GENIOMHE

Multivariate Statistics

by Samuel Ortion

Prof.: Cyril Dalmasso

Fall 2023

Contents

1 Introduction

Definition 1: Long Term Nonprocessor (LTNP)

Patient who will remain a long time in good health condition, even with a large viral load (cf. HIV).

Example 1: Genotype: Qualitative or Quantitative?

$$\text{SNP}: \begin{cases} \text{AA} \\ \text{AB} \\ \text{BB} \end{cases} \to \begin{pmatrix} 0 \\ 1 \\ 2 \end{pmatrix},$$

thus we might consider genotype either as a qualitative variable or quantitative variable.

When the variable are quantitative, we use regression, whereas for qualitative variables, we use an analysis of variance.

Part I.

1.1. Generalized Linear Model

$$g(\mathbb{E}(Y)) = X\beta$$

with g being

- Logistic regression: $g(v) = \log\left(\frac{v}{1-v}\right)$, for instance for boolean values,
- Poission regression: $g(v) = \log(v)$, for instance for discrete variables.

1.1.1. Penalized Regression

When the number of variables is large, e.g, when the number of explanatory variable is above the number of observations, if $p >> n$ (p: the number of explanatory variable, n is the number of observations), we cannot estimate the parameters. In order to estimate the parameters, we can use penalties (additional terms).

Lasso regression, Elastic Net, etc.

1.1.2. Simple Linear Model

$$\mathbf{Y} = \mathbf{X}\beta + \varepsilon$$

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix} = \begin{pmatrix} 1 & X_1 \\ 1 & X_2 \\ \vdots & \vdots \\ 1 & X_n \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

1.1.3. Assumptions

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1.1.4. Statistical Analysis Workflow

Step 1. Graphical representation;

Step 2. ...

$$Y = X\beta + \varepsilon,$$

is noted equivalently as

$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & x_{12} \\ 1 & x_{21} & x_{22} \\ 1 & x_{31} & x_{32} \\ 1 & x_{41} & x_{42} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{pmatrix}.$$

1.2. Parameter Estimation

1.2.1. Simple Linear Regression

1.2.2. General Case

If $\mathbf{X}^{\mathrm{T}}\mathbf{X}$ is invertible, the OLS estimator is:

$$\hat{\beta} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Y} \tag{1.1}$$

1.2.3. Ordinary Least Square Algorithm

We want to minimize the distance between $\mathbf{X}\beta$ and $\mathbf{Y}$:

$$\min \|\mathbf{Y} - \mathbf{X}\beta\|^2$$

(See chapter 2).

$$\begin{aligned}
&\Rightarrow \mathbf{X}\beta = proj^{(1,\mathbf{X})}\mathbf{Y} \\
&\Rightarrow \forall v \in w, vy = vproj^{w}(y) \\
&\Rightarrow \forall i : \\
&\quad \mathbf{X}_i\mathbf{Y} = \mathbf{X}_i X\hat{\beta} \qquad \text{where } \hat{\beta} \text{ is the estimator of } \beta \\
&\Rightarrow \mathbf{X}^{\mathrm{T}}\mathbf{Y} = \mathbf{X}^{\mathrm{T}}\mathbf{X}\hat{\beta} \\
&\Rightarrow (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Y} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}(\mathbf{X}^{\mathrm{T}}\mathbf{X})\hat{\beta} \\
&\Rightarrow \hat{\beta} = (X^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Y}
\end{aligned}$$

This formula comes from the orthogonal projection of $\mathbf{Y}$ on the subspace define by the explanatory variables $\mathbf{X}$

$\mathbf{X}\hat{\beta}$ is the closest point to $\mathbf{Y}$ in the subspace generated by $\mathbf{X}$.

If H is the projection matrix of the subspace generated by $\mathbf{X}$, $X\mathbf{Y}$ is the projection on $\mathbf{Y}$ on this subspace, that corresponds to $\mathbf{X}\hat{\beta}$.

1.3. Coefficient of Determination: R^2

Definition 2: R^2

$$0 \leq R^2 = \frac{\|\mathbf{X}\hat{\beta} - \bar{\mathbf{Y}}\mathbf{1}\|^2}{\|\mathbf{Y} - \bar{\mathbf{Y}}\mathbf{1}\|^2} = 1 - \frac{\|\mathbf{Y} - \mathbf{X}\hat{\beta}\|^2}{\|\mathbf{Y} - \bar{\mathbf{Y}}\mathbf{1}\|^2} \leq 1$$

proportion of variation of $\mathbf{Y}$ explained by the model.

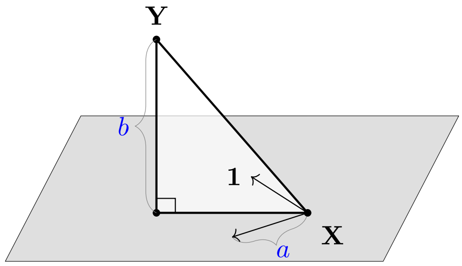

Figure 1.1. Orthogonal projection of $\mathbf{Y}$ on plan generated by the base described by $\mathbf{X}$. a corresponds to $\|\mathbf{X}\hat{\beta} - \bar{\mathbf{Y}}\|^2$ and b corresponds to $\|\mathbf{Y} - \hat{\beta}\mathbf{X}\|^2$

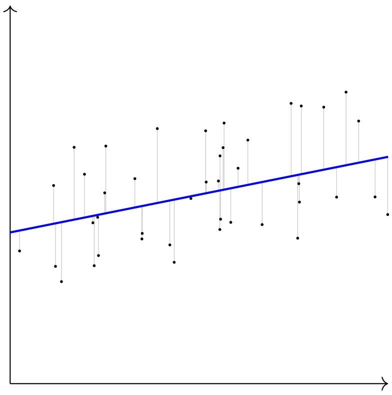

Figure 1.2. Ordinary least squares and regression line with simulated data.

2 Elements of Linear Algebra

Remark 1: vector

Let u a vector, we will use interchangeably the following notations: u and $\vec{u}$

Let $u = \begin{pmatrix} u_1 \\ \vdots \\ u_n \end{pmatrix}$ and $v = \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix}$

Definition 3: Scalar Product (Dot Product)

$$\begin{aligned} \langle u, v \rangle &= \begin{pmatrix} u_1, \dots, u_v \end{pmatrix} \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix} \\ &= u_1 v_1 + u_2 v_2 + \dots + u_n v_n \end{aligned}$$

We may use $\langle u, v \rangle$ or $u \cdot v$ notations.

Dot product properties

- $\langle u, v \rangle = \langle v, u \rangle$
- $\langle (u + v), w \rangle = \langle u, w \rangle + \langle v, w \rangle$
- $\langle u, v \rangle$
- $\langle \vec{u}, \vec{v} \rangle = \|\vec{u}\| \times \|\vec{v}\| \times \cos(\widehat{\vec{u}, \vec{v}})$

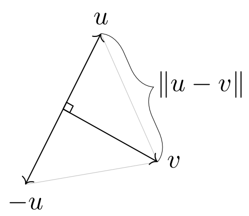

Figure 2.1. Scalar product of two orthogonal vectors.

Definition 4: Norm

Length of the vector.

$$\|u\| = \sqrt{\langle u, v\rangle}$$

$\|u, v\| > 0$

Definition 5: Distance

$$dist(u, v) = \|u - v\|$$

Definition 6: Orthogonality

Remark 2

$$(dist(u, v))^2 = \|u - v\|^2,$$

and

$$\langle v - u, v - u\rangle$$

$$\begin{aligned}\langle v - u, v - u\rangle &= \langle v, v\rangle + \langle u, u\rangle - 2\langle u, v\rangle \\ &= \|v\|^2 + \|u\|^2 \\ &= -2\langle u, v\rangle\end{aligned}$$

$$\begin{aligned}\|u - v\|^2 = \|u\|^2 + \|v\|^2 - 2\langle u, v\rangle \\ \|u + v\|^2 = \|u\|^2 + \|v\|^2 + 2\langle u, v\rangle\end{aligned}$$

Proposition 1: Scalar product of orthogonal vectors

$$u \perp v \Leftrightarrow \langle u, v\rangle = 0$$

Indeed. $\|u - v\|^2 = \|u + v\|^2$, as illustrated in Figure 2.1.

$$\begin{aligned} \Leftrightarrow & -2\langle u, v\rangle = 2\langle u, v\rangle \\ \Leftrightarrow & 4\langle u, v\rangle = 0 \\ \Leftrightarrow & \langle u, v\rangle = 0 \end{aligned}$$

□

Theorem 1

Pythagorean theorem If $u \perp v$, then $\|u + v\|^2 = \|u\|^2 + \|v\|^2$.

Definition 7: Orthogonal Projection

Let $y = \begin{pmatrix} y_1 \\ . \\ y_n \end{pmatrix} \in \mathbb{R}^n$ and w a subspace of $\mathbb{R}^n$ $\mathcal{Y}$ can be written as the orthogonal projection of y on w:

$$\mathcal{Y} = proj^w(y) + z,$$

where

$$\begin{cases} z \in w^\perp \\ proj^w(y) \in w \end{cases}$$

There is only one vector $\mathcal{Y}$ that ?

The scalar product between z and (?) is zero.

Property 1. *$proj^w(y)$ is the closest vector to y that belongs to w.*

Definition 8: Matrix

A matrix is an application, that is, a function that transform a thing into another, it is a linear function.

Example 2: Matrix application

Let A be a matrix:

$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$$

and

$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

Then,

$$\begin{aligned} Ax &= \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \\ &= \begin{pmatrix} ax_1 + bx_2 \\ cx_1 + dx_2 \end{pmatrix} \end{aligned}$$

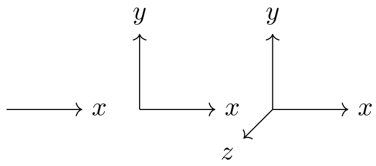

Figure 2.2. Coordinate systems

Example 2 continued

Similarly,

$$\begin{pmatrix} a & b & c & d \\ e & f & g & h \\ i & j & k & l \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} ax_1 + bx_2 + cx_3 \dots \end{pmatrix}$$

The number of columns has to be the same as the dimension of the vector to which the matrix is applied.

Definition 9: Tranpose of a Matrix

Let $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$, then $A^{\mathrm{T}} = \begin{pmatrix} a & c \\ b & d \end{pmatrix}$