



# Conjugate Prior Distribution I

- Let  $\mathcal{F}$  be a class of sampling distribution  $p(y|\theta)$ ,  $\mathcal{P}$  be a class of prior distribution  $p(\theta)$ .

- The class  $\mathcal{P}$  is conjugate for  $\mathcal{F}$  if

$$p(\theta|y) \in \mathcal{P}$$

for all  $p(\cdot|\theta) \in \mathcal{F}$  and  $p(\cdot) \in \mathcal{P}$ .

# Conjugate Prior Distribution II

## ■ Exponential family and sufficient statistics

### 1 Exponential family

$$p(y_i|\theta) = f(y_i)g(\theta) \exp\left(\phi(\theta)^T u(y_i)\right).$$

### 2 For i.i.d. $y_1, \dots, y_n$ , the density is

$$\left(\prod_{i=1}^n f(y_i)\right) g(\theta)^n \exp\left(\phi(\theta)^T \sum_{i=1}^n u(y_i)\right).$$

# Conjugate Prior Distribution III

3 If  $p(\theta) \propto g(\theta)^\eta \exp(\phi(\theta)^T \nu)$ , then

$$p(\theta|y) \propto g(\theta)^{n+\eta} \exp(\phi(\theta)^T (\nu + t(y))),$$

where  $t(y) = \sum_{i=1}^n u(y_i)$ .

# Negative Binomial Distribution I

■ If  $p(y|\theta) = \exp(-\theta) \theta^y / y!$  and  $\theta \sim \text{Gamma}(\alpha, \beta)$ , then

$$\begin{aligned}
 p(y) &= \frac{p(y|\theta)p(\theta)}{p(\theta|y)} \\
 &= \frac{\theta^y \exp(-\theta) \theta^{\alpha-1} \exp(-\beta\theta) \beta^\alpha \Gamma(\alpha+y)}{y! \theta^{\alpha+y-1} \exp(-(1+\beta)\theta) (1+\beta)^{\alpha+y} \Gamma(\alpha)} \\
 &= \frac{\Gamma(\alpha+y) \beta^\alpha}{\Gamma(\alpha) y! (1+\beta)^{\alpha+y}} = \binom{\alpha+y-1}{y} \left( \frac{\beta}{\beta+1} \right)^\alpha \left( \frac{1}{\beta+1} \right)^y.
 \end{aligned}$$

# Negative Binomial Distribution II

- Thus, we have

$$\text{Neg-bin}(y|\alpha, \beta) = \int \text{Poisson}(y|\theta) \text{Gamma}(\theta|\alpha, \beta) d\theta.$$

- Usually, this is related to over-dispersion model, it means that the variance is larger than mean. In Poisson model, mean and variance are equal.

# Asymptotic property of the posterior I

- In limit probability theory can be put in a Bayesian context to show:

$$\left( \frac{\theta - E[\theta|y]}{\sqrt{\text{Var}(\theta|y)}} \middle| y \right) \rightarrow N(0, 1),$$

where  $\theta \in \mathbb{R}$ .

$$\left( \text{Cov}(\theta|y)^{-1/2} (\theta - E[\theta|y]) \middle| y \right) \rightarrow N(0, I_p),$$

where  $\theta \in \mathbb{R}^p$ .

# Example of Data Analysis I

- Cancer of kidney/ureter in U. S. at 1980-1989.
  - 1 Data are gathered in each county.
  - 2 Population is varying through the counties.



## Example of Data Analysis II

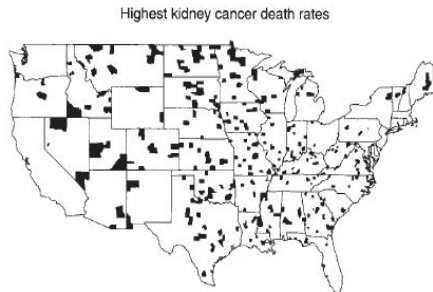


Figure 2.7 The counties of the United States with the highest 10% age-standardized death rates for cancer of kidney/ureter for U.S. white males, 1980–1989. Why are most of the shaded counties in the middle of the country? See Section 2.8 for discussion.

## Example of Data Analysis III

Lowest kidney cancer death rates

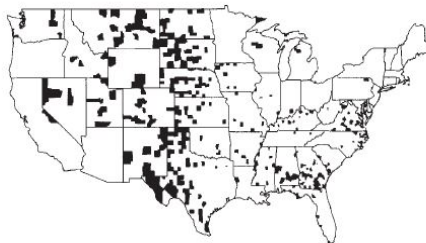


Figure 2.8 *The counties of the United States with the lowest 10% age-standardized death rates for cancer of kidney/ureter for U.S. white males, 1980–1989. Surprisingly, the pattern is somewhat similar to the map of the highest rates, shown in Figure 2.7.*

## Example of Data Analysis IV

- This data implies that variations are different along with the populations of the counties.
- Counties in the Great Plains in the middle of the country appear in the lowest 10% and highest 10% simultaneously.

# Example of Data Analysis V

- Thus we consider the model of

$$y_j \sim \text{Pois}(10n_j\theta_j),$$

where  $n_j$  is the population of the county, and prior of

$$\theta_j \sim \text{Gamma}(20, 430000).$$

## Example of Data Analysis VI

- Then  $\theta_j|y_j \sim \text{Gamma}(20 + y_j, 430000 + 10n_j)$ , it implies

$$E(\theta_j|y_j) = \frac{20 + y_j}{43000 + 10n_j},$$

$$\text{Var}(\theta_j|y_j) = \frac{20 + y_j}{(43000 + 10n_j)^2}.$$

- Small  $n_j$  results the relatively large weight of the prior in the posterior mean.

## Example of Data Analysis VII

- (Prior) predictive distribution gives that

$$y_j \sim \text{Neg-bin}\left(20, 430000/(10n_j)\right),$$

and variance of  $y_j/(10n_j)$  is larger when  $n_j$  is small, note that

$$\begin{aligned} E[y_j] &= 10n_j \frac{\alpha}{\beta}, \\ \text{Var}(y_j) &= 10n_j \frac{\alpha}{\beta} + (10n_j)^2 \frac{\alpha}{\beta^2}. \end{aligned}$$

# Example of Data Analysis VIII

- How to choose  $\alpha = 20$  and  $\beta = 430000$ ? Data driven.
- In some case, we consider the parameter should be estimated, empirical Bayes approach (not full Bayesian).

## Example of Data Analysis IX

- We have

$$y_j \sim \text{Neg-bin}(\alpha, \beta/(10n_j)),$$

and

$$E[y_j] = 10n_j \frac{\alpha}{\beta},$$

$$\text{Var}(y_j) = 10n_j \frac{\alpha}{\beta} + (10n_j)^2 \frac{\alpha}{\beta^2}.$$

- Using such as the moment method based on data.