



# Probability and Stochastic Processes

Lecture 28: Law of Iterated Expectations, Conditional Expectation as an MMSE Estimator, Generating Functions: Probability Generating Function, Moment Generating Function, Characteristic Function

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## Law of Iterated Expectations

### Theorem (Law of Iterated Expectations)

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Let  $X$  and  $Y$  be random variables. Suppose that  $\mathbb{E}[X]$  is well defined, i.e., not of the form  $\infty - \infty$ . Then,

$$\mathbb{E}[X] = \mathbb{E}[\mathbb{E}[X|Y]].$$

More generally, if  $g : \mathbb{R} \rightarrow \mathbb{R}$  is measurable and such that  $\mathbb{E}[g(X)]$  is well defined, then

$$\mathbb{E}[g(X)] = \mathbb{E}[\mathbb{E}[g(X)|Y]].$$

## Example

Let  $X_1, X_2, \dots$  be IID random variables. Let  $\mathbb{E}[X_1]$  be well-defined.

Let  $N$  be a discrete random variable taking values in  $\mathbb{N}$  and independent of  $\{X_1, X_2, \dots\}$ , and let  $\mathbb{E}[N]$  be well-defined.

Compute  $\mathbb{E}[S_N]$  assuming it is well-defined, where  $S_N = \sum_{n=1}^N X_n$ .

- Using the law of iterated expectations, we may write

$$\mathbb{E}[S_N] = \mathbb{E}\left[\mathbb{E}[S_N \mid N]\right].$$

- For any  $n \in \mathbb{N}$ , we have

$$\mathbb{E}[S_N \mid \{N = n\}] = \mathbb{E}[S_n \mid \{N = n\}] \stackrel{(a)}{=} \mathbb{E}[S_n] = n \cdot \mathbb{E}[X_1],$$

where (a) above follows from the fact that  $N \perp\!\!\!\perp \{X_1, X_2, \dots\}$

- Then, we have

$$\mathbb{E}[S_N \mid N] = N \cdot \mathbb{E}[X_1],$$

from which it follows that

$$\mathbb{E}[S_N] = \mathbb{E}\left[\mathbb{E}[S_N \mid N]\right] = \mathbb{E}[N] \cdot \mathbb{E}[X_1].$$

## Example + Caution!

Let  $Y$  be geometric with parameter  $p = 0.5$ .

Conditioned on  $\{Y = y\}$ , let  $X$  take the values  $\pm 2^y$  with equal probability, i.e.,

$$p_{X|Y=y}(x) = \frac{1}{2} \mathbf{1}_{\{-2^y, 2^y\}}(x).$$

1. Compute  $\mathbb{E}[X|Y]$ , and use it to compute  $\mathbb{E}[X]$ .
2. Compute  $p_X$  and use it to compute  $\mathbb{E}[X]$ .  
In particular, show that it is different from the answer of part (1).
3. Explain the discrepancy in the answers of parts (1.) and (2.).

## Solution – 1

- For any  $y \in \mathbb{N} \cup \{0\}$ , we have

$$\mathbb{E}[X \mid \{Y = y\}] = \frac{2^y}{2} + \frac{(-2^y)}{2} = 0.$$

- Hence, it follows that

$$\mathbb{E}[X|Y] = 0.$$

- Using the law of iterated expectations, we get

$$\mathbb{E}[X] = \mathbb{E}[\mathbb{E}[X|Y]] = 0.$$

## Solution - 2, 3

- The set of values that  $X$  takes is  $\{\pm 2, \pm 4, \pm 8, \dots\}$
- For any  $k \in \mathbb{N}$ ,

$$\mathbb{P}(\{X = 2^k\}) = \mathbb{P}(\{X = 2^k\} \mid \{Y = k\}) \cdot \mathbb{P}(\{Y = k\}) = \frac{1}{2} \cdot \left(\frac{1}{2}\right)^k = \frac{1}{2^{k+1}} = \mathbb{P}(\{X = -2^k\}).$$

- Then, we have

$$\mathbb{E}[X_+] = \sum_{k \in \mathbb{N}} 2^k \cdot \frac{1}{2^{k+1}} = +\infty = \mathbb{E}[X_-]$$

- Thus,  $\mathbb{E}[X]$  is not well-defined

The discrepancy in the answers of parts 1 and 2 is because of applying the law of iterated expectations **without checking** first whether  $\mathbb{E}[X]$  is well-defined.

## Conditional Expectation as MMSE Estimator

# Conditional Expectation as the Projection

## Proposition (Conditional Expectation as Projection)

Let  $g : \mathbb{R} \rightarrow \mathbb{R}$  be **measurable**, and let  $X, Y$  be random variables.

Suppose that  $X, Y, g(Y) \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathbb{P})$ . Then,

$$\mathbb{E}[X g(Y)] = \mathbb{E}\left[g(Y) \mathbb{E}[X|Y]\right].$$

Equivalently, we have

$$\mathbb{E}\left[(X - \mathbb{E}[X|Y]) g(Y)\right] = 0.$$



## Proof of Proposition

- By Hölder's inequality, we have

$$\left| \mathbb{E}[Xg(Y)] \right| \leq \mathbb{E}[|Xg(Y)|] \leq \sqrt{\mathbb{E}[X^2] \cdot \mathbb{E}[g(Y)^2]} < +\infty.$$

This implies that  $\mathbb{E}[Xg(Y)]$  is well-defined

- Using the law of iterated expectations, we may write

$$\mathbb{E}[Xg(Y)] = \mathbb{E}[\mathbb{E}[Xg(Y) | Y]].$$

- For any  $y \in \mathbb{R}$ ,

$$\mathbb{E}[Xg(Y) | \{Y = y\}] = \mathbb{E}[Xg(y) | \{Y = y\}] = g(y) \cdot \mathbb{E}[X | \{Y = y\}],$$

from which it follows that

$$\mathbb{E}[Xg(Y) | Y] = g(Y) \cdot \mathbb{E}[X | Y].$$

## Tidbits on Conditional Expectation

- Let  $\sigma(Y)$  denote the  $\sigma$ -algebra generated by  $Y$
- Let  $\mathcal{S}_{\sigma(Y)} \subset \mathcal{F}$  denote the collection of all random variables which are measurable with respect to  $\sigma(Y)$
- That is,

$$\mathcal{S}_{\sigma(Y)} := \left\{ Z : Z^{-1}(B) \in \sigma(Y) \text{ for every } B \in \mathcal{B}(\mathbb{R}) \right\}.$$

- If  $g : \mathbb{R} \rightarrow \mathbb{R}$  is **measurable**, then

$$Z = g(Y) \in \mathcal{S}_{\sigma(Y)}.$$

- Conversely, if  $Z \in \mathcal{S}_{\sigma(Y)}$ , then

$$Z = g(Y) \quad \text{for some measurable function } g$$

- $\mathbb{E}[X|Y] \in \mathcal{S}_{\sigma(Y)}$

## Conditional Expectation as the MMSE Estimator

### Theorem (Conditional Expectation as the MMSE Estimator)

Suppose that  $X, Y \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathbb{P})$ .

The conditional expectation  $\mathbb{E}[X|Y]$  is the **minimum mean-squared error (MMSE)** estimator for  $X$  given  $Y$ , i.e.,

$$\mathbb{E}[(X - \mathbb{E}[X|Y])^2] = \inf_{Z \in \mathcal{S}_{\sigma(Y)}} \mathbb{E}[(X - Z)^2].$$

**Proof:** Fix an arbitrary  $Z \in \mathcal{S}_{\sigma(Y)}$ . By definition, there exists  $g$  measurable such that  $Z = g(Y)$ .

- We have

$$\begin{aligned} \mathbb{E}[(X - Z)^2] &= \mathbb{E}[(X - g(Y))^2] = \mathbb{E}[(X - \mathbb{E}[X|Y] + \mathbb{E}[X|Y] - g(Y))^2] \\ &= \mathbb{E}[(X - \mathbb{E}[X|Y])^2] + \underbrace{\mathbb{E}[(\mathbb{E}[X|Y] - g(Y))^2]}_{\text{Term 1}} + 2 \underbrace{\mathbb{E}[(X - \mathbb{E}[X|Y])(\mathbb{E}[X|Y] - g(Y))]}_{\text{Term 2}} \end{aligned}$$

- From previous proposition, we have Term 2 = 0
- Also, Term 1  $\geq 0$ , with equality if and only if  $Z = \mathbb{E}[X|Y]$

# Generating Functions

# Probability Generating Function (PGF)

## Definition (Probability Generating Function)

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Let  $X$  be an **integer-valued** random variable. The **probability generating function (PGF)** of  $X$  is defined as

$$G_X(z) := \mathbb{E}[z^X] = \sum_{k \in \mathbb{Z}} z^k p_X(k), \quad z \in \mathbb{R}.$$

- The **region of convergence (ROC)** of a PGF is defined as the set

$$\text{ROC}(G_X) = \left\{ z \in \mathbb{R} : |G_X(z)| < +\infty \right\}.$$

- For any  $z \in \mathbb{R}$  such that  $|z| \leq 1$ , we have

$$|G_X(z)| = \left| \sum_{k \in \mathbb{Z}} z^k p_X(k) \right| \leq \sum_{k \in \mathbb{Z}} |z|^k p_X(k) \leq \sum_{k \in \mathbb{Z}} p_X(k) = 1,$$

thus proving that

$$\{z \in \mathbb{R} : |z| \leq 1\} \subseteq \text{ROC}(G_X).$$

## Examples

- If  $X \sim \text{Poisson}(\lambda)$ , then

$$G_X(z) = e^{\lambda(z-1)}, \quad z \in \mathbb{R}.$$

- If  $X \sim \text{Geometric}(p)$ , then

$$G_X(z) = \frac{pz}{1 - (1-p)z}, \quad |z| < \frac{1}{1-p}.$$

## Properties of PGF

- $G_X(1) = 1$
- $\left. \frac{d}{dz} G_X(z) \right|_{z=1} = \mathbb{E}[X]$
- More generally, for any  $k \in \mathbb{N}$ ,

$$\left. \frac{d^k}{dz^k} G_X(z) \right|_{z=1} = \mathbb{E}[X(X-1) \cdots (X-k+1)].$$

- $X \perp\!\!\!\perp Y \implies G_{X+Y}(z) = G_X(z) \cdot G_Y(z)$ . Furthermore,

$$\text{ROC}(G_{X+Y}) = \text{ROC}(G_X) \cap \text{ROC}(G_Y).$$

- Let  $Y = \sum_{i=1}^N X_i$ , where  $X_1, X_2, \dots$  are IID integer-valued and  $N$  is independent of  $\{X_1, X_2, \dots\}$  and taking values in  $\mathbb{N}$ . Then, for any  $z \in \mathbb{R}$  such that  $G_Y(z)$  is well-defined, we have

$$G_Y(z) = G_N(G_{X_1}(z)).$$

## Moment Generating Function (MGF)



## Moment Generating Function (MGF)

### Definition (Moment Generating Function)

Fix a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Let  $X$  be a random variable.

The **moment generating function (MGF)** of  $X$  is a function  $M_X : \mathbb{R} \rightarrow [0, +\infty]$  defined as

$$M_X(t) := \mathbb{E}[e^{tX}], \quad t \in \mathbb{R}.$$

The **region of convergence (ROC)** of MGF is defined as the set

$$\text{ROC}(M_X) = \left\{ t \in \mathbb{R} : M_X(t) < +\infty \right\}.$$

## Examples

- If  $X \sim \text{Exponential}(\mu)$ , then

$$M_X(t) = \begin{cases} \frac{\mu}{\mu - t}, & t < \mu, \\ +\infty, & t \geq \mu. \end{cases}$$

- If  $X \sim \mathcal{N}(0, 1)$ , then

$$M_X(t) = e^{\frac{t^2}{2}}, \quad t \in \mathbb{R}.$$

- If  $f_X(x) = \frac{1}{\pi} \frac{1}{1+x^2}$ ,  $x \in \mathbb{R}$ , then

$$M_X(t) = \begin{cases} 1, & t = 0, \\ +\infty, & t \neq 0. \end{cases}$$