

11 – Classification

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Recognition and Classification Problem

Face recognition

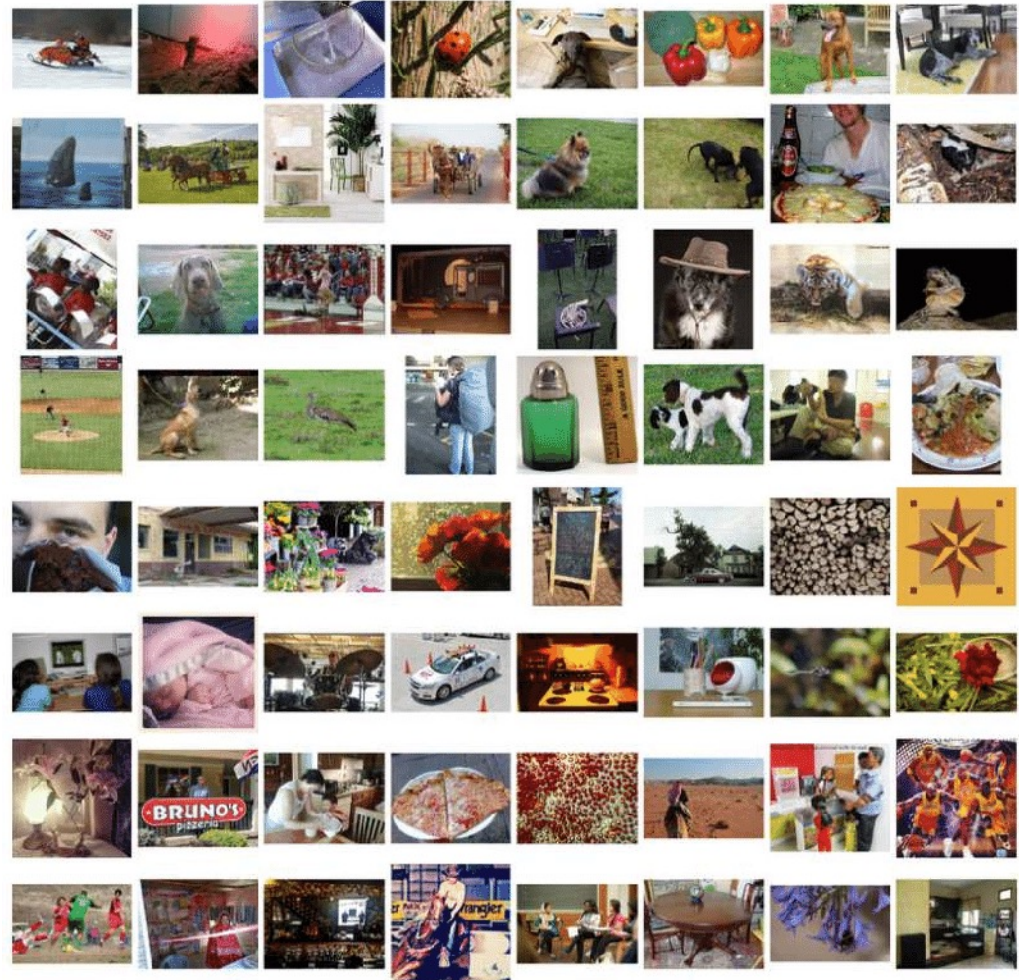


Handwriting recognition

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*Les bruyères ou un a de plantes
de la famille des hamacées.
Ce un des arbustes dicotylédones
à fleurs le plus saillant marces ou
violette disposées en épis dans la plupart.*

ImageNet (14 million images) – object recognition



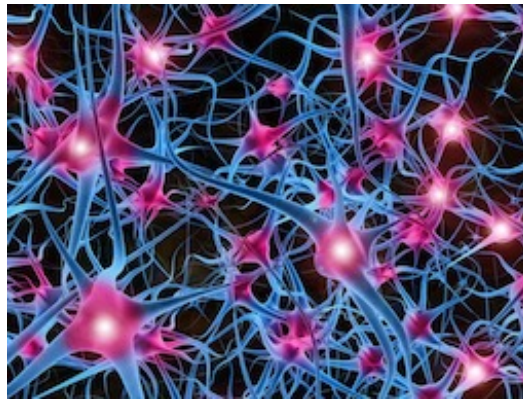
Brain is good in Recognition & Classification

Human brain



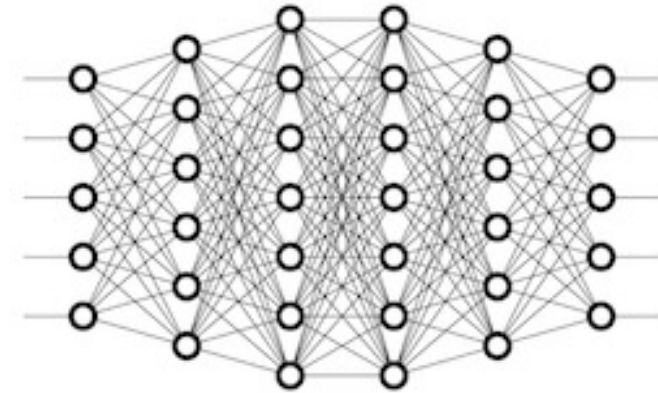
- ◆ Weight: 1.5 kg or 2% of total body
- ◆ Volume: $\approx \frac{1}{2}$ sphere with 6.5cm radius
- ◆ Consume 20% of our energy

Network of neurons



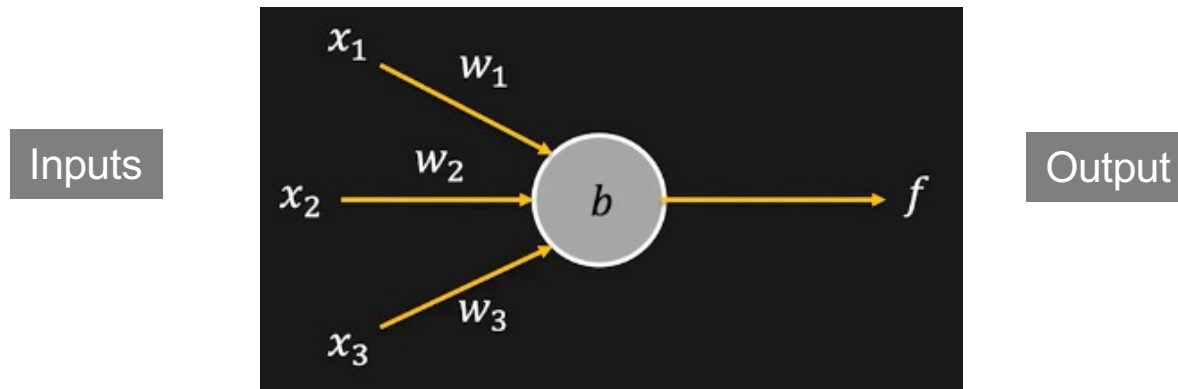
- ◆ 100 billion neurons
- ◆ 100 trillion synapses

Artificial neural network



- ◆ Largest today has 160 billion parameters
- ◆ Around 0.16% of human brain

Perceptron



$$f = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq -b \\ 1 & \text{if } \sum_j w_j x_j > -b \end{cases}$$

$$f = \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$$

$w_j = \text{weights},$
 $b = \text{threshold (or bias)}$

Source: Rosenblatt

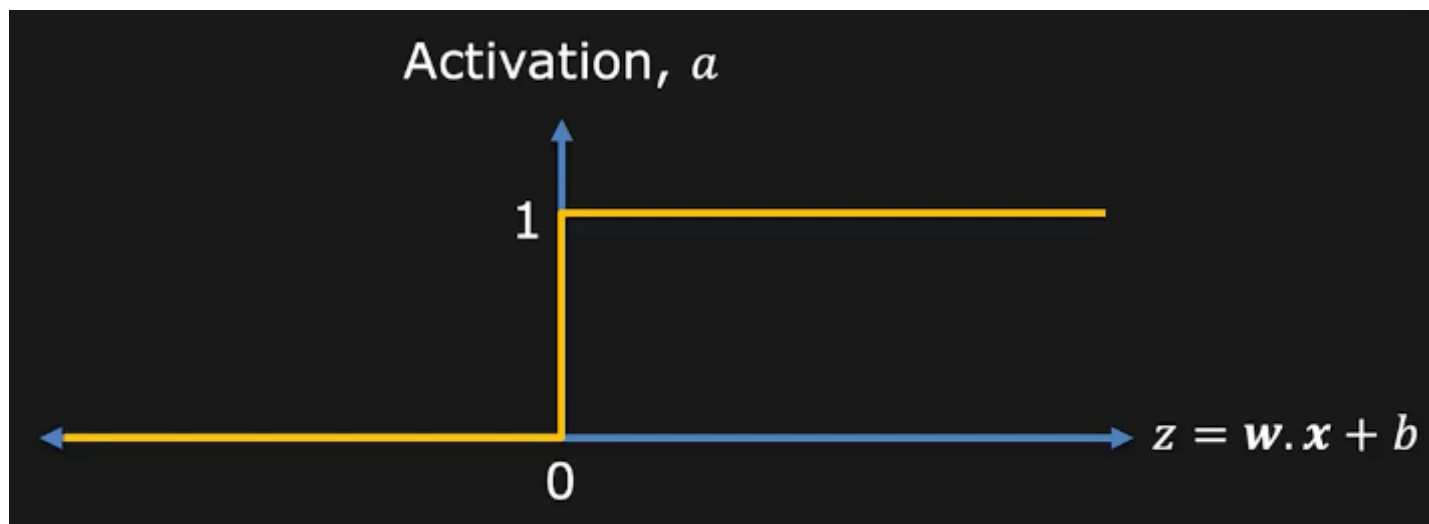
Activation Function of a Perceptron

Let $z = w \cdot x + b$

$$f = \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$$

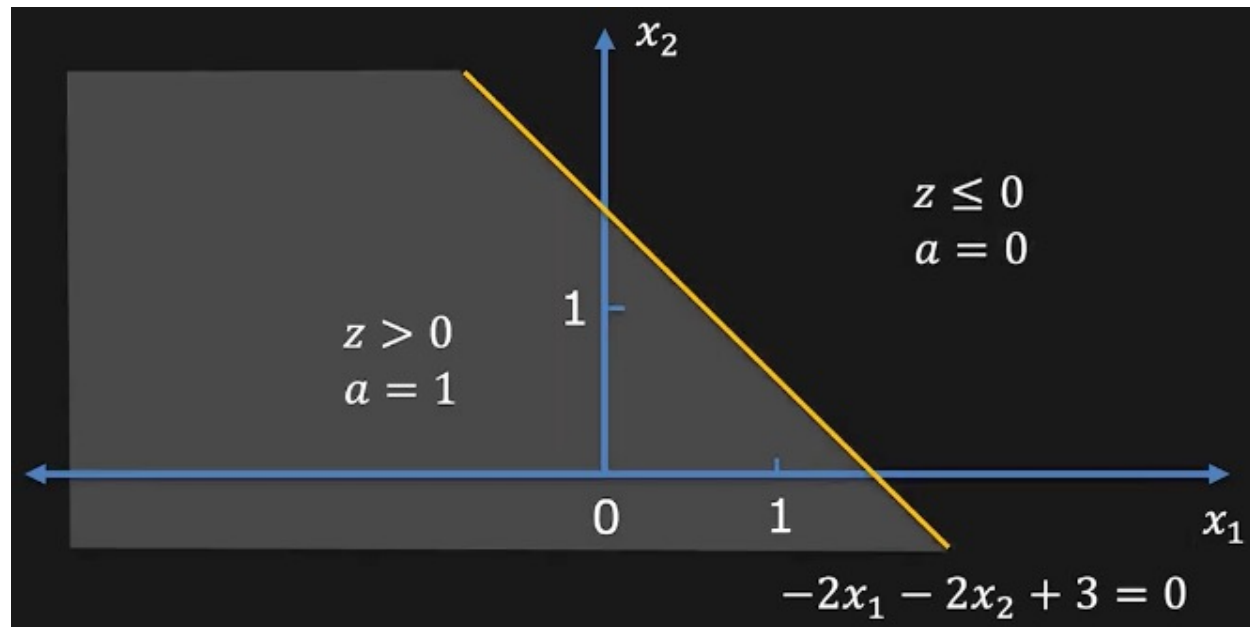
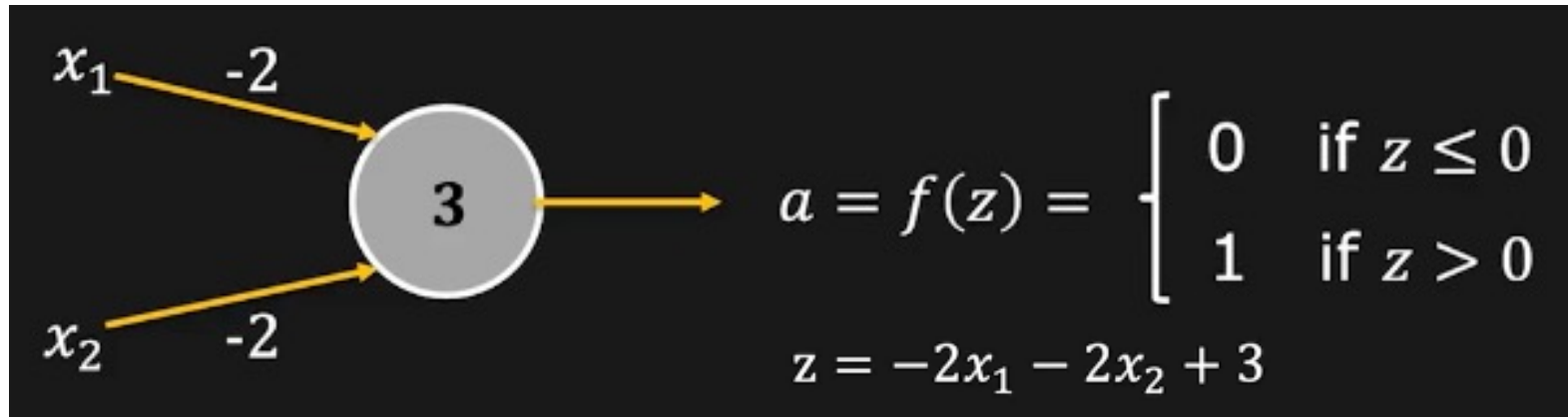
Activation Function is a unity step function $u(t)$

$$a = f(z) = \begin{cases} 0 & \text{if } z \leq 0 \\ 1 & \text{if } z > 0 \end{cases}$$



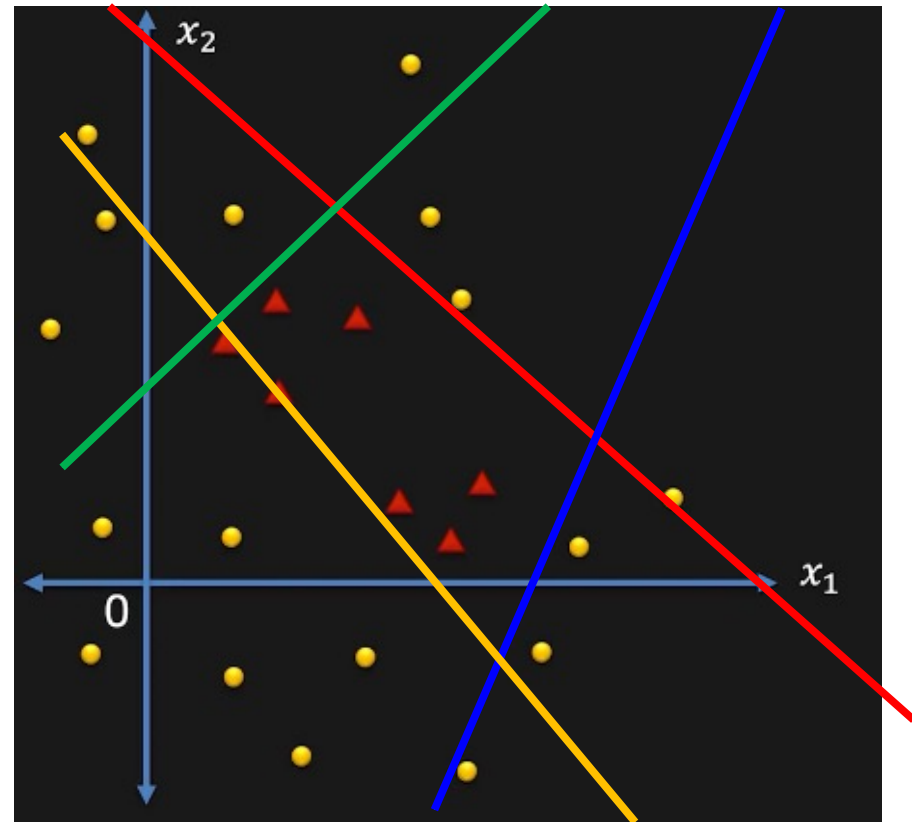
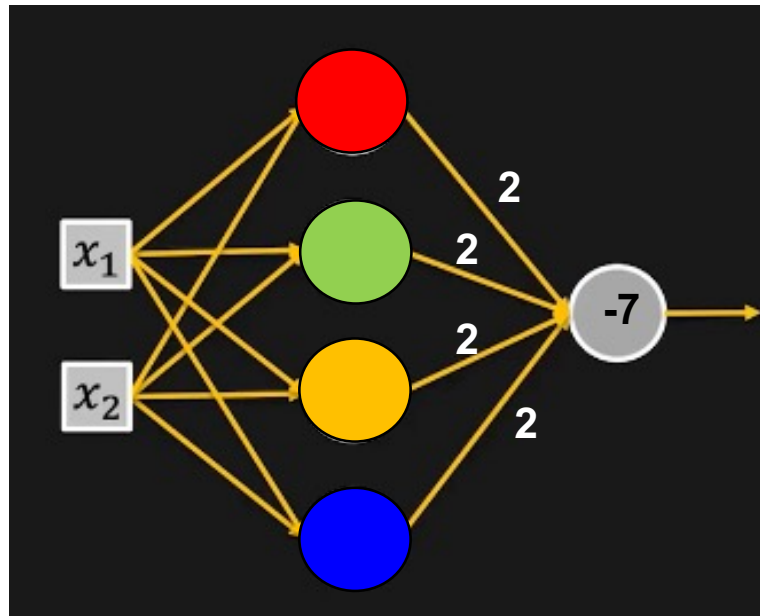
Source: Rosenblatt

Perceptron is a Linear Classifier



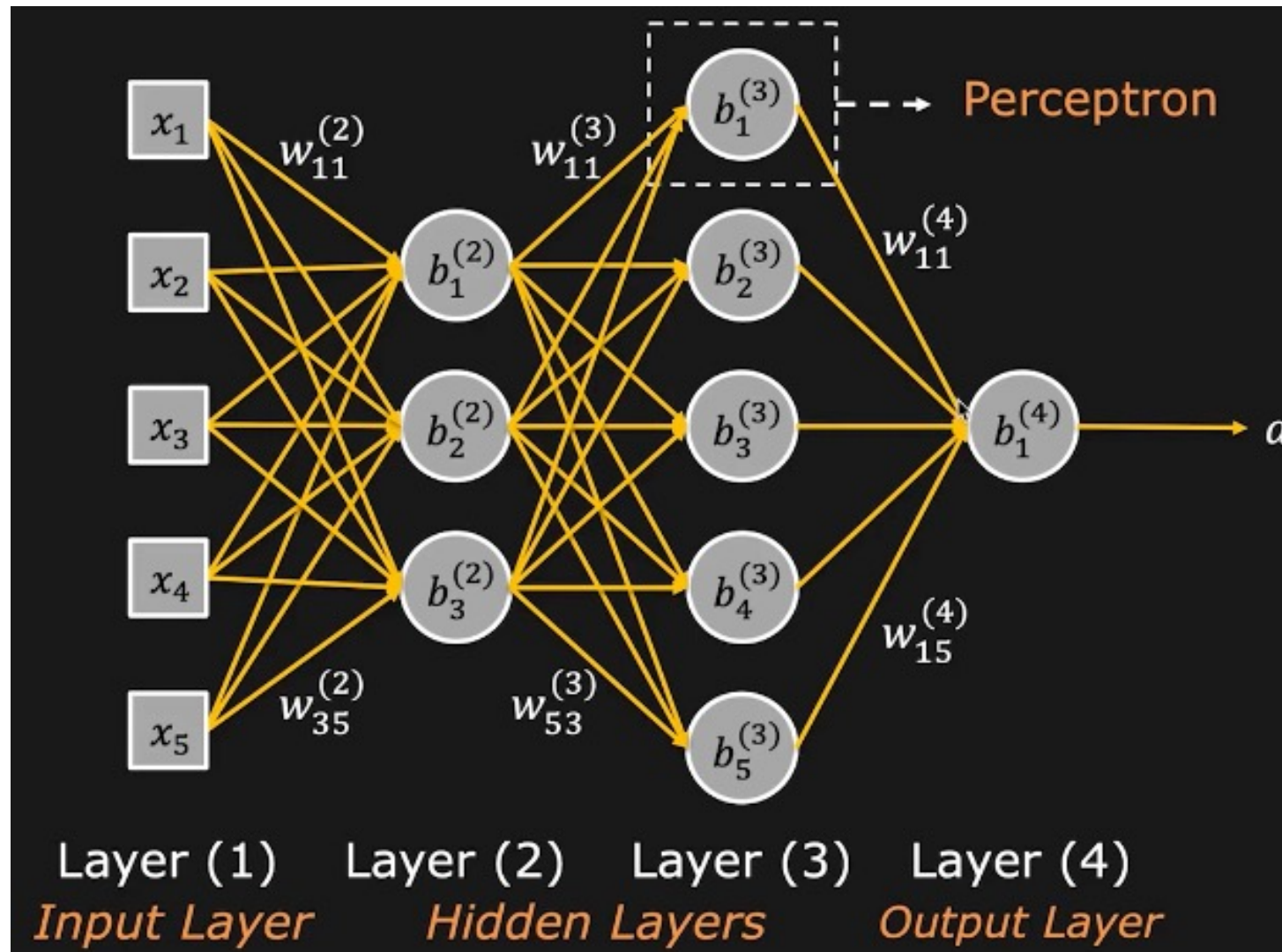
Source: Rosenblatt

A Network of Perceptrons

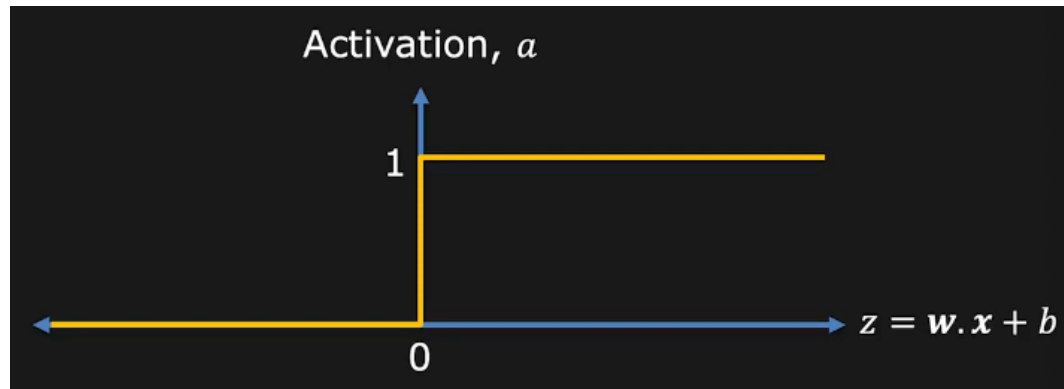


- ◆ We can use multiple layers of perceptrons to build a complex classifier.

A Multi-layer Perceptron

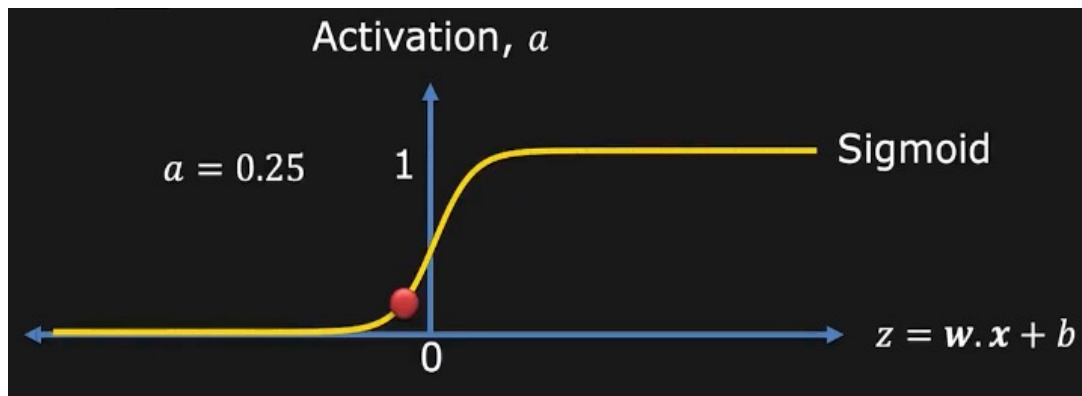


Sigmoid Activation Function



$$a = f(z) = \begin{cases} 0 & \text{if } z \leq 0 \\ 1 & \text{if } z > 0 \end{cases}$$

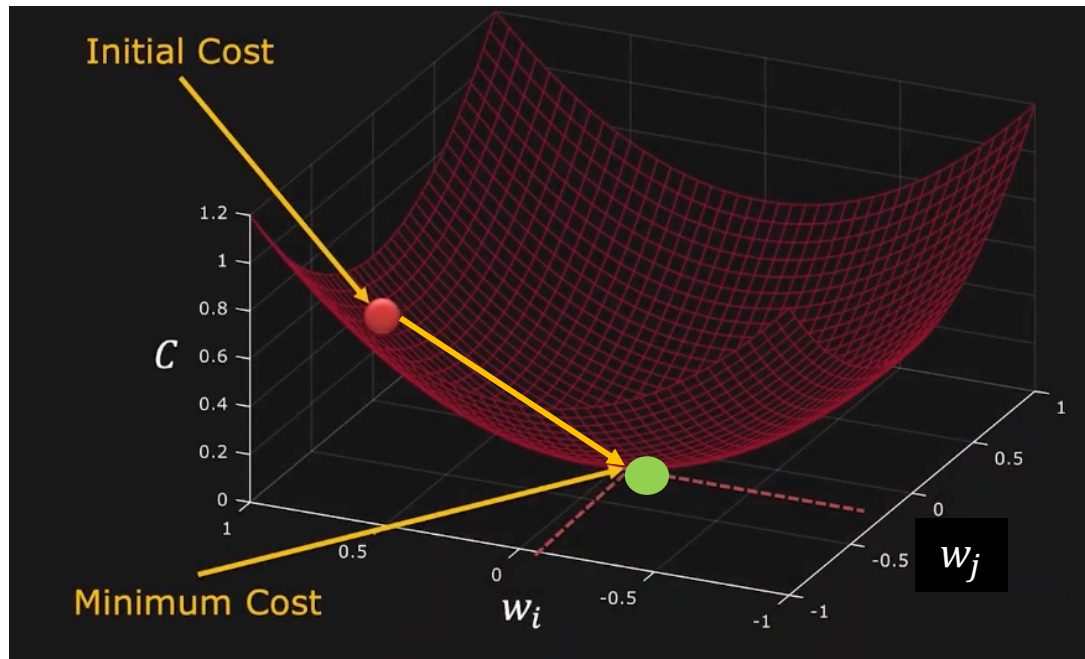
- ◆ Step function activation causes output to change abruptly.
- ◆ 1st derivatives $\rightarrow \infty$.
- ◆ Potential for unstable network.



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

- ◆ Sigmoid function activation has a gently transition.
- ◆ Function good for differentiation.
- ◆ Output changes smoothly with changing weights and threshold.
- ◆ Allow backpropagation training.

Optimize Weights in Neural Network - Training



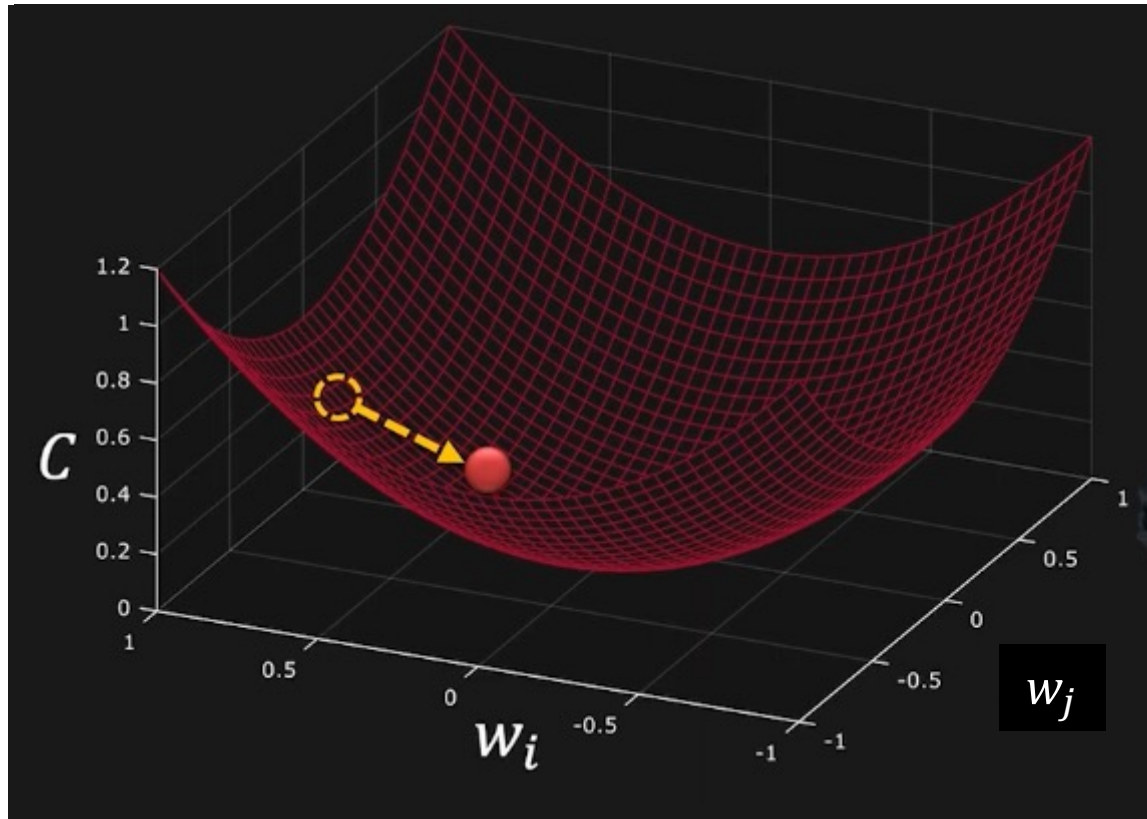
- ◆ Gradient of C with respect to $[w_i, w_j]$ is ∇C , where

$$\nabla C = \begin{bmatrix} \frac{\partial C}{\partial w_i} & \frac{\partial C}{\partial w_j} \end{bmatrix}$$

- ◆ If there is a change in weight of: $\Delta w = \begin{bmatrix} \Delta w_i \\ \Delta w_j \end{bmatrix}$

- ◆ The change in C will be: $\Delta C = \nabla C \cdot \Delta w = \begin{bmatrix} \frac{\partial C}{\partial w_i} & \frac{\partial C}{\partial w_j} \end{bmatrix} \begin{bmatrix} \Delta w_i \\ \Delta w_j \end{bmatrix}$

Training Network Weights by Gradient Descend



Let $\Delta w = -\eta \nabla C$

where η is the learning rate.

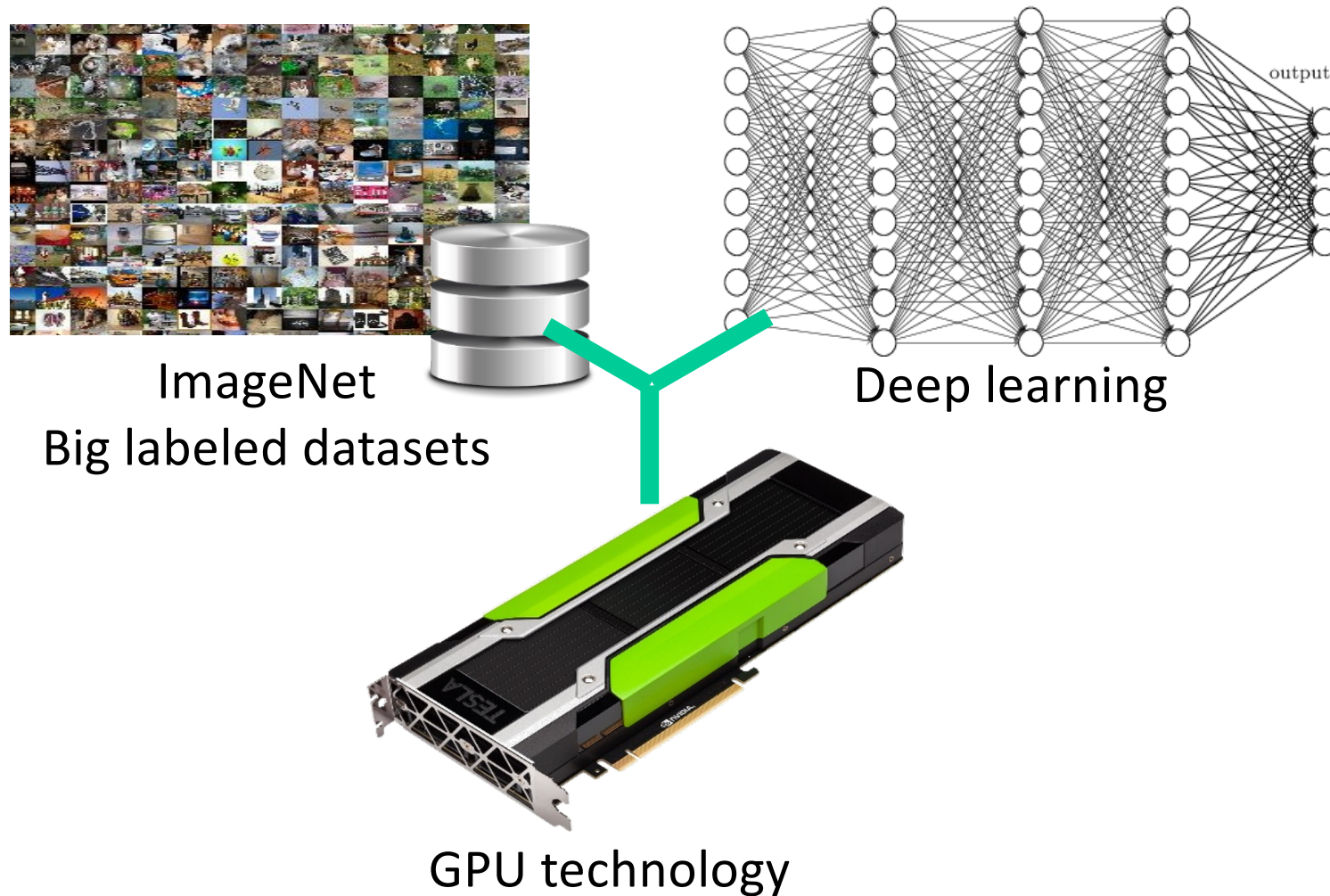
For each step:

$$w_i \rightarrow w'_i = w_i - \eta \frac{\partial C}{\partial w_i}$$

$$w_j \rightarrow w'_j = w_j - \eta \frac{\partial C}{\partial w_j}$$

- ◆ $\frac{\partial C}{\partial w}$ can be efficiently computer computed using the backpropagation algorithm.

Modern Neural Network System for Visual Data



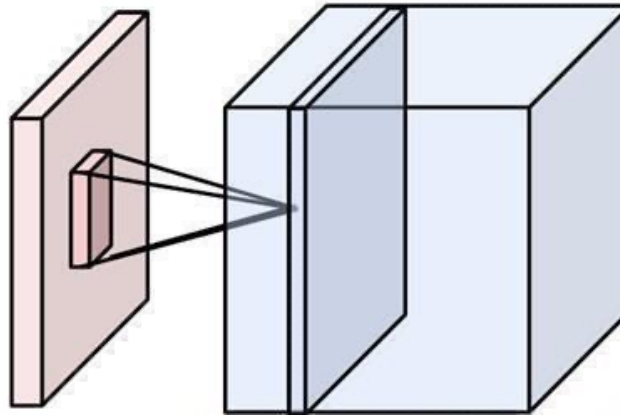
Source: Jayaraman

ImageNet



- ◆ Dataset containing ~14 million images in 20,000 classes.
- ◆ Manually labelled with name of main object.
- ◆ Images gathered from internet.
- ◆ Used for training neural networks.

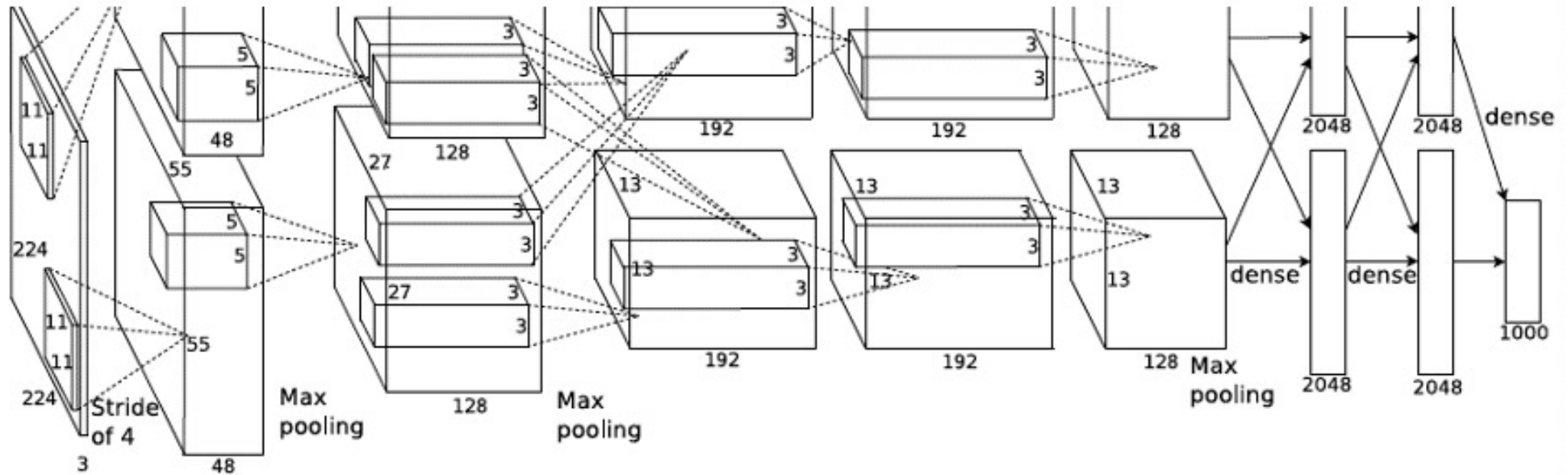
Convolutional Neural Network (CNN)



- ◆ Convolutional Neural Network (CNN):
 - ◆ Multi-layer network.
 - ◆ Use local connectivity, i.e. neurons feed from small group of neural in previous layer.
 - ◆ Weight parameters are shared across spatial positions by training shift-invariant filter kernels.
 - ◆ Popular in image recognition.

Source: Karpathy

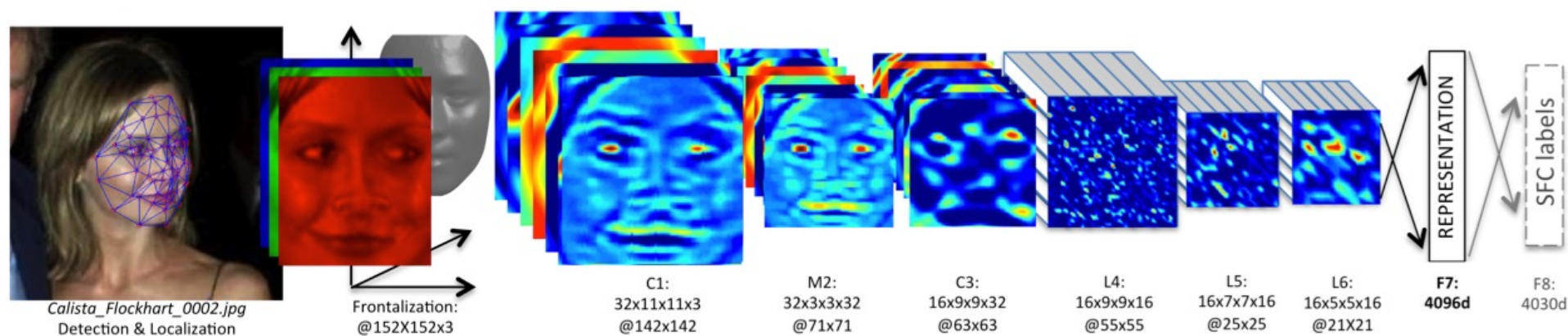
Popular Neural Network - AlexNet



- ◆ Very large CNN model with: 7 hidden layers, 650k neurons and 60 million parameters.
- ◆ Trained with 1 million images.
- ◆ Training ran for a week on two GPUs.

Source: Alex Krizhevsky

Popular Neural Network - DeepFace



- ◆ 9-layer network.
- ◆ >120 million parameters.
- ◆ Trained on 4 million facial images.
- ◆ Achieve accuracy of 97.35%.

Source: Taigman

Pre-trained Neural Network on Matlab

| Neural Network | Depth | Size | Parameters (Millions) | Image Input Size |
|-----------------------------------|-------|--------|-----------------------|------------------|
| squeezenet | 18 | 5.2 MB | 1.24 | 227-by-227 |
| googlenet | 22 | 27 MB | 7 | 224-by-224 |
| inceptionv3 | 48 | 89 MB | 23.9 | 299-by-299 |
| densenet201 | 201 | 77 MB | 20 | 224-by-224 |
| mobilenetv2 | 53 | 13 MB | 3.5 | 224-by-224 |
| resnet18 | 18 | 44 MB | 11.7 | 224-by-224 |
| resnet50 | 50 | 96 MB | 25.6 | 224-by-224 |
| resnet101 | 101 | 167 MB | 44.6 | 224-by-224 |
| xception | 71 | 85 MB | 22.9 | 299-by-299 |
| inceptionresnetv2 | 164 | 209 MB | 55.9 | 299-by-299 |
| shufflenet | 50 | 5.4 MB | 1.4 | 224-by-224 |
| nasnetmobile | * | 20 MB | 5.3 | 224-by-224 |
| nasnetlarge | * | 332 MB | 88.9 | 331-by-331 |
| darknet19 | 19 | 78 MB | 20.8 | 256-by-256 |
| darknet53 | 53 | 155 MB | 41.6 | 256-by-256 |
| efficientnetb0 | 82 | 20 MB | 5.3 | 224-by-224 |
| alexnet | 8 | 227 MB | 61 | 227-by-227 |
| vgg16 | 16 | 515 MB | 138 | 224-by-224 |
| vgg19 | 19 | 535 MB | 144 | 224-by-224 |