

$$\# \text{ Q1 } \# X = \begin{bmatrix} 1 \\ 3 \\ 6 \end{bmatrix} \# Y = \begin{bmatrix} 6 \\ 10 \\ 16 \end{bmatrix}$$

$$\# X^* = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\# Y = \begin{bmatrix} 6 \\ 10 \\ 6 \end{bmatrix}$$

$$\# \text{ Cost} = (0_0 + 0_1 - 6)^2 + (0_0 + 30_1 - 10)^2 + (0_0 + 60_1 - 16)^2$$

$$= 0_0^2 + 0_1^2 + 36 - 120_1 - 120_0 + 0_0^2 + 90_1^2 + 100 - 600_1 - 200_0 + 60_0 0_1 + 0_0^2 + 360_1^2 + 256 + 120_0 0_1 - 1920_1 - 320_0$$

$$\text{Cost} = 30_0^2 + 460_1^2 + 392 - 2640_1 - 640_0 + 180_0 0_1$$

① Now fix  $0_0 = 0$

$$\text{Cost} = (460_1^2 + 392) - 2640_1 (0, 0) = (0, 0)$$

$$\frac{dC}{d0_1} = 920_1 - 264 = 0 \Rightarrow 0_1 = 2.87$$

② Now fix  $0_1 = 2.87$

$$\text{Cost} = 30_0^2 + 46(2.87)^2 + 392 - 264(2.87)$$

$$= 640_0 - 64 + 180_0 \times 2.87$$

der

$$\frac{dC}{d0} = 60_0 - 64 + 18 \times 2.87 = 0$$

$$d0 = 0_0 = \frac{2}{3}$$

Now fix  $\theta_0 \approx 2$

$$\frac{\partial C}{\partial \theta_0} = 92\theta_0 - 264 + 18\theta_0 = 0$$

$$= 92\theta_0 - 264 + 36 = 0$$

$$= 92\theta_0 = 264 - 36$$

$$\# \theta_0 = 2.47$$

Q1(b) # Stochastic gradient descent with initial value of  $\theta_0$  &  $\theta_1$  & a learning rate of 0.01

# First fix  $\theta_0 = 0$  &  $\theta_1 = 0$

Now we take first training sample.

$$\# C = \theta_0 + \theta_1 (0 + \theta_1 - 6)^2$$

$$\rightarrow \# \frac{\partial C}{\partial \theta_0} = 2(\theta_0 + \theta_1 - 6) = -12$$

$$\rightarrow \# \frac{\partial C}{\partial \theta_1} = 2(\theta_0 + \theta_1 - 6) = -12$$

$$(\theta_0, \theta_1)_{\text{new}} = (\theta_0, \theta_1)_{\text{old}} - \alpha \left( \frac{\partial C}{\partial \theta_0}, \frac{\partial C}{\partial \theta_1} \right)$$

$$(\theta_0, \theta_1) \Rightarrow (0.12, 0.12)$$

②  $\theta_0 = 0.12$  &  $\theta_1 = 0.12$

$$\# C = (3\theta_0 + 3\theta_1 - 10)^2$$

$$\# \frac{\partial C}{\partial \theta_0} = 2(3\theta_0 + 3\theta_1 - 10) = 2(0.48 - 10) = -19.04$$

$$\# \frac{\partial C}{\partial \theta_1} = 6(3\theta_0 + 3\theta_1 - 10) = 6(0.48 - 10) = -57.12$$

$$\begin{aligned}
 (\theta_0, \theta_1) &= (0.12, 0.12) - 0.01(-19.04, -52.12) \\
 &= (0.12, 0.12) + (0.1904, 0.5212) \\
 &= (0.3104, 0.6412)
 \end{aligned}$$

# Iteration 3

$$\# \theta_0 = 0.3104, \theta_1 = 0.6412$$

~~(\theta\_0, \theta\_1)~~

$$C = (\theta_0 + 6\theta_1 - 16)^2$$

$$\# \frac{\partial C}{\partial \theta_0} = 2(\theta_0 + 6\theta_1 - 16) \quad \frac{\partial C}{\partial \theta_1} = 12(\theta_0 + 6\theta_1 - 16)$$

$$\# \frac{\partial C}{\partial \theta_0} = -23.08 \quad \frac{\partial C}{\partial \theta_1} = -138.5088$$

$$\begin{aligned}
 (\theta_0, \theta_1) &= (0.3104, 0.6412) - 0.01(-23.08, -138.5088) \\
 &= (0.5412, 2.07)
 \end{aligned}$$

# The final value of  $\theta_0$  &  $\theta_1$  is  
0.5412 & 2.07

Q

Q(c)

$$\theta_{opt} = (X^T X + \lambda I)^{-1} X^T Y$$

$$\# X = \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 6 \end{bmatrix} \# Y = \begin{bmatrix} 6 \\ 10 \\ 16 \end{bmatrix}$$

$$X^T X = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 3 & 6 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 1 & 6 \end{bmatrix}$$

$$= \begin{bmatrix} 3 & 10 \\ 10 & 46 \end{bmatrix}$$

$$\# X^T X + I = \begin{bmatrix} 4 & 10 \\ 10 & 47 \end{bmatrix}$$

$$\hat{\beta}_{\text{opt}} = \begin{bmatrix} 4 & 10 \\ 10 & 47 \end{bmatrix}^{-1} \left( \begin{bmatrix} 1 & 1 \\ 1 & 3 \\ 6 & 6 \end{bmatrix} \begin{bmatrix} 6 \\ 10 \\ -16 \end{bmatrix} \right)$$

$$= \frac{1}{28} \begin{bmatrix} 47 & -10 \\ -10 & 4 \end{bmatrix} \begin{bmatrix} 32 \\ 132 \end{bmatrix}$$

$$= \frac{1}{28} \begin{bmatrix} 184 \\ 208 \end{bmatrix} = \begin{bmatrix} 2.09 \\ 2.36 \end{bmatrix}$$

# The optimal value obtained by Ridge regression is  $\hat{\beta}_0 = 2.09$  &  $\hat{\beta}_1 = 2.36$

Q5(c)

The solution obtained by lasso regression is sparse compared to the one obtained by Ridge regression.



Q4 (b)

$$\theta_{opt} = (X^T X + \lambda I)^{-1} X^T Y$$

$$= \left[ \begin{bmatrix} 1 & 2 & 3 & 4 \\ 2 & 4 & 6 & 8 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 3 & 6 \\ 4 & 8 \end{bmatrix} + \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} \right]^{-1} X^T Y$$

$$\Rightarrow \left[ \begin{bmatrix} 30 & 60 \\ 60 & 120 \end{bmatrix} + \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} \right]^{-1} \begin{bmatrix} 1 & 2 & 3 & 4 \\ 2 & 4 & 6 & 8 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \\ 4 \\ 5 \end{bmatrix}$$

$$\theta_{opt} = \begin{bmatrix} 31 & 60 \\ 60 & 121 \end{bmatrix}^{-1} \begin{bmatrix} 40 \\ 80 \end{bmatrix}$$

$$\theta_{opt} = \begin{bmatrix} 121 & -60 \\ -60 & 31 \end{bmatrix} \begin{bmatrix} 40 \\ 80 \end{bmatrix} \times \frac{1}{150}$$

$$\Rightarrow \begin{bmatrix} 4840 - 4800 \\ -2400 + 2460 \end{bmatrix} \times \frac{1}{150}$$

$$= \begin{bmatrix} 40 \\ -80 \end{bmatrix} \times \frac{1}{150} = \begin{bmatrix} 0.26 \\ -0.53 \end{bmatrix}$$

$$\# \text{Opt} = \begin{bmatrix} 0.26 \\ +0.53 \end{bmatrix}$$

# Yes we can obtain a solution here  
 because of the regularization imposed  
 on variable  $\theta$