Homework 7

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Problem 1. A random sample of size n is obtained without replacement from a finite population of size N that has 3 separate categories A, B, C with sizes M_A, M_B, M_C , respectively, such that $M_A + M_B + M_C = N$.

- (a) Let X_A, X_B, X_C be the numbers of individuals sampled from the three categories. Find the joint pmf for (X_A, X_B, X_C) . Keep in mind that $X_A + X_B + X_C = n$.
- (b) Now let $Y = X_A + X_B$. Find the joint pmf for (X_A, Y) .
- (c) What is the marginal pmf for Y? Hint: think about the sampling and what happens if you ignore the distinction between categories A and B.
- (d) Find the conditional pmf for X_A , given Y = y. What distribution is this (name and parameters)?
- (a) The joint pmf for (X_A, X_B, X_C) is

$$P(X_A = x_a, X_B = x_b, X_C = x_c) = \frac{\binom{M_A}{x_a} \binom{M_B}{x_b} \binom{M_C}{x_c}}{\binom{N}{n}}$$

where $x_a + x_b + x_c = n$.

(b) The joint pmf for (X_A, Y) is

$$P(X_A = x_a, Y = y) = \frac{\binom{M_A}{x_a} \binom{M_B}{y - x_a} \binom{M_C}{n - y}}{\binom{N}{n}}$$

where $x_a \leq y$ and $y \leq n$.

(c) The marginal pmf for Y is

$$P(Y = y) = \frac{\binom{M_A + M_B}{y} \binom{M_C}{n-y}}{\binom{N}{n}}$$

where $y \leq n$.

(d) The conditional pmf for X_A , given Y = y is

$$P(X_A = x_a | Y = y) = \frac{\binom{M_A}{x_a} \binom{M_B}{y - x_a}}{\binom{M_A + M_B}{y}}$$

where $x_a \leq y$. This is a hypergeometric distribution with parameters $M_A + M_B$, M_A , y. **Problem 2.** Let (X,Y) have joint cdf $F(x,y) = P(X \leq x, Y \leq y)$.

(a) Show that, for a < b and c < d,

$$P(a < X < b, c < Y < d) = F(b, d) - F(b, c) - F(a, d) + F(a, c).$$

- (b) Simplify the expression in (a) for the independence case: $F(x,y) = F_X(x)F_Y(y)$.
- (a) We have 4 events to consider:

$$A = \{X \le b, Y \le d\}, B = \{X \le a, Y \le d\}, C = \{X \le b, Y \le c\}, D = \{X \le a, Y \le c\}.$$

Note that

$$\{a < X \le b, c < Y \le d\} = A \setminus (B \cup C) = A \cap B^c \cap C^c.$$

Also note that $B^c \cap C^c = (B \cup C)^c$. By inclusion-exclusion, we have

$$\mathsf{P}(B \cup C) = \mathsf{P}(B) + \mathsf{P}(C) - \mathsf{P}(B \cap C) = \mathsf{P}(B) + \mathsf{P}(C) - \mathsf{P}(D).$$

Therefore,

(b) For the independence case, we have

$$F(b,d) - F(a,d) - F(b,c) + F(a,c)$$

= $F_X(b)F_Y(d) - F_X(a)F_Y(d) - F_X(b)F_Y(c) + F_X(a)F_Y(c)$
= $(F_X(b) - F_X(a))(F_Y(d) - F_Y(c)).$

Problem 3. Suppose T has negative binomial(2, p) distribution and the conditional pmf for S, given T = t, is $f_{S|T}(s|t) = \frac{1}{t+1}$, $s \in \{0, ..., t\}$.

- (a) Find the joint pmf for (S, T). Be sure to indicate the range with any restrictions.
- (b) Find the marginal pmf for S and the conditional pmf for T, given S = s.
- (c) Show that S and R = T S are independent and have the same distribution.
- (a) The joint pmf for (S, T) is

$$f_{S,T}(s,t) = f_{S|T}(s|t)f_T(t) = \frac{1}{t+1} {t+1 \choose 1} p^2 (1-p)^{t-2} = p^2 (1-p)^t$$

where $t \in \{0, 1, ...\}$ and $s \in \{0, 1, ..., t\}$.

(b) The marginal pmf for S is

$$f_S(s) = \sum_{t=0}^{\infty} f_{S,T}(s,t)$$

$$= \sum_{t=s}^{\infty} p^2 (1-p)^t$$

$$= p^2 \frac{(1-p)^s}{p} = p(1-p)^s$$

The conditional pmf for T, given S = s is

$$f_{T|S}(t|s) = \frac{f_{S,T}(s,t)}{f_S(s)} = \frac{p^2(1-p)^t}{p(1-p)^s} = p(1-p)^{t-s}.$$

(c) The joint pmf for (S, R) is

$$f_{S,R}(s,r) = f_{S,T}(s,s+r) = p^2 (1-p)^{s+r} = p(1-p)^s \cdot p(1-p)^r = f_S(s) \cdot f_R(r).$$

Therefore, S and R are independent. Also, we have

$$f_R(r) = p(1-p)^r,$$

which is the same as the distribution of S.

Problem 4. Suppose $S \sim \text{binomial}(m, p)$ and $T \sim \text{binomial}(n, p)$ (same second parameter p), with S and T independent. Use the convolution formula to prove $S + T \sim \text{binomial}(m + n, p)$. Hint: factor out the result and observe that a hypergeometric pmf remains.

Let X = S + T. By the convolution formula, we have

$$f_X(x) = \sum_s f_S(s) f_T(x-s)$$

$$= \sum_s {m \choose s} p^s (1-p)^{m-s} {n \choose x-s} p^{x-s} (1-p)^{n-(x-s)}$$

$$= p^x (1-p)^{m+n-x} \sum_s {m \choose s} {n \choose x-s}$$

$$= p^x (1-p)^{m+n-x} {m+n \choose x}$$

where the last equality follows from Vandermonde's identity:

$$\sum_{s} \binom{m}{s} \binom{n}{x-s} = \binom{m+n}{x}.$$

Therefore, $X \sim \text{binomial}(m+n, p)$.

Problem 5. Statistical Inference by Casella and Berger, 2nd Edition, Chapter 4, Exercise 4.

4. A pdf is defined by

$$f(x,y) = \begin{cases} C(x+2y) & \text{if } 0 < y < 1 \text{ and } 0 < x < 2\\ 0 & \text{otherwise.} \end{cases}$$

- (a) Find the value of C.
- (b) Find the marginal distribution of X.
- (c) Find the joint cdf of X and Y, be sure to give the joint cdf for all (x, y) in the real plane, and then check yourself by deriving the joint pdf for all (x, y).
- (d) Find $P(Y^2 < X < \sqrt{Y})$.
- (e) Find $P(X + 2Y \le t)$ for $t \in [0, 4]$ and deduce the pdf for T = X + 2Y. You will need to consider a couple cases of the double integral separately. Be sure to check that your pdf is valid.

(a) To find C, we have

$$1 = \int_0^1 \int_0^2 C(x+2y) \, dx \, dy$$
$$= C \int_0^1 \left[\frac{x^2}{2} + 2yx \right]_0^2 dy$$
$$= C \int_0^1 (2+4y) \, dy$$
$$= C \left[2y + 2y^2 \right]_0^1 = 4C.$$

Therefore, $C = \frac{1}{4}$.

(b) The marginal distribution of X is

$$f_X(x) = \int_0^1 f(x, y) \, dy$$
$$= \int_0^1 \frac{1}{4} (x + 2y) \, dy$$
$$= \frac{1}{4} \left[xy + y^2 \right]_0^1 = \frac{x+1}{4}$$

where 0 < x < 2.

(c) The joint cdf of X and Y is

$$F(x,y) = \begin{cases} 0 & \text{if } x \le 0 \text{ or } y \le 0\\ \int_0^y \int_0^x \frac{1}{4} (u+2v) \, du \, dv & \text{if } 0 < x < 2 \text{ and } 0 < y < 1\\ \int_0^1 \int_0^x \frac{1}{4} (u+2v) \, du \, dv & \text{if } 0 < x < 2 \text{ and } y \ge 1\\ \int_0^y \int_0^2 \frac{1}{4} (u+2v) \, du \, dv & \text{if } x \ge 2 \text{ and } 0 < y < 1\\ 1 & \text{if } x \ge 2 \text{ and } y \ge 1 \end{cases}$$

Calculating the integrals, we have

$$F(x,y) = \begin{cases} 0 & \text{if } x \le 0 \text{ or } y \le 0\\ \frac{x^2y}{8} + \frac{xy^2}{4} & \text{if } 0 < x < 2 \text{ and } 0 < y < 1\\ \frac{x^2}{8} + \frac{x}{4} & \text{if } 0 < x < 2 \text{ and } y \ge 1\\ \frac{y}{2} + \frac{y^2}{2} & \text{if } x \ge 2 \text{ and } 0 < y < 1\\ 1 & \text{if } x \ge 2 \text{ and } y \ge 1 \end{cases}$$

Taking the partial derivatives with respect to both x and y, we have

$$\frac{\partial^2}{\partial x \partial y} F(x, y) = \begin{cases} \frac{1}{4} (x + 2y) & \text{if } 0 < x < 2 \text{ and } 0 < y < 1 \\ 0 & \text{otherwise.} \end{cases}$$

This matches the original joint pdf.

(d) We have

$$\begin{split} \mathsf{P}(Y^2 < X < \sqrt{Y}) &= \int_0^1 \int_{y^2}^{\sqrt{y}} \frac{1}{4} (x + 2y) \, dx \, dy \\ &= \int_0^1 \frac{1}{4} \left[\frac{x^2}{2} + 2yx \right]_{y^2}^{\sqrt{y}} \, dy \\ &= \int_0^1 \frac{1}{4} \left(\frac{y}{2} + 2y^{3/2} - \frac{y^4}{2} - 2y^3 \right) \, dy \\ &= \frac{1}{4} \left[\frac{y^2}{4} + \frac{4y^{5/2}}{5} - \frac{y^5}{10} - \frac{y^4}{2} \right]_0^1 = \frac{7}{80}. \end{split}$$

(e) For $t \in [0, 4]$, we have

$$P(X + 2Y \le t) = \int_0^1 \int_0^{\min(2, t - 2y)} \frac{1}{4} (x + 2y) \, dx \, dy$$

$$= \int_0^1 \frac{1}{4} \left[\frac{x^2}{2} + 2yx \right]_0^{\min(2, t - 2y)} \, dy$$

$$= \int_0^1 \frac{1}{4} \left(\frac{\min(2, t - 2y)^2}{2} + 2y \min(2, t - 2y) \right) \, dy.$$

We need to consider two cases:

- Case 1: $0 \le t < 2$. In this case, we have

$$P(X + 2Y \le t) = \int_0^{t/2} \int_0^{t-2y} \frac{1}{4} (x + 2y) \, dx \, dy$$
$$= \frac{t^3}{24}.$$

- Case 2: $2 \le t \le 4$. In this case, we have

$$P(X+2Y \le t) = \int_0^{(t-2)/2} \frac{1}{4} (2+4y) dy + \int_{(t-2)/2}^1 \frac{1}{4} \left(\frac{(t-2y)^2}{2} + 2y(t-2y) \right) dy$$
$$= -\frac{t^3}{24} + \frac{t^2}{4} - \frac{1}{3}.$$

Therefore, the cdf for T = X + 2Y is

$$F_T(t) = \begin{cases} 0 & \text{if } t < 0\\ \frac{t^3}{24} & \text{if } 0 \le t < 2\\ -\frac{t^3}{24} + \frac{t^2}{4} - \frac{1}{3} & \text{if } 2 \le t \le 4\\ 1 & \text{if } t > 4 \end{cases}$$

Taking the derivative with respect to t, we have the pdf for T:

$$f_T(t) = \begin{cases} \frac{t^2}{8} & \text{if } 0 \le t < 2\\ -\frac{t^2}{8} + \frac{t}{2} & \text{if } 2 \le t \le 4\\ 0 & \text{otherwise.} \end{cases}$$

To check that the pdf is valid, we have

$$\int_{-\infty}^{\infty} f_T(t) dt = \int_0^2 \frac{t^2}{8} dt + \int_2^4 \left(-\frac{t^2}{8} + \frac{t}{2} \right) dt$$

$$= \left[\frac{t^3}{24} \right]_0^2 + \left[-\frac{t^3}{24} + \frac{t^2}{4} \right]_2^4$$

$$= \frac{8}{24} + \left(-\frac{64}{24} + 4 - \left(-\frac{8}{24} + 1 \right) \right) = \frac{8 - 64 + 96 + 8 - 24}{24} = \frac{24}{24} = 1.$$

Problem 6. Suppose (R, S) has joint pdf $f_{R,S}(r, s) = 8s^2e^{-2s}$ for $0 \le r \le s$.

- (a) Find the marginal pdf for S and the conditional pdf for R, given S = s. Try to identify the distributions by name, giving appropriate values to the parameters.
- (b) Find the marginal pdf for R and the conditional pdf for S, given R = r.
- (a) The marginal pdf for S is

$$f_S(s) = \int_0^s 8s^2 e^{-2s} dr = 8s^3 e^{-2s}$$

where $s \ge 0$. This is a gamma distribution with parameters $\alpha = 3$ and $\beta = 2$. The conditional pdf for R, given S = s is

$$f_{R|S}(r|s) = \frac{f_{R,S}(r,s)}{f_{S}(s)} = \frac{8s^2e^{-2s}}{8s^3e^{-2s}} = \frac{1}{s}$$

where $0 \le r \le s$. This is a uniform distribution on the interval [0, s].

(b) The marginal pdf for R is

$$f_R(r) = \int_r^\infty 8s^2 e^{-2s} ds$$

$$= \left[-4s^2 e^{-2s} - 4se^{-2s} - 2e^{-2s} \right]_r^\infty$$

$$= 4r^2 e^{-2r} + 4re^{-2r} + 2e^{-2r}$$

$$= 2e^{-2r}(2r^2 + 2r + 1)$$

where $r \geq 0$. The conditional pdf for S, given R = r is

$$f_{S|R}(s|r) = \frac{f_{R,S}(r,s)}{f_{R}(r)} = \frac{8s^2e^{-2s}}{2e^{-2r}(2r^2 + 2r + 1)} = \frac{4s^2e^{-2(s-r)}}{2r^2 + 2r + 1}$$

where $s \geq r$.

Problem 7. (a) Prove Corollary 4.19.ii in the notes, by applying Theorem 4.18.

(b) Suppose X, Y are independent exponential(1) random variables and W = X + Y, Z = X - Y. Find the joint pdf for (W, Z). Be aware of the range for the random pair: Z can be positive or negative but it also is restricted by W.

(c) Find the marginal distributions for W and Z. (Note: W is a special case of Example 4.10 in the notes.)

Corollary 4.19.ii. Suppose (X, Y) has joint pdf $f_{X,Y}(x, y)$. Let W = aX + bY and Z = cX + dY. If $ad \neq bc$ then (W, Z) has joint pdf

$$f_{W,Z}(w,z) = \frac{1}{|ad - bc|} f_{X,Y}\left(\frac{dw - bz}{ad - bc}, \frac{az - cw}{ad - bc}\right).$$

Theorem 4.18. Suppose (X, Y) has pdf $f_{X,Y}(x, y)$, and let U = g(X, Y) and V = h(X, Y). Assume the transformation $(x, y) \to (g(x, y), h(x, y))$ is 1-1 and differentiable on a set A such that $P((X, Y) \in A) = 1$. Then (U, V) has pdf satisfying

$$f_{U,V}(u,v) = f_{X,Y}(x,y) \frac{dx \, dy}{du \, dv}$$

expressed as a function of (u, v).

(a) By Theorem 4.18, we have

$$f_{W,Z}(w,z) = f_{X,Y}(x,y) \frac{dx \, dy}{dw \, dz}.$$

Note that

$$\begin{bmatrix} dw \\ dz \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} dx \\ dy \end{bmatrix}.$$

Therefore,

$$\frac{dw\,dz}{dx\,dy} = \begin{vmatrix} a & b \\ c & d \end{vmatrix} = ad - bc.$$

Since $ad \neq bc$, we have

$$\frac{dx\,dy}{dw\,dz} = \frac{1}{|ad - bc|}.$$

Also, solving for x and y, we have

$$\begin{bmatrix} x \\ y \end{bmatrix} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} \begin{bmatrix} w \\ z \end{bmatrix} = \begin{bmatrix} \frac{dw - bz}{ad - bc} \\ \frac{az - cw}{ad - bc} \end{bmatrix}.$$

Combining the above results, we have

$$f_{W,Z}(w,z) = \frac{1}{|ad - bc|} f_{X,Y}\left(\frac{dw - bz}{ad - bc}, \frac{az - cw}{ad - bc}\right).$$

(b) The joint pdf for (W, Z) is

$$f_{W,Z}(w,z) = \frac{1}{|ad - bc|} f_{X,Y}\left(\frac{dw - bz}{ad - bc}, \frac{az - cw}{ad - bc}\right).$$

Here, a = 1, b = 1, c = 1, d = -1. Therefore,

$$f_{W,Z}(w,z) = \frac{1}{2} f_{X,Y}\left(\frac{w+z}{2}, \frac{w-z}{2}\right).$$

Since X and Y are independent exponential (1) random variables, we have

$$f_{X,Y}(x,y) = e^{-x}e^{-y} = e^{-(x+y)}.$$

Therefore,

$$f_{W,Z}(w,z) = \frac{1}{2}e^{-\left(\frac{w+z}{2} + \frac{w-z}{2}\right)} = \frac{1}{2}e^{-w}$$

where $w \ge 0$ and $-w \le z \le w$.

(c) The marginal distribution for W is

$$f_W(w) = \int_{-w}^w f_{W,Z}(w,z) dz = \int_{-w}^w \frac{1}{2} e^{-w} dz = \frac{1}{2} e^{-w} (2w) = we^{-w}.$$

This is a gamma distribution with parameters $\alpha = 2$ and $\beta = 1$. The marginal distribution for Z is

$$f_Z(z) = \int_0^\infty f_{W,Z}(w,z) dw = \int_{|z|}^\infty \frac{1}{2} e^{-w} dw = \frac{1}{2} e^{-|z|}.$$

This is a Laplace distribution with parameters $\mu = 0$ and b = 1.

- **Problem 8.** (a) Let T and U be independent with $T \sim \operatorname{gamma}(\alpha, \gamma)$ and $U \sim \operatorname{gamma}(\beta, \gamma)$ (with the same scale parameter γ). Let X = T + U and Y = T/(T + U). Determine the joint pdf for (X, Y). Identify the marginal distributions by name and describe, in words, what the joint distribution of (X, Y) is. Hint: review distributions defined in Section 3.3 of the notes.
 - (b) Using the result for the distribution of X in part (a), prove by mathematical induction (iteration) that if T_1, \ldots, T_k are independent random variables such that $T_i \sim \operatorname{gamma}(\alpha_i, \gamma)$, then $T_1 + \cdots + T_k \sim \operatorname{gamma}(\alpha_1 + \cdots + \alpha_k, \gamma)$.
 - (a) T = XY and U = X(1 Y). The Jacobian determinant is

$$J = \begin{vmatrix} Y & X \\ 1 - Y & -X \end{vmatrix} = -X.$$

Therefore, by the change of variables formula, we have

$$f_{X,Y}(x,y) = f_{T,U}(xy, x(1-y))|J|$$

$$= f_T(xy)f_U(x(1-y))x$$

$$= \frac{1}{\gamma^{\alpha}\Gamma(\alpha)}(xy)^{\alpha-1}e^{-\frac{xy}{\gamma}} \cdot \frac{1}{\gamma^{\beta}\Gamma(\beta)}(x(1-y))^{\beta-1}e^{-\frac{x(1-y)}{\gamma}} \cdot x$$

$$= \frac{x^{\alpha+\beta-1}y^{\alpha-1}(1-y)^{\beta-1}}{\gamma^{\alpha+\beta}\Gamma(\alpha)\Gamma(\beta)}e^{-\frac{x}{\gamma}}$$

where x > 0 and 0 < y < 1. We can factor the joint pdf as

$$f_{X,Y}(x,y) = \left(\frac{x^{\alpha+\beta-1}}{\gamma^{\alpha+\beta}\Gamma(\alpha+\beta)}e^{-\frac{x}{\gamma}}\right) \left(\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}y^{\alpha-1}(1-y)^{\beta-1}\right).$$

Notice the left factor is the marginal distribution for X

$$f_X(x) = \frac{x^{\alpha+\beta-1}}{\gamma^{\alpha+\beta}\Gamma(\alpha+\beta)}e^{-\frac{x}{\gamma}},$$

which is a gamma distribution with parameters $\alpha + \beta$ and γ . The right is the marginal distribution for Y

$$f_Y(y) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} y^{\alpha - 1} (1 - y)^{\beta - 1},$$

which is a beta distribution with parameters α and β .

(b) Base case: for k = 2, the result holds by part (a). Inductive hypothesis: assume the result holds for k = n, i.e.,

$$T_1 + \cdots + T_n \sim \operatorname{gamma}(\alpha_1 + \cdots + \alpha_n, \gamma).$$

Inductive step: for k = n + 1, we have

$$T_1 + \cdots + T_n + T_{n+1} = (T_1 + \cdots + T_n) + T_{n+1}.$$

By the inductive hypothesis, $(T_1 + \cdots + T_n) \sim \operatorname{gamma}(\alpha_1 + \cdots + \alpha_n, \gamma)$ and $T_{n+1} \sim \operatorname{gamma}(\alpha_{n+1}, \gamma)$. By part (a), we have

$$\operatorname{gamma}(\alpha_1 + \dots + \alpha_n, \gamma) + \operatorname{gamma}(\alpha_{n+1}, \gamma) \sim \operatorname{gamma}(\alpha_1 + \dots + \alpha_n + \alpha_{n+1}, \gamma).$$