

## Ordinary Least Squares

Targets  $\underline{y}$  Design matrix  $X$  ( $n \times p$ )

Linear comb of features:  $X\underline{w}$

$$\hat{\underline{w}}_{OLS} \text{ minimizes } \|\underline{y} - X\underline{w}\|^2.$$

$i^{\text{th}}$  example  $y_i = x_{i1}w_1 + x_{i2}w_2 + \dots + x_{ip}w_p + \epsilon_i$

OLS: minimize  $\sum \epsilon_i^2$ .

If  $\epsilon_i \sim N(0, \sigma^2)$ ,  $\epsilon_i$  independent

## Ridge Regression

(1)  $\hat{\underline{w}}_{\text{ridge}} = \arg \min_{\underline{w}} \|\underline{y} - X\underline{w}\|^2$

subject to  $\|\underline{w}\|^2 \leq B$ . — (v1)

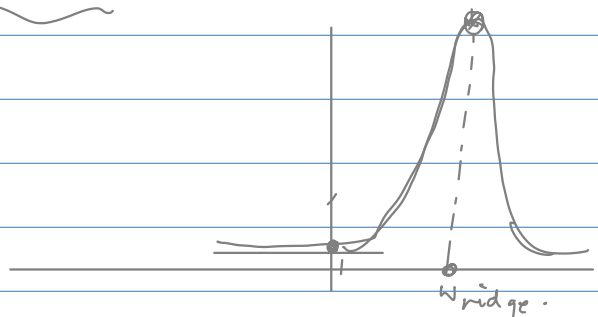
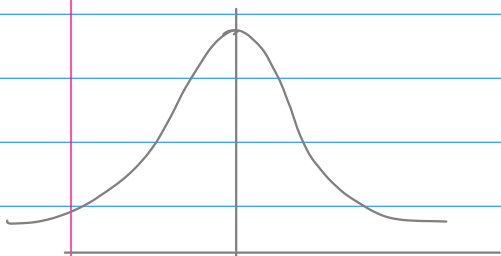
Completely equivalent

$\arg \min_{\underline{w}} \|\underline{y} - X\underline{w}\|^2 + \lambda \|\underline{w}\|^2$ . — (v2)

(2)  $y_i = x_{i1}w_1 + x_{i2}w_2 + \dots + x_{ip}w_p + \epsilon_i$

$\underline{w} \sim N(\underline{0}, I/\lambda)$ .

$\left\{ \text{If } \underline{w} \sim N(\underline{0}, \Sigma) \right.$   
 $\left. \arg \min_{\underline{w}} \|\underline{y} - X\underline{w}\|^2 + \underbrace{\underline{w}^T \Sigma^{-1} \underline{w}} \right\}$



$$\hat{w}_{OLS} = (X^T X)^{-1} X^T y = \arg \min_w \|y - Xw\|^2.$$

Predict on a new test case  $\underline{z}$ :  $\underline{z}^T \hat{w}_{OLS}$

$$\hat{w}_{ridge} = (X^T X + \lambda I)^{-1} X^T y = \arg \min_w \|y - Xw\|^2 + \lambda \|w\|^2.$$

Predict on a new test case  $\underline{z}$ :  $\underline{z}^T \hat{w}_{ridge}$ .

$$\text{But } \underline{z}^T \hat{w}_{ridge} = \underline{z}^T (X^T X + \lambda I)^{-1} X^T y \quad \left. \vphantom{\underline{z}^T (X^T X + \lambda I)^{-1} X^T y} \right\} \text{Matrix inversion lemma.}$$

$$= \underline{z}^T \underbrace{X^T}_{\text{red}} (X X^T + \lambda I)^{-1} y.$$

$$X = \begin{bmatrix} \underline{x}_1^T \\ \underline{x}_2^T \\ \underline{x}_3^T \\ \underline{x}_4^T \end{bmatrix} \quad X^T = \begin{bmatrix} | & | & | & | \\ \underline{x}_1 & \underline{x}_2 & \underline{x}_3 & \underline{x}_4 \\ | & | & | & | \end{bmatrix}$$

$$\underline{z}^T X^T = (\underline{z}^T) \begin{pmatrix} | & | & | & | \\ \underline{x}_1 & \underline{x}_2 & \underline{x}_3 & \underline{x}_4 \\ | & | & | & | \end{pmatrix} = (\underline{z}^T \underline{x}_1 \quad \underline{z}^T \underline{x}_2 \quad \dots \quad \underline{z}^T \underline{x}_4).$$

$$X X^T = \begin{bmatrix} \underline{x}_1^T \underline{x}_1 & \underline{x}_1^T \underline{x}_2 & \underline{x}_1^T \underline{x}_3 & \underline{x}_1^T \underline{x}_4 \\ \vdots & \vdots & \vdots & \vdots \\ \underline{x}_4^T \underline{x}_1 & \underline{x}_4^T \underline{x}_2 & \underline{x}_4^T \underline{x}_3 & \underline{x}_4^T \underline{x}_4 \end{bmatrix} \rightarrow k(x, x) = \begin{bmatrix} k(\underline{x}_1, \underline{x}_2) & \dots \\ k(\underline{x}_3, \underline{x}_1) & \dots \\ \vdots & \vdots \\ k(\underline{x}_4, \underline{x}_4) \end{bmatrix}$$

$$\begin{array}{lcl} \underline{x}_1 & \longrightarrow & \phi(\underline{x}_1) \\ \underline{x}_2 & \longrightarrow & \phi(\underline{x}_2) \end{array}$$