

$$\cancel{\mathbb{E}(X|\mathcal{F}) = E_{\mathcal{F}}(x)} \quad (\Omega, \mathcal{F}, P) \quad \mathcal{F} \subset \bar{\mathcal{F}}$$

$$\mathbb{E}(X; A)$$

$$E(X \cdot \mathbb{1}_A) = \mathbb{E}(E(x); A) \quad \forall A \in \mathcal{F}$$

if satisfies ...

we need (1) $E_{\mathcal{F}}(x) \in \mathcal{F}$

$$(2) E(x; A) = E(E_{\mathcal{F}}(x); A) \quad \forall A \in \mathcal{F}$$

then we say $E_{\mathcal{F}}(x)$ is "Conditional Expectation of X given \mathcal{F} "

example Assume X, Y are r.v. $\Psi(x, y) : \mathbb{R}^2 \rightarrow \mathbb{R}$ $\mathcal{F} = \sigma\{\underline{X}\} = \{\underline{X} \in A\}_{A \in \mathcal{B}(\mathbb{R})}$

claim $E_{\mathcal{F}}(\Psi(x, y)) = g(x)$

where $g(x) = \mathbb{E}(\Psi(x, y))$, $x \in \mathbb{R}$

$$\mathbb{E}[\Psi(x, y); A] = \int_{x \in A} \underbrace{\int_{y \in \mathbb{R}} \Psi(x, y) dF_Y(y)}_{g(x)} dF_X(x) \quad \text{use Fobini}$$

$$g(x) = \int_{y \in \mathbb{R}} \Psi(x, y) dF_Y(y)$$

$$= \int_{x \in A} g(x) dF_X(x) = \mathbb{E}(g(x); A)$$

now All sorts of Properties of Independent Expectation

Properties of $E_{\mathcal{F}}(\cdot)$

(1) linearity $E_{\mathcal{F}}(ax + by) = aE_{\mathcal{F}}(x) + bE_{\mathcal{F}}(y)$

(2) monotonicity if $Y \geq X$ then $E_{\mathcal{F}}(Y) \geq E_{\mathcal{F}}(X)$

(3) M.C.T. $X_n \geq 0$, $X_n \uparrow X$, $E(X) < \infty$, then $E_{\mathcal{F}}(X_n) \xrightarrow[n \rightarrow \infty]{a.s.} E_{\mathcal{F}}(X)$

④ Jensen inequality. Ψ is convex function, $E|X| < \infty$, $E|\Psi(X)| < \infty$
 Then $\Psi(E_Z(X)) \leq E_Z\Psi(X)$ as.

$$\Rightarrow E\Psi(E_Z(X)) \leq (\Psi(Z))$$

Application of 4. Let $X \in L_p$, $p \geq 1$ ($E(|X|^p) < \infty$), $\|X\|_p = (E|X|^p)^{1/p}$

$$\text{then } \|E_Z(X)\|_p \leq \|X\|_p \quad \text{say if true then } \|E_Z(X)\|_p^p \leq \|X\|_p^p$$

The conditional expectation is a contraction in L_p .
 That is the L_p norm shrinks.

$$\Psi(x) = |x|^p, \quad x \in \mathbb{R}, \quad p \geq 1$$

$$(5) \quad \text{if } \mathcal{F}_1 \subset \mathcal{F}_2 \text{ then } E_{\mathcal{F}_1}(E_{\mathcal{F}_2}(X)) = E_{\mathcal{F}_1}(X) = E_{\mathcal{F}_2}(E_{\mathcal{F}_1}(X))$$

Becomes the smaller of the two.

$$(6) \quad \text{if } X \in \mathcal{F}, \text{ then } E_{\mathcal{F}}(XY) = E_{\mathcal{F}}(XE_{\mathcal{F}}(Y)) \quad \text{we assume } E|XY| < \infty \\ E(Y) < \infty$$

$$\text{Proof we need to show } E(E_{\mathcal{F}}(XY)Z) = E(XE_{\mathcal{F}}(Y)Z)$$

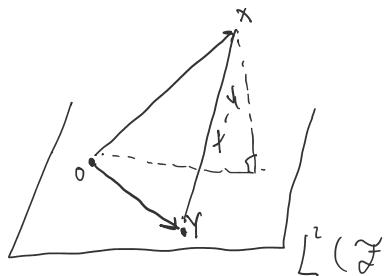
$$E(E_{\mathcal{F}}(XY)Z) = E(XYZ) \quad \begin{matrix} \text{if } Z \in \mathcal{F} \\ Z \text{ is bdd} \end{matrix}$$

$$E(E_{\mathcal{F}}(Y)XYZ) = E(XYZ) \quad \begin{matrix} \text{if } X \text{ is bounded} \\ \text{use procedure from §8} \end{matrix}$$

call this my new Z

$$(7) \quad \text{we assume } E|X|^2 < \infty \quad (X \in L_2) \quad \text{then } y \text{ is measurable with respect to } \mathcal{F}$$

$$\|X - E_{\mathcal{F}}(X)\|_{L_2} \leq \|X - Y\|_{L_2}, \quad Y \in L_2(\mathcal{F})$$



$$\|x - y\|_2^2 = \|x - E_F(x)\|_2^2 + \|E_F(x) - y\|_2^2$$

$$E(x-y)^2 = (x - E_F(x))^2 + (E_F(x) - y)^2 + 2(E(x - E_F(x))(E_F(x) - y))$$

↑ ↑ ↑ ↑

then take the expectation of every term $2E(bE_F(x) - y)$

J.L. Doob. invented martingales

$$E_F g(x)(\omega) = \int_R g(x) d\mu_\omega(x)$$

$\omega \longmapsto \mu_\omega$ PM on \mathbb{R}
 something important.

$$P_F(A)(\omega) \in E_F(1_A) \quad A \in \mathcal{F}$$

$$\text{if } P_F(A \cup B) = P_F(A) + P_F(B)$$

$$P_F(\bigcup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} P_F(A_i)$$

$$A_i \cap A_j = \emptyset \quad i \neq j$$

what was the trick of doob?

Focus on the Reelline.