Probability space $(\Omega, \mathcal{F}, \mathbb{P})$ is a special kind of general measure space. We require

$$\mathbb{P}(\Omega) = 1.$$

The finiteness of probability measure brings some convenient properties.

1. the continuity of probability measure.

If
$$A_k \uparrow A$$
, then $\mathbb{P}(A_k) \uparrow \mathbb{P}(A)$.
If $A_k \downarrow A$, then $\mathbb{P}(A_k) \downarrow \mathbb{P}(A)$.

2. there are at most countable atoms.

$$D:=\{\omega\in\Omega\;\Big|\;\mathbb{P}\{\omega\}>0\}\quad\text{is at most countable}.$$

3. boundness implies integrability.

$$|X| \le M < \infty \quad \Rightarrow \quad \mathbb{E}|X| < \infty.$$

4. high order moment exists ⇒ low order moment exists.

$$\mathbb{E} |X|^q < \infty \quad \Rightarrow \quad \mathbb{E} |X|^p < \infty, \qquad \forall 1 \le p \le q < \infty.$$

It is worth noting that we often require $(\Omega, \mathcal{F}, \mathbb{P})$ is **complete**, i.e.,

$$\mathbb{P}(N) = 0 \quad \Rightarrow \quad \forall N_0 \subset N, N_0 \in \mathcal{F}.$$

A **random variable (r.v.)** X refers to a measurable function from (Ω, \mathcal{F}) to $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$.

The **distribution** of X refers to the probability measure on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ induced by it,

$$\mu_X(B) := \mathbb{P}[X \in B].$$

Statistics of X: with μ_X , we can easily predict probabilistic behaviors of X,

$$\mathbb{E} X = \int_{\mathbb{R}} x \, \mu_X(dx),$$

$$\mathbb{E}\,X^2 = \int_{\mathbb{R}} x^2\,\mu_X(dx).$$

Generally, for a Borel function $g: \mathbb{R} \to \mathbb{R}$,

$$\mathbb{E}[g(X)] = \int_{\mathbb{D}} g(x) \, \mu_X(dx).$$

This equality should be understood that

- 1. the existence of one integral implies the existence of the other integral;
- 2. if these integral exist, then they must be equal.

The (cumulative) distribution function of a r.v. X refers to a nondecreasing function $F_X : \mathbb{R} \to [0,1]$,

$$F_X(x) := \mu_X(-\infty, x].$$

Note that F_X is **right continuous** in our definition. It could be **left continuous** if F_X is defined by $\mu_X(-\infty,x)$.

A r.v. X is called **discrete** if there exists a countable set $D \subset \mathbb{R}$ such that $\mu_X(D) = 1$.

Equivalently, this means X has at most countable possible values.

A r.v. X is called **(absolutely) continuous** if $\mu_X \ll \lambda$.

Equivalently, this means (by Radon-Nikodym theorem) there exists $f_X \ge 0$ such that

$$\mu_X(B) = \int_B f_X(x) dx, \quad \forall B \in \mathcal{B}(\mathbb{R}).$$

In this case, f_X , also known as the R-N derivative, is called the **probability density function (p.d.f.)** of X.

Statistics of continuous r.v. X: for a Borel function $g: \mathbb{R} \to \mathbb{R}$,

$$\mathbb{E}[g(X)] = \int_{\mathbb{R}} g(x) f_X(x) dx.$$

Note: if *X* is generalized as a measurable function from (Ω, \mathcal{F}) to $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$, then

- 1. μ_X is a probability measure on $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$;
- 2. F_X and f_X (if exists) are functions on \mathbb{R}^n .

Measurable set classes $\{A_t\}_{t \in T}$ are termed **independent** if for any *finite* subset $\{t_1, t_2, ..., t_n\} \subset T$,

$$\mathbb{P}\bigg(\bigcap_{k=1}^n A_{t_k}\bigg) = \prod_{k=1}^n \mathbb{P}(A_{t_k}), \qquad \forall A_{t_k} \in \mathcal{A}_{t_k}, \quad k = 1, 2, \dots, n.$$

This definition naturally applies to r.v.s $\{X_t\}_{t\in T}$, where A_t is replaced by $\sigma(X_t) := \{X_t^{-1}(B) \mid B \in \mathcal{B}(\mathbb{R})\}$.

Specifically, finite many r.v.s $\{X_1, X_2, \dots, X_n\}$ are independent if and only if

$$\mathbb{P}\Big(\bigcap_{k=1}^n [X_k \leq x_k]\Big) = \prod_{k=1}^n \mathbb{P}[X_k \leq x_k], \qquad \forall x_k \in \mathbb{R}, \quad k=1,2,\dots,n.$$

Independent-means-multiply: given independent variables X and Y, if $X, Y \in \mathcal{L}^1$ or $X, Y \in \mathcal{L}^0_+$, then

$$\mathbb{E}[XY] = \mathbb{E}[X] \cdot \mathbb{E}[Y].$$

Counterexample: it is possible that XY is not well defined when X,Y are independent and $X \in \mathcal{L}^1, Y \in \mathcal{L}^0_+$. We can construct such an example following this procedure:

- 1. fix $\Omega = [0, 1]$ and $P(B) = \lambda(B \cap [0, 1])$;
- 2. set $X(\omega) = \mathbb{1}_{[0,1/2]}(\omega) \mathbb{1}_{(1/2,1]}(\omega) \in \mathcal{L}^1$;
- 3. set $Y \in \mathcal{L}^0_{\perp}$ such that $\mathbb{E} Y = \infty$;
- 4. show that X and Y are independent if $\forall \omega \in [0,1], Y(\omega) = Y(1-\omega)$;
- 5. the last step uses the fact that Lebesgue measure is invariant under reflection and translation.

A sequence of probability measures $\{\mu_n\}$ on $\mathcal{B}(\mathbb{R})$ is said to **weakly converge** to a probability measure μ if

$$\int_{\mathbb{R}} f(x) \, \mu_n(dx) \to \int_{\mathbb{R}} f(x) \, \mu(dx), \qquad \text{for any bounded continous function } f: \mathbb{R} \to \mathbb{R}.$$

A sequence of r.v.s $\{X_n\}$ is said to **converge to** X **in distribution (or in law)** if

$$\mathbb{E}[f(X_n)] \to \mathbb{E}[f(X)],$$
 for any bounded continous function $f: \mathbb{R} \to \mathbb{R}$.

Note: X_n convenges to X in distribution, denoted by $X_n \overset{\mathcal{D}}{\longrightarrow} X$ or $X_n \overset{d}{\longrightarrow} X$, is equivalent to μ_{X_n} weakly converges to μ_X , denoted by $\mu_{X_n} \overset{w}{\longrightarrow} \mu_X$.

The characteristic function of a probability measure μ on $\mathcal{B}(\mathbb{R})$ is a complex-valued function defined on \mathbb{R}

$$\phi_{\mu}(t) := \int_{\mathbb{R}} e^{itx} \ \mu(dx) := \int_{\mathbb{R}} \cos tx \ \mu(dx) + i \int_{\mathbb{R}} \sin tx \ \mu(dx).$$

The **characteristic function of a r.v.** X on $\mathcal{B}(\mathbb{R})$ is a complex-valued function defined on \mathbb{R}

$$\phi_X(t) := \mathbb{E}[e^{itX}] := \mathbb{E}[\cos tX] + i \mathbb{E}[\sin tX].$$

We should note that the characteristic function is bounded by 1.

We should also bear in mind that convergence in law is equivalent to pointwise convergence of characteristic function.

(The implication in one direction is by definition, and the opposite one comes from Lévy's continuity theorem.)