

Deep Learning for Data Scientists

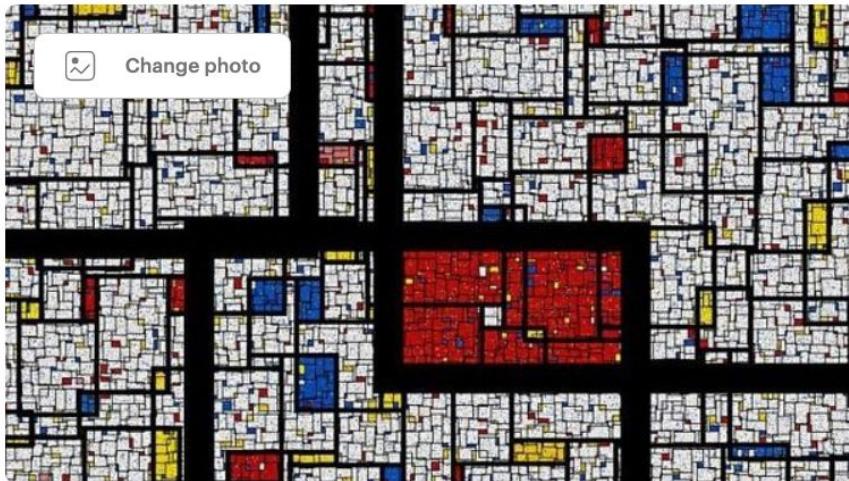
Antonio Rueda-Toicen
Data Science Retreat
October 2021

About me

- Machine Learning Engineer at Vinted
- Background in academia (computer science and bioengineering)
 - Organizer of the [Berlin Computer Vision Group](#)
 - Arepa-lover (try them, they're awesome)



Fig 1: Arepas



Berlin Computer Vision Group

Berlin, Germany

384 members · Public group ?

Organized by Antonio Rueda Toicen

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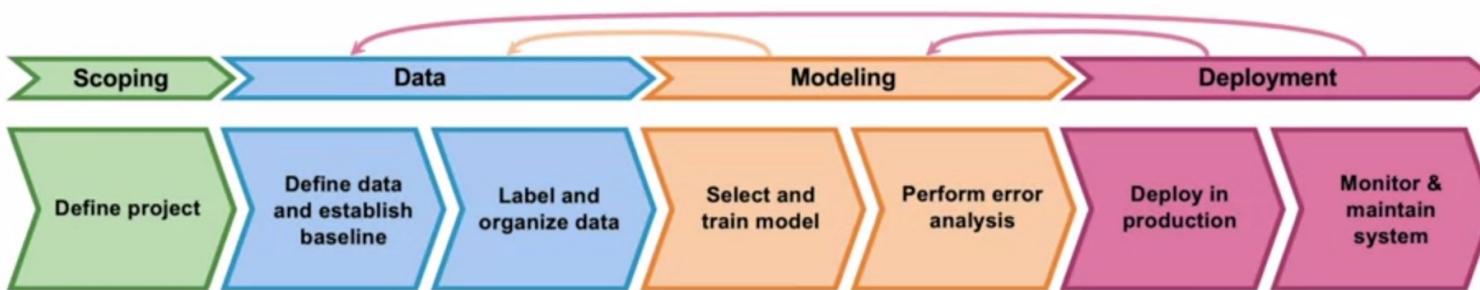
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<https://www.meetup.com/Berlin-Computer-Vision-Group/>

Agenda

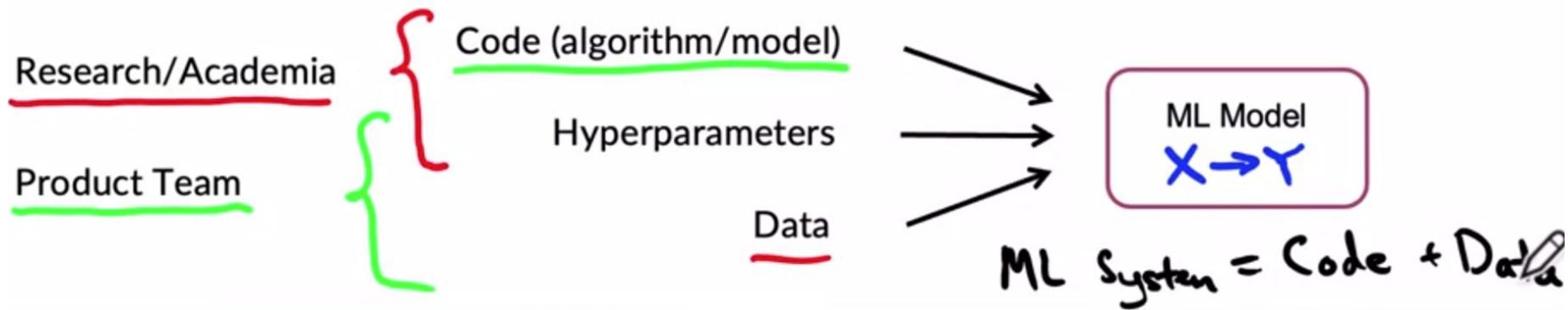
- Intro to deep learning
 - DL in the machine learning project-cycle
 - What is DL and why should we use it?
 - Neural networks
 - Perceptrons
 - The feedforward pass
 - Backpropagation
 - Activation functions
 - Stochastic gradient descent
 - Convolutional neural networks
 - Data augmentation
 - Residual networks (ResNet)
 - Binary vs multiclass classifiers
 - Transfer learning and embeddings
 - Our goal: build a cats vs dogs image classifier in PyTorch

The ML project lifecycle



[From Andrew Ng's Intro to ML in Production](#)

The data driven-approach to ML



[From Andrew Ng's Intro to ML in Production](#)

Knowing the jargon

Model aka network aka architecture (although a fine-grained distinction exists here with respect to training)

Weight aka parameter aka connection strength

Hyperparameter

Neuron aka processing unit

Loss aka cost aka error function

Error rate aka $1 - \text{accuracy}$

Sensitivity aka recall

Activation function

Transfer learning

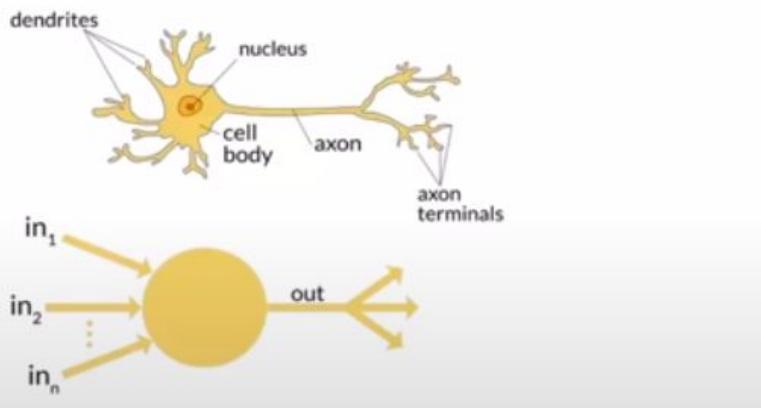
Epoch

Batch

What is an artificial neural network?

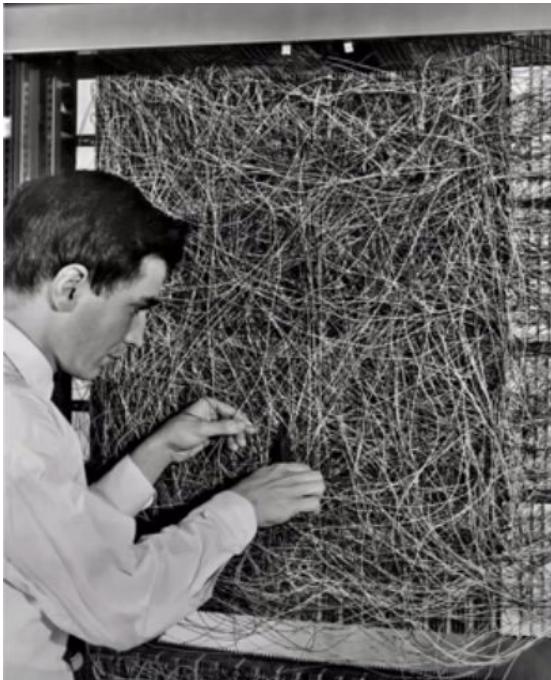
In 1943 Warren McCulloch, a neurophysiologist, and Walter Pitts, a logician, teamed up to develop a mathematical model of an artificial neuron. They declared that:

Because of the “all-or-none” character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms. (Pitts and McCulloch; A Logical Calculus of the Ideas Immanent in Nervous Activity)



Artificial “neurons” are also called “processing units”

What is an artificial neural network?



"we are about to witness the birth of such a machine – a machine capable of perceiving, recognizing and identifying its surroundings without any human training or control".

Frank Rosenblatt

Image: Frank Rosenblatt with the Mark I Perceptron at Cornell University (1961)

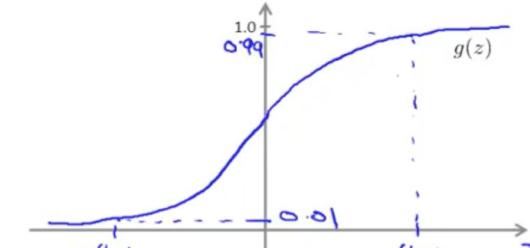
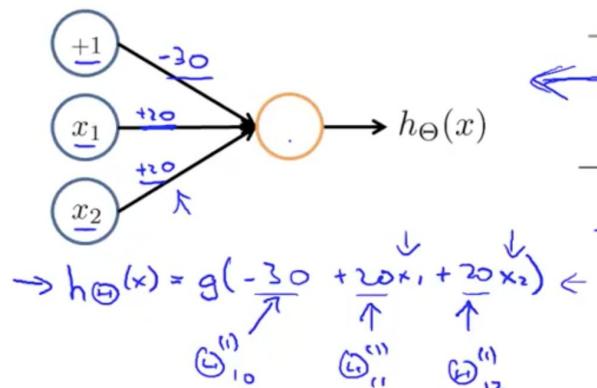
What does a neural network ‘learn’?

It learns “*weights*” aka “*parameters*” aka “*connection strengths*” that minimize a measure of error (aka “*loss*” aka “*cost*”) function given a set of training inputs x (aka “*a dataset*”)

Simple example: AND

$$\rightarrow x_1, x_2 \in \{0, 1\}$$

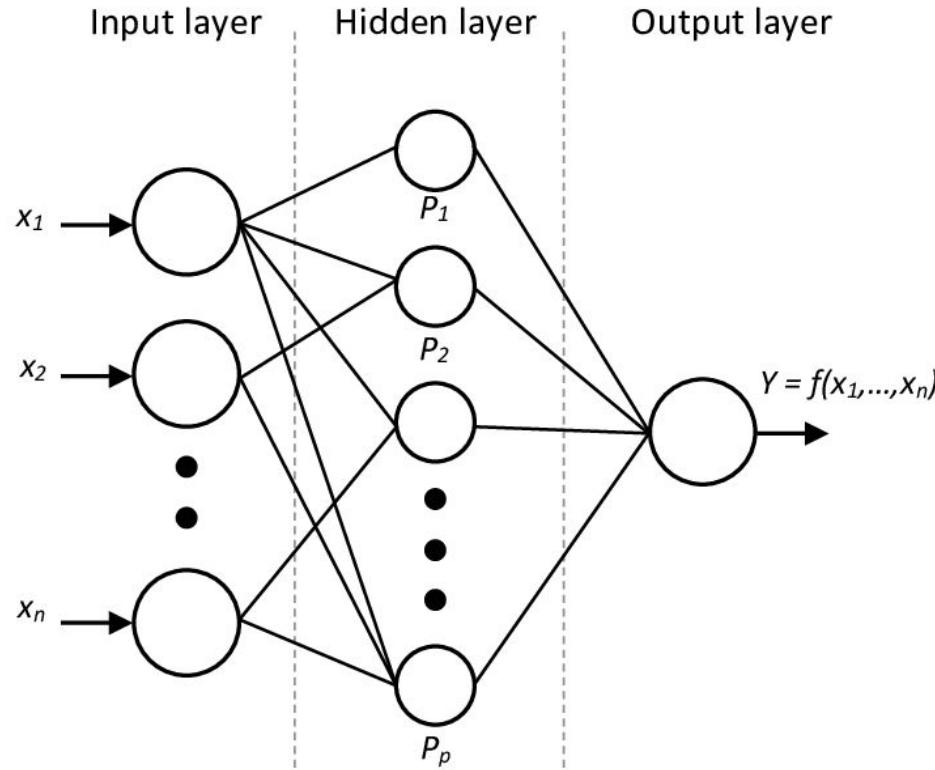
$$\rightarrow y = x_1 \text{ AND } x_2$$



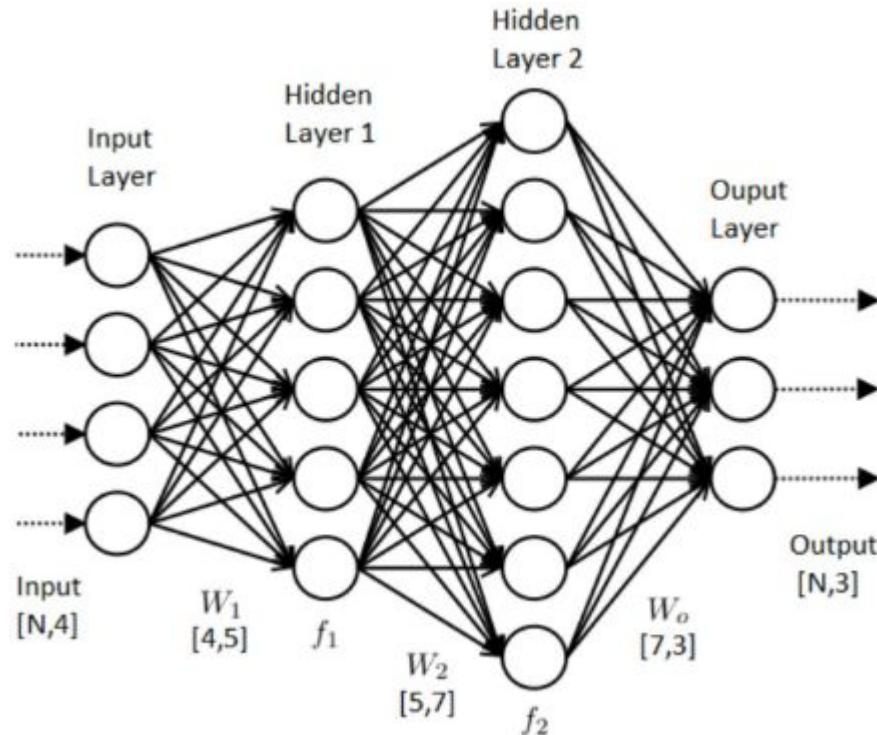
x_1	x_2	$h_{\Theta}(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

$h_{\Theta}(x) \approx x_1 \text{ AND } x_2$

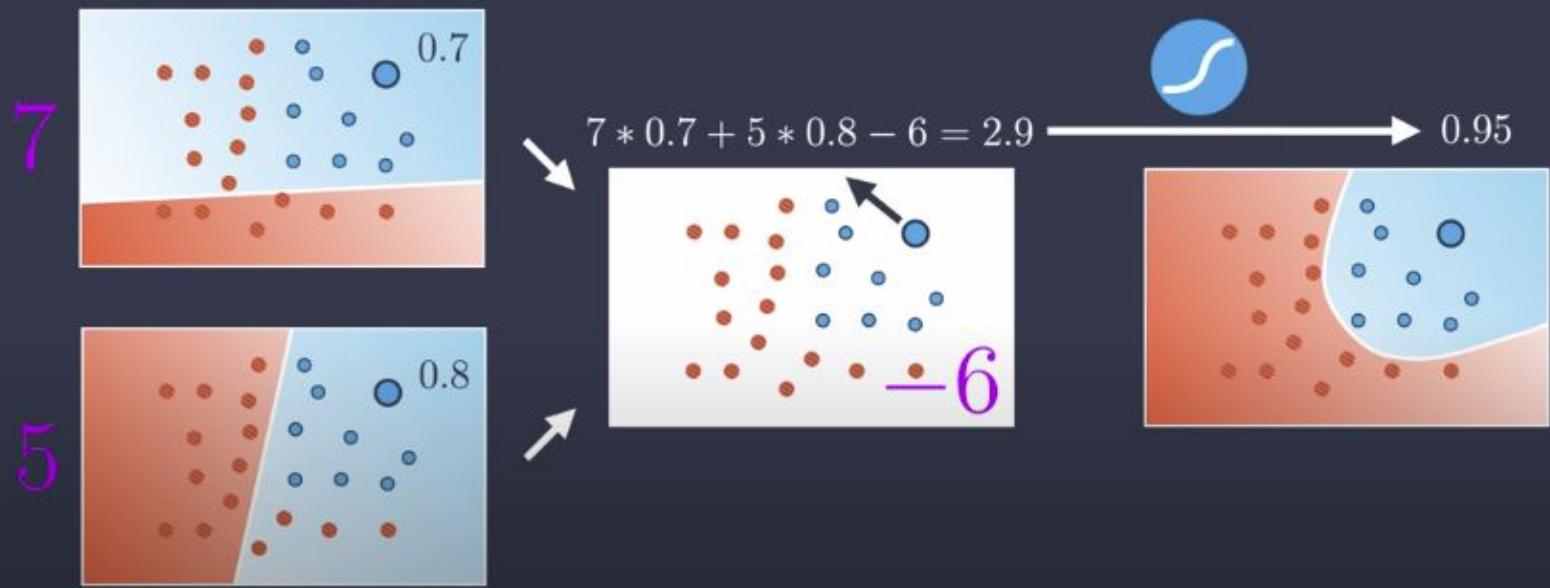
Hidden layers



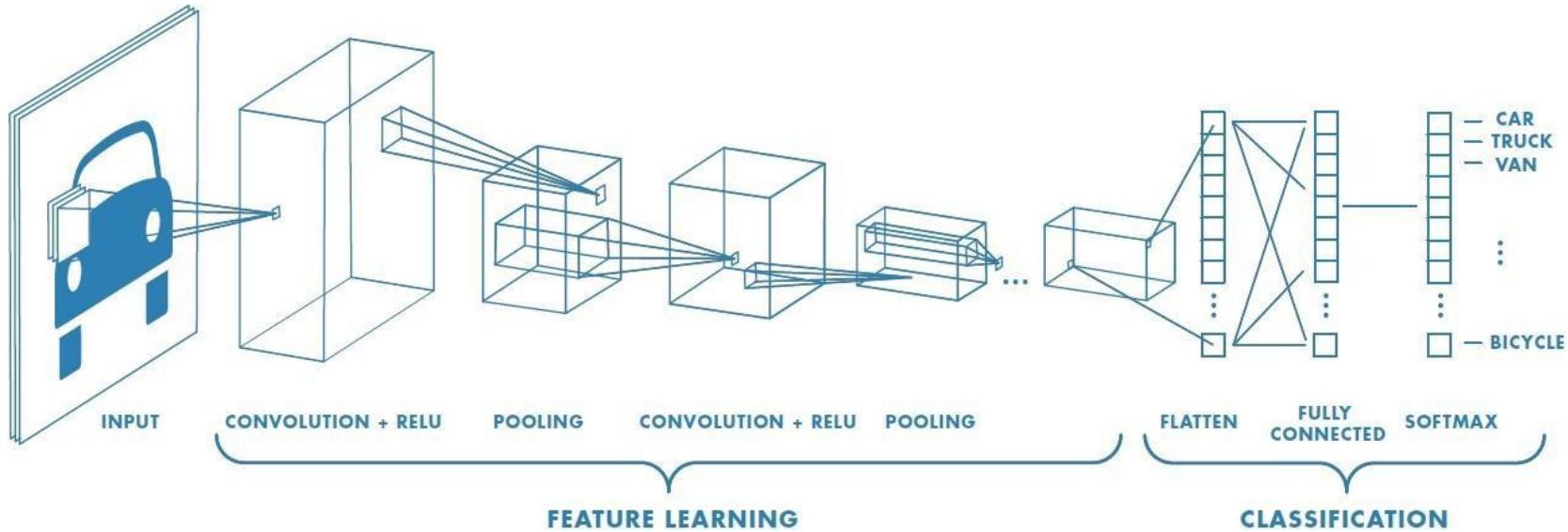
Hidden layers



Neural Network



What is deep learning?



What is a GPU?



Most deep learning libraries require the use of NVIDIA graphical processing units with CUDA capabilities

Why use a GPU for deep learning?

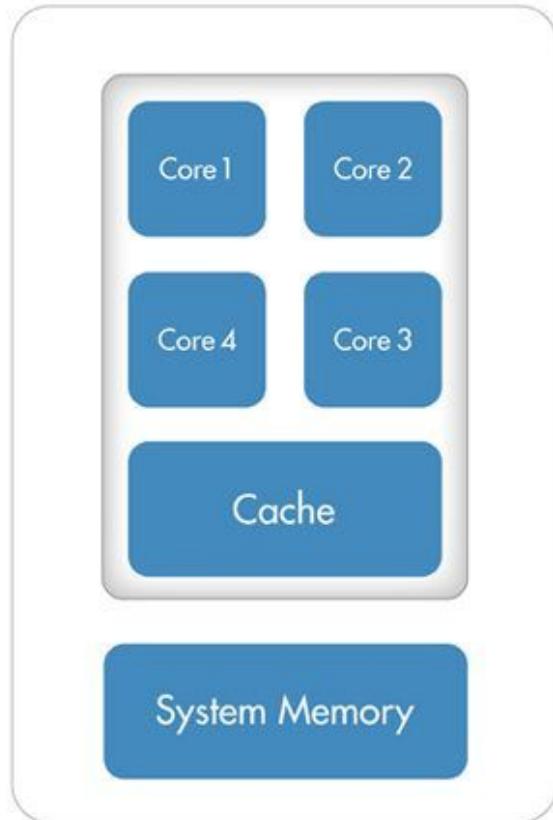
How is a CPU different from a GPU?

- More cores!

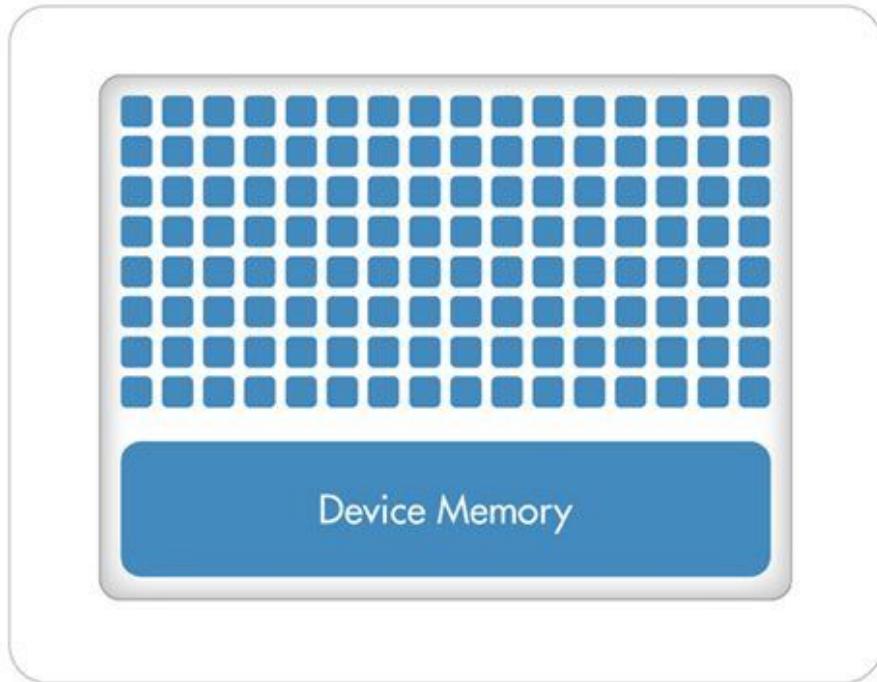
Why are CPUs less effective for deep learning?

- Less cores :(

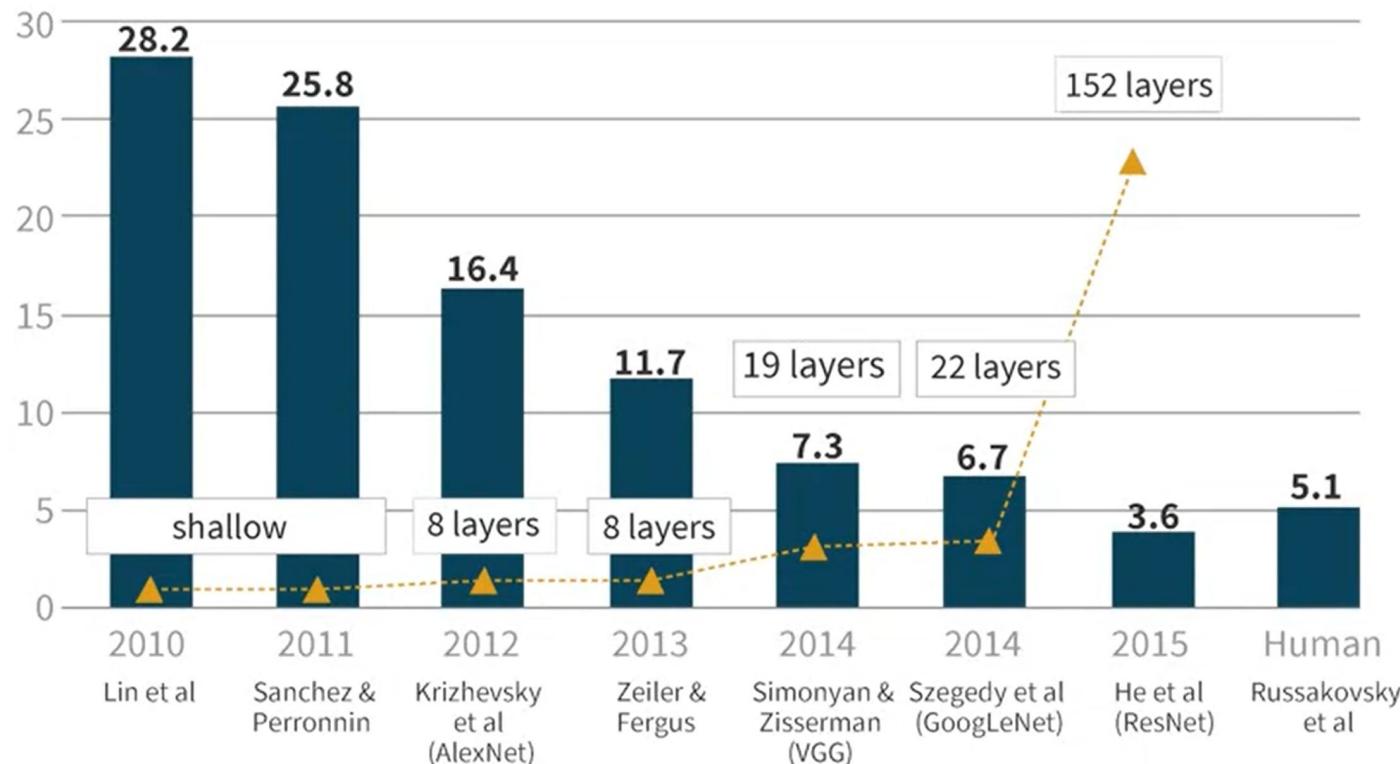
CPU (Multiple Cores)



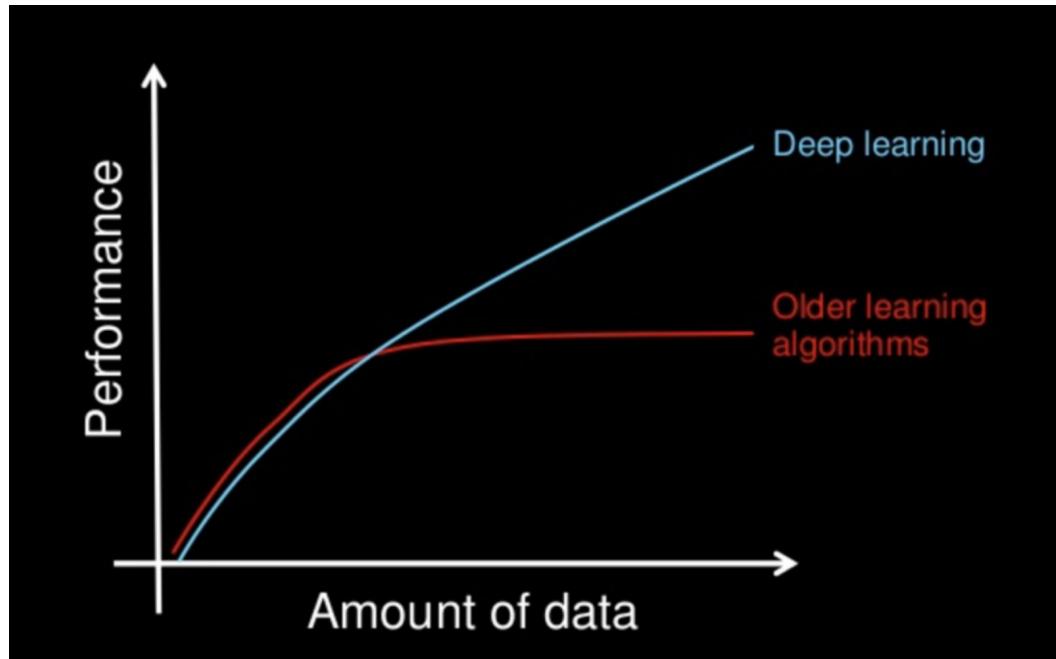
GPU (Hundreds of Cores)



IMAGENET LARGE SCALE VISUALrecognition CHALLENGE (ILSVRC) WINNERS



Why do we use deep learning?



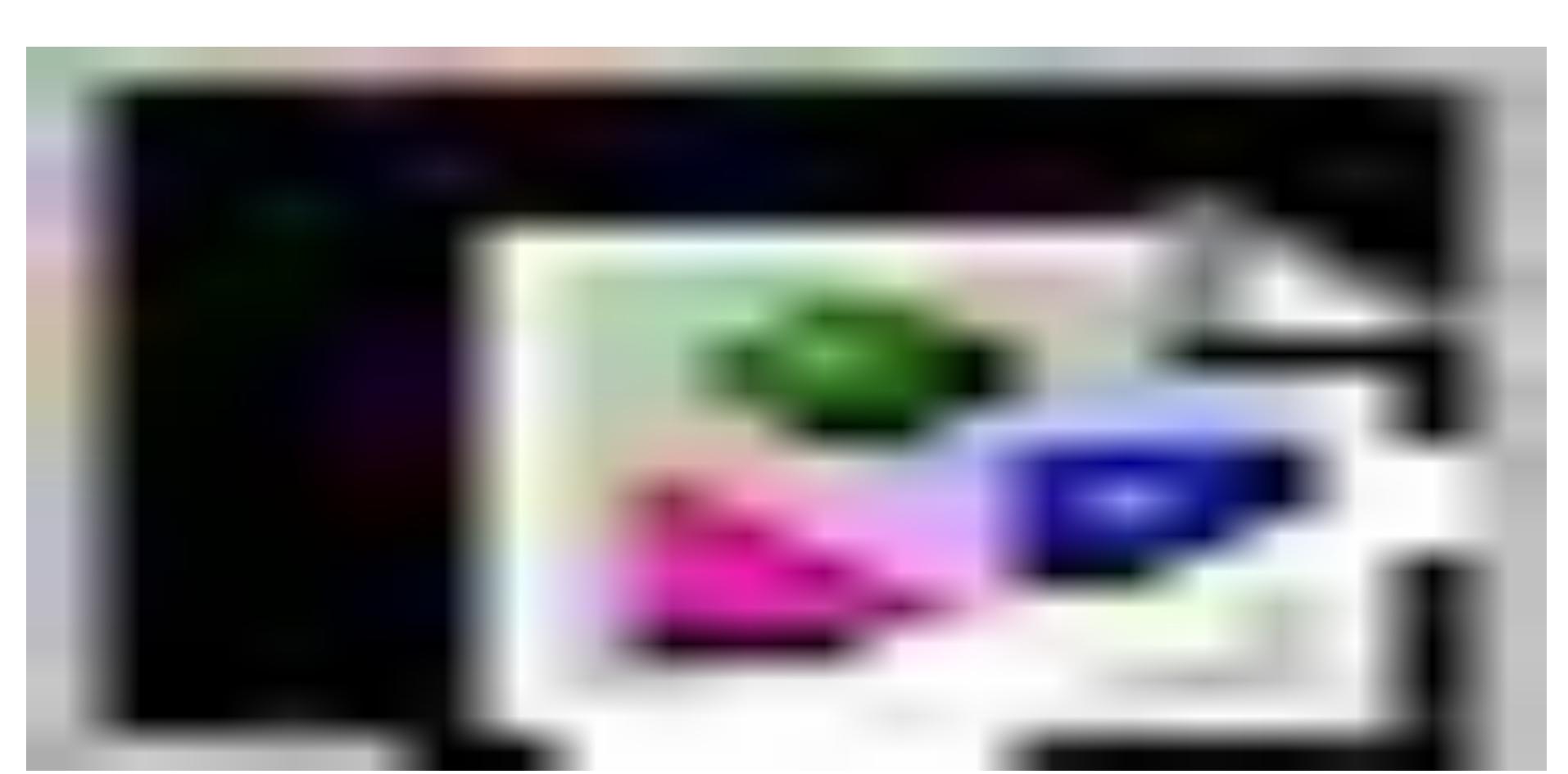
- Disclaimer: the [No Free Lunch Theorems](#) explain why this graph might be hype, although things like the [current GPT experiments](#) show promise

Applications of deep learning

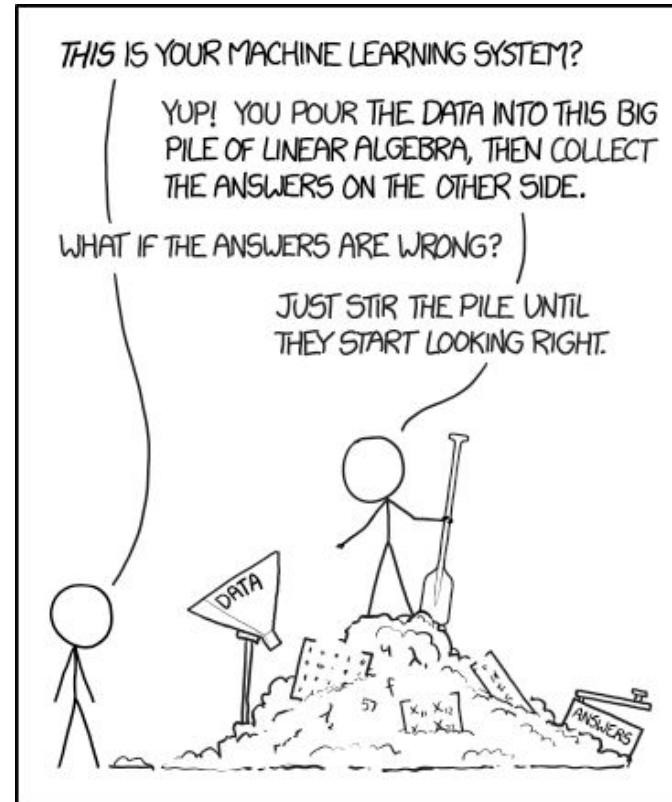
- Computer vision: image classification, object detection, segmentation, image description, image generation, satellite and drone image analysis
- Natural Language Processing: translation, text and DNA sequence prediction, text generation
- Audio understanding, audio generation, lip reading
- Playing games, finding optimal strategies (when paired with reinforcement learning)
- Any system that requires the finding of **significant correlations** or patterns/"intuitions" in the data, i.e. the 'thinking fast' systems referred by Daniel Kahneman in his famous book.

Why do we use deep learning?

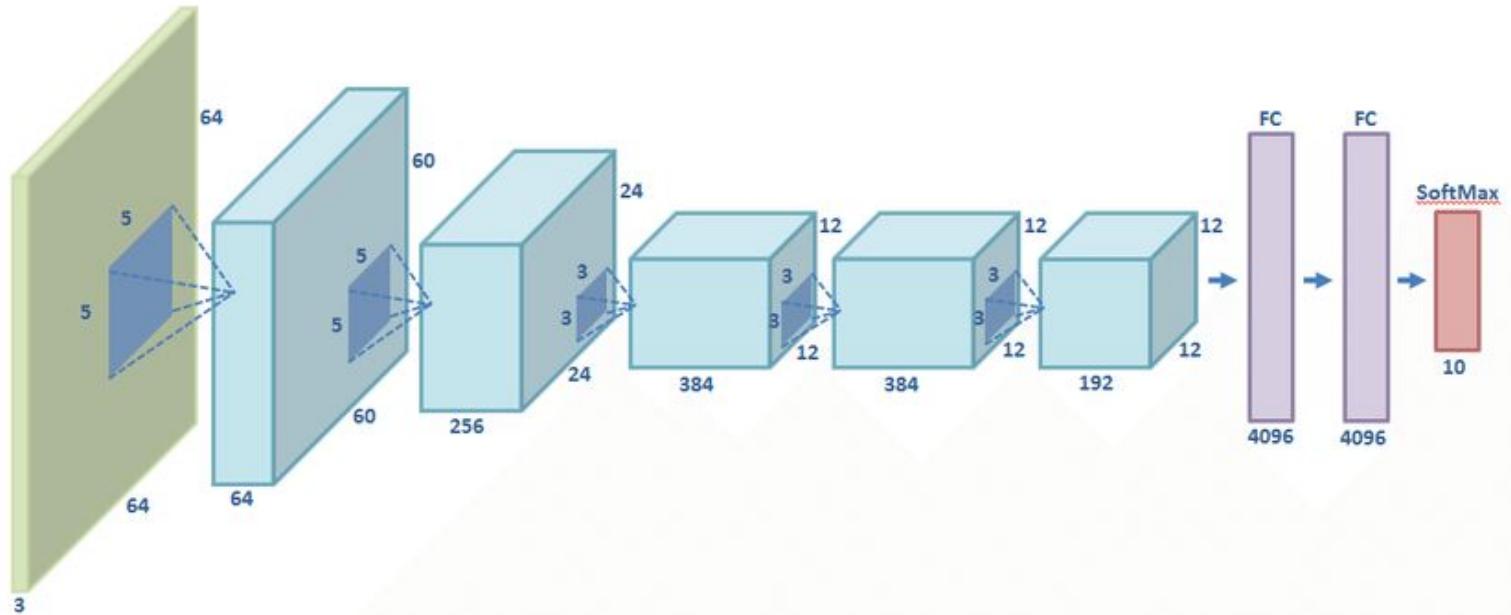
- Deep neural networks are ***universal function approximators***
 - *This means that given the right architecture and training, they can compute everything that's computable, just like a [Universal Turing Machine](#)*
 - *In practice this means that deep networks are very good at finding very sophisticated decision boundaries (aka “curve fitting”)*
 - *Finding the function means the finding **architecture and or training** of the neural network*
 - *It's fair to call deep neural networks “**linear regression on steroids**”*
 - *Deep neural networks pick hidden **correlations** in the data, but most architectures [don't pick on causality](#) (current research topic)*



Stir the pile

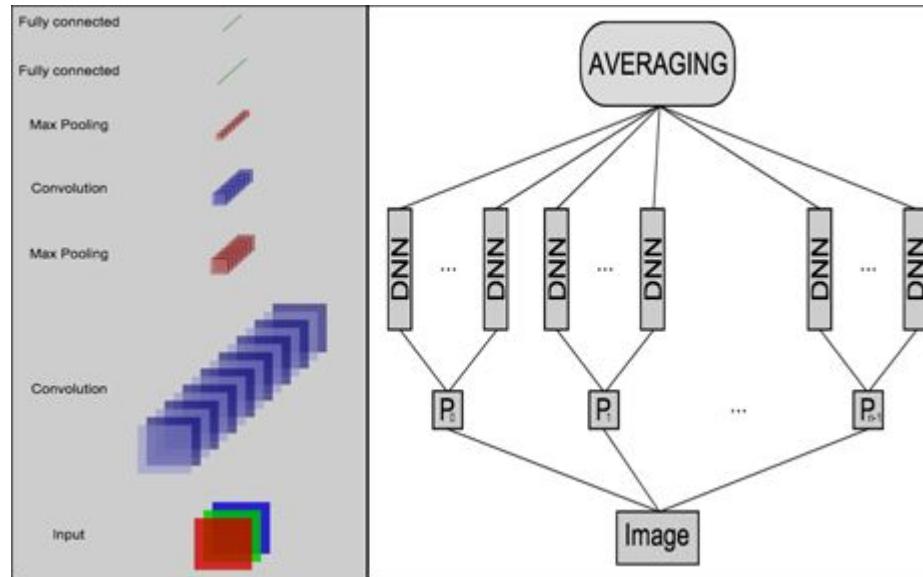


Different network architectures represent different ways to ‘stir the pile’



Architecture of the Alexnet network

Different network architectures represent different ways to ‘stir the pile’



Architecture of the Dannet network

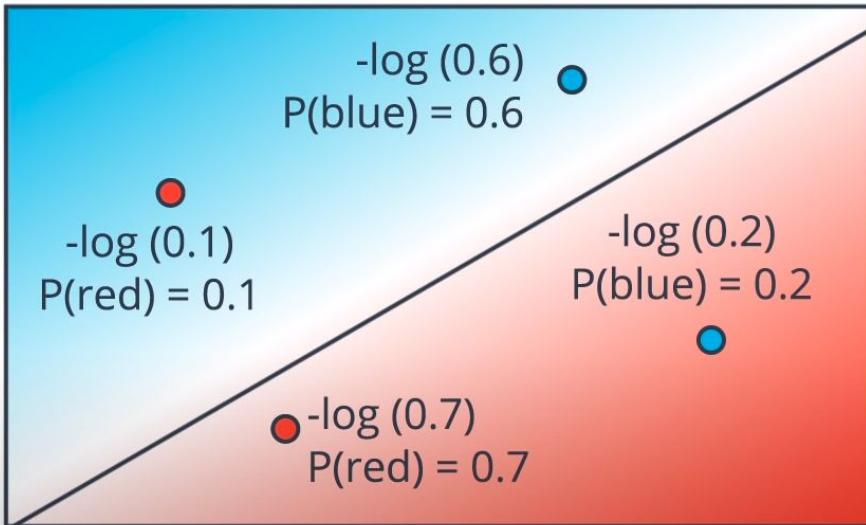
Choose the right loss function for the task

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \tilde{y}_i)^2$$

Choose the right loss function for the task

$$\text{Loss} = -\frac{1}{\text{output size}} \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log (1 - \hat{y}_i)$$

Error Function



$$-\log(0.6) - \log(0.2) - \log(0.1) - \log(0.7) = 4.8$$

0.51 1.61 2.3 0.36

If $y = 1$

$$P(\text{blue}) = \hat{y}$$

Error = $-\ln(\hat{y})$

If $y = 0$

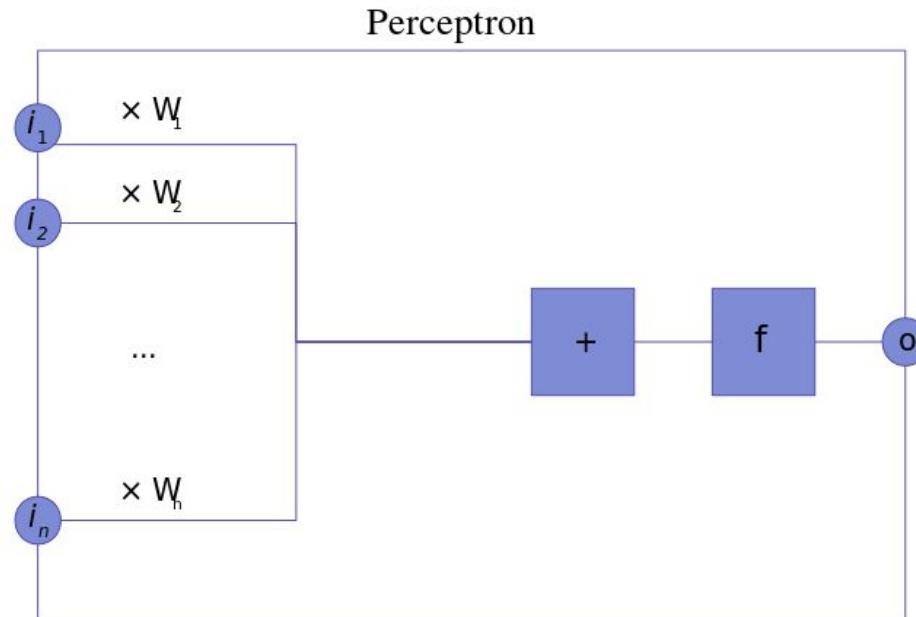
$$P(\text{red}) = 1 - P(\text{blue}) = 1 - \hat{y}$$

Error = $-\ln(1 - \hat{y})$

$$\text{Error} = -(1-y)(\ln(1-\hat{y})) - y\ln(\hat{y})$$

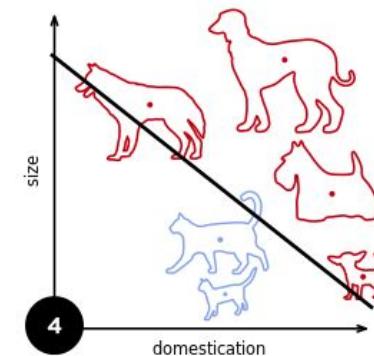
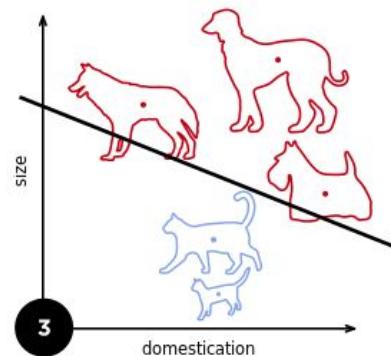
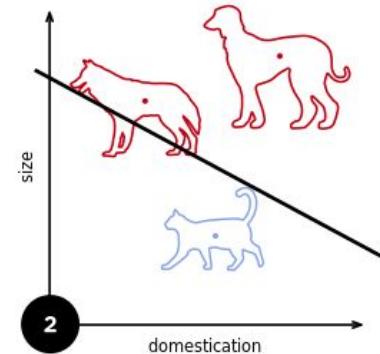
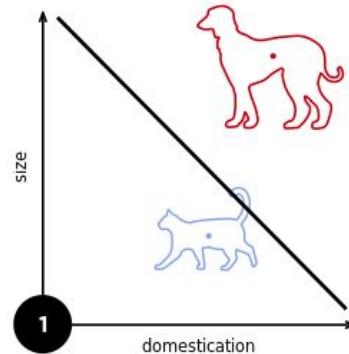
Error Function = $-\frac{1}{m} \sum_{i=1}^m (1-y_i)(\ln(1-\hat{y}_i)) + y_i\ln(\hat{y}_i)$

What is a perceptron?

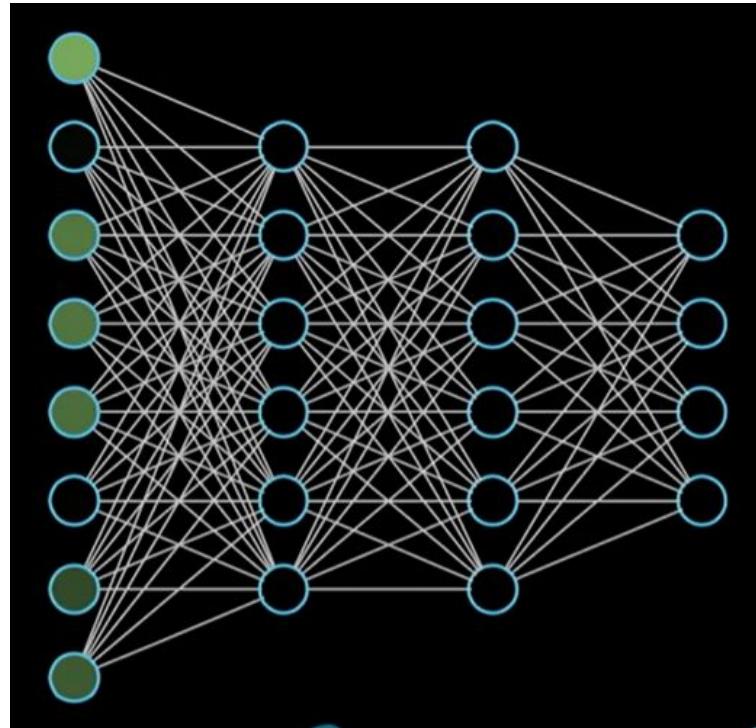


$$o = f\left(\sum_{k=1}^n i_k \cdot W_k\right)$$

What is a perceptron?



Multilayer perceptrons



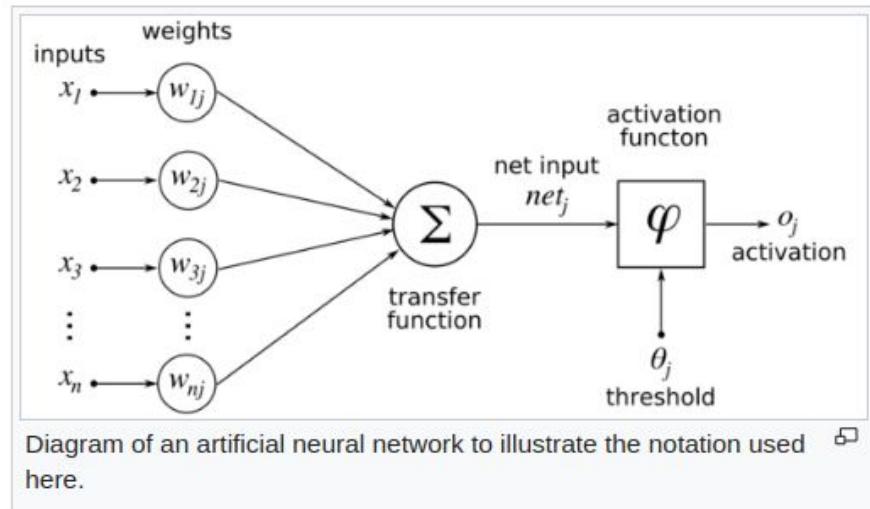
Backpropagation

Finding the derivative of the error [edit]

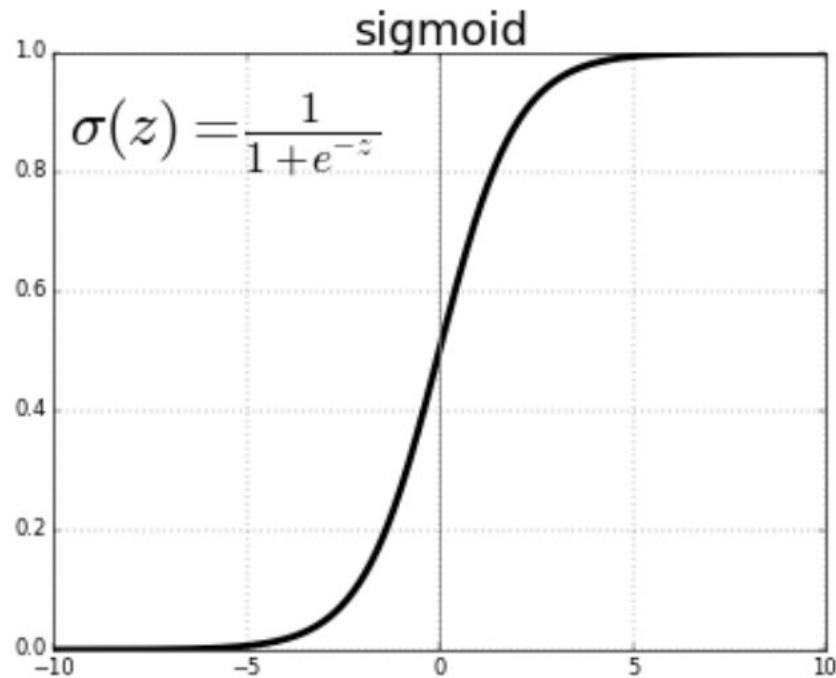
Calculating the [partial derivative](#) of the error with respect to a weight w_{ij} is done using the [chain rule](#) twice:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial o_j} \frac{\partial o_j}{\partial w_{ij}} = \frac{\partial E}{\partial o_j} \frac{\partial o_j}{\partial \text{net}_j} \frac{\partial \text{net}_j}{\partial w_{ij}} \quad (\text{Eq. 1})$$

In the last factor of the right-hand side of the above, only one term in the sum net_j depends on w_{ij} , so that

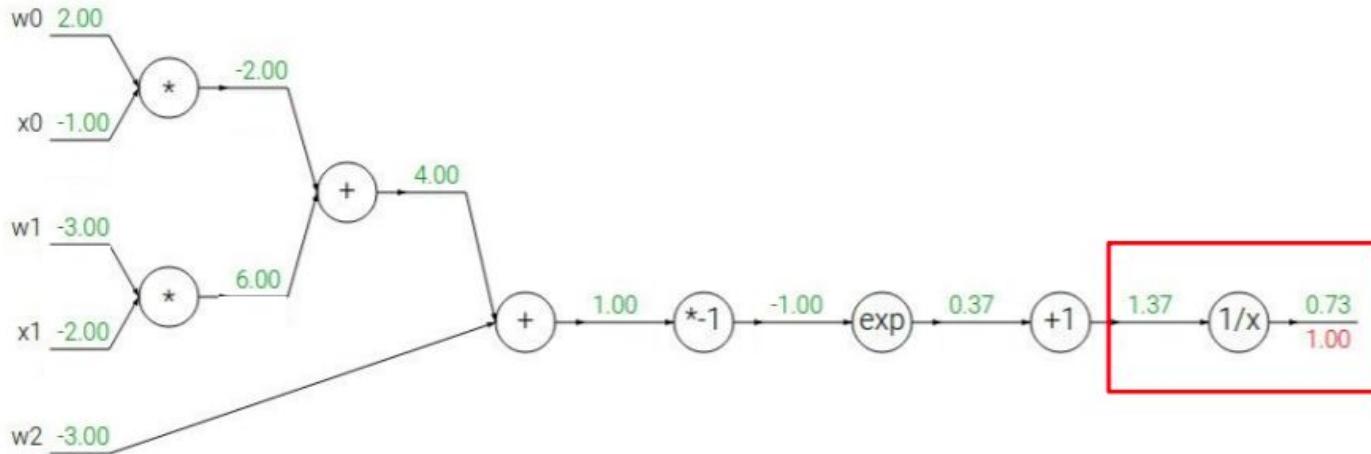


The sigmoid activation function



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

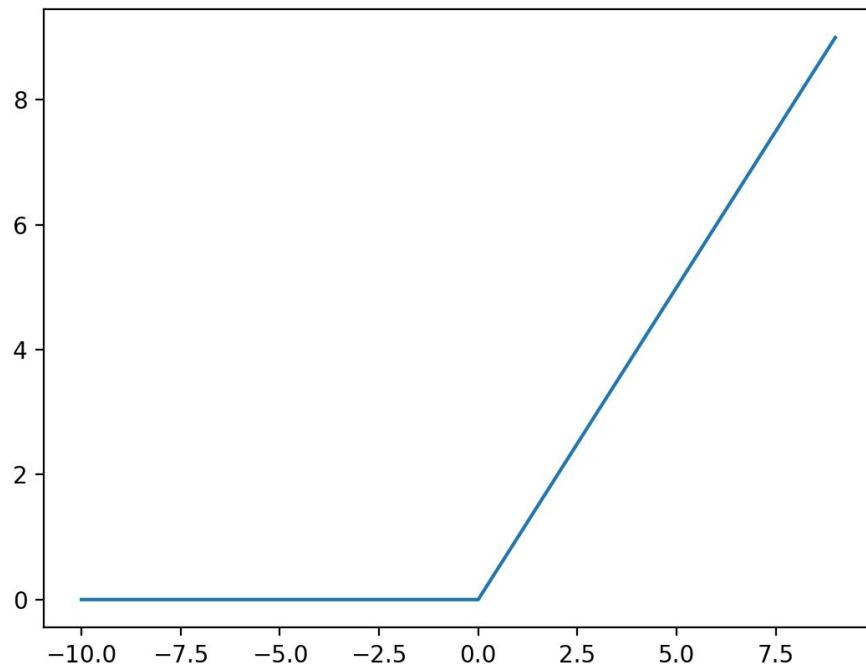
$$\frac{df}{dx} = -1/x^2$$

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

\rightarrow

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

The rectifier linear unit (ReLU) activation function

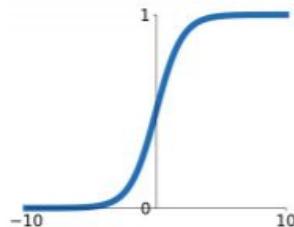


$$f(x) = x^+ = \max(0, x)$$

Activation functions

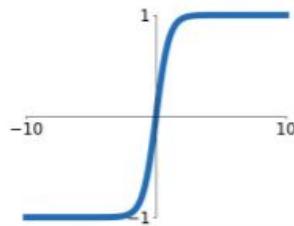
Sigmoid

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



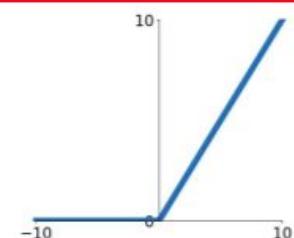
tanh

$$\tanh(x)$$



ReLU

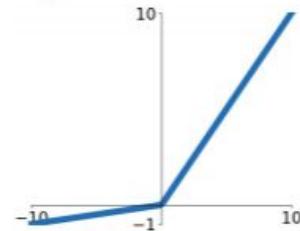
$$\max(0, x)$$



ReLU is a good default choice for most problems

Leaky ReLU

$$\max(0.1x, x)$$

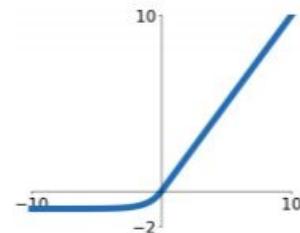


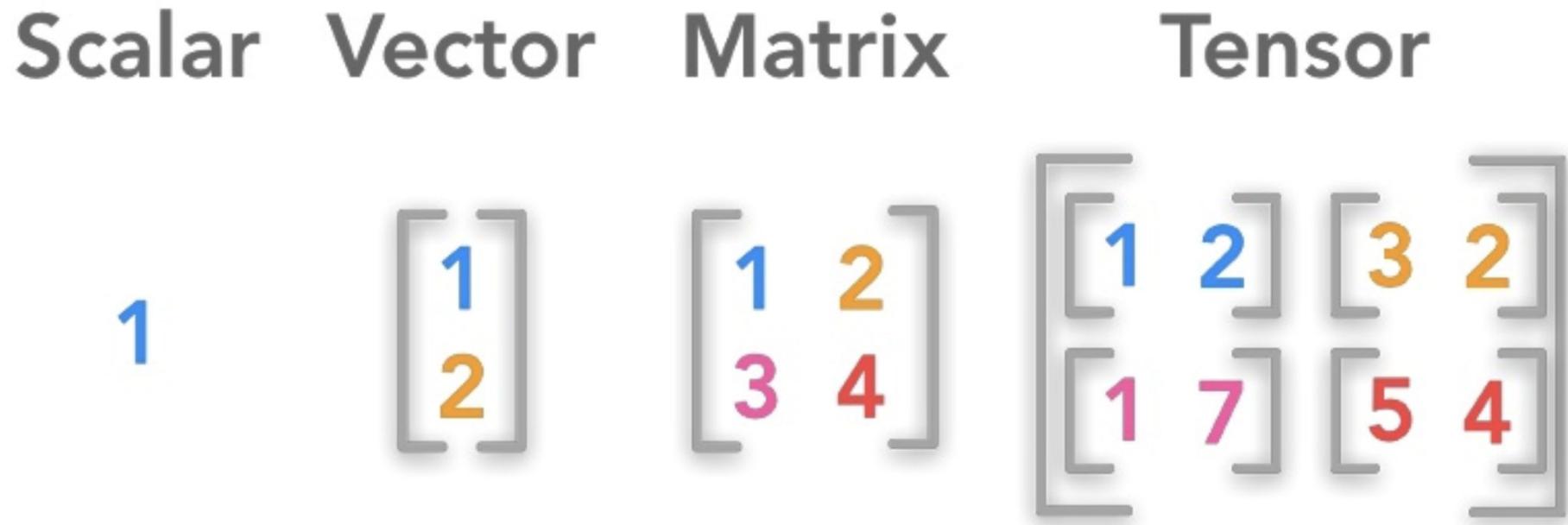
Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$





- [Read: scalars, vectors, matrices, and tensors](#)
 - [Understanding rank terminology](#)

Matrix multiplication

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 1 & 0 \\ 2 & 3 & 4 \end{bmatrix} \times \begin{bmatrix} 2 & 5 \\ 6 & 7 \\ 1 & 8 \end{bmatrix}$$

- + - +

► Multiply

<http://matrixmultiplication.xyz/>

Matrix multiplication

$$\begin{bmatrix} 2 & -2 \\ 5 & 3 \end{bmatrix} \times \begin{bmatrix} -1 & 7 \\ 7 & -6 \end{bmatrix} = \begin{bmatrix} (2)(-1) + (-2)(7) & 2 \cdot 4 + (-2)(-6) \\ 5(-1) + 3(7) & 5 \cdot 4 + 3(-6) \end{bmatrix}$$

[Khan Academy Tutorial](#)

Pay attention to the size of the input



Anthony Wang @aytwang · 15h

Replies to [@the_antlr_guy](#)

Wow, this is extraordinary. I can't count the number of hours I've spent in the debugger combing through every variable that could have gone wrong using `print(x.shape)` statements 😂

1

1

16

1



Terence Parr @the_antlr_guy · 15h

haha! Same here! Seems like `print(x.shape)` is the most common deep learning programming construct there is!

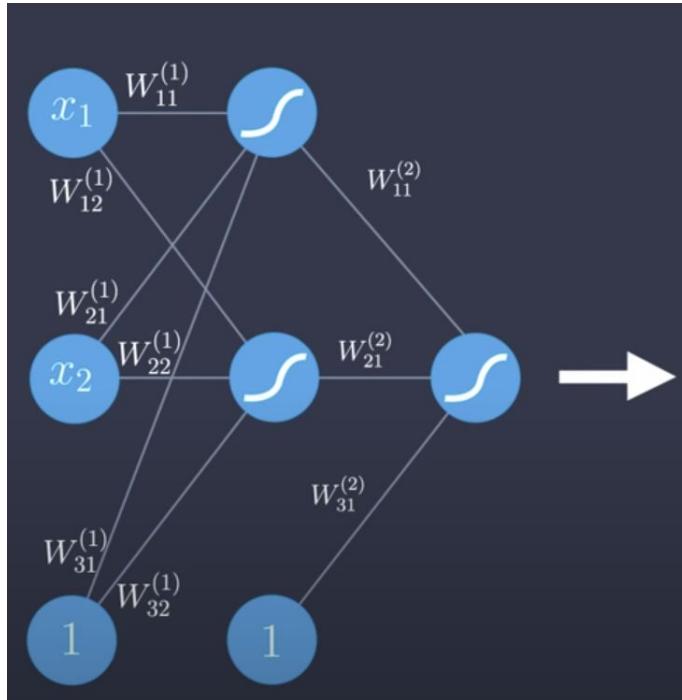
2

6

17

1

The feedforward pass



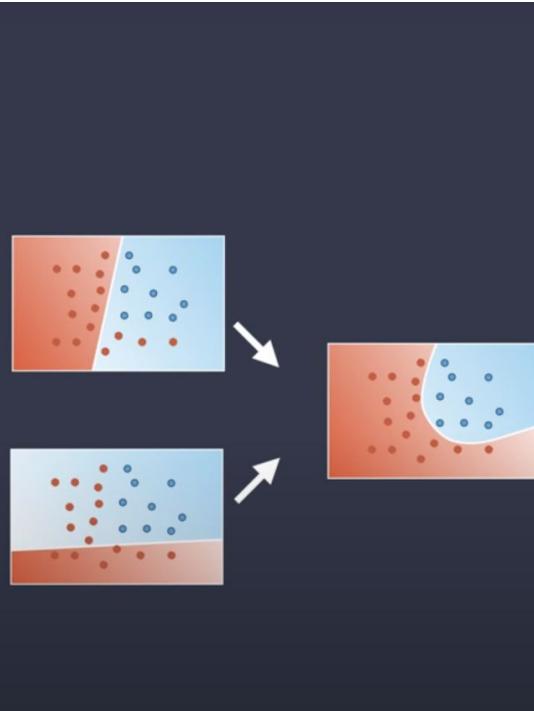
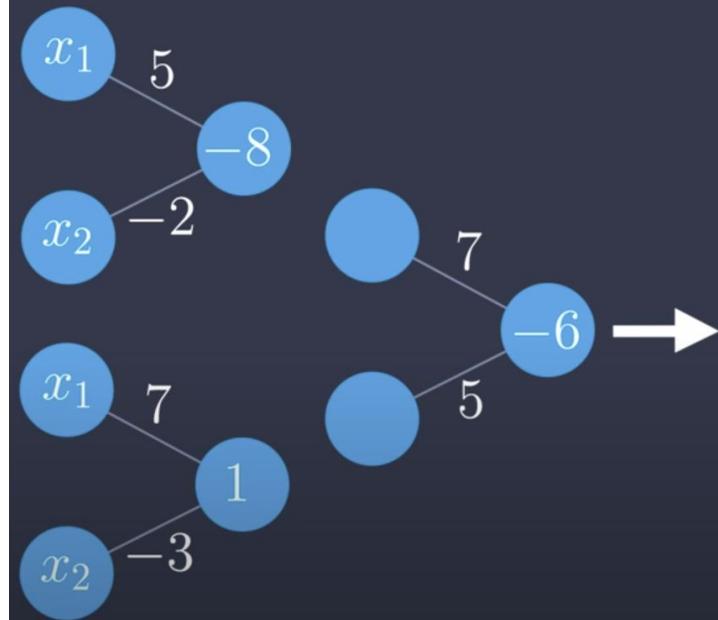
$$\hat{y} = \sigma \begin{pmatrix} W_{11}^{(2)} \\ W_{21}^{(2)} \\ W_{31}^{(2)} \end{pmatrix} \sigma \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} \\ W_{31}^{(1)} & W_{32}^{(1)} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 1 \end{pmatrix}$$

$$\hat{y} = \sigma \circ W^{(2)} \circ \sigma \circ W^{(1)}(x)$$

Understanding the feedforward pass

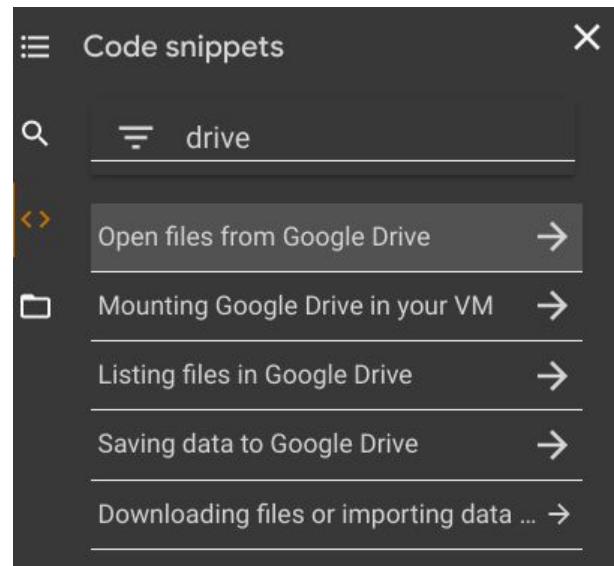
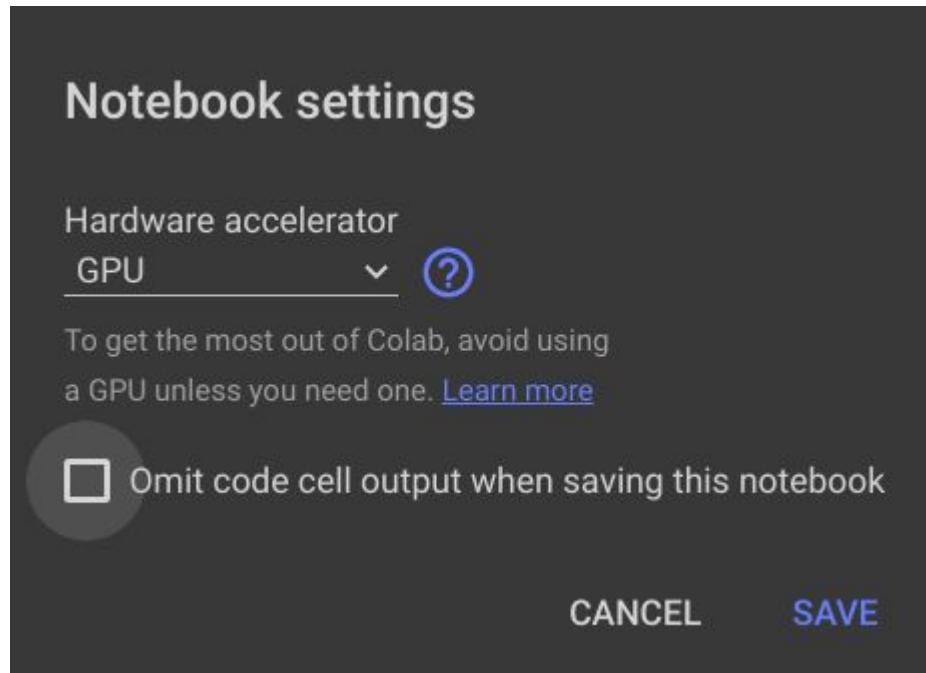
Learning non-linearities

Neural Network

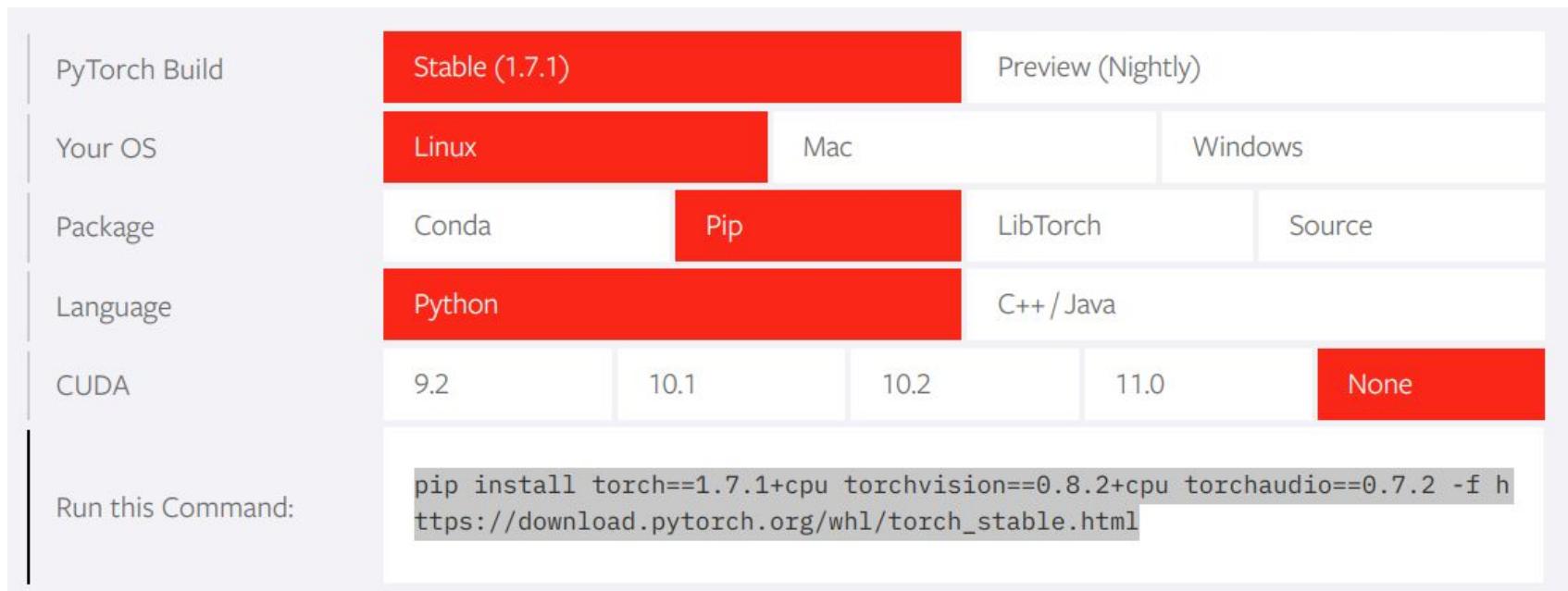


[How neural networks learn non-linearities](#)

Setting up Google Colab



Installing PyTorch



<https://pytorch.org/>

Practice: tensors in Pytorch

- [Notebook](#)
- [Solutions](#)

Questions:

- How is a torch tensor different from a numpy array?
- Is a torch tensor always run on a GPU?
- What is an in-place operation? How do we mark in-place operations in Python?

The Softmax function

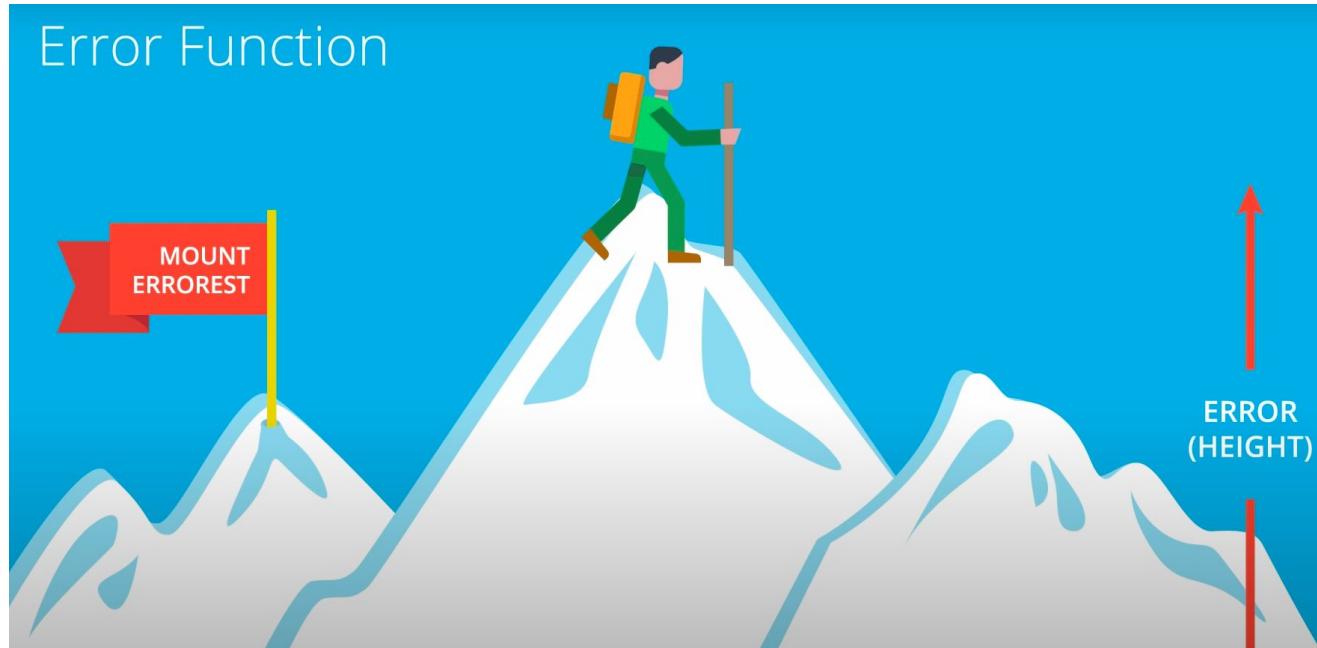
The softmax function takes as input a vector z of K real numbers, and normalizes it into a **probability distribution** consisting of K probabilities proportional to the exponentials of the input numbers. That is, prior to applying softmax, some vector components could be negative, or greater than one; and might not sum to 1; but after applying softmax, each component will be in the **interval** $(0, 1)$, and the components will add up to 1, so that they can be interpreted as probabilities. Furthermore, the larger input components will correspond to larger probabilities.

The standard (unit) softmax function $\sigma : \mathbb{R}^K \rightarrow \mathbb{R}^K$ is defined by the formula

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \text{ for } i = 1, \dots, K \text{ and } \mathbf{z} = (z_1, \dots, z_K) \in \mathbb{R}^K$$

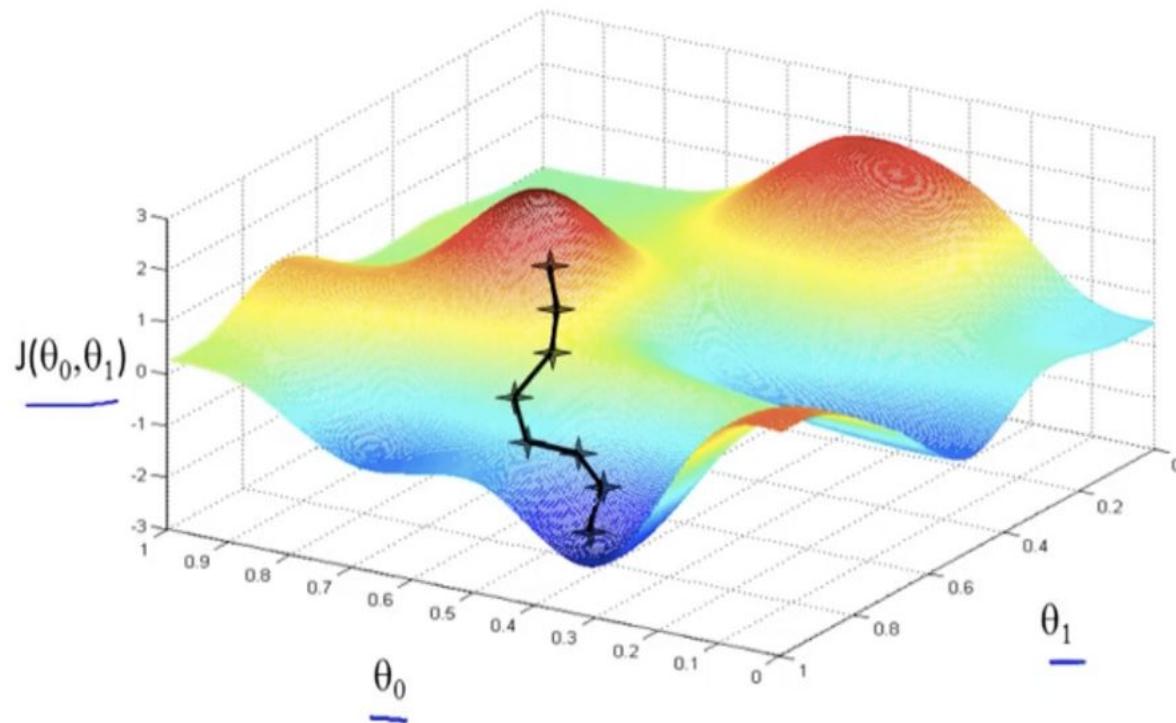
https://en.wikipedia.org/wiki/Softmax_function

Gradient descent

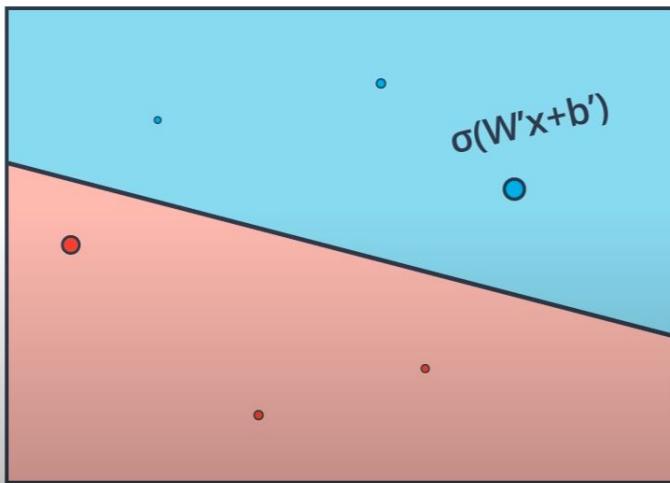


https://github.com/fastai/fastbook/blob/master/04_mnist_basics.ipynb

Stochastic gradient descent



Gradient Descent Algorithm



1. Start with random weights:

$$w_1, \dots, w_n, b$$

2. For every point (x_1, \dots, x_n) :

2.1. For $i = 1 \dots n$

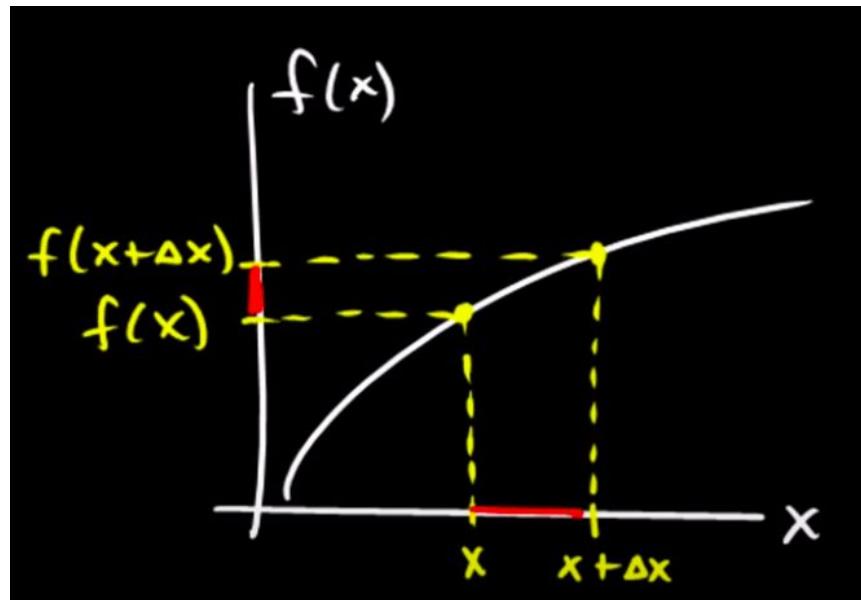
2.1.1. Update $w'_i \leftarrow w_i - \alpha \hat{y} x_i$

2.1.2. Update $b' \leftarrow b - \alpha \hat{y}$

3. Repeat until error is small

Implementing gradient descent

Numerical calculation of derivatives



Numerical derivatives

Numerical and analytic derivatives in Python

Gradient computation graphs

Backpropagation: a simple example

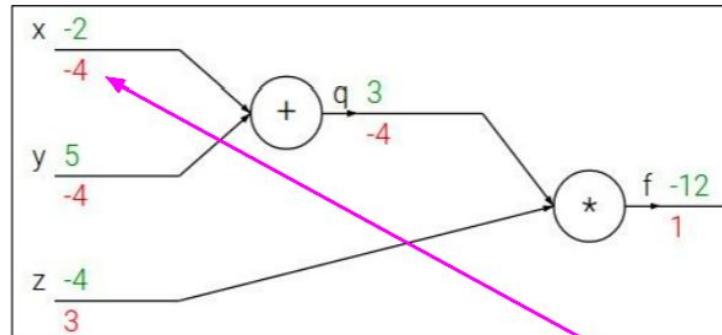
$$f(x, y, z) = (x + y)z$$

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

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

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

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

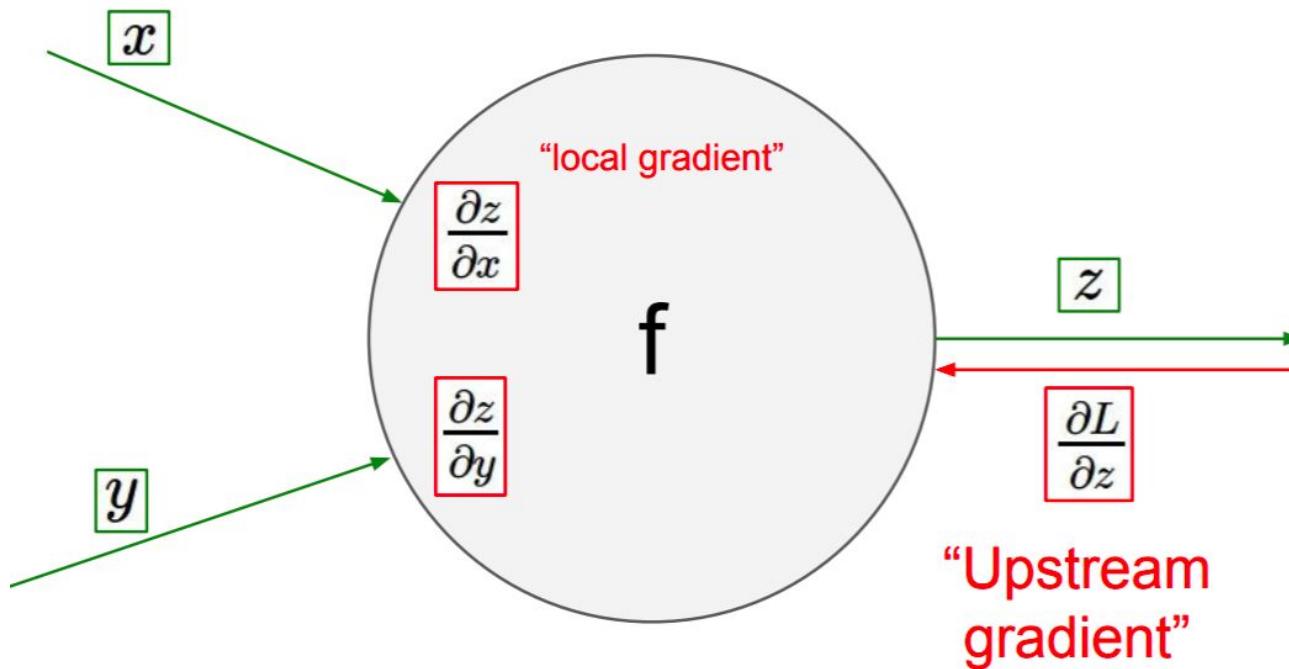


Chain rule:

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

Upstream gradient Local gradient

Gradient computation graphs



Scalar to Scalar

$$x \in \mathbb{R}, y \in \mathbb{R}$$

Regular derivative:

$$\frac{\partial y}{\partial x} \in \mathbb{R}$$

If x changes by a small amount, how much will y change?

Vector to Scalar

$$x \in \mathbb{R}^N, y \in \mathbb{R}$$

Derivative is **Gradient**:

$$\frac{\partial y}{\partial x} \in \mathbb{R}^N \quad \left(\frac{\partial y}{\partial x} \right)_n = \frac{\partial y}{\partial x_n}$$

For each element of x , if it changes by a small amount then how much will y change?

Vector to Vector

$$x \in \mathbb{R}^N, y \in \mathbb{R}^M$$

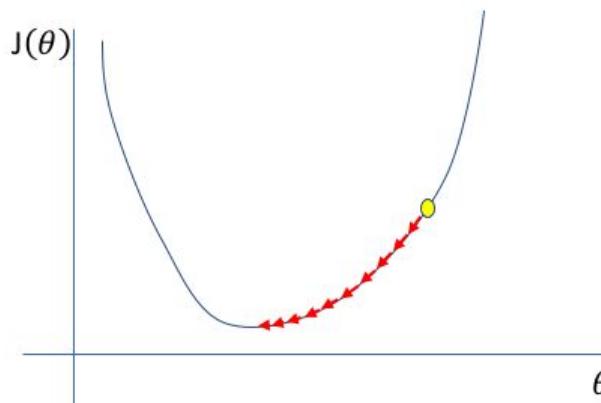
Derivative is **Jacobian**:

$$\frac{\partial y}{\partial x} \in \mathbb{R}^{N \times M} \quad \left(\frac{\partial y}{\partial x} \right)_{n,m} = \frac{\partial y_m}{\partial x_n}$$

For each element of x , if it changes by a small amount then how much will each element of y change?

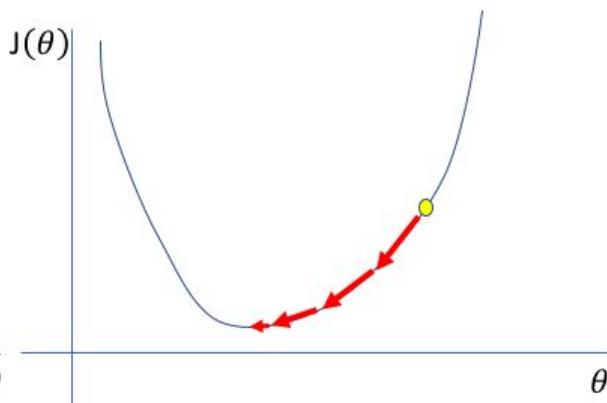
The importance of the learning rate

Too low



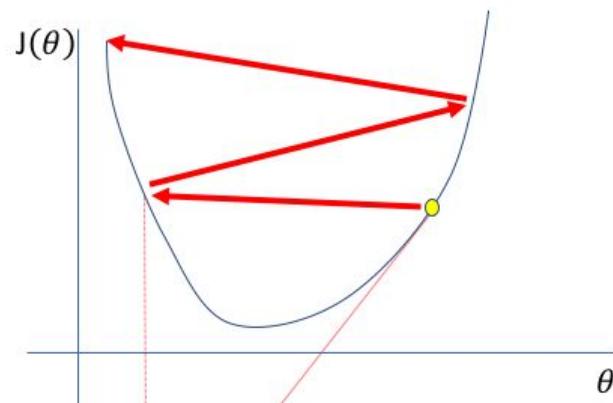
A small learning rate requires many updates before reaching the minimum point

Just right



The optimal learning rate swiftly reaches the minimum point

Too high



Too large of a learning rate causes drastic updates which lead to divergent behaviors

The importance of the learning rate

$$\Delta w_{ij} = (\eta * \frac{\partial E}{\partial w_{ij}})$$



weight
increment

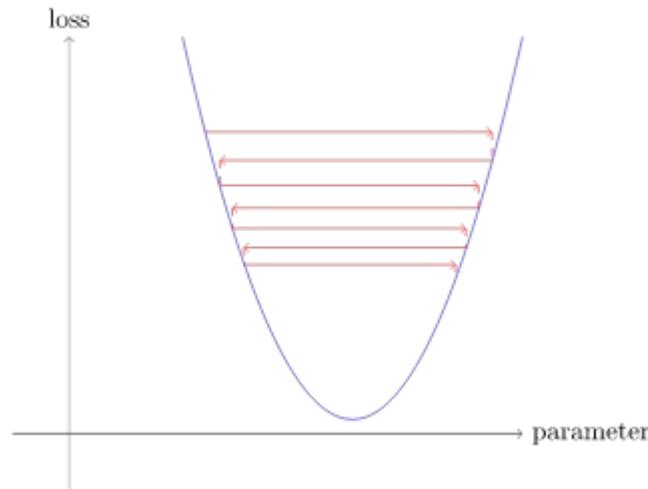


learning
rate

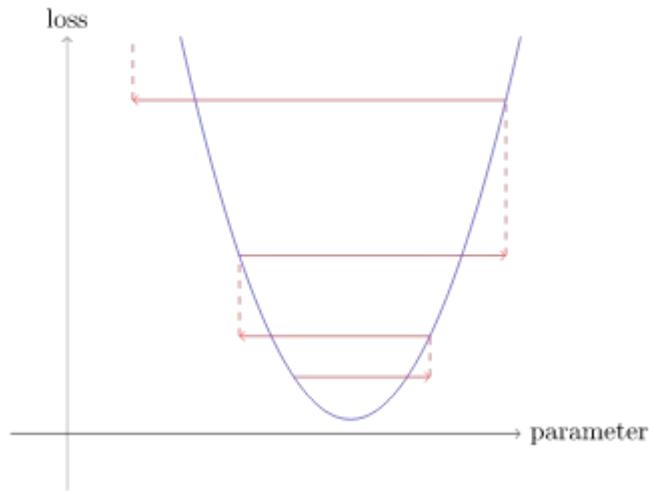
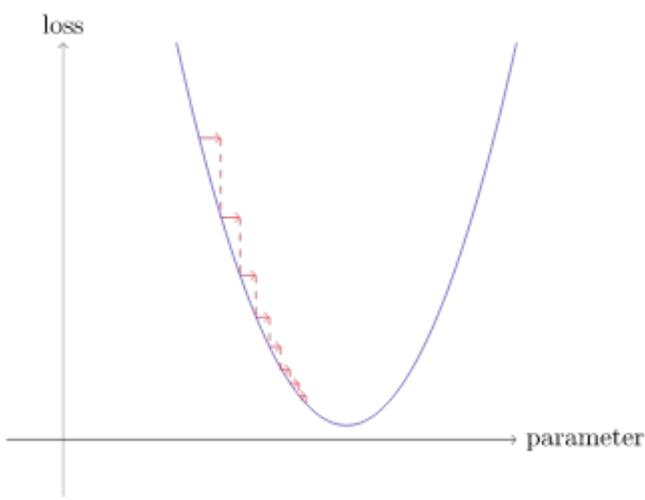


weight
gradient

Choosing a learning rate



Choosing a learning rate



Understanding momentum

$$\Delta w_{ij} = (\eta * \frac{\partial E}{\partial w_{ij}}) + (\gamma * \Delta w_{ij}^{t-1})$$


momentum factor

weight increment,
previous iteration

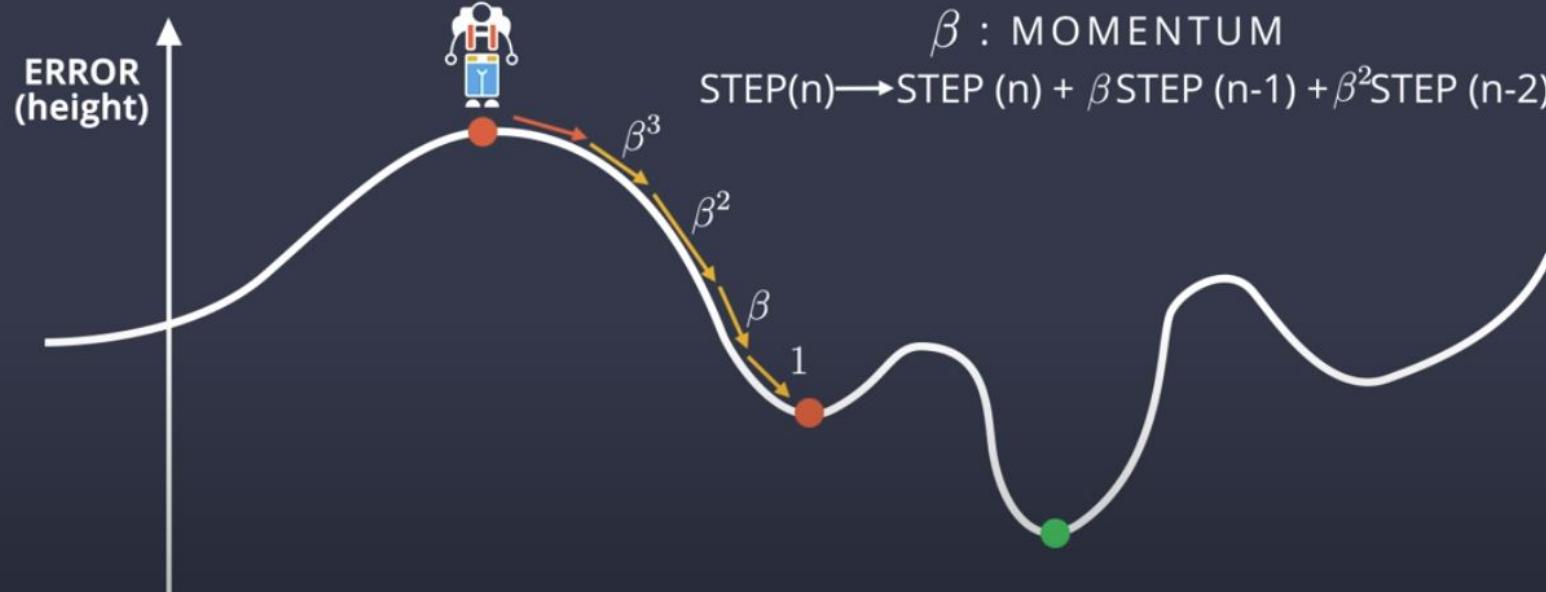
GRADIENT DESCENT

IDEA: MOMENTUM

STEP → AVERAGE OF PREVIOUS STEPS

β : MOMENTUM

STEP(n) → STEP (n) + β STEP (n-1) + β^2 STEP (n-2) + ...



The intuition of momentum

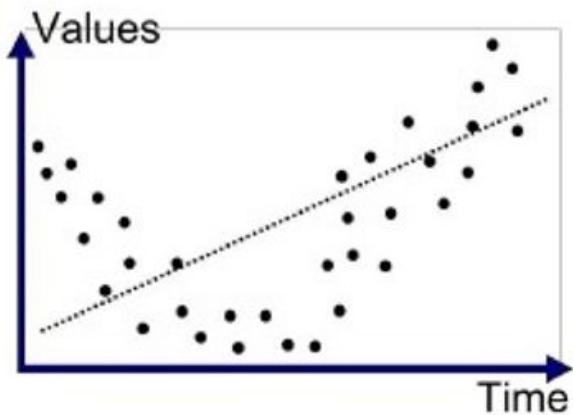
Weight decay aka $\|x\|$ -regularization

$$\text{L1 ERROR FUNCTION} = -\frac{1}{m} \sum_{i=1}^m (1 - y_i) \ln(1 - \hat{y}_i) + y_i \ln(\hat{y}_i) + \boxed{\lambda(|w_1| + \dots + |w_n|)}$$

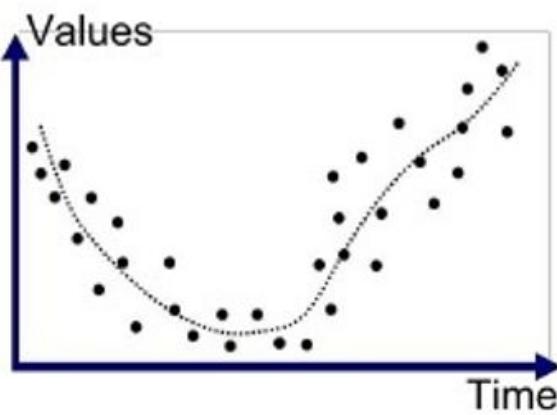
$$\text{L2 ERROR FUNCTION} = -\frac{1}{m} \sum_{i=1}^m (1 - y_i) \ln(1 - \hat{y}_i) + y_i \ln(\hat{y}_i) + \boxed{\lambda(w_1^2 + \dots + w_n^2)}$$

L1 and L2 regularization

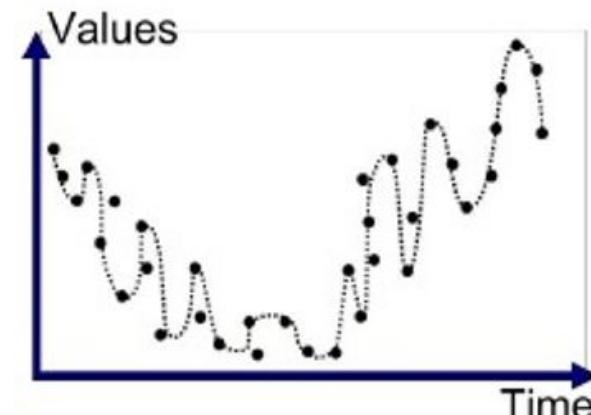
The bias vs variance tradeoff



Underfitted

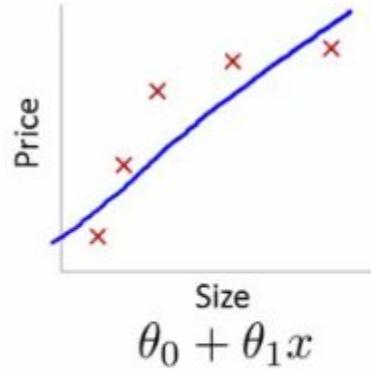


Good Fit/Robust

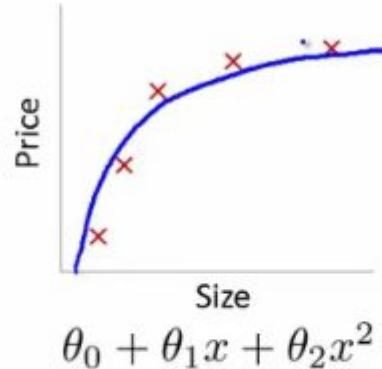


Overfitted

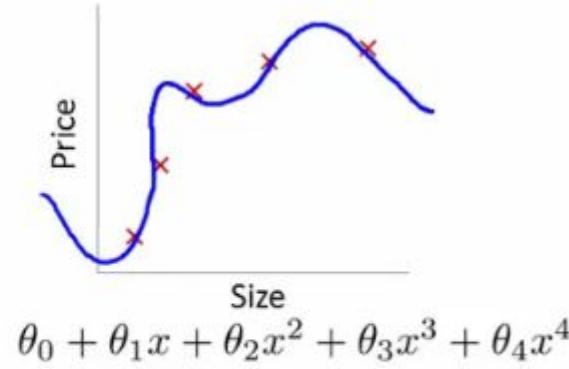
The bias vs variance tradeoff



High bias
(underfit)

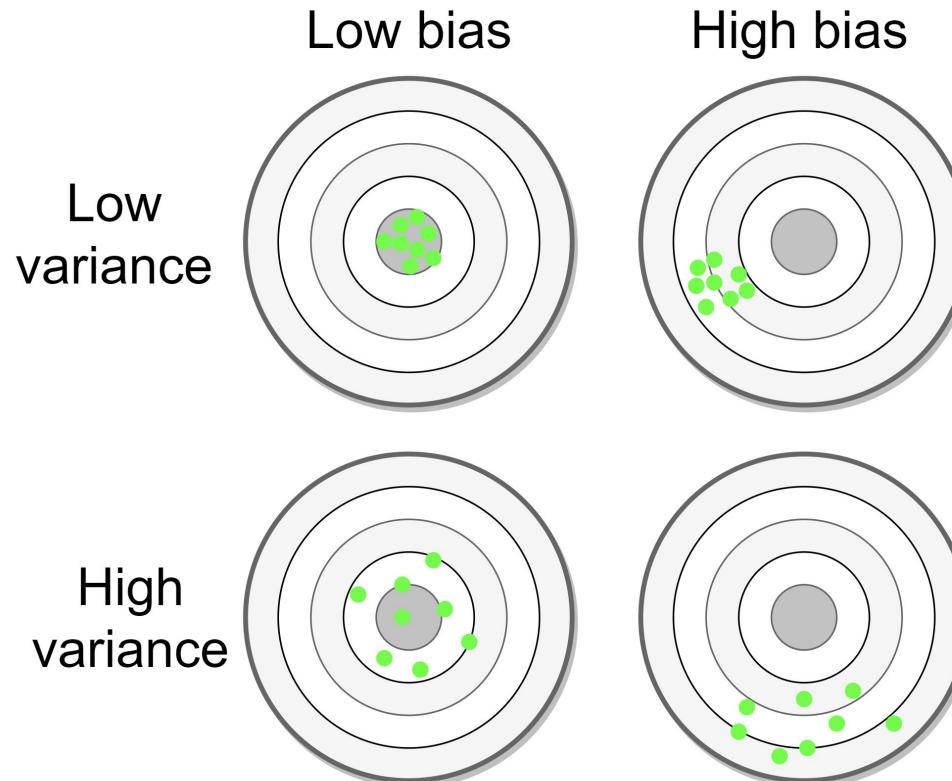


"Just right"

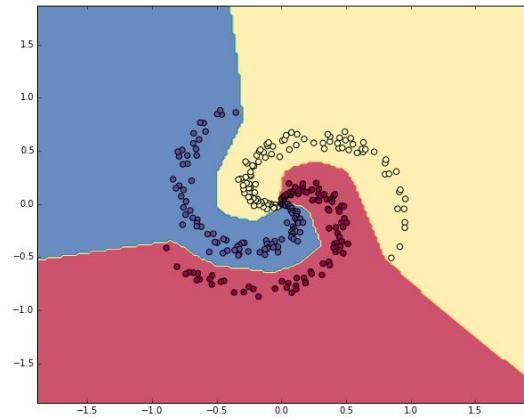
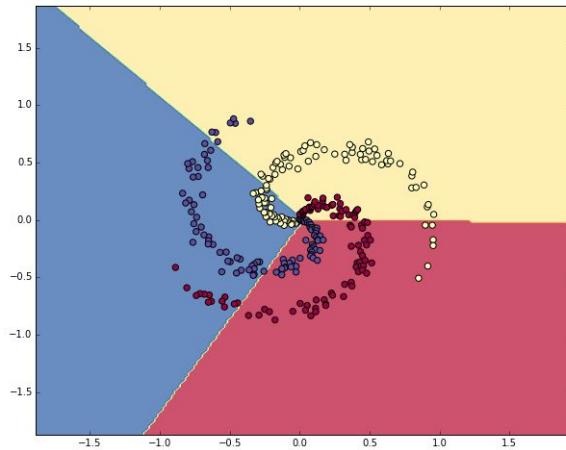


High variance
(overfit)

The bias vs variance tradeoff



Learning non-linearities



<https://cs231n.github.io/neural-networks-case-study>

[Experiment notebook](#)

Q: What happens with large learning rates? What happens with large coefficients for l2 regularization?

Practice: neural networks in PyTorch

- [Notebook](#)
- [Solutions](#)

Pay special attention to

- How to define datasets and dataloaders and their purpose
- How images are normalized
- How nn.Linear defines fully connected layers
- How we extend nn.Module
 - how the `__init__` and `forward()` methods are defined

Q: What is the purpose of nn.Sequential? Why would we use OrderedDict to define an architecture?

How do computers represent images?

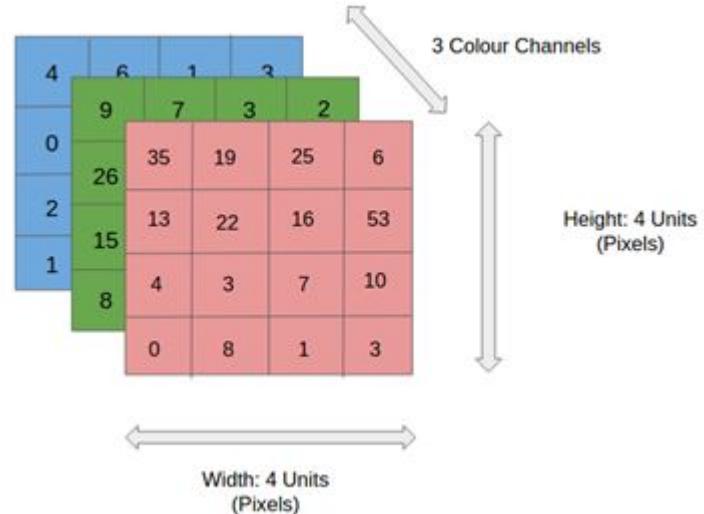


<https://setosa.io/ev/image-kernels/>

Images as tensors



What a human sees



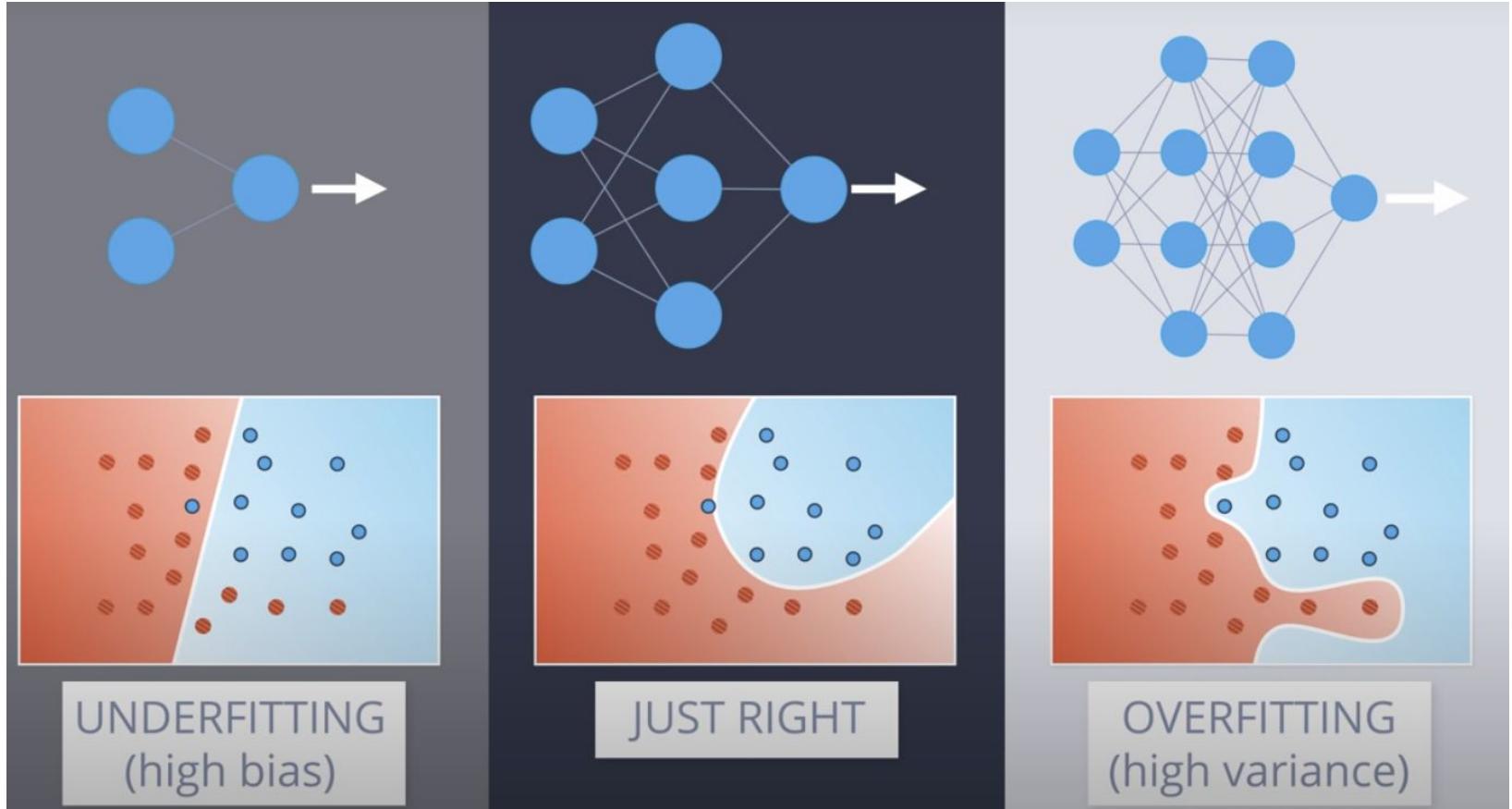
What the computer ‘sees’

Performance metrics vs loss functions

A model performance metric measures the quality of predictions in the validation or test sets. Accuracy, precision, recall, specificity, fbeta, f1, and ROC are performance metrics, not loss functions

The default classification error metric in fastai is `error_rate = 1 - accuracy`

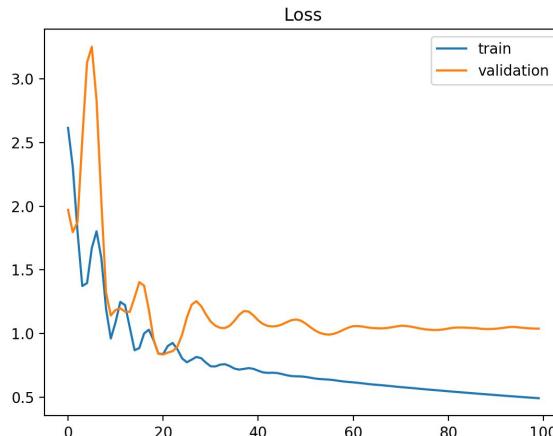
The loss function is used to adjust the weights of the model (through its gradient).
The error metric is a report of performance and it can be opposite to the loss function



Understanding the bias vs variance tradeoff in neural network architectures

How long should we train the network?

- Until it overfits! (Training loss goes down while validation loss goes up)
- This general principle applies to **all** hyperparameters related to model complexity



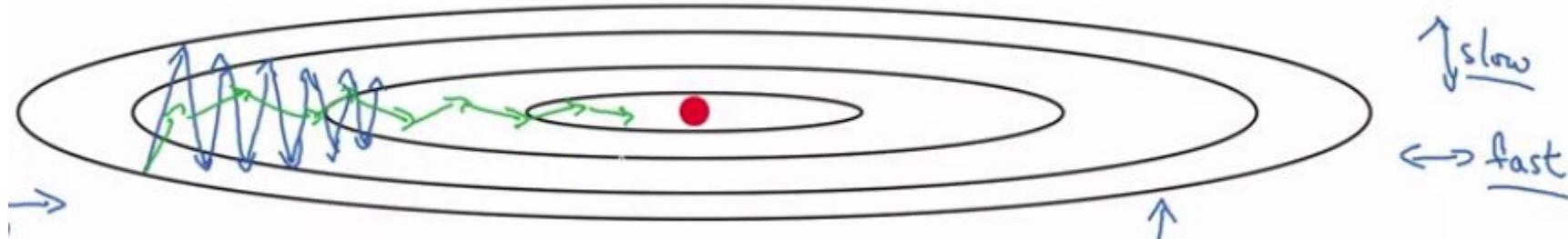
Practice: training in PyTorch

- [Notebook](#)
- [Solutions](#)

Questions:

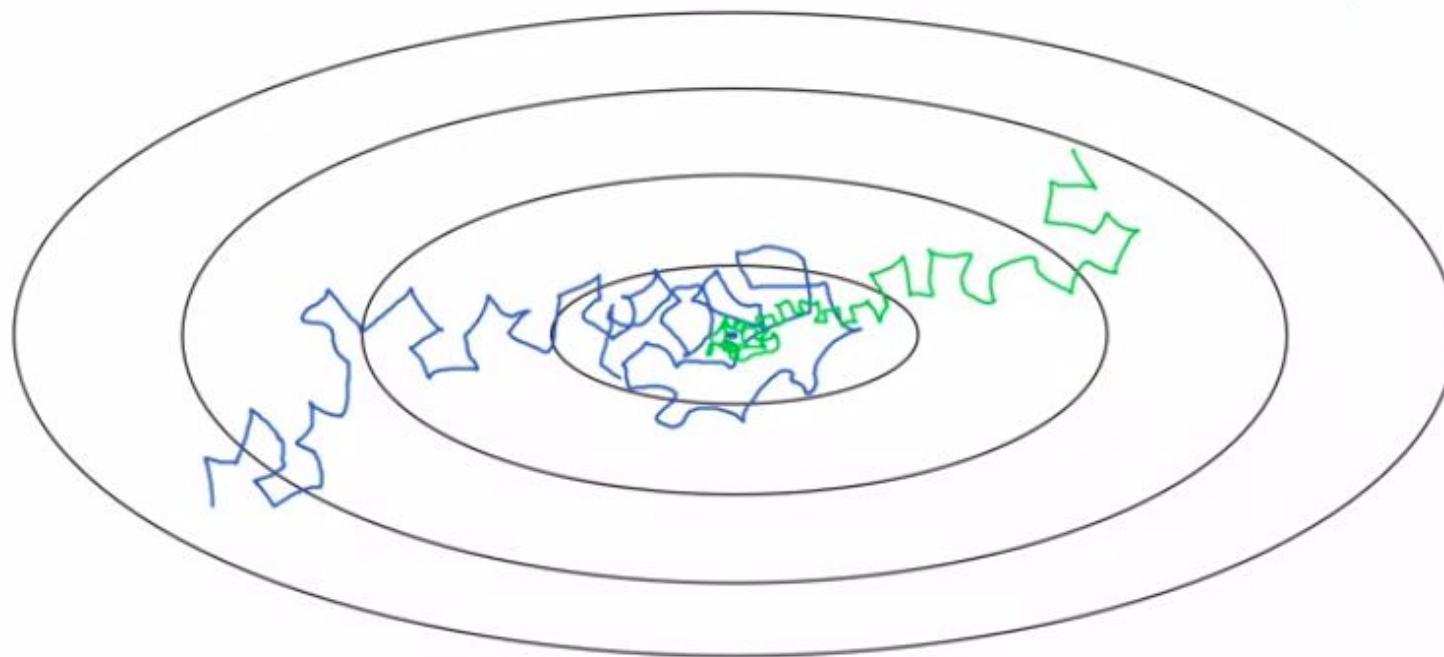
- Why shouldn't we use the network's accuracy as a Pytorch **criterion**?
- What criterion should we use if we change nn.LogSoftmax to Softmax? ([See](#))
- Where do we define the size of the training batch?

The ADAM optimizer



TLDR: [moving averages](#) and [momentum](#) are combined to smoothen the trajectory of the gradient descent. Averages are computed across training batches. This optimization algorithm usually trains faster than SGD

Learning rate decay



Practice: training fully connected networks

- [Notebook](#)
- [Solutions](#)

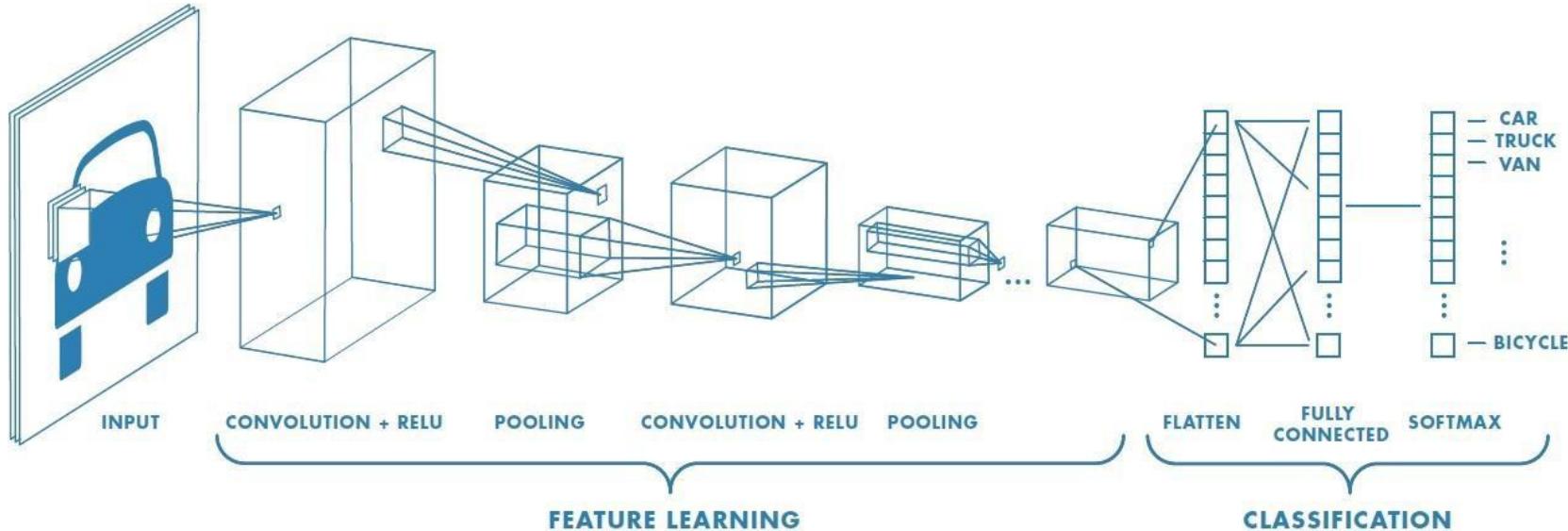
Questions:

- What is a logit (in the context of neural networks)?

Practice: Inference and validation

- [Notebook](#)
- [Solutions](#)
- [Saving models notebook](#)
- Does increasing the amount of dropout increase the bias or the variance of the network?
- If the validation loss is lower than the training loss is the network overfitted or underfitted?
- Experiment: try adding a ‘save model’ functionality to the Part 5 notebook. Save the model as pth file after a validation loss threshold of your choice has been satisfied.

Convolutional Neural Networks



CNNs vs multilayer perceptrons

Image Classification



what we see

- Outdoor
- Building
- Snow

Image Classification

5	9	23	32	33	0	0	0	0	0	0	0
3	28	30	47	0	0	0	0	0	0	0	0
7	1	3	0	0	0	0	0	0	0	0	0
14	21	20	25	27	38	40	0	0	0	0	0
18	29	0	0	0	0	0	0	0	0	0	0
12	13	15	0	0	0	0	0	0	0	0	0
20	26	27	11	25	38	40	0	0	0	0	0
32	33	34	0	0	0	0	0	0	0	0	0
29	18	0	0	0	0	0	0	0	0	0	0
5	9	8	24	0	0	0	0	0	0	0	0
28	16	17	0	0	0	0	0	0	0	0	0
18	29	0	0	0	0	0	0	0	0	0	0
25	26	20	11	0	0	0	0	0	0	0	0
7	1	3	0	0	0	0	0	0	0	0	0
33	32	9	5	23	0	0	0	0	0	0	0
28	16	17	0	0	0	0	0	0	0	0	0

- Outdoor
- Building
- Snow? *Do we care about snow?*
 - Enough of these images need to be shown to the algorithm

what the computer “sees”

Defining image taxonomies



- Bedroom
- Terrace
- Desk
- Vegetation
- Do we have enough images with these things?

Labels for hard cases



- Should we have added 'neon lights' to our taxonomy?
- How many of these things we have?
- Should we invest effort on this?
- **Stacks of binary models** are appropriate for this problem

Hot Dog not a Hot Dog



<https://www.youtube.com/watch?v=vlci3C4JkL0>

What is a convolution filter?

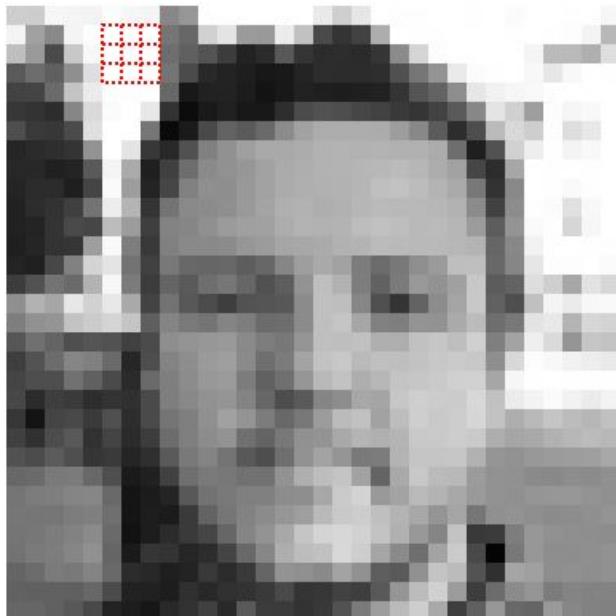
1	2	3	4	5	6	7
8	9	10	11	12	13	14
15	16	17	18	19	20	21
22	23	24	25	26	27	28
29	30	31	32	33	34	35
36	37	38	39	40	41	42
43	44	45	46	47	48	49

0.1	0.2	0.3
0.4	0.5	0.6
0.7	0.8	0.9

$$\begin{aligned} &= 0.1 \times 10 + 0.2 \times 11 + 0.3 \times 12 \\ &+ 0.4 \times 17 + 0.5 \times 18 + 0.6 \times 19 \\ &+ 0.7 \times 24 + 0.8 \times 25 + 0.9 \times 26 \\ &= 94.2 \end{aligned}$$

https://github.com/fastai/fastbook/blob/master/13_convolutions.ipynb

What is a convolution filter?



input image

$$\left(\begin{array}{c} 255 \times 0 + 254 \times -1 + 255 \times 0 \\ + 255 \times -1 + 255 \times 5 + 255 \times -1 \\ + 255 \times 0 + 255 \times -1 + 252 \times 0 \\ = 256 \end{array} \right)$$

kernel:
sharpen



output image

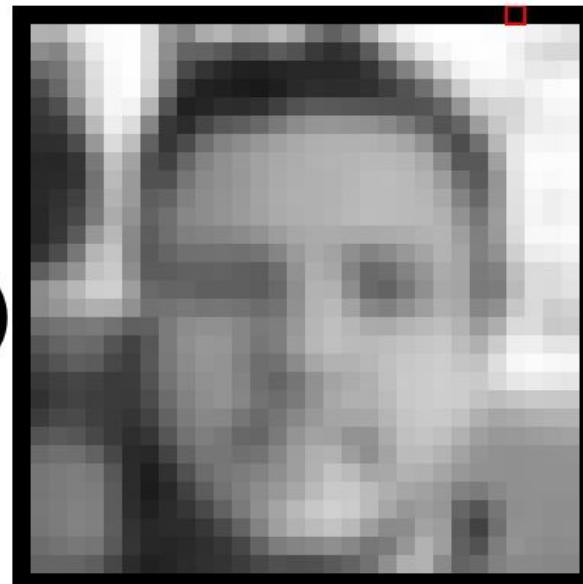
<https://setosa.io/ev/image-kernels/>

What is a convolution filter?



input image

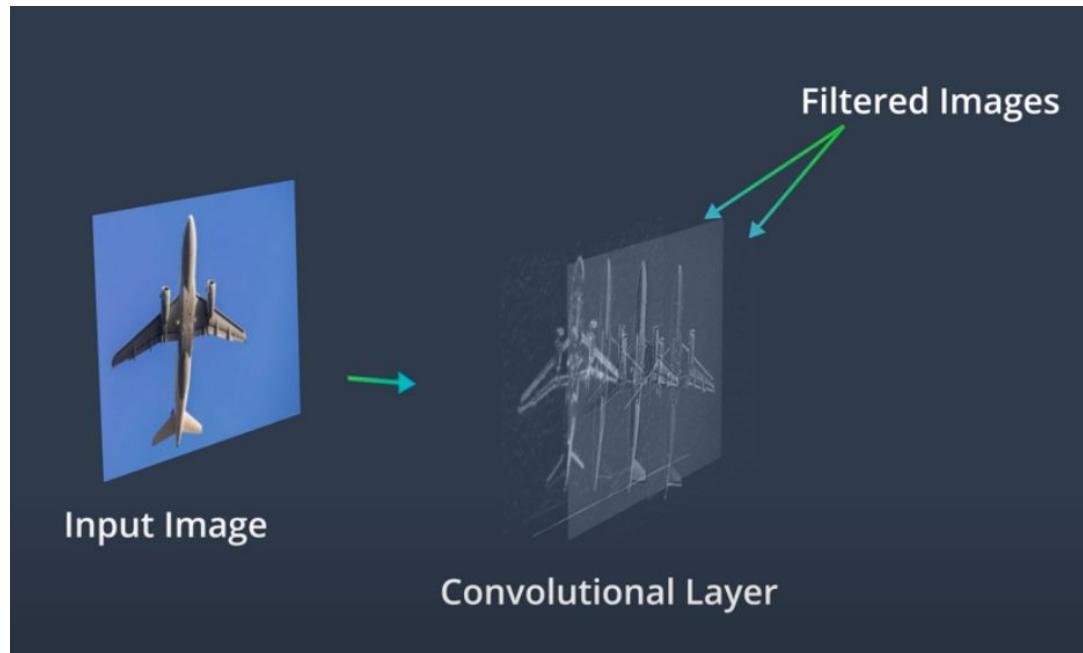
$$\begin{aligned} & \left(\begin{array}{ccc} ? & + & ? \\ \times 0.0625 & & \times 0.125 & \times 0.0625 \\ + & 252 & + & 255 & + & 255 \\ \times 0.125 & & \times 0.25 & & \times 0.125 \\ + & 254 & + & 255 & + & 254 \\ \times 0.0625 & & \times 0.125 & & \times 0.0625 \end{array} \right) \\ & = ? \\ & \text{kernel: } \text{blur} \end{aligned}$$



output image

<https://setosa.io/ev/image-kernels/>

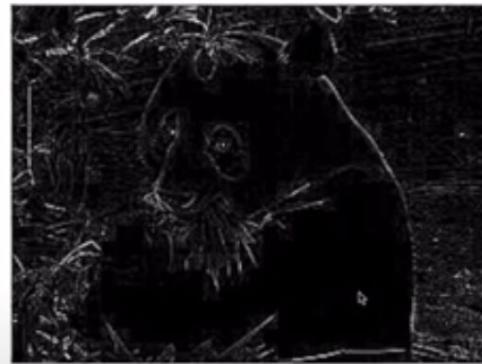
What is a convolution filter?



[Understanding the output of convolutional layers](#)

What is a convolution filter?

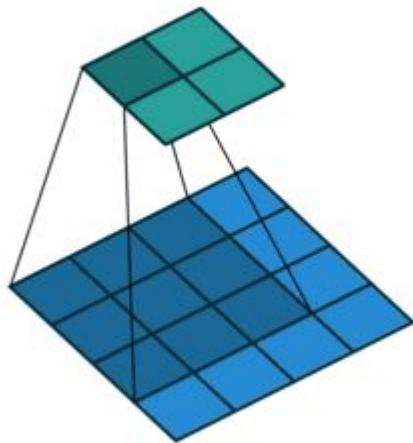
0	-1	0
-1	4	-2
0	-1	0



$$0 + -1 + 0 + -1 + 4 + \mathbf{-2} + 0 + -1 + 0 = -1$$

[Visualizing convolution kernels](#)

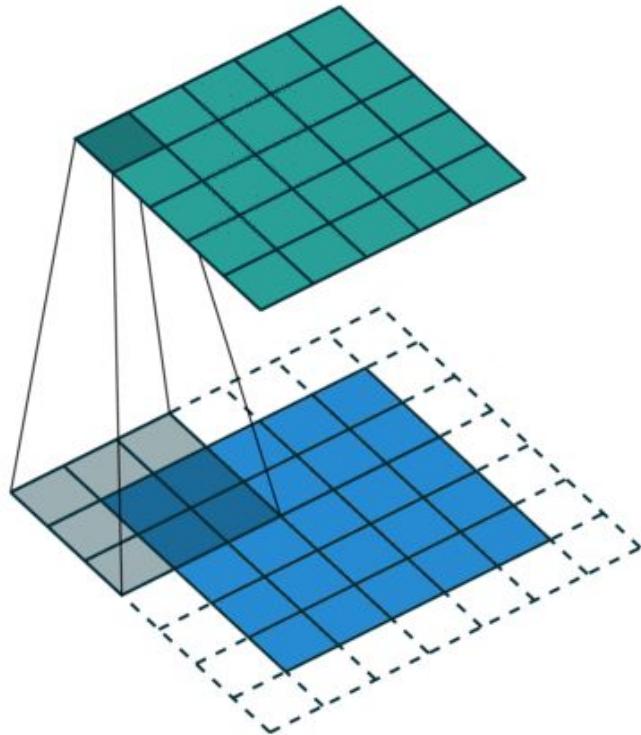
What is a convolution filter?



Convolution of 3×3 and stride = 1 without padding

Effect: the output loses one pixel on each dimension

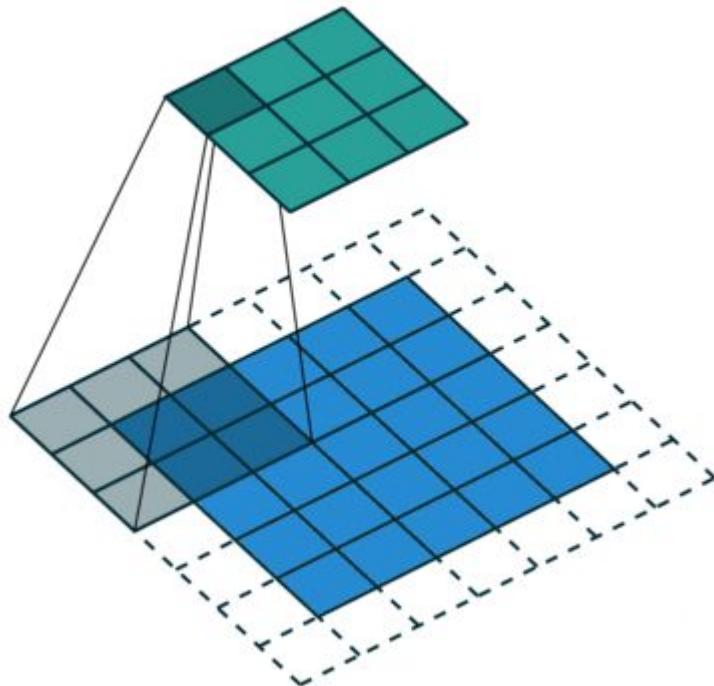
What is a convolution filter?



Convolution of 3×3 and stride = 1 with zero padding of one pixel

Effect: the output preserves original image size

What is a convolution filter?



Convolution of 3x3 and stride = 2 with zero padding

Effect: the output is downsampled to about half its size

[Activity: Conv2D in Pytorch \(Colab notebook\)](#)

Experiment: finding edges with convolutions

$$S_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}$$

$$S_y = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}$$

Finding edges with convolution kernels

Pooling

Max Pooling

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

Average Pooling

31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2
pool size

100	184
12	45

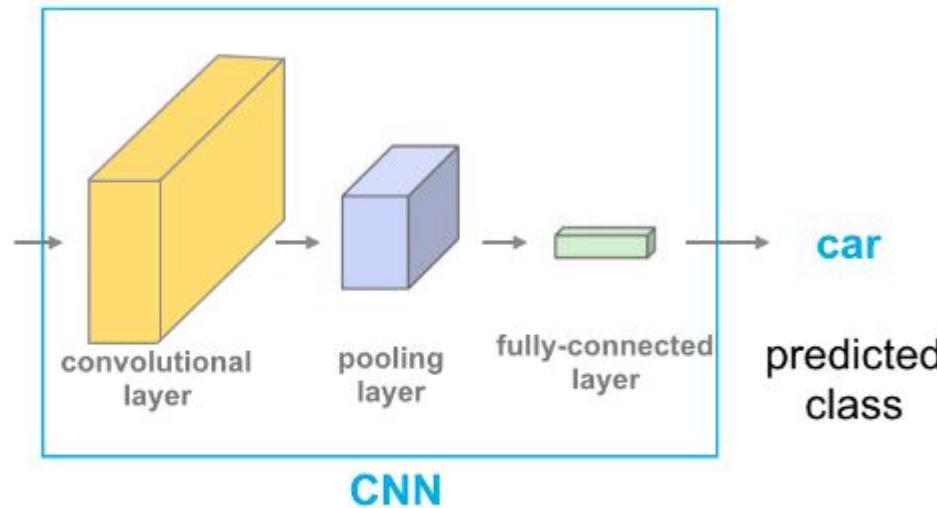
2 x 2
pool size

36	80
12	15

CNN architectures

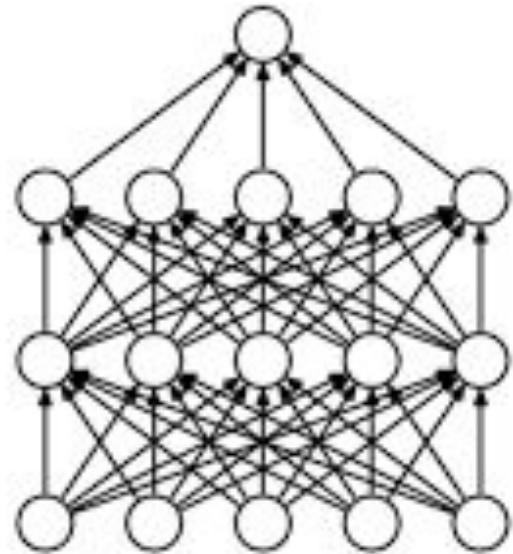


input image

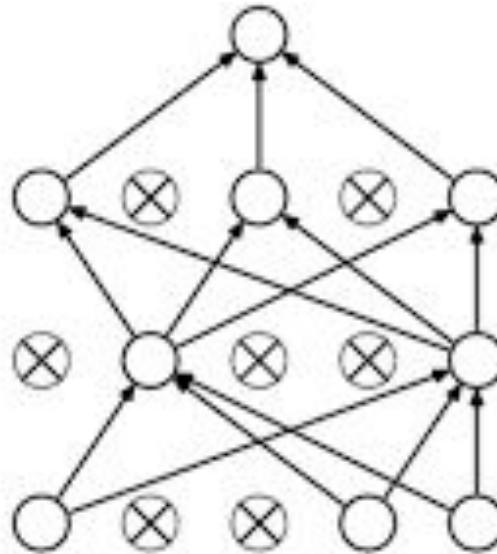


Layers in a CNN.

Dropout regularization

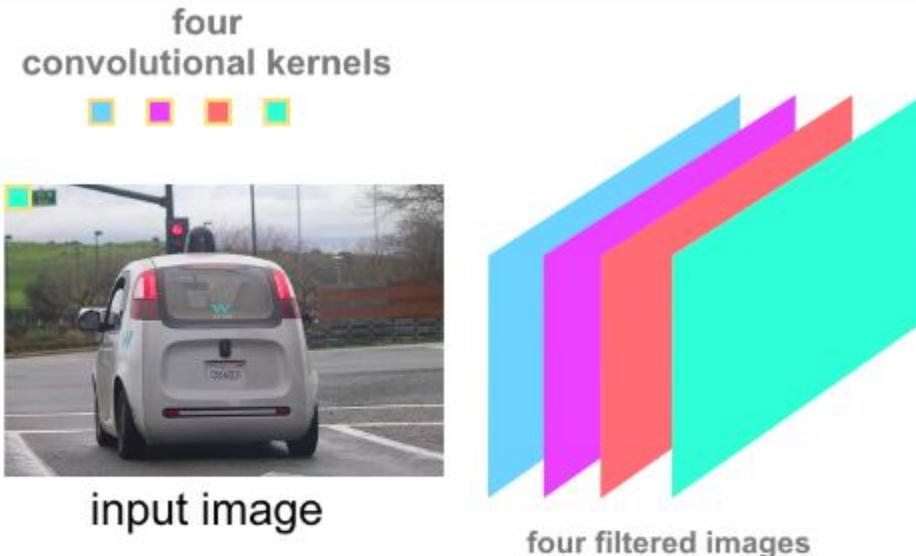


(a) Standard Neural Net



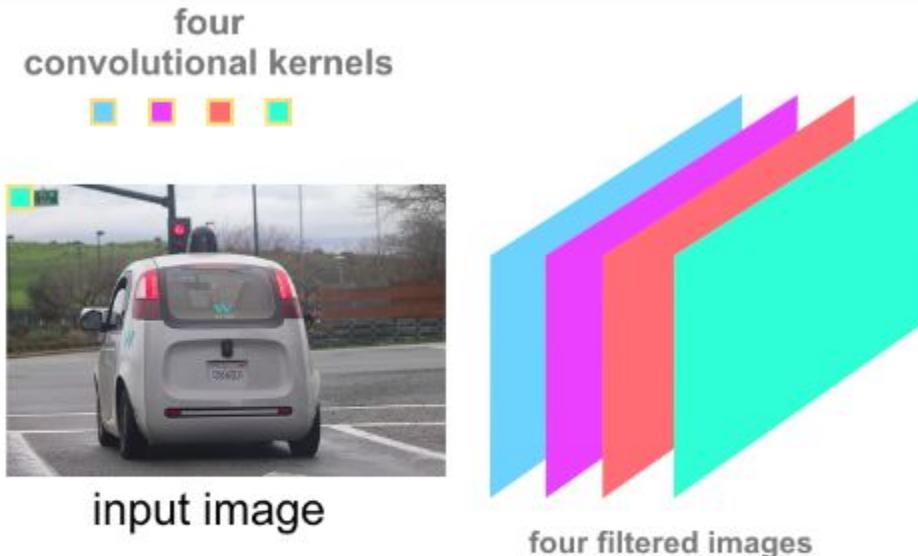
(b) After applying dropout.

CNN architectures



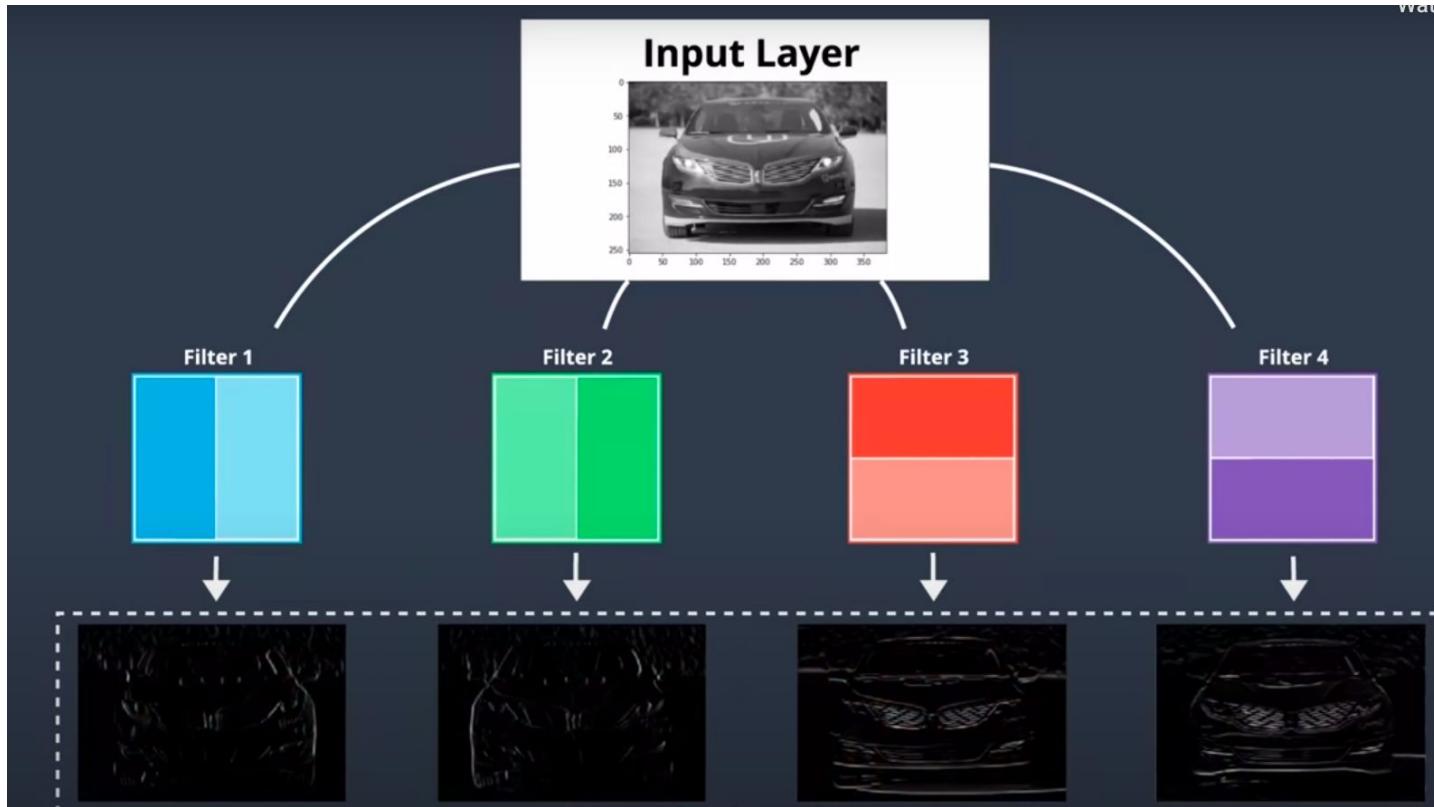
4 kernels = 4 filtered images.

CNN architectures

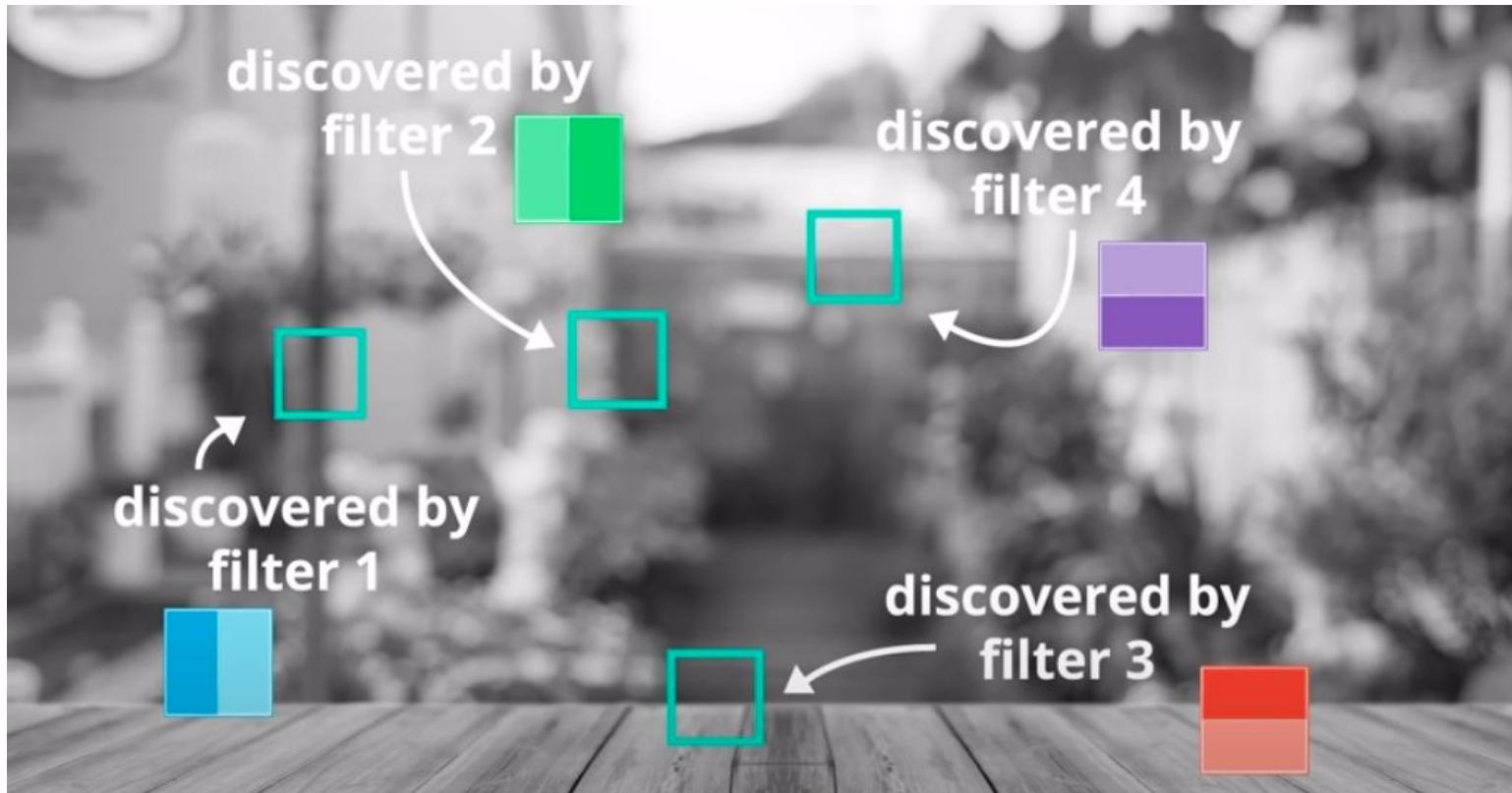


4 kernels = 4 filtered images.

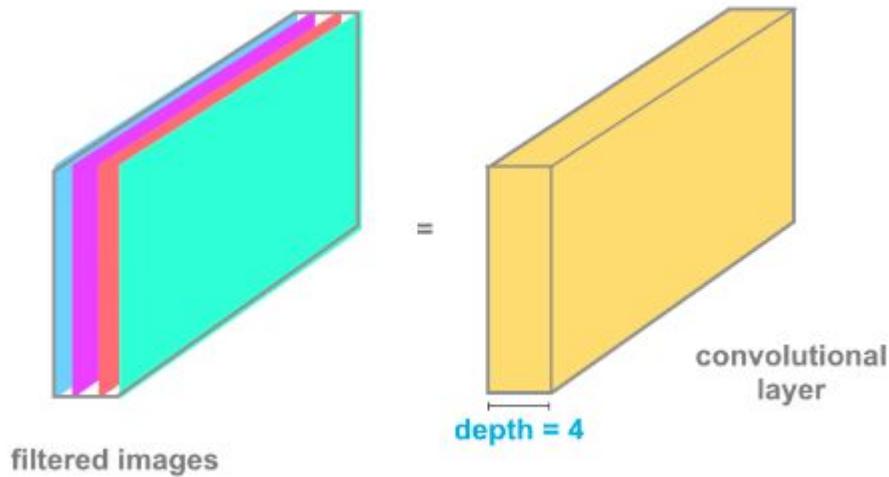
CNN architectures



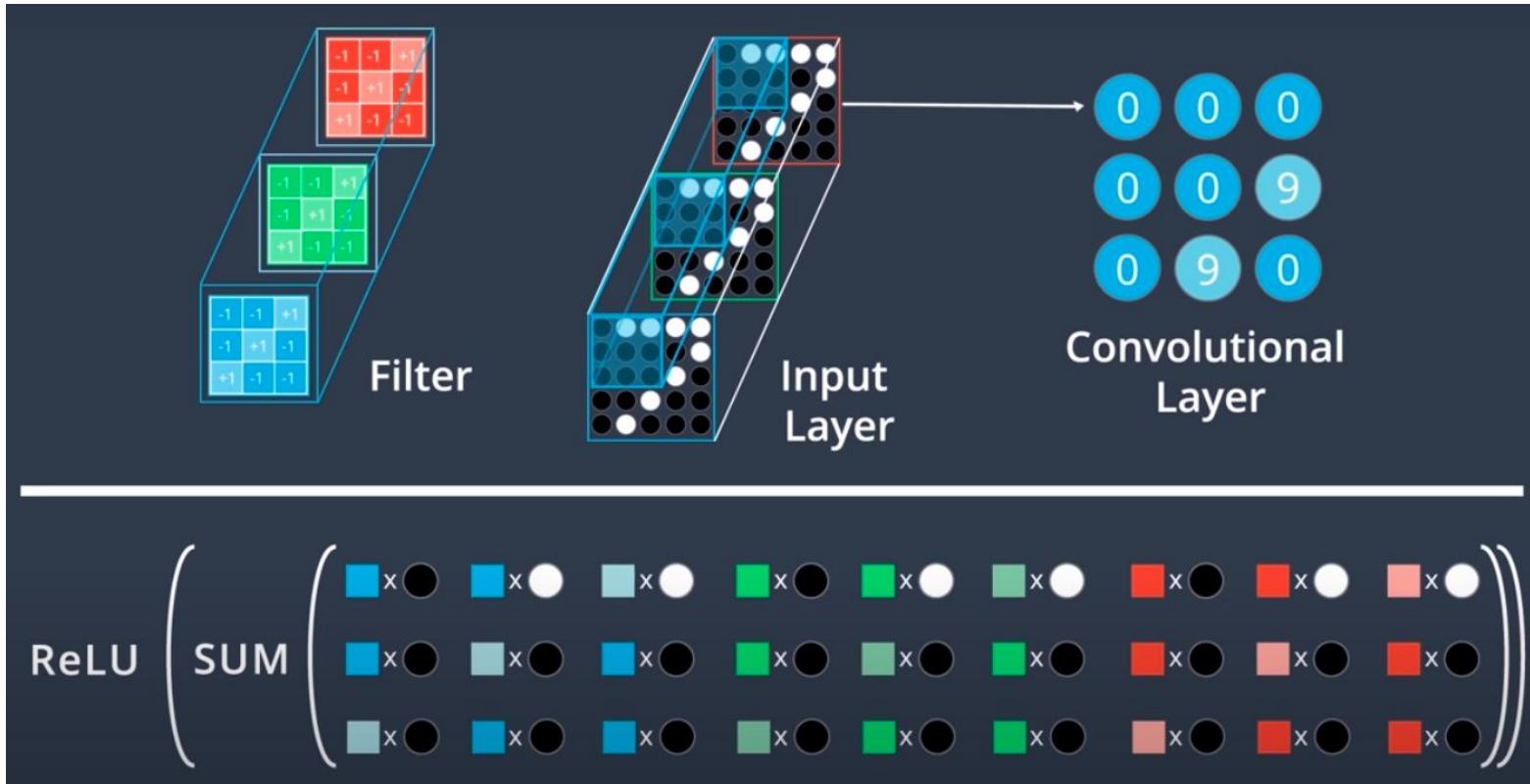
CNN architectures

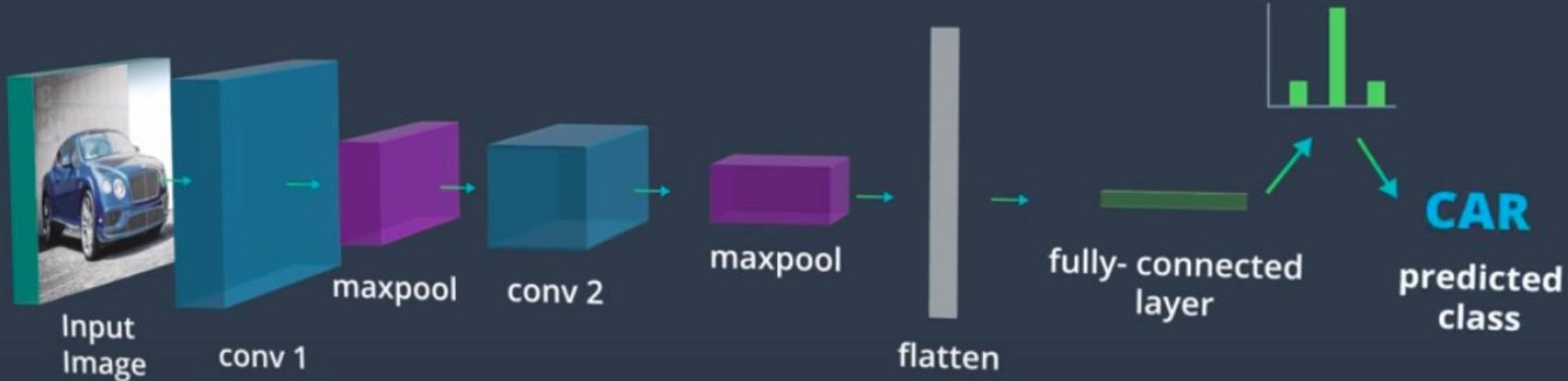


CNN architectures



CNN architectures





extracting more and more complex features

learns to distill the **content** of the image

Normalizing images

```
transforms = torch.nn.Sequential(  
    transforms.CenterCrop(10),  
    transforms.Normalize((0.485, 0.456, 0.406), (0.229, 0.224, 0.225)),  
)  
scripted_transforms = torch.jit.script(transforms)
```

<https://pytorch.org/docs/stable/torchvision/transforms.html#transforms-on-torch-tensor>

Images need to be resized for the GPU

zeros



border



reflection



Data augmentation



<https://docs.fast.ai/vision.augment>

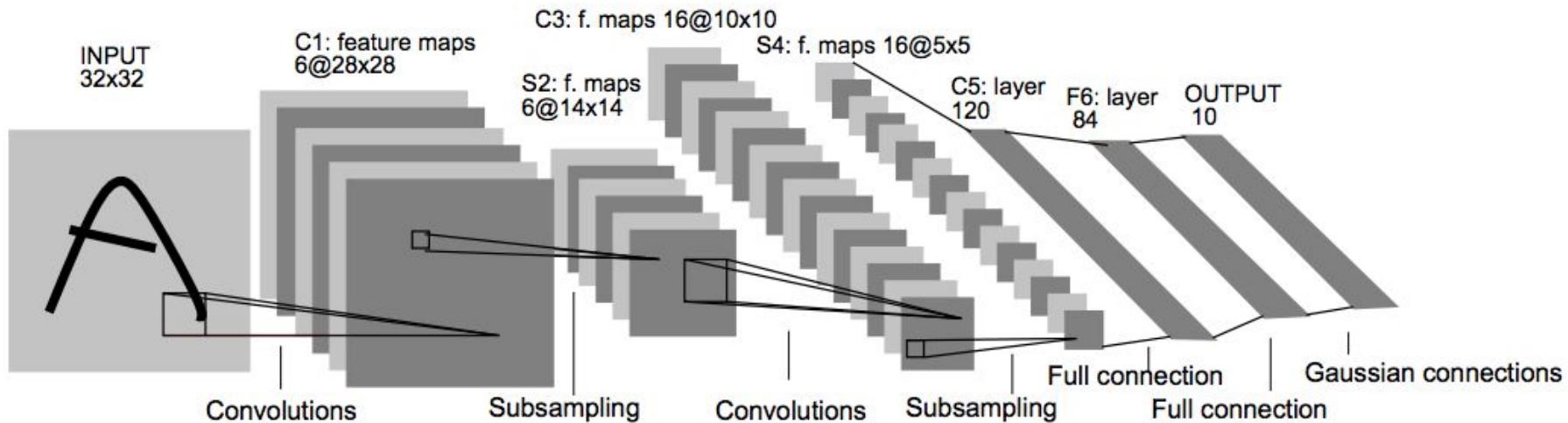
Augmentations composition in PyTorch

Practice: loading image data

- [Notebook](#)
- [Solutions](#)

Q: Why are we using different means and standard deviations to normalize each image channel?

Understanding architecture diagrams: LeNet



Understanding architecture diagrams: AlexNet

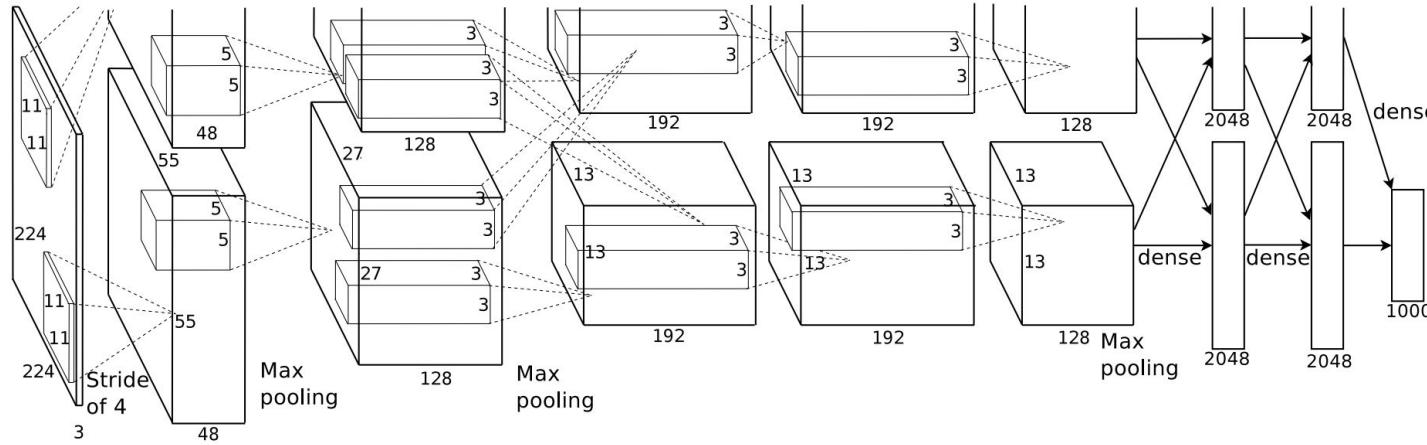


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Transfer learning

Using a pretrained model for a task different to what it was originally trained on is called *transfer learning*

ImageNet is the single most important dataset in computer vision, it contains 1.3 million labeled images of a thousand categories and has been used to benchmark classification models during the last decade. Most popular models have been pretrained and published on ImageNet

What a pretrained network already knows



Cornell University

arXiv.org > cs > arXiv:1311.2901

Computer Science > Computer Vision and Pattern Recognition

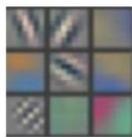
[Submitted on 12 Nov 2013 ([v1](#)), last revised 28 Nov 2013 (this version, v3)]

Visualizing and Understanding Convolutional Networks

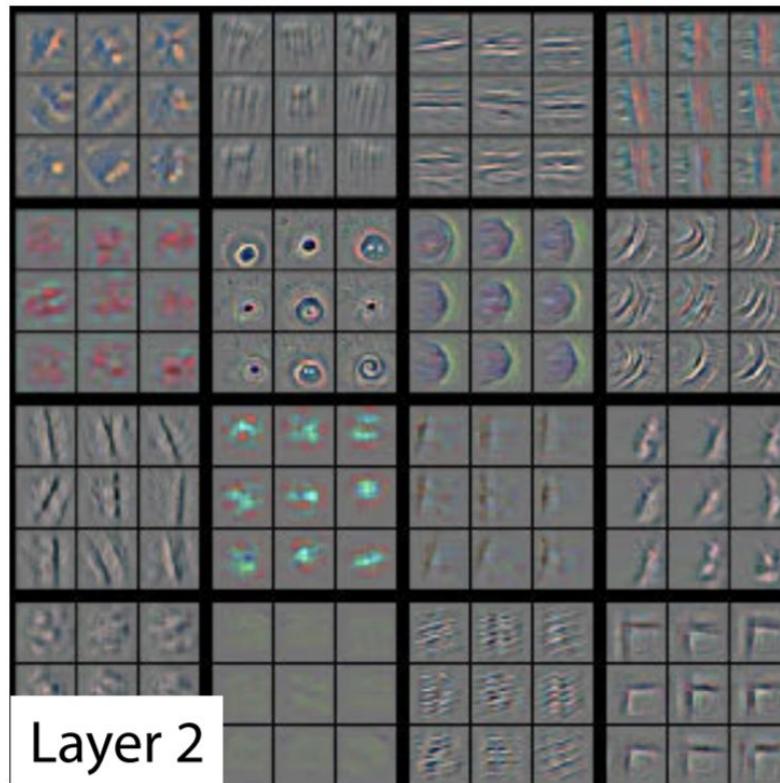
Matthew D Zeiler, Rob Fergus

<https://arxiv.org/pdf/1311.2901.pdf>

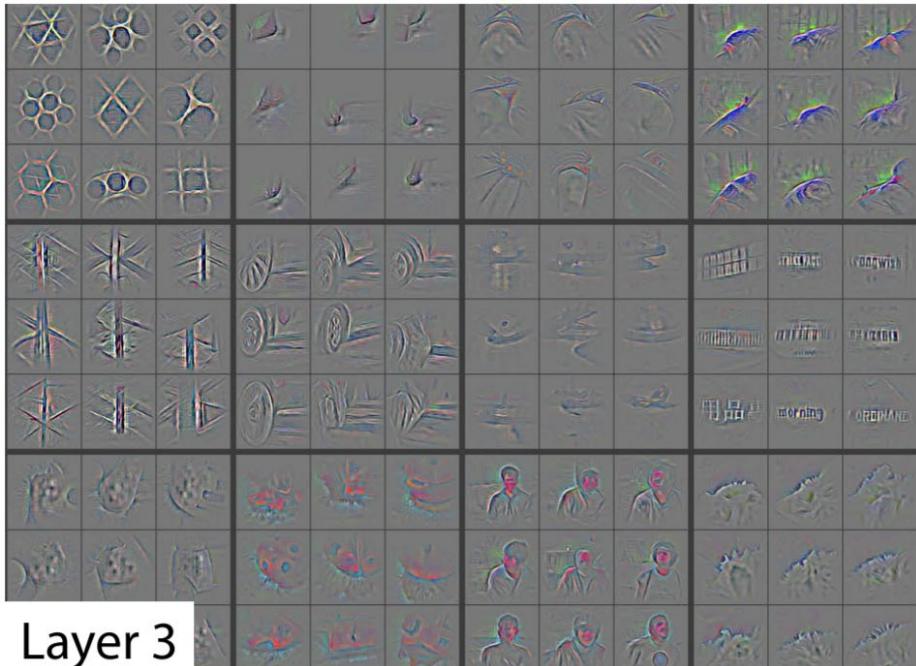
What a pretrained network already knows



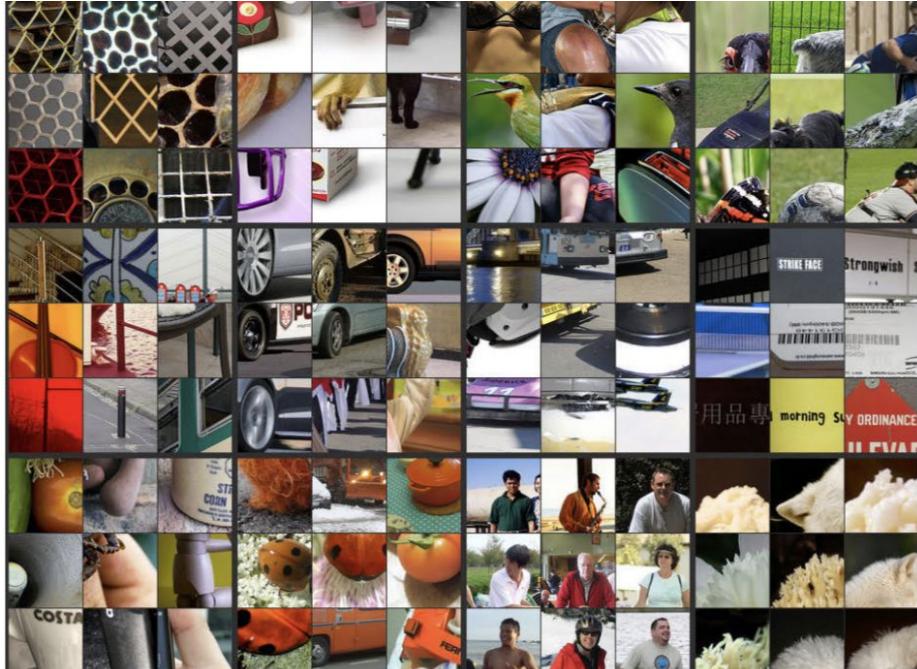
Layer 1



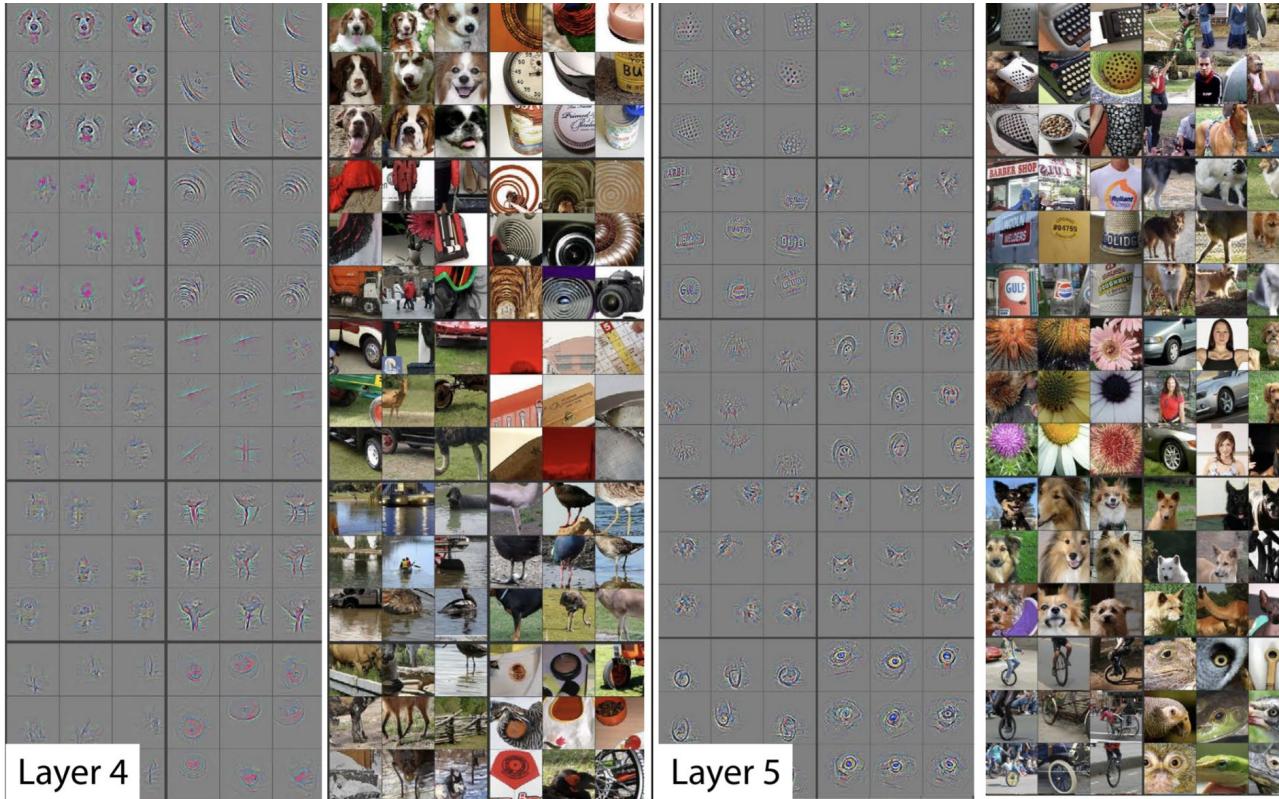
What a pretrained network already knows



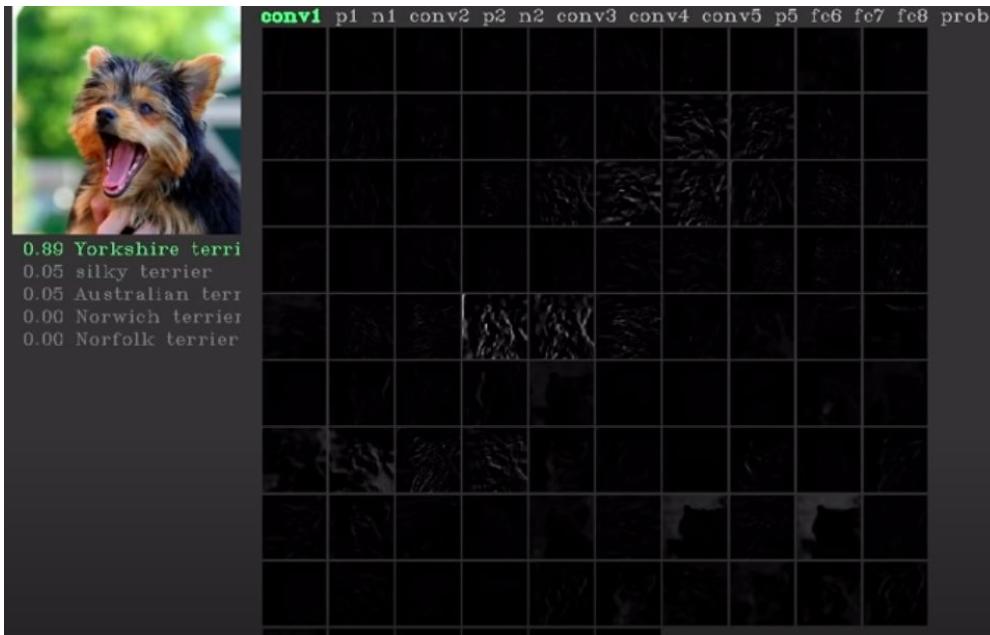
Layer 3



What a pretrained network already knows



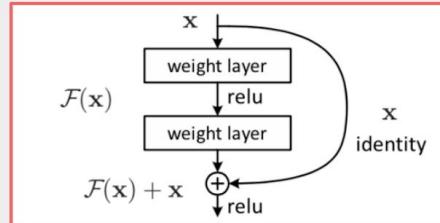
What a pretrained network already knows



Visualizing the layers of an Alexnet trained on Imagenet

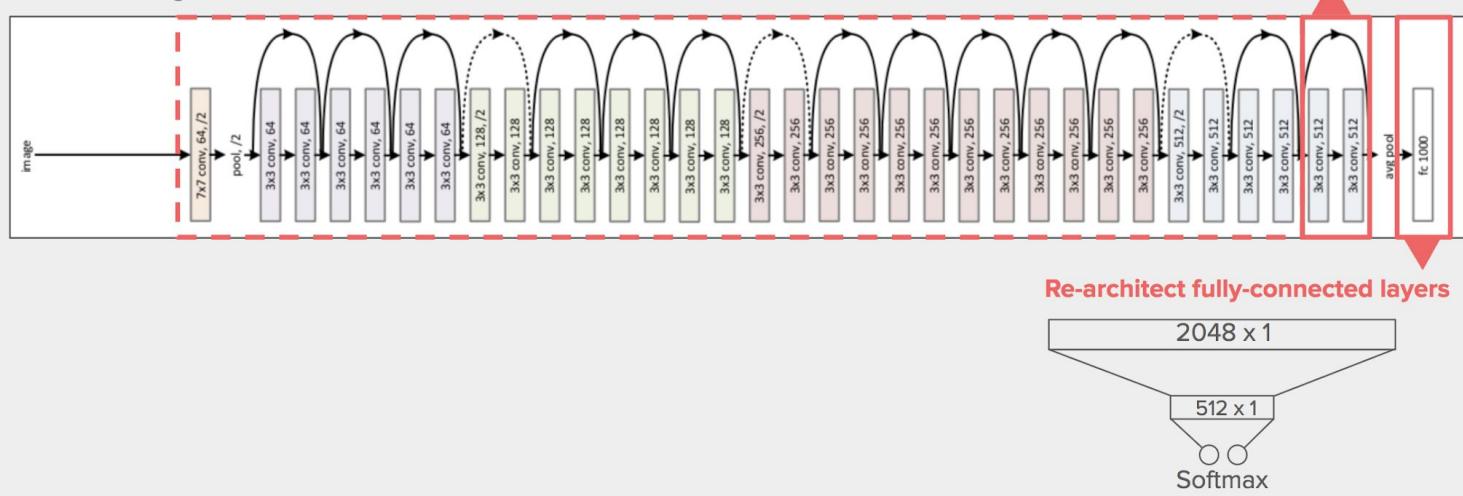
Resnet

Retrain ResNet50



Residual Learning Block

ResNet50 Diagram



Building a dogs vs cats image classifier



Playground Prediction Competition

Dogs vs. Cats

Create an algorithm to distinguish dogs from cats



Kaggle · 213 teams · 7 years ago

Overview

Data

Notebooks

Discussion

Leaderboard

Datasets

...

New Notebook

<https://www.kaggle.com/c/dogs-vs-cats/>

Practice: transfer learning

- [Notebook](#)
 - [Solution](#) with Resnet
 - [Solution](#) with Densenet
-
- Questions
 - Why do we need to explore the model architecture before defining our own final layers?

Review questions

- What is a loss function? Is the f1 measure a loss function or a performance metric?
- Can we use accuracy as a loss function? Can we use precision or recall as loss functions?
- Is the accuracy guaranteed to increase as the value of the loss function goes down?
- Why parts of the model need to be differentiable for an architecture to be trainable?
- What are we trying to minimize when using gradient descent? What is the learning rate?
- What is a GPU? Why are GPUs useful for deep learning?

Review questions

- What is an epoch? What is a batch? How does the batch size influence training?
- What is the difference between stochastic gradient descent (SGD) and ‘vanilla’ gradient descent?
- What is momentum? What is the difference between ADAM and SGD?
- What is a Jacobian? What is a Hessian? Do we use Hessians in deep learning?
- Suppose that we have a ground truth for a ‘cat’ label that is encoded as [0, 1]. We can assume that the ground truth for a ‘dog’ label is [1, 0].
 - The network first outputs [0.75, 0.25] as prediction
 - In the next epoch it outputs [0.99, 0.01] as prediction

Has the cross entropy loss increased or reduced?

Review questions

- What does it mean for a dataset to be ‘linearly separable’?
- How many layers does a neural network need in order to learn non-linear correlations?
- What’s the difference between a performance metric and a loss function?
- Why should we shuffle the data in every training epoch?
- Explain the bias vs variance tradeoff.
 - Effect of increasing the number of training epochs
 - Increasing the number of layers
 - Increasing the amount of dropped out connections
- How would you define ‘regularization’?
- What is the purpose of dropout? How does it work? Should dropout be active during inference time?

Review questions

- What is the vanishing gradient problem?
- How does a Resnet avoid the vanishing gradient problem?
- What does it mean to ‘freeze’ a layer?
- How does batch normalization work?
- Why should we call `model.eval()` before evaluating data from the validation set?
- What does it mean to “transfer a tensor” to the GPU?
- What is CUDA?
- How does the amount of RAM available in the GPU affect the types of models and data that we can use to train?
- What should we try when torch reports ‘CUDA out of memory’ errors?

Review questions

- Why do we need to call ``optimizer.zero_grad()`` in the training loop?
- What's the difference between a parameter and a hyperparameter? What's another common name for 'parameter' in a neural network?
- How can we know what's the "optimal" number of units in a hidden layer?
- How can we know the "optimal" number of layers in a network?
- Is data augmentation a regularization technique? Why should we apply data augmentations probabilistically?
- Why should we shuffle the data inside a training batch?
- If a model is increasing its loss through several epochs should we increase or decrease the learning rate?
- How do we evaluate training and validation loss to do early stopping?

Review questions

- What is weight decay? What is learning rate decay?
- Suppose that after going through certain number of epochs the training loss is higher than the validation loss. Is this an example of underfitting or overfitting?
- What is the vanishing gradient problem? Why does it appear?
- Are vanishing gradients more likely to appear when representing Jacobians and weight vectors with 8 bits, 16 bits, or 32 bits of precision?
- Why are ReLU activation functions less likely to display vanishing gradients than sigmoid activation functions?
- What is a skip connection?
- What is the difference between a Resnet and a Densenet?

Review questions

- Why do we resize images before training?
- If we retrain or do inference on a network pre-trained on Imagenet, why do we need to normalize its image channels using the mean and std of the intensities of the original dataset?
- What is a receptive field?
- What is a convolution?
- Why do we apply padding to images before doing convolutions?
- When calling `conv2d(..., ..., 64)` how many output channels are we producing? How are they different from each other?
- Why is the vanishing gradient a ‘numerical’ problem? What does that mean?
- Are we more likely to get vanishing gradients when using fp16 or fp32 data types for our weights?

Resources

- [Intro to Deep Learning with PyTorch at Udacity](#)
- [Convolutional Neural Networks at Coursera](#)
- [Fast.ai - Deep Learning for Coders](#)
- [Pylmagesearch Blog](#)
- [Stanford's CS231: Convolutional Neural Networks for Visual Recognition](#)
- [3blue1brown's series on neural networks](#)
- [Goodfellow's Deep Learning Book \(great for theory\)](#)
- [Visualizing and understanding neural networks \(Stanford lecture\)](#)