Random Networks (ER) Model

Introduction to Network Science
Carlos Castillo
Topic 07

Universitat Pompeu Fabra Barcelona

Contents

- The ER model
- Degree distribution under the ER model

Sources

- Albert László Barabási: Network Science. Cambridge University Press, 2016.
  - Follows almost section-by-section chapter 03
- Data-Driven Social Analytics course by Vicenç Gómez and Andreas Kaltenbrunner
- URLs cited in the footer of specific slides

Why studying random networks?

- One way of studying complex networks is by running stochastic models of network creation and then see if they generate networks that look like real ones
- The "random network" model is one specific stochastic model in which each link is created independently at random

Meeting people at a party

- You pick a random person
- Talk to that person for a while, if there are good vibes, you are connected
- Then pick another person
  - And repeat
- The result is what we call a **random network**

Formalization (Erdös-Rényi or ER)

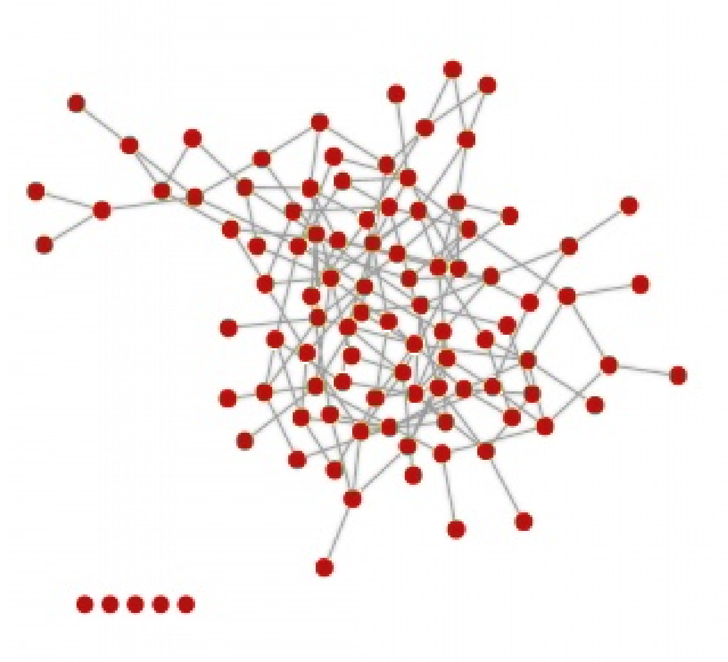
Sounds like "ERDOSH and REGN"

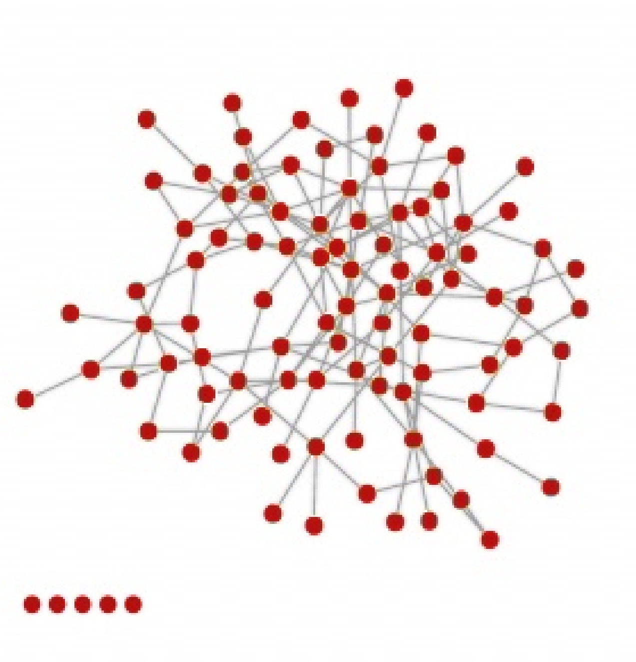
- For each pair of nodes in the graph
  - Perform a Bernoulli trial with probability p
    - "Toss a biased coin with probability p of landing heads"
  - If the trial succeeds, connect those nodes
    - "If the coin lands heads, connect those nodes"
- Repeat for all pairs $\frac{N(N-1)}{2}$

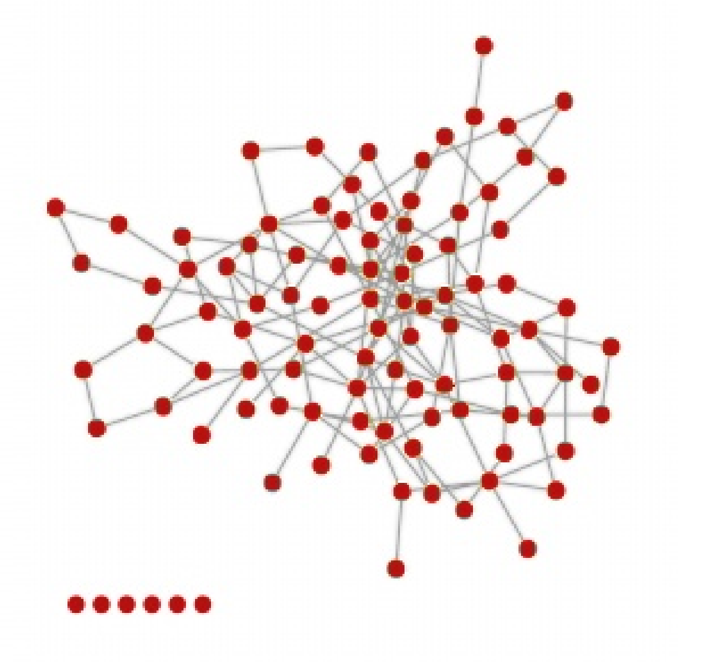
Example
(3 networks, same parameters)

$$N = 100, p = 0.03, \langle k \rangle \approx 3$$

Nodes at the bottom ended up isolated







A key characteristic of a network: its degree distribution

- One of the most evident characteristics of a network is its degree distribution
  - Is this distribution very skewed? Or every node is close to some average? Is there a “typical” degree?
  - Does it look like the degree distribution predicted by a network formation model?
- We will spend a fair amount of time studying the degree distribution under various models

The binomial distribution

- The distribution of the probability of obtaining x successes in n independent trials, in which each trial has probability of succeeding p

$$p_x = \binom{n}{x} p^x (1-p)^{n-x}$$

$$\langle x \rangle = \sum_{x=0}^{n} x p_x = np$$

Degree distribution in ER model

- Simply a Binomial distribution
- Note that the maximum number of "successes" (links) of a node is N-1, hence:

$$p_k = \binom{N-1}{k} p^k (1-p)^{N-1-k}$$

$$\langle k \rangle = p(N-1)$$

Expected number of links

- Expected number of links

$$\langle L \rangle = p \cdot L_{\max} = p \frac{N(N-1)}{2}$$

- Average degree

$$\langle k \rangle = \frac{2 \langle L \rangle}{N} = p(N-1)$$

Exercise [B. 2016, Ex. 3.11.1]

- Consider an ER graph with N=3,000 $p=10^{-3}$
  1) What is the expected number of links <L>?
  2) What is the average degree <k>?

$$\langle L \rangle = p \cdot L_{\max} = p\frac{N(N-1)}{2}$$

$$\langle k \rangle = \frac{2\langle L \rangle}{N} = p(N-1)$$

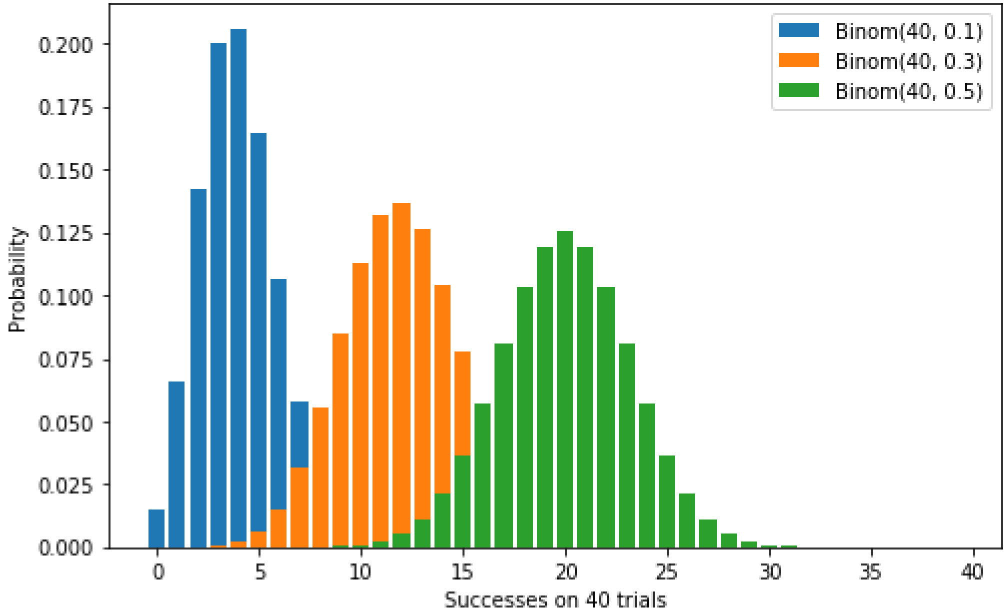
Answer in Nearpod Poll
https://nearpod.com/student/
Code to be given during class

Degree distribution examples

- The peak is always at $\langle k \rangle = p(N-1)$

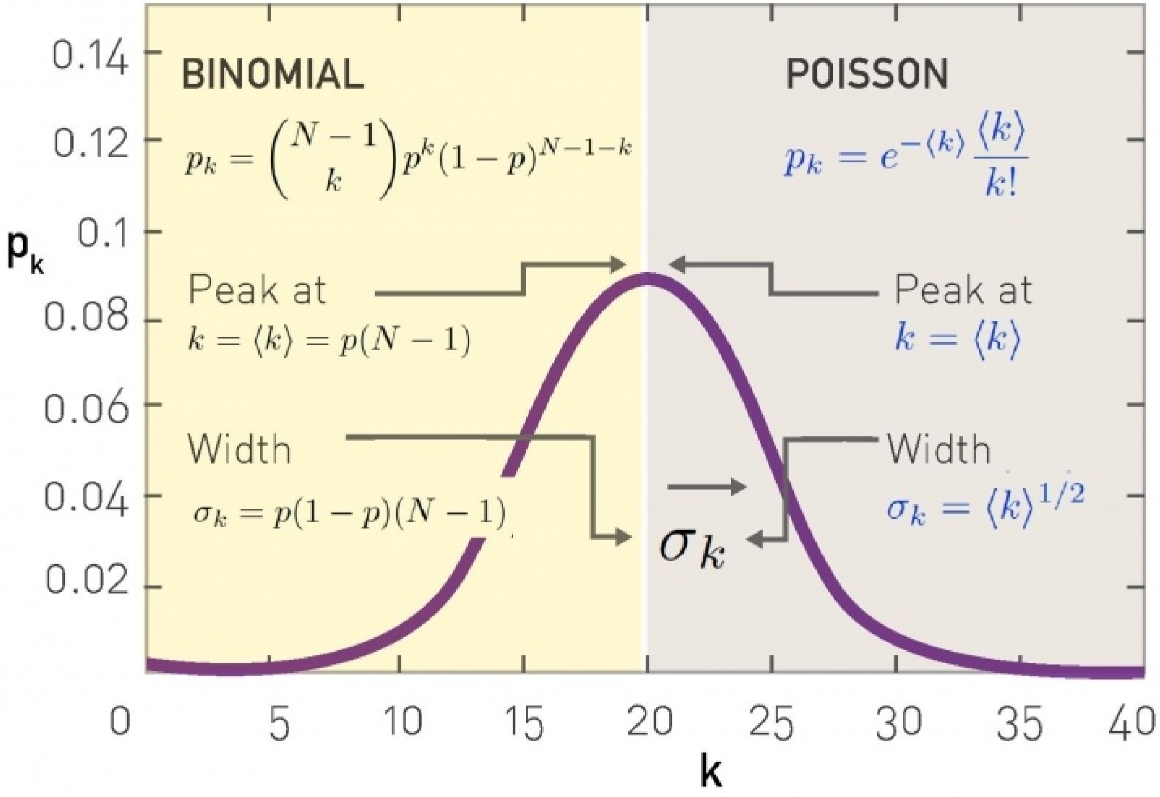
```
import numpy as np
from scipy.stats import binom
from matplotlib import pyplot as plt
```

```
x = np.arange(0, 40)
plt.figure(figsize=(8,5))
plt.bar(x, (binom(40, 0.1)).pmf(x), label='Binom(40, 0.1)')
plt.bar(x, (binom(40, 0.3)).pmf(x), label='Binom(40, 0.3)')
plt.bar(x, (binom(40, 0.5)).pmf(x), label='Binom(40, 0.5)')
plt.gca().legend()
plt.xlabel("Successes on 40 trials")
plt.ylabel("Probability")
plt.show()
```



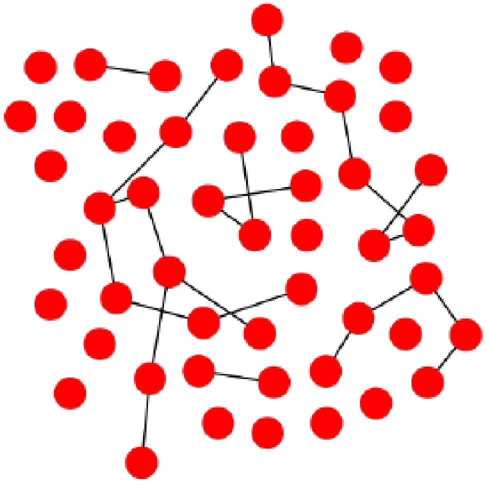
python™

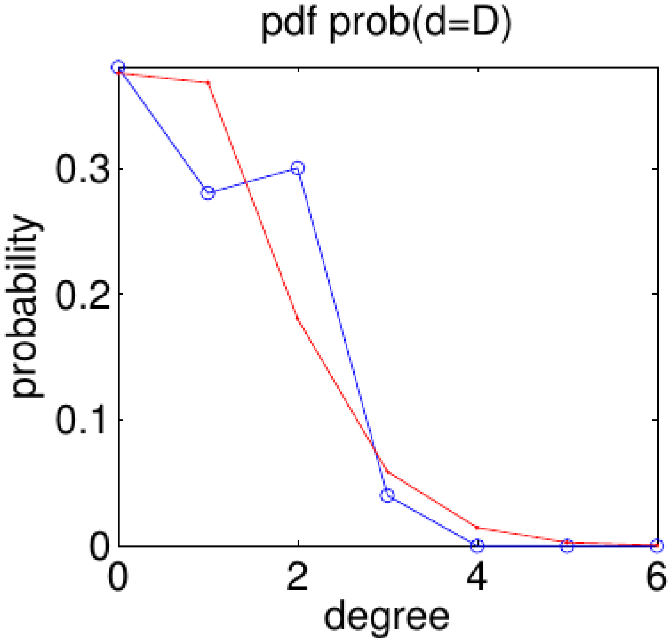
Approximation with a Poisson distribution for $\langle k \rangle \ll N$

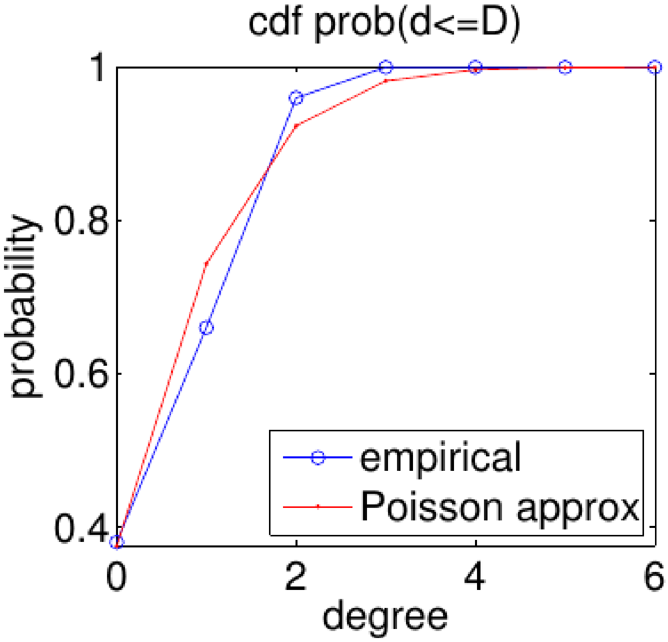


More examples (1/6)

$$N = 50, p = 0.02, \langle k \rangle \approx 1$$



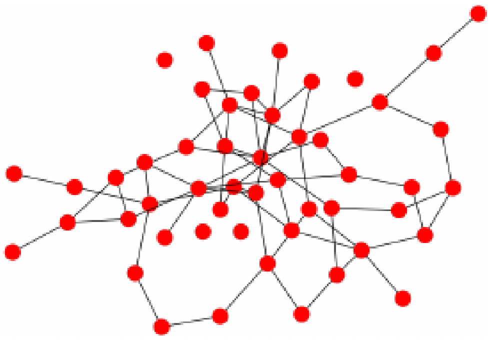


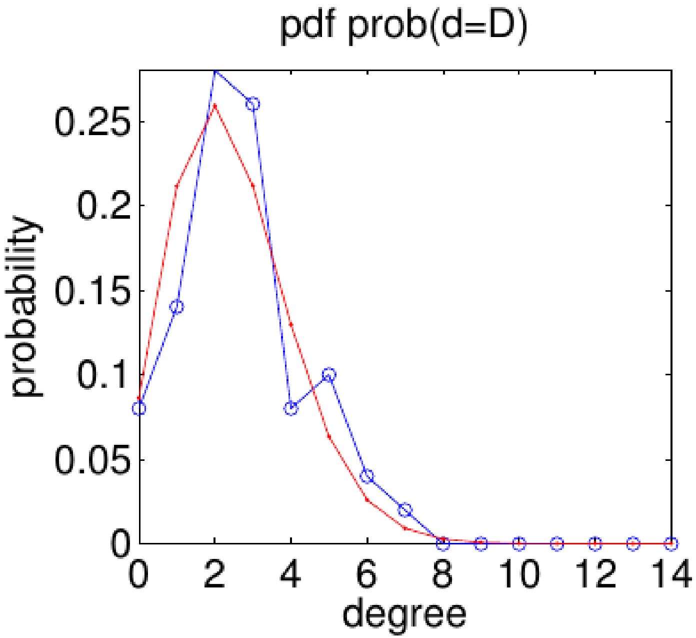


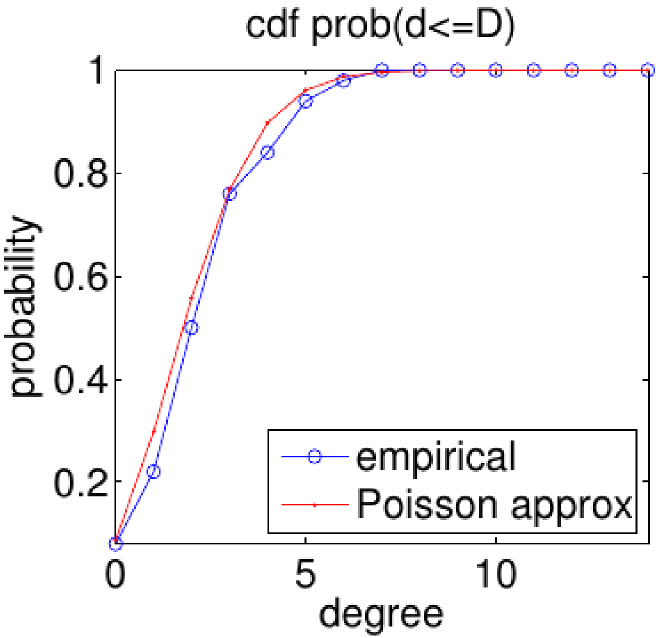
https://www.upf.edu/web/iis/DataDrivenSocialAnalytics

More examples (2/6)

$$N = 50, p = 0.05, \langle k \rangle \approx 2.5$$







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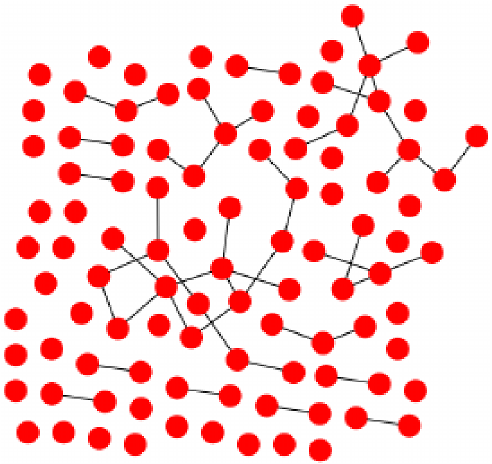
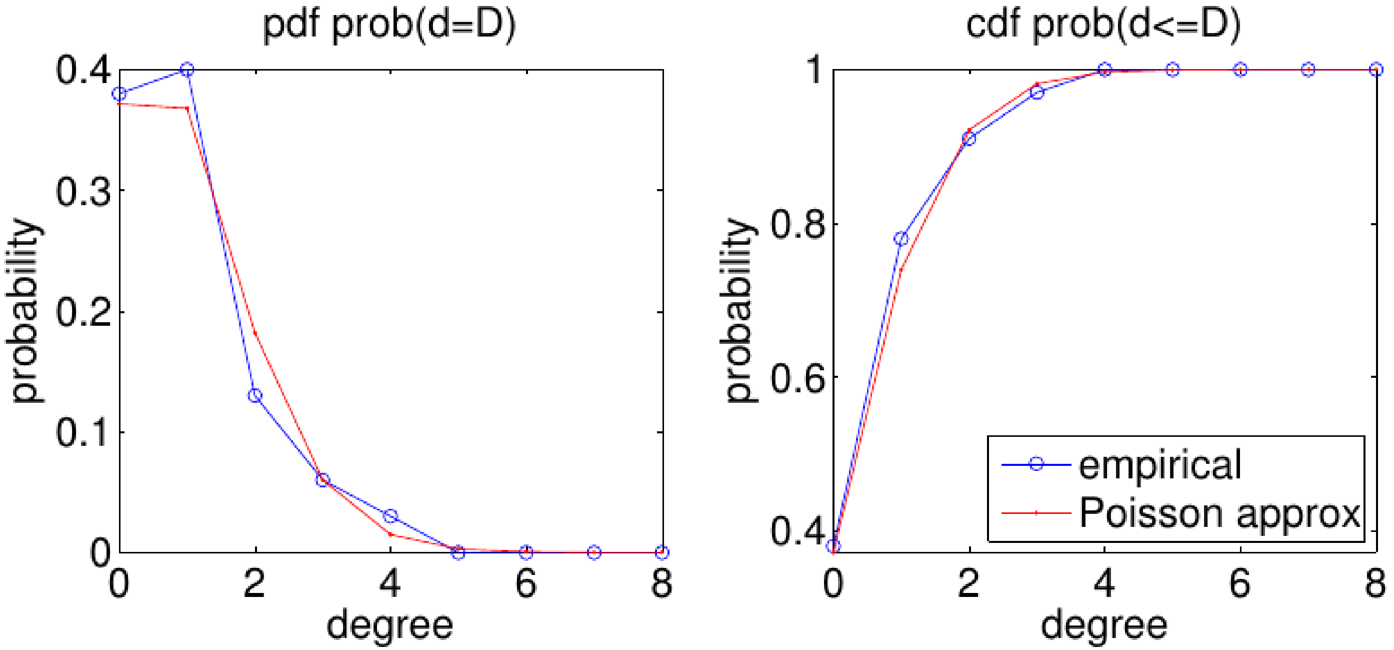
More examples (3/6)

$$N = 100, p = 0.01, \langle k \rangle \approx 1$$





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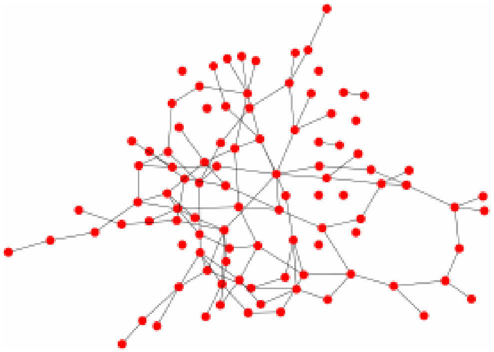
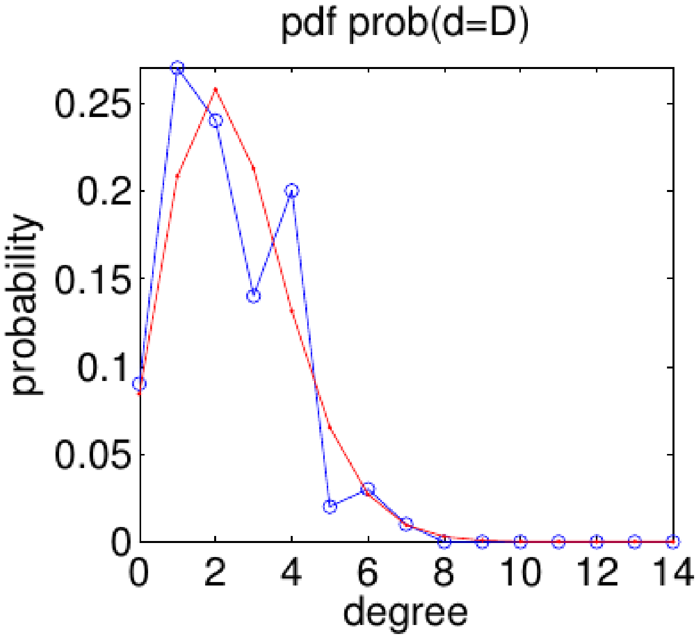
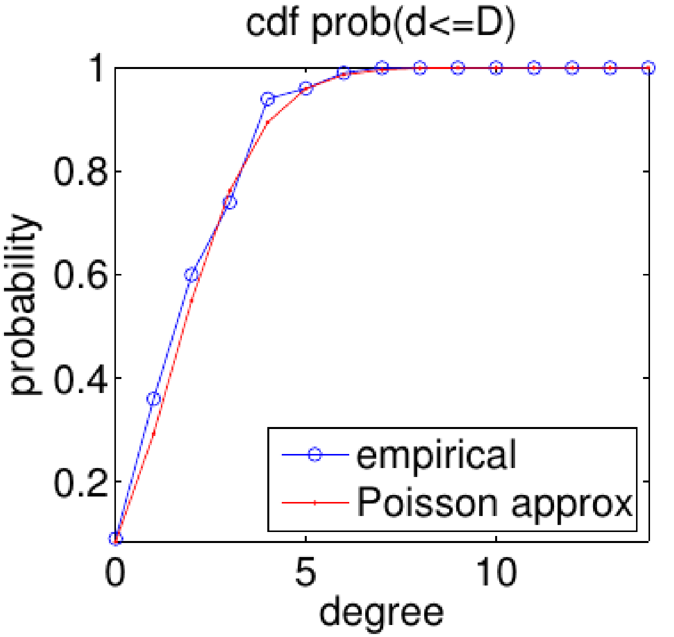
More examples (4/6)

$$N = 100, p = 0.025, \langle k \rangle \approx 2.5$$



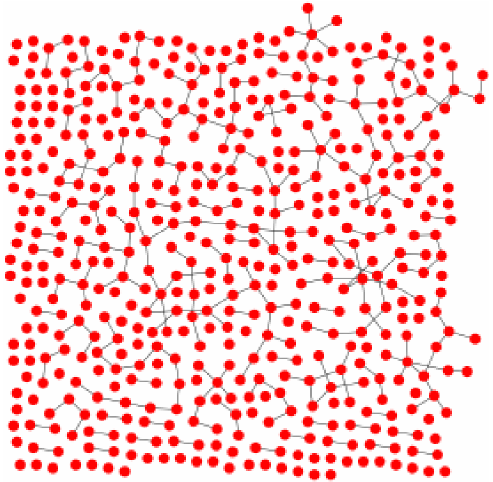


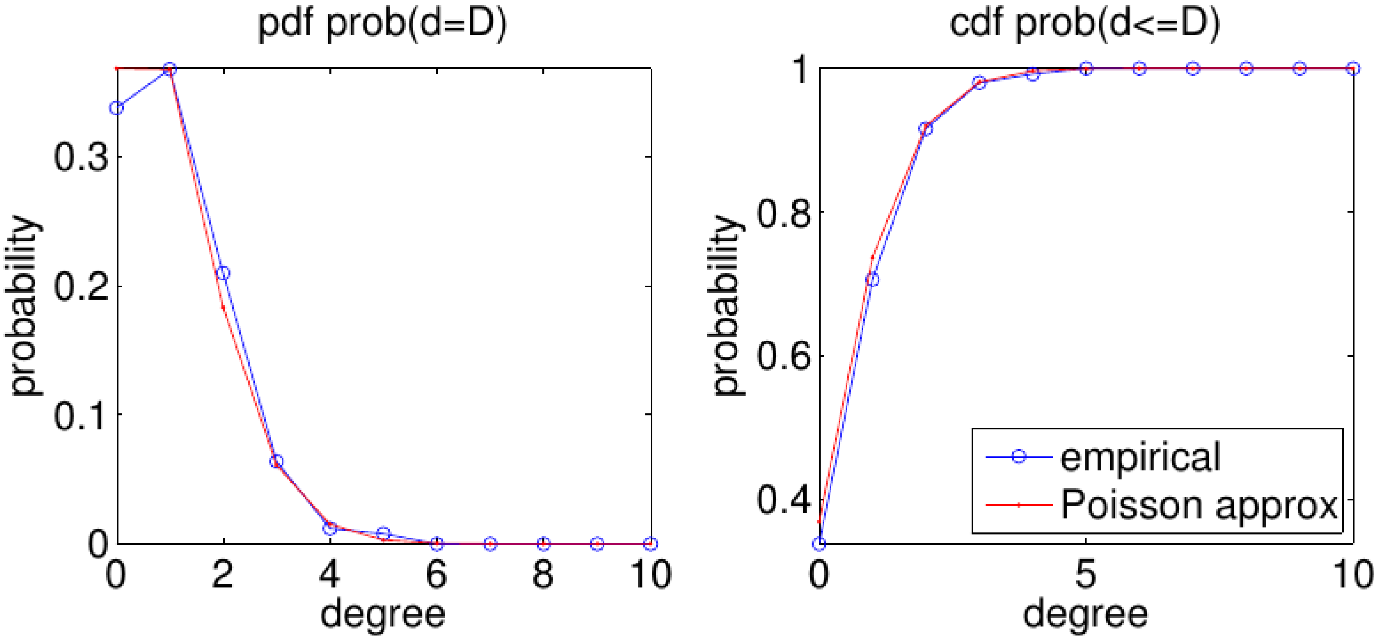


https://www.upf.edu/web/iis/DataDrivenSocialAnalytics

More examples (5/6)

$$N = 500, p = 0.002, \langle k \rangle \approx 1$$





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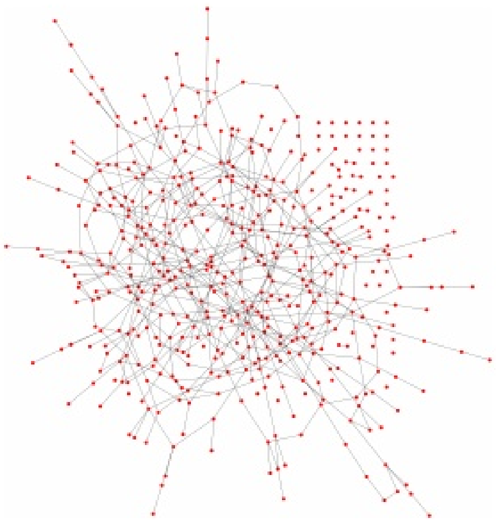
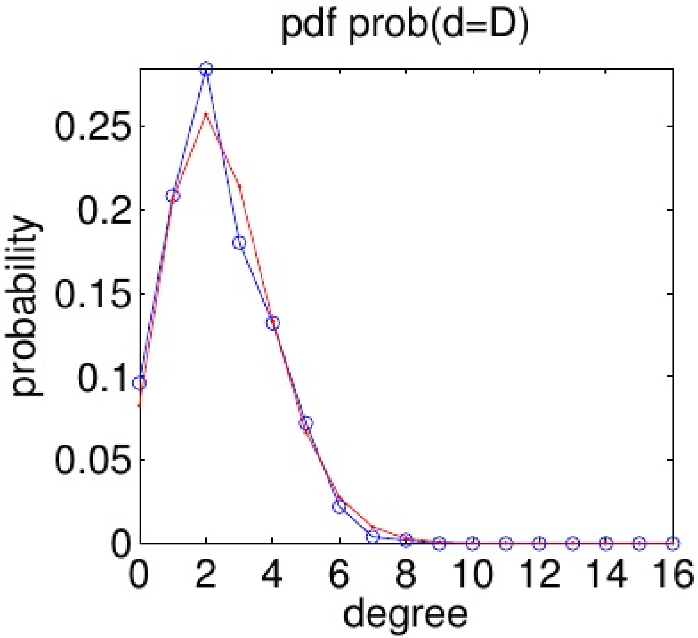
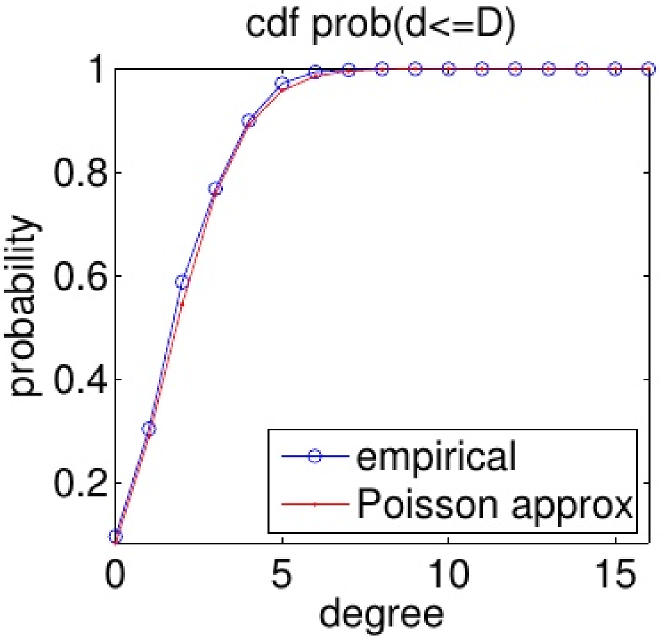
More examples (6/6)

$$N = 500, p = 0.005, \langle k \rangle \approx 2.5$$







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“Back of the envelope” calculations

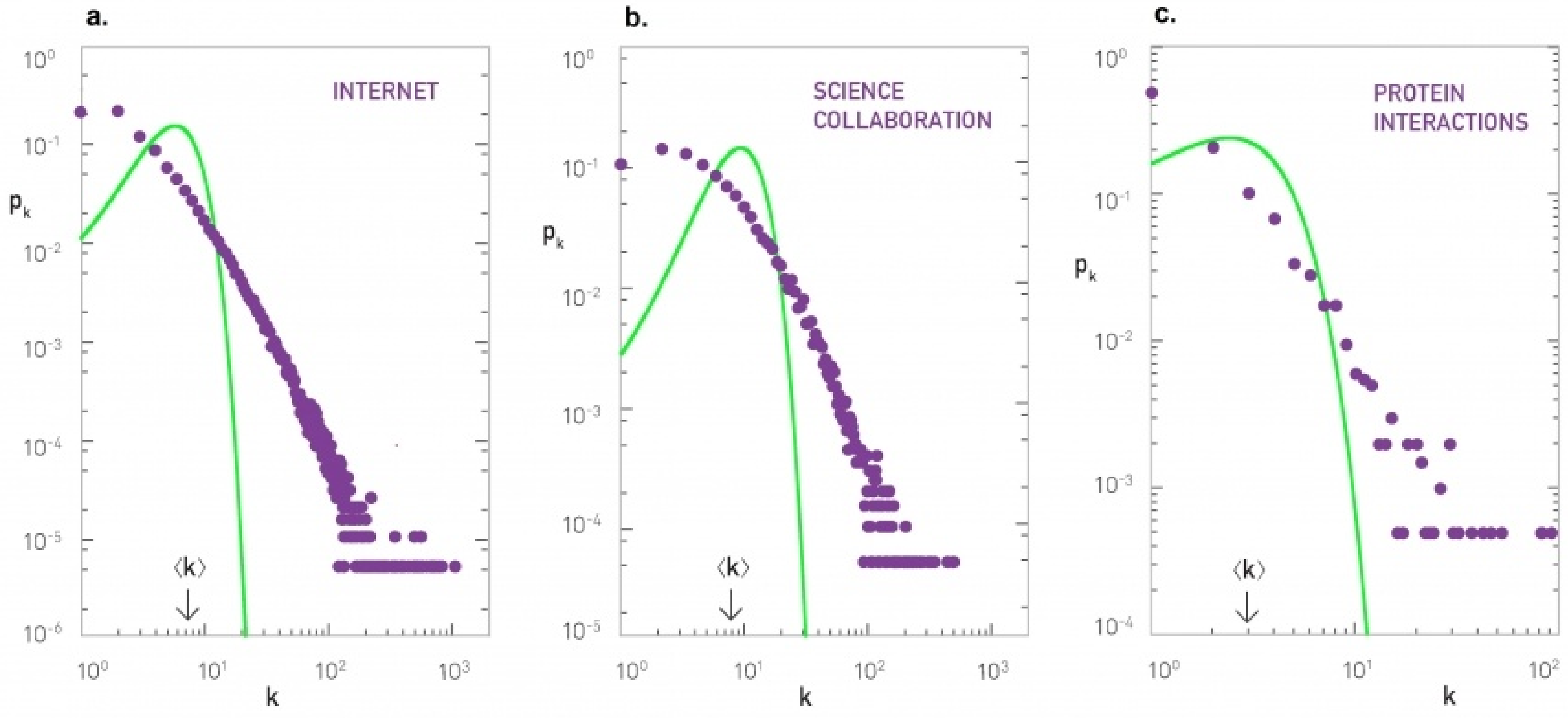
- Suppose $N = 7 \times 10^9$
- Suppose $\langle k \rangle = 1{,}000$
  - A person knows the name of approx. 1,000 others
- Then on expectation $k_{max} = 1{,}185$
- $\langle k \rangle \pm \sigma$ is the range from 968 to 1,032
- Is this realistic?

Survey: how many WhatsApp contacts do you have?

https://goo.gl/forms/ovVvdnlWmZgMWdiL2

Answer in
Google Forms

Real networks (green = $e^{-\langle k \rangle} \frac{\langle k \rangle^k}{k!}$)



Summary

Things to remember

- The ER model
- Degree distribution in the ER model

Practice on your own

- Write code to create ER networks
- Indicate the expected number of edges of a network with N=256, p=0.25; then compare your solution with the one on this video:

https://www.youtube.com/watch?v=2DckiyysQy4