EVML

ARTIFICIAL NEURAL NETWORKS

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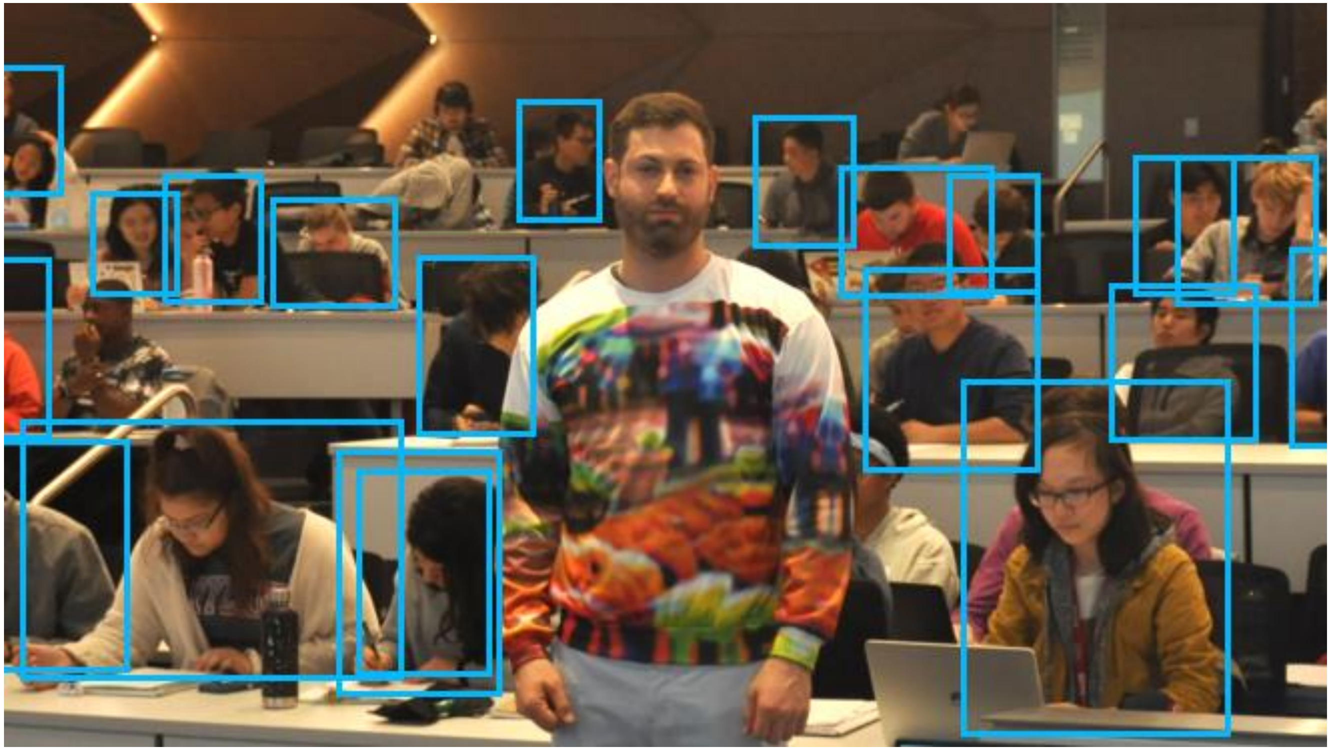
DEADLINES

- https://gitlab.com/jeroen_veen/evml-evd3/-/blob/main/schedule.md?ref_type=heads

ADVERSARIAL SWEATER OF DOOM



Render Yourself Invisible To AI With This Adversarial Sweater Of Doom | Hackaday, 20 October 2022

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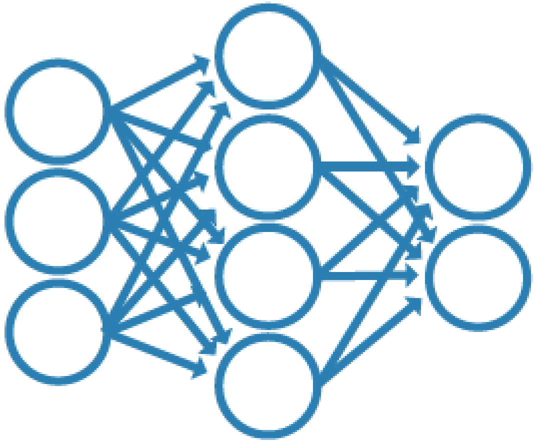
CONTENTS

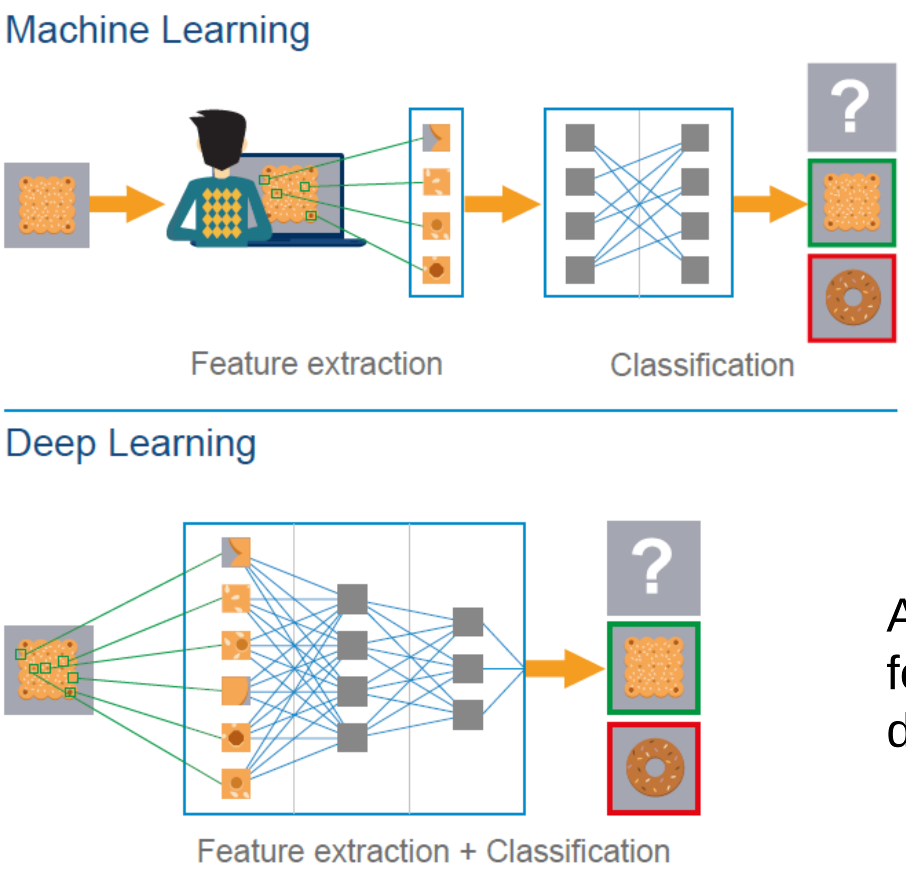
- Machine learning vs deep learning
- Biological neuron
- Perceptron
- Multi-layer perceptron (MLP)
- Backpropagation
- Regression and classification MLP



BACKGROUND MATERIAL

- https://deeplizard.com/learn/playlist/PLZbbT5o_s2xq7LwI2y8_QtvuXZedL6tQU
- https://www.3blue1brown.com/topics/neural-networks
- MIT Deep Learning 6.S191 (introtodeeplearning.com)

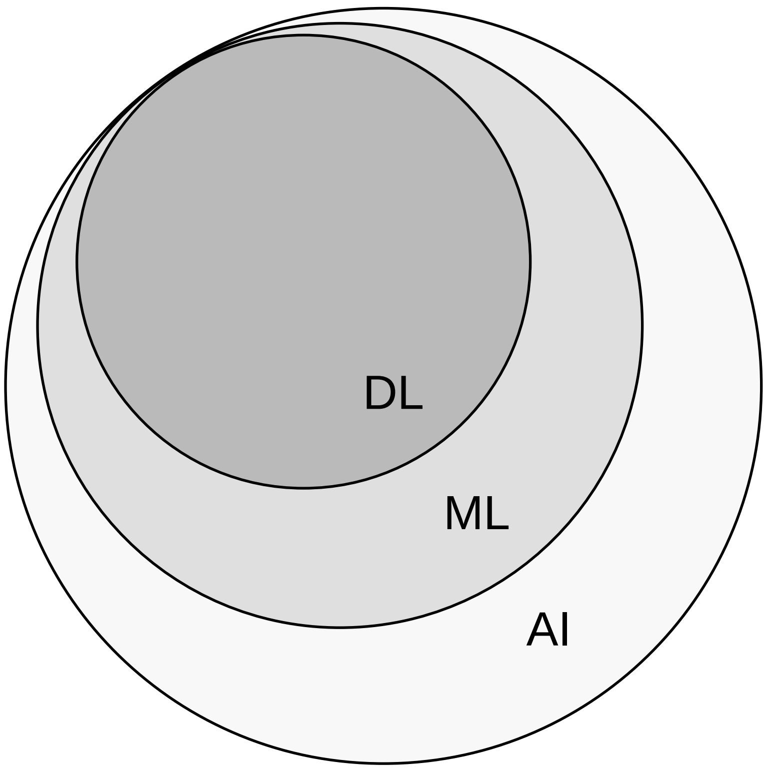
MACHINE LEARNING VS DEEP LEARNING



Autonomous feature definition

Source: Tilmann Zuper, Artificial Intelligence in Image Processing: Deep Learning Compared with Conventional Methods, Basler AG, Ahrensburg, Germany.

DEFINING AI, DL & ML



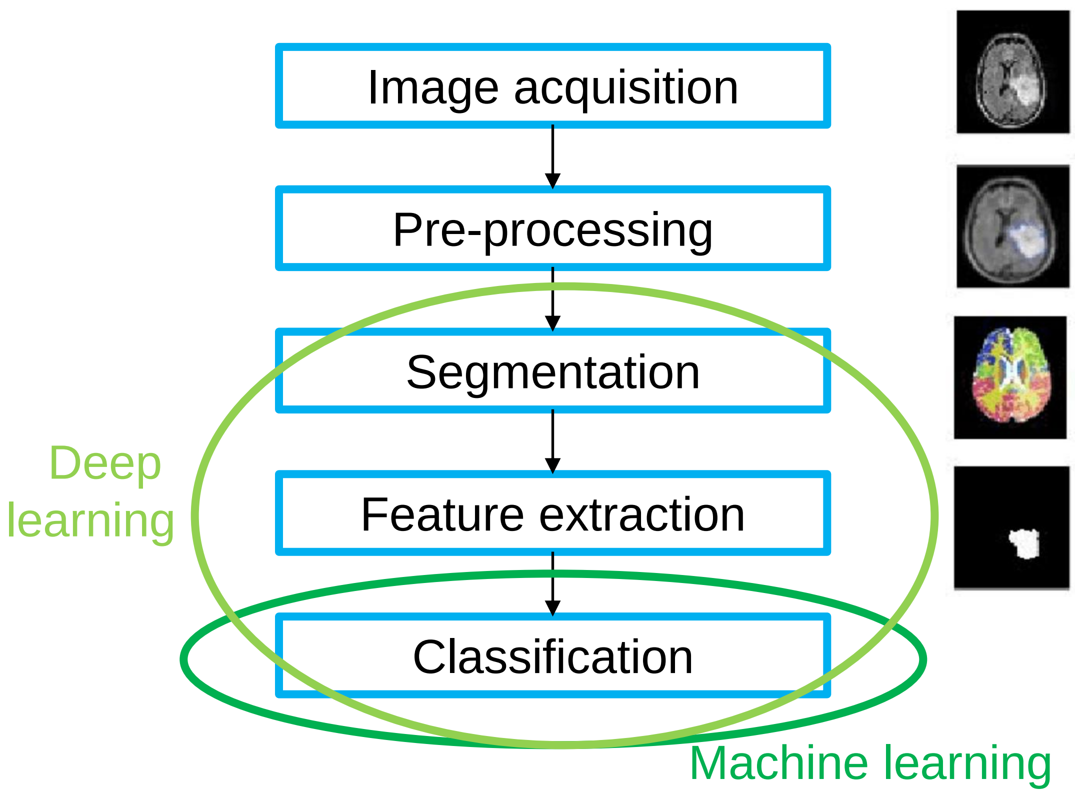
- Strong AI vs Applied AI
- Cognitive replication
- Rational process

Machine learning

- Performs predictive analysis
- Just fancy math & pattern matching

MACHINE LEARNING APPLIED TO VISION

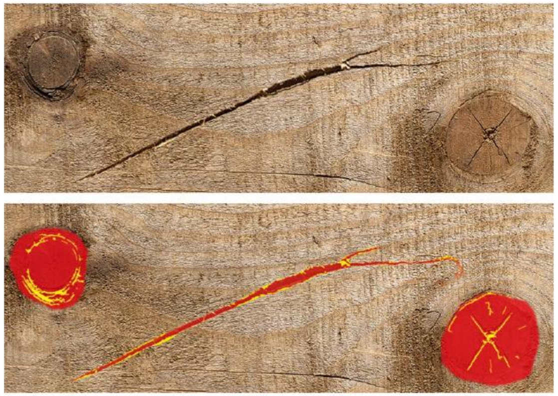
- Classical image processing

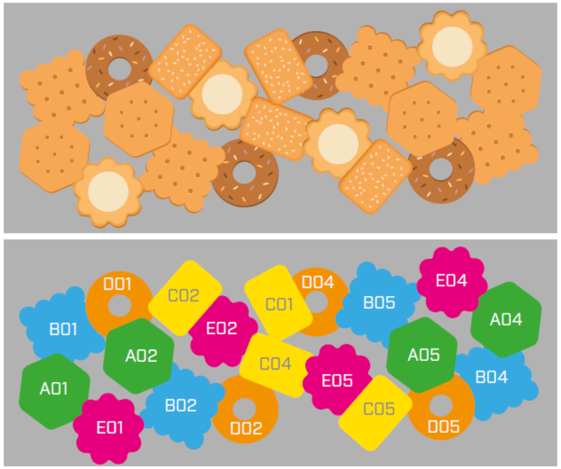


APPLICATION AREAS OF DEEP LEARNING

- Anomaly detection, image classification, image segmentation and object recognition.

- Higher precision and greater flexibility compared to conventional image analysis methods.





Source: Tilmann Zuper, Artificial Intelligence in Image Processing: Deep Learning Compared with Conventional Methods, Basler AG, Ahrensburg, Germany.

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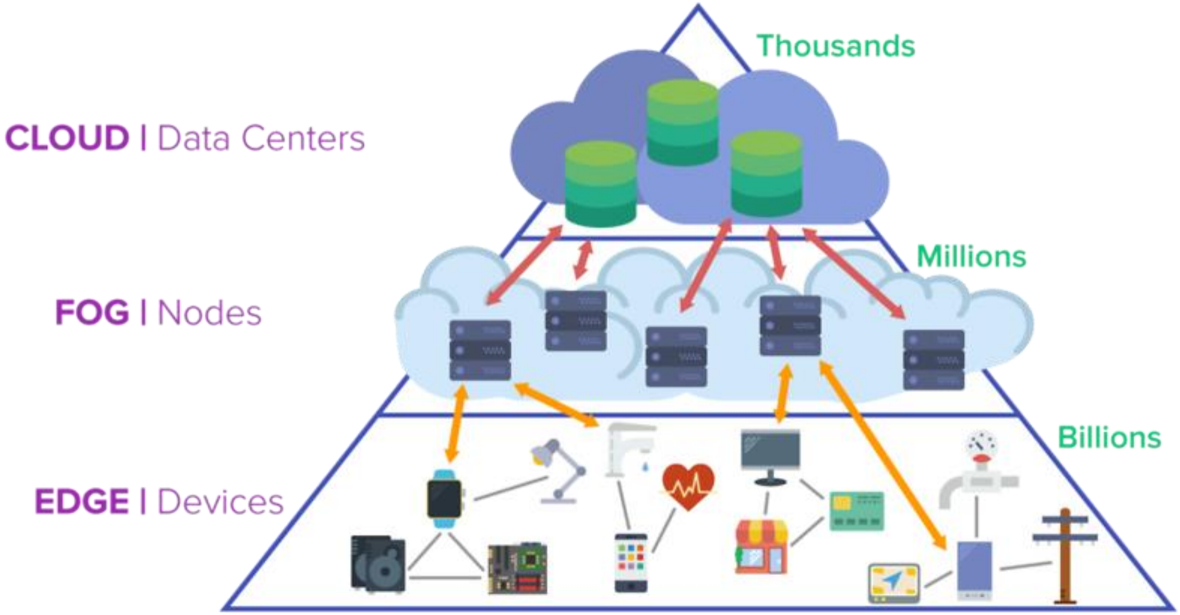
COSTS OF DEEP LEARNING

- Additional hardware
  Large memory and computing capacity is required, typically outsourced to e.g. GPUs (graphic cards).

- Power consumption:
  Large memory and computing capacity increase power consumption and thus the heat generation. This can be problematic for embedded systems.

- High amount of training data:
  Large number of training images required, which is sometimes difficult in the development of a Machine Vision application.

ON THE EDGE



Source: https://medium.com/da-labs/edge-ai-the-future-of-ai-d954ebc40a46

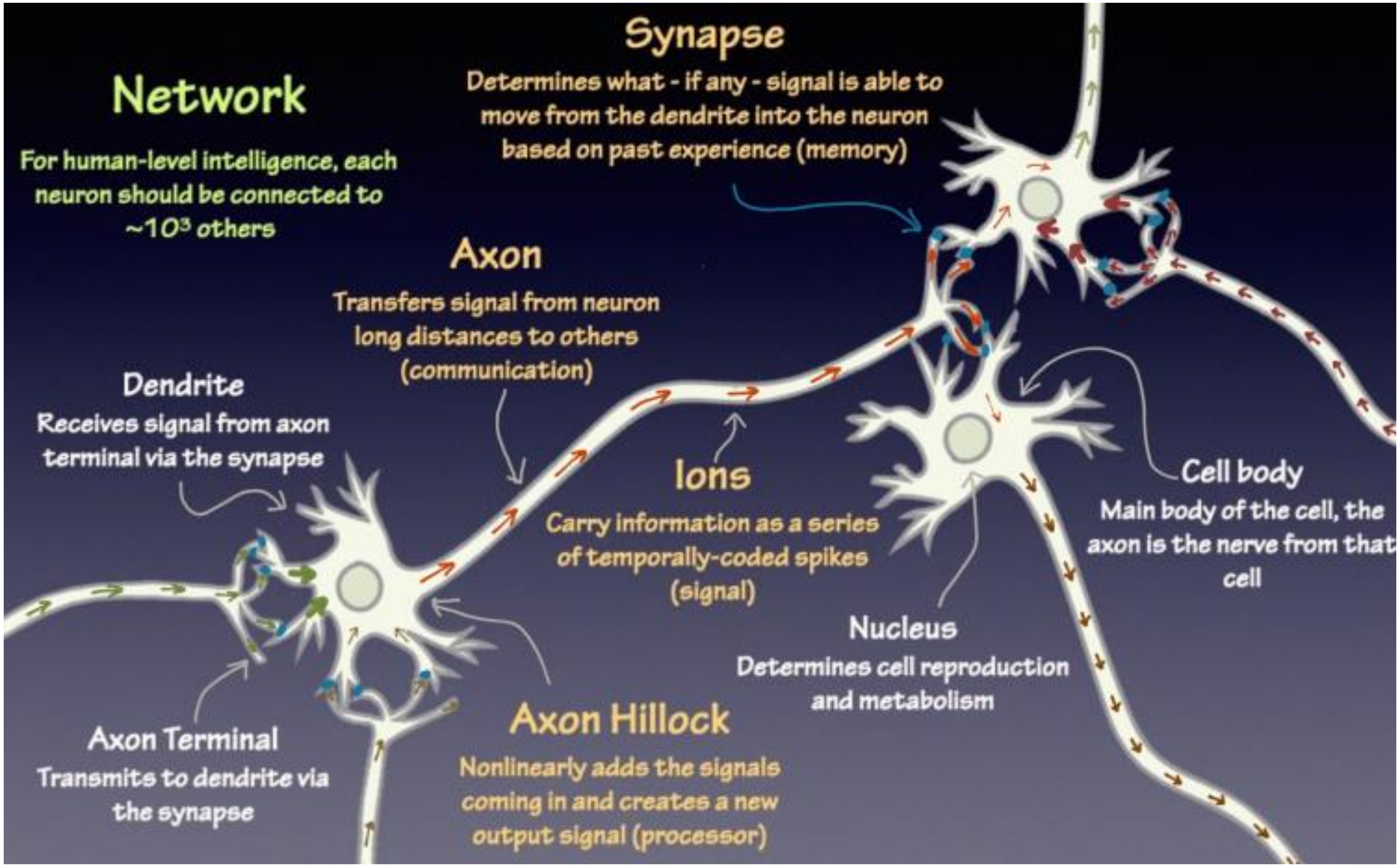
HYBRID APPROACH

- High performance with low memory and power requirement
- Image preprocessing with conventional methods.

- An artificial neural network then delivers the desired results with the preprocessed data.

- DL mingled with expert systems

BIOLOGICAL NEURONS

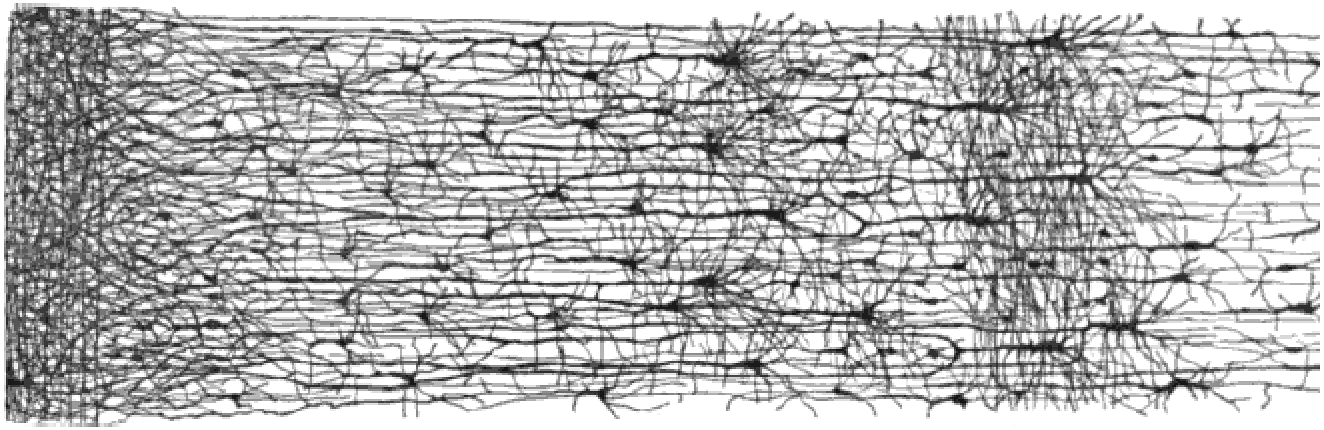


Source: S. Bains, The Promise and Pitfalls of Neuromorphic Computers, EETimes, 2020

NEURAL CIRCUITS

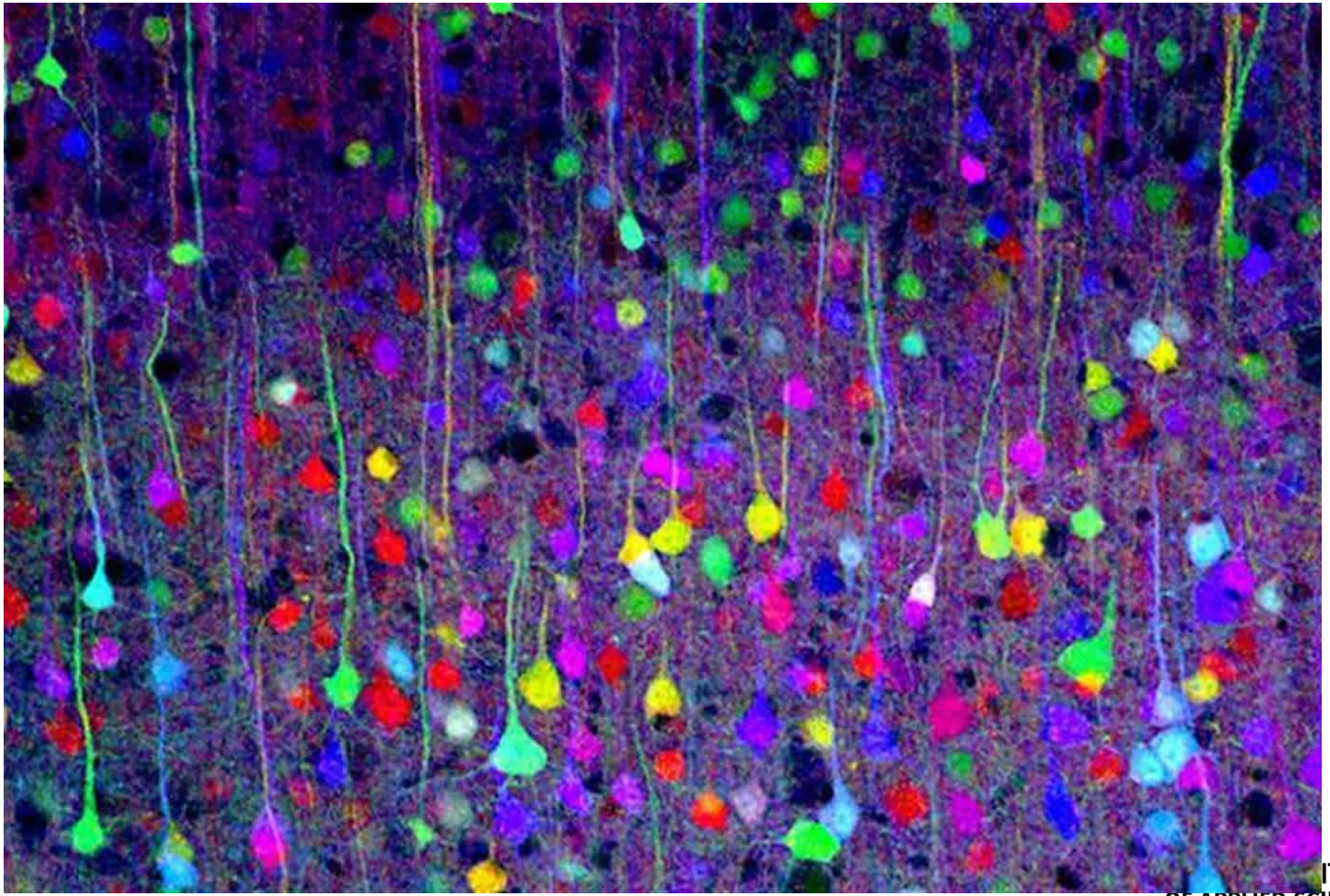
- Population of neurons interconnected by synapses to carry out a specific function when activated

- Highly complex computations can be performed by a network of fairly simple neurons



Source: Géron, ISBN: 9781492032632

BRAINBOW OF CEREBRAL CORTEX NEURONS LABELED WITH DIFFERENT COLORS



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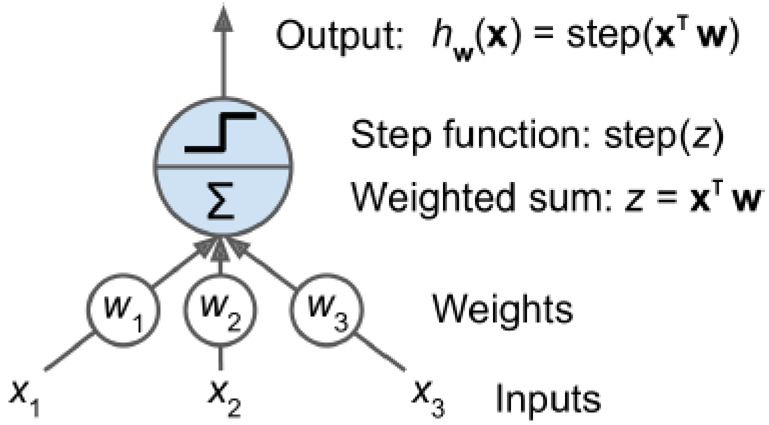
Source: Nature, Meet Nurture - Neuroscience News *credited to Lichtman Lab, Harvard University.*

THRESHOLD LOGIC UNIT (TLU)

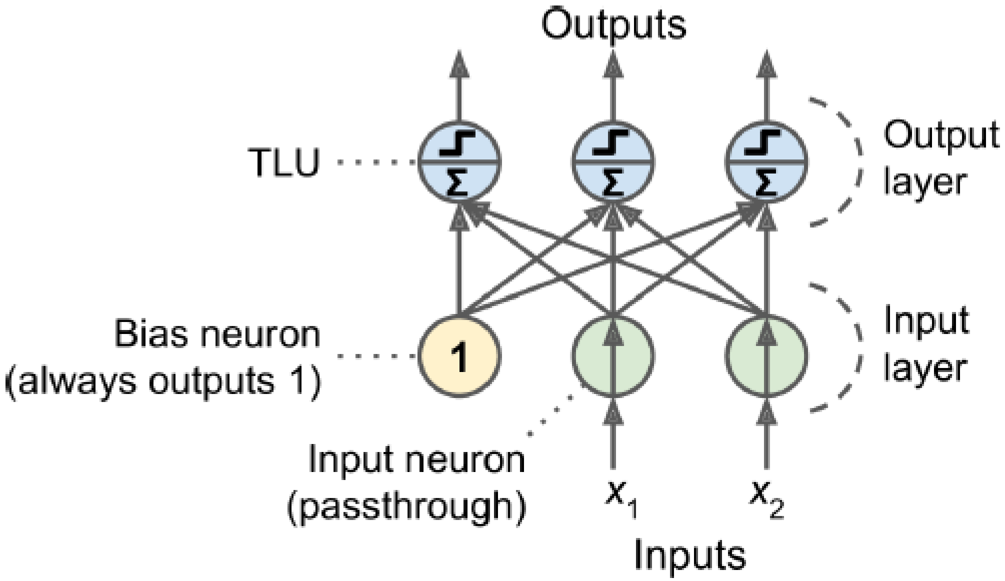
- Elementary unit of an ANN
- Simplified model of a biological neuron
- Dot product followed by a non-linear function
- Performs linear binary classification



Source: Géron, ISBN: 9781492032632

PERCEPTRON

- Single layer of TLUs
- Multioutput classifier
- Connection weights

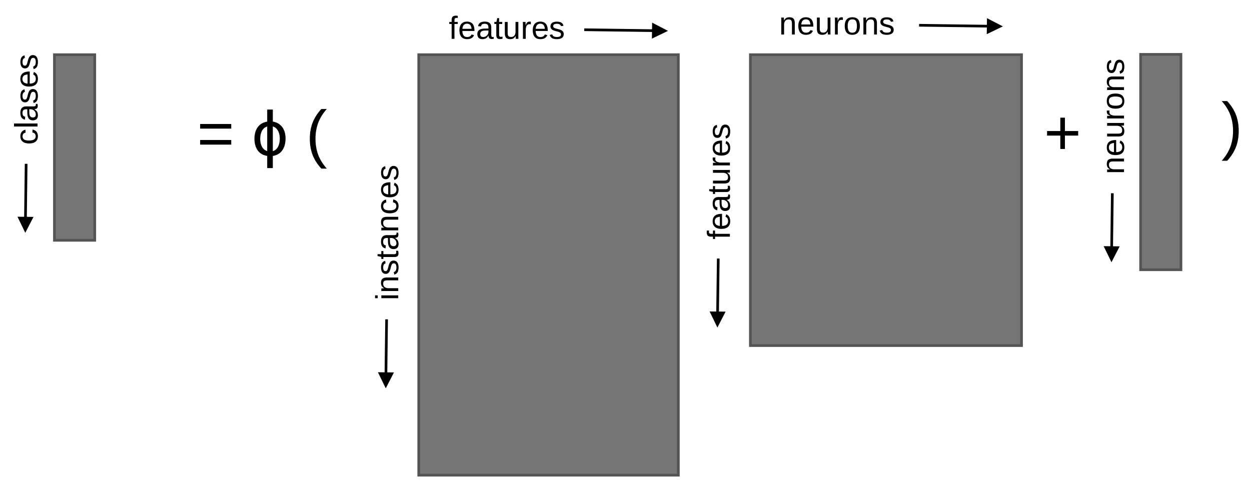


Source: Géron, ISBN: 9781492032632

OUTPUT COMPUTATION

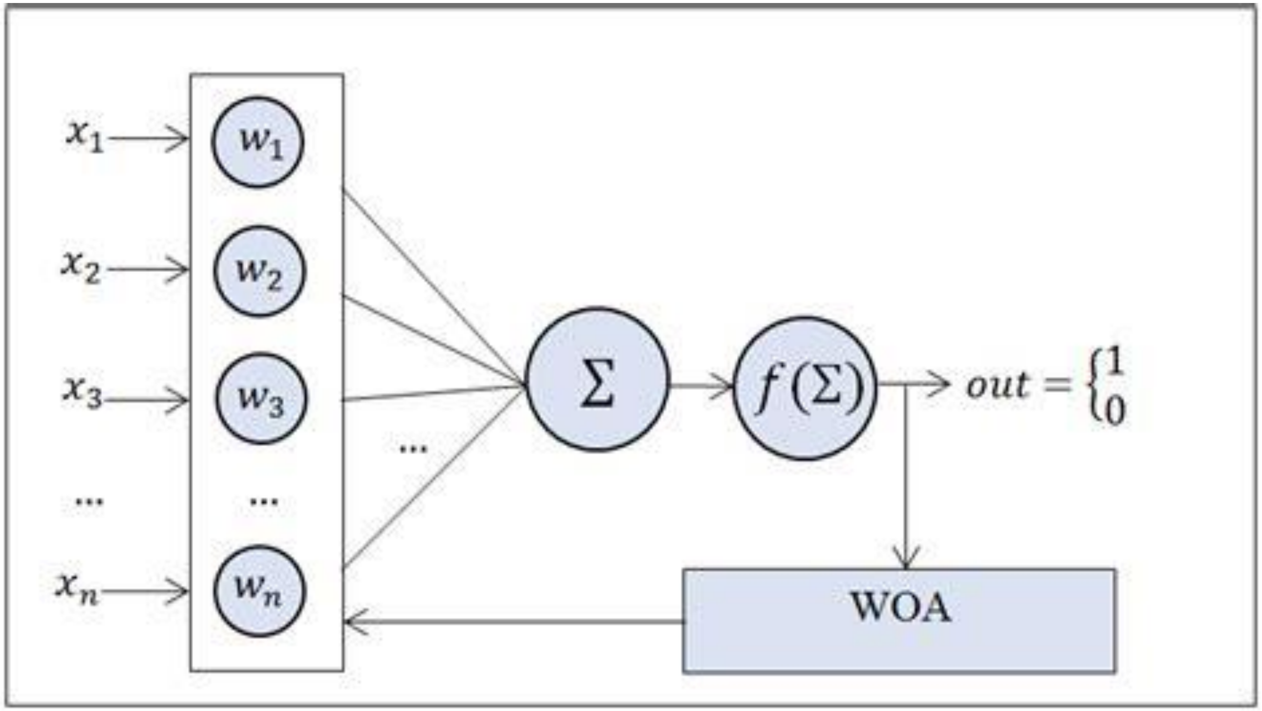
$$h_{\mathbf{W},\,\mathbf{b}}(\mathbf{X}) = \phi(\mathbf{X}\mathbf{W} + \mathbf{b})$$

Output vector | Matrix of input features | Activation function | Weight matrix | Bias vector



HOW TO FIND THE OPTIMAL WEIGHTS?

- Optimization
- Cost function



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PERCEPTRON TRAINING ALGORITHM

- Multi-dimensional optimization problem
- Gradient descent

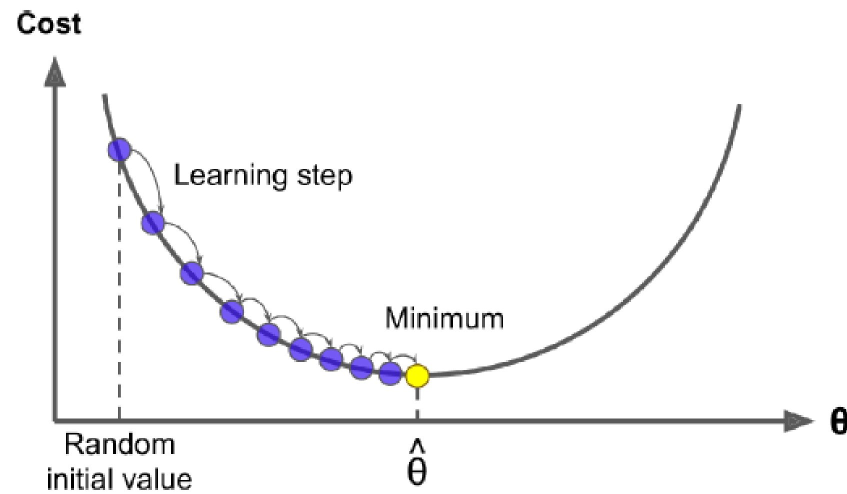
Learning rate

Input value

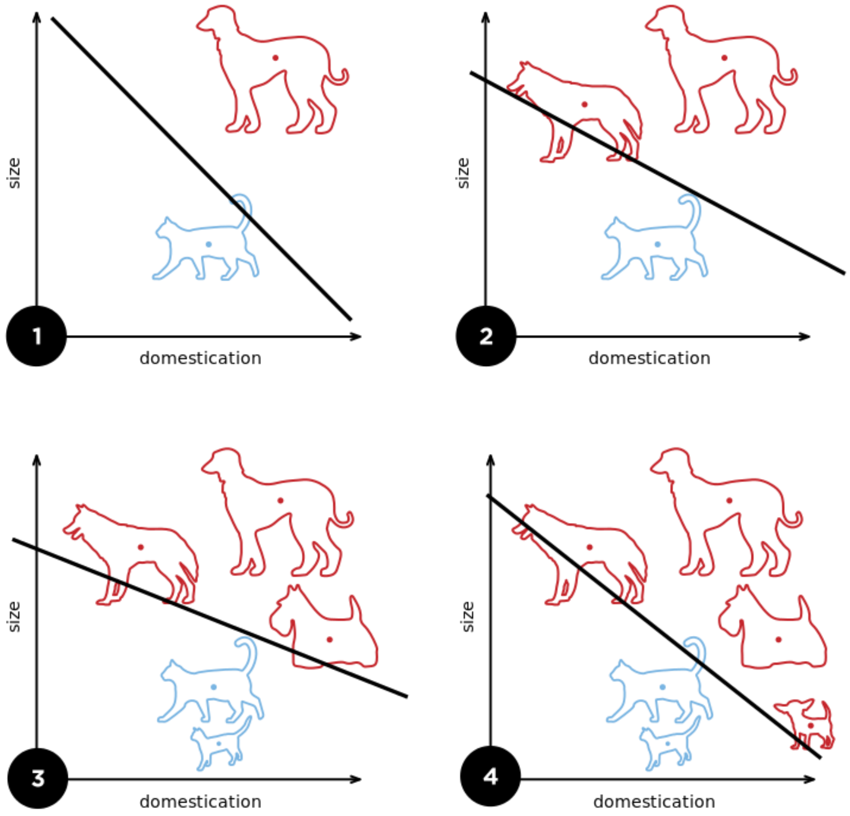
$$w_{i,j}^{(\text{next step})} = w_{i,j} + \eta \boxed{\left(y_j - \hat{y}_j\right)} x_i$$

Connection weights

error



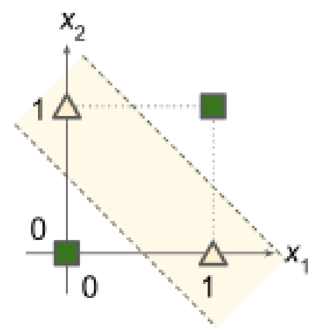
EXAMPLE OF ITERATIVE UPDATING

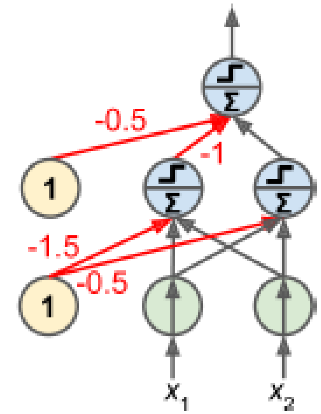


Source: https://en.wikipedia.org/wiki/Perceptron

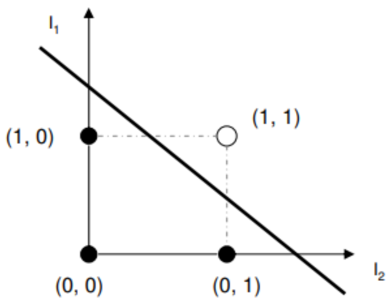
PERCEPTRON LIMITATIONS

- Linear decision boundary
- Incapable of learning complex patterns

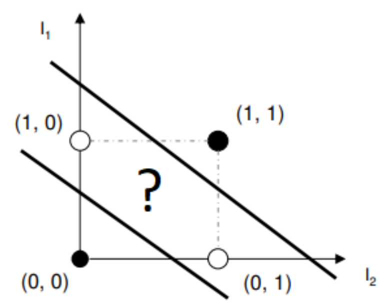




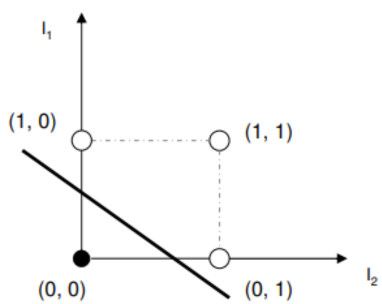
AND		
I_1	I_2	out
0	0	0
0	1	0
1	0	0
1	1	1



XOR		
I_1	I_2	out
0	0	0
0	1	1
1	0	1
1	1	0



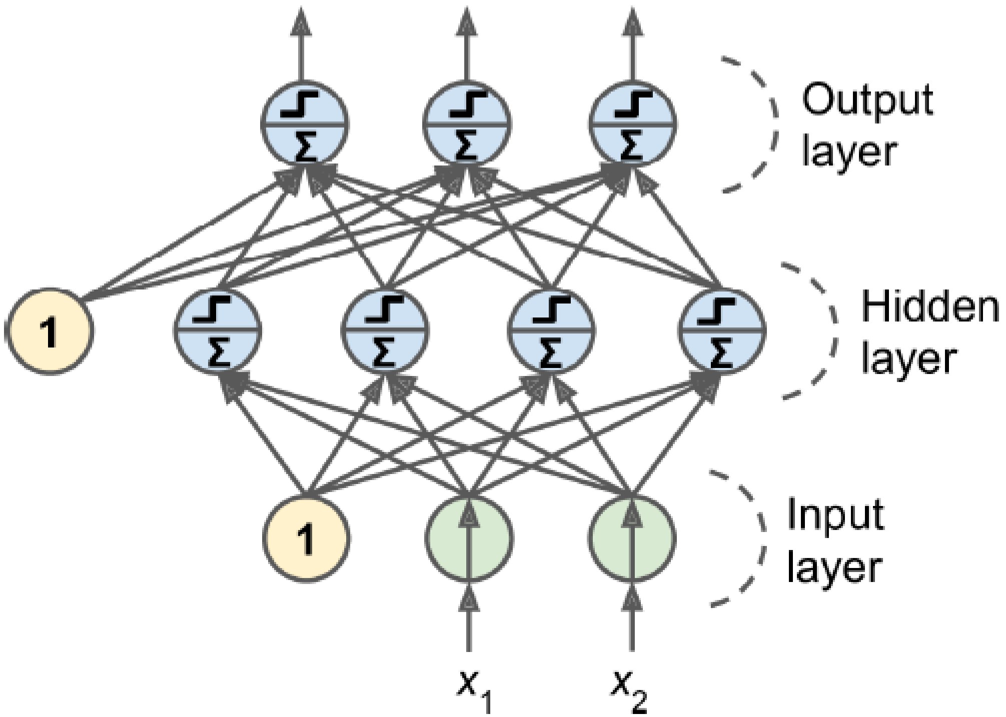
OR		
I_1	I_2	out
0	0	0
0	1	1
1	0	1
1	1	1



Source: https://mc.ai/solving-xor-with-a-single-perceptron/

MULTILAYER PERCEPTRON

- Feedforward neural network



Source: Géron, ISBN: 9781492032632

BACKPROPAGATION

Let's now watch

MIT's intro to deep learning
https://www.youtube.com/watch?v=7sB052Pz0sQ?t=35m38s

3BLUE1BROWN SERIES S3 • A3
What is backpropagation really doing?
https://www.youtube.com/watch?v=Ilg3gGewQ5U

BACKPROPAGATION

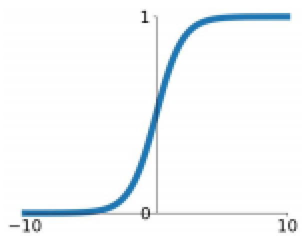
- for each training instance, the backpropagation algorithm first makes a prediction (forward pass) and measures the error,
- then goes through each layer in reverse to measure the error contribution from each connection (reverse pass),
- and finally tweaks the connection weights to reduce the error (Gradient Descent step).

break the symmetry: randomly initialize weights and biases

ACTIVATION FUNCTIONS

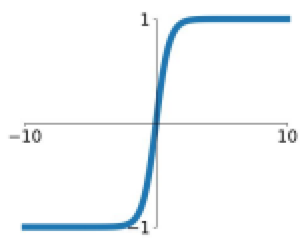
Sigmoid

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



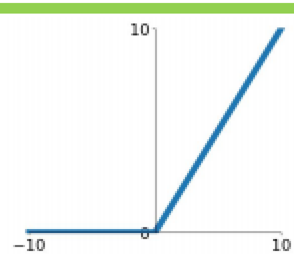
tanh

$\tanh(x)$



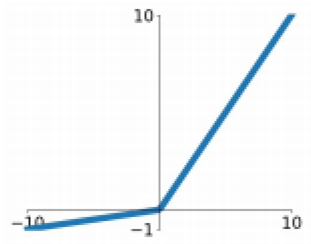
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

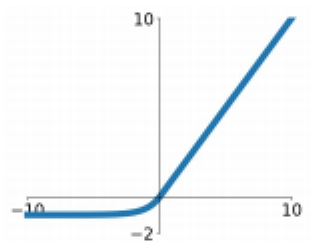


Maxout

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

ELU

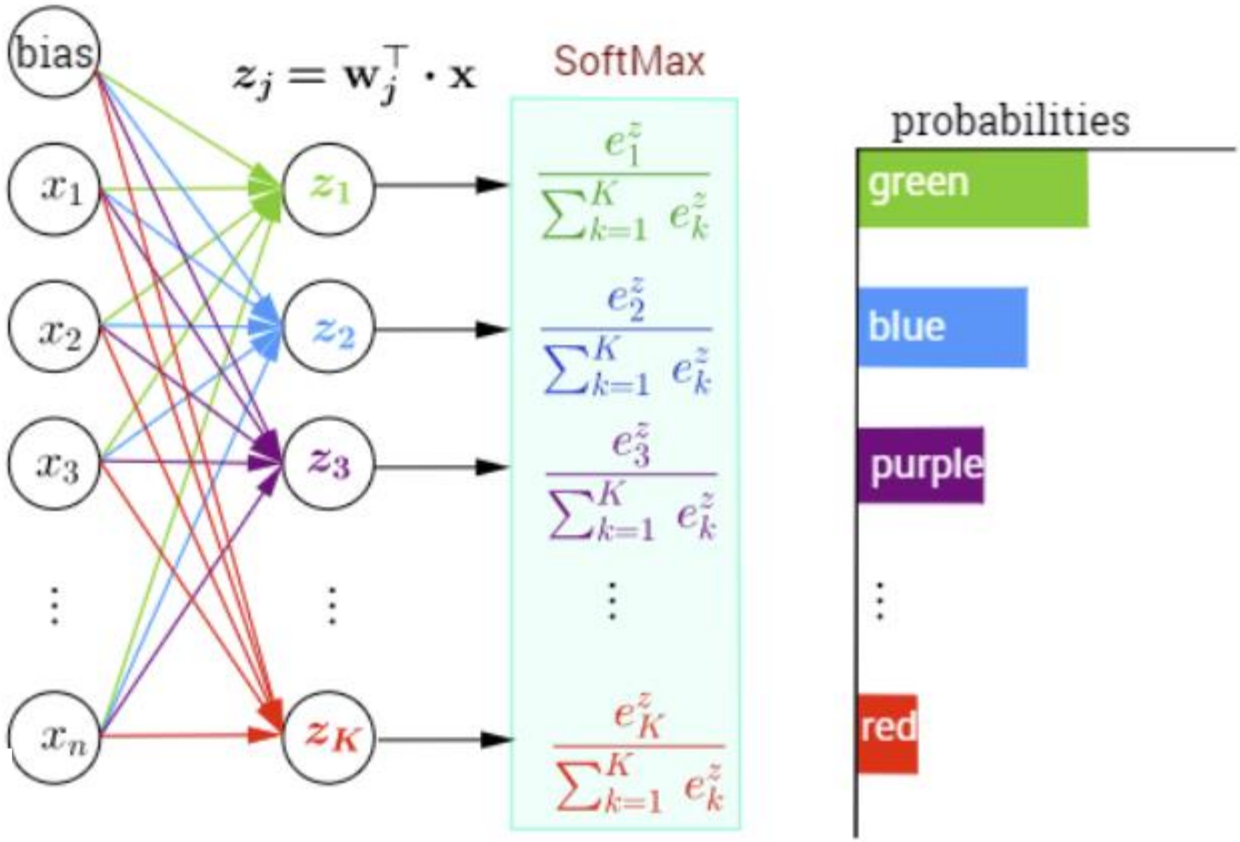
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Source: http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture6.pdf

CLASSIFICATION MLP

$$\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ \vdots \\ z_K \end{bmatrix} = \begin{bmatrix} \mathbf{w}_1^\top \\ \mathbf{w}_2^\top \\ \mathbf{w}_3^\top \\ \vdots \\ \mathbf{w}_K^\top \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$



$$\sigma(j) = \frac{\exp(\mathbf{w}_j^\top \mathbf{x})}{\sum_{k=1}^K \exp(\mathbf{w}_k^\top \mathbf{x})} = \frac{\exp(z_j)}{\sum_{k=1}^K \exp(z_k)}$$

Source: http://rinterested.github.io/statistics/softmax.html

REGRESSION MLP

- No activation function for output neurons required
- Use functions to bound outputs, e.g. relu, softplus, logistic function

Table 10-1 summarizes the typical architecture of a regression MLP.

Table 10-1. Typical regression MLP architecture

Hyperparameter	Typical value
# input neurons	One per input feature (e.g., 28 x 28 = 784 for MNIST)
# hidden layers	Depends on the problem, but typically 1 to 5
# neurons per hidden layer	Depends on the problem, but typically 10 to 100
# output neurons	1 per prediction dimension
Hidden activation	ReLU (or SELU, see Chapter 11)
Output activation	None, or ReLU/softplus (if positive outputs) or logistic/tanh (if bounded outputs)
Loss function	MSE or MAE/Huber (if outliers)

Source: Géron, ISBN: 9781492032632

EXERCISE

- https://developers.google.com/machine-learning/crash-course/reducing-loss/playground-exercise

- How did the lower learning rate impact convergence?

- Can you find a learning rate too slow to be useful?

- Better website:
  https://playground.tensorflow.org