

Conditional Expectation and Independence

$E_Y[X]$ is the "best guess" at X using only information in \mathcal{G} . What if \mathcal{G} has no information about X ?

Prop: Let $X: (\Omega, \mathcal{F}) \rightarrow (S, \mathcal{B})$ be a random variable, and let $\mathcal{G} \subseteq \mathcal{F}$ be a sub- σ -field.

If $\sigma(X), \mathcal{G}$ are independent, and $f: S \rightarrow \mathbb{R}$ is s.t. $f(X) \in L^1(\Omega, \mathcal{F}, P)$, then

$$E_{\mathcal{G}}[f(X)] = E[f(X)] \text{ a.s.}$$

Conversely, if \nearrow holds for all $f \in B(S, \mathcal{B})$, then $\sigma(X), \mathcal{G}$ are independent.

Pf. (\Rightarrow) Let $Y \in B(\Omega, \mathcal{G})$. Then $E[f(X)Y] = E[f(X)]E[Y] = \underbrace{E[f(X)]}_a E[Y] \Rightarrow E_{\mathcal{G}}[X] = a$

(\Leftarrow) $E[f(X)Y] = E[E_{\mathcal{G}}[f(X)]Y] = E[f(X)]E[Y]$.
 $\Rightarrow \sigma(X), \mathcal{G}$ are independent. //

Conditioning on a Random Variable / Vector

If $\underline{X}: (\Omega, \mathcal{F}) \rightarrow (S, \mathcal{B})$ (think $S = \mathbb{R}^d$),

and $Y \in L^1(\Omega, \mathcal{F}, P)$, we denote

$$\mathbb{E}_{\sigma(\underline{X})}[Y] = \mathbb{E}[Y | \sigma(\underline{X})] =: \mathbb{E}[Y | \underline{X}]$$

This is in $L^1(\Omega, \sigma(\underline{X}), P)$. In particular, it is $\sigma(\underline{X})/\mathcal{B}(\mathbb{R})$ -measurable.

By the Doob-Dynkin representation,
there is a $\mathcal{B}/\mathcal{B}(\mathbb{R})$ -measurable function $f_Y: S \rightarrow \mathbb{R}$

$$\text{s.t. } \mathbb{E}[Y | \underline{X}] = f_Y(\underline{X})$$

Notation: $f_Y(s) =: \mathbb{E}[Y | \underline{X}=s]$
 $(= \frac{\mathbb{E}[Y \mathbf{1}_{\{\underline{X}=s\}}]}{P(\underline{X}=s)})$

Equivalently: $f_Y: S \rightarrow \mathbb{R}$ is characterized by

$$\mathbb{E}[Y \cdot h(\underline{X})] = \mathbb{E}[f_Y(\underline{X})h(\underline{X})] \quad \forall h \in \mathcal{B}(S, \mathcal{B})$$

$$\hookrightarrow h = \mathbf{1}_{\{s\}} : \mathbb{E}[Y \mathbf{1}_{\{\underline{X}=s\}}] = \mathbb{E}[f_Y(s) \mathbf{1}_{\{\underline{X}=s\}}] = f_Y(s) P(\underline{X}=s)$$

If X, Y are independent, " Y is constant wst X ".

We can make this precise as follows.

Prop: Let $X: (\Omega, \mathcal{F}) \rightarrow (S, \mathcal{B})$, $Y: (\Omega, \mathcal{F}) \rightarrow (T, \mathcal{C})$

be random variables. Let \mathbb{P} be a probability measure on (Ω, \mathcal{F}) . If X, Y are independent, and $f \in \mathcal{B}(S \times T, \mathcal{B} \otimes \mathcal{C})$, then

$$\mathbb{E}[f(X, Y) | X = x] = \mathbb{E}[f(x, Y)] = \int_T f(x, y) \mu_Y(dy).$$

I.e. $\mathbb{E}[f(X, Y) | X] = \mathbb{E}[f(x, Y)]|_{x=X}$

Pf. Since X, Y are independent, $\mu_{(X, Y)} = \mu_X \otimes \mu_Y$. Thus, if $h \in \mathcal{B}(S, \mathcal{B})$,

$$\mathbb{E}[f(X, Y) h(X)] = \iint_{S \times T} f(x, y) h(x) \mu_X \otimes \mu_Y(dx dy)$$

$$= \int_S \mu_X(dx) h(x) \underbrace{\left(\int_T \mu_Y(dy) f(x, y) \right)}_{\mathbb{E}[f(x, Y)] = f_Y(x)} = \int_S f_Y(x) h(x) \mu_X(dx)$$

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E.g. Suppose (X, Y) has a joint density $\rho = \rho_{X,Y}$.

We want to identify $\mathbb{E}[f(X, Y) | X] = g(X)$

This means we want, $\forall h \in \mathcal{B}(\mathbb{R}, \mathcal{B}(\mathbb{R}))$,

$$\mathbb{E}[\mathbb{E}[f(X, Y) | X] h(X)] = \mathbb{E}[f(X, Y) h(X)]$$

$$\mathbb{E}[g(X) h(X)]$$

$$\int g(x) h(x) \mu_X(dx)$$

$$\iint f(x, y) h(x) \rho(x, y) dy$$

Note: since (X, Y) has a joint density, X has a **marginal** density

$$P(X \in A) = P((X, Y) \in A \times \mathbb{R}) = \iint_{A \times \mathbb{R}} \rho(x, y) dy dx = \int_A \left(\int_{\mathbb{R}} \rho(x, y) dy \right) dx$$

$$\text{I.e. } \rho_X(x) = \int_{\mathbb{R}} \rho(x, y) dy$$

$$\Rightarrow \int h(x) g(x) \rho_X(x) dx = \int h(x) \left(\int dy f(x, y) \rho(y) \right) dx$$

Prop: Let (X, Y) have density $\rho = \rho_{XY}$.

Let $\rho_X(x) = \int \rho_{XY}(x, y) dy$ be the marginal density of X . Define

$$\rho_{Y|X}(y|x) := \mathbb{1}_{0 < \rho_X < \infty} \frac{\rho_{XY}(x, y)}{\rho_X(x)}$$

Then for $f \in \mathcal{B}(\mathbb{R}^2)$,

$$\mathbb{E}[f(X, Y) | X = x] \approx$$

$$\mathbb{E}[f(X, Y) | X] = g(x) \quad \text{where } g(x) = \int f(x, y) \rho_{Y|X}(y|x) dy$$

Pf. We saw on the last slide, \uparrow holds provided g satisfies

$$g(x) \rho_X(x) = \int f(x, y) \rho_{XY}(x, y) dy \quad \text{for } (\lambda) \text{ a.e. } x \in \mathbb{R}$$

↑

We defined g to make this true if $\rho_X(x) > 0$.

Claim: If $\rho_X(x) = 0$ then $|\int f(x, y) \rho_{XY}(x, y) dy| = 0$.

$$\leq \sup_y |f(x, y)| \underbrace{\int |\rho_{XY}(x, y)| dy}_{\rho_X(x)} \quad \text{///}$$