

**Recitation 11**

**1 On taking limits of random variables**

Consider the following problem. Suppose

$$P(B|A) \geq \frac{1}{2} \text{ and } P(C|B) \geq \frac{1}{2}.$$

Is it necessarily true that

$$P(C|A) \geq \frac{1}{4}?$$

**Solution:** No; let  $X$  be a uniform random variable in the interval  $[0, 4]$ . Let  $A = \{X \in [0, 2]\}$ ,  $B = \{X \in [1, 3]\}$ ,  $C = \{X \in [2, 4]\}$ . Then,  $P(B|A) = P(C|B) = 1/2$ , but  $P(C|A) = 0$ .  $\square$

In fact, we can strengthen this example. Indeed, suppose  $X$  is uniform over  $[0, K]$ , and  $A = \{X \in [0, 1]\}$ ,  $B = \{X \in [0, K]\}$ ,  $C = \{X \in [1, K]\}$ . Then  $P(B|A) = 1$ ,  $P(C|A) = 0$ , and  $P(C|B) = (K - 1)/K$ . If we pick  $K$  large,  $P(C|B)$  approaches 1. So it is quite possible that

$$P(B|A) = 1, P(C|B) = 1 - \epsilon, P(C|A) = 0,$$

regardless of how small  $\epsilon > 0$  is.

It is somewhat surprising therefore that it is not possible to have

$$P(B|A) = 1, P(C|B) = 1, P(C|A) = 0.$$

Indeed, let us write  $A \sqsubset B$  if  $A \cap B^c$  has measure 0. Observe that  $P(B|A) = 1$  is equivalent to<sup>1</sup>

$$A \sqsubset B.$$

So the conditions  $P(B|A) = 1$  and  $P(C|B) = 1$  can be rewritten as

$$A \sqsubset B, B \sqsubset C,$$

<sup>1</sup>Provided  $P(A) > 0$ , which we implicitly assume.

which necessarily implies  $A \subset C$ . Indeed,

$$P(A \cap C^c) = P(A \cap B \cap C^c) + P(A \cap B^c \cap C^c) = 0 + 0,$$

the first term being a subset of the measure-0 set  $B \cap C^c$ , and the second set being a subset of the measure-0 set  $A \cap B^c$ . So  $A \subset C$  and thus  $P(C|A) = 1$ .

What is the source of this discontinuity? What happens if we simply let  $K \rightarrow \infty$  in our counterexample? Unfortunately,  $X$  was defined to be uniform over  $[1, K]$ , and when we let  $K \rightarrow \infty$ , we do not get a random variable.

## 2 Convergence of densities vs convergence of distributions

Suppose  $f_n$  is the density of the random variable  $X_n$ , and

$$f_n \rightarrow f,$$

pointwise. It does not follow that  $f$  is the density of a random variable. As we had just argued in the previous section,

$$\frac{1}{n}1_{[0,n]} \rightarrow 0,$$

and of course the zero function is not a valid density. Another example is  $1_{[n,n+1]}$  which also converges to the zero function.

But suppose  $f_n \rightarrow f$  everywhere, and moreover  $f_n, f$  are all valid densities. What is the relationship of this convergence to the convergence of the distributions  $F_n$  and  $F$ ?

We will prove the following two statements.

**Claim 1:** It is possible that  $F_n \rightarrow F$  everywhere, that  $F_n$  has density  $f_n$ ,  $F$  has density  $f$ , and yet nowhere does  $f_n$  converge to  $f$ .

**Claim 2:** If  $f_n \rightarrow f$ , and  $f, f_n$  are valid distributions, then  $F_n \rightarrow F$  everywhere.

**Proof of Claim 1:** Break up the the interval  $[0, 1]$  into  $2^i$  intervals

$$[0, 1] = [0, \frac{1}{2^i}] \cup [\frac{1}{2^i}, \frac{2}{2^i}] \cup \dots \cup [\frac{2^i - 1}{2^i}, 1],$$

and let  $f_i$  be 2 on the first, third, ... of these intervals and 0 on the second, fourth, ... of them.

If  $F$  is the cdf of the  $U[0, 1]$  distributions, then its not hard to see that  $F_n \rightarrow F$ . Indeed,

$$\max_{x \in R} |F_n(x) - F(x)| = \frac{1}{2^i}.$$

On the other hand,  $f = 1_{[0,1]}$ , so  $f_n$  does not approach  $f$  anywhere.  $\square$

**Proof of Claim 2:** Define  $g_i = f_i - f$ , and let  $g_i = g_i^+ - g_i^-$  be the standard decomposition of  $g_i$  into positive and negative parts. Since  $f_i$  converges to  $f$  almost everywhere, we have that  $g_i^+$  and  $g_i^-$  both converge to 0 almost everywhere.

Since  $f_i$  is a PDF, it is nonnegative almost everywhere; and therefore,  $g_i \geq -f$  almost everywhere, which in turn implies  $g_i^- \leq f$  almost everywhere. So  $g_i^-$  is upper bounded by an integrable function. Thus we can interchange limit and integration when it comes to  $g_i^-$ , and in particular

$$\lim_i \int_{-\infty}^{+\infty} g_i^- = \int_{-\infty}^{+\infty} \lim_i g_i^- = 0.$$

But since  $\int_{-\infty}^{+\infty} f_i = 1 = \int_{-\infty}^{+\infty} f$ , it follows that

$$\int_{-\infty}^{+\infty} g_i^+ = \int_{-\infty}^{+\infty} g_i^-,$$

and therefore

$$\lim_i \int_{-\infty}^{+\infty} g_i^+ = \lim_i \int_{-\infty}^{+\infty} g_i^- = 0.$$

Now passing from integrals involving  $g_i^+$  and  $g_i^-$  to integrals involving  $g$ :

$$\lim_i \int_{-\infty}^{+\infty} |g_i| = \lim_i \left[ \int_{-\infty}^{+\infty} g_i^+ + \int_{-\infty}^{+\infty} g_i^- \right] = 0.$$

Now we use the last equation to prove convergence in distribution:

$$\begin{aligned} |F(x) - F_n(x)| &\leq \int_{-\infty}^x |f(u) - f_n(u)| du \\ &\leq \int_{-\infty}^{+\infty} |f(u) - f_n(u)| du \\ &= \int_{-\infty}^{+\infty} |g_n(u)| du \end{aligned}$$

and we have just shown that the last expression approaches 0.

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