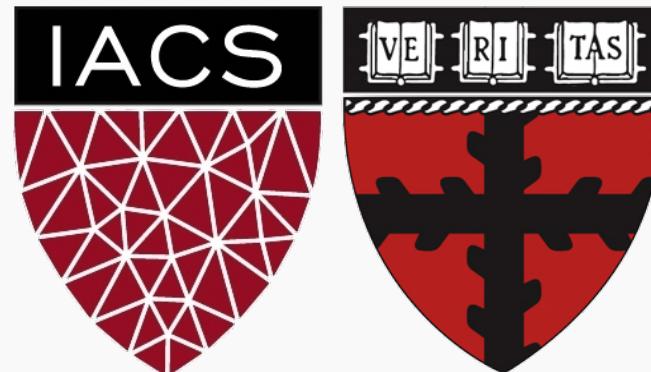


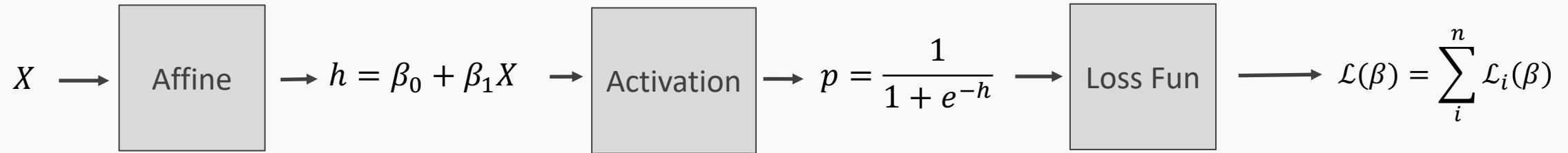
Backpropagation

CS109A Introduction to Data Science

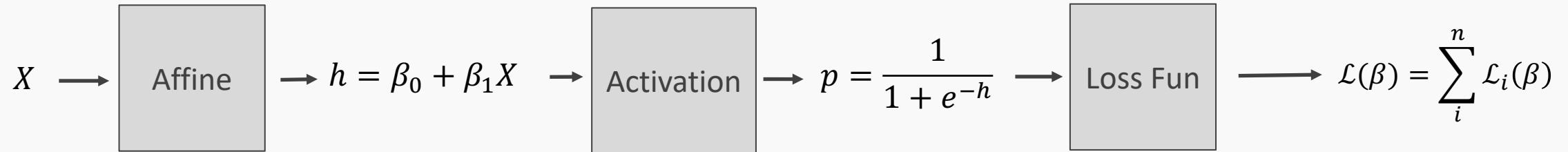
Pavlos Protopapas, Kevin Rader and Chris Tanner



Backpropagation: Logistic Regression Revisited



Backpropagation: Logistic Regression Revisited



$$\frac{\partial \mathcal{L}}{\partial p} \frac{\partial p}{\partial h} \frac{\partial h}{\partial \beta} \quad \leftarrow \quad \frac{\partial \mathcal{L}}{\partial p} \frac{\partial p}{\partial h} \quad \leftarrow \quad \frac{\partial \mathcal{L}}{\partial p}$$

$$\frac{\partial h}{\partial \beta_1} = X, \frac{d\mathcal{L}}{d\beta_0} = 1$$

$$\frac{\partial p}{\partial h} = \sigma(h)(1 - \sigma(h))$$

$$\frac{\partial \mathcal{L}}{\partial p} = -y \frac{1}{p} - (1 - y) \frac{1}{1 - p}$$

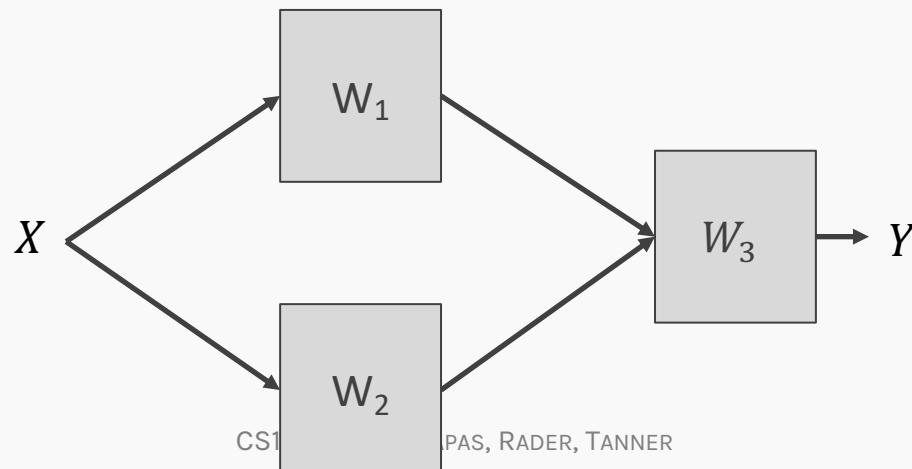
$$\frac{\partial \mathcal{L}}{\partial \beta_1} = -X\sigma(h)(1 - \sigma(h))\left[y \frac{1}{p} + (1 - y) \frac{1}{1 - p}\right]$$

$$\frac{\partial \mathcal{L}}{\partial \beta_0} = -\sigma(h)(1 - \sigma(h))\left[y \frac{1}{p} + (1 - y) \frac{1}{1 - p}\right]$$

Backpropagation

1. Derivatives need to be evaluated at some values of X , y , and W .
2. But since we have an expression, we can build a function that takes as input X , y , W , and returns the derivatives, and then we can use gradient descent to update.
3. This approach works well but it does not generalize. For example if the network is changed, we need to write a new function to evaluate the derivatives.

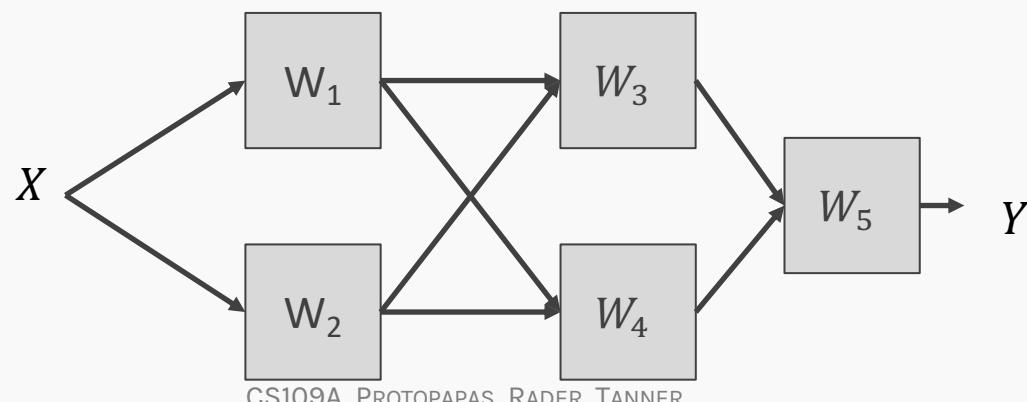
For example, this network will need a different function for the derivatives



Backpropagation

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For example, this network will need a different function for the derivatives



Backpropagation. Pavlos game #456

Need to find a formalism to calculate the derivatives of the loss w.r.t. weights that is:

1. Flexible enough that adding a node or a layer or changing something in the network will not require re-deriving the functional form from scratch.
2. It is exact.
3. It is computationally efficient.

Hints:

1. Remember we only need to evaluate the derivatives at X_i, y_i and $W^{(k)}$.
2. We should take advantage of the chain rule we learned before

Idea 1: Evaluate the derivative at: $X=\{3\}$, $y=1$, $W=3$

Variables	derivatives	Value of the variable	Value of the partial derivative	$\frac{d\xi_n}{dW}$
$\xi_1 = -W^T X$	$\frac{\partial \xi_1}{\partial W} = -X$	-9	-3	-3
$\xi_2 = e^{\xi_1} = e^{-W^T X}$	$\frac{\partial \xi_2}{\partial \xi_1} = e^{\xi_1}$	e^{-9}	e^{-9}	$-3e^{-9}$
$\xi_3 = 1 + \xi_2 = 1 + e^{-W^T X}$	$\frac{\partial \xi_3}{\partial \xi_2} = 1$	$1+e^{-9}$	1	$-3e^{-9}$
$\xi_4 = \frac{1}{\xi_3} = \frac{1}{1 + e^{-W^T X}} = p$	$\frac{\partial \xi_4}{\partial \xi_3} = -\frac{1}{\xi_3^2}$	$\frac{1}{1 + e^{-9}}$	$\left(\frac{1}{1 + e^{-9}}\right)^2$	$-3e^{-9} \left(\frac{1}{1 + e^{-9}}\right)^2$
$\xi_5 = \log \xi_4 = \log p = \log \frac{1}{1 + e^{-W^T X}}$	$\frac{\partial \xi_5}{\partial \xi_4} = \frac{1}{\xi_4}$	$\log \frac{1}{1 + e^{-9}}$	$1 + e^{-9}$	$-3e^{-9} \left(\frac{1}{1 + e^{-9}}\right)$
$\mathcal{L}_i^A = -y \xi_5$	$\frac{\partial \mathcal{L}}{\partial \xi_5} = -y$	$-\log \frac{1}{1 + e^{-9}}$	-1	$3e^{-9} \left(\frac{1}{1 + e^{-9}}\right)$
$\frac{\partial \mathcal{L}_i^A}{\partial W} = \frac{\partial \mathcal{L}_i}{\partial \xi_5} \frac{\partial \xi_5}{\partial \xi_4} \frac{\partial \xi_4}{\partial \xi_3} \frac{\partial \xi_3}{\partial \xi_2} \frac{\partial \xi_2}{\partial \xi_1} \frac{\partial \xi_1}{\partial W}$			-3	0.00037018372

Basic functions

We still need to derive derivatives ☹

Variables	derivatives	Value of the variable	Value of the partial derivative	$\frac{d\xi_n}{dW}$
$\xi_1 = -W^T X$	$\frac{\partial \xi_1}{\partial W} = -X$	-9	-3	-3
$\xi_2 = e^{\xi_1} = e^{-W^T X}$	$\frac{\partial \xi_2}{\partial \xi_1} = e^{\xi_1}$	e^{-9}	e^{-9}	$-3e^{-9}$
$\xi_3 = 1 + \xi_2 = 1 + e^{-W^T X}$	$\frac{\partial \xi_3}{\partial \xi_2} = 1$	$1+e^{-9}$	1	$-3e^{-9}$
$\xi_4 = \frac{1}{\xi_3} = \frac{1}{1 + e^{-W^T X}} = p$	$\frac{\partial \xi_4}{\partial \xi_3} = -\frac{1}{\xi_3^2}$	$\frac{1}{1 + e^{-9}}$	$\left(\frac{1}{1 + e^{-9}}\right)^2$	$-3e^{-9} \left(\frac{1}{1+e^{-9}}\right)^2$
$\xi_5 = \log \xi_4 = \log p = \log \frac{1}{1 + e^{-W^T X}}$	$\frac{\partial \xi_5}{\partial \xi_4} = \frac{1}{\xi_4}$	$\log \frac{1}{1 + e^{-9}}$	$1 + e^{-9}$	$-3e^{-9} \left(\frac{1}{1+e^{-9}}\right)$
$\mathcal{L}_i^A = -y \xi_5$	$\frac{\partial \mathcal{L}}{\partial \xi_5} = -y$	$-\log \frac{1}{1 + e^{-9}}$	-1	$3e^{-9} \left(\frac{1}{1+e^{-9}}\right)$
$\frac{\partial \mathcal{L}_i^A}{\partial W} = \frac{\partial \mathcal{L}_i}{\partial \xi_5} \frac{\partial \xi_5}{\partial \xi_4} \frac{\partial \xi_4}{\partial \xi_3} \frac{\partial \xi_3}{\partial \xi_2} \frac{\partial \xi_2}{\partial \xi_1} \frac{\partial \xi_1}{\partial W}$			-3	0.00037018372



Basic functions

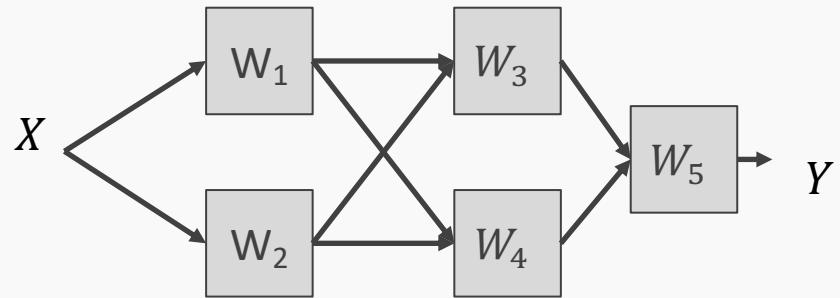
Notice though those are basic functions that my grandparent can do

$\xi_0 = X$	$\frac{\partial \xi_0}{\partial X} = 1$	<pre>def x0(x): return x</pre>	<pre>def derx0(): return 1</pre>
$\xi_1 = -W^T \xi_0$	$\frac{\partial \xi_1}{\partial W} = -X$	<pre>def x1(a, x): return -a*x</pre>	<pre>def derx1(a, x): return -a</pre>
$\xi_2 = e^{\xi_1}$	$\frac{\partial \xi_2}{\partial \xi_1} = e^{\xi_1}$	<pre>def x2(x): return np.exp(x)</pre>	<pre>def derx2(x): return np.exp(x)</pre>
$\xi_3 = 1 + \xi_2$	$\frac{\partial \xi_3}{\partial \xi_2} = 1$	<pre>def x3(x): return 1+x</pre>	<pre>def derx3(x): return 1</pre>
$\xi_4 = \frac{1}{\xi_3}$	$\frac{\partial \xi_4}{\partial \xi_3} = -\frac{1}{\xi_3^2}$	<pre>def der1(x): return 1/(x)</pre>	<pre>def derx4(x): return -(1/x)**(2)</pre>
$\xi_5 = \log \xi_4$	$\frac{\partial \xi_5}{\partial \xi_4} = \frac{1}{\xi_4}$	<pre>def der1(x): return np.log(x)</pre>	<pre>def derx5(x): return 1/x</pre>
$\mathcal{L}_i^A = -y \xi_5$	$\frac{\partial \mathcal{L}}{\partial \xi_5} = -y$	<pre>def der1(y, x): return -y*x</pre>	<pre>def derL(y): return -y</pre>



Putting it altogether

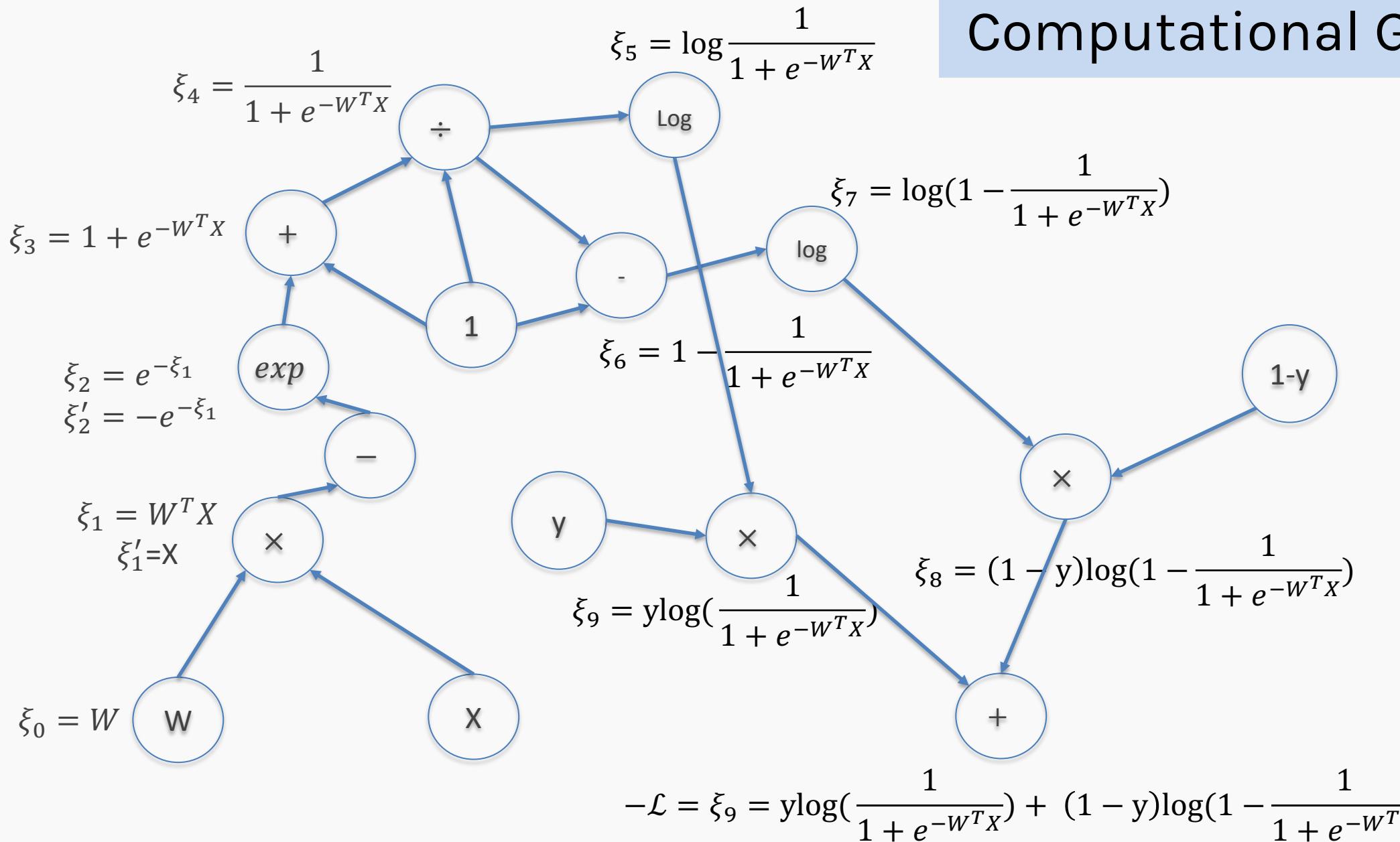
1. We specify the network structure



2. Following the computational graph ...

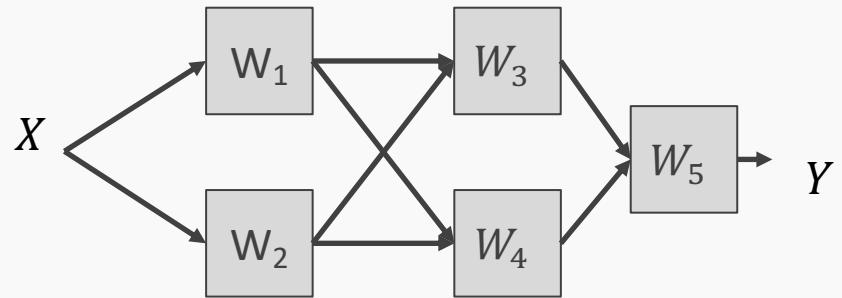
What is computational graph?

Computational Graph



Putting it altogether

1. We specify the network structure



- Envision the computational graph (only needed for the reverse mode).
- At each node of the graph we build two functions: the evaluation of the variable and its partial derivative with respect to the previous variable (as shown in the table 3 slides back)
- Now we can either go forward or backward depending on the situation. In general, forward is easier to implement and to understand. The difference is clearer when there are multiple nodes per layer.

Forward mode: Evaluate the derivative at: $X=\{3\}$, $y=1$, $W=3$

Variables	derivatives	Value of the variable	Value of the partial derivative	$\frac{d\mathcal{L}}{d\xi_n}$
$\xi_1 = -W^T X$	$\frac{\partial \xi_1}{\partial W} = -X$	-9	-3	-3
$\xi_2 = e^{\xi_1} = e^{-W^T X}$	$\frac{\partial \xi_2}{\partial \xi_1} = e^{\xi_1}$	e^{-9}	e^{-9}	$-3e^{-9}$
$\xi_3 = 1 + \xi_2 = 1 + e^{-W^T X}$	$\frac{\partial \xi_3}{\partial \xi_2} = 1$	$1+e^{-9}$	1	$-3e^{-9}$
$\xi_4 = \frac{1}{\xi_3} = \frac{1}{1 + e^{-W^T X}} = p$	$\frac{\partial \xi_4}{\partial \xi_3} = -\frac{1}{\xi_3^2}$	$\frac{1}{1 + e^{-9}}$	$\left(\frac{1}{1 + e^{-9}}\right)^2$	$-3e^{-9} \left(\frac{1}{1 + e^{-9}}\right)^2$
$\xi_5 = \log \xi_4 = \log p = \log \frac{1}{1 + e^{-W^T X}}$	$\frac{\partial \xi_5}{\partial \xi_4} = \frac{1}{\xi_4}$	$\log \frac{1}{1 + e^{-9}}$	$1 + e^{-9}$	$-3e^{-9} \left(\frac{1}{1 + e^{-9}}\right)$
$\mathcal{L}_i^A = -y \xi_5$	$\frac{\partial \mathcal{L}}{\partial \xi_5} = -y$	$-\log \frac{1}{1 + e^{-9}}$	-1	$3e^{-9} \left(\frac{1}{1 + e^{-9}}\right)$
$\frac{\partial \mathcal{L}_i^A}{\partial W} = \frac{\partial \mathcal{L}_i}{\partial \xi_5} \frac{\partial \xi_5}{\partial \xi_4} \frac{\partial \xi_4}{\partial \xi_3} \frac{\partial \xi_3}{\partial \xi_2} \frac{\partial \xi_2}{\partial \xi_1} \frac{\partial \xi_1}{\partial W}$			-3	0.00037018372



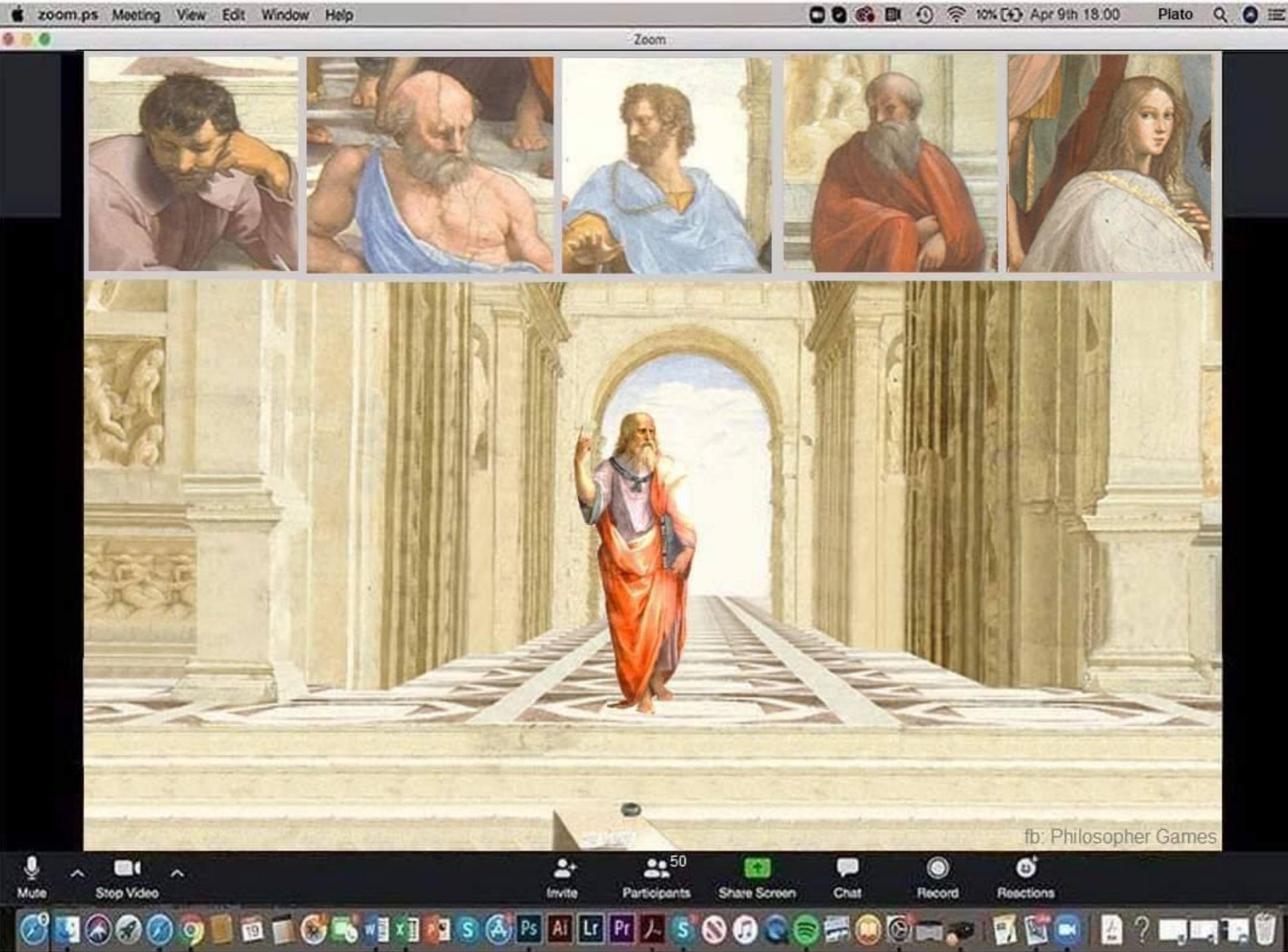
Backward mode: Evaluate the derivative at: $X=\{3\}$, $y=1$, $W=3$

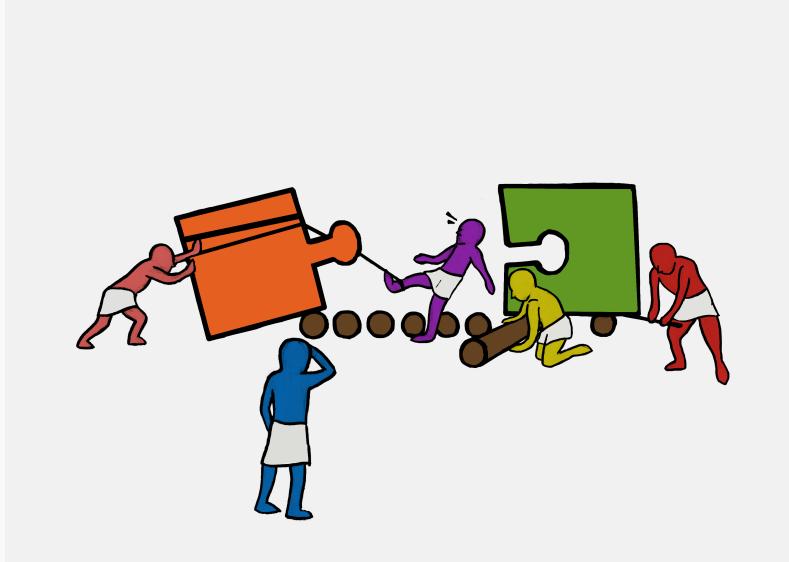
Variables	derivatives	Value of the variable	Value of the partial derivative
$\xi_1 = -W^T X$	$\frac{\partial \xi_1}{\partial W} = -X$	-9	-3
$\xi_2 = e^{\xi_1} = e^{-W^T X}$	$\frac{\partial \xi_2}{\partial \xi_1} = e^{\xi_1}$	e^{-9}	e^{-9}
$\xi_3 = 1 + \xi_2 = 1 + e^{-W^T X}$	$\frac{\partial \xi_3}{\partial \xi_2} = 1$	$1+e^{-9}$	1
$\xi_4 = \frac{1}{\xi_3} = \frac{1}{1 + e^{-W^T X}} = p$	$\frac{\partial \xi_4}{\partial \xi_3} = -\frac{1}{\xi_3^2}$	$\frac{1}{1 + e^{-9}}$	$\left(\frac{1}{1 + e^{-9}}\right)^2$
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$\mathcal{L}_i^A = -y\xi_5$	$\frac{\partial \mathcal{L}}{\partial \xi_5} = -y$	$-\log \frac{1}{1 + e^{-9}}$	-1
$\frac{\partial \mathcal{L}_i^A}{\partial W} = \frac{\partial \mathcal{L}_i}{\partial \xi_5} \frac{\partial \xi_5}{\partial \xi_4} \frac{\partial \xi_4}{\partial \xi_3} \frac{\partial \xi_3}{\partial \xi_2} \frac{\partial \xi_2}{\partial \xi_1} \frac{\partial \xi_1}{\partial W}$			Type equation here.

Store all these values

Check this: <https://autoed.herokuapp.com>







I suggest to use pen and paper to calculate the derivatives
Back-propagation by hand