Introduction

A Simulation Study

Characteristics

Results

Other Networks

More Types

# Network Characteristics and Efficient Coordination



## Frank Thuijsman

joint work with

## Abhimanyu Khan, Ronald Peeters, Philippe Uyttendaele

Maastricht University

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
Outline					



- A Simulation Study
- 3 Characteristics







Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
Coordina	ation Game				

	Ρ	R
Ρ	<i>a</i> , a	b, c
R	<i>c</i> , <i>b</i>	d, d

Assumptions:

- a > c, d > b: pure equilibria (P, P) and (R, R);
- 2 a > d: payoff on *P* Pareto dominates payoff on *R*;
- **(3)** c > b: in case of mis-coordination, *R* is safer.

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
Populatio	n of Players				

Assumptions:

- even number of players;
- Players are connected in (social) network;
- at discrete stages 1, 2, 3, ... players are randomly matched to other players;
- at each stage each player chooses P or R by imitating neighbor with highest realized payoff;
- neighbors include self.

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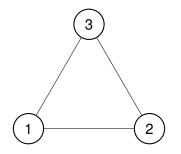
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
Goal of S	tudy				

We want to investigate the influence of network characteristics:

- on convergence to the efficient outcome P;
- on the speed of convergence to a homogeneous population.

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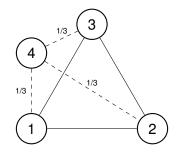


#### Motivation:

Scale-free networks match empirical data on networks Few nodes with high degree, many nodes with low degree.

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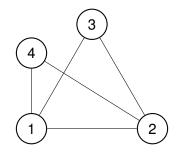


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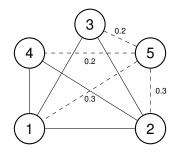


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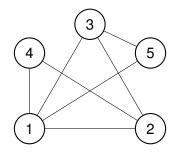


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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
	0000				
Network	s of Different S	ize and Degr	ee		

We created scale-free networks with 100, 200 and 300 nodes.

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We created scale-free networks with 100, 200 and 300 nodes.

For each of these we examined:

- 100 networks with average degree 4;
- 100 networks with average degree 6;
- 100 networks with average degree 8.

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We created scale-free networks with 100, 200 and 300 nodes.

For each of these we examined:

- 100 networks with average degree 4;
- 100 networks with average degree 6;
- 100 networks with average degree 8.

This gave a total of 900 different networks.

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
Network	Initializations				

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
Network	Initializations				

These initializations were made by creating 100 random colorings for each of 12 fixed fractions of P nodes.

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We used the following 12 fractions: 0.01, 0.02, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50.

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We used the following 12 fractions: 0.01, 0.02, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50.

This gave 1,080,000 different initializations.

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
Network	Simulations				

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
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This gave a total of 108,000,000 simulations.

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
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Each simulation ran until all nodes were of the same type.

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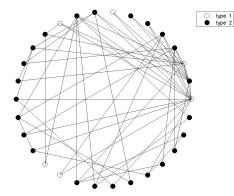
At each stage all nodes were randomly paired to other nodes.

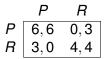
Each node played the strategy that did best among its neighbors (each node is one of its own neighbors).

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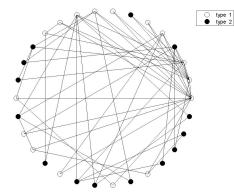
Initially 20% *P*, type 1, white

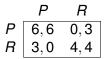
Average Degree 4

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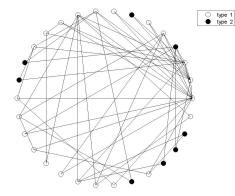
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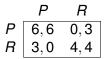
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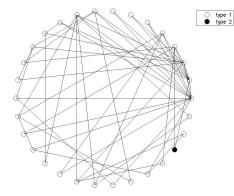
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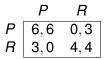
Average Degree 4

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#### An Example on a Scale Free Network





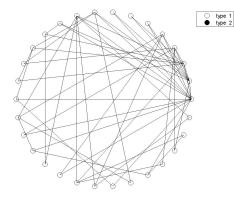
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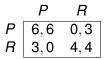
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#### An Example on a Scale Free Network





Initially 20% *P*, type 1, white

Average Degree 4

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types		
		000					
Network Specific Characteristics (NSC)							

- Size:
- Density:
- Degree:
- Power:



- Size: number of nodes
- Density:
- Degree:
- Power:



- Size: number of nodes
- Density: fraction of links used in network
- Degree:
- Power:



- Size: number of nodes
- Density: fraction of links used in network
- Degree: mean and s.d. of degree per node
- Power.



- Size: number of nodes
- Density: fraction of links used in network
- Degree: mean and s.d. of degree per node
- Power: mean and s.d. of power per node



- Share of P nodes:
- Degree of P nodes:
- Power of P nodes:
- Segregation of P nodes:
- Segregation of R nodes:



- Share of P nodes: fraction of P nodes
- Degree of P nodes:
- Power of P nodes:
- Segregation of P nodes:
- Segregation of R nodes:



- Share of P nodes: fraction of P nodes
- Degree of P nodes: mean and s.d. of degree per P node
- Power of P nodes:
- Segregation of P nodes:
- Segregation of R nodes:



- Share of P nodes: fraction of P nodes
- Degree of P nodes: mean and s.d. of degree per P node
- Power of P nodes: sum, mean and s.d.
- Segregation of P nodes:
- Segregation of R nodes:



- Share of P nodes: fraction of P nodes
- Degree of P nodes: mean and s.d. of degree per P node
- Power of P nodes: sum, mean and s.d.
- Segregation of P nodes: measure using random walks
- Segregation of R nodes: same

Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types		
Variables	Variables to Explain						

- Payoff Dominant Wins:
- Mean Convergence Time:

Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
Variables	to Explain				

- Payoff Dominant Wins: proportion of P wins
- Mean Convergence Time:

Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
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- Payoff Dominant Wins: proportion of P wins
- *Mean Convergence Time*: just what it says

Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
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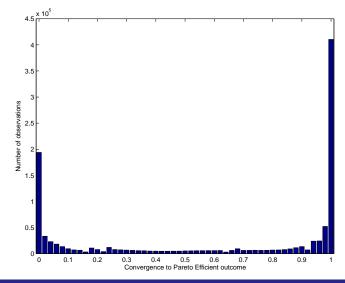
- Payoff Dominant Wins: proportion of P wins
- *Mean Convergence Time*: just what it says

Each of these is measured over 100 runs for any specific choice of initialized network.

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#### Number of Initializations for *P* Wins Proportions



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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types			
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Regression Analysis on Payoff Dominant Wins								
They cool	ricgression Analysis on rayon bonniant wins							

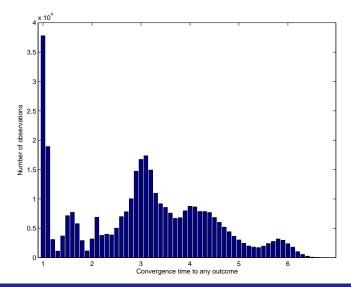
For the Scale Free Networks Examined:

Variable	Coef.	Effect
Size	0.000117	positive
Degree: mean	0.011441	positive
Share of <i>P</i> nodes	2.182151	positive
Degree of P nodes: stdev	0.014224	positive
Power of P nodes: stdev	-2.428675	negative
Segregation (norm.) of P nodes	-0.053563	negative
Segregation (norm.) of R nodes	-0.134324	negative
Constant	0.171971	_
Number of obs. R-squared	1,080 0.84	,

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#### Number of Initializations for Convergence Time



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Regression Analysis on <i>Convergence Time</i>						

For the Scale Free Networks Examined:

Variable	Coef.	Effect	
Size	0.00233	positive	
Degree: mean	-0.37935	negative	
Share of <i>P</i> nodes	0.30642	positive	
Degree of <i>P</i> nodes: stdev	0.10754	positive	
Power of P nodes: stdev	4.10292	positive	
Segregation (norm.) of P nodes	-0.81094	negative	
Segregation (norm.) of R nodes	1.66375	positive	
Constant	3.64648		
Number of obs.	1,080,000		
R-squared	0.4691		

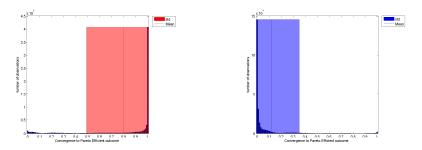
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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types

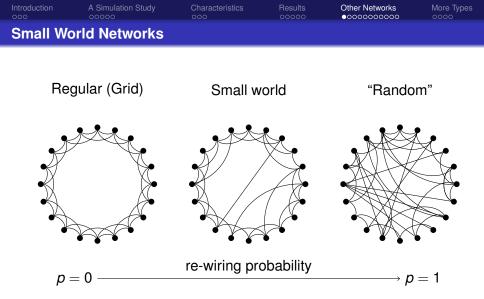
#### Classification Tree Analysis on *Payoff Dominant Wins*

# For the Scale Free Networks Examined:

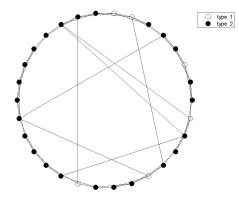
Selection	Converge mean	ence to P std	Number of Initializations	
Original dataset	63.2%	42.0%	(1,050,000)	
Segregation (norm.) of <i>P</i> nodes $< 1.302$ Segregation (norm.) of <i>P</i> nodes $\ge 1.302$	80.1% 12.0%	31.7% 23.7%	(788,193) (261,807)	



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$$\begin{array}{c|ccc}
P & R \\
P & 6,6 & 0,3 \\
R & 3,0 & 4,4
\end{array}$$

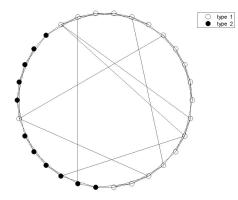
Initially 20% *P*, type 1, white

Re-wiring prob. 0.2

Average Degree 4

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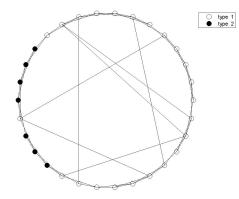
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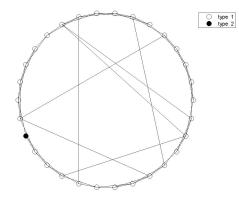
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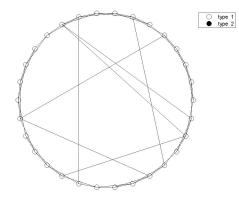
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For each of these we examined, for each of 11 re-wiring probabilities:

- 50 networks with average degree 4;
- 50 networks with average degree 6;
- 50 networks with average degree 8.

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For each of these we examined, for each of 11 re-wiring probabilities:

- 50 networks with average degree 4;
- 50 networks with average degree 6;
- 50 networks with average degree 8.

As re-wiring probabilities we used: 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.

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For each of these we examined, for each of 11 re-wiring probabilities:

- 50 networks with average degree 4;
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As re-wiring probabilities we used: 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.

This gave a total of 4,950 different networks.

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
Network	Initializations				

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
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These initializations were made by creating 50 random colorings, for each of 12 fixed fractions of P nodes.

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This gave 2,970,000 different initializations.

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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
Network	Simulations				

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
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This gave a total of 148,500,000 simulations.

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Each simulation ran until all nodes were of the same type.

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
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At each stage all nodes were randomly paired to other nodes.

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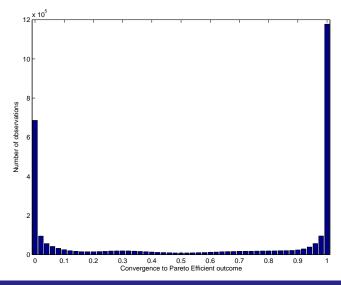
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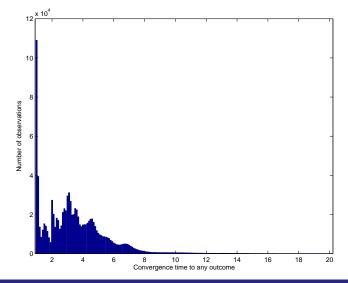
For the Small World Networks Examined:

Variable	Coef.	Effect
Size	0.000035	positive
Degree: mean	0.029864	positive
Share of <i>P</i> nodes	2.454443	positive
Degree of <i>P</i> nodes: stdev	0.016762	positive
Power of P nodes: stdev	-6.000691	negative
Segregation (norm.) of P nodes	-0.017797	negative
Segregation (norm.) of <i>R</i> nodes	-1.027209	negative
Constant	0.891018	—
Number of obs.	2,970	,000
R-squared	0.84	19

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#### Number of Initializations for Convergence Time for SWN



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For the Small World Networks Examined:

Variable	Coef.	Effect
Size	0.00381	positive
Degree: mean	-0.34104	negative
Share of <i>P</i> nodes	-0.22817	negative
Degree of <i>P</i> nodes: stdev	-0.95482	negative
Power of P nodes: stdev	-51.25889	negative
Segregation (norm.) of P nodes	-0.95487	negative
Segregation (norm.) of <i>R</i> nodes	-2.58388	negative
Constant	10.13382	—
Number of obs. R-squared	2,970,000 0.3658	

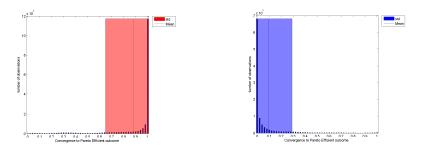
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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types
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#### Small World Classification Tree Analysis

# For the Small Data Set of Small World Networks Examined:

Selection	Converge mean	ence to P std	Number of Initializations	
Original dataset	58.3%	44.3%	(2,970,000)	
Segregation (norm.) of <i>P</i> nodes $< 1.208$ Segregation (norm.) of <i>P</i> nodes $\ge 1.208$	88.2% 9.1%	23.4% 19.9%	(1,845,824) (1,124,176)	



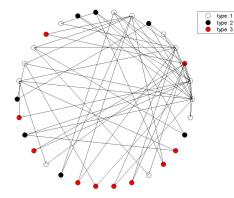
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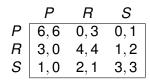


- In both cases Size, Mean degree, Share of P nodes and SD of P degree have a positive effect on efficient coordination.
- In both cases SD of power of P nodes, Segregation of P nodes and Segregation of R nodes have a negative effect on efficient coordination.
- In both cases Segregation of P nodes is the most important variable to decide on convergence to P or to R.
- Results differ for speed of convergence in general, but they are very similar when looking only at those initializations with at least 0.75 convergence: only size and segregation norms increase time to convergence.









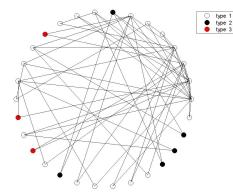
Initial distr. (0.4; 0.2; 0.2)

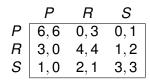
Average Degree 4

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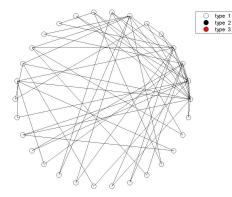
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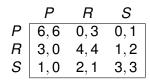
Average Degree 4

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## A Scale Free Network with 3 Types



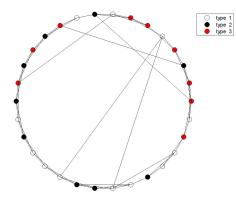


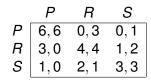
Initial distr. (0.4; 0.2; 0.2)

Average Degree 4

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Initial distr. (0.4; 0.2; 0.2)

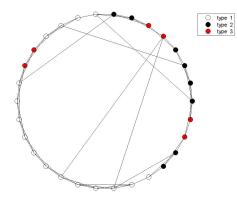
Re-wiring prob. 0.2

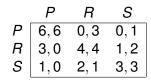
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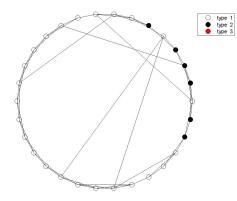
Initial distr. (0.4; 0.2; 0.2)

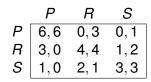
Re-wiring prob. 0.2

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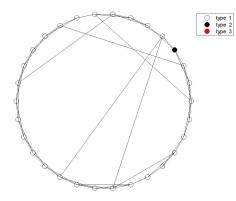
Initial distr. (0.4; 0.2; 0.2)

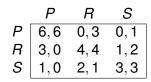
Re-wiring prob. 0.2

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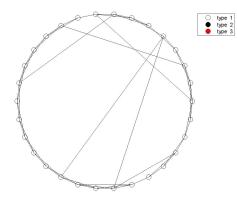
Initial distr. (0.4; 0.2; 0.2)

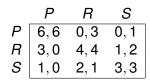
Re-wiring prob. 0.2

Average Degree 4

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Initial distr. (0.4; 0.2; 0.2)

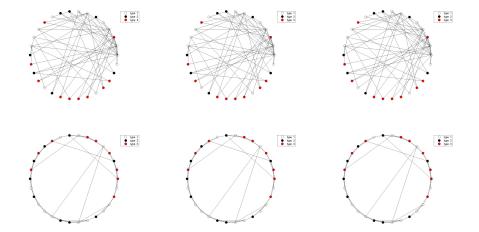
Re-wiring prob. 0.2

Average Degree 4

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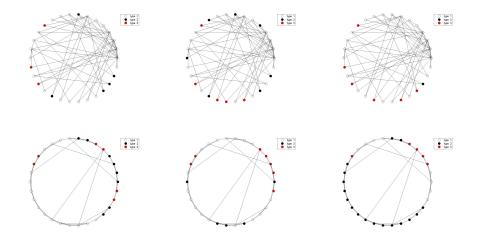
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
	in Devellel				





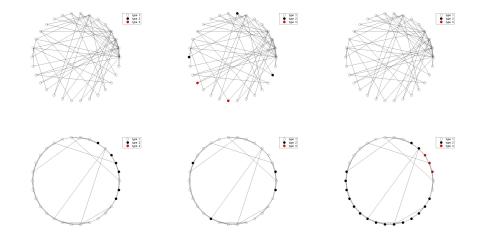
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
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#### Six Runs in Parallel

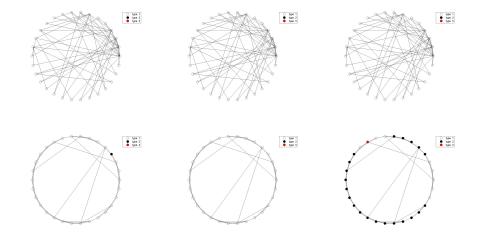


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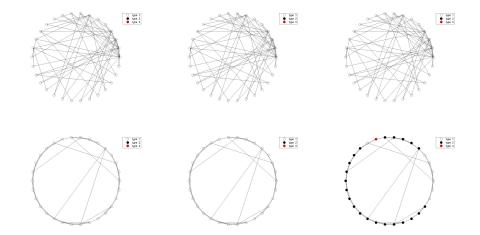
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



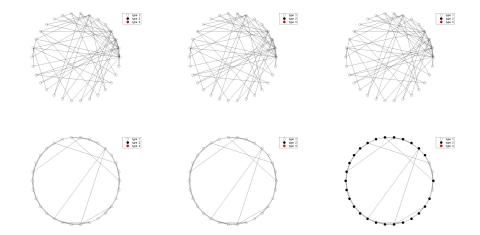
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



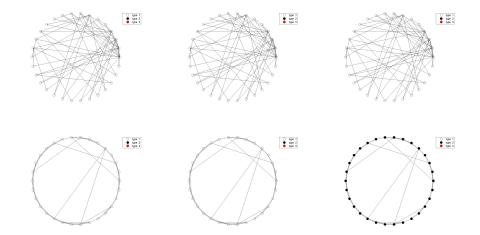
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



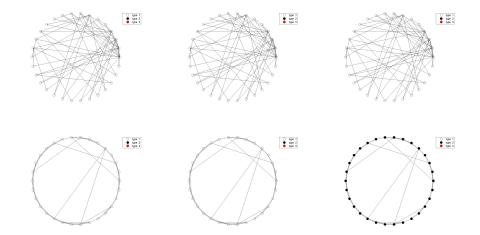
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○○●
Thanks					

# Thank you for your attention! Comments will be appreciated!

Presentation and paper will soon be available at https://dke.maastrichtuniversity.nl/f.thuijsman/

Frank Thuijsman, Department of Knowledge Engineering, Maastricht University