

CS174 Fall 98: Lecture Note 4

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Random graphs

- How many edges are needed to make a random graph on n nodes connected?

First, we need to define precisely what we mean by a “random graph.”

Experiment 1:

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start with  $n$  vertices  $V = \{1, 2, \dots, n\}$  and  $E = \emptyset$ 
do  $m$  times
    select an edge  $e = \{i, j\} \notin E$  uniformly at random
    add  $e$  to  $E$ 
output  $G = (V, E)$ 
```

Sample space: all $\binom{n}{m}$ labeled graphs G with n vertices and m edges, each equally likely

Ex: Enumerate the entire sample space for $n = 4, m = 3$. \square

Let G be a random graph (sample point) as above; we want to find the smallest value of m s.t. $\Pr[G \text{ is connected}]$ is close to 1.

Actually, it is much easier to answer a similar question for a slightly different sample space: then we'll translate the answer to the above sample space.

Experiment 2:

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start with  $n$  vertices  $V = \{1, 2, \dots, n\}$  and  $E = \emptyset$ 
do until  $G = (V, E)$  is connected
    select an edge  $e = \{i, j\} \notin E$  uniformly at random
    add  $e$  to  $E$ 
output  $G = (V, E)$ 
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Sample space: all connected graphs G obtained from the above experiment, with probabilities ???

Ex: Enumerate the entire sample space (including the probabilities) for $n = 4$. \square

We are interested in the random variable $X = |E|$, i.e., the number of edges in the graph G at the end of the experiment. Let's compute $E(X)$.

Idea: let $X_k =$ number of edges added to reduce number of components from k to $k - 1$.

Then $X = \sum_{k=2}^n X_k$ and $E(X) = \sum_{k=2}^n E(X_k)$.

What does X_k look like?

Well, $X_n = 1$ always (with probability 1) — why?

And $X_{n-1} = 1$ with probability 1 — why?

The distribution of X_{n-2} depends on the first two edges (why?); but presumably its expectation is not much bigger than 1 (again, why?)

Similarly, for $k < n - 2$, the distributions of the X_k become rather complicated, but maybe we can compute an upper bound on $E(X_k)$.

Claim: For all k , we have $E(X_k) \leq \frac{n-1}{k-1}$.

Proof: Suppose G has exactly $k > 1$ components. Consider *any* vertex i . Our experiment is equally likely to pick any of the edges $\{i, j\}$ that is not in E . There are at most $n - 1$ such edges, of course. How many of them reduce the number of components? Well, *at least* $k - 1$ (why?). Therefore, the probability that any such edge reduces the number of components is at least $\frac{k-1}{n-1}$. Since this holds for every vertex i , it holds in general. But now we see that $X_k \leq Y_k$, where $Y_k = \#$ coin flips up to and including first head for a coin with $\Pr[\text{heads}] = p = \frac{k-1}{n-1}$. And by qun. 2(a) of HW2, we know that $E(Y_k) = \frac{1}{p} = \frac{n-1}{k-1}$. Hence $E(X_k) \leq \frac{n-1}{k-1}$. \square

Now we are done:

$$E(X) = \sum_{k=2}^n E(X_k) \leq (n-1) \left\{ 1 + \frac{1}{2} + \frac{1}{3} + \cdots + \frac{1}{n-1} \right\} \sim (n-1)(\ln(n-1) + \gamma).$$

So the expected number of edges at the end of Experiment 2 is at most $(n-1)(\ln(n-1) + \gamma)$ as $n \rightarrow \infty$.

Note: This is only an upper bound on $E(X)$. The exact answer (which requires more effort) is $E(X) \sim \frac{n}{2} \ln n$. So we are off by only a factor of 2.

Ex: In the above proof, we said that $X_k \leq Y_k$. What does this mean, in view of the fact that X_k and Y_k are not numbers but random variables (over different sample spaces)? What it means, precisely, is that $\Pr[X_k \geq z] \leq \Pr[Y_k \geq z]$ for all z . Think about this statement, and convince yourself that it holds for the X_k and Y_k in the above proof. Also, show that $X_k \leq Y_k$ implies that $E(X_k) \leq E(Y_k)$, as we used in the proof. \square

We've seen that the *expected* number of edges required to make the graph connected is at most $M(n) = (n-1)(\ln(n-1) + \gamma)$. What's the probability that we need much more than this? We can get a bound on this probability using Markov's inequality:

Theorem [Markov's Inequality]: Let X be a r.v. taking non-negative values, and let $\mu = E(X)$. Then

$$\Pr[X \geq c\mu] \leq \frac{1}{c} \quad \text{for any } c \geq 1.$$

Proof:

$$\begin{aligned} \mu = E(X) &= \sum_k \Pr[X = k] \cdot k \\ &\geq \sum_{k \geq c\mu} \Pr[X = k] \cdot k \\ &\geq c\mu \sum_{k \geq c\mu} \Pr[X = k] \\ &= c\mu \Pr[X \geq c\mu]. \end{aligned}$$

Therefore, $\Pr[X \geq c\mu] \leq \frac{1}{c}$. \square

Ex: The above proof isn't formally valid when $\mu = 0$, since in the last step we cancel μ . Is the theorem still true when $\mu = 0$? \square

Ex: Give a simple counterexample which shows that Markov's inequality is definitely false if we drop the assumption that X is non-negative. \square

Applying Markov's inequality to our r.v. X , we get

$$\Pr[X \geq cM(n)] \leq \frac{1}{c} \quad \text{for any } c \geq 1. \quad (*)$$

So, for example, if we add $10M(n)$ edges, the probability that G is connected is at least $\frac{9}{10}$.

This will help us to analyze Experiment 1. First, suppose we modify Experiment 2 slightly so that, if G becomes connected before m edges have been added, we still continue to add random edges until G has exactly m edges. View each point of the sample space of this modified Experiment 2 as $G = G' + G''$, where G' is the graph consisting of the first m edges and G'' is the remainder. (Note that G'' will be empty if G' is connected.) Then it should be clear that

$$\Pr[X \leq m] = \Pr[G' \text{ is connected}].$$

What is the relationship with Experiment 1? Well, if you think about it you should see that the sample space of graphs G' is *exactly* the same as the sample space of Experiment 1 (why?). So we get

$$\Pr_1[G \text{ is connected}] = \Pr_2[G' \text{ is connected}] = \Pr_2[X \leq m],$$

where \Pr_1 and \Pr_2 denote probabilities in Experiments 1 and 2 respectively. Now, putting $m = cM(n)$ in Experiment 1, we get from (*) that

$$\Pr_1[G \text{ is connected}] = \Pr_2[X \leq cM(n)] \geq 1 - \frac{1}{c},$$

which gives a good answer to our original question about Experiment 1; i.e., a random graph with n vertices and $m = c(n-1)(\ln(n-1) + \gamma)$ edges is connected with probability at least $1 - \frac{1}{c}$.

A randomized algorithm for a graph problem

Let $G = (V, E)$ be an undirected graph. A cut in G is a set of edges whose removal separates G into two (or more) components.

The problem MINCUT involves finding a cut in G with the minimum number of edges.

Here is a very simple randomized algorithm (due to Karger) for MINCUT:

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while  $G$  has more than two vertices do
    pick an edge  $e = (u, v)$  u.a.r.
    contract  $e$ 
output the remaining edges

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The operation “contract e ” means that the endpoints, u and v , of e are merged into a single vertex, retaining all their connections to other vertices. More precisely, we retain all multiple edges that are created, but eliminate all self-loops.

Since the number of vertices decreases by 1 each time, there will be exactly $n - 2$ iterations, where n is the number of vertices in G . So the algorithm runs in $O(n^2)$ time. (Check this.) But does it work???

First, note that the algorithm always outputs a valid cut in G . (Why?) We need to analyze the probability that it outputs a minimum cut.

Let's focus on a particular minimum cut, which we'll call \mathcal{C} . We'll look at the probability that \mathcal{C} survives throughout the repeated contraction process of the algorithm.

Let E_i be the event that \mathcal{C} survives iteration i . We want to compute $\Pr[E_1 \wedge E_2 \wedge \dots \wedge E_{n-2}]$.

Using the fact that $\Pr[E \wedge F] = \Pr[F] \Pr[E|F]$, we can write this as

$$\Pr[\bigwedge_{i=1}^{n-2} E_i] = \Pr[E_1] \times \Pr[E_2|E_1] \times \Pr[E_3|E_1 \wedge E_2] \times \cdots \times \Pr[E_{n-2} | \bigwedge_{j=1}^{n-3} E_j]. \quad (\ddagger)$$

What is $\Pr[E_1]$, the probability that \mathcal{C} survives the first iteration?

Well, let the number of edges in \mathcal{C} be k . Then every vertex in G must have degree¹ at least k (why?). So G must have at least $\frac{kn}{2}$ edges.

Therefore, $\Pr[E_1] \geq 1 - \frac{k}{(kn/2)} = 1 - \frac{2}{n} = \frac{n-2}{n}$. (Why?)

Now let's look at $\Pr[E_2|E_1]$, the probability that \mathcal{C} survives the second iteration given that it survived the first.

By the same argument as above, G must now have at least $\frac{k(n-1)}{2}$ edges.

So $\Pr[E_2|E_1] \geq 1 - \frac{k}{k(n-1)/2} = 1 - \frac{2}{n-1} = \frac{n-3}{n-1}$.

In similar fashion, we can show for each i that

$$\Pr[E_i | \bigwedge_{j=1}^{i-1} E_j] \geq 1 - \frac{2}{n-i+1} = \frac{n-i-1}{n-i+1}.$$

Plugging this into (\ddagger) gives

$$\Pr[\bigwedge_{i=1}^{n-2} E_i] \geq \frac{n-2}{n} \times \frac{n-3}{n-1} \times \frac{n-4}{n-2} \times \cdots \times \frac{2}{4} \times \frac{1}{3} = \frac{2}{n(n-1)}.$$

So, our algorithm discovers the minimum cut \mathcal{C} with probability at least $\frac{2}{n^2}$.

Ex: If there were many – say, m – minimum cuts, show that this probability would improve to $\frac{2m}{n^2}$.

□

The observation in this exercise isn't much use, however, since in general we can't assume that G will have more than a single minimum cut. So the best lower bound we have on the success probability of the algorithm is about $\frac{2}{n^2}$.

Disappointing?

Not really: suppose we perform t independent trials of the algorithm, and choose the smallest cut we find. What is the probability that we fail to discover \mathcal{C} on all t attempts?

Clearly, this prob. is at most $(1 - \frac{2}{n^2})^t$. (Why?)

So if we take $t = cn^2$, with c a constant, the prob. is at most $(1 - \frac{2}{n^2})^{cn^2} \leq e^{-2c}$.

So, to make the probability that the algorithm fails as small as (say) $e^{-14} \approx 10^{-6}$, it is enough to perform only $7n^2$ repetitions.

Ex: The above proof shows that G can have at most $\frac{n(n-1)}{2}$ different minimum cuts. Why? □

Ex: Suppose that Karger's algorithm is applied to a tree G . Show that it finds a minimum cut with probability 1. □

Ex: Suppose we modify the algorithm so that, instead of choosing an edge u.a.r. and merging its endpoints, it chooses two vertices u.a.r. and merges them. Find a family of graphs G_n (where G_n has n vertices for each n) such that, when the modified algorithm is applied to G_n , the probability that it finds a minimum cut is *exponentially* small in n . How many times would you have to repeat this algorithm to have a reasonable chance of finding a minimum cut? □

¹The degree of a vertex is the number of neighbors it has.