

Conditional Expectation

- Say that we observe that $Y=y$ and wish to use this information to predict X . The conditional PMF $P_{X|Y}(x|y)$ or PDF $f_{X|Y}(x|y)$ tells us the distribution, but what about just the average value of X given that $Y=y$?

→ Examples: * Observe the temperature today and try to predict the average temperature tomorrow.

* Take a noisy measurement from a reactor and determine the best control input (on average).

- The conditional expected value $\mathbb{E}[X | Y=y]$ of X given the event $\{Y=y\}$ is

$$\text{Discrete: } \mathbb{E}[X | Y=y] = \sum_{x \in R_x} x P_{X|Y}(x|y)$$

$$\text{Continuous: } \mathbb{E}[X | Y=y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx$$

- Recall that the expected value $\mathbb{E}[X]$ is a number. All of the randomness in X is averaged out.
- In contrast, the conditional expected value $\mathbb{E}[X|Y=y]$ is a **function of y** . Roughly speaking, all of the randomness in X that does not depend on Y is averaged out.
 - Sometimes, it helps to write $h(y) = \mathbb{E}[X|Y=y]$ to remind ourselves this is a deterministic function of y .
- Recall also that if we plug in the random variable Y into a function $h(y)$, we get $h(Y)$, which is a **random variable** itself.
- In this sense, we use the notation $\mathbb{E}[X|Y]$ to represent $h(Y)$ where $h(y) = \mathbb{E}[X|Y=y]$. Thus, $\mathbb{E}[X|Y]$ is a **random variable**.

- The conditional expected value $\mathbb{E}[g(x) | Y = y]$ of a function $g(x)$ given the event $\{Y = y\}$ is

Discrete:	$\mathbb{E}[g(x) Y = y] = \sum_{x \in R_x} g(x) P_{X Y}(x y)$
Continuous:	$\mathbb{E}[g(x) Y = y] = \int_{-\infty}^{\infty} g(x) f_{X Y}(x y) dx$

- Writing $h(y) = \mathbb{E}[g(x) | Y = y]$ helps remind us that $\mathbb{E}[g(x) | Y = y]$ is a deterministic function of y .
- The notation $\mathbb{E}[g(x) | Y]$ refers to substituting the random variable Y into the function $h(y) = \mathbb{E}[g(x) | Y = y]$ and thus $\mathbb{E}[g(x) | Y]$ is a random variable.

• Conditional Expectation Properties:

→ If X and Y are independent, $\mathbb{E}[X|Y=y] = \mathbb{E}[X]$ and $\mathbb{E}[g(x)|Y=y] = \mathbb{E}[g(x)]$.

Why?

$$\mathbb{E}[X|Y=y] = \sum_{x \in R_x} x P_{X|Y}(x|y) \stackrel{\text{Independence}}{=} \sum_{x \in R_x} x P_x(x) = \mathbb{E}[X].$$

→ Law of Total Expectation: $\mathbb{E}[X] = \mathbb{E}[\mathbb{E}[X|Y]]$
 $\mathbb{E}[g(x)] = \mathbb{E}[\mathbb{E}[g(x)|Y]]$

Why?

$$\begin{aligned} \mathbb{E}[\mathbb{E}[X|Y]] &= \mathbb{E}[h(Y)] = \sum_{y \in R_Y} h(y) P_Y(y) \\ h(y) &= \mathbb{E}[X|Y=y] = \sum_{x \in R_x} x P_{X|Y}(x|y) \\ &= \sum_{y \in R_Y} \sum_{x \in R_x} x \underbrace{P_{X|Y}(x|y) P_Y(y)}_{\downarrow \text{Multiplication Rule}} \\ &= \sum_{y \in R_Y} \sum_{x \in R_x} x P_{X,Y}(x,y) = \mathbb{E}[X] \end{aligned}$$

• Example: $P_{X|Y}(x|y)$

		x		
		1	2	3
y	1	1	0	0
	2	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{2}$

→ Calculate $\mathbb{E}[X|Y=y]$.

$$\mathbb{E}[X|Y=y] = \sum_{x \in R_x} x P_{X|Y}(x|y) = \begin{cases} \sum_{x \in R_x} x P_{X|Y}(x|1) & y=1 \\ \sum_{x \in R_x} x P_{X|Y}(x|2) & y=2 \end{cases}$$

$$= \begin{cases} 1 \cdot 1 + 2 \cdot 0 + 3 \cdot 0 & y=1 \\ 1 \cdot \frac{1}{4} + 2 \cdot \frac{1}{4} + 3 \cdot \frac{1}{2} & y=2 \end{cases} = \begin{cases} 1 & y=1 \\ \frac{9}{4} & y=2 \end{cases}$$

→ Calculate $\mathbb{E}[\mathbb{E}[X|Y]]$. We don't have enough information! Need $P_Y(y)$.

Say $P_Y(y) = \begin{cases} \frac{1}{3} & y=1 \\ \frac{2}{3} & y=2 \end{cases}$

$$\mathbb{E}[\mathbb{E}[X|Y]] = \sum_{y \in R_Y} \mathbb{E}[X|Y=y] P_Y(y) = \mathbb{E}[X|Y=1] P_Y(1) + \mathbb{E}[X|Y=2] P_Y(2)$$

$$= 1 \cdot \frac{1}{3} + \frac{9}{4} \cdot \frac{2}{3} = \frac{2+9}{6} = \frac{11}{6} = \mathbb{E}[X]$$

- Example: X given $Y=y$ is Geometric(y).

$$P_Y(y) = \begin{cases} \frac{1}{4} & y = \frac{1}{2} \\ \frac{3}{4} & y = \frac{2}{3} \end{cases} \quad P_{X|Y}(x|y) = \begin{cases} y(1-y)^{x-1} & y = \frac{1}{2}, \frac{2}{3}, x = 1, 2, 3, \dots \\ 0 & \text{otherwise} \end{cases}$$

Determine $E[X|Y=y]$ and $E[X]$.

$$E[X|Y=y] = \frac{1}{y} \quad E[X] = E[E[X|Y]] = \sum_{y \in R_Y} \frac{1}{y} P_Y(y) = \left(\frac{1}{2}\right) \cdot \frac{1}{4} + \left(\frac{2}{3}\right) \cdot \frac{3}{4}$$

Geometric(p) Mean: $\frac{1}{p}$ Law of Total Expectation $= \frac{1}{2} + \frac{9}{8} = \frac{13}{8}$

- Example: X given $Y=y$ is Gaussian($\frac{y^2}{3}, 4$). Y is Exponential(2).

Determine $E[X|Y=y]$ and $E[X]$.

$$E[X|Y=y] = \frac{y^2}{3} \quad E[X] = E[E[X|Y]] = E\left[\frac{Y^2}{3}\right] = \frac{1}{3} \cdot \frac{1}{2} = \frac{1}{6}$$

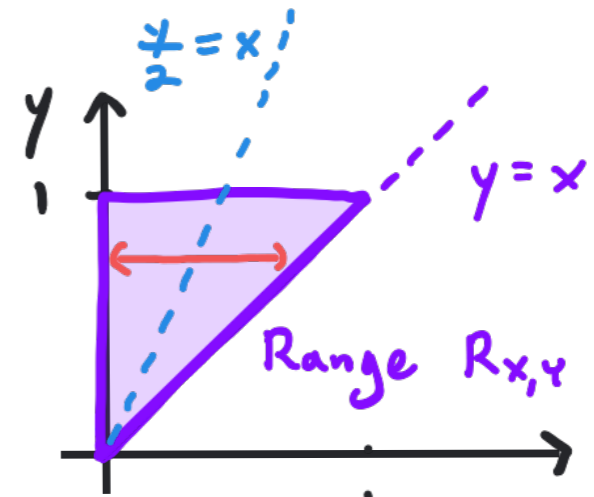
Gaussian(μ, σ^2) Mean: μ $E[Y^2] = \text{Var}[Y] + (E[Y])^2$

Alternate Variance Formula $= \frac{1}{2^2} + \frac{1}{2^2} = \frac{1}{2}$

$\text{Var}[Y] = E[Y^2] - (E[Y])^2$

Exponential(λ) Mean: $\frac{1}{\lambda}$
Variance: $\frac{1}{\lambda^2}$

• Example: $f_{x,y}(x,y) = \begin{cases} 2 & 0 \leq x \leq y, 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$



→ Calculate $\mathbb{E}[X|Y=y]$ and $\mathbb{E}[X]$.

Step 1 Determine conditional PDF $f_{x|y}(x|y)$.

→ First, need marginal PDF $f_y(y)$.

$$f_y(y) = \int_{-\infty}^{\infty} f_{x,y}(x,y) dx = \int_0^y 2 dx = (2x) \Big|_0^y = \begin{cases} 2y & 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

This makes sense!
Average is between 0 and y.

→ Now, plug into conditional PDF formula.

$$f_{x|y}(x|y) = \begin{cases} \frac{f_{x,y}(x,y)}{f_y(y)} & (x,y) \in R_{x,y} \\ 0 & \text{otherwise} \end{cases} = \begin{cases} \frac{2}{2y} & 0 \leq x \leq y, 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Step 2 Plug into conditional expectation formula.

$$\mathbb{E}[X|Y=y] = \int_{-\infty}^{\infty} x f_{x|y}(x|y) dx = \int_0^y x \cdot \frac{1}{y} dx = \left(\frac{1}{2} x^2\right) \Big|_0^y \cdot \frac{1}{y} = \frac{y}{2}$$

$$\mathbb{E}[X] = \mathbb{E}[\mathbb{E}[X|Y]] = \mathbb{E}\left[\frac{Y}{2}\right] = \int_{-\infty}^{\infty} \frac{y}{2} f_y(y) dy = \int_0^1 y^2 dy = \left(\frac{1}{3} y^3\right) \Big|_0^1 = \frac{1}{3}$$