

Solutions to the Extra Sample Problems.

1. Suppose that there are a amber and b beryl balls in an urn. Suppose that $k \leq a + b$ are randomly withdrawn without replacement. Let X be the number of amber balls withdrawn. Using the method of indicators or otherwise, find $\mathbf{E}(X)$ and $\mathbf{Var}(X)$.

X is distributed according to the hypergeometric distribution. If $p = a/(a+b)$ is the fraction of amber balls initially, then the answers can be compared to those for the binomial rv with $Y \sim \text{bin}(k, p)$. One way to do the problem is to take the pmf

$$f_X(x) = \frac{\binom{a}{x} \binom{b}{k-x}}{\binom{a+b}{k}}, \quad \text{for } 0 \leq x \leq k.$$

and use it to compute $\mathbf{E}(X)$ and $\mathbf{Var}(X) = \mathbf{E}(X^2) - \mathbf{E}(X)^2$ in the usual way. However, the method of indicators is far easier. Let $I_j = 1$ whenever the j th ball drawn is amber, and $I_j = 0$ otherwise. Then

$$X = \sum_{j=1}^k I_j \quad \text{and} \quad \mathbf{E}(X) = \sum_{j=1}^k \mathbf{E}(I_j).$$

Without knowing anything else about the draws, the probabilities are the same for each draw

$$\mathbf{E}(I_j) = \mathbf{E}(I_1) = \frac{a}{a+b} = p$$

for all j . Hence

$$\mathbf{E}(X) = \sum_{j=1}^k \mathbf{E}(I_j) = \sum_{j=1}^k \frac{a}{a+b} = \frac{ak}{a+b} = kp = \mathbf{E}(Y).$$

To compute $\mathbf{E}(X^2)$ we shall need for $i \neq j$ the probability $\mathbf{E}(I_i I_j)$ that both the i th and the j th draws are amber. Again, since the probability for any two pairs is as likely as any other two,

$$\mathbf{E}(I_i I_j) = \mathbf{E}(I_1 I_2) = \frac{a(a-1)}{(a+b)(a+b-1)}.$$

for all $i \neq j$. Hence using $X^2 = \left(\sum_{i=1}^k I_i\right) \left(\sum_{j=1}^k I_j\right) = \sum_{i=1}^k \sum_{j=1}^k I_i I_j$,

$$\begin{aligned} \mathbf{E}(X^2) &= \mathbf{E} \left(\sum_{i,j=1}^k I_i I_j \right) = \sum_{i,j=1}^k \mathbf{E}(I_i I_j) = \sum_i \mathbf{E}(I_i^2) + \sum_{i \neq j} \mathbf{E}(I_i I_j) \\ &= \frac{ak}{a+b} + \frac{a(a-1)k(k-1)}{(a+b)(a+b-1)} = \frac{ak}{a+b} \left(\frac{a+b-1+(a-1)(k-1)}{a+b-1} \right) \end{aligned}$$

since $I_i^2 = I_i$. The variance is thus

$$\begin{aligned} \mathbf{Var}(X) &= \mathbf{E}(X^2) - \mathbf{E}(X)^2 = \frac{ak}{a+b} \left(\frac{b+ak-k}{a+b-1} - \frac{ak}{a+b} \right) \\ &= \frac{abk(a+b-k)}{(a+b)^2(a+b-1)} = kpq \left(\frac{a+b-k}{a+b-1} \right). \end{aligned}$$

The variance of the hypergeometric is the same as the binomial $\mathbf{Var}(Y) = kpq$ except for the correction factor $(a+b-k)/(a+b-1)$ which is negligible when k is small compared to $a+b$.

2. Let X and Y be independent random variables, such that X is uniform on $\{1, 2, 3, \dots, m\}$ and Y is uniform on $\{1, 2, 3, \dots, n\}$ where $1 \leq m \leq n$. Let $Z = X + Y$. Find the pmf $f_Z(z)$, $\mathbf{E}(Z)$ and $\mathbf{Var}(Z)$.

Since X and Y are uniform, their pmf's are

$$f_X(x) = \begin{cases} \frac{1}{m}, & \text{if } 1 \leq x \leq m; \\ 0, & \text{otherwise.} \end{cases} \quad f_Y(y) = \begin{cases} \frac{1}{n}, & \text{if } 1 \leq y \leq n; \\ 0, & \text{otherwise.} \end{cases}$$

Since X and Y are independent, the joint pmf $f(x, y) = f_X(x)f_Y(y)$. Using $m \leq n$ we see that the pmf for $Z = X + Y$ is given for $z \in \{2, 3, \dots, m+n\}$ by

$$f_Z(z) = \mathbf{P}(X + Y = z) = \sum_{x+y=z} f_X(x)f_Y(y) \\ = \begin{cases} \sum_{j=1}^{z-1} f_X(j)f_Y(z-j), & \text{if } z \leq m; \\ \sum_{j=1}^m f_X(j)f_Y(z-j), & \text{if } m < z \leq n; \\ \sum_{j=z-n}^m f_X(j)f_Y(z-j), & \text{if } n < z; \end{cases} = \begin{cases} \frac{z-1}{mn} & \text{if } z \leq m; \\ \frac{1}{n}, & \text{if } m+1 \leq z \leq n+1; \\ \frac{m+n-z+1}{mn}, & \text{if } n+1 < z; \end{cases}$$

Notice that the distribution is symmetric about $(m+n+2)/2$ so that $\mathbf{E}(Z) = (m+n+2)/2$. To see this, observe that $f_Z(z) = f_Z(m+n+2-z)$. Thus

$$2\mathbf{E}(Z) = 2 \sum_{k=2}^{m+n} kf_Z(k) = \sum_{k=2}^{m+n} (kf_Z(k) + kf_Z(m+n+2-k)) \\ = \sum_{k=2}^{m+n} (kf_Z(k) + (m+n-k+2)f_Z(k)) = m+n+2.$$

Of course, we could have seen this using linearity

$$\mathbf{E}(Z) = \mathbf{E}(X + Y) = \mathbf{E}(X) + \mathbf{E}(Y) = \frac{m+1}{2} + \frac{n+1}{2}.$$

Similarly, by independence,

$$\mathbf{Var}(Z) = \mathbf{Var}(X + Y) = \mathbf{Var}(X) + \mathbf{Var}(Y) = \frac{m^2-1}{12} + \frac{n^2-1}{12}.$$

3. Suppose that there are n dice whose six sides instead of being numbered are labeled by an apple on one side, a banana on two sides and a cherry on three sides. Suppose all n dice are rolled. Let X be the number of apples showing, Y the number of bananas and Z the number of cherries. Find the joint probability $f(x, y)$. Find the marginal probability $f_X(x)$.

This is the multinomial distribution. Each roll of a die is independent. Also, for each roll, $p = \mathbf{P}(\text{apple}) = \frac{1}{6}$, $q = \mathbf{P}(\text{banana}) = \frac{1}{3}$ and $r = \mathbf{P}(\text{cherry}) = \frac{1}{2}$ such that $p + q + r = 1$. If there are $x \geq 0$ apples, $y \geq 0$ bananas and $z \geq 0$ cherries, such that $x + y + z = n$,

$$f(x, y, z) = \mathbf{P}(X = x \text{ and } Y = y \text{ and } Z = z) = \binom{n}{x, y, z} p^x q^y r^z = \frac{n!}{x! y! z!} \frac{2^y 3^z}{6^n}$$

The joint probability for $x \geq 0$, $y \geq 0$ and $x + y \leq n$ is

$$f(x, y) = \mathbf{P}(X = x \text{ and } Y = y) = f(x, y, n-x-y) \\ = \frac{n!}{x! y! (n-x-y)!} \left(\frac{1}{6}\right)^x \left(\frac{1}{3}\right)^y \left(\frac{1}{2}\right)^{n-x-y}.$$

Thus using the binomial formula, the marginal probability

$$\begin{aligned} f_X(x) &= \sum_y f(x, y) = \frac{n!}{x!(n-x)!} \left(\frac{1}{6}\right)^x \sum_{y=0}^{n-x} \frac{(n-x)!}{y!(n-x-y)!} \left(\frac{1}{3}\right)^y \left(\frac{1}{2}\right)^{n-x-y} \\ &= \frac{n!}{x!(n-x)!} \left(\frac{1}{6}\right)^x \left(\frac{1}{3} + \frac{1}{2}\right)^{n-x} = \binom{n}{x} \left(\frac{1}{6}\right)^x \left(\frac{5}{6}\right)^{n-x}. \end{aligned}$$

This is no surprise. If a “success” means an apple is rolled and “failure” means a banana or cherry is rolled, then the number of apples has the binomial distribution $X \sim \text{bin}(n, \frac{1}{6})$.

4. Let X and Y be random variables whose joint probability is $f(1, 1) = f(3, 2) = .2$, $f(1, 2) = .5$, $f(2, 2) = .1$ and $f(i, j) = 0$ for other (i, j) . Find $f_{X|Y}(x | y)$ and $\mathbf{E}(X | Y)$.

We obtain the marginal probabilities by summing rows of the pmf table using

$$f_X(x) = \sum_y f(x, y), \quad f_Y(y) = \sum_x f(x, y).$$

	$x = 1$	$x = 2$	$x = 3$	$f_Y(y)$
$y = 1$.2	0	0	.2
$y = 2$.5	.1	.2	.8
$f_X(x)$.7	.1	.2	1

The conditional probability mass function

$$f_{X|Y}(x | y) = \mathbf{P}(X = x | Y = y) = \frac{f(x, y)}{f_Y(y)}$$

so that

$$\begin{aligned} f_{X|Y}(1 | 1) &= \frac{f(1, 1)}{f_Y(1)} = \frac{.2}{.2} = 1, & f_{X|Y}(2 | 1) &= \frac{f(2, 1)}{f_Y(1)} = 0, \\ f_{X|Y}(3 | 1) &= \frac{f(3, 1)}{f_Y(1)} = 0, & f_{X|Y}(1 | 2) &= \frac{f(1, 2)}{f_Y(2)} = \frac{.5}{.8} = .625, \\ f_{X|Y}(2 | 2) &= \frac{f(2, 2)}{f_Y(2)} = \frac{.1}{.8} = .125, & f_{X|Y}(3 | 2) &= \frac{f(3, 2)}{f_Y(2)} = \frac{.2}{.8} = .25. \end{aligned}$$

The conditional expectation $\mathbf{E}(X | Y)$ is thus

$$\begin{aligned} \mathbf{E}(X | Y = 1) &= \sum_x x f_{X|Y}(x | 1) = (1)(1) + (2)(0) + (3)(0) = 1, \\ \mathbf{E}(X | Y = 2) &= \sum_x x f_{X|Y}(x | 2) = (1)(.625) + (2)(.125) + (3)(.25) = 1.625. \end{aligned}$$

5. Suppose that $\mathbf{E}(|X|^\alpha) = 0$ for some $\alpha > 0$. Show that $\mathbf{P}(X = 0) = 1$.

This follows from a version of Chebychov's Inequality. Let $h(x) = |x|^\alpha$ in the basic inequality Theorem 4.6.1. Then for $a = \varepsilon^\alpha > 0$,

$$\mathbf{P}(|X| \geq \varepsilon) = \mathbf{P}(|X|^\alpha \geq \varepsilon^\alpha) \leq \frac{\mathbf{E}(|X|^\alpha)}{\varepsilon^\alpha}. \quad (1)$$

Let A_n denote the event that $|X| \geq \frac{1}{n}$. Then the events are monotone $A_n \subset A_{n+1}$ for all n and the event

$$\{X \neq 0\} = \{|X| > 0\} = \bigcup_{n=1}^{\infty} A_n.$$

By the monotone convergence of probability, and (1) with $\varepsilon = 1/n$,

$$\begin{aligned} 0 \leq 1 - \mathbf{P}(X = 0) &= \mathbf{P}(|X| > 0) = \mathbf{P}\left(\bigcup_{n=1}^{\infty} A_n\right) = \lim_{n \rightarrow \infty} \mathbf{P}(A_n) \\ &\leq \lim_{n \rightarrow \infty} n^\alpha \mathbf{E}(|X|^\alpha) = \lim_{n \rightarrow \infty} 0 = 0. \end{aligned}$$

6. Let X_n be a sequence of independent Bernoulli trials ($X_n \in \{0, 1\}$) such that $\mathbf{P}(X_n = 1) = p$ for all n . Show that the sample means converge in probability as $n \rightarrow \infty$,

$$\frac{1}{n} (X_1 + \cdots + X_n) \xrightarrow{P} p.$$

Let $S_n = X_1 + \cdots + X_n$ as usual and observe that because of independence and the behavior of variance under multiplication by a constant, the random variable S_n/n satisfies

$$\begin{aligned} \mathbf{E}\left(\frac{1}{n} S_n\right) &= \frac{1}{n} \mathbf{E}\left(\sum_{j=1}^n X_j\right) = \frac{1}{n} \sum_{j=1}^n \mathbf{E}(X_j) = \frac{1}{n} \sum_{j=1}^n p = p; \\ \mathbf{Var}\left(\frac{1}{n} S_n\right) &= \frac{1}{n^2} \mathbf{Var}\left(\sum_{j=1}^n X_j\right) = \frac{1}{n^2} \sum_{j=1}^n \mathbf{Var}(X_j) = \frac{1}{n^2} \sum_{j=1}^n pq = \frac{pq}{n}. \end{aligned}$$

Recall the version of Chebychov's inequality, gotten by applying Theorem 4.6.1 to $h(x) = (x - \mathbf{E}(X))^2$. For all $a > 0$,

$$\mathbf{P}(|X - \mathbf{E}(X)| \geq a) \leq \frac{\mathbf{Var}(X)}{a^2}. \quad (2)$$

Recall also the meaning of $Z_n \xrightarrow{P} Z$ "convergence in probability." It means for every $\varepsilon > 0$,

$$\lim_{n \rightarrow \infty} \mathbf{P}(|Z_n - Z| \geq \varepsilon) = 0.$$

In our case, $Z_n = S_n/n$, $Z = p$ and apply (2) with $a = \varepsilon$, where $\varepsilon > 0$ is any positive number. Then

$$\mathbf{P}\left(\left|\frac{1}{n} S_n - p\right| \geq \varepsilon\right) \leq \frac{\mathbf{Var}\left(\frac{1}{n} S_n\right)}{\varepsilon^2} = \frac{pq}{\varepsilon^2 n} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

Thus the sample average converges in probability to its mean, as to be shown.

7. Urn 1 contains 10 white and 3 black balls; urn 2 contains 3 white and 5 black balls. Two randomly selected balls are transferred from No. 1 and placed in No. 2 and then 4 balls are taken from the latter. Let the rv X be the number of white balls chosen. Find $f_X(x)$.

This is an exercise in the total probability formula. Let us condition on the colors of the balls transferred from urn 1 to urn 2. Three mutually exclusive events are A , that both balls are white, B that one was white and the other was black, and C that both were black. The probabilities are computed as usual for drawing without replacement (*i.e.*, hypergeometric)

$$\begin{aligned}\mathbf{P}(A) &= \frac{\binom{10}{2}\binom{3}{0}}{\binom{13}{2}} = \frac{10 \cdot 9}{13 \cdot 12} = \frac{15}{26}, & \mathbf{P}(B) &= \frac{\binom{10}{1}\binom{3}{1}}{\binom{13}{2}} = \frac{10 \cdot 3 \cdot 2}{13 \cdot 12} = \frac{10}{26}, \\ \mathbf{P}(C) &= \frac{\binom{10}{0}\binom{3}{2}}{\binom{13}{2}} = \frac{3 \cdot 2}{13 \cdot 12} = \frac{1}{26}.\end{aligned}$$

The conditional pmf's may be computed using the given constitution of the second urn. For $0 \leq x \leq 4$,

$$f(x|A) = \frac{\binom{5}{x}\binom{5}{4-x}}{\binom{10}{4}}, \quad f(x|B) = \frac{\binom{4}{x}\binom{6}{4-x}}{\binom{10}{4}}, \quad f(x|C) = \frac{\binom{3}{x}\binom{7}{4-x}}{\binom{10}{4}}.$$

Of course we interpret $f(4|C) = 0$. Using the total probability formula for the pmf,

$$\begin{aligned}f(x) &= \mathbf{P}(A)f(x|A) + \mathbf{P}(B)f(x|B) + \mathbf{P}(C)f(x|C) \\ &= \frac{15}{26 \cdot 210} \binom{5}{x} \binom{5}{4-x} + \frac{10}{26 \cdot 210} \binom{4}{x} \binom{6}{4-x} + \frac{1}{26 \cdot 210} \binom{3}{x} \binom{7}{4-x}.\end{aligned}$$

8. Roll a die. Let X be the number showing. Then flip X fair coins. Let Y be the number of heads. Find $\mathbf{E}(Y)$.

We use the formula $\mathbf{E}(\mathbf{E}(Y|X)) = \mathbf{E}(Y)$. The variable X is uniform on $\{1, 2, 3, 4, 5, 6\}$ so that for integral x such that $1 \leq x \leq 6$,

$$f_X(x) = \mathbf{P}(X = x) = \frac{1}{6}, \quad \mathbf{E}(X) = \frac{7}{2}.$$

We assume that the coins are independent, thus the number of heads in X flips is distributed binomially $Y \sim \text{bin}(X, \frac{1}{2})$. Thus the conditional pmf and expectations are for $1 \leq y \leq x$,

$$f_{Y|X}(y|x) = \mathbf{P}(Y = y | X = x) = \binom{x}{y} p^y q^{x-y} = \binom{x}{y} \frac{1}{2^x}; \quad \mathbf{E}(Y | X = x) = px = \frac{x}{2}.$$

Thus

$$\mathbf{E}(Y) = \mathbf{E}(\mathbf{E}(Y|X)) = \mathbf{E}\left(\frac{X}{2}\right) = \frac{\mathbf{E}(X)}{2} = \frac{7}{4}.$$