

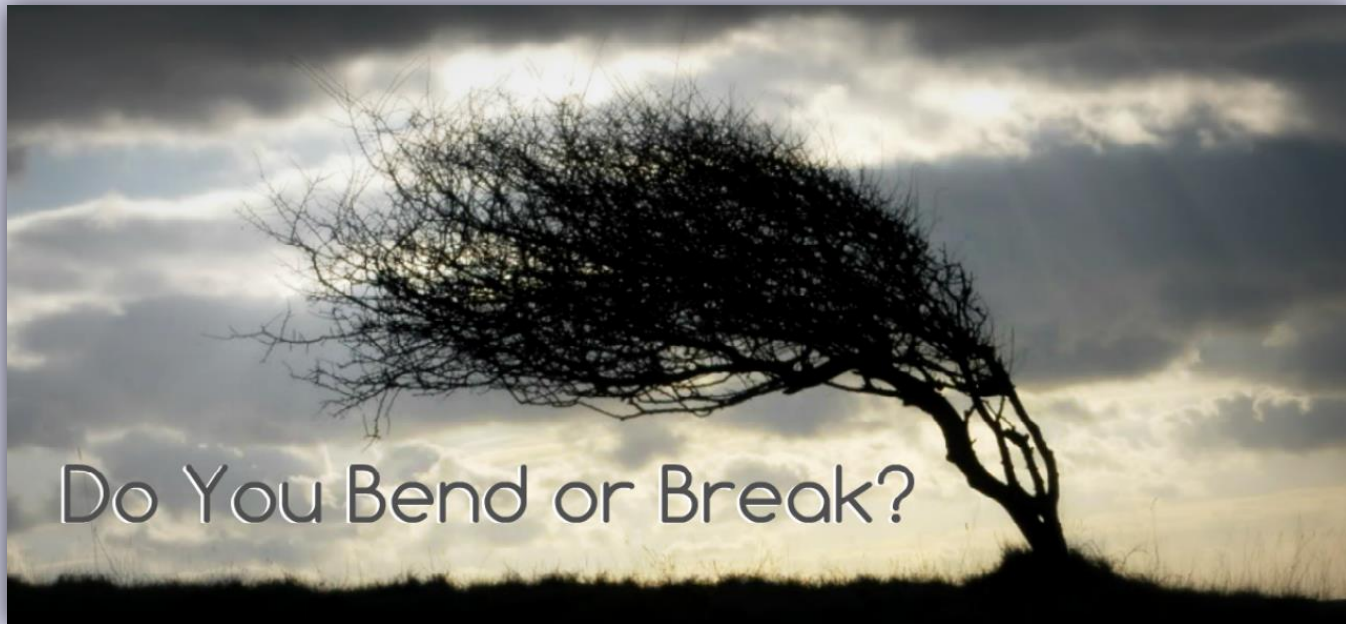
Baruch Barzel



# RESILIENCE

of COMPLEX NETWORKS

Universal resilience patterns in complex networks.  
*Nature* **530**, 307 (2016).



# RESILIENCE

# Resilience loss



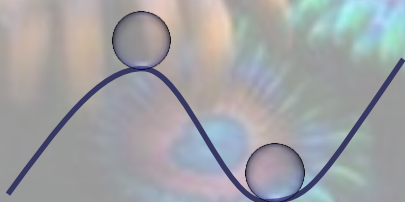
# Resilience function

$$\frac{dx}{dt} = f(\beta, x(t))$$

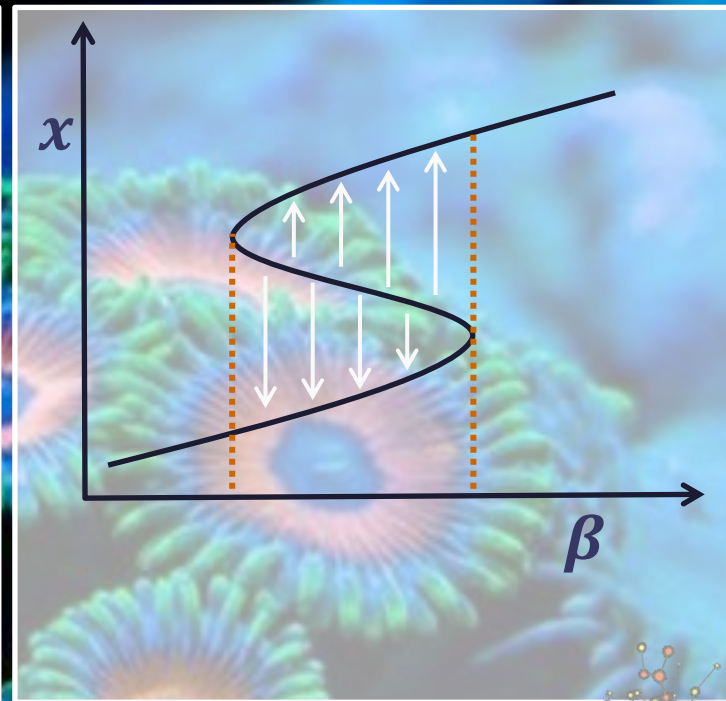
$$f(\beta, x) = 0$$

$$\frac{df}{dx} < 0$$

$\longrightarrow x(\beta)$



A diagram showing a potential energy curve with a local minimum. A grey ball is positioned in the minimum, representing a stable state. An arrow points from the text  $x(\beta)$  to the ball.

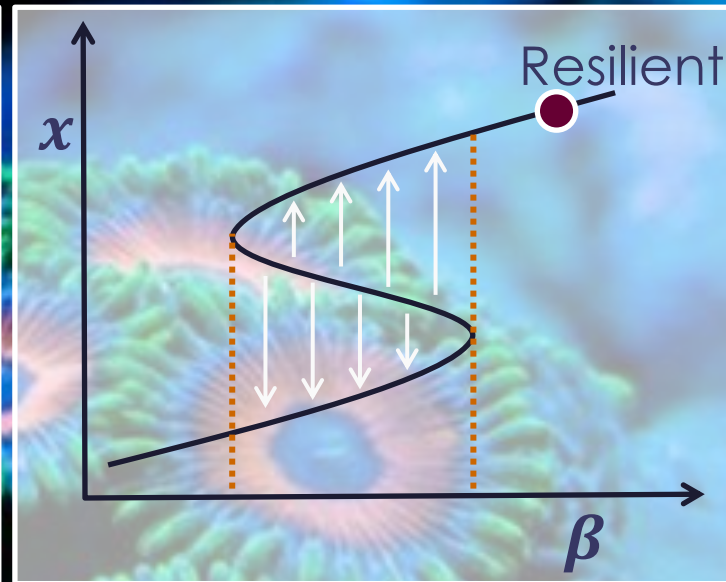


# Resilience function

$$\frac{dx}{dt} = f(\beta, x(t))$$

$$f(\beta, x) = 0 \longrightarrow x(\beta)$$

$$\frac{df}{dx} < 0$$



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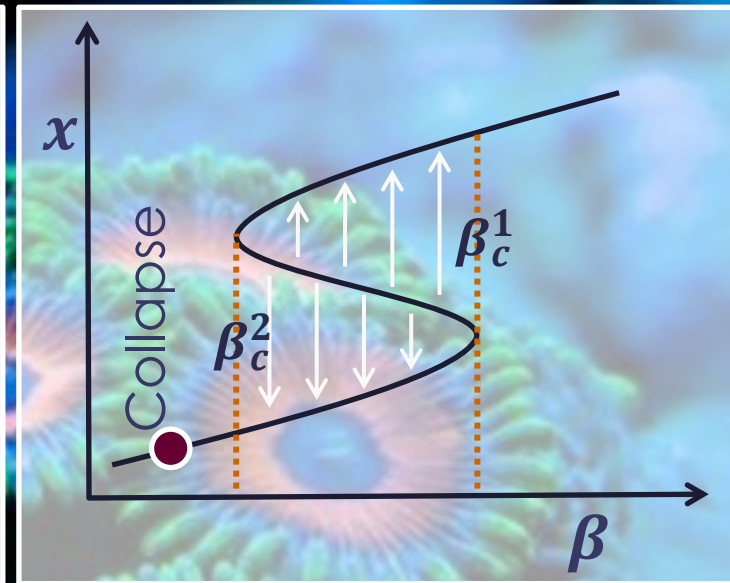


# Resilience function

$$\frac{dx}{dt} = f(\beta, x(t))$$

$$f(\beta, x) = 0$$

$$\frac{df}{dx} < 0 \quad \longrightarrow \quad x(\beta)$$



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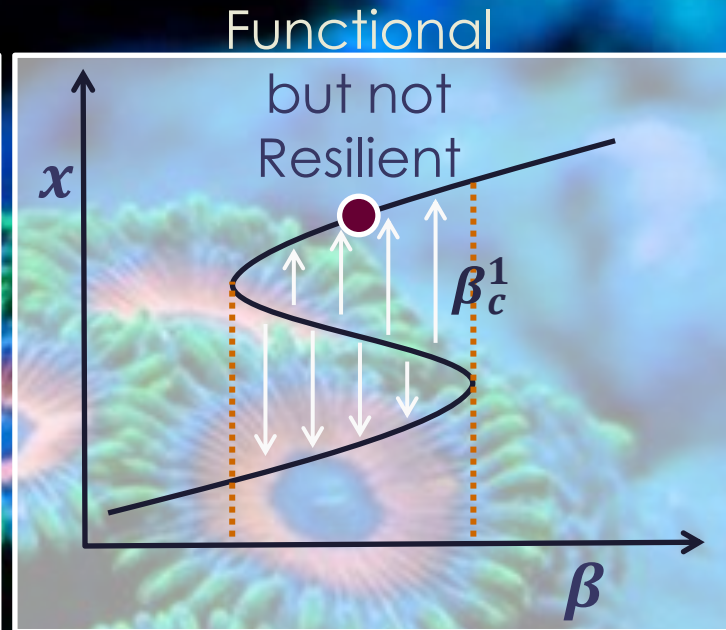


# Resilience function

$$\frac{dx}{dt} = f(\beta, x(t))$$

$$f(\beta, x) = 0 \longrightarrow x(\beta)$$

$$\frac{df}{dx} < 0$$



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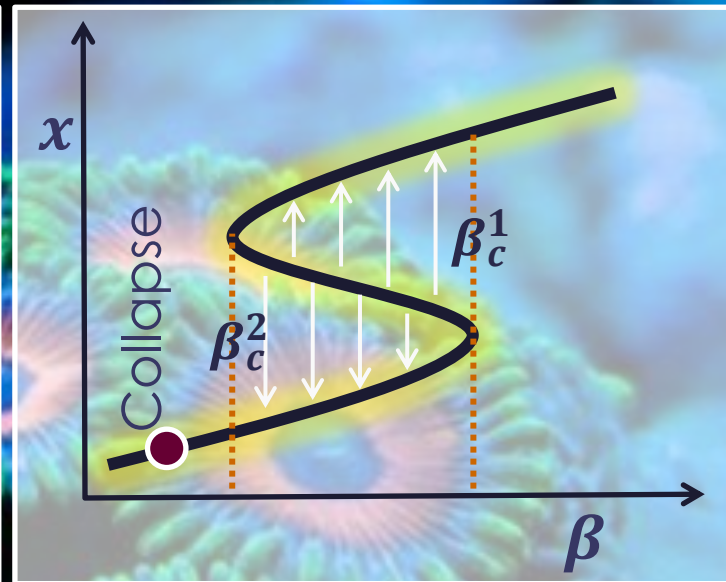


# Resilience function

$$\frac{dx}{dt} = f(\beta, x(t))$$

$$f(\beta, x) = 0$$

$$\frac{df}{dx} < 0 \quad \longrightarrow \quad x(\beta)$$



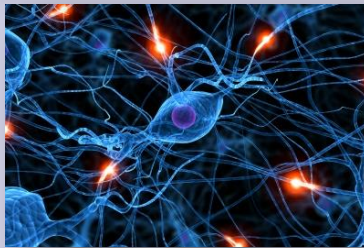
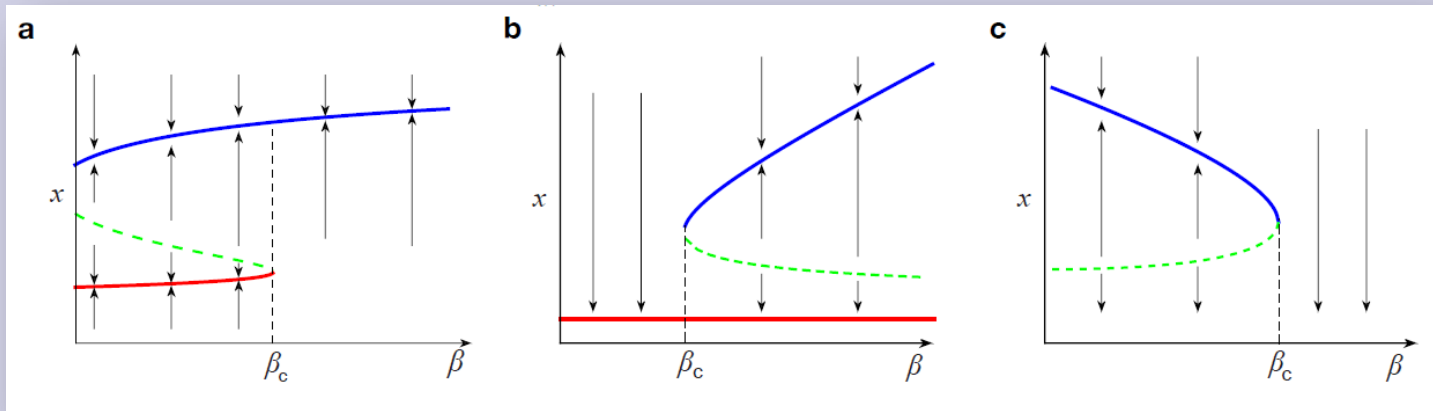
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# Resilience functions

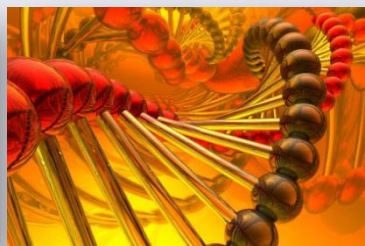
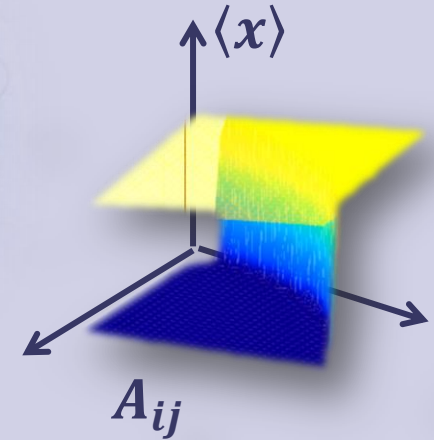
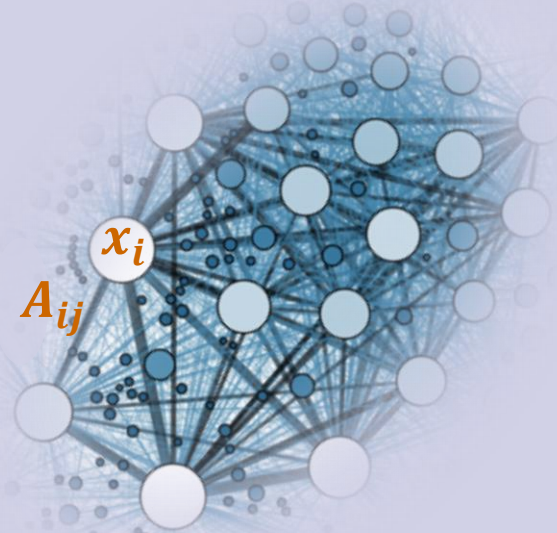
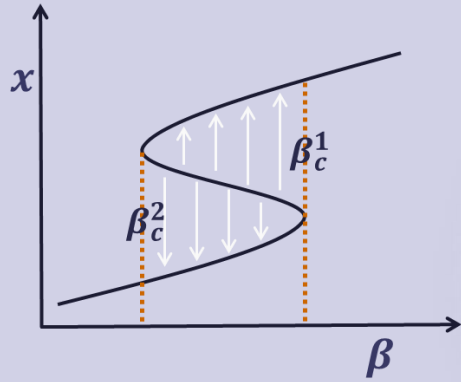
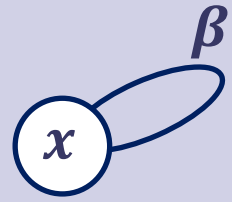
$$\frac{dx}{dt} = f(\beta, x(t))$$



# Multidimensional systems

$$\frac{dx}{dt} = f(\beta, x(t))$$

$$\frac{dx_i}{dt} = f(A_{ij}, \vec{x}(t))$$

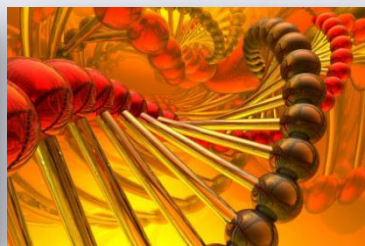
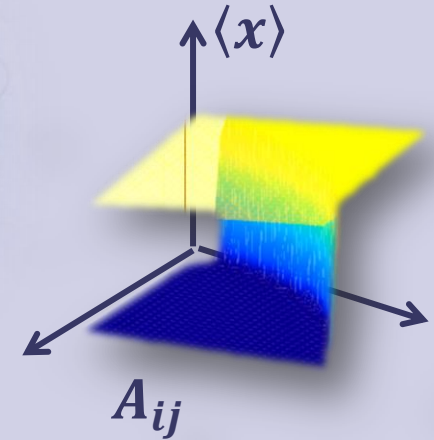
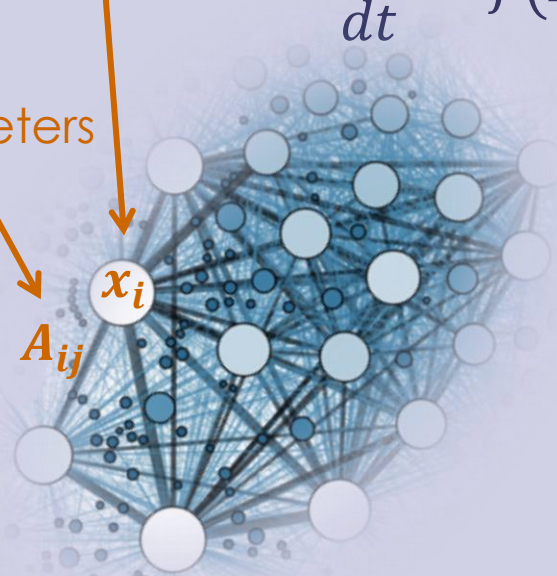
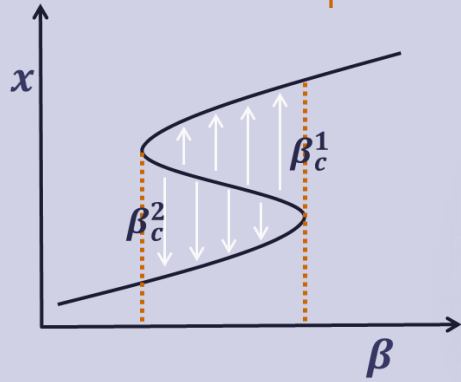
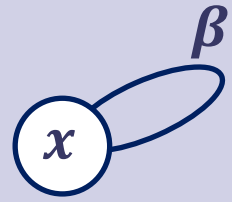


# Multidimensional systems

$$\frac{dx}{dt} = f(\beta, x(t))$$

Ndimensional  
 $N^2$   
parameters

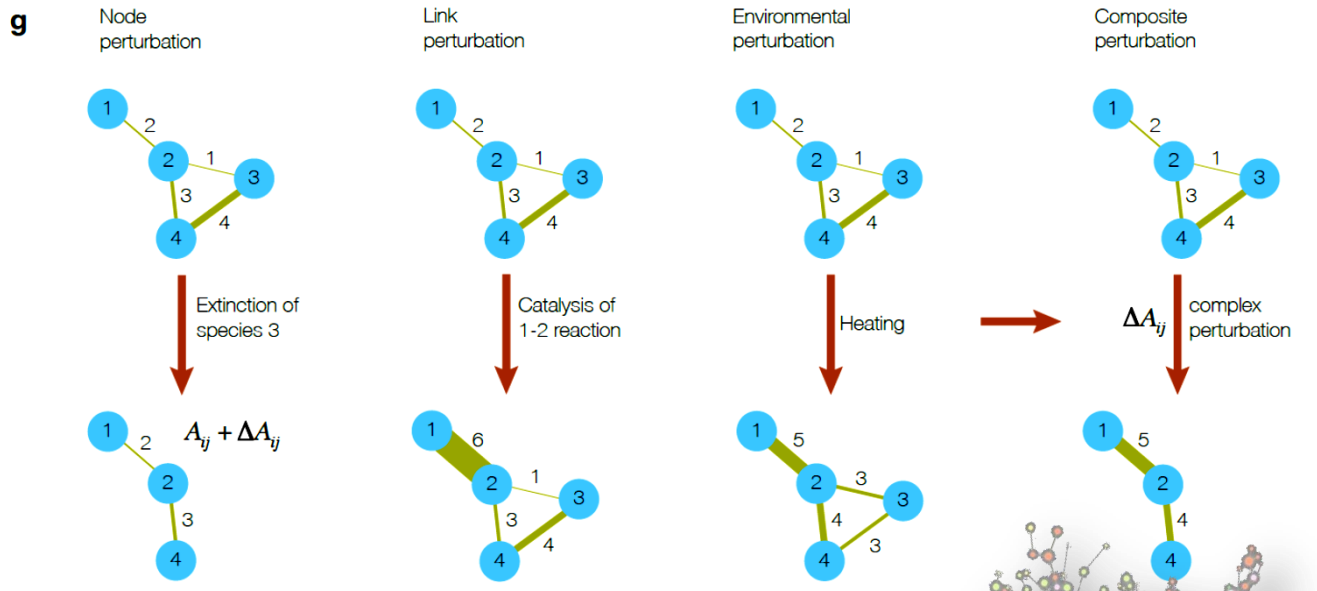
$$\frac{dx_i}{dt} = f(A_{ij}, \vec{x}(t))$$



# Multidimensional systems

$$\beta \rightarrow \beta + \Delta\beta \longrightarrow A_{ij} \rightarrow A_{ij} + \Delta A_{ij}$$

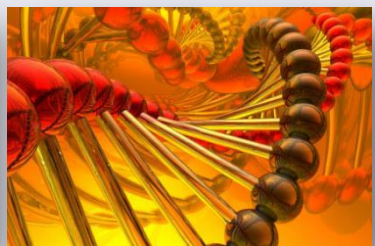
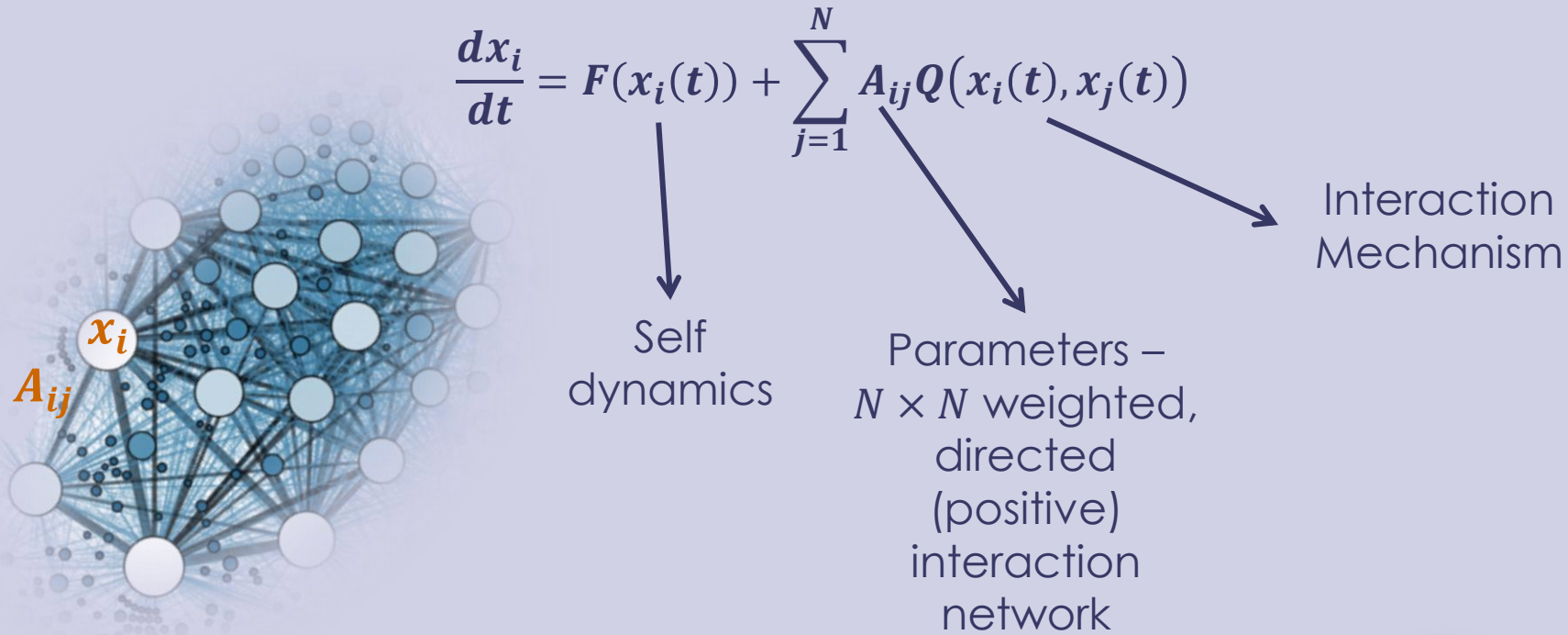
### Network Perturbations



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# Multidimensional systems



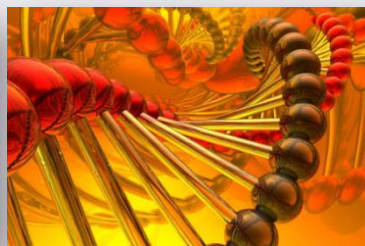
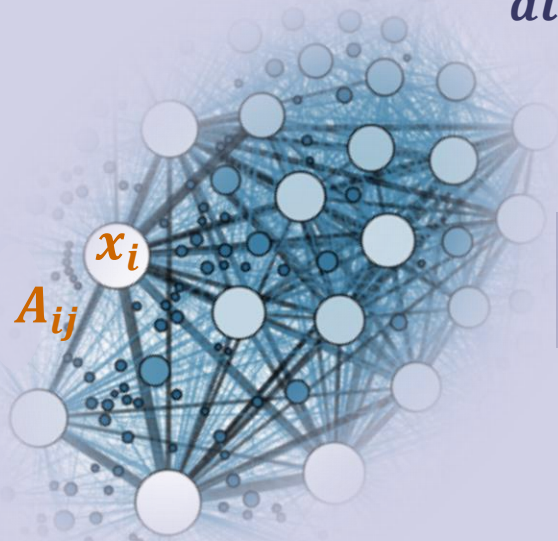
# Multidimensional systems

$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij} Q(x_i(t), x_j(t))$$

Self dynamics

Parameters –  
 $N \times N$  weighted,  
directed  
interaction  
network

Interaction  
Mechanism

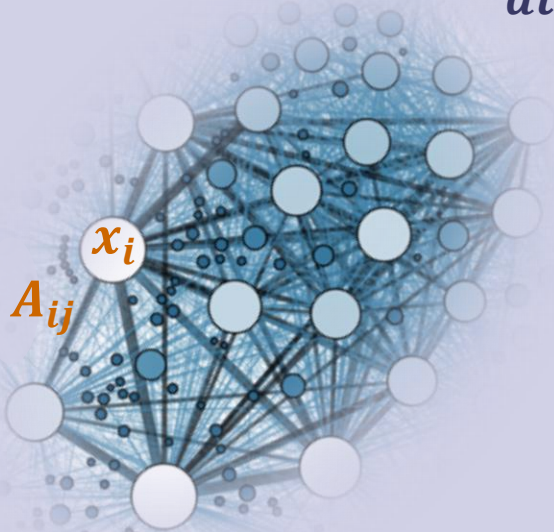


# Multidimensional systems

$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij} Q(x_i(t), x_j(t))$$

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

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



# Ecological Resilience

$$\frac{dx_i}{dt} = B_i + x_i \left( 1 - \frac{x_i}{\kappa_i} \right) \left( \frac{x_i}{\xi_i} - 1 \right) + \sum_{j=1}^N A_{ij} \frac{x_i x_j}{1 + \alpha x_i + \gamma x_j}$$

Self dynamics  
(Logistic growth  
+ Allee effect)  
 $F(x_i)$

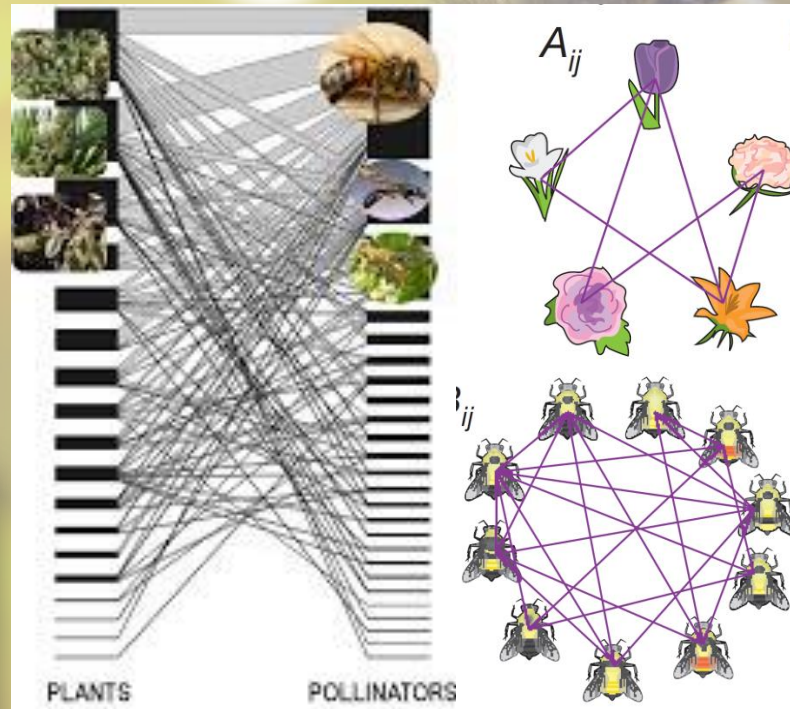
Interaction  
mechanism  
(Symbiosis)  
 $Q(x_i, x_j)$





# Ecological resilience

$$\frac{dx_i}{dt} = B_i + x_i \left( 1 - \frac{x_i}{\kappa_i} \right) \left( \frac{x_i}{\xi_i} - 1 \right) + \sum_{j=1}^N A_{ij} \frac{x_i x_j}{1 + \alpha x_i + \gamma x_j}$$



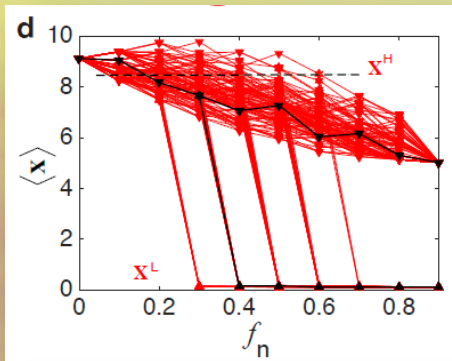
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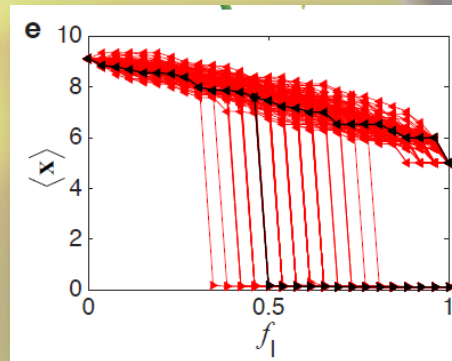
# Ecological Resilience

$$\frac{dx_i}{dt} = B_i + x_i \left( 1 - \frac{x_i}{\kappa_i} \right) \left( \frac{x_i}{\xi_i} - 1 \right) + \sum_{j=1}^N A_{ij} \frac{x_i x_j}{1 + \alpha x_i + \gamma x_j}$$

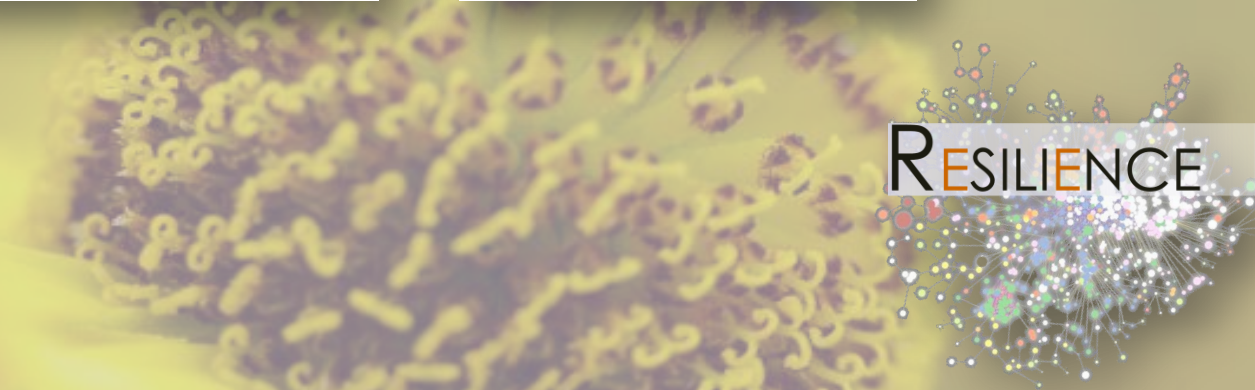
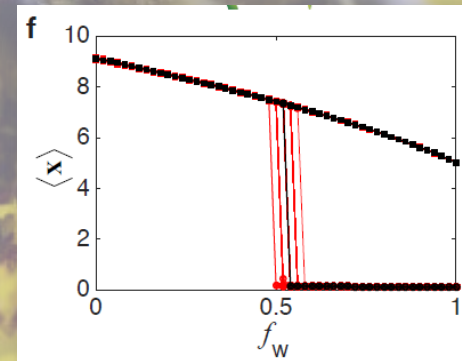
Plant Extinction



Pollinator Extinction

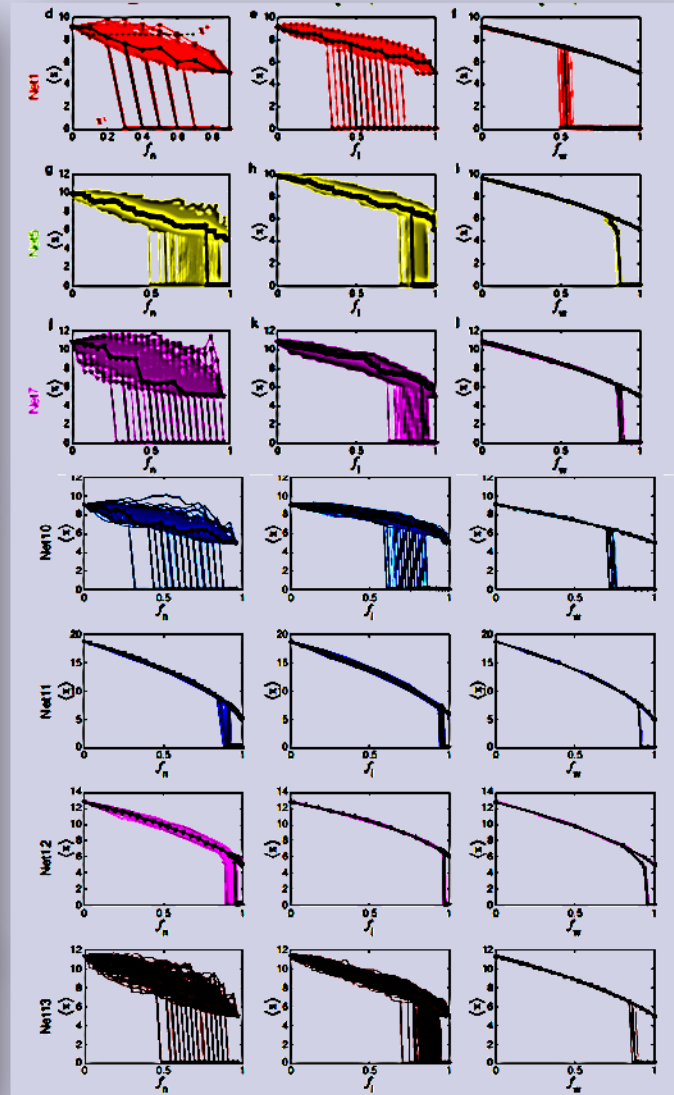
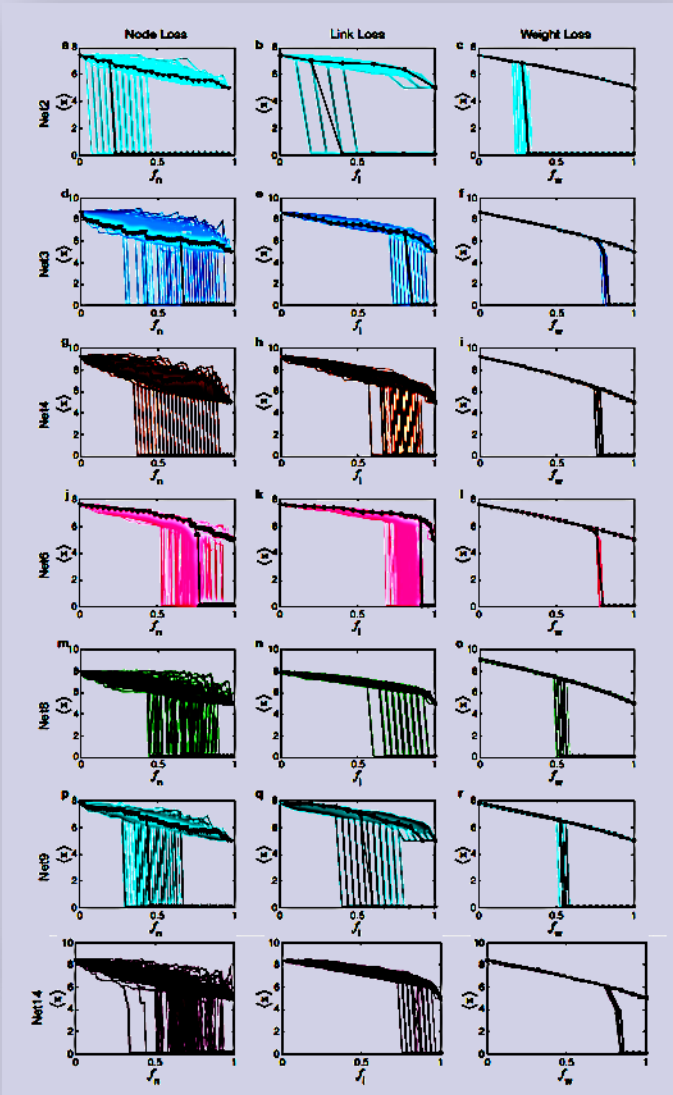


Environmental Change

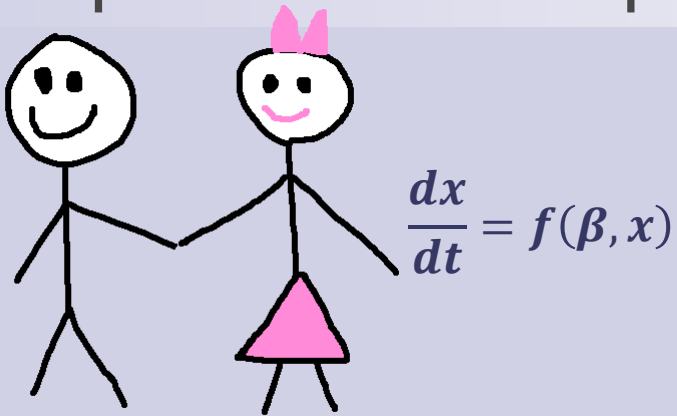


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# Ecological resilience

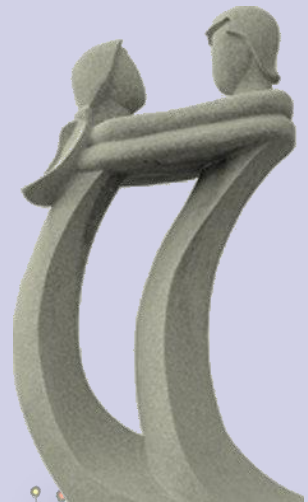


# Simple – Complex - Complexer



$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij} Q(x_i(t), x_j(t))$$

?



# Dimension reduction

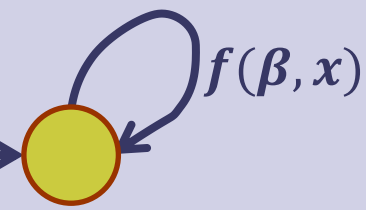
$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij}Q(x_i(t), x_j(t)) \longrightarrow \frac{dx}{dt} = f(\beta, x)$$



Naïvely

$$\beta = \langle k \rangle$$

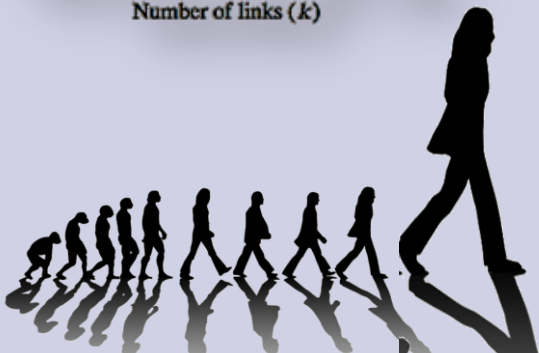
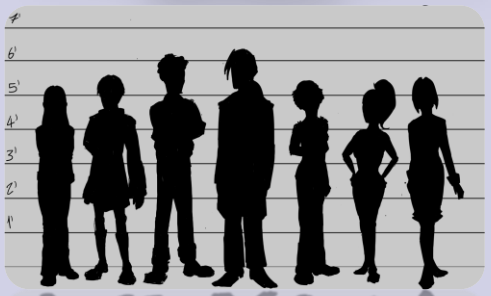
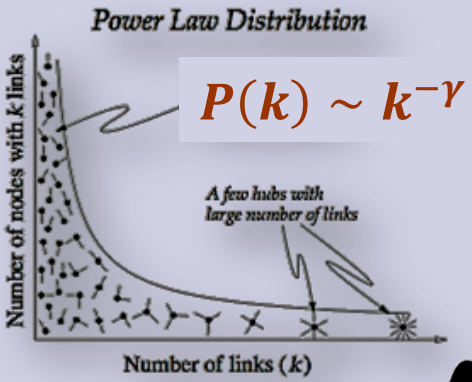
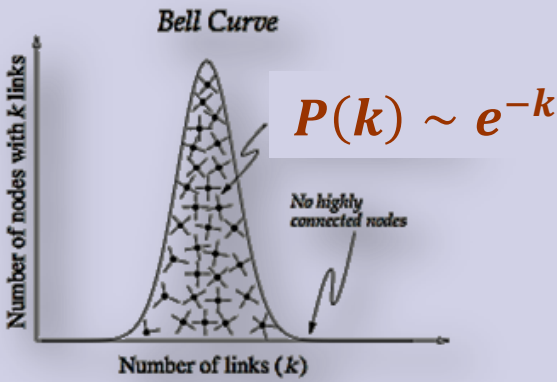
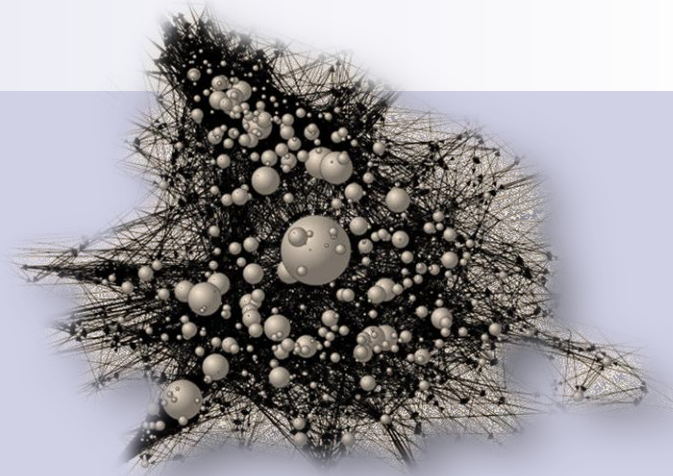
$$x = \langle x \rangle$$



# Averages are irrelevant

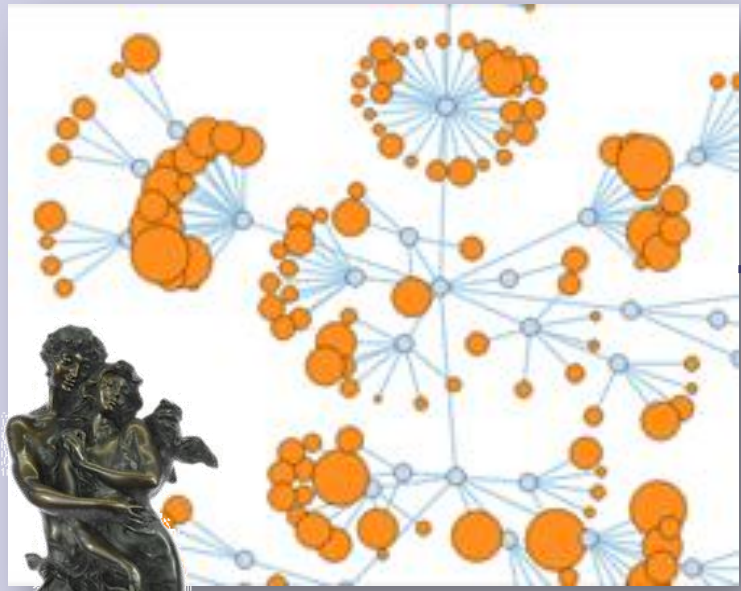
Degree heterogeneity  $P(k)$

Weighted links



# Dimension reduction

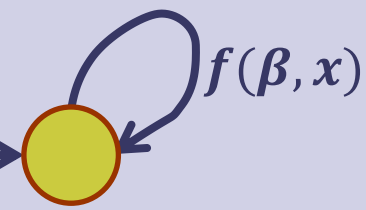
$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij}Q(x_i(t), x_j(t)) \longrightarrow \frac{dx}{dt} = f(\beta, x)$$



Naïvely

$$\beta = \langle k \rangle$$

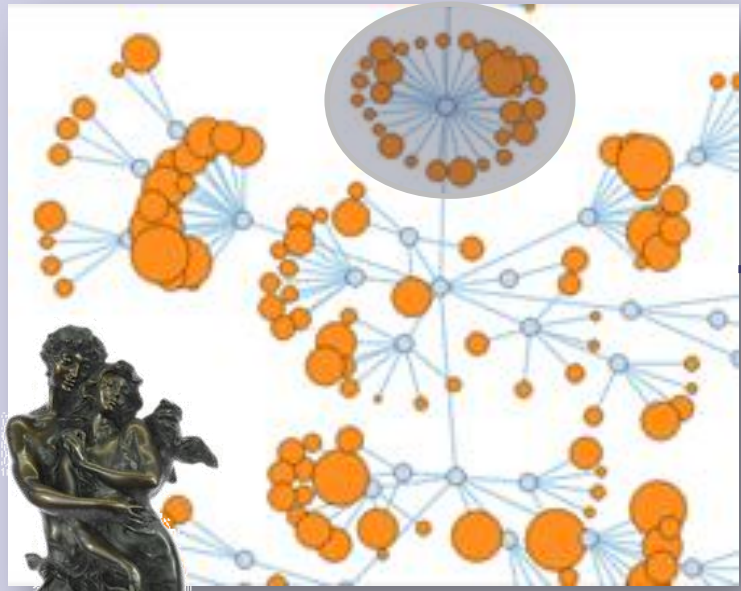
$$x = \langle x \rangle$$



# Dimension reduction

$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij} Q(x_i(t), x_j(t))$$

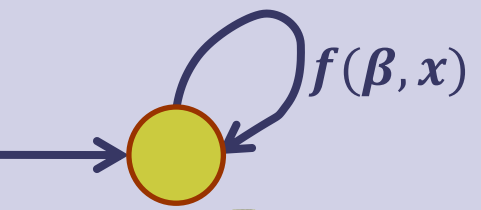
Weighted average over nearest neighbor nodes



Correctly

$$\beta = \frac{\mathbf{1}^T A \vec{s}^{in}}{\mathbf{1}^T A \mathbf{1}}$$

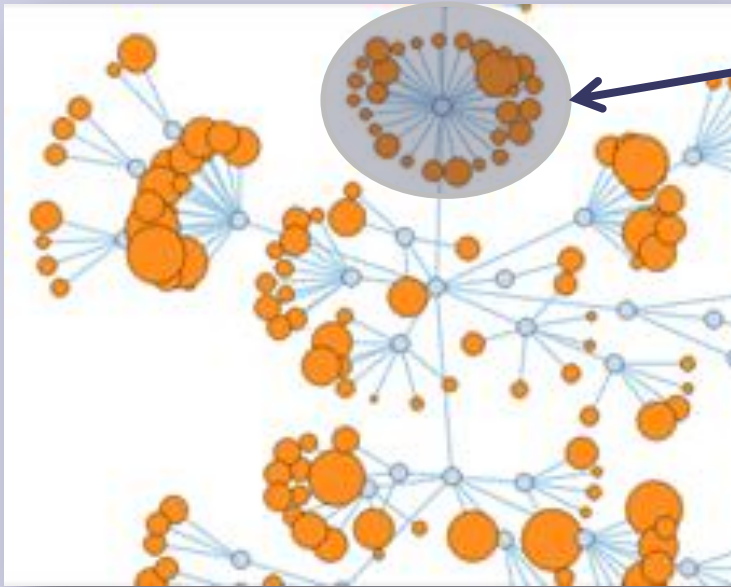
$$\vec{x} = \frac{\mathbf{1}^T A \vec{x}}{\mathbf{1}^T A \mathbf{1}}$$





# Dimension reduction

$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij} Q(x_i(t), x_j(t))$$



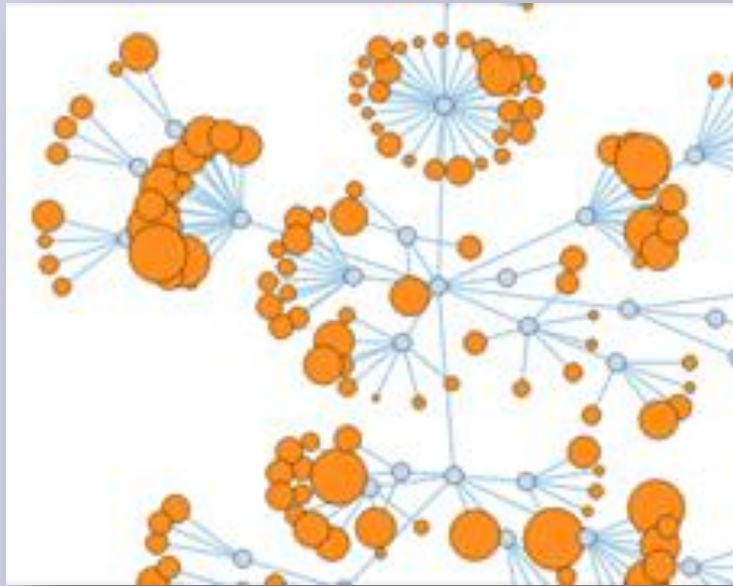
$$\mathcal{L}(\vec{v}) = \frac{\mathbf{1}^T A \vec{v}}{\mathbf{1}^T A \mathbf{1}}$$

Weighted  
average over  
nearest neighbor  
nodes

Configuration model:  
Nodes are unique.  
Neighborhoods are all alike.



# Your friends are more popular than you

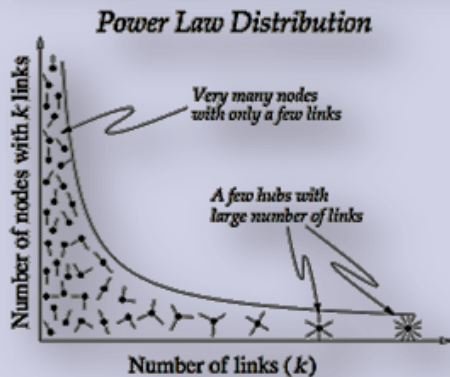


Ex. 1 – Pick a node  $i$ , measure  $k_i$

$$P(k), \quad \langle k \rangle = \sum_k kP(k)$$

Ex. 2 – Pick a node  $i$ , measure  $k_j$  of its neighbor  $j$

$$P_{nn}(k) = \frac{1}{\langle k \rangle} kP(k), \quad \langle k_{nn} \rangle = \frac{\langle k^2 \rangle}{\langle k \rangle} = \langle k \rangle + \frac{\sigma^2}{\langle k \rangle}$$



# Dimension reduction

$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij} Q(x_i(t), x_j(t))$$

Weighted  
average over  
nearest neighbor  
nodes

$$\mathcal{L}(\vec{v}) = \frac{\mathbf{1}^T A \vec{v}}{\mathbf{1}^T A \mathbf{1}}$$

$$\frac{dx_i}{dt} \approx F(x_i(t)) + s_i^{\text{in}} Q(x_i(t), \mathcal{L}(\vec{x}(t)))$$

$$s_i^{\text{in}} = \sum_{j=1}^N A_{ij} \quad \text{Weighted in-degree}$$



# Dimension reduction

$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij} Q(x_i(t), x_j(t))$$

$$\mathcal{L}(\vec{v}) = \frac{\mathbf{1}^T A \vec{v}}{\mathbf{1}^T A \mathbf{1}}$$

Weighted  
average over  
nearest neighbor  
nodes

$$\frac{dx_i}{dt} \approx F(x_i(t)) + s_i^{\text{in}} Q(x_i(t), \mathcal{L}(\vec{x}(t)))$$

$$s_i^{\text{in}} = \sum_{j=1}^N A_{ij} \quad \text{Weighted in-degree}$$

$$\frac{d\mathcal{L}(\vec{x})}{dt} \approx F(\mathcal{L}(\vec{x})) + \mathcal{L}(\vec{s}^{\text{in}}) Q(\mathcal{L}(\vec{x}), \mathcal{L}(\vec{x}))$$

$$\mathcal{L}(F(\vec{x})) \approx F(\mathcal{L}(\vec{x}))$$



# Dimension reduction

$$\frac{dx_i}{dt} = F(x_i(t)) + \sum_{j=1}^N A_{ij} Q(x_i(t), x_j(t))$$

$$\mathcal{L}(\vec{v}) = \frac{\mathbf{1}^T A \vec{v}}{\mathbf{1}^T A \mathbf{1}}$$

Weighted  
average over  
nearest neighbor  
nodes

$$\frac{dx_i}{dt} \approx F(x_i(t)) + s_i^{\text{in}} Q(x_i(t), \mathcal{L}(\vec{x}(t)))$$

$$\frac{d\mathcal{L}(\vec{x})}{dt} \approx F(\mathcal{L}(\vec{x})) + \mathcal{L}(\vec{s}^{\text{in}}) Q(\mathcal{L}(\vec{x}), \mathcal{L}(\vec{x}))$$

Mapping to  $\beta$ -space reduces the multidimensional system into an effective one dimensional resilience function

$$\frac{dx_{\text{eff}}}{dt} \approx F(x_{\text{eff}}) + \beta_{\text{eff}} Q(x_{\text{eff}}, x_{\text{eff}}) = f(\beta, x)$$

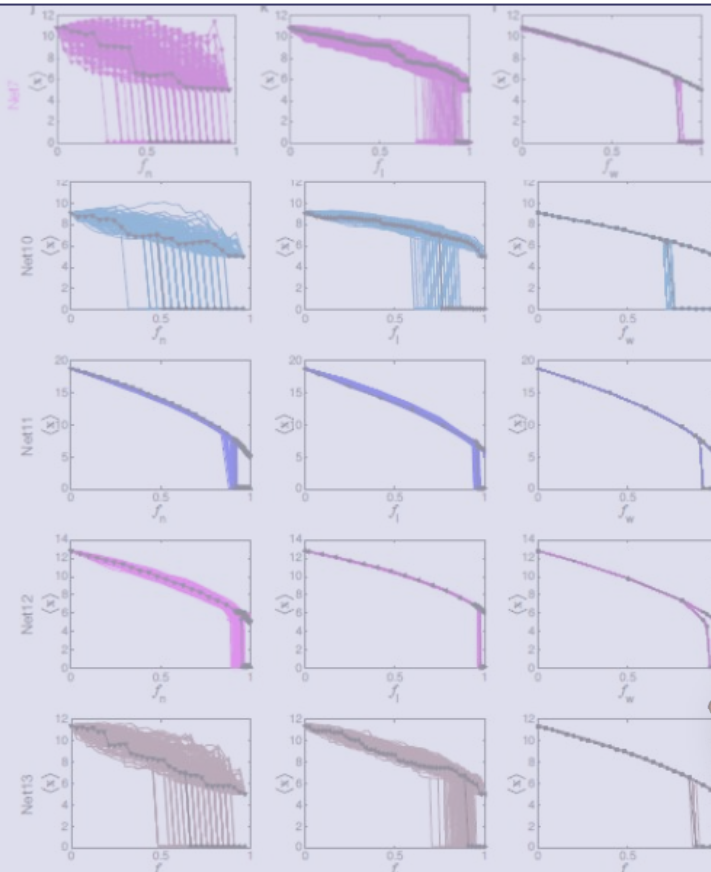
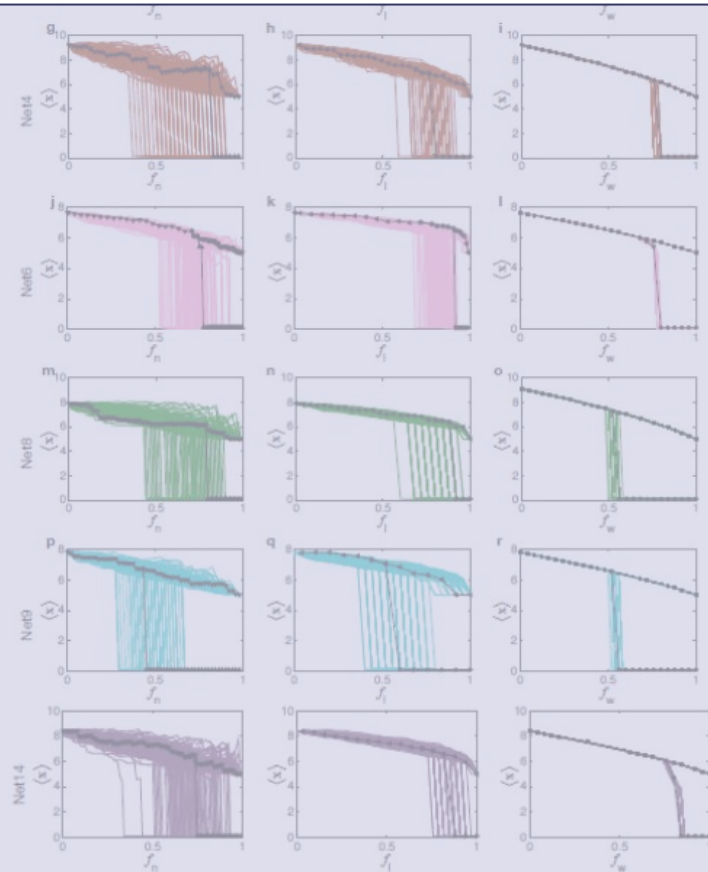
$$x_{\text{eff}} = \mathcal{L}(\vec{x}) = \frac{\mathbf{1}^T A \vec{x}}{\mathbf{1}^T A \mathbf{1}}$$

$$\beta_{\text{eff}} = \mathcal{L}(\vec{s}^{\text{in}}) = \frac{\mathbf{1}^T A \vec{s}^{\text{in}}}{\mathbf{1}^T A \mathbf{1}}$$



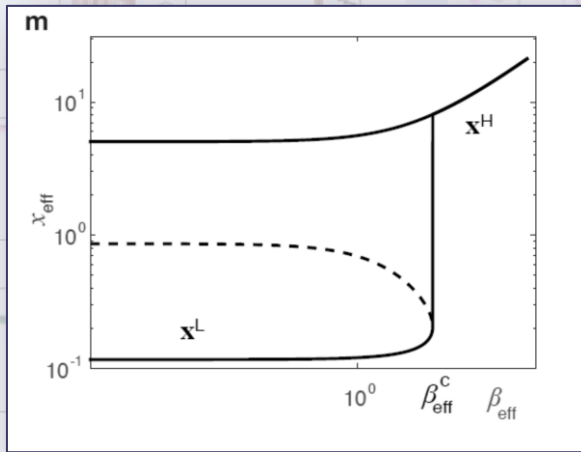
# Ecological Resilience

$$\frac{dx_{\text{eff}}}{dt} = B + x_{\text{eff}} \left( 1 - \frac{x_{\text{eff}}}{\kappa} \right) \left( \frac{x_{\text{eff}}}{\xi} - 1 \right) + \beta_{\text{eff}} \frac{x_{\text{eff}}^2}{1 + (\alpha + \gamma)x_{\text{eff}}}$$



# Ecological resilience

$$\frac{dx_{\text{eff}}}{dt} = B + x_{\text{eff}} \left( 1 - \frac{x_{\text{eff}}}{\kappa} \right) \left( \frac{x_{\text{eff}}}{\xi} - 1 \right) + \beta_{\text{eff}} \frac{x_{\text{eff}}^2}{1 + (\alpha + \gamma)x_{\text{eff}}}$$



$$A_{ij} \rightarrow \beta_{\text{eff}}$$

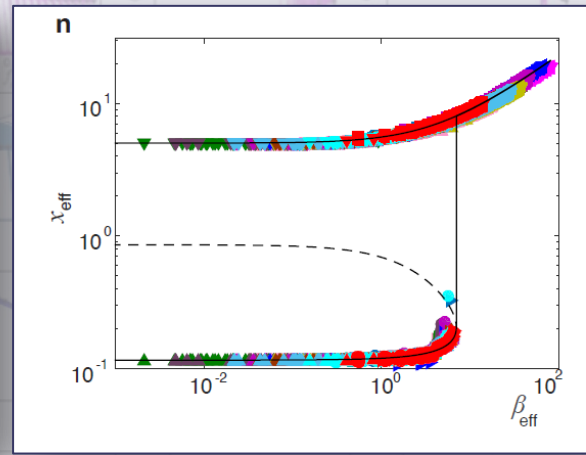
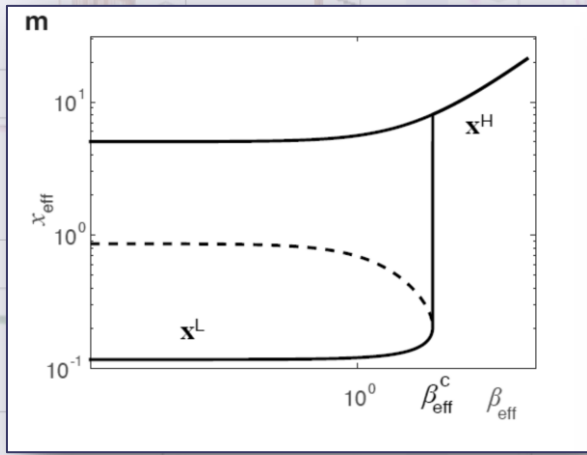
$$\Delta A_{ij} \rightarrow \Delta \beta_{\text{eff}}$$

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# Ecological resilience

$$\frac{dx_{\text{eff}}}{dt} = B + x_{\text{eff}} \left( 1 - \frac{x_{\text{eff}}}{\kappa} \right) \left( \frac{x_{\text{eff}}}{\xi} - 1 \right) + \beta_{\text{eff}} \frac{x_{\text{eff}}^2}{1 + (\alpha + \gamma)x_{\text{eff}}}$$



$A_{ij} \rightarrow \beta_{\text{eff}}$

$\Delta A_{ij} \rightarrow \Delta \beta_{\text{eff}}$

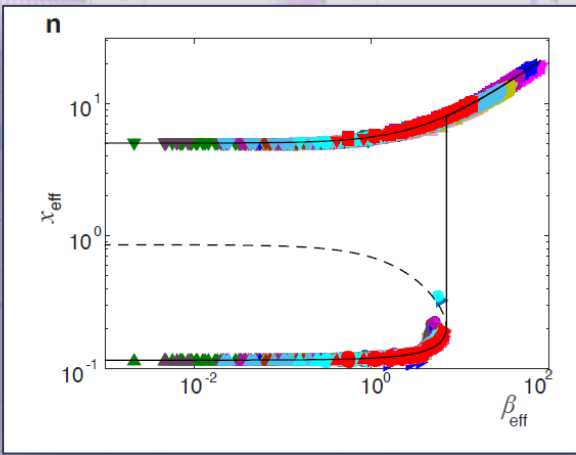
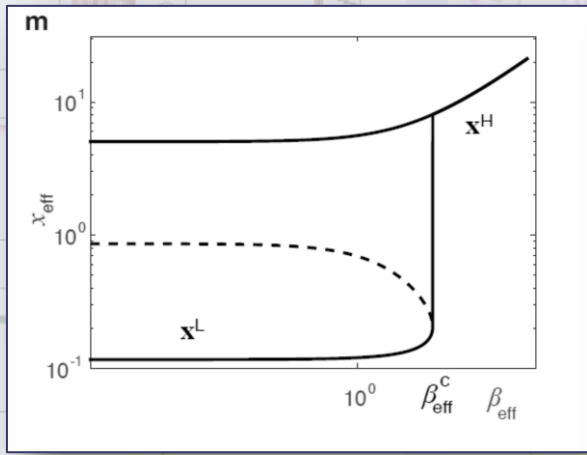
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# Ecological resilience

$$\frac{dx_{\text{eff}}}{dt} = B + x_{\text{eff}} \left( 1 - \frac{x_{\text{eff}}}{\kappa} \right) \left( \frac{x_{\text{eff}}}{\xi} - 1 \right) + \beta_{\text{eff}} \frac{x_{\text{eff}}^2}{1 + (\alpha + \gamma)x_{\text{eff}}}$$



$A_{ij} \rightarrow \beta_{\text{eff}}$   
 $\Delta A_{ij} \rightarrow \Delta \beta_{\text{eff}}$

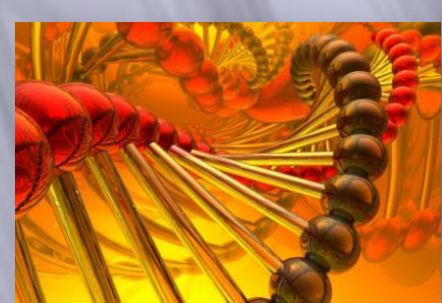
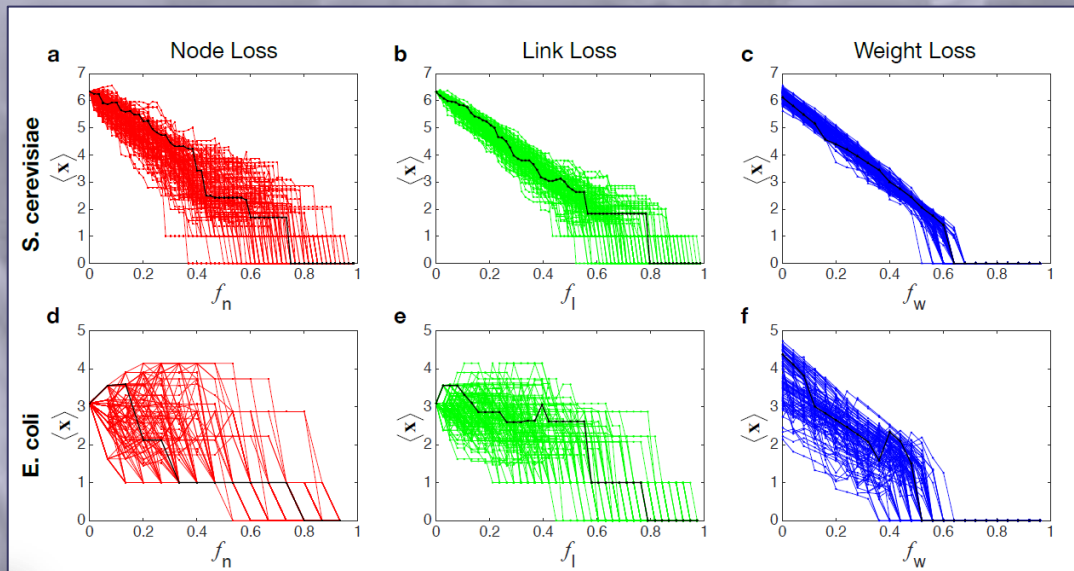
$\beta$ -space exposes the hidden universality of the system's resilience function



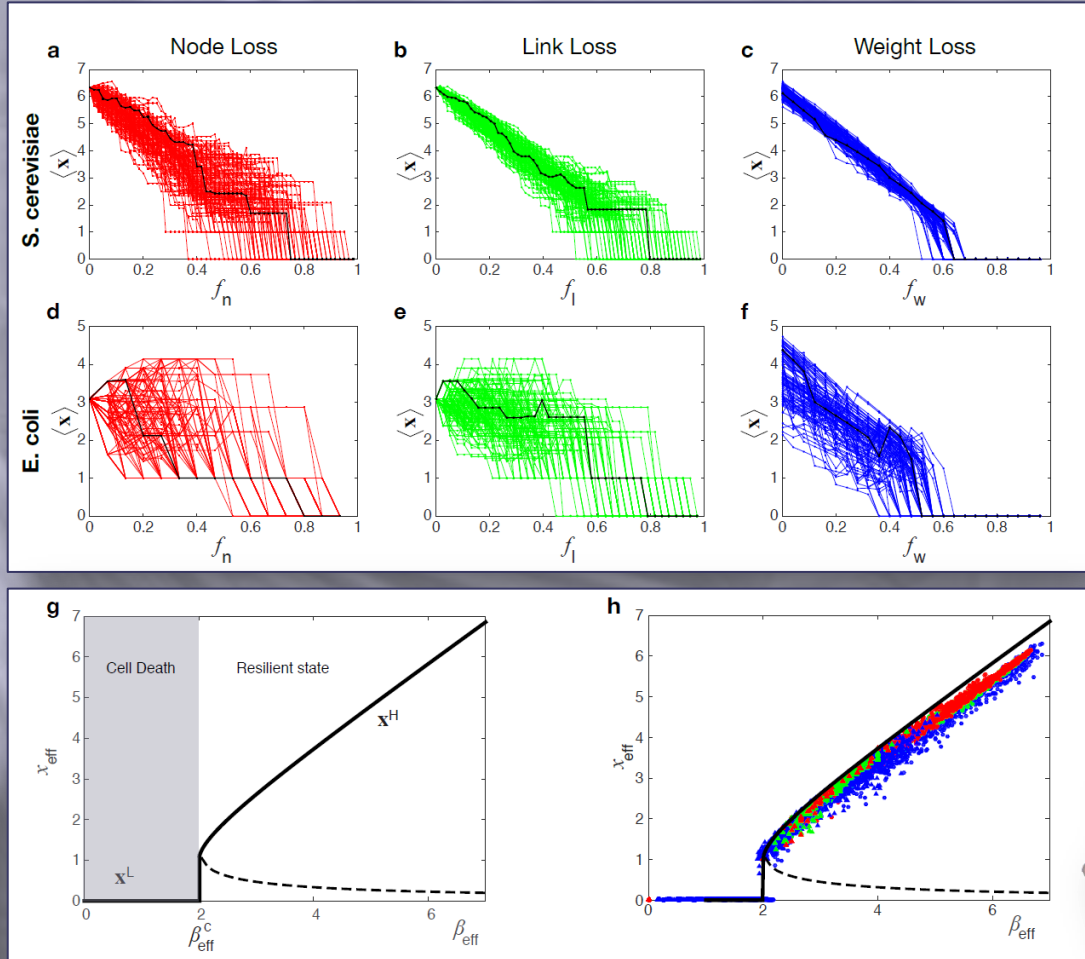
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# Biological Resilience

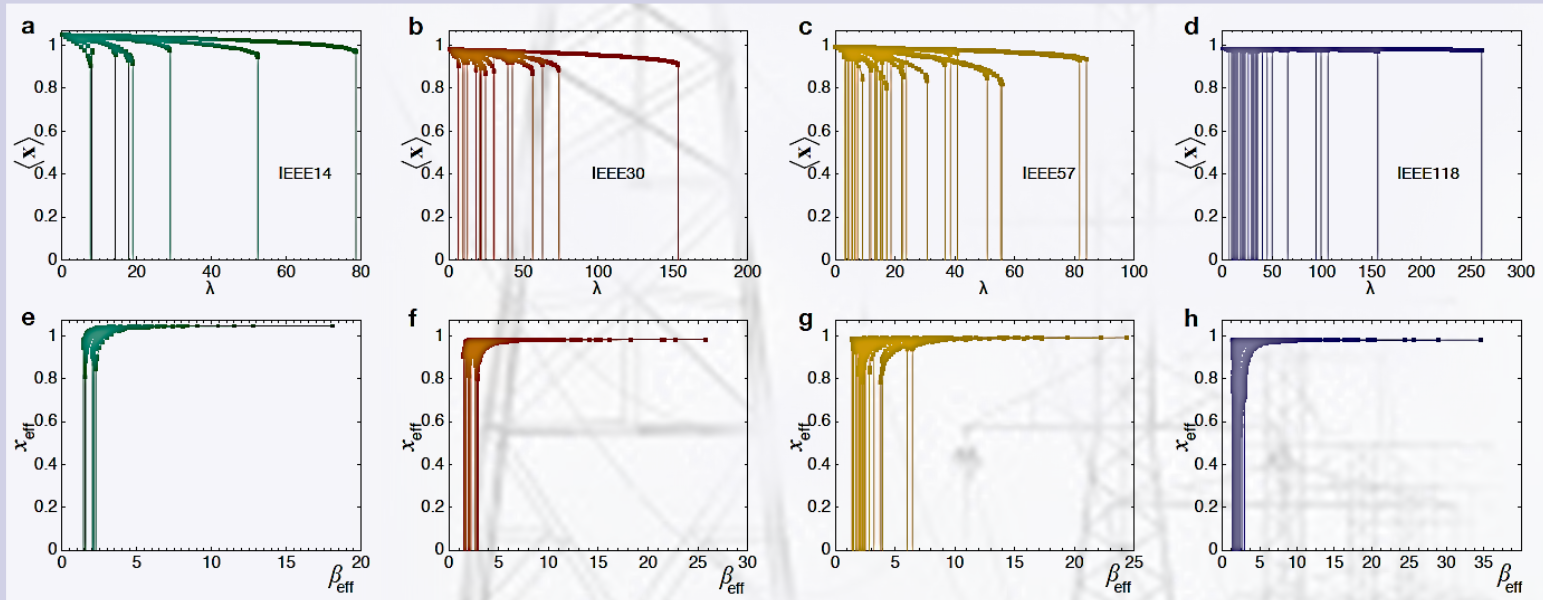
$$\frac{dx_i}{dt} = -Bx_i^\alpha + \sum_{j=1}^N A_{ij} \frac{x_j^h}{1 + x_j^h}$$



# Biological Resilience



# Power supply



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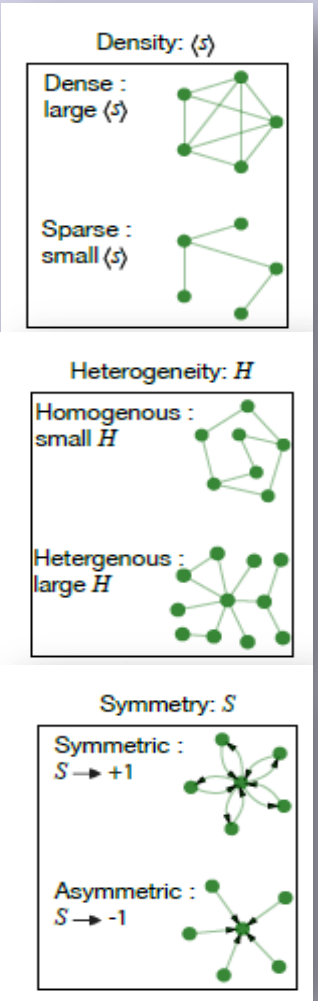
# The parameters of resilience

$$\beta_{\text{eff}} = \mathcal{L}(\vec{s}^{\text{in}}) = \langle s \rangle + \mathcal{H}\mathcal{S}$$

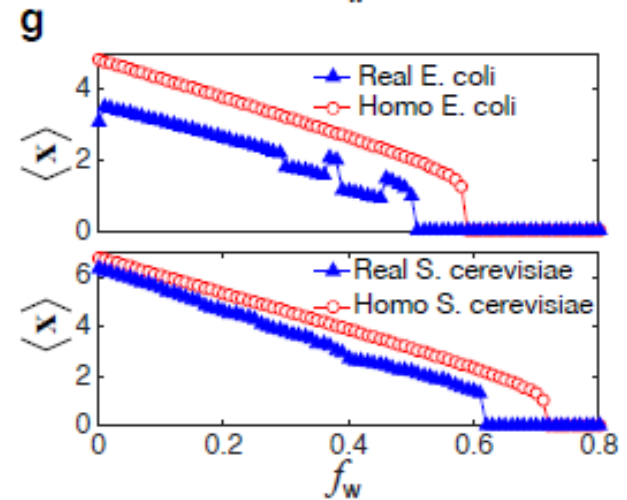
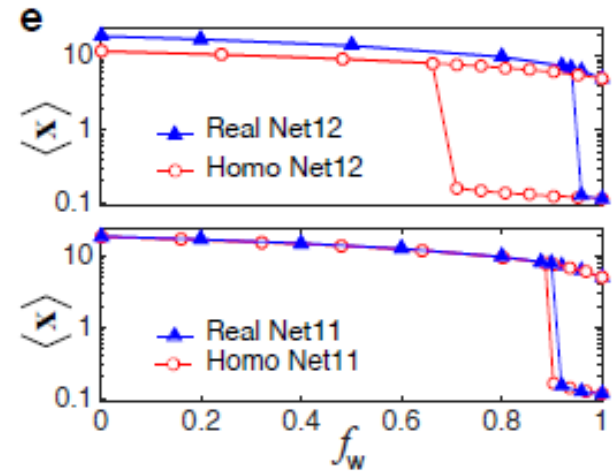
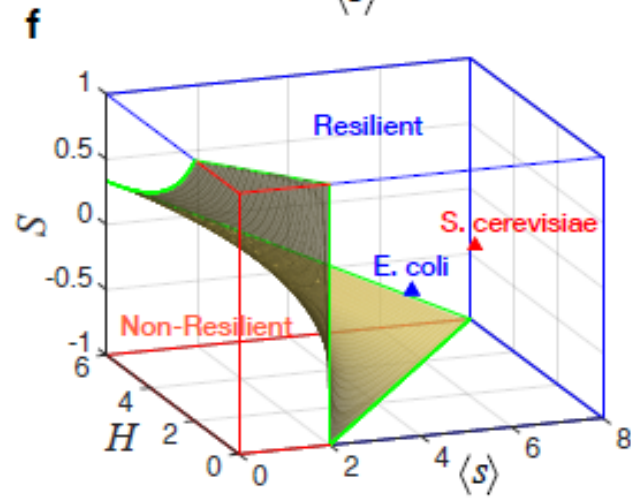
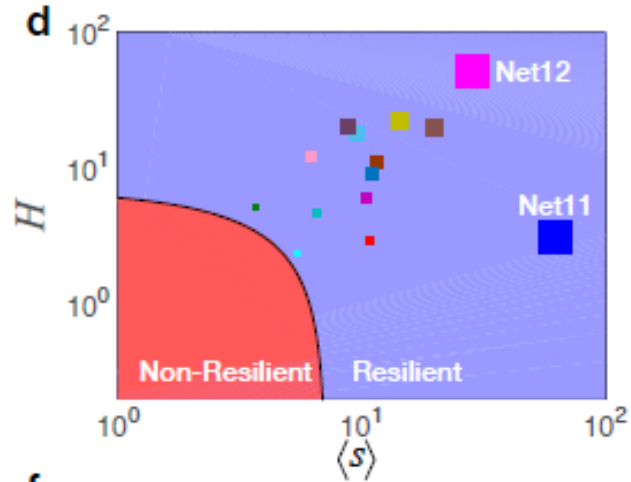
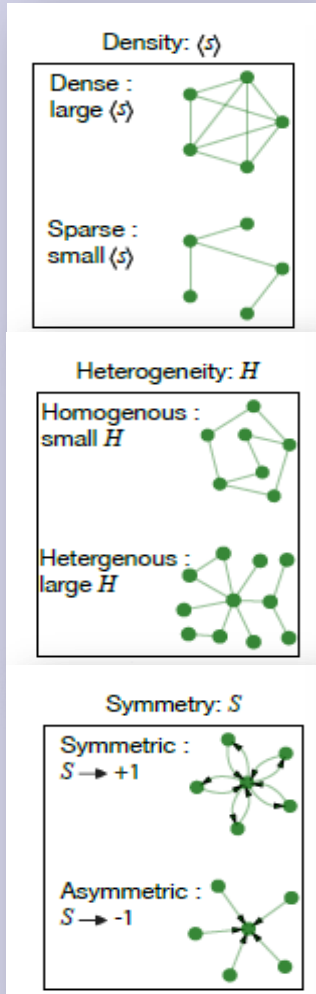
$$\langle s \rangle = \sum_{i=1}^N s_i = \langle s^{\text{in}} \rangle = \langle s^{\text{out}} \rangle$$

$$\mathcal{H} = \frac{\sigma^{\text{in}} \sigma^{\text{out}}}{\langle s \rangle}$$

$$\mathcal{S} = \frac{\langle s^{\text{in}} s^{\text{out}} \rangle - \langle s^{\text{in}} \rangle \langle s^{\text{out}} \rangle}{\sigma^{\text{in}} \sigma^{\text{out}}}$$



# The parameters of resilience





Universal resilience patterns in complex networks.  
*Nature* **530**, 307 (2016)



Constructing minimal models for complex system dynamics.  
*Nature Communications* **6**, 7186 (2015)

Universality in network dynamics.  
*Nature Physics* **9**, 673 (2013)



Patterns of information flow in complex networks.  
*Nature Communications*. In press (2017)

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