Graph Mining
SD212
3. Graph structure

Thomas Bonald

2018 – 2019

Motivation

- How many clicks are needed to go from Platini to Plato on Wikipedia?

  Only 3!
  Platini $\rightarrow$ Naples $\rightarrow$ Ancient Greek $\rightarrow$ Plato

- And from Plato to Platini?

  Only 3 as well!
  Plato $\rightarrow$ Louvre $\rightarrow$ France $\rightarrow$ Platini

Motivation

- How many pages are accessible in k clicks from Plato on Wikipedia?

  Using **Wikipedia for Schools** (4,591 pages):

# clicks	# nodes	proportion
1	76	1.6%
2	1505	32.8%
3	4527	98.6%
4	4584	99.8%

  In 1 click, you already get some central nodes:
  Plato $\rightarrow$ Latin, Italy, Arabic language, Iran, 19th century,...

Outline

1. Small-world property
2. Clustering coefficient
3. Watts-Strogatz graphs
4. Sparse matrices

The six degrees of separation

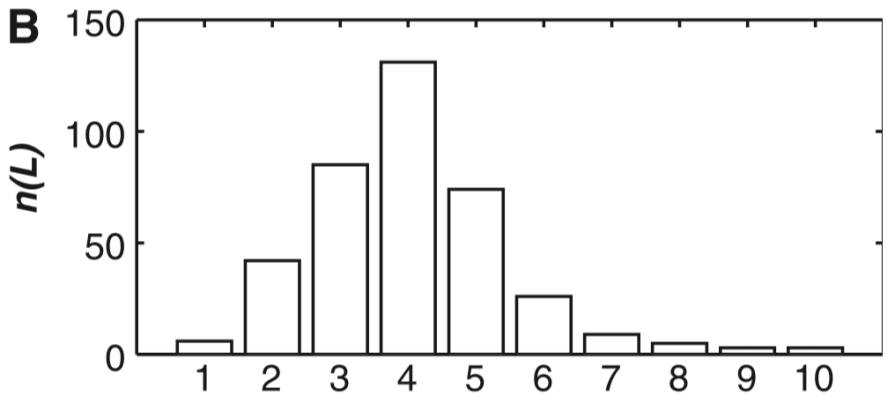
- Stated by Karinthy in 1929!
- Verified experimentally by Milgram in 1967

Source: Wikipedia

Emails

Dodds, Muhamad, Watts 2003

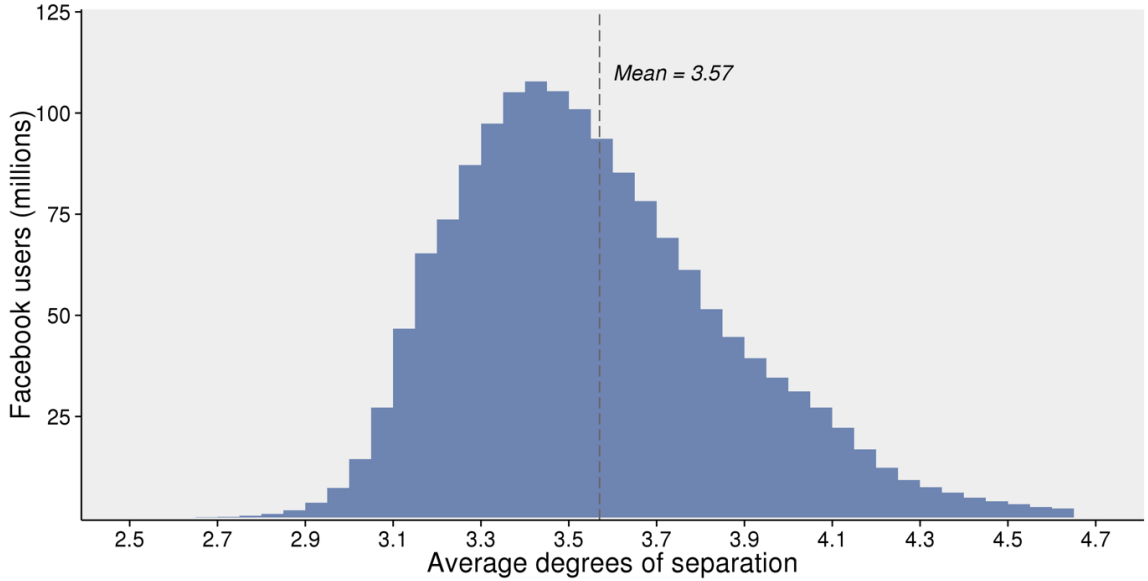
- 18 target people from all over the world
- 24,163 volunteers
- 384 successful chains
  Length of successful chains



Facebook

Bhagat, Burke, Diuk, Filiz, Edunov 2016

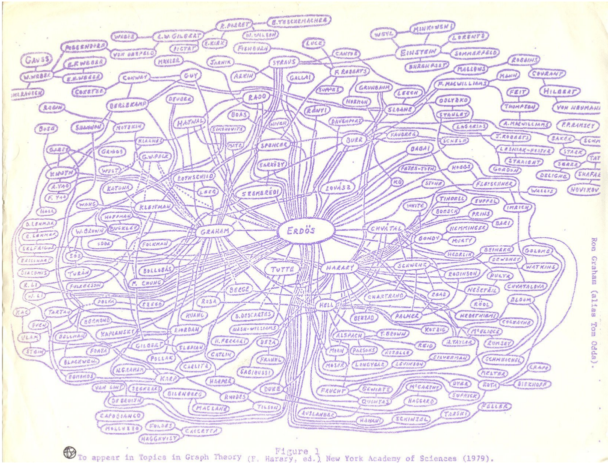
- Based on the 1.59 billion people active on Facebook
- Compute the average path length to any other people



The 3 and a half degrees of separation of Facebook

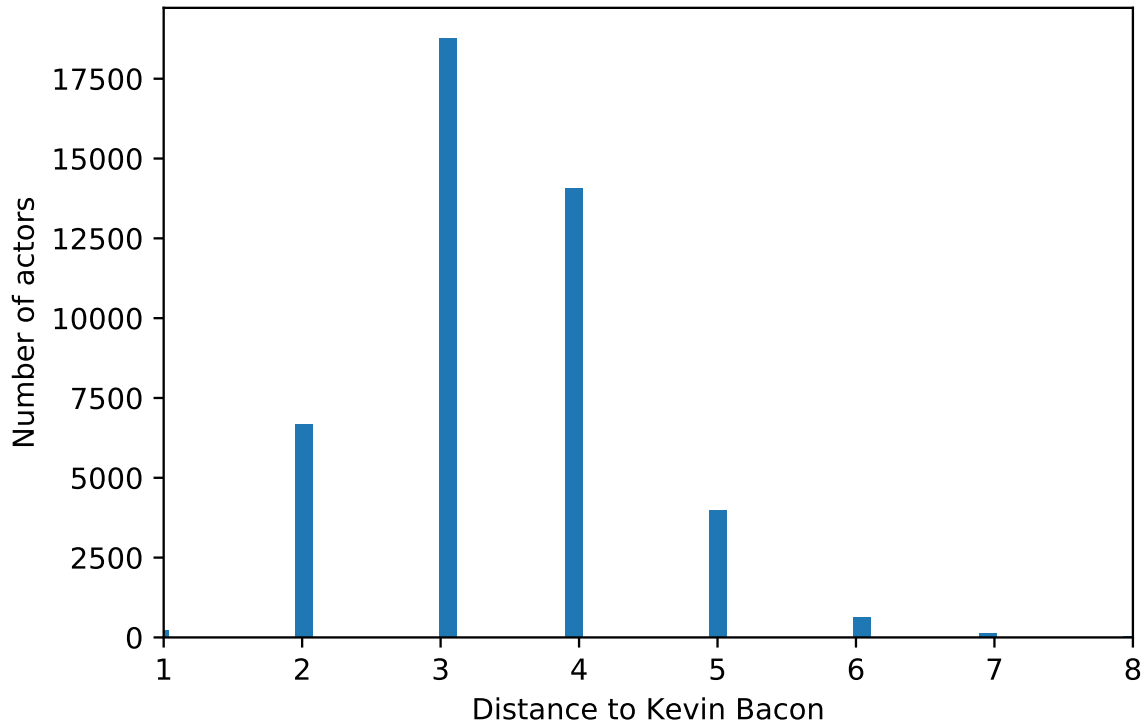
Erdös number

- Graph of co-authors of scientific papers
- Distance to Erdös (1913-1996)



The Bacon number

- Originated from an interview of Kevin Bacon by Premiere Magazine in 1994
- Graph of co-staring in movies



Results from YaGo database (44,586 actors)

The small-world property

- Is it universal?
- Example of a ring / a grid

The small-world property

- How does it emerge?
- Example of a random graph

Outline

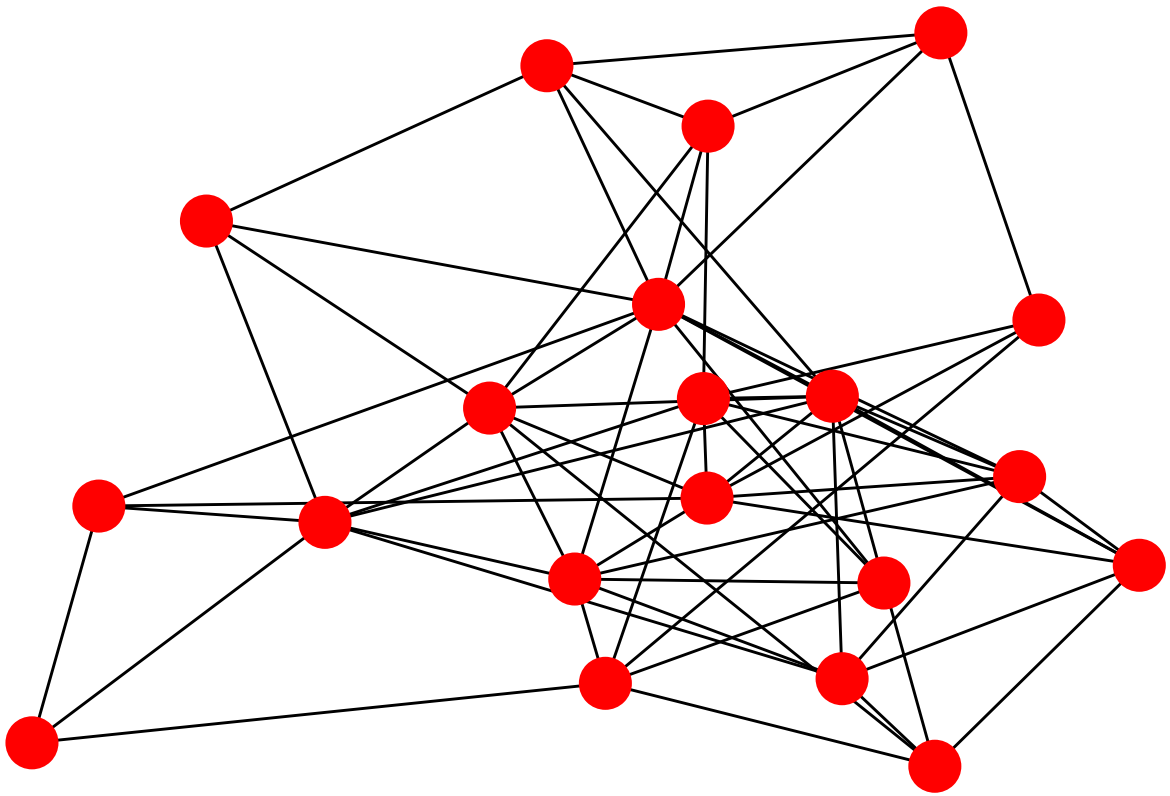
1. Small-world property
2. **Clustering coefficient**
3. Watts-Strogatz graphs
4. Sparse matrices

Structure vs. randomness

- The small-world property can be explained by randomness
- Can real graphs be considered as purely **random**?

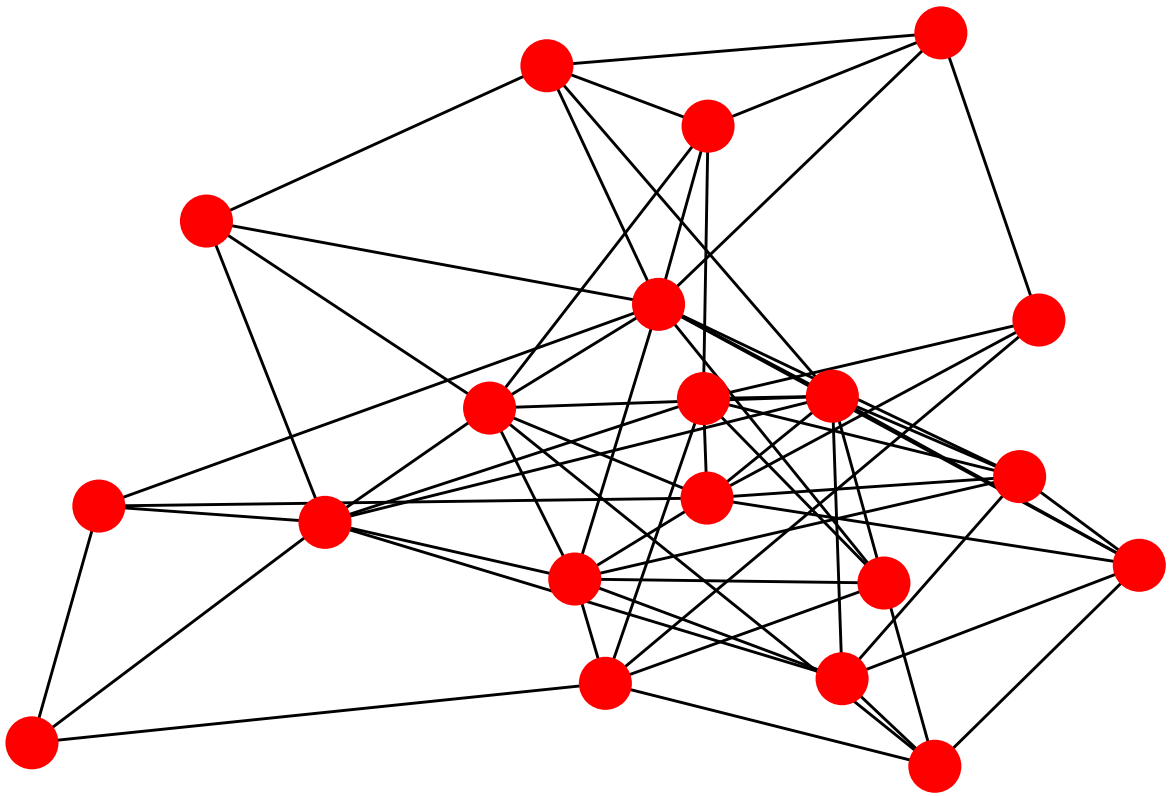
Clustering coefficient

Fraction of closed triangles



Local clustering coefficient

Proportion of my friends that are friends



Average local clustering coefficient

Some real graphs

Graph	C
Les Miserables	0.57
Openflights	0.25
Wikipedia for schools	0.28
Actor graph	0.79
Openstreet	0.001

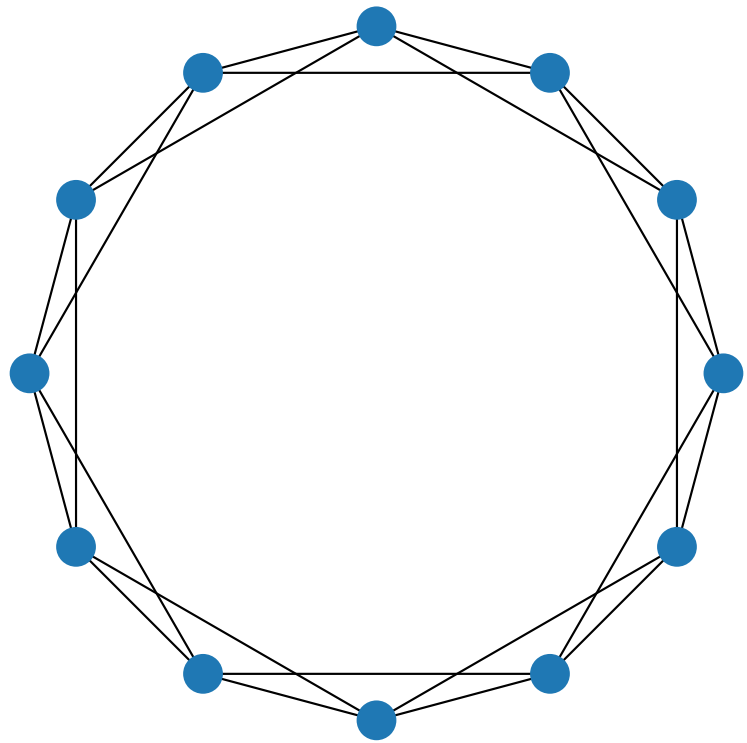
Case of Erdös-Rényi graphs

Outline

1. Small-world property
2. Clustering coefficient
3. **Watts-Strogatz graphs**
4. Sparse matrices

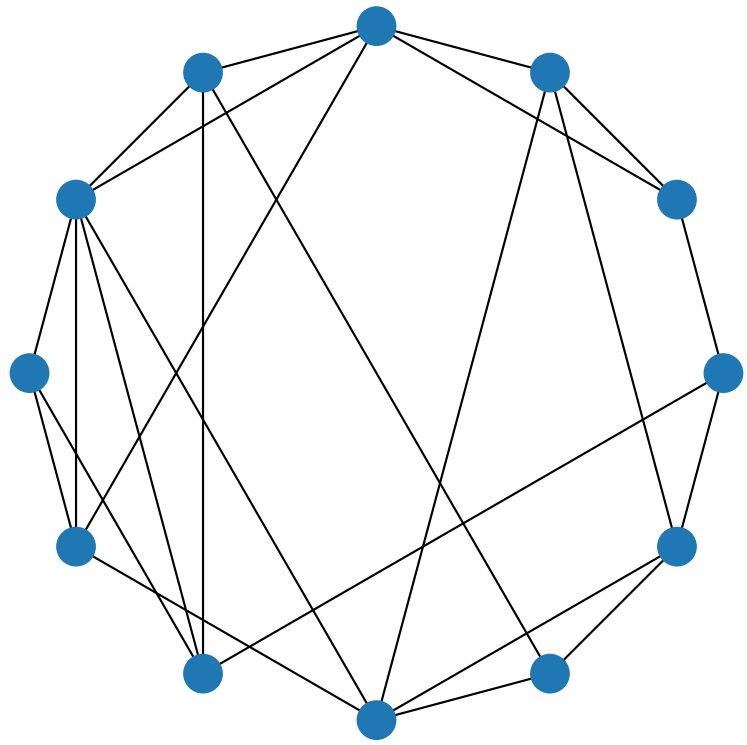
Watts-Strogatz graphs

1. Start from a ring of n nodes where each node is connected to its d nearest neighbors (d even)
2. Modify each edge at random with probability p



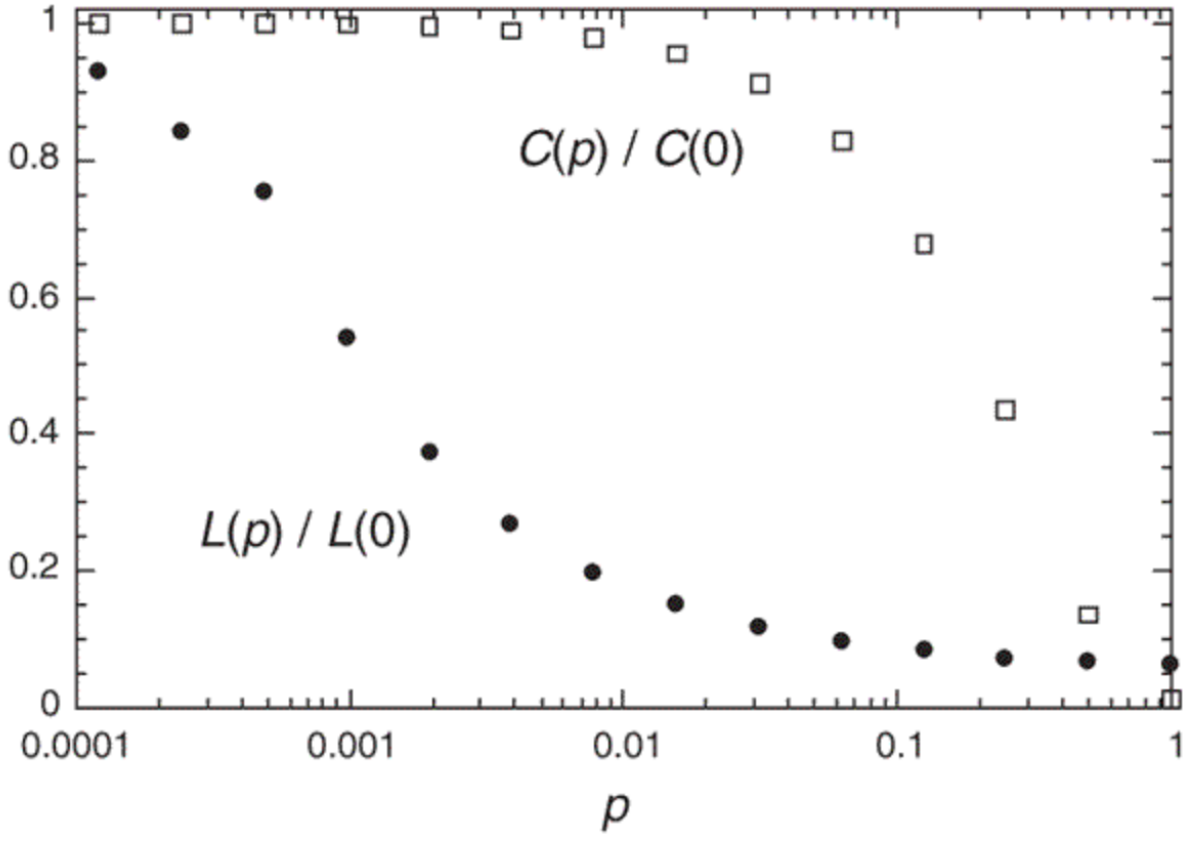
$n = 12, d = 4$

Example



$n = 12, d = 4, p = 0.4$

Small-world vs clustering structure



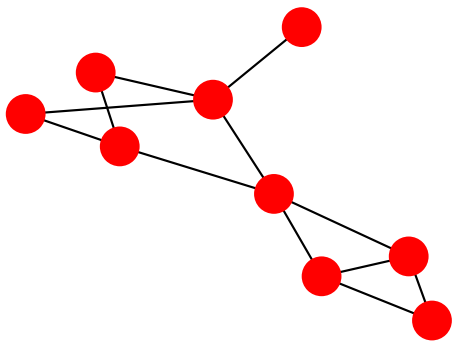
$n = 1000, d = 10$

Source: Watts & Strogatz 1998

Outline

1. Small-world property
2. Clustering coefficient
3. Watts-Strogatz graphs
4. **Sparse matrices**

Adjacency matrix



```
[[0 1 0 0 0 0 0 0 1 1]
 [1 0 0 0 0 1 0 1 1 0]
 [0 0 0 0 0 0 0 1 0 0]
 [0 0 0 0 0 1 0 1 0 0]
 [0 0 0 0 0 1 0 1 0 0]
 [0 1 0 1 1 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0]
 [0 1 1 1 1 0 0 0 0 0]
 [1 1 0 0 0 0 0 0 0 1]
 [1 0 0 0 0 0 0 0 1 0]]
```

Compressed Sparse Row (CSR) format

```
[[0 1 0 0 0 0 0 0 1 1]
 [1 0 0 0 0 1 0 1 1 0]
 [0 0 0 0 0 0 0 1 0 0]
 [0 0 0 0 0 1 0 1 0 0]
 [0 0 0 0 0 1 0 1 0 0]
 [0 1 0 1 1 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0]
 [0 1 1 1 1 0 0 0 0 0]
 [1 1 0 0 0 0 0 0 0 1]
 [1 0 0 0 0 0 0 0 1 0]]
```

```
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
[1 8 9 0 5 7 8 7 5 7 5 7 1 3 4 1 2 3 4 0 1 9 0 8]
[ 0  3  7  8 10 12 15 15 19 22 24]
```

Pros and cons

Pros

- Efficient storage
- Fast row slicing
- Fast matrix-vector product

Cons

- Slow column slicing
- Slow modification (e.g., add an entry)

Some applications

- Neighbors / degrees
- Path lengths
- Breadth-first search (BFS)
- Clustering coefficient

Summary

- Most real graphs have both the **small-world property** and a **high clustering** coefficient
- **Watts-Strogatz graphs** have both properties (for properly chosen parameters)
- **Sparse matrices** are key to efficient computation of path lengths and clustering coefficients