



## 1. Measure theory

## 1.1 Measure spaces and probability spaces.

Def. Let  $\Omega \neq \emptyset$ . A collection  $\mathcal{F}$  of subsets of  $\Omega$  is said to be a  $\sigma$ -algebra on  $\Omega$  if

- (1) If  $F \in \mathcal{F}$ , then  $F^c \in \mathcal{F}$ , where  $F^c = \Omega \setminus F$   
 (2) If  $F_n \in \mathcal{F}$ ,  $n \geq 1$ , then  $\bigcup_{n=1}^{\infty} F_n \in \mathcal{F}$ .

Remark: • A  $\sigma$ -algebra is closed under the complement, countable union and countable intersection

$$\left( \bigcap_{n=1}^{\infty} F_n = \left( \bigcup_{n=1}^{\infty} F_n^c \right)^c \right)$$

- Let  $\{\mathcal{F}_i\}_{i \in \mathcal{I}}$  be a family of  $\sigma$ -algebras on  $\Omega$ .  
 Then  $\bigcap_{i \in \mathcal{I}} \mathcal{F}_i$  is also a  $\sigma$ -algebra on  $\Omega$ .

Def. Let  $\mathcal{A}$  be a collection of subsets of  $\Omega$ .  
 Let  $\sigma(\mathcal{A})$  denote the smallest  $\sigma$ -algebra on  $\Omega$  that contains  $\mathcal{A}$ .  
 We call  $\sigma(\mathcal{A})$  the  $\sigma$ -algebra generated by  $\mathcal{A}$ .

Example • Let  $X$  be a topological space. Let  $\beta(X)$  denote the  $\sigma$ -algebra generated by the collection of open sets in  $X$ .  
 We call  $\beta(X)$  the Borel  $\sigma$ -algebra.

Let  $\mathcal{B}(\mathbb{R})$  denote the Borel  $\sigma$ -algebra on  $\mathbb{R}$ . Each element in  $\mathcal{B}(\mathbb{R})$  is called a Borel set in  $\mathbb{R}$ .

Def. (Measurable space)  $(\Omega, \mathcal{F})$  is called a measurable space if  $\Omega \neq \emptyset$  and  $\mathcal{F}$  is a  $\sigma$ -algebra on  $\Omega$ .

Def. (measure) A function  $\mu: \mathcal{F} \rightarrow [0, \infty]$  is called a measure on  $(\Omega, \mathcal{F})$  if

$$(i) \quad \mu(\emptyset) = 0.$$

$$(ii) \quad \mu\left(\bigcup_{n=1}^{\infty} A_n\right) = \sum_{n=1}^{\infty} \mu(A_n) \quad \text{if}$$

$A_n, n \geq 1$ , are disjoint elements in  $\mathcal{F}$ .

Prop 1.1. Let  $\mu$  be a measure on  $(\Omega, \mathcal{F})$ . Then

$$(i) \quad \mu(A) \leq \mu(B) \quad \text{if } A \subset B \quad (\text{monotonicity})$$

$$(ii) \quad \mu\left(\bigcup_{n=1}^{\infty} A_n\right) \leq \sum_{n=1}^{\infty} \mu(A_n) \quad \text{for } A_n \in \mathcal{F}. \quad (\text{Sub-additivity})$$

$$(iii) \quad \text{If } A_n \uparrow A, \text{ then } \mu(A_n) \rightarrow \mu(A) \text{ as } n \rightarrow \infty$$

$$(iv) \quad \text{If } A_n \downarrow A \text{ and } \mu(A_1) < \infty, \text{ then } \quad (\text{continuity from below})$$

$$\lim_{n \rightarrow \infty} \mu(A_n) = \mu(A). \quad (\text{continuity from above}).$$

- Def. • A triple  $(\Omega, \mathcal{F}, \mu)$  is called a measure space if  $\mu$  is a measure on  $(\Omega, \mathcal{F})$ .
- If  $\mu(\Omega) = 1$ , we call  $\mu$  a prob. measure. Correspondingly,  $(\Omega, \mathcal{F}, \mu)$  is called a prob. space.
- Usually a prob. measure is denoted as P.

### Example. (discrete prob. space)

Let  $\Omega$  be a countable set. Let

$$\mathcal{F} = 2^\Omega := \{A : A \subset \Omega\}.$$

Then  $(\Omega, \mathcal{F})$  is a measurable space.

Let  $\{p(\omega)\}_{\omega \in \Omega}$  be a prob. vector, i.e.  $p(\omega) \geq 0$  and  $\sum_{\omega \in \Omega} p(\omega) = 1$ .

Define

$$P(A) = \sum_{\omega \in A} p(\omega) \quad \text{for all } A \subset \Omega.$$

Then  $(\Omega, \mathcal{F}, P)$  is a (discrete) prob. space.

Example (Borel measure on  $\mathbb{R}$ ) A measure  $\mu$  on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  is called a Borel measure on  $\mathbb{R}$ .

Prop 1.2. Let  $\mu$  be a Borel prob. measure on  $\mathbb{R}$ . Set

$$F(x) = \mu((-\infty, x]) \quad \text{for } x \in \mathbb{R}.$$

Then

(1)  $F$  is non-decreasing, i.e.  $F(x) \leq F(y)$  if  $x < y$ .

(2)  $F$  is right-continuous, i.e.

$$\lim_{y \rightarrow x^+} F(y) = F(x).$$

(3)  $\lim_{x \rightarrow +\infty} F(x) = 1$ ,  $\lim_{x \rightarrow -\infty} F(x) = 0$ .

Pf. (1) is trivial, (2) & (3) follow from the continuity property of a prob. measure.  $\square$ .

## 1.2 Random variables and their distributions.

Let  $(\Omega, \mathcal{F}, P)$  be a probability space.

Def. A function  $X: \Omega \rightarrow \mathbb{R}$  is said to be  $\mathcal{F}$ -measurable if

$$X^{-1}(A) \in \mathcal{F} \quad \text{for every Borel set } A \subset \mathbb{R}.$$

If so, we call  $X$  a random variable (r.v.).

Example: • Let  $(\Omega, \mathcal{F}, P)$  be a discrete prob. space. Then any function  $X: \Omega \rightarrow \mathbb{R}$  is a r.v.

- Let  $(\Omega, \mathcal{F}, P)$  be a general prob. space and let  $A \in \mathcal{F}$ .

Define  $\mathbb{1}_A : \Omega \rightarrow \mathbb{R}$  by

$$\mathbb{1}_A(x) = \begin{cases} 1 & \text{if } x \in A, \\ 0 & \text{otherwise.} \end{cases}$$

Then  $\mathbb{1}_A$  is a r.v. which is called the indicator function of  $A$ .

(check:  $\mathbb{1}_A^{-1}\{1\} = A$ ,  $\mathbb{1}_A^{-1}\{0\} = A^c$ )

Def. Let  $X$  be a r.v. on  $(\Omega, \mathcal{F}, P)$ . Then  $X$  induces a prob. measure  $\mu$  on  $\mathbb{R}$  by

$$\mu(A) = P(X \in A) := P(X^{-1}(A)), \quad A \in \mathcal{B}(\mathbb{R}).$$

We call  $\mu$  the distribution of  $X$ .

Moreover, set  $F(x) = P\{X \leq x\} = \mu((-\infty, x])$  for  $x \in \mathbb{R}$ ; we call it the distribution function of  $X$ .

If  $F(x)$  has the form

$$F(x) = \int_{-\infty}^x f(y) dy,$$

then we say  $X$  has the density function  $f$ .

Example: ① (Uniform distribution on  $(0, 1)$ )

$$f(x) = \begin{cases} 1 & \text{for } x \in (0, 1) \\ 0 & \text{otherwise} \end{cases}$$

$$F(x) = \begin{cases} 1 & \text{if } x \geq 1 \\ x & \text{if } 0 \leq x < 1 \\ 0 & \text{if } x < 0 \end{cases}$$

② (exponential distribution with parameter  $\lambda$ )

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$F(x) = \begin{cases} 1 - e^{-\lambda x} & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

③ (standard norm distribution)

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \quad x \in \mathbb{R}$$

### 1.3. Random elements and random vectors.

Now we generalize the concept of r.v.

**Def.** A map  $X: \Omega \rightarrow T$  from  $(\Omega, \mathcal{F}, P)$  to a measurable space  $(T, \mathcal{T})$  is said to be measurable if

$$X^{-1}(A) \in \mathcal{F} \text{ for every } A \in \mathcal{T}.$$

In this case, we call  $X$  a random element of  $(T, \mathcal{T})$ .

If  $(T, \mathcal{T}) = (\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ , then we call  $X$  a random vector.

**Def.** Let  $X: \Omega \rightarrow T$  be a random element. Set

$$\sigma(X) = \{ X^{-1}(A) : A \in \mathcal{T} \}.$$

We call it the  $\sigma$ -algebra generated by  $X$ .

Below we give a useful result to check the measurability of  $X: \Omega \rightarrow T$ .

Prop 1.3. Let  $X: \Omega \rightarrow T$  be a map. Suppose  $\mathcal{A}$  is a collection of subsets of  $T$  such that  $\sigma(\mathcal{A}) = \mathcal{T}$ . Then

$$X \text{ is } \mathcal{F}\text{-measurable} \Leftrightarrow X^{-1}(A) \in \mathcal{F} \text{ for all } A \in \mathcal{A}.$$

**Pf.**  $\checkmark$  Let  $\mathcal{Y} := \{ A \subset T : X^{-1}(A) \in \mathcal{F} \}$ . Then  $\mathcal{Y}$  is a  $\sigma$ -algebra and contains  $\mathcal{A}$ . Hence  $\mathcal{Y} \supset \sigma(\mathcal{A}) = \mathcal{T}$ .  $\square$



Prop 1.4. If  $X: (\Omega, \mathcal{F}) \rightarrow (\mathcal{T}, \mathcal{T})$   
 and  $f: (\mathcal{T}, \mathcal{T}) \rightarrow (U, \mathcal{U})$  are measurable,  
 then so is  $f(X): (\Omega, \mathcal{F}) \rightarrow (U, \mathcal{U})$ .

**pf.** Let  $A \in \mathcal{U}$ . Then  $f^{-1}(A) \in \mathcal{T}$ . Thus

$$X^{-1}(f^{-1}(A)) \in \mathcal{F}.$$

$$\text{Hence } (f(X))^{-1}(A) = X^{-1}(f^{-1}(A)) \in \mathcal{F}. \quad \square$$

- Extended real line  $\mathbb{R}^* = [-\infty, \infty]$ .  
 Endow  $\mathbb{R}^*$  with the topology generated by  
 $[-\infty, a), (a, b), (b, +\infty]$

Let  $\mathcal{B}(\mathbb{R}^*)$  denote the Borel  $\sigma$ -algebra on  $\mathbb{R}^*$ .

A measurable map  $X: (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}^*, \mathcal{B}(\mathbb{R}^*))$  is also  
 called a random variable.

Prop. 1.5. Let  $X_1, X_2, \dots$  be r.v.'s. Then

$$\inf_n X_n, \sup_n X_n, \underline{\lim}_n X_n, \overline{\lim}_n X_n$$

are all r.v.'s.

## 1.4 Integration

Let  $(\Omega, \mathcal{F}, \mu)$  be a measure space and  $f: \Omega \rightarrow \mathbb{R}^*$  be measurable.

Then we can define

$$\int f \, d\mu = \int f^+ \, d\mu - \int f^- \, d\mu$$

if one of  $\int f^+ \, d\mu$ ,  $\int f^- \, d\mu$  is finite.

We call  $f$  integrable if  $\int |f| \, d\mu < \infty$ , and write  $f \in L^1(\Omega, \mathcal{F}, \mu)$  or  $L^1(\mu)$ .

Moreover we write  $f \in L^p(\mu)$  if  $\int |f|^p \, d\mu < \infty$   
and  $\|f\|_p := \left( \int |f|^p \, d\mu \right)^{1/p} \rightarrow p \text{ norm of } f$

Basic inequalities:

Hölder inequality: Let  $p, q > 1$  be such that  $\frac{1}{p} + \frac{1}{q} = 1$ . Then

$$\int |fg| \, d\mu \leq \left( \int |f|^p \, d\mu \right)^{1/p} \left( \int |g|^q \, d\mu \right)^{1/q}.$$

Minkowski inequality:

$$\|f + g\|_p \leq \|f\|_p + \|g\|_p \quad \text{for all } p \geq 1.$$

Jensen inequality: <sup>Let  $\mu$  be a prob. measure,</sup> Let  $\varphi: \mathbb{R} \rightarrow \mathbb{R}$  be convex, i.e.

$p\varphi(x) + (1-p)\varphi(y) \geq \varphi(px + (1-p)y)$   
for all  $0 \leq p \leq 1$  and  $x, y \in \mathbb{R}$ . Suppose  $f$  and  $\varphi(f)$  are integrable. Then

$$\varphi\left(\int f d\mu\right) \leq \int \varphi \circ f d\mu.$$

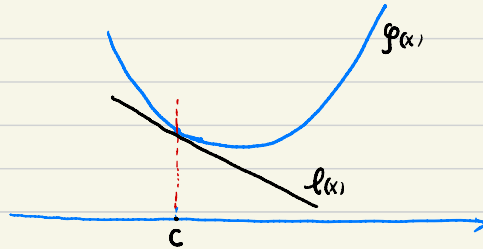
Pf. Write  $c = \int f d\mu$ .

Since  $\varphi$  is convex, there exists a function

$$l(x) = ax + b$$

such that  $l(c) = \varphi(c)$  and  $\varphi(x) \geq l(x)$  for all  $x \in \mathbb{R}$ .

See the following picture.



Hence

$$\varphi(f(x)) \geq l(f(x)) = af(x) + b$$

Taking integration gives

$$\begin{aligned} \int \varphi \circ f d\mu &\geq \int (af(x) + b) d\mu = a \int f d\mu + b \\ &= l(c) = \varphi(c). \quad \square \end{aligned}$$

Next we recall some convergence results.

- (Monotone convergence Thm) Let  $f_n, n \geq 1$ , be non-negative functions such that  $f_n \uparrow f$  a.e. Then

$$\int f_n d\mu \rightarrow \int f d\mu \text{ as } n \rightarrow \infty$$

- Fatou's lemma: Let  $f_n, n \geq 1$ , be non-negative measurable functions.

$$\text{Then } \liminf_{n \rightarrow \infty} \int f_n d\mu \geq \int \liminf_{n \rightarrow \infty} f_n d\mu.$$

- Dominated convergence Thm:

Suppose  $f_n \rightarrow f$  a.e. and  $|f_n| \leq g$  for all  $n$  and  $\int g d\mu < \infty$ . Then

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