Review of some probability concepts: random vectors, large-sample results

(A quick tour)

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Random vectors

Random vectors

In statistics multiple variables are usually observed, and vectors of random variables (**random vectors**) are required. The two-dimensional case is useful to illustrate the main concepts, and will be used here.

For continuous r.v., the **joint (probability) density function** extends the one-dimensional case: it is the $f(x, y)$ function such that, for any $A \subseteq \mathbb{R}^2$

$$\Pr\{(X, Y) \in A\} = \int\int_A f(x, y) dx\, dy\,.$$

Note that $f(x, y) \geq 0$ and $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x, y) dx\, dy = 1$.

The probability density function defines the **joint distribution** of the random vector (X, Y).

Marginal distribution

The joint distribution embodies information about each components, so that the distribution of X, ignoring Y, can be obtained from $f(x, y)$.

The *marginal* density function of X is given by

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

and similarly for the other variable.

(Note: here and elsewhere we always use the symbol f for any p.d.f., identifying the specific case by the argument of the function).

Conditional distribution

The *conditional density function* of Y given $X = x_0$ updates the distribution of Y by incorporating the information that $X = x_0$.

It is given by the important formula

$$f(y|X = x_0) = \frac{f(x_0, y)}{f(x_0)}, \qquad \text{provide } f(x_0) > 0\,.$$

The simplified notation $f(y|x_0)$ is often employed.

The conditional p.d.f. is properly defined, since $f(y|X = x_0) \geq 0$ and $\int_{-\infty}^{\infty} f(y|x_0) dy = 1$.

A symmetric definition applies to X given $Y = y_0$.

Conditional distribution: useful properties

In the two dimensional case, it is readily possible to write

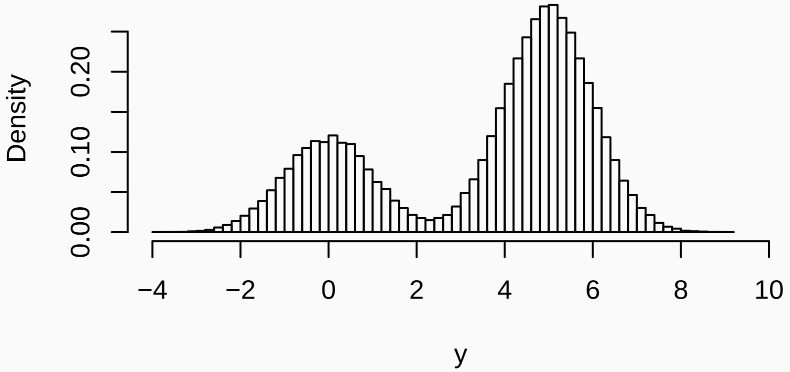
$$f(x, y) = f(x)\, f(y|x)\,.$$

Extensions to higher dimensions require some care:

$$\begin{aligned}
f(x, y, z) &= f(x, y|z)\, f(z) \\
f(x, y|z) &= f(x|z)\, f(y|x, z) \\
f(x, y, z) &= f(x|y, z)\, f(y, z) \\
f(x, y, z) &= f(x|y, z)\, f(y|z)\, f(z) \\
f(x_1, x_2, \ldots, x_n) &= f(x_1)\, f(x_2|x_1)\, f(x_3|x_2, x_1)\, \ldots f(x_n|x_{n-1}, \ldots, x_2, x_1)
\end{aligned}$$

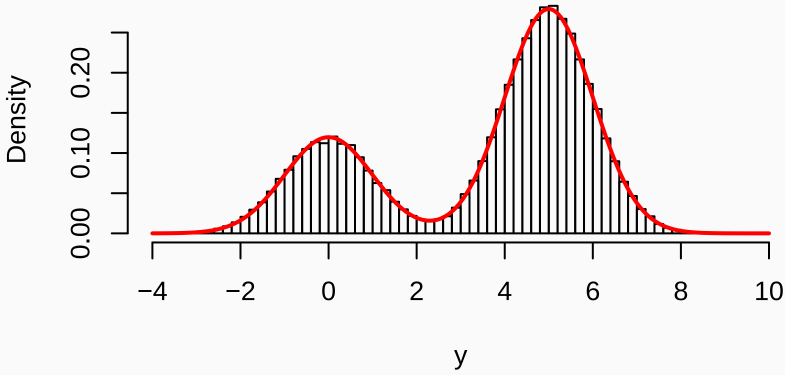
R lab: simulation from joint distributions

```
x <- rbinom(10^5, size = 1, prob = 0.7)
y <- rnorm(10^5, m = x * 5, s = 1) ### Y| X = x ~ N(x * 5, 1)
hist.scott(y, main = "", xlim = c(-4, 10))
```



R lab: simulation from joint distributions (cont'd.)

```
xx <- seq(-4, 10, l = 1000)
ff <- 0.3 * dnorm(xx, 0) + 0.7 * dnorm(xx, 5)
### This is a mixture of normal distributions
hist.scott(y, main = "",  xlim = c(-4, 10))
lines(xx, ff, col = "red", lwd = 2)
```



Bayes theorem

From the factorization of the joint distribution it readily follows that

$$f(x, y) = f(x)\, f(y|x) = f(y)\, f(x|y)$$

from which we obtain the **Bayes theorem**

$$f(x|y) = \frac{f(x)\, f(y|x)}{f(y)}\,.$$

This is a cornerstone of statistics, leading to an entire school of statistical modelling.

Independence and conditional independence

When $f(y|x)$ does not depend on the value of y, the r.v. X and Y are *independent*, and

$$f(x, y) = f(y)\, f(x)$$

More in general, n r.v. are independent if and only if

$$f(x_1, x_2, \ldots, x_2) = f(x_1)\, f(x_2) \ldots f(x_n)\,.$$

Conditional independence arises when two r.v. are independent given a third one:

$$f(y, x|z) = f(x|z)\, f(y|z)$$

An important part of statistical modelling exploits some sort of conditional independence.

Example of conditional independence: the Markov property

The general factorization defined above

$$f(x_1, x_2, \ldots, x_n) = f(x_1)\, f(x_2|x_1)\, f(x_3|x_2, x_1)\, \ldots f(x_n|x_{n-1}, \ldots, x_2, x_1)$$

will simplify considerably when the *first order Markov property* holds:

$$f(x_i|x_1, \ldots, x_{i-1}) = f(x_i|x_{i-1})$$

which means that X_i is independent of $X_1, \ldots, X_{i-2}$ given X_{i-1}. We get

$$f(x_1, x_2, \ldots, x_n) = f(x_1) \prod_{i=2}^{n} f(x_i|x_{i-1})\,.$$

When the variables are observed over time, this means that the process has *short memory*, a property quite useful in the statistical modelling of **time series**.

Mean and variance of linear transformations

For two r.v. X and Y and two constants a, b we get

$$E(a\,X + b\,Y) = a\,E(X) + b\,E(Y)\,.$$

The result follows from the more general one

$$E\{g(X, Y)\} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x, y)\, f(x, y)\, dx\, dy\,.$$

For variances we need first to introduce the **covariance** between X and Y

$$\mathrm{cov}(X, Y) = E\{(X - \mu_x)\,(Y - \mu_y)\} = E(X\,Y) - \mu_x\,\mu_y\,,$$

where $\mu_x = E(X)$ and $\mu_y = E(Y)$. Then

$$\mathrm{var}(a\,X + b\,Y) = a^2\,\mathrm{var}(X) + b^2\,\mathrm{var}(Y) + 2\,a\,b\,\mathrm{cov}(X, Y)\,.$$

Note: for X, Y independent it follows that $\mathrm{cov}(X, Y) = 0$. The reverse is not true, unless the joint distribution of X and Y is multivariate normal.

Mean vector

For a random vector $\mathbf{X} = (X_1, X_2, \dots, X_n)^\top$, the **mean vector** is just

$$E(\mathbf{X}) = \begin{pmatrix} E(X_1) \\ E(X_2) \\ \vdots \\ E(X_n) \end{pmatrix} .$$

The mean vector has the same properties of the scalar case, so that for example $E(\mathbf{X} + \mathbf{Y}) = E(\mathbf{X}) + E(\mathbf{Y})$, and for $\mathbf{A}$ and $\mathbf{b}$ a $n \times n$ matrix and a $n \times 1$ vector, respectively, it follows that

$$E(\mathbf{A}\,\mathbf{X} + \mathbf{b}) = \mathbf{A}\,E(\mathbf{X}) + \mathbf{b}\,.$$

Variance-covariance matrix

The variance-covariance matrix of the random vector $\mathbf{X}$ collects all the variances (on the main) diagonal and all the pairwise covariances (off the main diagonal), being the $n \times n$ symmetric semi-definite matrix

$$\boldsymbol{\Sigma} = E\{(\mathbf{X}-\boldsymbol{\mu}_x)\,(\mathbf{X}-\boldsymbol{\mu}_x)^\top\} = \begin{pmatrix} \mathrm{var}(X_1) & \mathrm{cov}(X_1, X_2) & \cdots & \mathrm{cov}(X_1, X_n) \\ \mathrm{cov}(X_1, X_2) & \mathrm{var}(X_2) & \cdots & \mathrm{cov}(X_2, X_n) \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{cov}(X_1, X_n) & \mathrm{cov}(X_2, X_n) & \cdots & \mathrm{var}(X_n) \end{pmatrix}$$

Useful properties:

$$\begin{aligned} \boldsymbol{\Sigma}_{\mathbf{A}\,\mathbf{X}+\mathbf{b}} &= \mathbf{A}\,\boldsymbol{\Sigma}\,\mathbf{A}^\top \\ \boldsymbol{\Sigma}_{\mathbf{X}^\top\mathbf{A}\,\mathbf{X}} &= \boldsymbol{\mu}_x^\top\mathbf{A}\,\boldsymbol{\mu}_x + \mathrm{tr}(\mathbf{A}\,\boldsymbol{\Sigma}) \end{aligned}$$

Transformation of random variables and random vectors

Given a continuous r.v. X and a transformation $Y = g(X)$, with g an invertible function, it readily follows that

$$f_y(y) = f_x\{g^{-1}(x)\} \left| \frac{dx}{dy} \right| .$$

The result is extended to two continuous random vectors with the same dimension

$$f_{\mathbf{y}}(\mathbf{y}) = f_{\mathbf{x}}\{g^{-1}(\mathbf{x})\} \left| \mathbf{J} \right| ,$$

with $J_{ij} = \partial x_i / \partial y_j$.

For discrete r.v., the results are simpler, with no need of including the Jacobian of the transformation.

The multivariate normal distribution

The multivariate normal distribution

Start from a set of n i.i.d. $Z_i \sim \mathcal{N}(0, 1)$, so that $E(\mathbf{Z}) = \mathbf{0}$ and covariance matrix $\mathbf{I}_n$. If $\mathbf{B}$ is $m \times n$ matrix of coefficients and $\boldsymbol{\mu}$ a m-vector of coefficients, then the m-dimensional random vector $\mathbf{X}$

$$\mathbf{X} = \mathbf{B}\,\mathbf{X} + \boldsymbol{\mu}$$

has a **multivariate normal distribution** with covariance matrix $\boldsymbol{\Sigma} = \mathbf{B}\,\mathbf{B}^\top$.

The notation is

$$\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})\,.$$

Joint p.d.f.

Using basic results on transformation of random vectors, starting from the joint p.d.f of $Z_1, Z_2, \ldots, Z_n$ we obtain

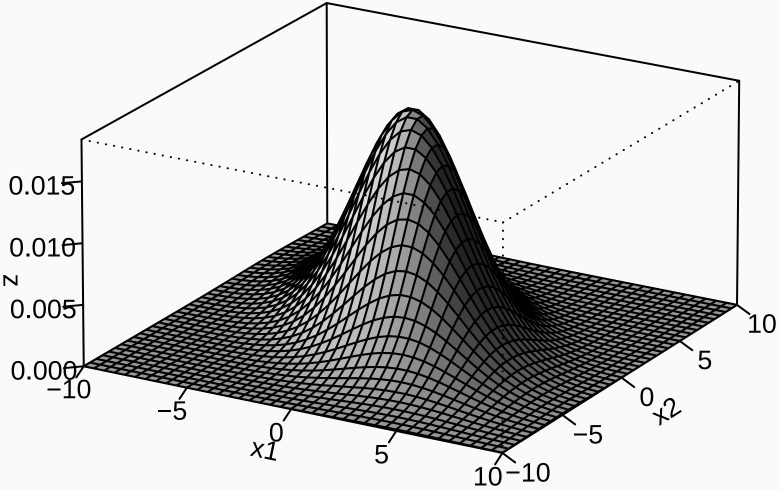
$$f_{\mathbf{x}}(\mathbf{x}) = \frac{1}{\sqrt{(2\,\pi)^m\,|\boldsymbol{\Sigma}|}}\, exp\left\{-\frac{1}{2}\,(\mathbf{x}-\boldsymbol{\mu})^\top\,\boldsymbol{\Sigma}^{-1}\,(\mathbf{x}-\boldsymbol{\mu})\right\}, \qquad \text{for } \mathbf{x} \in \mathbb{R}^m,$$

provide that $\boldsymbol{\Sigma}$ has full rank m. The result can be extended to *singular* $\boldsymbol{\Sigma}$ by recourse to the *pseudo-inverse* of $\boldsymbol{\Sigma}$: this is used, for example, in the analysis of *compositional data*.

A useful property which holds only for this distribution: *two r.v. with multivariate normal distribution and* **zero covariance** *are* **independent**.

Example: bivariate case

We take $\mu_1 = \mu_2 = 0$, $\sigma_1^2 = 10$, $\sigma_2^2 = 10$, $\sigma_{12} = 15$



Linear transformations

It is simple to verify that if $\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ and $\mathbf{A}$ is a $k \times m$ matrix of constants then

$$\mathbf{A}\,\mathbf{X} \sim \mathcal{N}(\mathbf{A}\,\boldsymbol{\mu}, \mathbf{A}\,\boldsymbol{\Sigma}\,\mathbf{A}^\top)\,.$$

A special case is obtained when $k = 1$, in that for a m-dimensional vector $\mathbf{a}$

$$\mathbf{a}^\top\,\mathbf{X} \sim \mathcal{N}(\mathbf{a}^\top\,\boldsymbol{\mu}, \mathbf{a}^\top\,\boldsymbol{\Sigma}\,\mathbf{a})\,.$$

Note that for suitable choices of $\mathbf{a}$ (when all the elements 0s or 1s) it follows that **the marginal distribution of any subvector of $\mathbf{X}$ is multivariate normal**.

Normality of the marginal distributions, instead, does not imply multivariate normality.

Conditional distributions

Consider two random vectors $\mathbf{X}$ and $\mathbf{Y}$ with multivariate normal joint distribution, and partition their joint covariance matrix as

$$\boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Sigma}_{xx} & \boldsymbol{\Sigma}_{xy} \\ \boldsymbol{\Sigma}_{yx} & \boldsymbol{\Sigma}_{yy} \end{pmatrix},$$

and similarly for the mean vector $\boldsymbol{\mu} = (\boldsymbol{\mu}_x, \boldsymbol{\mu}_y)^\top$.

Using results on *partitioned matrices*, it follows that the **conditional distributions are multivariate normal**.

For instance

$$\mathbf{Y}|\mathbf{x} \sim \mathcal{N}(\boldsymbol{\mu}_y + \boldsymbol{\Sigma}_{yx}\,\boldsymbol{\Sigma}_{xx}^{-1}\,(\mathbf{x} - \boldsymbol{\mu}_x), \boldsymbol{\Sigma}_{yy} - \boldsymbol{\Sigma}_{yx}\,\boldsymbol{\Sigma}_{xx}^{-1}\,\boldsymbol{\Sigma}_{xy}).$$

Statistics

Random sample

The collection of r.v. $X_1, X_2, \ldots, X_n$ is said to be a **random sample** of size n if they are *independent and identically distributed*, that is

- $X_1, X_2, \ldots, X_n$ are independent r.v.
- They have the same distribution, namely the same c.d.f.

The concept is central in statistics, and it is the suitable mathematical model for the outcome of sampling units from a very large population. The definition is, however, more general.

(For more details: https://www.probabilitycourse.com/chapter8/8_1_1_random_sampling.php)

Statistics

A **statistic** is a r.v. defined as a function of a set of r.v.

Obvious examples are the sample mean and variance of data $y_1, y_2, \dots, y_n$

$$\overline{y} = \frac{1}{n} \sum_{i=1}^{n} y_i \,, \qquad s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (y_i - \overline{y})^2 \,.$$

Consider a random vector $\mathbf{y}$ with p.d.f. $f_{\boldsymbol{\theta}}(\mathbf{y})$ depending on a vector $\boldsymbol{\theta}$ (which is the *parameter*, as we will see).

If a statistic $t(\mathbf{y})$ is such that $f_{\boldsymbol{\theta}}(\mathbf{y})$ can be written as

$$f_{\boldsymbol{\theta}}(\mathbf{y}) = h(\mathbf{y})\, g_{\boldsymbol{\theta}}\{t(\mathbf{y})\} \,,$$

where h does not depend on $\boldsymbol{\theta}$, and g depends on $\mathbf{y}$ only through $t(\mathbf{y})$, then t is a **sufficient statistic** for $\boldsymbol{\theta}$: all the *information* available on $\boldsymbol{\theta}$ contained in $\mathbf{y}$ is supplied by $t(\mathbf{y})$.

The concepts of information and sufficiency are central in statistical inference.

Example: sufficient statistic for the normal distribution

Given a vector of independent normal r.v. $Y_i \sim \mathcal{N}(\mu, \sigma^2)$, it follows that $\boldsymbol{\theta} = (\mu, \sigma^2)$ and

$$
\begin{aligned}
f_{\boldsymbol{\theta}}(\mathbf{y}) &= \prod_{i=1}^{n} \frac{1}{\sqrt{2\,\pi}\,\sigma} \exp\left\{-\frac{1}{2\,\sigma^2}(y_i - \mu)^2\right\} \\
&= \frac{1}{\left(\sqrt{2\,\pi}\right)^n \sigma^n} \exp\left\{-\frac{1}{2\,\sigma^2} \sum_i (y_i - \mu)^2\right\} .
\end{aligned}
$$

By some simple algebra, it is possible to show that the two-dimensional statistic $t(\mathbf{y}) = (\bar{y}, s^2)$ is sufficient for (μ, σ^2).

Complements & large-sample results

Moment generating function

The **moment generating function** (m.g.f.) characterises the distribution of a r.v. X, and it is defined as

$$M_X(t) = E(e^{t\,X})\,, \qquad \text{for } t \text{ real}\,.$$

The name derives from the fact the k^{th} derivative of the m.g.f. at $t = 0$ gives the k^{th} uncentered moment:

$$\frac{d^k\,M_X(t)}{d\,t^k}\Big|_{t=0} = E(X^k)\,.$$

Two useful properties:

- If $M_X(t) = M_Y(t)$ for some small interval around $t = 0$, then X and Y have the same distribution.
- If X and Y are independent, $M_{X+Y}(t) = M_X(t)\,M_Y(t)$.

The central limit theorem

For i.i.d. r.v. $X_1, X_2, \ldots, X_n$ with mean μ and finite variance σ^2, the **central limit theorem** states that for large n the distribution of the r.v. $\overline{X}_n = \sum_{i=1}^n X_i/n$ is approximately

$$\overline{X}_n \sim \mathcal{N}(\mu, \sigma^2/n)\,.$$

More formally, the theorem says that for any $x \in \mathbb{R}$ the c.d.f. of $Z_n = (\overline{X}_n - \mu)/\sqrt{\sigma^2/n}$ satisfies

$$\lim_{n\to\infty} F_{Z_n}(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\,\pi}}\, e^{-z^2/2}\, dz\,.$$

The proof is simple, and it uses the m.g.f.

The theorem generalizes to multivariate and non-identical settings.

It has a central importance in statistics, since it supports the normal approximation to the distribution of a r.v. that can be viewed as the sum of other r.v.

The law of large numbers

Consider i.i.d. (independent and identically distributed) r.v. $X_1, \ldots, X_n$, with mean μ and $(E|X_i|) < \infty$.

The **strong law of large numbers** states that, for any positive ϵ

$$\Pr\left(\lim_{n\to\infty} |\overline{X}_n - \mu| < \epsilon\right) = 1\,,$$

namely $\overline{X}_n$ *converges almost surely to* μ.

With the further assumption $\mathrm{var}(X_i) = \sigma^2$, the **weak law of large numbers** follows

$$\lim_{n\to\infty} \Pr\left(|\overline{X}_n - \mu| \geq \epsilon\right) = 0\,.$$

Proof of the weak law of large numbers

First we recall the *Chebyshev's inequality*: given a r.v. X such that $E(X^2) < \infty$ and a constant $a > 0$, then

$$\Pr(|X| \geq a) \leq \frac{E(X^2)}{a^2}\,.$$

We apply the inequality to the case of interest, so that

$$\Pr\left(|\overline{X}_n - \mu| \geq \epsilon\right) \leq \frac{E\{(\overline{X}_n - \mu)^2\}}{\epsilon^2} = \frac{\mathrm{var}(\overline{X}_n)}{\epsilon^2} = \frac{\sigma^2}{n\,\epsilon^2}\,,$$

which tends to zero when $n \to \infty$.

The result may hold also for non-i.i.d. cases, provided $\mathrm{var}(\overline{X}_n) \to 0$ for large n.

Jensen's inequality

This is another useful result, that states that for a r.v. X and a concave function g

$$g\{E(X)\} \geq E\{g(X)\}\,.$$

(Note: a concave function is such that

$$g\{\alpha\, x_1 + (1-\alpha)\, x_2\} \geq \alpha\, g(x_1) + (1-\alpha)\, g(x_2)\,,$$

for any x_1, x_2, and $0 \leq \alpha \leq 1$).

An example is $g(x) = -x^2$, so that

$$-E(X)^2 \geq -E(X^2) \quad \Rightarrow \quad E(X)^2 \leq E(X^2)\,,$$

which is obviously true since $E(X^2) = \mathrm{var}(X) + E(X)^2$.