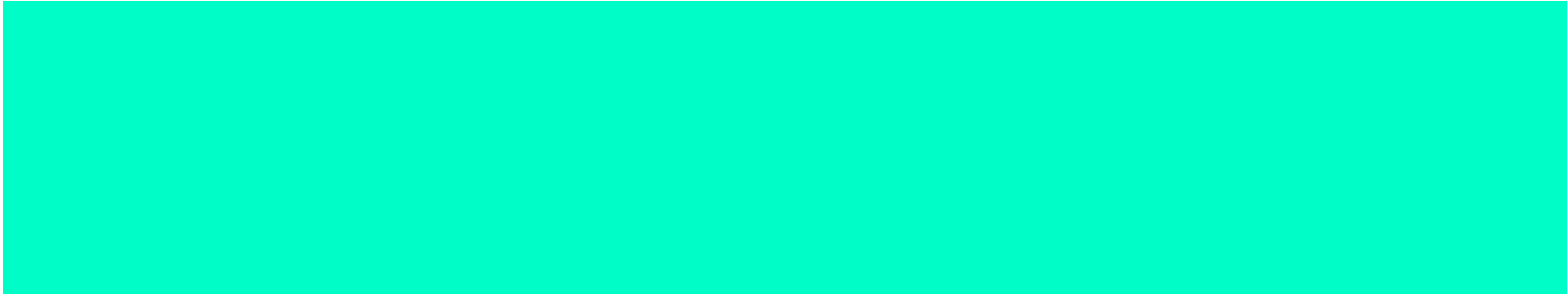


5.3 LAW OF TOTAL EXPECTATION



AGENDA

- CONDITIONAL EXPECTATION
- LAW OF TOTAL EXPECTATION (LTE)
- LAW OF TOTAL PROBABILITY (CONTINUOUS VERSION)

CONDITIONAL EXPECTATION

Conditional Expectation: Let X be a discrete random variable. Then, the conditional expectation of X given A is

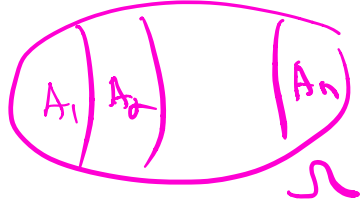
$$\mathbb{E}[X | A] = \sum_{x \in \Omega_X} x \mathbb{P}(X = x | A)$$

Linearity of expectation still applies to conditional expectation: $\mathbb{E}[X + Y | A] = \mathbb{E}[X | A] + \mathbb{E}[Y | A]$

LAW OF TOTAL EXPECTATION

Law of Total Expectation (Event Version): Let X be a random variable, and let events A_1, \dots, A_n partition the sample space. Then,

$$\mathbb{E}[X] = \sum_{i=1}^n \mathbb{E}[X | A_i] \mathbb{P}(A_i)$$



$$\mathbb{E}(X) = \sum_{x \in \Omega_X} x \cdot \underbrace{\Pr(X=x)}_{\substack{\text{LTP} \\ \text{by defn}}}$$

$$\sum_{i=1}^n \Pr(X=x | A_i) \Pr(A_i)$$

Interchange
order
of summation

$$= \sum_{i=1}^n \Pr(A_i) \sum_{x \in \Omega_X} x \cdot \Pr(X=x | A_i) = \sum_{i=1}^n \mathbb{E}(X | A_i) \Pr(A_i)$$

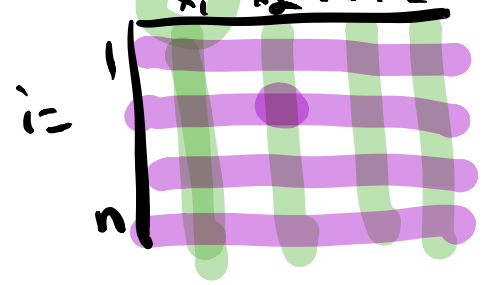
by defn $\mathbb{E}(X | A_i)$

LINEARITY OF EXPECTATION APPLIES

To conditional expectation too!!

$$E(X + Y \mid A) = E(X \mid A) + E(Y \mid A)$$

$$E(aX + b \mid A) = a E(X \mid A) + b$$



LAW OF TOTAL EXPECTATION (RV VERSION)

Law of Total Expectation (Event Version): Let X be a random variable, and let events A_1, \dots, A_n partition the sample space. Then,

$$\mathbb{E}[X] = \sum_{i=1}^n \mathbb{E}[X | A_i] \mathbb{P}(A_i)$$

Law of Total Expectation (RV Version): Suppose X and Y be discrete random variables. Then,

$$\mathbb{E}[X] = \sum_{y \in \Omega_Y} \mathbb{E}[X | Y = y] p_Y(y)$$

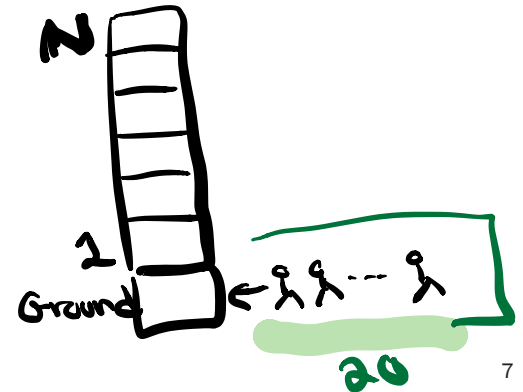
$$\begin{aligned} \Omega_Y &= \{y_1, y_2, \dots\} \\ Y &= y_1 \\ Y &= y_2 \\ &\vdots \end{aligned}$$

PROBLEM

The number of people who enter an elevator on the ground floor is a Poisson random variable with mean 10. If there are N floors above the ground floor, and if each person is equally likely to get off at any one of the N floors, independently of where the others get off, compute the expected number of stops that the elevator will make before discharging all the passengers.

Y # stops elevator make.

$$E(Y) = ?$$



X : # people who enter elevator

$$X \sim \text{Poi}(10)$$

Special
Case
Problems

Suppose 20 people enter
elevator.

$$Y_i = \begin{cases} 1 & \text{elevator stops} \\ & \text{on } i^{\text{th}} \text{ floor} \\ 0 & \text{o.w.} \end{cases}$$

$$Y_i = \begin{cases} 1 & \text{elevator} \\ & \text{stops on } i^{\text{th}} \text{ floor} \\ 0 & \text{otherwise} \end{cases}$$

$$E(Y_i) = \Pr(\text{elevator stops at } i^{\text{th}} \text{ floor})$$

$[i \in \{1, \dots, N\}]$

$$= \Pr(\text{somebody chooses } i^{\text{th}} \text{ floor})$$

$\geq 1 \text{ person}$

$$= 1 - \Pr(\text{nobody chooses that floor})$$

$$= 1 - \left(1 - \frac{1}{N}\right)^{20}$$

- $E(Y_i) = ?$
- a) $\frac{20}{N}$
 - b) $1 - \left(1 - \frac{1}{N}\right)^{20}$
 - c) 1
 - d) I don't know

who stop on i^{th} floor
 $\sim \text{Bin}\left(20, \frac{1}{N}\right)$

20 people
N floors.

k people \Rightarrow

$$E(Y_i) = \Pr(\text{elevator stops at } i^{\text{th}} \text{ floor})$$
$$= 1 - \left(1 - \frac{1}{N}\right)^k$$

X # people enter $\sim \text{Poi}(10)$

Y # steps elev.

$$E(Y) = \sum_{k=0}^{\infty} E(Y | X=k) \underbrace{\text{Pr}(X=k)}_{e^{-10} \frac{10^k}{k!}}$$

simplifying r.v. Y

$$E(Y_1 + Y_2 + \dots + Y_N | X=k)$$

$Y_i = \begin{cases} 1 & \text{elev steps at time } t_i \\ 0 & \text{o.w.} \end{cases}$

$$\stackrel{\text{L.o.E.}}{=} \underbrace{E(Y_1 | X=k)} + \underbrace{E(Y_2 | X=k)} + \dots + \underbrace{E(Y_N | X=k)}$$

$$= N \left(1 - \left(1 - \frac{1}{N} \right)^k \right)$$

$$= \sum_{k=0}^{\infty} N \left(1 - \left(1 - \frac{1}{N} \right)^k \right) e^{-10} \frac{10^k}{k!} \ll$$

SOLUTION

X number of people who enter

Y number of stops

$$Pr(X = k) = e^{-10} \frac{10^k}{k!}$$

$$E(Y) = \sum_{k=0}^{\infty} E(Y|X = k)P(X = k)$$

$$E(Y|X = k) = E(Y_1 + \dots + Y_N|X = k)$$

Y_i indicates a stop on floor i

$$E(Y_i|X = k) = (1 - (1 - 1/N)^k)$$

LTP discrete (r.v.)

$$\Pr(E) = \sum_{y \in \mathcal{Y}} \Pr(E|Y=y) \underbrace{\Pr(Y=y)}_{p_Y(y)}$$

LAW OF TOTAL PROBABILITY (CONT VERSION)

$$\Pr(E) = \int_{-\infty}^{\infty} \Pr(E|Y=y) f_Y(y) dy \quad (*)$$

(Note: In the original image, a pink arrow points from the $f_Y(y)$ term to the text $\approx \Pr(y \leq Y \leq y+dy)$ below it.)

X_1, X_2, \dots, X_k i.i.d. density \underline{f} CDF \underline{F}

$$\Pr(X_1 = \min(X_1, \dots, X_k))$$

$$= \Pr(X_1 < X_2, X_1 < X_3, \dots, X_1 < X_k)$$

$$\stackrel{\text{LTP}}{=} \int_{-\infty}^{\infty} \Pr(X_2 > x, X_3 > x, \dots, X_k > x \mid X_1 = x) f(x) dx$$

$$= \Pr(X_2 > x, X_3 > x, \dots, X_k > x \mid X_1 = x)$$

$$= \prod_{i=2}^k \Pr(X_i > x)$$

\uparrow
 $1 - \Pr(X_i \leq x)$
 $F(x)$

$$= (1 - F(x))^{k-1}$$

$$= \int_{-\infty}^{\infty} \underbrace{(1 - F(x))^{k-1}}_{u^{k-1}} \underbrace{f(x) dx}_{-du}$$

- $\prod_{i=2}^k \Pr(X_i > x) = ?$
- \Rightarrow
- a) $(1 - F(x))^{k-1}$
 - b) $F(x)^{k-1}$
 - c) $(1 - F(x))^k$
 - d) I don't know

- $du = ?$
- a) $f(x)$
 - b) $f(x) dx$
 - c) $-f(x) dx$
 - d) I don't know

change of variable

$$u = 1 - F(x)$$

$$du = -f(x) dx$$

as x goes $-\infty \rightarrow \infty$
 u goes from $1 \rightarrow 0$

u goes from

a) $-\infty \rightarrow \infty$

b) $0 \rightarrow 1$

c) $1 \rightarrow 0$

d) I don't know

$$\frac{d}{dx} F(x) = f(x)$$

$$F(x) = \int_{-\infty}^x f(w) dw$$

$$F(x) \rightarrow \begin{matrix} -\infty & \rightarrow & \infty \\ 0 & \rightarrow & 1 \end{matrix}$$

$$\int_0^1 u^{k-1} du = \int_0^1 u^{k-1} du = \frac{u^k}{k} \Big|_0^1 = \frac{1}{k}$$

$$\Pr(X_1 = \min(X_1, \dots, X_k)) = \frac{1}{k}$$

$$\Pr(X_k = \min(X_1, \dots, X_k)) = \frac{1}{k}$$

MULTIVARIATE: FROM DISCRETE TO CONTINUOUS

	Discrete	Continuous
Joint PMF/PDF	$p_{X,Y}(x, y) = P(X = x, Y = y)$	$f_{X,Y}(x, y) \neq P(X = x, Y = y)$
Joint CDF	$F_{X,Y}(x, y) = \sum_{t \leq x} \sum_{s \leq y} p_{X,Y}(t, s)$	$F_{X,Y}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(t, s) ds dt$
Normalization	$\sum_x \sum_y p_{X,Y}(x, y) = 1$	$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x, y) dx dy = 1$
Marginal PMF/PDF	$p_X(x) = \sum_y p_{X,Y}(x, y)$	$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy$
Expectation	$E[g(X, Y)] = \sum_x \sum_y g(x, y) p_{X,Y}(x, y)$	$E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{X,Y}(x, y) dx dy$
Conditional PMF/PDF	$p_{X Y}(x y) = \frac{p_{X,Y}(x, y)}{p_Y(y)}$	$f_{X Y}(x y) = \frac{f_{X,Y}(x, y)}{f_Y(y)}$
Conditional Expectation	$E[X Y = y] = \sum_x x p_{X Y}(x y)$	$E[X Y = y] = \int_{-\infty}^{\infty} x f_{X Y}(x y) dx$
Independence	$\forall x, y, p_{X,Y}(x, y) = p_X(x) p_Y(y)$	$\forall x, y, f_{X,Y}(x, y) = f_X(x) f_Y(y)$



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	Discrete	Continuous
Joint PMF/PDF	$p_{X,Y}(x, y) = P(X = x, Y = y)$	$f_{X,Y}(x, y) \neq P(X = x, Y = y)$
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LAW OF TOTAL EXPECTATION (EXAMPLE FROM LAST TIME)



Show that if $X \sim \text{Geo}(p)$, then $\mu = E[X] = 1/p$ by using the LTE conditioning on the first flip.

$$\mu = E[X] = E[X | H]P(H) + E[X | T]P(T) \quad (\text{LTE})$$

LAW OF TOTAL EXPECTATION (EXAMPLE FROM LAST TIME)



Show that if $X \sim \text{Geo}(p)$, then $\mu = E[X] = 1/p$ by using the LTE conditioning on the first flip.

$$\mu = E[X] = E[X | H]P(H) + E[X | T]P(T) \quad (\text{LTE})$$

$$= 1 \cdot p + (E[1 + X]) \cdot (1 - p)$$

$$= p + (1 + E[X]) \cdot (1 - p)$$

So,

$$\cancel{\mu} = p + (1 + \mu)(1 - p) = p + 1 - p + \mu - \mu p = 1 + \cancel{\mu} - \mu p$$

$$0 = 1 - \mu p \rightarrow \mu = \frac{1}{p}$$