

# Math Homework #1

Eric C. Miller

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## Questions from the Book

### Problem 3.6: Proof:

**Contradiction:** Assume that  $\exists A$  s.t.  $P(A) \neq \sum_{i \in I} P(A \cap B_i)$ . This implies that  $\exists a \in A$  s.t.  $a \notin \bigcup_{i \in I} B_i = \Omega$ , as since all  $B_j$  are disjoint. Here we have a contradiction, as  $A \in F$  and  $\exists a \in A, a \notin \Omega$ .

### Problem 3.8: Proof

$$1 - \prod_{k=1}^n (1 - P(E_k)) = 1 - \prod_{k=1}^n (P(E_k^c)) = 1 - P\left(\bigcap_{k=1}^n E_k^c\right) = P\left(\bigcup_{k=1}^n E_k\right) \quad (1)$$

### Problem 3.11:

We have that  $P(s = \text{crime} | \text{test} = +)$  cannot be solved directly. Hence, we use Bayes Rule:

$$\begin{aligned} P(s = \text{crime} | \text{test} = +) &= \frac{P(\text{test} = + | s = \text{crime})P(s = \text{crime})}{P(\text{test} = + | s = \text{crime})P(s = \text{crime}) + P(\text{test} = + | s = \text{innocent})P(s = \text{innocent})} \\ &= \frac{(1)\left(\frac{1}{250,000,000}\right)}{(1)\left(\frac{1}{250,000,000}\right) + \left(\frac{1}{3,000,000}\right)\left(\frac{249,999,999}{250,000,000}\right)} \\ &= 0.0118 \end{aligned} \quad (2)$$

### Problem 3.12:

Let  $w_1$  = the contestant's chosen window, of the set  $W = \{w_1, w_2, w_3\}$ . Each has an equal  $1/3$  chance of being correct, and  $2/3$  chance of being a goat. Window  $w_3$  is exposed as a goat (this can be done without loss of generality). While  $w_1$  still has a  $1/3$  chance of containing the prize,  $w_2$  now represents the entire original chance of either  $w_2$  and  $w_3$  having a combined  $2/3$  chance of having the prize behind one of them. Hence, it is wiser to switch.

For a larger problem, let the chosen window be  $w_1$  of the set of windows  $W = \{w_1, w_2, \dots, w_9, w_{10}\}$ . If 8 are opened to reveal goats, leaving  $w_1$  and  $w_2$  (also possible without loss of generality, as  $\binom{9}{8} = 9$ ), we have that you have an  $9/10$  chance of winning by switching and a  $1/10$  chance of winning by staying.

### Problem 3.16: Proof:

$$V(X) = E[(X - \mu)^2] = E[X^2 - 2\mu X + \mu^2] = E[X^2] - 2\mu E[X] + \mu^2 = E[X^2] - \mu^2 \quad (3)$$

**Problem 3.33: Proof:**

We observe that the binomial random variable  $B$  has a mean  $\mu = np$  and variance  $\sigma^2 = np(1-p)$ . However, this is simply a sum of iid Bernoulli random variables  $X_k$  with  $\mu_s = p$ ,  $\sigma_s^2 = p(1-p)$ , and  $\sum_{k=1}^n X_k = B$ . If we then divide  $B$  by  $n$ , as long as  $n$  is sufficiently large we can use the Weak Law of Large Numbers to show:

$$\begin{aligned} P\left(\left|\frac{\sum_{k=1}^n X_k}{n} - \mu_s\right| \geq \epsilon\right) &= \frac{\sigma_s^2}{n\epsilon^2} \\ P\left(\left|\frac{\sum_{k=1}^n X_k}{n} - p\right| \geq \epsilon\right) &= \frac{p(1-p)}{n\epsilon^2} \\ P\left(\left|\frac{B}{n} - p\right| \geq \epsilon\right) &= \frac{p(1-p)}{n\epsilon^2} \end{aligned} \quad (4)$$

**Problem 3.36: Proof:**

Let  $X_i$  = a Bernoulli trial (with  $\mu = 0.801$  and  $\sigma \approx 0.1594$ ) determining whether student  $i$  will attend the University, with  $i \in I = \{1, 2, 3, \dots, 6241, 6242\}$ ,  $\forall i$ . From this, we can infer that  $S = \sum_{i \in I} X_i$  is a Binomial random variables with  $n = 6242$ . We may then use the Central Limit Theorem to determine the probability that over 5500 students will attend:

$$1 - P(S < 5500) = 1 - P\left(\frac{S - n\mu}{\sqrt{n}\sigma} < \frac{5500 - (6242)(0.801)}{(79)(0.1594)}\right) = 1 - P(Z < 39.7) \approx 0 \quad (5)$$

Hence, we predict with almost absolute certainty that the University will not have over 5500 students enroll for the coming academic year.

**Question #2****Part A:**

Let  $\Omega = \{1, 2, 3, 4, 5, 6, 7, 8\}$ , where  $P(i) = \frac{1}{8} \forall i \in \Omega$ . Let  $A = \{1, 3, 5, 7\}$ ,  $B = \{2, 4, 6, 8\}$ , and  $C = \{1, 2, 3, 4\}$ . We then have that:

$$\begin{aligned} P(A \cap B) &= P(1, 3, 5, 7)P(2, 4, 6, 8) = \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) = \frac{1}{4} \\ P(B \cap C) &= P(2, 4, 6, 8)P(1, 2, 3, 4) = \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) = \frac{1}{4} \\ (A \cap C) &= P(1, 3, 5, 7)P(1, 2, 3, 4) = \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) = \frac{1}{4} \end{aligned} \quad (6)$$

However, we have that:

$$0 = P(A \cap B \cap C) \neq P(1, 3, 5, 7)P(2, 4, 6, 8)P(1, 2, 3, 4) = \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) = \frac{1}{8} \quad (7)$$

**Part B:**

Let  $\Omega = \{1, 2, 3, 4, 5, 6, 7, 8\}$ , where  $P(i) = \frac{1}{8} \forall i \in \Omega$ . Let  $A = \{1, 3, 5, 8\}$ ,  $B = \{1, 4, 6, 8\}$ , and  $C = \{2, 4, 7, 8\}$ . We then have that:

$$\begin{aligned} P(A \cap B) &= P(1, 3, 5, 8)P(2, 4, 7, 8) = \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) = \frac{1}{4} \\ P(B \cap C) &= P(1, 4, 6, 8)P(2, 4, 7, 8) = \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) = \frac{1}{4} \\ P(A \cap B \cap C) &= P(1, 3, 5, 8)P(1, 4, 6, 8)P(2, 4, 7, 8) = \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) = \frac{1}{8} \end{aligned} \quad (8)$$

However, we have that:

$$\frac{1}{8} = (A \cap C) \neq P(1, 3, 5, 8)P(2, 4, 7, 8) = \left(\frac{1}{2}\right) \left(\frac{1}{2}\right) = \frac{1}{4} \quad (9)$$

### Question #3

**Proof:** Let  $B$  be a "Bedford random variable", whose domain is  $\Omega = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ . In order for a distribution to qualify as a valid discrete distribution,  $B$  must follow the following properties:

$$\begin{aligned} \forall \omega \in \Omega, P(\omega) &\geq 0 \\ \sum_{i \in I} P(\omega_i) &= 1 \end{aligned} \quad (10)$$

where  $I$  is the index set  $\forall \omega_i \in \Omega$ . We see that both of these properties exist, as both the probabilities for each element of  $\Omega$  is non-negative, and all add to 1. This is observable in the table below:

First significant digit	Predicted frequency
1	0.301
2	0.176
3	0.125
4	0.097
5	0.079
6	0.067
7	0.058
8	0.051
9	0.046
Total	1.00

Hence, we have that Bedford's Law follows a well-defined discrete distribution.

### Question #4

**Part A Proof:**

$$E[X] = \sum_{n=1}^{\infty} 2^n \left(\frac{1}{2}\right)^n = \sum_{n=1}^{\infty} \left(\frac{2}{2}\right)^n = \sum_{n=1}^{\infty} 1 = +\infty \quad (11)$$

**Part B Proof:**

$$E[X] = \sum_{n=1}^{\infty} \ln(2^n) \left(\frac{1}{2}\right)^n = \sum_{n=1}^{\infty} n \ln(2) \left(\frac{1}{2}\right)^n = \ln(2) \sum_{n=1}^{\infty} n \left(\frac{1}{2}\right)^n = 2 \ln(2) \quad (12)$$

### Question #5

If one investor bought an asset in the country they are from, they would neither gain nor lose money, and have an estimated return of 0%. However, if they invest in the other country, they would have an estimated return of  $(0.5)(1.25) + (0.5)(0.80) = 1.025$  units of their home currency. Hence, each investor should buy the risk-free investment in the other country they do not currently reside in.

## Question #6

### Part A

Let  $X : \Omega \rightarrow \mathbb{R}$  be a continuous random variable. We assuming some valid mapping between our sample space and  $\mathbb{R}$ . Because  $E[x^2] = V[X] + E[X]^2 = \infty$ , and we know  $E[X]$  must be finite, and subsequently  $V[X]$  must be infinite. This allows us to identify our random variable as following the Pareto distribution with parameter  $\alpha \in (1, 2]$ :

$$X = \begin{cases} \frac{\alpha x_m^\alpha}{X^{\alpha+1}} & \text{if } x_m \leq x \\ 0 & \text{if } x_m > x \end{cases}$$

### Part B

Let  $X \sim \text{Exponential}(\lambda = \frac{3}{2})$  and  $Y \sim \text{Unif}(0, 1)$ . As  $E[X] = \frac{1}{\lambda} = \frac{2}{3} < \frac{2}{3} = E[Y]$ , and the following is true:

$$P(X > Y) = 1 - P(X < Y) = 1 - P(X - Y < 0) = 0.8512 \quad (13)$$

Hence, we have that the conditions are satisfied.

### Part C

Let  $X, Y, Z \sim \text{Unif}(-1, 1)$ . All have an identical expected value of 0, and have a strictly positive probability of being larger than one another. Hence, the conditions are satisfied.

## Question #7

Let  $X \sim N(0, 1)$ ,  $P(Z = 1) = P(Z = -1) = \frac{1}{2}$ , and  $Y = XZ$

### Part A

We seek to demonstrate  $Y \sim N(0, 1)$ . This can be done by equating its CDF to that of  $X$ , which is a standard normal (due to CDFs being uniquely defined). This is as follows:

$$\begin{aligned} P(Y < y) &= P(X * Z < y) \\ &= P(X < y|Z = 1)P(Z = 1) + P(-X < y|Z = 1)P(Z = -1) \\ &= P(X < y) \left(\frac{1}{2}\right) + P(X > -y) \left(\frac{1}{2}\right) \\ &= \left(\frac{1}{2}\right) [P(X < y) + P(X < y)] \text{ (as standard normal is symmetrical about 0)} \\ &= P(X < y) \end{aligned} \quad (14)$$

### Part B

For any value of  $X$ ,  $P(Y = X) = P(-Y = X) = \frac{1}{2}$ . However, if we have the absolute value of both sides, both are constrained to be positive. Hence, we have  $P(|Y| = |X|) = P(|-Y| = |X|) = 1$ .

### Part C

As we are simply attempting to show X and Y are *not* independent, it is sufficient to show that they lack a necessary property of independence. This can be done with the following:

$$\begin{aligned}
 P(X < x | Y < x) &= P(X < x | XZ < x) \\
 &= P(X < x | X < x)P(Z = 1) + P(X < x | -X < x)P(Z = -1) \\
 &= P(X < x) \left( \frac{1}{2} \right) + P(X < x | -X < x) \left( \frac{1}{2} \right) \\
 &\neq P(X < x)
 \end{aligned} \tag{15}$$

### Part D

$$\begin{aligned}
 Cov[X, Y] &= E[(X - \mu_x)(Y - \mu_y)] = E[XY] + \mu_x \mu_y = (0) + (0)(0) = 0 \\
 &\text{as} \\
 E[XY] &= E[XXZ] = (1) \left( \frac{1}{2} \right) E[X^2] + (-1) \left( \frac{1}{2} \right) E[X^2] = 0
 \end{aligned} \tag{16}$$

### Part E

This contradicts our answers for Parts C and D; hence, this is not true, and extends from the fact that  $Cov[X, Y] = 0$  is not a sufficient condition for independence of X and Y.

### Question #8

Let  $F(X) = x$  be the CDF of the continuous uniform distribution between 0 and 1. For some  $x \in (0, 1)$ , the probability that at least one variable  $X_i$  is larger than  $x$  is simply the product of  $nF(X)$ s; this then represents distribution of the maximum  $M$ . Likewise, the probability that at least one random variables is below  $x$  is  $1 - [1 - F(X)]^n$  (of which  $[1 - F(X)]^n$  represents the probability that at all variables are above  $x$ ). Given  $\forall i, X_i \sim U(0, 1)$ , we can identify the CDFs of  $M$  and  $m$  as follows:

$$\begin{aligned}
 M &\sim F(x)^n = x^n \\
 m &\sim 1 - [1 - F(x)]^n = 1 - (1 - x)^n
 \end{aligned} \tag{17}$$

The PDFs of the minimum and maximum are then simply the derivative of these functions, and their expected values are easily computable:

$$\begin{aligned}
 M &\sim \frac{\partial}{\partial x}[x^n] = nx^{n-1}, \quad E[M] = \int_0^1 nx^n = \frac{n}{n+1} \\
 m &\sim \frac{\partial}{\partial x}[1 - [1 - x]^n] = n[1 - x]^{n-1}, \quad E[m] = \int_0^1 xn[1 - x]^n = \frac{1}{n+1}
 \end{aligned} \tag{18}$$

### Question #9

We define  $X_i$  = a random variable denoting the state of the economy, with  $P(X = 0) = P(X = 1) = \frac{1}{2}$ . Hence each  $X_i$  is a Bernoulli trial with  $\mu = \frac{1}{2}$  and  $\sigma^2 = \frac{1}{4}$ . Further, let  $\Upsilon = \{X_i\}_{i=1}^n$ , and  $S_n = \sum_{k=1}^n X_k$ .

**Part A**

Let  $n = 1000$ . We then use the Central Limit Theorem:

$$\begin{aligned}
 1 - P(S < 490) - P(S > 510) &= P(S < 510) - P(S < 490) \\
 &= P\left(\frac{S - n\mu}{\sqrt{n}\sigma} < \frac{510 - (0.5)(1000)}{\sqrt{250}}\right) - P\left(\frac{S - n\mu}{\sqrt{n}\sigma} < \frac{490 - (0.5)(1000)}{\sqrt{250}}\right) \\
 &= P(Z < 0.632) - P(Z < -0.632) \\
 &= 0.7363 - 0.2637 \\
 &= 0.4726
 \end{aligned} \tag{19}$$

**Part B**

We can use the Weak Law of Large Numbers:

$$P\left(\left|\frac{S}{n} - \mu\right| \geq \epsilon\right) \leq \frac{\sigma^2}{n\epsilon^2} \Rightarrow P\left(\left|\frac{S}{n} - 0.5\right| \geq 0.005\right) \leq \frac{10,000}{n} \tag{20}$$

Hence, we see that  $n = 1,000,000$ .

**Question #10**

**Contradiction:** Assume  $\theta < 0$ . We observe that  $e^{\theta X}$  for some  $\theta \neq 0$  is a convex function; hence, we can use Jensen's inequality to show:

$$\begin{aligned}
 e^{\theta E[X]} &\leq E[e^{\theta X}] = 1 \\
 \ln[e^{\theta E[X]}] &\leq 0 \\
 \theta E[X] &\leq 0
 \end{aligned} \tag{21}$$

This leads to a contradiction because as  $\theta < 0$ ,  $\theta E[X] > 0$  as both  $\theta$  and  $E[X]$  are strictly negative. Thus, as  $\theta \neq 0$  by hypothesis,  $\theta > 0$ .