

# Math 275A: Homework 3

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## 1.5.4

Claim: If  $f$  is integrable and  $E_m$  are disjoint sets with union  $E$  then

$$\sum_{m=0}^{\infty} \int_{E_m} f \, d\mu = \int_E f \, d\mu$$

So if  $f \geq 0$ , then  $\nu(E) = \int_E f \, d\mu$  defines a measure.

Proof: The easiest way to show this is to apply the dominated convergence theorem. Define  $f_n = f \mathbf{1}_{A_n}$  for  $A_n = \cup_{m=0}^n E_m$ . Since  $A_n \uparrow E$  it follows that  $f_n \rightarrow f$  on  $E$  a.e. By construction, each  $f_n$  is dominated by  $|f|$  in that  $|f_n| \leq |f|$ . Given that  $f$ , and therefore  $|f|$ , is integrable, we can apply the DCT to our sequence. Thus  $\int_E f_n \, d\mu \rightarrow \int_E f \, d\mu$ .

To prove the claim, note that each  $A_n$  over which each  $f_n$  is defined is a union of  $n$  disjoint sets so that

$$\int_E f_n \, d\mu = \lim_n \int_{A_n} f \, d\mu = \lim_n \sum_{m=0}^n \int_{E_m} f \, d\mu = \sum_{m=0}^{\infty} \int_{E_m} f \, d\mu$$

The second equality comes from the linearity property of integration and the fact that we can write  $f_n$  as  $\sum_{m=0}^n f \mathbf{1}_{E_m}$  for disjoint sets  $E_m$ . If, in addition,  $f \geq 0$  such that  $\nu(E) = \int_E f \, d\mu \geq 0$  for every set  $E$ , then  $\nu(E)$  satisfies the definition of a measure.

## 1.5.8

Claim: Show that if  $f$  is integrable on  $[a, b]$ ,  $g(x) = \int_{[a, x]} f(y) \, dy$  is continuous on  $(a, b)$ .

Proof: Given that  $g : \mathbb{R} \rightarrow \mathbb{R}$  we just need to show continuity in terms of limits of sequences. Take any sequence  $x_n \rightarrow x$  where  $x_n, x \in (a, b)$ . Then define  $f_n = f \mathbf{1}_{[a, x_n]}$  such that the functions  $f_n$  converge to  $f \mathbf{1}_{[a, x]}$  a.e. Since  $f$  is integrable over  $[a, b]$ , the absolute value of each  $f_n$  is upper-bounded by an integrable function  $|f|$  on  $[a, b]$ . Thus we can apply the Dominated Convergence Theorem to conclude that

$$g(x_n) = \int_{[a, x_n]} f(y) \, dy = \int_{[a, b]} f_n(y) \, dy \rightarrow \int_{[a, b]} f(y) \mathbf{1}_{[a, x]} \, dy = \int_{[a, x]} f(y) \, dy = g(x)$$

We did not make any assumptions about the sequence  $x_n$  other than convergence to  $x$ , so continuity follows.

## 1.6.5

Claim: Show that: (i) if  $\epsilon > 0$ ,  $\inf\{P(|X| > \epsilon) : EX = 0, \text{ var}(X) = 1\} = 0$ ; (ii) if  $y \geq 1$ ,  $\sigma^2 \in (0, \infty)$ ,  $\inf\{P(|X| > y) : EX = 1, \text{ var}(X) = \sigma^2\} = 0$

Proof: Given that my own understanding of set theory is lacking, I'll make the assumption that the infimums in the claim are taken over all possible random variables  $X$  defined on  $([0, 1], \mathcal{R}, \mu)$  where  $\mu$  is taken to be the Lebesgue measure.

(i) For a given  $\epsilon > 0$ , define a sequence of random variables  $X_n = \epsilon\sqrt{n}\mathbf{1}_{E_n} - \epsilon\sqrt{n}\mathbf{1}_{E_{-n}}$  where  $E_n = (0, \frac{1}{2n\epsilon^2})$  and  $E_{-n} = (-\frac{1}{2n\epsilon^2}, 0)$ . Then

$$EX_n = \sqrt{n}\epsilon\mu(E_n) - \sqrt{n}\epsilon\mu(E_{-n}) = 0$$

and

$$\text{var}(X_n) = n\epsilon^2\mu(E_n) + n\epsilon^2\mu(E_{-n}) = \frac{2n\epsilon^2}{2n\epsilon^2} = 1$$

while

$$P(|X_n| > \epsilon) = \mu(E_n) + \mu(E_{-n}) = \frac{1}{n\epsilon^2} \quad \text{for } n > 1$$

This probability goes to zero as  $n \rightarrow \infty$ , proving the claim.

(ii) Given  $y \geq 1$  and  $\sigma^2 \in (0, \infty)$ , define a sequence of random variables  $X_n = \sqrt{ny}\mathbf{1}_{E_n} - \sqrt{ny}\mathbf{1}_{E_{-n}} + \mathbf{1}_{[0,1]}$  where  $E_n = (0, \frac{\sigma^2}{2ny^2})$  and  $E_{-n} = (-\frac{\sigma^2}{2ny^2}, 0)$ . Then

$$EX_n = \sqrt{ny}\mu(E_n) - \sqrt{ny}\mu(E_{-n}) + \mu([0, 1]) = 1$$

and

$$\text{var}(X_n) = E(X_n - 1)^2 = ny^2\mu(E_n) + ny^2\mu(E_{-n}) = \frac{2ny^2\sigma^2}{2ny^2} = \sigma^2$$

Due to the way we've defined  $X_n$  and because  $y \geq 1$ ,  $|X_n(\omega)|$  only has the potential to be greater than  $y$  when  $\omega$  falls within  $E_n$  or  $E_{-n}$ . Thus

$$P(|X_n| > y) \leq \mu(E_n) + \mu(E_{-n}) = \frac{\sigma^2}{ny^2} \quad \text{for } n > 1$$

which goes to zero as  $n \rightarrow \infty$ , proving the claim.

## 1.6.8

Claim: Suppose that the probability measure  $\mu$  has  $\mu(A) = \int_A f(x) dx$  for all  $A \in \mathcal{R}$ . Use the proof technique of Theorem 1.6.9 to show that for any  $g$  with  $g \geq 0$  or  $\int |g(x)| \mu(dx) < \infty$  we have

$$\int g(x) \mu(dx) = \int g(x)f(x) dx$$

Proof: Let's go through the cases as in 1.6.9.

Case 1 (Indicator Functions): For some  $A \in \mathcal{R}$ , let  $g = \mathbf{1}_A$ . Then

$$\int g(x) \mu(dx) = \int \mathbf{1}_A \mu(dx) = P(X \in A) = \mu(A) = \int_A f(x) dx = \int \mathbf{1}_A(x)f(x)dx = \int g(x)f(x)dx$$

Case 2 (Simple Functions): Let  $g(x) = \sum_{n=1}^m c_n \mathbf{1}_{A_n}$  be some simple function where  $c_n \in \mathbb{R}$  and  $A_n \in \mathcal{R}$ . Then linearity of integration lets us write

$$\begin{aligned} \int g(x) \mu(dx) &= \int \sum_{n=1}^m c_n \mathbf{1}_{A_n}(x) \mu(dx) = \sum_{n=1}^m c_n \int \mathbf{1}_{A_n}(x) \mu(dx) \\ &= \sum_{n=1}^m c_n \int \mathbf{1}_{A_n}(x)f(x) dx = \int \sum_{n=1}^m c_n \mathbf{1}_{A_n}(x)f(x) dx = \int g(x)f(x) dx \end{aligned}$$

where Case 1 was applied to get the third equality.

Case 3 (Nonnegative Functions): If  $g \geq 0$  define

$$g_n(x) = ([2^n g(x)/2^n]) \wedge n$$

where  $[x]$  is the largest integer less than or equal to  $x$  and  $a \wedge b = \min\{a, b\}$ . As defined  $g_n$  are simple nonnegative functions such that  $g_n \uparrow g$  and  $g_n f \uparrow g f$ . Applying Case 2 and the Monotone Convergence Theorem (twice) yields

$$\int g(x) \mu(dx) = \lim_n \int g_n(x) \mu(dx) = \lim_n \int g_n(x) f(x) dx = \int g(x) f(x) dx$$

Case 4 (Integrable Functions): For the general case can write  $g(x) = g^+(x) - g^-(x)$ . That  $\int |g(x)| \mu(dx) < \infty$  guarantes  $\int g^+(x) \mu(dx)$  and  $\int g^-(x) \mu(dx)$  are finite. Thus

$$\int g(x) \mu(dx) = \int g^+(x) \mu(dx) - \int g^-(x) \mu(dx) = \int g^+(x) f(x) dx - \int g^-(x) f(x) dx = \int g(x) f(x) dx$$

thereby completing the proof.

### 1.6.13

Claim: If  $EX_1^- < \infty$  and  $X_n \uparrow X$ , then  $EX_n \uparrow EX$ .

Proof: Each  $X_n$  can be decomposed as  $X_n = X_n^+ - X_n^-$ .  $X_n \uparrow X$  implies that  $X_n^+ \uparrow X^+$  so the Monotone Convergence Theorem tells us that  $EX_n^+ \uparrow EX^+$ .

Similarly,  $X_n^- \downarrow X^-$  where each  $X_n^-$  is a nonnegative function. This implies that  $|X_n| \leq X_1$  for which we know that  $EX_1$  is finite. Thus we can apply the Dominated Convergence Theorem to determine  $EX_n^- \rightarrow EX^-$ .

Combing results, we have that

$$EX_n = EX_n^+ - EX_n^- \rightarrow EX^+ - EX^- = EX$$

To get monotonic convergence from bellow, observe that since  $X_n^- \downarrow X^-$  it follows that  $EX_n^-$  decreases with each  $n$  as  $n \rightarrow \infty$ . This combined with the monotonicity of  $EX_n^+$  implies  $EX_n \uparrow EX$ .