Random Graph theory

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February 27, 2020

Most materials from this note is taken from [1, 3]

1 Erdos-Renyi Graph Model

- We use $G(n, p)$ to denote an undirected (Erdos-Renyi) graph with n nodes.
- An edge is formed between 2 nodes with probability $p \in (0,1)$ **independently** of other edges.
- A graph is **connected** when there is a path between every pair of vertices.

When $p = p(n)$ is a function of n, we may be interested in the behavior of $G(n, p(n))$ as $n \to \infty$.

1.1 Warm-up

Q1. What is the probability that a vertex is isolated in $G(n, p)$? Ans: A given node i cannot form an edge with each of the remaining $n-1$ nodes. Thus the probability is $(1-p)^{n-1}$.

Q2. What is the expected number of edges in $G(n, p)$? The total number of edges in a graph is $\binom{n}{2}$, and each of these edges form with probability p. So we expect $p\binom{n}{2}$ edges overall.

2 Sharp Threshold for Connectivity

The first lecture will be a proof of the following result. This proof uses several techniques you learned in this class.

Theorem 2.1 Erdos-Renyi 1961

Consider a graph $g \sim G(n, p(n))$ where $p(n) = \lambda \frac{\ln(n)}{n}$. Then as $n \to \infty$,

$$\begin{aligned} P(g \text{ connected}) &\to 0 \quad \text{if } \lambda < 1 \\ P(g \text{ connected}) &\to 1 \quad \text{if } \lambda > 1 \end{aligned}$$

Proof. Suppose $\lambda < 1$. Since $P(\text{connected}) = 1 - P(\text{disconnected})$, we will show $P(\text{disconnected}) \to 1$ by showing that **there is at least 1 isolated node**. Define

- X_n to be a random variable that counts the number of isolated nodes
- I_i to be a (Bernoulli) indicator random variable such that $I_i = 1$ when node i is isolated and is 0 otherwise
- Let $p = p(n)$ and $q = q(n) = (1 - p(n))^{n-1}$ be the probability of a node being isolated

We want to show $P(X_n > 0) \to 1$, or equivalently, $P(X_n = 0) \to 0$ by rules of probability complements. To get a bound on $P(X_n = 0)$, we observe:

$$\begin{aligned}
\text{Var}(X_n) &= E\left(X_n - E(X_n)\right) \\
&= P(X_n = 0)(0 - E(X_n))^2 + P(X_n = 1)(1 - E(X_n))^2 + \ldots \\
&\geq P(X_n = 0)E(X_n)^2.
\end{aligned}$$

Thus

$$\frac{\text{Var}(X_n)}{E(X_n)^2} \geq P(X_n = 0). \tag{2.1}$$

We will now calculate $\text{Var}(X_n)$ and $E(X_n)$ explicitly to show that the left hand side of (2.1) goes to 0. By linearity of expectation and applying definition of indicators,

$$\mathbb{E}(X_n) = \mathbb{E}\left(\sum_{i=1}^{n} I_i\right) = \sum_{i=1}^{n} \mathbb{E}(I_i) = \sum_{i=1}^{n} P(I_i) = nq.$$

Since indicators I_i are **not independent** (why?), we use equation (1.10) in your book [2]:

$$\begin{aligned}
\text{Var}(X_n) = \text{Var}\left(\sum_{i=1}^{n} I_i\right) &= \sum_{i=1}^{n} \text{Var}(I_i) + \sum_{i=1}^{n}\sum_{j\neq i} \text{Cov}(I_i, I_j) \\
&= \sum_{i=1}^{n} q(1-q) + \sum_{i=1}^{n}\sum_{j\neq i} \left[E(I_i I_j) - E(I_i)E(I_j)\right] \quad (\text{since Var(Bernoulli)} = p(1-p)) \\
&= nq(1-q) + \sum_{i=1}^{n}\sum_{j\neq i} \left[P(I_i \cap I_j) - P(I_i)P(I_j)\right] \\
&= nq(1-q) + \sum_{i=1}^{n}\sum_{j\neq i} \left[(1-p)^{n-1}(1-p)^{n-2} - (1-p)^{n-1}(1-p)^{n-1}\right] \\
&= nq(1-q) + \sum_{i=1}^{n}\sum_{j\neq i} \left[\frac{q^2}{1-p} - q^2\right] \\
&= nq(1-q) + n(n-1)q^2 \frac{p}{1-p}.
\end{aligned}$$

Thus

$$\frac{\text{Var}(X_n)}{E(X_n)^2} = \frac{nq(1-q) + n(n-1)q^2 \frac{p}{1-p}}{(nq)^2} = \frac{1-q}{nq} + \frac{n-1}{n}\frac{p}{1-p}.$$

We will now show these terms approach 0 as $n \to \infty$, then eq (2.1) will give us what we need. The first term is dominated by nq, and

$$
\begin{aligned}
\lim_{n\to\infty} nq &= \lim_{n\to\infty} n(1-p)^{n-1} = \lim_{n\to\infty} \exp\left\{\ln(n) + (n-1)\ln(1-p)\right\} \\
&= \lim_{n\to\infty} \exp\left\{\ln(n) + (n-1)\ln\left(1 - \frac{\lambda \ln(n)}{n}\right)\right\} \\
&\approx \lim_{n\to\infty} \exp\left\{\ln(n) - \lambda \frac{n-1}{n}\ln(n)\right\} \quad \left(\ln(1-x) = 1 - x + \frac{x^2}{2} - \ldots \approx -x + O(x^2) \text{ for small } x\right) \\
&= \lim_{n\to\infty} \exp\left\{\ln(n)\left(1 - \lambda\frac{n-1}{n}\right)\right\} \\
&= \infty \quad (\text{since } \lambda < 1)
\end{aligned}
$$

For the second term, observe that $p = \lambda \frac{\ln(n)}{n} \to 0$ as $n \to \infty$. So $\frac{p}{1-p} \to 0$ as well. This completes the case for $\lambda < 1$.

Part II. Now suppose $\lambda > 1$. We want to show $P(\text{connected}) \to 1$, or equivalently $P(\text{disconnected}) \to 0$. A graph is disconnected if there is a subgraph of k nodes that does not connect to any of the other $n-k$ nodes (draw a picture). By symmetry, we only have to consider $k \in \{1, 2, \ldots \lfloor n/2 \rfloor\}$. So

$$
\begin{aligned}
P(\text{disconnected}) &= \bigcup_{k=1}^{\lfloor n/2 \rfloor} P(\text{some set of } k \text{ nodes not connected to the rest}) \\
&\leq \sum_{k=1}^{\lfloor n/2 \rfloor} P(\text{some set of } k \text{ nodes not connected to the rest}) \quad (\text{inclusion-exclusion picture}) \\
&= \sum_{k=1}^{\lfloor n/2 \rfloor} \binom{n}{k} \left[(1-p)^{(n-k)}\right]^k \\
&\leq \sum_{k=1}^{\lfloor n/2 \rfloor} \binom{n}{k} e^{p(n-k)k} \quad \left(e^{-x} = 1 - x + \frac{x^2}{2} - \ldots \approx 1 - x + O(x^2) \text{ for small } x\right) \\
&= \sum_{k=1}^{\lfloor n/2 \rfloor} \binom{n}{k} \exp\left\{\frac{-\lambda \ln(n)(n-k)k}{n}\right\} \\
&= \sum_{k=1}^{\lfloor n/2 \rfloor} \binom{n}{k} n^{\frac{-\lambda}{n}(n-k)k} \\
&= \sum_{k=1}^{n^*} \binom{n}{k} n^{\frac{-\lambda}{n}(n-k)k} + \sum_{k=n^*+1}^{\lfloor n/2 \rfloor} \binom{n}{k} n^{\frac{-\lambda}{n}(n-k)k} \quad \left(\text{Choose } n^* s.t. \frac{\lambda(n-n^*)}{n} > 1 \iff n^* = \lfloor n(1-\frac{1}{\lambda}) \rfloor\right)
\end{aligned}
$$

For the first term,

$$
\begin{aligned}
\sum_{k=1}^{n^*}\binom{n}{k}n^{\frac{-\lambda}{n}(n-k)k} &\le \sum_{k=1}^{n^*} n^k n^{\frac{-\lambda}{n}(n-k)k} = \sum_{k=1}^{n^*}\left[n^{1-\frac{\lambda}{n}(n-k)}\right]^k \\
&\le \sum_{k=1}^{n^*}\left[n^{1-\frac{\lambda}{n}(n-n^*)}\right]^k \qquad \text{(judiciously bound inner} k \text{ with something bigger)} \\
&= \sum_{k=1}^{n^*} r^k \qquad \left(\text{define } r = n^{1-\frac{\lambda}{n}(n-n^*)}\right) \\
&= \left(\sum_{k=0}^{n^*} r^k\right) - 1 \\
&= \frac{r}{1-r} \qquad \left(\text{geometric series; } 1-\frac{\lambda}{n}(n-n^*) < 0, \text{ so } r<1\right) \\
&= \frac{1}{n^{\frac{\lambda}{n}(n-n^*)-1}-1} \\
&\longrightarrow 0 \qquad (\text{since } n\to\infty \text{ and exponent} > 0)
\end{aligned}
$$

For the second term, we use a better bound than before (see homework):

$$
\binom{n}{k} \le \frac{n^k}{k!} = \binom{n}{k}^k \frac{k^k}{k!} < \left(\frac{n}{k}\right)^k \sum_{j=0}^{\infty}\frac{k^j}{j!} = \left(\frac{ek}{k}\right)^k.
$$

Thus

$$
\begin{aligned}
\sum_{k=n^*+1}^{\lfloor n/2\rfloor}\binom{n}{k}n^{\frac{-\lambda}{n}(n-k)k} &\le \sum_{k=n^*+1}^{\lfloor n/2\rfloor}\left(\frac{en}{k}\right)^k n^{\frac{-\lambda(n-k)k}{n}} = \sum_{k=n^*+1}^{\lfloor n/2\rfloor}\left[\frac{en^{1-\frac{\lambda(n-k)}{n}}}{k}\right]^k \\
&\le \sum_{k=n^*+1}^{\lfloor n/2\rfloor}\left[\frac{en^{1-\frac{\lambda(n-\frac{n}{2})}{n}}}{n^*+1}\right]^k \qquad \text{(bound inner } k \text{ with something from above)} \\
&= \sum_{k=n^*+1}^{\lfloor n/2\rfloor}\left[\frac{en^{1-\frac{\lambda}{2}}}{n(1-\frac{1}{\lambda})+1}\right]^k \le \sum_{k=n^*+1}^{\lfloor n/2\rfloor}\left[\frac{en^{\frac{-\lambda}{2}}}{1-\frac{1}{\lambda}}\right]^k \\
&\le \sum_{k=n^*+1}^{\lfloor n/2\rfloor} r^k \qquad \left(r = \frac{en^{\frac{-\lambda}{2}}}{1-\frac{1}{\lambda}}, 0<r<1 \text{ for large } n\right) \\
&\le \sum_{k=n^*+1}^{\infty} r^k = \sum_{k=0}^{\infty} r^k - \sum_{k=n^*+1}^{n^*} r^k \\
&= \frac{1}{1-r} - \frac{1-r^{n^*+1}}{1-r} \qquad \left(\text{finite geometric series } \sum_{k=0}^{m} r^k = \frac{1-r^{m+1}}{1-r}\right) \\
&= \frac{r^{n^*+1}}{1-r} \longrightarrow 0 \qquad \text{since } n^*\to\infty.
\end{aligned}
$$

$\square$

Problem 2.2 Bounds of binomial coefficients

For integers n and k, prove the following inequalities

$$\frac{n^k}{k^k} \leq \binom{n}{k} \leq \frac{n^k}{k!} < \left(\frac{ne}{k}\right)^k.$$

References

[1] Acemoglu, D. and Ozdaglar, A. (2009). Lecture 3: Erdos-Renyi graphs and Branching Processes. http://economics.mit.edu/files/4621.

[2] Lange, K. (2010). *Applied probability*. Springer Science & Business Media.

[3] Ramchandran, K. (2009). Random Graphs. https://inst.eecs.berkeley.edu/~ee126/sp18/random-graphs.pdf.