УНИВЕРСИТЕТ ИТМО

Introduction to deep learning

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Outline

- Neural nets
- Introduction to deep learning
- Convolutional Neural Network (CNN)
- DNN best practices
- DNN applications

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- **Neural nets**
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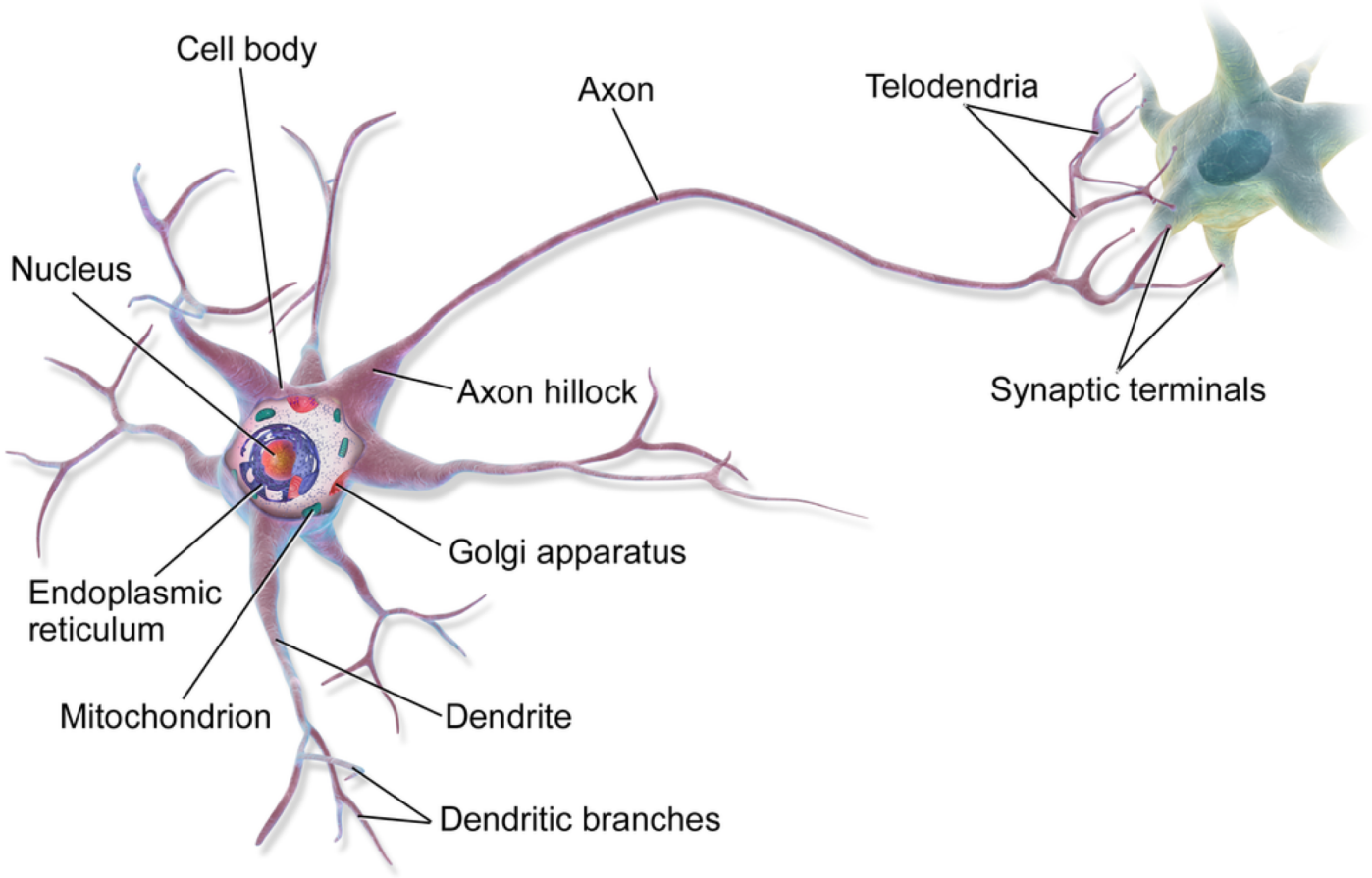
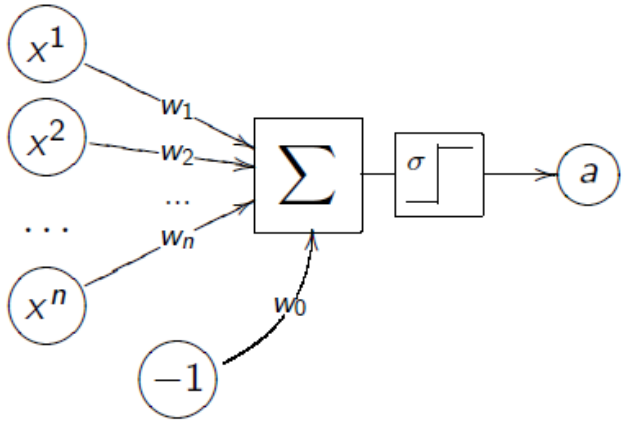
Biological neuron



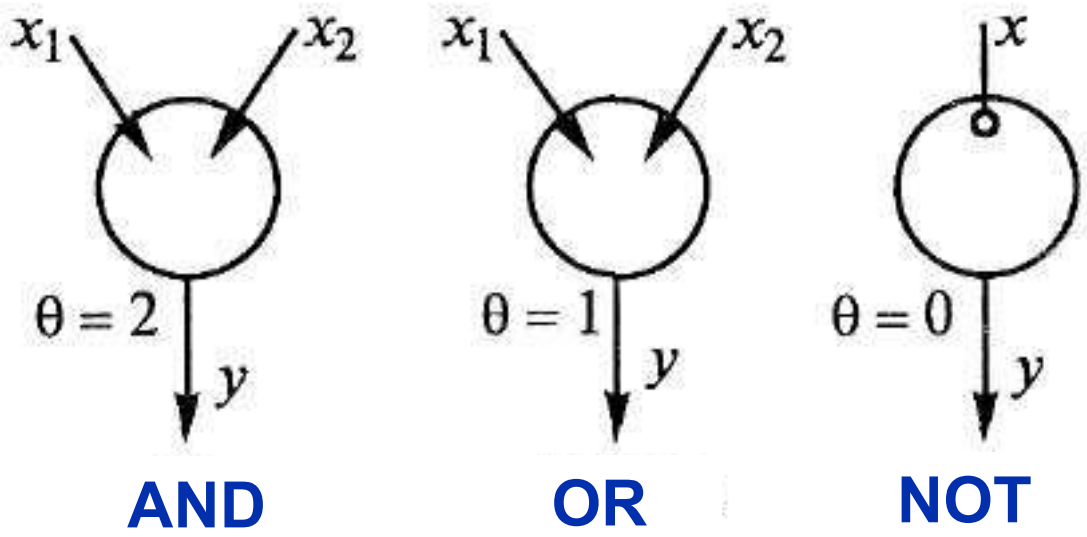
Generalized McCulloch-Pitts neuron

$$y_w(x, T^m) = \sigma\left(\sum_{i=1}^{n} w_i x^i - w_0\right),$$

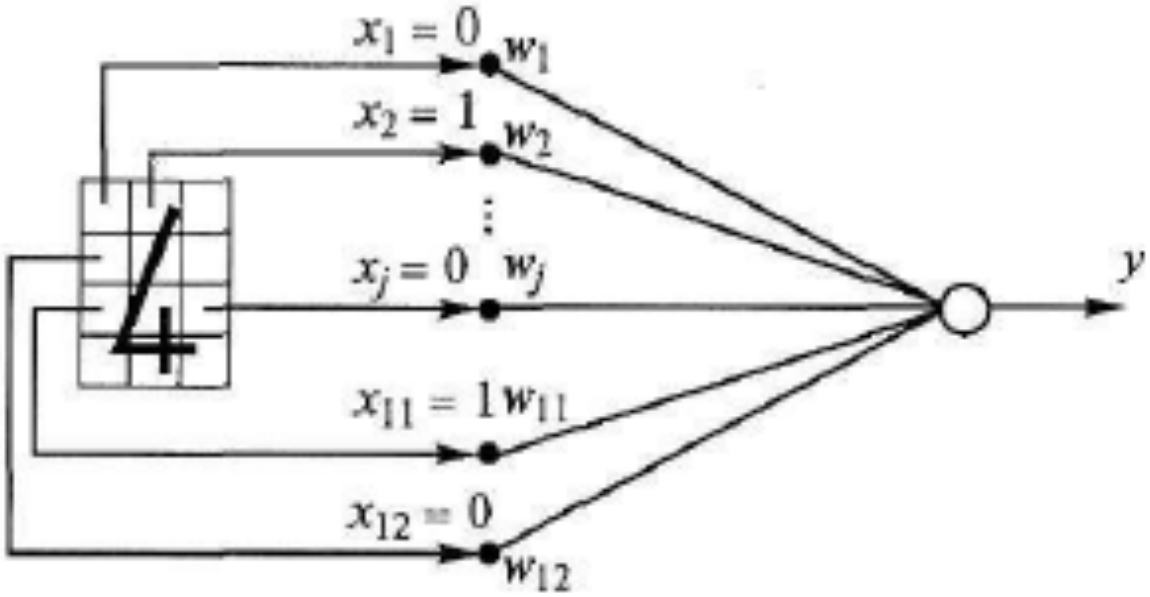
where $\sigma(x) = 1$ if $x > 0$ and 0 otherwise.



Generalized McCulloch-Pitts neuron



Rosenblatt's perceptron



Rosenblatt's rule and Hebb's rule

Rosenblatt's rule for $\{1; 0\}$ classification case for weight learning is for each object $x_{(k)}$ change weight vector:

$$w^{[k+1]} := w^{[k]} - \eta(a_w(x_{(k)}) - y_{(k)}).$$

Hebb's rule for $\{1; -1\}$ classification case for weight learning is for each object $x_{(k)}$ change weight vector:

If $\langle w^{[k]} x_{(k)} \rangle y_{(k)} < 0$ then $w^{[k+1]} := w^{[k]} + \eta x_{(k)} y_{(k)}$.

Perceptron Convergence Theorem

If $X_m = \{(x_1, y_1), \ldots, (x_m, y_m)\}$ describes a linearly separable dichotomy, then the fixed-increment perceptron algorithm terminates after a finite number of weight updates.

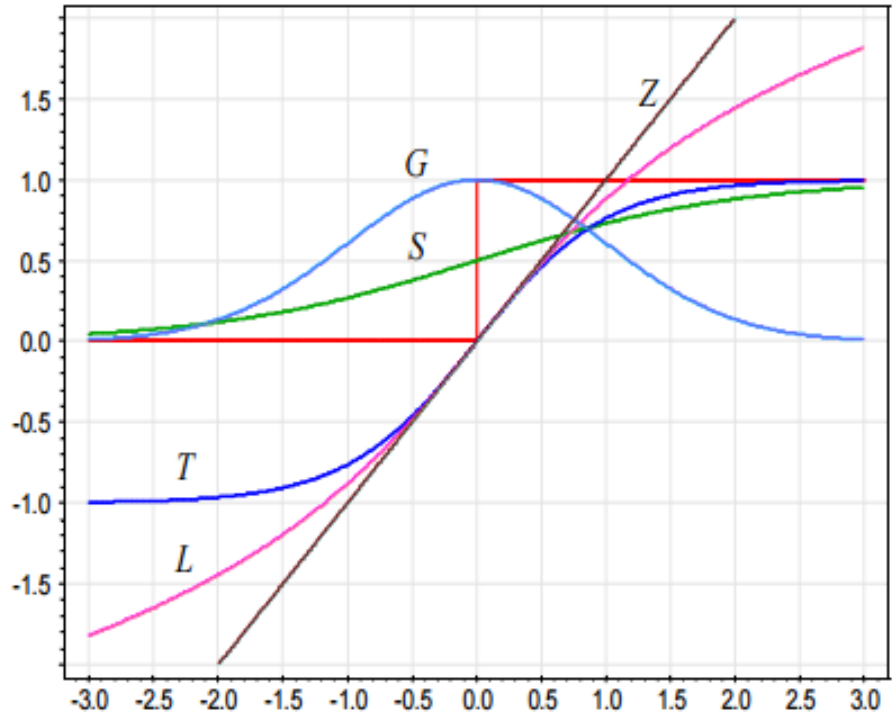
Delta-rule

Let $L(a_w, x) = (\langle w, x \rangle - 1)^2$.

Delta-rule for weight learning is for each object $x_{(k)}$ change weight vector:

$$w^{[k+1]} := w^{[k]} - \eta\left(\langle w, x_{(k)} \rangle - y_{(k)}\right).$$

Activation functions



$\sigma(z) = (1 + e^{-z})^{-1}$ S

$\mathrm{th}(z) = 2\sigma(2z) - 1$ T

$\ln(z + \sqrt{z^2 + 1})$ L

$\exp(-z^2/2)$ G

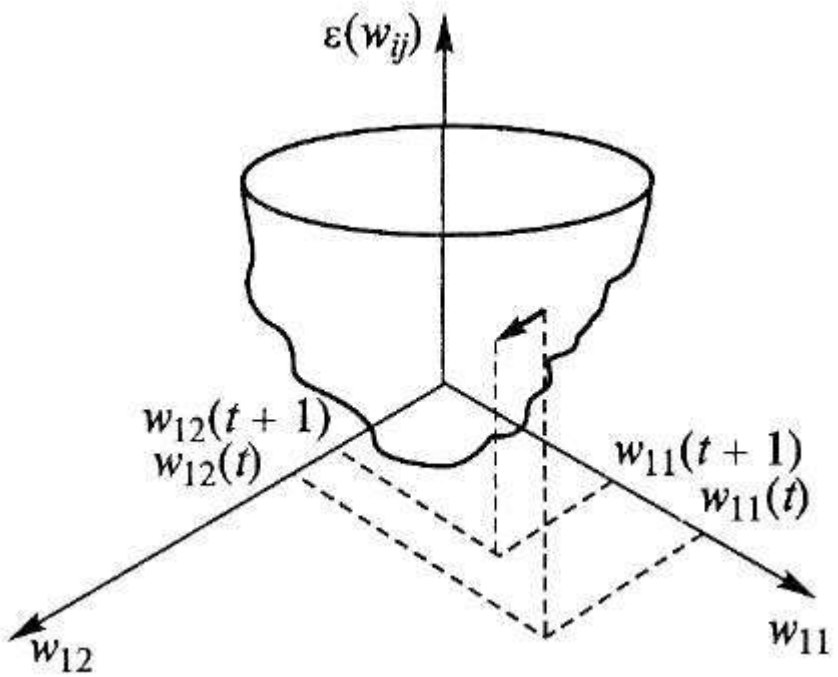
z Z

Gradient descent

Widrow, Hoff, 1960

$$\varepsilon = \frac{1}{2}\sum_{i=1}^{I}(d_i - y_i)^2$$

$$\varepsilon = \varepsilon(w_{ij})$$



Gradient descent

Changing Δw_{ij} in the direction opposite to the gradient of the hypersurface :

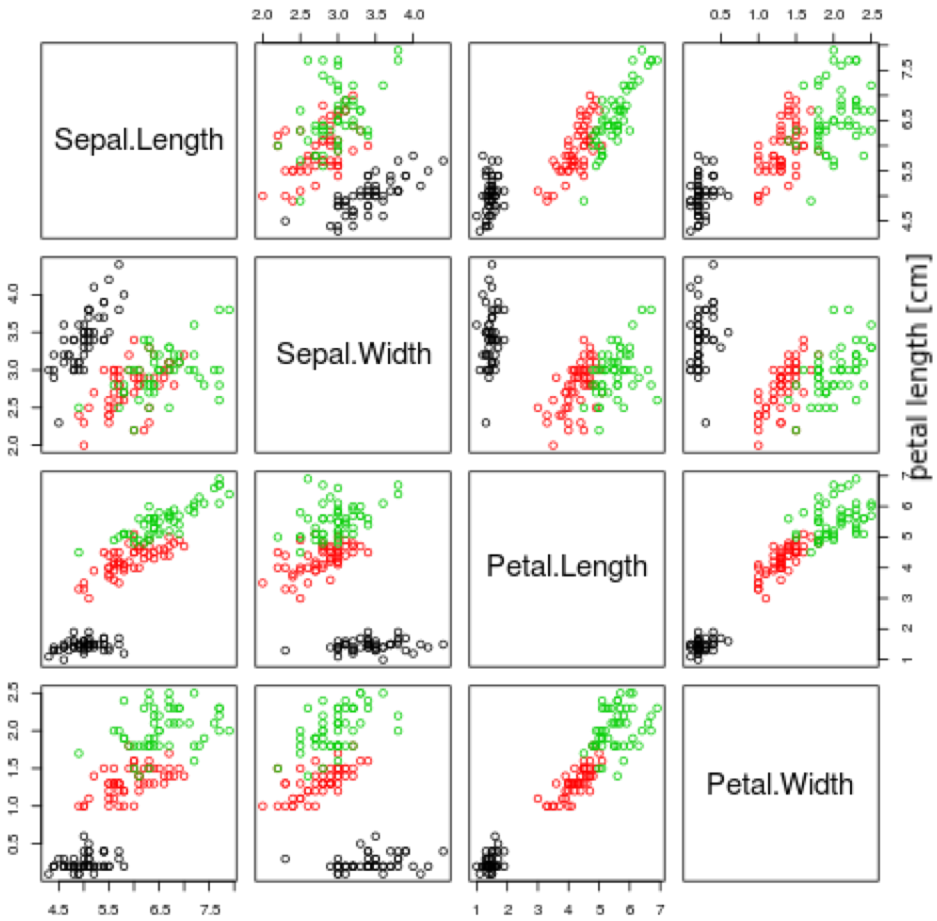
$$\Delta w_{ij} = -\eta \frac{\partial \varepsilon}{\partial w_{ij}}, \qquad \frac{\partial \varepsilon}{\partial w_{ij}} = \frac{\partial \varepsilon}{\partial y_i} \frac{\partial y_i}{\partial w_{ij}}$$

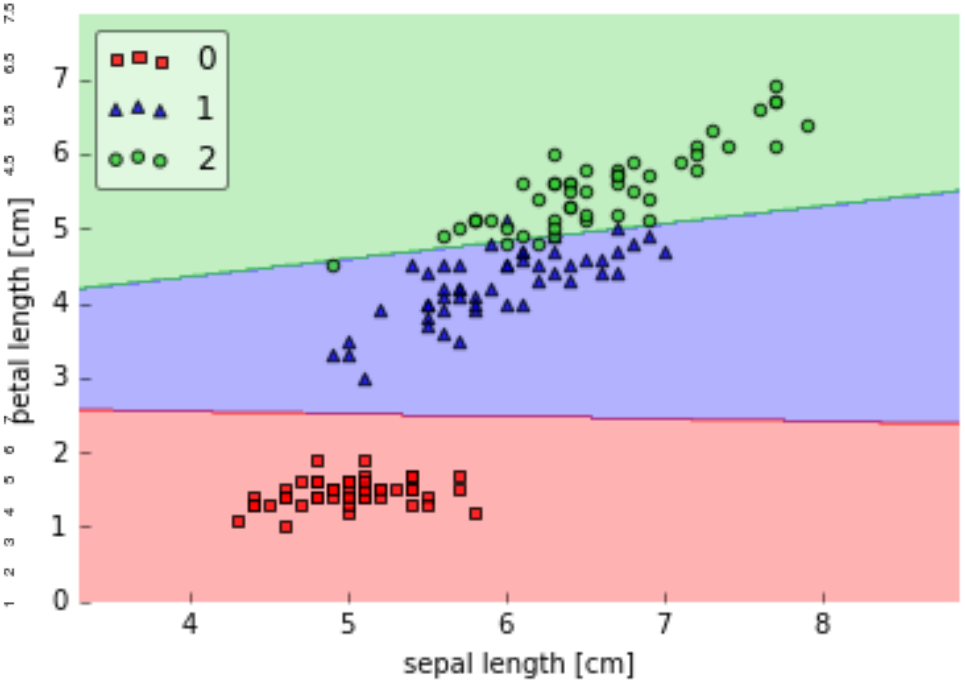
$$\frac{\partial y_i}{\partial w_{ij}} = \frac{\partial f_\sigma(S_i)}{\partial S_i} \frac{\partial S_i}{\partial w_{ij}} = f'_\sigma(S_i) x_j$$

$$\frac{\partial \varepsilon}{\partial y_i} = -(d_i - y_i)$$

$$\Delta w_{ij} = -\eta\left(-(d_i - y_i) f'_\sigma(S_i) x_j\right) = \eta(d_i - y_i) f'_\sigma(S_i) x_j$$

Linear decision boundary

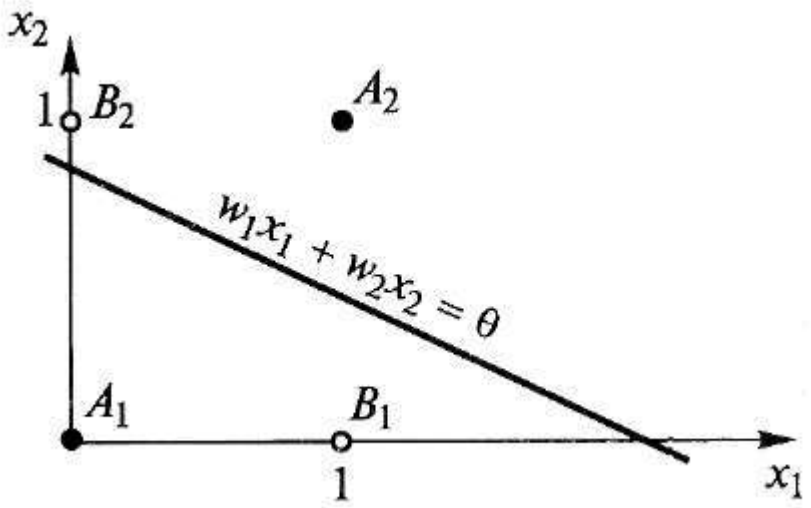




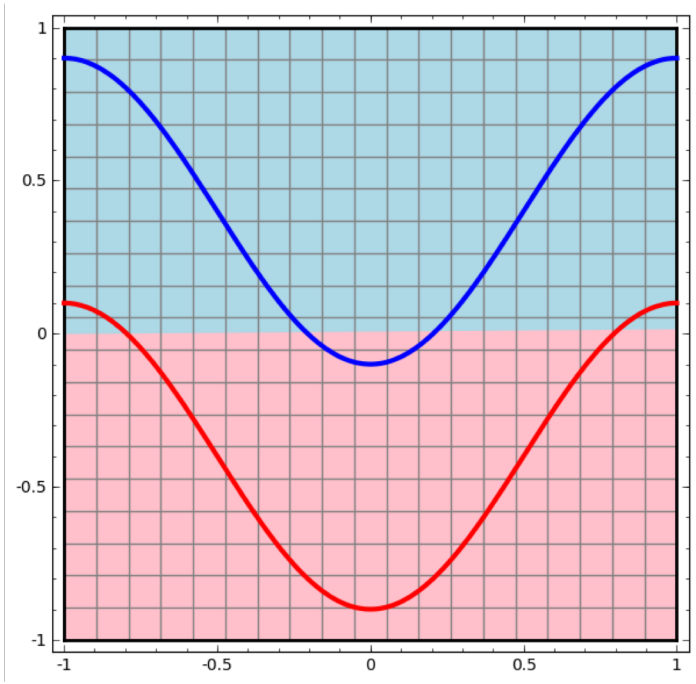
Linear Separability and the XOR Problem

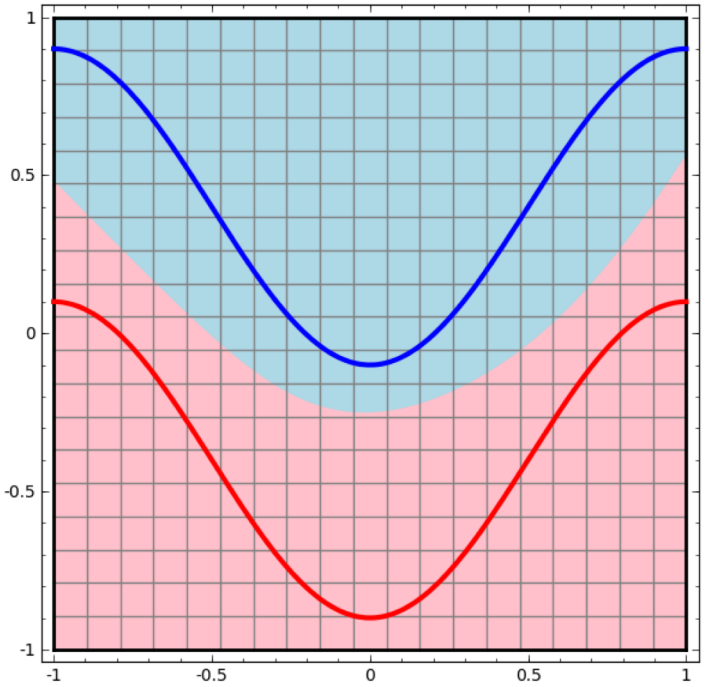
Minsky, Papert, 1969

- «XOR»

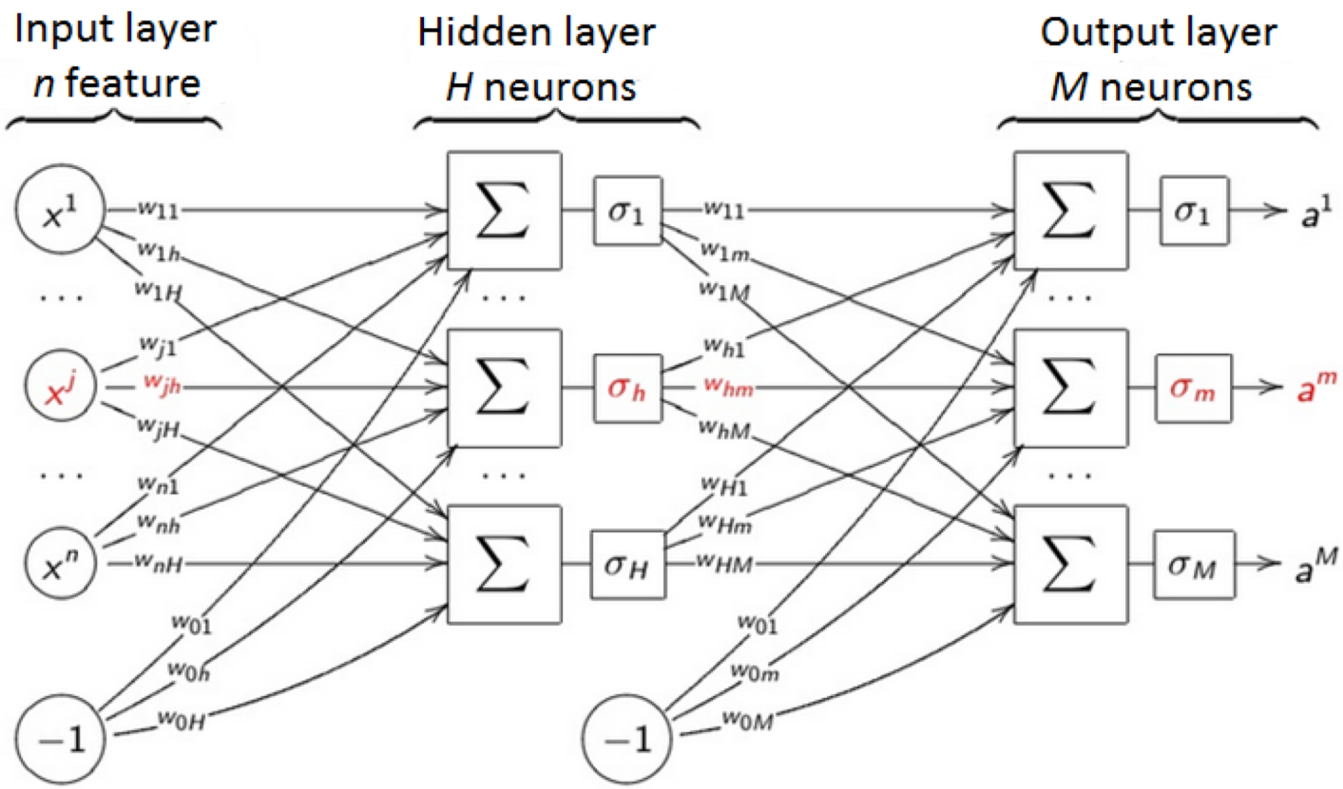


Linear Separability

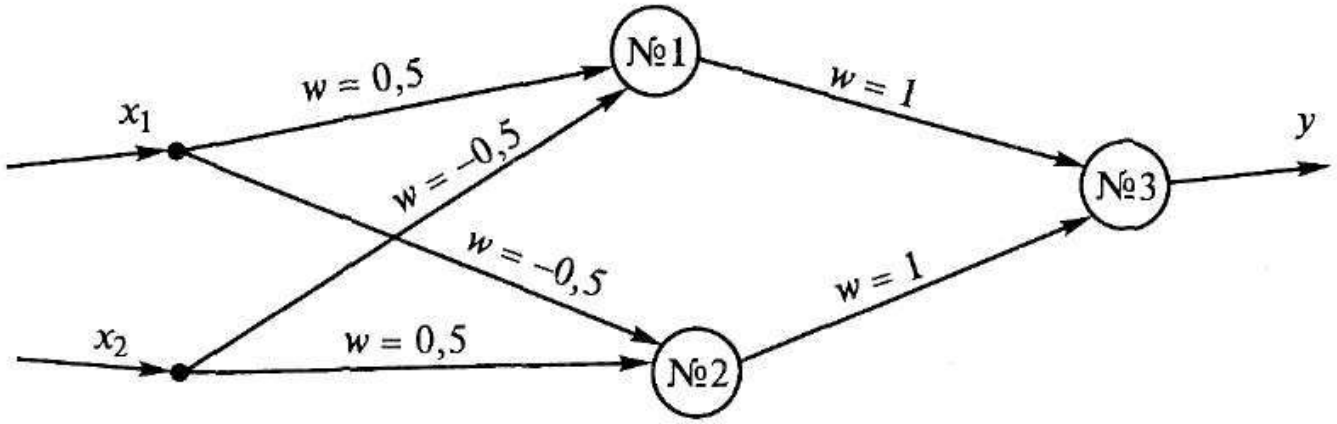




Multilayer perceptron (MLP)



MLP. The modeling of XOR



№ 1:

$$S_1 = 0,5 \times x_1 + (-0,5) \times x_2;$$
$$y_1 = 1, \quad S_1 \geq \theta;$$
$$y_1 = 0, \quad S_1 < \theta.$$

№ 2:

$$S_2 = (-0,5) \times x_1 + 0,5 \times x_2;$$
$$y_2 = 1, \quad S_2 \geq \theta;$$
$$y_2 = 0, \quad S_2 < \theta.$$

№ 3:

$$S_3 = 1 \times y_1 + 1 \times y_2;$$
$$y_3 = 1, \quad S_3 \geq \theta;$$
$$y_3 = 0, \quad S_3 < \theta.$$

Back propogation

LeCun, Werbos, Galushkin, 1974

- For output layer:

$$w_{ij}^{(k)}(t+1) = w_{ij}^{(k)}(t) + \Delta w_{ij}^{(k)}(t+1),$$

$$\Delta w_{ij}^{(k)}(t+1) = \eta \delta_i^{(k)} y_j^{(k-1)}, \quad \delta_i^{(K)} = (d_i - y_i) f_\sigma'(S_i).$$

- For hidden layers:

$$(d_j - y_j) = \sum_{i=1}^{I} \delta_i w_{ij}$$

$$\delta_i^{(K)} = f_\sigma'(S_i) \sum_{l=1}^{H_{k+1}} \delta_l^{(k+1)} w_{li}^{(k+1)}.$$

Flexibility MLP

- 13th Hilbert problem
- Solved by Kolmogorov, in case of neural nets – by Hecht-Nielsen

Problems with MLP

Main problems:

- Too much connections
- Lose complex structure of objects
- Tend to overfitting

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Deep architecture

Definition: Deep architectures are composed of multiple levels of non-linear operations, such as neural nets with many hidden layers

- Most machine learning algorithms have shallow (1-3 layers) architecture (SVM, PCA, kNN, LogisticRegression, etc.)

Goal**:** Deep learning methods aim at:

- Learning feature hierarchies, no more feature engineering!
- Where features from higher levels of the hierarchy are formed by lower level features.

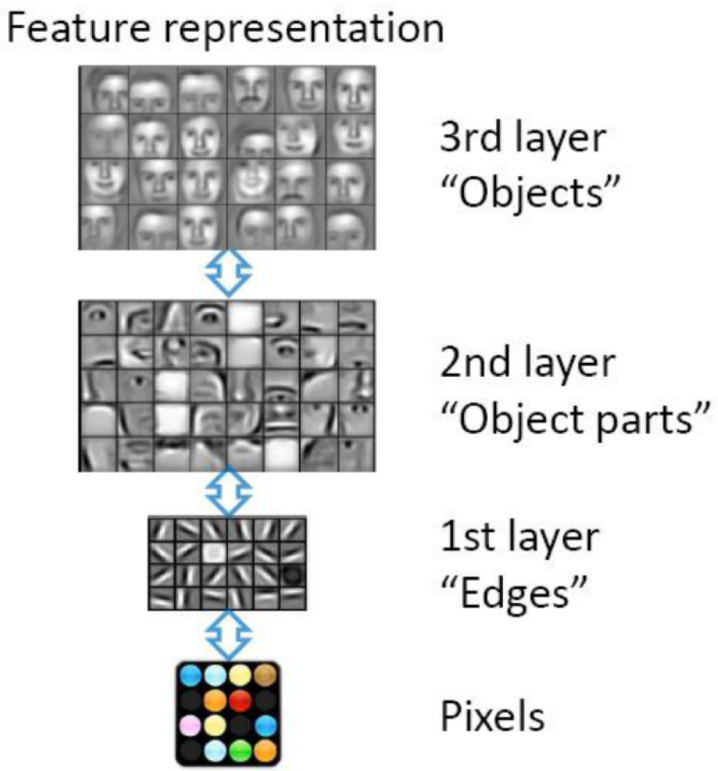
Why to go deep?

- Some functions cannot be efficiently represented by shallow
- architectures
- Functions that can be compactly represented by a depth k architecture might require an exponential number of computational elements to be represented by a depth k − 1 architecture
- Allow non-local generalization and comprehensibility
- State of the art results in many fields

Levels of abstraction

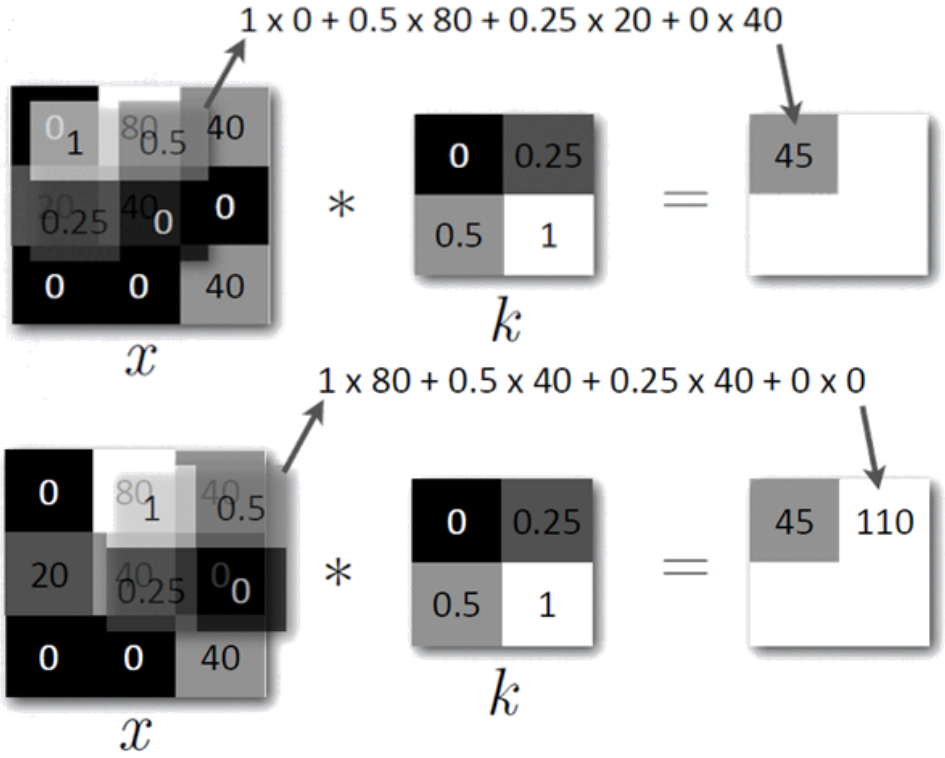
Hierarchical Learning:

- Natural progression from low level to high level structure as seen in natural complexity
- Easier to monitor what is being learnt
- A good lower level representation can be used for many tasks



Discrete convolution

$$(x \times k)_{ij} = \sum_{pq} x_{i+p,j+q}\, k_{r-p,r-q}$$



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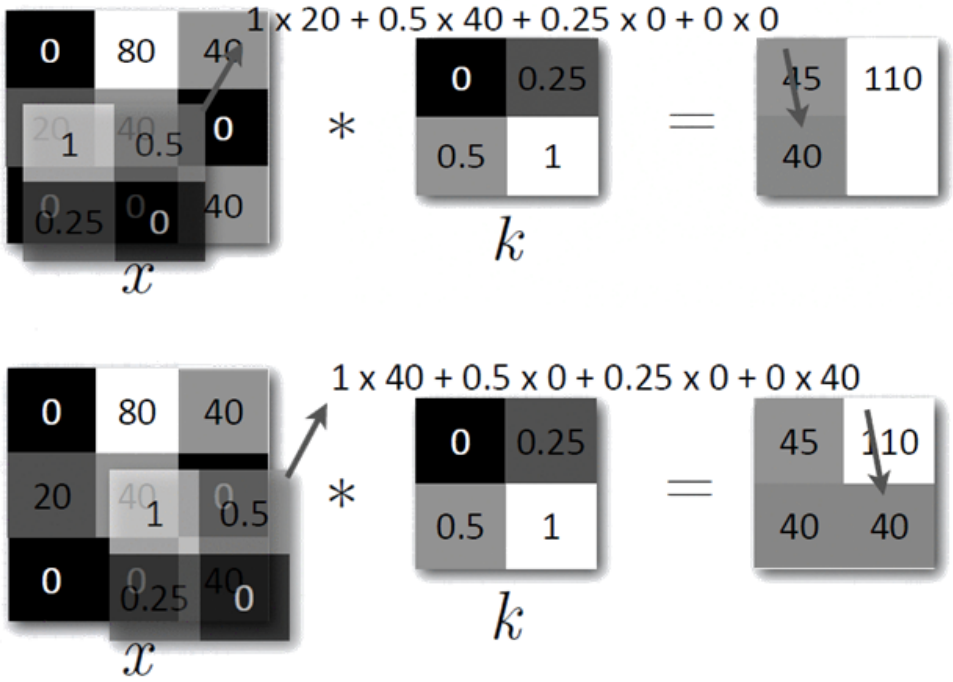

What can kernels do?

$*$

0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

$=$

blur

$*$

	0	1	0	
	1	-4	1	
	0	1	0	

$=$

edge detection

$*$

0	0	0	0	0
0	0	-1	0	0
0	-1	5	-1	0
0	0	-1	0	0
0	0	0	0	0

$=$

sharpen

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Convolutional Neural Network (CNN)

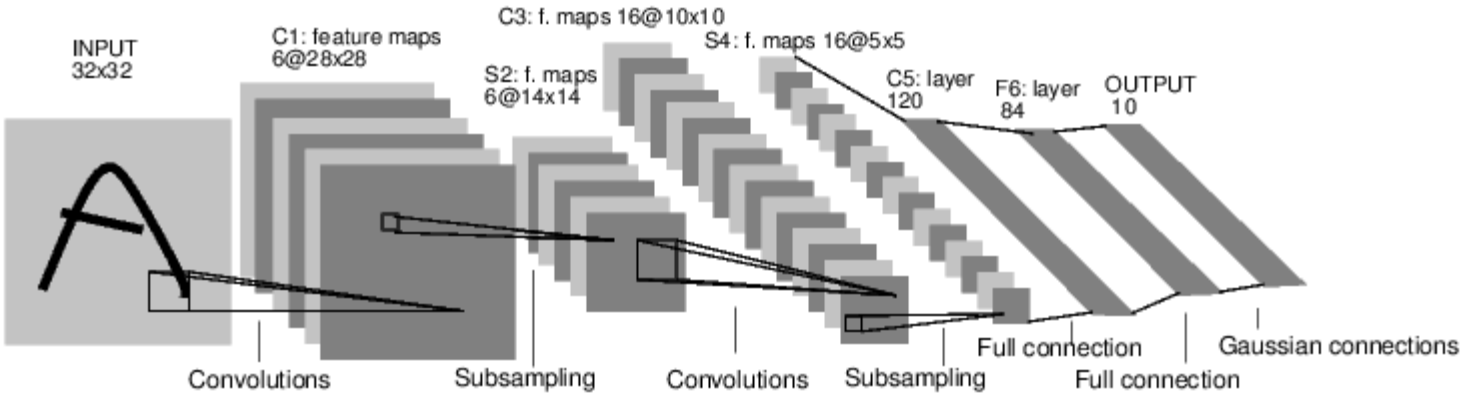
Core concepts:

- Local perception – each neuron sees a small part of the object. Use kernels (filters) to capture 1D or 2D structure of objects. For instance, capture all pixel's neighbors for an image
- Weight sharing – use small and the same sets of kernels for all objects, this leads to less adjusting parameters than MLP
- Subsampling/pooling – use dimensionality reduction in order, for images, to provide invariance to scale

Convolutional Neural Network

- Convolutional layers
- Subsampling (pooling) layers
- Fully connected layers

LeNet



LeCun, Yann, et al. "Gradient-based learning applied to document recognition." *Proceedings of the IEEE* 86.11 (1998): 2278-2324.

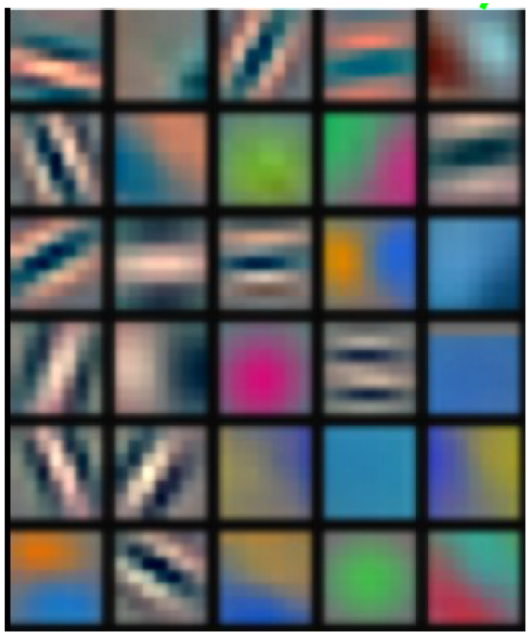
GoogLeNet

Convolution
Pooling
Softmax
Other

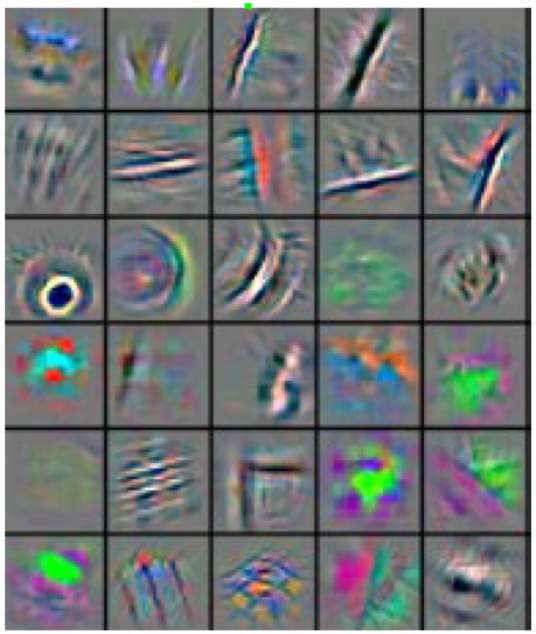
Szegedy, Christian, et al. "Going deeper with convolutions." *arXiv preprint arXiv:1409.4842* (2014).

What do trained kernels look like?

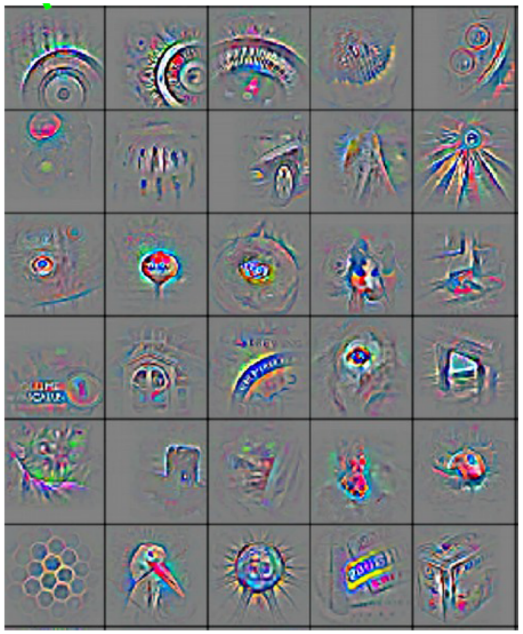
low feature



medium feature



high feature



- Each kernel composes a local patch of lower-level features into high level representation

Pros and cons of deep learning

- **Universal**, flexible and powerful tool
- Suitable for any task of AI
- Shows **the best results** in complex tasks

- It is difficult, long and **expensive to adjust**
- For good results, you need **a lot of data**

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Data augmentation

- Image shifting, rotation
- Horizontal/vertical flips + cropping
- Changing RGB intensities

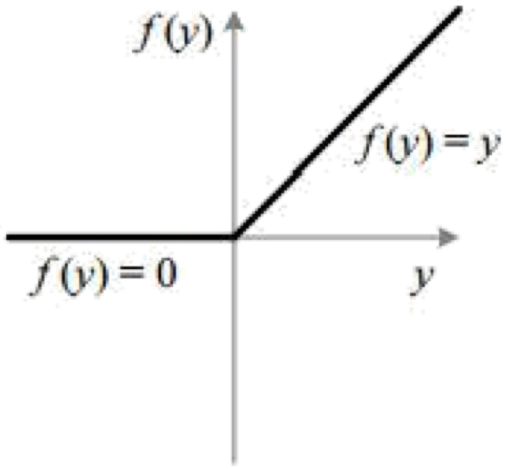
Dropout

Dropout: set the output of each hidden neuron to zero w.p. 0.5

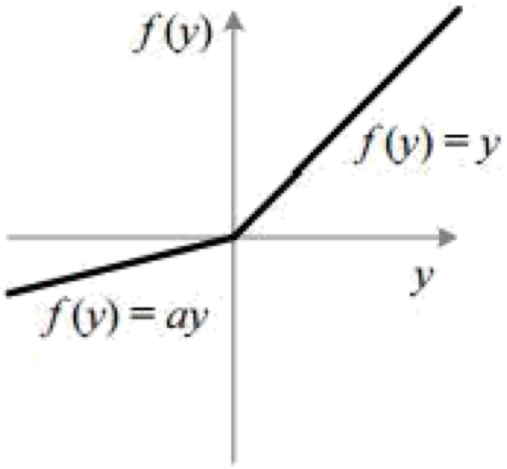
- The neurons do not contribute to the forward pass and in backpropagation
- Allows to try different architectures
- It is forced to learn more robust features
- Allows to avoid overfitting

ReLU, PReLU

ReLU



PReLU



- Sigmoid, hyperbolic tangent activation functions have a problem with vanishing of gradients and tend to overfitting

Loss functions

- Softmax
- $L = \frac{1}{N}\sum_i -log\frac{e^{f y_i}}{\sum_j e^{f j}}$
- Where $j \in [1, K]$, N – number of samples

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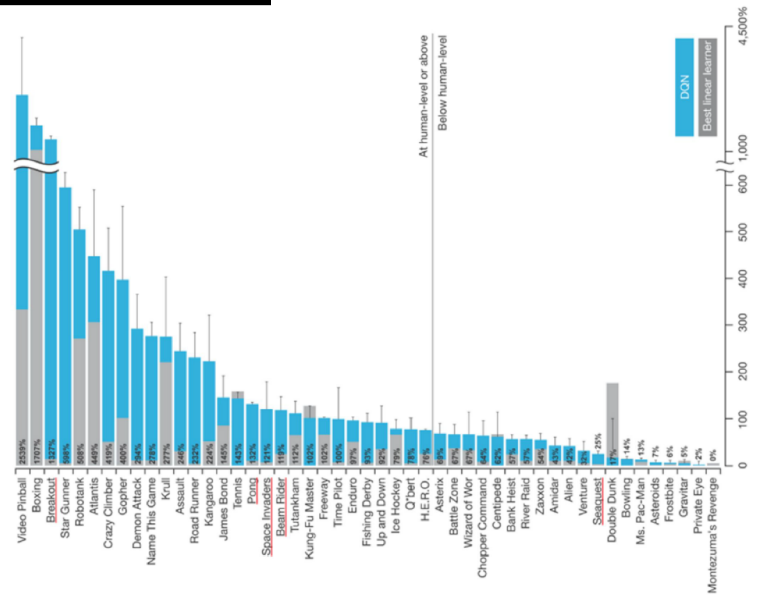
Deep learning applications

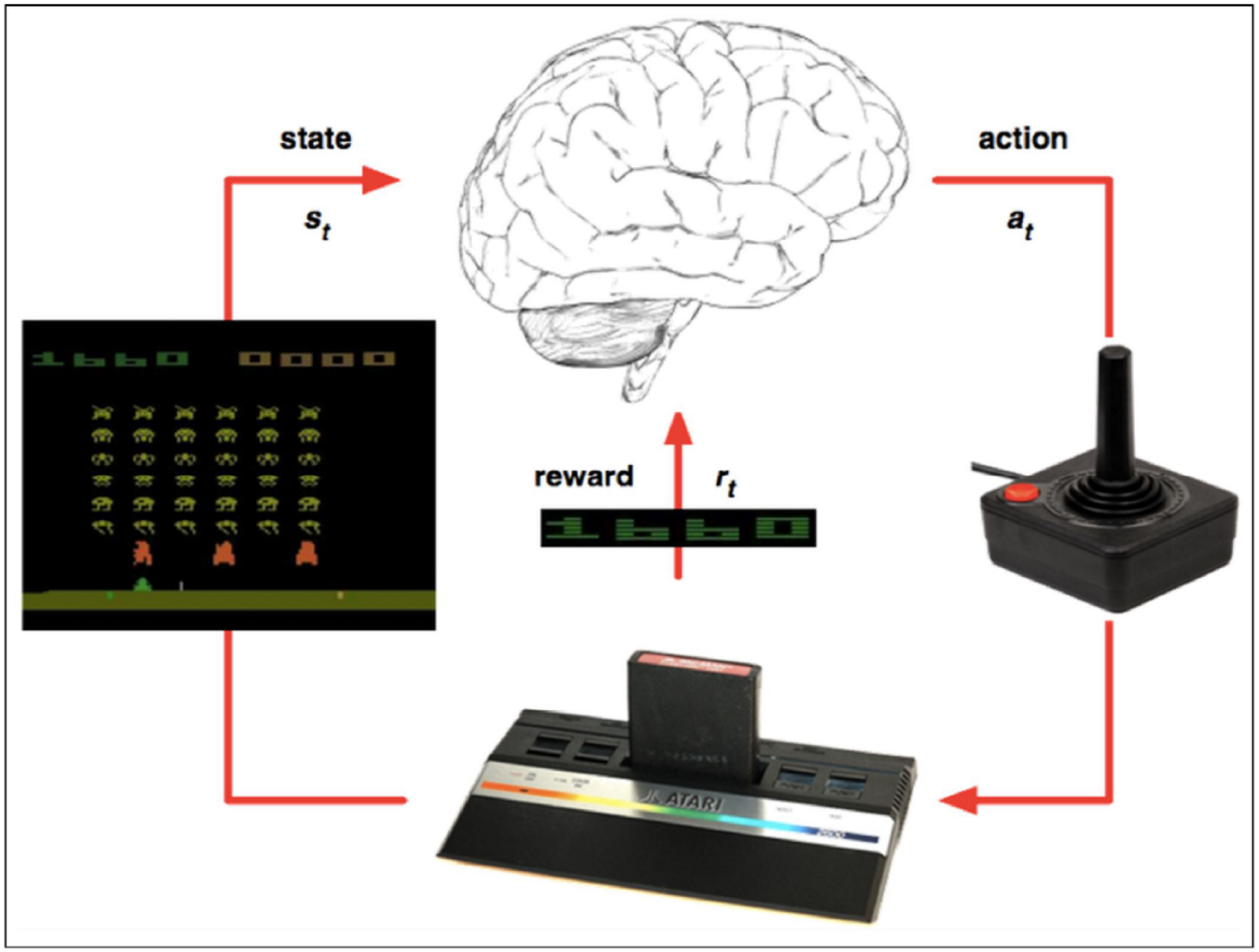
- Image Recognition
- Image Search
- Visual Question Answering
- NLP
- Speech Recognition
- …

Atari

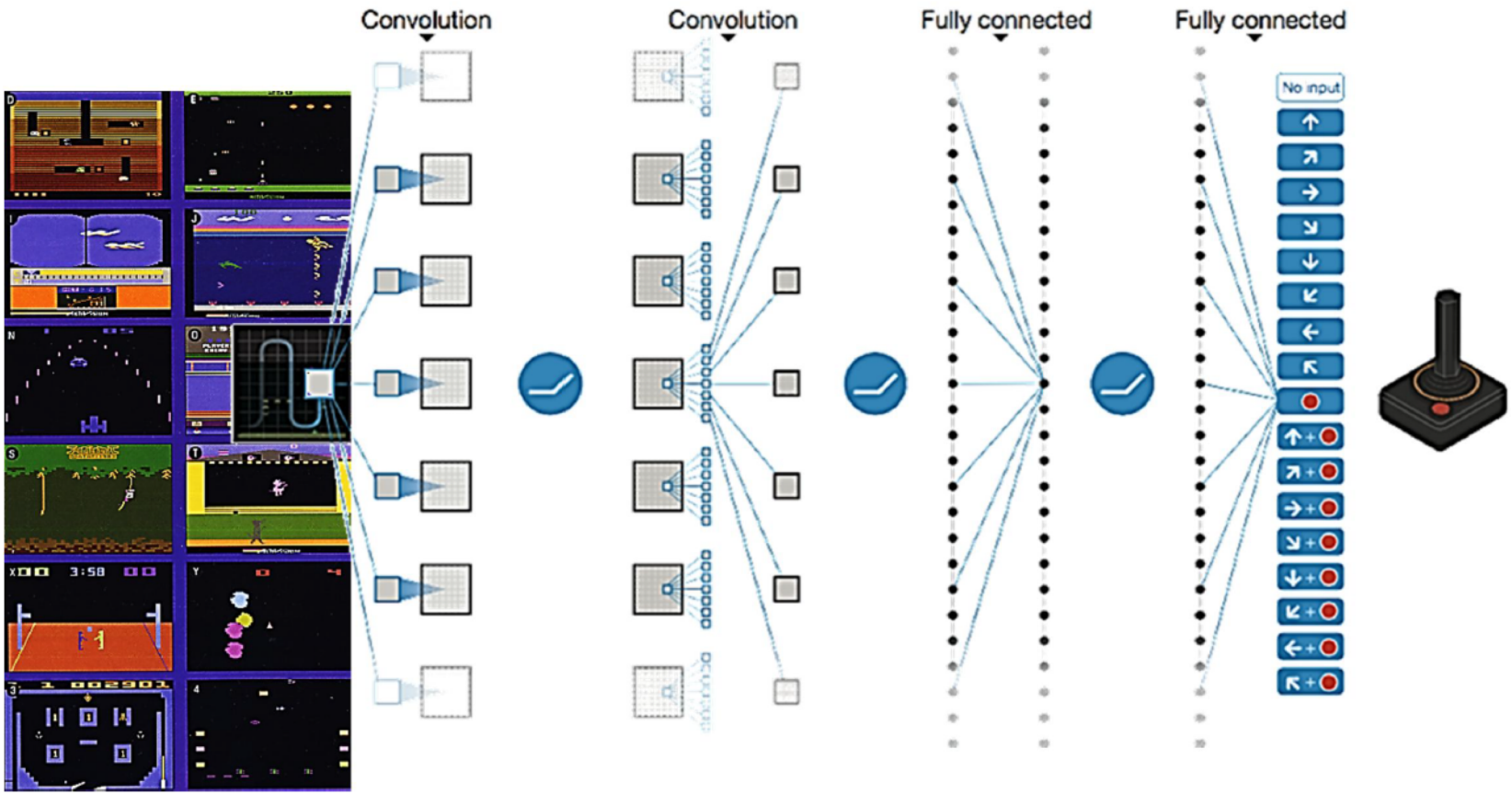


Mnih, Volodymyr, et al. "Human-level control through deep reinforcement learning." *nature* 518.7540 (2015): 529-533.

Atari: how it works

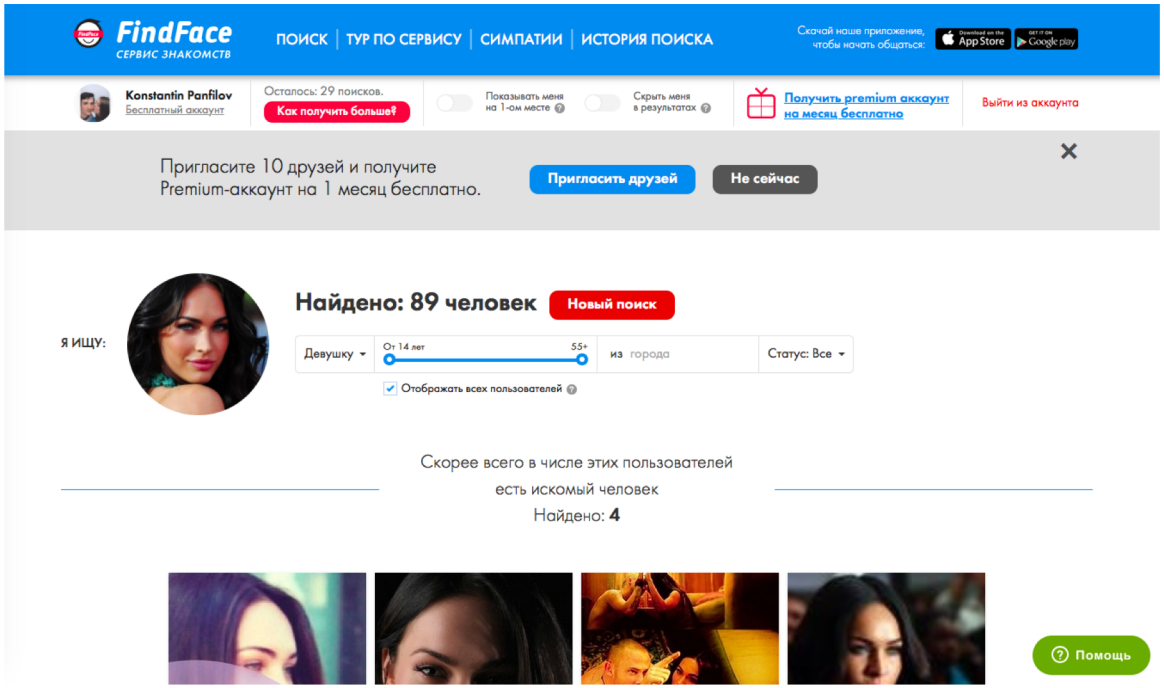


DQN architecture

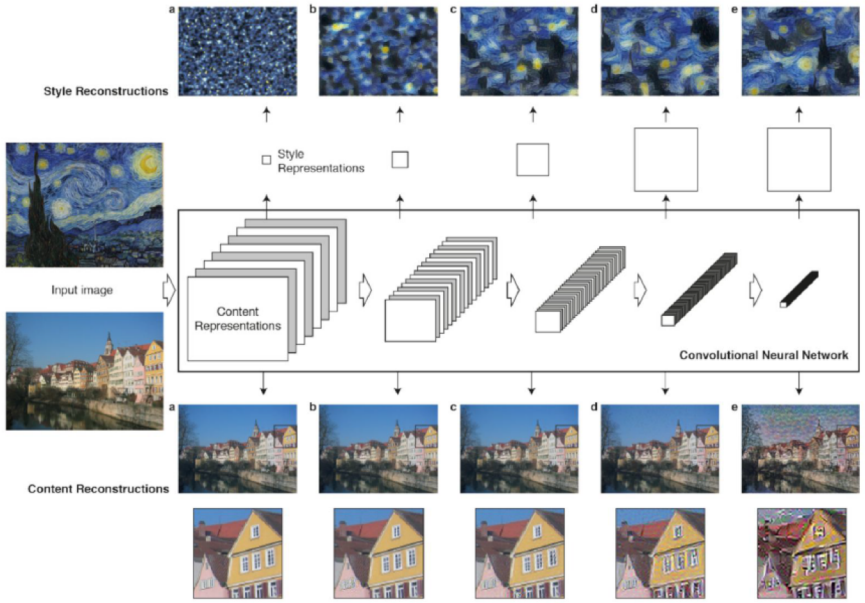


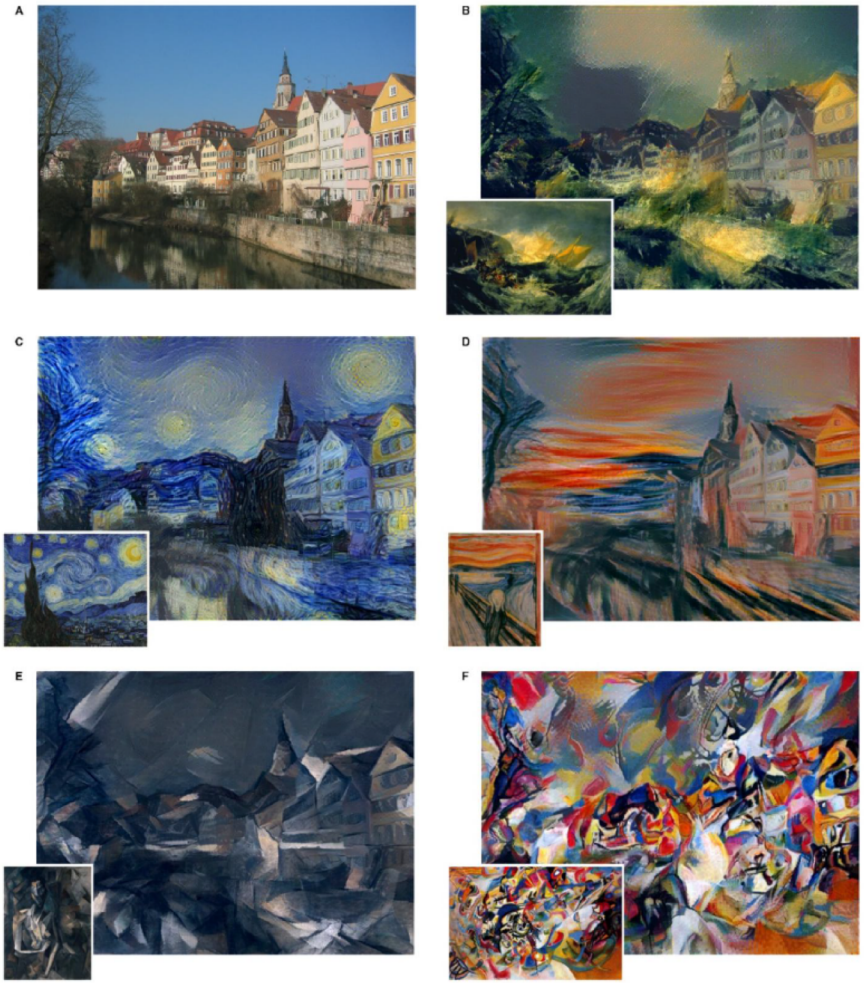
Faces recognition

FindFace uses CNN to provide the search of faces that look similar



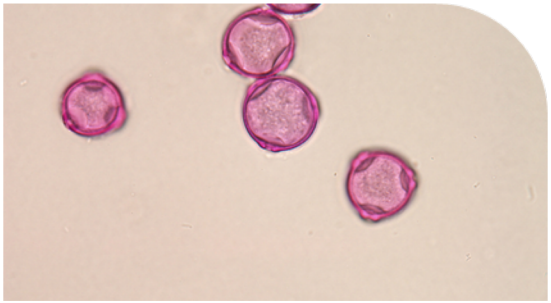
Prisma, DeepArt





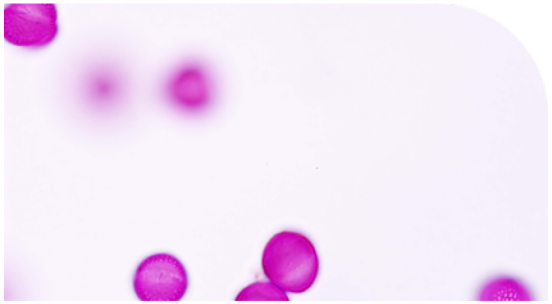
Gatys, L.A., Ecker, A.S. and Bethge, M., 2015. A neural algorithm of artistic style.
arXiv preprint arXiv:1508.06576.

Pollen recognition

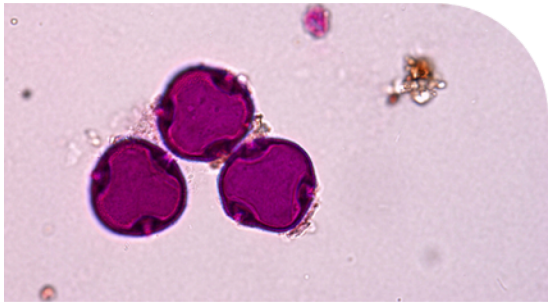


Береза повислая

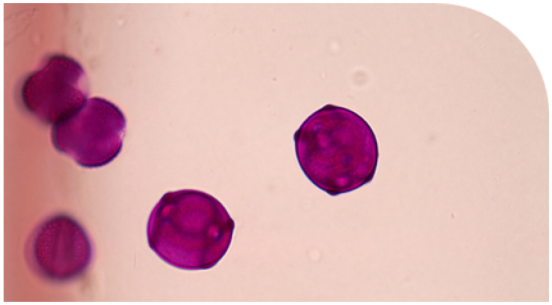
Свербига восточная



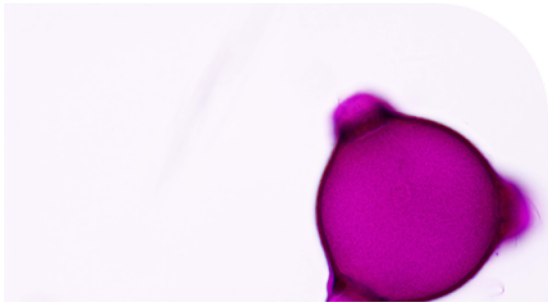
Ива белая



Липа сердцевидная



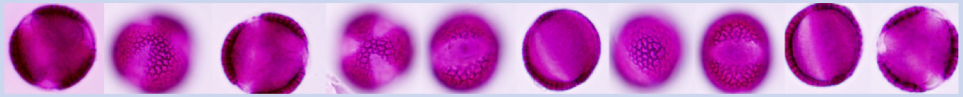
Ольха клейкая



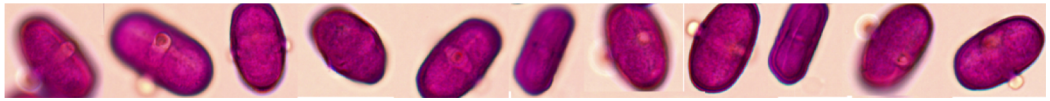
Иван-чай узколистный

Multiple focuses and forms

Свербига восточная

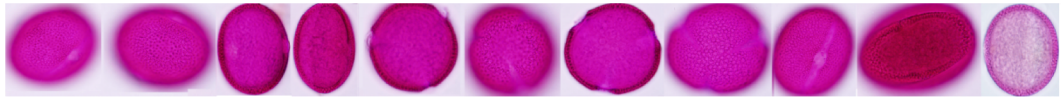


Дудник лесной



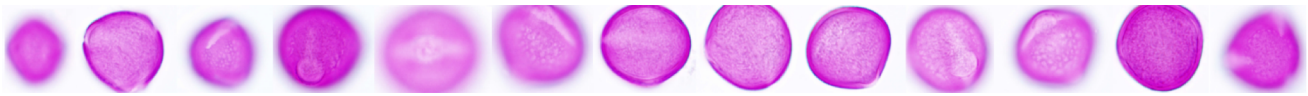
Гвоздика-травянка

Гречиха посевная

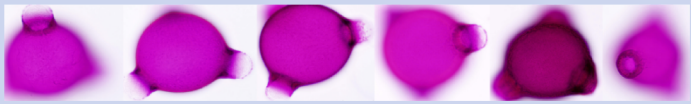


Дудник лекарственный

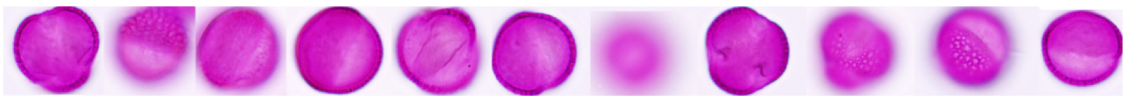
Клевер гибридный



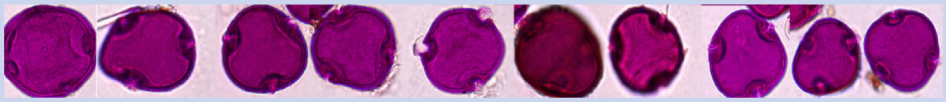
Иван-чай узколистный



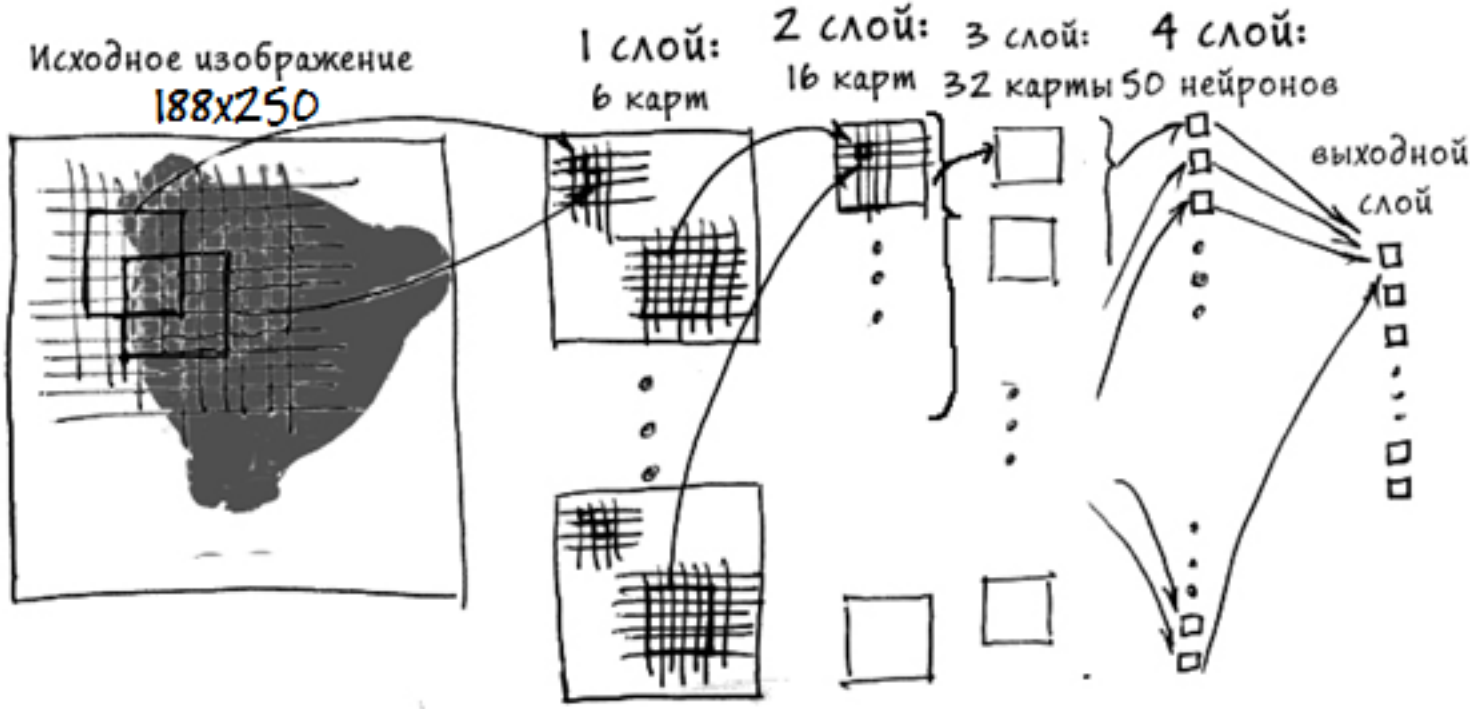
Ива белая



Липа сердцевидная

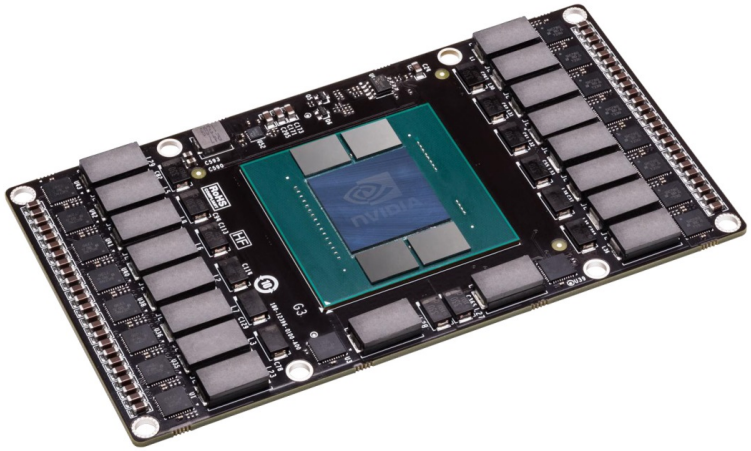


CNN architecture



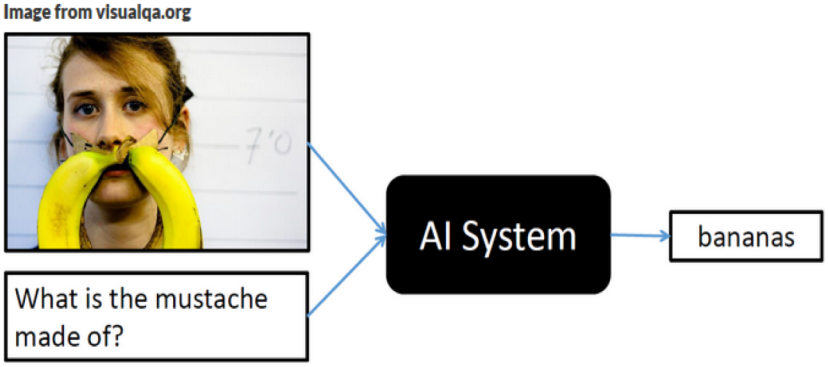
On 5 classes the accuracy **= 99.7%** (RF 85.6%)

What else?



NVIDIA Pascal

Image from visualqa.org



Tools

- Python:
  Keras, Theano, TensorFlow, Caffe, Pylearn2, Deepnet
- C:
  Torch
- C++:
  Caffe, nnForge, CXXNET, Cuda-convent
- Matlab:
  Caffe, DeepLearningToolbox, Deepmat, Cuda CNN