

## Lecture 7 Network Laplacian

## 1. Diffusion

$\psi_i$  — amount of certain physical quantity at node  $i$   
 Rate of flow from  $j$  to  $i$  =  $C(\psi_j - \psi_i)$

$$\frac{d\psi_i}{dt} = C \sum_{j=1}^n A_{ij}(\psi_j - \psi_i) \quad C > 0 - \text{diffusion constant}$$

$$\delta_{ij} = \begin{cases} 1, & i=j \\ 0, & i \neq j \end{cases} \quad = C \sum_j A_{ij} \psi_j - C \psi_i \sum_j A_{ij} = C \sum_j (A_{ij} - \delta_{ij} k_i) \psi_j$$

$$\psi \equiv \begin{pmatrix} \psi_1 \\ \vdots \\ \psi_n \end{pmatrix} \Rightarrow \frac{d\psi}{dt} = C(A - D) \cdot \psi - \text{matrix form}$$

$$D \equiv \begin{pmatrix} k_1 & 0 \\ 0 & k_n \end{pmatrix} \quad L \equiv D - A - \text{Laplacian matrix}$$

Diffusion equation:  $\frac{d\psi}{dt} + CL \cdot \psi = 0$

$$L = \begin{cases} k_i, & i=j \\ -1, & i \neq j \text{ but } A_{ij}=1 \\ 0, & \text{otherwise} \end{cases}$$

Why "Diffusion"?

$$\text{C.f. } \frac{\partial \phi}{\partial t} = D \frac{\partial^2 \phi}{\partial x^2} - \text{usual diffusion eq. in 1D}$$

space discretization

$$\phi = \begin{pmatrix} \phi_1 \\ \vdots \\ \phi_n \end{pmatrix} \quad \frac{\partial^2}{\partial x^2} \rightarrow \frac{1}{\delta^2} (\phi_{i+1} + \phi_{i-1} - 2\phi_i)$$

$$\Rightarrow \frac{\partial \phi}{\partial t} = D L \phi \quad \text{with } L \equiv \frac{1}{\delta^2} \begin{pmatrix} -2 & 1 & 0 \\ 1 & -2 & 1 \\ 0 & 1 & -2 \end{pmatrix}$$

## 2. Solution of diffusion equation

$$L \cdot \psi_i = \lambda_i \psi_i, \quad \psi_j^T \cdot \psi_i = \delta_{ij}$$

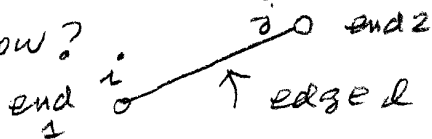
$$\psi(t) = \sum a_i(t) \psi_i$$

$$\Rightarrow \sum_i \left( \frac{da_i}{dt} + C \lambda_i a_i \right) \psi_i = 0$$

$$\psi_j^T \cdot \Rightarrow \frac{da_j}{dt} + C \lambda_j a_j = 0 \Rightarrow \boxed{a_j(t) = a_j(0) e^{-C \lambda_j t}}$$

Physical constraint:

How?



$B_{mxn}$  — edge incidence matrix

$$\lambda_i \geq 0$$

$$B_{lj} = \begin{cases} +1, & \text{if end 1 of edge } l \rightarrow \text{node } j \\ -1, & \text{"end 2"} \\ 0, & \text{otherwise} \end{cases}$$

Each row: one "1" (adixed edge) one "-1"

1 edge between a pair of nodes



$$\sum_l B_{li} B_{lj} = -1 \quad i \neq j$$

$$\sum_l B_{li} B_{li} = \sum_l B_{li}^2 = k_i$$

$$\Rightarrow L_{ij} = \sum_k B_{ki} B_{kj} ; L = B^T \cdot B$$

$$\lambda_i = \tilde{v}_i^T \cdot (B^T \cdot B) \tilde{v}_i = (B \tilde{v}_i)^T (B \tilde{v}_i) \geq 0 \quad \square$$

Usually,  $L$  has at least one zero eigenvalue

with  $\tilde{v} = (1, 1, \dots, 1)^T$

$L$  is non-invertible

$\lambda_2 > 0$   
 $\nwarrow$  algebraic connectivity

$0 = \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n \Rightarrow$  if the network is connected

### 3. Network Synchronizability

$$\sum_{j=1}^n L_{ij} = 0 \quad \frac{dx_i}{dt} = F(x_i) + \varepsilon \sum_{j=1}^n L_{ij} H(x_j) \quad \dots (1)$$

Isolated oscillator:  $\frac{dx}{dt} = F(x)$  — identical oscillator

Solution  $\underline{s}(t)$ :  $\frac{ds}{dt} = F(s)$

$x_i(t) = \underline{s}(t)$  (for all  $i$ ) — synchronized solution

Substituting this into Eq. (1)  $\Rightarrow \frac{ds}{dt} = F(s) + \varepsilon \sum_{j=1}^n L_{ij} H(s) = F(s)$

Key issue: is  $x_i(t) = \underline{s}(t)$  stable?

Variational equation: say  $x_i(t) = \underline{s}(t) + \delta x_i(t)$

How does  $\delta x_i(t)$  evolve?

$$\delta \underline{x} = \begin{pmatrix} \delta x_1 \\ \delta x_2 \\ \vdots \\ \delta x_n \end{pmatrix}$$

$$\frac{d(\delta x_i(t))}{dt} = \underbrace{DF(\underline{s}(t))}_{\text{matrix}} \cdot \delta x_i(t) + \varepsilon \sum_{j=1}^n L_{ij} \underbrace{DH(\underline{s}(t))}_{\text{matrix}} \cdot \delta x_j(t)$$

$$\frac{d\delta \underline{x}}{dt} = \underbrace{[DF(\underline{s}(t))]}_{\text{block-diagonal}} \cdot \delta \underline{x} + \varepsilon \underbrace{[DH(\underline{s}(t))]}_{\text{block-diagonal}} \cdot L \cdot \delta \underline{x}(t)$$

$L \cdot \tilde{v}_i = \lambda_i \tilde{v}_i$  components decoupled —  $\underline{y}(t) \equiv \underline{U} \cdot \delta \underline{x}(t)$

$$L = \underline{U}^{-1} \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix} \underline{U}$$

determined by nodal & coupling dyn., not by network structure

$\rightarrow \Lambda_{\max}$

$$\frac{dy_i}{dt} = DF(\underline{s}(t)) \cdot y_i + \varepsilon \lambda_i DH(\underline{s}(t)) \cdot y_i$$

$\lambda_1 = 0$ :  $\frac{dy_1}{dt} = DF(\underline{s}(t)) \cdot y_1$  — within synchronization manifold

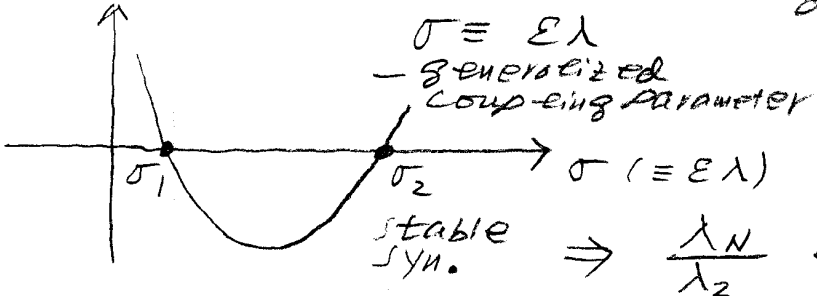
All others:  $\frac{dy}{dt} = [DF(\underline{s}) + \sigma DH(\underline{s})] \cdot y$  — linear diff. Eq.

$y(t) = y(0) e^{\Lambda t}$

$\Lambda_{\max}$  — Master stability function

$\Lambda_{\max} < 0 \Rightarrow$  stable syn.

$\frac{\lambda_N}{\lambda_2}$  — measure of synchronizability!



## Heterogeneity in Oscillator Networks: Are Smaller Worlds Easier to Synchronize?

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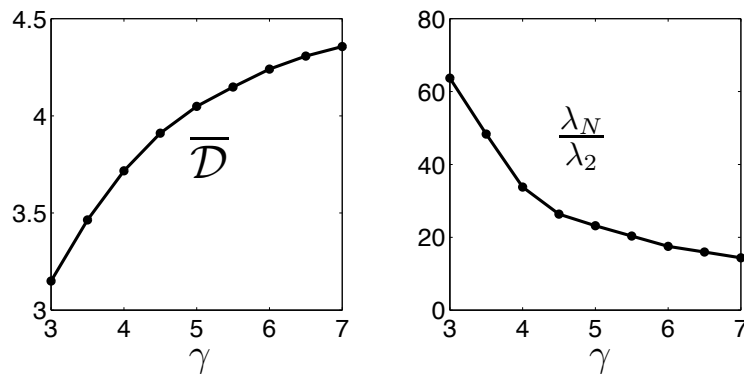
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Small-world and scale-free networks are known to be more easily synchronized than regular lattices, which is usually attributed to the smaller network distance between oscillators. Surprisingly, we find that networks with a homogeneous distribution of connectivity are more synchronizable than heterogeneous ones, even though the average network distance is larger. We present numerical computations and analytical estimates on synchronizability of the network in terms of its heterogeneity parameters. Our results suggest that some degree of homogeneity is expected in naturally evolved structures, such as neural networks, where synchronizability is desirable.

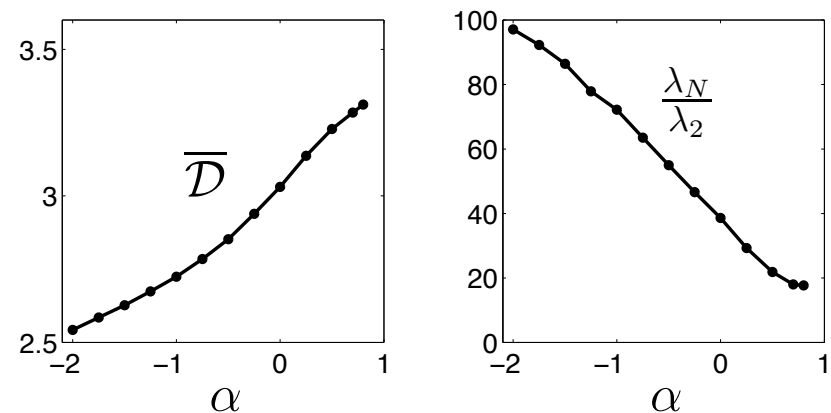
### Semi-random scale-free network model

Smaller  $\gamma \longleftrightarrow$  More heterogeneous degree distribution



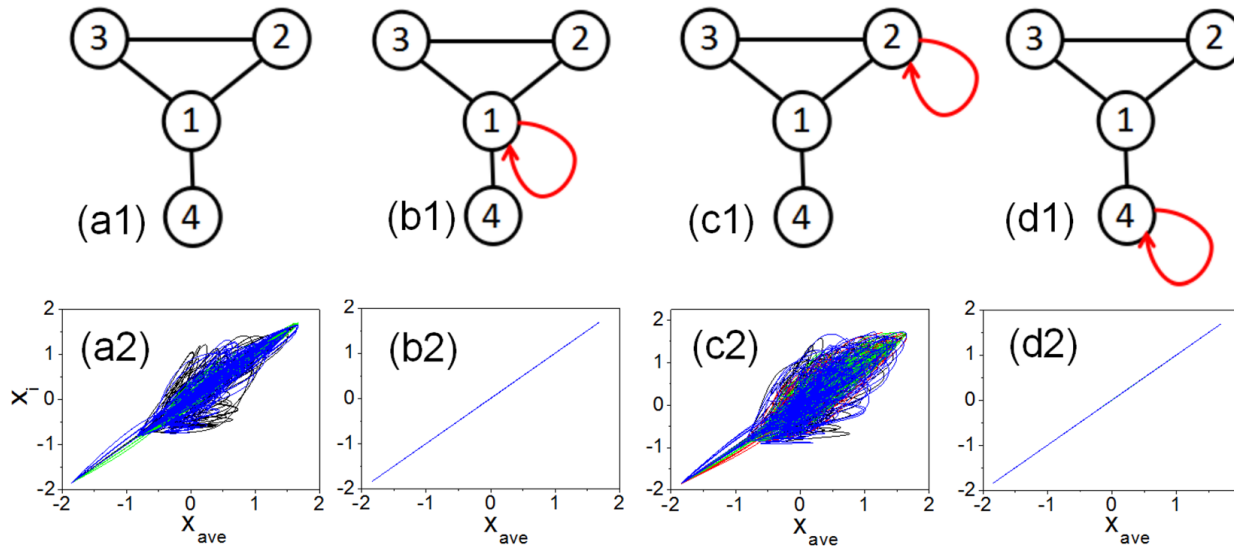
### Growing scale-free network model

Smaller  $\alpha \longleftrightarrow$  More heterogeneous degree distribution



*Heterogeneity  $\Rightarrow$  { Smaller  $\overline{D}$ , but  
More difficult to synchronize*

# Autapses Promote Synchronization in Neuronal Networks



**Figure 1.** The impact of a single autapse on synchronization in a toy neuronal network. (a1) Without any autapse, the network has four nodes and four edges, where each node is a Hindmarsh-Rose neuron. (b1–d1) Network structure when a single autapse (represented by the red curve with an arrow) is present at node 1, 2, and 4, respectively. (a2–d2) For the network structures in (a1–d1), respectively, the dynamical behaviors of the network in terms of synchronization. Shown in each panel is a plot of the  $x$  variable from each node versus the averaged value of this variable over all the nodes during the time evolution. When there is global synchronization, all the variables are equal to their average value at any instant of time, tracing out a straight line segment along the diagonal. Any deviation from the diagonal signifies lack of synchronization. The uniform coupling parameter is  $\varepsilon = 1$  and the time delay associated with the autapse is  $\tau = 4$ .

- Autapses – first discovered in 1972
- For 25 years, autapses were thought to be “useless”
- After 1997 – biological roles of autapses gradually recognized
- Still much is to be learned

H.-W. Fan, Y.-F. Wang, H.-T. Wang, Y.-C. Lai, and X.-G. Wang, “Autapses promote synchronization in neuronal networks,” *Scientific Reports* **8**, article number 580 (2018).