

# First Bayes #1

1. a)

$$f_{Y|\theta}(y_i|\theta) = \theta e^{-\theta y_i}$$

Derive maximum likelihood estimate

$$\begin{aligned} l(\theta; y) &= \log(f(y; \theta)) = \log(\theta^n e^{-\theta \sum_{i=1}^n y_i}) \\ &= n \log(\theta) - \theta \sum_{i=1}^n y_i \end{aligned}$$

$$l'(\theta; y) = n \log \theta - \theta \sum_{i=1}^n y_i \quad d\theta$$

Set derivative to zero

$$\begin{aligned} \frac{n}{\theta} &= \sum_{i=1}^n y_i \\ \theta &= \frac{n}{\sum y_i} \end{aligned}$$

For MLE we get  $\frac{1}{\bar{y}}$

b)

$$\begin{aligned} f_{\theta|Y}(y|\theta) &\propto f_{\theta}(\theta) f_{Y|\theta}(y|\theta) \\ &= \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta} \theta^n e^{-\theta \sum y_i} \\ &= \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha+n-1} e^{-\beta\theta - \theta \sum y_i} \\ &\propto \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha+n-1} e^{-\theta(\beta + \sum y_i)} \\ &= \theta^{\alpha+n-1} e^{-\theta(\beta + \sum y_i)} \end{aligned}$$

We can see that this is a gamma distribution

$$= \text{Gamma}(\alpha+n, \beta + \sum y_i)$$

2 a) We need to derive the posterior predictive distribution, that is

$$\begin{aligned} f_{\tilde{Y}|Y}(\tilde{y}|y) &= \int_0^\infty f_{\tilde{Y}|\theta}(\tilde{y}|\theta) f_{\theta|Y}(\theta|y) d\theta \\ &= \int_0^\infty \theta e^{-\theta \tilde{y}} \frac{(\beta + \sum y_i)^{\alpha+n}}{\Gamma(\alpha+n)} \theta^{\alpha+n-1} e^{-(\beta + \sum y_i)\theta} d\theta \\ &= \frac{(\beta + \sum y_i)^{\alpha+n}}{\Gamma(\alpha+n)} \int_0^\infty \theta^{\alpha+n} e^{-\theta(\beta + \sum y_i + \tilde{y})} d\theta \\ &= \frac{(\beta + \sum y_i)^{\alpha+n}}{\Gamma(\alpha+n)} \frac{\Gamma(\alpha+n+1)}{(\beta + \sum y_i + \tilde{y})^{\alpha+n+1}} \underbrace{\int_0^\infty \frac{(\beta + \sum y_i + \tilde{y})^{\alpha+n+1}}{\Gamma(\alpha+n+1)} \theta^{\alpha+n} e^{-\theta(\beta + \sum y_i + \tilde{y})} d\theta}_{\text{gamma density} = 1} \\ &= \frac{(\beta + \sum y_i)^{\alpha+n}}{\Gamma(\alpha+n)} \frac{\Gamma(\alpha+n+1)}{(\beta + \sum y_i + \tilde{y})^{\alpha+n+1}} \\ &= \frac{(\beta + \sum y_i)^{\alpha+n} (\alpha+n)}{(\beta + \sum y_i + \tilde{y})^{\alpha+n+1}} \end{aligned}$$

Now substitute  $\alpha := \alpha + n$   $\lambda := \beta + \sum_{i=1}^n y_i$

$$= \frac{\alpha \lambda^\alpha}{(\lambda + \tilde{y})^{\alpha+1}}$$

$$\text{Thus } f(x) = \frac{\alpha \lambda^\alpha}{(\lambda + x)^{\alpha+1}}$$

3.  $Y = (Y_1, \dots, Y_d)$

$\theta = (\theta_1, \dots, \theta_d)$

$Y|\theta \sim \text{Multin}(n, \theta)$

$$\begin{aligned} f_{\theta|Y}(\theta|y) &\propto f_{Y|\theta}(y|\theta) f_{\theta}(\theta) \\ &= \binom{n}{y_1, \dots, y_d} \prod_{i=1}^d \theta_i^{y_i} \frac{\Gamma(\alpha_1, \dots, \alpha_d)}{\Gamma(\alpha_1) \dots \Gamma(\alpha_d)} \prod_{i=1}^d \theta_i^{\alpha_i-1} \\ &\propto \prod_{i=1}^d \theta_i^{y_i} \prod_{i=1}^d \theta_i^{\alpha_i-1} \\ &= \prod_{i=1}^d \theta_i^{y_i + \alpha_i - 1} \end{aligned}$$

So the posterior is a Dirichlet distribution

$$\alpha = (\alpha_1 + y_1, \dots, \alpha_d + y_d)$$

Dir( $\alpha$ )