# CS-671: DEEP LEARNING AND ITS APPLICATIONS Lecture: 09 Backpropagation and Neural Networks

Aditya Nigam, Assistant Professor School of Computing and Electrical Engineering (SCEE) Indian Institute of Technology, Mandi http://faculty.iitmandi.ac.in/ãditya/ aditya@iitmandi.ac.in

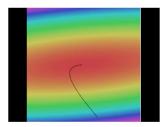


Presentation for CS-671@IIT Mandi (7 March, 2019) (\*Slides Credit : Stanford University CS231n, Spring 2017) https://www.youtube.com/watch?v=vT1JzLTH4G4&list= PLC1qU-LWwrF64f4QKQT-Vg5Wr4qEE1Zxk

February - May, 2019

## Optimization





# Vanilla Gradient Descent

while True:

Landscape image is CC0 1.0 public domain Welking man image is CC0 1.0 public domain

weights\_grad = evaluate\_gradient(loss\_fun, data, weights)
weights += - step size \* weights grad # perform parameter update

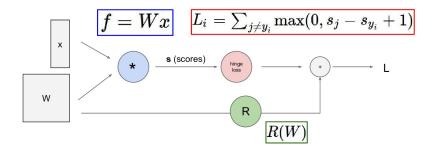
Gradient descent

$$rac{df(x)}{dx} = \lim_{h o 0} rac{f(x+h) - f(x)}{h}$$

**Numerical gradient**: slow :(, approximate :(, easy to write :) **Analytic gradient**: fast :), exact :), error-prone :(

In practice: Derive analytic gradient, check your implementation with numerical gradient

Computational graphs



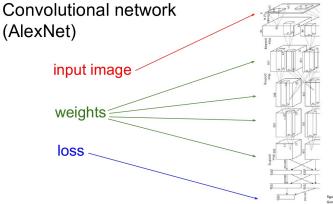
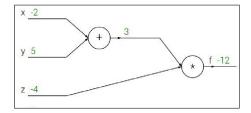


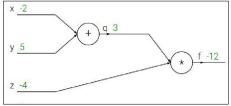
Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission. Backpropagation: a simple example

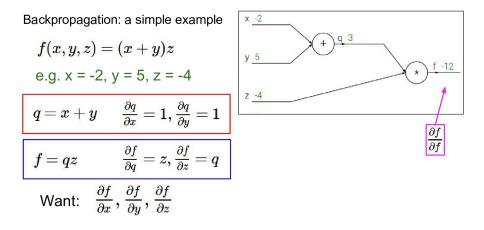
$$f(x, y, z) = (x + y)z$$

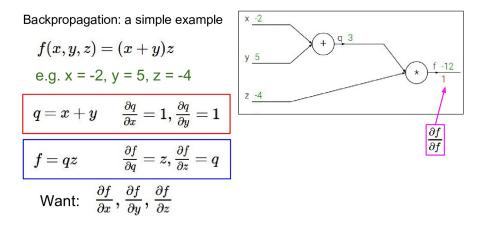
e.g. 
$$x = -2$$
,  $y = 5$ ,  $z = -4$ 

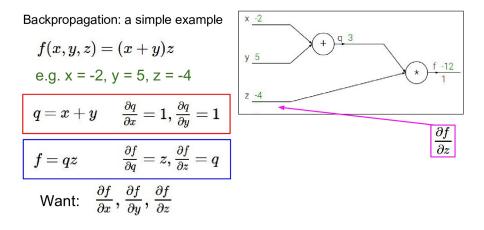


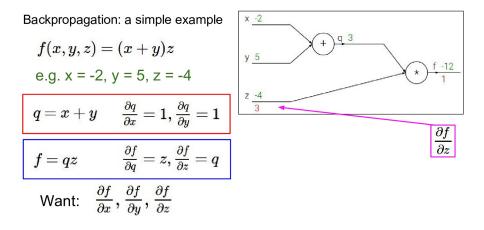
Backpropagation: a simple example f(x, y, z) = (x + y)ze.g. x = -2, y = 5, z = -4 q=x+y  $rac{\partial q}{\partial x}=1, rac{\partial q}{\partial y}=1$  $rac{\partial f}{\partial q}=z, rac{\partial f}{\partial z}=q$ f = qz $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$ Want:

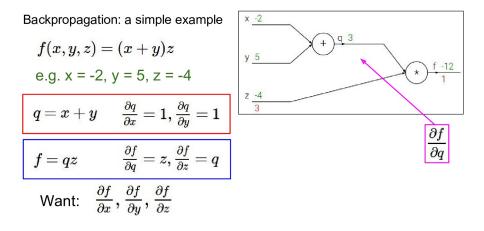


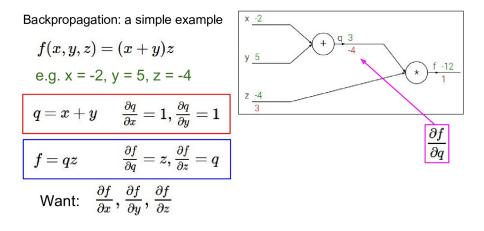


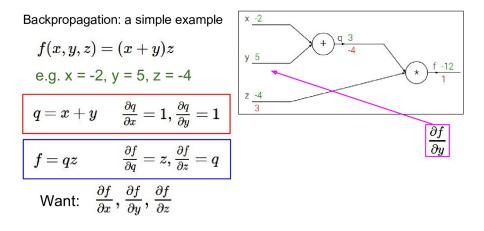


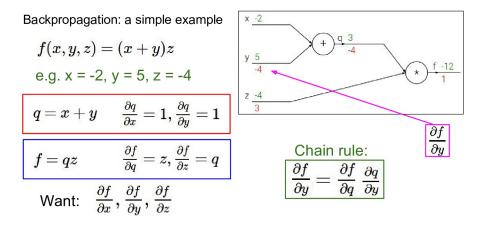






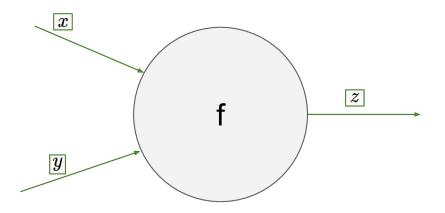


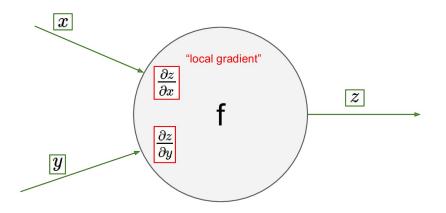


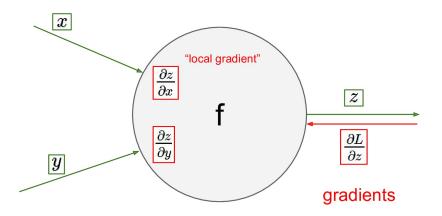


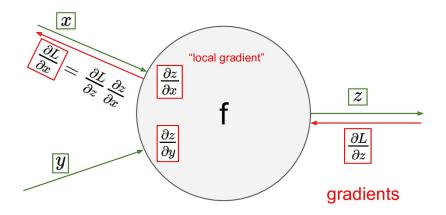
Backpropagation: a simple example x -2 q 3 f(x, y, z) = (x + y)zy 5 -12 -4 e.q. x = -2, y = 5, z = -4z <u>-4</u> 3 q=x+y  $rac{\partial q}{\partial x}=1, rac{\partial q}{\partial y}=1$  $\partial f$  $\partial x$  $rac{\partial f}{\partial q}=z, rac{\partial f}{\partial z}=q$ f = qz $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$ Want:

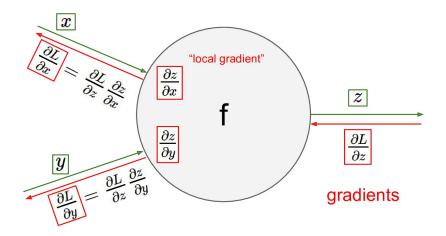
Backpropagation: a simple example	x -2
f(x,y,z)=(x+y)z	y 5 + q 3 -4
e.g. x = -2, y = 5, z = -4	-4 * f-12 1
$q=x+y$ $rac{\partial q}{\partial x}=1, rac{\partial q}{\partial y}=1$	$\left[\frac{z-4}{3}\right]$
$f=qz$ $rac{\partial f}{\partial q}=z, rac{\partial f}{\partial z}=q$	Chain rule: $\frac{\partial f}{\partial x}$ $\partial f \ df \ \partial f \ \partial q$
Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$	$\overline{\partial x} = \overline{\partial q} \overline{\partial x}$

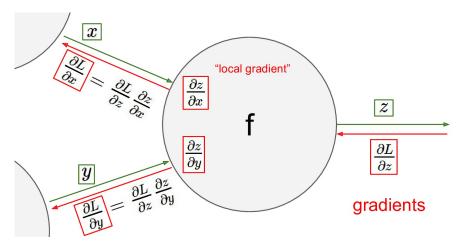






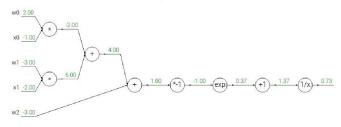


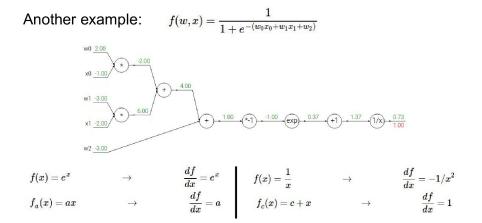


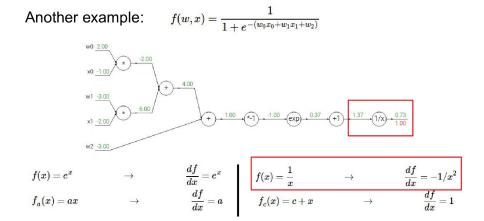


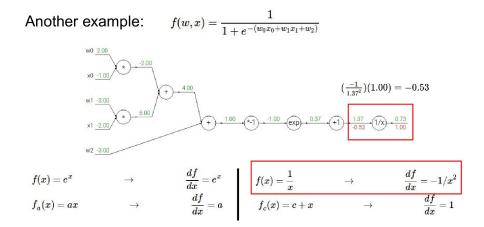
### Another example:

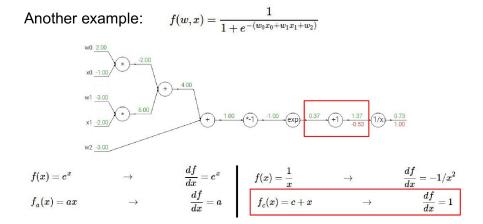
$$f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

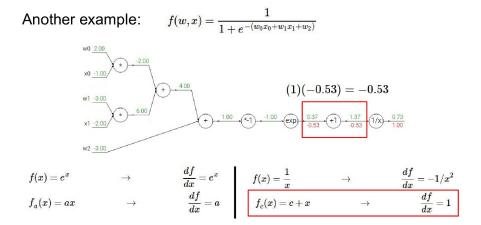


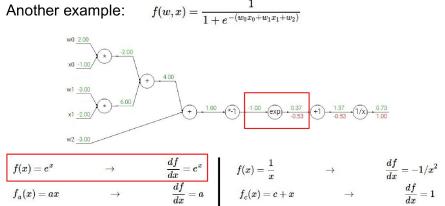




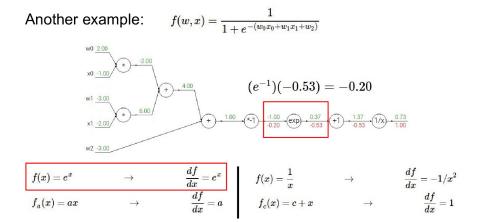




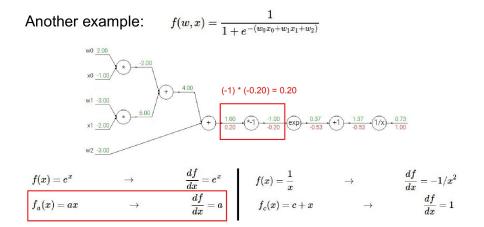


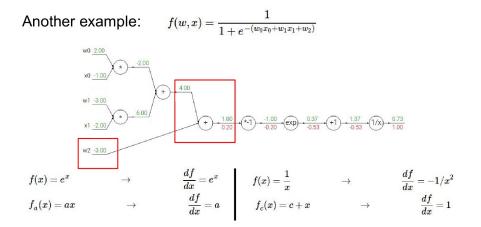


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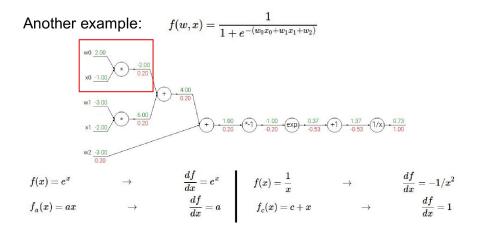


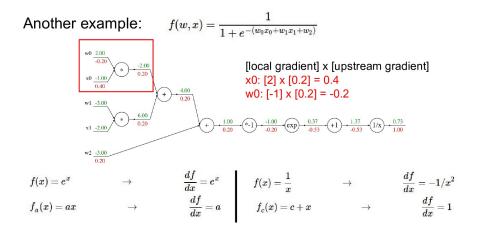
#### $f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$ Another example: w0 2.00 x0 -1.0 4.00 w1 -3.00 6.00 1.00 -1.00 $+ \frac{0.37}{-0.53} + (+1) + \frac{1.37}{-0.53} + (1/x) + \frac{0.73}{1.00}$ (exp)x1 -2.00 w2 -3.00 $f(x) = e^x$ $f_a(x) = ax$ $\rightarrow$

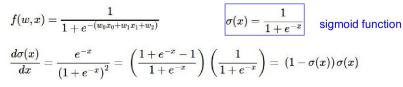


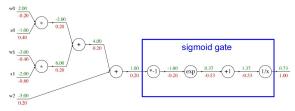


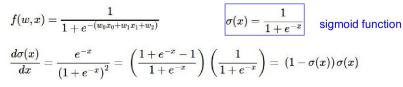
#### Another example: $f(w,x) = \frac{1}{1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}}$ [local gradient] x [upstream gradient] [1] x [0.2] = 0.2 [1] x [0.2] = 0.2 (both inputs!) (1] x [0.2] = 0.2 (both inputs!) (2] x [0.2] = 0.2 (both inputs!) (3] x [0.2] = 0.2 (both inputs!) (both inputs!) (4] x [0.2] = 0.2 (both inputs!) (b

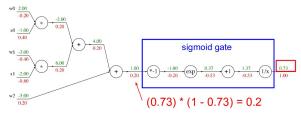




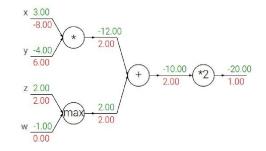




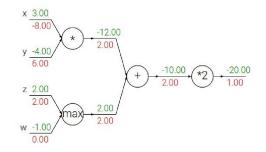




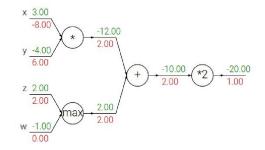
add gate: gradient distributor



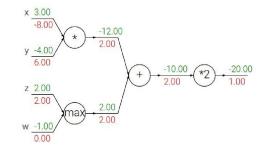
add gate: gradient distributor Q: What is a max gate?



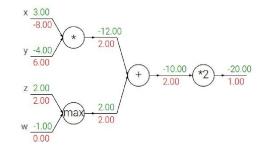
add gate: gradient distributor max gate: gradient router

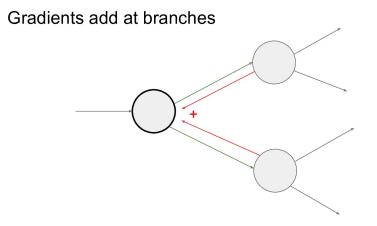


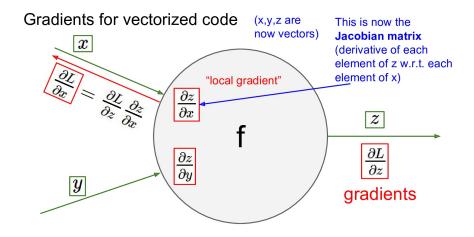
add gate: gradient distributor max gate: gradient router Q: What is a mul gate?



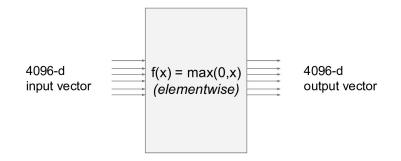
add gate: gradient distributor max gate: gradient router mul gate: gradient switcher

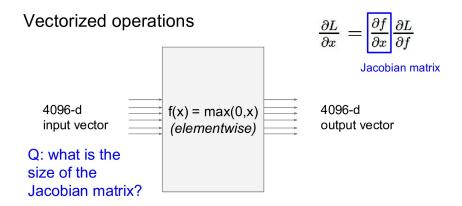


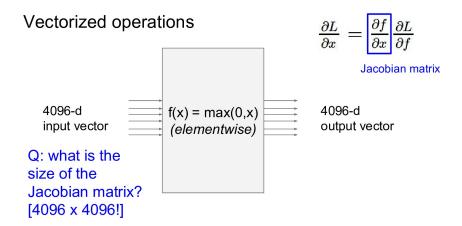




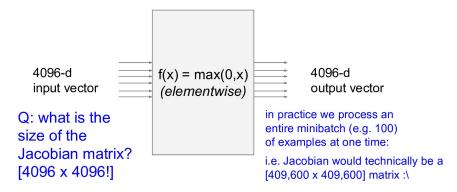
### Vectorized operations

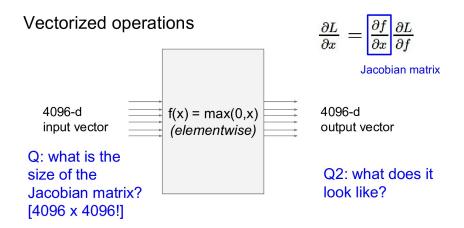






## Vectorized operations

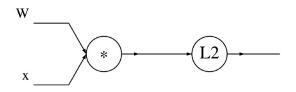


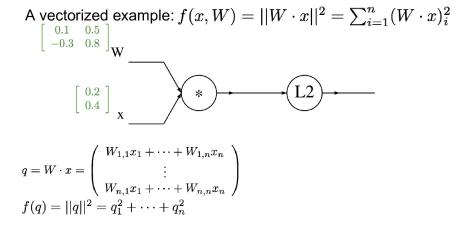


A vectorized example:  $f(x, W) = ||W \cdot x||^2 = \sum_{i=1}^n (W \cdot x)_i^2$ 

# A vectorized example: $f(x, W) = ||W \cdot x||^2 = \sum_{i=1}^{n} (W \cdot x)_i^2$ $\in \mathbb{R}^n \in \mathbb{R}^{n \times n}$

A vectorized example:  $f(x, W) = ||W \cdot x||^2 = \sum_{i=1}^{n} (W \cdot x)_i^2$ 





A vectorized example: 
$$f(x, W) = ||W \cdot x||^2 = \sum_{i=1}^{n} (W \cdot x)_i^2$$
  
 $\begin{bmatrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{bmatrix}_W$   
 $\begin{bmatrix} 0.2 \\ 0.4 \end{bmatrix}_x$   
 $q = W \cdot x = \begin{pmatrix} W_{1,1}x_1 + \dots + W_{1,n}x_n \\ \vdots \\ W_{n,1}x_1 + \dots + W_{n,n}x_n \end{pmatrix}$   
 $f(q) = ||q||^2 = q_1^2 + \dots + q_n^2$ 

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$$\begin{bmatrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{bmatrix}_W$$

$$\begin{bmatrix} 0.2 \\ 0.4 \end{bmatrix}_x$$

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$$\begin{bmatrix} 0.22 \\ 0.26 \end{bmatrix}$$

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$$\begin{bmatrix} 0.22 \\ 0.26 \end{bmatrix}$$

$$\begin{bmatrix} 0.116 \\ 1.00 \end{bmatrix}$$

$$\begin{bmatrix} 0.2 \\ 0.44 \\ 0.52 \end{bmatrix}$$

$$\begin{bmatrix} 0.116 \\ 1.00 \end{bmatrix}$$

$$g = W \cdot x = \begin{pmatrix} W_{1,1}x_1 + \dots + W_{1,n}x_n \\ \vdots \\ W_{n,1}x_1 + \dots + W_{n,n}x_n \end{pmatrix}$$

$$\frac{\partial f}{\partial q_i} = 2q_i$$

$$\begin{bmatrix} \nabla_q f = 2q \end{bmatrix}$$

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A vectorized example: 
$$f(x, W) = ||W \cdot x||^2 = \sum_{i=1}^{n} (W \cdot x)_i^2$$
  

$$\begin{bmatrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{bmatrix}_W$$

$$\begin{bmatrix} 0.2 \\ 0.4 \end{bmatrix}_x$$

$$\begin{bmatrix} 0.2 \\ 0.4 \end{bmatrix}_x$$

$$\begin{bmatrix} 0.22 \\ 0.26 \end{bmatrix}_{i=1}^{i=1} (U \cdot x)_i^2$$

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$$f(x, W) = ||W \cdot x||^2 = \sum_{i=1}^{n} (W \cdot x)_i^2$$
  

$$\begin{bmatrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{bmatrix}_W$$

$$\begin{bmatrix} 0.2 \\ 0.4 \end{bmatrix}_x$$

$$\begin{bmatrix} 0.2 \\ 0.4 \end{bmatrix}_x$$

$$\begin{bmatrix} 0.2 \\ 0.4 \end{bmatrix}_{k=ix_j}$$

$$\frac{\partial q_k}{\partial W_{i,j}} = \mathbf{1}_{k=ix_j}$$

$$\frac{\partial f}{\partial W_{i,j}} = \sum_{k=ix_j} \frac{\partial f}{\partial q_k} \frac{\partial q_k}{\partial W_{i,j}}$$

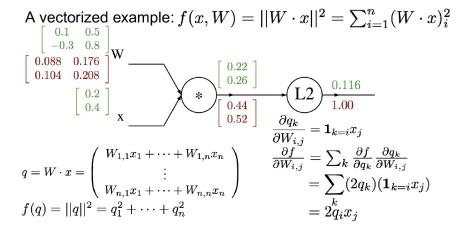
$$f(q) = ||q||^2 = q_1^2 + \dots + q_n^2$$

$$= 2 q_i^k x_j$$

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Lecture, February - May, 2019

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A vectorized example: 
$$f(x, W) = ||W \cdot x||^2 = \sum_{i=1}^{n} (W \cdot x)_i^2$$
  

$$\begin{bmatrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{bmatrix} W$$

$$\begin{bmatrix} 0.088 & 0.176 \\ 0.104 & 0.208 \end{bmatrix} W$$

$$\begin{bmatrix} 0.22 \\ 0.2 \\ 0.4 \end{bmatrix} \times \underbrace{\begin{bmatrix} 0.22 \\ 0.26 \end{bmatrix}} U$$

$$\begin{bmatrix} 0.22 \\ 0.26 \end{bmatrix} U$$

$$\begin{bmatrix} 0.22 \\ 0.26 \end{bmatrix} U$$

$$\begin{bmatrix} 0.22 \\ 0.4 \end{bmatrix} U$$

$$\begin{bmatrix} 0.22 \\ 0.$$

. .

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A vectorized example: 
$$f(x, W) = ||W \cdot x||^2 = \sum_{i=1}^n (W \cdot x)_i^2$$
  

$$\begin{bmatrix} 0.1 & 0.5 \\ -0.3 & 0.8 \end{bmatrix} W$$

$$\begin{bmatrix} 0.088 & 0.176 \\ 0.104 & 0.208 \end{bmatrix} W$$

$$\begin{bmatrix} 0.22 \\ 0.26 \end{bmatrix} (D.104 - 0.208)$$

$$\begin{bmatrix} 0.2 \\ 0.4 \end{bmatrix} (D.22 - 0.116)$$

$$\begin{bmatrix} 0.22 \\ 0.4 \end{bmatrix} (D.116)$$

$$\begin{bmatrix} 0.22 \\ 0.4 \end{bmatrix} (D.116)$$

$$\begin{bmatrix} 0.21 \\ 0.44 \\ 0.52 \end{bmatrix} (D.116)$$

$$\begin{bmatrix} 0.116 \\ 1.00 \end{bmatrix}$$

$$\begin{bmatrix} 0.4wy \text{ scheck: The gradient with respect to a variable should have the same shape as the variable}$$

$$\frac{\partial q_k}{\partial W_{i,j}} = \mathbf{1}_{k=i}x_j$$

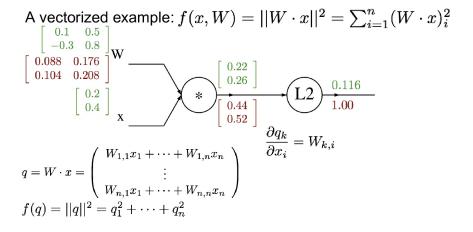
$$\frac{\partial f}{\partial q_k} \frac{\partial q_k}{\partial W_{i,j}} = \sum_{k=i} \frac{\partial f}{\partial q_k} \frac{\partial q_k}{\partial W_{i,j}}$$

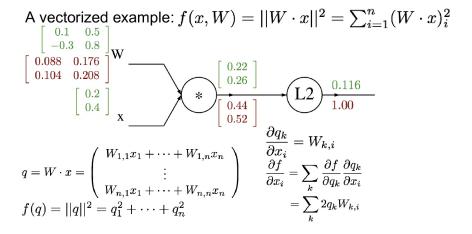
$$f(q) = ||q||^2 = q_1^2 + \dots + q_n^2$$

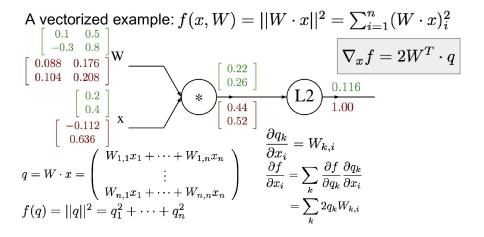
$$= 2 q^k x_j$$

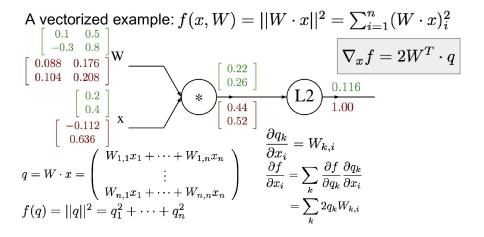
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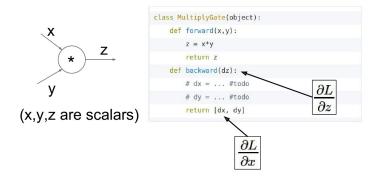
### Modularized implementation: forward / backward API



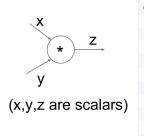
#### Graph (or Net) object (rough psuedo code)

ass (	ComputationalGraph(object):
#.	
det	f forward(inputs):
	<pre># 1. [pass inputs to input gates]</pre>
	# 2. forward the computational graph:
	<pre>for gate in self.graph.nodes_topologically_sorted():</pre>
	gate.forward()
	<pre>return loss # the final gate in the graph outputs the loss</pre>
det	f backward():
	<pre>for gate in reversed(self.graph.nodes_topologically_sorted()):</pre>
	<pre>gate.backward() # little piece of backprop (chain rule applied)</pre>
	<pre>return inputs_gradients</pre>

### Modularized implementation: forward / backward API



### Modularized implementation: forward / backward API



lass Mu	<pre>iltiplyGate(object):</pre>
def	<pre>forward(x,y):</pre>
	z = x*y
	<pre>self.x = x # must keep these around!</pre>
	self.y = y
	return z
def	backward(dz):
	dx = self.y * dz # [dz/dx * dL/dz]
	dy = self.x * dz # [dz/dy * dL/dz]
	return [dx, dy]

# Summary so far...

- neural nets will be very large: impractical to write down gradient formula by hand for all parameters
- backpropagation = recursive application of the chain rule along a computational graph to compute the gradients of all inputs/parameters/intermediates
- implementations maintain a graph structure, where the nodes implement the **forward**() / **backward**() API
- **forward**: compute result of an operation and save any intermediates needed for gradient computation in memory
- **backward**: apply the chain rule to compute the gradient of the loss function with respect to the inputs