

# Preliminary Research Exam

Ronak Mehta

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# A Foundations

## A.1 Measure Theory

Here, we state fundamental definitions and results of measure theory without proof, to be used primarily in Section A.2.

**Notation** We write  $f : (\Omega, \mathcal{F}) \rightarrow (S, \mathcal{S})$  to mean  $f : \Omega \rightarrow S$  is an  $(\mathcal{F}, \mathcal{S})$ -measurable function. We say  $f$  is  $\mathcal{F}$ -measurable if the codomain's  $\sigma$ -algebra  $\mathcal{S}$  is understood from context. When no such  $\mathcal{S}$  is specified, we understand it to be  $\mathcal{R}$ , the Borel  $\sigma$ -algebra.

**Proposition A.1.** *Given any measurable nonnegative function  $f : \Omega \rightarrow [0, \infty]$ , there is a sequence of nonnegative simple functions  $(f_n)_n$  with  $f_n \uparrow f$  pointwise.*

**Theorem A.2** (Monotone convergence theorem). *Let  $(\Omega, \mathcal{F}, \mu)$  be a common measure space,  $(f_n)_{n \geq 0}$  be a sequence of measurable functions from  $\Omega$  into  $[0, \infty]$ , which are increasing pointwise to limit function  $f : \Omega \rightarrow \mathbb{R}$ . Then,  $f$  is measurable, and*

$$\int f_n d\mu \uparrow \int f d\mu.$$

**Theorem A.3** (Dominated convergence theorem). *Let  $(\Omega, \mathcal{F}, \mu)$  be a common measure space,  $(f_n)_{n \geq 0}$  be a sequence of measurable functions from  $\Omega$  into  $[-\infty, \infty]$ , which converge pointwise to limit function  $f : \Omega \rightarrow \mathbb{R}$ . Suppose that there exists an integrable function  $h$  such that for each  $n$ ,  $|f_n| \leq h$  everywhere. Then,*

$$\lim_{n \rightarrow \infty} \int f_n d\mu = \int f d\mu.$$

**Definition A.4** (Generated  $\sigma$ -algebra). For a measurable function  $Z : \Omega \rightarrow \mathbb{R}$ , we define  $\sigma(Z)$  as the smallest  $\sigma$ -algebra (in the sense of inclusion)  $\mathcal{F}$  on  $\Omega$  such that  $Z$  is  $\mathcal{F}$ -measurable.

**Definition A.5** (Absolute continuity). Let  $\nu$  and  $\mu$  be measures defined on the same measurable space. Then,  $\nu$  is absolutely continuous with respect to  $\mu$  (written  $\nu \ll \mu$ ), if  $\mu(A) = 0$  implies  $\nu(A) = 0$  for all measurable sets  $A$ .

**Definition A.6** ( $\sigma$ -finite measure). A measure  $\mu$  on measurable space  $(\Omega, \mathcal{F})$  is called  $\sigma$ -finite if there exists a sequence  $A_1, A_2, \dots \in \mathcal{F}$  such that

- $\mu(A_i) < \infty$  for each  $i = 1, 2, \dots$ , and
- $\bigcup_{i=1}^{\infty} A_i = \Omega$ .

In other words, the entire set can be written as a countable union of sets of finite measure.

**Theorem A.7** (Radon-Nikodym theorem). *Let  $\nu$  and  $\mu$  be two  $\sigma$ -finite measures on  $(\Omega, \mathcal{F})$ . If  $\nu \ll \mu$ , then there is a  $(\mathcal{F}, \mathcal{R})$ -function  $f : \Omega \rightarrow \mathbb{R}$  such that for all  $A \in \mathcal{F}$ ,*

$$\int_A f d\mu = \nu(A).$$

The function  $f$  is written  $\frac{d\nu}{d\mu}$  and called the Radon-Nikodym derivative.

## A.2 Conditional Probability

In this section, we define conditional probability in the language of measure theory. Let  $(\Omega, \mathcal{F}_0, P)$  be a probability space,  $\mathcal{F} \subseteq \mathcal{F}_0$  be a  $\sigma$ -algebra,  $(\mathbb{R}, \mathcal{R})$  be the real line equipped with the Borel  $\sigma$ -algebra, and  $X : \Omega \rightarrow \mathcal{R}$  be a  $(\mathcal{F}_0, \mathcal{R})$ -measurable random variable.

**Definition A.8** (Conditional expectation). Let  $\mathbb{E}[|X|] < \infty$ . We define the *conditional expectation of  $X$  given  $\mathcal{F}$* , or  $\mathbb{E}[X|\mathcal{F}]$ , to be any random variable  $Y$  that satisfies

- (i)  $Y$  is  $(\mathcal{F}, \mathcal{R})$ -measurable, and
- (ii) for all  $A \in \mathcal{F}$ ,  $\int_A X dP = \int_A Y dP$ .

Such a  $Y$  is called a *version of  $\mathbb{E}[X|\mathcal{F}]$* .

The  $\sigma$ -algebra  $\mathcal{F}$  represents a subset of events which is analogous to the conditioning random variable in the undergraduate probability notion of conditional expectation.

**Definition A.9** (Variants of conditional expectation). For conditional probability, we define the following function on  $\mathcal{R}$ :

$$A \mapsto \mathbb{P}[X \in A|\mathcal{F}] = \mathbb{E}[1_{X^{-1}(A)}|\mathcal{F}].$$

For an arbitrary measurable function  $Z : \Omega \rightarrow \mathbb{R}$ , we define

$$\mathbb{E}[X|Z] = \mathbb{E}[X|\sigma(Z)].$$

Next, we establish some properties of conditional expectation.

**Lemma A.10** (Integrability). *If  $Y = \mathbb{E}[X|\mathcal{F}]$  (a.e.), then  $Y$  is integrable.*

*Proof.* Let  $A = \{\omega \in \Omega : Y(\omega) > 0\}$ , which is a  $\mathcal{F}$ -measurable set, as  $(0, \infty) \in \mathcal{R}$  and  $Y$  is a measurable function. Then, use property (ii) twice.

$$\begin{aligned} \int_A Y dP &= \int_A X dP \leq \int_A |X| dP. \\ \int_{A^c} -Y dP &= \int_{A^c} -X dP \leq \int_{A^c} |X| dP. \end{aligned}$$

Then,

$$\mathbb{E}[|Y|] = \int_A Y dP + \int_{A^c} -Y dP \leq \int_A |X| dP + \int_{A^c} |X| dP = \mathbb{E}[|X|] < \infty.$$

□

**Lemma A.11** (Uniqueness). *If  $Y'$  also satisfies (i) and (ii),*

$$\int_A Y dP = \int_A Y' dP \text{ for all } A \in \mathcal{F}.$$

*Proof.* Take any  $\epsilon > 0$  and let  $A = \{\omega \in \Omega : Y(\omega) - Y'(\omega) \leq \epsilon\}$ , which is  $\mathcal{F}$  measurable because  $Y - Y'$  is measurable and  $[\epsilon, \infty) \in \mathcal{R}$ . Then,

$$\begin{aligned} 0 &= \int_A X - X dP \\ &= \int_A X dP - \int_A X dP \\ &= \int_A Y dP - \int_A Y' dP \\ &= \int_A Y - Y' dP \\ &\geq \epsilon P(A), \end{aligned}$$

indicating that  $P(A) = P(Y - Y' \geq \epsilon) = 0$ , or that  $Y \geq Y'$  a.e.. Switching the roles of  $Y$  and  $Y'$  gives that  $Y = Y'$  a.e..  $\square$

**Lemma A.12** (Existence). *There exists a  $Y$  that satisfies the defining properties of conditional expectation.*

*Proof.* First, suppose that  $X \geq 0$ , let  $\mu = P$ , and define

$$\nu(A) := \int_A X dP \text{ for any } A \in \mathcal{F}.$$

The monotone convergence theorem, along with a sequence of non-negative simple functions  $X_n : \Omega \rightarrow [0, \infty)$  that approach  $X$  pointwise, can be used to show that  $\nu$  is a measure. Then, the definition clearly shows that  $\mu(A) = 0 \implies \nu(A) = 0$ , so  $\nu \ll \mu$ . Thus, by the Radon-Nikodym theorem,

$$\int_A X dP = \nu(A) = \int_A \frac{d\nu}{d\mu} dP.$$

Letting  $A = \Omega$ , we have that  $Y := \frac{d\nu}{d\mu}$  is  $(\mathcal{F}, \mathcal{R})$ -measurable and integrable, and because its non-negative,  $\mathbb{E}[|Y|] < \infty$ . Thus, both properties are satisfied, and  $Y$  is a version of  $\mathbb{E}[X|\mathcal{F}]$ .

For the general case, let  $X^+$  and  $X^-$  be the nonnegative and nonpositive parts of  $X$ , and let  $Y_1 = \mathbb{E}[X^+|\mathcal{F}]$  and  $Y_2 = \mathbb{E}[X^-|\mathcal{F}]$ . Now,  $Y_1 - Y_2$  is integrable, and for all  $A \in \mathcal{F}$ , we have

$$\begin{aligned} \int_A X dP &= \int_A X^+ dP - \int_A X^- dP \\ &= \int_A Y_1 dP - \int_A Y_2 dP \\ &= \int_A (Y_1 - Y_2) dP. \end{aligned}$$

Thus,  $Y_1 - Y_2$  is a version of  $\mathbb{E}[X|\mathcal{F}]$ .  $\square$

**Proposition A.13** (Properties of conditional expectation). *The following hold:*

1. **Linearity:** For any  $a \in \mathbb{R}$ ,

$$\mathbb{E}[aX + Y|\mathcal{F}] = a\mathbb{E}[X|\mathcal{F}] + \mathbb{E}[Y|\mathcal{F}].$$

2. **Monotonicity:** If  $X \leq Y$  a.e., then

$$\mathbb{E}[X|\mathcal{F}] \leq \mathbb{E}[Y|\mathcal{F}] \text{ a.e..}$$

3. **Preservation of limits:** If  $X_n \geq 0$  and  $X_n \uparrow X$ , then

$$\mathbb{E}[X_n|\mathcal{F}] \uparrow \mathbb{E}[X|\mathcal{F}].$$

*Proof.* 1. The RHS is  $\mathcal{F}$ -measurable, as it is a linear combination of  $\mathcal{F}$ -measurable functions. Then, for any  $A \in \mathcal{F}$ ,

$$\begin{aligned} \int_A a\mathbb{E}[X|\mathcal{F}] + \mathbb{E}[Y|\mathcal{F}] dP &= a \int_A \mathbb{E}[X|\mathcal{F}] dP + \int_A \mathbb{E}[Y|\mathcal{F}] dP \\ &= a \int_A X dP + \int_A Y dP \\ &= \int_A aX + Y dP. \end{aligned}$$

2. Take any  $\epsilon$ , and let  $A = \{\omega : \mathbb{E}[X|\mathcal{F}](\omega) - \mathbb{E}[Y|\mathcal{F}](\omega) \geq \epsilon\}$ . Then,

$$\int_A \mathbb{E}[X|\mathcal{F}] dP = \int_A X dP \leq \int_A Y dP = \int_A \mathbb{E}[Y|\mathcal{F}] dP.$$

Then,

$$\begin{aligned} 0 &\geq \int_A \mathbb{E}[X|\mathcal{F}] dP - \int_A \mathbb{E}[Y|\mathcal{F}] dP \\ &\geq \epsilon P(A), \end{aligned}$$

so the set  $A$  has zero measure for all  $\epsilon$ . This means that  $\mathbb{E}[X|\mathcal{F}] \leq \mathbb{E}[Y|\mathcal{F}]$  a.e..

3. First, let  $Y_n = X - X_n$ . Due to linearity and monotonicity, it suffices to show that  $Z_n := \mathbb{E}[Y_n|\mathcal{F}] \downarrow 0$ . Because  $Y_n(\omega)$  is monotonically non-increasing in  $n$ , there exists a set  $\Omega_0$  of measure one such that for each  $\omega \in \Omega_0$ , we have that  $Z_n(\omega)$  is bounded (within  $[0, X(\omega)]$ ) and non-increasing, indicating convergence. String together these limits on  $\Omega_0$  to be the function  $Z_\infty$ , defined arbitrarily on  $\Omega_0^c$ .

Then, for any  $A \in \mathcal{F}$ ,

$$\lim_{n \rightarrow \infty} \int_A Z_n dP = \lim_{n \rightarrow \infty} \int_A Y_n dP \stackrel{\text{DCT}}{=} \int_A \lim_{n \rightarrow \infty} Y_n dP = 0.$$

The dominated convergence theorem applies because  $0 \leq Y_n(\omega) \leq X(\omega)$ , with  $X$  integrable by definition of conditional expectation.

□

**Definition A.14** (Regular conditional distribution). Let  $(\Omega, \mathcal{F}, P)$  be a probability space,  $\mathcal{G} \subseteq \mathcal{F}$  be a  $\sigma$ -algebra,  $X : \Omega \rightarrow S$  be a  $(\mathcal{F}, S)$ -measurable map. The function  $\mu : \Omega \times S \rightarrow [0, 1]$  is said to be a *regular conditional distribution (r.c.d.)* for  $X$  given  $\mathcal{G}$  if

- (i) For each  $A$ , the function  $\omega \mapsto \mu(\omega, A)$  is a version of  $\mathbb{P}[X \in A|\mathcal{G}]$ .

(ii) For a.e.  $\omega$ , the function  $A \mapsto \mu(\omega, A)$  is a probability measure on  $(S, \mathcal{S})$ .

**Theorem A.15.** *If  $(S, \mathcal{S}) = (\mathbb{R}, \mathcal{R})$ , that is that  $X$  is measurable with respect to  $\mathcal{F}$  and the Borel  $\sigma$ -algebra, then there exists an r.c.d..*

*Proof.* lol

□