

# Complex Networks

## random graphs

2016.1.4(Mon)

# Goal

metrics

algorithms

models

processes

# contents of this chapter

- random graphs (12)
- models of network formation (14)
  - BA model
- other network models (15)
  - the small-world model
- percolation

# network models

- “If I know a network as some particular property, such as a particular degree distribution, what effect will that have on the wider behavior of the system?”
- building mathematical models of networks
  - mimic the patterns of connections in real networks
  - understand the implications of the patterns

# random graph

- a model network in which some specific set of parameters take fixed values, but the network is random in other respects
- simplest example:  $G(n, m)$ 
  - take  $n$  vertices and place  $m$  edges at random
  - simple graph (no multiedges or self-edges)

⇒ a probability distribution  $P(G)$  over possible networks

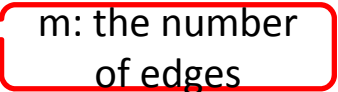
$$P(G) = \begin{cases} 1/\Omega & \text{if } G \text{ is a simple graph with } n \text{ vertices and } m \text{ edges} \\ 0 & \text{otherwise} \end{cases}$$

$\Omega$ : the total number of simple graphs with  $n$  vertices and  $m$  edges

# random graph model = an ensemble of networks

- properties of random graphs = the average properties of the ensemble
- diameter of  $G(n,m)$  :  $\langle l \rangle = \sum_G P(G) l(G) = \frac{1}{\Omega} \sum_G l(G)$
- this is a useful definition for several reasons:
  - many average properties can be calculated exactly
  - we are often interested in typical properties of the networks
  - distributions of values for many network measures is sharply peaked
- average degree :  $\langle k \rangle = 2m/n$

# another random graph model

- $G(n,p)$ 
  - $n$  : the number of vertices
  - $p$  : the probability of edges between vertices
- $G(n,p)$  is the ensemble of networks with  $n$  vertices in which each simple  $G$  appears with probability  $P(G) = p^m (1-p)^{\binom{n}{2}-m}$ 
  - $m$ : the number of edges
- often called as “Erdos-Renyi model”, “Poisson random graph”, “Bernoulli random graph”, or “the random graph”

# mean number of edges and mean degree of $G(n,p)$

- total probability of drawing a graph with  $m$  edges from the ensemble is

$$P(m) = \binom{\binom{n}{2}}{m} p^m (1-p)^{\binom{n}{2}-m}$$

the expected value of binomially distributed variable (see the next page)

- the mean value of  $m$  is  $\langle m \rangle = \sum_{m=0}^{\binom{n}{2}} m P(m) = \binom{n}{2} p$
- the mean degree is  $\langle k \rangle = \sum_{m=0}^{\binom{n}{2}} \frac{2m}{n} P(m) = \frac{2}{n} \binom{n}{2} p = (n-1)p$

often denoted as  $c$

$$c = (n-1)p$$

$$n(n-1)/2$$



# the expected value of binomially distributed variable

$$\langle m \rangle = \sum_{m=0}^{\binom{n}{2}} m P(m) = \sum_{m=1}^{\binom{n}{2}} m P(m) = \sum_{m=1}^{\binom{n}{2}} m \binom{\binom{n}{2}}{m} p^m (1-p)^{\binom{n}{2}-m}$$

0 · P(0) = 0

$$\binom{N}{k} = \frac{N!}{k!(N-k)!} = \frac{N \cdot (N-1)!}{k \cdot (k-1)!((N-1)-(k-1))!}$$

$$= \frac{N}{k} \cdot \frac{(N-1)!}{(k-1)!((N-1)-(k-1))!} = \frac{N}{k} \cdot \binom{N-1}{k-1}$$

$N = \binom{n}{2}, k = m$

$$\langle m \rangle = \sum_{m=1}^{\binom{n}{2}} m \binom{\binom{n}{2}}{m} p^m (1-p)^{\binom{n}{2}-m} = \binom{n}{2} p \sum_{m=1}^{\binom{n}{2}} \binom{\binom{n}{2}-1}{m-1} p^{m-1} (1-p)^{\binom{n}{2}-m}$$

$j = m - 1$

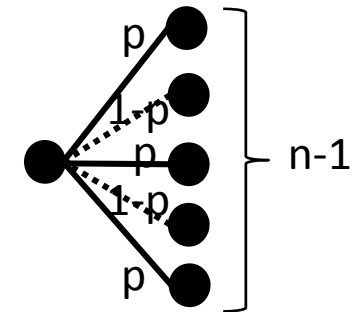
$$\langle m \rangle = \binom{n}{2} p \sum_{j=0}^{\binom{n}{2}-1} \binom{\binom{n}{2}-1}{j} p^j (1-p)^{\binom{n}{2}-1-j} = \binom{n}{2} p (p + (1-p))^{\binom{n}{2}-1} = \binom{n}{2} p$$

binomial theorem 1

# degree distribution of $G(n,p)$ (1)

- a vertex is connected with probability  $p$  to each of the  $n-1$  other vertices

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



- we are interested in large networks
  - a mean degree is approximately constant
  - $p = c/(n-1)$  becomes vanishingly small as  $n \rightarrow \infty$

$$\ln[(1-p)^{n-1-k}] = (n-1-k) \ln\left(1 - \frac{c}{n-1}\right) \cong -(n-1-k) \frac{c}{n-1} \cong -c$$

$$(1-p)^{n-1-k} = e^{-c}$$

for large  $n$

$$\begin{aligned} \ln(1+x) &= \sum_{n=1}^{\infty} \frac{(-1)^{n+1}}{n} x^n \quad \text{for all } |x| < 1 \\ &= x - \frac{1}{2} x^2 + \frac{1}{3} x^3 - \dots \end{aligned} \quad \text{Taylor expansion}$$

# degree distribution of $G(n,p)$ (2)

- for large  $n$

$$\binom{n-1}{k} = \frac{(n-1)!}{(n-1-k)!k!} \cong \frac{(n-1)^k}{k!}$$

$(n-1)(n-2)\dots(n-k)/k!$

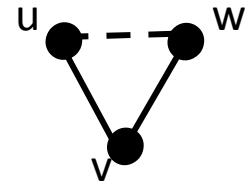
- $p_k$  becomes as follows in the limit of large  $n$

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k} = \frac{(n-1)^k}{k!} p^k e^{-c} = \frac{(n-1)^k}{k!} \left(\frac{c}{n-1}\right)^k e^{-c} = e^{-c} \frac{c^k}{k!}$$

Poisson distribution

# clustering coefficient of $G(n,p)$

- clustering coefficient : the probability that two network neighbors of a vertex are also neighbors of each other



- in a random graph, the probability is  $p = c/(n-1)$

$$C = \frac{c}{n-1}$$

- tends to zero in the limit  $n \rightarrow \infty$
- differs sharply from most of the real-world networks (quite high clustering coefficient)

# Giant component (1)

- the size of the largest component in a network

- $p=0 \rightarrow \text{size}=1$

independent of the size of the network

- $p=1 \rightarrow \text{size}=n$

it will grow with the network

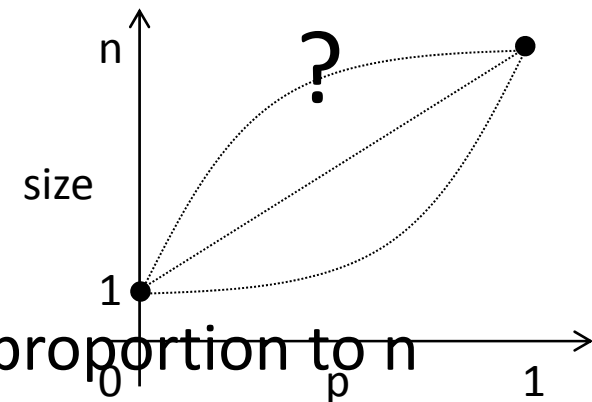
- giant component

- a component whose size grows in proportion to  $n$

- $u$  : average fraction of vertices that do not belong to the giant component

- $u = 1$  if there is no giant component

- $u$  is the probability that a randomly chosen vertex does not belong to the giant component



# Giant component (2)

- if vertex  $i$  does not belong to the giant component, for every other vertex  $j$ 
  - $i$  is not connected to  $j$  by an edge probability:  $1-p$
  - $i$  is connected to  $j$ , but  $j$  is not a member of the giant component probability:  $pu$
- total probability of not being connected to g.c. via any of  $n-1$  vertices:

probability of not being connected to g.c. via  $j$ :  $1-p+pu$

probability:  $1-p$

probability:  $pu$

$$u = (1 - p + pu)^{n-1} = \left[ 1 - \frac{c}{n-1} (1-u) \right]^{n-1}$$

# Giant component (3)

- taking logs of both sides

$$\ln u = (u - 1) \ln \left[ 1 - \frac{c}{n-1} (1-u) \right] \cong -(n-1) \frac{c}{n-1} (1-u) = -c(1-u)$$

- taking exponentials of both sides

$$u = e^{-c(1-u)}$$

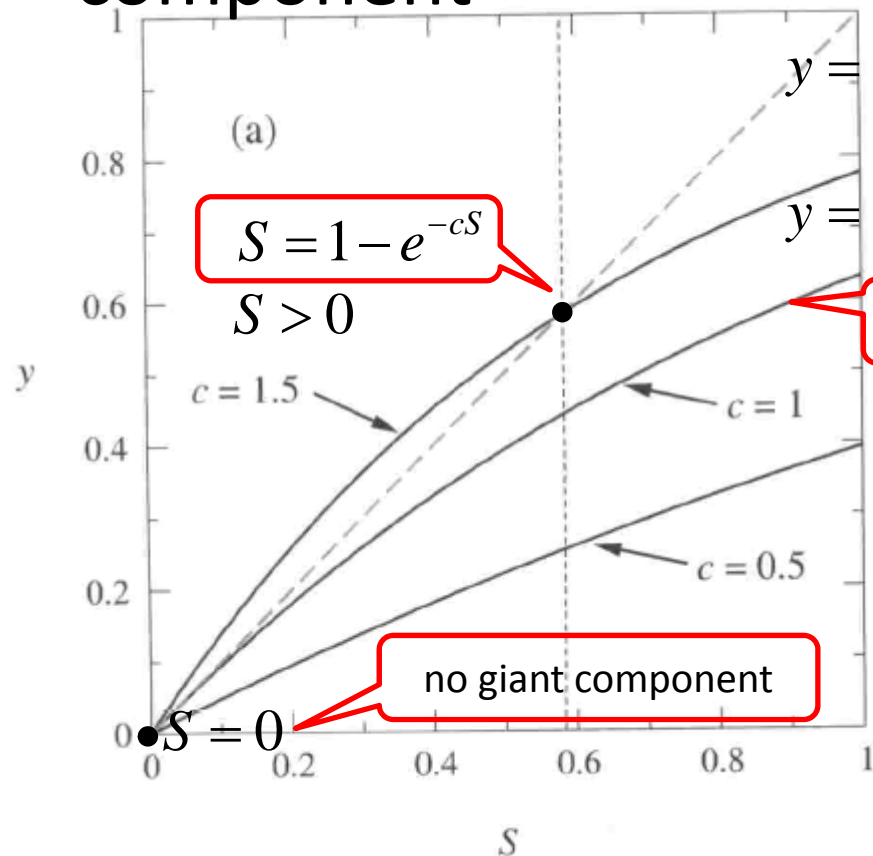
- $u$  is the fraction of vertices not in the giant component
- the fraction of vertices that are in the giant component is  $S = 1 - u$

$$S = 1 - e^{-cS}$$

it doesn't have a  
simple solution for  $S$

# Giant component (4)

- graphical solution for the size of the giant component



$$\frac{d}{dS}(1 - e^{-cS}) = 1$$

$$ce^{-cS} = 1$$

$$S = 0 \rightarrow c = 1$$

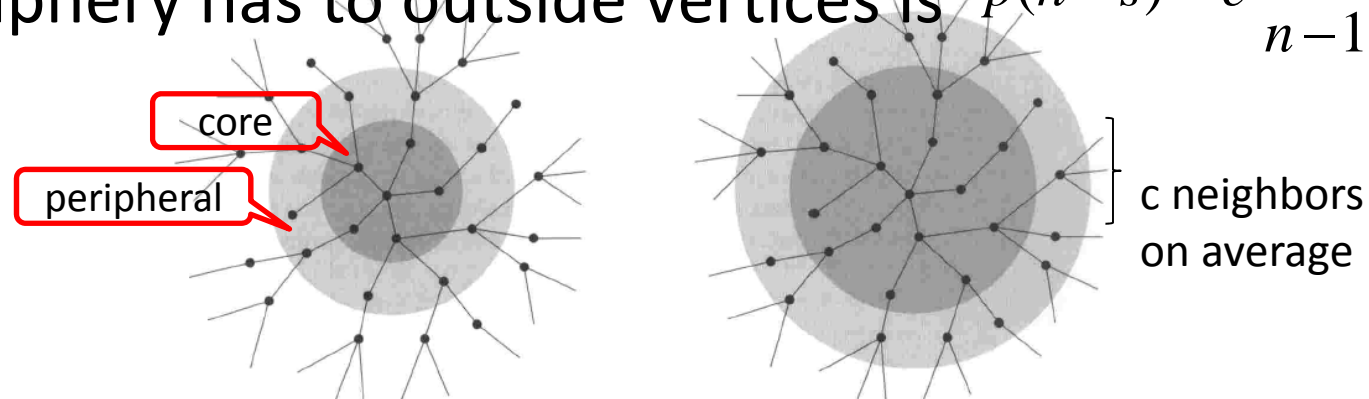
if  $c \leq 1$ , no giant component

if  $c > 1$ , two solutions for  $S$  ( $S=0$  &  $S>0$ )



# the value of $c$ and the growth of a set (1)

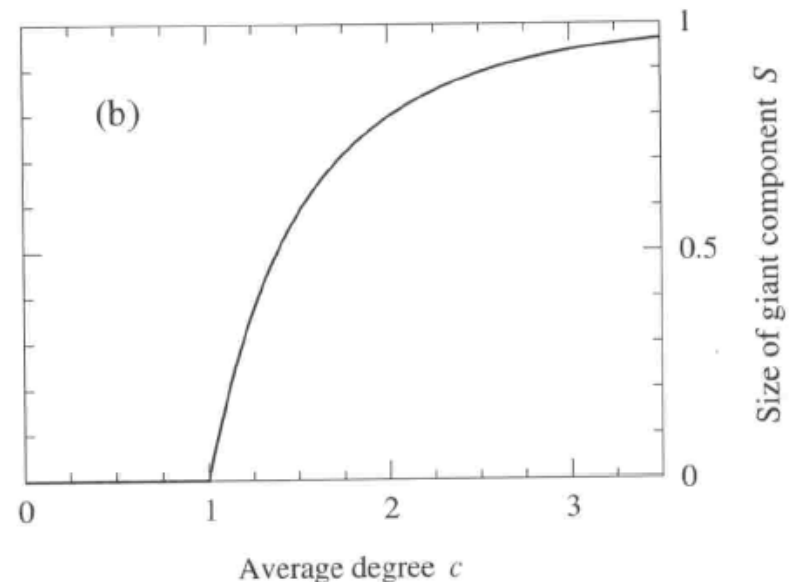
- core : all neighbor are inside the set
- peripheral : at least one neighbor is outside
- enlarging the set by adding immediate neighbor
  - $s$  vertices in the set,  $n-s$  vertices outside the set
  - the average number of connections a vertex in the periphery has to outside vertices is  $p(n-s) = c \frac{n-s}{n-1} \cong c$



the value of  $c$  and the growth of a set

(2)

- each peripheral has  $c$  neighbors outside
  - (# of new peripheral) =  $c \times$  (# of old peripheral)
- if  $c > 1$ , the average size of the periphery will grow exponentially  $\rightarrow$  giant component
- the size of the giant component is the larger solution of  $S = 1 - e^{-cS}$



# small components (1)

- when  $c > 1$ , there exist a giant component
- what is the structure of the remainder of the network?
  - it is made up of many small components whose average size is constant and doesn't increase with the size of the network
- there is only one giant component
  - suppose there are two giant components which have size  $S_1 n$  and  $S_2 n$ 
    - the number of distinct pairs of vertices between the two is  $S_1 S_2 n^2$
    - the probability that there is no edge between the two component is  
is
$$q = (1 - p)^{S_1 S_2 n^2} = \left(1 - \frac{c}{n-1}\right)^{S_1 S_2 n^2}$$

## small components (2)

- taking logs of both sides and going to the limit

$$\begin{aligned}
 \ln q &= S_1 S_2 \lim_{n \rightarrow \infty} \left[ n^2 \ln \left( 1 - \frac{c}{n-1} \right) \right] = S_1 S_2 \left[ -c(n+1) + \frac{1}{2} c^2 \right] \\
 &= c S_1 S_2 \left[ -n + \left( \frac{1}{2} c - 1 \right) \right]
 \end{aligned}$$

Taylor expansion

$$\begin{aligned}
 \ln(1+x) &= \sum_{n=1}^{\infty} \frac{(-1)^{n+1}}{n} x^n \quad \text{for all } |x| < 1 \\
 &= x - \frac{1}{2} x^2 + \frac{1}{3} x^3 - \dots
 \end{aligned}$$

- taking the exponential again

$$q = q_0 e^{-c S_1 S_2 n}$$

$$q_0 = e^{c(c/2-1)S_1 S_2}$$

constant

- the probability that the two giant components are really components dwindles exponentially with increasing  $n$

# sizes of small components (1)

- $\pi_s$  : probability that a randomly chosen vertex belongs to a small component of size  $s$

$$\sum_{s=0}^{\infty} \pi_s = 1 - S$$


- small components are trees

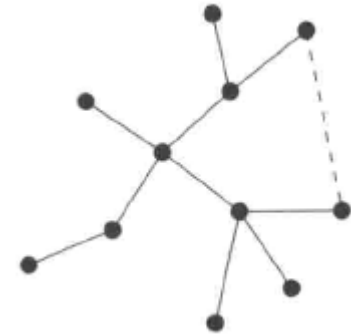
- a tree of  $s$  vertices contains  $s-1$  edges

- the total number of places where we could add an extra edge to the tree:  $\binom{s}{2} - (s-1) = \frac{1}{2}(s-1)(s-2)$

- the total number of extra edges :

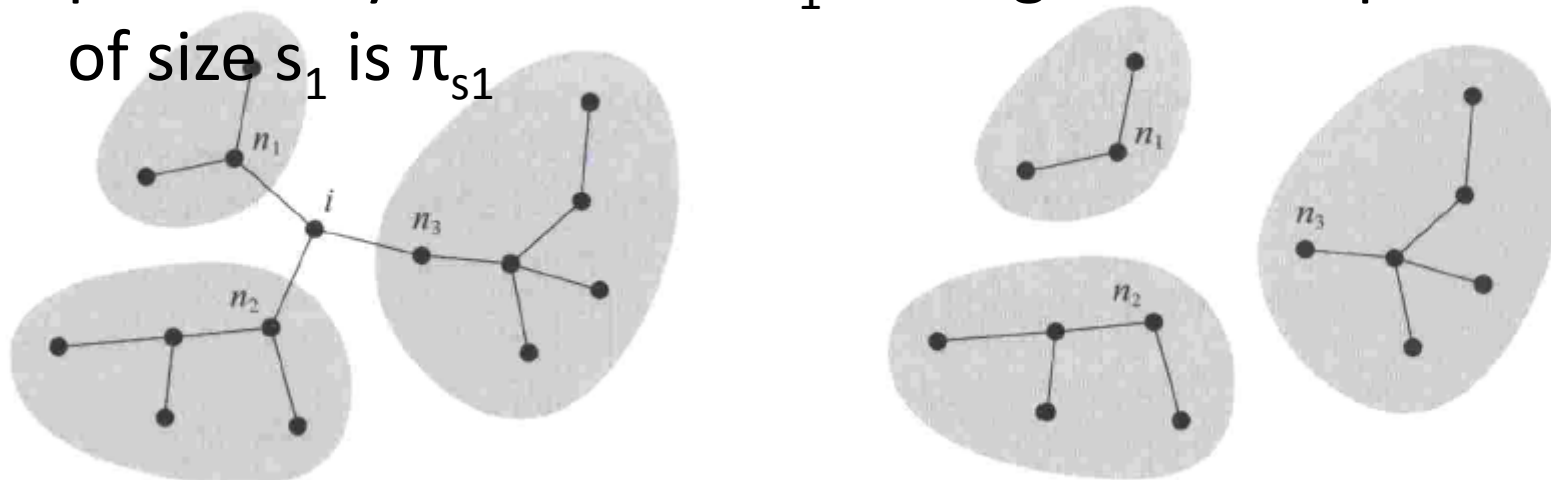
$$\frac{1}{2}(s-1)(s-2)p = \frac{1}{2}(s-1)(s-2)\frac{c}{n-1}$$

- $s$  increases more slowly than  $\sqrt{n}$   extra edges  $\rightarrow 0$



## sizes of small components (2)

- because the component is a tree,
  - (size of the component) =  $\sum(\text{size of } n_i) + 1$
- if vertex  $i$  is removed, the subcomponents become components in their own right
  - probability that vertex  $n_1$  belongs to a component of size  $s_1$  is  $\pi_{s1}$



## size of small components (3)

- suppose that vertex  $i$  has degree  $k$
- probability  $P(s | k)$  that vertex  $i$  belongs to small component of size  $s$  is

$$P(s | k) = \sum_{s_1=1}^{\infty} \dots \sum_{s_k=1}^{\infty} \left[ \prod_{j=1}^k \pi_{s_j} \right] \delta(s-1, \sum_j s_j)$$

- to get  $\pi_s$ , just average  $P(s | k)$  over the distribution  $p_k$  of the degree

$$\begin{aligned} \pi_s &= \sum_{k=1}^{\infty} p_k P(s | k) = \sum_{k=0}^{\infty} p_k \sum_{s_1=1}^{\infty} \dots \sum_{s_k=1}^{\infty} \left[ \prod_{j=1}^k \pi_{s_j} \right] \delta(s-1, \sum_j s_j) \\ &= e^{-c} \sum_{k=0}^{\infty} \frac{c^k}{k!} \sum_{s_1=1}^{\infty} \dots \sum_{s_k=1}^{\infty} \left[ \prod_{j=1}^k \pi_{s_j} \right] \delta(s-1, \sum_j s_j) \end{aligned}$$

$\because p_k = e^{-c} \frac{c^k}{k!}$   
 in the limit of large  $k$

# size of small components (4)

- generating function encapsulates all of the information about the degree distribution in a single function

$$h(z) = \pi_1 z + \pi_2 z^2 + \pi_3 z^3 + \dots = \sum_{s=1}^{\infty} \pi_s z^s$$

- we can recover the probabilities by differentiating  $\pi_s = \frac{1}{s!} \left. \frac{d^s h}{dz^s} \right|_{z=0}$
- substituting  $\pi_s$  into the equation of  $h(z)$

$$h(z) = \sum_{s=1}^{\infty} z^s e^{-c} \sum_{k=0}^{\infty} \frac{c^k}{k!} \sum_{s_1=1}^{\infty} \dots \sum_{s_k=1}^{\infty} \left[ \prod_{j=1}^k \pi_{s_j} \right] \delta(s-1, \sum_j s_j)$$



# size of small components (5)

$$\begin{aligned}
 h(z) &= \sum_{s=1}^{\infty} z^s e^{-c} \sum_{k=0}^{\infty} \frac{c^k}{k!} \sum_{s_1=1}^{\infty} \dots \sum_{s_k=1}^{\infty} \left[ \prod_{j=1}^k \pi_{s_j} \right] \delta(s-1, \sum_j s_j) \\
 &= e^{-c} \sum_{k=0}^{\infty} \frac{c^k}{k!} \sum_{s_1=1}^{\infty} \dots \sum_{s_k=1}^{\infty} \left[ \prod_{j=1}^k \pi_{s_j} \right] z^{1+\sum_j s_j} \\
 &= z e^{-c} \sum_{k=0}^{\infty} \frac{c^k}{k!} \sum_{s_1=1}^{\infty} \dots \sum_{s_k=1}^{\infty} \left[ \prod_{j=1}^k \pi_{s_j} z^{s_j} \right] \\
 &= z e^{-c} \sum_{k=0}^{\infty} \frac{c^k}{k!} \left[ \sum_{s=1}^{\infty} \pi_s z^s \right]^k = z e^{-c} \sum_{k=0}^{\infty} \frac{c^k}{k!} [h(z)]^k = z \exp[c(h(z)-1)]
 \end{aligned}$$

$\because \exp x = \sum_{n=0}^{\infty} \frac{1}{n!} x^n$

$\delta=1 \text{ only when } s-1=\sum_j s_j$

- it doesn't have a known closed-form solution for  $h(z)$ , but we can calculate many useful things from it without solving for  $h(z)$  explicitly

# size of small components (6)

- mean size of the component to which a randomly chosen vertex belongs

$$\langle s \rangle = \frac{\sum_s s \pi_s}{\sum_s \pi_s} = \frac{h'(1)}{1-S}$$

$h'(z)$  : the first derivative of  $h(z)$

- from the equation of  $h(z)$

$$h'(z) = \exp[c(h(z)-1)] + cz h'(z) \exp[c(h(z)-1)] = \frac{h(z)}{z} + ch(z)h'(z)$$

$$h'(z) = \frac{h(z)}{z[1-ch(z)]}$$

$$h(1) = \sum_s \pi_s = 1-S$$

$$h'(1) = \frac{h(1)}{1-ch(1)} = \frac{1-S}{1-c+cS}$$

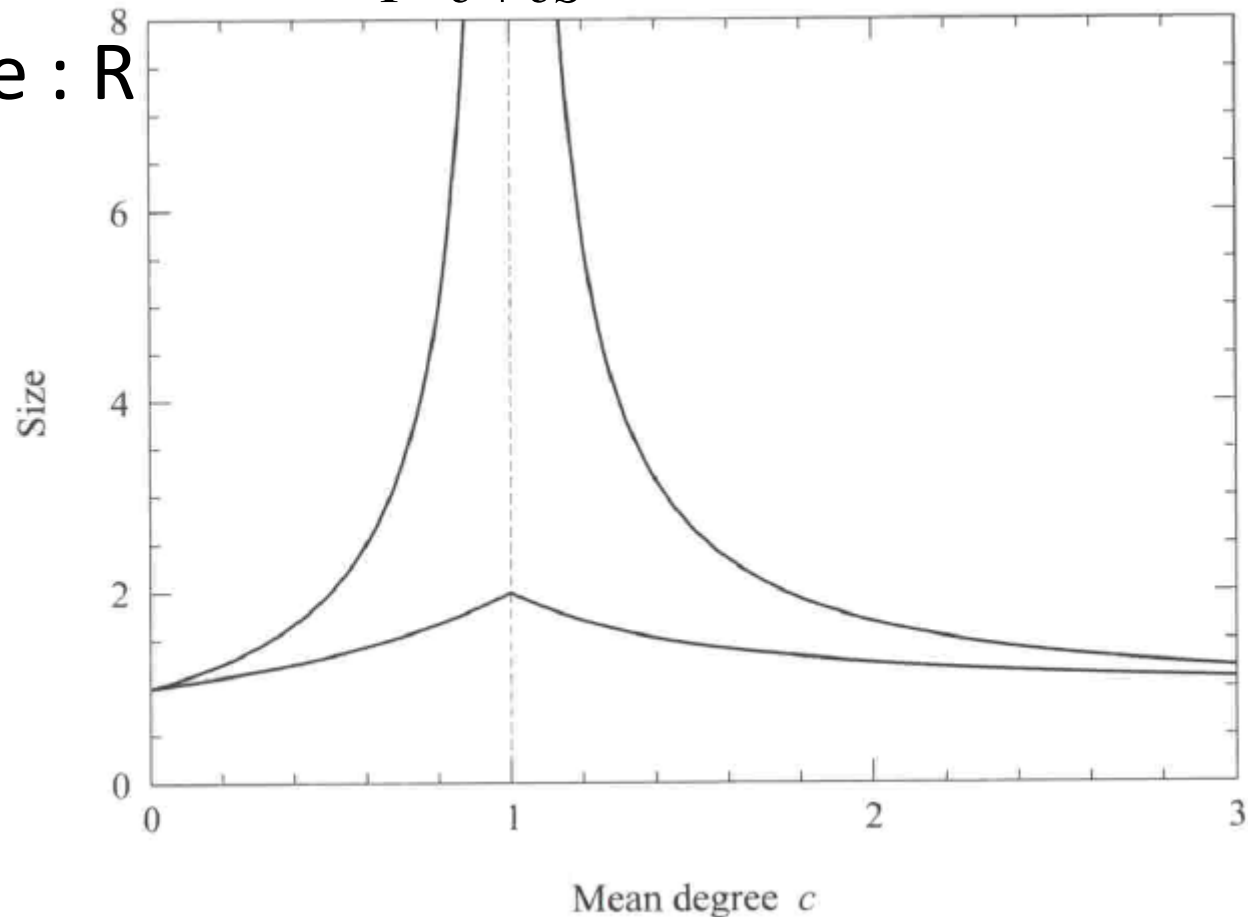
$$\langle s \rangle = \frac{1}{1-c+cS}$$

it doesn't grow with the number of vertices  $n$

when  $c < 1$  and there is no giant component,  
 $\langle s \rangle = 1/(1-c)$

# divergence of the average size $\langle s \rangle$

- upper curve :  $\langle s \rangle = \frac{1}{1-c+cS}$  diverges when  $c=1$
- lower curve :  $R$



# average size of a small component

- $\langle s \rangle$ : the average size of the component to which a randomly chosen vertex belongs  
 $\neq$  average size of a component
- $n_s$  : the actual number of components of size  $s$
- $sn_s$ : the number of vertices that belong to components of size  $s$
- the probability that a randomly chosen vertex belongs to a component of size  $s$  is  $\pi_s = \frac{sn_s}{n}$

# average size of a small component

- R: average size of a component

$$R = \frac{\sum_s s n_s}{\sum_s n_s} = \frac{n \sum_s \pi_s}{n \sum_s \pi_s / s} = \frac{1 - S}{\sum_s \pi_s / s}$$

$$\int_0^1 \frac{h(z)}{z} dz = \sum_{s=1}^{\infty} \pi_s \int_0^1 z^{s-1} dz = \sum_{s=1}^{\infty} \frac{\pi_s}{s}$$

$$h(z) = \sum_{s=1}^{\infty} \pi_s z^s$$

$$\frac{h(z)}{z} = [1 - ch(z)] \frac{dh}{dz} \quad \because h'(z) = \frac{h(z)}{z[1 - ch(z)]}$$

$$\sum_{s=1}^{\infty} \frac{\pi_s}{s} = \int_0^1 [1 - ch(z)] \frac{dh}{dz} dz = \int_0^{1-S} (1 - ch) dh = 1 - S - \frac{1}{2} c(1 - S)^2$$

$$\because h(1) = \sum_s \pi_s = 1 - S$$

$$\therefore R = \frac{2}{2 - c + cS}$$

it does not  
diverge at  $c=1$

# the complete distribution of component sizes

- p.416

# path lengths (1)

- small world effect : typical length of paths between vertices in network tend to be short
- the diameter of a random graph varies with the number  $n$  of vertices as  $\ln n$ 
  - the average number of vertices  $s$  steps away from a randomly chosen vertex in a random graph is  $c^s$
  - it grows exponentially with  $s$   $c^s \cong n$
  - diameter of the network is approximately  $s \cong \ln n / \ln c$
- this argument is true when  $c^s$  is much less than  $n$

## path lengths (2)

- two different starting vertices (i and j)
- if there is a dashed line between the surfaces, the shortest path between i and j is  $s+t+1$
- the absence of an edge between the surfaces is a necessary and sufficient condition for  $d_{ij} > s+t+1$

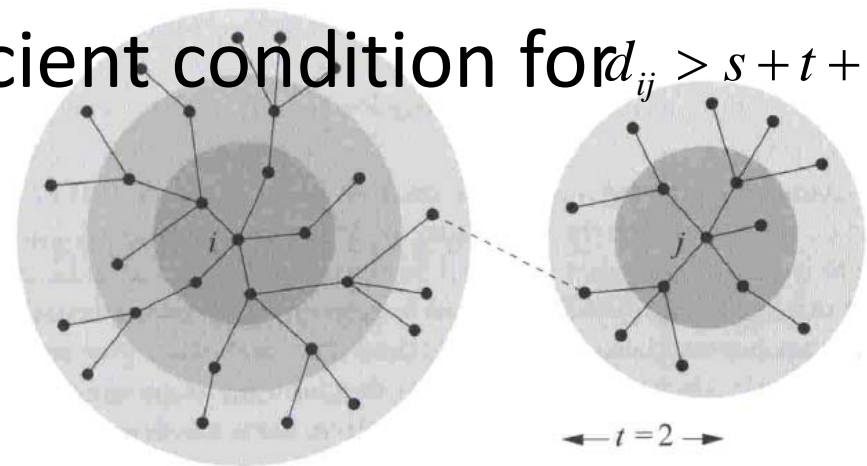
- $c^s \times c^t$  pairs of vertices

$$P(d_{ij} > s+t+1) = (1-p)^{c^{s+t}}$$

$$l = s+t+1$$

$$P(d_{ij} > l) = (1-p)^{c^{l-1}} = \left(1 - \frac{c}{n}\right)^{c^{l-1}}$$

$$\ln P(d_{ij} > l) = c^{l-1} \ln \left(1 - \frac{c}{n}\right) \cong -\frac{c^l}{n}$$



$$\ln(1+x) = \sum_{n=1}^{\infty} \frac{(-1)^{n+1}}{n} x^n \quad \text{for all } |x| < 1$$



# path length (3)

$$P(d_{ij} > l) = \exp\left(-\frac{c^l}{n}\right)$$

tend to zero only if  $c^l$  grows faster than  $n$

$c^l = an^{1+\varepsilon}$   
 $\varepsilon \rightarrow 0$

- diameter : the smallest value of  $l$  s.t.  $P(d_{ij} > l) = 0$

$$l = \frac{\ln a}{\ln c} + \lim_{\varepsilon \rightarrow 0} \frac{(1 + \varepsilon) \ln n}{\ln c} = A + \frac{\ln n}{\ln c}$$

diameter increases slowly with  $n$

- logarithmic dependence of the diameter on  $n$ 
  - acquaintance network of the entire world (7 billion people)

$$l = \frac{\ln n}{\ln c} = \frac{\ln(7 \times 10^9)}{\ln 1000} = 3.3..$$

small enough to account for the results of the small-world experiments of Milgram

# problems with the random graph (1)

- no transitivity or clustering
  - $C = \frac{c}{n-1}$  tends to zero in the limit of large  $n$
  - the acquaintance network of the human population in the world
    - $n \cong 7,000,000,000$
    - $C \cong \frac{1000}{7,000,000,000} \cong 10^{-7}$
- no correlation between the degrees of adjacent vertices (no communities)

clustering coefficient of  
real acquaintance  
network is much bigger  
(0.01 or 0.5)

## problems with the random graph (2)

- the shape of degree distribution is different
  - real network : right-skewed

