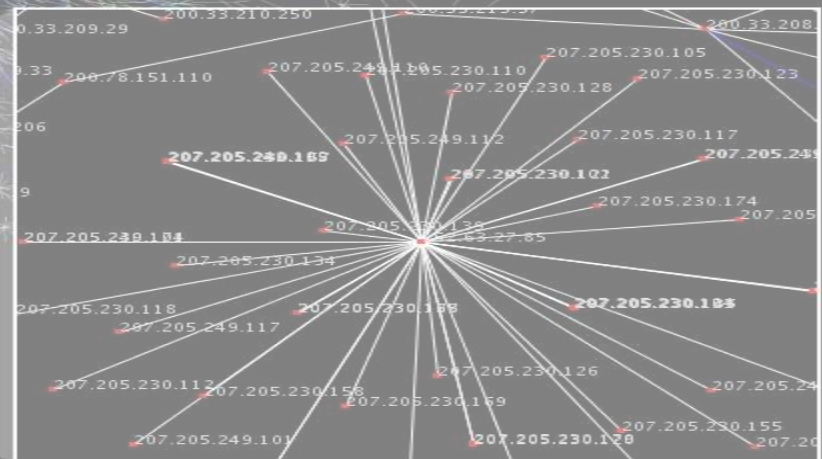


Topics in Algorithms and Data Science

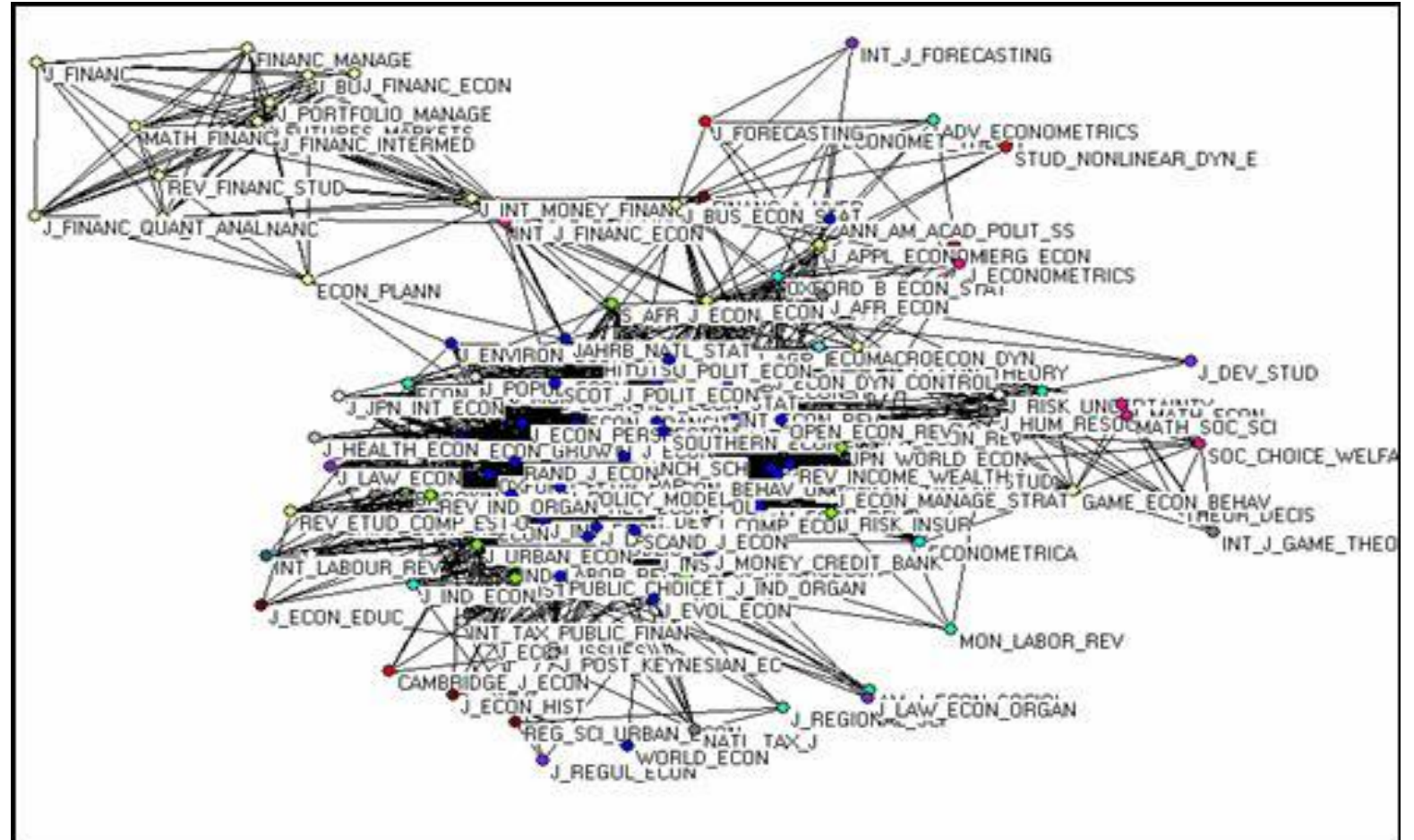
Random Graphs

Omid Etesami



Large graphs

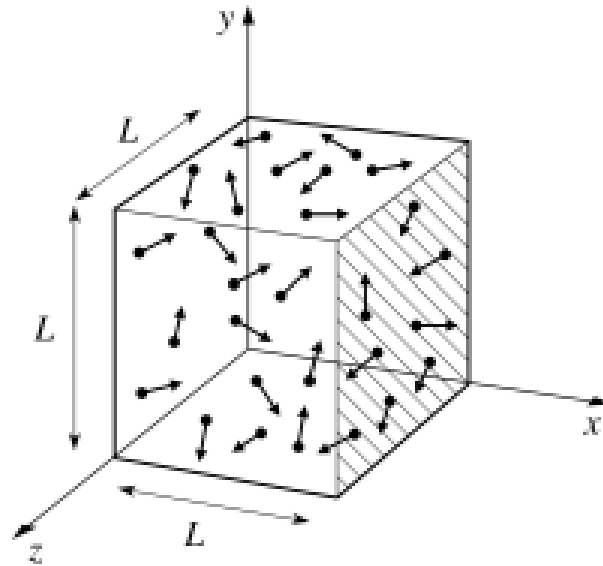
- World Wide Web
- Internet
- Social Networks
- Journal Citations
- ...



Economics Journals Citations

Random graphs

- Unlike traditional graph theory, we are interested in **statistical** properties of large graphs
- Similar to the shift in physics in late 19th century from mechanics to statistical mechanics



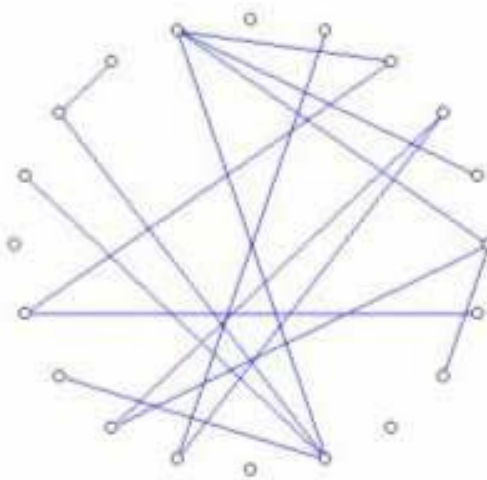
$G(n, p)$ graphs

Erdos-Renyi graphs

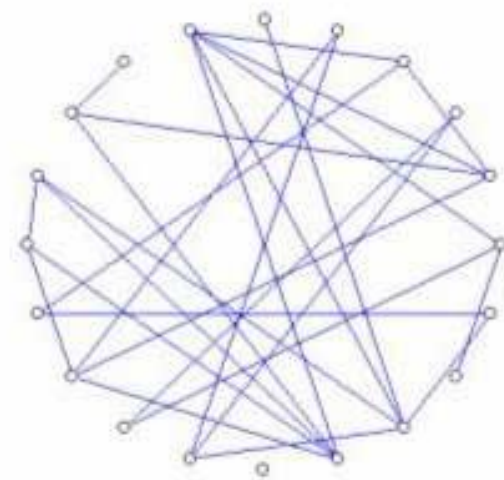
- $G(n, p)$ random graph with n vertices
- Each edge appears with probability p independently of other edges



$p = 0$
(a)



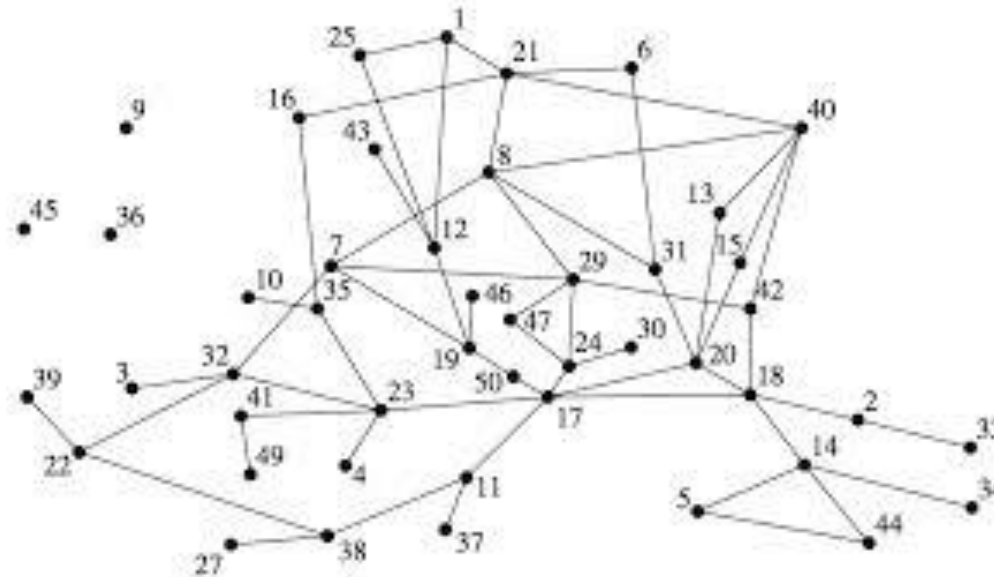
$p = 0.1$
(b)



$p = 0.2$
(c)

Erdos-Renyi graphs with constant expected degree

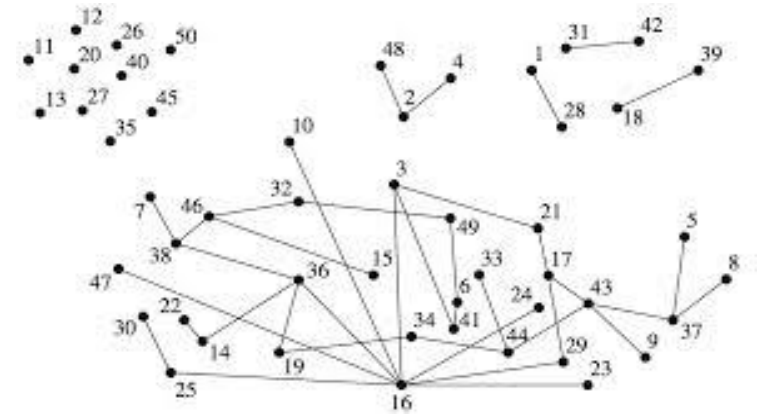
- The probability p may depend on n .
- If $p = d/n$, the expected degree is $(n-1)d/n \approx d$.



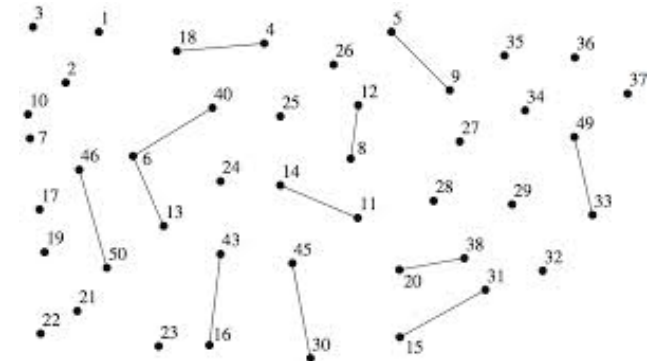
Global property emerges from independent choices

With no “collusion”, the following happens:

$d > 1$: with probability almost 1, there is a giant component of size $\Omega(n)$

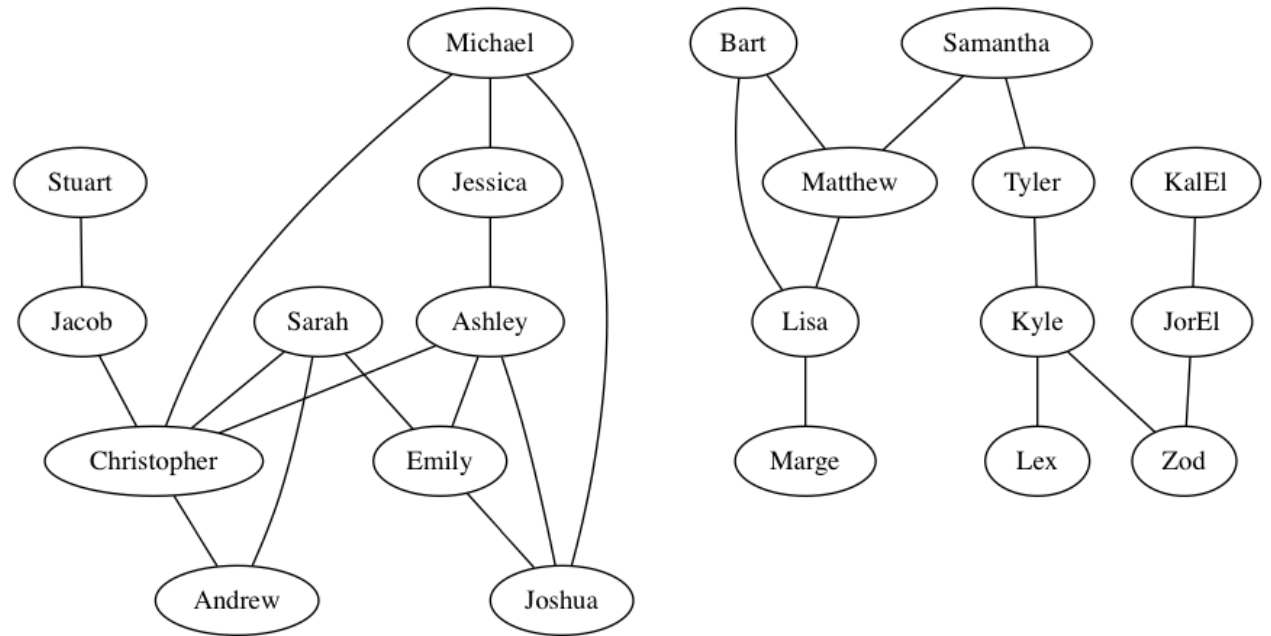


$d < 1$: with probability almost 1, each connected component is of size $o(n)$

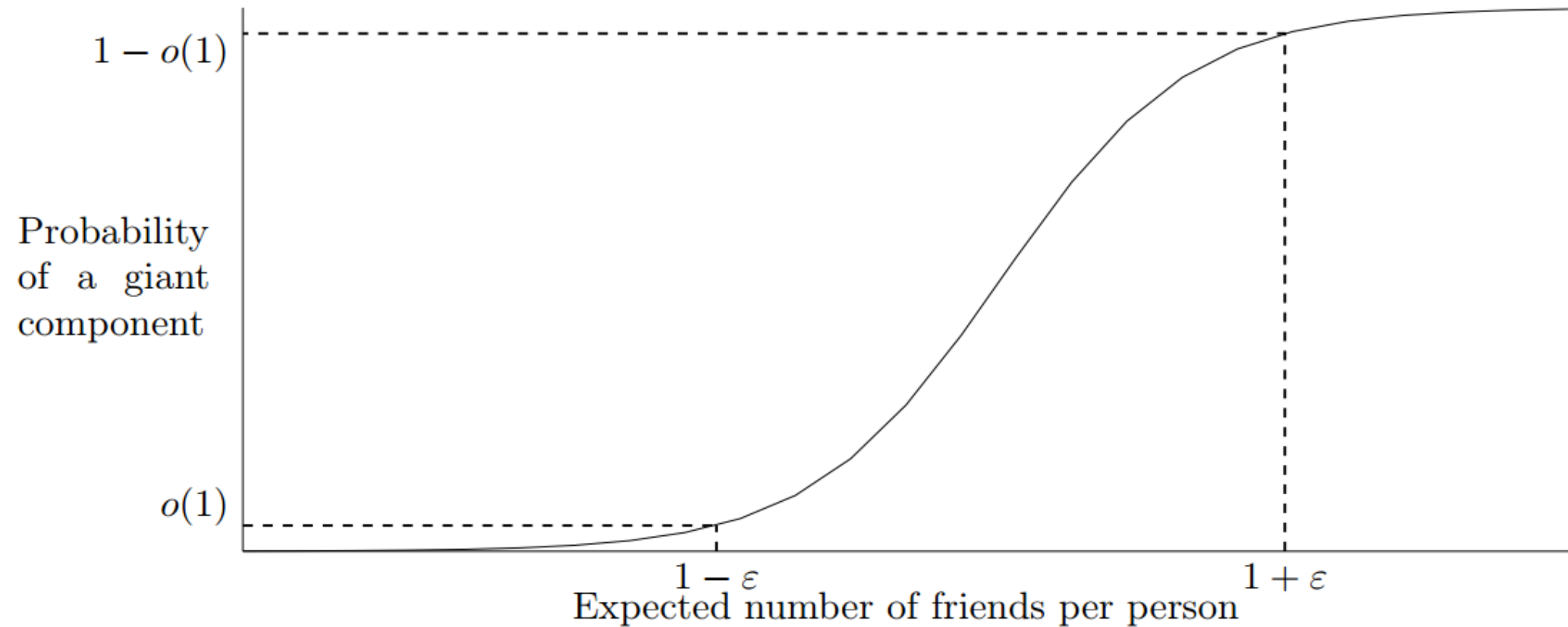


Friendship graph

- vertices = people, edges = knowing each other
- two persons in the same connected component if they indirectly know each other
- each pair of persons become friends with probability p
- average degree = expected # friends

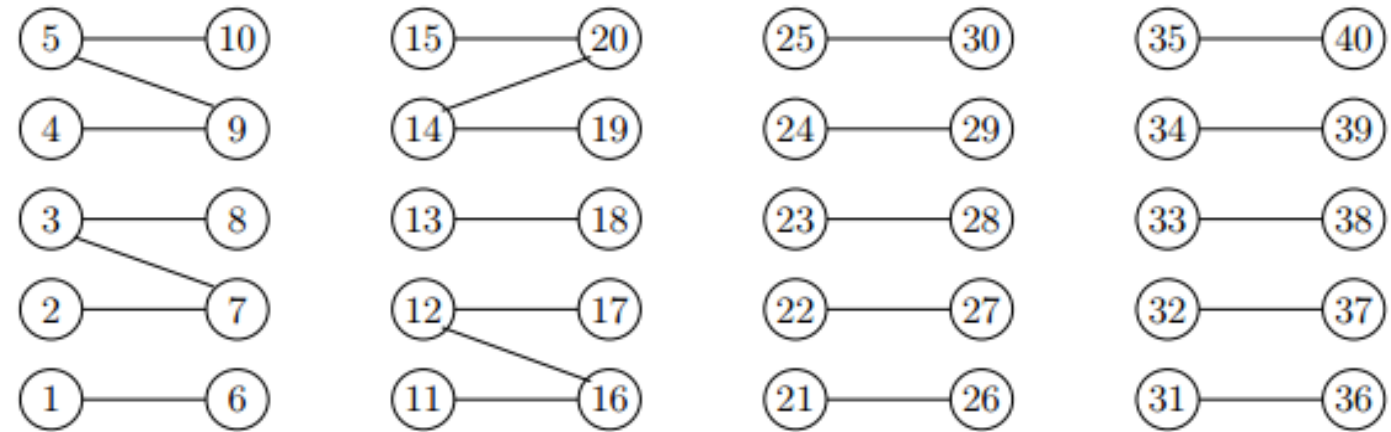


Existence of giant component



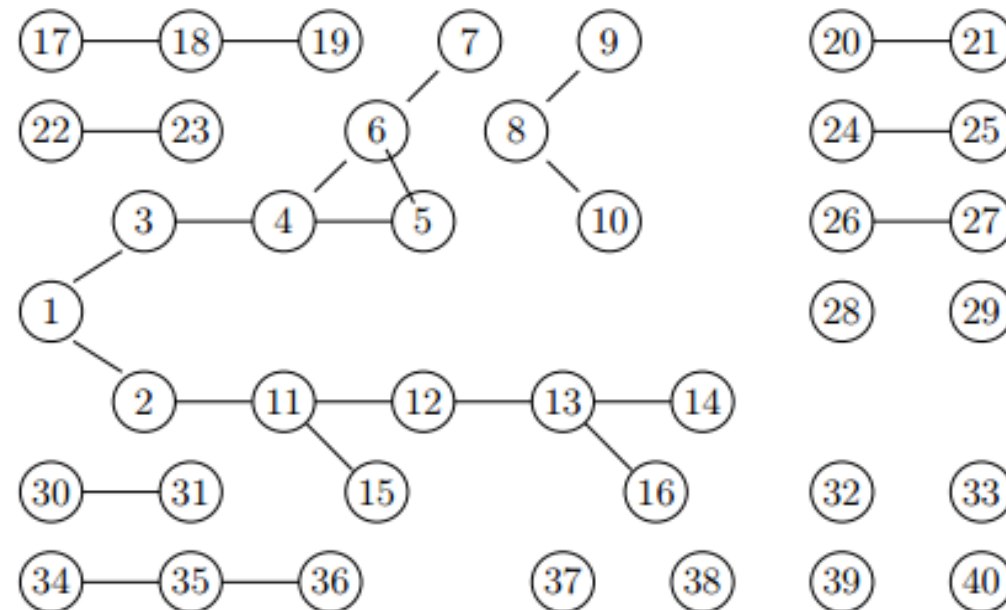
Random vs not random

The bottom graph looks more random.



A graph with 40 vertices and 24 edges

average degree > 1
so we expect a giant component.



Small components are mostly trees.

A randomly generated $G(n, p)$ graph with 40 vertices and 24 edges

Degree distribution

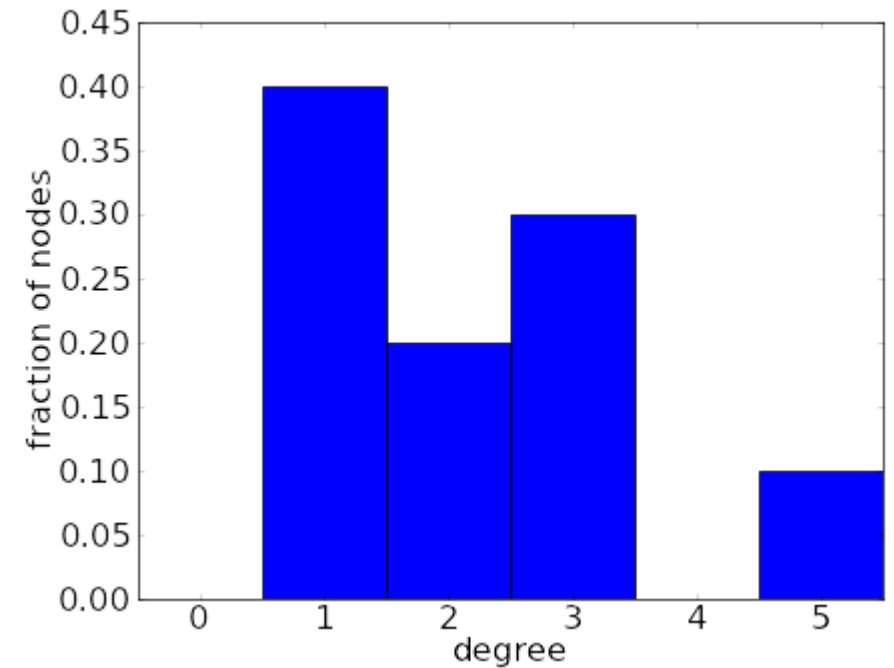
Degree distribution

is the number of vertices of each given degree.

Easy to calculate in real-world graphs.

In $G(n,p)$: degree of each vertex is sum of $n-1$ independent Bernoulli random variables, resulting in the binomial distribution.

For large n , we replace $n-1$ with n .

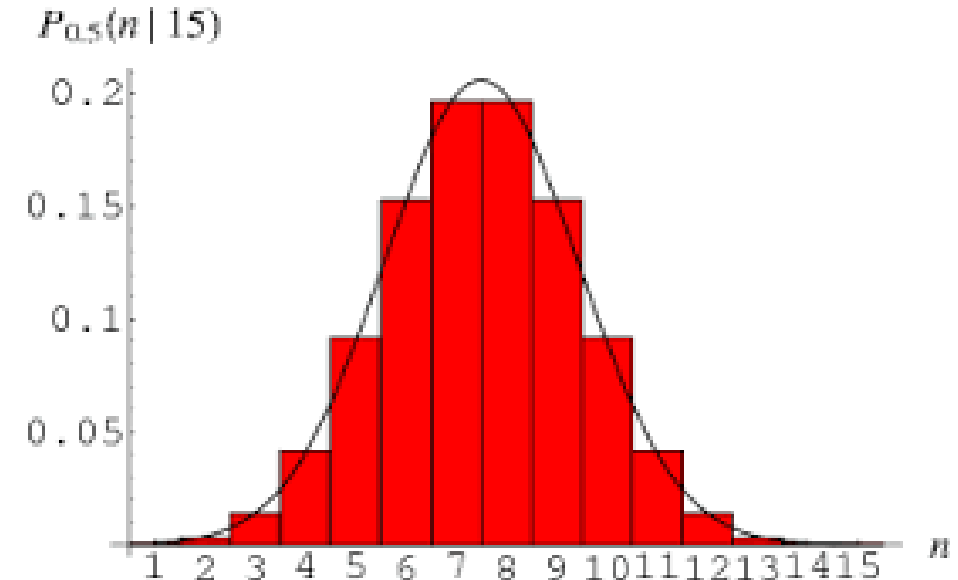


Example: $G(n, 1/2)$

$$\text{Prob}(\text{deg} = k) = \binom{n-1}{k} / 2^{n-1} \approx \binom{n}{k} / 2^n.$$

- Mean $m = n/2$ (sum of Bernoulli expected values)
- Variance $\sigma^2 = n/4$ (sum of Bernoulli variances)

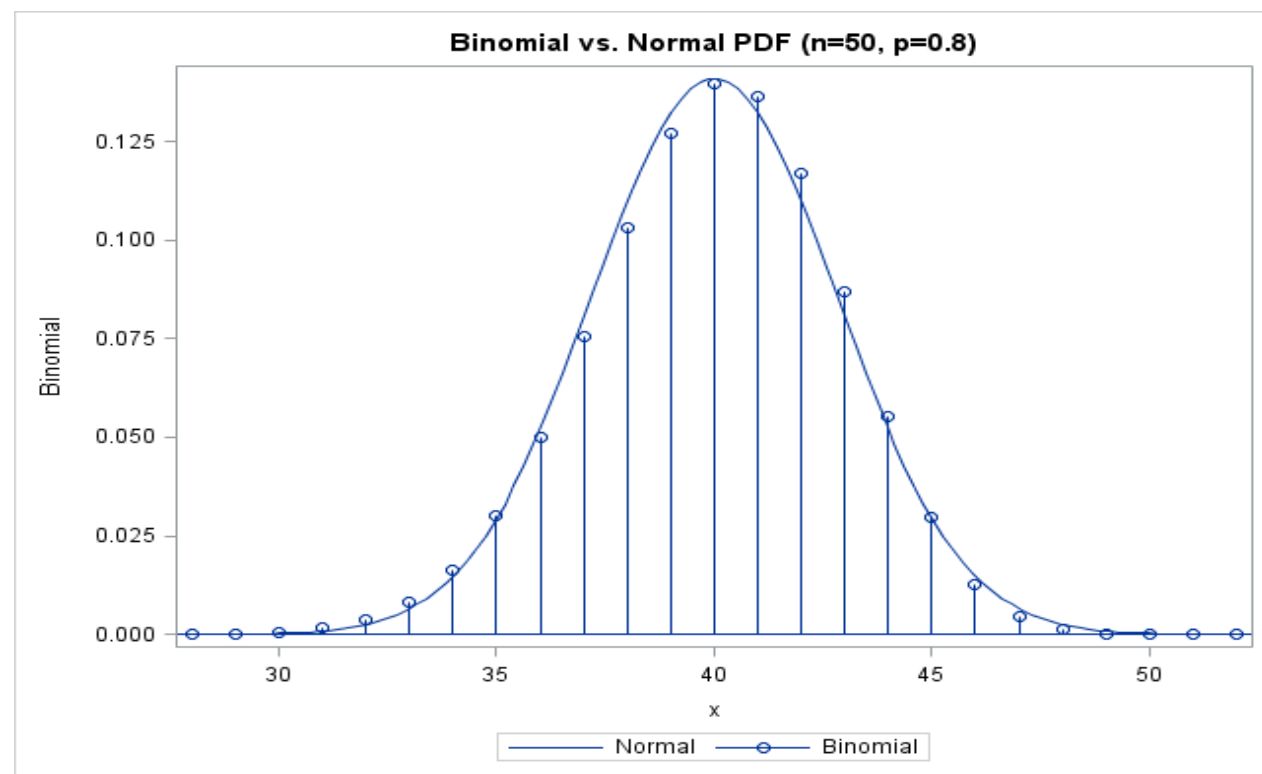
For each $\varepsilon > 0$, almost surely
the degree of each vertex is within $1 \pm \varepsilon$ of $n/2$



$G(n, 1/2)$ (continued): normal approximation

binomial distribution \approx normal distribution of same mean and variance

$$\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(k-m)^2}{2\sigma^2}}$$

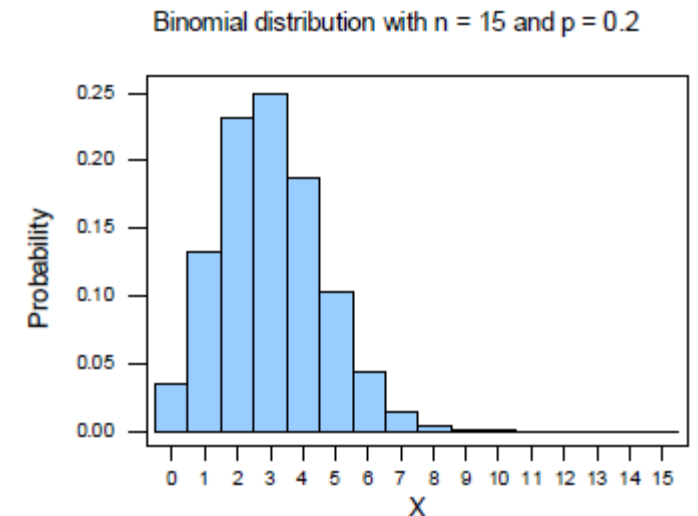


most mass have value $\text{mean} \pm c n^{1/2}$ for constant c .

$G(n, p)$ for general p

$$\text{Prob}(\text{degree} = k) = \binom{n-1}{k} p^k (1-p)^{n-k-1} \approx \binom{n}{k} p^k (1-p)^{n-k}$$

The approximation is valid for $k \approx np$.

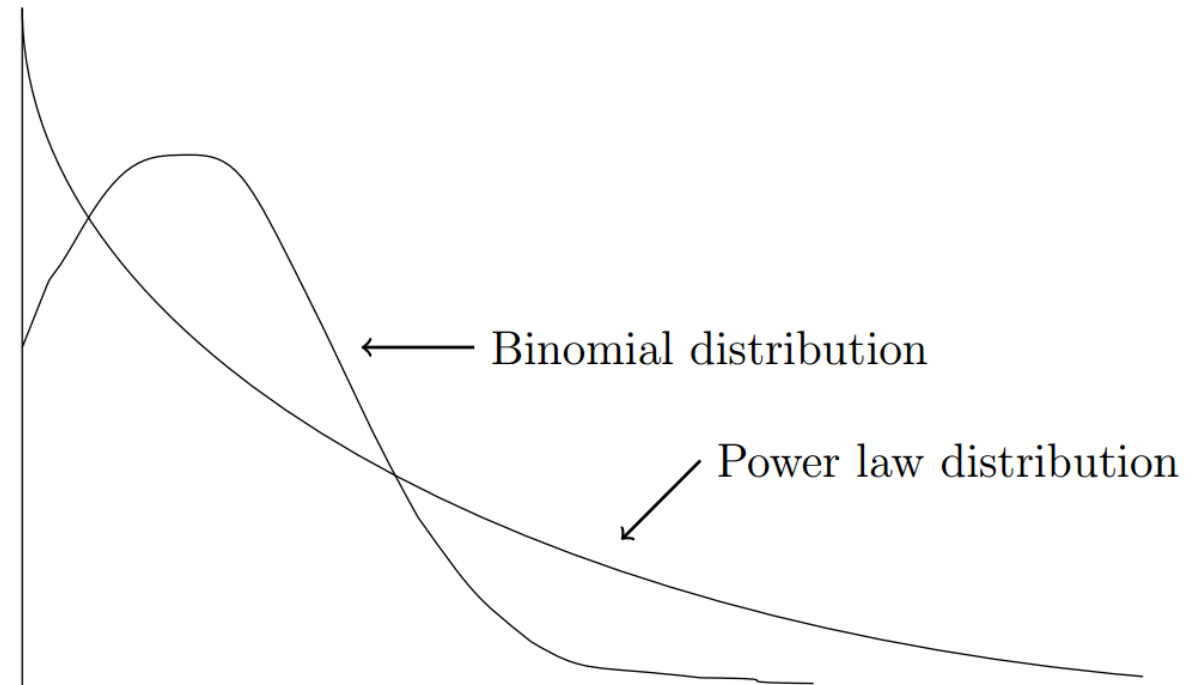


Real-world degree distributions

tail of a random variable = values far from mean (measured in number of standard variations)

- Tail of binomial distribution falls off exponentially fast
- Many graphs in applications have “heavy” tails

Models more complex than $G(n,p)$ needed
for real-world applications



Airline route graph

- Small cities have degree 1 or 2
- Major hubs have degree 100 or more

Power law distribution:

$$\Pr(\text{degree } k) = c/k^r.$$

r often slightly less than 3.

Later in the course,
we see models that
give power law distributions.



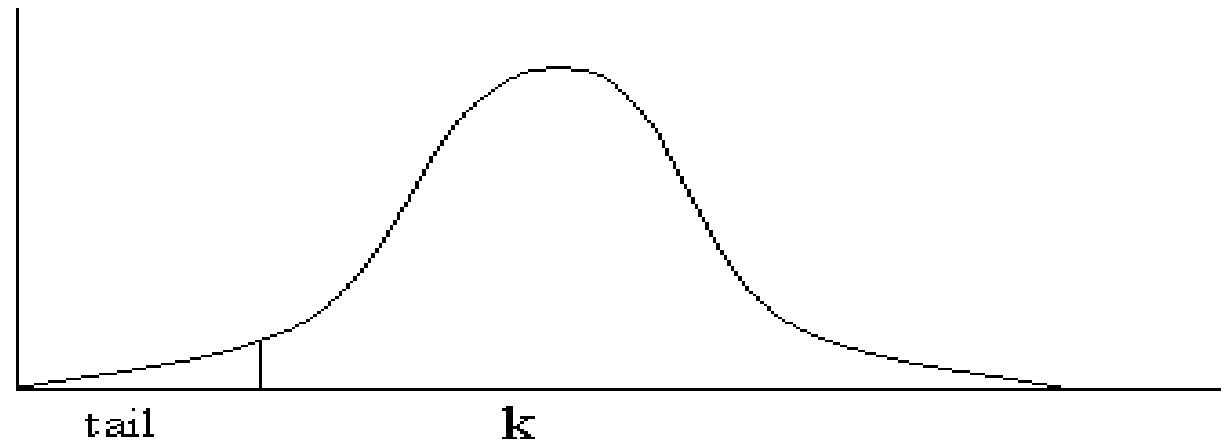
Concentration of degree

By Chernoff bounds (which we do not prove), for a fixed vertex v ,

$$\Pr(|np - \deg(v)| \geq \alpha\sqrt{np}) \leq 2e^{-\alpha^2/3} \text{ when } 0 < \alpha < \sqrt{np}.$$

Let $\epsilon < 1$. Applying union bound to the above,

almost surely the degree of all vertices are in $[np(1 - \epsilon), np(1 + \epsilon)]$
if $p = \Omega(\ln n / (n\epsilon^2))$.



The lower bound on p is necessary:

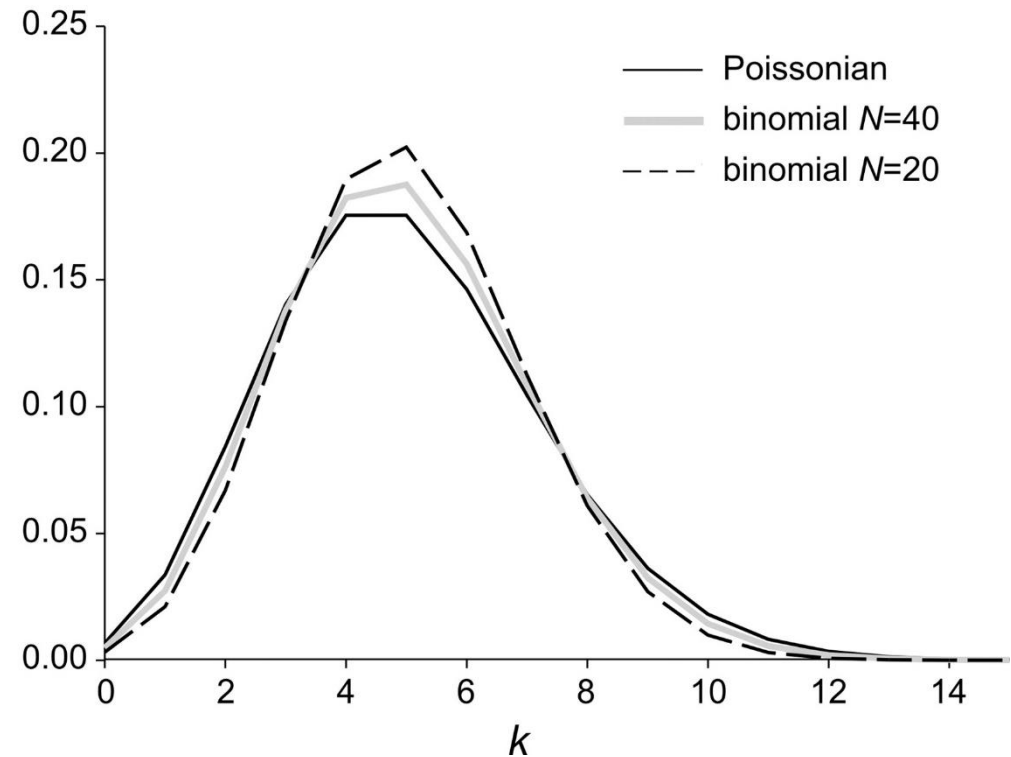
When $p = 1/n$, vertices of degree $\Omega(\log n / \log \log n)$ exist with high probability.

Graphs with constant expected value

When graphs have constant degree, $G(n, p=d/n)$ for constant d is a better model. In this case, the binomial distribution approaches the Poisson distribution.

$$\binom{n}{k} p^k (1-p)^{n-k} \approx \frac{n^k}{k!} \left(\frac{d}{n}\right)^k (1-d/n)^{n-k} \approx d^k e^{-d} / k!$$

For $\binom{n}{k} \approx n^k / k!$ we need $k = o(\sqrt{n})$.



A vertex of high degree

When $p = 1/n$, we have

$$\Pr(k) = \binom{n}{k} (1/n)^k (1 - 1/n)^{n-k} \approx e^{-1}/k! \geq e^{-1}/k^k.$$

If $k = \ln n / \ln \ln n$,

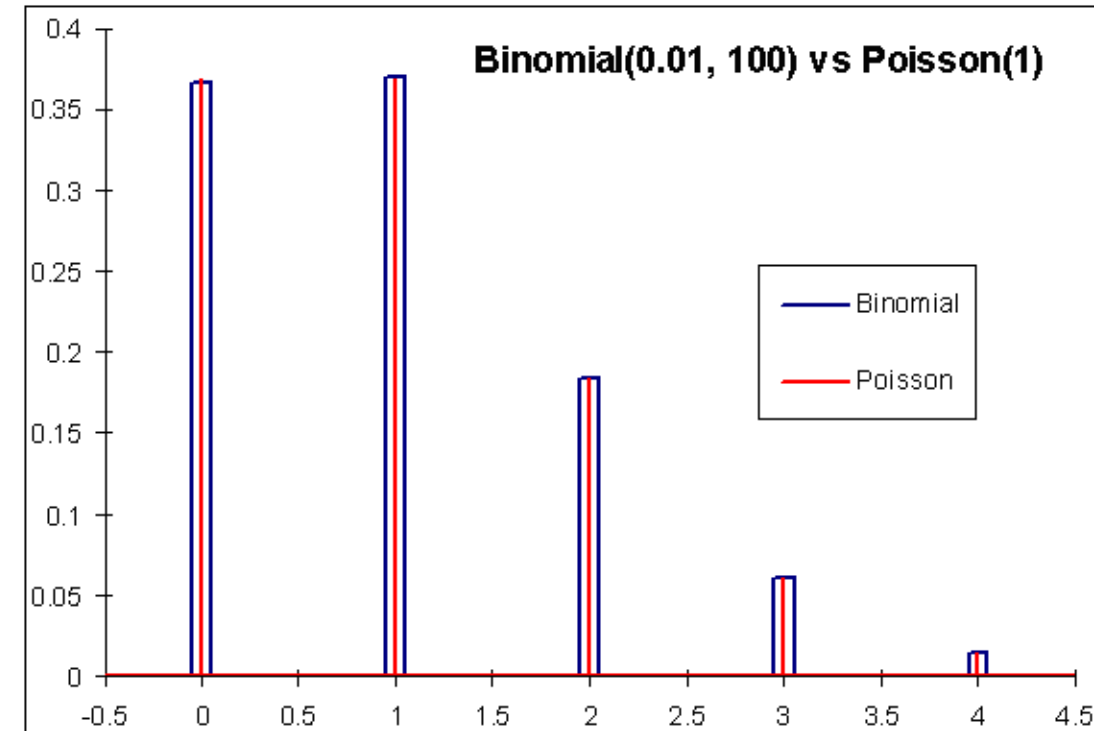
we have $\Pr(k) \geq 1/(en)$.

(Without giving the proof)

with high probability

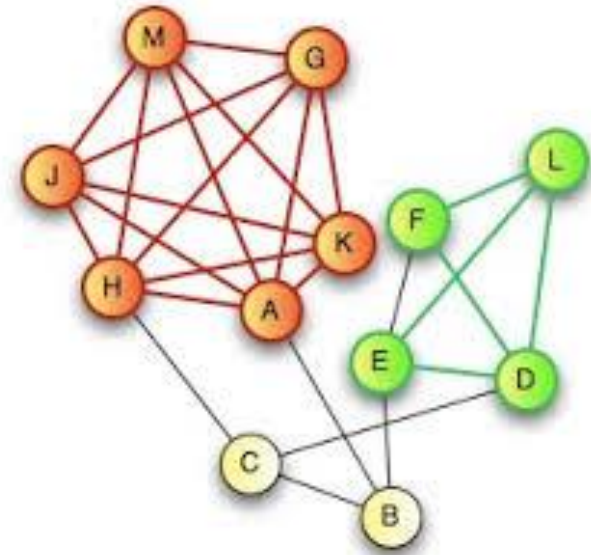
a vertex of degree k exists

(even though the degrees of different vertices are not independent).



Today's open problem: finding max clique in $G(n, \frac{1}{2})$

- Almost surely $G(n, \frac{1}{2})$ has a max clique of size $\approx 2 \lg_2 n$.
- Can you find it in polynomial time?
- Best current algorithm is greedy and finds only a clique of size $\approx \lg_2 n$.
- It is open if one can find a clique of size $(1 + \varepsilon) \lg_2 n$ for constant $\varepsilon > 0$.



Existence of triangles

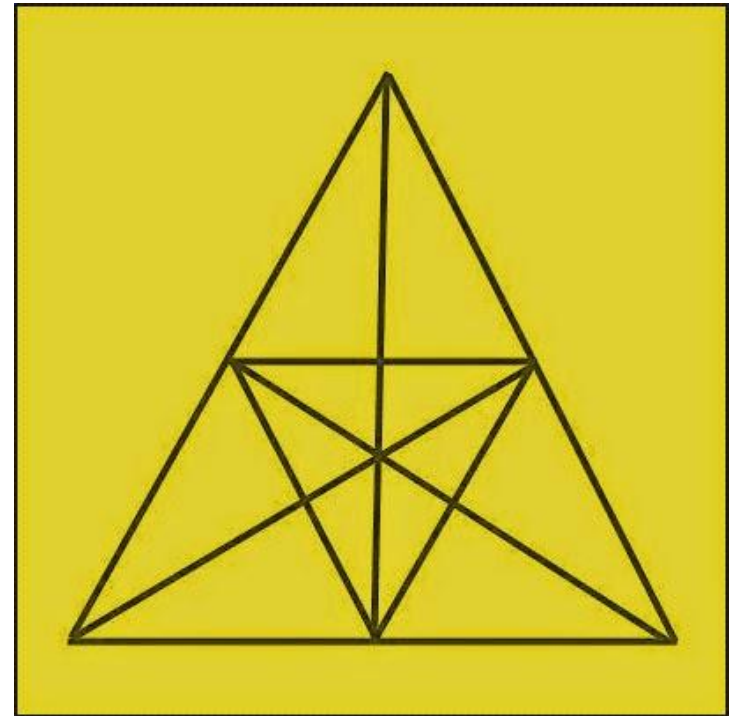
Triangles in $G(n, d/n)$

There are $\binom{n}{3}$ potential triangles.

Each is a triangle with probability $(d/n)^3$.

The expected number of triangles is $\binom{n}{3}(d/n)^3 \approx d^3/6$

by indicator random variables and linearity of expectation.

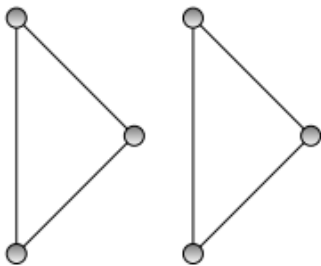


Second moment

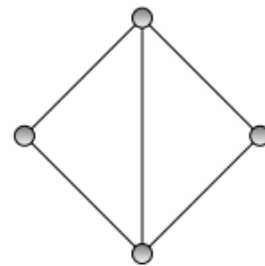
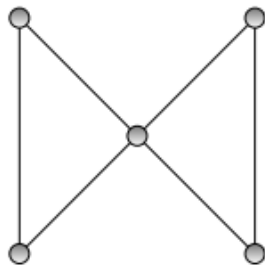
To rule out the possibility that all triangles are on a small fraction of graphs, we bound the second moment of # triangles.

$$X = \sum_{ijk} \Delta_{ijk}.$$

$$E[X^2] = \sum_{ijk, i'j'k'} E[\Delta_{ijk} \Delta_{i'j'k'}].$$



or



The two triangles of Part 1 are either disjoint or share at most one vertex

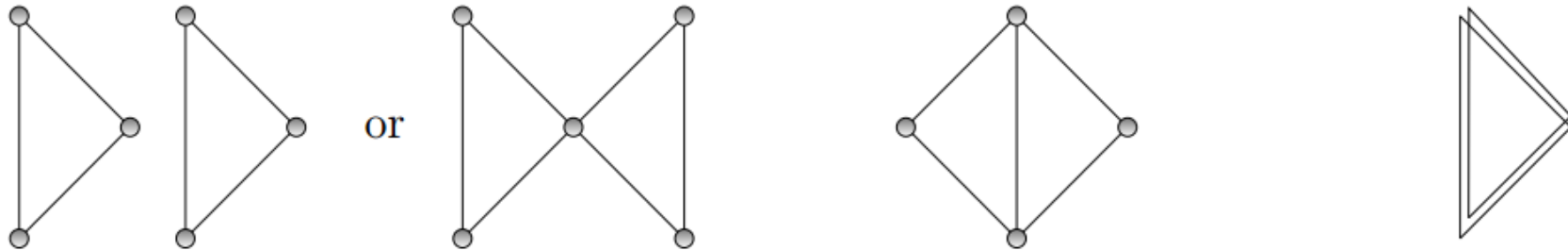
The two triangles of Part 2 share an edge

The two triangles in Part 3 are the same triangle

Splitting $E[X^2] = \sum_{ijk, i'j'k'} E[\Delta_{ijk} \Delta_{i'j'k'}]$.
 into three parts

- For Part 1, $E[\Delta_{ijk} \Delta_{i'j'k'}] = E[\Delta_{ijk}] E[\Delta_{i'j'k'}]$. Thus, the sum for Part 1 is at most $E^2[X]$.
- For part 2, the number of terms is $O(n^4)$, each term $(d/n)^5$.
- For part 3, the sum equals $E[X]$.

Thus, $\text{Var}[X] = E[X^2] - E^2[X] \leq d^3/6 + o(1)$.



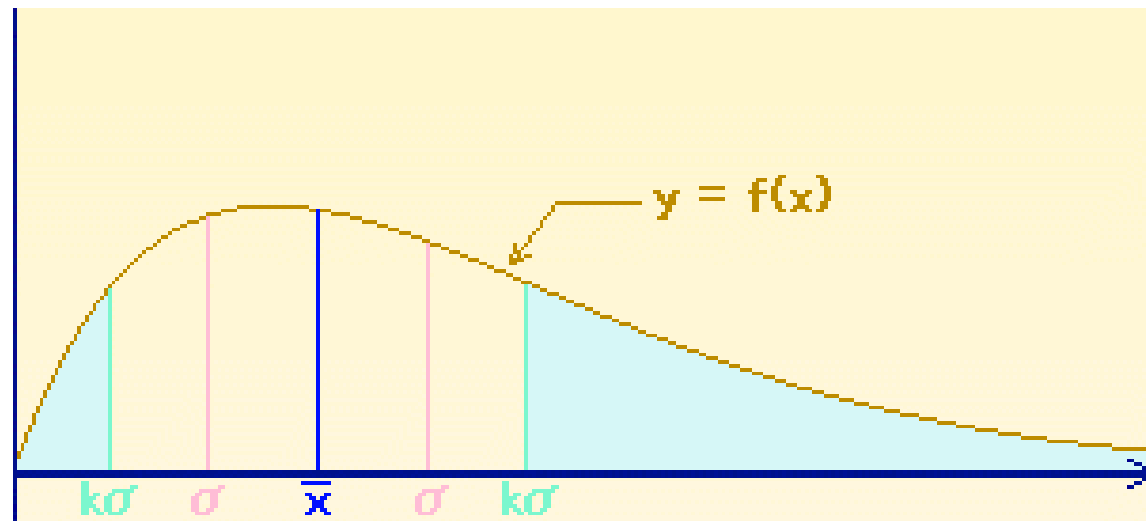
The two triangles of Part 1 are either disjoint or share at most one vertex

The two triangles of Part 2 share an edge

The two triangles in Part 3 are the same triangle

Chebyshev inequality

$$\Pr[X = 0] \leq \Pr[|X - E[X]| \geq E[X]] \leq \text{Var}[X] / E^2[X] \leq 6/d^3 + o(1).$$



When $d > 6^{1/3}$ there exists a triangle with constant nonzero probability.

Phase transitions

Phase transitions in physics

When temperature or pressure slightly increases, abrupt change in the phase of the matter happens,

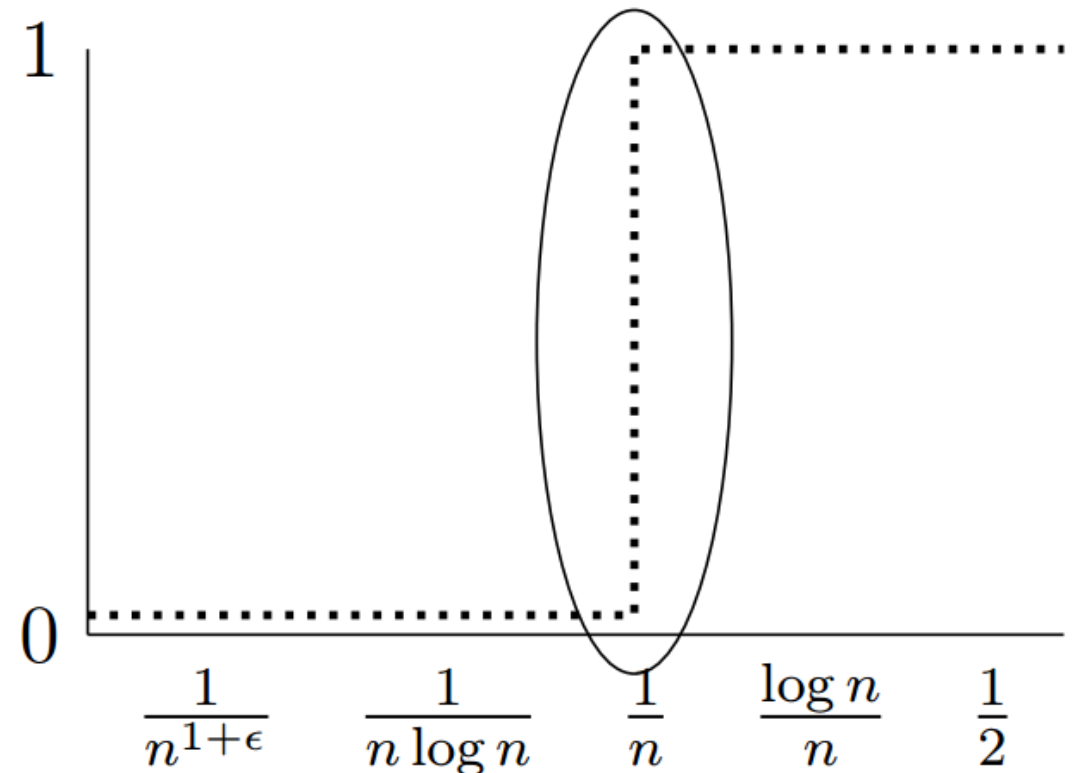
e.g. liquid \rightarrow gas.



Phase transition for random graphs

When the edge probability passes some **threshold** $p(n)$, there is an abrupt transition from not having a property to having that property.

- When $p_1(n) = o(p(n))$, almost surely $G(n, p_1)$ does not have the property.
- When $p_2(n) = \omega(p(n))$, almost surely $G(n, p_2)$ has the property.
- Example: for appearance of cycles, $p(n) = 1/n$.
- Example: for disappearance of isolated vertices, $p(n) = \log n / n$.

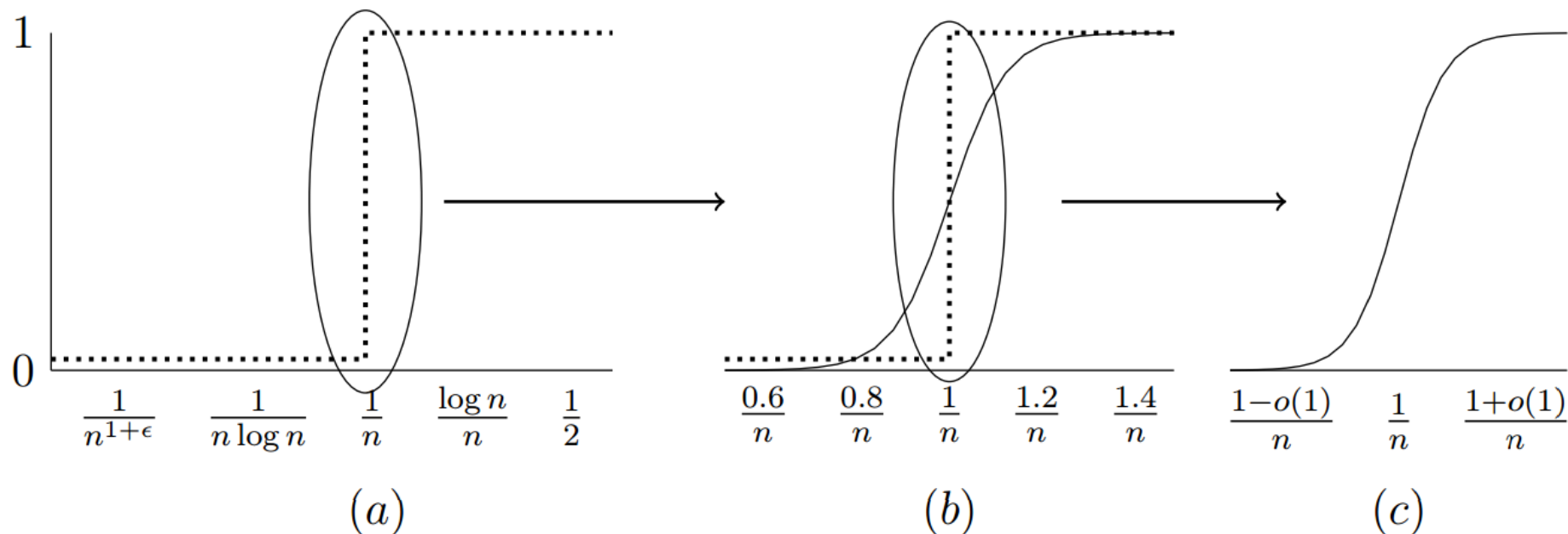


Sharp threshold

$p(n)$ is called a *sharp* threshold if

- when $p_1(n) = p(n)(1-\Omega(1))$, almost surely $G(n, p_1)$ does not have the property;
- when $p_2(n) = p(n)(1+\Omega(1))$, almost surely $G(n, p_2)$ has the property.

Example: existence of a giant component has sharp threshold at $p(n) = 1/n$.



Dotted line has threshold.

Solid line has threshold;
dotted line has sharp threshold.

Solid line has sharp threshold.

1st and 2nd moment method

We already know that existence of a triangle has a threshold at $p(n) = 1/n$.

Let X be number of triangles.

Below threshold, $E[X] = o(1)$ so $\Pr[X > 0] = o(1)$ [Markov inequality, 1st moment]

Above threshold, $E[X^2] = E^2[X](1+o(1))$ so $\Pr[X = 0] = o(1)$ [Chebyshev, 2nd moment]

(That $E[X] = \omega(1)$ is not enough for the “above threshold” case.)

No items

At least one
occurrence
of item in
10% of the
graphs

$$E(x) \geq 0.1$$

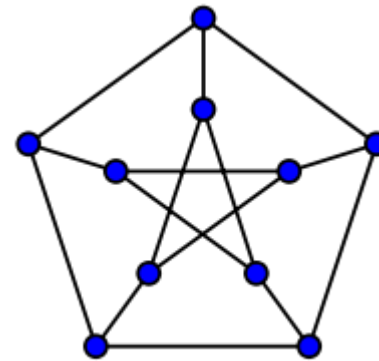
For 10% of the
graphs, $x \geq 1$

Graph diameter 2

Graph diameter 2 has a sharp threshold at

$$p = \sqrt{2 \ln n / n}$$

- Two vertices have a common neighbor if the size of their neighbors is approximately $n^{1/2}$. (Birthday paradox)
- The extra factor of $(\ln n)^{1/2}$ is to ensure **all** pairs of vertices have distance at most two.

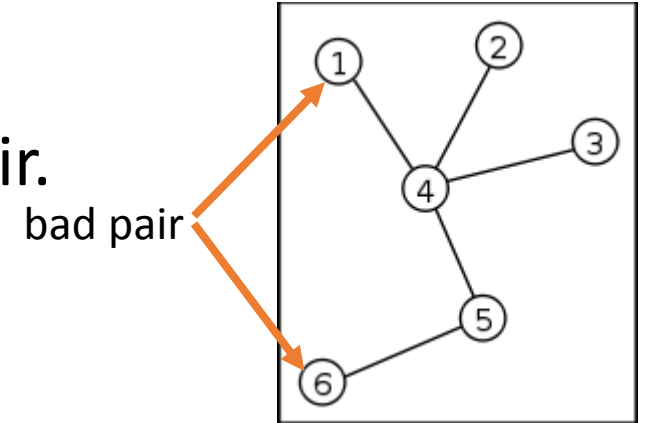


Petersen has diameter 2

bad pairs

- (i, j) bad pair of vertices iff $\text{dist}(i, j) > 2$.
- I_{ij} indicator random variable for whether (i, j) bad pair.

$$x = \sum_{i < j} I_{ij} = 0 \text{ iff graph has diameter } \leq 2$$



For $p = c\sqrt{\ln n/n}$, $E[x] = \binom{n}{2}(1-p)(1-p^2)^{n-2} \approx n^{2-c^2}/2$.

- By first moment method,
if $c > 2^{1/2}$, almost surely graph has diameter 2.

For $c < 2^{1/2}$, we apply the second moment method.

$$E[x^2] = \sum_{i < j, k < l} E[I_{ij} I_{kl}].$$

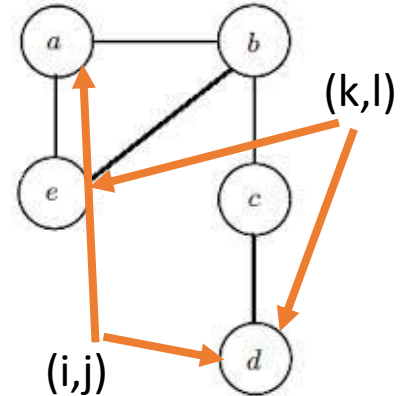
Split the sum into three parts according to $|\{i, j, k, l\}| = 2, 3, 4$.

Case 1. i, j, k, l all distinct: $E[I_{ij} I_{kl}] \leq (1 - p^2)^{2(n-4)} \approx n^{-2c^2}$.

Case 2. i, j, k, l has one repetition: $E[I_{ij} I_{kl}] \leq (1 - 2p^2 + p^3)^{n-3} \approx n^{-2c^2}$.

Case 3. $i = k, j = l$: $E[I_{ij} I_{kl}] = E[I_{ij}]$.

$$\begin{aligned} E[X^2] &\leq \frac{n^4}{4} n^{-2c^2} (1 + o(1)) + O(n^3 n^{-2c^2}) + O(n^2 n^{-c^2}) \\ &= E[X]^2 (1 + o(1)). \end{aligned}$$



Isolated vertices

The disappearance of isolated vertices has a sharp threshold at $p = \ln n / n$

In fact, at this point, the giant component has absorbed all small components of size ≥ 2 ,

so with the disappearance of isolated vertices, the graph becomes connected.



related to balls and bins

1st and 2nd moment when $p = c \ln n / n$

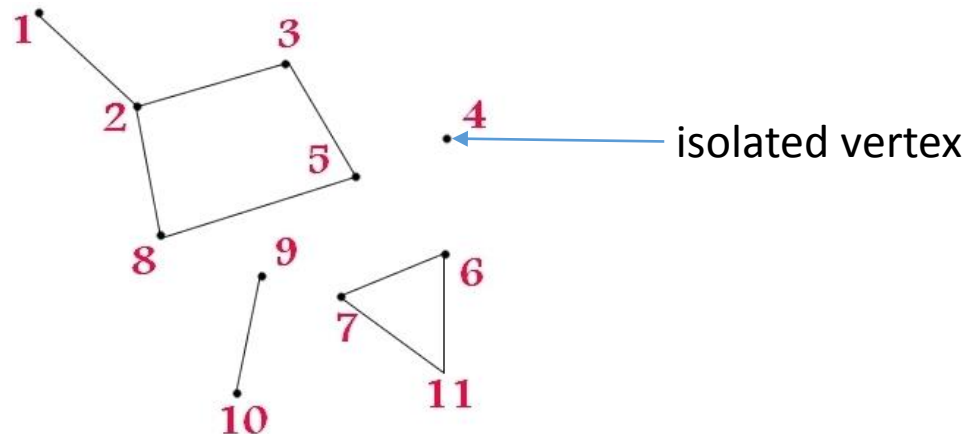
$x = I_1 + \dots + I_n$, where I_j is indicator random variable for j being isolated.

$$E[x] = n(1 - p)^{n-1} \approx n^{1-c}.$$

When $c > 1$, $E[x]$ tends to zero and we can use 1st moment method.

$$E[x^2] = \sum_{i,j} E[I_i I_j] = E[x] + n(n-1)(1-p)^{2(n-1)-1} \leq E[x] + n^{2-2c}.$$

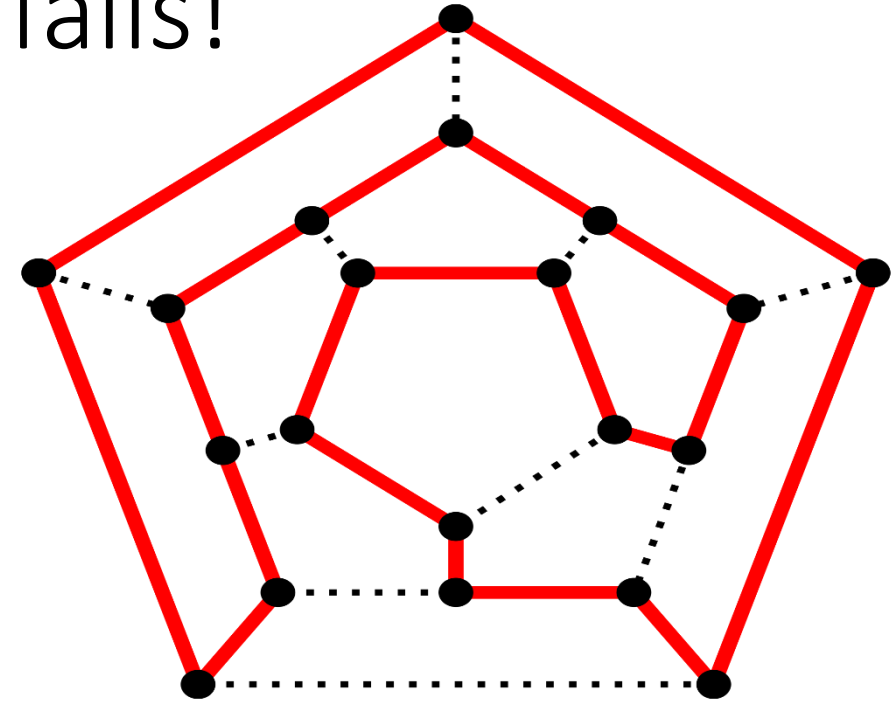
For $c < 1$, an isolated vertex exists almost surely by 2nd moment method.



Hamilton circuits

A situation where 1st moment fails!

Let $x = \#$ of Hamilton circuits



The value of p for which $E[x]$ goes from zero to infinity is not the threshold for having a Hamilton cycle

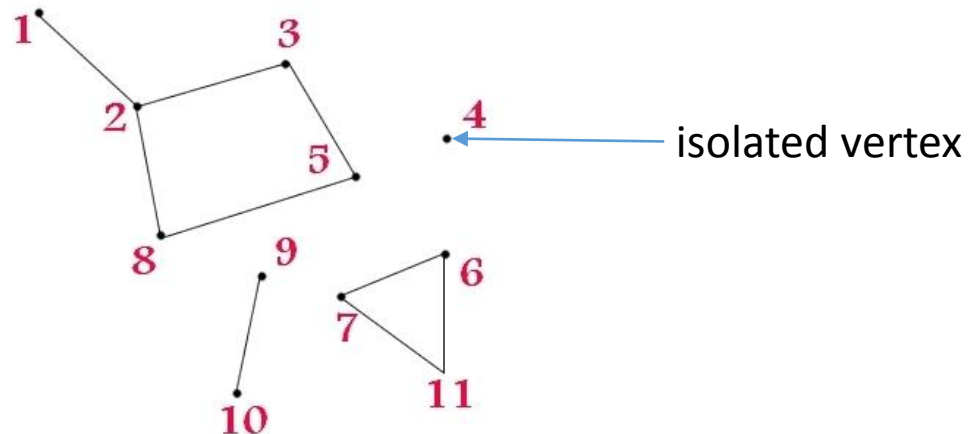
because Hamilton circuits are very concentrated on a small fraction of random graphs.

Expected # Hamilton circuits

For $p = d/n$,

$$E[x] = \frac{(n-1)!}{2} (d/n)^n \approx \Theta(n^{-1/2}) (n/e)^n (d/n)^n = \begin{cases} o(1) & \text{if } d < e \\ w(1) & \text{if } d > e \end{cases}$$

but for constant d , isolated vertices exist and the graph is not even connected.



Actual threshold for Hamilton circuits

If $d = \ln n + \ln \ln n + \omega(1)$, almost surely $G(n, d/n)$ is Hamiltonian.

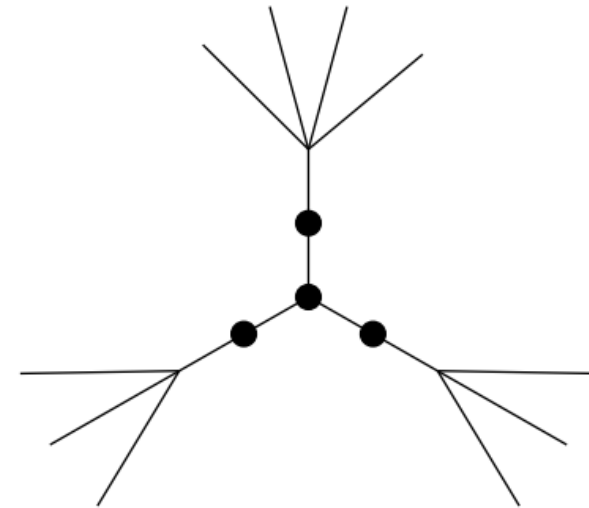
If $d = \ln n + \ln \ln n - \omega(1)$, almost surely $G(n, d/n)$ is not Hamiltonian.

Same threshold as the moment of disappearance of degree-1 vertices!

Why not a subgraph like this

(a degree-3 vertex connected to 3 degree-2 vertices)

happen at that moment?



Frequency of degree 2 and 3 vertices is low. The probability that such a configuration of such vertices occur **together** is low.

The giant component

The evolution of $G(n,p)$ as p increases

- $p = 0$: no edges

a

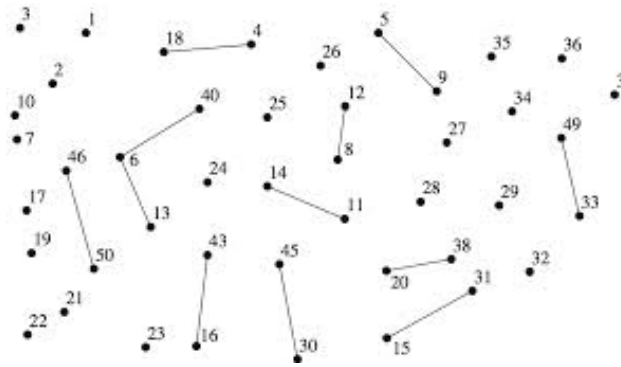
b

e

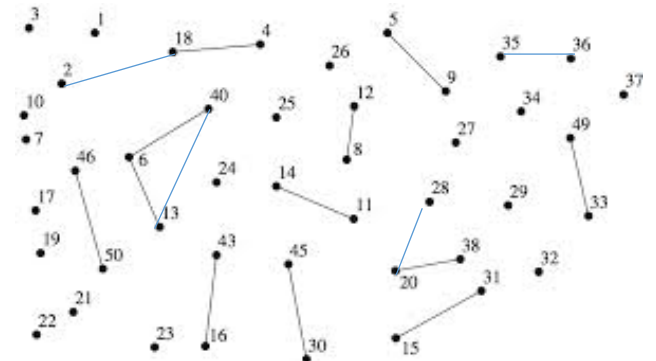
c

d

- $p = o(1/n)$: forest, i.e. no cycle

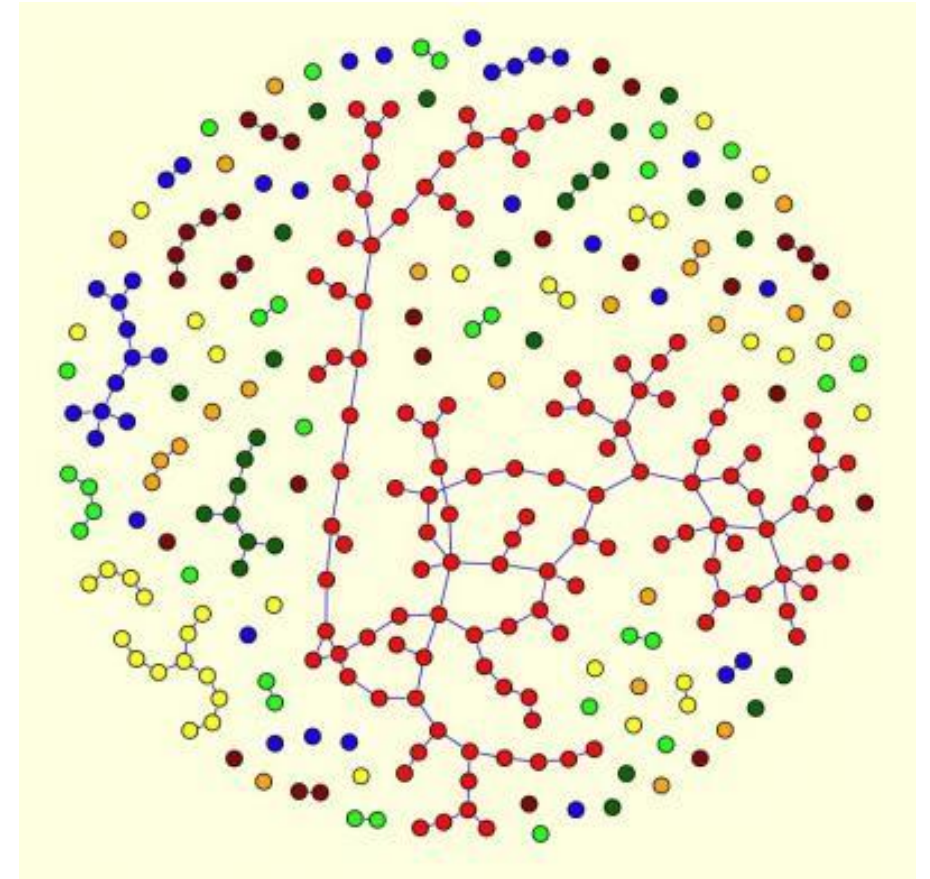


- $p = d/n$, d constant < 1 :
all components of size $O(\lg n)$,
no component has more than one cycle,
expected # components containing single cycles = $O(1)$,
there is a cycle with probability $\Omega(1)$



The evolution of $G(n, p)$ as p further increases

- $p = 1/n$: for any function $f = \omega(1)$,
tree of size $\geq n^{2/3}/f$ exists
all components have size $\leq n^{2/3}f$
- $p = d/n$, d constant > 1 :
there exists a single giant component
of size $\Omega(n)$



A giant component happens also in real graphs like portions of the web.

Example: protein interactions

- vertices = proteins,
- edges = proteins interact, i.e. two amino acids bind for an action
- 2735 vertices, 3602 edges: $\text{edges/vertices} > \frac{1}{2}$

Size of component	1	2	3	4	5	6	7	8	9	10	11	12	...	15	16	...	1851
Number of components	48	179	50	25	14	6	4	6	1	1	1	0	0	0	1	0	1

- As more proteins added, the giant component absorbs the smaller components

Further examples of giant component

<ftp://ftp.cs.rochester.edu/pub/u/joel/papers.lst>

Vertices are papers and edges mean that two papers shared an author.

1	2	3	4	5	6	7	8	14	27488
2712	549	129	51	16	12	8	3	1	1

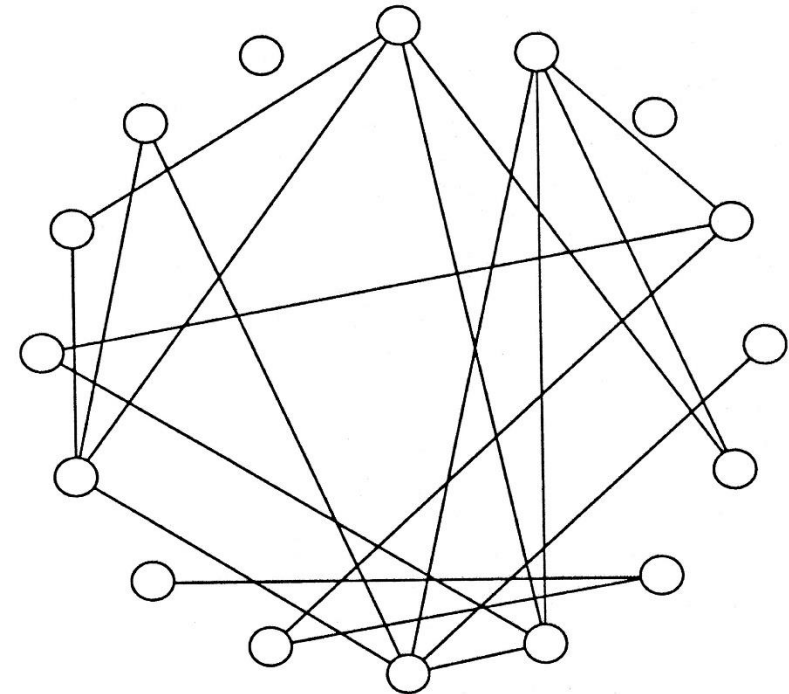
<http://www.gutenberg.org/etext/3202>

Vertices represent words and edges connect words that are synonyms of one another.

1	2	3	4	5	14	16	18	48	117	125	128	30242
7	1	1	1	0	1	1	1	1	1	1	1	1

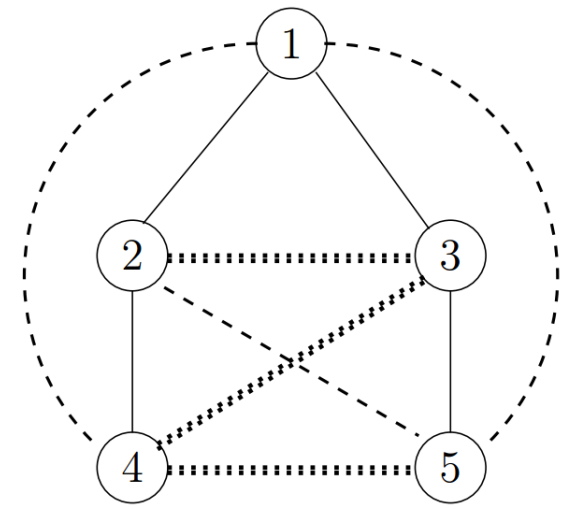
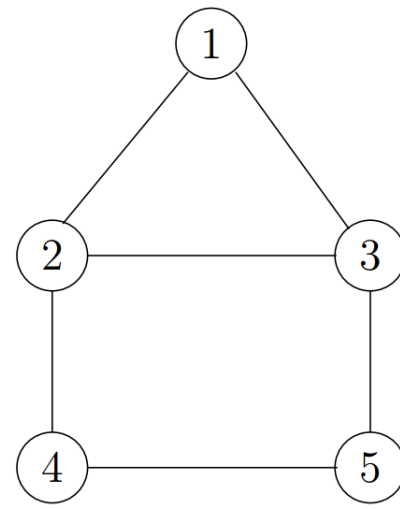
The evolution of $G(n, p)$ as p increases even more

- $p = \ln n / (2n)$:
all non-isolated vertices are absorbed in the giant component,
i.e. graph consists of giant component + isolated vertices
- $p = \ln n / n$: $G(n, p)$ becomes connected
- $p = 1/2$: $G(n, p)$ even has a clique of size $\approx 2 \lg_2 n$



Breadth-first search

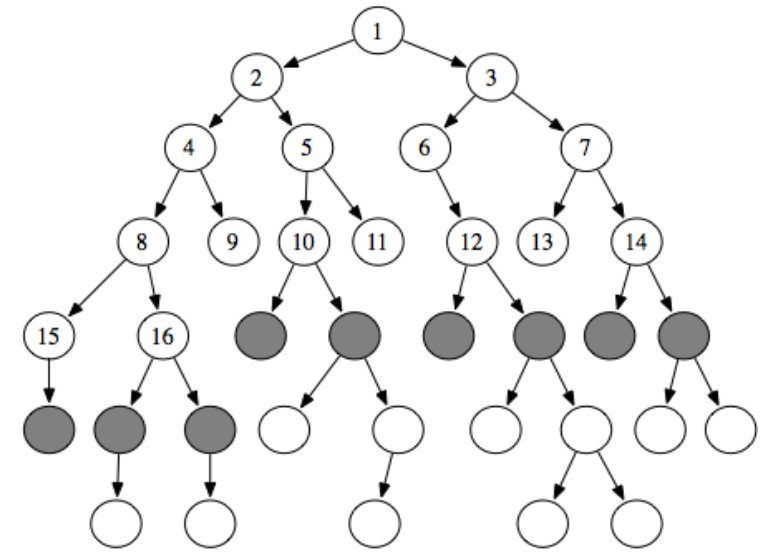
- Generate an edge only when the BFS needs to know if the edge exists
- Start BFS from an arbitrary vertex and mark it discovered and unexplored
- frontier = set of discovered and unexplored vertices
- At each step select v from frontier, and explore it as follows: for each undiscovered vertex u , independently with probability $p = d/n$ add edge (v, u) and add u to the frontier
- BFS finishes when the frontier becomes empty, i.e. when the connected component has been entirely explored



dotted line: unexplored edge
dashed line: edge does not exist
solid line: edge exists

A process equivalent to BFS

- $S = \{v\}, i = 1$
- While $|S| - i \geq 0$
 - add each vertex in $V - S$ to S independently with probability $p = d/n$
 - $i++$



If we replace **while $|S| - i \geq 0$** with **while true**,

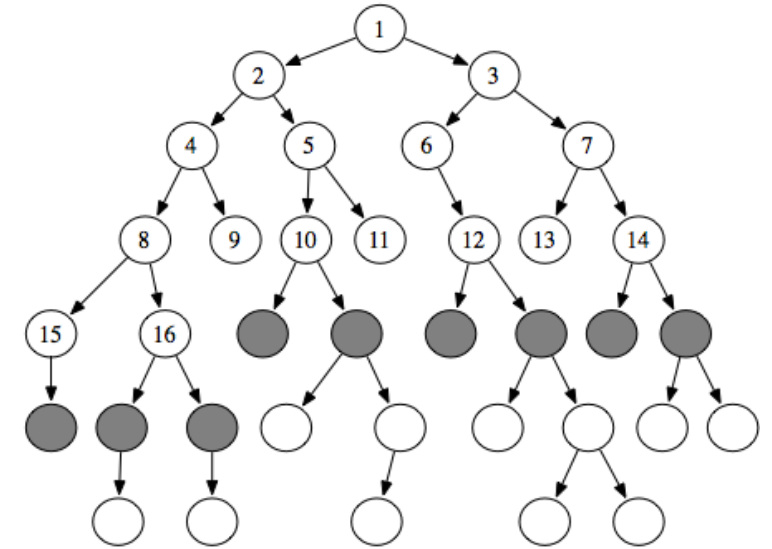
any vertex other than v is not added to S at the first i steps w.p. exactly $(1 - d/n)^i$.

$|S|$ after i iterations has distribution $1 + \text{Binomial}(n-1, 1 - (1 - d/n)^i)$.

For small i , the expected size of S is $\approx id$.

Rough analysis of the process

- The expected size of the “frontier”, i.e. $|S| - i$, is approximately $\approx id - i = i(d - 1)$.



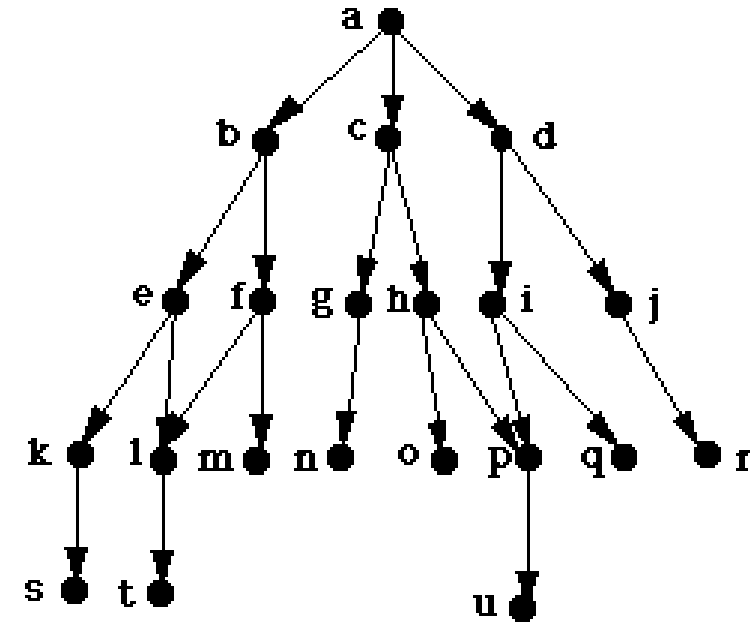
- For $d < 1$, the expected size of the “frontier” is negative.
- For $d > 1$, the expected size of the “frontier” increases, but the rate of discovering new vertices decreases when more vertices have been discovered.

When $(d-1)/d$ fraction of vertices are discovered, this rate is 1.

After that, the “frontier” shrinks.

Before threshold: $d < 1$

Thm. If $p = d/n$, with probability $1 - 1/n$, the sizes of all components are at most $\frac{4 \ln n}{(1-d)^2}$



Proof: By union bound, it suffices to show for each vertex that w.p. $\leq 1/n^2$, its component is of size greater than $k = \frac{4 \ln n}{(1-d)^2}$.

If component size is bigger, then $|S| - k \geq 1$ at step k , i.e. random variable $\text{Binomial}(n-1, 1-(1-d/n)^k)$ with mean at most dk is at least k . This happens with probability at most $(e^{1-d}d)^k$ by Chernoff bound:

$$\Pr(X > (1 + \delta)\mu) < \left(\frac{e^\delta}{(1 + \delta)^{(1+\delta)}} \right)^\mu.$$

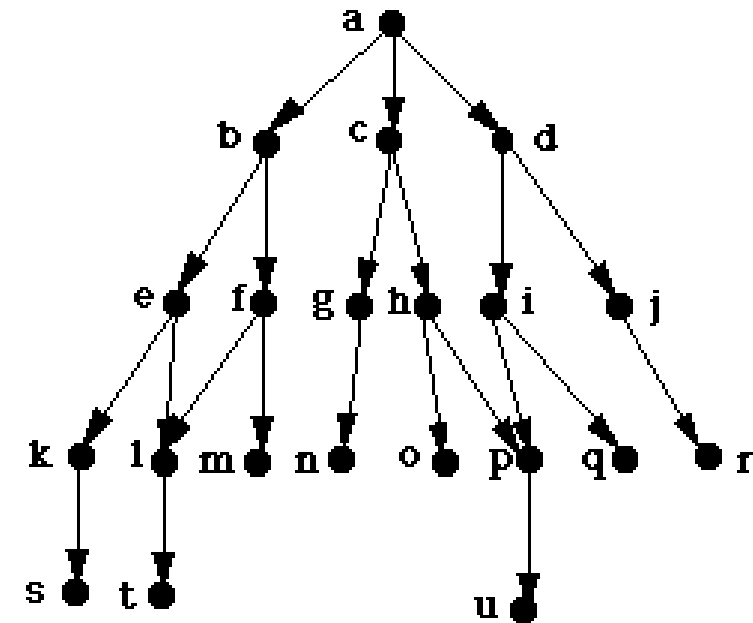
After threshold: $d > 1$

Thm. For each $d > 1$, there are constants c_1 and c_2 such that w.p. $\geq 1 - 1/n$, all component sizes are either $\leq c_1 \ln n$ or $\geq c_2 n$.

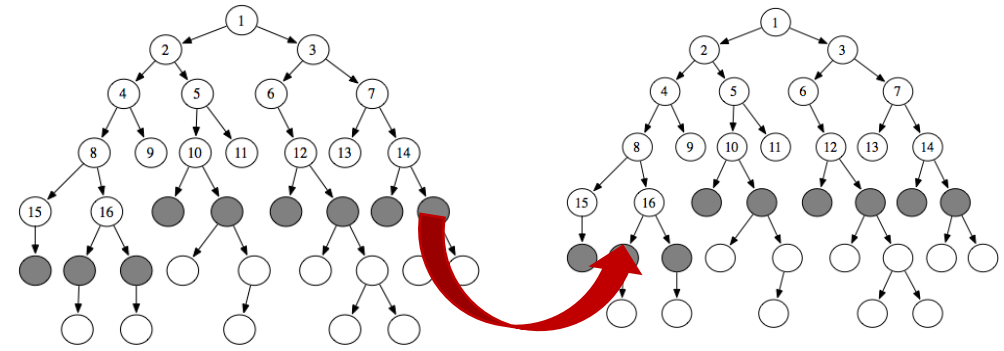
Proof: By union bound, it suffices to show for each vertex and $c_1 \ln n \leq i \leq c_2 n$ that the size of the component of that vertex is i w.p. at most $1/n^3$.

The probability is at most $\Pr[\text{Binomial}(n-1, 1-(1-d/n)^i) = i]$.

The mean of the binomial variable is $id - O(i^2 d^2/n)$, which is $i(1 + \Omega(1))$ for $i \leq c_2 n$ when c_2 is suitably small. By Chernoff bound, the probability is at most $\exp(-\Omega(i))$, which is $\leq 1/n^3$ for $i \geq c_1 \ln n$ when c_1 is suitably large.



Two big components cannot coexist!



- Thm. Assume $d > 1$. The probability that at least two components of size $\geq n^{2/3}$ exists is at most $1/n$.

Proof.

- Let u and v be two vertices. Do BFS from both of them for $n^{2/3}$ steps.
- Either one of the BFSs finishes before that many steps, or the two BFS trees share vertices, or else w.p. $\geq 1 - 1/n^3$ by Chernoff bound both frontiers at step $i = n^{2/3}$ are of size $\Omega(n^{2/3})$.
- Since the frontier has not yet been explored, each pair of vertices from the two frontiers are independently connected with probability d/n .
- The probability that the two components are distinct is
$$\leq (1 - d/n)^{\Omega(n^{4/3})} \leq 1/n^3.$$

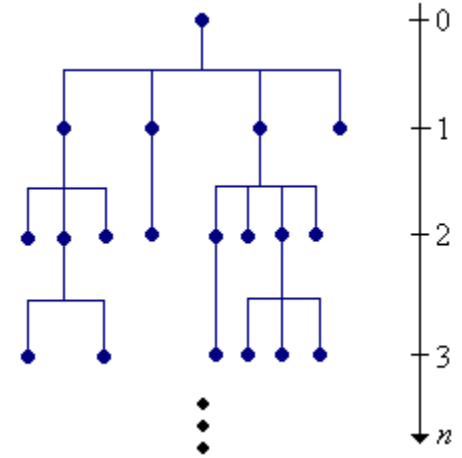
Branching process

- A method for creating a possibly infinite tree:

Let Y be a non-negative integer random variable

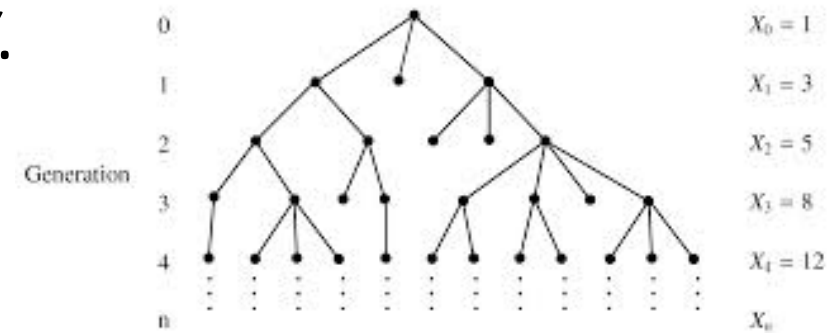
- Start from the root
- Choose a value according to the distribution of Y and spawn that many children
- For each of the root children, choose their # children independently according to the distribution of Y

...



Thm. If $E[Y] > 1$,
extinction probability is < 1 .

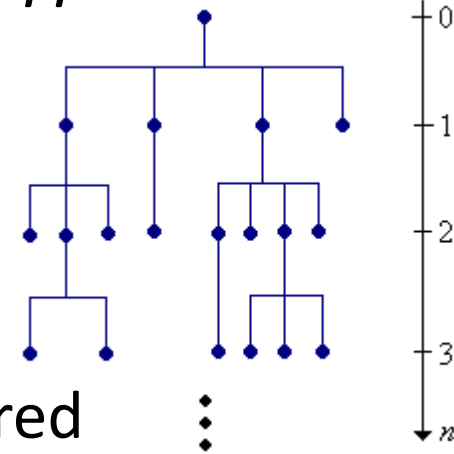
- We assume Y is bounded; otherwise truncate Y .
- Let $p_i = \Pr[Y = i]$.
- $p_0 < 1$.



- There exists $p_0 \leq \alpha < 1$ such that $f(\alpha) = \sum_i p_i \alpha^i \leq \alpha$
(because $f(1) = 1, f'(1) > 1$)
- By induction on t , $\Pr[\text{extinction in } t \text{ levels}] \leq \alpha$.
- $\Pr[\text{extinction}] = \lim_{t \rightarrow \infty} \Pr[\text{extinction in } t \text{ levels}] \leq \alpha$.

For $d > 1$, each vertex is with constant positive probability not in a component of size $\leq c_1 \ln n$

- Do BFS from vertex v .
- While # discovered vertices $\leq c_1 \ln n$,
the distribution of # undiscovered neighbors of a vertex being explored
dominates $\text{Binomial}(n - c_1 \ln n, d/n)$, which in turn
dominates a random variable Y (depending on d but independent of n)
with mean > 1 .
- The probability that this branching process does not become extinct is positive independent of n .



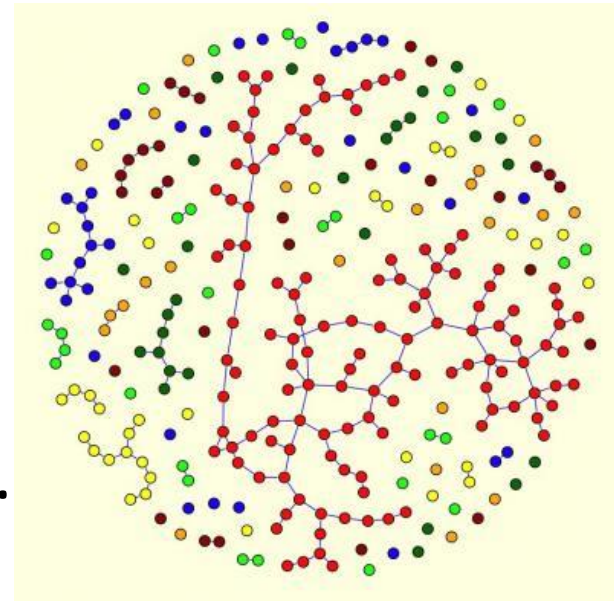
There exists a giant component when $d > 1$.

- Choose a vertex. With $\Omega(1)$ probability it is in a giant component.
- Otherwise, almost surely, it is in a component of size $O(\ln n)$.
- Remove that component from the graph.
- The remaining graph is an Erdos-Renyi graph, still with average degree $1 + \Omega(1)$.
- Now repeat the above for the remaining graph.

You can do the above for $\omega(1)$ steps.

Then almost surely a giant component is found.

For another proof using second moment, see the textbook.

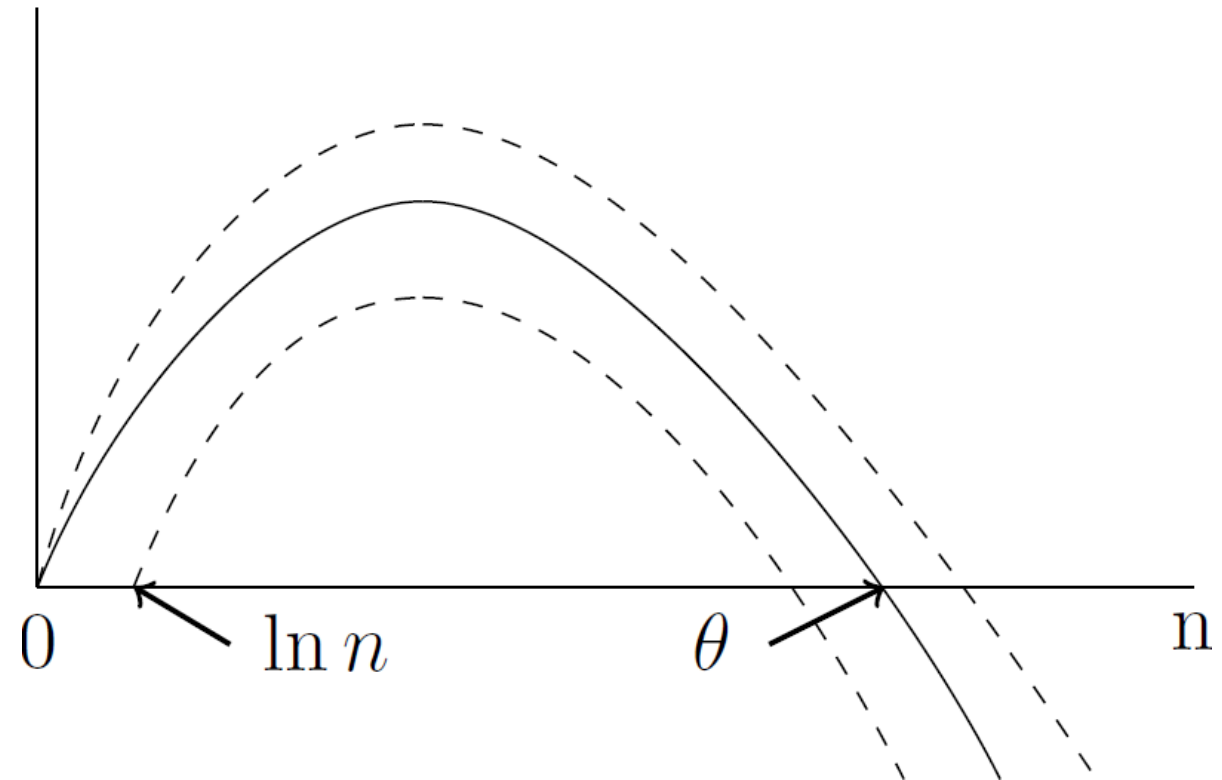


Size of the giant component?

Expected size of frontier = 0
when $n(1-d/n)^\theta = n - \theta$.

In other words
 $\exp(-d (\theta/n)) = 1 - \theta/n$.

(Without giving the proof)
the expected size of the giant
component is approximately this θ .



Solid curve = expected value of the frontier
Dashed curve = probable range for the frontier

Branching Processes

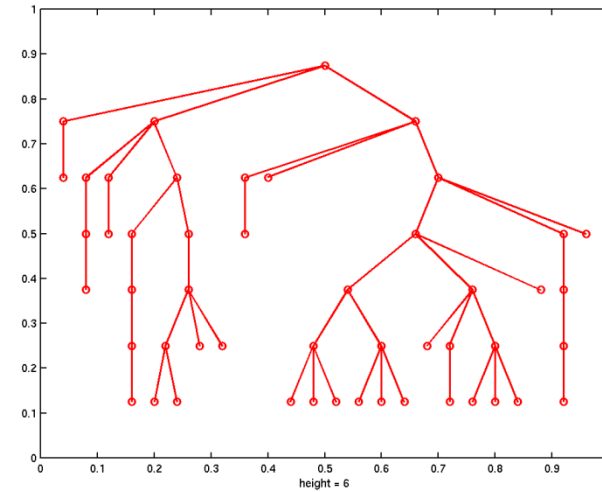
What do we study about branching processes?

We will derive the exact value of

- the **extinction probability**
- the **expected size of the tree conditioned on extinction**

In particular, when the expected number of children is not 1, the conditional expected size is finite.

We know that $G(n, d/n)$, when $d > 1$, consists of a giant component of size $\Omega(n)$ and small components of size $O(\lg n)$. This suggests that the expected size of the small components is constant.



Generating function

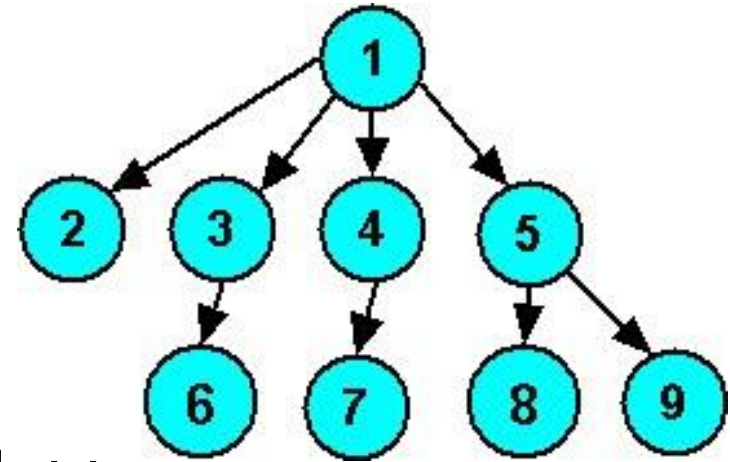
- Let Y be the random variable equal to the number of children of a node.
- Let $p_i = \Pr[Y = i]$.
- The generating function for Y is the function $f(x) = \sum_{i=0}^{\infty} p_i x^i$.



“A generating function is a clothesline on which we hang up a sequence of numbers for display.” Herbert Wilf, Generatingfunctionology

Composition of generating functions

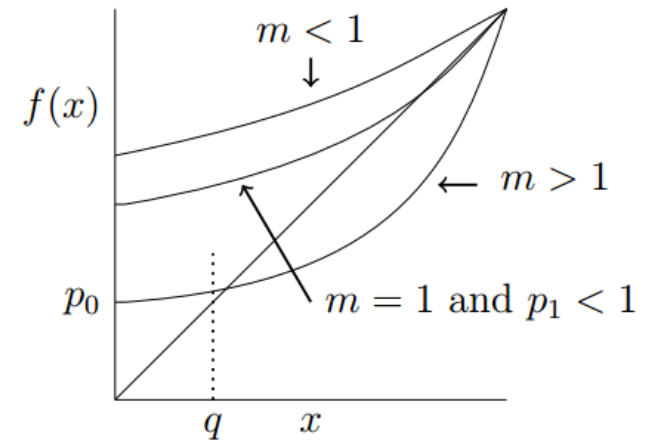
If $f(x)$ is probability generating function for # children
for every node in 1st generation and
 $g(x)$ is probability generating function for # children
for every node in 2nd generation,
 $f(g(x))$ is probability generating function for # grandchildren.



Proof. If $g(x)$ is p.g.f. for Y and $h(x)$ is p.g.f. for Z ,
and Y, Z are independent, then
 $g(x)h(x)$ is the p.g.f. for $Y + Z$.

children in j th generation

- The generating function for total #children in j th generation is $f_j(x)$, where $f_{j+1}(x) = f(f_j(x))$ and $f_1(x) = f(x)$.
- The functions $f_j(x)$ are power series with non-negative coefficients. Therefore, they are non-decreasing and convex on $[0, 1]$.
- If $p_0 < 1$, they are also strictly increasing.



Probability of extinction

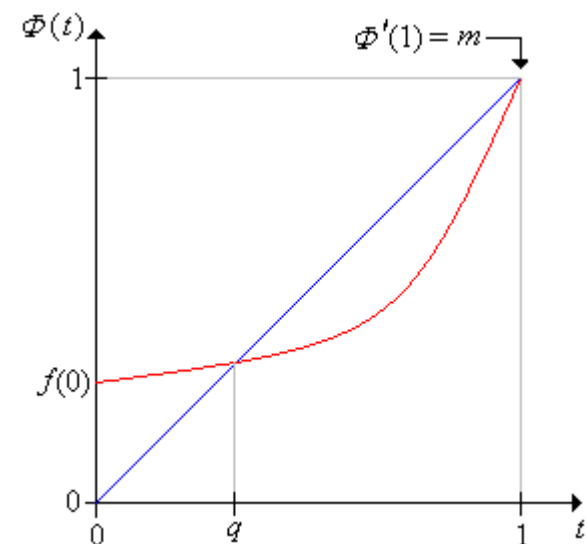
If q is the probability of extinction, we have $q = \sum_{i=0}^{\infty} p_i q^i$.

In other words, q is a root of $f(x) = x$.

1 is always a root of $f(x) = x$.

- If $(E[Y] < 1)$ or $(E[Y] = 1, p_1 < 1)$, then the only root is $q = 1$ because $f'(1) \leq 1$ and f is strictly convex.
- If $Y = 1$, then $q = 0$.
- If $E[Y] > 1$, there is only one root < 1 since $f'(1) > 1$ and f is convex.

Since q is not 1, q is this other root.

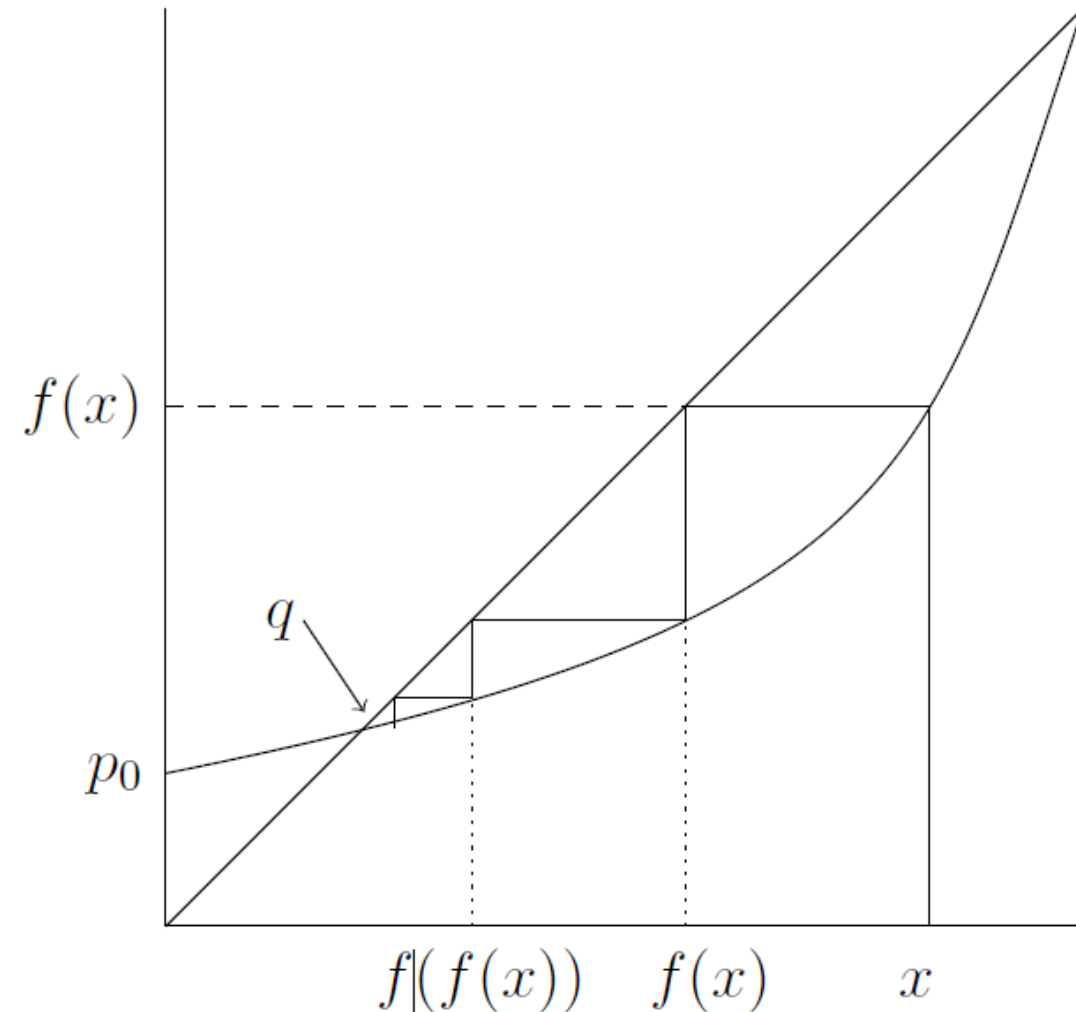


Another way of deriving extinction probability

If q is the smallest root of $f(x) = x$,
then $f_j(0)$ tends to q as j gets larger.
Therefore, extinction probability is q .

Also for any x , $f_j(x)$ tends to q
as j gets larger.

Thus, coefficients of non-constant terms
in $f_j(x)$ tends to zero.



Real biological systems

- In the branching processes we analyzed, the population either dies out or the population size goes to infinity.
- In real world, processes often go to *stable* populations.
- This is due to other factors, like the distribution of # children depends on the size of whole population.

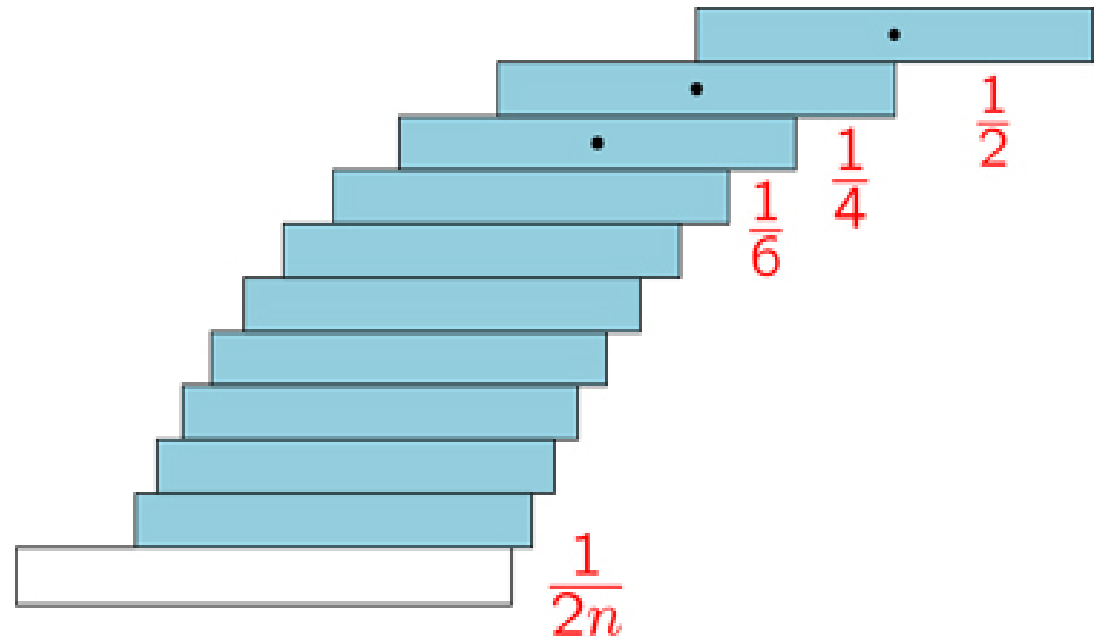


Expected size of extinct families

Finite random variable may have infinite expected value

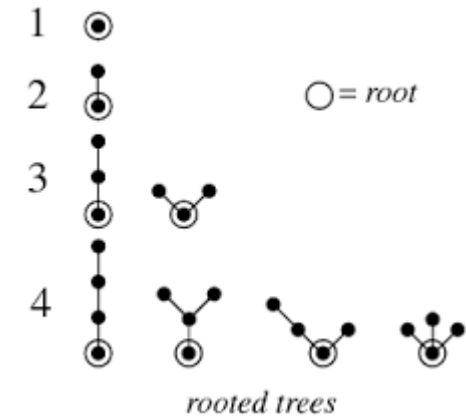
Let X be a positive integer random variable with $p_i = 6/(i^2 \pi^2)$.

$$EX = \sum_{i=1}^{\infty} i \cdot 6/(i^2 \pi^2) = 6/\pi^2 \sum_{i=1}^{\infty} 1/i = \infty$$



Expected size of extinct families (easy cases)

- $E[Y] < 1$: It dies out with probability 1.
Expected size of level l is $E[Y]^l$.
Expected tree size = $1/(1 - E[Y])$.

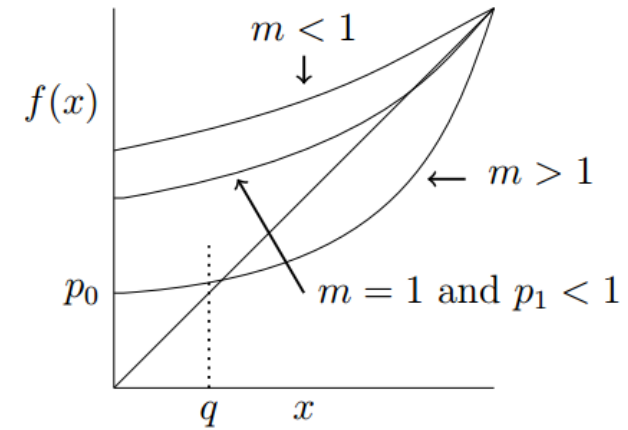


- $E[Y] = 1, Pr[Y = 1] = 1$: The tree never dies.
- $E[Y] = 1, Pr[Y = 1] < 1$: The tree dies out with probability 1.
Expected size at level l is 1.
Expected tree size is infinity.

Expected size of extinct families: case $E[Y] > 1$

- Let the root have i children.
- $\Pr[\text{tree finite} \mid i] = q^i$.

Note $f'(q) < 1$



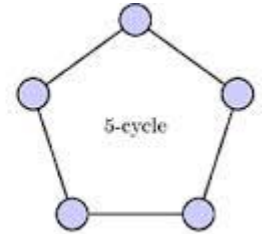
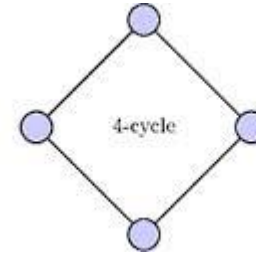
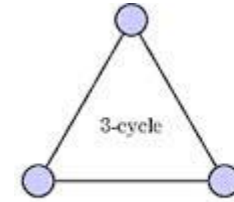
- By Bayes rule, $\Pr[i \mid \text{tree finite}] = \Pr[\text{tree finite} \mid i] p_i / \Pr[\text{tree finite}]$
$$= q^i p_i / q = p_i q^{i-1}$$
- We now have a new branching process with probabilities $p_i q^{i-1}$.
- Expected number of children in this branching process is $f'(q)$.
- Expected size of extinct families = $1/(1 - f'(q))$.

Emergence of cycles

Theorem. Threshold for emergence of cycles is $p = 1/n$.

- Expected # cycles = $\sum_{k=3}^n \frac{n(n-1)\dots(n-k+1)}{k!} \frac{(k-1)!}{2} (d/n)^k.$

- The above sum is at most $\sum_{k=3}^{\infty} d^k.$

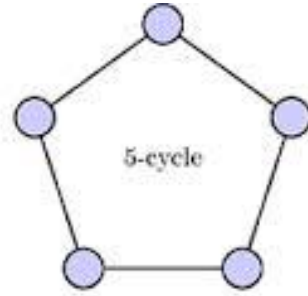
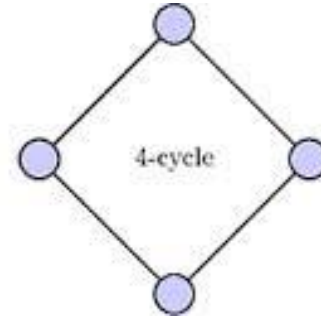
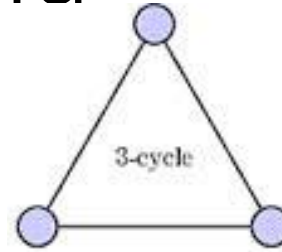


- When $d = o(1)$, the expected # cycles is $o(1)$, so by 1st moment method, there is a cycle with probability only $o(1)$.

- When $d = \omega(1)$, we already showed there is a triangle almost surely.

cycles around the threshold

- Suppose d is constant.



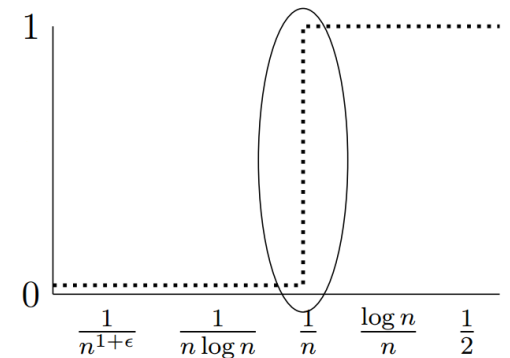
- If $d < 1$, expected # cycles $\leq \sum_{k=3}^{\infty} d^k = O(1)$.

- If $d \geq 1$, expected # cycles is at least

$$\sum_{k=3}^{\lg n} \frac{n(n-1)\dots(n-k+1)}{2kn^k} = \sum_{k=3}^{\lg n} \frac{1-o(1)}{2k} = \omega(1).$$

Threshold for emergence of cycles is not sharp.

- When $d = 1 + \Omega(1)$, there is a giant component in $G(n, (1+d)/(2n))$.
- $G(n, d/n)$ has a lot more edges than $G(n, (1+d)/(2n))$, and each extra edge forms a cycle in the giant component with constant probability.
- Therefore, there are $\omega(1)$ cycles in $G(n, d/n)$ almost surely.



- When $d = 1 - \Omega(1)$, do BFS over the whole graph.
- In each connected component, other than the BFS tree we have not finalized existence of other edges.
- There are on average $O(n)$ non-finalized edges (since expected size of components is $O(1)$ by branching processes).
- Therefore, with at least positive constant probability, there is no cycle.
- Also, with at least positive constant probability, there is a cycle.

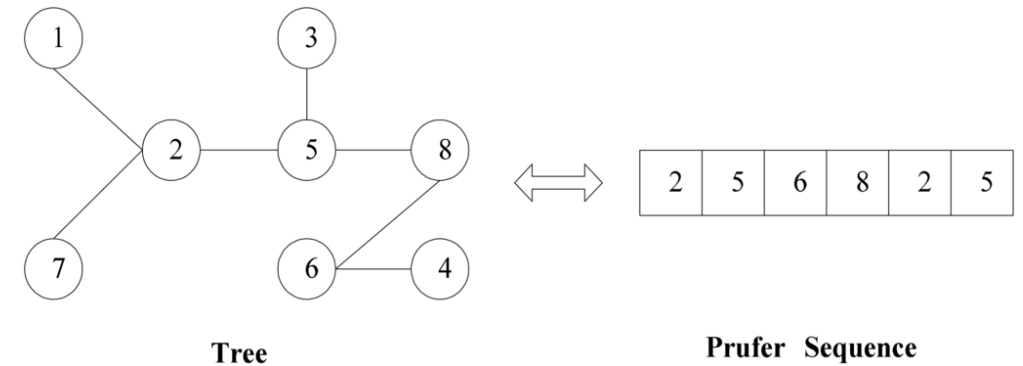
Full connectivity

connected components of size k

The expected # connected components of size k is at most

$$\binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k)}.$$

- # trees on k vertices is k^{k-2} .
- # tree edges = $k - 1$
- # edges crossing the component = $k(n-k)$.

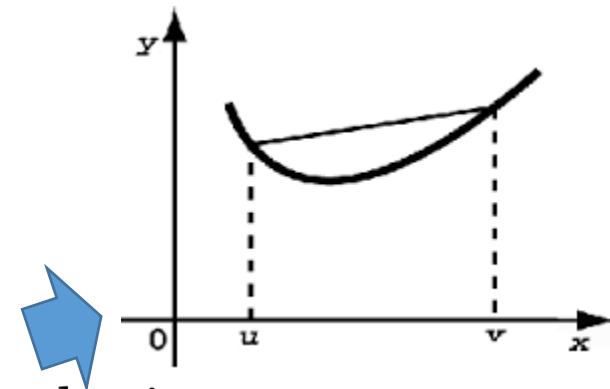


When $p = c \ln n / n$ for constant $c > 1/2$, there is no component of size between 2 and $n/2$.

$$\binom{n}{k} k^{k-2} p^{k-1} (1-p)^{k(n-k)} \leq e^{f(k)}$$

for $f(k) = \ln n + k + k \ln \ln n - 2 \ln k + k \ln c - ck \ln n + ck^2 \ln n / n$.

using $\binom{n}{k} \leq (ne/k)^k$ and $1-p \leq e^{-p}$.



$f''(x) > 0$ so $f(k)$ attains maximum over $k \in [2, n/2]$ at the endpoints.

$f(k) \approx (1 - kc) \ln n$ for constant k and $f(n/2) \approx -cn \ln n / 4$.

Thus, expected number of components of size in $[2, n/2]$ is $O(n^{(1-2c)(1+o(1))})$.

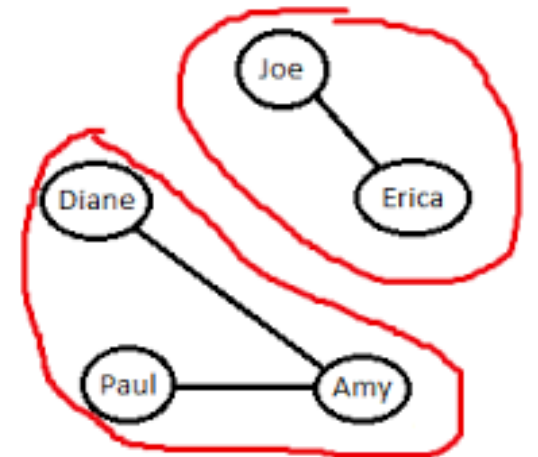
Now use 1st moment method.

Thm. $p = \ln n / n$ is sharp threshold for connectivity.

- Let $p = c \ln n / n$.
- For $c < 1$, we already showed there is an isolated vertex.
- For $c > 1$, there is no isolated vertex.

So almost surely all components are of size $> n/2$.

But there cannot be two components of size $> n/2$. 



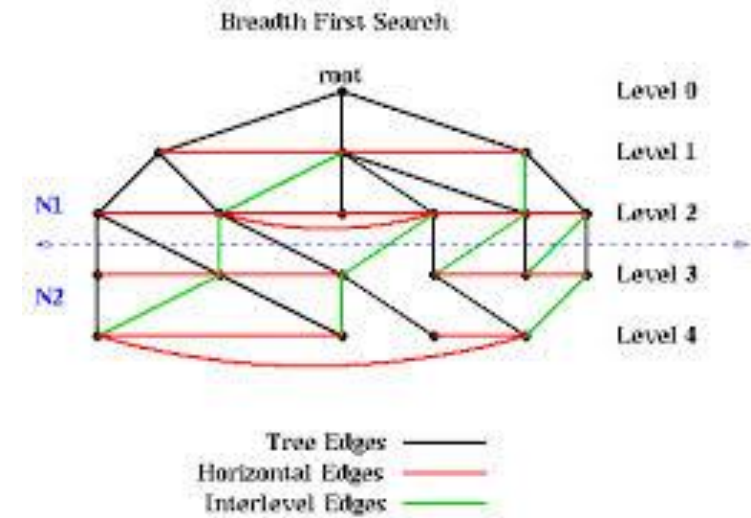
Threshold for logarithmic
diameter

When $p = c \ln n / n$ for large constant c , the graph has diameter $O(\log n)$.

If you run BFS from a vertex,
 the first level has $\geq c(1 - \varepsilon) \ln n$ vertices for large c .
 (We proved concentration for degrees at the beginning of course.)

If S_l is nodes at level l , while $|S_1| + \dots + |S_l| \leq n/1000$,
 by Chernoff w.p. $1 - \exp(-\Omega(|S_l|))$, $|S_{l+1}| \geq 2 |S_l|$.
 (The expected size of S_{l+1} is at least $200 |S_l|$.)

By union bound, the neighborhood of each vertex at distance $O(\lg n)$ is of size $\geq n/1000$.



Almost surely, there is an edge between any two disjoint sets of vertices of size $n/1000$.

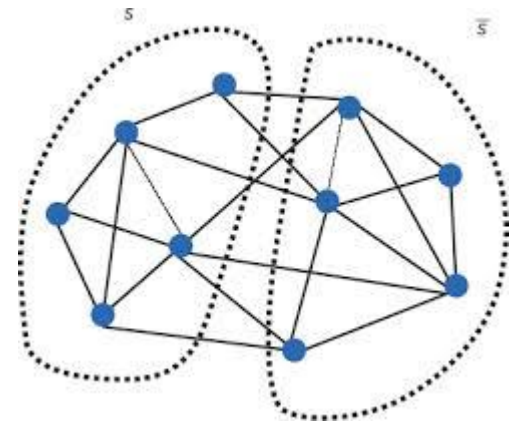
The probability that there is no edge between sets S and T is

$$(1 - p)^{|S||T|} \leq e^{-p|S||T|} \leq e^{-c(\ln n)n/10^6}.$$

There are only 2^{2n} such pairs of sets.

By union bound, almost surely
all such sets S and T are connected.

In particular, neighborhoods of logarithmic depth for any two vertices are connected.



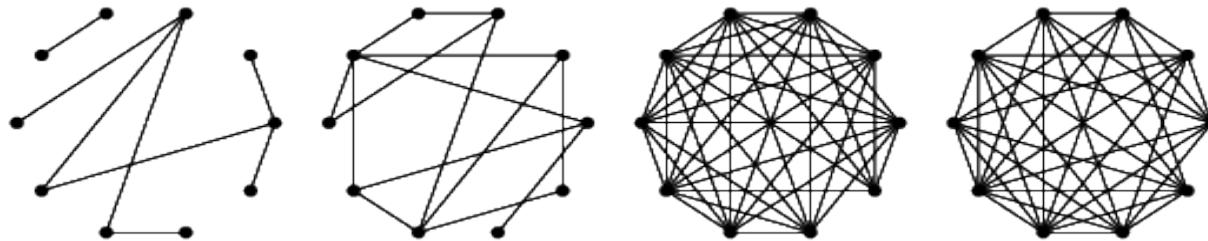
Summary of phase transitions we proved

Property	Threshold
cycles	$1/n$
giant component	$1/n$
giant component + isolated vertices	$\frac{1}{2} \frac{\ln n}{n}$
connectivity, disappearance of isolated vertices	$\frac{\ln n}{n}$
diameter two	$\sqrt{\frac{2 \ln n}{n}}$

Phase transitions for increasing
properties

Do all graph properties have thresholds for Erdos-Renyi graphs?

- All increasing properties have a threshold.
- A property is increasing if when G has the property, adding edges it still has the property.

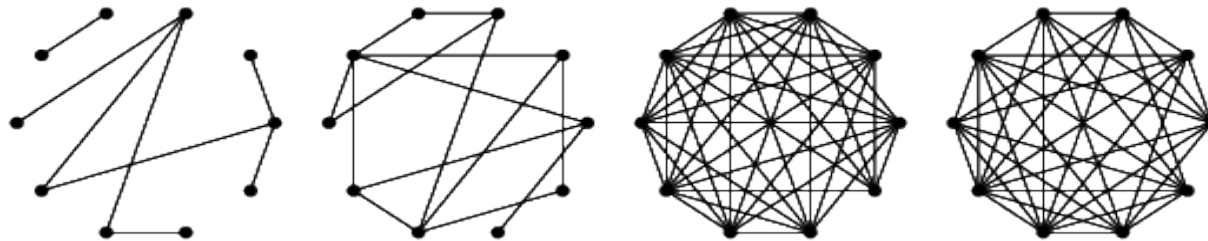


- Examples of increasing properties: having cycle, connectivity, no isolated vertices, having giant component, Hamiltonicity, ...

For increasing property Q , and $0 \leq p \leq q \leq 1$,
 $\Pr[G(n, p) \text{ has } Q] \leq \Pr[G(n, q) \text{ has } Q]$

Proof. Generate $G(n, q)$ as follows:

- first sample $G(n, p)$
- Between every pair of nodes that is not an edge in $G(n, p)$, add an edge with probability $(q - p) / (1 - p)$.

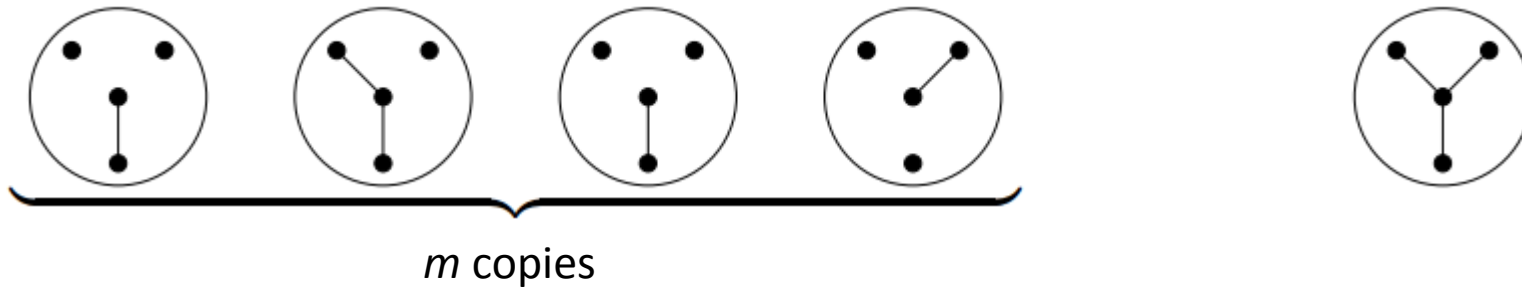


With the above sampling, if $G(n, p)$ has property Q , so does $G(n, q)$.

m -fold replication of $G(n, p)$

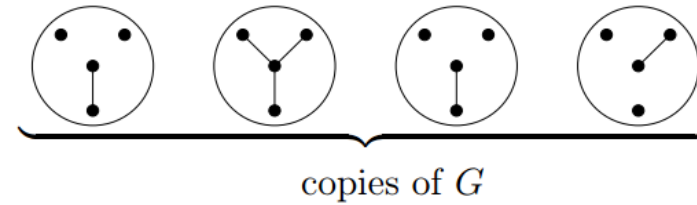
is a new graph with n vertices whose edges are the union of m independent copies of $G(n, p)$.

It is equivalent to $G(n, q)$ for $q = 1 - (1 - p)^m \leq mp$.

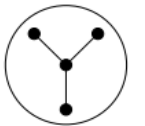


Relation of m -fold replication with $G(n, p)$

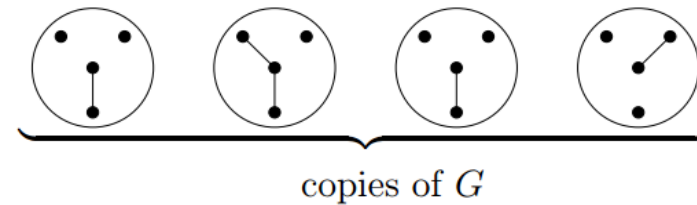
- $\Pr[G(n, mp) \text{ has } Q] \geq \Pr[G(n, q) \text{ has } Q]$



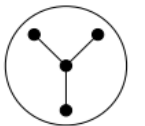
If any graph has three or more edges, then the m -fold replication has three or more edges.



The m -fold replication H



Even if no graph has three or more edges, the m -fold replication might have three or more edges.



The m -fold replication H

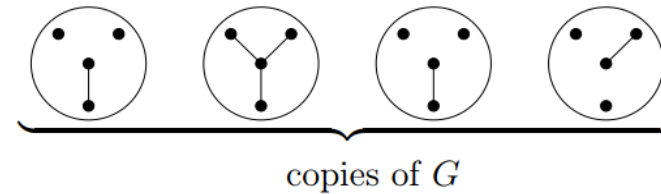
- $\Pr[G(n, q) \text{ has } Q] \geq 1 - (1 - \Pr[G(n, p) \text{ has } Q])^m.$

Thm. Increasing properties have thresholds.

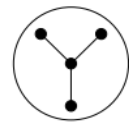
Let p be such that $\Pr[G(n, p) \text{ has } Q] = 1/2$.

- If $p' = mp$, $\Pr[G(n, p') \text{ has } Q] \geq 1 - (1 - \Pr[G(n, p) \text{ has } Q])^m = 1 - 2^{-m}$.
- If $p' = p/m$, $1/2 = \Pr[G(n, p) \text{ has } Q] \geq 1 - (1 - \Pr[G(n, p') \text{ has } Q])^m$.

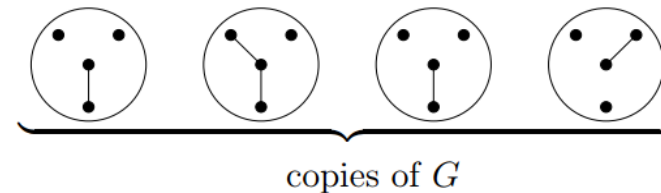
Thus, p is a threshold.



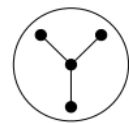
If any graph has three or more edges, then the m -fold replication has three or more edges.



The m -fold replication H



Even if no graph has three or more edges, the m -fold replication might have three or more edges.



The m -fold replication H