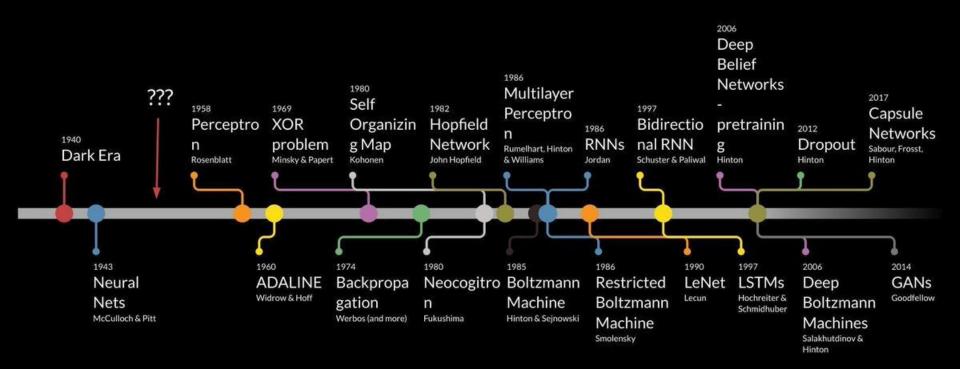
Machine Learning Course

Introduction to Deep Learning

Outline

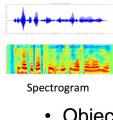
- 1. Neural Networks in different areas. Historical overview.
- 2. Backpropagation.
- 3. Activation functions.
- 4. Playground.
- 5. Neural network from scratch.

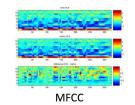
Deep Learning Timeline



Audio Features

Real world problems

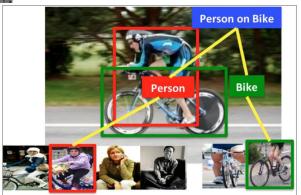




- Object detection
- Action classification
- Image captioning
- ...



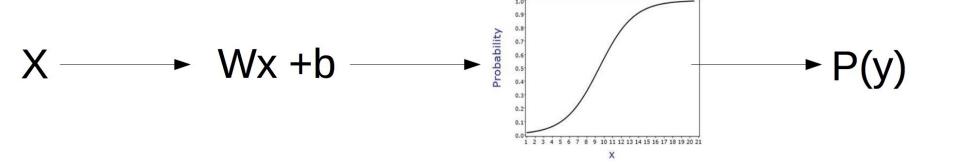






"man in black shirt is playing guitar."

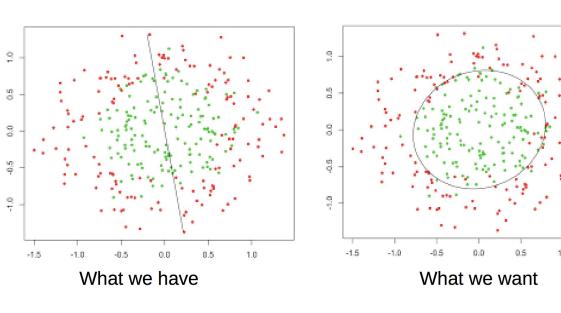
Logistic regression



$$P(y|x) = \sigma(w \cdot x + b)$$

$$L = -\sum_{i} y_{i} \log P(y|x_{i}) + (1 - y_{i}) \log (1 - P(y|x_{i}))$$

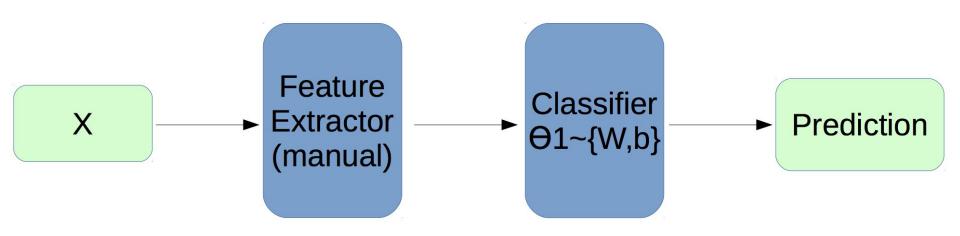
Problem: nonlinear dependencies



Logistic regression (generally, linear model) need feature engineering to show good results.

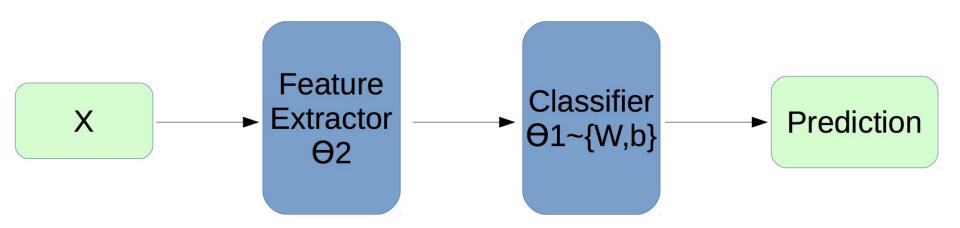
And feature engineering is an *art*.

Classic pipeline



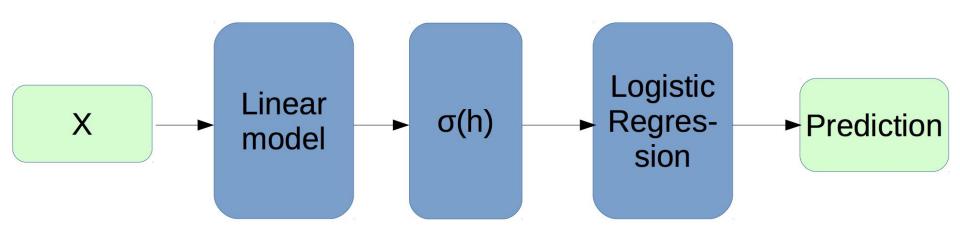
Handcrafted features, generated by experts.

NN pipeline



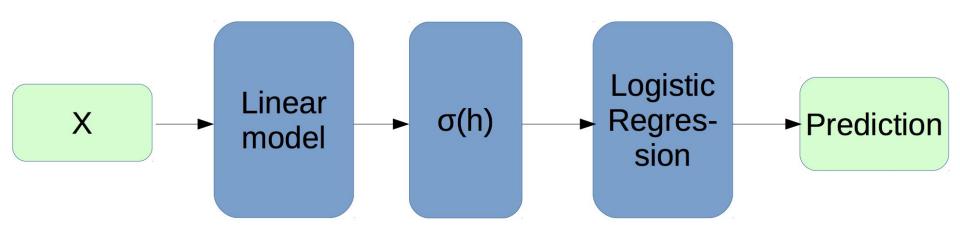
Automatically extracted features.

NN pipeline: example



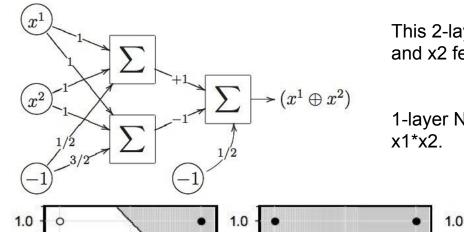
E.g. two logistic regressions one after another.

NN pipeline: example



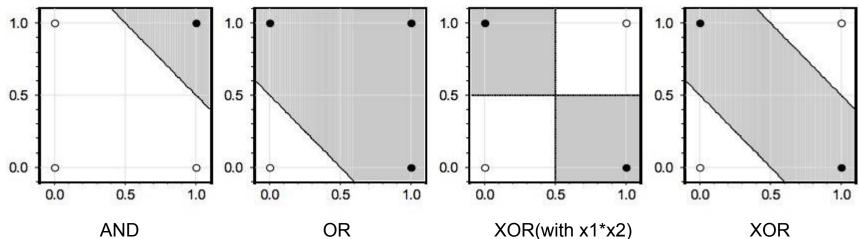
Actually, it's a neural network.

XOR problem



This 2-layer NN (on the left) implements XOR with only x1 and x2 features.

1-layer NN also can succeed, but only with extra feature x1*x2.



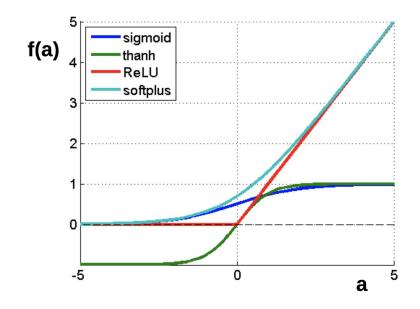
Activation functions: nonlinearities

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

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

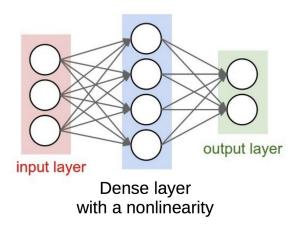
$$f(a) = \max(0, a)$$

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



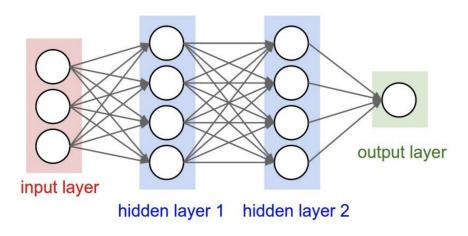
Some generally accepted terms

- Layer a building block for NNs :
 - o Dense layer: f(x) = Wx+b
 - Nonlinearity layer: $f(x) = \sigma(x)$
 - Input layer, output layer
 - A few more we will cover later
- Activation function function applied to layer output
 - Sigmoid
 - o tanh
 - ReLU
 - Any other function to get nonlinear intermediate signal in NN
- Backpropagation a fancy word for "chain rule"

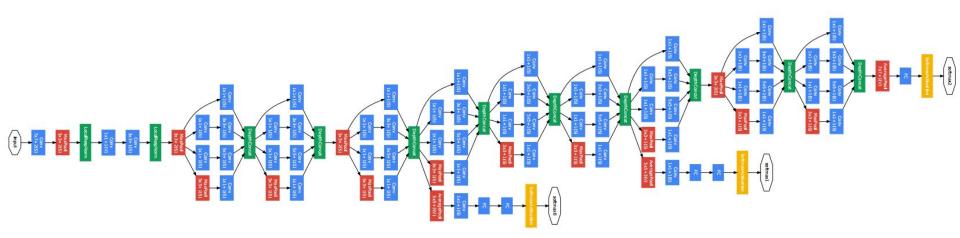


"Train it via backprop!"

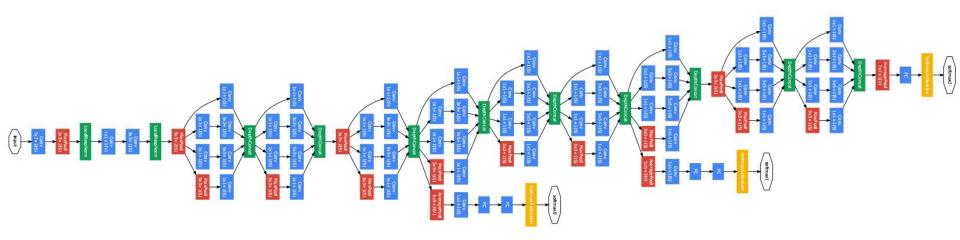
Actually, it can be deeper



Much deeper...



Much deeper...



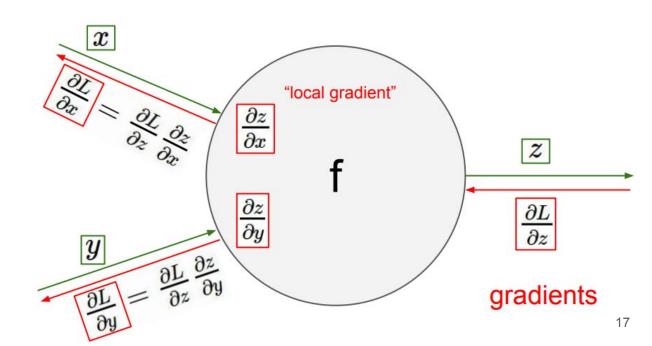
How to train it?

Backpropagation and chain rule

Chain rule is just simple math:

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

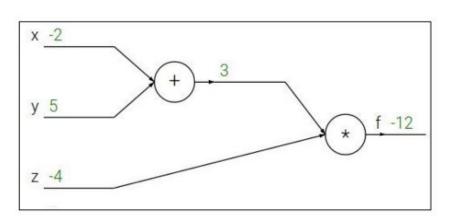
Backprop is just way to use it in NN training.



source: http://cs231n.github.io

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

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



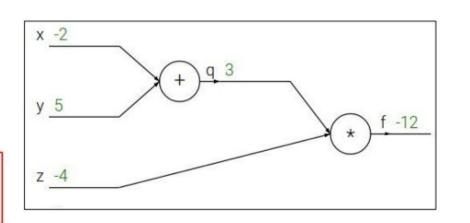
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e.g. x = -2, y = 5, z = -4

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

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

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

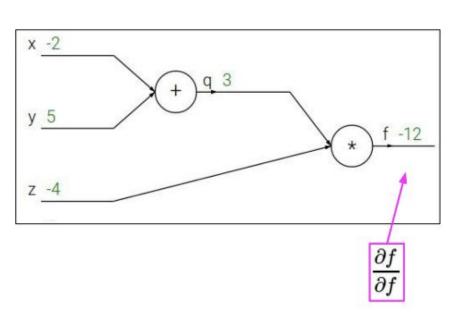


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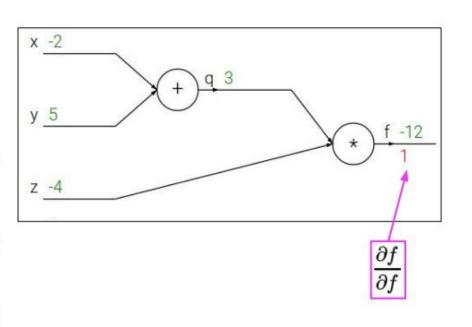


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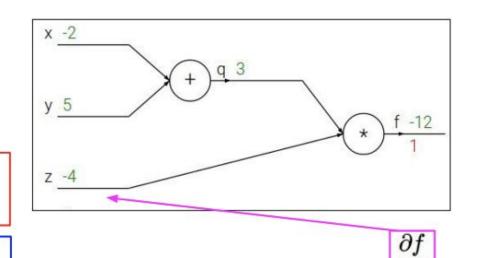


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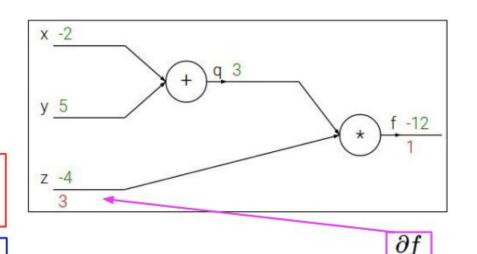


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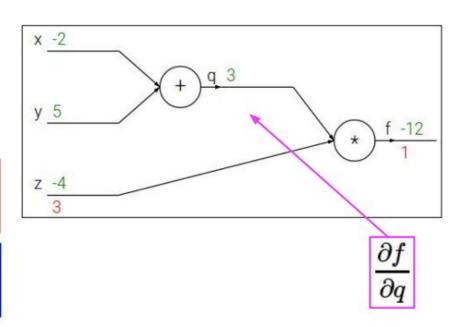


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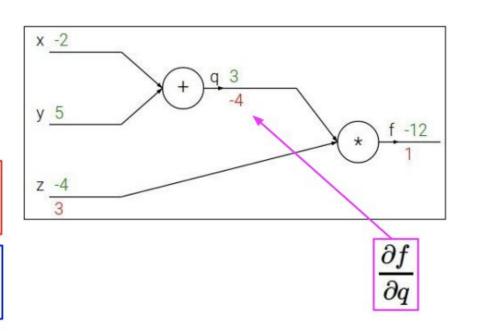


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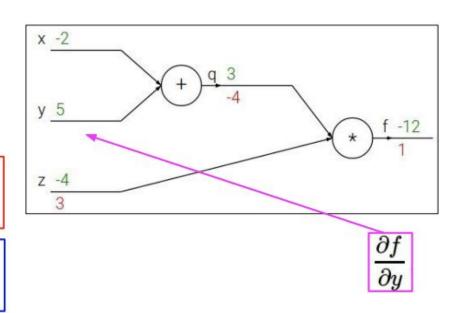


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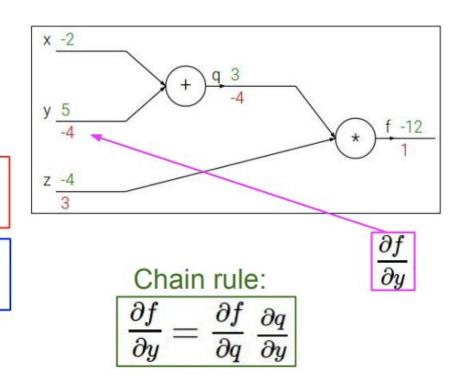


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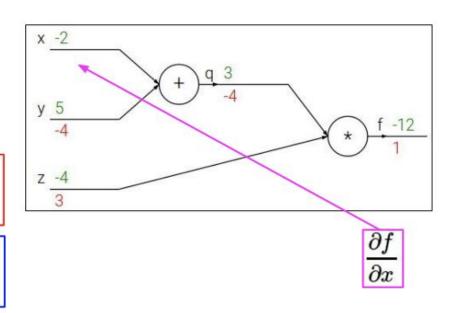


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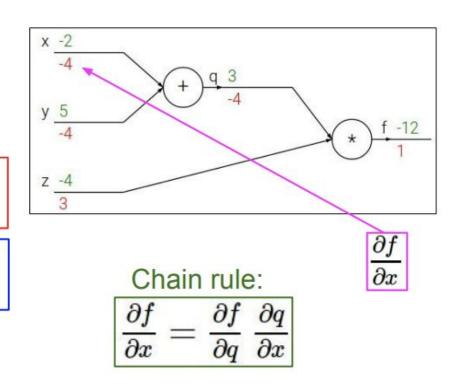


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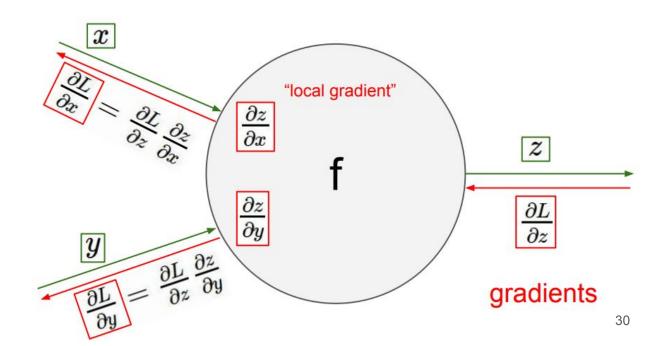


Backpropagation and chain rule

Chain rule is just simple math:

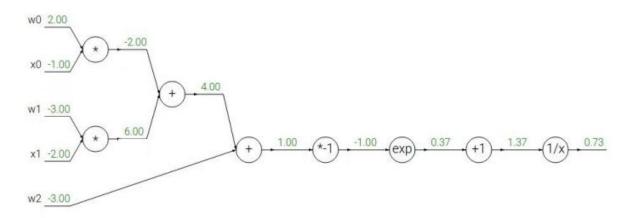
$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x}$$

Backprop is just way to use it in NN training.

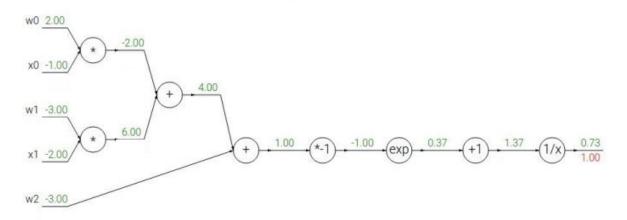


source: http://cs231n.github.io

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

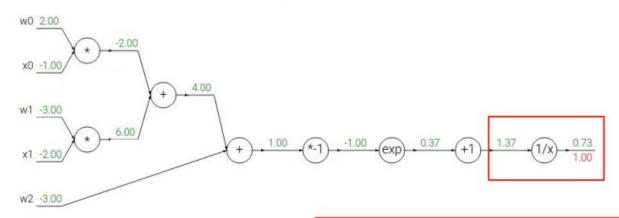


$$f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



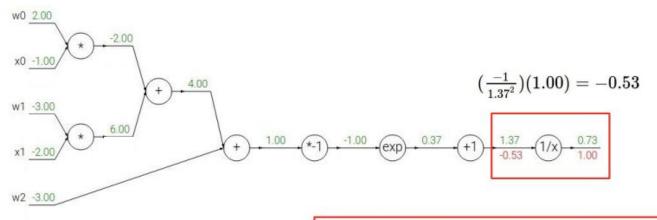
$$egin{array}{lll} f(x)=e^x &
ightarrow & rac{df}{dx}=e^x & f(x)=rac{1}{x} &
ightarrow & rac{df}{dx}=-1/x^2 \ f_a(x)=ax &
ightarrow & rac{df}{dx}=a & f_c(x)=c+x &
ightarrow & rac{df}{dx}=1 \end{array}$$

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

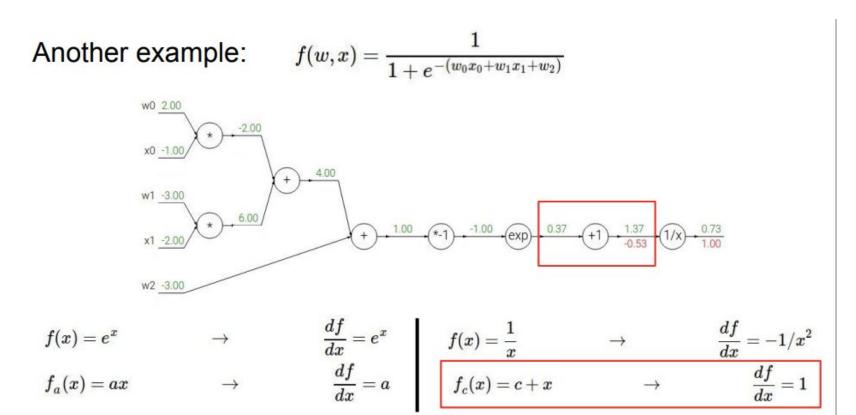


$$f(x)=e^x \qquad \qquad
ightarrow \qquad rac{df}{dx}=e^x \qquad \qquad f(x)=rac{1}{x} \qquad
ightarrow \qquad rac{df}{dx}=-1/x^2 \qquad \qquad f_c(x)=c+x \qquad \qquad
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$$f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

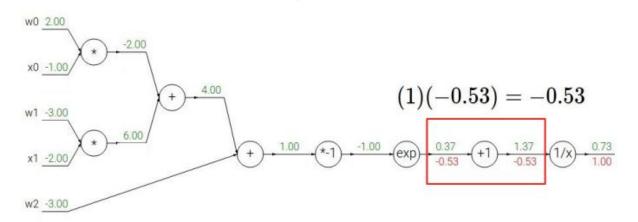


$$f(x)=e^x \hspace{1cm} o \hspace{1cm} rac{df}{dx}=e^x \hspace{1cm} f(x)=rac{1}{x} \hspace{1cm} o \hspace{1cm} rac{df}{dx}=-1/x^2 \hspace{1cm} f_c(x)=c+x \hspace{1cm} o \hspace{1cm} rac{df}{dx}=1$$



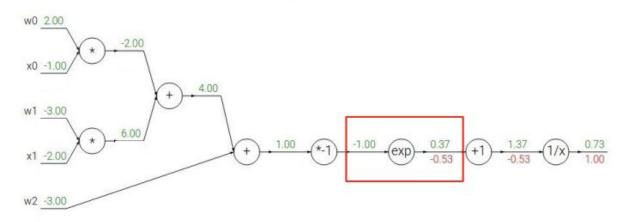
35

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



$$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 \$$

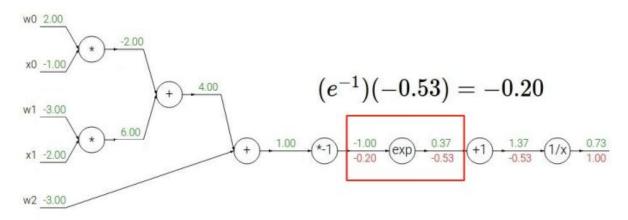
$$f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



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

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ightarrow \qquad rac{df}{dx} = -1/x^2 \ \hline f_c(x) = c + x \qquad
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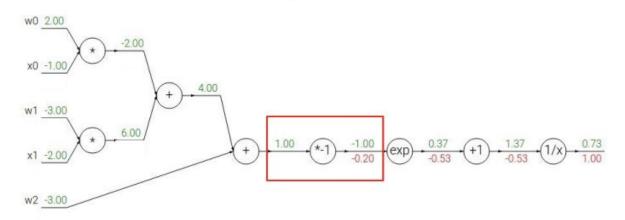
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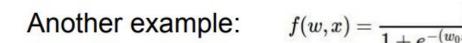
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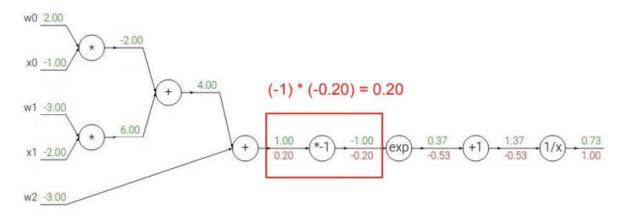
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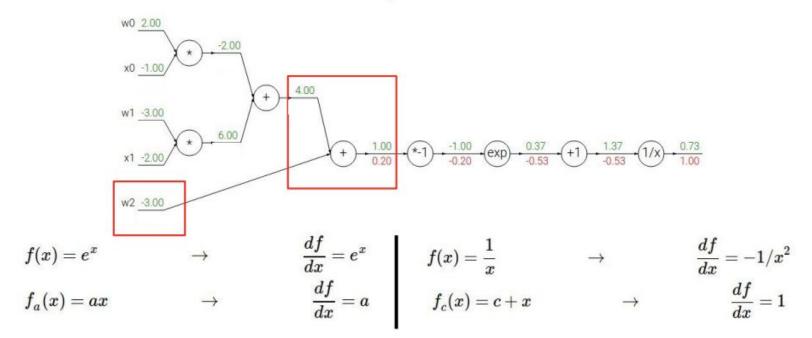




$$\frac{df}{dx} = -1/x^2$$

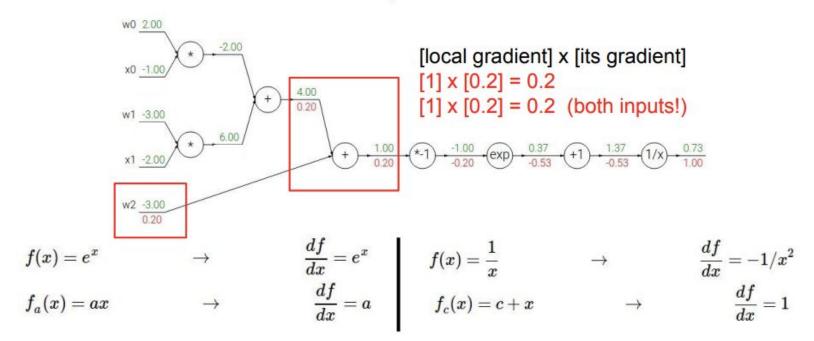
$$\frac{df}{dx} = 1$$

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

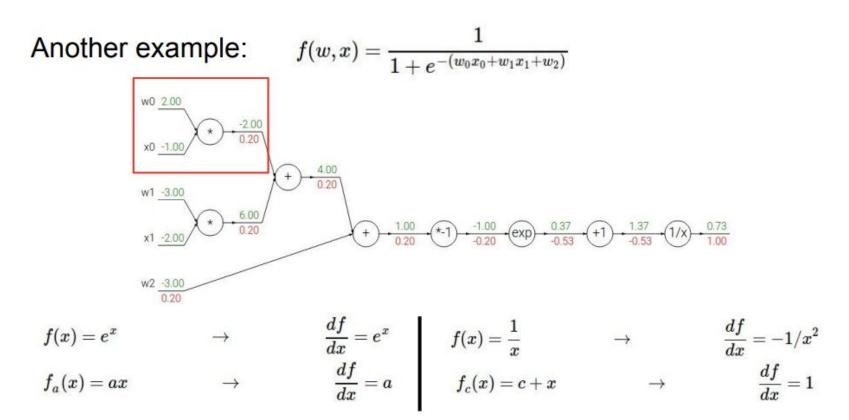


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$$f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

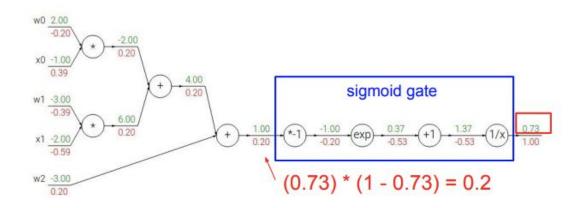


42



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

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

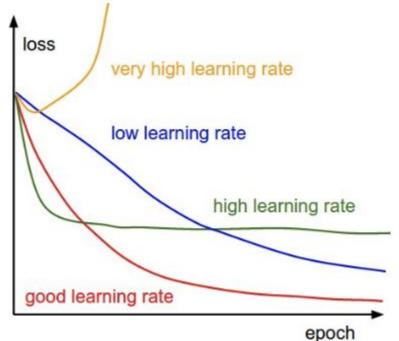


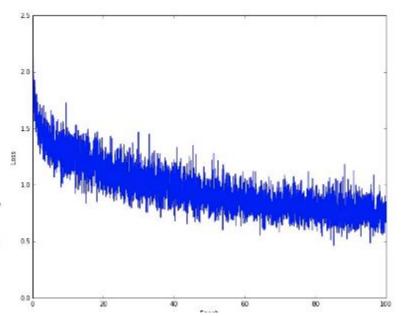
Gradient optimization

Stochastic gradient descent (and variations)

is used to optimize NN parameters.

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





source: http://cs231n.github.io/neural-networks-3/

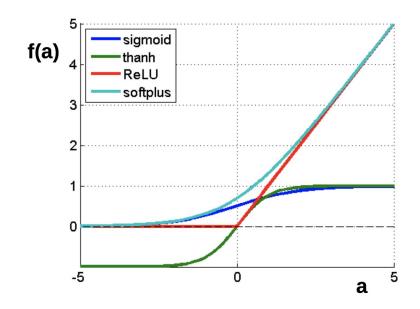
Once more: nonlinearities

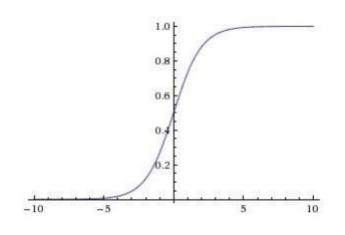
$$f(a) = \frac{1}{1 + e^a}$$

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

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

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





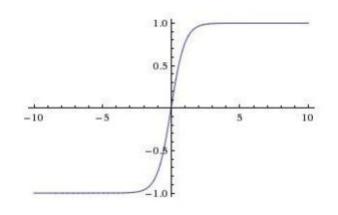
Sigmoid

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

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

3 problems:

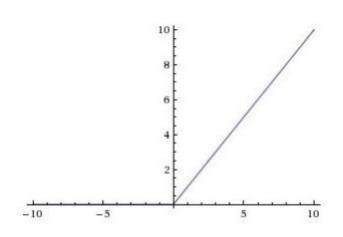
- Saturated neurons "kill" the gradients
- Sigmoid outputs are not zerocentered
- exp() is a bit compute expensive



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

tanh(x)

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

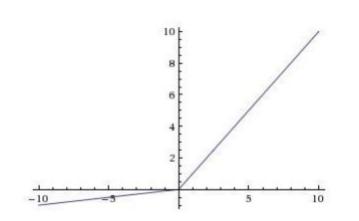


ReLU (Rectified Linear Unit)

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

- 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:

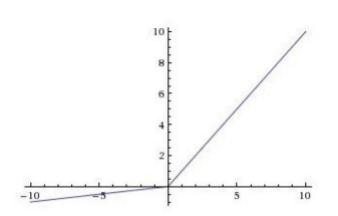
hint: what is the gradient when x < 0?



- 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

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

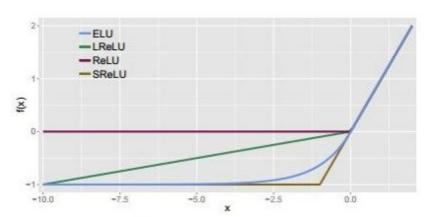
- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- will not "die".

Parametric Rectifier (PReLU)

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

backprop into \alpha (parameter)

Exponential Linear Units (ELU)



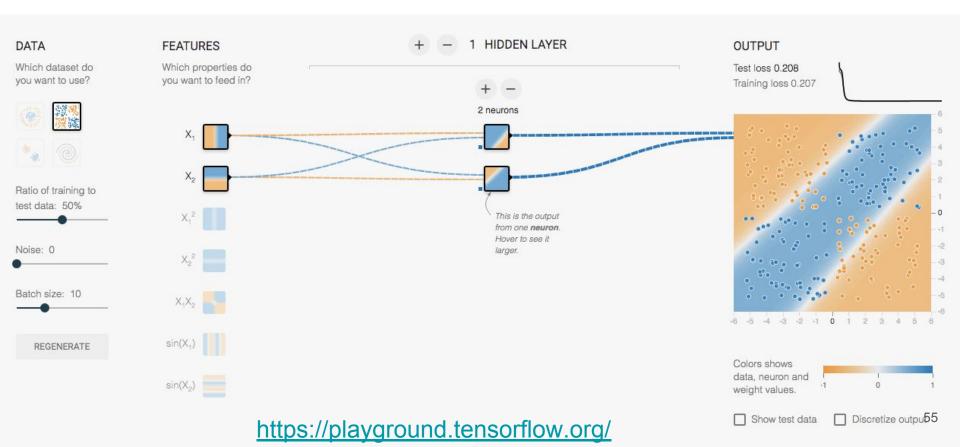
$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha (\exp(x) - 1) & \text{if } x \le 0 \end{cases}$$

- 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

Practice time: interactive playground



That's all. Time to build some NN.

