Backpropagation Classwork

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All We Want in Life is Gradients

$$\begin{bmatrix}
\frac{\partial h}{\partial b_1} \\
\frac{\partial h}{\partial b_2} \\
\frac{\partial h}{\partial w_1} \\
\frac{\partial h}{\partial w_2}
\end{bmatrix}$$

Partial Derivatives

$$f(x,y) = x^2 + xy + y^2$$

$$\frac{\partial f}{\partial y} = x + 2y$$
 $\frac{\partial f}{\partial x} = 2x + y$

For a function of with multiple variables, how does the *function change* when you change a *single* variable

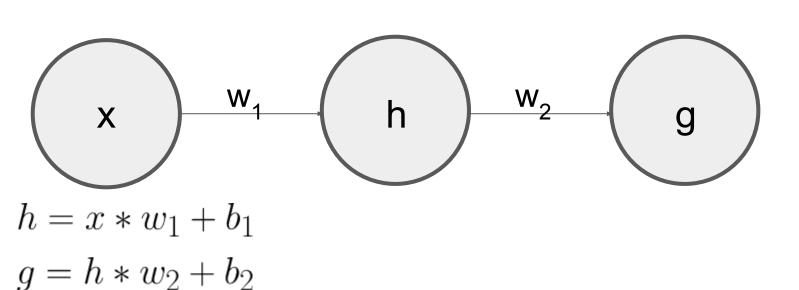
The Chain-Rule

$$f(x) = cos(x)$$
$$g(x) = x^{2}$$
$$f(g(x)) = cos(x^{2})$$

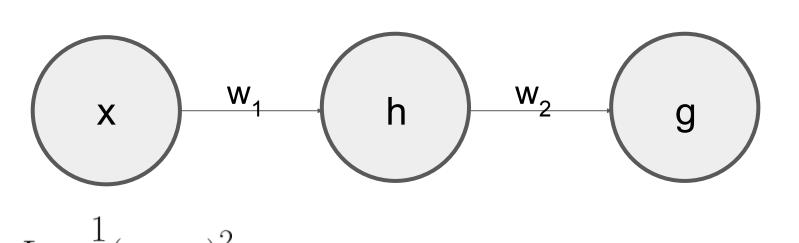
If we want to know how changing x affects f(g(x)) we first need to think about how changing x affects g(x) then how changing g(x) affects f(g(x))

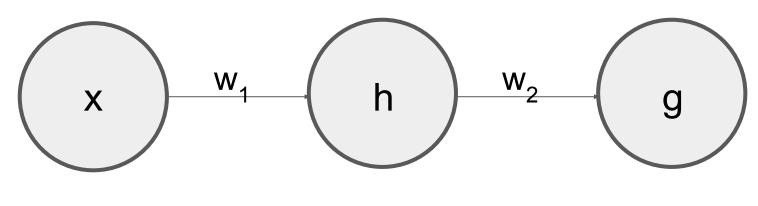
$$\frac{\partial f(g(x))}{\partial x} = \frac{\partial f}{\partial g} \frac{\partial g}{\partial x}$$

Simple Network



Loss



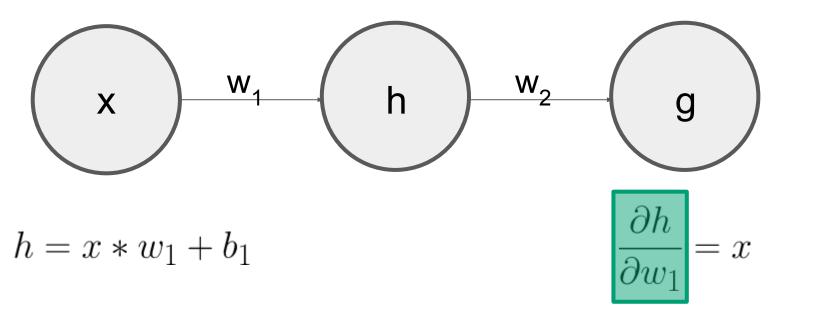


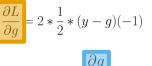
 $g = h * w_2 + b_2$

 b_2 $\frac{\partial g}{\partial h} = w$

$$\frac{\partial g}{\partial g} = 2 * \frac{1}{2} * (y - g)(-1)$$

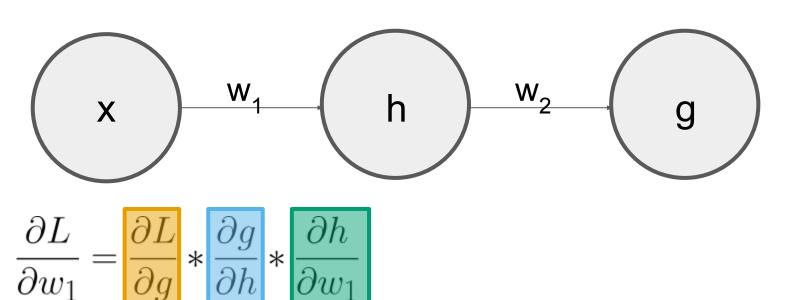
$$\frac{\partial g}{\partial g} = w_2$$

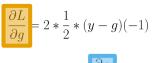






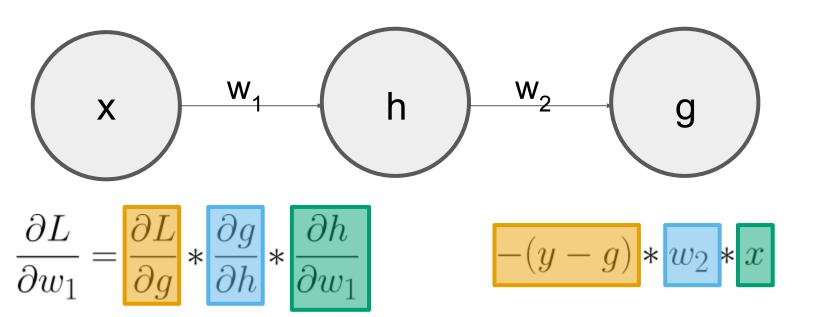


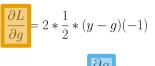






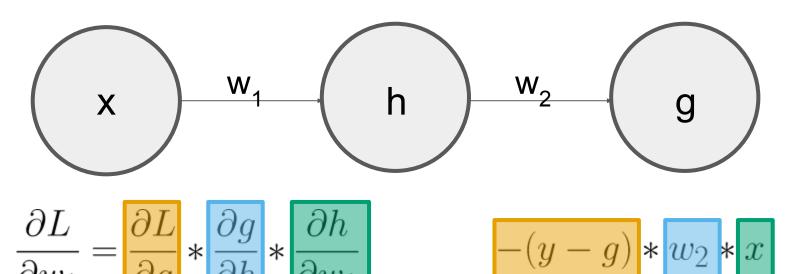




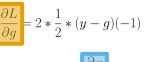






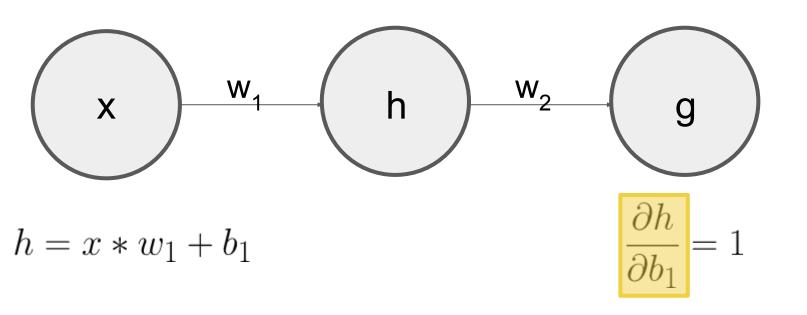










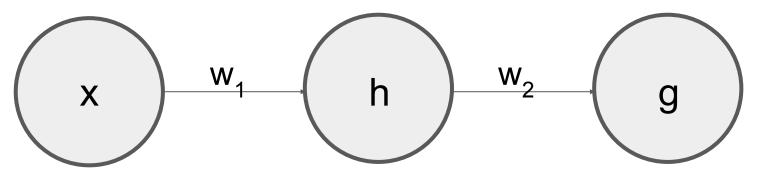


$\frac{\partial L}{\partial g} = 2 * \frac{1}{2} * (y - g)(-1)$





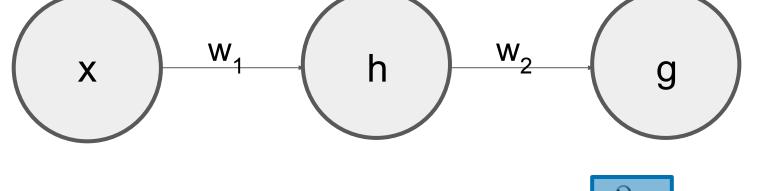




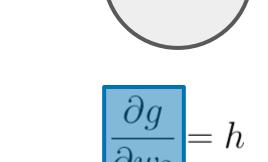
$$\frac{\partial L}{\partial b_1} = \frac{\partial L}{\partial g} * \frac{\partial g}{\partial h} * \frac{\partial h}{\partial b_1}$$

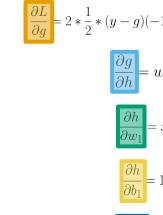
$$-(y-g)*w_2*1$$

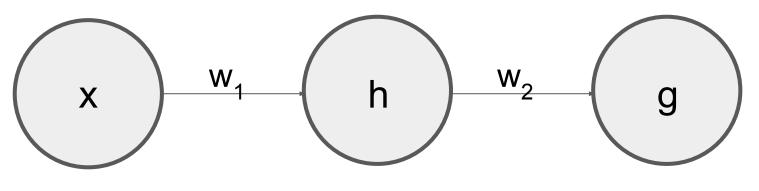




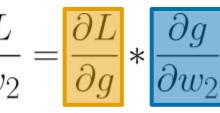
$$g = h * w_2 + b_2$$



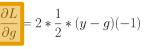








$$-(y-g)*h$$



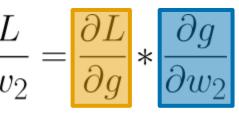


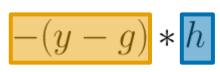






$$\begin{pmatrix} x \end{pmatrix}$$
 $\begin{pmatrix} w_1 \end{pmatrix}$ $\begin{pmatrix} h \end{pmatrix}$ $\begin{pmatrix} w_2 \end{pmatrix}$ $\begin{pmatrix} g \end{pmatrix}$

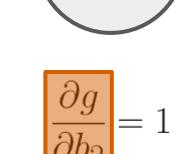


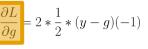




$$W_1$$
 W_2 Q

$$g = h * w_2 + b_2$$











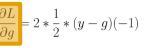


$$\frac{\partial g}{\partial b_2} = 1$$

$$\begin{pmatrix} x \end{pmatrix} \qquad \begin{pmatrix} w_1 \end{pmatrix} \qquad \begin{pmatrix} h \end{pmatrix} \qquad \begin{pmatrix} w_2 \end{pmatrix} \qquad \begin{pmatrix} g \end{pmatrix}$$

$$\frac{\partial L}{\partial b_2} = \boxed{\frac{\partial L}{\partial g}} * \boxed{\frac{\partial g}{\partial b_2}}$$

$$-(y-g)*1$$











$$\frac{\partial g}{\partial b_2} = 1$$

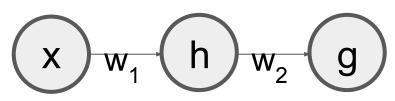
$$\begin{pmatrix} x \end{pmatrix} \qquad \begin{pmatrix} w_1 \end{pmatrix} \qquad \begin{pmatrix} h \end{pmatrix} \qquad \begin{pmatrix} w_2 \end{pmatrix} \qquad \begin{pmatrix} g \end{pmatrix}$$

$$\frac{\partial L}{\partial b_2} = \frac{\partial L}{\partial g} * \frac{\partial g}{\partial b_2}$$

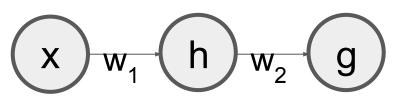


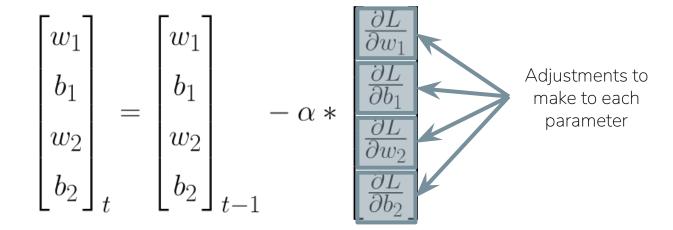
$$x$$
 w_1 h w_2 g

$$\nabla L = \begin{bmatrix} \frac{\partial w_1}{\partial L} \\ \frac{\partial L}{\partial b_1} \\ \frac{\partial L}{\partial w_2} \\ \frac{\partial L}{\partial b_2} \end{bmatrix}$$



$$\begin{bmatrix} w_1 \\ b_1 \\ w_2 \\ b_2 \end{bmatrix}_t = \begin{bmatrix} w_1 \\ b_1 \\ w_2 \\ b_2 \end{bmatrix}_{t-1} - \alpha * \begin{bmatrix} \frac{\partial L}{\partial w_1} \\ \frac{\partial L}{\partial b_1} \\ \frac{\partial L}{\partial w_2} \\ \frac{\partial L}{\partial b_2} \end{bmatrix}$$

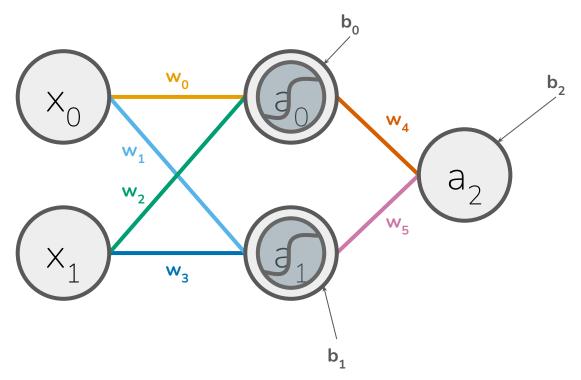


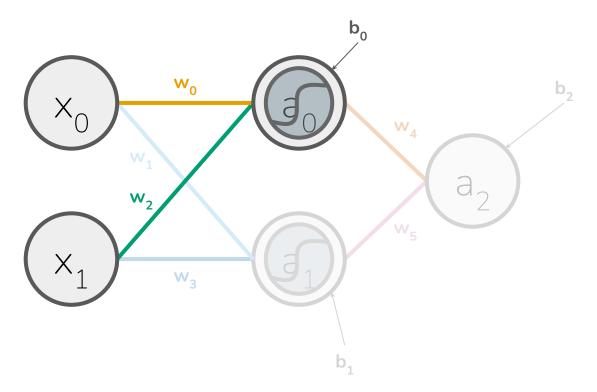


Note: We have only 1 hidden layer and NO activation parameter functions...

A More Complicated Network

A More Complicated Network

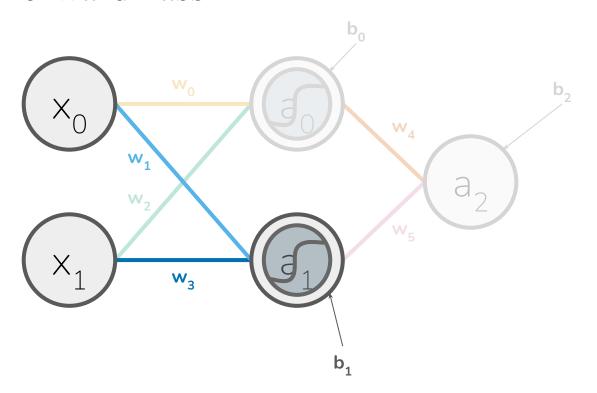




$$z_0 = (x_0 * w_0) + (x_1 * w_2) + b_0$$
$$a_0 = \sigma(z_0)$$

$$z_1 = (x_0 * w_1) + (x_1 * w_3) + b_1$$
$$a_1 = \sigma(z_1)$$

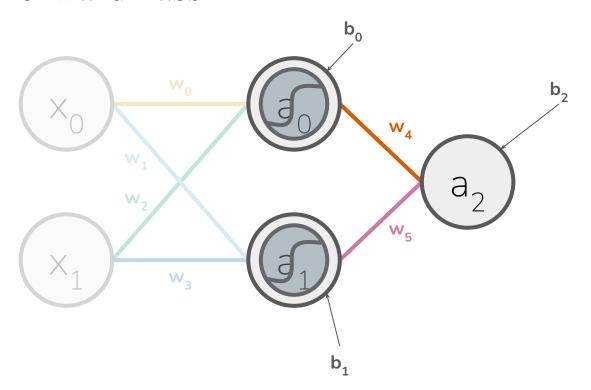
$$a_2 = (a_0 * w_4) + (a_1 * w_5) + b_2$$



$$z_0 = (x_0 * w_0) + (x_1 * w_2) + b_0$$
$$a_0 = \sigma(z_0)$$

$$z_1 = (x_0 * w_1) + (x_1 * w_3) + b_1$$
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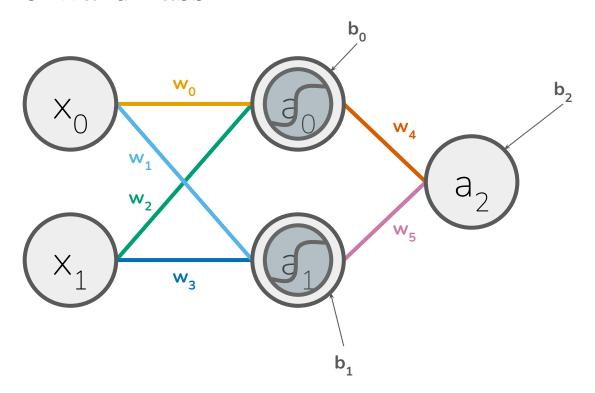
$$a_2 = (a_0 * w_4) + (a_1 * w_5) + b_2$$



$$z_0 = (x_0 * w_0) + (x_1 * w_2) + b_0$$
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$$z_1 = (x_0 * w_1) + (x_1 * w_3) + b_1$$
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$$a_2 = (a_0 * w_4) + (a_1 * w_5) + b_2$$



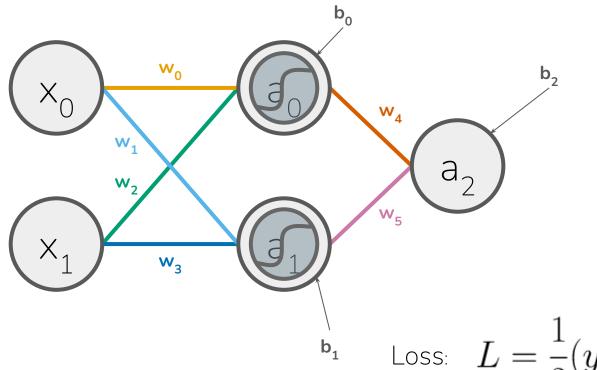
$$z_0 = (x_0 * w_0) + (x_1 * w_2) + b_0$$
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$$a_2 = (a_0 * w_4) + (a_1 * w_5) + b_2$$

Loss

$$z_0 = (x_0 * w_0) + (x_1 * w_2) + b_0$$
$$a_0 = \sigma(z_0)$$



$$z_1 = (x_0 * w_1) + (x_1 * w_3) + b_1$$

 $a_1 = \sigma(z_1)$

$$a_2 = (a_0 * w_4) + (a_1 * w_5) + b_2$$

Loss: $L = \frac{1}{2}(y - a_2)^2$

Questions

- 1. What is the dimension of our gradient (i.e. how many parameters are there in the model?)
- 2. How many individual partial derivatives do we need to calculate in order to compute all the terms in the gradient?
- 3. What is the partial derivative of L with respect to w_4 ? (Don't calculate the derivatives, just use the chain rule to figure out which partial derivatives you'd need in order to calculate it)
- 4. What is the partial derivative of L with respect to w_0 ? (Don't calculate the derivatives, just use the chain rule to figure out which partial derivatives you'd need in order to calculate it)
- 5. Do earlier weights (nearer the input layer) have *longer* or *shorter* chains of partial derivatives?

Notes:

Notes:

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