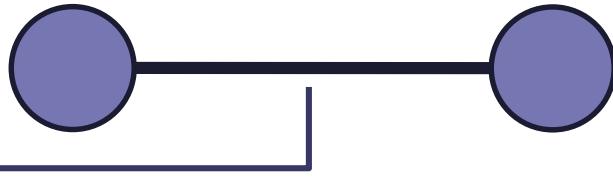
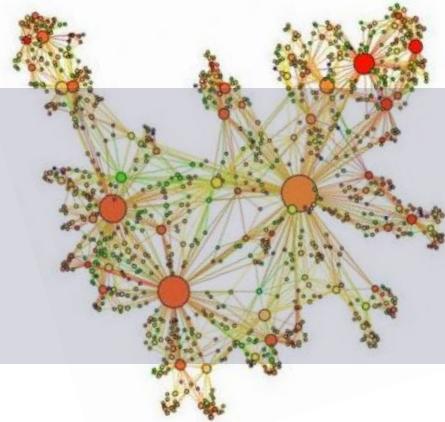
Degree distribution: scale free $P(k) \sim k^{-\gamma}$

Nonlinear dynamics (sometimes hidden)

Dynamics layer

$x_i(t) \rightarrow \text{Activity}$

$$\frac{dx_i}{dt} = \mathbf{M}_0(x_i) + \sum_{j=1}^N A_{ij} \mathbf{M}_1(x_i) \mathbf{M}_2(x_j)$$



A_{ij} Weighted, directed topology

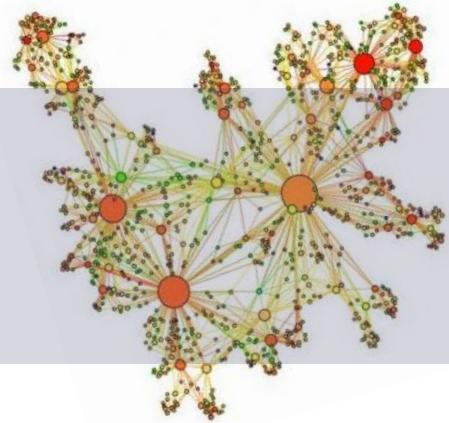
$x_i(t)$ Concentration, Infection probability, Species abundance

M_0, M_1, M_2 Intrinsic nonlinear interaction mechanisms

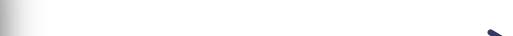
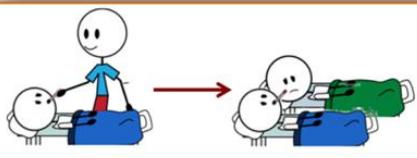
Dynamics layer

$x_i(t) \rightarrow \text{Activity}$

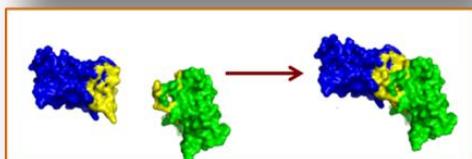
$$\frac{dx_i}{dt} = \mathbf{M}_0(x_i) + \sum_{j=1}^N A_{ij} \mathbf{M}_1(x_i) \mathbf{M}_2(x_j)$$



$$\frac{dx_i}{dt} = Bx_i(1 - x_i) + \sum_{j=1}^N A_{ij} \frac{x_i x_j^a}{1 + x_j^a}$$

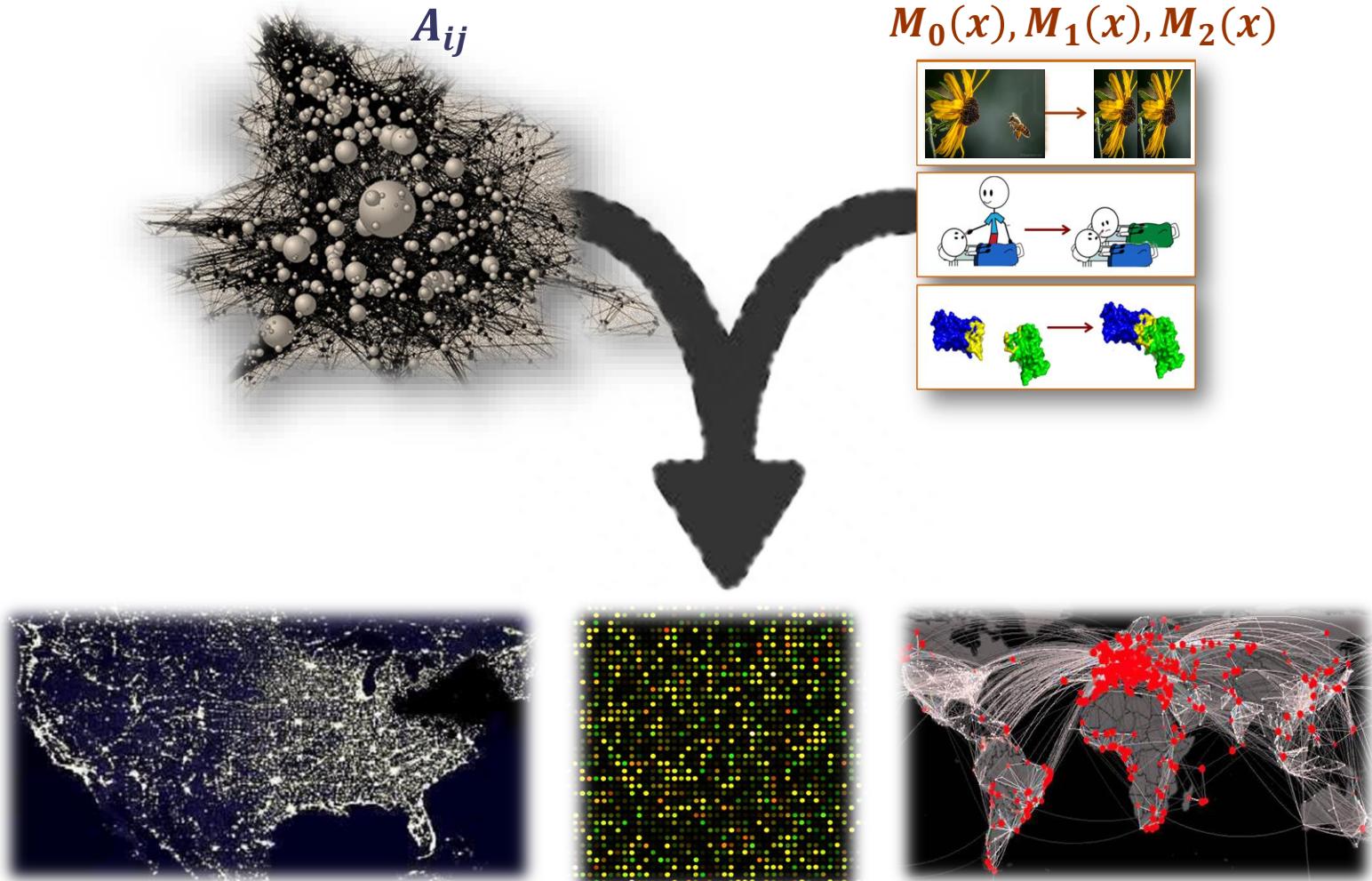


$$\frac{dx_i}{dt} = -Bx_i + \sum_{j=1}^N A_{ij}(1 - x_i)x_j$$



$$\frac{dx_i}{dt} = -Bx_i + \sum_{j=1}^N A_{ij} \frac{x_j^h}{1 + x_j^h}$$

Bringing networks to life

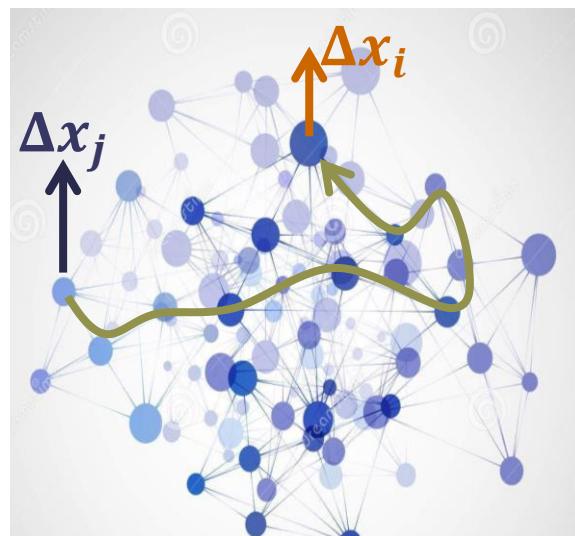


patterns of information spread

Information flow in complex networks

$$x_j \rightarrow x_j + \Delta x_j \longrightarrow x_i + \Delta x_i(t)$$

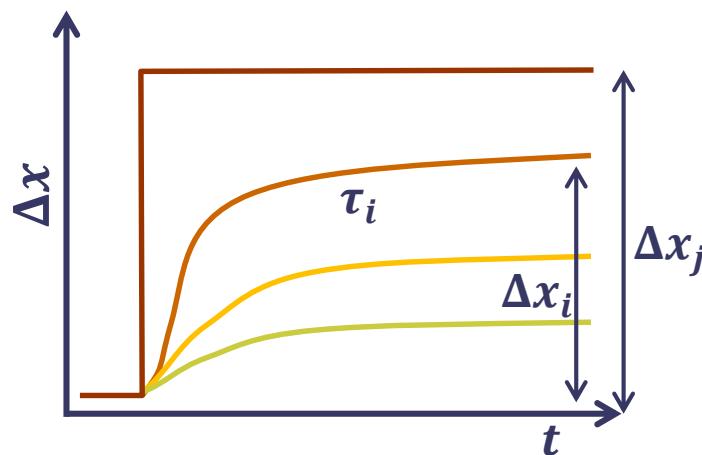
signal response



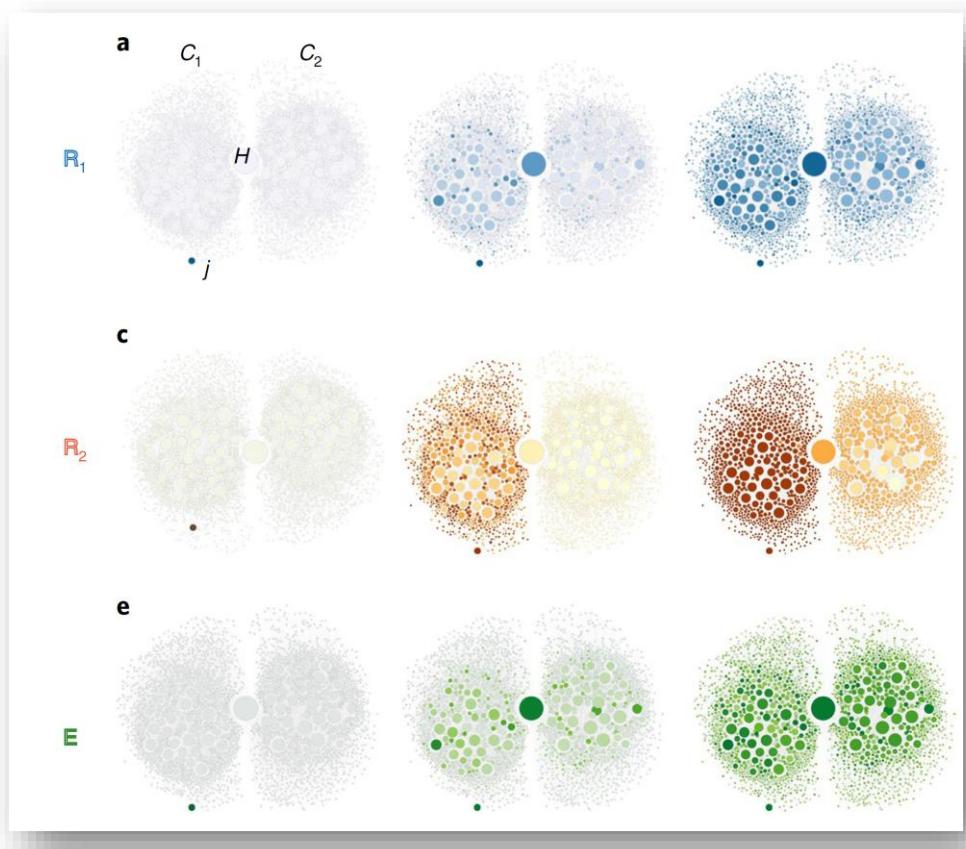
Response patterns to fixed-point perturbations

Information flow in complex networks

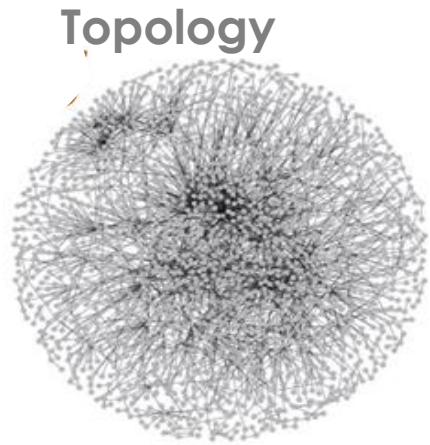
- When $T(j \rightarrow i)$
- Where $l_{ij}(t)$
- How strongly Δx_i
- How $(\mathcal{F}_i, \mathcal{F}_{ij})$



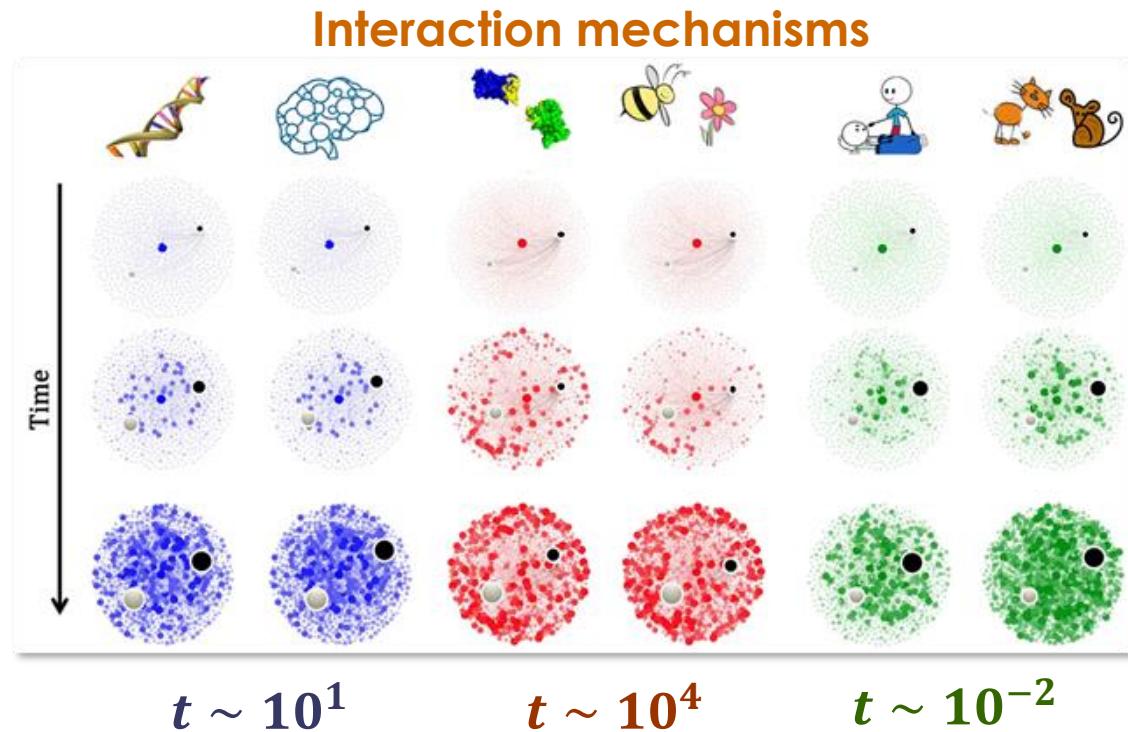
Spatiotemporal propagation



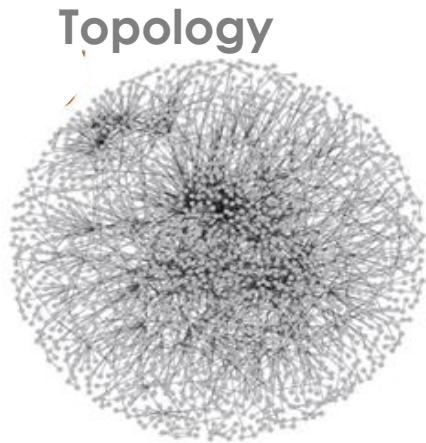
The zoo of propagation patterns



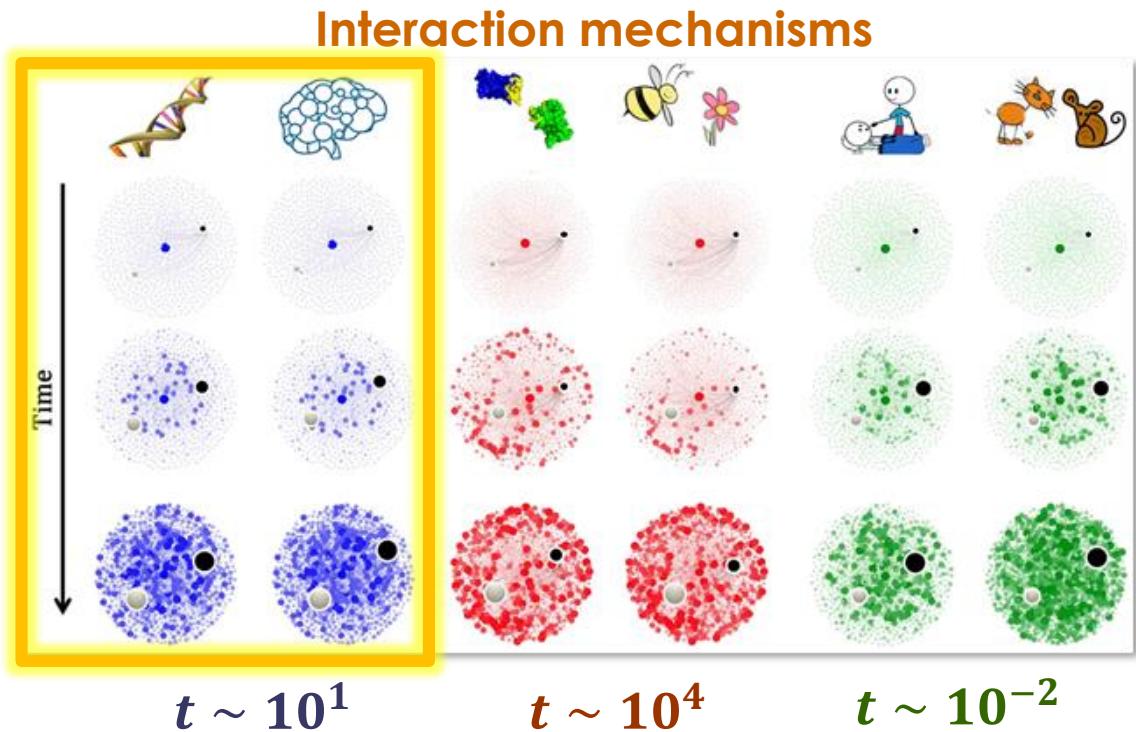
Identical networks
yield visibly distinct
propagation patterns



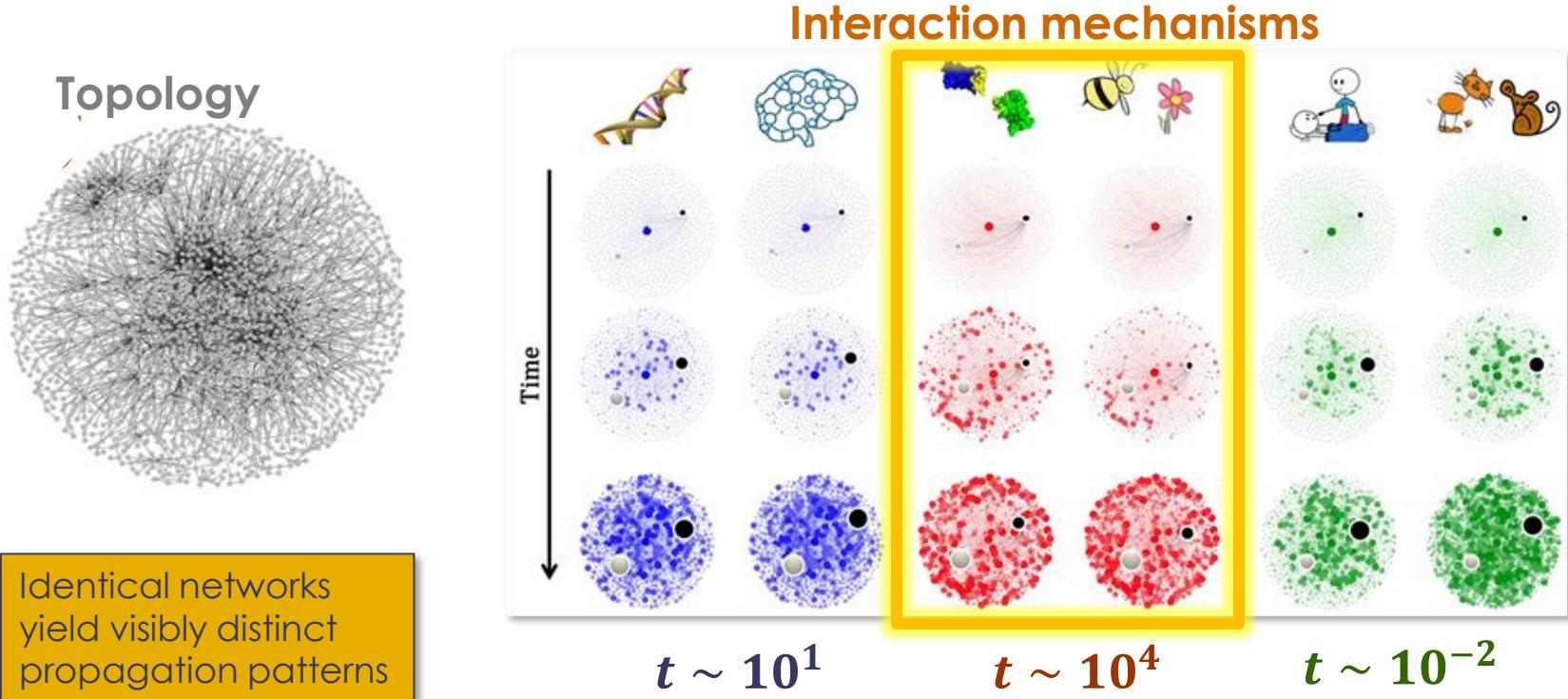
The zoo of propagation patterns



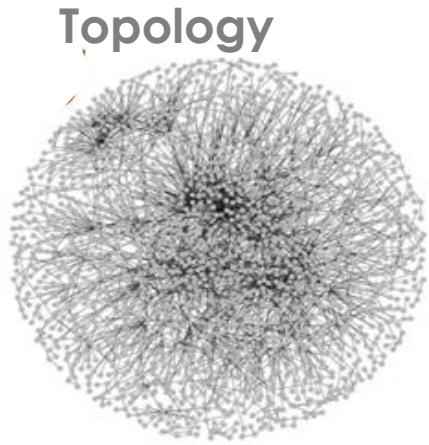
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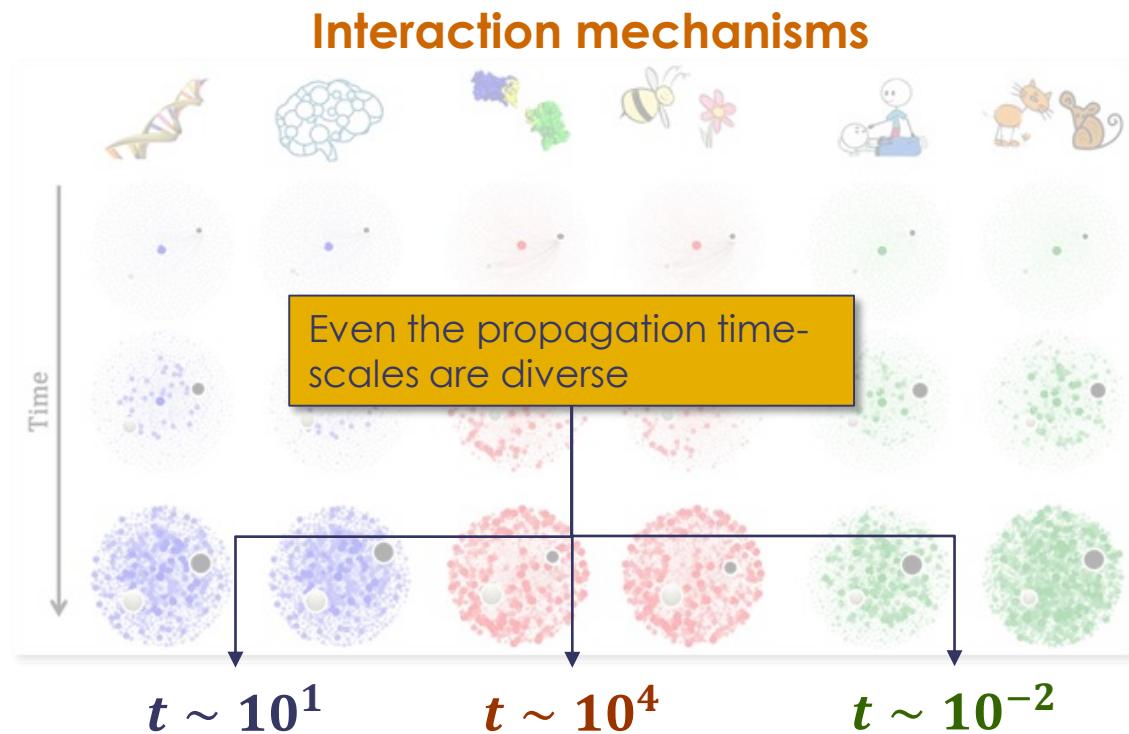
The zoo of propagation patterns



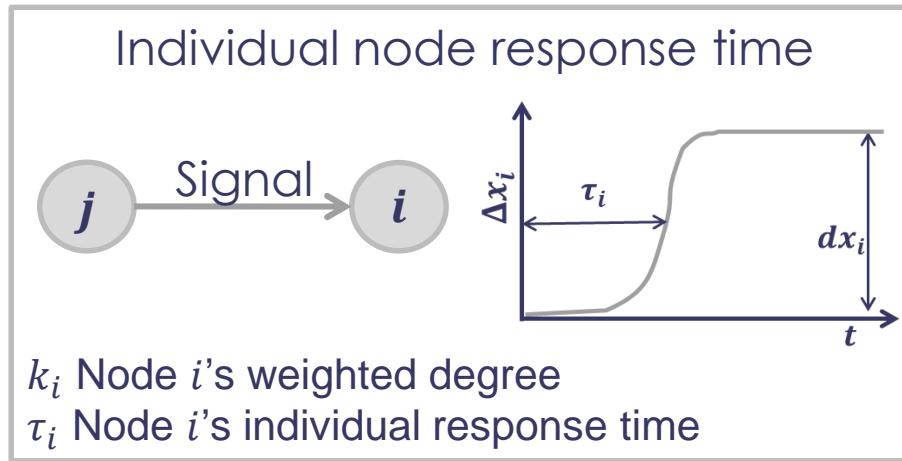
The zoo of propagation patterns



Identical networks
yield visibly distinct
propagation patterns



Taming the zoo of propagation patterns

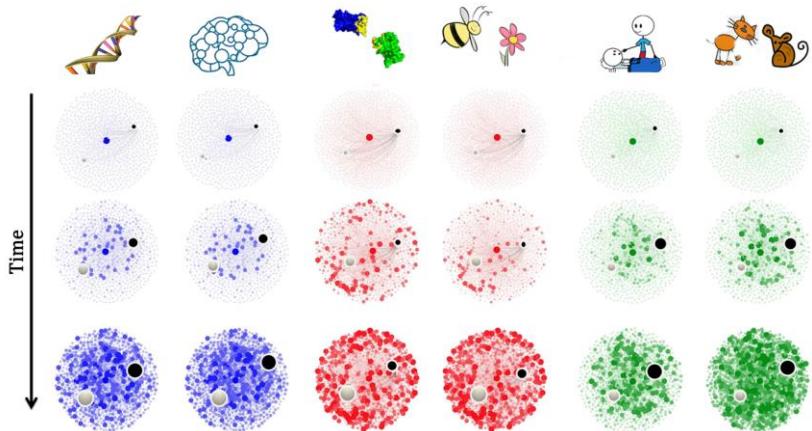


$$\tau_i \sim k_i^\theta$$

A node's intrinsic response time scales with its weighted degree

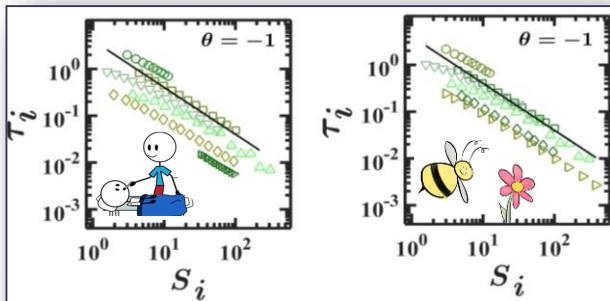
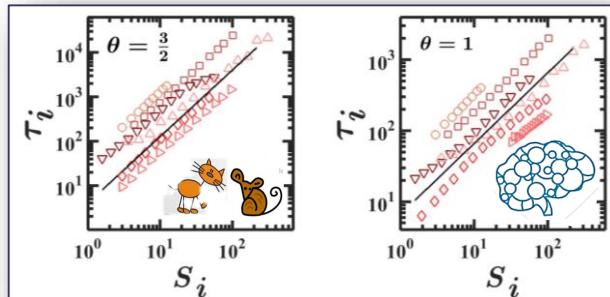
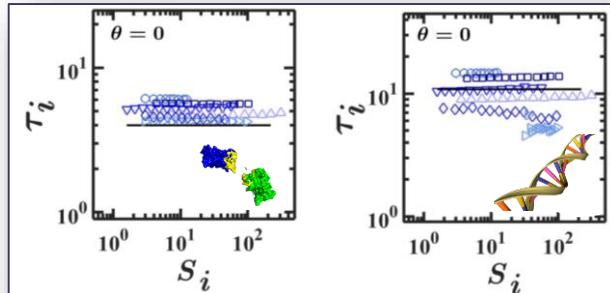
Why should you care?

Diverse & unpredictable



Universal

$$\tau_i \sim k_i^\theta$$



Why should you care?

How do we obtain the exponent θ ?

$$\frac{dx_i}{dt} = \mathbf{M}_0(x_i) + \sum_{j=1}^N A_{ij} \mathbf{M}_1(x_i) \mathbf{M}_2(x_j)$$



$$R(x) = -\frac{M_1(x)}{M_0(x)}$$

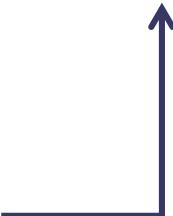
$$\tau_i \sim k_i^\theta$$

$$Y(x) = \left(\frac{d(M_1(x)R(x))}{dx} \right)^{-1}$$



$$Y(R^{-1}(x)) = \sum_{n=0}^{\infty} C_n x^{\Gamma(n)}$$

$$\theta = -2 - \Gamma(0)$$



Why should you care:

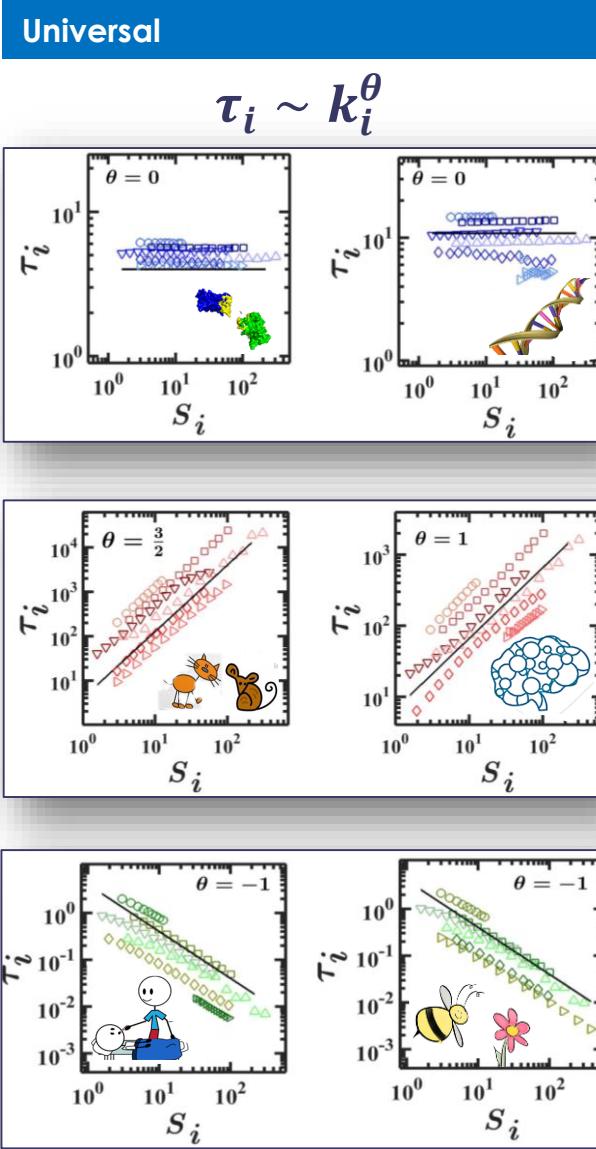
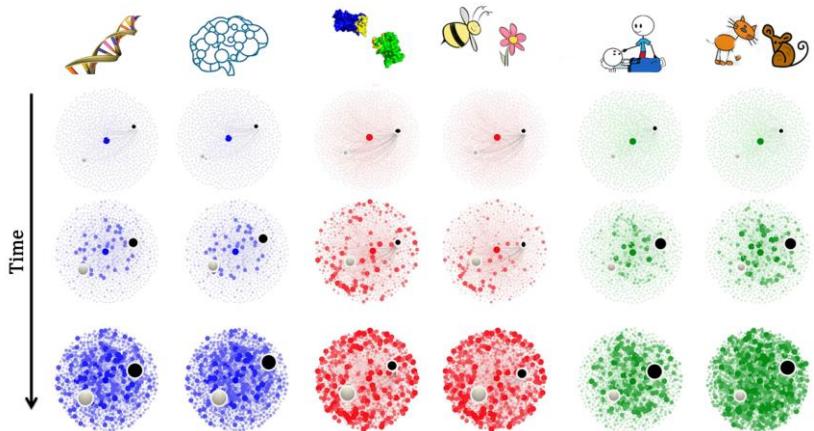
θ depends on the system's Dynamics (M_0, M_1, M_2)

Only on leading powers (through $\Gamma(0)$)

Not on coefficients (C_n)

Universality

Diverse & unpredictable



Dynamic insight

Response time

Dynamic observable of interest.

$$\tau_i \sim k_i^\theta$$

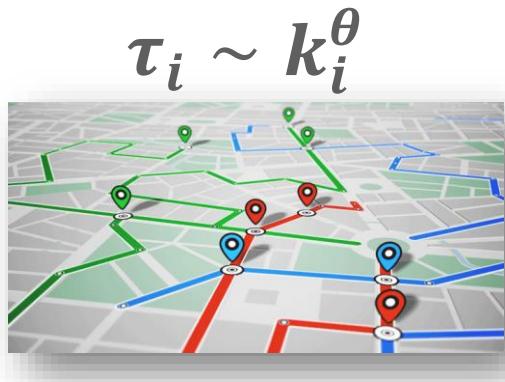
Weighted degree

Known topological element

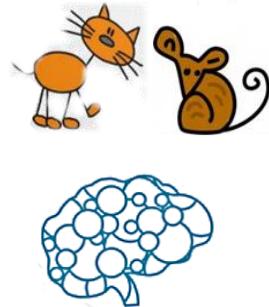
Dynamic determinant

Mapping topology into dynamics

Network GPS – how signals navigate the network



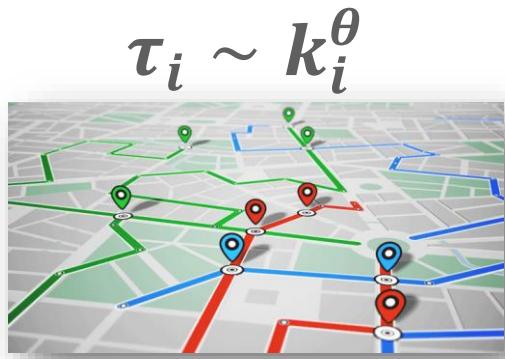
$\theta > 0$
Hubs
=
Bottlenecks



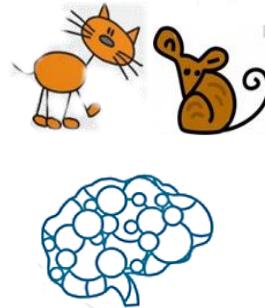
$\theta < 0$
Hubs
=
Free flow



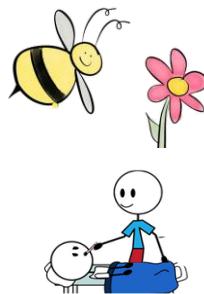
Network GPS – how signals navigate the network



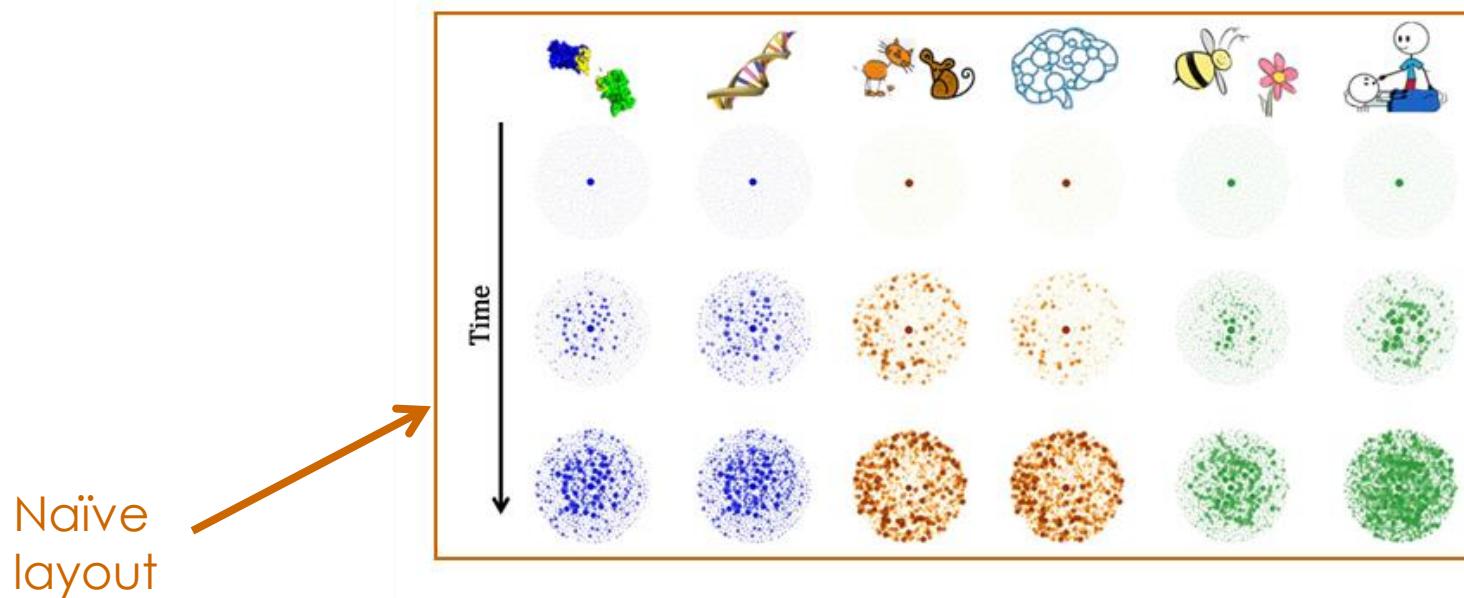
$\theta > 0$
Hubs
=
Bottlenecks



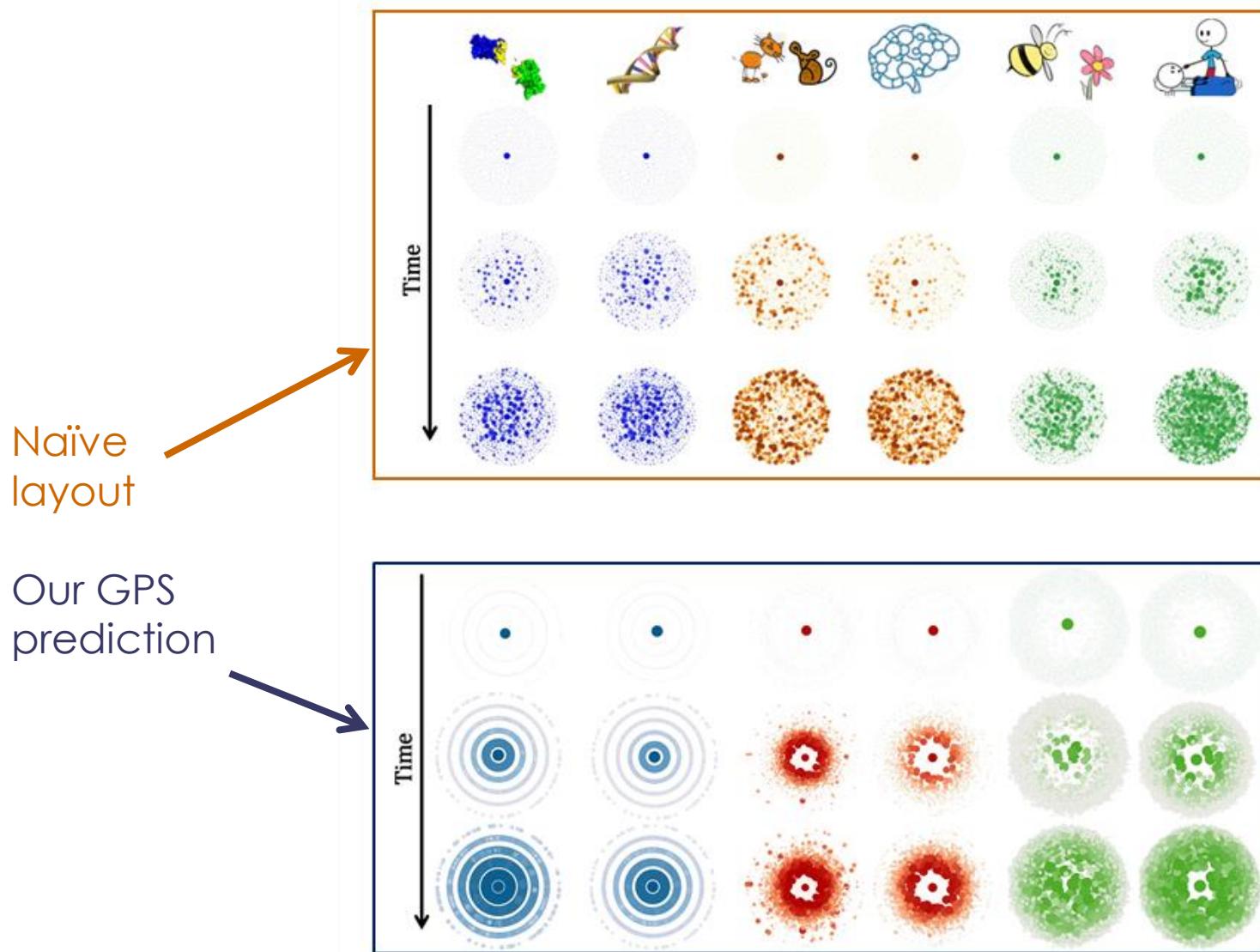
$\theta < 0$
Hubs
=
Free flow



Network GPS – how signals navigate the network

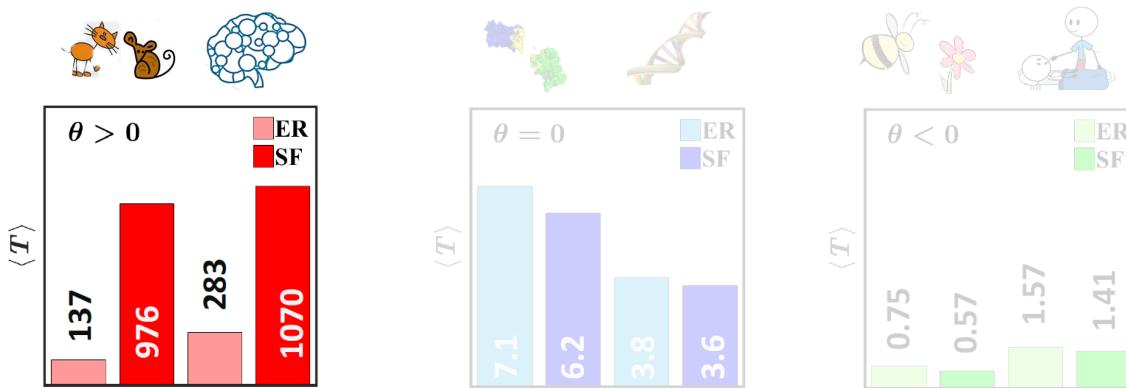


Network GPS – how signals navigate the network



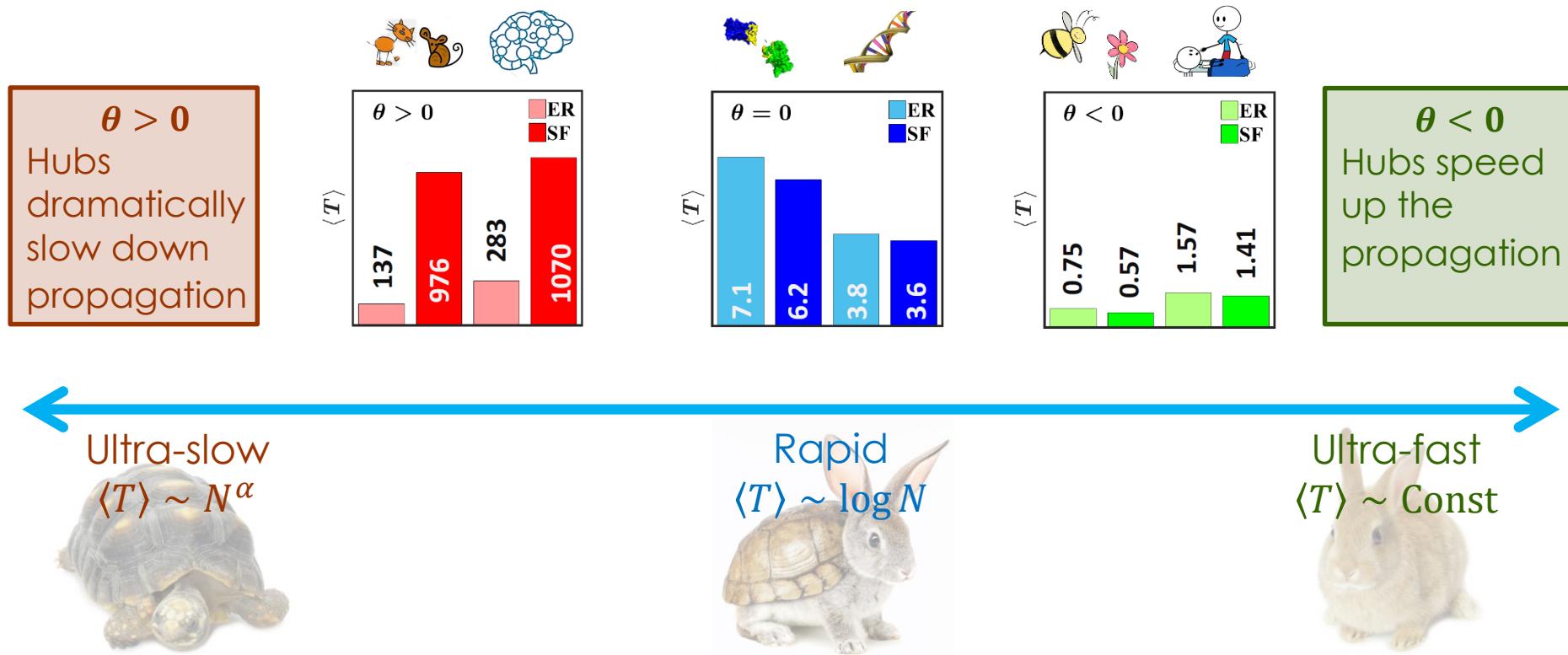
Same topology – different spreading rules

$\theta > 0$
Hubs
dramatically
slow down
propagation



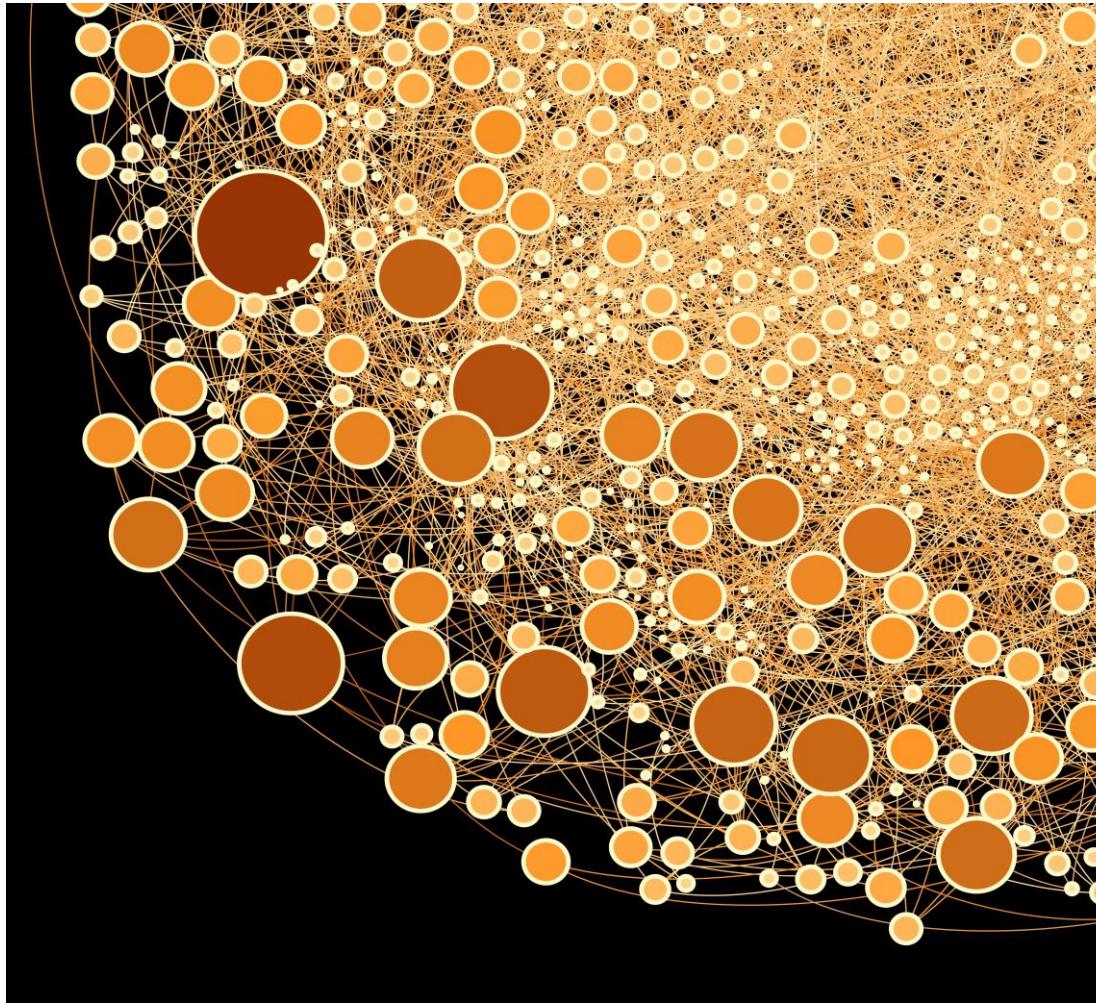
Hubs speed
up the
propagation

Same topology – different spreading rules

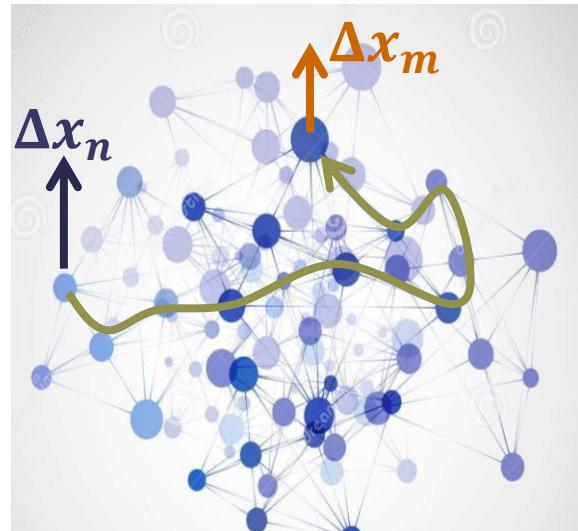


Different interpretations of scale-freeness. All boiled down to a single analytically predictable parameter θ

Flow



Information flow

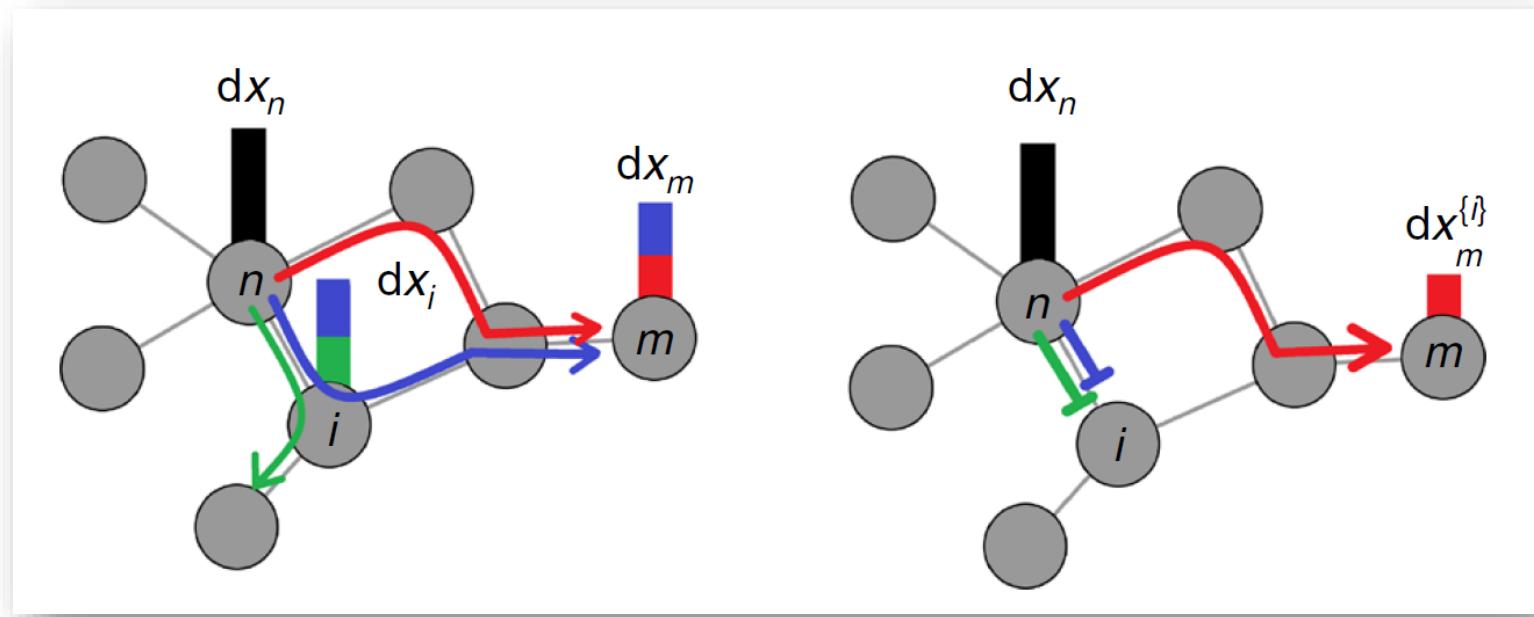
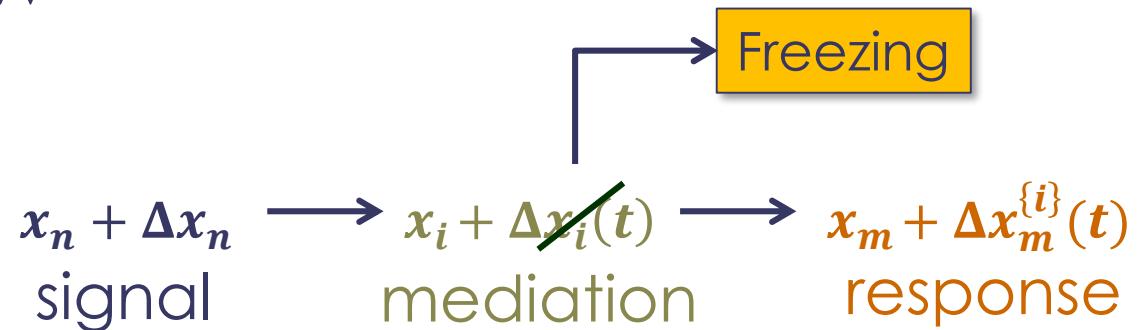


$x_n + \Delta x_n$ → signal $x_i + \Delta x_i(t)$ → mediation $x_m + \Delta x_m(t)$ response

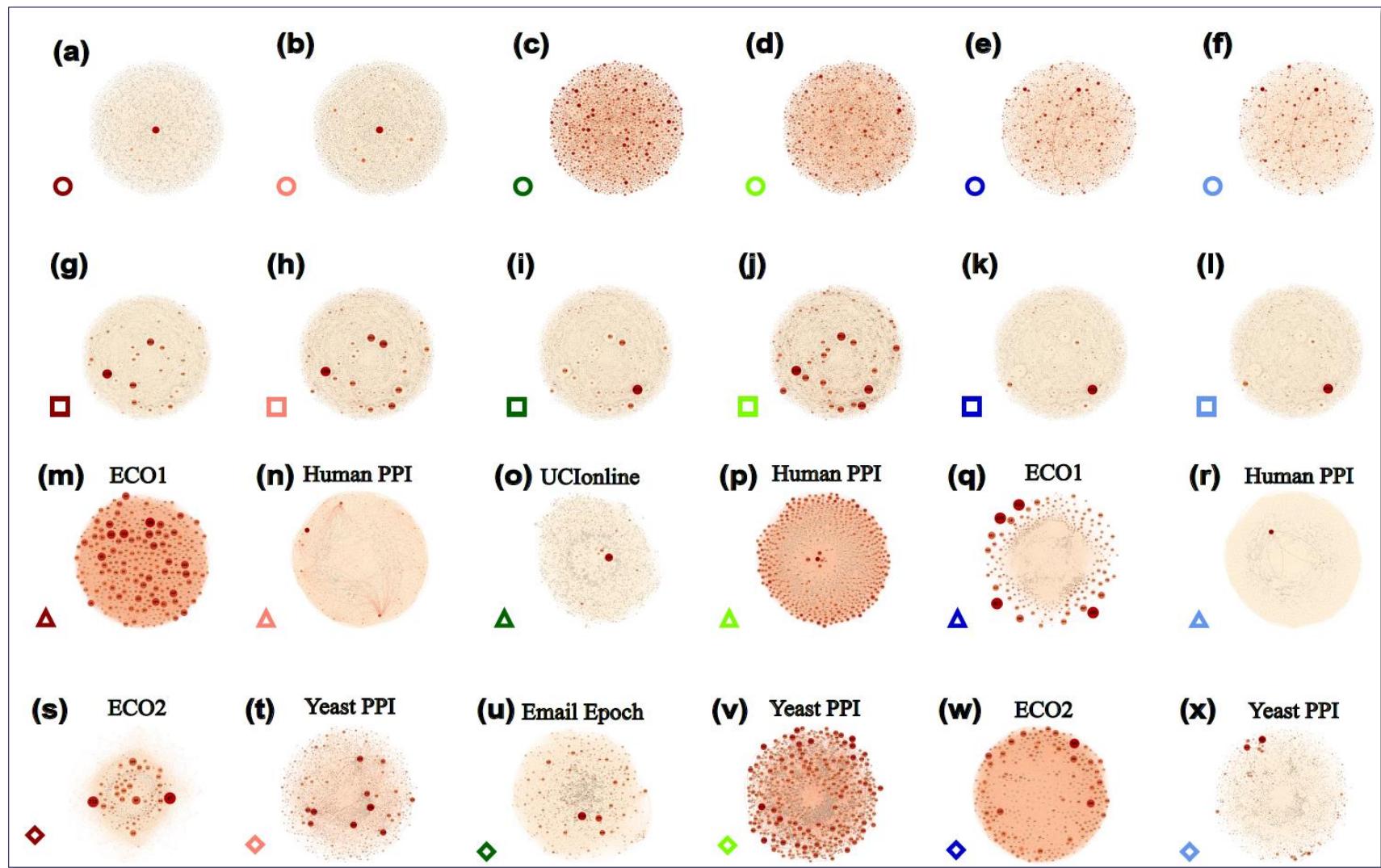
Node flow \mathcal{F}_i : how effective is each node in *transferring* information?

Link flow \mathcal{F}_{ij} : How effective is each link, pathway?

Information flow



The zoo of information flow patterns



Taming the zoo of information flow patterns

$$\mathcal{F}_i \sim k_{i,\text{out}} k_{i,\text{in}}^{\omega-1}$$

$$\mathcal{F}_{ij} \sim A_{ij} k_{i,\text{out}} k_{i,\text{in}}^{\xi-1} k_{j,\text{in}}^{\xi}$$

Node/link flow

Dynamic function
of interest.

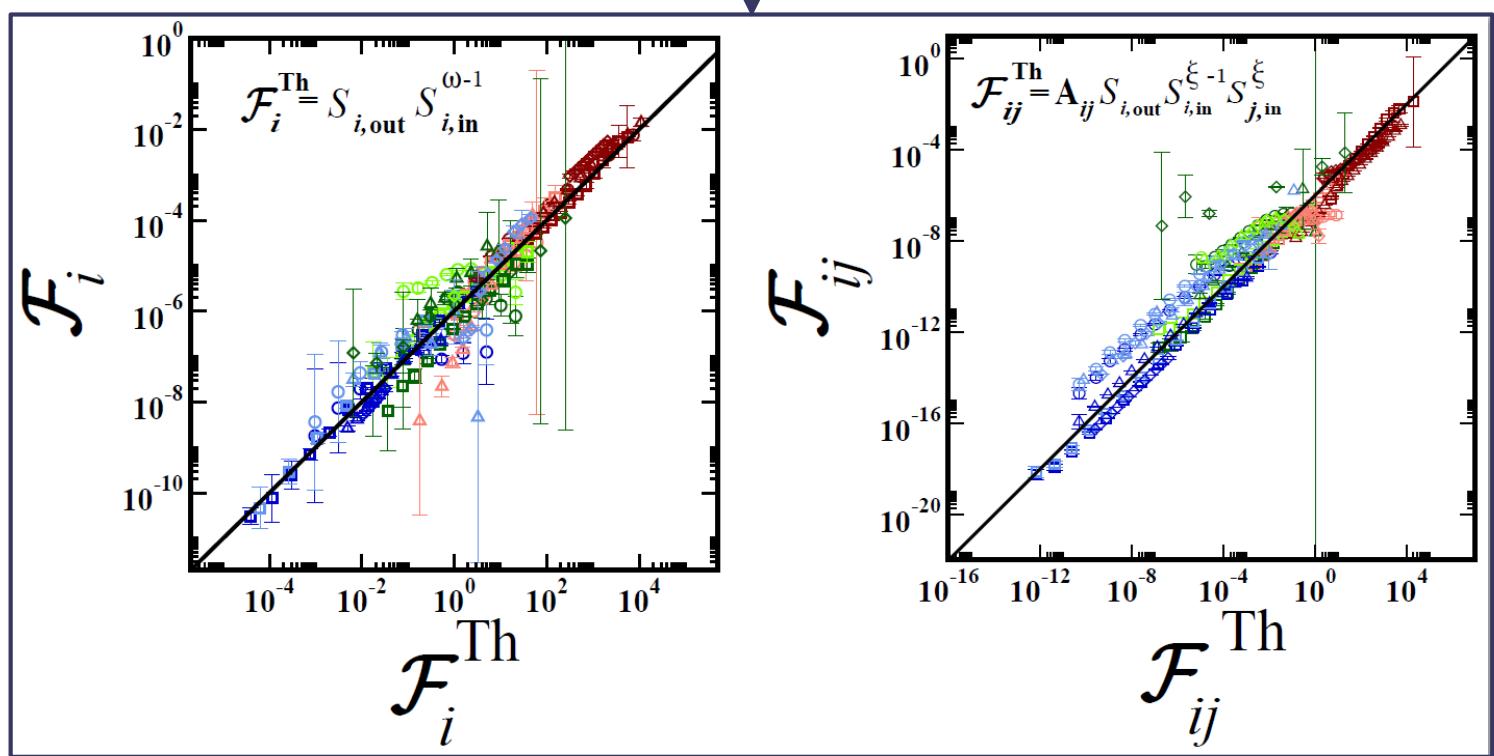
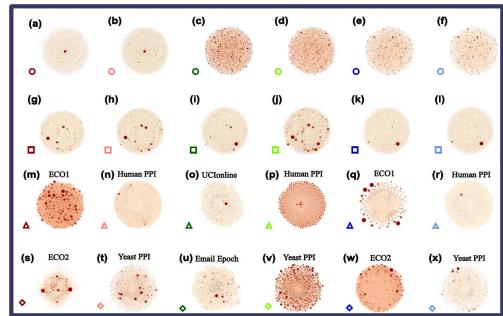
**Dynamic
determinants**

Mapping topology into
dynamics

$\mathcal{F}_i, \mathcal{F}_{ij}, k_{\text{in/out}}$, ω, ξ

Weighted in/out degrees
Known topological elements

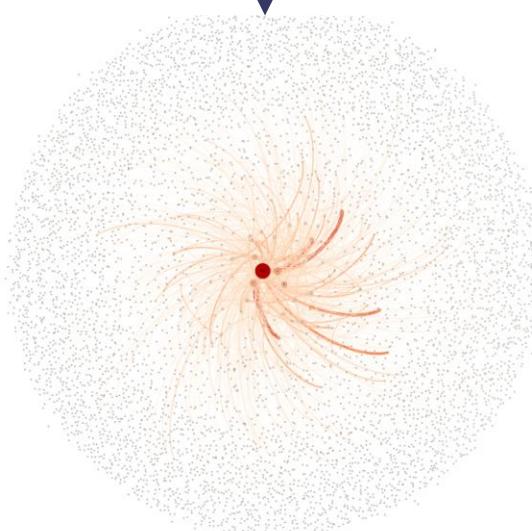
The ~~zoo~~ universal information flow patterns



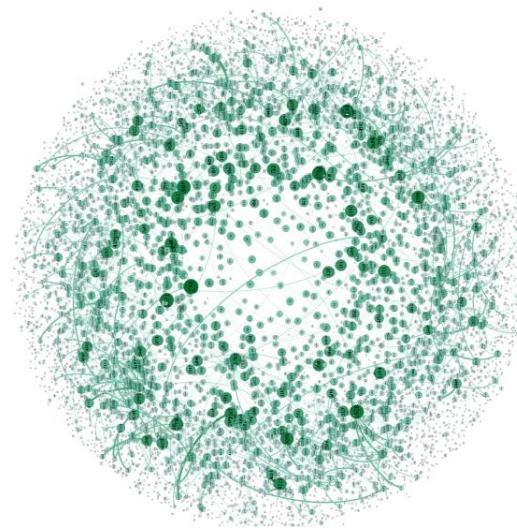
Universal classes of information flow patterns

$$\mathcal{F}_i \sim k_{i,\text{out}} k_{i,\text{in}}^{\omega-1}$$

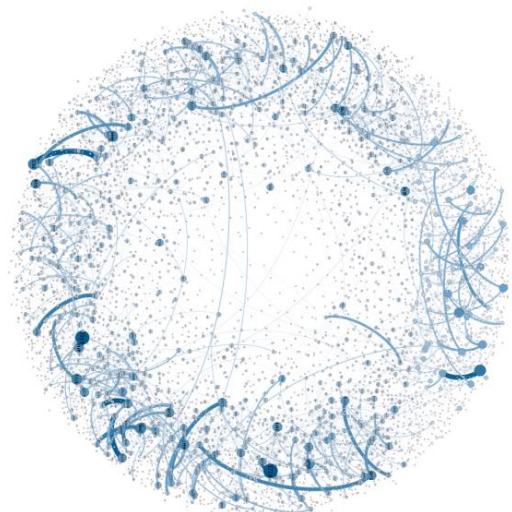
$$\mathcal{F}_{ij} \sim A_{ij} k_{i,\text{out}} k_{i,\text{in}}^{\xi-1} k_{j,\text{in}}^\xi$$



Hub centric

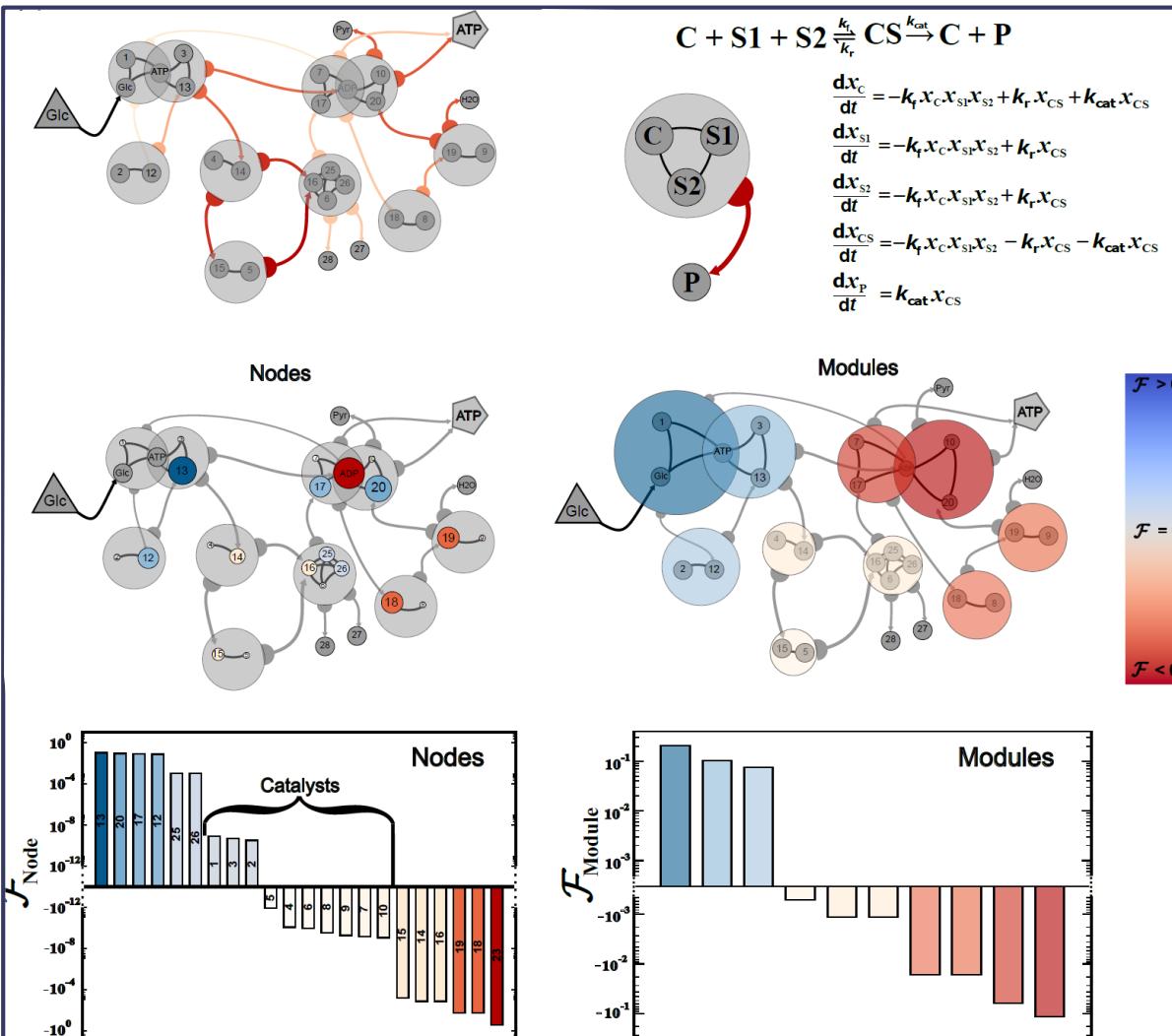


Egalitarian



Peripheral

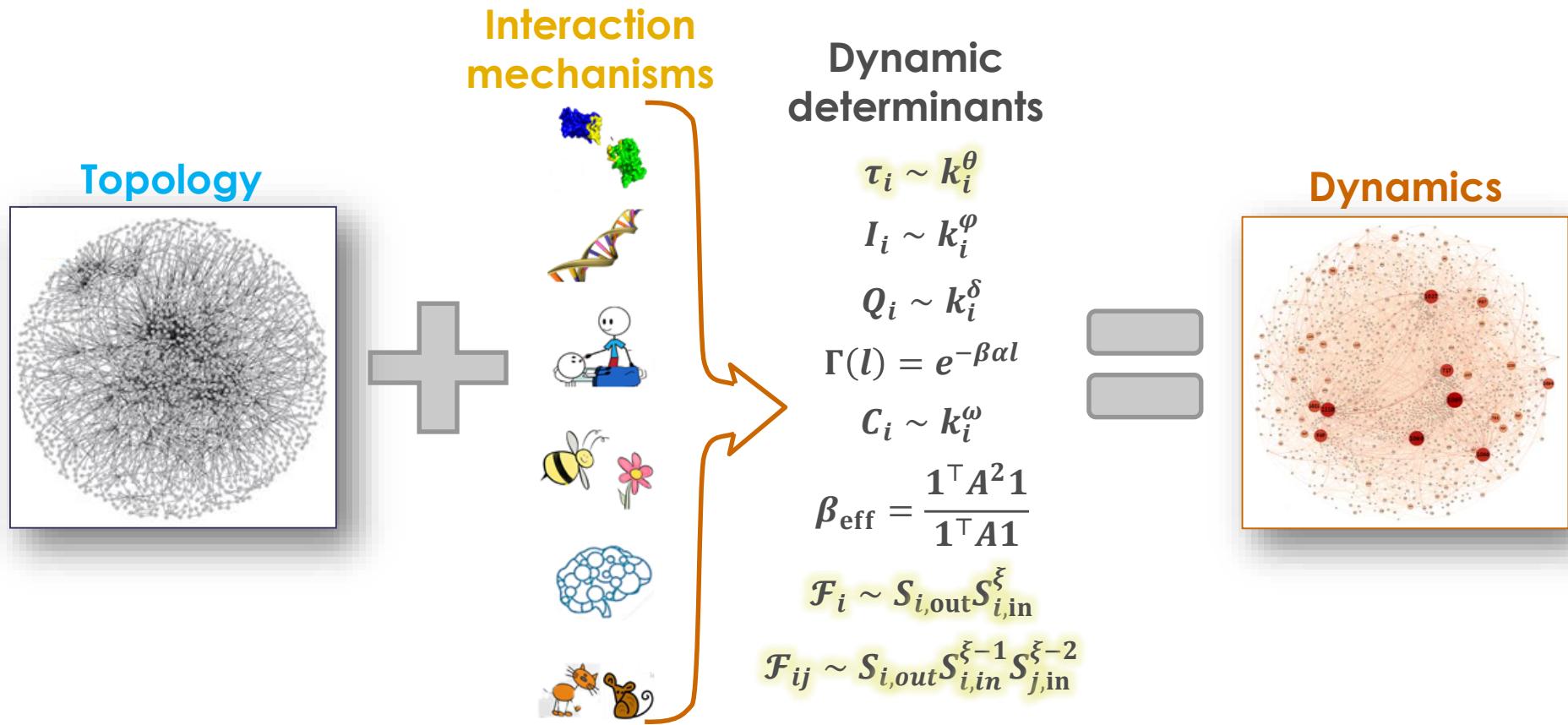
Flow analysis in Glycolysis: what is a biological network?



Metabolism: Designed to push the mean information flow towards zero.

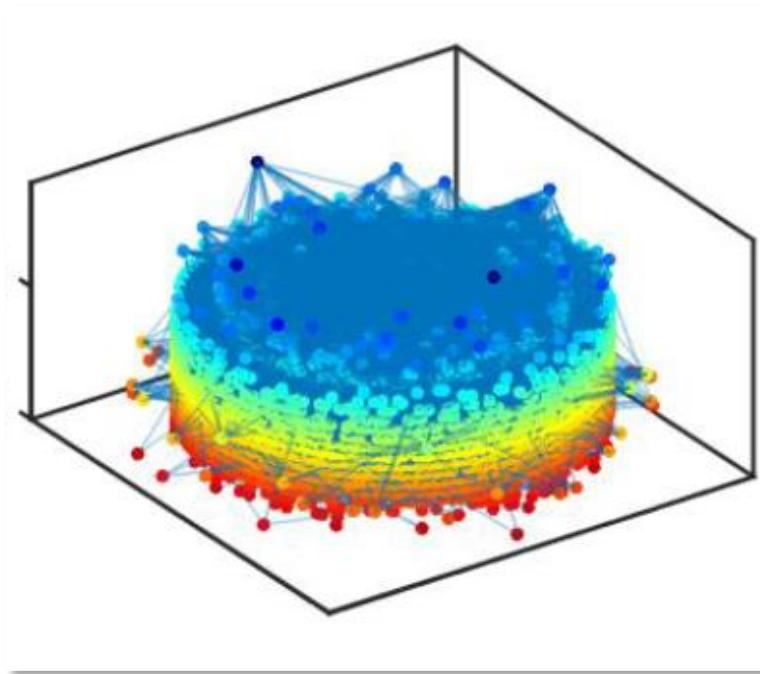
Output (response) independent of Input (perturbation)

Dictionary of network dynamics

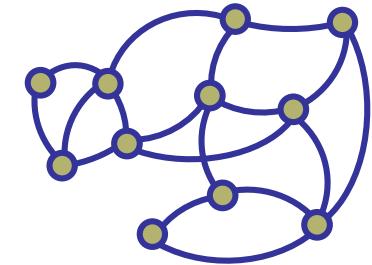
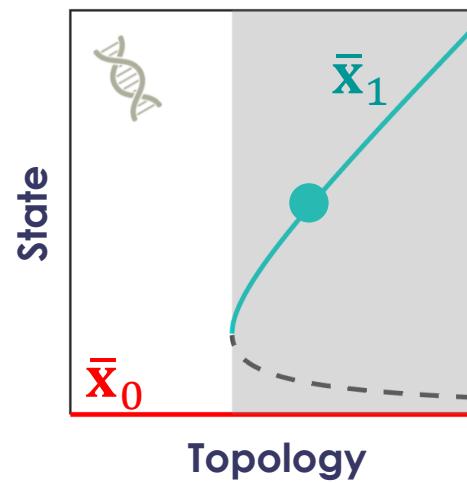
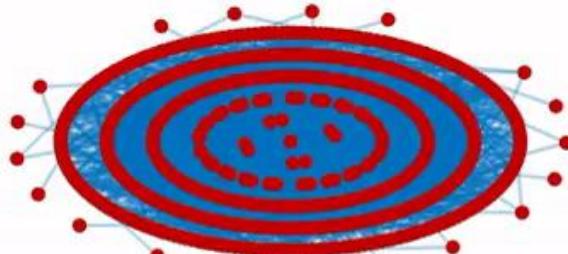


Microscopic Diversity condenses into a discrete set of
Universality classes that determine how
Topology translates into Dynamics

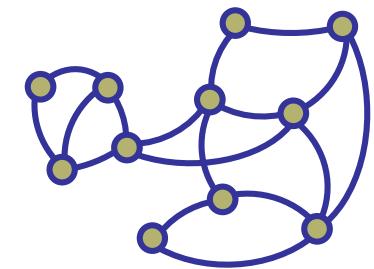
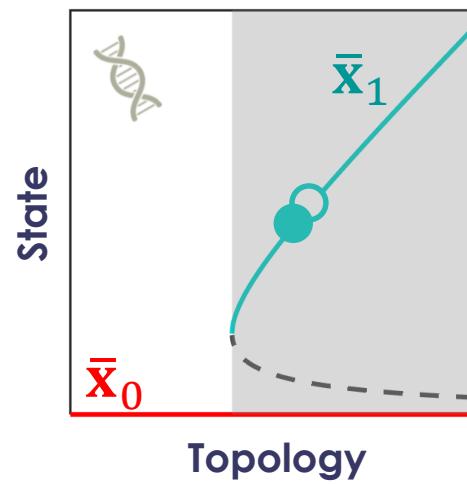
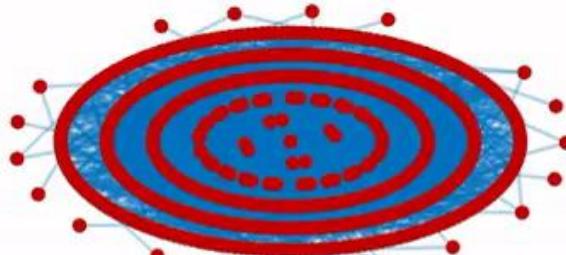
Recoverability



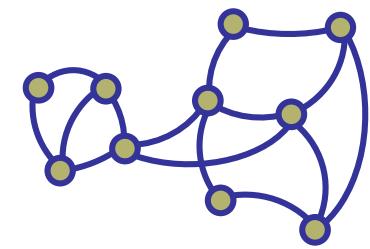
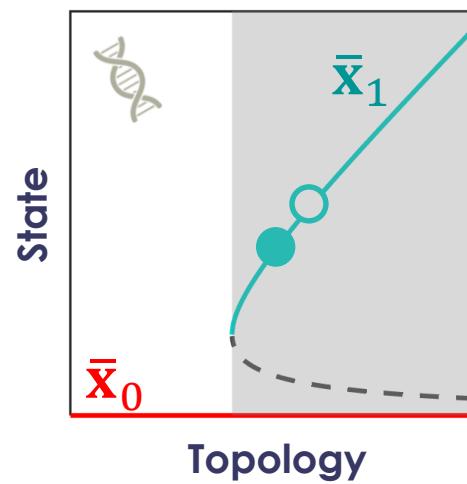
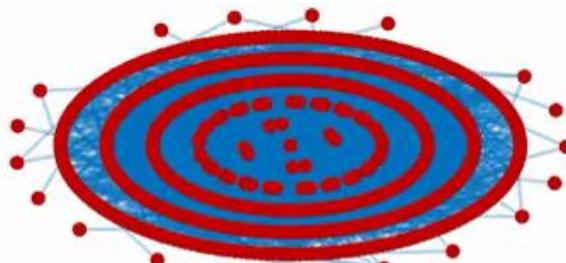
Dynamic transitions



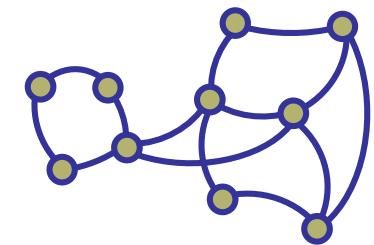
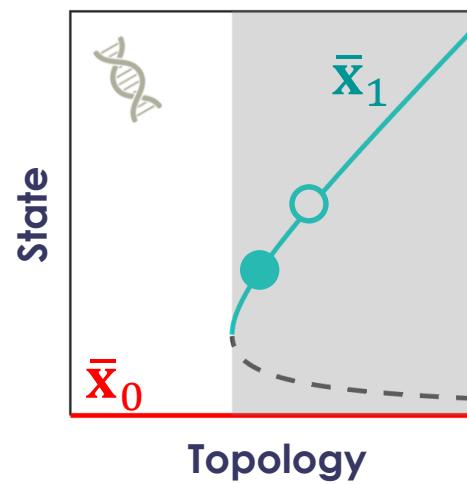
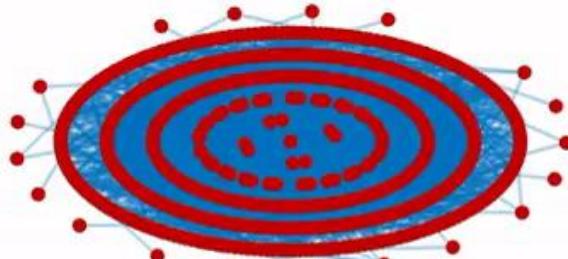
Dynamic transitions



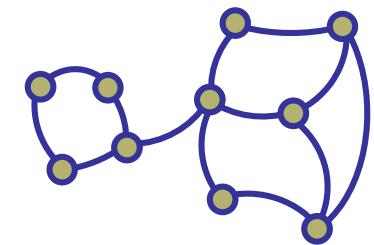
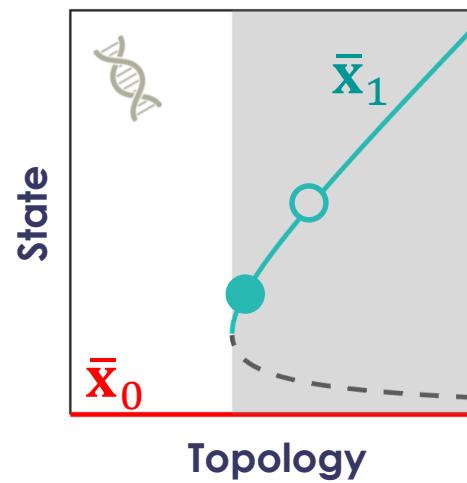
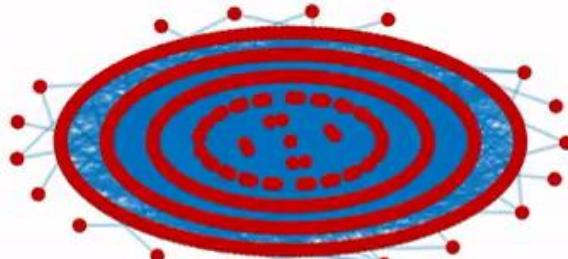
Dynamic transitions



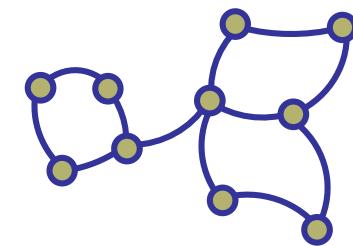
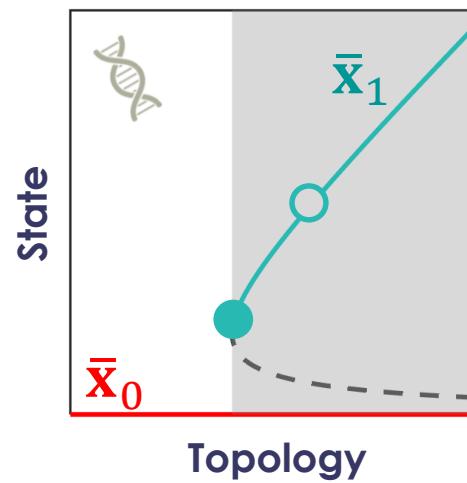
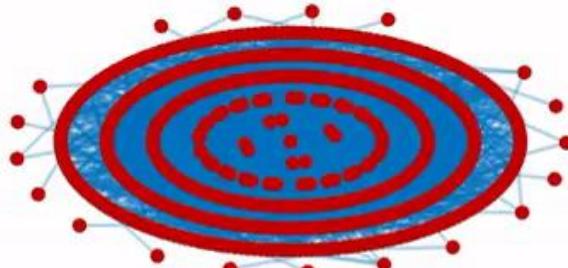
Dynamic transitions



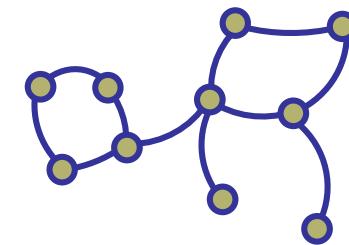
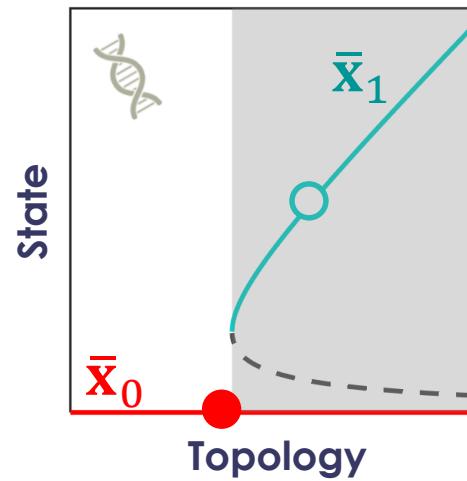
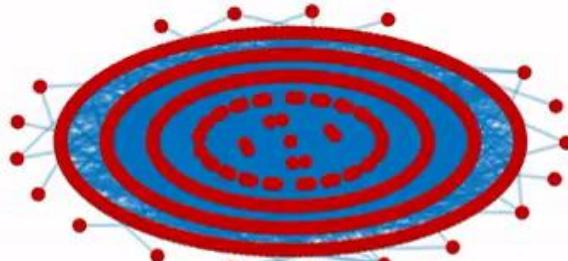
Dynamic transitions



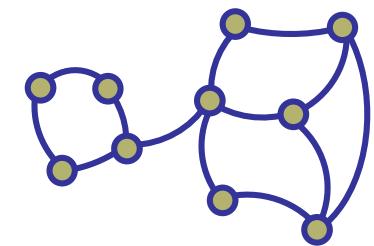
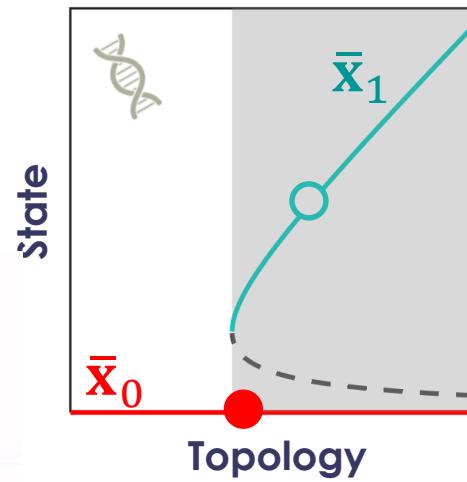
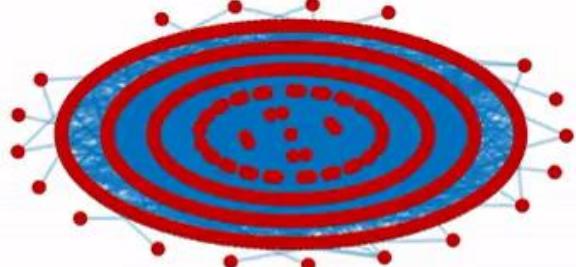
Dynamic transitions



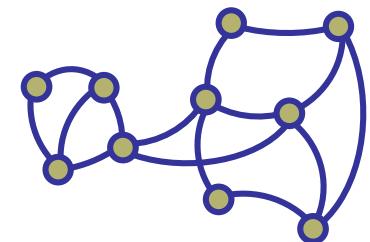
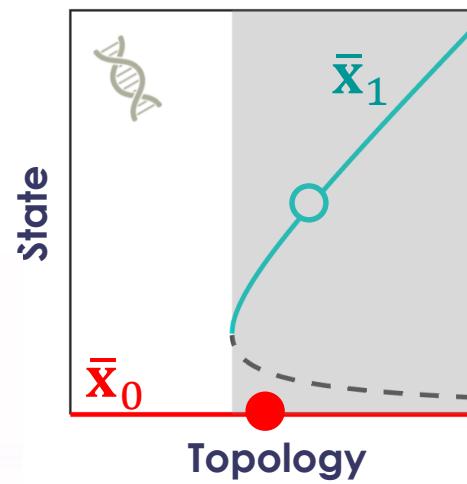
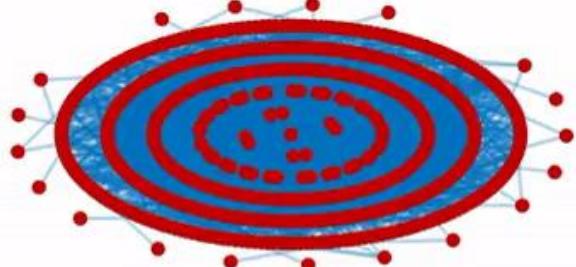
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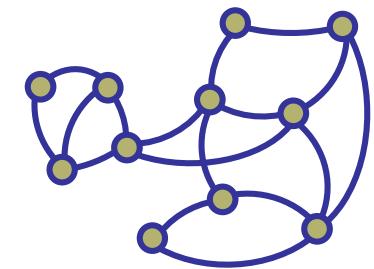
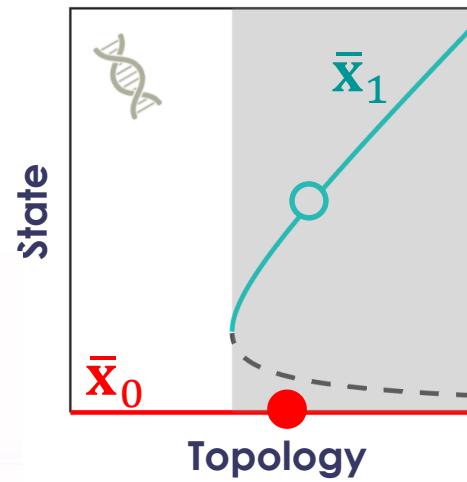
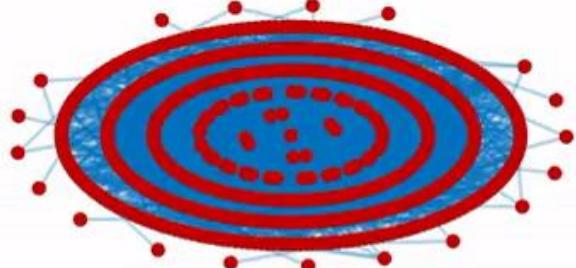
Dynamic transitions - irreversible



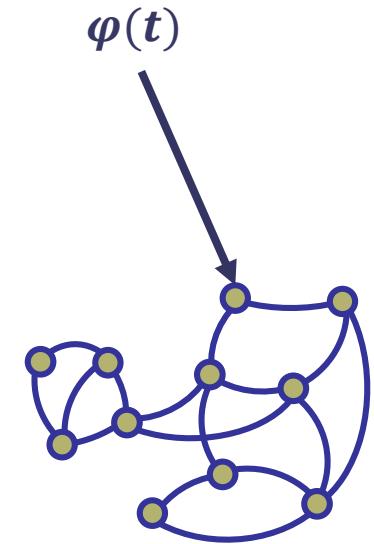
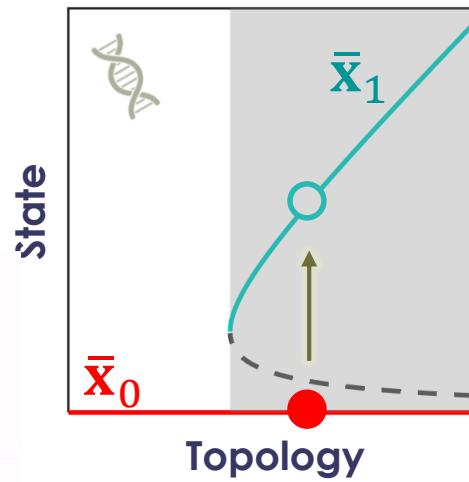
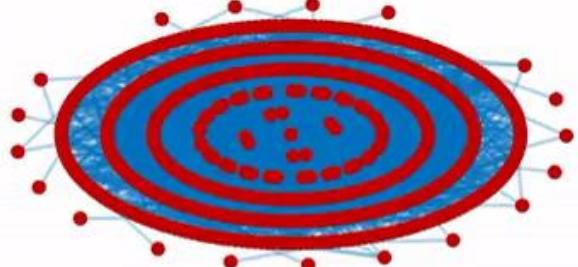
Dynamic transitions - irreversible



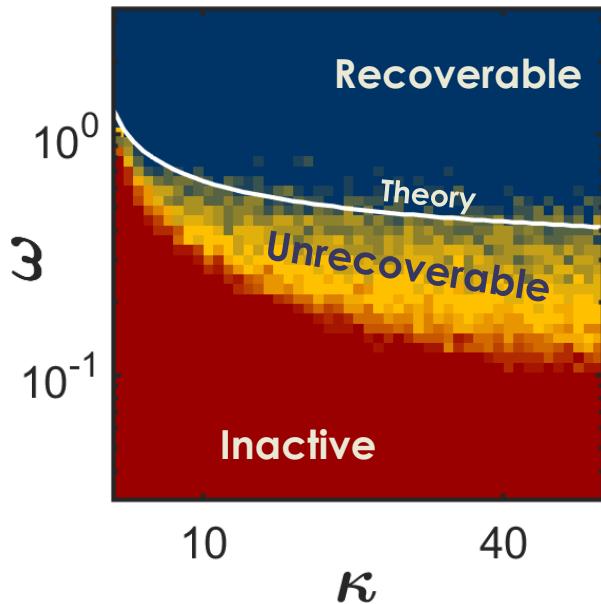
Dynamic transitions - irreversible



Reigniting the network activity

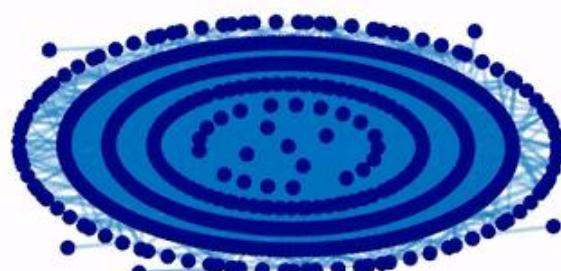
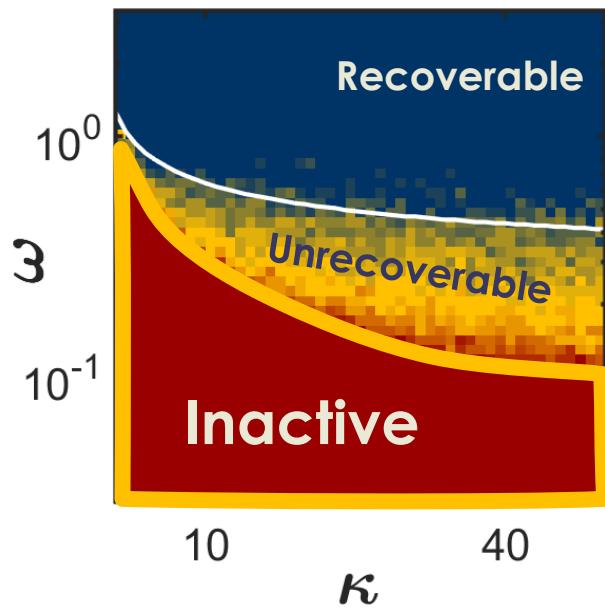


The recoverable phase

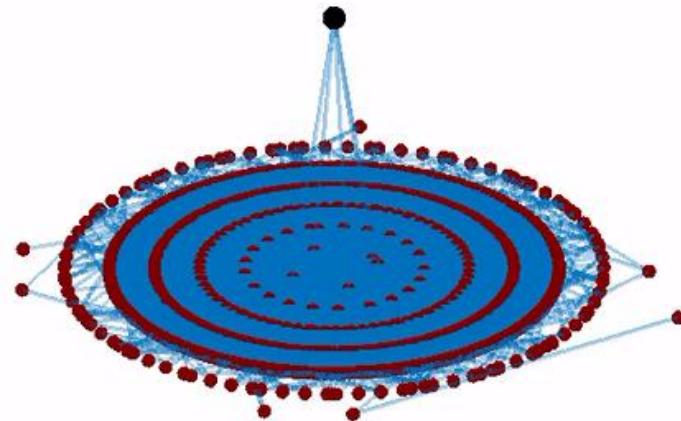
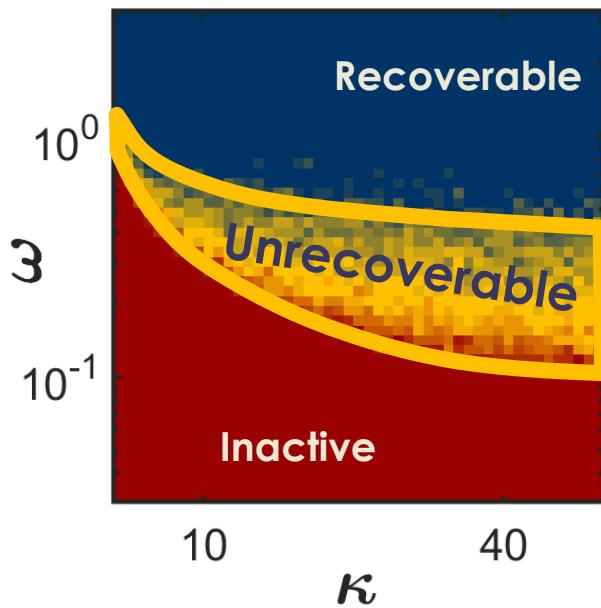


Can you reignite a failed system by controlling just one node?

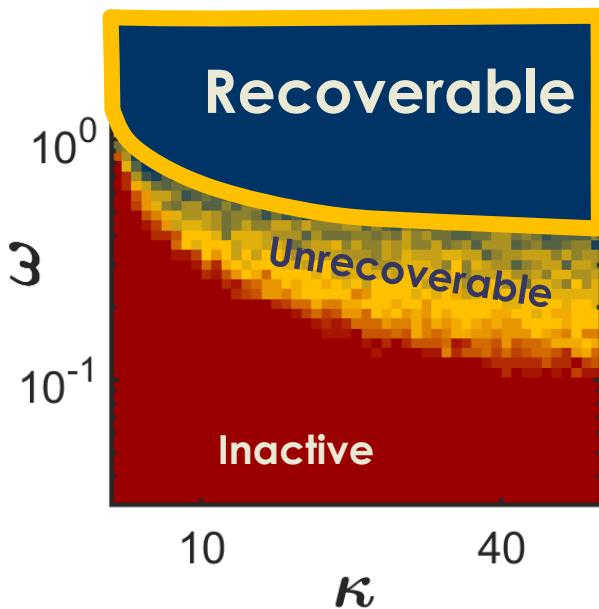
The recoverable phase



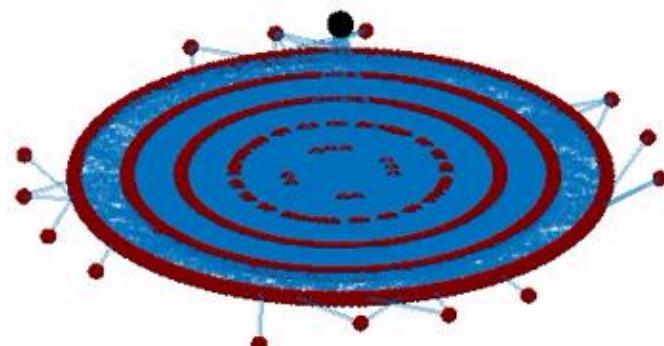
The recoverable phase



The recoverable phase



Single node reigniting –
reviving the failed system by
activating one node



Theory of network dynamics was brought to you by



Dr. Nir Lahav



Dr. Chittaranjan Hens



Dr. Chandrakala Meena



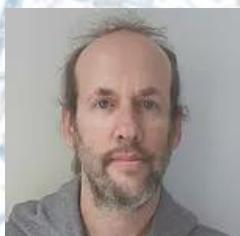
Dr. Aradhana Singh



Uzi Harush



Dr. Suman Acharyya



Dr. Nir Schreiber



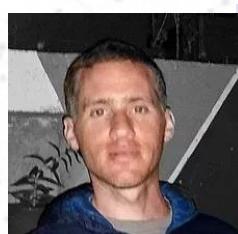
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