

7.22 a) $f(\bar{x}, \theta) = f(\bar{x}|\theta)\pi(\theta) = \frac{\sqrt{n}}{\sqrt{2\pi\sigma}} e^{-n(\bar{x}-\theta)^2/(2\sigma^2)} \frac{1}{\sqrt{2\pi\tau}} e^{-(\theta-\mu)^2/2\tau^2}$.

b) Factor the exponent in part a) as

$$\frac{-n}{2\sigma^2}(\bar{x}-\theta)^2 - \frac{1}{2\tau^2}(\theta-\mu)^2 = -\frac{1}{2v^2}(\theta-\delta(x))^2 - \frac{1}{\tau^2 + \sigma^2/n}(\bar{x}-\mu)^2,$$

where $\delta(x) = (\tau^2\bar{x} + (\sigma^2/n)\mu)/(\tau^2 + \sigma^2/n)$ and $v = (\sigma^2\tau^2/n) / (\tau + \sigma^2/n)$. Let $n(a, b)$ denote the pdf of a normal distribution with mean a and variance b . The above factorization shows that

$$f(x, \theta) = n(\theta, \sigma^2/n) \times n(\mu, \tau^2) = n(\delta(x), v^2) \times n(\mu, \tau^2 + \sigma^2/n),$$

where the marginal distribution of \bar{X} is $n(\mu, \tau^2 + \sigma^2/n)$ and the posterior distribution of $\theta|x$ is $n(\delta(x), v^2)$. This also completes part c).

7.23 Let $t = s^2$ and $\theta = \sigma^2$. Since $(n-1)S^2/\sigma^2 \sim \chi_{n-1}^2$, we have

$$f(t|\theta) = \frac{1}{\Gamma((n-1)/2) 2^{(n-1)/2}} \left(\frac{n-1}{\theta}\right)^{[(n-1)/2]-1} e^{-(n-1)t/2\theta} \frac{n-1}{\theta}.$$

With $\pi(\theta)$ as given, we have (ignoring terms that do not depend on θ)

$$\begin{aligned} \pi(\theta|t) &\propto \left(\frac{1}{\theta}\right)^{((n-1)/2)-1} e^{-(n-1)t/2\theta} \frac{1}{\theta} \left[\frac{1}{\theta^{\alpha+1}} e^{-1/\beta\theta}\right] \\ &\propto \left(\frac{1}{\theta}\right)^{((n-1)/2)+\alpha+1} \exp\left\{-\frac{1}{\theta}\left[\frac{(n-1)t}{2} + \frac{1}{\beta}\right]\right\}, \end{aligned}$$

which we recognize as the kernel of an inverted gamma pdf, $IG(a, b)$, with $a = ((n-1)/2) + \alpha$ and

$b = \left[\frac{(n-1)t}{2} + \frac{1}{\beta}\right]^{-1}$. Direct calculation shows that the mean of an $IG(a, b)$ is $1/((a-1)b)$, so

$$E(\theta|t) = \frac{\frac{n-1}{2}t + \frac{1}{\beta}}{\frac{n-1}{2} + \alpha - 1} = \frac{\frac{n-1}{2}s^2 + \frac{1}{\beta}}{\frac{n-1}{2} + \alpha - 1}.$$

This is a Bayes estimator of σ^2 .

7.24 For n observations, $Y = \sum X_i \sim \text{Poisson}(n\lambda)$.

a) The marginal pmf of Y is

$$\begin{aligned} m(y) &= \int_0^\infty \frac{(n\lambda)^y e^{-n\lambda}}{y!} \frac{1}{\Gamma(\alpha)\beta^\alpha} \lambda^{\alpha-1} e^{-\lambda/\beta} d\lambda \\ &= \frac{n^y}{y!\Gamma(\alpha)\beta^\alpha} \int_0^\infty \lambda^{(y+\alpha)-1} e^{-\lambda/\beta} d\lambda = \frac{n^y}{y!\Gamma(\alpha)\beta^\alpha} \cdot \Gamma(y+\alpha) \cdot \left(\frac{\beta}{n\beta+1}\right)^{y+\alpha}. \end{aligned}$$

Thus,

$$\pi(\lambda|y) = \frac{f(y|\lambda)\pi(\lambda)}{m(y)} = \frac{\lambda^{(y+\alpha)-1} e^{-\lambda/\beta}}{\Gamma(y+\alpha) \left(\frac{\beta}{n\beta+1}\right)^{y+\alpha}} \sim \text{gamma}\left(y + \alpha, \frac{\beta}{n\beta+1}\right).$$

b) $E(\lambda|y) = (y + \alpha) \frac{\beta}{n\beta+1} = \frac{\beta}{n\beta+1} y + \frac{1}{n\beta+1} (\alpha\beta).$

$$\text{Var}(\lambda|y) = (y + \alpha) \frac{\beta^2}{(n\beta+1)^2}.$$

9.53 ~~100~~ a) $E[b \text{Len}(C) - I_C(\mu)] = 2c\sigma b - P(|Z| \leq c)$, where $Z \sim n(0,1)$.

b) $\frac{d}{dc}[2c\sigma b - P(|Z| \leq c)] = 2\sigma b - 2\left(\frac{1}{\sqrt{2\pi}}e^{-c^2/2}\right)$.

c) If $b\sigma > 1/\sqrt{2\pi}$ the derivative is always positive since $e^{-c^2/2} < 1$.

9.55 ~~100~~

$$\begin{aligned} E[L((\mu, \sigma), C)] &= E[L((\mu, \sigma), C) | S < K] P(S < K) + E[L((\mu, \sigma), C) | S > K] P(S > K) \\ &= E[L((\mu, \sigma), C') | S < K] P(S < K) + E[L((\mu, \sigma), C) | S > K] P(S > K) \\ &= R[L((\mu, \sigma), C')] + E[L((\mu, \sigma), C) | S > K] P(S > K), \end{aligned}$$

where the last equality follows because C' is \emptyset if $S > K$.

The conditional expectation in the second term is bounded by

$$\begin{aligned} E[L((\mu, \sigma), C) | S > K] &= E[b \text{Len}(C) - I_C(\mu) | S > K] \\ &= E[2bcS - I_C(\mu) | S > K] \\ &> E[2bcK - 1 | S > K] && \text{(since } S > K \text{ and } I_C \leq 1) \\ &= 2bcK - 1, \end{aligned}$$

which is positive if $K > 1/2bc$. For those values of K , C' dominates C .