Conditional expectation

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Outline

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General definition

Definition 1.

Let

- (X, Y) couple of discrete random variables
- Joint pmf p
- Marginal pmf's p_X, p_Y
- y such that $p_Y(y) > 0$

Then the conditional pmf of X given $Y = y$ is defined by

$$p_{X|Y}(x|\, y) = \mathbf{P}\left(X = x|\, Y = y\right) = \frac{p(x,y)}{p_Y(y)}$$

Example ctd: tossing 3 coins (1)

Experiment:
Tossing a coin 3 times

Events: We consider

$$A = \text{"At most one Head"}$$
$$B = \text{"At least one Head and one Tail"}$$

Random variables: Set

$$X_1 = \mathbf{1}_A, \qquad X_2 = \mathbf{1}_B, \qquad X = (X_1, X_2)$$

Example ctd: tossing 3 coins (2)

Joint distribution of (X_1, X_2):

$X_1 \backslash X_2$	0	1	Marg. X_1
0	$1/8$	$3/8$	$1/2$
1	$1/8$	$3/8$	$1/2$
Marg. X_2	$1/4$	$3/4$	1

Conditional probabilities given $X_1 = 0$:

$$p_{X_2|X_1}(0|\,0) = \frac{1/8}{1/2} = \frac{1}{4}, \quad p_{X_2|X_1}(1|\,0) = \frac{3/8}{1/2} = \frac{3}{4}$$

Conditional probabilities given $X_2 = 1$:

$$p_{X_1|X_2}(0|\,1) = \frac{3/8}{3/4} = \frac{1}{2}, \quad p_{X_1|X_2}(1|\,1) = \frac{3/8}{3/4} = \frac{1}{2}$$

Conditioning Poisson random variables

Proposition 2.

Let

- $X \sim \mathcal{P}(\lambda_1)$, $Y \sim \mathcal{P}(\lambda_2)$
- $X \perp\!\!\!\perp Y$
- $p = \frac{\lambda_1}{\lambda_1+\lambda_2}$

Then

$$\mathcal{L}\left(X \middle| X+Y=n\right) = \text{Bin}(n, p)$$

Proof (1)

Expression for the conditional probabilities:
Let $0 \leq k \leq n$. Then invoking $X \perp\!\!\!\perp Y$,

$$\mathbf{P}\left(X = k \,|\, X + Y = n\right) = \frac{\mathbf{P}\left(X = k\right)\mathbf{P}\left(Y = n - k\right)}{\mathbf{P}\left(X + Y = n\right)}$$

Law of $X + Y$: One can prove that

$$X + Y \sim \mathcal{P}(\lambda_1 + \lambda_2)$$

Proof (2)

Computation of the conditional probabilities:

$$\begin{aligned}
&\mathbf{P}\left(X=k \mid X+Y=n\right) \\
&= e^{-\lambda_1}\frac{\lambda_1^k}{k!}e^{-\lambda_2}\frac{\lambda_2^{n-k}}{(n-k)!}\left[e^{-(\lambda_1+\lambda_2)}\frac{(\lambda_1+\lambda_2)^n}{n!}\right]^{-1} \\
&= \binom{n}{k}p^k(1-p)^{n-k}
\end{aligned}$$

Conclusion:

$$\mathcal{L}\left(X \mid X+Y=n\right) = \text{Bin}(n,p)$$

Cond. expectation in the discrete case

Definition 3.

Let

- (X, Y) couple of discrete random variables
- Joint pmf p
- Marginal pmf's p_X, p_Y, y such that $p_Y(y) > 0$
- $p_{X|Y}(x|\,y)$ conditional distribution

Then the conditional exp. of X given $Y = y$ is defined by

$$\mathbf{E}\,[X|\,Y = y] = \sum_{x \in \mathcal{E}} x\, p_{X|Y}(x|\,y)$$

Binomial example (1)

Situation: Let

- $X, Y \sim \text{Bin}(n, p)$
- $X \perp\!\!\!\perp Y$
- $Z = X + Y$

Problem: We wish to compute

$$\mathbf{E}\left[X \middle| Z = m \right]$$

Binomial example (2)

Distribution for Z:

$$Z = \sum_{i=1}^{n} X_i + \sum_{j=1}^{n} Y_j \sim \text{Bin}(2n, p)$$

Computation for conditional pmf: For $k \le \min(n, m)$ we have

$$\begin{aligned} \mathbf{P}\left(X = k \middle| Z = m\right) &= \frac{\mathbf{P}(X = k,\, X + Y = m)}{\mathbf{P}(Z = m)} \\ &= \frac{\mathbf{P}(X = k,\, Y = m - k)}{\mathbf{P}(Z = m)} \\ &= \frac{\binom{n}{k}\binom{n}{m-k}}{\binom{2n}{m}} \end{aligned}$$

Hypergeometric random variable (1)

Use: Consider the experiment

- Urn containing N balls
- m white balls, $N - m$ black balls
- Sample of size n is drawn without replacement
- Set $X = \#$ white balls drawn

Then

$$X \sim \text{HypG}(n, N, m)$$

Hypergeometric random variable (2)

Notation:

$$X \sim \text{HypG}(n, N, m), \quad \text{for } N \in \mathbb{N}^*, \; m, n \leq N$$

State space:

$$\{0, \ldots, n\}$$

Pmf:

$$\mathbf{P}(X = k) = \frac{\binom{m}{k}\binom{N-m}{n-k}}{\binom{N}{n}}, \quad 0 \leq k \leq n$$

Expected value and variance: Set $p = \frac{m}{N}$. Then

$$\mathbf{E}[X] = np, \qquad \mathbf{Var}(X) = np(1-p)\left(\frac{N-n}{N-1}\right)$$

Binomial example (3)

Conditional pmf: For $k \leq \min(n, m)$ we have seen

$$p_{X|Z}(k|\, m) = \frac{\binom{n}{k}\binom{n}{m-k}}{\binom{2n}{m}}$$

Recall: If $V \sim \text{HypG}(n, N, m)$ then

$$\mathbf{P}(X = k) = \frac{\binom{m}{k}\binom{N-m}{n-k}}{\binom{N}{n}}$$

Identification of the conditional pmf: We have

$$p_{X|Z}(k|\, m) = \text{Pmf of HypG}(m, 2n, n)$$

Binomial example (4)

Conditional expectation: Let $V \sim \text{HypG}(m, 2n, n)$. Then

$$\mathbf{E}[X|\, Z = m] = \mathbf{E}[V]$$

Numerical value:
According to the values for hypergeometric distributions,

$$\mathbf{E}[X|\, Z = m] = m \times \frac{n}{2n} = \frac{m}{2}$$

Outline

General definition

Definition 4.

Let

- (X, Y) couple of continuous random variables
- Joint density f
- Marginal densities f_X, f_Y
- y such that $f_Y(y) > 0$

Then the conditional density of X given $Y = y$ is defined by

$$f_{X|Y}(x|\, y) = \frac{f(x, y)}{f_Y(y)}$$

Justification of the definition

Heuristics: $f_{X|Y}(x|\, y)$ can be interpreted as

$$
\begin{aligned}
f_{X|Y}(x|\, y)\, dx &= \frac{f(x,y)\, dxdy}{f_Y(y)\, dy} \\
&\simeq \frac{\mathbf{P}\left(x \le X \le x+dx,\ y \le Y \le y+dy\right)}{\mathbf{P}\left(y \le Y \le y+dy\right)} \\
&= \mathbf{P}\left(x \le X \le x+dx|\, y \le Y \le y+dy\right)
\end{aligned}
$$

Use of the conditional probability: compute probabilities like

$$\mathbf{P}\left(X \in A|\, Y = y\right) = \int_A f_{X|Y}(x|\, y)\, dx$$

Rigorous definition: see next sections

Simple example of continuous conditioning (1)

Density: Let (X, Y) be a random vector with density

$$\frac{e^{-\frac{x}{y}} e^{-y}}{y} \mathbf{1}_{(0,\infty)}(x) \mathbf{1}_{(0,\infty)}(y)$$

Question: Compute

$$\mathbf{P}(X > 1 | Y = y)$$

Simple example of continuous conditioning (2)

Marginal distribution of Y: We have

$$\begin{aligned} f_Y(y) &= \int_0^\infty f(x,y)\,dx \\ &= \frac{e^{-y}}{y}\left(\int_0^\infty e^{-\frac{x}{y}}\,dx\right)\mathbf{1}_{(0,\infty)}(y) \\ &= e^{-y}\,\mathbf{1}_{(0,\infty)}(y) \end{aligned}$$

Conditional density: For $y > 0$ we have

$$f_{X|Y}(x|\,y) = \frac{f(x,y)}{f_Y(y)} = \frac{e^{-\frac{x}{y}}}{y}\,\mathbf{1}_{(0,\infty)}(x)$$

Namely $\mathcal{L}(X|\,Y=y) = \mathcal{E}(\frac{1}{y})$

Simple example of continuous conditioning (3)

Conditional probability:

$$\begin{aligned}
\mathbf{P}(X > 1 | Y = y) &= \int_1^{\infty} f_{X|Y}(x| y)\, dx \\
&= \int_1^{\infty} \frac{e^{-\frac{x}{y}}}{y}\, dx \\
&= e^{-\frac{1}{y}}
\end{aligned}$$

Cond. expectation in the continuous case

Definition 5.

Let

- (X, Y) couple of continuous random variables
- Joint density f
- Marginal densities f_X, f_Y, y such that $f_Y(y) > 0$
- $f_{X|Y}(x|\, y)$ conditional density

Then the conditional exp. of X given $Y = y$ is defined by

$$\mathbf{E}[X|\, Y = y] = \int_{\mathbb{R}} x\, f_{X|Y}(x|\, y)\, dx$$

Example of continuous conditional expectation (1)

Density: Let (X, Y) be a random vector with density

$$\frac{e^{-\frac{x}{y}} e^{-y}}{y} \mathbf{1}_{(0,\infty)}(x) \mathbf{1}_{(0,\infty)}(y)$$

Question: Compute

$$\mathbf{E}[X | Y = y]$$

Example of continuous conditional expectation (2)

Conditional density: For $y > 0$ we have seen that

$$f_{X|Y}(x|\,y) = \frac{f(x,y)}{f_Y(y)} = \frac{e^{-\frac{x}{y}}}{y}\,\mathbf{1}_{(0,\infty)}(x)$$

Namely $\mathcal{L}(X|\,Y=y) = \mathcal{E}(\frac{1}{y})$

Conditional expectation: We have

$$\begin{aligned}\mathbf{E}\,[X|\,Y=y] &= \int_{\mathbb{R}} x\,f_{X|Y}(x|\,y)\,dx \\ &= \int_0^\infty x\,\frac{e^{-\frac{x}{y}}}{y} \\ &= y\end{aligned}$$

Outline

Formal definition

Definition 6.

We are given a probability space $(\Omega, \mathcal{F}_0, \mathbf{P})$ and

- A σ-algebra $\mathcal{F} \subset \mathcal{F}_0$.
- $X \in \mathcal{F}_0$ such that $\mathbf{E}[|X|] < \infty$.

Conditional expectation of X given $\mathcal{F}$:

- Denoted by $\mathbf{E}[X|\mathcal{F}]$
- Defined by: $\mathbf{E}[X|\mathcal{F}]$ is the $L^1(\Omega)$ r.v Y such that
  - (i) $Y \in \mathcal{F}$.
  - (ii) For all $A \in \mathcal{F}$, we have

$$\mathbf{E}[X\mathbf{1}_A] = \mathbf{E}[Y\mathbf{1}_A],$$

or otherwise stated $\int_A X \, d\mathbf{P} = \int_A Y \, d\mathbf{P}$.

Remarks

Notation: We use the notation $Y \in \mathcal{F}$ to say that a random variable Y is $\mathcal{F}$-measurable.

Interpretation: More intuitively

- $\mathcal{F}$ represents a given information
- Y is the best prediction of X given the information in $\mathcal{F}$.

Existence and uniqueness:
To be seen after the examples.

Outline

Easy examples (1)

Example 1: Assume

$$X \in \mathcal{F}.$$

Then

$$\mathbf{E}[X|\mathcal{F}] = X$$

Independence of a r.v and a σ-field

Definition 7.

We say that $X \perp\!\!\!\perp \mathcal{F}$ if
$\hookrightarrow$ for all $A \in \mathcal{F}$ and $B \in \mathcal{B}(\mathbb{R})$, we have

$$\mathbf{P}((X \in B) \cap A) = \mathbf{P}(X \in B)\, \mathbf{P}(A),$$

or otherwise stated:

$$X \perp\!\!\!\perp \mathbf{1}_A$$

Easy examples (2)

Example 2: Assume

$$X \perp\!\!\!\perp \mathcal{F}.$$

Then

$$\mathbf{E}[X|\mathcal{F}] = \mathbf{E}[X]$$

Proof: example 2

We have

(i) $\mathbf{E}[X] \in \mathcal{F}$ since $\mathbf{E}[X]$ is a constant.

(ii) If $A \in \mathcal{F}$,

$$\mathbf{E}[X \mathbf{1}_A] = \mathbf{E}[X]\ \mathbf{E}[\mathbf{1}_A] = \mathbf{E}\Big[\mathbf{E}[X] \mathbf{1}_A\Big].$$

Discrete conditional expectation

Example 3: We consider

- $\left\{\Omega_j; j \geqslant 1\right\}$ partition of Ω such that $\mathbf{P}(\Omega_j) > 0$ for all $j \geqslant 1$.
- $\mathcal{F} = \sigma(\Omega_j; j \geqslant 1)$.

Then

$$\mathbf{E}[X|\mathcal{F}] = \sum_{j\geqslant 1} \frac{\mathbf{E}[X\,\mathbf{1}_{\Omega_j}]}{\mathbf{P}(\Omega_j)}\,\mathbf{1}_{\Omega_j} \equiv Y. \tag{1}$$

Proof: example 3

Strategy: Verify (i) and (ii) for the random variable Y.

(i) For all $j \geq 1$, we have $\mathbf{1}_{\Omega_j} \in \mathcal{F}$. Thus, for any sequence $(\alpha_j)_{j\geq 1}$,

$$\sum_{j\geq 1} \alpha_i \mathbf{1}_{\Omega_j} \in \mathcal{F}.$$

(ii) It is enough to verify (1) for $A = \Omega_n$ and $n \geq 1$ fixed. However,

$$\mathbf{E}[Y\,\mathbf{1}_{\Omega_n}] = \mathbf{E}\left\{\frac{\mathbf{E}[X\mathbf{1}_{\Omega_n}]}{\mathbf{P}(\Omega_n)}\,\mathbf{1}_{\Omega n}\right\} = \frac{\mathbf{E}[X\,\mathbf{1}_{\Omega_n}]}{\mathbf{P}(\Omega_n)}\mathbf{E}[\mathbf{1}_{\Omega_n}] = \mathbf{E}[X\,\mathbf{1}_{\Omega_n}].$$

Undergrad conditional probability

Definition: For a generic measurable set $A \in \mathcal{F}_0$, we set

$$\mathbf{P}(A|\mathcal{F}) \equiv \mathbf{E}[\mathbf{1}_A|\mathcal{F}]$$

Discrete example setting:
Let B, B^c be a partition of Ω, and $A \in \mathcal{F}_0$. Then

1. $\mathcal{F} = \sigma(B) = \left\{\Omega, \emptyset, B, B^c\right\}$
2. We have
$$\mathbf{P}(A|\mathcal{F}) = \mathbf{P}(A|B)\,\mathbf{1}_B + \mathbf{P}(A|B^c)\,\mathbf{1}_{B^c}.$$

Dice throwing

Example: We consider

- $\Omega = \left\{1, 2, 3, 4, 5, 6\right\}$, $A = \{4\}$, $B =$ "even number".

Then

$$\mathbf{P}(A|\mathcal{F}) = \frac{1}{3}\,\mathbf{1}_B.$$

Conditioning a r.v by another r.v

Definition 8.

Let

- X random variable such that $X \in L^1(\Omega)$
- Y random variable

We set

$$\mathbf{E}[X|Y] = \mathbf{E}[X|\sigma(Y)].$$

Characterizing $\sigma(Y)$

How to know if $A \in \sigma(Y)$:
We have $A \in \sigma(Y)$ iff

$$A = \left\{\omega;\ Y(\omega) \in B\right\}, \quad \text{or} \quad \mathbf{1}_A = \mathbf{1}_B(Y)$$

How to know if $Z \in \sigma(Y)$:
Let Z and Y be two random variables. Then

$$Z \in \sigma(Y) \quad \text{iff we can write} \quad Z = U(Y), \quad \text{with} \quad U \in \mathcal{B}(\mathbb{R}).$$

Conditioning a r.v by a discrete r.v

Example 4: Whenever X and Y are discrete random variables
$\hookrightarrow$ Computation of $\mathbf{E}[X|Y]$ can be handled as in example 3.

More specifically:

- Assume $Y \in E$ with $E = \{y_i;\, i \geq 1\}$
- Hypothesis: $\mathbf{P}(Y = y_i) > 0$ for all $i \geq 1$.

Then $\mathbf{E}[X|Y] = h(Y)$ with $h : E \to \mathbb{R}$ defined by:

$$h(y) = \frac{\mathbf{E}[X\,\mathbf{1}_{(Y=y)}]}{\mathbf{P}(Y = y)}.$$

Conditioning a r.v by a continuous r.v

Example 5: Let (X, Y) couple of real random variables with measurable density $f : \mathbb{R}^2 \to \mathbb{R}_+$. We assume that

$$\int_{\mathbb{R}} f(x, y) dx > 0, \quad \text{for all } y \in \mathbb{R}.$$

Let $g : \mathbb{R} \to \mathbb{R}$ a measurable function such that $g(X) \in L^1(\Omega)$. Then $\mathbf{E}[g(X)|Y] = h(Y)$, with $h : \mathbb{R} \to \mathbb{R}$ defined by:

$$h(y) = \frac{\int_{\mathbb{R}} g(x) f(x, y) dx}{\int_{\mathbb{R}} f(x, y) dx}.$$

Heuristic proof

Formally one can use a conditional density:

$$\mathbf{P}(X = x | Y = y)\text{''} = \text{''}\frac{\mathbf{P}(X = x, Y = y)}{\mathbf{P}(Y = y)} = \frac{f(x,y)}{\int f(x,y)dx},$$

Integrating against this density we get:

$$\begin{aligned}\mathbf{E}[g(X)|Y = y] &= \int g(x)\mathbf{P}(X = x|Y = y)\,dx \\ &= \frac{\int g(x)f(x,y)dx}{\int f(x,y)dx}.\end{aligned}$$

Rigorous proof

Strategy: Check (i) and (ii) in the definition for the r.v $h(Y)$.

(i) If $h \in \mathbb{B}(\mathbb{R})$, we have seen that $h(Y) \in \sigma(Y)$.

(ii) Let $A \in \sigma(Y)$ Then

$$A = \left\{\omega;\ Y(\omega) \in B\right\} \quad \Longrightarrow \quad \mathbf{1}_A = \mathbf{1}_B(Y)$$

Thus

$$\begin{aligned}
\mathbf{E}[h(Y)\mathbf{1}_A] &= \mathbf{E}[h(Y)\mathbf{1}_B(Y)] \\
&= \int_B \int_{\mathbb{R}} h(y) f(x,y)\, dx dy \\
&= \int_B dy \int_{\mathbb{R}} \left\{ \frac{\int g(z) f(z,y)\, dz}{\int f(z,y)\, dz} \right\} f(x,y)\, dx \\
&= \int_B dy \int g(z) f(z,y)\, dz = \mathbf{E}[g(X)\mathbf{1}_B(Y)].
\end{aligned}$$

Weird example

Example 6: We take

- $\Omega = (0,1)$, $\mathcal{F}_0 = \mathcal{B}((0,1))$ and $\mathbf{P} = \lambda$.

We set $X(\omega) = \cos(\pi\omega)$, and

$$\mathcal{F} = \{A \subset (0,1);\, A \text{ or } A^c \text{countable}\}.$$

Then $\mathbf{E}[X|\mathcal{F}] = 0$.

Proof

Strategy: Check (i) and (ii) in the definition for the r.v $Y = 0$.

(i) Obviously $0 \in \mathcal{F}$.

(ii) Let $A \in \mathcal{F}$, such that A is countable. Then

$$\mathbf{E}[X \mathbf{1}_A] = \int_A cos(\pi x) dx = 0.$$

Similarly, if $A \in \mathcal{F}$ is such that A^c is countable, we have

$$\mathbf{E}[X \mathbf{1}_A] = \int_0^1 cos(\pi x) dx - \int_{A^c} cos(\pi x) dx = 0,$$

which ends the proof.

Weird example: heuristics

Intuition: One could think that

1. We know that $\{x\}$ occurred for all $x \in [0, 1]$
2. $\{x\} \in \mathcal{F}$
3. Thus $\mathbf{E}[X|\mathcal{F}] = X$.

Paradox: This is wrong because $X \notin \mathcal{F}$.

Correct intuition: If we know $\omega \in A_i$ for a finite number of $A_i \in \mathcal{F}$ then nothing is known about X.

Outline

Conditional expectation: uniqueness

Proposition 9.

On the probability space $(\Omega, \mathcal{F}_0, \mathbf{P})$ consider

- A σ-algebra $\mathcal{F} \subset \mathcal{F}_0$.
- $X \in \mathcal{F}_0$ such that $\mathbf{E}[|X|] < \infty$.

Then if it exists, the random variable

$$\mathbf{E}[X|\mathcal{F}]$$

is uniquely defined.

Proof of uniqueness

Aim: Let Y, Y' satisfying (i) + (ii).
$\hookrightarrow$ Let us show $Y = Y'$ a.s

General property: For all $A \in \mathcal{F}$, we have $\mathbf{E}[Y \mathbf{1}_A] = \mathbf{E}[Y' \mathbf{1}_A]$.

Particular case: Let $\epsilon > 0$, and set

$$A_\epsilon \equiv (Y - Y' \geqslant \epsilon).$$

Then $A_\epsilon \in \mathcal{F}$, and thus

$$0 = \mathbf{E}[(Y - Y') \mathbf{1}_{A_\epsilon}] \geq \epsilon \mathbf{E}[\mathbf{1}_{A_\epsilon}] = \epsilon \mathbf{P}(A_\epsilon)$$

$\Rightarrow \mathbf{P}(A_\epsilon) = 0.$

Proof of uniqueness (2)

Set A_+: Let

$$A_+ \equiv (Y - Y' > 0) = \bigcup_{n \geqslant 1} A_{1/n}.$$

We have $n \mapsto A_{1/n}$ increasing, and thus

$$\mathbf{P}(A_+) = \mathbf{P}\left(\bigcup_{n \geqslant 1} A_{1/n}\right) = \lim_{n \to \infty} \mathbf{P}(A_{1/n}) = 0.$$

Set A_-: In the same way, if

$$A_- = \{Y - Y' < 0\}$$

we have $P(A_-) = 0$.

Proof of uniqueness (3)

Conclusion: We obtain, setting

$$A_{\neq} \equiv \{Y \neq Y'\} = A_{+} \cup A_{-},$$

that $\mathbf{P}(A_{\neq}) = 0$, and thus $Y = Y'$ a.s.

Absolute continuity

Definition 10.

Let μ, ν two σ-finite measures on $(\Omega, \mathcal{F})$.
We say that $\nu \ll \mu$ (μ is absolutely continuous w.r.t ν) if

$$\mu(A) = 0 \implies \nu(A) = 0 \text{ for all } A \in \mathcal{F}.$$

Radon-Nykodym theorem

Theorem 11.

Let

- μ, ν σ -finite measures on $(\Omega, \mathcal{F})$, such that $\nu \ll \mu$.

Then there exists $f \in \mathcal{F}$ such that for all $A \in \mathcal{F}$ we have

$$\nu(A) = \int_A f \, d\mu.$$

The function f:

- Is called Radon-Nykodym derivative of μ with respect to ν
- Is denoted by $f \equiv \frac{d\nu}{d\mu}$.
- We have $f \geq 0$ μ-almost everywhere
- $f \in L^1(\mu)$.

Conditional expectation: existence

Proposition 12.

On the probability space $(\Omega, \mathcal{F}_0, \mathbf{P})$ consider

- A σ-algebra $\mathcal{F} \subset \mathcal{F}_0$.
- $X \in \mathcal{F}_0$ such that $\mathbf{E}[|X|] < \infty$.

Then the random variable

$$\mathbf{E}[X|\mathcal{F}]$$

exists and is uniquely defined.

Proof of existence

Hypothesis: We have

- A σ-algebra $\mathcal{F} \subset \mathcal{F}_0$.
- $X \in \mathcal{F}_0$ such that $\mathbf{E}[|X|] < \infty$.
- $X \geqslant 0$.

Defining two measures: we set

1. $\mu = P$, measure on $(\Omega, \mathcal{F})$.
2. $\nu(A) \equiv \mathbf{E}[X \mathbf{1}_A] = \int_A X \, d\mathbf{P}$.

Then ν is a measure (owing to Beppo-Levi).

Proof of existence (2)

Absolute continuity: we have

$$\mathbf{P}(A) = 0 \Rightarrow \mathbf{1}_A = 0 \quad P\text{-a.s.}$$
$$\Rightarrow X\,\mathbf{1}_A = 0 \quad P\text{-a.s.}$$
$$\Rightarrow \nu(A) = 0$$

Thus $\nu \ll P$

Conclusion: invoking Radon-Nykodym, there exists $f \in \mathcal{F}$ such that, for all $A \in \mathcal{F}$, we have $\nu(A) = \int_A f\, d\mathbf{P}$.
$\hookrightarrow$ We set $f = \mathbf{E}[X|\mathcal{F}]$.

Outline

Linearity, expectation

Proposition 13.

Let $X \in L^1(\Omega)$. Then

$$\mathbf{E}\left\{\mathbf{E}[X|\mathcal{F}]\right\} = \mathbf{E}[X].$$

Proposition 14.

Let $\alpha \in \mathbb{R}$, and $X, Y \in L^1(\Omega)$. Then

$$\mathbf{E}[\alpha X + Y|\mathcal{F}] = \alpha\,\mathbf{E}[X|\mathcal{F}] + \mathbf{E}[Y|\mathcal{F}] \quad \text{a.s.}$$

Proof

Strategy: Check (i) and (ii) in the definition for the r.v

$$Z \equiv \alpha\,\mathbf{E}[X|\mathcal{F}] + \mathbf{E}[Y|\mathcal{F}].$$

Verification: we have

(i) Z is a linear combination of $\mathbf{E}[X|\mathcal{F}]$ and $\mathbf{E}[Y|\mathcal{F}]$
$\hookrightarrow Z \in \mathcal{F}$.

(ii) For all $A \in \mathcal{F}$, we have

$$\begin{aligned}
\mathbf{E}[Z\,\mathbf{1}_A] &= \mathbf{E}\left\{(\alpha\,\mathbf{E}[X|\mathcal{F}] + \mathbf{E}[Y|\mathcal{F}])\,\mathbf{1}_A\right\} \\
&= \alpha\,\mathbf{E}\left\{\mathbf{E}[X|\mathcal{F}]\,\mathbf{1}_A\right\} + \mathbf{E}\left\{\mathbf{E}[Y|\mathcal{F}]\,\mathbf{1}_A\right\} \\
&= \alpha\,\mathbf{E}[X\,\mathbf{1}_A] + \mathbf{E}[Y\,\mathbf{1}_A] \\
&= \mathbf{E}[(\alpha X + Y)\,\mathbf{1}_A].
\end{aligned}$$

Monotonicity

Proposition 15.

Let $X, Y \in L^1(\Omega)$ such that $X \leqslant Y$ almost surely. We have

$$\mathbf{E}[X|\mathcal{F}] \leqslant \mathbf{E}[Y|\mathcal{F}],$$

almost surely.

Proof: Along the same lines as proof of uniqueness for the conditional expectation. For instance if we set

$$A_\varepsilon = \{\mathbf{E}[X|\mathcal{F}] - \mathbf{E}[Y|\mathcal{F}] \geqslant \varepsilon > 0\},$$

then it is readily checked that

$$\mathbf{P}(A_\varepsilon) = 0.$$

Monotone convergence

Proposition 16.

Let $\{X_n; n \geq 1\}$ be a sequence of random variables such that

- $X_n \geqslant 0$
- $X_n \nearrow X$ almost surely
- $\mathbf{E}[X] < \infty$.

Then

$$\mathbf{E}[X_n|\mathcal{F}] \nearrow \mathbf{E}[X|\mathcal{F}].$$

Proof

Strategy: Set $Y_n \equiv X - X_n$. We are reduced to show $Z_n \equiv \mathbf{E}[Y_n|\mathcal{F}] \searrow 0$.

Existence of a limit: $n \mapsto Y_n$ is decreasing, and $Y_n \geqslant 0$
$\hookrightarrow$ Z_n is decreasing and $Z_n \geqslant 0$.
$\hookrightarrow$ Z_n admits a limit a.s, denoted by Z_∞.

Aim: Show that $Z_\infty = 0$.

Proof (2)

Expectation of Z_∞: we will show that $\mathbf{E}[Z_\infty] = 0$. Indeed

- X_n converges a.s. to X.
- $0 \leqslant X_n \leqslant X \in L^1(\Omega)$.

Thus, by dominated convergence, $\mathbf{E}[X_n] \to \mathbf{E}[X]$.

We deduce:

- $\mathbf{E}[Y_n] \to 0$
- Since $\mathbf{E}[Y_n] = \mathbf{E}[Z_n]$, we also have $\mathbf{E}[Z_n] \to 0$.
- By monotone convergence, we have $\mathbf{E}[Z_n] \to \mathbf{E}[Z_\infty]$

This yields $\mathbf{E}[Z_\infty] = 0$.

Conclusion: $Z_\infty \geq 0$ and $\mathbf{E}[Z_\infty] = 0$
$\hookrightarrow$ $Z_\infty = 0$ almost surely.

Cauchy-Schwarz inequality

Proposition 17.

Let $X, Y \in L^2(\Omega)$. Then

$$\mathbf{E}^2[X\,Y|\mathcal{F}] \leqslant \mathbf{E}[X^2|\mathcal{F}]\,\mathbf{E}[Y^2|\mathcal{F}] \quad \text{a.s.}$$

Proof of Cauchy-Schwarz (1)

A family positive random variables:
For all $\theta \in \mathbb{R}$, we have

$$\mathbf{E}[(X + \theta Y)^2 | \mathcal{F}] \geqslant 0 \quad \text{a.s.}$$

Thus almost surely we have: for all $\theta \in \mathbb{Q}$,

$$\mathbf{E}[(X + \theta Y)^2 | \mathcal{F}] \geqslant 0,$$

Proof of Cauchy-Schwarz (2)

Expansion: For all $\theta \in \mathbb{Q}$

$$\mathbf{E}[Y^2|\mathcal{F}]\theta^2 + 2\mathbf{E}[XY|\mathcal{F}]\theta + \mathbf{E}[X^2|\mathcal{F}] \geqslant 0.$$

Recall: If a polynomial satisfies $a\theta^2 + b\theta + c \geqslant 0$ for all $\theta \in \mathbb{Q}$
$\hookrightarrow$ then we have $b^2 - 4ac \leqslant 0$

Application: Almost surely, we have

$$E^2[XY|\mathcal{F}] - \mathbf{E}[X^2|\mathcal{F}]\mathbf{E}[Y^2|\mathcal{F}] \leqslant 0.$$

Jensen's inequality

Proposition 18.

Let $X \in L^1(\Omega)$, and $\varphi : \mathbb{R} \to \mathbb{R}$ such that $\varphi(X) \in L^1(\Omega)$ and φ convex. Then

$$\varphi(\mathbf{E}[X|\mathcal{F}]) \leqslant \mathbf{E}[\varphi(X)|\mathcal{F}] \quad \text{a.s.}$$

Contraction in $L^p(\Omega)$

Proposition 19.

The conditional expectation is a

contraction in $L^p(\Omega)$ for all $p \geqslant 1$

Proof of contraction in L^p

Application of Jensen's inequality: We have

$$X \in L^p(\Omega) \Rightarrow \mathbf{E}[X|\mathcal{F}] \in L^p(\Omega)$$

and

$$|\mathbf{E}[X|\mathcal{F}]|^p \leq \mathbf{E}[|X|^p|\mathcal{F}] \quad \Longrightarrow \quad \mathbf{E}\left\{|\mathbf{E}[X|\mathcal{F}]|^p\right\} \leqslant \mathbf{E}[|X|^p]$$

Successive conditionings

Theorem 20.

Let

- Two σ-algebras $\mathcal{F}_1 \subset \mathcal{F}_2$.
- $X \in L^1(\Omega)$.

Then

$$\mathbf{E}\left\{\mathbf{E}[X|\mathcal{F}_1]|\mathcal{F}_2\right\} = \mathbf{E}[X|\mathcal{F}_1] \quad (2)$$

$$\mathbf{E}\left\{\mathbf{E}[X|\mathcal{F}_2]|\mathcal{F}_1\right\} = \mathbf{E}[X|\mathcal{F}_1]. \quad (3)$$

Proof

Proof of (2): We set $Z \equiv \mathbf{E}[X|\mathcal{F}_1]$. Then

$$Z \in \mathcal{F}_1 \subset \mathcal{F}_2.$$

According to Example 1, we have $\mathbf{E}[Z|\mathcal{F}_2] = Z$, i.e. (2).

Proof of (3): We set $U = \mathbf{E}[X|\mathcal{F}_2]$.
$\hookrightarrow$ We will show that $\mathbf{E}[U|\mathcal{F}_1] = Z$, via (i) and (ii) of Definition 6.

(i) $Z \in \mathcal{F}_1$.

(ii) If $A \in \mathcal{F}_1$, we have $A \in \mathcal{F}_1 \subset \mathcal{F}_2$, and thus

$$\mathbf{E}[Z\mathbf{1}_A] = \mathbf{E}[X\mathbf{1}_A] = \mathbf{E}[U\mathbf{1}_A].$$

Conditional expectation for products

Theorem 21.

Let $X, Y \in L^2(\Omega)$, such that $X \in \mathcal{F}$. Then

$$\mathbf{E}[X\,Y|\mathcal{F}] = X\,\mathbf{E}[Y|\mathcal{F}].$$

Proof: We use a 4 steps methodology

Proof

Step 1: Assume $X = \mathbf{1}_B$, with $B \in \mathcal{F}$
We check (i) and (ii) of Definition 6.

(i) We have $\mathbf{1}_B \mathbf{E}[Y|\mathcal{F}] \in \mathcal{F}$.

(ii) For $A \in \mathcal{F}$, we have

$$\begin{aligned} \mathbf{E}\left\{(\mathbf{1}_B \mathbf{E}[Y|\mathcal{F}])\, \mathbf{1}_A\right\} &= \mathbf{E}\left\{\mathbf{E}[Y|\mathcal{F}]\, \mathbf{1}_{A\cap B}\right\} \\ &= \mathbf{E}[Y\, \mathbf{1}_{A\cap B}] \\ &= \mathbf{E}[(\mathbf{1}_B Y)\, \mathbf{1}_A], \end{aligned}$$

and thus

$$\mathbf{1}_B\, \mathbf{E}[Y|\mathcal{F}] = \mathbf{E}[\mathbf{1}_B\, Y|\mathcal{F}].$$

Proof (2)

Step 2: If X is of the form

$$X = \sum_{i \leqslant n} \alpha_i \mathbf{1}_{B_i},$$

with $\alpha_i \in \mathbb{R}$ and $B_i \in \mathcal{F}$, then, by linearity we also get

$$\mathbf{E}[XY|\mathcal{F}] = X\,\mathbf{E}[Y|\mathcal{F}].$$

Step 3: If $X, Y \geqslant 0$

$\hookrightarrow$ There exists a sequence $\{X_n; n \geqslant 1\}$ of simple random variables such that

$$X_n \nearrow X.$$

Then applying the monotone convergence we end up with:

$$\mathbf{E}[XY|\mathcal{F}] = X\,\mathbf{E}[Y|\mathcal{F}].$$

Proof (3)

Step 4: General case $X \in L^2$

$\hookrightarrow$ Decompose $X = X^+ - X^-$ and $Y = Y^+ - Y^-$, which gives

$$\mathbf{E}[XY|\mathcal{F}] = X\mathbf{E}[Y|\mathcal{F}]$$

by linearity.

Conditional expectation and independence

Theorem 22.

Let

- X, Y two independent random variables
- $\alpha : \mathbb{R}^2 \to \mathbb{R}$ such that $\alpha(X, Y) \in L^1(\Omega)$

We set, for $x \in \mathbb{R}$,

$$g(x) = \mathbf{E}[\alpha(x, Y)].$$

Then

$$\mathbf{E}[\alpha(X, Y)|X] = g(X).$$

Proof: with 4 steps method applied to α.

Generalization of the previous theorem

Theorem 23.

Let

- $\mathcal{F} \subset \mathcal{F}_0$
- $X \in \mathcal{F}$ and $Y \perp\!\!\!\perp \mathcal{F}$ two random variables
- $\alpha : \mathbb{R}^2 \to \mathbb{R}$ such that $\alpha(X, Y) \in L^1(\Omega)$

We set, for $x \in \mathbb{R}$,

$$g(x) = \mathbf{E}[\alpha(x, Y)].$$

Then

$$\mathbf{E}[\alpha(X, Y)|\mathcal{F}] = g(X).$$

Outline

Orthogonal projection

Definition: Let

- H Hilbert space
  $\hookrightarrow$ complete vectorial space equipped with inner product.
- F closed subspace of H.

Then, for all $x \in H$

- There exists a unique $y \in F$, denoted by $y = \pi_F(x)$

Satisfying one of the equivalent conditions (i) or (ii).

(i) For all $z \in F$, we have $\langle x - y, z \rangle = 0$.

(ii) For all $z \in F$, we have $\|x - y\|_H \leqslant \|x - z\|_H$.

$\pi_F(x)$ is denoted orthogonal projection of x onto F.

Conditional expectation and projection

Theorem 24.

Consider

- The space $L^2(\mathcal{F}_0) \equiv \{Y \in \mathcal{F}_0;\ \mathbf{E}[Y^2] < \infty\}$.
- $X \in L^2(\mathcal{F}_0)$.
- $\mathcal{F} \subset \mathcal{F}_0$

Then

1. $L^2(\mathcal{F}_0)$ is a Hilbert space
   $\hookrightarrow$ Inner product $\langle X, Y \rangle = \mathbf{E}[XY]$.
2. $L^2(\mathcal{F})$ is a closed subspace of $L^2(\mathcal{F}_0)$.
3. $\pi_{L^2(\mathcal{F})}(X) = \mathbf{E}[X|\mathcal{F}]$.

Proof

Proof of 2:
If $X_n \to X$ in $L^2 \Rightarrow$ There exists a subsequence $X_{n_k} \to X$ a.s.
Thus, if $X_n \in \mathcal{F}$, we also have $X \in \mathcal{F}$.

Proof of 3: Let us check (i) in our definition of projection

Let $Z \in L^2(\mathcal{F})$.
$\hookrightarrow$ We have $\mathbf{E}[Z\,X|\mathcal{F}] = Z\,\mathbf{E}[X|\mathcal{F}]$, and thus

$$\mathbf{E}\left\{Z\,\mathbf{E}[X|\mathcal{F}]\right\} = \mathbf{E}\left\{\mathbf{E}[X\,Z|\mathcal{F}]\right\} = \mathbf{E}\left[X\,Z\right],$$

which ensures (i) and $\mathbf{E}[X|\mathcal{F}] = \pi_{L^2(\mathcal{F})}(X)$.

Application to Gaussian vectors

Example: Let

- (X, Y) centered Gaussian vector in $\mathbb{R}^2$
- Hypothesis: $V(Y) > 0$.

Then

$$\mathbf{E}[X|Y] = \alpha Y, \quad \text{with} \quad \alpha = \frac{\mathbf{E}[X\,Y]}{V(Y)}.$$

Proof

Step 1: We look for α such that

$$Z = X - \alpha Y \quad \Longrightarrow \quad Z \perp\!\!\!\perp Y.$$

Recall: If (Z, Y) is a Gaussian vector
$\hookrightarrow Z \perp\!\!\!\perp Y$ iff $\text{cov}(Z, Y) = 0$

Application: $\text{cov}(Z, Y) = \mathbf{E}[Z\, Y]$. Thus

$$\text{cov}(Z, Y) = \mathbf{E}[(X - \alpha Y)\, Y] = \mathbf{E}[X\, Y] - \alpha V(Y),$$

et

$$\text{cov}(Z, Y) = 0 \quad \text{iff} \quad \alpha = \frac{\mathbf{E}[XY]}{V(Y)}.$$

Proof (2)

Step 2: We invoke (i) in the definition of π.
$\hookrightarrow$ Let $V \in L^2(\sigma(Y))$. Then

$$Y \perp\!\!\!\perp (X - \alpha Y) \quad \Longrightarrow \quad V \perp\!\!\!\perp (X - \alpha Y)$$

and

$$\mathbf{E}[(X - \alpha Y) V] = \mathbf{E}[X - \alpha Y] \, \mathbf{E}[V] = 0.$$

Thus

$$\alpha Y = \pi_{\sigma(Y)}(X) = \mathbf{E}[X| \, Y].$$

Outline

Aim of this section

Recall: We have seen that if

- $X \sim \mathcal{P}(\lambda_1)$, $Y \sim \mathcal{P}(\lambda_2)$
- $X \perp\!\!\!\perp Y$
- $p = \frac{\lambda_1}{\lambda_1+\lambda_2}$,

then

$$\mathcal{L}\left(X \middle| X+Y=n\right) = \text{Bin}(n, p)$$

Question:

How to translate this

$\hookrightarrow$ to the non-baby conditional expectation language?

Outline

Characterizing r.v by expected values

Notation:

$C_b(\mathbb{R}) \equiv$ set of continuous and bounded functions on $\mathbb{R}$.

Theorem 25.

Let X be a r.v. We assume that

$$\mathbf{E}[\varphi(X)] = \int_{\mathbb{R}} \varphi(x)\, f(x)\, dx, \quad \text{for all functions } \varphi \in C_b(\mathbb{R}).$$

Then X is continuous, with density f.

Application: change of variable

Problem: Let

- X random variable with density f.
- Set $Y = h(X)$ with $h : \mathbb{R} \to \mathbb{R}$.

We wish to find the density of Y.

Application: change of variable (2)

Recipe: One proceeds as follows

1. For $\varphi \in C_b(\mathbb{R})$, write

$$\mathbf{E}[\varphi(Y)] = \mathbf{E}[\varphi(h(X))] = \int_{\mathbb{R}} \varphi(h(x))\, f(x)\, dx.$$

2. Change variables $y = h(x)$ in the integral.
   After some elementary computations we get

$$\mathbf{E}[\varphi(Y)] = \int_{\mathbb{R}} \varphi(y)\, g(y)\, dy.$$

3. This characterizes Y, which admits a density g

Example: normal r.v and linear transformations

Proposition 26.

Let

- $X \sim \mathcal{N}(0,1)$
- $\mu \in \mathbb{R}$ and $\sigma > 0$
- Set $Y = \sigma X + \mu$

Then

$$Y \sim \mathcal{N}(\mu, \sigma^2)$$

Proof

Recipe, item 1: for $\varphi \in C_b(\mathbb{R})$, write

$$\mathbf{E}[\varphi(Y)] = \mathbf{E}[\varphi(\sigma X + \mu)] = \int_{\mathbb{R}} \varphi(\sigma x + \mu) \frac{e^{-x^2/2}}{\sqrt{2\pi}} \, dx.$$

Recipe, item 2: Change of variable: $y = \sigma x + \mu$:

$$\mathbf{E}[\varphi(Y)] = \int_{\mathbb{R}} \varphi(y) \, g(y) \, dx, \quad \text{with} \quad g(y) = \frac{e^{-(y-\mu)^2/(2\sigma^2)}}{\sqrt{2\pi\sigma^2}}.$$

Recipe, item 3:
Y is continuous with density g, therefore $Y \sim \mathcal{N}(\mu, \sigma^2)$.

Characterizing r.v by expected values (ctd)

Theorem 27.

Let $X : \Omega \to \mathbb{R}$ be a r.v. Then

$$\{\mathbf{E}[\varphi(X)];\ \varphi \in C_b(\mathbb{R})\} \text{ characterizes the law of } X$$

Outline

CRL

Definition 28.

Let

- $(\Omega, \mathcal{F}, P)$ a probability space
- $(S, \mathcal{S})$ a measurable space of the form $\mathbb{R}^d, \mathbb{Z}^d$
- $X : (\Omega, \mathcal{F}) \to (S, \mathcal{S})$ a random variable in $L^1(\Omega)$
- $\mathcal{G}$ a σ-algebra such that $\mathcal{G} \subset \mathcal{F}$.

We say that $\mu : \Omega \times \mathcal{S} \to [0, 1]$ is a Conditional regular law of X given $\mathcal{G}$ if

(i) For all $f \in C_b(S)$, the map $\omega \mapsto \mu(\omega, f)$ is a random variable, equal to $\mathbf{E}[f(X)|\, \mathcal{G}]$ a.s.

(ii) ω-a.s. $f \mapsto \mu(\omega, f)$ is a probability measure on $(S, \mathcal{S})$.

Discrete example

Poisson law case: Let

- $X \sim \mathcal{P}(\lambda)$ and $Y \sim \mathcal{P}(\mu)$
- $X \perp\!\!\!\perp Y$

We set $S = X + Y$.

Then

CRL of X given S is $\text{Bin}(S, p)$, with $p = \frac{\lambda}{\lambda+\mu}$

Proof for the discrete example

Proof: we have seen that for $n \leqslant m$

$$\mathbf{P}(X = n | S = m) = \binom{m}{n} p^n (1-p)^{m-n} \quad \text{with } p = \frac{\lambda}{\lambda + \mu}.$$

Then we consider

- State space $= \mathbb{N}$, $\mathcal{G} = \sigma(S)$

and we verify that these conditional probabilities define a CRL.

Continuous example

Exponential law case: Let

- $X \sim \mathcal{E}(1)$ and $Y \sim \mathcal{E}(1)$
- $X \perp\!\!\!\perp Y$

We set $S = X + Y$.

Then

CRL of X given S is $\mathcal{U}([0, S])$.

Continuous example

Proof: The joint density of (X, S) is given by

$$f(x, s) = e^{-s}\mathbf{1}_{\{0\le x\le s\}}.$$

Let then $\psi \in \mathcal{B}_b(\mathbb{R}_+)$. Thanks to Example 5, we have

$$\mathbf{E}[\psi(X)|S] = u(S),$$

with

$$u(s) = \frac{\int_{\mathbb{R}_+} \psi(x) f(x, s)dx}{\int_{\mathbb{R}_+^2} f(x, s)dx} = \frac{1}{s}\int_0^s \psi(x)dx.$$

Proof

In addition, $S \neq 0$ almost surely, and thus if $A \in \mathcal{B}(\mathbb{R})$ we have:

$$\mathbf{E}[\psi(X)|S] = \frac{\int_0^S \psi(x)dx}{S}.$$

Considering the state space as $= \mathbb{R}_+$, $\mathcal{S} = \mathcal{B}(\mathbb{R}_+)$ and setting

$$\mu(\omega, f) = \frac{1}{S(\omega)} \int_0^{S(\omega)} \psi(x)dx,$$

one can verify that we have defined a conditional regular law.

Existence of the CRL

Theorem 29.

Let

- X a random variable on $(\Omega, \mathcal{F}_0, P)$.
- Taking values in a space of the form $(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$.
- $\mathcal{G} \subset \mathcal{F}_0$ a σ-algebra.

Then the CRL of X given $\mathcal{G}$ exists.

Proof: nontrivial and omitted.

Computation rules for CRL

(1) If $\mathcal{G} = \sigma(Y)$, with Y random variable with values in $\mathbb{R}^m$, we have

$$\mu(\omega, f) = \mu(Y(\omega), f),$$

and one can define a CRL of X given Y as a family $\{\mu(y, .); y \in \mathbb{R}^m\}$ of probabilities on $\mathbb{R}^n$, such that for all $f \in C_b(\mathbb{R}^n)$ the function

$$y \mapsto \mu(y, f)$$

is measurable.

(2) If Y is a discrete r.v, this can be reduced to:

$$\mu(y, A) = \mathbf{P}\left(X \in A | Y = y\right) = \frac{\mathbf{P}\left(X \in A, Y = y\right)}{\mathbf{P}\left(Y = y\right)}.$$

Computation rules for CRL (2)

(3) When one knows the CRL, quantities like the following (for $\phi \in \mathcal{B}(\mathbb{R}^n)$) can be computed:

$$\mathbf{E}\left[\phi(X)|\mathcal{G}\right] = \int_{\mathbb{R}^n} \phi(x)\,\mu(\omega, dx)$$

$$\mathbf{E}\left[\phi(X)|Y\right] = \int_{\mathbb{R}^n} \phi(x)\,\mu(Y, dx).$$

(4) The CRL is not unique.
However if N_1, N_2 are 2 CRL of X given $\mathcal{G}$
$\hookrightarrow$ we have ω-almost surely:

$$N_1(\omega, f) = N_2(\omega, f) \quad \text{for all} \quad f \in C_b(\mathbb{R}^n).$$