

# 1 Exponential Family

Let

- $\mu$  be a measure on  $\mathbb{R}^n$ ,
- $h : \mathbb{R}^n \mapsto [0, \infty)$  be a non-negative function,
- $\eta_1, \dots, \eta_s$  be measurable functions from  $\mathbb{R}^p$  to  $\mathbb{R}$ ,
- $T_1, \dots, T_s$  be measurable functions from  $\mathbb{R}^n$  to  $\mathbb{R}$ ,
- let  $\theta \in \mathbb{R}^p$  be a  $p \times 1$  column vector.

**Definition 1** (Exponential family). Suppose that

$$K(\theta) \equiv \log \int \exp \left\{ \sum_{i=1}^s \eta_i(\theta) T_i(x) \right\} h(x) d\mu(x) < \infty.$$

The family of densities  $\{p(\cdot | \theta) : \theta \in \Theta\}$  is called an  $s$ -parameter (or  $s$ -dimensional [maybe better]) exponential family, where

$$p(x | \theta) = \exp \left\{ \sum_{i=1}^s \eta_i(\theta) T_i(x) - K(\theta) \right\} h(x).$$

We can also do a reparametrization and define  $\eta = \eta(\theta) \in \mathbb{R}^s$ .

**Definition 2** (Exponential family in Canonical Form). Suppose that

$$A(\eta) \equiv \log \int \exp \left\{ \sum_{i=1}^s \eta_i T_i(x) \right\} h(x) d\mu(x) < \infty.$$

The family of densities  $\{p(\cdot | \eta) : \eta \in \mathcal{N}\}$  is called an  $s$ -dimensional exponential family in canonical form, where

$$p(x | \eta) = \exp \left\{ \sum_{i=1}^s \eta_i T_i(x) - A(\eta) \right\} h(x),$$

$\eta$  is called a natural parameter, and  $\mathcal{N}$  is called the natural parameter space.

**Example 1** (Examples of Exponential Family).

1. Gaussian  $N(\mu, \sigma^2)$  with  $\theta = (\mu, \sigma^2)$ ,  $\mu \in \mathbb{R}$ ,  $\sigma^2 \in (0, \infty)$ :

$$p(x | \theta) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{(x - \mu)^2}{2\sigma^2} \right\} = \exp \left\{ \frac{\mu}{\sigma^2} x - \frac{1}{2\sigma^2} x^2 - \frac{1}{2} \log(2\pi\sigma^2) - \frac{\mu^2}{2\sigma^2} \right\},$$

where  $T_1 = x$ ,  $\eta_1(\theta) = \frac{\mu}{\sigma^2}$ ,  $T_2 = x^2$ ,  $\eta_2(\theta) = -\frac{1}{2\sigma^2}$ ,  $K(\theta) = \frac{1}{2} \log(2\pi\sigma^2) + \frac{\mu^2}{2\sigma^2}$ , and  $h(x) = 1$ .

2. Bernoulli( $\theta$ ) with  $\theta \in (0, 1)$ :

$$P(X = x | \theta) = \theta^x (1 - \theta)^{1-x} = \exp \{x \log \theta + (1 - x) \log(1 - \theta)\},$$

where  $T_1 = x$ ,  $\eta_1(\theta) = \log \theta$ ,  $T_2 = 1 - x$ ,  $\eta_2(\theta) = \log(1 - \theta)$ ,  $K(\theta) = 1$ , and  $h(x) = 1$ .

3. If  $X_1, \dots, X_n$  are iid  $N(\mu, \sigma^2)$ , their joint density is

$$p(x_1, \dots, x_n | \theta) = \exp \left\{ \frac{\mu}{\sigma^2} \sum_{i=1}^n x_i - \frac{1}{2\sigma^2} \sum_{i=1}^n x_i^2 - \frac{n}{2} \log(2\pi\sigma^2) - \frac{n\mu^2}{2\sigma^2} \right\},$$

where  $T_1 = \sum_{i=1}^n x_i$ ,  $\eta_1(\theta) = \frac{\mu}{\sigma^2}$ ,  $T_2 = \sum_{i=1}^n x_i^2$ ,  $\eta_2(\theta) = -\frac{1}{2\sigma^2}$ ,  $K(\theta) = \frac{1}{2} \log(2\pi\sigma^2) + \frac{\mu^2}{2\sigma^2}$ , and  $h(x) = 1$ .

Several important properties of exponential family is in the following theorem.

**Theorem 1.** Consider a  $k$ -parameter exponential family with natural parameter  $\eta$ . Let  $\mathcal{Z}$  be an open subset of the natural parameter space and the function  $\phi(x)$  to be integrable, i.e.,

$$\int |\phi(x)| p(x | \eta) d\mu(x) < \infty,$$

for all  $\eta \in \mathcal{Z}$ . Then

$$\frac{\partial \int \phi(x) p(x | \eta) d\mu(x)}{\partial \eta} = \int \frac{\partial \phi(x) p(x | \eta)}{\partial \eta} d\mu(x),$$

that is, the derivative can be computed under integration sign.

An importance application of the theorem is to compute the moments of  $T(x)$ .

1. Let  $\phi(x) \equiv 1$ , we get

$$E[T_i(x) | \eta] = \frac{\partial A(\eta)}{\partial \eta_i}.$$

2. If we take one more derivative, we get

$$\begin{aligned} \text{cov}[T_i(X), T_j(X) | \eta] &= \frac{\partial^2 A(\eta)}{\partial \eta_i \partial \eta_j}, \\ \text{var}[T_i(X) | \eta] &= \frac{\partial^2 A(\eta)}{\partial \eta_i^2}. \end{aligned}$$

**Example 2** (Examples of Moments of Exponential Family).

We reparametrize Bernoulli( $\theta$ ) with  $\theta \in (0, 1)$  to  $\eta = \log \frac{\theta}{1-\theta} \in \mathbb{R}$ , such that

$$P(X = x | \eta) = \exp \{x\eta - \log(1 + e^\eta)\}.$$

where  $T(x) = x$ , and  $A(\eta) = \log(1 + e^\eta)$ . Hence,

$$\begin{aligned} E[X | \eta] &= \frac{\partial \log(1 + e^\eta)}{\partial \eta} = \frac{e^\eta}{1 + e^\eta} = \theta, \\ \text{Var}[X | \eta] &= \frac{\partial^2 \log(1 + e^\eta)}{\partial \eta^2} = \frac{e^\eta}{(1 + e^\eta)^2} = \theta(1 - \theta). \end{aligned}$$

If we want the derivative with respect to  $\theta$ , we can apply the chain rule to the natural parameter.

**Theorem 2** (Convex set). The natural parameter space  $\mathcal{N}$  is a convex set.

**Example 3** (Uniqueness in  $T$  and  $s$ ). We need to note that the functions  $\{T\}$  and  $\{\eta\}$  are not unique. The number  $s$  is not unique either. Bernoulli( $\theta$ ) with  $\theta \in (0, 1)$ :

$$P(X = x | \theta) = \theta^x (1 - \theta)^{1-x} = \exp \{x \log \theta + (1 - x) \log (1 - \theta)\},$$

where  $T_1 = x$ ,  $\eta_1(\theta) = \log \theta$ ,  $T_2 = 1 - x$ ,  $\eta_2(\theta) = \log (1 - \theta)$ ,  $K(\theta) = 1$ , and  $h(x) = 1$ , that is 2-dimensional exponential family. But  $x$  and  $1 - x$  are not linearly independent.

1. We can write  $P(X = x)$  as

$$P(X = x | \theta) = \exp \left\{ x \log \frac{\theta}{1-\theta} + \log(1-\theta) \right\},$$

where  $T(x) = x$ ,  $\eta(\theta) = \log \frac{\theta}{1-\theta}$ ,  $K(\theta) = -\log(1-\theta)$ , and  $h(x) = 1$ . That is, 1-dimensional Exponential family, but not in canonical form.

2. If we reparametrize  $\eta = \log \frac{\theta}{1-\theta} \in \mathbb{R}$ , then

$$P(X = x | \eta) = \exp \{x\eta - \log(1 + e^\eta)\}$$

where  $T(x) = x$ , and  $A(\eta) = \log(1 + e^\eta)$ . That is, 1-dimensional Exponential family, in canonical form.

**Definition 3** (Minimal or strictly  $s$ -dimensional exponential family). If  $s$  in  $\sum_{i=1}^s \eta_i(\theta) T_i(x)$  cannot be reduced, then we say the exponential family is minimal or it is a strictly  $s$ -dimensional exponential family.

Minimal exponential family essentially means that the functions  $1, \eta_1, \dots, \eta_s$  are linearly independent and the statistics  $T_1, \dots, T_s$  are affine independent (i.e., a positive definite covariance matrix), i.e.,

$$\begin{aligned} \sum_{i=1}^s \lambda_i \eta_i(\theta) = \lambda_0 &\Rightarrow \lambda_i = 0, \forall i, \\ \sum_{i=1}^s \lambda_i T_i(x) = \lambda_0 &\Rightarrow \lambda_i = 0, \forall i. \end{aligned}$$

There is no special reason to keep the exponential family non-minimal.

**Definition 4** (Full rank and curved exponential family). Consider a strictly  $s$ -dimensional exponential family in canonical form

$$p(x | \eta) = \exp \left\{ \sum_{i=1}^s \eta_i T_i(x) - A(\eta) \right\} h(x),$$

where  $\eta \in \Delta$  is the natural parameter and  $\Delta$  is the natural parameter space. If  $\Delta$  contains an  $s$ -dimensional open set, then the family is said to be [full rank](#). Otherwise, it is a curved exponential family.

Curved exponential family typically means the exponential family is minimal and  $\{\eta_i\}$  are affine independent, but they are related in a nonlinear way. That is, we cannot reduce  $s$ , but the dimension of  $\theta$  is lower than  $s$ .

**Example 4** (Examples of Curved Exponential Family).

Gaussian  $N(\theta, \theta^2)$  with  $\theta > 0$ :

$$p(x | \theta) = \frac{1}{\sqrt{2\pi\theta^2}} \exp \left\{ -\frac{(x-\theta)^2}{2\theta^2} \right\} = \exp \left\{ \frac{1}{\theta}x - \frac{1}{2\theta^2}x^2 - \frac{1}{2} \log(2\pi\theta^2) - \frac{1}{2} \right\},$$

where  $T_1 = x$ ,  $\eta_1(\theta) = \frac{1}{\theta}$ ,  $T_2 = x^2$ ,  $\eta_2(\theta) = -\frac{1}{2\theta^2}$ ,  $K(\theta) = \frac{1}{2} \log(2\pi\theta^2) + \frac{1}{2}$ , and  $h(x) = 1$ . We only have one parameter  $\theta$ , but we need  $s = 2$  [cannot be reduced further].