Lecture 3 Introduction to Deep Learning

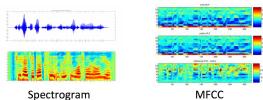
Vladislav Goncharenko

Outline

- 1. Neural Networks in different areas, historical overview
- 2. Backpropagation
- 3. More on backpropagation
- 4. Activation functions
- 5. Playground

Audio Features

Real world applications



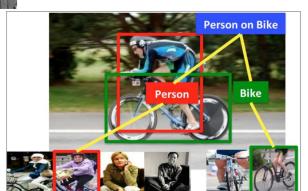


person

- Object detection
- Action classification
- Image captioning

• ...



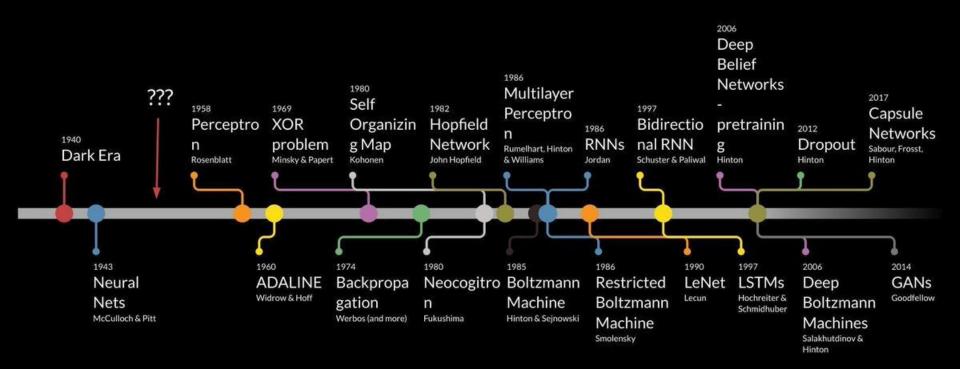




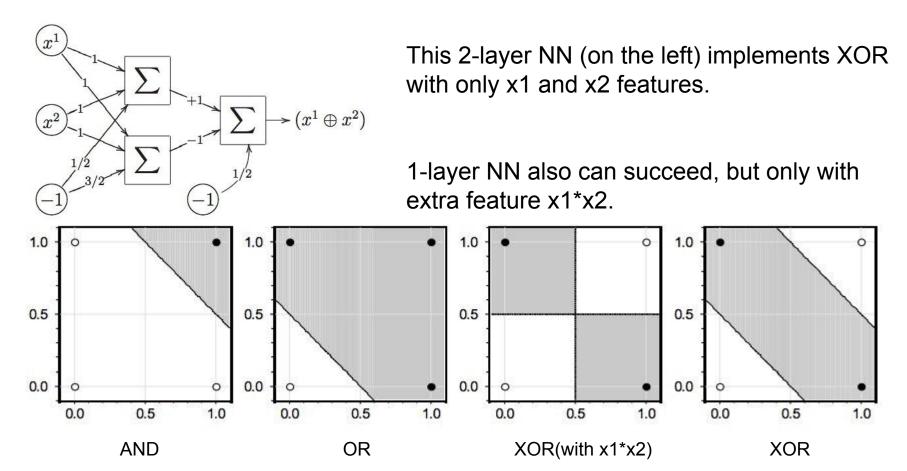
"man in black shirt is playing guitar."



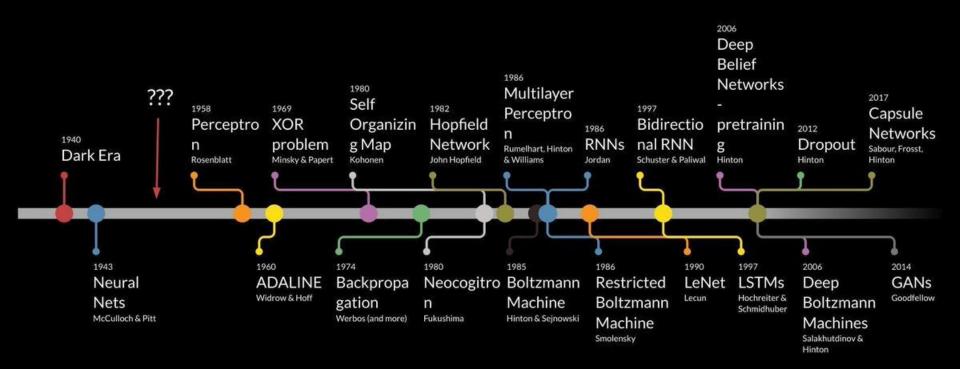
Deep Learning Timeline

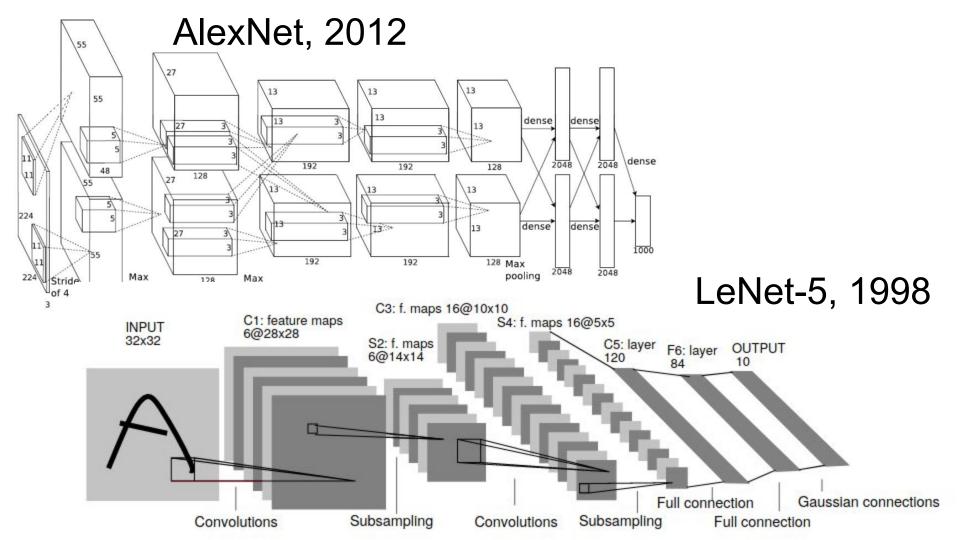


XOR problem

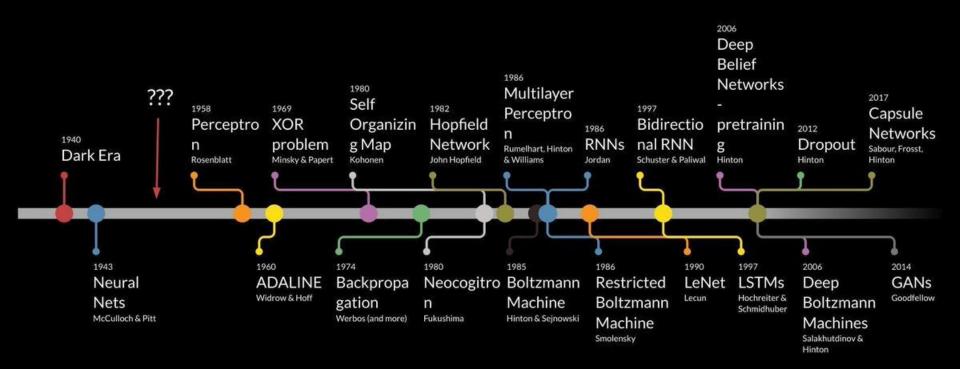


Deep Learning Timeline



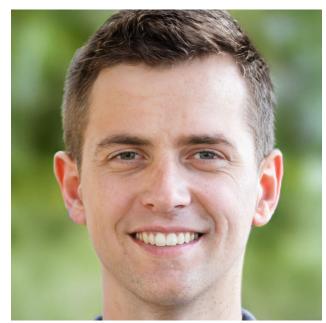


Deep Learning Timeline



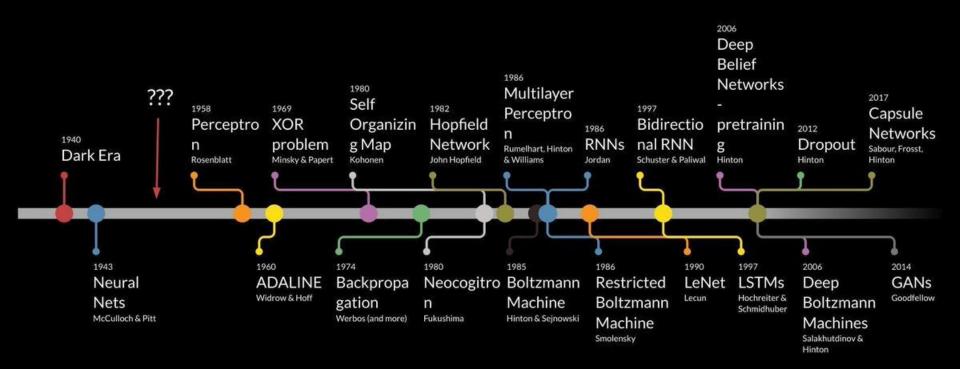
GANs, 2014+





https://thispersondoesnotexist.com/

Deep Learning Timeline



Transformer, BERT, GPT-2 and more, 2017+



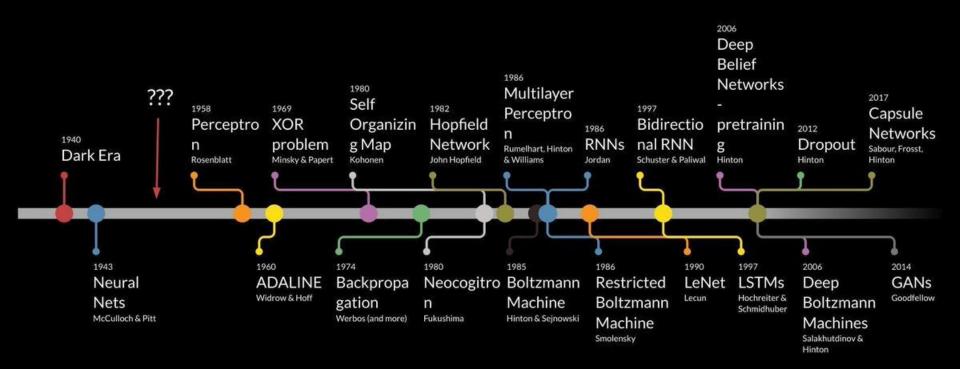








Deep Learning Timeline



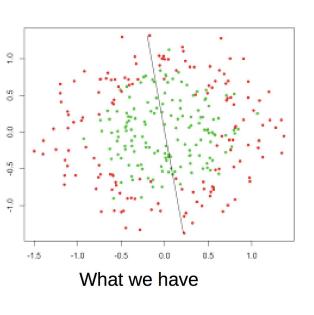
Logistic regression

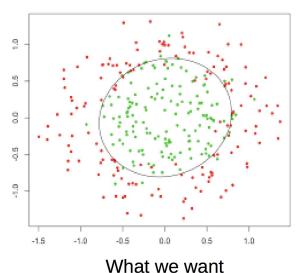
$$X \longrightarrow Wx +b \longrightarrow \mathbb{Q} = 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5 \ 0.5$$

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

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

Problem: nonlinear dependencies

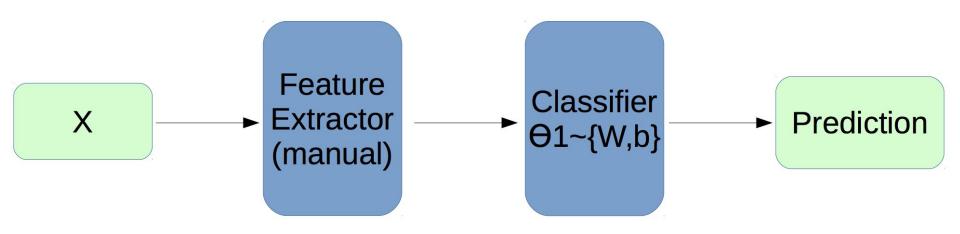




Logistic regression (generally, linear model) need feature engineering to show good results.

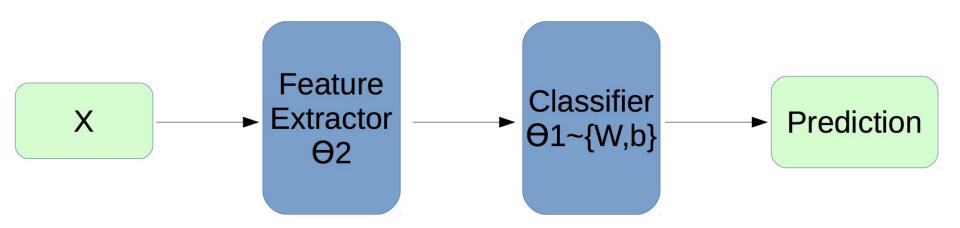
And feature engineering is an *art*.

Classic pipeline



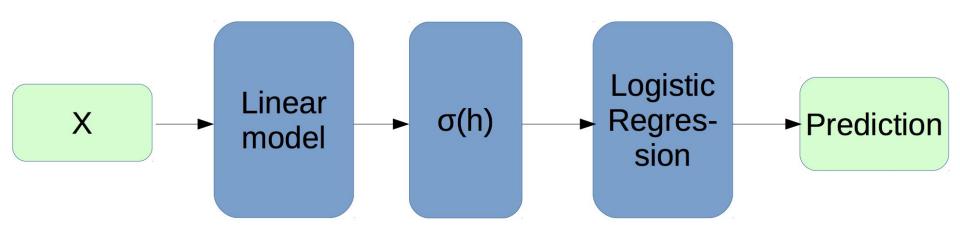
Handcrafted features, generated by experts.

NN pipeline



Automatically extracted features.

NN pipeline: example



E.g. two logistic regressions one after another.

Actually, it's a neural network.

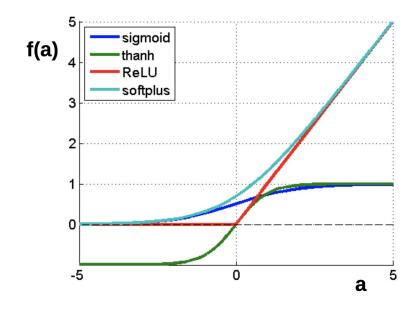
Activation functions: nonlinearities

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

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

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

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



Some generally accepted terms

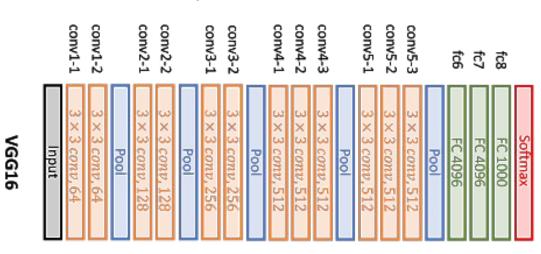
- Layer a building block for NNs :
 - Dense/Linear/FC layer: f(x) = Wx+b
 - Nonlinearity layer: $f(x) = \sigma(x)$
 - Input layer, output layer
 - A few more we will cover later
- Activation function function applied to

layer output

- Sigmoid
- tanh
- ReLU
- Any other function to get nonlinear intermediate signal in NN
- Backpropagation a fancy word for

"chain rule"

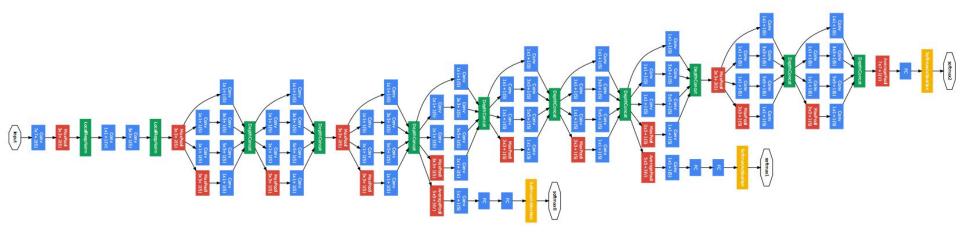
Actually, networks can be deep



And deeper...

	conv1-1	conv1-2		conv2-1	conv2-2		conv3-1	conv3-2		conv4-1	conv4-2	conv4-3		conv5-1	conv5-2	conv5-3		fc6	fc7	fc8			
Input	3 × 3 conv, 64	3 × 3 conv, 64	Pool	3×3 conv, 128	3×3 conv, 128	Pool	3×3 conv, 256	3 × 3 conv, 256	Pool	$3 \times 3 conv, 512$	$3 \times 3 conv, 512$	$3 \times 3 conv, 512$	Pool	3×3 conv, 512	3×3 conv, 512	3 × 3 conv, 512	Pool	FC 4096	FC 4096	FC 1000	Softmax		
Input	3 × 3 conv, 64	3 × 3 conv, 64	Pool	$3 \times 3 conv, 128$	3 × 3 conv, 128	Pool	3 × 3 conv, 256	3 × 3 conv, 256	Pool	3×3 conv, 512	3×3 conv, 512	3 × 3 conv, 512	3 × 3 conv, 512	Pool	3 × 3 conv, 512	3 × 3 conv, 512	3 × 3 conv, 512	$3 \times 3 conv, 512$	Pool	FC 4096	FC 4096	FC 1000	Softmax

Much deeper...

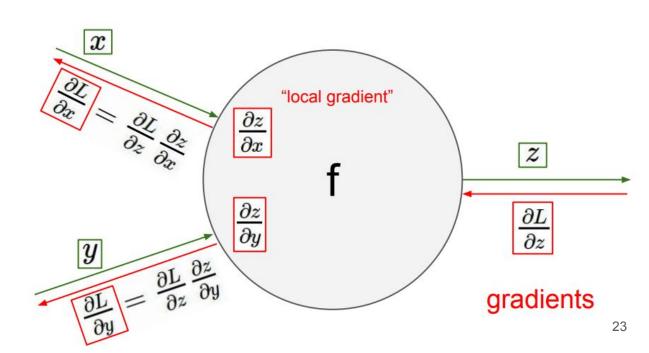


How to train it?

Backpropagation and chain rule

Chain rule is just simple math: $\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x}$

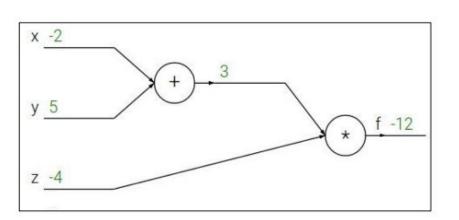
Backprop is just way to use it in NN training.



source: http://cs231n.github.io

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

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

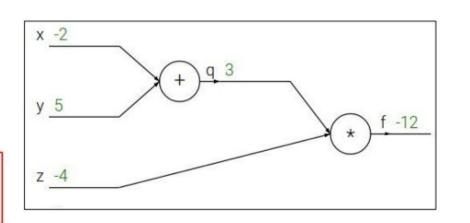


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$$q=x+y \qquad rac{\partial q}{\partial x}=1, rac{\partial q}{\partial y}=1$$

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

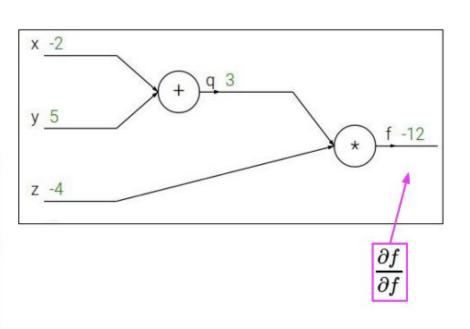


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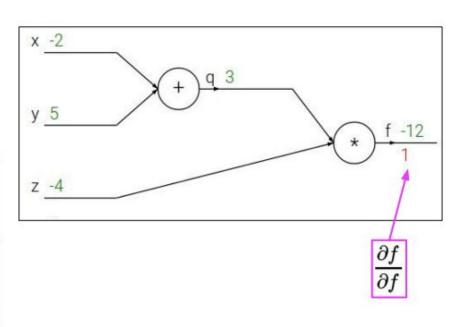


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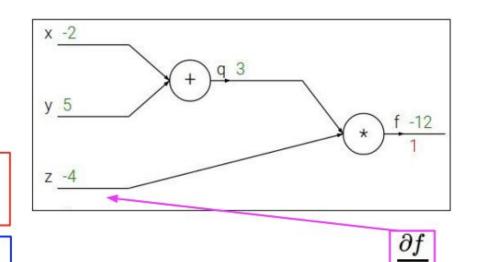


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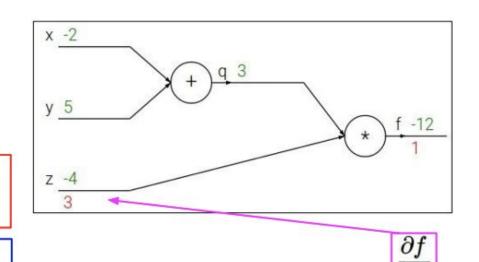


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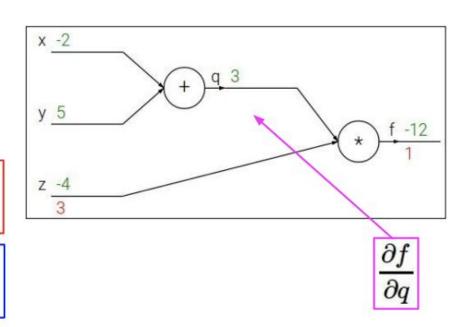


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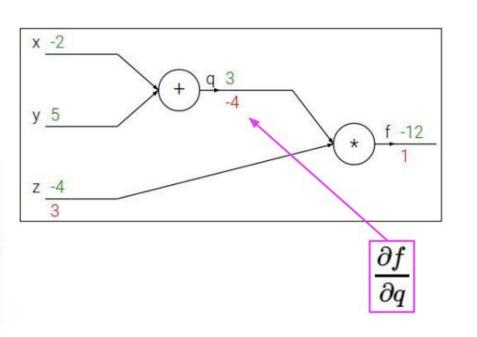


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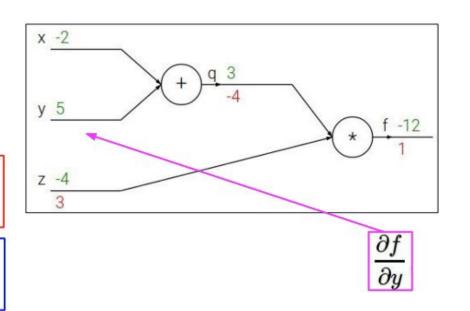


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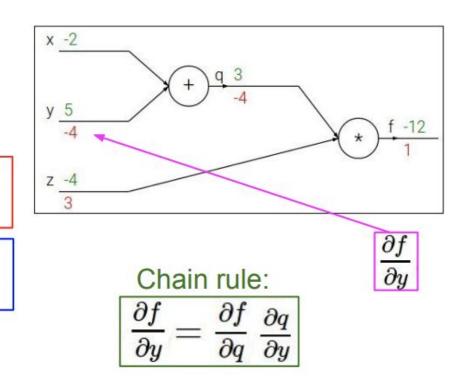


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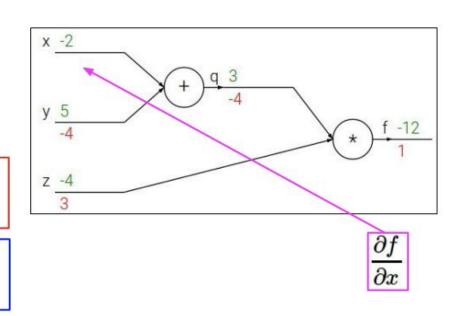


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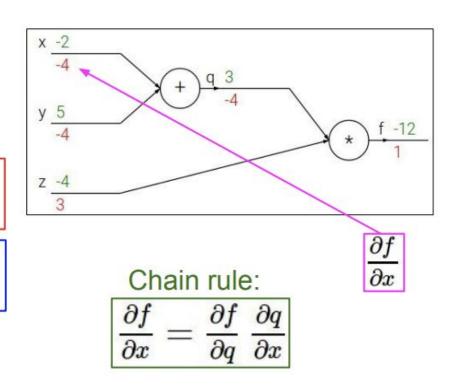


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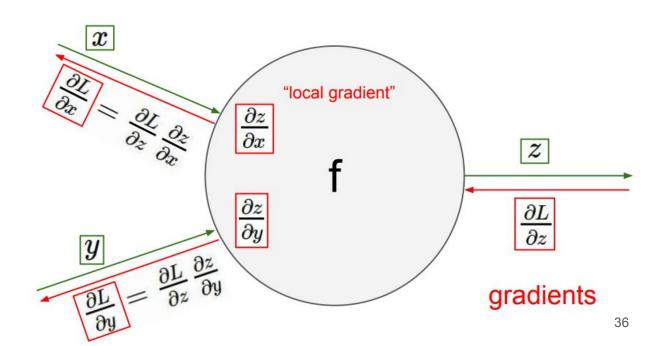


Backpropagation and chain rule

Chain rule is just simple math:

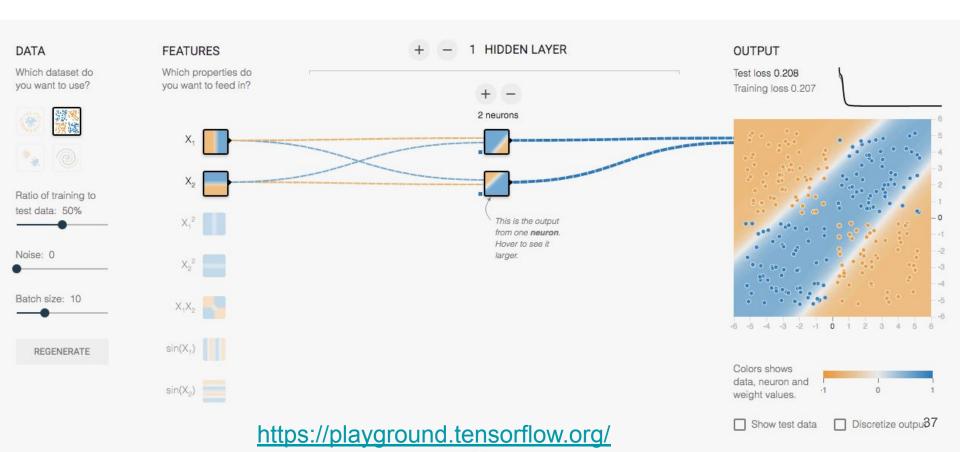
$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x}$$

Backprop is just way to use it in NN training.

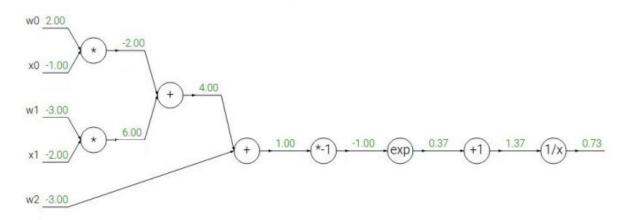


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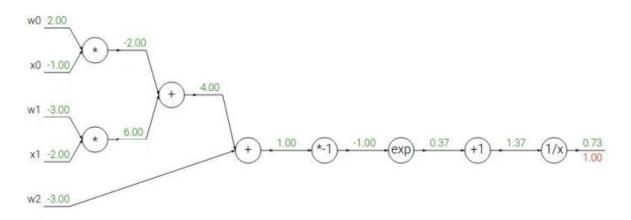
Interactive playground



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

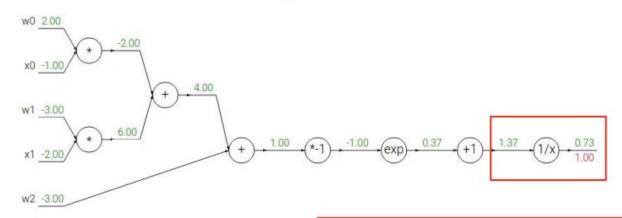


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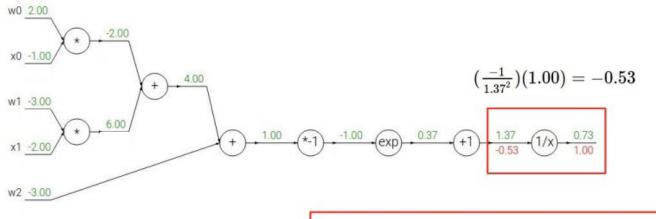


$$f(x) = e^x \hspace{1cm} o \hspace{1cm} rac{df}{dx} = e^x \hspace{1cm} f(x) = rac{1}{x} \hspace{1cm} o \hspace{1cm} rac{df}{dx} = -1/x^2 \ f_a(x) = ax \hspace{1cm} o \hspace{1cm} rac{df}{dx} = a \hspace{1cm} f_c(x) = c + x \hspace{1cm} o \hspace{1cm} rac{df}{dx} = 1$$

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



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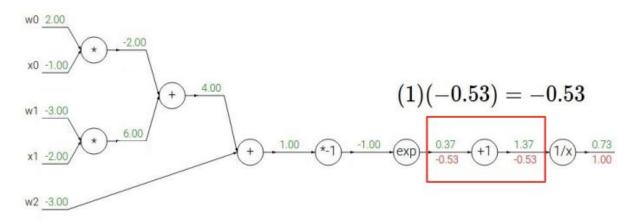


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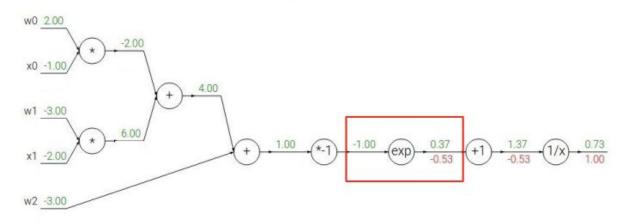
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$$f(x)=e^x \hspace{1cm} o \hspace{1cm} rac{df}{dx}=e^x \hspace{1cm} f(x)=rac{1}{x} \hspace{1cm} o \hspace{1cm} rac{df}{dx}=-1/x^2 \ f_a(x)=ax \hspace{1cm} o \hspace{1cm} rac{df}{dx}=a \hspace{1cm} f(x)=c+x \hspace{1cm} o \hspace{1cm} rac{df}{dx}=1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

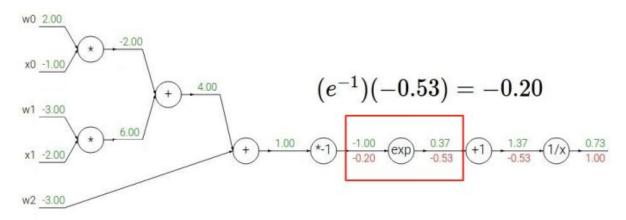
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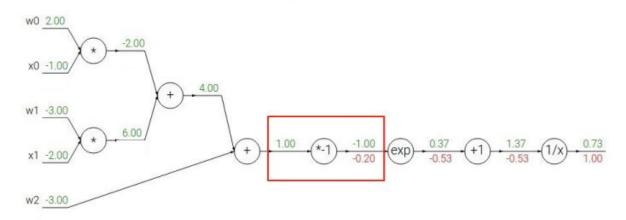
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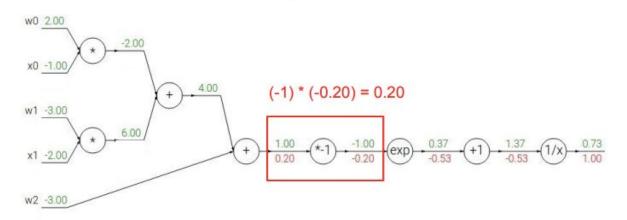
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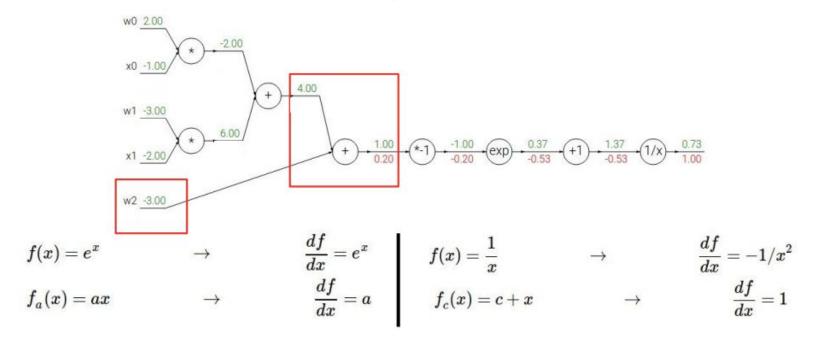


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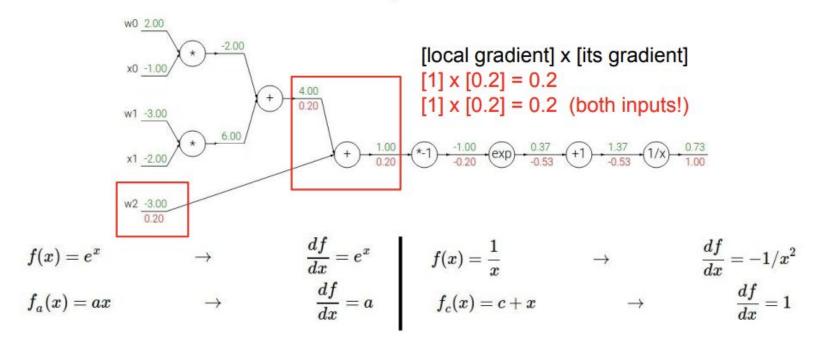


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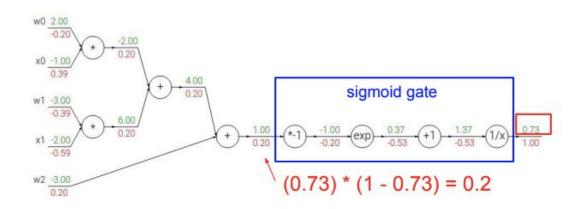
$$f(w,x)=rac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



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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 $rac{d\sigma(x)}{dx}=rac{e^{-x}}{(1+e^{-x})^2}=\left(rac{1+e^{-x}-1}{1+e^{-x}}
ight)\left(rac{1}{1+e^{-x}}
ight)=(1-\sigma(x))\,\sigma(x)$

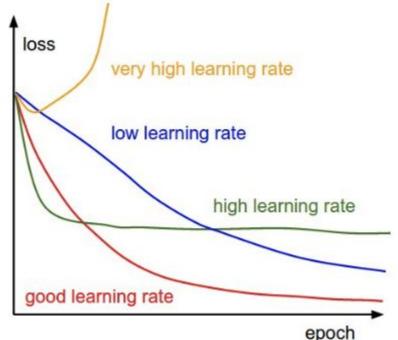


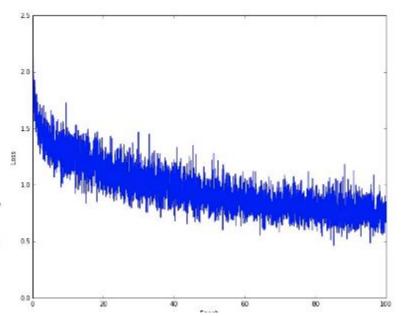
Gradient optimization

Stochastic gradient descent (and variations)

is used to optimize NN parameters.

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





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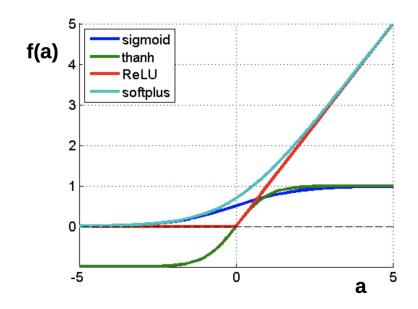
Once more: nonlinearities

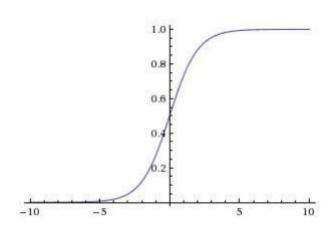
$$f(a) = \frac{1}{1 + e^a}$$

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

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

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





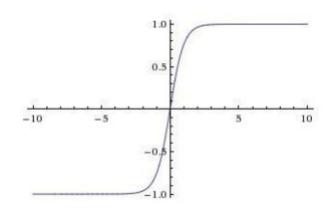
Sigmoid

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

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

3 problems:

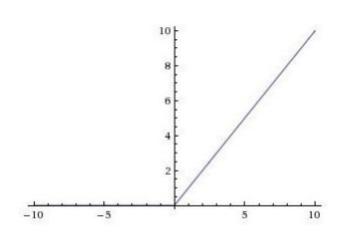
- Saturated neurons "kill" the gradients
- Sigmoid outputs are not zerocentered
- exp() is a bit compute expensive



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

tanh(x)

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

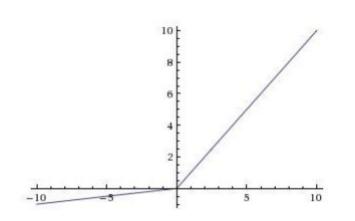


ReLU (Rectified Linear Unit)

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

- 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:

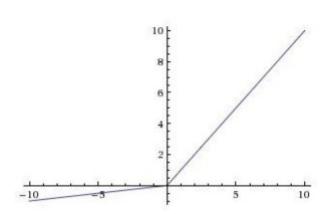
hint: what is the gradient when x < 0?



- 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

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

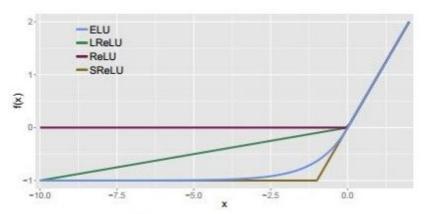
- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- will not "die".

Parametric Rectifier (PReLU)

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

backprop into \alpha (parameter)

Exponential Linear Units (ELU)



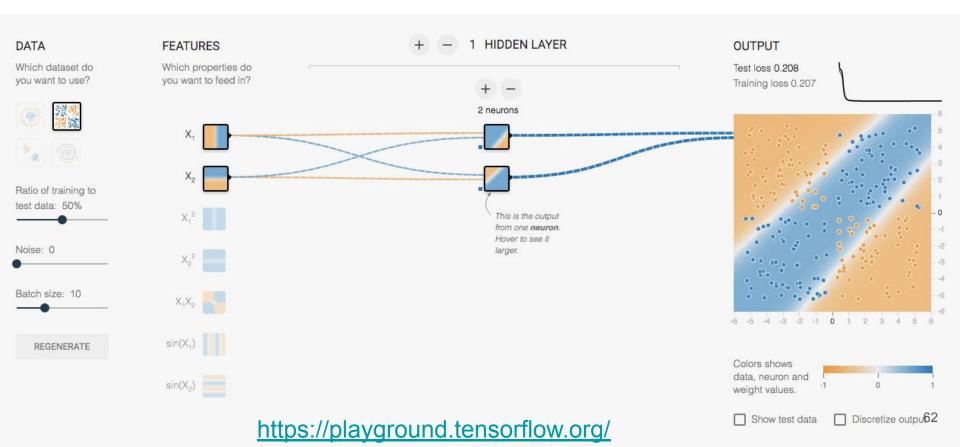
$$f(x) = \begin{cases} x & \text{if } x > 0\\ \alpha (\exp(x) - 1) & \text{if } x \le 0 \end{cases}$$

- 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

Don't miss the interactive playground





WHO'S AWESOME?