

HW7

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1. CB4.32

a. $Y|A \sim \text{Pois}(A)$ $A \sim \text{Gamma}(\alpha, \beta)$ $\text{FIND } Y, E(Y), \text{Var}(Y)$, AND $Y \sim \text{NEG-BINOM } \alpha=1,2,3\dots$

$$f_Y = \int_0^\infty f_Y(y|a) f_A(a) da = \int_0^\infty \frac{a^y e^{-a}}{y!} \cdot \frac{1}{\Gamma(\alpha)\beta^\alpha} a^{\alpha-1} e^{-a/\beta} da = \frac{1}{y! \Gamma(\alpha) \beta^\alpha} \int_0^\infty \frac{(a+y-1)!}{(a-1)!} e^{-a(1+1/\beta)} da$$

KERNEL OF GAMMA: $\alpha = \alpha+y$
 $\beta = \frac{1}{1+1/\beta}$

$$f_Y = \frac{\Gamma(\alpha+y) \left(\frac{1}{1+1/\beta}\right)^{\alpha+y}}{y! \Gamma(\alpha) \beta^\alpha}$$

$$E_Y = E_A(E_{Y|A}(Y|A)) = E_A(A) = \alpha\beta \quad \underline{E_Y = \alpha\beta}$$

$$\sqrt{\text{Var}_Y} = \sqrt{E(\text{Var}_Y(Y|A)) + \text{Var}(E(Y|A))} = \sqrt{E(A) + \text{Var}(A)} = \sqrt{\alpha\beta + \alpha\beta^2} = \sqrt{\text{Var}_Y}$$

If α is integer, $f_Y = \frac{(\alpha+y)!}{y! \alpha!} \left(\frac{\beta}{1+\beta}\right)^{\alpha+y} \cdot \frac{1}{\beta} = \binom{y+\alpha-1}{y} \cdot \left(\frac{\beta}{1+\beta}\right)^y \left(\frac{1}{1+\beta}\right)^\alpha = \text{NEG-BINOM}(\alpha, \frac{1}{1+\beta})$

b. $Y|N \sim \text{Binom}(N, p)$ $N|A \sim \text{Pois}(A)$ $A \sim \text{Gamma}(\alpha, \beta)$

$$f_{Y|N} = P(Y=y|N) = P(Y=y|N=n, \lambda) P(N=n|\lambda) = \sum_{n=y}^{\infty} \binom{n}{y} p^y (1-p)^{n-y} \frac{e^{-\lambda} \lambda^n}{n!}$$

$$= \sum \frac{1}{y!(n-y)!} \left(\frac{p}{1-p}\right)^y \left((1-p)\lambda\right)^{n-y} e^{-\lambda} = \frac{e^{-\lambda}}{y!} \left(\frac{p}{1-p}\right)^y \sum_{m=0}^{\infty} \frac{((1-p)\lambda)^{m+y}}{m!} = \frac{e^{-\lambda}}{y!} \left(\frac{p(1-p)\lambda}{1-p}\right)^y \sum_{m=0}^{\infty} \frac{((1-p)\lambda)^m}{m!}$$

$$= \frac{e^{-\lambda}}{y!} (p\lambda)^y e^{-(p\lambda)} = \frac{(p\lambda)^y e^{-(p\lambda)}}{y!} = \text{Pois}(p\lambda)$$

$\therefore f_{Y|N} \sim \text{Pois}$ WHICH IS THE SAME START AS (a), BUT WITH $p\lambda$ INSTEAD OF β :

$$f_Y = \frac{(\alpha+y)!}{y! \Gamma(\alpha) (p\lambda)^{\alpha+y}}$$

2. 4.35 $x|p \sim \text{Binom}(n, p)$ $\eta \sim \text{Beta}(\alpha, \beta)$

a. $\text{Var}(x) = E(\text{Var}(x|p)) + \text{Var}(E(x|p)) = E(np(1-p) + \text{Var}(np)) = nE(p(1-p)) + n(n-1)\text{Var}(p)$

$$= nE(p)(1-E(p)) + n(n-1)\text{Var}(p) = \text{Var}(x)$$

b. $Y|A = \text{Poisson}(A)$ $A \sim \text{Gamma}(\alpha, \beta)$

As shown in 4.32(a), $\text{Var}(Y) = \alpha\beta + \alpha\beta^2$ $E(A) = \alpha\beta \Rightarrow \sqrt{\text{Var}(Y)} = \sqrt{E(A) + \frac{1}{\alpha} E(A)^2} = \sqrt{m + \frac{1}{\alpha} m^2}$ WHERE $m = E(A)$

3. X, Y HAVE FINITE VARIANCES. PROVE:

$$a) E(XY) = E(X E(Y|X)) \quad E(XY) = \iint_{\mathbb{R}^2} xy f_{XY} dx dy = \iint_{\mathbb{R}^2} xy f_{Y|X} f_X dx dy$$

$$= \int_X x f_X \left[\int_Y y f_{Y|X} dy \right] dx = \int_X x f_X E(Y|X) dx = \underline{E[X E(Y|X)]}$$

$$b) \text{Cov}(X, Y) = \text{Cov}(X, E(Y|X)) \quad \text{Cov}(X, Y) = \underline{E(XY) - E(X)E(Y)}$$

$$\text{Cov}(X, E(Y|X)) = E(X E(Y|X)) - E(X) E(E(Y|X)) = \underline{E(XY) - E(X)E(Y)}$$

$$c) X, Y - E(Y|X) \text{ ARE UNCORRELATED: } \text{Cov}(X, Y - E(Y|X)) = E(XY - xE(Y|X)) - E(X) E(Y - E(Y|X))$$

$$= E(XY) - E(XY) - E(X) E(Y) + E(X) E(E(Y|X)) = 0 - E(X) E(Y) + E(X) E(Y) = 0$$

4. FIND $E(X)$

$$a) X|Y \sim \text{Binom}(n, Y) \quad Y \sim \text{Beta}(a, b) \quad E(X) = E_Y(E_{X|Y}(X|Y)) = E_Y(nY) = nE_Y(Y) = \underline{\frac{na}{a+b}}$$

$$b) X|Y \sim \text{Exp}(Y) \quad Y \sim \text{Gamma}(a, b) \quad E(X) = E_Y(E_{X|Y}(X|Y)) = E_Y(Y) = \underline{ab}$$

5. FIND $\text{VAR}(X)$ FOR $Y \sim \text{...}$

$$\begin{aligned} \text{VAR}(X) &= E(\text{VAR}(X|Y)) + \text{VAR}(E(X|Y)) = E(nY(1-Y)) + \text{VAR}(nY) = nE(Y - Y^2) + n(n-1)\text{VAR}Y \\ &= \frac{na}{a+b} + \frac{n(n-1)ab}{(a+b)^2(a+b+1)} - nE(Y^2) \\ &\quad \hookrightarrow \text{VAR}(Y) + E(Y)^2 = \frac{a(a+1)}{(a+b)(a+b+1)} \\ &= \frac{na}{a+b} \left[1 + \frac{(n-1)b}{(a+b)(a+b+1)} - \frac{a+1}{a+b+1} \right] \end{aligned}$$

6. $P(Y=1) = .3 \quad P(Y=2) = .7 \quad X|Y \sim \text{Poisson}(Y) \quad \text{FIND } M_X(t)$

$$\begin{aligned} X &\sim .3 \text{ Pois}(1) + .7 \text{ Pois}(2) \quad M_X(t) = M_{\text{Pois}(1)}(.3t) \cdot M_{\text{Pois}(2)}(.7t) = e^{(e^{.3t}-1)} \cdot e^{(e^{.7t}-1)} \\ &= e^{.3t + 2e^{.7t} - 3} = M_X(t) \end{aligned}$$

7. CB 4.41 SHOW ANY R.V. IS UNCORRELATED WITH A CONSTANT

$$\text{NEED TO SHOW: } \text{Cov}(X, c) = 0 \quad \text{Cov}(X, c) = E(Xc) - E(X)E(c) = cE(X) - cE(X) = 0 = \underline{\text{Cov}(X, c)}$$

$$\therefore \text{CORR} = \frac{\text{Cov}}{\sigma_X \sigma_c} = 0$$

8. CB 4.42 $X \perp\!\!\!\perp Y, \mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2$ EXPRESS $\text{Cov}(XY, Y)$ IN THOSE TERMS

$$\text{Cov}(XY, Y) = \frac{\text{Cov}(XY, Y)}{\pi} \quad \text{Cov}(XY, Y) = E(XY Y) - E(XY) E(Y)$$

$\text{Cov}(X, Y)$

$$\text{Var}(XY) = E(X^2Y^2) - E(XY)^2 = E(X^2)E(Y^2) - E(X^2)E(Y)^2 = (\text{Var}(X) + \mu_X^2)(\text{Var}(Y) + \mu_Y^2) - \mu_X^2\mu_Y^2$$

$$\text{Var}(XY) = \sigma_X^2\sigma_Y^2 + \sigma_X^2\mu_Y^2 + \sigma_Y^2\mu_X^2 + \mu_X^2\mu_Y^2 - \mu_X^2\mu_Y^2 = \sigma_X^2\sigma_Y^2 + \sigma_X^2\mu_Y^2 + \sigma_Y^2\mu_X^2$$

$$E(XY) = E(X)E(Y) = \mu_X\mu_Y \quad E(Y) = \mu_Y$$

$$E(XY^2) = E(X)E(Y^2) = E(X)(\text{Var}(Y) + E(Y)^2) = \mu_X(\sigma_Y^2 + \mu_Y^2)$$

$$\text{Cov}(XY, Y) = \mu_X\sigma_Y^2 + \mu_X\mu_Y^2 - \mu_X\mu_Y^2 = \mu_X\sigma_Y^2$$

$$\text{Corr}(XY, Y) = \frac{\mu_X\sigma_Y^2}{\sigma_Y(\sigma_X^2 + \sigma_Y^2 + \mu_X^2)^{1/2}} = \frac{\mu_X\sigma_Y^2}{(\sigma_X^2 + \sigma_Y^2 + \mu_X^2)^{1/2}}$$

9. CB 4.43 X_1, X_2, X_3 UNCORRELATED, μ_i, σ^2 FIND $\text{Cov}(X_1 + X_2, X_2 + X_3) \text{ & } \text{Cov}(X_1 + X_2, X_1 - X_2)$

a. $\text{Cov}(X_1 + X_2, X_2 + X_3) = E[(X_1 + X_2)(X_2 + X_3)] - E(X_1 + X_2)E(X_2 + X_3) = E(X_1X_2 + X_1X_3 + X_2^2 + X_2X_3) - (E(X_1) + E(X_2))(E(X_2) + E(X_3))$

$$= E(X_1X_2) + E(X_1X_3) + E(X_2^2) + E(X_2X_3) - (\mu_1 + \mu_2)(\mu_2 + \mu_3) = E(X_1)E(X_2) + E(X_1)E(X_3) + \text{Var}(X_2) + E(X_2)^2 + E(X_2)E(X_3) - 4\mu^2$$
$$= \mu^2 + \mu^2 + \sigma^2 + \mu^2 + \mu^2 - 4\mu^2 = \sigma^2$$

$$\text{Cov}(X_1 + X_2, X_2 + X_3) = \sigma^2$$

b. $\text{Cov}(X_1 + X_2, X_1 - X_2) = E(X_1^2 - X_1X_2 + X_1X_2 - X_2^2) - (E(X_1) + E(X_2))(E(X_1) - E(X_2)) = E(X_1^2) - E(X_2^2) - (\mu_1 + \mu_2)(\mu_1 - \mu_2)$

$$= \text{Var}(X_1) + E(X_1)^2 - \text{Var}(X_2) - E(X_2)^2 - (\mu_1 + \mu_2)(0) = \sigma^2 + \mu^2 - \sigma^2 - \mu^2 - 0 = 0$$

$$\text{Cov}(X_1 + X_2, X_1 - X_2) = 0$$

10. CB 4.65 PROVE COV. INEQUALITY BY GENERALIZING: $E(g(x)(x - \mu)) \geq 0$

PROVE: LET $X \perp\!\!\!\perp Y$ $g = (g(x) - g(y))(h(x) - h(y))$

a) FOR $g(x)$ MONO + & $h(x)$ MONO - : $E(g(x)h(x)) \leq E(g(x))E(h(x))$

$$E(g) = E[(g(x) - g(y))(h(x) - h(y))] = [E(g(x)) - E(g(y))][E(h(x)) - E(h(y))]$$

WHEN $y = x$: $E(g) = 0$

$\forall x: E(g(y)) \geq E(g(x)), E(h(y)) \leq E(h(x)) \therefore E(g) = [\text{NEGATIVE}][\text{POSITIVE}] \therefore E(g) \leq 0$

$\forall x: E(g(y)) \leq E(g(x)), E(h(y)) \geq E(h(x)) \therefore E(g) = [\text{POSITIVE}][\text{NEGATIVE}] \therefore E(g) \leq 0$

$$E(g) \leq 0 \therefore E[(g(x) - g(y))(h(x) - h(y))] \leq 0 \quad E[g(x)h(x) - g(x)h(y) - g(y)h(x) + g(y)h(y)] \leq 0$$

$\therefore E[g(x)h(x) - g(x)h(y) - g(y)h(x) + g(y)h(y)] \leq 0$

$$E[g(x)h(x)] = E[g(x)h(y)] + E[g(y)h(x)] - E[g(y)h(y)] = E[g(x)]E[h(x)]$$

$$\therefore \underline{E[g(x)h(x)] \leq E[g(x)]E[h(x)]}$$

b) For $g(x), h(x)$ Both Mono + or - : $E(g(x)h(x)) \geq E(g(x))E(h(x))$

when $y=x$: $E(q) \geq 0$

Monot + : $\forall x: E(g(y)) \geq E(g(x)), E(h(y)) \geq E(h(x)) : E(q) = [\text{positive}][\text{positive}] \therefore E(q) \geq 0$

$\forall x: E(g(y)) \leq E(g(x)), E(h(y)) \leq E(h(x)) : E(q) = [\text{positive}][\text{positive}] \therefore E(q) \geq 0$

Monot - : $\forall x: E(g(y)) \geq E(g(x)), E(h(y)) \leq E(h(x)) : E(q) = [\text{negative}][\text{negative}] \therefore E(q) \geq 0$

$\forall x: E(g(y)) \leq E(g(x)), E(h(y)) \leq E(h(x)) : E(q) = [\text{positive}][\text{positive}] \therefore E(q) \geq 0$

WE CAN DO THE SAME EXPECTATION MOVEMENT FROM (a) TO SHOW

$$\underline{E[g(x)h(x)] \geq E[g(x)]E[h(x)]}$$