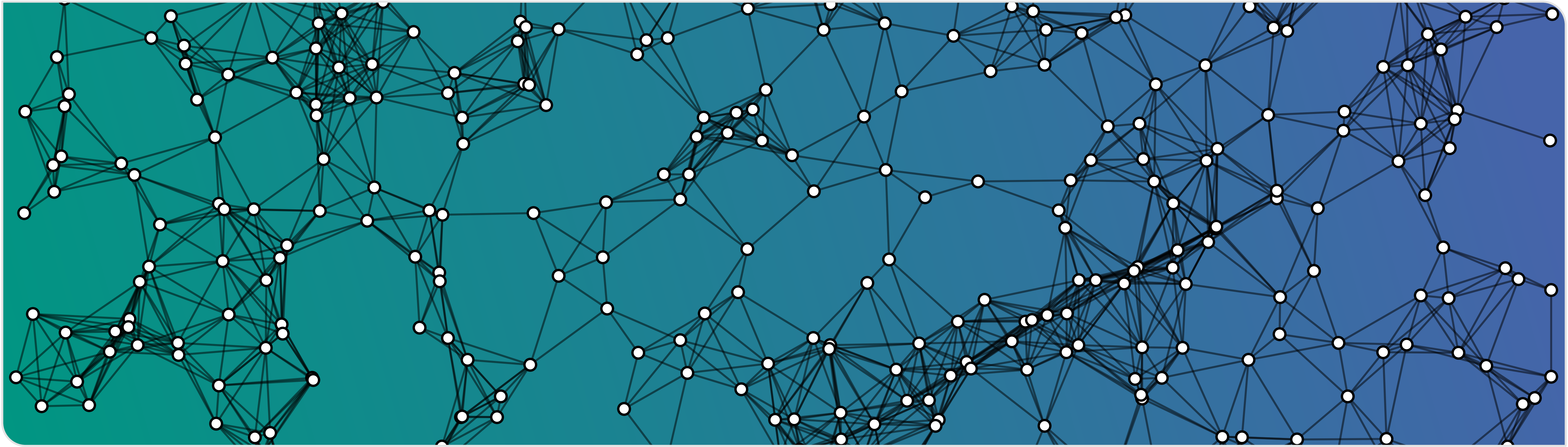
Karlsruher Institut für Technologie

Praktikum – Beating the Worst Case

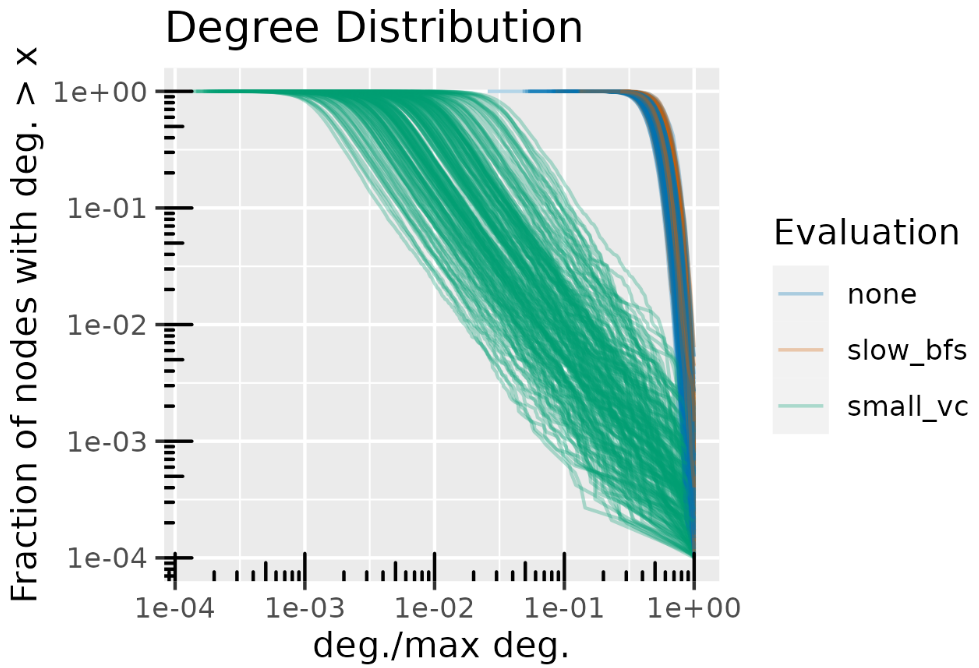
Jean-Pierre von der Heydt und Marcus Wilhelm | 29.11.2023



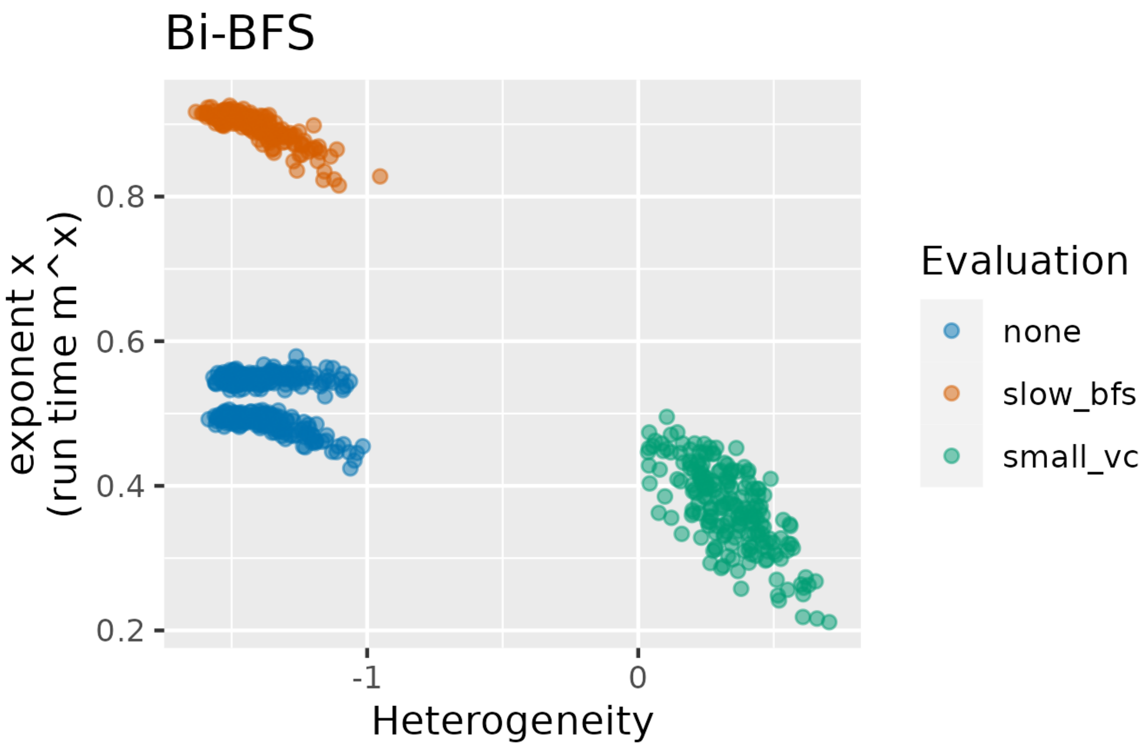
Vorstellung Übungsblatt 1

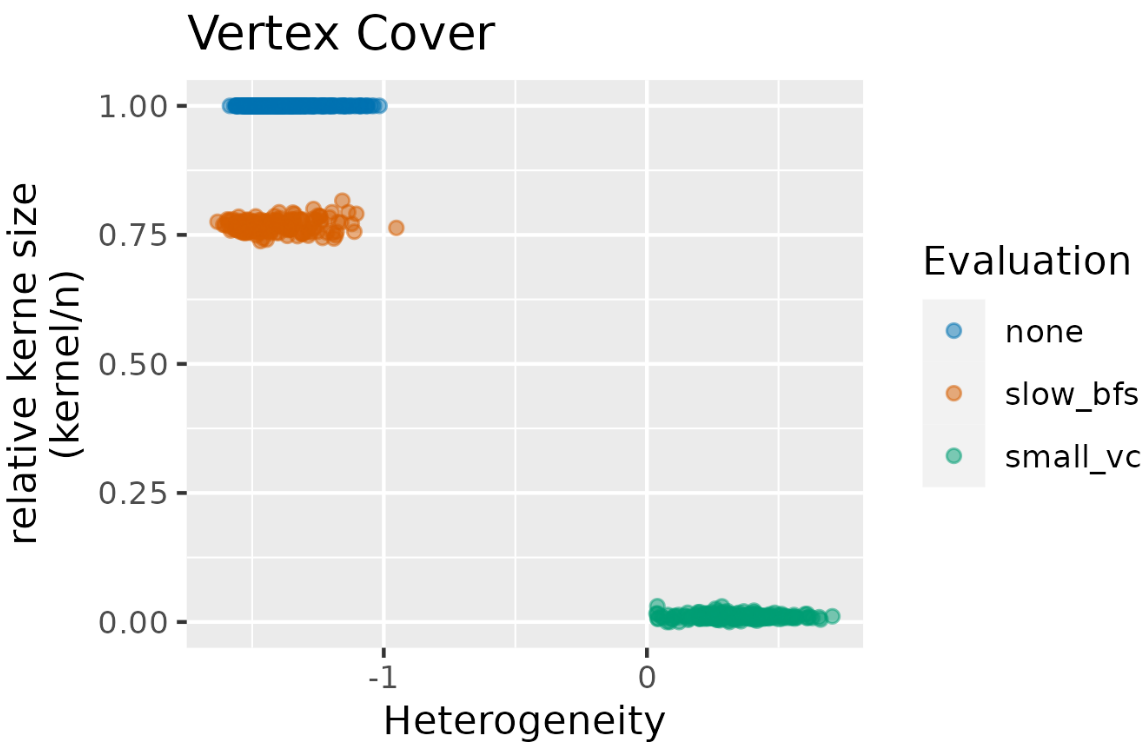
Heterogenität

- Berechne Standartabweichung σ und Durchschnitt μ der Gradverteilung
- Variationskoeffizient: $\frac{\sigma}{\mu}$
- Heterogenität: $\log(\frac{\sigma}{\mu})$



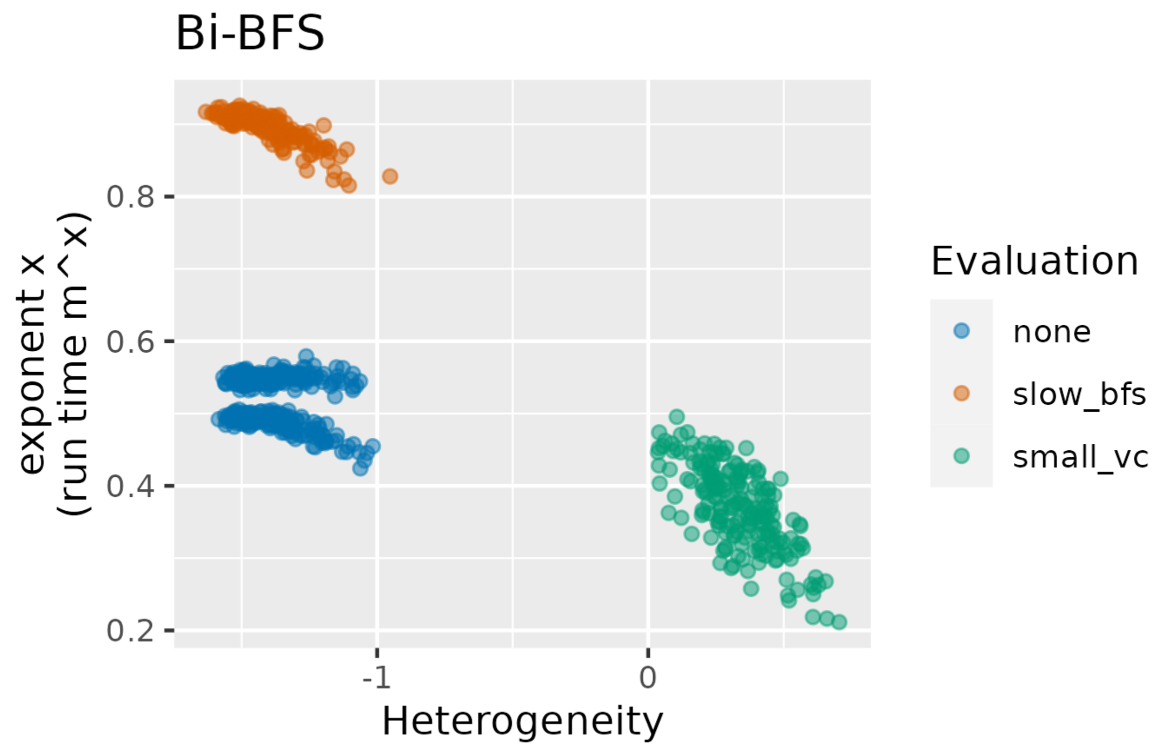
Heterogenität

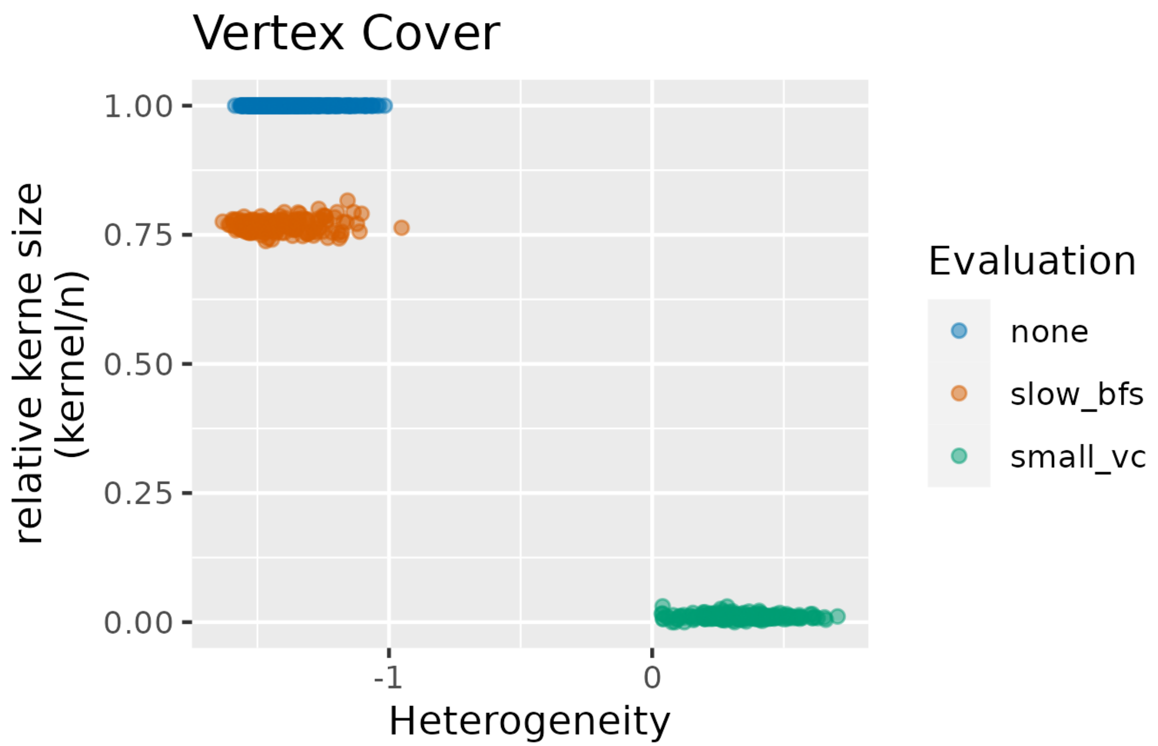




- Heterogenität: $\log(\frac{\sigma}{\mu})$

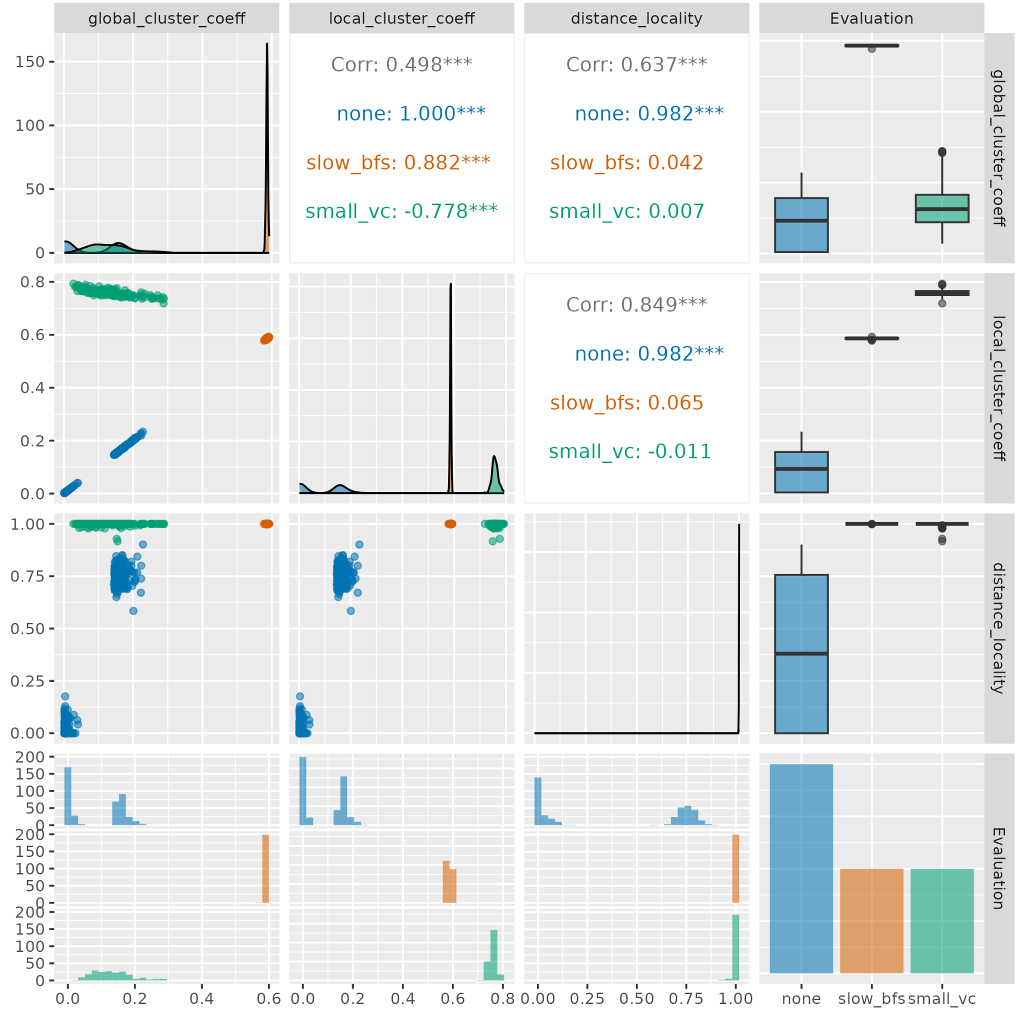
Heterogenität



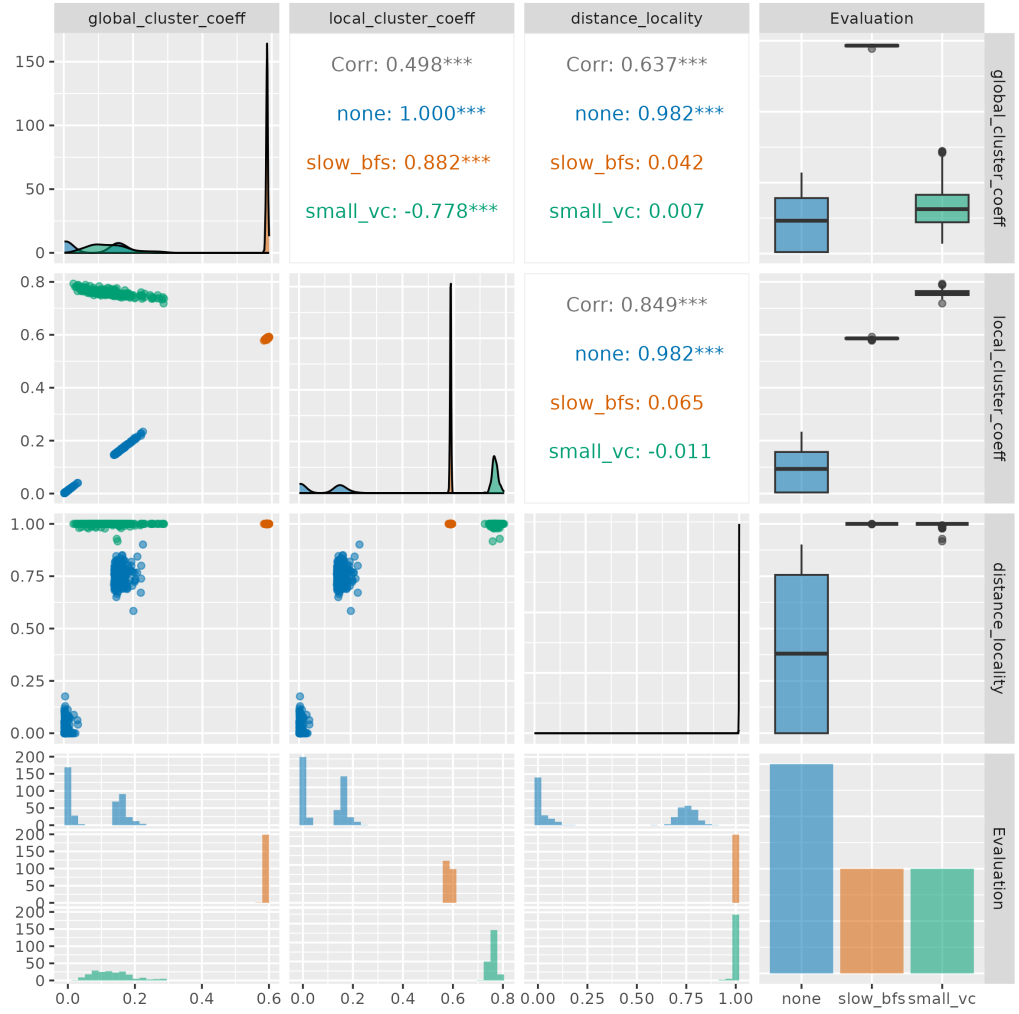


- Heterogenität: $\log(\frac{\sigma}{\mu})$
- Heterogenität reicht nicht aus, um die Graphen zu unterscheiden oder die Algorithmenperformance zu erklären

Korrelation zwischen Lokalitätsmetriken

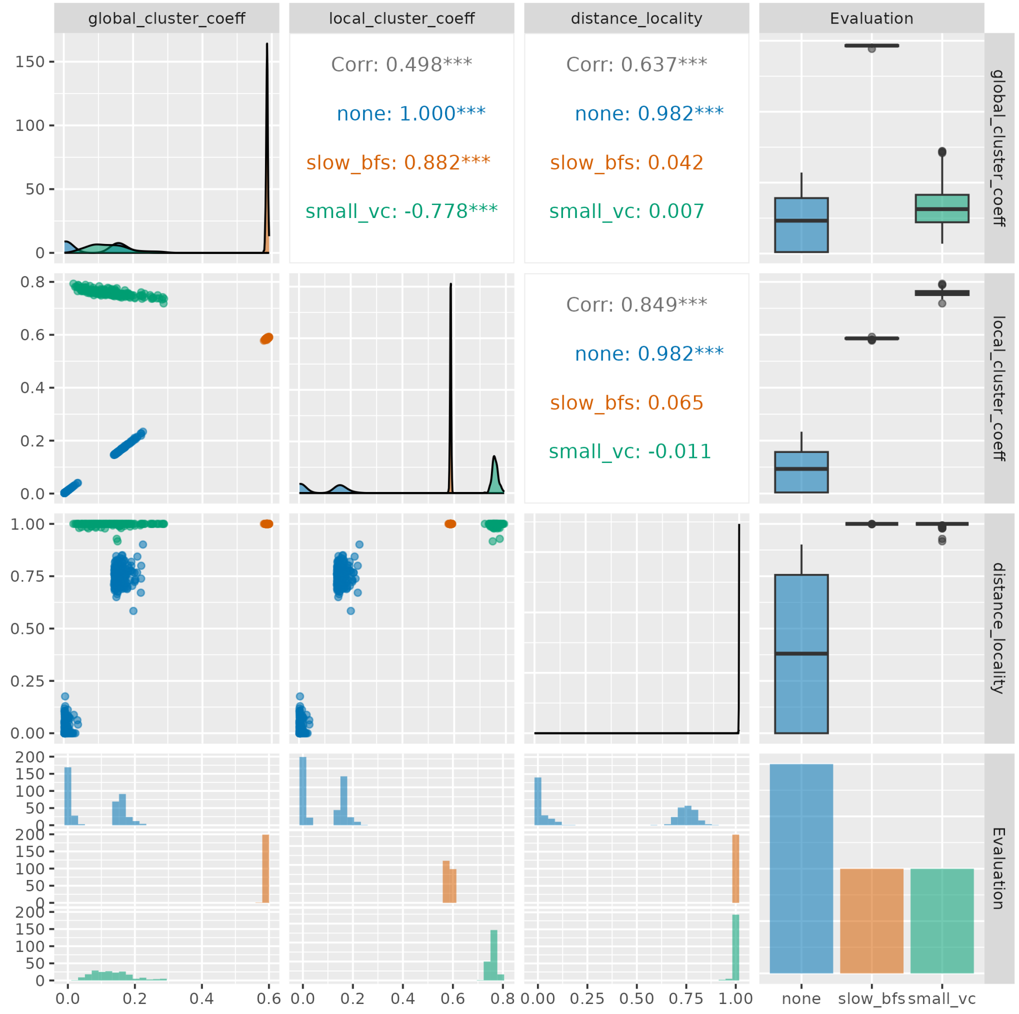


Korrelation zwischen Lokalitätsmetriken



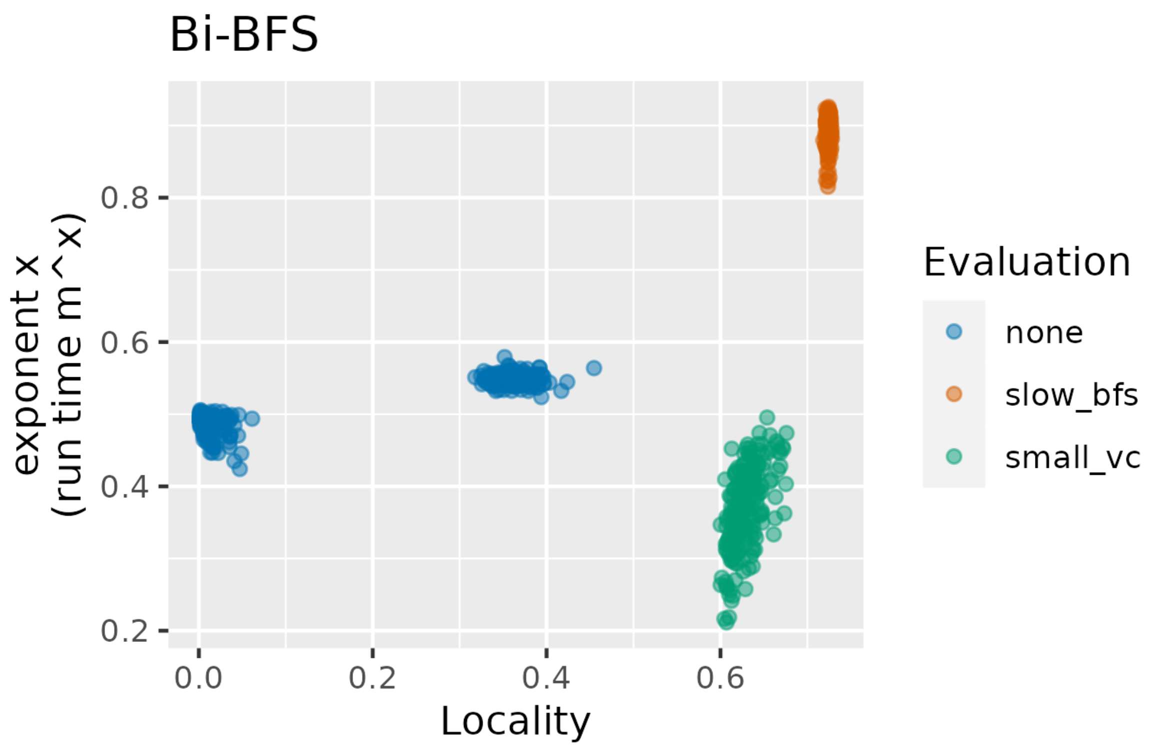
- Lokalitätsmetriken sind sich nicht immer einig

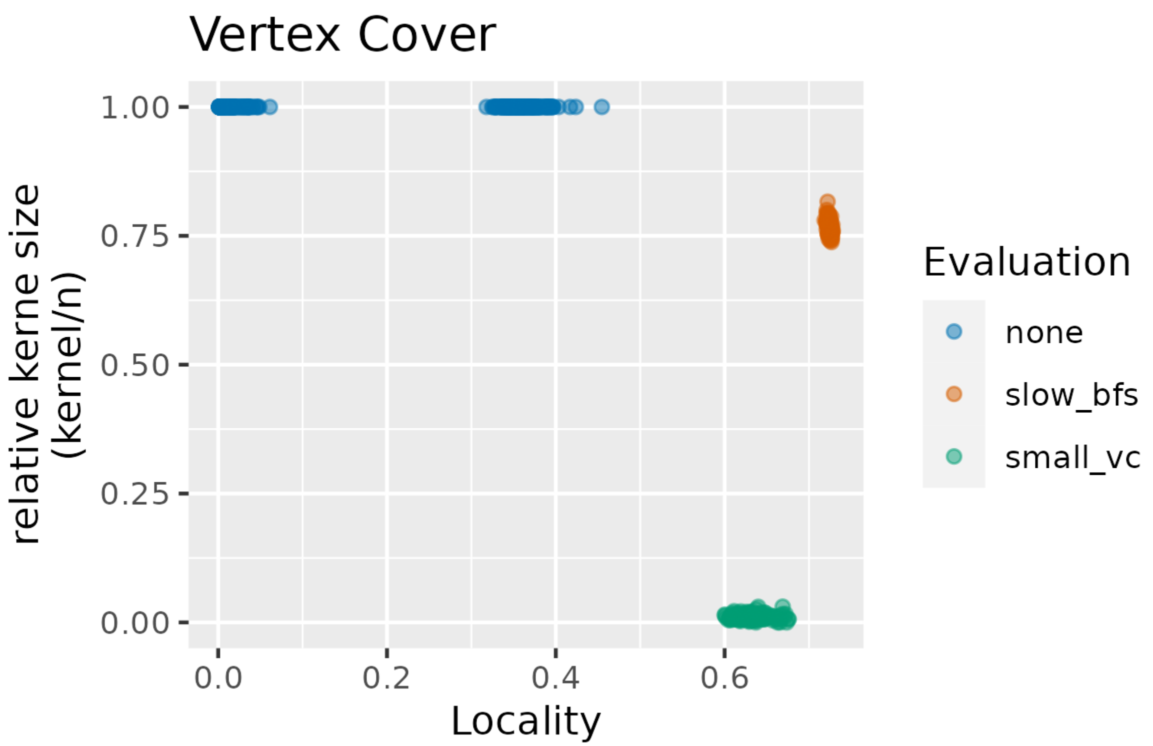
Korrelation zwischen Lokalitätsmetriken



- Lokalitätsmetriken sind sich nicht immer einig
- Lokalität: $\frac{1}{3}(\text{cluster}_{\text{local}} + \text{cluster}_{\text{global}} + \text{cluster}_{\text{dist}})$

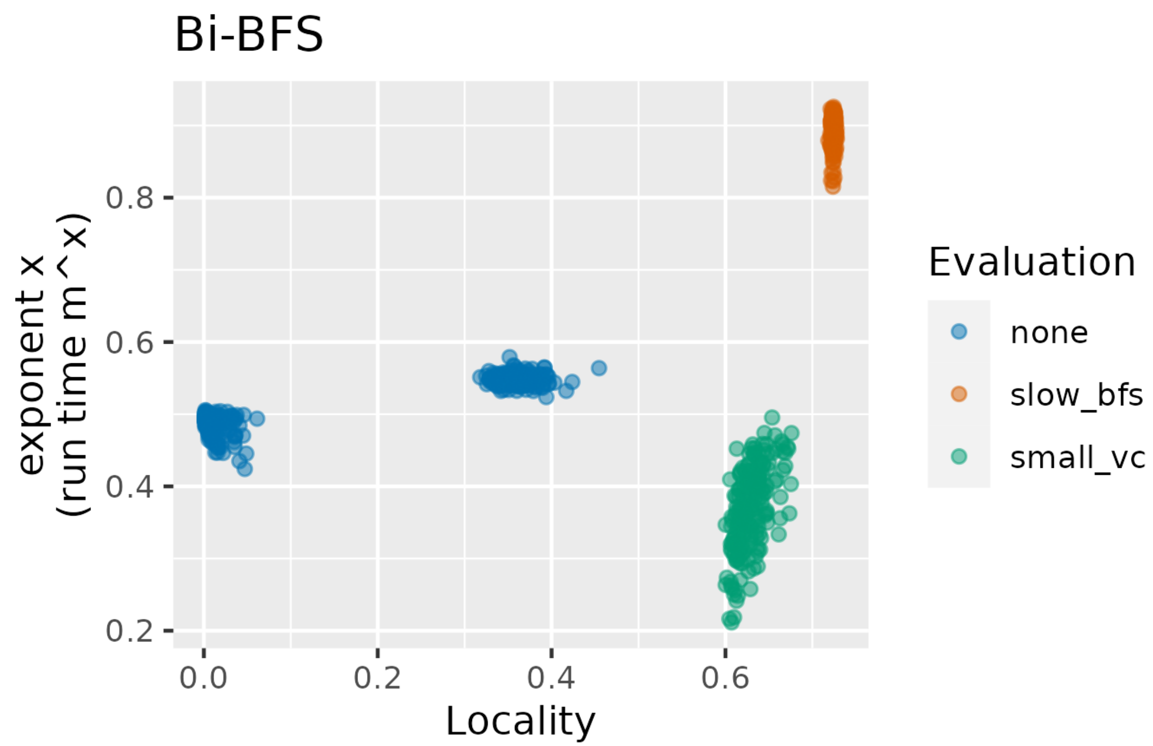
Lokalität

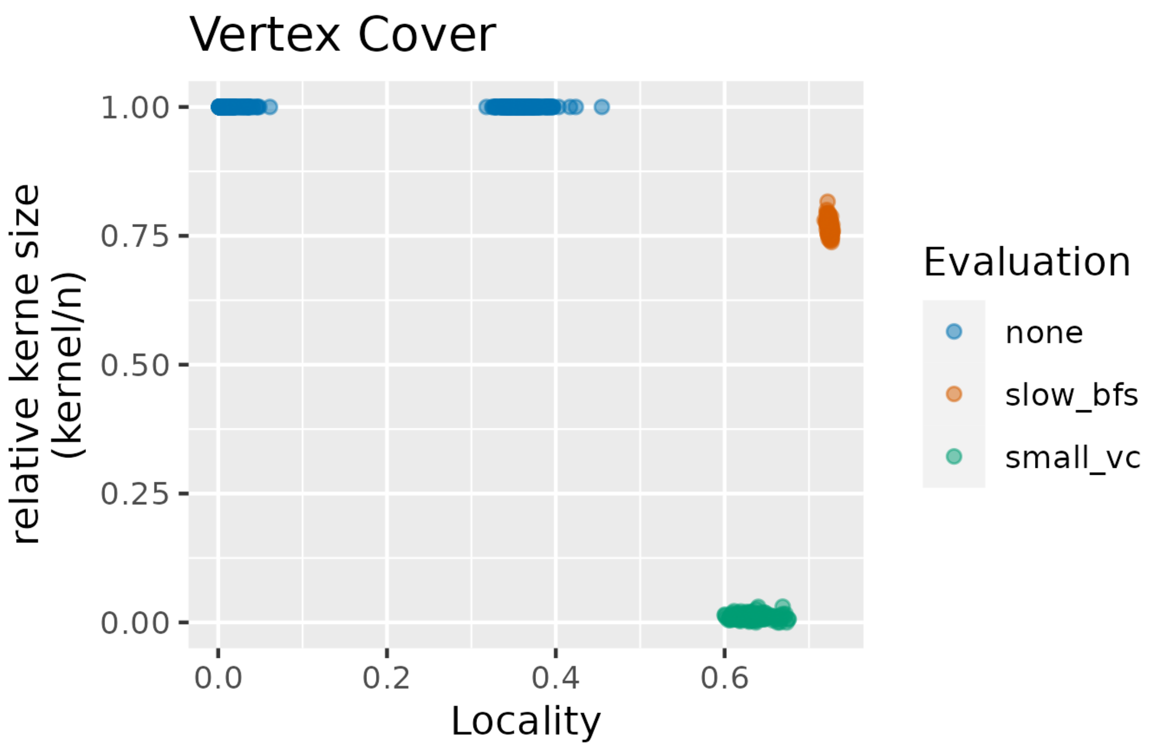




- Lokalität: $\frac{1}{3}(\text{cluster}_{\text{local}} + \text{cluster}_{\text{global}} + \text{cluster}_{\text{dist}})$

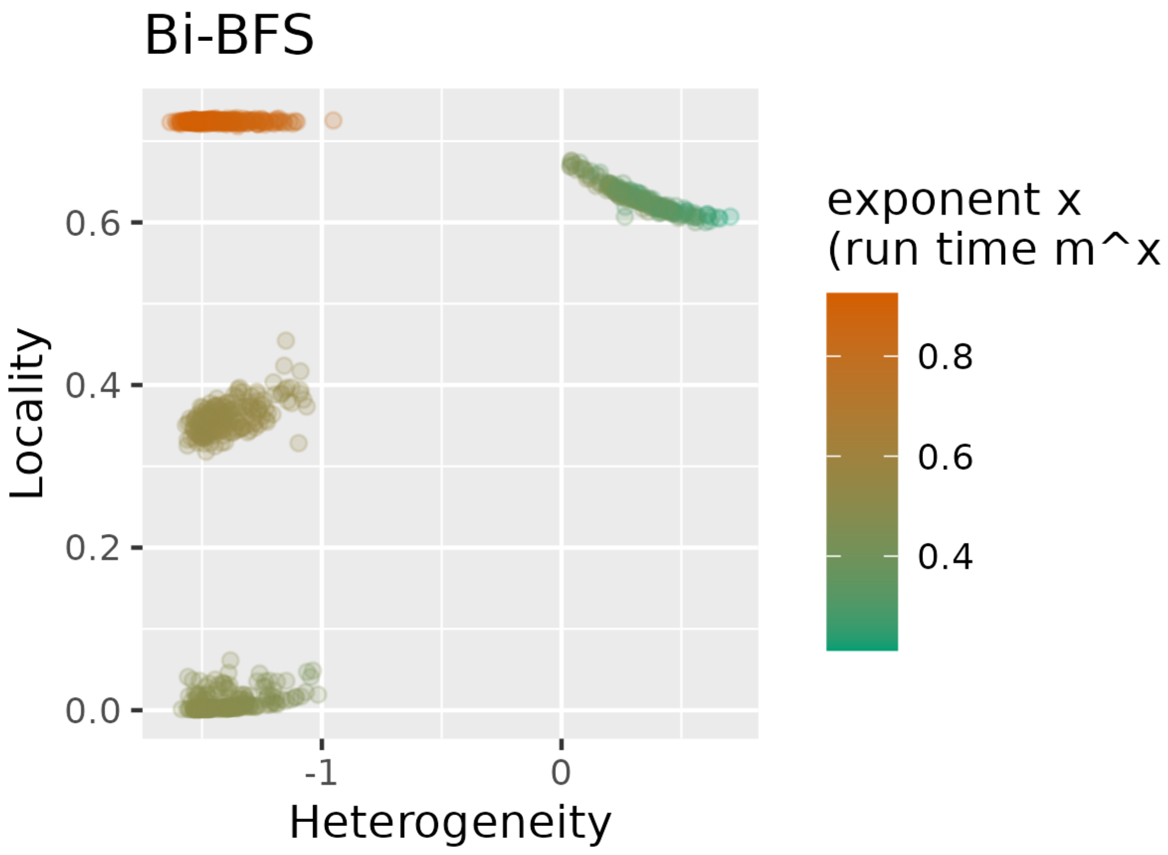
Lokalität

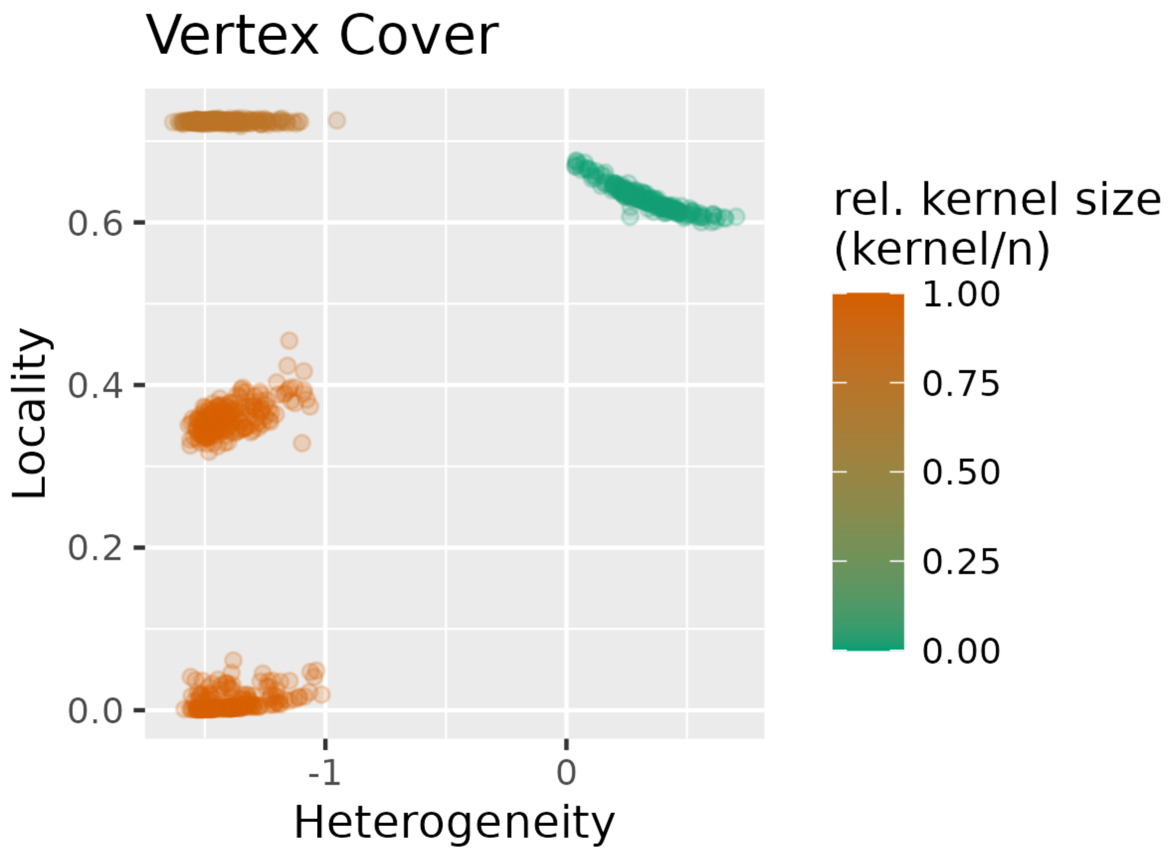




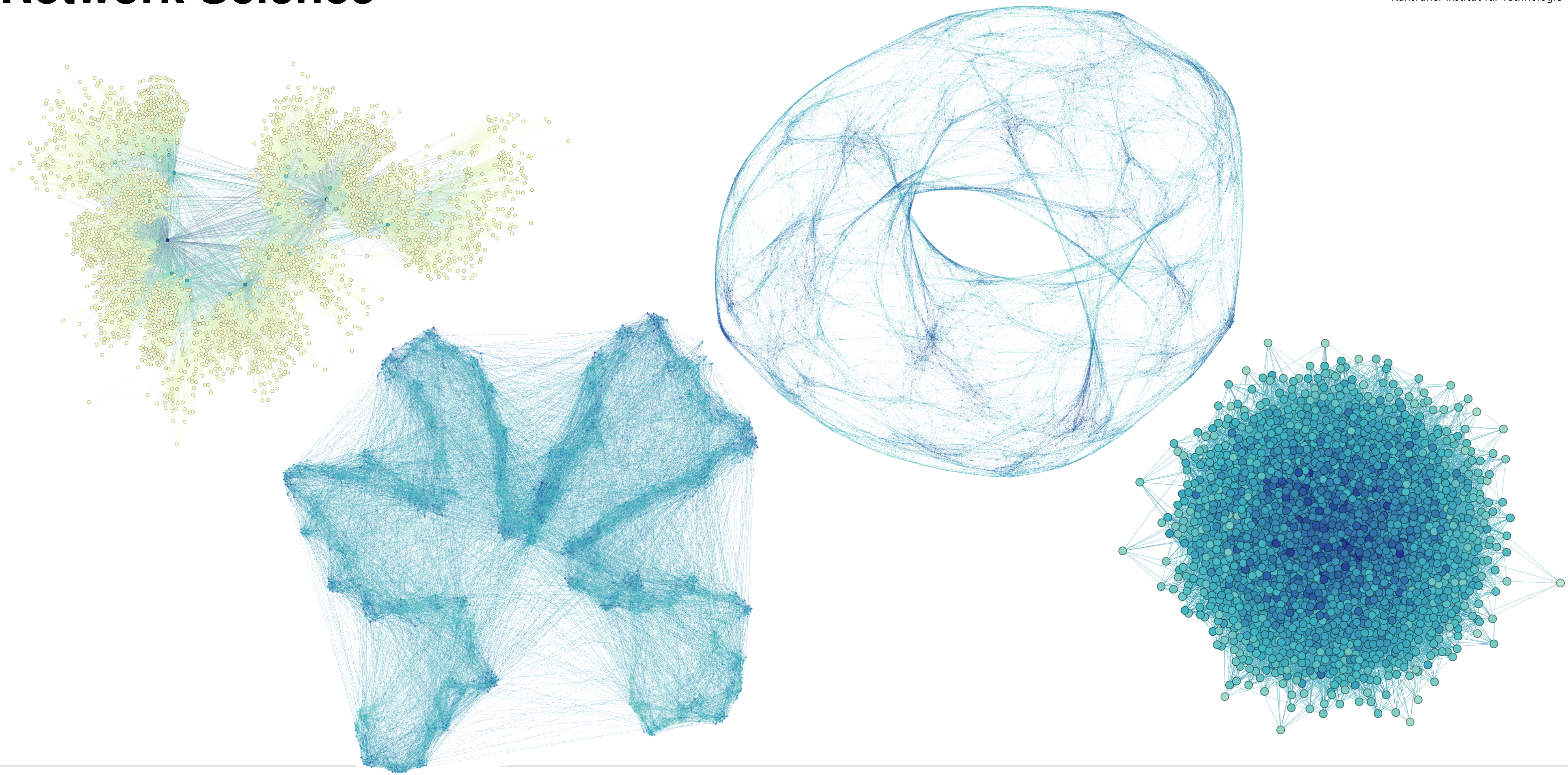
- Lokalität: $\frac{1}{3}(\text{cluster}_{\text{local}} + \text{cluster}_{\text{global}} + \text{cluster}_{\text{dist}})$
- Auch Lokalität reich nicht aus, zum Differenzieren

Heterogenität und Lokalität



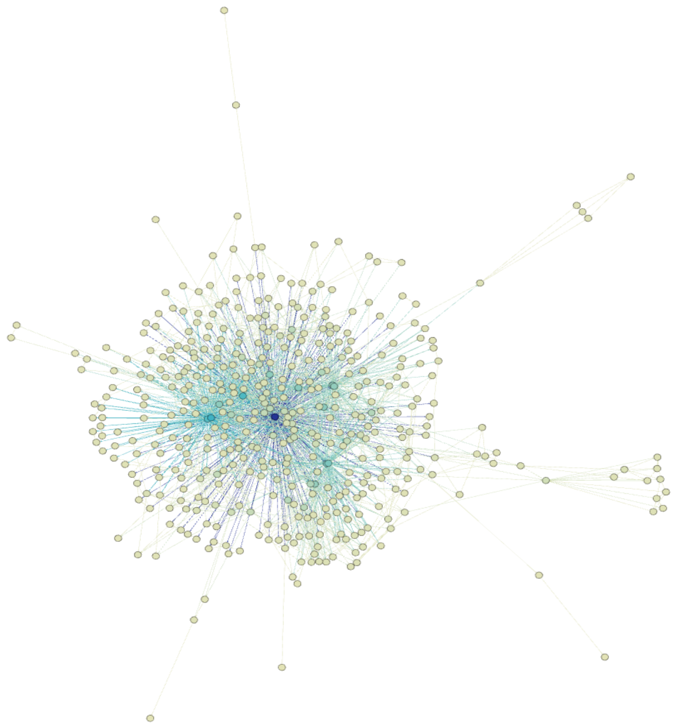


Network Science



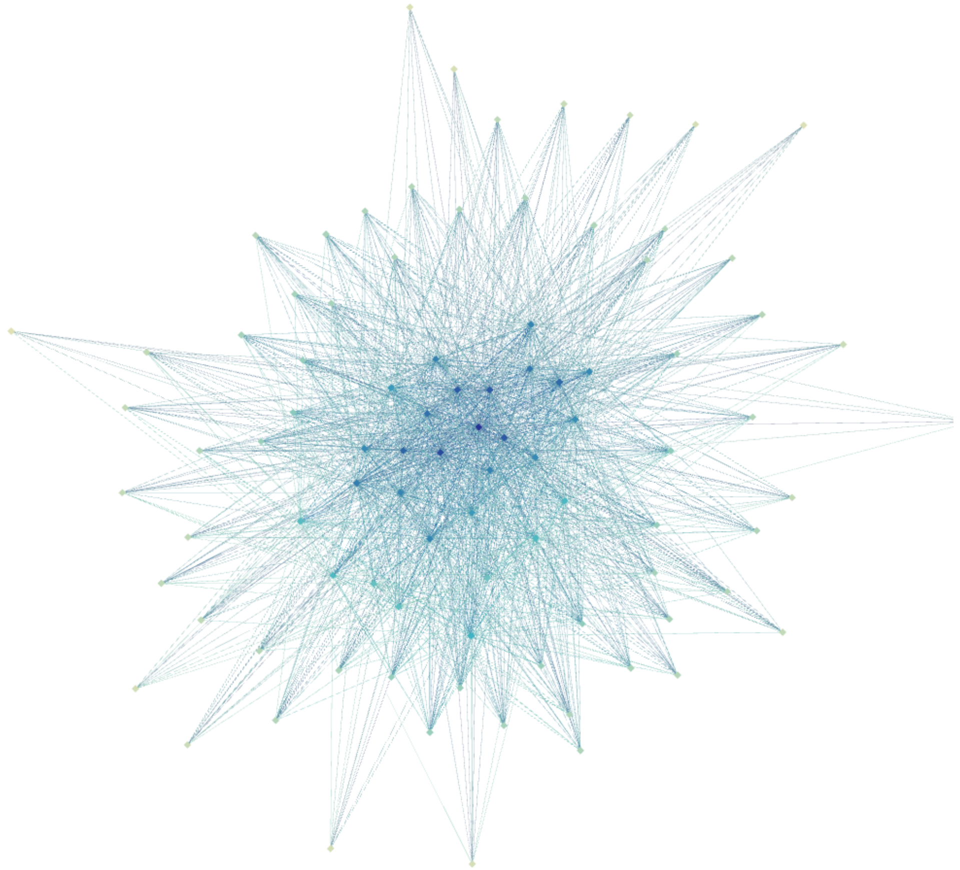
Beispiele für reale Netzwerke

- bio-celegans



Beispiele für reale Netzwerke

- `bio-celegans`
- `bn-macaque-rhesus_cerebral-cortex_1`

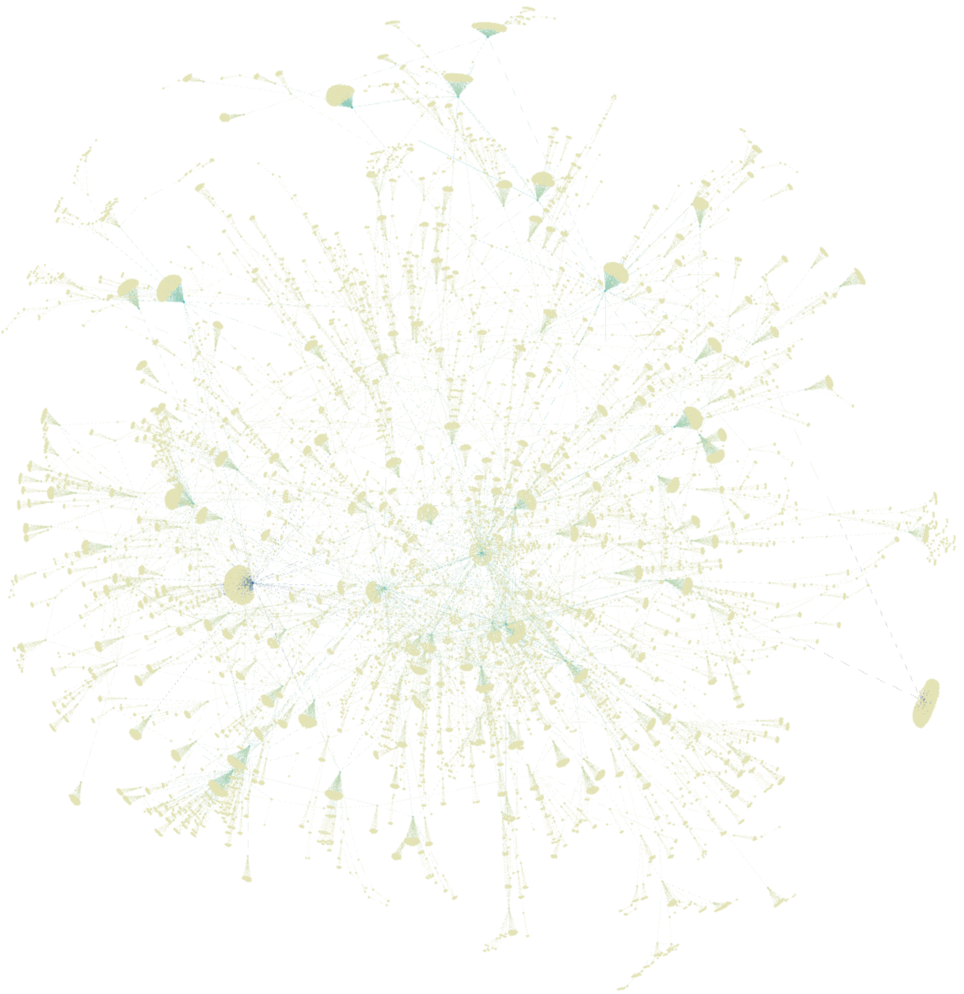


Beispiele für reale Netzwerke

- bio-celegans
- bn-macaque-rhesus_cerebral-cortex_1
- opsahl-powergrid

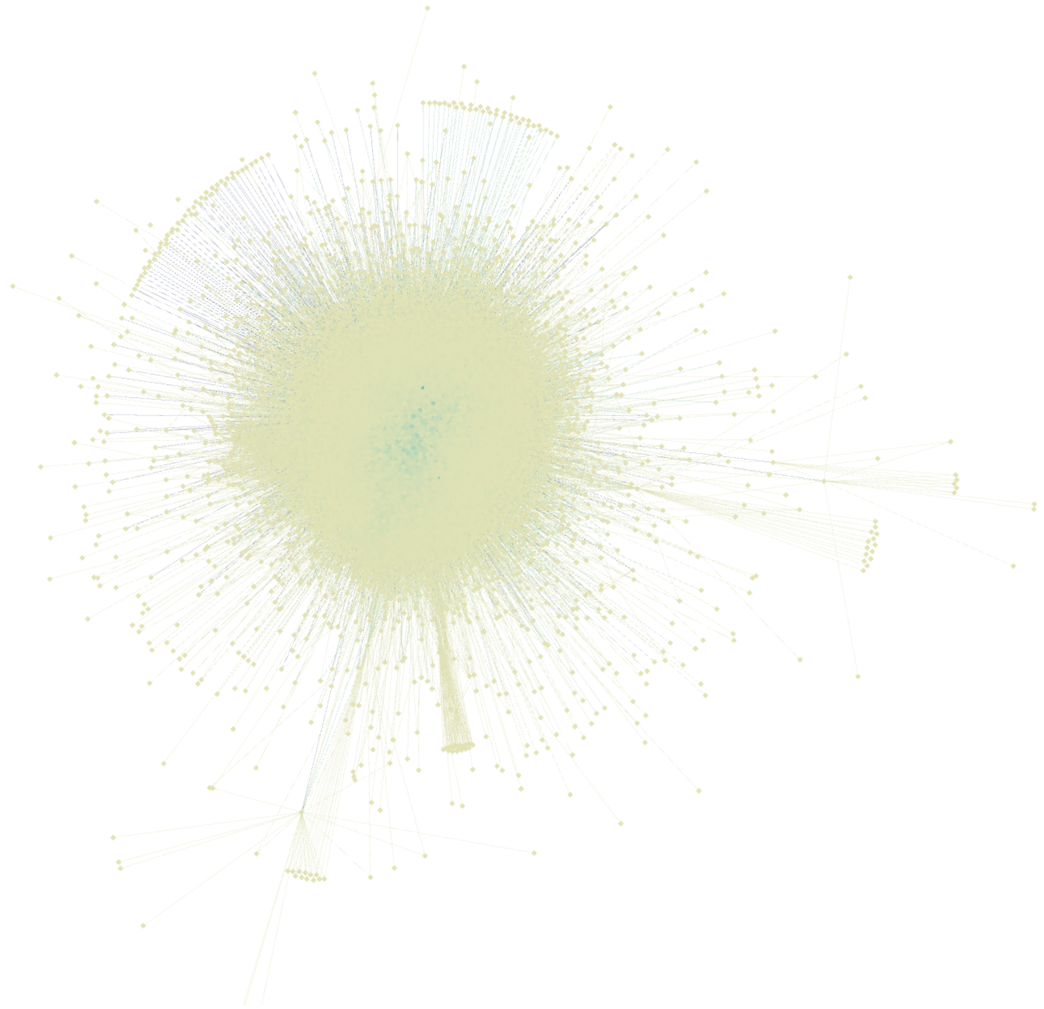
Beispiele für reale Netzwerke

- `bio-celegans`
- `bn-macaque-rhesus_cerebral-cortex_1`
- `opsahl-powergrid`
- `econ-poli-large`



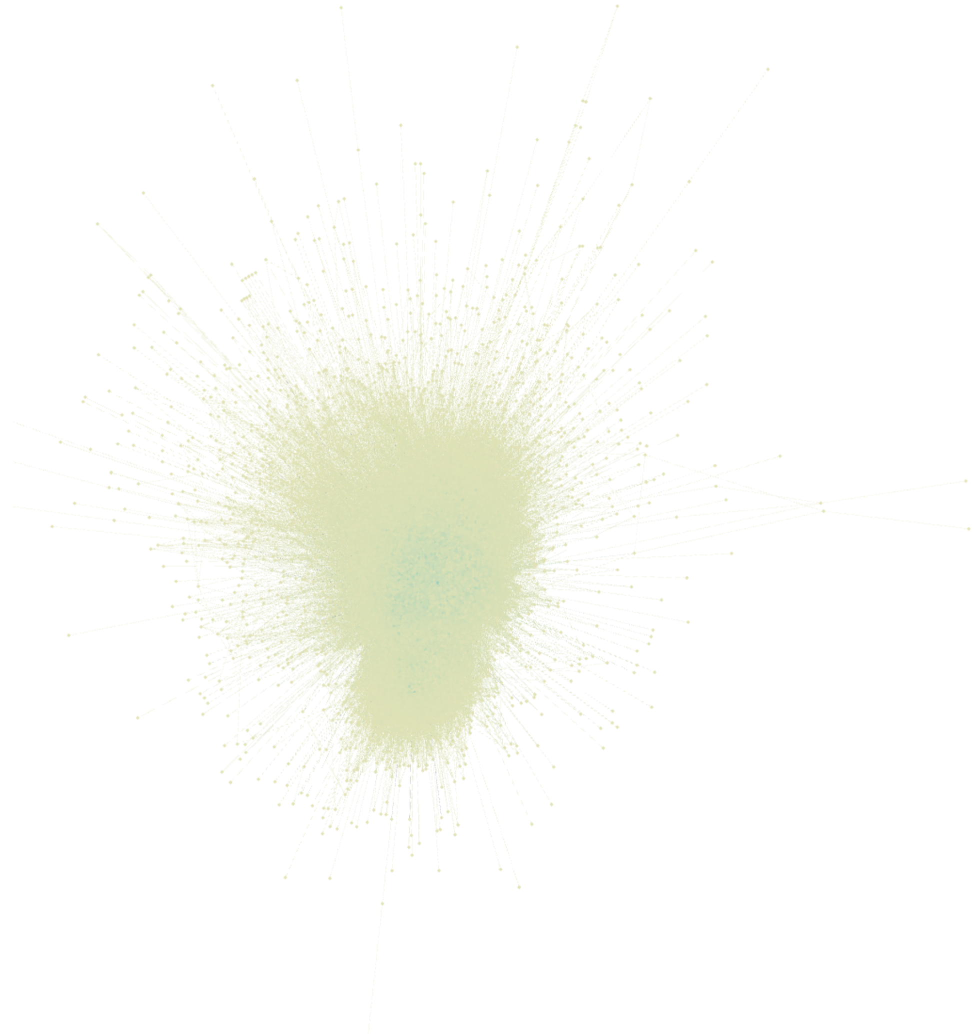
Beispiele für reale Netzwerke

- `bio-celegans`
- `bn-macaque-rhesus_cerebral-cortex_1`
- `opsahl-powergrid`
- `econ-poli-large`
- `bio-grid-yeast`



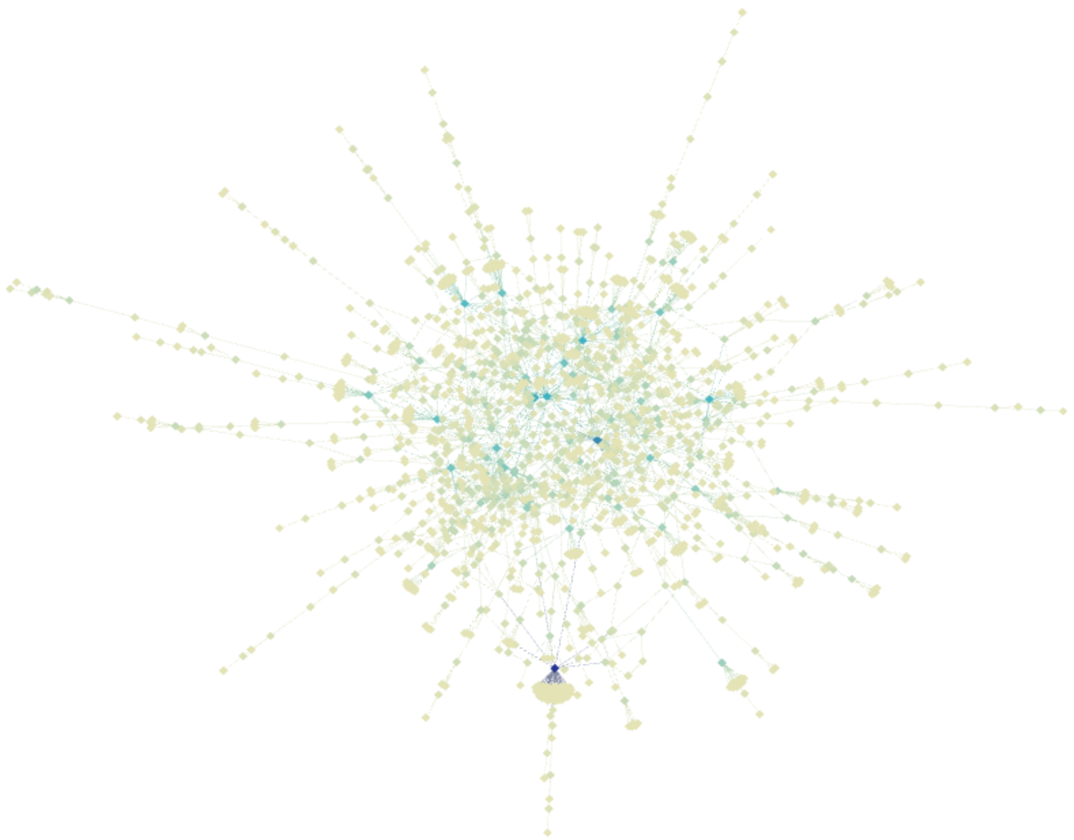
Beispiele für reale Netzwerke

- bio-celegans
- bn-macaque-rhesus_cerebral-cortex_1
- opsahl-powergrid
- econ-poli-large
- bio-grid-yeast
- socfb-Yale4



Beispiele für reale Netzwerke

- `bio-celegans`
- `bn-macaque-rhesus_cerebral-cortex_1`
- `opsahl-powergrid`
- `econ-poli-large`
- `bio-grid-yeast`
- `socfb-Yale4`
- `bio-yeast-protein-inter`



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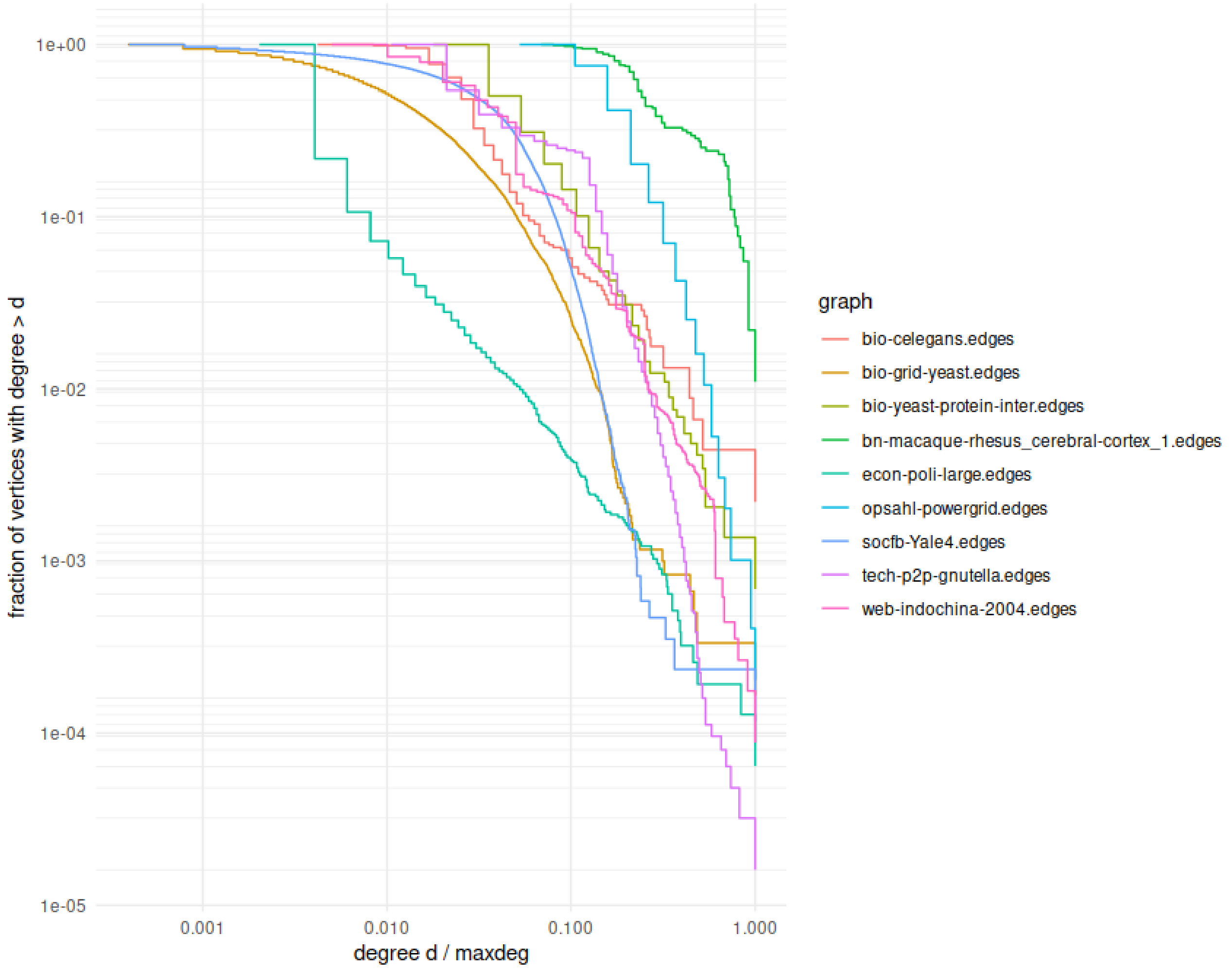

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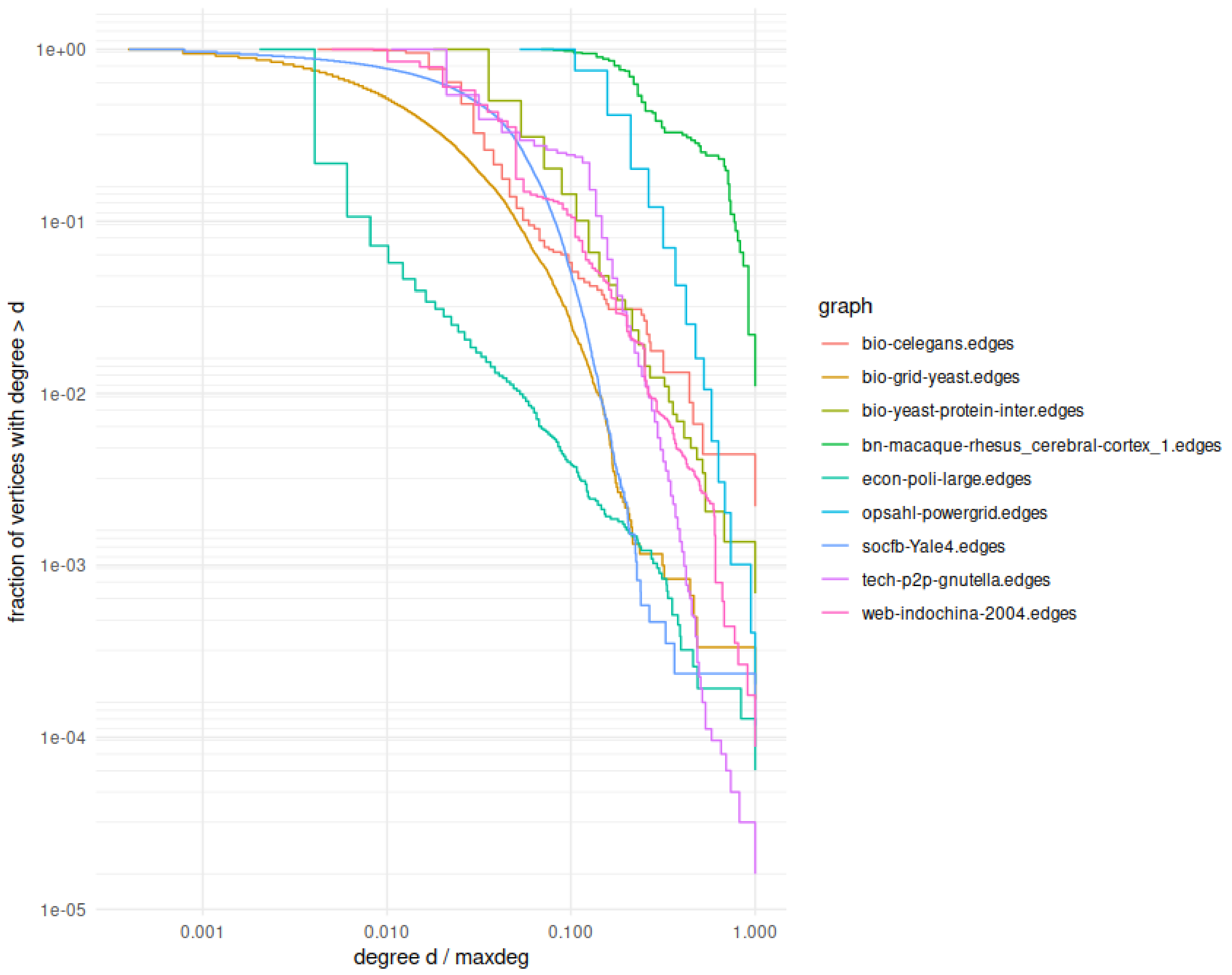

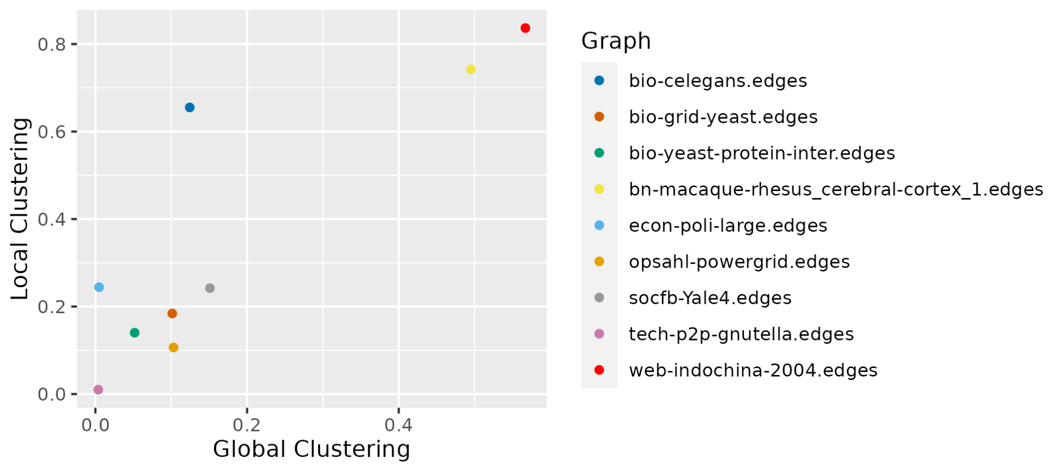

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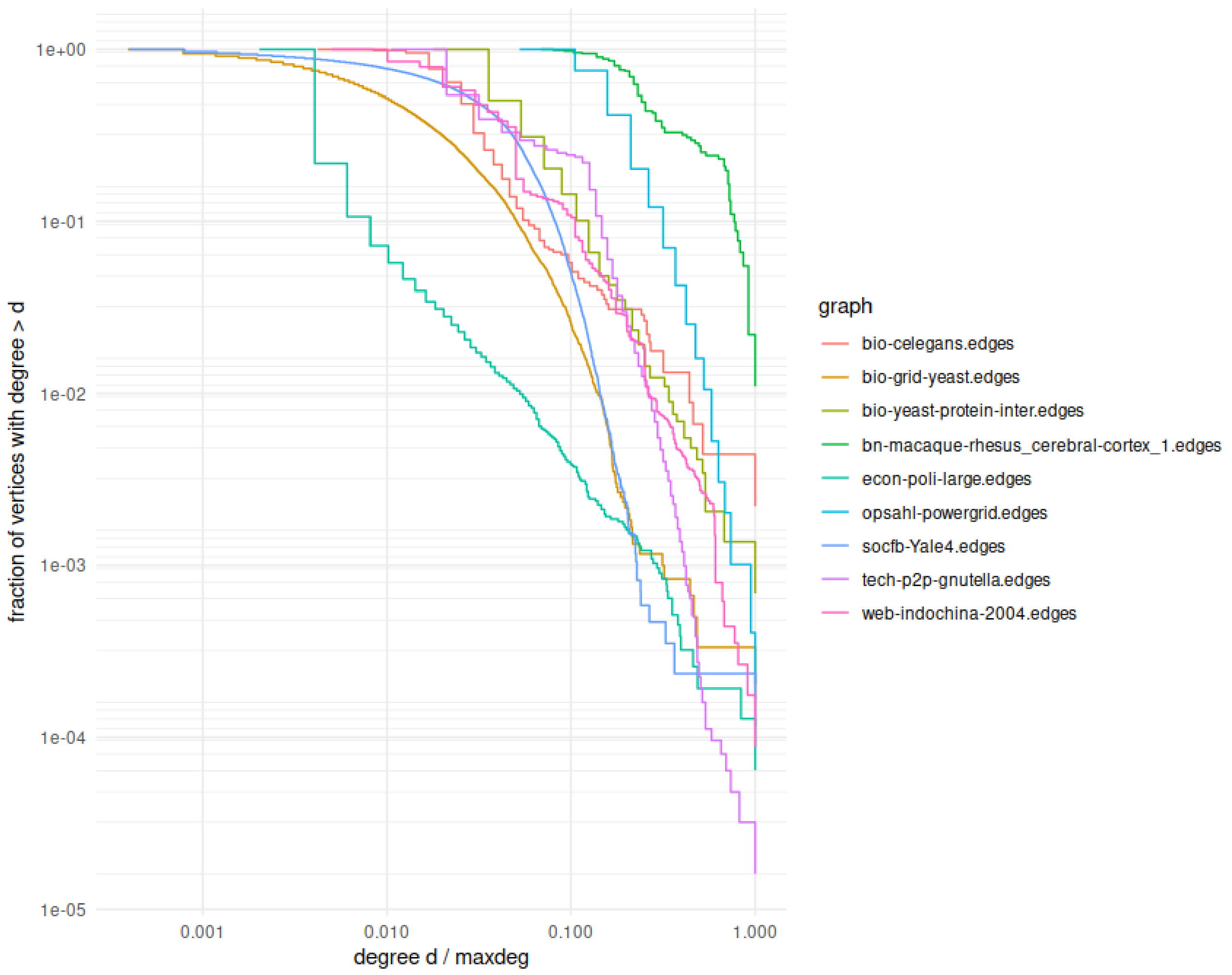

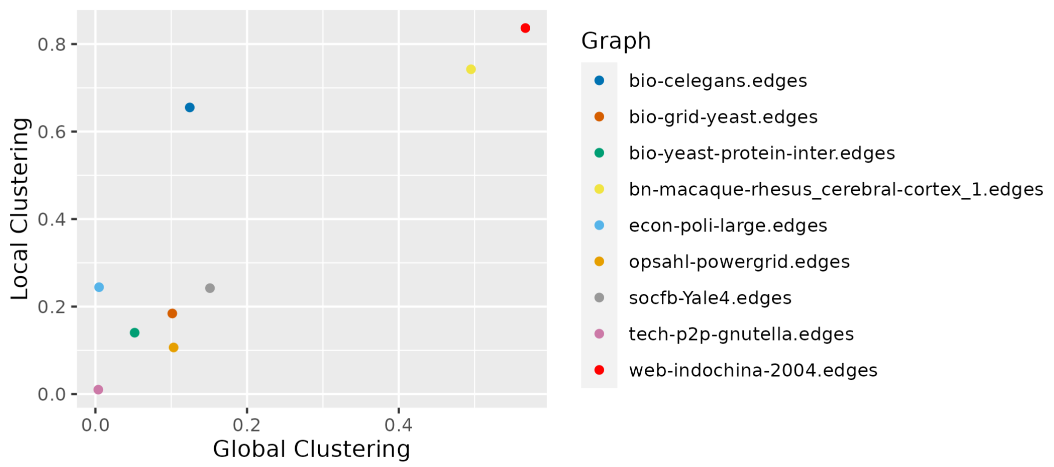

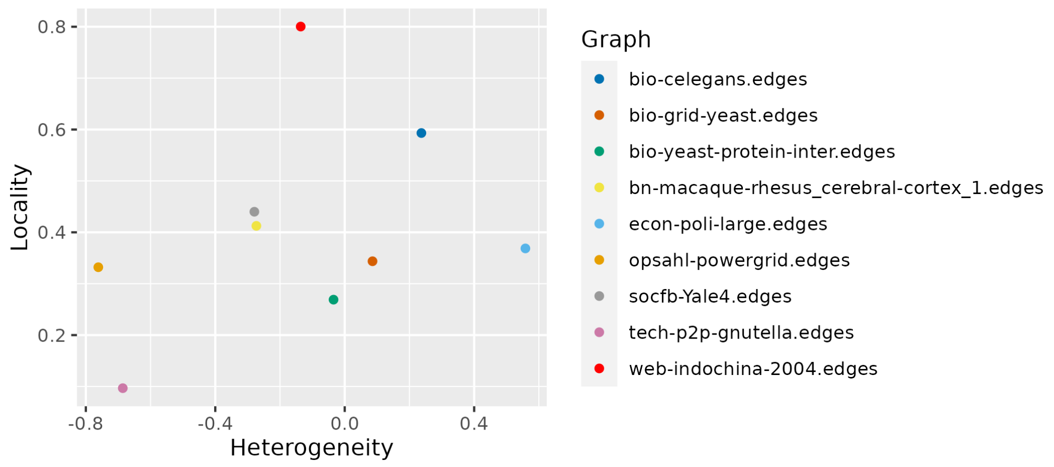

Eigenschaften komplexer Netzwerke

Begriff: complex network, scale-free network

Eigenschaften komplexer Netzwerke

Begriff: complex network, scale-free network

Drei Charakteristika:

Eigenschaften komplexer Netzwerke

Begriff: complex network, scale-free network

Drei Charakteristika:

- heterogene Gradverteilung

Eigenschaften komplexer Netzwerke

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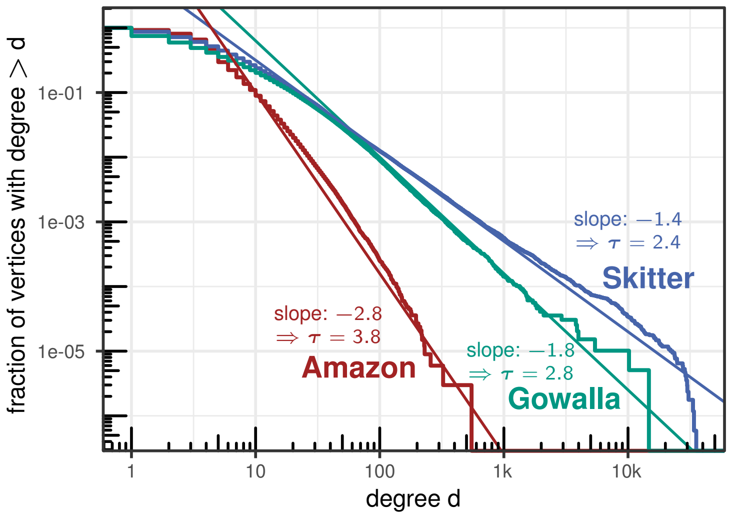
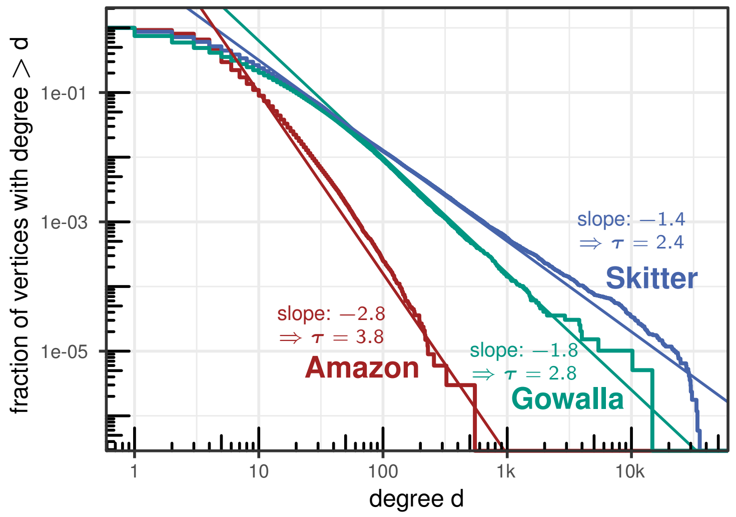


Eigenschaften komplexer Netzwerke

Begriff: complex network, scale-free network

Drei Charakteristika:

- heterogene Gradverteilung
- kurze Wege / „small-world“



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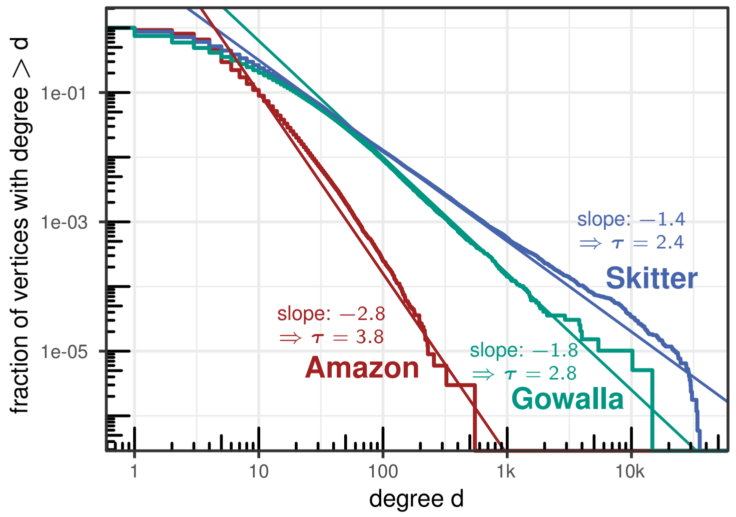

six-degrees of . . .

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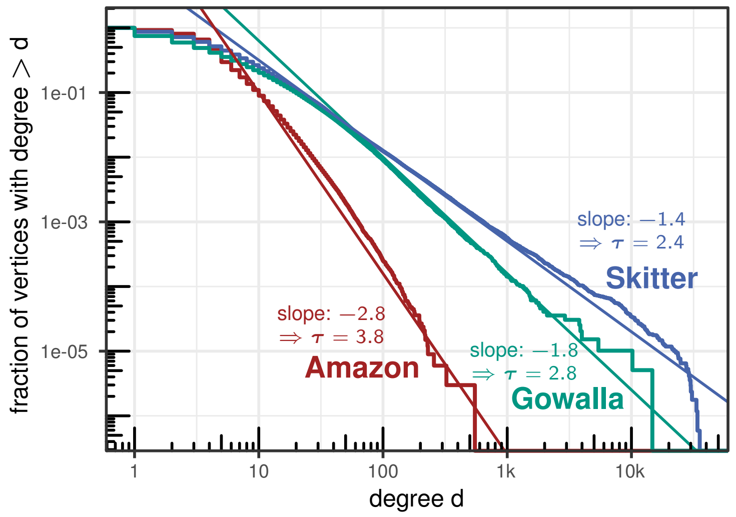

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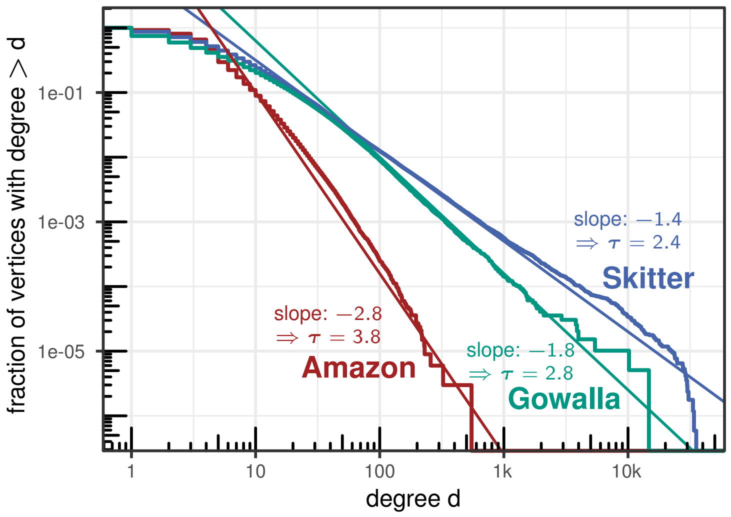

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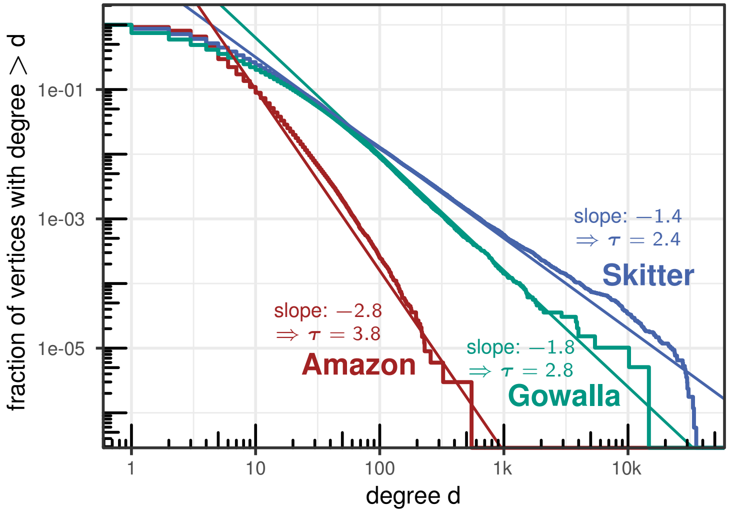

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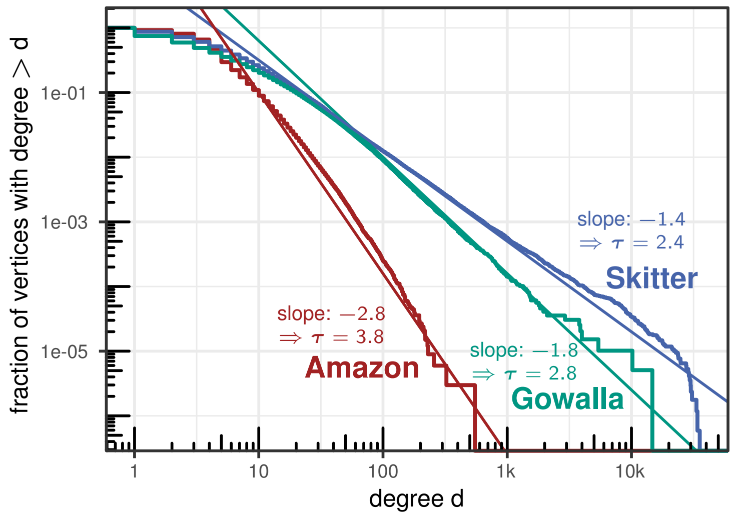
. . . Kevin Bacon

Eigenschaften komplexer Netzwerke

Begriff: complex network, scale-free network

Drei Charakteristika:

- heterogene Gradverteilung
- kurze Wege / „small-world“
- hohe Lokalität / Clustering



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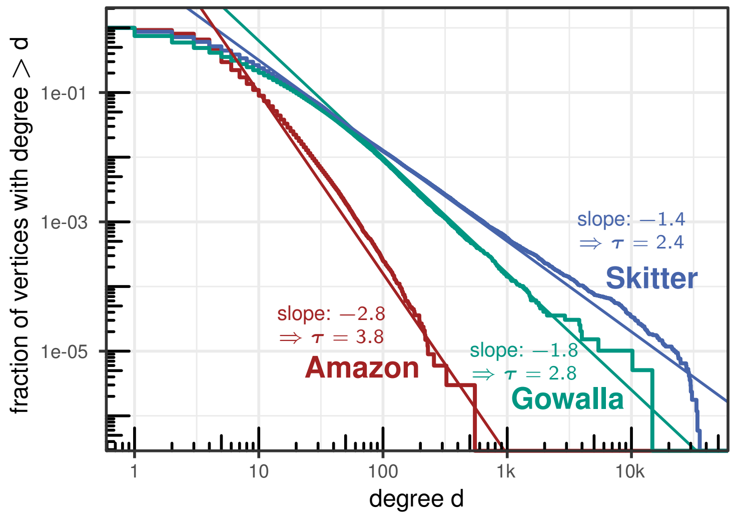

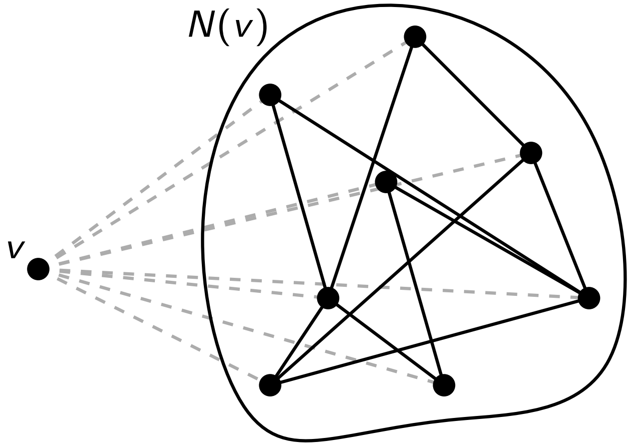

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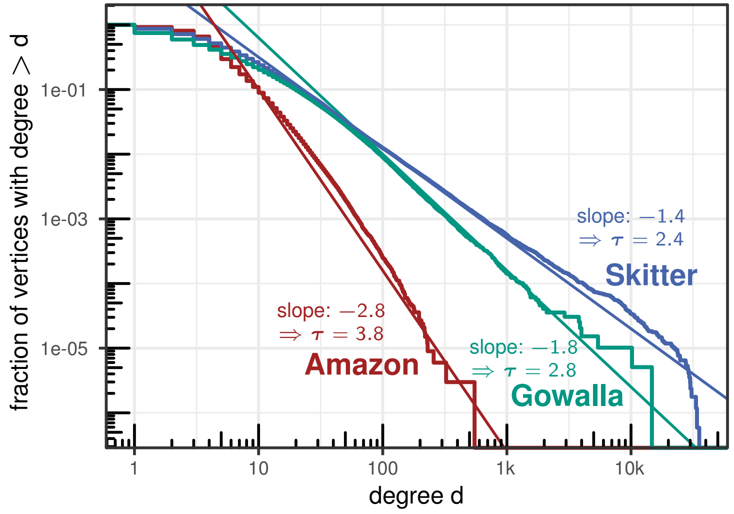
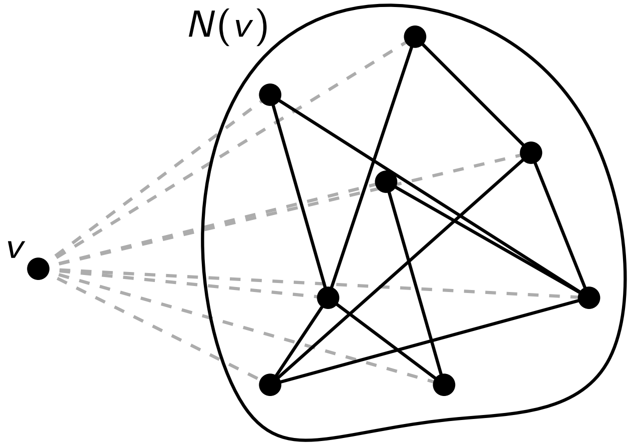
Ziel: Erklären / Modellieren





six-degrees of …

…Separation

…Wikipedia

…Kevin Bacon

Modelle für komplexe Netzwerke

Karlsruher Institut für Technologie

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:

- heterogene Gradverteilung
- kurze Wege / „small-world"
- hohe Lokalität / Clustering

1959 1923 / 1999 2002 1998 2010 2019

Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:

- heterogene Gradverteilung
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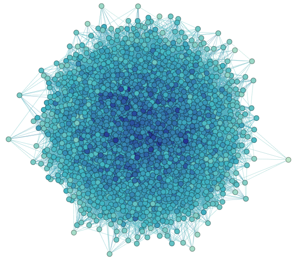
1959 1923 / 1999 2002 1998 2010 2019

Erdős–Rényi model

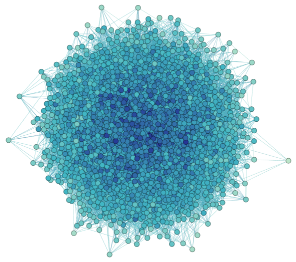


Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	1923 / 1999	2002	1998	2010	2019
heterogene Gradverteilung						
kurze Wege / „small-world“	✓					
hohe Lokalität / Clustering						

Erdős–Rényi model

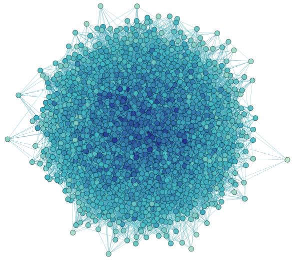


Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	2002	1998	2010	2019
■ heterogene Gradverteilung						
■ kurze Wege / „small-world“	✓					
■ hohe Lokalität / Clustering						

Erdős–Rényi model



Modelle für komplexe Netzwerke

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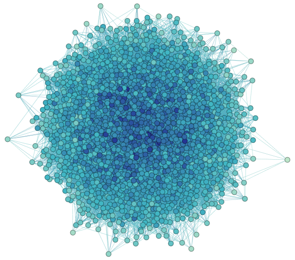
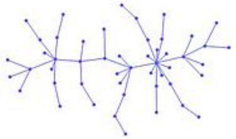
Erdős–Rényi model



Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree

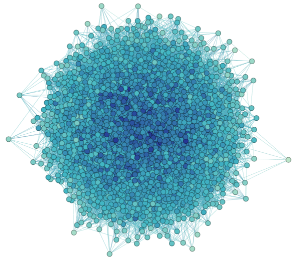


Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	2002	1998	2010	2019
heterogene Gradverteilung		✓				
kurze Wege / „small-world“	✓	✓				
hohe Lokalität / Clustering						

Erdős–Rényi model



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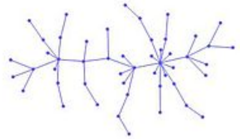
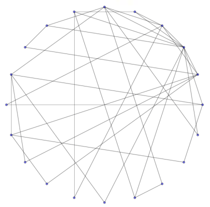


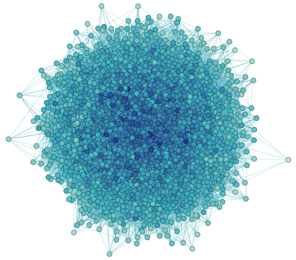


Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	1998	2010	2019
heterogene Gradverteilung		✓				
kurze Wege / „small-world“	✓	✓				
hohe Lokalität / Clustering						

Erdős–Rényi model



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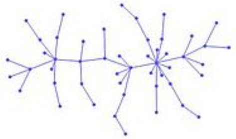

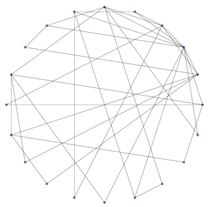

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heterogene Gradverteilung		✓				
kurze Wege / „small-world"	✓	✓				
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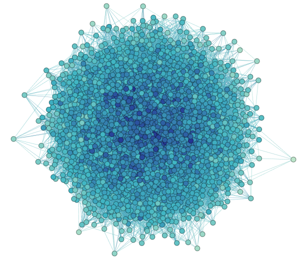

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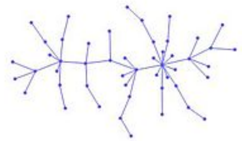
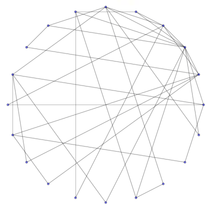




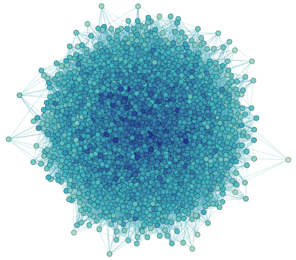
Chung-Lu / Configuration model

Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

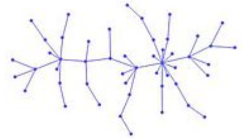
Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	1998	2010	2019
heterogene Gradverteilung		✓				
kurze Wege / „small-world“	✓	✓				
hohe Lokalität / Clustering						

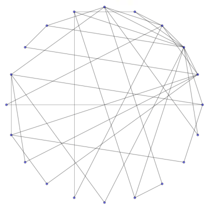
Erdős–Rényi model



Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree





Chung-Lu / Configuration model

vertices with weights w_i (following power-law distribution);

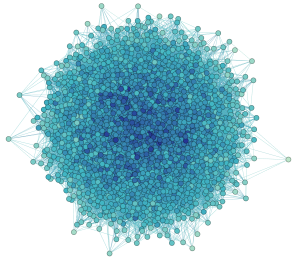
$\Pr\left[\{e_i, e_j\} \in E\right] \sim \frac{w_i \cdot w_j}{W}$

Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	1998	2010	2019
heterogene Gradverteilung		✓	✓			
kurze Wege / „small-world“	✓	✓	✓			
hohe Lokalität / Clustering						

Erdős–Rényi model



Preferential Attachment

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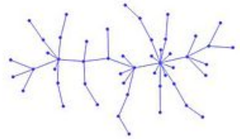

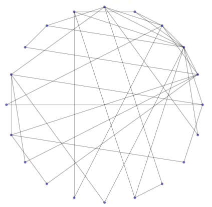

Chung-Lu / Configuration model

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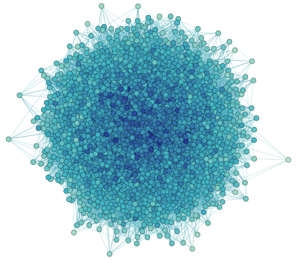
Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	2010	2019
heterogene Gradverteilung		✓	✓			
kurze Wege / „small-world“	✓	✓	✓			
hohe Lokalität / Clustering						

Erdős–Rényi model



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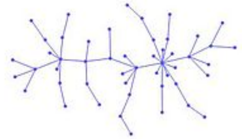

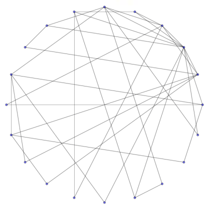

Chung-Lu / Configuration model

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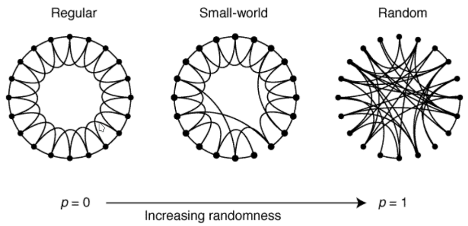
Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

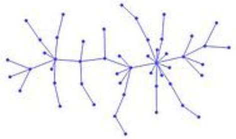
Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	2010	2019
heterogene Gradverteilung		✓	✓			
kurze Wege / „small-world“	✓	✓	✓			
hohe Lokalität / Clustering						

Watts–Strogatz model

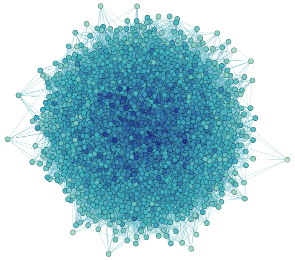


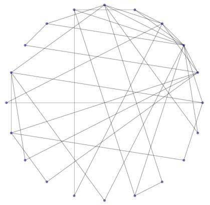
Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree



Erdős–Rényi model





Chung-Lu / Configuration model

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Modelle für komplexe Netzwerke

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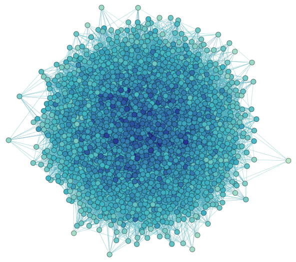
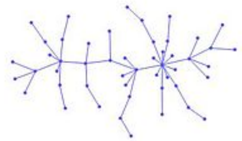
Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	2010	2019
heterogene Gradverteilung		✓	✓			
kurze Wege / „small-world“	✓	✓	✓	✓		
hohe Lokalität / Clustering				✓		

Erdős–Rényi model

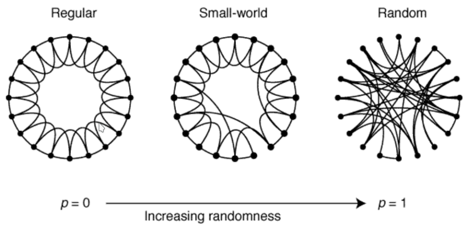


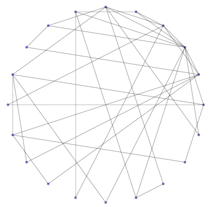
Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree



Watts–Strogatz model





Chung-Lu / Configuration model

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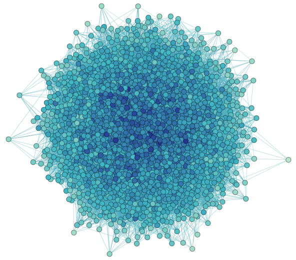
Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

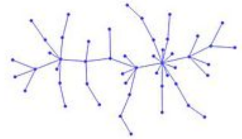
Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	2010	2019
■ heterogene Gradverteilung		✓	✓				
■ kurze Wege / „small-world“	✓	✓	✓	✓			
■ hohe Lokalität / Clustering				✓			

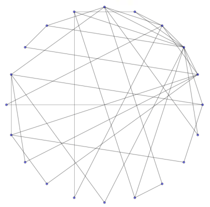
Erdős–Rényi model



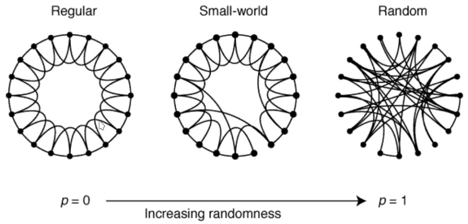
Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree





Watts–Strogatz model



Chung-Lu / Configuration model

vertices with weights w_i (following power-law distribution);
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Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

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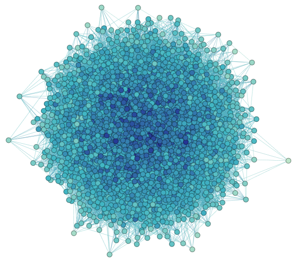
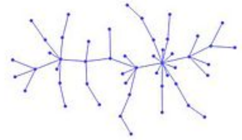
kurze Wege / „small-world“	✓	✓	✓	✓			
hohe Lokalität / Clustering				✓			

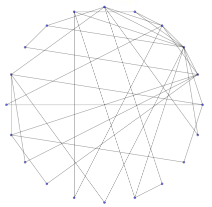
Erdős–Rényi model



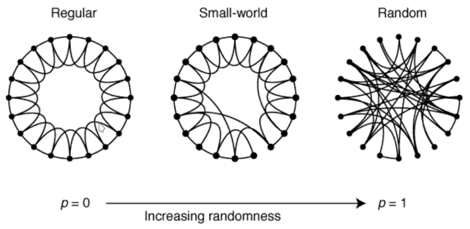
Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree





Watts–Strogatz model



Chung-Lu / Configuration model

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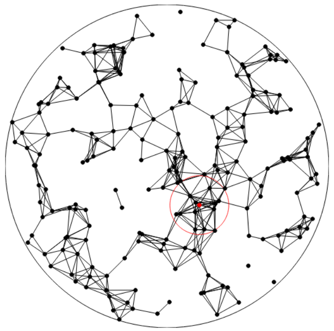
Geometric Random Graph

sample vertices uniformly in geometry, connect if distance below threshold

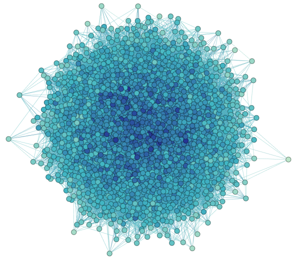


Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

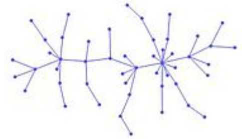
Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG 2010	2019
heterogene Gradverteilung		✓	✓			
kurze Wege / „small-world“	✓	✓	✓	✓		
hohe Lokalität / Clustering				✓	✓	

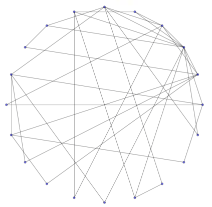
Erdős–Rényi model



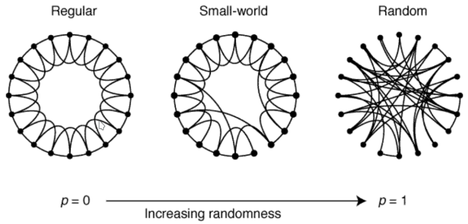
Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree





Watts–Strogatz model



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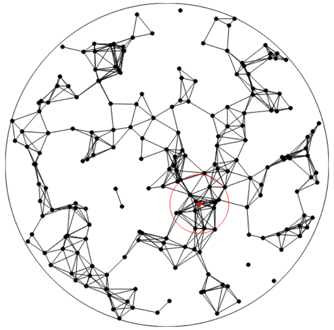

Modelle für komplexe Netzwerke

Karlsruher Institut für Technologie

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	HRG 2010	2019
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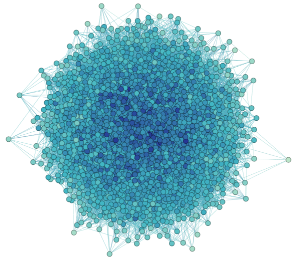
kurze Wege / „small-world“	✓	✓	✓	✓			
hohe Lokalität / Clustering				✓	✓		

Erdős–Rényi model



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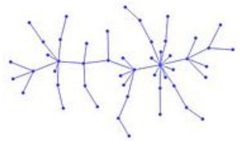
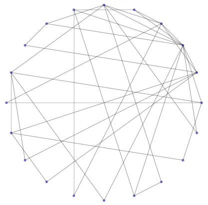
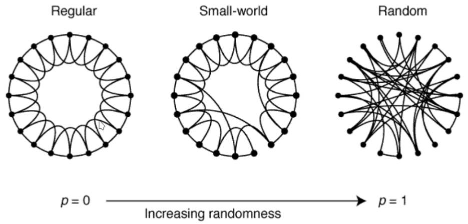




Watts–Strogatz model



Chung-Lu / Configuration model

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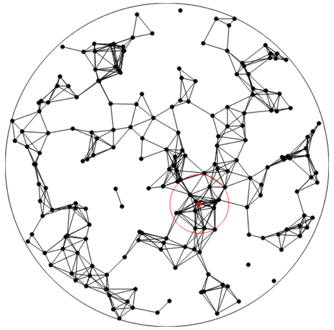

Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	HRG 2010	2019
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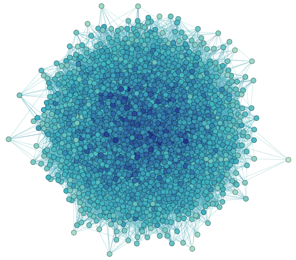
kurze Wege / „small-world“	✓	✓	✓	✓			
hohe Lokalität / Clustering				✓	✓		

Erdős–Rényi model



Preferential Attachment

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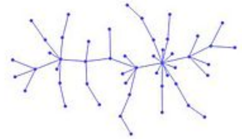
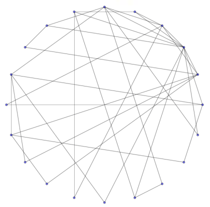
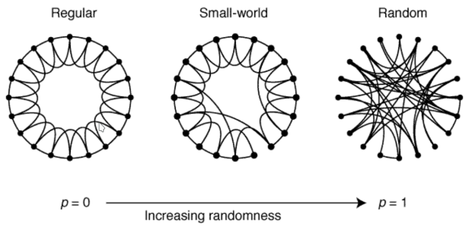




Watts–Strogatz model



Chung-Lu / Configuration model

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Geometric Random Graph (Hyperbolic)

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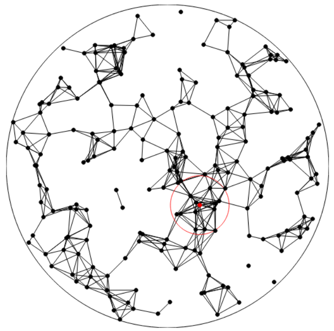

Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	HRG 2010	2019
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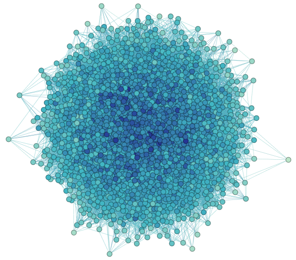
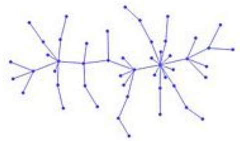
kurze Wege / „small-world“	✓	✓	✓	✓			
hohe Lokalität / Clustering				✓	✓		

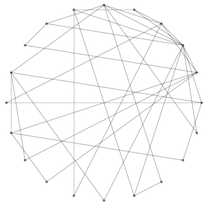
Erdős–Rényi model



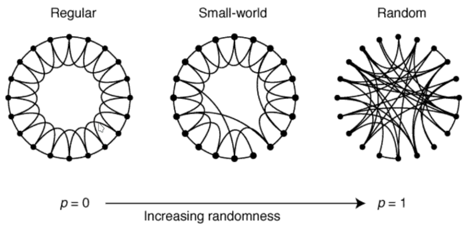
Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree





Watts–Strogatz model



Chung-Lu / Configuration model

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Geometric Random Graph (Hyperbolic)

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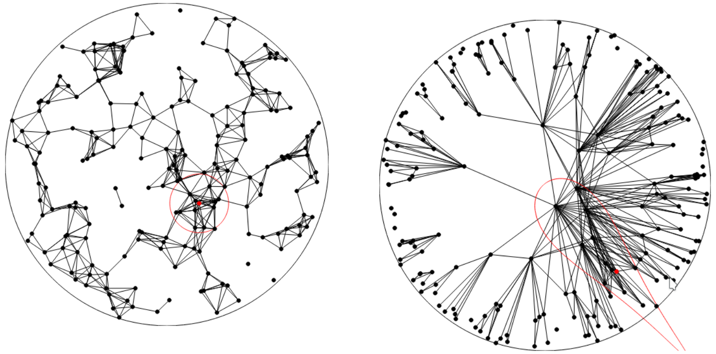

Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG 2010	HRG 2019
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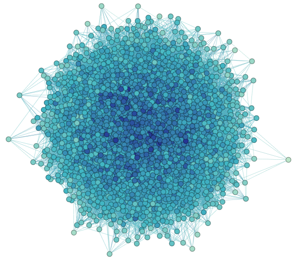
■ kurze Wege / „small-world“	✓	✓	✓	✓		✓
■ hohe Lokalität / Clustering				✓	✓	✓

Erdős–Rényi model



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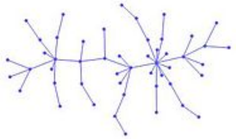
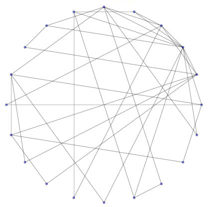
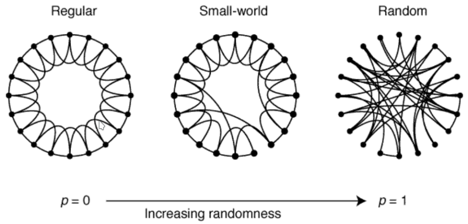




Watts–Strogatz model



Chung-Lu / Configuration model

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Geometric Random Graph (Hyperbolic)

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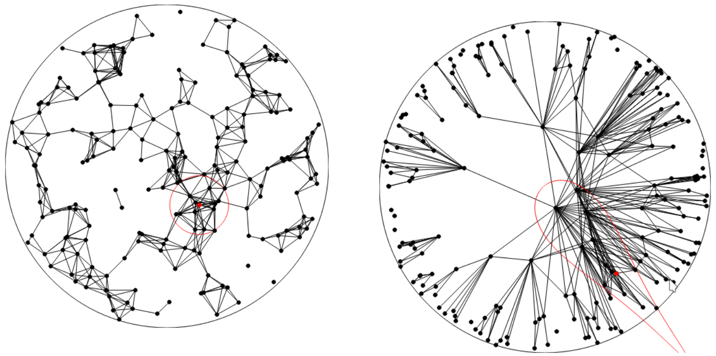
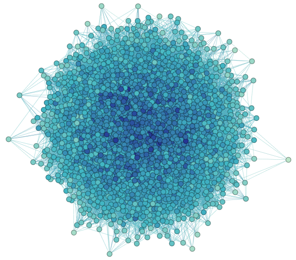


Modelle für komplexe Netzwerke

Ziel: Modellieren und Erklären der Eigenschaften

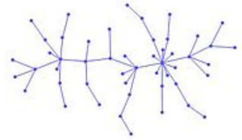
Drei Charakteristika:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	HRG 2010	GIRG 2019
■ heterogene Gradverteilung		✓	✓			✓	
■ kurze Wege / „small-world“	✓	✓	✓	✓		✓	
■ hohe Lokalität / Clustering				✓	✓	✓	

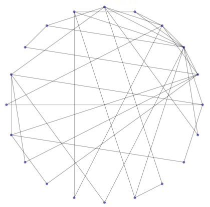
Erdős–Rényi model



Preferential Attachment

iteratively add vertices, choose edges with probability proportional to current degree





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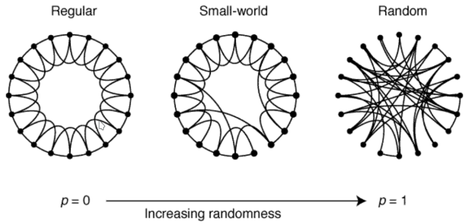

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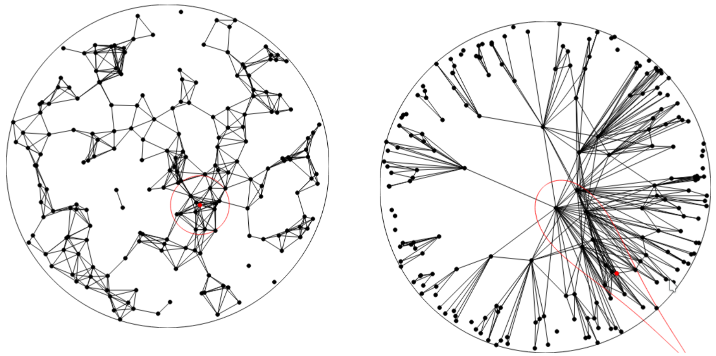

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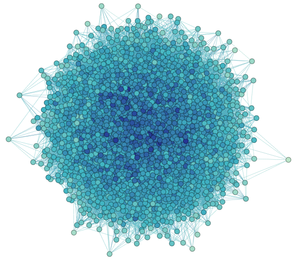

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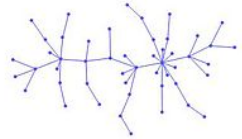

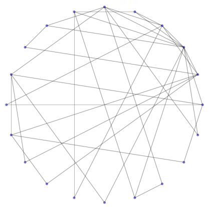

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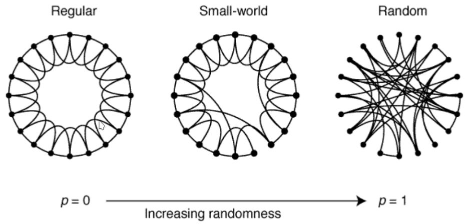

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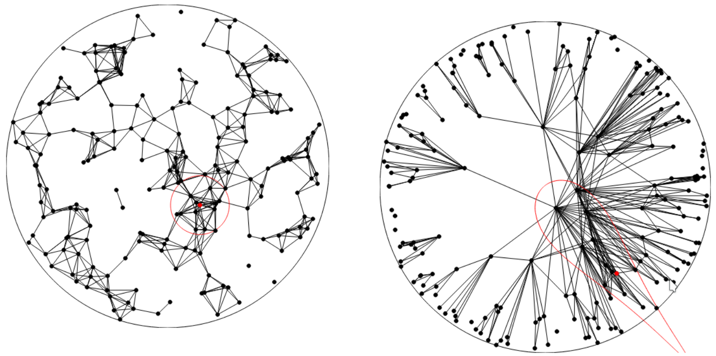

Modelle für komplexe Netzwerke

Karlsruher Institut für Technologie

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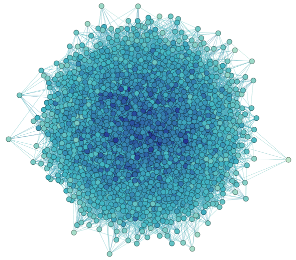

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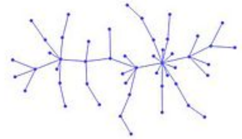

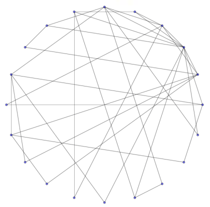

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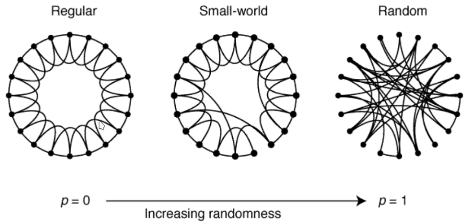

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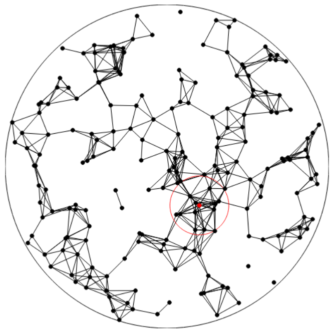
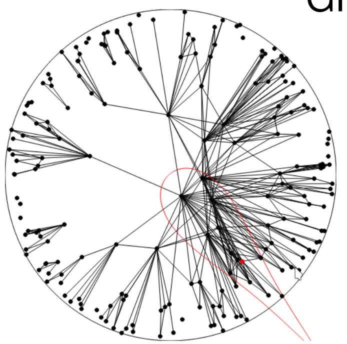


GIRG

GRG + IRG



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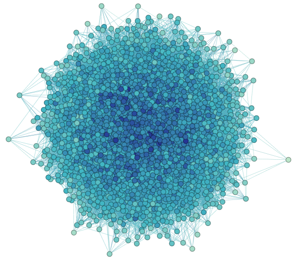

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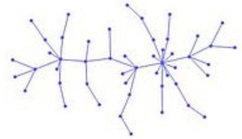

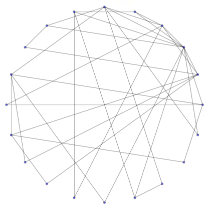

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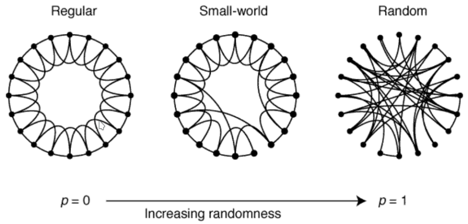

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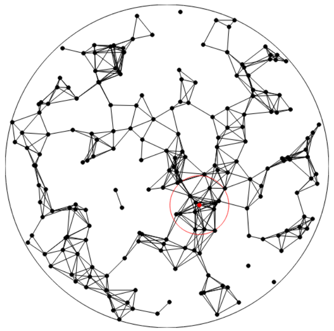

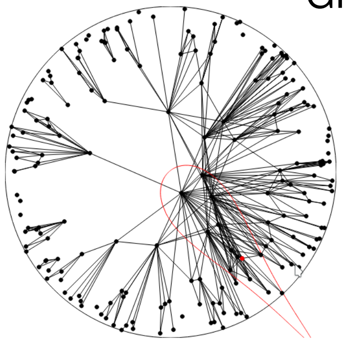

GIRG

GRG $\times$ IRG

Modelle für komplexe Netzwerke

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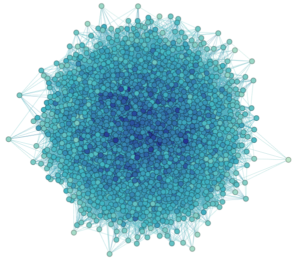

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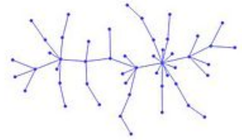

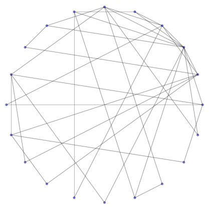

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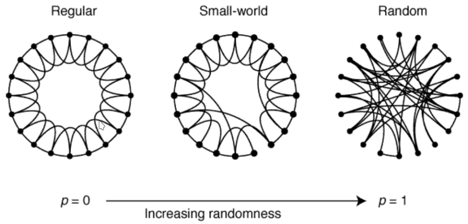

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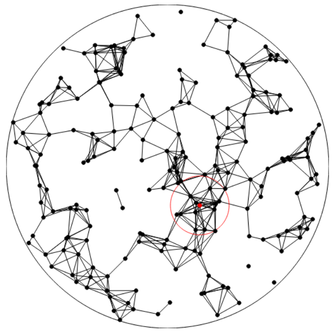

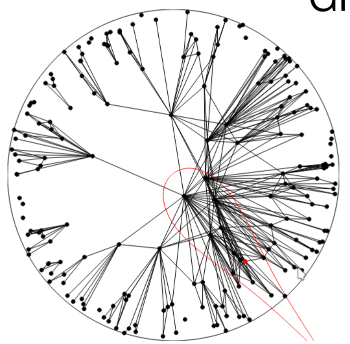

GIRG

GRG $\times$ IRG

Übungsblatt 2

Generierte Graphen

Echtwelt-Graphen

Übungsblatt 2

Generierte Graphen

- Sucht euch mehrere Modelle zum Generieren von Graphen raus
- Könnt ihr herausfinden, wie wir die Graphen generiert haben?

Echtwelt-Graphen

Übungsblatt 2

Karlsruher Institut für Technologie

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igraph

chistopher / girgs

NetworkX
Network Analysis in Python

NetworKit
Large-scale Network Analysis

Echtwelt-Graphen

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REPOSITORY

External Validity of Average-Case Analyses

Networks

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REPOSITORY

External Validity of Average-Case Analyses

Networks

- Wie gut funktionieren die Algorithmen auf den neuen Graphen?
- Wie sehen Graphen mit hoher Heterogenität und geringer Lokalität aus?
- Wie sieht es mit der Heterogenität und Lokalität der Graphen aus?