

# 1 Measure theory basics

Given a set  $X$ , a *measure* maps subsets  $A \subset X$  to  $\mu(A)[0, +\infty]$ .

**Example 1.1.**  $X$  countable. The *counting measure*  $\#(A) = \# \text{ elements in } A$

**Example 1.2.**  $X = \mathbb{R}^n$ . The *Lebesgue measure*  $\lambda(A) = \int_A dx_1 \cdots dx_n$  ("volume of  $A$ ")

**Definition 1.3.** A  $\sigma$ -field  $\mathcal{F}$  is a collection of subsets for which  $\mu$  is defined.

**Example 1.4.**  $X$  countable,  $\mathcal{F} = \mathcal{P}(X)$ .

**Example 1.5.**  $X = \mathbb{R}^n$ ,  $\mathcal{F} = \mathcal{B}(\mathbb{R}^n) = \sigma\{\text{open sets of } \mathbb{R}^n\}$  is the *Borel  $\sigma$ -field*

**Definition 1.6.**  $(X, \mathcal{F})$  is a *measurable space*. A *measure*  $\mu : \mathcal{F} \rightarrow [0, +\infty]$  satisfies

$$\mu\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \mu(A_i) \quad (1.1)$$

for disjoint  $A_i \in \mathcal{F}$ .

**Definition 1.7.** A *probability measure*  $\mathbb{P}$  is a measure where  $\mathbb{P}(X) = 1$ .

We notate an *integral* wrt measure  $\mu$  as  $\int_X f(X) \mu(dx)$ .

**Example 1.8. Counting:**  $\int_X f(x) \mu(dx) = \sum_{x \in X} f(x)$

**Lebesgue:**  $\int f(x) \lambda(dx) = \int_{\mathbb{R}^n} f(x) dx_1 \cdots dx_n$

# 2 Densities

Given  $(X, \mathcal{F})$  measurable space and two measures  $P, \mu$

**Definition 2.1.**  $P$  is *dominated by*  $\mu$  (denoted  $P \ll \mu$ ) if  $\mu(A) = 0 \implies P(A) = 0$ . If  $\mu = \lambda$ , we say  $P$  is *absolutely continuous*.

If  $P \ll \mu$ , then by the Radon-Nikodym theorem the *density*  $p(x) = \frac{dP}{d\mu}(x)$  exists, is essentially unique, and satisfies

$$P(A) = \int_A p(x) d\mu(x) \quad (2.1)$$

$$\int_X f(x) dP(x) = \int_X f(x) p(x) d\mu(x) \quad (2.2)$$

$\frac{dP}{d\mu}$  is essentially unique: If  $p_0(x)$  and  $p_1(x)$  are both densities for  $\frac{dP}{d\mu}$ , then  $p_0 \stackrel{\text{a.s.}}{=} p_1$  i.e.  $P(\{p_0(x) \neq p_1(x)\}) = 0$ .

**Example 2.2.**  $\mathcal{N}(0, 1)$ ,  $p(x) = (2\pi)^{-1/2} e^{-x^2/2}$ .  $P((a, b)) = \int_a^b p(x) dx$ .

### 3 Random variables

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

- $\omega \in \Omega$  is an *outcome*
- $A \in \mathcal{F}$  is an *event*
- $\mathbb{P}(A)$  is the probability of event  $A$

**Definition 3.1.** A *random variable* (vector, matrix) is a measurable function  $X : \Omega \rightarrow \mathbb{R}$  ( $\mathbb{R}^n$ ). That is,  $X^{-1}(A) = \{\omega : X(\omega) \in A\} \in \mathcal{F}$  for all  $A \in \mathcal{B}$ .

We say  $X \sim Q$  if  $\mathbb{P}(X \in B) = \mathbb{P}(X^{-1}(B)) = Q(B)$ .

**Definition 3.2.** An *expectation* is an integral wrt  $\mathbb{P}$ :

$$\mathbb{E}[X] = \int_{\Omega} X(\omega) d\mathbb{P}(\omega) = \int_{\mathbb{R}} x dQ(x) \quad (3.1)$$

**Corollary 3.3.**  $Q$  is a probability measure, since  $B = \mathbb{R} \implies Q(\mathbb{R}) = P(X \in \mathbb{R}) = 1$ .

### 4 Estimation

**Statistical model:** a family of candidate probability distributions  $\mathcal{P} = \{P_{\theta} : \theta \in \Theta\}$  for observed data  $X \sim P_{\theta}$ .

**Goal:** observe  $X$ , estimate  $g(\theta)$  (*estimand*)

**Example 4.1.** Flip a coin  $n$  times.  $\theta$  = probability of heads.  $X$  = # heads in  $n$  trials  $\sim \text{Binom}(n, \theta) = \theta^x (1 - \theta)^{n-x} \binom{n}{x}$ .

**Definition 4.2.** A *statistic*  $\Gamma(X)$  is a function of the data  $X$ . Statistics are generally used as intermediate quantities to summarize data within a statistical procedure.

An *estimator*  $\delta(X)$  is also a function  $\delta(X)$ , usually chosen to be “close” to a function of the parameters  $g(\theta)$ .

**Example 4.3.** For the binomial example,  $\delta_0(X) = X/n$  is an estimator of  $\theta$ .

### 5 Loss and Risk

**Loss function:**  $L(\theta, \delta)$  measures how good an estimator  $\delta$  is.

**Example 5.1.** Squared error loss  $L(\theta, \delta) = (\delta - g(\theta))^2$

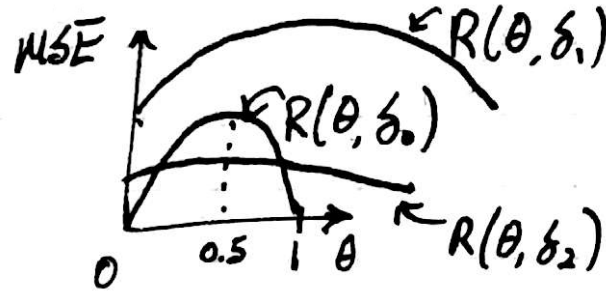
**Definition 5.2.** The *risk*

$$R(\theta, \delta(\cdot)) = \mathbb{E}_{\theta}[L(\theta, \delta(X))] = \mathbb{E}_{X \sim P_{\theta}}[L(\theta, \delta(X))] \quad (5.1)$$

**Notation:**  $\mathbb{E}_\theta$  denotes an expectation where the subscript  $\theta$  is fixed and all other random quantities are integrated over.

**Example 5.3.**  $R(\theta, \delta_0) = \frac{1}{n}\theta(1 - \theta)$ ,  $L = \text{squared error}$ ,  $R = \text{MSE}$ .

Consider  $\delta_1 = \frac{X+3}{n}$  and  $\delta_2 = \frac{X+3}{n+6}$ .



$\delta_1$  is inadmissible:  $\forall \theta : R(\theta, \delta_0) < R(\theta, \delta_1)$ .

Comparing  $\delta_0$  to  $\delta_2$  shows that different estimators may perform better for different values of  $\theta$ .