

1. [3 Points] Write the stochastic gradient descent update rules for  $w_j$  and  $b$  for ridge regression.

$$\begin{aligned}
 \mathcal{L} &\approx (\hat{y}^{(i)} - y^{(i)})^2 + \lambda \sum_{j=1}^n w_j^2 \\
 &= (\sum w_j x_j^{(i)} + b - y^{(i)})^2 + \lambda \sum_{j=1}^n w_j^2 \\
 \frac{d\mathcal{L}}{dw_j} &= [2(\hat{y}^{(i)} - y^{(i)})x_j + 2\lambda w_j] \\
 &\Rightarrow w_j \leftarrow w_j - \eta(2(\hat{y}^{(i)} - y^{(i)})x_j + 2\lambda w_j) \\
 &\Rightarrow w_j \leftarrow (1 - 2\lambda\eta)w_j - 2\eta(\hat{y}^{(i)} - y^{(i)})x_j
 \end{aligned}$$

$$b \leftarrow b - \eta \times 2(\hat{y}^{(i)} - y^{(i)})$$

#### 5.4.2 Lasso regression

The loss for  $L_1$  regularization can be written as

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^n (\hat{y}^{(i)} - y^{(i)})^2 + \lambda \sum_{j=1}^m \|w_j\|$$

Note that we do not regularize  $b$ . With the SGD approximation, this becomes

$$\mathcal{L} \approx (\hat{y}^{(i)} - y^{(i)})^2 + \lambda \sum_{j=1}^m |w_j|$$

1. [3 Points] Write the stochastic gradient descent update rules for  $w_j$  and  $b$  for lasso regression.

$$\begin{aligned}
 &\text{if } w_j \geq 0: \\
 &\quad w_j \leftarrow w_j - 2\eta(\hat{y}^{(i)} - y^{(i)})x_j - \eta\lambda \\
 &\text{else:} \\
 &\quad w_j \leftarrow w_j - 2\eta(\hat{y}^{(i)} - y^{(i)})x_j + \eta\lambda \\
 &b \leftarrow b - 2\eta(\hat{y}^{(i)} - y^{(i)})
 \end{aligned}$$