already know : $\frac{\partial}{\partial w_k} g(w^T x^{(i)}) = g\cdot(1-g)\, x_k^{(i)}$.

We have $l(w) = \frac{1}{2}\sum (y^{(i)} - g)^2$

$$\frac{\partial}{\partial w_j} l(w) = \sum_i (y^{(i)} - g)\cdot g\cdot(1-g)\cdot x_j^{(i)}$$

$$H[k,j] = \frac{\partial}{\partial w_k}\frac{\partial}{\partial w_j} l(w) = \frac{\partial}{\partial w_k}\sum (y^{(i)} - g)\cdot g(1-g)\cdot x_j^{(i)}$$

$$= \sum \frac{\partial}{\partial w_k} y^{(i)} x_j^{(i)} g(1-g) - \frac{\partial}{\partial w_k} x_j^{(i)} g^2(1-g)$$

$$= \sum \underset{1}{\frac{\partial}{\partial w_k} y^{(i)} x_j^{(i)} g} - \underset{2}{\frac{\partial}{\partial w_k} y^{(i)} x_j^{(i)} g^2} - \underset{3}{\frac{\partial}{\partial w_k} x_j^{(i)} g^2} + \underset{4}{\frac{\partial}{\partial w_k} x_j^{(i)} \cdot g^3}$$

$$= \sum \underset{1}{y^{(i)} x_j^{(i)} \cdot g(1-g) x_k^{(i)}} - \underset{2}{2y^{(i)} x_j^{(i)} g\cdot g(1-g) x_k^{(i)}} - \underset{3}{2x_j^{(i)} g\cdot g(1-g) x_k^{(i)}}$$

$$+ \underset{4}{3g^2\cdot g(1-g) x_k^{(i)}}.$$

$$= \sum g(1-g) x_k^{(i)} x_j^{(i)} y^{(i)} - 2g^2(1-g) x_j^{(i)} x_k^{(i)} y^{(i)} - 2g^2(1-g) x_j^{(i)} x_k^{(i)}$$

$$+ 3g^3(1-g) x_j^{(i)} x_k^{(i)}.$$

$$= \sum g(1-g) x_j^{(i)} x_k^{(i)} \underline{\left[y^{(i)} - 2g y^{(i)} - 2g + 3g^2\right]}$$

$$\boxed{\begin{aligned} &H[l(w)] = X^T\, \mathrm{DIAG}\left(g(1-g)\right), X. \left[\mathrm{sum}\left[y^{(i)} - 2g y^{(i)} - 2g + 3g^2\right]\right] \\ &H(k,j) = \sum g(1-g) x_k^{(i)} x_j^{(i)} . \left[y^{(i)} - 2g y^{(i)} - 2g + 3g^2\right] \end{aligned}}$$

$$W := W + \eta \underset{\text{inverse Hessian}}{\left[X^T . \mathrm{diag}\left(g(1-g)\right) . X * \mathrm{sum}\left(y^{(i)} - 2g y^{(i)} - 2g + 3g^2\right)\right]^{-1}} . \underset{\text{gradient}}{X * ydiff . g(1-g)}$$