Multi-Agent Systems and Evolution

Days 3-4: Games on networks

Elias Fernández Domingos

Outline of the course

- Day 1: Introduction to Game Theory
- Day 2: Evolutionary Game Theory
- **Day 3-4: Games on Networks, connecting theory to Behavioural Experiments**
- Day 5: Final remarks and Project presentations

Day 3: Games on networks

1. Complex networks
2. Games on networks

Why should you care about EGT?

The Evolution of Sectarianism

Sebastian Ille

New College of the Humanities, London

Human cooperation for reasons other than self-interest has long intrigued social scientists leading to a substantial literature in economics. Its complement – sectarianism – has not received closer attention in economics despite its significant impact. Based on a dynamic model, the paper shows that sectarianism can be understood as the outcome of a repeated bargaining process in which sectarian affiliation evolves into a pure coordination signal that attributes economic and political benefits. It demonstrates that such sectarian social contracts co-evolve with the sects' degree of coerciveness and are self-reinforcing. Sectarian conflict may then not be a result of diverging religious ideologies but is shown to be caused by external manipulations of the signal (e.g. via identity politics), and internal political and economic grievances within a sect that spill over to the inter-sectarian level while adopting a sectarian appearance. Theoretical results are supported by empirical findings from the Middle East.

nature climate change

LETTERS

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A bottom-up institutional approach to cooperative governance of risky commons

Vítor V. Vasconcelos[1,2,3], Francisco C. Santos[1,3] and Jorge M. Pacheco[1,4,5]★

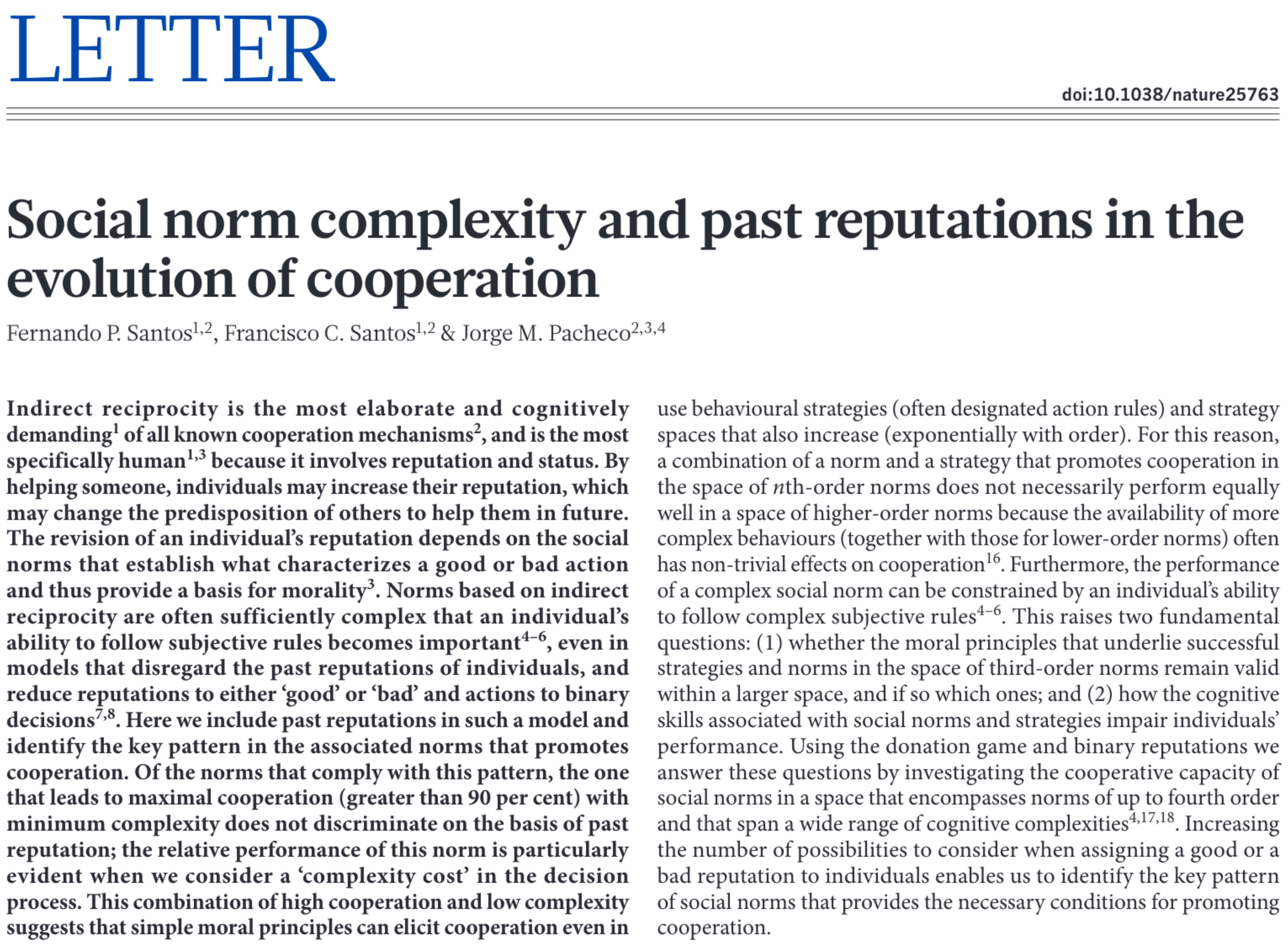
Avoiding the effects of climate change may be framed as a public goods dilemma[1], in which the risk of future losses is non-negligible[2–7], while realizing that the public good may be far in the future[3,7–9]. The limited success of existing attempts to reach global cooperation has been also associated with a lack of sanctioning institutions and mechanisms to deal with those who do not contribute to the welfare of the planet or fail to abide by agreements[1,3,10–13]. Here we investigate the emergence and impact of different types of sanctioning to deter non-cooperative behaviour in climate agreements. We show that a bottom-up approach, in which parties create local

through time[18–21] (Methods and Supplementary Information for further details). Behavioural experiments[4,5,22], as well as other theoretical models[23,24], have implemented thresholds through repeated interactions, and other authors have highlighted the role played by pledges and communication during negotiations[1,5,25], bringing about additional layers of complexity to this problem (details and comparison with other models in the Supplementary Information).

Besides contributing to this public good, Ps also contribute with a punishment tax (π_t) to an institution that, whenever endowed with enough funding ($n_p\pi_t$) will effectively punish Ds by an amount Δ. Hence, establishing an institution stands as a second-order

Descriptive modelling framework

Why should you care about EGT?



LETTER

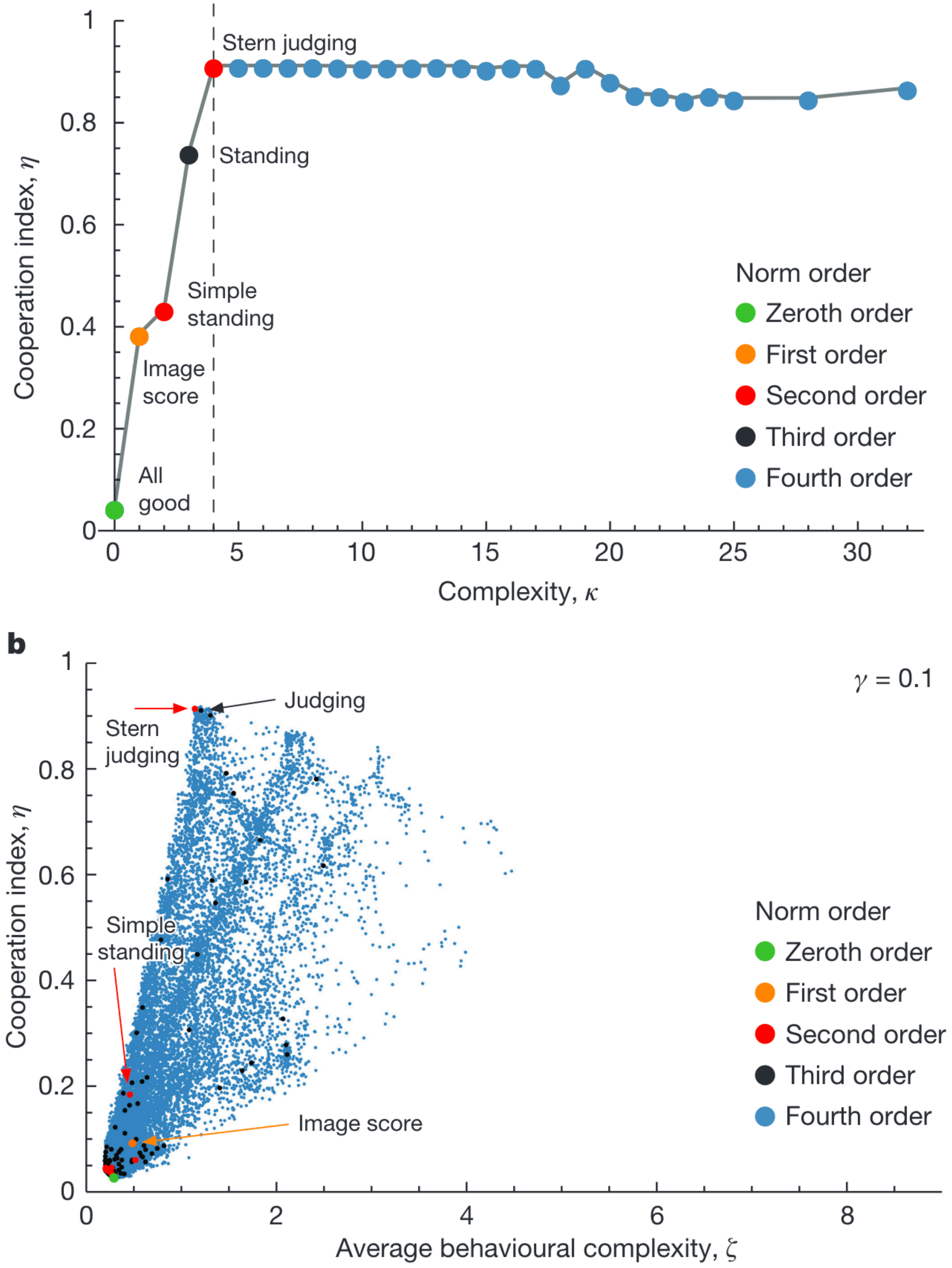
doi:10.1038/nature25763

Social norm complexity and past reputations in the evolution of cooperation

Fernando P. Santos[1,2], Francisco C. Santos[1,2] & Jorge M. Pacheco[2,3,4]

Indirect reciprocity is the most elaborate and cognitively demanding[1] of all known cooperation mechanisms[2], and is the most specifically human[1,3] because it involves reputation and status. By helping someone, individuals may increase their reputation, which may change the predisposition of others to help them in future. The revision of an individual's reputation depends on the social norms that establish what characterizes a good or bad action and thus provide a basis for morality[3]. Norms based on indirect reciprocity are often sufficiently complex that an individual's ability to follow subjective rules becomes important[4–6], even in models that disregard the past reputations of individuals, and reduce reputations to either 'good' or 'bad' and actions to binary decisions[7,8]. Here we include past reputations in such a model and identify the key pattern in the associated norms that promotes cooperation. Of the norms that comply with this pattern, the one that leads to maximal cooperation (greater than 90 per cent) with minimum complexity does not discriminate on the basis of past reputation; the relative performance of this norm is particularly evident when we consider a 'complexity cost' in the decision process. This combination of high cooperation and low complexity suggests that simple moral principles can elicit cooperation even in

use behavioural strategies (often designated action rules) and strategy spaces that also increase (exponentially with order). For this reason, a combination of a norm and a strategy that promotes cooperation in the space of *n*th-order norms does not necessarily perform equally well in a space of higher-order norms because the availability of more complex behaviours (together with those for lower-order norms) often has non-trivial effects on cooperation[16]. Furthermore, the performance of a complex social norm can be constrained by an individual's ability to follow complex subjective rules[4–6]. This raises two fundamental questions: (1) whether the moral principles that underlie successful strategies and norms in the space of third-order norms remain valid within a larger space, and if so which ones; and (2) how the cognitive skills associated with social norms and strategies impair individuals' performance. Using the donation game and binary reputations we answer these questions by investigating the cooperative capacity of social norms in a space that encompasses norms of up to fourth order and that span a wide range of cognitive complexities[4,17,18]. Increasing the number of possibilities to consider when assigning a good or a bad reputation to individuals enables us to identify the key pattern of social norms that provides the necessary conditions for promoting cooperation.



Descriptive modelling framework

Why should you care about EGT?

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Modeling behavioral experiments on uncertainty and cooperation with population-based reinforcement learning

Elias Fernández Domingos [a,b,c], Jelena Grujić [a,b], Juan C. Burguillo [c], Francisco C. Santos [d,b], Tom Lenaerts [a,b,*]

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A R T I C L E   I N F O

Keywords:
Public goods game
Population dynamics
Individual learning
Collective risk
Uncertainty

A B S T R A C T

From climate action to public health measures, human collective endeavors are often shaped by different uncertainties. Here we introduce a novel population-based learning model wherein a group of individuals facing a collective risk dilemma acquire their strategies over time through reinforcement learning, while handling different sources of uncertainty. In such an N-person collective risk dilemma players make step-wise contributions to avoid a catastrophe that would result in a loss of wealth for all players. Success is attained if they collectively reach a certain contribution level over time, or, when the threshold is not reached, they were lucky enough

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Committing to the wrong artificial delegate in a collective-risk dilemma is better than directly committing mistakes

Inês Terrucha[1,2✉], Elias Fernández Domingos[2,3,4], Pieter Simoens[1] & Tom Lenaerts[2,3,4,5✉]

While autonomous artificial agents are assumed to perfectly execute the strategies they are programmed with, humans who design them may make mistakes. These mistakes may lead to a misalignment between the humans' intended goals and their agents' observed behavior, a problem of value alignment. Such an alignment problem may have particularly strong consequences when

Descriptive modelling framework

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α-Rank: Multi-Agent Evaluation by Evolution

Shayegan Omidshafiei[1], Christos Papadimitriou[5], Georgios Piliouras[4], Karl Tuyls[1], Mark Rowland[2], Jean-Baptiste Lespiau[1], Wojciech M. Czarnecki[2], Marc Lanctot[3], Julien Perolat[2] & Remi Munos[1]

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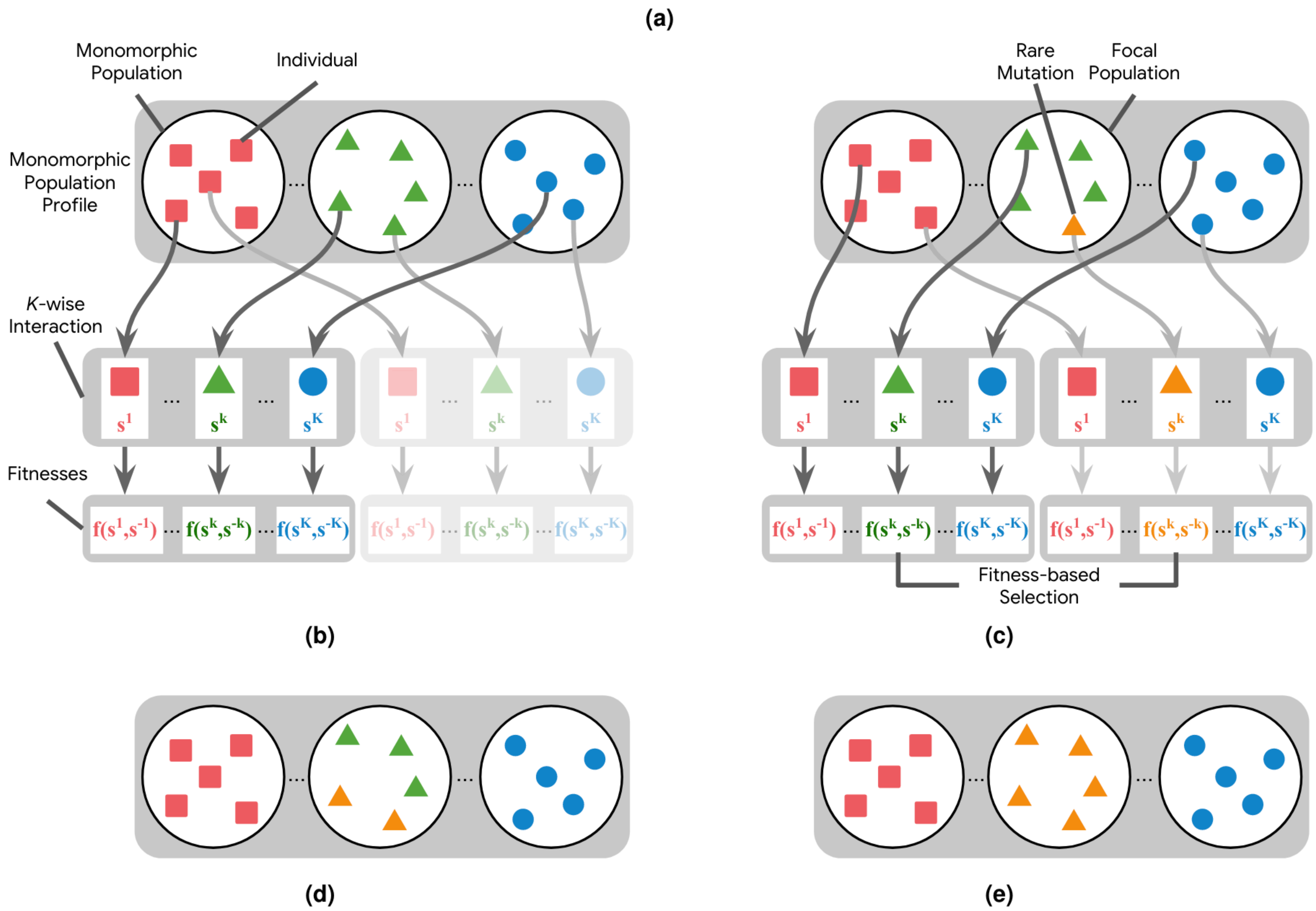
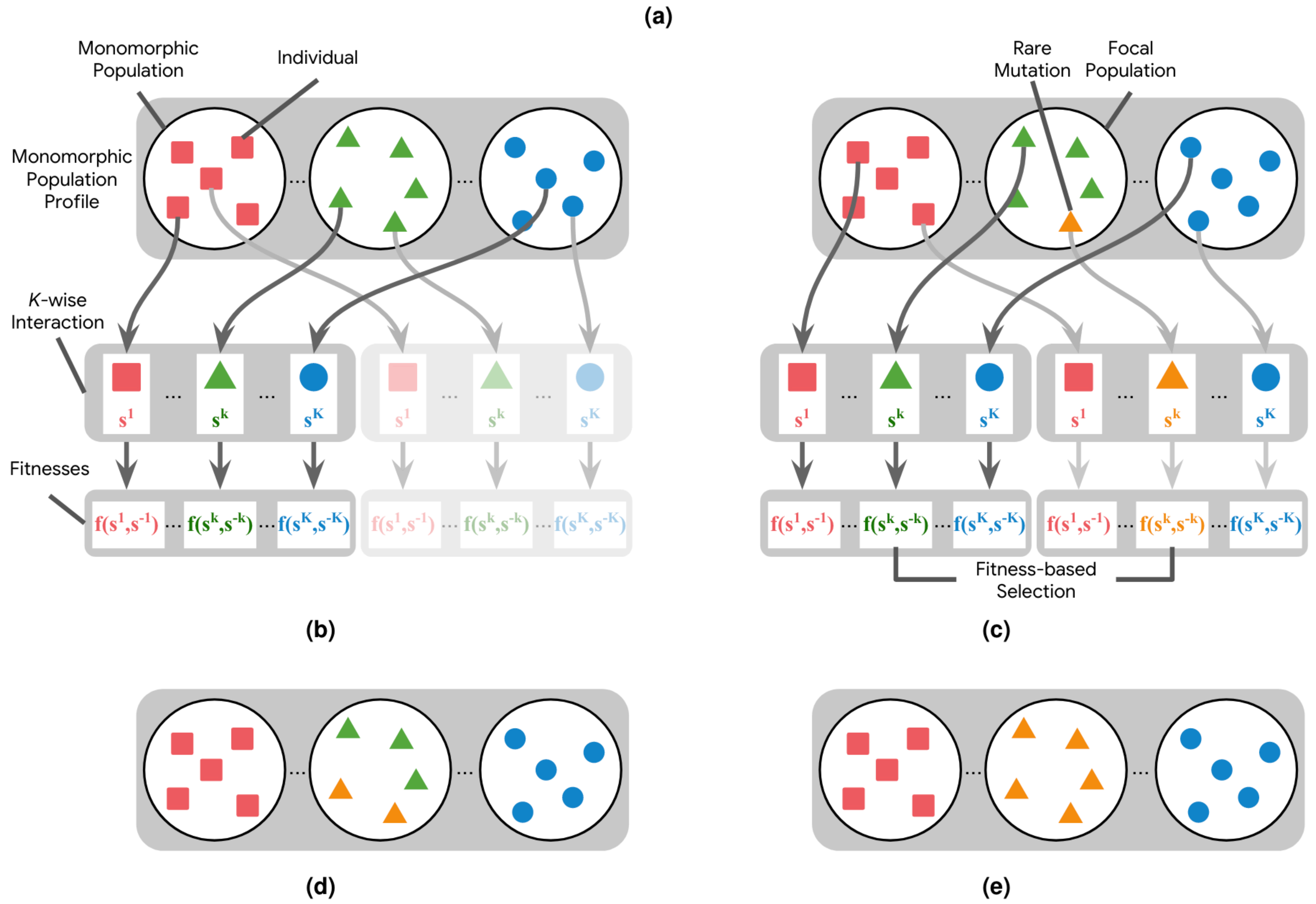
We introduce α-*Rank*, a principled evolutionary dynamics methodology, for the *evaluation* and *ranking* of agents in large-scale multi-agent interactions, grounded in a novel dynamical game-theoretic solution concept called *Markov-Conley chains* (MCCs). The approach leverages continuous-time and discrete-time evolutionary dynamical systems applied to empirical games, and scales tractably in the number of agents, in the type of interactions (beyond dyadic), and the type of empirical games (symmetric and asymmetric). Current models are fundamentally limited in one or more of these dimensions, and are not guaranteed to converge to the desired game-theoretic solution concept (typically the Nash equilibrium). α-Rank automatically provides a ranking over the set of agents under evaluation and provides insights into their strengths, weaknesses, and long-term dynamics in terms of basins of attraction and sink components. This is a direct consequence of the correspondence we establish to the dynamical MCC solution concept when the underlying evolutionary model's ranking-intensity parameter, α, is chosen to be large, which exactly forms the basis of α-Rank. In contrast to the



Improve AI self-play in large deep-RL agents

Why should you care about EGT?



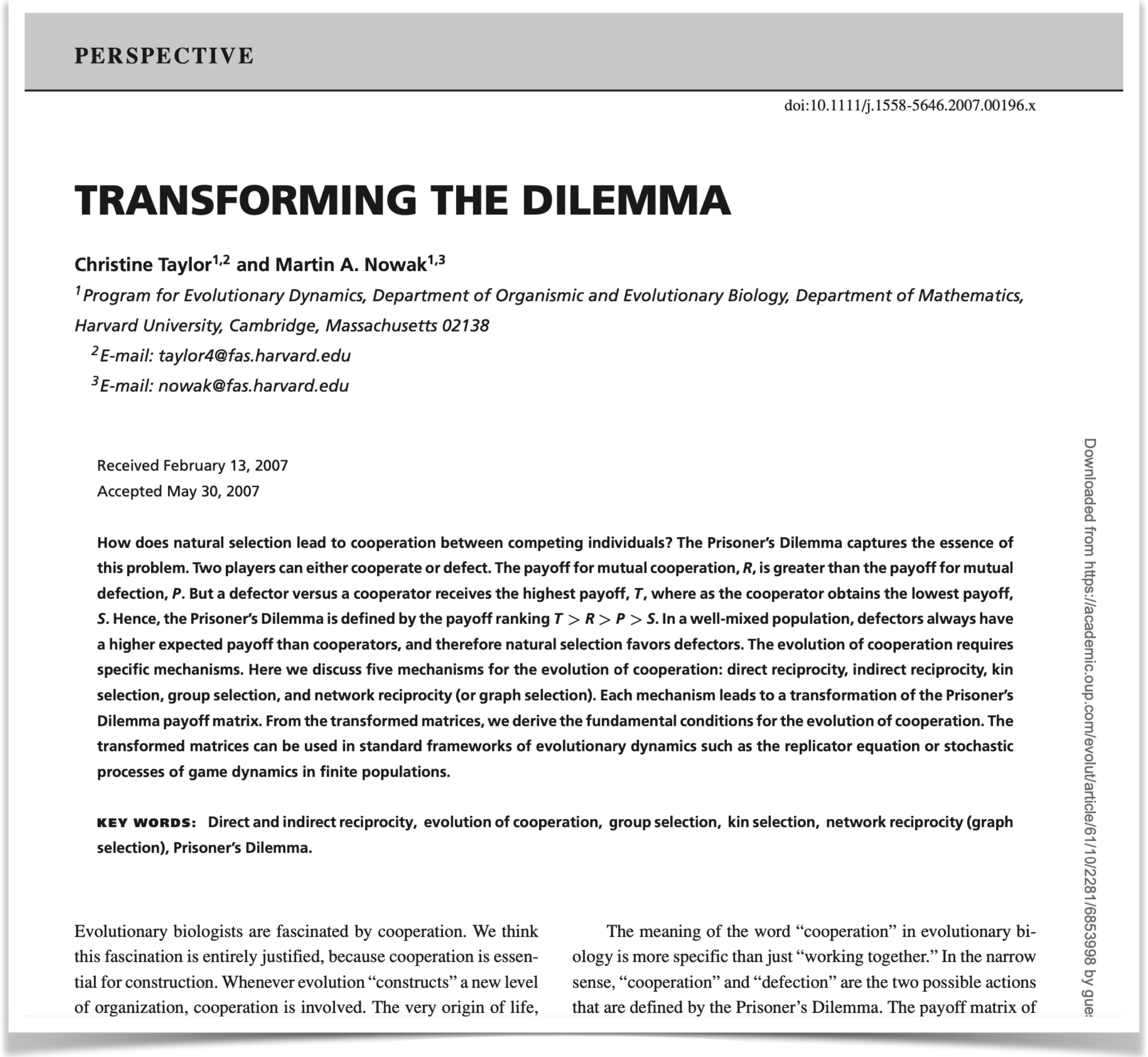
Improve AI self-play in large deep-RL agents

1.

Omidshafiei, S., Papadimitriou, C., Piliouras, G., Tuyls, K., Rowland, M., Lespiau, J. B., ... & Munos, R. (2019). α-rank: Multi-agent evaluation by evolution. *Scientific reports*, *9*(1), 9937.

Why should you care about EGT?

Prescriptive Framework?


PERSPECTIVE

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TRANSFORMING THE DILEMMA

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How does natural selection lead to cooperation between competing individuals? The Prisoner's Dilemma captures the essence of this problem. Two players can either cooperate or defect. The payoff for mutual cooperation, R, is greater than the payoff for mutual defection, P. But a defector versus a cooperator receives the highest payoff, T, where as the cooperator obtains the lowest payoff, S. Hence, the Prisoner's Dilemma is defined by the payoff ranking $T > R > P > S$. In a well-mixed population, defectors always have a higher expected payoff than cooperators, and therefore natural selection favors defectors. The evolution of cooperation requires specific mechanisms. Here we discuss five mechanisms for the evolution of cooperation: direct reciprocity, indirect reciprocity, kin selection, group selection, and network reciprocity (or graph selection). Each mechanism leads to a transformation of the Prisoner's Dilemma payoff matrix. From the transformed matrices, we derive the fundamental conditions for the evolution of cooperation. The transformed matrices can be used in standard frameworks of evolutionary dynamics such as the replicator equation or stochastic processes of game dynamics in finite populations.

KEY WORDS: Direct and indirect reciprocity, evolution of cooperation, group selection, kin selection, network reciprocity (graph selection), Prisoner's Dilemma.

Evolutionary biologists are fascinated by cooperation. We think this fascination is entirely justified, because cooperation is essential for construction. Whenever evolution "constructs" a new level of organization, cooperation is involved. The very origin of life,

The meaning of the word "cooperation" in evolutionary biology is more specific than just "working together." In the narrow sense, "cooperation" and "defection" are the two possible actions that are defined by the Prisoner's Dilemma. The payoff matrix of

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REVIEW

Five Rules for the Evolution of Cooperation

Martin A. Nowak

Cooperation is needed for evolution to construct new levels of organization. Genomes, cells, multicellular organisms, social insects, and human society are all based on cooperation. Cooperation means that selfish replicators forgo some of their reproductive potential to help one another. But natural selection implies competition and therefore opposes cooperation unless a specific mechanism is at work. Here I discuss five mechanisms for the evolution of cooperation: kin selection, direct reciprocity, indirect reciprocity, network reciprocity, and group selection. For each mechanism, a simple rule is derived that specifies whether natural selection can lead to cooperation.

Evolution is based on a fierce competition between individuals and should therefore reward only selfish behavior. Every gene, every cell, and every organism should be designed to promote its own evolutionary success at the expense of its competitors. Yet we observe cooperation on many levels of biological organization. Genes cooperate in genomes. Chromosomes cooperate in eukaryotic cells. Cells cooperate in multicellular organisms. There are many examples of cooperation among animals. Humans are the champions of cooperation: From hunter-gatherer societies to nation-states, cooperation is the decisive organizing principle of human society. No other life form on Earth is engaged in the same complex games of cooperation and defection. The question of how natural selection can lead to cooperative behavior has fascinated evolutionary biologists for several decades.

A cooperator is someone who pays a cost, c, for another individual to receive a benefit, b. A defector has no cost and does not deal out benefits. Cost and benefit are measured in terms of fitness. Reproduction can be genetic or cultural. In any mixed population, defectors have a higher average fitness than cooperators (Fig. 1). Therefore, selection acts to increase the relative abundance of defectors. After some

well-mixed populations needs help for establishing cooperation.

Kin Selection

When J. B. S. Haldane remarked, "I will jump into the river to save two brothers or eight cousins," he anticipated what became later known as Hamilton's rule (*1*). This ingenious idea is that natural selection can favor cooperation if the donor and the recipient of an altruistic act are genetic relatives. More precisely, Hamilton's rule states that the coefficient of relatedness, r, must exceed the cost-to-benefit ratio of the altruistic act:

$$r > c/b \tag{1}$$

Relatedness is defined as the probability of sharing a gene. The probability that two brothers share the same gene by descent is 1/2; the same probability for cousins is 1/8. Hamilton's theory became widely known as "kin selection" or "inclusive fitness" (*2–7*). When evaluating the fitness of the behavior induced by a certain gene, it is important to include the behavior's effect on kin who might carry the same gene. Therefore, the "extended phenotype" of cooperative behavior is the consequence of "selfish genes" (*8*, *9*).

Direct Reciprocity

observe cooperation between unrelated individuals or even between members of different species. Such considerations led Trivers (*10*) to propose another mechanism for the evolution of cooperation, direct reciprocity. Assume that there are repeated encounters between the same two individuals. In every round, each player has a choice between cooperation and defection. If I cooperate now, you may cooperate later. Hence, it might pay off to cooperate. This game theoretic framework is known as the repeated Prisoner's Dilemma.

But what is a good strategy for playing this game? In two computer tournaments, Axelrod (*11*) discovered that the "winning strategy" was the simplest of all, tit-for-tat. This strategy always starts with a cooperation, then it does whatever the other player has done in the previous round: a cooperation for a cooperation, a defection for a defection. This simple concept captured the fascination of all enthusiasts of the repeated Prisoner's Dilemma. Many empirical and theoretical studies were inspired by Axelrod's groundbreaking work (*12–14*).

But soon an Achilles heel of the world champion was revealed: If there are erroneous moves caused by "trembling hands" or "fuzzy minds," then the performance of tit-for-tat declines (*15*, *16*). Tit-for-tat cannot correct mistakes, because an accidental defection leads to a long sequence of retaliation. At first, tit-for-tat was replaced by generous-tit-for-tat (*17*), a strategy that cooperates whenever you cooperate, but sometimes cooperates although you have defected [with probability $1 - (c/b)$]. Natural selection can promote forgiveness.

Subsequently, tit-for-tat was replaced by win-stay, lose-shift, which is the even simpler idea of repeating your previous move whenever you are doing well, but changing otherwise (*18*). By various measures of success, win-stay, lose-shift is more robust than either tit-for-tat or generous-tit-for-tat (*15*, *18*). Tit-for-tat is an efficient catalyst of cooperation in a society where nearly everybody is a defector,

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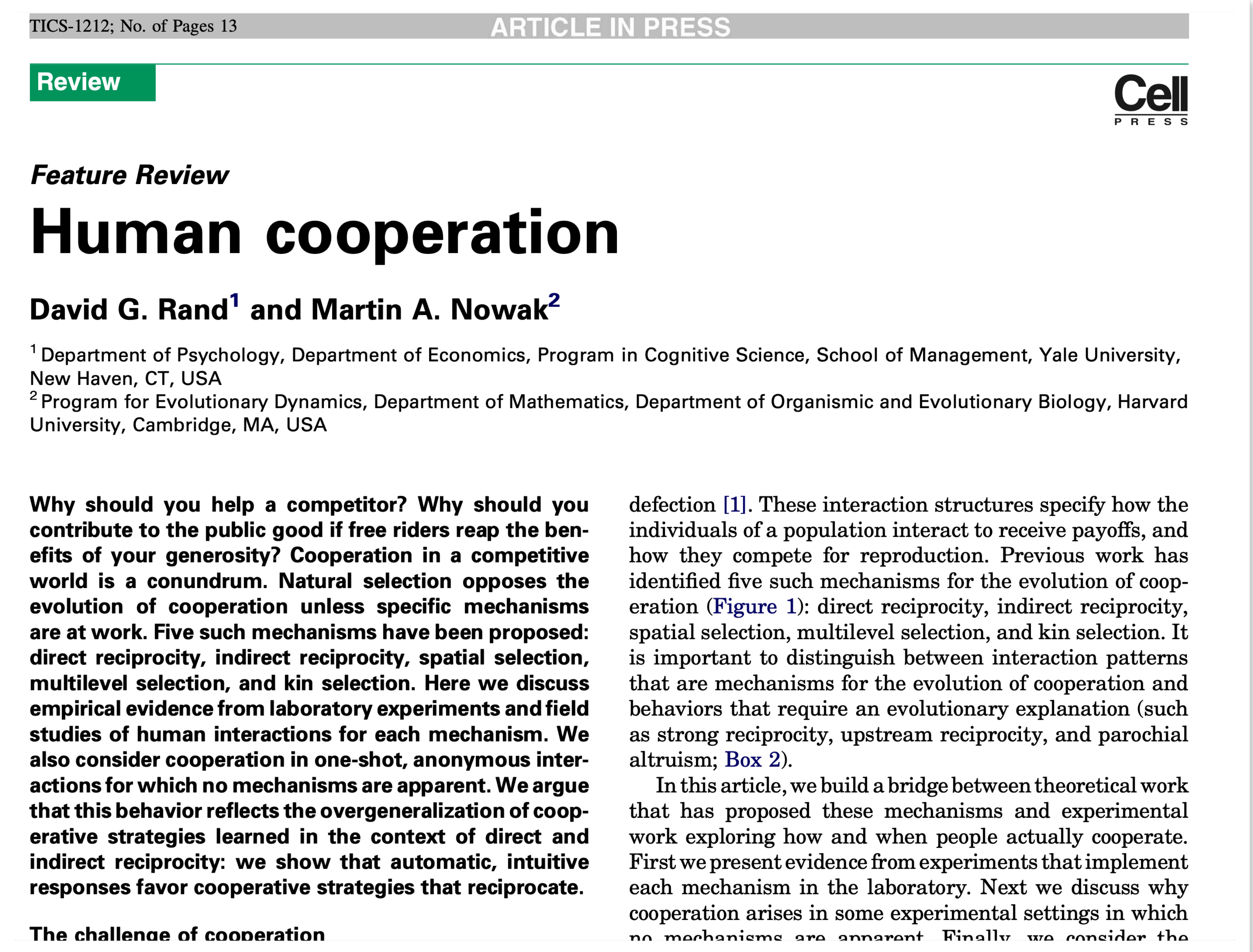
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Review

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Feature Review

Human cooperation

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[2] Program for Evolutionary Dynamics, Department of Mathematics, Department of Organismic and Evolutionary Biology, Harvard University, Cambridge, MA, USA

Why should you help a competitor? Why should you contribute to the public good if free riders reap the benefits of your generosity? Cooperation in a competitive world is a conundrum. Natural selection opposes the evolution of cooperation unless specific mechanisms are at work. Five such mechanisms have been proposed: direct reciprocity, indirect reciprocity, spatial selection, multilevel selection, and kin selection. Here we discuss empirical evidence from laboratory experiments and field studies of human interactions for each mechanism. We also consider cooperation in one-shot, anonymous interactions for which no mechanisms are apparent. We argue that this behavior reflects the overgeneralization of cooperative strategies learned in the context of direct and indirect reciprocity: we show that automatic, intuitive responses favor cooperative strategies that reciprocate.

The challenge of cooperation

defection [1]. These interaction structures specify how the individuals of a population interact to receive payoffs, and how they compete for reproduction. Previous work has identified five such mechanisms for the evolution of cooperation (Figure 1): direct reciprocity, indirect reciprocity, spatial selection, multilevel selection, and kin selection. It is important to distinguish between interaction patterns that are mechanisms for the evolution of cooperation and behaviors that require an evolutionary explanation (such as strong reciprocity, upstream reciprocity, and parochial altruism; Box 2).

In this article, we build a bridge between theoretical work that has proposed these mechanisms and experimental work exploring how and when people actually cooperate. First we present evidence from experiments that implement each mechanism in the laboratory. Next we discuss why cooperation arises in some experimental settings in which no mechanisms are apparent. Finally, we consider the

Taylor, C., & Nowak, M. A. (2007). Transforming the dilemma. Evolution, 61(10), 2281-2292.

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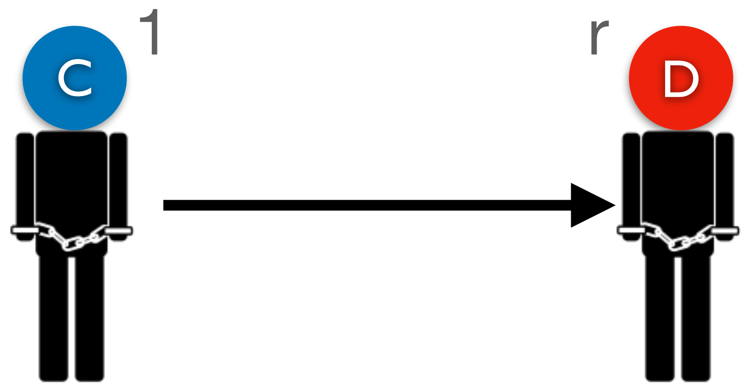
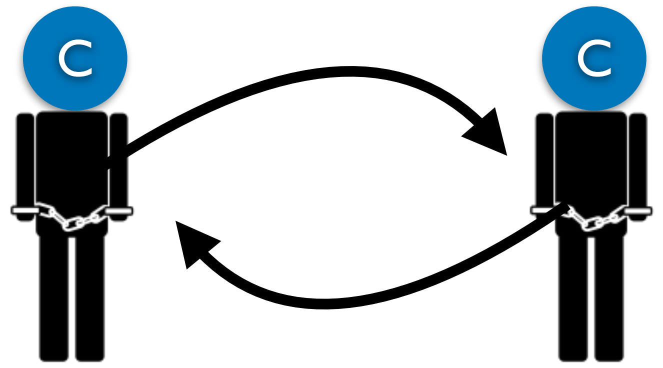
Four of the five rules

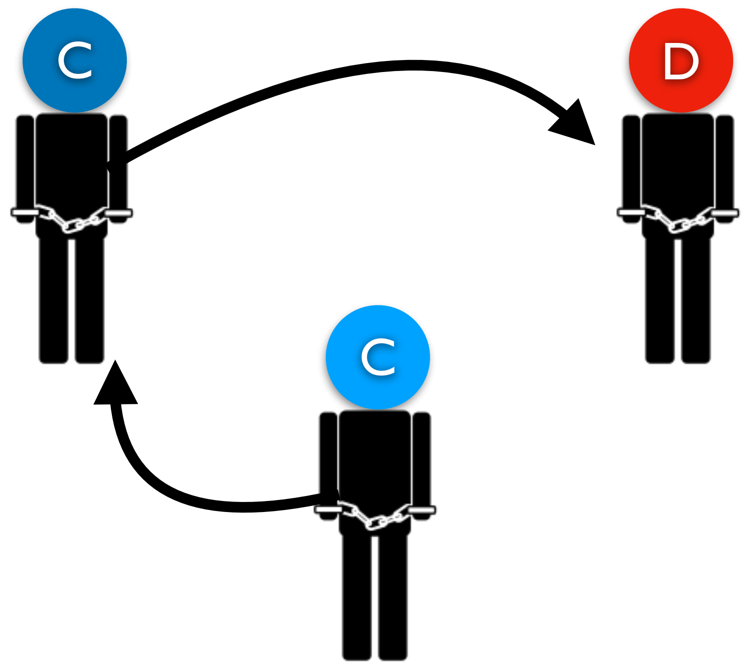


kin selection

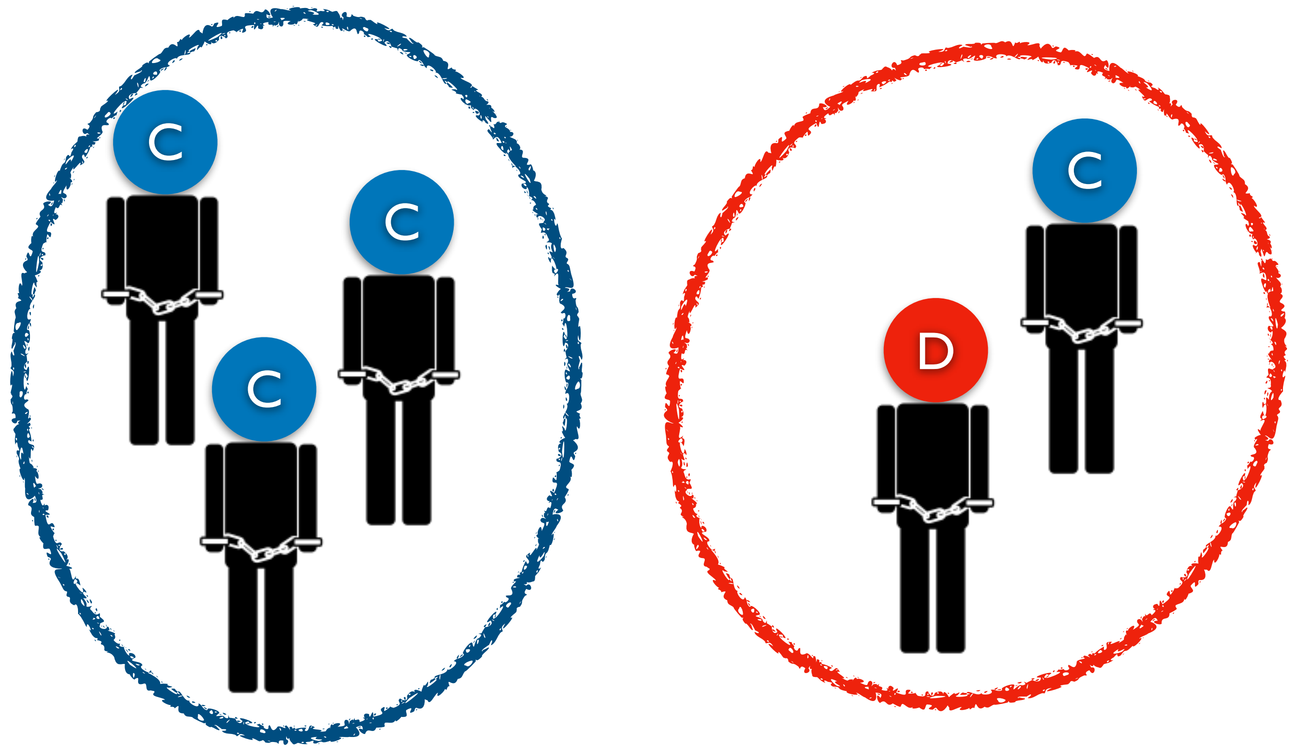


direct reciprocity

indirect reciprocity



group selection



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Rule number five

Part 1: Complex networks

Some good references

Statistical physics of human cooperation

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:ooperation among unrelated individuals is unique to humans, who often sacrifice p
ıon good and work together to achieve what they are unable to execute alone. T
ur species is indeed due, to a large degree, to our unparalleled other-regarding a
ve understanding of human cooperation remains a formidable challenge. Recent re
:ates that it is important to focus on the collective behavior that emerges as the res
ıg individuals, groups, and even societies. Non-equilibrium statistical physics, in pa
ds and the theory of collective behavior of interacting particles near phase transit
very valuable for understanding counterintuitive evolutionary outcomes. By study
eration as classical spin models, a physicist can draw on familiar settings from stat
like pairwise interactions among particles that typically govern solid-state physics
g humans often involve group interactions, and they also involve a larger number of
most simplified description of reality. The complexity of solutions therefore often
physical systems. Here we review experimental and theoretical research that ad
of human cooperation, focusing on spatial pattern formation, on the spatiotempor
utions, and on self-organization that may either promote or hinder socially favorabl

Contents

Statistical Mechanics of Complex Networks

Réka Albert[1,2] and Albert-László Barabási[2]

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Complex networks describe a wide range of systems in nature and society, much quoted examples including the cell, a network of chemicals linked by chemical reactions, or the Internet, a network of routers and computers connected by physical links. While traditionally these systems were modeled as random graphs, it is increasingly recognized that the topology and evolution of real networks is governed by robust organizing principles. Here we review the recent advances in the field of complex networks, focusing on the statistical mechanics of network topology and dynamics. After reviewing the empirical data that motivated the recent interest in networks, we discuss the main models and analytical tools, covering random graphs, small-world and scale-free networks, as well as the interplay between topology and the network's robustness against failures and attacks.

CONTENTS

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Complex networks: Structure and dynamics

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75651 Paris CEDEX 13, France

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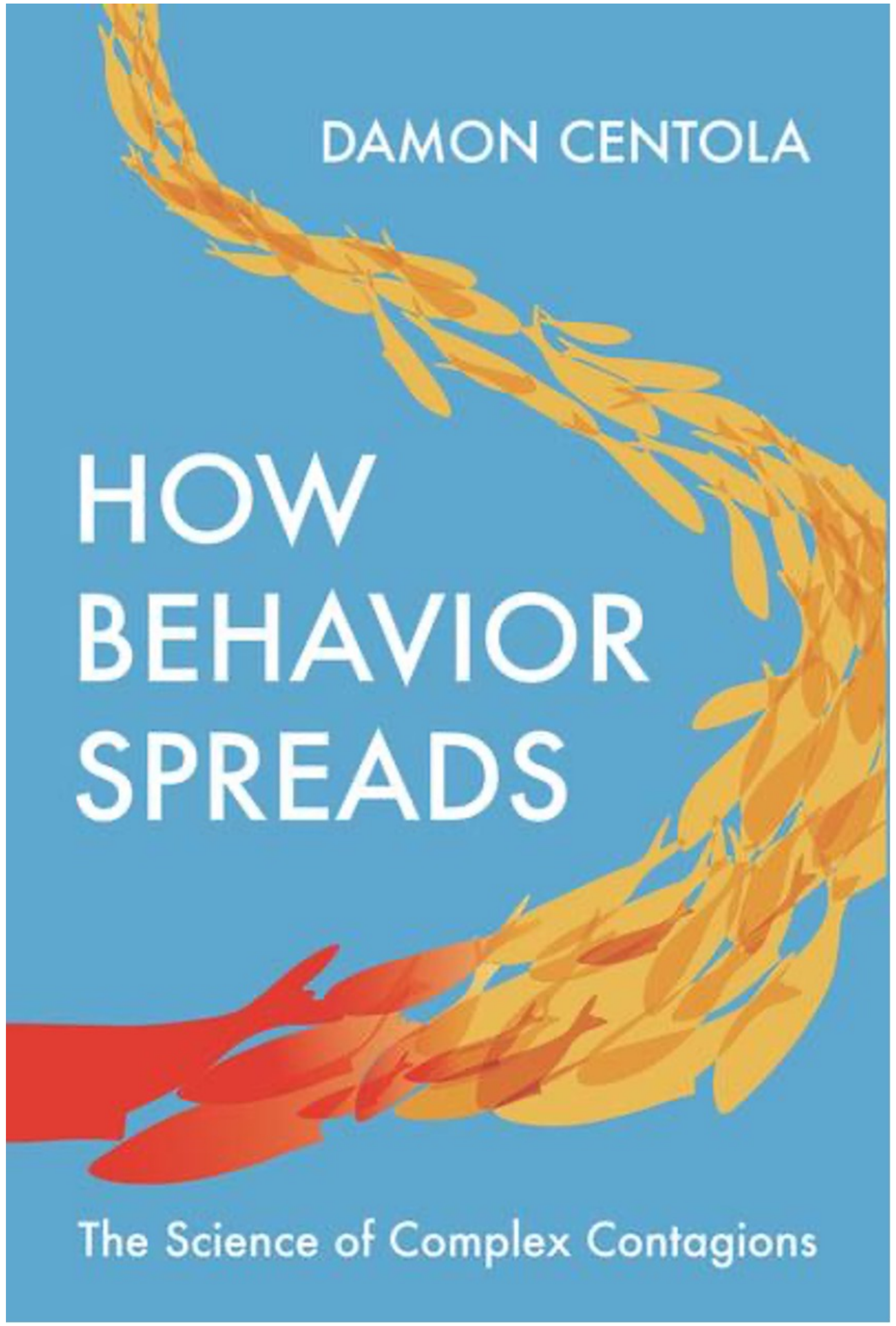
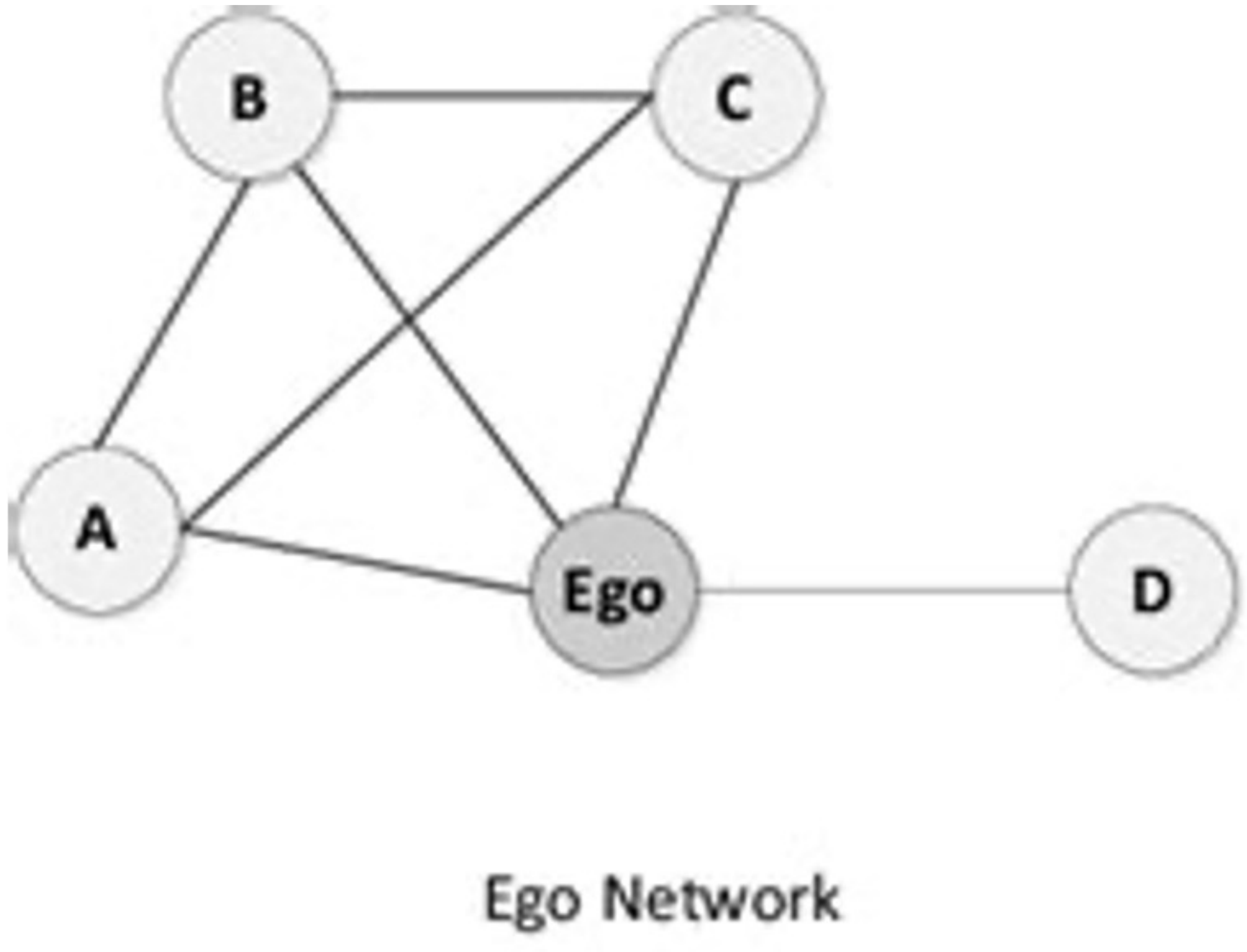
Available online 10 January 2006
editor: I. Procaccia

iological and chemical systems, neural networks, social interacting species, the Internet and the V
v examples of systems composed by a large number of highly interconnected dynamical units. The
lobal properties of such systems is to model them as graphs whose nodes represent the dynamical
r the interactions between them. On the one hand, scientists have to cope with structural issues, such
of a complex wiring architecture, revealing the unifying principles that are at the basis of real network
nic the growth of a network and reproduce its structural properties. On the other hand, many relevai
; complex networks' dynamics, such as learning how a large ensemble of dynamical systems that i
ıg topology can behave collectively. We review the major concepts and results recently achieved i
dynamics of complex networks, and summarize the relevant applications of these ideas in many dif
nonlinear science to biology, from statistical mechanics to medicine and engineering.

Some good references



What are social networks?



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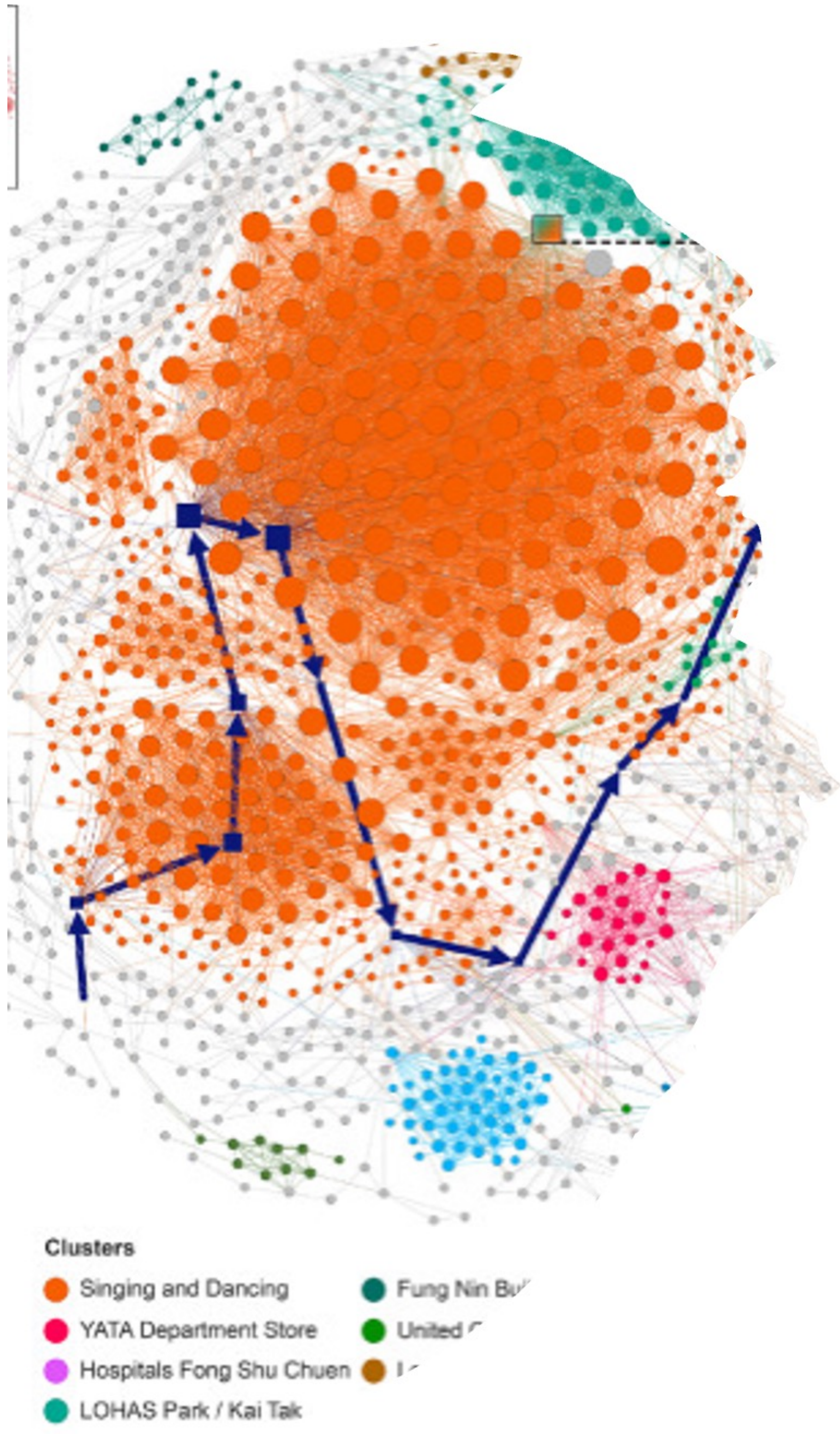
What are social networks?



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What are social networks?

https://www.youtube.com/watch?v=4fHufyIWmX0

Important concepts

https://www.youtube.com/watch?v=-ckaLBsCoxo&t=1s

Important concepts

- A graph **G** can be defined as $G = (V, E)$ where **V** is the set of vertices or **nodes** of the graph, and **E** the set of edges connecting every two nodes in the graph.
- We can also represent a finite graph using an **adjacency matrix A**. This $n \times n$ square matrix indicate whether pairs of vertices in the graph are connected by an edge, i.e., every $A_{ij} = 1$ where there is and edge between nodes v_i and v_j, otherwise $A_{ij} = 0$.
- Graphs can be **directed** or **undirected**. In undirected graphs, the adjacency matrix is symmetric.
-

Important concepts

- The edges of a graph can also be weighted, i.e., some edges are more important than others.
- The **distance matrix** is a weighted adjacency matrix, and the **distance** between two nodes $d(v_i, v_j)$ in the network can be defined as the minimum sum of the sum of the weights on the shortest path between two nodes. Or simply, for binary networks (non-weighted) **the distance between two nodes is defined as the number of edges along the shortest path connecting them.**
-

Important concepts

- The **degree (**k**)** of a node is the total number of edged incident on that node in a binary undirected network.
- In directed networks, we differentiate between **in-degree (**k_{in}**)** and **out-degree (**k_{out}**)**.
- In weighted networks, the strength measure is also considered.
-

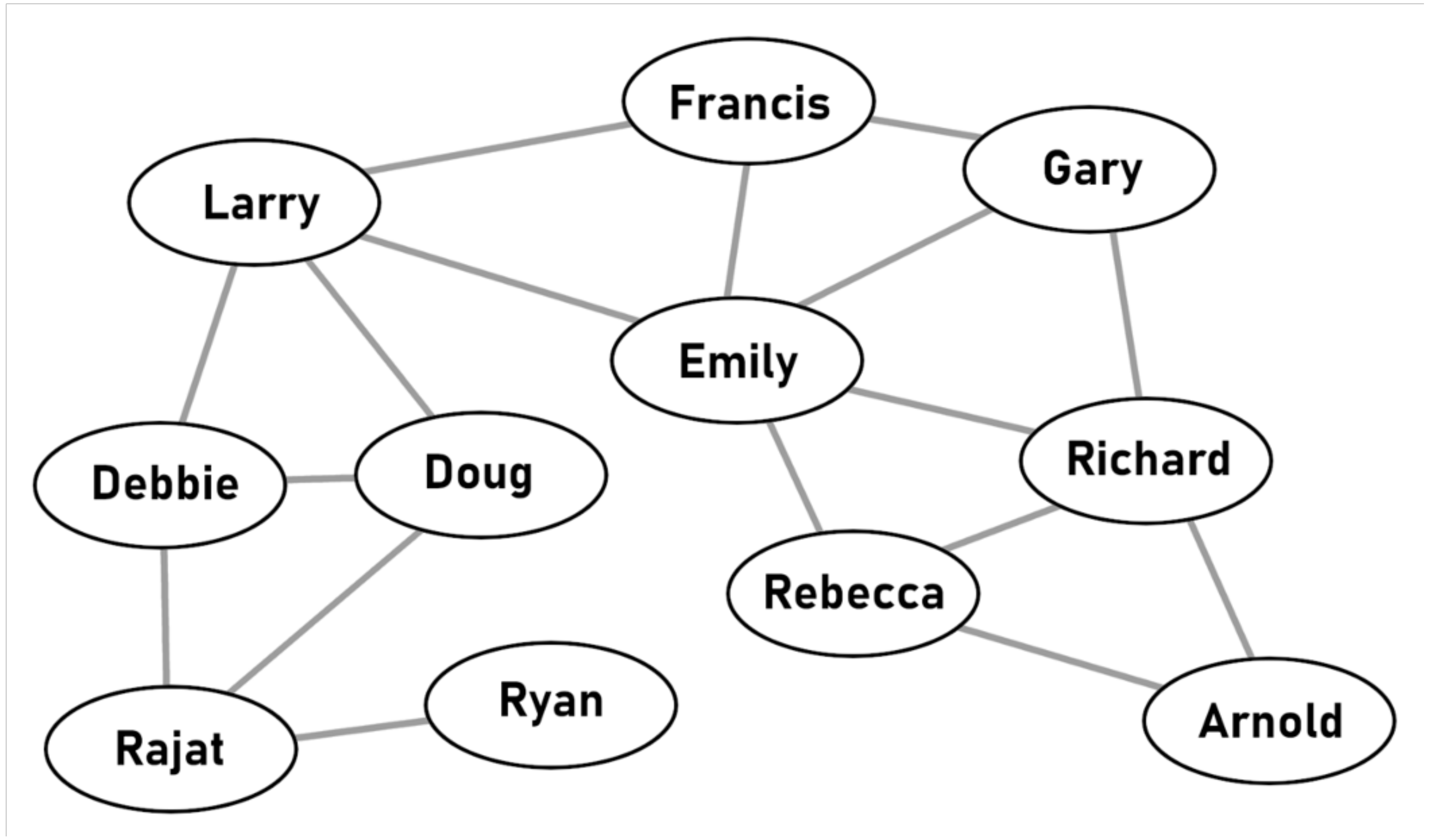
Important concepts

- A **clique** is a subset of nodes of an undirected graph (or network) such that every two distinct nodes in the clique are adjacent. That is, a clique in a graph G is a complete subgraph of G.
-

Important concepts: Small worlds

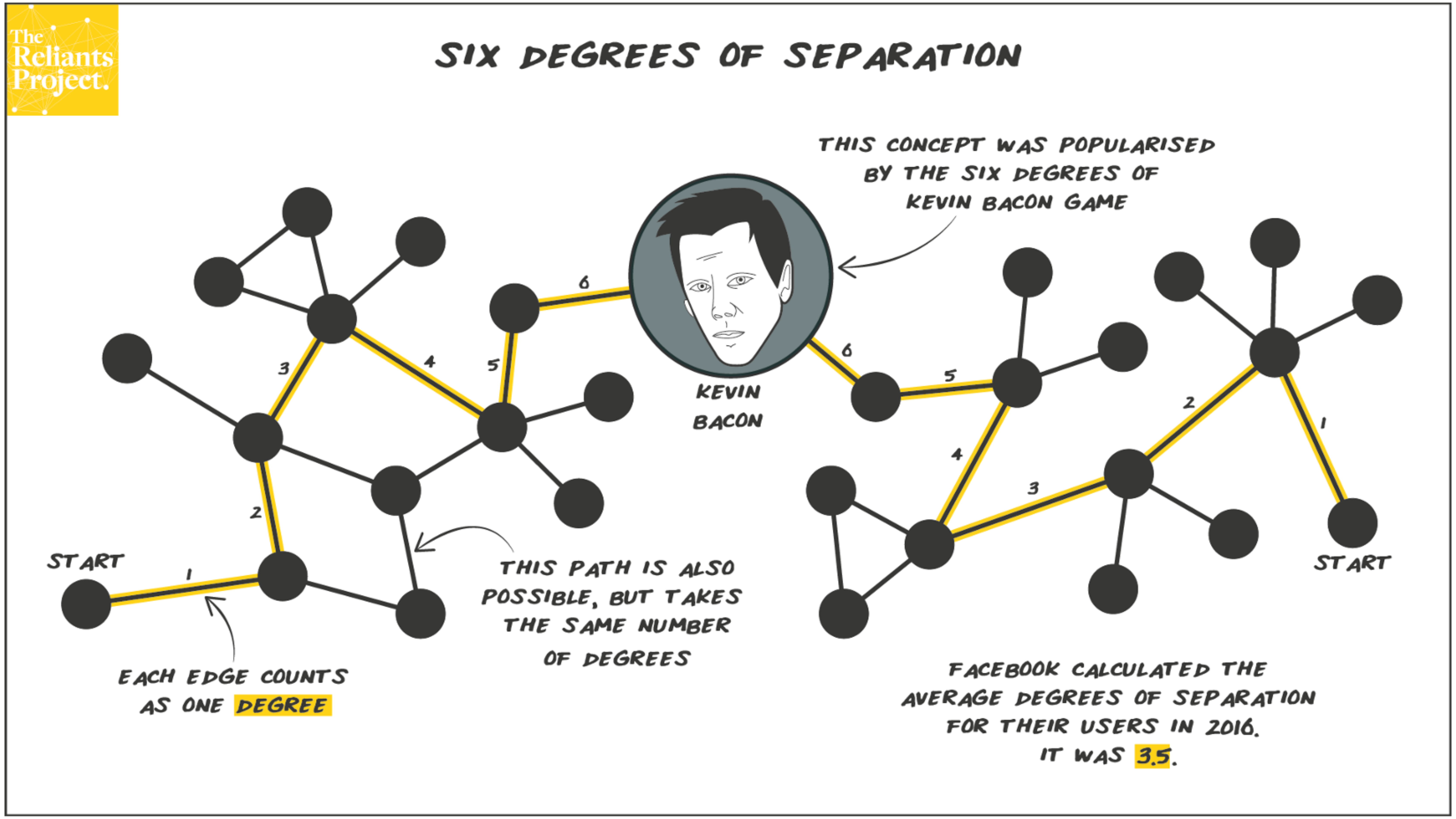
There are many important measures and indicators of a network topology. We will focus on the following three concepts:

- **Small worlds**
- **Clustering**
- **Degree distribution**



Watts, Duncan J., and Steven H. Strogatz. "Collective dynamics of 'small-world'networks." *nature* 393.6684 (1998): 440-442.

Important concepts: Small worlds



Important concepts: Clustering

Clustering: cliques tend to form in social networks, representing circles of close friends. This effect can be quantified using the **clustering coefficient** (Watts and Strogatz 1998).

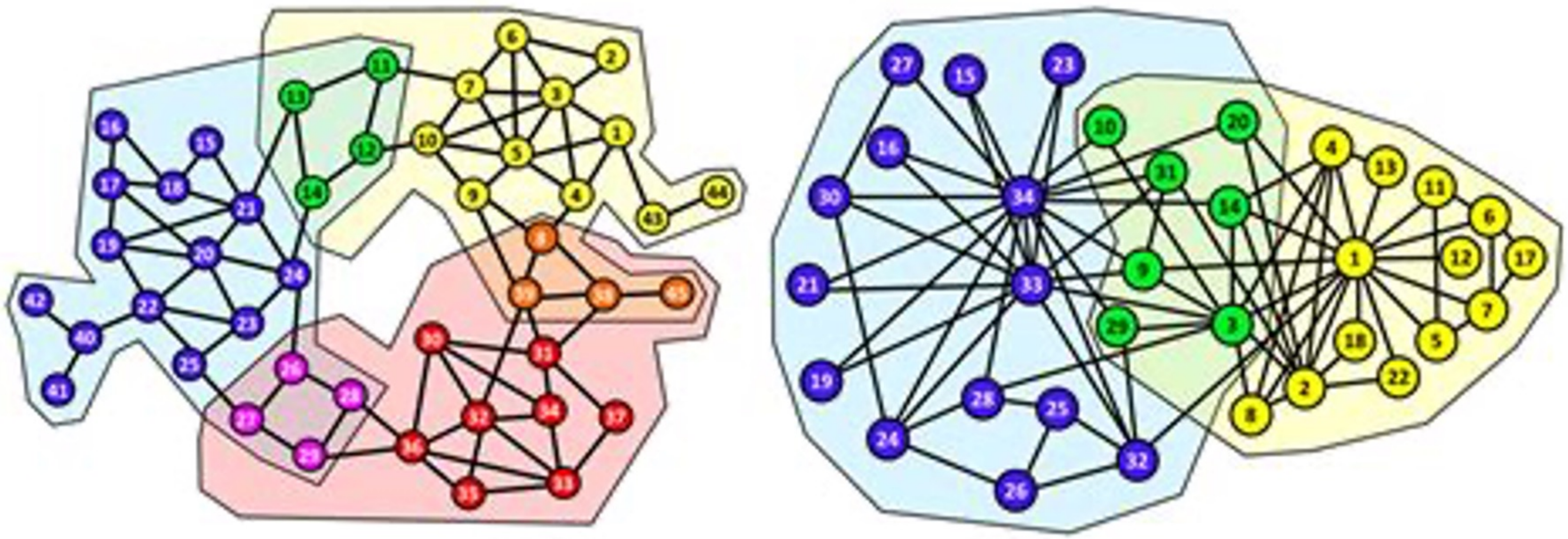
Let's assume we have a node i in the network, with k_i edges which connect it to k_i other nodes. If the first neighbours of the original node were part of a clique, there would be $k_i(k_i - 1)/2$ **edges between them.**

The ratio between the number E_i of edges that actually exist between these k_i nodes and the total number of nodes in a clique $k_i(k_i - 1)/2$ gives the value of the clustering coefficient of node i:

$$C_i = \frac{2E_i}{k_i(k_i - 1)}$$

The **clustering coefficient** of the whole network is an average of all individual C_i**'s.**

Important concepts: Clustering



Important concepts: Clustering

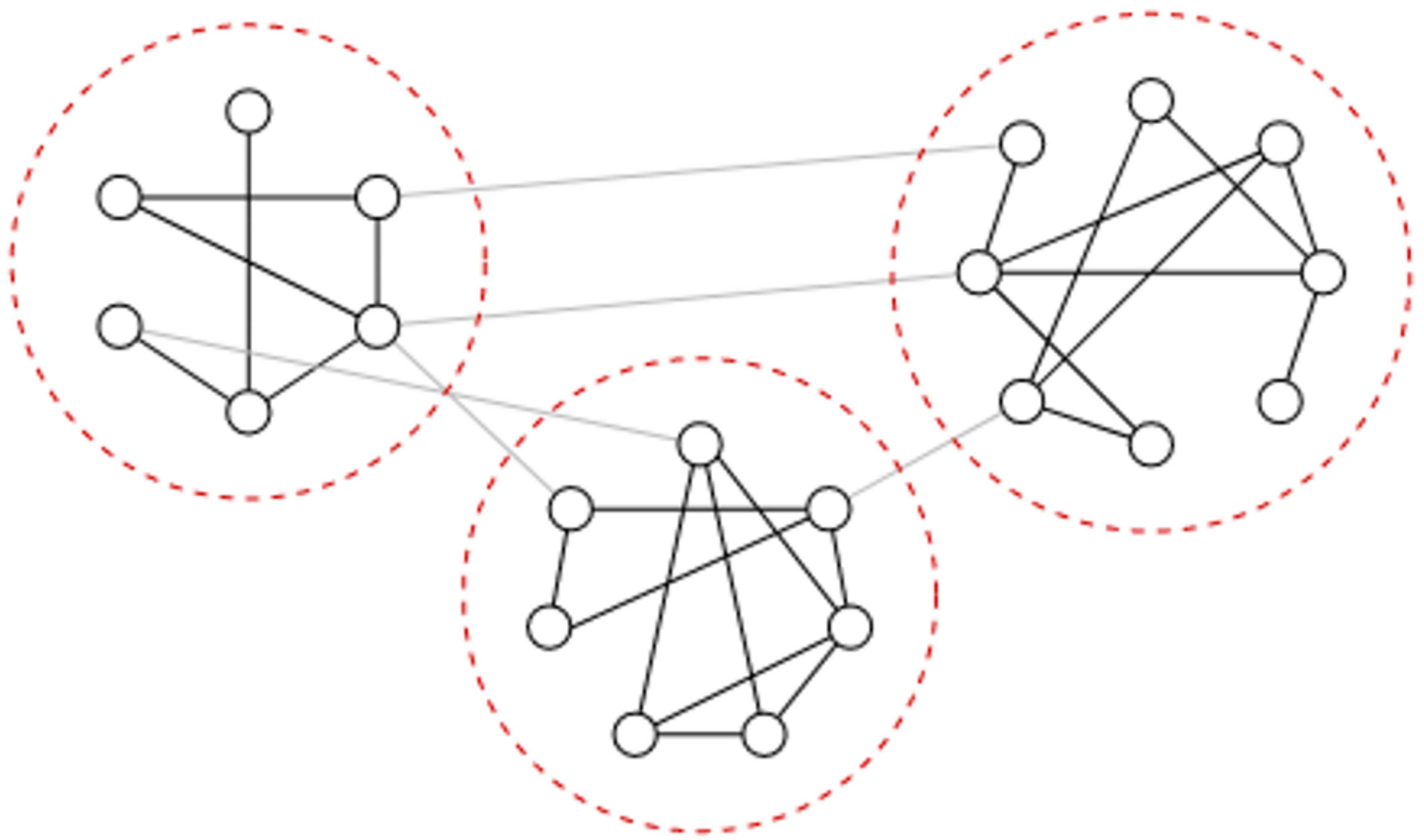


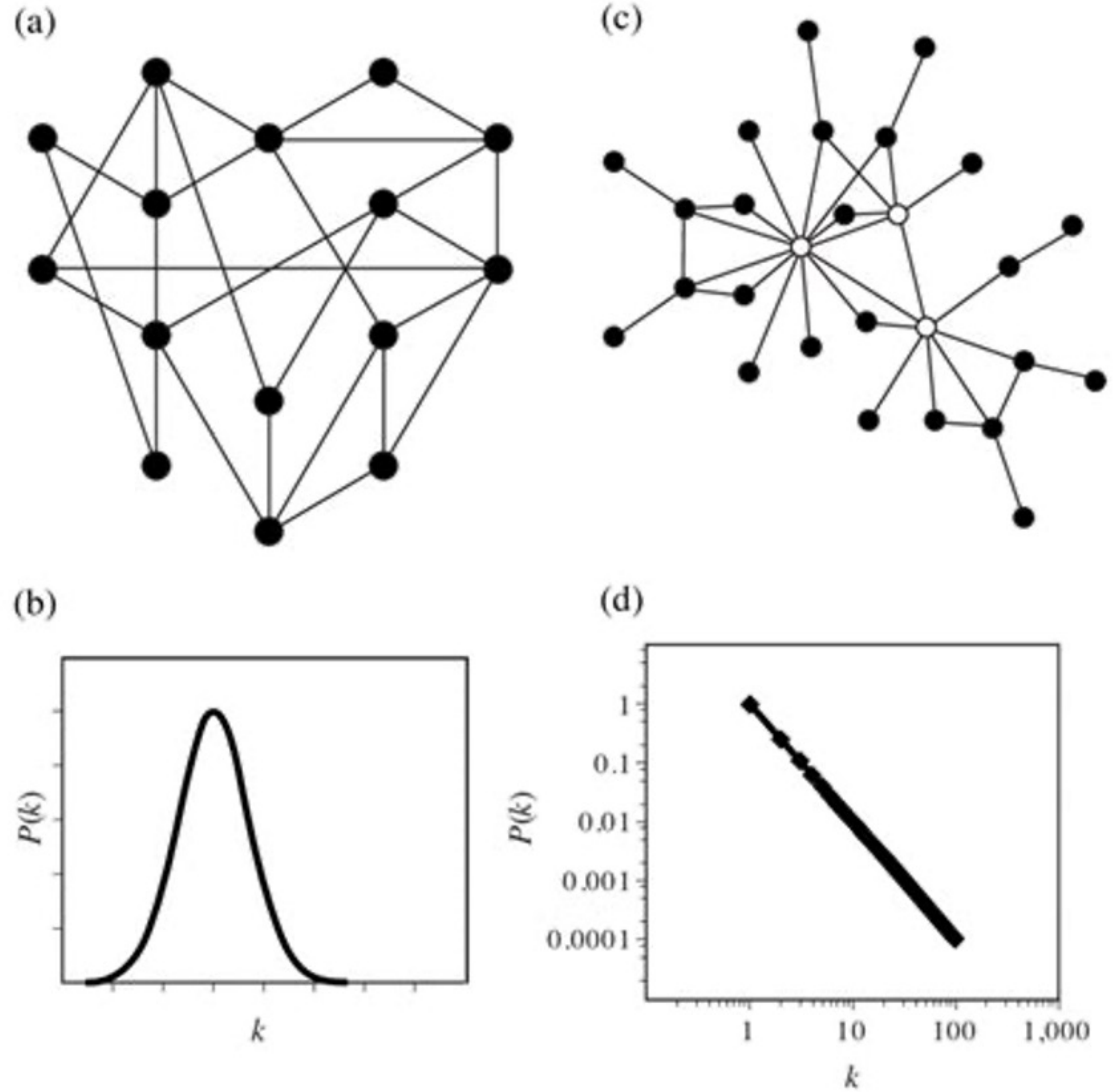
Fig. 2.3. Communities can be defined as groups of nodes such that there is a higher density of edges within groups than between them. In the case shown in figure there are three communities, denoted by the dashed circles. Reprinted figure with permission from Ref. [51]. © 2004 by the American Physical Society.

Boccaletti et al., ‘Complex Networks’.

Important concepts: Degree distribution

Degree distribution: The spread in the number of edges a node has, or node degree, is characterized by the distribution function $P(k)$.

$P(k)$ gives the probability that a randomly selected node has exactly k edges.



Random / Erdös-Rényi (ER) network

Power-law / Scale-free network

Important concepts

Characterization and Traversal of Large Real-World Networks

A. Garcia-Robledo, ... G. Morales-Luna, in Big Data, 2016

5.3 Characterization and Measurement

A complex network $G = V, E$ is a non-empty set V of nodes or vertices and a set E of links or edges, such that there is a mapping between the elements of E and the set of pairs $\{i, j\}$, $i, j \in V$. Let $n = V$ be the number of vertices and $m = E$ be the number of edges of G. The degree k_i of a vertex $i \in V$ is the number of neighbors of i. Let n_k be the number of vertices of degree k in G, such that $\sum_k n_k = n$. Let $Pk = n_k / n$ be the degree distribution of G.

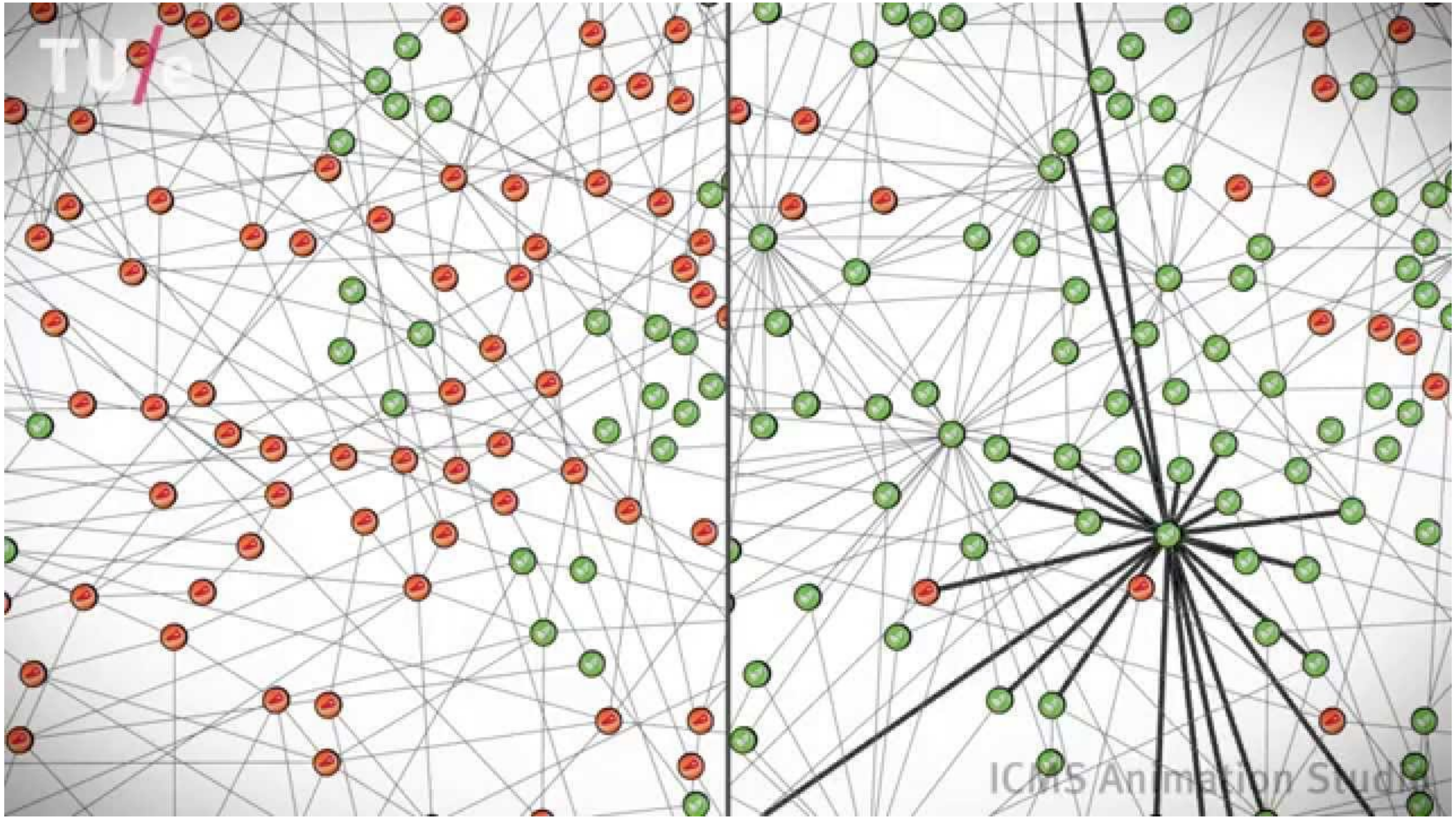
Complex networks, random graphs, and graphs arising in scientific computing (e.g., meshes and lattices) are all sparse. However, unlike these kinds of graphs, complex networks present the combined

https://www.sciencedirect.com/science/article/pii/B9780128053942000052

Important concepts

Metric	Symbol	Type	Equations
Density	d	Degree	$2m \,/\, nn - 1$
Clustering coefficient	CC_i	Clustering	$\frac{2e_{jk}}{k_i k_i - 1} : j, k \in N_i, e_{jk} \in E$
Avg. path length	$\langle L \rangle$	Distance	$\frac{1}{nn-1} \sum_{i,j \in V : i \neq j} d_{ij}$
Diameter	D	Distance	$\max_{i,j \in V : i \neq j} d_{ij}$
Betweenness centrality	nBc_u	Centrality	$\sum_{i,j \in V : i \neq j} \frac{\sigma i,u,j}{\sigma i,j}$
Central point dominance	CPD	Centrality	$\frac{1}{n-1} \sum_{i \in V} nBc_{\max} - nBc_i$
Closeness centrality	Cc_i	Centrality	$\frac{1}{\sum_{j \in V} d_{ij}}$
Avg. neighbor degree	$\langle k_n \rangle$	Centrality	$\frac{k_u}{k_i} : u \in N_i$

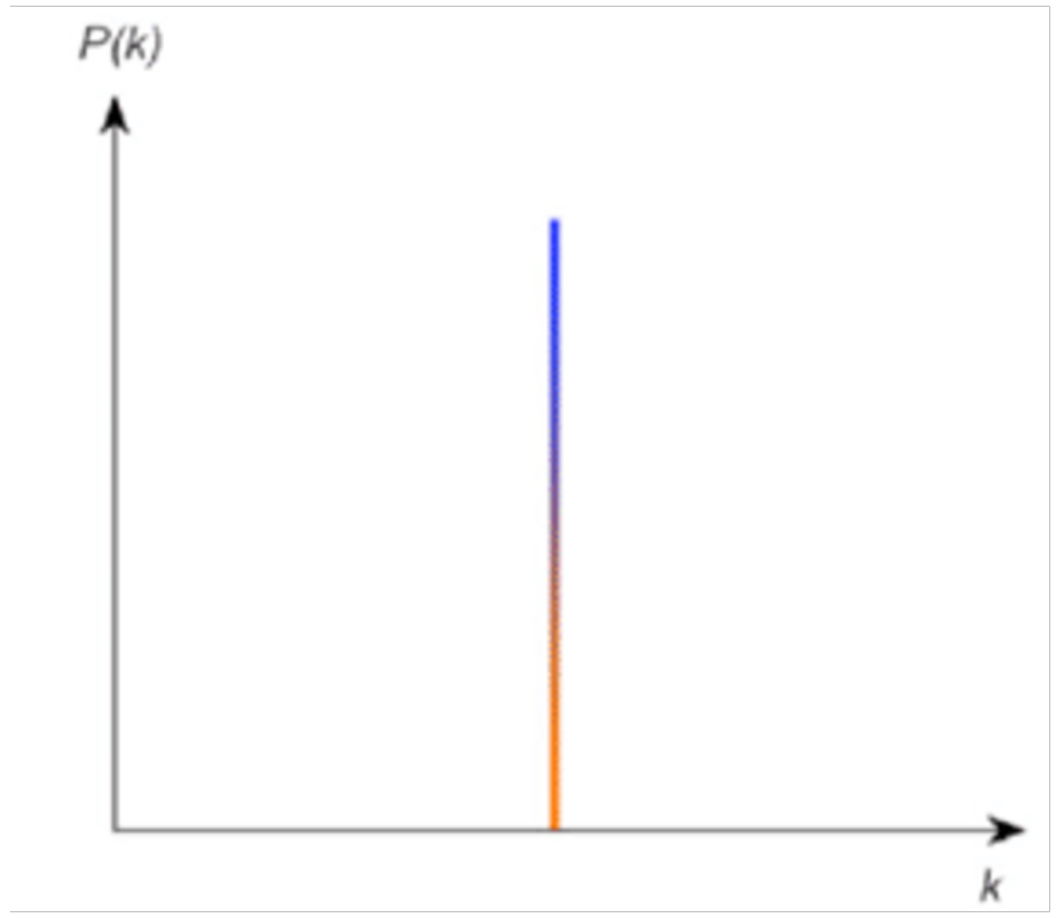
Structure and social ties

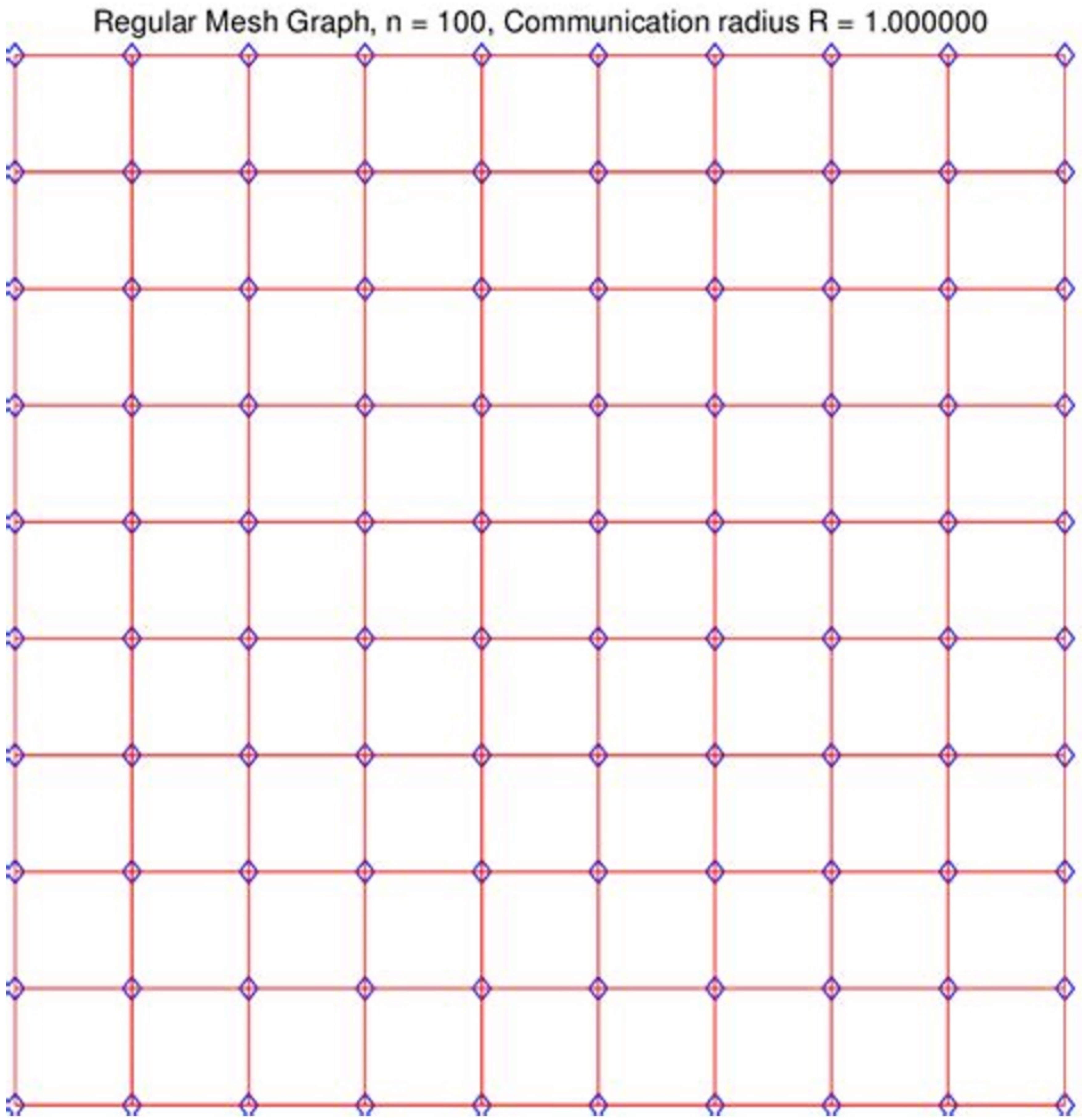


https://www.youtube.com/watch?v=sI8TK2mETrk&source_ve_path=MjM4NTE

Regular Networks

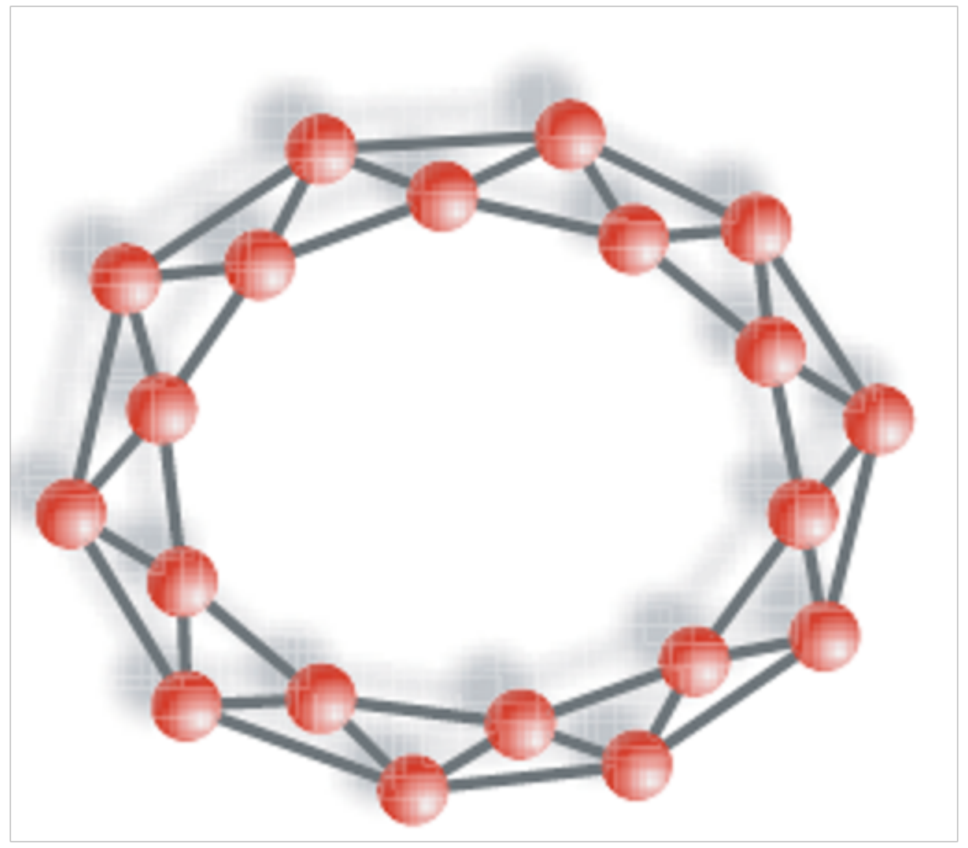
$$\langle k \rangle = 4$$
$$P(k) = \delta(4)$$

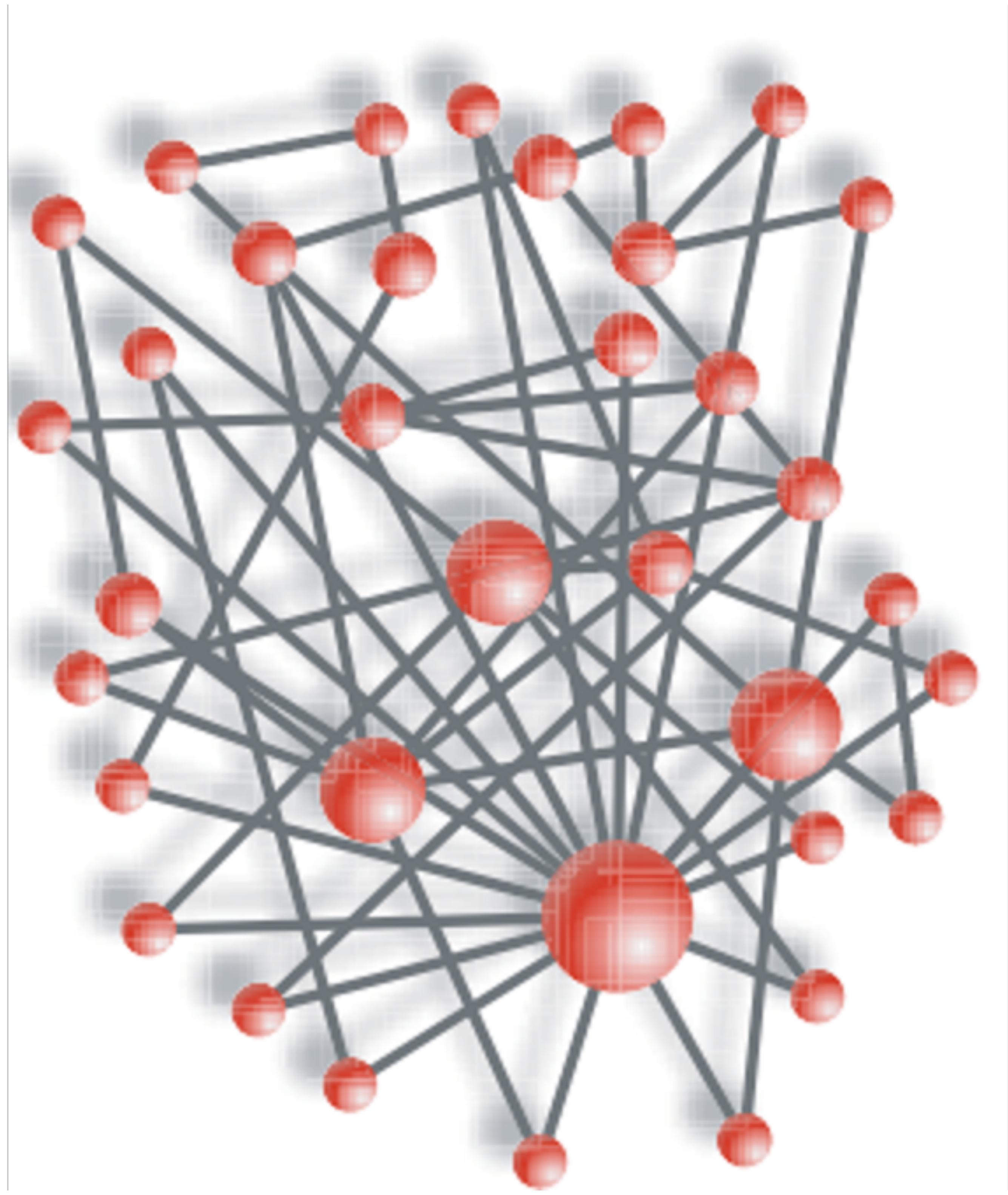




Complex Networks

- Random graphs
- Small world
- Scale free

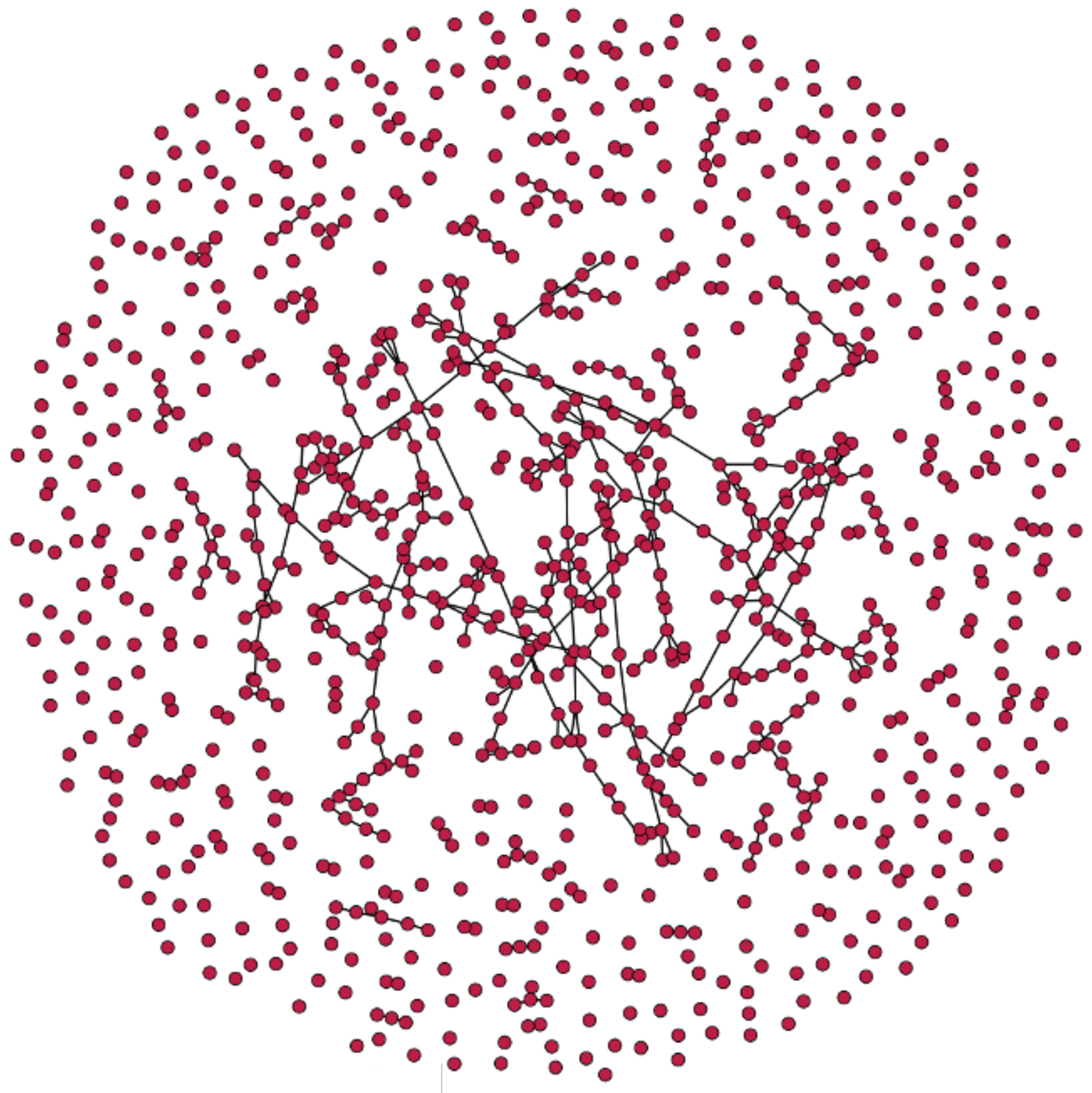


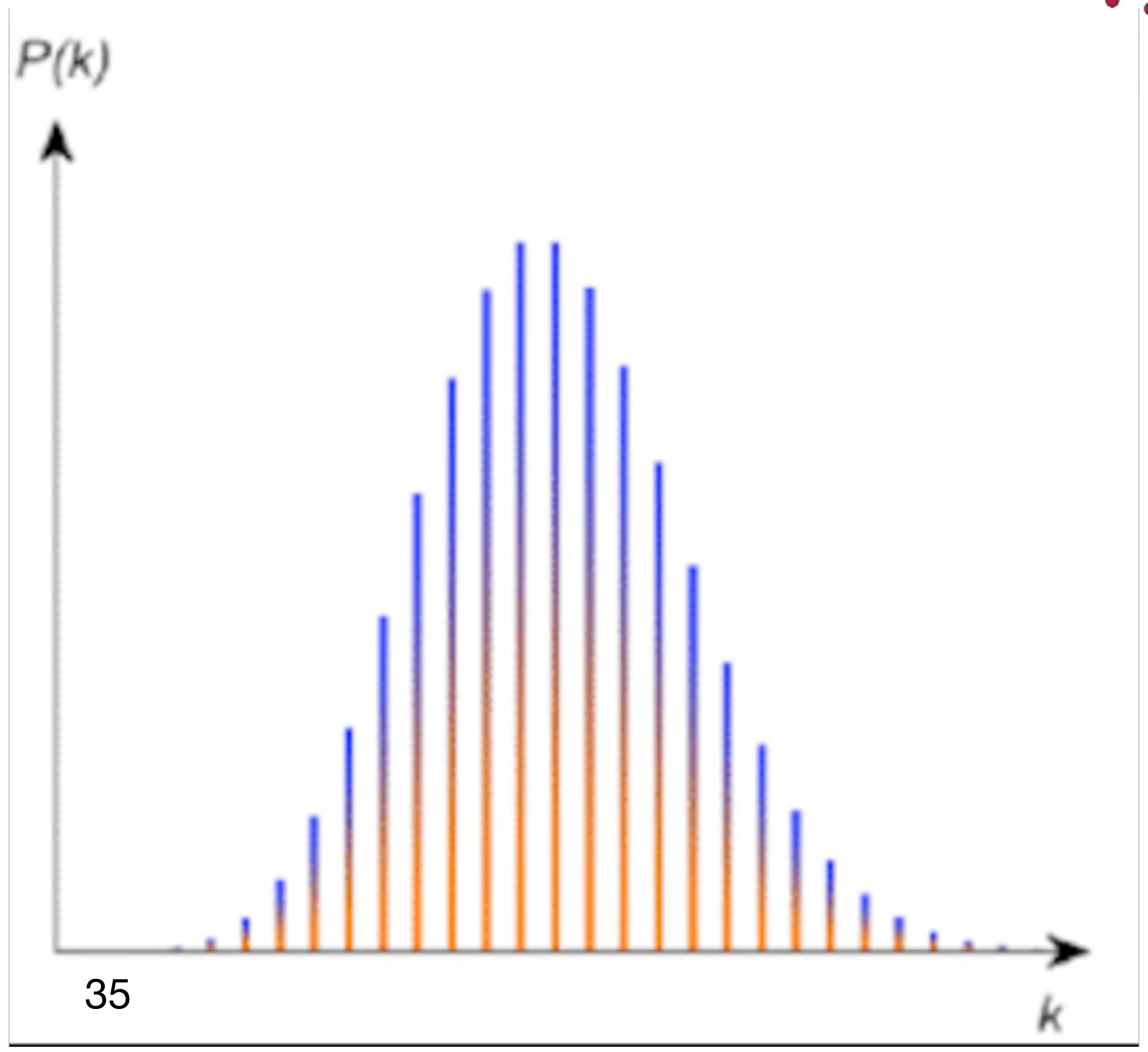


Complex Networks: Erdös-Rényi (ER) Random Network

- The Erdös-Rényi model defines a random graph as N labeled nodes connected by n edges which are chosen randomly from the $N(N-1)/2$ possible edges.

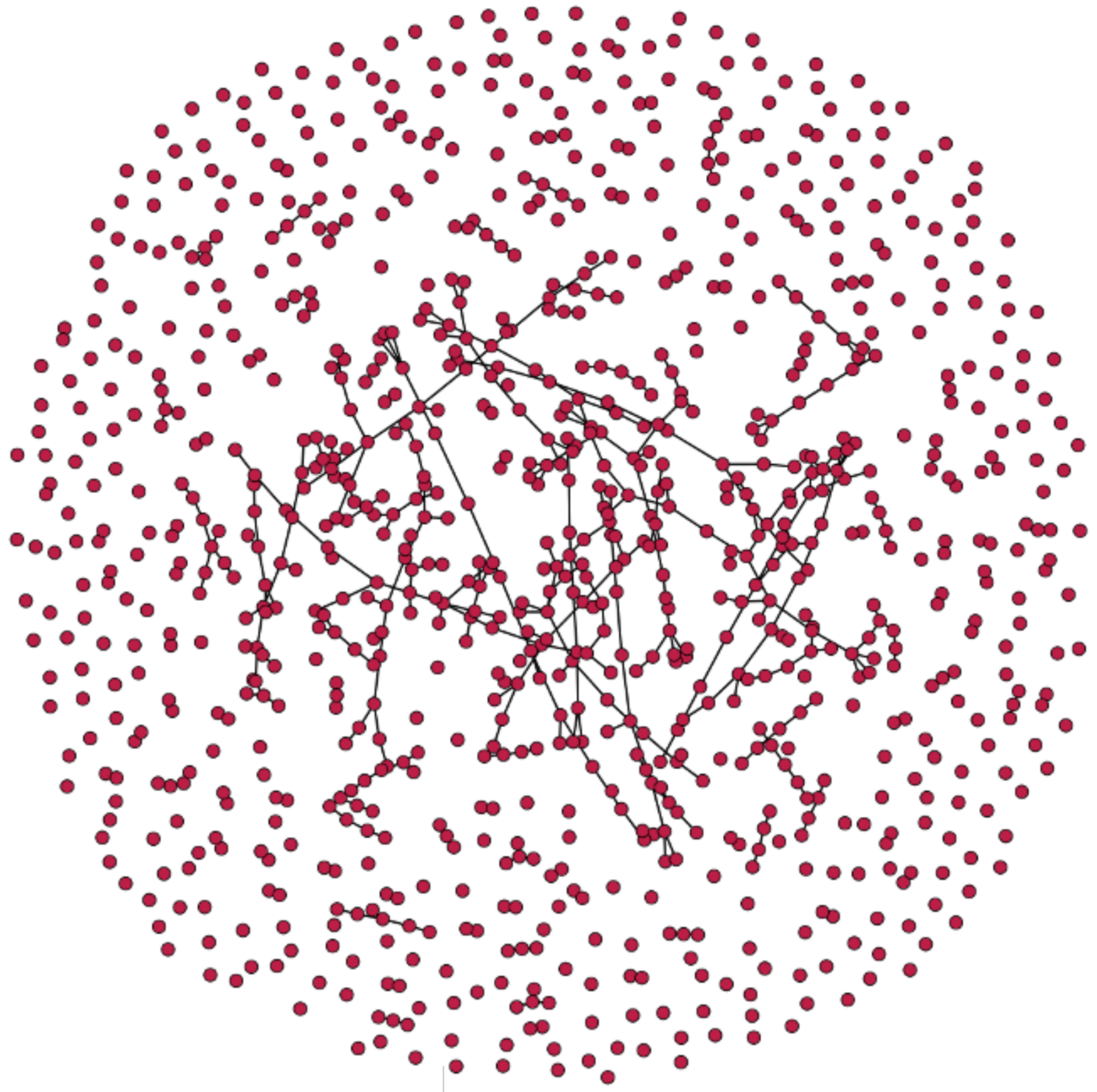
- This defines $\frac{C^{n}_{N(N-1}}{2}$ possible graphs with N nodes and n edges. A random network can be generating by choosing one of these possible graphs with equal probability

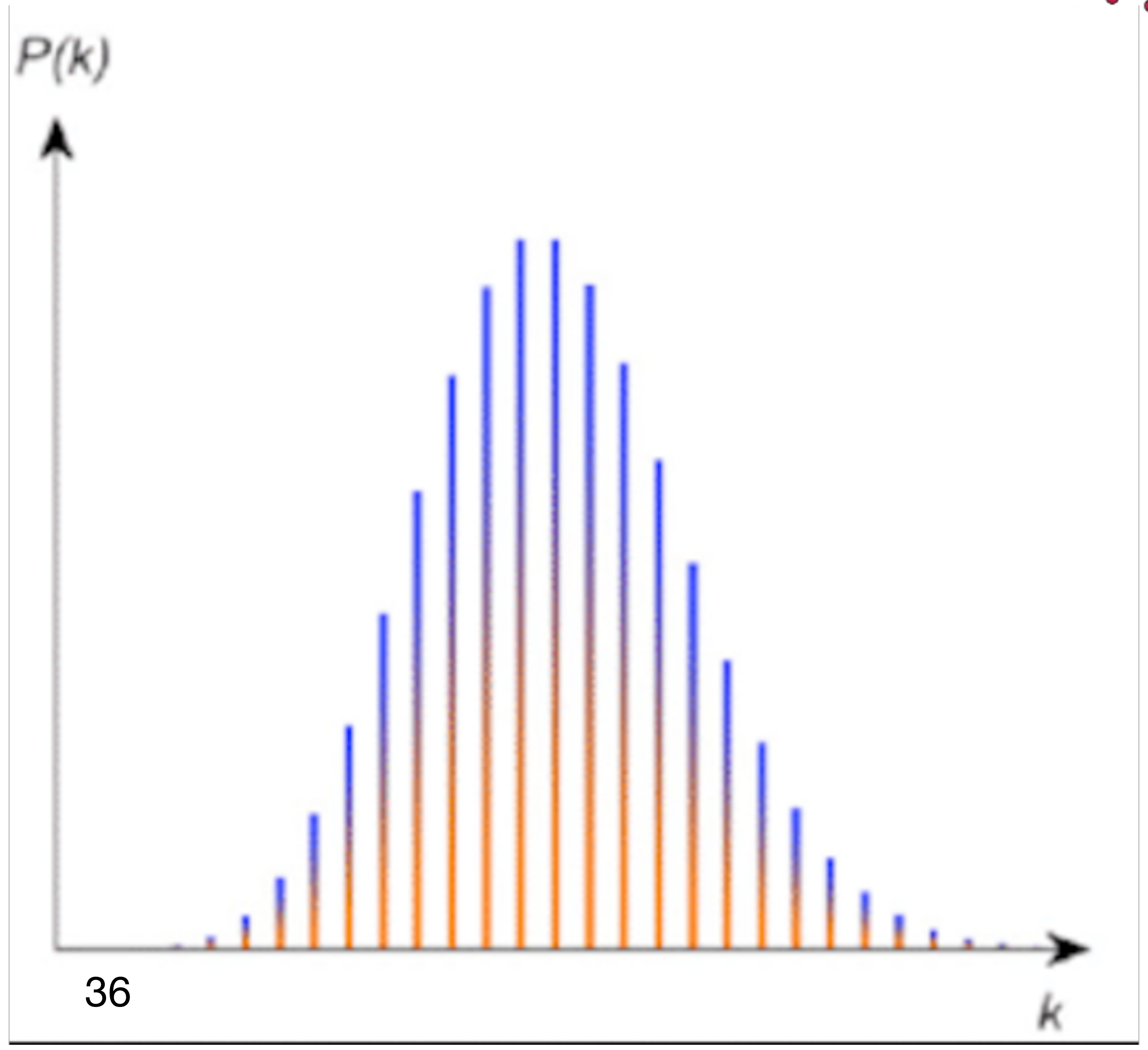




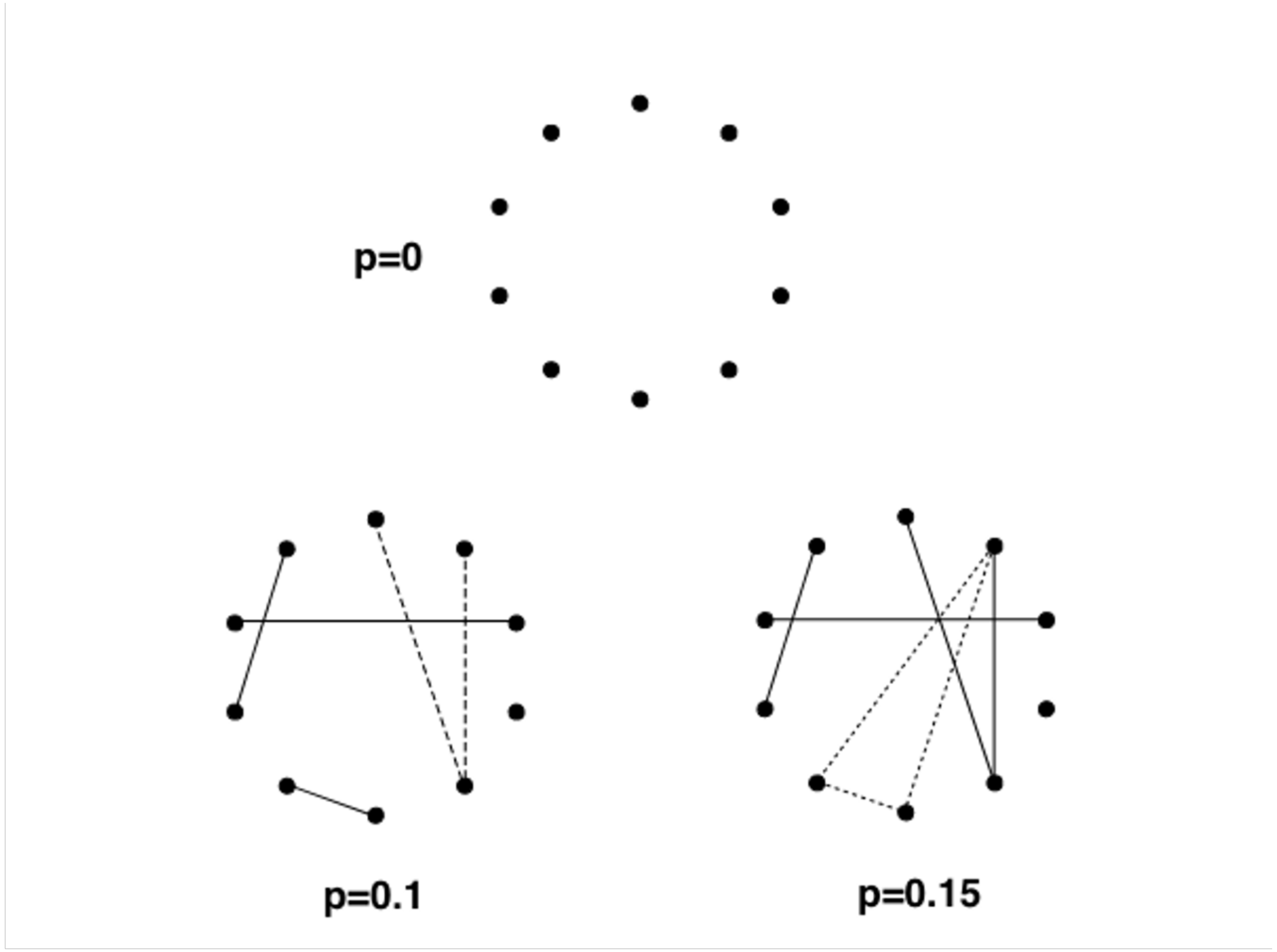
Complex Networks: Erdös-Rényi (ER) Random Network

- Alternatively, we can construct a random graph using what is known as the **binomial model.**
- Start with N nodes, and then connect every pair of nodes with probability p.
- In this case, the total number of edges is a random variable with expectation $E(n) = pN(N-1)/2$. Thus, the probability of obtaining a graph with N nodes and n edges is $P(N, n) = e^{n}(1-p)^{(}N(N-1)/2 - n)$.
- The degree distribution $P(k)$ of a random graph is a Poisson distribution with a peak at $P(< k >)$.





Complex Networks: Erdös-Rényi (ER) Random Network



Albert and Barabasi, ‘Statistical Mechanics of Complex Networks’.

Complex Networks: Erdös-Rényi (ER) Random Network

$$P(k) \simeq e^{-pN}\frac{(pN)^k}{k!} = e^{-\langle k \rangle}\frac{\langle k \rangle^k}{k!}$$

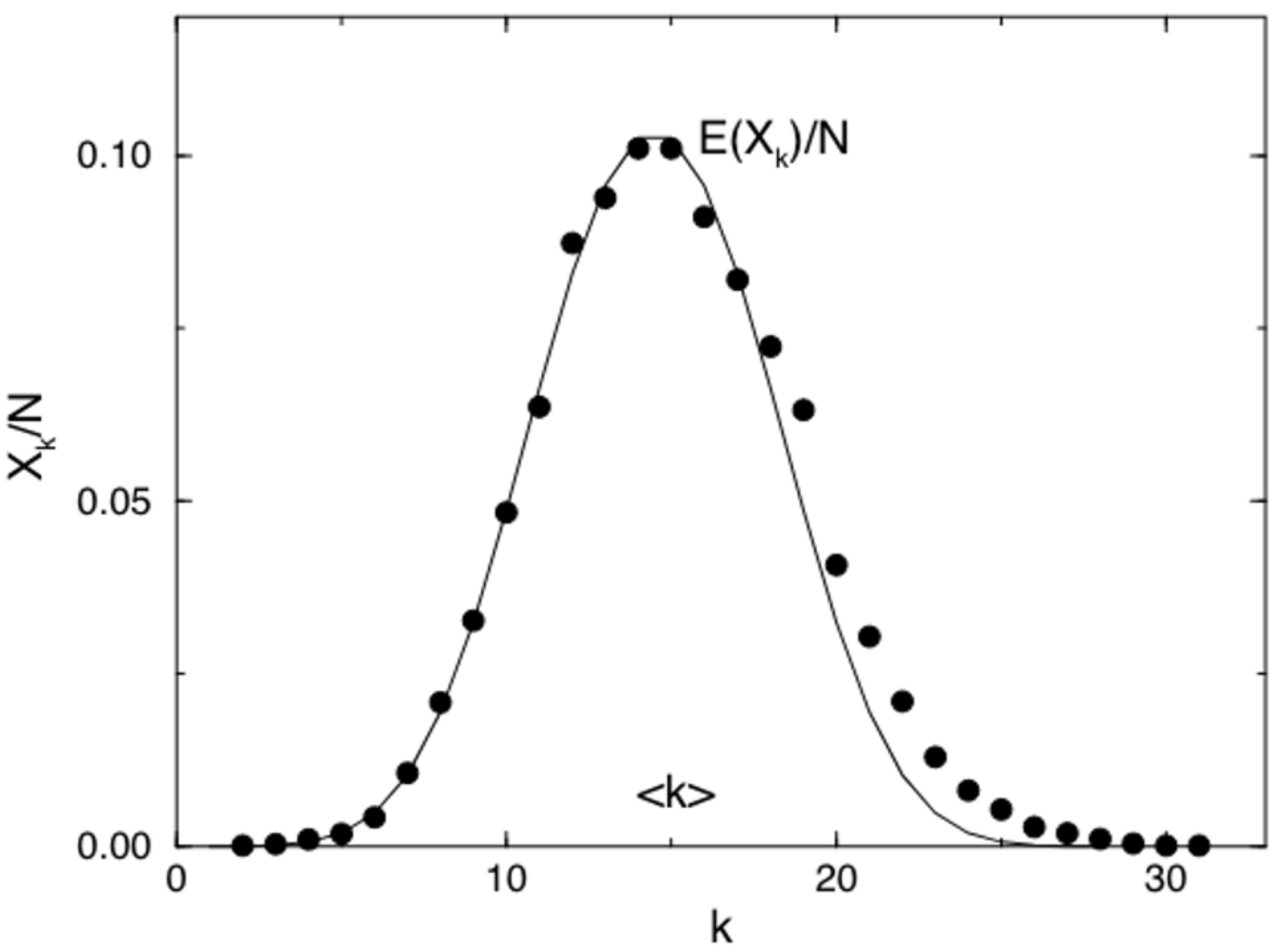


FIG. 7. The degree distribution that results from the numerical simulation of a random graph. We generated a single random graph with $N = 10,000$ nodes and connection probability $p = 0.0015$, and calculated the number of nodes with degree k, X_k. The plot compares X_k/N with the expectation value of the Poisson distribution (13), $E(X_k)/N = P(k_i = k)$, and we can see that the deviation is small.

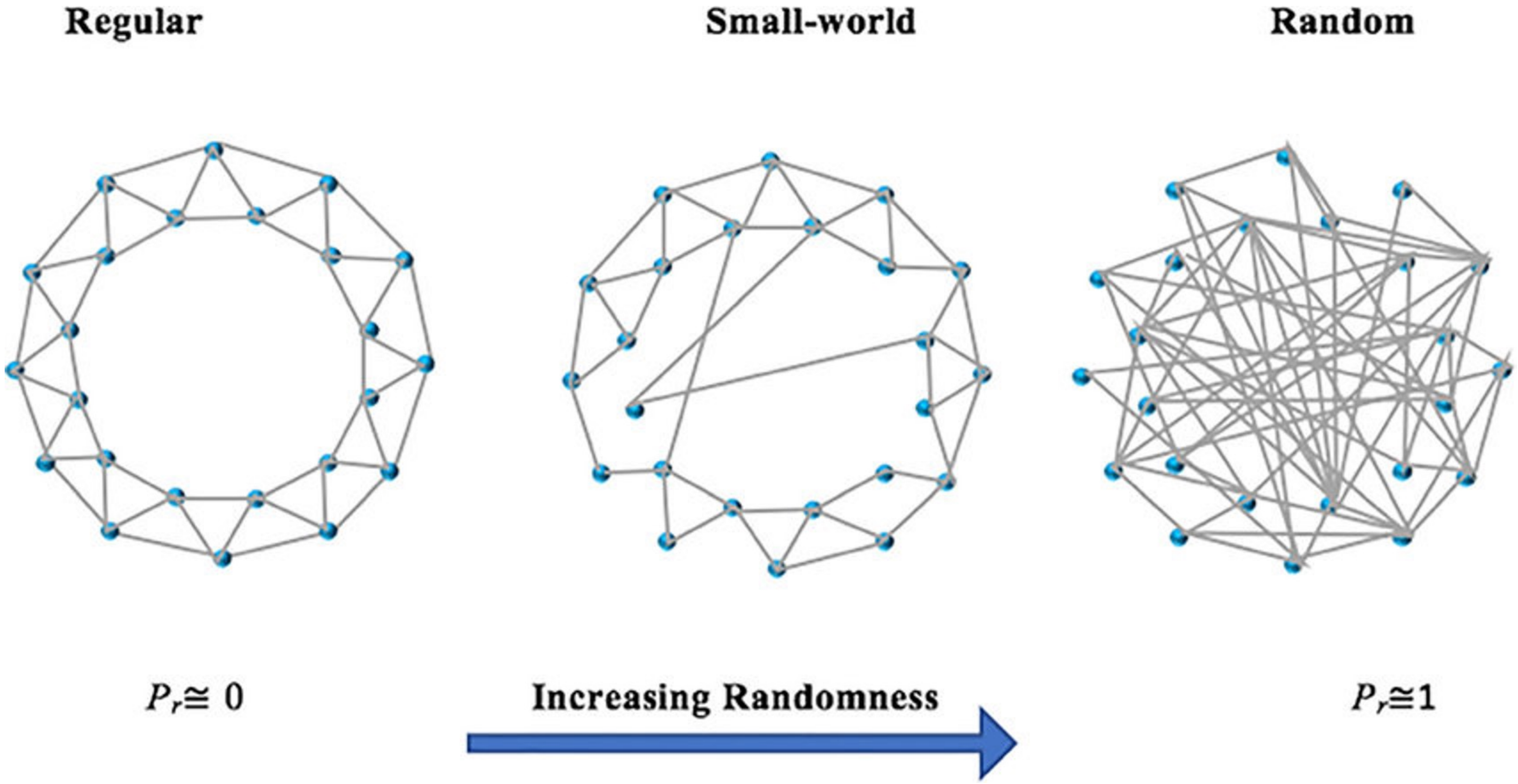
Albert and Barabasi, 'Statistical Mechanics of Complex Networks'.

Complex Networks: Small-World Networks

- Also known as the Wattz and Strogatz model, proposed in (Wattz & Strogatz 1998).
- Algorithm:
  1. **Start with order**: start with a ring lattice with N nodes in which every node is connected to its first K neighbours ($K/2$ on either side). In order to have a sparse, but connected network at all times, consider $N \gg K \gg ln(N) \gg 1$.
  2. **Randomise**: Randomly rewire each edge of the lattice with probability p, such that self-connections and duplicate edges are excluded. This process introduces $pNk/2$ long-range edges which connect to nodes that otherwise would be part of different neighbourhoods. p gives control over the transition between order (regular lattice) and full randomness.

Albert and Barabasi, 'Statistical Mechanics of Complex Networks'.

Complex Networks: Small-World Networks



Saadat, Yalda, et al. 2018

Complex Networks: Small-World Networks

Albert and Barabasi, 'Statistical Mechanics of Complex Networks'.

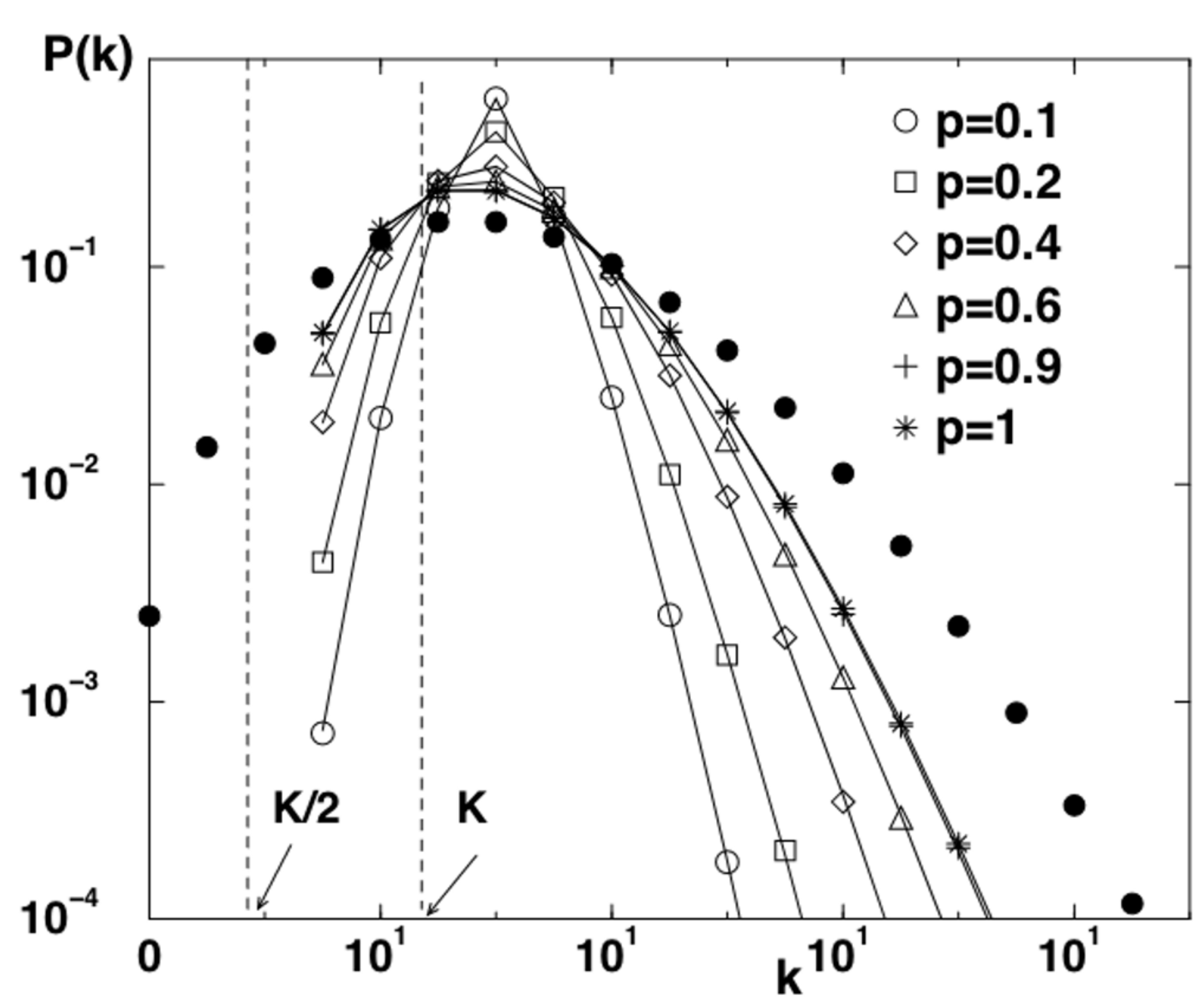
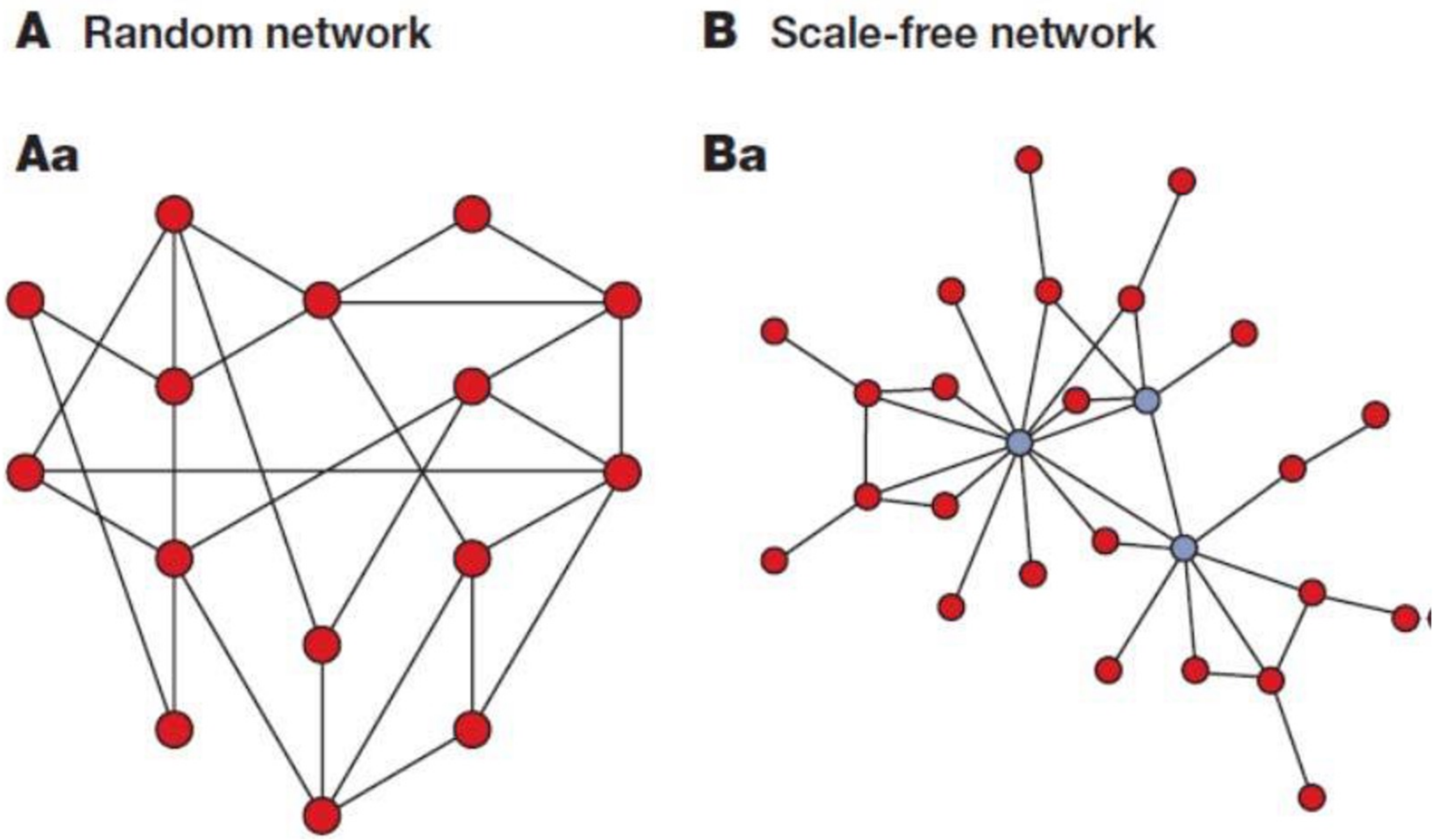


FIG. 19. Degree distribution of the WS model for $K = 3$ and various p. We can see that only $k \geq K/2$ values are present, and the mean degree is $\langle k \rangle = K$. The symbols are obtained from numerical simulations of the WS model with $N = 1000$, and the lines correspond to Eq. (76). As a comparison, the degree distribution of a random graph with the same parameters is plotted with filled symbols. After Barrat and Weigt (2000).

Complex Networks: Scale-Free Networks



Brigandt, Ingo, Sara Green, and Maureen A. O'Malley 2017.

Complex Networks: Scale-Free Networks

- Graph degree distribution follows a power law $P(k) \sim Ak^{-\lambda}$.
- It was found that many of the real-world networks display a degree distribution that is shaped as a power law with exponents varying in the range $2 < \lambda < 3$.

Complex Networks: Scale-Free Networks

Barabási and Albert (1999) argued that the scale-free nature of real networks is rooted in two generic mechanisms common in many real networks:

- **Growth**: most real networks grow by continuously attaching new nodes to a small nucleolus.
- **Preferential attachment:** the likelihood of connecting to a node depends on the node's degree.

Complex Networks: Scale-Free Networks

Algorithm:

1. **Growth**: Growth: starting with a small number (m_0) of nodes, at every time-step we add a new node with m ($\leq m_0$) edges that link the new node to m different nodes already present in the system.
2. **Preferential attachment**: when choosing the nodes to which the new node connects, we assume that the probability P that a new node will be connected to node i depends on the degree k_i such that $P(k_i) = \frac{k_i}{\sum_j k_j}$.

- After t time-steps this algorithm results in a network with $N = t + m_0$ nodes and mt edges.
- Numerical simulations indicate that this network evolves into a scale-invariant state with the probability that a node has k edges following a power-law with an exponent $\lambda_{SF} = 3$.

Complex Networks: Scale-Free Networks

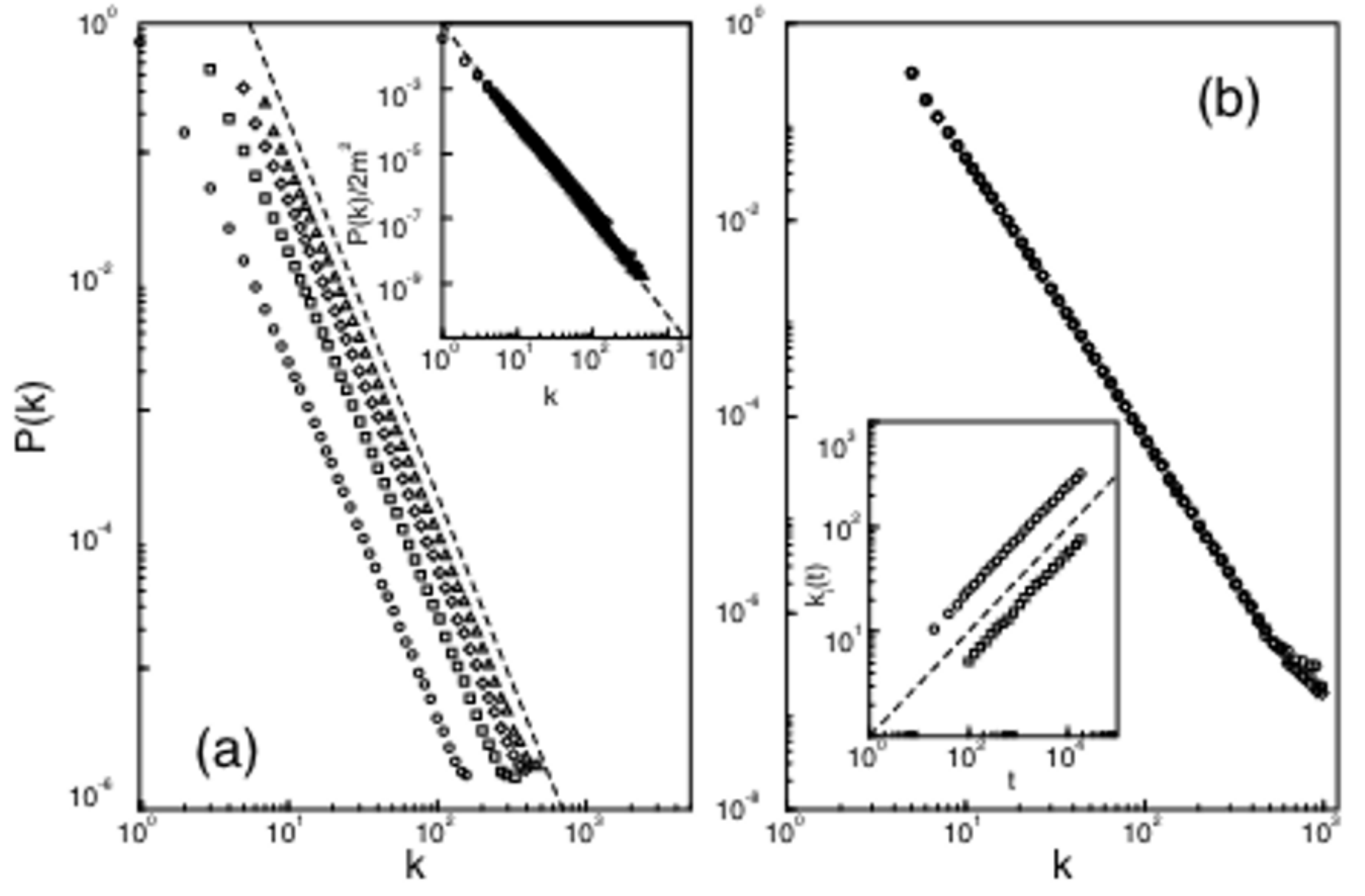
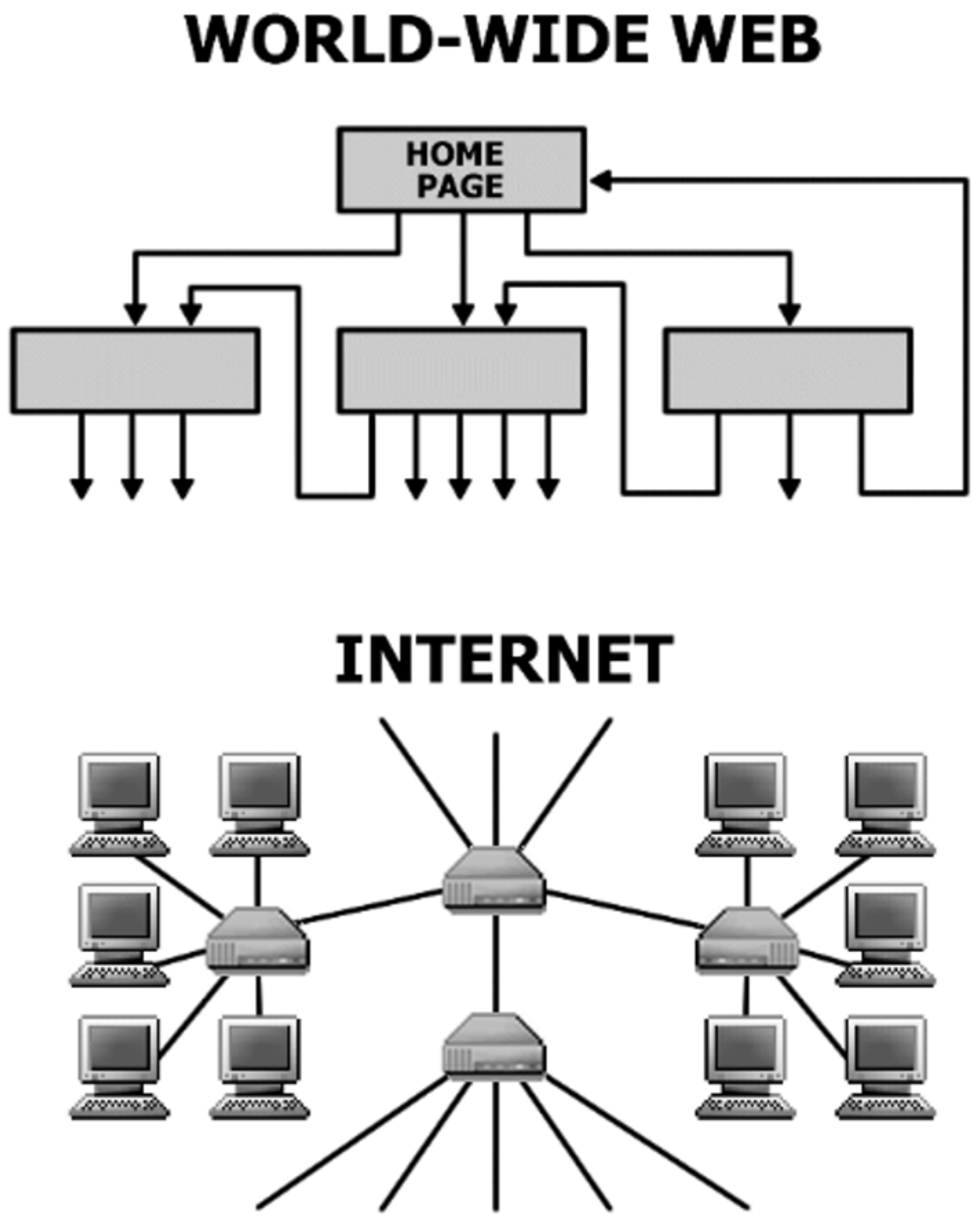
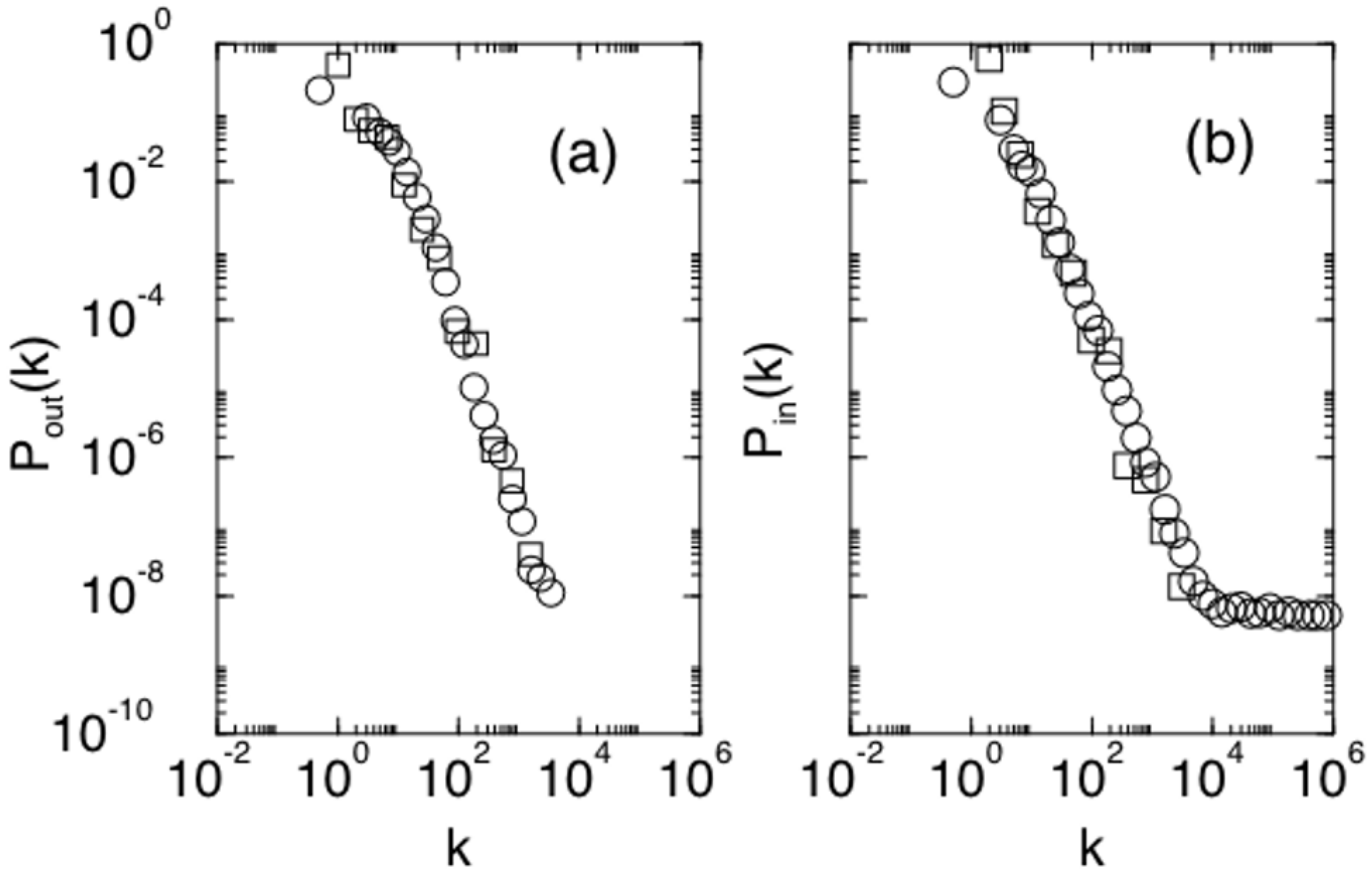


FIG. 21. (a) Degree distribution of the scale-free model, with $N = m_0 + t = 300,000$ and $m_0 = m = 1$ (circles), $m_0 = m = 3$ (squares), $m_0 = m = 5$ (diamonds) and $m_0 = m = 7$ (triangles). The slope of the dashed line is $\gamma = 2.9$. The inset shows the rescaled distribution (see text) $P(k)/2m^2$ for the same values of m, the slope of the dashed line being $\gamma = 3$. (b) $P(k)$ for $m_0 = m = 5$ and system sizes $N = 100,000$ (circles), $N = 150,000$ (squares) and $N = 200,000$ (diamonds). The inset shows the time-evolution for the degree of two vertices, added to the system at $t_1 = 5$ and $t_2 = 95$. Here $m_0 = m = 5$, and the dashed line has slope 0.5, as predicted by Eq. (80). After Barabási, Albert, Jeong (1999).

Albert and Barabasi, 'Statistical Mechanics of Complex Networks'.

Complex Networks: Real-world examples





$\lambda_{in} = 2.45$ $\lambda_{out} = 2.1$

(Albert, Jeong and Barabási 1999)

Albert and Barabasi, 'Statistical Mechanics of Complex Networks'.

Complex Networks: how to infer the network topology from data?

number of poorly connected elements.

In finite-size networks, fat-tailed degree distributions have natural cut-offs [83]. When analyzing real networks, it may happen that the data have a rather strong intrinsic noise due to the finiteness of the sampling. Therefore, when the size of the system is small and the degree distribution $P(k)$ is heavy-tailed, it is sometimes advisable to measure the *cumulative* degree distribution $P_{\text{cum}}(k)$, defined as $P_{\text{cum}}(k) = \sum_{k'=k}^{\infty} P(k')$. Indeed, when summing up the original distribution $P(k)$, the statistical fluctuations generally present in the tails of the distribution are smoothed. Consequently, if $P(k) \sim k^{-\gamma}$, the exponent γ can be obtained from $P_{\text{cum}}(k)$ as one plus the slope of $P_{\text{cum}}(k)$ in a log–log plot, i.e., $\gamma = 1 + \gamma_{\text{cum}}$. Another possibility is that of performing an exponential binning of data [8].

Boccaletti et al., 'Complex Networks: structure and dynamics'.

Complex Networks: how to infer the network topology from data?

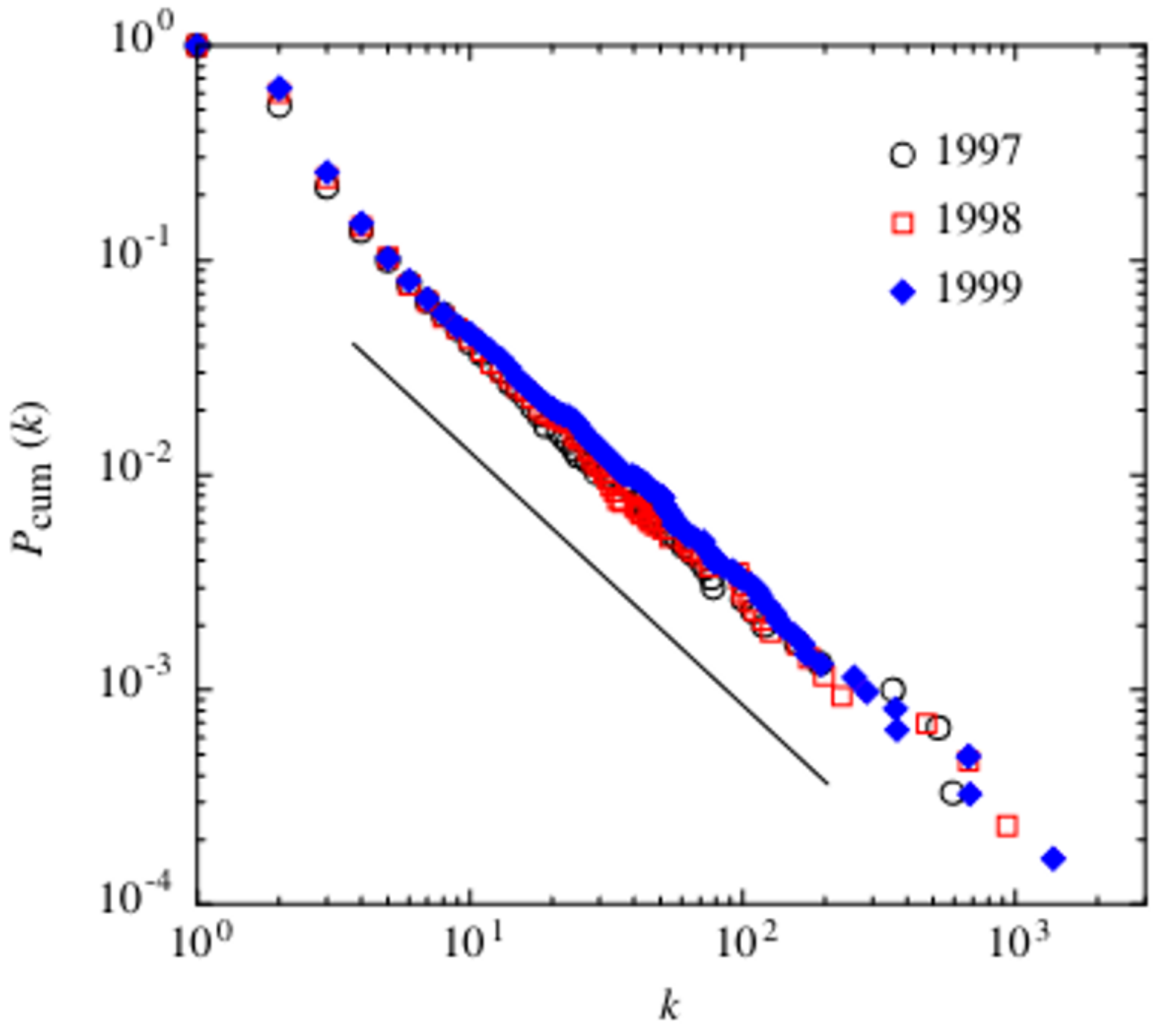


Fig. 2.4. Cumulative degree distributions of the Internet AS graph representation for three different years. The power-law behavior is clear, as well as the fact that, regardless of the very dynamic nature of the Internet, the exponent γ is constant with time. Reprinted figure with permission from Ref. [25]. © 2001 by the American Physical Society.

Boccaletti et al., 'Complex Networks: structure and dynamics'.

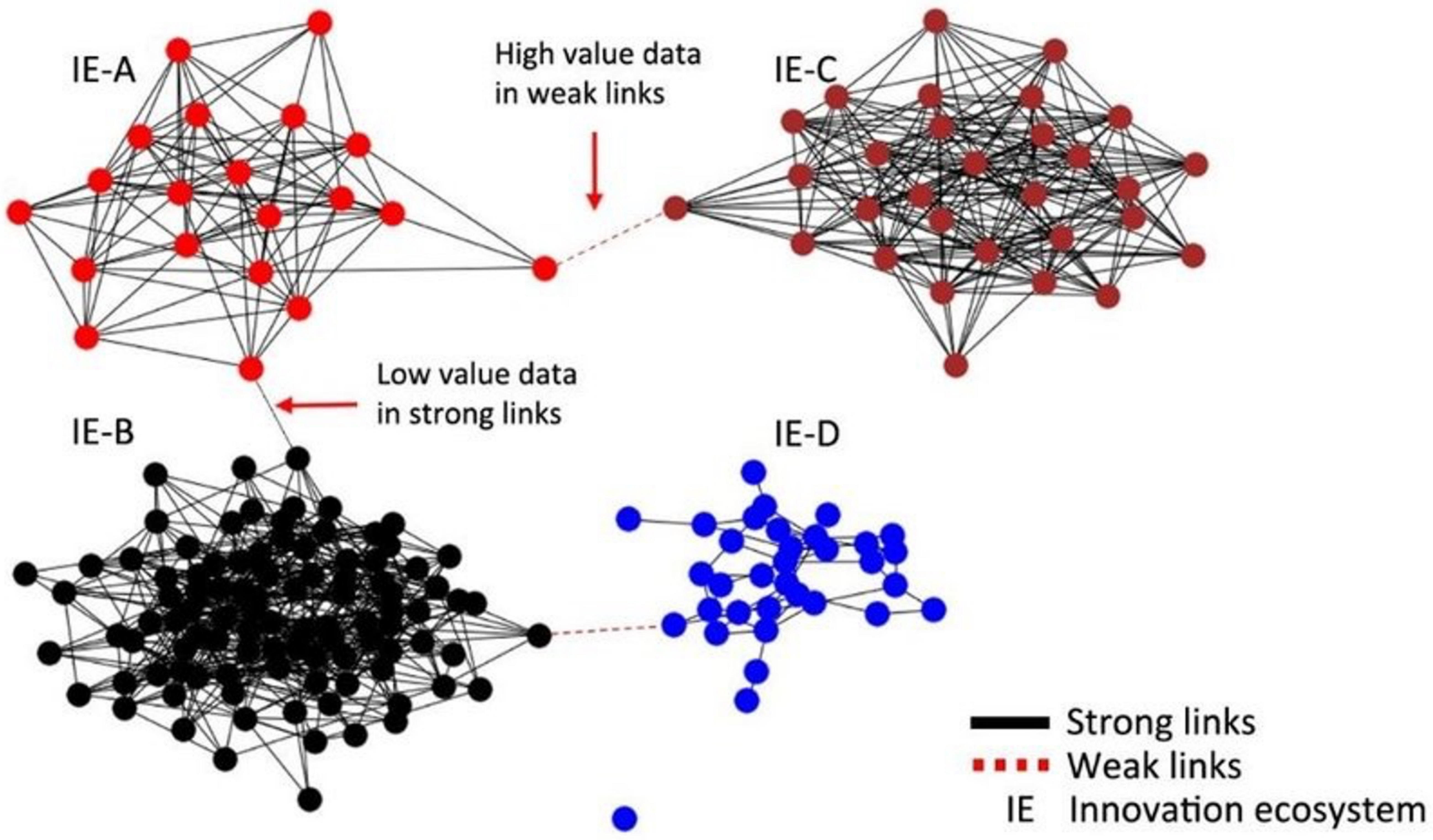
Complex Networks: how to infer the network topology from data?

Use Maximum Likelihood (MLE) to fit distribution like the Power Law, not the Least-Squares (LSE)!

If the estimation errors belong to a normal distribution, then MLE are LSE, but this does not have to be true for other distributions.

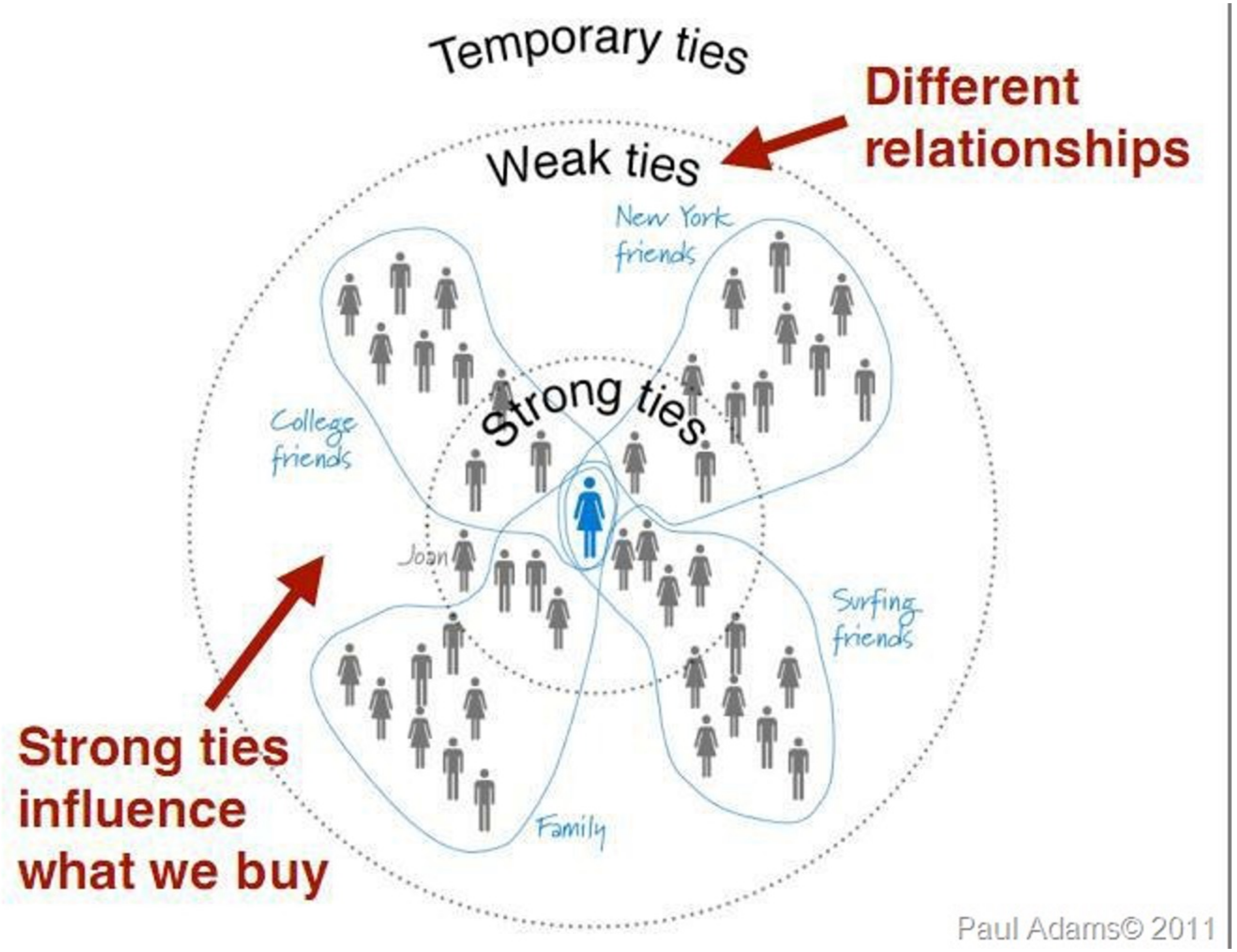
https://www.youtube.com/watch?v=UdADuHJUX6Q

Network diffusion and contagion



https://www.researchgate.net/profile/Badziili-Nthubu/publication/333902908/figure/fig2/AS:772952572301312@1561297662054/Visualisation-of-weak-ties-vs-strong-ties-IE-A-link-to-IE-C-represents-a-weak-tie-which.jpg

Network diffusion and contagion

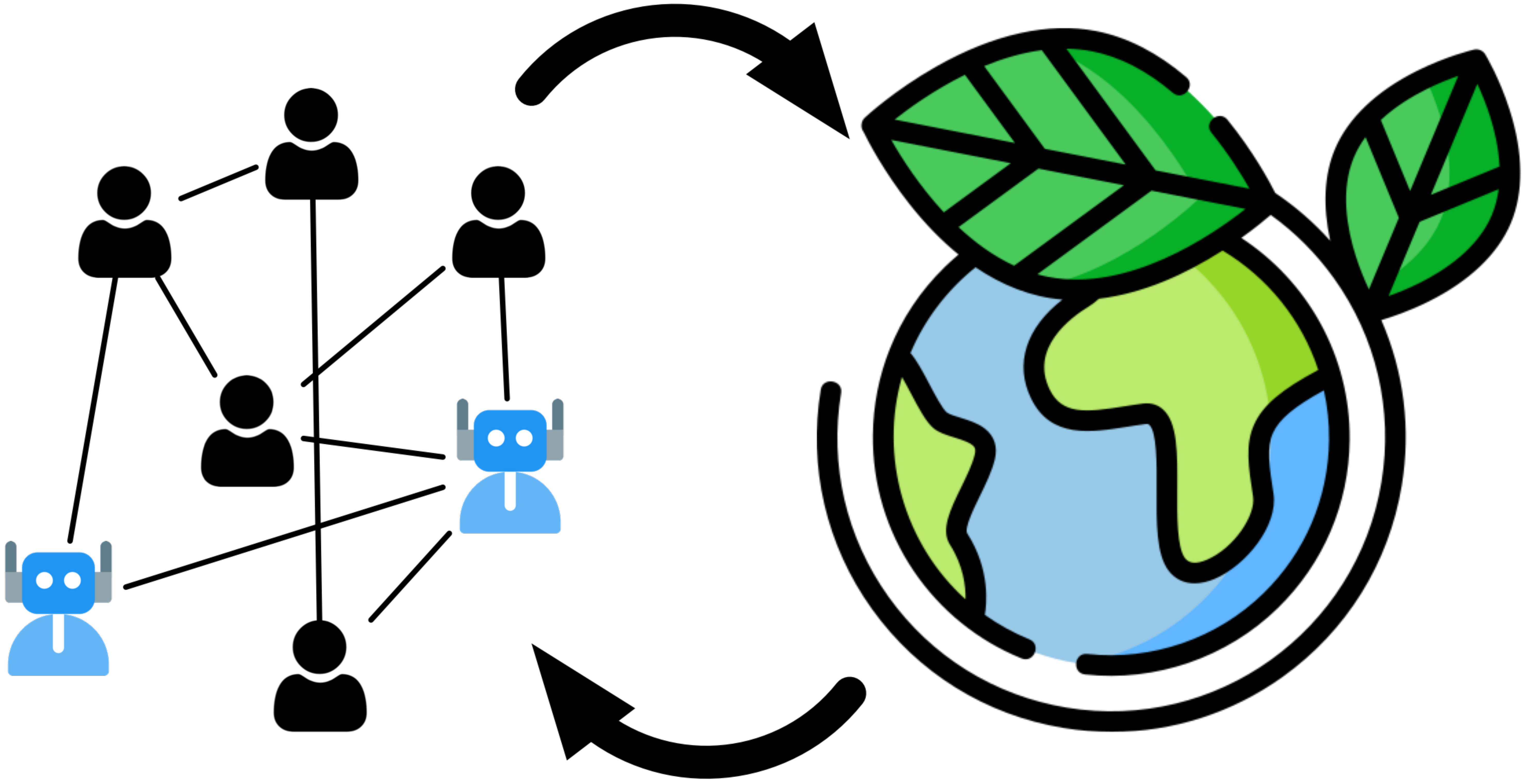


https://mspoweruser.com/the-ties-that-bind/

Part 2: Games on networks

Levels of abstraction

Actors/Players Game/Environment



Levels of abstraction

These processes may happen at different time scales!

Structured populations: Spatial games

- Spatial structure among plants or animals in an ecosystem
- The graph can also describe the architecture of cells in a multicellular organism, including the cellular differentiation hierarchy
- Relationships in a social network
- Dynamics on graph describe cultural evolution and the spread of new inventions and ideas

Some good references

PNAS

Evolutionary dynamics of social dilemmas in structured heterogeneous populations

F. C. Santos*, J. M. Pacheco†, and Tom Lenaerts*‡§

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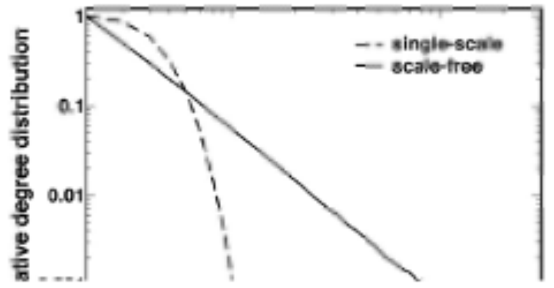
Edited by Brian Skyrms, University of California, Irvine, CA, and approved December 15, 2005 (received for review September 21, 2005)

Real populations have been shown to be heterogeneous, in which some individuals have many more contacts than others. This fact contrasts with the traditional homogeneous setting used in studies of evolutionary game dynamics. We incorporate heterogeneity in the population by studying games on graphs, in which the variability in connectivity ranges from single-scale graphs, for which heterogeneity is small and associated degree distributions exhibit a Gaussian tale, to scale-free graphs, for which heterogeneity is large with degree distributions exhibiting a power-law behavior.



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PLoS COMPUTATIONAL BIOLOGY

Cooperation Prevails When Individuals Adjust Their Social Ties

Francisco C. Santos[1], Jorge M. Pacheco[2,3], Tom Lenaerts[4,5*]

1 Computer and Decision Engineering Department, Institut de Recherches Interdisciplinaires et de Développements en Intelligence Artificielle, Université Libre de Bruxelles, Brussels, Belgium, 2 Program for Evolutionary Dynamics, Harvard University, Cambridge, Massachusetts, United States of America, 3 Department of Physics of the Faculty of Science, Center for Theoretical and Computational Physics, University of Lisbon, Lisbon, Portugal, 4 SWITCH Laboratory, Flanders Interuniversity Institute for Biotechnology, Vrije Universiteit Brussel, Brussels, Belgium, 5 Department of Computer Science, Vrije Universiteit Brussel, Brussels, Belgium

Conventional evolutionary game theory predicts that natural selection favours the selfish and strong even though cooperative interactions thrive at all levels of organization in living systems. Recent investigations demonstrated that a limiting factor for the evolution of cooperative interactions is the way in which they are organized, cooperators becoming evolutionarily competitive whenever individuals are constrained to interact with few others along the edges of networks with low average connectivity. Despite this insight, the conundrum of cooperation remains since recent empirical data shows that real networks exhibit typically high average connectivity and associated single-to-broad–

Original Paper

Adaptive Behavior

Adaptive Behavior
18(5) 416–427

DOI: 10.1177/1059712310384282
adb.sagepub.com
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Learning to coordinate in complex networks

Sven Van Segbroeck[1,2], Steven de Jong[1,3], Ann Nowé[1], Francisco C Santos[4] and Tom Lenaerts[1,2]

Abstract

Designing an adaptive multi-agent system often requires the specification of interaction patterns between the different agents. To date, it remains unclear to what extent such interaction patterns influence the dynamics of the learning mechanisms inherent to each agent in the system. Here, we address this fundamental problem, both analytically and via computer simulations, examining networks of agents that engage in stag-hunt games with their neighbors and thereby learn to coordinate their actions. We show that the specific network topology does not affect the game strategy the agents learn on average. Yet, network features such as heterogeneity and clustering

PRL **108,** 158104 (2012) PHYSICAL REVIEW LETTERS week ending 13 APRIL 2012

Emergence of Fairness in Repeated Group Interactions

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[2]*Departamento de Matemática e Aplicações, Universidade do Minho, Braga, Portugal*
[3]*ATP-group, CMAF, Instituto para a Investigação Interdisciplinar, Lisboa, Portugal*
[4]*AI-lab, Vrije Universiteit Brussel, Brussels, Belgium*
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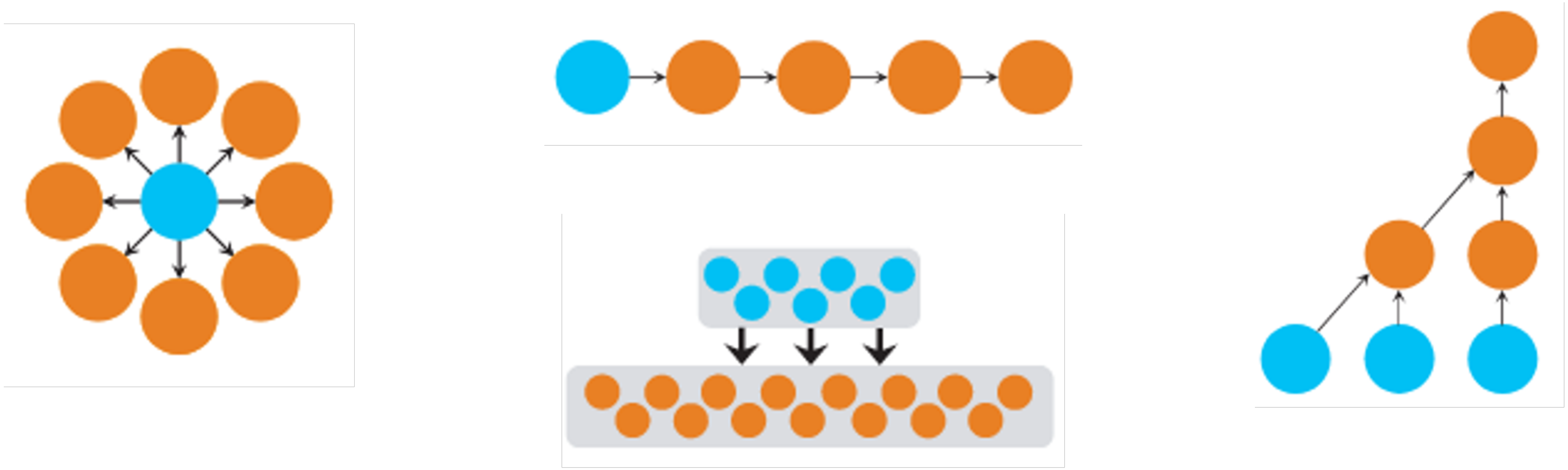
(Received 26 August 2011; published 10 April 2012)

Often groups need to meet repeatedly before a decision is reached. Hence, most individual decisions will be contingent on decisions taken previously by others. In particular, the decision to cooperate or not will depend on one's own assessment of what constitutes a fair group outcome. Making use of a repeated *N*-person prisoner's dilemma, we show that reciprocation towards groups opens a window of opportunity for cooperation to thrive, leading populations to engage in dynamics involving both coordination and coexistence, and characterized by cycles of cooperation and defection. Furthermore, we show that this process leads to the emergence of fairness, whose level will depend on the dilemma at stake.

DOI: 10.1103/PhysRevLett.108.158104 PACS numbers: 87.23.Kg, 89.75.Fb

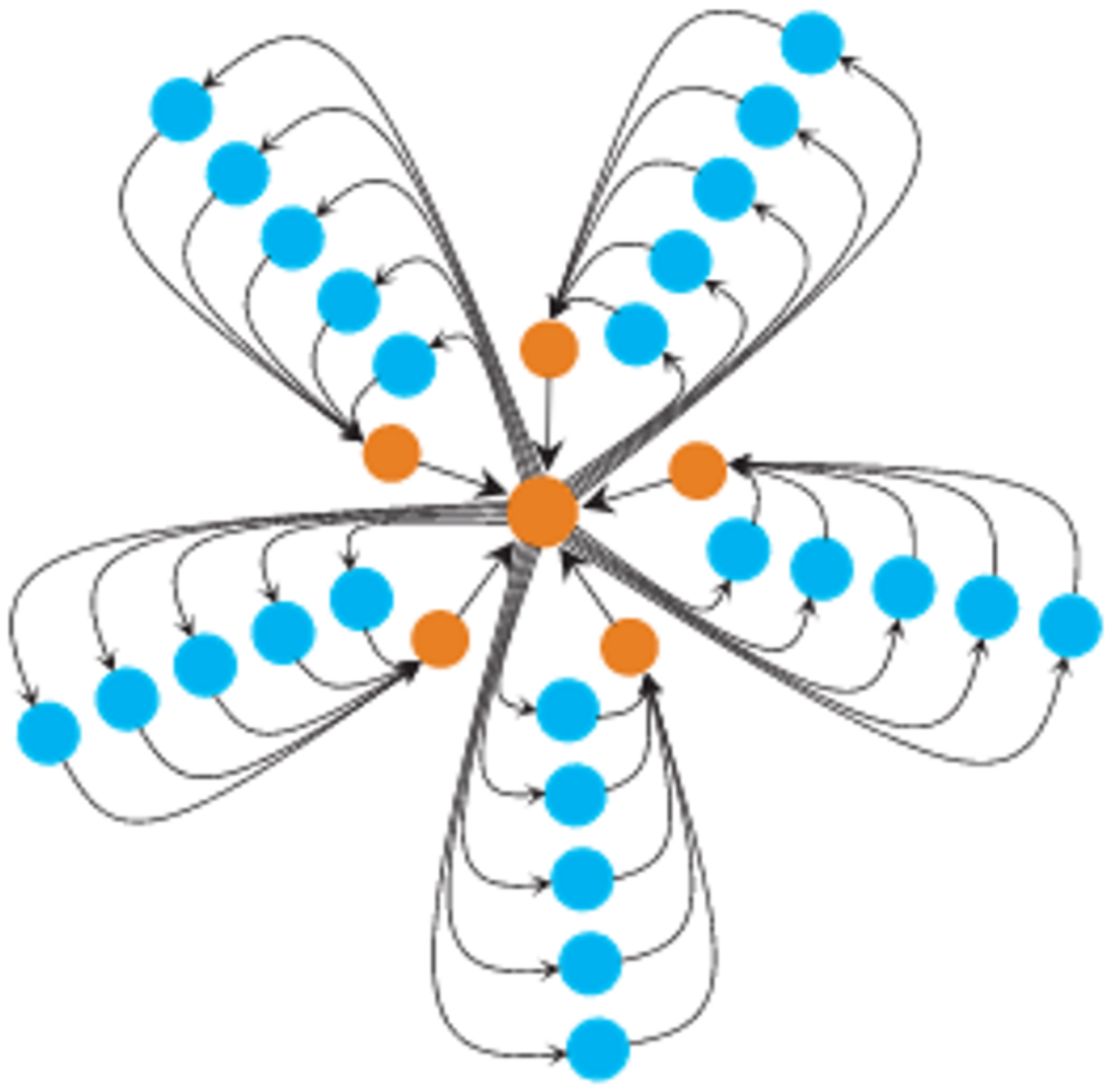
Suppressors of selection



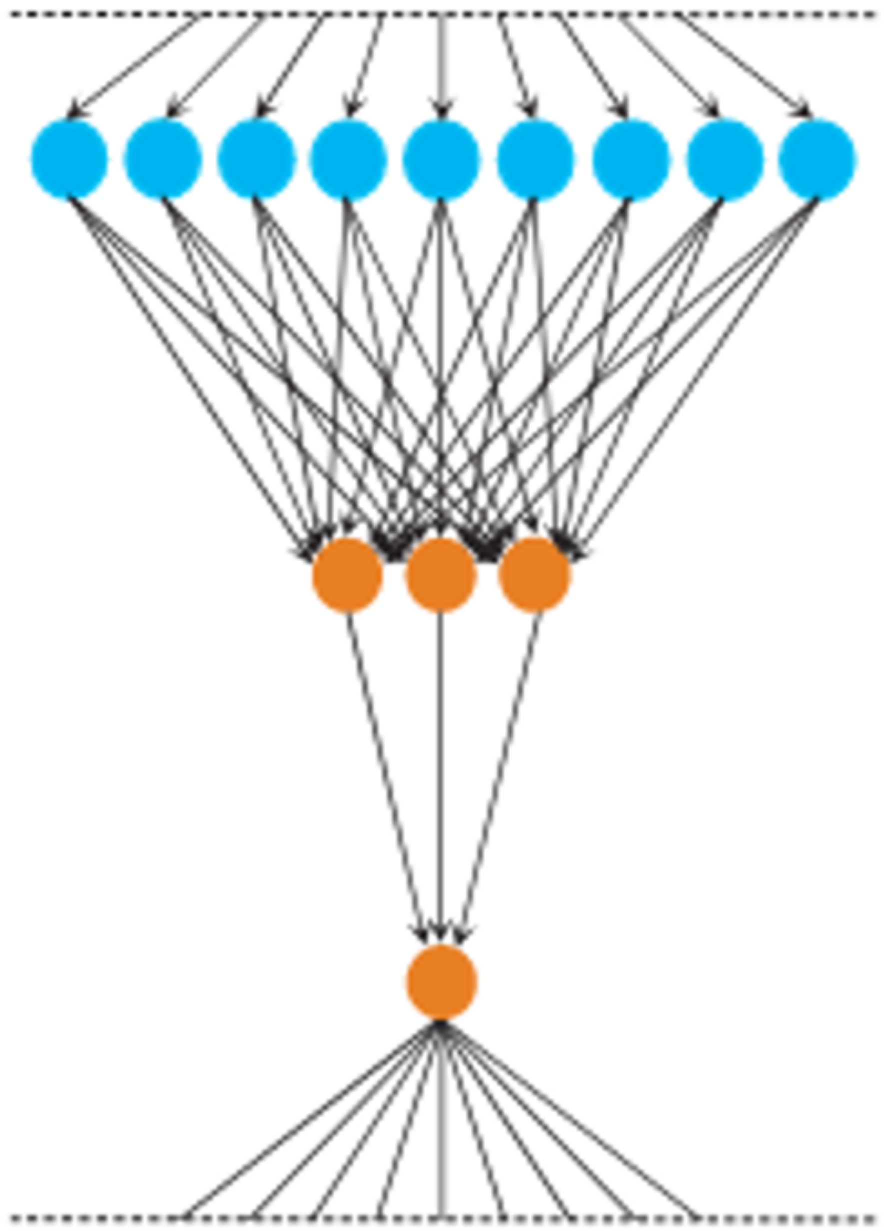
Lieberman, Erez, Christoph Hauert, and Martin A. Nowak. "Evolutionary dynamics on graphs." *Nature* 433.7023 (2005): 312-316.

Amplifiers of selection

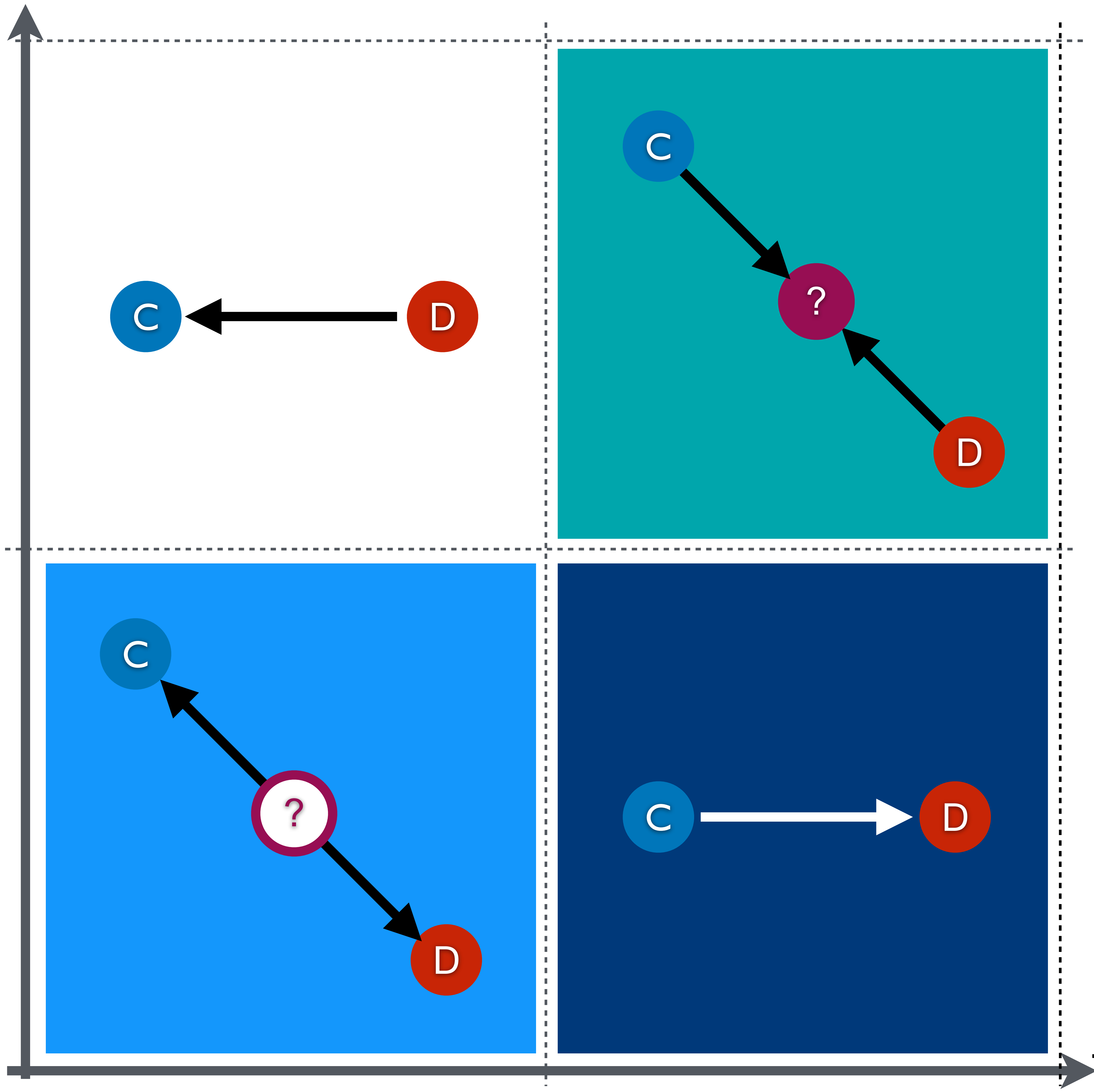
superstar



funnel



Lieberman, Erez, Christoph Hauert, and Martin A. Nowak. "Evolutionary dynamics on graphs." *Nature* 433.7023 (2005): 312-316.


Sucker
Sucker > Punish
Punish
Sucker < Punish
C
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Temptation
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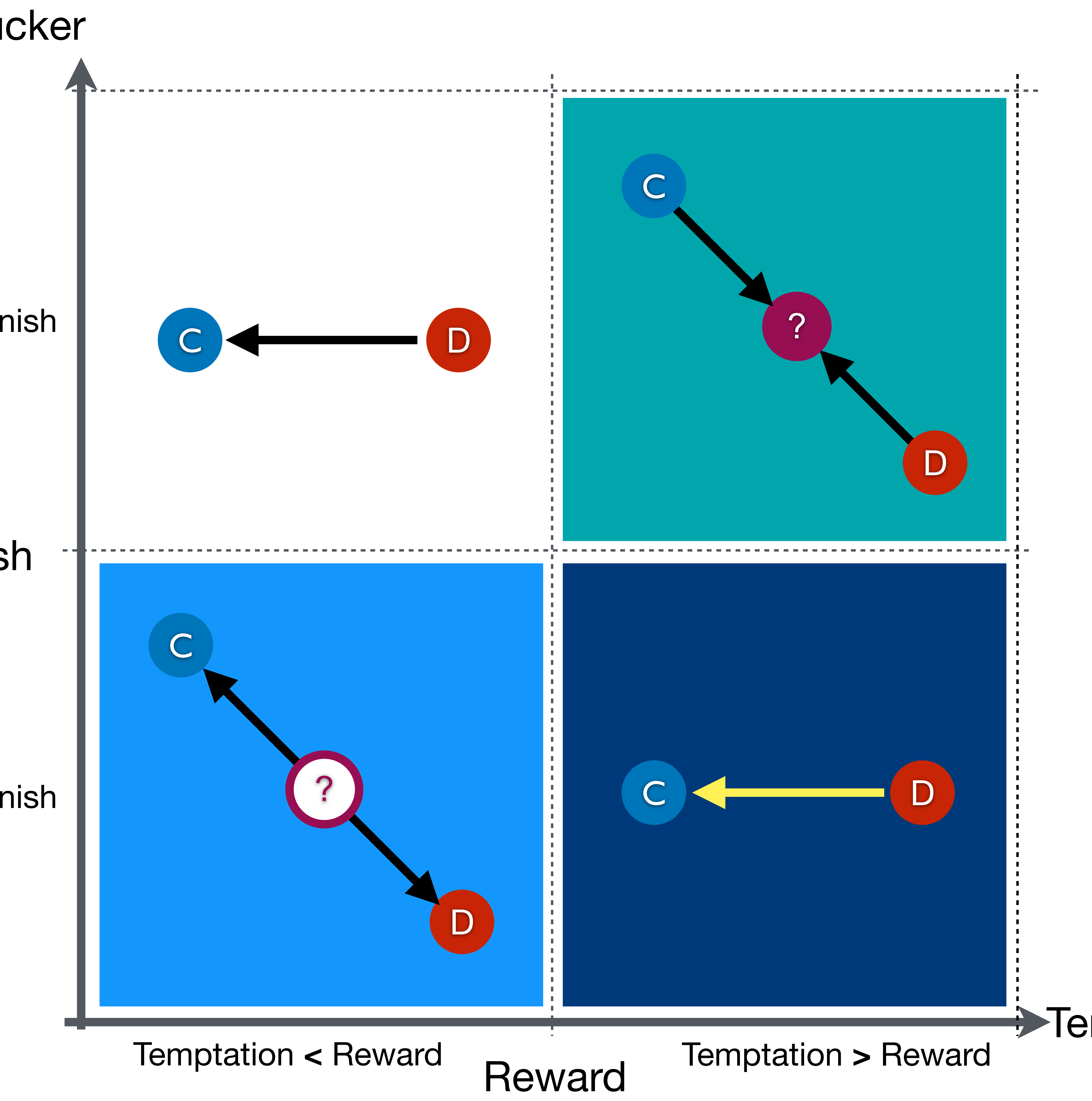
Reward
Temptation > Reward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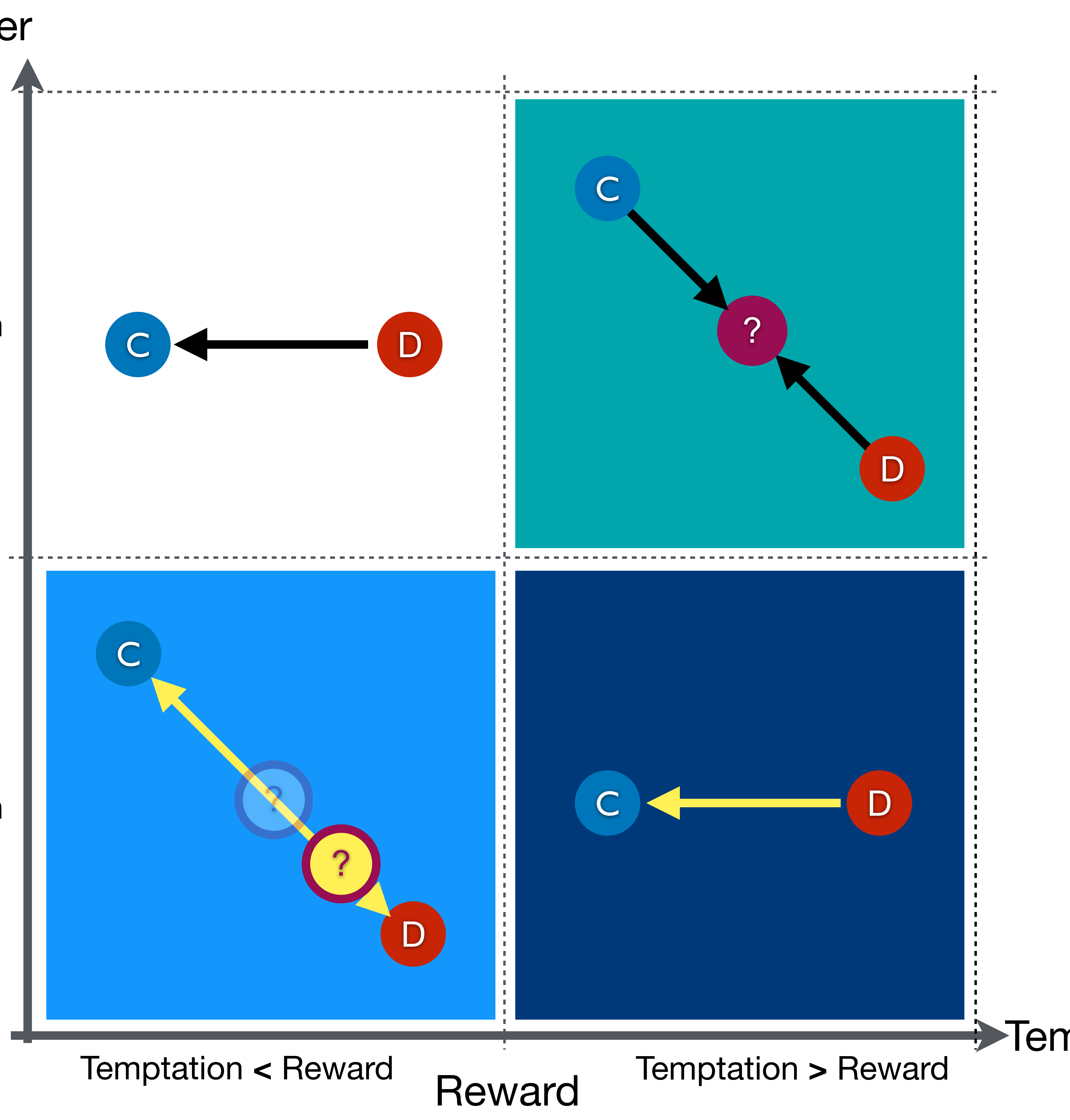
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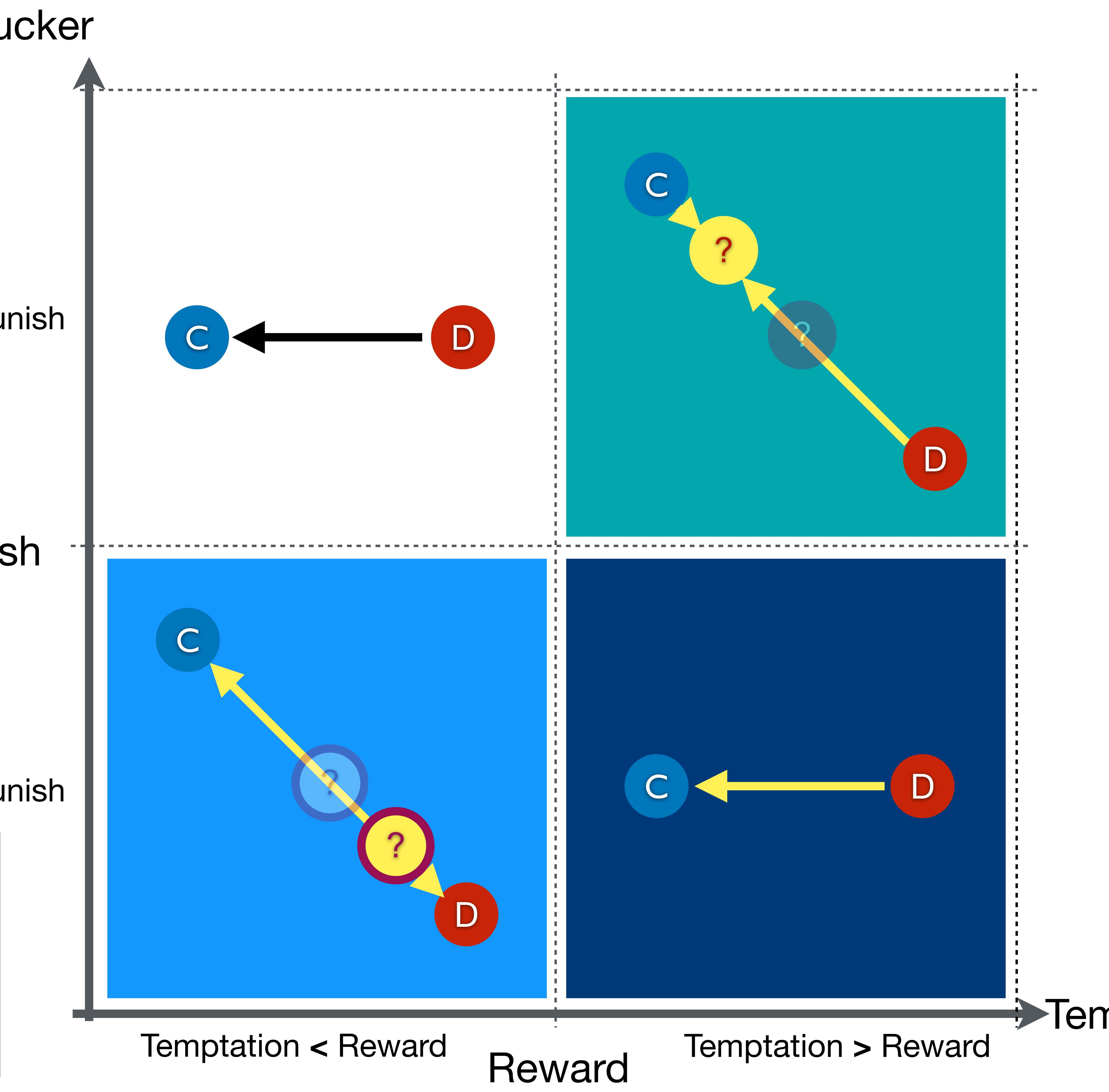
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Proc. Natl. Acad. Sci. USA
Vol. 79, pp. 1331–1335, February 1982
Population Biology

Assortment of encounters and evolution of cooperativeness

(altruism/evolutionary stable strategies/assortative meetings)

ILAN ESHEL† AND L. L. CAVALLI-SFORZA

Departments of Mathematics and Genetics, Stanford University, Stanford, California 94305

Contributed by L. L. Cavalli-Sforza, October 13, 1981

ABSTRACT The method of evolutionary stable strategies (ESS), in its current form, is confronted with a difficulty when it tries to explain how some social behaviors initiate their evolution. We show that this difficulty may be removed by changing the assumption made tacitly in game theory (and in ESS) of randomness

In the case of nonrandom encounters due to active individuals may actively seek or avoid encounters wit individuals of their phenotype or strategy. These choic be the result of learning by the individual, or they may netically or culturally inherited traits that have spread

Homogeneous interactions in space

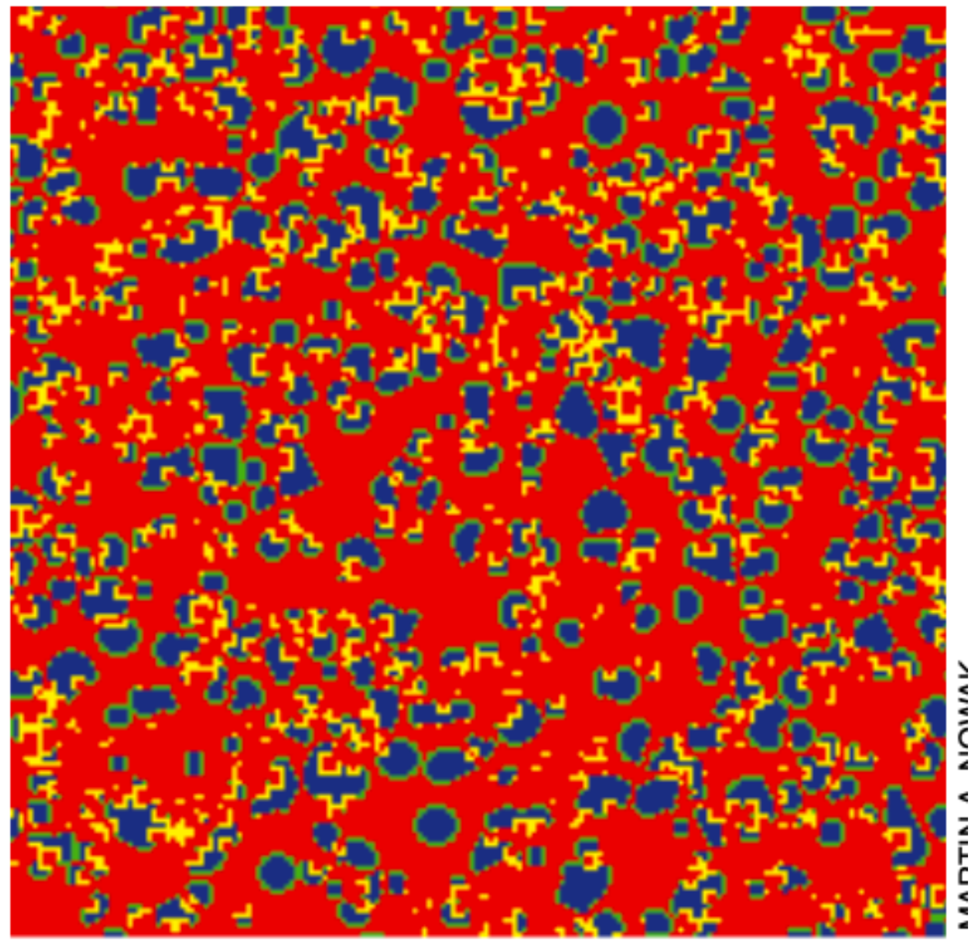
The Arithmetics of Mutual Help

Computer experiments show how cooperation rather than exploitation can dominate in the Darwinian struggle for survival

by Martin A. Nowak, Robert M. May and Karl Sigmund

The principle of give and take pervades our society. It is older than commerce and trade. All members of a household, for example, are want of natural weapons, & c., are more than counterbalanced by his…social qualities, which lead him to give and receive aid from his fellow-men." "possibly the most important book of the year" (1902), he drew a vast fresco of cooperation acting among Siberian herds, Polynesian islanders and medie-

Spatial games

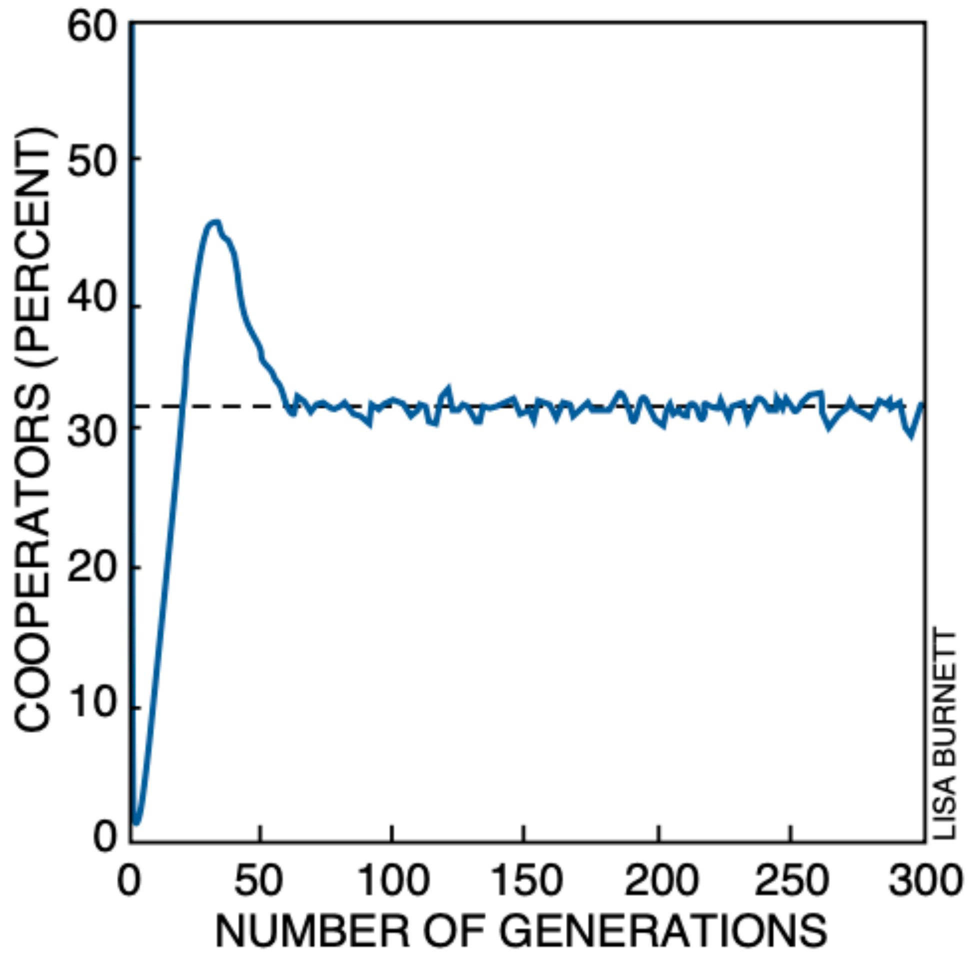


Red is a D who was a D before

Blue is a C who was a C before

Green is a C who was a D before

Yellow is a D who was a C before



The fraction of C **stabilises** over time in the grid

Nowak, M. A., May, R. M., & Sigmund, K. (1995). The arithmetics of mutual help. Scientific American, 272(6), 76-81.

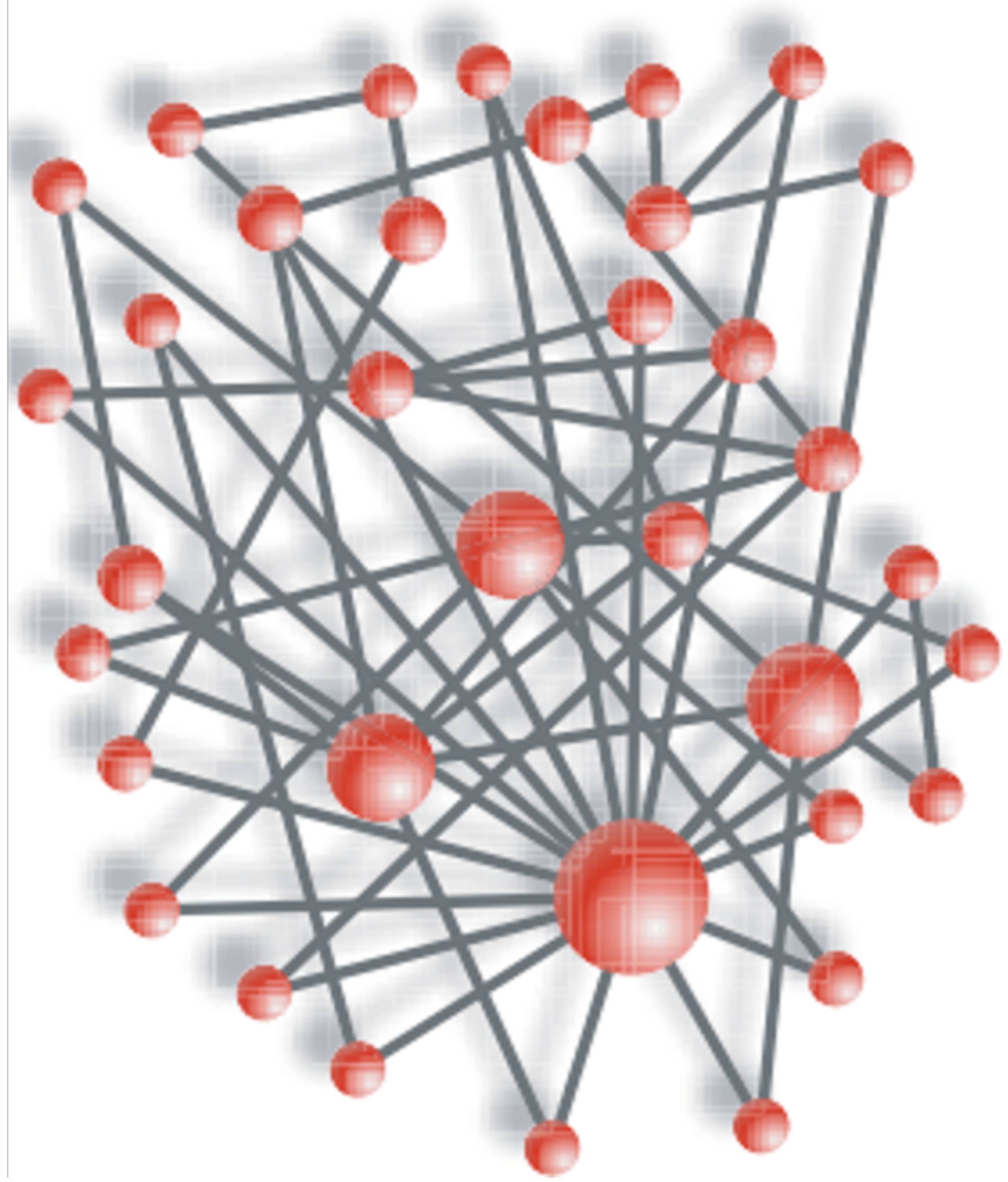
Nowak, M. A., & May, R. M. (1992). Evolutionary games and spatial chaos. nature, 359(6398), 826-829.

Games on networks

What is the network structure?

How are strategies updated?

Can individual change their social ties?



Neighbourhood

contribute. The total contribution is multiplied by an enhancement

sence of spatial and network reciprocity[...].

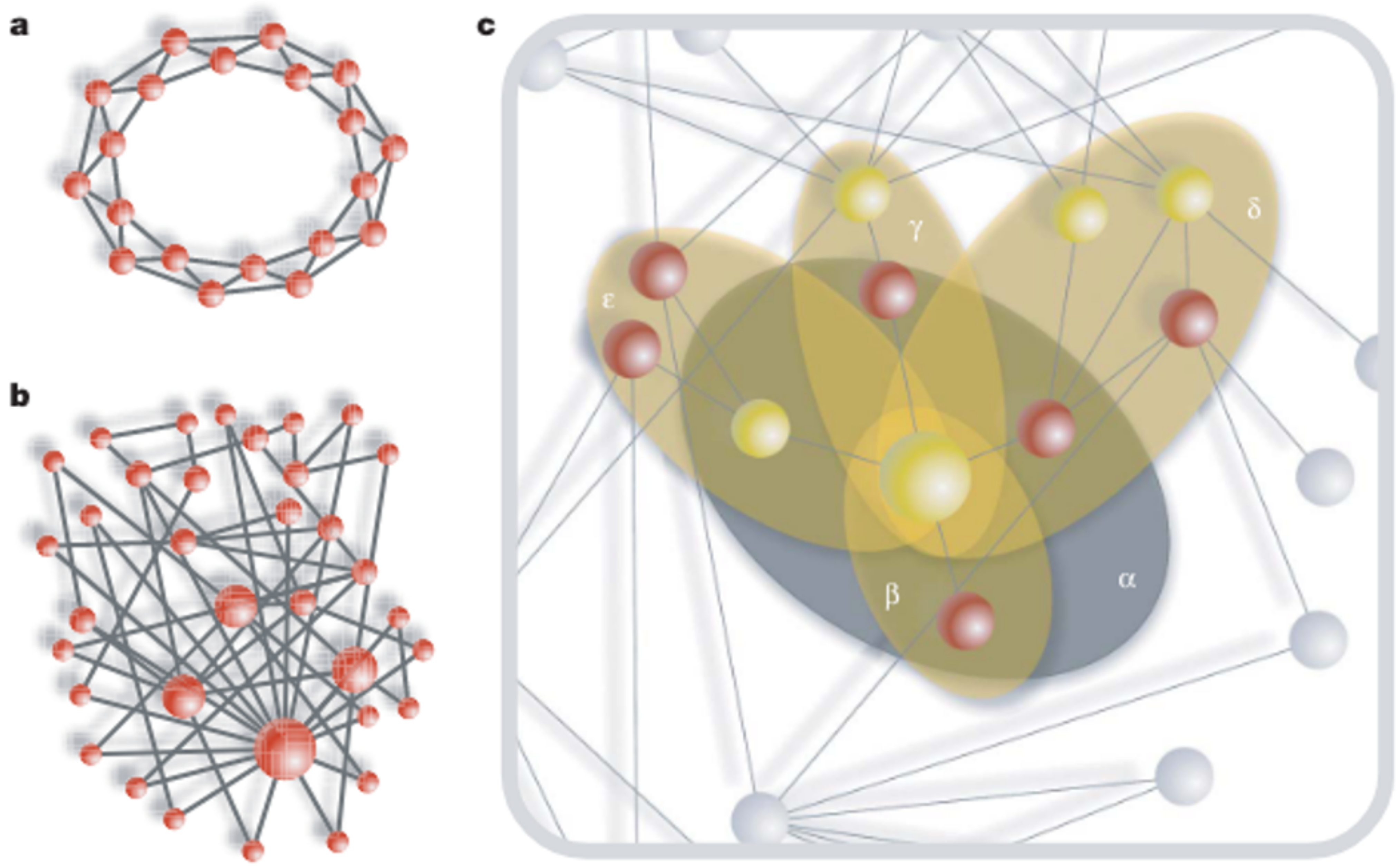


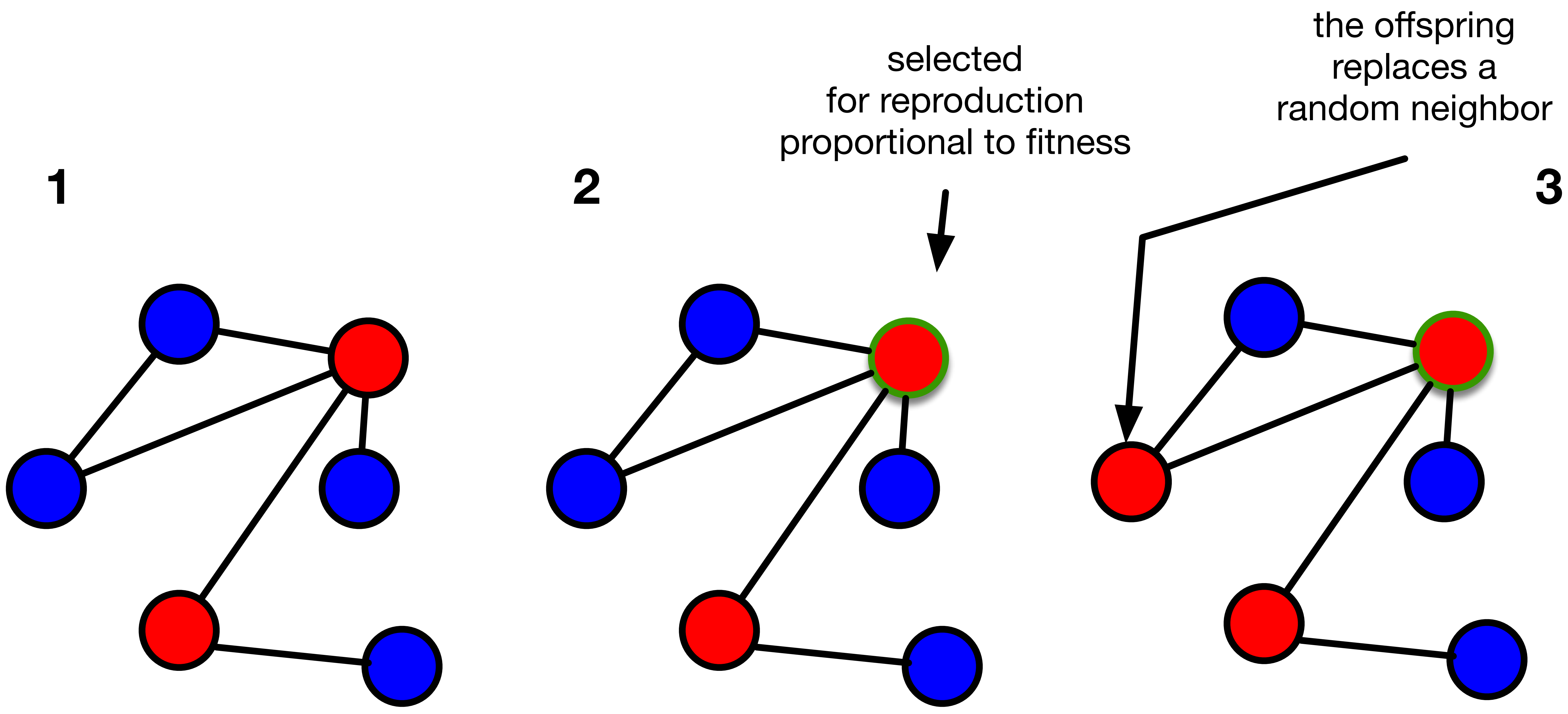
Figure 1 | Population structure and local neighbourhoods. **a**, Regular graphs studied so far, which mimic spatially extended systems. **b**, Scale-free graphs[9] in which small-world effects coexist with a large heterogeneity in neighbourhood size. **c**, The focal individual (largest sphere) belongs to different groups (neighbourhoods) of different sizes in a heterogeneous graph. Given his/her connectivity $k = 4$, we identify five neighbourhoods, each centred on one of the members of the focal individual's group, such that individual fitness derives from the payoff accumulated in all five neighbourhoods (α, β, γ, δ and ε).

Santos, Santos, and Pacheco, 'Social Diversity Promotes the Emergence of Cooperation in Public Goods Games'.

Common rules for behavioural update/adaptation

There are many…, but the most common ones are:

1. “Birth-death”

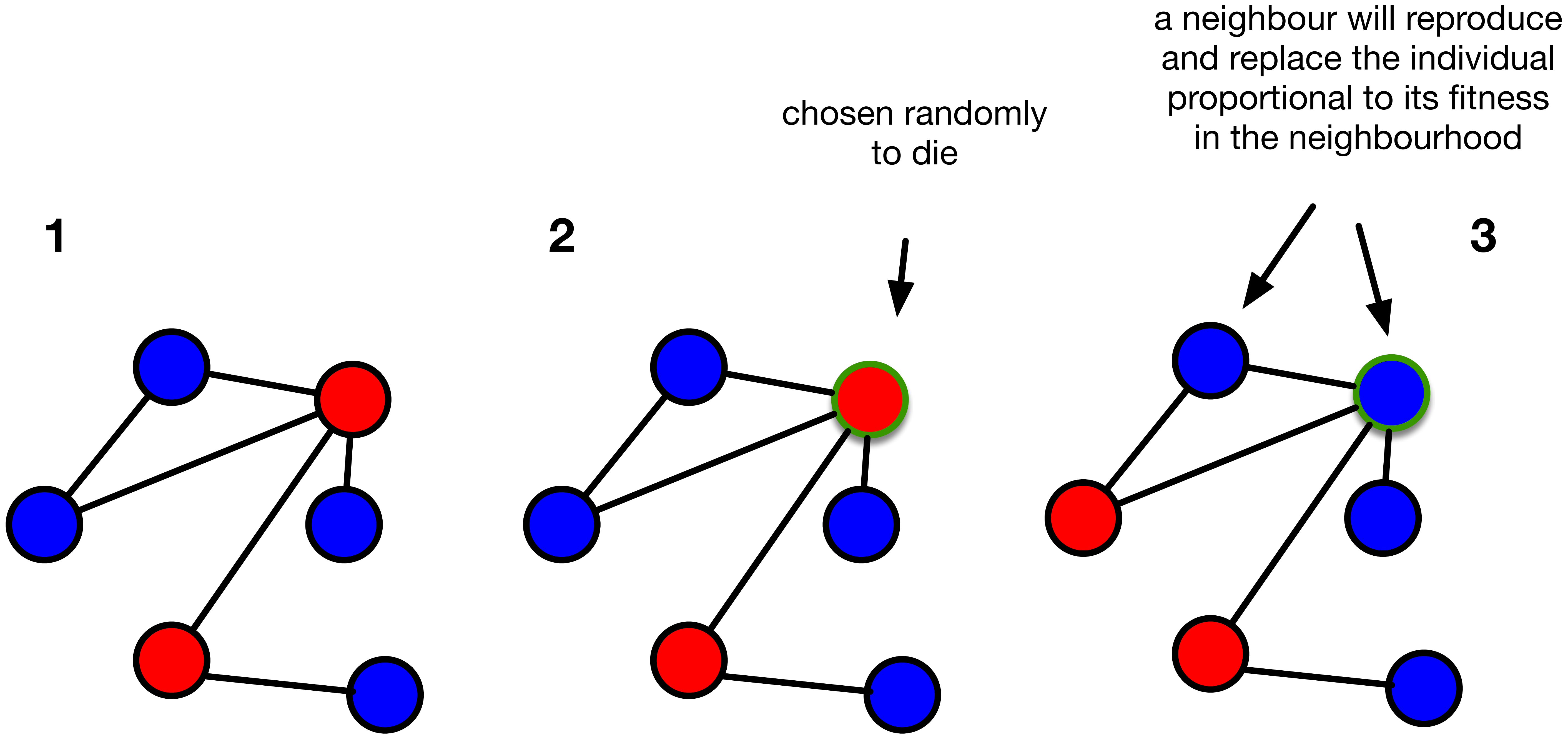


This process can also be **synchronous** or **asynchronous**

Common rules for behavioural update/adaptation

There are many…, but the most common ones are:

2. “Death-Birth”

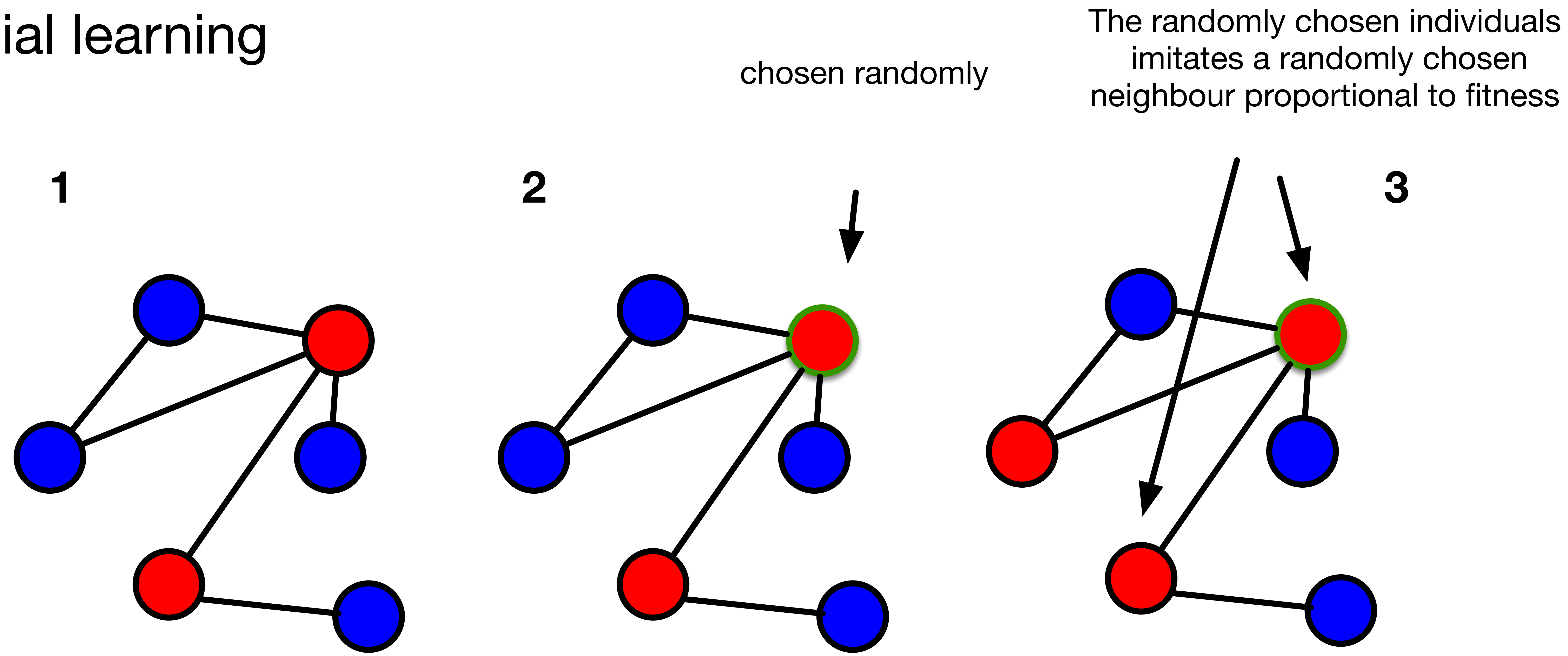


This process can also be **synchronous** or **asynchronous**

Common rules for behavioural update/adaptation

There are many…, but the most common ones are:

3. Imitation or social learning



This process can also be **synchronous** or **asynchronous**

The role of heterogeneity

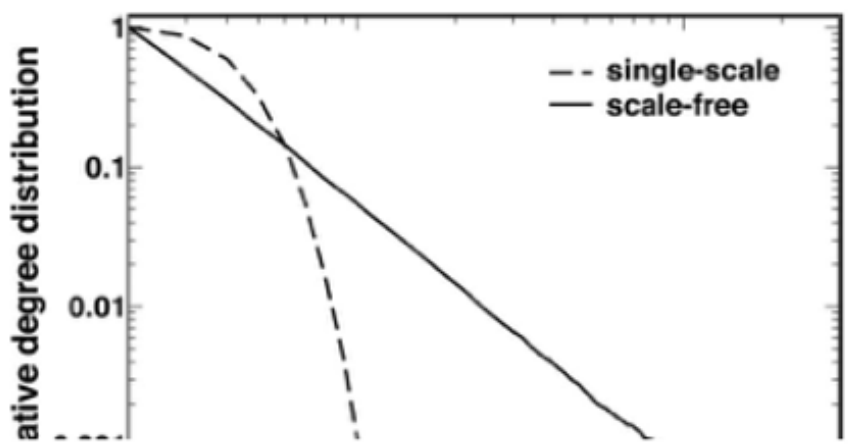
Evolutionary dynamics of social dilemmas in structured heterogeneous populations

F. C. Santos*, J. M. Pacheco†, and Tom Lenaerts*‡§

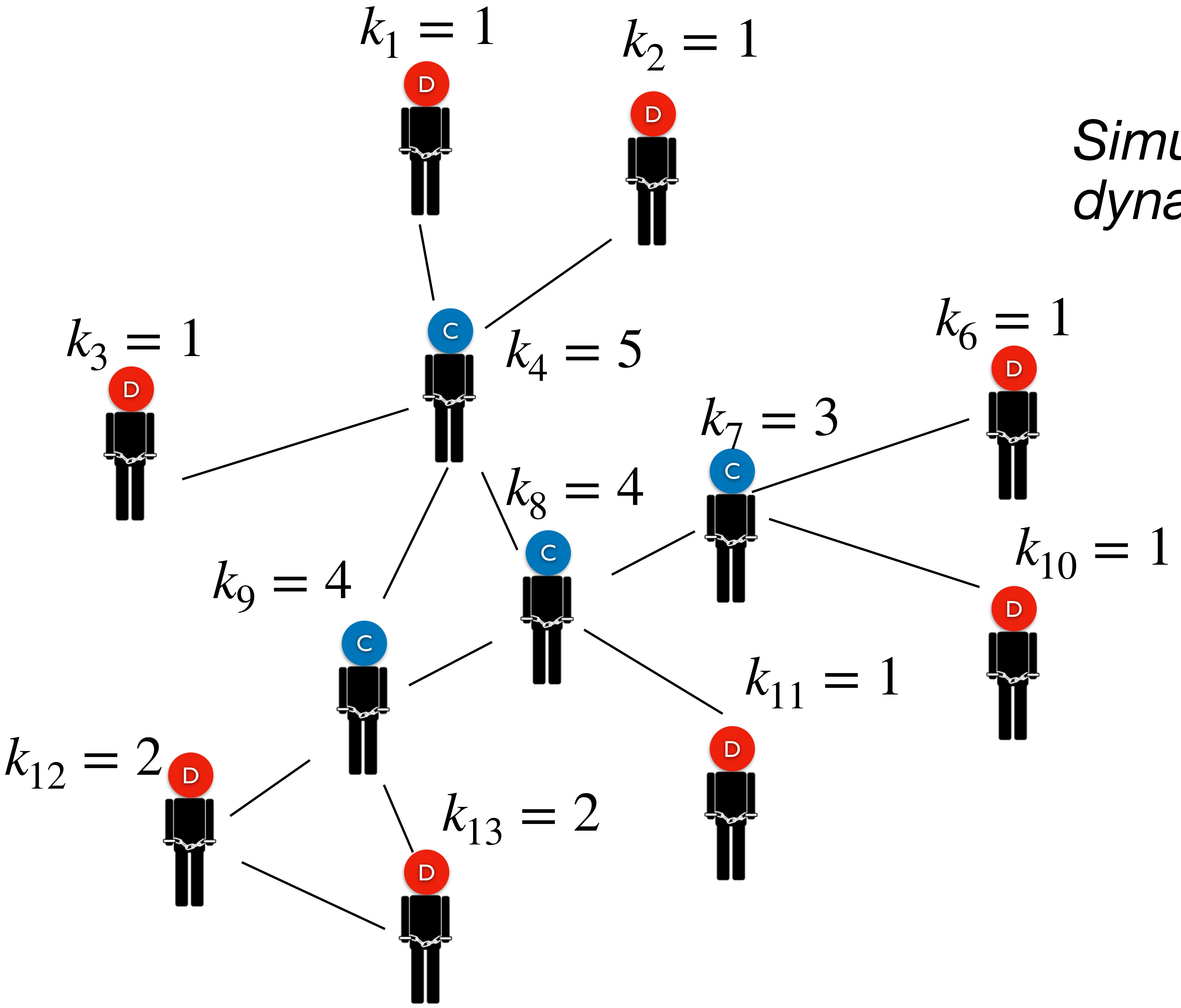
*Institut de Recherches Interdisciplinaires et de Développements en Intelligence Artificielle, CP 194/6, Université Libre de Bruxelles, Avenue Franklin Roosevelt 50, 1050 Brussels, Belgium; †Centro de Física Teórica e Computacional and Departamento de Física da Faculdade de Ciências, Universidade de Lisboa, P-1649-003 Lisbon, Portugal; and ‡Department of Computer Science, Vrije Universiteit Brussel, Pleinlaan 2, 1050 Brussels, Belgium

Edited by Brian Skyrms, University of California, Irvine, CA, and approved December 15, 2005 (received for review September 21, 2005)

Real populations have been shown to be heterogeneous, in which some individuals have many more contacts than others. This fact contrasts with the traditional homogeneous setting used in studies of evolutionary game dynamics. We incorporate heterogeneity in the population by studying games on graphs, in which the variability in connectivity ranges from single-scale graphs, for which heterogeneity is small and associated degree distributions exhibit a Gaussian tale, to scale-free graphs, for which heterogeneity is large with degree distributions exhibiting a power-law behavior.



Modelling evolution on networks



Simulating stochastic evolutionary dynamics

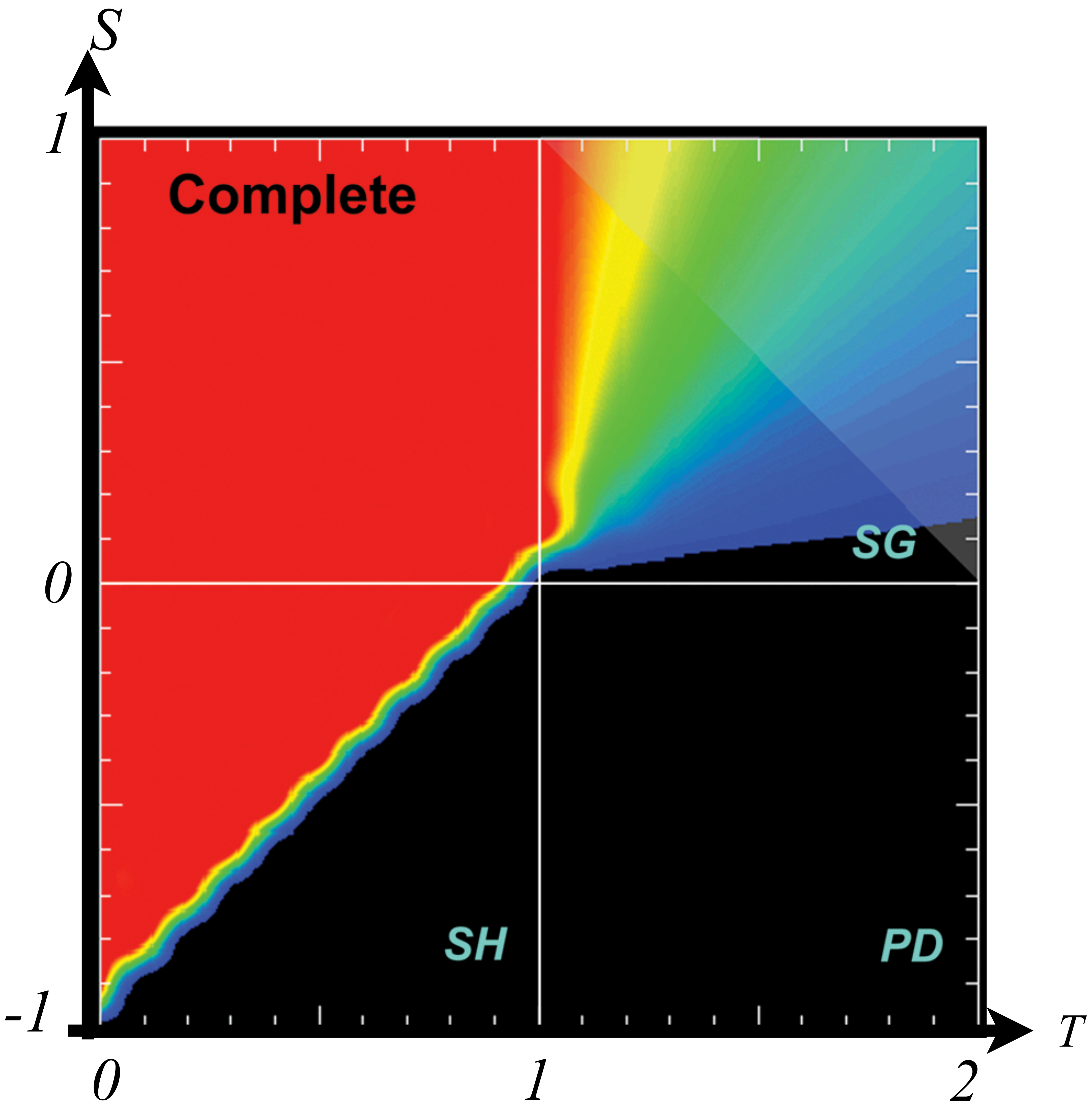
Vertex x **plays** k_x times **and accumulates** payoff F_x

Choose a neighbour y with payoff F_y

Replace strategy s_x in node x by strategy s_y of node y with probability

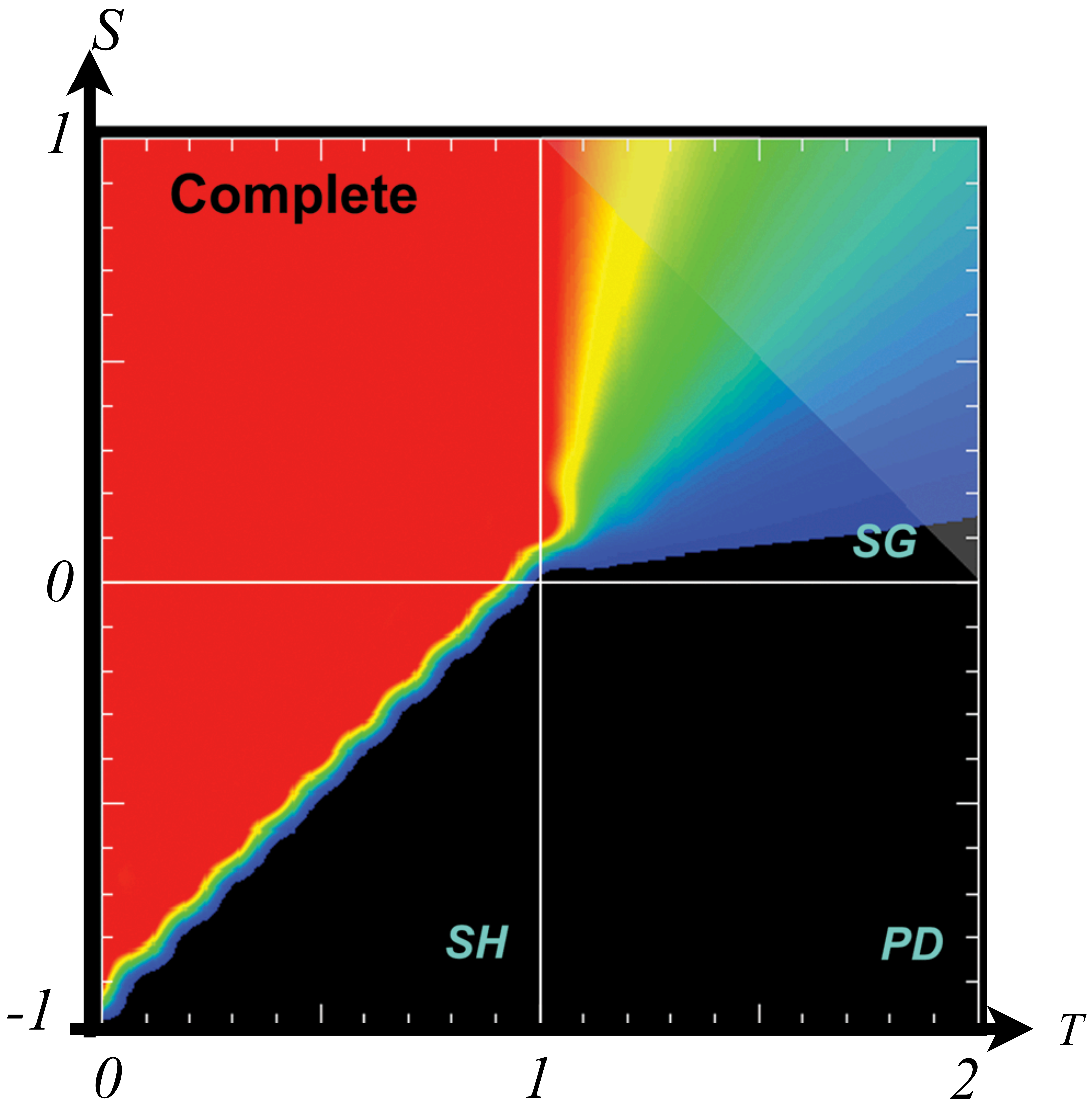
$$p = \max\left[0, \frac{F_y - F_x}{k_>(T - S)}\right]$$

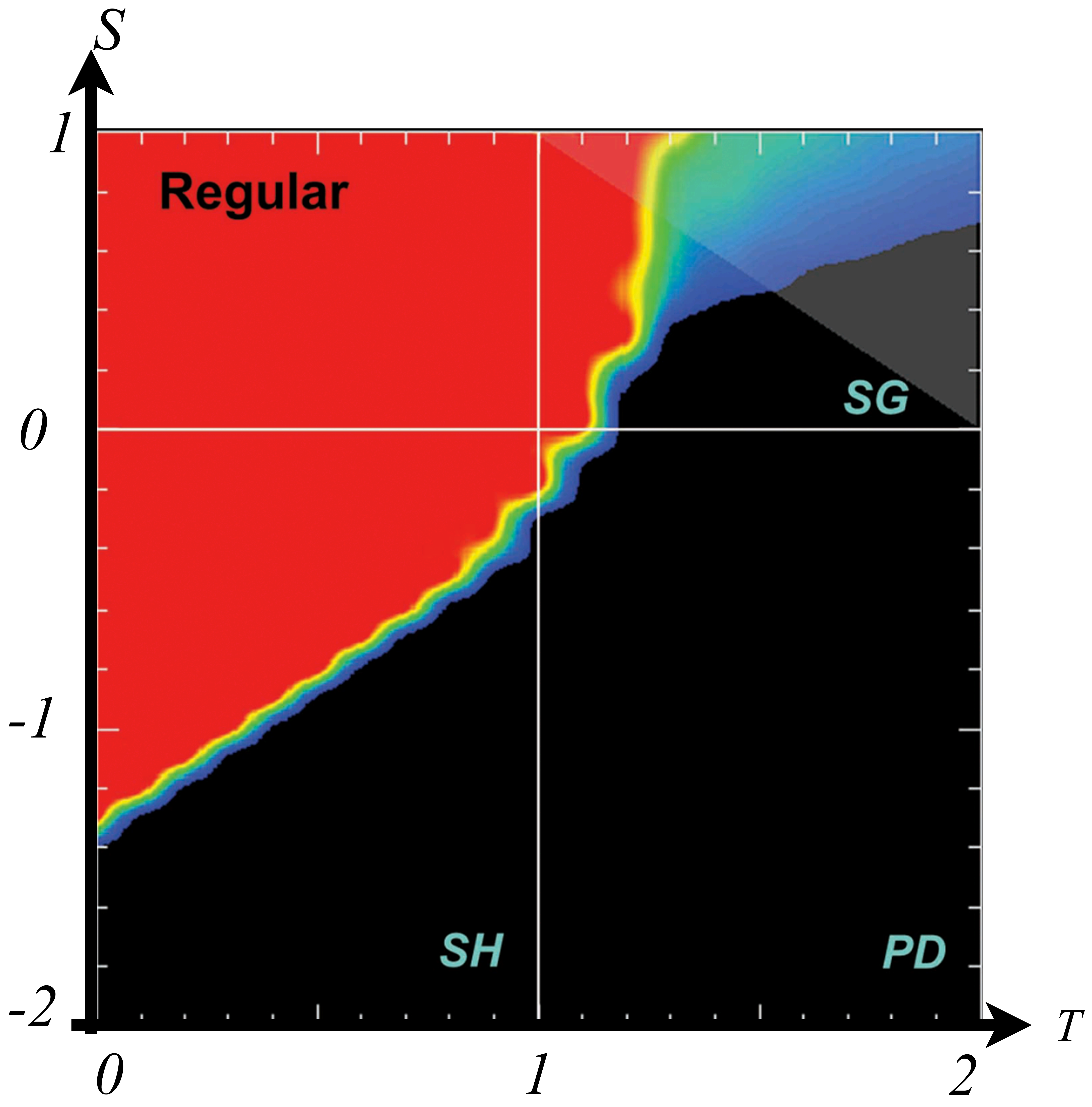
Well-mixed, the baseline



$Z = 10^4$, 100 runs, 50% C, R=1 and P=0

Regular networks

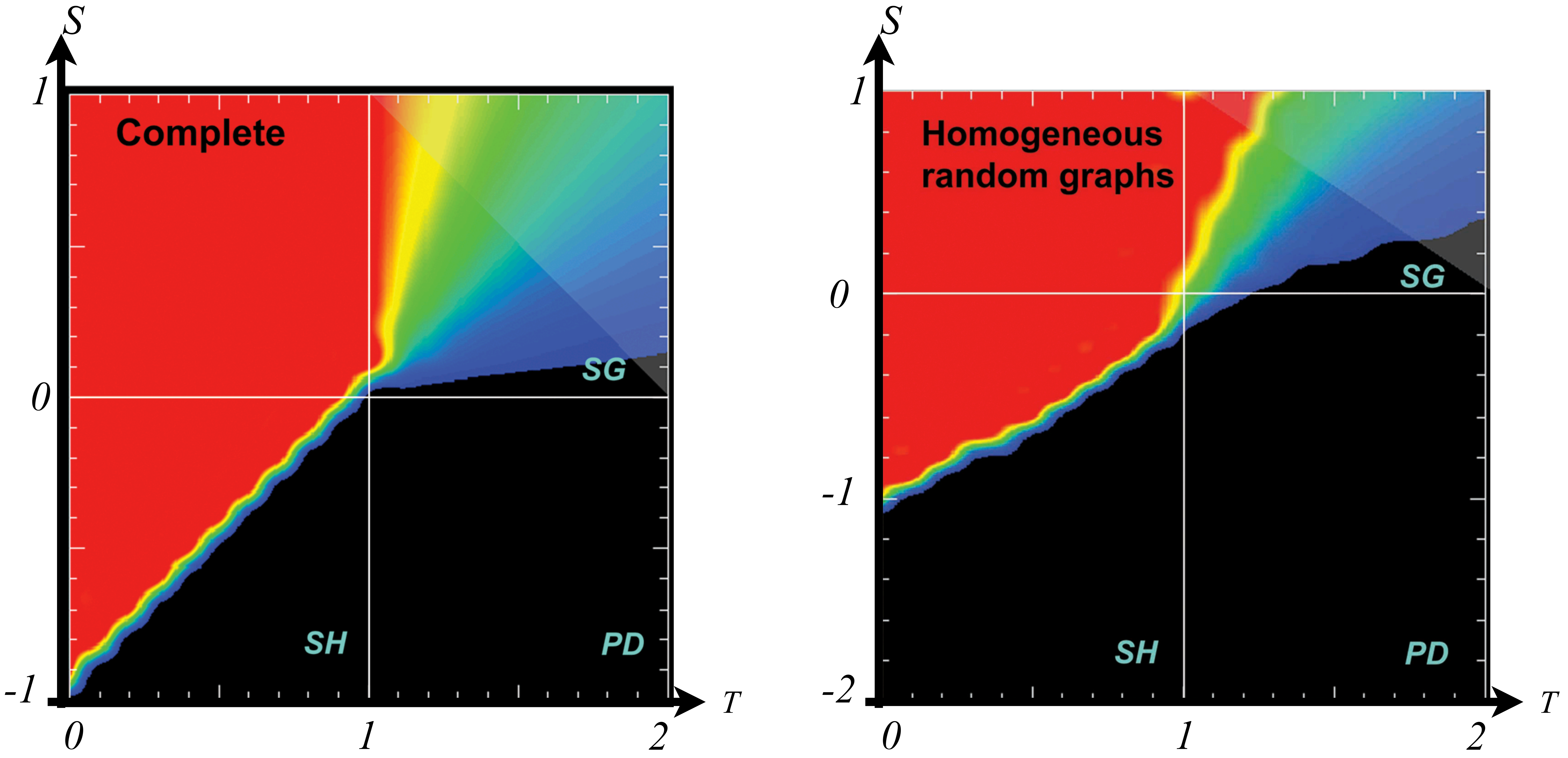




$Z = 10^4$, 100 runs, 50% C, R=1 and P=0

Low average degree $\hat{k} = 4$

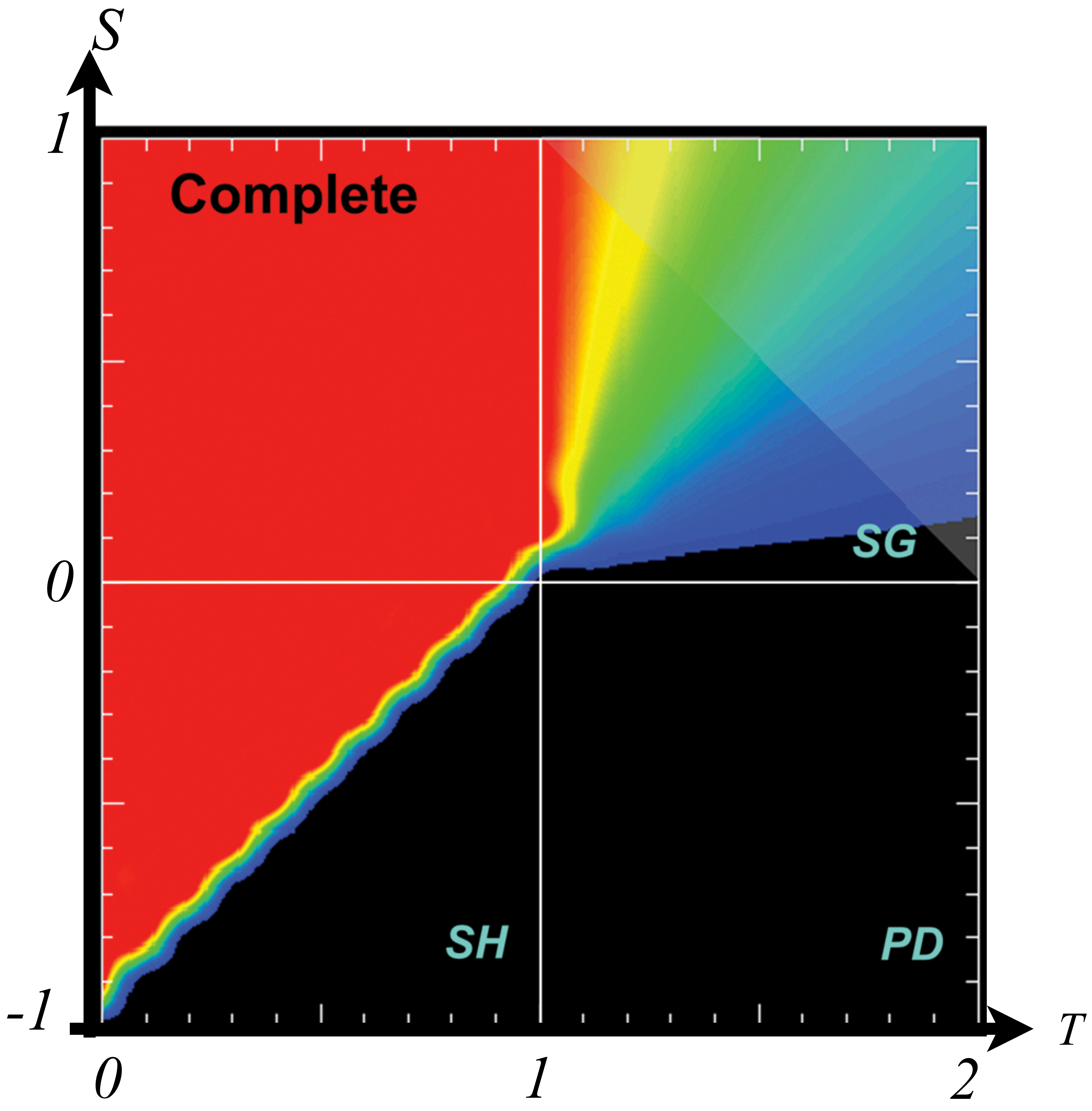
Random (Erdös-Rényi) networks



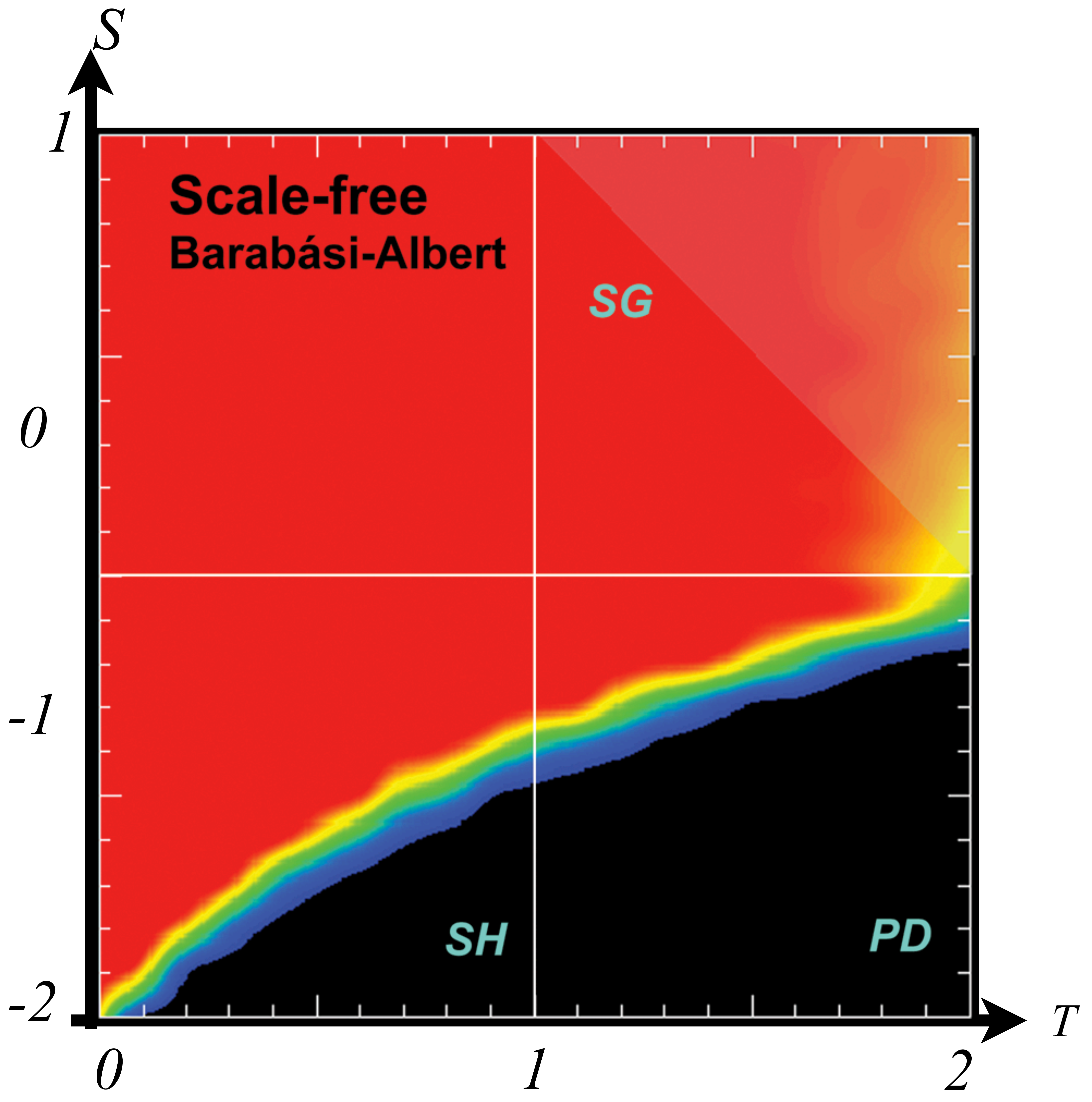
$Z = 10^4$, 100 runs, 50% C, R=1 and P=0

Low average degree $\hat{k} = 4$

Scale-free (Barabasi) networks

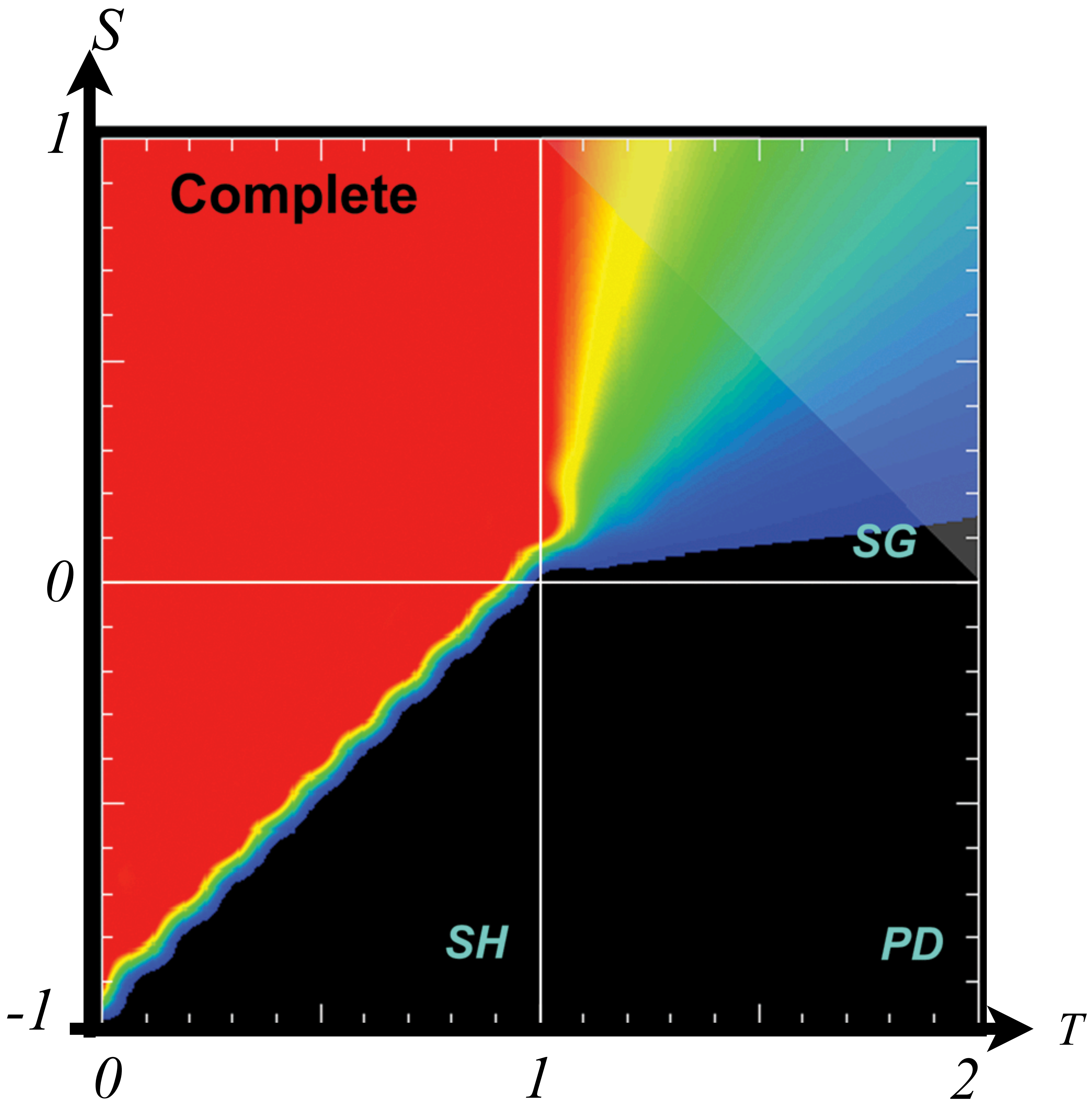


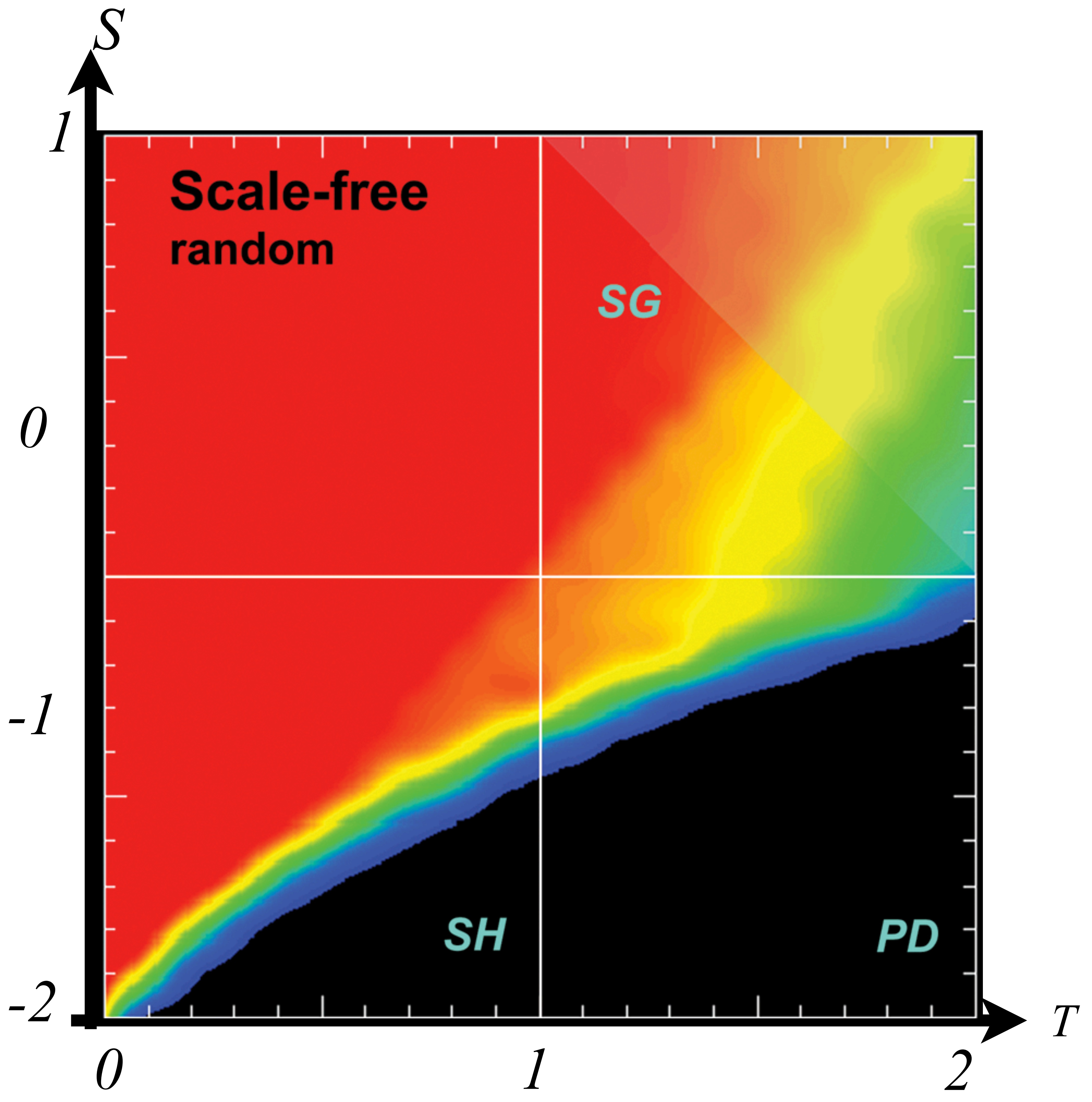
$Z = 10^4$, 100 runs, 50% C, R=1 and P=0



Low average degree $\hat{k} = 4$

Randomized Scale-free (Barabasi) networks

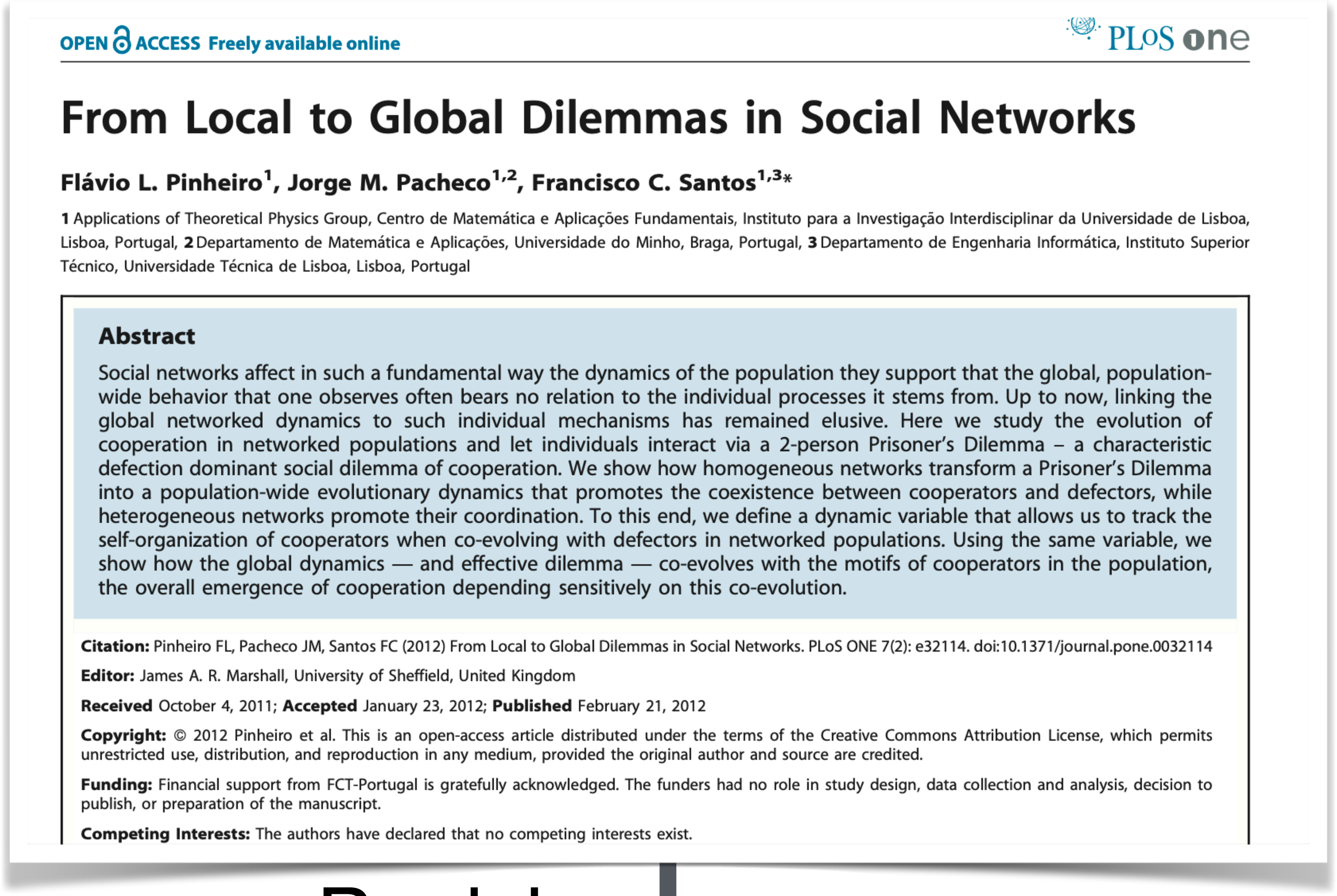




$Z = 10^4$, 100 runs, 50% C, R=1 and P=0

Low average degree $\hat{k} = 4$

Transforming the PD in an SH or SD


OPEN ACCESS Freely available online
PLoS one

From Local to Global Dilemmas in Social Networks

Flávio L. Pinheiro[1], Jorge M. Pacheco[1,2], Francisco C. Santos[1,3*]

1 Applications of Theoretical Physics Group, Centro de Matemática e Aplicações Fundamentais, Instituto para a Investigação Interdisciplinar da Universidade de Lisboa, Lisboa, Portugal, 2 Departamento de Matemática e Aplicações, Universidade do Minho, Braga, Portugal, 3 Departamento de Engenharia Informática, Instituto Superior Técnico, Universidade Técnica de Lisboa, Lisboa, Portugal

Abstract

Social networks affect in such a fundamental way the dynamics of the population they support that the global, population-wide behavior that one observes often bears no relation to the individual processes it stems from. Up to now, linking the global networked dynamics to such individual mechanisms has remained elusive. Here we study the evolution of cooperation in networked populations and let individuals interact via a 2-person Prisoner's Dilemma – a characteristic defection dominant social dilemma of cooperation. We show how homogeneous networks transform a Prisoner's Dilemma into a population-wide evolutionary dynamics that promotes the coexistence between cooperators and defectors, while heterogeneous networks promote their coordination. To this end, we define a dynamic variable that allows us to track the self-organization of cooperators when co-evolving with defectors in networked populations. Using the same variable, we show how the global dynamics — and effective dilemma — co-evolves with the motifs of cooperators in the population, the overall emergence of cooperation depending sensitively on this co-evolution.

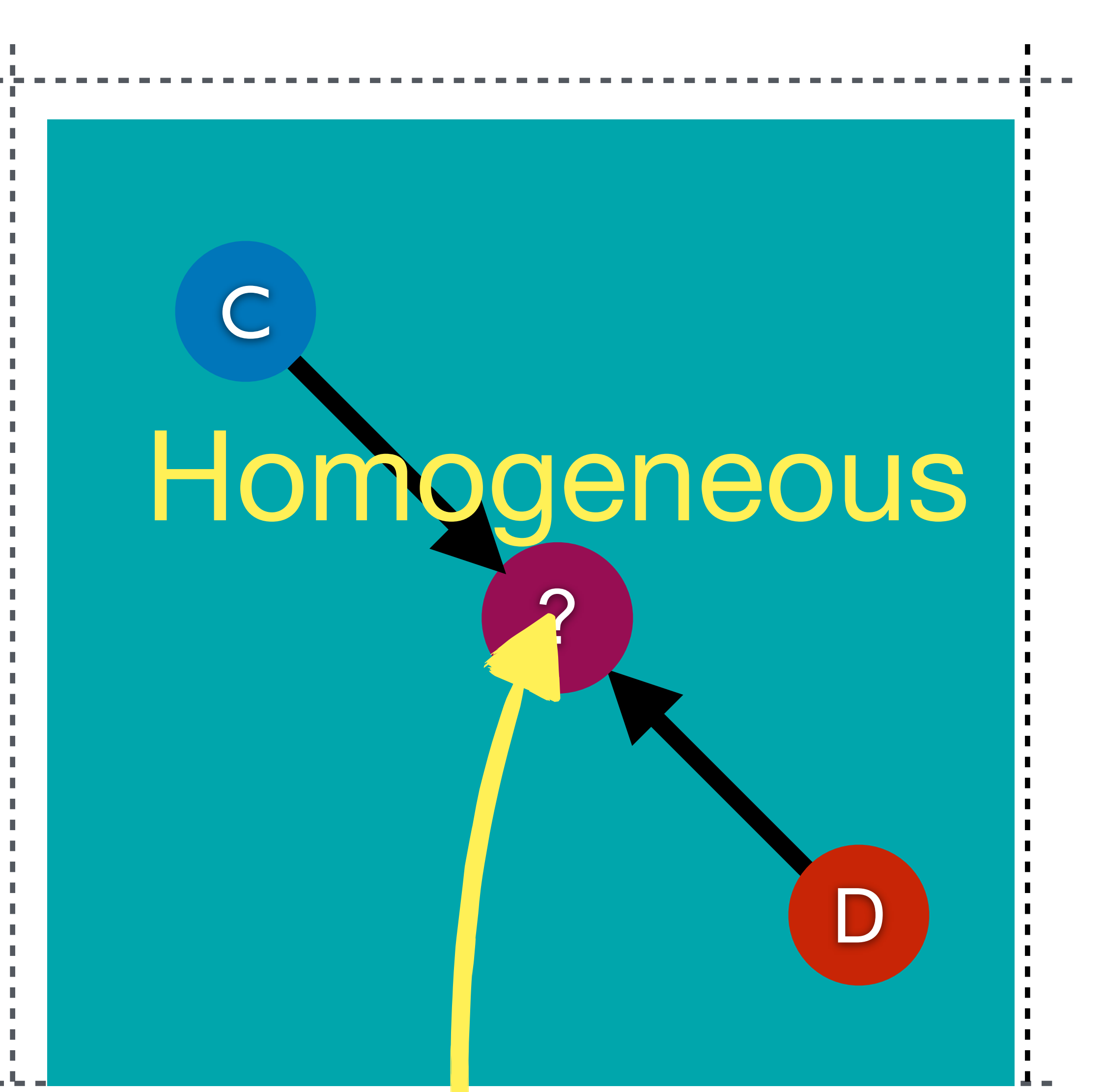
Citation: Pinheiro FL, Pacheco JM, Santos FC (2012) From Local to Global Dilemmas in Social Networks. PLoS ONE 7(2): e32114. doi:10.1371/journal.pone.0032114

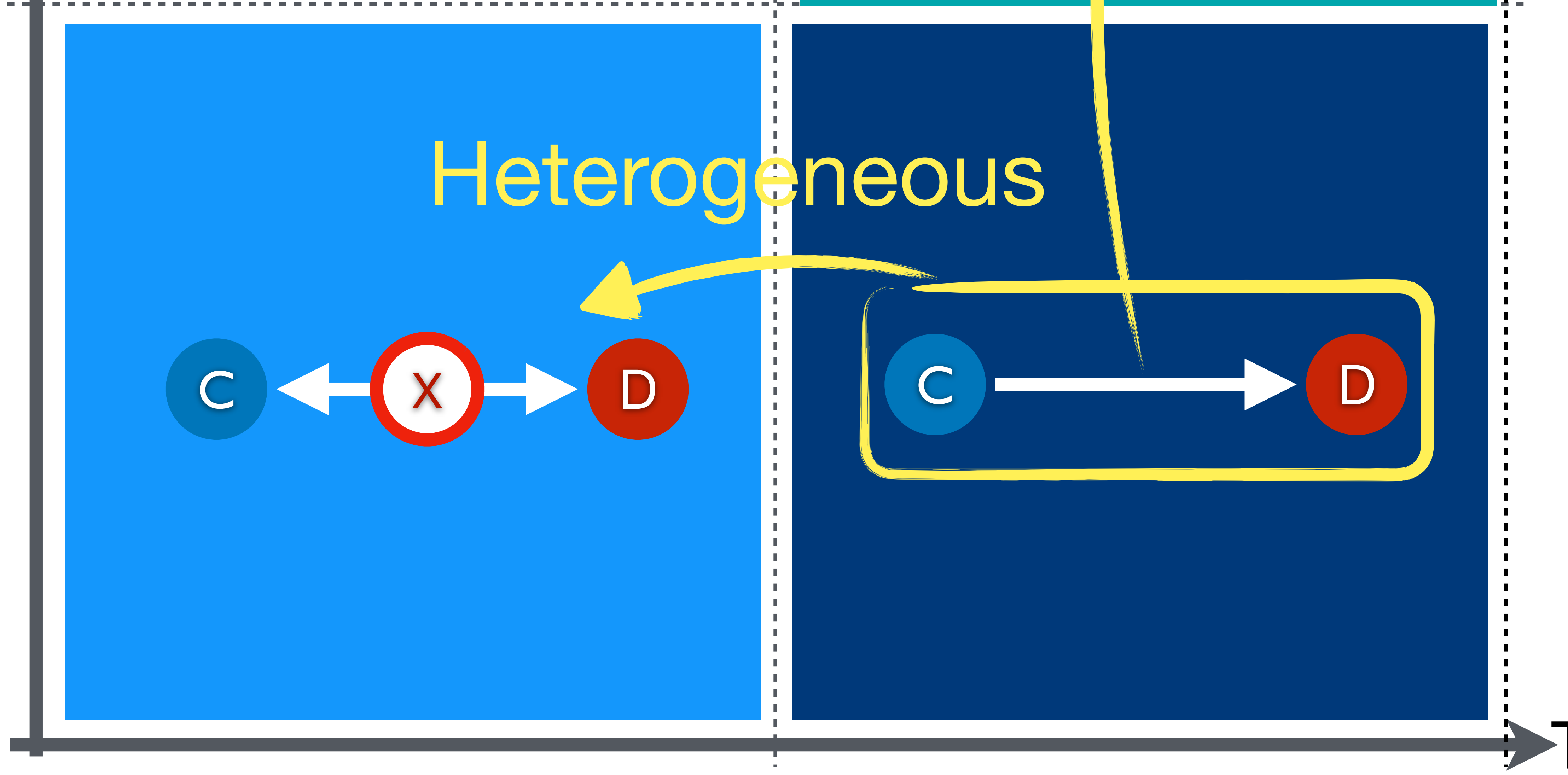
Editor: James A. R. Marshall, University of Sheffield, United Kingdom

Received October 4, 2011; **Accepted** January 23, 2012; **Published** February 21, 2012

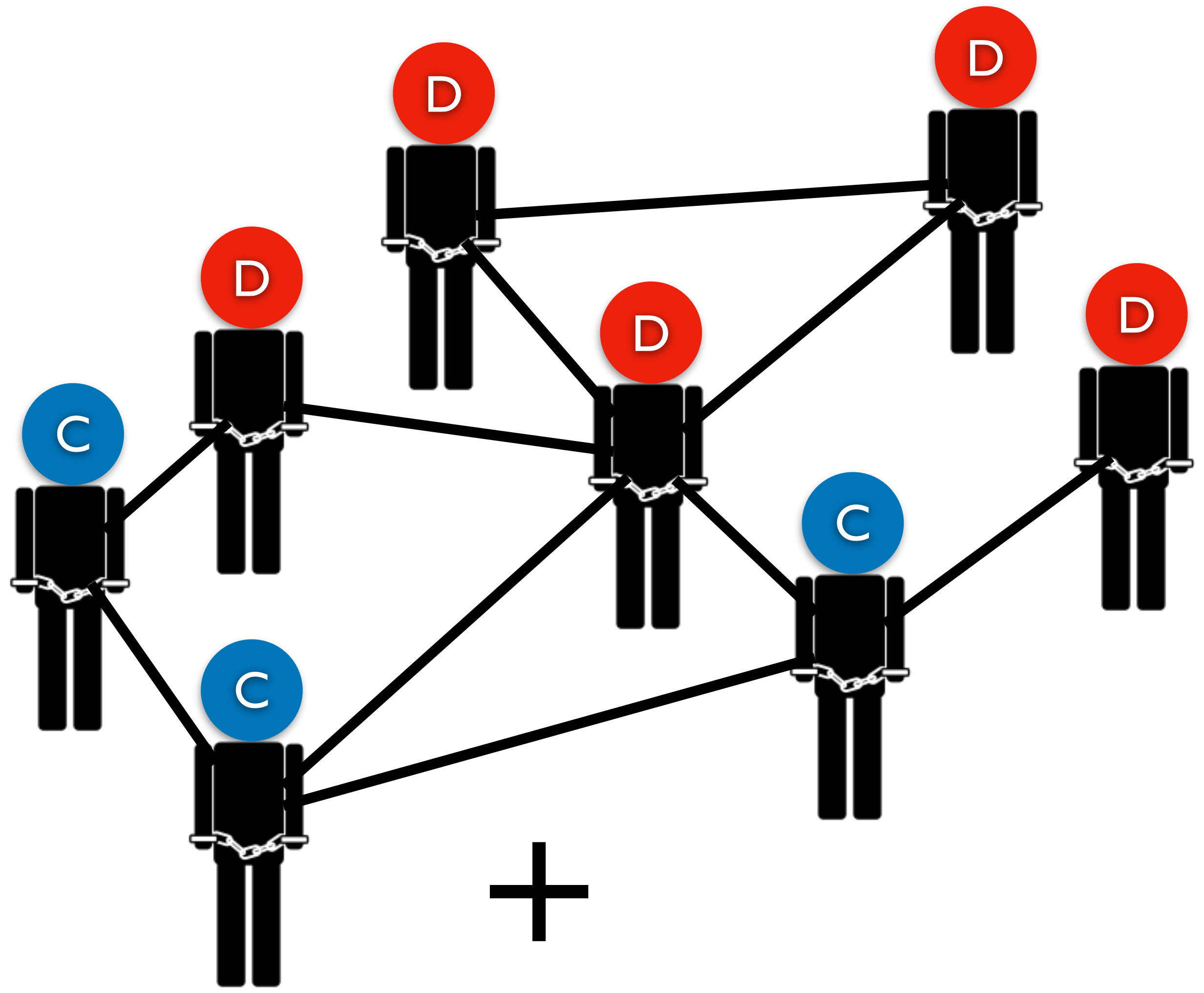
Funding: Financial support from FCT-Portugal is gratefully acknowledged. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing Interests: The authors have declared that no competing interests exist.





Introduces a new tool: the **averaged gradient of selection**

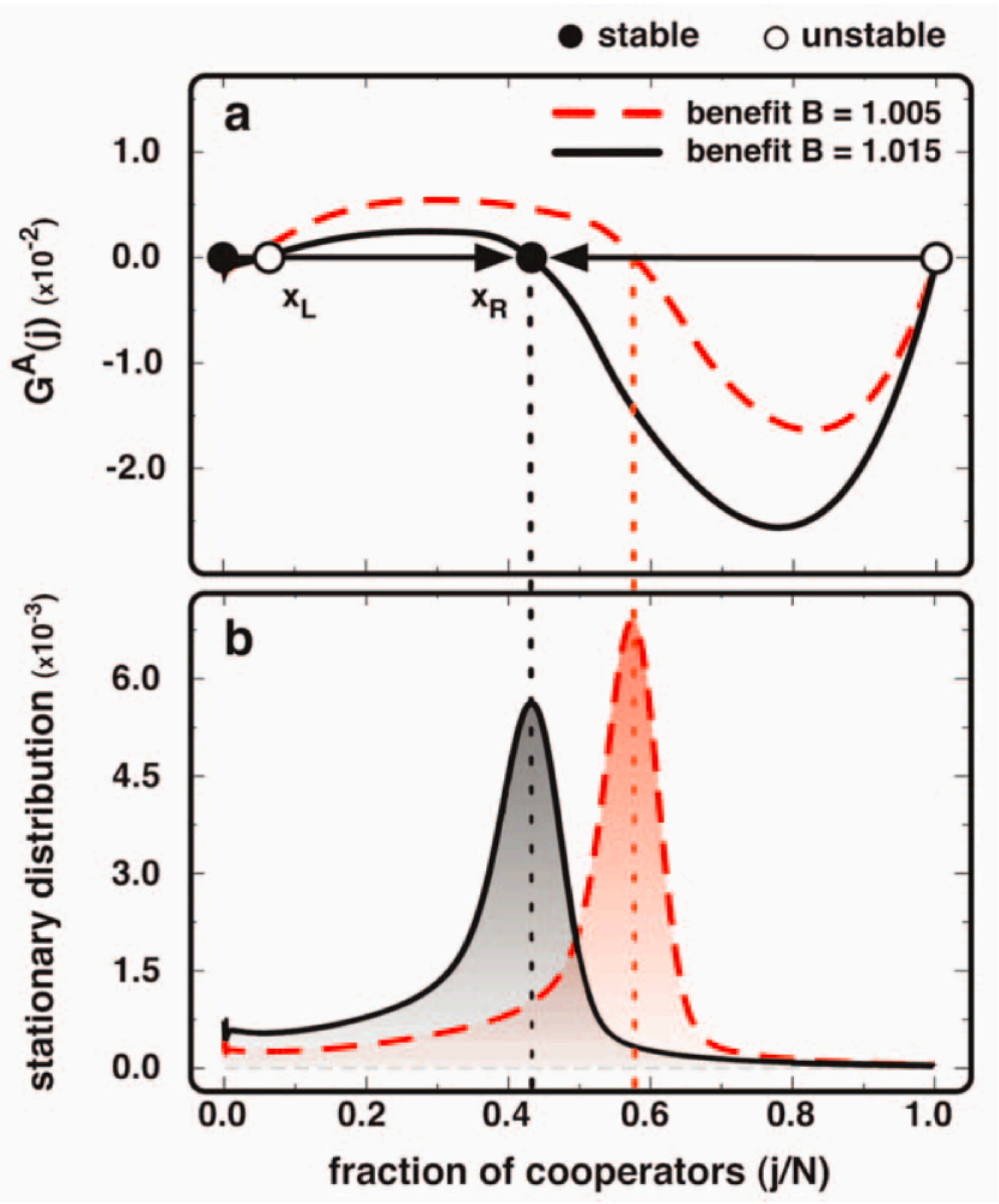


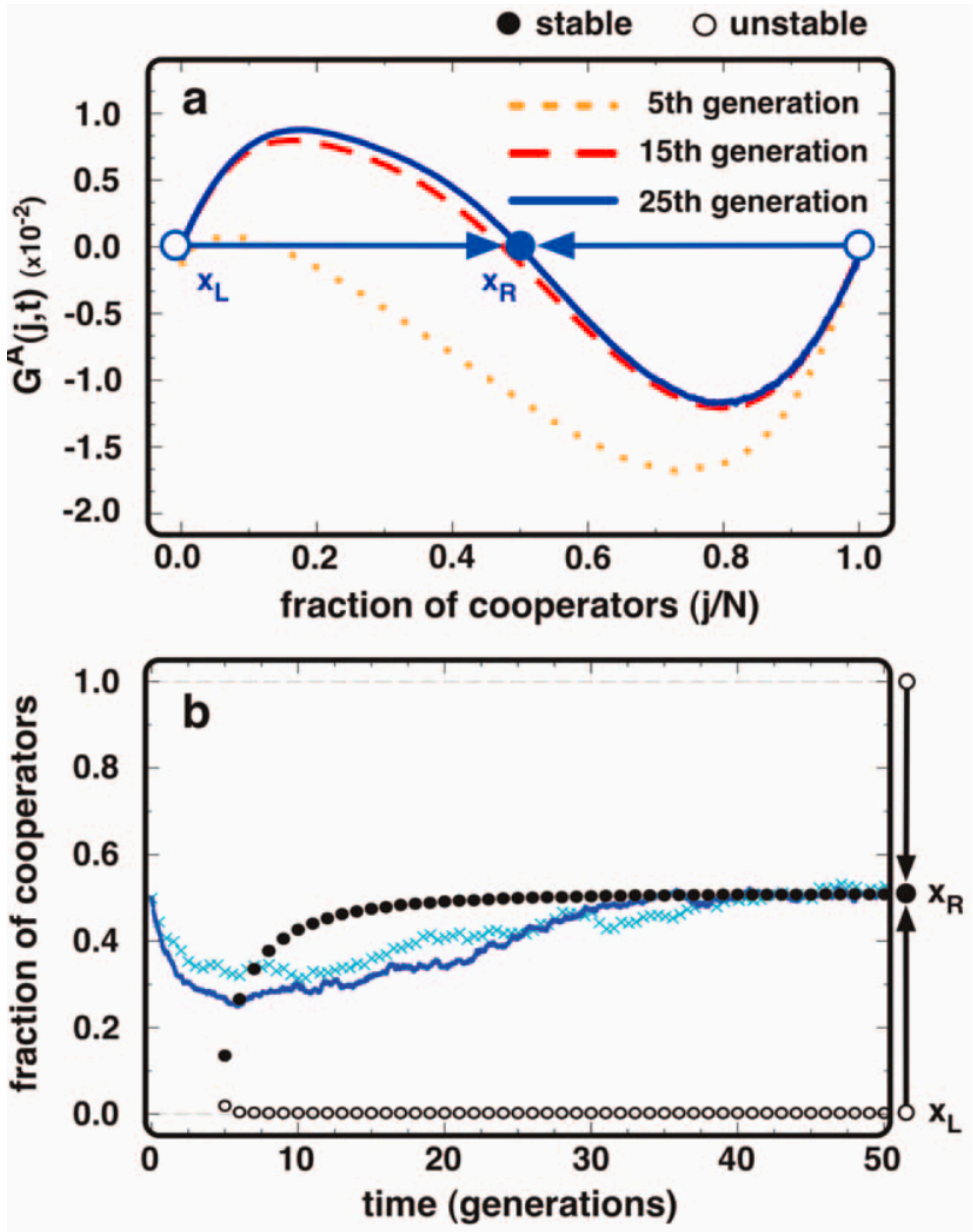
Nowak, M. A. (2006). Five rules for the evolution of cooperation. *science*, *314*(5805), 1560-1563.

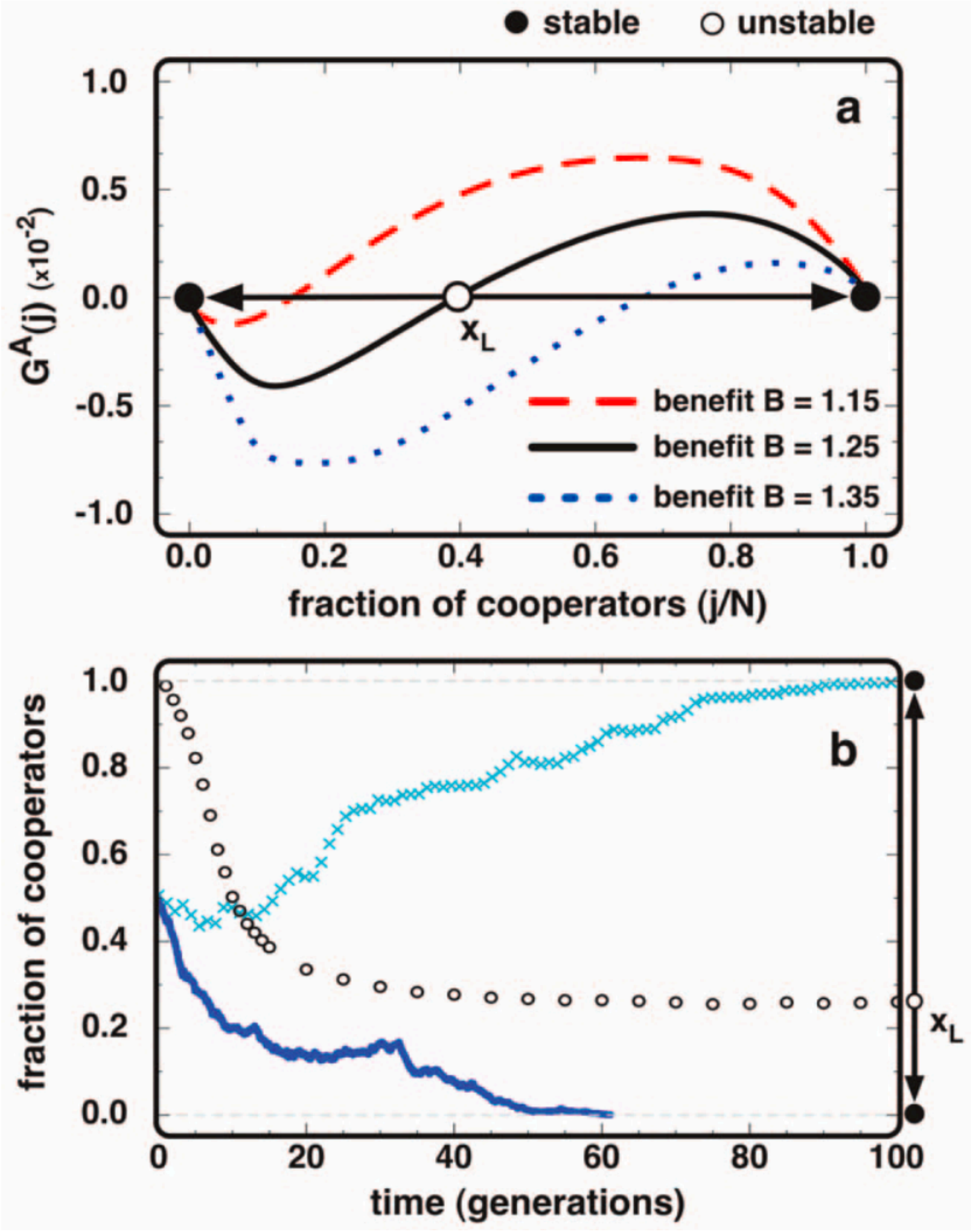
Assortment leads to the transformation of the game

homogeneous random network

Scale-Free
(Barrabassi-Albert)



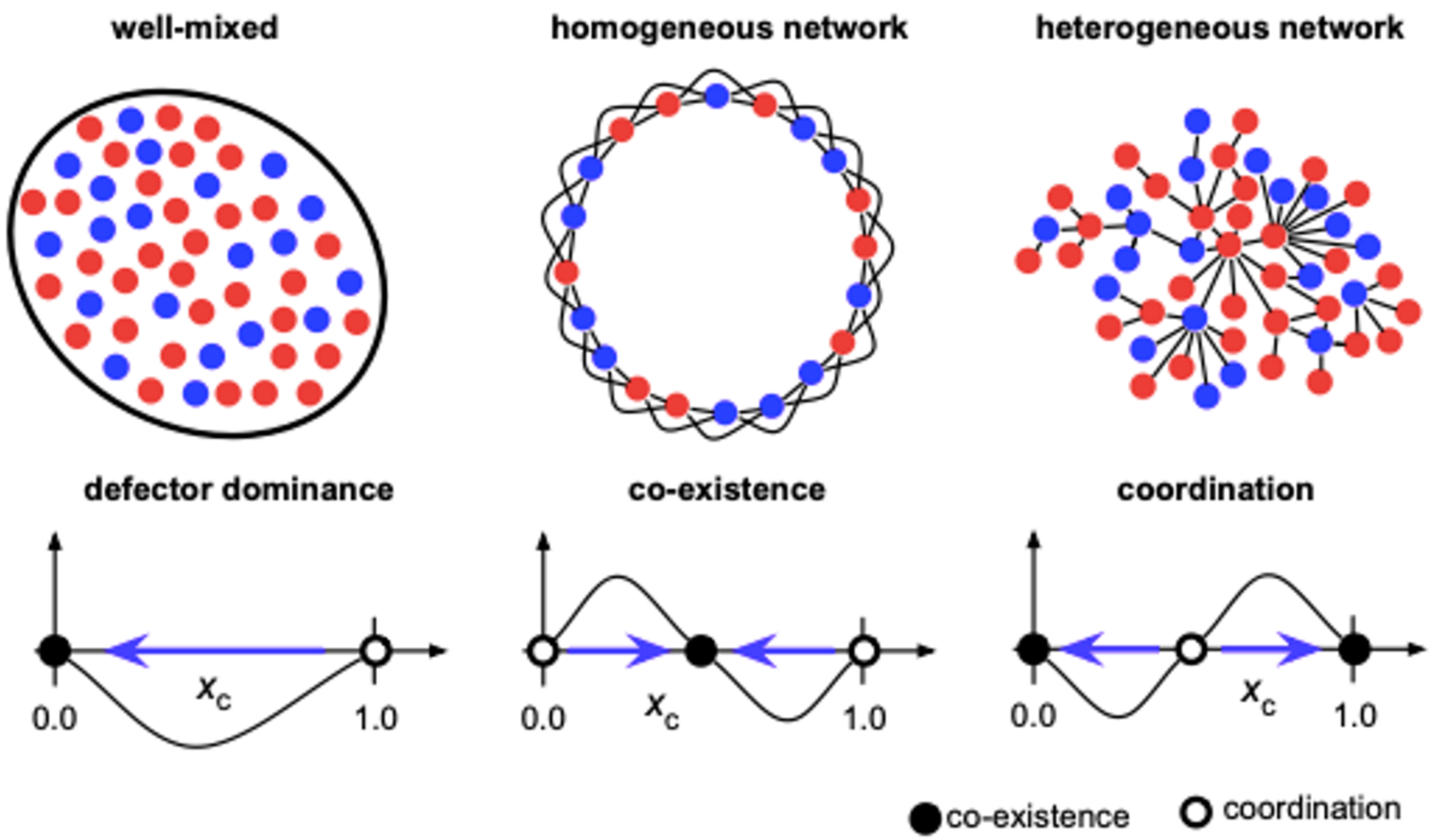




1. Pinheiro, F. L., Pacheco, J. M. & Santos, F. C. From Local to Global Dilemmas in Social Networks. *PLoS ONE* **7**, e32114 (2012).

Increasing heterogeneity favours cooperation

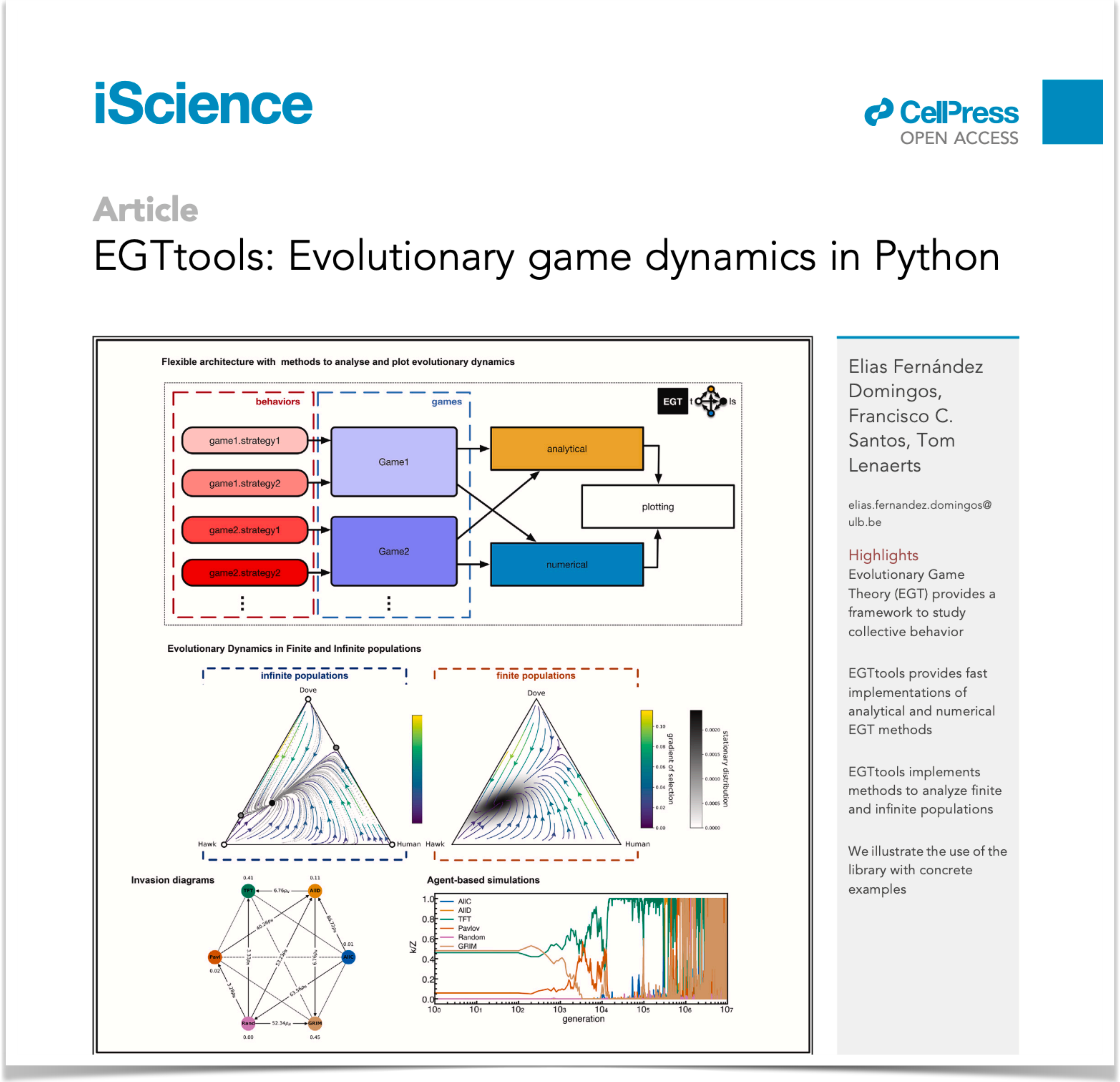
1. Heterogeneity in structure also leads to heterogeneous payoffs among individuals (even if they adopt the same strategy), since some individuals interact more often than others
2. **Local** information may be different from **global**



From Prof. Francisco C. Santos

Pinheiro F L, Pacheco J M and Santos F C 2012 From Local to Global Dilemmas in Social Networks *PLoS One* 7 e32114

EGTtools demo


iScience

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Article

EGTtools: Evolutionary game dynamics in Python

Flexible architecture with methods to analyse and plot evolutionary dynamics

Elias Fernández Domingos, Francisco C. Santos, Tom Lenaerts

elias.fernandez.domingos@ulb.be

Highlights

Evolutionary Game Theory (EGT) provides a framework to study collective behavior

EGTtools provides fast implementations of analytical and numerical EGT methods

EGTtools implements methods to analyze finite and infinite populations

We illustrate the use of the library with concrete examples

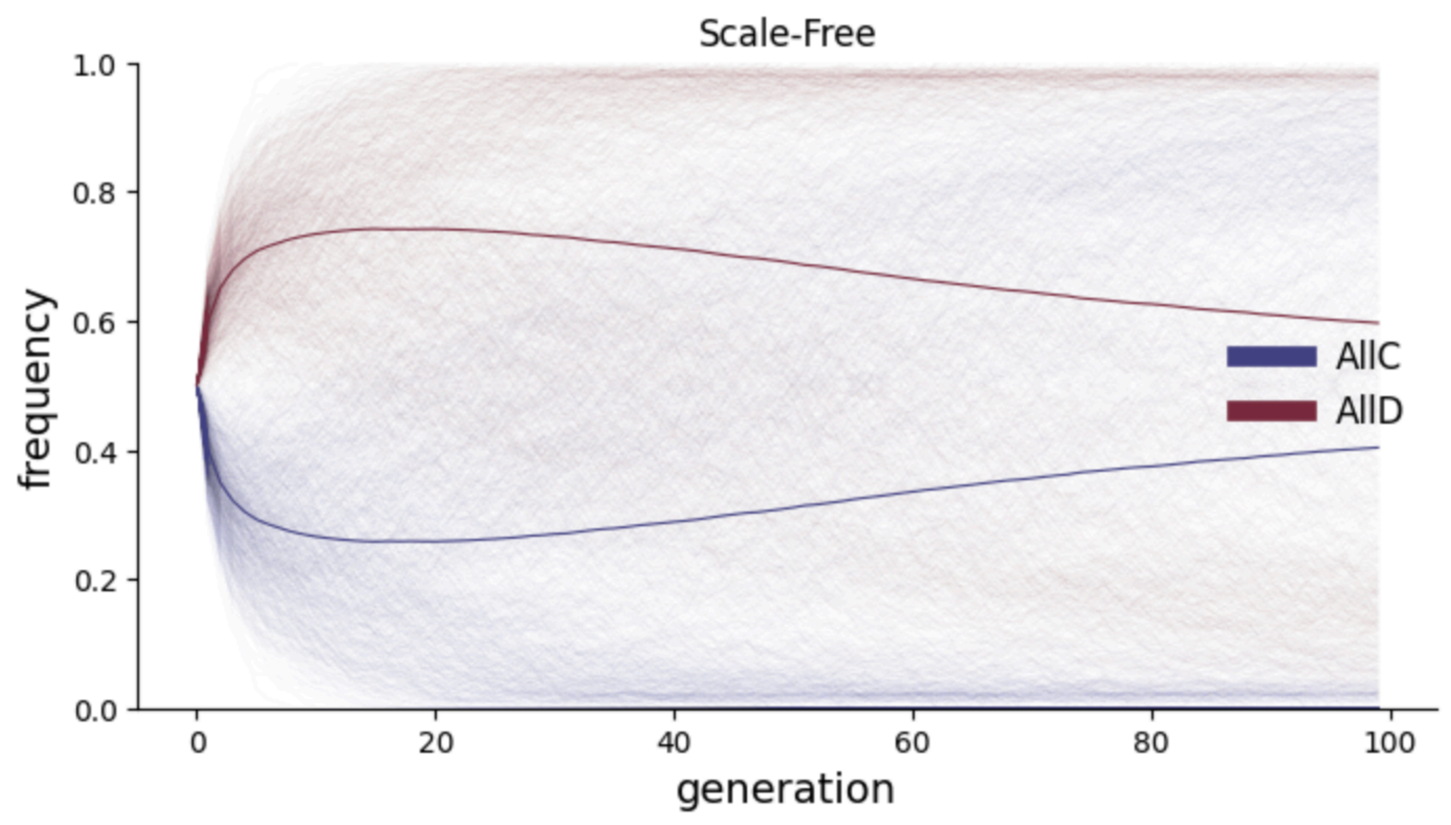
Domingos, E. F., Santos, F. C., & Lenaerts, T. (2023). EGTtools: Evolutionary game dynamics in Python. Iscience, 26(4): 106419 https://doi.org/10.1016/j.isci.2023.106419

https://github.com/Socrats/EGTTools

jupyter Network Last Checkpoint: 1 minute ago

File Edit View Run Kernel Settings Help

```
[18]: results_array = np.asarray(results)

[19]: colors = sns.color_palette("icefire", nb_strategies)

[20]: # Plot each year's time series in its own facet
fig, ax = plt.subplots(figsize=(8, 4))

for run in results:
    for i in range(len(strategies)):
        ax.plot(run[:, i] / Z, linewidth=.01, alpha=0.6, color=colors[i])

for i in range(len(strategies)):
    ax.plot(np.mean(results_array[:, :, i] / Z, axis=0), linewidth=.8,
            alpha=1, color=colors[i], label=strategy_labels[i])

ax.set_ylabel('frequency', fontsize=14)
ax.set_xlabel('generation', fontsize=14)
ax.set_ylim(0, 1)
ax.set_title("Scale-Free")
legend = ax.legend(fontsize=12,frameon=False)
# make legend lines thiker
for line in legend.get_lines():
    line.set_linewidth(7)

sns.despine()
```



What about n-player games?

Vol 454 | 10 July 2008 | doi:10.1038/nature06940 nature

LETTERS

Social diversity promotes the emergence of cooperation in public goods games

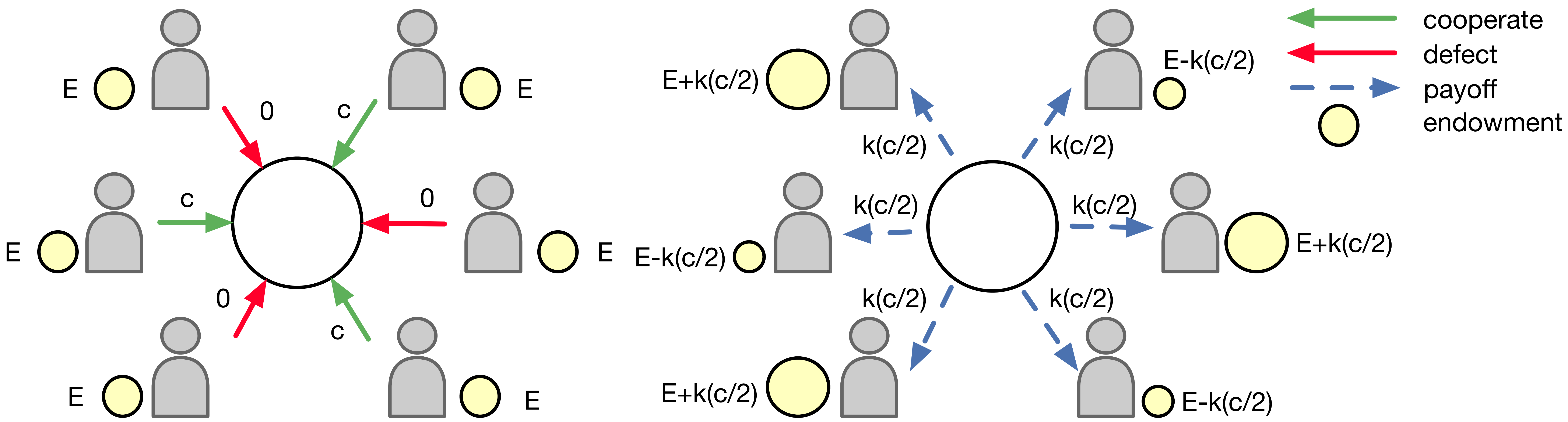
Francisco C. Santos[1], Marta D. Santos[2] & Jorge M. Pacheco[2]

Humans often cooperate in public goods games[1–3] and situations ranging from family issues to global warming[4,5]. However, evolutionary game theory predicts[4,6] that the temptation to forgo the public good mostly wins over collective cooperative action, and this is often also seen in economic experiments[7]. Here we show how social diversity provides an escape from this apparent paradox. Up to now, individuals have been treated as equivalent in all respects[4,8], in sharp contrast with real-life situations, where diversity is ubiquitous. We introduce social diversity by means of heterogeneous graphs and show that cooperation is promoted by the diversity associated with the number and size of the public goods game in which each individual participates and

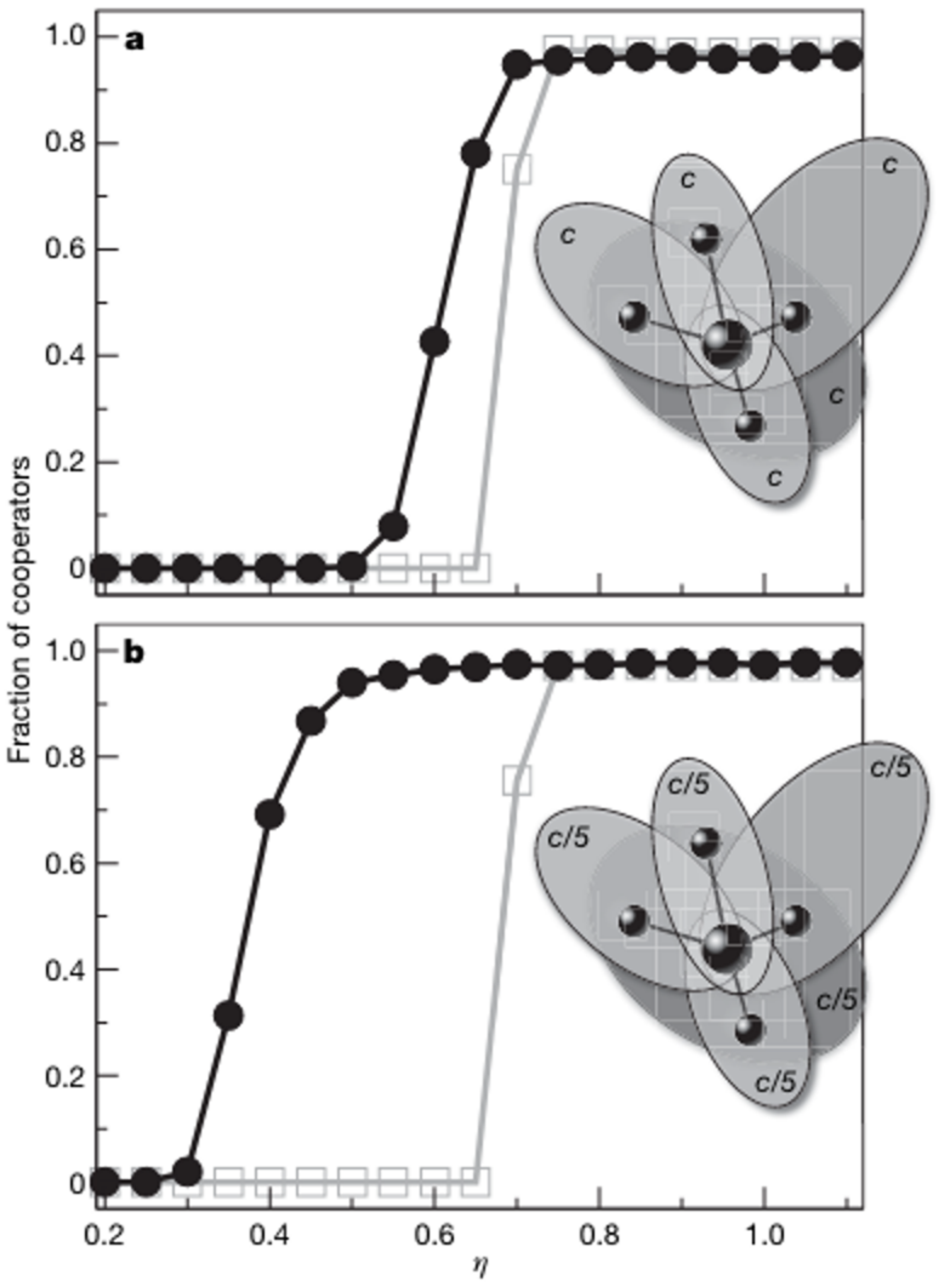
factor *r* and the result is equally distributed between all *N* members of the group. Hence, Ds get the same benefit of the Cs at no cost. Collective action to shelter, protect and nourish, which abounds in the animal world, provides examples of PGGs, because the cooperation of group members is required. Ultimately, the success (and survival)[5] of the human species relies on the capacity of humans for large-scale cooperation. In the absence of enforcement mechanisms[7,13,14], conventional evolutionary game theory predicts that the temptation to defect leads individuals to forgo the public good[4] in the *N*-person prisoner's dilemma. Whenever interactions are not repeated, and reward and punishment[4,8,13] can be ruled out, several mechanisms were explored that promote cooperation. Individuals

What about n-player games?

Public good game



Heterogeneous networks also promote cooperation in public good games



Fixed cost per game

Fixed cost per individual

And non-linear games?

Risk of collective failure provides an escape from the tragedy of the commons

Francisco C. Santos[a,b] and Jorge M. Pacheco[b,c,1]

[a]Departamento de Informática and Centro de Inteligência Artificial, Faculdade de Ciências e Tecnologia, Universidade Nova de Lisboa, 2829-516 Caparica, Portugal; [b]Applications of Theoretical Physics Group, Centro de Matemática e Aplicações Fundamentais, Instituto de Investigação Interdisciplinar, P-1649-003 Lisbon Codex, Portugal; and [c]Departamento de Matemática e Aplicações, Universidade do Minho, 4710-057 Braga, Portugal

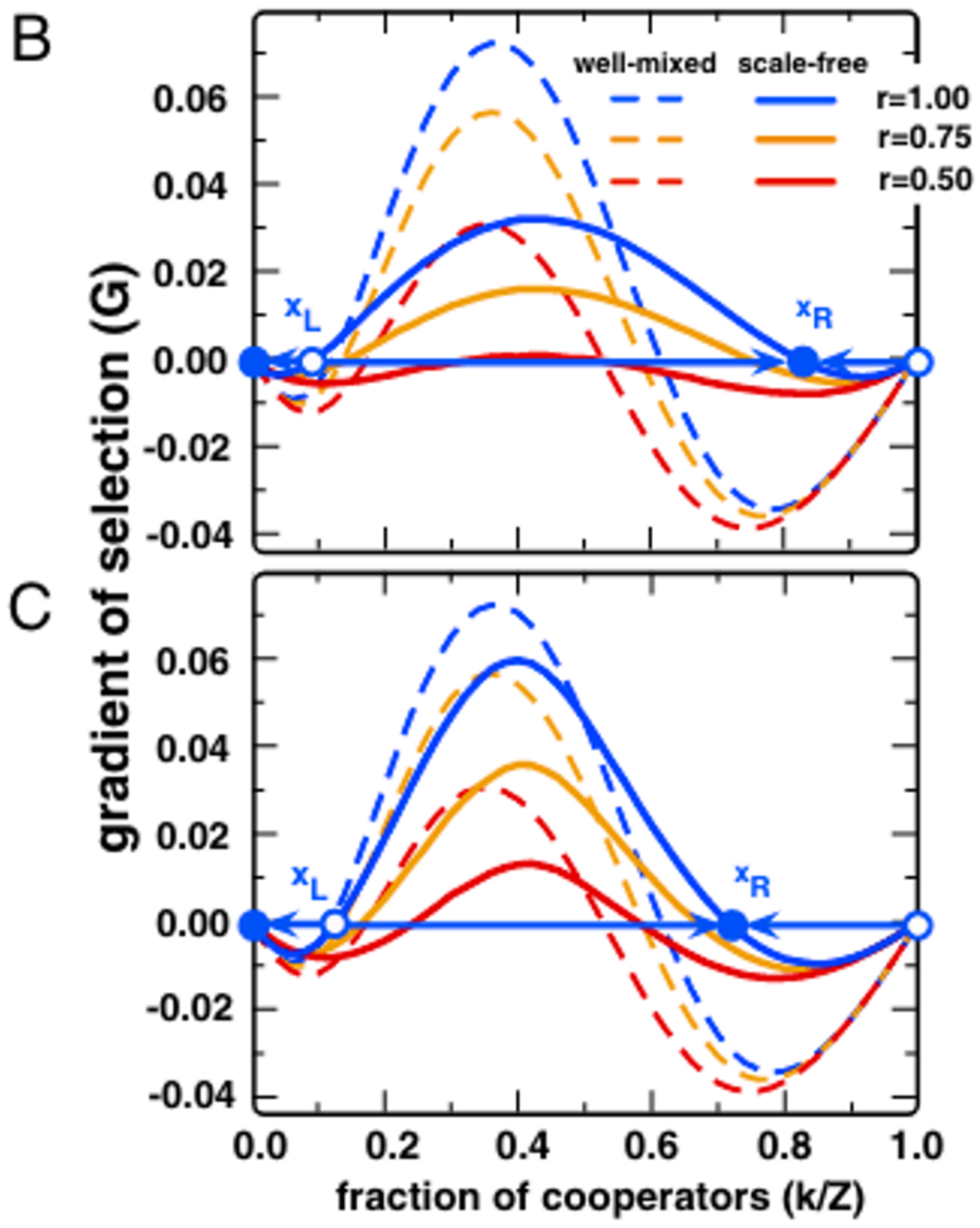
Edited by Simon A. Levin, Princeton University, Princeton, NJ, and approved May 11, 2011 (received for review October 18, 2010)

From group hunting to global warming, how to deal with collective action may be formulated in terms of a public goods game of cooperation. In most cases, contributions depend on the risk of future losses. Here, we introduce an evolutionary dynamics approach to a broad class of cooperation problems in which attempting to minimize future losses turns the risk of failure into a central issue in individual decisions. We find that decisions within small groups under high risk and stringent requirements to success significantly raise the chances of coordinating actions and escaping the tragedy of the commons. We also offer insights on the scale at which public goods problems of cooperation are best

contain at least M Cs (or equivalently, a collective effort of Mcb), all members will lose their remaining endowments with a probability r (the risk); otherwise, everyone will keep whatever they have. Imposing such a threshold mimics situations common to most of the public endeavors described above, and it also extends to nonhuman dilemmas (21–23), where a minimum combined effort is needed to achieve a collective goal. This is also the case in international environmental agreements (extensive reviews in refs. 5, 6, 11, and 12), which demand a minimum number of ratifications to come into practice (3, 24, 25).

Rational players facing this one-shot dilemma will opt for

Heterogeneity also fosters cooperation in the Collective Risk Dilemma



Fixed threshold

Variable threshold

Problematic to confirm experimentally

PNAS

Heterogeneous networks do not promote cooperation when humans play a Prisoner's Dilemma

Carlos Gracia-Lázaro[a], Alfredo Ferrer[a], Gonzalo Ruiz[a], Alfonso Tarancón[a,b], José A. Cuesta[a,c], Angel Sánchez[a,c,1], and Yamir Moreno[a,b,1]

[a]Instituto de Biocomputación y Física de Sistemas Complejos (BIFI), Universidad de Zaragoza, 50018 Zaragoza, Spain; [b]Departamento de Física Teórica, Universidad de Zaragoza, 50009 Zaragoza, Spain; and [c]Grupo Interdisciplinar de Sistemas Complejos (GISC), Departamento de Matemáticas, Universidad Carlos III de Madrid, 28911 Leganés, Madrid, Spain

Edited by Simon A. Levin, Princeton University, Princeton, NJ, and approved June 8, 2012 (received f

It is not fully understood why we cooperate with strangers on a daily basis. In an increasingly global world, where interaction networks and relationships between individuals are becoming more complex, different hypotheses have been put forward to explain the foundations of human cooperation on a large scale and to account for the true motivations that are behind this phenomenon. In this context, population structure has been suggested to foster cooperation in social dilemmas, but theoretical studies of this mechanism have yielded contradictory results so far; additionally, the issue lacks a proper experimental test in large systems. We have performed the largest experiments to date with humans playing a spatial Prisoner's Dilemma on a lattice and a scale-free network (1,229 subjects). We observed that the level of cooperation reached in both networks is the same, comparable with the level of cooperation of smaller networks or unstructured populations. We have also found that subjects respond to the cooperation that they observe in a reciprocal manner, being more likely to cooperate if, in the previous round, many of their neighbors and themselves did so, which implies that humans do not consider neighbors' payoffs when making their decisions in this dilemma but only their actions. Our results, which are in agreement with recent theoretical predictions based on this behavioral rule, suggest that population structure has little relevance as a cooperation promoter or inhibitor among humans.

evolutionary game dynamics | network reciprocity | conditional cooperation

with some except
Interestingly, the
account the behav
predicts that neith
would influence t
lemma (i.e., the c
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Here, we close
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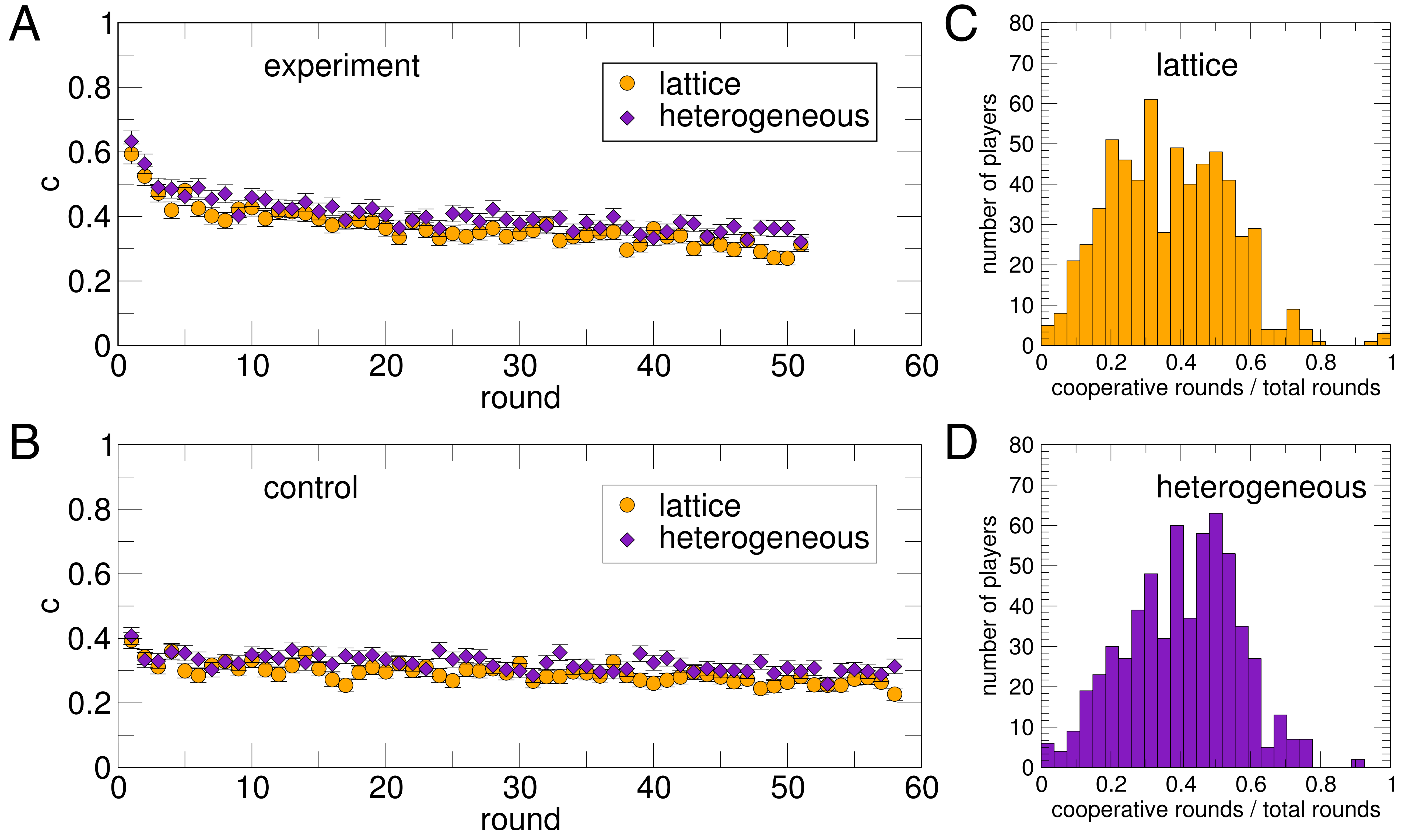

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Social Experiments in the Mesosc
Spatial Prisoner's Dilemma

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UCM, Cantoblanco, Madrid, Spain, 4 Instituto de Biocomputación y Física de Sistemas Complejos

Abstract

Background: The evolutionary origin of cooperation among unrelated
several disciplines. Prominent among the several mechanisms propose
existence of a population structure that determines the interactions
analytically and by simulation the effects of such a structure, particularly
the results of these models largely depend on details such as the type
Therefore, experimental work suitably designed to address this questio

Methods and Findings: We have designed an experiment to test the
Prisoner's Dilemma on a network whose size is comparable to that of
declines to an asymptotic state with low but nonzero cooperation. R
population is heterogeneous, consisting of a high percentage of defecto
that shares features of the conditional cooperators of public goods game
coexistence of these different strategies that is in good agreement with

Conclusions: In our large experimental setup, cooperation was not promo
level (around 20%) typical of public goods experiments. Our findings also

Experiments reveal condition

PLOS | COMPUTATIONAL BIOLOGY

RESEARCH ARTICLE

Reinforcement Learning Explains Conditional Cooperation and Its Moody Cousin

Takahiro Ezaki[1,2,3,4], Yutaka Horita[3,4], Masanori Takezawa[5,6], Naoki Masuda[7]*

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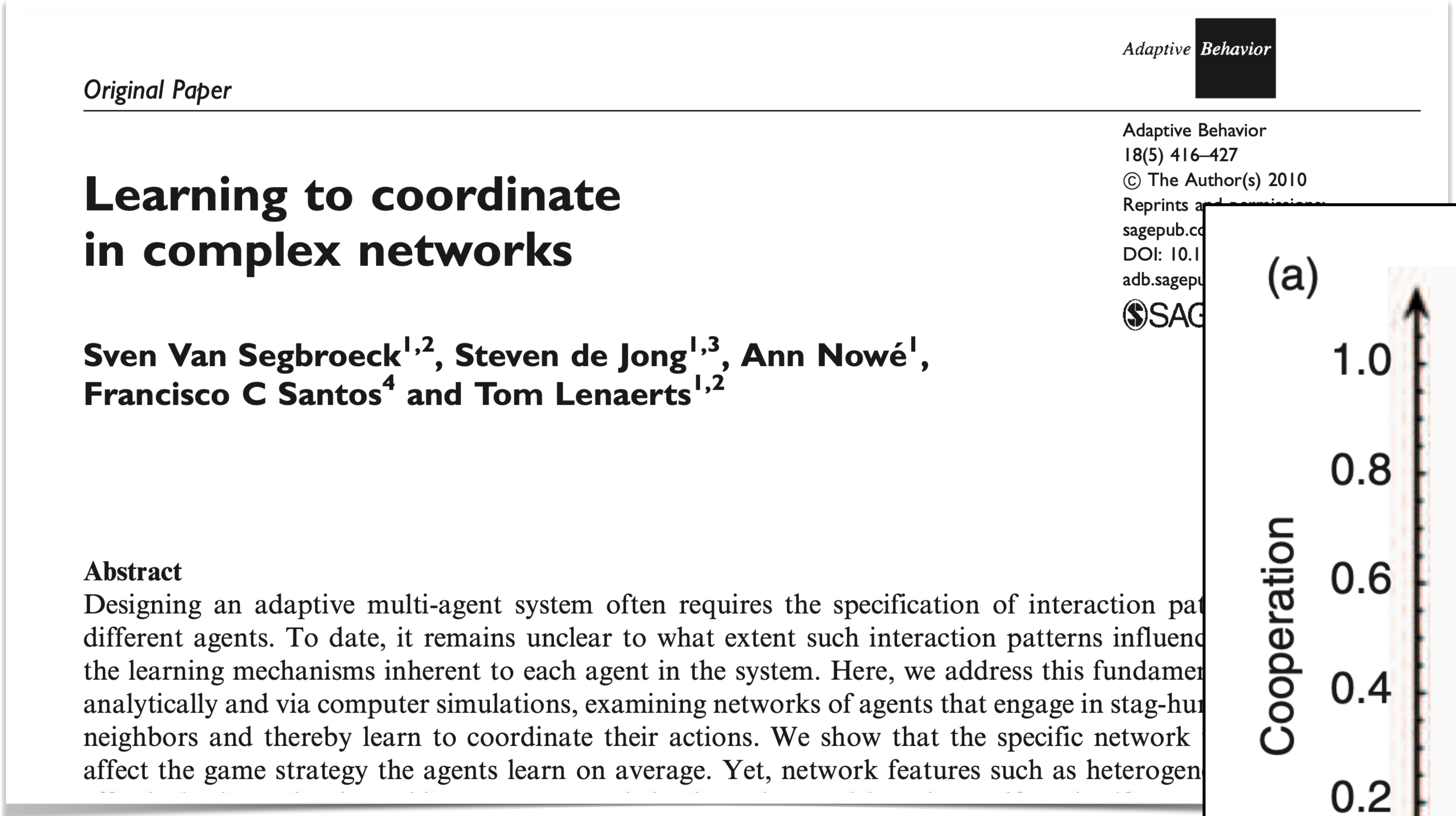
Editor: Natalia L. Komarova, University of California,

Abstract

Direct reciprocity, or repeated interaction, is a main mechanism to sustain cooperation under social dilemmas involving two individuals. For larger groups and networks, which are probably more relevant to understanding and engineering our society, experiments employing repeated multiplayer social dilemma games have suggested that humans often show conditional cooperation behavior and its moody variant. Mechanisms underlying these behaviors largely remain unclear. Here we provide a proximate account for this behavior by showing that individuals adopting a type of reinforcement learning, called aspiration learn-

Reinforcement learning = individual learning by experience (see part 2)

Individual learning (alone) has no effect in networks


Adaptive Behavior

Original Paper

Adaptive Behavior
18(5) 416–427

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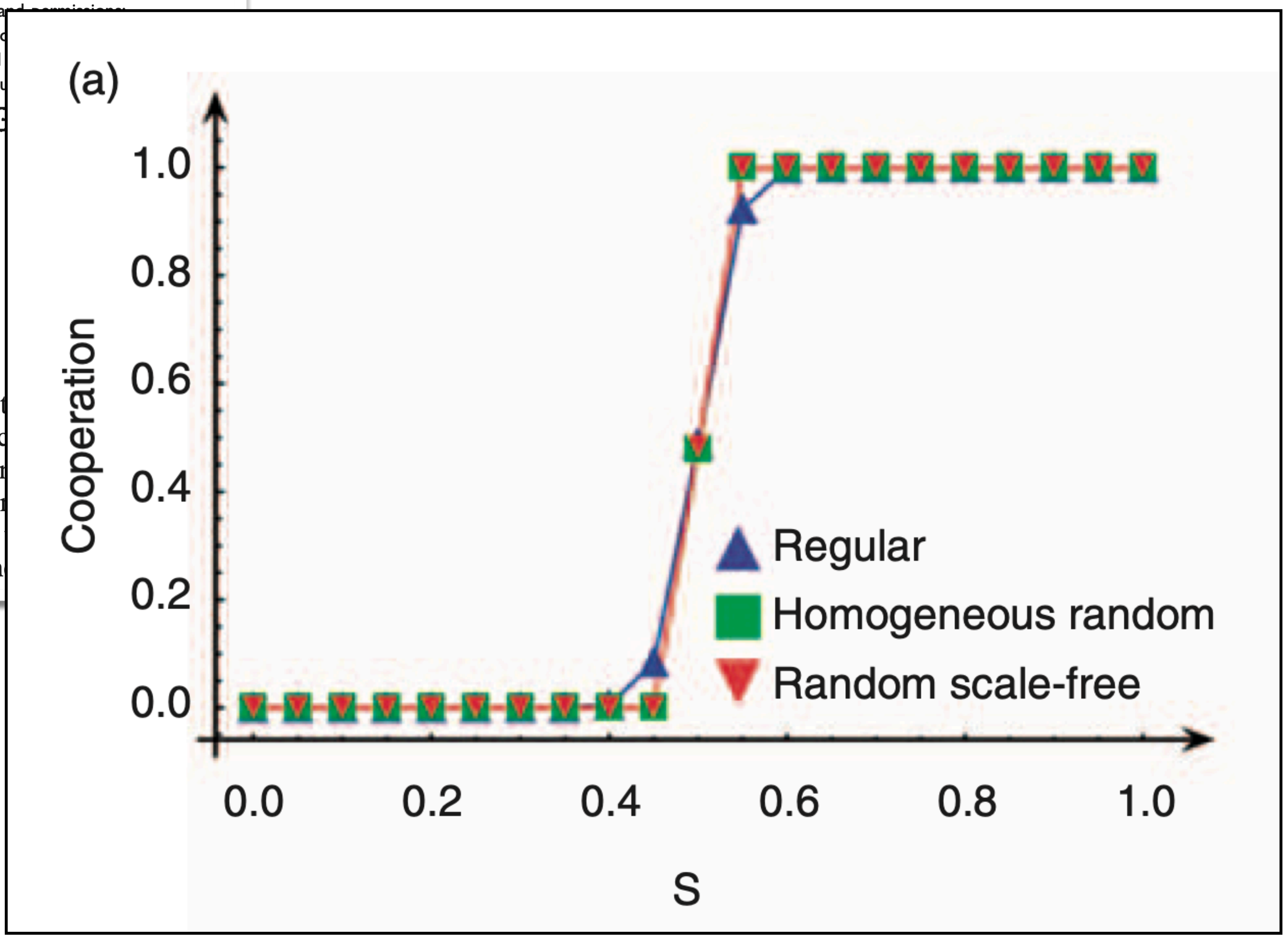
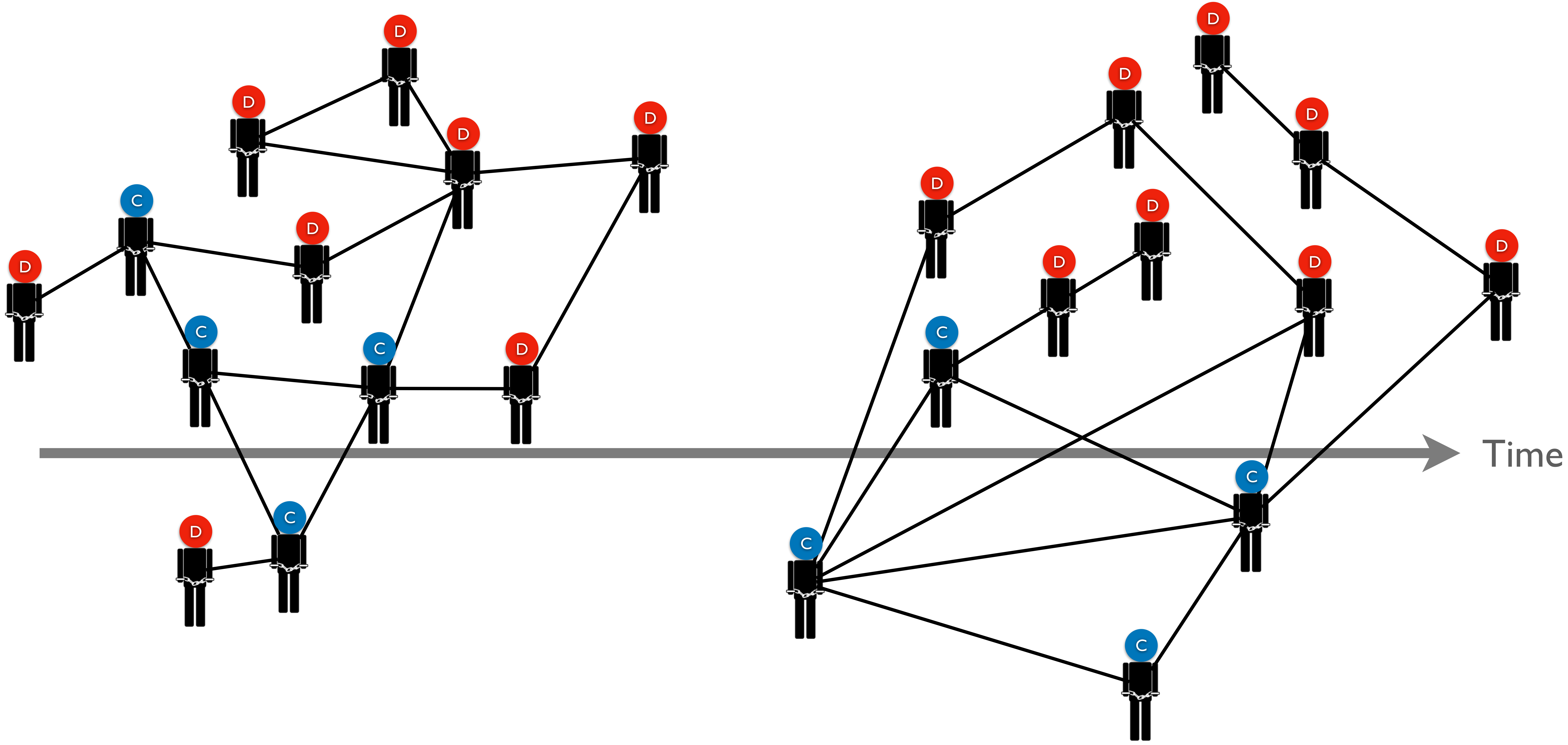
Learning to coordinate in complex networks

Sven Van Segbroeck[1,2], Steven de Jong[1,3], Ann Nowé[1], Francisco C Santos[4] and Tom Lenaerts[1,2]

Abstract
Designing an adaptive multi-agent system often requires the specification of interaction pat
different agents. To date, it remains unclear to what extent such interaction patterns influen
the learning mechanisms inherent to each agent in the system. Here, we address this fundame
analytically and via computer simulations, examining networks of agents that engage in stag-hu
neighbors and thereby learn to coordinate their actions. We show that the specific network
affect the game strategy the agents learn on average. Yet, network features such as heterogen

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Cooperation Prevails When Individuals Adjust Their Social Ties

Francisco C. Santos[1], Jorge M. Pacheco[2,3], Tom Lenaerts[4,5*]

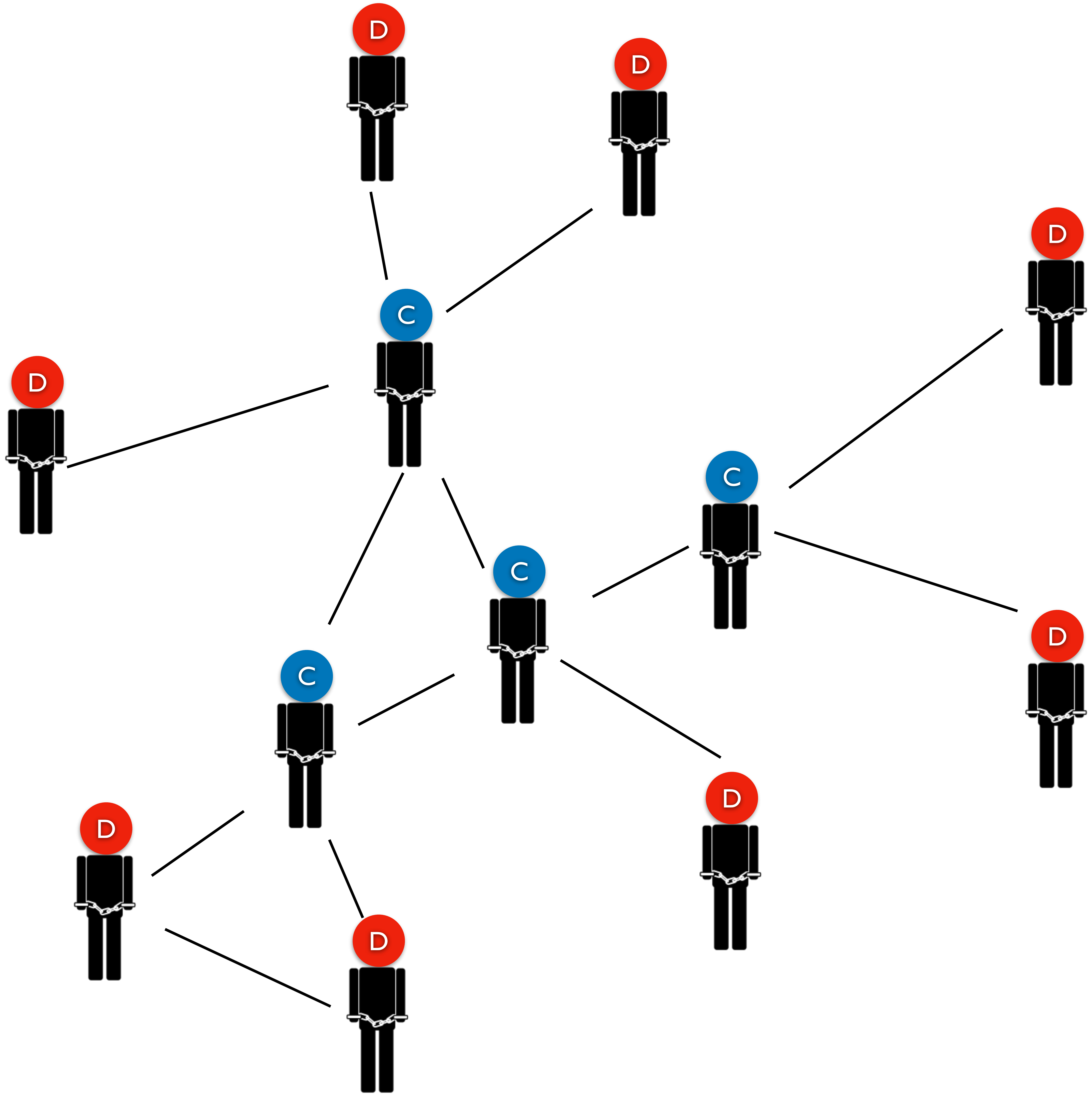
1 Computer and Decision Engineering Department, Institut de Recherches Interdisciplinaires et de Développements en Intelligence Artificielle, Université Libre de Bruxelles, Brussels, Belgium, **2** Program for Evolutionary Dynamics, Harvard University, Cambridge, Massachusetts, United States of America, **3** Department of Physics of the Faculty of Science, Center for Theoretical and Computational Physics, University of Lisbon, Lisbon, Portugal, **4** SWITCH Laboratory, Flanders Interuniversity Institute for Biotechnology, Vrije Universiteit Brussel, Brussels, Belgium, **5** Department of Computer Science, Vrije Universiteit Brussel, Brussels, Belgium

Conventional evolutionary game theory predicts that natural selection favours the selfish and strong even though cooperative interactions thrive at all levels of organization in living systems. Recent investigations demonstrated that a limiting factor for the evolution of cooperative interactions is the way in which they are organized, cooperators becoming evolutionarily competitive whenever individuals are constrained to interact with few others along the edges of networks with low average connectivity. Despite this insight, the conundrum of cooperation remains since recent empirical data shows that real networks exhibit typically high average connectivity and associated single-to-broad–

What is the effect of changing topologies?

Both numerical and analytical approaches have been proposed

How to rewire ?



C likes to interact with C and D likes to interact with C

C wants to change the link with D. This rewire with probability p to a neighbour of D

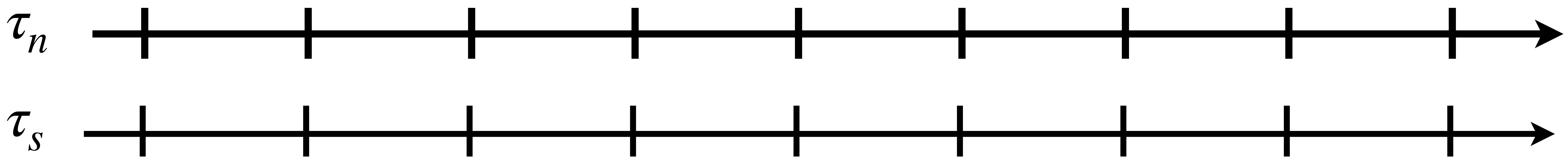
$$p = (1 + e^{-\beta(F_a - F_b)})^{-1}$$

D wants to change the link with D.

- The first can rewire with probability p to a neighbour of the other D.

- The second can rewire with probability $(1 - p)$

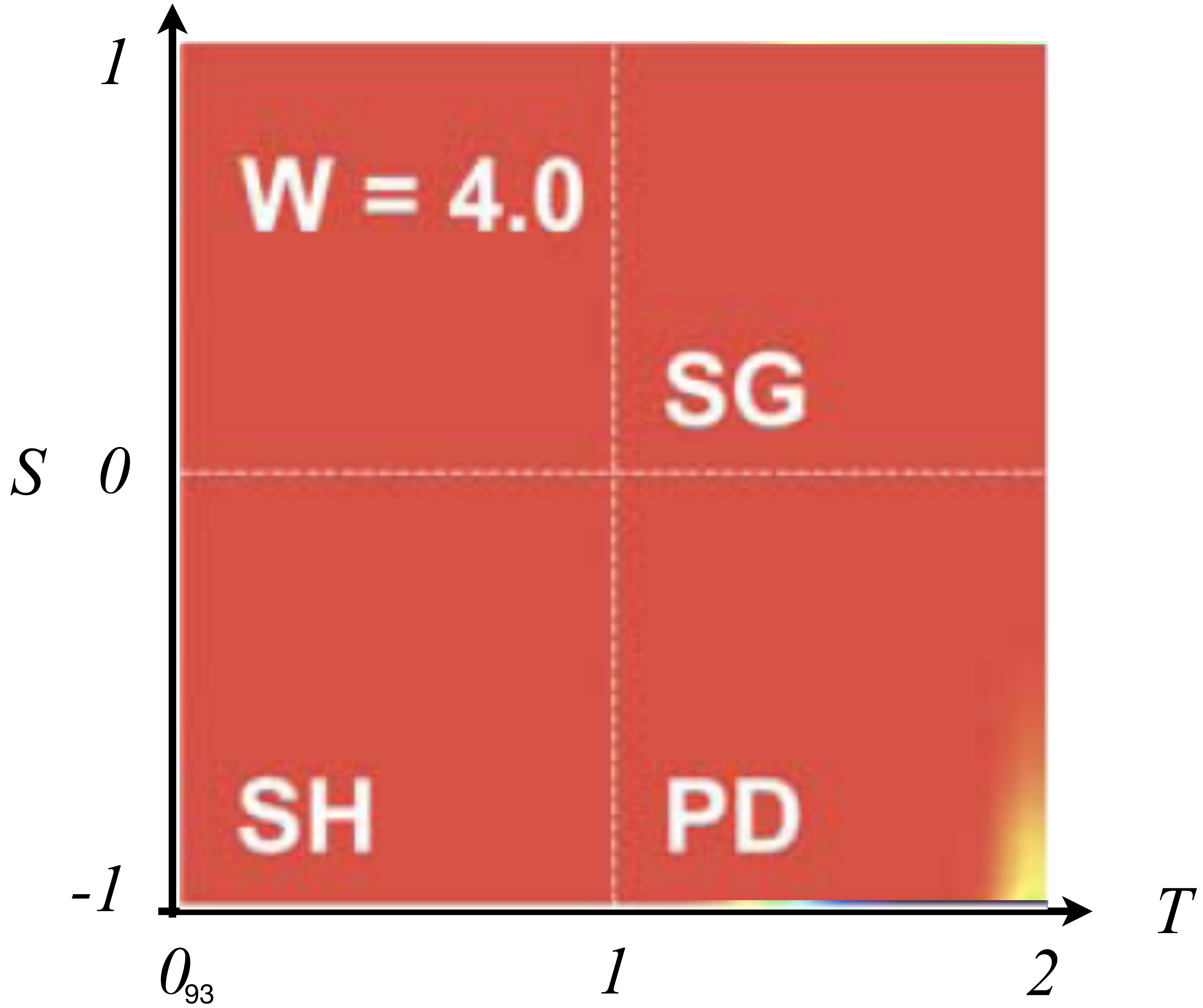
Time-scale differences



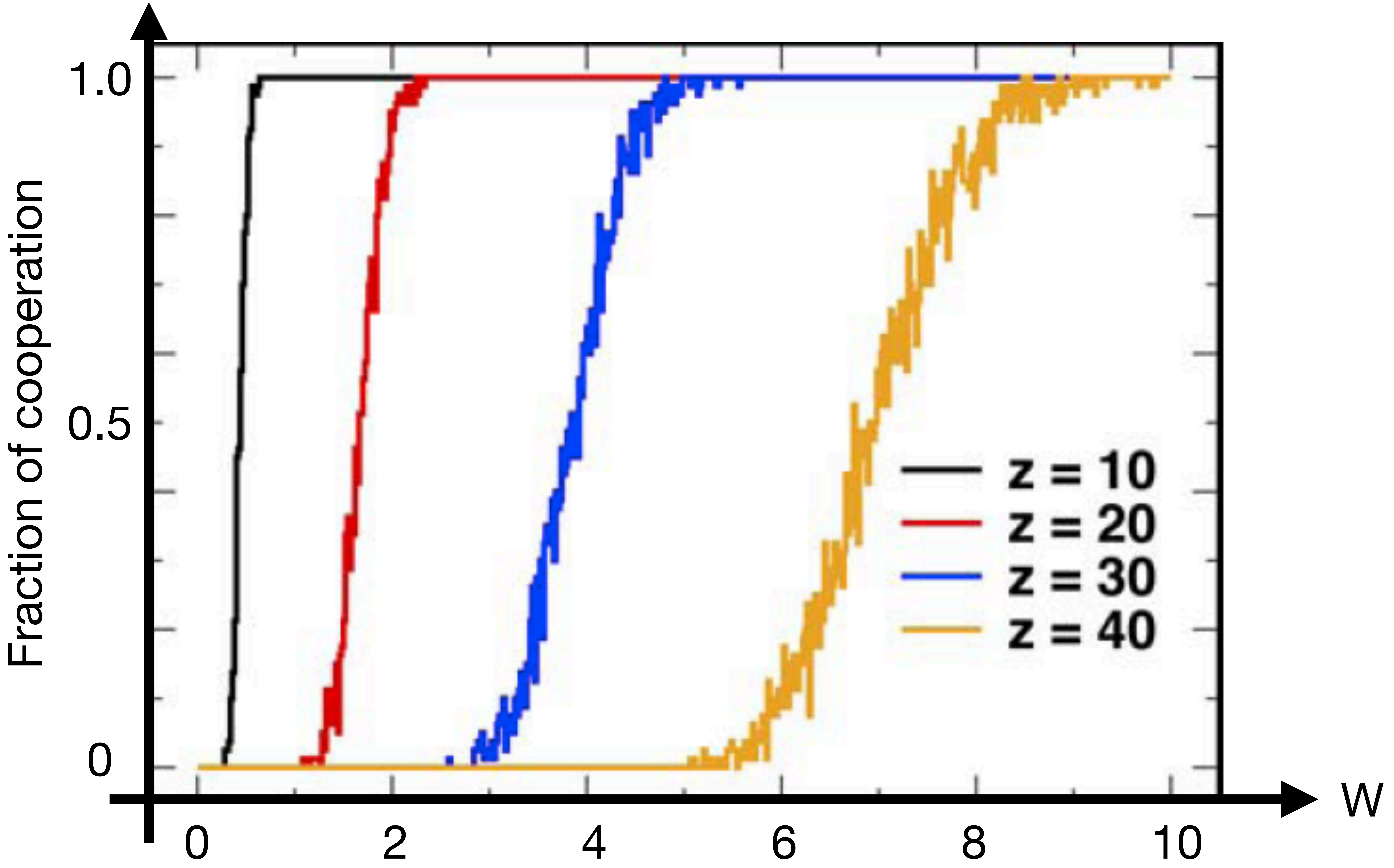
$$W = \frac{\tau_n}{\tau_s}$$

High average degree $\hat{k} = 30$

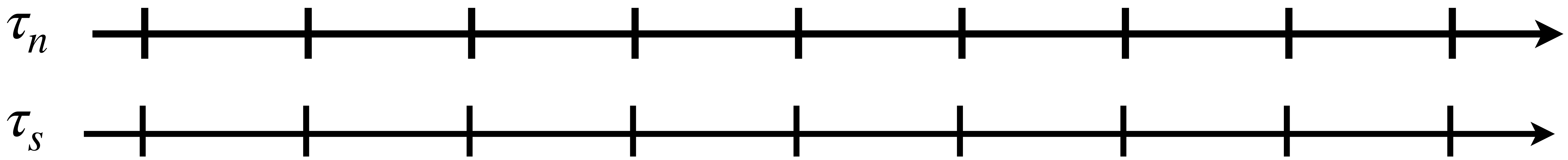
$Z = 10^4$, 100 runs,
$\beta = 0.5\,\%$, 50% C, R=1 and P=0



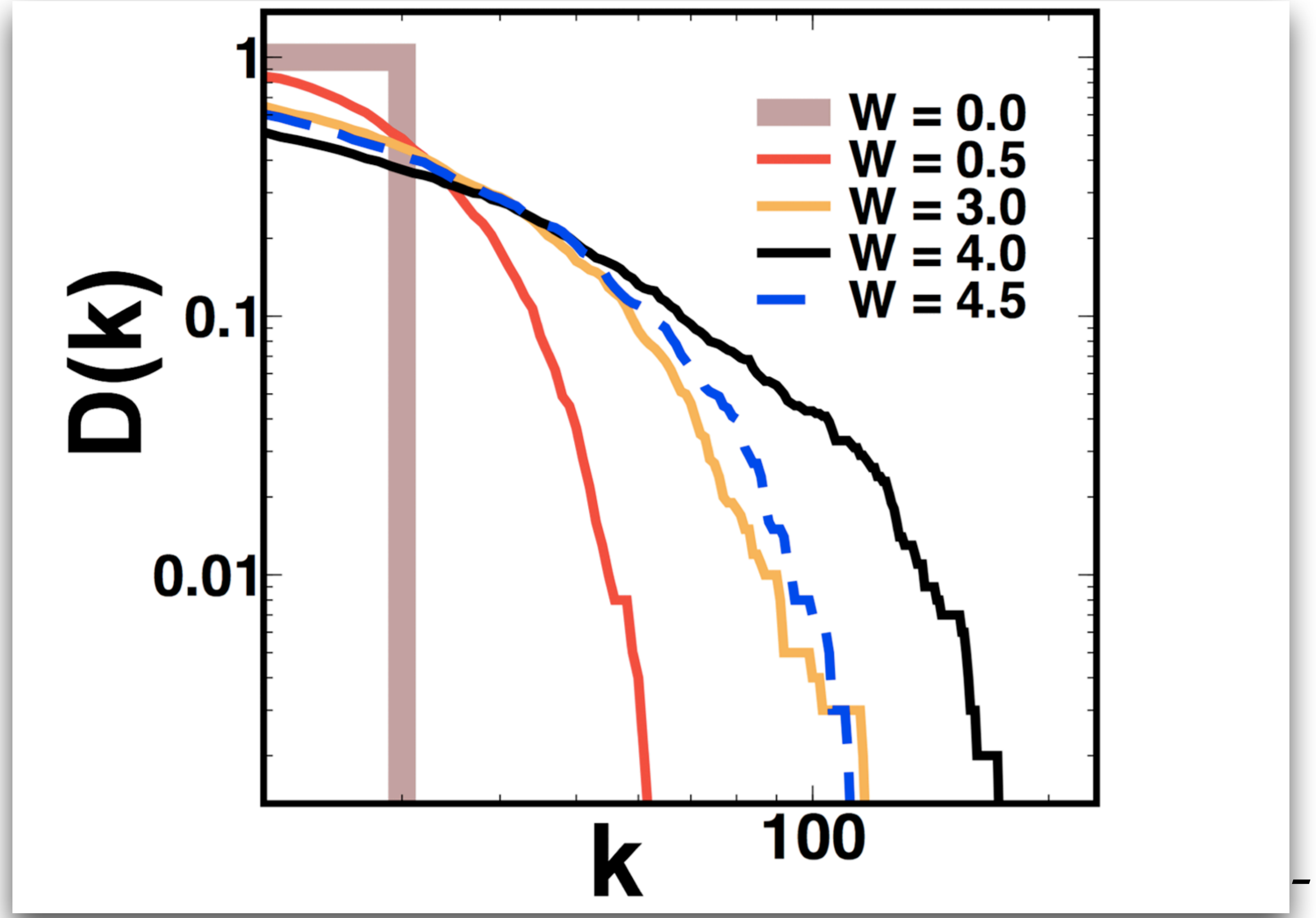
Time scale and degree are linked

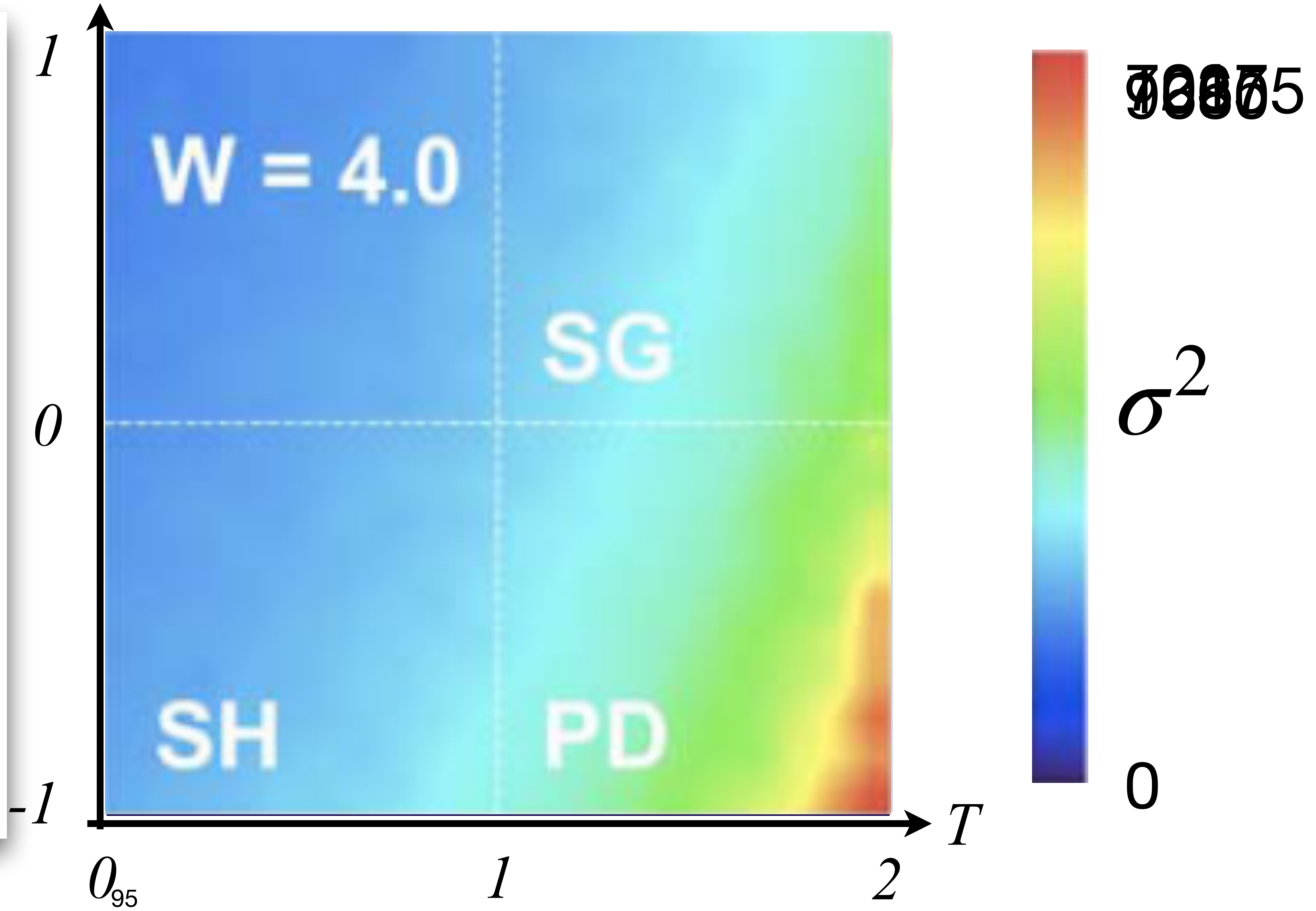


Time-scale differences



$$W = \frac{\tau_n}{\tau_s}$$





Confirmation ...

ECOLOGY LETTERS

Ecology Letters, (2011) **14**: 546–551 doi: 10.1111/j.1461-0248.2011.01615.x

LETTER

Co-evolution of behaviour and social network structure promotes human co

Katrin Fehl, Daniel J. van der Post and Dirk Semmann*
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**Correspondence: E-mail: dirk.semmann@bio.uni-goettingen.de*

Abstract

The ubiquity of cooperation in n
theoretical work shows that if
favoured by natural selection. To
repeated games between participa
links after each social interaction
Through biased link breaking (i.e
this link-breaking behaviour lead
these clusters. This assortment is
direct reciprocity and beyond
Our results highlight the importa
cooperation.

Keywords

Assortment, co-evolution, cooper
social behaviour.

Ecology Letters (2011) **14**: 546–551

PNAS

Dynamic social networks promote cooperation in experiments with humans

David G. Rand[a,b,1], Samuel Arbesman[c,d,1], and Nicholas A. Christakis[c,d,e,f,2]

[a]Program for Evolutionary Dynamics, [b]Department of Psychology, [c]Institute for Quantitative Social Science, and [e]Department of Sociology, Harvard University, Cambridge, MA 02138; and [d]Department of Health Care Policy and [f]Department of Medicine, Harvard Medical School, Boston, MA 02115

Edited by Douglas S. Massey, Princeton University, Princeton, NJ, and approved October 18, 2011 (received for review May 23, 2011)

Human populations are both highly cooperative and highly organized. Human interactions are not random but rather are structured in social networks. Importantly, ties in these networks often are dynamic, changing in response to the behavior of one's social partners. This dynamic structure permits an important form of conditional action that has been explored theoretically but has received little empirical attention: People can respond to the cooperation and defection of those around them by making or breaking network links. Here, we present experimental evidence of the power of using strategic link formation and dissolution, and the network modification it entails, to stabilize cooperation in sizable groups. Our experiments explore large-scale cooperation, where subjects' cooperative actions are equally beneficial to all those with whom they interact. Consistent with previous research, we find that cooperation decays over time when social networks are shuffled randomly every round or are fixed across all rounds. We also find that, when networks are dynamic but are updated only infrequently, cooperation again fails. However, when subjects can update their network connections frequently, we see a qualitatively different outcome: Cooperation is maintained at a high level through network rewiring. Subjects preferentially break links with defectors and form new links with cooperators, creating an incentive to cooperate and leading to substantial changes in network structure. Our experiments confirm the predictions of a set of evolutionary game theoretic models and demonstrate the important role that dynamic social networks can play in supporting large-scale human cooperation.

collective action | economic games | evolutionary game theory |

conditional action, one that occurs via changes in network structure rather than via changes in cooperation behavior.

Behavioral reciprocity is a central mechanism for the evolution of cooperation (1, 20, 21). In evolutionary game theory, reciprocity is defined as occurring when my actions toward you depend on your actions in the past. Reciprocity traditionally has been conceptualized in two-player game theory as the emergence of concordant behaviors within dyads. For example, the "tit-for-tat" strategy engages in reciprocity by cooperating only if the opponent cooperated in the previous round. Reciprocity creates future consequences for one's choices and has been shown experimentally to promote cooperation in repeated two-player interactions (22–25). However, reciprocity is problematic in group interactions involving more than two players: If the only way to sanction defectors is to defect, this action also harms the other cooperators in one's group (26).

Strategic tie formation and dissolution in dynamic networks offer a solution to this problem by providing players with an additional method of responding to the past actions of others. Players can reciprocate not only by changing their cooperation behaviors but also by creating or dissolving ties. Thus, cooperators need not switch to defection to punish defectors in their group; instead they can establish and maintain links with cooperators but sever connections with defectors, engaging in what we call "link reciprocity." (Note that this reciprocity is different from the use of the term in social network analysis, where reciprocity refers to the existence of tie concordance in directed graphs—that is, if ego nominates alter, alter also nominates ego, and a mutually reciprocated tie exists.)

ENCES

But, do people really use social learning on networks?

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Research

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http://dx.doi.org/10.1098/rsos.200618

Do people imitate when making decisions? Evidence from a spatial Prisoner's Dilemma experiment

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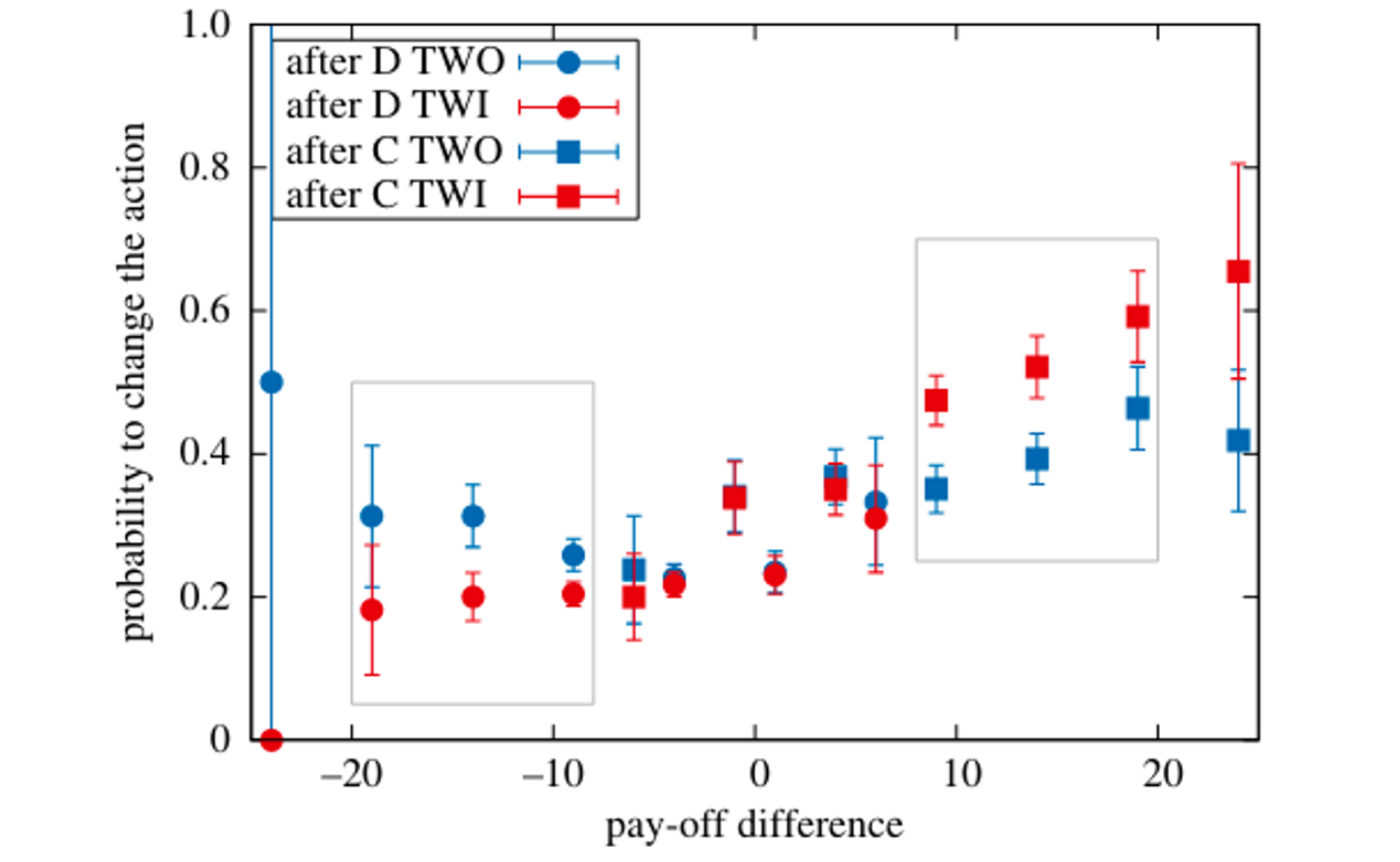
[2]MLG, Université Libre de Bruxelles, Brussels, Belgium

JG, 0000-0002-2688-6191; TL, 0000-0003-3645-1455

Humans do imitate more successful individuals on a local scale

TWO: Treatment without payoff difference information

TWI: Treatment with payoff difference information



Grujić, J., & Lenaerts, T. (2020). Do people imitate when making decisions? Evidence from a spatial prisoner's dilemma experiment. *Royal Society open science*, *7*(7), 200618.

Is this still relevant?

Hindawi
Complexity
Volume 2021, Article ID 6851477, 11 pages
https://doi.org/10.1155/2021/6851477

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Research Article

Eliciting Fairness in N-Player Network Games through Degree-Based Role Assignment

Andreia Sofia Teixeira,[1,2,3,4] **Francisco C. Santos**,[2,4] **Alexandre P. Francisco**,[2] **and Fernando P. Santos**[4,5,6]

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Evolutionary Game Theoretic Insights on the SIRS Model of the COVID-19 Pandemic

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Abstract: The effectiveness of control measures against the diffusion of the COVID-19 pandemic is grounded on the assumption that people are prepared and disposed to cooperate. From a strategic decision point of view, cooperation is the unreachable strategy of the prisoner's dilemma game, where the temptation to exploit the others and the fear to be betrayed by them drives the people behavior, which eventually results fully defective. In this work, we integrate the SIRS epidemic model with the replicator equation of evolutionary games in order to study the interplay between the infection spreading and the propensity of people to become cooperative under the pressure of the epidemic. We find that the developed model possesses several steady states, including fully or partially cooperative ones and that the presence of such states allows to take the disease under control. Moreover, assuming a seasonal variation of the infection rate, the system presents rich dynamics, including chaotic behavior and epidemic extinction.

Is this still relevant?

Chaos, Solitons and Fractals 155 (2022) 111655

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

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Frontiers

Cooperation dynamics under pandemic risks ar economic interdependence

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Network Diversity Promotes Safety Adoption in Swift Artificial Intelligence Development

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[5] Artificial Intelligence Lab, Vrije Universiteit Brussel

Abstract

Regulating the development of advanced technology such as Artificial Intelligence (AI) has become a principal topic, given the potential threat they pose to humanity's long term future. First deploying such technology promises innumerable benefits, which might lead to the disregard of safety precautions or societal consequences in favour of speedy devel- which innovation dynamics are pictured through the lens of Evolutionary Game Theory (EGT) and where all race participants are equally well-connected in the system. The baseline results have showed the importance of accounting for different time-scales of development, and also exposed the dilemmas that arise when what is individually preferred by developers differs from what is globally beneficial. How-

Is this still relevant?

SPECIAL FEATURE

Check for updates

Link recommendation algorithms and dynamics of polarization in online social networks

Fernando P. Santos[a,b,1], Yphtach Lelkes[c], and Simon A. Levin[a]

[a]Department of Ecology and Evolutionary Biology, Princeton University, Princeton, NJ 08544; [b]Informatics Institute, University of Amsterdam,1098XH Amsterdam, The Netherlands; and [c]Annenberg School for Communication Research, University of Pennsylvania, Philadelphia, PA 19104

Edited by Charles Perrings, Arizona State University, Tempe, AZ, and accepted by Editorial Board Member Kenneth W. Wachter July 14, 2021 (received for review March 1, 2021)

The level of antagonism between political groups has risen in the past years. Supporters of a given party increasingly dislike members of the opposing group and avoid intergroup interactions, leading to homophilic social networks. While new connections offline are driven largely by human decisions, new connections on online social platforms are intermediated by link recommendation algorithms, e.g., "People you may know" or "Whom to follow" suggestions. The long-term impacts of link recommendation in polarization are unclear, particularly as exposure to opposing viewpoints has a dual effect: Connections with out-group members can lead to opinion convergence and prevent group polarization or further separate opinions. Here, we provide a complex adaptive–systems perspective on the effects of link recommendation algorithms. While several models justify polarization through rewiring based on opinion similarity, here we explain it through rewiring

That is not an easy task. As pointed out by Woolley and Howard, "to understand contemporary political communication we must now investigate the politics of algorithms and automation" (16). While traditional media outlets are curated by humans, online social media resorts to computer algorithms to personalize contents through automatic filtering. To understand information dynamics in online social networks, one needs to take into account the interrelated subtleties of human decision making [e.g., only share specific contents (17), actively engage with other users, follow or befriend particular individuals, interact offline] and the outcomes of automated decisions (e.g., news sorting and recommendation systems) (18, 19). In this regard, much attention has been placed on the role of news filters and sorting (1, 18, 19). Shmargad and Klar (20) provide

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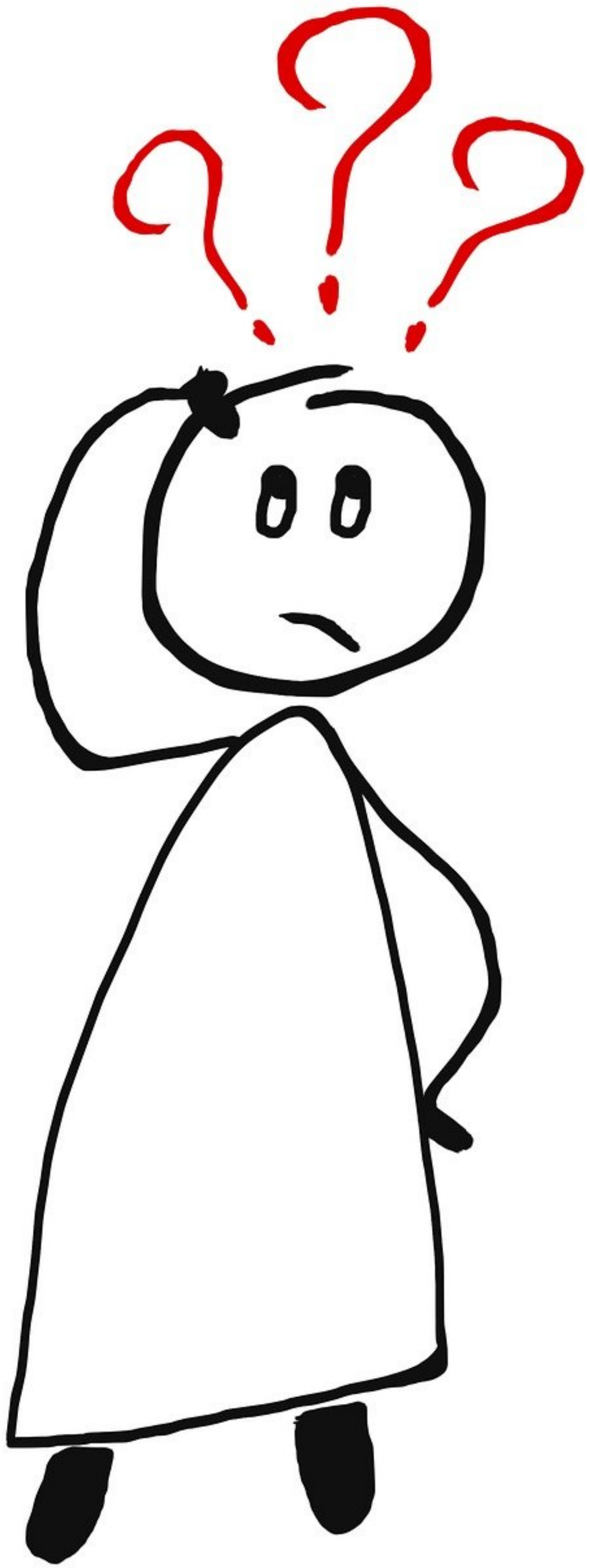

Questions ?

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https://github.com/Socrats