

Stability analysis of ecosystems with random modular interactions

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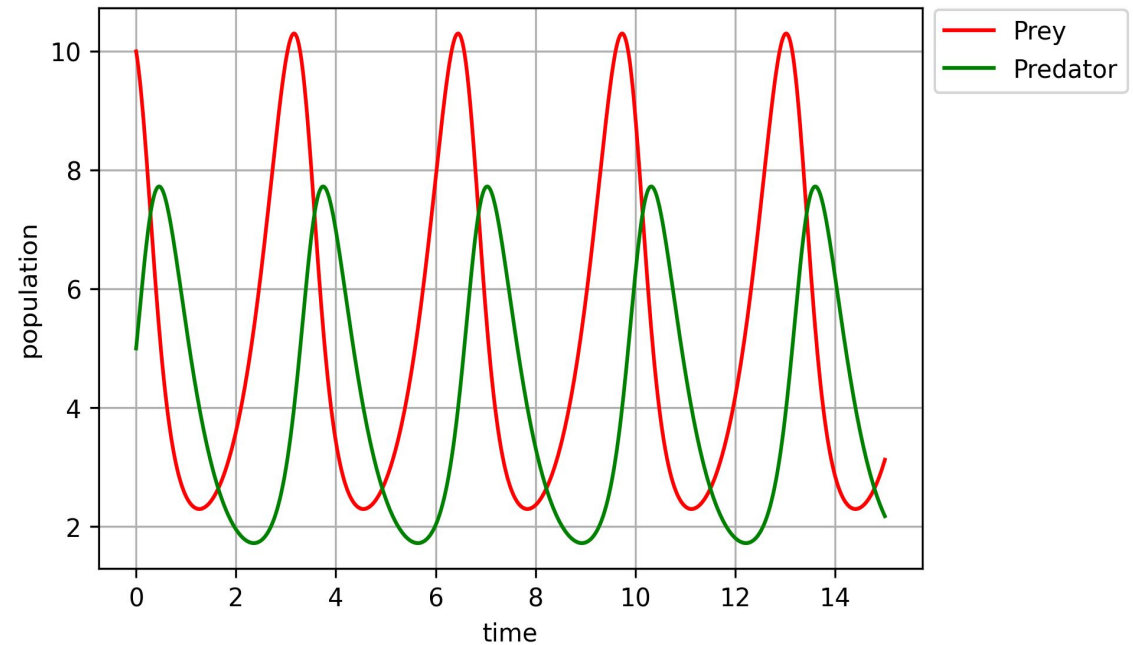
Outline of Presentation

- I. Introduction
- II. Description of the Model
- III. Theoretical Analysis
- IV. Numerical Simulations
- V. Conclusions

Introduction: Population dynamics in ecosystems

$$\frac{dx_i}{dt} = f_i(\mathbf{x}(t))$$

x_i : population of species i

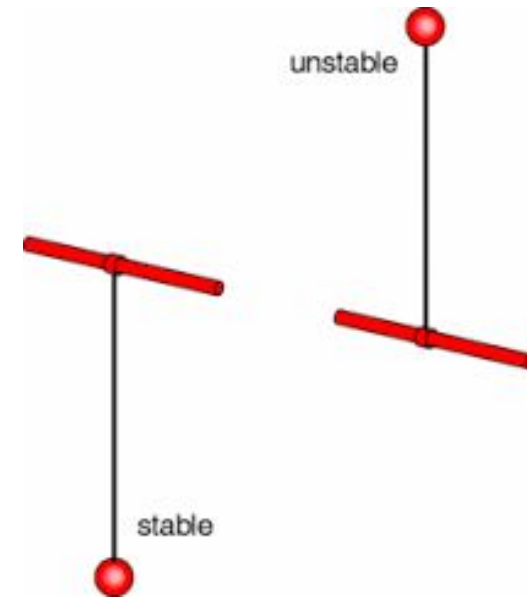


Introduction: Population dynamics in ecosystems

Get equilibrium points \boldsymbol{x}^*

$$\left. \frac{dx_i}{dt} \right|_{\boldsymbol{x}^*} = f_i(\boldsymbol{x}^*) = 0$$

\boldsymbol{x}^* can be either stable and unstable



Introduction: The Community Matrix

Using Multivariate Taylor Series

$$\frac{d\mathbf{x}}{dt} = \cancel{\mathbf{f}(\mathbf{x}^*)} + \left. \frac{\partial \mathbf{f}}{\partial \mathbf{x}} \right|_{\mathbf{x}^*} (\mathbf{x} - \mathbf{x}^*) + \dots$$

Jacobian Matrix : $\tilde{J}_{ij} = \frac{\partial f_i(\mathbf{x})}{\partial x_j}$

Community Matrix: $A = \tilde{J} \Big|_{\mathbf{x}^*}$

Introduction: Using Eigenvalue to determine stability

if we let $\tilde{\mathbf{x}} = (\mathbf{x} - \mathbf{x}^*)$

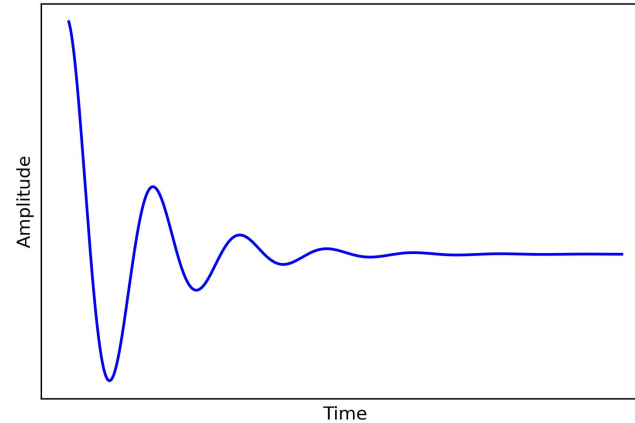
$$\frac{d\tilde{\mathbf{x}}}{dt} = \mathbf{A}\tilde{\mathbf{x}}$$

$$\tilde{\mathbf{x}}(t) = c_1 e^{\lambda_1 t} \mathbf{v}_1 + c_2 e^{\lambda_2 t} \mathbf{v}_2 + \dots + c_n e^{\lambda_n t} \mathbf{v}_n$$

where $\text{Re}(\lambda_1) > \text{Re}(\lambda_2) > \dots > \text{Re}(\lambda_n)$

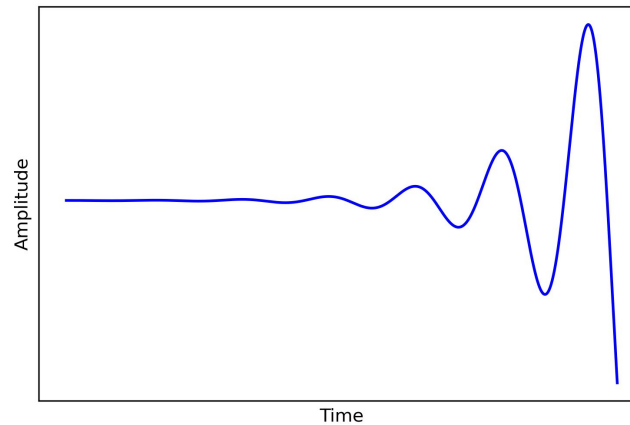
Introduction: Using Eigenvalue to determine stability

$$\operatorname{Re}(\lambda_1) < 0$$



stable

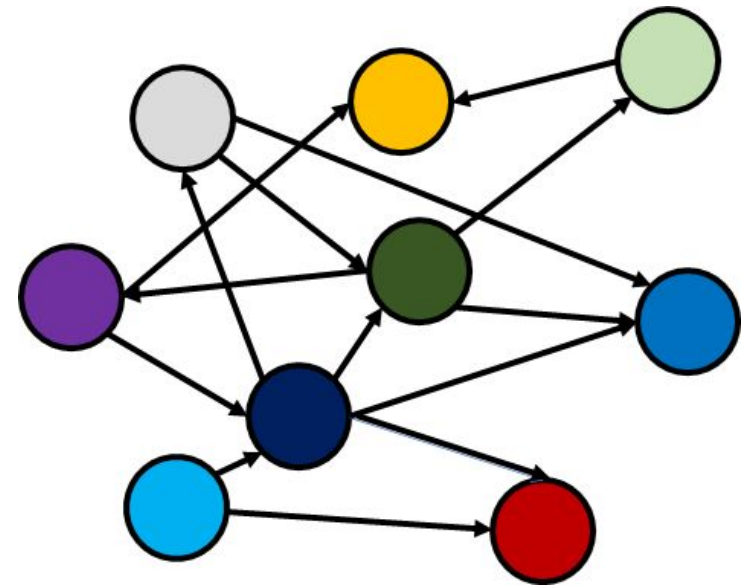
$$\operatorname{Re}(\lambda_1) > 0$$



unstable

Introduction: Community matrix as the Adjacency Matrix

$$\mathbf{A} = \begin{pmatrix} 3.546 & 2.234 & \dots & 1 \\ \vdots & \ddots & 0 & -0.2 \\ -1.456 & 0.45 & \dots & 3 \end{pmatrix}$$



Introduction: Using Random matrices in ecological dynamics analysis



Robert May

- Robert May: Random Matrix as Community Matrix
- Condition of stability for a general (fully-connected) random matrix:

$$\sqrt{SC\sigma^2} < d$$

where

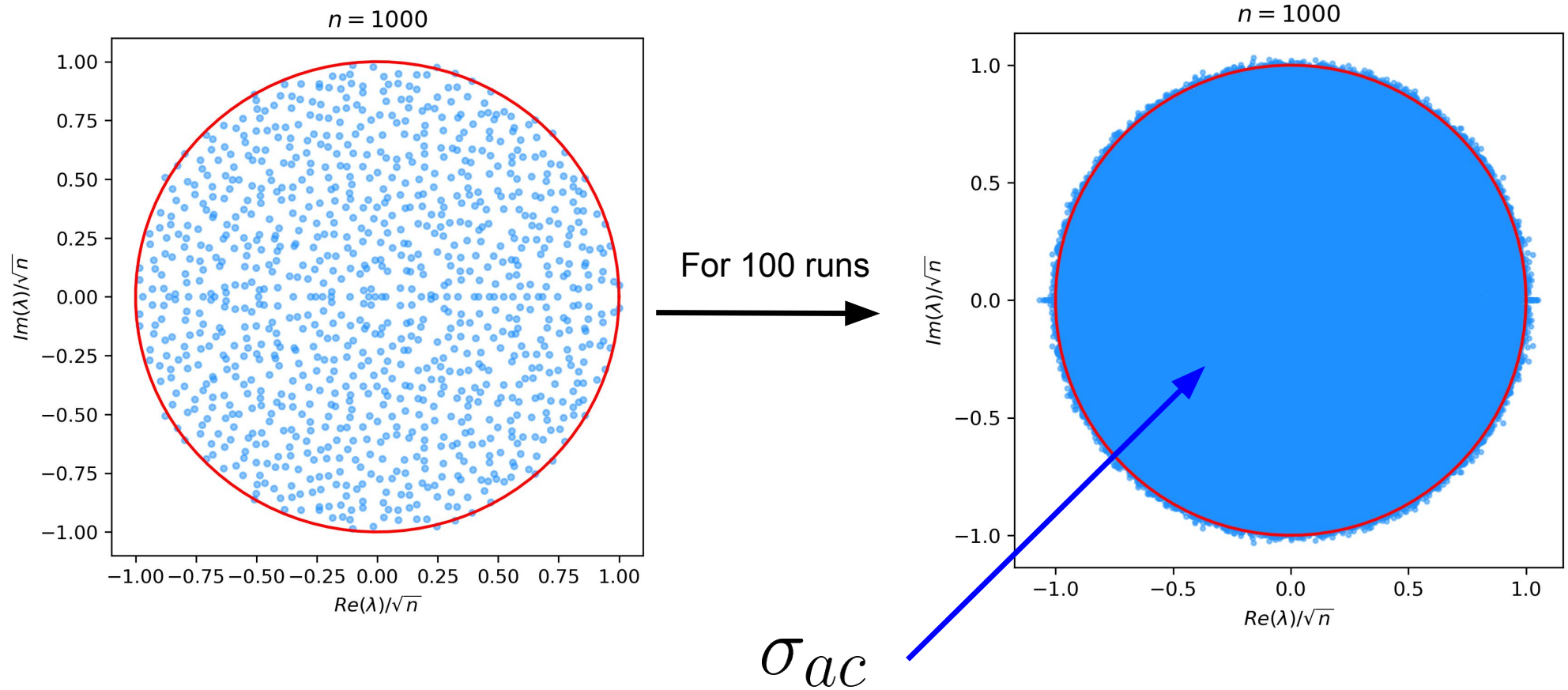
S : size of matrix

C : connentance of matrix

σ^2 : variance of the elements

d : diagonal elements

Self-Averaging of Random Matrices



Introduction: Problems of May's approach

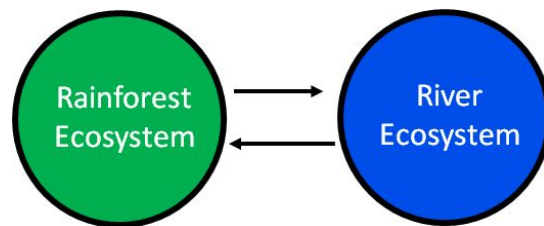


Robert May

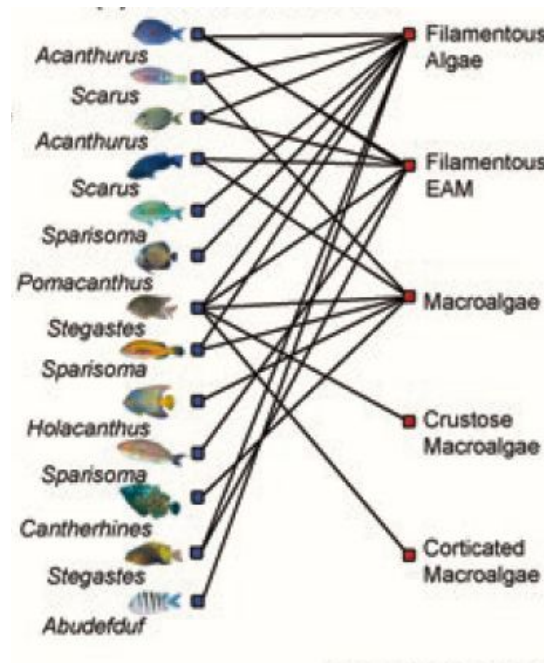
- However, May emphasize the importance of studying different network structures to model ecological communities realistically.
- For very large food webs, the connection between nodes are sparse. What happens if the matrix becomes sparser and more structured?

Introduction: Network Structures in an Ecosystem

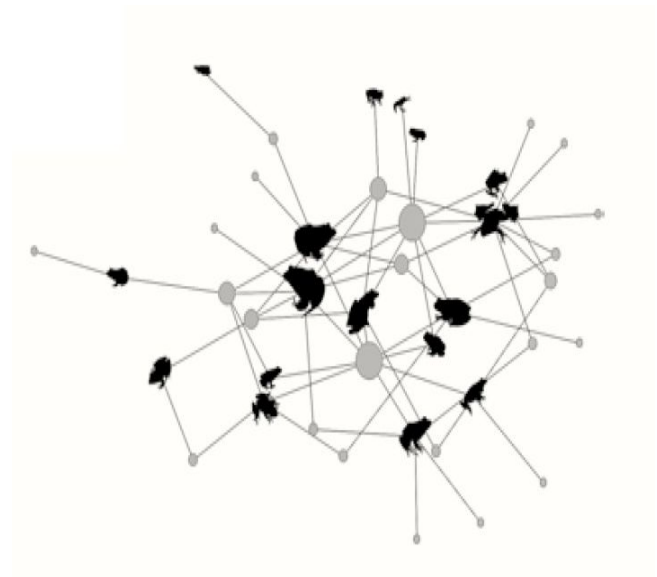
In reality, food webs can be of the following structure (but not limited to):



Modular



Bipartite



Core-periphery

Description of the model

$$A_{ij} = C_{ij} - D\delta_{ij}$$

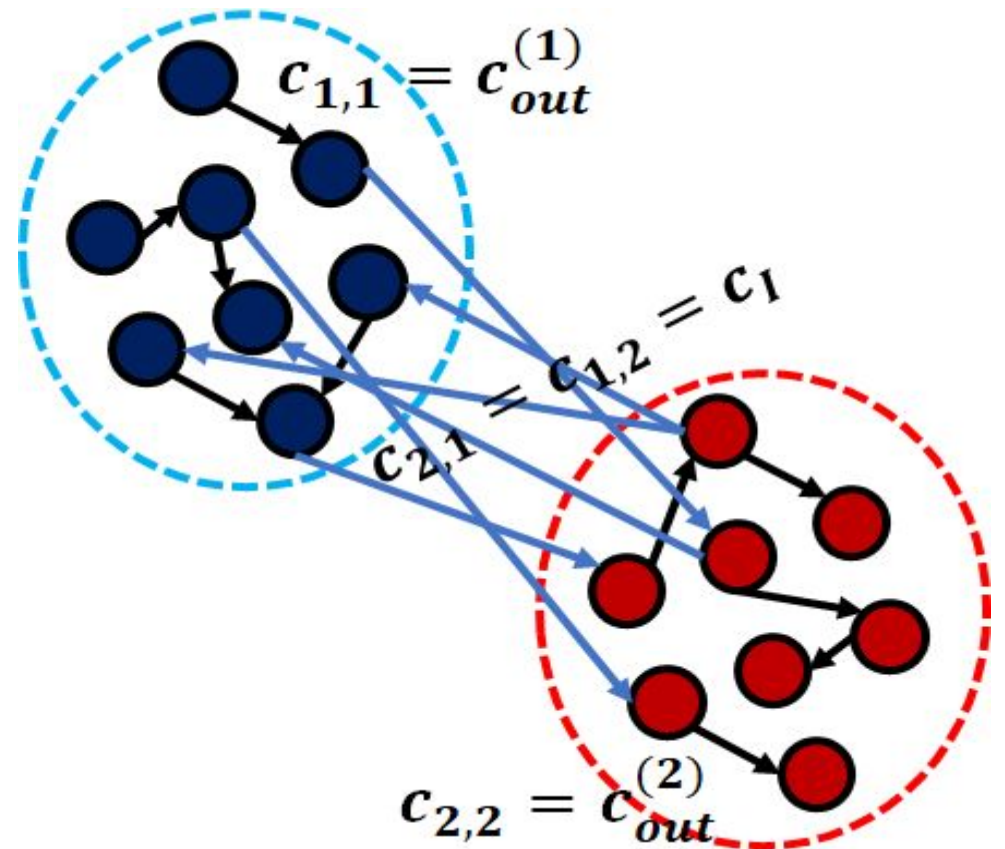
where $C_{ij} \in \{0, 1\}$

$$\mathbf{A} = \begin{pmatrix} \mathbf{C}^{(1)} & \boldsymbol{\alpha} \\ \boldsymbol{\beta} & \mathbf{C}^{(2)} \end{pmatrix}$$

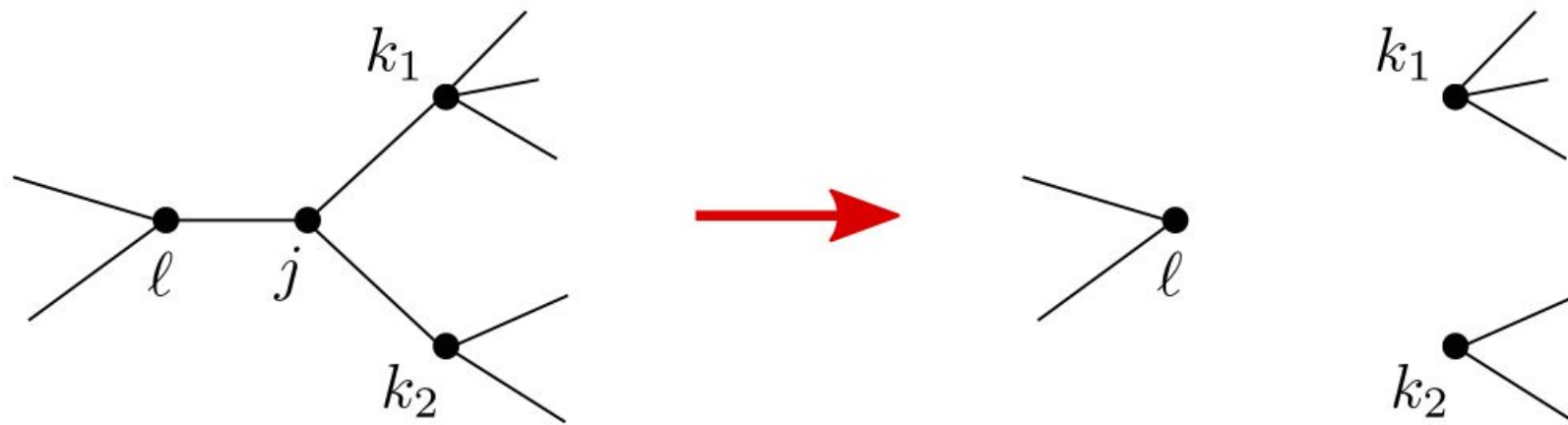
Each block is controlled by a connectivity parameter:

$$p_{u,v} = c_{u,v}/n$$

u, v : communities , n : no. of species per community



Right eigenvector of oriented sparse locally tree-like matrices

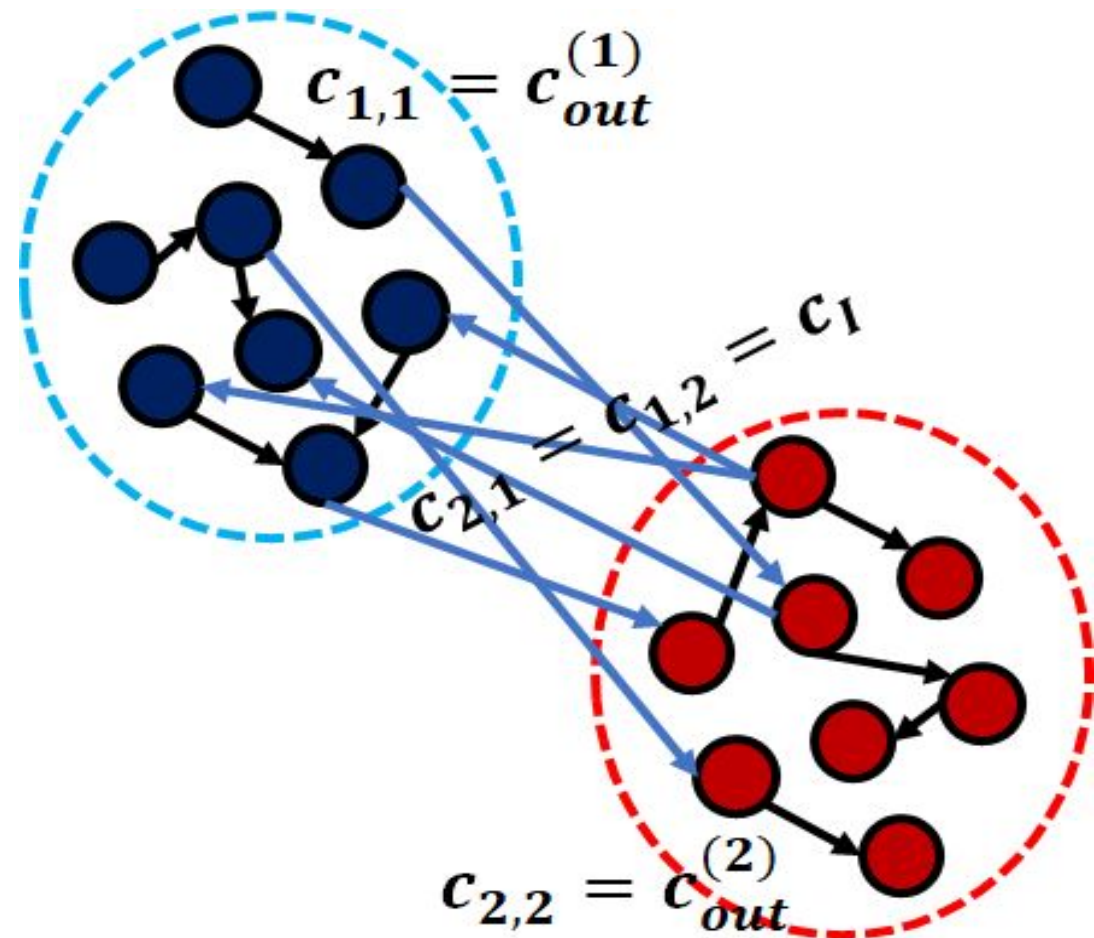


$$R_j = \frac{1}{z + D} \sum_{k \in \partial_j^{\text{out}}} R_k, \quad z \notin \sigma_{\text{ac}}$$

Two-community structure

Splitting the right eigenvector into $R^{(1)}$ and $R^{(2)}$

$$R = \begin{pmatrix} R^{(1)} \\ R^{(2)} \end{pmatrix}$$



Two-community structure

$$R_j^{(1)} = \frac{1}{z + D} \sum_{k \in \partial_j^{\text{out}}, k \in \mathbf{C}^{(1)}} R_k^{(1)} + \frac{1}{z + D} \sum_{k' \in \partial_j^{\text{out}}, k' \in \mathbf{C}^{(2)}} R_{k'}^{(2)}$$

$$R_j^{(2)} = \frac{1}{z + D} \sum_{k \in \partial_j^{\text{out}}, k \in \mathbf{C}^{(1)}} R_k^{(1)} + \frac{1}{z + D} \sum_{k' \in \partial_j^{\text{out}}, k' \in \mathbf{C}^{(2)}} R_{k'}^{(2)}$$

Equations for the first moments

$$\langle R^{(1)} \rangle = \frac{1}{z + D} \left[c_{\text{out}}^{(1)} \langle R^{(1)} \rangle \right] + \frac{1}{z + D} \left[c_I \langle R^{(2)} \rangle \right]$$

$$\langle R^{(2)} \rangle = \frac{1}{z + D} \left[c_I \langle R^{(1)} \rangle \right] + \frac{1}{z + D} \left[c_{\text{out}}^{(2)} \langle R^{(2)} \rangle \right]$$

The outlier

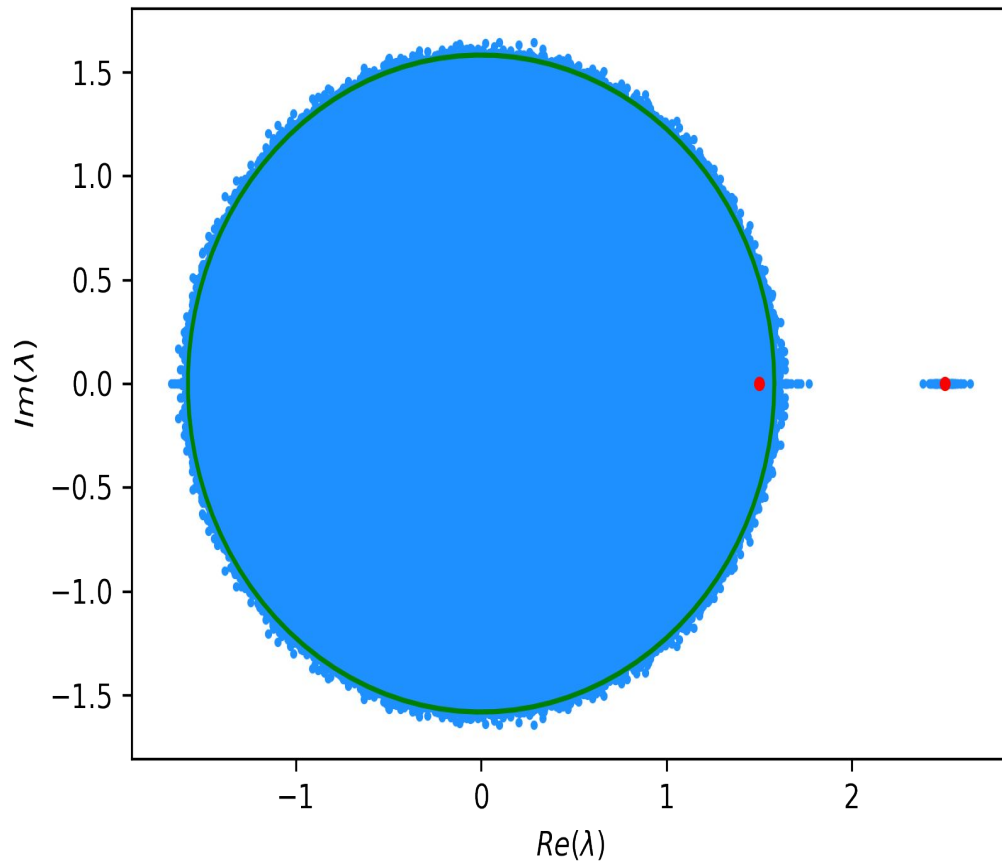
$$z = -D + \frac{c_{\text{out}}^{(2)} + c_{\text{out}}^{(1)}}{2} \pm \frac{\sqrt{\left(c_{\text{out}}^{(2)} - c_{\text{out}}^{(1)}\right)^2 + 4c_I^2}}{2},$$

The boundary of the continuous part

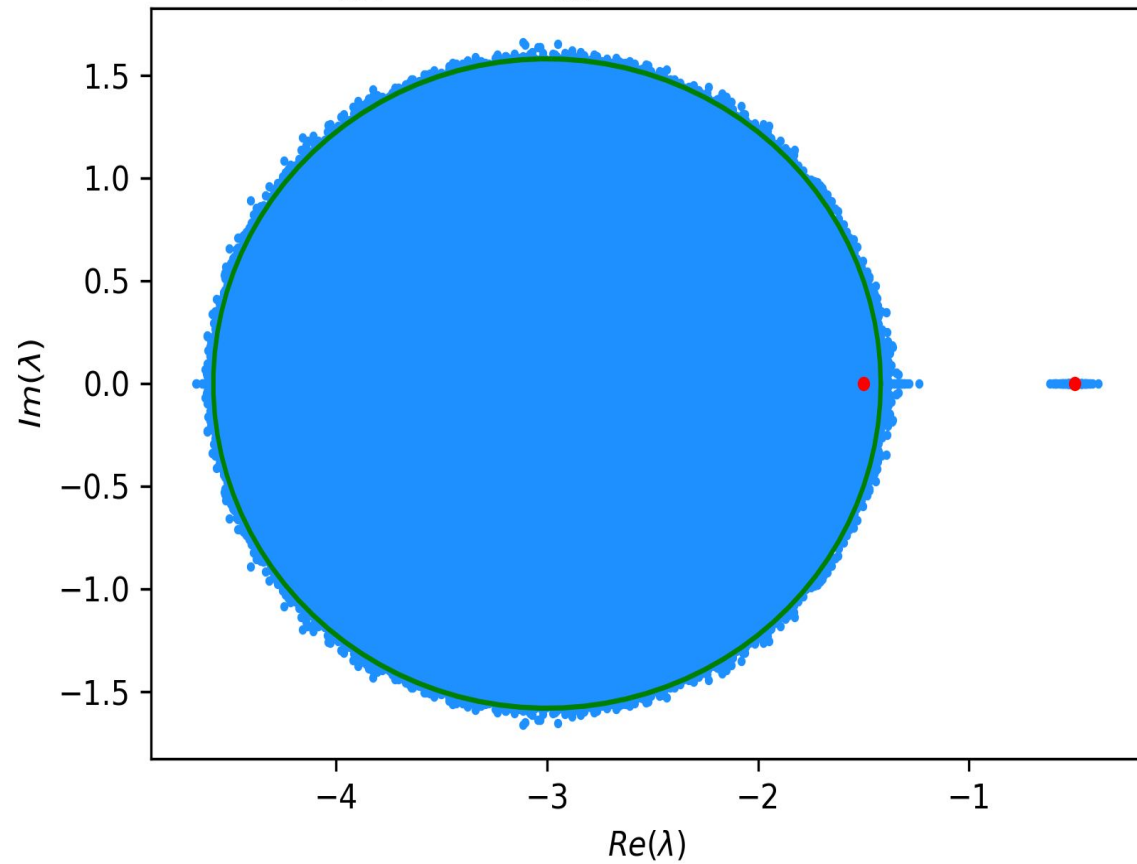
$$|z + D|^2 = \frac{c_{\text{out}}^{(2)} + c_{\text{out}}^{(1)}}{2} \pm \frac{\sqrt{\left(c_{\text{out}}^{(2)} - c_{\text{out}}^{(1)}\right)^2 + 4c_I^2}}{2},$$

Two-modular networks

$$c_{out}^{(1)} = 2.01, c_{out}^{(2)} = 1.99, c_l = 0.5$$

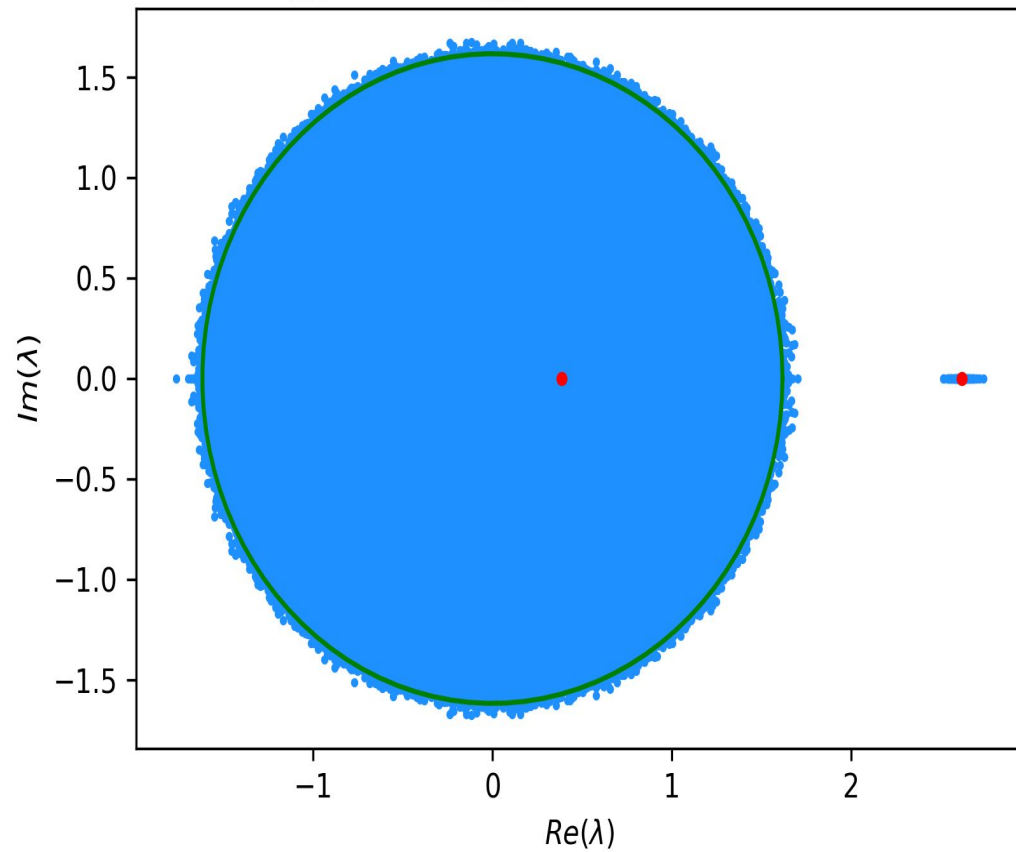


$$c_{out}^{(1)} = 2.0, c_{out}^{(2)} = 2.0, c_l = 0.5, D = 3$$

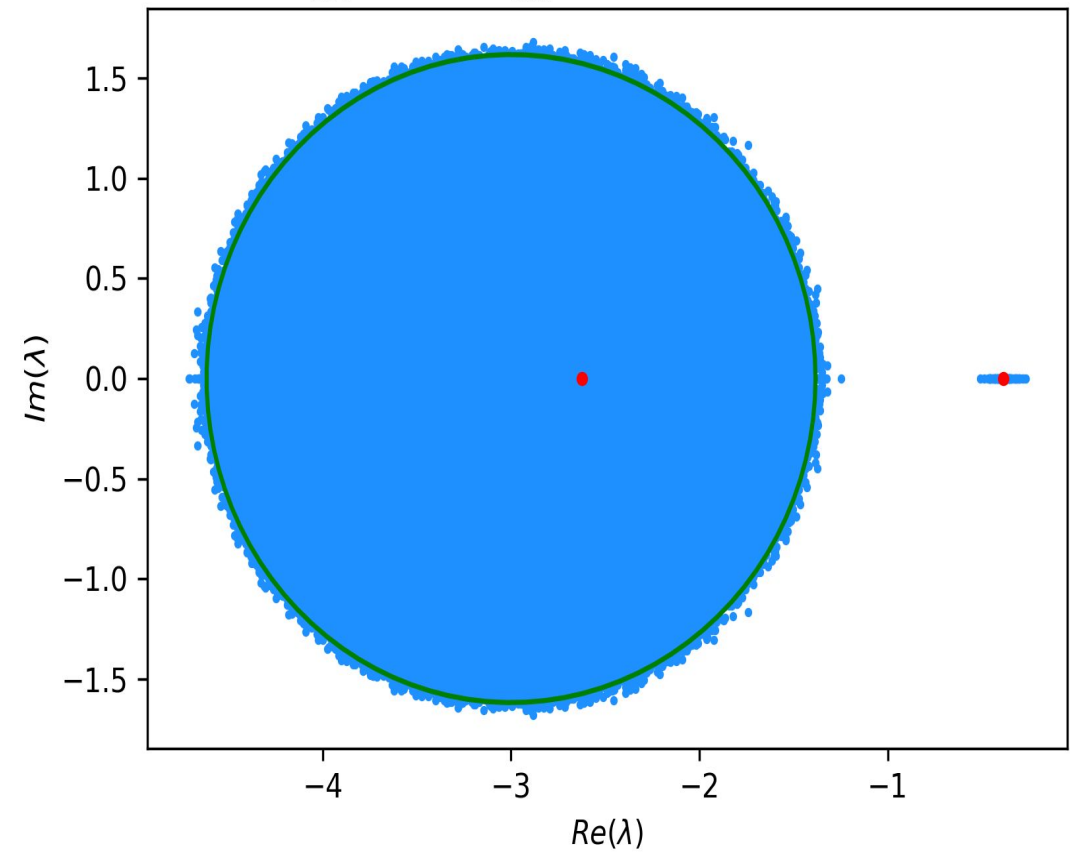


Core-periphery networks

$c_{out}^{(1)} = 2.0$, $c_{out}^{(2)} = 1.0$, $c_l = 1.0$, $D = 0$

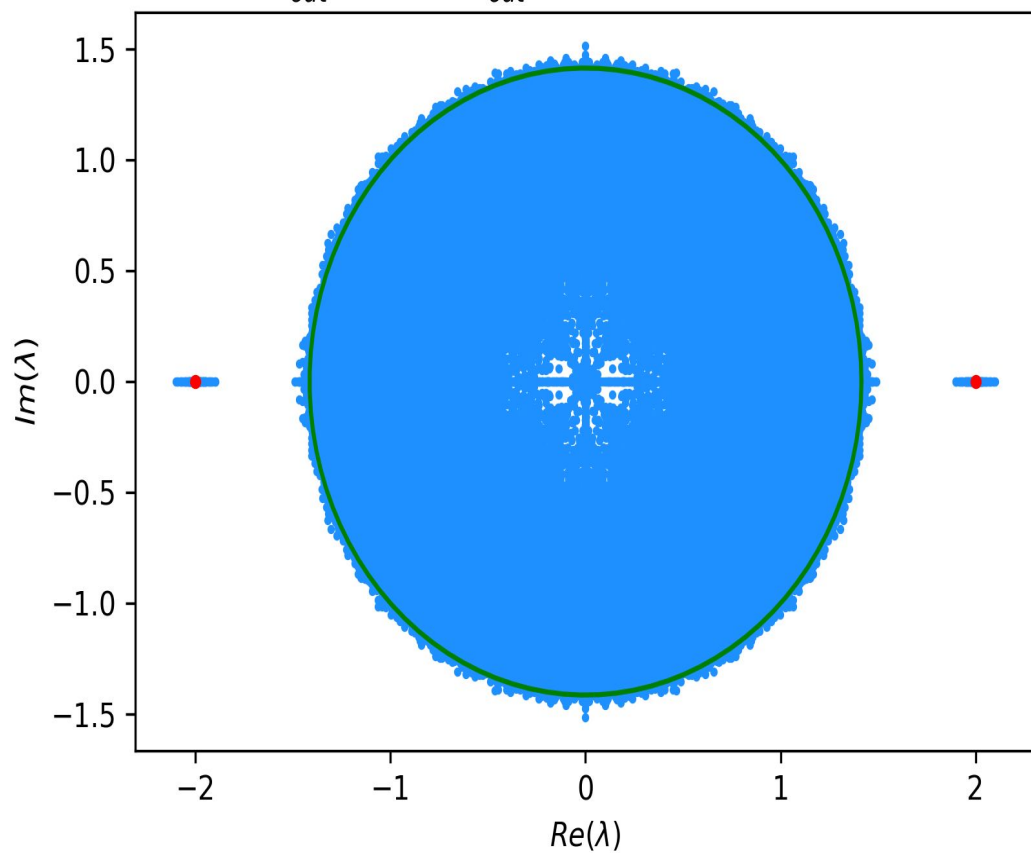


$c_{out}^{(1)} = 2.0$, $c_{out}^{(2)} = 0.99$, $c_l = 1.0$, $D = 3$

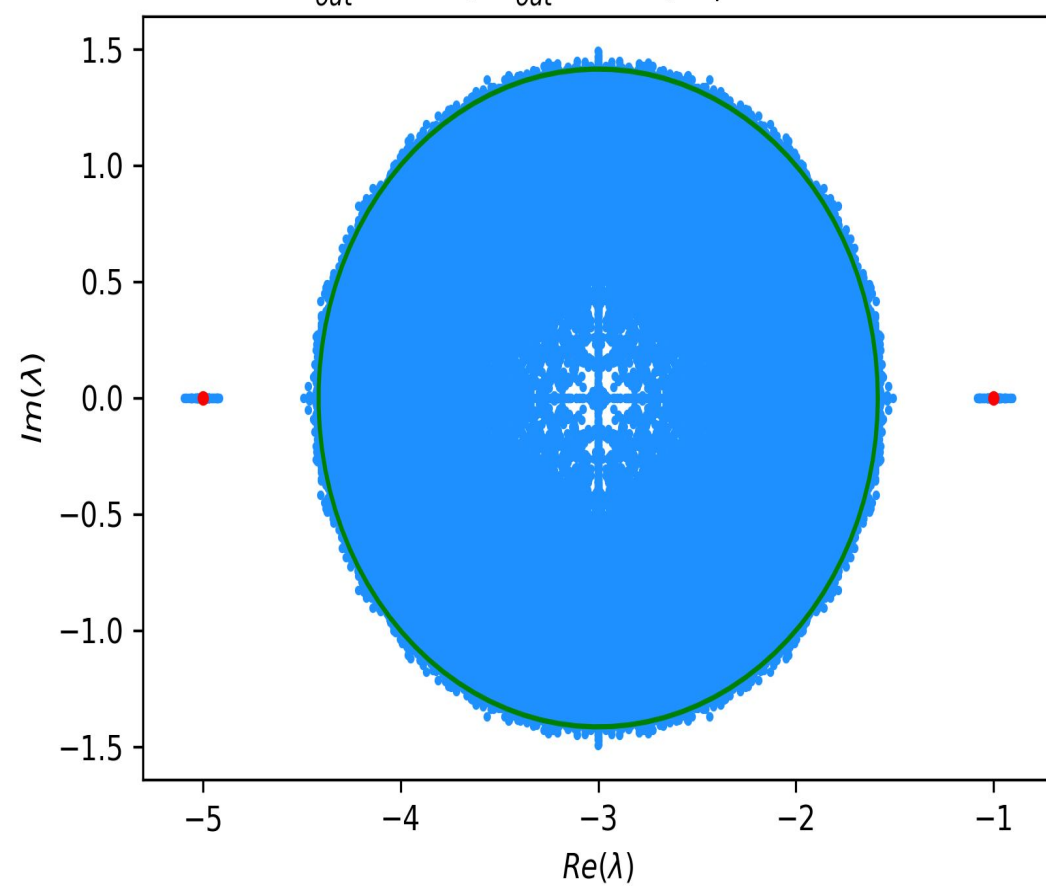


Bi-partite networks

$c_{out}^{(1)} = 0.0$, $c_{out}^{(2)} = 0.0$, $c_I = 2.0$, $D = 0$

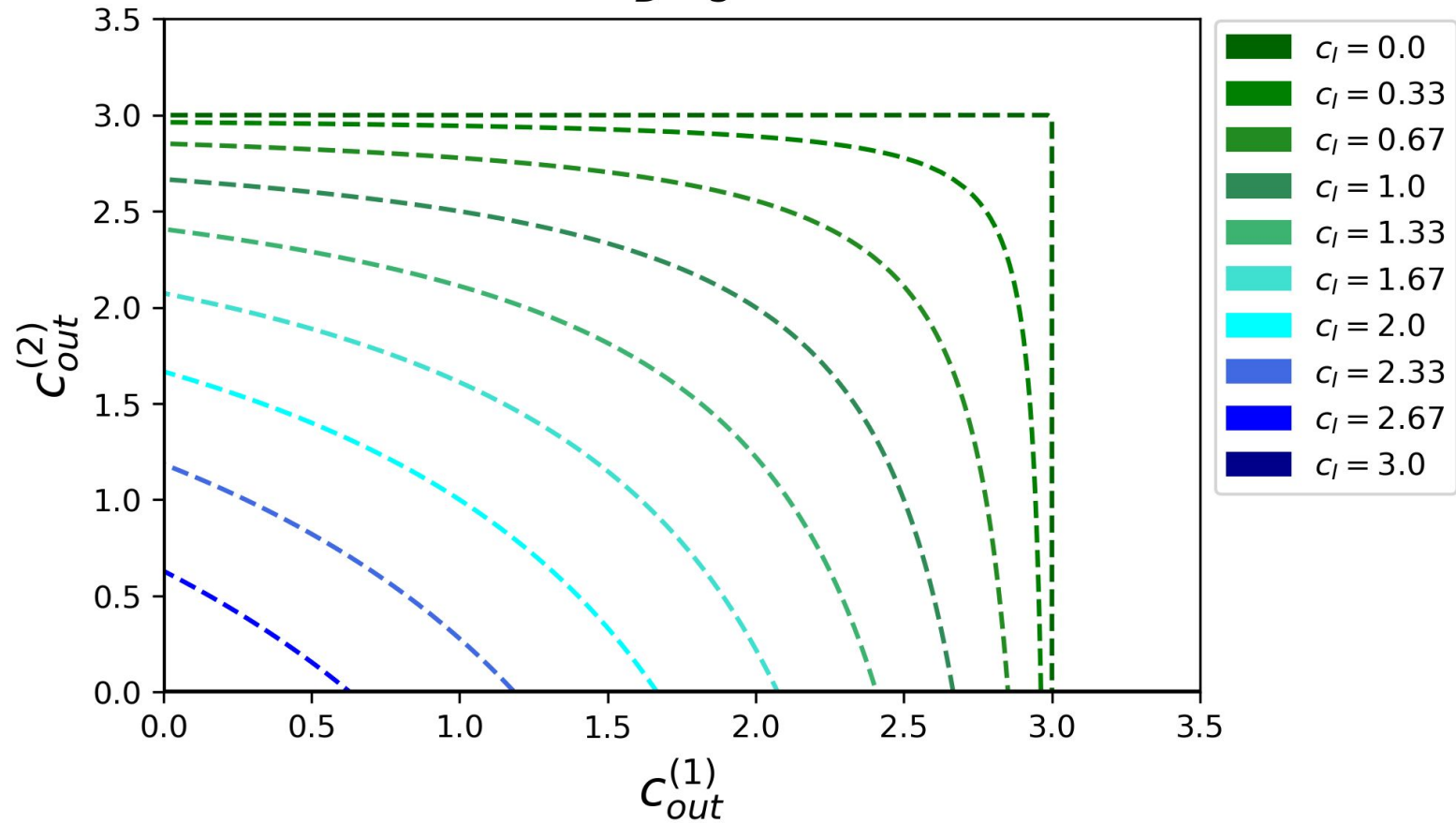


$c_{out}^{(1)} = 0.0$, $c_{out}^{(2)} = 0.0$, $c_I = 2.0$, $D = 3$



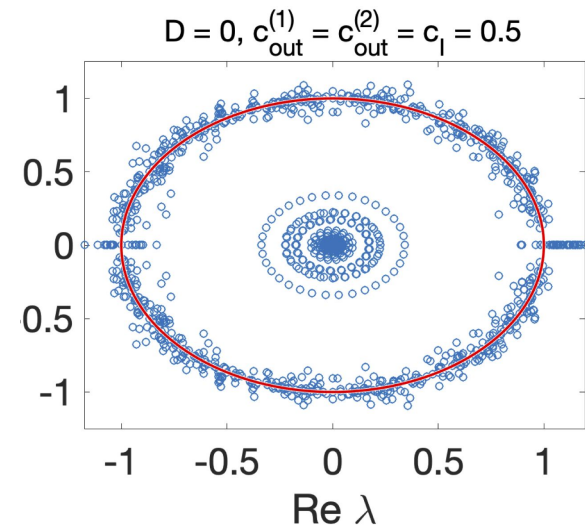
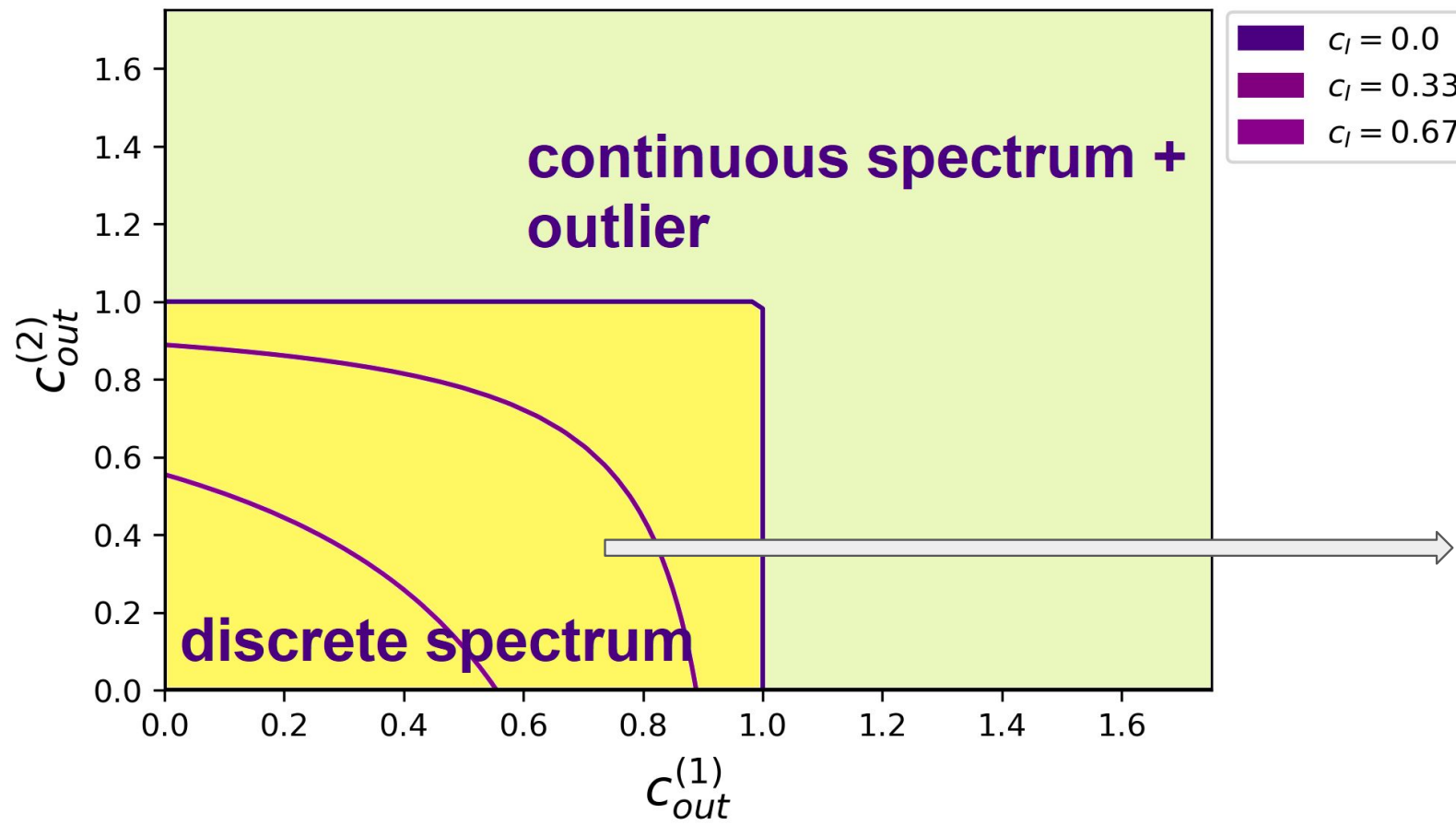
Stability -- Instability diagram

$D = 3$



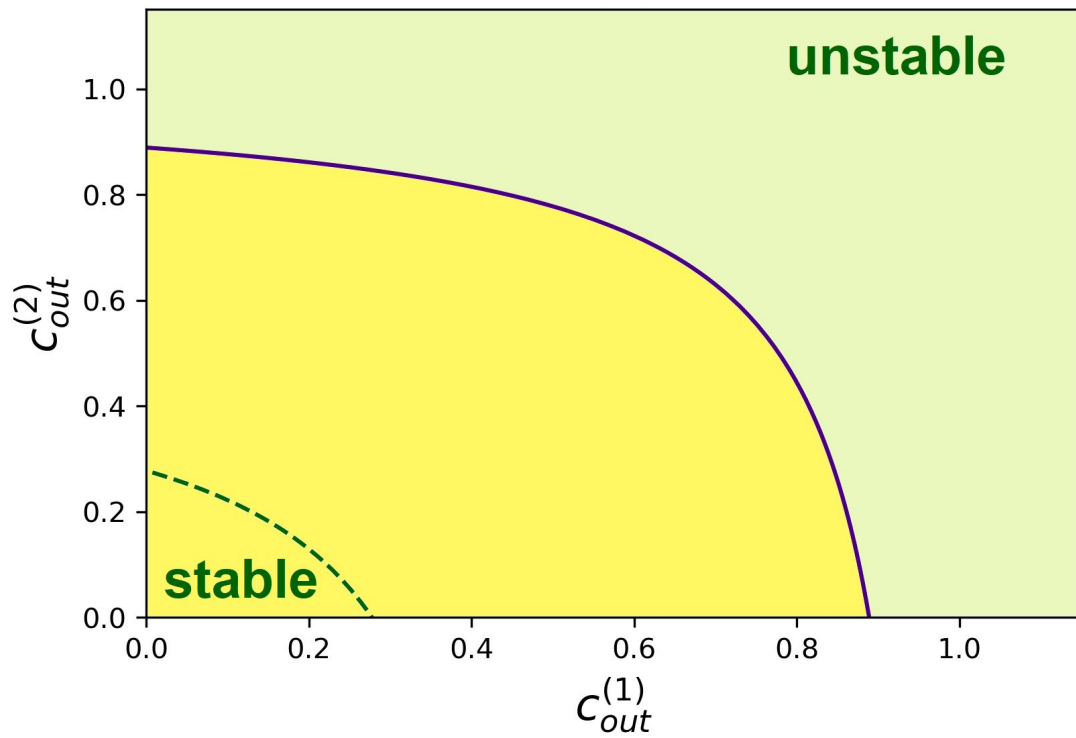
$$c_I^2 - c_{out}^{(1)} c_{out}^{(2)} + D(c_{out}^{(1)} + c_{out}^{(2)}) < D^2$$

The existence of spectral gap

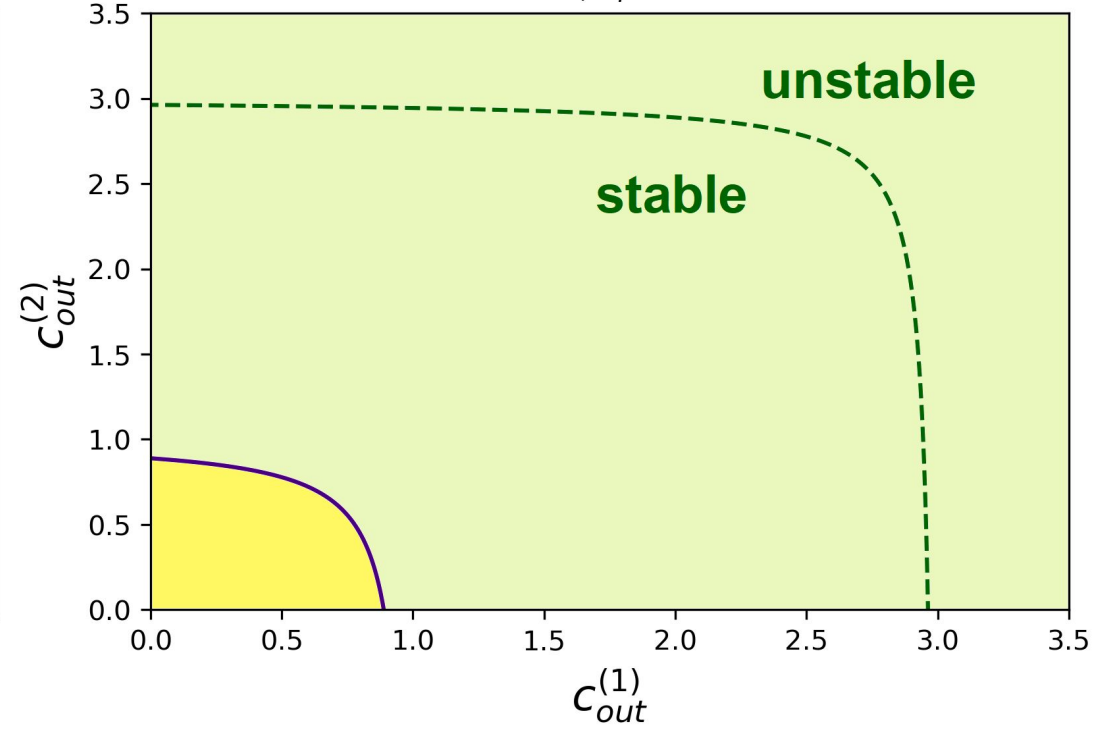


Combination of the two diagrams

$D = 0.5, c_l = 0.33$



$D = 3, c_l = 0.33$



Conclusion & Future work

- Outlier and boundary of the bulk of the spectrum are found analytically
- Condition for the existence of gap between the outlier and the bulk
- Condition for the system stability
- Modular structure is more stable than the core-periphery one

Future work

Localisation of the eigenvectors

Multimodular structure

Weighted and degree-correlated graphs