

Diversity of Core-Periphery Structure in Real Networks

Ryan J. Gallagher

 @ryanjgallag



Northeastern University
Network Science Institute

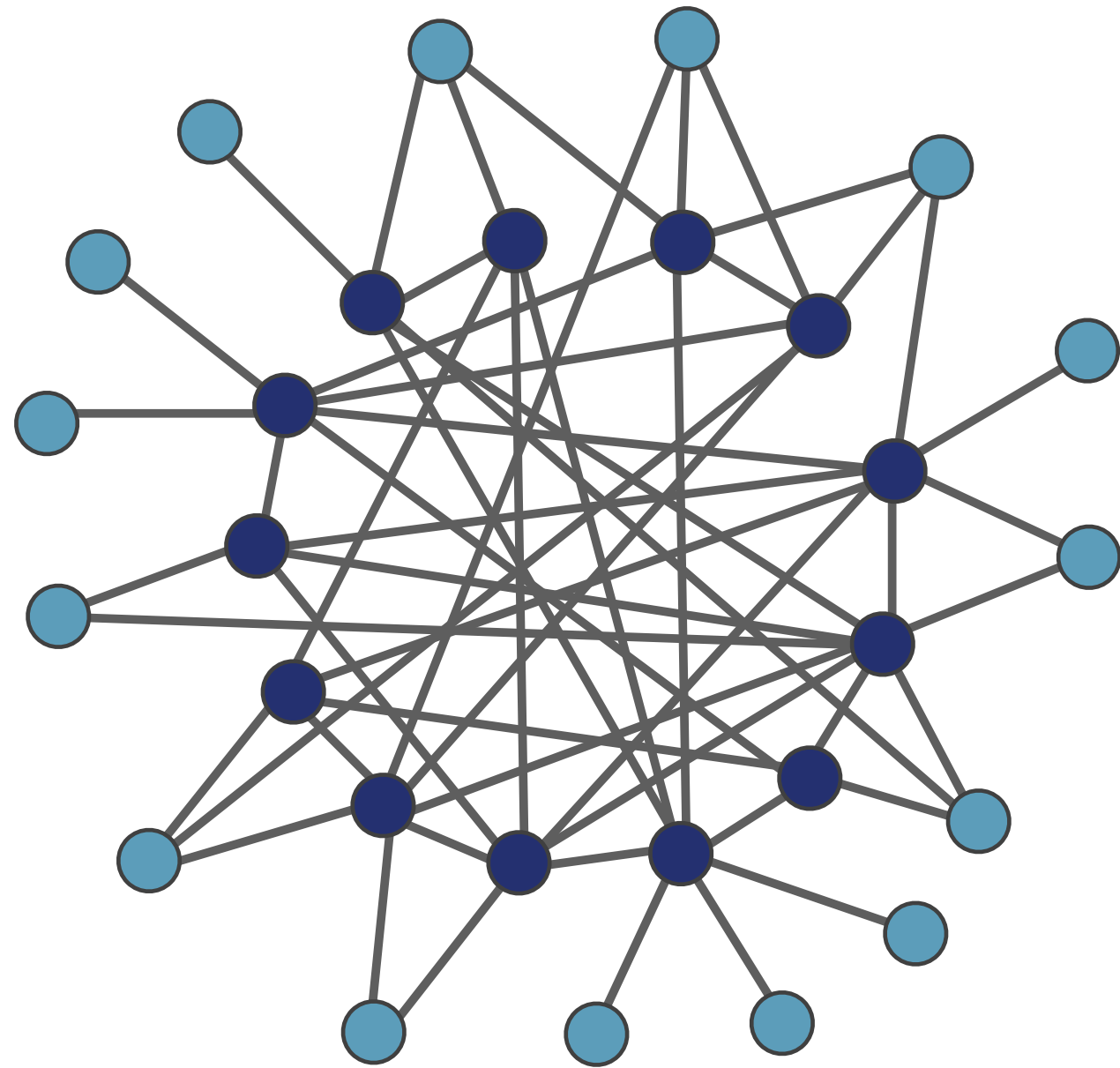
What is core-periphery structure?

Core-Periphery Structure

Two-Block Model

“Core nodes are adjacent to other core nodes, core nodes are adjacent to some periphery nodes, and periphery nodes do not connect with other periphery nodes.”

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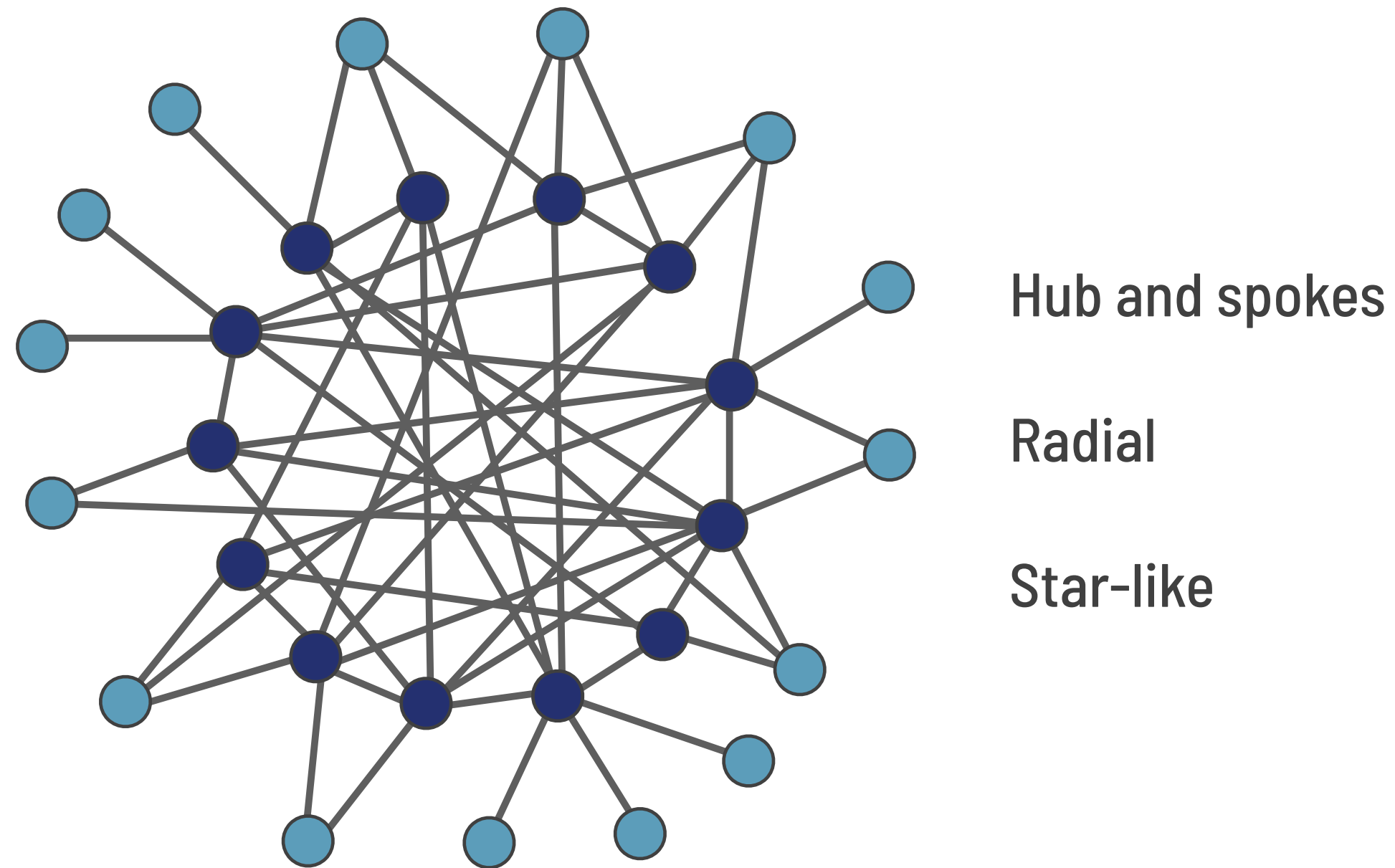


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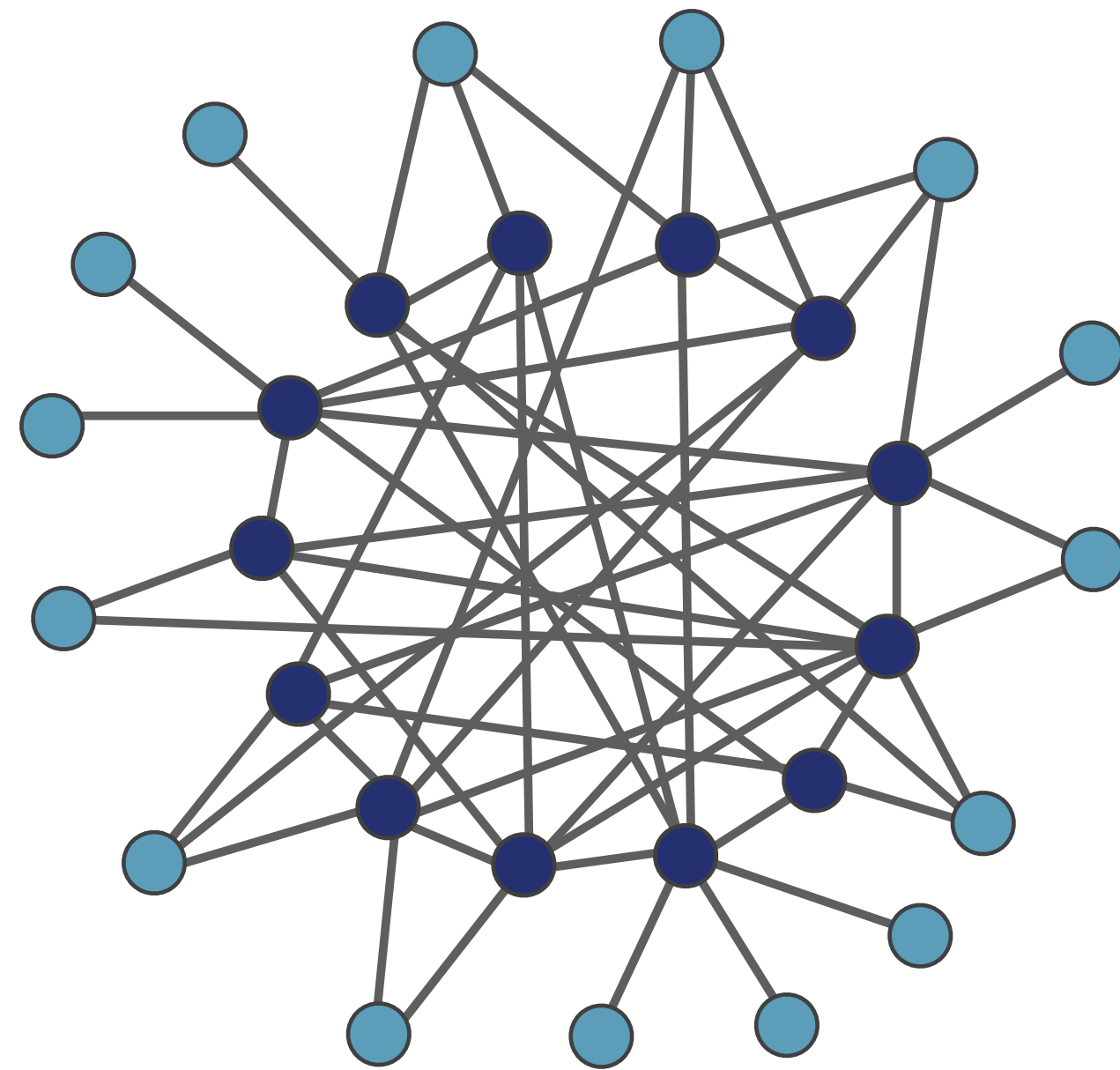


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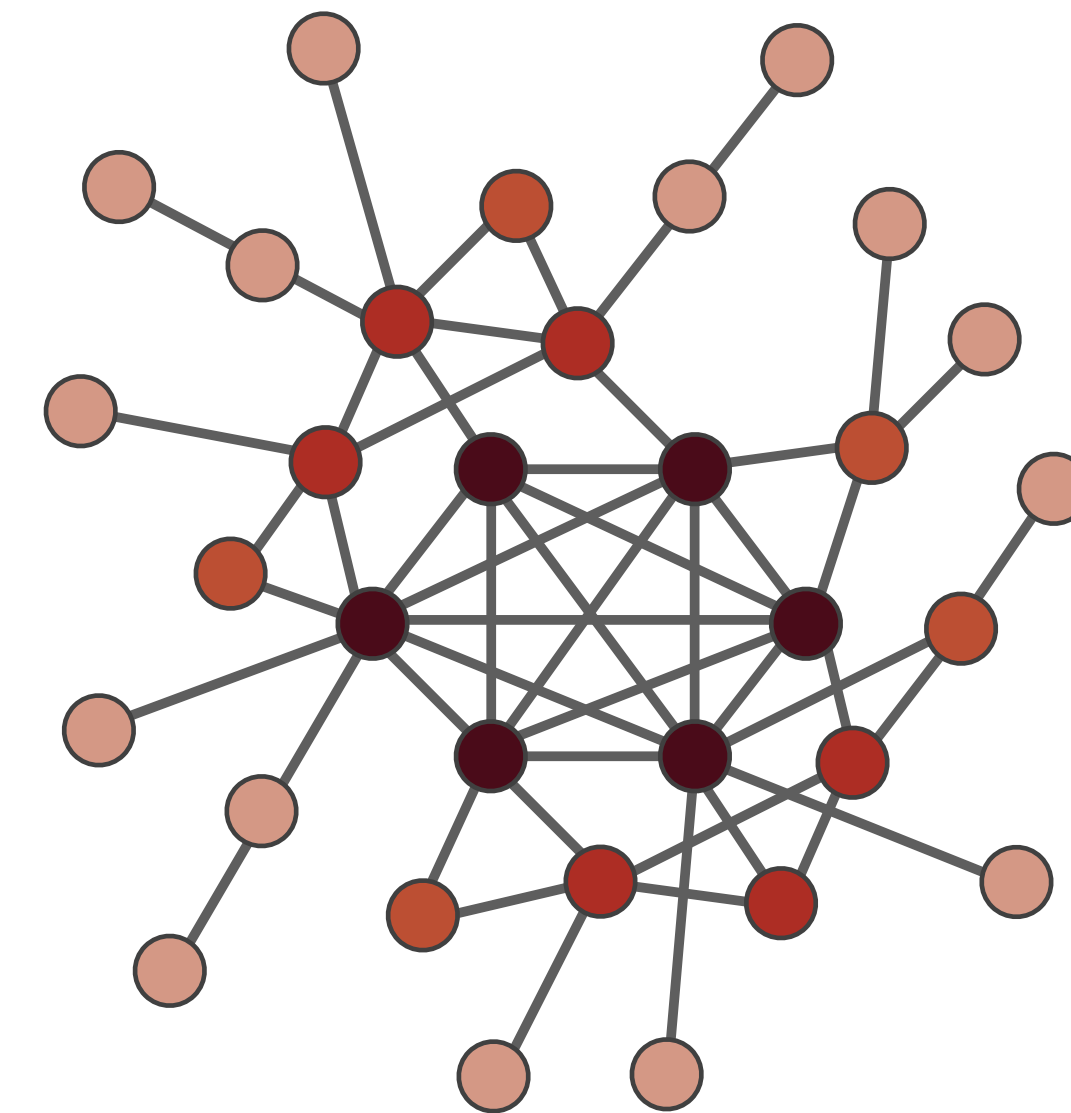
Hub and spokes

Radial

Star-like

k -Cores Decomposition

The k -core of a network is the maximal subnetwork such that every node has at least k connections.

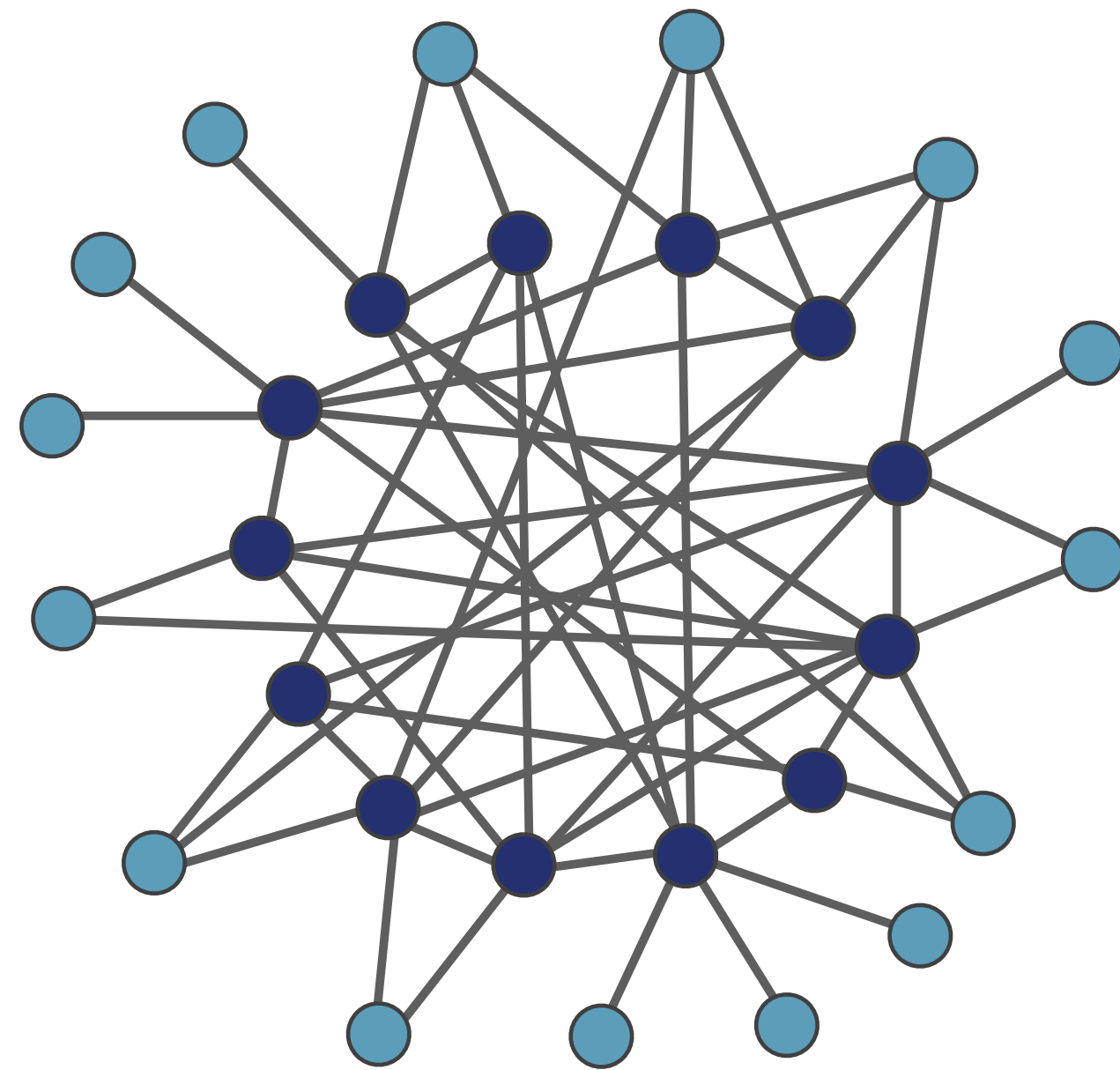


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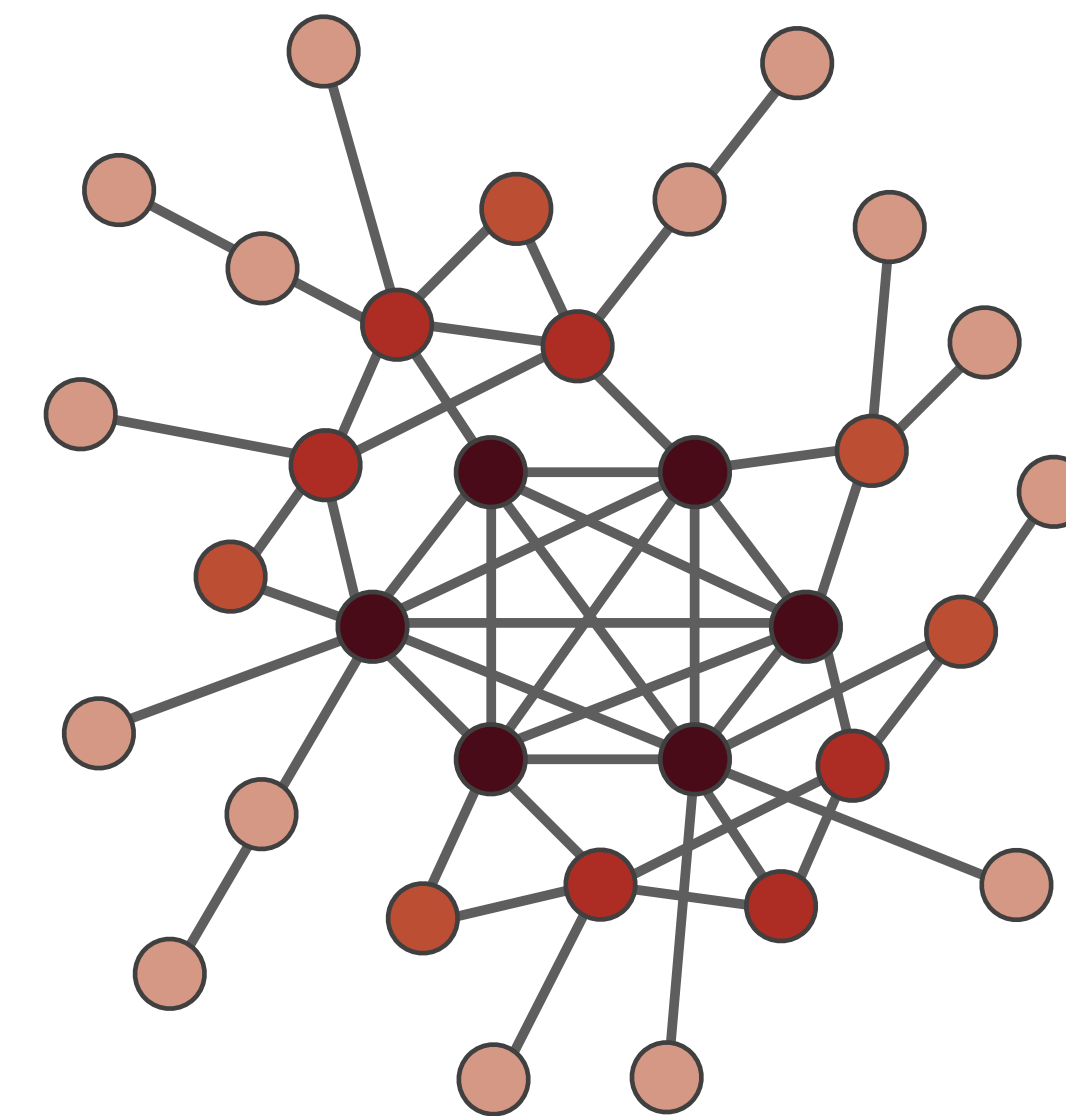
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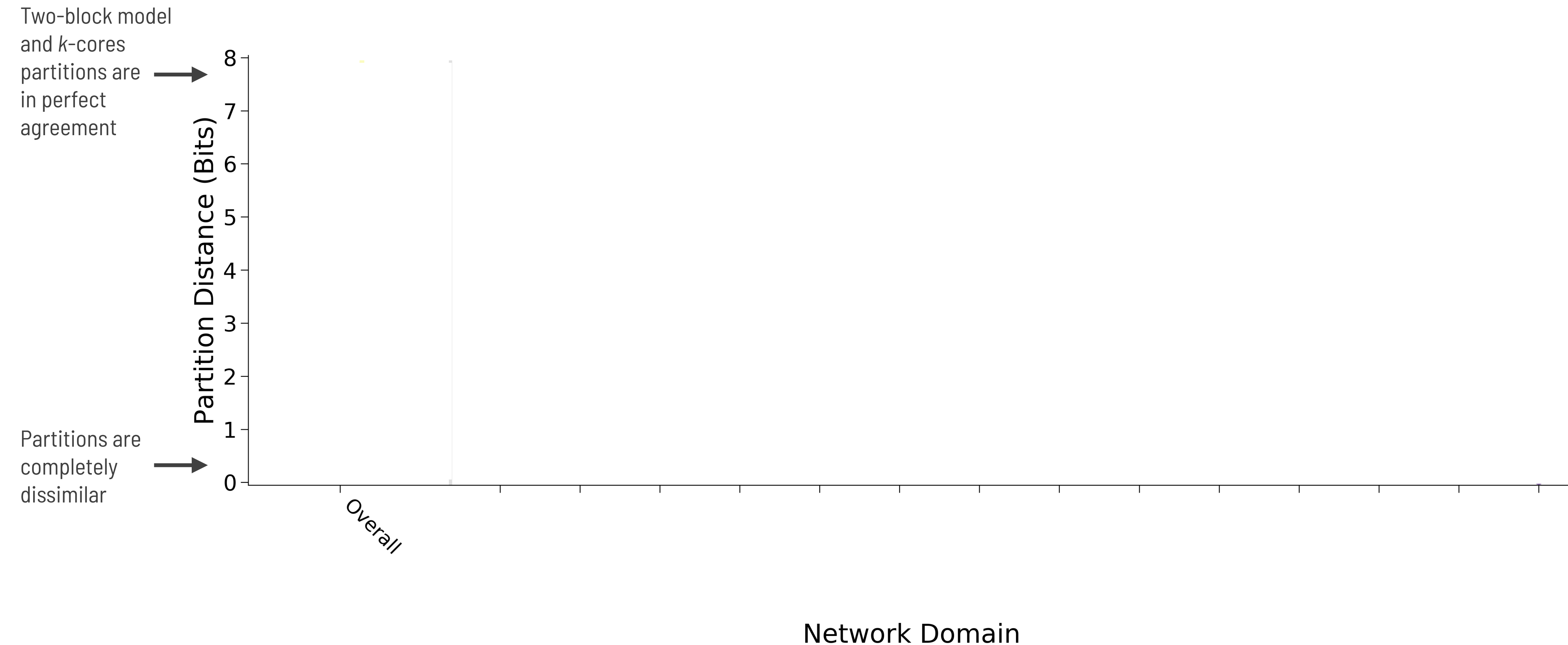


Layers

Hierarchy

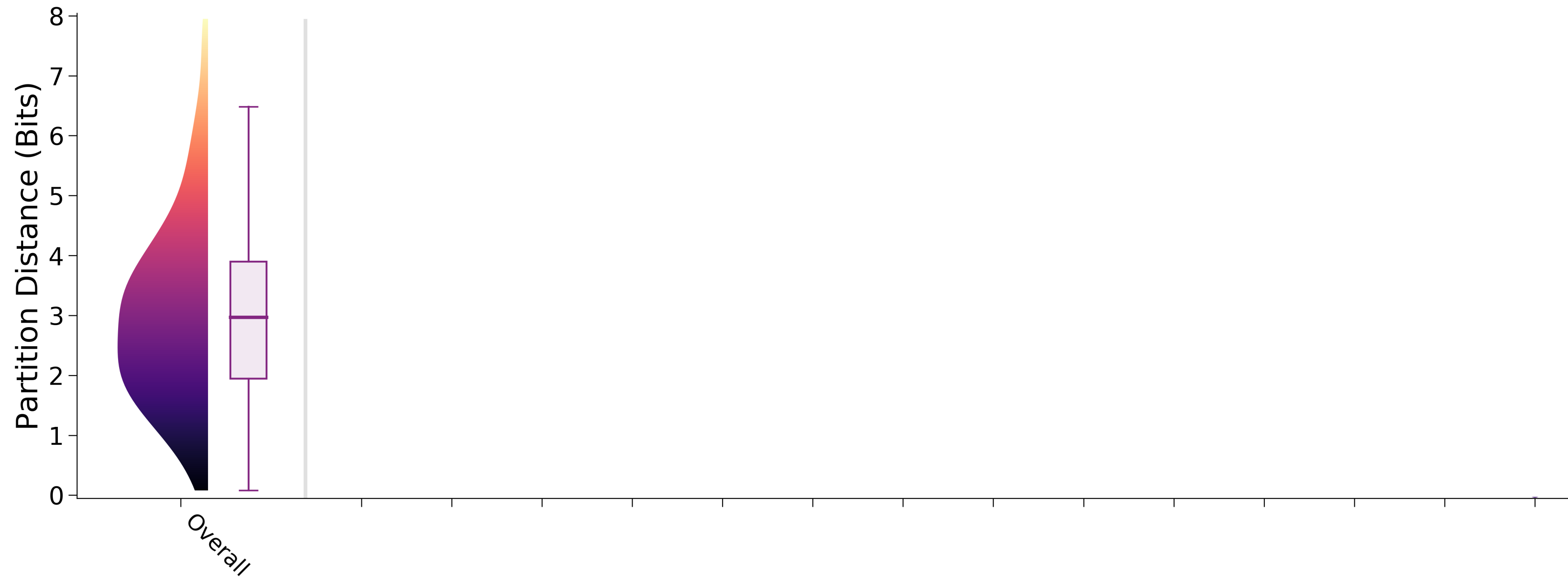
Shells

Core-Periphery Partition Comparison



Jérôme Kunegis. "KONECT—The Koblenz Network Collection." In *Proceedings Int. Conf. on World Wide Web Companion*, 2013.

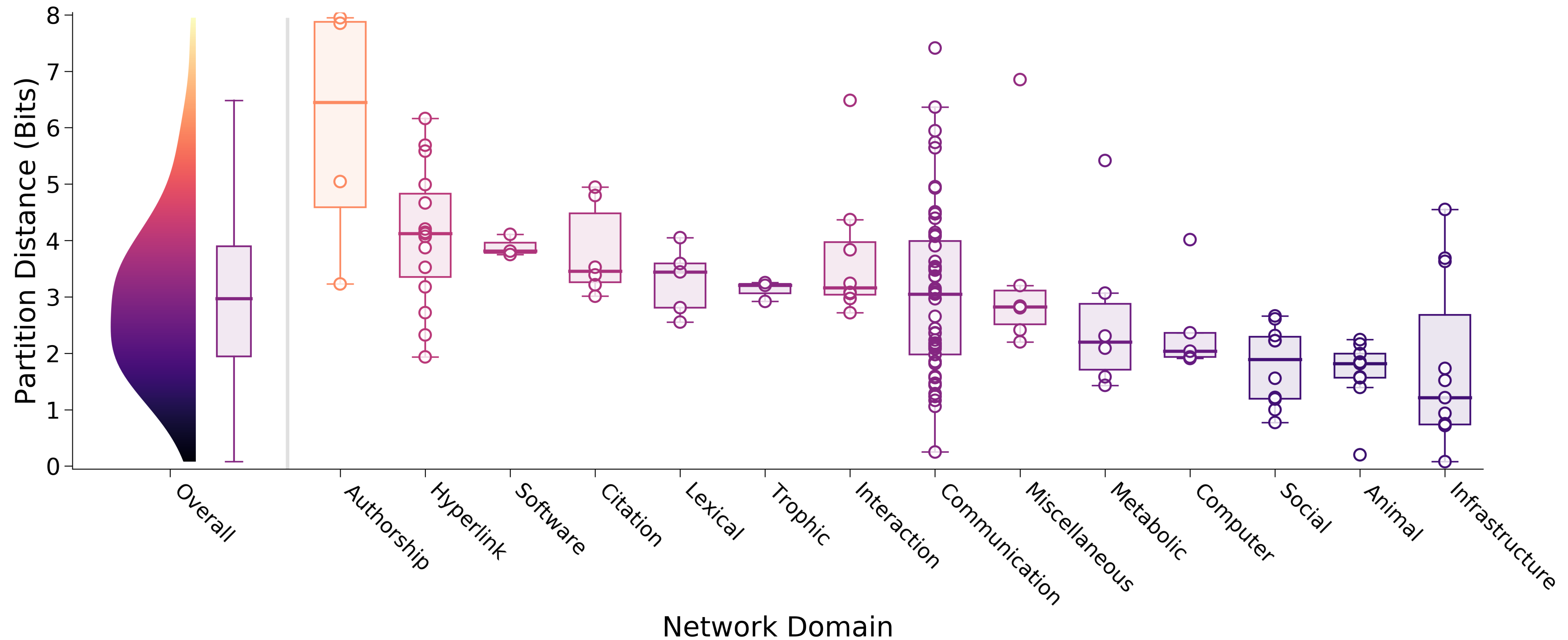
Core-Periphery Partition Comparison



Network Domain

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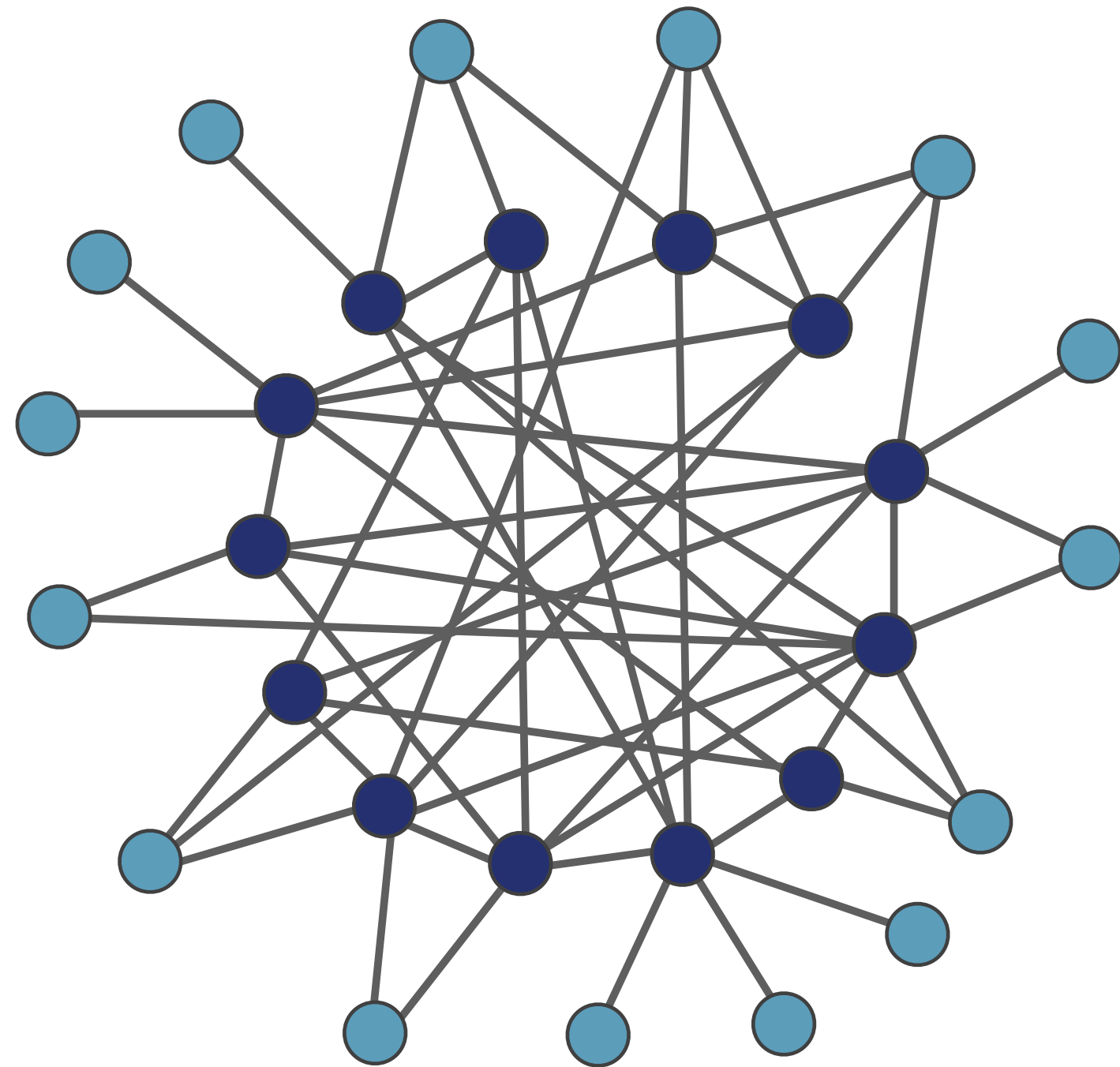


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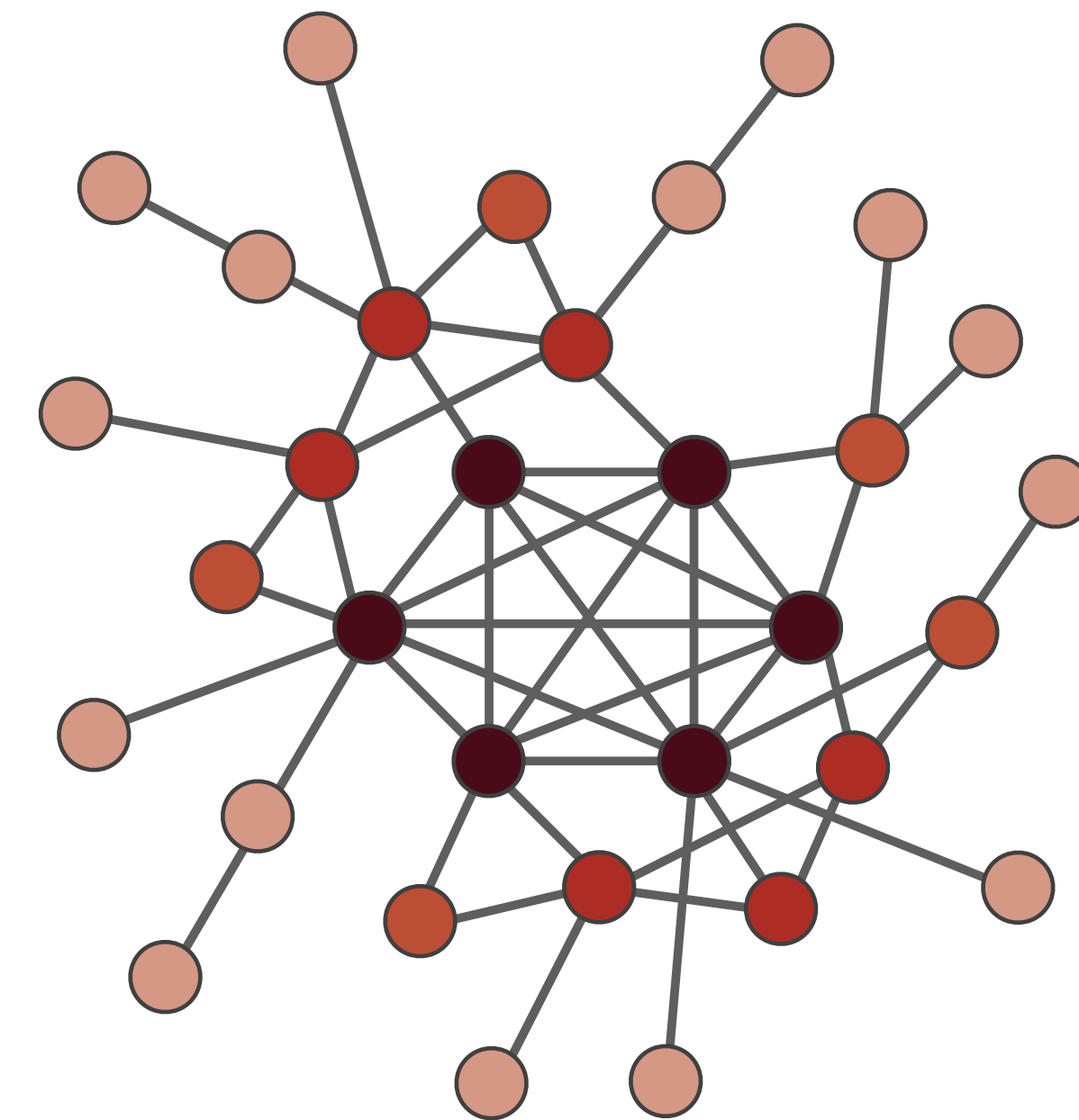
Core-Periphery Typology

The two-block model and the k -cores decomposition exemplify a *typology of core-periphery structure*

Hub-and-spoke



Layered



How do we determine which type of core-periphery structure best describes a network?

Core-Periphery Stochastic Block Models

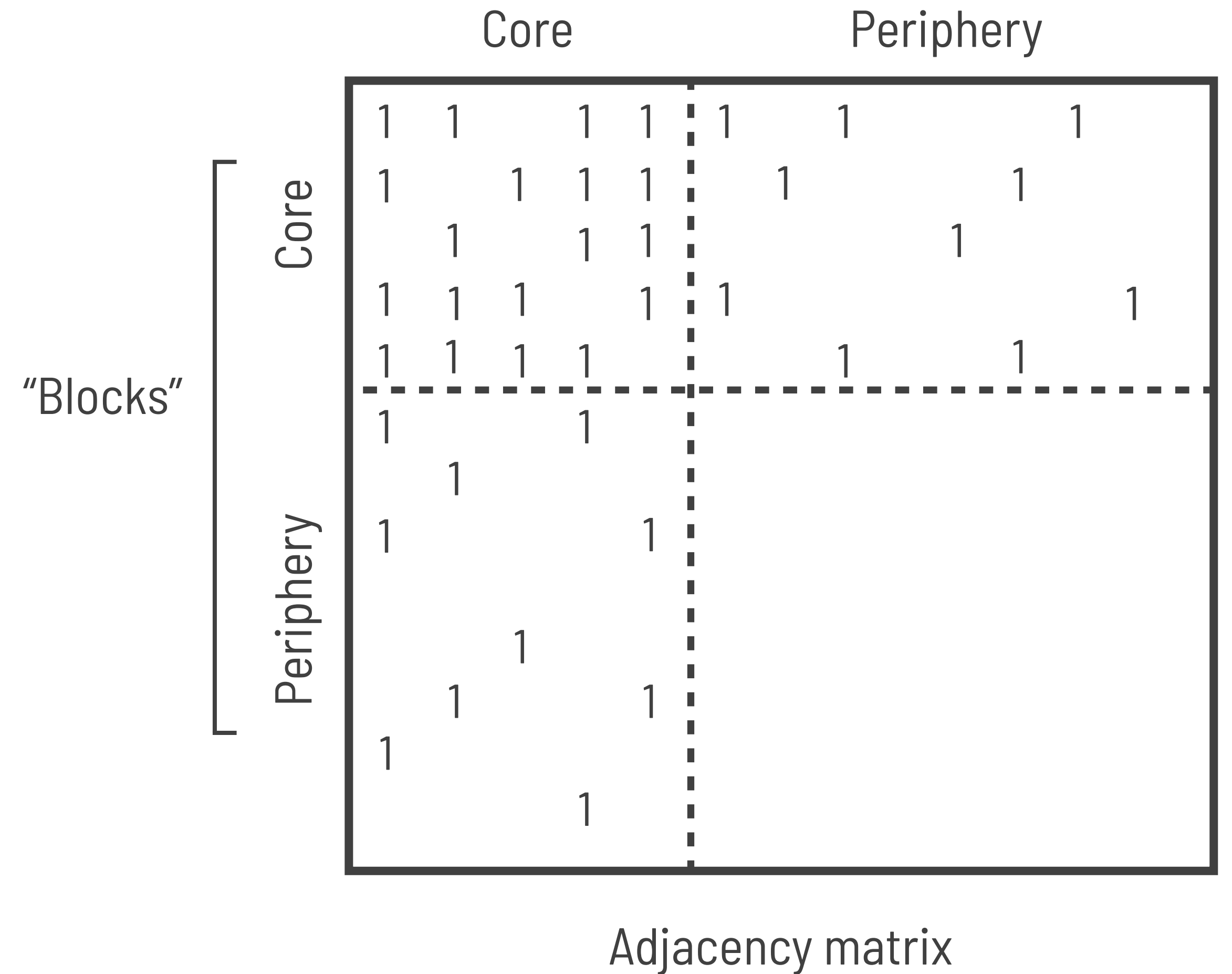
We can encode our prior notions of core-periphery structure through *Bayesian stochastic block models*

1	1		1	1	1		1		1
1		1	1	1		1		1	
	1		1	1			1		
1	1	1		1	1				1
1	1	1	1			1		1	
1			1						
	1								
1				1					
		1							
	1			1					
1									
			1						

Adjacency matrix

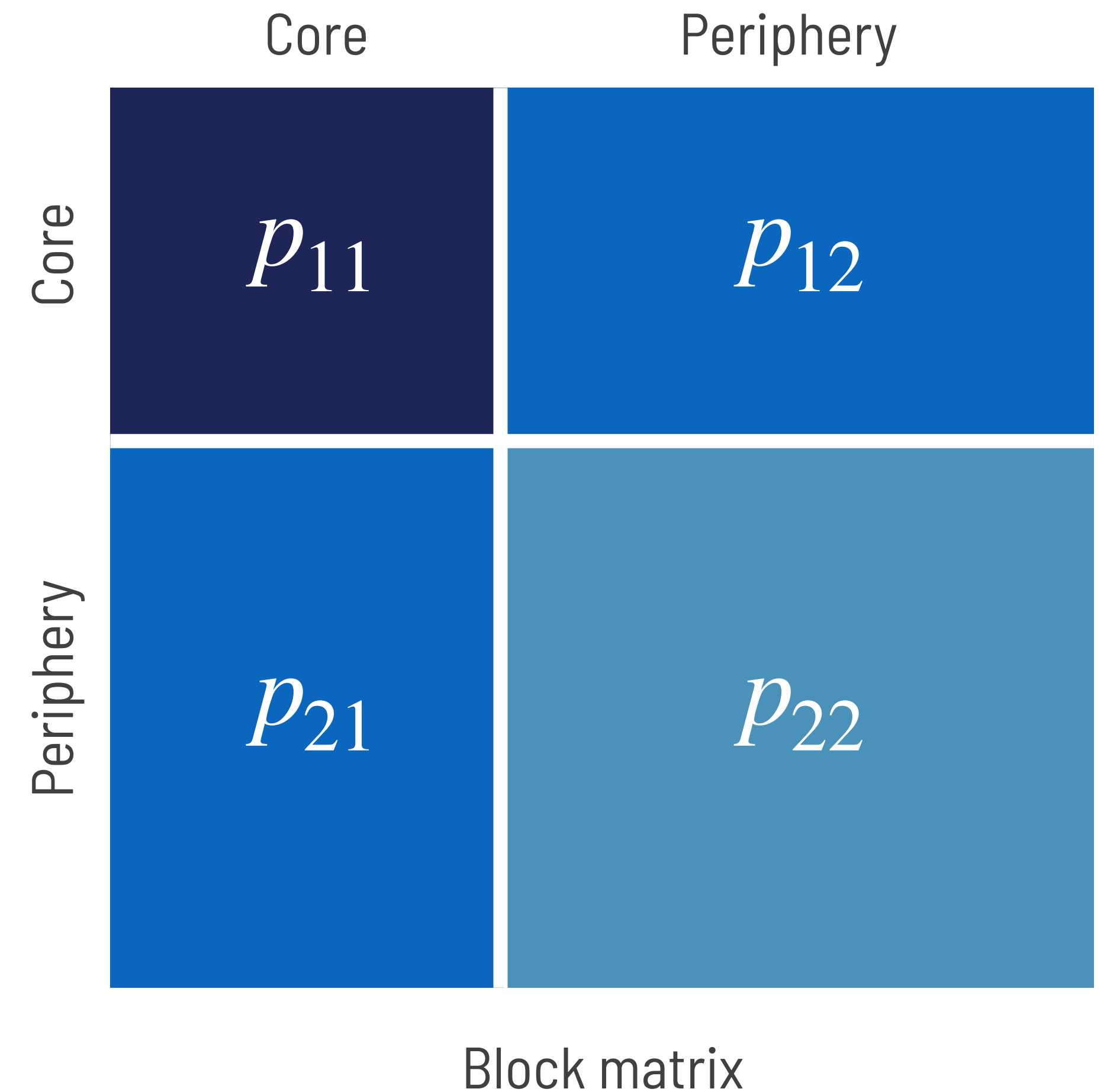
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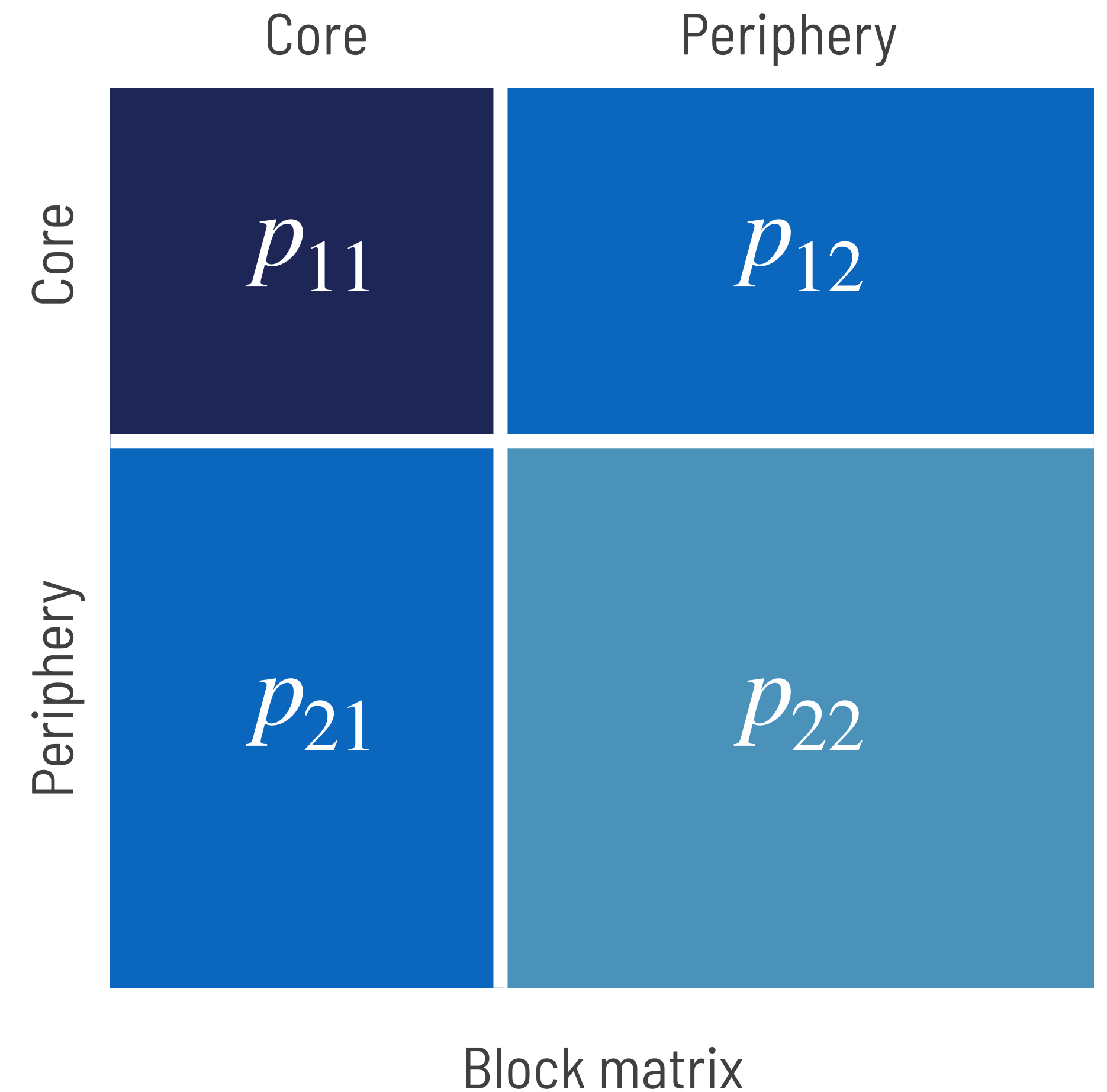
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Core-Periphery Stochastic Block Models

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$$P(\theta, \mathbf{p} \mid \mathbf{A})$$

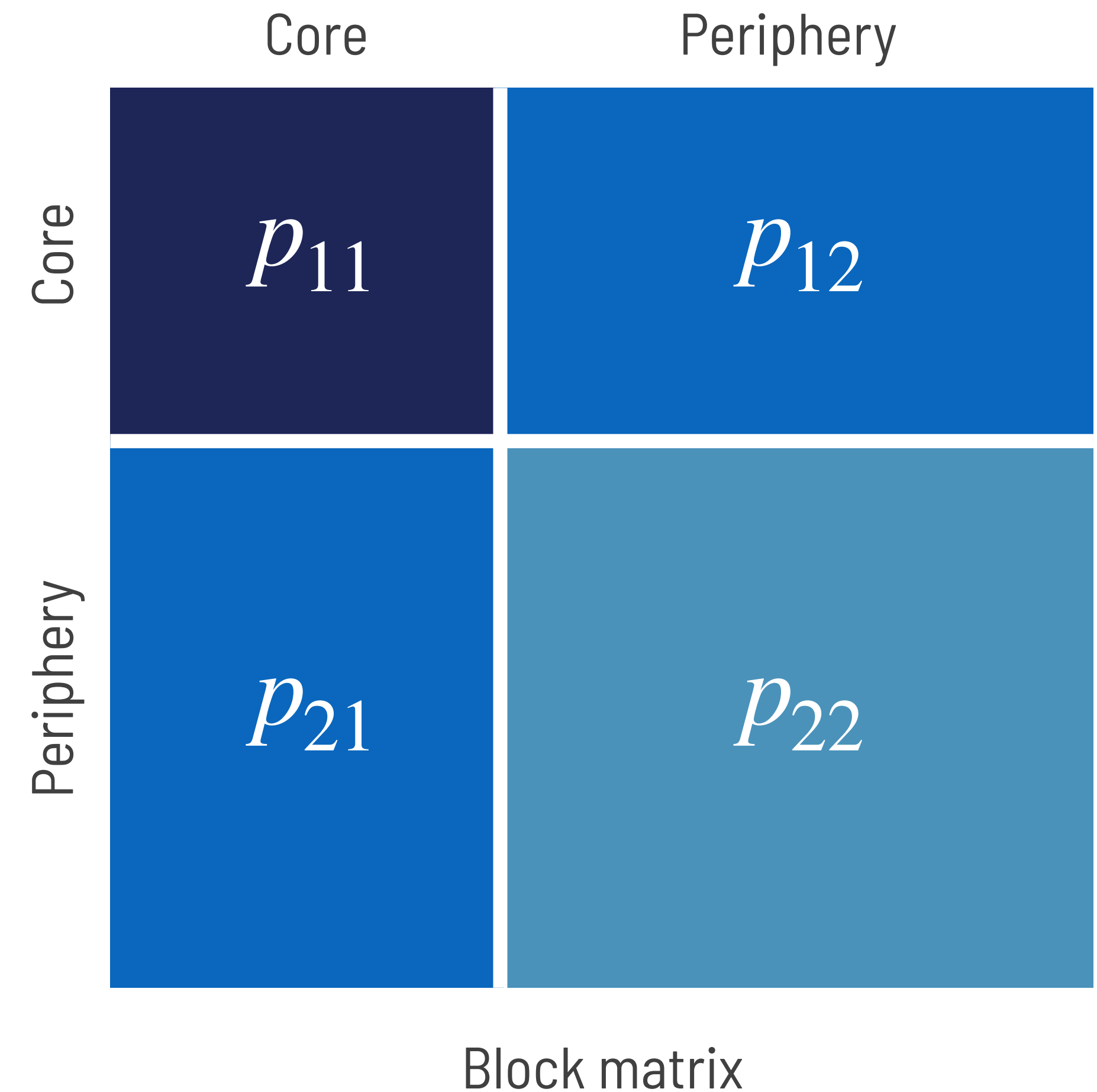


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Assignments of
nodes to blocks

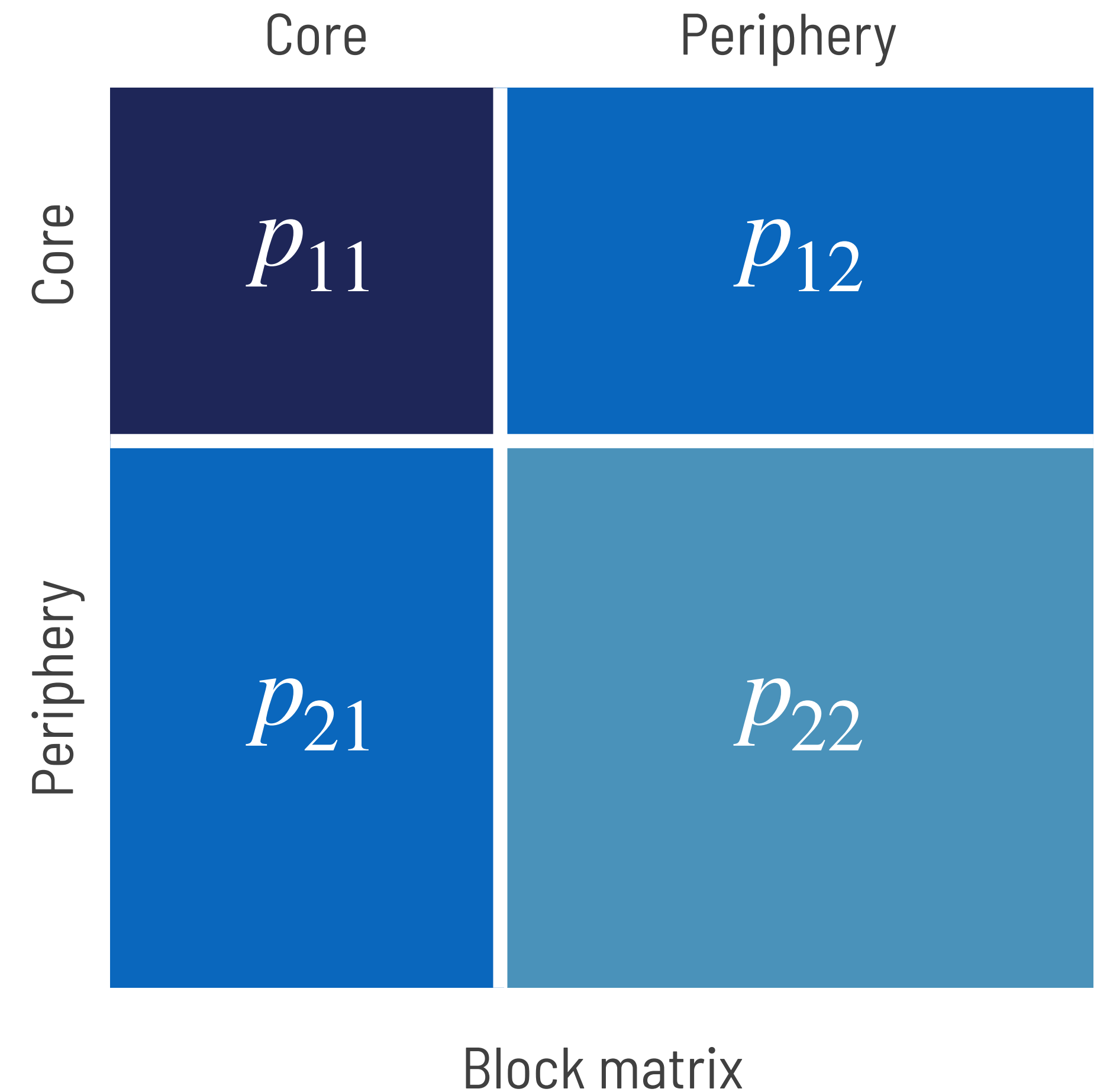


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Block
matrix

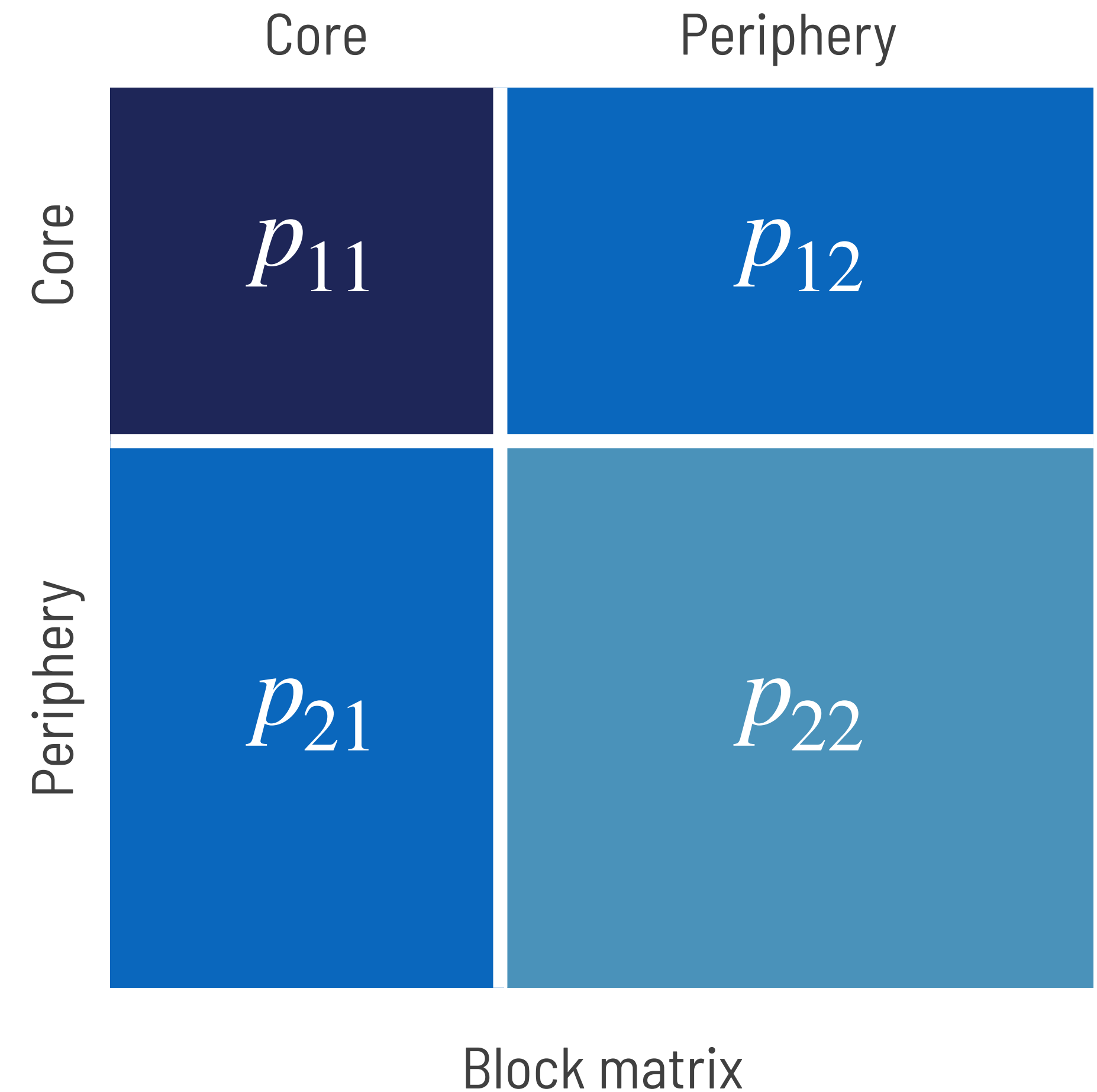


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Network
data

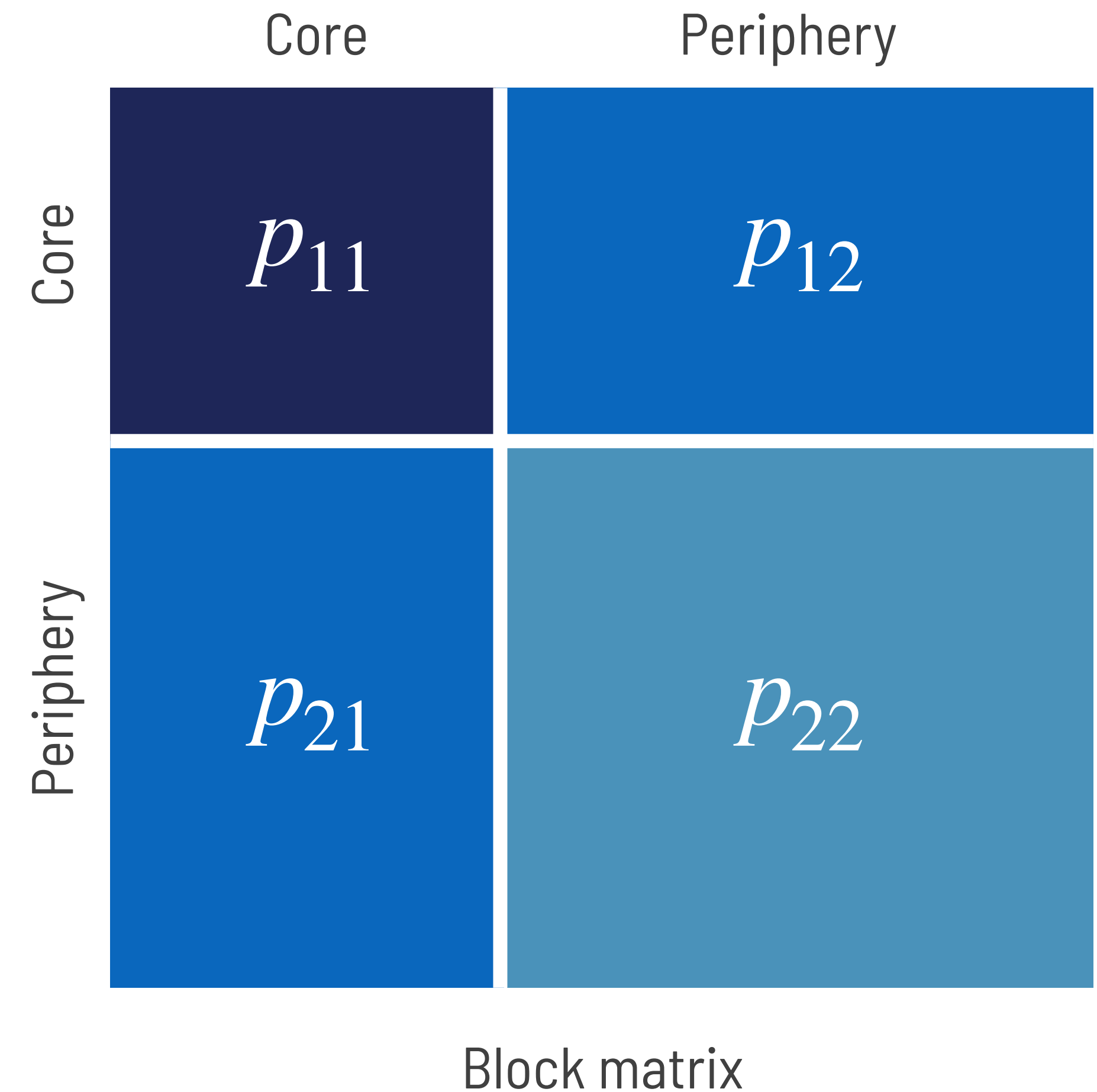


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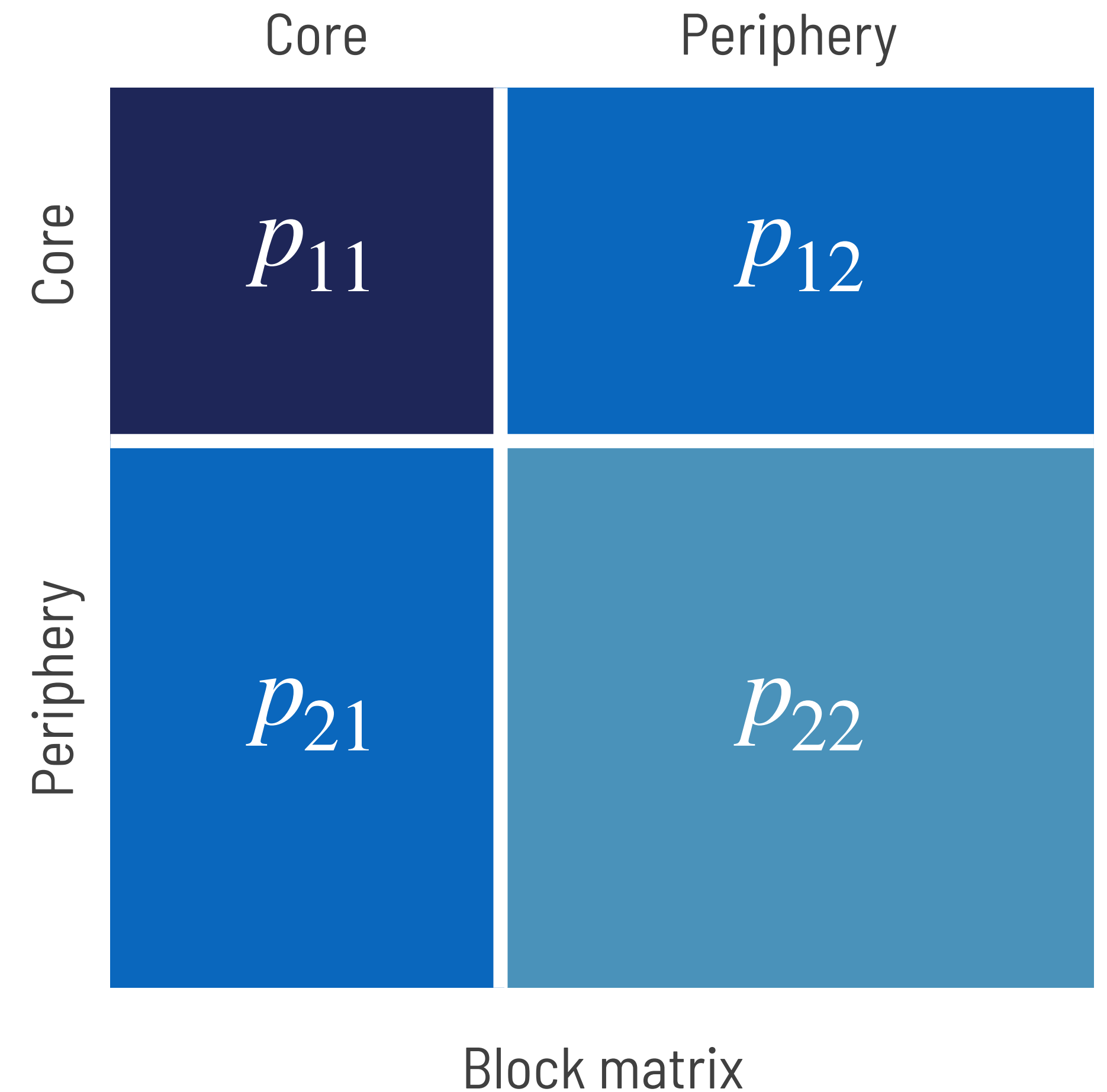
Posterior
distribution



Core-Periphery Stochastic Block Models

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$$P(\theta, \mathbf{p} \mid \mathbf{A}) \propto P(\mathbf{A} \mid \theta, \mathbf{p}) P(\theta) P(\mathbf{p})$$

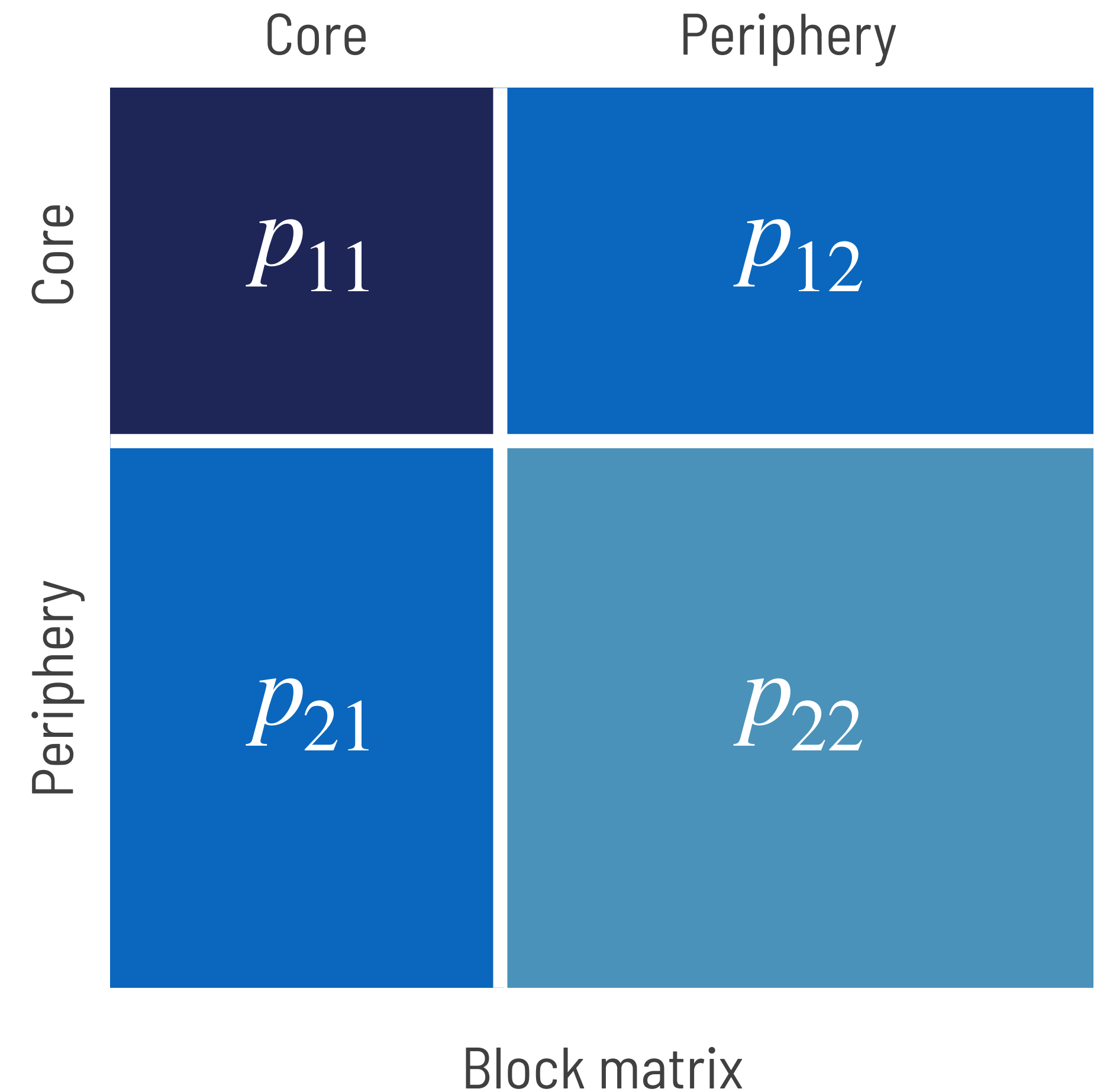


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Covered by
prior work



Karrer, B., & Newman, M. E. (2011). Stochastic blockmodels and community structure in networks. *Physical Review E*, 83(1), 016107.

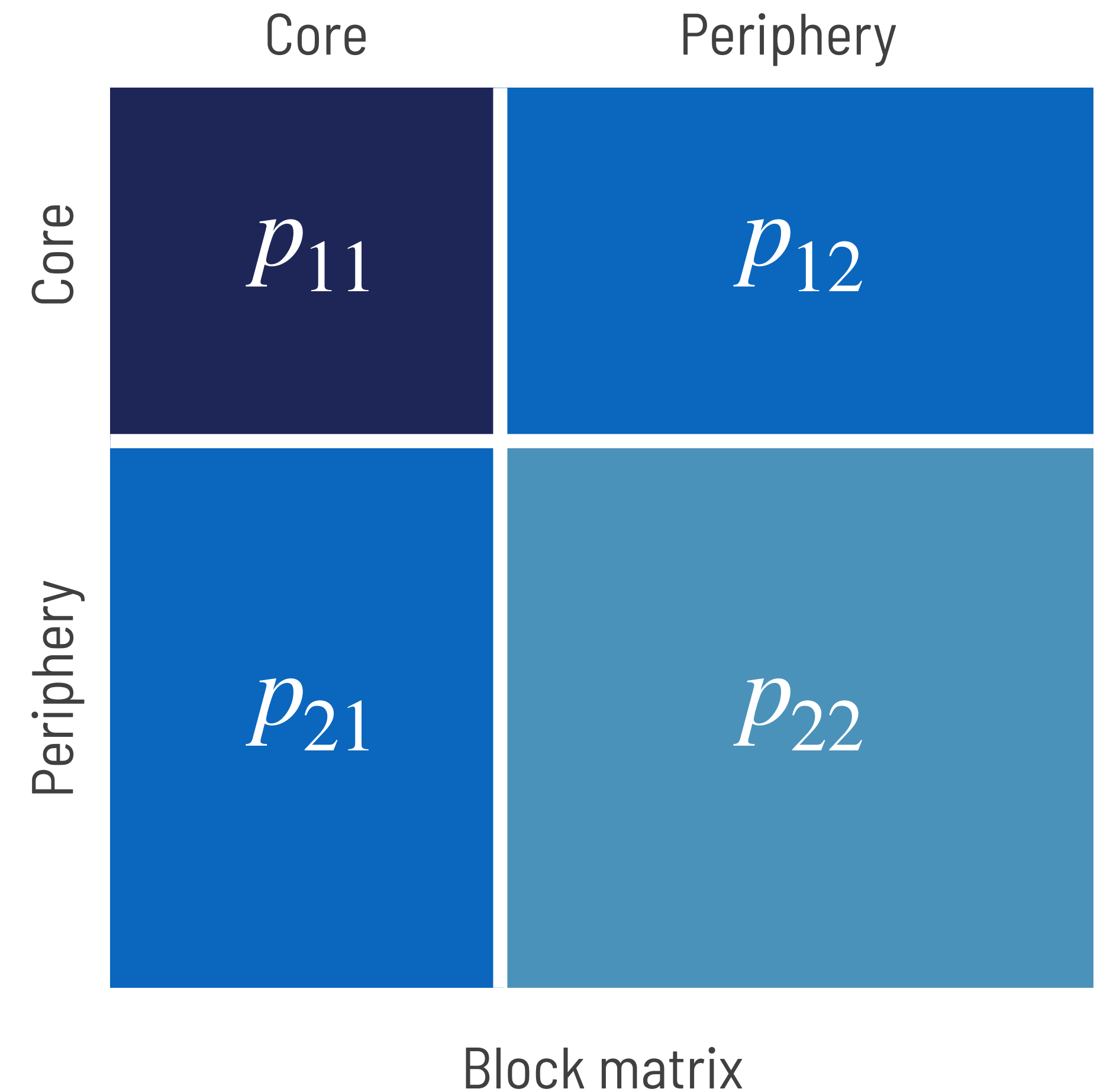
Peixoto, T. P. (2019). Bayesian stochastic blockmodeling. *Advances in Network Clustering and Blockmodeling*, 289-332.

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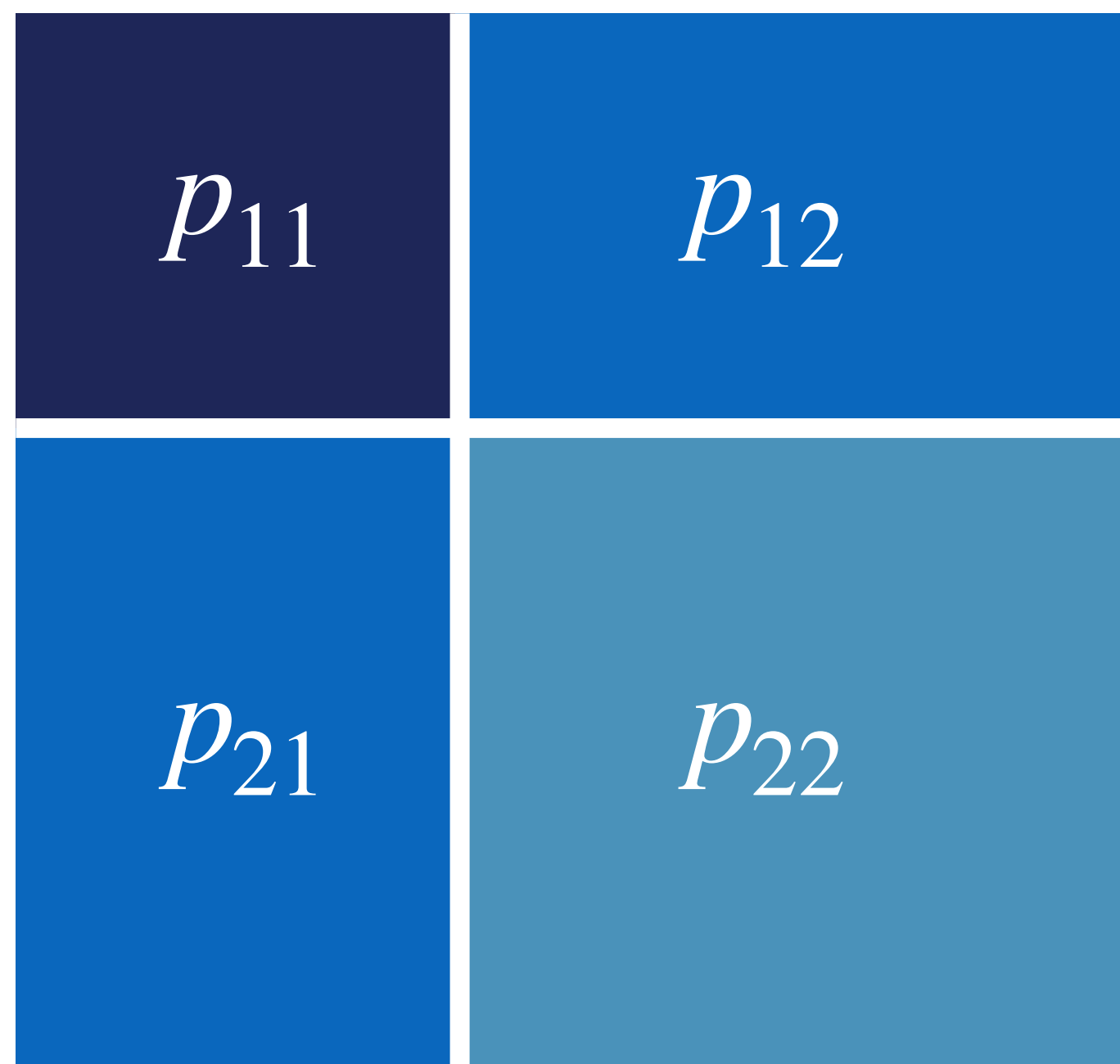
Prior on
block matrix



Block Connectivity Priors

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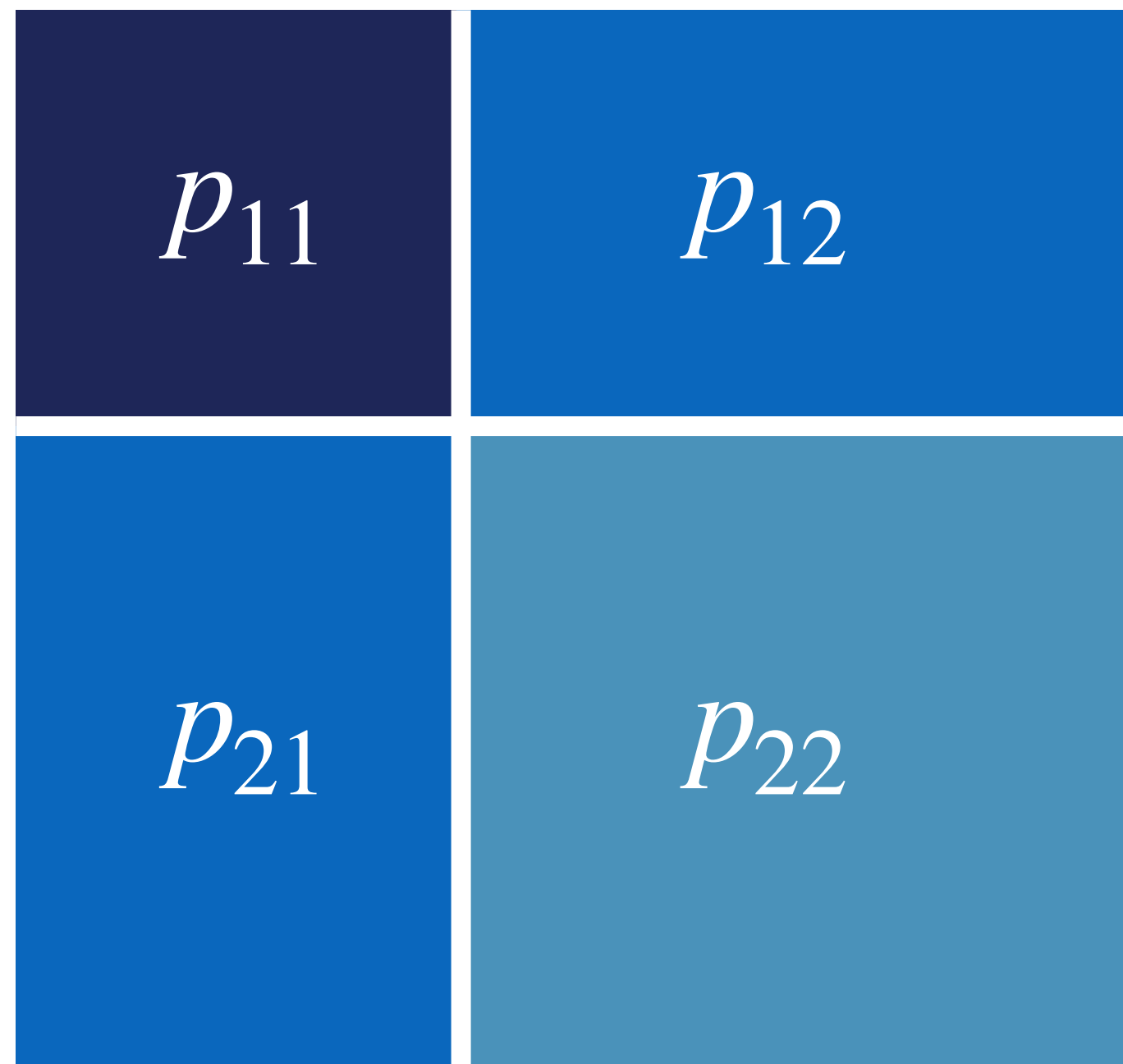
Hub-and-spoke



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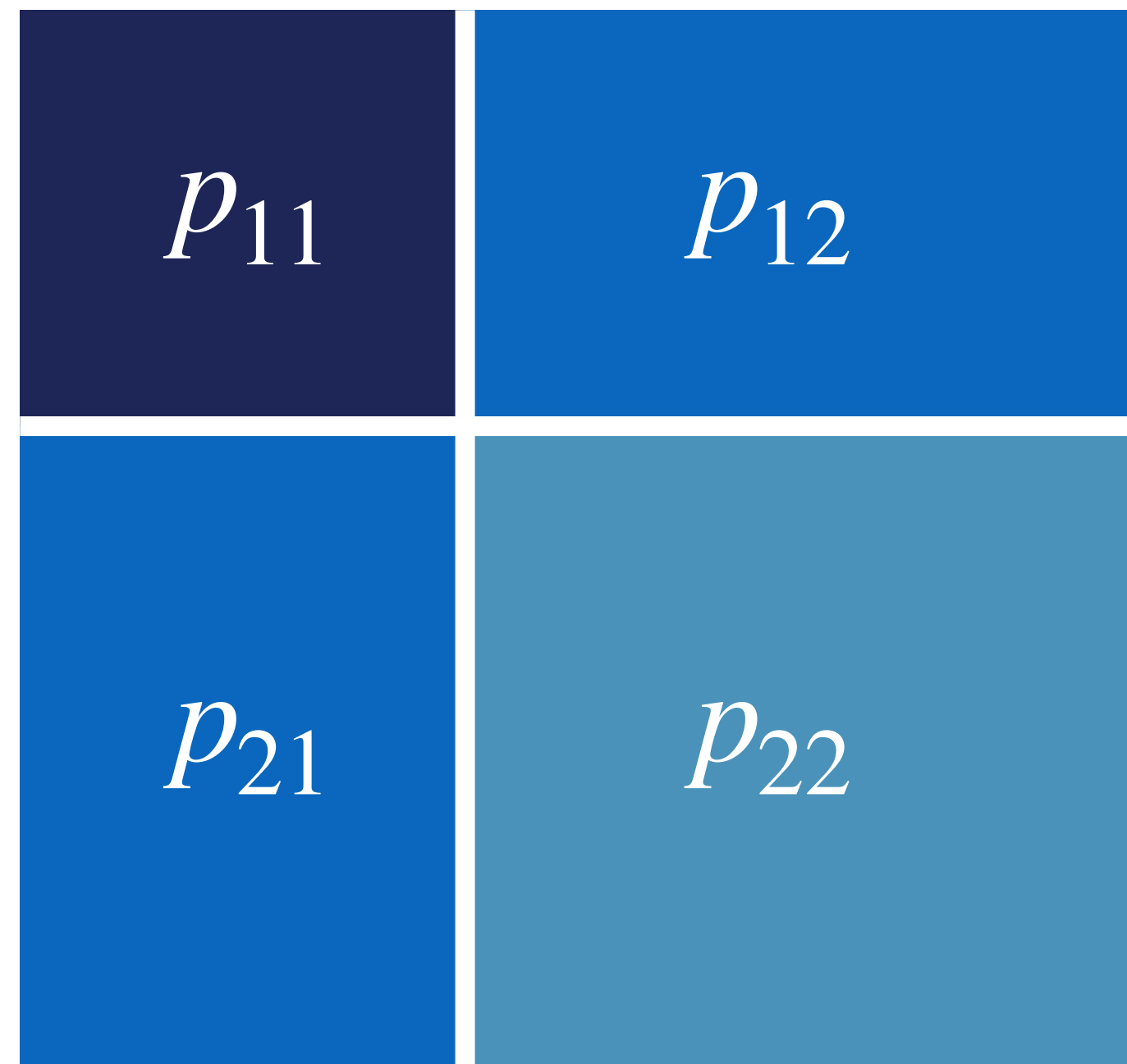


$$p_{11} > p_{12} > p_{22}$$

Block Connectivity Priors

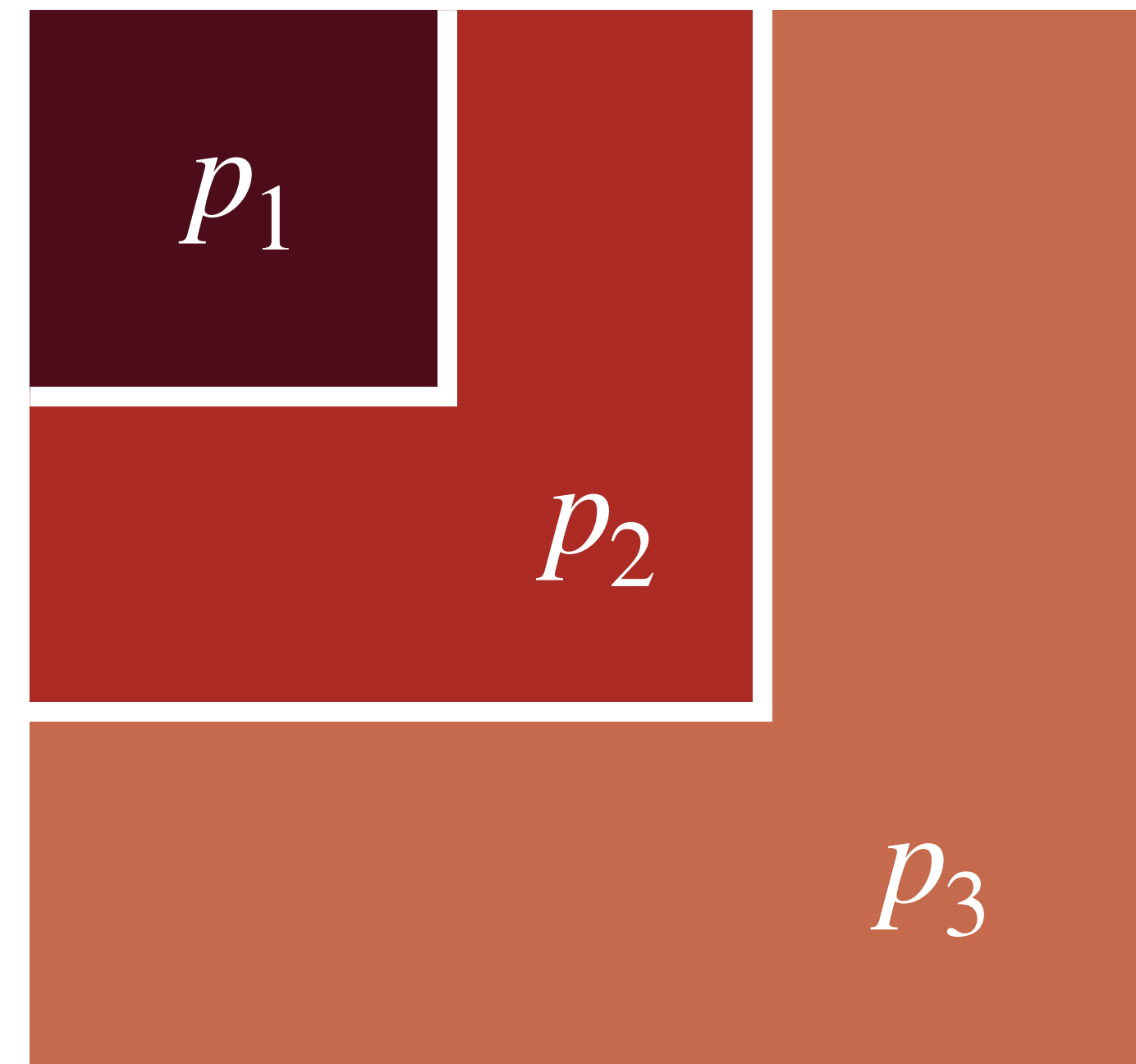
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Layered



$$p_1 > p_2 > \dots > p_\ell$$

Model Selection and Description Length

The Bayesian framework allows us to perform model selection between the hub-and-spoke model \mathcal{H} and the layered model \mathcal{L}

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If the hub-and-spoke model is a better fit...

Posterior odds ratio

$$\Lambda = \frac{P(\hat{\theta}_{\mathcal{H}}, \mathcal{H} \mid \mathbf{A})}{P(\hat{\theta}_{\mathcal{L}}, \mathcal{L} \mid \mathbf{A})} > 1$$

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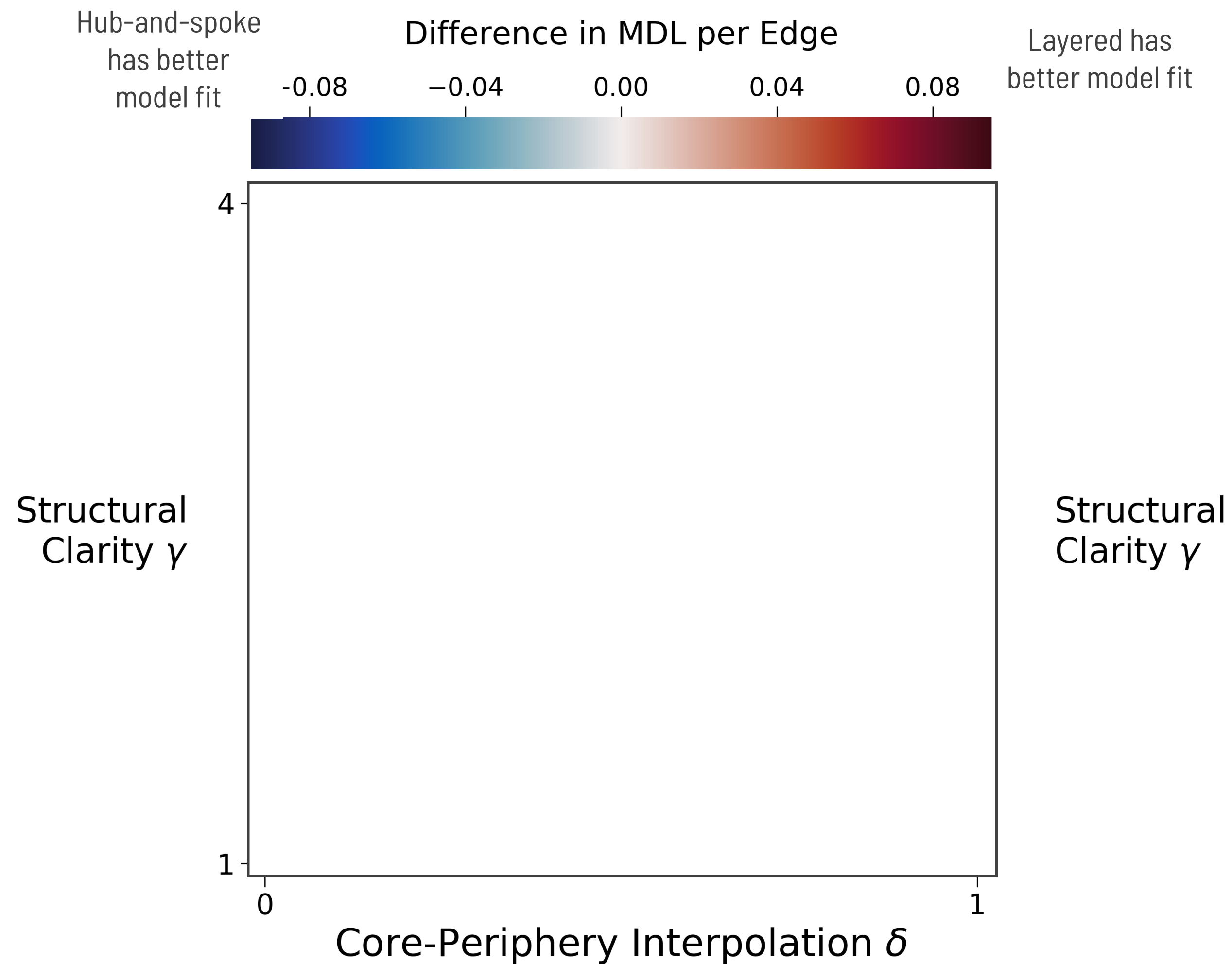


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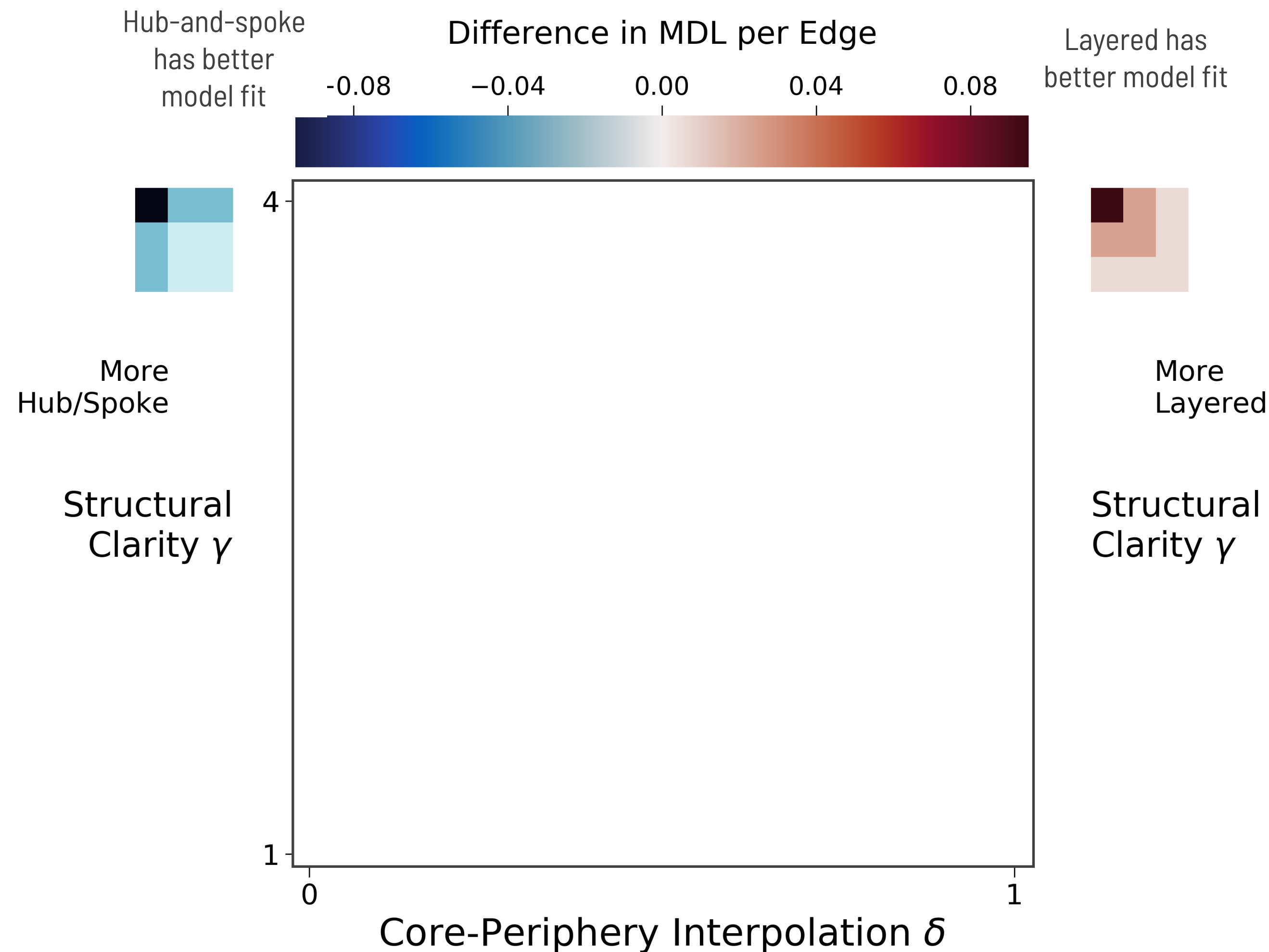
The smaller the description length,
the better the model fit

Synthetic Validation: Discerning Models



We generate synthetic core-periphery networks according to the stochastic block model, and validate that our models can discern the planted structure

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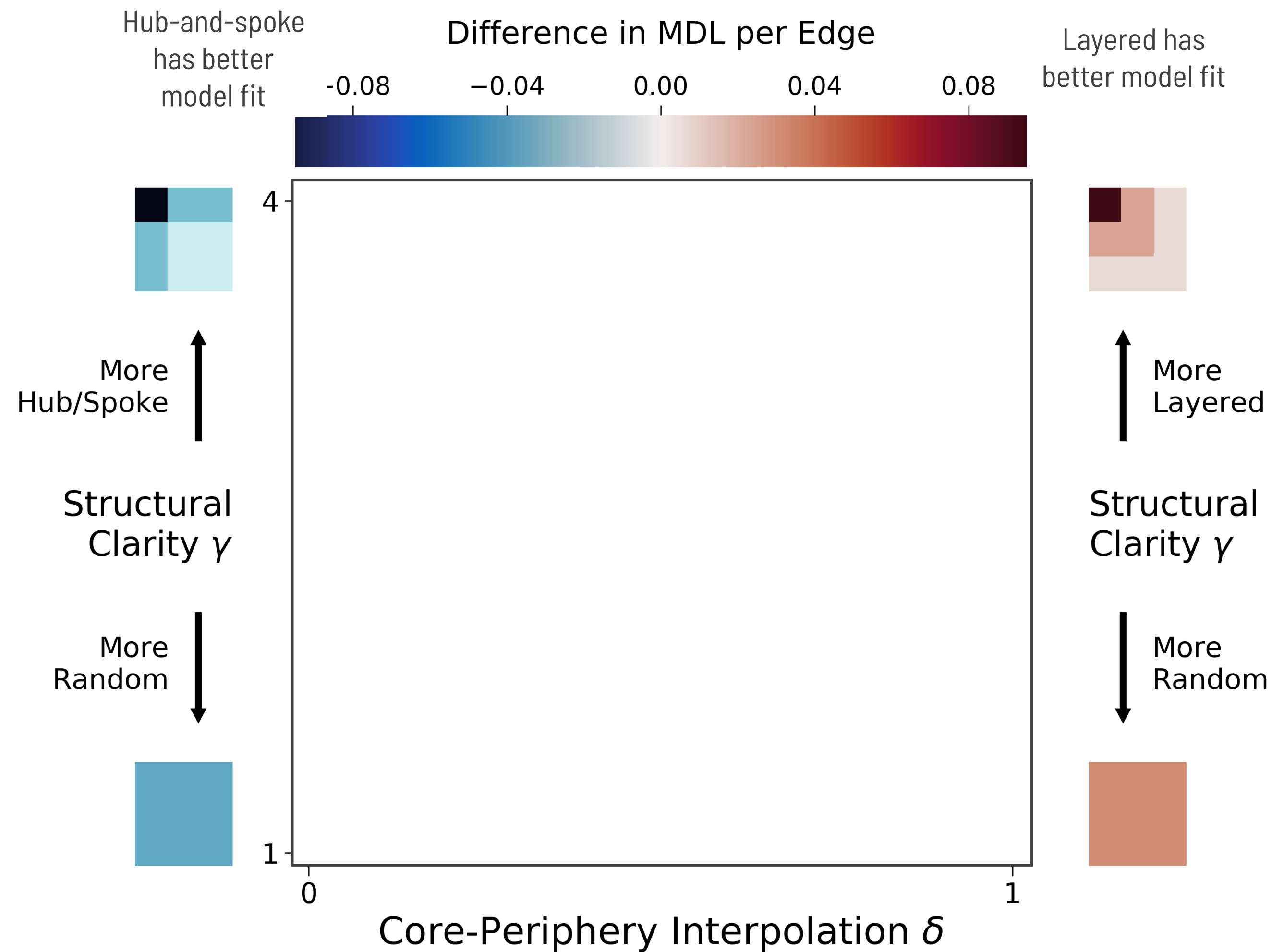


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Core-periphery interpolation

- $\delta = 0$, hub-and-spoke structure
- $\delta = 1$, layered structure (3 layers)

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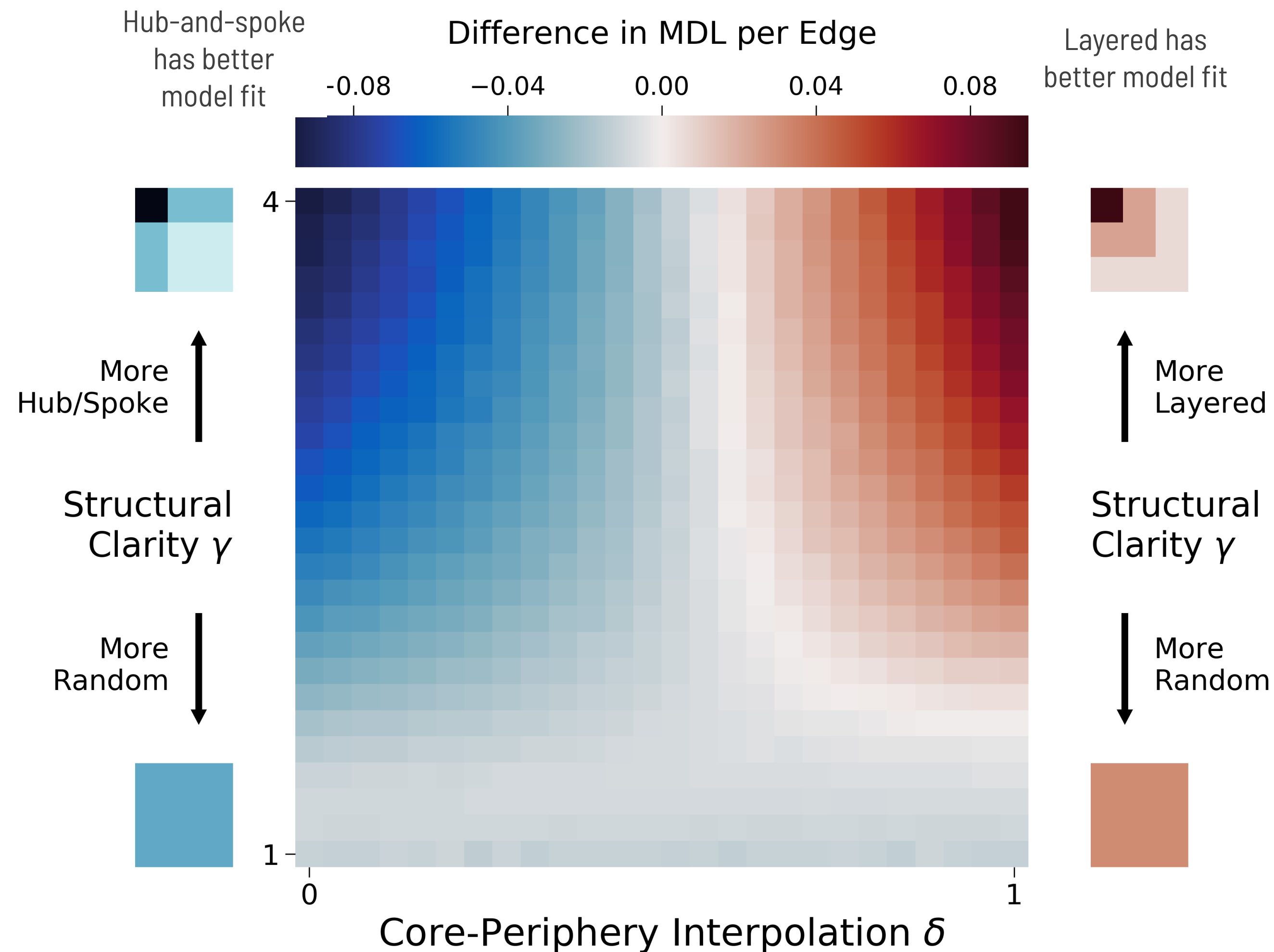
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- $\gamma = 1$, random structure
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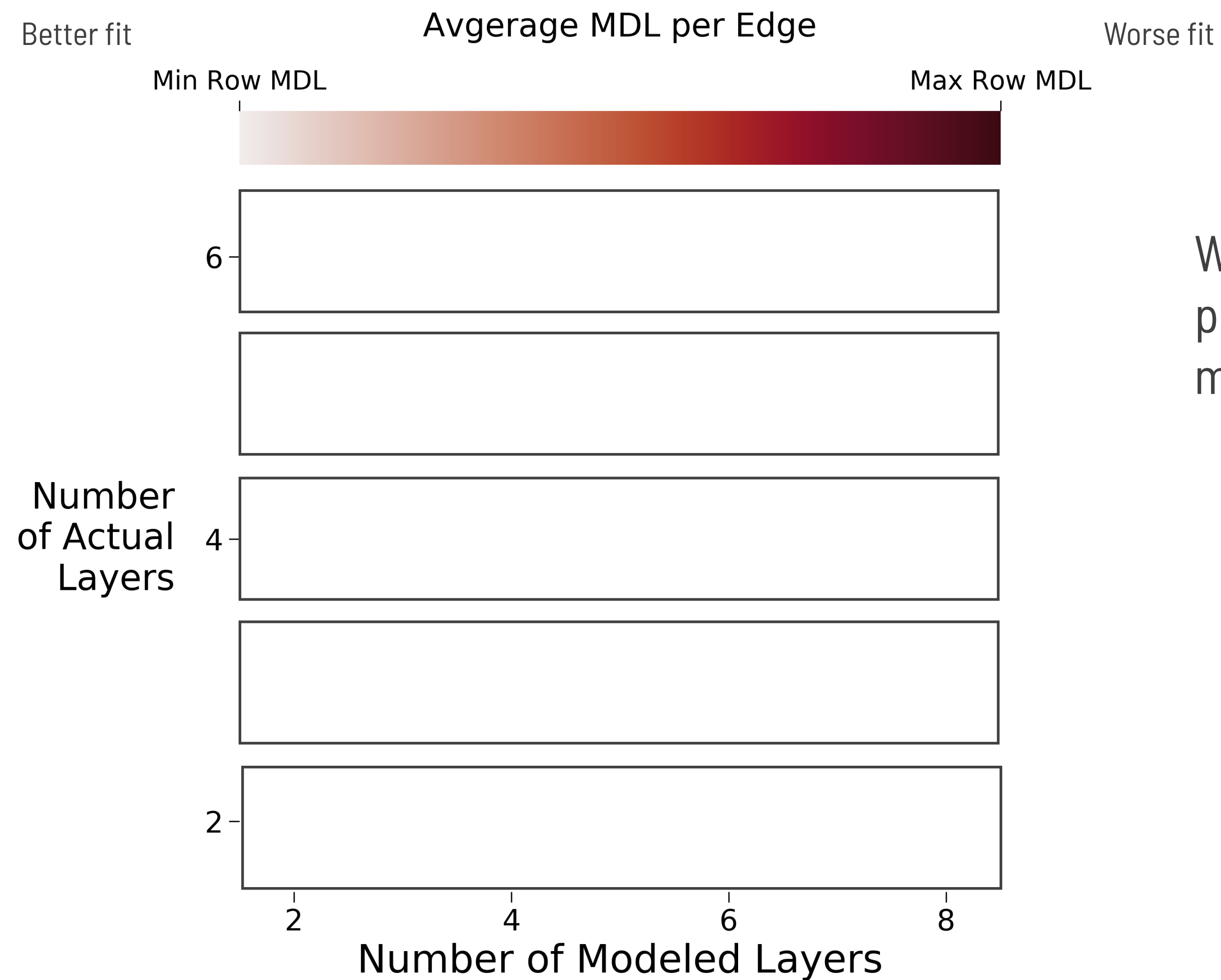
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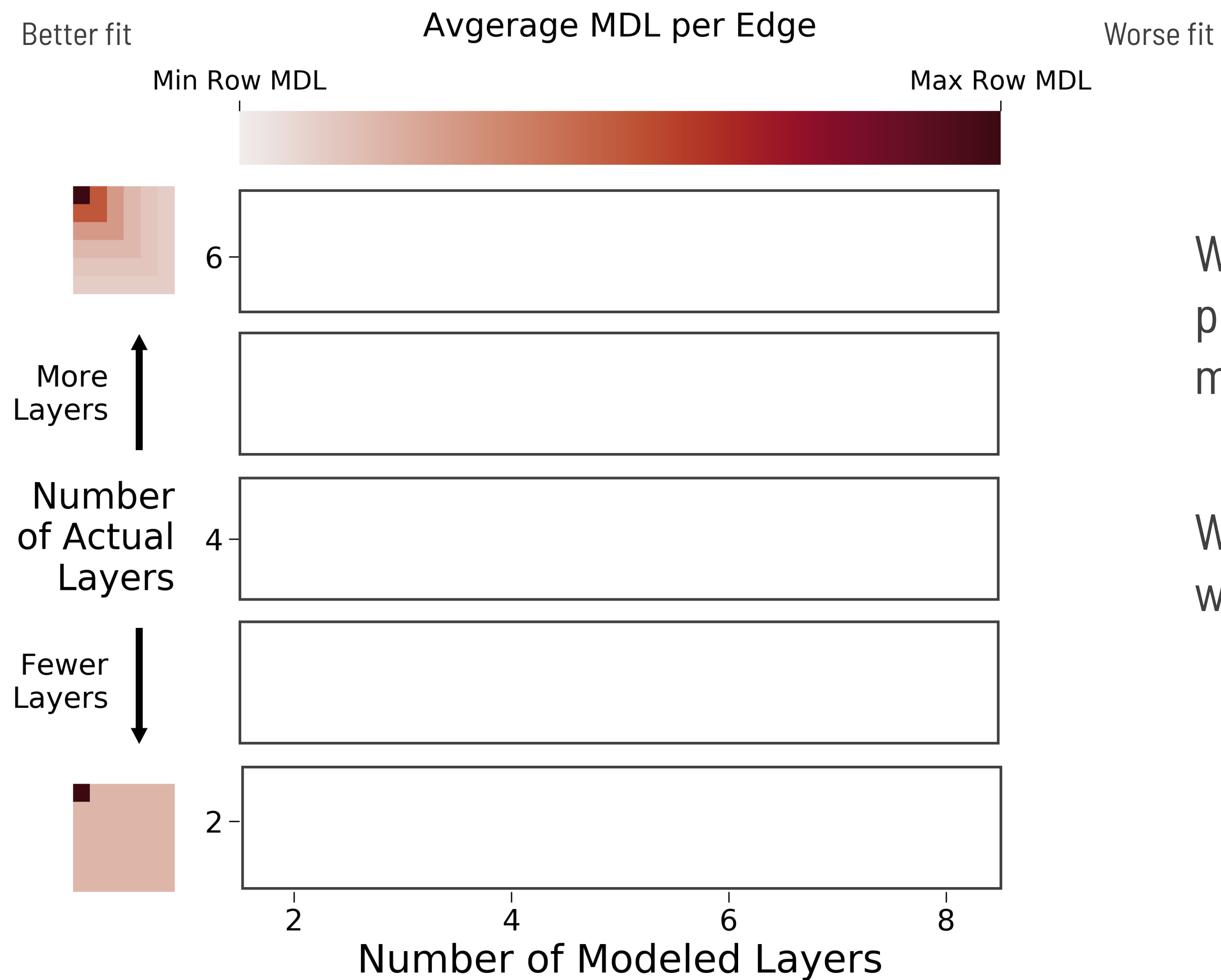
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We generate synthetic networks with layered core-periphery structure and validate that our layered model can discern the planted number of layers

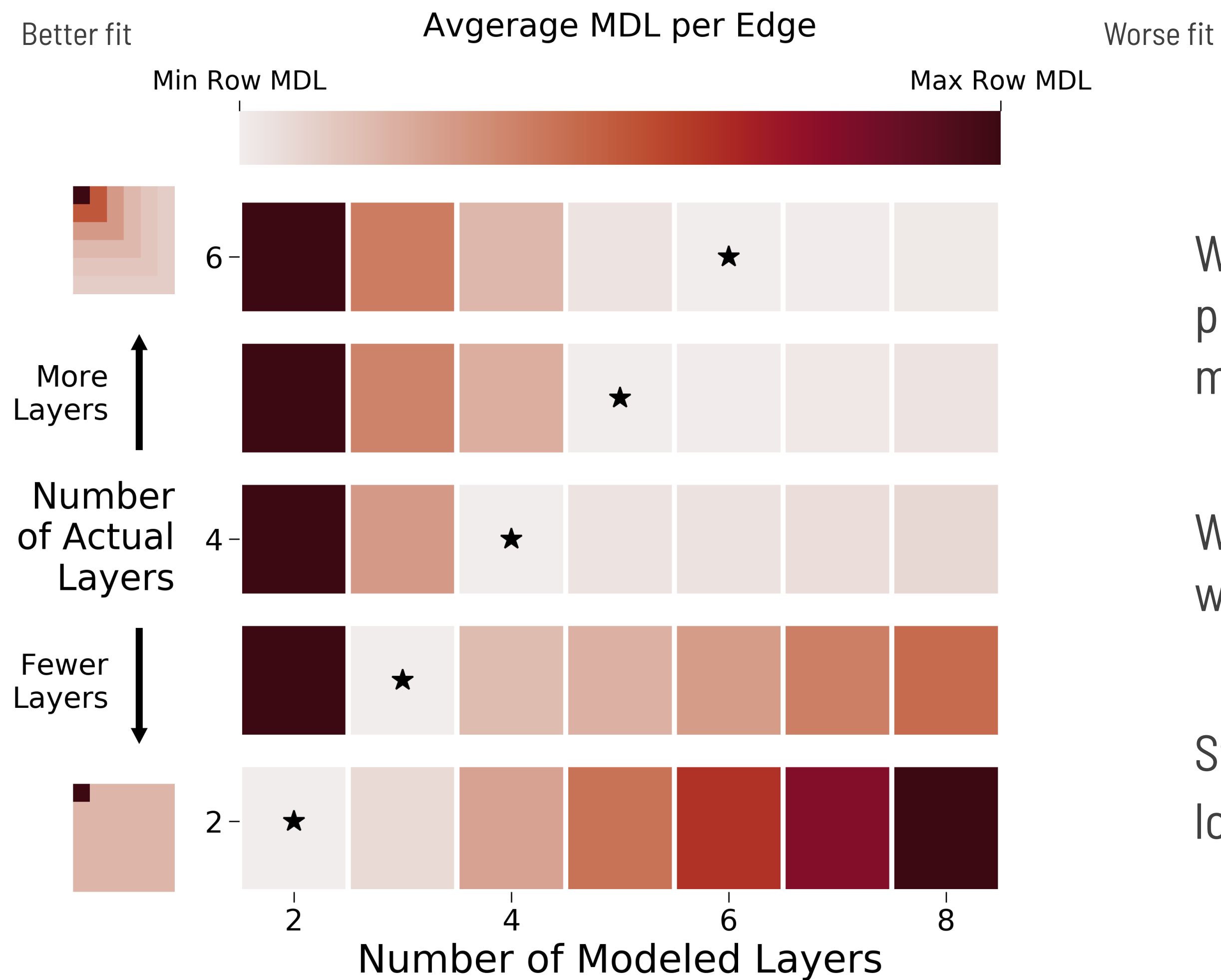
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We vary the number of planted layers in the networks while holding the average degree constant

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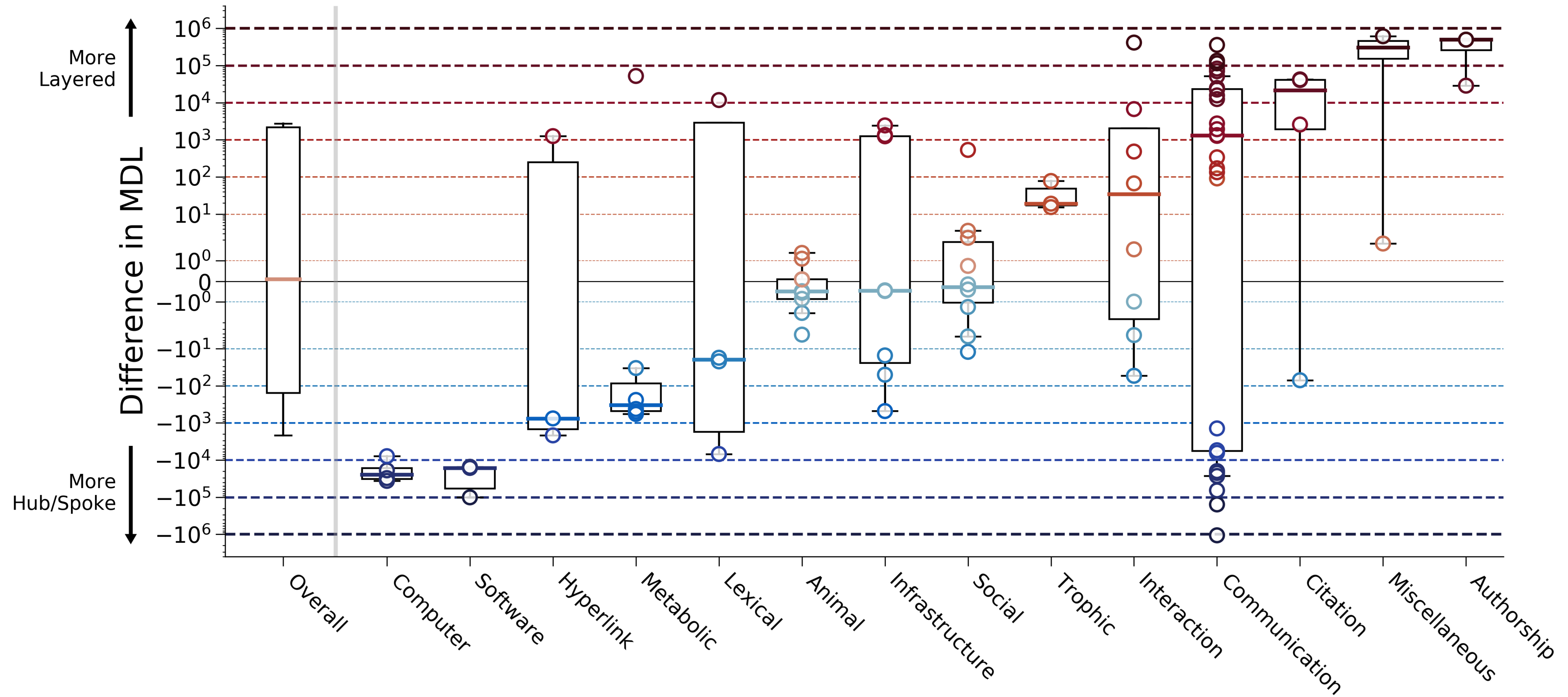


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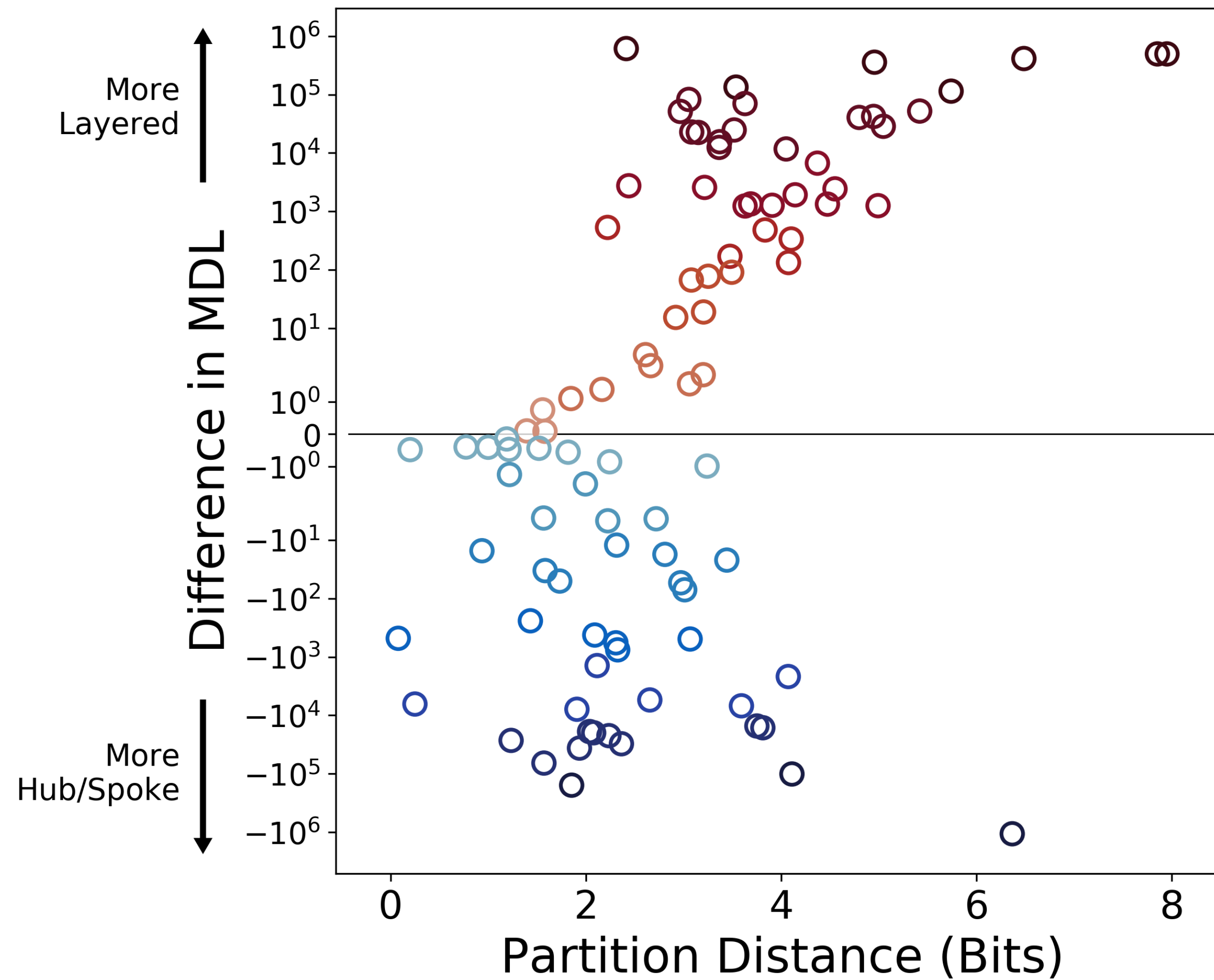
Stars (★) in each row indicate the model with the lowest description length on average

Diversity of Core-Periphery Structure



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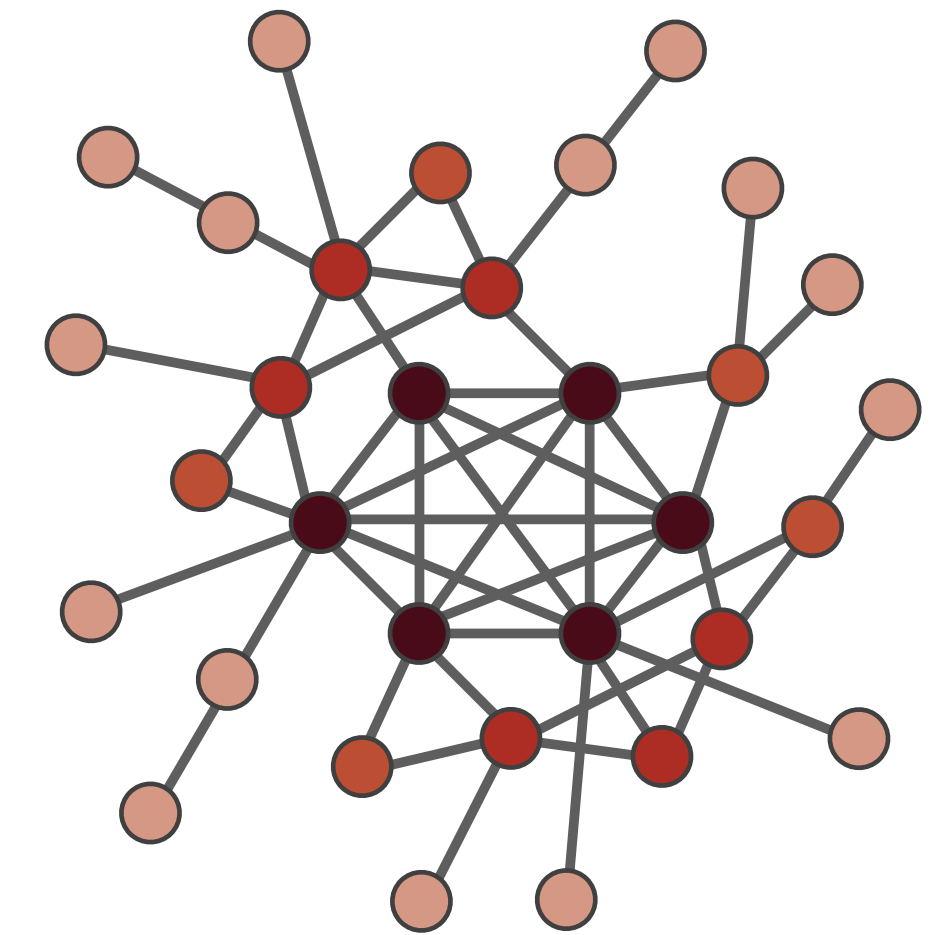
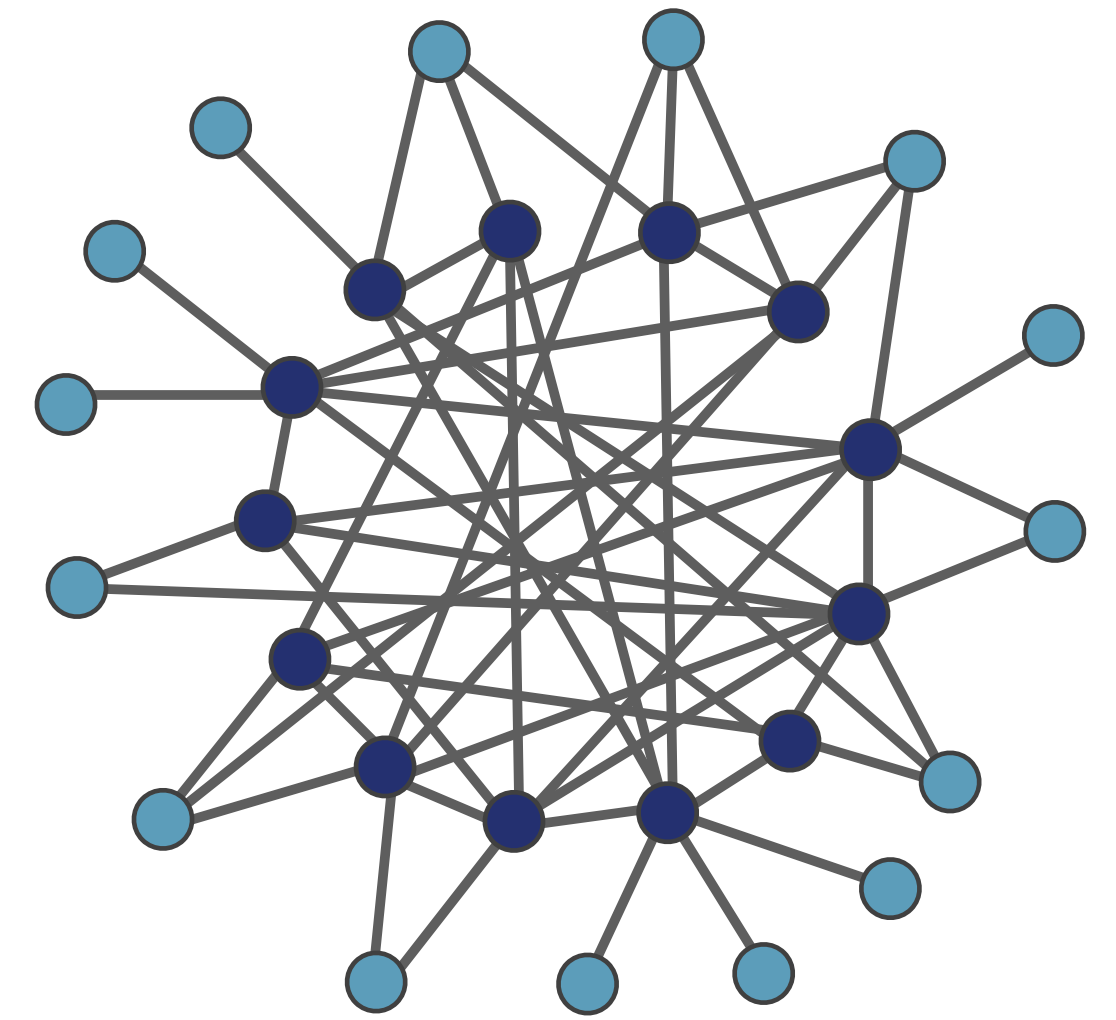
Partition Dissimilarity is Explained by the Core-Periphery Typology



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A Clarified Typology of Core-Periphery Structure

1. The two most popular core-periphery algorithms, the two-block model and the k -cores decomposition, give inconsistent descriptions of core-periphery structure
2. We have proposed a clarified typology of core-periphery structure:
There are hub-and-spoke and layered core-periphery structures
3. We have constructed two stochastic block models for measuring hub-and-spoke and layered structures, and a measure of model fit for network data
4. We have shown there is a diversity of core-periphery structure among real networks



Collaborators



Jean-Gabriel Young

Postdoctoral Fellow

Center for the Study of Complex Systems
University of Michigan



JAMES S. McDONNELL FOUNDATION



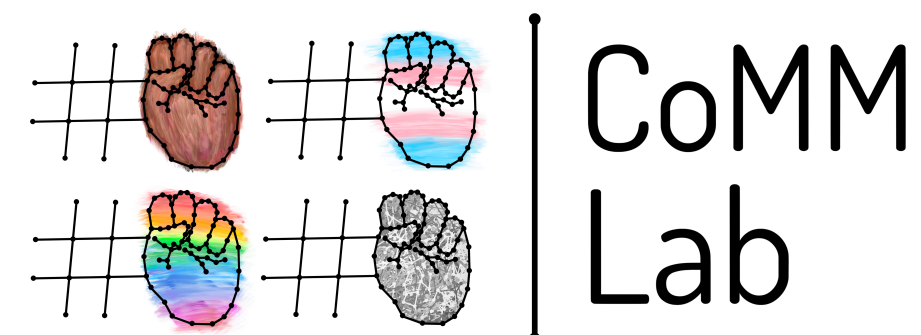
Brooke Foucault Welles

Associate Professor

Communication Studies
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