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

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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*;
- **(**) 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 payoff;
- neighbors include self.

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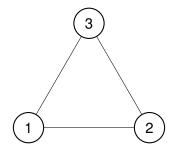


We want to investigate the influence of network characteristics:

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

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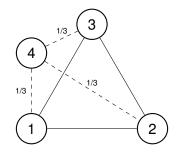


#### Motivation:

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

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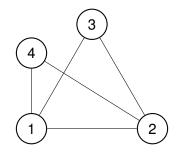


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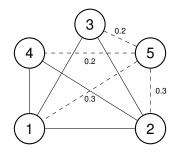


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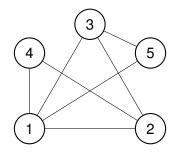


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Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types			
	0000							
Network	Networks of Different Size and Degree							

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:

- 25 networks with average degree 4;
- 25 networks with average degree 6;
- 25 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:

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

This gave a total of 225 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 25 random colorings for each of 12 fixed fractions of P nodes.

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

These initializations were made by creating 25 random colorings for each of 12 fixed fractions of P nodes.

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 67,500 different initializations.

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
Network	Simulations				

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

This gave a total of 1,687,500 simulations.

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

This gave a total of 1,687,500 simulations.

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

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

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

This gave a total of 1,687,500 simulations.

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

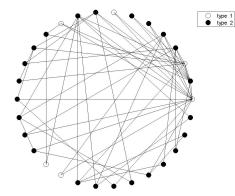
At each stage all nodes were randomly paired to other nodes.

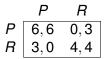
Each node played the strategy that did best among its neighbors (each node is one of its own neighbors).

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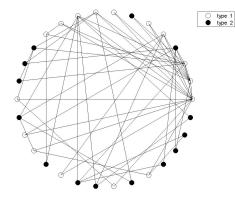


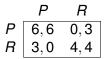
Initially 20% *P*, type 1, white

Average Degree 4

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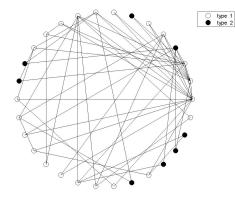


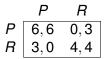
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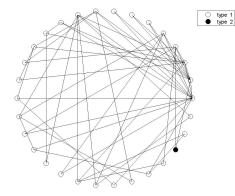


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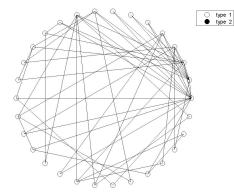
$$\begin{array}{c|ccc}
P & R \\
\hline
P & 6,6 & 0,3 \\
R & 3,0 & 4,4
\end{array}$$

Initially 20% *P*, type 1, white

Average Degree 4

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

- Payoff Dominant Wins:
- Mean Convergence Time:

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

- Payoff Dominant Wins: proportion of P 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*: just what it says

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

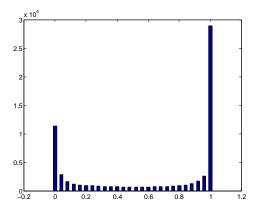
- Payoff Dominant Wins: proportion of P wins
- *Mean Convergence Time*: just what it says

Each of these is measured over 25 runs for any specific choice of initialized network.

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Introduction	A Simulation Study	Characteristics	Results o●ooo	Other Networks	More Types		
Regression Analysis on Payoff Dominant Wins							

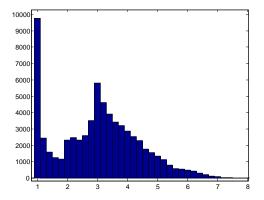
For the Scale Free Networks Examined:

Variable	Coef.	Effect	
Size	.000166	positive	
Degree: mean	.013205	positive	
Share of <i>P</i> nodes	2.175143	positive	
Degree of P nodes: stdev	.012700	positive	
Segregation (norm.) of P nodes	053167	negative	
Segregation (norm.) of R nodes	107330	negative	
Constant	.121343	_	
Number of obs.	67,5	500	
R-squared	0.8402		

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Introduction	A Simulation Study	Characteristics	Results oo●oo	Other Networks	More Types		
Number of Initializations for Convergence Time							

Number of Initializations for *Convergence Time* 



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	ion Analysis or	Convorgon			
Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types

# For the Scale Free Networks Examined:

Variable	Coef.	Effect	
Size	.002208	positive	
Degree: mean	379215	negative	
Share of <i>P</i> nodes	.302001	positive	
Degree of P nodes: stdev	.113038	positive	
Segregation (norm.) of P nodes	806758	negative	
Segregation (norm.) of R nodes	1.765975	positive	
Constant	3.551547		
Number of obs.	67,500		
R-squared	0.4596		

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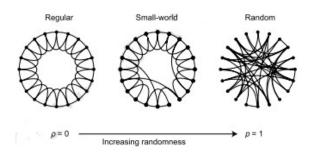
Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types		
Classification Tree Analysis on Payoff Dominant Wins							

# For the Scale Free Networks Examined:

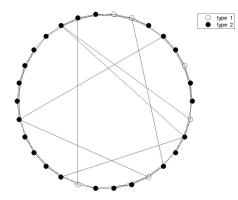
Selection	Converge mean	ence to P std	Number of observations	
Original dataset	63.2%	42.2%	(65,625)	
Segregation (norm.) of <i>P</i> nodes $< 1.313$ Segregation (norm.) of <i>P</i> nodes $\ge 1.313$	79.7% 11.2%	32.2% 23.0%	(49,742) (15,883)	

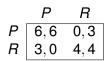
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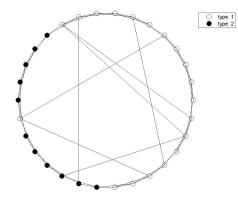
Initially 20% *P*, type 1, white

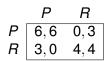
Rewiring prob. 0,2

Average Degree 4

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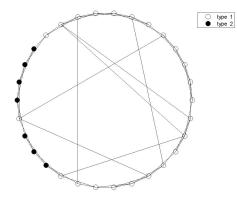
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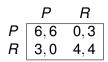
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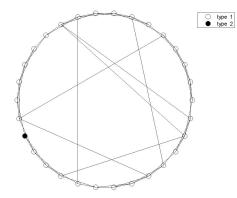
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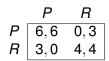
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Average Degree 4

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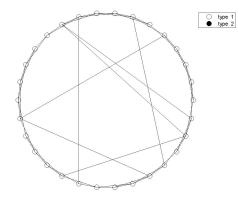
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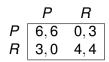
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Average Degree 4

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Initially 20% *P*, type 1, white

Rewiring prob. 0,2

Average Degree 4

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types		
Networks of Different Size and Degree							

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:

- 10 networks with average degree 4;
- 10 networks with average degree 6;
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We created scale-free networks with 100, 200 and 300 nodes.

For each of these we examined:

- 10 networks with average degree 4;
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- 10 networks with average degree 8.

This gave a total of 90 different networks.

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
Network I	nitializations				

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These initializations were made by creating 10 random colorings, for each of 12 fixed fractions of P nodes, for each of 6 different re-wiring probabilities.

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These initializations were made by creating 10 random colorings, for each of 12 fixed fractions of P nodes, for each of 6 different re-wiring probabilities.

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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These initializations were made by creating 10 random colorings, for each of 12 fixed fractions of P nodes, for each of 6 different re-wiring probabilities.

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.

And re-wiring probabilities: 0, 0.2, 0.4, 0.6, 0.8, 1

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These initializations were made by creating 10 random colorings, for each of 12 fixed fractions of P nodes, for each of 6 different re-wiring probabilities.

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And re-wiring probabilities: 0, 0.2, 0.4, 0.6, 0.8, 1

This gave 64,800 different initializations.

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks oooo●ooooooo	More Types
Network	Simulations				

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
Network	Simulations				

This gave a total of 648,000 simulations.

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This gave a total of 648,000 simulations.

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

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This gave a total of 648,000 simulations.

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

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

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks oooo●ooooooo	More Types
Network	Simulations				

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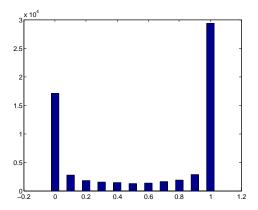
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At each stage all nodes were randomly paired to other nodes.

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

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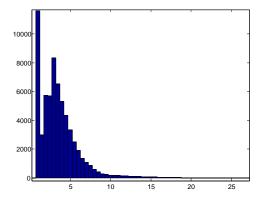


For the Small Data Set of Small World Networks Examined:

Variable	Coef.	Effect		
Size	.000085	positive		
Degree: mean	.033065	positive		
Degree: stdev	005834	negative		
Share of <i>P</i> nodes	2.456533	positive		
Degree of <i>P</i> nodes: stdev	.015220	positive		
Segregation (norm.) of <i>P</i> nodes	014965	negative		
Segregation (norm.) of <i>R</i> nodes	931433	negative		
Constant	.757578	—		
Number of obs.	64,8	64,800		
R-squared	0.8261			

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

Variable	Coef.	Effect	
Size	.004134	positive	
Degree: mean	256099	negative	
Degree: stdev	-1.742573	negative	
Share of <i>P</i> nodes	590169	negative	
Segregation (norm.) of <i>P</i> nodes	954044	negative	
Segregation (norm.) of <i>R</i> nodes	-5.030866	negative	
Constant	13.109070	—	
Number of obs.	64,799		
R-squared	0.33	82	

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Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types
Small W	and Classifiest		lucio		

#### Small World Classification Tree Analysis

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

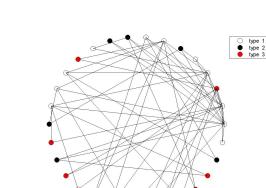
Selection	Converge mean	ence to P std	Number of observations
Original dataset	59.8%	40.2%	(63,000)
Segregation (norm.) of $P$ nodes $< 1.210$ Segregation (norm.) of $P$ nodes $\ge 1.210$	88.3% 10.5%	24.2% 22.6%	(39,947) (23,053)

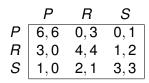
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- In both cases Size and Share of P nodes have a positive effect on efficient coordination.
- In both cases Segregation of P nodes and Segregation of R nodes have a negative effect on efficient coordination.
- In both cases Segregation of P nodes is the most important variable to decide on convergence to P or to R.







Initial distr. (0.4; 0.2; 0.2)

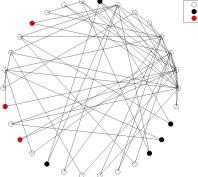
Average Degree 4

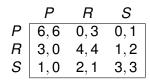
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type 1 type 2 type 3







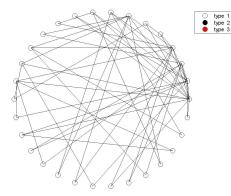
Initial distr. (0.4; 0.2; 0.2)

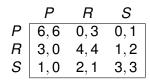
Average Degree 4

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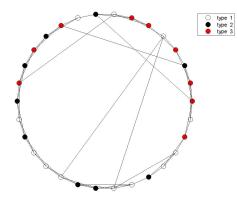


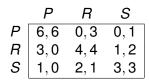
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Average Degree 4

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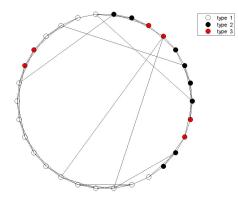
Initial distr. (0.4; 0.2; 0.2)

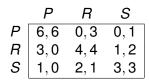
Rewiring prob. 0,2

Average Degree 4

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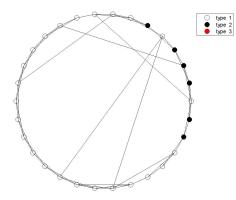
Initial distr. (0.4; 0.2; 0.2)

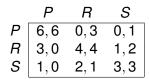
Rewiring prob. 0,2

Average Degree 4

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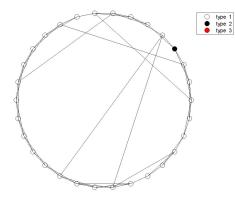
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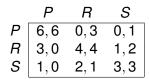
Rewiring prob. 0,2

Average Degree 4

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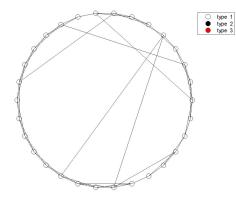
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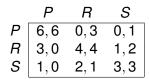
Rewiring prob. 0,2

Average Degree 4

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Initial distr. (0.4; 0.2; 0.2)

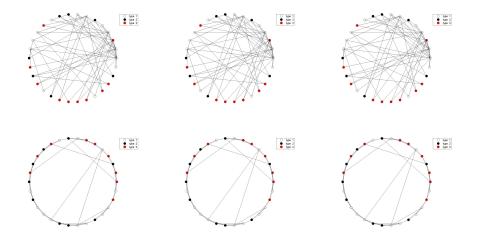
Rewiring prob. 0,2

Average Degree 4

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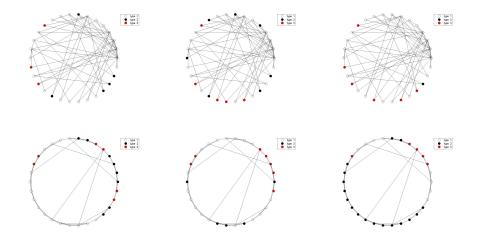
#### Six Runs in Parallel



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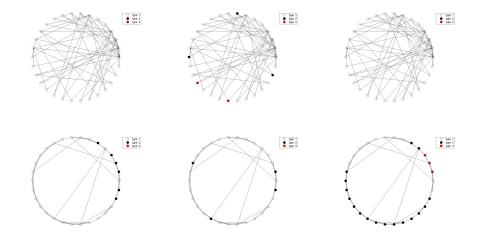
Introduction	A Simulation Study	Characteristics	Results	Other Networks	More Types ○○●○
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#### Six Runs in Parallel

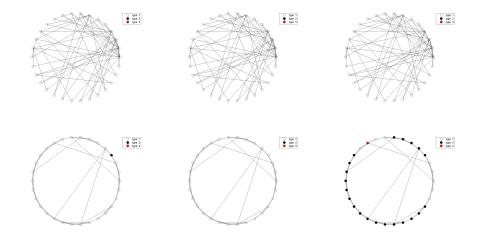


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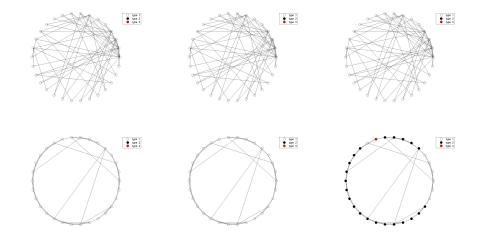
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



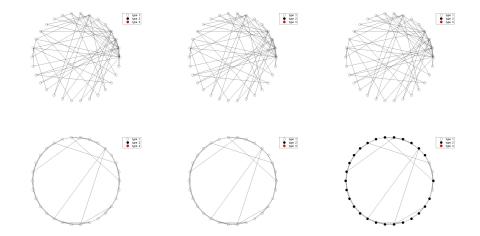
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



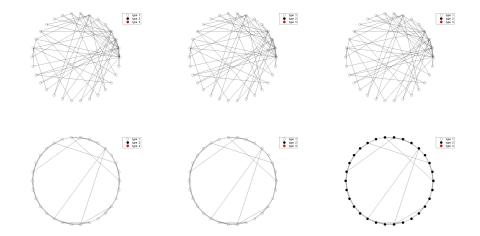
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



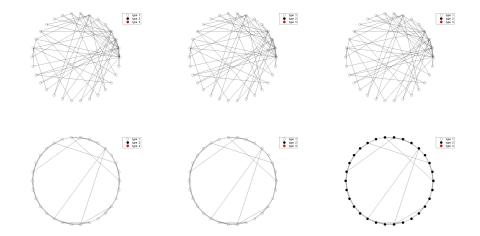
Introduction	A Simulation Study	Characteristics	Results 00000	Other Networks	More Types ○○●○
Six Runs	s in Parallel				



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	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/

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