

Problem Set 2 – Supervised Learning

DS598 B1 – DL4DS

Spring, 2024

Problem 2.1

To walk “downhill” on the loss function (equation 2.5), we measure its gradient with respect to the parameters ϕ_0 and ϕ_1 . Calculate expressions for the slopes $\partial L / \partial \phi_0$ and $\partial L / \partial \phi_1$.

Assuming that $L = \text{MSE} \dots$

$$L = \frac{1}{N} * \sum_{i=1}^N (y_i - (\phi_0 + \phi_1 * x_i))^2$$

Then, for calculating the gradient the slopes, we would need to calculate the partial derivative with respect to ω_0 , the intercept of the line, which shows how it will be affected by the Loss function....

$$\frac{\partial L}{\partial \phi_0} = \frac{u^* \left[\frac{1}{N} * \sum_{i=1}^N (y_i - (\phi_0 + \phi_1 * x_i))^2 \right]}{u \phi_0} \Rightarrow = \frac{1}{N} * \sum_{i=1}^N [-2 * (y_i - (\phi_0 + \phi_1 * x_i))] \Rightarrow$$

$$\frac{\partial L}{\partial \phi_0} = \frac{-2}{N} * \sum_{i=1}^N (y_i - (\phi_0 + \phi_1 * x_i))$$

Then, for calculating the gradient the slopes, we would need to calculate the partial derivative with respect to ω_1 , the slope of the line, which will show how it will be affected by the Loss function....

$$\frac{\partial L}{\partial \phi_1} = \frac{u^* \left[\frac{1}{N} * \sum_{i=1}^N (y_i - (\phi_0 + \phi_1 * x_i))^2 \right]}{u \phi_1} \Rightarrow = \frac{1}{N} * \sum_{i=1}^N [-2 x_i * (y_i - (\phi_0 + \phi_1 * x_i))] \Rightarrow$$

$$\frac{\partial L}{\partial \phi_1} = \frac{-2}{N} * \sum_{i=1}^N x_i * (y_i - (\phi_0 + \phi_1 * x_i))$$

Problem 2.2

Show that we can find the minimum of the loss function in closed-form by setting the expression for the derivatives from problem 2.1 to zero and solving for ϕ_0 and ϕ_1 .

We will need to set both of the gradient expressions equal to 0....

Starting with omega_0...

$$0 = \frac{-2}{N} * \sum_{i=1}^N (y_i - (\phi_0 + \phi_1 * x_i)) \Rightarrow \sum_{i=1}^N (y_i - (\phi_0 + \phi_1 * x_i)) \Rightarrow (\sum_{i=1}^N y_i) - (N\phi_0 + \phi_1 * \sum_{i=1}^N x_i) \Rightarrow$$

$$N\phi_0 = (\sum_{i=1}^N y_i) - \phi_1 * \sum_{i=1}^N x_i \Rightarrow$$

$$\phi_0 = \frac{(\sum_{i=1}^N y_i) - \phi_1 * \sum_{i=1}^N x_i}{N}$$

Now, omega_1

$$0 = \frac{-2}{N} * \sum_{i=1}^N x_i (y_i - (\phi_0 + \phi_1 * x_i)) \Rightarrow \sum_{i=1}^N x_i (y_i - (\phi_0 + \phi_1 * x_i)) \Rightarrow (\sum_{i=1}^N x_i y_i) - (\sum_{i=1}^N x_i \phi_0 + \sum_{i=1}^N x_i \phi_1 x_i) \Rightarrow$$

$$0 = (\sum_{i=1}^N x_i y_i) - (\sum_{i=1}^N x_i \phi_0 + \sum_{i=1}^N x_i \phi_1 x_i) \Rightarrow 0 = (\sum_{i=1}^N x_i y_i) - \sum_{i=1}^N x_i (\phi_0 + \phi_1 x_i) \Rightarrow$$

$$\sum_{i=1}^N x_i (\phi_0 + \phi_1 x_i) = (\sum_{i=1}^N x_i y_i) \Rightarrow \sum_{i=1}^N x_i^2 \phi_1 = (\sum_{i=1}^N x_i y_i) - \sum_{i=1}^N x_i \phi_0 \Rightarrow$$

$$\phi_1 = \frac{(\sum_{i=1}^N x_i y_i) - \sum_{i=1}^N x_i \phi_0}{\sum_{i=1}^N x_i^2}$$