

Problem 4) part 1:

$$\min_{\beta} : \|X\hat{\beta} - y\|_2^2 = \sum (x_i \hat{\beta} - y_i)^2$$

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

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

$$= y^T y - 2\hat{\beta}^T X^T y + \hat{\beta}^T X^T X \hat{\beta}$$

$$\frac{d}{d\hat{\beta}} LS = \frac{d}{d\hat{\beta}} (y^T y - 2\hat{\beta}^T X^T y + \hat{\beta}^T X^T X \hat{\beta})$$

set derivative
to zero
to optimize \rightarrow

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

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

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

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

Both are scalars and
the transpose of a
scalar is a scalar
so $y^T X \hat{\beta} = (y^T X \hat{\beta})^T$
 $= \hat{\beta}^T X^T y$

part 2 Ridge

$$\lambda \|\beta\|_2^2 = \lambda \beta^T \beta$$

$$\min_{\beta} \left[\|X\beta - y\|_2^2 + \lambda \|\beta\|_2^2 \right]$$

↓ using derivation from previous part

$$= y^T y - 2 \hat{\beta}^T X^T y + \hat{\beta}^T X^T X \hat{\beta} + \lambda \hat{\beta}^T \hat{\beta}$$

$$\frac{d}{d\beta} RR = -2 X^T y + 2 X^T X \hat{\beta} + 2 \lambda \hat{\beta}$$

Set to
Zero

$$0 = -2 X^T y + 2 X^T X \hat{\beta} + 2 \lambda \hat{\beta}$$

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

$$(X^T X + \lambda I) \hat{\beta} = X^T y$$

$$\boxed{\hat{\beta} = (X^T X + \lambda I)^{-1} X^T y}$$