

§5. Martingales

§5.1 Conditional expectation

- Let X be a r.v. on a prob. space $(\Omega, \mathcal{F}, P)$ such that

$$E|X| < \infty.$$

Let $\beta = \mathcal{F}$ be a sub- σ -algebra. Then

$$\mu(A) = \int_A X dP, \quad A \in \beta$$

defines a signed measure on (Ω, β) and μ is absolutely continuous with respect to P , i.e. $P(A)=0 \Rightarrow \mu(A)=0$.

By the Radon-Nikodym Theorem, there is a function

$$g \in L^1(\Omega, \beta, P)$$

such that

$$\mu(A) = \int_A g dP, \quad A \in \beta.$$

Moreover, any other such function g' must coincide with g almost surely wrt μ .

Def.

We use the notation $E(X|\beta)$ for g , and call

$E(X|\beta)$ the conditional expectation of X with respect to β .

- As an element of $L^1(\Omega, \mathcal{F}, P)$, $E(X|\beta)$ is completely characterized by the following two properties:

(1) $E(X|\beta)$ is β -measurable;

(2)
$$\int_A E(X|\beta) dP = \int_A X dP \quad \text{for all } A \in \beta.$$

Example 5.1. Let $\beta = \{\emptyset, E, E^c, \Omega\}$ with $E \in \mathcal{F}$.

Then β is a finite sub-sigma algebra of $\mathcal{F}$.

Let $X = \mathbb{1}_A$ with $A \in \mathcal{F}$. Let $g = E(\mathbb{1}_A | \beta)$.
Since g is β -measurable, it must be constant on E and E^c .

By property (2),

$$g(x) = \begin{cases} \int_E X dP / P(E) & \text{if } x \in E; \\ \int_{E^c} X dP / P(E^c) & \text{if } x \in E^c. \end{cases}$$

Since $X = \mathbb{1}_A$,

$$g(x) = \begin{cases} P(A \cap E) / P(E) & \text{if } x \in E. \\ P(A \cap E^c) / P(E^c) & \text{if } x \in E^c. \end{cases}$$

Thus, $g(x)$ gives the prob. of the occurrence of A once we know to which element of $\mathcal{F}$ the point x belongs to.

Example 5.2. Similarly let $\beta = \sigma(\Omega_1, \dots, \Omega_k)$ be the σ -algebra generated by a finite partition $\Omega_1, \dots, \Omega_k$ of Ω .

Then

$$E(X|\beta)(x) = \int_{\Omega_i} X dP / P(\Omega_i)$$

if $x \in \Omega_i$.

The following properties of conditional expectations can be proved easily by using the characterization by (i) and (ii):

Prop 5.3. (1) If $X \geq 0$ a.s., then $E(X|\beta) \geq 0$ a.s.

(2) $E(aX + bY|\beta) = aE(X|\beta) + bE(Y|\beta)$ a.s. for $X, Y \in L^1$, $a, b \in \mathbb{R}$.

(2) If X is β -measurable, then $E(X|\beta) = X$ a.s.

(3) If X is β -measurable and $X \in L^\infty(\Omega, \mathcal{F}, P)$, then for each $Y \in L^1(\Omega, \mathcal{F}, P)$
 $E(XY|\beta) = X E(Y|\beta)$ a.s.

(4) $E(E(X|\beta)) = EX$.

(5) If $\beta_2 \subset \beta_1$, then

$$E(E(X|\beta_1)|\beta_2) = E(X|\beta_2) \text{ a.s.}$$

(6) If X is independent of β , then

$$E(X|\beta) = E(X) \text{ a.s.}$$

pf. We prove (5), (6) only.

$$\text{Let } \beta_2 \subset \beta_1. \quad \text{Let } g = E(E(X|\beta_1)|\beta_2).$$

clearly g is β_2 -measurable. Moreover, for any $A \in \beta_2$,

$$\int_A g \, dP = \int_A E(X|\beta_1) \, dP = \int_A X \, dP,$$

where the second equality follows from the fact that $A \in \beta_1$.

Hence by the characterization of the conditional expectation,

$$g = E(X|\beta_1).$$

This proves (5).

To see (6), recall that X is independent of β , so

X and $\mathbb{1}_B$ are independent for each $B \in \beta$

$$\begin{aligned} \text{Hence } \int_B X \, dP &= \int \mathbb{1}_B \cdot X \, dP = \int \mathbb{1}_B^{dP} \int X \, dP \\ &= P(B) E(X). \\ &= \int_B E(X) \, dP. \end{aligned}$$

It follows that $E(X|\beta) = E(X)$ a.s.

Prop. 5.4. Suppose $X_n \rightarrow X$ a.s. and $|X_n| \leq Y$ and $EY < \infty$.

Then $E(X_n | \beta) \rightarrow E(X | \beta)$ a.s.

pf. Let $Z_n = \sup_{k \geq n} |X_k - X|$. Then $Z_n \searrow 0$ a.s. and $0 \leq Z_n \leq Y$

Now

$$\begin{aligned} |E(X_n | \beta) - E(X | \beta)| &= |E(X_n - X | \beta)| \\ &\leq E(Z_n | \beta). \end{aligned}$$

Since Z_n is non-increasing, so is $E(Z_n | \beta)$.

Hence $E(Z_n | \beta)$ has a limit Z with $Z \geq 0$.

Notice that

$$\begin{aligned} E(Z) &= \int Z \, dP \leq \int E(Z_n | \beta) \, dP \\ &= E(Z_n) \rightarrow 0. \end{aligned}$$

(by the DCT)

Hence $Z \equiv 0$ a.s.

It follows that $E(Z_n | \beta) \rightarrow 0$ a.s., and thus

$$E(X_n | \beta) \rightarrow E(X | \beta). \quad \square$$

Prop 5.5 (Jensen inequality).

Let $\phi: \mathbb{R} \rightarrow \mathbb{R}$ be convex. Suppose that X and $\phi(X)$ are integrable.

Then $\phi(E(X|\mathcal{B})) \leq E(\phi(X)|\mathcal{B})$ a.s.

Pf. Since ϕ is convex, it is known that

$\phi'(q+)$ exists at each $q \in \mathbb{R}$

and

$$\phi(x) \geq \phi'(q+) (x - q) + \phi(q) \text{ for all } x \in \mathbb{R}.$$

Hence, we have

$$\phi(x) = \sup_{q \in \mathbb{R}} \phi'(q+) (x - q) + \phi(q) \quad \text{for all } x \in \mathbb{R}$$

Notice that $\phi'(q)$ exists and is continuous, except for at most countable many points. It follows that $\exists$ a sequence $(a_n), (b_n)$ in $\mathbb{R}$ such that

$$\textcircled{1} \quad \phi(x) = \sup_n a_n x + b_n \quad \text{for all } x \in \mathbb{R}.$$

Now for fixed n ,

$$\phi(X) \geq a_n X + b_n$$

So

$$E(\phi(X)|\mathcal{B}) \geq a_n E(X|\mathcal{B}) + b_n \quad \text{a.s.}$$

$$\begin{aligned} \text{Hence } E(\phi(X)|\mathcal{B}) &\geq \sup_n a_n E(X|\mathcal{B}) + b_n \quad \text{a.s.} \\ &= \phi(E(X|\mathcal{B})) \quad \text{a.s.} \quad (\text{by (1)}). \end{aligned}$$



§ 5.2 Martingales and examples.

Def. Let $(\Omega, \mathcal{F}, P)$ be a prob. space, and $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots$ an increasing sequence of sub- σ -algebras of $\mathcal{F}$.

A sequence $X_1, X_2, \dots$ of r.v.'s such that $E|X_n| < \infty$ is said to be

a submartingale if $E(X_{n+1} | \mathcal{F}_n) \geq X_n$ a.s.

a martingale if $E(X_{n+1} | \mathcal{F}_n) = X_n$ a.s.

a supermartingale if $E(X_{n+1} | \mathcal{F}_n) \leq X_n$ a.s.

Remark: • the word 'martingale' was formerly used for a certain betting system.

- If X_n is the fortune of a gambler after n plays, in case of a submartingale the game is favorable to the player; in case of a supermartingale, the game is unfavorable to the player.

Examples:

(a) Sums of independent r.v.'s of zero mean.

Let $S_n = X_1 + \dots + X_n$, where $X_1, \dots, X_n, \dots$ are independent r.v.'s with $E|X_n| < \infty$ and $E X_n = 0$.

Let $\mathcal{F}_n = \sigma(X_1, \dots, X_n)$.

$$\begin{aligned} \text{Then } E(S_{n+1} | \mathcal{F}_n) &= E(S_n | \mathcal{F}_n) + E(X_{n+1} | \mathcal{F}_n) \\ &= S_n + E(X_{n+1} | \mathcal{F}_n) \\ &\quad \text{(since } S_n \text{ is } \mathcal{F}_n\text{-measurable)} \\ &= S_n + E(X_{n+1}) \quad \text{(since } X_{n+1} \text{ is independent of } \mathcal{F}_n) \\ &= S_n. \end{aligned}$$

(b) Product of non-negative independent r.v.'s of mean 1.

Let $X_1, X_2, \dots$ be non-negative independent r.v.'s with $E(X_n) = 1$.

Let $M_n = X_1 \dots X_n$.

Then for $n \geq 1$,

$$\begin{aligned} E(M_{n+1} | \mathcal{F}_n) &= E(X_{n+1} M_n | \mathcal{F}_n) \\ &= M_n E(X_{n+1} | \mathcal{F}_n) \quad \text{(since } M_n \text{ is } \mathcal{F}_n\text{-measurable)} \\ &= M_n E(X_{n+1}) = M_n. \\ &\quad \uparrow \text{(since } X_{n+1} \text{ and } \mathcal{F}_n \text{ are independent)} \end{aligned}$$

So (M_n) is a martingale.