

# QBS 108: Homework 1 Key

April 14, 2020

1. From the L2-regularized cross-entropy loss function given below, write the formula for a single gradient descent update for  $w_k \in \mathbf{w}$ . Why would L1 be more difficult than calculating the formula for an L2 regularized model?

Cross entropy:

$$L = - \sum y_i \ln(p(x_i)) + (1 - y_i) \ln(1 - p(x_i)) + \lambda ||w||^2$$

Where;

$$p(x_i) = \frac{1}{1 + e^{-w'x}}$$

It is helpful to calculate the derivative of  $p(x)$  separately.

$$\begin{aligned} p(x_i) &= (1 + e^{-w'x})^{-1} \\ \frac{\partial p(x_i)}{\partial w_k} &= -1 \frac{1}{(1 + e^{-w'x})^2} * -x e^{-w'x} \\ \frac{\partial p(x_i)}{\partial w_k} &= \frac{x e^{-w'x}}{(1 + e^{-w'x})^2} \\ \frac{\partial p(x_i)}{\partial w_k} &= x \frac{e^{-w'x}}{(1 + e^{-w'x})^2} \end{aligned}$$

This is 'the trick'- add and subtract 1 to rewrite the expression (alternatively, you can multiply by  $\frac{1+e^{-x}}{1+e^{-x}}$  and reduce). This lets you reduce the squared term on one denominator.

$$\begin{aligned} \frac{\partial p(x_i)}{\partial w_k} &= x \left[ \frac{-1 + 1 + e^{-w'x}}{(1 + e^{-w'x})^2} \right] \\ \frac{\partial p(x_i)}{\partial w_k} &= x \left[ \frac{-1}{(1 + e^{-w'x})^2} + \frac{1}{(1 + e^{-w'x})} \right] \\ \frac{\partial p(x_i)}{\partial w_k} &= \frac{x}{(1 + e^{-w'x})} \left[ 1 - \frac{1}{(1 + e^{-w'x})} \right] \end{aligned}$$

Recognizing this as similar to  $p(x_i)$  we can rewrite to yield:

$$\frac{\partial p(x_i)}{\partial w_k} = xp(x_i)(1 - p(x_i))$$

Now we can derive the rest of the expression. From loss;

$$-L = \sum y_i \ln(p(x_i)) + (1 - y_i) \ln(1 - p(x_i)) + \lambda ||w||^2$$

Plug in our derivative and use chain rule to calculate out the derivatives.

$$-\frac{\partial L}{\partial w_k} = \sum y_i \frac{\partial \ln(p(x_i))}{\partial w_k} + (1 - y_i) \frac{\partial \ln(1 - p(x_i))}{\partial w_k} + 2\lambda w_k$$

We calculated  $\frac{\partial p(x_i)}{\partial w_k}$  above, and recall  $\frac{\partial \ln(x)}{\partial y} = (\frac{1}{x}) \frac{\partial x}{\partial y}$ ;

$$-\frac{\partial L}{\partial w_k} = \sum y_i \frac{1}{p(x_i)} \frac{\partial p(x_i)}{\partial w_k} + (1 - y_i) \frac{1}{1 - p(x_i)} \frac{\partial 1 - p(x_i)}{\partial w_k} + 2\lambda w_k$$

Replace the term that we calculated above, and notice that  $\frac{\partial 1 - p(x_i)}{\partial w_k} = -\frac{\partial p(x_i)}{\partial w_k}$  as the constant drops off.

$$-\frac{\partial L}{\partial w_k} = \sum y_i \left( \frac{1}{p(x_i)} \right) (xp(x_i)(1 - p(x_i))) + (1 - y_i) \left( \frac{1}{(1 - p(x_i))} \right) (-xp(x_i)(1 - p(x_i))) + 2\lambda w_k$$

Canceling out terms and combining yields;

$$\begin{aligned} -\frac{\partial L}{\partial w_k} &= \sum y_i (x_i(1 - p(x_i))) + (1 - y_i)(-x_i p(x_i)) + 2\lambda w_k \\ -\frac{\partial L}{\partial w_k} &= \sum y_i (x_i - x_i p(x_i)) + ((-x_i p(x_i)) - y_i(-x_i) p(x_i)) + 2\lambda w_k \\ -\frac{\partial L}{\partial w_k} &= \sum (y_i x_i - y_i x_i p(x_i)) + ((-x_i p(x_i)) + (y_i x_i p(x_i))) + 2\lambda w_k \\ -\frac{\partial L}{\partial w_k} &= \sum (y_i x_i - y_i x_i p(x_i)) + ((-x_i p(x_i)) + (y_i x_i p(x_i))) + 2\lambda w_k \\ -\frac{\partial L}{\partial w_k} &= \sum (y_i x_i) + ((-x_i p(x_i)) + 2\lambda w_k) \\ -\frac{\partial L}{\partial w_k} &= \sum_i^N (y_i - p(x_i)) x_i + 2\lambda w_k \end{aligned}$$

Making each update  $w_k \rightarrow w'_k$ ;

$$\boxed{w'_k = w_k + \alpha \left[ \frac{\partial L}{\partial w_k} \right] = w_k + \alpha \left[ \sum_i^N (y_i - p(x_i)) x_i + 2\lambda w_k \right]}$$

L1 is more difficult to derive than L2 because L1 penalty term is non-differentiable (continuity issues at 0).