# Stat511(Section001): Homework #3

Due on Feb. 2, 2021 at  $5:00 \mathrm{pm}$ 

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#### Problem 1

For every  $i, X_i$  is a Bernoulli distribution, and we can rewrite the pmf of  $X_i$  in one line;

$$P(X_i = x) = \left(\frac{e^{\theta - a_i}}{1 + e^{\theta - a_i}}\right)^x \left(\frac{1}{1 + e^{\theta - a_i}}\right)^{1 - x} = exp[xlog(e^{\theta - a_i}) - log(1 + e^{\theta - a_i})] = \frac{exp(x(\theta - a_i))}{1 + e^{\theta - a_i}}$$

Hence we can get:

$$f(X) = \frac{exp(\theta \sum_{i=1}^{n} x_i - \sum_{i=1}^{n} a_i x_i)}{\prod_{i=1}^{n} (1 + e^{\theta - a_i})} = \frac{exp(\theta \sum_{i=1}^{n} x_i)}{\prod_{i=1}^{n} (1 + e^{\theta - a_i})} exp(-\sum_{i=1}^{n} a_i x_i) = g_{\theta}(T)h(x)$$

Hence the one-dim sufficient statistics for  $\theta$  is  $\sum_{i=1}^{n} x_i$ 

### Problem 2

(i)

we can get:

$$f(x) = \frac{\beta^{n\alpha}}{\Gamma(\alpha)^n} (\prod_{i=1}^n x_i)^{\alpha - 1} e^{-\beta(\sum_{i=1}^n x_i)}$$

Hence, we can get:

$$T(x) = (\prod_{i=1}^{n} x_i, \sum_{i=1}^{n} x_i)$$

is a two dimension sufficient statistic for  $(\alpha, \beta)$ .

(ii)

when we know the  $\alpha$ . Then  $(\prod_{i=1}^n x_i)^{\alpha-1}$  is no longer one part of  $g_{\theta}(T(x))$  and become one part of h(x). And thus  $g_{\theta}(T(x)) = \beta^{n\alpha} e^{-\beta(\sum_{i=1}^n x_i)}, h(x) = \frac{1}{\Gamma(\alpha)^n} (\prod_{i=1}^n x_i)^{\alpha-1}$ . Thus we can get:

$$T(x) = \sum_{i=1}^{n} x_i$$

is one-dim sufficient statistic for  $\beta$ .

#### Problem 3

(a)

we can know:

$$f(x) = (\frac{1}{\theta})^n \prod_{i=1}^n I(x_i > \theta) \prod_{i=1}^n I(x_i < 2\theta)$$

Also we get  $\prod_{i=1}^{n} I(x_i > \theta)$  is equivalence to  $I(x_{(1)} > \theta)$  and  $\prod_{i=1}^{n} I(x_i < 2\theta)$  is equivalence to  $I(x_{(n)} < 2\theta)$ . Thus, we can get;

$$f_{\theta}(x) = (\frac{1}{\theta})^n I(x_{(1)} > \theta) I(x_{(n)} < 2\theta)$$

Where we can see f(x) is  $g_{\theta}(T(x))$  and h(x) = 1. Thus:

$$T(x) = (x_{(1)}, x_{(n)})$$

is sufficient for  $\theta$ . Now we prove it is minimal. We can find:

$$x_{(1)} = \sup\{\theta : f_{\theta}(x) > 0\}, x_{(n)} = 2\inf\{\theta : f_{\theta}(x) > 0\}$$

Thus, if S(x) is a sufficient statistics for  $\theta$ , we can get there exists functions h and  $g_{\theta}$  so that  $f_{\theta}(x) = g_{\theta}(S(x))h(x)$ . And since h(x) > 0, we have:

$$x_{(1)} = \sup\{\theta : f_{\theta}(S(x)) > 0\}, x_{(n)} = 2\inf\{\theta : f_{\theta}(S(x)) > 0\}$$

Therefore, there is a function  $\Phi$  such that  $T(x) = \Phi(S(x))$  for every S(x). Hence, we conclude that T(x) is minimal sufficient statistics.

(b)

We know if sample mean and sample variance are the sufficient statistics for  $\theta$ , then by factorization theorem(Assumed  $S(x) = \bar{X}, S^2$ ):

$$f_{\theta}(x) = (\frac{1}{\theta})^n I(x_{(1)} > \theta) I(x_{(n)} < 2\theta) = g_{\theta}(S(x)) h(x)$$

Hence  $g_{\theta}(S(x))$  must contain  $(\frac{1}{\theta})^n I(x_{(1)} > \theta) I(x_{(n)} < 2\theta)$ . Therefore,  $g_{\theta}(S(x))$  must contain  $x_{(1)}$  and  $x_{(n)}$ , which is contradicted with the fact that  $g_{\theta}(S(x))$  is the function of only sample mean and sample variance. Thus we prove sample mean and sample variance are not sufficient for  $\theta$ .

## Problem 4

(a)

We have:

$$f_{\theta}(x) = \frac{n!}{x_1! x_2! x_3! x_4!} p_1^{x_1} p_2^{x_2} p_3^{x_3} p_4^{x_4} = h(x) exp[x_1 log(p_1) + x_2 log(p_2) + x_3 log(p_3) + x_4 log(p_4)]$$

We place  $x_4$  by  $n - x_1 - x_2 - x_3$ . And we can get:

$$\begin{split} f_{\theta}(x) &= h(x) exp[x_1 log(p_1) + x_2 log(p_2) + x_3 log(p_3) + (n - x_1 - x_2 - x_3) log(p_4)] \\ &= h(x) exp(n log(p_4)) exp[x_1 log(\frac{p_1}{p_4}) + x_2 log(\frac{p_2}{p_4}) + x_3 log(\frac{p_3}{p_4})] \\ &= h(x) a(\theta) exp[x_1 log(\frac{2 + \theta}{\theta}) + x_2 log(\frac{1 - \theta}{\theta}) + x_3 log(\frac{1 - \theta}{\theta})] \\ &= h(x) a(\theta) exp[x_1 log(\frac{2 + \theta}{\theta}) + (x_2 + x_3) log(\frac{1 - \theta}{\theta})] \end{split}$$

And thus this is an exponential family with  $b(\theta) = (log(\frac{2+\theta}{\theta}), log(\frac{1-\theta}{\theta})), T(x) = (x_1, x_2 + x_3)$ . Now we prove T(x) is minimal sufficient for  $\theta$ . For two sample point x and y. We have:

$$\frac{f(x|\theta)}{f(y|\theta)} = \frac{y_1!y_2!y_3!y_4!}{x_1!x_2!x_3!x_4!} exp(((x_1 - y_1)log(\frac{2 + \theta}{\theta}) + (x_2 + x_3 - y_2 - y_3)log(\frac{1 - \theta}{\theta}))$$

if  $\frac{f(x|\theta)}{f(y|\theta)}$  is constant if and only if  $x_1 = y_1, x_2 + x_3 = y_2 + y_3$  since we see that  $\frac{y_2!y_3!}{x_2!x_3!}$  is the constant when we think it is a function of  $\theta$ . Hence, we get the minimal sufficient statistics is  $(x_1, x_2 + x_3)$ .

(b)

It is. We see the two term in  $b(\theta)$ . Assumed  $log(\frac{2+\theta}{\theta}) = t$ , Then we have:

$$log(\frac{2+\theta}{\theta}) = t \Rightarrow \frac{\theta+2}{\theta} = e^t \Rightarrow \frac{2-2\theta}{\theta} = e^t - 3 \Rightarrow log(\frac{1-\theta}{\theta}) = log(\frac{e^t - 3}{2})$$

which is one to one relationship. One term is the function of another. Hence it will be a curved exponential family.