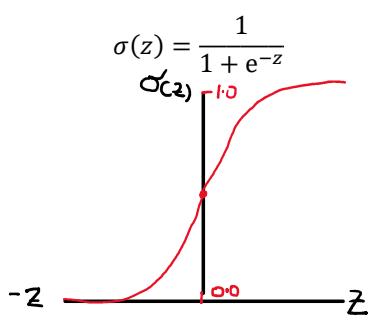


Gradient Descent - Logistic Regression

Wednesday, February 28, 2024 4:35 PM



$$z = w^T x + b$$

$$\hat{y} = a = \sigma(z)$$

Binary Classification:

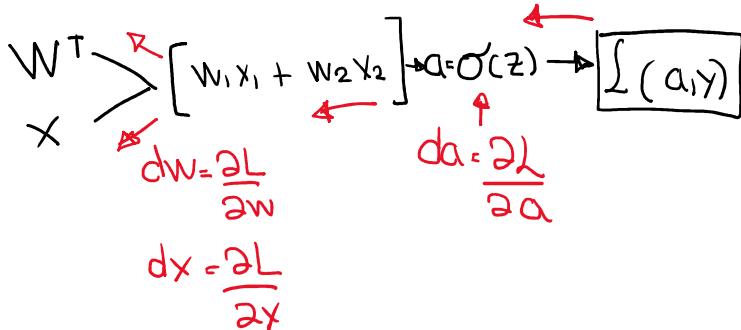
$$L(a, y) = -[y \log(a) + (1 - y) \log(1 - a)]$$

We need
to minimize
loss

$$x = [x_1 \ x_2]$$

$$w = [w_1 \ w_2]$$

From R to L



Chain rule:

$$dw = \frac{\partial L}{\partial a} \cdot \frac{\partial a}{\partial z} \cdot \frac{\partial z}{\partial w}$$

$$dx = \frac{\partial L}{\partial a} \cdot \frac{\partial a}{\partial z} \cdot \frac{\partial z}{\partial x}$$

Sigmoid derivative:

$$a \cdot \sigma'(z) = \frac{1}{1+e^{-z}} \cdot \frac{\partial a}{\partial z} = \frac{\partial a}{\partial z} \left(\frac{1}{1+e^{-z}} \right)$$

$$\frac{\partial a}{\partial z} = (1+e^{-z})^{-1} = -[1+e^{-z}]^{-2} \cdot (-1)e^{-z}$$

$$\frac{\partial a}{\partial z} = \frac{e^{-z}}{[1+e^{-z}]^2} = \frac{e^{-z}}{1+e^{-z}} \cdot \frac{1}{1+e^{-z}}$$

$$\frac{\partial a}{\partial z} = [1-\sigma(z)]\sigma(z)$$

Loss derivative:

$$L = -[y \log a + (1-y) \log(1-a)]$$

$$\frac{\partial L}{\partial a} = -\frac{\partial}{\partial a}(y \log a) - \frac{\partial}{\partial a}((1-y) \log(1-a))$$

$$\frac{\partial L}{\partial a} = \frac{-y}{a} + \frac{1-y}{1-a}$$

Derivative $\frac{\partial L}{\partial z}$

Gradient.

Derivative $\frac{\partial L}{\partial z}$

$$\frac{\partial L}{\partial z} = \frac{\partial L}{\partial a} \cdot \frac{\partial a}{\partial z}$$

$$\frac{\partial L}{\partial z} = \left[\frac{y}{a} + \frac{1-y}{1-a} \right] \cdot [1-a]^a$$

$$\frac{\partial L}{\partial z} = \left[-y(1-a) + (1-y)a \right] = \left[-y + ya + a - ya \right]$$

$$\frac{\partial L}{\partial z} = a - y$$

Gradients:

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial z} \cdot \frac{\partial z}{\partial w_1} = [a-y] x_1$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial L}{\partial z} \cdot \frac{\partial z}{\partial b_1} = [a-y]$$