

Desarrollo del algoritmo de aprendizaje Backpropagation para un Perceptrón Multicapa (MLP) con 1 capa oculta

Ajuste de pesos sinápticos según el descenso por el gradiente:

$$\delta w'_{kj} = -\varepsilon \frac{\partial E}{\partial w'_{kj}} \quad (1)$$

$$\delta w_{ji} = -\varepsilon \frac{\partial E}{\partial w_{ji}} \quad (2)$$

Salida de la red MLP:

$$z_k^u = g \left(\sum_j w'_{kj} f \left(\underbrace{\sum_i w_{ji} x_i^u}_{y_j^u} - \theta_j \right) - \theta'_k \right) \quad (3)$$

Función de error (error cuadrático medio):

$$E(w_{ji}, w'_{kj}) = \frac{1}{2} \sum_u \sum_k [t_k^u - z_k^u]^2 \quad (4)$$

Reemplazando (3) en (4)

$$E(w_{ji}, w'_{kj}) = \frac{1}{2} \sum_u \sum_k \left[t_k^u - g \left(\underbrace{\sum_j w'_{kj} y_j^u}_{h_k^u} - \theta'_k \right) \right]^2 = \frac{1}{2} \sum_u \sum_k \left[t_k^u - g(h_k^u) \right]^2 \quad (5)$$

Cálculo de (1): Derivando (5) respecto a cada peso w'_{kj} y aplicando la regla de la cadena, tenemos:

$$\begin{aligned} \frac{\partial E}{\partial w'_{kj}} &= \frac{\partial E}{\partial h_k^u} \frac{\partial h_k^u}{\partial h_k^u} \frac{\partial h_k^u}{\partial w'_{kj}} = \frac{1}{2} 2 \sum_u [t_k - g(h_k^u)] \left(-\frac{\partial g(h_k^u)}{\partial h_k^u} \right) \underbrace{\frac{\partial h_k^u}{\partial w'_{kj}}}_{y_j^u \text{ (por (5))}} = \\ &= -\sum_u [t_k - g(h_k^u)] \frac{\partial g(h_k^u)}{\partial h_k^u} y_j^u \end{aligned} \quad (6)$$

Reemplazando (6) en (1) tenemos

$$\delta w'_{kj} = -\varepsilon \frac{\partial E}{\partial w'_{kj}} = \varepsilon \sum_u \underbrace{[t_k - g(h_k^u)] \frac{\partial g(h_k^u)}{\partial h_k^u}}_{\Delta_k^u} y_j^u$$

Por lo tanto

$$\delta w'_{kj} = \varepsilon \sum_{\mu} \Delta^{\mu}_k y^{\mu}_j \left[\begin{array}{l} \Delta^{\mu}_k = [t^{\mu}_k - g(h^{\mu}_k)] \frac{\partial g(h^{\mu}_k)}{\partial h^{\mu}_k} \\ h^{\mu}_k = \sum_j w'_{kj} y^{\mu}_j - \theta'_k \end{array} \right]$$

De manera similar se calcula (2). Expandiendo y^{μ}_j en (5) tenemos:

$$E(w_{ji}, w'_{kj}) = \frac{1}{2} \sum_{\mu} \sum_k \left[t^{\mu}_k - g \left(\underbrace{\sum_j w'_{kj} f \left(\underbrace{\sum_i w_{ji} x^{\mu}_i - \theta_j}_{h^{\mu}_j} \right)}_{h^{\mu}_k} \right) - \theta'_k \right]^2 \quad (7)$$

Cálculo de (2): derivando (5) respecto a cada peso w_{ji} y aplicando la regla de la cadena, tenemos:

$$\begin{aligned} \frac{\partial E}{\partial w_{ji}} &= \frac{\partial E}{\partial h^{\mu}_k} \frac{\partial h^{\mu}_k}{\partial h^{\mu}_j} \frac{\partial h^{\mu}_j}{\partial w_{ji}} = \frac{1}{2} 2 \sum_{\mu} \sum_k \left[[t_k - g(h^{\mu}_k)] \left(-\frac{\partial g(h^{\mu}_k)}{\partial h^{\mu}_k} \right) w'_{kj} \frac{\partial f(h^{\mu}_j)}{\partial h^{\mu}_j} \frac{\partial h^{\mu}_j}{\partial w_{ji}} \right] = \\ &= - \sum_{\mu} \sum_k \left[[t_k - g(h^{\mu}_k)] \frac{\partial g(h^{\mu}_k)}{\partial h^{\mu}_k} w'_{kj} \frac{\partial f(h^{\mu}_j)}{\partial h^{\mu}_j} \right] x^{\mu}_i \quad (8) \end{aligned}$$

Reemplazando (8) en (2) tenemos

$$\delta w_{ji} = -\varepsilon \frac{\partial E}{\partial w_{ji}} = \varepsilon \sum_{\mu} \sum_k \underbrace{\left[[t_k - g(h^{\mu}_k)] \frac{\partial g(h^{\mu}_k)}{\partial h^{\mu}_k} w'_{kj} \frac{\partial f(h^{\mu}_j)}{\partial h^{\mu}_j} \right]}_{\Delta^{\mu}_j} x^{\mu}_i$$

Por lo tanto

$$\delta w_{ji} = \varepsilon \sum_{\mu} \Delta^{\mu}_j x^{\mu}_i \left[\begin{array}{l} \Delta^{\mu}_j = \left[\sum_k \Delta^{\mu}_k w'_{kj} \right] \frac{\partial f(h^{\mu}_j)}{\partial h^{\mu}_j} \\ \Delta^{\mu}_k = [t^{\mu}_k - g(h^{\mu}_k)] \frac{\partial g(h^{\mu}_k)}{\partial h^{\mu}_k} \\ h^{\mu}_k = \sum_j w'_{kj} y^{\mu}_j - \theta'_k \\ h^{\mu}_j = \sum_i w_{ji} x^{\mu}_i - \theta_j \end{array} \right]$$