



Probability and Stochastic Processes

Conditional Expectations, Law of Iterated Expectations, Conditional Expectation as an MMSE Estimator

Karthik P. N.

Assistant Professor, Department of AI

Email: pnkarthik@ai.iith.ac.in

28/30 October 2024

Conditional Expectations

Conditional Expectation

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X, Y be random variables with respect to \mathcal{F} .

Objective

To define the following quantities:

- $\mathbb{E}[X|\{Y = y\}]$, for any $y \in \mathbb{R}$.
- $\mathbb{E}[X|Y]$.

Programme:

We shall define the above quantities by considering X discrete/continuous, and Y discrete/continuous.

Case 1: X, Y Jointly Discrete

Let X, Y have the joint PMF $p_{X,Y}$.

- Step 1: Conditional PMF of X , conditioned on the event $\{Y = y\}$:

$$p_{X|Y=y}(x) = \frac{p_{X,Y}(x, y)}{p_Y(y)}, \quad x \in \mathbb{R}.$$

- Step 2: The quantity $\mathbb{E}[X|\{Y = y\}]$ is defined as the expectation with respect to the conditional PMF $p_{X|Y=y}$, i.e.,

$$\mathbb{E}[X|\{Y = y\}] := \sum_{x \in \mathbb{R}} x \cdot p_{X|Y=y}(x).$$

Case 1: X, Y Jointly Discrete

Let X, Y have the joint PMF $p_{X,Y}$.

- Step 3: Define the function $\psi_1 : \mathbb{R} \rightarrow \mathbb{R}$ as

$$\psi_1(y) := \begin{cases} \mathbb{E}[X|\{Y = y\}], & p_Y(y) > 0, \\ 0, & p_Y(y) = 0. \end{cases}$$

- Step 4: The quantity $\mathbb{E}[X|Y]$ is simply defined as

$$\mathbb{E}[X|Y] = \psi_1(Y).$$

Example

Suppose that X takes values uniformly in the set $\{-1, 0, 1\}$.

Suppose that

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

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

Exercise: Determine $\mathbb{E}[X|Y]$.

Case 2: X, Y Jointly Continuous

Let X, Y have the joint PDF $f_{X,Y}$.

- Step 1: Conditional PDF of X , conditioned on the event $\{Y = y\}$:

$$f_{X|Y=y}(x) = \frac{f_{X,Y}(x, y)}{f_Y(y)}, \quad x \in \mathbb{R}.$$

- Step 2: The quantity $\mathbb{E}[X|\{Y = y\}]$ is defined as the expectation with respect to the conditional PDF $f_{X|Y=y}$, i.e.,

$$\mathbb{E}[X|\{Y = y\}] := \int_{-\infty}^{+\infty} x \cdot f_{X|Y=y}(x).$$

Case 2: X, Y Jointly Continuous

Let X, Y have the joint PDF $p_{X,Y}$.

- Step 3: Define the function $\psi_2 : \mathbb{R} \rightarrow \mathbb{R}$ as

$$\psi_2(y) := \begin{cases} \mathbb{E}[X|\{Y = y\}], & f_Y(y) > 0, \\ 0, & f_Y(y) = 0. \end{cases}$$

- Step 4: The quantity $\mathbb{E}[X|Y]$ is simply defined as

$$\mathbb{E}[X|Y] = \psi_2(Y).$$

Example

- Let X and Y have the joint PDF

$$f_{X,Y}(x,y) = \begin{cases} \frac{1}{x}, & 0 \leq y \leq x < +\infty, \\ 0, & \text{otherwise.} \end{cases}$$

What is $\mathbb{E}[Y|X]$?

Exercise: Compute $\mathbb{E}[X|Y]$.

Case 3: X Continuous, Y Discrete

- Step 1: Conditional CDF of X , conditioned on the event $\{Y = y\}$:

$$F_{X|\{Y=y\}}(x) = \mathbb{P}(\{X \leq x\}|\{Y = y\}), \quad x \in \mathbb{R}.$$

Case 3: X Continuous, Y Discrete

- Step 1: Conditional CDF of X , conditioned on the event $\{Y = y\}$:

$$F_{X|\{Y=y\}}(x) = \mathbb{P}(\{X \leq x\}|\{Y = y\}), \quad x \in \mathbb{R}.$$

- Step 2: Get the conditional PDF of X , conditioned on the event $\{Y = y\}$:

$$h_y(x) = \frac{d}{dx} F_{X|\{Y=y\}}(x).$$

Case 3: X Continuous, Y Discrete

- Step 1: Conditional CDF of X , conditioned on the event $\{Y = y\}$:

$$F_{X|\{Y=y\}}(x) = \mathbb{P}(\{X \leq x\}|\{Y = y\}), \quad x \in \mathbb{R}.$$

- Step 2: Get the conditional PDF of X , conditioned on the event $\{Y = y\}$:

$$h_y(x) = \frac{d}{dx} F_{X|\{Y=y\}}(x).$$

- Step 3: The quantity $\mathbb{E}[X|\{Y = y\}]$ is defined as the expectation with respect to the conditional PDF $h_y(x)$, i.e.,

$$\mathbb{E}[X|\{Y = y\}] := \int_{-\infty}^{+\infty} x \cdot h_y(x).$$

Case 3: X Continuous, Y Discrete

- Step 4: Define the function $\psi_3 : \mathbb{R} \rightarrow \mathbb{R}$ as

$$\psi_3(\gamma) := \begin{cases} \mathbb{E}[X|\{Y = \gamma\}], & p_Y(\gamma) > 0, \\ 0, & p_Y(\gamma) = 0. \end{cases}$$

Case 3: X Continuous, Y Discrete

- Step 4: Define the function $\psi_3 : \mathbb{R} \rightarrow \mathbb{R}$ as

$$\psi_3(\gamma) := \begin{cases} \mathbb{E}[X|\{Y = \gamma\}], & p_Y(\gamma) > 0, \\ 0, & p_Y(\gamma) = 0. \end{cases}$$

- Step 5: The quantity $\mathbb{E}[X|Y]$ is simply defined as

$$\mathbb{E}[X|Y] = \psi_3(Y).$$

Case 4: X Discrete, Y Continuous

- Step 1: The joint probability

$$i(x, y) = \mathbb{P}(\{X = x\} \cap \{Y \leq y\}).$$

Case 4: X Discrete, Y Continuous

- Step 1: The joint probability

$$i(x, y) = \mathbb{P}(\{X = x\} \cap \{Y \leq y\}).$$

- Step 2: Construction of the conditional PMF of X , conditioned on the event $\{Y = y\}$:

$$i_y(x) = \frac{1}{f_Y(y)} \cdot \frac{d}{dy} i(x, y), \quad x \in \mathbb{R}.$$

Case 4: X Discrete, Y Continuous

- Step 1: The joint probability

$$i(x, y) = \mathbb{P}(\{X = x\} \cap \{Y \leq y\}).$$

- Step 2: Construction of the conditional PMF of X , conditioned on the event $\{Y = y\}$:

$$i_y(x) = \frac{1}{f_Y(y)} \cdot \frac{d}{dy} i(x, y), \quad x \in \mathbb{R}.$$

- Step 3: The quantity $\mathbb{E}[X|\{Y = y\}]$ is defined as the expectation with respect to the conditional PMF $i_y(x)$, i.e.,

$$\mathbb{E}[X|\{Y = y\}] := \sum_{x \in \mathbb{R}} x \cdot i_y(x).$$

Case 4: X Discrete, Y Continuous

- Step 4: Define the function $\psi_4 : \mathbb{R} \rightarrow \mathbb{R}$ as

$$\psi_4(y) := \begin{cases} \mathbb{E}[X|\{Y = y\}], & f_Y(y) > 0, \\ 0, & f_Y(y) = 0. \end{cases}$$

Case 4: X Discrete, Y Continuous

- Step 4: Define the function $\psi_4 : \mathbb{R} \rightarrow \mathbb{R}$ as

$$\psi_4(y) := \begin{cases} \mathbb{E}[X|\{Y = y\}], & f_Y(y) > 0, \\ 0, & f_Y(y) = 0. \end{cases}$$

- Step 5: The quantity $\mathbb{E}[X|Y]$ is simply defined as

$$\mathbb{E}[X|Y] = \psi_4(Y).$$

Example

- Let $Y \sim \mathcal{N}(0, 1)$. Suppose that the conditional PMF of X , conditioned on the event $\{Y = y\}$, is

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

where $\text{sgn}(y)$ denotes the sign of y , and is defined as

$$\text{sgn}(y) = \begin{cases} 1, & y > 0, \\ 0, & y = 0, \\ -1, & y < 0. \end{cases}$$

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

Law of Iterated Expectations

Law of Iterated Expectations

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X and Y be random variables w.r.t. \mathcal{F} .

Theorem (Law of Iterated Expectations)

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 a function such that $\mathbb{E}[g(X)]$ is well defined, then

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

Proof – X, Y Jointly Discrete

$$\mathbb{E}[\mathbb{E}[g(X)|Y]] = \sum_y \mathbb{E}[g(X)|\{Y = y\}] p_Y(y)$$

Proof – X, Y Jointly Discrete

$$\begin{aligned}\mathbb{E}[\mathbb{E}[g(X)|Y]] &= \sum_y \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\ &= \sum_{y:p_Y(y)>0} \mathbb{E}[g(X)|\{Y = y\}] p_Y(y)\end{aligned}$$

Proof – X, Y Jointly Discrete

$$\begin{aligned}\mathbb{E}[\mathbb{E}[g(X)|Y]] &= \sum_y \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) p_{X|\{Y=y\}}(x) p_Y(y)\end{aligned}$$

Proof – X, Y Jointly Discrete

$$\begin{aligned}\mathbb{E}[\mathbb{E}[g(X)|Y]] &= \sum_y \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) p_{X|\{Y=y\}}(x) p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) \frac{p_{X,Y}(x, y)}{p_Y(y)} p_Y(y)\end{aligned}$$

Proof – X, Y Jointly Discrete

$$\begin{aligned}\mathbb{E}[\mathbb{E}[g(X)|Y]] &= \sum_y \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) p_{X|\{Y=y\}}(x) p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) \frac{p_{X,Y}(x, y)}{p_Y(y)} p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) p_{X,Y}(x, y)\end{aligned}$$

Proof – X, Y Jointly Discrete

$$\begin{aligned}\mathbb{E}[\mathbb{E}[g(X)|Y]] &= \sum_y \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) p_{X|\{Y=y\}}(x) p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) \frac{p_{X,Y}(x, y)}{p_Y(y)} p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) p_{X,Y}(x, y) = \sum_x g(x) \sum_{y:p_Y(y)>0} p_{X,Y}(x, y)\end{aligned}$$

Proof – X, Y Jointly Discrete

$$\begin{aligned}\mathbb{E}[\mathbb{E}[g(X)|Y]] &= \sum_y \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \mathbb{E}[g(X)|\{Y = y\}] p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) p_{X|\{Y=y\}}(x) p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) \frac{p_{X,Y}(x, y)}{p_Y(y)} p_Y(y) \\&= \sum_{y:p_Y(y)>0} \sum_x g(x) p_{X,Y}(x, y) = \sum_x g(x) \sum_{y:p_Y(y)>0} p_{X,Y}(x, y) \\&= \mathbb{E}[g(X)].\end{aligned}$$

Example

Let X_1, X_2, \dots be i.i.d. random variables with $|\mathbb{E}[X_1]| < +\infty$.
Let N be a discrete random variable independent of $\{X_n\}_{n=1}^\infty$.
Compute $\mathbb{E}[S_N]$, where $S_N = \sum_{i=1}^N X_i$.

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.).

Conditioning on Events – 1

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X be a random variable w.r.t. \mathcal{F} .

Let $A \in \mathcal{F}$ with $\mathbb{P}(A) > 0$.

Proposition (Conditioning on an Event)

- Suppose that X is discrete. Then,

$$\mathbb{E}[X|A] = \sum_x x p_{X|A}(x),$$

where $p_{X|A}(x)$ is defined as

$$p_{X|A}(x) = \frac{\mathbb{P}(\{X = x\} \cap A)}{\mathbb{P}(A)}.$$

Conditioning on Events – 2

Fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Let X be a random variable w.r.t. \mathcal{F} .

Let $A \in \mathcal{F}$ with $\mathbb{P}(A) > 0$.

Proposition (Conditioning on an Event)

- Suppose that X is continuous. Then,

$$\mathbb{E}[X|A] = \int_{-\infty}^{\infty} x f_{X|A}(x) \, dx,$$

where $f_{X|A}(x)$ is defined as

$$f_{X|A}(x) = \frac{d}{dx} F_{X|A}(x).$$

Miscellaneous Problems on Conditional Expectations

Miscellaneous Problems

- Let $Y \sim \text{Geometric}(p)$ for some $p > 0$.
Compute $\mathbb{E}[Y]$ using the law of iterated expectations.

Miscellaneous Problems

- Let $Y \sim \text{Geometric}(p)$ for some $p > 0$.
Compute $\mathbb{E}[Y]$ using the law of iterated expectations.
- Suppose that $X \sim \text{Exponential}(\lambda)$ for some $\lambda > 0$.
Compute $\mathbb{E}[X | \{X > 1\}]$.

Miscellaneous Problems

- Let $Y \sim \text{Geometric}(p)$ for some $p > 0$.
Compute $\mathbb{E}[Y]$ using the law of iterated expectations.

- Suppose that $X \sim \text{Exponential}(\lambda)$ for some $\lambda > 0$.
Compute $\mathbb{E}[X|\{X > 1\}]$.

- Let X and Y be jointly continuous with the joint PDF

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{2} y e^{-xy}, & x > 0, 0 < y < 2, \\ 0, & \text{otherwise.} \end{cases}$$

Compute $\mathbb{E}[e^{X/2}|Y]$.

Miscellaneous Problems

- What is $\mathbb{E}[g(X)|X]$?
- If $X \perp\!\!\!\perp Y$, what is $\mathbb{E}[X|Y]$?

Conditional Expectation as MMSE Estimator

Conditional Expectation as MMSE Estimator

Recall: if $|\mathbb{E}[X]| < +\infty$, then

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

More generally, the following holds.

Conditional Expectation as MMSE Estimator

Recall: if $|\mathbb{E}[X]| < +\infty$, then

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

More generally, the following holds.

Proposition

Let f be Borel-measurable, and let $|\mathbb{E}[Xf(Y)]| < +\infty$. Then,

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

The previous result simply follows by taking $f \equiv 1$.

Conditional Expectation as MMSE Estimator

Recall: if $|\mathbb{E}[X]| < +\infty$, then

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

More generally, the following holds.

Proposition

Let f be Borel-measurable, and let $|\mathbb{E}[Xf(Y)]| < +\infty$. Then,

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

The previous result simply follows by taking $f \equiv 1$.

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

Conditional Expectation as MMSE Estimator

Recall: if $|\mathbb{E}[X]| < +\infty$, then

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

More generally, the following holds.

Proposition

Let f be Borel-measurable, and let $|\mathbb{E}[Xf(Y)]| < +\infty$. Then,

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

The previous result simply follows by taking $f \equiv 1$.

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

$$\text{Cov}(X - \mathbb{E}[X|Y], f(Y)) = 0.$$

Theorem (Conditional Expectation as the MMSE Estimator)

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

$$\mathbb{E}[(X - \mathbb{E}[X|Y])^2] \leq \mathbb{E}[(X - h(Y))^2].$$