

# Lecture 3

Instructor: Quan Zhou

For more details about the materials covered in this note, see Chapters 3.1 and 3.2 of Resnick [3] and Chapter 1.3 of Durrett [2].

## 3.1 Inverse maps

**Definition 3.1.** Let  $\Omega, \Lambda$  be two sets and consider a function  $f: \Omega \rightarrow \Lambda$ . For  $A \subset \Lambda$ , the inverse image of  $A$  under  $f$  is

$$f^{-1}(A) = \{\omega \in \Omega : f(\omega) \in A\}.$$

**Example 3.1.** A simple function means a function with a finite range (finite number of possible values). For a real-valued simple function (i.e.  $\Lambda = \mathbb{R}$ ), we may denote the range by  $\{a_1, \dots, a_k\}$ , where  $a_i$ 's are distinct real numbers. Define  $A_i = f^{-1}(\{a_i\})$ . Then,  $\{A_i : i = 1, \dots, k\}$  partitions  $\Omega$ . ("Partition" means  $\cup_{i=1}^k A_i = \Omega$  and  $A_i$ 's are disjoint.) Further, the function can be expressed by  $f = \sum_{i=1}^k a_i \mathbb{1}_{A_i}$ .

**Proposition 3.1.**  $f^{-1}$  preserves complementation, unions and intersections; that is,  $f^{-1}(A^c) = (f^{-1}(A))^c$ ,  $f^{-1}(\cup_{t \in T} A_t) = \cup_{t \in T} f^{-1}(A_t)$  and  $f^{-1}(\cap_{t \in T} A_t) = \cap_{t \in T} f^{-1}(A_t)$ .

*Proof.* Try it yourself. □

**Lemma 3.1.** Let  $\mathcal{G}$  be a  $\sigma$ -algebra on  $\Lambda$ . Then,  $f^{-1}(\mathcal{G}) = \{f^{-1}(A) : A \in \mathcal{G}\}$  is a  $\sigma$ -algebra on  $\Omega$ .

*Proof.* We only need to verify the three postulates. (i) Since  $\Lambda \in \mathcal{G}$ , we have  $\Omega = f^{-1}(\Lambda) \in f^{-1}(\mathcal{G})$ . (ii) If  $f^{-1}(A) \in f^{-1}(\mathcal{G})$ , so is  $(f^{-1}(A))^c = f^{-1}(A^c)$  by Proposition 3.1. (iii) If  $f^{-1}(A_i) \in f^{-1}(\mathcal{G})$  for  $i = 1, 2, \dots$ , we have  $\cup_i f^{-1}(A_i) = f^{-1}(\cup_i A_i) \in f^{-1}(\mathcal{G})$  since  $\cup_i A_i \in \mathcal{G}$  and  $f^{-1}$  preserves unions by Proposition 3.1. □

**Remark 3.1.** Sometimes we also use the notation  $\sigma(f) = f^{-1}(\mathcal{G})$ , and we say that  $\sigma(f)$  is the  $\sigma$ -algebra generated by  $f$ . Of course, when  $\sigma(f)$  is used, it is assumed that  $\mathcal{G}$  is clear from context; for example, when  $\Lambda = \mathbb{R}$ , the notation  $\sigma(f)$  means  $f^{-1}(\mathcal{B}(\mathbb{R}))$ .

**Theorem 3.1.** *If  $\mathcal{A} \subset \mathcal{P}(\Lambda)$  (i.e.  $\mathcal{A}$  is a collection of subsets of  $\Lambda$ ), then  $f^{-1}(\sigma(\mathcal{A})) = \sigma(f^{-1}(\mathcal{A}))$ .*

*Proof.* First, by Lemma 3.1  $f^{-1}(\sigma(\mathcal{A}))$  is a  $\sigma$ -algebra and thus  $f^{-1}(\sigma(\mathcal{A})) \supset \sigma(f^{-1}(\mathcal{A}))$ . Second, define  $\mathcal{C} = \{B \subset \Lambda : f^{-1}(B) \in \sigma(f^{-1}(\mathcal{A}))\}$  and show that  $\mathcal{C}$  is also a  $\sigma$ -algebra. Clearly,  $\mathcal{A} \subset \mathcal{C}$  and thus  $\sigma(\mathcal{A}) \subset \mathcal{C}$ . It follows that the other direction also holds, i.e.  $f^{-1}(\sigma(\mathcal{A})) \subset \sigma(f^{-1}(\mathcal{A}))$ , which concludes the proof.  $\square$

## 3.2 Measurable functions and random variables

**Definition 3.2.** Let  $(\Omega, \mathcal{F})$  and  $(\Lambda, \mathcal{G})$  be two measurable spaces and  $f: \Omega \rightarrow \Lambda$  be a function. We say  $f$  is a measurable function if  $f^{-1}(\mathcal{G}) \subset \mathcal{F}$  and we write  $f: (\Omega, \mathcal{F}) \rightarrow (\Lambda, \mathcal{G})$ . When  $\Omega$  and  $\Lambda$  are clear from text and we only want to emphasize the  $\sigma$ -algebra, we may write  $f \in \mathcal{F}/\mathcal{G}$ .

If  $(\Lambda, \mathcal{G}) = (\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ , we say  $f$  is Borel measurable or a Borel function and often simply write  $f \in \mathcal{F}$ .

**Definition 3.3.** In probability theory, a real valued Borel function is called a random variable for  $d = 1$  and a random vector for  $d > 1$  and is often denoted by  $X, Y, \dots$ .

**Example 3.2.** Consider a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Let  $X = \mathbb{1}_A$  for some  $A \in \mathcal{F}$ . Then  $X$  is a random variable and  $\sigma(X) = \{\emptyset, \Omega, A, A^c\}$ .

**Proposition 3.2** (Test for measurability). *Consider measurable spaces  $(\Omega, \mathcal{F})$ ,  $(\Lambda, \mathcal{G})$  and function  $f: \Omega \rightarrow \Lambda$ . If  $f^{-1}(\mathcal{A}) \subset \mathcal{F}$  for some  $\mathcal{A}$  that generates  $\mathcal{G}$ , then  $f$  is measurable.*

*Proof.* If  $f^{-1}(\mathcal{A}) \subset \mathcal{F}$ , we have  $\sigma(f^{-1}(\mathcal{A})) \subset \mathcal{F}$  by the minimality of the generated  $\sigma$ -algebra. Then apply Theorem 3.1.  $\square$

**Corollary 3.1.** *The real valued function  $X: \Omega \rightarrow \mathbb{R}$  is a random variable iff  $X^{-1}((-\infty, b]) \in \mathcal{F}$  for any  $b \in \mathbb{R}$ .*

*Proof.* Try it yourself.  $\square$

**Proposition 3.3.** *Let  $X$  be a random variable. If  $\mathcal{A}$  generates  $\mathcal{B}(\mathbb{R})$ , then  $\sigma(X) = \sigma(\{X^{-1}(A) : A \in \mathcal{A}\})$ .*

*Proof.* Try it yourself.  $\square$

**Proposition 3.4** (Composition). *Let  $f : (\Omega_1, \mathcal{B}_1) \rightarrow (\Omega_2, \mathcal{B}_2)$  and  $g : (\Omega_2, \mathcal{B}_2) \rightarrow (\Omega_3, \mathcal{B}_3)$  where  $(\Omega_i, \mathcal{B}_i)$  ( $i = 1, 2, 3$ ) are measurable spaces. Define the composition  $g \circ f : \Omega_1 \rightarrow \Omega_3$  by  $g \circ f(\omega_1) = g(f(\omega_1))$  for  $\omega_1 \in \Omega_1$ . Then  $g \circ f \in \mathcal{B}_1/\mathcal{B}_3$ .*

*Proof.* Try it yourself. □

**Proposition 3.5** (Converse to Proposition 3.4). *Let  $f : (\Omega_1, \mathcal{B}_1) \rightarrow (\Omega_2, \mathcal{B}_2)$  and  $h : \Omega_1 \rightarrow \mathbb{R}$ . Then,  $h \in \sigma(f)/\mathcal{B}(\mathbb{R})$  if and only if there exists some  $g : (\Omega_2, \mathcal{B}_2) \rightarrow (\mathbb{R}, \mathcal{B}(\mathbb{R}))$  such that  $h = g \circ f$ .*

*Proof.* Try it yourself after Lecture 4. □

**Proposition 3.6.** *Let  $f : \mathbb{R}^m \rightarrow \mathbb{R}^d$  be a continuous function. Then  $f \in \mathcal{B}(\mathbb{R}^m)/\mathcal{B}(\mathbb{R}^d)$ .*

*Proof.* It follows from the definition of Borel  $\sigma$ -algebra and the fact that  $f^{-1}(A)$  is open if  $A \subset \mathbb{R}^d$  is open and  $f$  is continuous. □

**Lemma 3.2.**  *$X = (X_1, \dots, X_n)$  is a random vector iff  $X_i$  is a random variable for every  $i$ .*

*Proof.* The proof relies on the fact that  $\mathcal{B}(\mathbb{R}^n)$  is generated by the collection of all the rectangles in  $\mathbb{R}^n$ . See Durrett [2, Theorem 1.3.5]. □

**Theorem 3.2.** *If  $X_1, \dots, X_n$  are random variables and  $f : (\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n)) \rightarrow (\mathbb{R}, \mathcal{B}(\mathbb{R}))$ , then  $f(X_1, \dots, X_n)$  is a random variable and  $X = (X_1, \dots, X_n)$  is a random vector.*

*Proof.* By Proposition 3.4, if  $(X_1, \dots, X_n)$  is a measurable function which maps from  $(\Omega, \mathcal{F})$  to  $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$ , then  $f(X_1, \dots, X_n)$  is a random variable. In other words, we need to show  $(X_1, \dots, X_n)$  is a random vector. But this follows from Lemma 3.2. □

**Theorem 3.3.** *If  $X_1, X_2, \dots$ , are random variables, then  $\inf_n X_n, \sup_n X_n, \liminf_n X_n, \limsup_n X_n$  are measurable. Note that they take value in the measurable space  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ .*

*Proof.* Observe that  $\{\inf_n X_n < x\} = \cup_n \{X_n < x\}$  and  $\{\sup_n X_n > x\} = \cup_n \{X_n > x\}$ . Then use the property that a  $\sigma$ -algebra is closed under countable unions/intersections. □

**Proposition 3.7.** Let  $(\Omega, \mathcal{F}, \mu)$  be a measure space,  $(\Lambda, \mathcal{G})$  be a measurable space and  $f : (\Omega, \mathcal{F}) \rightarrow (\Lambda, \mathcal{G})$ . Define a function on  $\mathcal{G}$ , denoted by  $\mu \circ f^{-1}$  (or  $f_{\#}\mu$ ), as  $(\mu \circ f^{-1})(A) = \mu(f^{-1}(A))$  for any  $A \in \mathcal{G}$ . Then  $\mu \circ f^{-1}$  is a measure on  $(\Lambda, \mathcal{G})$ . It is called the push-forward measure of  $\mu$  or the measure induced by  $f$ .

*Proof.* Try it yourself. □

**Definition 3.4.** For a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  and a random variable  $X$  defined on it,  $\mathbb{P} \circ X^{-1}$  is called the distribution or the law of  $X$ .

**Example 3.3.** Consider tossing two dice, which corresponds to the sample space  $\Omega = \{(i, j) : 1 \leq i, j \leq 6\}$ . Let  $\Lambda = \{2, 3, \dots, 12\}$ . Define  $X : \Omega \rightarrow \Lambda$  by  $X((i, j)) = i + j$ . Then  $X^{-1}(\{2, 3\}) = \{(1, 1), (1, 2), (2, 1)\}$ . The distribution of  $X$  is given by the push-forward measure  $\mathbb{P} \circ X^{-1}$  where  $\mathbb{P}$  denotes the probability measure on  $\Omega$ . Hence,  $\mathbb{P} \circ X^{-1}(\{2, 3\}) = 3/36$ .

## References

- [1] Dennis D. Cox. *The Theory of Statistics and Its Applications*. Unpublished.
- [2] Rick Durrett. *Probability: Theory and Examples*, volume 49. Cambridge university press, 2019.
- [3] Sidney Resnick. *A Probability Path*. Springer, 2019.