## AMS 261: Probability Theory (Fall 2017)

## Homework 4 solutions

1. Consider a sequence  $\{X_n:n=1,2,...\}$  of  $\overline{\mathbb{R}}$ -valued random variables defined on the same probability space  $(\Omega,\mathcal{F},P)$ . Assume that the sequence is (pointwise) increasing, that is, for all n and for each  $\omega\in\Omega,\,X_n(\omega)\leq X_{n+1}(\omega)$ . Moreover, assume that  $\mathrm{E}(X_1)>-\infty$ . Denote by X the pointwise limit of  $\{X_n:n=1,2,...\}$ , that is, for each  $\omega\in\Omega,\,X(\omega)=\lim_{n\to\infty}X_n(\omega)$ . Prove that  $\mathrm{E}(X)=\lim_{n\to\infty}\mathrm{E}(X_n)$ . Solution: Since  $\{X_n:n=1,2,...\}$  is a (pointwise) increasing sequence of random variables, it is easy to show that the sequence of the corresponding positive parts,  $\{X_n^+:n=1,2,...\}$ , is increasing with limit given by  $X^+$ . Therefore, applying the MCT to the  $\overline{\mathbb{R}}^+$ -valued random variables  $X_n^+$ , we obtain

$$\lim_{n \to \infty} \mathcal{E}(X_n^+) = \mathcal{E}(X^+). \tag{1.1}$$

Similarly, note that  $\{-X_n^-:n=1,2,...\}$  is an increasing sequence of  $\overline{\mathbb{R}}^-$ -valued random variables. Since  $X_1 \leq X_2$  and  $\mathrm{E}(X_1) > -\infty$ , we have that  $\mathrm{E}(X_2)$  exists and  $-\infty < \mathrm{E}(X_1) \leq \mathrm{E}(X_2)$  (Fristedt & Gray, 1997, Chapter 4, Theorem 9(iv)). Applying the same argument, we get that  $\mathrm{E}(X_n) > -\infty$ , for each n, as well as that  $\mathrm{E}(X) > -\infty$ , which implies that  $\mathrm{E}(X_n^-) < \infty$ , for all n, as well as  $\mathrm{E}(X^-) < \infty$ . Next, since  $\mathrm{E}(X_1^-) < \infty$ , we conclude that  $X_1^-$  is almost surely finite, that is,  $-X_1^- > -\infty$ , almost surely, and thus  $c = \inf\{-X_1^-(\omega): \omega \in \Omega\} > -\infty$ . Now,  $\{-X_n^- - c: n=1,2,...\}$  is an increasing sequence of  $\overline{\mathbb{R}}^+$ -valued random variables, and the MCT yields

$$\lim_{n \to \infty} \mathcal{E}(X_n^-) = \mathcal{E}(X^-). \tag{1.2}$$

The result can now be obtained by combining (1.1) and (1.2), noting that  $\lim_{n\to\infty} (\mathbb{E}(X_n^+) - \mathbb{E}(X_n^-))$  is well defined because  $\mathbb{E}(X_n^-) < \infty$ , for all n.

2. Let  $\{X_n : n = 1, 2, ...\}$  be a countable sequence of  $\overline{\mathbb{R}}^+$ -valued random variables defined on a common probability space  $(\Omega, \mathcal{F}, P)$ , and assume that  $\mathrm{E}(\sum_{n=1}^{\infty} X_n) < \infty$ . Show that  $\mathrm{E}\left(\sum_{n=1}^{\infty} X_n\right) = \sum_{n=1}^{\infty} \mathrm{E}(X_n)$ .

**Solution:** For n=1,2,..., define  $Y_n=\sum_{j=1}^n X_j$ . Then the sequence of  $\overline{\mathbb{R}}^+$ -valued random variables  $\{Y_n:n=1,2,...\}$ , defined on  $(\Omega,\mathcal{F},P)$ , is increasing, since each of the  $X_j$  is  $\overline{\mathbb{R}}^+$ -valued. Denote by Y the pointwise limit of the  $Y_n$ , i.e., for each  $\omega\in\Omega$ ,  $Y(\omega)=\lim_{n\to\infty}\sum_{j=1}^n X_j(\omega)=\sum_{n=1}^\infty X_n(\omega)$ . Then, using the MCT and additivity of expectation,

$$E\left(\sum_{n=1}^{\infty} X_n\right) = E(Y) = \lim_{n \to \infty} E(Y_n) = \lim_{n \to \infty} \sum_{j=1}^{n} E(X_j) = \sum_{n=1}^{\infty} E(X_n).$$

(Note that the assumption  $E(\sum_{n=1}^{\infty} X_n) < \infty$  implies that  $\sum_{n=1}^{\infty} X_n$  is an almost surely finite random variable, but is not strictly needed.)

3. Let  $\{X_n : n = 1, 2, ...\}$ ,  $\{Y_n : n = 1, 2, ...\}$ , and  $\{Z_n : n = 1, 2, ...\}$  be sequences of  $\mathbb{R}$ -valued random variables (all the random variables are defined on the same probability space). Assume that: (a)  $\mathrm{E}(X_n)$  and  $\mathrm{E}(Z_n)$  exist for all n and are finite; (b) each of the three sequences converges almost surely (denote by X, Y, and Z the respective almost sure limits); (c)  $\mathrm{E}(X)$ ,  $\mathrm{E}(Y)$ , and  $\mathrm{E}(Z)$  exist and are finite; (d)  $X_n \leq Y_n \leq Z_n$  almost surely; (e)  $\lim_{n\to\infty} \mathrm{E}(X_n) = \mathrm{E}(X)$ , and  $\lim_{n\to\infty} \mathrm{E}(Z_n) = \mathrm{E}(Z)$ . Show that  $\lim_{n\to\infty} \mathrm{E}(Y_n) = \mathrm{E}(Y)$ .

Solution: Consider the sequence of random variables  $\{Z_n - Y_n : n = 1, 2, ...\}$ . Based on assumption (d),  $Z_n - Y_n \ge 0$ , almost surely, and, therefore, using the Fatou lemma,

$$E(\liminf_{n \to \infty} (Z_n - Y_n)) \le \liminf_{n \to \infty} E(Z_n - Y_n).$$
(3.1)

Using assumption (b), we obtain that the almost sure limit of the sequence  $\{Z_n - Y_n : n = 1, 2, ...\}$  is given by Z - Y, and so  $\liminf_{n \to \infty} (Z_n - Y_n) = \lim_{n \to \infty} (Z_n - Y_n) = Z - Y$ , almost surely. Therefore, using properties of the  $\liminf$  for numerical sequences, (3.1) yields

$$\begin{array}{ll} \mathrm{E}(Z-Y) & \leq & \lim\inf_{n\to\infty}\mathrm{E}(Z_n-Y_n) = \liminf_{n\to\infty}\{\mathrm{E}(Z_n)-\mathrm{E}(Y_n)\} \\ & = & \liminf_{n\to\infty}\mathrm{E}(Z_n) + \liminf_{n\to\infty}\{-\mathrm{E}(Y_n)\} = \mathrm{E}(Z) - \limsup_{n\to\infty}\mathrm{E}(Y_n), \end{array}$$

since  $E(Z) = \lim_{n\to\infty} E(Z_n) = \liminf_{n\to\infty} E(Z_n)$  (assumption (e)). Rearranging terms in the above inequality, we have  $E(Y) \ge \limsup_{n\to\infty} E(Y_n)$ .

Analogously, consider the sequence  $\{Y_n - X_n : n = 1, 2, ...\}$ , which is, almost surely, non-negative, and

Analogously, consider the sequence  $\{Y_n-X_n:n=1,2,...\}$ , which is, almost surely, non-negative, and converges, almost surely, to Y-X, based on assumptions (d) and (b), respectively. Hence,  $\mathrm{E}(Y)-\mathrm{E}(X)=\mathrm{E}(Y-X)=\mathrm{E}(\lim_{n\to\infty}(Y_n-X_n))=\mathrm{E}(\liminf_{n\to\infty}(Y_n-X_n))$ , and, thus, using, again, the Fatou lemma and properties of the  $\liminf_{n\to\infty}\mathrm{E}(Y)-\mathrm{E}(X)\leq \liminf_{n\to\infty}\mathrm{E}(Y_n-X_n)=\liminf_{n\to\infty}\{\mathrm{E}(Y_n)-\mathrm{E}(X_n)\}=\lim\inf_{n\to\infty}\mathrm{E}(Y_n)-\mathrm{E}(X)$ , since  $\liminf_{n\to\infty}\mathrm{E}(X_n)=\lim_{n\to\infty}\mathrm{E}(X_n)=\mathrm{E}(X)$  from assumption (e). Hence,  $\mathrm{E}(Y)\leq \liminf_{n\to\infty}\mathrm{E}(Y_n)$ , which, combined with  $\mathrm{E}(Y)\geq \limsup_{n\to\infty}\mathrm{E}(Y_n)$ , proves the result.

- 4. Let  $\{X_n:n=1,2,...\}$  be a countable sequence of  $\mathbb{R}$ -valued random variables defined on a common probability space  $(\Omega,\mathcal{F},P)$ . Assume that there exist finite real constants p>1 and K>0 such that  $\sup_n \mathbb{E}(|X_n|^p) \leq K$ . Show that  $\{X_n:n=1,2,...\}$  is uniformly integrable. Solution: For any c>0, we can write  $\mathbb{E}(|X_n|1_{(|X_n|\geq c)})=\mathbb{E}(|X_n|^p|X_n|^{1-p}1_{(|X_n|\geq c)})\leq c^{1-p}\mathbb{E}(|X_n|^p),$  since p>1. Therefore,  $\sup_n \mathbb{E}(|X_n|1_{(|X_n|\geq c)})\leq c^{1-p}\sup_n \mathbb{E}(|X_n|^p)\leq Kc^{1-p},$  using the assumption. Hence, finally,  $\lim_{c\to\infty}\sup_n \mathbb{E}(|X_n|1_{(|X_n|\geq c)})\leq \lim_{c\to\infty}(Kc^{1-p})=0$ , proving the result.
- 5. Let X be an  $\mathbb{R}$ -valued random variable, defined on probability space  $(\Omega, \mathcal{F}, P)$ , with finite expectation  $\mu = \mathrm{E}(X)$  and finite standard deviation  $\sigma = \{\mathrm{Var}(X)\}^{1/2}$ . Prove that for any  $0 \le z \le \sigma$ ,

$$P(\{\omega \in \Omega: |X(\omega) - \mu| \geq z\}) \geq \frac{\sigma^4 \{1 - (z/\sigma)^2\}^2}{\operatorname{E}(|X - \mu|^4)}.$$

**Solution:** Let  $Y = |X - \mu|^2$ . We have  $E(Y) = E(|X - \mu|^2) = Var(X) < \infty$ , by assumption. If  $E(Y^2) = E(|X - \mu|^4) = \infty$ , the inequality holds true (the right hand side is 0 in this case). The case  $E(Y^2) = 0$  is not of interest for the inequality (the right hand side is not well defined in this case); note that if  $E(Y^2) = 0$  (and since  $E(Y) < \infty$ ), Y is almost surely equal to a finite constant. Therefore, consider the case  $0 < E(Y^2) < \infty$ . The result is obtained by applying to random variable Y the inequality that can be viewed as a complement to Chebyshev inequality (Fristedt & Gray, 1997, Corollary 5.5; proved in class). In particular, setting  $\lambda = z^2/\sigma^2$ , for any  $0 \le z \le \sigma$ , we have (note that  $\lambda \in [0,1]$ )

$$P(\left\{\omega \in \Omega : |X(\omega) - \mu|^2 \ge z^2 \sigma^{-2} \mathrm{E}(|X - \mu|^2)\right\}) \ge \left(1 - \frac{z^2}{\sigma^2}\right)^2 \frac{\{\mathrm{E}(|X - \mu|^2)\}^2}{\mathrm{E}(|X - \mu|^4)},$$

which yields the result noting that  $\sigma^2 = E(|X - \mu|^2) < \infty$ .

- 6. Let  $\{X_n:n=1,2,...\}$  be a sequence of  $\mathbb{R}$ -valued random variables defined on a common probability space  $(\Omega,\mathcal{F},P)$ . Suppose there exists an  $\mathbb{R}^+$ -valued random variable Y, defined on  $(\Omega,\mathcal{F},P)$ , such that  $\mathrm{E}(Y)<\infty$  and  $|X_n|\leq Y$ , almost surely, for all n. Show that  $\{X_n:n=1,2,...\}$  is uniformly integrable. Solution: Fix c>0. Because  $|X_n|\leq Y$ , almost surely, for all n, we have  $1_{(|X_n|\geq c)}\leq 1_{(Y\geq c)}$ , almost surely, for all n. By combining the above inequalities,  $|X_n|1_{(|X_n|\geq c)}\leq Y1_{(Y\geq c)}$ , almost surely, for all n. Therefore,  $\mathrm{E}(|X_n|1_{(|X_n|\geq c)})\leq \mathrm{E}(Y1_{(Y\geq c)})$ , for all n, and so  $\sup_n \mathrm{E}(|X_n|1_{(|X_n|\geq c)})\leq \mathrm{E}(Y1_{(Y\geq c)})$ . Next,  $\lim_{c\to\infty}\sup_n \mathrm{E}(|X_n|1_{(|X_n|\geq c)})\leq \lim_{c\to\infty}\mathrm{E}(Y1_{(Y\geq c)})=0$ , and thus  $\lim_{c\to\infty}\sup_n \mathrm{E}(|X_n|1_{(|X_n|\geq c)})=0$ . (Note that the result  $\lim_{c\to\infty}\mathrm{E}(Y1_{(Y\geq c)})=0$  was proved in class, using the assumptions that  $Y\geq 0$  and  $\mathrm{E}(Y)<\infty$ , and applying the DCT to the sequence  $Z_k=Y1_{(Y\geq k)}\leq Y$ .)
- 7. Consider a countable sequence  $\{X_n: n=1,2,...\}$  of  $\overline{\mathbb{R}}$ -valued random variables, defined on a common probability space  $(\Omega,\mathcal{F},P)$ , and an increasing function  $G:[0,\infty)\to[0,\infty)$ , which satisfies  $\lim_{t\to\infty}\{t^{-1}G(t)\}=\infty$  and  $0<\sup_n\mathbb{E}\{G(|X_n|)\}<\infty$ . Prove that  $\{X_n: n=1,2,...\}$  is uniformly integrable. Solution: Fix  $\varepsilon>0$  and let  $A=\varepsilon^{-1}\sup_n\mathbb{E}\{G(|X_n|)\}$  (we have  $0< A<\infty$ , by assumption). Because  $\lim_{t\to\infty}\{t^{-1}G(t)\}=\infty$ , we can find large c (which depends on  $\varepsilon$ ) such that

$$t^{-1}G(t) \ge A, \quad \forall t \ge c. \tag{7.1}$$

For n=1,2,..., let  $Y_n=|X_n|1_{(|X_n|\geq c)}$ . For any  $\omega\in\Omega$  with  $|X_n(\omega)|\geq c$ , we have  $Y_n(\omega)\geq c$ , and using (7.1),  $G(Y_n(\omega))\geq AY_n(\omega)$ . Moreover, for any  $\omega\in\Omega$  with  $|X_n(\omega)|< c$ , we have  $Y_n(\omega)=0$ , and since  $G(0)\geq 0$ , the inequality  $G(Y_n(\omega))\geq AY_n(\omega)$  is still valid. Therefore, for any n=1,2,...,  $A|X_n|1_{(|X_n|\geq c)}\leq G(|X_n|1_{(|X_n|\geq c)})\leq G(|X_n|)$ , using the assumption that G is increasing. Taking expectations,  $E(|X_n|1_{(|X_n|\geq c)})\leq A^{-1}E\{G(|X_n|)\}$ , and therefore,  $\sup_n E(|X_n|1_{(|X_n|\geq c)})\leq A^{-1}\sup_n E\{G(|X_n|)\}=\varepsilon$ , which provides the result, since the inequality above holds true for any  $\varepsilon>0$  and any c'>c.