# 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 n = 109, we get n = 37234. In the case where the number of digits is n = 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  $(m-1)m=c_1^2n-c_1\sqrt{n} \geq 2n$ ,  $(c_1^2-2)\sqrt{n} \geq c_1$ . 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.  $\prod_{i=0}^{m-1} (1-\frac{i}{n}) \geq \prod_{i=0}^{m-1} \exp(-\frac{i}{n}-\frac{i^2}{n^2}) = \exp(-\frac{m(m-1)}{2n}-\frac{(m-1)m(2m-1)}{6n^2}) = \exp(-\frac{m(m-1)}{2n}(1+\frac{2m-1}{3n})) \geq \exp(-\frac{m^2}{2n}(1+\frac{2m}{3\sqrt{n}})) \geq \frac{1}{2}$  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,  $\prod_{i=1}^{i} {2j \choose 2}$  ways to distribute *i* birthdays to 2i people and  $\prod_{i=1}^{100-2i} (366 - 1)^{-2i}$ (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  $Y \sim Poisson(\mu p)$ .

$$\Pr(Y = k) = \sum_{i=k}^{\infty} \Pr(X = i) {i \choose k} p^k (1-p)^{i-k} = \sum_{i=k}^{\infty} \frac{e^{-\mu} \mu^i}{i!} \frac{i!}{k!(i-k)!} p^k (1-p)^{i-k}$$
$$= \frac{e^{-\mu} (p\mu)^k}{k!} \sum_{i=k}^{\infty} \frac{(\mu(1-p))^{i-k}}{(i-k)!} = \frac{e^{-\mu} (p\mu)^k}{k!} e^{\mu(1-p)} = \frac{e^{-\mu p} (\mu p)^k}{k!}.$$

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, Z = j)

$$X = I + Z \text{ by definition. This allows us to write } \Pr(I = i, Z = j) \text{ as } \Pr(I = i, X = i + j) = \Pr(X = i + j) {i+j \choose i} p^i (1-p)^j = \frac{e^{-\mu} \mu^{i+j}}{i!j!} p^i (1-p)^j.$$
 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

$$P = \sum_{k=0}^{\lfloor n/2 \rfloor} {n \choose 2k} {2k \choose k} {(\frac{1}{n})^{2k}} (1 - \frac{2}{n})^{n-2k}.$$
 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  $Y_0 = \sum_{i>0} X_{ik}$  where  $0 < \delta < 1$ .

$$\Pr(Y_0 \ge (1+\delta)\mathbf{E}[Y_0]) \le \exp(-\frac{1}{3}\frac{\mathbf{E}[X]}{k}\delta^2), \text{ and } \Pr(Y_0 \le (1-\delta)\mathbf{E}[Y_0]) \le \exp(-\frac{1}{2}\frac{\mathbf{E}[X]}{k}\delta^2)$$
 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  $\Pr(|X - \mathbf{E}[X]| \ge \delta \mathbf{E}[X]) \le 2k \exp(-\frac{1}{3} \frac{\mathbf{E}[X]}{k} \delta^2)$ . 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  $n \ge 2$ .

Since  $x_{j+1} = x_j(1 - (1 - \frac{1}{n})^{x_j - 1}) \le x_j(1 - (1 - \frac{x_j - 1}{n})) = x_j \frac{x_j - 1}{n} \le \frac{x_j^2}{n}$ , the inequality given in the hint is true.

With  $x_1 = n(1 - (1 - \frac{1}{n})^{n-1})$ , cascading the inequality yields  $x_k \le n(\frac{x_1}{n})^{2^{k-1}} = n(1 - (1 - \frac{1}{n})^{n-1})^{2^{k-1}} \le n(1 - (1 - \frac{1}{n})^n)^{2^{k-1}}$ .

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  $\ln n + 2^{k^*-1} \ln \frac{3}{4} \le 0$ , which is equivalent to  $2^{k^*-1} \ge \frac{\ln n}{\ln \frac{4}{3}}$ . Therefore, we get  $k^*-1 \ge \ln \frac{\ln n}{\ln \frac{4}{3}}$ , which shows that  $k^* = O(\log \log n)$ .

# 5.13