

[Sp-10]

1. Conditional Expectation & Conditional Variance

1.

$$\begin{aligned} & E[(Y - E[Y|X])^2 | X] \\ &= E[Y^2 - 2Y E[Y|X] + (E[Y|X])^2 | X] \\ &= E[Y^2 | X] - 2 E[Y E[Y|X] | X] + (E[Y|X])^2 \\ &= E[Y^2 | X] - 2 E[Y|X] \cdot E[Y|X] + (E[Y|X])^2 \\ &= E[Y^2 | X] - (E[Y|X])^2. \quad \text{Q.E.D.} \end{aligned}$$



2. Prove Eve's Law .

Pf:

$$\begin{aligned} \text{Var}(E[Y|X]) &= E[(E[Y|X])^2] - (E[E[Y|X]])^2 \\ &= E[(E[Y|X])^2] - (E[Y])^2 \dots (1) \end{aligned}$$

$$\begin{aligned} \text{Var}(Y|X) &= E[Y^2 | X] - (E[Y|X])^2 \\ \Rightarrow E[\text{Var}(Y|X)] &= E[Y^2] - E[(E[Y|X])^2] \dots (2) \end{aligned}$$

By (1) + (2),

$$\begin{aligned} & E[\text{Var}(Y|X)] + \text{Var}(E[Y|X]) \\ &= E[Y^2] - (E[Y])^2 = \text{Var}(Y) \end{aligned}$$

Q.E.D.



3.

$$(a). E[w] = E[Y - E[Y|X]] = 0. \quad \checkmark$$

$$\begin{aligned} E[w|X] &= E[Y - E[Y|X]|X] \\ &= E[Y|X] - E[E[Y|X]|X] \\ &= E[Y|X] - E[Y|X] = 0 \quad \checkmark \end{aligned}$$

(b). By Eve's Law,

$$\begin{aligned} \text{Var}(w) &= E[\text{Var}(w|X)] + \text{Var}(E[w|X]) \\ &= E[X^2] + 0 \\ &= 1 \quad \checkmark \end{aligned}$$

4.

(a). Write

$$\begin{aligned} X &= X_1 + \dots + X_N \\ \text{where } N &\sim \text{Geom}(p), \quad X|N \sim \text{Gamma}(N, \lambda) \\ \text{Then,} \quad E[X] &= E[E[X|N]] = E[N/\lambda] = \frac{1}{\lambda p} \quad \checkmark \end{aligned}$$

$$\begin{aligned} \text{Var}(x) &= E[\text{Var}(x|N)] + \text{Var}(E[x|N]) \\ &= E[N/\lambda^2] + \text{Var}(N/\lambda) \\ &= \left(\frac{1}{\lambda p}\right)^2 \quad \checkmark \end{aligned}$$

$$(b). E[e^{tX}] = E[E[e^{tX}|N]]$$

$$= E\left[\left(\frac{\lambda}{\lambda-t}\right)^N\right] \text{ for } t < \lambda.$$

By LOTUS,

$$\begin{aligned} & E\left[\left(\frac{\lambda}{\lambda-t}\right)^N\right] \\ &= \sum_{n=1}^{\infty} \left(\frac{\lambda}{\lambda-t}\right)^n P(N=n) \\ &= \sum_{n=1}^{\infty} \left(\frac{\lambda}{\lambda-t}\right)^n p q^{n-1} \\ &= \frac{p}{q} \sum_{n=1}^{\infty} (qr)^n \quad \left\{ \text{where } r = \frac{\lambda}{\lambda-t} \right\} \\ &= \frac{p}{q} \left(\frac{1}{1-qr} - 1 \right) \quad \left\{ \text{Geometric Series} \right\} \\ &= \frac{p}{q} \frac{qr}{1-qr} = \frac{p\lambda}{p\lambda-t} \quad \text{for } t < p\lambda \quad \checkmark \\ \Rightarrow X &\sim \text{Exp}(p\lambda) \quad \left\{ \text{makes sense} \right\}. \end{aligned}$$

5.

Let $Y \sim \text{Bern}(\frac{1}{2})$ s.t.

$Y=1$ if choosing coin with p_1 .

$$\begin{aligned} X|Y=1 &\sim \text{Bin}(n, p_1) \\ X|Y=0 &\sim \text{Bin}(n, p_2) \end{aligned}$$

$$\begin{aligned} E[X] &= E[E[X|Y]] \\ &= \frac{1}{2} E[X|Y=1] + \frac{1}{2} E[X|Y=0] \\ &= \frac{1}{2} n p_1 + \frac{1}{2} n p_2 = \frac{n}{2} (p_1 + p_2) \quad \checkmark \end{aligned}$$

$$\begin{aligned} E[X^2] &= E[E[X^2|Y]] \\ &= \frac{1}{2} E[X^2|Y=1] + \frac{1}{2} E[X^2|Y=0] \\ &= \frac{1}{2} [n p_1 (q_1 + np_1)] + \frac{1}{2} [n p_2 (q_2 + np_2)] \end{aligned}$$

$$\begin{aligned}
 \Rightarrow \text{Var}(X) &= E[X^2] - E[X]^2 \\
 &= \frac{1}{n}(np_1q_1 + np_2q_2) + \frac{1}{2}n^2p_1^2 + \frac{1}{2}n^2p_2^2 \\
 &\quad - \frac{1}{4}n^2(p_1 + p_2)^2 \\
 &= \frac{1}{2}(np_1q_1 + np_2q_2) + \frac{1}{4}n^2(p_1 - p_2)^2
 \end{aligned}$$

where $q_1 = 1 - p_1$, $q_2 = 1 - p_2$

3 Note on 4, 5:

In 4. $X = X_1 + \dots + X_N$. We shall understand that

$$E[X|N] = E[X_1 + \dots + X_N] = N \frac{1}{2}$$

instead of

$$E[X] = E[X_1 + \dots + X_N] = N \frac{1}{2}$$

because

$E[X]$ is a number, $N \frac{1}{2}$ is a fun of N .
a r.v.

Similarly, in 5, we can write

$$X = I X_1 + (1-I) X_2$$

where $X_i \sim \text{Bin}(n, p_i)$, $I = 1$ if having p_1 coin.

$\{I, X_1, X_2\}$ indep. f.

We shall understand that

$$\begin{aligned}
 E[X|I] &= I \cdot E[X_1] + (1-I) E[X_2] \\
 &= I n p_1 + (1-I) n p_2
 \end{aligned}$$

because $X|I$ means that we treat " I " as constant \Rightarrow we can take it out.

3

II. Inequality

1.

Given X, Y are i.i.d. positive r.v.s. and $c > 0$

(a). $E[\ln X] \leq \ln E[X]$ ✓
because $\ln x$ is concave.

(b). $E[X] \leq \sqrt{E[X^2]}$
because $\text{Var}(X) = E[X^2] - (E[X])^2 \geq 0$ ✓

(c). Since
 $\sin^2 X + \cos^2 X = 1$
 $\Rightarrow E[\sin^2 X] + E[\cos^2 X] = 1$ ✓

(d). Since $X > 0$,
 $E[|X|] = E[X] \leq \sqrt{E[X^2]}$. ✓

(e). By Markov inequality,
 $P(X > c) = P(|X^3| > c^3) \leq \frac{E[|X|^3]}{c^3} = \frac{E[X^3]}{c^3}$.
 $\Rightarrow P(X > c) \leq \frac{E(X^3)}{c^3}$. ✓

(f). Since X, Y are i.i.d. positive r.v.s.,
by symmetry,
 $P(X \leq Y) = P(X > Y)$ ✓

(g). $E[XY] = |E[XY]| \leq \sqrt{E[X^2]E[Y^2]}$
by Cauchy-Schwarz inequality. ✓

(h). We have

$$P(X > 5 \text{ or } Y > 5) = 1 - P(X \leq 5 \text{ and } Y \leq 5)$$

$$P(X+Y > 10) = 1 - P(X+Y \leq 10)$$

Since

$$X \leq 5 \text{ and } Y \leq 5 \subseteq X+Y \leq 10$$

$$\Rightarrow P(X \leq 5 \text{ and } Y \leq 5) \leq P(X+Y \leq 10)$$

$$\Rightarrow P(X+Y > 10) \leq P(X > 5 \text{ or } Y > 5)$$



(i). We know

$$E[X] = E[Y] \text{ . (i.i.d.)}$$

$$\Rightarrow \min(E[X], E[Y]) = E[X] = E[Y] .$$

And

$$\begin{cases} \min(X, Y) \leq X \\ \min(X, Y) \leq Y \end{cases}$$

$$\Rightarrow E[\min(X, Y)] \leq \min(E[X], E[Y])$$



(j). Since X, Y are i.i.d.

$$E\left[\frac{X}{Y}\right] = E[X] E\left[\frac{1}{Y}\right]$$

Since $g(y) = \frac{1}{y}$ for $y > 0$ is convex,

by Jensen's inequality,

$$E\left[\frac{1}{Y}\right] \geq \frac{1}{E[Y]}$$

$$\Rightarrow E\left[\frac{X}{Y}\right] \geq \frac{E[X]}{E[Y]} .$$



(k). Comparing $E[X^2(Y^2+1)]$ and $E[X^2(Y^2+1)]$

is equivalent to comparing

$$E[X^4] \text{ and } E[X^2 Y^2].$$

Since X, Y are i.i.d.,

$$E[X^2 Y^2] = E[X^2] E[Y^2] = (E[X^2])^2 .$$

$$\text{Since } \text{Var}(X^2) = E[X^4] - (E[X^2])^2 > 0$$

$$\Rightarrow E[X^4] \geq (E[X^2])^2 \Rightarrow E[X^2(X^2+1)] \geq E[X^2(Y^2+1)]$$



(1). $E\left[\frac{X^3}{X^3+Y^3}\right] = E\left[\frac{Y^3}{X^3+Y^3}\right]$ by symmetry. ✓

2.
(a). Since $g(x) = \frac{1}{x}$ for $x > 0$ is convex,
 $\Rightarrow E[1/X] > 1/E[X]$
for any positive nonconstant r.v..

(b). Given X, Y are two positive
nonconstant r.v.s.

By Cauchy-Schwarz inequality,

$$\sqrt{E\left[\frac{X}{Y}\right]E\left[\frac{Y}{X}\right]} \geq E\left[\sqrt{\frac{X}{Y}} \cdot \sqrt{\frac{Y}{X}}\right] = 1$$

Let $W = \frac{X}{Y}$, $\Rightarrow \frac{1}{W} = \frac{Y}{X}$.

$$\Rightarrow E\left[\frac{X}{Y}\right]E\left[\frac{Y}{X}\right] = E[W]E\left[\frac{1}{W}\right]$$

$$> E[W] \cdot \frac{1}{E[W]} = 1$$

by Jensen's inequality

3.
Let sample mean be

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

We want to find an "n" s.t.

$$P(|\bar{X}_n - \mu| > 2\delta) \leq 0.01$$

$$\text{Var}(\bar{X}_n) = \frac{1}{n^2} \cdot n \text{Var}(X_i) = \frac{\sigma^2}{n}.$$

By Chebyshov inequality,

$$\begin{aligned} P(|\bar{X}_n - \mu| > 2\sigma) &\leq \frac{\text{Var}(\bar{X}_n)}{4\sigma^2} \\ &= \frac{\sigma^2/n}{4\sigma^2} \\ &= \frac{1}{4n}. \end{aligned}$$

$$\Rightarrow \frac{1}{4n} \leq 0.01 \Rightarrow n \geq 25.$$



4. Suppose $g(x) = \log x$ for $x > 0$.

$g''(x) = -x^{-2} < 0 \Rightarrow g(x)$ is concave.

$\Rightarrow E[\log(X)] \leq \log(E[X])$ by Jensen's inequality

Assume a_j 's are distinct. Let X be a random variable which takes values from a_1, \dots, a_n with equal prob.

Then, for left hand side, by LOTUS,

$$\begin{aligned} E[\log X] &= \frac{1}{n} \sum_{j=1}^n \log a_j \\ &= \log \left(\prod_{j=1}^n a_j \right)^{\frac{1}{n}}. \end{aligned}$$

For right hand side,

$$\log E[X] = \log \frac{1}{n} \sum_{j=1}^n a_j$$

$$\Rightarrow \log \left(\prod_{j=1}^n a_j \right)^{1/n} \leq \log \frac{1}{n} \sum_{j=1}^n a_j$$

$$\Rightarrow \frac{1}{n} \sum_{j=1}^n a_j \geq \left(\prod_{j=1}^n a_j \right)^{1/n}.$$



} If a_j have some repeated values,

(et $P(X=a_j) = \frac{m_j}{n}$, where
 m_j is # a_j 's)

$$\Rightarrow E[X] = \sum_x x \cdot P(X=x) \\ = \frac{1}{n} \cdot (\text{Sum of all } a_j \text{'s}) \quad \{ \quad \checkmark$$