Beating the Worst Case

Practical Course – 5th Meeting

Jean-Pierre, Marcus

Sheet 2: Recapitulation

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Concepts

- explain the performance of bi-BFS and VC with graph parameters
- degree distribution
- locality

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Task

Determine suitable measures for heterogeneity and locality

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Task

Determine suitable measures for heterogeneity and locality

- can they predict algorithm performance
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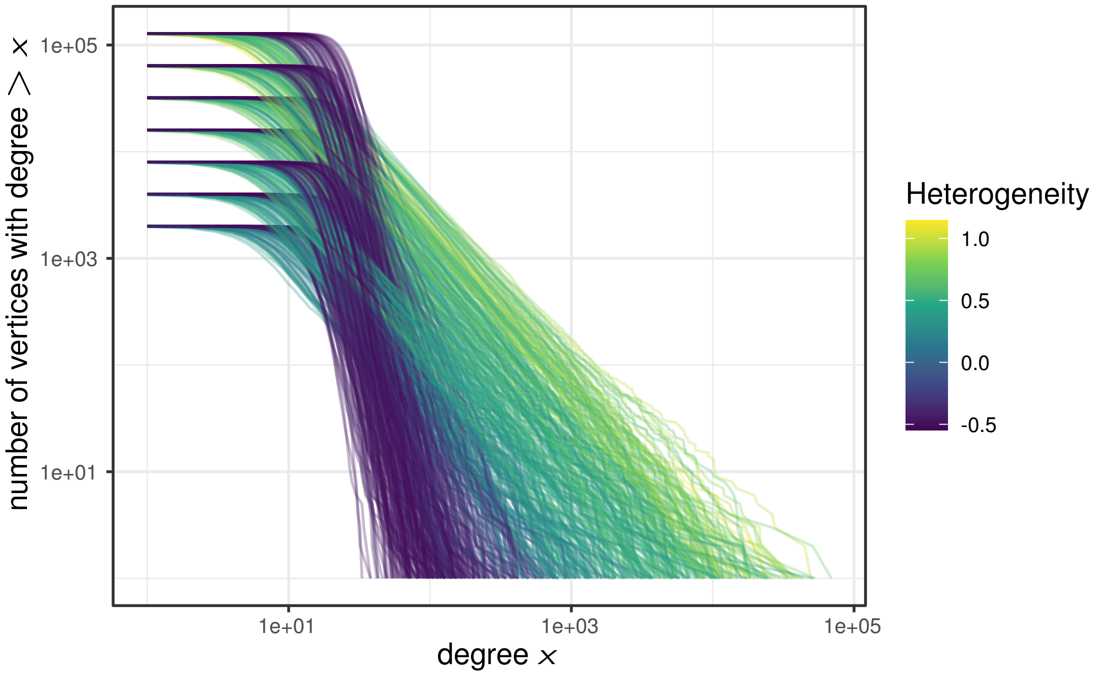
Methods / Tools

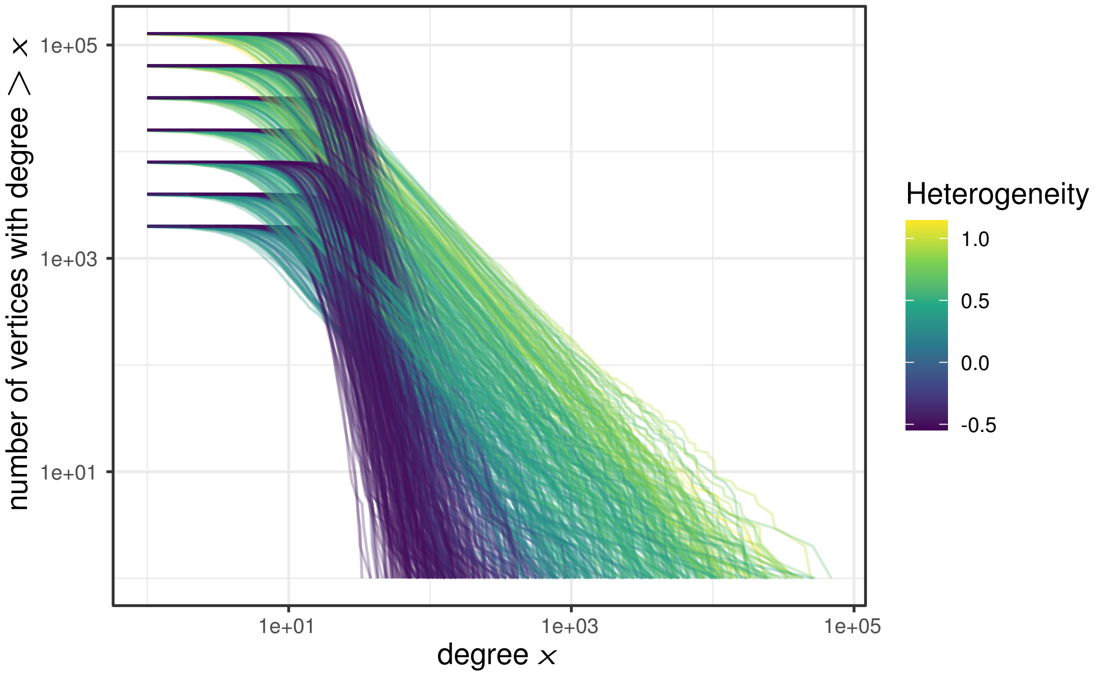
- did you change your experiment setup?
- did you establish a useful pipeline?

Presentations

Heterogeneity

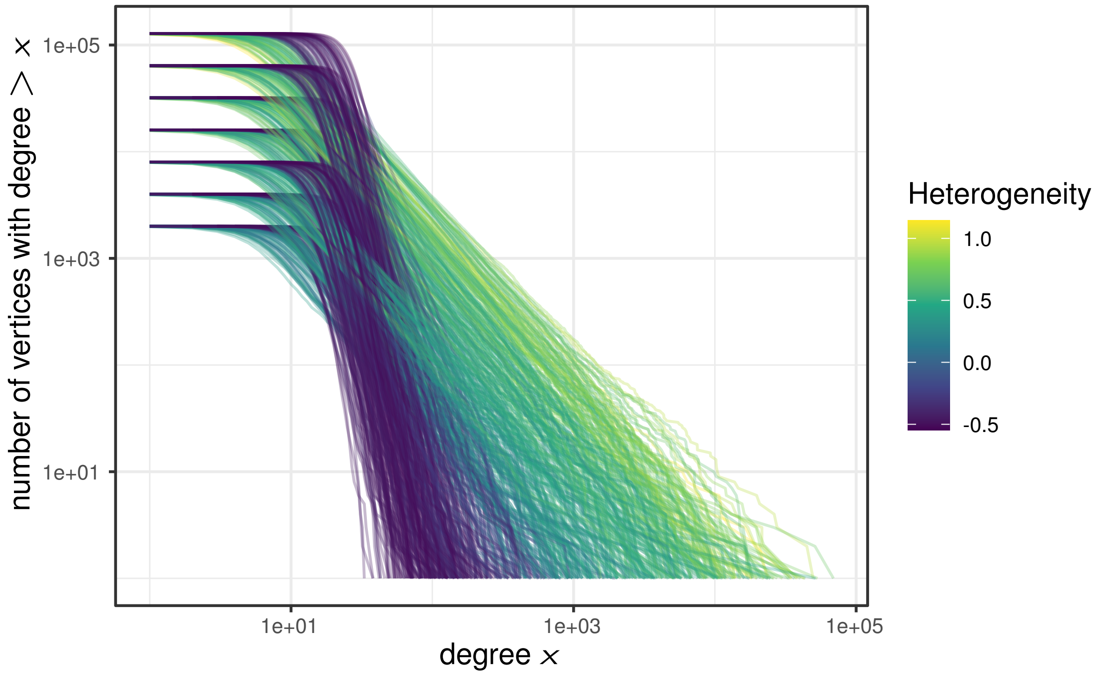


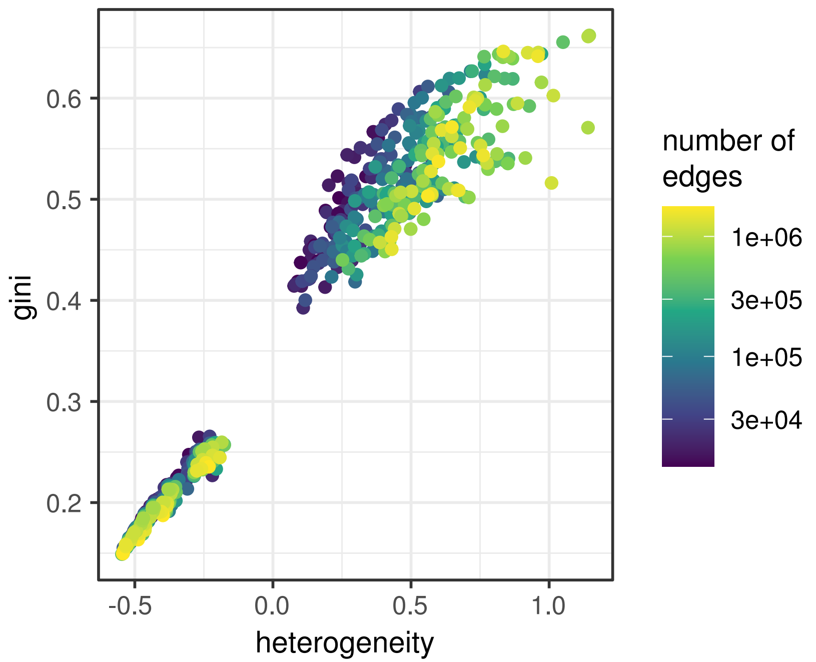
Heterogeneity



- Compute the standard deviation σ average μ of the degree distribution
- Coefficient of Variation: $\frac{\sigma}{\mu}$
- Heterogeneity: $\log(\frac{\sigma}{\mu})$

Heterogeneity

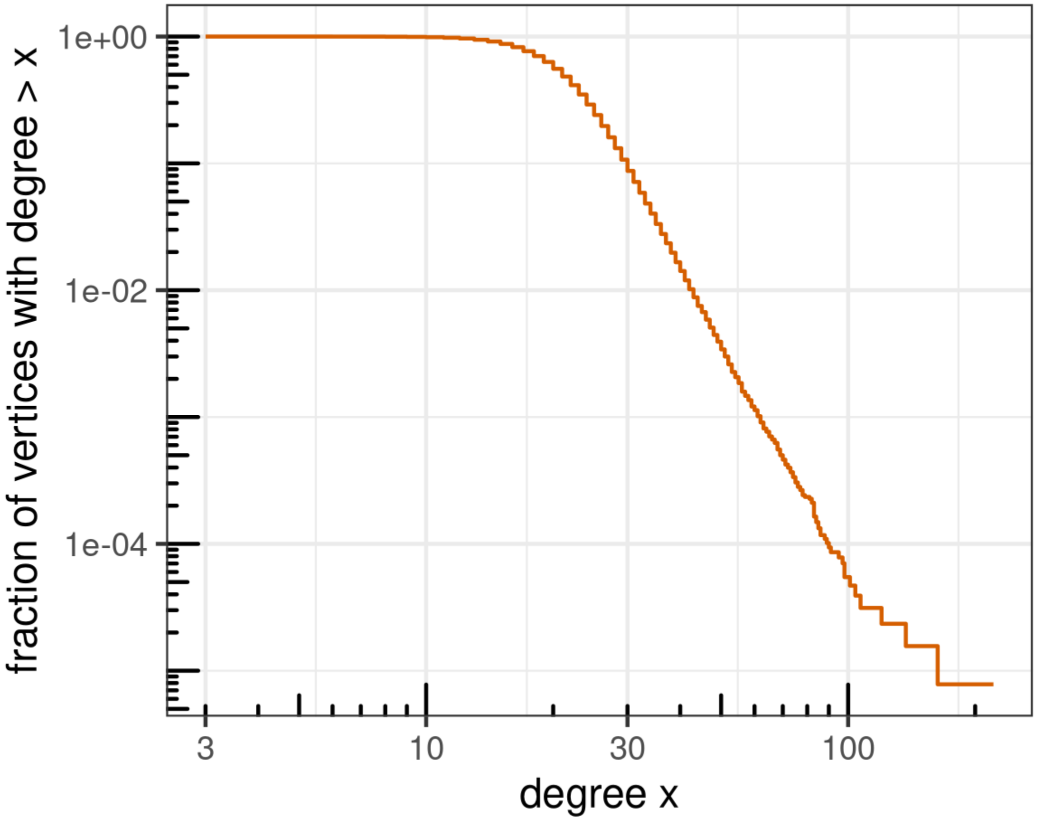




- Compute the standard deviation σ average μ of the degree distribution
- Coefficient of Variation: $\frac{\sigma}{\mu}$
- Heterogeneity: $\log(\frac{\sigma}{\mu})$

- strong correlation with gini coefficent
- slight dependence on graph size

Why is the CCDF Flat?



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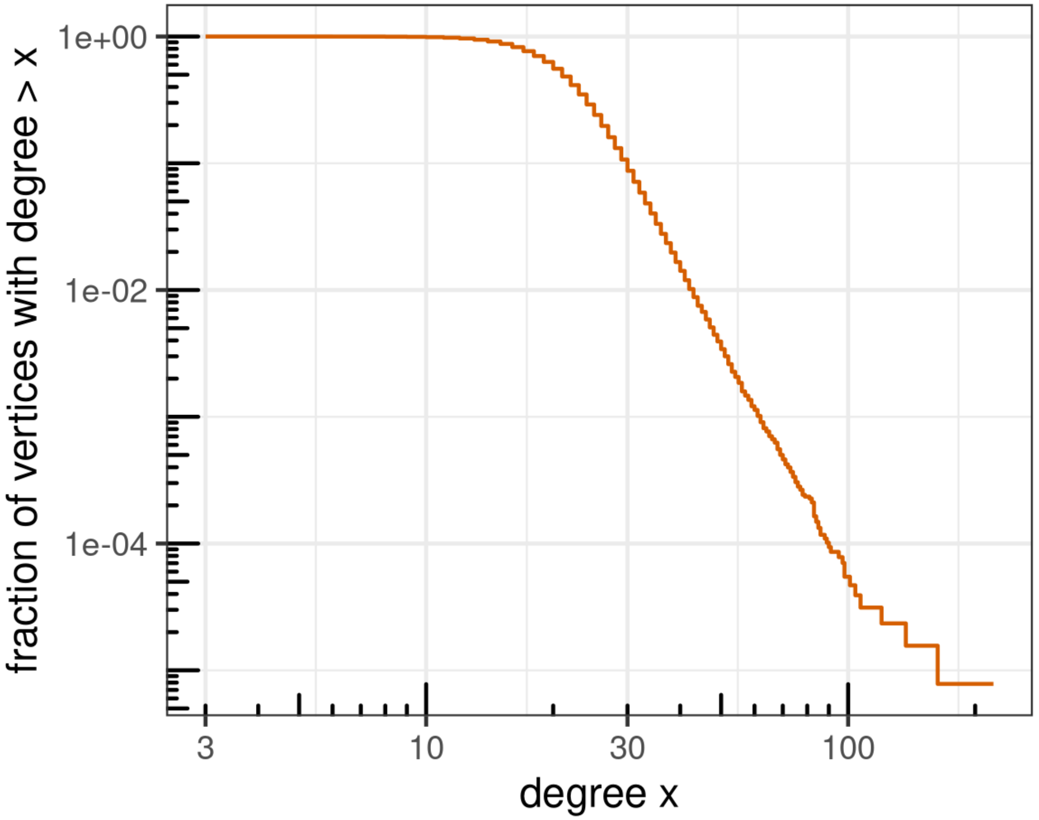
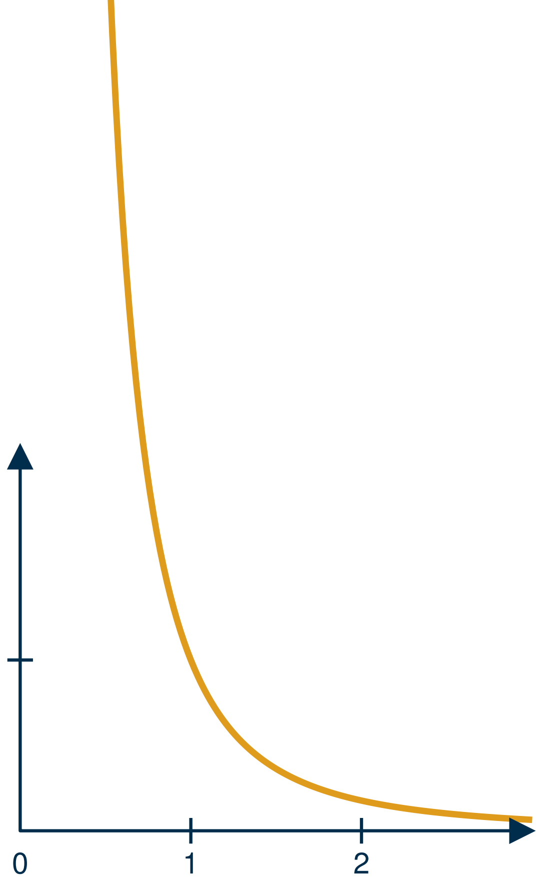


Power-Law Distribution

- $f(x) = cx^{-\tau}$



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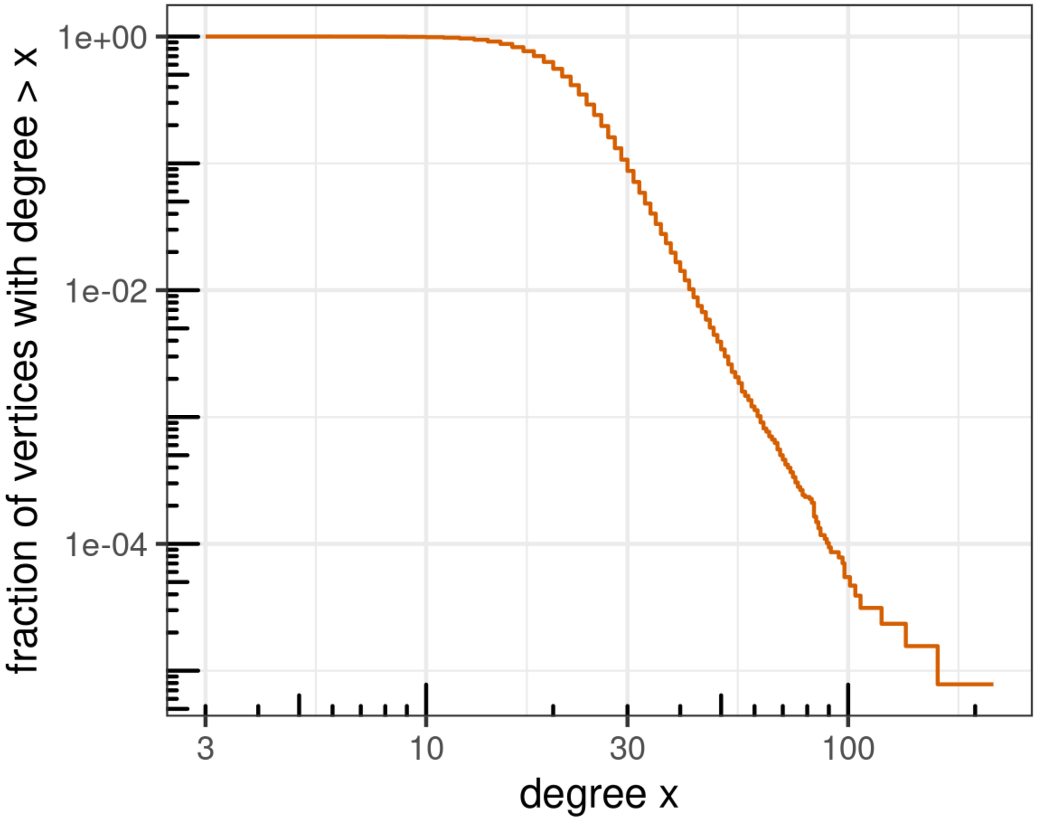

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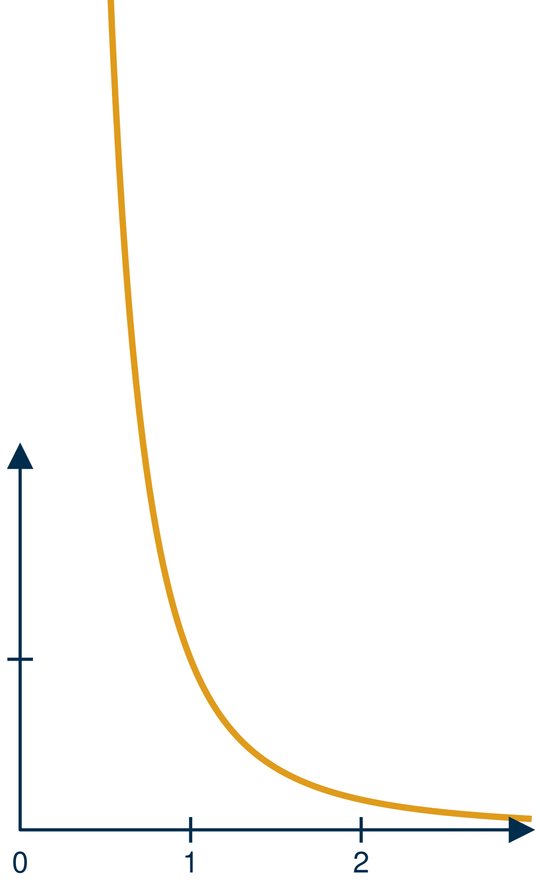

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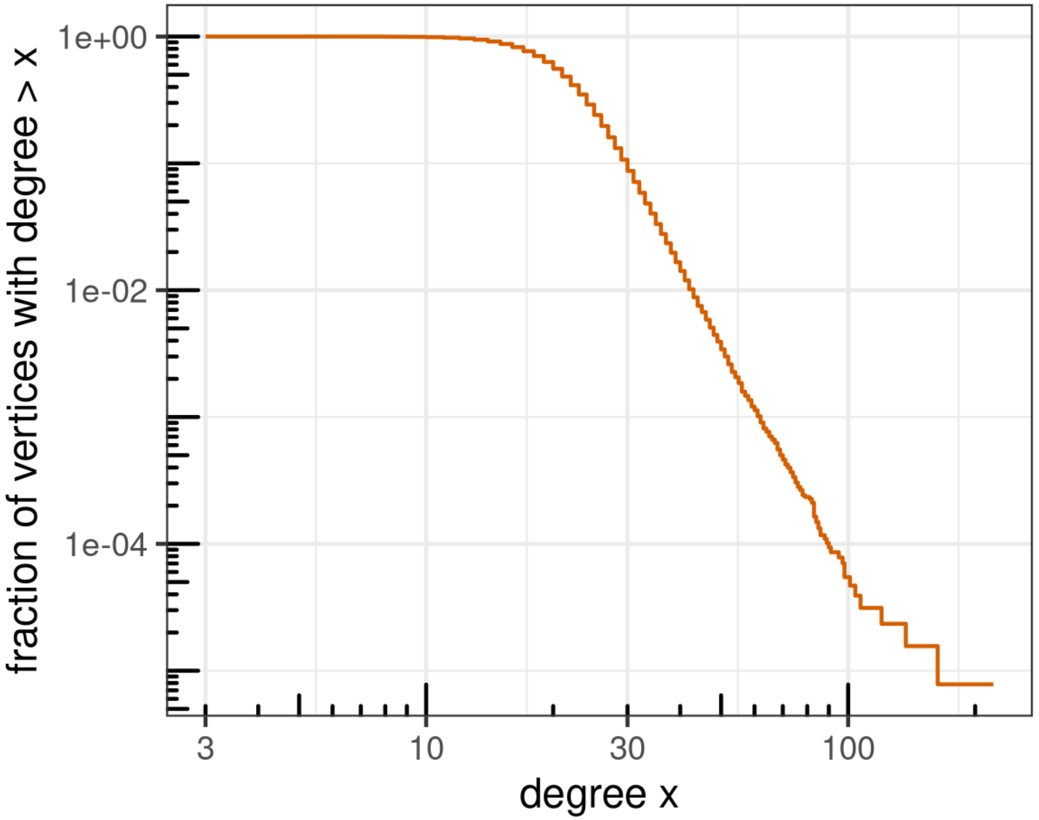
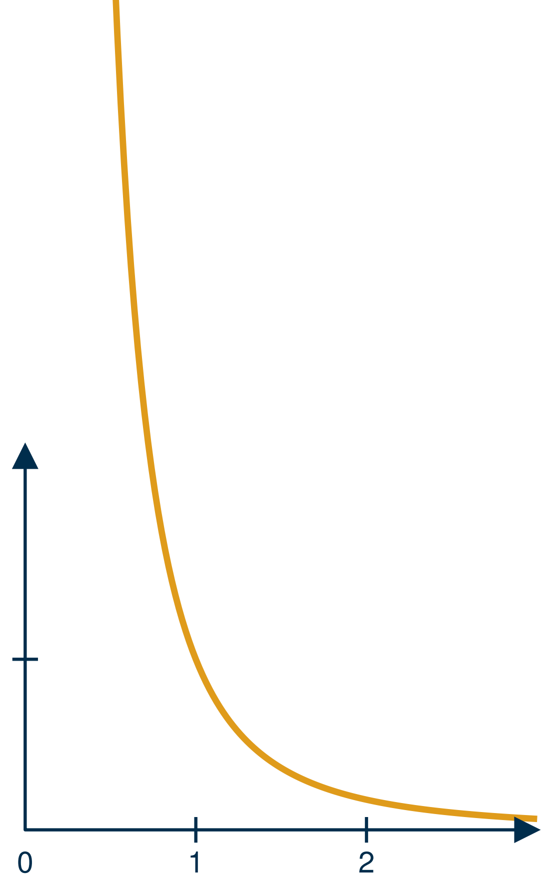
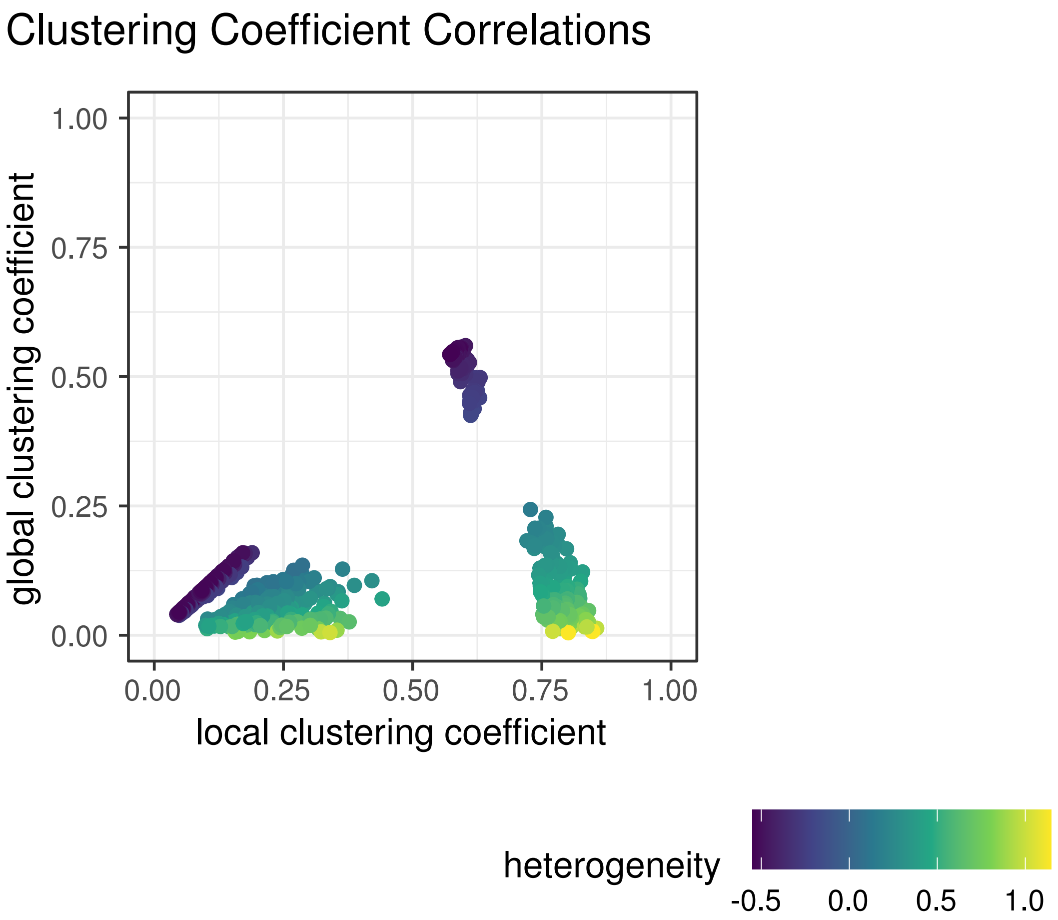


Power-Law Distribution

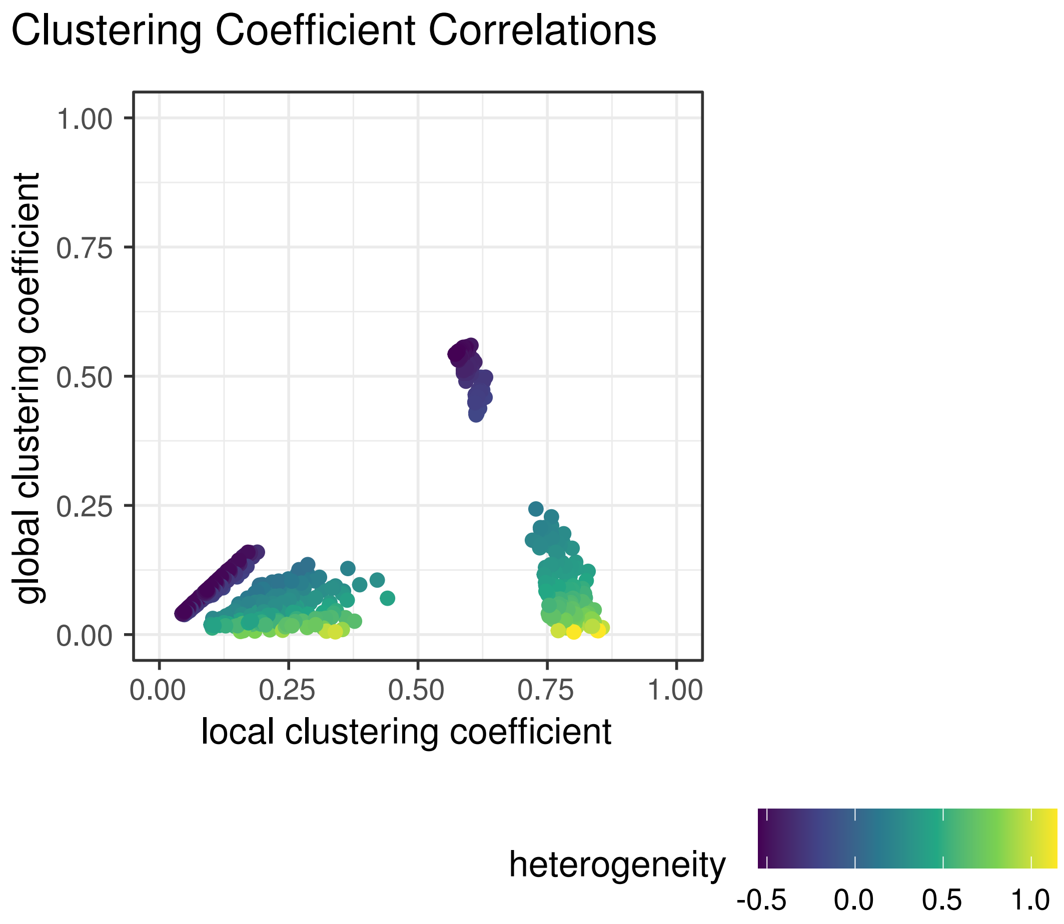
- $f(x) = cx^{-\tau}$
- needs $x_{\min}$ to be well defined, otherwise probability goes towards infinity
- Distribution follows a power law: it follows $f(x)$ for $x > x_{\min}$
  - $x \leq x_{\min}$ are irelevant



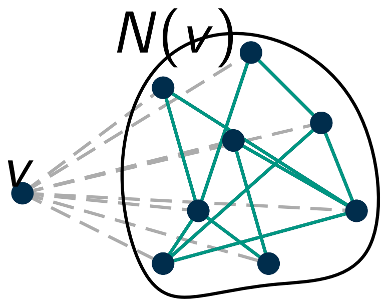
Locality


Clustering Coefficient Correlations
global clustering coefficient
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
local clustering coefficient
heterogeneity
-0.5
0.0
0.5
1.0

Locality

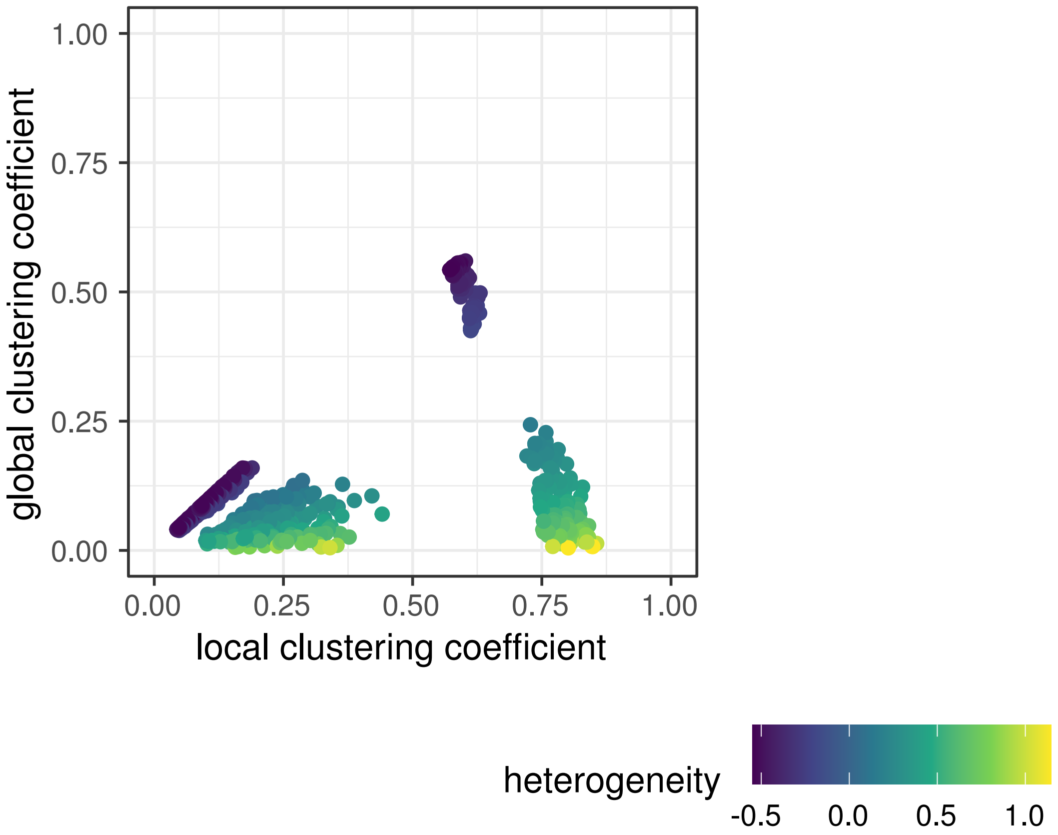


Local Clustering Coefficient



Locality

Clustering Coefficient Correlations



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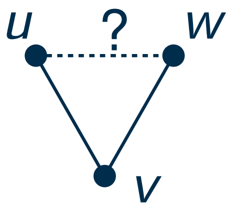
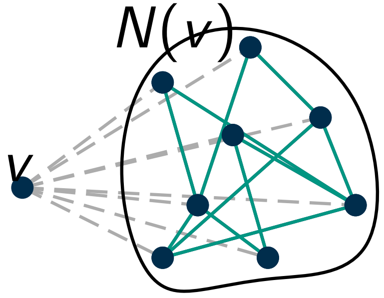
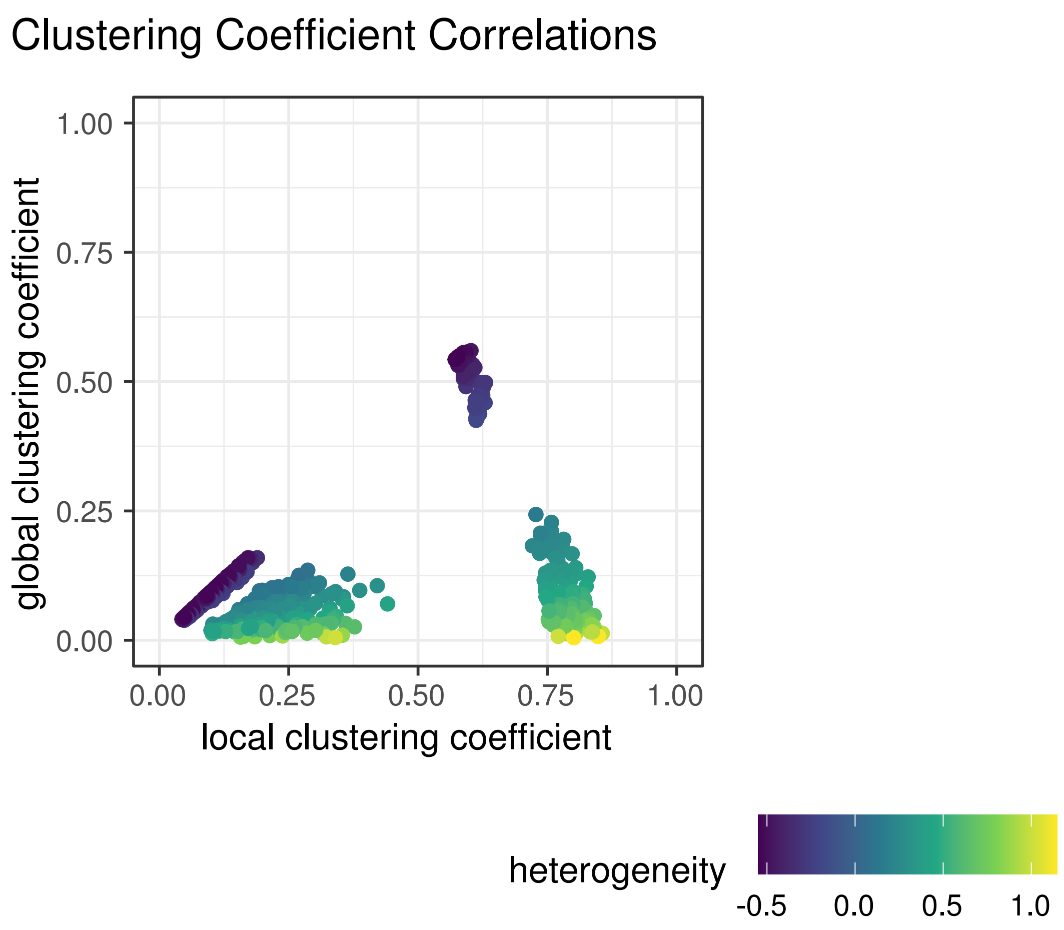




Global Clustering Coefficient

Locality



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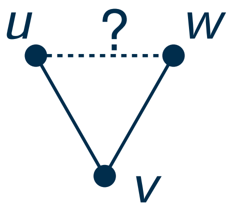
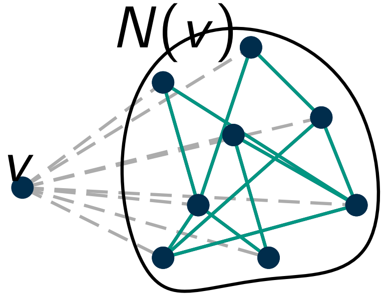


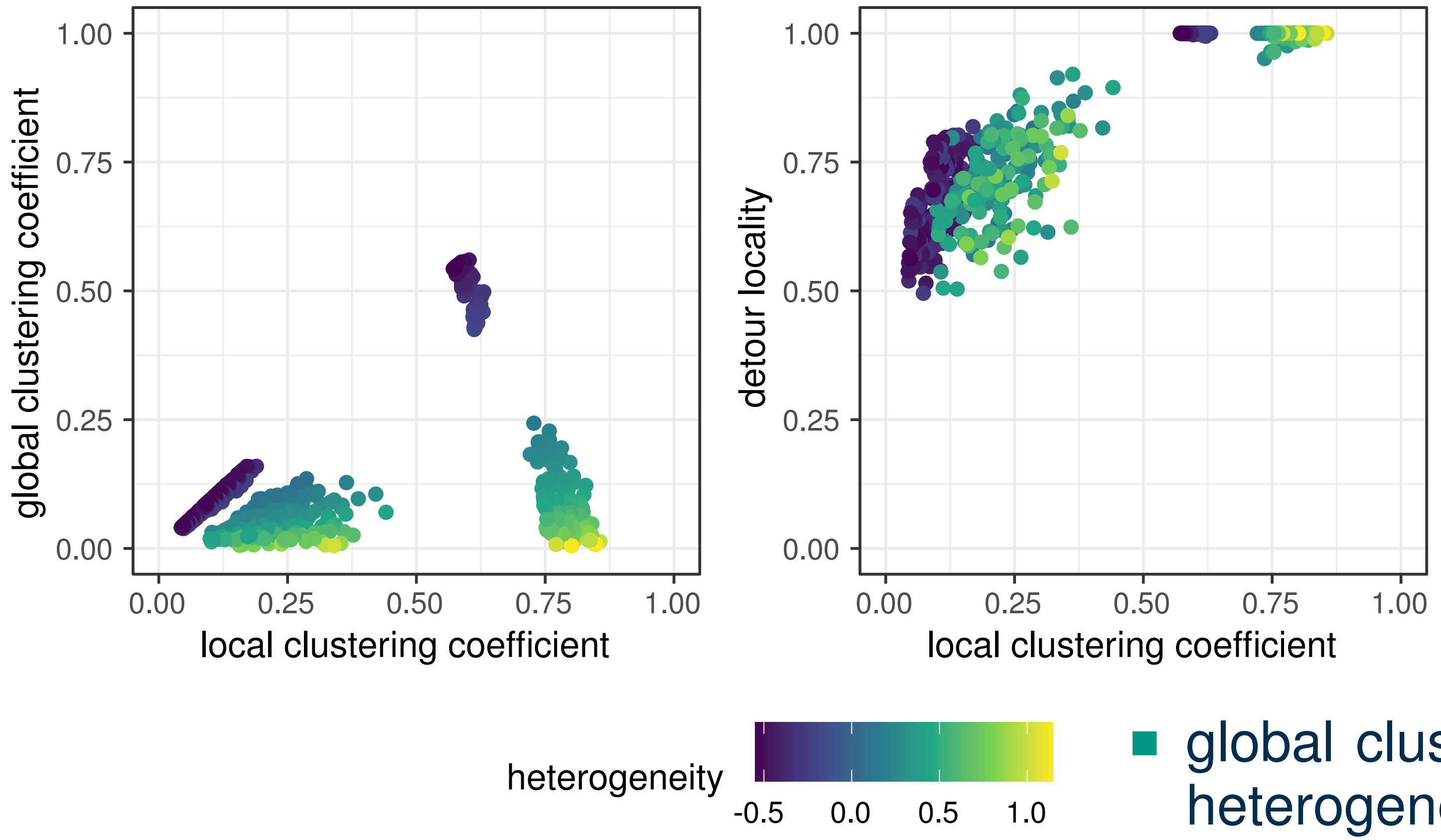


Global Clustering Coefficient

- global clustering coefficent does not work on heterogeneous graphs

Locality

Clustering Coefficient Correlations



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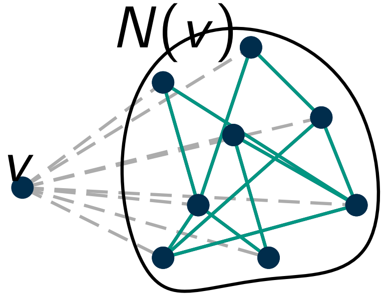
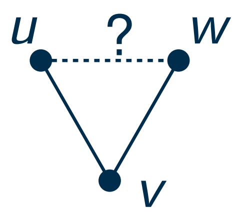
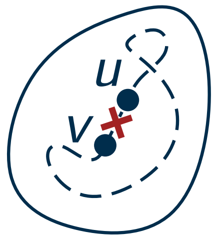




Global Clustering Coefficient

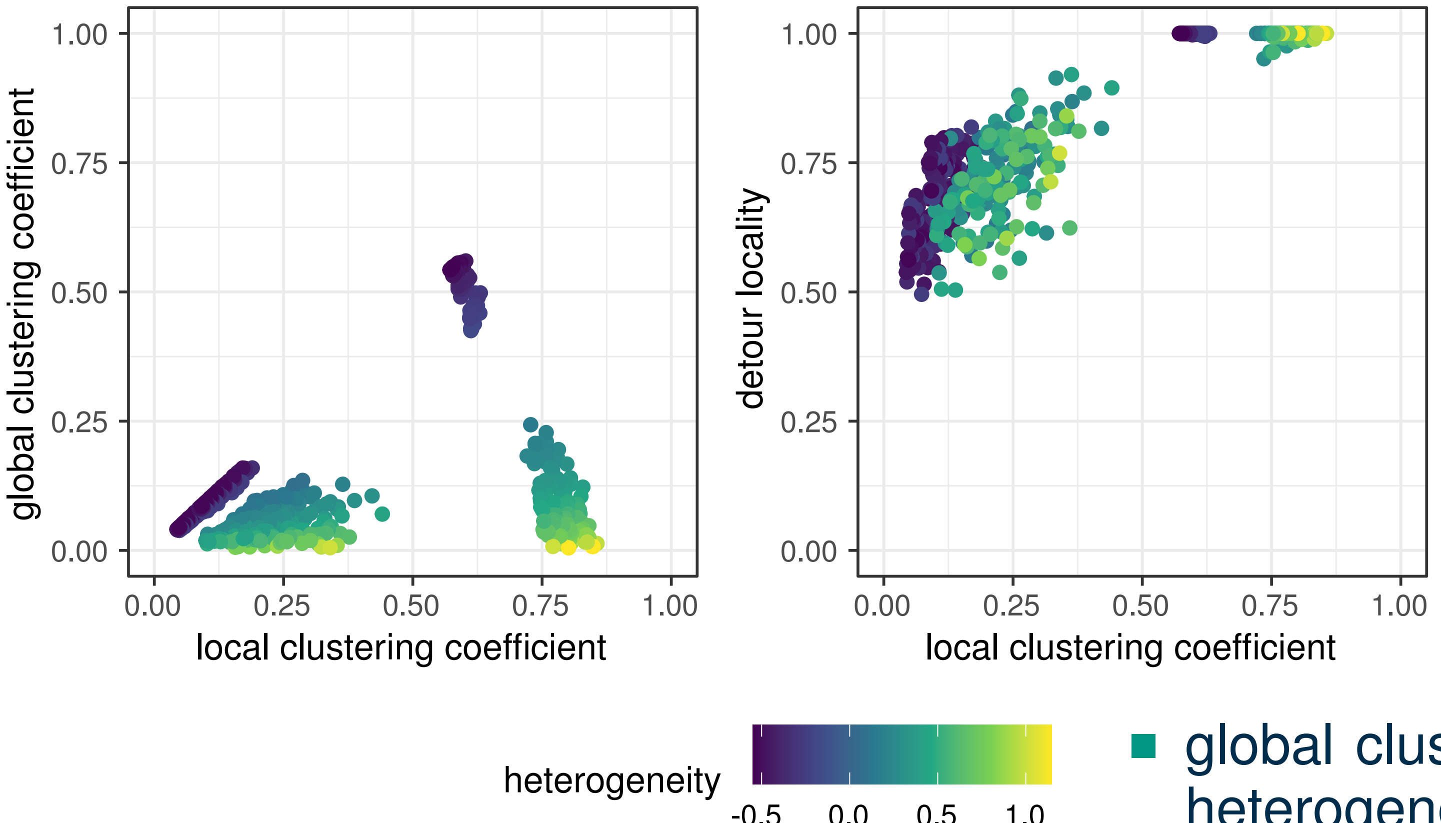
Detour Locality



- global clustering coefficent does not work on heterogeneous graphs

Locality

Clustering Coefficient Correlations



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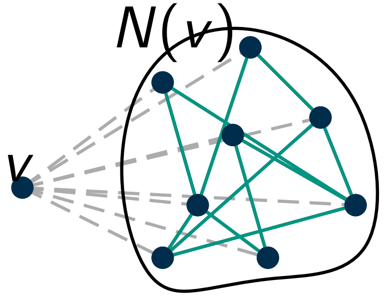

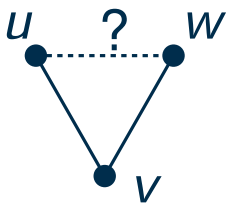

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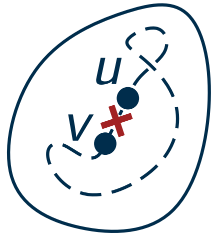
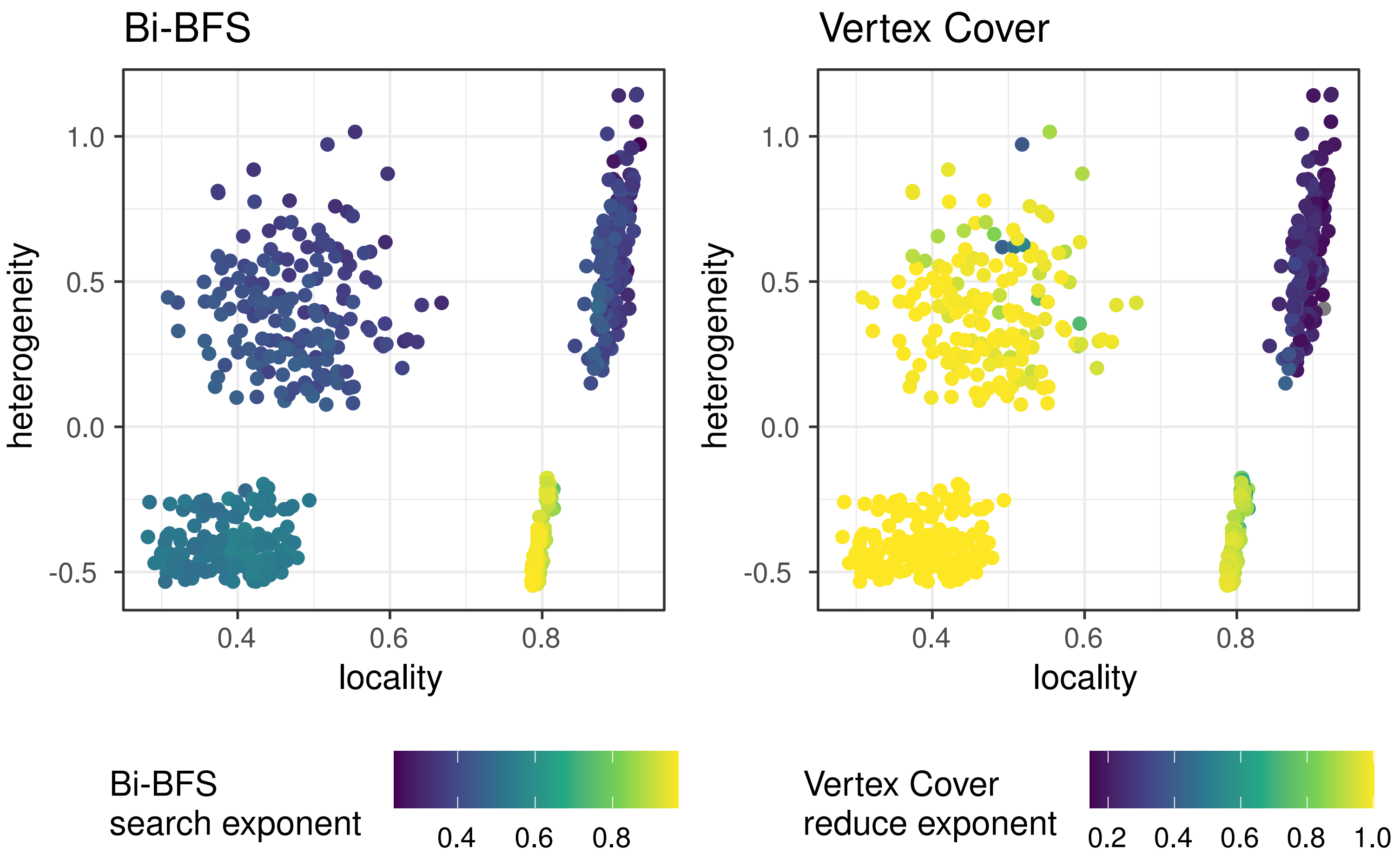
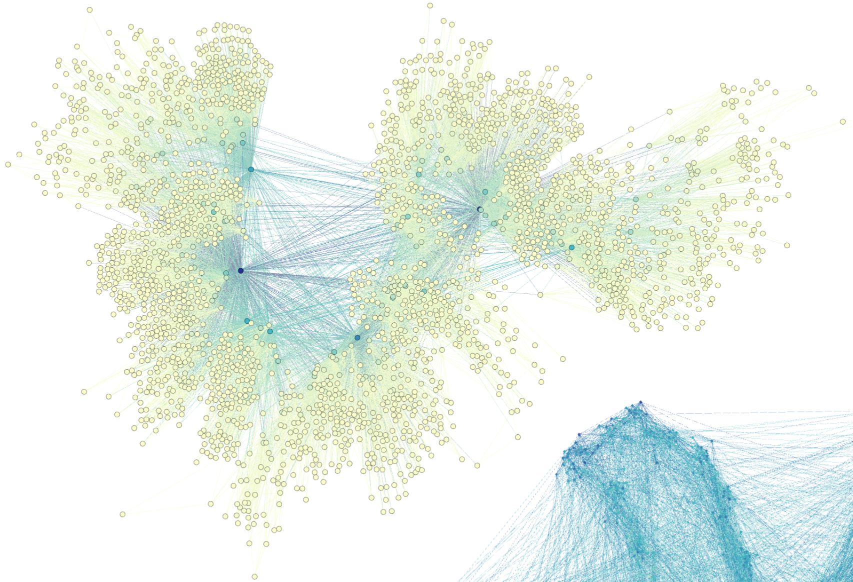


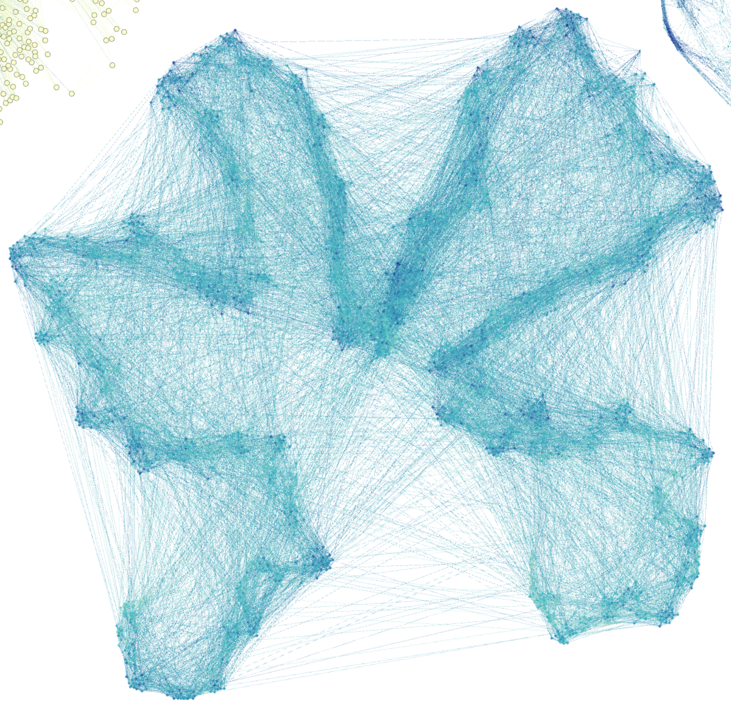
- global clustering coefficent does not work on heterogeneous graphs
- Locality $= \frac{1}{2}(\text{local} + \text{detour})$

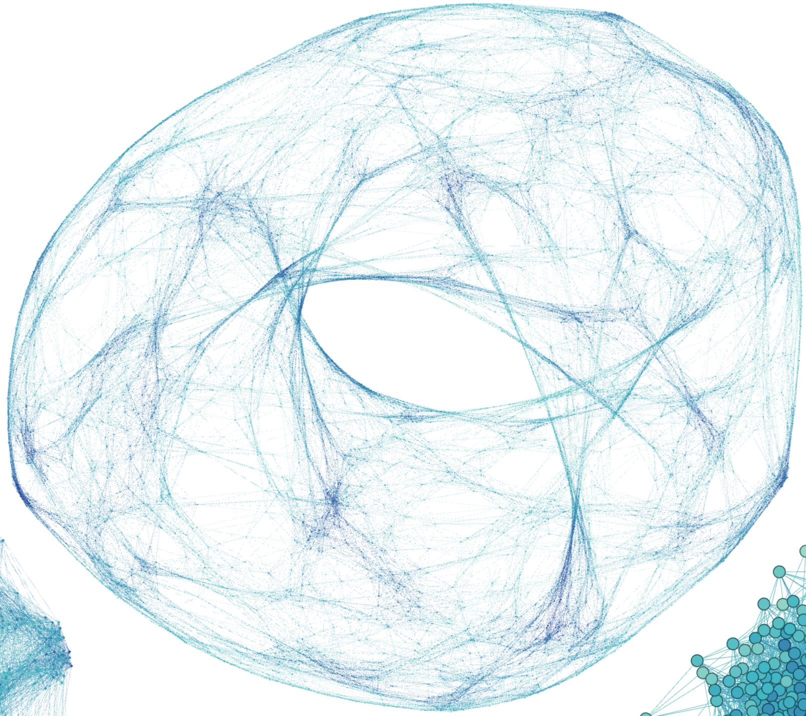
Heterogeneity + Locality

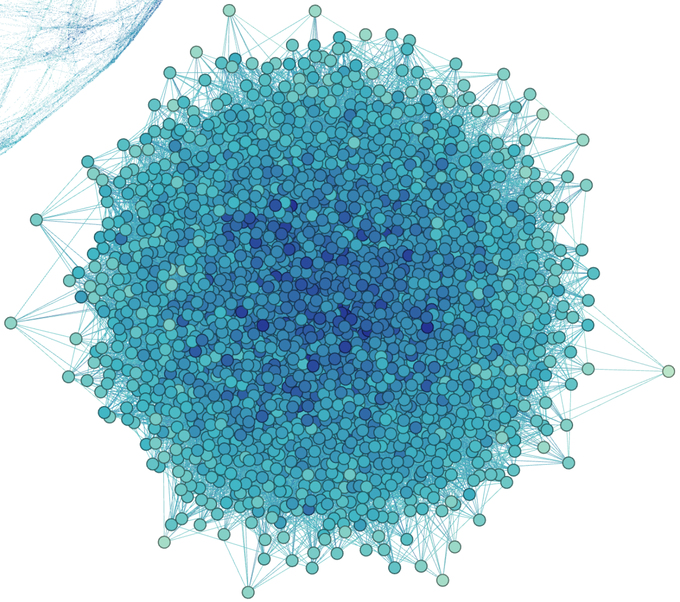


Network Science



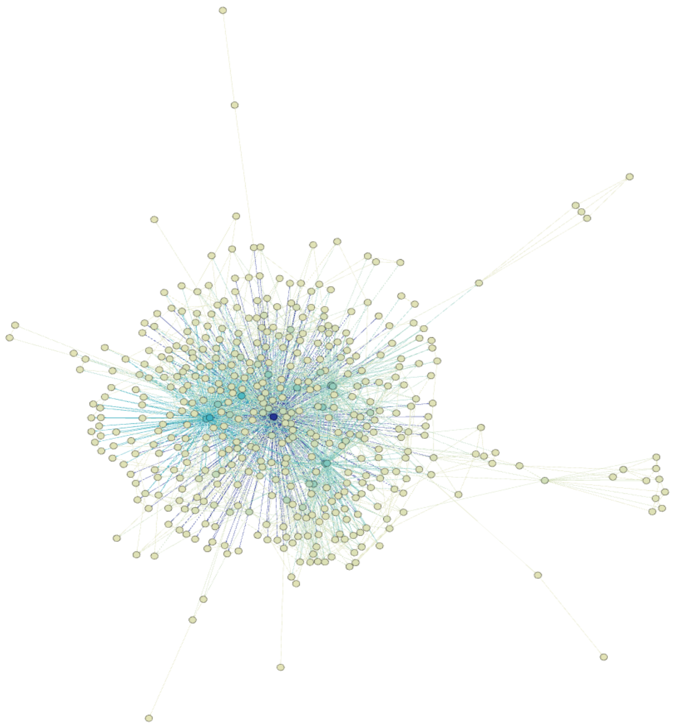






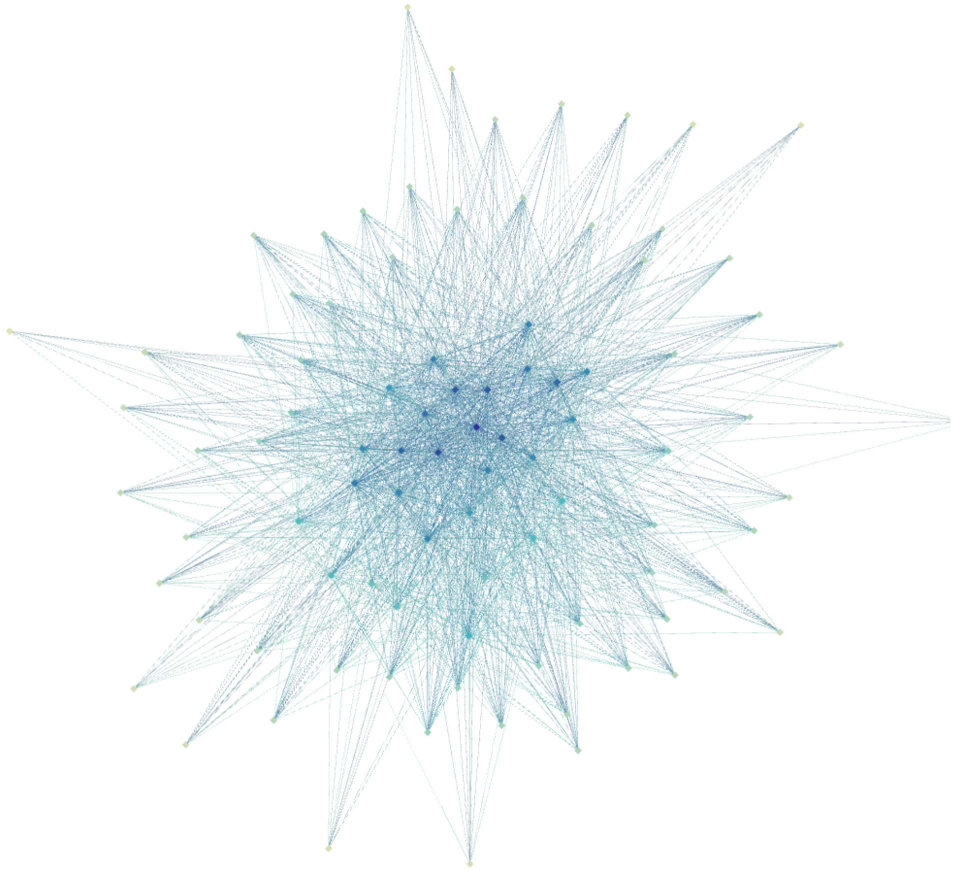
Examples for Real-World Networks

- `bio-celegans`



Examples for Real-World Networks

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



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Examples for Real-World Networks

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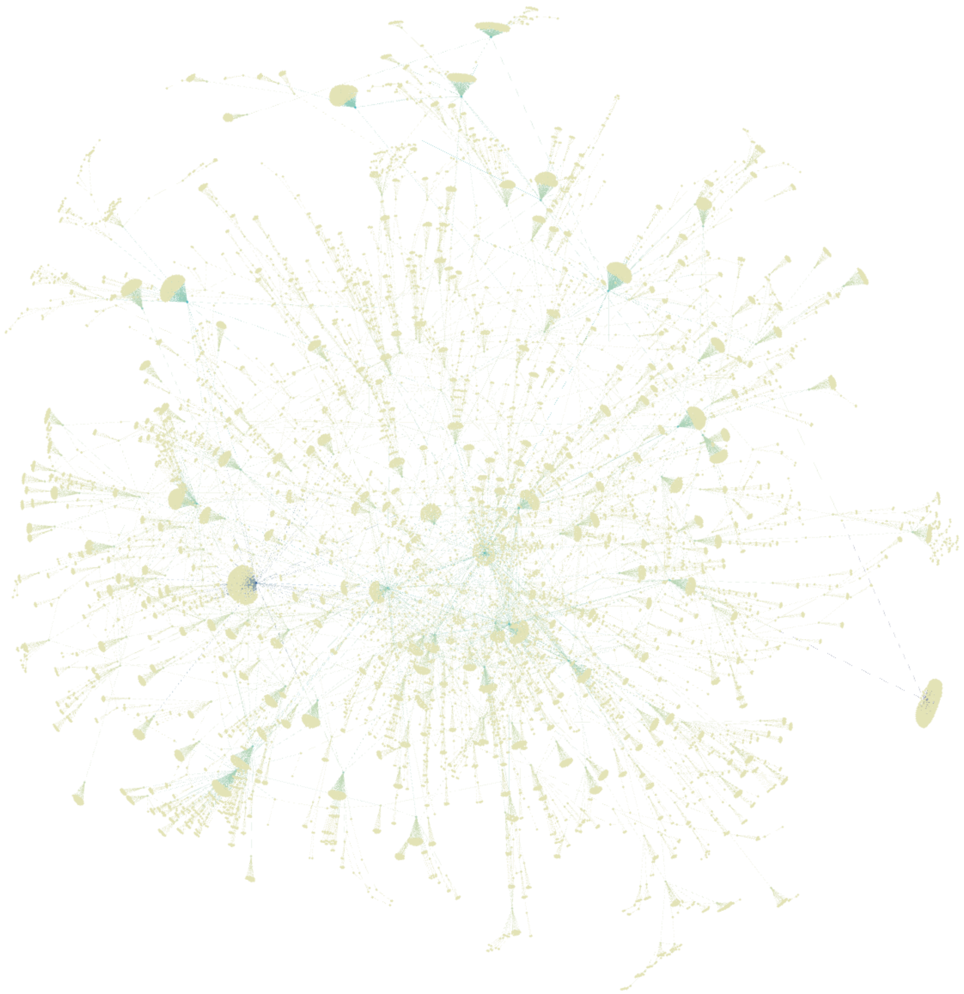
- `econ-poli-large`



Examples for Real-World Networks

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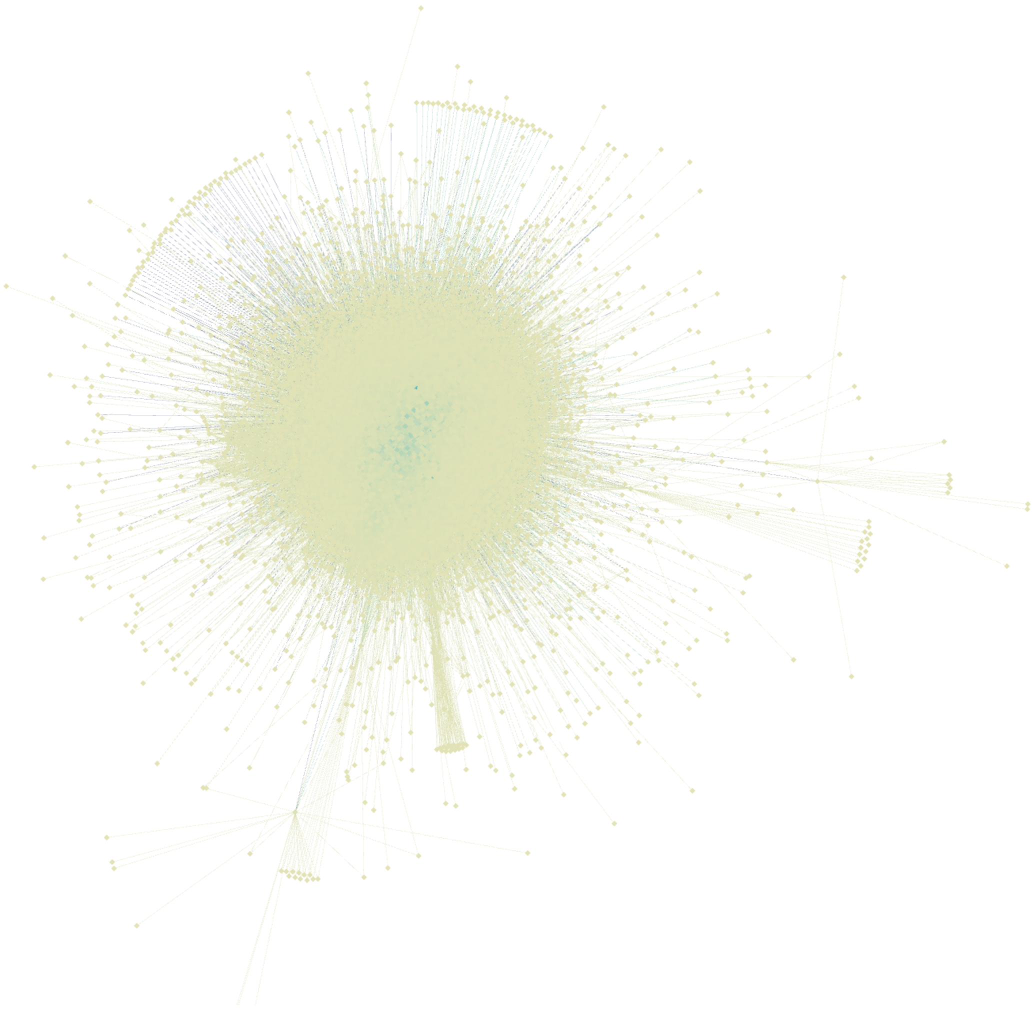
- opsahl-powergrid
- econ-poli-large
- bio-grid-yeast



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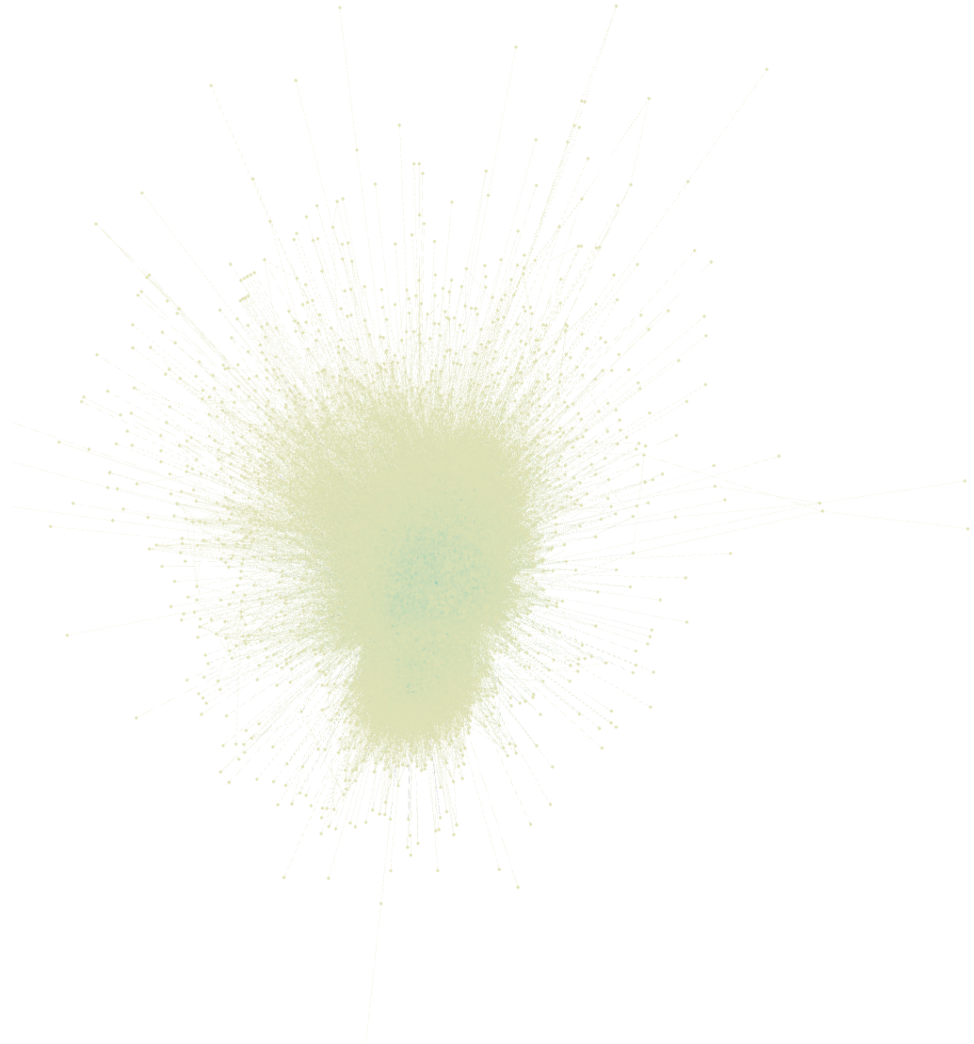
- socfb-Yale4



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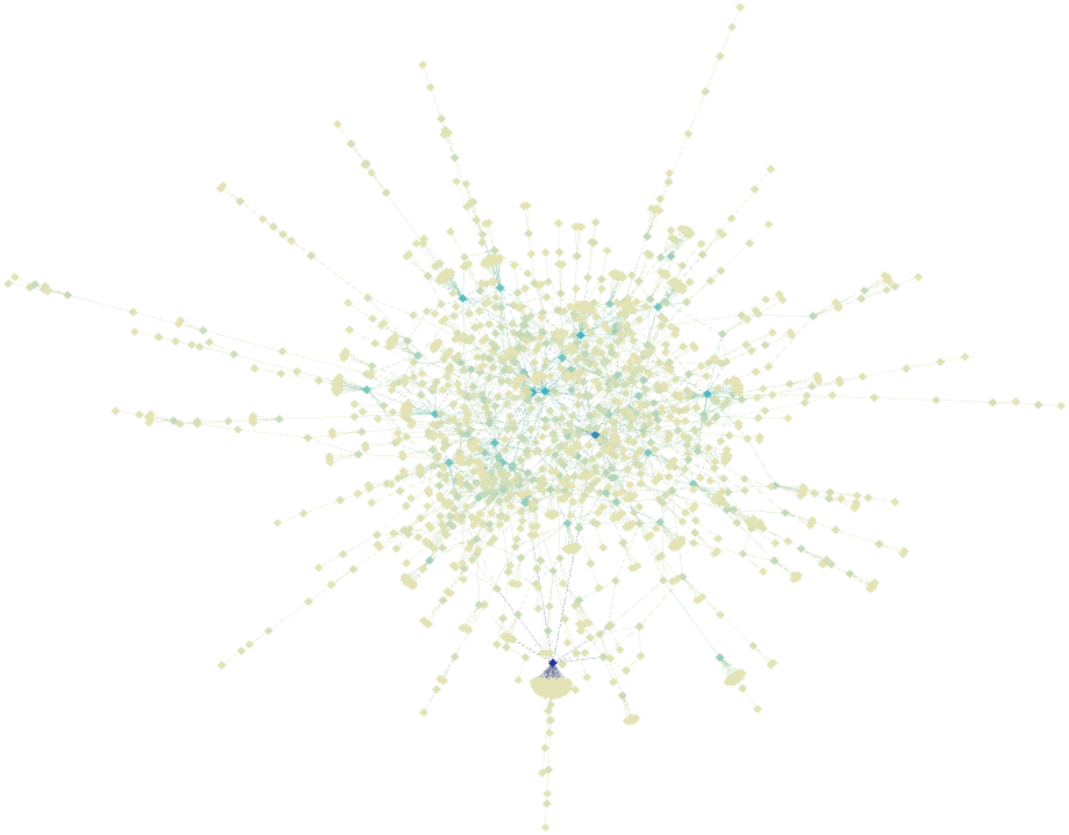
- `socfb-Yale4`
- `bio-yeast-protein-inter`



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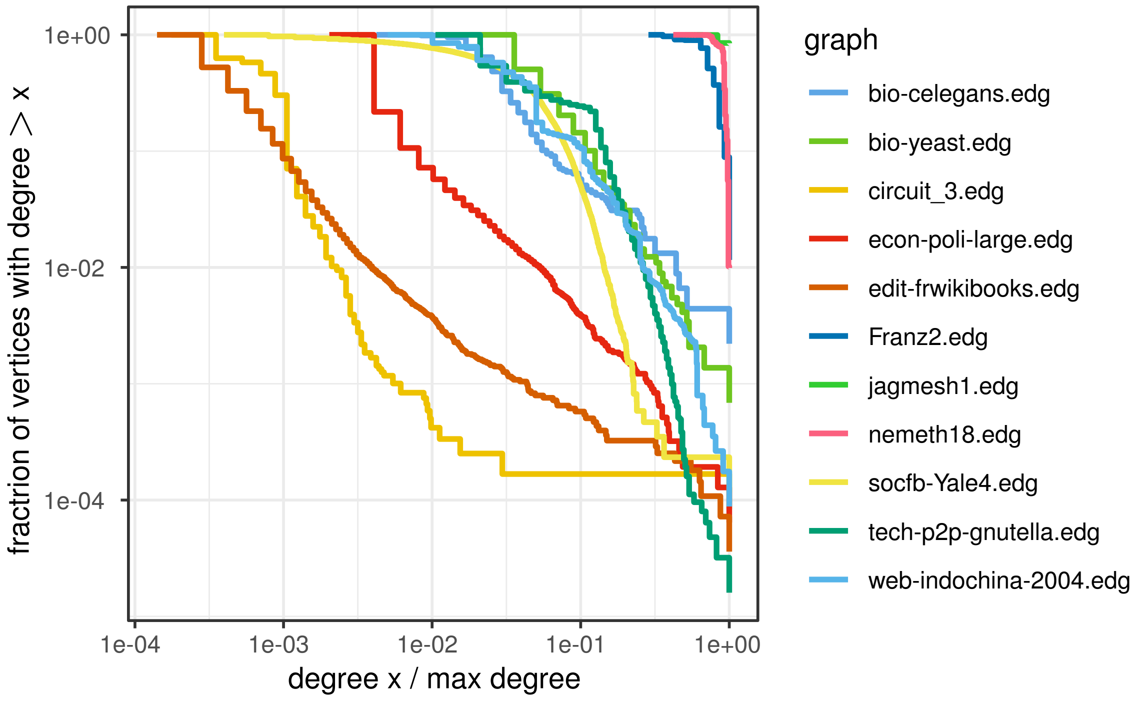

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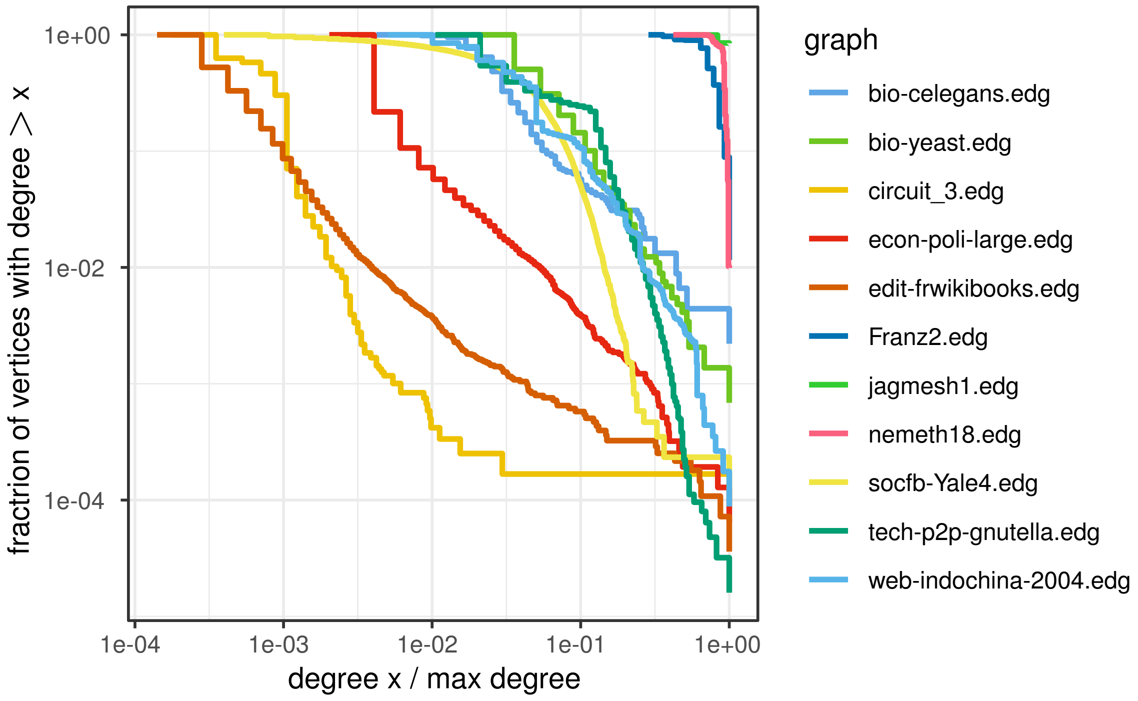

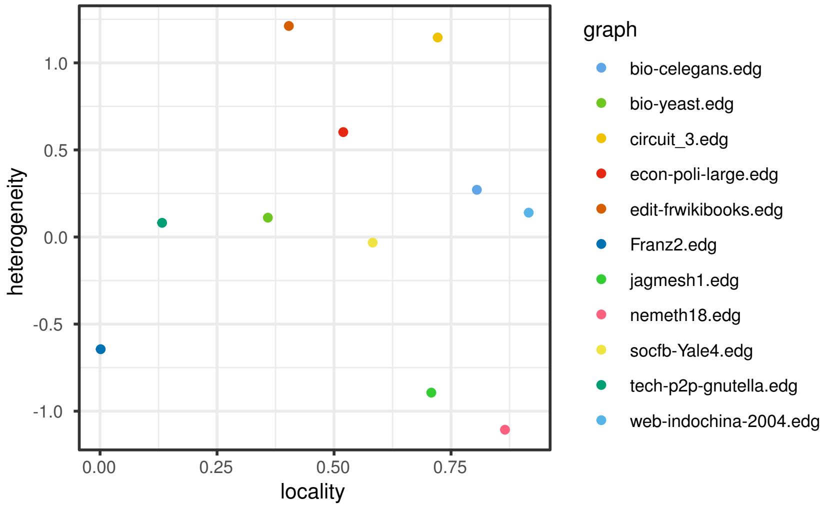

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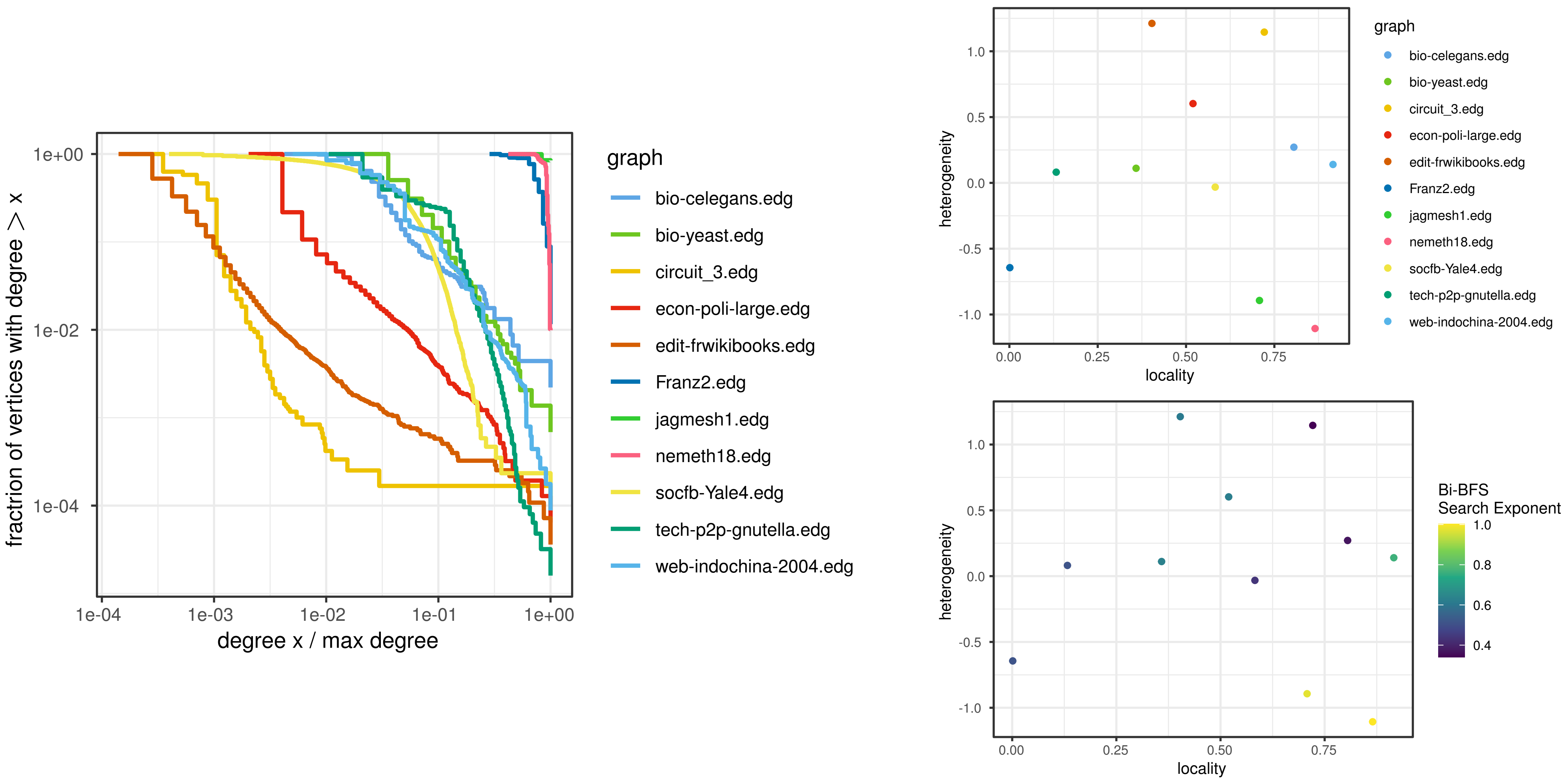

Complex Networks

Keyword: complex network, scale-free network

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Three Characteristics:

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- heterogeneous degree distribution

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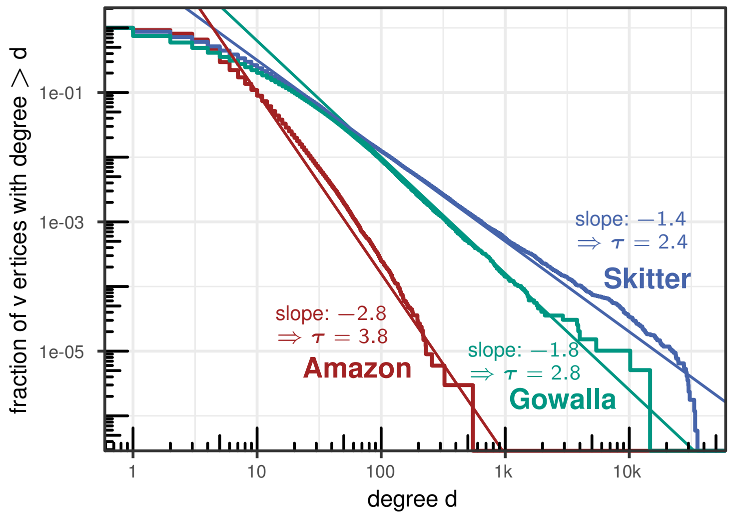

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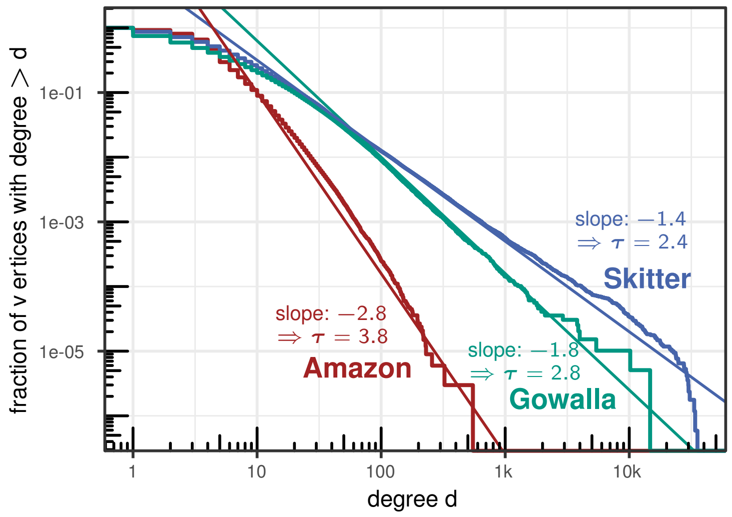
Keyword: complex network, scale-free network

Three Characteristics:

- heterogeneous degree distribution
- short distances / „small-world“



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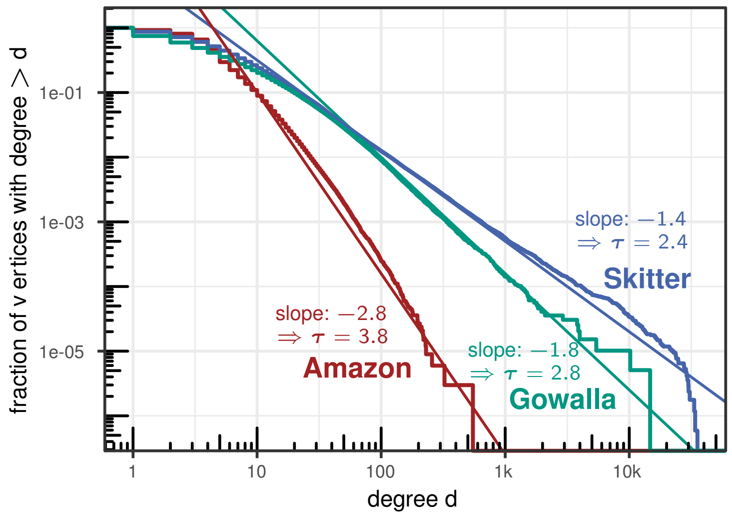

six-degrees of . . .

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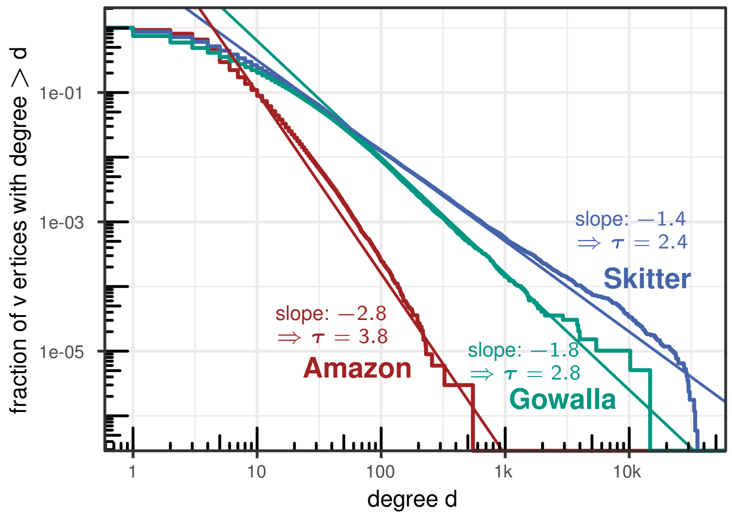

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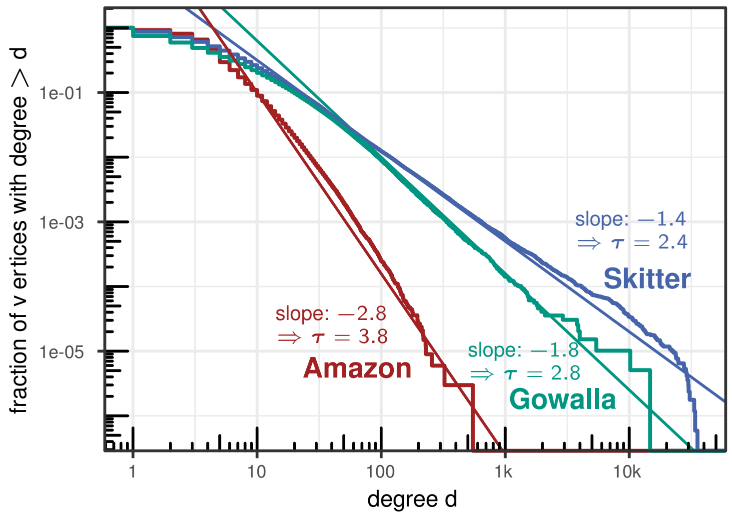

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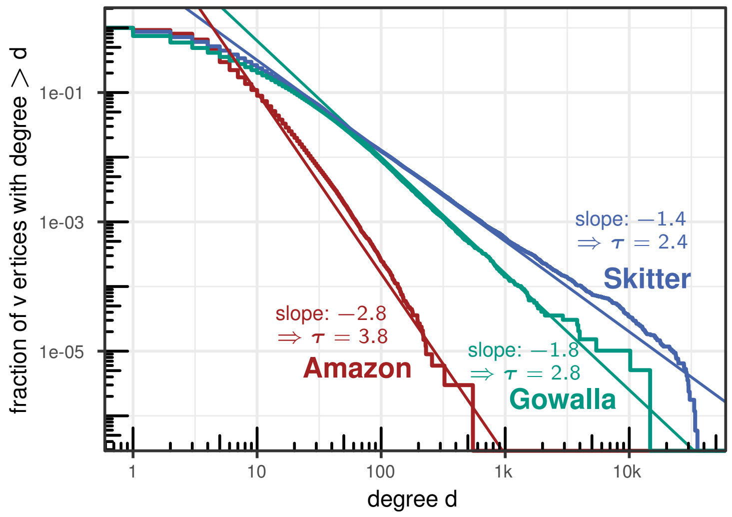

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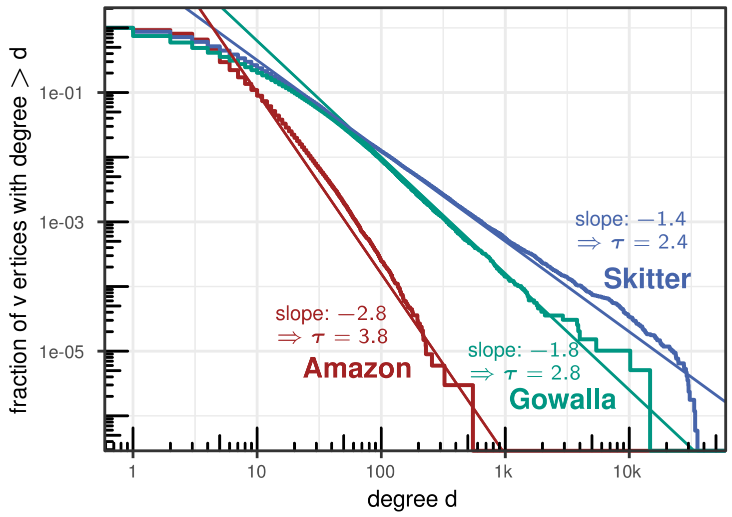

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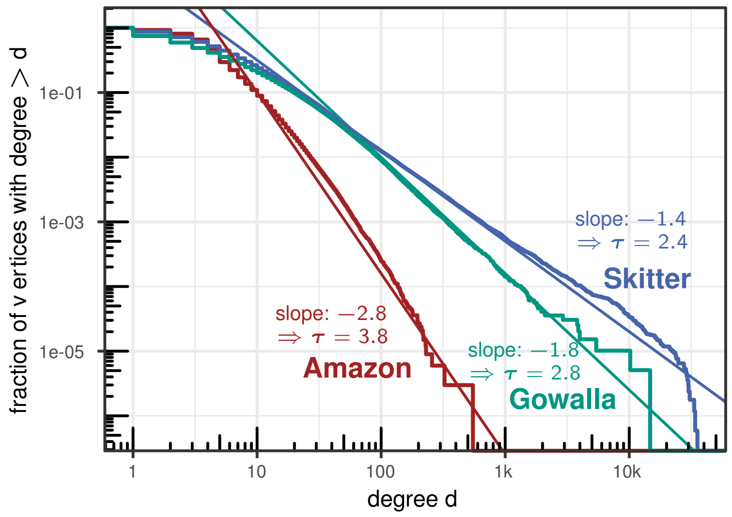

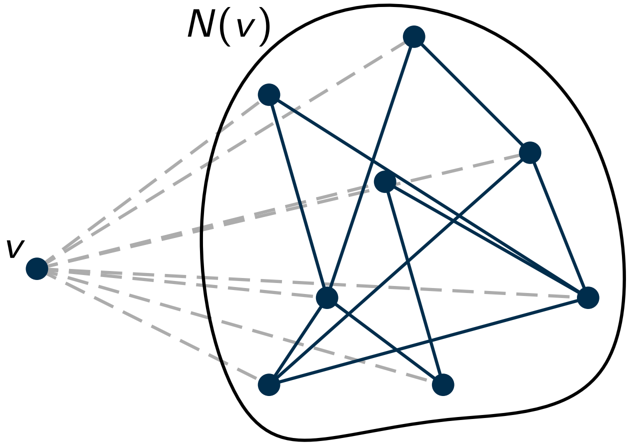

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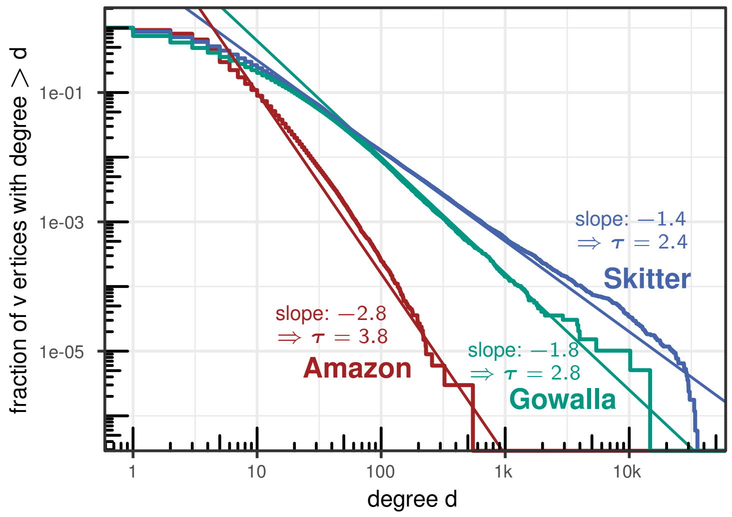
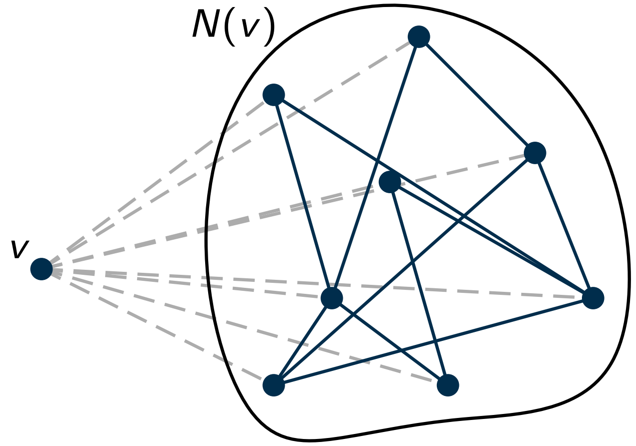
goal: explain / model





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Models for Complex Networks

Goal: model and explain characteristics

Three characteristics:

1959 1923 / 1999 2002 1998 2010 2019

- heterogeneous degrees
- short distances / „small-world“
- high locality / clustering

Models for Complex Networks

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1959

1923 / 1999

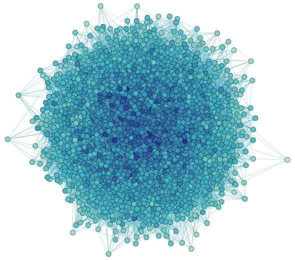
2002

1998

2010

2019

Erdős–Rényi model



Models for Complex Networks

Goal: model and explain characteristics

Three characteristics:	ER 1959	1923 / 1999	2002	1998	2010	2019
■ heterogeneous degrees						
■ short distances / „small-world“	✓					
■ high locality / clustering						

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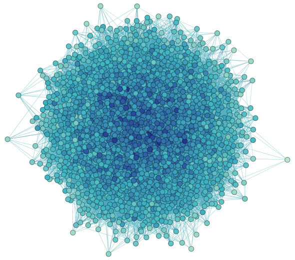

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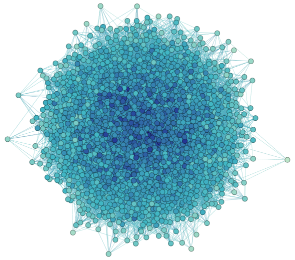

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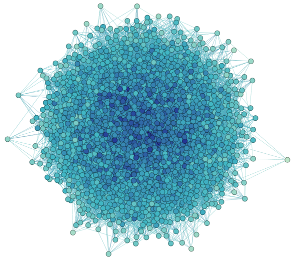
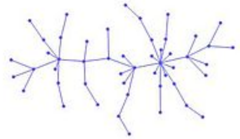
■ high locality / clustering						

Erdős–Rényi model



Preferential Attachment

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

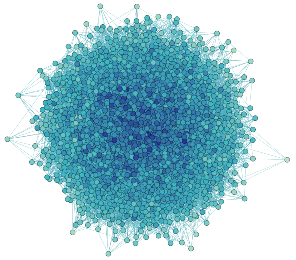


Models for Complex Networks

Goal: model and explain characteristics

Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	2002	1998	2010	2019
heterogeneous degrees		✓				
short distances / „small-world“	✓	✓				
high locality / clustering						

Erdős–Rényi model



Preferential Attachment

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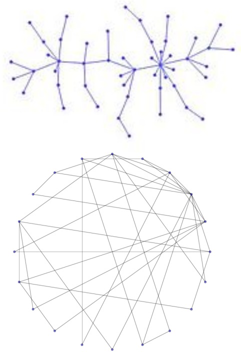
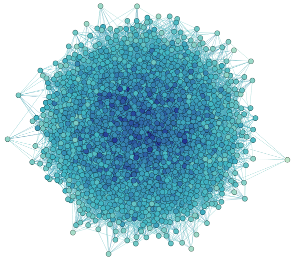


Models for Complex Networks

Goal: model and explain characteristics

Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	1998	2010	2019
▪ heterogeneous degrees		✓				
▪ short distances / „small-world“	✓	✓				
▪ high locality / clustering						

Erdős–Rényi model



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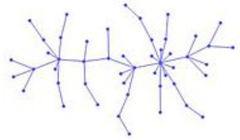
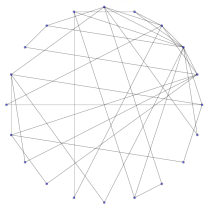


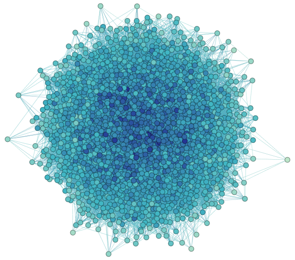


Models for Complex Networks

Goal: model and explain characteristics

Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	1998	2010	2019
heterogeneous degrees		✓				
short distances / „small-world“	✓	✓				
high locality / clustering						

Erdős–Rényi model



Preferential Attachment

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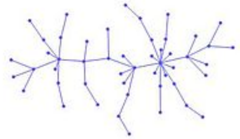
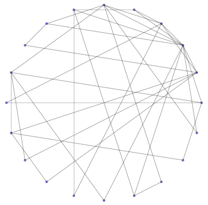




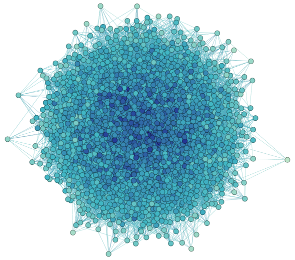
Chung-Lu / Configuration model

Models for Complex Networks

Goal: model and explain characteristics

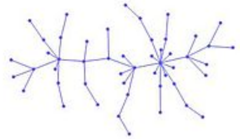
Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	1998	2010	2019
heterogeneous degrees		✓				
short distances / „small-world“	✓	✓				
high locality / clustering						

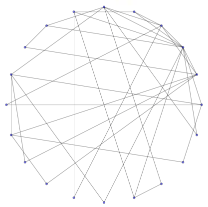
Erdős–Rényi model



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);

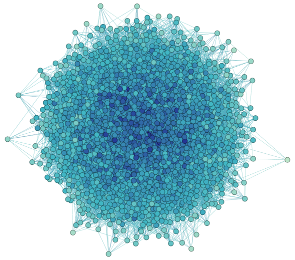
$\Pr\left[\{e_i, e_j\} \in E\right] \sim \frac{w_i \cdot w_j}{W}$

Models for Complex Networks

Goal: model and explain characteristics

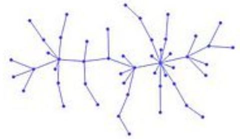
Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	1998	2010	2019
heterogeneous degrees		✓	✓			
short distances / „small-world“	✓	✓	✓			
high locality / clustering						

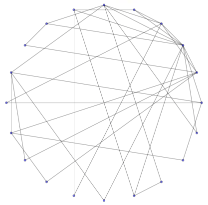
Erdős–Rényi model



Preferential Attachment

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





Chung-Lu / Configuration model

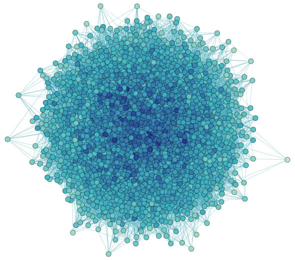
vertices with weights w_i (following power-law distribution);
$\Pr\left[\{e_i, e_j\} \in E\right] \sim \frac{w_i \cdot w_j}{W}$

Models for Complex Networks

Goal: model and explain characteristics

Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	2010	2019
■ heterogeneous degrees		✓	✓			
■ short distances / „small-world“	✓	✓	✓			
■ high locality / clustering						

Erdős–Rényi model



Preferential Attachment

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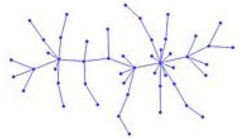

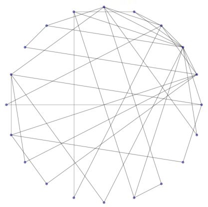

Chung-Lu / Configuration model

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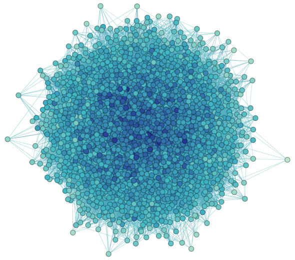
$\Pr\left[\{e_i, e_j\} \in E\right] \sim \frac{w_i \cdot w_j}{W}$

Models for Complex Networks

Goal: model and explain characteristics

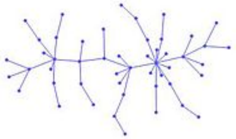
Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	2010	2019
heterogeneous degrees		✓	✓			
short distances / „small-world“	✓	✓	✓			
high locality / clustering						

Erdős–Rényi model

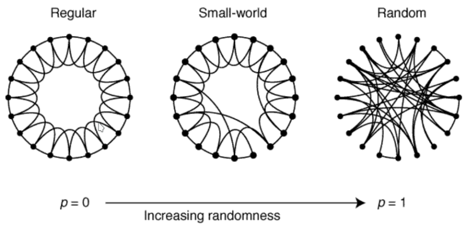


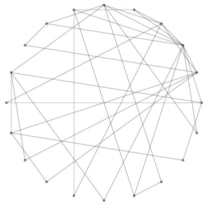
Preferential Attachment

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);

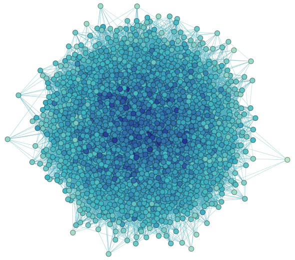
$\Pr\left[\{e_i, e_j\} \in E\right] \sim \frac{w_i \cdot w_j}{W}$

Models for Complex Networks

Goal: model and explain characteristics

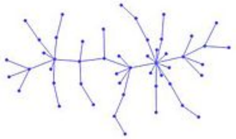
Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	2010	2019
■ heterogeneous degrees		✓	✓			
■ short distances / „small-world“	✓	✓	✓	✓		
■ high locality / clustering				✓		

Erdős–Rényi model

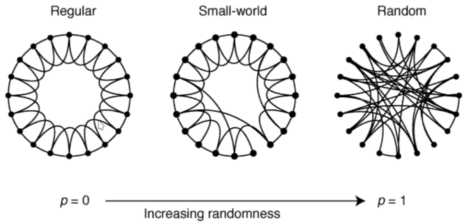


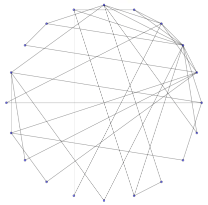
Preferential Attachment

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



Watts–Strogatz model





Chung-Lu / Configuration model

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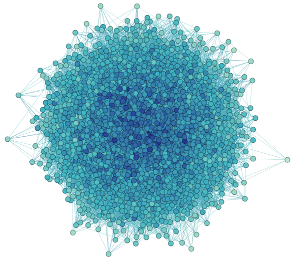
Models for Complex Networks

Goal: model and explain characteristics

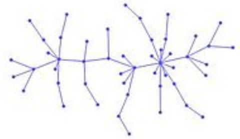
Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG 2010	2019
heterogeneous degrees		✓	✓			
short distances / „small-world“	✓	✓	✓	✓		
high locality / clustering				✓		

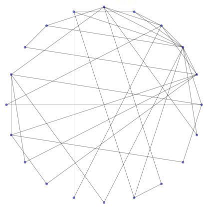
Erdős–Rényi model



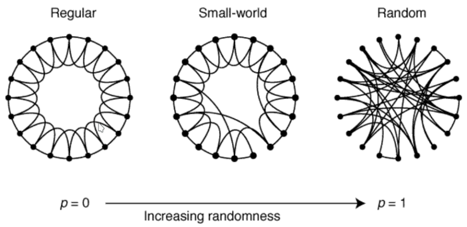
Preferential Attachment

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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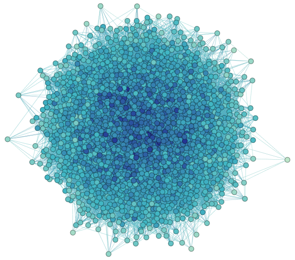
Models for Complex Networks

Goal: model and explain characteristics

Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	2010	2019
■ heterogeneous degrees		✓	✓				
■ short distances / „small-world“	✓	✓	✓	✓			
■ high locality / clustering				✓			

Erdős–Rényi model



Preferential Attachment

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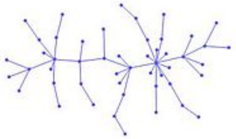
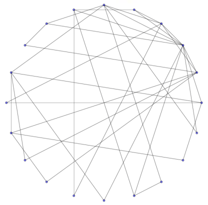
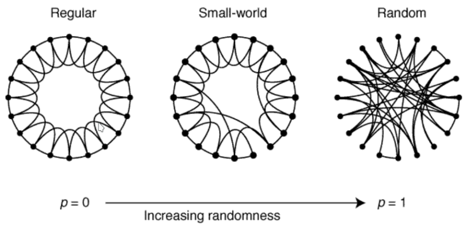




Watts–Strogatz model



Chung-Lu / Configuration model

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

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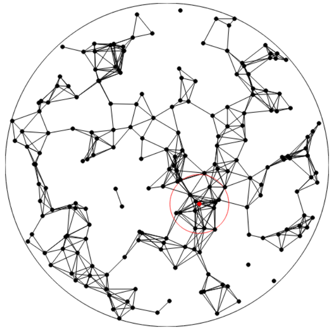
Geometric Random Graph

sample vertices uniformly in geometry, connect if distance below threshold

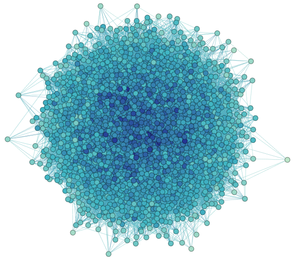


Models for Complex Networks

Goal: model and explain characteristics

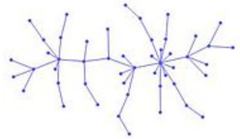
Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	2010	2019
■ heterogeneous degrees		✓	✓				
■ short distances / „small-world“	✓	✓	✓	✓			
■ high locality / clustering				✓	✓		

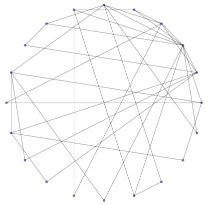
Erdős–Rényi model



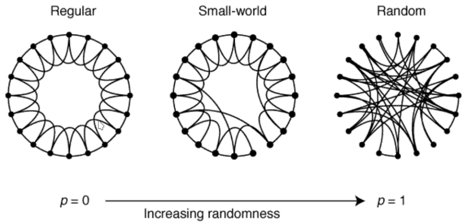
Preferential Attachment

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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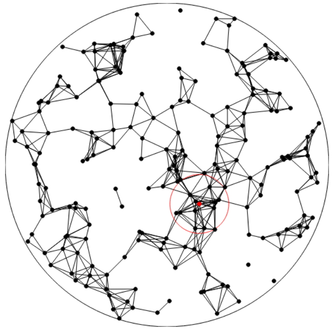
Geometric Random Graph

sample vertices uniformly in geometry, connect if distance below threshold

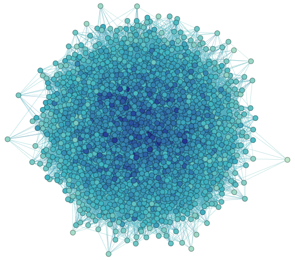


Models for Complex Networks

Goal: model and explain characteristics

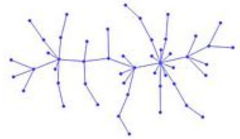
Three characteristics:	ER	Pref. Attach. / Barabási-Albert	Chung-Lu	Watts-Strogatz model	GRG	HRG	
	1959	1923 / 1999	2002	1998		2010	2019
■ heterogeneous degrees		✓	✓				
■ short distances / „small-world“	✓	✓	✓	✓			
■ high locality / clustering				✓	✓		

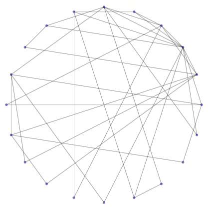
Erdős–Rényi model



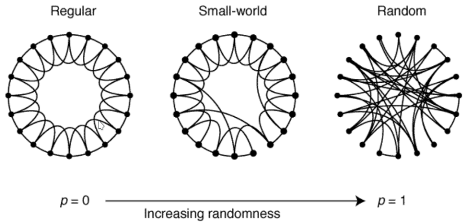
Preferential Attachment

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





Watts–Strogatz model



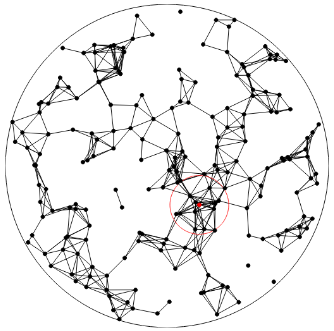
Chung-Lu / Configuration model

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

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

Geometric Random Graph

sample vertices uniformly in geometry, connect if distance below threshold

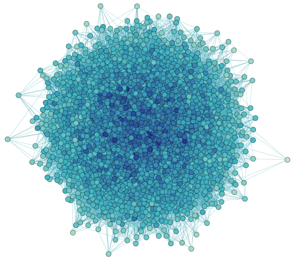


Models for Complex Networks

Goal: model and explain characteristics

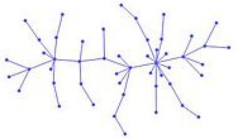
Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	HRG 2010	2019
■ heterogeneous degrees		✓	✓				
■ short distances / „small-world“	✓	✓	✓	✓			
■ high locality / clustering				✓	✓		

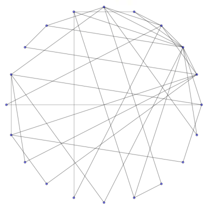
Erdős–Rényi model



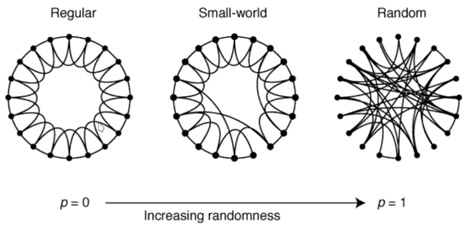
Preferential Attachment

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





Watts–Strogatz model



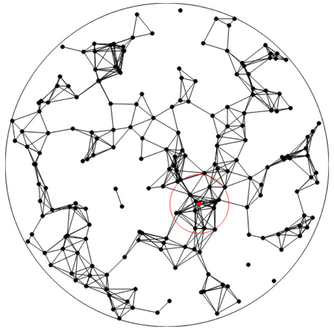
Chung-Lu / Configuration model

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

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

Geometric Random Graph (Hyperbolic)

sample vertices uniformly in geometry, connect if distance below threshold

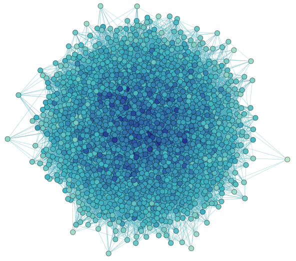


Models for Complex Networks

Goal: model and explain characteristics

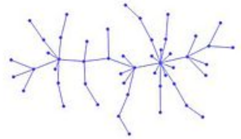
Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	HRG 2010	2019
■ heterogeneous degrees		✓	✓				
■ short distances / „small-world"	✓	✓	✓	✓			
■ high locality / clustering				✓	✓		

Erdős–Rényi model

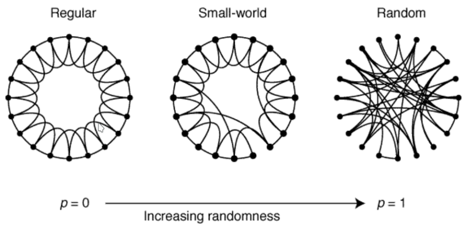


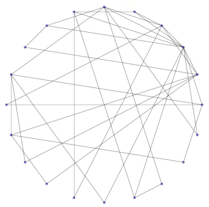
Preferential Attachment

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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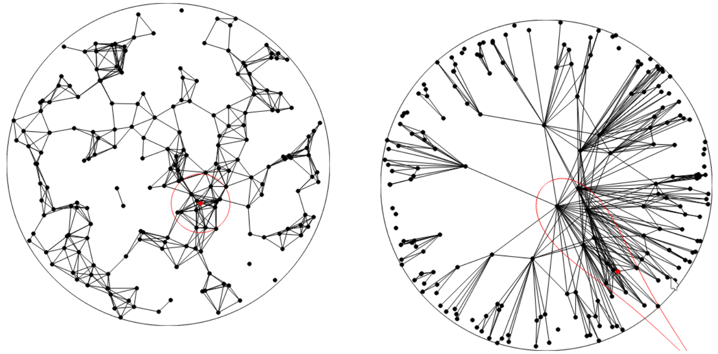

Models for Complex Networks

Goal: model and explain characteristics

Three characteristics:	ER 1959	Pref. Attach. / Barabási-Albert 1923 / 1999	Chung-Lu 2002	Watts-Strogatz model 1998	GRG	HRG 2010	2019
■ heterogeneous degrees		✓	✓			✓	
■ short distances / „small-world“	✓	✓	✓	✓		✓	
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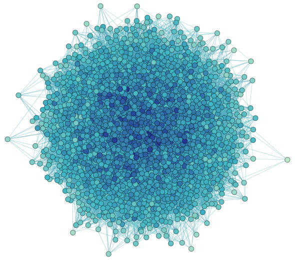
Erdős–Rényi model



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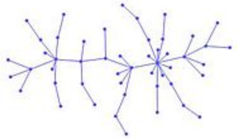

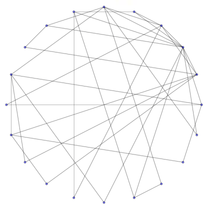

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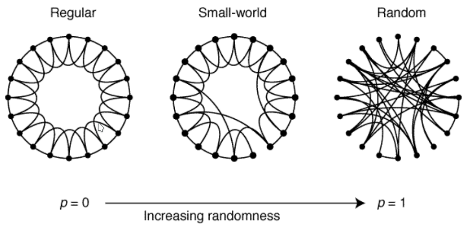

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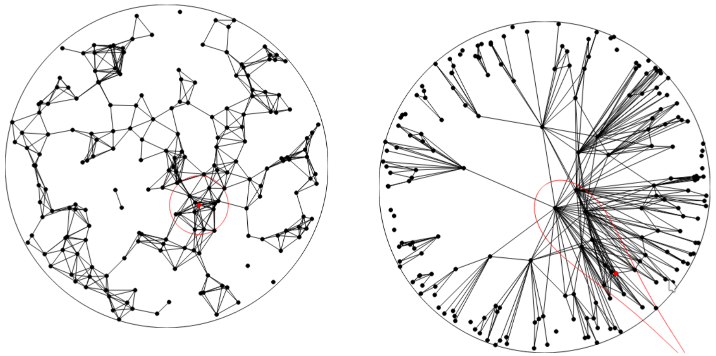

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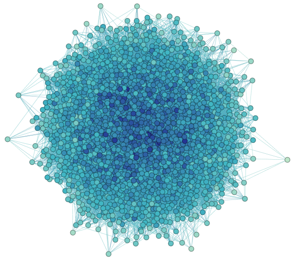

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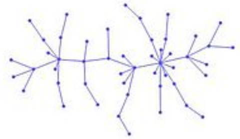

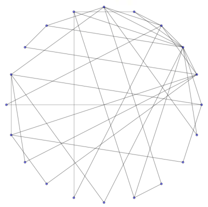

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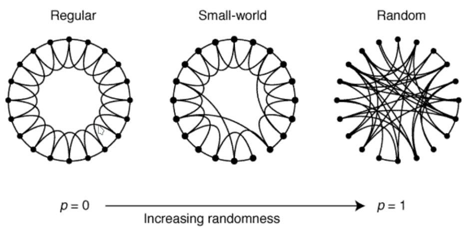

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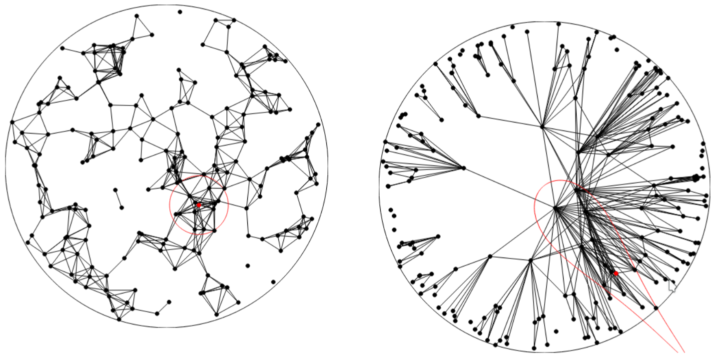

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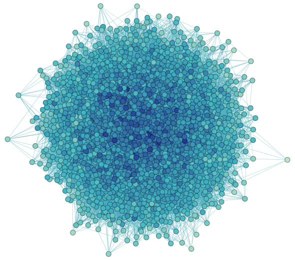

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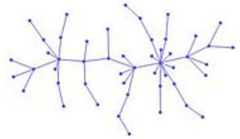

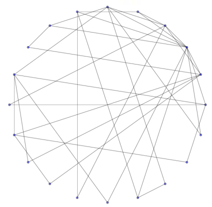

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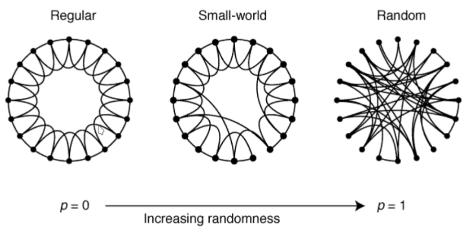

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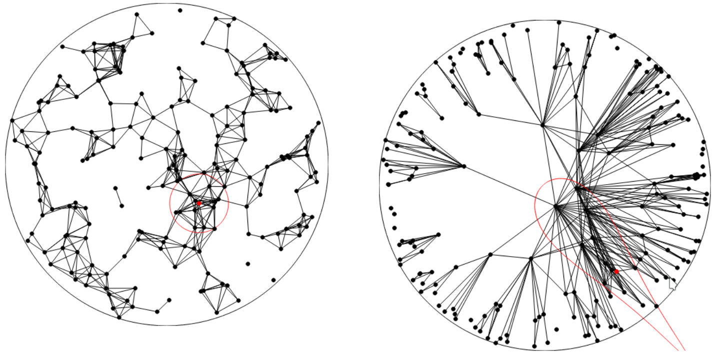

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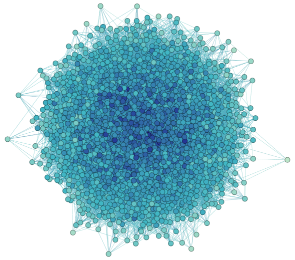

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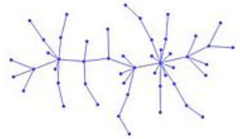

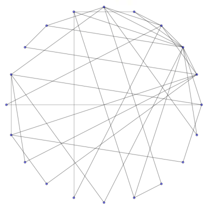

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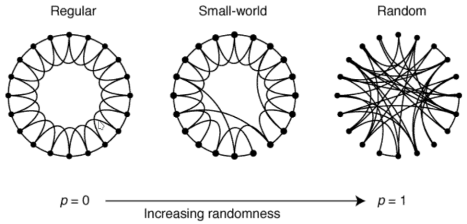

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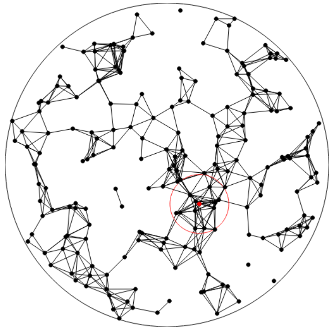
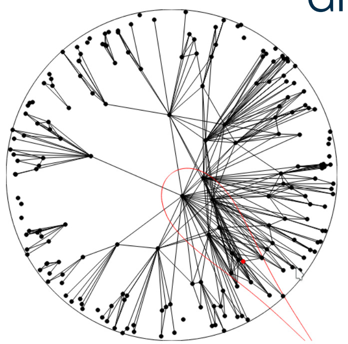


GIRG

GRG + IRG



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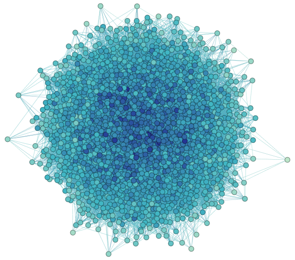

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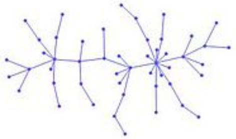

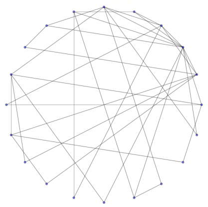

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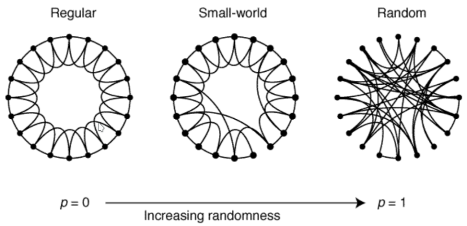

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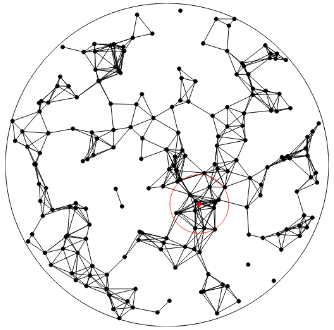

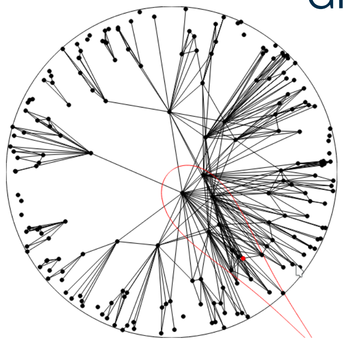

GIRG

GRG + IRG

Sheet 3

Generated Graphs

Real-World Graphs

Sheet 3

Generated Graphs

- select multiple random models to generate graphs
- can you determine, how we generated the initial test set?

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igraph

chistopher / girgs

NetworkX
Network Analysis in Python

NetworKit
Large-scale Network Analysis

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REPOSITORY

External Validity of Average-Case Analyses

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REPOSITORY

External Validity of Average-Case Analyses

Networks

- How fast are Bi-BFS and VC on the new graphs?
- What is the heterogeneity and locality of the new graphs?
- How do graphs with high heterogeneity and low locality look like?