

MU5IN075

Network Analysis and Mining

4. Random Graph Models I

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Outline

- 1 Motivation
- 2 Graphs with given density: Erdős-Rényi graphs
- 3 Watts-Strogatz small-world model
- 4 Barabási-Albert scale-free model

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Random graphs – Motivation

1: understand the structure

Are the observed properties **normal**?

Answer: compare to a **synthetic random graph**

Draw randomly (**uniform probability**) in the set of graphs
→ observe **common** properties to the large majority of graphs
→ they are the **expected** properties

2: simulate processes

3/30

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Erdős-Rényi model

version 1: $G_{n,p}$

- n nodes
- any edge exists with a given probability p

Exercise: write a pseudocode to generate $G_{n,p}$

Complexity: $O(n^2)$

5/30

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Erdős-Rényi model

version 2: $G_{n,m}$

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- m edges chosen uniformly at random

Exercise: write a pseudocode to generate $G_{n,m}$

Complexity: $\mathcal{O}(m)$

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Complexity: $\mathcal{O}(m)$

What about multiple edges and self-loops?

Equivalence between $G_{n,p}$ and $G_{n,m}$

In a $G_{n,p}$ ER graph, probability p is the density (δ)

$$p = \frac{2m}{n(n-1)} = \delta$$

$G_{n,m}$ and $G_{n,p}$ are similar if p and m verify this relationship

(note: strictly speaking, the 2 models are not equivalent)

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Degree distributions of ER graphs

Quiz: what is the expected degree distribution?

- probability of having exactly degree k for one node?

$$\mathcal{P}(k) = \binom{n-1}{k} p^k \cdot (1-p)^{n-1-k} \rightarrow \text{binomial law}$$

- average number of neighbors $\langle k \rangle$?

$$\langle k \rangle = \sum_{k=0}^{n-1} \mathcal{P}(k) \cdot k = \dots = (n-1)p$$

- standard deviation σ_k of the degree distribution?

$$\sigma_k = \sqrt{\langle k^2 \rangle - \langle k \rangle^2} = \dots = \sqrt{\langle k \rangle}$$

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Notion of expected property

Example: Erdős-Rényi random graph $G_{n,m}$, $n = m = 4950$

Result: clique of 100 nodes and other 4850 nodes degree 0

Surprising?

Probability to have degree 0: $\mathcal{P}(k=0) = (1-p)^m \sim 0.135$.

\Rightarrow Expected number of degree 0 nodes:

$\mathcal{P}(k=0) \cdot n \sim 670$ to be compared with 4850...

\rightarrow seems **very unlikely**

how unlikely? **statistical tests**, out of NAM scope (\rightarrow NDA)

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Connectedness of ER graphs

Do ER graphs exhibit a giant component?

Experimental approach: the percolation phenomenon

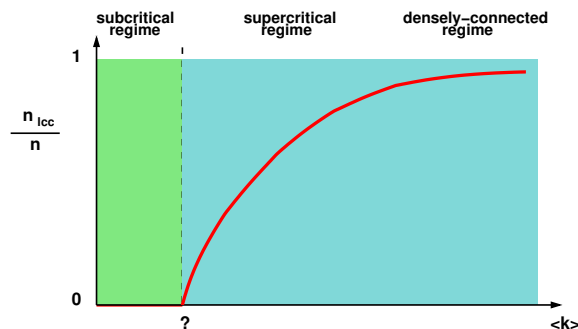
<https://www.complexity-explorables.org/explorables/the-blob/>

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Some real graphs:

- Internet AS level (CAIDA data): $\langle k \rangle \simeq 4.03$
- US power grid (T. Opsahl data): $\langle k \rangle \simeq 2.67$
- Scientific collaborations (GaTech data): $\langle k \rangle \simeq 3.75$
- Yeast metabolic network (Y. Moreno data): $\langle k \rangle \simeq 2.44$
- Actor collaborations (Notre-Dame data): $\langle k \rangle \simeq 173.3$

⇒ Existence of a giant component explained by density alone

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Clustering of ER graphs

Quiz: What clustering coefficient do you expect for ER graphs?

clue: think of the probabilistic interpretation of the cc

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Clustering of ER graphs

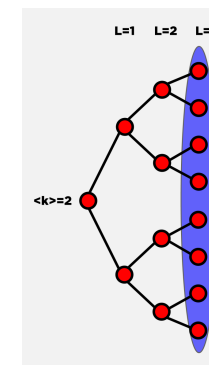
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Distances in ER graphs

Rough hypothesis: no cycles. . .



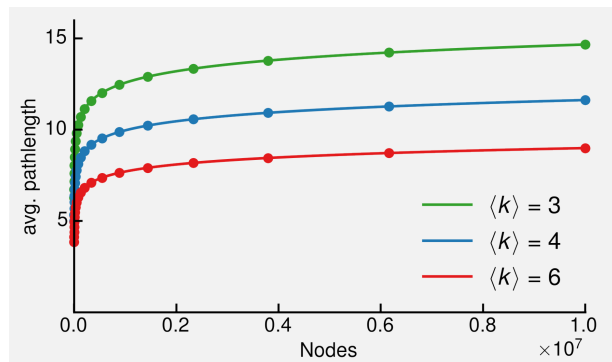
credits image: V.Gauthier

⇒ Short distances explained by density alone

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Summary of ER graphs properties

- Density
- Connectedness
- Average distance, diameter

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Summary of ER graphs properties

- Density set by operator
- Connectedness **giant component, size $\mathcal{O}(n)$** (if $m \geq n$)
- Average distance, diameter $\sim \log(n)$ (if $m \geq n$)

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Summary of ER graphs properties

- Degree distribution
- Clustering coefficient
- Communities

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Summary of ER graphs properties

- Degree distribution **homogeneous**
- Clustering coefficient \simeq **density**
- Communities **no**

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Summary of ER graphs properties

	real	ER
density	low	?
connectedness	giant comp.	?
distances	low	?
degree distrib.	heterogeneous	?
clustering	high	?
communities	yes	?

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Summary of ER graphs properties

	real	ER
density	low	low
connectedness	giant comp.	giant comp.
distances	low	low
degree distrib.	heterogeneous	homogeneous
clustering	high	low
communities	yes	no

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Conclusion on Erdős-Rényi graphs

Real-world complex networks are very different from random Erdős-Rényi graphs

Consequences

- Resemblances (connectedness, distances) can be explained with this simple model
- In general, not a good model for simulations, proofs ...

→ **Other models?**

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General idea of the Small-World model

Reminder: Milgram's Small-World experiment

Small-world: small average distance, high clustering

From a regular network, random reconnections of edges with probability p :

Watts et Strogatz - *Nature*, 1998

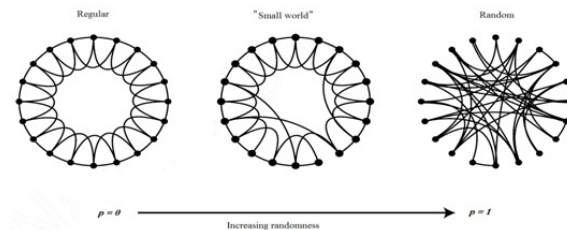
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- regular graph?
- random graph?
- intermediary case?

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- intermediary case? somewhere inbetween

⇒ homogeneous

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Clustering in SW graphs

Quiz: what is expected for the average clustering coefficient?

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- regular graph? neighbors are connected: 1
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18/30

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Paths length in SW graphs

Quiz: what is the expected for the path length?

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Paths length in SW graphs

Quiz: what is the expected for the path length?

- regular graph? some nodes are far away
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Paths length in SW graphs

Quiz: what is the expected for the path length?

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- random graph? Erdős-Rényi case $\sim \log(n)$, short
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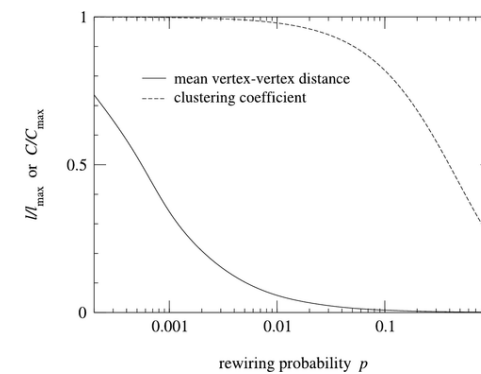
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Trade-off clustering/path length in SW graphs



https://mathinsight.org/applet/small_world_network

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Small-World model implementation

Algorithm 1: WS generation

Parameters: p (rewiring proba); $G = (V, E)$: k -regular graph

```

foreach  $u = (i, j)$  in  $E$  do
  *  $i' \leftarrow i; j' \leftarrow j$ 
   $r_i$  random float  $\in [0; 1]$ 
  if  $r_i < p$  then
    draw a random node  $n_i \in V \setminus \{i\}$ 
     $i' \leftarrow n_i$ 
  end
   $r_j$  random float  $\in [0; 1]$ 
  if  $r_j < p$  then
    draw a random node  $n_j \in V \setminus \{j\}$ 
     $j' \leftarrow n_j$ 
  end
  if no loop and no multi-edge then  $u \leftarrow (i', j')$  else go to *
end
  
```

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Summary of SW graphs properties

	real	small-world
density	low	?
connectedness	giant comp.	?
distances	low	?
degree distrib.	heterogeneous	?
clustering	high	?
communities	yes	?

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Meaning of scale-free

fr: sans échelle ou invariant d'échelle

Reminder: degree distribution follows a power-law:

$$\mathcal{P}(k) = A \cdot k^\alpha + B$$

In practice for real networks:

$$\mathcal{P}(k) \propto k^{-\gamma} \text{ with } 2 \leq \gamma \leq 3$$

⇒ degree distrib. in log-scale is a line with slope $(-\gamma)$

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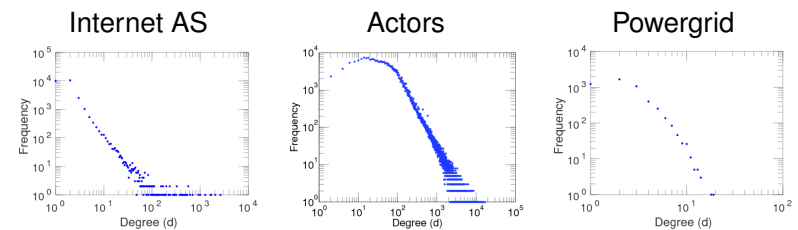
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Scale-Free model

fr: modèle sans échelle

Barabási and Albert - *Science*, 1999

Graph built according to the **preferential attachment** law:

probability for a node i to be connected to a new comer
 proportional to degree k_i

Motivation: this process leads to a **power-law degree distribution** (not proved here)

Ad hoc justification: generative process in agreement with the *"rich gets richer"* rule (or Merton's *"Matthew's effect"*)

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Barabási-Albert scale-free model

Algorithm 2: BA generation (n nodes, $(n - n_0)\alpha + m_0$ edges)

Parameters: n , G , α (degree arriving node)

with G connected graph with n_0 nodes and m_0 edges,

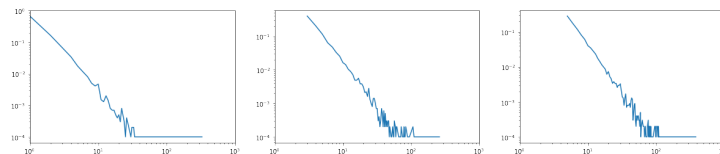
```

for  $i$  from  $(n_0 + 1)$  to  $n$  do
    add node  $i$  to  $G$ 
     $num = 0$  //  $num$ : number of links of  $i$ 
    while  $num < \alpha$  do
        draw  $j \in \llbracket 0; i - 1 \rrbracket$  with probability  $\mathcal{P}(j) = \frac{k_j}{\sum_{q=0}^{i-1} k_q}$ 
        if  $(i, j) \notin G$  then
            add edge  $(i, j)$  in  $G$ 
             $num++$ 
        end
    end
end
    
```

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Degree distributions of BA graphs: influence of the parameters

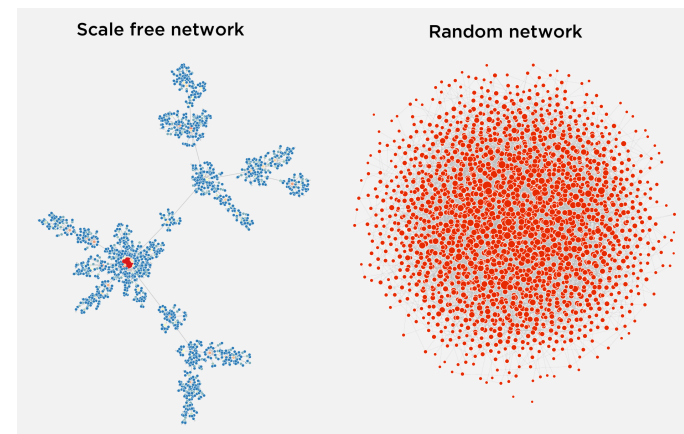
For $\alpha = 1, 3, 5$:



Slope independent of m
 Theoretical slope: $\gamma \simeq 3$

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Visual comparison to ER graphs



credits image: V.Gauthier

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Quiz: what is the clustering coefficient in the $\alpha = 1$ case? other cases?

→ clustering is very low, even null

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Quiz: spreading experiment: what do you expect comparing spreading on a real network and on a BA model?

→ clustering (local density) tends to slow down spreading

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Properties of the *Scale-Free* model

	real	scale-free
density	low	?
connectedness	giant comp.	?
distances	low	?
degree distrib.	heterogeneous	?
clustering	high	?
communities	yes	?

Properties of the *Scale-Free* model

	real	scale-free
density	low	low
connectedness	giant comp.	giant comp.
distances	low	low
degree distrib.	heterogeneous	scale-free
clustering	high	low, even 0
communities	yes	no