Deep Learning
Lecture 6:
Intro to DL

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Outline

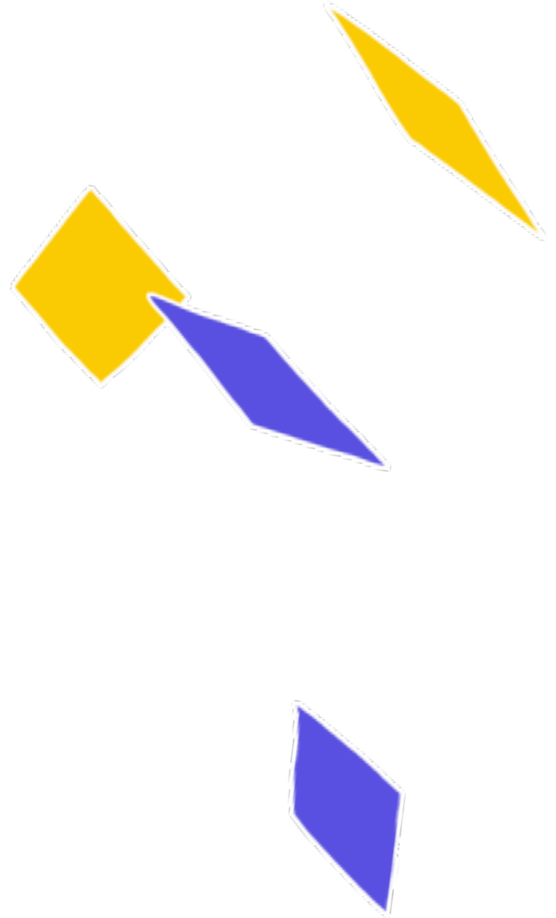
01 Neural Networks in different areas.
Historical overview

02 Backpropagation

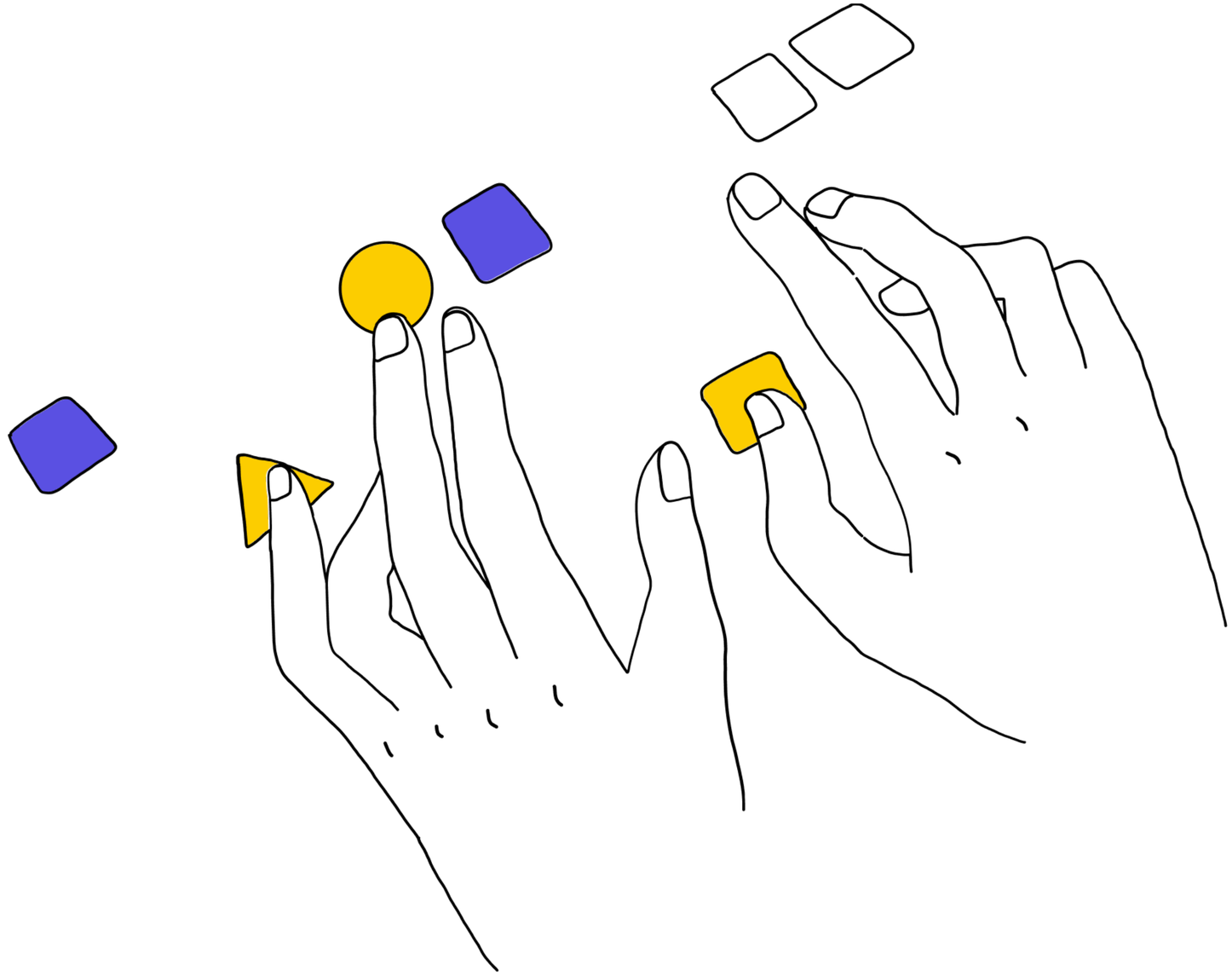
03 More on backpropagation

04 Activation functions

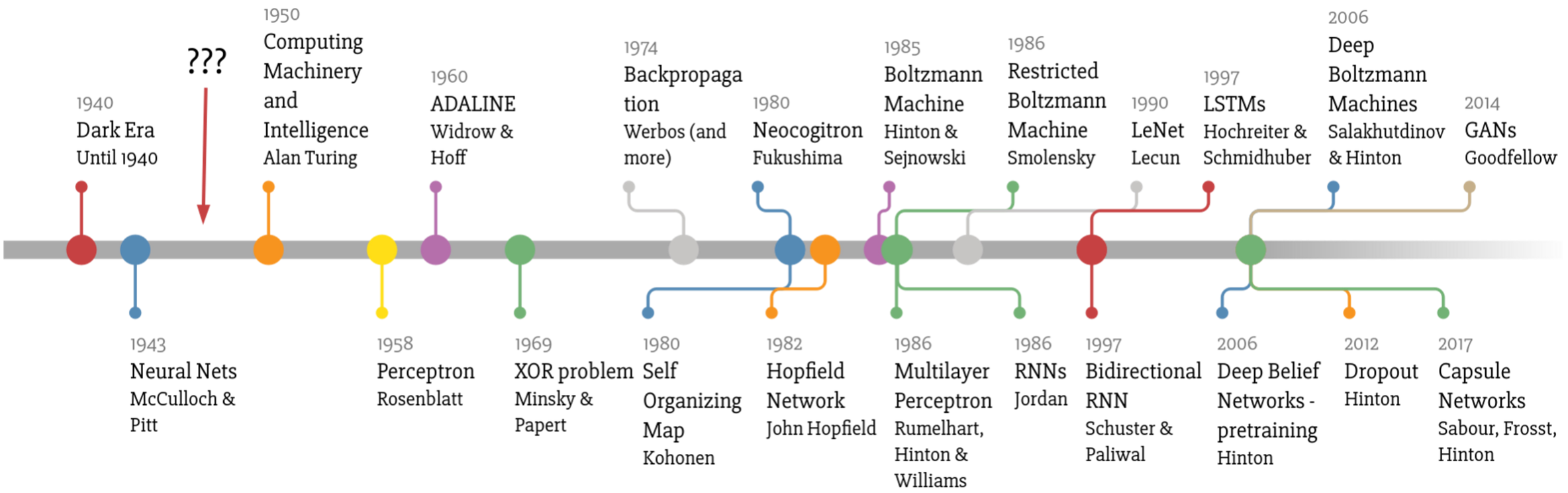
05 Playground



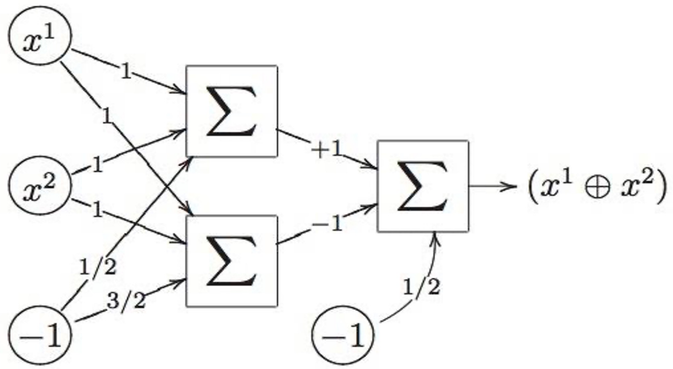
History of Deep Learning



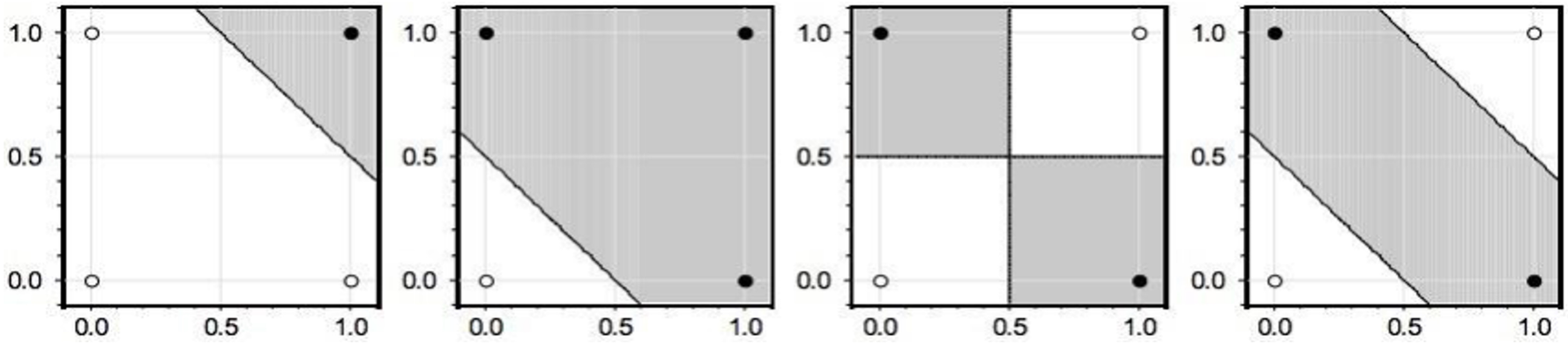
Deep Learning Timeline



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



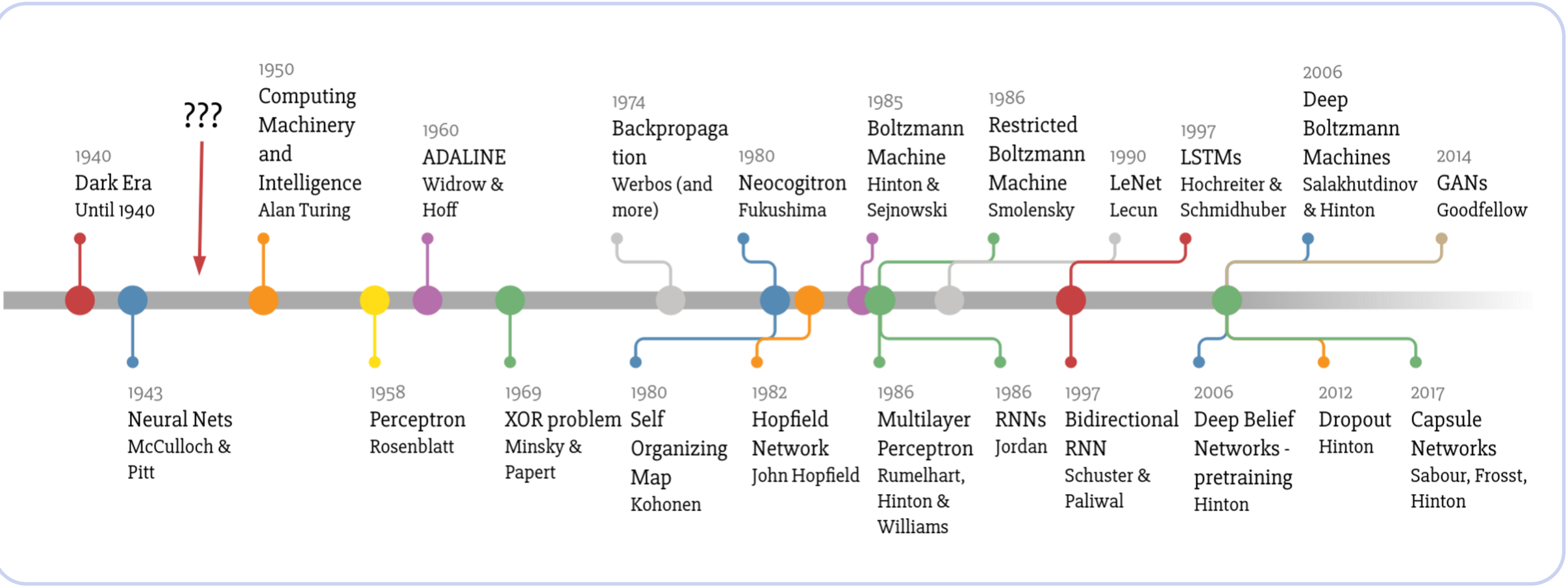
AND

XOR(with x1*x2)

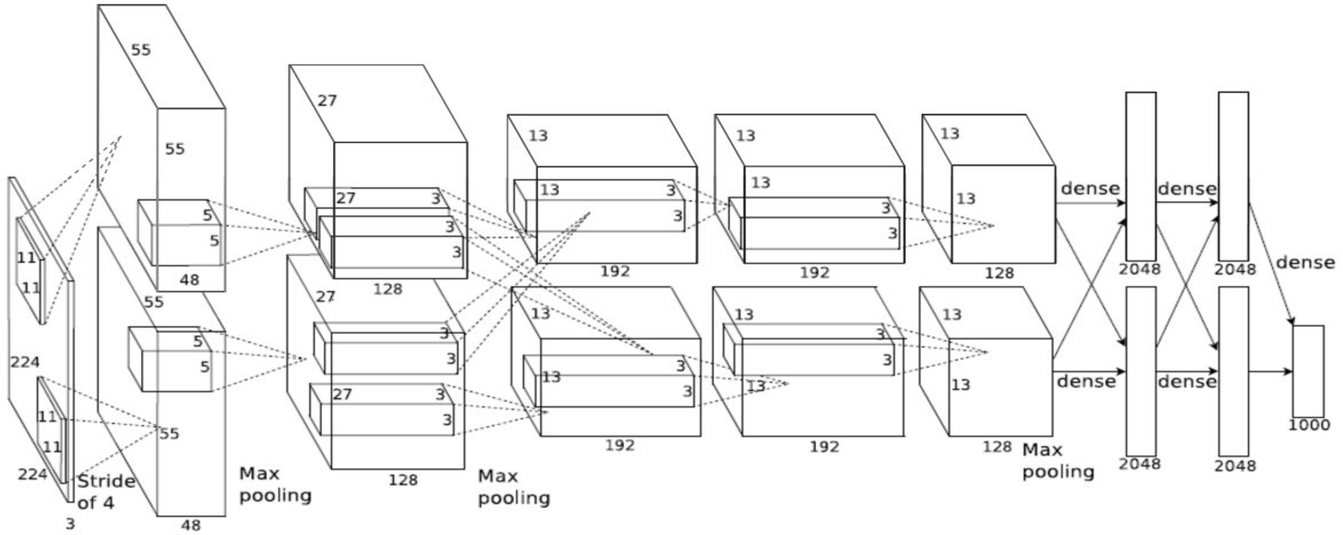
OR

XOR

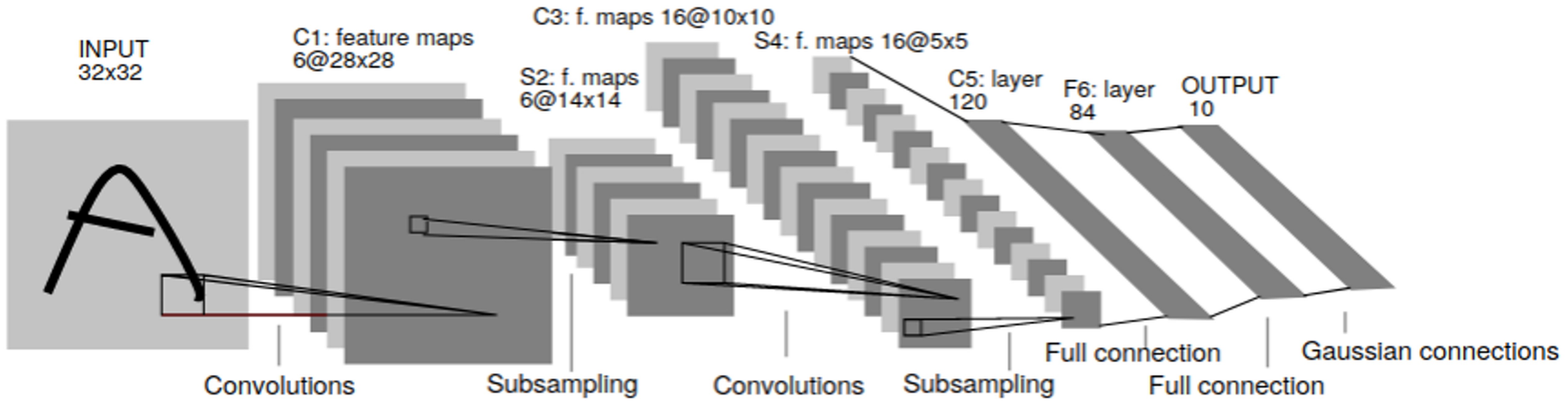
Deep Learning Timeline



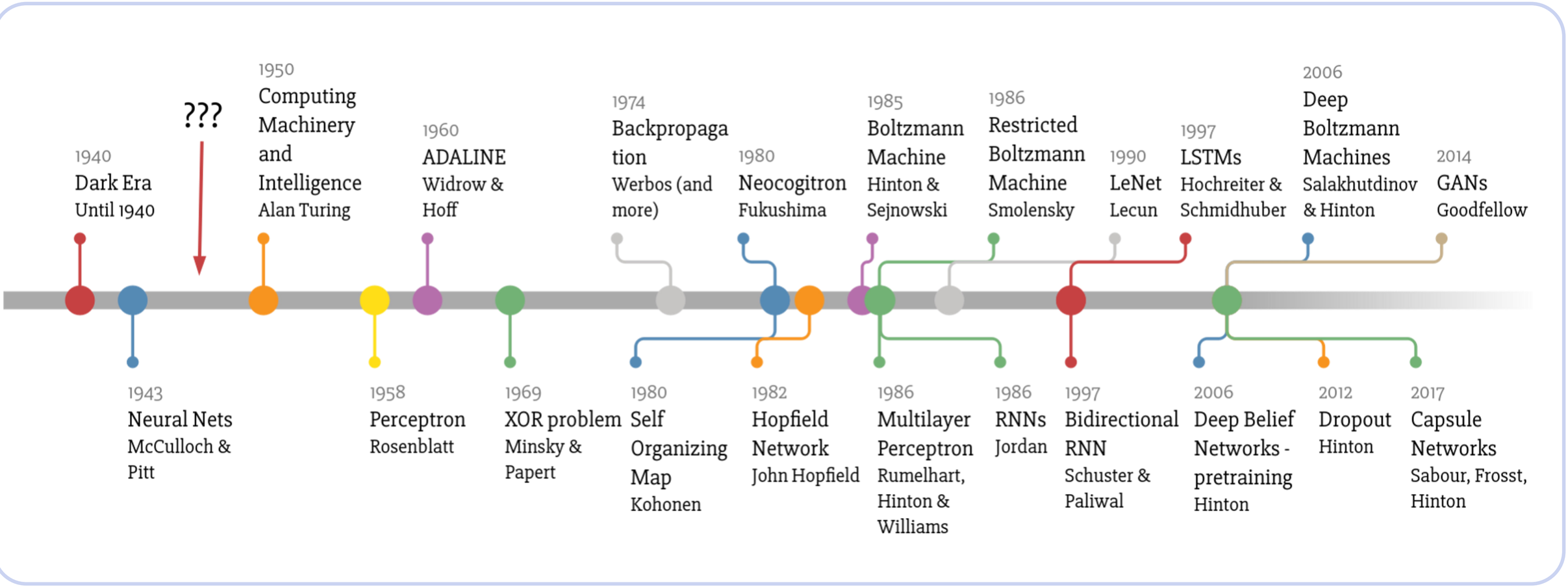
AlexNet, 2012



LeNet-5, 1998



Deep Learning Timeline



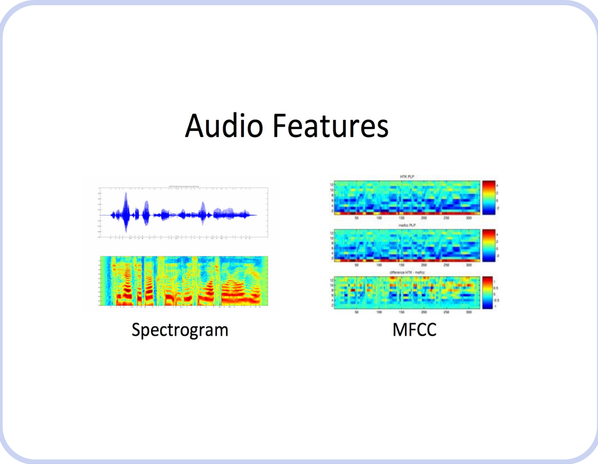
Real world applications

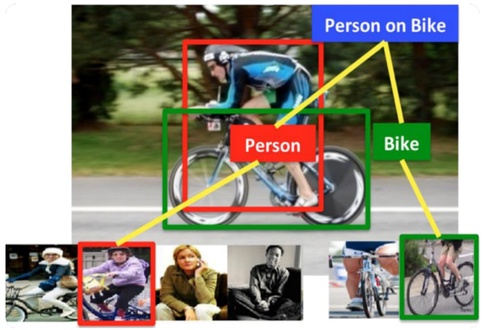
01 Object detection

02 Action classification

03 Image captioning

04 ...

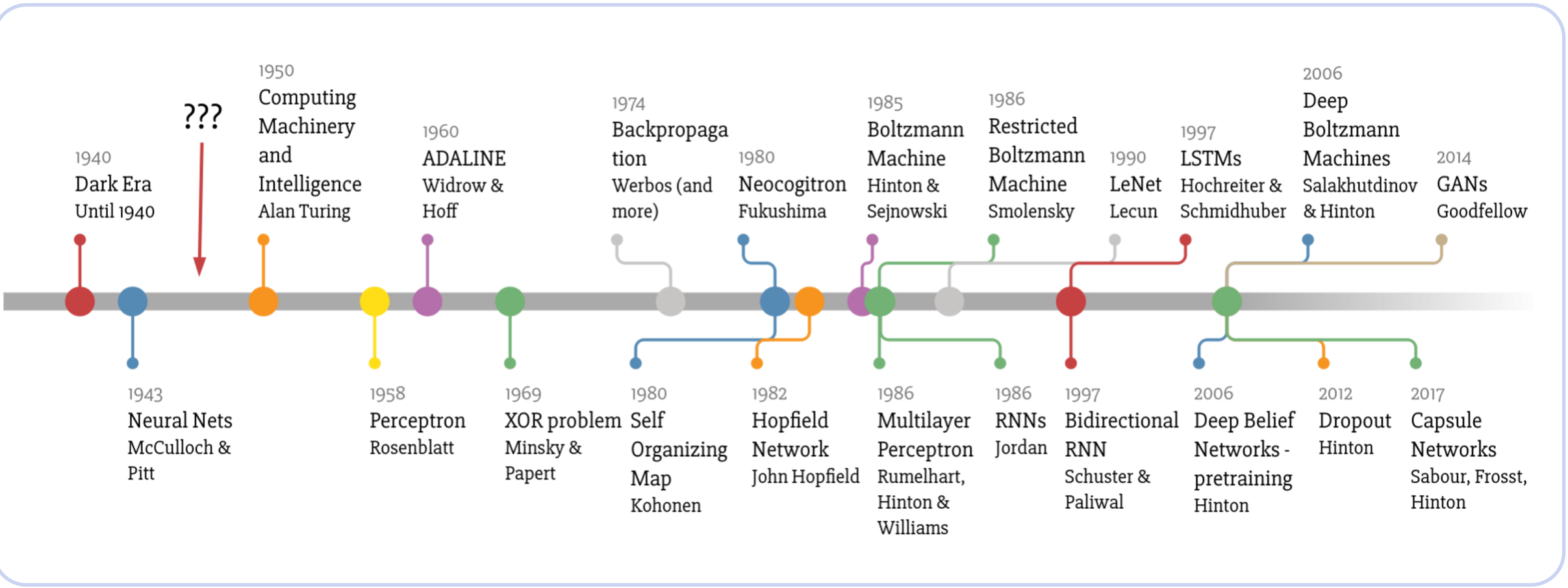




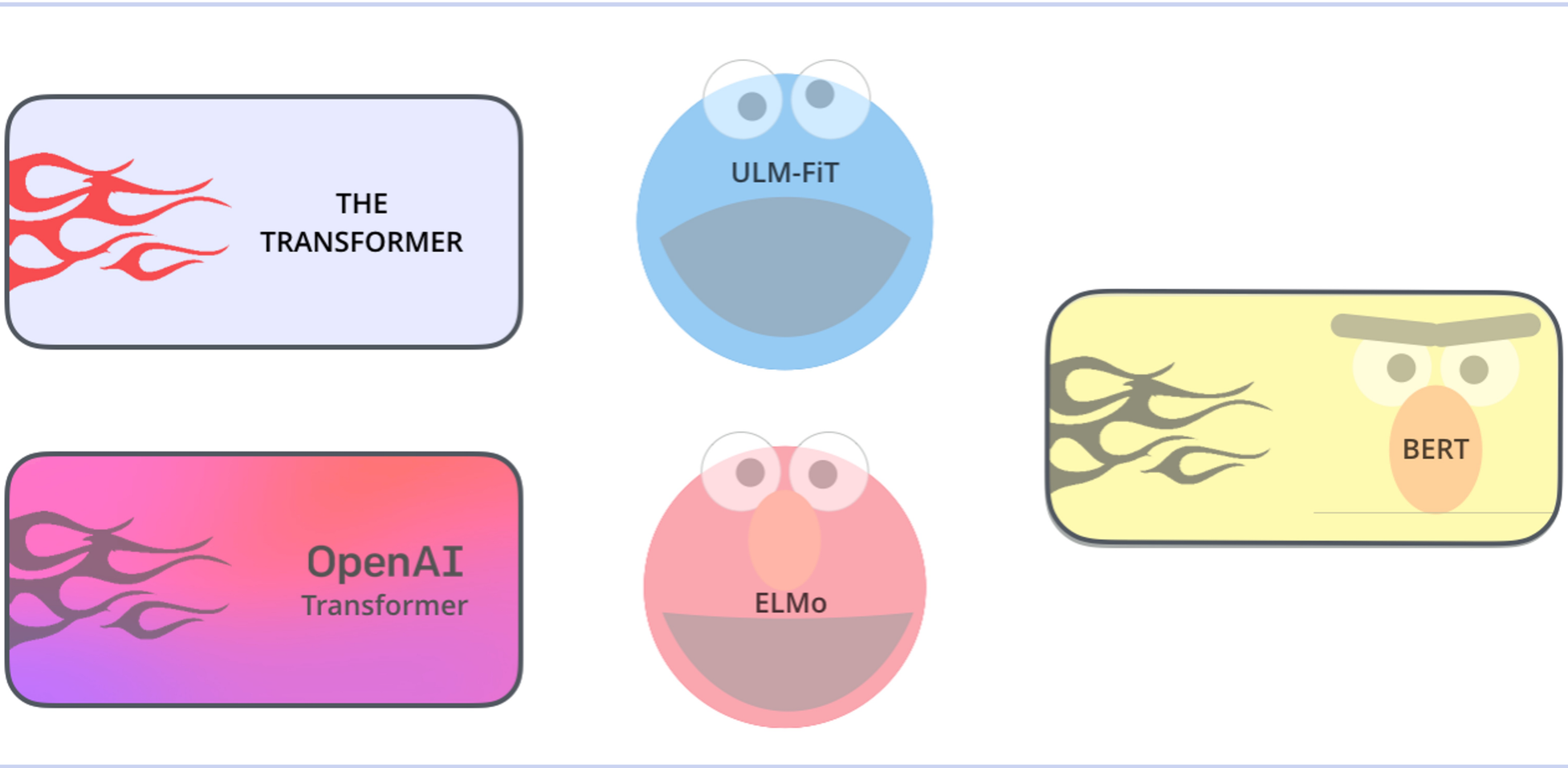
GANs, 2014+

https://thispersondoesnotexist.com/

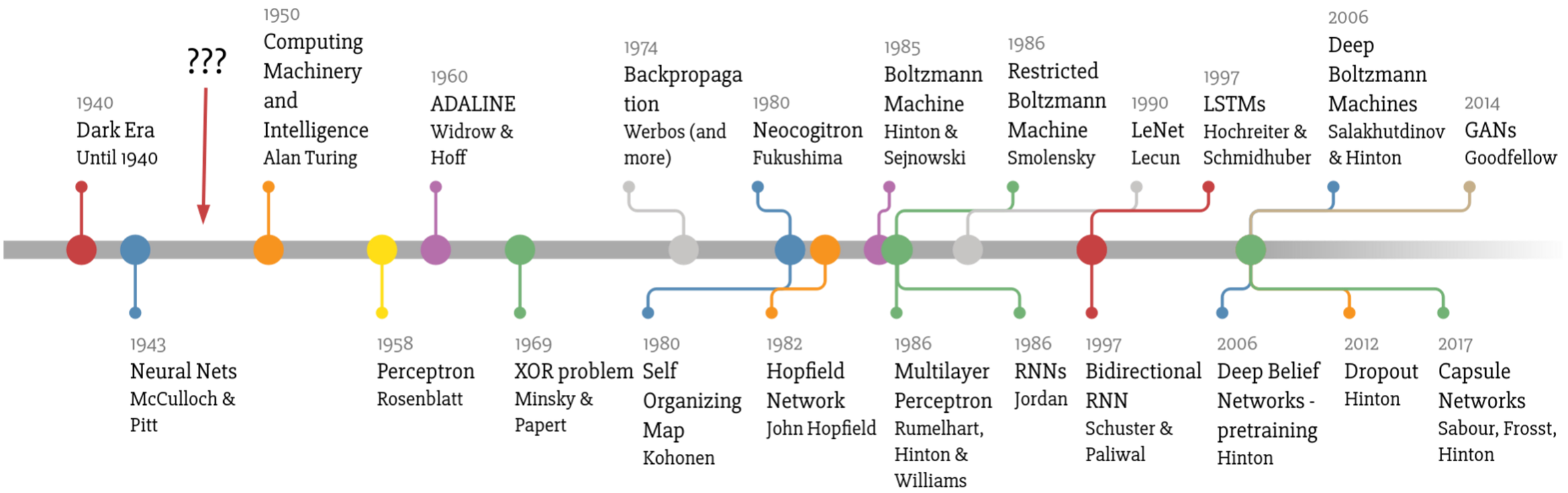
Deep Learning Timeline



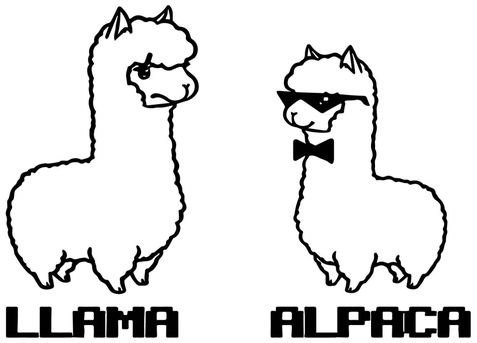
Transformer, BERT, GPT-2 and more, 2017+



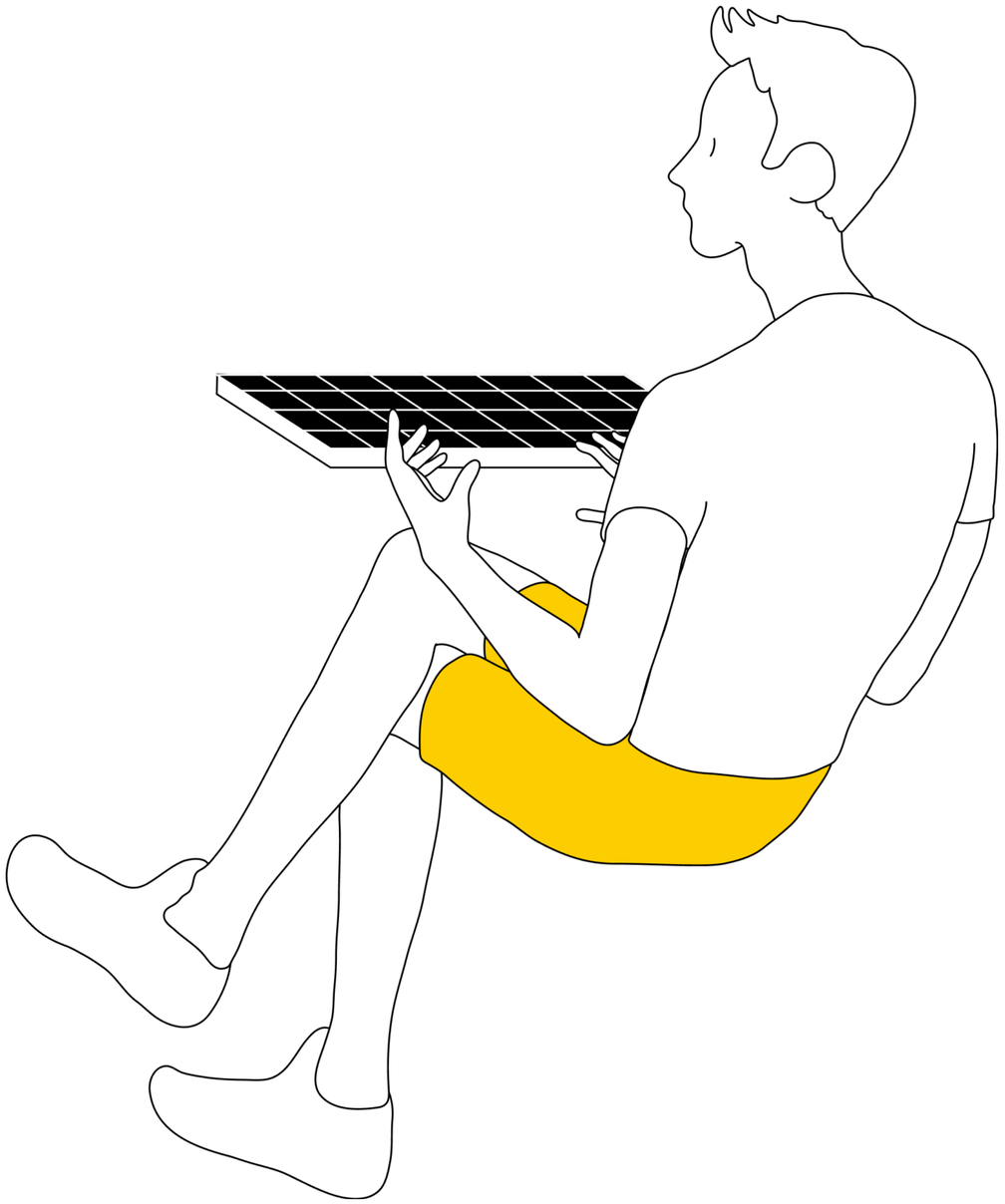
Deep Learning Timeline



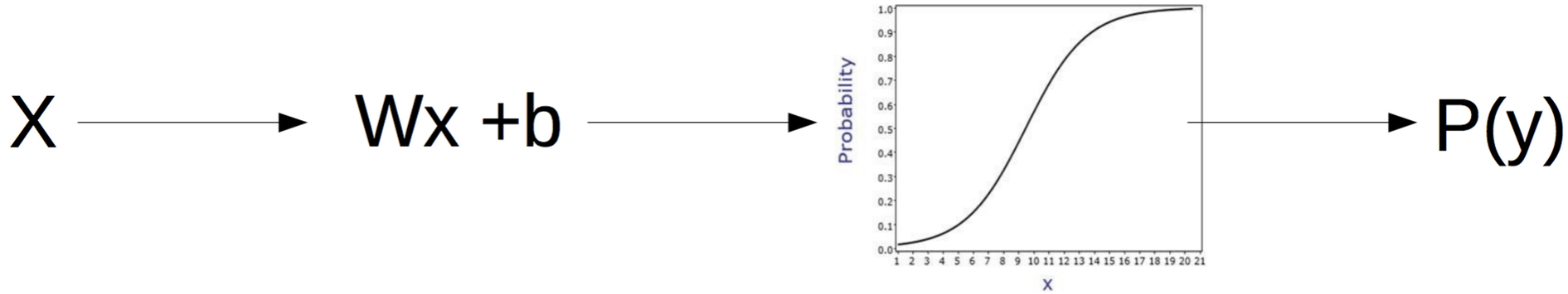
2022: (Instruct)ChatGPT, StableDiffusion
2023: GPT boom: GPT-4, YaGPT, GigaChat, LLaMa



Deep Learning: intuition



Logistic regression



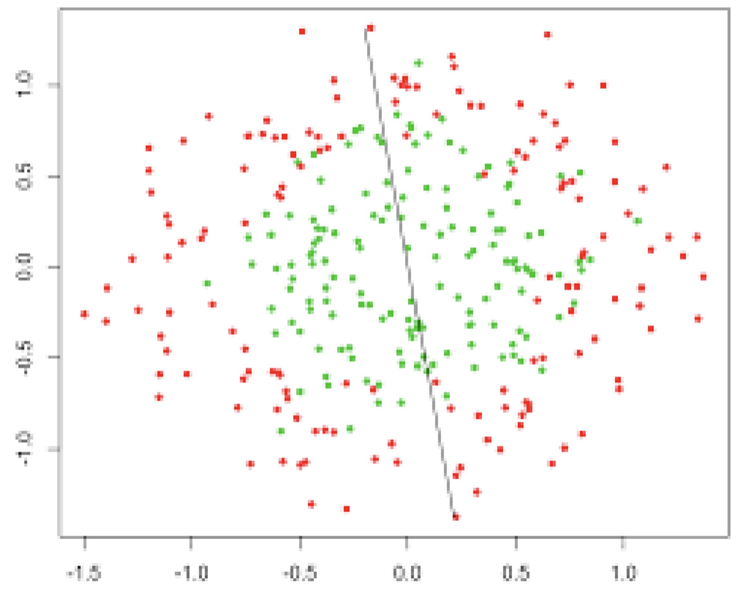
$$P(y = 1|\boldsymbol{x}) = \sigma(\boldsymbol{w}^\top \boldsymbol{x} + b)$$

$$L = -\sum_i \left(y^{(i)} \log P(y = 1|\boldsymbol{x}^{(i)}) + (1 - y^{(i)}) \log \left(1 - P(y = 1|\boldsymbol{x}^{(i)})\right) \right)$$

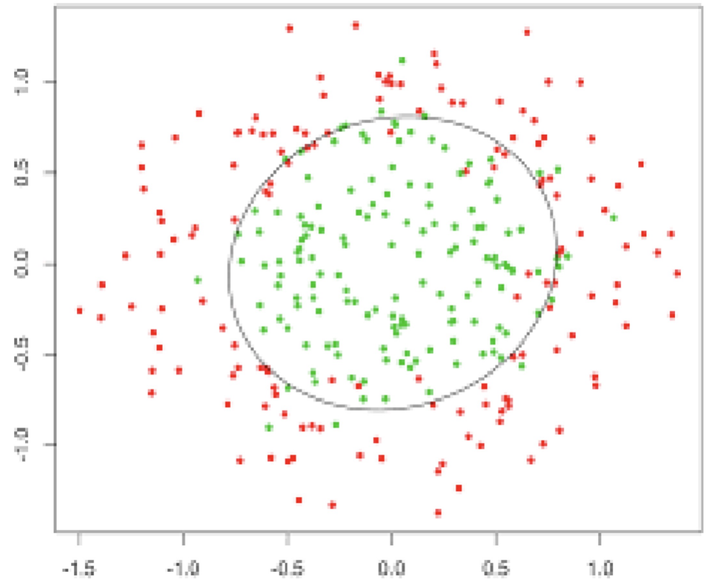
Problem: nonlinear dependencies

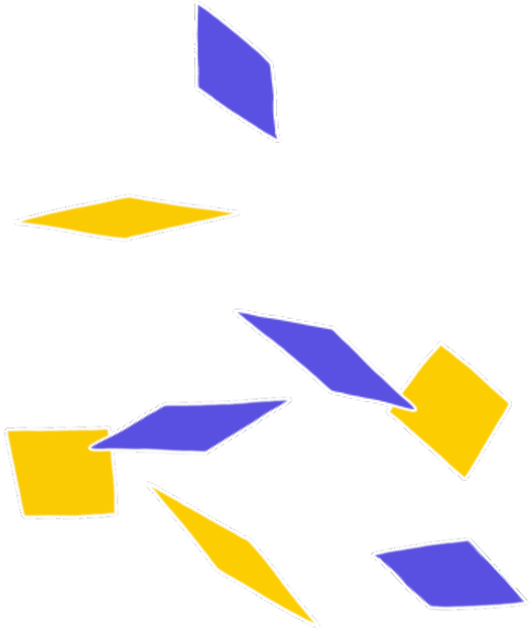
Logistic regression (generally, linear model) need feature engineering to show good results

What we have



What we want



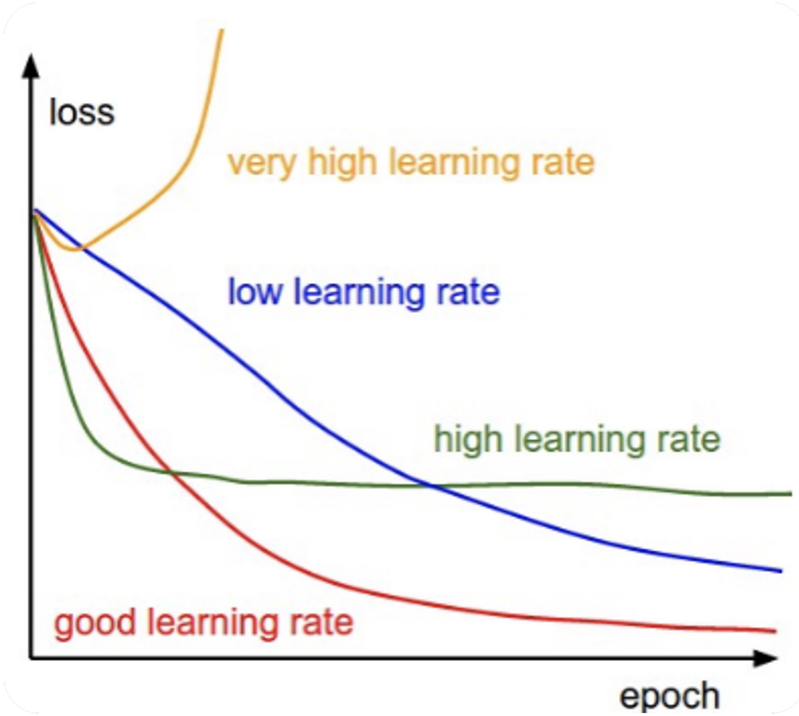


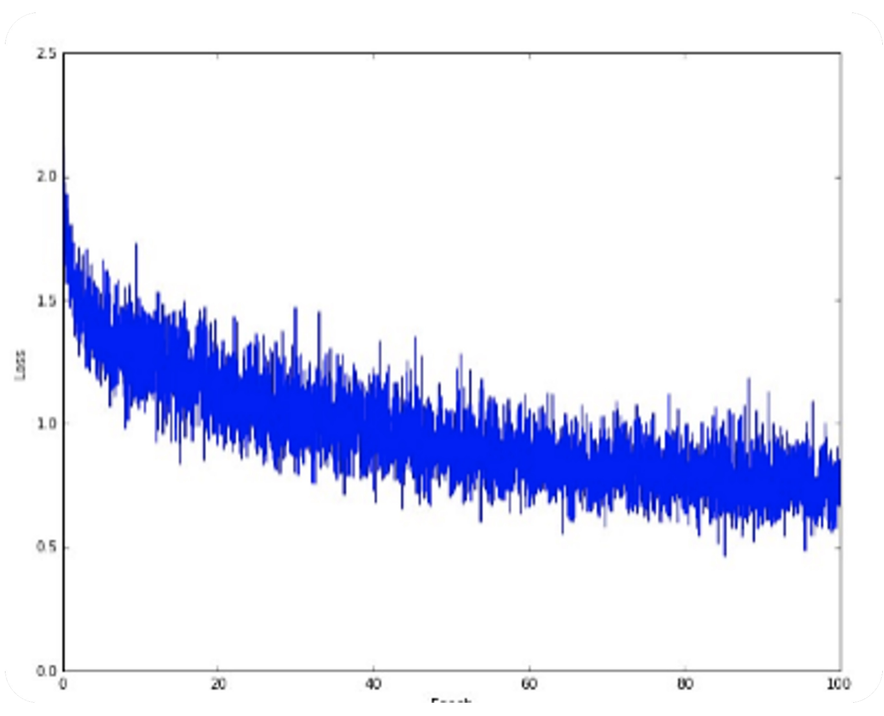
And feature engineering is an art

Gradient optimization

Stochastic gradient descent is used to optimize NN parameters

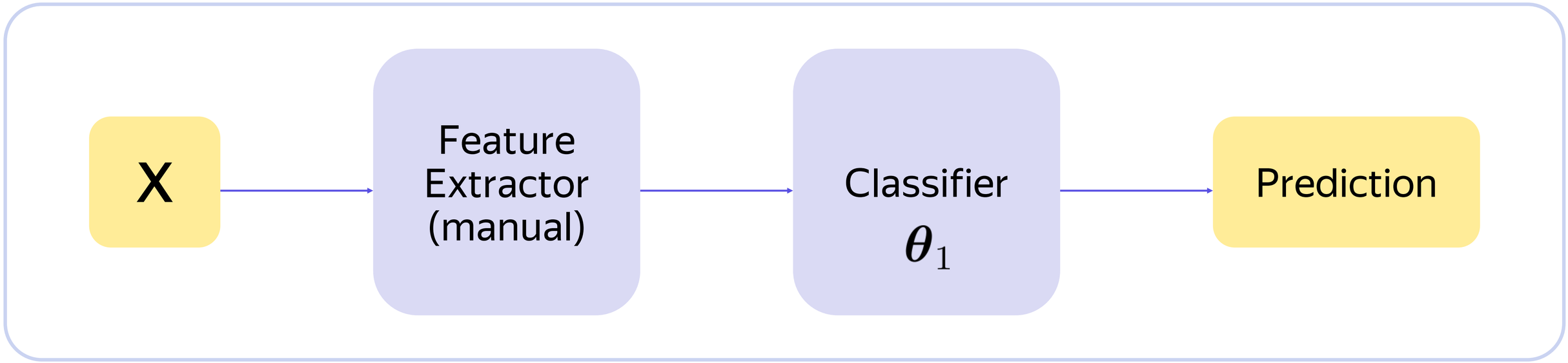
$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \frac{dL}{d\boldsymbol{w}}$$





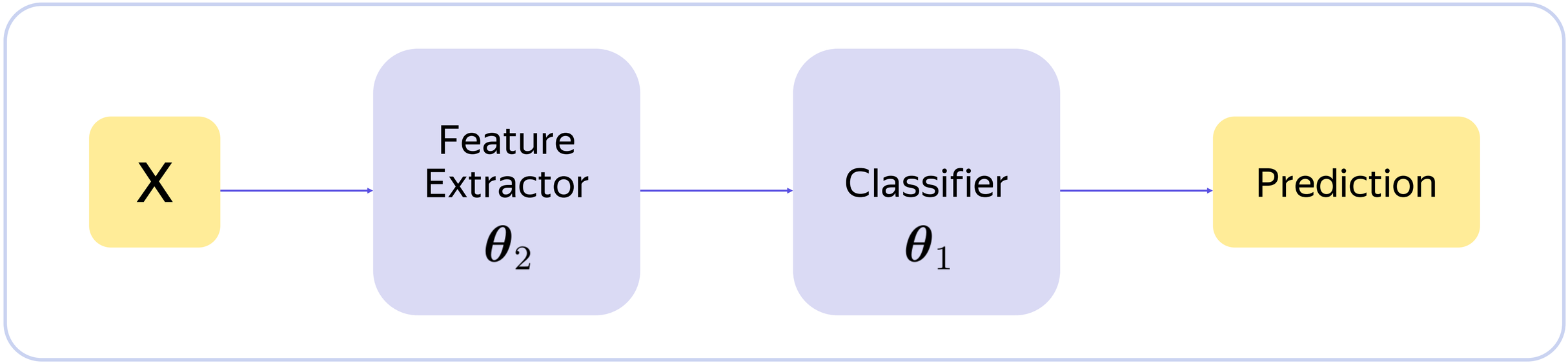
source

Classic pipeline



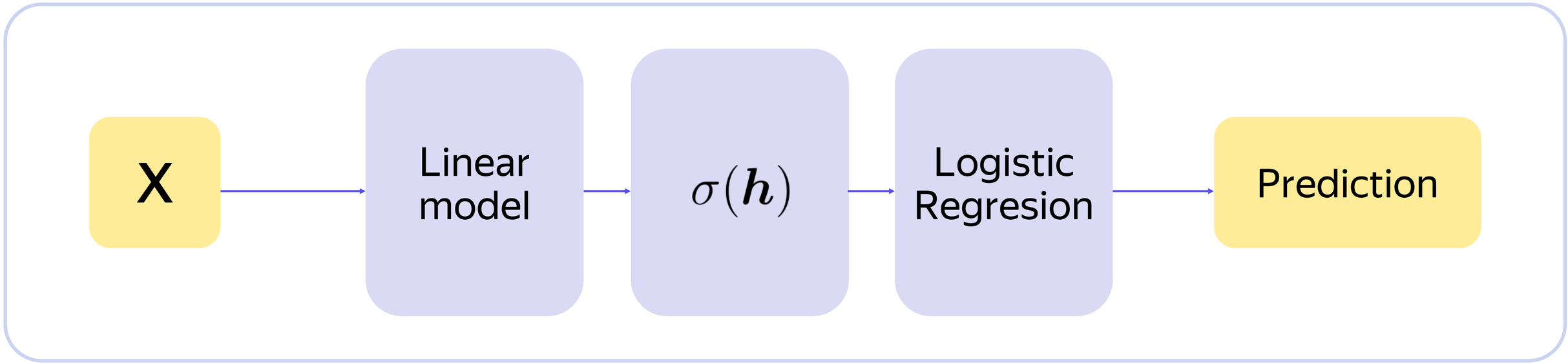
Handcrafted features, generated by experts

NN pipeline



Automatically extracted features

NN pipeline: example



E.g. two logistic regressions one after another.

Actually, it’s a neural network

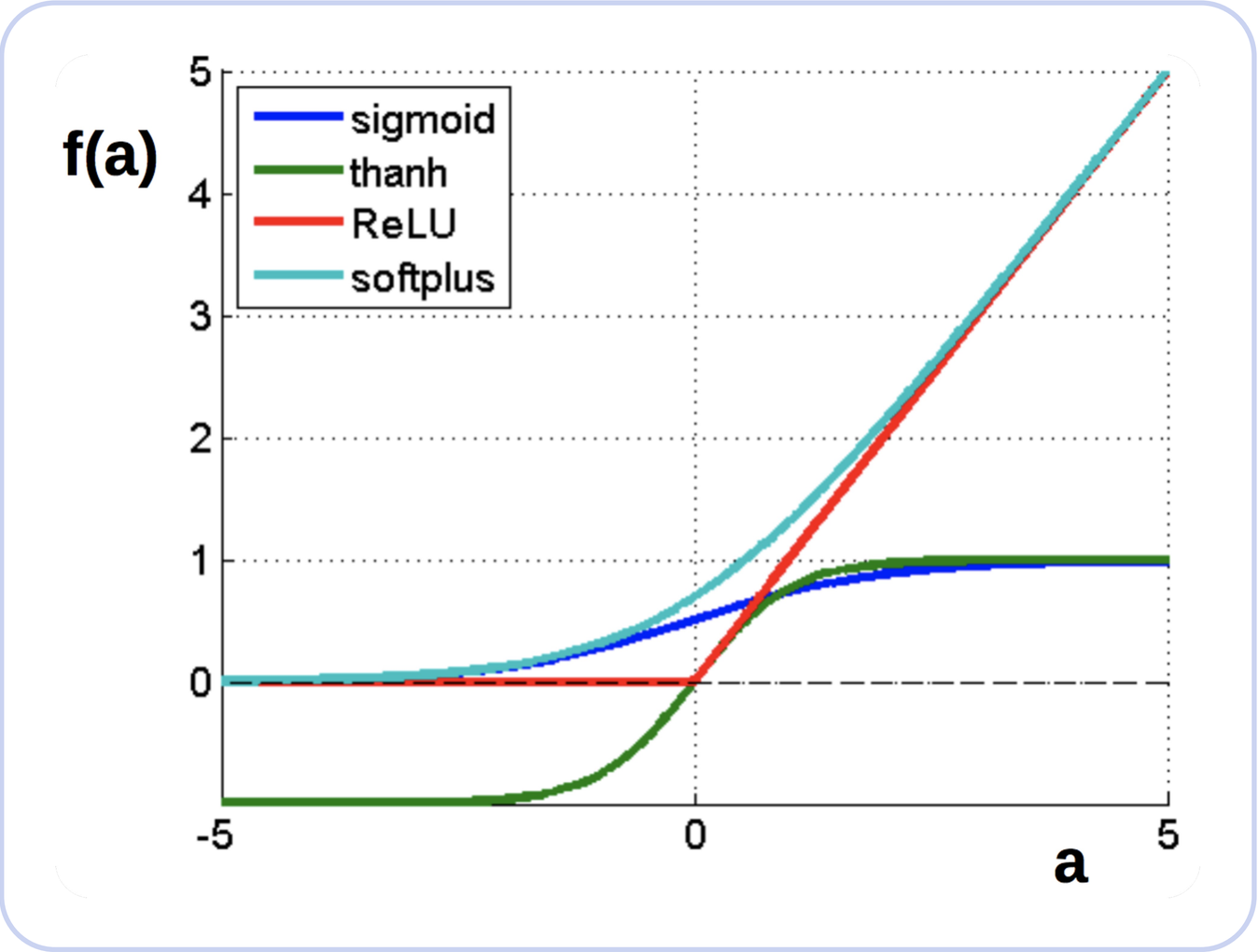
Activation functions: nonlinearities

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

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

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

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



Some generally accepted terms

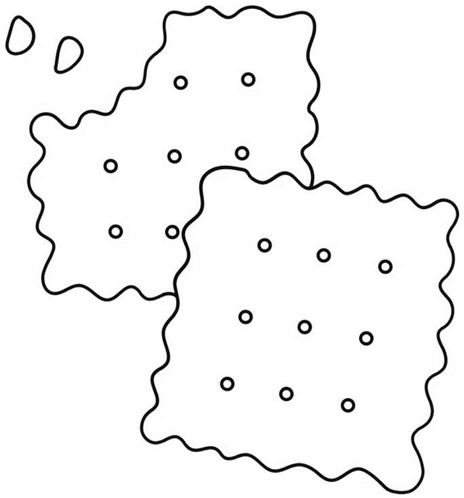
01 Layer — a building block for NNs :

- Dense/Linear/FC layer: $\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}$
- Nonlinearity layer, e.g. $\sigma(\boldsymbol{h})$
- Input layer, output layer
- etc.

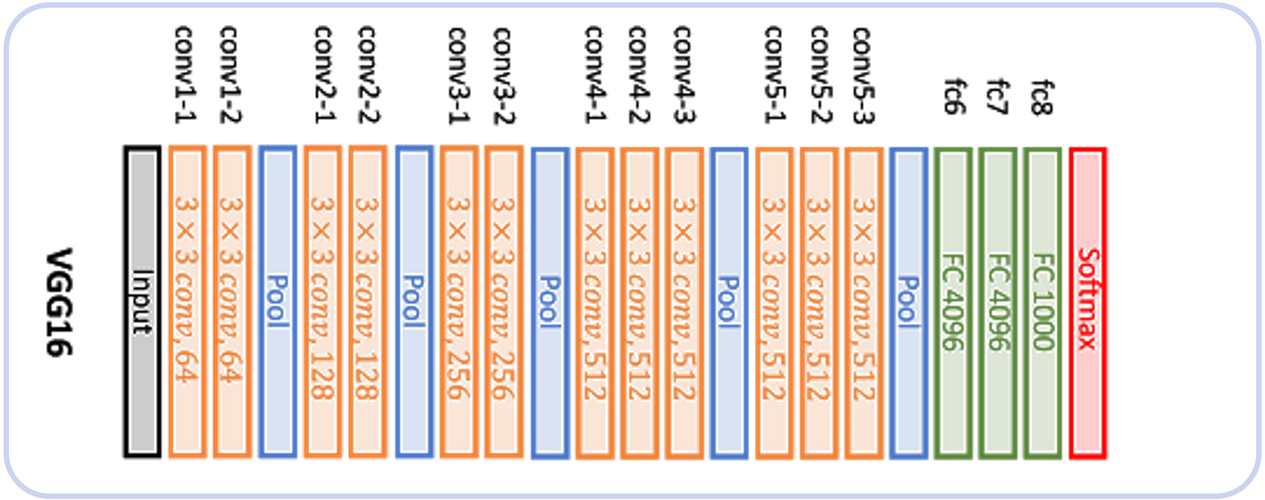
02 Activation function — function applied to layer output

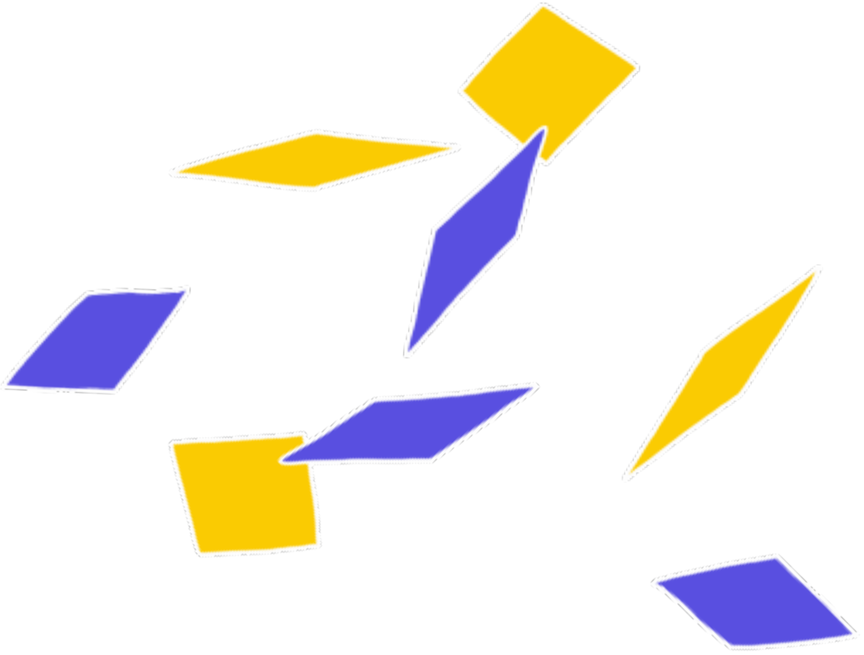
- Sigmoid
- tanh
- ReLU
- Any other function to get nonlinear intermediate signal in NN

03 Backpropagation — a fancy word for “chain rule”

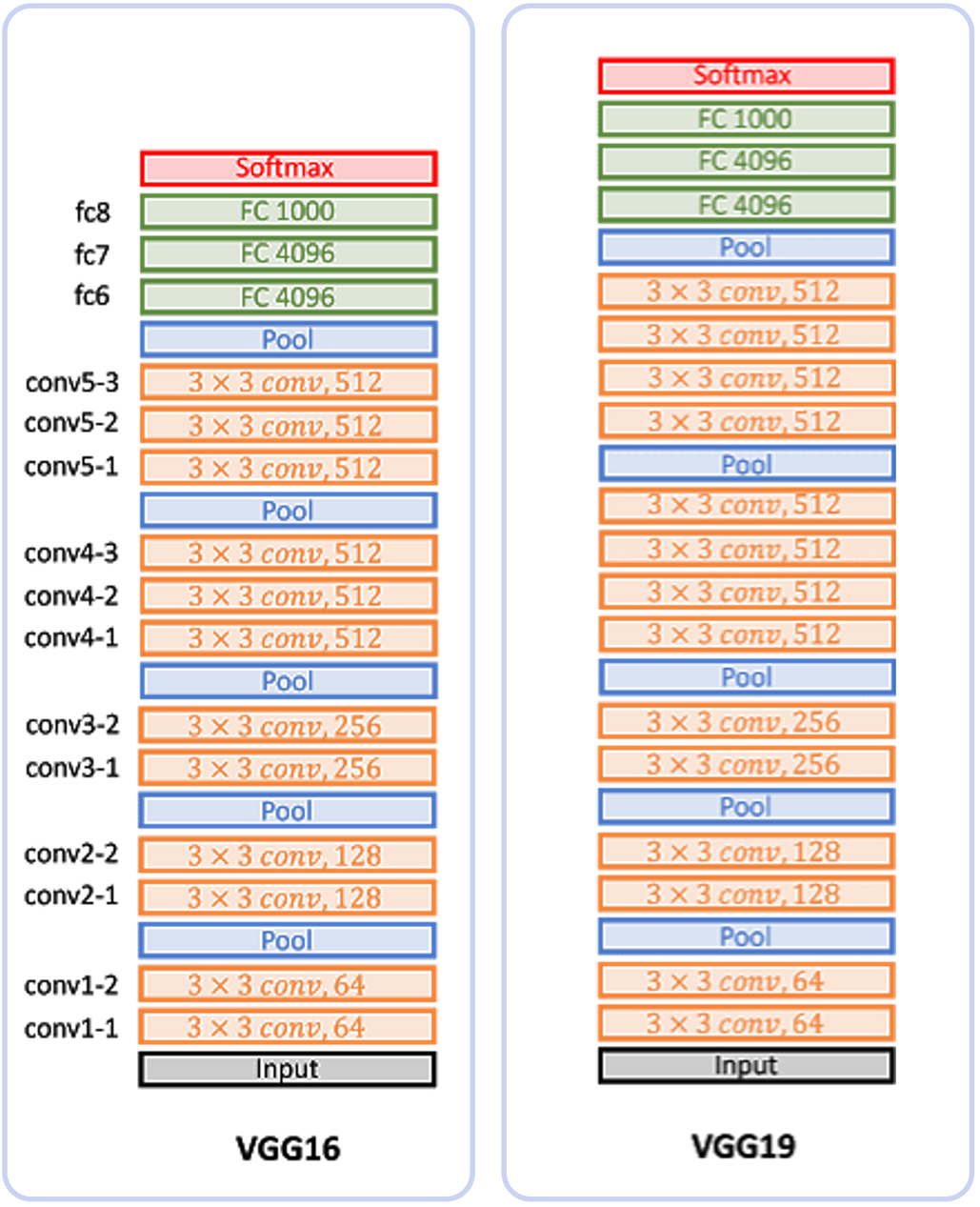


Actually, networks can be deep



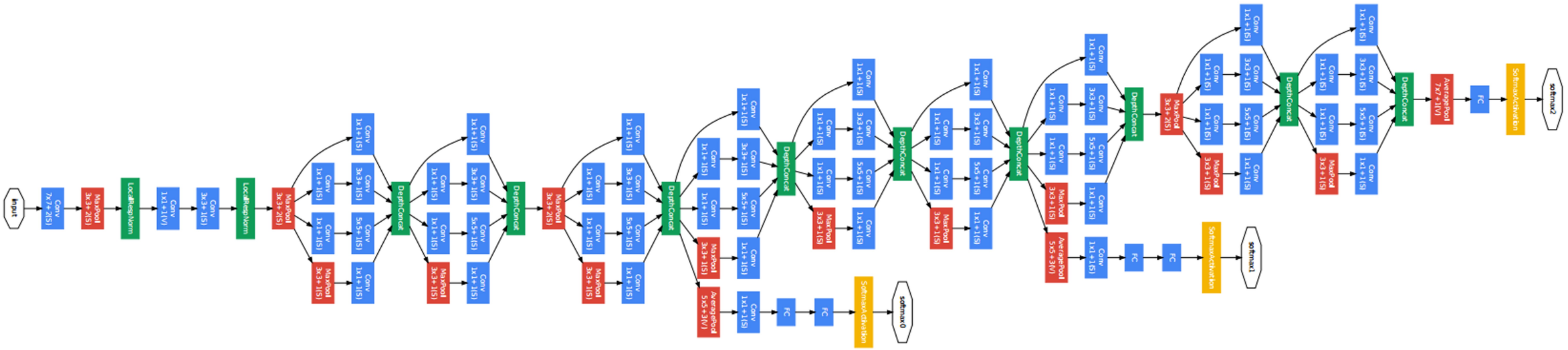


And deeper...


Softmax
fc8
FC 1000
fc7
FC 4096
fc6
FC 4096
Pool
conv5-3
3 × 3 conv, 512
conv5-2
3 × 3 conv, 512
conv5-1
3 × 3 conv, 512
Pool
conv4-3
3 × 3 conv, 512
conv4-2
3 × 3 conv, 512
conv4-1
3 × 3 conv, 512
Pool
conv3-2
3 × 3 conv, 256
conv3-1
3 × 3 conv, 256
Pool
conv2-2
3 × 3 conv, 128
conv2-1
3 × 3 conv, 128
Pool
conv1-2
3 × 3 conv, 64
conv1-1
3 × 3 conv, 64
Input
VGG16
Softmax
FC 1000
FC 4096
FC 4096
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 × 3 conv, 512
Pool
3 × 3 conv, 256
3 × 3 conv, 256
Pool
3 × 3 conv, 128
3 × 3 conv, 128
Pool
3 × 3 conv, 64
3 × 3 conv, 64
Input
VGG19

Much deeper...

How to train it?

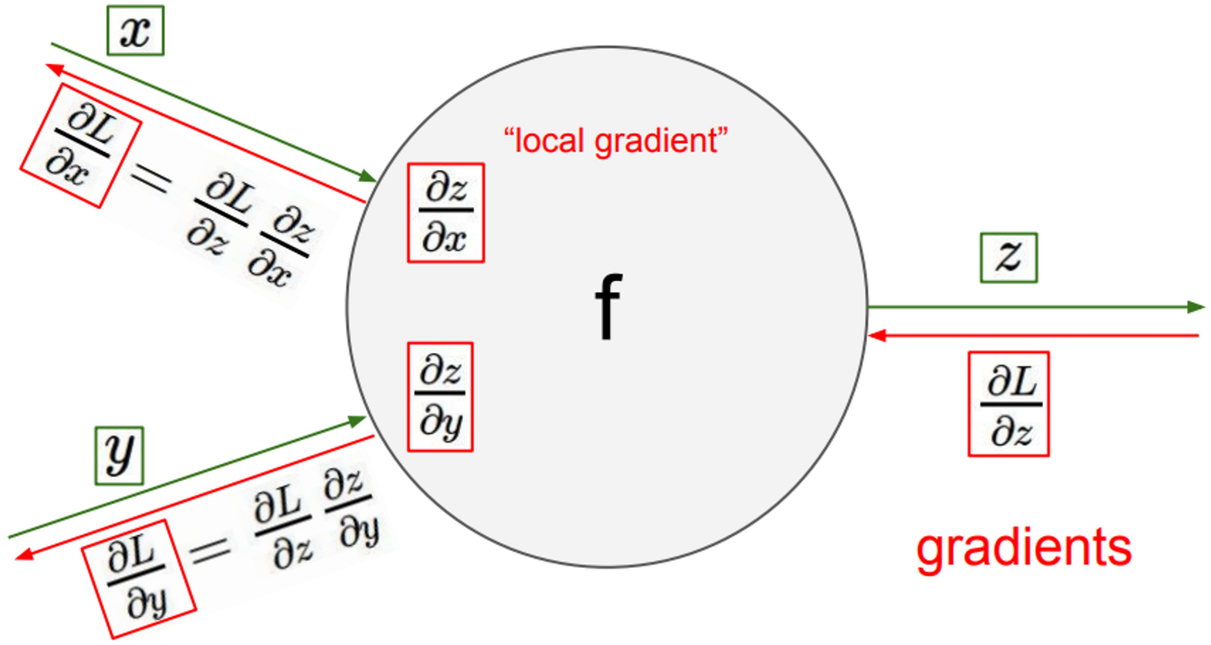


Backpropagation and chain rule

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



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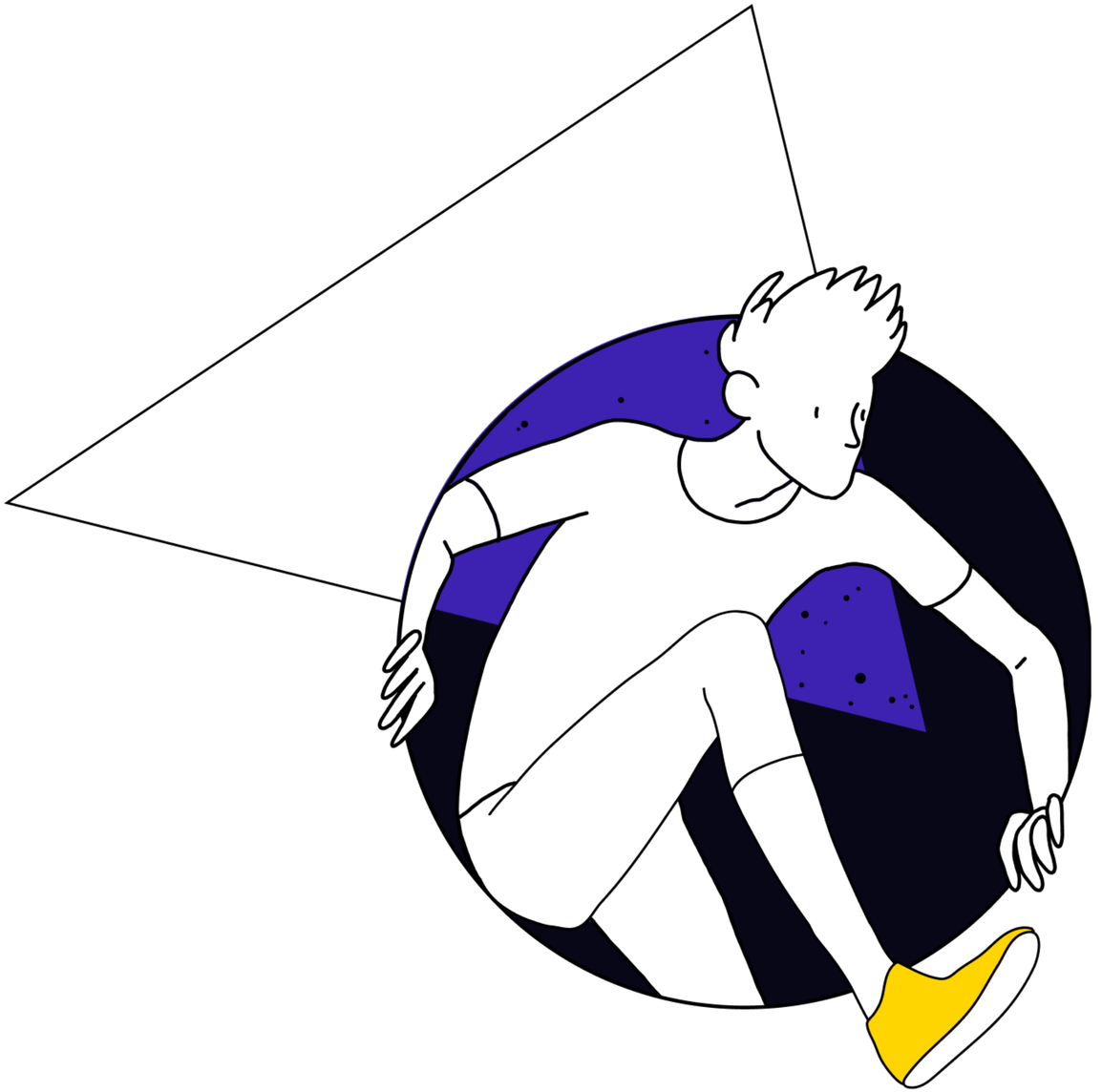
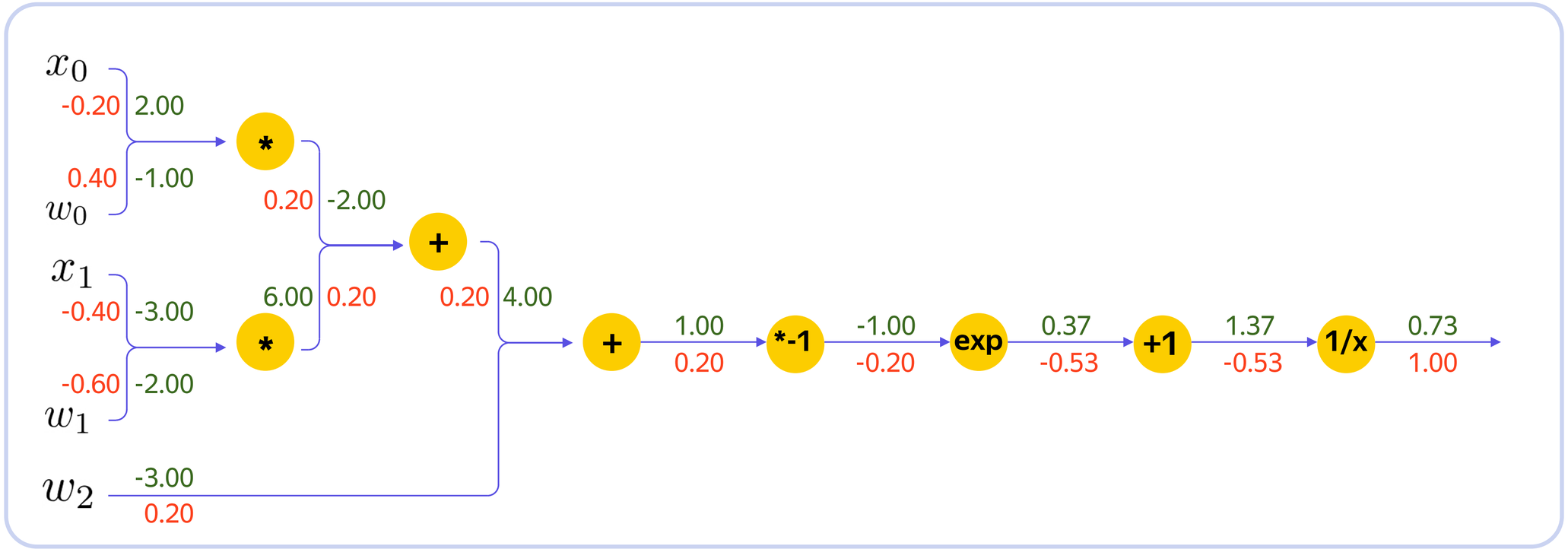
Backpropagation



Backpropagation example

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



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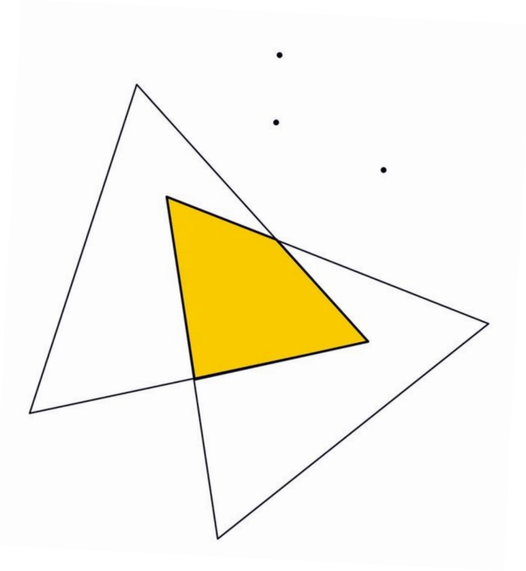
Backpropagation: matrix form



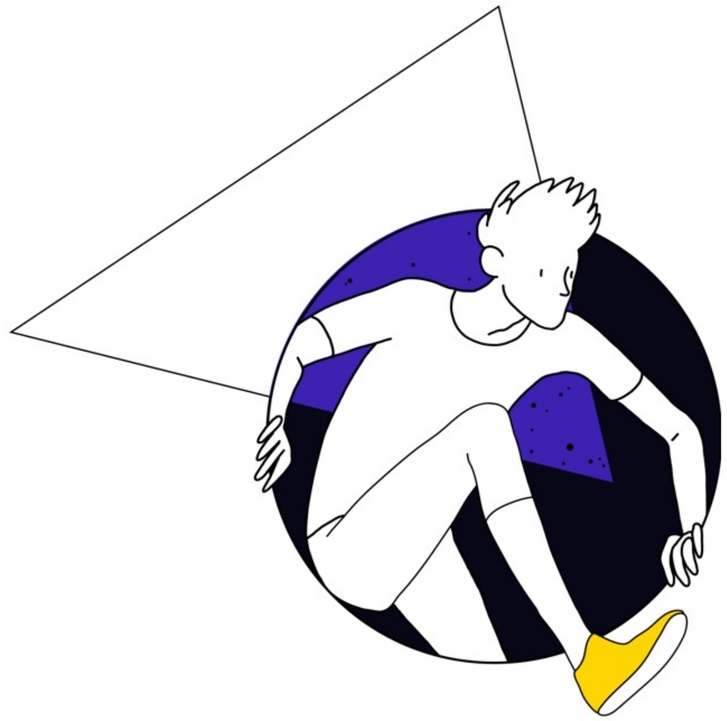
$$
\begin{aligned}
y_1 &= f_1(\mathbf{x}) = x_1 \\
y_2 &= f_2(\mathbf{x}) = x_2 \\
&\vdots \\
y_n &= f_n(\mathbf{x}) = x_n
\end{aligned}
$$

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

source

Backpropagation: matrix form

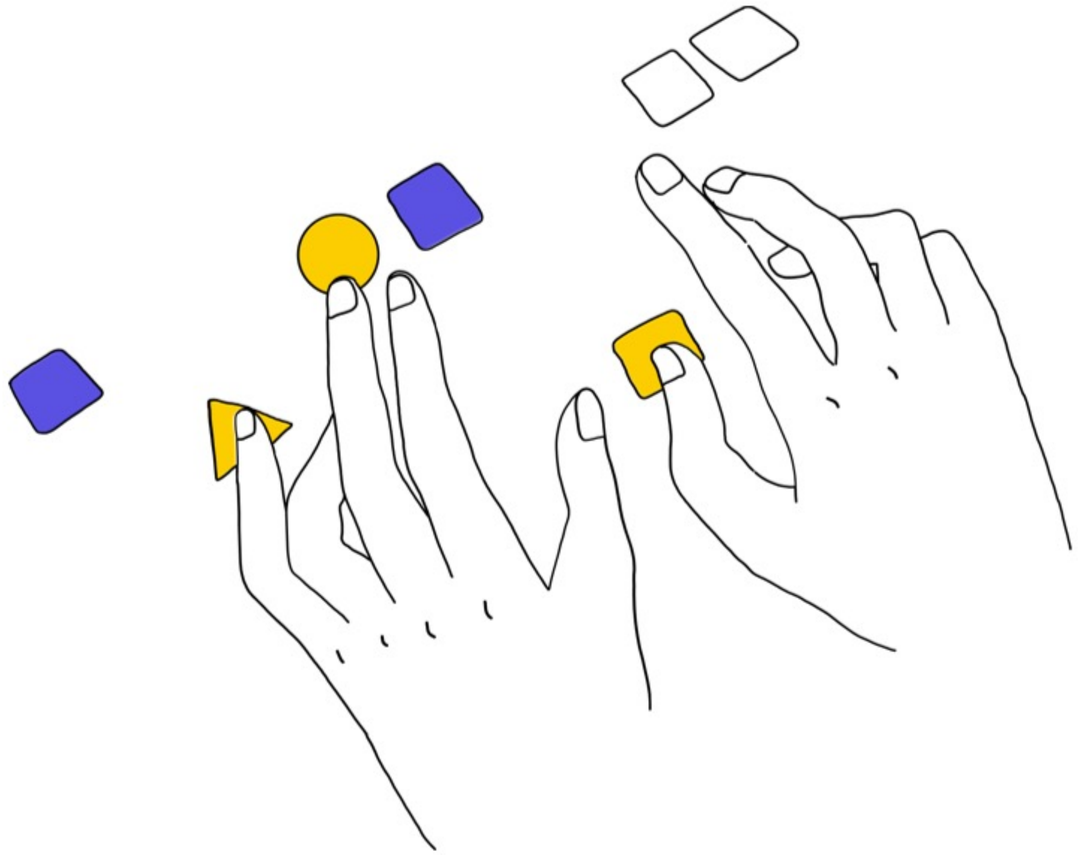
	scalar	vector
	x	$\mathbf{x}$
scalar		
f	$\frac{\partial f}{\partial x}$	$\frac{\partial f}{\partial \mathbf{x}}$
vector		
$\mathbf{f}$	$\frac{\partial \mathbf{f}}{\partial x}$	$\frac{\partial \mathbf{f}}{\partial \mathbf{x}}$



source

Backpropagation: matrix form

$$
\begin{aligned}
\frac{\partial \mathbf{y}}{\partial \mathbf{x}} &= \begin{bmatrix} \frac{\partial}{\partial \mathbf{x}} f_1(\mathbf{x}) \\ \frac{\partial}{\partial \mathbf{x}} f_2(\mathbf{x}) \\ \cdots \\ \frac{\partial}{\partial \mathbf{x}} f_m(\mathbf{x}) \end{bmatrix} \\
&= \begin{bmatrix} \frac{\partial}{\partial x_1} f_1(\mathbf{x}) & \frac{\partial}{\partial x_2} f_1(\mathbf{x}) & \cdots & \frac{\partial}{\partial x_n} f_1(\mathbf{x}) \\ \frac{\partial}{\partial x_1} f_2(\mathbf{x}) & \frac{\partial}{\partial x_2} f_2(\mathbf{x}) & \cdots & \frac{\partial}{\partial x_n} f_2(\mathbf{x}) \\ & & \cdots & \\ \frac{\partial}{\partial x_1} f_m(\mathbf{x}) & \frac{\partial}{\partial x_2} f_m(\mathbf{x}) & \cdots & \frac{\partial}{\partial x_n} f_m(\mathbf{x}) \end{bmatrix} \\
&= \begin{bmatrix} \frac{\partial}{\partial x_1} x_1 & \frac{\partial}{\partial x_2} x_1 & \cdots & \frac{\partial}{\partial x_n} x_1 \\ \frac{\partial}{\partial x_1} x_2 & \frac{\partial}{\partial x_2} x_2 & \cdots & \frac{\partial}{\partial x_n} x_2 \\ & & \cdots & \\ \frac{\partial}{\partial x_1} x_n & \frac{\partial}{\partial x_2} x_n & \cdots & \frac{\partial}{\partial x_n} x_n \end{bmatrix} \\
&\quad \text{(and since } \frac{\partial}{\partial x_j} x_i = 0 \text{ for } j \neq i\text{)} \\
&= \begin{bmatrix} \frac{\partial}{\partial x_1} x_1 & 0 & \cdots & 0 \\ 0 & \frac{\partial}{\partial x_2} x_2 & \cdots & 0 \\ & & \ddots & \\ 0 & 0 & \cdots & \frac{\partial}{\partial x_n} x_n \end{bmatrix} \\
&= \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ & & \ddots & \\ 0 & 0 & \cdots & 1 \end{bmatrix} \\
&= I \quad (I \text{ is the identity matrix with ones down the diagonal})
\end{aligned}
$$



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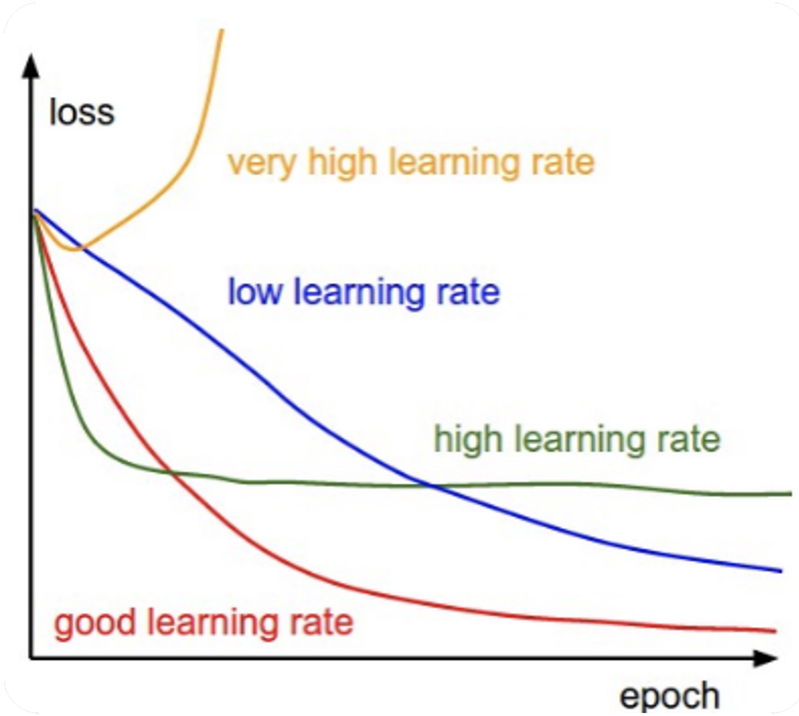
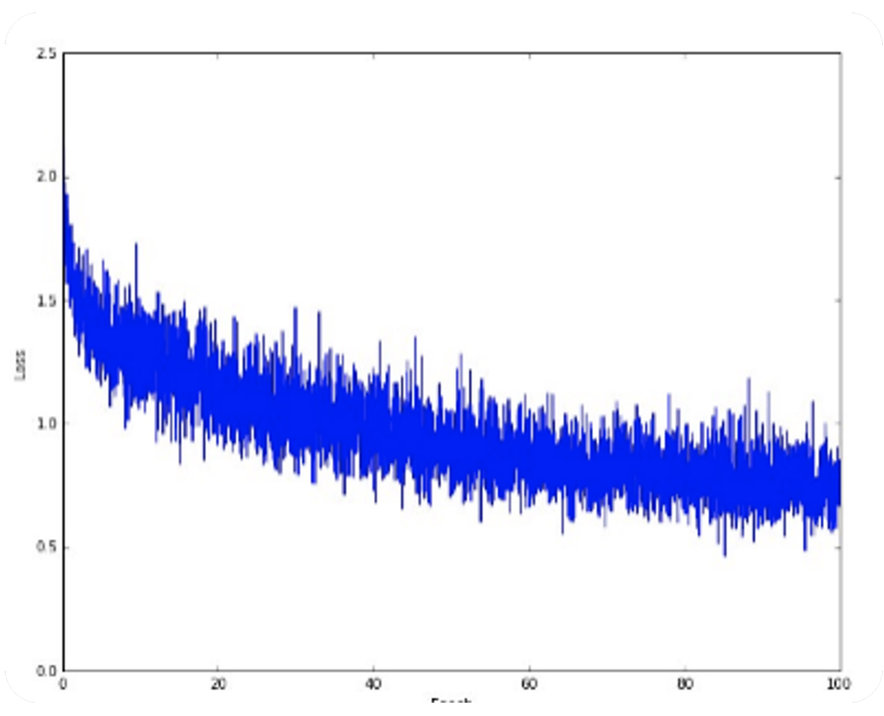
Gradient optimization

Stochastic gradient descent is used to optimize NN parameters

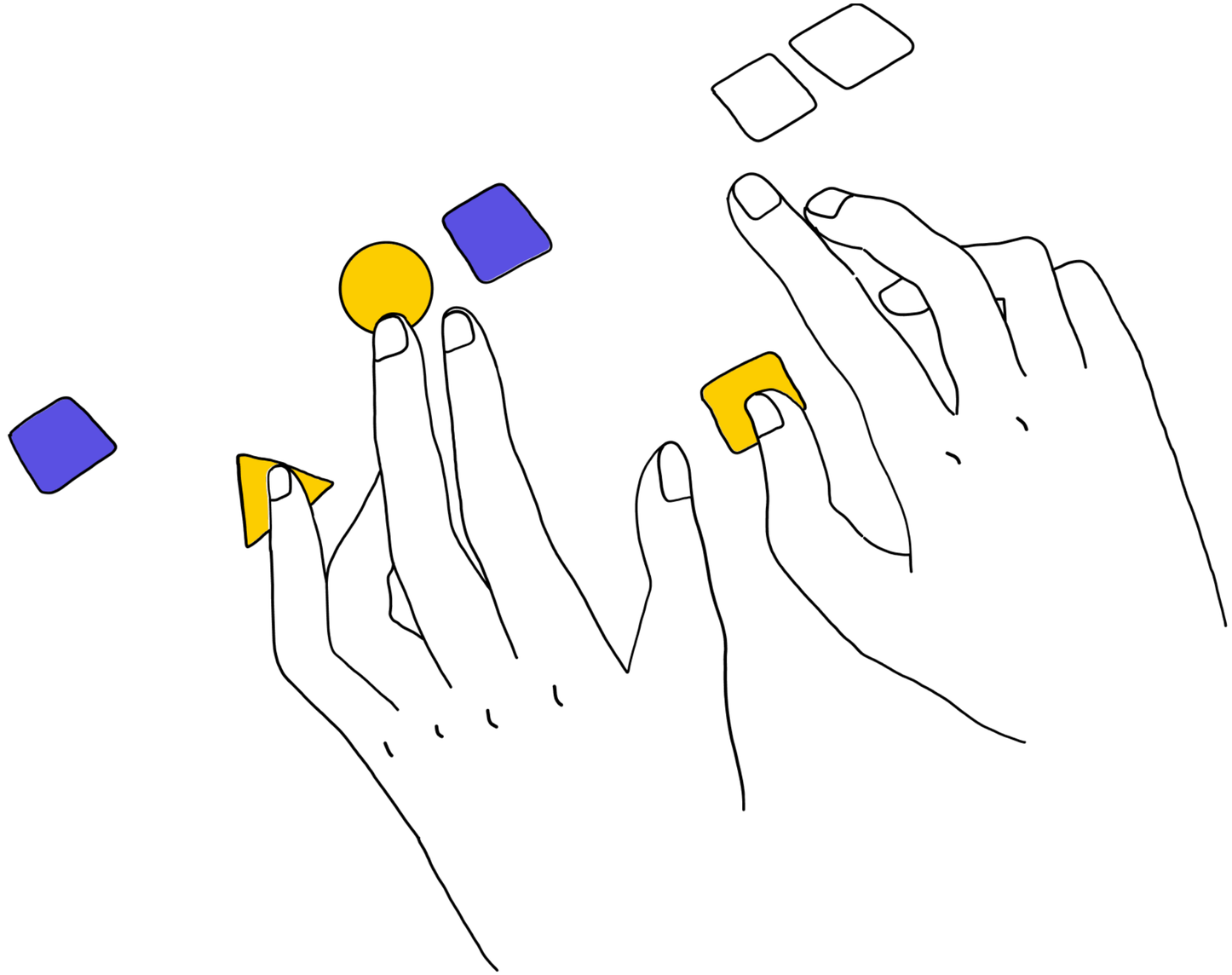
$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \frac{dL}{d\boldsymbol{w}}$$





source

Activation functions



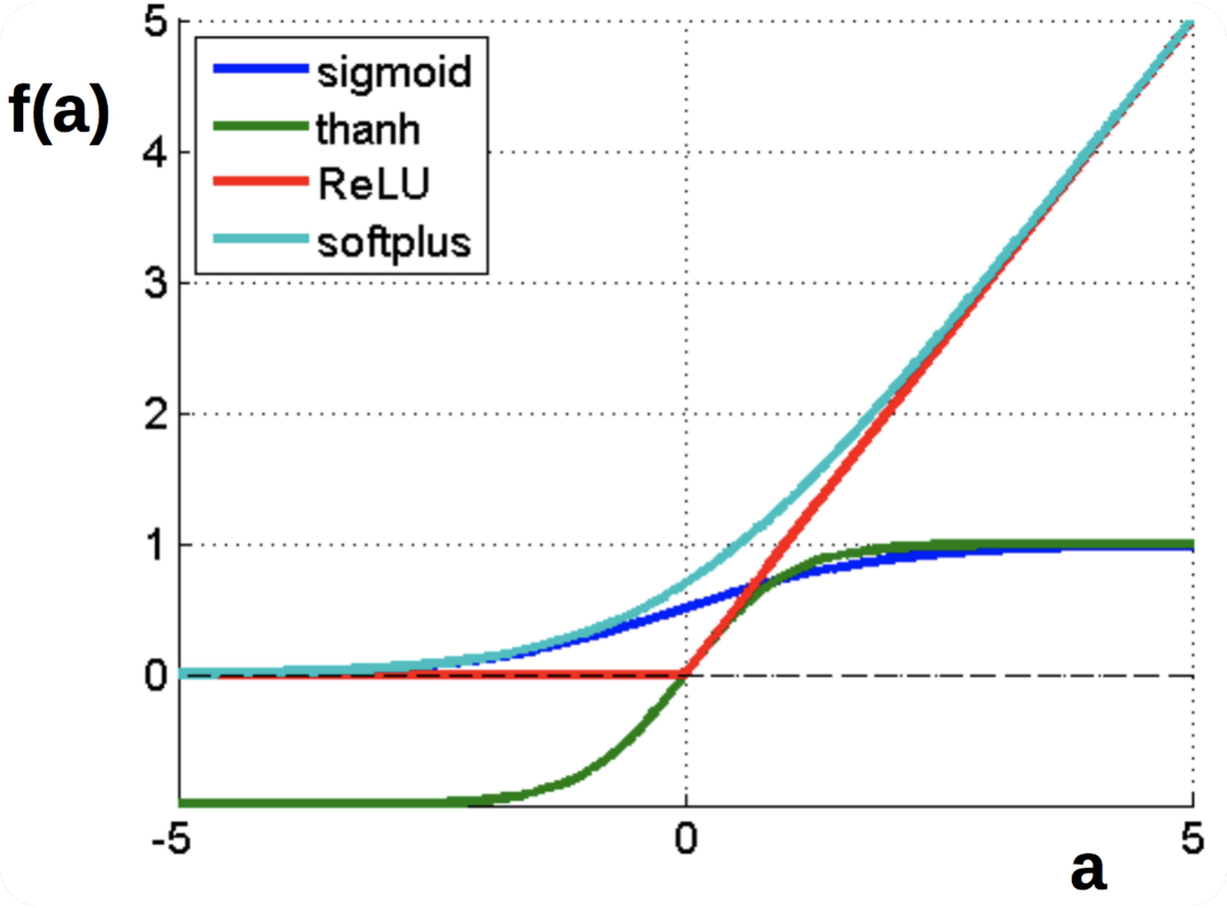
Once again: nonlinearities

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

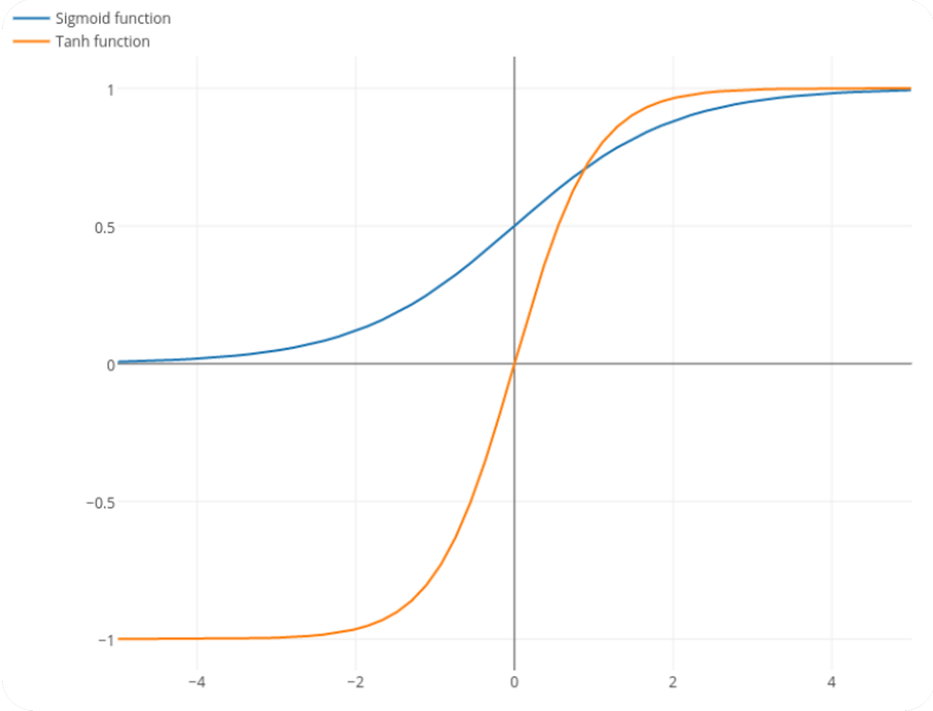
$$f(a) = \tanh(a)$$

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

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



Activation functions: Sigmoid



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

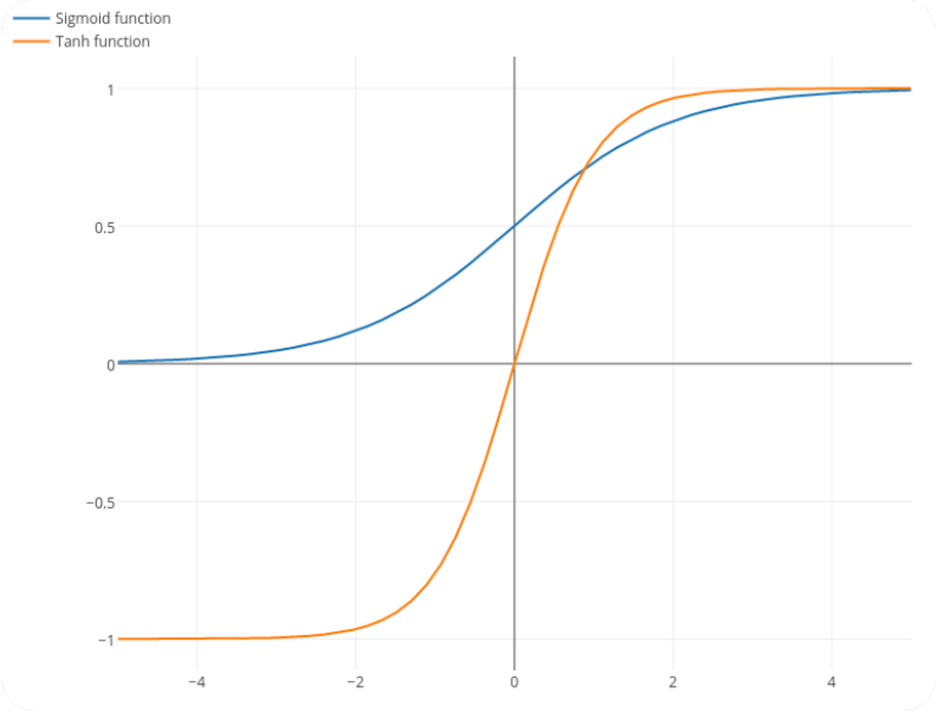
Maps R to (0,1)

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



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

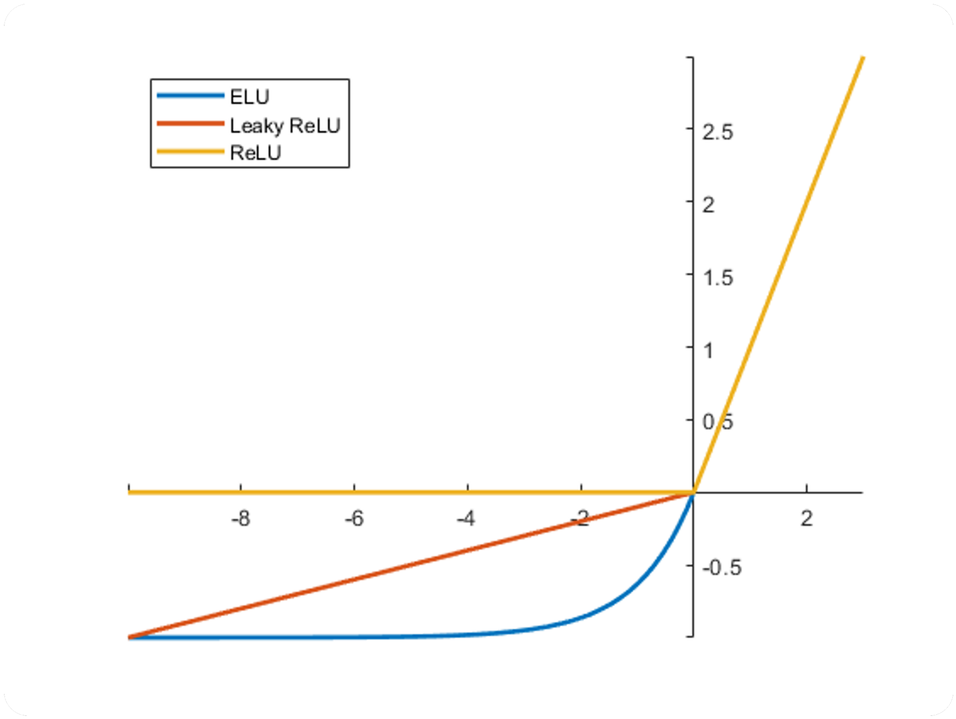
Maps R to (0,1)

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



$$\mathrm{ReLU}(a) = \max(\{0, a\})$$

Very simple to compute
(both forward and backward)

Up to 6 times faster than Sigmoid

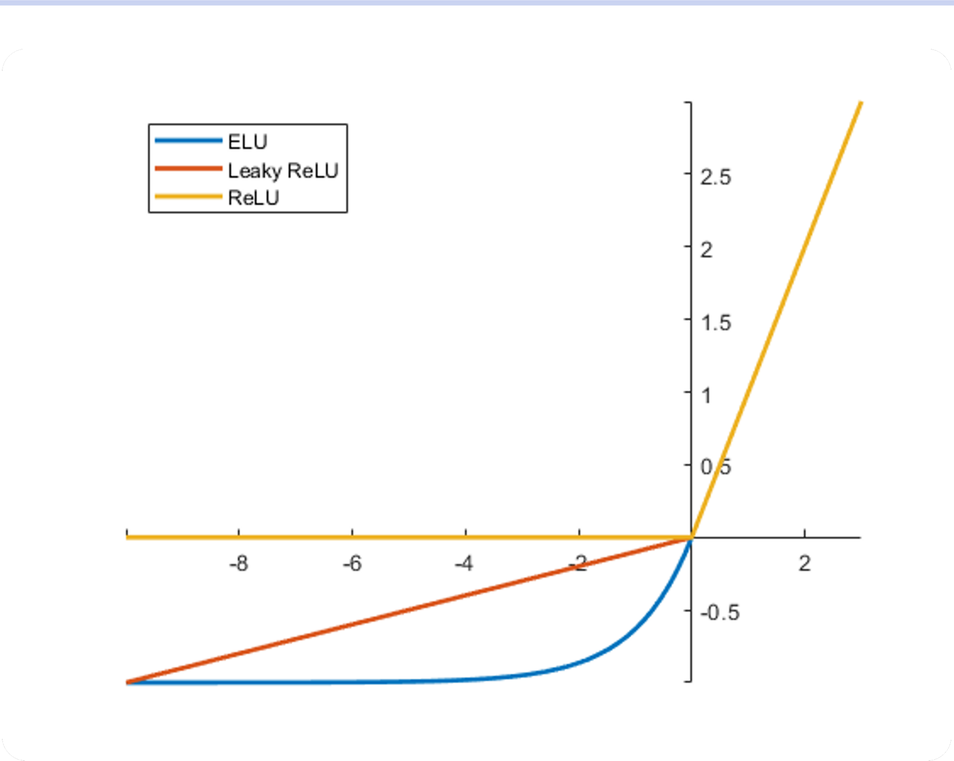
Does not saturate when x > 0

So the gradients are not 0

Problems:

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

Activation functions: Leaky ReLU



Very simple to compute
(both forward and backward)

Up to 6 times faster than Sigmoid

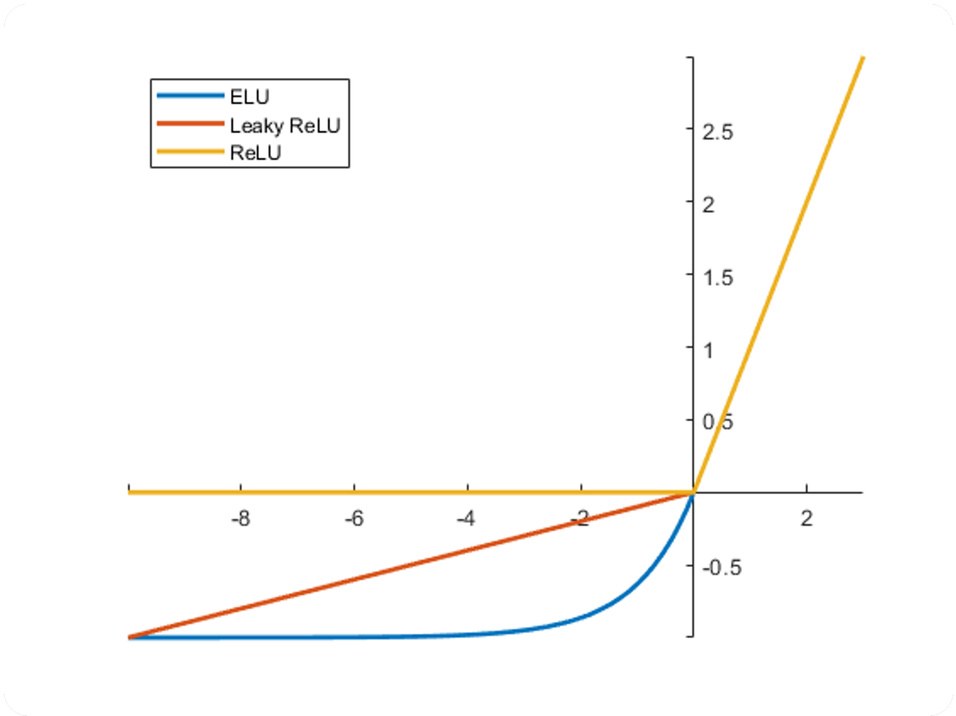
Does not saturate when x > 0

Problems:

- Shifted (not zero-centered) output

$$\text{Leaky ReLU}(a) = \max(\{0.01a, a\})$$

Activation functions: ELU



Similar to ReLU

Does not saturate

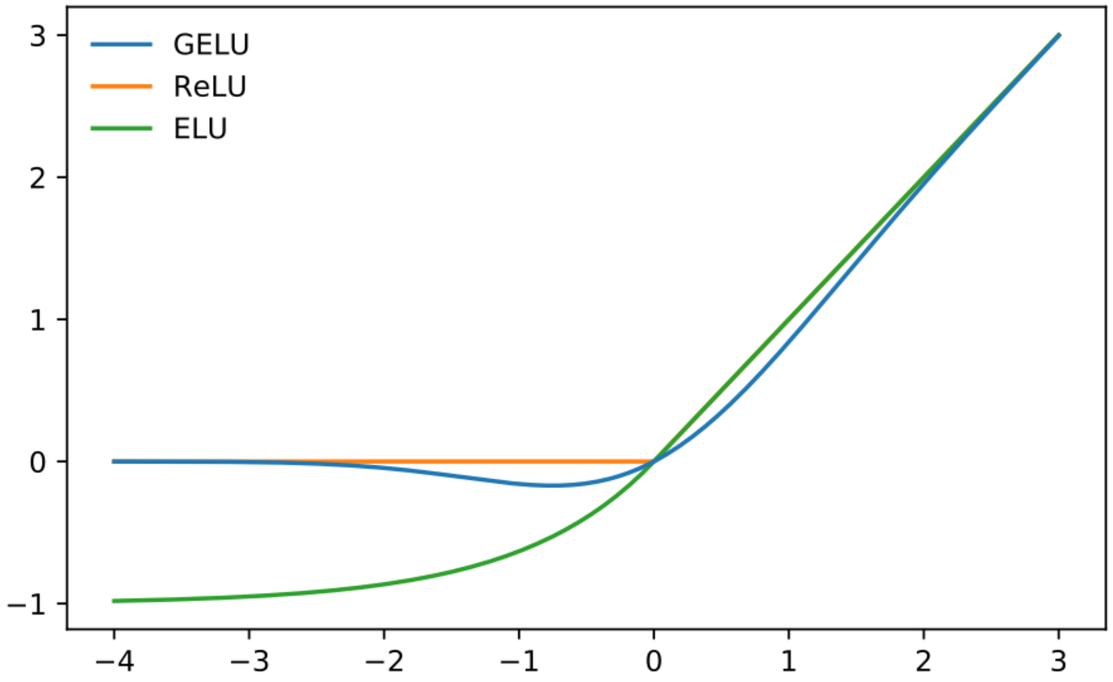
Close to zero mean outputs

Problems:

Requires exponent computation

$$\mathrm{ELU}(a) = \begin{cases} a & \text{if } a > 0 \\ \beta(\exp(a) - 1) & \text{if } a \leq 0 \end{cases}$$

Activation functions: GELU
Gaussian error linear unit



Outperforms ReLU and ELU according to the experiments

PyTorch's exact implementation is sufficiently fast such that these approximations may be unnecessary.

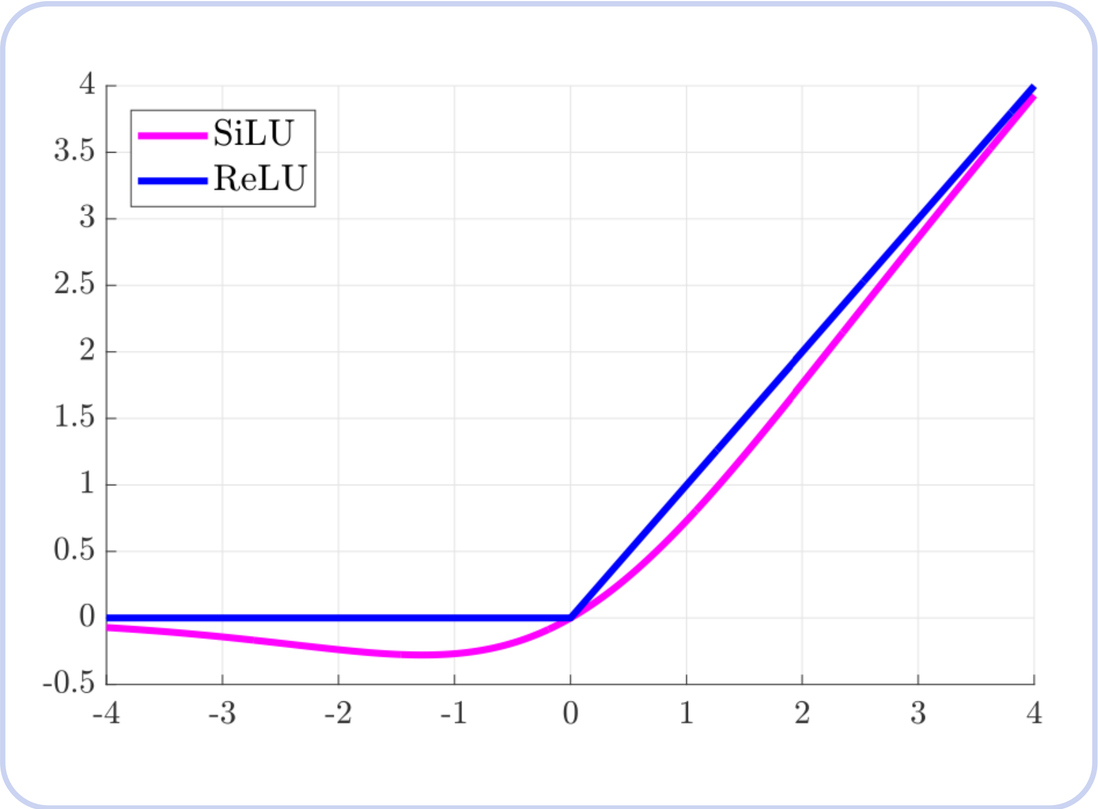
Problems:

Requires exponent computation

$$\mathrm{GELU}(a) = aP(X \leq a) = x\Phi(a) = \frac{1}{2}a\left[1 + \mathrm{erf}\left(\frac{a}{\sqrt{2}}\right)\right],\ X \in \mathcal{N}(0,1)$$

Paper link

Activation functions: SiLU
Sigmoid-weighted linear unit



Special case of Swish activation function

Originally proposed for RL algorithms

Problems:

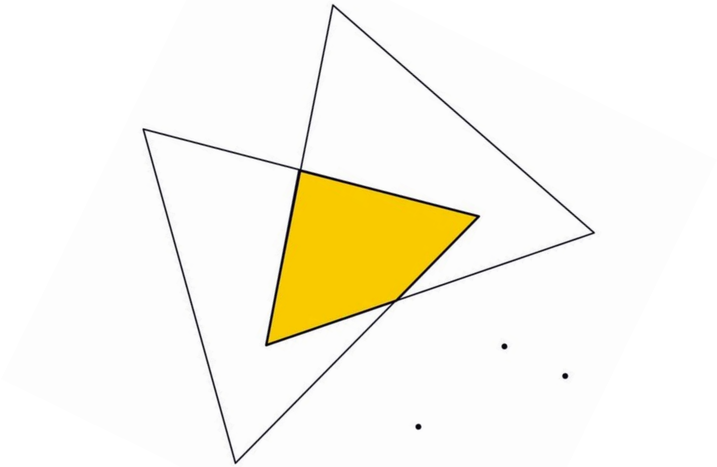
Requires exponent computation

$$\mathrm{SiLU}(a) = a\sigma(a)$$

Paper link

Activation functions: sum up

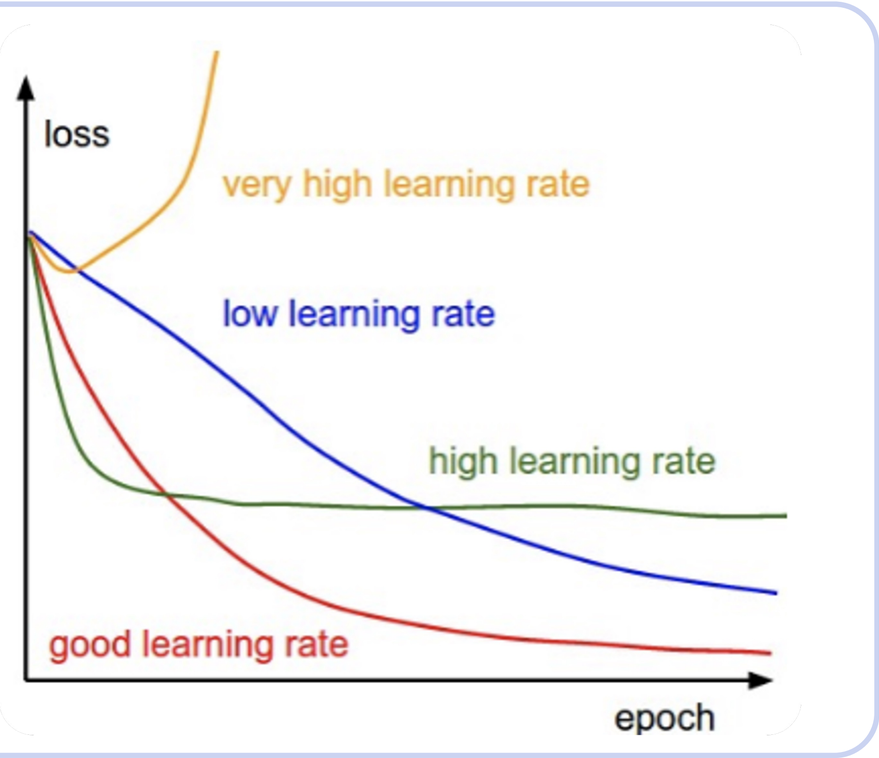
- Use ReLU as baseline approach
- Be careful with the learning rates
- Try out Leaky ReLU or ELU
- Try out tanh but do not expect much from it
- Sigmoid usually means binary classification somewhere close

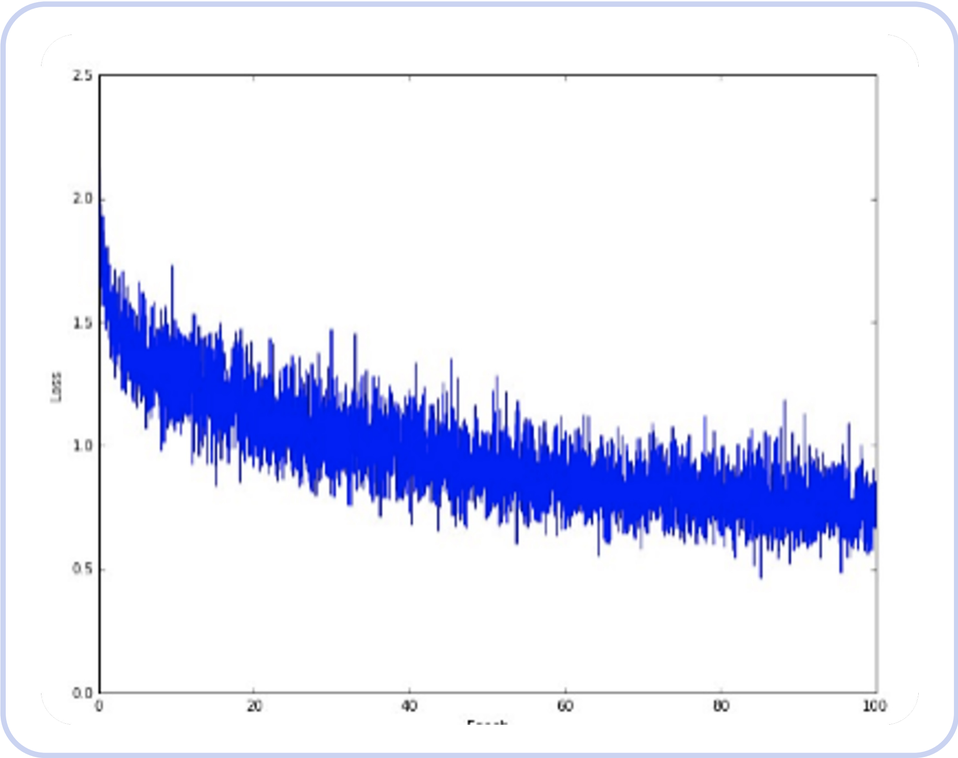


Once again: gradient optimization

Stochastic gradient descent is used to optimize NN parameters

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \frac{dL}{d\boldsymbol{w}}$$



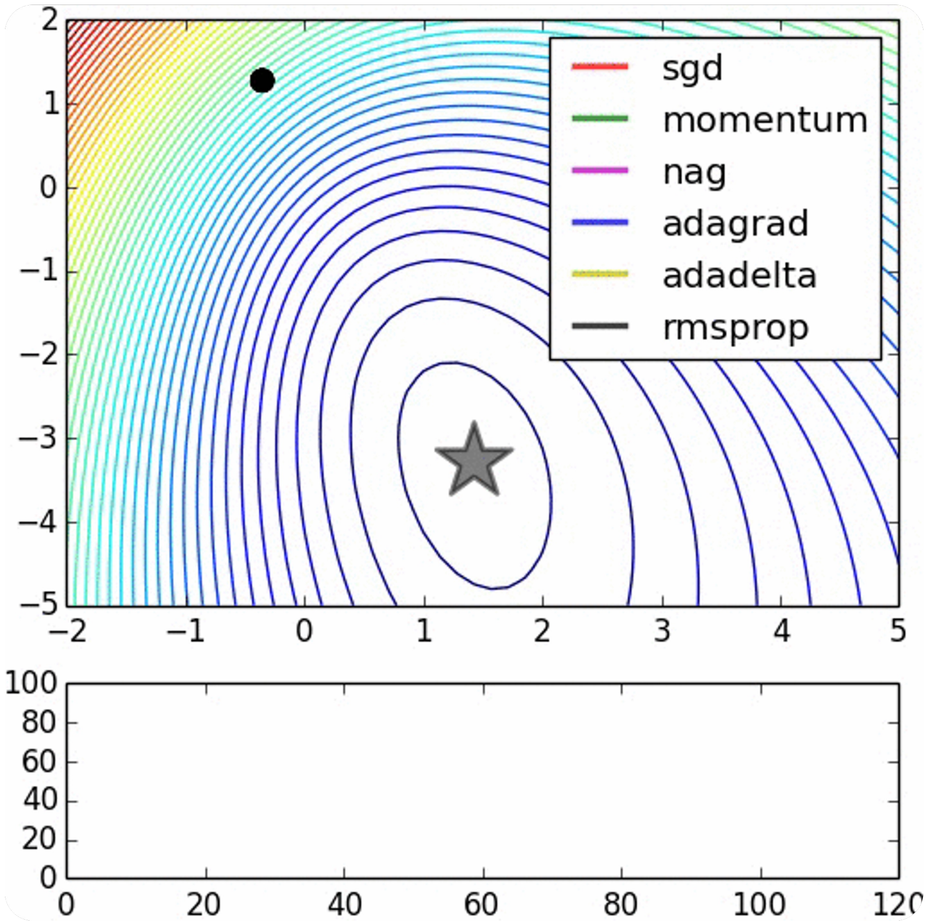


source

Optimizers

There are much more optimizers:

- Momentum
- Adagrad
- Adadelta
- RMSprop
- Adam
- ...
- even other NNs



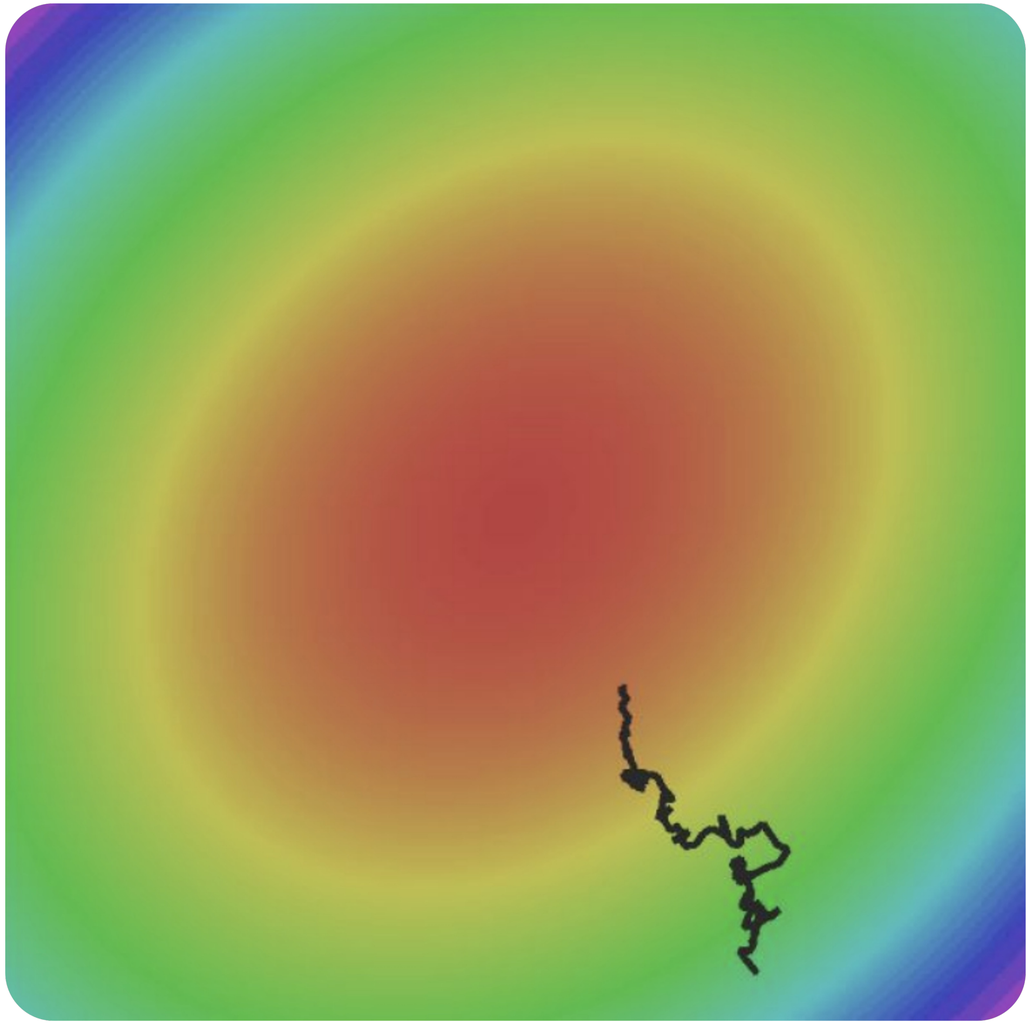
source

Optimization: SGD

$$L(\boldsymbol{w}) = \frac{1}{K}\sum_{i=1}^{K} L(\boldsymbol{x}^{(i)}, y^{(i)}, \boldsymbol{w})$$

$$\nabla_{\boldsymbol{w}} L(\boldsymbol{w}) = \frac{1}{K}\sum_{i=1}^{K} \nabla_{\boldsymbol{w}} L(\boldsymbol{x}^{(i)}, y^{(i)}, \boldsymbol{w})$$

Averaging over minibatches leads to noisy gradient estimation



source

First idea: momentum

Simple SGD

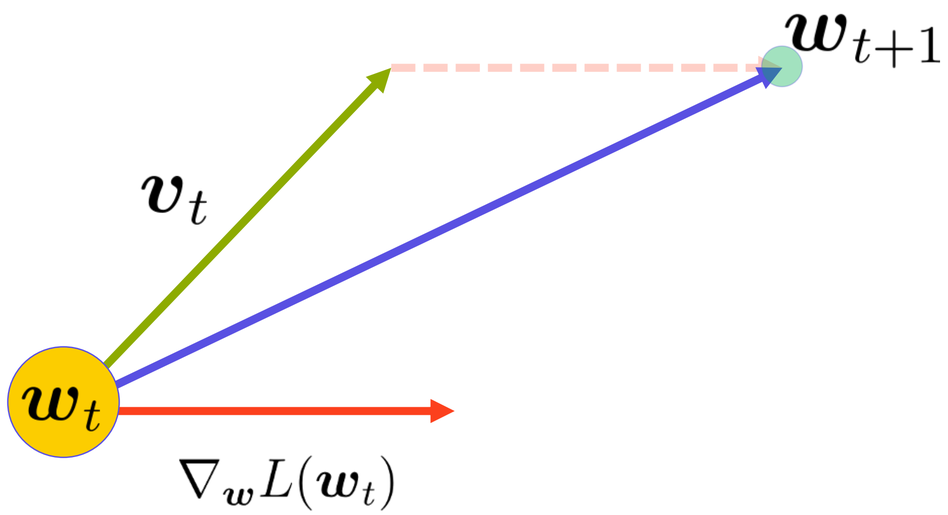
$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \nabla_{\boldsymbol{w}} L(\boldsymbol{w}_t)$$

SGD with momentum

$$\boldsymbol{v}_{t+1} = \rho \boldsymbol{v}_t + \nabla_{\boldsymbol{w}} L(\boldsymbol{w}_t)$$

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \boldsymbol{v}_{t+1}$$

Momentum update:



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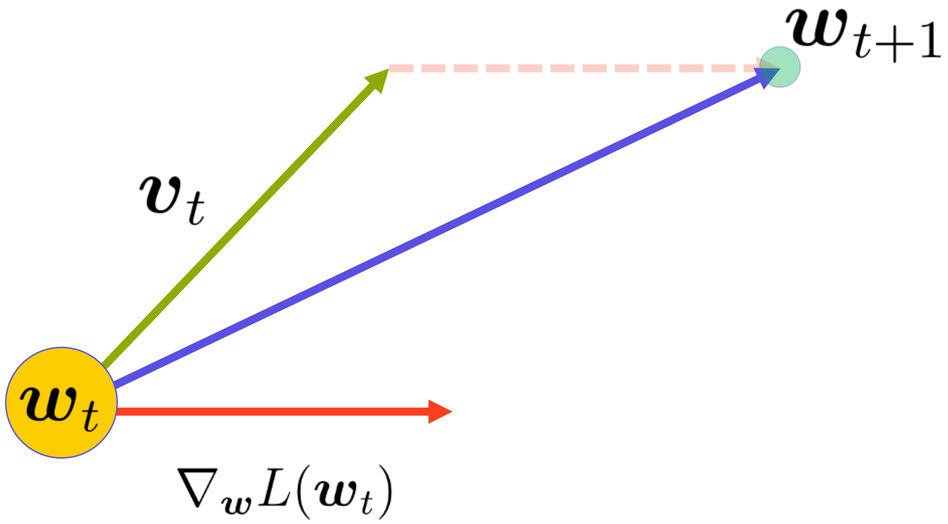
Nesterov momentum

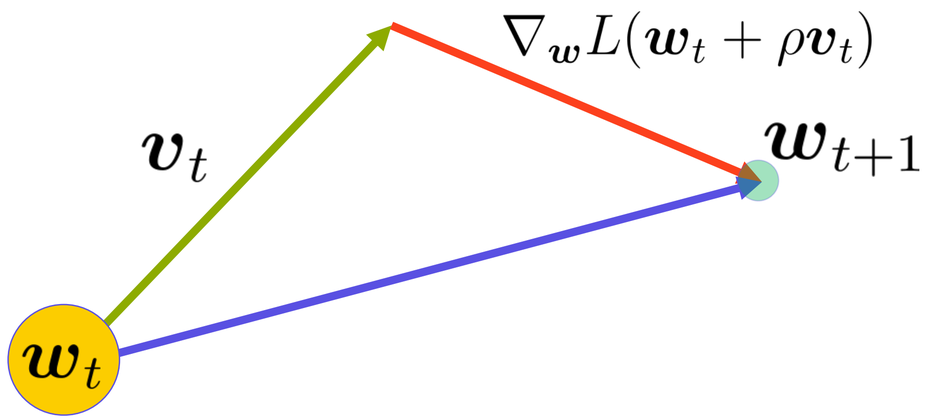
Momentum update:



$$\boldsymbol{v}_{t+1} = \rho \boldsymbol{v}_t + \nabla_{\boldsymbol{w}} L(\boldsymbol{w}_t)$$

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \boldsymbol{v}_{t+1}$$

Nesterov Momentum

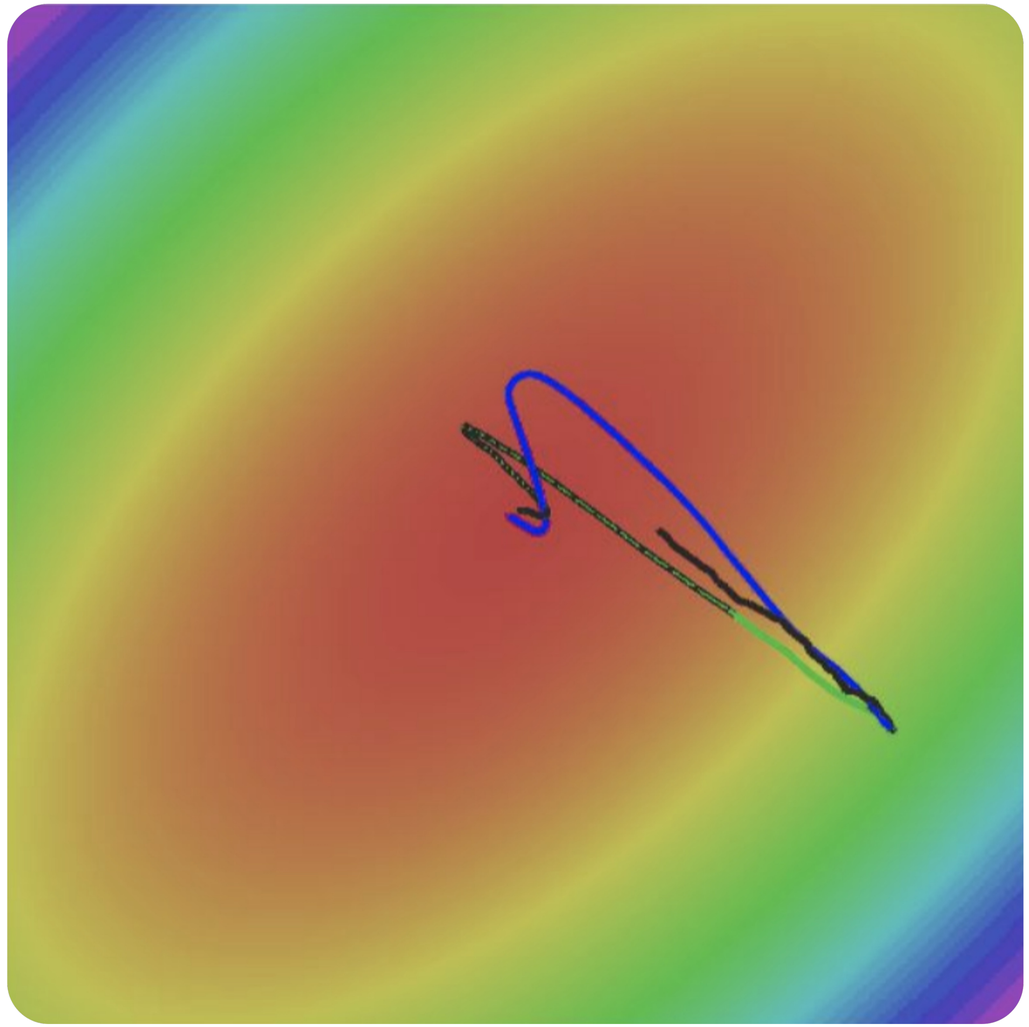


$$\boldsymbol{v}_{t+1} = \rho \boldsymbol{v}_t + \nabla_{\boldsymbol{w}} L(\boldsymbol{w}_t + \rho \boldsymbol{v}_t)$$

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \eta \boldsymbol{v}_{t+1}$$

source

Comparing momentums



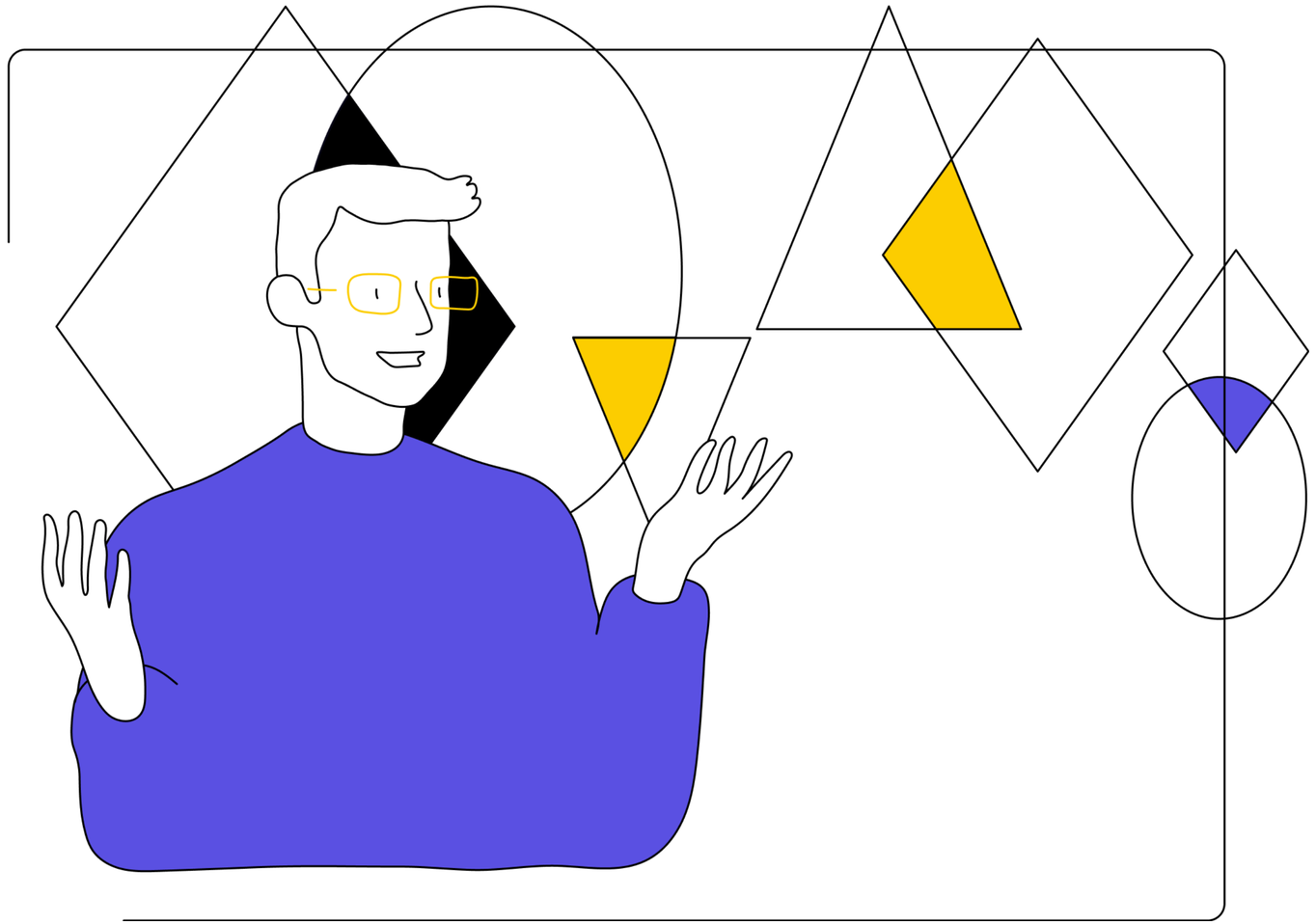
SGD

SGD+Momentum

Nesterov

source

Fancy (tiny) 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 $X_{\acute{e}tale}$ 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

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

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

Proof. Omitted. □

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(1) $\mathcal{F}$ is an algebraic space over S.
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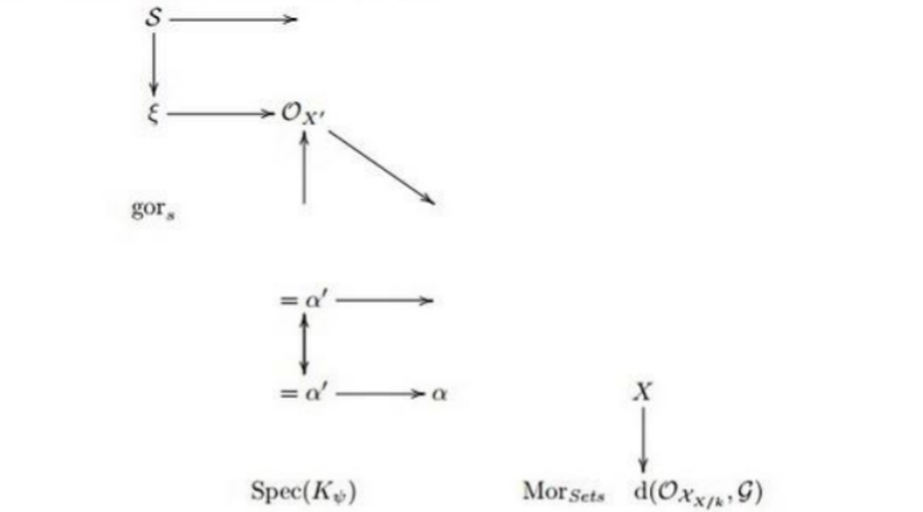
Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. □

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

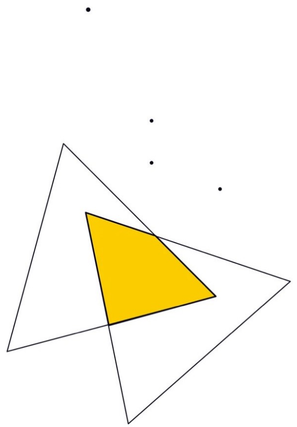
$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} \quad \text{-1}(\mathcal{O}_{X_{étale}}) \longrightarrow \mathcal{O}_{X_\ell}^{-1}\mathcal{O}_{X_\lambda}(\mathcal{O}_{X_\eta}^{\overline{v}})$$

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.

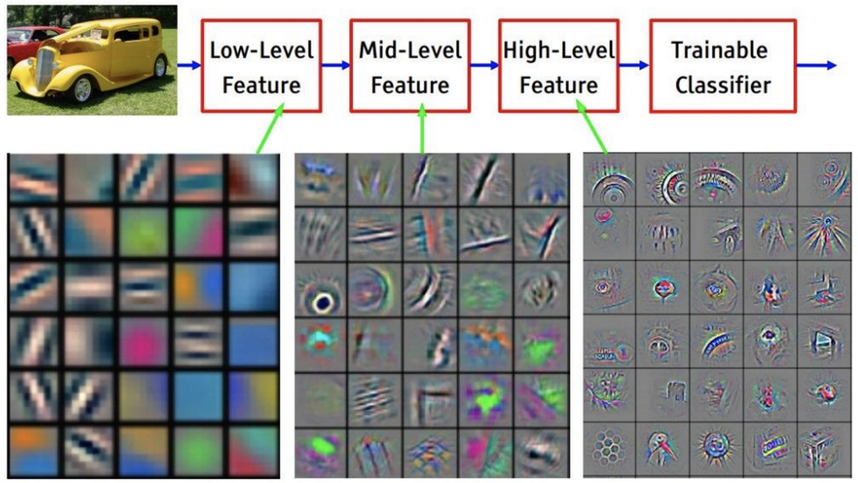
source

```
#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;
}
```

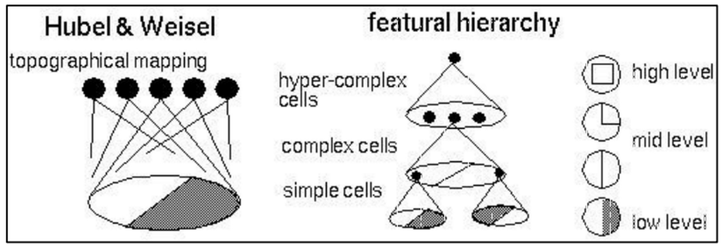


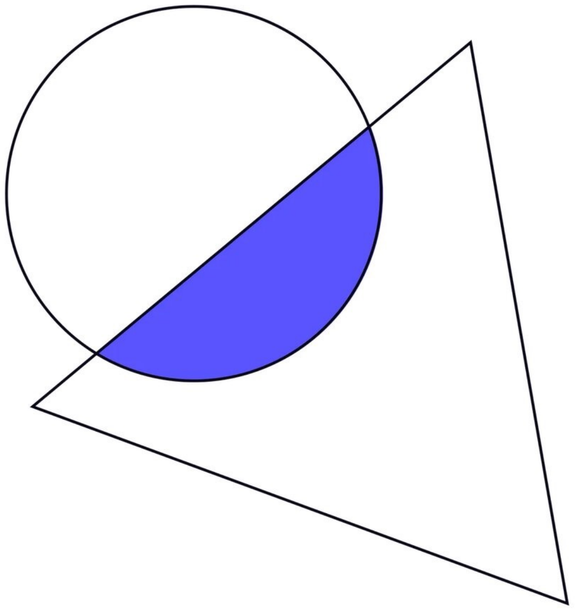
source

CNN:
Convolutional layer and visual cortex



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





[From Yann LeCun slides]

CNN:
Convolutional layer and visual cortex

source

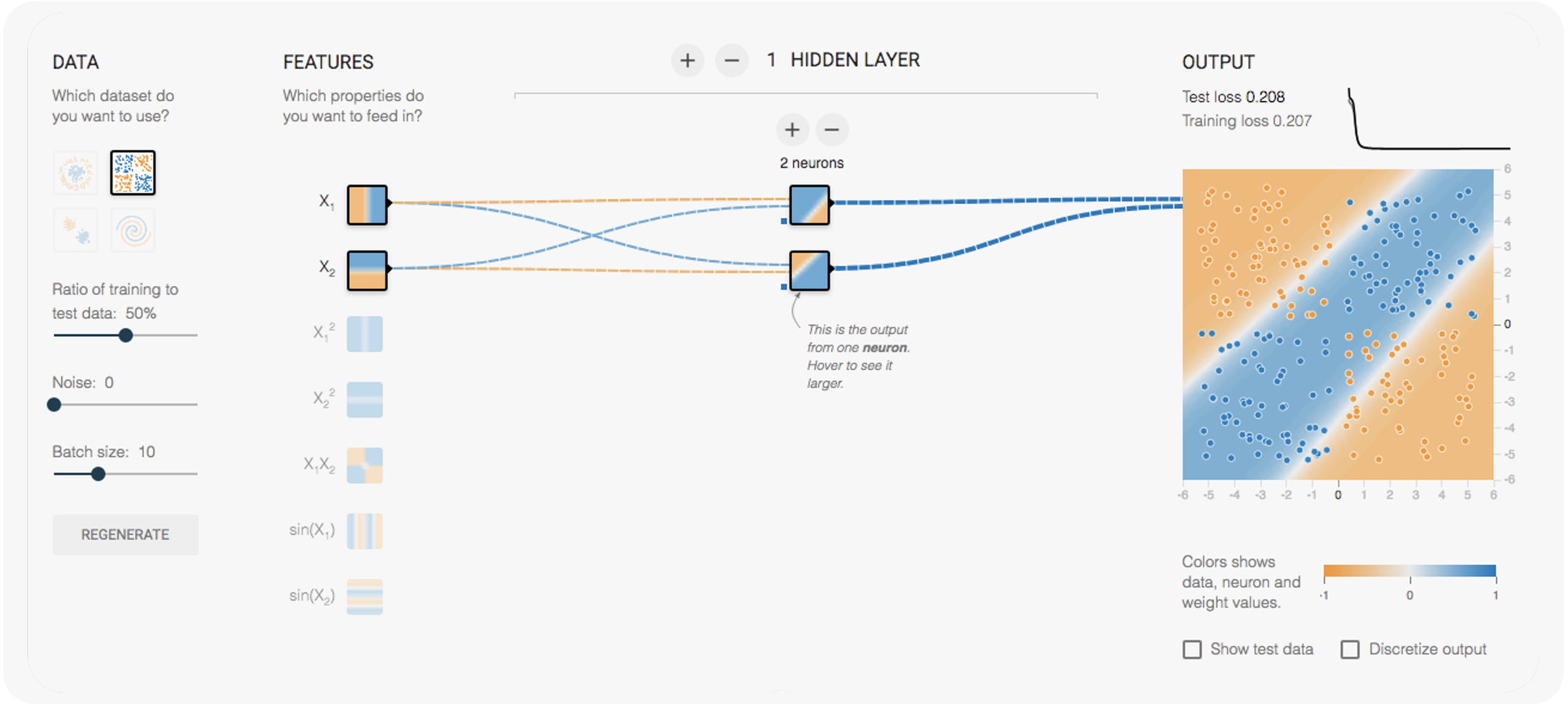
nanoGPT

available GPT implementations

~~minGPT~~ nanoGPT

Repo link

Don’t miss the interactive playground



source

WHO’S AWESOME?

You’re Awesome

Outro

01 Neural Networks are great

Especially for data with specific structure

02 All operations should be differentiable to use backpropagation mechanics

And still it is just basic differentiation

03 Many techniques in Deep Learning are inspired by nature

Or general sense

04 Do not hesitate to ask questions (and answer them as well)

More materials for self-study: link

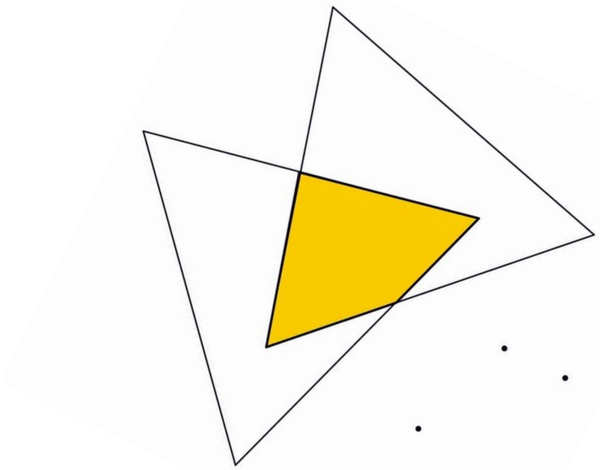
Backup

Second idea: different dimensions are different

01 Adagrad:
SGD with cache

$$\text{cache}_{t+1} = \text{cache}_t + (\nabla f(x_t))^2$$

$$x_{t+1} = x_t - \alpha \frac{\nabla f(x_t)}{\text{cache}_{t+1} + \varepsilon}$$



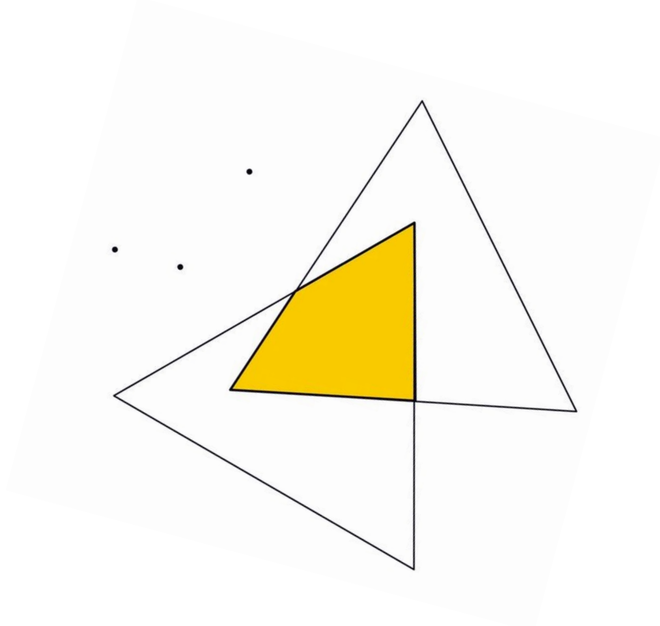
Second idea: different dimensions are different

01 Adagrad:
SGD with cache

$$\text{cache}_{t+1} = \text{cache}_t + (\nabla f(x_t))^2$$

$$x_{t+1} = x_t - \alpha \frac{\nabla f(x_t)}{\text{cache}_{t+1} + \varepsilon}$$

Problem: gradient fades with time



Second idea: different dimensions are different

01 Adagrad:
SGD with cache

$$\text{cache}_{t+1} = \text{cache}_t + (\nabla f(x_t))^2$$

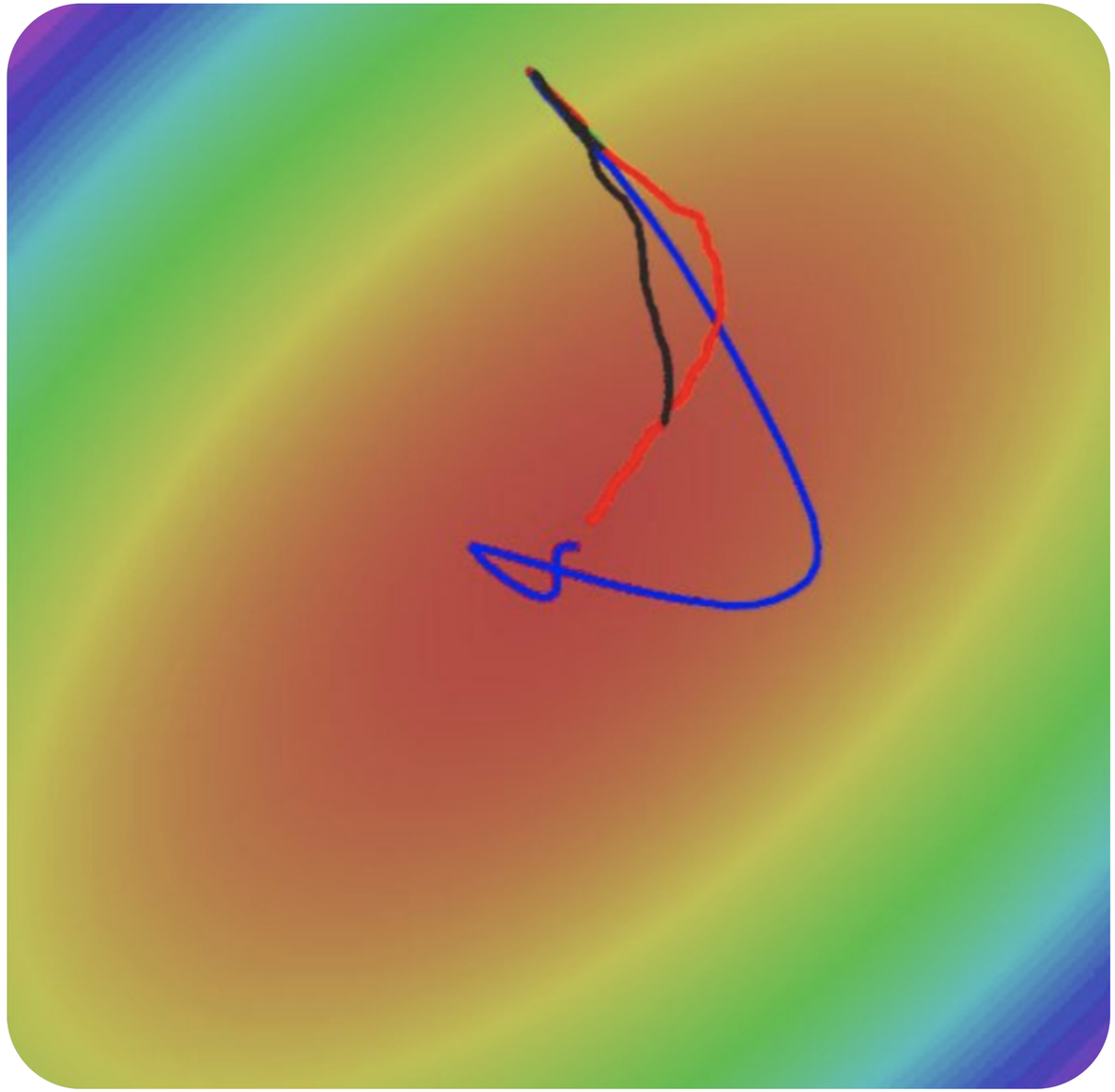
$$x_{t+1} = x_t - \alpha \frac{\nabla f(x_t)}{\text{cache}_{t+1} + \varepsilon}$$

02 RMSProp: SGD with cache
with exp. Smoothing

$$\text{cache}_{t+1} = \beta \text{cache}_t + (1-\beta)(\nabla f(x_t))^2$$

$$x_{t+1} = x_t - \alpha \frac{\nabla f(x_t)}{\text{cache}_{t+1} + \varepsilon}$$

Slide 29 Lecture 6 of Geoff Hinton's Coursera class



SGD

SGD+Momentum

RMSProp

source

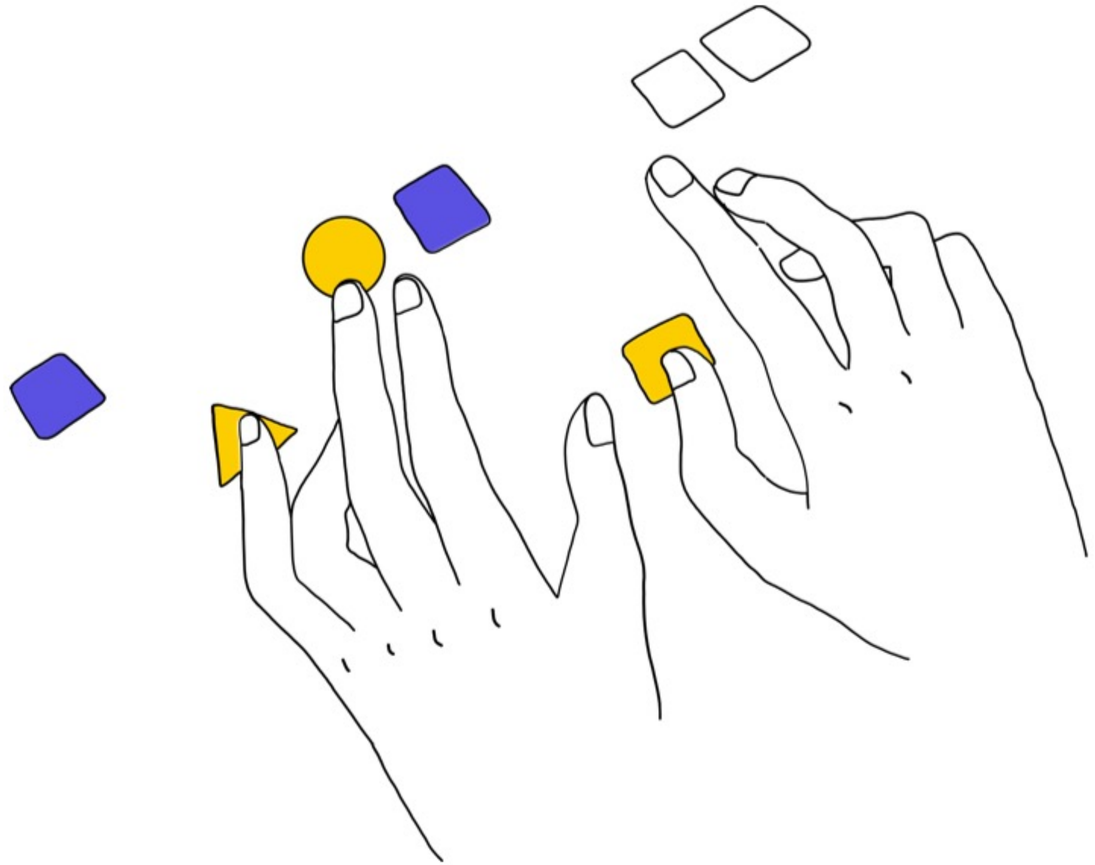
Adam

Let’s combine the momentum idea and RMSProp normalization:

$$v_{t+1} = \gamma v_t + (1-\gamma)\nabla f(x_t)$$

$$\text{cache}_{t+1} = \beta \text{cache}_t + (1-\beta)(\nabla f(x_t))^2$$

$$x_{t+1} = x_t - \alpha \frac{v_{t+1}}{\text{cache}_{t+1} + \varepsilon}$$



Adam full form involves bias correction term. See link for more info.

Adam

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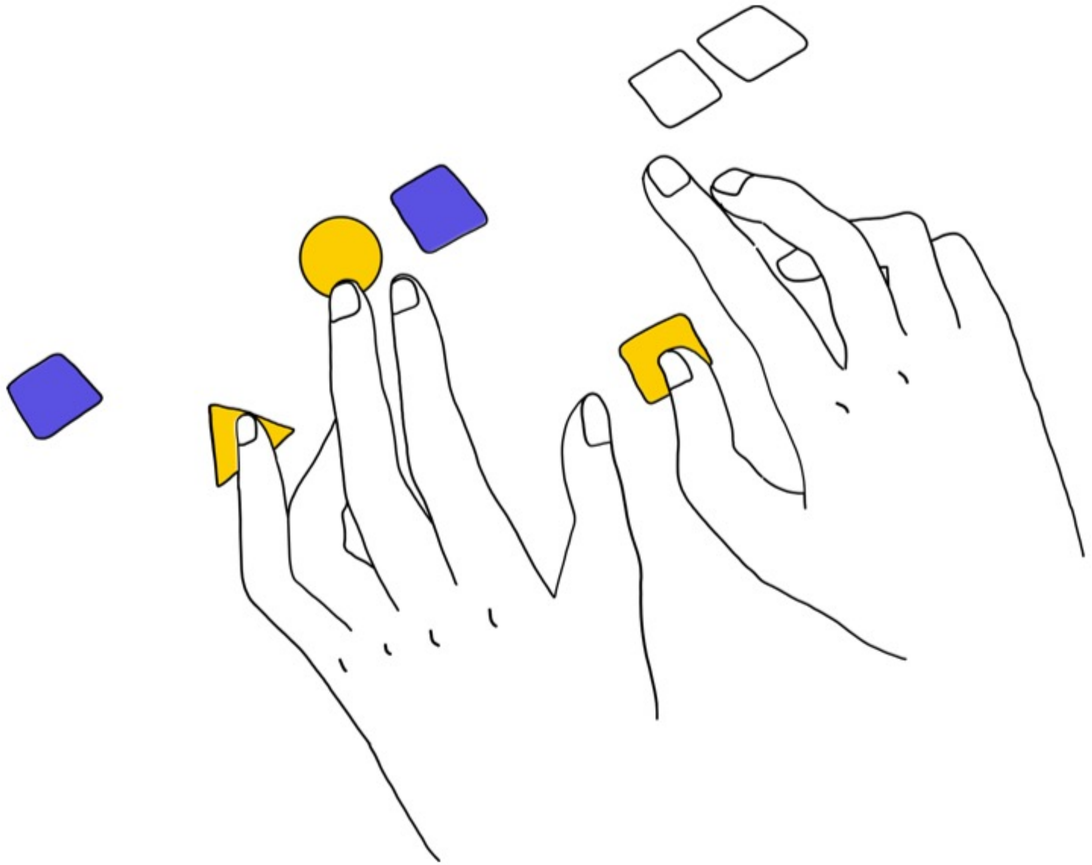
$$v_{t+1} = \gamma v_t + (1-\gamma)\nabla f(x_t)$$
$$\text{cache}_{t+1} = \beta \text{cache}_t + (1-\beta)(\nabla f(x_t))^2$$
$$x_{t+1} = x_t - \alpha \frac{v_{t+1}}{\text{cache}_{t+1} + \varepsilon}$$

Actually, that's not quite Adam



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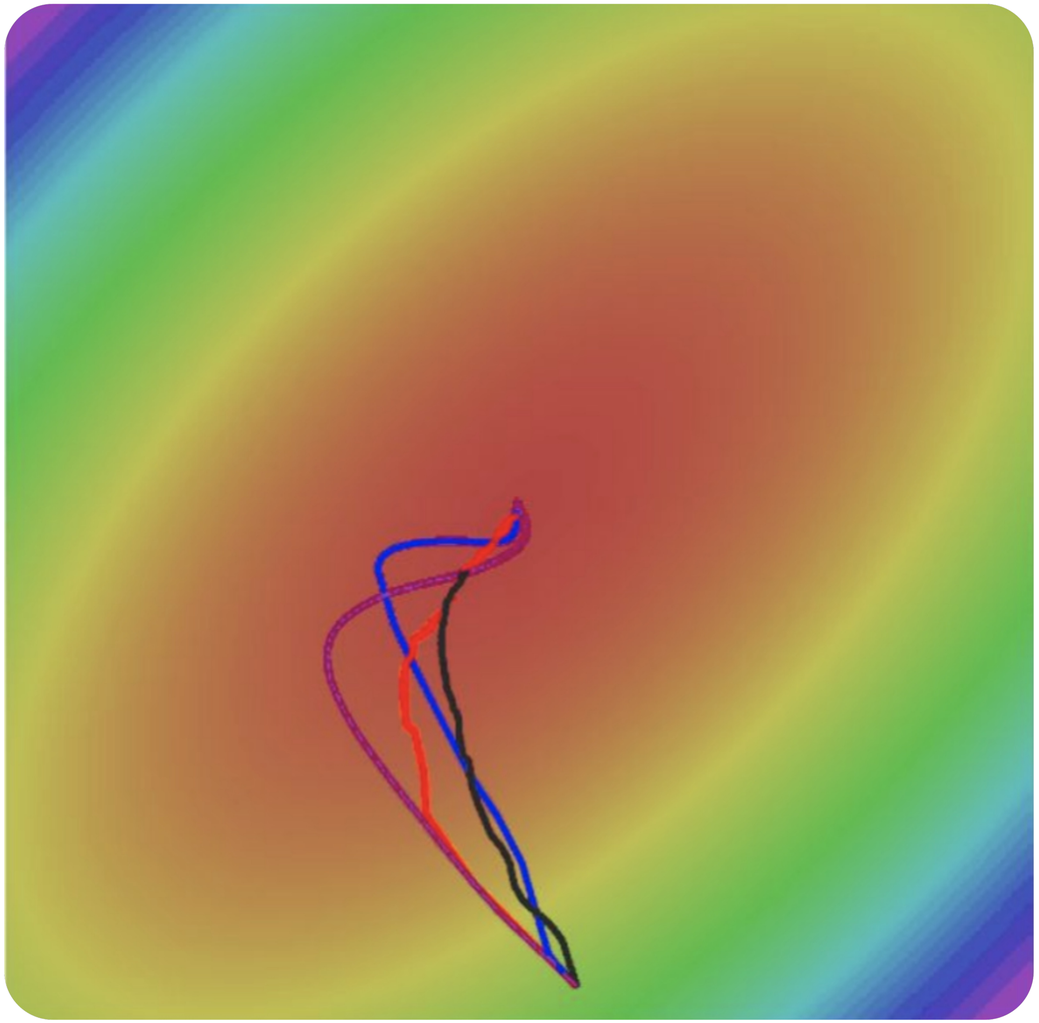
Comparing optimizers



SGD

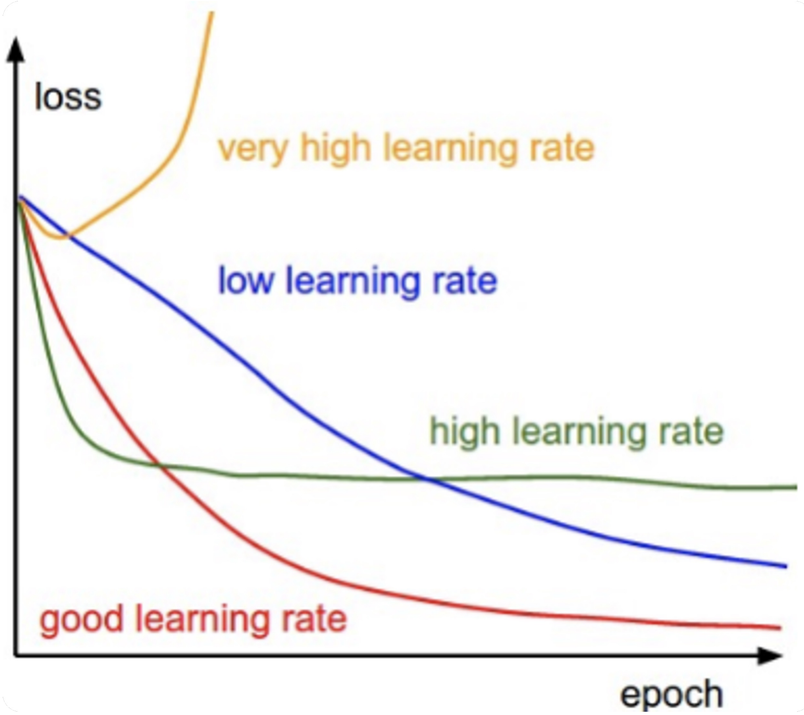
SGD+Momentum

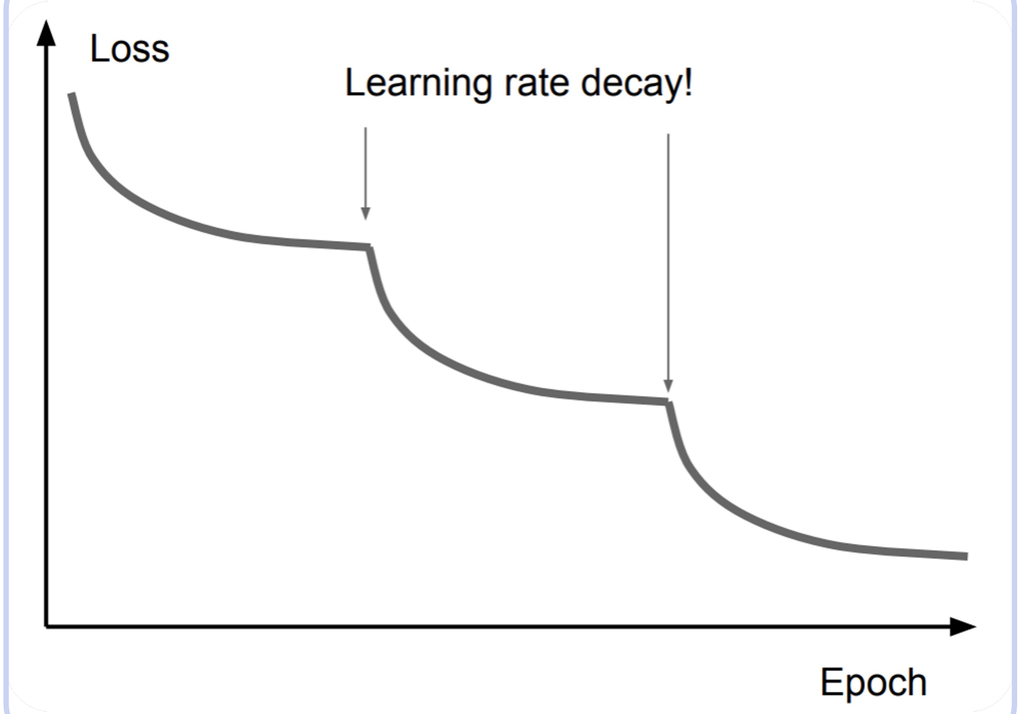
RMSProp

Adam

source

Once more: learning rate





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Sum up: optimization

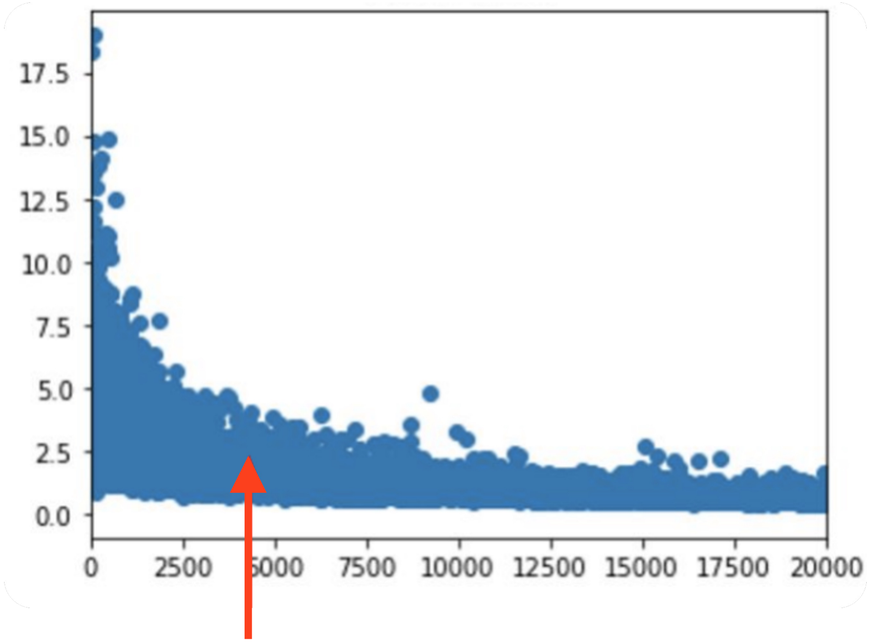
01 Adam is great basic choice

02 Even for Adam/RMSProp learning rate matters

03 Use learning rate decay

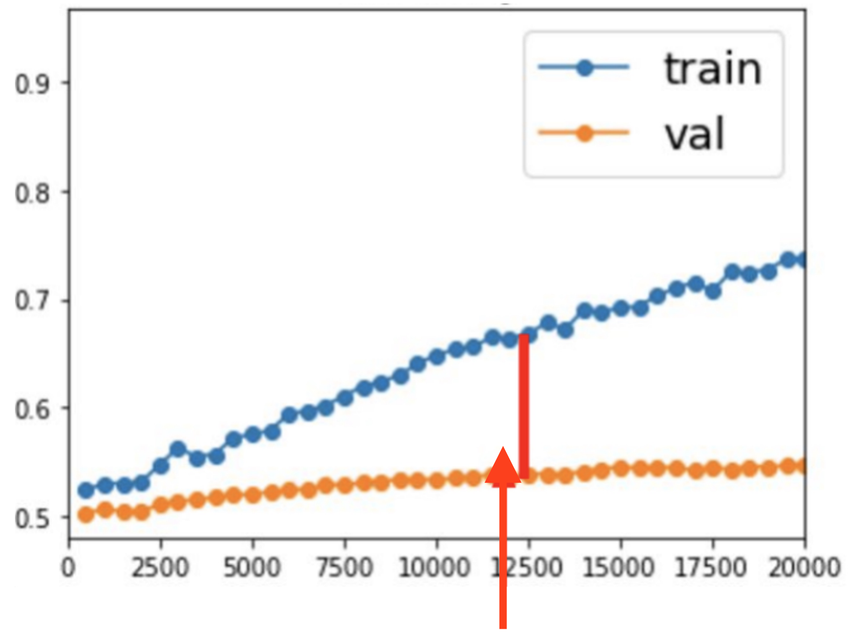
04 Monitor your model quality

Train Loss



Better optimization algorithms help reduce training loss

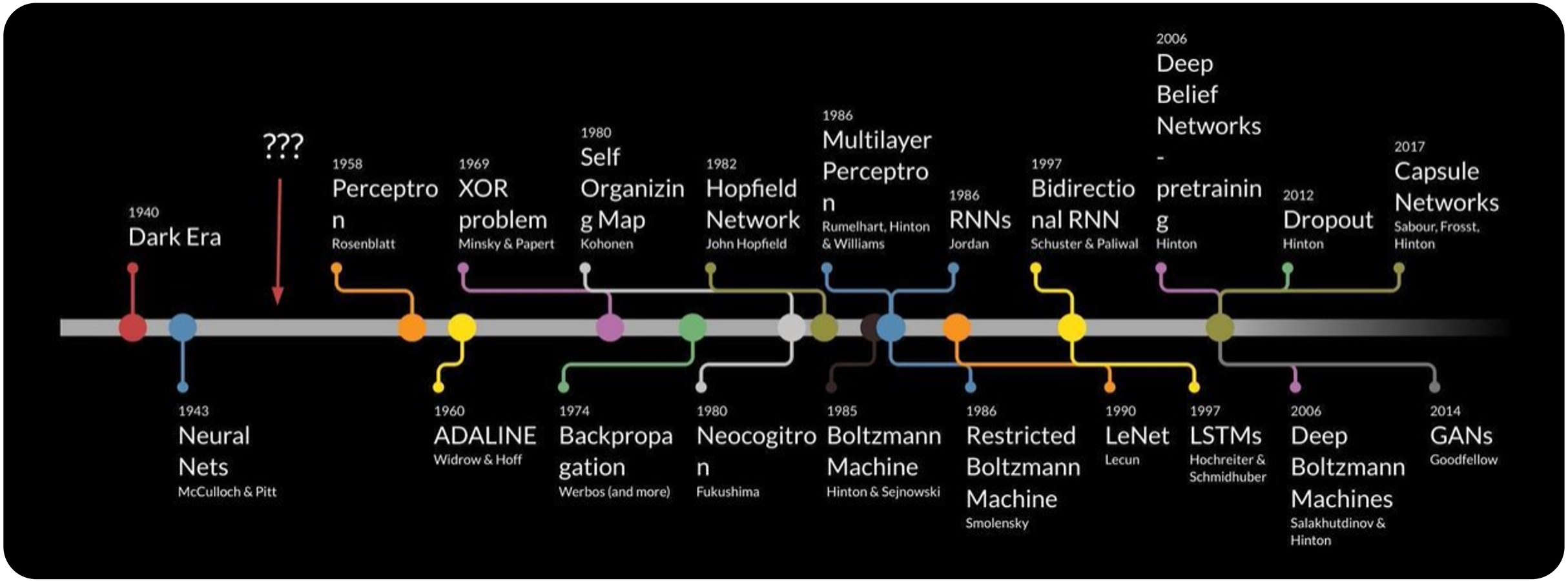
Accuracy



But we really care about error on new data — how to reduce the gap?

source

Deep Learning Timeline



Revise

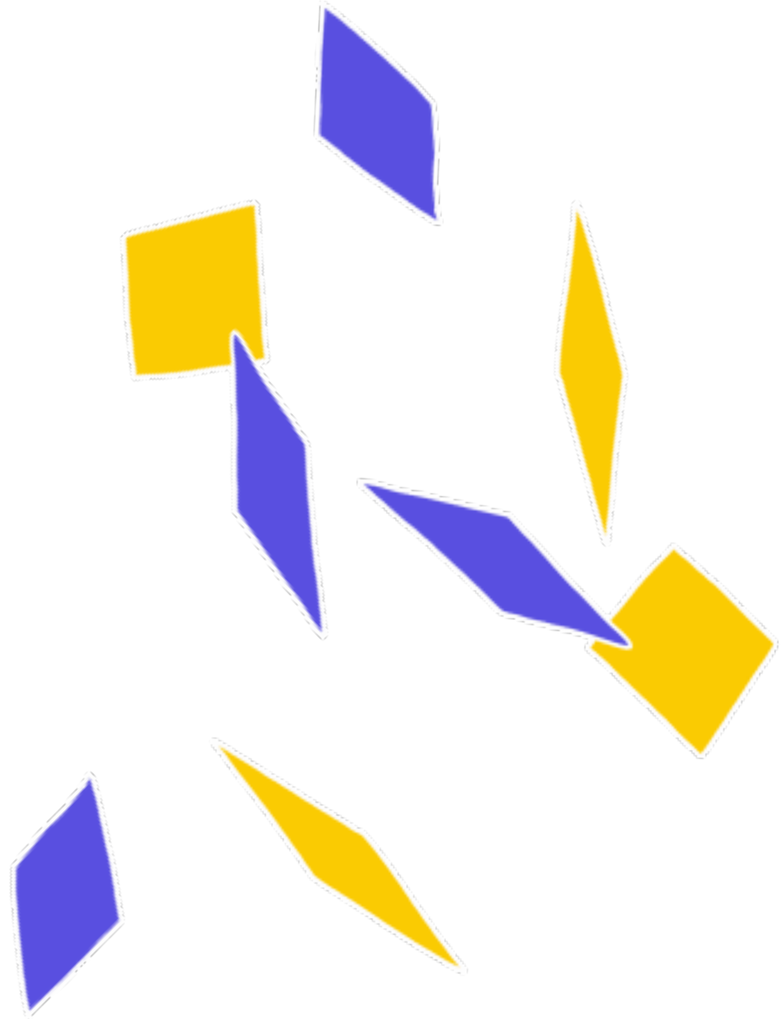
01 Neural Networks in different areas.
Historical overview

02 Backpropagation

03 More on backpropagation

04 Activation functions

05 Playground



Thanks for attention!

Questions?

girafe ai