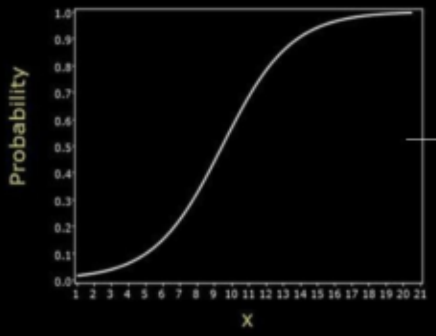
Deep Learning: intuition

Logistic regression

X → Wx +b →

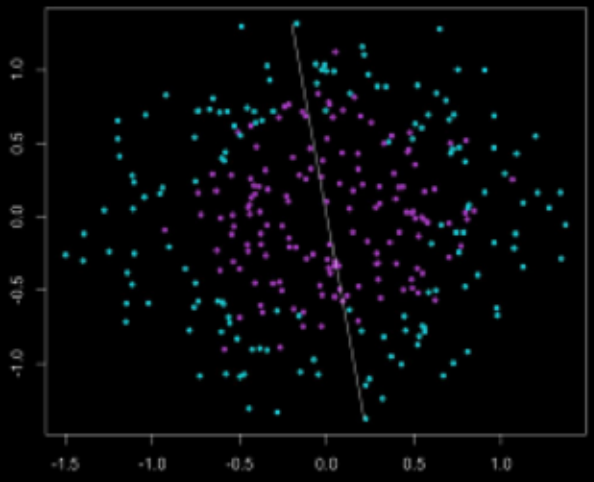


→ P(y)

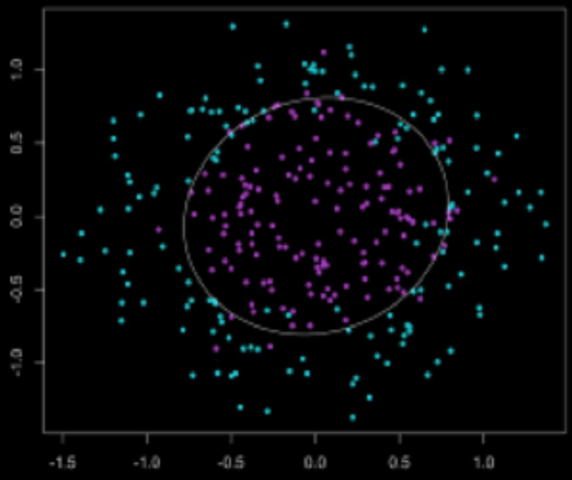
$$P(y|x)=\sigma(w\cdot x+b)$$

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

Problem: nonlinear dependencies



What we have

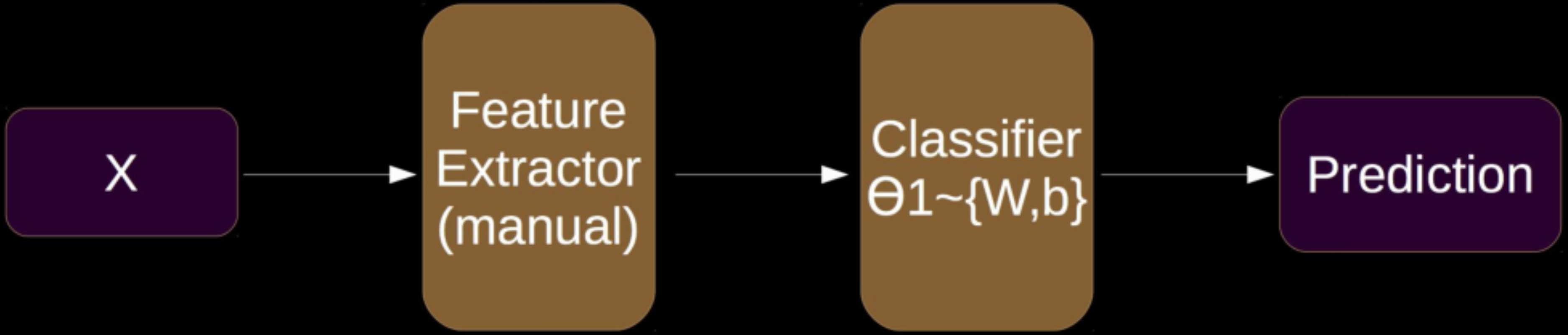


What we want

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

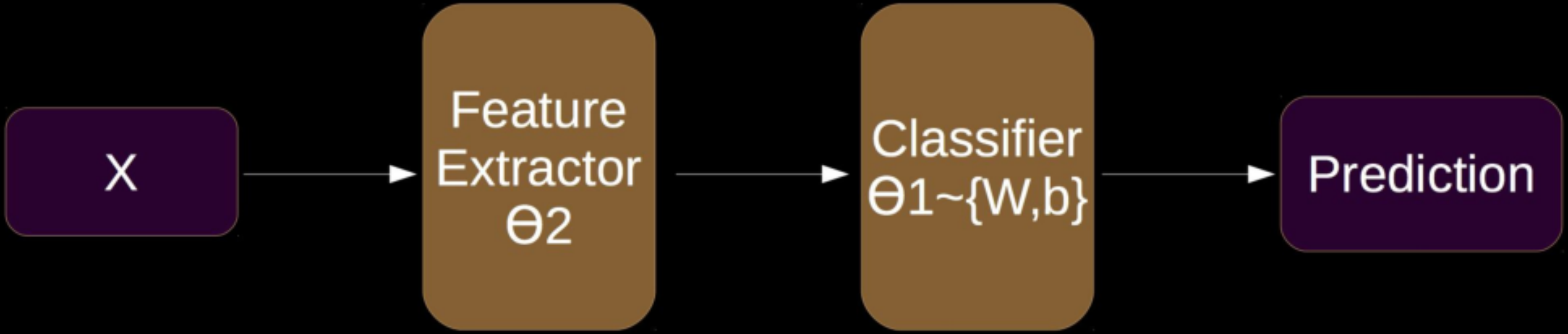
And feature engineering is an *art*.

Classic pipeline



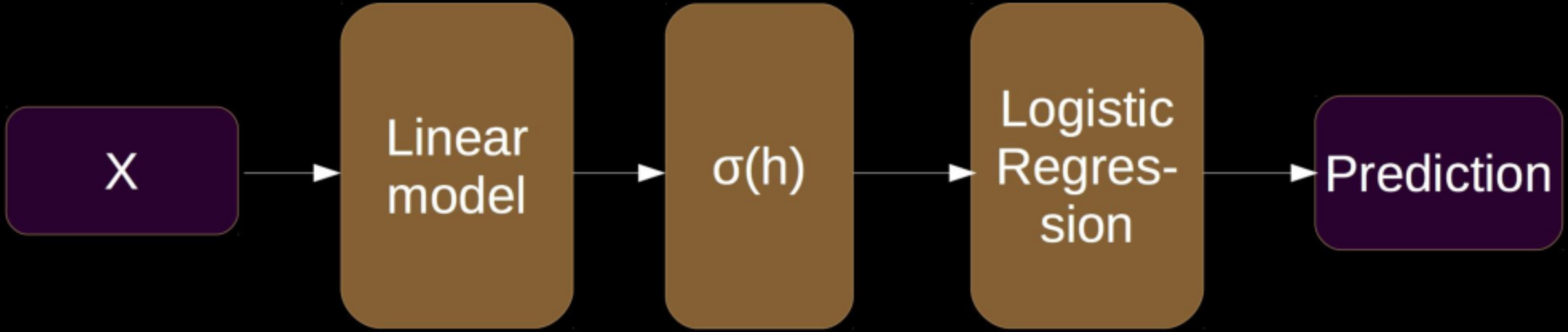
Handcrafted features, generated by experts.

NN pipeline



Automatically extracted features.

NN pipeline: example



E.g. two logistic regressions one after another.

Actually, it's a neural network.

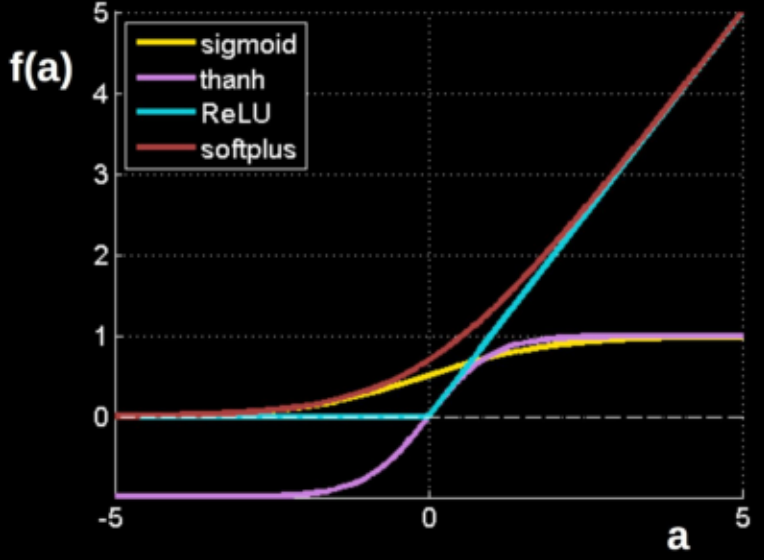
Activation functions: nonlinearities

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

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

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

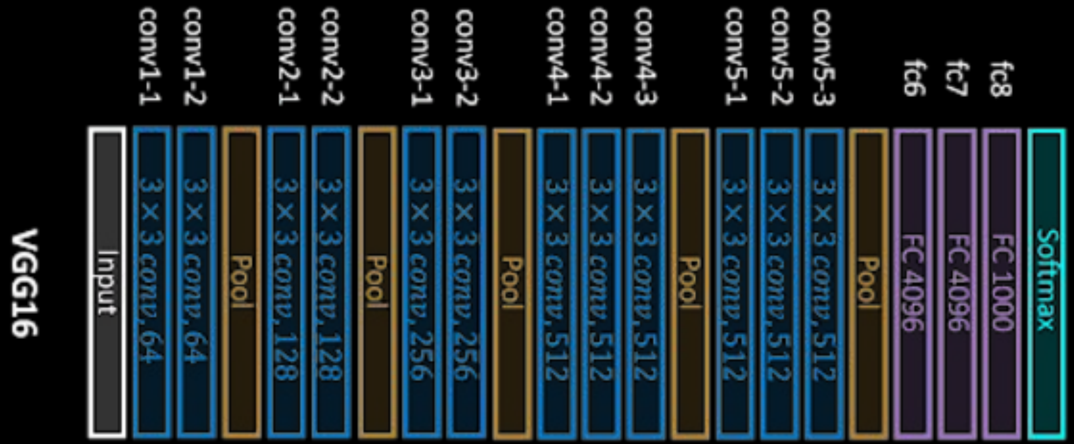
$$f(a) = \log(1+e^{a})$$



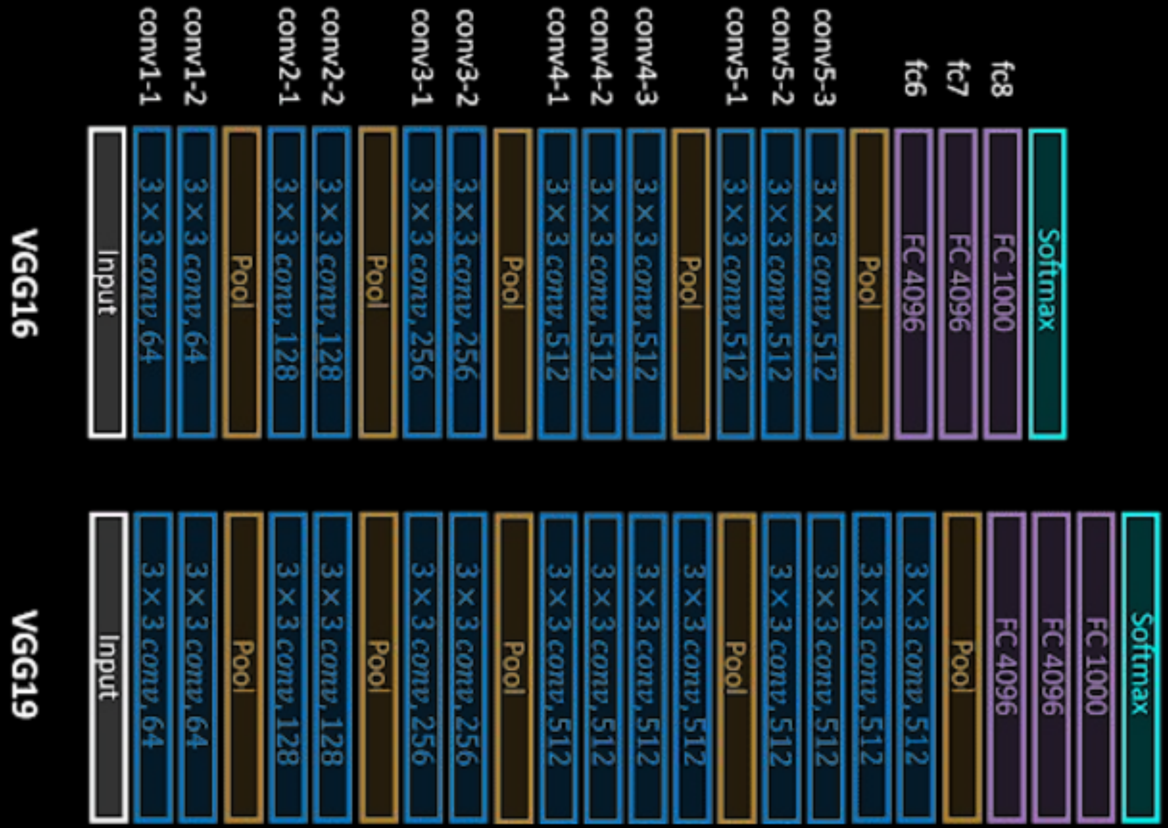
Some generally accepted terms

- 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"

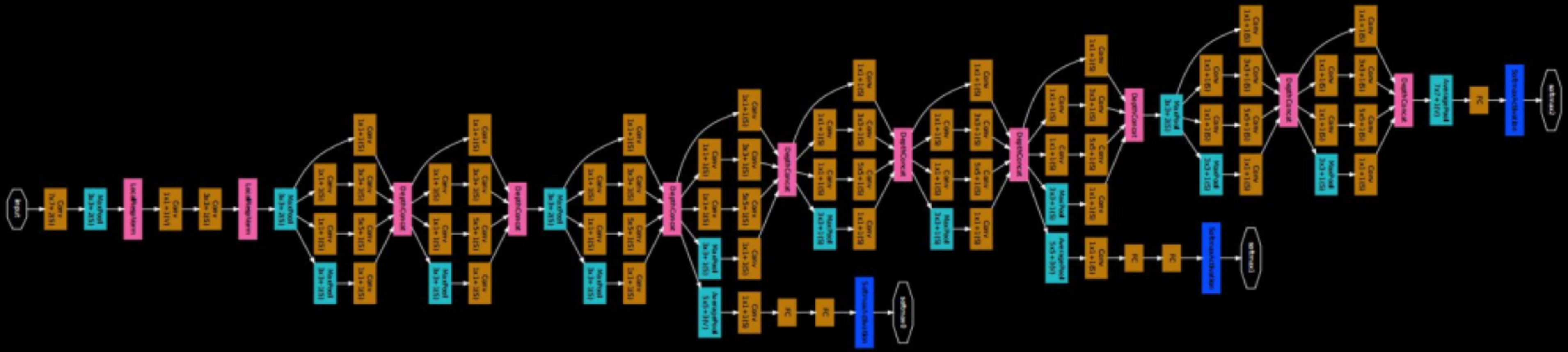
Actually, networks can be deep



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
Pool
3 × 3 conv, 128
3 × 3 conv, 256
3 × 3 conv, 512
FC 4096
FC 1000
Softmax
VGG19

Much deeper...

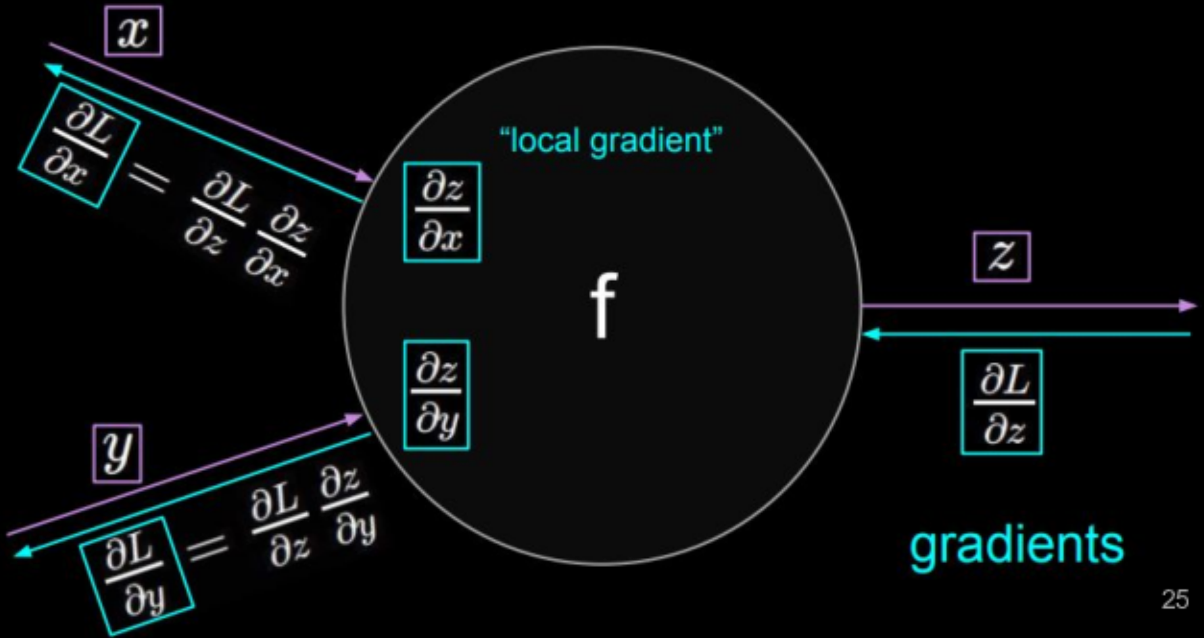


How to train it?

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.

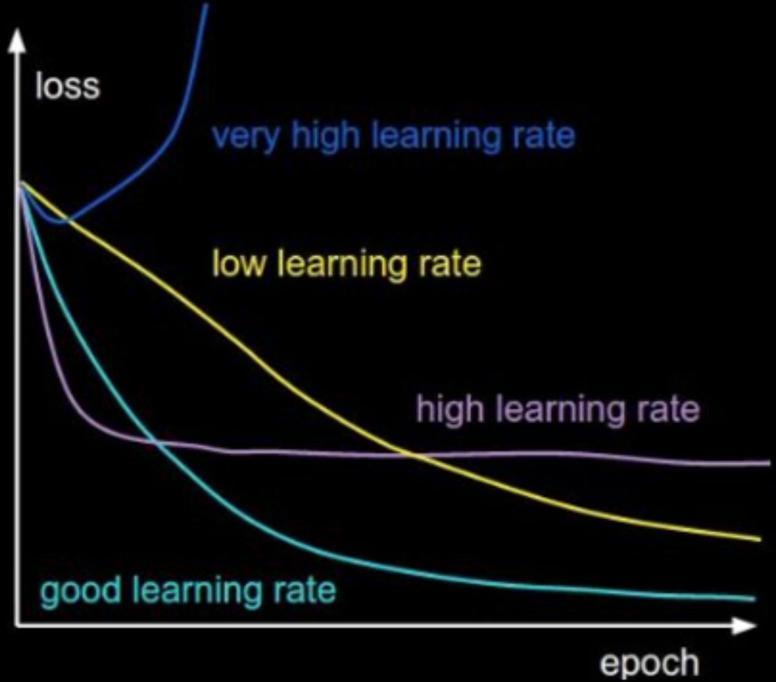


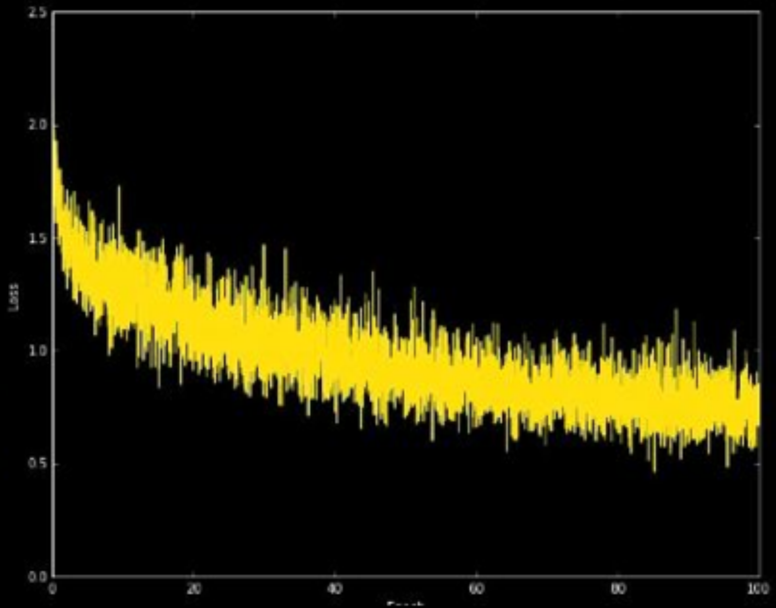
source: http://cs231n.github.io

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

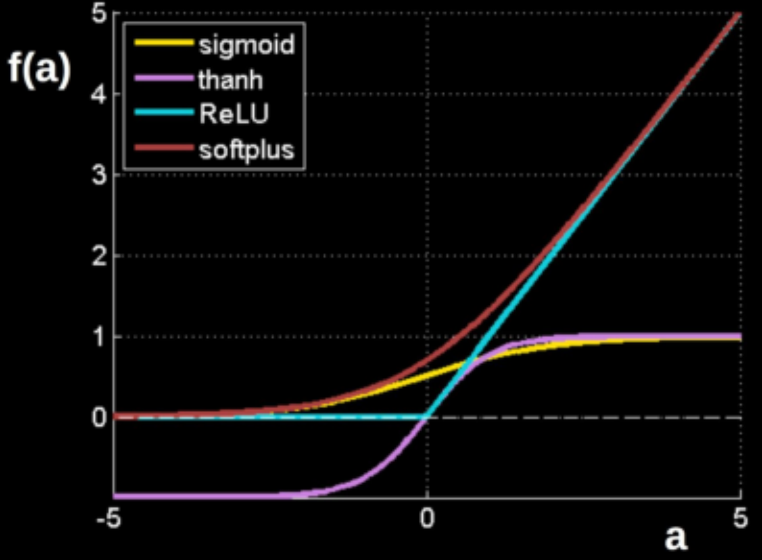
Once more: nonlinearities

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

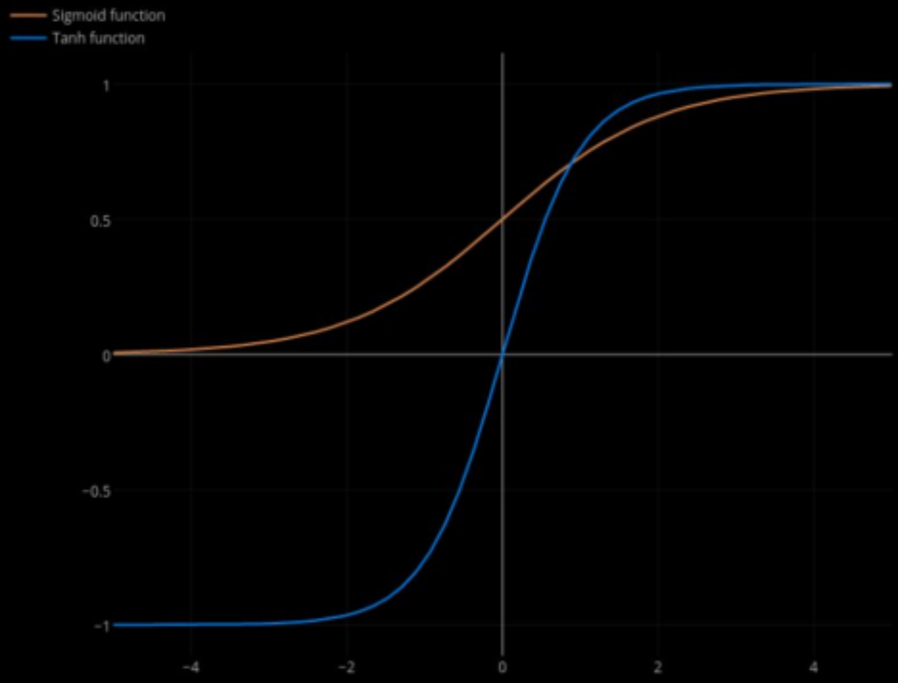
$$f(a) = \tanh(a)$$

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

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



Activation functions: Sigmoid



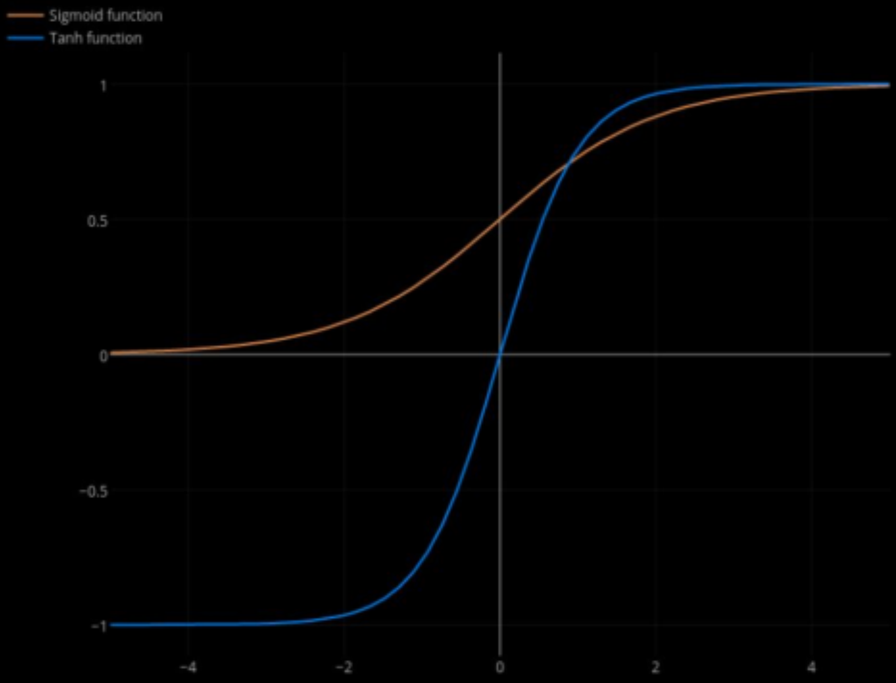
$$f(a) = \frac{1}{1 + e^{-a}}$$

- 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



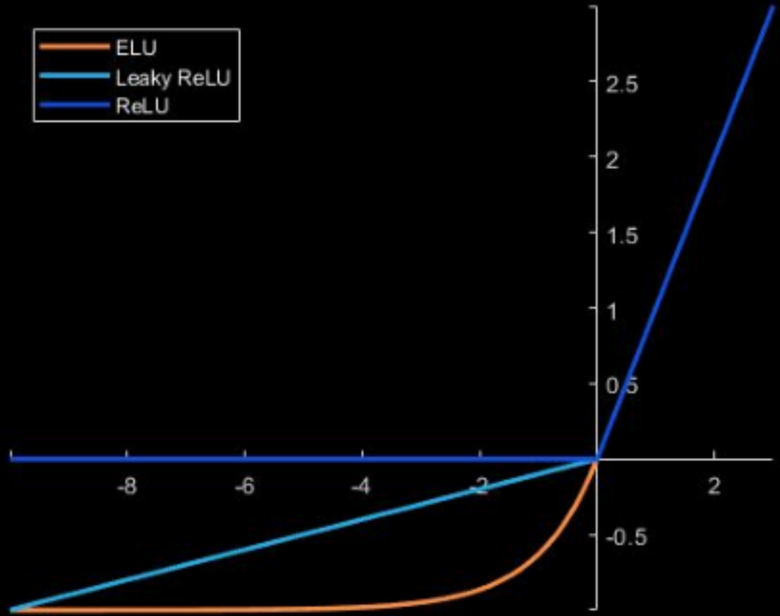
$$f(a) = \tanh(a)$$

- 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



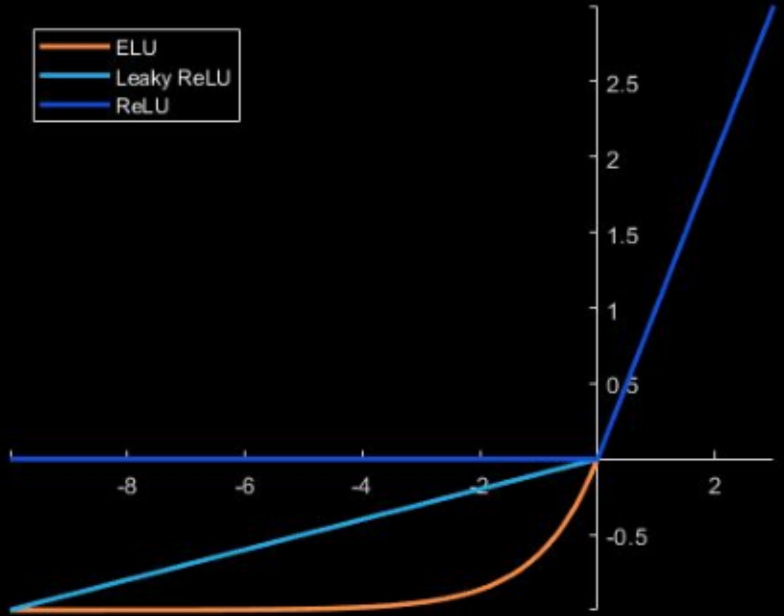
$$f(a) = \max(0, a)$$

- 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



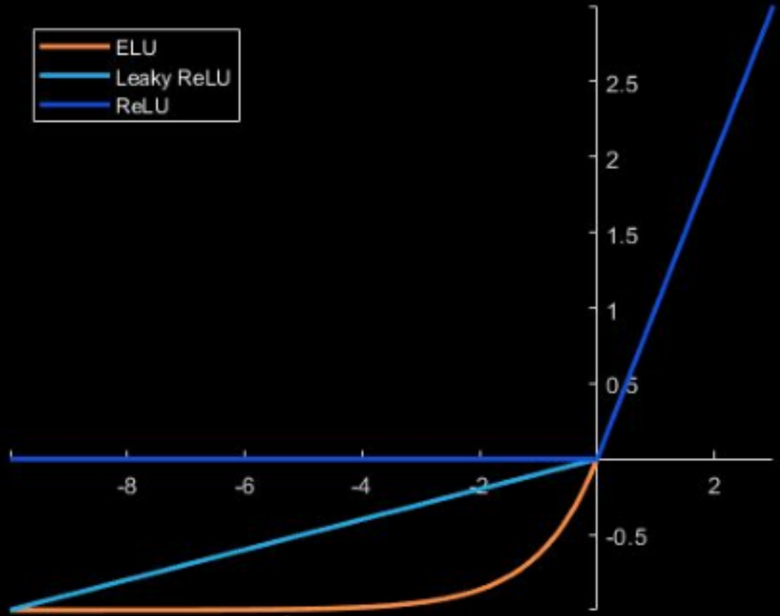
- Very simple to compute (both forward and backward)
  - Up to 6 times faster than Sigmoid
- Does not saturate when

Problems:

- Shifted, but not so much output

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

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 $X_{étale}$ 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. □

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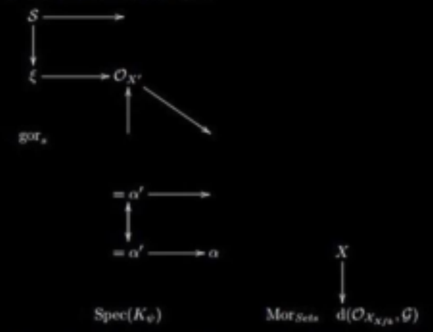
This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram



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

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

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. □

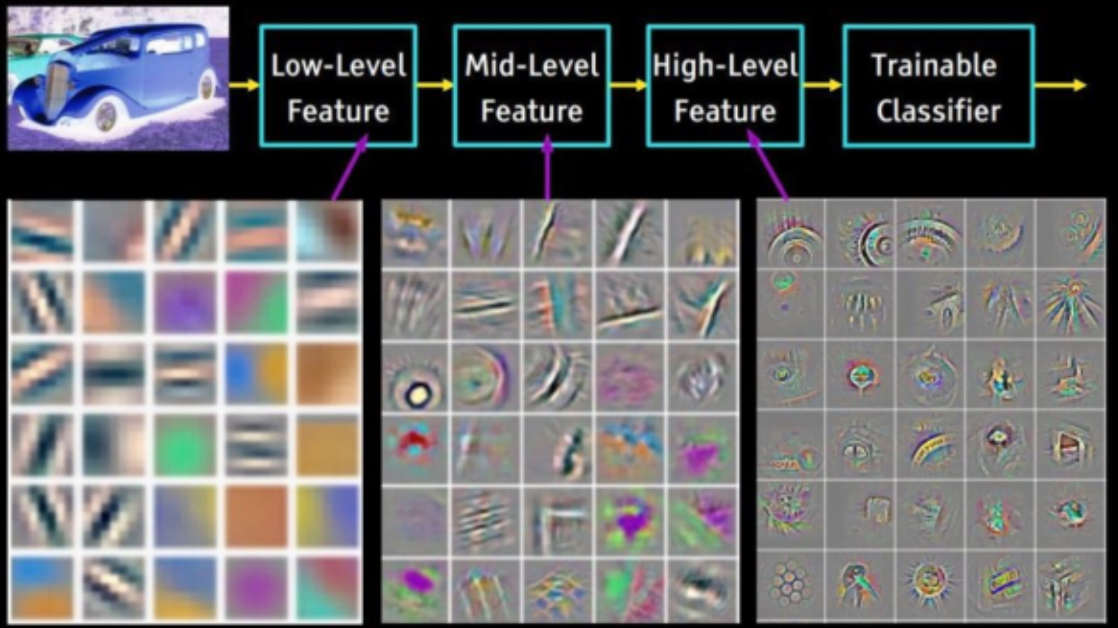
If $\mathcal{F}$ is a finite direct sum $\mathcal{O}_{X_\lambda}$ is a closed immersion, see Lemma ??. This is a sequence of $\mathcal{F}$ is a similar morphism.

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

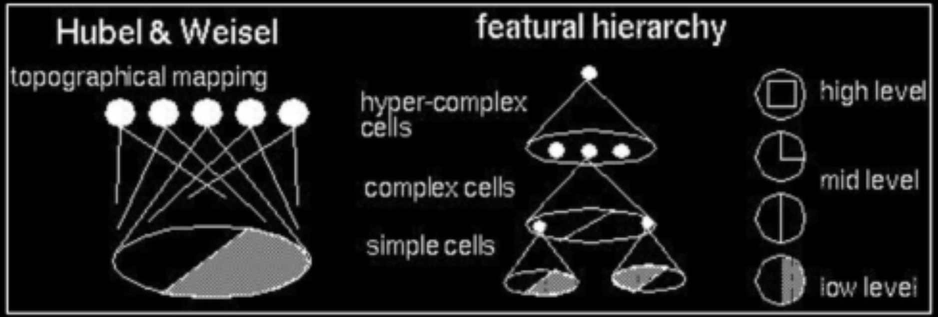
```c
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>

#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]

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