

Image classification and intro to neural networks

Vlad Shakhuro



9 October 2025

Outline

- I. Image classification task and datasets
2. Linear classification and MLPs
3. Convolutional neural networks
4. Milestone: AlexNet

Binary classification



Does this image contain a pedestrian?

Binary answer $y \in \begin{cases} 0, & \text{no} \\ 1, & \text{yes} \end{cases}$

Alternatively, the estimated probability
of the positive answer $p_{\text{yes}} \in [0; 1]$

Multiclass classification



Which object is shown on this image?

The set of *allowed* object classes is determined in advance

Integer answer $y \in \left\{ \begin{smallmatrix} 1, & 2, & \dots, & S \\ \text{car}, & \text{sign}, & & \text{bike} \end{smallmatrix} \right\}$

Alternatively, a list of estimated probabilities:

$$p_i \in [0; 1] \quad i \in 1, \dots, S \quad \sum_{i=1}^S p_i = 1$$

Attribute recognition



Male
Asian
Bearded
Smiling

Attributes are properties or characteristics that are commonly expressed by some object

Human attributes may include race, sex, age, color of hair, current emotional state or the presence of wearable accessories such as masks, glasses and hats

Attribute recognition can often be reduced to one or more classification tasks, for example:

- sex → binary
- race → multiclass
- age → multiclass (over discrete age groups)

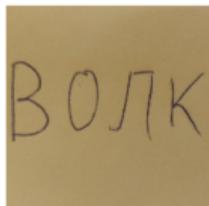
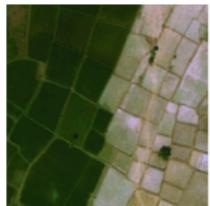
Metrics

Accuracy — percentage of correctly classified samples

Dataset	CNN	Original	BP[23]	CBP[11]	KP	Others
CUB [43]	VGG-16 [38]	73.1*	84.1	84.3	86.2	82.0 84.1
	ResNet-50 [15]	78.4	N/A	81.6	84.7	[18] [16]
Stanford Car [19]	VGG-16	79.8*	91.3	91.2	92.4	92.6 82.7
	ResNet-50	84.7	N/A	88.6	91.1	[18] [14]
Aircraft [27]	VGG-16	74.1*	84.1	84.1	86.9	80.7
	ResNet-50	79.2	N/A	81.6	85.7	[14]
Food-101 [4]	VGG-16	81.2	82.4	82.4	84.2	50.76
	ResNet-50	82.1	N/A	83.2	85.5	[4]

Top-K Accuracy (Rank K) — percentage of sample for which the correct class is within K most likely predicted classes (often K=5)

Data domains and modalities

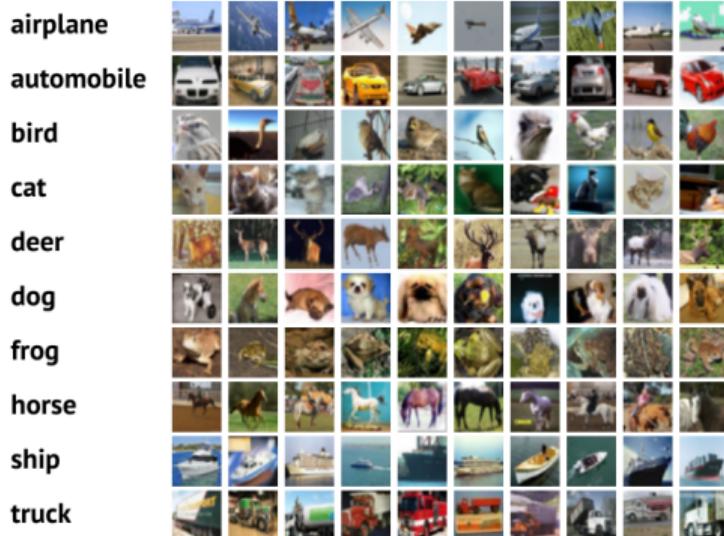


Every computer vision algorithm is designed to operate on images sampled from some *statistical population*. This population is described by an empirical distribution over the set of all “valid” (for that algorithm) images:

$$img \sim P(\mathbb{I}) \quad \mathbb{I} \subseteq \mathbb{R}^{H \times W \times C}$$

These algorithms work by exploiting the inherent properties and invariants of the *statistical population* they support

CIFAR-10 and CIFAR-100



Subset of the TinyImages collection
60000 images total

CIFAR-10: 10 classes

- 5000 training images per class
- 1000 testing images per class

CIFAR-100: 100 classes

- 500 training images per class
- 100 testing images per class

ImageNet

Goal: create a dataset with at least 1000 images for each of the original 117000 synsets/classes

~14 000 000 images

(~1 000 000 images with bounding box annotations)

~22 000 non-empty classes (~10 000 classes with at least 1000 examples)

planet housing animal weight drop headquarters egg white
teacher computer albumin albumin albumin albumin
register intensive court key structure light date television
gallery house church press market lighter
king fireplace church press market lighter
road paper cup concern concern
hotel road paper cup concern concern
sport screen tree file side site door pack
sky plant wall means fan hill cap coffee
in the tree house school railcar
bread table top man car study bird
weapon cover range man net button
cloud cover range man net button
spring range man net button
range man net button
bed shop train camera
kitchen train camera
engine train camera
dinner stone train
apple girl train
flagbank home room office club
cross chair man
radio Support level line street golf
beach library stage video food building
base material player machine security call clock
tool match equipment cell phone mountain telephone
football hospital match equipment cell phone mountain telephone
short circuit bridge scale equipment cell phone mountain telephone
gas pedal microphone recording



ImageNet: annotation problems



mite

mite
black widow
cockroach
tick
starfish

container ship

container ship
lifeboat
amphibian
fireboat
drilling platform

motor scooter

motor scooter
go-kart
moped
bumper car
golfcart

leopard

leopard
jaguar
cheetah
snow leopard
Egyptian cat



grille

convertible
grille
pickup
beach wagon
fire engine



mushroom

agaric
mushroom
jelly fungus
gill fungus
dead-man's-fingers



cherry

dalmatian
grape
elderberry
ffordshire bulterrier
currant



Madagascar cat

squirrel monkey
spider monkey
titi
indri
howler monkey

OpenImages



Goal: create the largest **open** dataset of real-life photographs with diverse annotations

- ~9 000 000 images
licensed under CC BY 2.0
- ~60 000 000 annotations for
~20 000 categories
- Various supplementary
annotations are also available
(for example, localized text descriptions)

Fine-grained classification



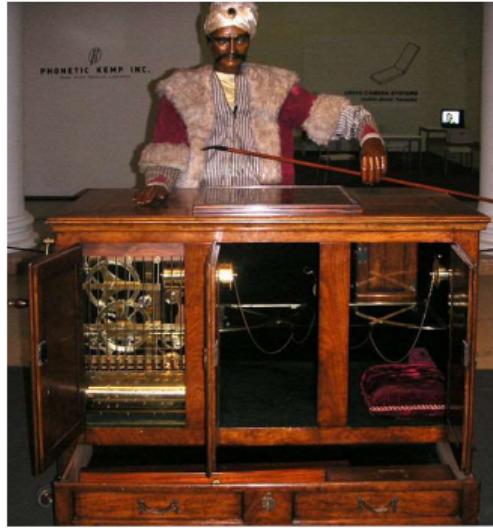
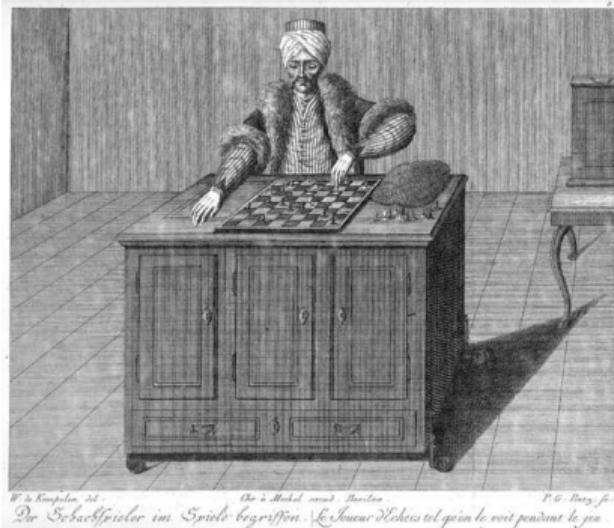
Galaxy Zoo



GALAXY ZOO galaxyzoo.org

- Classification of galaxy images
- The first large scale project of this kind
- More than 150 000 volunteers created over 60 000 000 annotations in a single year **for free**

Mechanical Turk



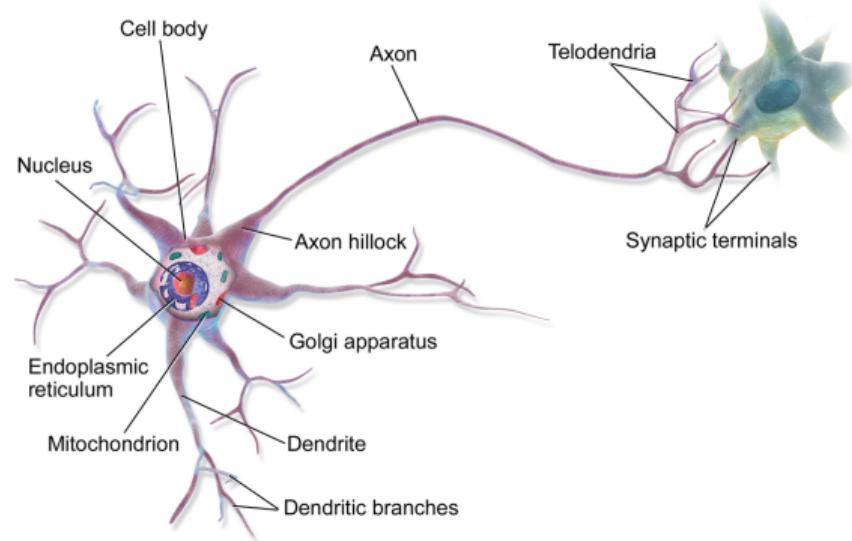
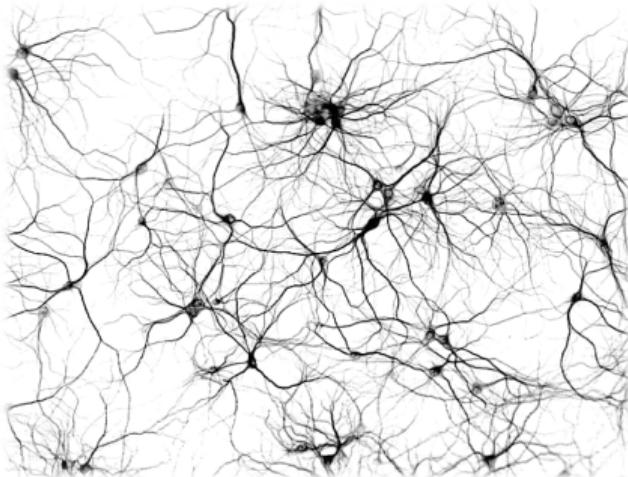
"Mechanical Turk, Automaton Chess Player" was a robot created **in 1770** that could play chess (and even beat competent players). In 1820 it was revealed that the robot couldn't actually play chess by itself and that it was instead **controlled by a human sitting in a hidden compartment**

Annotation as a service

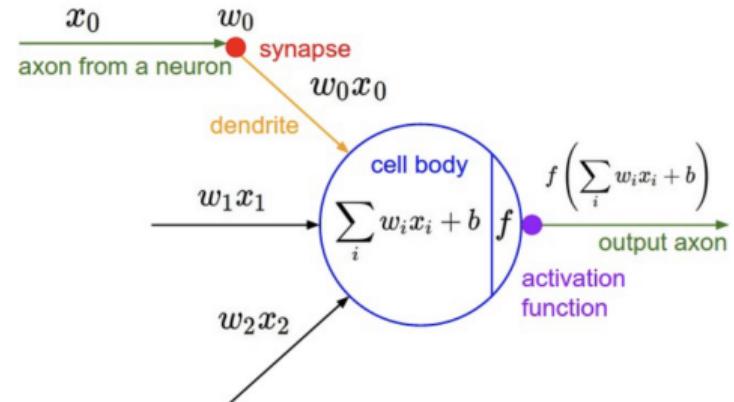
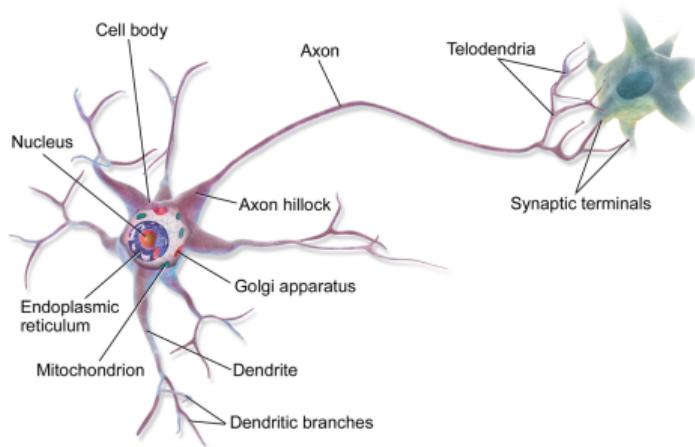
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Biological neurons

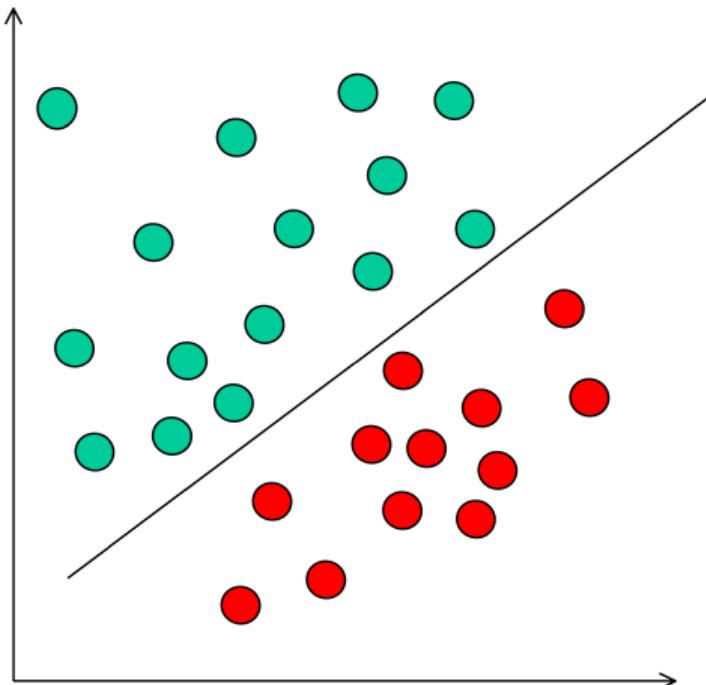


McCulloch-Pitts neuron model



$$a(x, w) = f \left(\sum_{i=1}^n w_i x_i + b \right)$$

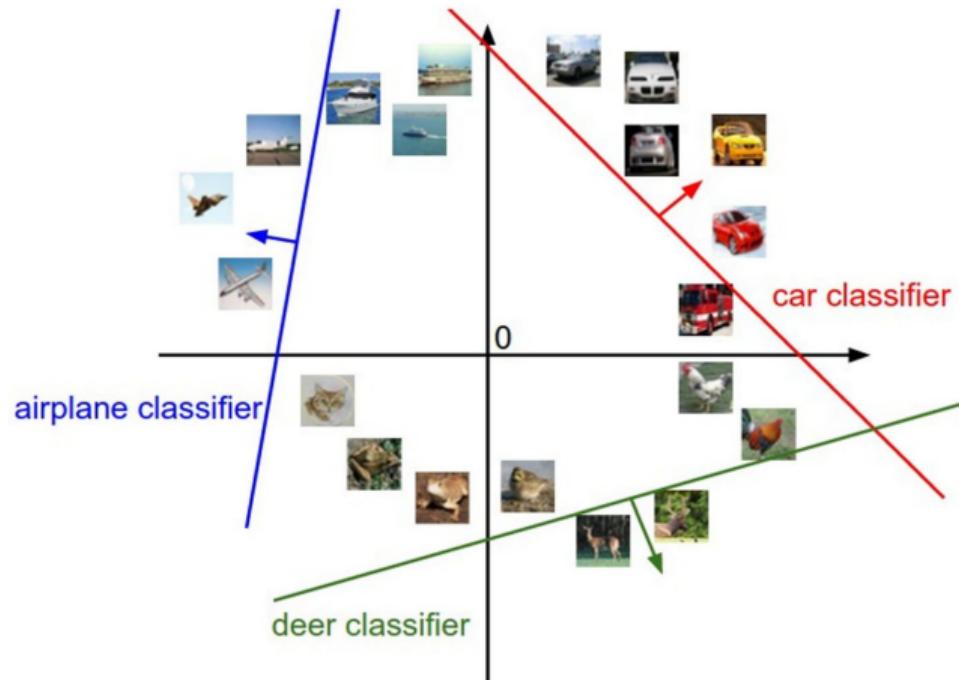
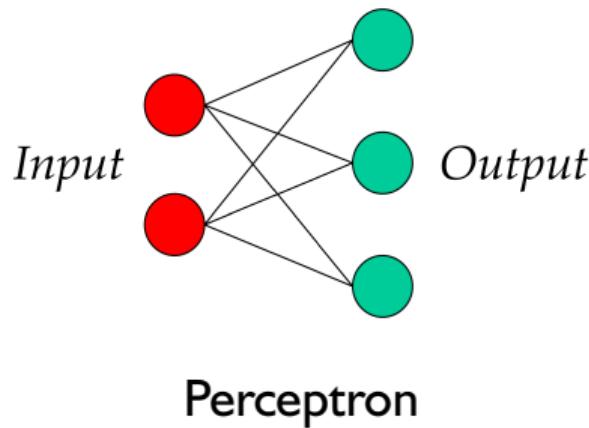
Neuron as linear classifier



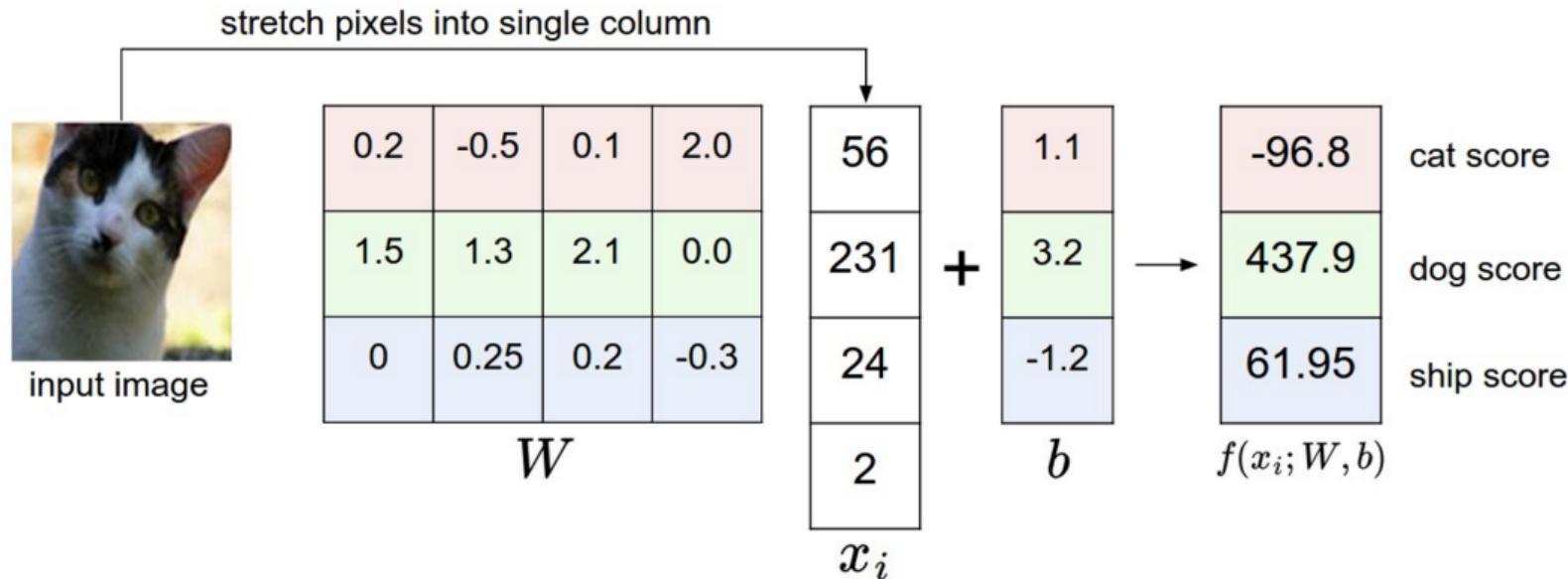
$$a(x, w) = f \left(\sum_{i=1}^n w_i x_i + b \right)$$

Optimal parameters w_i can be found using classical iterative methods

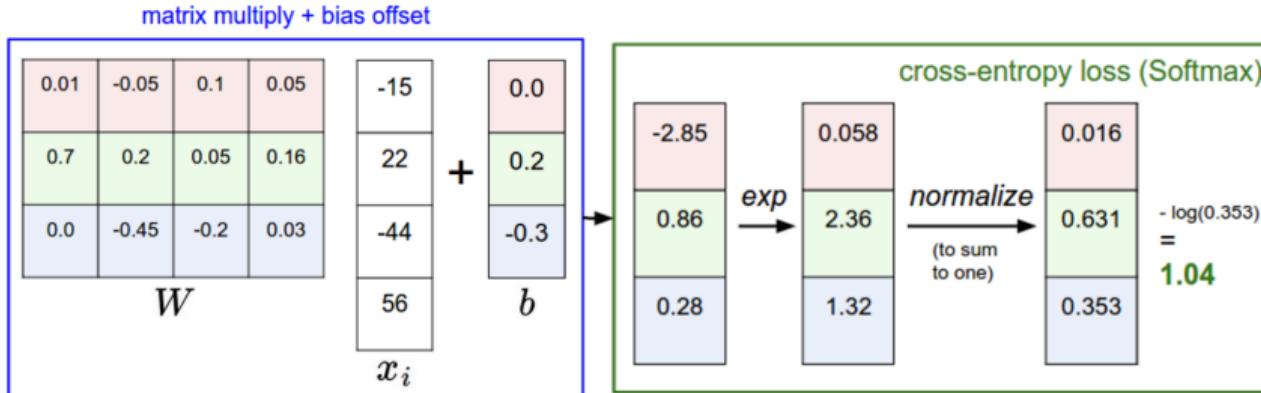
Multiclass classification



Multiclass classification for images



Loss function



Normalize scores with softmax activation:

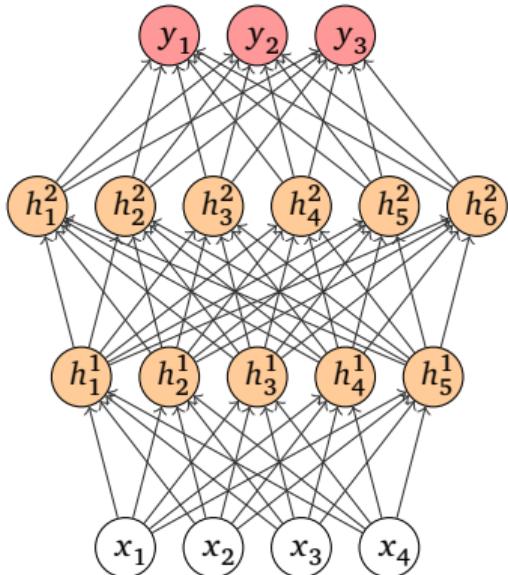
$$p_i^{\text{pr}} = \frac{e^{y_i}}{\sum_{j=1}^N e^{y_j}}$$

and compute categorical cross-entropy:

$$L(p^{\text{pr}}, p^{\text{gt}}) = - \sum_{i=1}^N p_i^{\text{gt}} \cdot \log(p_i^{\text{pr}})$$

Then we can train neuron using SGD with minibatches

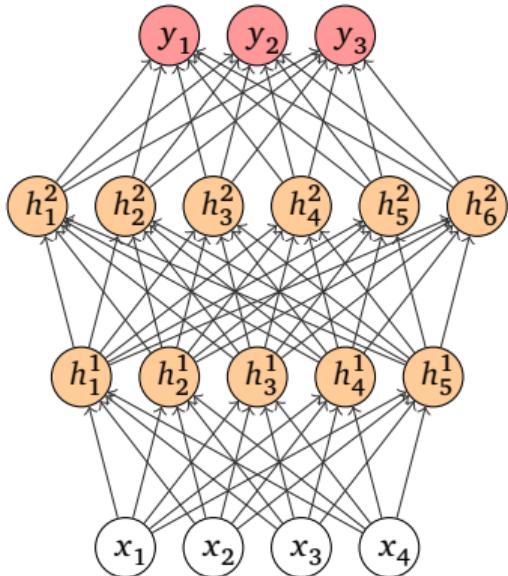
Multilayer perceptron (MLP)



Chained perceptrons may be called **deep neural networks**. Hidden layer neurons usually have nonlinear activation function (sigmoid, ReLU). Number of outputs depends on task

Layers in NN may have two meanings: a set of neuron activations (also called representations) and a set of connections with weights

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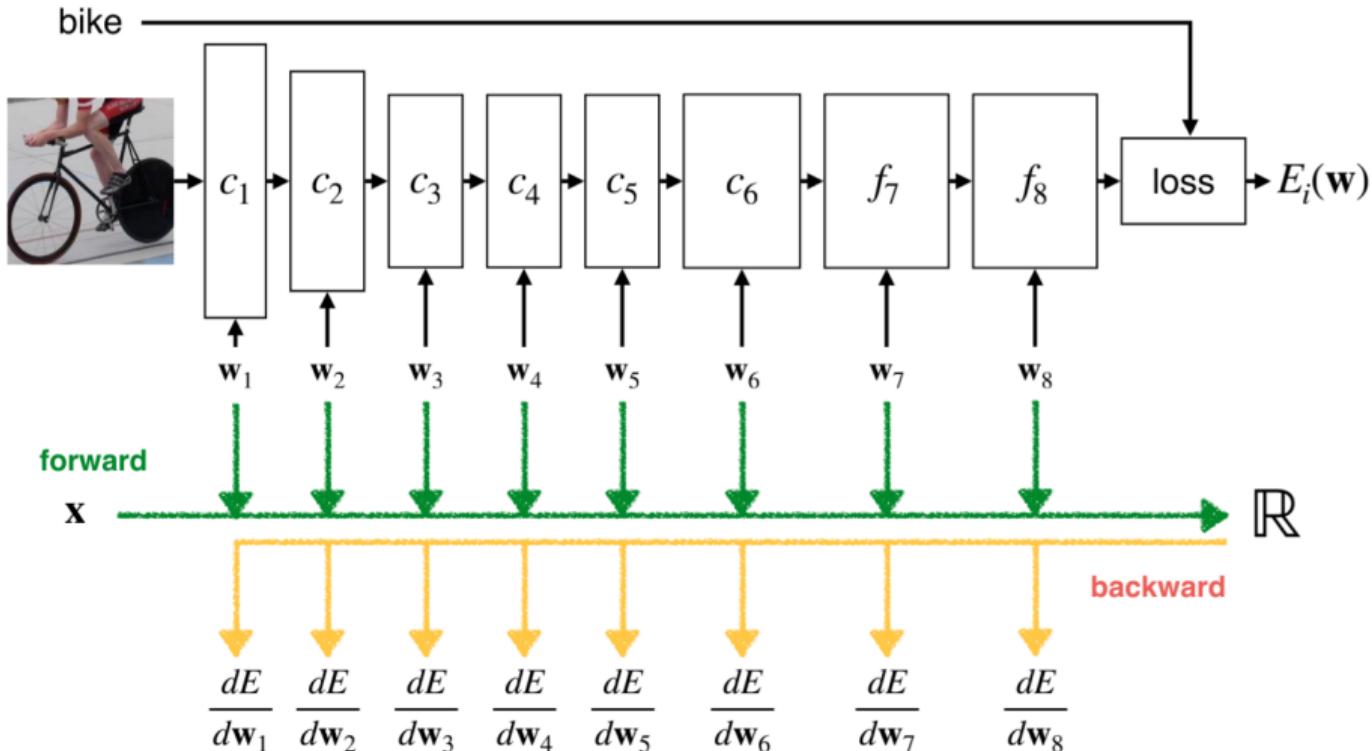
Layers in NN may have two meanings: a set of neuron activations (also called representations) and a set of connections with weights

How can we define architecture?

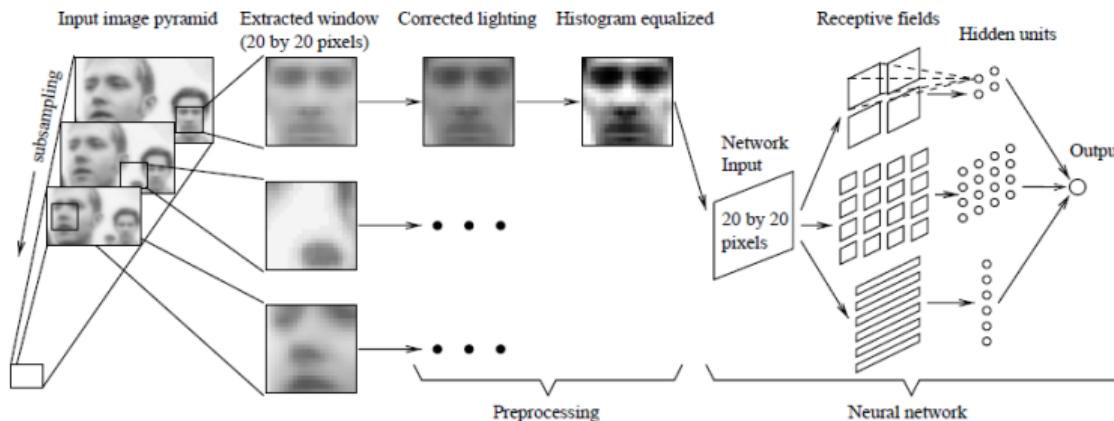
Backpropagation

class c_i

image \mathbf{x}_i



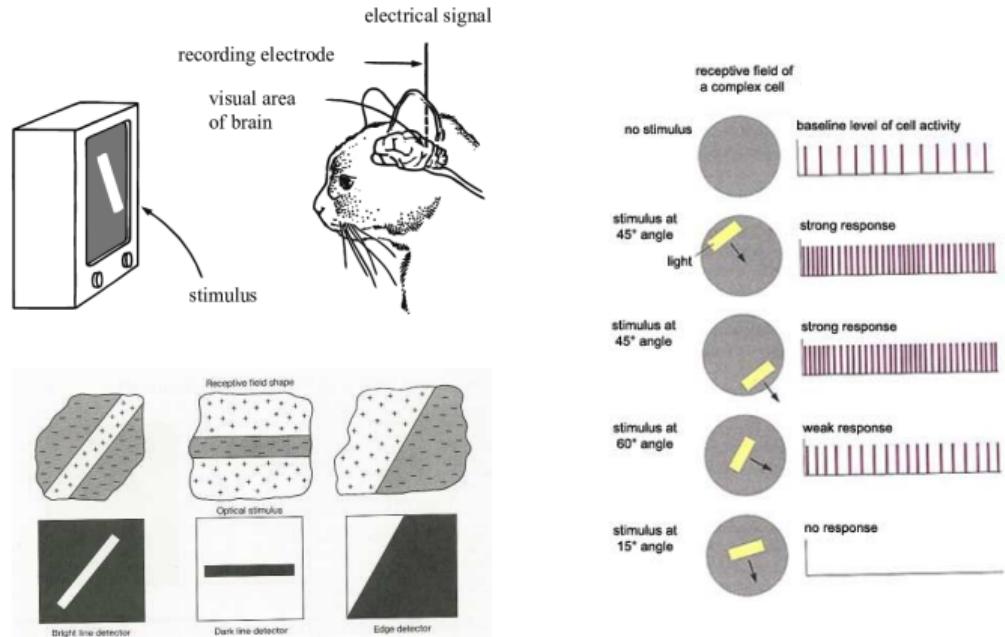
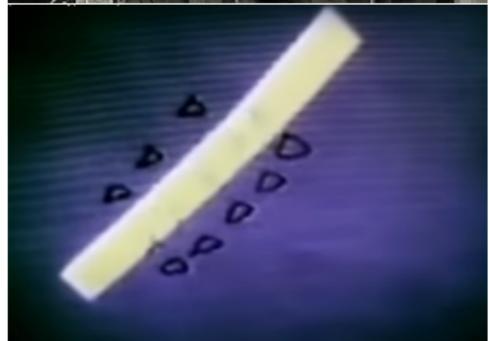
Rowley face detector



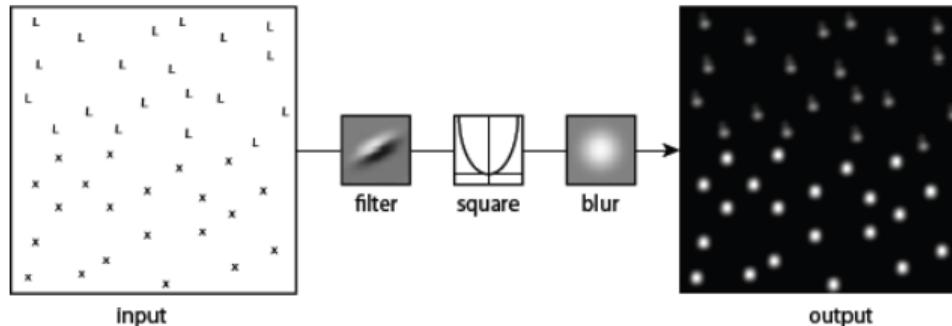
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Hubel and Wiesel visual cortex experiments



Modelling texture



Texture may be described using a bank of filters. Every pixel convolved with filters will give vector of features

Gabor filter as a model for simple cells

Bank of filters may be obtained using gabor filters for different orientations:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda} + \psi\right)$$

$$x' = x \cos \theta + y \sin \theta$$

$$y' = -x \sin \theta + y \cos \theta$$

Parameters:

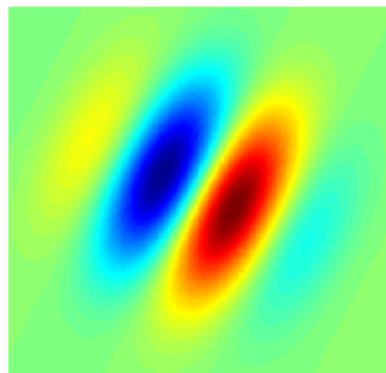
σ — gaussian stdev

γ — aspect ratio

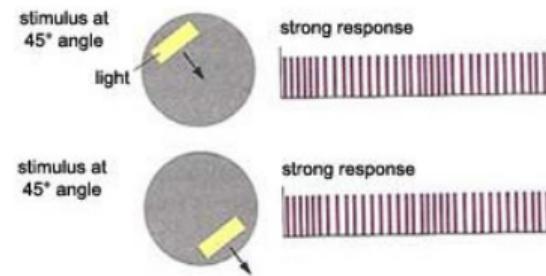
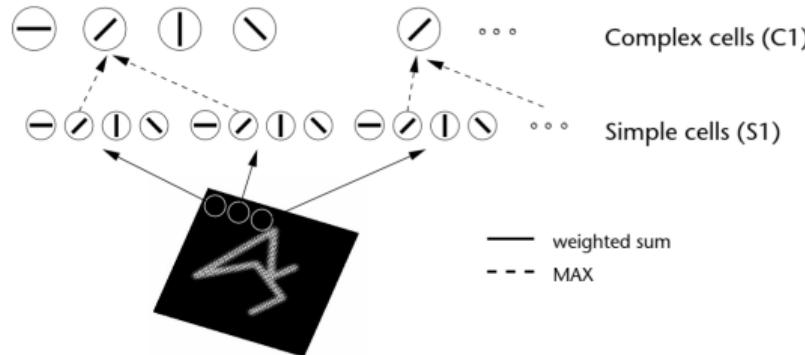
θ — orientation

λ — wave length

ψ — phase shift

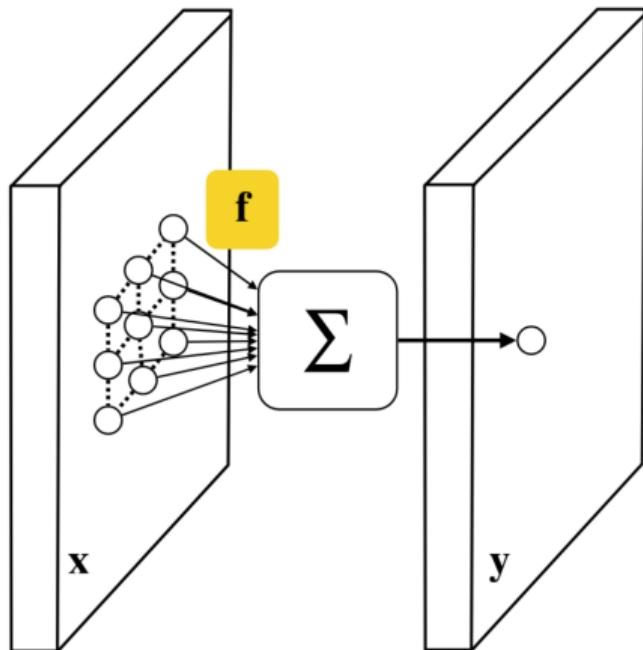


Max operation as a model for complex cells



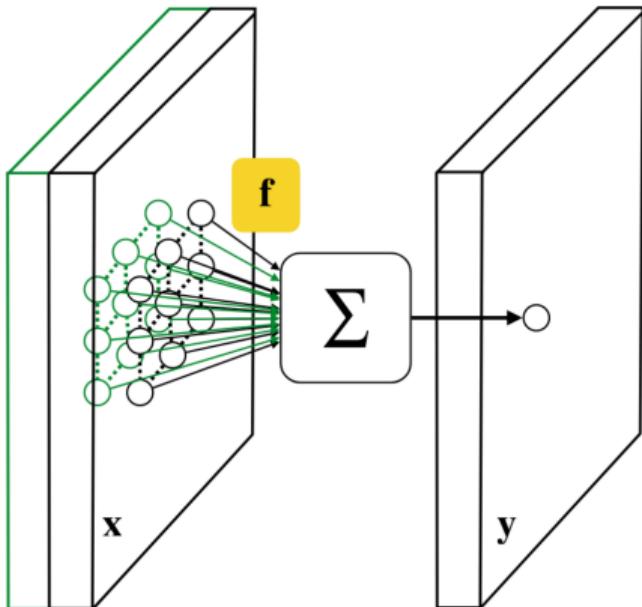
Position invariance (complex cells) may be obtained using MAX operation on top of simple convolutional cells

Convolutional layer



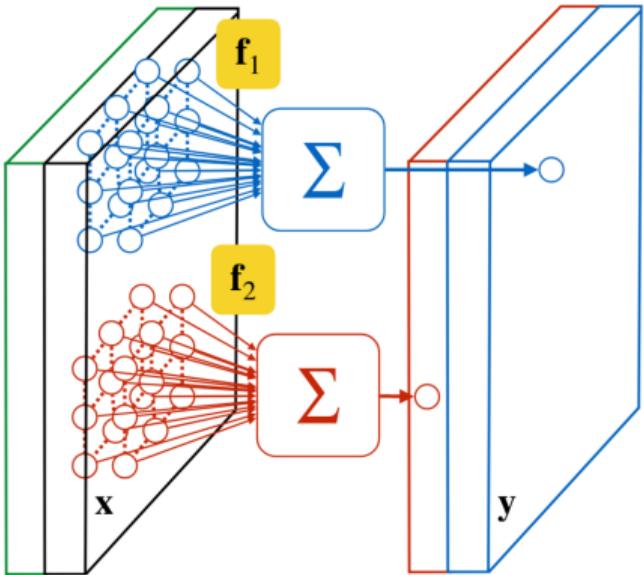
Convolution (linear filtering) for whole image may be modelled using a layer of neurons with shared weights.

Convolutional layer



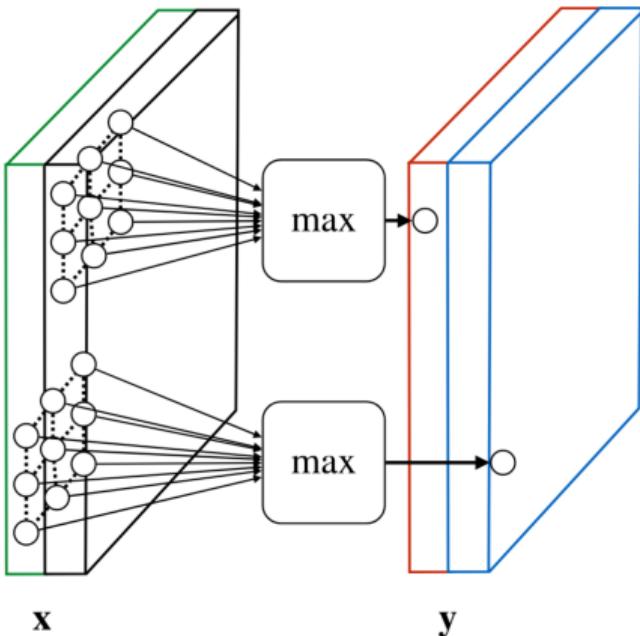
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Convolutional layer

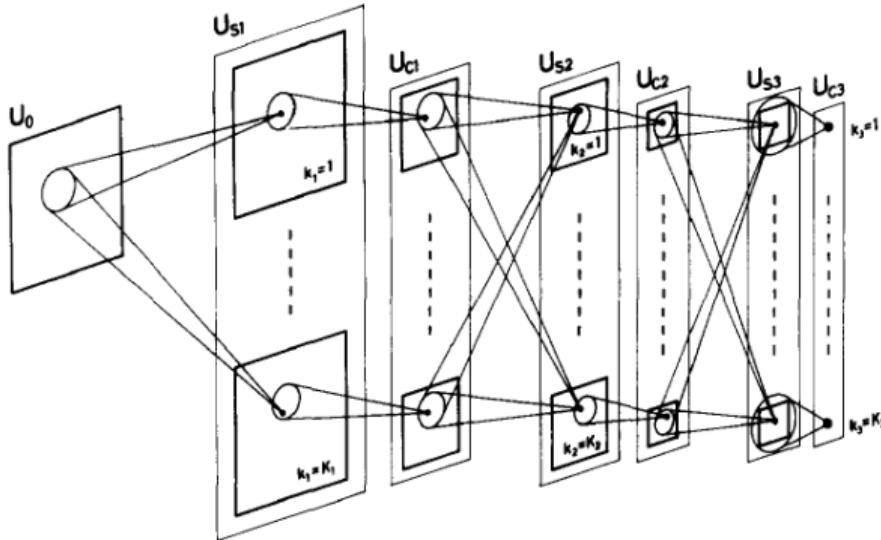


Convolution (linear filtering) for whole image may be modelled using a layer of neurons with shared weights. Convolutional layer is a set of convolutions over the same input

Max pooling layer



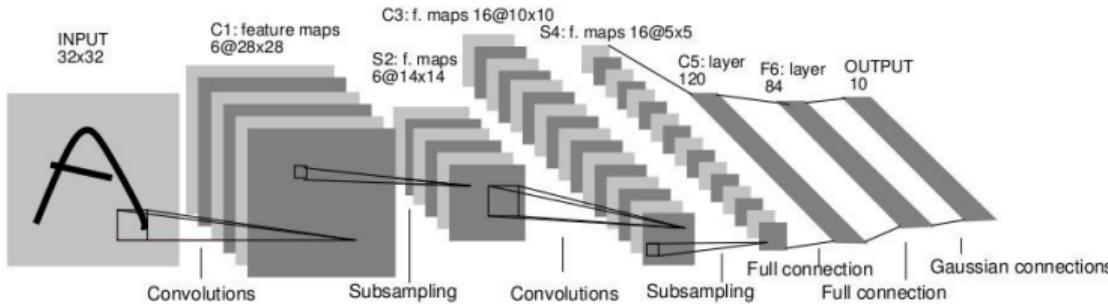
Neocognitron



Multilayer network with interleaved S and C layers. Last layer neurons are invariant to shifts in image

Fukushima. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. Biological Cybernetics 1980

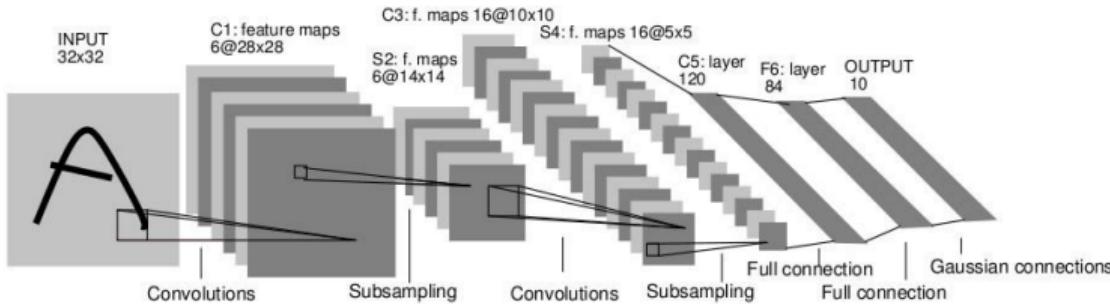
LeNet



Neocognitron idea + error backpropagation method
→ Convolutional Neural Network (CNN)

Since convolutional neurons share parameters and look at a small neighbourhood, convolutional networks are very effective

LeNet



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→ Convolutional Neural Network (CNN)

Since convolutional neurons share parameters and look at a small neighbourhood, convolutional networks are very effective

How many trained weights are there in different layers? (C1, S2, ..., F6, Output)?

LeCun et al. Gradient-based learning applied to document recognition. 1998

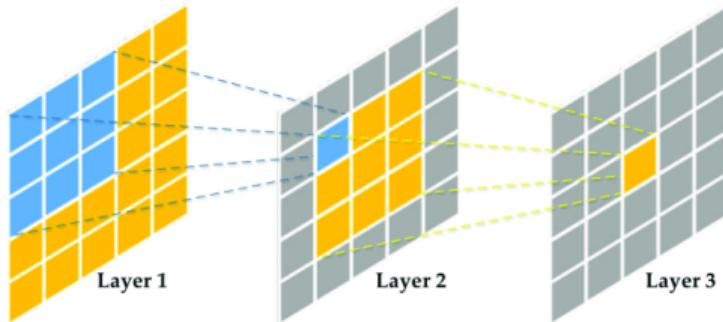
Convolutional filters for RGB images



Neural networks trained on RGB image classification task have first layers very similar to Gabor filter

Some layers may duplicate each other

Receptive field



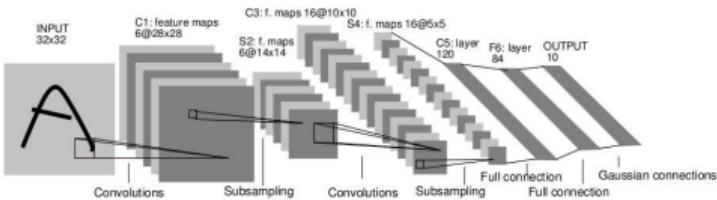
Receptive field is an area of image that *may* influence neuron output.
Depends on network architecture

Effective receptive field is an area that depends on trained weights

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LeNet and AlexNet comparison

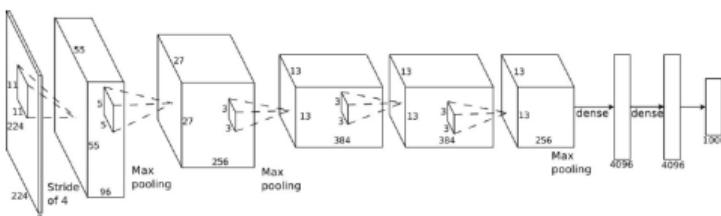


1998:

- 2 conv layers (6, 16 filters)
- 2 fully connected layers (120, 84 neurons)

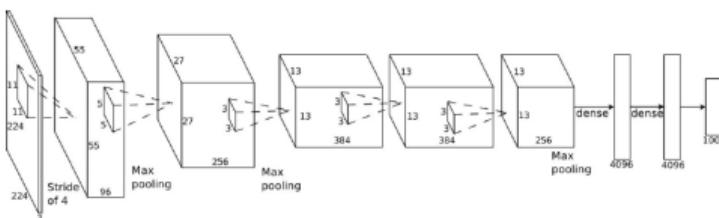
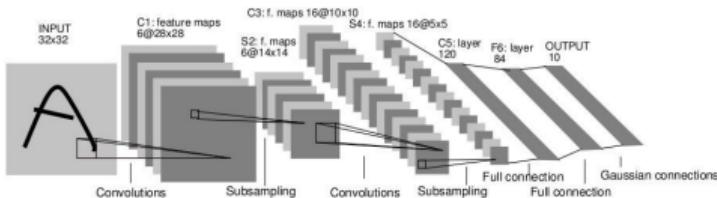
2012:

- 5 conv layers (96, 256, 384, 384, 256 filters)
- 2 fully connected layers (4096, 4096 neurons)



Krizhevsky A., Sutskever I., Hinton G. E. Imagenet classification with deep convolutional neural networks. NIPS 2012

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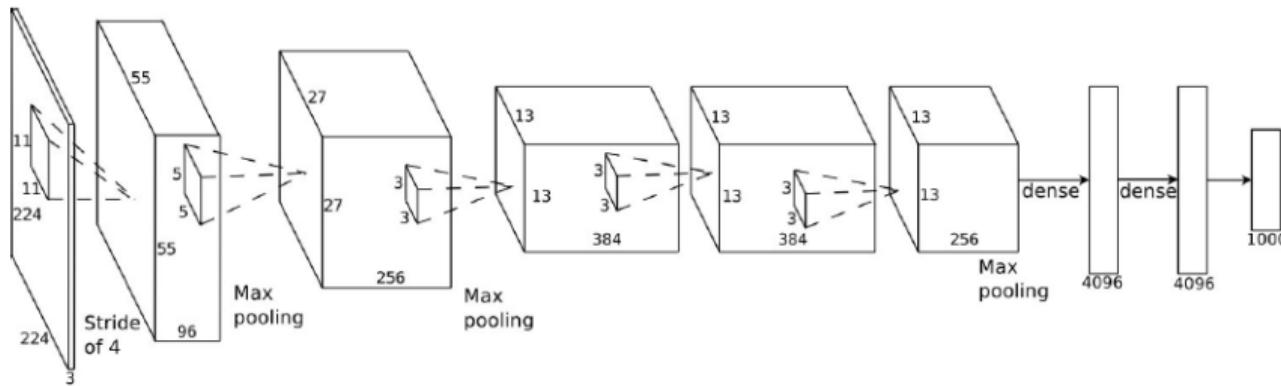
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What else has changed?

Krizhevsky A., Sutskever I., Hinton G. E. Imagenet classification with deep convolutional neural networks. NIPS 2012

AlexNet

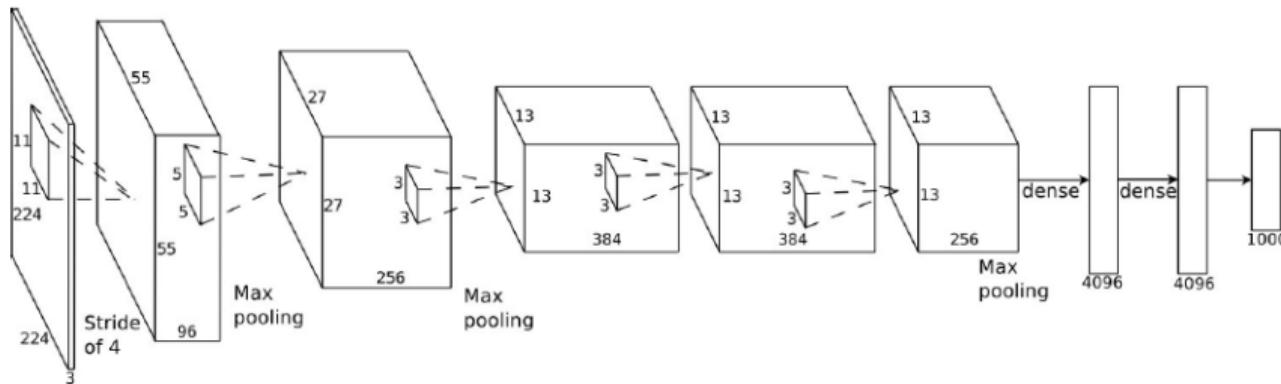


- 60M parameters
- 2GPU \times 3GB, 5GB RAM, 27GB HDD
- 1 week to train

Key ideas:

- ReLU activation
- image augmentations
- dropout

AlexNet



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- 2GPU \times 3GB, 5GB RAM, 27GB HDD
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Key ideas:

- ReLU activation
- image augmentations
- dropout

HW: compute *manually* number of parameters for AlexNet

Conclusion

We reviewed following topics:

- image classification tasks
- how to obtain and label data
- classification with single neuron and MLP
- main biological principles behind convolutional neural networks