

Conditional Expectation and Independence

$\mathbb{E}_{\mathcal{G}}[X]$ 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. $f(X) \in L^1(\Omega, \mathcal{F}, \mathbb{P})$, then

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

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

Pf. (\Rightarrow) Let $Y \in \mathcal{B}(\Omega, \mathcal{G})$. Then $\mathbb{E}[f(X)Y]$

\downarrow
 $(\Leftarrow) \mathbb{E}[f(X)Y]$

Conditioning on a Random Variable / Vector

If $X: (\Omega, \mathcal{F}) \rightarrow (S, \mathcal{B})$ (think $S = \mathbb{R}^d$),
and $Y \in L^1(\Omega, \mathcal{F}, \mathbb{P})$, we denote

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

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

By the Doob-Dynkin representation,

there is a $\mathcal{B} / \mathcal{B}(\mathbb{R})$ -measurable function $f_Y: S \rightarrow \mathbb{R}$

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

Notation: $f_Y(s) =:$

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

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

If X, Y are independent, "Y is constant wrt 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

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

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

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

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

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

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

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

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

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

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

It is $\rho_X(x) = \int_{\mathbb{R}} \rho(x, y) dy$

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

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

$$\rho_{Y|X}(y|x) := \frac{\rho_{X, Y}(x, y)}{\rho_X(x)}$$

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

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

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

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

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

Claim: If $\rho_X(x) = 0$ then