

$$\textcircled{1} \quad p(\theta|y, \sigma^2) \propto p(y|\theta, \sigma^2) p(\theta|\sigma^2)$$

$$= \exp\left(-\frac{1}{2\sigma^2}(x\theta - y)^T(x\theta - y)\right) \exp\left(-\frac{1}{2}(m_0 - \theta)^T S_0^{-1}(m_0 - \theta)\right)$$

$\uparrow$  we expect  $\theta|y, \sigma^2$  to be normally distributed

$$\Rightarrow (\theta - \hat{\theta})^T k^{-1}(\theta - \hat{\theta}) = \frac{1}{\sigma^2}(x\theta - y)^T(x\theta - y) + (m_0 - \theta)^T S_0^{-1}(m_0 - \theta)$$

$$\theta^T k^{-1} \theta - 2\theta^T k^{-1} \hat{\theta} + \hat{\theta}^T k^{-1} \hat{\theta} = \theta^T \left( \frac{x^T x}{\sigma^2} \right) \theta - 2\theta^T \left( \frac{x^T y}{\sigma^2} \right) + \frac{y^T y}{\sigma^2} + m_0^T S_0^{-1} m_0 - 2\theta^T S_0^{-1} m_0 + \theta^T S_0^{-1} \theta$$

Rearranging and dropping irrelevant constants:

$$\theta^T k^{-1} \theta - 2\theta^T k^{-1} \hat{\theta} = \theta^T \left( \frac{x^T x}{\sigma^2} + S_0^{-1} \right) \theta - 2\theta^T \left( \frac{x^T y}{\sigma^2} + S_0^{-1} m_0 \right)$$

Let  $k^{-1} = \frac{x^T x}{\sigma^2} + S_0^{-1}$ , Then,

$$-2\theta^T k^{-1} \hat{\theta} = -2\theta^T \left( \frac{x^T y}{\sigma^2} + S_0^{-1} m_0 \right)$$

$$\Rightarrow k^{-1} \hat{\theta} = \frac{x^T y}{\sigma^2} + S_0^{-1} m_0$$

$$\Rightarrow \hat{\theta} = k \left( \frac{x^T y}{\sigma^2} + S_0^{-1} m_0 \right)$$

So,  $\theta|y, \sigma^2 \sim N(\hat{\theta}, K\sigma^2)$

where  $\hat{\theta} = k \left( \frac{x^T y}{\sigma^2} + S_0^{-1} m_0 \right)$

and  $K = \left( \frac{x^T x}{\sigma^2} + S_0^{-1} \right)^{-1}$

2) a)  $\left( Q \begin{pmatrix} a_1 & & 0 \\ & \ddots & \\ 0 & & a_n \end{pmatrix} Q^T \right)^{-1} = (Q^T)^{-1} \begin{pmatrix} a_1 & & 0 \\ & \ddots & \\ 0 & & a_n \end{pmatrix} Q^{-1}$   $\leftarrow Q \text{ is orthogonal}$

$$= Q \begin{pmatrix} a_1 & & 0 \\ & \ddots & \\ 0 & & a_n \end{pmatrix}^{-1} Q^T = Q \begin{pmatrix} \frac{1}{a_1} & & 0 \\ & \ddots & \\ 0 & & \frac{1}{a_n} \end{pmatrix} Q^T$$

diagonal matrix

b)  $\hat{y} = X \hat{\theta}^{LS} = X (X^T X)^{-1} X^T y = (U \Sigma V^T) ((U \Sigma V^T)^T (U \Sigma V^T))^{-1} (U \Sigma V^T)^T y$

$$= U \Sigma V^T (V \Sigma^T U^T U \Sigma V^T)^{-1} (V \Sigma^T U^T) y$$

$$= U \Sigma V^T (V \Sigma \Sigma^T V^T)^{-1} V \Sigma^T U^T y = U \Sigma V^T (V \Sigma^{-1} \Sigma^{-1} V^T)^{-1} V \Sigma U^T y$$

$$= U \Sigma V^T V \Sigma^{-1} \Sigma^{-1} V^T V \Sigma U^T y = U \Sigma \Sigma^{-1} \Sigma^{-1} \Sigma U^T y$$

$$= \underline{U U^T y}$$

c)  $\hat{y} = X \hat{\theta}^{RR} = X (X^T X + \lambda I)^{-1} X^T y = U \Sigma V^T ((U \Sigma V^T)^T (U \Sigma V^T) + \lambda I) (U \Sigma V^T)^T y$

$$= U \Sigma V^T (V \Sigma^T U^T U \Sigma V^T + \lambda I)^{-1} V \Sigma^T U^T y$$

$$= U \Sigma V^T (V \Sigma \Sigma^T V^T + \lambda I)^{-1} V \Sigma U^T y$$

$$= U \Sigma V^T (V (\Sigma \Sigma + \lambda I) V^T)^{-1} V \Sigma U^T y = U \Sigma V^T (V (\Sigma \Sigma + \lambda I)^{-1} V^T) V \Sigma U^T y$$

$$= U \Sigma (\Sigma \Sigma + \lambda I)^{-1} \Sigma U^T y = U \Sigma \begin{pmatrix} \sigma_1^2 + \lambda & & 0 \\ & \ddots & \\ 0 & & \sigma_m^2 + \lambda \end{pmatrix}^{-1} \Sigma U^T y$$

$$= U \Sigma \begin{pmatrix} \frac{1}{\sigma_1^2 + \lambda} & & 0 \\ & \ddots & \\ 0 & & \frac{1}{\sigma_m^2 + \lambda} \end{pmatrix} \Sigma U^T y = \underline{U \begin{pmatrix} \frac{\sigma_1^2}{\sigma_1^2 + \lambda} & & 0 \\ & \ddots & \\ 0 & & \frac{\sigma_m^2}{\sigma_m^2 + \lambda} \end{pmatrix} U^T y}$$