

Lecture 10: Conditional Expectation and σ -Algebras

Definition- A σ -algebra \mathcal{F} of a sample space Ω is a collection of events $A \in \mathcal{F}$ such that

1. $\Omega \in \mathcal{F}$
2. If $A \in \mathcal{F}$ then $A^c \in \mathcal{F}$
3. If $A_1, A_2, \dots \in \mathcal{F}$ then $\bigcup_{n=1}^{\infty} A_n \in \mathcal{F}$.

Examples:

1. $\{\emptyset, \Omega\}$ = trivial σ -algebra
2. $\{\emptyset, \Omega, A, A^c\}$ = σ -algebra generated by an event A .

More Important Example:

Let X_i be a sequence of random variables satisfying

$$P(X_i = 1) = 1/2 \quad P(X_i = -1) = 1/2$$

and define

$$S_n = \sum_{i=1}^n X_i.$$

We take $\Omega = \{(x_1, x_2, \dots) \text{ where } x_i = \pm 1\}$.

1. $S_0 = 0$

$$\begin{aligned} \Rightarrow P(S_0 \in [a, b]) &= P(\{\omega : 0 \in [a, b]\}) \\ &= \begin{cases} P(\emptyset) & \text{if } 0 \notin [a, b] \\ P(\Omega) & \text{if } 0 \in [a, b] \end{cases} \end{aligned}$$

The only events needed are \emptyset, Ω

$$\Rightarrow \mathcal{F}_0 = \{\emptyset, \Omega\}$$

information you know at $i=0$.

$$2. S_1 = X_1$$

$$\Rightarrow P(S_1 \in [a, b]) = P(\{\omega : X_1 \in [a, b]\})$$

$$= \begin{cases} P(\emptyset) & \text{if } 1 \text{ or } -1 \notin [a, b] \\ P(\Omega) & \text{if } 1 \text{ and } -1 \in [a, b] \\ P(\{\omega \in \Omega : \omega = (1, \dots, \dots)\}) & \text{if } 1 \in [a, b] \text{ and } -1 \notin [a, b] \\ P(\{\omega \in \Omega : \omega = (-1, \dots, \dots)\}) & \text{if } -1 \in [a, b] \text{ and } 1 \notin [a, b] \end{cases}$$

$$\Rightarrow \mathcal{F}_2 = \{\emptyset, \Omega, \{\omega : \omega = (1, \dots, \dots)\}, \{\omega : \omega = (-1, \dots, \dots)\}\}$$

is a new σ -algebra containing information you know at $i=1$.

$$\Rightarrow \mathcal{F}_0 \subset \mathcal{F}_1 \subset \mathcal{F}_2 \text{ is a } \sigma\text{-algebra generated by } S_1$$

$$3. S_2 = X_1 + X_2$$

$$\text{Let } A = \{\omega : \omega = (1, 1, \dots, \dots)\}, B = \{\omega : \omega = (-1, -1, \dots, \dots)\}, C = \{\omega : \omega = (-1, 1, \dots, \dots)\}, \\ D = \{\omega : \omega = (1, -1, \dots, \dots)\}.$$

$$\Rightarrow P(S_2 \in I) = \begin{cases} P(\emptyset) & \text{if } -2, 0, 2 \notin I \\ P(\Omega) & \text{if } -2, 0, 2 \in I \\ P(A) & \text{if } 2 \in I, -2, 0 \notin I \\ P(B) & \text{if } -2 \in I, 0, 2 \notin I \\ P(C \cup D) & \text{if } 0 \in I, -2, 2 \notin I \\ P(A \cup B) & \text{if } -2, 2 \in I, 0 \notin I \\ P(A \cup C \cup D) & \text{if } 2, 0 \in I, -2 \notin I \\ P(B \cup C \cup D) & \text{if } -2, 0 \in I, 2 \notin I \end{cases}$$

$$\Rightarrow \mathcal{F}_2 = \{\emptyset, \Omega, \{1, 1, \dots\}, \{-1, -1, \dots\}, \{1, -1, \dots\}, \{-1, 1, \dots\}\}$$

* \mathcal{F}_2 is σ -algebra generated by S_2 .

$$\Rightarrow \mathcal{F}_0 \subset \mathcal{F}_1 \subset \mathcal{F}_2$$

Notation - $\sigma(X)$ is the σ -algebra generated by a random variable X . It is the smallest σ -algebra for which X is measurable on (Ω, \mathcal{F}, P) .

Definition - Let X be a random variable on (Ω, \mathcal{F}, P) . Consider another $\mathcal{G} \subset \mathcal{F}$. Then X is said to be \mathcal{G} -measurable if and only if

$$\{\omega: X(\omega) \in I\} \in \mathcal{G}$$

for all intervals I in \mathbb{R} .

Example:

Let $\mathcal{G} = \{\emptyset, \Omega\}$. If X is \mathcal{G} -measurable then X is a constant.

proof:

If X is \mathcal{G} -measurable then for all $[a, b)$,

$$\{\omega: X(\omega) \in [a, b)\} = \emptyset \text{ or } \{\omega: X(\omega) \in [a, b)\} = \Omega$$

Now, suppose there exists x_1, x_2 and ω_1, ω_2 such that $X_1(\omega_1) = x_1$ and $X_2(\omega_2) = x_2$. Therefore,

$$\Omega = \bigcap_{n=1}^{\infty} \{\omega: X(\omega) \in [x_1 - \frac{1}{n}, \frac{1}{n})\} = \bigcap_{n=1}^{\infty} \{\omega: X(\omega) \in [x_2 - \frac{1}{n}, \frac{1}{n})\}.$$

$$\Rightarrow \Omega = \{\omega: X(\omega) = x_1\} = \{\omega: X(\omega) = x_2\}.$$

$$\Rightarrow x_1 = x_2.$$

Theorem - If Y is $\sigma(X)$ -measurable then $Y = g(X)$ for some function g .

Definition - Let Y be a random variable on (Ω, \mathcal{F}, P) and $\mathcal{G} \subset \mathcal{F}$ be another σ -field. The conditional expectation of Y given \mathcal{G} , denoted $E[Y|\mathcal{G}]$, satisfies

- $E[Y|\mathcal{G}]$ is \mathcal{G} -measurable
- If W is \mathcal{G} -measurable then $E[WY] = E[W E[Y|\mathcal{G}]]$.

Properties:

1. If Y - \mathcal{G} -measurable then

$$\mathbb{E}[Y | \mathcal{G}] = Y$$

2. If Y - \mathcal{G} -measurable and X is another random variable then

$$\mathbb{E}[XY | \mathcal{G}] = Y \mathbb{E}[X | \mathcal{G}]$$

3. If Y is independent of \mathcal{G} , i.e. for all $A \in \mathcal{G}$

$$P(\{Y \in I\} \cap A) = P(\{Y \in I\})P(A)$$

then

$$\mathbb{E}[Y | \mathcal{G}] = \mathbb{E}[Y]$$

$$4. \mathbb{E}[aX + bY | \mathcal{G}] = a \mathbb{E}[X | \mathcal{G}] + b \mathbb{E}[Y | \mathcal{G}].$$

$$5. \mathbb{E}[Y^2] = \mathbb{E}[\mathbb{E}[Y | \mathcal{G}]^2] + \mathbb{E}[(Y - \mathbb{E}[Y | \mathcal{G}])^2]$$

$$\Rightarrow \mathbb{E}[\mathbb{E}[Y | \mathcal{G}]^2] \leq \mathbb{E}[Y^2].$$

Example:

$$\begin{aligned} \mathbb{E}[e^{xB_1} | B_{1/2}] &= \mathbb{E}[e^{x(B_1 - B_{1/2} + B_{1/2})} | B_{1/2}] \\ &= \mathbb{E}[e^{xB_{1/2}} e^{x(B_1 - B_{1/2})} | B_{1/2}] \\ &= e^{xB_{1/2}} \mathbb{E}[e^{x(B_1 - B_{1/2})} | B_{1/2}] \\ &= e^{xB_{1/2}} \mathbb{E}[e^{x(B_1 - B_{1/2})}] \\ &= e^{xB_{1/2}} e^{x^2/4} \\ &= e^{xB_{1/2} + x^2/4} \end{aligned}$$

Recall, for a Gaussian Random variable with mean μ and variance σ^2 that

$$\mathbb{E}[e^{tX}] = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$$