

- Synchronization: A phenomenon in which multiple oscillators vibrate homogeneously through interaction
- A system where clocks spinning at different speeds adjust their speed by looking at the clock connected to them?
- Synchronization of fireflies, synchronization of applause at concert halls, etc.

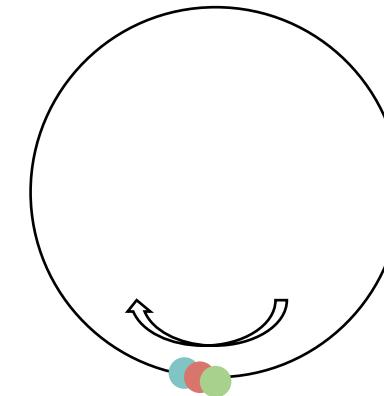
Angular velocity of node i

$$\frac{d\theta_i}{dt} = \Omega_i + \sum_j K_{ij} \sin(\theta_j - \theta_i)$$

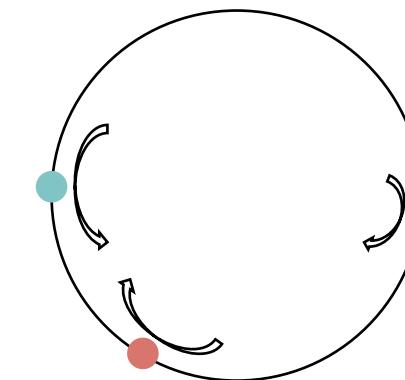
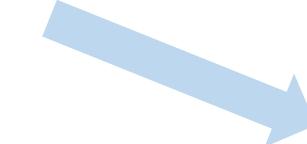
Interaction intensity

natural frequency

Interaction with surrounding nodes



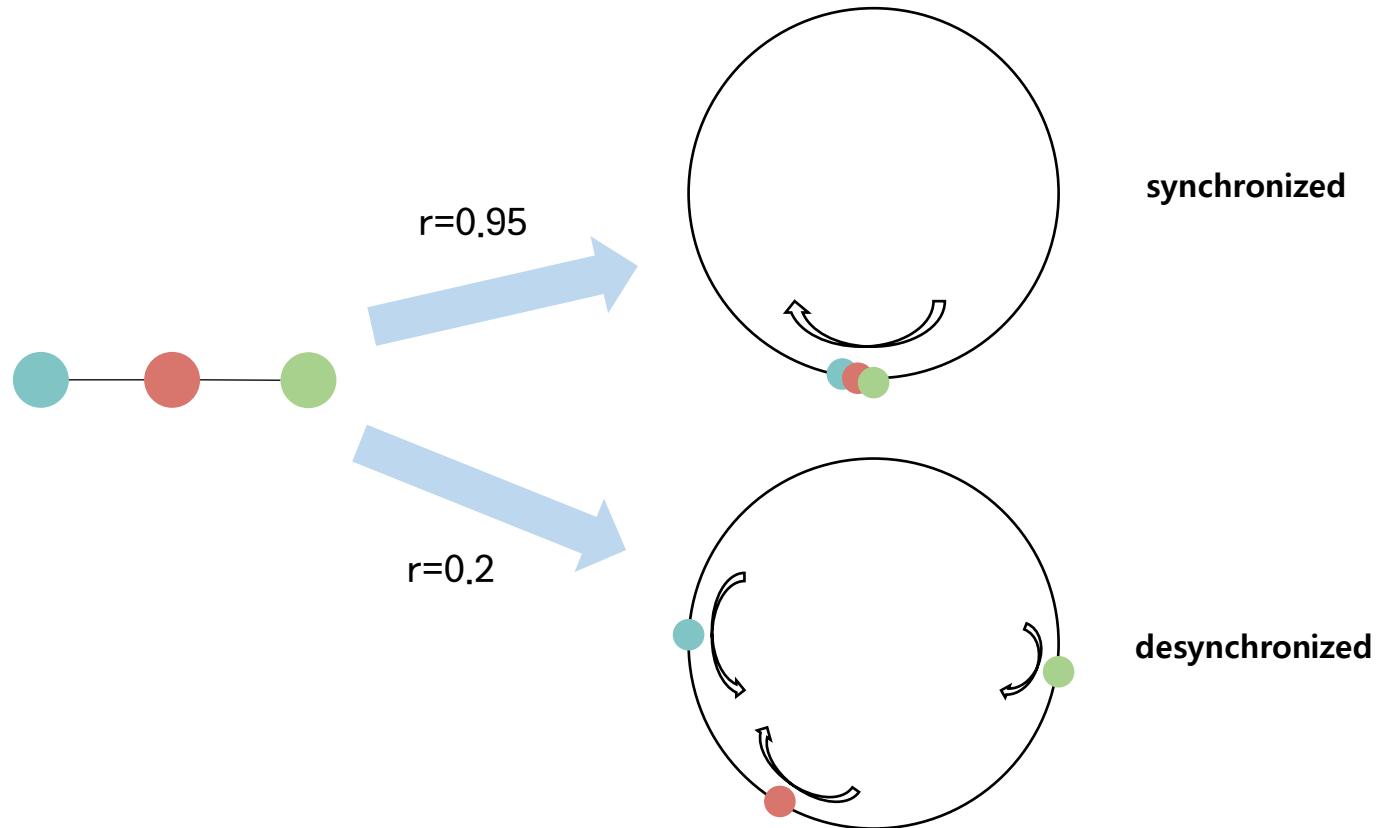
synchronized



desynchronized

- Kuramoto model: the simplest model for synchronization
- A state where everyone looks at each other and applauds.
- Depending on the interaction strength (K), the system can be synchronized or desynchronized.

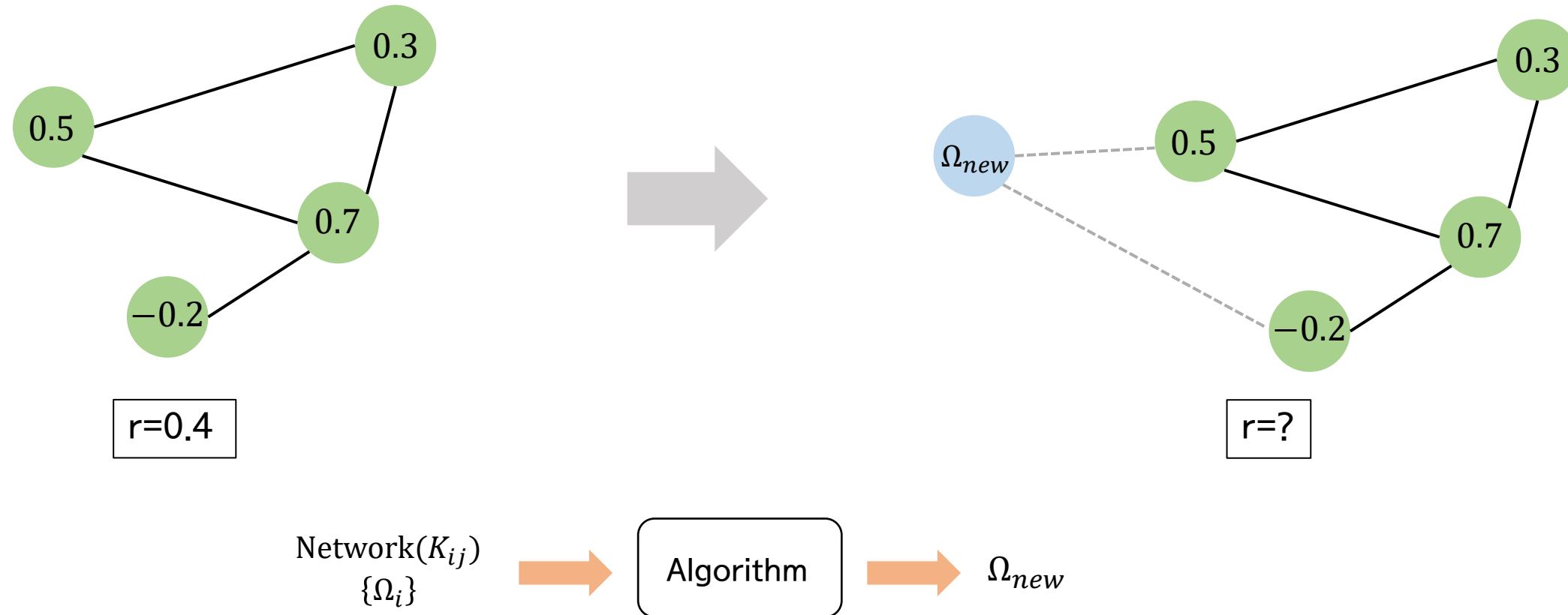
$$re^{i\psi} = \frac{1}{N} \sum_{j=1}^N e^{i\theta_j}$$



- Order parameter: A variable that expresses how well the synchronization is (0~1)
- The larger r , the better the synchronization.

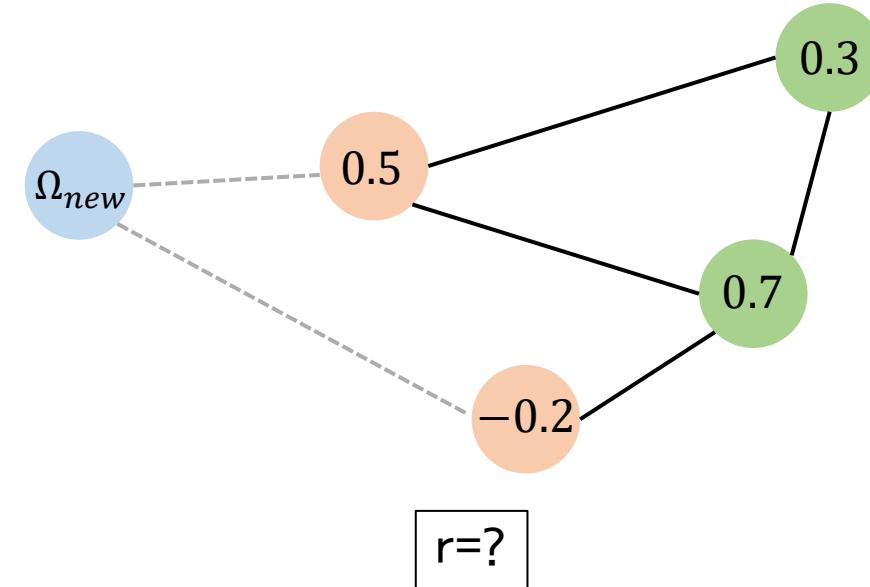
Optimal frequency for growing network

Introduction



- Question: When adding a new node to a network, how should its natural frequency be assigned?
- Compute the frequency to preserve or improve the original network's order parameter r .
- An algorithm that infers the new node's frequency from the existing network and its frequency distribution.

- Global: Average of all existing node frequencies
- Local: Average value of adjacent nodes (red)
- Random: Just random (normal distribution)
- SAF
- ALF



- Grow a given network (30 nodes) to 40 and assign frequencies to new nodes in 5 ways.
- Comparison of r at the beginning and r at the end
- What is the best way to increase the r of the network?

Optimal frequency for growing network

Introduction

SAF: I want to increase the order parameter as much as possible.

$$\omega_{N+1}^* = \operatorname{argmin}_{\omega_{N+1}} \left\{ \omega^T (\mathbf{L}^\dagger)^2 \omega \right\}$$

ALF: We want to reduce the power loss of the entire network as much as possible.

$$\omega_{N+1}^* = \operatorname{argmin}_{\omega_{N+1}} \left\{ \omega^T \mathbf{L}^\dagger \omega \right\}$$



induction:

with

$$\tilde{\mathbf{E}} = \begin{pmatrix} \mathbf{E} & \mathbf{0} \\ \mathbf{0}^T & 0 \end{pmatrix}, \quad \tilde{\mathbf{D}} = \begin{pmatrix} \mathbf{1}\mathbf{1}^T & \mathbf{1} \\ \mathbf{0} & 0 \end{pmatrix}, \quad \mathbf{I} = \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & 0 \end{pmatrix}$$

By using the relation

$$\mathbf{I}^T \mathbf{E} \mathbf{I} \mathbf{I}^T \mathbf{I}^T = \begin{pmatrix} \mathbf{1}\mathbf{1}^T \mathbf{E} \mathbf{I} \mathbf{I}^T & \mathbf{1}\mathbf{1}^T \mathbf{E} \mathbf{I} \\ \mathbf{I}^T \mathbf{E} \mathbf{I} \mathbf{I}^T & \mathbf{I}^T \mathbf{E} \mathbf{I} \end{pmatrix} = \begin{pmatrix} \mathbf{1}\mathbf{1}^T & \mathbf{1} \\ \mathbf{0} & 0 \end{pmatrix}^T \begin{pmatrix} \mathbf{E} & \mathbf{0} \\ \mathbf{0}^T & 0 \end{pmatrix} \begin{pmatrix} \mathbf{1}\mathbf{1}^T & \mathbf{1} \\ \mathbf{0} & 0 \end{pmatrix} = \mathbf{D}^T \tilde{\mathbf{E}} \tilde{\mathbf{D}},$$

we obtain

$$\begin{aligned} (\mathbf{L} + \varepsilon \mathbf{D})^{-1} - \frac{1}{\varepsilon(n+1)} \tilde{\mathbf{I}} \tilde{\mathbf{I}}^T &= \begin{pmatrix} \mathbf{E} & \mathbf{0} \\ \mathbf{0}^T & 0 \end{pmatrix} - \frac{1}{n+1} \tilde{\mathbf{B}} + \frac{\mathbf{I}^T \mathbf{E} \mathbf{I}}{(n+1)^2} \tilde{\mathbf{I}} \tilde{\mathbf{I}}^T + \mathcal{O}(\varepsilon) \\ &= \mathbf{I} \tilde{\mathbf{E}} \mathbf{I} - \frac{1}{n+1} \mathbf{D}^T \tilde{\mathbf{E}} \mathbf{I} - \frac{1}{n+1} \mathbf{I} \tilde{\mathbf{E}} \mathbf{D} + \frac{1}{(n+1)^2} \mathbf{D}^T \tilde{\mathbf{E}} \tilde{\mathbf{D}} + \mathcal{O}(\varepsilon) \\ &= \left(\mathbf{I} - \frac{1}{n+1} \tilde{\mathbf{B}} \right)^T \tilde{\mathbf{E}} \left(\mathbf{I} - \frac{1}{n+1} \tilde{\mathbf{D}} \right) + \mathcal{O}(\varepsilon) \\ &\equiv \tilde{\mathbf{C}}^T \tilde{\mathbf{E}} \tilde{\mathbf{C}} + \mathcal{O}(\varepsilon) \end{aligned}$$

with

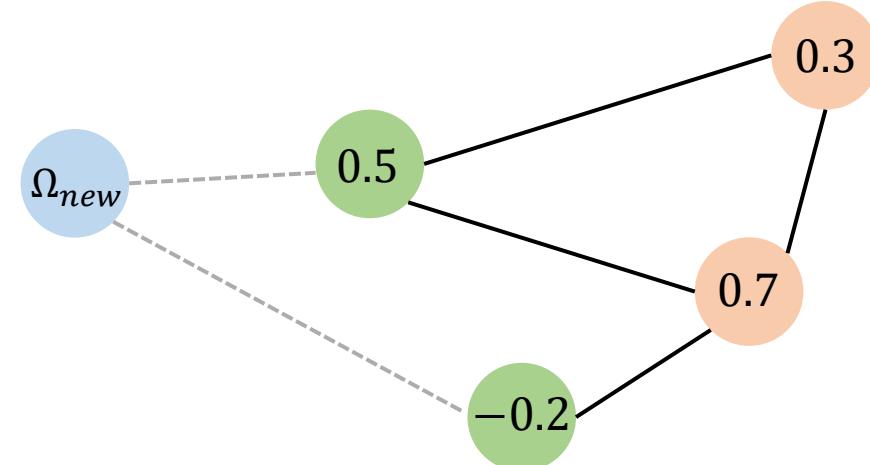
$$\tilde{\mathbf{C}} = \mathbf{I} - \frac{1}{n+1} \tilde{\mathbf{D}} = \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & 0 \end{pmatrix} - \frac{1}{n+1} \begin{pmatrix} \mathbf{1}\mathbf{1}^T & \mathbf{1} \\ \mathbf{0} & 0 \end{pmatrix}$$

It leads to

$$\mathbf{L}' = \lim_{\varepsilon \rightarrow 0} \left[(\mathbf{L} + \varepsilon \mathbf{D})^{-1} - \frac{1}{\varepsilon(n+1)} \tilde{\mathbf{I}} \tilde{\mathbf{I}}^T \right] = \tilde{\mathbf{C}}^T \begin{pmatrix} \mathbf{E} & \mathbf{0} \\ \mathbf{0}^T & 0 \end{pmatrix} \tilde{\mathbf{C}}$$

with $\mathbf{E} = (\mathbf{L} + \mathbf{W})^{-1}$ and

$$\tilde{\mathbf{C}} = \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & 0 \end{pmatrix} - \frac{1}{n+1} \begin{pmatrix} \mathbf{1}\mathbf{1}^T & \mathbf{1} \\ \mathbf{0} & 0 \end{pmatrix}$$



- SAF and ALF compute the natural frequency of a new node in a growing network based on established results.
- SAF: approximates the frequency that maximizes the order parameter.
- ALF: approximates the frequency that minimizes mutual interactions (\approx power loss)

SAF method [P. S. Skardal, D. Taylor, and J. Sun, PRL 113, 144101 (2014)]

Strong coupling regime ($r \approx 1$; $|\theta_i(t)| \ll 1$)

Equation of motion

$$\dot{\theta}_i(t) = \omega_i - K \sum_{j=1}^N A_{ij} \sin(\theta_i(t) - \theta_j(t))$$

$$\rightarrow \dot{\theta}_i(t) = \omega_i - K \sum_{j=1}^N L_{ij} \theta_j(t)$$

$L_{ij} = \delta_{ij} k_i - A_{ij}$: Laplace matrix

$k_i = \sum_j A_{ij}$: degree of node i

Order parameter

$$r^* e^{i\psi^*} = \frac{1}{N} \sum_{i=1}^N e^{i\theta_i^*}$$

$$\rightarrow r^* = 1 - \frac{1}{2N} \sum_{i=1}^N (\theta_i^*)^2$$

$$\dot{\boldsymbol{\theta}}(t) = \boldsymbol{\omega} + K \mathbf{L} \boldsymbol{\theta}(t), \quad r^* = 1 - \frac{1}{2N} (\boldsymbol{\theta}^*)^\text{T} \boldsymbol{\theta}^*$$

SAF method [P. S. Skardal, D. Taylor, and J. Sun, PRL 113, 144101 (2014)]

Strong coupling regime ($r \approx 1$; $|\theta_i(t)| \ll 1$)

Equation of motion

$$\dot{\boldsymbol{\theta}}(t) = \boldsymbol{\omega} - K\mathbf{L}\boldsymbol{\theta}(t) \rightarrow \boldsymbol{\theta}^* = \frac{1}{K}\mathbf{L}^\dagger \boldsymbol{\omega}$$

Order parameter

$$r^* = 1 - \frac{1}{2N}(\boldsymbol{\theta}^*)^\text{T} \boldsymbol{\theta}^*$$

$\mathbf{L}^\dagger = \sum_{i=2}^N \lambda_i^{-1} \boldsymbol{\nu}_i \boldsymbol{\nu}_i^\text{T}$: Moore-Penrose inverse

$$\rightarrow r^* = 1 - \frac{1}{2K^2N} \boldsymbol{\omega}^\text{T} (\mathbf{L}^\dagger)^2 \boldsymbol{\omega}$$

r^* is larger $\leftrightarrow \boldsymbol{\omega}^\text{T} (\mathbf{L}^\dagger)^2 \boldsymbol{\omega}$ is smaller

Measure for the optimization

$$\boldsymbol{\omega}_{N+1}^* = \underset{\boldsymbol{\omega}_{N+1}}{\operatorname{argmin}} \left\{ \boldsymbol{\omega}^\text{T} (\mathbf{L}^\dagger)^2 \boldsymbol{\omega} \right\}$$

ALF method [Y. Lei, et. al., to be published]

Strong coupling regime ($r \approx 1$; $|\theta_i(t)| \ll 1$)

Equation of motion

$$\dot{\boldsymbol{\theta}}(t) = \boldsymbol{\omega} - K\mathbf{L}\boldsymbol{\theta}(t) = \boldsymbol{\omega} - \nabla_{\boldsymbol{\theta}}V(\boldsymbol{\theta}(t)) \rightarrow \boldsymbol{\theta}^* = \frac{1}{K}\mathbf{L}^\dagger\boldsymbol{\omega}$$

$V(\boldsymbol{\theta}) = \frac{1}{2}K\boldsymbol{\theta}^T\mathbf{L}\boldsymbol{\theta}$: power loss (effective potential)

$$V(\boldsymbol{\theta}^*) = \frac{1}{2K}\boldsymbol{\omega}^T\mathbf{L}^\dagger\mathbf{L}\boldsymbol{\omega} = \frac{1}{2K}\boldsymbol{\omega}^T\mathbf{L}^\dagger\boldsymbol{\omega} \quad (\mathbf{L}^\dagger\mathbf{L}\mathbf{L}^\dagger = \mathbf{L}^\dagger)$$

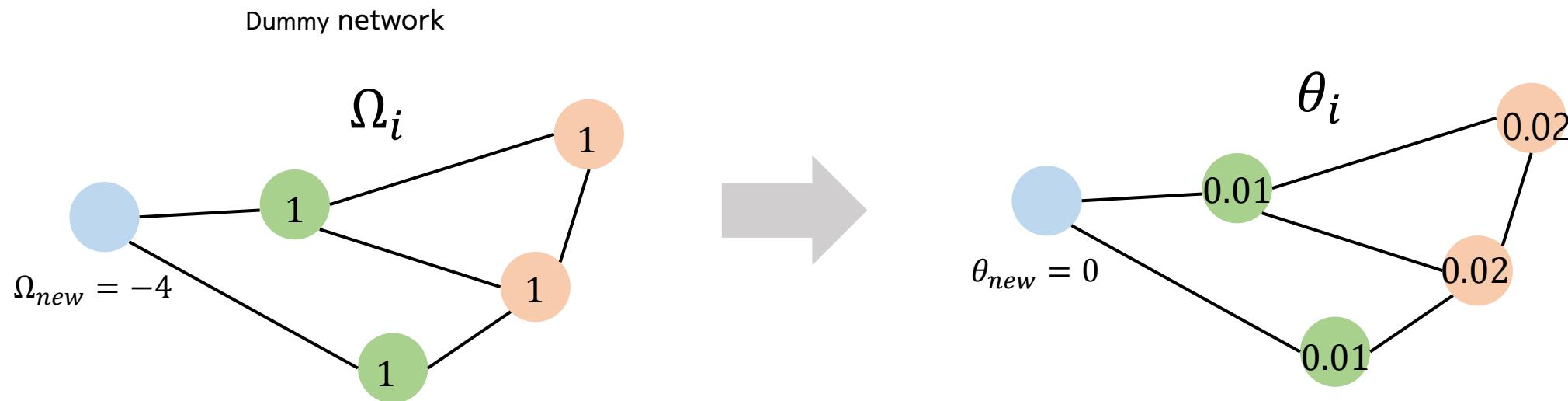
smaller $V(\boldsymbol{\theta}^*)$ would be better (?)

Measure for the optimization

$$\omega_{N+1}^* = \underset{\omega_{N+1}}{\operatorname{argmin}}\{\boldsymbol{\omega}^T\mathbf{L}^\dagger\boldsymbol{\omega}\}$$

ALF: We want to reduce the power loss of the entire network as much as possible.

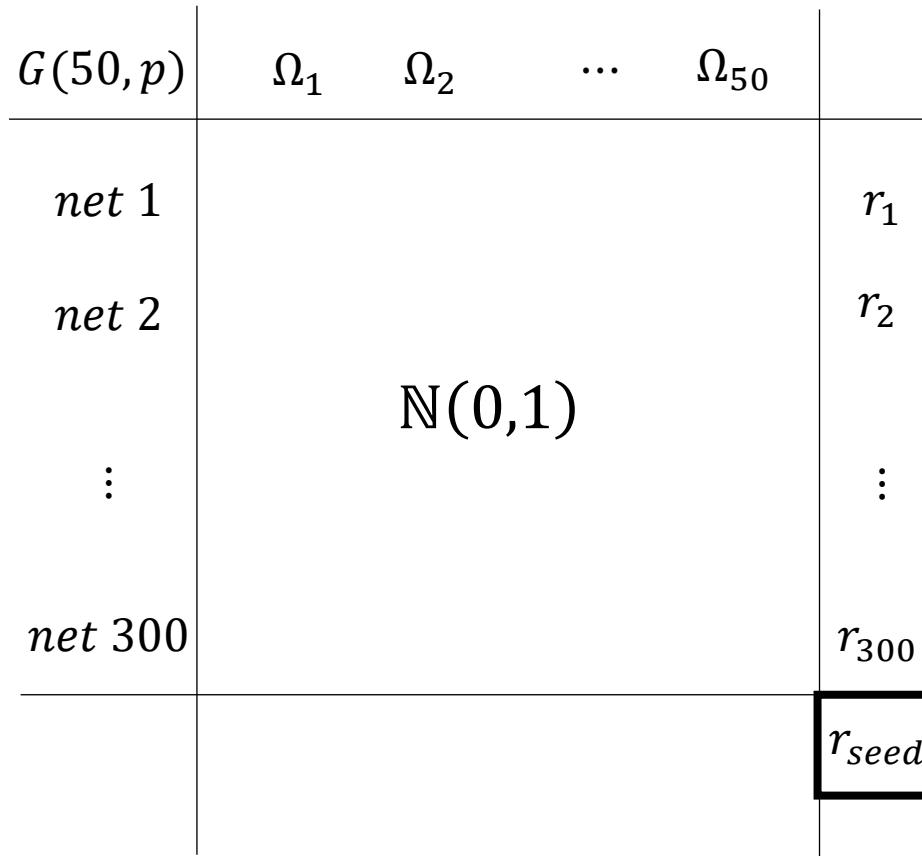
$$\omega_{N+1}^* = \operatorname{argmin}_{\omega_{N+1}} \{\boldsymbol{\omega}^T \mathbf{L}^\dagger \boldsymbol{\omega}\}$$



- Another interpretation of ALF: construct a dummy network where all existing nodes are assigned an angular velocity of 1.
- In its synchronized state, a larger phase difference with the new node leads to stronger influence on its assigned frequency.
- The new node's angular velocity is determined by weighting green nodes by 1 and red nodes by 2.

Optimal frequency for growing network

Introduction

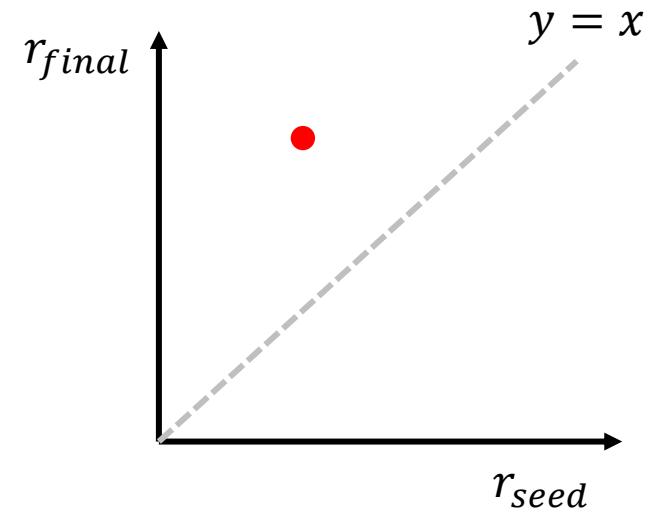


- Test method: Create several seed networks using the same settings
- Generating the natural frequency of each node as a normal distribution.
- The average value of r obtained from 300 networks becomes the representative value of the seed network.

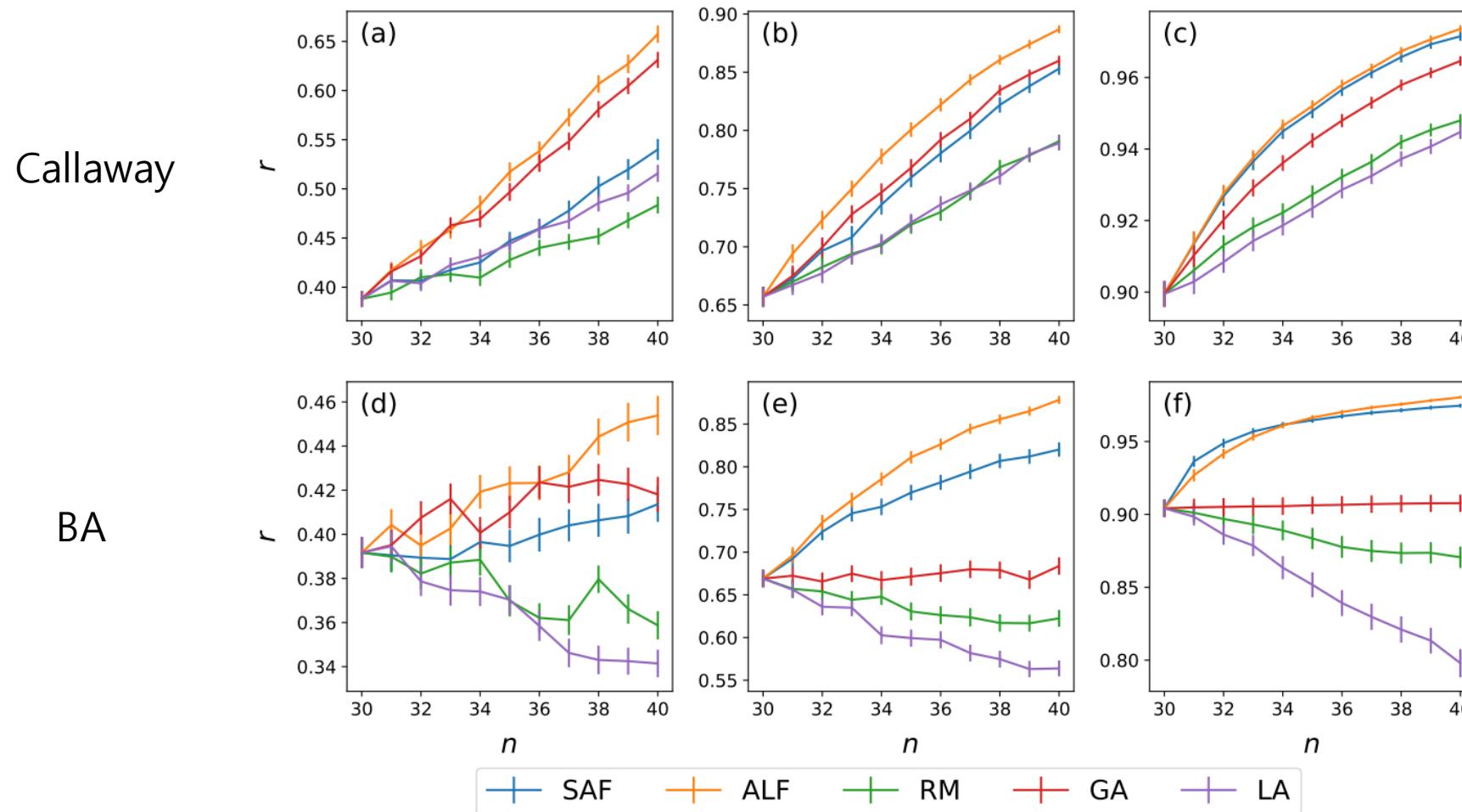
Optimal frequency for growing network

Introduction

$G(50, p)$	Ω_1	Ω_2	\dots	Ω_{50}		$\Omega_{51} \sim \Omega_{60}$	
<i>net 1</i>				r_1		r_1	
<i>net 2</i>				r_2		r_2	
\vdots				\vdots		\vdots	
<i>net 300</i>				r_{300}		r_{300}	
				r_{seed}		r_{final}	



- Test method: Create several seed networks using the same settings
- Generating the natural frequency of each node as a normal distribution.
- The average value of r obtained from 300 networks becomes the representative value of the seed network.

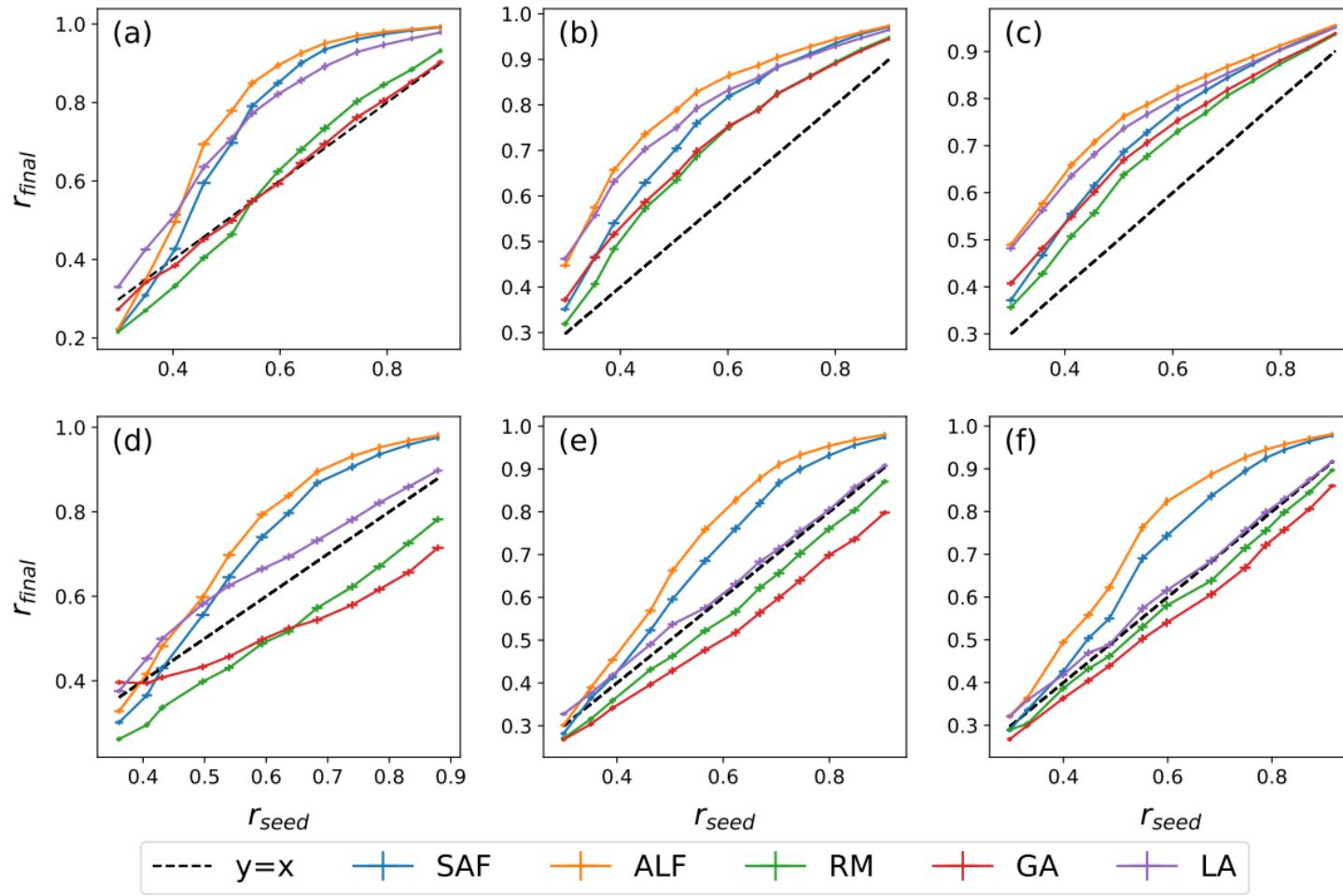


- Comparison of order parameters while growing 10 more seed networks with $N=30$
- When each column starts from a low r region, a middle region, or a high region
- ALF is good in most areas, SAF is a bit ambiguous

Optimal frequency for growing network

Introduction

Callaway



BA

- Difference between r of seed network and final r according to network size
- In rows 1, 2, and 3, the network sizes are 10~20, 30~40, and 50~60.
- ALF is good except for small networks.