

Gaussian sampling model  $y \sim N(X\beta, \sigma^2 I)$   
and Gaussian prior  $\beta \sim N(0, \tau I)$

Posterior distribution is given as;

$$P(\theta | \text{Data}) = \frac{P(\text{Data} | \theta) P(\theta)}{P(\text{Data})}$$

Taking log of above

$$\log P(\theta | \text{Data}) = \log P(\text{Data} | \theta) + \log P(\theta) - \log P(\text{Data}) \quad \text{--- (1)}$$

$$\begin{aligned} \log P(\text{Data} | \theta) &= P(Y=y_1, X=x_1) P(Y=y_2, X=x_2) \dots \\ &= \prod_{i=1}^N P(Y=y_i | X=x_i) \end{aligned}$$

$$\log P(\text{Data} | \theta) = \log \prod_{i=1}^N P(Y=y_i | X=x_i)$$

Assume  $x$  is not random.

$$y = x^T \beta + \epsilon \quad \text{where } \epsilon \sim N(0, \sigma^2)$$

as  $x$  is fixed  $\beta$  has normal distribution with mean 0 & variance  $\tau$

$$\therefore \log P(\text{Data} | \theta) = \log P(Y=y, X=x)$$

$$\log P(\theta) = \log P(\beta)$$

Now using the expression of Gaussian distribution

$$\begin{aligned} \log P(\text{Data} | \theta) &= \log P(Y=y, X=x) \\ &= \log \left( \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{(y_i - x_i^T \beta)^2}{2\sigma^2} \right\} \right) \end{aligned}$$

$$\text{and } \log P(\theta) = \log \left( \frac{1}{\sqrt{2\pi}\tau} \exp \left\{ -\frac{\beta^2}{2\tau} \right\} \right)$$

Substituting above in Eq<sup>n</sup> (1) we get;



$$\log P(\theta | \text{Data}) = \log \left( \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{(y_i - x_i^T \beta)^2}{2\sigma^2} \right\} \right) + \log \left( \frac{1}{\sqrt{2\pi}\tau} \exp \left\{ -\frac{\beta^2}{2\tau} \right\} \right) - \log P(\text{Data})$$

Taking derivative w.r.t  $\beta$

$$\frac{d \log P(\theta | \text{Data})}{d\beta} = \frac{d}{d\beta} \left\{ \log \frac{1}{\sqrt{2\pi}\sigma} - \frac{(y_i - x_i^T \beta)^2}{2\sigma^2} + \log \frac{1}{\sqrt{2\pi}\tau} - \frac{\beta^2}{2\tau} - \log P(\text{Data}) \right\}$$

$$\frac{d}{d\beta} \left( \frac{1}{\sigma^2} - \frac{(y_i - x_i^T \beta)^2}{2\sigma^2} - \frac{\beta^2}{\tau} \right)$$

$$= \left( -\frac{2x_i^T y_i}{\sigma^2} + \frac{2x_i^T x_i \beta}{\sigma^2} \right) - \frac{2\beta}{\tau}$$

Setting the above  $E_q^1$  to 0

$$0 = X^T Y - X^T X \beta - \frac{\sigma^2}{\tau} \beta$$

$$\therefore \beta = \left( X^T X + \frac{\sigma^2}{\tau} I \right)^{-1} X^T Y \quad - (2)$$

Now the  $\hat{\beta}$  for Ridge regression is given by

$$\hat{\beta} = (X^T X + \lambda I)^{-1} X^T Y \quad - (3)$$

$\therefore$  from Eq<sup>n</sup> (2) & (3) we can say that  $\lambda = \frac{\sigma^2}{\tau}$

$\therefore$  It is clear that  $P(\beta | Y)$  is Gaussian and its mean & median coincide.