

4.32 (a) For the hierarchical model

$$Y|\Lambda \sim \text{Poisson}(\Lambda) \quad \text{and} \quad \Lambda \sim \text{gamma}(\alpha, \beta)$$

find the marginal distribution, mean, and variance of Y . Show that the marginal distribution of Y is a negative binomial if α is an integer.

(b) Show that the three-stage model

$$Y|N \sim \text{binomial}(N, p), \quad N|\Lambda \sim \text{Poisson}(\Lambda), \quad \text{and} \quad \Lambda \sim \text{gamma}(\alpha, \beta)$$

$$(a): f(Y|\Lambda) = \frac{e^{-\Lambda} \Lambda^y}{y!}, \quad \begin{cases} \Lambda > 0 \\ y = 0, 1, 2, 3, \dots \end{cases}$$

$$f(\Lambda) = \frac{1}{P(\alpha) \beta^\alpha} \Lambda^{\alpha-1} e^{-\Lambda/\beta}, \quad \begin{cases} \alpha > 0 \\ \beta > 0 \\ \Lambda > 0 \end{cases}$$

$$f(Y, \Lambda) = f(Y|\Lambda) \cdot f(\Lambda)$$

$$= \frac{1}{P(\alpha) \beta^\alpha y!} \Lambda^{y+\alpha-1} e^{-\Lambda(1+\frac{1}{\beta})}$$

$$f_Y(y) = \int_{-\infty}^{\infty} f(Y, \Lambda) d\Lambda$$

$$= \int_0^{\infty} \frac{1}{P(\alpha) \beta^\alpha y!} \Lambda^{y+\alpha-1} e^{-\Lambda(1+\frac{1}{\beta})} d\Lambda$$

$$= \frac{1}{y!} \int_0^\infty \frac{1}{P(\alpha) \beta^\alpha} \lambda^{y+\alpha-1} e^{-\lambda(1+\frac{1}{\beta})} d\lambda$$

... (*)

$$\int_0^\infty \frac{1}{P(\alpha) \beta^\alpha} \lambda^{\alpha-1} e^{-\lambda/\beta} d\lambda = 1$$

$$\left\{ \begin{array}{l} \alpha'-1 = y + \alpha - 1 \\ \frac{1}{\beta'} = 1 + \frac{1}{\beta} \end{array} \right. \Rightarrow \left\{ \begin{array}{l} \alpha = \alpha' - y \\ \beta = \frac{\beta'}{1 - \beta'} \end{array} \right. \left\{ \begin{array}{l} \alpha' = \alpha + y \\ \beta' = \frac{\beta}{1 + \beta} \end{array} \right.$$

$$(*) = \frac{1}{y!} \int_0^\infty \frac{1}{P(\alpha'-y) (\frac{\beta'}{1-\beta'})^{\alpha'-y}} \lambda^{\alpha'-1} e^{-\lambda/\beta'} d\lambda$$

$$\begin{aligned}
 &= \frac{\frac{P(d') \beta'^{\alpha'}}{y! P(d'-y) \left(\frac{\beta'}{1+\beta}\right)^{d-y}}}{\frac{1}{P(d', \beta', \alpha')}} \int d^{\alpha'-1} e^{-\lambda/\beta'} d\lambda \\
 &\quad = 1 \\
 &= \frac{P(d+y) \left(\frac{\beta}{1+\beta}\right)^{d+y}}{y! P(d) \beta^d}
 \end{aligned}$$

$$\begin{aligned}
 &= \frac{P(d+y)}{y! P(d)} \cdot \underbrace{\beta^{(d+y)} \cdot \beta^{-d} \cdot \left[\frac{1}{(1+\beta)}\right]^d \cdot \left[\frac{1}{(1+\beta)}\right]^y}_{\sim} \\
 &= \frac{(d+y-1)!}{y! (d-1)!} \cdot \left(\frac{\beta}{1+\beta}\right)^y \cdot \left(\frac{1}{1+\beta}\right)^d
 \end{aligned}$$

$$= \binom{\alpha+y-1}{y} \cdot \left(\frac{\beta}{\alpha+\beta}\right)^y \cdot \left(\frac{1}{\alpha+\beta}\right)^{\alpha}, \quad y=0, 1, 2, \dots$$

= negative binomial , $\begin{cases} \alpha > 0 \\ \beta > 0 \end{cases}$

$$f(y | \alpha, \frac{1}{\alpha+\beta})$$

↑ ↑
γ p

$$\begin{aligned} E(y) &= \frac{\gamma(1-p)}{p} = \alpha \cdot \left(1 - \frac{1}{\alpha+\beta}\right) \cdot \left(\frac{1}{\alpha+\beta}\right) \\ &= \alpha \cdot (1+\beta - 1) = \alpha\beta \end{aligned}$$

$$\text{Var}(y) = \frac{\gamma(1-p)}{p^2} = \frac{E(x)}{p} = \alpha\beta(1+\beta)$$

$$(b) f(Y|N) = \binom{N}{y} P \cdot (1-P)^{N-y}, \quad y \in \{0, 1, 2, \dots, N\}$$

$P \in [0, 1]$

$$f(N|\lambda) = \frac{e^{-\lambda} \lambda^N}{N!}, \quad N \in \{0, 1, 2, \dots\}$$

$\lambda > 0$

$$f(\lambda) = \frac{1}{P(c_1 \beta)} \lambda^{d-1} e^{-\lambda/\beta}, \quad \begin{cases} \lambda > 0 \\ d > 0 \\ \beta > 0 \end{cases}$$

$$f(N, \lambda) = f(N|\lambda) \cdot f(\lambda)$$

According to (a)

$f(N) \sim \text{negative binomial}$

$$f^{(N)} = \binom{d+N-1}{N} \cdot \left(\frac{\beta}{\gamma+\beta}\right)^N \cdot \left(\frac{1}{\gamma+\beta}\right)^d, \quad N=0,1,2,\dots$$

$$\alpha > 0$$

$$\beta > 0$$

$$f_{(N,y)} = f_{(y|N)} \cdot f^{(N)}$$

$$= \binom{N}{y} P^y \cdot (1-P)^{N-y} \cdot \binom{d+N-1}{N} \cdot \left(\frac{\beta}{\gamma+\beta}\right)^N \cdot \left(\frac{1}{\gamma+\beta}\right)^d$$

$$= \frac{N!}{y!(N-y)!} \cdot \frac{(d+N-1)!}{N!(d-1)!} P^y \cdot (1-P)^{N-y} \cdot \left(\frac{\beta}{\gamma+\beta}\right)^y$$

$$\left(\frac{\beta}{\gamma+\beta}\right)^{N-y} \cdot \left(\frac{1}{\gamma+\beta}\right)^d$$

$$= \frac{(\alpha + N - 1)!}{y!(N-y)!(\alpha-1)!} \cdot \left(\frac{P\beta}{1+\beta}\right)^y \cdot \left(\frac{(1-P)\beta}{1+\beta}\right)^{N-y} \cdot \left(\frac{1}{1+\beta}\right)^2$$

$$f_Y(y) = \sum_{N=0}^{\infty} \frac{(\alpha + N - 1)!}{y!(N-y)!(\alpha-1)!} \cdot \left(\frac{P\beta}{1+\beta}\right)^y \cdot \left(\frac{(1-P)\beta}{1+\beta}\right)^{N-y} \cdot \left(\frac{1}{1+\beta}\right)^2$$

$$= \left(\frac{P\beta}{1+\beta}\right)^y \left(\frac{1}{1+\beta}\right)^2 \cdot \frac{1}{(\alpha-1)!y!} \sum_{N=0}^{\infty} \frac{(\alpha + N - 1)!}{(N-y)!} \left(\frac{(1-P)\beta}{1+\beta}\right)^{N-y} \dots \times$$

$$\sum_{N=0}^{\infty} \frac{(\alpha+y-1+N-y)!}{(N-y)!(\alpha+y-1)!} \cdot (\alpha+y-1)! \cdot \left(\frac{\beta-P\beta}{1+\beta}\right)^{N-y} \cdot \left(\frac{P\beta}{1+\beta}\right)^{\alpha+y-1} \cdot \left(\frac{1+\beta}{P\beta+1}\right)^{\alpha+y-1}$$

$$= \left(\frac{1+\beta}{P\beta+1}\right)^{\alpha+y} \cdot (\alpha+y-1)! \cdot \sum_{N=0}^{\infty} \binom{\alpha+N-1}{N-y} \left(\frac{\beta-P\beta}{1+\beta}\right)^{N-y} \left(\frac{P\beta+1}{1+\beta}\right)^{\alpha+y}$$

= 1

$$\therefore (*) = \left(\frac{PB}{1+B} \right)^y \cdot \left(\frac{1}{1+B} \right)^d \cdot \underbrace{\frac{1}{(d-y)!y!}}_{\text{binomial coefficient}} \cdot \left(\frac{1+B}{PB+1} \right)^{d+y} \cdot \underbrace{(d+y-1)!}_{\text{Gamma function}}$$

$$= \binom{d+y-1}{y} (PB)^y \cdot \left(\frac{1}{1+B} \right)^{d+y} \cdot (1+B)^{d+y} \cdot \left(\frac{1}{PB+1} \right)^{d+y}$$

$$= \binom{d+y-1}{y} (PB)^y \cdot \left(\frac{1}{PB+1} \right)^{d+y}$$

$$= \binom{d+y-1}{y} \left(\frac{PB}{PB+1} \right)^y \cdot \left(\frac{1}{PB+1} \right)^d$$

If it is negative $y = 0, 1, 2, 3, \dots$

binomial $\Rightarrow P \in [0, 1] \quad \beta, d > 0$

$$f(y|d, \frac{1}{PB+1})$$

$$Z(x) = \frac{d\left(1 - \frac{1}{PB+1}\right)}{\frac{1}{PB+1}} = d(PB+1-1) = dPB$$

$$\text{Var}(x) = \frac{Z(x)}{\frac{1}{PB+1}} = dPB(PB+1)$$

4.36 One generalization of the Bernoulli trials hierarchy in Example 4.4.6 is to allow the success probability to vary from trial to trial, keeping the trials independent. A standard model for this situation is

$$X_i | P_i \sim \text{Bernoulli}(P_i), \quad i = 1, \dots, n,$$

$$P_i \sim \text{beta}(\alpha, \beta).$$

This model might be appropriate, for example, if we are measuring the success of a drug on n patients and, because the patients are different, we are reluctant to assume that the success probabilities are constant. (This can be thought of as an *empirical Bayes model*; see Miscellanea 7.5.6.)

A random variable of interest is $Y = \sum_{i=1}^n X_i$, the total number of successes.

- (a) Show that $EY = n\alpha/(\alpha + \beta)$.
- (b) Show that $\text{Var } Y = n\alpha\beta/(\alpha + \beta)^2$, and hence Y has the same mean and variance as a $\text{binomial}(n, \frac{\alpha}{\alpha + \beta})$ random variable. What is the distribution of Y ?
- (c) Suppose now that the model is

$$X_i | P_i \sim \text{binomial}(n_i, P_i), \quad i = 1, \dots, k,$$

$$P_i \sim \text{beta}(\alpha, \beta).$$

Show that for $Y = \sum_{i=1}^k X_i$, $EY = \frac{\alpha}{\alpha + \beta} \sum_{i=1}^k n_i$ and $\text{Var } Y = \sum_{i=1}^k \text{Var } X_i$, where

$$\text{Var } X_i = n_i \frac{\alpha\beta(\alpha + \beta + n_i)}{(\alpha + \beta)^2(\alpha + \beta + 1)}.$$

$$(a): E(Y) = E\left(\sum_{i=1}^n X_i\right) = E(X_1 + X_2 + \dots + X_n) = E(X_1) + E(X_2) + \dots + E(X_n) = \sum_{i=1}^n E(X_i) \quad \dots \quad \textcircled{1}$$

$$E(X_i) = E_P\left(E(X_i | P_i)\right) = E_P(P_i)$$

$$\begin{aligned} & \text{mean of binomial} & \text{mean of Beta} \\ & = P_i & = \frac{\alpha}{\alpha + \beta} \end{aligned}$$

$$\begin{aligned} \therefore \textcircled{1} &= \sum_{i=1}^n \frac{\alpha}{\alpha + \beta} \\ &= \frac{n\alpha}{\alpha + \beta} \end{aligned}$$

$$(b) : \text{Var}(Y) = \text{Var}\left(\sum_{i=1}^n X_i\right) = \text{Var}(X_1 + X_2 + X_3 + \dots + X_n) = \text{Var}(X_1) + \text{Var}(X_2) + \dots + \text{Var}(X_n)$$

$$= \sum_{i=1}^n \text{Var}(X_i) \quad \cdots \quad \textcircled{2}$$

$$\text{Var}(X_i) = E_{P_i} \left(V(X|P_i) \right) + V_{P_i} \left(E(X|P_i) \right)$$

$$= P_i(1-P_i) \quad P_i$$

$$= E(P_i) - E(P_i^2) + V(P_i)$$

$$= E(P_i) \cdot E(P_i^2) + E(P_i^2 - E(P_i))^2$$

$$= Z(P_i) - Z(P_i)^2$$

$$= \frac{\alpha}{\alpha+\beta} - \frac{\alpha^2}{(\alpha+\beta)^2}$$

$$= \frac{\alpha(\alpha+\beta) - \alpha^2}{(\alpha+\beta)^2} = \frac{\alpha\beta}{(\alpha+\beta)^2}$$

$$\therefore \textcircled{2} = \sum_{i=1}^n \frac{\alpha \beta}{(\alpha + \beta)^2} = \frac{n \alpha \beta}{(\alpha + \beta)^2}$$

||
Var(Y)

$$Y \sim \text{Binomial}(n, \frac{\alpha}{\alpha + \beta})$$

$$f(y) = \binom{n}{y} \left(\frac{\alpha}{\alpha + \beta} \right)^y \left(\frac{\beta}{\alpha + \beta} \right)^{n-y}.$$

4.43 Let X_1, X_2 , and X_3 be uncorrelated random variables, each with mean μ and variance σ^2 . Find, in terms of μ and σ^2 , $\text{Cov}(X_1 + X_2, X_2 + X_3)$ and $\text{Cov}(X_1 + X_2, X_1 - X_2)$.

$$\text{Cov}(X_1 + X_2, X_2 + X_3) = \mathbb{E}((X_1 + X_2)(X_2 + X_3)) - \mathbb{E}(X_1 + X_2)\mathbb{E}(X_2 + X_3)$$

$$= \mathbb{E}(X_1 X_2 + X_1 X_3 + X_2^2 + X_2 X_3) - (\mu_1 + \mu_2)(\mu_2 + \mu_3)$$

$$= \mathbb{E}(X_1 X_2) + \mathbb{E}(X_1 X_3) + \mathbb{E}(X_2^2) + \mathbb{E}(X_2 X_3) - (\mu_1 + \mu_2)(\mu_2 + \mu_3)$$

$\because X_1, X_2, X_3$ are independent

$$= \mathbb{E}(X_1) - \mathbb{E}(X_2) + \mathbb{E}(X_1)\mathbb{E}(X_3) + \mathbb{E}(X_2^2) + \mathbb{E}(X_2)\mathbb{E}(X_3) -$$

$$(\mu_1 \mu_2 + \mu_1 \mu_3 + \mu_2 \mu_3 + \mu_2^2 + \mu_2 \mu_3)$$

$$= \underbrace{\mu_1 \mu_2}_{\mu_2^2} + \underbrace{\mu_1 \mu_3}_{\mu_2 \mu_3} + \underbrace{\mu_2^2}_{\mu_2^2} + \underbrace{\mu_2^2}_{\mu_2 \mu_3} - \underbrace{\mu_1 \mu_2}_{\mu_1 \mu_2} - \underbrace{\mu_1 \mu_3}_{\mu_1 \mu_3} -$$

$$\underbrace{\mu_2^2}_{\sigma^2} - \underbrace{\mu_2 \mu_3}_{\sigma^2} = \sigma^2$$

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

$$= \mathbb{E}((X_1+X_2)(X_1-X_2)) - \mathbb{E}(X_1+X_2) \cdot \mathbb{E}(X_1-X_2)$$

$$= \mathbb{E}(X_1^2 - X_2^2) - (\mu + \mu) \cdot (\mu - \mu)$$

$$= \mathbb{E}(X_1^2 - X_2^2) = \mathbb{E}(X_1^2) - \mathbb{E}(X_2^2)$$

$$= \mu^2 + \mu^2 - (\mu^2 + \mu^2) = 0$$

4.45 Show that if $(X, Y) \sim \text{bivariate normal}(\mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2, \rho)$, then the following are true.

- (a) The marginal distribution of X is $n(\mu_X, \sigma_X^2)$ and the marginal distribution of Y is $n(\mu_Y, \sigma_Y^2)$.
- (b) The conditional distribution of Y given $X = x$ is

$$n(\mu_Y + \rho(\sigma_Y/\sigma_X)(x - \mu_X), \sigma_Y^2(1 - \rho^2)).$$

- (c) For any constants a and b , the distribution of $aX + bY$ is

$$n(a\mu_X + b\mu_Y, a^2\sigma_X^2 + b^2\sigma_Y^2 + 2ab\rho\sigma_X\sigma_Y).$$

$$(a): f(x, y) = \frac{1}{2\pi\sqrt{\lambda_x}\sqrt{\lambda_y}\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)}\left(\left(\frac{x-\mu_x}{\lambda_x}\right)^2 + \left(\frac{y-\mu_y}{\lambda_y}\right)^2 - 2\rho\left(\frac{x-\mu_x}{\lambda_x}\right)\left(\frac{y-\mu_y}{\lambda_y}\right)\right)\right)$$

$$f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy = \int_{-\infty}^{\infty} \frac{1}{2\pi\sqrt{\lambda_x}\sqrt{\lambda_y}\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)}\left(\left(\frac{x-\mu_x}{\lambda_x}\right)^2 + 2\rho\left(\frac{x-\mu_x}{\lambda_x}\right)\left(\frac{y-\mu_y}{\lambda_y}\right) + \left(\frac{y-\mu_y}{\lambda_y}\right)^2\right)\right) dy$$

use $\rho = \frac{y-\mu_y}{\lambda_y}$ $\therefore dy = \lambda_y d\rho$

$$q = \frac{x-\mu_x}{\lambda_x} \quad \therefore dx = \lambda_x dq.$$

$$f_X(x) = \frac{1}{2\pi\Delta x\sqrt{1-p^2}} e^{-\frac{w^2}{2(1-p^2)}} \int_{-\infty}^{\infty} e^{-\frac{1}{2(1-p^2)}((p^2-2pq+q^2)-p^2q^2)} dp$$

$$= \frac{1}{2\pi\Delta x\sqrt{1-p^2}} \cdot e^{-\frac{w^2}{2(1-p^2)}} \cdot e^{p^2q^2/2(1-p^2)} \int_{-\infty}^{\infty} e^{-\frac{1}{2(1-p^2)}(p-q)^2} dp$$

$$\cdot \frac{1}{\sqrt{2\pi}\sqrt{1-p^2}} \cdot \sqrt{2\pi} \sqrt{1-p^2}$$

red part = 1

$$= \frac{e^{-\frac{q^2}{2}} \sqrt{2\pi} \sqrt{1-p^2}}{2\pi\Delta x\sqrt{1-p^2}} = \frac{1}{\sqrt{2\pi}\Delta x} e^{-\frac{1}{2} \left(\frac{x-\mu_x}{\Delta x}\right)^2}$$

$$X \sim N(\mu_x, \sigma_x^2)$$

Using the same method for y

$$Y \sim N(\mu_y, \sigma_y^2)$$

(b) .

$$f(Y|X=x) = \frac{f(X=x, Y)}{f_X(x)}$$

$$= \frac{\frac{1}{2\pi\Delta x\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)} \left[\left(\frac{x-\mu_x}{\Delta x}\right)^2 - 2\rho \left(\frac{x-\mu_x}{\Delta x}\right) \left(\frac{y-\mu_y}{\Delta y}\right) + \left(\frac{y-\mu_y}{\Delta y}\right)^2 \right]}}{\frac{1}{\sqrt{2\pi\Delta x}} e^{-\frac{(x-\mu_x)^2}{2\Delta x^2}}}$$

$$= \frac{1}{\sqrt{2\pi\Delta x\sqrt{1-\rho^2}}} e^{-\frac{1}{2(1-\rho^2)} \left[\rho^2 \left(\frac{x-\mu_x}{\Delta x}\right)^2 - 2\rho \left(\frac{x-\mu_x}{\Delta x}\right) \left(\frac{y-\mu_y}{\Delta y}\right) + \left(\frac{y-\mu_y}{\Delta y}\right)^2 \right]}$$

$$= \frac{1}{\sqrt{2\pi\Delta x\sqrt{1-\rho^2}}} e^{-\frac{1}{2\Delta x^2\sqrt{1-\rho^2}} \left[(y-\mu_y) - \left(\rho \frac{\Delta y}{\Delta x} (x-\mu_x)\right) \right]^2}$$

thus, $f_{Y|X}(y|x) \sim$

Normal distribution

$$N\left(\mu_Y - \rho \left(\frac{\delta_Y}{\delta_X}\right)(x - \mu_X), \delta_Y \sqrt{1 - \rho^2}\right)$$

(C)

$$\mathbb{E}(ax+by) = a\mathbb{E}(x)+b\mathbb{E}(y)$$

$$= a\mu_x + b\mu_y$$

$$\text{Var}(ax+by) = a^2 \text{Var}(x) + b^2 \text{Var}(y) + 2ab \text{Cov}(x, y) \quad \dots \quad \textcircled{1}$$

$$\frac{\text{Cov}(x, y)}{\text{Var}(x)} = \rho \quad \text{Cov}(x, y) = \rho \Delta x \Delta y$$

$$\textcircled{1} = \text{Var}(aX+bY) = a^2 \Delta_x^2 + b^2 \Delta_y^2 + 2ab \Delta_x \Delta_y \rho$$

$$M = aX+bY, \quad n = Y$$

$$\frac{\partial X}{\partial m} = \frac{1}{a} \quad \frac{\partial X}{\partial n} = \frac{-b}{a}$$

$$\frac{\partial Y}{\partial m} = 0 \quad \frac{\partial Y}{\partial n} = 1$$

$$|J| = \left| \frac{1}{a} \times [-0 \cdot \left(-\frac{b}{a} \right)] \right| = \frac{1}{a}$$

$$f_{mn}(m, n) = \frac{1}{2\pi a \sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)} \left(\left(\frac{1}{a}(cm - bn) \right)^2 - 2\frac{\rho}{a}(m - bn) + n^2 \right)} \dots \textcircled{1}$$

$$\mu = a\mu_x + b\mu_y \quad \Delta^2 = a^2 \Delta x^2 + b^2 \Delta y^2 + 2ab \rho \Delta x \Delta y$$

$$\Delta = \sqrt{a^2 \Delta x^2 + b^2 \Delta y^2 + 2ab \rho \Delta x \Delta y}$$

$$\rho' = \frac{\text{Cov}(m, n)}{\Delta m \Delta n} = \frac{a\rho + b}{\sqrt{a^2 + b^2 + 2ab\rho}} \quad \dots \quad \textcircled{2}$$

$$\Delta_n^2 = 1 \quad \mu_m = 0$$

$$\Delta_m^2 = a^2 + 2ab\rho + b^2 \quad \mu_n = 0$$

$$1 - \rho'^2 = 1 - \textcircled{2}^2 = \frac{(1 - \rho^2)a^2}{a^2 + b^2 + 2ab\rho}$$

$$= \frac{(1 - \rho^2)a^2}{\Delta m^2}$$

$$\textcircled{1} =$$

$$J_{mn}(m, n) = \frac{1}{2\pi \Delta m \Delta n \sqrt{1 - p^2}} e^{(-\frac{1}{2\Delta p^2} \left(\frac{m^2}{\Delta m^2} - 2\frac{mn}{\Delta mn} + \frac{n^2}{\Delta n^2} \right))}$$

In part (a), I have proved the relationship between $f_m(m)$ and $f_{mn}(m, n)$

$$f_m(m) \sim N(\bar{f}_m, \Delta_m^2)$$

$$f(ax+by) = N(a\bar{f}_x + b\bar{f}_y, a^2 \Delta_x^2 + b^2 \Delta_y^2 + 2ab \Delta_x \Delta_y)$$