Probability and Computing, 2nd Edition

Solutions to Chapter 5: Balls, Bins, and Random Graphs

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5.1

As $(1+1/n)^n$ increases, we find the smallest n to reach the threshold.
$(1+1/n)^n$ first reaches $0.99e$ at $n=50$, and $0.999999e$ at $n=499982$.
Since $(1-1/n)^n$ also increases, we solve in a similar way. $(1-1/n)^n$ first reaches $0.99/e$ at $n=51$ and $0.999999/e$ at $n=499991$.

5.2

Recall the formula used in the birthday paradox: If there are N possibilities, then we solve for the smallest n that satisfies $\prod_{i=1}^{n-1}(1-\frac{i}{N}) \approx \prod_{i=1}^{n-1} e^{-i/n} = e^{-(n-1)n/2N} < 1/2$. Note that we omitted the final approximation to derive exact numerical answers.
Regardless of whether the number of Social Security number digits is 9 or 13, using the last four digits gives $N=10000$ and this gives $n=119$.
In the case where the number of digits is 9 ($N=10^9$), we get $n=37234$.
In the case where the number of digits is 13 ($N=10^{13}$), we get $n=3723298$.

5.3

Let the number of balls thrown be m. Then the desired probability is $\prod_{i=0}^{m-1}(1-\frac{i}{n})$.
We first determine c_1. $m=c_1\sqrt{n}$ should satisfy $\prod_{i=0}^{m-1}(1-\frac{i}{n}) \leq \prod_{i=0}^{m-1} e^{-i/n} = e^{-(m-1)m/2n} \leq e^{-1}$. Since $(m-1)m = c_1^2 n - c_1\sqrt{n} \geq 2n$, $(c_1^2-2)\sqrt{n} \geq c_1$. Therefore, we choose c_1 that is greater than or equal to $\frac{1}{2}\left(\frac{1}{\sqrt{n}} + \sqrt{\frac{1}{n}+8}\right)$.
Now we determine c_2. To use the given hint, assume that $2m < n$.
$\prod_{i=0}^{m-1}(1-\frac{i}{n}) \geq \prod_{i=0}^{m-1}\exp(-\frac{i}{n}-\frac{i^2}{n^2}) = \exp(-\frac{m(m-1)}{2n} - \frac{(m-1)m(2m-1)}{6n^2})$
$= \exp(-\frac{m(m-1)}{2n}(1+\frac{2m-1}{3n})) \geq \exp(-\frac{m^2}{2n}(1+\frac{2m}{3n})) \geq \frac{1}{2}$ should be satisfied for $m=c_2\sqrt{n}$. This is equivalent to satisfying $\frac{c_2^2}{2}(1+\frac{2c_2}{3\sqrt{n}}) \leq \ln 2$.
Since n is sufficiently large, choosing $c_2 = \sqrt{2\ln 2 - \frac{1}{\ln n}}$ yields the desired result.

5.4

Let event A indicate that there exist two or more people who share a birthday, and event B indicate that exactly two people share a birthday. Then our desired probability would be $\Pr(A-B) = \Pr(A) - \Pr(B)$ since $B \subset A$.
We first determine $\Pr(A)$, which is easy: $\Pr(A) = 1 - \prod_{i=1}^{100}\frac{366-i}{365}$.
We now determine $\Pr(B)$. If there are i shared birthdays in which each day is

shared by exactly two people, then the number of possible permutations would be the product of the following terms:
$\binom{365}{i}$ ways to choose i shared days, $\binom{100}{2i}$ ways to choose $2i$ people to share birthdays, $\prod_{j=1}^{i} \binom{2j}{2}$ ways to distribute i birthdays to $2i$ people and $\prod_{j=1}^{100-2i} (366 - i - j)$ ways to distribute unique birthdays to the rest.
Thus, $\Pr(B) = \sum_{i=0}^{50} \frac{365!100!}{i!(100-2i)!(265+i)!2^i} \times \frac{1}{365^{100}}$.
Therefore, we can determine our desired probability $\Pr(A-B) = \Pr(A) - \Pr(B)$.

5.5

Let $X \sim Poisson(\lambda)$. Then $M_X(t) = \mathbf{E}[e^{tX}] = e^{\lambda(e^t-1)}$ holds. By computing the second derivative of $M_X(t)$ with respect to t and plugging $t = 0$ in, we get $\mathbf{E}[X^2] = \lambda + \lambda^2$. Thus, $\mathbf{Var}[X] = \lambda$ follows.

5.6

We first show that $Y \sim Poisson(\mu p)$.
$\Pr(Y = k) = \sum_{i=k}^{\infty} \Pr(X = i)\binom{i}{k} p^k (1-p)^{i-k} = \sum_{i=k}^{\infty} \frac{e^{-\mu}\mu^i}{i!} \frac{i!}{k!(i-k)!} p^k (1-p)^{i-k}$
$= \frac{e^{-\mu}(p\mu)^k}{k!} \sum_{i=k}^{\infty} \frac{(\mu(1-p))^{i-k}}{(i-k)!} = \frac{e^{-\mu}(p\mu)^k}{k!} e^{\mu(1-p)} = \frac{e^{-\mu p}(\mu p)^k}{k!}$.
We can also similarly show that $Z \sim Poisson(\mu(1-p))$.
Now we show that $\Pr(Y = i, Z = j) = \Pr(Y = i)\Pr(Z = j)$. Note that $X = Y + Z$ by definition. This allows us to write $\Pr(Y = i, Z = j)$ as $\Pr(Y = i, X = i + j) = \Pr(X = i + j)\binom{i+j}{i} p^i (1-p)^j = \frac{e^{-\mu}\mu^{i+j}}{i!j!} p^i (1-p)^j$.
Since $\Pr(Y = i)\Pr(Z = j) = \frac{e^{-p\mu}(p\mu)^i}{i!} \frac{e^{-(1-p)\mu}((1-p)\mu)^j}{j!} = \frac{e^{-\mu}\mu^{i+j}p^i(1-p)^j}{i!j!} = \Pr(Y = i, X = i + j)$, $Y \perp\!\!\!\perp Z$. ■

5.7

We first prove that $\ln(1 + x) \le x$, which is equivalent to $1 + x \le e^x$.
Since $\ln(1 + x) - x = -\frac{x^2}{2} + \frac{x^3}{3} - \cdots$, this can be seen as an alternating series as $\frac{x^n}{n}$ is monotonically decreasing in $|x| \le 1$. We can apply rearrangements to the alternating series as $\ln(1 + x) - x = -\sum_{n=1}^{\infty} \left(\frac{x^{2n}}{2n} - \frac{x^{2n+1}}{2n+1}\right)$, since the Taylor expansion of $\ln(1 + x)$ is absolutely convergent (to $e^x - 1$). The rearrangement gives $\ln(1 + x) - x \le 0$, which is the desired result.
We now prove $x + \ln(1 - x^2) \le \ln(1 + x)$, which is equivalent to $e^x(1 - x^2) \le 1 + x$. Since $\ln(1 - x^2) = \ln(1 + x) + \ln(1 - x)$, $x + \ln(1 - x^2) \le \ln(1 + x)$ is reduced to $\ln(1 - x) \le -x$. At $|x| \le 1$, this is equivalent to $\ln(1 + x) \le x$, which we have previously proved. ■

5.8

(a) Since the ball is equally likely to fall in one of the three bins, the desired probability is 1/3.
(b) Since the bin 2 did not receive balls, we can simply think of this as throwing balls n into $n-1$ bins. The conditional expectation would be $n/(n-1)$.
(c) Note that the probability that bin 1 receives more balls than bin 2 is the same as that of bin 2 receiving more balls than bin 1. Thus, we first compute the probability that two bins receive the same number of balls, which is $P = \sum_{k=0}^{\lfloor n/2 \rfloor} \binom{n}{2k}\binom{2k}{k}(\frac{1}{n})^{2k}(1-\frac{2}{n})^{n-2k}$. The desired probability would be $(1-P)/2$.

5.9

In the given condition, the expected number of elements in a single bucket is at most a. Since $a = O(1)$, sorting all buckets can still be done in linear time.

5.10

(a) By the Poisson approximation, the probability p is bounded as $p \le e\sqrt{n}(\frac{1}{e})^n$.
(b) $\frac{n!}{n^n}$.
(c) Since $\Pr(Z = n) = \frac{e^{-n}n^n}{n!}$ when $Z \sim Poisson(n)$, $\frac{n!}{n^n} \times \frac{e^{-n}n^n}{n!} = e^{-n}$ shows the claim. Theorem 5.6 states that the distribution $(Y_1, ..., Y_n)$ constrained on $\sum_{i=1}^{n} Y_i = n$ is equivalent to the balls and bins model. Note that each Y_i follows $Poisson(1)$ and each X_i denotes the load of the ith bin in the balls and bins model. Then using theorem 5.6, $(1/e)^n/(\frac{e^{-n}n^n}{n!}) = \frac{\Pr(\forall i, Y_i=1)}{\Pr(\sum_i Y_i = n)} = \Pr(\forall i, Y_i = 1 | \sum_i Y_i = n) = \Pr(\forall i, X_i = 1) = \frac{n!}{n^n}$.

5.11

Let X_i be the indicator variables that are 1 if there is a k-gap starting at i.
Let $X = \sum_{i=0}^{n-k} X_i$.
(a) The expected number of k-gaps would be $\sum_{i=0}^{n-k} \mathbf{E}[X_i] = (n-k+1)(1-\frac{k}{n})^m$.
(b) First, we assume that the bin loads follow the Poisson distribution to derive the Poisson-approximated Chernoff bound. We divide $\{X_i\}$ into k subsets, so that all indicator variables in the same subset are independent. First, we derive the Chernoff bound for $Y_0 = \sum_{i \ge 0} X_{ik}$ where $0 < \delta < 1$.
$\Pr(Y_0 \ge (1+\delta)\mathbf{E}[Y_0]) \le \exp(-\frac{1}{3}\frac{\mathbf{E}[X]}{k}\delta^2)$, and $\Pr(Y_0 \le (1-\delta)\mathbf{E}[Y_0]) \le \exp(-\frac{1}{2}\frac{\mathbf{E}[X]}{k}\delta^2)$ holds. Therefore, $\Pr(|Y_0 - \mathbf{E}[Y_0]| \ge \delta \mathbf{E}[Y_0]) \le 2\exp(-\frac{1}{3}\frac{\mathbf{E}[X]}{k}\delta^2)$.

With the union bound for all Y_i, we get $\Pr(|X-\mathbf{E}[X]| \geq \delta\mathbf{E}[X]) \leq 2k\exp(-\frac{1}{3}\frac{\mathbf{E}[X]}{k}\delta^2)$. Since we have used the Poisson approximation to compute the Chernoff bound, the computed upper bound should be multiplied by $e\sqrt{m}$.

5.12

Let X_i be the indicator variables that are 1 if a ball landed in bin i by itself.
(a) The expected number of balls to be *served* in this round would be $\sum_{i=1}^{n} \mathbf{E}[X_i] = \sum_{i=1}^{n} b \times \frac{1}{n}(1-\frac{1}{n})^{b-1} = b(1-\frac{1}{n})^{b-1}$. Therefore, the expected number of balls at the start of the next round would be $b(1-(1-\frac{1}{n})^{b-1})$.
(b) Note that if $n = 1$, then the number of rounds required would be trivially 1. Therefore, we only consider the cases where $n \geq 2$.
Since $x_{j+1} = x_j(1-(1-\frac{1}{n})^{x_j-1}) \leq x_j(1-(1-\frac{x_j-1}{n})) = x_j\frac{x_j-1}{n} \leq \frac{x_j^2}{n}$, the inequality given in the hint is true.
With $x_1 = n(1-(1-\frac{1}{n})^{n-1})$, cascading the inequality yields $x_k \leq n(\frac{x_1}{n})^{2^{k-1}} = n(1-(1-\frac{1}{n})^{n-1})^{2^{k-1}} \leq n(1-(1-\frac{1}{n})^n)^{2^{k-1}}$.
Now, let k^* be the minimum k that satisfies $n(1-(1-\frac{1}{n})^n)^{2^{k-1}} \leq 1$, so that the operation ends after no more than k^*+1 rounds. Since $1-(1-\frac{1}{n})^n \leq \frac{3}{4}$ at $n \geq 2$, we calculate the minimum k that satisfies $n(\frac{3}{4})^{2^{k-1}} \leq 1$.
Taking log on both sides gives $\ln n + 2^{k^*-1}\ln\frac{3}{4} \leq 0$, which is equivalent to $2^{k^*-1} \geq \frac{\ln n}{\ln\frac{4}{3}}$. Therefore, we get $k^*-1 \geq \ln\frac{\ln n}{\ln\frac{4}{3}}$, which shows that $k^* = O(\log\log n)$.

5.13

Let the load of bin i be X_i, and let $Y_k = X_{kn/\log_2 n}$ where $k \in \mathbb{N}_0$. Then for all i, there exists $k \in \mathbb{N}$ such that $kn/\log_2 n \leq i \leq (k+1)n/\log_2 n$.
When a ball is thrown into the bin i, only one of the two bins (bin $kn/\log_2 n$ and bin $(k+1)n/\log_2 n$) must be chosen together. This means that $X_i \leq Y_k + Y_{k+1}$. Since only one of the bins in $S = \{i | i = kn/\log_2 n\}$ gets a ball within a player's round, we can see Y_k as each bin in the model of balls and bins with $\log_2 n$ bins and $\log_2 n$ balls.
Recall that the probability that the maximum load is more than $3\ln n/\ln\ln n$ is at most $1/n$ in the model of n balls and n bins (Lemma 5.1). Therefore, we bound the probability that the maximum load is greater than $6M = 6\ln\log_2 n/\ln\ln\log_2 n$, considering $X_i \leq Y_k + Y_{k+1}$. Thus, we can derive the upper bound as $\Pr(\sum_{i=0}^{n-1}\mathbf{1}_{X_i \geq 6M} > 0) \leq \Pr(\sum_{i=0}^{\log_2 n-1}\mathbf{1}_{Y_i \geq 3M} > 0) \leq \frac{1}{\log_2 n}$. Thus, the maximum load is less than $6\ln\log_2 n/\ln\ln\log_2 n = O(\log\log n/\log\log\log n)$ with probability $1-\frac{1}{\log_2 n}$ which approaches 1 as $n \to \infty$.

5.14

(a) $\Pr(Z = \mu + h) - \Pr(Z = \mu - h - 1) = \frac{e^{-\mu}\mu^{\mu+h}}{(\mu+h)!} - \frac{e^{-\mu}\mu^{\mu-h-1}}{(\mu-h-1)!} = \frac{\mu^{\mu-h}}{(\mu+h)!}(\mu^{2h} - \sum_{i=1}^{h}(\mu^2 - i^2))$. Since $\mu^2 > \mu^2 - i^2$, $\Pr(Z = \mu + h) - \Pr(Z = \mu - h - 1) \geq 0$ holds and the claim is proved.
(b) $\Pr(Z \geq \mu) \geq \sum_{h=0}^{\mu-1} \Pr(Z = \mu + h) \geq \sum_{h=0}^{\mu-1} \Pr(Z = \mu - h - 1) = \Pr(Z < \mu) = 1 - \Pr(Z \geq \mu)$ shows that $2\Pr(Z \geq \mu) \geq 1$, proving the claim.
(c) Numerical validation can show that $\Pr(Z \geq \mu) \leq 1/2$ for all integers μ from 1 to 10.

5.15

(a) $\mathbf{E}[f(Y_1^{(m)}, ..., Y_n^{(m)})] = \sum_{k=0}^{\infty} \mathbf{E}[f(X_1^{(k)}, ..., X_n^{(k)})] \Pr(\sum_{i=1}^{n} Y_i^{(m)} = k)$ holds (recall the proof of Theorem 5.7).
If $\mu(m) = \mathbf{E}[f(X_1^{(m)}, ..., X_n^{(m)})]$ is monotonically increasing in m, then we have $\mu(k) \geq \mu(m)$ for $k \geq m$ for some m. Thus, $\mathbf{E}[f(Y_1^{(m)}, ..., Y_n^{(m)})] = \sum_{k<m} \mu(k) \Pr(\sum_{i=1}^{n} Y_i^{(m)} = k) + \sum_{k \geq m} \mu(k) \Pr(\sum_{i=1}^{n} Y_i^{(m)} = k)$ $(f \geq 0)$
$\geq \sum_{k \geq m} \mu(m) \Pr(\sum_{i=1}^{n} Y_i^{(m)} = k) = \mathbf{E}[f(X_1^{(m)}, ..., X_n^{(m)})] \Pr(\sum Y_i^{(m)} \geq m)$.
Similarly, if $\mu(m)$ is monotonically decreasing in m, then we have $\mu(k) \geq \mu(m)$ for $k \leq m$ for some m. Thus,
$\mathbf{E}[f(Y_1^{(m)}, ..., Y_n^{(m)})] = \sum_{k \leq m} \mu(k) \Pr(\sum_{i=1}^{n} Y_i^{(m)} = k) + \sum_{k > m} \mu(k) \Pr(\sum_{i=1}^{n} Y_i^{(m)} = k)$
$\geq \sum_{k \leq m} \mu(m) \Pr(\sum_{i=1}^{n} Y_i^{(m)} = k) = \mathbf{E}[f(X_1^{(m)}, ..., X_n^{(m)})] \Pr(\sum Y_i^{(m)} \leq m)$.
(b) Since the sum of independent Poisson random variables is also a Poisson random variable, $\sum Y_i^{(m)} \sim Poisson(m)$. Using the result of exercise 5.14.(b) and 5.15.(a), $\mathbf{E}[f(Y_1^{(m)}, ..., Y_n^{(m)})] \geq \mathbf{E}[f(X_1^{(m)}, ..., X_n^{(m)})] \Pr(\sum Y_i^{(m)} \geq m)$
$\geq \mathbf{E}[f(X_1^{(m)}, ..., X_n^{(m)})] \times \frac{1}{2}$. Thus, Theorem 5.10 is proved for the monotonically increasing case.
If one can derive a formal proof on the statement of exercise 5.14.(c), Theorem 5.10 can also be proved for the monotonically decreasing case.

5.16

(a) Expectations are computed as $\mathbf{E}[X_1 X_2 \cdots X_k] = \Pr(X_1 X_2 \cdots X_k = 1) = (1 - \frac{k}{n})^n$ and $\mathbf{E}[Y_1 Y_2 \cdots Y_k] = \Pr(Y_1 Y_2 \cdots Y_k = 1) = p^k = (1 - \frac{1}{n})^{k \times n}$.
Since $1 - \frac{k}{n} \leq (1 - \frac{1}{n})^k$ by the Bernoulli inequality, $\mathbf{E}[X_1 X_2 \cdots X_k] \leq \mathbf{E}[Y_1 Y_2 \cdots Y_k]$.

(b) $\mathbf{E}[e^{tX}] = \mathbf{E}\left[\sum_{k=0}^{\infty} \frac{(tX)^k}{k!}\right] = \sum_{k=0}^{\infty} \mathbf{E}[\frac{(tX)^k}{k!}]$ holds since $\mathbb{N}$ is countable, and the same applies to $\mathbf{E}[e^{tY}]$. Therefore, we show $\mathbf{E}[X^k] \leq \mathbf{E}[Y^k]$ for $\forall k \in \mathbb{N}$.
$\mathbf{E}[X^k] = \mathbf{E}[(X_1+X_2+\cdots+X_n)^k]$ holds, and $(X_1+X_2+\cdots+X_n)^k$ is the sum of products where each product is in the form of $X_{i_1}X_{i_2}\cdots X_{i_k}$ $(|\{i_1, i_2, ...i_k\}| \leq k)$. Since X_i are indicator variables, $X_i^n = X_i$ holds for $\forall n \in \mathbb{N}$, so the repeats can be ignored from the product.
Suppose that $|\{i_1, i_2, ...i_k\}| = m$. Then the result of 5.16.(a) applies with $k = m$. Thus, $\mathbf{E}[X^k] \leq \mathbf{E}[Y^k]$ holds and, therefore, $\mathbf{E}[e^{tX}] \leq \mathbf{E}[e^{tY}]$ holds.
(c) $\Pr(X \geq (1+\delta)\mu) \leq \frac{\mathbf{E}[e^{tX}]}{e^{t(1+\delta)\mu}} \leq \frac{\mathbf{E}[e^{tY}]}{e^{t(1+\delta)\mu}}$ holds. Since $\mathbf{E}[e^{tY}] = (1-p+pe^t)^n$, we can choose $t = \ln(1+\delta)$ to derive $\Pr(X \geq (1+\delta)\mu) \leq \left(\frac{e^\delta}{(1+\delta)^{1+\delta}}\right)^\mu$.

5.17

(a) Since there are $\binom{n}{5}$ possible 5-cliques and each 5-clique has $\binom{5}{2} = 10$ edges, the expected number of 5-cliques is $\binom{n}{5} \times p^{10}$. Solving $\binom{n}{5} \times p^{10} = 1$ for p gives $p = \binom{n}{5}^{-1/10}$.
(b) Since there are $\frac{1}{2}\binom{n}{6}\binom{6}{3}$ possible $K_{3,3}$ subgraphs and each $K_{3,3}$ subgraph has nine edges, the expected number of $K_{3,3}$ subgraphs is $\frac{1}{2}\binom{n}{6}\binom{6}{3} \times p^9$. Solving $\frac{1}{2}\binom{n}{6}\binom{6}{3} \times p^9 = 1$ for p gives $p = \left\{\frac{1}{2}\binom{n}{6}\binom{6}{3}\right\}^{-1/9}$.
(c) Since there are $(n-1)!/2$ possible Hamiltonian cycles and each Hamiltonian cycle has n edges, the expected number of Hamiltonian cycles is $\frac{1}{2}(n-1)! \times p^n$. Solving $\frac{1}{2}(n-1)! \times p^n = 1$ for p gives $p = \left\{\frac{1}{2}(n-1)!\right\}^{-1/n}$.

5.18

For any nonnegative function f, $\mathbf{E}[f(G_{n,p})||E| = k] = \mathbf{E}[f(G_{n,k})]$ holds.
Thus, $\mathbf{E}[f(G_{n,p})] = \sum_{k=0}^{M} \mathbf{E}[f(G_{n,k})]\Pr(|E| = k) \geq \mathbf{E}[f(G_{n,N})]\Pr(|E| = N)$ holds ($M = \binom{n}{2}$). Now we bound the probability $\Pr(|E| = N)$ for the $G_{n,p}$ model to derive the statement. Note that $p = N/M$. Using Stirling's bounds, $\Pr(|E| = N) = \binom{M}{N}p^N(1-p)^{M-N} = \frac{M!}{(M-N)!N!}(\frac{N}{M})^N(\frac{M-N}{M})^{M-N} \geq \frac{\sqrt{2\pi}}{e^2}\frac{\sqrt{M}}{\sqrt{MN-N^2}}$ $= \frac{\sqrt{2\pi}}{e^2}\frac{1}{\sqrt{N(1-p)}} \geq \frac{\sqrt{2\pi}}{e^2}\frac{1}{\sqrt{N}}$. Thus, we let f be an indicator of an event and prove that every event that happens with a small probability P in the $G_{n,p}$ model also happens with small probability (at most $\frac{e^2}{\sqrt{2\pi}}\sqrt{N} \times P$) in the $G_{n,N}$ model.

5.19

We use the result of exercise 5.18 to use the $G_{n,p}$ model. Let $M = \binom{n}{2}$ and $G \sim G_{n,p}$ where $p = \frac{r \ln n}{n}$ $(r > 2)$.
The probability that G is a disconnected graph containing a disconnected set of size $k < n/2$ is upper bounded by $\binom{n}{k}(1-p)^{k(n-k)}$ (union bound).
We can derive $\binom{n}{k} = \frac{(n-k+1)\cdots(n-1)n}{k!} \leq \frac{n^k}{k!} \leq (\frac{en}{k})^k$, where the last inequality is from $e^k = \sum_{i=0}^{\infty} \frac{k^i}{i!} > \frac{k^k}{k!}$. Using this, $\binom{n}{k}(1-p)^{k(n-k)} \leq (\frac{en}{k})^k e^{-pk(n-k)} \leq (\frac{en}{k})^k e^{-pkn/2} = (\frac{en^{1-r/2}}{k})^k$.
We can then upper-bound the probability that G is a disconnected graph again by the union bound: $\sum_{k=1}^{n/2} (\frac{en^{1-r/2}}{k})^k = en^{1-r/2} + \sum_{k=2}^{n/2} (\frac{en^{1-r/2}}{k})^k = O(n^{1-r/2})$.
Since $r > 2$, $O(n^{1-r/2}) = o(1)$. Thus, G is connected with probability $1 - o(1)$.
Now, to use the result of exercise 5.18, let $N = Mp = \frac{r}{2}(n-1)\ln n$. Since $N = O(n \log n)$, $r > 3$ guarantees that $G_{n,N}$ is disconnected with probability $o(1)$, i. e. connected with probability $1 - o(1)$. Thus, any $c > 3/2$ can be the desired constant.

5.20