SuperDataScience

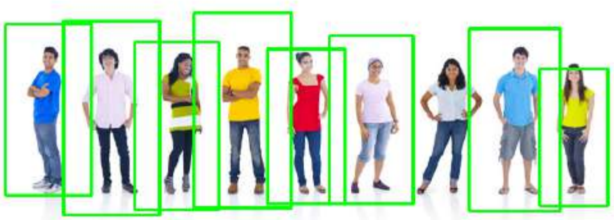
COMPUTER VISION

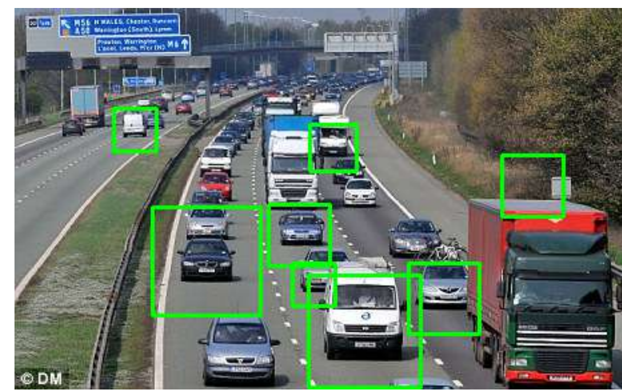
Part 1 Face detection	**Part 2** Face recognition	**Part 3** Object tracking	**Part 4** Neural networks for image classification	**Part 5** Convolutional neural networks for image classification
Part 6 Transfer learning and fine tuning	**Part 7** Neural networks for classification of emotions	**Part 8** Autoencoders	**Part 9** Object detection with YOLO	**Part 10** Recognition of gestures and actions
Part 11 Deep dream	**Part 12** Style transfer	**Part 13** GANs (Generative Adversarial Networks)	**Part 14** Image segmentation	

- Basic python programming
- Only the basic intuition (except for neural networks)
- Libraries
  - OpenCV
  - Dlib
  - TensorFlow
  - Darknet
  - Caffe framework
- Homeworks

PLAN OF ATTACK – FACE DETECTION

1. Face detection with Haarcascade and OpenCV
2. Face detection with HOG and Dlib
3. Face detection with CNN and Dlib
4. Face detection using webcam

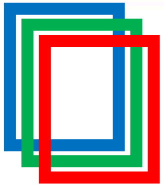


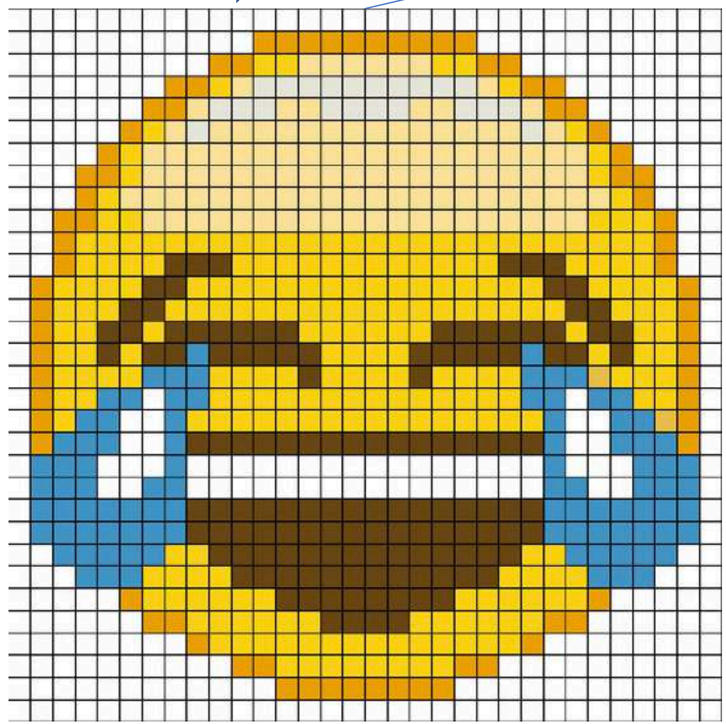


PIXELS

32 pixels

RGB

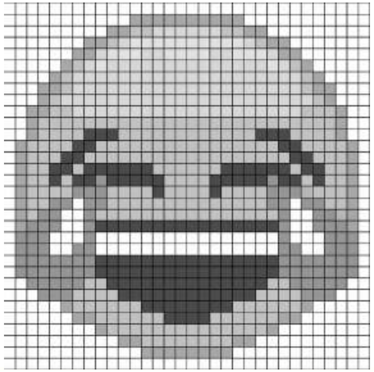




32 pixels

32 x 32 = 1024 pixels

32 x 32 x 3 = 3072



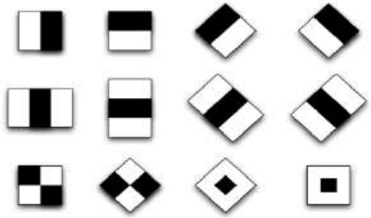
CASCADE CLASSIFIER

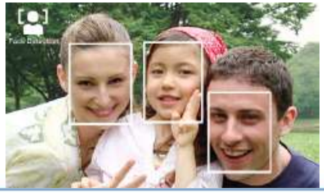
Faces

Not faces

AdaBoost Training

Feature selection



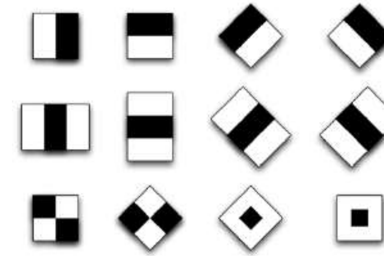


Apply to each “sub-window”

CASCADE CLASSIFIER

Sum of white pixels – sum of black pixels

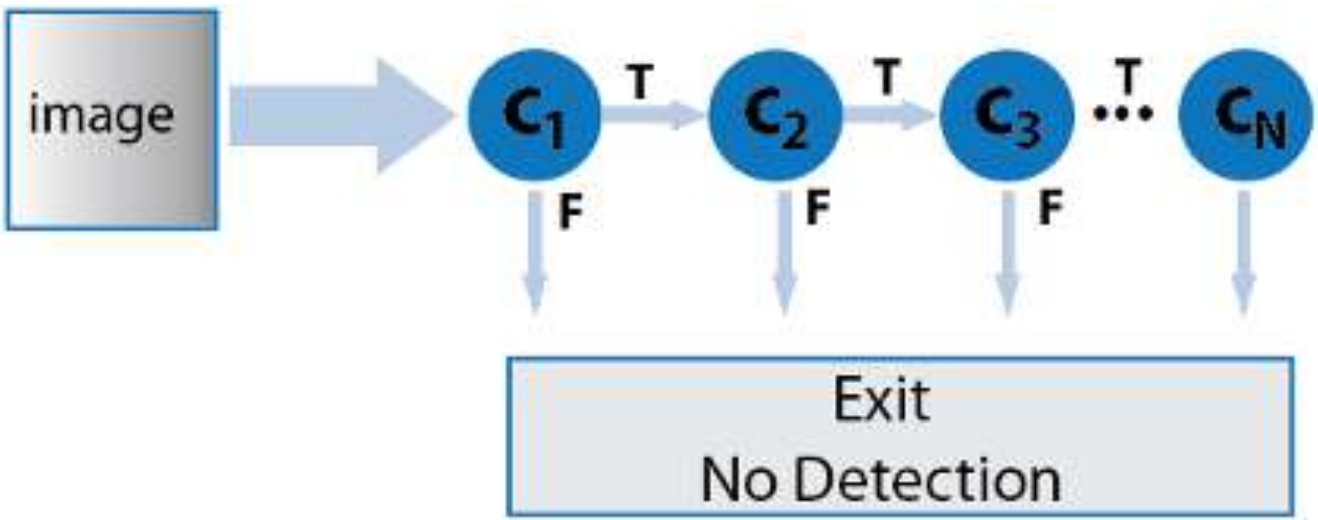
More than 160.000 combinations in a 24x24 image!



2 3 5 6
8 9 2 1

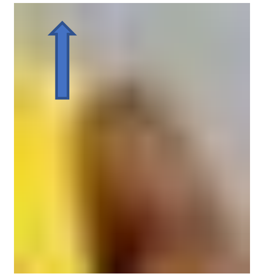
CASCADE CLASSIFIER

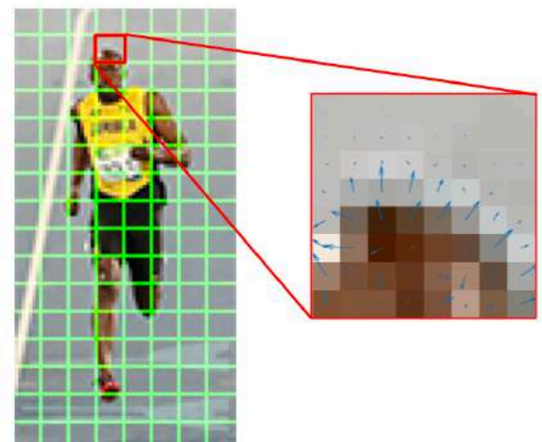
CASCADE CLASSIFIER



HOG – HISTOGRAMS OF ORIENTED GRADIENTS

Original Image : 720 x 475





2	3	4	4	3	4	2	2
5	11	17	13	7	9	3	4
11	21	23	27	22	17	4	6
23	99	165	135	85	32	26	2
91	155	133	136	144	152	57	28
98	196	76	38	26	60	170	51
165	60	60	27	77	85	43	136
71	13	34	23	108	27	48	110

Gradient Magnitude

80	36	5	10	0	64	90	73
37	9	9	179	78	27	169	166
87	136	173	39	102	163	152	176
76	13	1	168	159	22	125	143
120	70	14	150	145	144	145	143
58	86	119	98	100	101	133	113
30	65	157	75	78	165	145	124
11	170	91	4	110	17	133	110

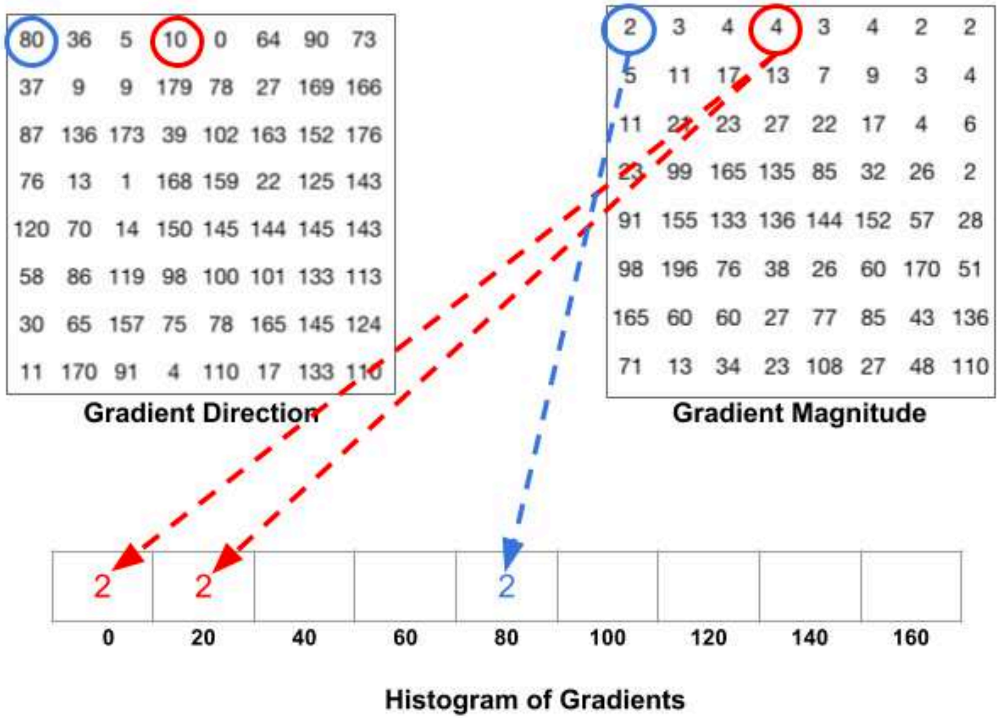
Gradient Direction

Derivative allows to measure the rate of change
(zero derivative, small derivative and high derivative)

Gradient vector (direction that the values increase)

Source of images: https://www.learnopencv.com/histogram-of-oriented-gradients/

HOG – HISTOGRAMS OF ORIENTED GRADIENTS



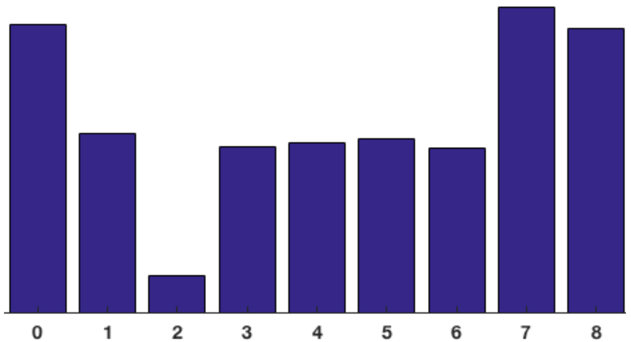
80	36	5	10	0	64	90	73
37	9	9	179	78	27	169	166
87	136	173	39	102	163	152	176
76	13	1	168	159	22	125	143
120	70	14	150	145	144	145	143
58	86	119	98	100	101	133	113
30	65	157	75	78	165	145	124
11	170	91	4	110	17	133	110

Gradient Direction

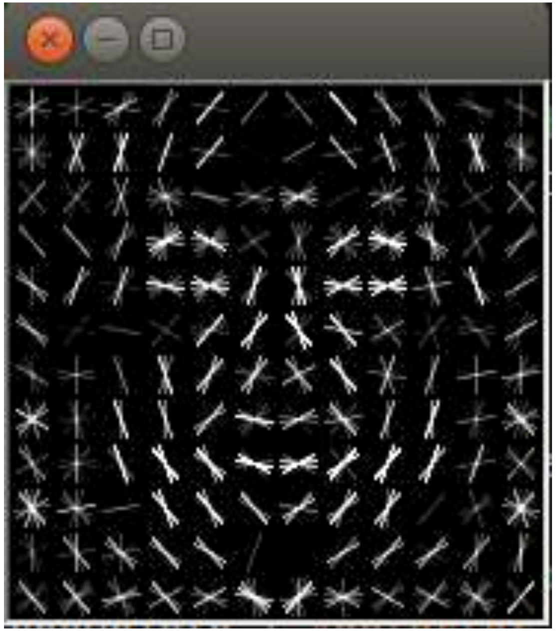
2	3	4	4	3	4	2	2
5	11	17	13	7	9	3	4
11	21	23	27	22	17	4	6
23	99	165	135	85	32	26	2
91	155	133	136	144	152	57	28
98	196	76	38	26	60	170	51
165	60	60	27	77	85	43	136
71	13	34	23	108	27	48	110

Gradient Magnitude

Histogram of Gradients

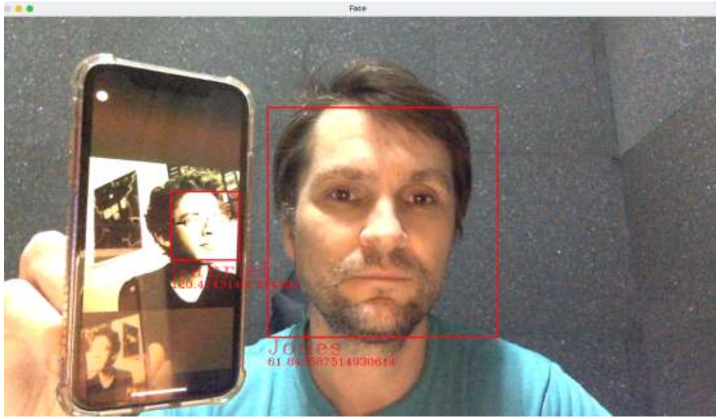


HOG – HISTOGRAMS OF ORIENTED GRADIENTS



PLAN OF ATTACK – FACE RECOGNITION

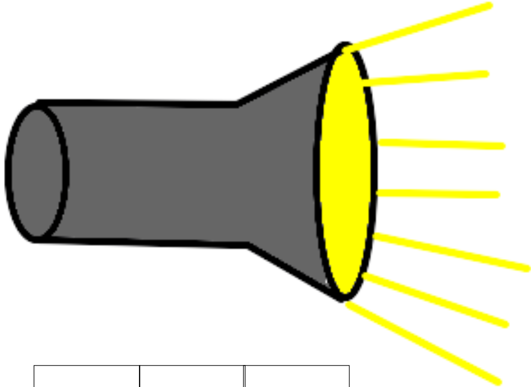
1. Face recognition with LBPH and OpenCV
2. Face recognition with Dlib, CNN and distance calculation
3. Face recognition using the webcam



LBPH (LOCAL BINARY PATTERNS HISTOGRAMS)

12	15	18
5	8	3
8	1	2

If >= 8: 1
If < 8: 0



42	55	48
35	38	33
38	30	32

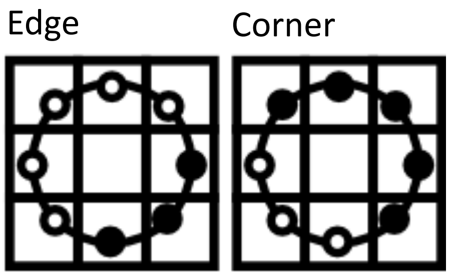
Binary = 11100010

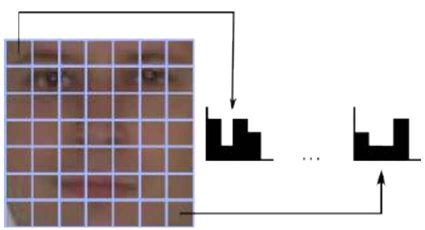
1	1	1
0	8	0
1	0	0

Binary = 11100010

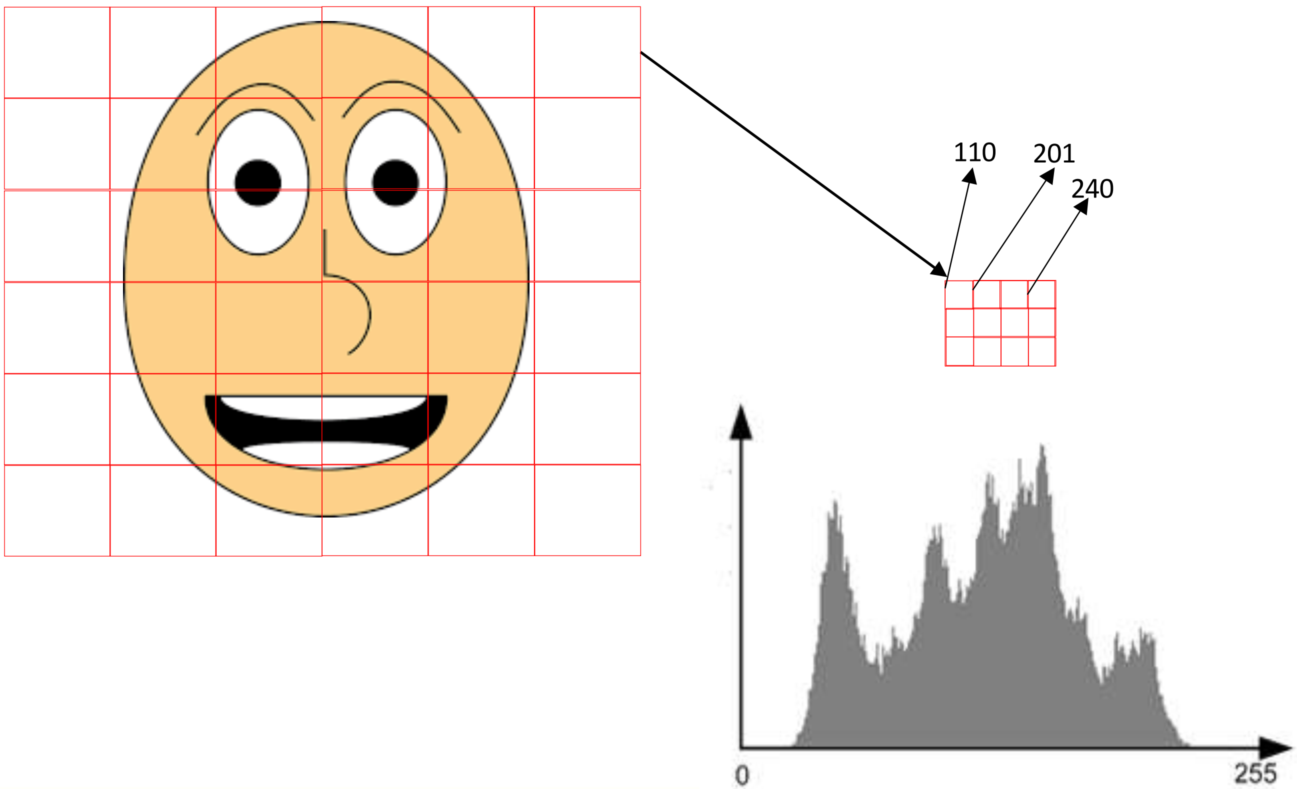
Decimal = 226

LBPH (LOCAL BINARY PATTERNS HISTOGRAMS)





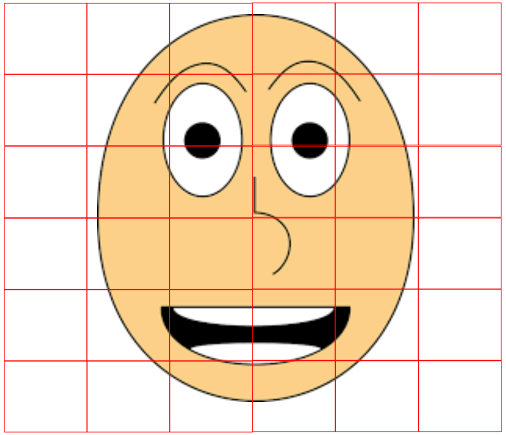
Source: https://bytefish.de/blog/local_binary_patterns/

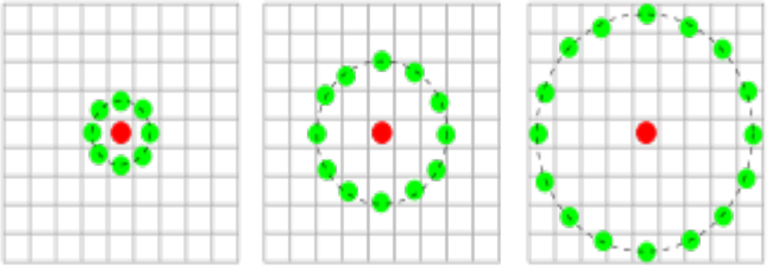


LBPH (LOCAL BINARY PATTERNS HISTOGRAMS)

1. Radius
2. Neighbors
3. grid_x and grid_y
4. Threshold

12	15	18
5	8	3
8	1	2

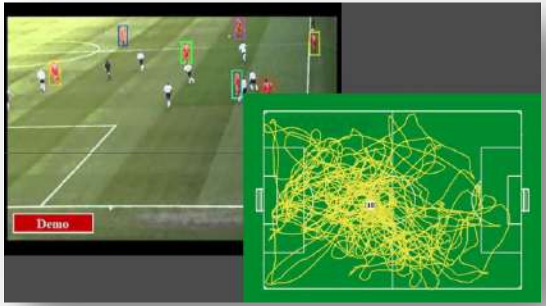




Source: https://en.wikipedia.org/wiki/Local_binary_patterns

PLAN OF ATTACK – OBJECT TRACKING

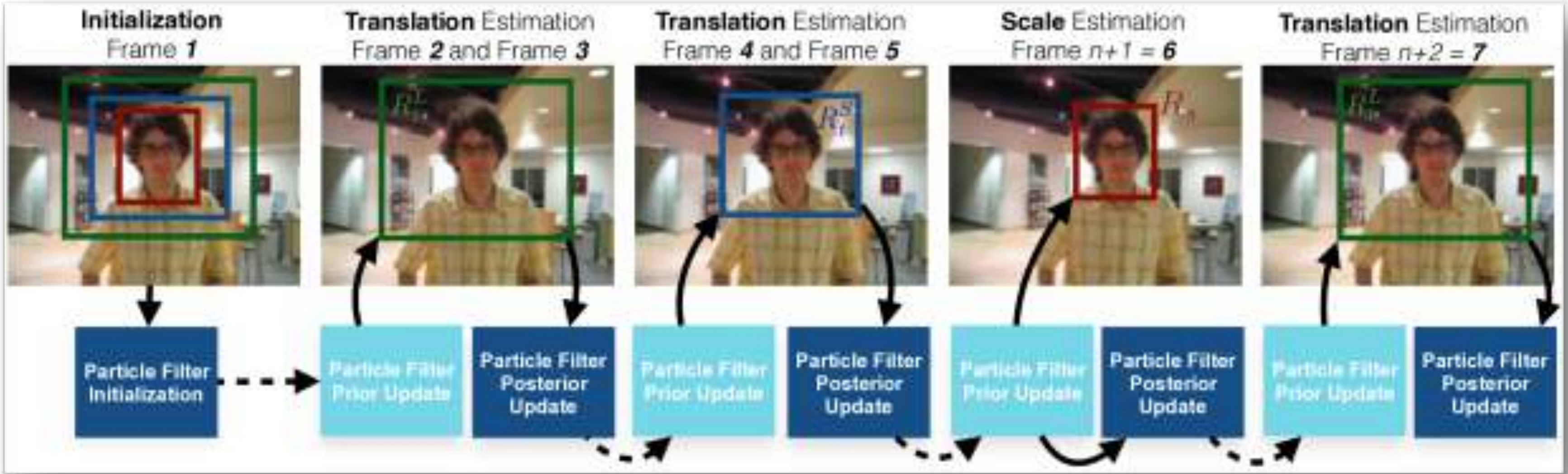
1. Object tracking vs. Object detection
2. KCF (Kernel Correlation Filters) algorithm
3. CSRT (Discriminative Correlation Filter with Channel and Spatial Reliability) algorithm
4. KCF and CSRT implementation



OBJECT TRACKING vs. OBJECT DETECTION

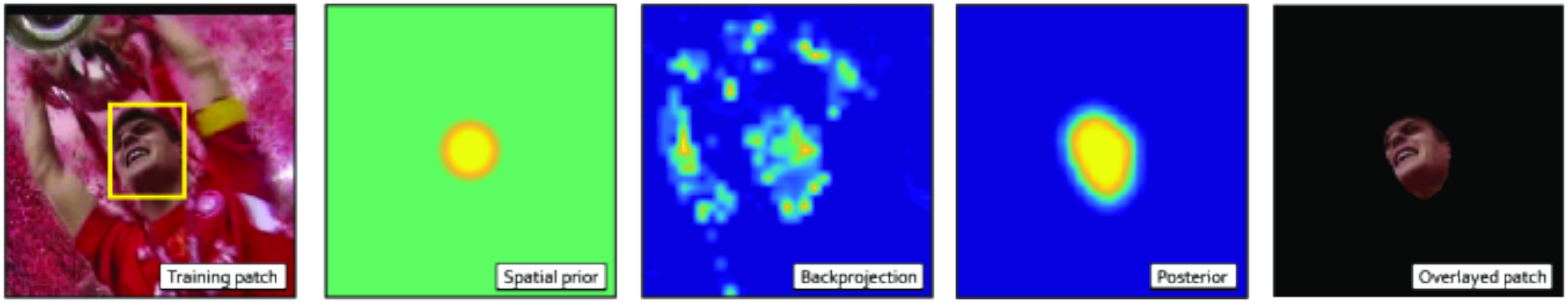
- Object tracking vs. Object detection

KCF (KERNAL CORRELATION FILTERS)



Source: https://www.groundai.com/project/enkcf-ensemble-of-kernelized-correlation-filters-for-high-speed-object-tracking/1

CSRT (DISCRIMINATIVE CORRELATION FILTER WITH CHANNEL AND SPATIAL RELIABILITY)



1. From left to right: training patch with the bounding box of the object
2. HOG to extract useful information of the image
3. Application of Random Markov Test to generate probabilities
4. Training patch masked using the confidence map

Source: https://www.arxiv-vanity.com/papers/1611.08461/

PLAN OF ATTACK

1. Part 1

    Biological fundamentals

    Single layer perceptron

2. Part 2

    Multi-layer perceptron

3. Part 3

    Pybrain

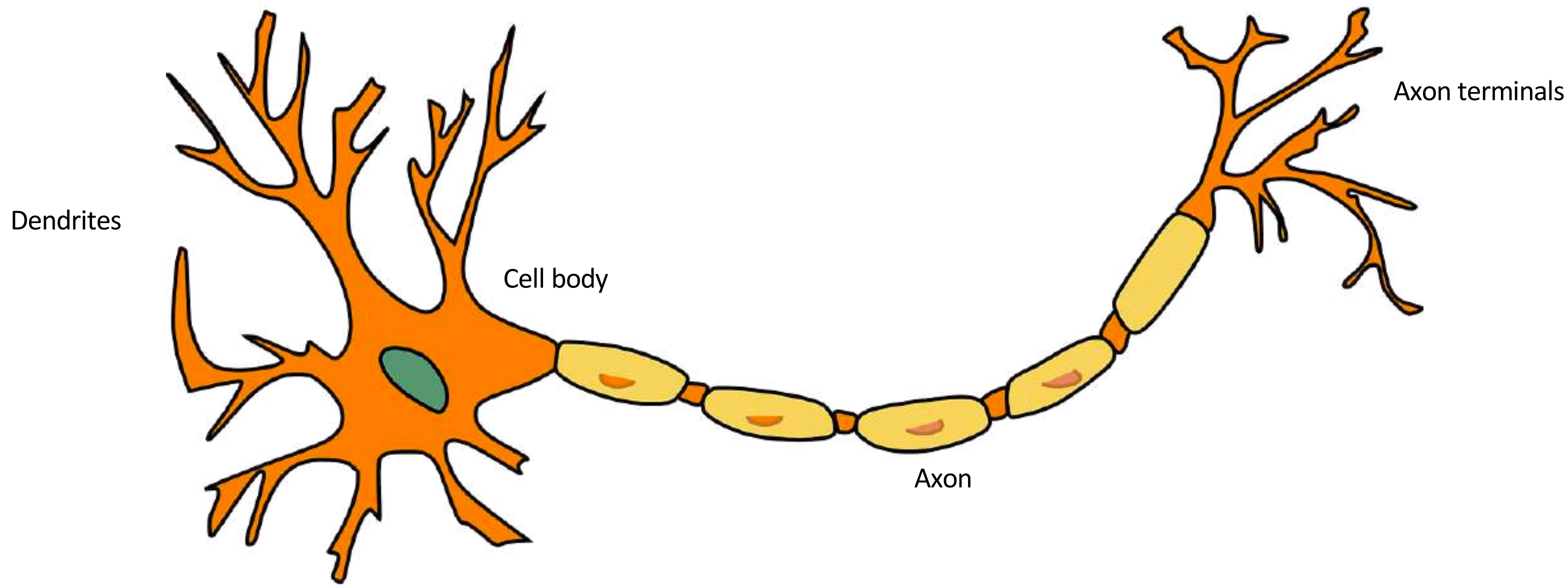
    Sklearn

    TensorFlow

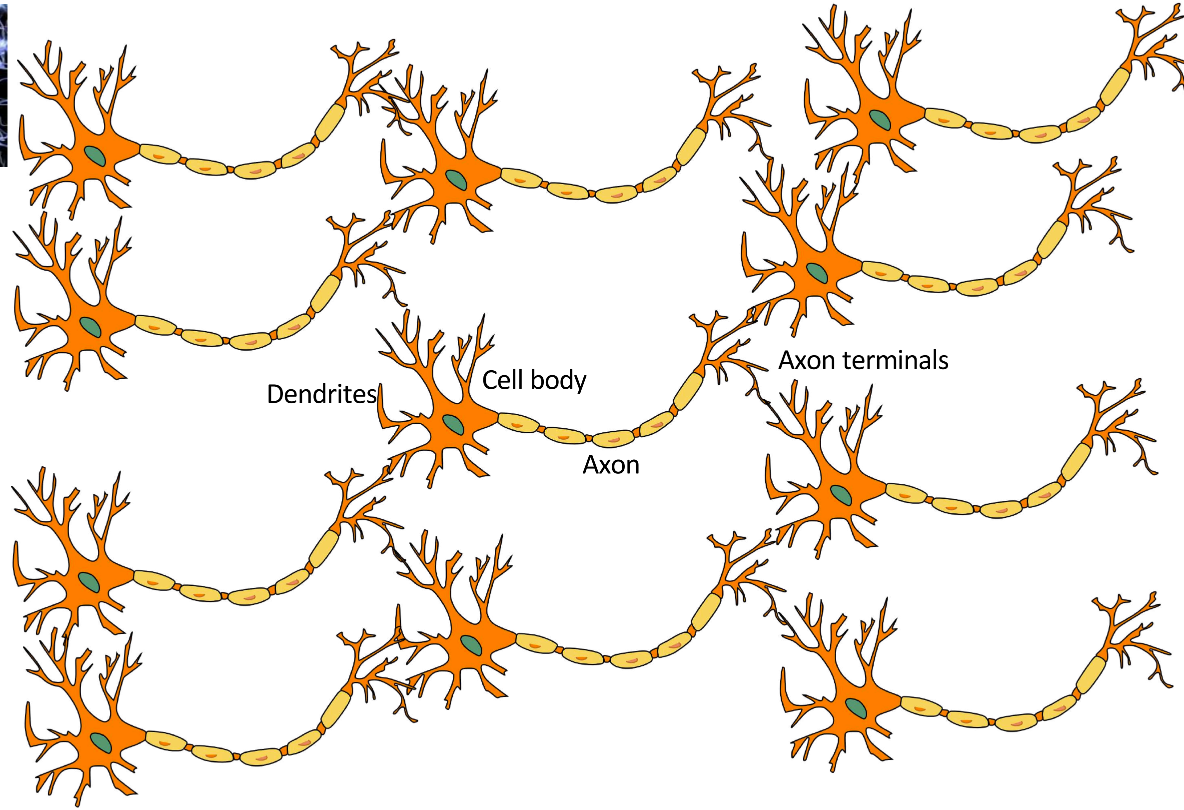
    PyTorch

BIOLOGICAL FUNDAMENTALS

BIOLOGICAL FUNDAMENTALS



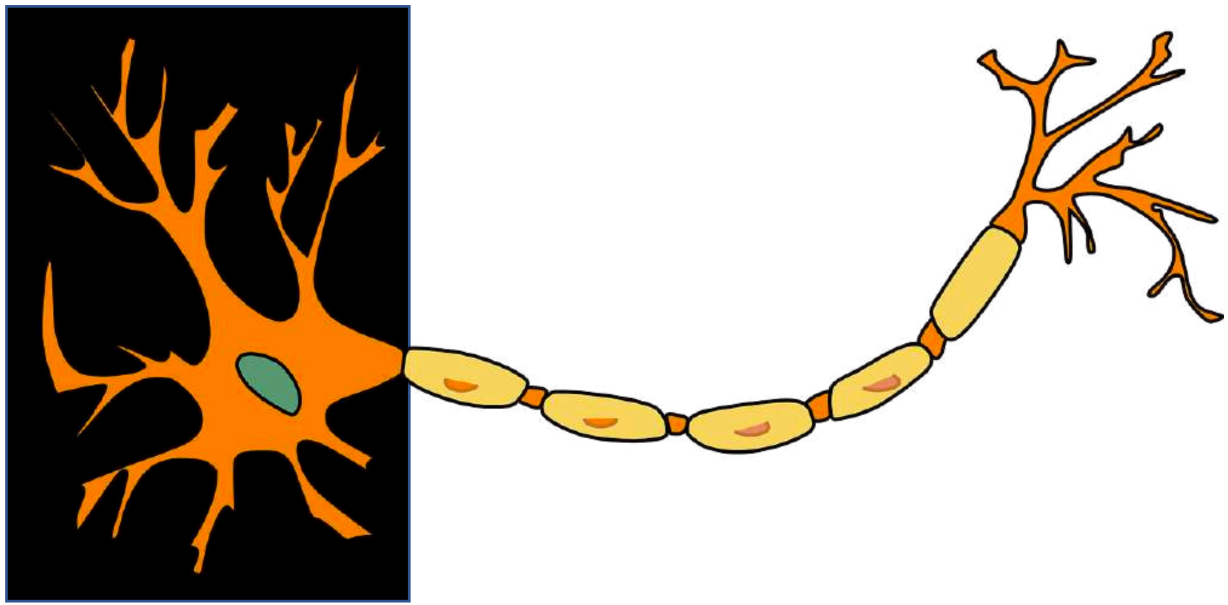
BIOLOGICAL FUNDAMENTALS



Synapse

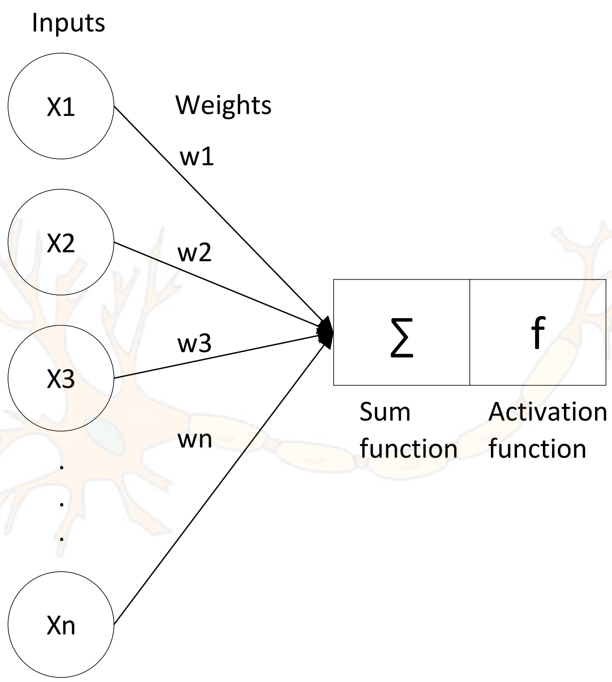
ARTIFICIAL NEURON

Input



Output

ARTIFICIAL NEURON

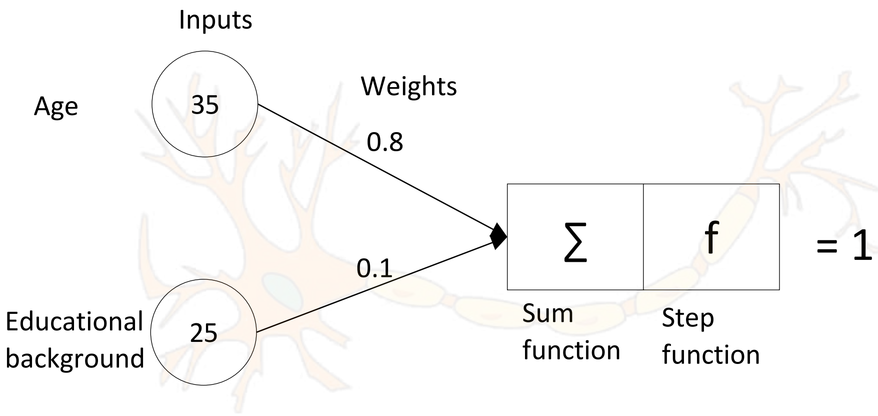


$$sum = \sum_{i=1}^{n} xi \ * wi$$

X1 * w1 + X2 * w2 + X3 * w3

python

PERCEPTRON



$$sum = \sum_{i=1}^{n} xi \ * wi$$

$$sum = (35 * 0.8) + (25 * 0.1)$$

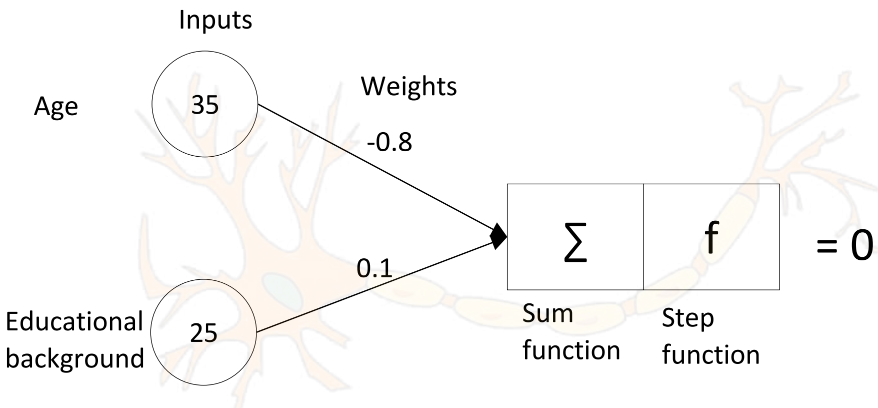
$$sum = 28 + 2.5$$

$$sum = 30.5$$

Greater or equal to 1 = 1
Otherwise = 0

"All or nothing" representation

PERCEPTRON



$$sum = \sum_{i=1}^{n} xi * wi$$

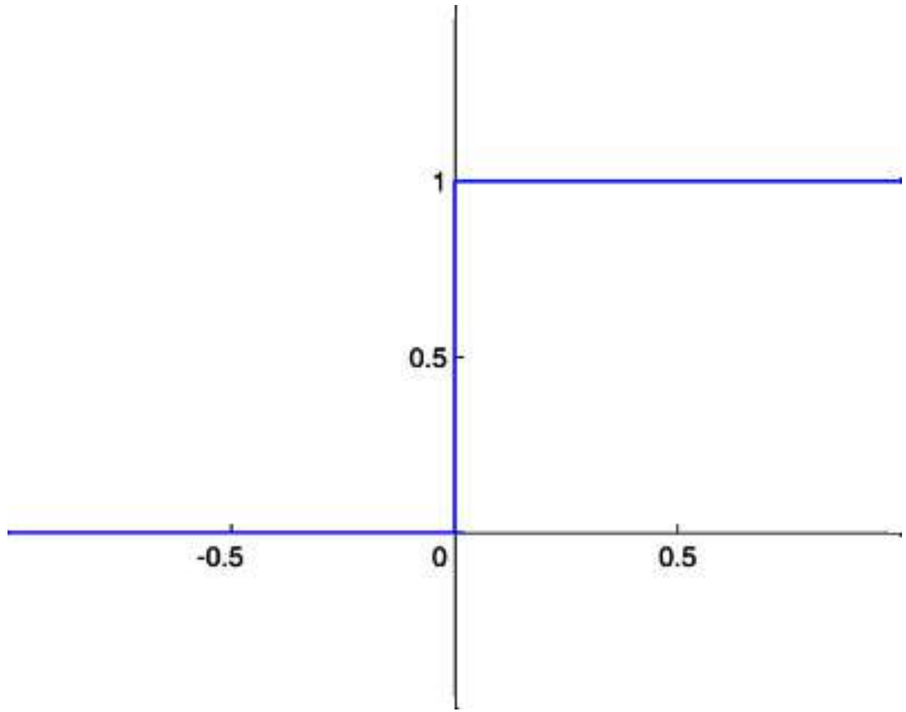
sum = (35 * -0.8) + (25 * 0.1)

sum = -28 + 2.5

sum = -25.5

Greater or equal to 1 = 1
Otherwise = 0

STEP FUNCTION



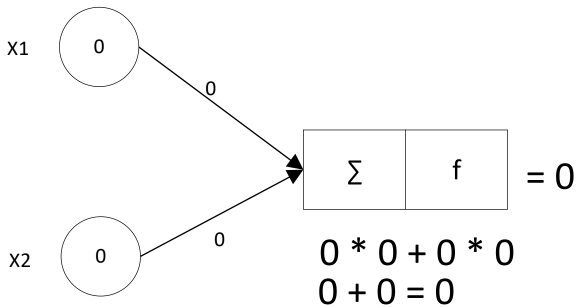
PERCEPTRON

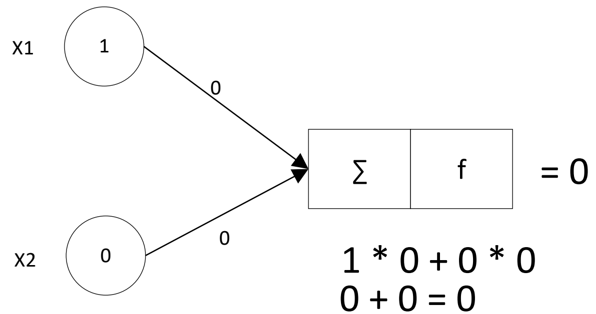
- Positive weight – exciting synapse
- Negative weight – inhibitory synapse
- Weights are the synapses
- Weights amplify or reduce the input signal
- The knowledge of a neural network is the weights

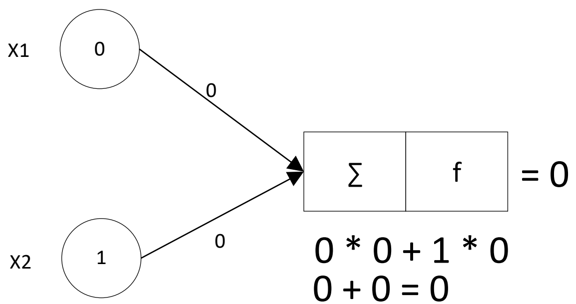
“AND” OPERATOR

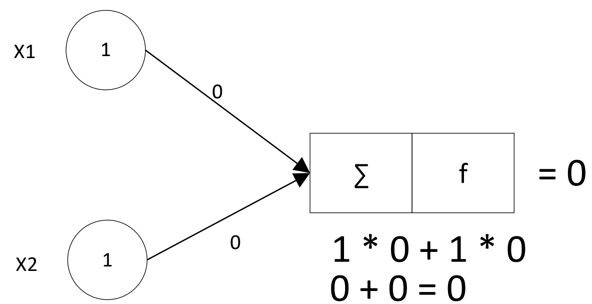
X1	X2	Class
0	0	0
0	1	0
1	0	0
1	1	1

"AND" OPERATOR









X1	X2	Class
0	0	0
0	1	0
1	0	0
1	1	1

error = correct - prediction

Class	Prediction	Error
0	0	0
0	0	0
0	0	0
1	0	1

75%

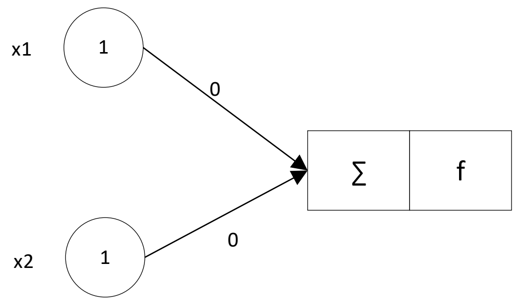
weight (n + 1) = weight(n) + (learning_rate * input * error)

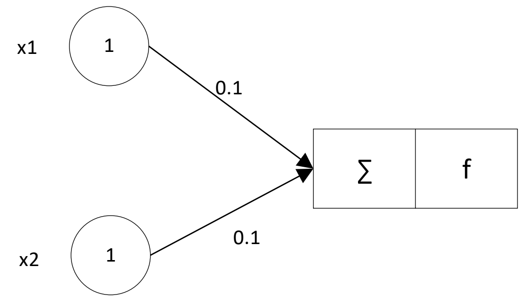
“AND” OPERATOR

weight (n + 1) = weight(n) + (learning_rate * input * error)
weight (n + 1) = 0 + (0.1 * 1 * 1)
weight (n + 1) = 0.1

error = correct - prediction

Class	Prediction	Error
0	0	0
0	0	0
0	0	0
1	0	1

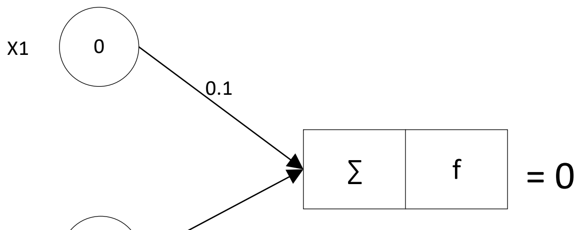




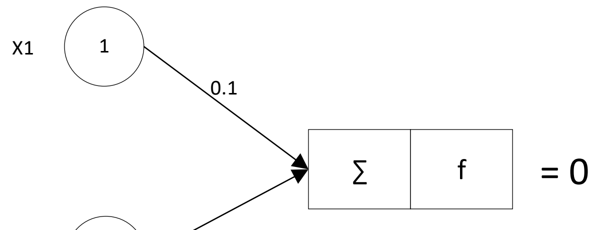
weight (n + 1) = weight(n) + (learning_rate * input * error)
weight (n + 1) = 0 + (0.1 * 1 * 1)
weight (n + 1) = 0.1

python

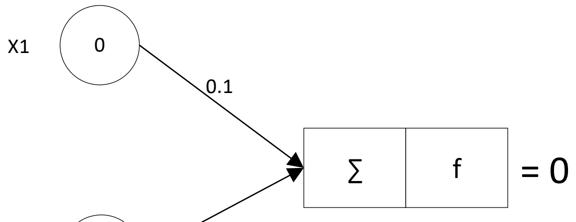
"AND" OPERATOR



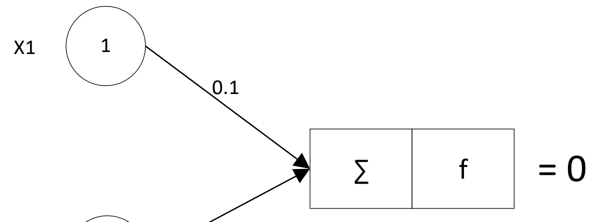
0 * 0.1 + 0 * 0.1
0 + 0 = 0



1 * 0.1 + 0 * 0.1
0.1 + 0 = 0



0 * 0.1 + 1 * 0.1
0 + 0.1 = 0.1



1 * 0.1 + 1 * 0.1
0.1 + 0.1 = 0.2

X1	X2	Class
0	0	0
0	1	0
1	0	0
1	1	1

error = correct - prediction

Class	Prediction	Error
0	0	0
0	0	0
0	0	0
1	0	1

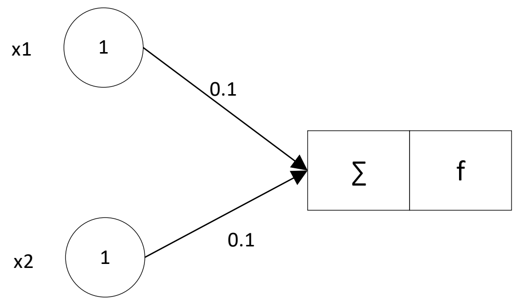
75%

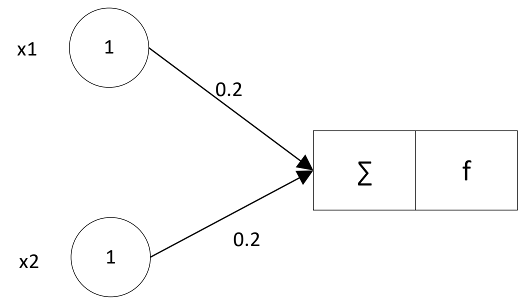
"AND" OPERATOR

weight (n + 1) = weight(n) + (learning_rate * input * error)
weight (n + 1) = 0.1 + (0.1 * 1 * 1)
weight (n + 1) = 0.2

error = correct - prediction

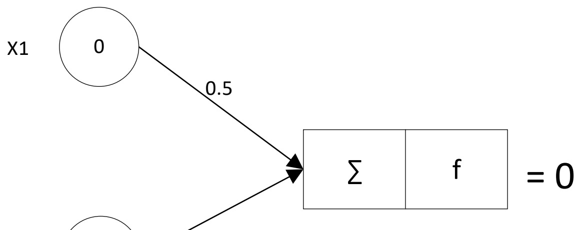
Class	Prediction	Error
0	0	0
0	0	0
0	0	0
1	0	1





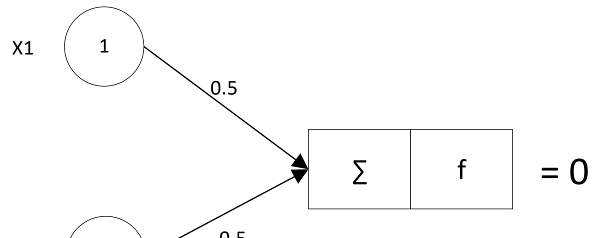
weight (n + 1) = weight(n) + (learning_rate * input * error)
weight (n + 1) = 0.1 + (0.1 * 1 * 1)
weight (n + 1) = 0.2

“AND” OPERATOR



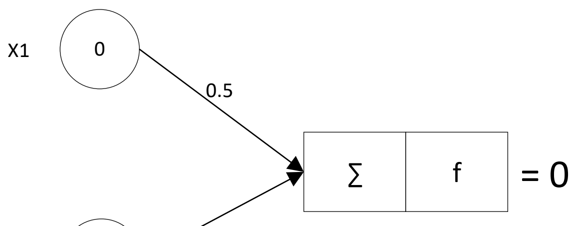
$0 * 0.5 + 0 * 0.5$

$0 + 0 = 0$



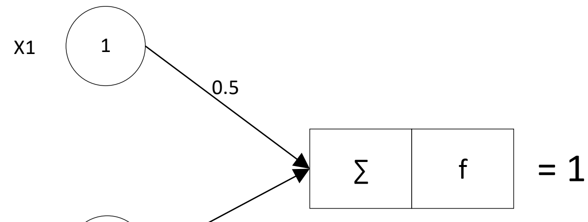
$1 * 0.5 + 0 * 0.5$

$0.5 + 0 = 0.5$



$0 * 0.5 + 1 * 0.5$

$0 + 0.5 = 0.5$



$1 * 0.5 + 1 * 0.5$

$0.5 + 0.5 = 1.0$

X1	X2	Class
0	0	0
0	1	0
1	0	0
1	1	1

error = correct - prediction

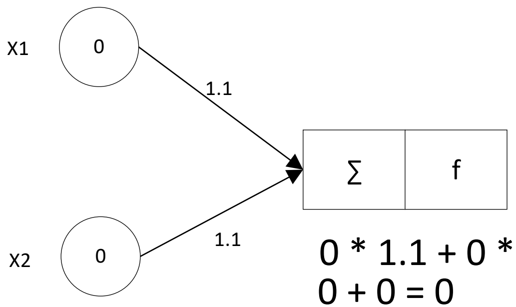
Class	Prediction	Error
0	0	0
0	0	0
0	0	0
1	1	0

100%

BASIC ALGORITHM

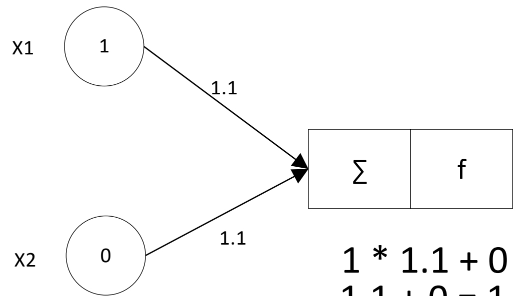
```
While error <> 0
  For each row
    Calculate output
    Calculate error (correct - prediction)
    If error > 0
        For each weight
            Update the weights
```

"OR" OPERATOR



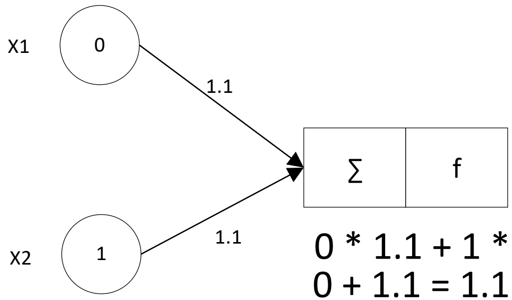
= 0

0 * 1.1 + 0 * 1.1
0 + 0 = 0



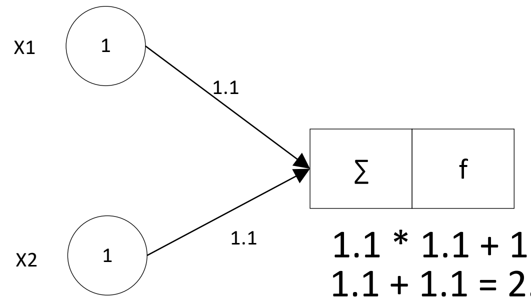
= 1

1 * 1.1 + 0 * 1.1
1.1 + 0 = 1.1



= 1

0 * 1.1 + 1 * 1.1
0 + 1.1 = 1.1



= 1

1.1 * 1.1 + 1 * 1.1
1.1 + 1.1 = 2.2

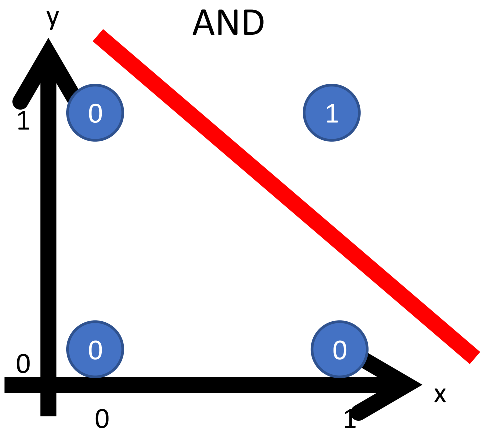
X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	1

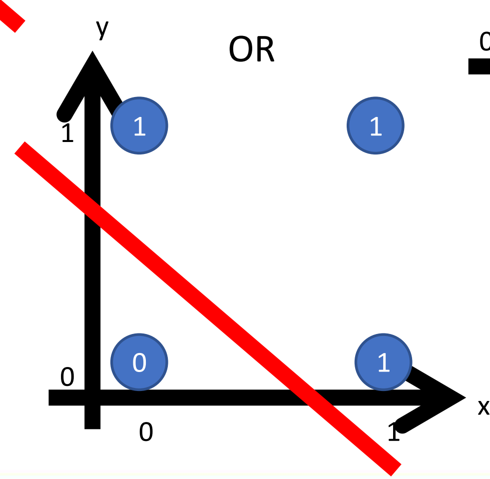
error = correct - prediction

Class	Prediction	Error
0	0	0
1	1	0
1	1	0
1	1	0

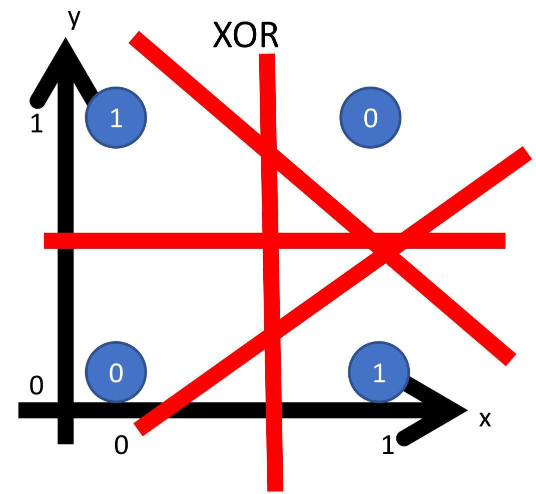
100%

“XOR” OPERATOR



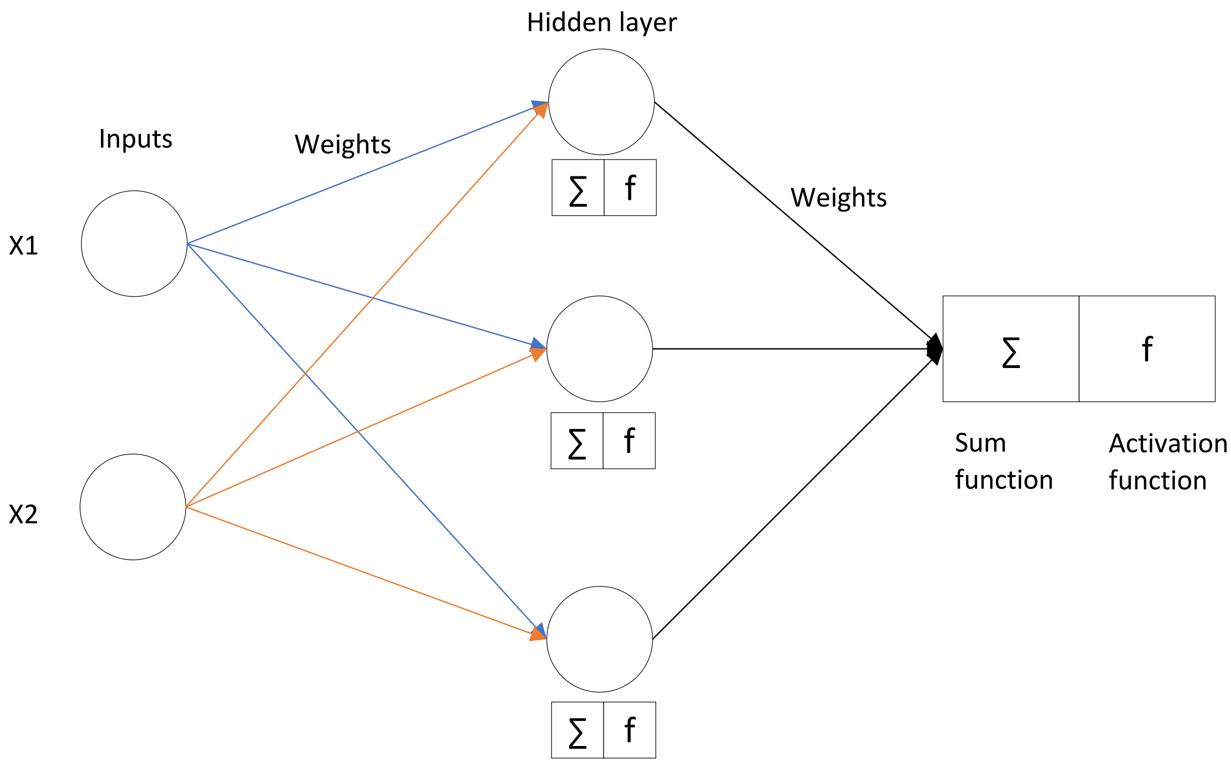


Linearly separable

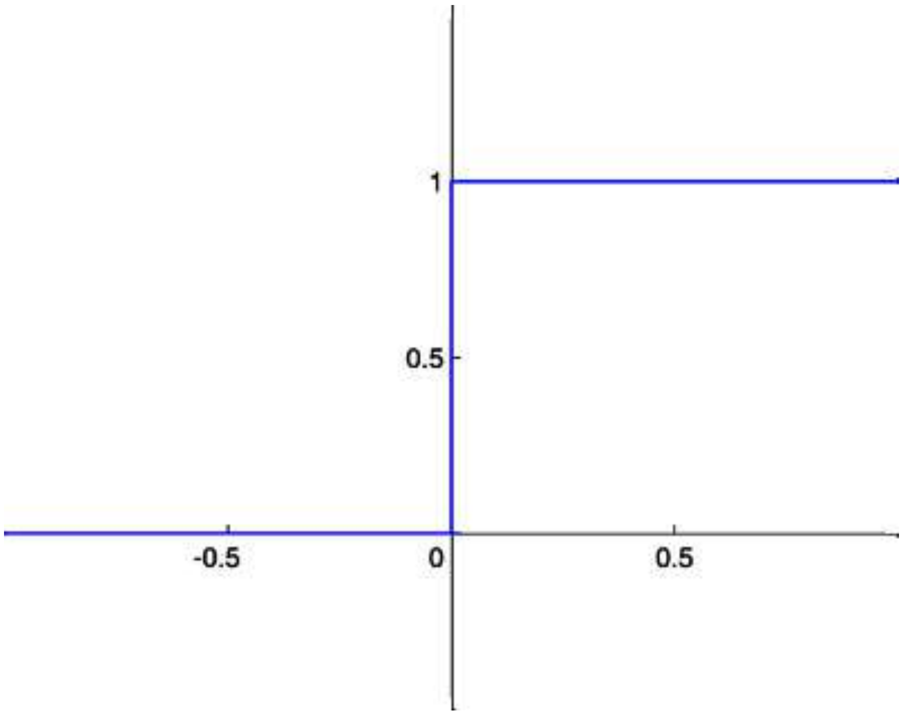


Non-linearly separable

MULTI-LAYER PERCEPTRON

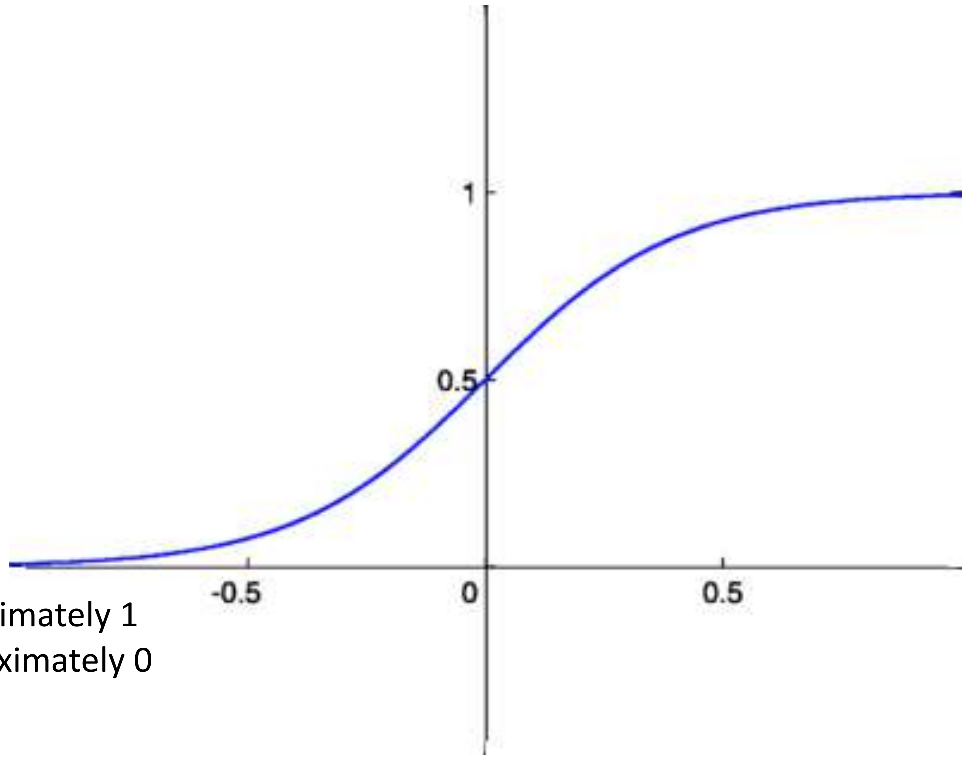


STEP FUNCTION



SIGMOID FUNCTION

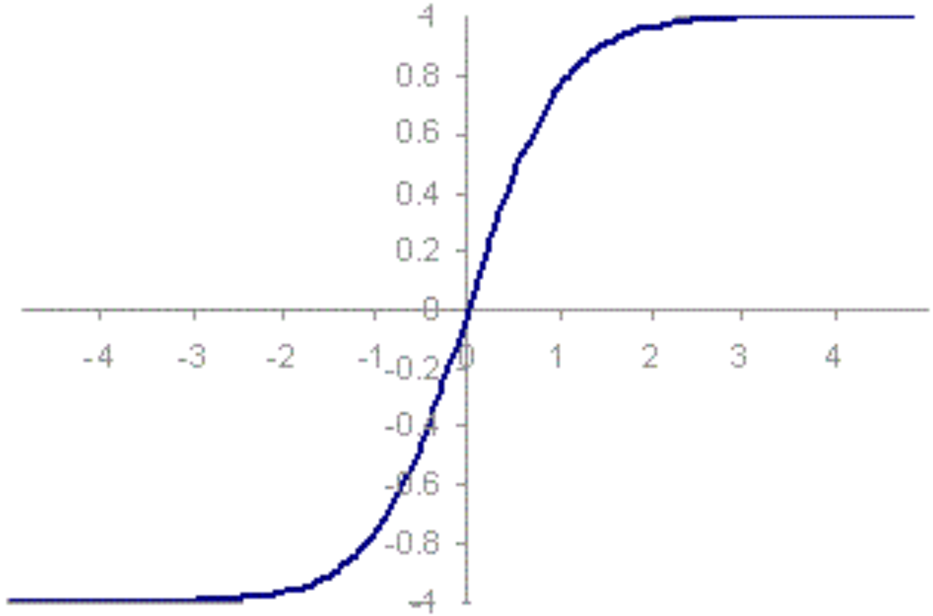
$$y = \frac{1}{1 + e^{-x}}$$



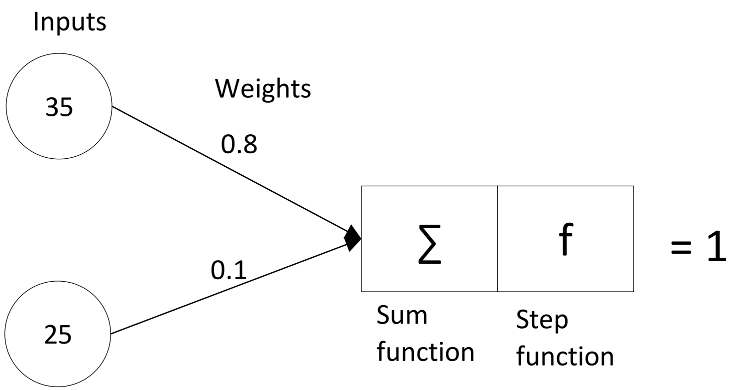
If X is high, the value is approximately 1
If X is small, the value is approximately 0

HYPERBOLIC TANGENT FUNCTION

$$Y = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$



STEP FUNCTION

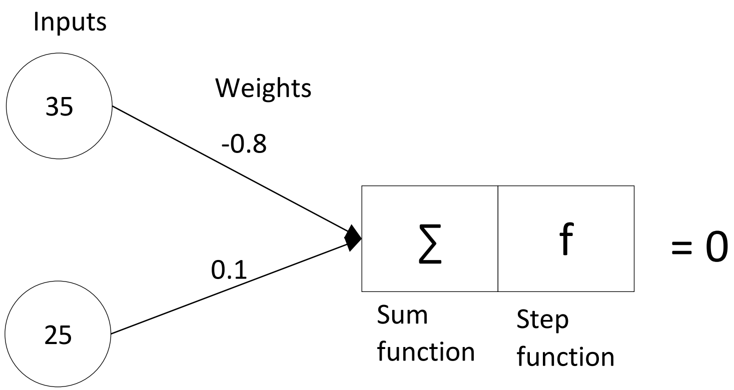


$$sum = \sum_{i=1}^{n} xi \ * wi$$

sum = (35 * 0.8) + (25 * 0.1)

sum = 28 + 2.5

sum = 30.5



$$sum = \sum_{i=1}^{n} xi \ * wi$$

sum = (35 * -0.8) + (25 * 0.1)

sum = -28 + 2.5

sum = -25.5

"XOR" OPERATOR

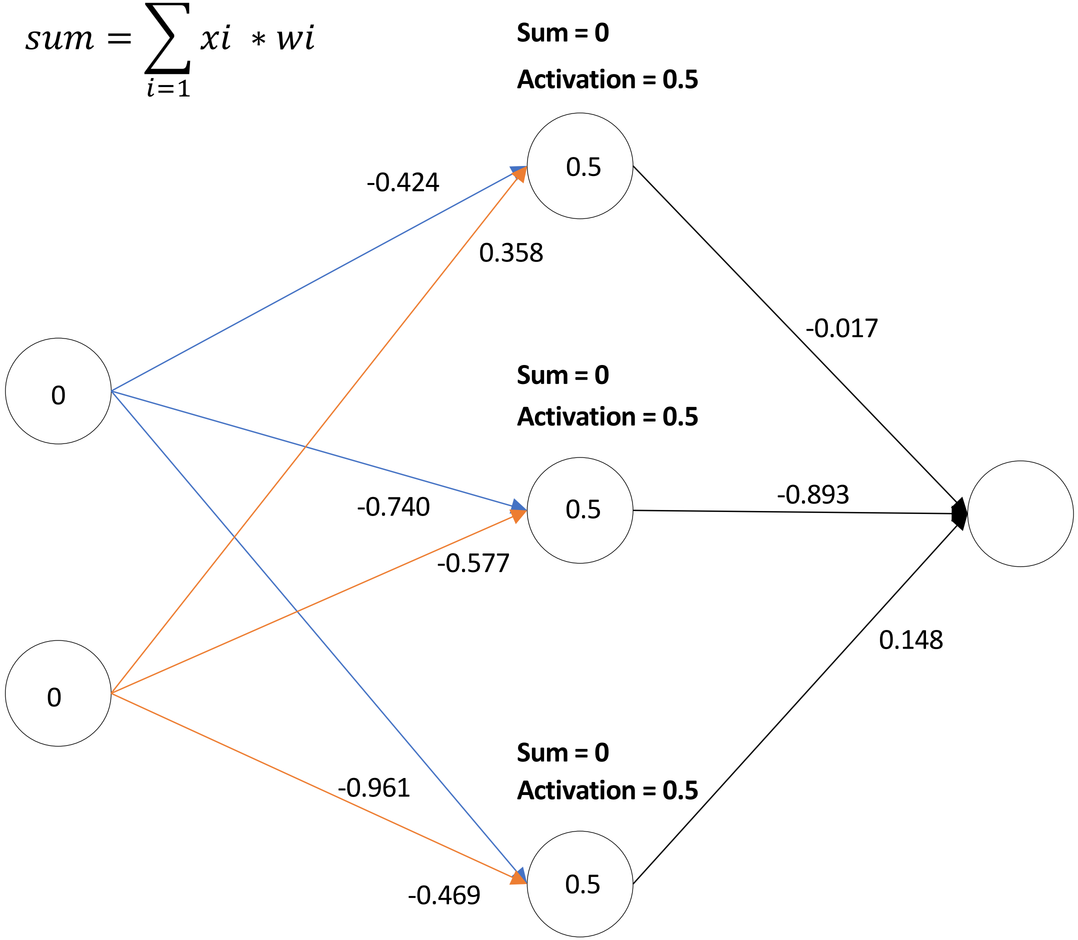
X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0

INPUT LAYER TO HIDDEN LAYER

$$sum = \sum_{i=1}^{n} xi \ * wi$$

$$y = \frac{1}{1 + e^{-x}}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



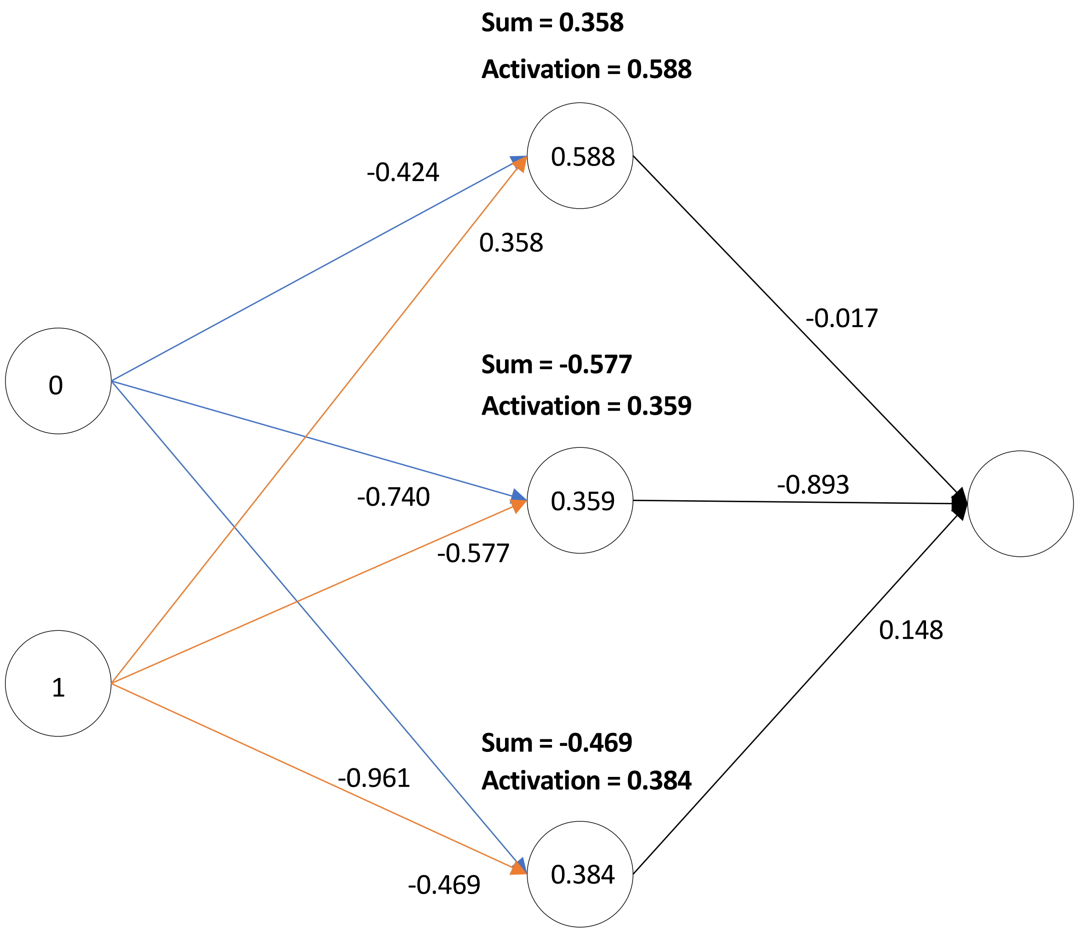
0 * (-0.424) + 0 * 0.358 = 0

0 * (-0.740) + 0 * (-0.577) = 0

0 * (-0.961) + 0 * (-0.469) = 0

INPUT LAYER TO HIDDEN LAYER

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0

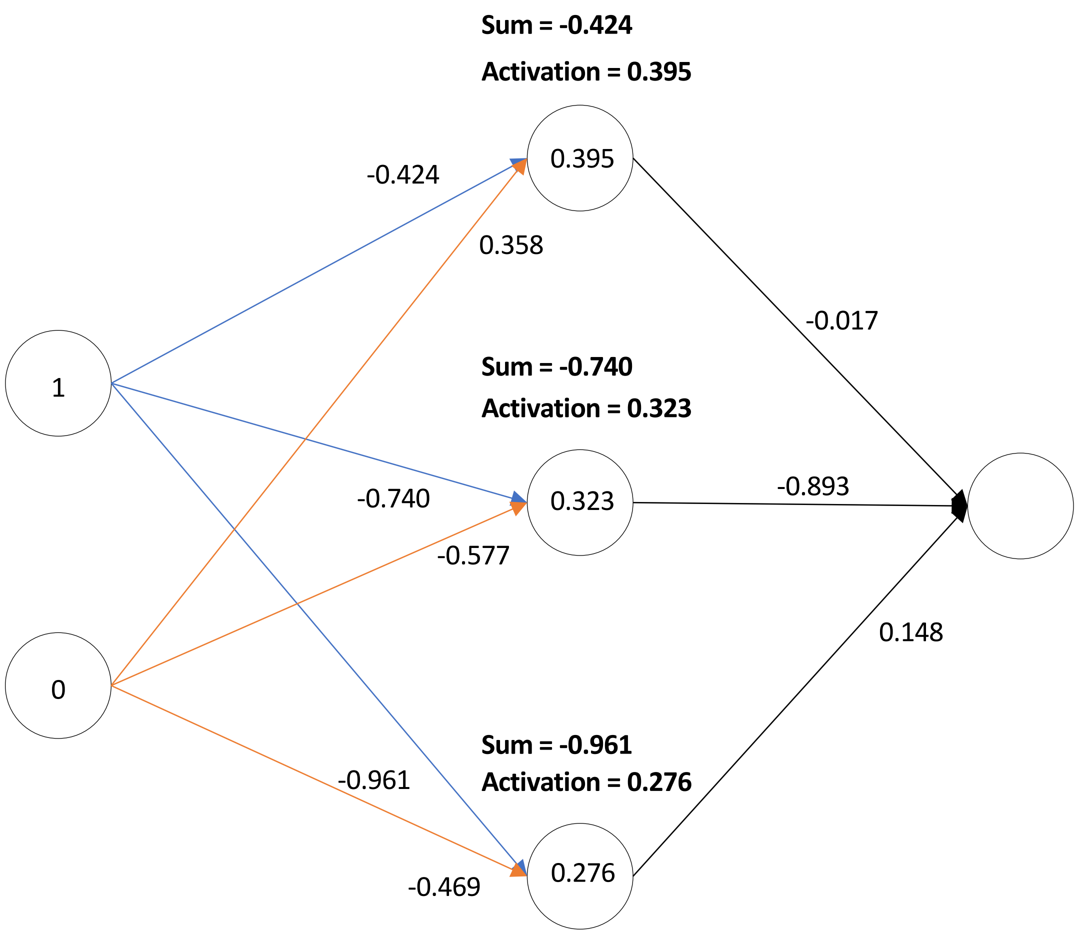


0 * (-0.424) + 1 * 0.358 = 0.358

0 * (-0.740) + 1 * (-0.577) = -0.577

0 * (-0.961) + 1 * (-0.469) = -0.469

INPUT LAYER TO HIDDEN LAYER



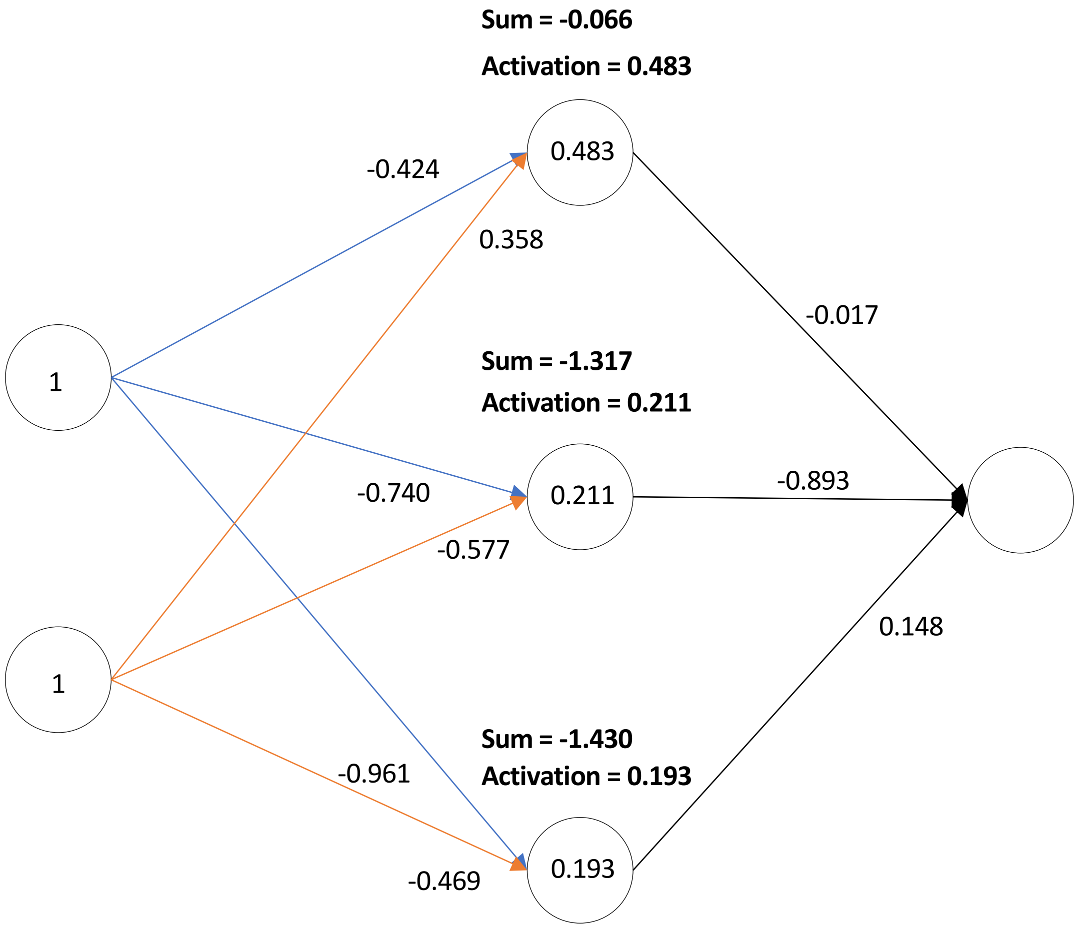
X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0

$$1 * (-0.424) + 0 * 0.358 = -0.424$$

$$1 * (-0.740) + 0 * (-0.577) = -0.740$$

$$1 * (-0.961) + 0 * (-0.469) = -0.961$$

INPUT LAYER TO HIDDEN LAYER



X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0

$$1 * (-0.424) + 1 * 0.358 = -0.066$$

$$1 * (-0.740) + 1 * (-0.577) = -1.317$$

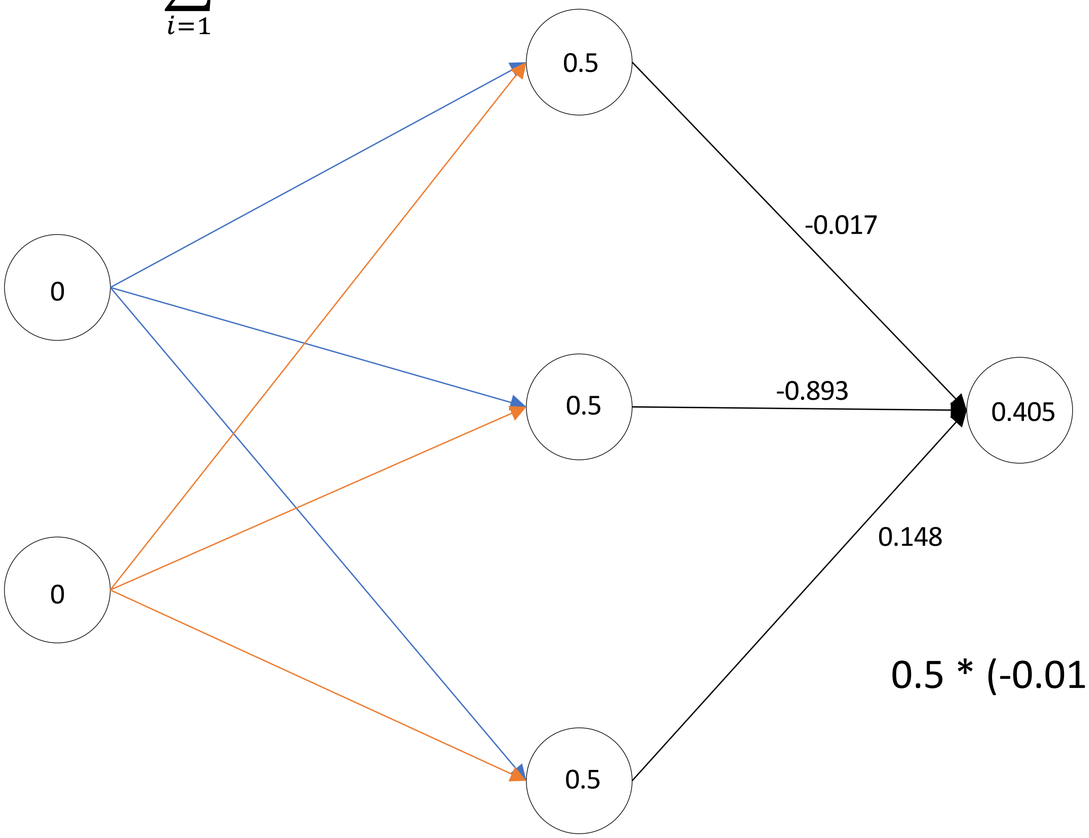
$$1 * (-0.961) + 1 * (-0.469) = -1.430$$

HIDDEN LAYER TO OUTPUT LAYER

$$sum = \sum_{i=1}^{n} xi \; * wi$$

$$y = \frac{1}{1 + e^{-x}}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



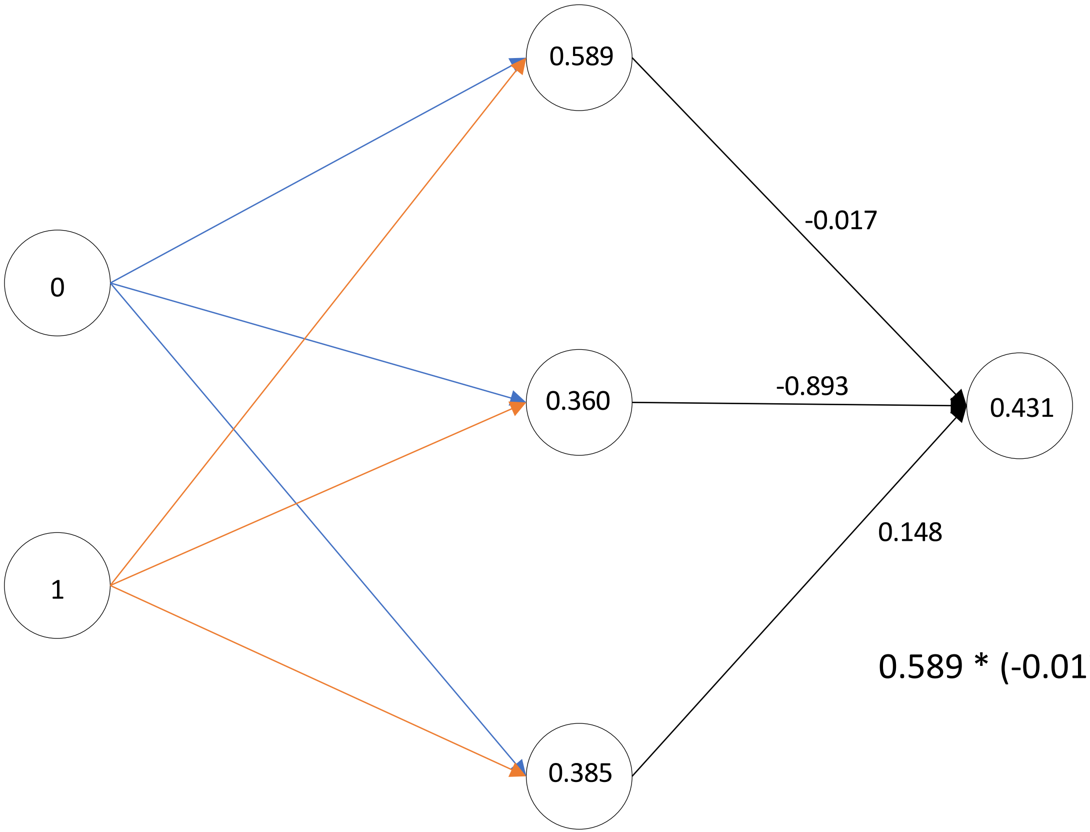
Sum = -0.381

Activation = 0.405

0.5 * (-0.017) + 0.5 * (-0.893) + 0.5 * 0.148 = -0.381

HIDDEN LAYER TO OUTPUT LAYER

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



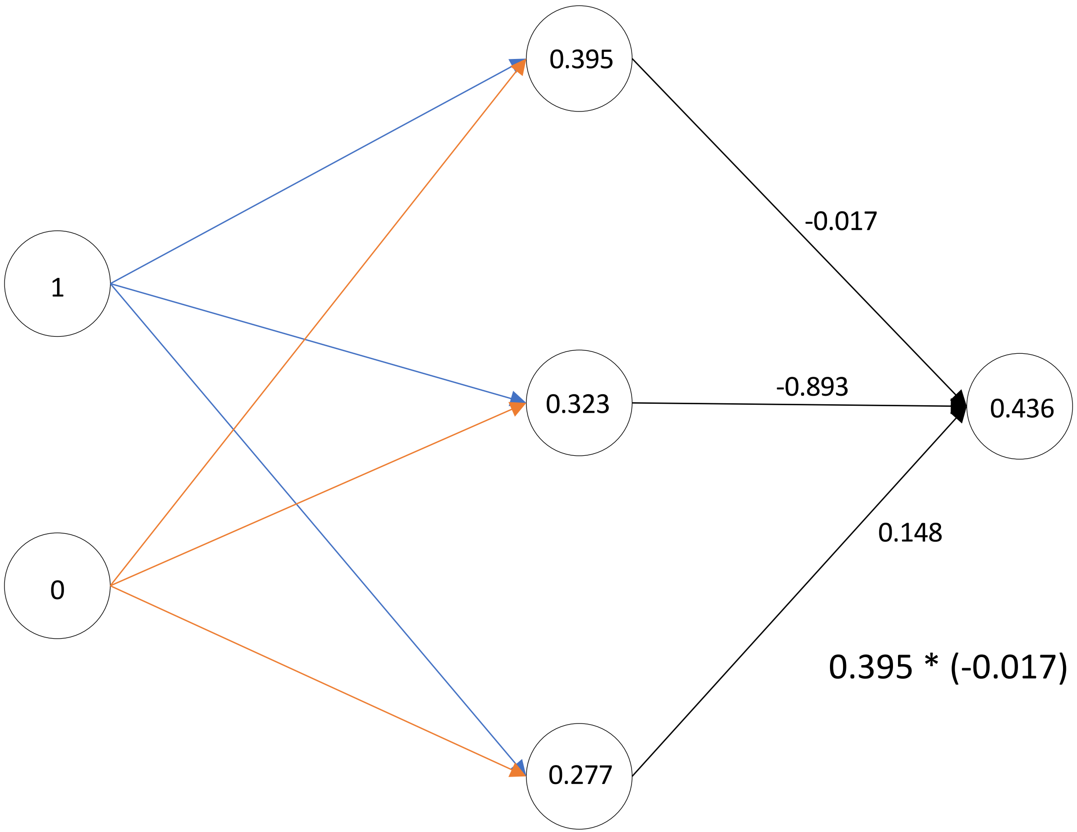
Sum = -0.274

Activation = 0.431

$$0.589 * (-0.017) + 0.360 * (-0.893) + 0.385 * 0.148 = -0.274$$

HIDDEN LAYER TO OUTPUT LAYER

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



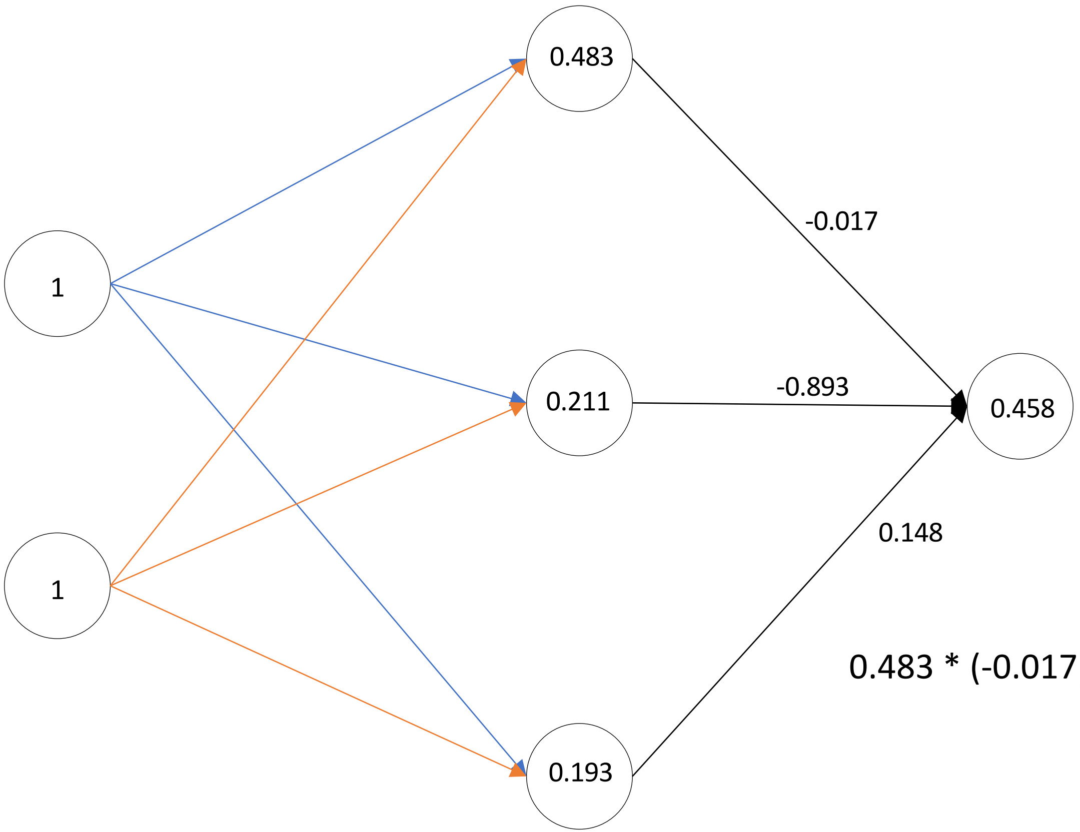
Sum = -0.254

Activation = 0.436

$$0.395 * (-0.017) + 0.323 * (-0.893) + 0.277 * 0.148 = -0.254$$

HIDDEN LAYER TO OUTPUT LAYER

X1	X2	Classe
0	0	0
0	1	1
1	0	1
1	1	0



Sum = -0.168

Activation = 0.458

$$0.483 * (-0.017) + 0.211 * (-0.893) + 0.193 * 0.148 = -0.168$$

"XOR" OPERATOR – ERROR (LOSS FUNCTION)

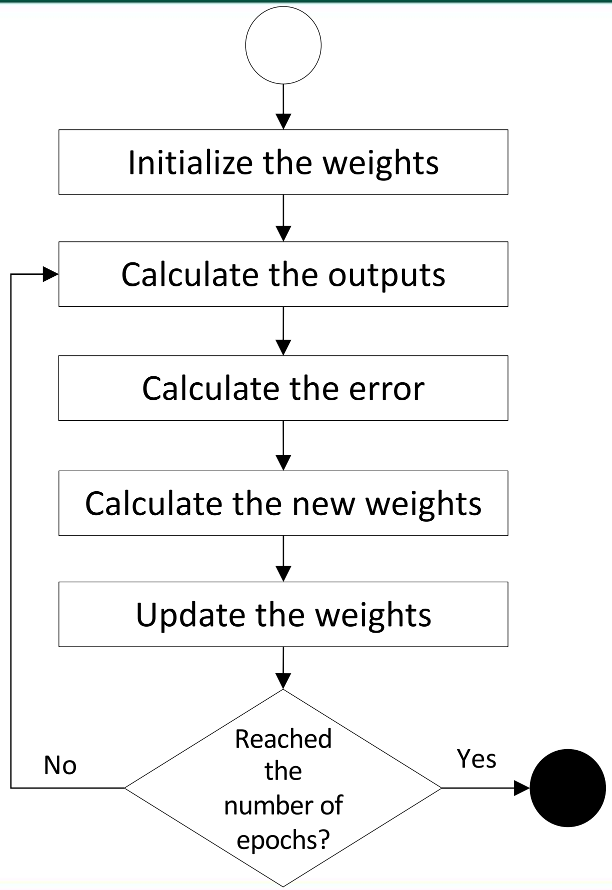
The simplest algorithm

error = correct – prediction

X1	X2	Class	Prediction	Error
0	0	0	0.405	-0.405
0	1	1	0.431	0.569
1	0	1	0.436	0.564
1	1	0	0.458	-0.458

Average = 0.499

ALGORITHM



Cost function (loss function)

Gradient descent

Derivative

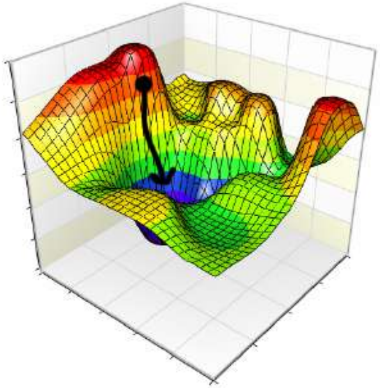
Delta

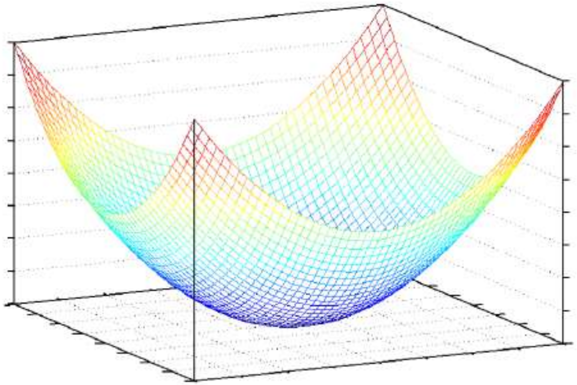
Backpropagation

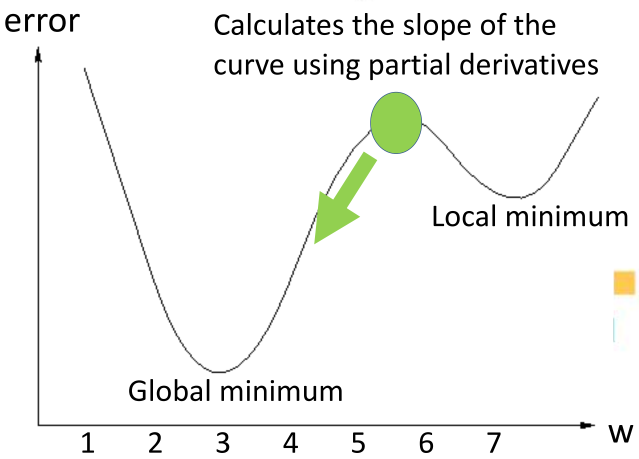
GRADIENT DESCENT

$\min C(w_1, w_2 \ldots w_n)$

Calculate the partial derivative to move to the gradient direction







GRADIENT DESCENT (DERIVATIVE)

$$y = \frac{1}{1 + e^{-x}}$$

$$d = \mathrm{y} * (1 - \mathrm{y})$$

$$d = 0.1 * (1 - 0.1)$$

DELTA PARAMETER

Activation function

↓

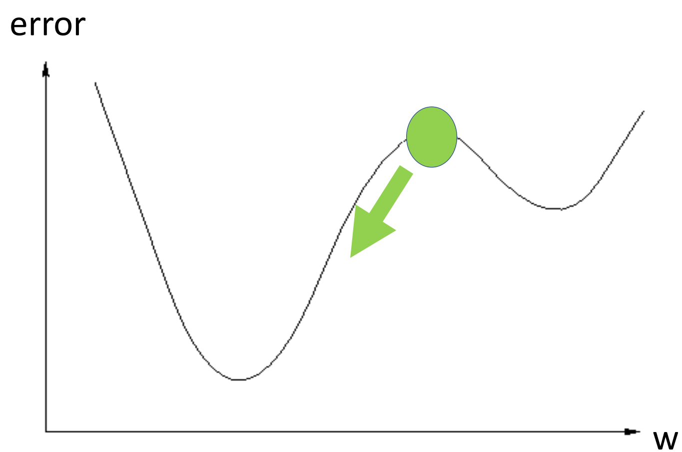
Derivative

↓

Delta

↓

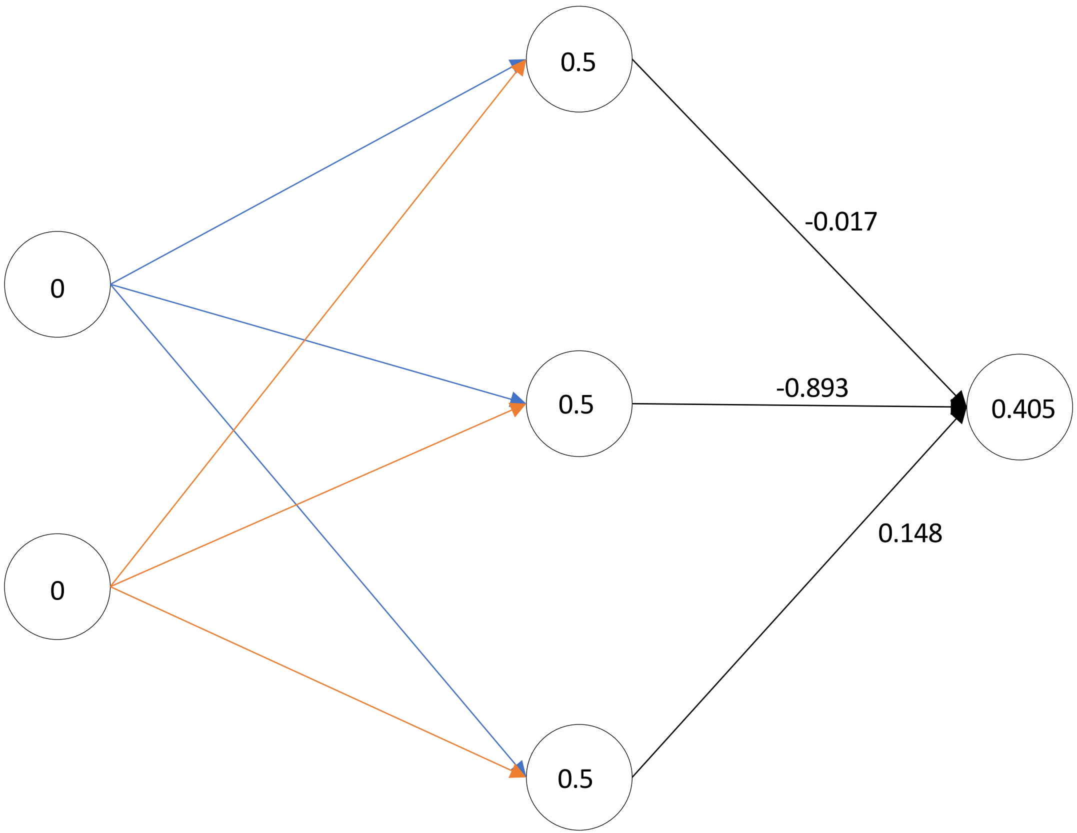
Gradient



OUTPUT LAYER – DELTA

$$delta_{output} = error * sigmoid_{derivative}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



Sum = -0.381

Activation = 0.405

Error = 0 – 0.405 = -0.405

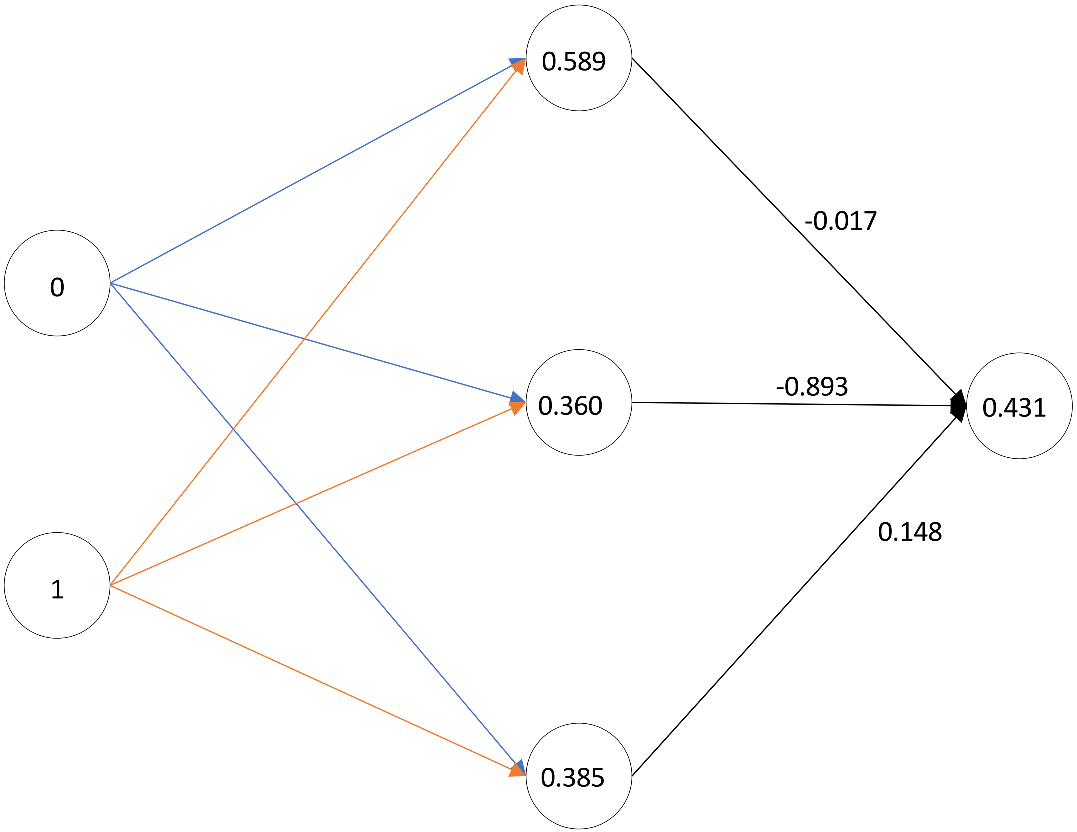
Derivative activation (sigmoid) = 0.241

Delta (output) = -0.405 * 0.241 = -0.097

OUTPUT LAYER – DELTA

$$delta_{output} = error * sigmoid_{derivative}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



Sum = -0.274

Activation = 0.431

Error = 1 – 0.431 = 0.569

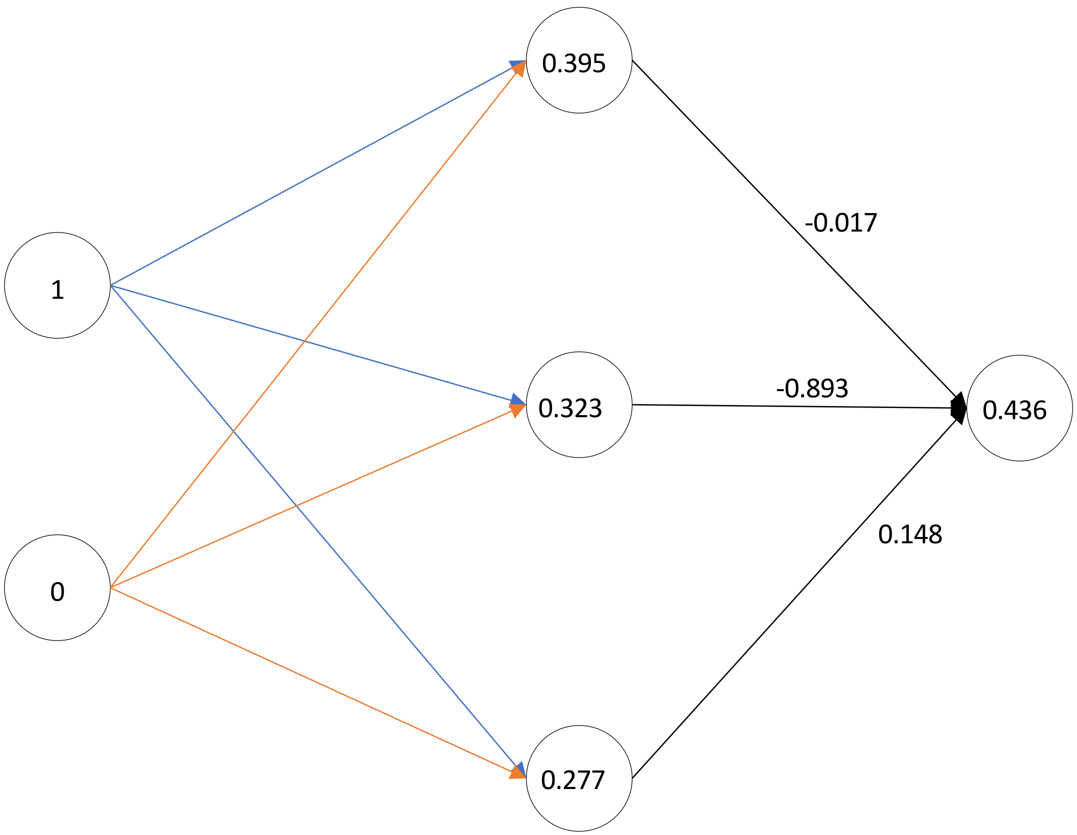
Derivative activation (sigmoid) = 0.245

Delta (output) = 0.569 * 0.245 = 0.139

OUTPUT LAYER – DELTA

$$delta_{output} = error * sigmoid_{derivative}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



Sum = -0.254

Activation = 0.436

Error = 1 – 0.436 = 0.564

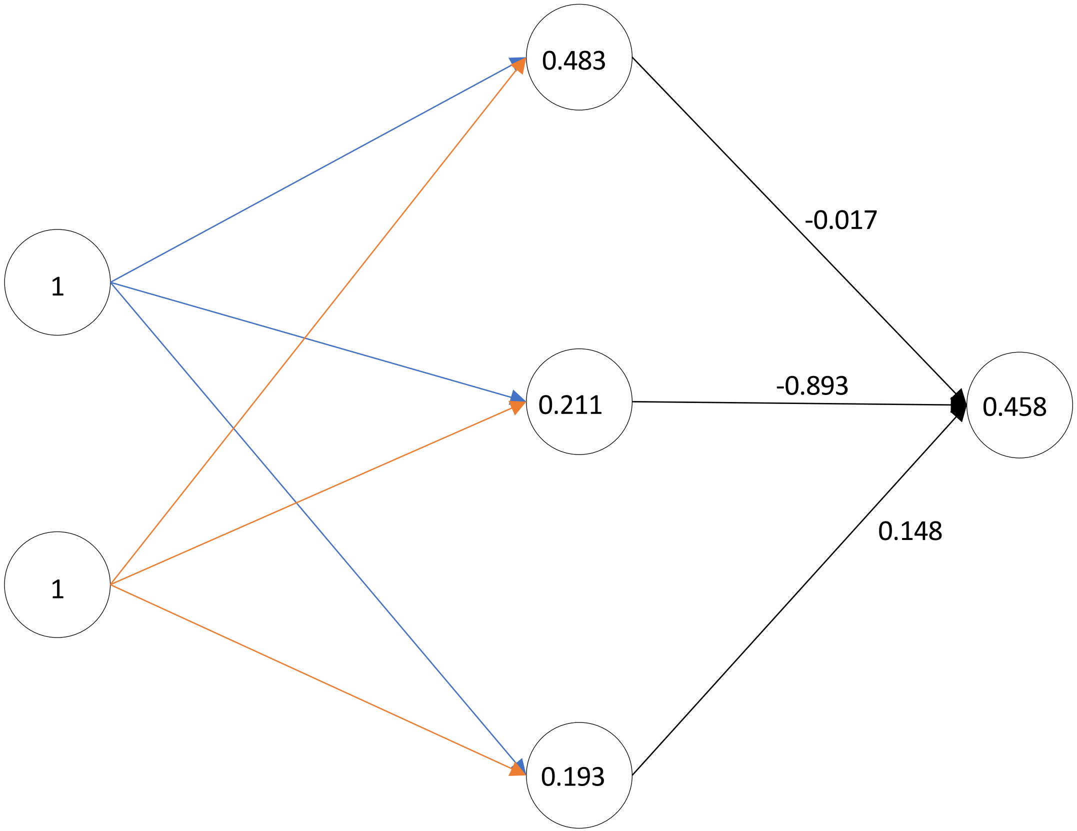
Derivative activation (sigmoid) = 0.246

Delta (output) = 0.564 * 0.246 = 0.138

OUTPUT LAYER – DELTA

$$delta_{output} = error * sigmoid_{derivative}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



Sum = -0.168

Activation = 0.458

Error = 0 – 0.458 = -0.458

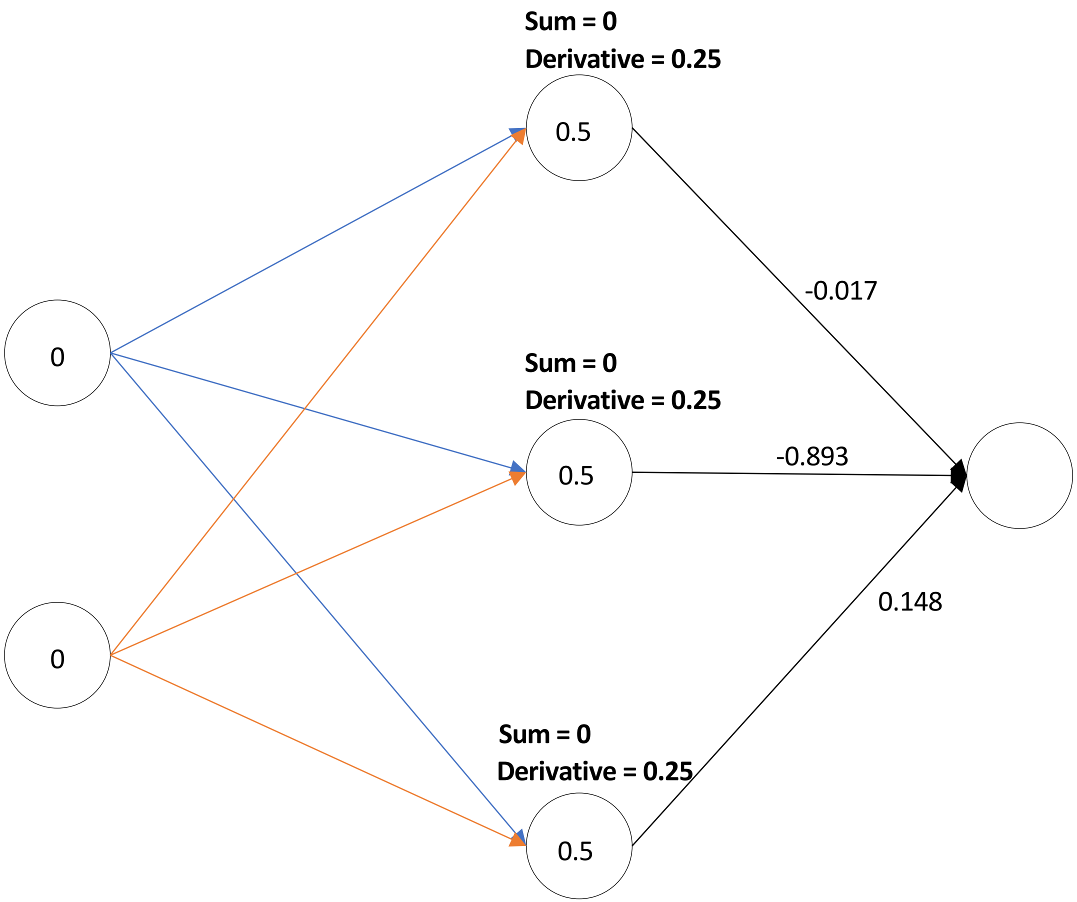
Derivative activation (sigmoid) = 0.248

Delta (output) = -0.458 * 0.248 = -0.113

HIDDEN LAYER – DELTA

$$delta_{hidden} = sigmoid_{derivative} * weight * delta_{output}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



Delta (output) = -0.097

0.25 * (-0.017) * (-0.097) = 0.000

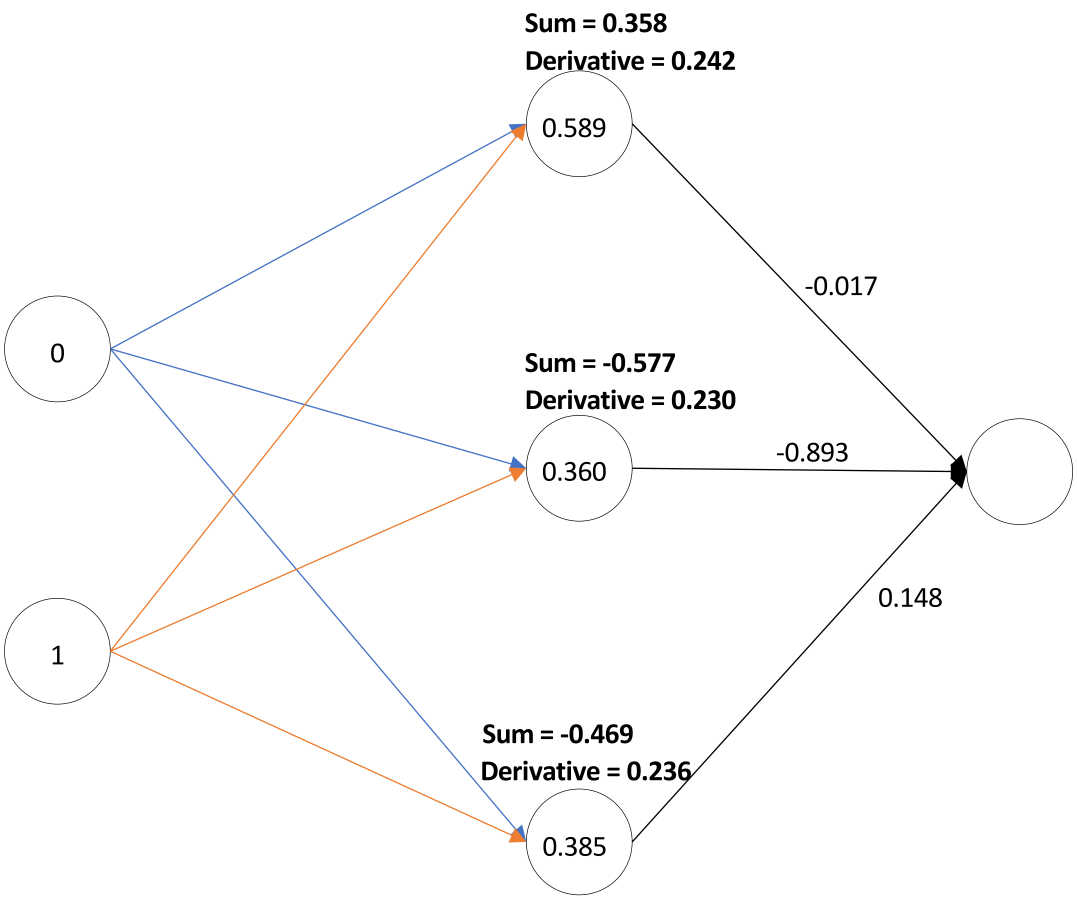
0.25 * (-0.893) * (-0.097) = 0.021

0.25 * 0.148 * (-0.097) = -0.003

HIDDEN LAYER – DELTA

$$delta_{hidden} = sigmoid_{derivative} * weight * delta_{output}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



Delta (output) = 0.139

0.242 * (-0.017) * 0.139 = -0.000

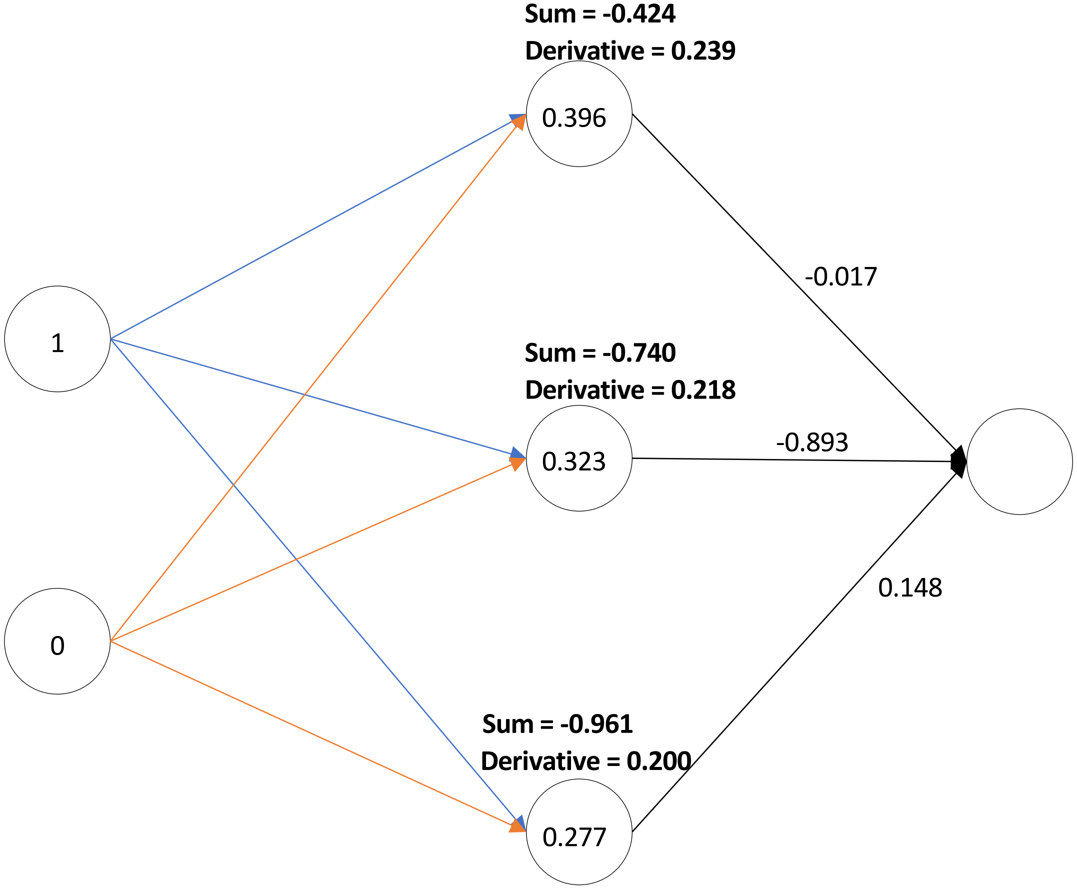
0.230 * (-0.893) * 0.139 = -0.028

0.236 * 0.148 * 0.139 = 0.004

HIDDEN LAYER – DELTA

$$delta_{hidden} = sigmoid_{derivative} * weight * delta_{output}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



Delta (output) = 0.138

0.239 * (-0.017) * 0.138 = -0.000

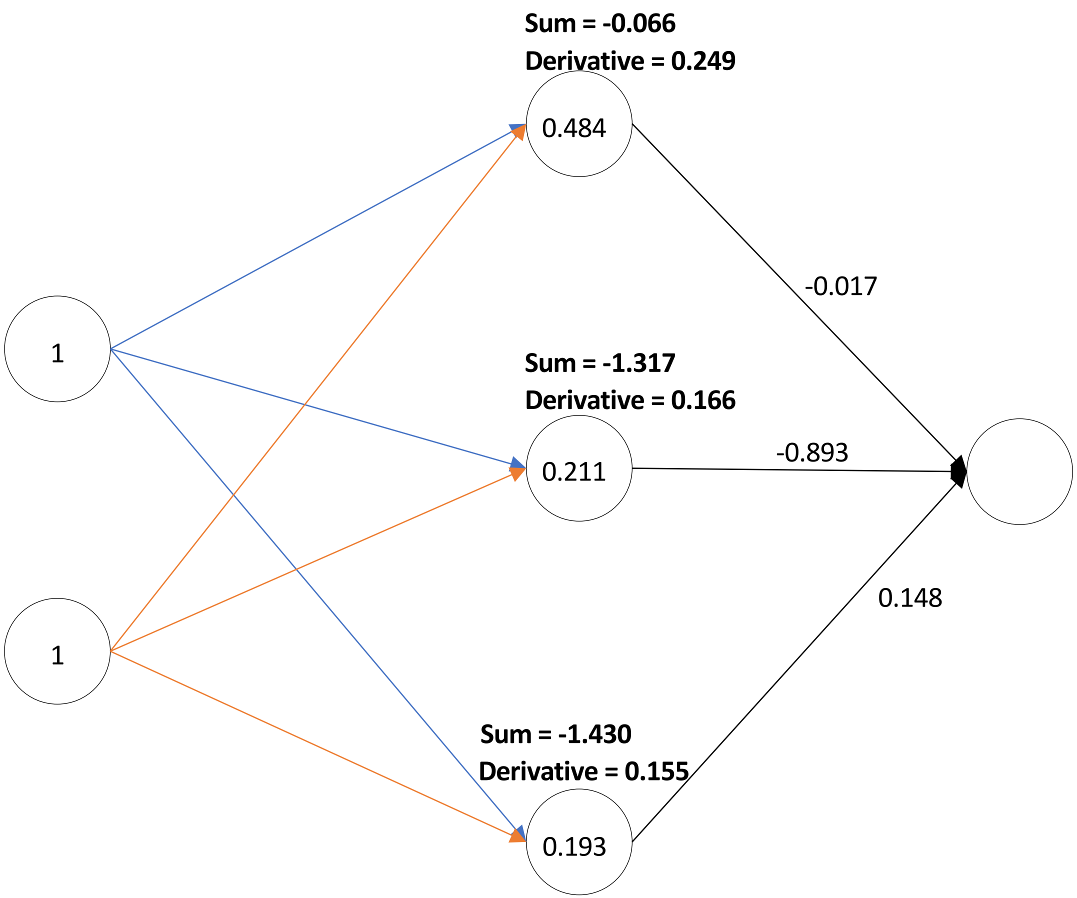
0.218 * (-0.893) * 0.138 = -0.026

0.200 * 0.148 * 0.138 = 0.004

HIDDEN LAYER – DELTA

$$delta_{hidden} = sigmoid_{derivative} * weight * delta_{output}$$

X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



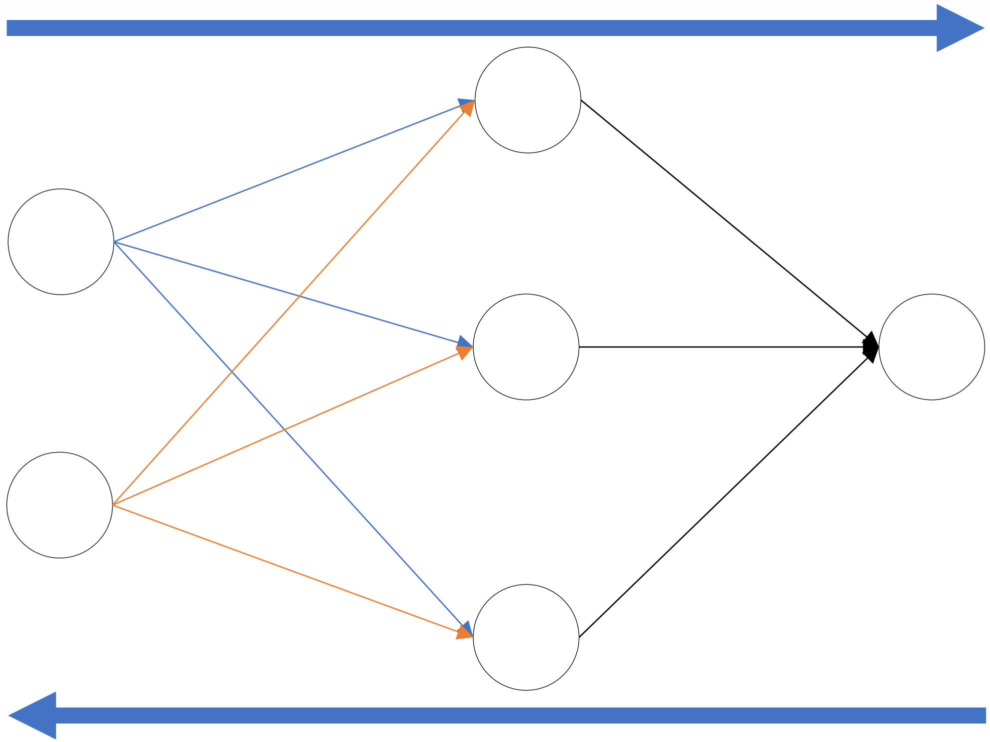
Delta (output) = -0.113

0.249 * (-0.017) * (-0.113) = 0.000

0.166 * (-0.893) * (-0.113) = 0.016

0.155 * 0.148 * (-0.113) = -0.002

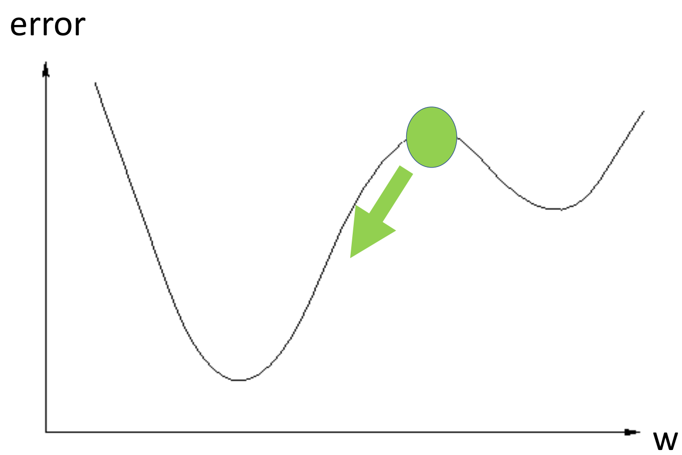
WEIGHT UPDATE



$$weight_{n+1} = weight_n + (input \ * delta \ * learing\_rate)$$

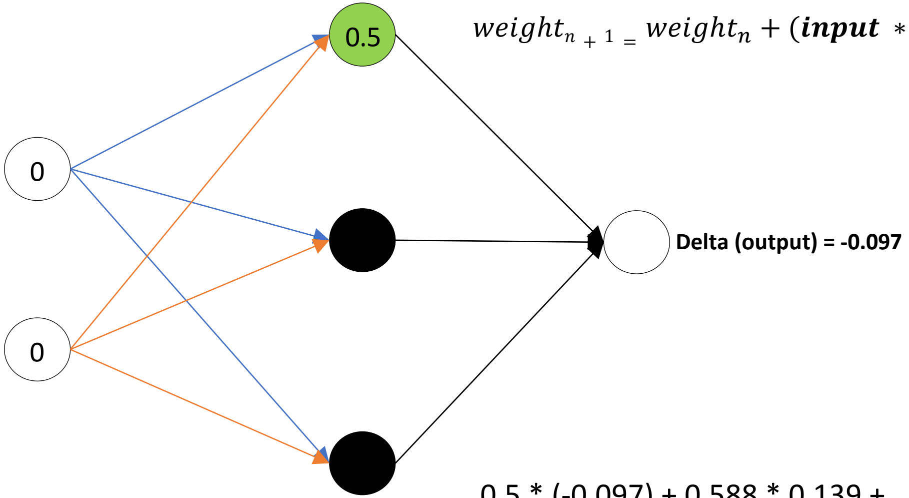
LEARNING RATE

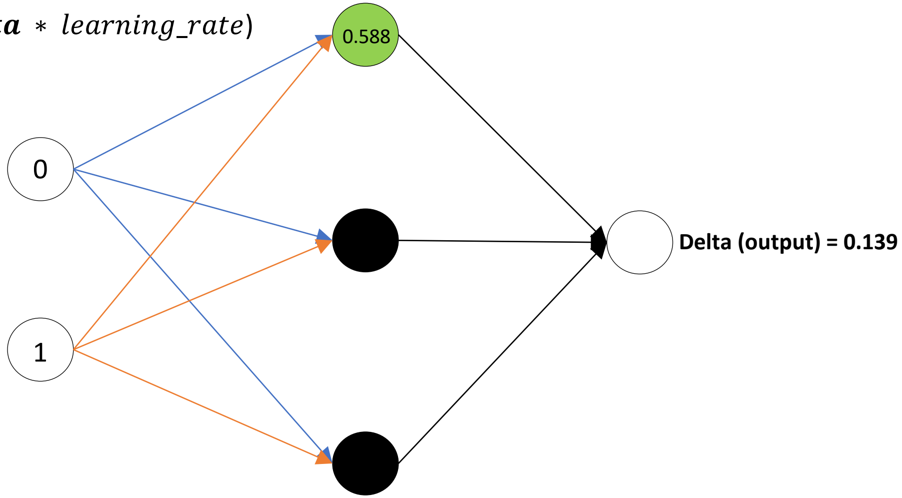
- Defines how fast the algorithm will learn
- High: the convergence is fast but may lose the global minimum
- Low: the convergence will be slower but more likely to reach the global minimum



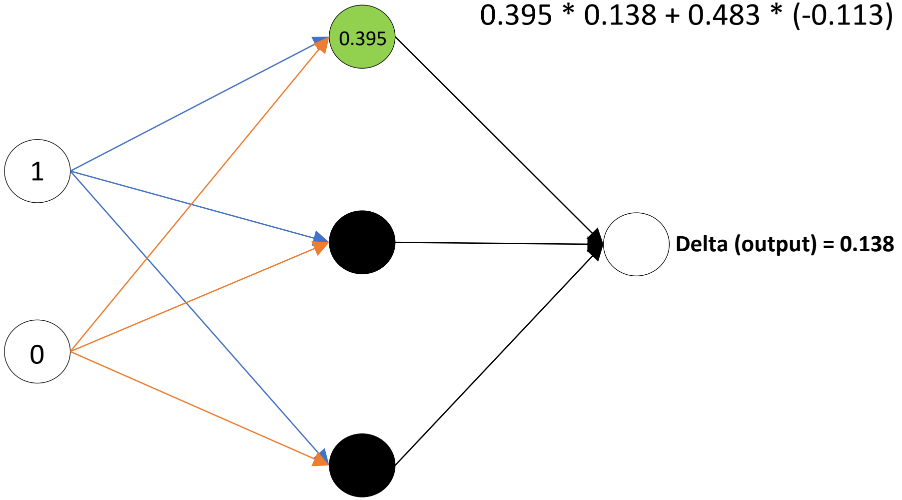
WEIGHT UPDATE – OUTPUT LAYER TO HIDDEN LAYER

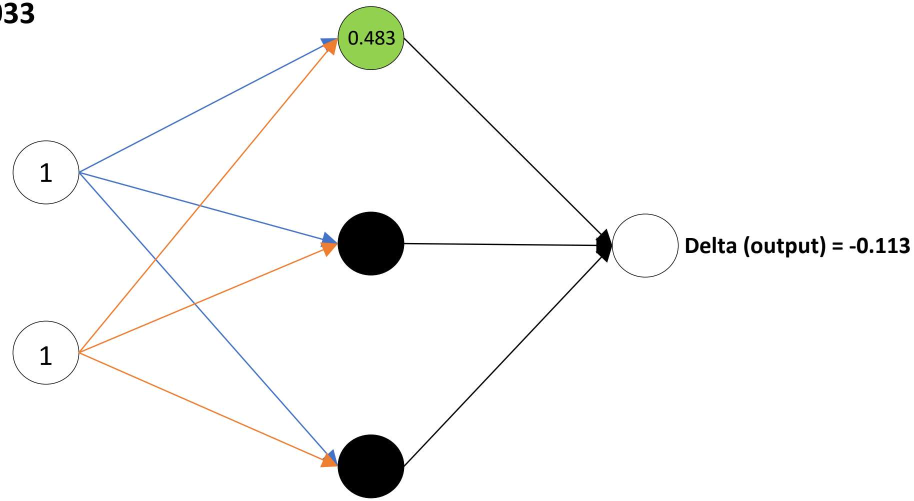
$$weight_{n+1} = weight_n + (\boldsymbol{input} * \boldsymbol{delta} * learning\_rate)$$





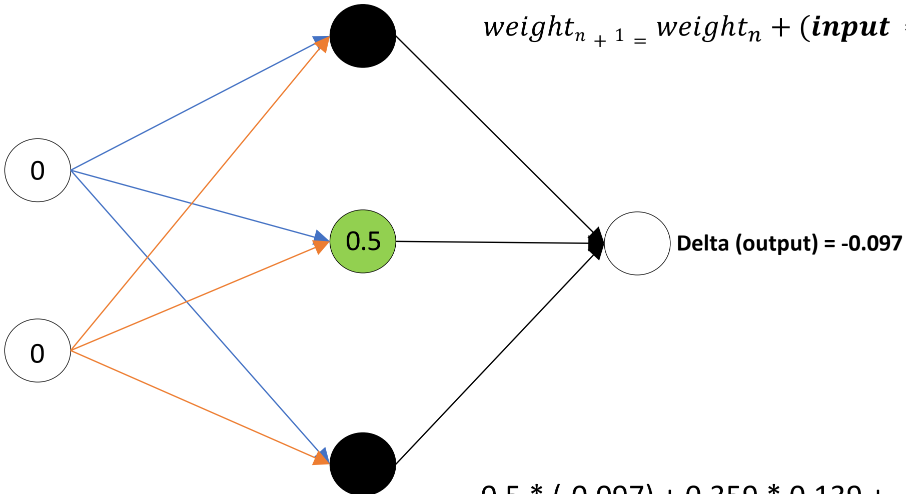
0.5 * (-0.097) + 0.588 * 0.139 +
0.395 * 0.138 + 0.483 * (-0.113) = **0.033**

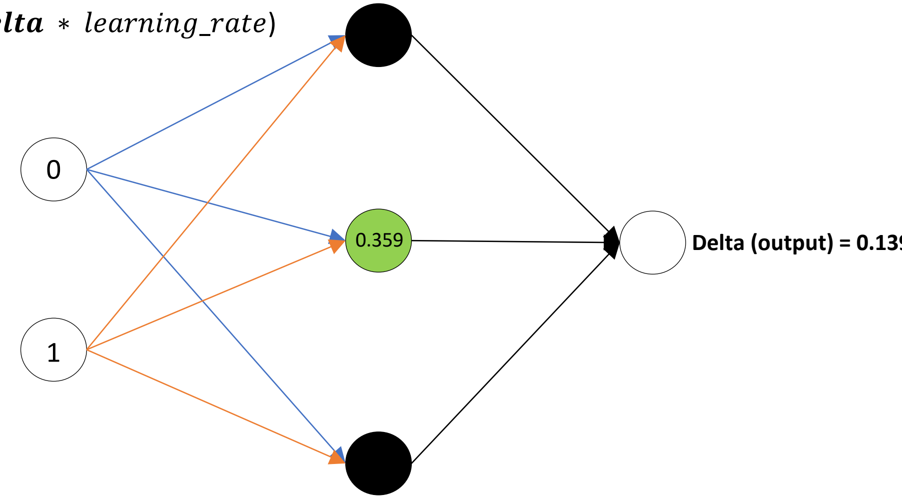




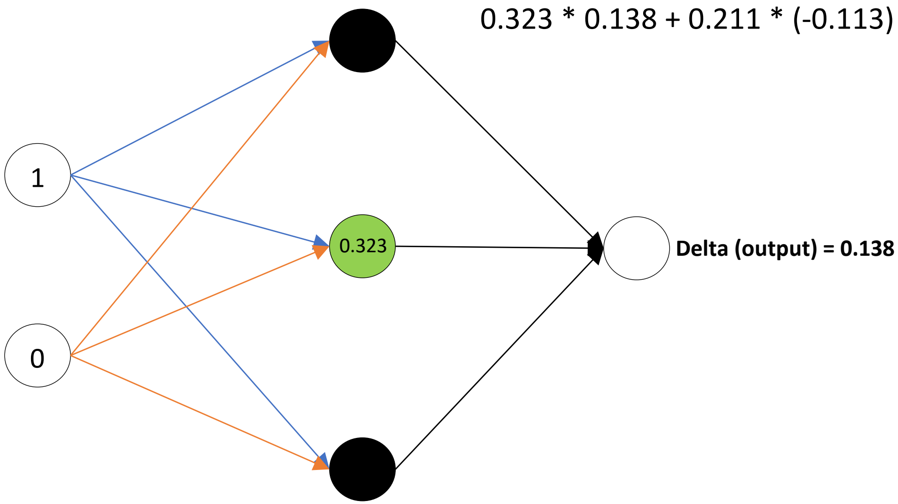
WEIGHT UPDATE – OUTPUT LAYER TO HIDDEN LAYER

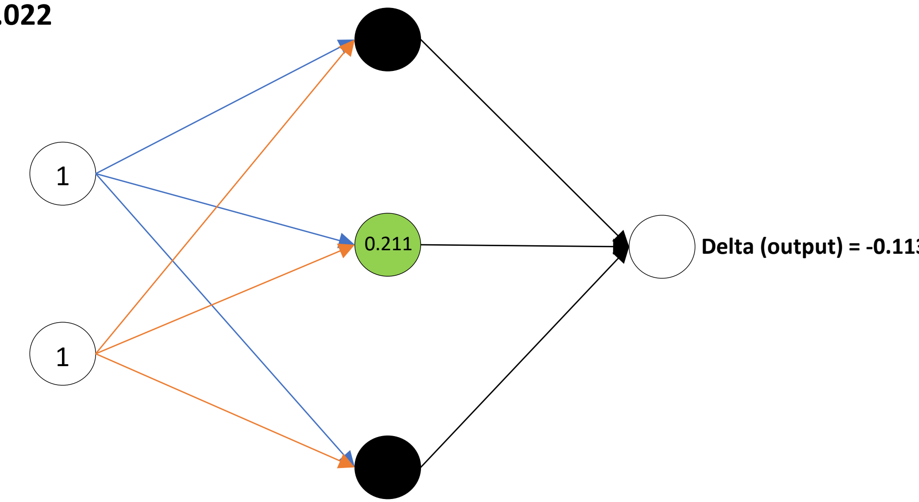
$$weight_{n+1} = weight_n + (\boldsymbol{input} * \boldsymbol{delta} * learning\_rate)$$





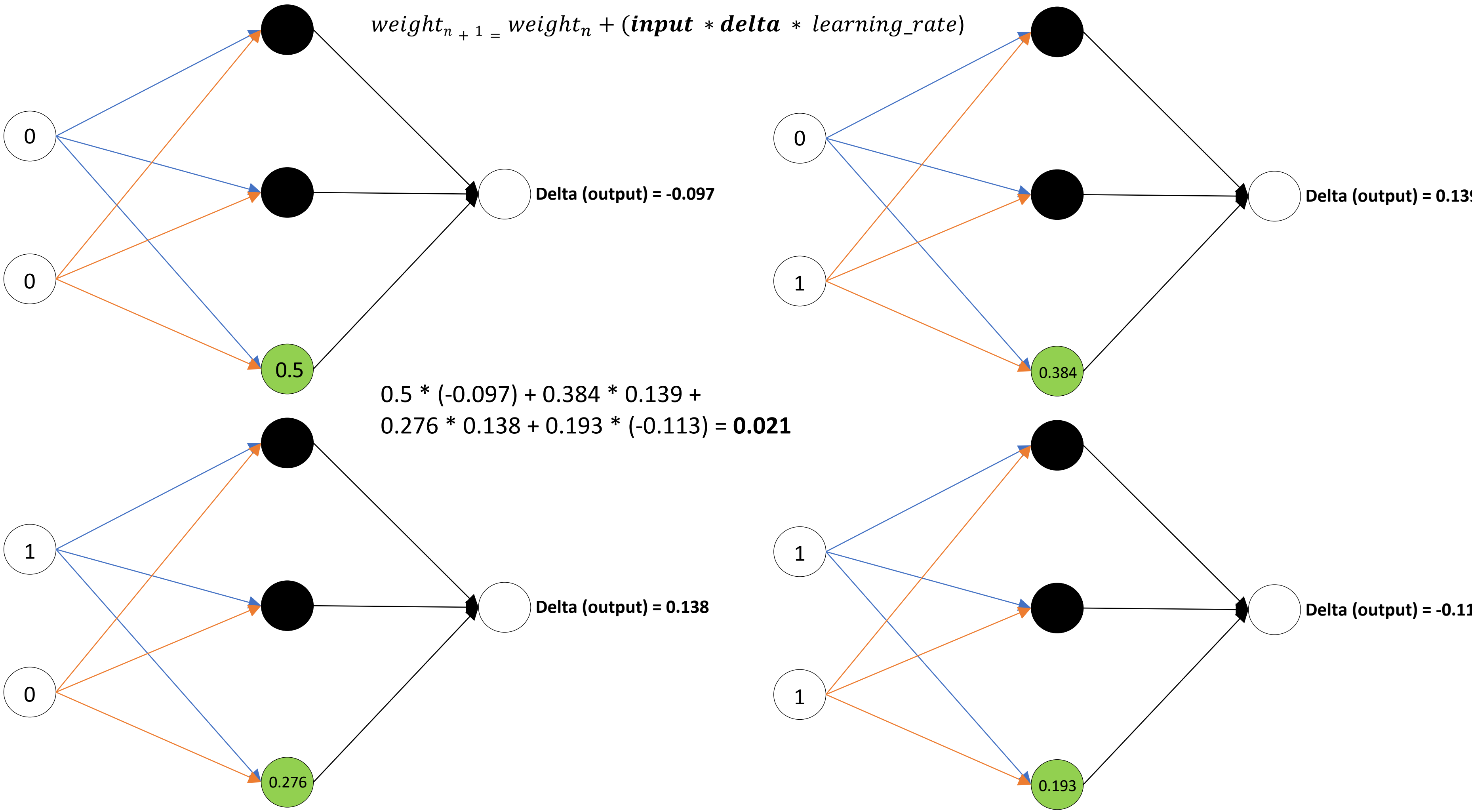
0.5 * (-0.097) + 0.359 * 0.139 +
0.323 * 0.138 + 0.211 * (-0.113) = **0.022**





WEIGHT UPDATE – OUTPUT LAYER TO HIDDEN LAYER

$$weight_{n+1} = weight_n + (\boldsymbol{input} * \boldsymbol{delta} * learning\_rate)$$



0.5 * (-0.097) + 0.384 * 0.139 +
0.276 * 0.138 + 0.193 * (-0.113) = **0.021**

WEIGHT UPDATE – OUTPUT LAYER TO HIDDEN LAYER

Learning rate = 0.3

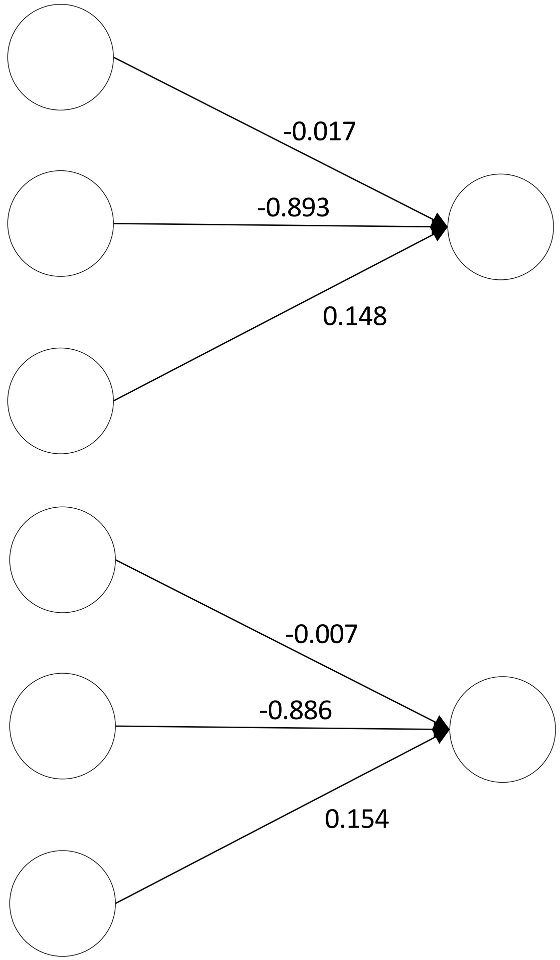
Input x delta
0.033
0.022
0.021

$$weight_{n+1} = weight_n + (\boldsymbol{input} * \boldsymbol{delta} * learning\_rate)$$

-0.017 + 0.033 * 0.3 = **-0.007**

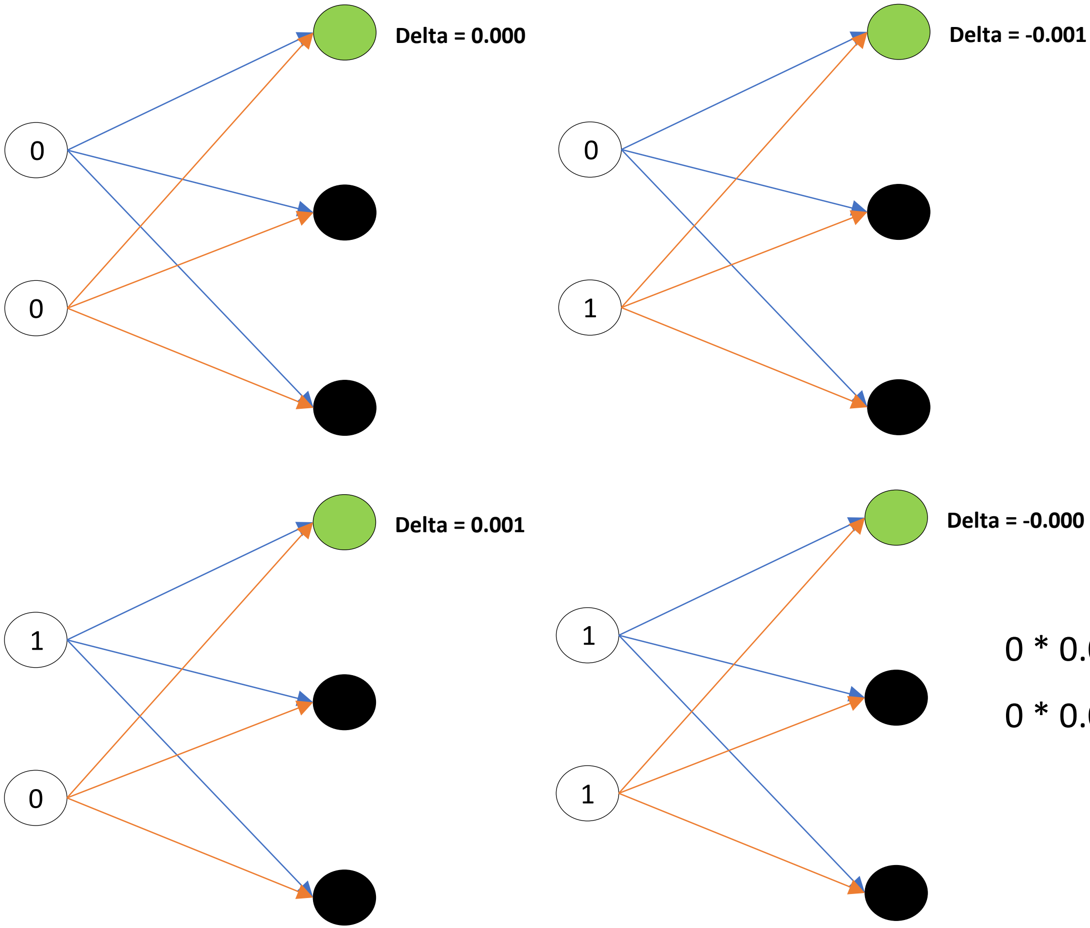
-0.893 + 0.022 * 0.3 = **-0.886**

0.148 + 0.021 * 0.3 = **0.154**



WEIGHT UPDATE – HIDDEN LAYER TO INPUT LAYER

$$weight_{n+1} = weight_n + (\boldsymbol{input} * \boldsymbol{delta} * learning\_rate)$$

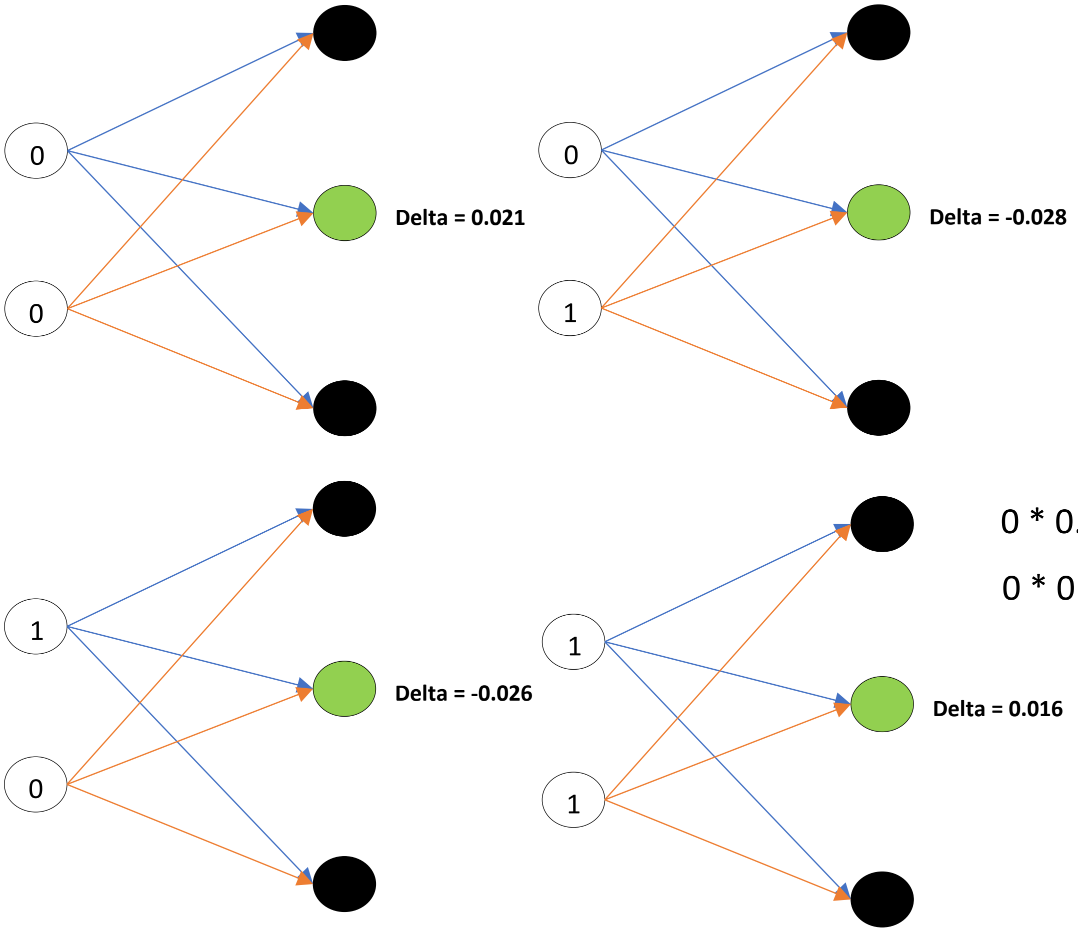


0 * 0.000 + 0 * (-0.001) + 1 * (0.001) + 1 * -0.000 = -0.000

0 * 0.000 + 1 * (-0.001) + 0 * (0.001) + 1 * -0.000 = -0.000

WEIGHT UPDATE – HIDDEN LAYER TO INPUT LAYER

$$weight_{n+1} = weight_n + (\boldsymbol{input} * \boldsymbol{delta} * learning\_rate)$$

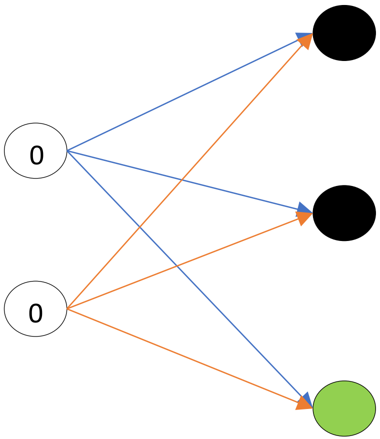


0 * 0.021 + 0 * (-0.028) + 1 * (-0.026) + 1 * 0.016 = -0.009

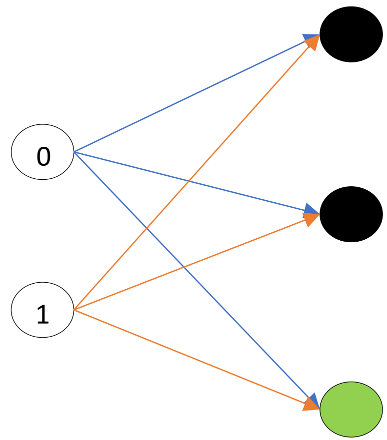
0 * 0.021 + 1 * (-0.028) + 0 * (-0.026) + 1 * 0.016 = -0.012

WEIGHT UPDATE – HIDDEN LAYER TO INPUT LAYER

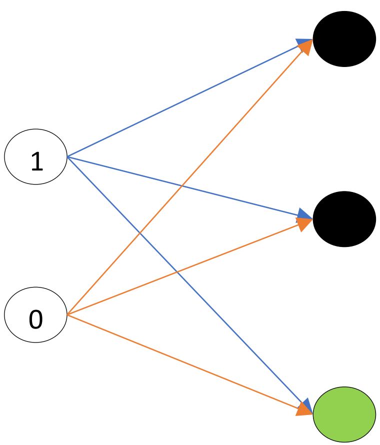
$$weight_{n+1} = weight_n + (\boldsymbol{input} * \boldsymbol{delta} * learning\_rate)$$



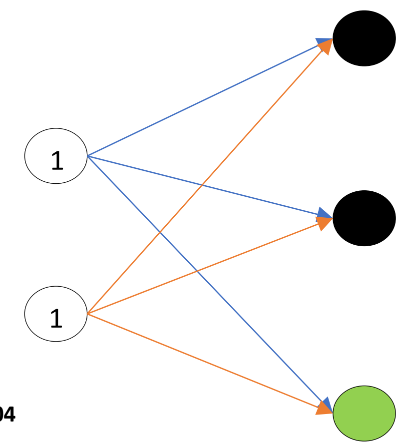
Delta = -0.003



Delta = 0.004



Delta = 0.004



Delta = -0.002

0 * (-0.003) + 0 * 0.004 + 1 * 0.004 + 1 * (-0.002) = 0.002

0 * (-0.003) + 1 * 0.004 + 0 * 0.004 + 1 * (-0.002) = 0.002

WEIGHT UPDATE – HIDDEN LAYER TO INPUT LAYER

Learning rate = 0.3

Input x delta

-0.000 -0.009 0.002

-0.000 -0.012 0.002

$$weight_{n+1} = weight_n + (\boldsymbol{input} * \boldsymbol{delta} * learning\_rate)$$

-0.424 + (-0.000) * 0.3 = **-0.424**

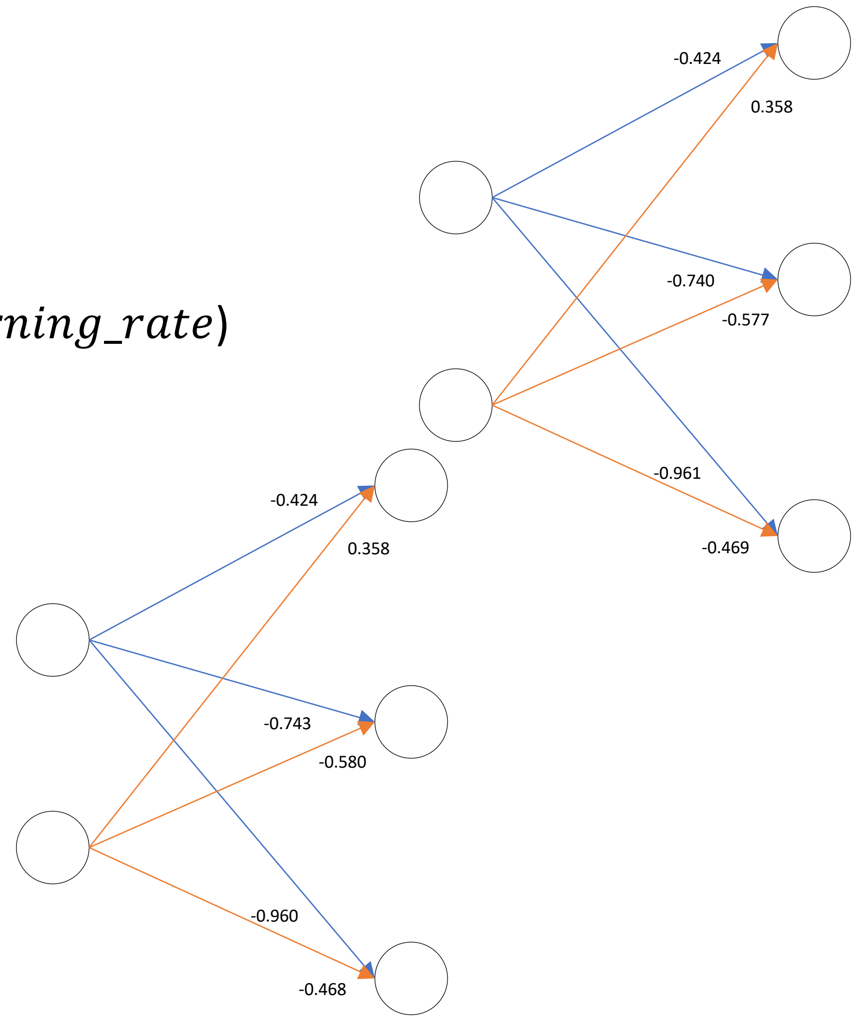
0.358 + (-0.000) * 0.3 = **0.358**

-0.740 + (-0.009) * 0.3 = **-0.743**

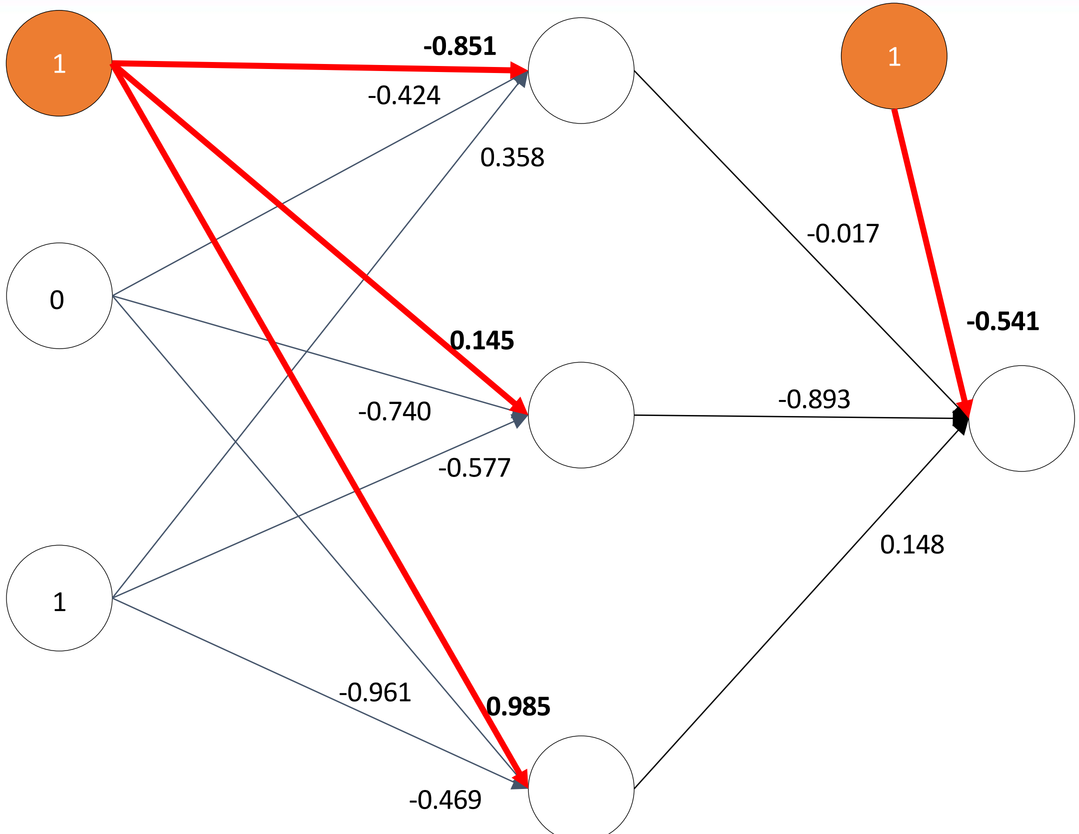
-0.577 + (-0.012) * 0.3 = **-0.580**

-0.961 + 0.002 * 0.3 = **-0.960**

-0.469 + 0.002 * 0.3 = **-0.468**



BIAS



$$output = sum(inputs * weights) + bias$$

ERROR (LOSS FUNCTION)

The simplest algorithm

error = correct – prediction

X1	X2	Class	Prediction	Error
0	0	0	0.405	-0.405
0	1	1	0.431	0.569
1	0	1	0.436	0.564
1	1	0	0.458	-0.458

Average = 0.499

MEAN SQUARED ERROR (MSE) AND ROOT MEAN SQUARED ERROR (RMSE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_i - y_i)^2$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i - o_i)^2}$$

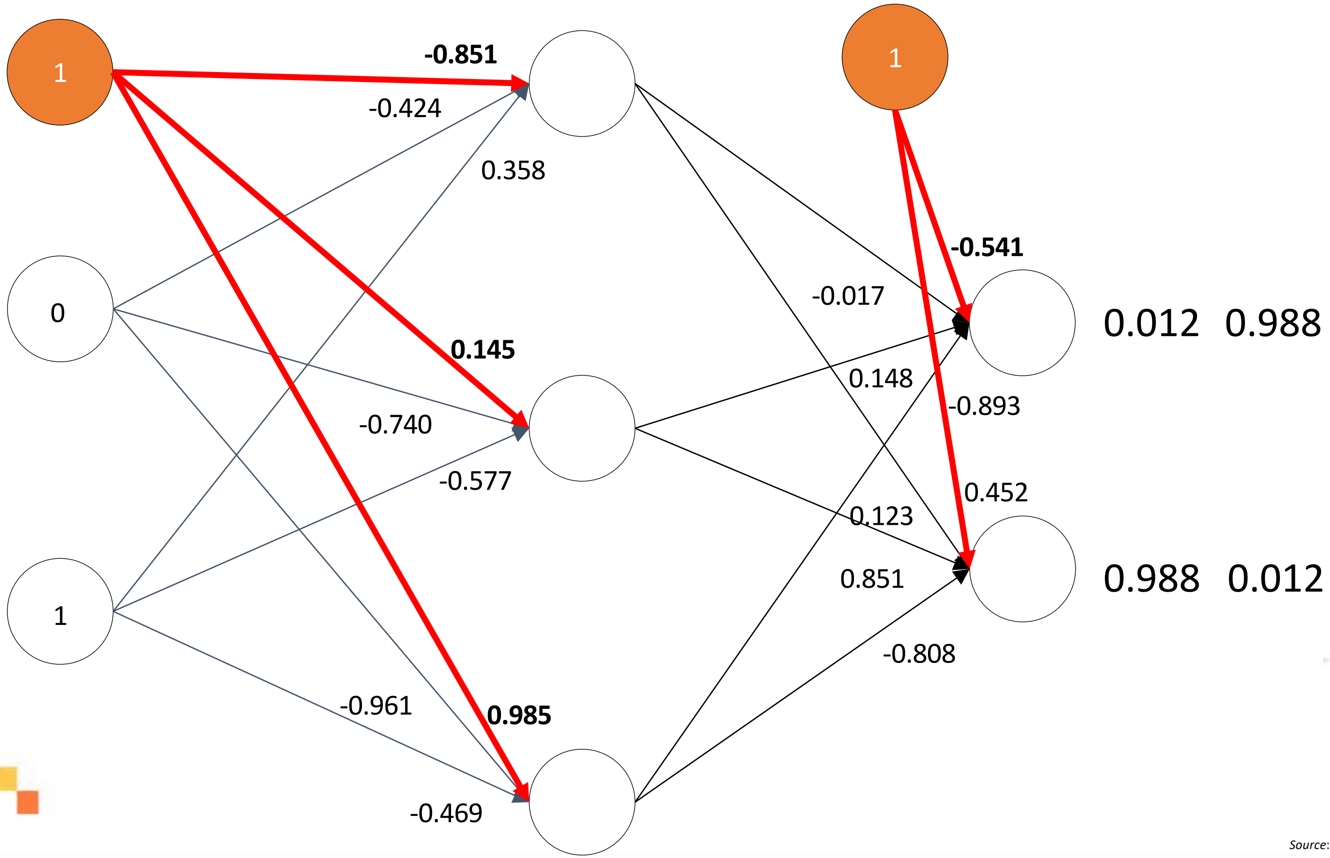
X1	X2	Class	Prediction	Error
0	0	0	0.405	$(0 – 0.405)^2 = 0.164$
0	1	1	0.431	$(1 – 0.431)^2 = 0.322$
1	0	1	0.436	$(1 – 0.436)^2 = 0.316$
1	1	0	0.458	$(0 - 0.458)^2 = 0.209$

10 (expected) – 5 (prediction) = 5 ($5^2 = 25$)
10 (expected) – 8 (prediction) = 2 ($2^2 = 4$)

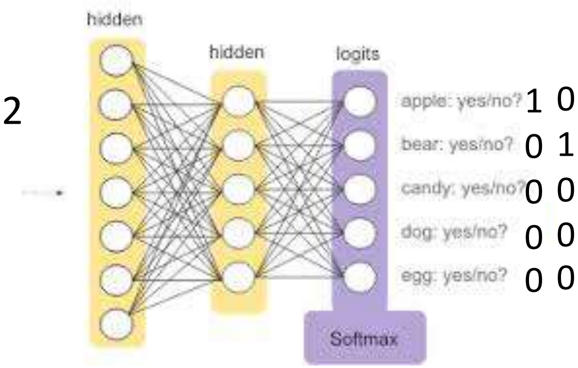
Sum = 1.011
MSE = 1.011 / 4 = 0.252
RMSE = 0.501

python

MULTIPLE OUTPUTS



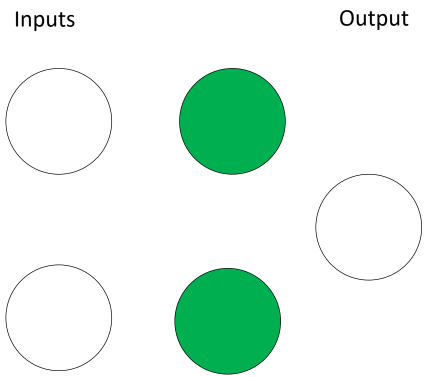
X1	X2	Class
0	0	0
0	1	1
1	0	1
1	1	0



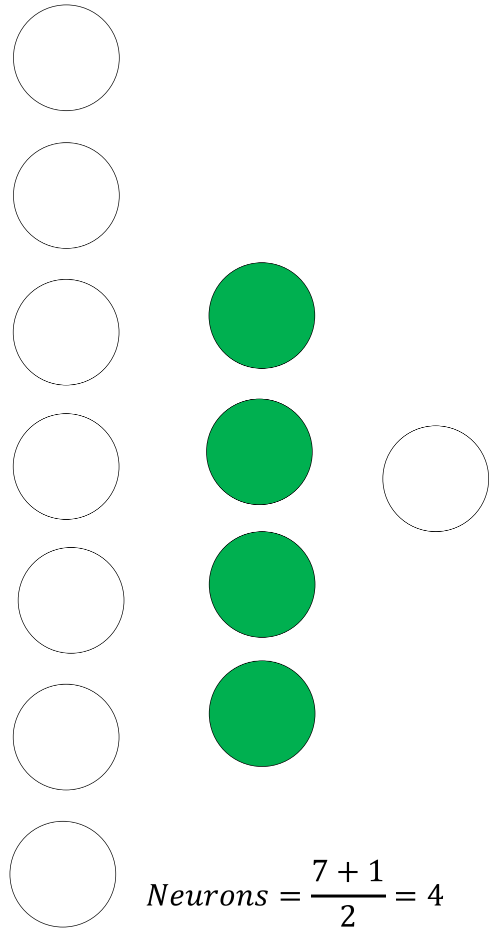
Source: https://developers.google.com/machine-learning/crash-course/multi-class-neural-networks/softmax

HIDDEN LAYERS

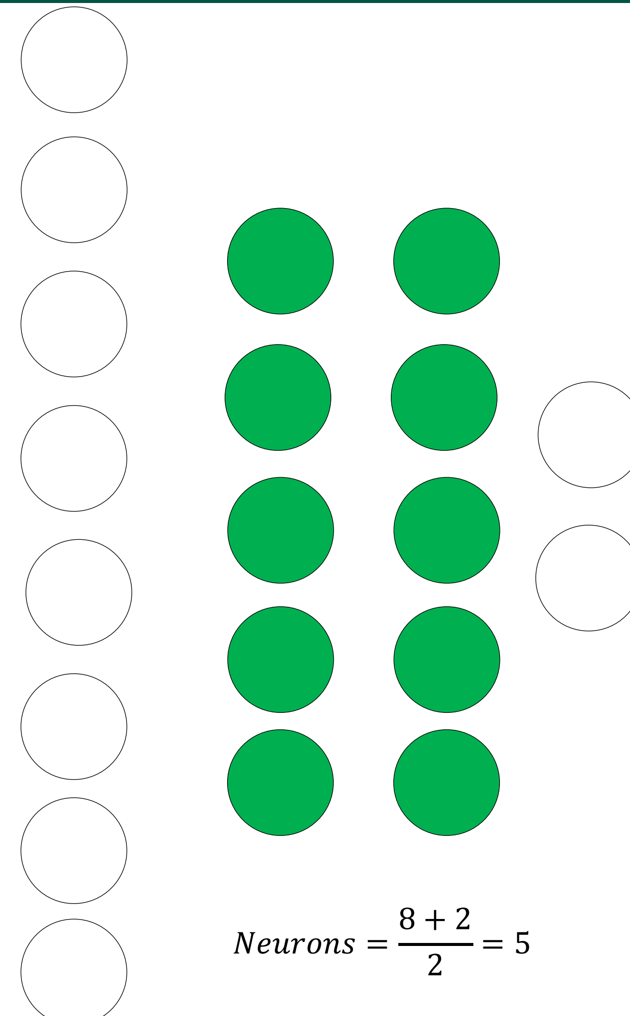
$$Neurons = \frac{Inputs + Outputs}{2}$$



$$Neurons = \frac{2+1}{2} = 1.5$$



$$Neurons = \frac{7+1}{2} = 4$$



$$Neurons = \frac{8+2}{2} = 5$$

HIDDEN LAYERS

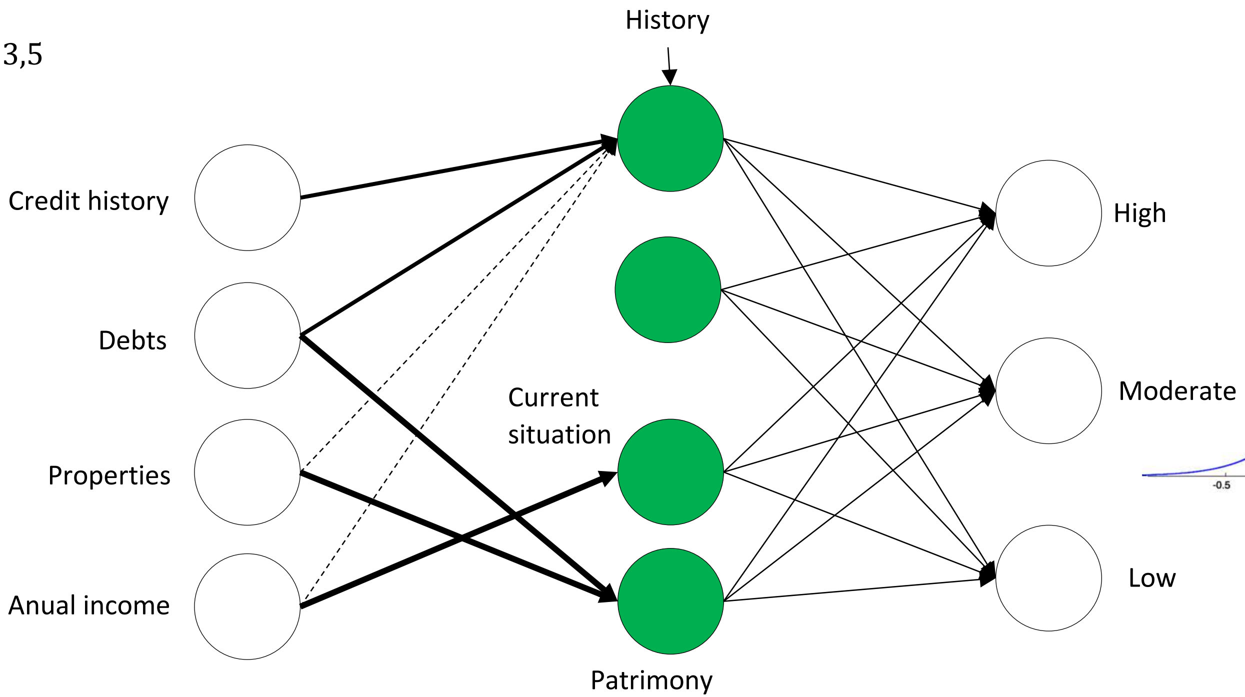
- Linearly separable problems do not require hidden layers
- In general, two layers work well
- Deep learning research shows that more layers are essential for more complex problems

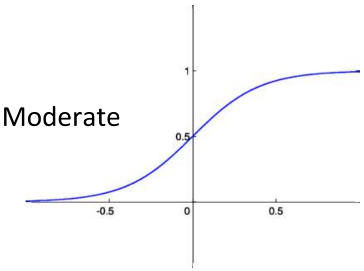
HIDDEN LAYERS

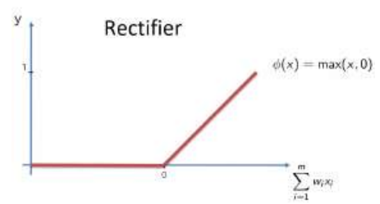
Credit history	Debts	Properties	Anual income	Risk
Bad	High	No	< 15.000	High
Unknown	High	No	>= 15.000 a <= 35.000	High
Unknown	Low	No	>= 15.000 a <= 35.000	Moderate
Unknown	Low	No	> 35.000	High
Unknown	Low	No	> 35.000	Low
Unknown	Low	Yes	> 35.000	Low
Bad	Low	No	< 15.000	High
Bad	Low	Yes	> 35.000	Moderate
Good	Low	No	> 35.000	Low
Good	High	Yes	> 35.000	Low
Good	High	No	< 15.000	High
Good	High	No	>= 15.000 a <= 35.000	Moderate
Good	High	No	> 35.0000	Low
Bad	High	No	>= 15.000 a <= 35.000	High

HIDDEN LAYERS

$$Neurons = \frac{4+3}{2} = 3{,}5$$

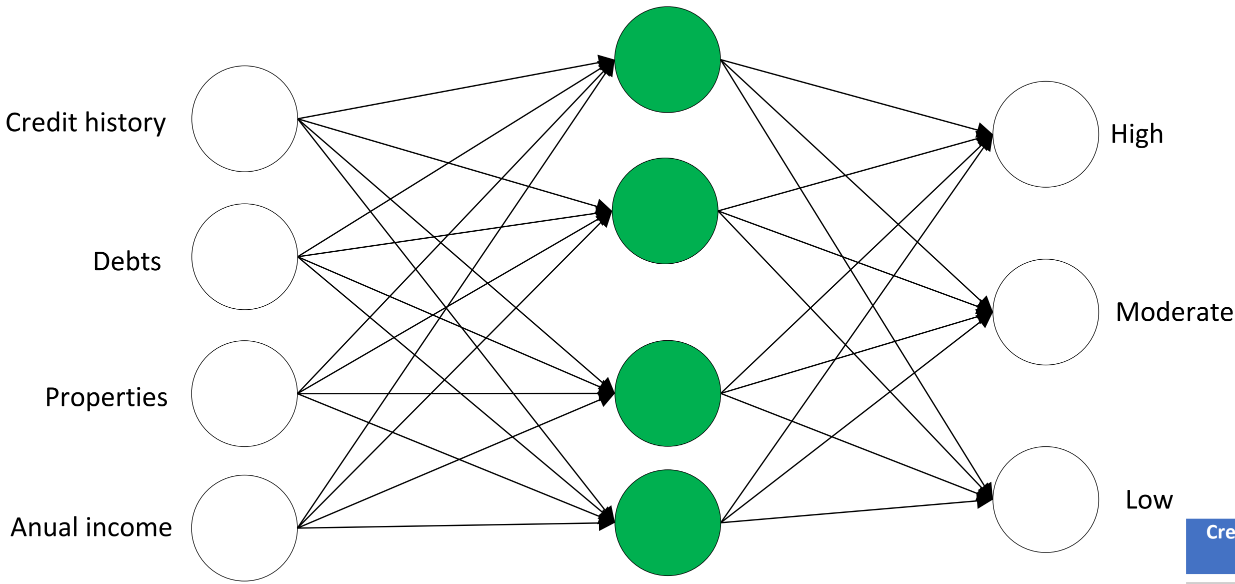






The higher the activation value, the more impact the neuron has

OUTPUT LAYER WITH CATEGORICAL DATA



error = correct – prediction

expected output = 1 0 0

prediction = 0.95 0.02 0.03

error = (1 – 0.95) + (0 – 0.02) + (0 – 0.03)

error = 0.05 + 0.02 + 0.03 = 0.08

Credit history	Debts	Properties	Anual income	Risk
3	1	1	1	1 0 0
2	1	1	2	1 0 0
2	2	1	2	0 1 0
2	2	1	3	1 0 0
2	2	1	3	0 0 1
2	2	2	3	0 0 1
3	2	1	1	1 0 0
3	2	2	3	0 1 0
1	2	1	3	0 0 1
1	1	2	3	0 0 1
1	1	1	1	1 0 0
1	1	1	2	0 1 0
1	1	1	3	0 0 1
3	1	1	2	1 0 0

STOCHASTIC GRADIENT DESCENT

Credit history	Debts	Properties	Anual income	Risk
3	1	1	1	1 0 0
2	1	1	2	1 0 0
2	2	1	2	0 1 0
2	2	1	3	1 0 0
2	2	1	3	0 0 1
2	2	2	3	0 0 1
3	2	1	1	1 0 0
3	2	2	3	0 1 0
1	2	1	3	0 0 1
1	1	2	3	0 0 1
1	1	1	1	1 0 0
1	1	1	2	0 1 0
1	1	1	3	0 0 1
3	1	1	2	1 0 0

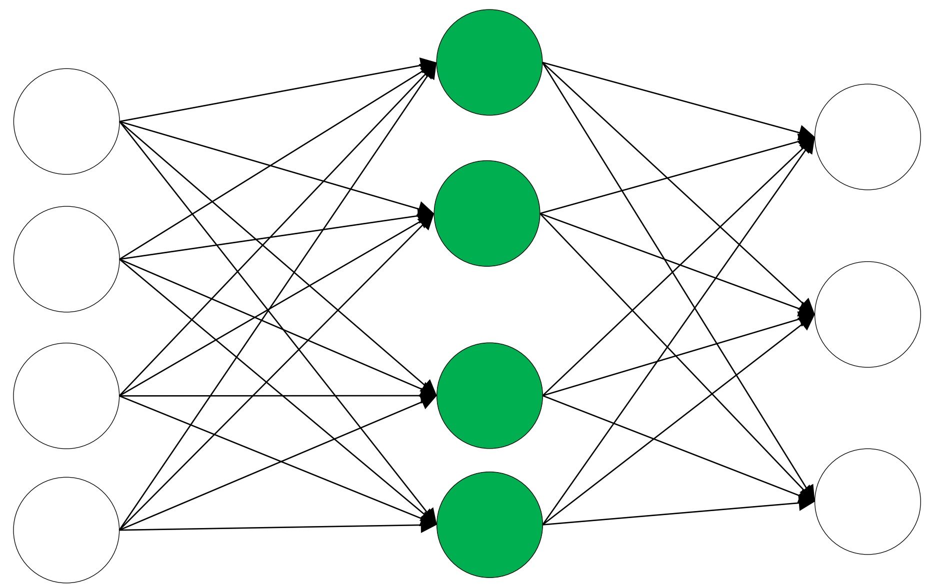
Credit history	Debts	Properties	Anual income	Risk
3	1	1	1	1 0 0
2	1	1	2	1 0 0
2	2	1	2	0 1 0
2	2	1	3	1 0 0
2	2	1	3	0 0 1
2	2	2	3	0 0 1
3	2	1	1	1 0 0
3	2	2	3	0 1 0
1	2	1	3	0 0 1
1	1	2	3	0 0 1
1	1	1	1	1 0 0
1	1	1	2	0 1 0
1	1	1	3	0 0 1
3	1	1	2	1 0 0

Batch gradient descent

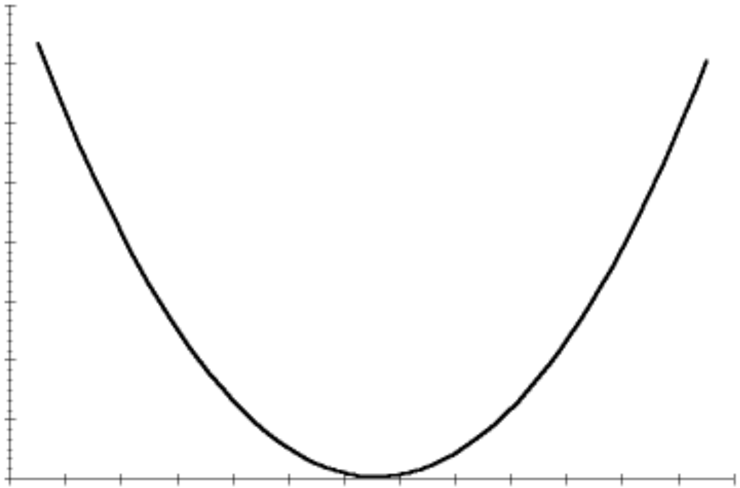
Calculate the error for all instances and then update the weights

Stochastic gradient descent

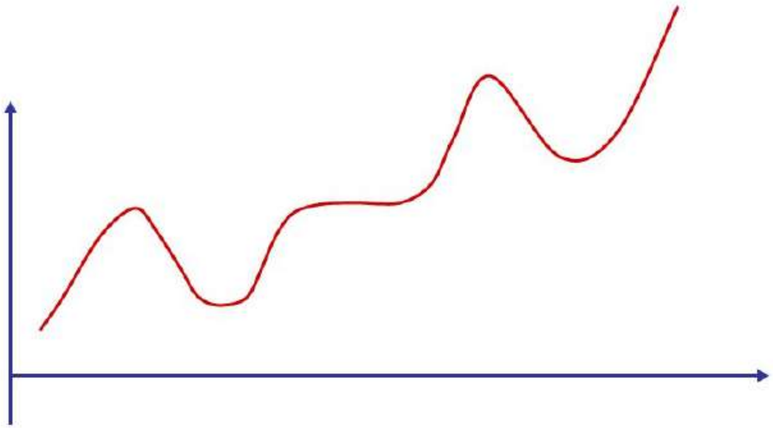
Calculate the error for each instance and then update the weights



CONVEX AND NON CONVEX



Convex



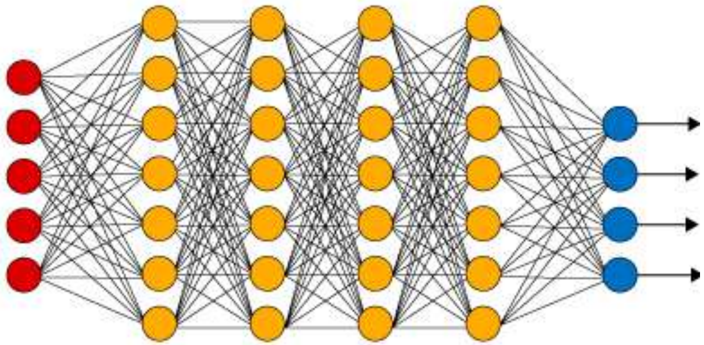
Non convex

python

GRADIENT DESCENT

- Stochastic gradient descent
  - Prevent local minimums (non convex)
  - Faster
- Mini batch gradient descent
  - Select a pre-defined number of instances in order to calculate the error and update the weights

- 90’s: SVM (Support Vector Machines)
- From 2006, several algorithms were created for training neural networks
- Two or more hidden layers

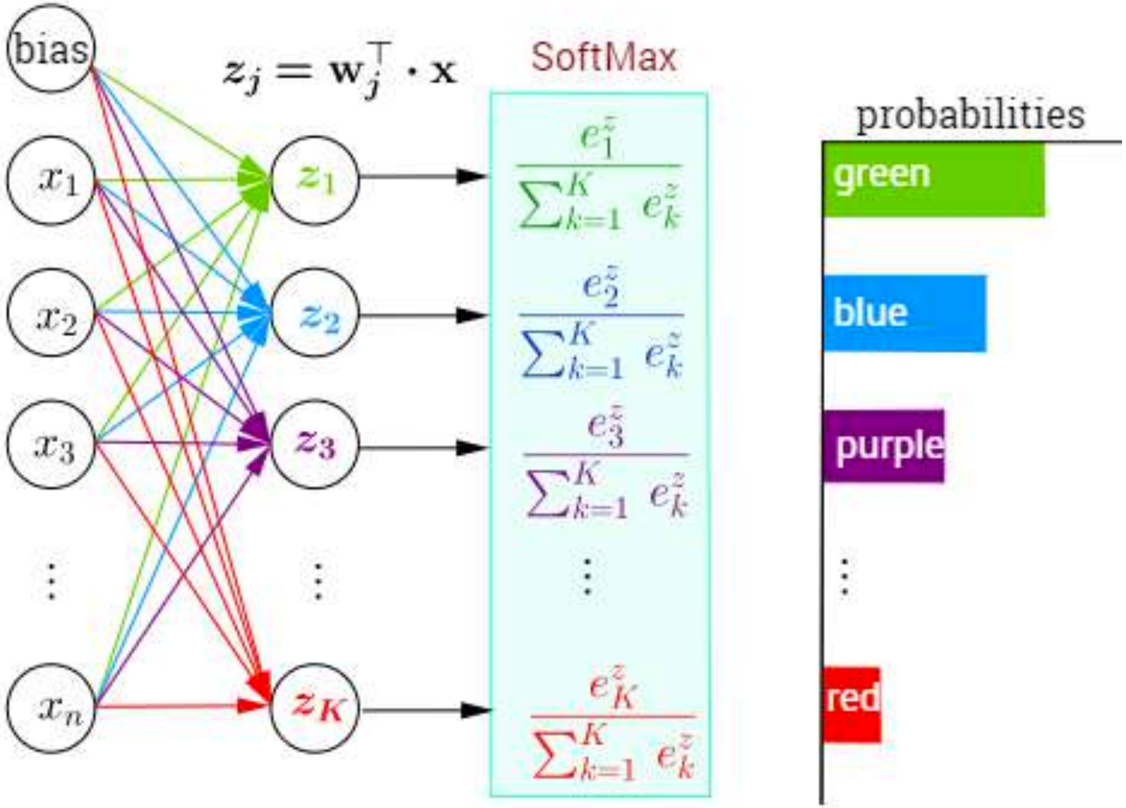


DEEP LEARNING

- Convolutional neural networks
- Recurrent neural networks
- Autoencoders
- GANs (Generative adversarial networks)

SOFTMAX

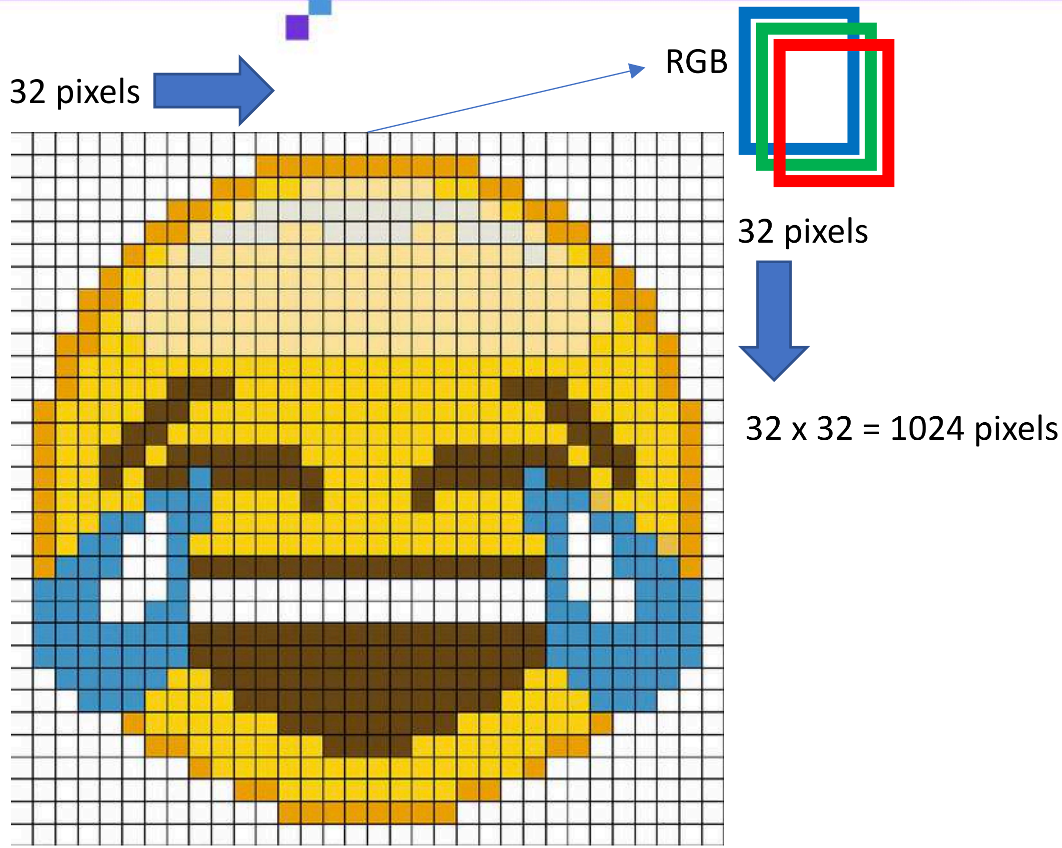
$$Y = \frac{e(x)}{\sum \quad e(x)}$$



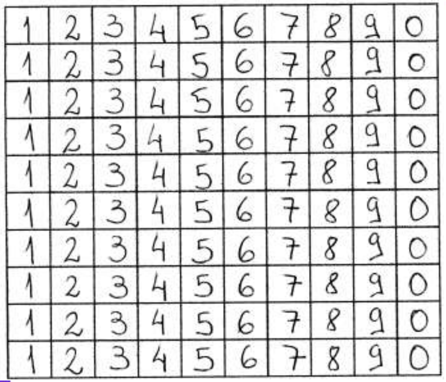
PLAN OF ATTACK – NEURAL NETWORKS FOR IMAGE CLASSIFICATION

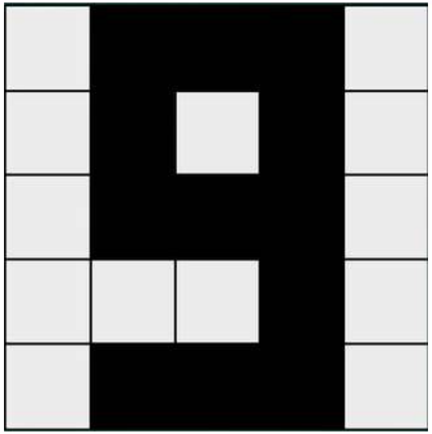
1. Intuition about neural networks
2. Neural network using the pixels of the images
3. Feature extractor with OpenCV
4. Neural network using feature extraction

PIXELS

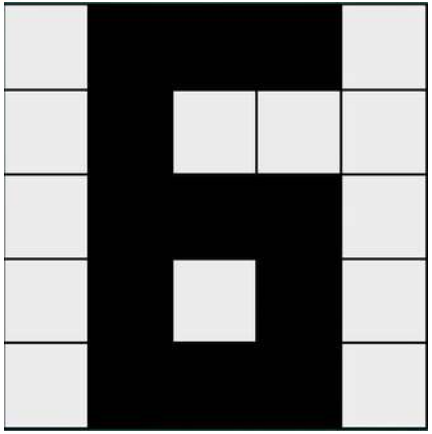


PIXELS

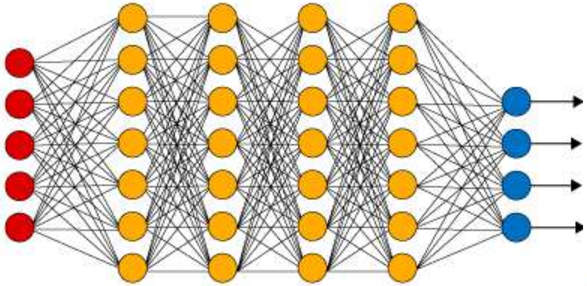




0,1,1,1,0,0,1,0,1,0,0,1,1,1,0,0,0,0,1,0,0,1,1,1,0,**9**



0,1,1,1,0,0,1,0,0,0,0,1,1,1,0,0,1,0,1,0,0,1,1,1,0,**6**

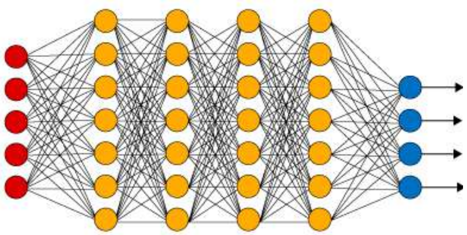


FEATURE EXTRACTION

Brown (mouth)
Blue (pants)
Gray (shoes)

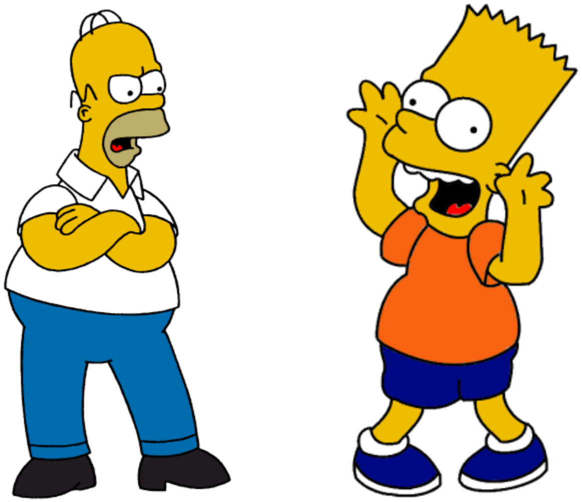
Orange (T-Shirt)
Blue (shorts)
Blue (sneakers)

```
0.0,0.0,0.087449393,9.861538462,8.660728745,2.257489879,0
0.0,0.0,0.012995452,4.980506823,0.0,0.0,0
0.0,0.0,0.014219662,9.668452534,1.034365711,1.034365711,0
0.0,0.0,0.013168984,10.734478157,5.981352718,2.126352016,0
0.979401078,16.958948664,2.349976559,2.48769339,0.0,0.0,1
0.058665773,15.566543748,0.306738183,0.0,0.0,0.0,1
1.829063147,14.074792961,2.135093168,0.0,0.0,0.0,1
2.804717308,0.152271939,0.026014568,0.0,0.0,0.0,1
2.510348847,0.0,0.037677839,0.0,0.0,0.0,1
```



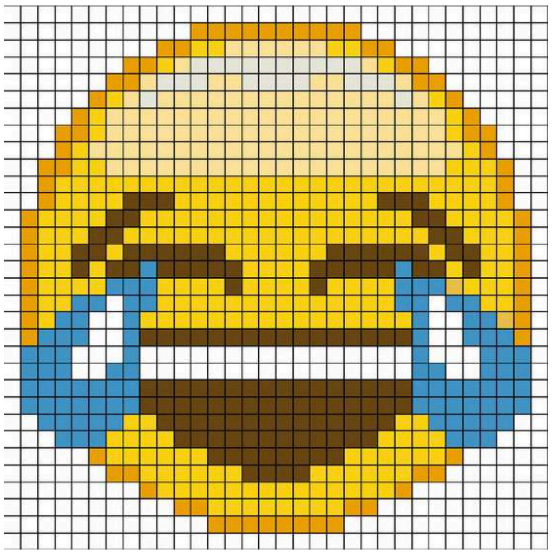
PLAN OF ATTACK – CONVOLUTIONAL NEURAL NETWORKS FOR IMAGE CLASSIFICATION

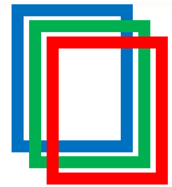
1. Intuition about convolutional neural networks
2. Types of neural networks for image classification
3. Convolutional neural network for image classification

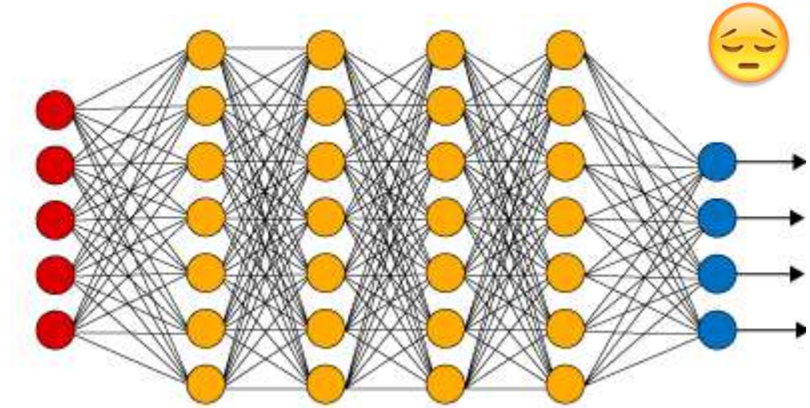


PIXELS

32 x 32 = 1.024 x 3 = **3.072 inputs**







- It does not use all pixels
- It applies a dense neural network, but at the beginning it transforms the data
- What are the most important features?

CONVOLUTIONAL NEURAL NETWORK STEPS

1. Convolution operation
2. Pooling
3. Flattening
4. Dense neural network

STEP 1: CONVOLUTION OPERATION

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

Image

X

1	0	0
1	0	1
0	1	1

Feature detector

=

0				

Feature map

0 * 1 + 0 * 0 + 0 * 0 + 0 * 1 + 1 * 0 + 0 * 1 + 0 * 0 + 0 * 1 + 0 * 1 = 0

STEP 1: CONVOLUTION OPERATION

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

Image

X

1	0	0
1	0	1
0	1	1

Feature detector

=

0	1			

Feature map

$$0 * 1 + 0 * 0 + 0 * 0 + 1 * 1 + 0 * 0 + 0 * 1 + 0 * 0 + 0 * 1 + 0 * 1 = 1$$

STEP 1: CONVOLUTION OPERATION

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

Image

X

1	0	0
1	0	1
0	1	1

Feature detector

=

0	1	0		

Feature map

0 * 1 + 0 * 0 + 0 * 0 + 0 * 1 + 0 * 0 + 0 * 1 + 0 * 0 + 0 * 1 + 0 * 1 = 0

STEP 1: CONVOLUTION OPERATION

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

Image

X

1	0	0
1	0	1
0	1	1

Feature detector

=

0	1	0	1	

Feature map

0 * 1 + 0 * 0 + 0 * 0 + 0 * 1 + 0 * 0 + 1 * 1 + 0 * 0 + 0 * 1 + 0 * 1 = 1

STEP 1: CONVOLUTION OPERATION

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

Image

X

1	0	0
1	0	1
0	1	1

Feature detector

=

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

$$1 * 1 + 0 * 0 + 0 * 0 + 1 * 1 + 0 * 0 + 1 * 1 + 0 * 0 + 1 * 1 + 1 * 1 = 5$$

STEP 1: CONVOLUTION OPERATION – RELU

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

Image

X

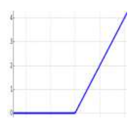
1	0	0
1	0	1
0	1	1

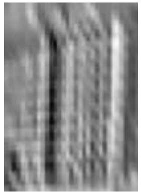
Feature detector

=

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

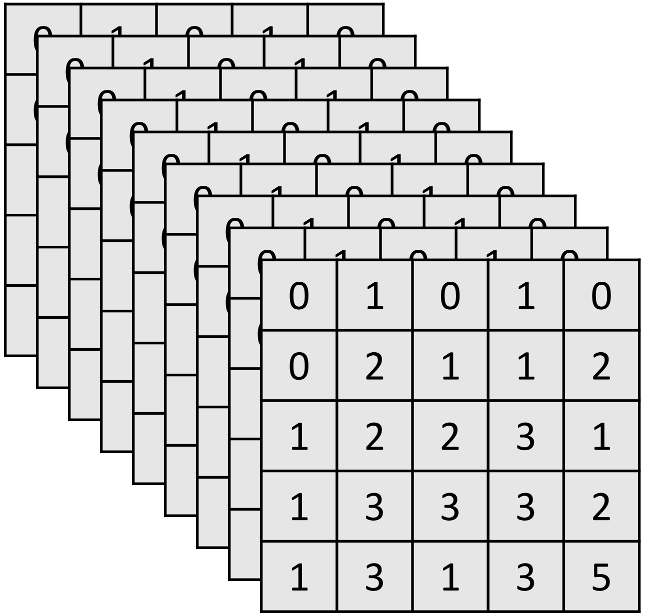




STEP 1: CONVOLUTIONAL LAYER

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

Image

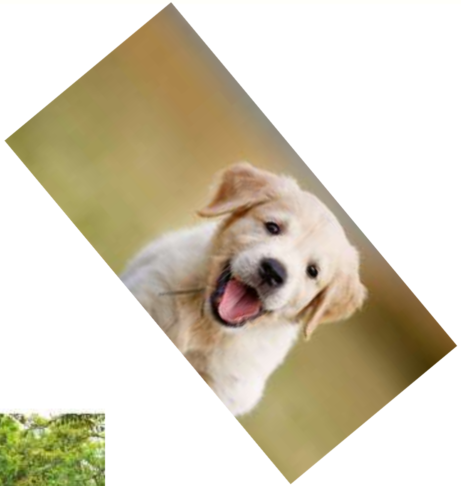


Feature maps

The network will decide which feature detector to use

The convolutional layer is the set of feature maps

STEP 2: POOLING



STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

2		

STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

2	1	

STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

2	1	2

STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

2	1	2
3		

STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

2	1	2
3	3	

STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

2	1	2
3	3	2

STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

2	1	2
3	3	2
3		

STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

Feature map

2	1	2
3	3	2
3	3	

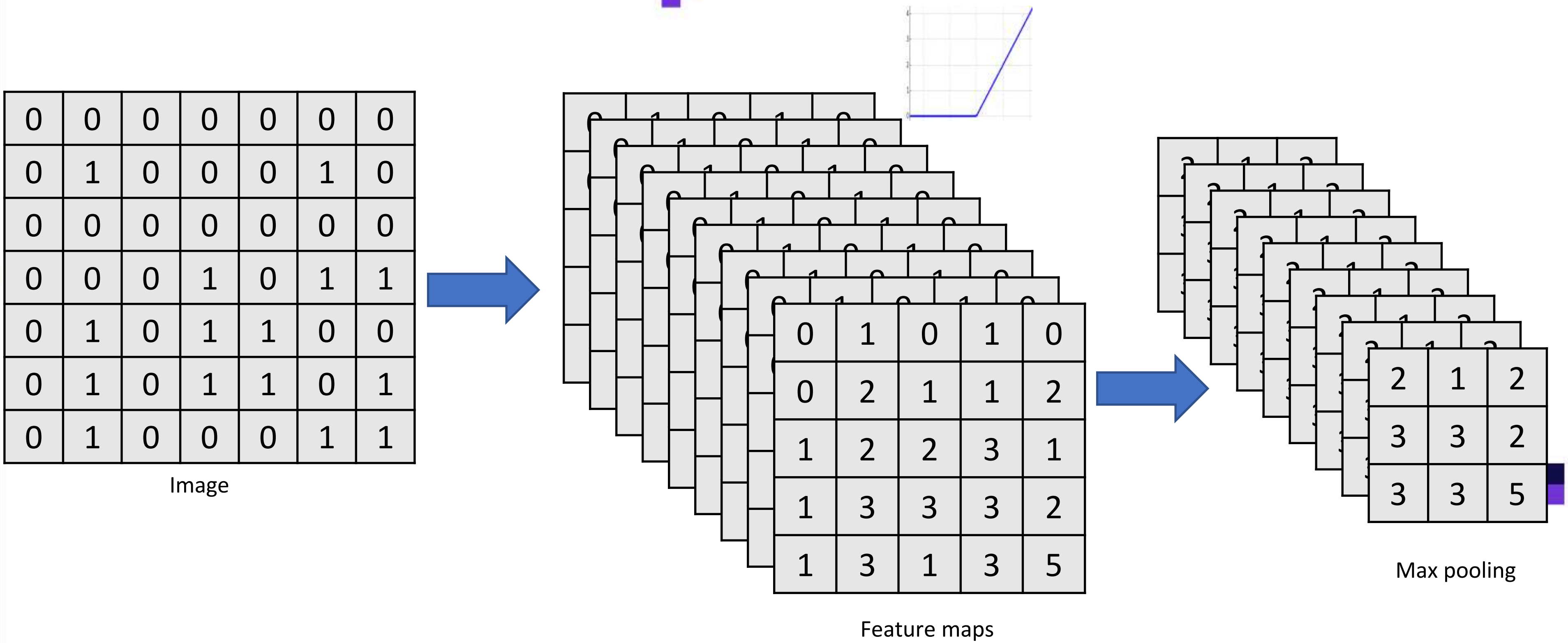
STEP 2: POOLING

0	1	0	1	0
0	2	1	1	2
1	2	2	3	1
1	3	3	3	2
1	3	1	3	5

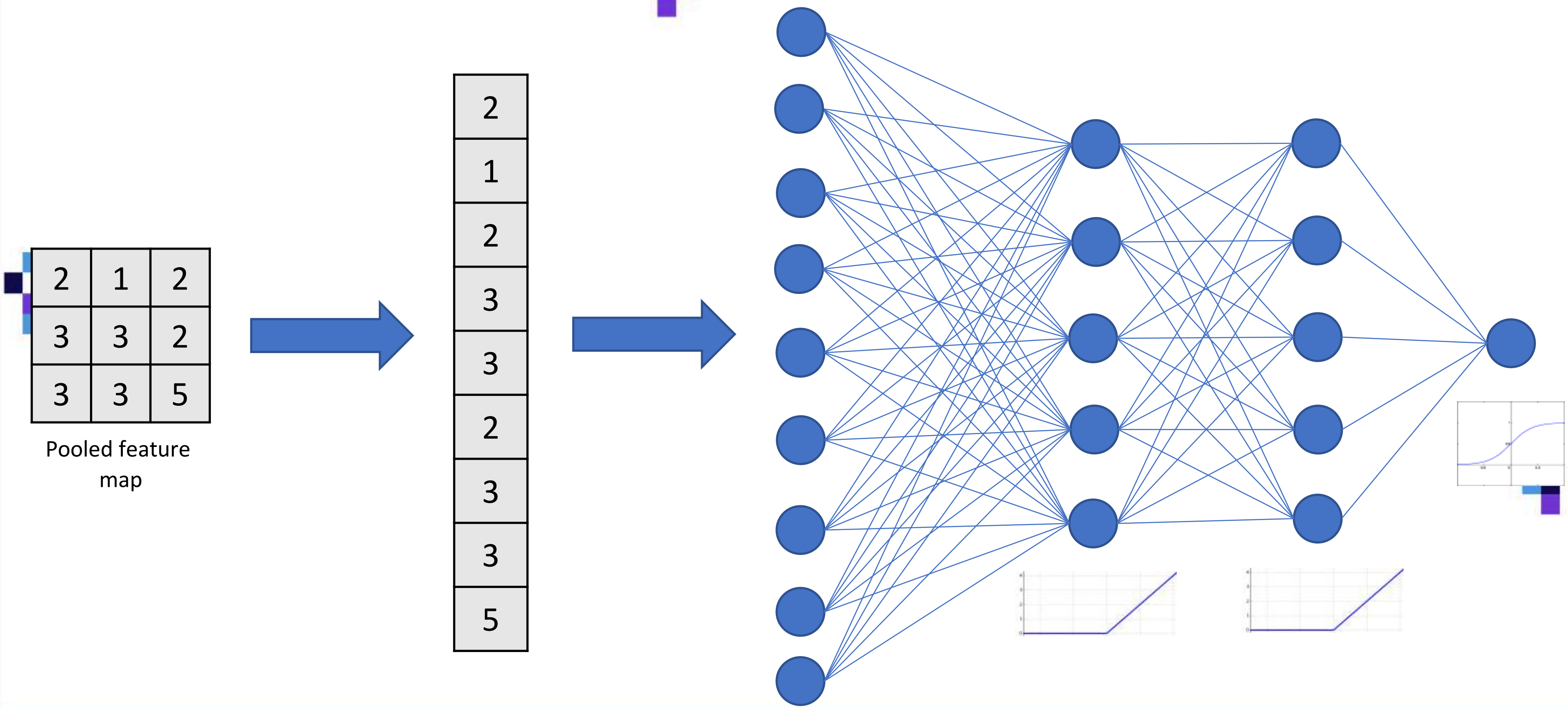
Feature map

2	1	2
3	3	2
3	3	5

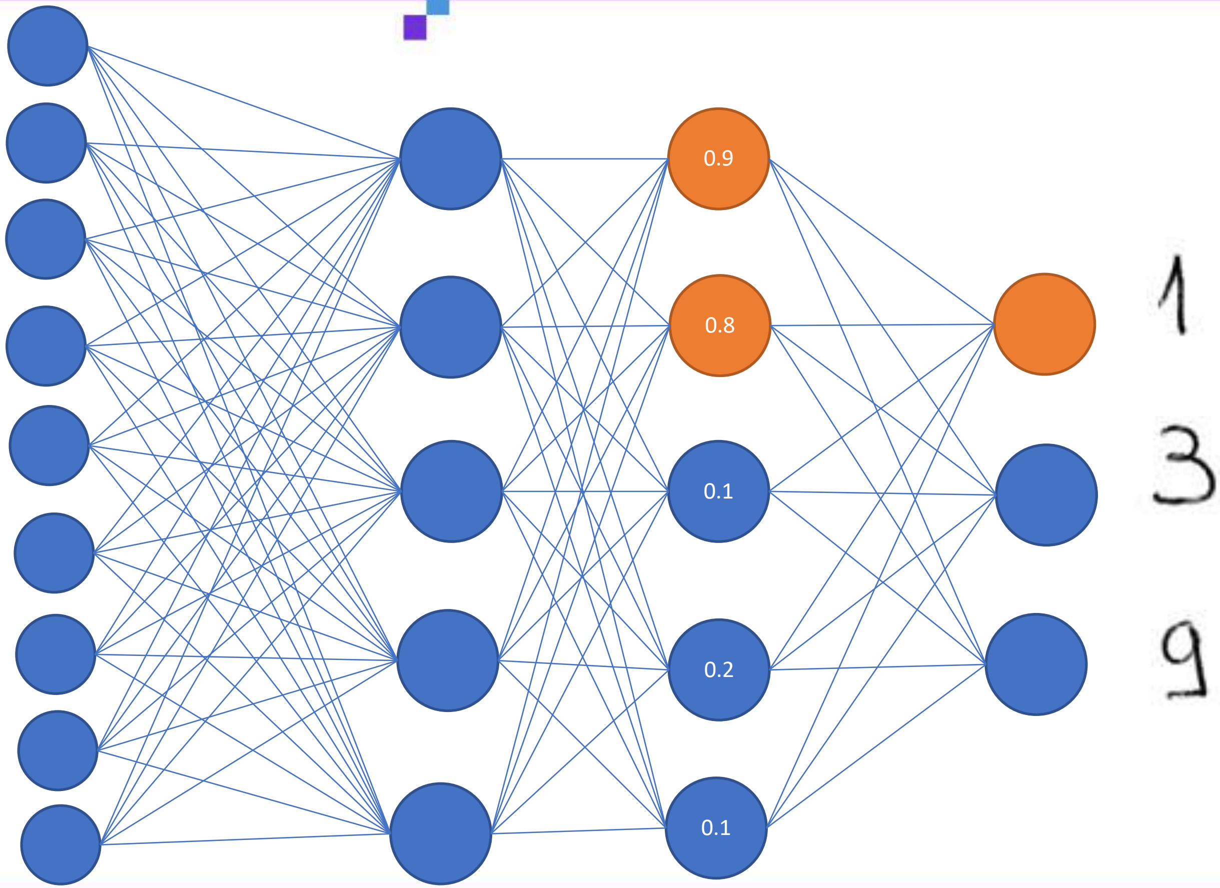
CONVOLUTIONAL NEURAL NETWORK – POOLING



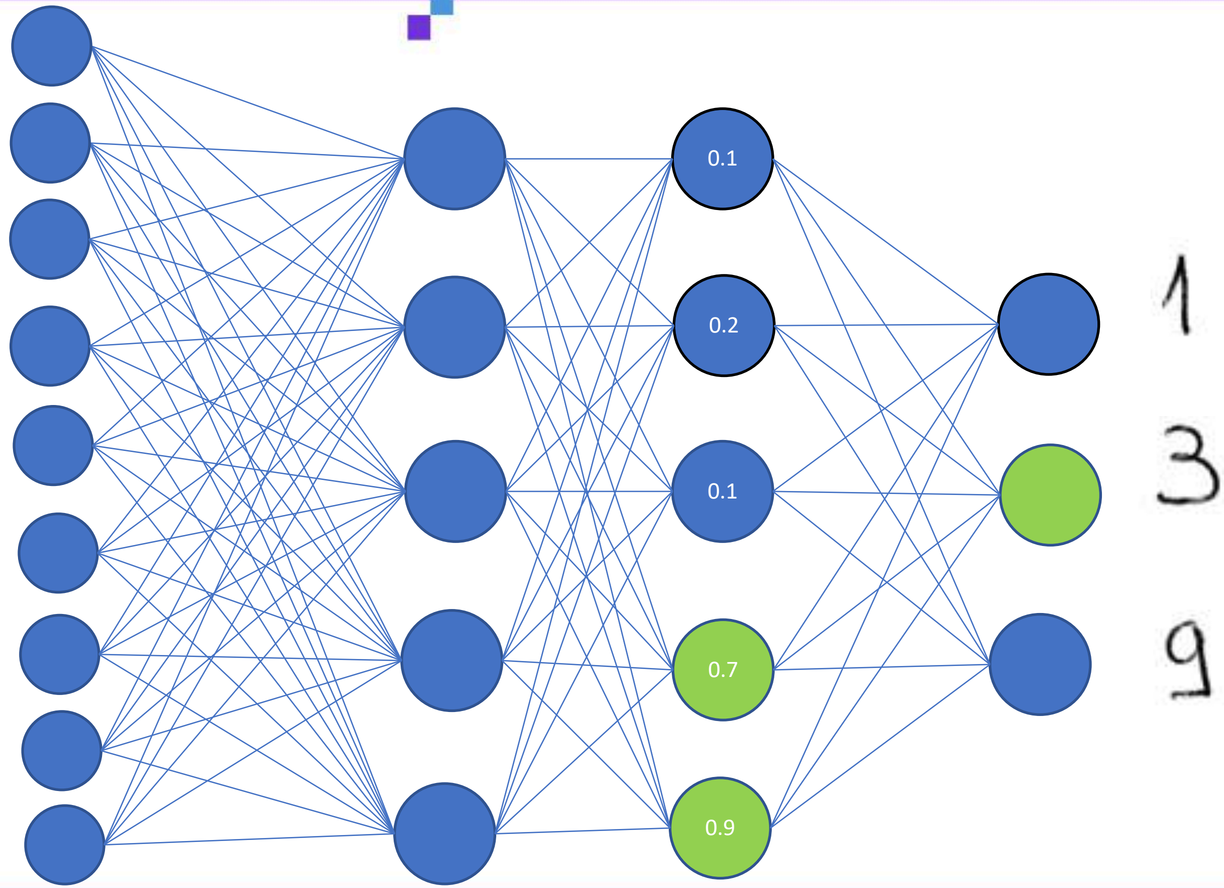
STEP 3: FLATTENING



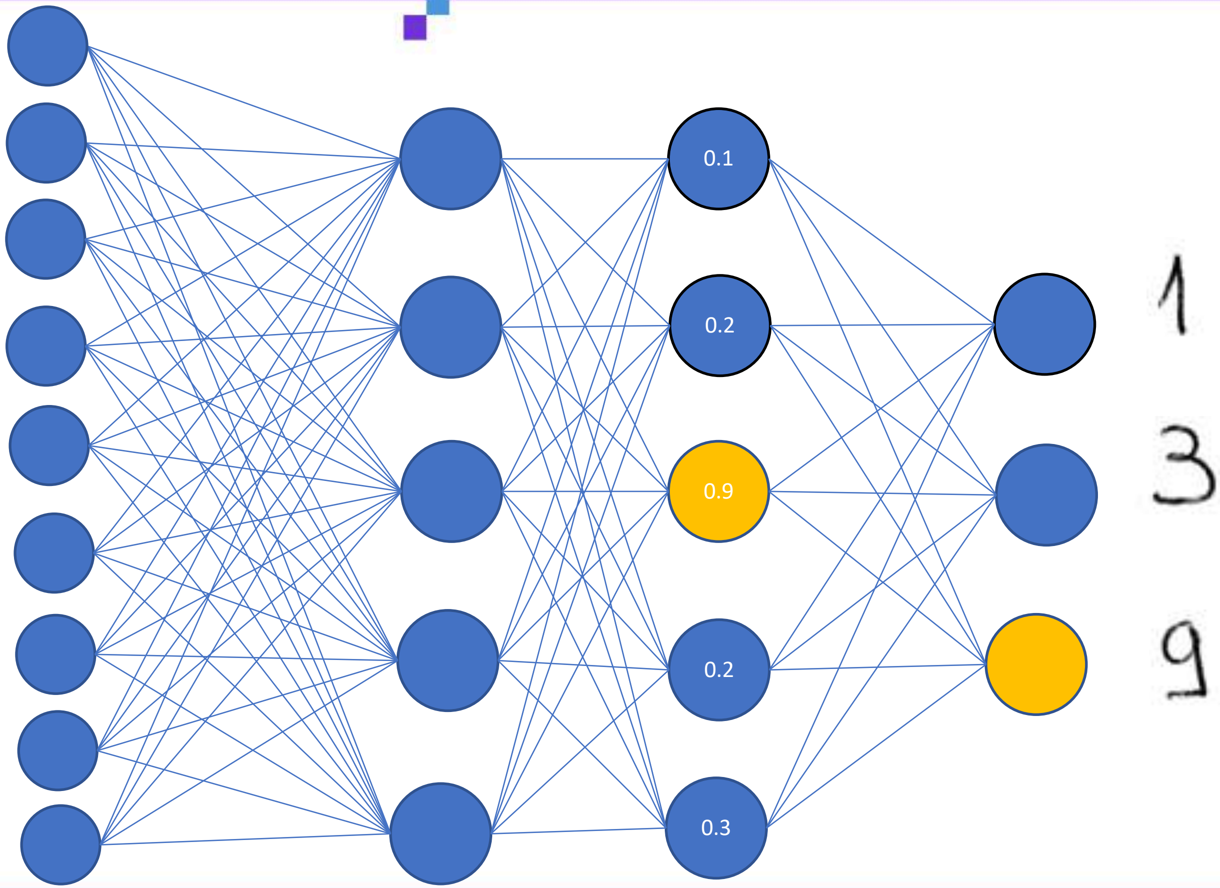
STEP 3: DENSE NEURAL NETWORK



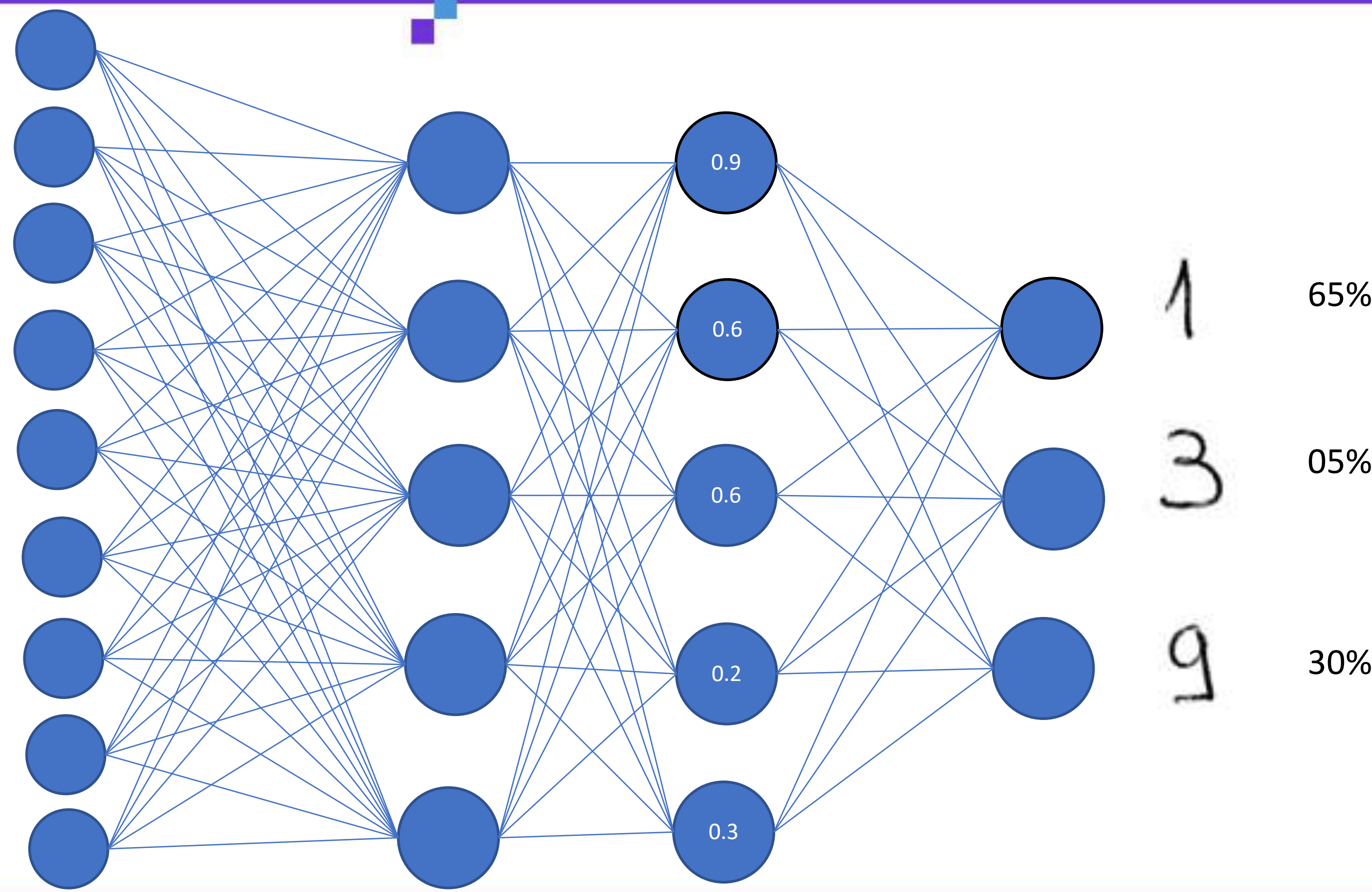
STEP 3: DENSE NEURAL NETWORK



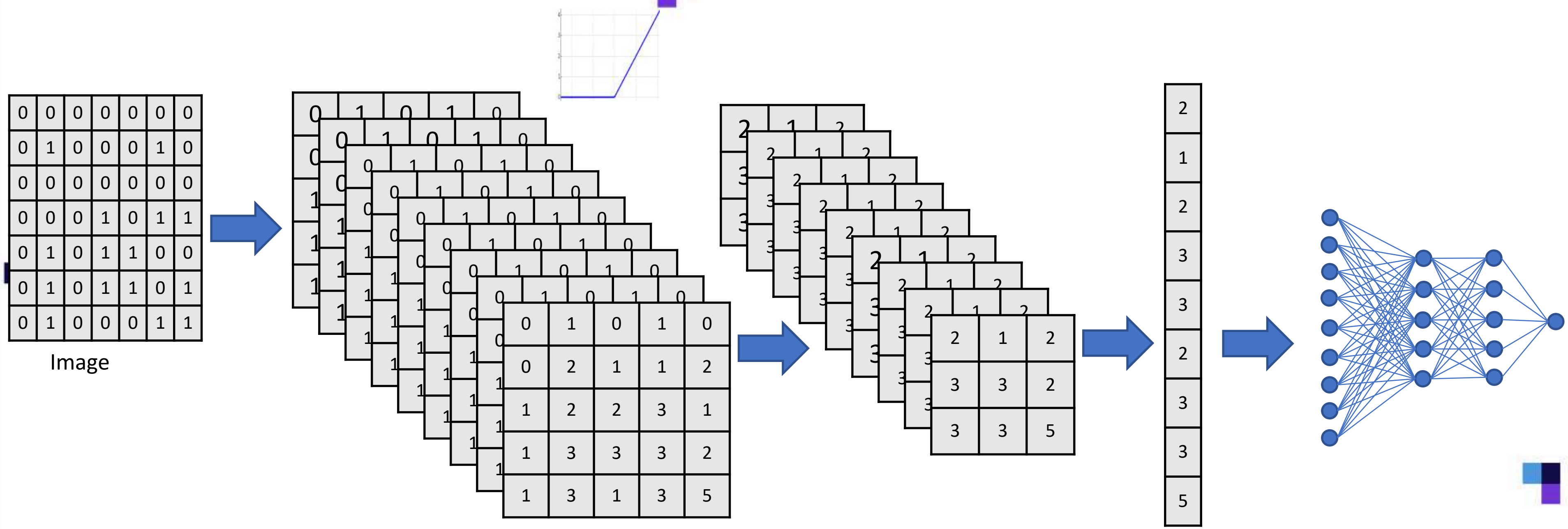
STEP 3: DENSE NEURAL NETWORK



STEP 3: DENSE NEURAL NETWORK



CONVOLUTIONAL NEURAL NETWORK

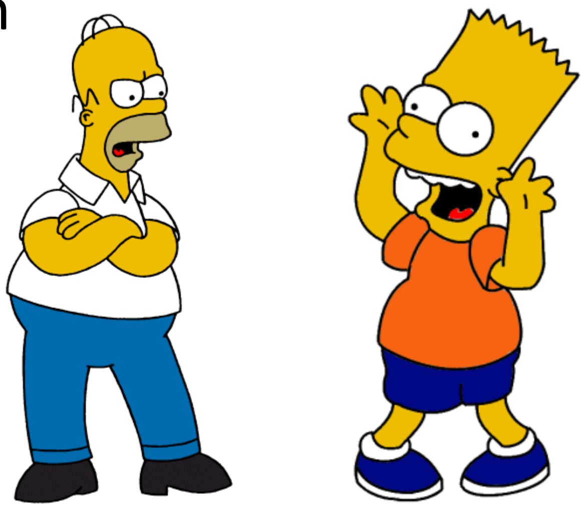


Training using gradient descent

In addition to adjusting the weights, the feature detector is also changed

PLAN OF ATTACK – TRANSFER LEARNING AND FINE TUNING FOR IMAGE CLASSIFICATION

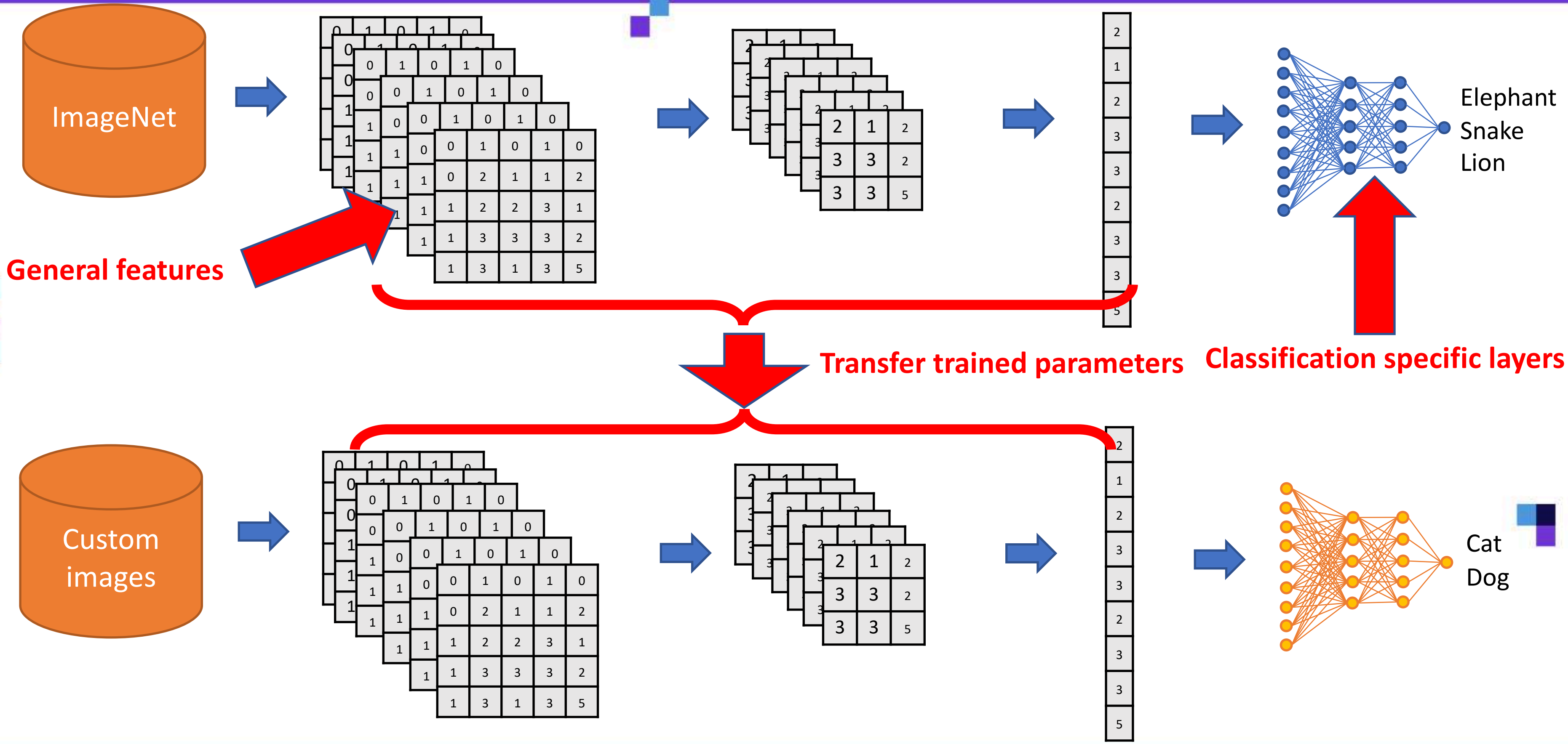
1. Intuition about transfer learning
2. Implementation
3. Intuition about fine tuning
4. Implementation



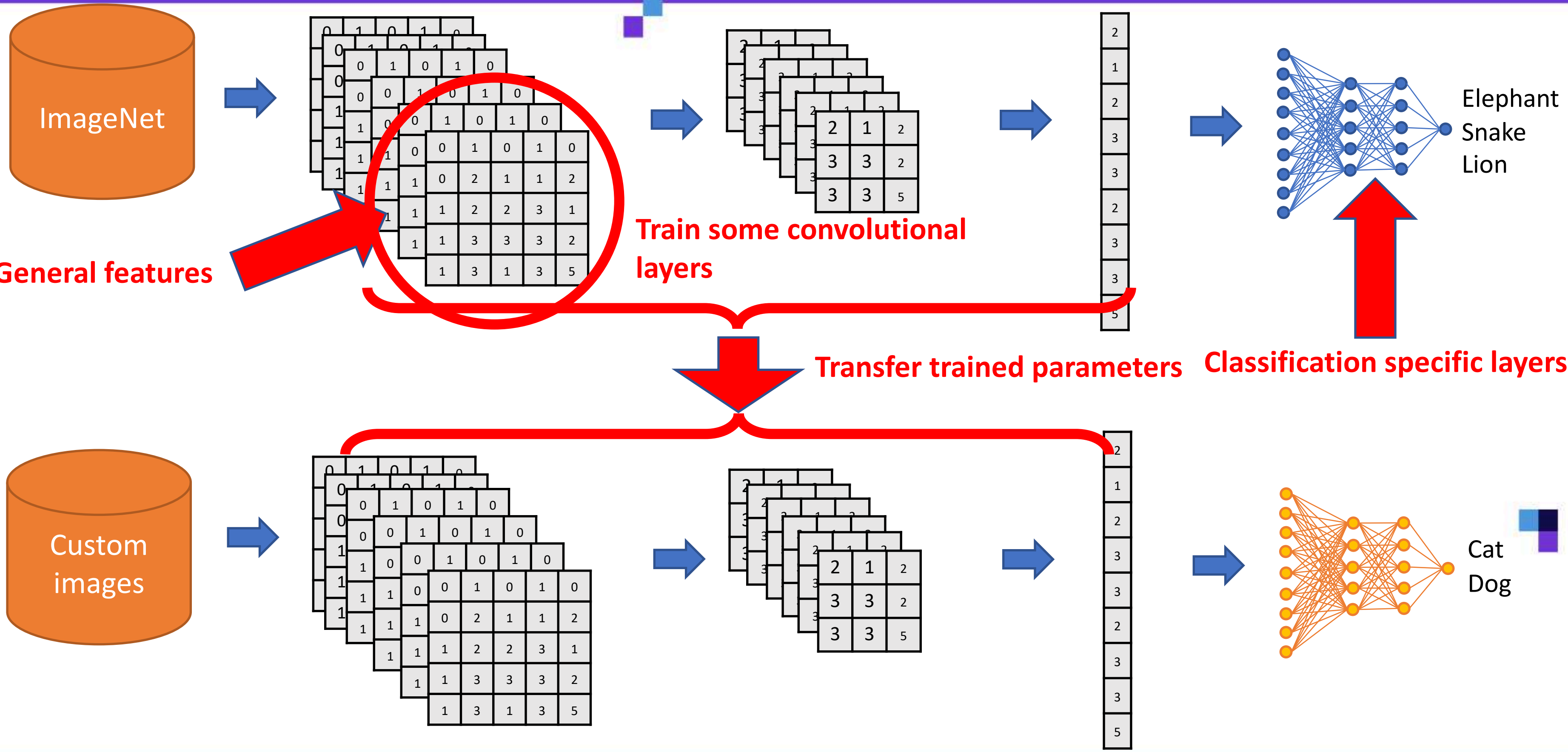
TRANSFER LEARNING

KNOWLEDGE TRANSFER

TRANSFER LEARNING



FINE TUNING


ImageNet
General features
Train some convolutional layers
Elephant
Snake
Lion
Transfer trained parameters
Classification specific layers
Custom images
Cat
Dog

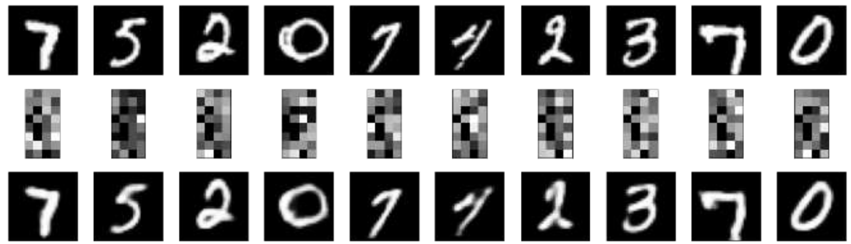
PLAN OF ATTACK – NEURAL NETWORKS FOR CLASSIFICATION OF EMOTIONS

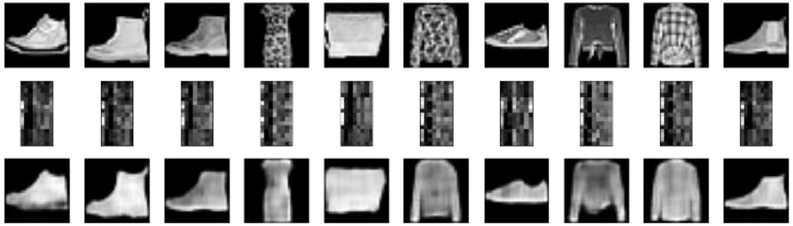
1. Implementation of convolutional neural networks
2. Detecting emotions in images
3. Detecting emotions in videos

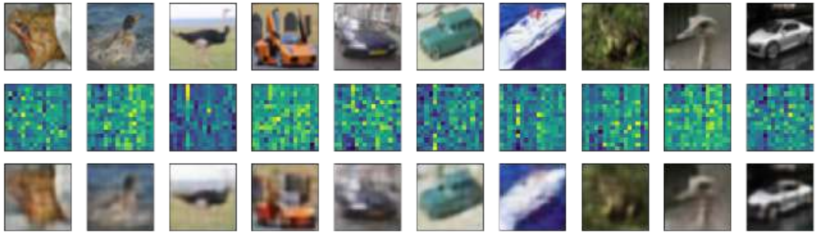
Source: EPFL

PLAN OF ATTACK – AUTOENCODERS

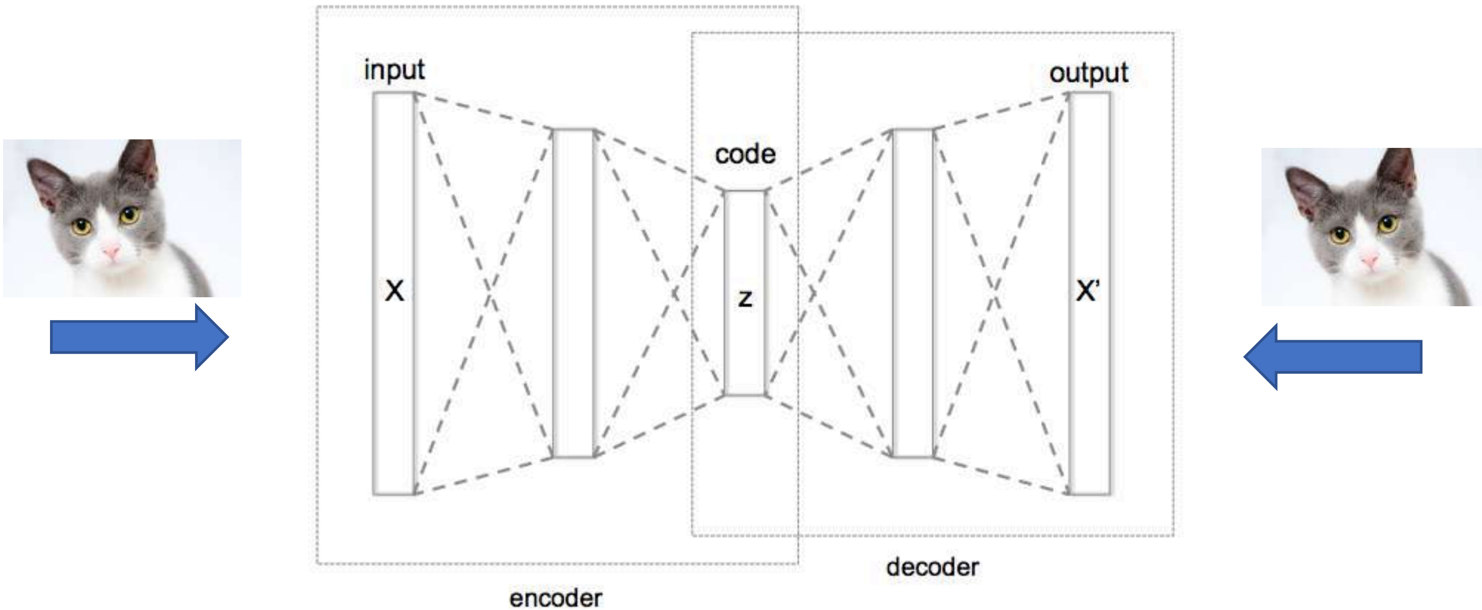
1. Intuition about autoencoders
2. Implementation of linear autoencoders
3. Implementation of convolutional autoencoders



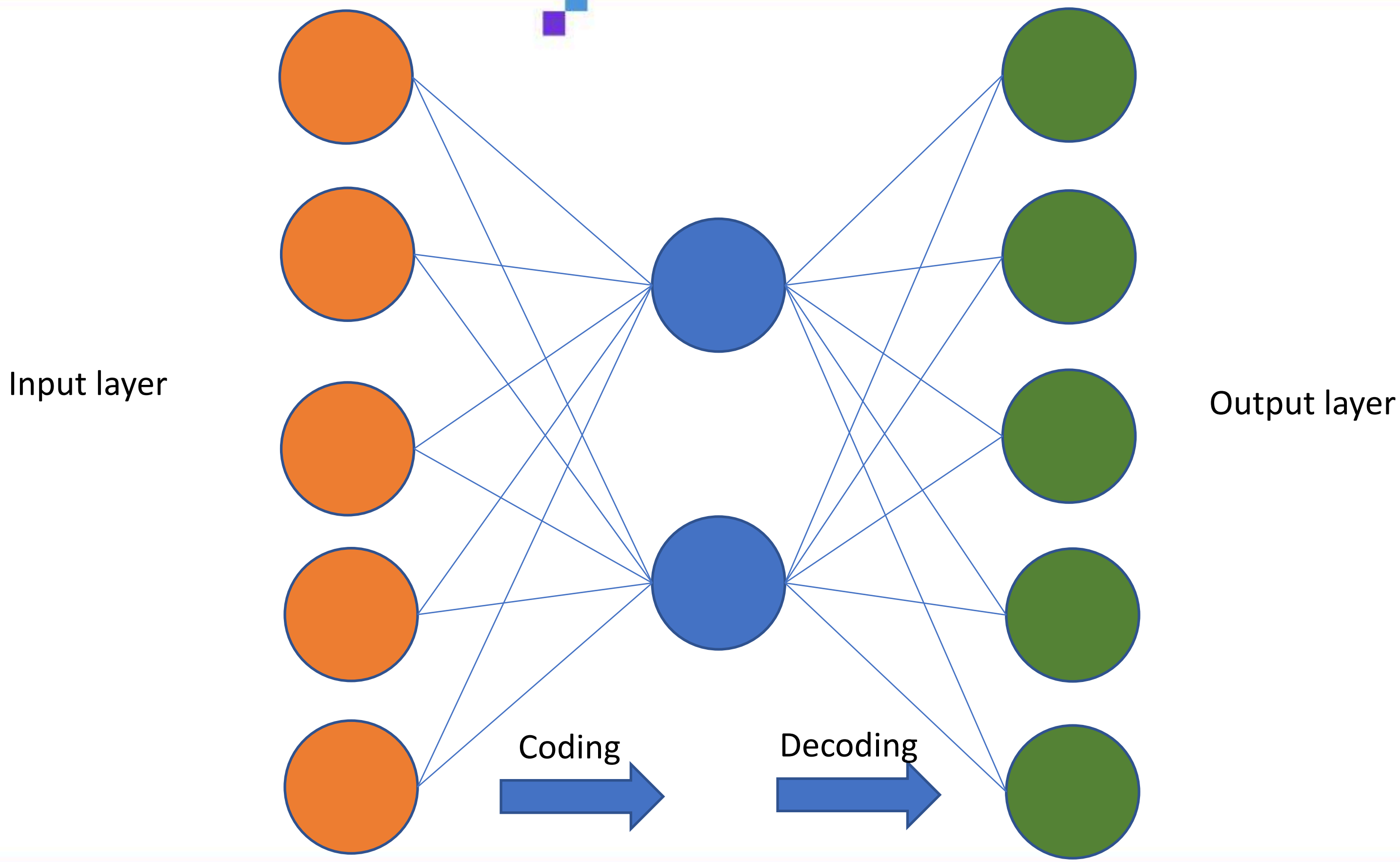




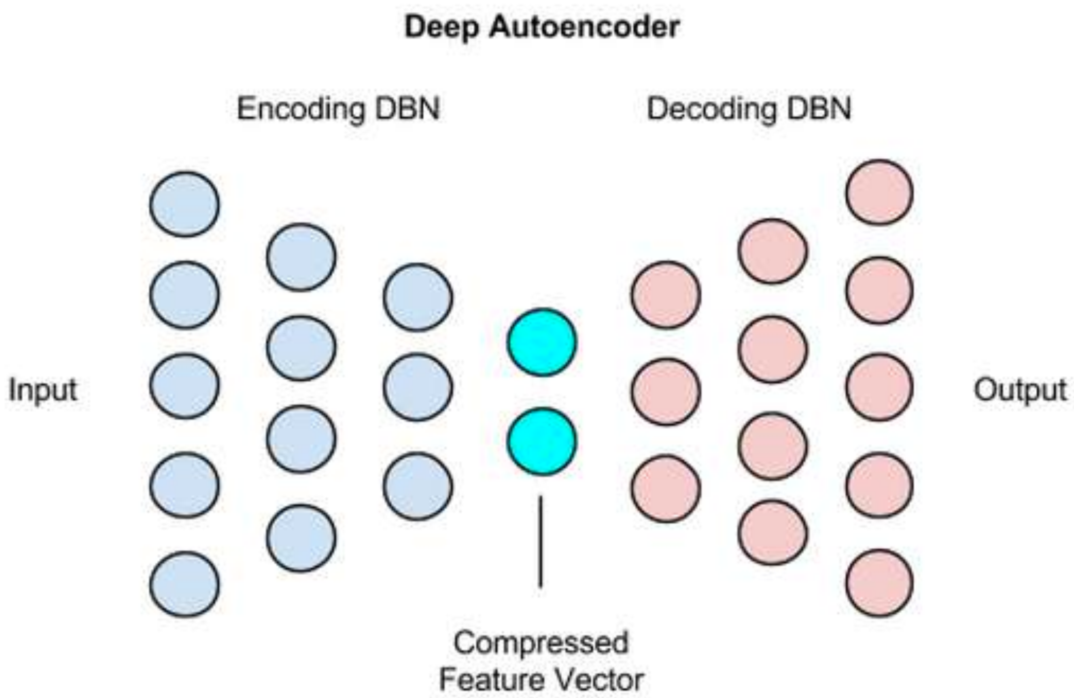
AUTOENCODERS



LINEAR AUTOENCODERS

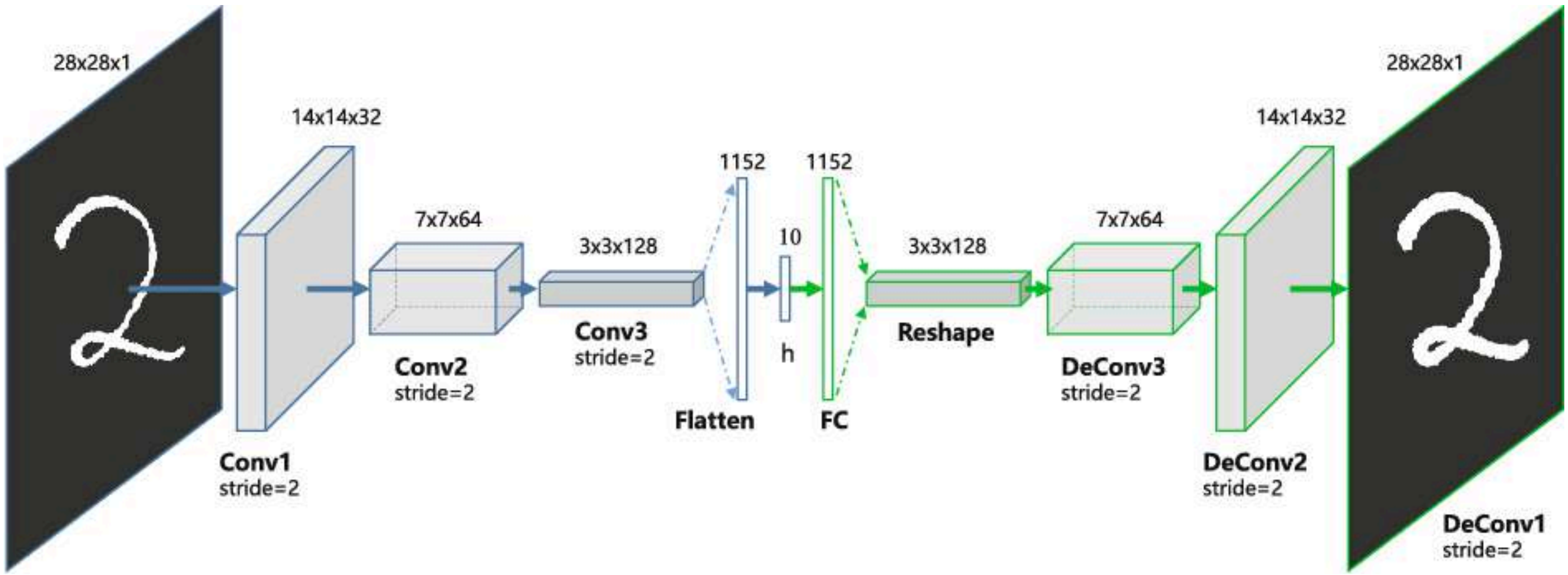


LINEAR AUTOENCODERS



Source: https://skymind.ai/wiki/deep-autoencoder

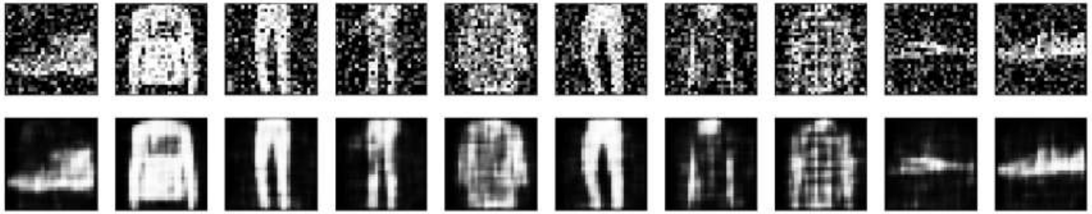
CONVOLUTIONAL AUTOENCODERS

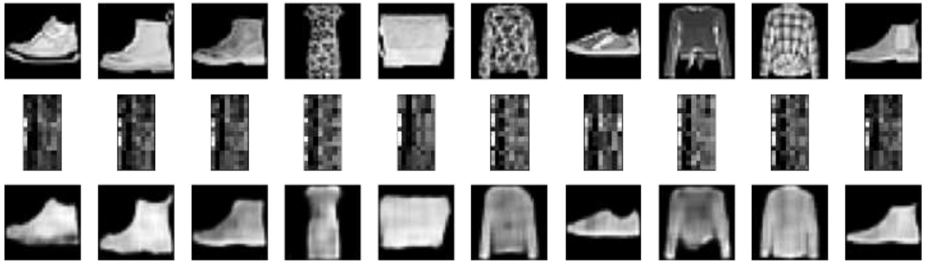


Source: https://www.semanticscholar.org/paper/Deep-Clustering-with-Convolutional-Autoencoders-Guo-Liu/b4c8c77fe8ac7aa07a9e41827955d38a24f6137f

AUTOENCODERS – APPLICATIONS

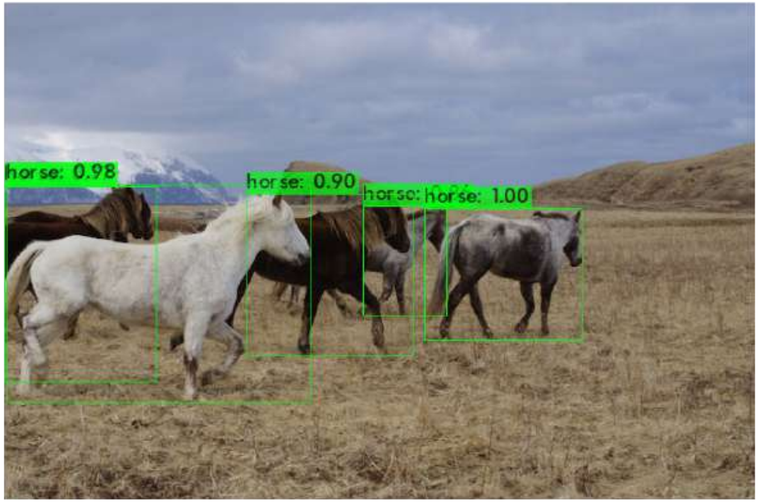
1. Noise removal
2. Image compression
3. Fraud detection
4. Dimensionality reduction (similar to PCA)

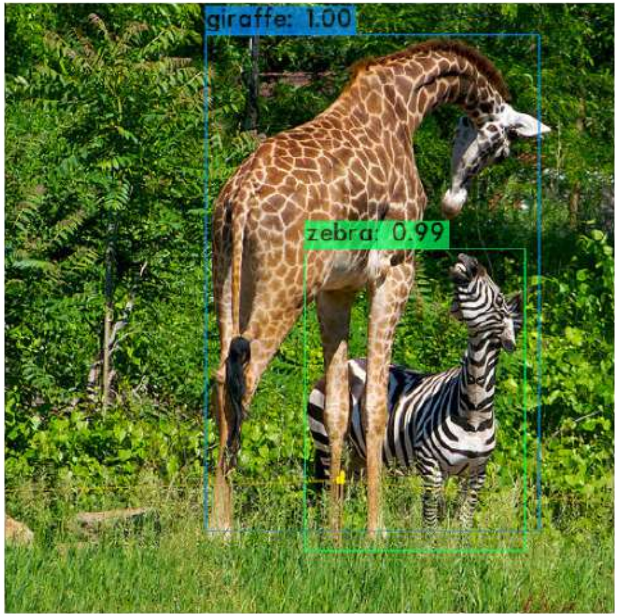




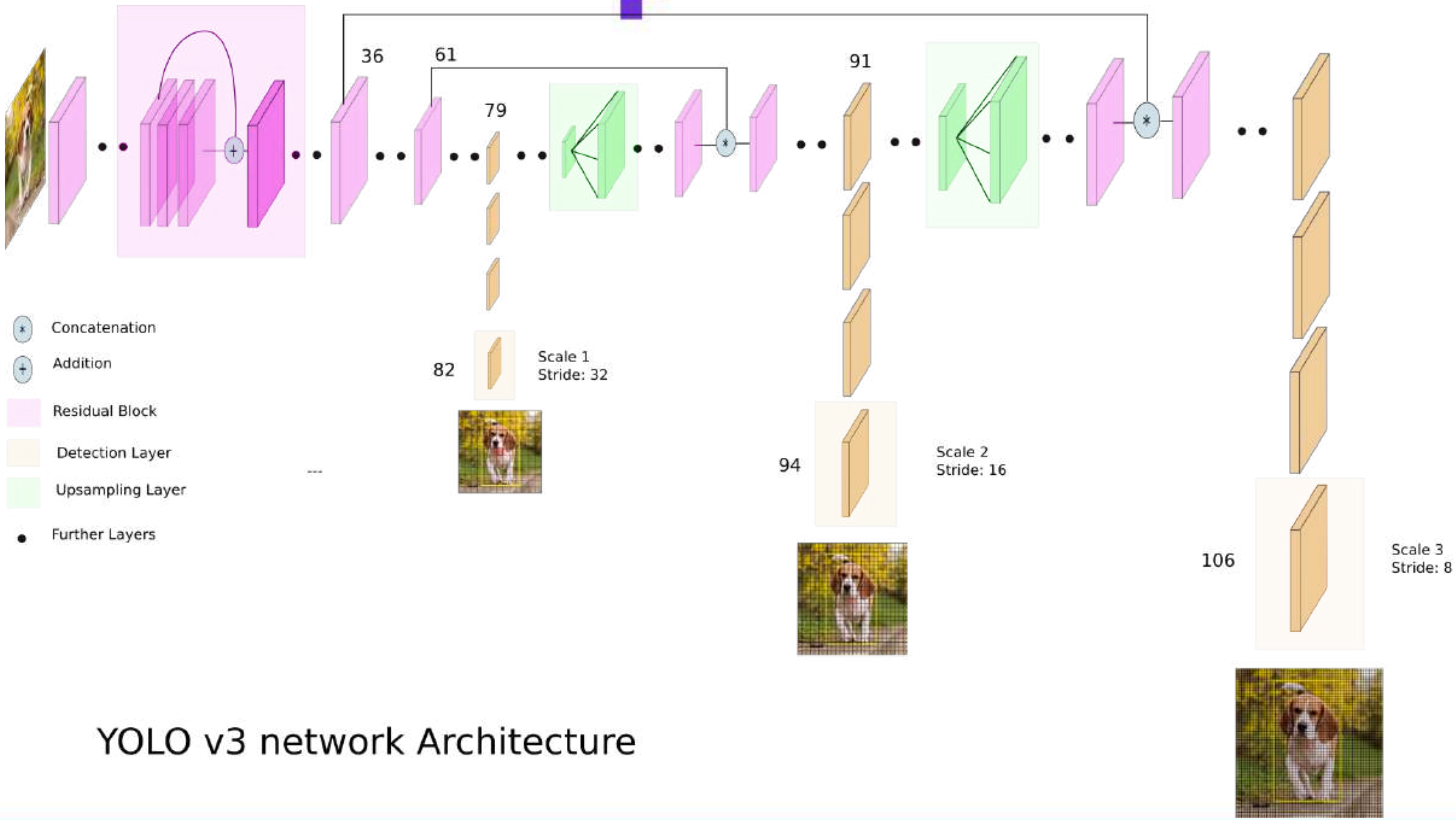
PLAN OF ATTACK – YOLO (YOU ONLY LOOK ONCE)

1. Intuition about YOLO
2. Object detection in images (Darknet)
3. Object detection in videos





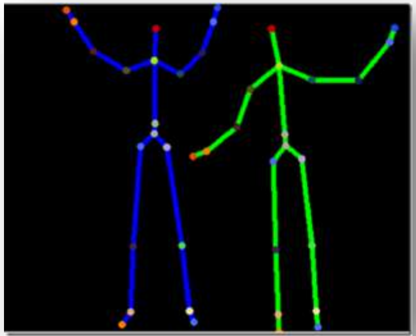
YOLO (YOU ONLY LOOK ONCE)



YOLO v3 network Architecture

PLAN OF ATTACK – RECOGNITION OF GESTURES AND ACTIONS

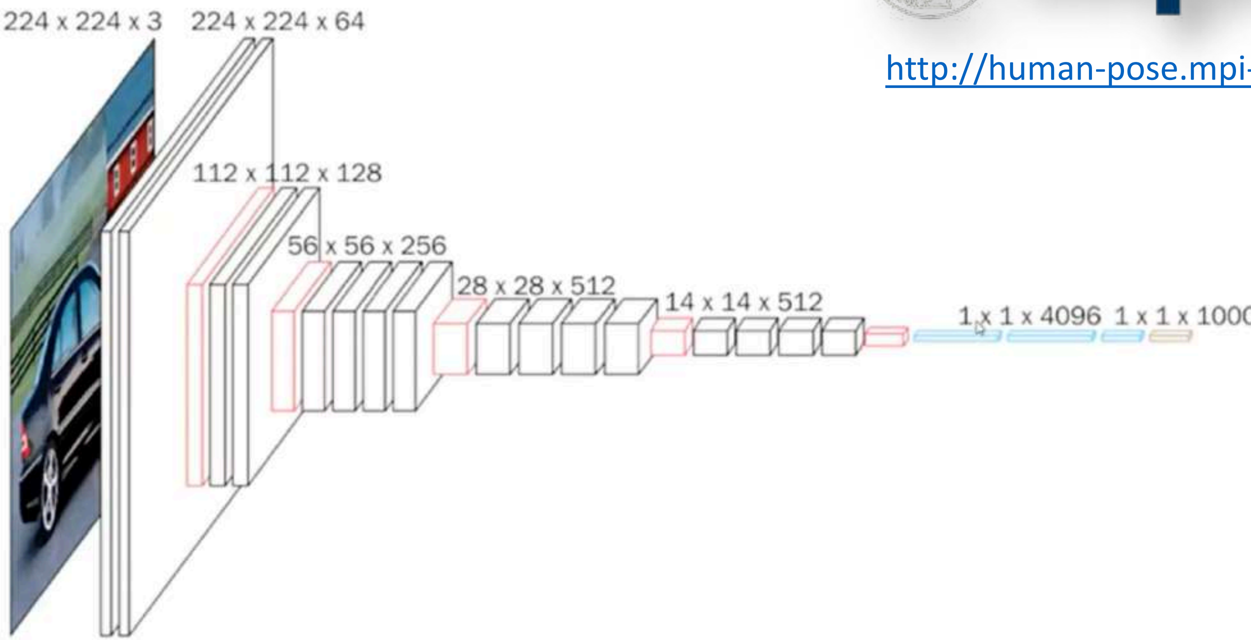
1. Intuition about recognition of gestures and actions
2. Implementation using images and videos



MPII MODEL

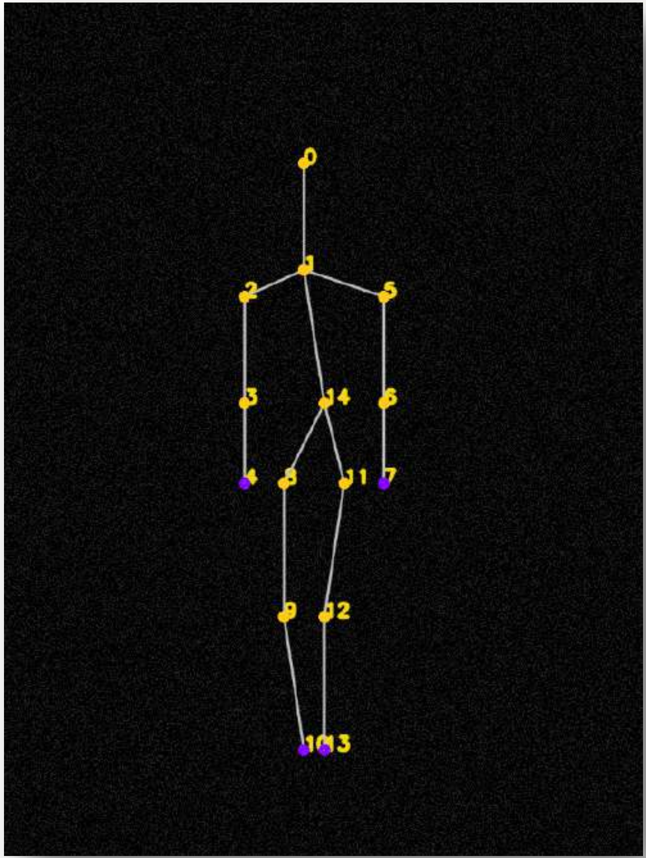
max planck institut
informatik

http://human-pose.mpi-inf.mpg.de/



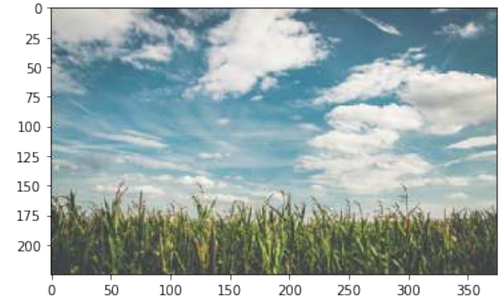
MPII – BODY POINTS

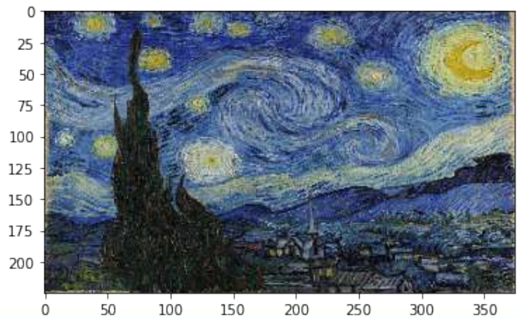
0	Head	9	Rigth knee
1	Neck	10	Rigth ankle
2	Rigth shoulder	11	Left hip
3	Rigth elbow	12	Left knee
4	Rigth wrist	13	Left ankle
5	Left shoulder	14	Chest
6	Left elbow	15	Background
7	Left wrist		
8	Rigth hip		



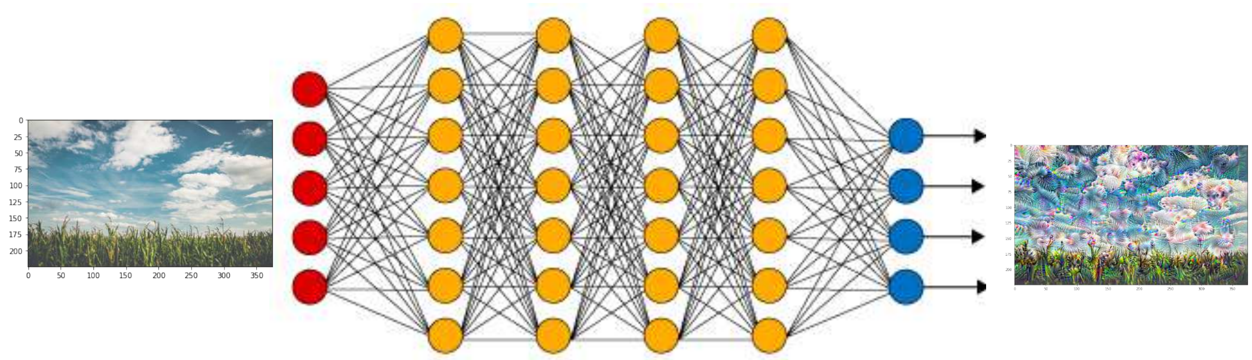
PLAN OF ATTACK – DEEP DREAM

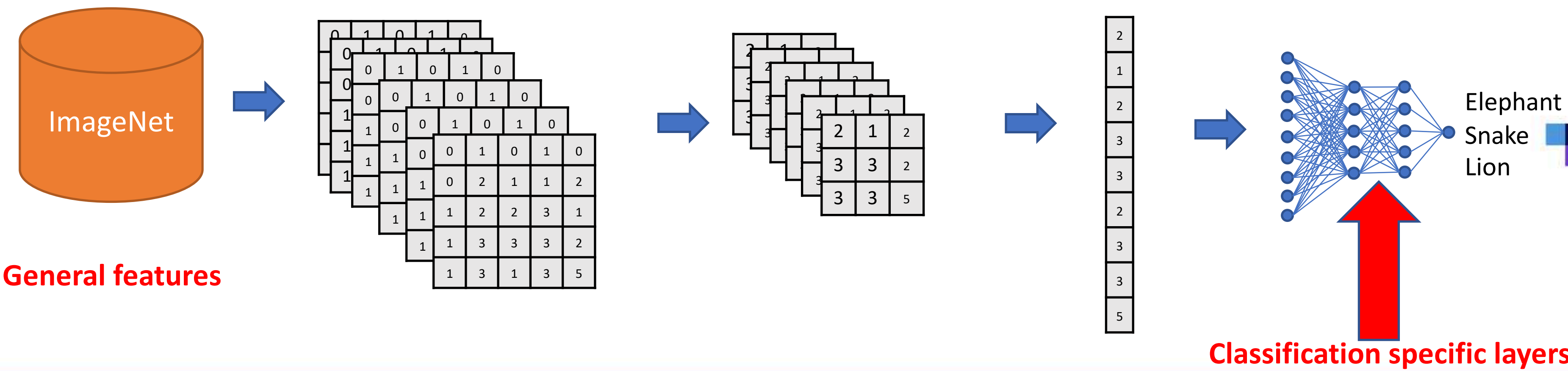
1. Intuition about Deep Dream
2. Implementation





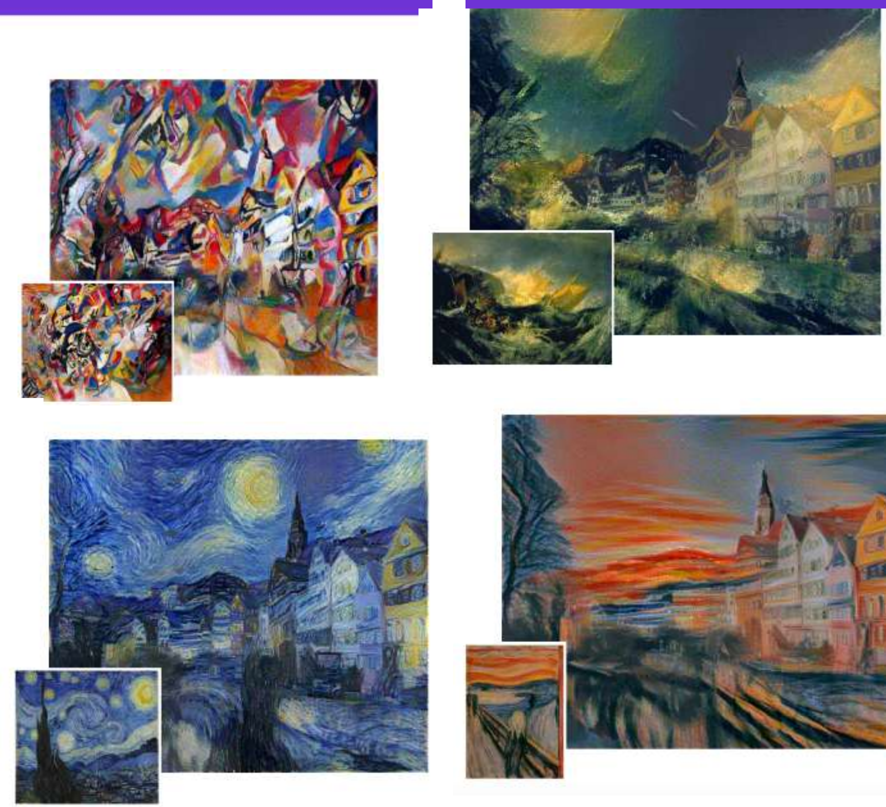
DEEP DREAM




ImageNet
General features
Elephant
Snake
Lion
Classification specific layers

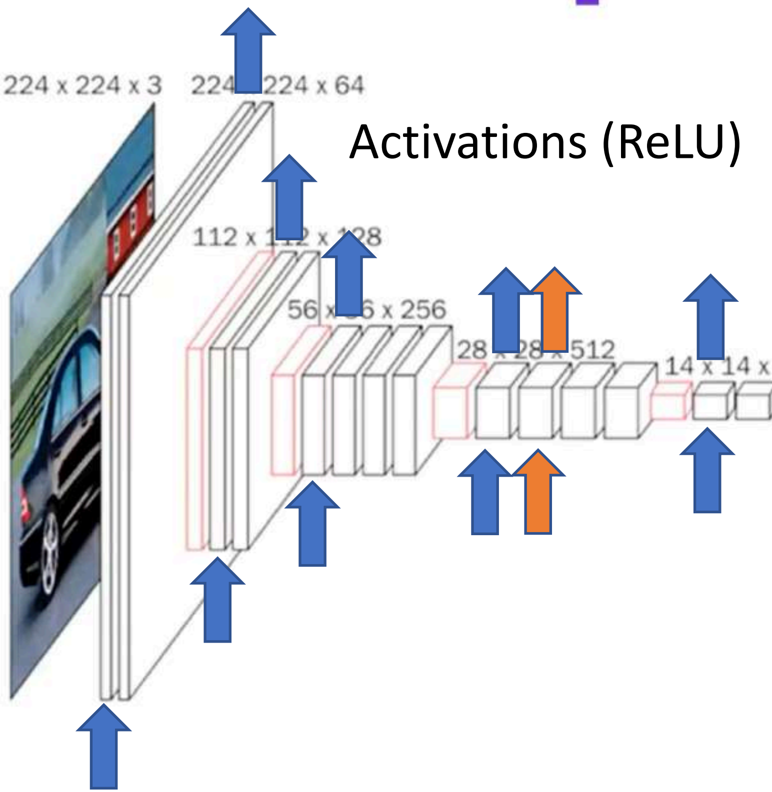
PLAN OF ATTACK – STYLE TRANSFER

1. Intuition about Style Transfer
2. Implementation

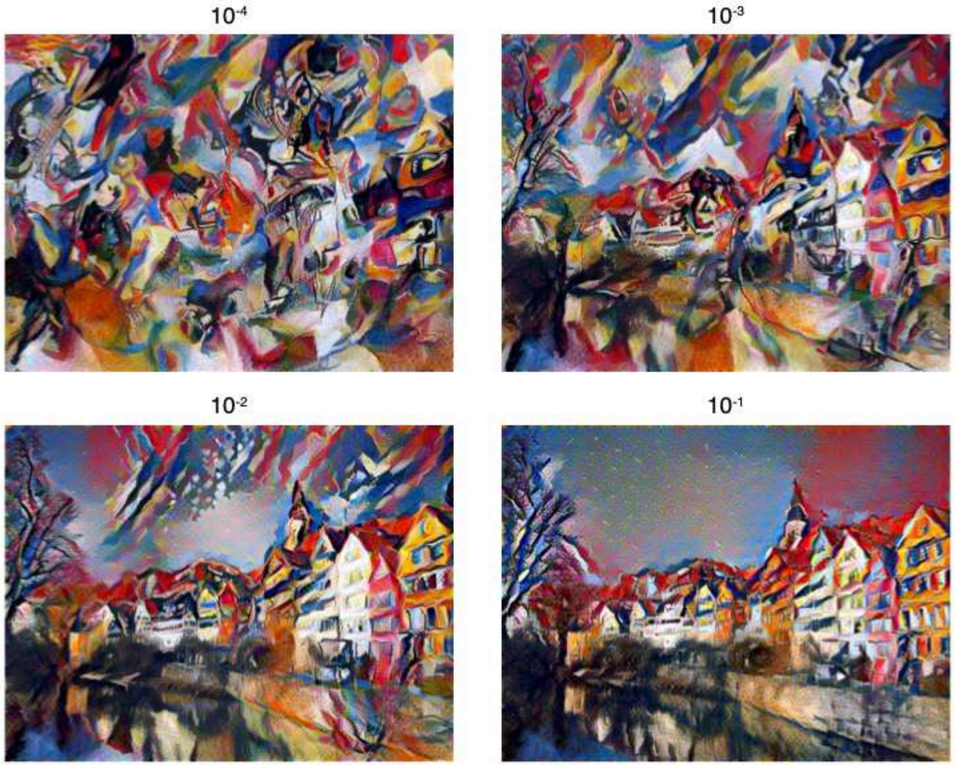


Source of images: https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Gatys_Image_Style_Transfer_CVPR_2016_paper.pdf

STYLE TRANSFER

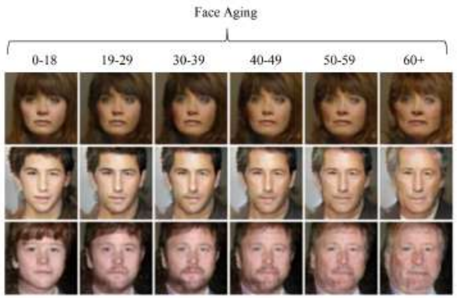


STYLE TRANSFER



PLAN OF ATTACK – GANs (GENERATIVE ADVERSARIAL NETWORKS)

1. Intuition about GANs
2. Implementation



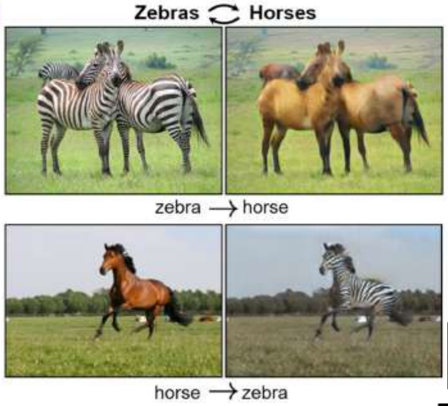
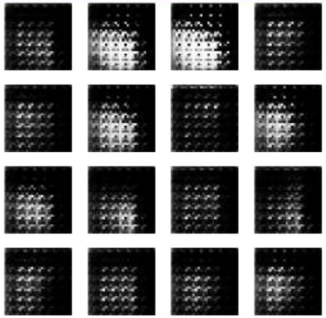
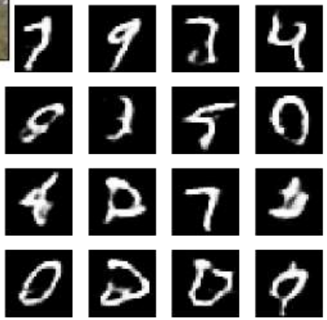
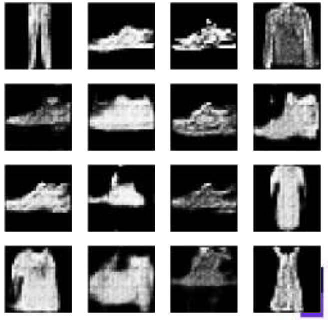


Figure 5: 1024 × 1024 images generated using the CELEBA-HQ dataset. See Appendix F for a larger set of results, and the accompanying video for latent space interpolations.



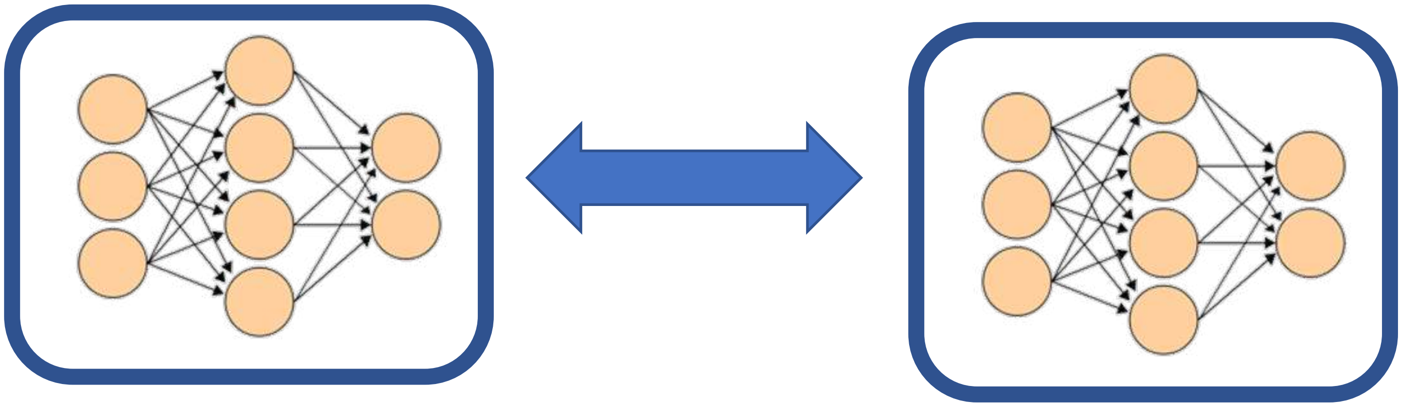




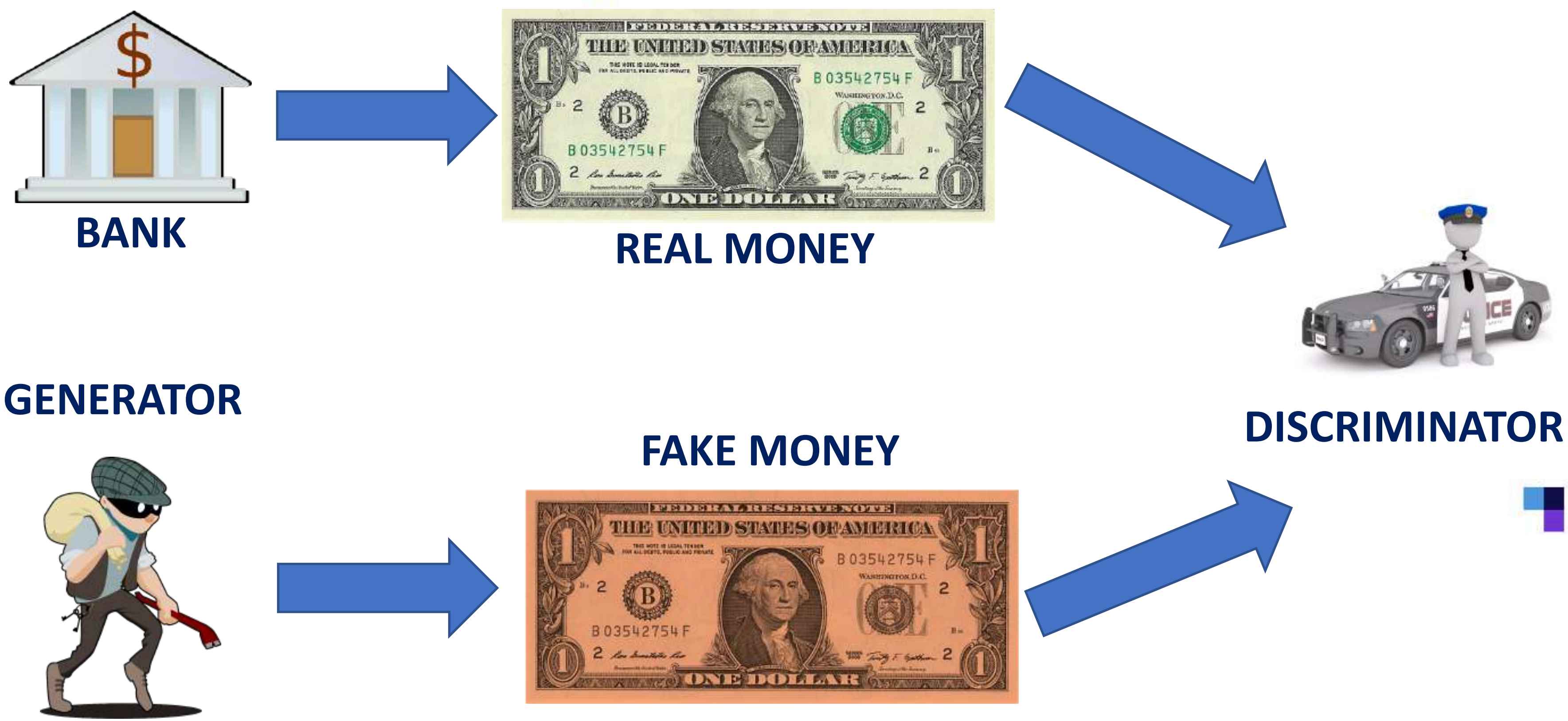
Source of images: https://jonathan-hui.medium.com/gan-some-cool-applications-of-gans-4c9ecca35900

GANs (GENERATIVE ADVERSARIAL NETWORKS)

GENERATOR **DISCRIMINATOR**



GANs (GENERATIVE ADVERSARIAL NETWORKS)

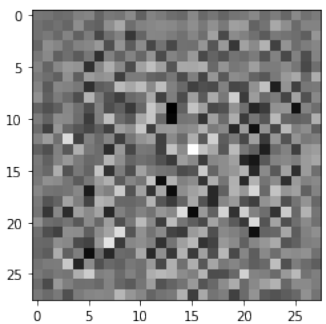


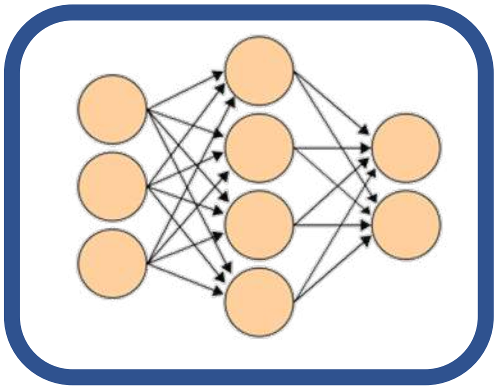
GANs – GENERATOR

1 – Real images

0 – Fake images

GENERATOR



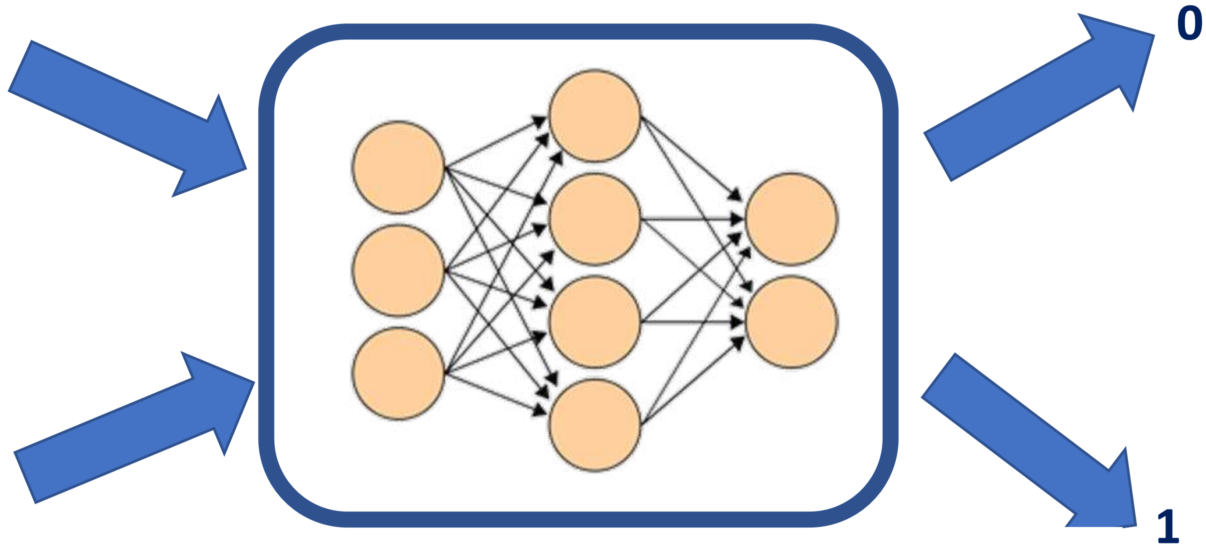


GANs - DISCRIMINATOR

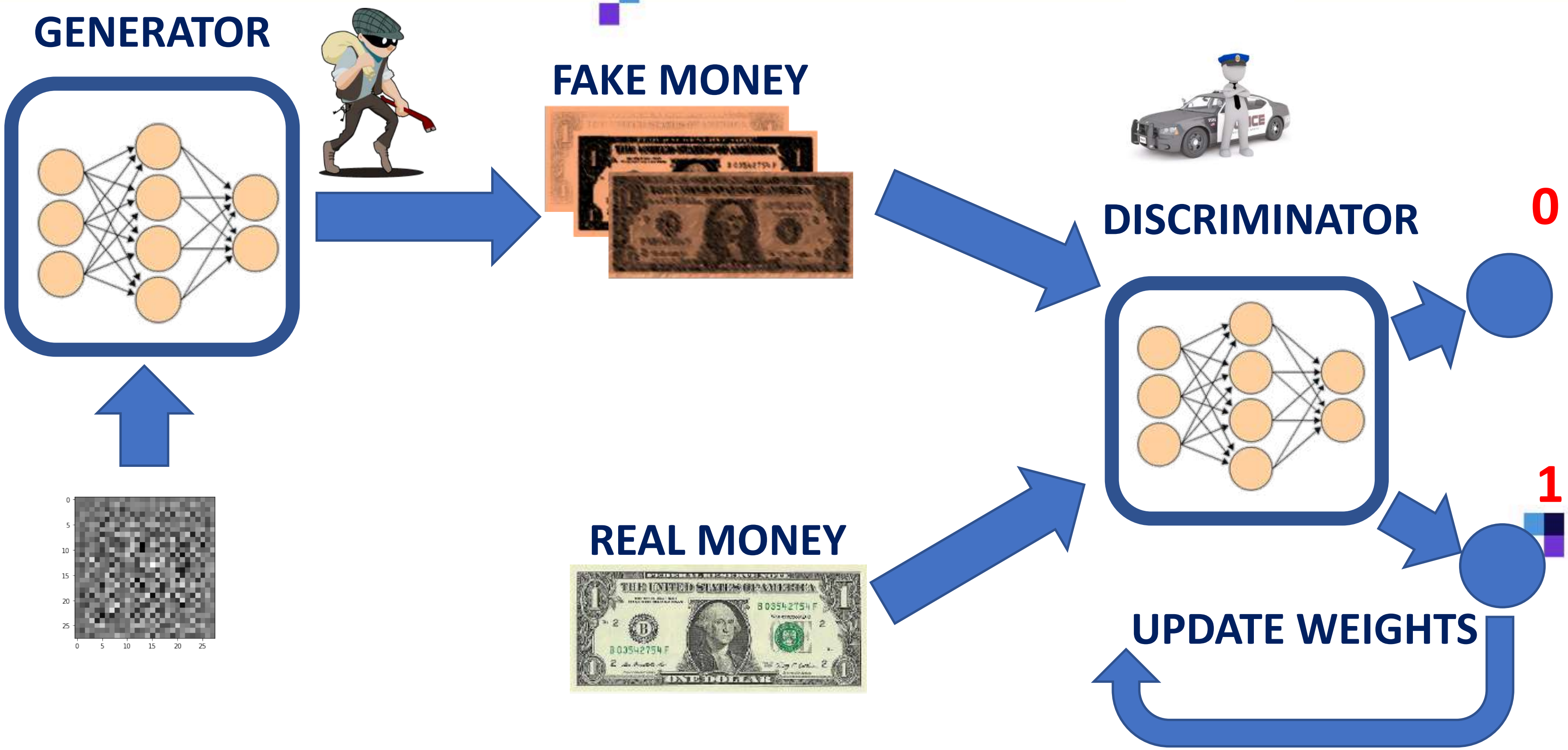
FAKE MONEY

REAL MONEY

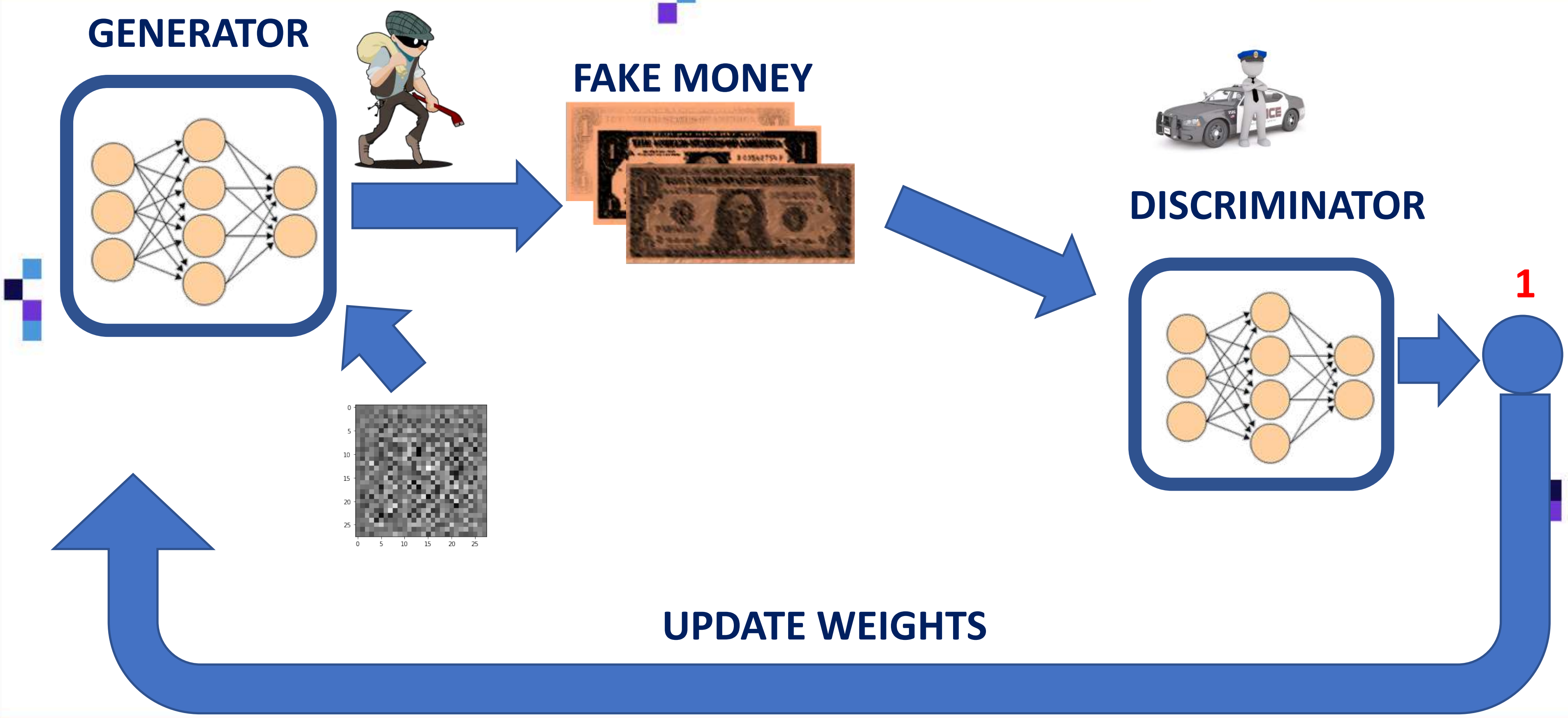
DISCRIMINATOR



GANs – DISCRIMINATOR TRAINING

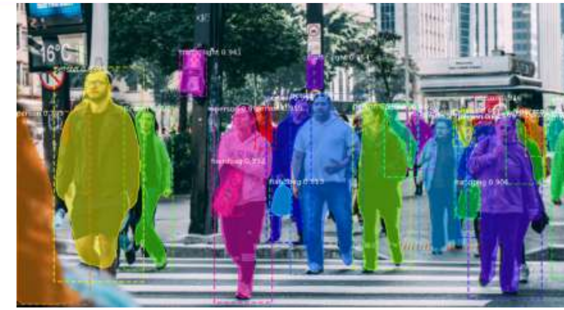


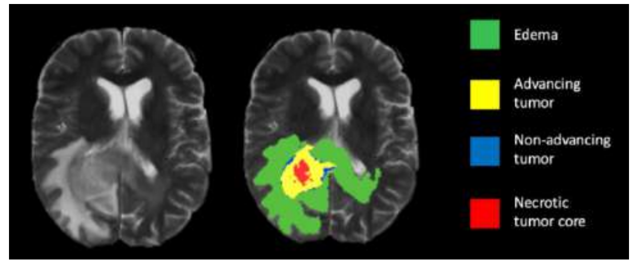
GANs – GENERATOR TRAINING

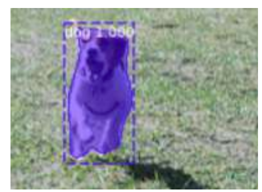


PLAN OF ATTACK – IMAGE SEGMENTATION

1. Intuition about segmentation
2. Implementation

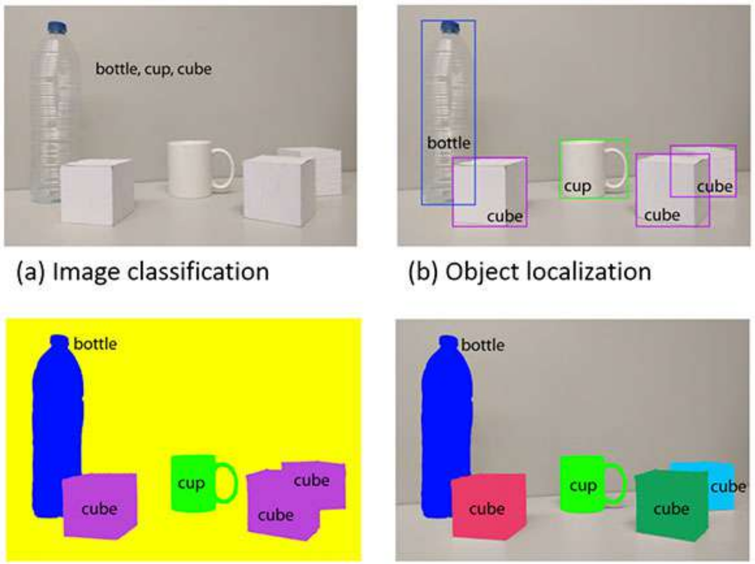






Source of images: data-flair.training & deepsense.ai

INSTANCE VS. SEMANTIC SEGMENTATION



(a) Image classification (b) Object localization

(c) Semantic segmentation (d) Instance segmentation

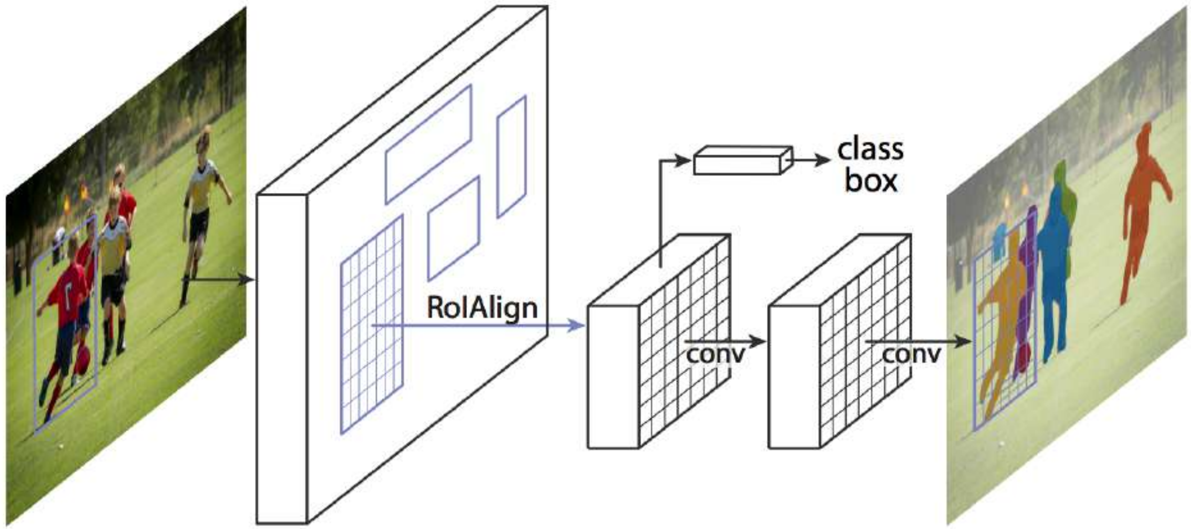
Source: [Garcia et al]()

Source: [NVIDIA Developer Blog]()

Source: [Pexels]()

MASK R-CNN

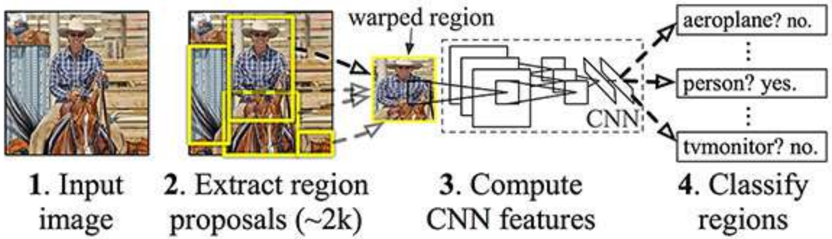
- It was built based on the previous object detection works: R-CNN (2013), Fast R-CNN (2015), and Faster R-CNN (2015), all by Girshick et al.



Source: https://arxiv.org/abs/1703.06870

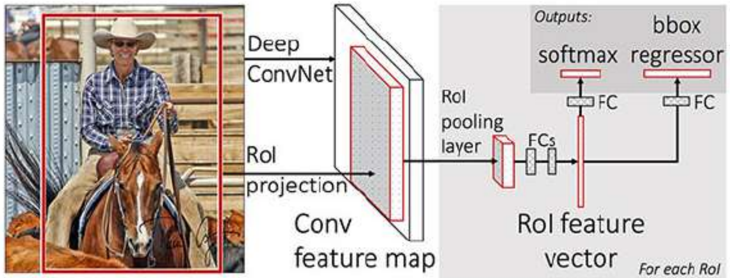
R-CNN, FAST R-CNNs AND FASTER R-CNN

Original R-CNN Architecture



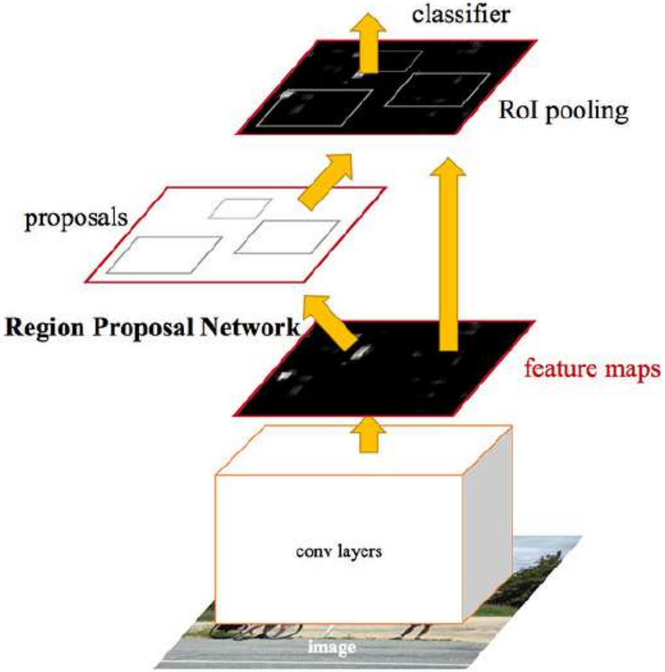
Source: Girshick et al,. 2013)

Fast R-CNN Architecture



Source: Girshick et al., 2015)

Faster R-CNN Architecture



Source: Girshick et al., 2015)