Machine Learning
Lecture 8:
Intro to Deep Learning

Radoslav Neychev

girafe ai

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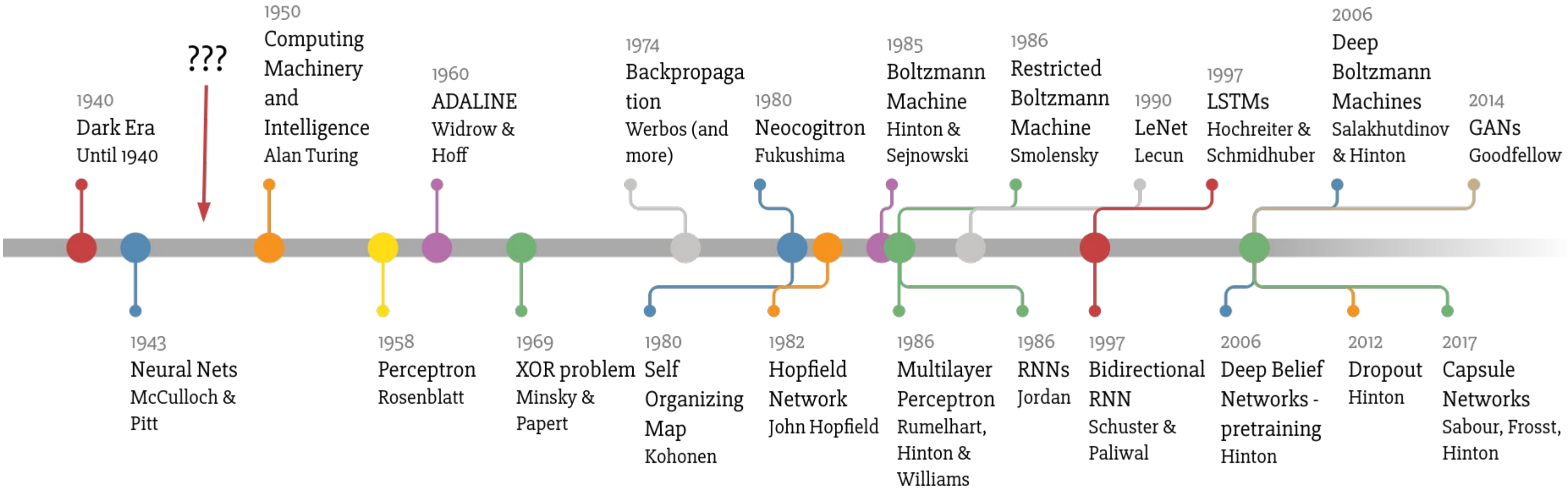
Outline

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

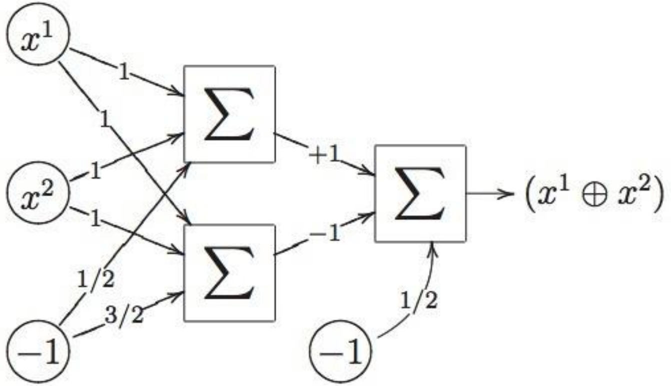
History of Deep Learning

Deep Learning Timeline



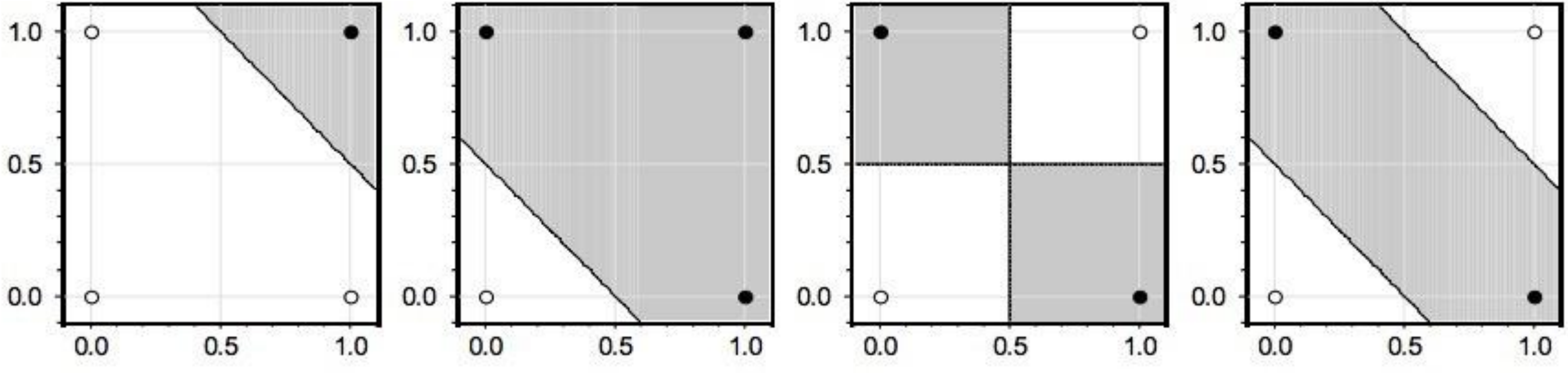
Made by Favio Vázquez

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.



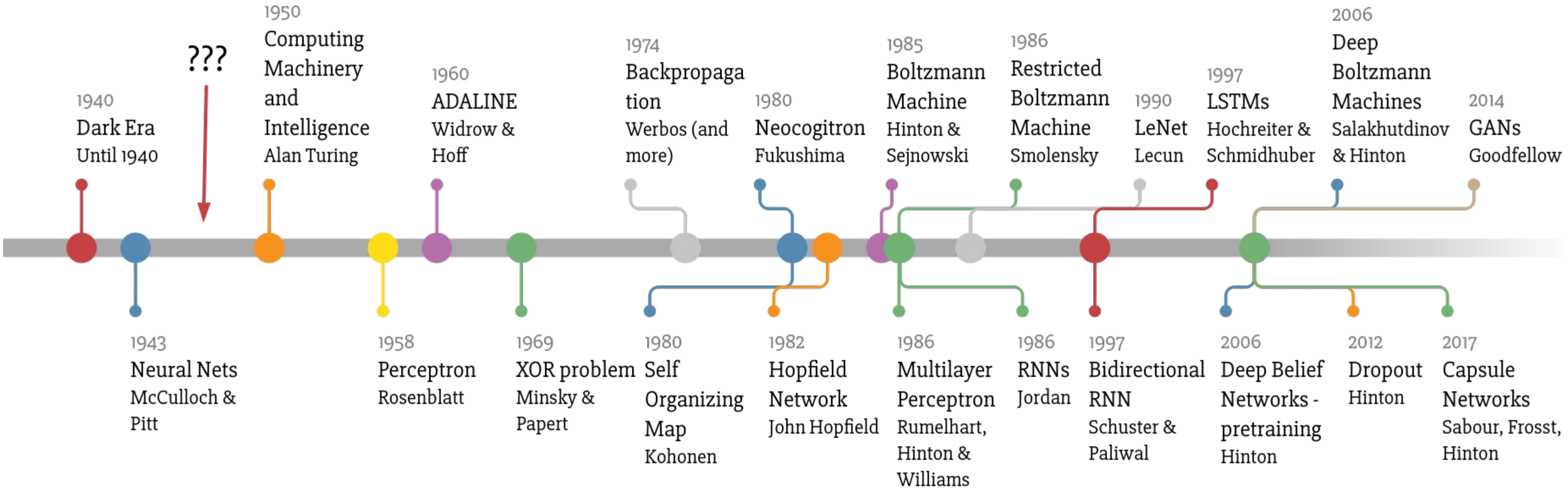
AND

OR

XOR(with x1*x2)

XOR

Deep Learning Timeline



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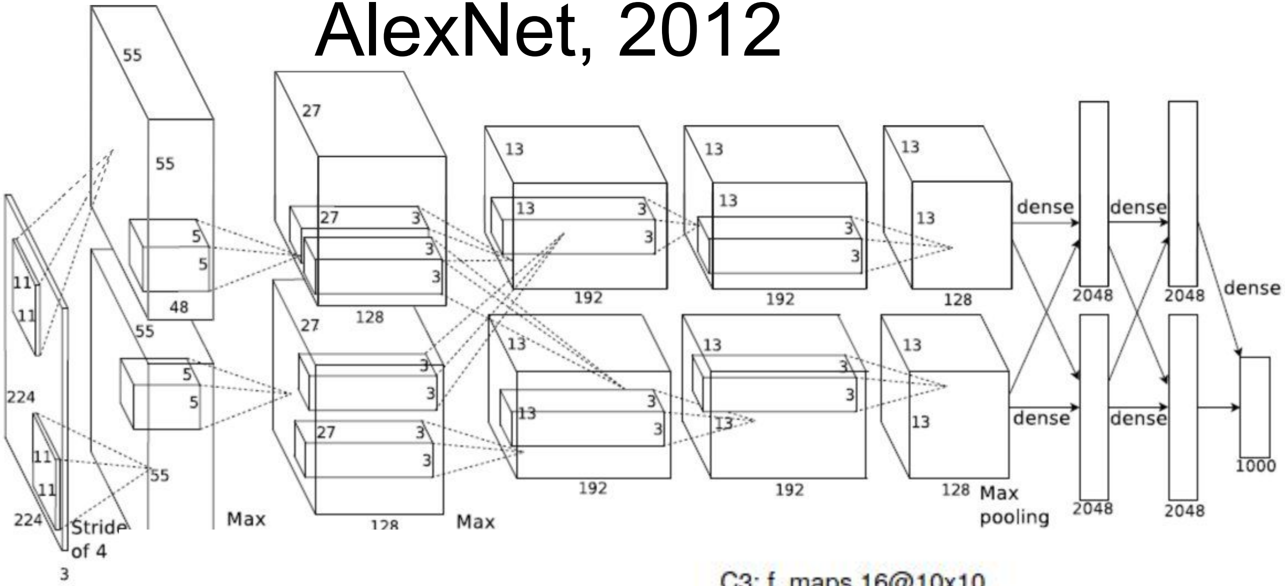
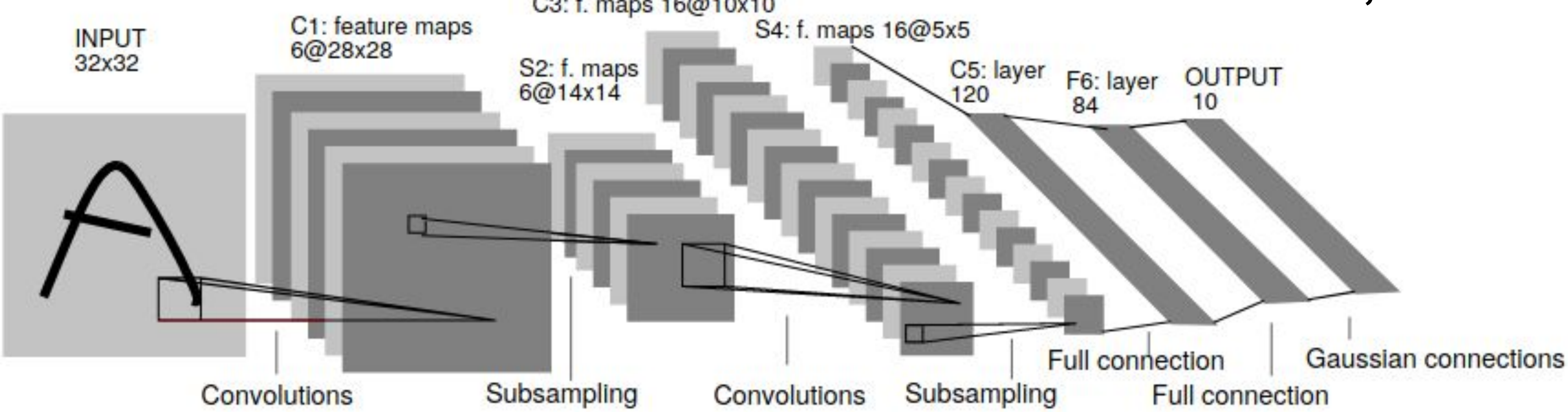
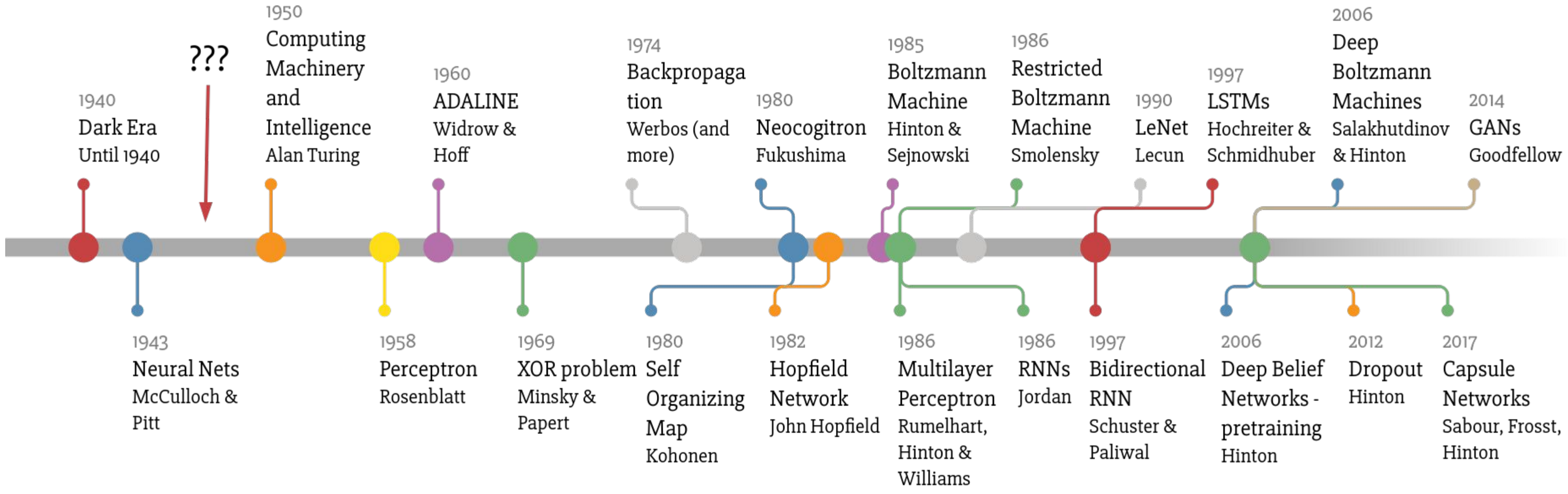
AlexNet, 2012



LeNet-5, 1998

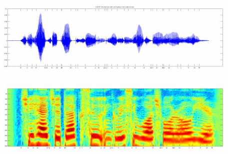


Deep Learning Timeline

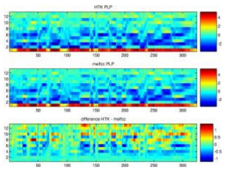


Real world applications

Audio Features

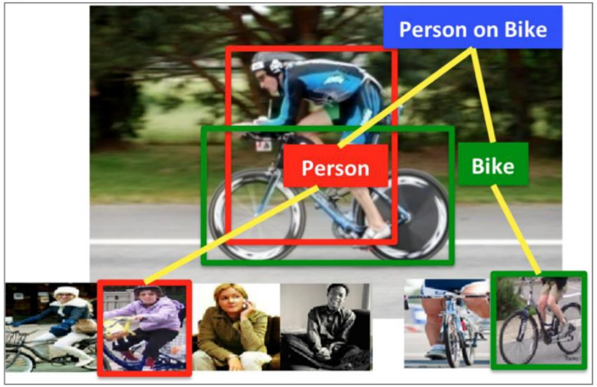


Spectrogram



MFCC

- Object detection
- Action classification
- Image captioning
- …

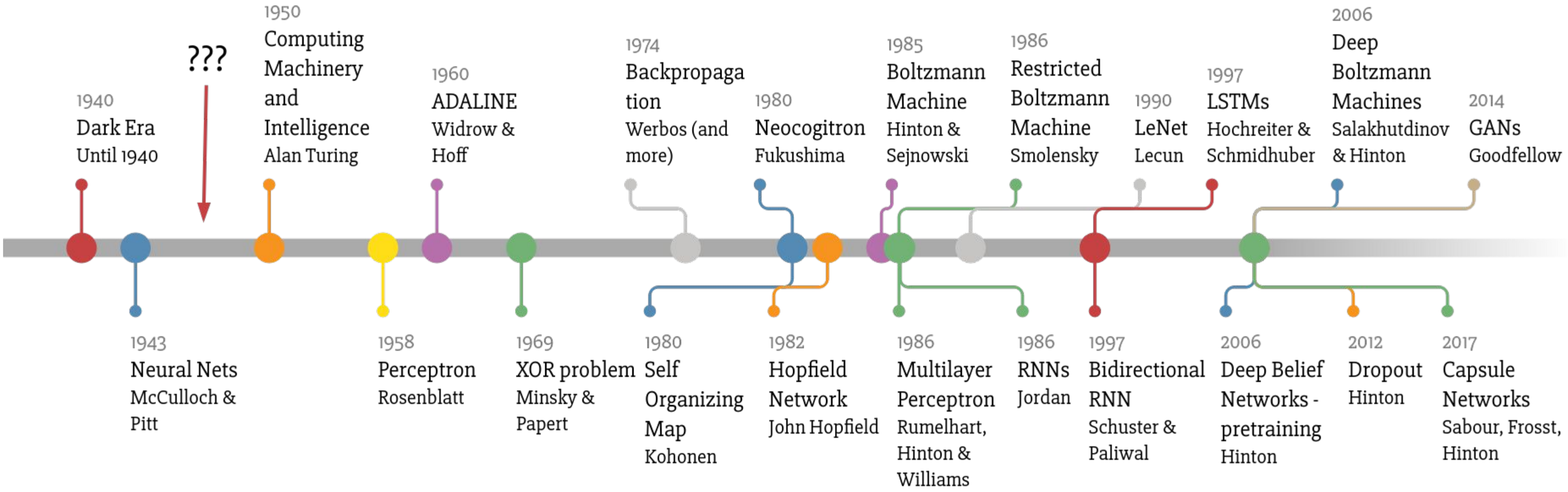


"man in black shirt is playing guitar."

GANs, 2014+

https://thispersondoesnotexist.com/

Deep Learning Timeline



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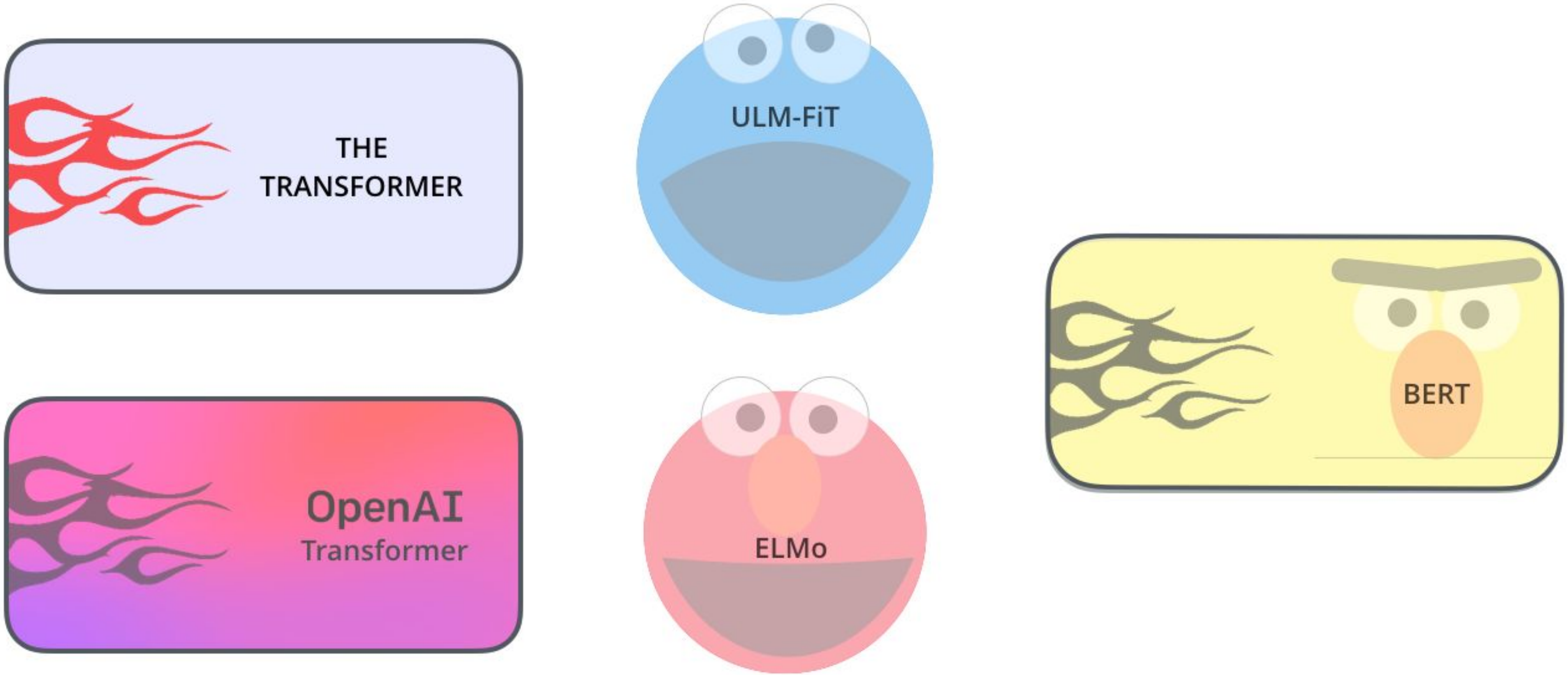
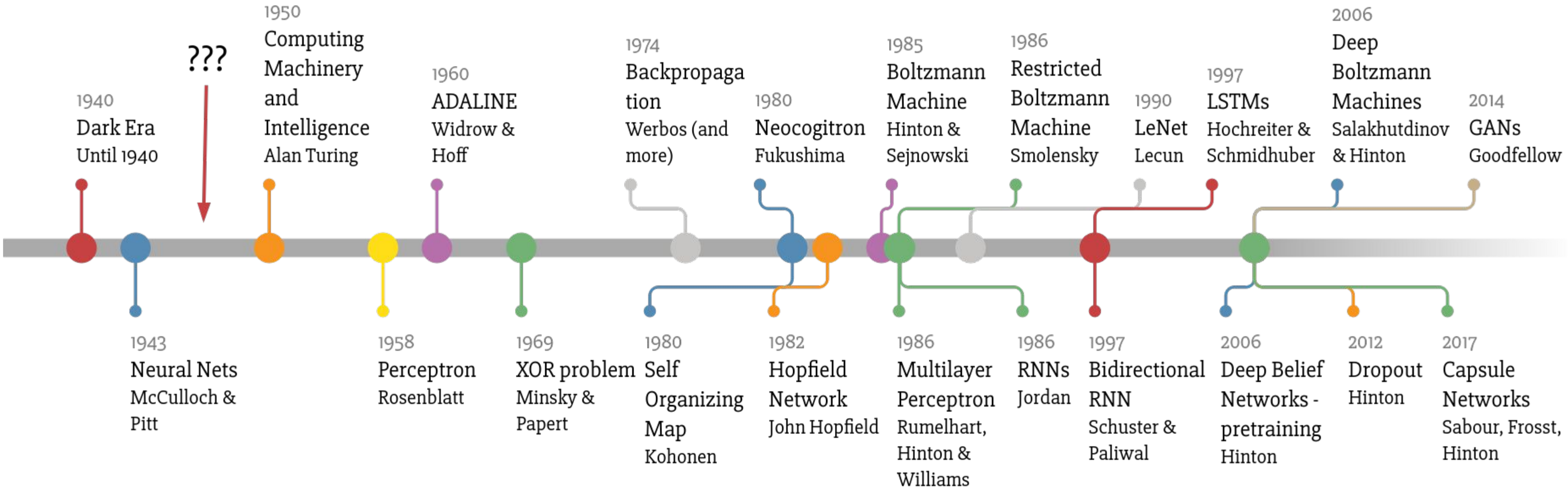
Transformer, BERT, GPT-2 and more, 2017+



Deep Learning Timeline



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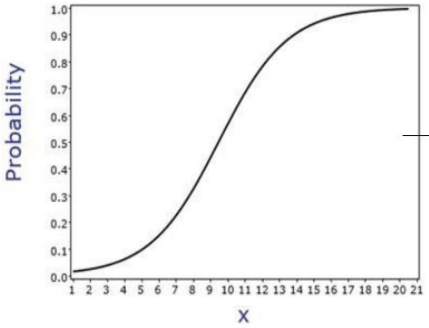
Deep Learning: intuition

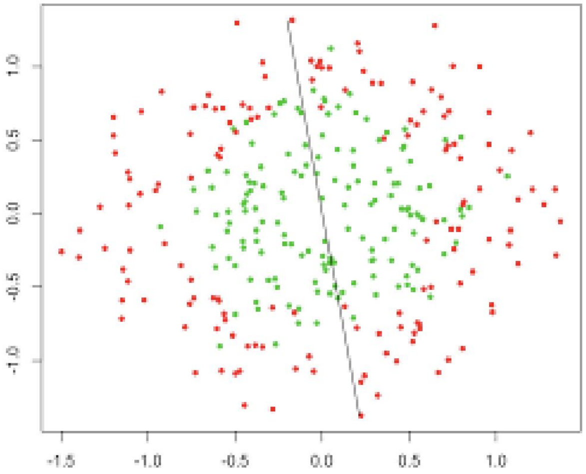
Logistic regression

X ⟶ Wx +b ⟶  ⟶ P(y)

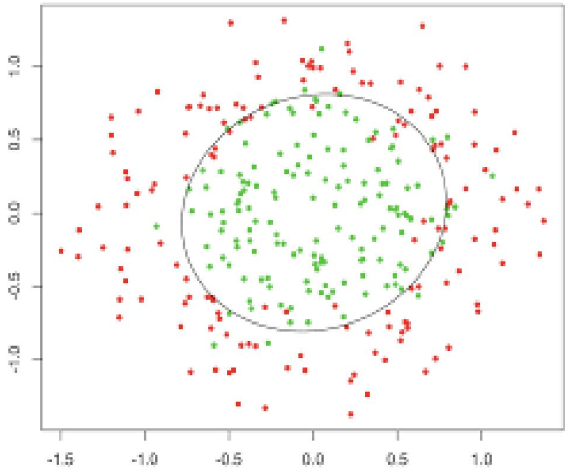
$$P(y|x) = \sigma(w \cdot x + b)$$

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

Problem: nonlinear dependencies



What we have

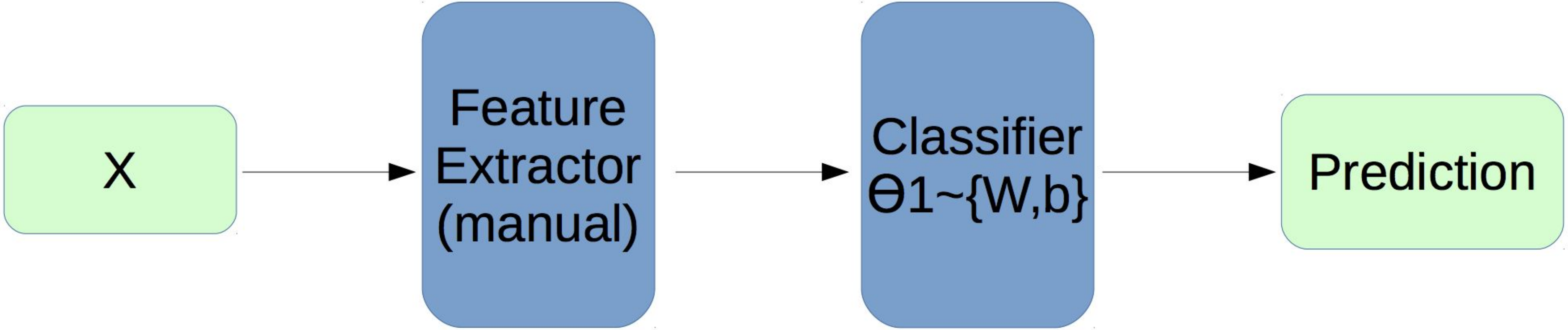


What we want

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

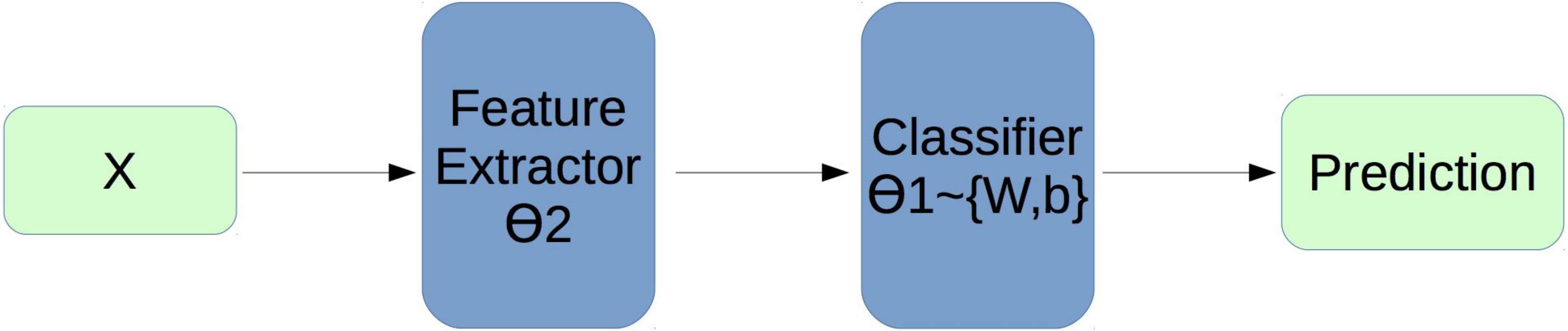
And feature engineering is an *art*.

Classic pipeline



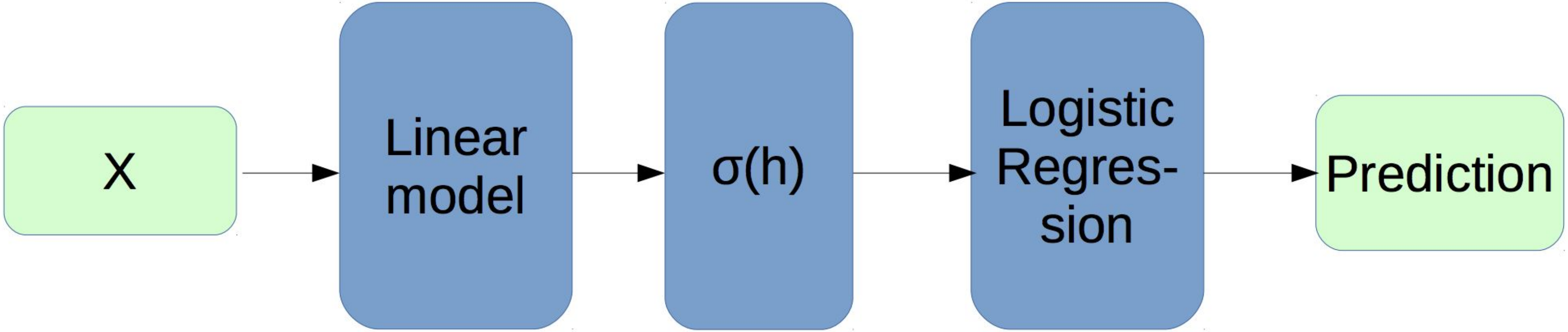
Handcrafted features, generated by experts.

NN pipeline



Automatically extracted features.

NN pipeline: example



E.g. two logistic regressions one after another.

Actually, it's a neural network.

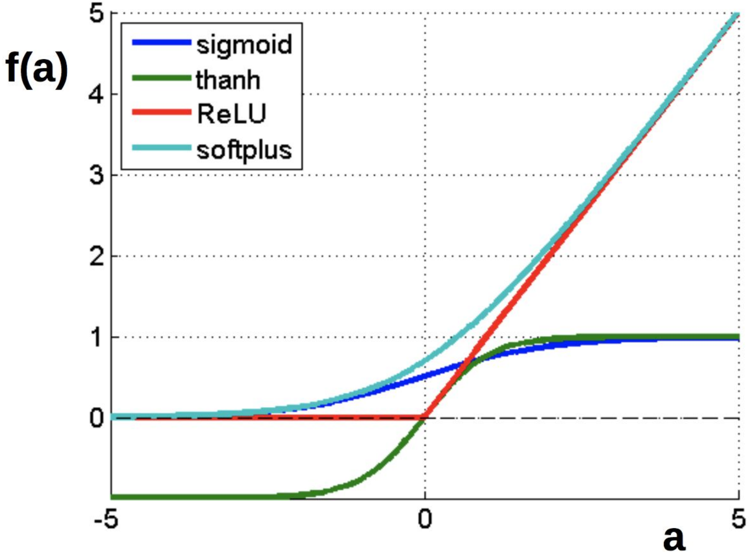
Activation functions: nonlinearities

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

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

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

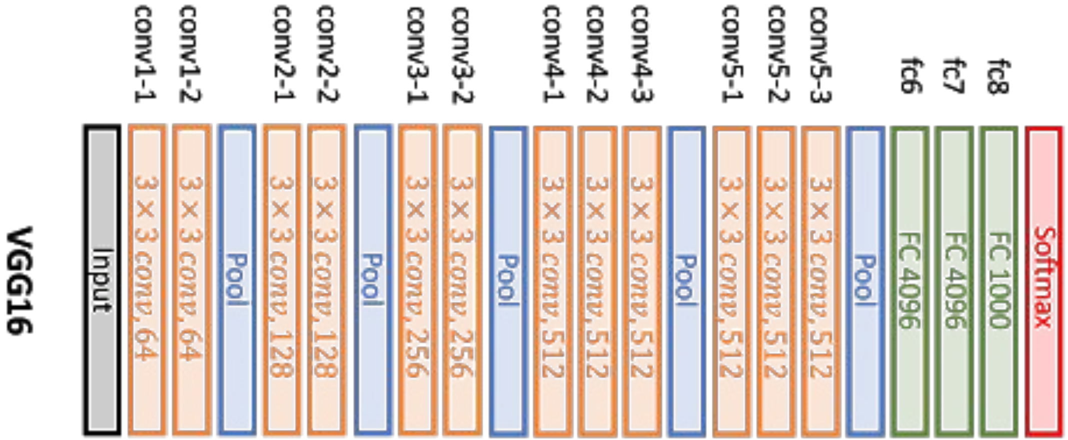
$$f(a) = \log(1 + e^{a})$$



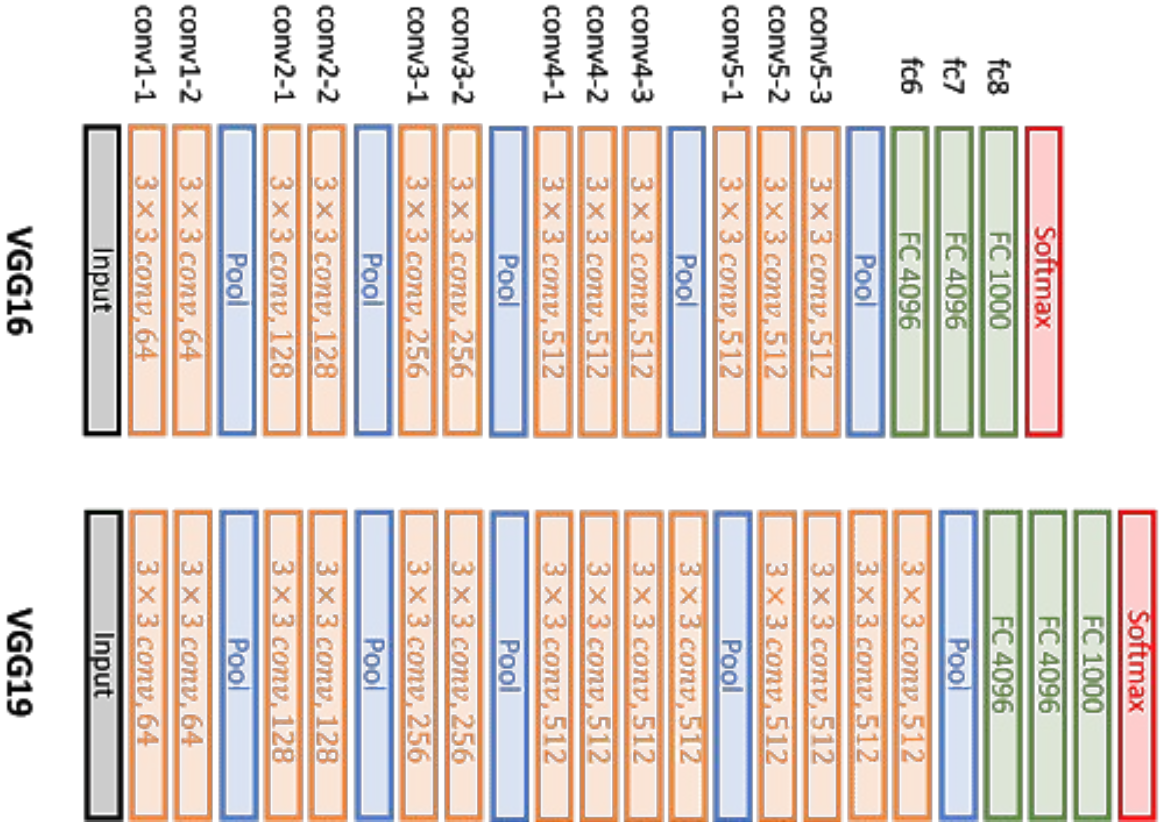
Some generally accepted terms

- 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



And deeper...



VGG16
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 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
Pool
3 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
Pool
FC 4096
FC 4096
FC 1000
Softmax
VGG19
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 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
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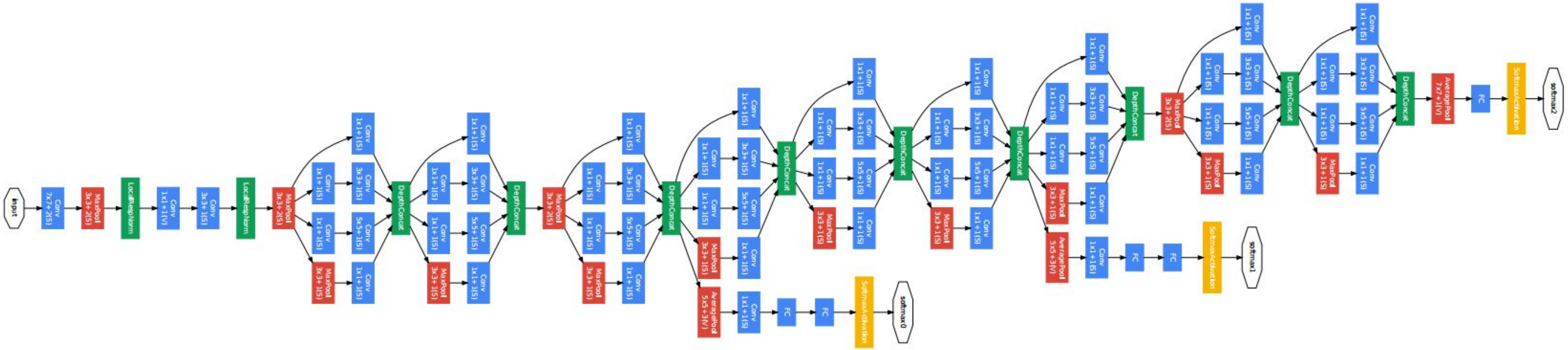
Pool
3 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
3 × 3 conv, 512
Pool
FC 4096
FC 4096
FC 1000
Softmax

Much deeper...

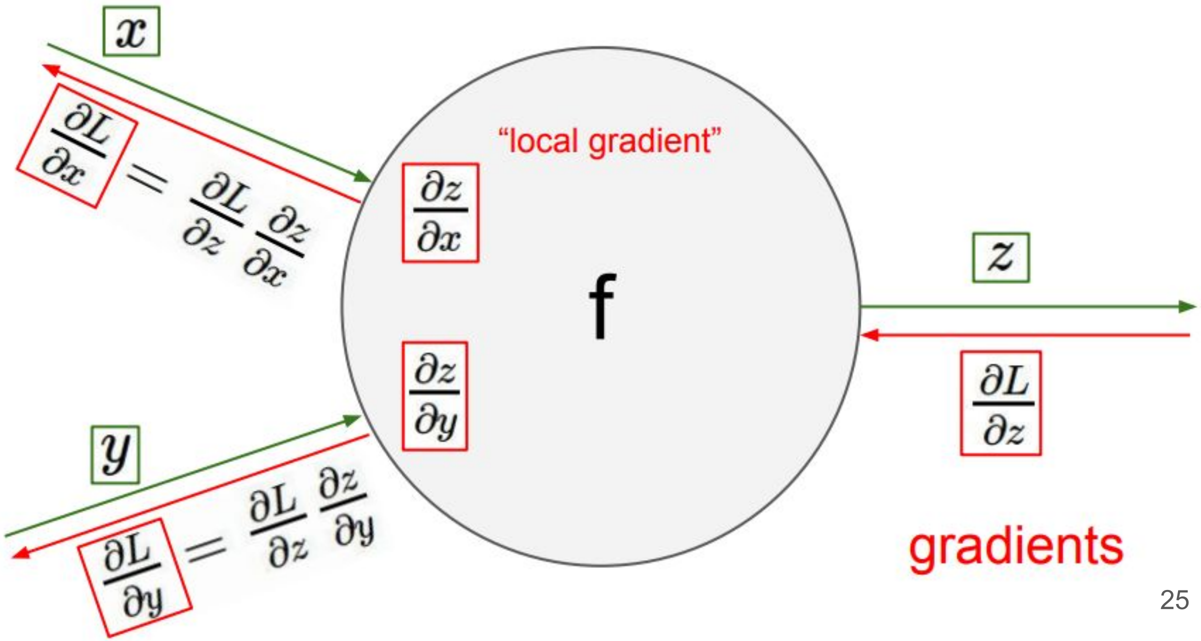


How to train it?

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

Backpropagation

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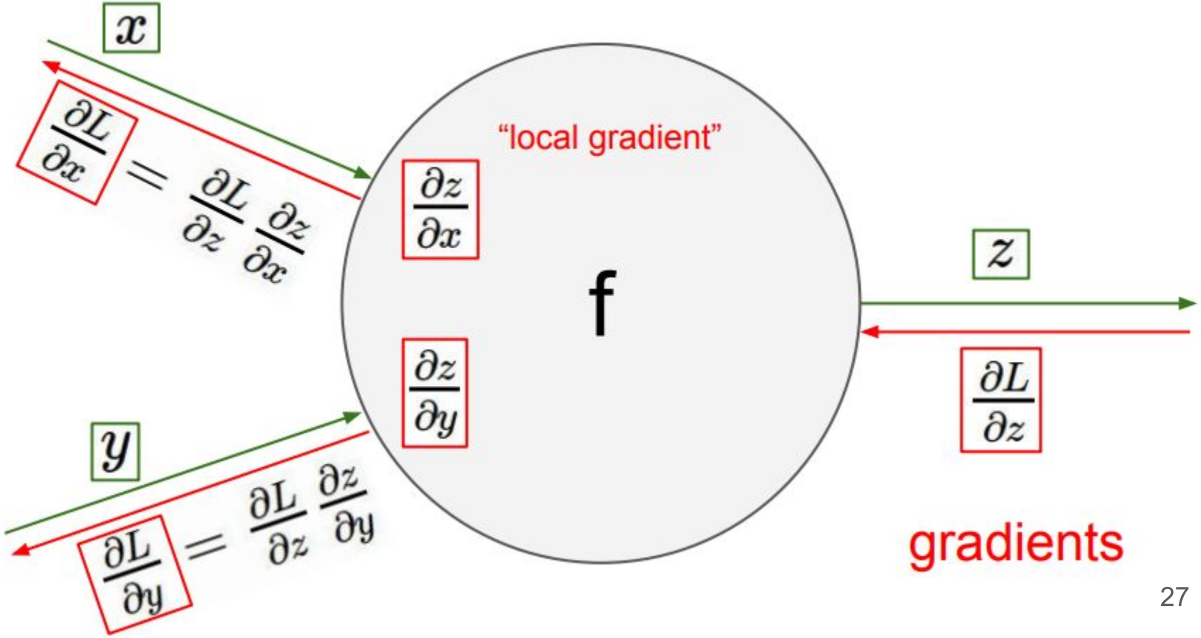

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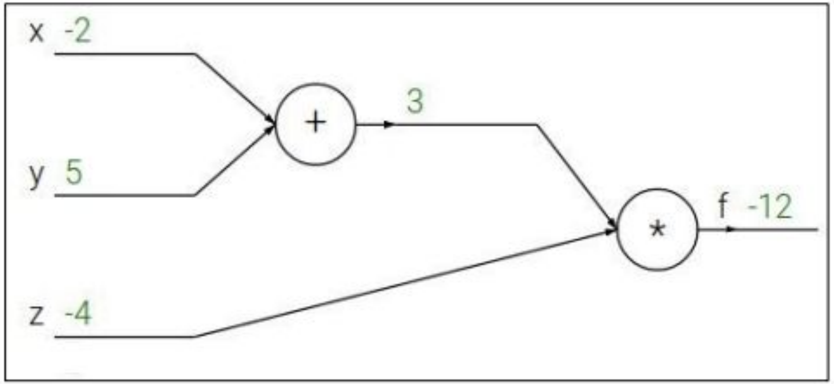
Backpropagation example

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

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



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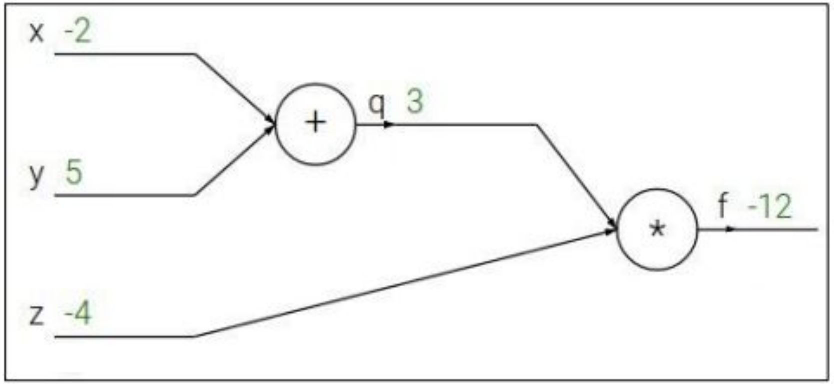
Want: $\dfrac{\partial f}{\partial x}, \dfrac{\partial f}{\partial y}, \dfrac{\partial f}{\partial z}$



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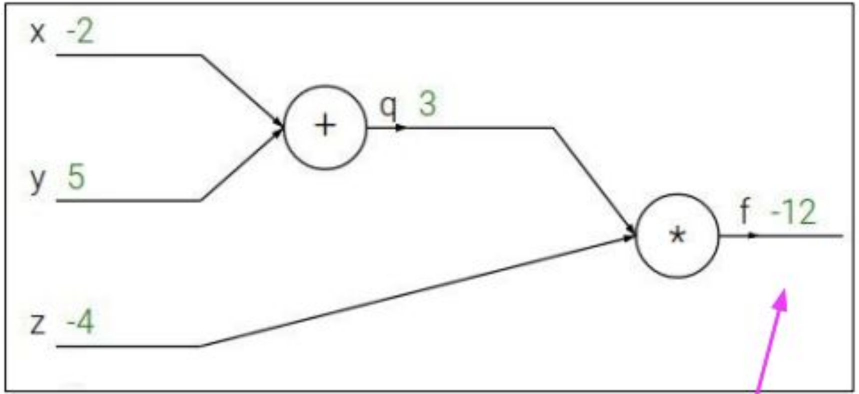

$$\frac{\partial f}{\partial f}$$

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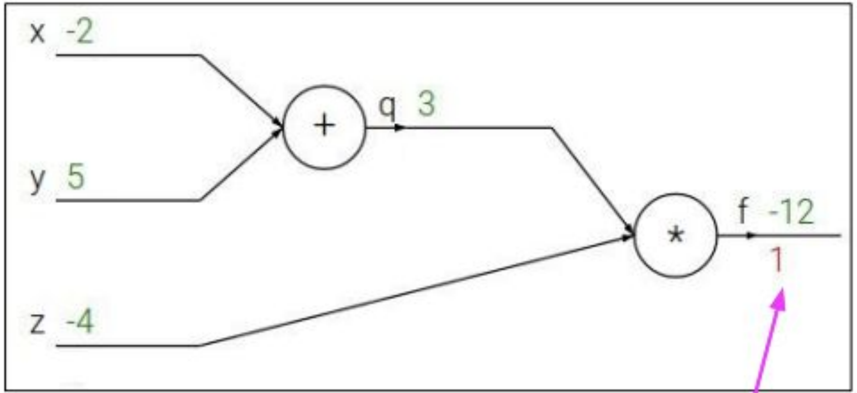

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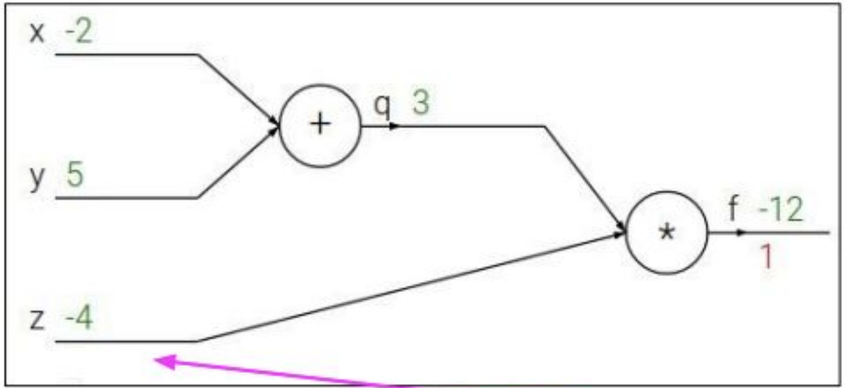

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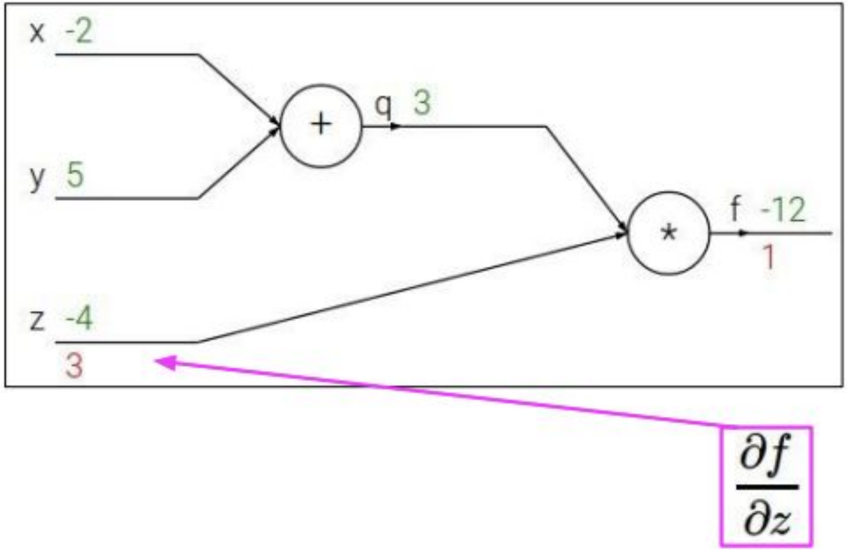

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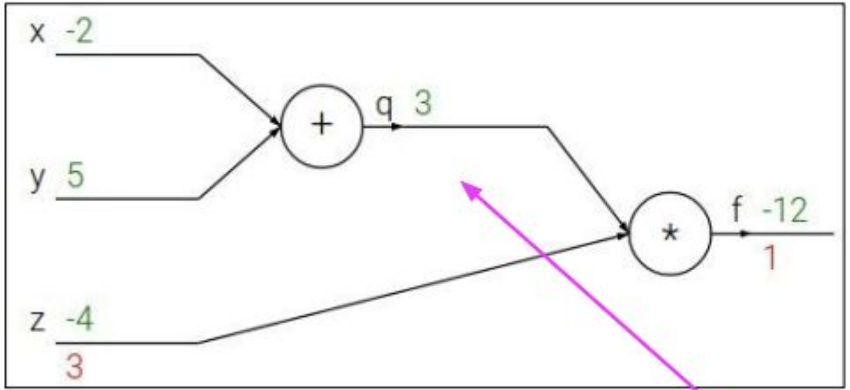

$$\frac{\partial f}{\partial q}$$

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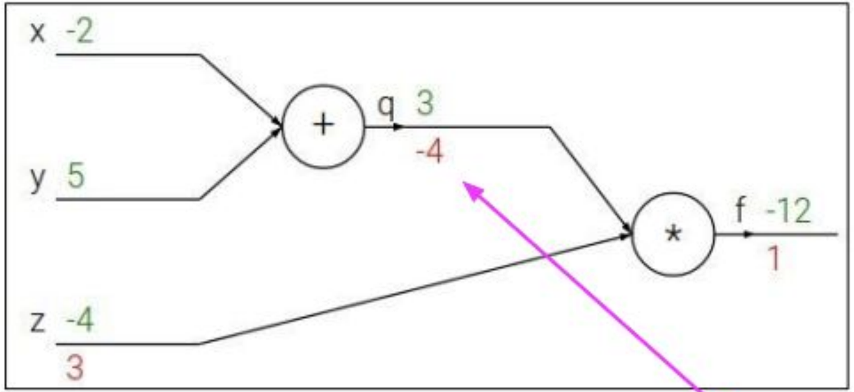

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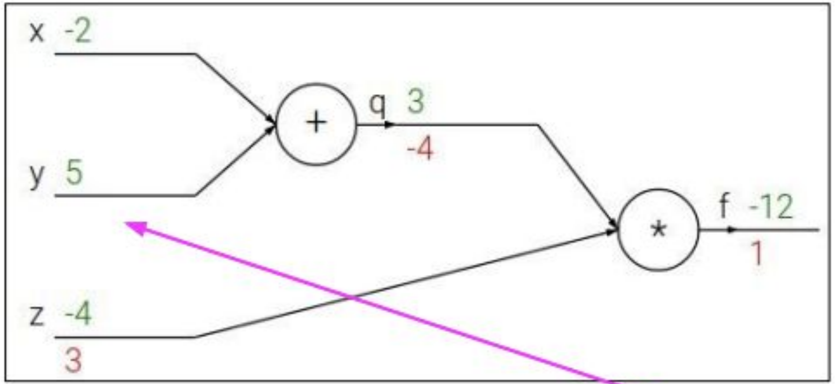

$$\boxed{\frac{\partial f}{\partial y}}$$

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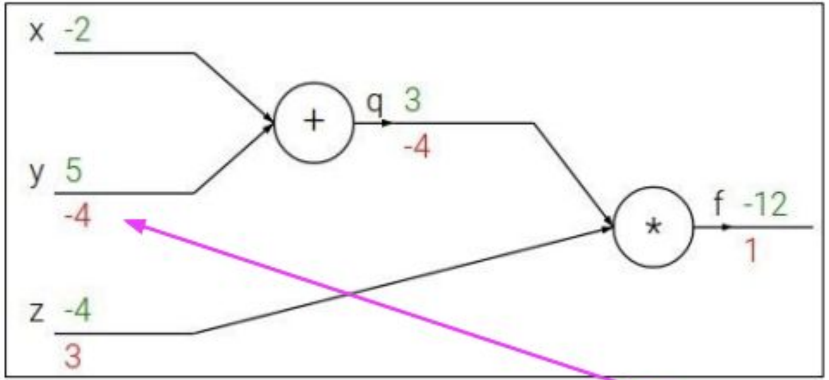

$$\frac{\partial f}{\partial y}$$

Chain rule:

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

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Backpropagation example

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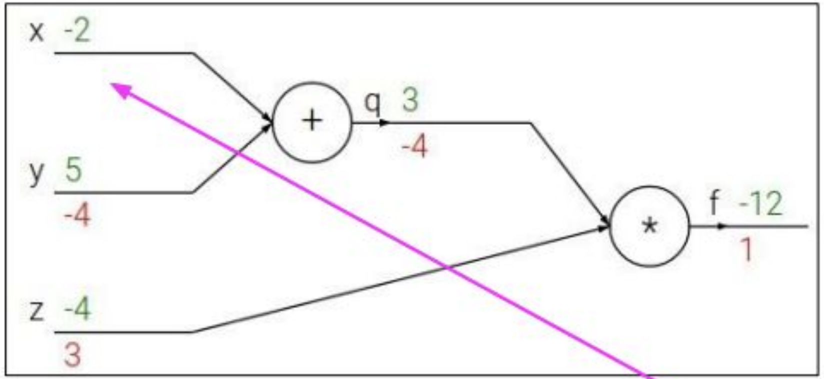

$$\frac{\partial f}{\partial x}$$

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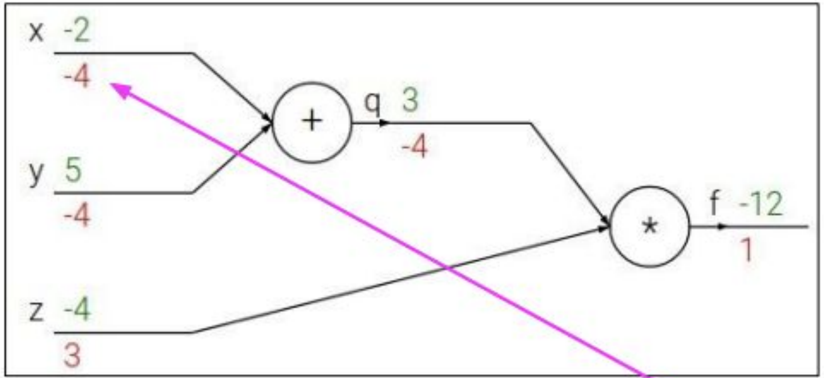

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Chain rule:

$$\boxed{\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x}}$$

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Backpropagation and chain rule

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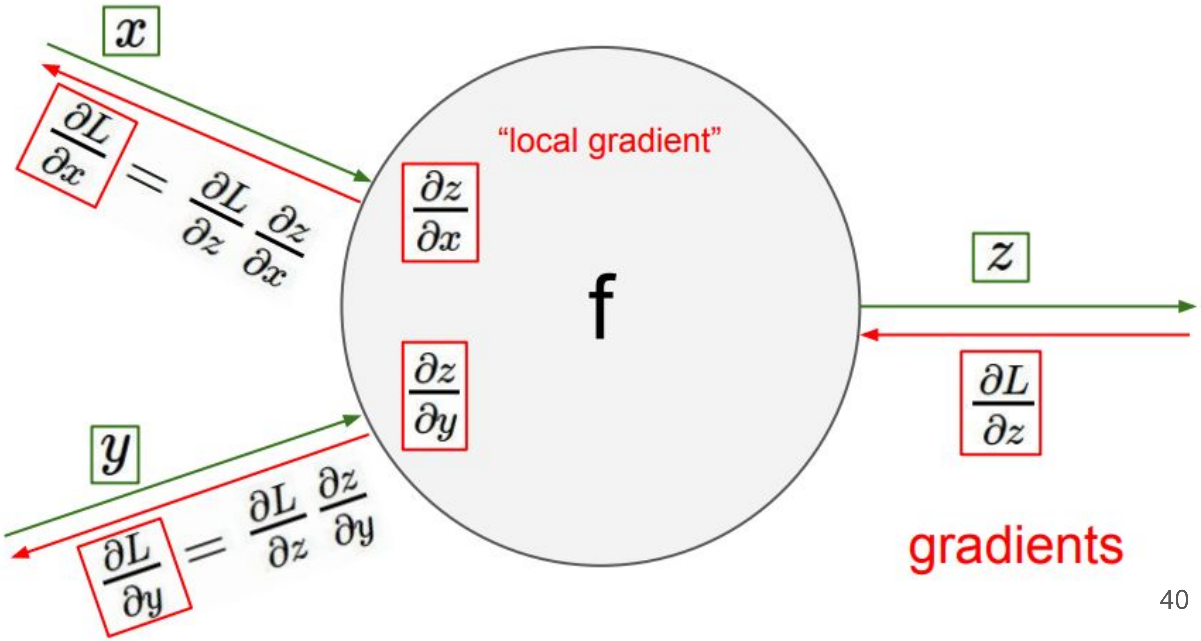

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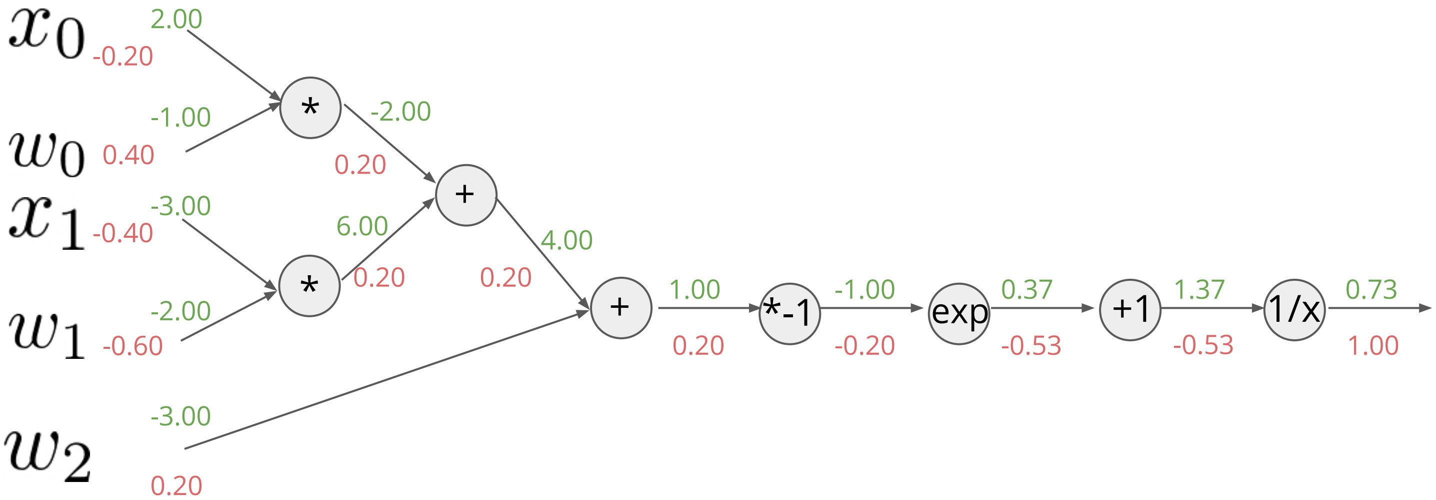
Backpropagation example

$$L(w,x) = \frac{1}{1+\exp(-(x_0 w_0 + x_1 w_1 + w_2))}$$



Based on: http://cs231n.github.io

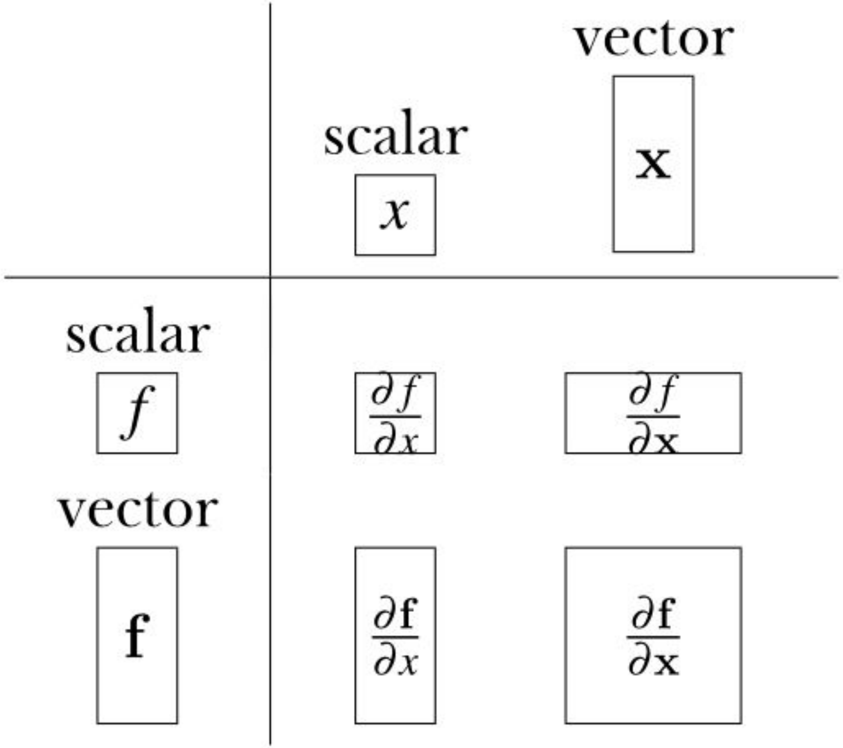
Backpropagation: matrix form

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

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

source: https://explained.ai/matrix-calculus/

Backpropagation: matrix form



source: https://explained.ai/matrix-calculus/

Backpropagation: matrix form

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

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

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

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

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

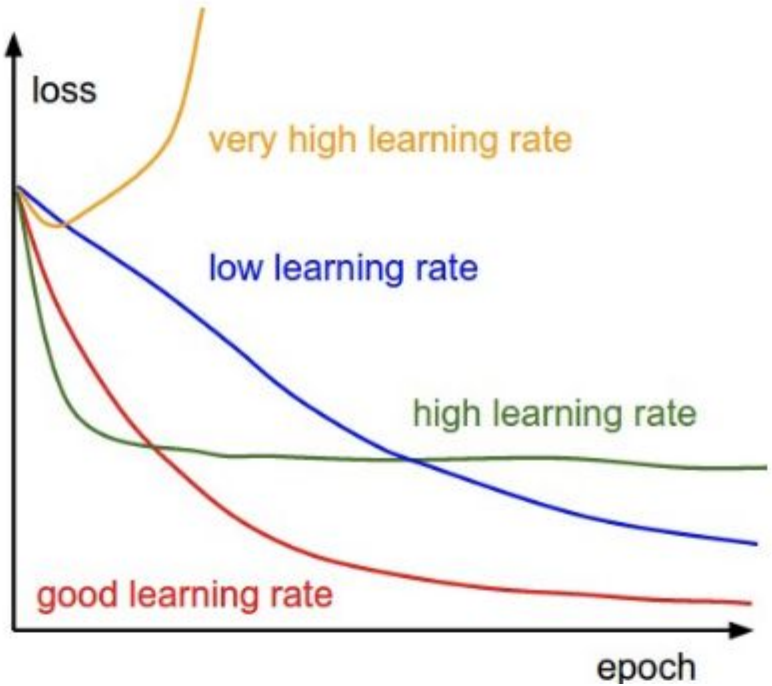
$$= I \quad (I \text{ is the identity matrix with ones down the diagonal})$$

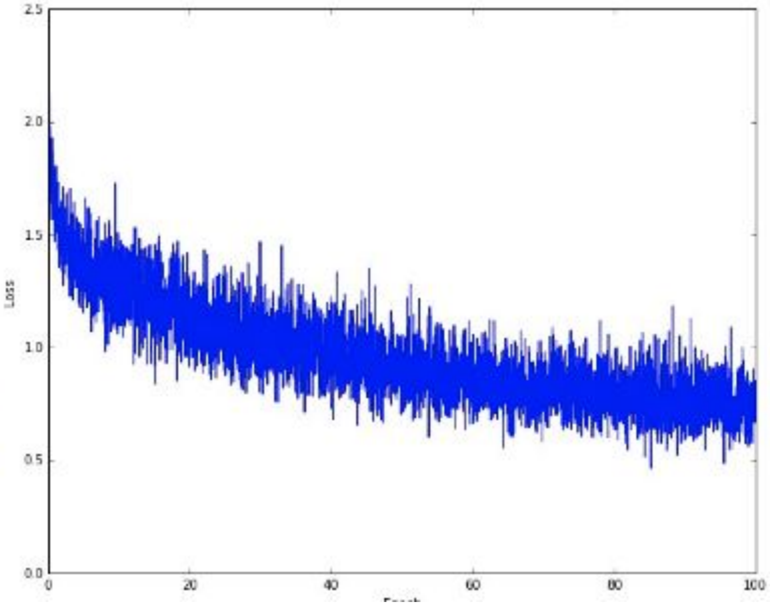
source: https://explained.ai/matrix-calculus/

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/

Activation functions

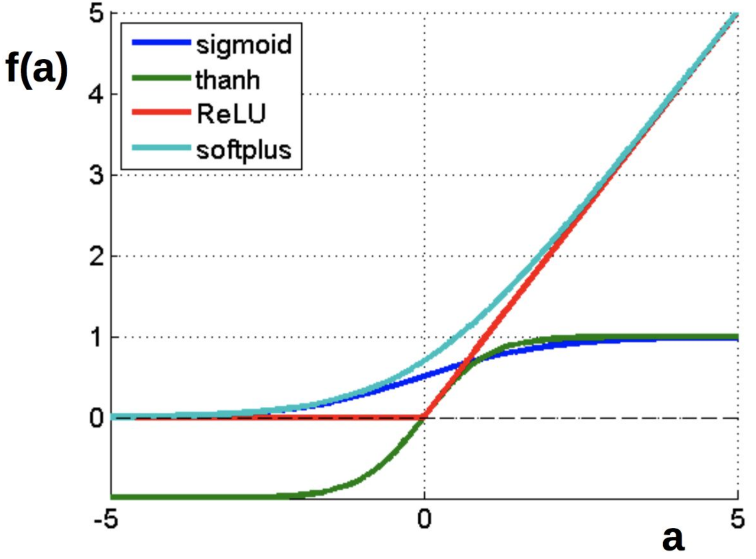
Once more: nonlinearities

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

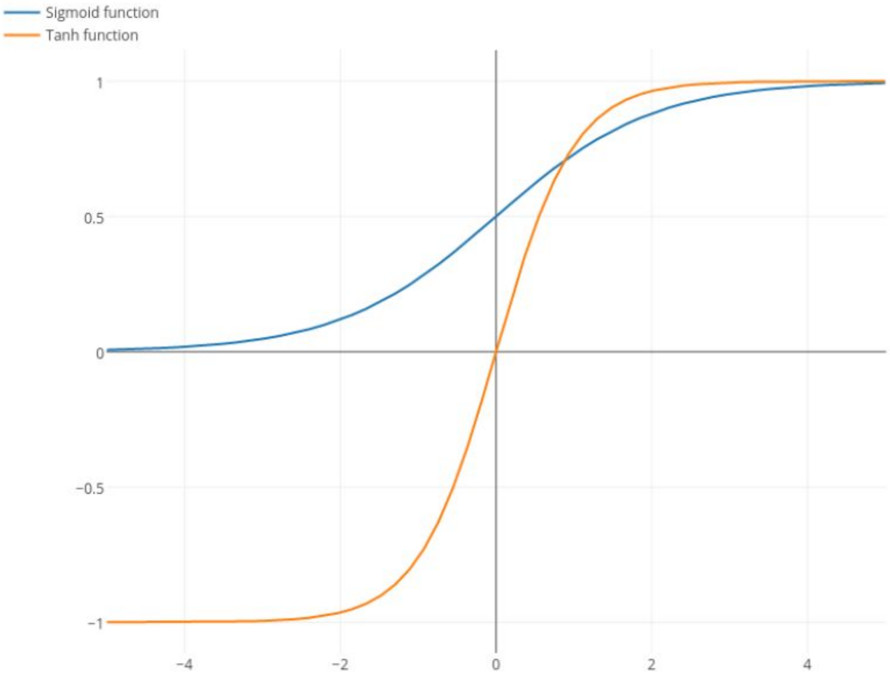
$$f(a) = \tanh(a)$$

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

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



Activation functions: Sigmoid



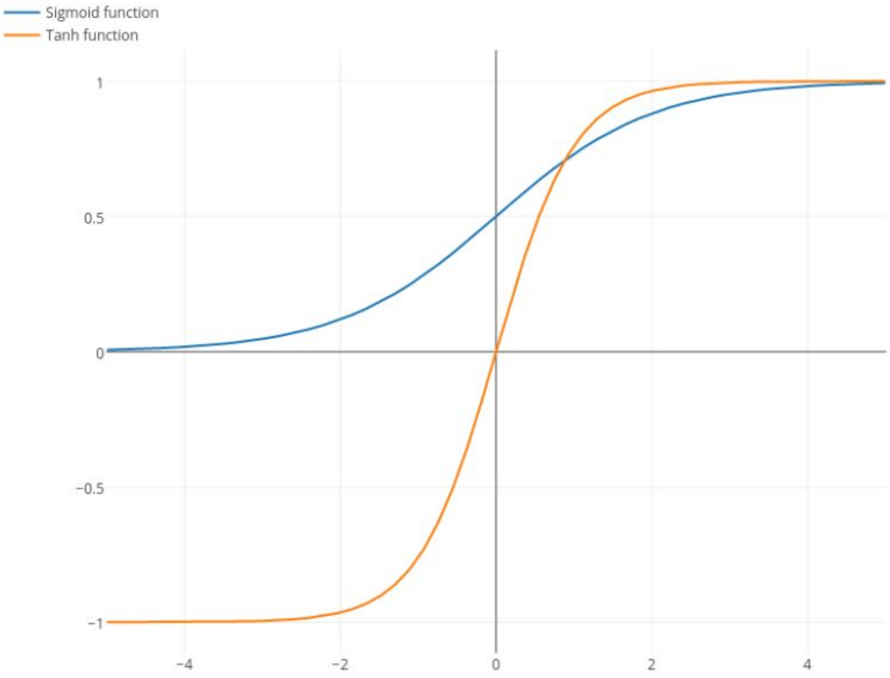
$$f(a) = \frac{1}{1 + e^{-a}}$$

- Maps R to (0,1)
- Historically popular, one of the first approximations of neuron activation

Problems:

- Almost zero gradients on the both sides (saturation)
- Shifted (not zero-centered) output
- Expensive computation of the exponent

Activation functions: tanh



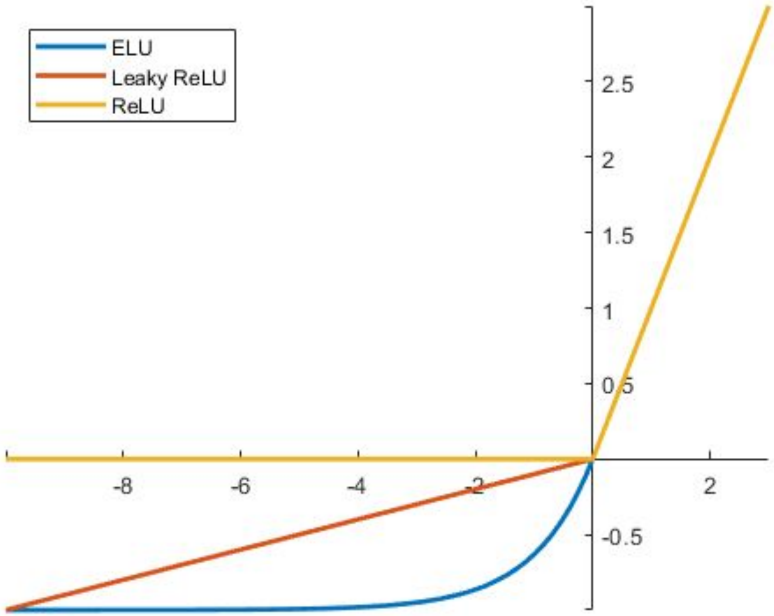
$$f(a) = \tanh(a)$$

- Maps R to (-1,1)
- Similar to the Sigmoid in other ways

Problems:

- Almost zero gradients on the both sides (saturation)
- ~~Shifted (not zero-centered) output~~
- Expensive computation of the exponent

Activation functions: ReLU



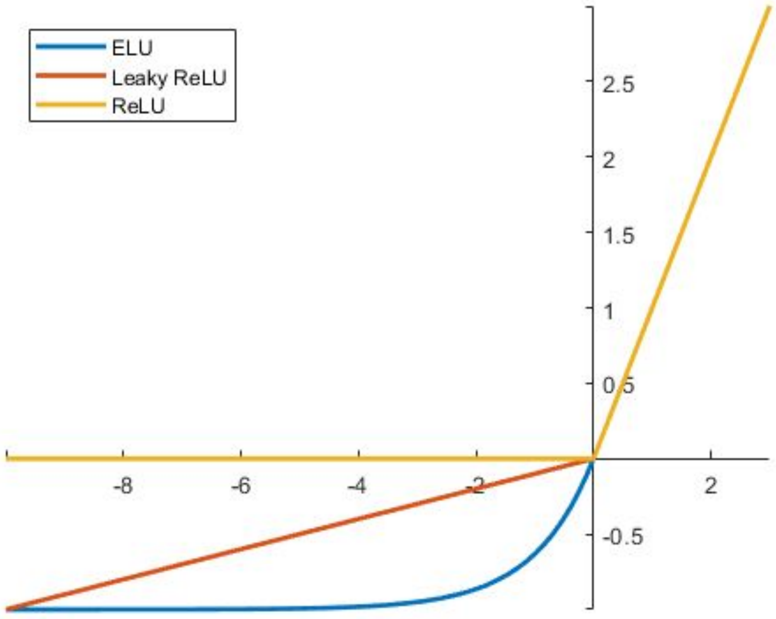
$$f(a) = \max(0, a)$$

- Very simple to compute (both forward and backward)
  - Up to 6 times faster than Sigmoid
- Does not saturate when x > 0
  - So the gradients are not 0

Problems:

- Zero gradients when x < 0
- Shifted (not zero-centered) output

Activation functions: Leaky ReLU



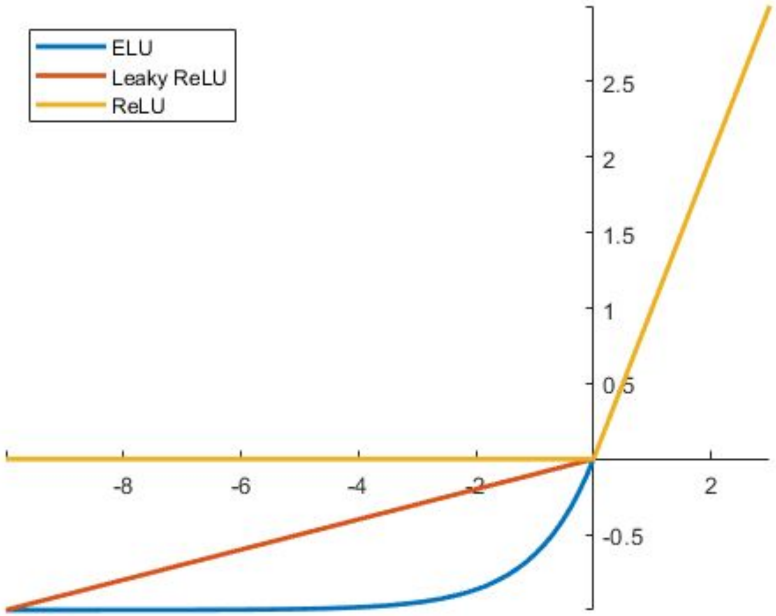
$$f(a) = \max(0.01a, a)$$

- Very simple to compute (both forward and backward)
  - Up to 6 times faster than Sigmoid
- Does not saturate when

Problems:

- Shifted, but not so much output

Activation functions: ELU



- Similar to ReLU
- Does not saturate
- Close to zero mean outputs

Problems:

- Requires exponent computation

$$f(a) = \begin{cases} a, & a > 0 \\ \alpha(\exp(a) - 1), & a \leq 0 \end{cases}$$

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

RNN

Shakespeare

```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain 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. □

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

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

.

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

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

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

Lemma 0.2. *This is an integer $\mathcal{Z}$ 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

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

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. □

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, inb_p);
  spin_unlock(&disk->queue_lock);
  mutex_unlock(&s->sock->mutex);
  mutex_unlock(&func->mutex);
  return disassemble(info->pending_bh);
}
```


Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Proof. Omitted. □

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

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

.

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

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

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

Lemma 0.2. *This is an integer $\mathcal{Z}$ 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

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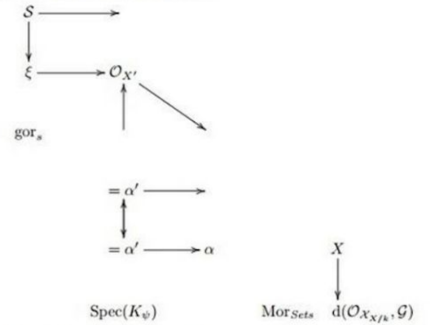
(1) $\mathcal{F}$ is an algebraic space over S.
(2) If X is an affine open covering.

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

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



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.

□

Proof. We have see that $X = \mathrm{Spec}(R)$ 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. □

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 $\mathcal{C}$. The functor $\mathcal{F}$ is a "field

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} \quad \text{-}1(\mathcal{O}_{X_{\acute{e}tale}}) \longrightarrow \mathcal{O}_{X_\ell}^{-1}\mathcal{O}_{X_\lambda}(\mathcal{O}_{X_\eta}^{\overline{v}})$$

is an isomorphism of covering of $\mathcal{O}_{X_i}$. 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. □

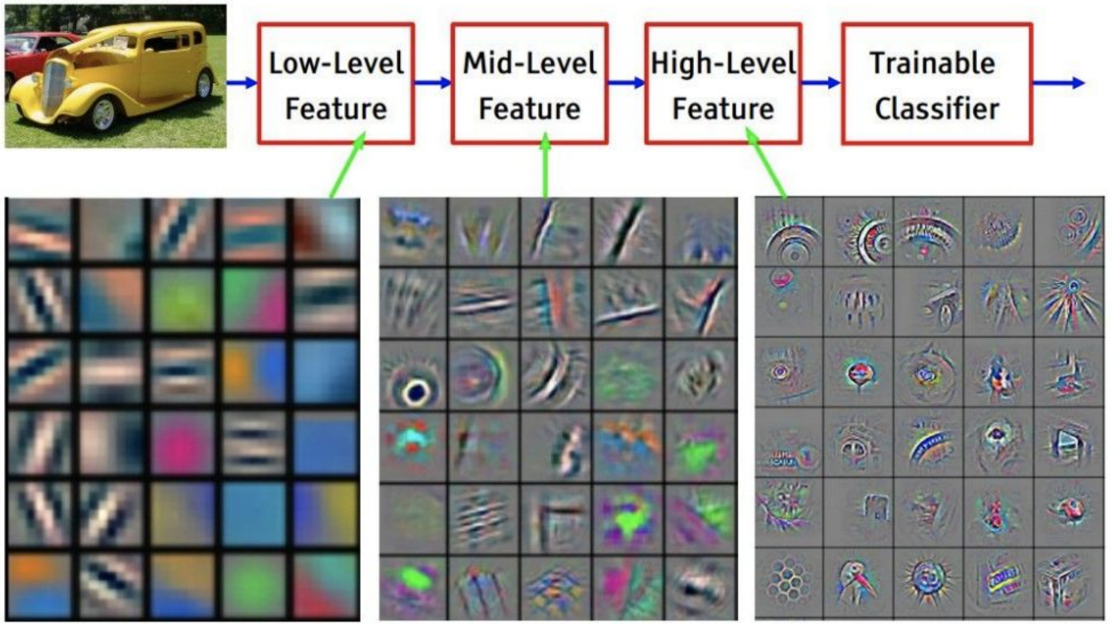
If $\mathcal{F}$ is a finite direct sum $\mathcal{O}_{X_\lambda}$ is a closed immersion, see Lemma ??. This is a sequence of $\mathcal{F}$ is a similar morphism.

Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

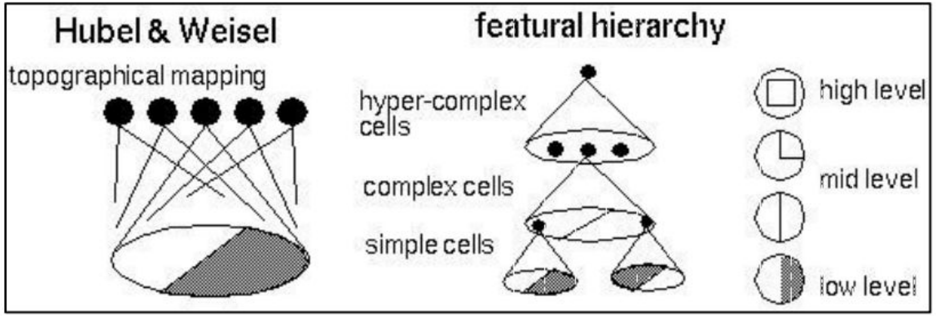
```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>

#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;
}
```


Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

CNN: Convolutional layer and visual cortex



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

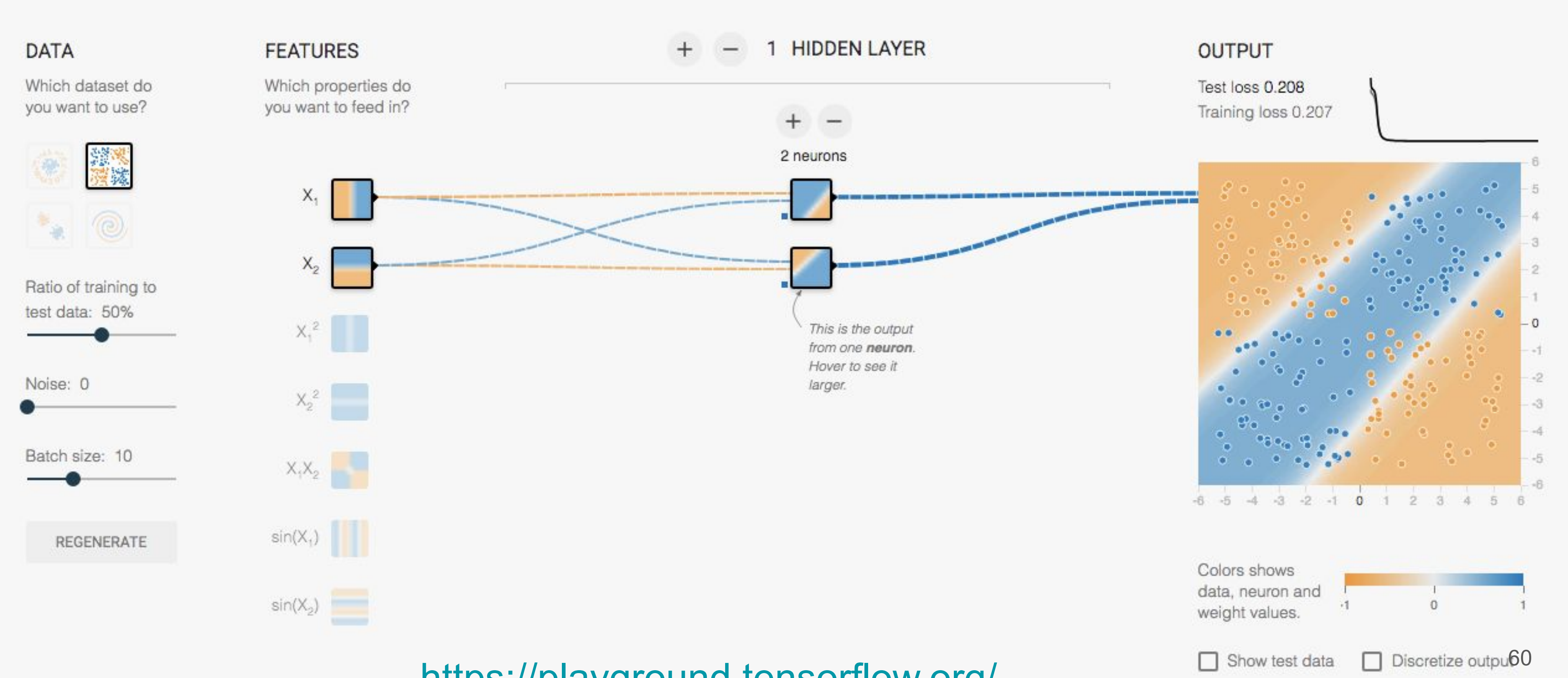


[From Yann LeCun slides]

Convolutional layer and visual cortex

Source: https://habr.com/ru/post/370541/

Don’t miss the interactive playground



https://playground.tensorflow.org/


WHO'S AWESOME?
You're Awesome

Outro

- 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