

Gradient derivation for FFNN for binary data

Model - No hidden layers + L neurons

$$z_{\ell i} = \phi\left(b_{\ell} + \sum_{j=1}^p w_{\ell j} x_{ij}\right) \quad \text{for } i \in \{1, \dots, n\}$$

$$\ell \in \{1, \dots, L\}$$

$$n_i = \beta_0 + \sum_{\ell=1}^L z_{\ell i} \beta_{\ell}$$

$$p_i = \text{Prob}(Y_i = 1 | X_i) = \frac{e^{n_i}}{1 + e^{n_i}}$$

$$\theta = \{b_{\ell}, w_{\ell j}, \beta_{\ell}\}$$

Likelihood

$$\log f(Y|\theta) = \sum_{i=1}^n Y_i \log(p_i) + (1 - Y_i) \log(1 - p_i)$$

$$= \sum_{i=1}^n Y_i n_i - Y_i \log(1 + e^{n_i}) - (1 - Y_i) \log(1 + e^{n_i})$$

$$(1) \quad = \sum_{i=1}^n Y_i n_i - \log(1 + e^{n_i})$$

$$(2) \quad = \sum_{i=1}^n Y_i \left(\beta_0 + \sum_{\ell} z_{\ell i} \beta_{\ell}\right) + \sum_{i=1}^n \log\left(1 + e^{\beta_0 + \sum_{\ell} z_{\ell i} \beta_{\ell}}\right)$$

$$(3) \quad = \sum_{i=1}^n Y_i \left(\beta_0 + \sum_{\ell} \beta_{\ell} \phi\left(b_{\ell} + \sum_j w_{\ell j} x_{ij}\right)\right) - \sum_{i=1}^n \log\left(1 + e^{\beta_0 + \sum_{\ell} \phi\left(b_{\ell} + \sum_j w_{\ell j} x_{ij}\right) \beta_{\ell}}\right)$$

Output layer gradients

using (2)

$$\frac{\partial \log(f(y_i))}{\partial \beta_0} = \sum_{i=1}^n y_i - \sum_{i=1}^n \frac{e^{h_i}}{1+e^{h_i}} = \sum_{i=1}^n (y_i - p_i)$$

$$\begin{aligned} \frac{\partial \log(f(y_i))}{\partial \beta_x} &= \sum_{i=1}^n y_i z_{xi} - \sum_{i=1}^n \frac{e^{h_i}}{1+e^{h_i}} z_{xi} \\ &= \sum_{i=1}^n z_{xi} (y_i - p_i) \end{aligned}$$

Input layer gradients

$$\begin{aligned} \frac{\partial \log(f(y_i))}{\partial b_x} &= \sum_{i=1}^n y_i \frac{\partial h_i}{\partial b_x} - \sum_{i=1}^n \frac{e^{h_i}}{1+e^{h_i}} \frac{\partial h_i}{\partial b_x} \\ &= \sum_{i=1}^n (y_i - p_i) \frac{\partial h_i}{\partial b_x} \end{aligned}$$

$$\frac{\partial h_i}{\partial b_x} = \frac{\partial}{\partial b_x} \beta_0 + \sum_{x=1}^L z_{xi} \beta_x$$

$$= \frac{\partial}{\partial b_x} z_{xi} \beta_x$$

$$= \beta_x \frac{\partial}{\partial b_x} \phi \left(b_x + \sum_{j=1}^p w_{xj} x_{ij} \right)$$

$$= \beta_x \phi' \left(b_x + \sum_{j=1}^p w_{xj} x_{ij} \right)$$

~~$$= \beta_x \phi' \left(b_x + \sum_{j=1}^p w_{xj} x_{ij} \right)$$~~

$$\frac{\partial \log(f(y|\theta))}{\partial w_{kj}} = \sum_{i=1}^n (y_i - p_i) \frac{\partial n_i}{\partial w_{kj}}$$

as in previous result

$$\begin{aligned} \frac{\partial n_i}{\partial w_{kj}} &= \frac{\partial}{\partial w_{kj}} \beta_0 + \sum_{\ell=1}^L z_{\ell i} \beta_{\ell} \\ &= \beta_{\ell} \frac{\partial z_{\ell i}}{\partial w_{kj}} \\ &= \beta_{\ell} \frac{\partial}{\partial w_{kj}} \phi \left(b_{\ell} + \sum_{j=1}^p w_{kj} x_{ij} \right) \\ &= \beta_{\ell} \phi' \left(b_{\ell} + \sum_{j=1}^p w_{kj} x_{ij} \right) x_{ij} \end{aligned}$$