

Network Science: Clustered models for network formation

Ozalp Babaoglu
Dipartimento di Informatica — Scienza e Ingegneria
Università di Bologna
www.cs.unibo.it/babaoglu/

Clustered models

- How to extend the ER model to be a better predictor of real network properties
- First, address the poor prediction of clustering
- ER model ignorant of current network structure in adding edges — all edges have exactly the same probability of appearing in the network regardless of their position
- In real networks, the formation of edges is often highly biased
- Bias towards connecting friends of friends

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Clustered models

- In social networks, people introduce their friends to each other
- People that have common friends have more occasions to meet each other and become friends themselves — *triadic closure*
- People who have common friends often also have common interests — *homophily*
- First idea: select edges randomly, but with a bias towards friends of friends
- The more common neighbors two nodes share, the more likely they will be connected

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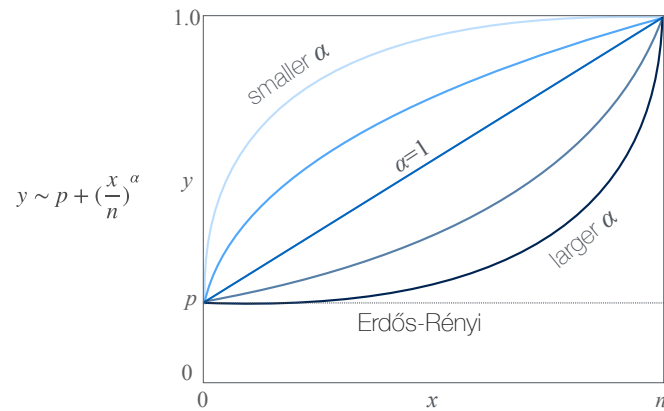
Clustered models The α model

- Bias the connections towards nodes that have common neighbors
- For some arbitrary pair of nodes, let x denote the number of neighbors they currently have in common
- Let y be the probability of adding an edge between a pair of nodes that have x common neighbors
- Assume that $y \sim p + (x/n)^\alpha$ for some constants p and α

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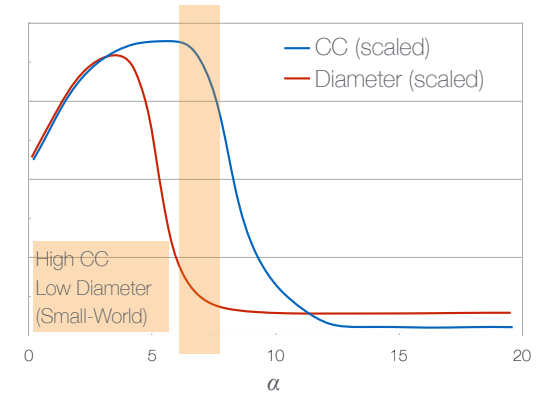
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Clustered models The α model



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Clustered models The α model



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Clustered models The α model

- The model needs to be “tuned” (setting α) and is able to achieve high clustering
- Get small diameter “for free”

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Clustered models Watts-Strogatz

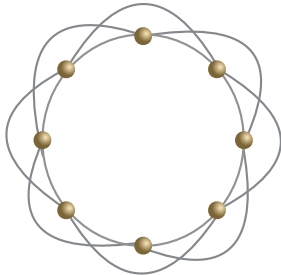
- Start with a highly regular network capturing relations that correspond to geographic, social proximity
- Such a network typically has high clustering but large diameter
- Idea (“rewire”): replace (a few) local edges with random “long distance” (short-cut) edges corresponding to occasional contacts outside of usual social circles
- A balanced set of “local” and “long distance” edges may exhibit high clustering while reducing the diameter

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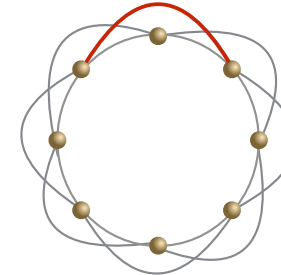
Clustered models Watts-Strogatz

- Start with a K -regular lattice (ring, grid, cube, etc.) where each node is connected to its K nearest neighbors
- Example: $n=8, K=4$



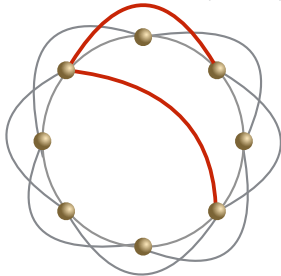
Clustered models Watts-Strogatz

- Clustering coefficient is 0.5 while the diameter is order n (need to go half-way around the ring)
- "Rewire" with probability q to a random node (no duplicates, no self edges)



Clustered models Watts-Strogatz

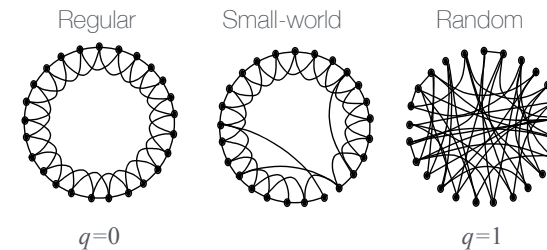
- Clustering coefficient is 0.5 while the diameter is order n (need to go half-way around the ring)
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- NetLogo Library/Networks/Small Worlds and "SmallWorldWS"

Clustered models Watts-Strogatz

- As the rewiring probability q increases from 0 to 1, we get more and more random networks passing through a region called "small-world" networks

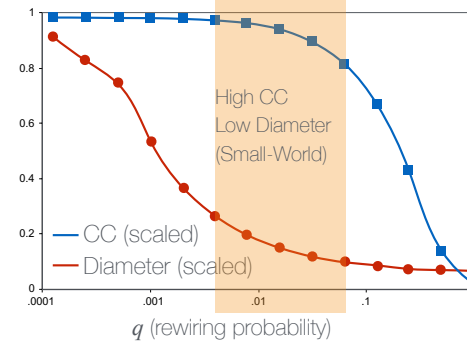


Clustered models Watts-Strogatz

- Origin of small-world networks
 - Diameter is governed by the *number* of random shortcuts (qn)
 - Clustering is governed by the *fraction* of random shortcuts (q)
- *Fact*: roughly 5 random shortcuts reduce average path length by factor of 2, independent of n
- For large n , a small number of random shortcuts will reduce the diameter substantially while leaving clustering mostly unchanged

Clustered models Watts-Strogatz

- Just like the α model, Watts-Strogatz needs to be “tuned” by setting the rewiring probability q



Clustered models Watts-Strogatz

- Clustering coefficient of K -regular lattice is $\frac{3(K-2)}{4(K-1)}$
- Converges to $3/4$ in the limit for large K
- Average path length for a d -dimensional hypercube scales as $n^{1/d}$ which grows much faster than logarithmic
- For the WS model, the clustering coefficient is

$$\frac{3K(K-1)}{2K(2K-1) + 8qK^2 + 4q^2K^2}$$

- While the average path length is

$$\frac{n^{1/d}}{K} f(qKn)$$

where $f(qKn)$ is a universal scaling function