

# Complex Networks and their Analysis with Random Walks

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# Objectives and Organization

□ First contact

**1h**

○ “networks everywhere”

□ Empirical findings of networks

**Daniel**

○ important commonalities

□ Mathematical models for networks

**1h**

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**break**

□ Random walk premier

**.5h**

○ simple yet profound

**Kostia**

□ Applications of random walks

**1.5h**

○ sampling, ranking, clustering, etc



# How to study networks?

- ❑ Networks obtained empirically provide one, complicated instance
  - eg., Facebook, Web, Neurons
- ❑ Need to work with abstractions

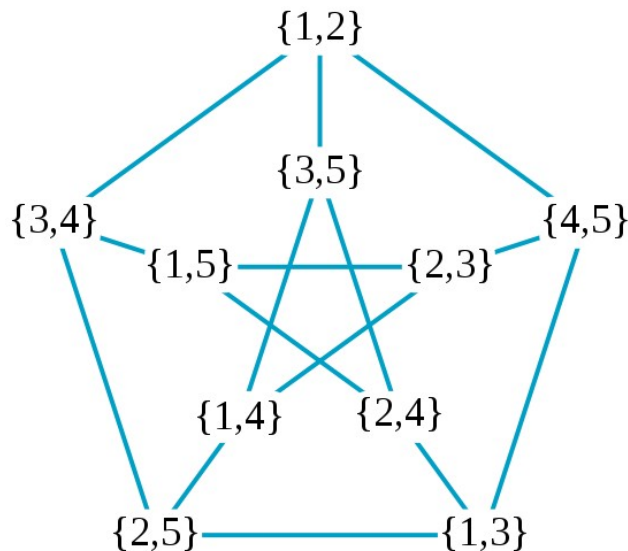
## **Mathematical models to the rescue!**

- ❑ Simplify reality for fundamental understanding of various properties
- ❑ Models for network structure (connectedness)

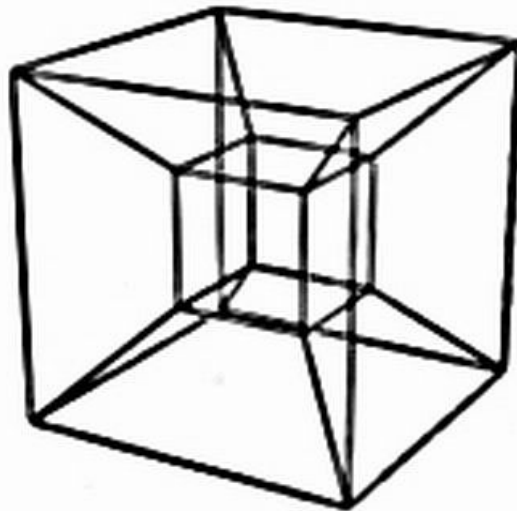
# Deterministic Models

- ❑ Network structure is deterministic
  - rules uniquely determine network formation
- ❑ Structural properties are deterministic

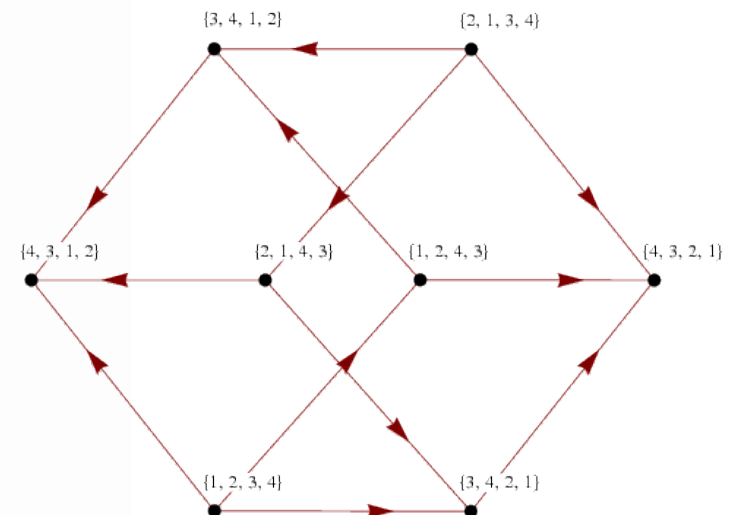
## Examples of models?



Kneser Graph



Hypercube

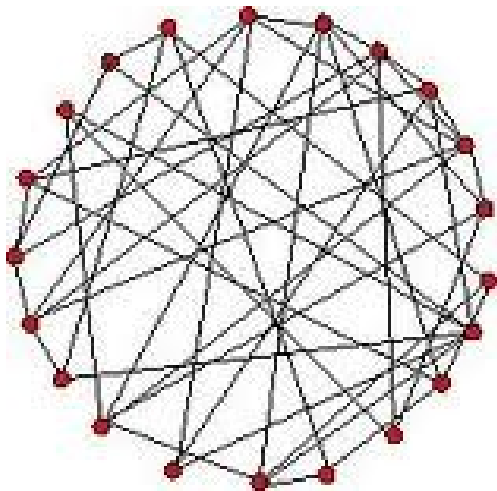


Caley Graphs

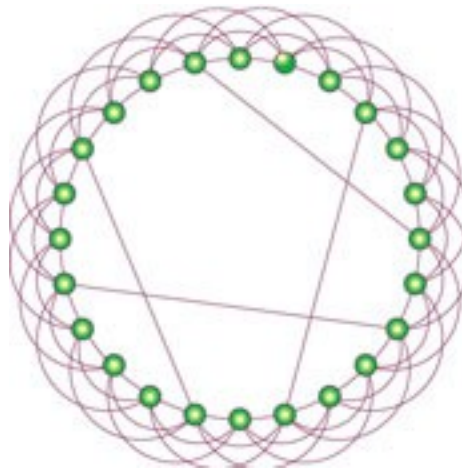
# Probabilistic Models

- ❑ Network structure is random
  - probabilistic rules determine network formation
- ❑ Structural properties are random

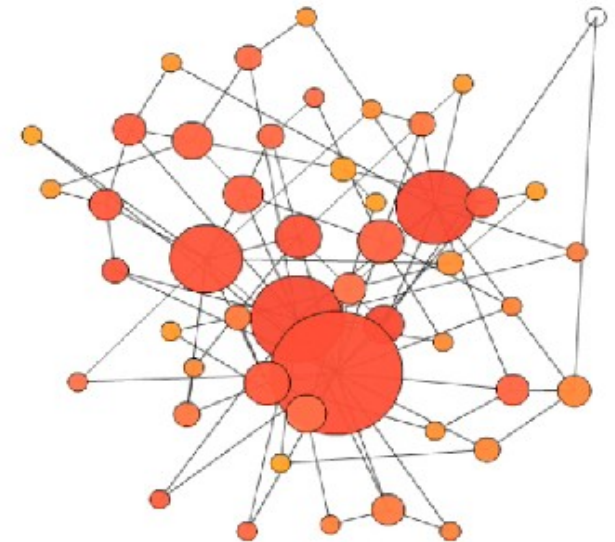
## Examples of models?



Erdős-Rényi



Watts-Strogatz



Barabási-Albert

# $G(n,p)$ Model

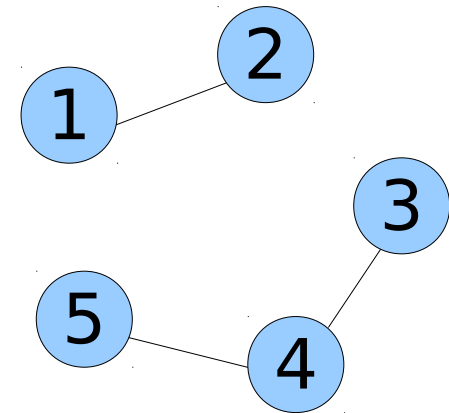
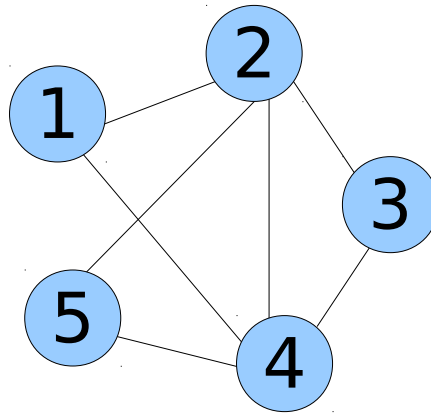
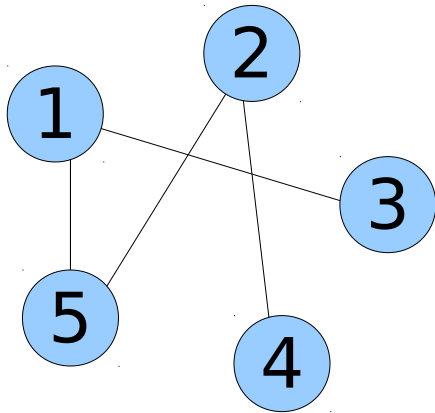
- ❑ Classic and most widely studied model for random graphs
  - first studied by Erdős and Rényi in 50s
  - aka. Binomial model, Erdős-Rényi model
- ❑ The model
  - network has  $n$  labeled nodes
  - each possible edge is present with probability  $p$ , independently

**Very simple model!**

- ❑ yet surprisingly rich structures emerge

# $G(n,p)$ Example

- ❑ Given its two parameter,  $n$  and  $p$ , what network is formed?
- ❑ Ex.  $n=5$ ,  $p=0.25$



- ❑ Network is random! A realization of the random process (choosing edges)

# Characterizing the $G(n,p)$

## What kind of networks does $G(n,p)$ generates?

- ❑ Is it a connected graph? What is the degree distribution? What is the clustering? Etc
- ❑ Random structure depends on  $n$  and  $p$
- ❑ Characterize structural properties for large  $n$  and scaling  $p$
- ❑ Determine conditions for properties to be present with high probability



# Simple Properties

❑ Sample space of  $G(n,p)$ ?

○  $S$  = all possible graphs with  $n$  nodes

❑ What is the sample space size?

$$|S| = 2^{\binom{n}{2}} \longleftarrow \text{Every possible edge can either be present or absent}$$

❑  $n=15$ ,  $|S| >$  number of atoms on universe!

❑ Probability of generating a given graph, defined by  $E = \{e_1, e_2, \dots, e_k\}$ ?

$$P(\text{generate set } E) = p^{|E|} (1-p)^{\binom{n}{2} - |E|}$$

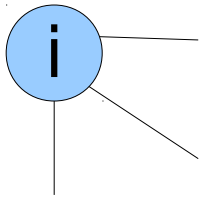
❑ depends only on  $k$ , and not the set  $E$

# Degree in $G(n,p)$

❑ What is the degree of a given node?

○ degree is random!

❑ What is degree distribution of a given node?



$$P[D=k]? \quad k = 0, 1, \dots, n-1$$

❑ Each edge incident on node  $i$  with probability  $p$

$$P[D=k] = \binom{n-1}{k} p^k (1-p)^{n-1-k}$$

Binomial  
distribution

❑ Expected degree

$$E[D] = (n-1)p$$

# Connected Components

- ❑ Is  $G(n,p)$  connected? Size of connected components?
- ❑ Let  $p$  be a function of  $n$ , thus  $p(n)$ 
  - if  $p(n) = z/(n-1)$  for constant  $z$ , then  $E[D] = z$
- ❑  $z < 1$  (subcritical)
  - all CC have size  $O(\log n)$ , many components
- ❑  $z > 1$  (supercritical)
  - largest CC has size  $\Omega(n)$ , all others  $O(\log n)$
- ❑  $z = \Omega(\log n)$ 
  - single CC, network is connected

**Phase transitions on graph structure!**

- ❑ results valid with high probability as  $n$  grows

# $G(n,p)$ and Real Networks



- ❑ Is  $G(n,p)$  a good model for real networks?

## **(most) Real Networks**

- ❑ Short distances
- ❑ High clustering
- ❑ Heavy-tailed degree distribution

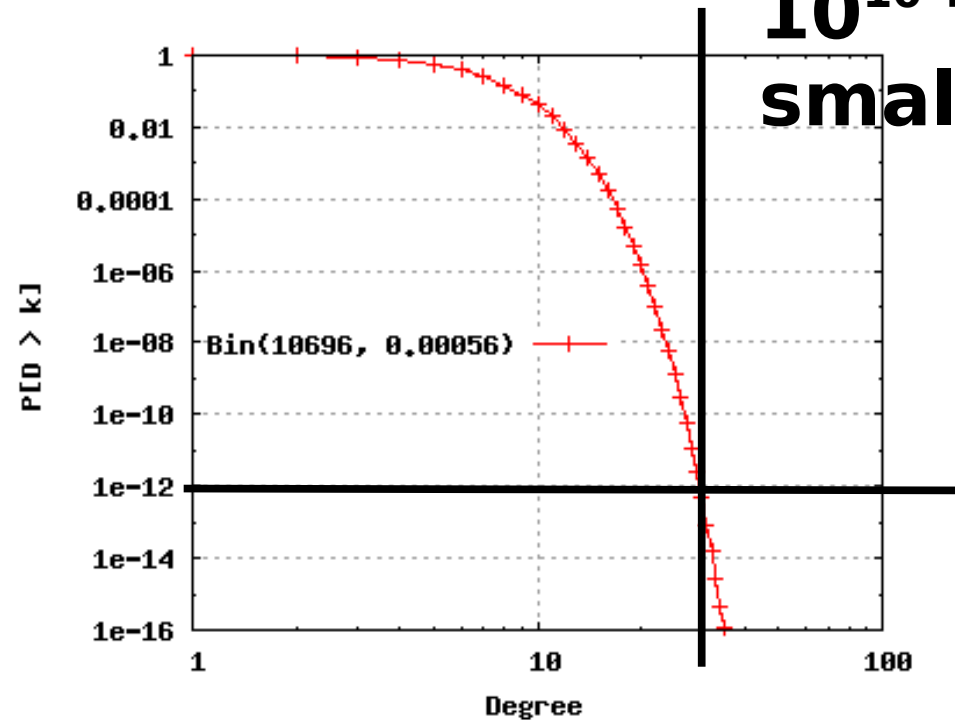
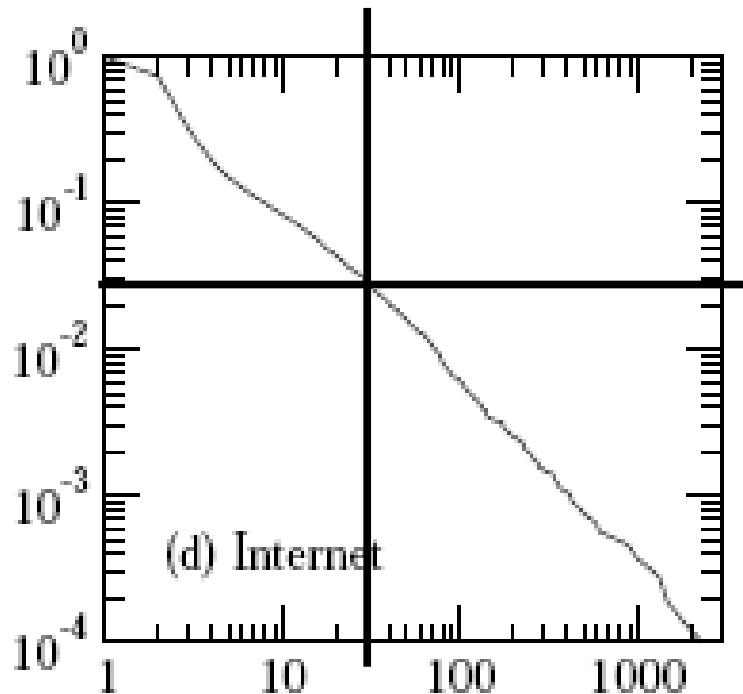
## **$G(n,p)$**

- ❑ Short distances
- ❑ Low clustering ( $p$ )
- ❑ Binomial degree distribution

**Fundamentally important,  
yet fundamentally different**

# Example

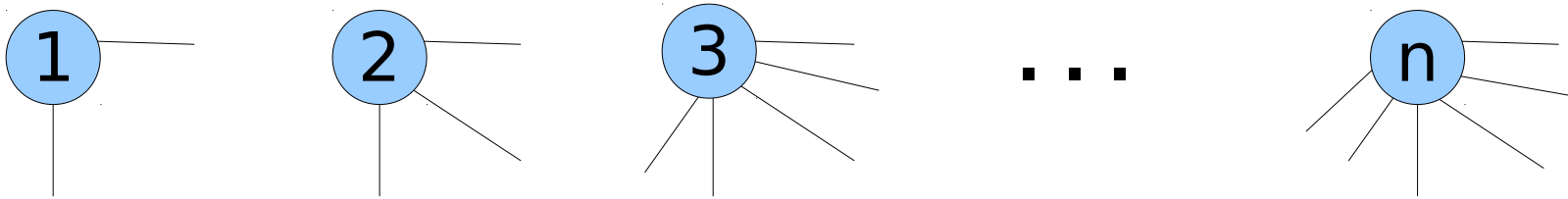
- ❑ AS Graph, 11K nodes, 32K edges
- ❑ Apply  $G(n,p)$  preserving  $n$  and avg deg (=6.16)
  - $n=11K$ ,  $p=0.00056$
- ❑ Clustering: data=0.39, model=0.00056
  - almost **1000** times smaller
- ❑ Degree distribution



**$P[D > 30]$  is  
 $10^{10}$  times  
smaller!**

# Configuration Model

- ❑ **Idea:** specify degree of network nodes, connect them at random
- ❑ Parameters: degree sequence  $d_1, d_2, \dots, d_n$ 
  - degree sum has to be even



- ❑ Connect edge points at random
  - multiple edges unlikely if network is very large
- ❑ Generalization of  $G(n,p)$ 
  - allows for arbitrary degree distribution
  - still very low clustering

# Generative Models

- ❑ Grow network iteratively
  - add nodes and edges over time
- ❑ Capture some fundamental aspect of network formation
  - structure is consequence of iterative rules

**Various models proposed  
in this class**

# Preferential Attachment

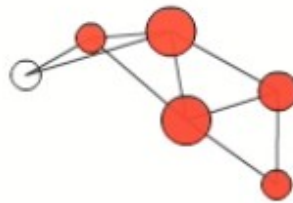
- ❑ Old phenomenon for growing dynamics
  - cumulative advantage, rich-gets-richer, Matthew effect, etc
- ❑ **Idea:** accumulated resources promote the accumulation of further resources
- ❑ Various empirical observations
  - word usage, city growth, etc
- ❑ Applied to networks
  - paper citation networks: Solla Price, 50's
  - hyperlinks on web: Barabasi-Albert, 99



# BA Model

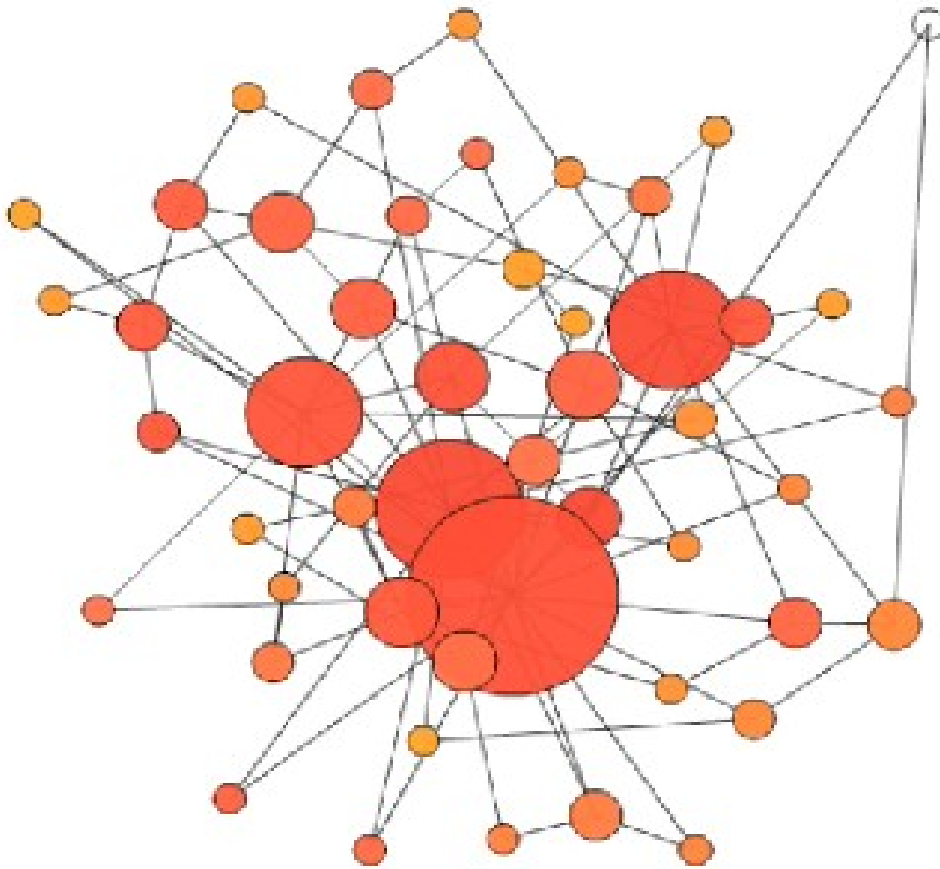
- ❑ Barabási-Albert model, proposed in 1999  
(*Science* paper with over 23K citations)
  - preferential attachment based on node degree
- ❑ At each step
  - add one node with degree  $m$
  - choose each neighbor with probability proportional to their degree
- ❑ Parameters
  - small initial network
  - $m$ , number of edges added with each node

# BA Model Example

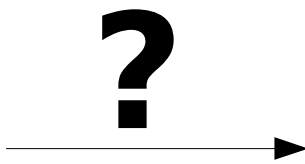


- ❑ Initial network is a triangle,  $m = 2$ 
  - size of node proportional to node degree

# BA Model Example



- ☐ What is happening?
- ☐ many small degree, few high degree

**Preferential attachment**  **Heavy-tailed degree distribution**

# BA Model Properties

□ Analysis via continuous approximations with differential equations

□  $d_u(t)$  : average degree of node  $u$  at time  $t$

○  $t_u$  : time node  $u$  entered network

$$d_u(t) = m \left( \frac{t}{t_u} \right)^{1/2}$$

□ Assuming  $t_u$  is uniformly chose  $[1, t]$

$$P[d_u(t) = k] \approx \frac{2m^2}{k^3}$$

**Power law degree distribution!**

# Limitations of BA

- ❑ Power law exponent is fixed, equal to 3
  - real networks have various decays
- ❑ Older nodes always have higher degrees
  - real networks new nodes can take over; Facebook
- ❑ Clustering coefficient is very low
- ❑ No new edges among existing nodes

**Many, many more models!**

- ❑ to address these and other limitations

# References

## Textbooks

- ❑ Mark Newman, *Networks: An Introduction*, 2010
- ❑ Albert-László Barabási, *Network Science*, 2015
- ❑ B. Bollobas, *Random Graphs*, 2001

## Papers

- ❑ A.-L. Barabási, R. Albert, *Emergence of scaling in random networks*, Science 1999
- ❑ *Scale-Free Networks: A Decade and Beyond*, Science (special issue) 2009