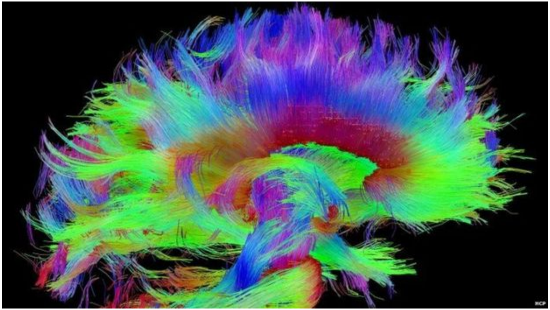
CS 4984: Erdös-Renyi and Small World Networks

T. M. Murali

February 8 and 13, 2018



Collective dynamics of ‘small-world’ networks

Duncan J. Watts & Steven H. Strogatz

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- Question is under-specified. There are many approaches:
  1. Idea 1: From the set of all graphs of n nodes, pick one uniformly at random.
  2. Idea 2: Specify the number of edges m. From the set of all graphs of n nodes and m edges, pick one uniformly at random.
  3. Idea 3: Specify a probability $0 \leq p \leq 1$. For every pair of nodes, add an edge between the nodes with probability p.

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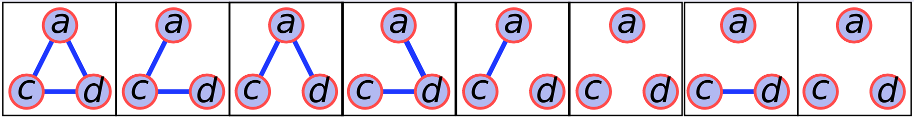

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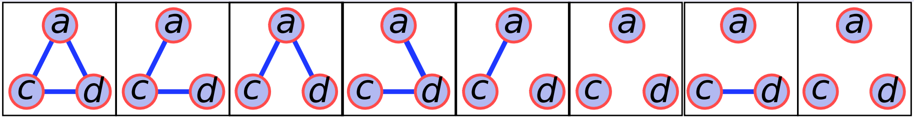

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  - To make a graph, we have two options for each edge: include it or exclude it.
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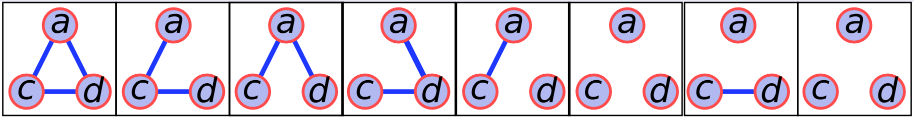

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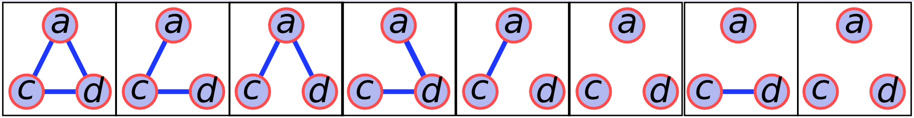

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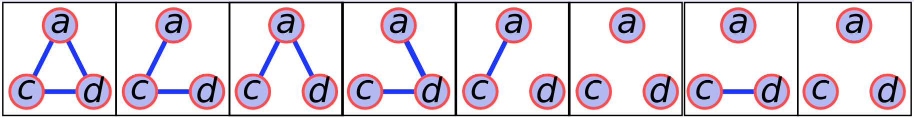

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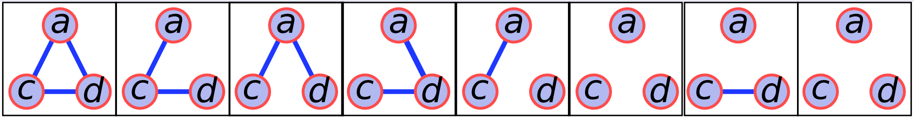

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- Explicitly construct all $2^{\binom{n}{2}}$ and then select one uniformly at random. Running time is $O(n^2 2^{\binom{n}{2}})$. Too slow!
- For every pair of nodes, add an edge with probability $1/2$. Running time is $O(n^2)$.

Properties of Random Graphs Created by Idea 1

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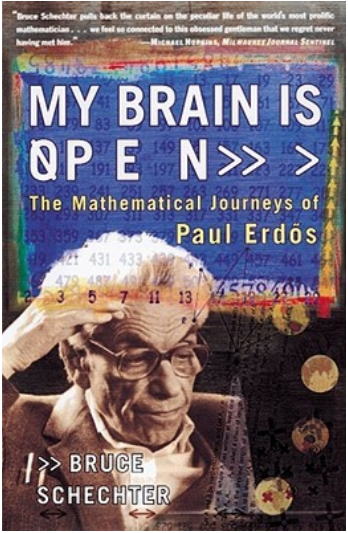
- What is the expected degree of a node? $(n-1)/2$.
- What is the expected number of edges in the graph? $n(n-1)/4$.
- On average, these graphs are very dense.

Erdős-Rényi Graphs



A mathematician is a device for turning coffee into theorems.

Erdős-Rényi Graphs

Idea 3: Specify a probability $0 \leq p \leq 1$.
For every pair of nodes, add an edge between the nodes with probability p.

- Series of papers in the 1960s setting the foundation of random graph theory.
- Framework for generating a random graph.
- $G(n, p)$: an undirected, unweighted graph (family) with n nodes.
- To generate a graph in $G(n, p)$:
  - For each pair (u, v) of $\binom{n}{2}$ node pairs, connect u and v by an edge with probability p.

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  - Generate a random number x between 0 and 1 under the uniform distribution. If $x \leq p$, then "do something", else "do the other thing".

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Degrees and Connectivity in Erdős-Rényi Graphs

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- To generate a graph in $G(n, p)$: For each pair (u, v) of $\binom{n}{2}$ nodes, connect u and v by an edge with probability p.
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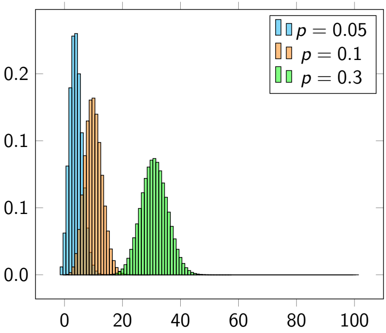

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- The expected degree of a node is $(n-1)p$.
- The expected number of edges in $G(n,p)$ is $n(n-1)p/2$.

Evolution of $G(n, p)$

- When p is close to 0, graph has many small connected components.
- When p is close to 1, graph is very dense (has almost all the edges).
- When do all nodes in the graph become connected into one component?

The evolution of the $G(n, p)$ random graph (Video, 4 min 51 sec)

Phase Transitions

If $p = 0$,

If $p < \frac{(1-\varepsilon)}{n}$,
If $p > \frac{(1+\varepsilon)}{n}$,

If $p < \frac{(1-\varepsilon)\ln n}{n}$,

If $p > \frac{(1+\varepsilon)\ln n}{n}$,

If $p = 1$,

Statements hold with high probability.

Phase Transitions

If $p = 0$, $G(n, p)$ has no edges.

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If $p > \frac{(1+\varepsilon)\ln n}{n}$, $G(n, p)$ is connected! The average shortest path length is $\frac{\ln n}{\ln(1+\varepsilon)+\ln\ln n}$. Path lengths are logarithmic in the number of nodes!

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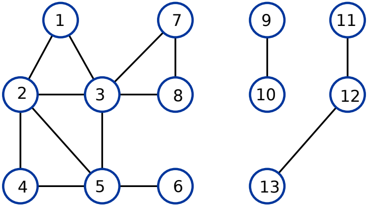
Clustering Coefficient



- Measures the extent of clusters/cliques around a node, on average.
- *Clustering coefficient $c(v)$* for a node v is the fraction of pairs of its neighbours that are themselves connected.
- *Clustering coefficient $c(G)$* of a graph G is the average of the clustering coefficients of its nodes.
  - Note that I am using lowercase c (since c is a number), whereas the paper uses uppercase C.
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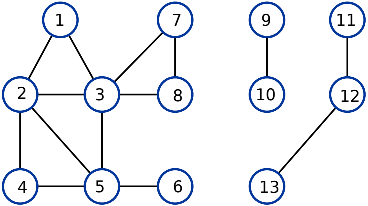

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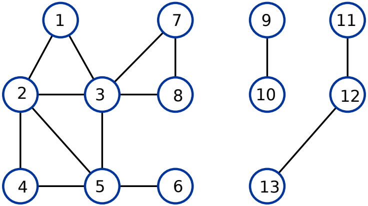

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Clustering Coefficient of an Erdős-Rényi Graph

- Assume $p > \frac{(1+\varepsilon)\ln n}{n}$.
- We know that the average shortest path length in $G(n,p)$ is $\approx \frac{\ln n}{\ln(1+\varepsilon)}$.

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  - Hence, the clustering coefficient of $G(n, p)$ is $p < 1$.

Milgram's Experiment

It's a small world! (Video, 1 min 36 sec)

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Criticisms

- Overestimates path lengths.
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Burning question

How do networks with small average shortest path length arise?

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- Consider two measures for a graph G:
  - $l(G)$, the average shortest path length in G.
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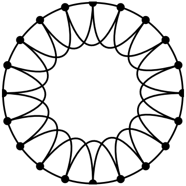

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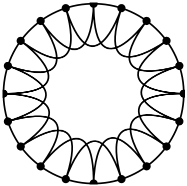

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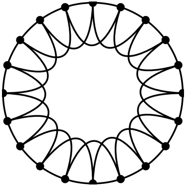
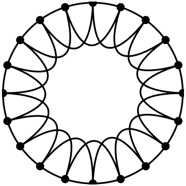


- $l(G) = n/2k$ (large).
- $c(G) =$

- Real world networks have small average shortest path lengths (like $G(n, p)$) but large clustering coefficients (like ring graph).

Motivation

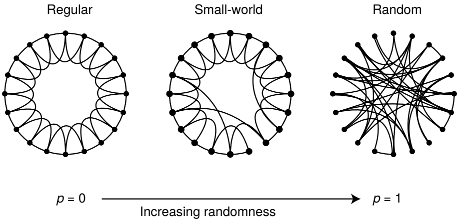
- Consider two measures for a graph G:
  - $l(G)$, the average shortest path length in G.
  - $c(G)$, the clustering coefficient of G.
- $G(n, p)$, $p > \frac{(1+\varepsilon)\ln n}{n}$:
  - $l(G) = \frac{\ln n}{\ln np}$ (small).
  - $c(G) = p$ (small).
- *Regular ring graph*: n nodes in a ring, each node connected to the next $k/2$ nodes appearing in clockwise order around the ring.



- $l(G) = n/2k$ (large).
- $c(G) = \approx 3/4$ (large).

- Real world networks have small average shortest path lengths (like $G(n, p)$) but large clustering coefficients (like ring graph).

Watts-Strogatz Model



- Three parameters: n, number of nodes; k: degree of each node; p: rewiring probability. This p is different from the p in E-R graphs.
- Rewire regular ring graph in $k/2$ rounds. In round j,
  1. For each node i, consider edge $(i, i+j)$.
  2. Pick a candidate node l uniformly at random between 1 and n.
  3. With probability p, replace (i, j) with (i, l) if

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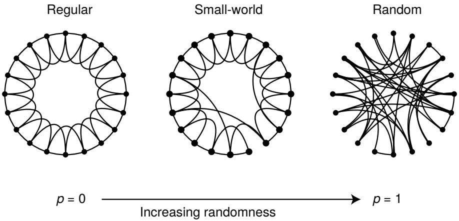

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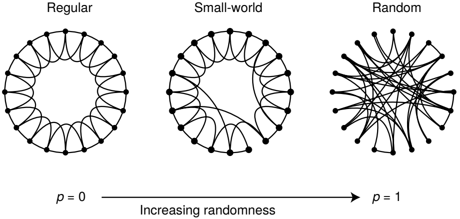
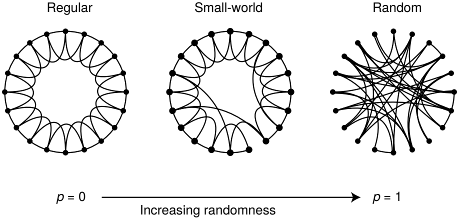
l and c for Watts-Strogatz Graphs



$l(p)$: average shortest path length for ring graph rewired with prob. p.
$c(p)$: average clustering coefficient for ring graph rewired with prob. p.
What is $l(0)$?

l and c for Watts-Strogatz Graphs



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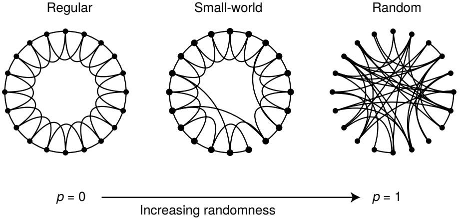
What is $c(0)$?

l and c for Watts-Strogatz Graphs



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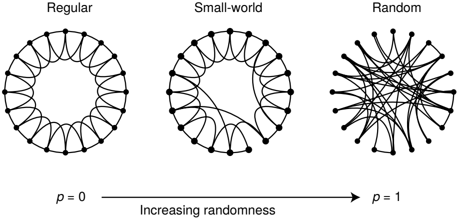

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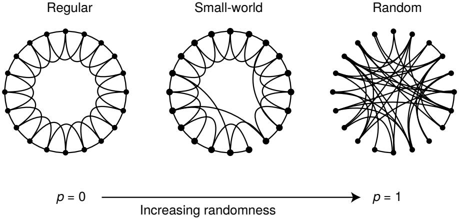
Ring lattice is large-world and highly clustered.
What is $l(1)$?

l and c for Watts-Strogatz Graphs



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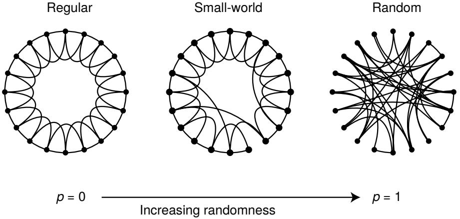
What is $c(1)$?

l and c for Watts-Strogatz Graphs



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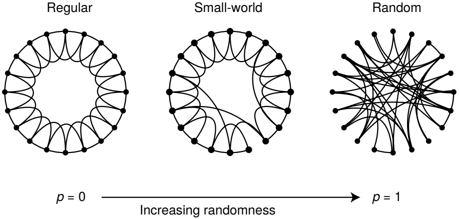

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Ring lattice is large-world and highly clustered.

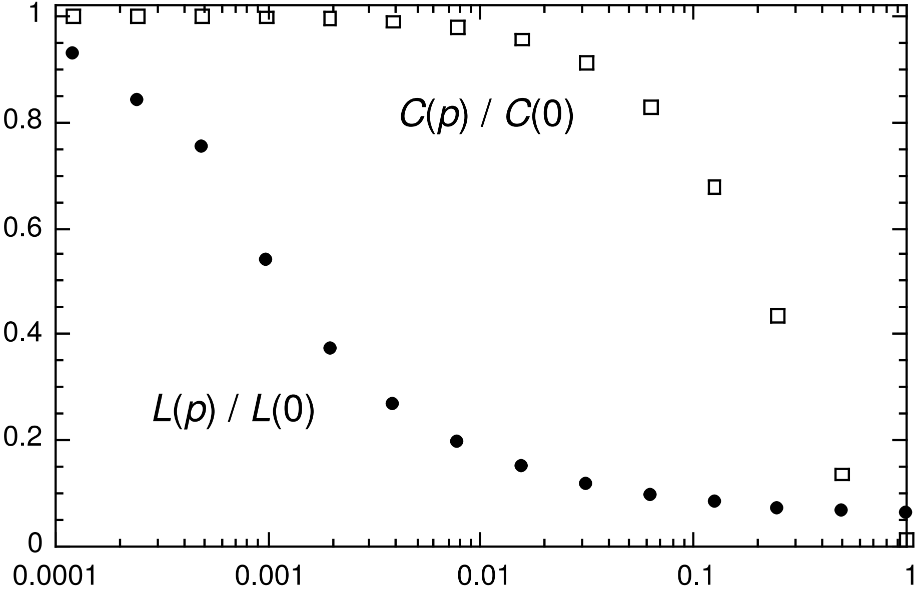
What is $l(1)$? $\ln n/\ln k$

What is $c(1)$? k/n.

Random graph is small-world but poorly clustered.

Are there values of p for which $l(p)$ is small but $c(p)$ is large?

l and c for Watts-Strogatz Graphs



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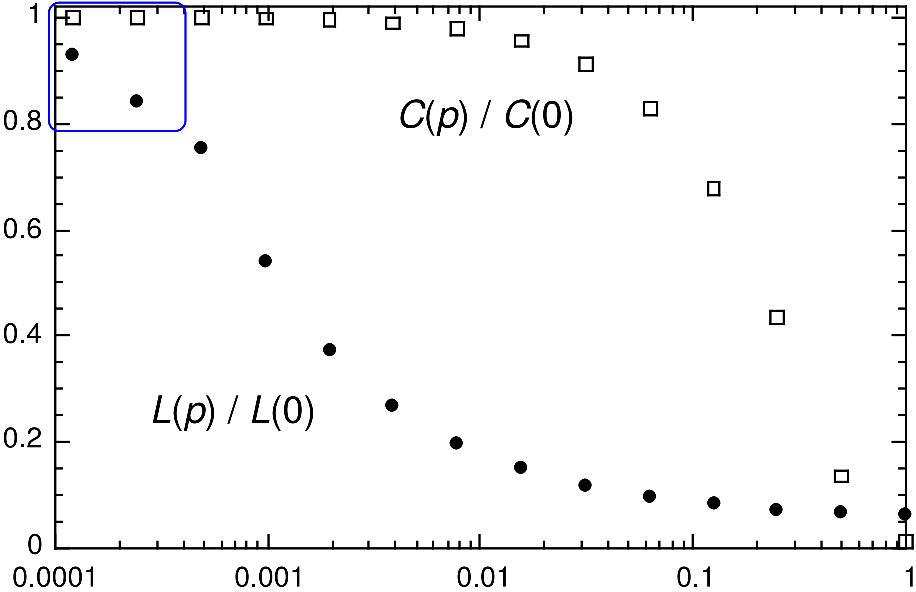

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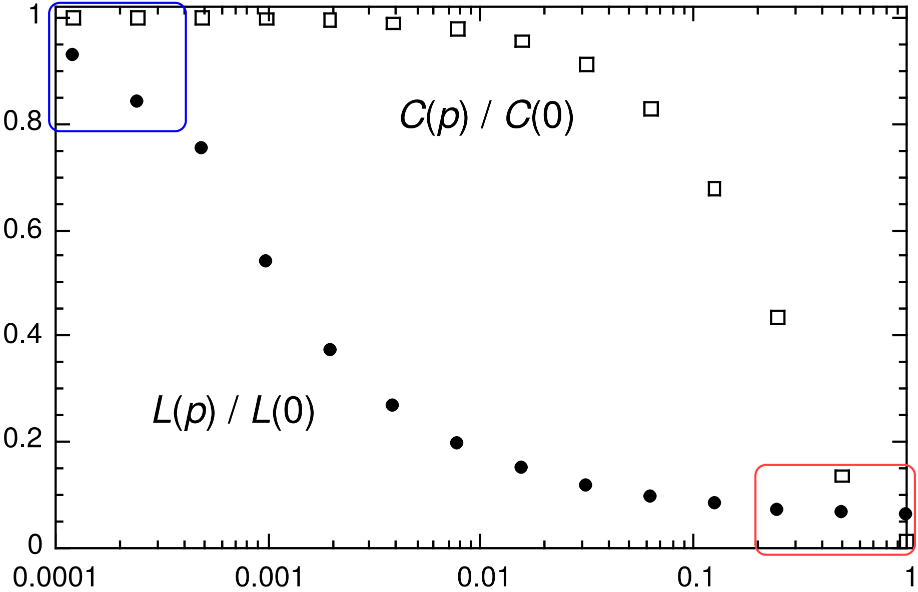
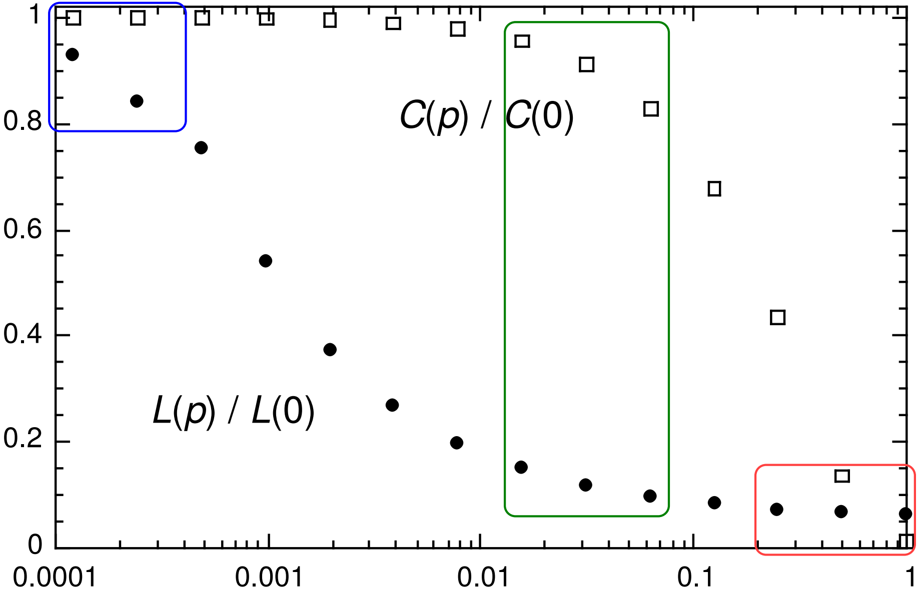


l and c for Watts-Strogatz Graphs



Observations

- $l(p)$ becomes small due to the addition of a small number of "long-range" edges.
- These short cuts connect nodes that would otherwise be very far apart.
- Non-linear effect on $l(p)$: Short cuts also contract the distance between neighbours of the connected nodes, their neighbours, and so on.

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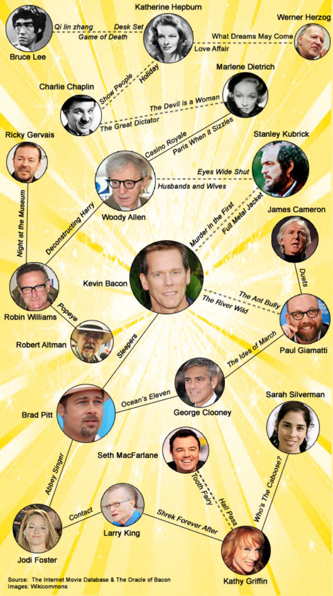
Do real-world networks have small l and large c?

Actor Network



Node $\equiv$

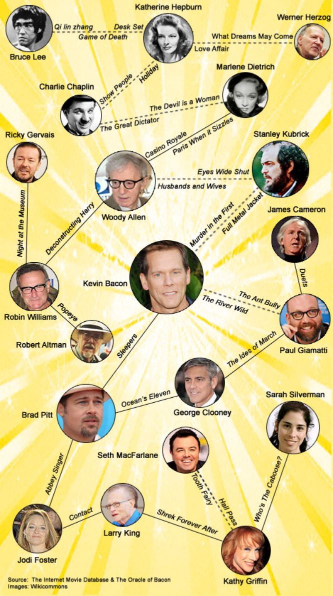
Edge $\equiv$

Edge weight $\equiv$

$n =$

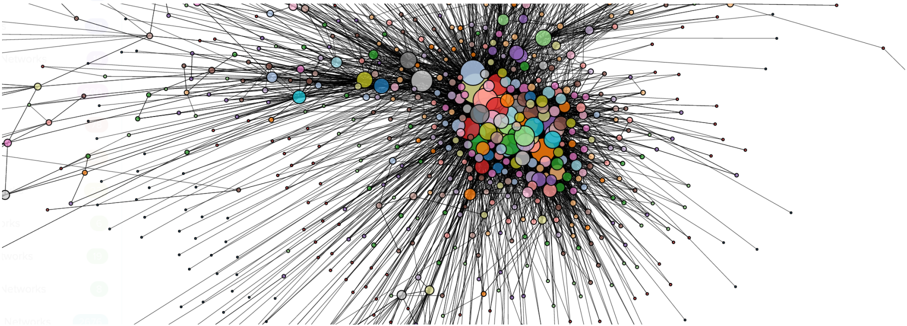
$m =$

Actor Network



Node $\equiv$ Actor
Edge $\equiv$ Collaboration
Edge weight $\equiv 1$
$n = 225,226$
$m = (225,226 \times 61)/2 = 6,869,393$

Power Network



Node $\equiv$

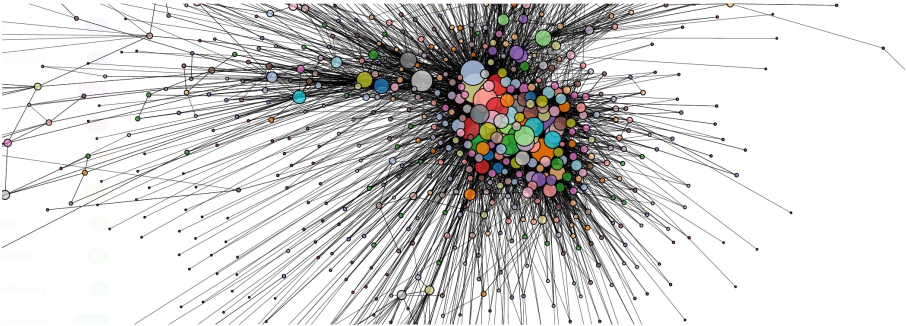
Edge $\equiv$

Edge weight $\equiv$

$n =$

$m =$

Power Network



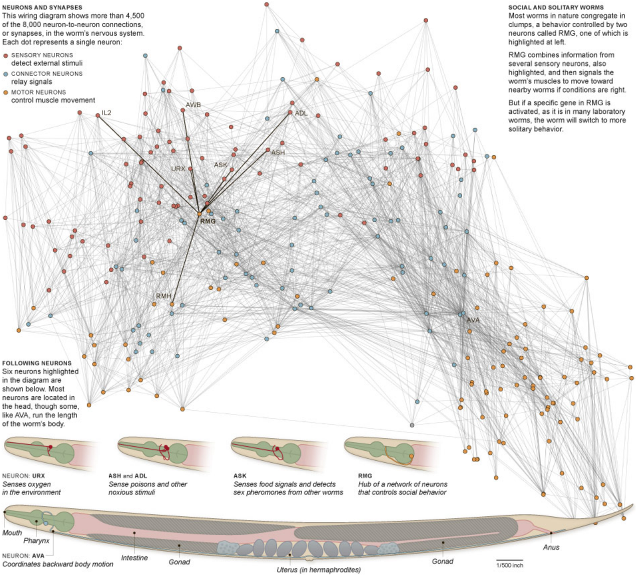
Node $\equiv$ Generators, transformers, and substations

Edge $\equiv$ High-voltage transmission line

Edge weight $\equiv 1$

$n = 4,941$
$m = (4,941 \times 2.67)/2 = 6,596$

C elegans connectome



Node $\equiv$

Edge $\equiv$

Edge weight $\equiv$

$n =$

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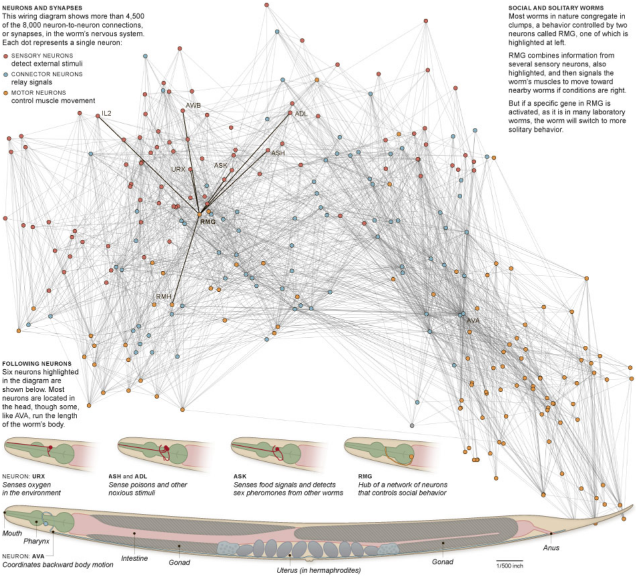
C elegans connectome



Node $\equiv$ Neuron
Edge $\equiv$ Synpase
Edge weight $\equiv 1$
$n = 282$
$m = (282 \times 14)/2 = 1974$

Real-world Networks are Small World

Table 1 Empirical examples of small-world networks

	L_{actual}	L_{random}	C_{actual}	C_{random}
Film actors	3.65	2.99	0.79	0.00027
Power grid	18.7	12.4	0.080	0.005
C. elegans	2.65	2.25	0.28	0.05

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The pattern in Nature's networks (Video, 3 min 25 sec)