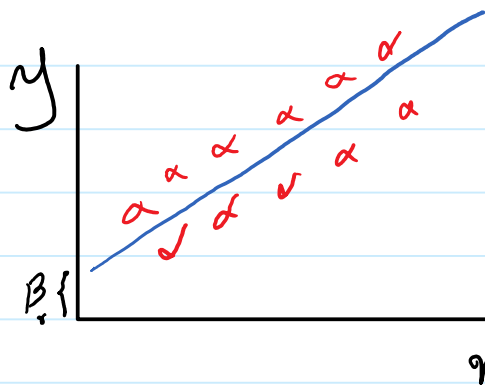


$$y = \beta_0 + \beta_1 x$$



$x$	$y$	$\hat{y}$	$e$	$e^2$
$\vdots$	$\vdots$	$\hat{\beta}_0 + \hat{\beta}_1 x_1$	$y_1 - \hat{y}_1$	$(y_1 - \hat{y}_1)^2$
$\vdots$	$\vdots$	$\hat{\beta}_0 + \hat{\beta}_1 x_2$	$y_2 - \hat{y}_2$	$(y_2 - \hat{y}_2)^2$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
				$\hline e^2$

$$\hat{\beta}_0, \hat{\beta}_1, \dots$$

$$\hat{y} = \hat{\beta}_0 + x \hat{\beta}_1$$

$$e = y - \hat{y}$$

$$e^2 = (y - \hat{y})^2$$

$$RSS = S = \sum_{i=1}^P e_i^2 = \sum_{i=1}^P (y_i - \hat{y}_i)^2$$

OLS : Ordinary least squares

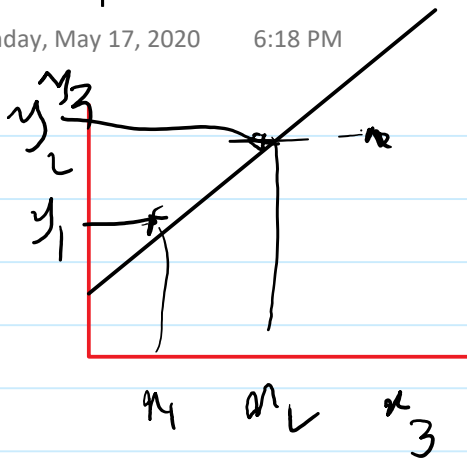


$$\frac{\partial S}{\partial \hat{\beta}_0} = 0, \quad \frac{\partial S}{\partial \hat{\beta}_1} = 0$$

# LM. Eq. 2

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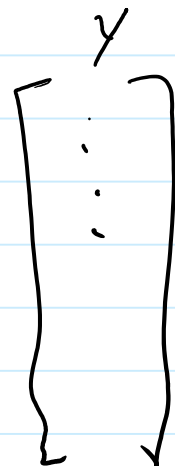
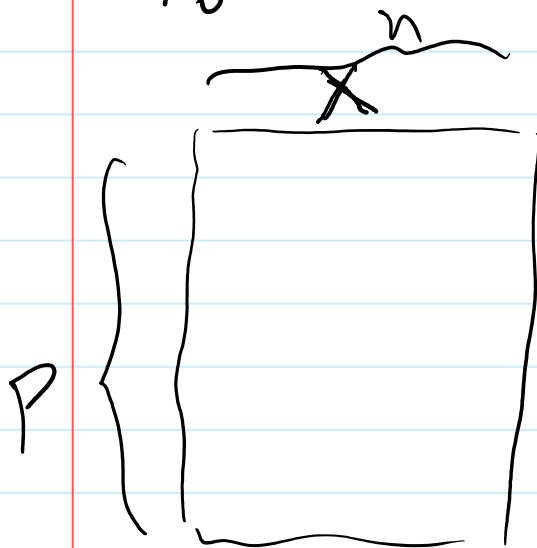


$n$	$y$	$\hat{y}$	$e$
1	2	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 - 2$
2	4	$\beta_0 + 2\beta_1$	$\beta_0 + 2\beta_1 - 4$
3	4	$\beta_0 + 3\beta_1$	$\beta_0 + 3\beta_1 - 4$

$$S = (\hat{\beta}_0 + \hat{\beta}_1 - 2)^2 + (\hat{\beta}_0 + 2\hat{\beta}_1 - 4)^2 + (\hat{\beta}_0 + 3\hat{\beta}_1 - 4)^2$$

$$\frac{\partial S}{\partial \beta_0} = 0$$

$$\frac{\partial S}{\partial \beta_1} = 0$$



$X$ : Features,  
variables  
predictors  
covariates

$y$ : target  
Response

$$p \geq n$$

$$p < n$$

# LM. Eq. 3

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$$y = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \dots + \hat{\beta}_n x_n$$

$$S = \sum_{i=1}^p e^2 = \sum_{i=1}^p (y_i - \hat{y}_i)^2$$

$$e = \begin{bmatrix} y_1 - \hat{y}_1 \\ y_2 - \hat{y}_2 \\ \vdots \\ y_p - \hat{y}_p \end{bmatrix}$$

$$S = e^T \cdot e$$

$$S = \begin{bmatrix} e_1 & e_2 & \dots & e_p \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_p \end{bmatrix}$$

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1n} \\ 1 & x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{p1} & x_{p2} & \dots & x_{pn} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{bmatrix}$$

$p \times n$        $n \times 1$        $p \times 1$

$$X \cdot \hat{\beta} = \hat{y}$$

$$S = e^T e = (y - \hat{y})^T (y - \hat{y})$$

$$= (y - X\hat{\beta})^T (y - X\hat{\beta}) \quad A^2 = A^T A$$

$$= (y^T - \hat{\beta}^T X^T) (y - X\hat{\beta}) \quad (AB)^T = B^T A^T$$

$$A^T A = I = 1$$

$$= y^T y - y^T X \hat{\beta} - \hat{\beta}^T X^T y + \hat{\beta}^T X^T X \hat{\beta}$$

$$\frac{\partial S}{\partial \beta} = -2X^T y + 2X^T X \hat{\beta} = 0$$

$$X^T X \hat{\beta} = X^T y$$

$$(X^T X)^{-1} X^T X \hat{\beta} = (X^T X)^{-1} X^T y$$

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1n} \\ 1 & \vdots & \vdots & & \vdots \\ \vdots & & & & \\ 1 & & & & x_{pn} \end{bmatrix}$$

numpy

$$(y^T X)^T = X^T y$$

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

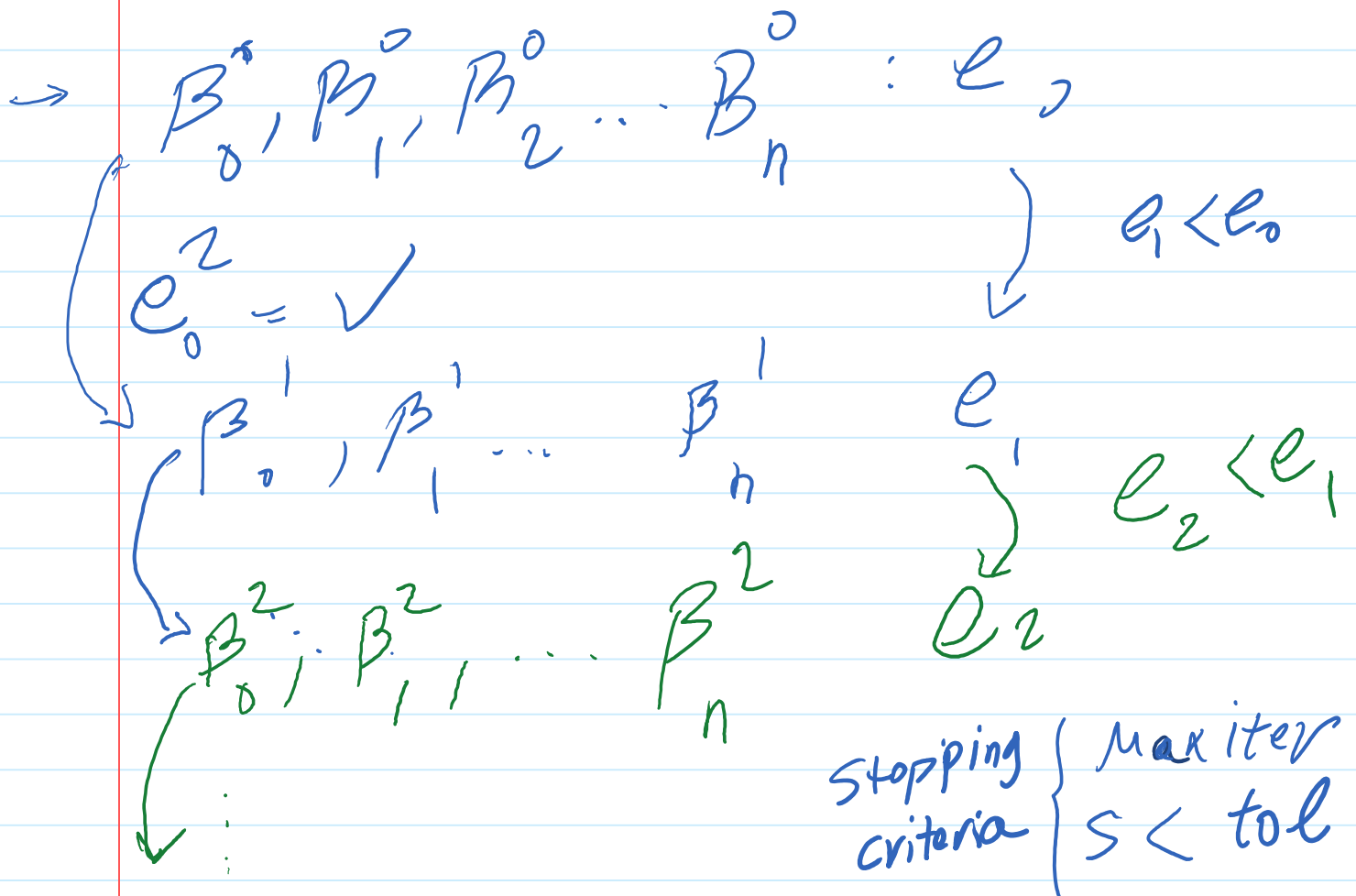
Closed Form Solution

closed for solution:

$$ax^2 + bx + c = 0$$

$$x_{1,2} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

## Numerical Solution



# LM. Lp Regularization

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overfit

$e > e$

$e < e$

CV

$$S = \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \alpha \sum_{j=1}^p |\beta_j|^p$$

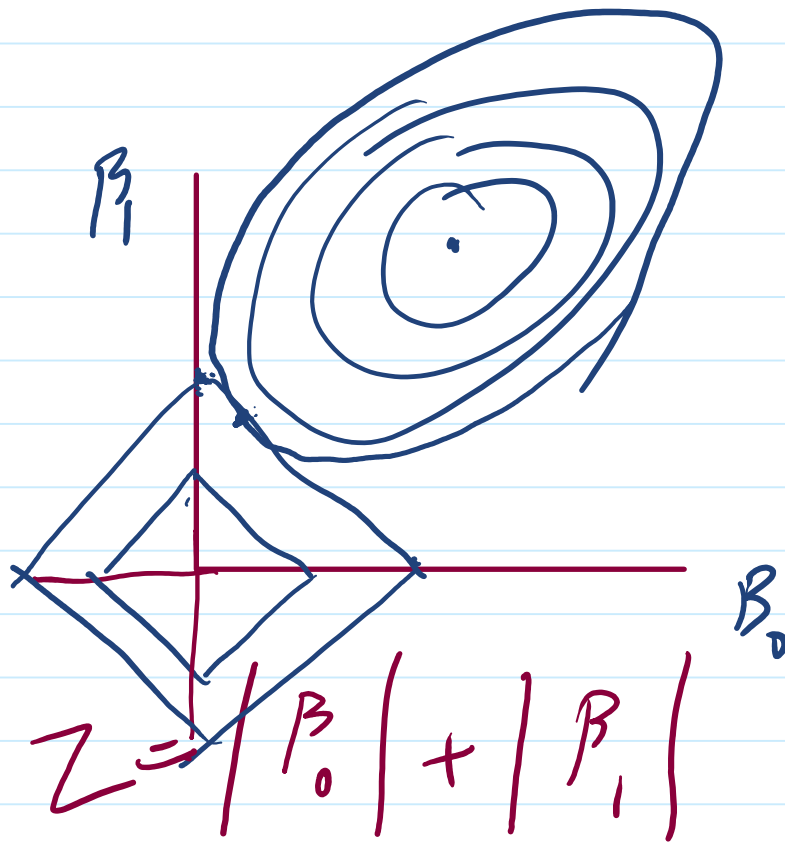
$0 < \alpha < \infty$

$\alpha \rightarrow 0 : S \rightarrow \text{lm}$

$\alpha \rightarrow \infty : \ell^p$

$$\mathcal{L}_1 \Rightarrow p=1$$

$$S = \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \alpha \sum_{j=0}^n |\beta_j|$$



$$\mathcal{L}_1 \rightarrow \beta_0 \rightarrow 0$$



$$l_2$$

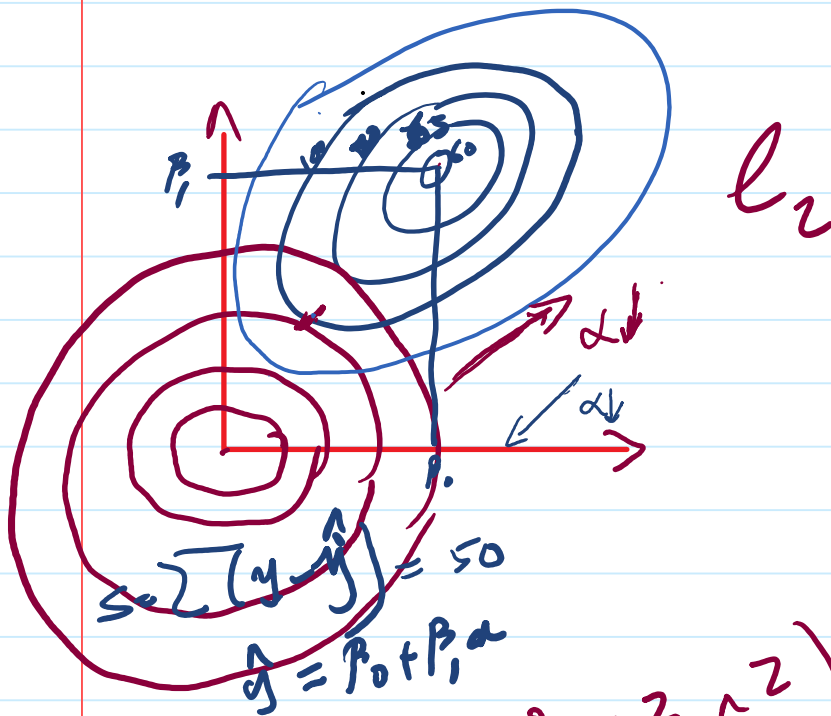
$$S = \sum_{i=1}^P (y_i - \hat{y}_i)^2 + \alpha \sum_{i=0}^n \beta_i^2$$

(2)  $\rightarrow P=2$

$$0 < \alpha < \infty$$

$$\alpha = 0 \rightarrow \text{Ridge} \rightarrow \text{Lm}$$

$$\alpha > 0 \rightarrow l_2 \text{ regularization}$$



$$y = \beta_1 x + \beta_0$$

$$Z = \beta_0^2 + \beta_1^2$$

$$S = \sum (y_i - \hat{y}_i)^2 + (\hat{\beta}_0^2 + \hat{\beta}_1^2)$$

$Z$

$l_1 / l_2$

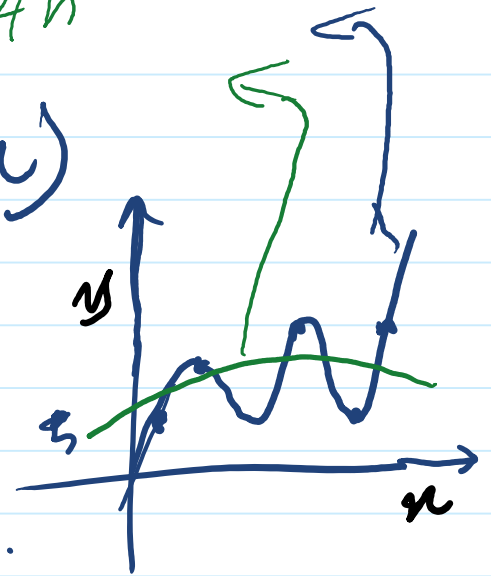
$$J = \sum_{i=1}^p (y_i - \hat{y}_i)^2 + \alpha \delta \sum_{i=1}^n |\hat{\beta}_i| + \alpha (1 - \delta) \sum_{i=1}^n \hat{\beta}_i^2$$

$$\delta = l_1 / l_2$$

w/o regularization  
with

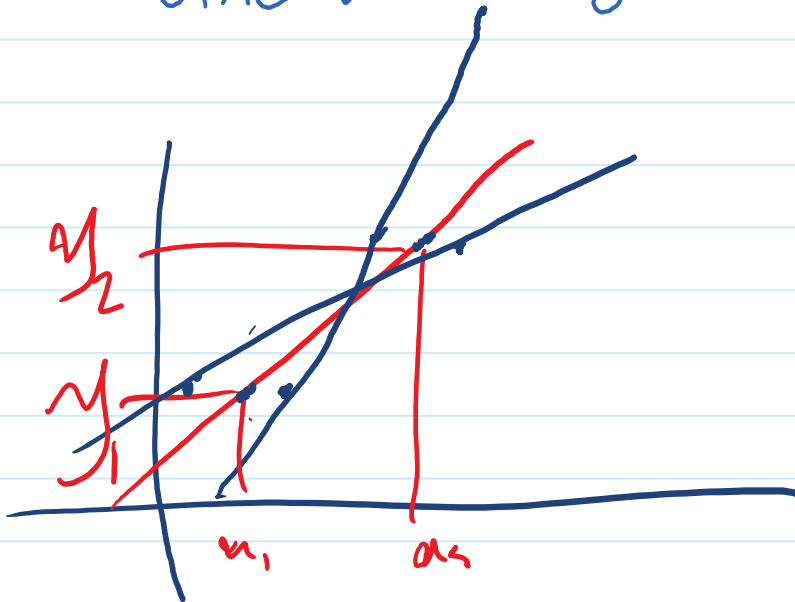
1. Reduce complexity  
i.e. reduce overfitting

$$y = f(x)$$



2. More robust to noise

Linear Regression Ridge



3.  $l_1$  can make  $\beta_i = 0$