



$$\hat{y}_p = \sum_{i=0}^{n-1} x_{i,p} w_i$$

$$p \in [0 \dots m-1]$$

Training set: x_0, y_0
 \vdots
 x_{m-1}, y_{m-1}

E was formulated a little differently in the code than what we had been doing on the board:

$$E = \frac{1}{m} \sum_{p=0}^{m-1} E_p = \frac{1}{m} \sum_{p=0}^{m-1} (\hat{y}_p - y_p)^2$$

$$\begin{aligned} \frac{\partial E}{\partial w_i} &= \frac{1}{m} \sum_p \frac{\partial}{\partial w_i} (\hat{y}_p - y_p)^2 \\ &= \frac{1}{m} \sum_p 2(\hat{y}_p - y_p) \frac{\partial}{\partial w_i} \hat{y}_p \end{aligned}$$

$$= \frac{2}{m} \sum_p (\hat{y}_p - y_p) x_{i,p}$$

$$= \frac{2}{m} \sum_p \text{error}_p \cdot x_{i,p}$$

In the code, gradients is a vector:

$$\text{gradients} = \frac{\partial E}{\partial w} = \frac{2}{m} \begin{bmatrix} \sum_p \text{error}_p \cdot x_{0,p} \\ \sum_p \text{error}_p \cdot x_{1,p} \\ \vdots \\ \sum_p \text{error}_p \cdot x_{n-1,p} \end{bmatrix}$$

Part 1:

HW 1: add a bias term to our model:

$$\hat{y}_p = \left(\sum x_{i,p} \cdot w_i \right) + b$$

- add a 'b' variable
- make any changes to the forward model that are necessary
- make any changes to 'gradients' that are necessary
- compute a gradient for b
- add a new training operation for b
- run this training op in your learning loop.

Part 2: add regularization terms

$$E = \frac{1}{m} \sum_{p=0}^{m-1} E_p + \gamma \left(\sum_{i=0}^{n-1} w_i^2 + b^2 \right)$$

- modify the gradients computation
- modify the gradients-bias computation
- Select $\gamma = 2$