

### 3.4 Exponential families.

Assume  $X \sim N(\mu, \sigma^2)$

$$\Rightarrow f(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad -\infty < x < \infty, -\infty < \mu < \infty, \sigma > 0$$

$$= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sigma} e^{-\frac{\mu^2}{2\sigma^2}} \cdot e^{-\frac{x^2}{2\sigma^2} + \frac{2x\mu}{2\sigma^2}}$$

Define  $h(x) = \frac{1}{\sqrt{2\pi}}$ ,  $c(\mu, \sigma^2) = \frac{1}{\sigma} e^{-\frac{\mu^2}{2\sigma^2}}$ ,  $w_1(\mu, \sigma^2) = \frac{-1}{2\sigma^2}$ ,  $t_1(x) = x^2$

$$w_2(\mu, \sigma^2) = \frac{\mu}{\sigma^2}, \quad t_2(x) = x$$

$$\Rightarrow f(x|\mu, \sigma^2) = h(x) \cdot c(\mu, \sigma^2) e^{\sum_{i=1}^2 w_i(\mu, \sigma^2) t_i(x)}$$

A family of pdfs or pmfs is called an exponential family if it can be expressed as:

$$f(x|\underline{\theta}) = h(x) c(\underline{\theta}) e^{\sum_{i=1}^k w_i(\underline{\theta}) t_i(x)}$$

where  $h(x) \geq 0$ ,  $t_1(x), \dots, t_k(x)$  are real valued functions of  $x$  that cannot depend on  $\theta$ .

$c(\underline{\theta}) \geq 0$  and  $w_1(\underline{\theta}), \dots, w_k(\underline{\theta})$  are real valued functions of  $\underline{\theta}$  that cannot depend on  $x$ .

#### Binomial distribution

$$f(x|p) = \binom{m}{x} p^x (1-p)^{m-x}, \quad x=0, 1, 2, \dots, m$$

$$f(x|p) = \binom{m}{x} \left(\frac{p}{1-p}\right)^x (1-p)^m = \binom{m}{x} (1-p)^m e^{x \log\left(\frac{p}{1-p}\right)}$$

$$h(x) = \begin{cases} \binom{m}{x}, & x=0, 1, 2, \dots, m \\ 0 & \text{otherwise} \end{cases}, \quad c(p) = (1-p)^m, \quad w(p) = \log\left(\frac{p}{1-p}\right), \quad t(x) = x.$$

## Uniform distribution

$$f(x|\theta) = \begin{cases} \frac{1}{\theta}, & 0 \leq x \leq \theta \\ 0 & \text{otherwise} \end{cases} = e^{-\log \theta} \mathbb{I}_{[0, \theta]}(x)$$

$\mathbb{I}_{[0, \theta]} = g(x, \theta) \Rightarrow f(x|\theta)$  is not a member of an exponential family, but.

Binomial, negative binomial, Poisson, normal, gamma and beta are.

## Some useful results.

Suppose  $f(x|\theta)$  is a pdf.

Then  $\int_{-\infty}^{\infty} f(x|\theta) dx = 1$  and  ~~$\int_{-\infty}^{\infty} f(x|\theta) dx = 1$~~   $\int_{-\infty}^{\infty} \frac{d}{d\theta} f(x|\theta) dx = 0$

$$\Rightarrow \int_{-\infty}^{\infty} \frac{\frac{d}{d\theta} f(x|\theta)}{f(x|\theta)} f(x|\theta) dx = 0 \Rightarrow \int_{-\infty}^{\infty} \frac{d}{d\theta} [\log f(x|\theta)] f(x|\theta) dx = 0$$

$$\Rightarrow E \left[ \frac{d}{d\theta} \log f(X|\theta) \right] = 0 \quad (1)$$

Score statistic.

Further

$$\int_{-\infty}^{\infty} \frac{d}{d\theta} \left[ \frac{d}{d\theta} \log f(x|\theta) f(x|\theta) \right] dx = 0$$

$$\Rightarrow \int_{-\infty}^{\infty} \frac{d^2}{d\theta^2} \log f(x|\theta) f(x|\theta) dx + \underbrace{\int_{-\infty}^{\infty} \frac{d}{d\theta} f(x|\theta) \frac{d}{d\theta} \log f(x|\theta) dx}_{=0} = 0$$
$$\frac{d}{d\theta} [\log f(x|\theta)] \cdot f(x|\theta)$$

$$\text{or } \int_{-\infty}^{\infty} \left( \frac{d}{d\theta} \log f(x|\theta) \right)^2 \cdot f(x|\theta) dx = - \int_{-\infty}^{\infty} \frac{d^2}{d\theta^2} \log f(x|\theta) \cdot f(x|\theta) dx$$

which gives:

$$\text{Var} \left[ \underbrace{\frac{d}{d\theta} \log f(X|\theta)} \right] = - E \left[ \frac{d^2}{d\theta^2} \log f(X|\theta) \right] \quad (2)$$

Score Statistic.

Now assume

$$f(x|\theta) = h(x) c(\theta) e^{\sum_{i=1}^k w_i(\theta) t_i(x)}$$

$$\text{Then } \log f(x|\theta) = \log h(x) + \log c(\theta) + \sum_{i=1}^k w_i(\theta) t_i(x) \quad (3)$$

$$\frac{\partial}{\partial \theta_j} \log f(x|\theta) = \frac{\partial}{\partial \theta_j} \log c(\theta) + \sum_{i=1}^k \frac{\partial}{\partial \theta_j} w_i(\theta) t_i(x)$$

$$\text{From (1): } 0 = E \left[ \frac{\partial}{\partial \theta_j} \log f(X|\theta) \right] = \frac{\partial}{\partial \theta_j} \log c(\theta) + E \left[ \sum_{i=1}^k \frac{\partial}{\partial \theta_j} w_i(\theta) t_i(X) \right]$$

$$\Rightarrow E \left[ \sum_{i=1}^k \frac{\partial}{\partial \theta_j} w_i(\theta) t_i(X) \right] = - \frac{\partial}{\partial \theta_j} \log c(\theta) \quad 3.4.4$$

$$\text{From (3): } \text{Var} \left[ \frac{\partial}{\partial \theta_j} \log f(X|\theta) \right] = \text{Var} \left[ \sum_{i=1}^k \frac{\partial}{\partial \theta_j} w_i(\theta) t_i(X) \right] \stackrel{(2)}{=} - E \left[ \frac{\partial^2}{\partial \theta_j^2} \log f(X|\theta) \right]$$

$$\frac{\partial^2}{\partial \theta_j^2} \log f(x|\theta) = \frac{\partial^2}{\partial \theta_j^2} \log c(\theta) + \sum_{i=1}^k \frac{\partial^2}{\partial \theta_j^2} w_i(\theta) t_i(x)$$

$$E \left[ \frac{\partial^2}{\partial \theta_j^2} \log f(X|\theta) \right] = \frac{\partial^2}{\partial \theta_j^2} \log c(\theta) + E \left[ \sum_{i=1}^k \frac{\partial^2}{\partial \theta_j^2} w_i(\theta) t_i(X) \right]$$

$$\text{Hence } \text{Var} \left[ \sum_{i=1}^k \frac{\partial}{\partial \theta_j} w_i(\theta) t_i(X) \right] = - \frac{\partial^2}{\partial \theta_j^2} \log c(\theta) - E \left[ \sum_{i=1}^k \frac{\partial^2}{\partial \theta_j^2} w_i(\theta) t_i(X) \right] \quad 3.4.5$$

Example Binomial distribution.

$$f(x|p) = \binom{n}{x} (1-p)^{n-x} p^x e^{x \log\left(\frac{p}{1-p}\right)}$$

$$c(p) = (1-p)^n, \quad w(p) = \log\left(\frac{p}{1-p}\right), \quad t(x) = x$$

$$w'(p) = \frac{1}{p(1-p)},$$

$$\log c(p) = n \log(1-p) \Rightarrow \frac{d}{dp} \log c(p) = -\frac{n}{1-p}$$

From 3.4.4

$$E\left[\frac{1}{p(1-p)} x\right] = \frac{n}{1-p} \Rightarrow E[x] = \frac{p(1-p) \cdot n}{1-p} = np.$$

$$\frac{d^2}{dp^2} \log c(p) = -\frac{n}{(1-p)^2}, \quad \frac{d^2}{dp^2} w(p) = -\frac{(1-2p)}{(p(1-p))^2}$$

$$\begin{aligned} \text{Var}\left[\frac{1}{p(1-p)} x\right] &= \frac{n}{(1-p)^2} + \frac{(1-2p)E[x]}{(p(1-p))^2} \Rightarrow \text{Var}[x] = np^2 + (1-2p)np \\ &= np - np^2 = np(1-p). \end{aligned}$$

Definition 3.4.7.

A curved exponential family is a family of densities of the form  $f(x|\underline{\theta}) = h(x) c(\underline{\theta}) e^{\sum_{i=1}^k w_i(\underline{\theta}) t_i(x)}$  for which the dimension of  $\underline{\theta}$  is equal to  $d \leq k$ .

Example:  $X \sim N(\mu, \sigma^2)$ .