Introduction to Deep Learning

Himanshu Singh

Github

Perceptron

$\hat{y} = g(w_o + X^T W)$

Common activation Functions:

1) Sigmoid

$$g(z) = \frac{1}{1+e^{-z}}$$

$g'(z) = g(z)(1-g(z))$

2) Hyperbolic Tangent

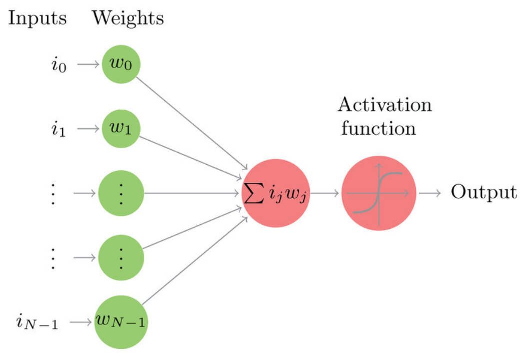
$$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

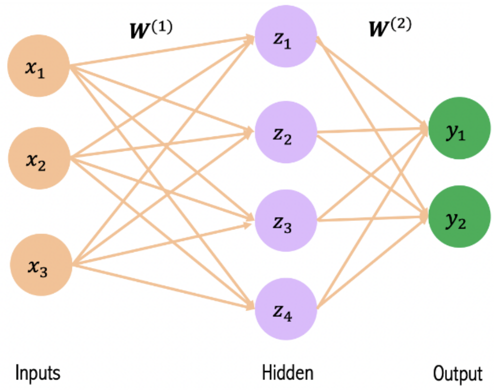
$g'(z) = 1 - g(z)^2$

3) Rectified Linear Unit (ReLU)

$$g(z) = max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$





MultiLayer Perceptron

$$z_j = \sum_{i=1}^{3} x_i w_{ij}^{(1)} + w_{0j}^{(1)}$$

$$y_k = \sum_{j=1}^{4} g(z_j) w_{jk}^{(2)} + w_{0k}^{(2)}$$

Emperical Loss

$$J(W) = \frac{1}{n} \sum_{i=1}^{n} L(\underbrace{f(x^{(i)}; W)}_{Predicted}, \underbrace{y^{(i)}}_{Actual})$$

Binary Cross Entropy Loss

$$J(W) = -\frac{1}{n} \sum_{i=1}^{n} \underbrace{y^{(i)}}_{Actual} \log(\underbrace{f(x^{(i)}; W)}_{Predicted}) + (1 - \underbrace{y^{(i)}}_{Actual}) \log(1 - \underbrace{f(x^{(i)}; W)}_{Predicted})$$

Mean Square Error Loss

$$J(W) = \frac{1}{n} \sum_{i=1}^{n} (\underbrace{f(x^{(i)}; W)}_{Predicted} - \underbrace{y^{(i)}}_{Actual})^2$$

Loss Optimization

$$W^* = \underset{W}{argmin} \frac{1}{n} \sum_{i=1}^{n} L(f(x^{(i)}; W), y^{(i)})$$

$$W^* = \underset{W}{argmin}\, J(W)$$

Gradient Descent Algorithm:

1. Initialize weight randomly $\sim N(0, \sigma^2)$
2. Loop until convergence
3. Compute gradient, $\frac{\partial J(w)}{\partial W}$
4. Update weights, $W \leftarrow w - \eta \frac{\partial J(w)}{\partial W}$
5. Return weights

#BACKPROPAGATION ALGORITHM