

# Problem Set 10

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## Problem 1.

1. We have this result from problem 2 in Problem Set 3:

$$l(\theta) = \sum_{i=1}^n \left( -\frac{1}{2} \log(\theta) - \frac{1}{2\theta} X_i^2 \right)$$

Taking deravite ans set to equal 0, we get:

$$\frac{\partial l(\theta)}{\partial \theta} = \sum_{i=1}^n \left( -\frac{1}{2\theta} + \frac{1}{2\theta^2} X_i^2 \right) = 0 \iff \theta^{MLE} = \frac{\sum_{i=1}^n X_i^2}{n} \quad (1)$$

2. From (1), we have the second deraviate of log-likelihood:

$$\frac{\partial^2 l(\theta)}{\partial \theta^2} = \sum_{i=1}^n \left( \frac{1}{2\theta^2} - \frac{1}{\theta^3} X_i^2 \right) \iff I(\theta) = -\sum_{i=1}^n \mathbb{E} \left[ \frac{1}{2\theta^2} - \frac{1}{\theta^3} X_i^2 \right] = \frac{n}{2\theta^2}$$

Hence,

$$(\theta^{MLE} - \theta) \xrightarrow[n \rightarrow \infty]{(d)} N(0, \frac{2\theta^2}{n})$$

3.

a) From previous question, we know:  $I(\theta) = \frac{n}{2\theta^2}$ . Hence,  $\pi(\theta) = c\sqrt{\det I(\theta)} = c\sqrt{\frac{n}{2\theta^2}}$ . This is improper prior

b) We have

$$\pi(\theta|X_1, \dots, X_n) = \frac{\pi(\theta)p_n(X_1, \dots, X_n|\theta)}{\int_0^\infty p_n(X_1, \dots, X_n|t)d\pi(t)} = \frac{c\sqrt{\frac{n}{2\theta^2}} \frac{1}{(2\pi\theta)^{\frac{n}{2}}} e^{-\frac{1}{2\theta} \sum_{i=1}^n X_i^2}}{\int_0^\infty p_n(X_1, \dots, X_n|t)d\pi(t)} = \frac{c\sqrt{n}}{(2\pi\theta)^{\frac{n}{2}} \sqrt{2\theta^2}} e^{-\frac{1}{2\theta} \sum_{i=1}^n X_i^2}$$

Hence, we can rewrite the posterio:

$$\frac{c\sqrt{n}}{(2\pi\theta)^{\frac{n}{2}} \sqrt{2\theta^2}} e^{-\frac{1}{2\theta} \sum_{i=1}^n X_i^2} = \frac{c\sqrt{n}}{(2\pi)^{\frac{n}{2}} \sqrt{2}} \frac{e^{-\frac{\frac{1}{2} \sum_{i=1}^n X_i^2}{\theta}}}{\theta^{\frac{n}{2}+1}} = \frac{c\sqrt{n}}{(2\pi)^{\frac{n}{2}} \sqrt{2}} \frac{e^{-\frac{\beta}{\theta}}}{\theta^{\alpha+1}}$$

Where  $\alpha = \frac{n}{2}$ ,  $\beta = \frac{\sum_{i=1}^n X_i^2}{2}$  and  $c$  is the constant satisfied  $\frac{c\sqrt{n}}{(2\pi)^{\frac{n}{2}} \sqrt{2}} = \frac{\beta^\alpha}{\Gamma(\alpha)}$ . This posterior is Gamma distribution with parameters  $\alpha$  and  $\beta$ . c)

We know  $\theta(\hat{\pi}) = \int_0^\infty \theta d\pi(\theta|X_1, \dots, X_n)$  is the expectation of Gamma distribution with parameters  $\alpha$  and  $\beta$ .

Hence,  $\theta(\hat{\pi}) = \frac{\beta}{\alpha-1} = \frac{\sum_{i=1}^n X_i^2}{n-2}$ .

## Problem 2.

1. Conditionally on  $\beta$ , we have  $Y - X\beta \sim N_p(0, \sigma^2 I_n)$ . Hence,  $Y \sim N_p(X\beta, \sigma^2 I_n)$ .

2.

a) We know:

$$\pi(\beta|X_1, \dots, X_n) \propto \pi(\beta)p_n(X_1, \dots, X_n|\beta) \propto e^{\frac{1}{\sigma^2}\|Y-X\beta\|_2^2} e^{\frac{1}{\tau^2}\|\beta\|_2^2} = e^{\frac{1}{\sigma^2}\left(\|Y-X\beta\|_2^2 + \frac{\sigma^2}{\tau^2}\|\beta\|_2^2\right)}$$

b) Let  $\pi(\beta|X_1, \dots, X_n) = K e^{\frac{1}{\sigma^2}\left(\|Y-X\beta\|_2^2 + \frac{\sigma^2}{\tau^2}\|\beta\|_2^2\right)}$

We know:

$$\begin{aligned} \frac{1}{\sigma^2}\left(\|Y-X\beta\|_2^2 + \frac{\sigma^2}{\tau^2}\|\beta\|_2^2\right) &= \frac{1}{\sigma^2}\left((Y-X\beta)^T(Y-X\beta) + \frac{\sigma^2}{\tau^2}\beta^T\beta\right) \\ &= \frac{1}{\sigma^2}\left(Y^TY - 2\beta^TX^TY + \beta^TX^TX\beta + \frac{\sigma^2}{\tau^2}\beta^T\beta\right) = \frac{1}{\sigma^2}\left(Y^TY - 2\beta^TX^TY\right) + \beta^T\left(\frac{1}{\sigma^2}X^TX + \frac{1}{\tau^2}I\right)\beta \end{aligned}$$

Hence,

$$\begin{aligned} \pi(\beta|X_1, \dots, X_n) &= K e^{\frac{1}{\sigma^2}\left(Y^TY - 2\beta^TX^TY\right) + \beta^T\left(\frac{1}{\sigma^2}X^TX + \frac{1}{\tau^2}I\right)\beta} = K_1 e^{\frac{-2}{\sigma^2}\beta^TX^TY + \beta^T\left(\frac{1}{\sigma^2}X^TX + \frac{1}{\tau^2}I\right)\beta} \\ &= K_1 e^{\beta^T\left(\frac{1}{\sigma^2}X^TX + \frac{1}{\tau^2}I\right)\beta - \frac{2}{\sigma^2}\beta^TX^TY} \end{aligned}$$

Let  $\Sigma^{-1} = \frac{1}{\sigma^2}X^TX + \frac{1}{\tau^2}I$  and  $\mu = (X^TX + \frac{\sigma^2}{\tau^2}I)^{-1}X^TY$ . We can see that  $\frac{1}{\sigma^2}X^TY = \Sigma^{-1}\mu$ . Therefore, we can rewrite

$$\pi(\beta|X_1, \dots, X_n) = K_1 e^{\beta^T \Sigma^{-1} \beta - 2\beta^T \Sigma^{-1} \mu} = K_1 e^{\beta^T \Sigma^{-1} \beta - 2\beta^T \Sigma^{-1} \mu + \mu^T \Sigma^{-1} \mu - \mu^T \Sigma^{-1} \mu}$$

We see that  $\mu^T \Sigma^{-1} \mu$  depends on  $X$  and  $Y$  which are constants, hence we can get rid this constant by rewrite:

$$\pi(\beta|X_1, \dots, X_n) = K_2 e^{\beta^T \Sigma^{-1} \beta - 2\beta^T \Sigma^{-1} \mu + \mu^T \Sigma^{-1} \mu} = K_2 e^{(\beta - \mu)^T \Sigma^{-1} (\beta - \mu)}$$

c)) The posterior mean of  $\beta$  is the expectation of  $g(\beta)$  which is  $\mu = (X^TX + \frac{\sigma^2}{\tau^2}I)^{-1}X^TY$

**Problem 3.**