

## 2.4 TA Session (2019.01.11)

### 2.4.1 Sufficient Statistics

**Example 2.6.** (Sufficient statistics for normal distribution) We have a density  $f_X(x)$  such that we can factorize it into

$$f_X(x) = \exp(g(\theta)K(x) + s(\theta) + h(x))$$

then  $K(x)$  is your sufficient statistic. Once you pin down the value of  $K(x)$  then you don't have to care about the part where  $\theta$  and  $x$  interact. For example, the sufficient statistics for

$$x_1, \dots, x_N \sim N(\mu, \sigma^2)$$

$$f_X(x_1, \dots, x_N) = (2\pi\sigma^2)^{-n/2} \exp\left(-\sum_{i=1}^n \frac{(x_i - \mu)^2}{\sigma^2}\right) = (2\pi\sigma^2) \exp\left(-\sum_{i=1}^n \frac{x_i^2}{\sigma^2} + 2\sum_{i=1}^n \frac{\mu x_i}{\sigma^2} - \frac{n\mu^2}{\sigma^2}\right)$$

is  $T(X) = (\sum X_i, \sum X_i^2)$ .

To see this, note that

$$f_{X|T}(x|t) = \frac{f_{X,T}(x, t)}{f_T(t)} = \frac{f_X(x) \cdot 1\{t, x \text{ are compatible}\}}{f_T(t)}$$

**Example 2.7.** (Sufficient statistics for Poisson) Given  $x_1, \dots, x_N \sim \text{Poisson}(\lambda)$ , we have

$$f_X(x) = \prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} = e^{-n\lambda} \lambda^{\sum x_i} \prod_{i=1}^n \frac{1}{x_i!}$$

In this case,  $\sum x_i$  is the sufficient statistic. To see this more explicitly,

$$f_{X,T}(x, t) = f_X(x) \cdot 1\{t, x \text{ are compatible}\}$$

Furthermore,  $T = \sum x_i \sim \text{Poisson}(n\lambda)$  so the marginal density should be

$$f_T(t) = e^{-n\lambda} (n\lambda)^t \frac{1}{t!}$$

and the conditional density is then obtained as

$$f_{X|T}(x|t) = \frac{f_{X,T}(x, t)}{f_T(t)} = \frac{1}{n^t t!} \prod_{i=1}^n \frac{1}{x_i!}$$

which is *Multinomial*  $(\frac{1}{n}, \dots, \frac{1}{n}, N)$

### 2.4.2 Conjugate Prior

**Example 2.8.** Prior  $\theta \sim \text{Beta}(\alpha, \beta)$  and conditional  $x|\theta \sim \text{Binomial}(p, \theta)$  yields posterior

$$\theta|x \sim \text{Beta}(\alpha + x, \beta + n - x)$$

where the density of a Beta distribution is given as

$$\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha-1} (1 - \theta)^{\beta-1} 1\{0 \leq \theta \leq 1\}$$

and the density of a Binomial distribution is given as

$$\frac{n!}{x!(n-x)!} \theta^x (1-\theta)^{n-x} \mathbf{1}_{\{x=0,1,\dots,n\}}$$

Then

$$f_{\Theta|X}(\theta|x) = \frac{f_{X|\Theta}(x|\theta)f_{\Theta}(\theta)}{f_X(x)}$$

Note that  $P(x=1) = P(x=0) = 1/2$ , so we have

$$f(\theta|x) = 2\theta^x(1-\theta)^{1-x} \mathbf{1}_{\{0 \leq \theta \leq 1\}} \sim \text{Beta}(1+x, 2-x)$$