

Deep Learning School

Intro to Deep Learning

Deep Learning School, Moscow
Fall 2020

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Assistant Professor, [Machine Learning course](#) Lecturer, MIPT. Visiting lecturer at Harbour.Space University, Barcelona, Spain.

Useful materials for self-study: [link](#)

ex. Яндекс-CERN (Research Engineer),

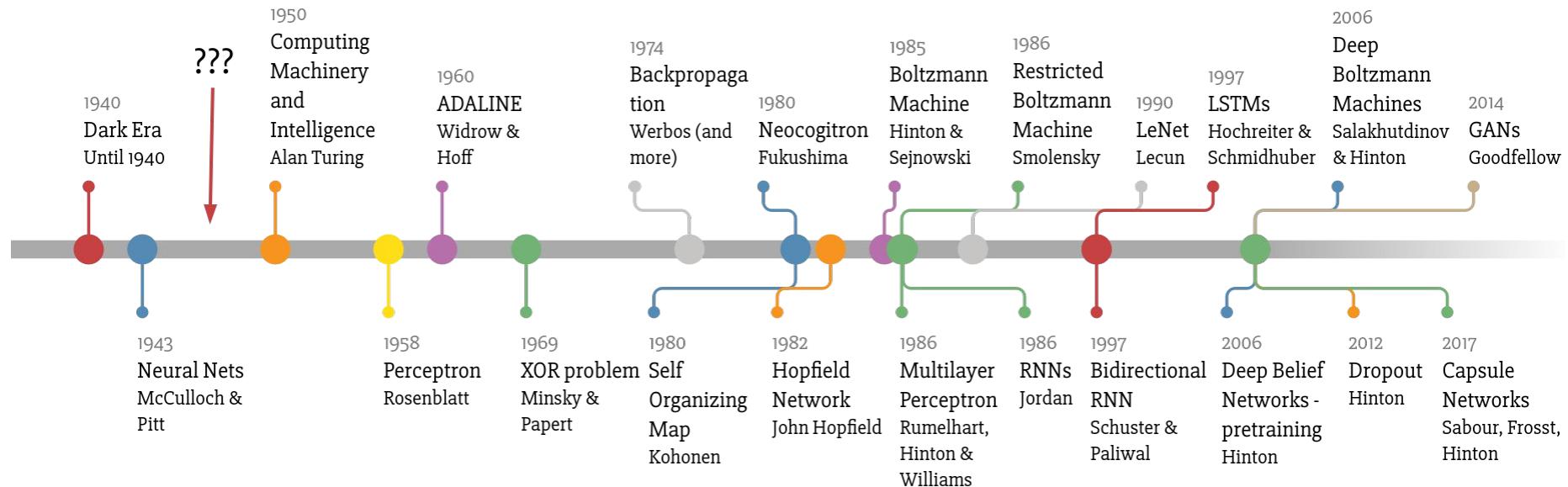
ex. Raiffeisen Bank Russia (Senior Quantitative Analysis Officer)

Outline

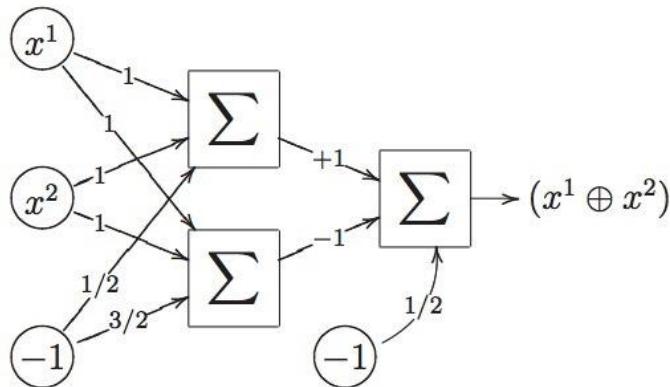
1. Neural Networks in different areas. Historical overview.
2. Backpropagation.
3. More on backpropagation.
4. Activation functions.
5. Playground.

History of Deep Learning

Deep Learning Timeline

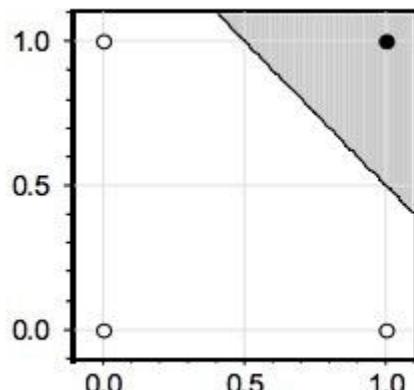


XOR problem

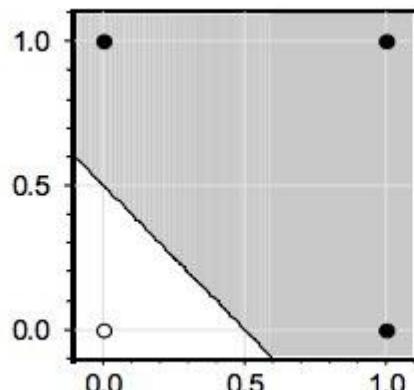


This 2-layer NN (on the left) implements XOR with only x_1 and x_2 features.

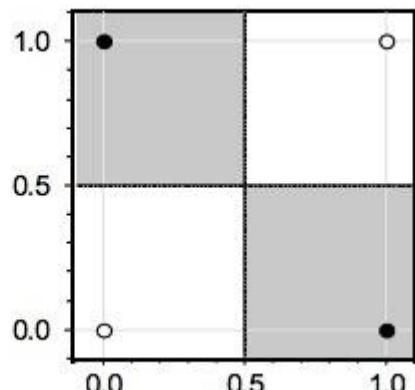
1-layer NN also can succeed, but only with extra feature $x_1 \cdot x_2$.



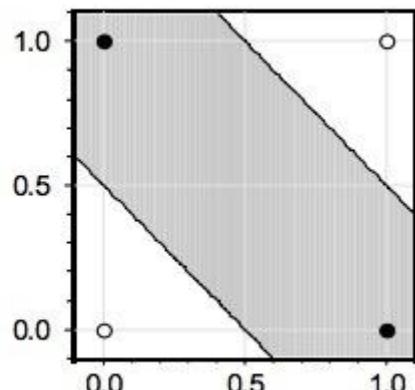
AND



OR

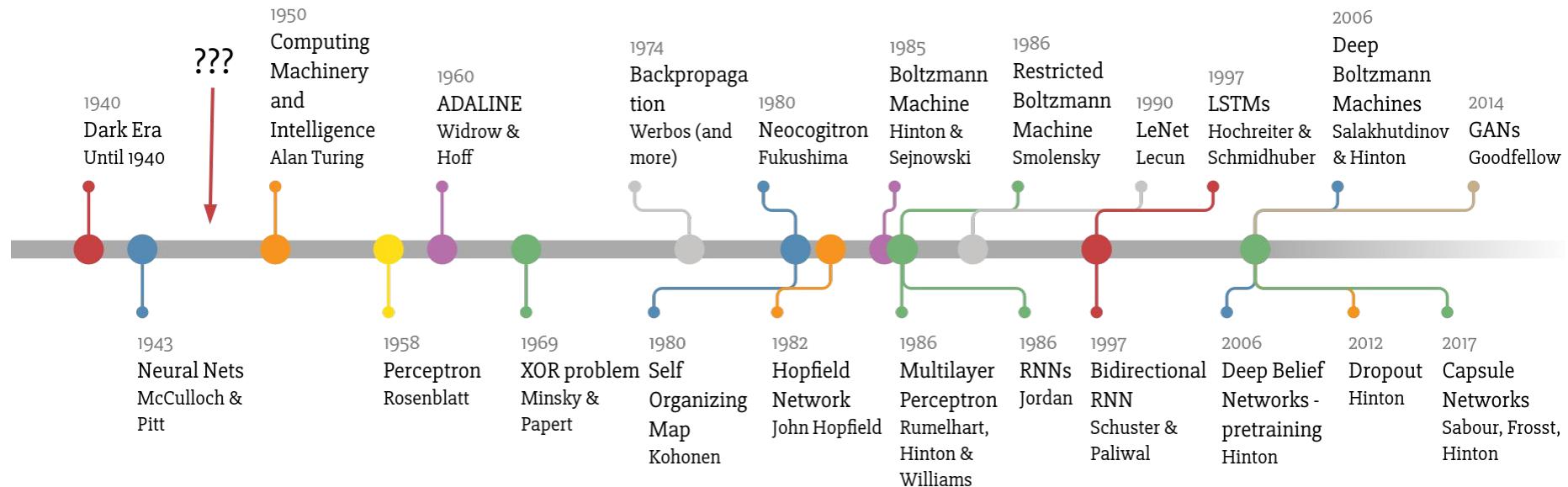


XOR(with $x_1 \cdot x_2$)

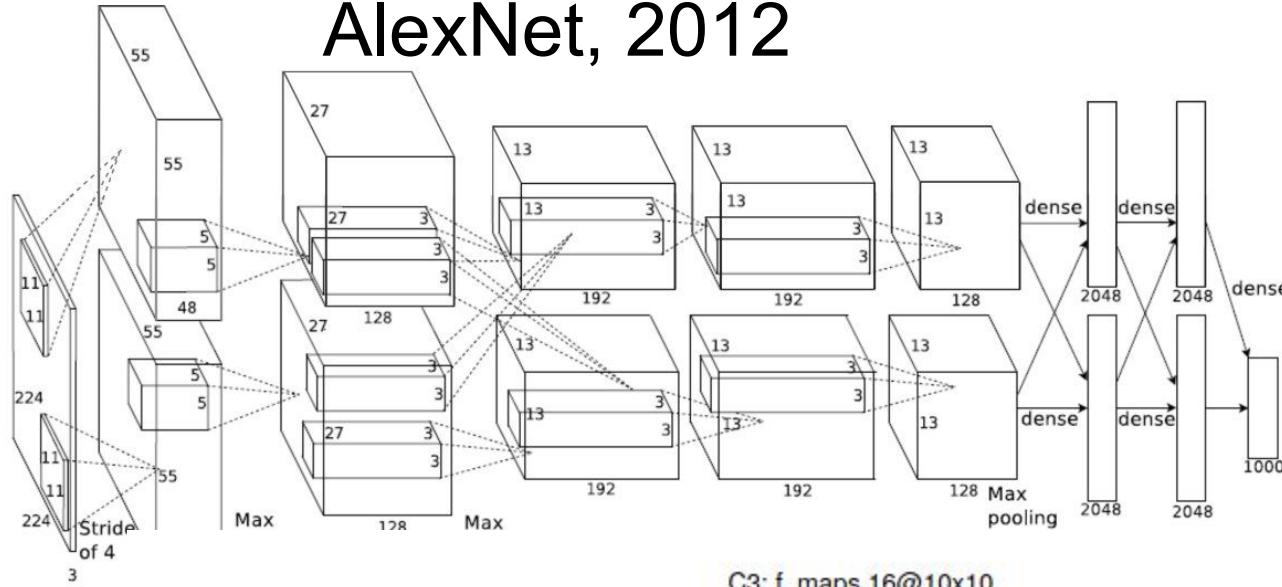


XOR

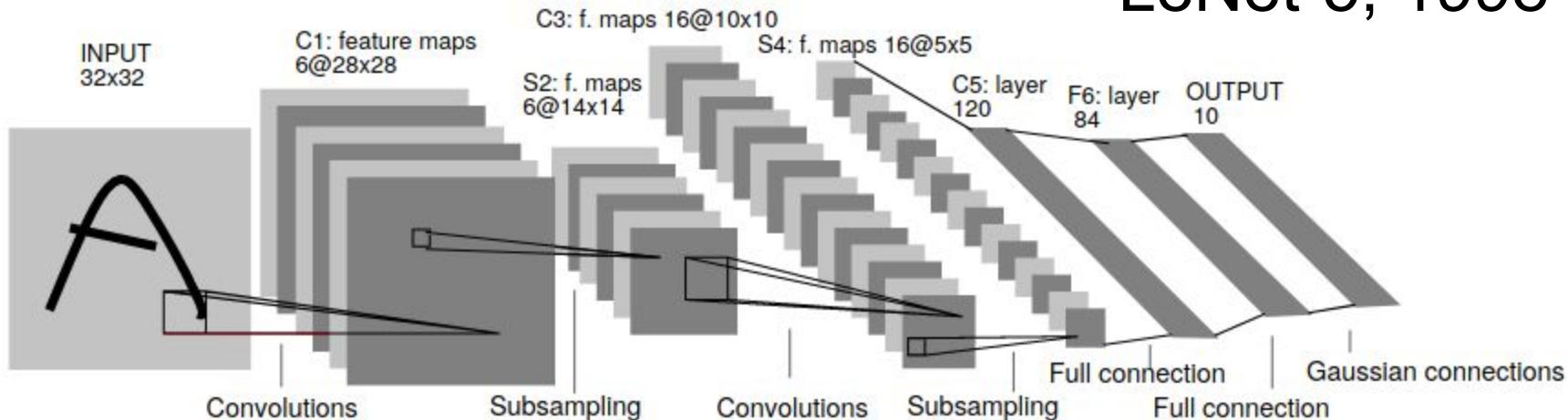
Deep Learning Timeline



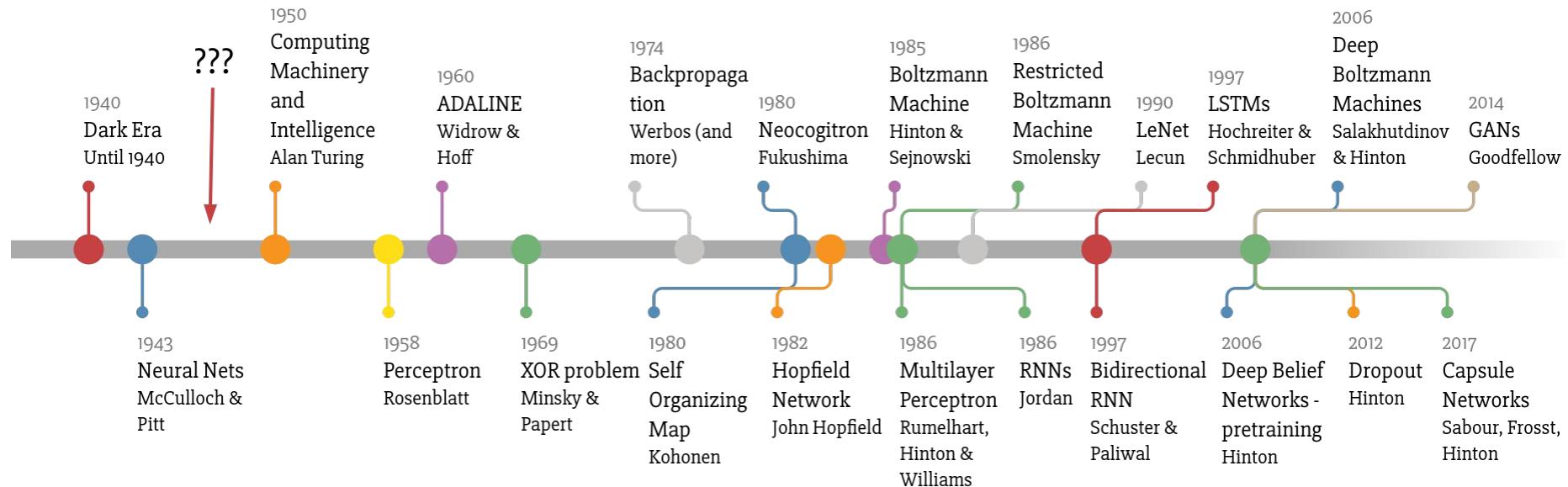
AlexNet, 2012



LeNet-5, 1998

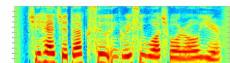
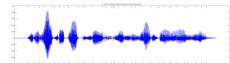


Deep Learning Timeline

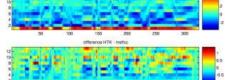
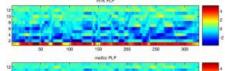


Audio Features

Real world applications



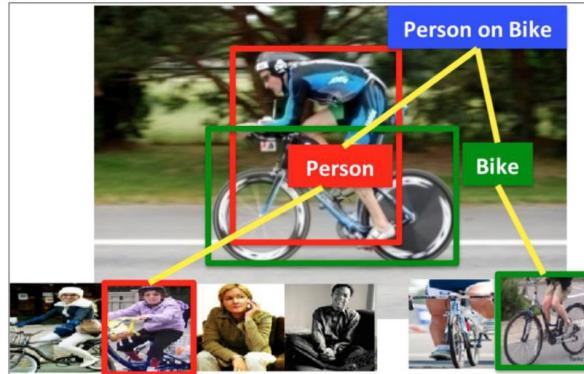
Spectrogram



MFCC

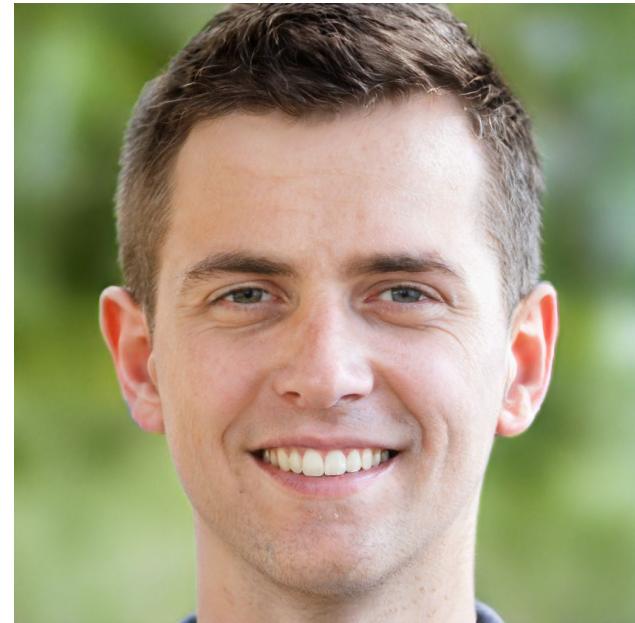


- Object detection
- Action classification
- Image captioning
- ...



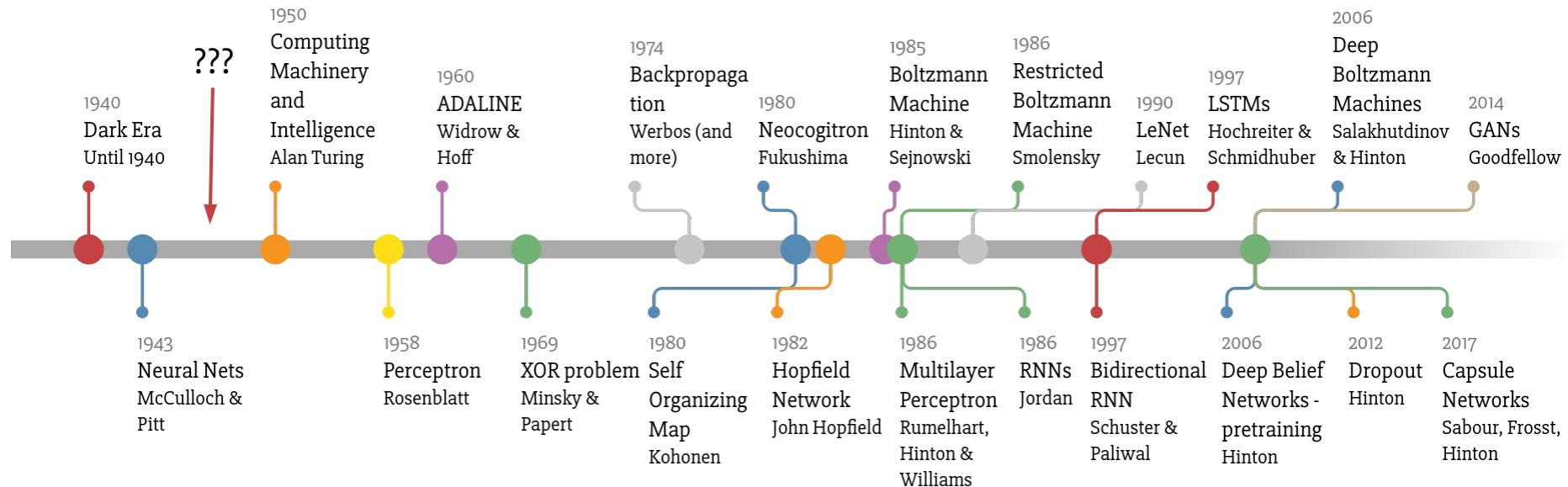
"man in black shirt is playing guitar."

GANs, 2014+



<https://thispersondoesnotexist.com/>

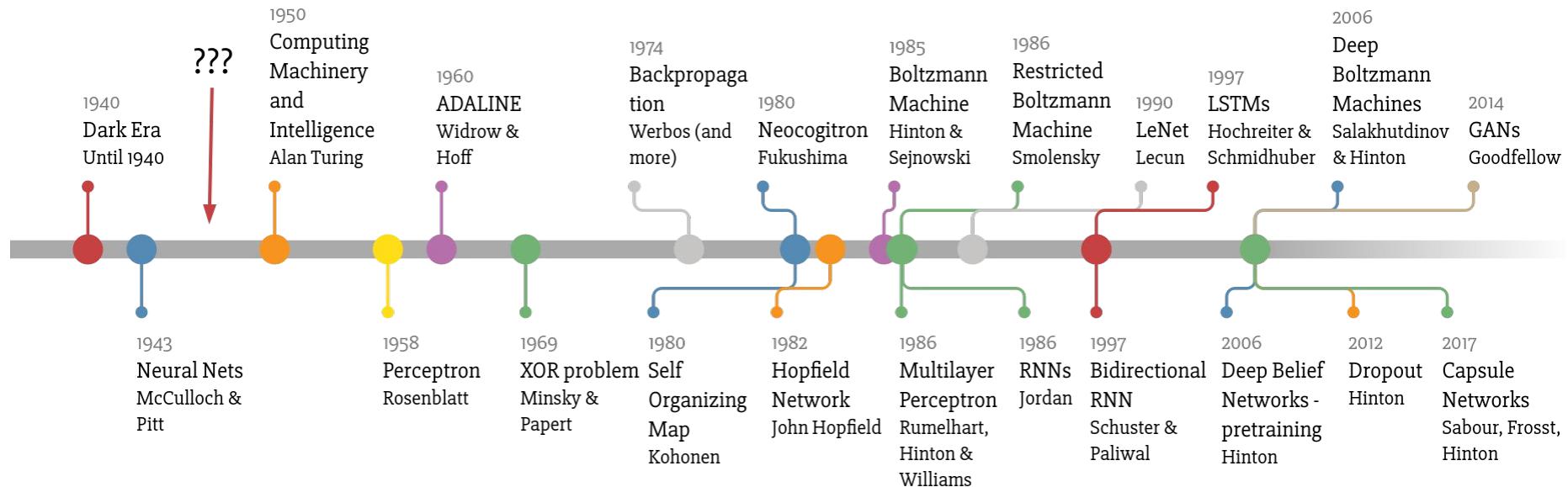
Deep Learning Timeline



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

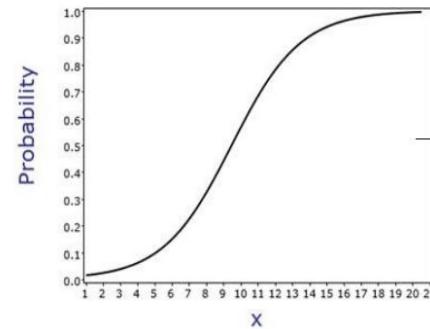
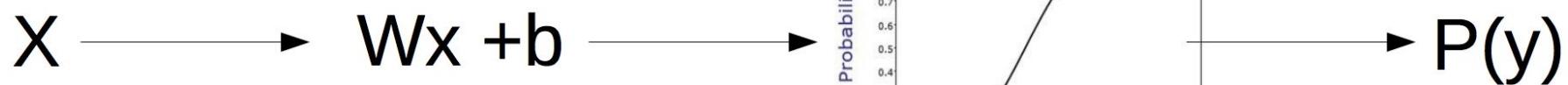


Deep Learning Timeline



Deep Learning: intuition

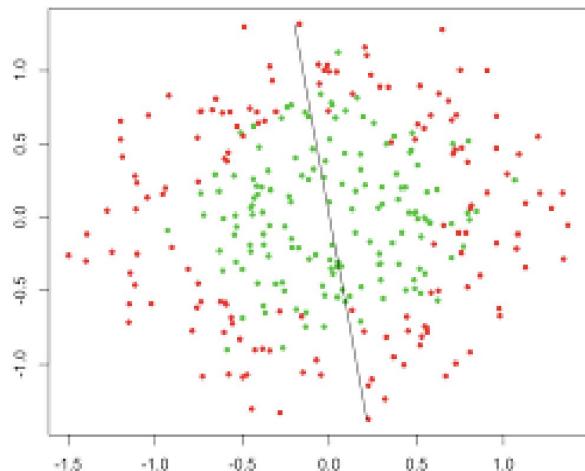
Logistic regression



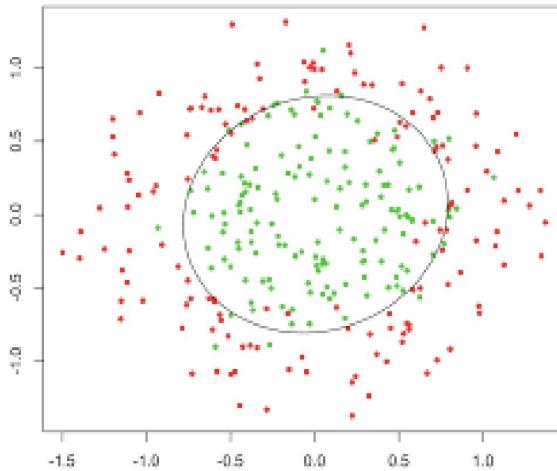
$$P(y|x) = \sigma(w \cdot x + b)$$

$$L = -\sum_i y_i \log P(y|x_i) + (1 - y_i) \log (1 - P(y|x_i))$$

Problem: nonlinear dependencies



What we have

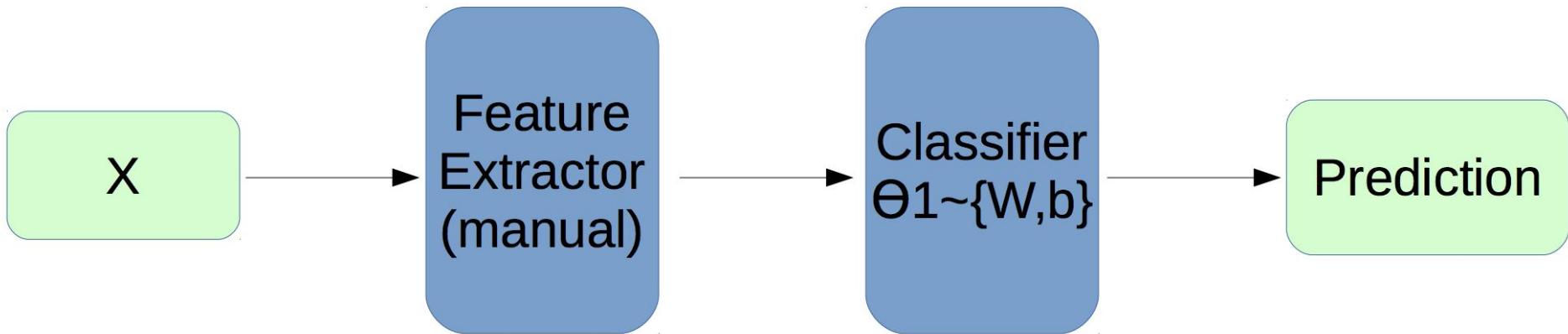


What we want

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

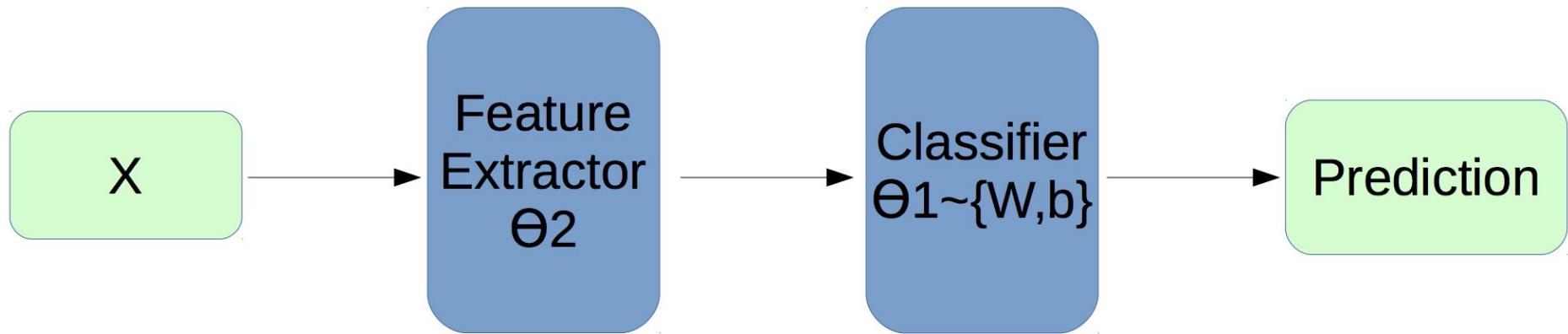
And feature engineering is
an *art*.

Classic pipeline



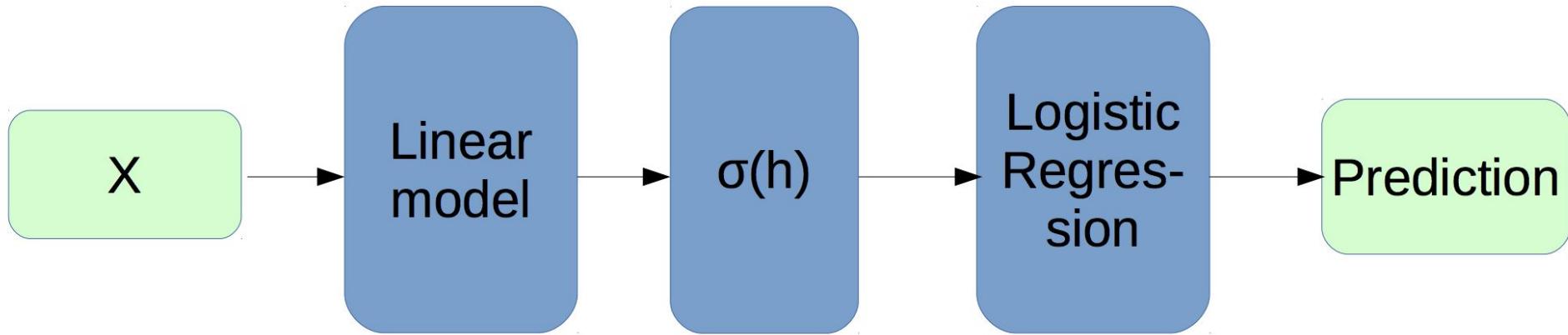
Handcrafted features, generated by experts.

NN pipeline



Automatically extracted features.

NN pipeline: example



E.g. two logistic regressions one after another.

Actually, it's a neural network.

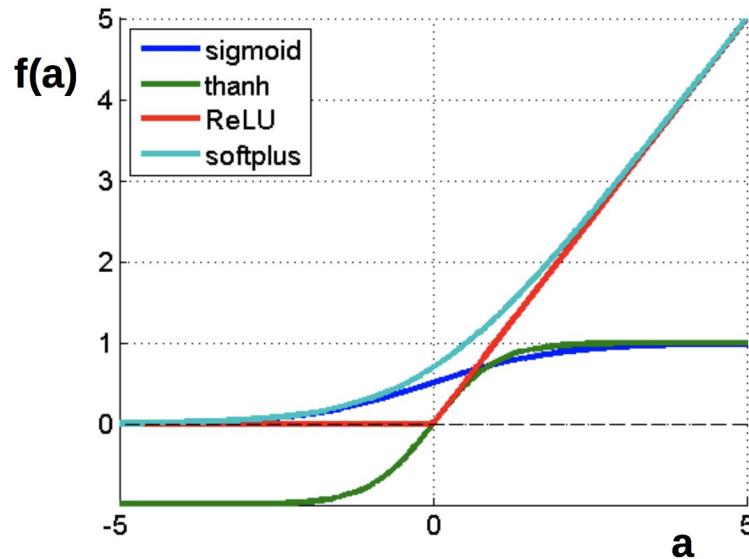
Activation functions: nonlinearities

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

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

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

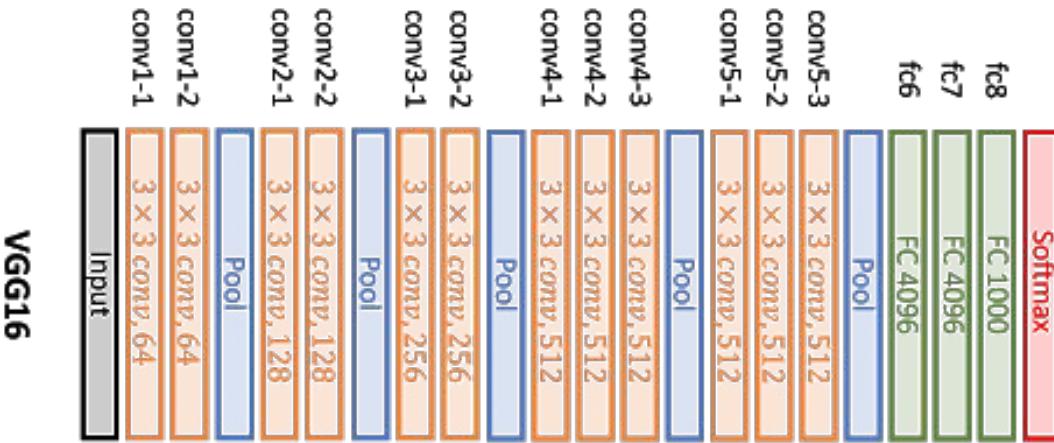
$$f(a) = \log(1 + e^a)$$



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



VGG16

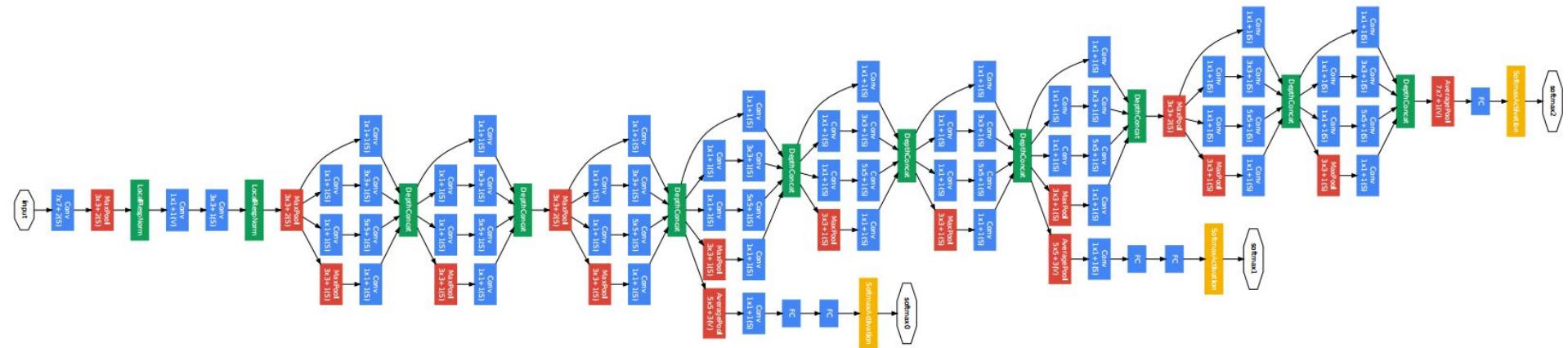
And deeper...



VGG16

VGG19

Much deeper...



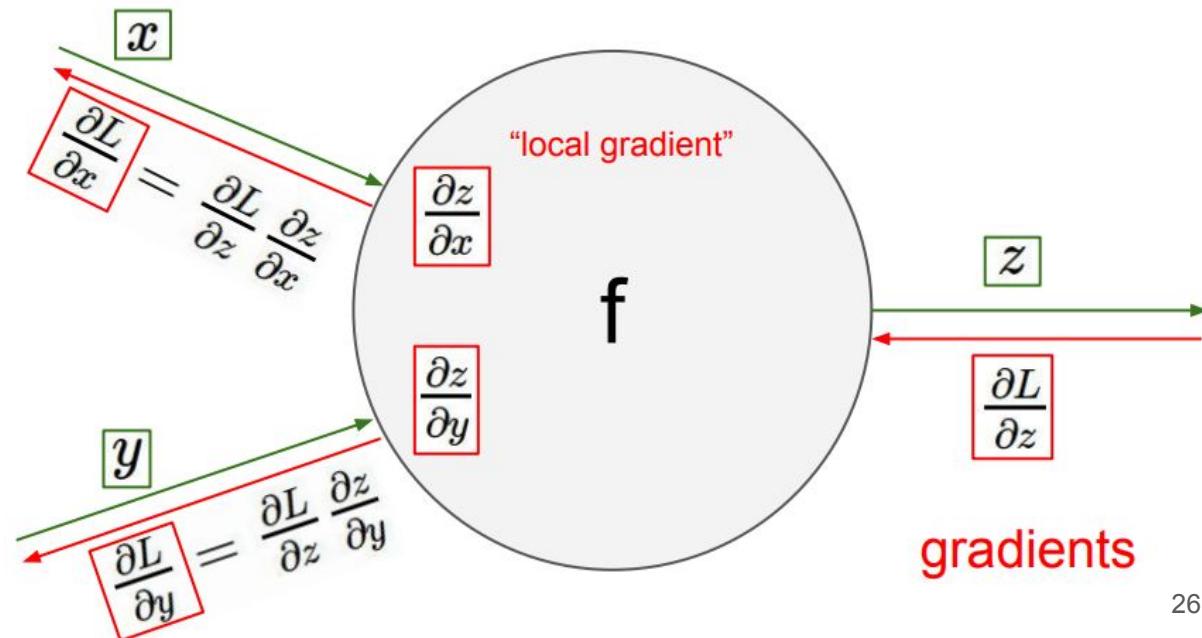
How to train it?

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.



gradients

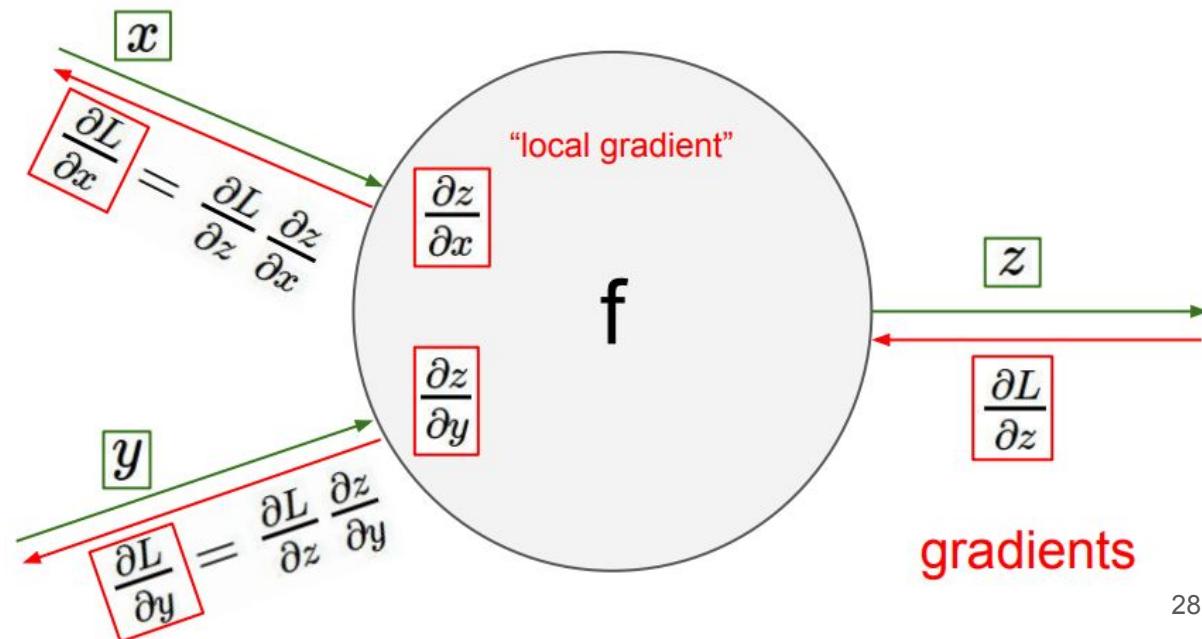
Backpropagation

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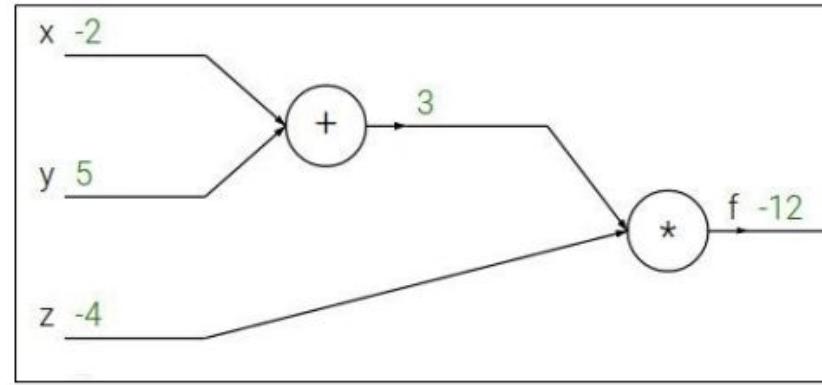
Backprop is just
way to use it in NN
training.



Backpropagation example

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

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



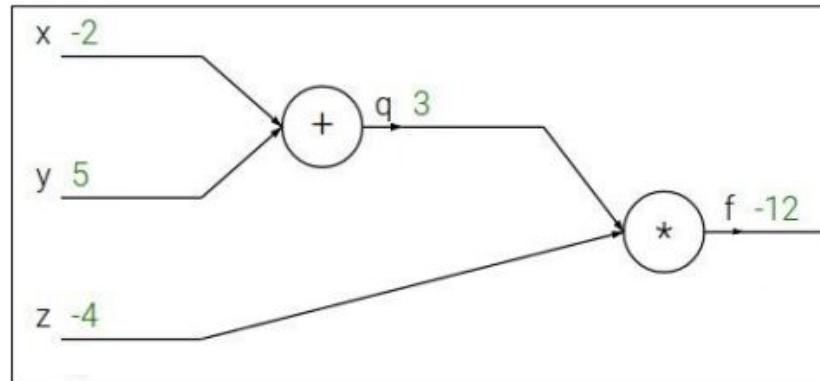
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$$q = x + y \quad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \quad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$



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

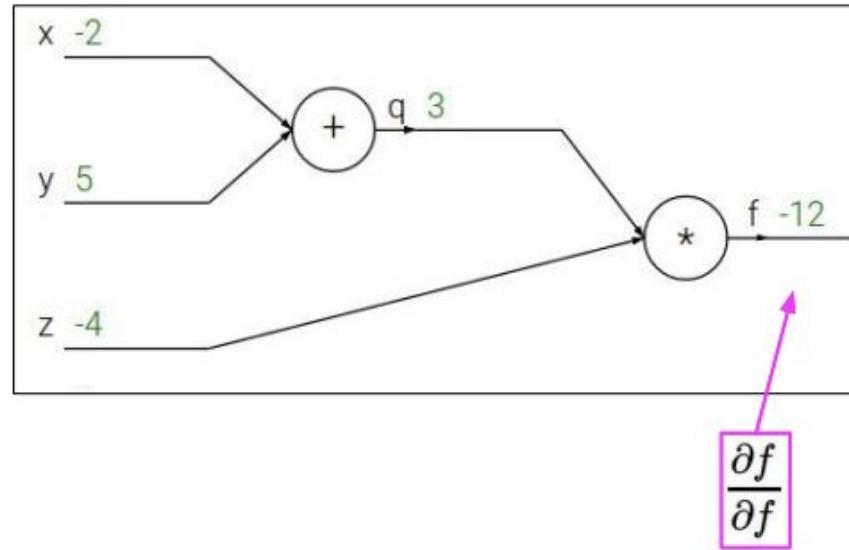
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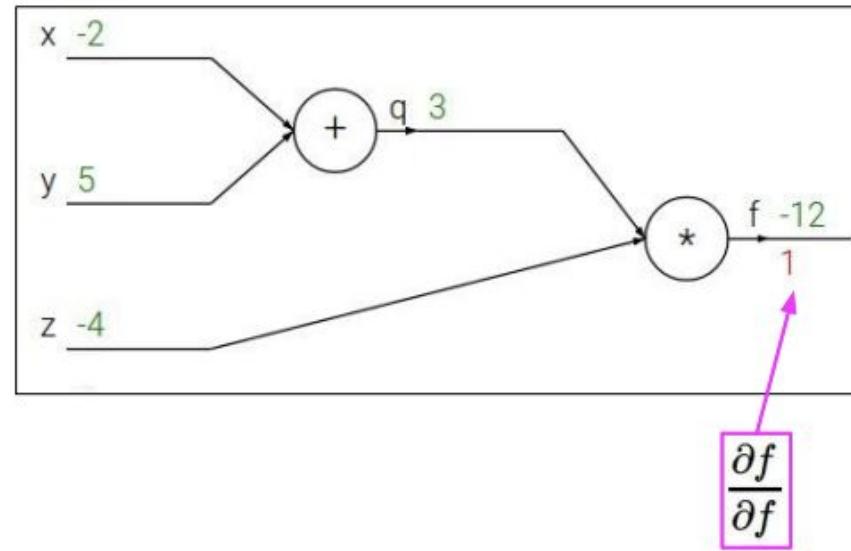
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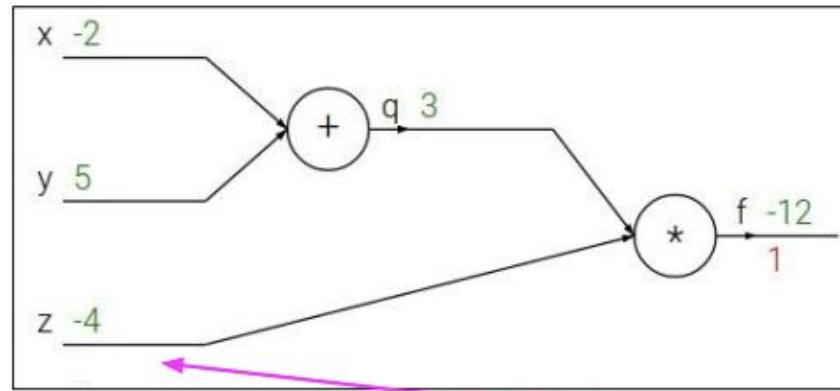
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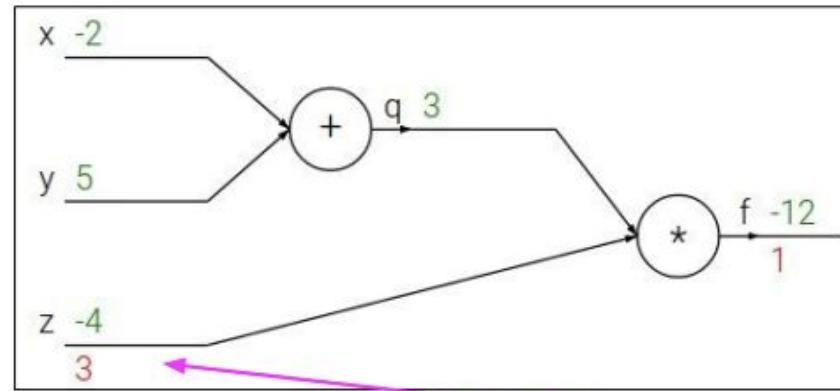
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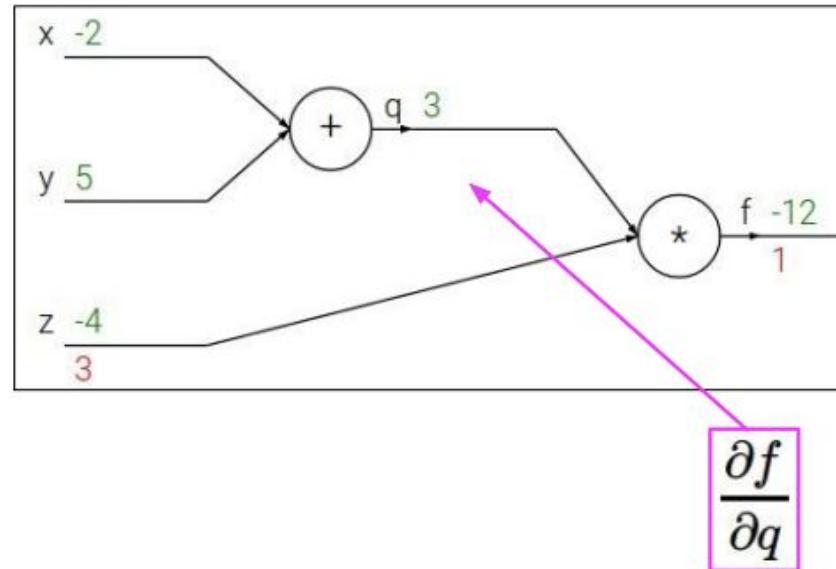
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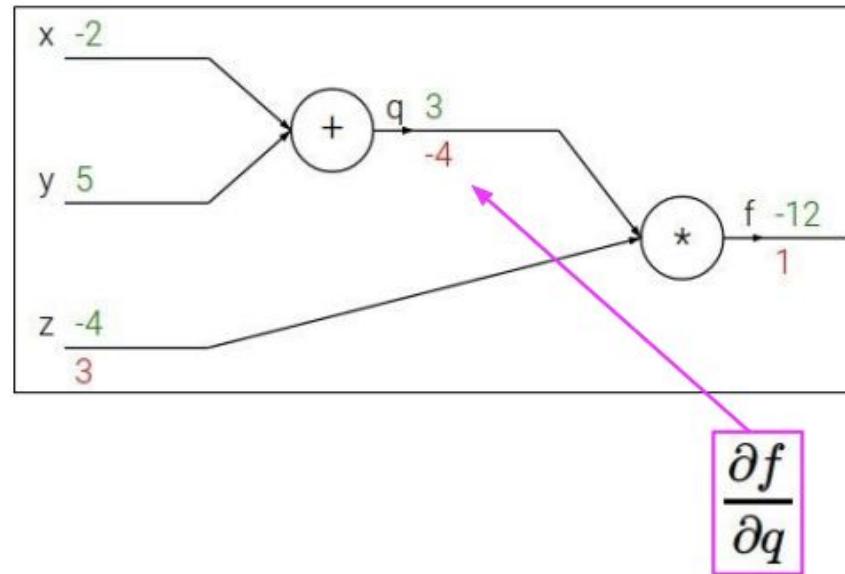
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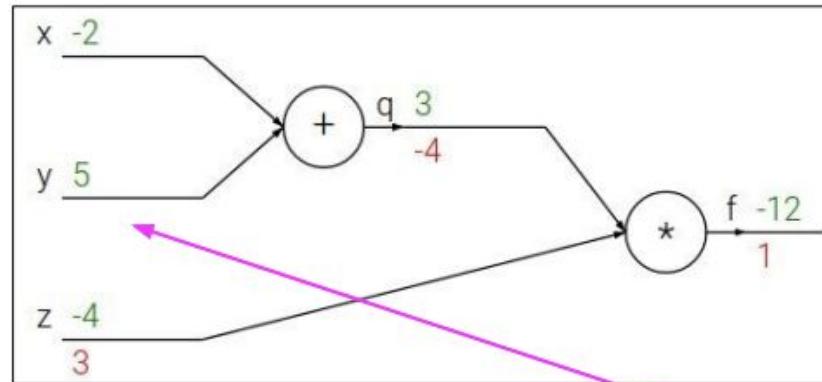
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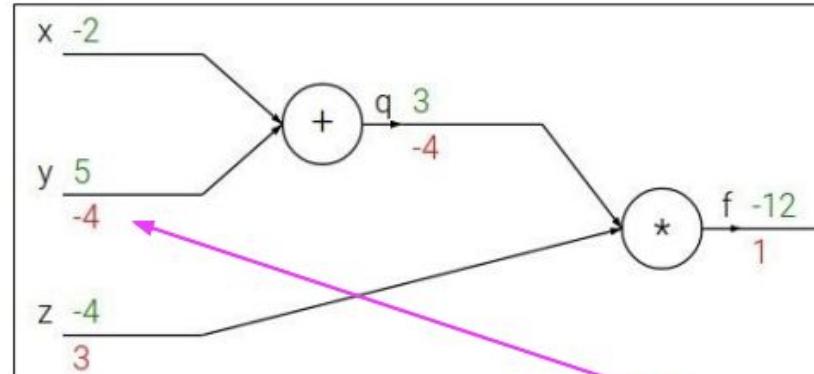
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Chain rule:

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y}$$

$$\frac{\partial f}{\partial y}$$

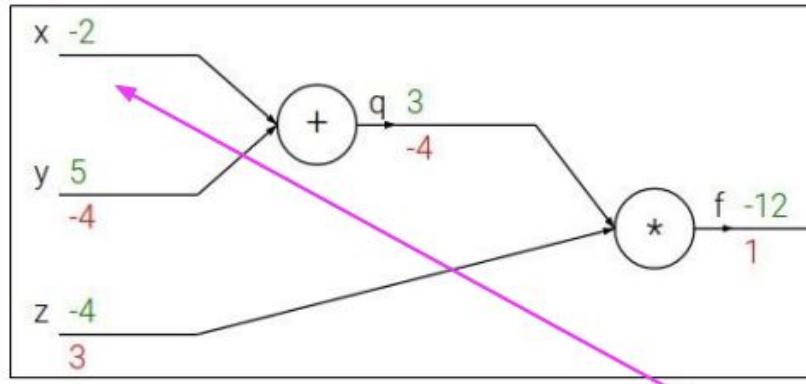
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$$\frac{\partial f}{\partial x}$$

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

Backpropagation example

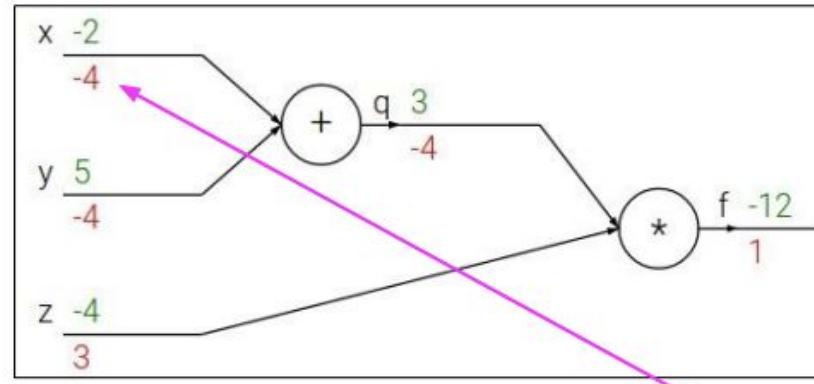
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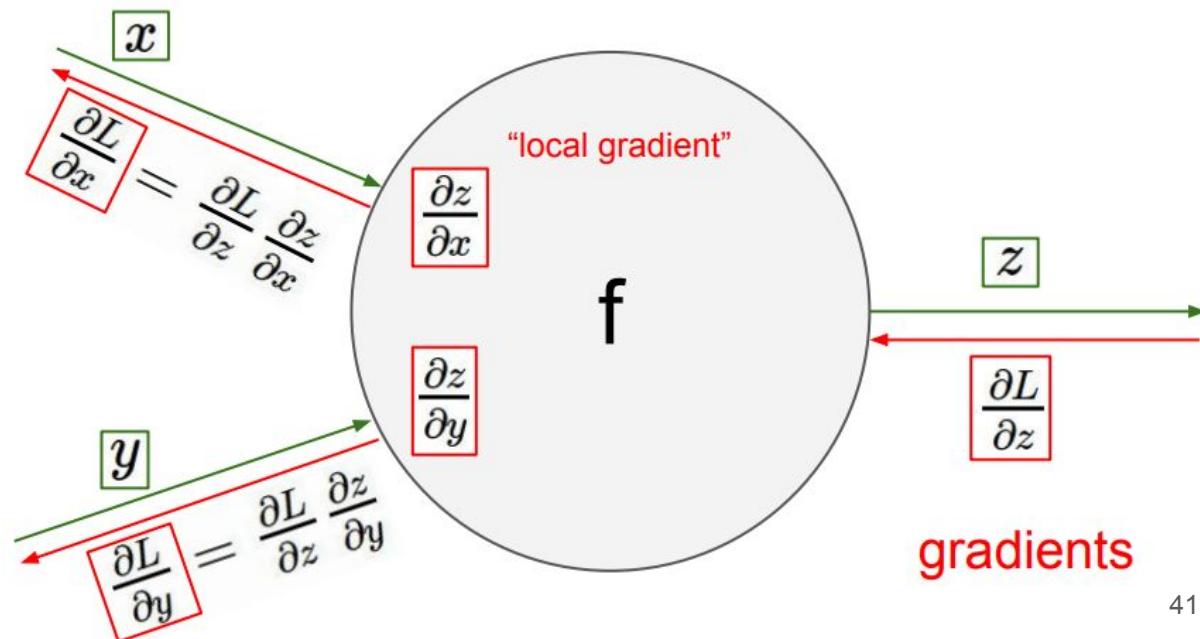
$$\frac{\partial f}{\partial x}$$

Backpropagation and chain rule

Chain rule is just simple math:

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

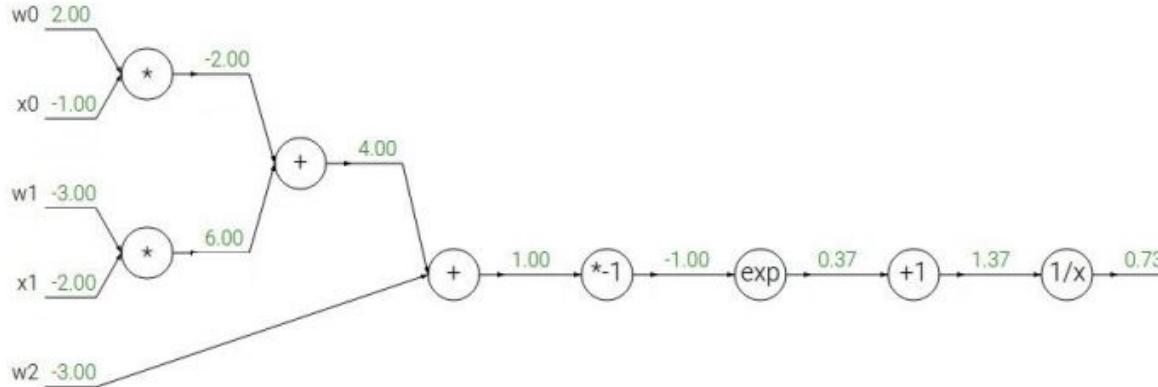
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Backpropagation example

Another example:

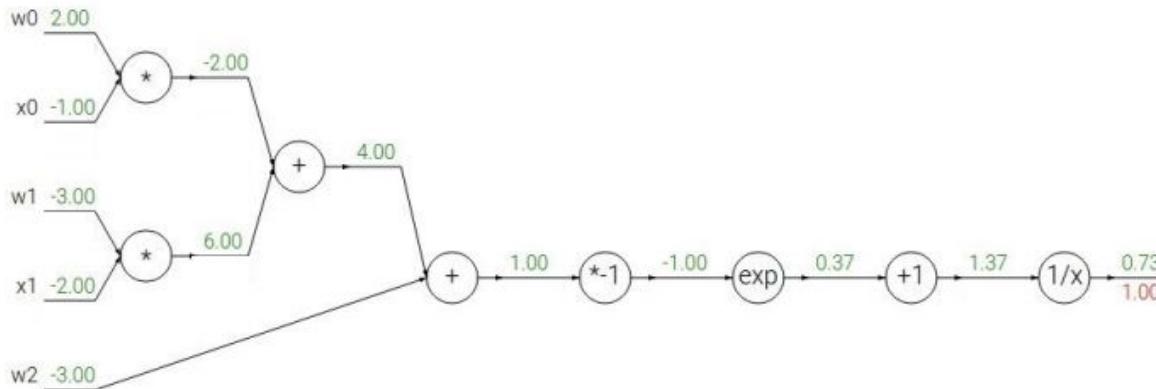
$$f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$$



Backpropagation example

Another example:

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



$$f(x) = e^x$$

→

$$\frac{df}{dx} = e^x$$

$$f_a(x) = ax$$

→

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

$$f(x) = \frac{1}{x}$$

→

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

$$f_c(x) = c + x$$

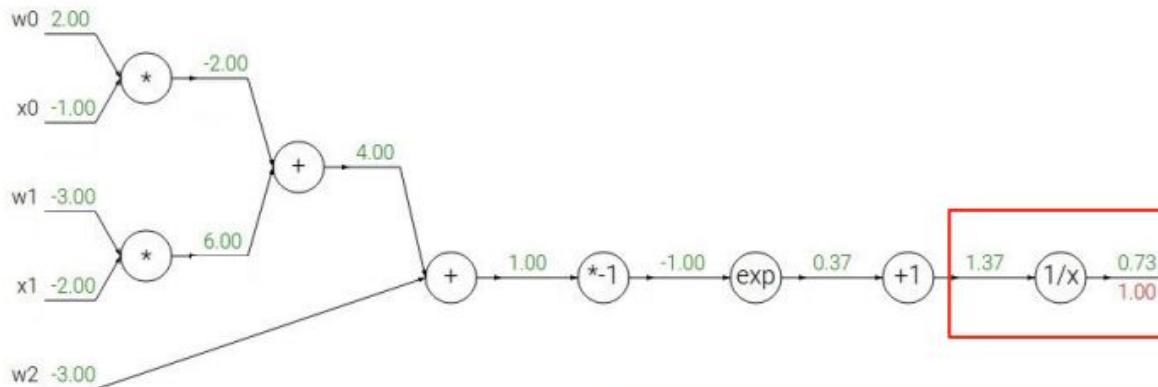
→

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

Backpropagation example

Another example:

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



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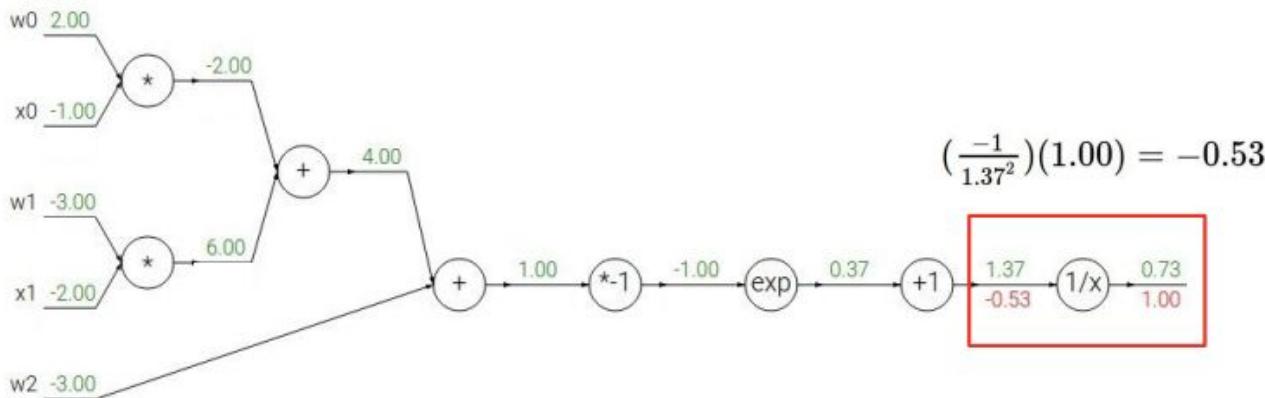
→

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

Backpropagation example

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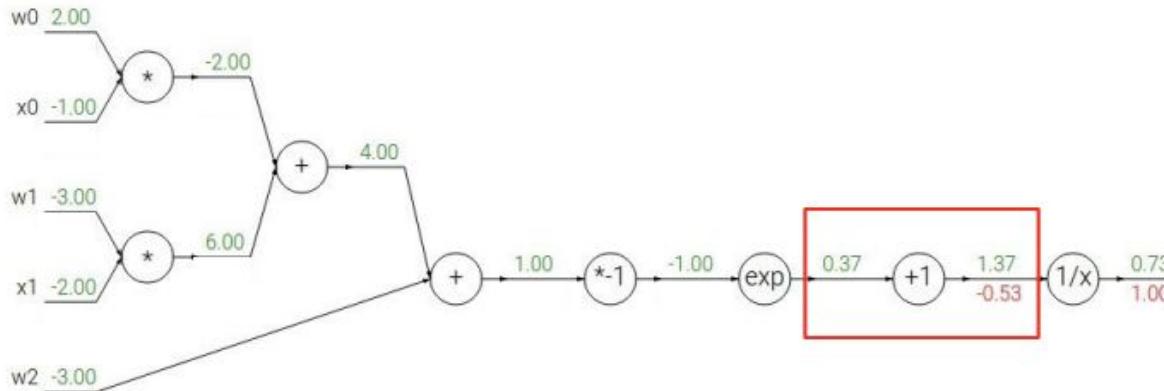
→

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

Backpropagation example

Another example:

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



$$f(x) = e^x$$

\rightarrow

$$\frac{df}{dx} = e^x$$

$$f_a(x) = ax$$

\rightarrow

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

$$f(x) = \frac{1}{x}$$

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

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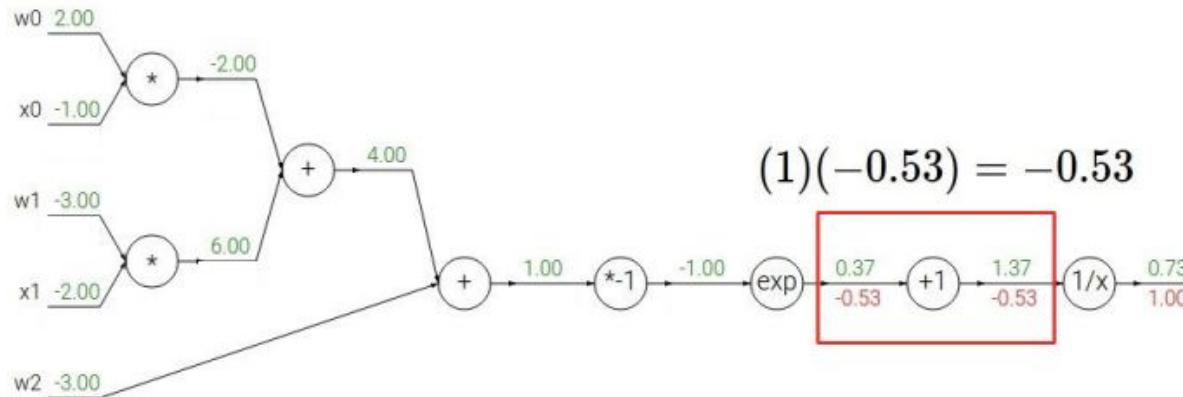
\rightarrow

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

Backpropagation example

Another example:

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



$$f(x) = e^x$$

→

$$\frac{df}{dx} = e^x$$

$$f_a(x) = ax$$

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

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

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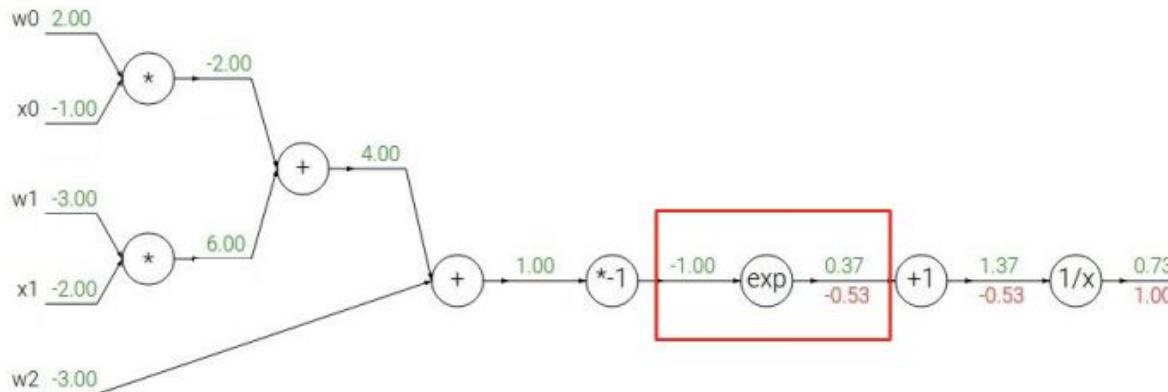
→

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

Backpropagation example

Another example:

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



$$\boxed{f(x) = e^x \rightarrow \frac{df}{dx} = e^x}$$

$$f_a(x) = ax \rightarrow \frac{df}{dx} = a$$

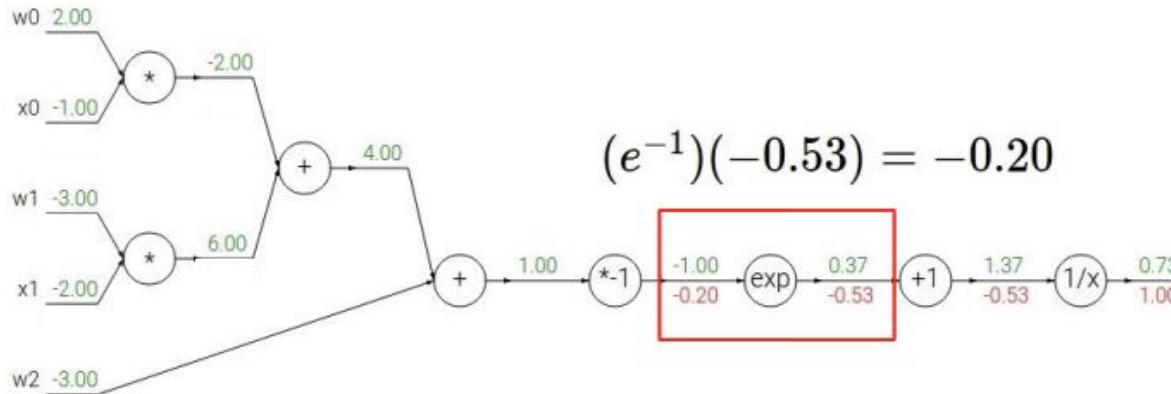
$$f(x) = \frac{1}{x} \rightarrow \frac{df}{dx} = -1/x^2$$

$$f_c(x) = c + x \rightarrow \frac{df}{dx} = 1$$

Backpropagation example

Another example:

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



$$f(x) = e^x \rightarrow \frac{df}{dx} = e^x$$

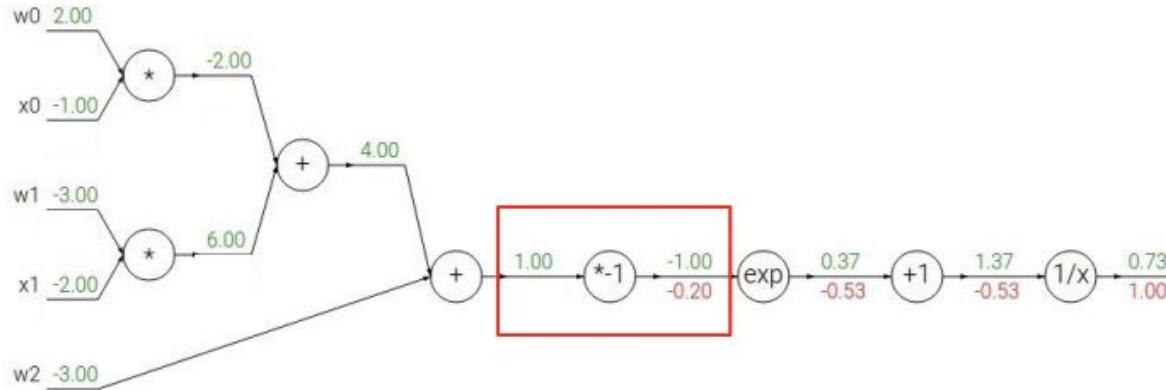
$$f_a(x) = ax \rightarrow \frac{df}{dx} = a$$

$$f(x) = \frac{1}{x} \rightarrow \frac{df}{dx} = -1/x^2$$

$$f_c(x) = c + x \rightarrow \frac{df}{dx} = 1$$

Backpropagation example

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



$$f(x) = e^x$$

→

$$\frac{df}{dx} = e^x$$

$$f_a(x) = ax$$

→

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

$$f(x) = \frac{1}{x}$$

→

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

$$f_c(x) = c + x$$

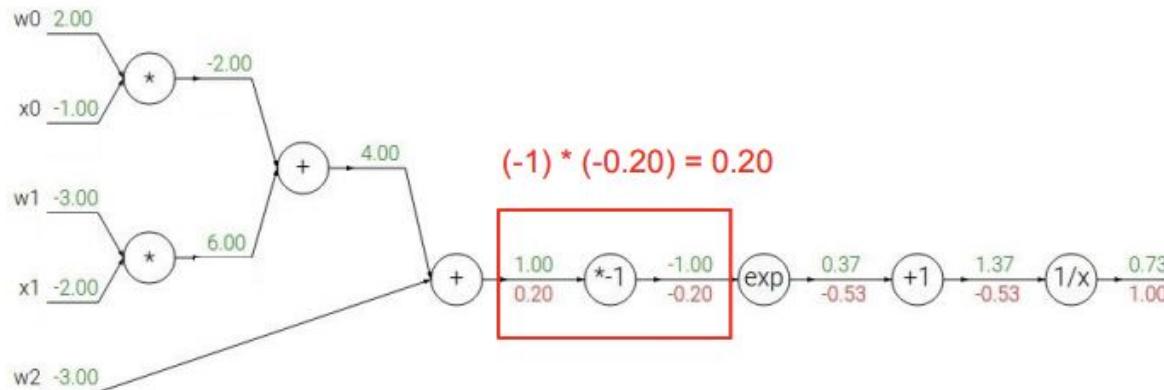
→

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

Backpropagation example

Another example:

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



$$f(x) = e^x$$

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→

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

$$f_c(x) = c + x$$

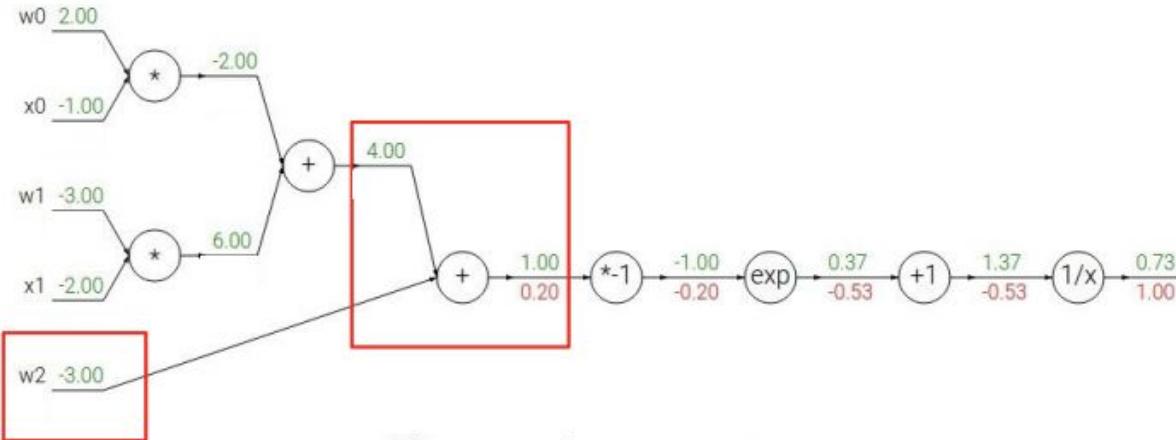
→

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

Backpropagation example

Another example:

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$$f(x) = e^x$$

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$$\frac{df}{dx} = e^x$$

$$f_a(x) = ax$$

→

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

$$f(x) = \frac{1}{x}$$

→

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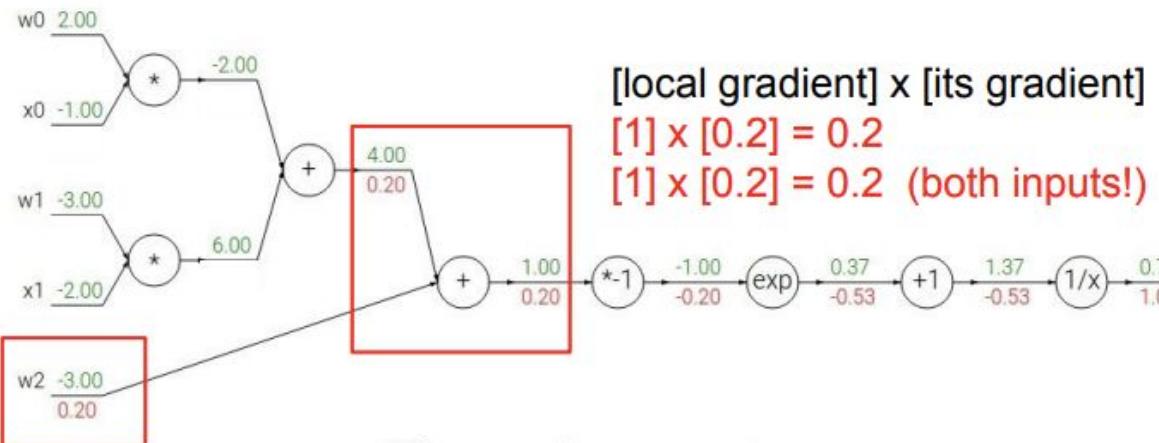
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$$f(x) = \frac{1}{x}$$

$$f_a(x) = ax$$

→

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

$$f_c(x) = c + x$$

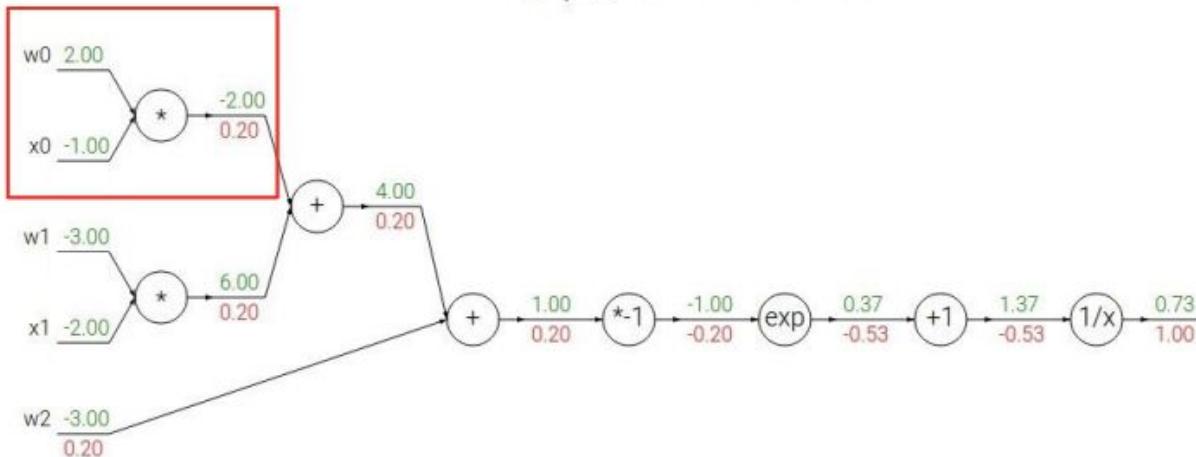
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Backpropagation example

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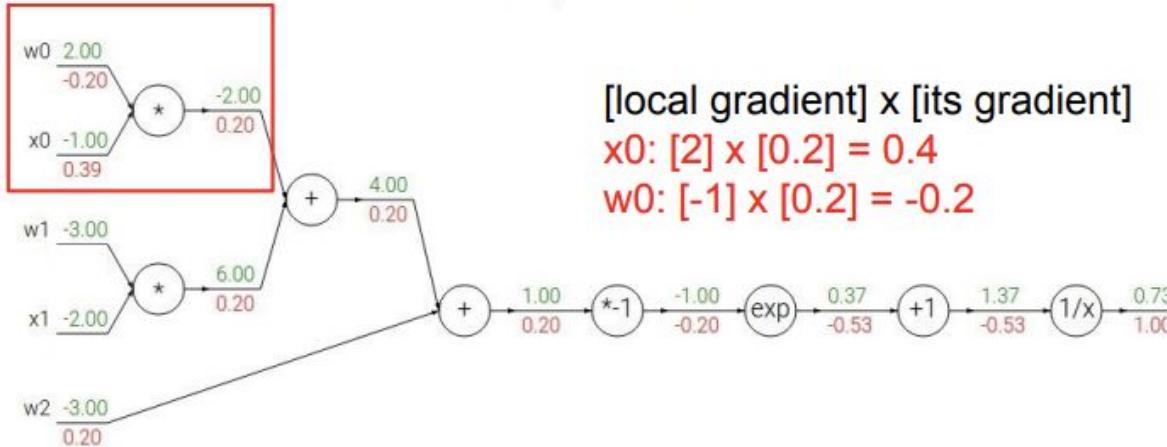
→

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

Backpropagation example

Another example:

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



$$f(x) = e^x$$

→

$$\frac{df}{dx} = e^x$$

$$f_a(x) = ax$$

→

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

$$f(x) = \frac{1}{x}$$

→

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

$$f_c(x) = c + x$$

→

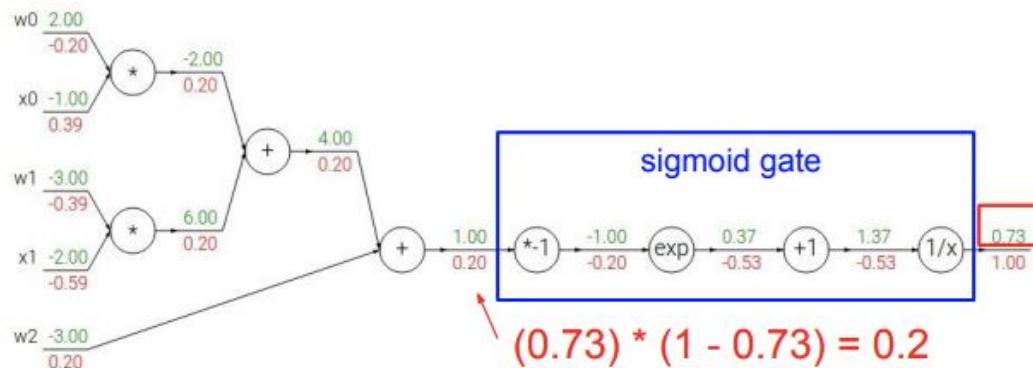
$$\frac{df}{dx} = 1$$

Backpropagation example

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

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad \text{sigmoid function}$$

$$\frac{d\sigma(x)}{dx} = \frac{e^{-x}}{(1 + e^{-x})^2} = \left(\frac{1 + e^{-x} - 1}{1 + e^{-x}} \right) \left(\frac{1}{1 + e^{-x}} \right) = (1 - \sigma(x))\sigma(x)$$



Backpropagation: matrix form

$$y_1 = f_1(\mathbf{x}) = x_1$$

$$y_2 = f_2(\mathbf{x}) = x_2$$

⋮

$$y_n = f_n(\mathbf{x}) = x_n$$

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \begin{bmatrix} \nabla f_1(\mathbf{x}) \\ \nabla f_2(\mathbf{x}) \\ \dots \\ \nabla f_m(\mathbf{x}) \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial \mathbf{x}} f_1(\mathbf{x}) \\ \frac{\partial}{\partial \mathbf{x}} f_2(\mathbf{x}) \\ \dots \\ \frac{\partial}{\partial \mathbf{x}} f_m(\mathbf{x}) \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial x_1} f_1(\mathbf{x}) & \frac{\partial}{\partial x_2} f_1(\mathbf{x}) & \dots & \frac{\partial}{\partial x_n} f_1(\mathbf{x}) \\ \frac{\partial}{\partial x_1} f_2(\mathbf{x}) & \frac{\partial}{\partial x_2} f_2(\mathbf{x}) & \dots & \frac{\partial}{\partial x_n} f_2(\mathbf{x}) \\ \dots \\ \frac{\partial}{\partial x_1} f_m(\mathbf{x}) & \frac{\partial}{\partial x_2} f_m(\mathbf{x}) & \dots & \frac{\partial}{\partial x_n} f_m(\mathbf{x}) \end{bmatrix}$$

Backpropagation: matrix form

$$\begin{aligned}y_1 &= f_1(\mathbf{x}) = x_1 \\y_2 &= f_2(\mathbf{x}) = x_2 \\&\vdots \\y_n &= f_n(\mathbf{x}) = x_n\end{aligned}$$

		vector
	scalar	\mathbf{x}
scalar	f	$\frac{\partial f}{\partial \mathbf{x}}$
vector	\mathbf{f}	$\frac{\partial \mathbf{f}}{\partial \mathbf{x}}$

Backpropagation: matrix form

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial}{\partial \mathbf{x}} f_1(\mathbf{x}) \\ \frac{\partial}{\partial \mathbf{x}} f_2(\mathbf{x}) \\ \vdots \\ \frac{\partial}{\partial \mathbf{x}} f_m(\mathbf{x}) \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial x_1} f_1(\mathbf{x}) & \frac{\partial}{\partial x_2} f_1(\mathbf{x}) & \cdots & \frac{\partial}{\partial x_n} f_1(\mathbf{x}) \\ \frac{\partial}{\partial x_1} f_2(\mathbf{x}) & \frac{\partial}{\partial x_2} f_2(\mathbf{x}) & \cdots & \frac{\partial}{\partial x_n} f_2(\mathbf{x}) \\ \vdots \\ \frac{\partial}{\partial x_1} f_m(\mathbf{x}) & \frac{\partial}{\partial x_2} f_m(\mathbf{x}) & \cdots & \frac{\partial}{\partial x_n} f_m(\mathbf{x}) \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\partial}{\partial x_1} x_1 & \frac{\partial}{\partial x_2} x_1 & \cdots & \frac{\partial}{\partial x_n} x_1 \\ \frac{\partial}{\partial x_1} x_2 & \frac{\partial}{\partial x_2} x_2 & \cdots & \frac{\partial}{\partial x_n} x_2 \\ \vdots \\ \frac{\partial}{\partial x_1} x_n & \frac{\partial}{\partial x_2} x_n & \cdots & \frac{\partial}{\partial x_n} x_n \end{bmatrix}$$

(and since $\frac{\partial}{\partial x_j} x_i = 0$ for $j \neq i$)

$$= \begin{bmatrix} \frac{\partial}{\partial x_1} x_1 & 0 & \cdots & 0 \\ 0 & \frac{\partial}{\partial x_2} x_2 & \cdots & 0 \\ \ddots \\ 0 & 0 & \cdots & \frac{\partial}{\partial x_n} x_n \end{bmatrix}$$

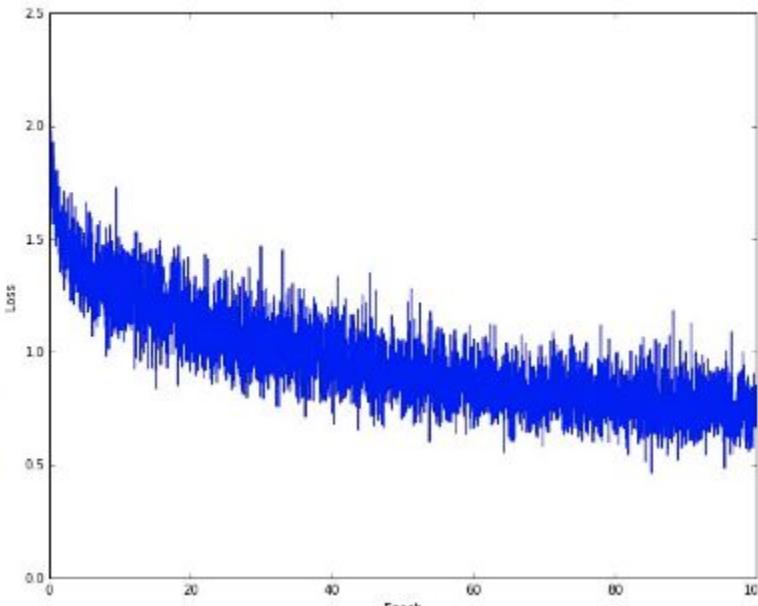
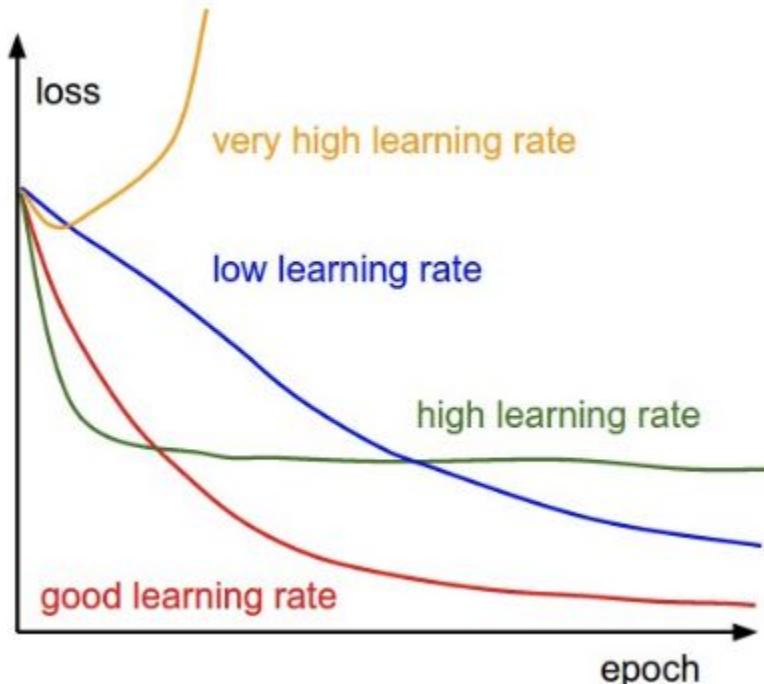
$$= \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \ddots \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$

$= I$ (I is the identity matrix with ones down the diagonal)

Gradient optimization

Stochastic gradient descent (and variations)
is used to optimize NN parameters.

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



Activation functions

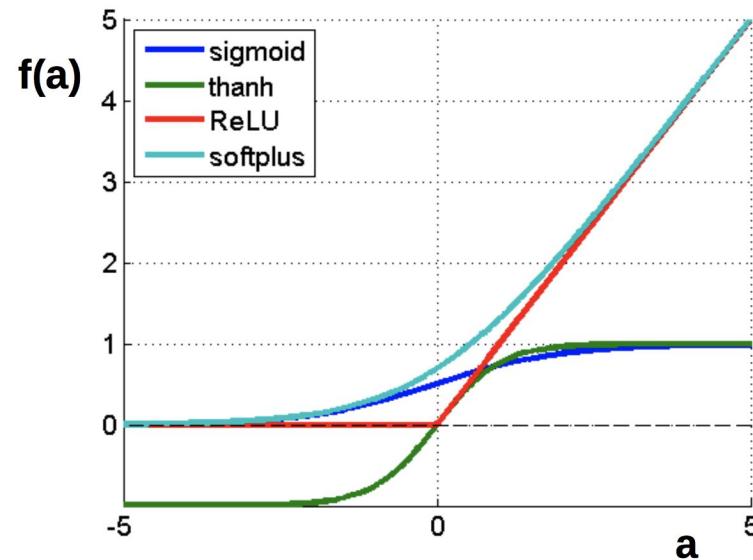
Once more: nonlinearities

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

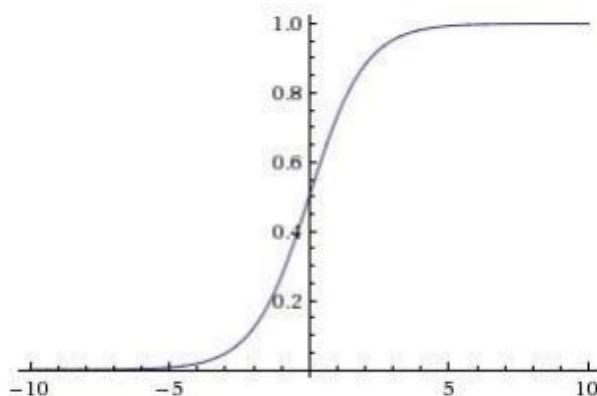
$$f(a) = \tanh(a)$$

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

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



Activation functions



Sigmoid

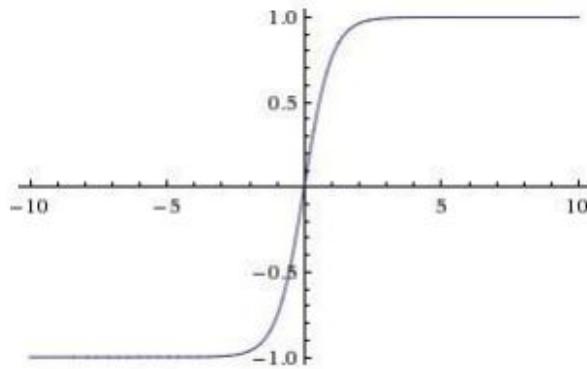
$$f(a) = \frac{1}{1 + e^a}$$

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

3 problems:

1. Saturated neurons “kill” the gradients
2. Sigmoid outputs are not zero-centered
3. $\exp()$ is a bit compute expensive

Activation functions

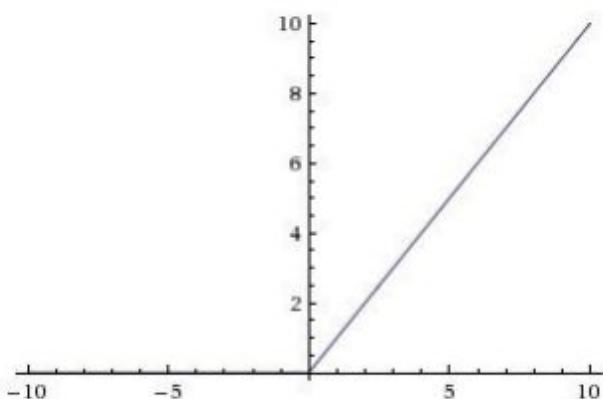


tanh(x)

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

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

Activation functions



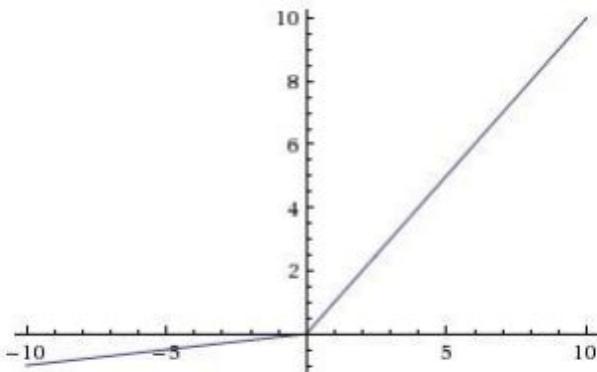
ReLU
(Rectified Linear Unit)

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

- 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 $x < 0$?

Activation functions

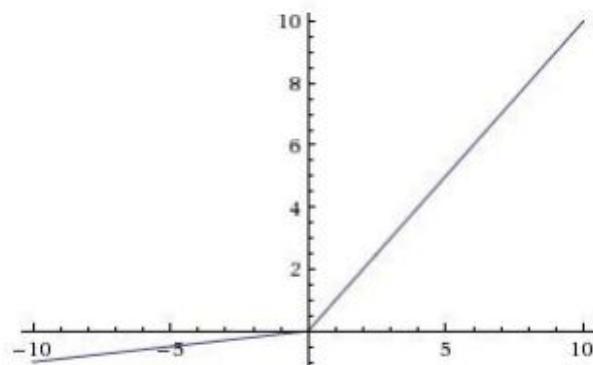


- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- **will not “die”.**

Leaky ReLU

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

Activation functions



Leaky ReLU

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

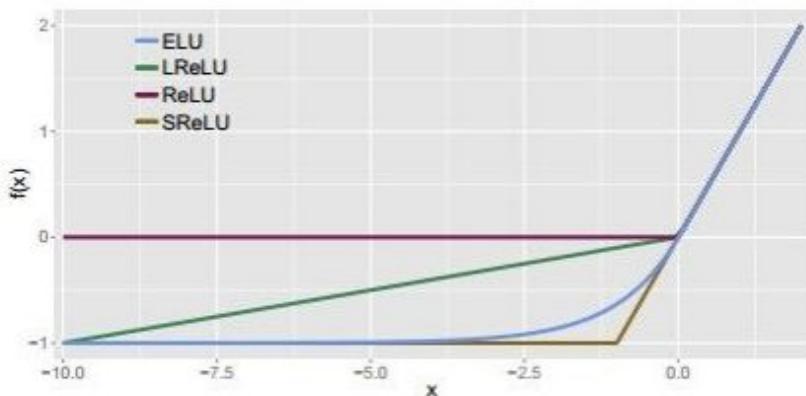
- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- will not “die”.

Parametric Rectifier (PReLU)

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

backprop into α
(parameter)

Exponential Linear Units (ELU)



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

- 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**

Fancy neural networks

Shakespeare

PANDARUS:

Alas, I think he shall be come approached and the day
 When little strain would be attain'd into being never fed,
 And who is but a chain and subjects of his death,
 I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul,
 Breaking and strongly should be buried, when I perish
 The earth and thoughts of many states.

DUKE VINCENTIO:

Well, your wit is in the care of side and that.

Second Lord:

They would be ruled after this chamber, and
 my fair nues begun out of the fact, to be conveyed,
 Whose noble souls I'll have the heart of the wars.

Clown:

Come, sir, I will make did behold your worship.

VIOLA:

I'll drink it.

Algebraic Geometry (Latex)

Proof. Omitted. \square

Lemma 0.1. Let \mathcal{C} be a set of the construction.

Let \mathcal{C} be a gerber covering. Let \mathcal{F} be a quasi-coherent sheaves of \mathcal{O} -modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{C})$$

Proof. This is an algebraic space with the composition of sheaves \mathcal{F} on X_{state} we have

$$\mathcal{O}_X(\mathcal{F}) = \{\text{morph}_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where \mathcal{G} defines an isomorphism $\mathcal{F} \rightarrow \mathcal{G}$ of \mathcal{O} -modules. \square

Lemma 0.2. This is an integer Z is injective.

Proof. See Spaces, Lemma ??.

Lemma 0.3. Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \rightarrow Y^t \rightarrow Y \rightarrow Y \rightarrow Y' \times_X Y \rightarrow X,$$

be a morphism of algebraic spaces over S and Y .

Proof. Let X be a nonzero scheme of X . Let X be an algebraic space. Let \mathcal{F} be a quasi-coherent sheaf of \mathcal{O}_X -modules. The following are equivalent

- (1) \mathcal{F} is an algebraic space over S .
- (2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. \square

Linux kernel (source code)

```
/*
 * If this error is set, we will need anything right after that BSD.
 */
static void action_new_function(struct s_stat_info *wb)
{
    unsigned long flags;
    int lel_idx_bit = e->edd->sys & -((unsigned long) *FIRST_COMPAT);
    buf[0] = 0xffffffff & (bit << 4);
    min(inc, slist->bytes);
    printk(KERN_WARNING "Memory allocated %02x/%02x, "
           "original MLL instead\n",
           min(min(multi_run - s->len, max) * num_data_in),
           frame_pos, sz + first_seg);
    div_u64 w(val, imh_p);
    spin_unlock(&disk->queue_lock);
    mutex_unlock(&s->sock->mutex);
    mutex_unlock(&func->mutex);
    return disassemble(info->pending_bh);
}
```

Proof. Omitted. \square

Lemma 0.1. Let \mathcal{C} be a set of the construction.

Let \mathcal{C} be a gerber covering. Let \mathcal{F} be a quasi-coherent sheaves of \mathcal{O} -modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

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Lemma 0.3. Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \rightarrow Y' \rightarrow Y \rightarrow Y \rightarrow Y' \times_X Y \rightarrow X.$$

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Proof. Let X be a nonzero scheme of X . Let X be an algebraic space. Let \mathcal{F} be a quasi-coherent sheaf of \mathcal{O}_X -modules. The following are equivalent

- (1) \mathcal{F} is an algebraic space over S .
- (2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. \square

This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

$$\begin{array}{ccccc}
 S & \xrightarrow{\quad} & & & \\
 \downarrow & & & & \\
 \xi & \longrightarrow & \mathcal{O}_{X'} & & \\
 \text{gor}_s & & \uparrow & \searrow & \\
 & & =\alpha' \longrightarrow & & \\
 & & \uparrow & & \\
 & & =\alpha' \longrightarrow \alpha & & \\
 & & \text{Spec}(K_\psi) & \text{Mor}_{\text{Sets}} & X \\
 & & & & \downarrow d(\mathcal{O}_{X_{/\mathbb{k}}}, \mathcal{G})
 \end{array}$$

is a limit. Then \mathcal{G} is a finite type and assume S is a flat and \mathcal{F} and \mathcal{G} is a finite type f_* . This is of finite type diagrams, and

- the composition of \mathcal{G} is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

\square

Proof. We have see that $X = \text{Spec}(R)$ and \mathcal{F} is a finite type representable by algebraic space. The property \mathcal{F} is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U . \square

Proof. This is clear that \mathcal{G} is a finite presentation, see Lemmas ??.

A reduced above we conclude that U is an open covering of C . The functor \mathcal{F} is a “field”

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\bar{x}} \dashv (\mathcal{O}_{X_{\text{étale}}}) \longrightarrow \mathcal{O}_{X_\ell}^{-1} \mathcal{O}_{X_\lambda}(\mathcal{O}_{X_\eta}^\pi)$$

is an isomorphism of covering of \mathcal{O}_{X_ℓ} . If \mathcal{F} is the unique element of \mathcal{F} such that X is an isomorphism.

The property \mathcal{F} is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme \mathcal{O}_X -algebra with \mathcal{F} are opens of finite type over S . If \mathcal{F} is a scheme theoretic image points. \square

If \mathcal{F} is a finite direct sum \mathcal{O}_{X_λ} is a closed immersion, see Lemma ???. This is a sequence of \mathcal{F} is a similar morphism.

```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/seteew.h>
#include <asm/pgproto.h>

#define REG_PG      vesa_slot_addr_pack
#define PFM_NOCOMP  AFSR(0, load)
#define STACK_DDR(type)      (func)

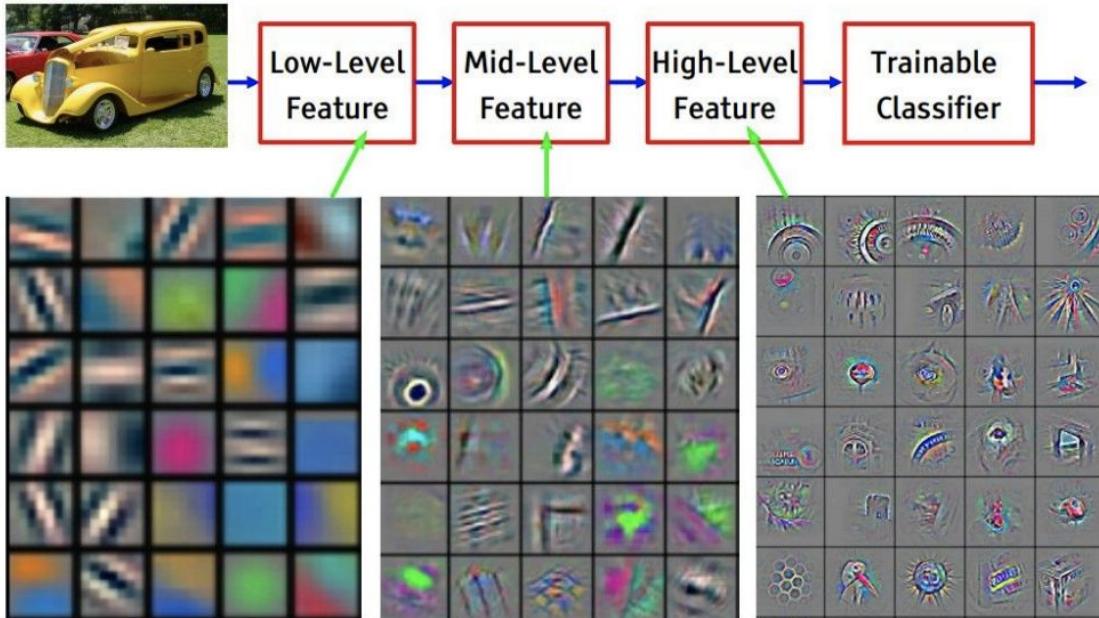
#define SWAP_ALLOCATE(nr)      (e)
#define emulate_sigs()  arch_get_unaligned_child()
#define access_rw(TST)  asm volatile("movd %%esp, %0, %3" : : "r" (0)); \
    if (_type & DO_READ)

static void stat_PC_SEC __read_mostly offsetof(struct seq_argsqueue, \
    pC>[1]);

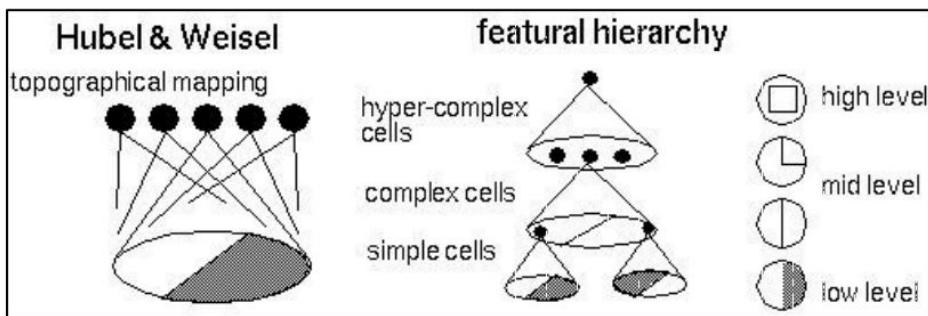
static void
os_prefix(unsigned long sys)
{
#ifdef CONFIG_PREEMPT
    PUT_PARAM_RAID(2, sel) = get_state_state();
    set_pid_sum((unsigned long)state, current_state_str(),
                (unsigned long)-1->lr_full; low;
}

```

CNN: Convolutional layer and visual cortex



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]



[From Yann LeCun slides]

Convolutional layer and visual cortex



Don't miss the interactive playground

DATA

Which dataset do you want to use?



Ratio of training to test data: 50%

Noise: 0

Batch size: 10

REGENERATE

FEATURES

Which properties do you want to feed in?

X_1



X_2



X_1^2



X_2^2



$X_1 X_2$



$\sin(X_1)$



$\sin(X_2)$



+

-

1 HIDDEN LAYER

+

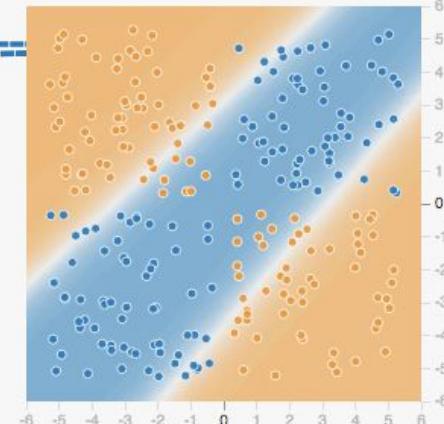
-

2 neurons

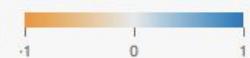
This is the output from one **neuron**. Hover to see it larger.

OUTPUT

Test loss 0.208
Training loss 0.207



Colors shows data, neuron and weight values.



Show test data

Discretize output



WHO'S AWESOME?

You're Awesome

- Neural Networks are great
 - Especially for data with specific structure
- All operations should be differentiable to use backpropagation mechanics
 - And still it is just basic differentiation
- Many techniques in Deep Learning are inspired by nature
 - Or general sense
- Do not hesitate to ask questions (and answer them as well)

More materials for self-study: [link](#)