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SDS 383 D - Statistical Modeling 2
Homework

Exercise 1.1

$$X_1, \dots, X_n \sim \text{Bernoulli}(p), \quad h(p) \sim \text{Beta}(\alpha, \beta)$$

$$\begin{aligned} p|X_1, \dots, X_N &\propto f(x_1, \dots, x_n|p) \cdot h(p) \\ &\propto p^{\sum x_i} (1-p)^{n-\sum x_i} \cdot p^{\alpha-1} (1-p)^{\beta-1} \\ &\propto p^{\sum x_i + \alpha - 1} (1-p)^{\beta + n - \sum x_i - 1} \end{aligned}$$

$$p|X_1, \dots, X_N \sim \text{Beta}(\sum x_i + \alpha, \beta + n - \sum x_i)$$

Exercise 1.2

$$\begin{aligned} X_1, \dots, X_N &\stackrel{iid}{\sim} \text{Cat}(p), \quad p = (p_1, \dots, p_K), \quad f(x|p) = \prod_{i=1}^n \prod_{k=1}^K p_k^{I(x_i=k)} \\ p &\sim \text{Dirichlet}(\alpha_1, \dots, \alpha_K) \end{aligned}$$

$$\pi(p) = \frac{\Gamma(\sum_k \alpha_k)}{\prod_K \Gamma(\alpha_k)} \prod_{k=1}^K p^{\alpha_k - 1} I(\sum_{k=1}^{K-1} p_k \leq 1, p_k \geq 0)$$

$$\begin{aligned} p|X_{1:n} &\propto f(x_{1:n}|p) \cdot \pi(p) \\ &\propto \prod_{i=1}^n \prod_{k=1}^K p_k^{I(x_i=k)} \cdot \prod_{k=1}^K p_k^{\alpha_k - 1} \\ &\propto \prod_{k=1}^K p_k^{n_k + \alpha_k - 1}, \quad \text{where } n_k = \sum_{i=1}^N I(x_i = k) \\ p|X_{1:n} &\sim \text{Dir}(n_1 + \alpha_1, \dots, n_K + \alpha_K) \end{aligned}$$

Exercise 1.3

$X \sim \text{Gam}(\alpha, b)$ and $Y \sim \text{Gam}(\beta, b)$ and X is independent of Y .

1.3.a

Let $W = X+Y$ and $Z = X/(X+Y)$. Show that W and Z are independent with $W \sim \text{Gam}(\alpha + \beta, b)$ and $Z \sim \text{Beta}(\alpha, \beta)$.

This is a bivariate random variable transformation:

Change of variables equation: $f_{w,z} = f_{x,y}(h_1(w, z), h_2(w, z))|J|$

$$g_1(X, Y) = W = X + Y$$

$$g_2(X, Y) = Z = X/(X + Y)$$

$$h_1(Z, W) = X = ZW$$

$$h_2(Z, W) = Y = W(1 - Z)$$

$$|J| = \text{abs}\left(\begin{vmatrix} \frac{\partial X}{\partial W} & \frac{\partial X}{\partial Z} \\ \frac{\partial Y}{\partial W} & \frac{\partial Y}{\partial Z} \end{vmatrix}\right) = \begin{vmatrix} Z & W \\ 1 - Z & -W \end{vmatrix} = \text{abs}(-w) = w$$

$$f_{w,z} = f_x(zw)f_y(w - zw)w$$

$$f_{w,z} = \frac{b^\alpha (zw)^{\alpha-1} e^{-bzw} \cdot b^\beta (w(1-z))^{\beta-1} e^{-bw(1-z)} w}{\Gamma(\alpha)\Gamma(\beta)} \cdot I(zw \geq 0) \cdot I(w - zw \geq 0)$$

$$f_{w,z} = \frac{w^{\alpha+\beta-1} b^{\alpha+\beta} e^{-bw} \cdot z^{\alpha-1} (1-z)^{\beta-1}}{\Gamma(\alpha)\Gamma(\beta)} \cdot I(0 \leq z \leq 1) \cdot I(w \geq 0)$$

$$f_{w,z} = \frac{b^{\alpha+\beta} w^{\alpha+\beta-1} e^{-bw} I(w \geq 0)}{\Gamma(\alpha + \beta)} \cdot \frac{\Gamma(\alpha + \beta) z^{\alpha-1} (1-z)^{\beta-1} I(0 \leq z \leq 1)}{\Gamma(\alpha)\Gamma(\beta)}$$

So W and Z are independent by factorization theorem and $W \sim \text{Gam}(\alpha + \beta, b)$ and $Z \sim \text{Beta}(\alpha, \beta)$

1.3.b

Explain how to use a random gamma sampler to sample from a $\text{Beta}(\alpha, \beta)$ random variable using R:

We can use the R function `(rgamma(n, shape, rate))` to sample two gamma random variables with shape parameters $\alpha = 10, \beta = 2$ and rate parameters equal $b = 5, b = 5$ and then use the transformation from the previous step to get a sample from a $\text{Beta}(\alpha = 10, \beta = 2)$ distribution.

```
x <- rgamma(1, 10, 5)
y <- rgamma(1, 2, 5)
z = x / (x + y)
```

Exercise 1.4

Suppose $X_1 \dots X_n \stackrel{iid}{\sim} \text{Normal}(\theta, \sigma_0^2)$ where σ_0^2 is known. Suppose $\theta \sim \text{Normal}(m, v)$, find posterior of $\theta|X_{1:N}$

$$\begin{aligned}
\theta|X_{1:N} &\propto \exp\left\{\frac{-1}{2\sigma_0^2} \sum_{i=1}^N (x_i - \theta)^2\right\} \cdot \exp\left\{\frac{-1}{2v^2} (\theta - m)^2\right\} \\
&\propto \exp\left\{\frac{-1}{2\sigma_0^2} \left(\sum_{i=1}^N (x_i^2 + \theta^2 - 2\theta x_i)\right) + \frac{-1}{2v^2} (\theta^2 + m^2 - 2\theta m)\right\} \\
&\propto \exp\left\{\frac{-\theta^2}{2} \cdot \left(\frac{1}{v^2} + \frac{n}{\sigma_0^2}\right) + \theta \left(\frac{m}{v^2} + \frac{\sum x_i}{\sigma_0^2}\right) - \left(\frac{m^2}{2v^2} + \frac{\sum x_i^2}{2\sigma_0^2}\right)\right\} \\
&\propto \exp\left\{\frac{-\theta^2}{2} \cdot \left(\frac{1}{v^2} + \frac{n}{\sigma_0^2}\right) + \theta \left(\frac{m}{v^2} + \frac{\sum x_i}{\sigma_0^2}\right)\right\} \\
&\propto \exp\left\{\frac{-1}{2} \left(\theta^2 \left(\frac{1}{v^2} + \frac{n}{\sigma_0^2}\right) - 2\theta \left(\frac{m}{v^2} + \frac{\sum x_i}{\sigma_0^2}\right)\right)\right\}
\end{aligned}$$

Completing the square:

$$\begin{aligned}
a &= \frac{1}{v^2} + \frac{n}{\sigma_0^2} \\
b &= \frac{m}{v^2} + \frac{\sum x_i}{\sigma_0^2} \\
a\theta^2 - 2\theta b &= a\left(\theta^2 - \frac{2\theta b}{a}\right) = a\left(\left(\theta - \frac{b}{a}\right)^2 - \frac{b^2}{a^2}\right)
\end{aligned}$$

$$\begin{aligned}
\theta|X_{1:N} &\propto \exp\left\{\frac{-1}{2} a \left(\theta - \frac{b}{a}\right)^2\right\} \\
&\propto \exp\left\{\frac{-1}{2} \frac{\left(\theta - \frac{b}{a}\right)^2}{\frac{1}{a}}\right\} \\
\theta|X_{1:N} &\sim \text{Normal}\left(m = \frac{b}{a}, v = a^{-1}\right) \\
m &= \frac{b}{a} = \frac{\frac{m}{v^2} + \frac{\sum x_i}{\sigma_0^2}}{\frac{1}{v^2} + \frac{n}{\sigma_0^2}}, \quad v = \left(\frac{1}{v^2} + \frac{n}{\sigma_0^2}\right)^{-1}
\end{aligned}$$