

Supplemental Notes

Topics

① Conditioning

- total expectation
- total variance
- total covariance

② "SIT" technique

Conditional Estimation

$$P(B|A) = \frac{P(A \cap B)}{P(A)} \quad \text{for } P(A) > 0$$

Conditional pdf

$$f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)}$$

Annotations: "conditional" points to $f_{Y|X}(y|x)$, "joint" points to $f_{XY}(x,y)$, "marginal" points to $f_X(x)$.

$$f_{X|Y}(x|y) = \frac{f_{XY}(x,y)}{f_Y(y)}$$

Total Probability: $P(B) = P(B|A) \cdot P(A) + P(B|A^c) \cdot P(A^c)$

$$P(E) = \sum_k P(E|H_k) \cdot P(H_k) \quad \text{if } \{H_k\} \text{ partition } \Omega$$

Thm: $P(X \in A) = \int_{y=-\infty}^{y=\infty} P(X \in A | Y=y) \cdot f_Y(y) dy$
 $= E_Y [P(X \in A | Y)]$ ← r.v.

Prf: $P(X \in A) = P((X, Y) \in A \times \mathbb{R})$ if $A \subset \mathbb{R}$.

$$= \iint_{A \times \mathbb{R}} f_{XY}(x, y) dy dx$$

(Fubini) $= \int_A \int_{y=-\infty}^{y=\infty} f_{XY}(x, y) \cdot dy dx$

$$= \int_{y=-\infty}^{y=\infty} \left(\int_A f_{XY}(x|y) dx \right) f_Y(y) dy.$$

since $f(x|y) = \frac{f(x,y)}{f(y)}$

$$= \int_{y=-\infty}^{y=\infty} P[X \in A | Y=y] f_Y(y) dy.$$

QED

Similarly:

Thm: $P[(X, Y) \in B] = \int_{x=-\infty}^{x=\infty} P[(X, Y) \in B | X=x] \cdot f_X(x) dx.$

★ "SIT" technique for solving problems

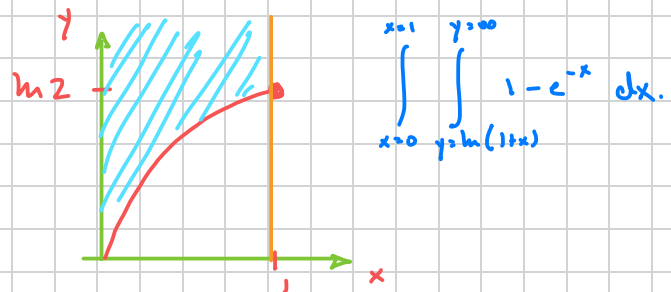
(1) T: use Total probability (or expectation/variance/etc.)

(2) S: Substitute x for r.v. X if $X=x$.

(3) I: Use Independence of X and Y (if appropriate)

Ex: Independent X and Y : $X \sim U[0,1]$, $Y \sim \text{Exp}(1)$

find $P(Y > \ln(1+X))$



(use SIT)

$$P(Y > \ln(1+X)) = P((X,Y) \in B)$$

$$\stackrel{\text{Total prob}}{=} \int_{x=-\infty}^{x=\infty} P(Y > \ln(1+X) | X=x) f_X(x) dx$$

$$\stackrel{x \sim U[0,1]}{=} \int_0^1 P(Y > \ln(1+X) | X=x) dx$$

$$\stackrel{\text{Sub}}{=} \int_0^1 P(Y > \ln(1+x) | X=x) dx$$

$$\stackrel{\text{Ind}}{=} \int_0^1 P(Y > \ln(1+x)) dx$$

$$\stackrel{Y \sim \text{Exp}(1)}{=} \int_0^1 e^{-\ln(1+x)} dx$$

$$= \int_0^1 e^{\ln\left(\frac{1}{1+x}\right)} dx$$

$$= \int_0^1 \frac{dx}{1+x}$$

put $u=1+x$
 $du=dx$

$\therefore x=0 \rightarrow u=1$
 $x=1 \rightarrow u=2$

$$\therefore = \int_1^2 \frac{du}{u} = \ln u \Big|_1^2 = \ln 2 - \ln 1 = \ln 2 \approx 0.693$$

Thm: (Total Expectation)

$$E_x[X] = E_y[E[X|Y]] \quad (\text{if exists})$$

Prf: $E_y[E[X|Y]] = \int_{y=-\infty}^{y=\infty} E[X|Y=y] \cdot f_y(y) dy$ (assume exists)

$$= \int_{y=-\infty}^{y=\infty} \int_{x=-\infty}^{x=\infty} x \cdot f(x|y) \cdot f_y(y) dx dy$$

Fubini $= \int_{x=-\infty}^{x=\infty} x \left[\int_{y=-\infty}^{y=\infty} f_{xy}(x,y) dy \right] dx$ since $f(x|y) = \frac{f(x,y)}{f(y)}$

$$= \int_{x=-\infty}^{x=\infty} x \cdot f_x(x) dx$$

$$= E_x[X]$$

QED

Ex: Bernoulli, H: \$10, T: \$2

$$E_x[X] = E_y[E[X|Y]]$$

$$\therefore E_x[X] = P(Y=0) \cdot E[X|Y=0] + P(Y=1) \cdot E[X|Y=1]$$

Similarly:

$$(1) E_{xy}[g(x,y)] = \int_{x=-\infty}^{x=\infty} E[g(x,y)|X=x] \cdot f_x(x) dx$$

$$(2) E_{xyz}[g(x,y,z)] = \int_{z=-\infty}^{z=\infty} \int_{y=-\infty}^{y=\infty} E[g(x,y,z)|Y=y, Z=z] \cdot f_{yz}(y,z) dy dz$$

Conditioning

Total Expectation

$$E_x[X] = E_y[E[X|Y]].$$

Total Variance

$$V_x[X] = E_y[V[X|Y]] + V_y[E[X|Y]].$$

Total Covariance

$$\text{Cov}(X, Y) = E_z[\text{Cov}(X, Y|Z)] + \text{Cov}_z(E[X|Z], E[Y|Z])$$

Ex: Dependent X and Y : $X \sim \text{Exp}(1)$, $Y_{|X=x} \sim N(0, x^2)$
 \uparrow
 $x > 0$

Find $E[Y^2 X^4]$

use TB of "STT"

$$\therefore E[Y^2 X^4] \stackrel{\text{total exp.}}{=} \int_{x=-\infty}^{x=\infty} E[Y^2 X^4 | X=x] f_x(x) dx.$$

$E_x[E[Y^2 X^4 | X]]$

$$\stackrel{X \sim \text{Exp}(1)}{=} \int_0^{\infty} E[Y^2 X^4 | X=x] e^{-x} dx$$

$$\stackrel{\text{Sub}}{=} \int_0^{\infty} E[Y^2 x^4 | X=x] e^{-x} dx$$

$$= \int_0^{\infty} x^4 \cdot E[Y^2 | X=x] e^{-x} dx \quad (\text{Proposition 1, below})$$

$$= \int_0^{\infty} x^4 x^2 e^{-x} dx \quad \text{since } Y_{|X=x} \sim N(0, x^2)$$

$$= \int_0^{\infty} x^6 e^{-x} dx$$

$$= E_x[X^6]$$

$$= \underline{6!} = 720$$

Since $X \sim \text{Exp}(1)$

Ex: Suppose $X, Y \sim \exp(1)$. Put $Z = X/Y$. find $f_z(z)$.

Suppose $Y = y$. (i.e. Y is constant)

then $Z = X/y$ is a scaled version of X (scaled by constant $1/y$)

$$\therefore f_z(z|y) = |y| \cdot f_x(yz|y) \quad \text{see earlier example } Y = aX + b \rightarrow Y = aX \quad (a \neq 0)$$

$$f_Y(y) = \frac{1}{|a|} f_x\left(\frac{y}{a}\right)$$

$$\therefore f_z(z) = \int_{-\infty}^{\infty} |y| \cdot \overset{\text{conditional}}{f_x(yz|y)} \cdot \overset{\text{marginal}}{f_Y(y)} dy$$

$$\stackrel{\text{indep.}}{=} \int_{-\infty}^{\infty} |y| \cdot f_x(yz) \cdot f_Y(y) dy \stackrel{\text{exp}}{=} \int_0^{\infty} y e^{-yz} e^{-y} dy = \int_0^{\infty} y e^{-(1+z)y} dy$$

$$\text{let } u = y \\ du = dy$$

$$dv = e^{-ay} dy \\ v = e^{-ay} / -a$$

$$= \frac{y e^{-ay}}{-a} \Big|_{y=0}^{y=\infty} + \int_0^{\infty} \frac{e^{-ay}}{+a} dy$$

$$= -\frac{e^{-ay}}{a^2} \Big|_{y=0}^{y=\infty} = \frac{1}{(1+z^2)} \quad \text{for } z \geq 0$$

Proposition 1: $E[g(X)Y|X] = g(X) \cdot E[Y|X]$.

Prf: $\forall x$:

$$E[g(X)Y|X=x] = \int_{y=-\infty}^{y=\infty} g(x) \cdot y \cdot f(y|x) dy$$

$$= g(x) \cdot \int_{y=-\infty}^{y=\infty} y \cdot f(y|x) dy$$

$$= g(x) \cdot E[Y|X=x].$$

$$\therefore E[g(X) \cdot Y|X] = g(X) \cdot E[Y|X].$$

Defn: Conditional Variance $V[Y|X] = E[(Y - E[Y|X])^2 | X]$
(if exists)

Fact: If X and Y are jointly Gaussian (JG)

$$f_{XY}(x,y) = \frac{\exp\left[-\frac{\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2 - 2\rho_{XY}\left(\frac{x-\mu_x}{\sigma_x}\right)\left(\frac{y-\mu_y}{\sigma_y}\right)}{2(1-\rho_{XY}^2)}\right]}{2\pi\sigma_x\sigma_y\sqrt{1-\rho_{XY}^2}}$$

then:

$$(1) E[Y|X] = \mu_y + \rho_{XY} \frac{\sigma_Y}{\sigma_X} (X - \mu_x)$$

$$(2) V[Y|X] = \sigma_Y^2 (1 - \rho_{XY}^2)$$

$$\therefore \sigma_{Y|X}^2 < \sigma_Y^2 \quad \text{if} \quad \rho_{XY} = \frac{\sigma_{XY}}{\sigma_X\sigma_Y} \neq 0.$$

Ex: Q1: roll 6 dice (iid)

$$E\left[\sum_{k=1}^6 X_k\right] = \sum_{k=1}^6 E[X_k] = 6 E[X] = 6 \cdot 3.5 = 21$$

Q2: roll 1 die, X = outcome.

Roll X dice

roll random # of dice

$$E\left[\sum_{k=1}^{\overset{\text{random}}{N}} X_k\right] = ?$$

Proposition 2: $V[Y|X] = E[Y^2|X] - E^2[Y|X]$

Prf: $V[Y|X] = E[(Y - E[Y|X])^2 | X]$

$$\stackrel{\text{Lin}}{=} E[Y^2 + E^2[Y|X] - 2 \cdot Y \cdot E[Y|X] | X]$$

$$\stackrel{\text{Lin}}{=} E[Y^2|X] + E[\underbrace{E^2[Y|X]}_{g(x)} | X] - 2 \cdot E[\underbrace{Y \cdot E[Y|X]}_{h(x)} | X]$$

$$\stackrel{\text{prop 1}}{=} E[Y^2|X] + E^2[Y|X] \cdot E[1|X] - 2 \cdot E[Y|X] \cdot E[Y|X]$$

$$= E[Y^2|X] + E^2[Y|X] - 2 \cdot E^2[Y|X]$$

$$= E[Y^2|X] - E^2[Y|X]$$

QED

Thrm: (Total Variance)

$$V_x[X] = E_y[V(X|Y)] + V_y[E(X|Y)] \quad \text{"ev-ve"}$$

Prf: $E_y[V(X|Y)] + V_y[E(X|Y)]$

$$= E_y[V(X|Y)] + E_y[E^2(X|Y)] - (E_y[E(X|Y)])^2$$

$$\stackrel{\text{total exp}}{=} E_y[V(X|Y)] + E_y[E^2(X|Y)] - E_x^2[X]$$

$$\stackrel{\text{prop 2}}{=} E_y[E(X^2|Y) - E^2(X|Y)] + E_y[E^2(X|Y)] - E_x^2[X]$$

$$= E_y[E(X^2|Y)] - \cancel{E_y[E^2(X|Y)]}$$

$$+ \cancel{E_y[E^2(X|Y)]} - E_x^2[X]$$

$$\stackrel{\text{total exp}}{=} E_x[X^2] - E_x^2[X]$$

$$= V_x[X]$$

QED

★ Thm: (Doubly Random Sum) If iid $X_1, \dots, X_n \forall n$

and $\sigma_x^2 < \infty$ ($\because \mu_x < \infty$).

- Positive \mathbb{Z}^+ r.v. N
- N is independent of $X_1, \dots, X_n \forall n$.

$$(1) E\left[\sum_{k=1}^N X_k\right] = E_N[N] \cdot \mu_x$$

$$(2) V\left[\sum_{k=1}^N X_k\right] = E_N[N] \sigma_x^2 + V_N[N] \mu_x^2$$

Prf:

(SIT technique)

$$\begin{aligned} (1) E\left[\sum_{k=1}^N X_k\right] &\stackrel{\text{total exp}}{=} E_N\left[E\left[\sum_{k=1}^N X_k \mid N\right]\right] \\ &= \sum_{n=1}^{\infty} p_N(n) \cdot E\left[\sum_{k=1}^n X_k \mid N=n\right] \quad \text{since } N > 0 \\ &\stackrel{\text{sub}}{=} \sum_{n=1}^{\infty} p_N(n) E\left[\sum_{k=1}^n X_k \mid N=n\right] \\ &\stackrel{\text{ind}}{=} \sum_{n=1}^{\infty} p_N(n) \cdot E\left[\sum_{k=1}^n X_k\right] \\ &\stackrel{\text{lin}}{=} \sum_{n=1}^{\infty} p_N(n) \cdot \sum_{k=1}^n E[X_k] \\ &\stackrel{\text{iid}}{=} \sum_{n=1}^{\infty} p_N(n) (n \cdot \mu_x) \\ &= \mu_x \cdot \sum_{n=1}^{\infty} n \cdot p_N(n) \\ &= \mu_x E_N[N] = E_N[N] \cdot \mu_x \end{aligned}$$

$$\begin{aligned}
(2) \quad V\left[\sum_{k=1}^N X_k\right] & \stackrel{\text{total var}}{=} E_N\left[V\left[\sum_{k=1}^N X_k \mid N\right]\right] + V_N\left[E\left[\sum_{k=1}^N X_k \mid N\right]\right] \\
& = \sum_{n=1}^{\infty} p_N(n) \cdot V\left[\sum_{k=1}^n X_k \mid N=n\right] + V_N\left[E\left[\sum_{k=1}^N X_k \mid N\right]\right] \\
& \stackrel{\text{sub}}{=} \sum_{n=1}^{\infty} p_N(n) \cdot V\left[\sum_{k=1}^n X_k \mid N=n\right] + V_N\left[E\left[\sum_{k=1}^N X_k \mid N\right]\right] \\
& \stackrel{\text{ind}}{=} \sum_{n=1}^{\infty} p_N(n) \cdot V\left[\sum_{k=1}^n X_k\right] + V_N\left[E\left[\sum_{k=1}^N X_k \mid N\right]\right] \\
& \stackrel{\text{iid}}{=} \sigma_x^2 \sum_{n=1}^{\infty} n \cdot p_N(n) + V_N\left[E\left[\sum_{k=1}^N X_k \mid N\right]\right] \\
& = E_N[N] \sigma_x^2 + V_N\left[E\left[\sum_{k=1}^N X_k \mid N\right]\right] \\
& = E_N[N] \sigma_x^2 + E_N\left[\left(E\left[\sum_{k=1}^n X_k \mid N=n\right]\right)^2\right] \\
& \quad - \left(E_N\left[E\left[\sum_{k=1}^n X_k \mid N=n\right]\right]\right)^2 \\
& \stackrel{\text{sub}}{=} E_N[N] \sigma_x^2 + E_N\left[\left(E\left[\sum_{k=1}^n X_k \mid N=n\right]\right)^2\right] \\
& \quad - \left(E_N\left[E\left[\sum_{k=1}^n X_k \mid N=n\right]\right]\right)^2 \\
& \stackrel{\text{ind}}{=} E_N[N] \sigma_x^2 + E_N\left[\left(E\left[\sum_{k=1}^n X_k\right]\right)^2\right] \\
& \quad - \left(E_N\left[E\left[\sum_{k=1}^n X_k\right]\right]\right)^2 \\
& \stackrel{\text{iid}}{=} E_N[N] \sigma_x^2 + \mu_x^2 \sum_{n=1}^{\infty} n^2 \cdot p_N(n) - \mu_x^2 \left(\sum_{n=1}^{\infty} n \cdot p_N(n)\right)^2 \\
& = E_N[N] \sigma_x^2 + \mu_x^2 \cdot E_N[N^2] - \mu_x^2 \cdot E_N^2[N] \\
& = E_N[N] \sigma_x^2 + \mu_x^2 \left(E_N[N^2] - E_N^2[N]\right) \\
& = E_N[N] \sigma_x^2 + \mu_x^2 V_N[N].
\end{aligned}$$

QED

