

Pseudocode:

Initialize inputs:

$x\_in, y\_in, y1\_in, z\_in$  (input arrays for data).

Set initial parameters  $w = [-2, 3, 1]$  (initial guess for the weights).

Define constants:  $maxit = 1000000$ ,  $\epsilon = 1.e-3$ .

Define objective function:

Compute  $z = w[0] + w[1] * x\_in + w[2] * z\_in$ .

Calculate  $z1 = \log(1 + \exp(-z))$  and  $z2 = \log(1 + \exp(z))$ .

Compute the value of the objective function:

$objective\_value = \text{dot}(y\_in, z1) + \text{dot}(y1\_in, z2)$ .

Define gradient function:

Compute  $hi = 1 / (1 + \exp(-w[0] - w[1] * x\_in - w[2] * z\_in))$ .

Calculate the difference  $yh = hi - y\_in$ .

Return gradient as  $[\text{sum}(yh), \text{dot}(yh, x\_in), \text{dot}(yh, z\_in)]$ .

Define line search function:

Set  $\beta = 0.1$ ,  $stepsize = 1$ ,  $trial = 100$ ,  $\tau = 0.5$ .

For each iteration (up to trial times):

Compute  $fx1 = objective\_function(x)$ .

Compute  $fx2 = objective\_function(x - stepsize * gradient)$ .

Calculate condition  $c = -\beta * stepsize * \text{dot}(gradient, gradient)$ .

If  $fx2 - fx1 \leq c$ , break loop (valid step size found).

Else, reduce stepsize by multiplying by  $\tau$ .

Return the final step size.

Optimization loop:

For each iteration (up to  $maxit$  times):

Compute  $gradient = gradient\_function(w)$ .

Calculate norm of the gradient  $b = \text{norm}(\text{gradient})$ .

If  $b < \text{epsilon}$ , break loop (convergence achieved).

Perform line search to compute stepsize.

Update  $w = w - \text{stepsize} * \text{gradient}$ .

Print the iteration count and gradient norm.

After the loop:

Calculate the minimum objective function value:

$\text{minimum\_value} = \text{objective\_function}(w)$ .

Print the minimum value, location ( $w$ ), and number of iterations ( $i$ ).