

## Math 563 - Take Home Midterm Solutions

1. Let  $f(x)$  be a Borel measurable real-valued function on  $[0, 1]$  with  $\int_0^1 f^2(x) dx < \infty$ . Let  $\{U_n\}_{n=1}^\infty$  be an independent sequence of random variables, each of which is uniformly distributed on  $[0, 1]$ , i.e., the distribution of  $U_n$  is Lebesgue measure on  $[0, 1]$ . Let

$$S_n = \frac{1}{n} \sum_{i=1}^n f(U_i)$$

Prove that  $S_n$  converges to the constant  $\int_0^1 f(x) dx$  in probability.

**SOLUTION:** By a theorem from class, the independence of the  $U_i$  implies that the sequence  $f(U_i)$  is independent. By the law of the unconscious statistician,

$$E[f^2(U_i)] = \int_0^1 f^2(x) dx < \infty$$

The finiteness of the second moment implies the first moment is finite and

$$E[f(U_i)] = \int_0^1 f(x) dx$$

It is easy to check that the  $f(U_i)$  are identically distributed since the  $U_i$  are. So by the weak law of large numbers,  $S_n$  converges in probability to the mean of  $f(U_i)$ , i.e., to the constant  $\int_0^1 f(x) dx$ .

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2. Let  $X_n$  be an independent, identically distributed sequence of non-negative random variables. Prove that  $EX_1 < \infty$  if and only if  $P(X_n \geq n \text{ i.o.}) = 0$ .

**SOLUTION:** By the Borel-Cantelli lemma,  $P(X_n > n \text{ i.o.}) = 0$  if and only if  $\sum_n P(X_n > n) < \infty$ . Since they are identically distributed,  $P(X_n > n) = P(X_1 > n)$ . So we have reduced the problem to showing that  $EX_1 < \infty$  if and only if  $\sum_n P(X_1 > n) < \infty$ . By a homework problem,

$$E[X_1] = \int_0^\infty P(X_1 \geq x) dx$$

Note that  $P(X_1 \geq x)$  is a decreasing function of  $x$ . So

$$\sum_{n=1}^\infty P(X_1 \geq n) \leq \int_0^\infty P(X_1 \geq x) dx \leq \sum_{n=0}^\infty P(X_1 \geq n)$$

which proves the needed result.

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3. Let  $A_n$  be a sequence of events which converges to the event  $A$  in the following sense. If  $\omega \in A$ , then there is an  $N$  such that that  $n \geq N$  implies  $\omega \in A_n$ . If  $\omega \notin A$ , then there is an  $N$  such that that  $n \geq N$  implies  $\omega \notin A_n$ . Prove that  $P(A_n)$  converges to  $P(A)$ .

**SOLUTION:** If  $1_A(\omega) = 1$ , then there is an  $N$  such that that  $n \geq N$  implies  $1_{A_n}(\omega) = 1$ . And if  $1_A(\omega) = 0$ , then there is an  $N$  such that that  $n \geq N$  implies  $1_{A_n}(\omega) = 0$ . Thus  $1_{A_n}$  converges to  $1_A$  pointwise for all  $\omega$ . We have  $|1_{A_n}| \leq 1$  and  $E[1] < \infty$ . So by the dominated convergence theorem,  $E[1_{A_n}]$  converges to  $E[1_A]$ . Since  $E[1_{A_n}] = P(A_n)$  and  $E[1_A] = P(A)$ , this proves the result.

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4. Let  $A$  be an event in  $(\Omega, \mathcal{F}, P)$  with  $P(A) > 0$ . Define a new probability measure on  $(\Omega, \mathcal{F})$  by  $Q(B) = P(A \cap B)/P(A)$ . Let  $X$  be a nonnegative random variable which is independent of  $A$ , meaning that  $\sigma(X)$  and  $\sigma(A)$  are independent. ( $\sigma(A)$  is just  $\{A, A^c, \Omega, \emptyset\}$ .) Prove that  $\int X dP = \int X dQ$ . Hint: start with a simple random variable  $X$ .

**SOLUTION:** Let  $Z$  be a simple random variable which is measurable with respect to  $\sigma(X)$ . (The hint notwithstanding, it is confusing to call the simple random variable  $X$ .) So

$$Z = \sum_{j=1}^m c_j 1_{E_j}$$

where the  $E_j$  are disjoint and in  $\sigma(X)$ . So  $E_j$  and  $A$  are independent. So  $Q(E_j) = P(E_j \cap A)/P(A) = P(E_j)P(A)/P(A) = P(E_j)$ . Thus  $\int Z dP = \int Z dQ$ .

Now we let  $X_n$  be a sequence of simple nonnegative random variables which increase to  $X$  pointwise and (this is crucial) are measurable with respect to  $\sigma(X)$ . In the standard construction of the  $X_n$ , the events involved in the definition of  $X_n$  are of the form  $X^{-1}(B)$  where  $B$  is an interval or half-infinite interval. So these events are in  $\sigma(X)$  and so these  $X_n$  are measurable with respect to  $\sigma(X)$ . So  $\int X_n dP = \int X_n dQ$ . Now let  $n \rightarrow \infty$  and use the monotone convergence theorem on both sides to get  $\int X dP = \int X dQ$ .

Here is different solution due to Ben. By a homework problem,  $\int X dQ = \int_0^\infty Q(X \geq x) dx$ . Now for all  $x$ , the event  $X \geq x$  is in  $\sigma(X)$  and so is independent of  $A$ . So  $Q(X \geq x) = P(\{X \geq x\} \cap A)/P(A) = P(\{X \geq x\})P(A)/P(A) = P(X \geq x)$

Thus  $\int_0^\infty Q(X \geq x)dx = \int_0^\infty P(X \geq x)dx = \int X dP$ , again using the homework problem.

5. Let  $X$  and  $Y$  be independent real valued random variables. Suppose that  $P(X = x) = 0$  for all real  $x$ .

- (a) Prove that  $P(X = Y) = 0$ .  
 (b) Prove that  $P(XY = 1) = 0$ .

**SOLUTION:**

Since  $X$  and  $Y$  are independent, their joint distribution is  $\mu_X \times \mu_Y$ . So

$$P(X = Y) = \int 1_A(x, y)d(\mu_X \times \mu_Y)$$

where  $A$  is the subset of the plane :  $A = \{(x, y) : x = y\}$ . So the indicator function  $1_A(x, y)$  is 1 if and only if  $x = y$ . So we will write it as  $1(x = y)$ . Using Fubini (note the integrand is nonnegative),

$$\begin{aligned} \int 1(x = y)d(\mu_X \times \mu_Y) &= \int \left( \int 1(x = y) d\mu_X(dx) \right) d\mu_Y(dy) \\ &= \int P(X = y)d\mu_Y(dy) = \int 0 d\mu_Y(dy) = 0 \end{aligned}$$

The proof of (b) is almost the same. Now  $A = \{(x, y) : xy = 1\}$ . So in place of  $P(X = y)$  we get  $P(X = 1/y)$ , which is also zero.

Another approach is to write  $P(X = Y)$  as  $P(X + (-Y) = 0)$ . Now  $X$  and  $-Y$  are independent, so the distribution their sum is the convolution of their distributions ...

6. Suppose  $X$  and  $Y$  are independent, identically distributed *non-negative* random variables. They have a density  $f(x)$ . Let  $Z = X - Y$ . The density of  $Z$  is  $\exp(-|x|)/2$ . ( $Z$  takes on all real values.) Find  $f(x)$ .

**SOLUTION:** Compute the characteristic function of  $Z$  :

$$\begin{aligned} \int e^{itx} \frac{1}{2} e^{-|x|} dx &= \frac{1}{2} \int_0^\infty e^{itx-x} dx + \frac{1}{2} \int_{-\infty}^0 e^{itx+x} dx \\ &= \frac{1}{2} \left( \frac{1}{1-it} + \frac{1}{1+it} \right) = \frac{1}{1+t^2} \end{aligned}$$

Let  $\beta(t)$  be the characteristic function of  $X$  and  $Y$ . Then the characteristic function of  $-Y$  is  $\beta(-t)$ . So the characteristic function of  $X - Y = X + (-Y)$  is  $\beta(t)\beta(-t)$ . We can factor  $1/(1+t^2)$  as the product of  $1/(1+it)$  and  $1/(1-it)$ . Note that  $1/(1+it)$  is the characteristic function of an exponential distribution with mean 1. So we can take  $X$  and  $Y$  to have this distribution.