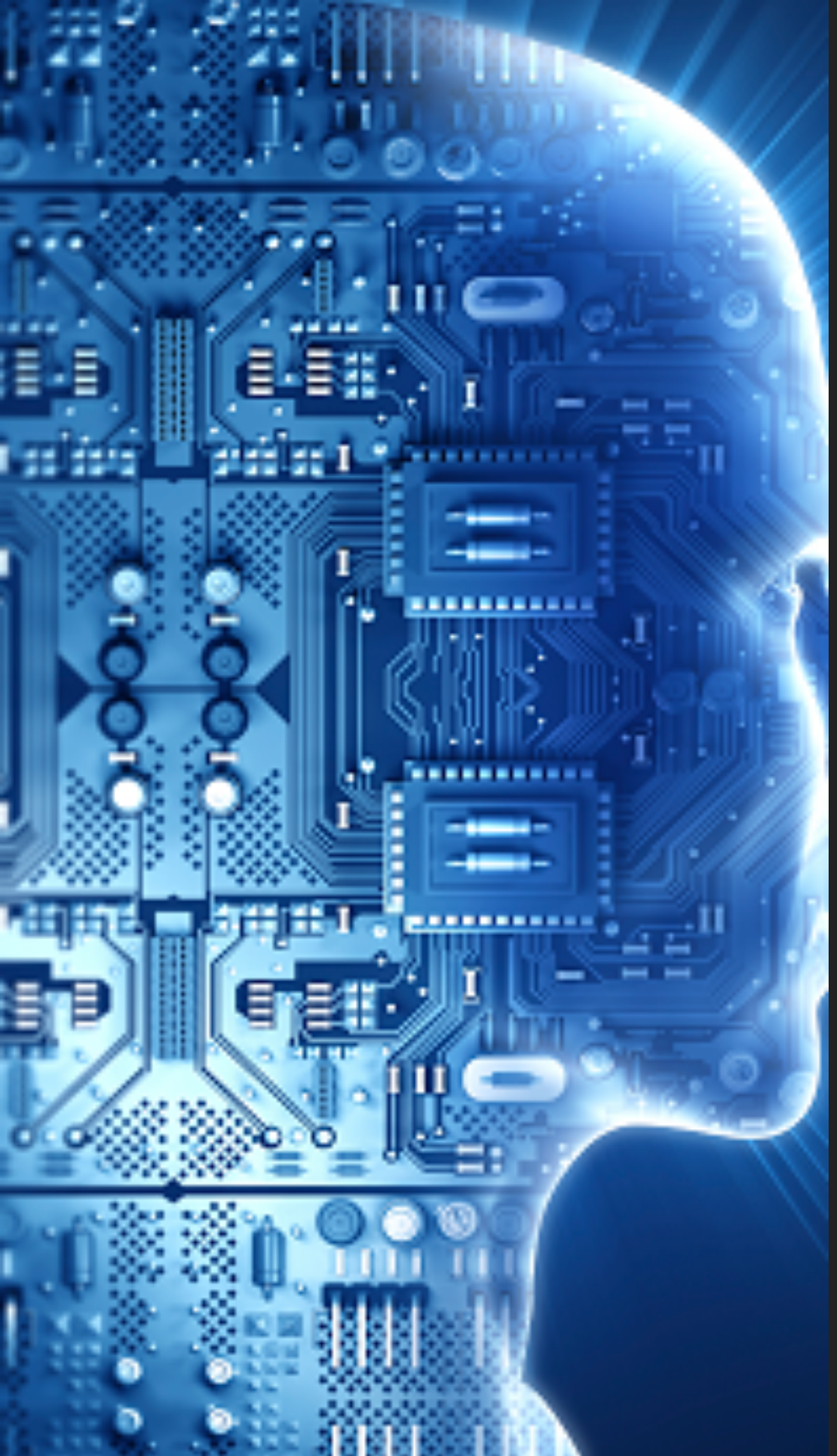


INTRODUCTION TO AI AND MACHINE LEARNING

SESSION #4

COURSE AGENDA

Session #1: Introduction to machine learning, concepts, basics, capabilities. Classification basics. ✓

Session #2: Feature engineering, data wrangling. Regression basics. ✓

Session #3: Working with textual data, text classification, NLP basics ✓

Session #4: Introduction to neural networks, deep learning, image recognition

SESSION #4 AGENDA

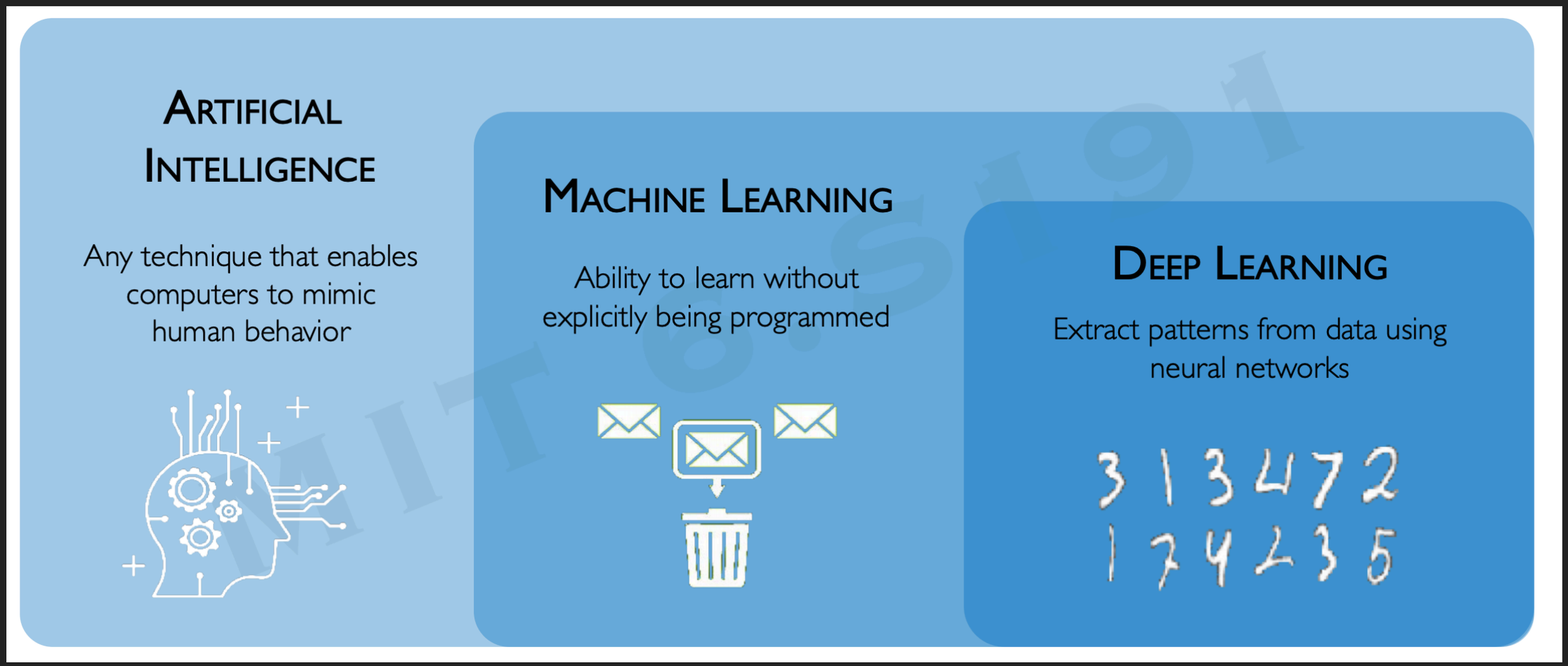
SECTION 1

- Machine learning vs. deep learning
- Neural network fundamentals
- Convolutional Neural Networks for image processing
- Transfer Learning

SECTION 2

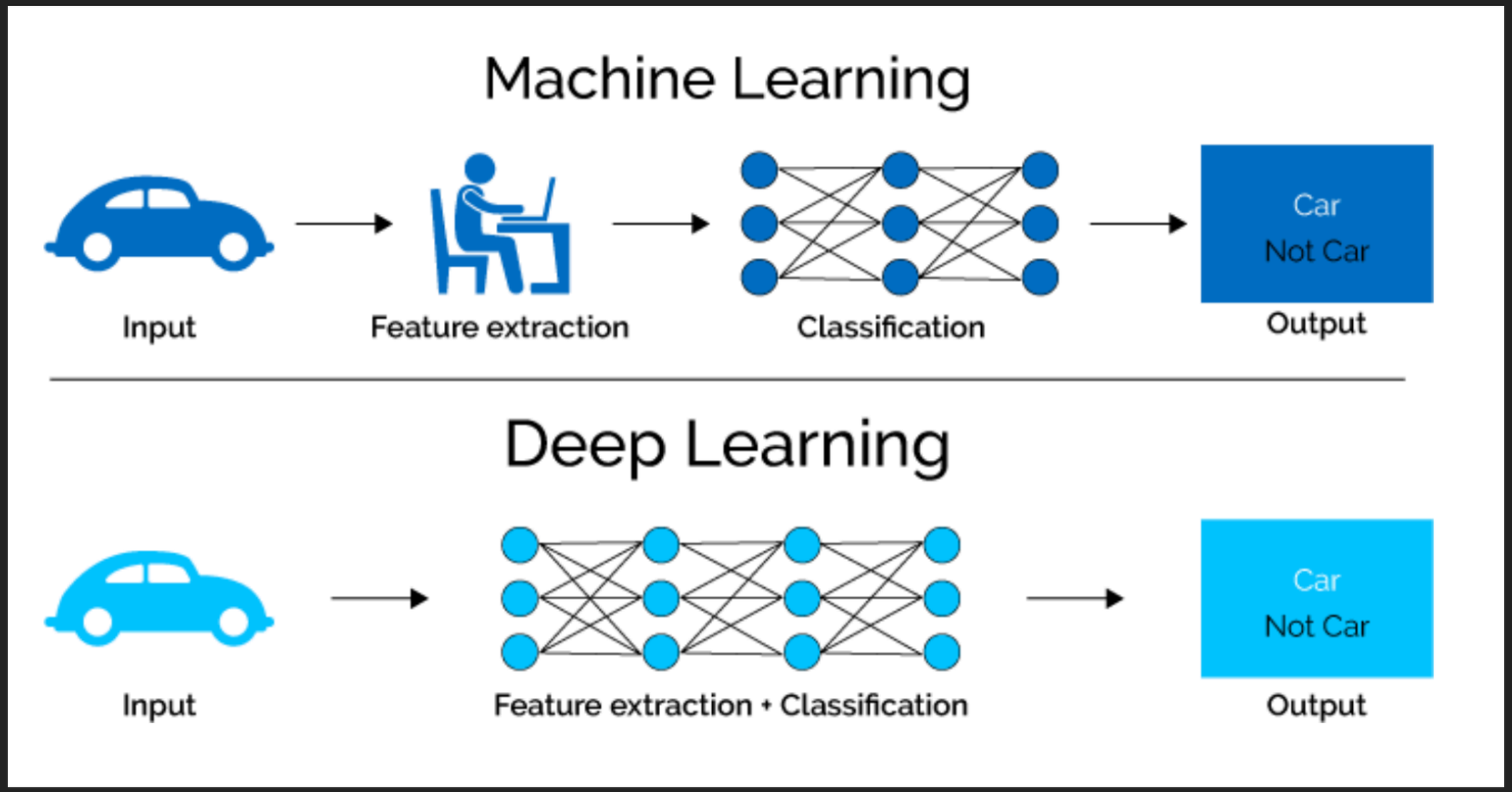
- Case Study: Cat or dog?

MACHINE LEARNING VS. DEEP LEARNING



Source: http://introtodeeplearning.com/

MACHINE LEARNING VS. DEEP LEARNING



Source: https://towardsdatascience.com/why-deep-learning-is-needed-over-traditional-machine-learning-1b6a99177063

THE RISE OF DEEP LEARNING

Neural network concepts have been here with us for 60 years. Why now?

DATA

- available in huge amounts
- easy to collect and store

HARDWARE

- the rise of GPUs
- massively parallelizable

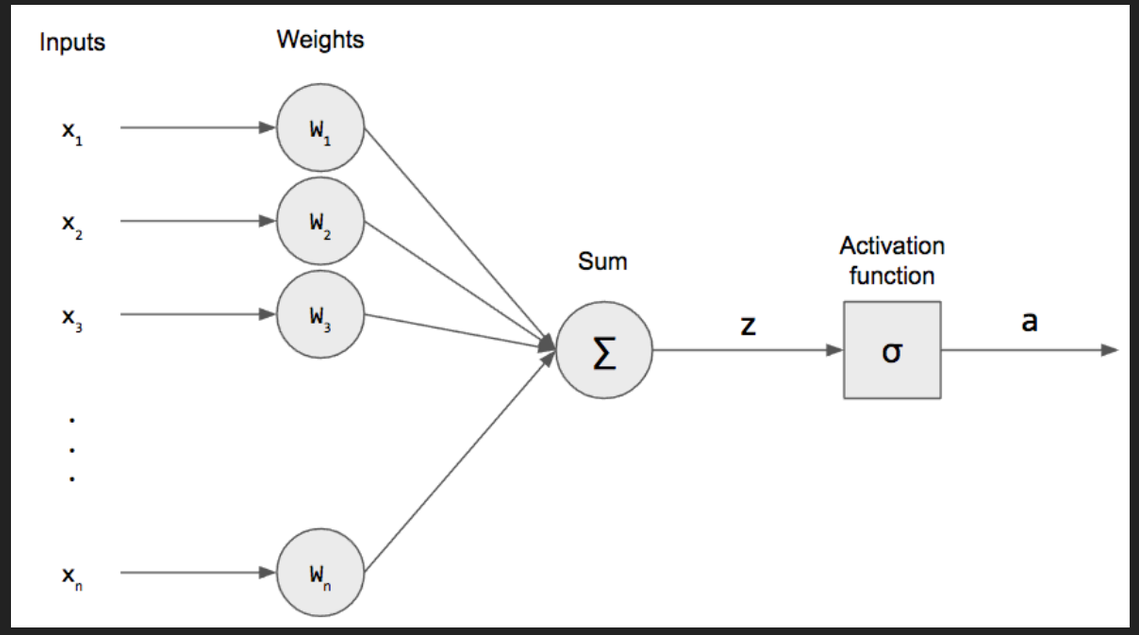
SOFTWARE

- transferrable models
- advanced toolboxes (Tensorflow)

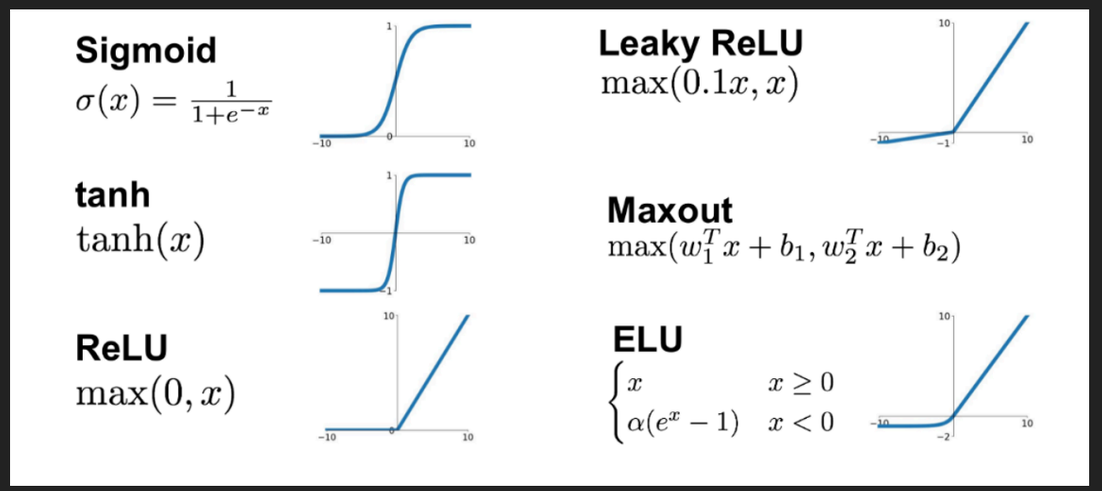
FUNDAMENTALS OF NEURAL NETWORKS

Neural network is a machine learning architecture loosely inspired by human brain

A perceptron / artificial neuron



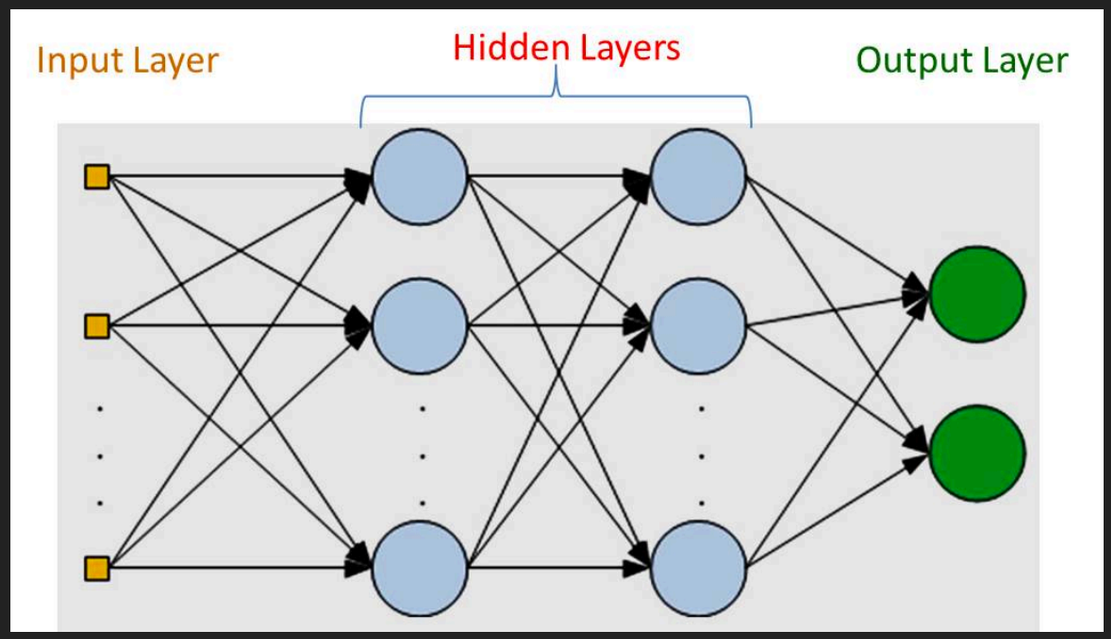
Various activation functions



FUNDAMENTALS OF NEURAL NETWORKS

In practice the neurons are organized into layers.

A multi layer perceptron



Input layer: the input features

Hidden layers: all layers between the input and output layers are called hidden layer

Output layer: the neural network output

HOW NEURAL NETWORKS LEARN?

The objective of training a neural network is to reduce the error on the output layer

Loss function

- the result of loss function is a number that describe how good a model is
- an improvement on this number means a better model
- before training we define a loss function for the whole population of the input data points
    - for classification it can be: maximum likelihood estimation (MLE)
    - for regression it can be: mean squared error (MSE)

HOW NEURAL NETWORKS LEARN?

Backpropagation

1. You know the desired output for a given input
2. Send the input through the network
3. Calculate the error of the network
4. Go back and change the weights throughout the whole network so that the error is reduced
5. Repeat step 2 to 4 until error is the minimal

Input	Desired Output
0	0
1	2
2	4

Now the output of your model when 'W" value is 3:

Input	Desired Output	Model output (W=3)
0	0	0
1	2	3
2	4	6

Notice the difference between the actual output and the desired output:

Input	Desired Output	Model output (W=3)	Absolute Error	Square Error
0	0	0	0	0
1	2	3	1	1
2	4	6	2	4

Let's change the value of 'W'. Notice the error when 'W' = '4'

Input	Desired Output	Model output (W=3)	Absolute Error	Square Error	Model output (W=4)	Square Error
0	0	0	0	0	0	0
1	2	3	1	1	4	4
2	4	6	2	4	8	16

Now if you notice, when we increase the value of 'W' the error has increased. So, obviously there is no point in increasing the value of 'W' further. But, what happens if I decrease the value of 'W'? Consider the table below:

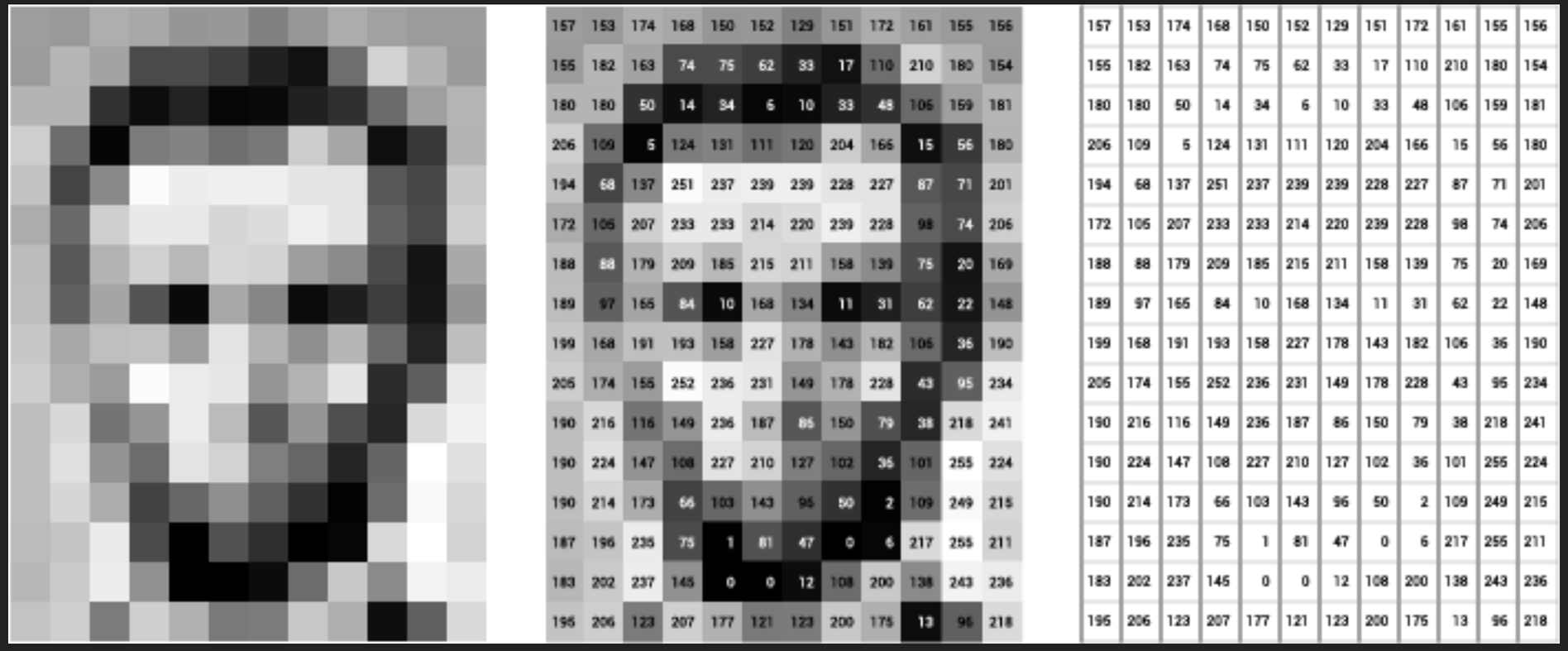
Input	Desired Output	Model output (W=3)	Absolute Error	Square Error	Model output (W=2)	Square Error
0	0	0	0	0	0	0
1	2	3	2	4	3	0
2	4	6	2	4	4	0

IMAGE PROCESSING

How do computers “see”?

For black and white images each pixel carries a value between 0 and 255.

For an RGB colored image each pixel is described by 3 values between 0 and 255.



157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
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172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
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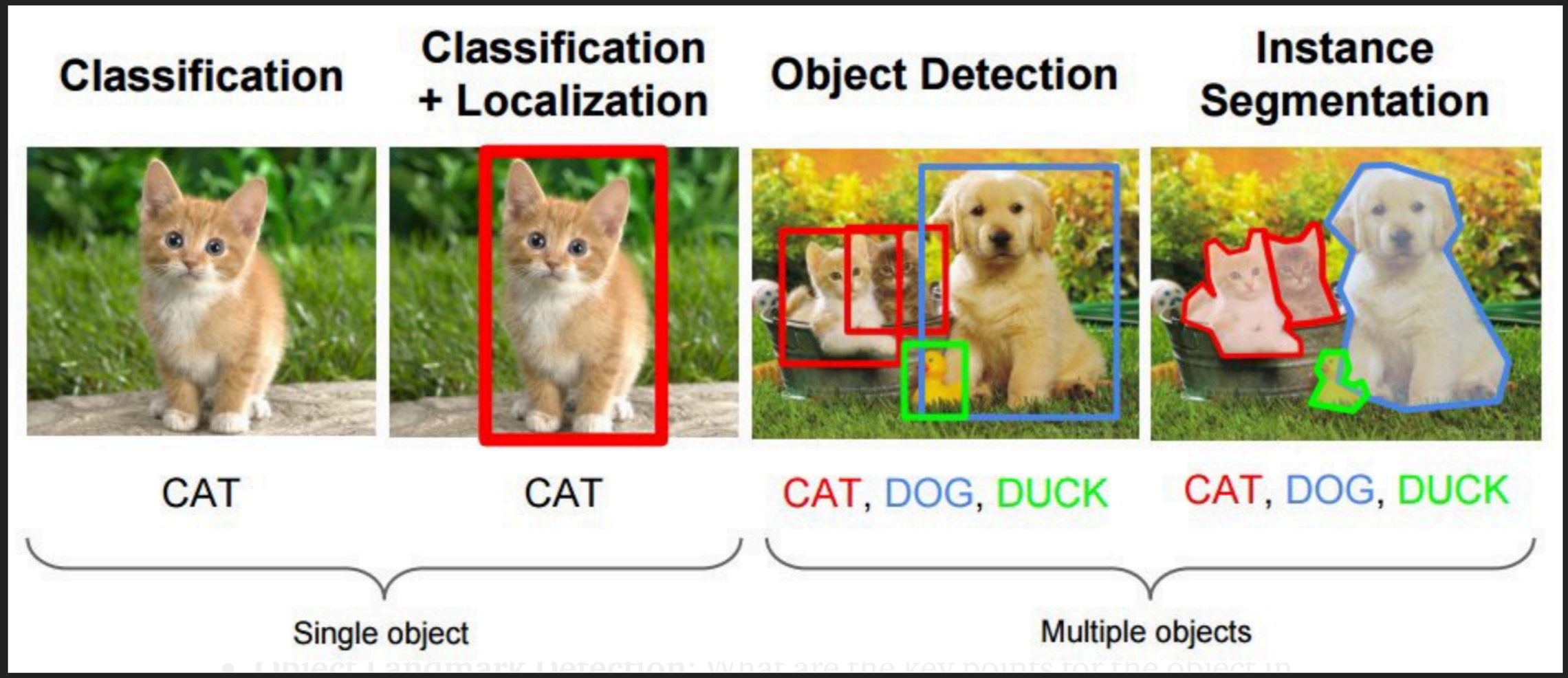
Source: https://towardsdatascience.com/everything-you-ever-wanted-to-know-about-computer-vision-heres-a-look-why-it-s-so-awesome-e8a58dfb641e

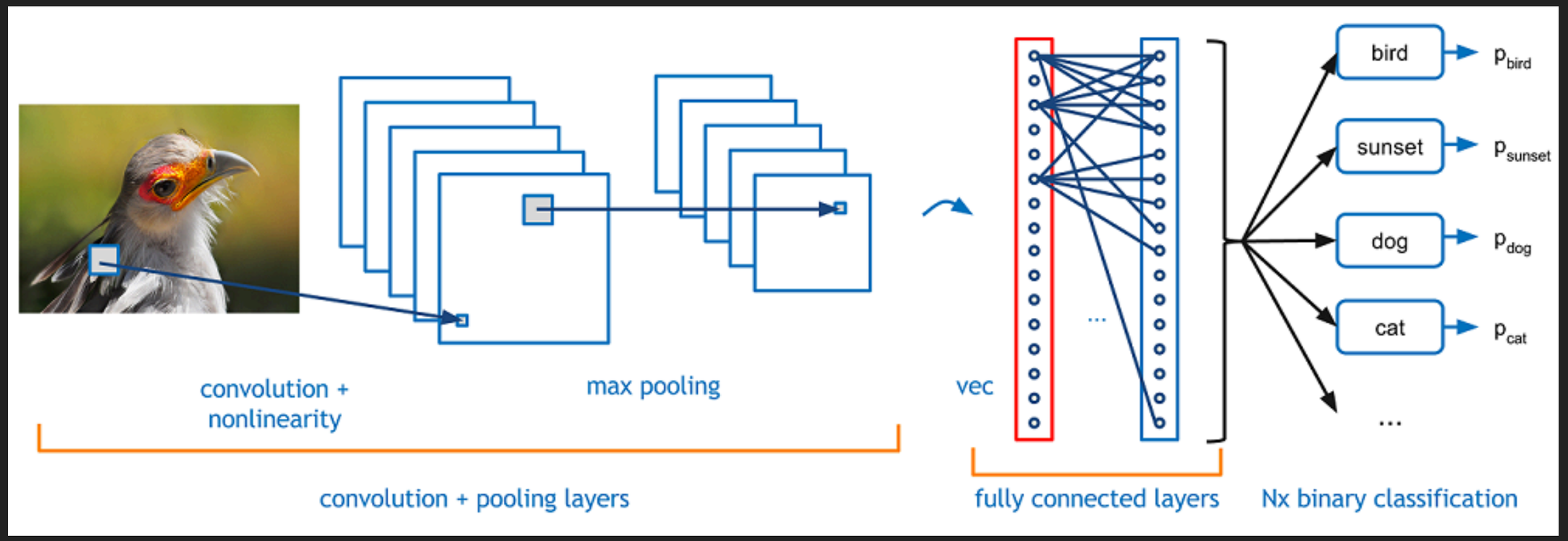
COMPUTER VISION TASKS



Source: https://towardsdatascience.com/everything-you-ever-wanted-to-know-about-computer-vision-heres-a-look-why-it-s-so-awesome-e8a58dfb641e

CONVOLUTIONAL NEURAL NETWORKS (CNN/CONVNET)

CNN is a deep learning algorithm which can take in an input image, assign importance to various aspects in the image and be able to differentiate one from the other.



Source: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

CONVOLUTIONAL NEURAL NETWORKS (CNN/CONVNET)

In the layered architecture each layer is capable of extracting different features from the image.

Source: https://medium.com/@pallawi.ds/ai-starter-build-your-first-convolution-neural-network-in-keras-from-scratch-to-perform-a059eaa6d4ff

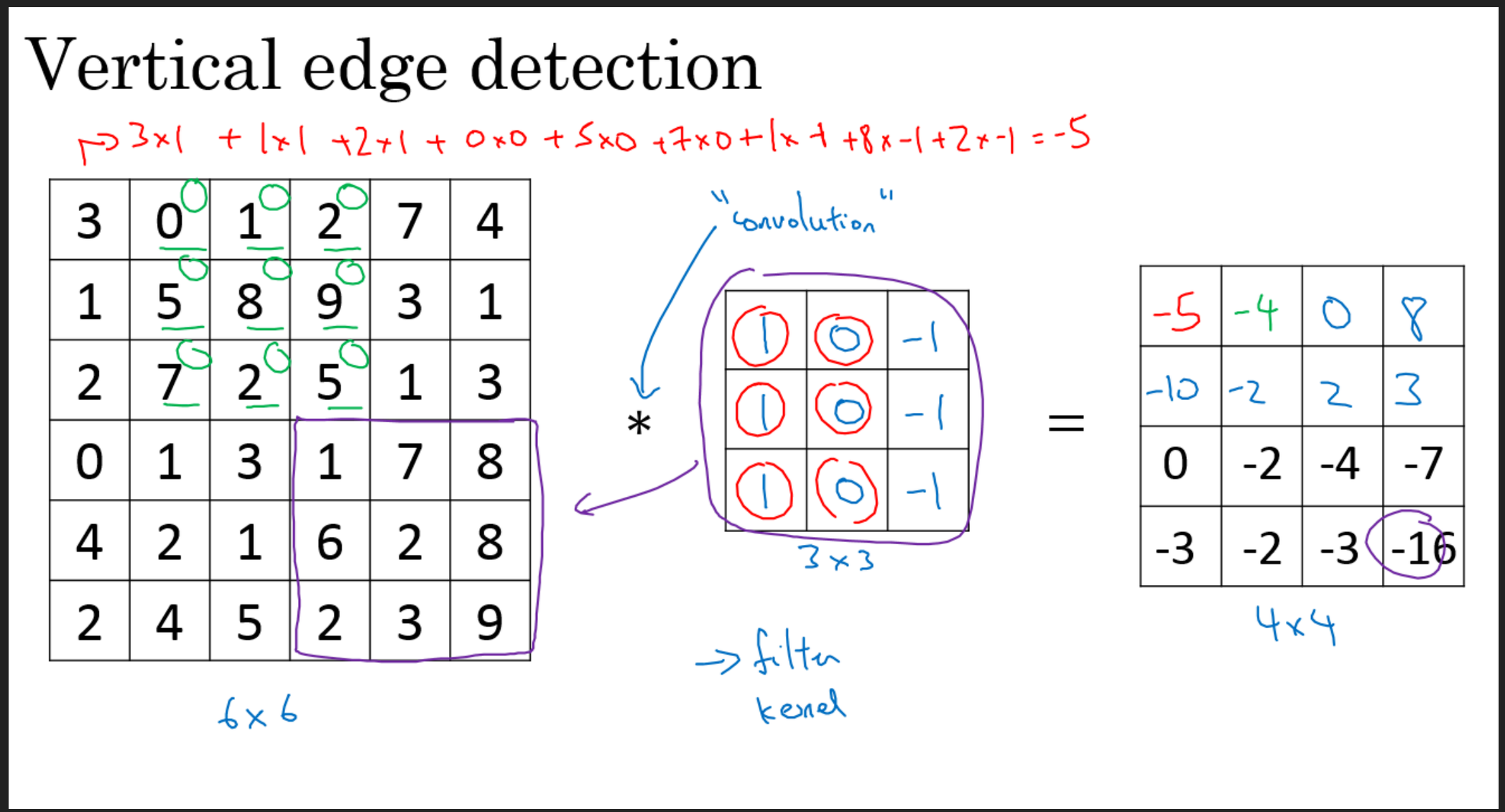
Low-level features: edge or curve detection

Mid-level features: eye, ear or mouth detection

High-level features: face detection

CONVOLUTIONAL NEURAL NETWORKS (CNN/CONVNET)

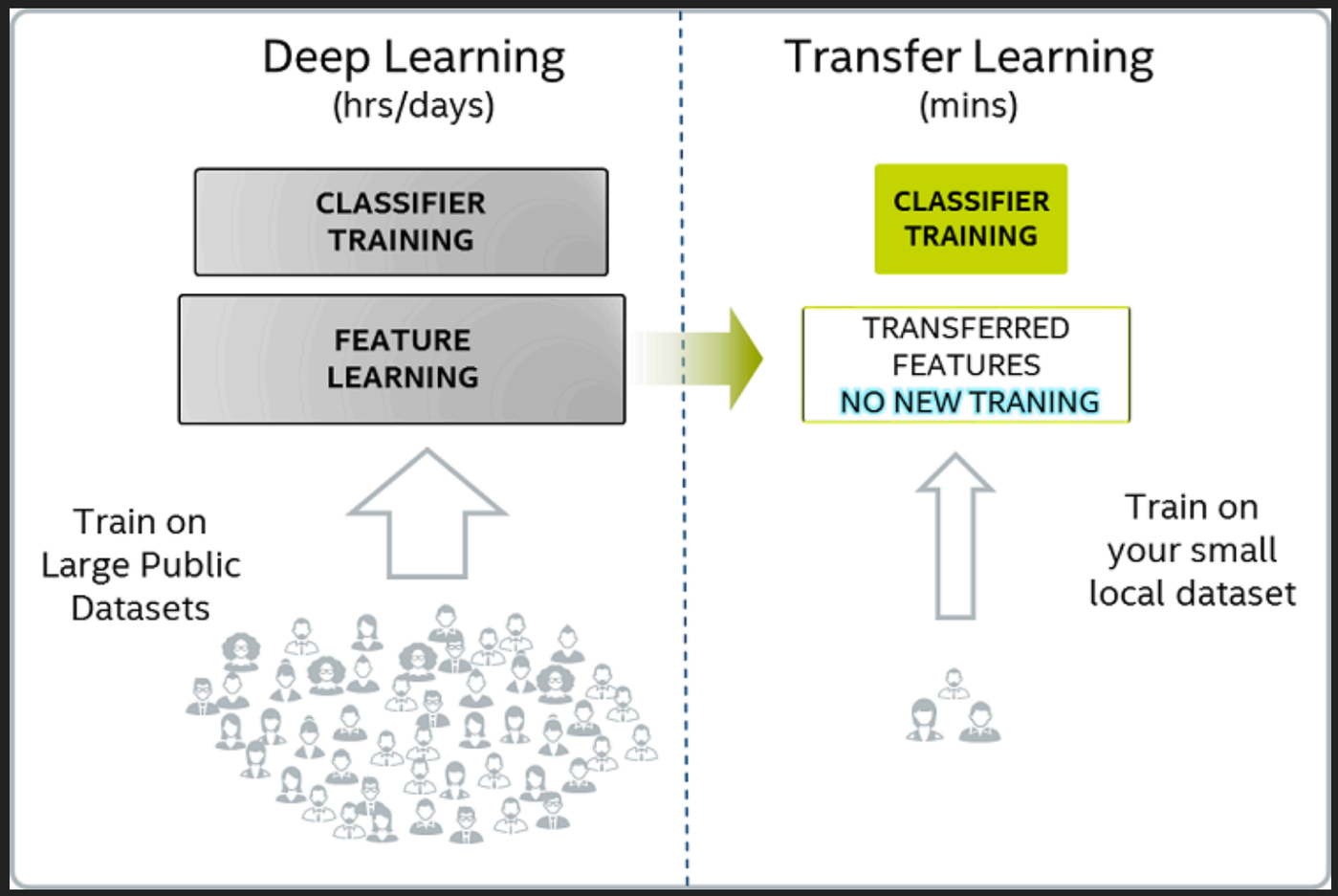
Edge detection example:



Source: https://zhangruochi.com/Convolutional-Neural-Networks/2019/03/27/

TRANSFER LEARNING

Transfer learning is storing knowledge gained solving a problem and applying it to solve a similar problem



Source: https://www.freecodecamp.org/news/asl-recognition-using-transfer-learning-918ba054c004/

TRANSFER LEARNING

ImageNet: collection of 15 million human-labelled images belonging to 22k categories.

Popular pre-trained neural networks for image processing:

- VGG-16
- AlexNet
- U-Net
- ResNet
- R-CNN
- Inception

DEMO