Probabilities and Statistics

In this section, we present some results in probability and statistics within the framework of this course. For more information, you can refer to the STT-1000 course, Wasserman (2010) (in English) and Delmas (2013) (in French).

1 Modeling randomness

Many real-world phenomena are unpredictable, and their outcomes generally contain a certain amount of variability. This variability is taken into account using a measure of uncertainty called **probability measure**.

Definition

The **sample space** S is the set of all possible outcomes of a phenomenon. An **event** is a subset of the sample space S.

Examples

1. If the experiment consists of tossing a coin, $S = \{0, 1\}$. The result of this experiment cannot be known in advance. For example, $E = \{1\}$ is an event of S.

2. If we are interested in the lifespan of a phone, $S = \mathbb{R}_+$. We can also choose $S = [0, M]$, because this lifespan is probably not infinite! The event $E = [10, \infty)$ represents the event "the lifespan of more than 10 time units."

3. For the number of days without snow in Quebec City in a year, we can choose $S = \mathbb{N}$. The event $E = (0, 5]$ represents the event "fewer than 5 days without snow in Quebec City in a year."

Definition

A **probability measure** $\mathbb{P}$ on S is an application (function) defined on the sample space and satisfying the following properties:

1. For each event E, $\mathbb{P}(E) \in [0, 1]$.
2. $\mathbb{P}(S) = 1$.
3. Let $E_1, E_2, ...$ be a sequence of mutually exclusive events (finite or infinite), i.e. $\forall i \neq j, E_i \cap E_j = \emptyset$. We have
$$\mathbb{P}(\bigcup_{n=1}^{\infty} E_n) = \sum_{n=1}^{\infty} \mathbb{P}(E_n).$$

We call $\mathbb{P}(E)$ the probability of event E.

The definition of probability measures can be subjective and linked to the statistician's experience. Let's take example 3 on the number of days without snow in Quebec City during the year. Someone who has just arrived in Canada may want to give the same probability to each day, while a Quebecer will have more information and will be able to vary the probabilities based on this knowledge.

Definition

Two events E and F are said to be **independent** if $\mathbb{P}(E \cap F) = \mathbb{P}(E) \times \mathbb{P}(F)$.

Definition

Let E and F be two events. The **conditional probability** that E occurs given that F has occurred is defined by:
$$\mathbb{P}(E \mid F) = \frac{\mathbb{P}(E \cap F)}{\mathbb{P}(F)}.$$

Intuitively, two events are independent if knowledge of one provides no information about the occurrence of the other. We also have $\mathbb{P}(E \mid F) = \mathbb{P}(E)$.

2 Random variables

In probability theory, it is customary to express the outcome of experiments as the value of a function called a **random variable**. This characterization is always possible.

Definition

Let X be a random variable. The **distribution** of this random variable is defined by the application $A \mapsto \mathbb{P}(X \in A)$.

Definition

Let X be a random variable. This random variable is **discrete** if it takes, at most, a countable number of values. In this case, the distribution of X is given by the probabilities $\mathbb{P}(X = x)$ for all outcomes x.

Definition

Let X be a random variable. This random variable is **continuous** if the probabilities $\mathbb{P}(X \in A)$ are given by integrals of the form $\int_A f(x)dx$ where $f : \mathbb{R}^d \to \mathbb{R}_+$ is an integrable function such that $\int_{\mathbb{R}^d} f(x)dx = 1$. Note that, for a fixed outcome x, $\mathbb{P}(X = x) = 0$.

Definition

Let X be a random variable. The **mathematical expectation** $\mathbb{E}(X)$ of X is the average value of the outcome of X with respect to its probability distribution. The expectation is usually denoted by μ.

Let F be a countable set. A discrete random variable X has an expectation $\mathbb{E}(X) = \sum_{x \in F} x\mathbb{P}(X = x)$. Let X be a continuous random variable with density f. Its expectation is given by $\mathbb{E}(X) = \int_{\mathbb{R}^d} xf(x)dx$.

Transfer theorem

Let X be a random variable. Let $g : \mathbb{R}^d \mapsto \mathbb{R}$ be a function such that $\mathbb{E}[g(X)]$ exists. We have:

1. If X is a discrete random variable, $\mathbb{E}[g(X)] = \sum_{x \in F} g(x)\mathbb{P}(X = x)$;
2. If X is a continuous random variable with density f, $\mathbb{E}[g(X)] = \int_{\mathbb{R}^d} g(x)f(x)dx$.

Properties: Linearity of expectation

Let X and Y be two random variables whose expectations exist, and let $\lambda \in R$. We have:

1. $\mathbb{E}(X + Y) = \mathbb{E}(X) + \mathbb{E}(Y)$;
2. $\mathbb{E}(\lambda X) = \lambda \mathbb{E}(X)$.

Proof

The proof is derived from the transfer theorem and the linearity of addition and integration.

Definition

Let X be a random variable such that the expectation of its square exists. The **variance** of X is defined by

$$\mathrm{Var}(X) = \mathbb{E}\left[(X - \mathbb{E}(X))^2\right] = \mathbb{E}\left[X^2\right] - \mathbb{E}\left[X\right]^2.$$

The variance measures the dispersion of a random variable around its mean. We can also look at the **standard deviation**, defined as the square root of the variance: $\sigma(X) = \sqrt{\mathrm{Var}(X)}$.

Definition

Let X and Y be two random variables and A and B be two events. If the events $\{X \in A\}$ and $\{Y \in B\}$ are independent, then we say that the random variables X and Y are **independent**.

From this definition, we can deduce that:

1. for functions f and g, the random variables $f(X)$ and $g(Y)$ are independent;
2. if the random variables X and Y are real-valued and their expectation exists, then the expectation of the product XY exists and $\mathbb{E}(XY) = \mathbb{E}(X) \times \mathbb{E}(Y)$.

Definition

Let X be a random variable. The **distribution function** $F : \mathbb{R} \mapsto [0, 1]$ of X is defined by

$$F(t) = \mathbb{P}(X \leq t), \quad t \in \mathbb{R}.$$

3 Random vectors

Suppose that $X = (X_1, X_2)$ is a random variable of dimension 2 with density f_X. Random variables of dimension greater than 1 are generally referred to as **random vectors**. The densities of X_1 and X_2 are called **marginal densities**. When X_1 and X_2 are independent, we have:

$$f_X(x, y) = f_{X_1}(x) \cdot f_{X_2}(y), \quad (x, y) \in \mathbb{R}^2.$$

Example of the multivariate normal distribution

A random vector X of dimension p is said to follow a multivariate normal distribution with mean μ and variance Σ if its density is given by

$$f_X(x) = \frac{1}{(2\pi)^{p/2}} \cdot \frac{1}{(\det \Sigma)^{1/2}} \cdot \exp\left\{ -\frac{1}{2} (x-\mu)^\top \Sigma^{-1} (x-\mu) \right\}, \quad x \in \mathbb{R}^p.$$

We denote $X \sim \mathcal{N}_p(\mu, \Sigma)$.

In statistics, an important quantity to measure is the linear dependence between X_1 and X_2. For this, we can use the covariance or the correlation.

Definition

Let $X = (X_1, X_2)$ be a random vector such that the expectation of the square of X_1 and X_2 exists. The **covariance** between X_1 and X_2 is given by

$$\mathrm{Cov}(X_1, X_2) = \mathbb{E}\left[(X_1 - \mathbb{E}(X_1))(X_2 - \mathbb{E}(X_2)) \right].$$

The **correlation** between X_1 and X_2 is a version of the covariance normalized by the standard deviation of the random variables. It is given by

$$\mathrm{Corr}(X_1, X_2) = \frac{\mathrm{Cov}(X_1, X_2)}{\sigma(X_1)\sigma(X_2)}.$$

The sign of the covariance and correlation can be interpreted. If they are strictly positive, X_1 and X_2 tend to move in the same direction. If X_1 increases, then X_2 also increases, and vice versa. If they are strictly negative, X_1 and X_2 tend to move in opposite directions. If X_1 increases, then X_2 decreases, and vice versa. If the covariance is equal to 0, there are no rules and X_1 and X_2 are said to be orthogonal.

Properties

Let $X = (X_1, X_2)$ be a random vector. We have

1. $\mathrm{Cov}(X_1, X_2) = \mathbb{E}(X_1 X_2) - \mathbb{E}(X_1)\mathbb{E}(X_2)$;
2. $\mathrm{Cov}(X_1, X_2) = \mathrm{Cov}(X_2, X_1)$;
3. $\mathrm{Cov}(X_1 + \lambda Y_1, X_2) = \mathrm{Cov}(X_1, X_2) + \lambda \mathrm{Cov}(Y_1, X_2)$.

Proof

1. We find the result by expanding the product in the definition of the covariance.
2. Using point 1. and the commutativity of multiplication.
3. Using point 1. and the linearity of expectation.

4 Estimation

In practice, we do not have perfect knowledge of our random vectors, but only some of their realizations (called samples). Let $x_1, \dots, x_n$ be n independent realizations of a random vector X with mean μ and variance Σ.

The estimator of the mean μ is given by

$$\hat{\mu} = \overline{X} := \frac{1}{n}\sum_{i=1}^{n} x_i.$$

The estimator of the variance Σ is given by

$$\widehat{\Sigma} := \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \hat{\mu})(x_i - \hat{\mu})^\top.$$

Why do we divide this sum by $n-1$ and not by n to estimate the variance? If we divide by n, $\hat{\Sigma}$ is a biased estimator of the variance. Indeed, we must take into account that we are using a biased estimator of the mean in the variance estimator and therefore correct for this estimate.

Let $D = \{\mathrm{diag}(\widehat{\Sigma})\}^{1/2}$ be the matrix of standard deviations calculated on the sample. We can estimate the correlation matrix on the sample by

$$\widehat{R} = D^{-1}\widehat{\Sigma}D^{-1}.$$

References

Delmas, Jean-François. 2013. *Introduction au calcul des probabilités et à la statistique : exercices, problèmes et corrections (2e édition)*. Les Presses de l'ENSTA.

Wasserman, Larry. 2010. *All of Statistics: A Concise Course in Statistical Inference*. Springer Publishing Company, Incorporated.