

A Gentle Introduction to Probability Theory

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Section 1

Probability Spaces

Let Ω denote the set of all potential outcomes or results ω of a random experiment.

Then Ω is called sample space or possibility space.

Any subset $A \subset \Omega$ is called an event.

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- $A \in \mathcal{A} \implies A^C \in \mathcal{A}$
- $A_1, A_2, A_3, \dots \in \mathcal{A} \implies \bigcup_{I \in \mathbb{N}} A_I \in \mathcal{A}$

The power set of a set A is given by

$$\mathcal{P}(A) := \{M \mid M \subset A\},$$

being the set of all subsets M of A . It holds that $|\mathcal{P}(A)| = 2^{|A|}$.

Given an arbitrary family of subsets F of a sample space Ω , the σ -algebra

$$\sigma(F) := \bigcap_{F \subset \mathcal{A}} \mathcal{A}, \quad \text{with } \mathcal{A} \text{ being } \sigma\text{-algebras on } \Omega$$

denotes the smallest σ -algebra on Ω , which contains F .

Given $\Omega = \mathbb{R}$ and $I := \{(s, t) : -\infty \leq s \leq t \leq \infty\}$, the σ -algebra generated by the open intervals I are usually denoted

$$\mathcal{B}(\mathbb{R}) := \sigma(I)$$

This is called the Borel σ algebra on \mathbb{R} . By definition of σ -algebras, \mathcal{B} contains all open, closed and half open intervals.

A tuple (Ω, \mathcal{A}) , consisting of a sample space Ω and a σ -algebra $\mathcal{A} \subset \mathcal{P}(\Omega)$ is called measurable space.

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- μ is σ -additive, i.e. for all sequences of pairwise disjoint sets A_1, A_2, \dots holds:

$$\mu\left(\dot{\bigcup}_{i \in \mathbb{N}} A_i\right) = \sum_{i \in \mathbb{N}} \mu(A_i)$$

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- P is σ -additive, that is, for all sequences of pairwise disjoint sets A_1, A_2, \dots holds:

$$P\left(\bigcup_{i \in \mathbb{N}} A_i\right) = \sum_{i \in \mathbb{N}} P(A_i)$$

The triple (Ω, \mathcal{A}, P) , consisting of a sample space Ω , a σ -algebra \mathcal{A} on Ω and a probability measure P defined on \mathcal{A} , is called probability space.

A function on the sample space Ω

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The function does **not** have to be real valued, but the concept generalises trivially!

In order to facilitate the notation of the following concepts, we define:

$$X^{-1}(]-\infty, z]) = \{\omega \in \Omega \mid -\infty < X(\omega) \leq z\} =: \{X \leq z\}$$

A random quantity $X : \Omega \rightarrow \mathbb{R}^d$ is called measurable with respect to the σ -algebra \mathcal{A} , if:

$$\forall z \in \mathbb{R}^d : \{X \leq z\} \in \mathcal{A}$$

with $\{X \leq z\} \in \mathcal{A}$ being shorthand for the set of outcomes $\omega \in \Omega$, for which the function $X = (X_1, \dots, X_d)$ results in values below $z = (z_1, \dots, z_d)$, i.e.:

$$\{X \leq z\} = \{\omega \in \Omega \mid X(\omega) \leq z\} = \{\omega \in \Omega \mid X_1(\omega) \leq z_1, \dots, X_d(\omega) \leq z_d\}$$

Let $X : \Omega \rightarrow \mathbb{R}^d$ be a measurable random variable on the measure space (Ω, \mathcal{A}) . The probabilities of *all* events belonging to X as a whole are called *probability distribution* or *cumulative distribution* of the random variable X . The entire distribution is determined by the function:

$$F_X : \mathbb{R}^d \rightarrow [0, 1] \tag{1}$$

$$z \mapsto F_X(z) := P(\{X \leq z\}) = P(\{X_1 \leq z_1, \dots, X_d \leq z_d\}), \tag{2}$$

leading to F_X being called *distribution function* of X

Using *Riemann-Stieltjes integrals*, one can write:

$$P(\{a < X \leq b\}) = F_X(b) - F_X(a) = \int_a^b dF_X(z)$$

, given that F_X is continuous.

In case F_X is differentiable, the probabilities can be given as:

$$\int_a^b dF_X(z) = \int_a^b F'_X(z) dz$$

Under the further restriction that F'_X be continuous, the following holds for infinitesimal changes dz :

$$P(\{z < X \leq z + dz\}) = F_X(z + dz) - F_X(z) = F'_X(z) dz = dF_X(z)$$

If a function $f : \mathbb{R} \rightarrow \mathbb{R}$ exists with

$$F_X(z) = \int_{-\infty}^z f(s) ds$$

, it is called density function of X . In case f is continuous, $F'_X = f$ follows.

The expected value $\mathbb{E}(X)$ of a random variable X is defined as its mean function value

$$\mathbb{E}(X) = \int_{\mathbb{R}^d} z \, dF_X(z)$$

Variance and Standard Deviation

The variance $\text{Var}(X)$ of a random variable X is defined as the quadratic deviation of X from its expected value, i.e.

$$\text{Var}(X) = \mathbb{E}(|X - \mathbb{E}(X)|^2)$$

A better intuition of the strength of dispersion can be had by examining the *standard deviation* $s(X)$

$$s(X) := \sqrt{\text{Var}(X)}$$

Deterministic Convergence

Recall that convergence towards a limit L for a deterministic sequence S_n , with $n \in \mathbb{N}$, can be expressed by

$$\forall \epsilon > 0 \quad \exists N : \quad \forall n \geq N : \quad |S_n - L| < \epsilon$$

Convergence in Probability

A sequence of random variables X_1, X_2, \dots , denoted by X_n , is said to converge in probability towards X , written as $X_n \xrightarrow{P} X$ or $\text{plim}_{n \rightarrow \infty} X_n = X$, if

$$\forall \epsilon > 0 : \quad P(|X_n - X| > \epsilon) \rightarrow 0 \quad \text{as} \quad n \rightarrow \infty$$

X_n is said to *converge in distribution* towards X , written as $X_n \xrightarrow{D} X$, if

$$\forall x \in \mathbb{R} : P(X_n \leq x) \rightarrow P(X \leq x) \quad \text{as } n \rightarrow \infty$$

, given that $P(X \leq x)$ is continuous at x .

Convergence in r th Mean

X_n converges in r th mean (for $r \geq 1$), written as $X_n \xrightarrow{r} X$, if

$$\forall n \in \mathbb{N} : \quad \mathbb{E}(|X_n|^r) < \infty$$

and

$$\mathbb{E}(|X_n - X|^r) \rightarrow 0 \quad \text{as} \quad n \rightarrow \infty$$