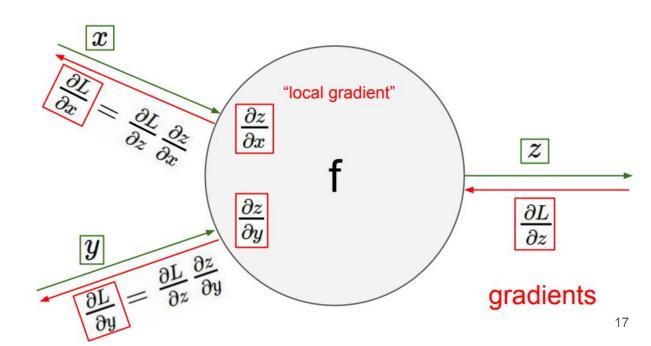
Backpropagation and chain rule

Chain rule is just simple math:

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x}$$

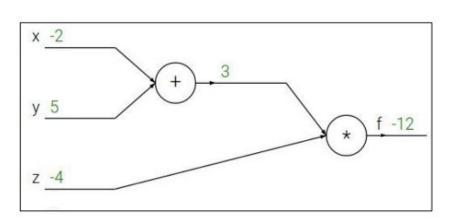
Backprop is just way to use it in NN training.



source: http://cs231n.github.io

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

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



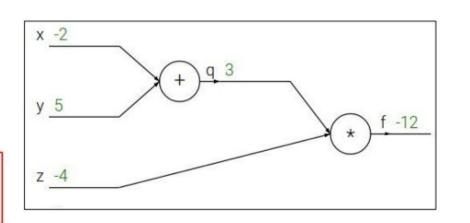
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$$q=x+y \qquad rac{\partial q}{\partial x}=1, rac{\partial q}{\partial y}=1$$

$$f=qz$$
 $rac{\partial f}{\partial q}=z, rac{\partial f}{\partial z}=q$

Want:
$$\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$$

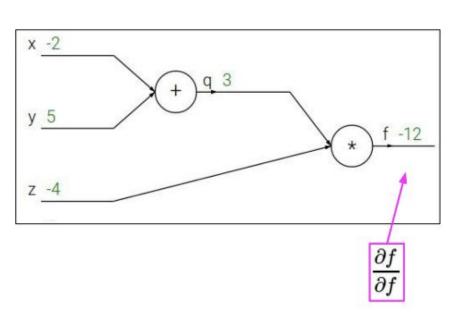


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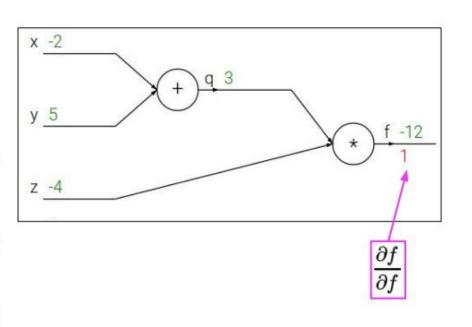


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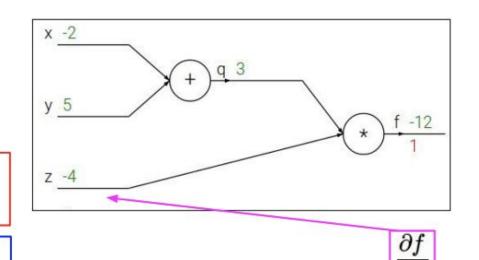


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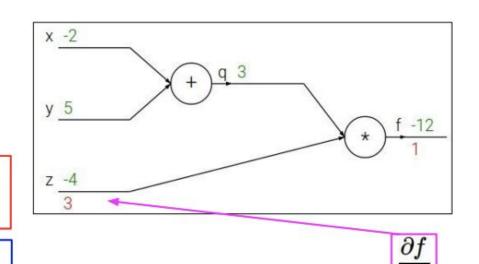


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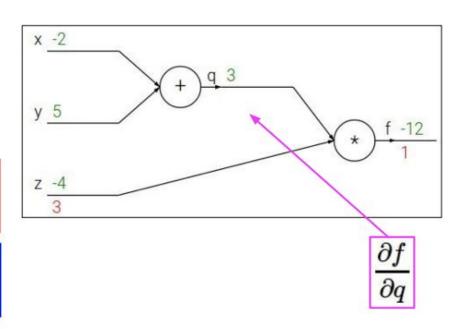


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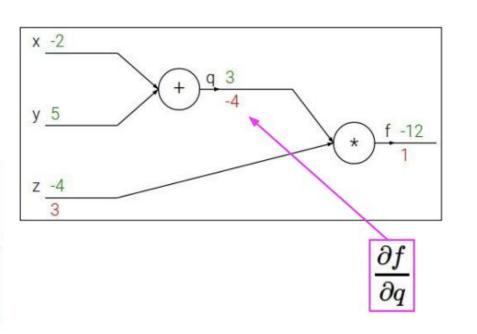


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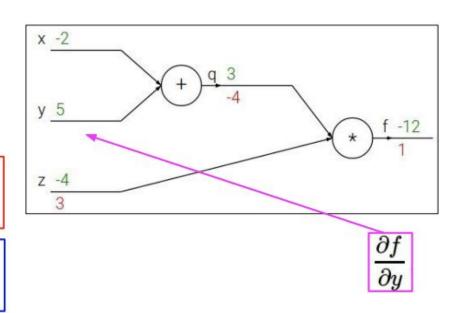


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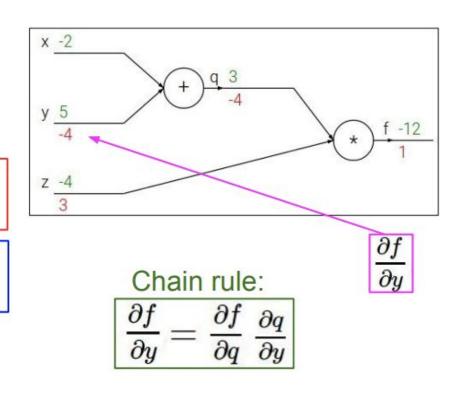


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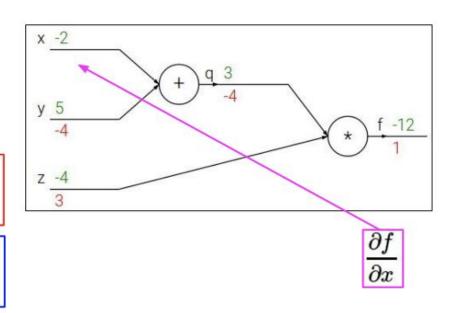


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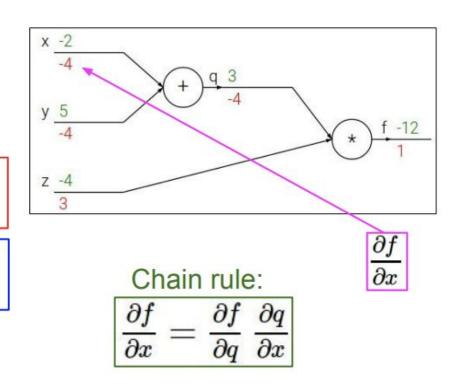


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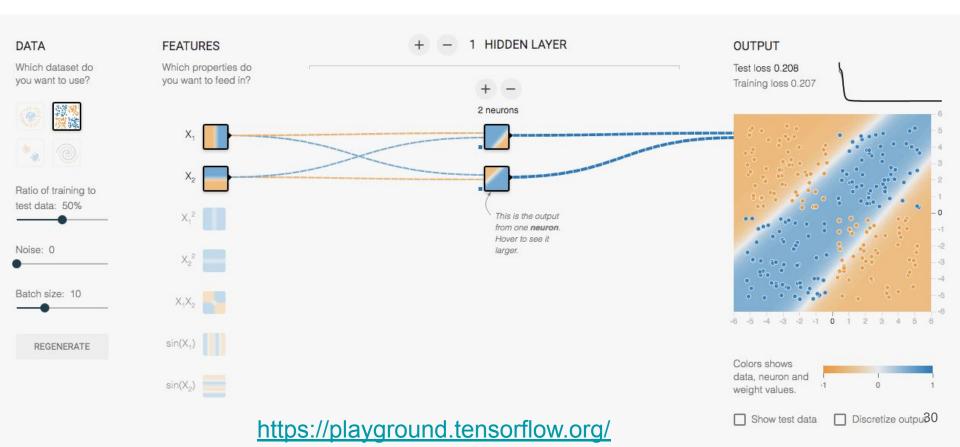
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Practice time: interactive playground

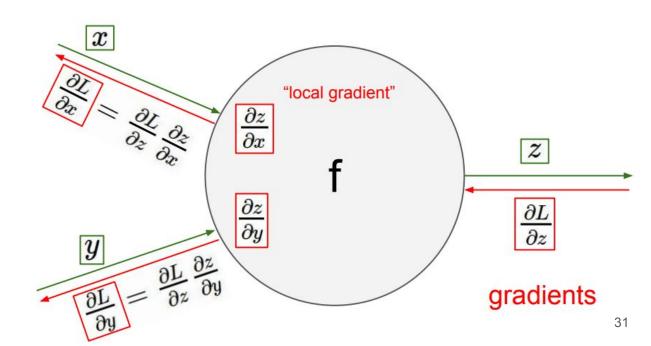


Backpropagation and chain rule

Chain rule is just simple math:

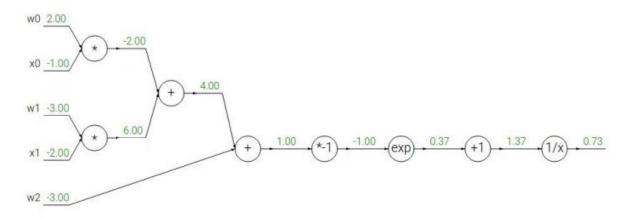
$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x}$$

Backprop is just way to use it in NN training.



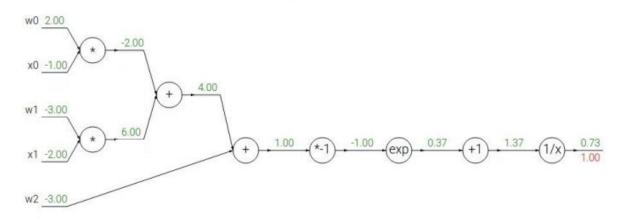
source: http://cs231n.github.io

Another example:
$$f(w,x) = \frac{1}{1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}}$$



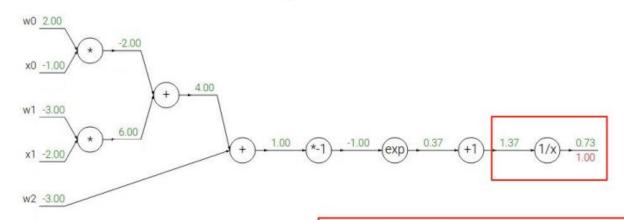
32

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

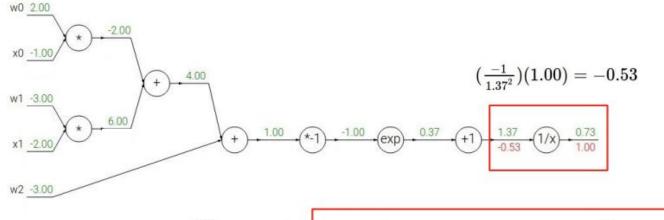


$$egin{array}{lll} f(x) = e^x &
ightarrow & rac{df}{dx} = e^x & f(x) = rac{1}{x} &
ightarrow & rac{df}{dx} = -1/x^2 \ f_a(x) = ax &
ightarrow & rac{df}{dx} = a & f_c(x) = c + x &
ightarrow & rac{df}{dx} = 1 \end{array}$$

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



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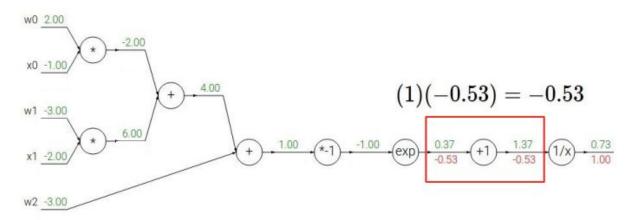


$$f(x)=e^x \hspace{1cm} o \hspace{1cm} rac{df}{dx}=e^x \hspace{1cm} f(x)=rac{1}{x} \hspace{1cm} o \hspace{1cm} rac{df}{dx}=-1 \ f_c(x)=c+x \hspace{1cm} o \hspace{1cm} o \hspace{1cm} rac{df}{dx}=-1 \ f_c(x)=c+x \hspace{1cm} o \hspace{$$

Another example:
$$f(w,x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$$

36

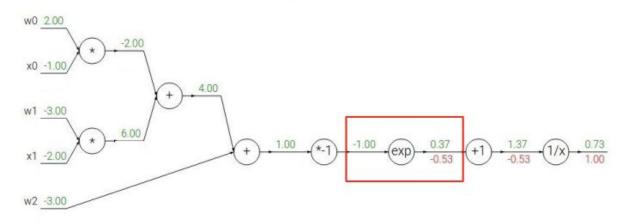
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$$f(x)=e^x \hspace{1cm} o \hspace{1cm} rac{df}{dx}=e^x \hspace{1cm} f(x)=rac{1}{x} \hspace{1cm} o \hspace{1cm} rac{df}{dx}=-1/x^2 \ f_a(x)=ax \hspace{1cm} o \hspace{1cm} rac{df}{dx}=a \hspace{1cm} f(x)=c+x \hspace{1cm} o \hspace{1cm} rac{df}{dx}=1 \$$

37

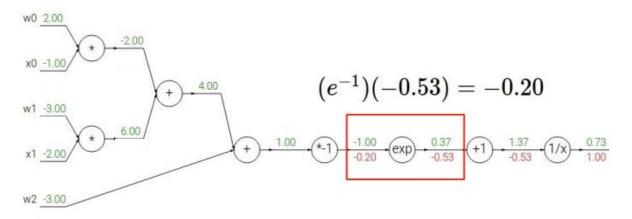
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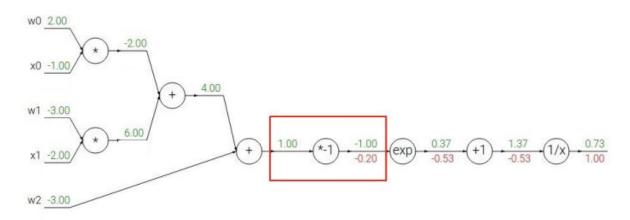
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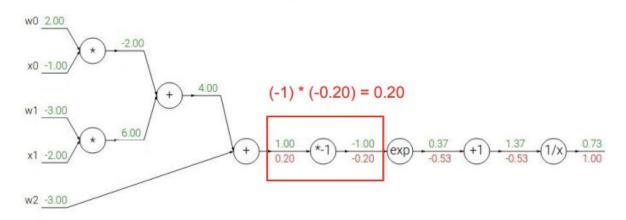


$$f(x) = e^x \hspace{1cm} o \hspace{1cm} rac{df}{dx} = e^x \ f_a(x) = ax \hspace{1cm} o \hspace{1cm} rac{df}{dx} = a$$

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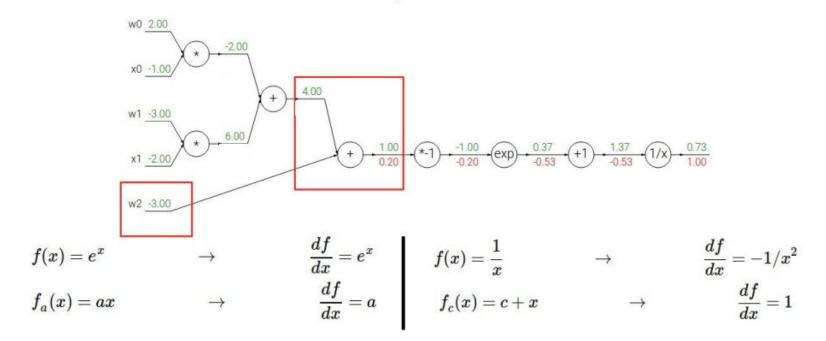


$$f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



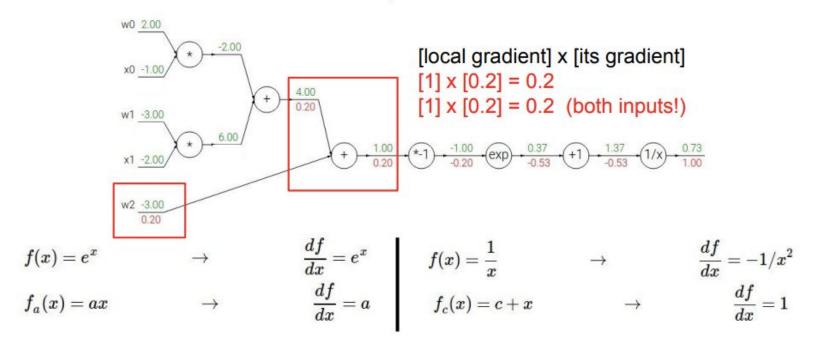
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$$f(w,x) = \frac{1}{1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}}$$



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



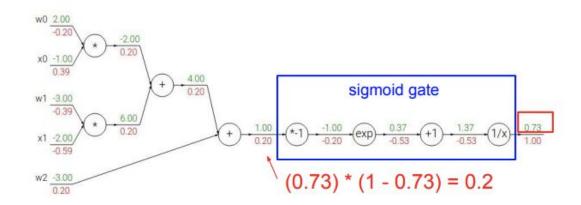
43

Another example:
$$f(w,x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$$
 [local gradient] x [its gradient]
$$x0: [2] \times [0.2] = 0.4$$

$$w0: [-1] \times [0.2] = -0.2$$

$$w1 \xrightarrow{-3.00} x1 \xrightarrow{-2.00} x1 \xrightarrow{-2.00} x1 \xrightarrow{-2.00} x1 \xrightarrow{-2.00} x1 \xrightarrow{-2.00} x1 \xrightarrow{-2.00} x1 \xrightarrow{-3.00} x1$$

$$f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$
 $\sigma(x)=rac{1}{1+e^{-x}}$ sigmoid function $rac{d\sigma(x)}{dx}=rac{e^{-x}}{(1+e^{-x})^2}=\left(rac{1+e^{-x}-1}{1+e^{-x}}
ight)\left(rac{1}{1+e^{-x}}
ight)=(1-\sigma(x))\,\sigma(x)$

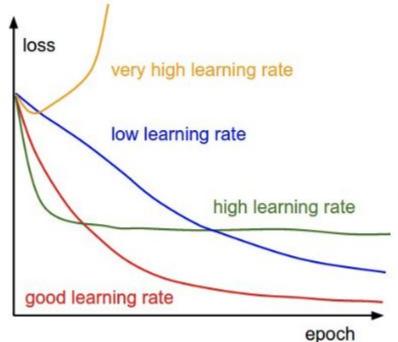


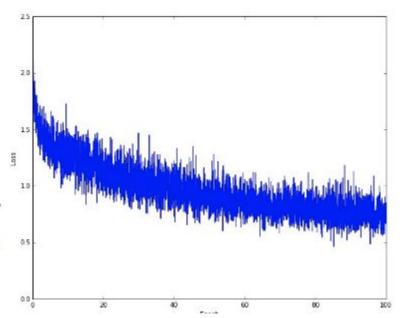
Gradient optimization

Stochastic gradient descent (and variations)

is used to optimize NN parameters.

 $x_{t+1} = x_t - \text{learning rate} \cdot dx$





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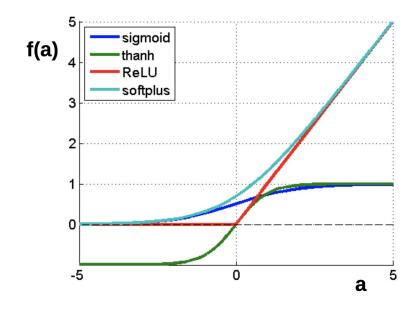
Once more: nonlinearities

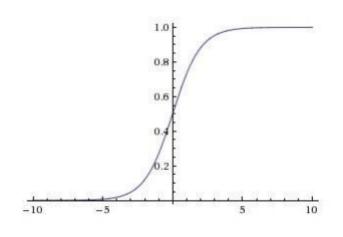
$$f(a) = \frac{1}{1 + e^a}$$

$$f(a) = \tanh(a)$$

$$f(a) = \max(0, a)$$

$$f(a) = \log(1 + e^a)$$





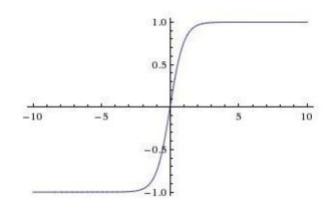
Sigmoid

$$f(a) = \frac{1}{1 + e^a}$$

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating "firing rate" of a neuron

3 problems:

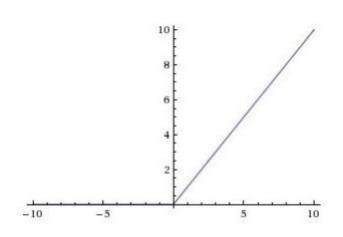
- Saturated neurons "kill" the gradients
- Sigmoid outputs are not zerocentered
- exp() is a bit compute expensive



- Squashes numbers to range [-1,1]
- zero centered (nice)
- still kills gradients when saturated :(

tanh(x)

$$f(a) = \tanh(a)$$

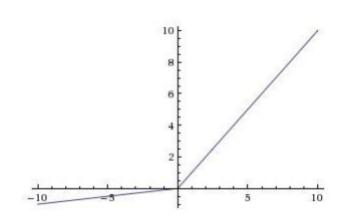


ReLU (Rectified Linear Unit)

$$f(a) = \max(0, a)$$

- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)
- Not zero-centered output
- An annoyance:

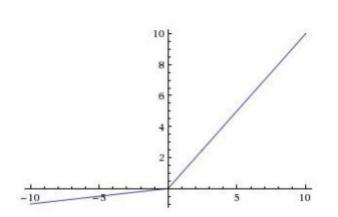
hint: what is the gradient when x < 0?



- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- will not "die".

Leaky ReLU

$$f(x) = \max(0.01x, x)$$



Leaky ReLU

$$f(x) = \max(0.01x, x)$$

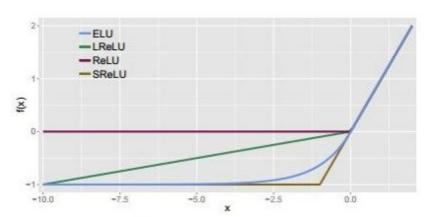
- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- will not "die".

Parametric Rectifier (PReLU)

$$f(x) = \max(\alpha x, x)$$

backprop into \alpha (parameter)

Exponential Linear Units (ELU)



$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha (\exp(x) - 1) & \text{if } x \le 0 \end{cases}$$

- All benefits of ReLU
- Does not die
- Closer to zero mean outputs
- Computation requires exp()

Activation functions: sum up

- Use ReLU as baseline approach
- Be careful with the learning rates
- Try out Leaky ReLU or ELU
- Try out tanh but do not expect much from it
- Do not use Sigmoid