

ERASMUS D4 course

Week 10: Linear regression, part 1

Subject: The concept of conditional distribution and
conditional Expected Value - part 2.

Introduction

In stochastic methods, for instance in Statistics, Econometrics
the general problem has a following form:

for given R.V. $(X_1, X_2, \dots, X_n)$ we are looking for
the interaction between the coordinates $X_1, \dots, X_n$ and we
try to establish the measure of this interaction.

To do this we can use: the covariance value, the correlation
coefficient, the notion of stochastic independence and others.

Among them is also the concept of conditional distribution
and conditional expected value.

Of course we are going to explain these concepts only
to the case $n=2$, so (X, Y) with finite
discrete joint distribution.

The concept of conditional distributions & cond. exp. value

Suppose we have a R.V. (X, Y) and its joint dist P ,
so

$$(X, Y) \longrightarrow P = [p_{ij}]_{n \times m},$$

where $n = |X(\Omega)|$, $m = |Y(\Omega)|$.

Then the marginal distributions are as follows:

$$d_X: P_{i\cdot} = \sum_{j=1}^m p_{ij}, \quad i = 1, \dots, n$$

$$d_Y: P_{\cdot j} = \sum_{i=1}^n p_{ij}, \quad j = 1, \dots, m,$$

where

$$P_{i\cdot} = P(\{\omega \in \Omega: X(\omega) = x_i\})$$

$$P_{\cdot j} = P(\{\omega \in \Omega: Y(\omega) = y_j\}).$$

Def 1.

The conditional distribution of X with respect of condition that $Y = y_k$ or of Y with respect of condition that $X = x_i$ we understand respectively

$$\frac{P_{i,k}}{P_{i,k}} = \frac{P(\{\omega \in \Omega: X(\omega) = x_i \& Y(\omega) = y_k\})}{P(\{\omega \in \Omega: Y(\omega) = y_k\})}, \text{ for } i=1, \dots, n$$

and fixed k , $k=1, 2, \dots, m$
or

$$\frac{P_{i,k}}{P_{i,\cdot}} = \frac{P(\{\omega \in \Omega: X(\omega) = x_i \& Y(\omega) = y_k\})}{P(\{\omega \in \Omega: X(\omega) = x_i\})}.$$

So,
$$\frac{P_{i,k}}{P_{\cdot,k}} = P(\{\omega \in \Omega: X(\omega) = x_i\} | \{\omega \in \Omega: Y(\omega) = y_k\})$$

and
$$\frac{P_{i,k}}{P_{i,\cdot}} = P(\{\omega \in \Omega: Y(\omega) = y_k\} | \{\omega \in \Omega: X(\omega) = x_i\})$$

Remark. Since
$$\sum_{i=1}^n \frac{P_{i,k}}{P_{i,k}} = \frac{1}{P_{\cdot,k}} \sum_{i=1}^n P_{i,k} = \frac{P_{\cdot,k}}{P_{i,k}} = 1$$

and
$$\sum_{k=1}^m \frac{P_{i,k}}{P_{i,\cdot}} = \frac{1}{P_{i,\cdot}} \sum_{k=1}^m P_{i,k} = \frac{P_{i,\cdot}}{P_{i,\cdot}} = 1,$$

The sequences given in def 1 define the probability distributions.

Having such distributions we can calculate the corresponding ~~math~~ mathematical expectations which we denote as follows:

$$\begin{aligned} (\#1) \quad E(Y | X = x_i) &= \sum_{k=1}^m y_k P(\{ \omega \in \Omega : Y(\omega) = y_k \} | \{ \omega \in \Omega : X(\omega) = x_i \}) \\ &= \sum_{k=1}^m y_k \frac{P_{i,k}}{P_{i \cdot}} \quad (i=1, \dots, n) \quad \text{and similarly} \end{aligned}$$

$$\begin{aligned} (\#2) \quad E(X | Y = y_k) &= \sum_{i=1}^n x_i \cdot P(\{ \omega \in \Omega : X(\omega) = x_i \} | \{ \omega \in \Omega : Y(\omega) = y_k \}) \\ &= \sum_{i=1}^n x_i \frac{P_{i,k}}{P_{\cdot k}} \quad (k=1, \dots, m) \end{aligned}$$

which are called the conditional math. expectations.

Now for R.V. (X, Y) as above let the set

$$O = \{ (x_i, y_k) \in \mathbb{R}^2, \quad i=1, 2, \dots, n, \quad k=1, 2, \dots, m \}$$

be a result of observation of $\omega \rightarrow (X(\omega), Y(\omega))$.

then the set

$$A = \{ (x, y) \in \mathbb{R}^2 : x = x_i, y = E(Y | X = x_i), i=1, \dots, n \},$$

and similarly

$$B = \{ (x, y) \in \mathbb{R}^2 : y = y_k, x = E(X | Y = y_k), k=1, \dots, m \}$$

is called the regression curve of the first type
Y with respect to X or X with respect to Y.

These curves are used for the determination of relationships
between X and Y, what is important in econometrics
and in general in statistics.

Now we show how it works on example.

Example.

We have

$$(X, Y) \longrightarrow P = \begin{matrix} & \begin{matrix} -1 & 1 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \end{matrix} & \begin{bmatrix} \frac{11}{50} & \frac{1}{10} \\ \frac{8}{50} & \frac{13}{50} \\ \frac{3}{50} & \frac{1}{5} \end{bmatrix} \end{matrix}$$

where $X(n) = \{1, 2, 3\}$, $Y(n) = \{-1, 1\}$,

$$\text{so } d_X = \left(\frac{16}{50}, \frac{21}{50}, \frac{13}{50} \right)$$

$$d_Y = \left(\frac{22}{50}, \frac{28}{50} \right).$$

We will find the regression curve of Y with respect to X
and vice-versa.

First we need conditional distributions for X & Y .

$$X : \begin{cases} P(X=1 | Y=-1) = \frac{\frac{11}{50}}{\frac{22}{50}} = \frac{1}{2} \\ P(X=2 | Y=-1) = \frac{\frac{8}{50}}{\frac{22}{50}} = \frac{8}{22} \\ P(X=3 | Y=-1) = \frac{\frac{3}{50}}{\frac{22}{50}} = \frac{3}{22} \end{cases}$$

$$\begin{cases} P(X=1 | Y=1) = \frac{\frac{1}{10}}{\frac{28}{50}} = \frac{5}{28} \\ P(X=2 | Y=1) = \frac{\frac{13}{50}}{\frac{28}{50}} = \frac{13}{28} \\ P(X=3 | Y=1) = \frac{\frac{1}{5}}{\frac{28}{50}} = \frac{10}{28} \end{cases}$$

$$Y : \begin{cases} P(Y=-1 | X=1) = \frac{\frac{11}{50}}{\frac{16}{50}} = \frac{11}{16} \\ P(Y=1 | X=1) = \frac{\frac{5}{10}}{\frac{16}{50}} = \frac{5}{16} \end{cases}$$

$$\begin{cases} P(Y=-1 | X=2) = \frac{\frac{8}{50}}{\frac{21}{50}} = \frac{8}{21} \\ P(Y=1 | X=2) = \frac{\frac{13}{50}}{\frac{21}{50}} = \frac{13}{21} \end{cases}$$

$$\begin{cases} P(Y=-1 | X=3) = \frac{\frac{3}{50}}{\frac{13}{50}} = \frac{3}{13} \\ P(Y=1 | X=3) = \frac{\frac{1}{5}}{\frac{13}{50}} = \frac{10}{13} \end{cases}$$

No we can calculate the conditional expectations:

$$E(X|Y=-1) = 1 \cdot \frac{1}{22} + 2 \cdot \frac{8}{22} + 3 \cdot \frac{7}{22} = \frac{36}{22}$$

$$E(X|Y=1) = \frac{61}{22}$$

and similarly

$$E(Y|X=1) = -1 \cdot \frac{11}{16} + 1 \cdot \frac{5}{16} = -\frac{6}{16}$$

$$E(Y|X=2) = \frac{5}{21}$$

$$E(Y|X=3) = \frac{7}{15}$$

Finally

$$A = \left\{ \left(1, -\frac{6}{16} \right), \left(2, \frac{5}{21} \right), \left(3, \frac{7}{15} \right) \right\}$$

$$B = \left\{ \left(\frac{36}{22}, -1 \right), \left(\frac{61}{22}, 1 \right) \right\}.$$