

**Statistics 522, Problem Set 4 Solutions**

Wellner; 2/5/99

1. Exercise 8.4.2, PFS page 141. Repeat Example 8.4.1 for sampling without replacement.

**Solution:** (a) When the sampling is done without replacement the joint probability distribution for  $(X_1, X_2)$  is as follows:

			$X_1$		
		1	2	3	
$X_2$	1	0	2/30	3/30	5/30
	2	2/30	2/30	6/30	10/30
	3	3/30	6/30	6/30	15/30
		5/30	10/30	15/30	1

Hence the marginal distribution of  $S = X_1 + X_2$  is given by

$k$	2	3	4	5	
$P(S = k)$	4/30	8/30	12/30	6/30	1

It is easy to compute the conditional distribution of  $Y = X_2$  given  $S$  (or given  $\mathcal{D} = S^{-1}(\mathcal{B})$ ): letting  $D_j = [S = j]$ ,

		$Y$			
	1	2	3		$E(Y \mathcal{D})$
$D_3$	1/2	1/2	0		3/2
$D_4$	3/8	2/8	3/8		2
$D_5$	0	1/2	1/2		5/2
$D_6$	0	0	1		3
$P(Y = i)$	5/30	10/30	15/30		

Note that

$$P(Y = i|\mathcal{D}) = \sum_{j=3}^6 \frac{P([Y = i] \cap D_j)}{P(D_j)} 1_{D_j}$$

satisfies  $P(Y = i) = E\{P(Y = i|\mathcal{D})\}$ . Also note that  $E(Y) = 7/3$ , and

$$E(E(Y|\mathcal{D})) = (3/2)(4/30) + 2(8/30) + (5/2)(12/30) + 3(6/30) = 7/3.$$

2. Exercise 8.4.3, PfS page 141. Let  $Y$  denote a rv on some  $(\Omega, \mathcal{A}, P)$  that takes on the eight values  $1, \dots, 8$  with probabilities  $1/32, 2/32, 3/32, 4/32, 15/32, 4/32, 1/32, 1/32$ . Let  $\mathcal{C} = \mathcal{F}(Y)$ , and let  $C_i \equiv [Y = i]$  and  $p_i = P(C_i)$  for  $i = 1, \dots, 8$ . Let  $\mathcal{D} \equiv \sigma\{[C_1 + C_5, C_2 + C_6, C_3 + C_7, C_4 + C_8]\}$ ,  $\mathcal{E} \equiv \sigma\{[C_1 + C_5 + C_2 + C_6, C_3 + C_7 + C_4 + C_8]\}$ , and  $\mathcal{F} \equiv \{\Omega, \}$ .
- (a) Represent  $\Omega$  as a  $2 \times 4$  rectangle having eight cells representing  $C_1, \dots, C_4$  in the first row and  $C_5, \dots, C_8$  in the second row. Enter the appropriate values of  $Y(\omega)$  and  $p_i$  in each cell, forming a table. Evaluate  $E(Y)$ .
- (b) Evaluate  $E(Y|\mathcal{D})$  and  $E(E(Y|\mathcal{D}))$ .
- (c) Evaluate  $E(Y|\mathcal{E})$  and  $E(E(Y|\mathcal{E}))$ .
- (d) Evaluate  $E(Y|\mathcal{F})$  and  $E(E(Y|\mathcal{F}))$ .

**Solution:** (a) With the events  $C_i$  as given, we compute the following probability distribution:

$i$	1	2	3	4
$P(Y = i)$	1/32	2/32	3/32	4/32
$P(Y = i + 4)$	15/32	4/32	1/32	2/32
$P(Y = i \text{ or } i + 4)$	16/32	6/32	4/32	6/32

This results in

$$E(Y) = (1 \cdot 1 + 2 \cdot 2 + 3 \cdot 3 + 4 \cdot 4 + 5 \cdot 15 + 6 \cdot 4 + 7 \cdot 1 + 8 \cdot 2)/32 = 152/32.$$

(b) With  $\mathcal{D}$  as given we compute the conditional probability distribution and conditional expectations to be:

$D_i$	1	2	3	4
$P(Y = i \mathcal{D})$	1/16	2/6	3/4	4/6
$P(Y = i + 4 \mathcal{D})$	15/16	4/6	1/4	2/6
$E(Y \mathcal{D})$	76/16	28/6	16/4	32/6

This yields

$$E(E(Y|\mathcal{D})) = \frac{76}{16} \cdot \frac{16}{32} + \frac{28}{6} \cdot \frac{6}{32} + \frac{16}{4} \cdot \frac{4}{32} + \frac{32}{6} \cdot \frac{6}{32} = \frac{152}{32} = E(Y).$$

(c) With  $\mathcal{E}$  as given, we compute the conditional probability distribution and conditional expectations to be:

$i$	1	2	3	4
$P(Y = i \mathcal{E})$	1/22	2/22	3/10	4/10
$P(Y = i + 4 \mathcal{E})$	15/22	4/22	1/10	2/10
$P(E_j)$	22/32		10/32	

This yields

$$E(Y|\mathcal{E})(\omega) = \frac{1 + 4 + 75 + 24}{22} = \frac{104}{22} \quad \omega \in E_1,$$

and

$$E(Y|\mathcal{E})(\omega) = \frac{9 + 16 + 7 + 16}{10} = \frac{48}{10} \quad \omega \in E_2,$$

and hence

$$E(E(Y|\mathcal{E})) = \frac{104}{22} \frac{22}{32} + \frac{48}{10} \frac{10}{32} = \frac{152}{32} = E(Y).$$

3. Exercise 8.4.4, PfS page 145: i.e. prove (24) and (26) on page 142:  
 (24) The  $C_r$ -, Hölder, Liapounov, Minkowski, and Jensen inequalities hold for  $E(\cdot|\mathcal{D})$ .  
 (26)  $h$  is a determination of  $E(Y|\mathcal{D})$  if and only if  $E(XY) = E(Xh)$  for all  $\mathcal{D}$ -measurable rv's  $X$ .

**Solution:** (24):  $C_r$ : For  $r \geq 1$ ,  $|x|^r$  is a convex function of  $x$ , so  $|(x+y)/2|^r \leq (1/2)(|x|^r + |y|^r)$ . Thus  $|X+Y|^r \leq 2^{r-1}\{|X|^r + |Y|^r\}$ .

Taking condition expectations across this inequality and using (16) yields  $E(|X + Y|^r|\mathcal{D}) \leq 2^{r-1}\{E(|X|^r|\mathcal{D}) + E(|Y|^r|\mathcal{D})\}$ . For  $0 < r \leq 1$ ,  $|X + Y|^r \leq |X|^r + |Y|^r$ , so taking conditional expectations across this inequality yields  $E(|X + Y|^r|\mathcal{D}) \leq E(|X|^r|\mathcal{D}) + E(|Y|^r|\mathcal{D})$ .

Hölder's inequality: for arbitrary  $a, b \in \mathbb{R}$  and  $r, s$  satisfying  $(1/r) + (1/s) = 1$ , we have

$$|ab| \leq \frac{|a|^r}{r} + \frac{|b|^s}{s}$$

with equality only if  $|b| = |a|^{1/(s-1)}$ . Taking  $a = |X|/E^{1/r}(|X|^r|\mathcal{D})$  and  $b = |Y|/E^{1/s}(|Y|^s|\mathcal{D})$ , we find that

$$\frac{|X||Y|}{E^{1/r}(|X|^r|\mathcal{D})E^{1/s}(|Y|^s|\mathcal{D})} \leq \frac{|X|^r}{rE(|X|^r|\mathcal{D})} + \frac{|Y|^s}{sE(|Y|^s|\mathcal{D})},$$

and taking conditional expectations across this inequality and using (16) gives

$$\frac{E\{|X||Y|\}|\mathcal{D}\}}{E^{1/r}(|X|^r|\mathcal{D})E^{1/s}(|Y|^s|\mathcal{D})} \leq \frac{1}{r} + \frac{1}{s} = 1.$$

This yields  $E\{|X||Y|\}|\mathcal{D}\} \leq E^{1/r}(|X|^r|\mathcal{D})E^{1/s}(|Y|^s|\mathcal{D})$  with equality if and only if

$$\frac{|Y|}{E^{1/s}(|Y|^s|\mathcal{D})} = \left( \frac{|X|}{E^{1/r}(|X|^r|\mathcal{D})} \right)^{1/(s-1)} \quad \text{a.s.}$$

Liapunov's inequality: Suppose that  $E|X|^q < \infty$ . and let  $0 < p \leq q$ . Then by the conditional Hölder inequality with  $1/r = p/q$ ,  $1/s = 1 - p/q$ , we find that

$$E(|X|^p|\mathcal{D}) \leq E(|X|^q|\mathcal{D})^{p/q} E(1^{1/(1-p/q)}|\mathcal{D})^{1-p/q} = E(|X|^q|\mathcal{D})^{p/q} \quad \text{a.s.}$$

This implies that  $E(|X|^p|\mathcal{D})^{1/p} \leq E(|X|^q|\mathcal{D})^{1/q}$  a.s.

Minkowski's inequality: This follows from the conditional Hölder inequality in the same way that Minkowski's inequality follows from the unconditional Hölder inequality.

Jensen's inequality: see the nice proof in Williams, page 89, and note the "important corollary" to Williams' (h).

(26): Suppose that  $E(XY) = E(Xh)$  for all  $\mathcal{D}$ -measurable rv's  $X$ . Then, in particular with  $h = 1_D$  for  $D \in \mathcal{D}$ , we have  $E(1_D Y) = E(1_D h)$

for  $D \in \mathcal{D}$ , and hence  $h$  is a version (or “determination”) of  $E(Y|\mathcal{D})$ . On the other hand, suppose that  $h$  is a version of  $E(Y|\mathcal{D})$ ; i.e.  $E(1_D Y) = E(1_D h)$  for all  $D \in \mathcal{D}$ . Note that this implies  $E(1_D Y^+) = E(1_D h^+)$  and  $E(1_D Y^-) = E(1_D h^-)$  for all  $D \in \mathcal{D}$ .

Suppose first that  $X \geq 0$ . Then there is a sequence of  $\mathcal{D}$ -measurable simple functions  $X_n = \sum_{j=1}^n d_j 1_{D_j} \nearrow X$ . Then by the monotone convergence theorem

$$\begin{aligned}
E(XY) &= E(X(Y^+ - Y^-)) = E(XY^+) - E(XY^-) \\
&= \lim_n E(X_n Y^+) - \lim_n E(X_n Y^-) \quad \text{by the MCT} \\
&= \lim_n E\left(\sum_1^n d_j 1_{D_j} Y^+\right) - \lim_n E\left(\sum_1^n d_j 1_{D_j} Y^-\right) \\
&= \lim_n \sum_1^n d_j E(1_{D_j} Y^+) - \lim_n \sum_1^n d_j E(1_{D_j} Y^-) \\
&= \lim_n \sum_1^n d_j E(1_{D_j} h^+) - \lim_n \sum_1^n d_j E(1_{D_j} h^-) \text{ by the equality for sets} \\
&= \lim_n E(X_n h^+) - \lim_n E(X_n h^-) \quad \text{by reversing the above steps} \\
&= E(X h^+) - E(X h^-) \quad \text{by the MCT} \\
&= E(X(h^+ - h^-)) = E(Xh).
\end{aligned}$$

Now suppose that  $X$  is arbitrary with  $E|XY| < \infty$ . Then

$$\begin{aligned}
E(XY) &= E((X^+ - X^-)Y) = E(X^+Y) - E(X^-Y) \\
&= E(X^+h) - E(X^-h) \quad \text{by the result for } X \geq 0 \\
&= E((X^+ - X^-)h) = E(Xh).
\end{aligned}$$

4. Exercise E9.2, PwMG, page 231. Suppose that  $X, Y \in L_1(\Omega, \mathcal{F}, P)$  and that  $E(Y|X) = X$  a.s. and  $E(X|Y) = Y$  a.s. Prove that  $P(X = Y) = 1$ .

**Solution:** Suppose first that  $X, Y \in L_2(P)$ . Then, by Pythagoras,

$$EX^2 = E(E(X|Y)^2) + E((X - E(X|Y))^2),$$

and since  $E(X|Y) = Y$  a.s. this yields

$$(1) \quad E(X^2) = E(Y^2) + E((X - Y)^2).$$

Reversing the roles of  $X$  and  $Y$ , we also obtain, upon using  $E(Y|X) = X$  a.s.,

$$(2) \quad E(Y^2) = E(X^2) + E((Y - X)^2).$$

Adding (1) and (2) gives

$$E(X^2) + E(Y^2) = E(X^2) + E(Y^2) + 2E((X - Y)^2),$$

and this implies that  $E(X - Y)^2 = 0$ , which in turn implies  $P(X = Y) = 1$ .

Now one way to proceed is to reduce the general case of  $X, Y \in L_1(P)$  to the  $L_2(P)$  case treated above. Instead I will prove it using the hint.

Note that

$$\begin{aligned} & E(X - Y)1_{[X > c, Y \leq c]} + E(X - Y)1_{[X \leq c, Y \leq c]} \\ &= E(X - Y)1_{[Y \leq c]} = E(X1_{[Y \leq c]}) - E(Y1_{[Y \leq c]}) \\ &= E(E(X1_{[Y \leq c]}|Y)) - E(Y1_{[Y \leq c]}) \\ &= E(1_{[Y \leq c]}E(X|Y)) - E(Y1_{[Y \leq c]}) \\ (3) \quad &= E(1_{[Y \leq c]}Y) - E(Y1_{[Y \leq c]}) = 0 \end{aligned}$$

using  $E(X|Y) = Y$  a.s. in the last line. Similarly, reversing the roles of  $X$  and  $Y$ ,

$$(4) \quad \begin{aligned} & E(Y - X)1_{[Y > c, X \leq c]} + E(Y - X)1_{[Y \leq c, X \leq c]} \\ &= E(Y - X)1_{[X \leq c]} = 0. \end{aligned}$$

Adding (3) and (4) yields

$$\begin{aligned} 0 &= E(X - Y)1_{[X > c, Y \leq c]} + E(X - Y)1_{[X \leq c, Y \leq c]} \\ &\quad - E(X - Y)1_{[Y > c, X \leq c]} - E(X - Y)1_{[Y \leq c, X \leq c]} \\ &= E(X - Y)1_{[X > c, Y \leq c]} - E(X - Y)1_{[Y > c, X \leq c]}. \end{aligned}$$

Since  $[X - Y > 0] = [X > Y] = \cup_{q \in \mathbf{Q}} [X > q \geq Y]$  and similarly for  $[X - Y < 0]$ , this yields, by summing over rationals  $q$ ,

$$0 = E(X - Y)1_{[X - Y > 0]} - E(X - Y)1_{[X - Y < 0]} = E|X - Y|.$$

But this implies  $P(|X - Y| = 0) = 1$ , or  $P(X = Y) = 1$ .

5. Exercise E9.1, PwMG, page 231: show that if  $X \in L_1(\Omega, \mathcal{F}, P)$ ,  $Y \in L_1(\Omega, \mathcal{G}, P)$ , and  $E(X1_G) = E(Y1_G)$  for all  $G$  in a  $\bar{\pi}$ -system  $\mathcal{G}_0$  generating  $\mathcal{G}$ , then the same equality holds for all  $G \in \mathcal{G}$ . (And then  $Y = E(X|\mathcal{G})!$ )

**Solution:** One way to do this is from the  $\pi - \lambda$ -theorem: Let the  $\bar{\pi}$ -system be denoted by  $\mathcal{G}_0$ . Let  $\mathcal{H} \equiv \{G \in \mathcal{F} : E(X1_G) = E(Y1_G)\}$ . Then  $\mathcal{G}_0 \subset \mathcal{H}$ . Suppose that  $A, B \in \mathcal{H}$  with  $A \supset B$ . Then

$$\begin{aligned} E(X1_{A \setminus B}) &= E(X(1_A - 1_B)) = E(X1_A) - E(X1_B) \\ &= E(Y1_A) - E(Y1_B) = E(Y(1_A - 1_B)) = E(Y1_{A \setminus B}) \end{aligned}$$

and hence  $A \setminus B \in \mathcal{H}$ . Now suppose that  $\{A_n\} \subset \mathcal{H}$  with  $A_n \nearrow A$ . Then  $E(X1_{A_n}) = E(Y1_{A_n})$  for each  $n$ , and we have both  $X1_{A_n} \rightarrow X1_A$ , and  $Y1_{A_n} \rightarrow Y1_A$ , with  $|X1_{A_n}| \leq |X|$  and  $|Y1_{A_n}| \leq |Y|$  where  $X, Y \in L_1$ . Hence, by the above equality for each  $n$  and the dominated convergence theorem twice,

$$E(X1_A) = \lim_n E(X1_{A_n}) = \lim_n E(Y1_{A_n}) = E(Y1_A).$$

Therefore  $A \in \mathcal{H}$ . Thus  $\mathcal{H}$  is a  $\lambda$ -system. So by the  $\pi - \lambda$ -theorem,  $\sigma[\mathcal{G}_0] = \mathcal{G} \subset \mathcal{H}$ ; i.e. the equality holds for all  $G \in \mathcal{G}$ .