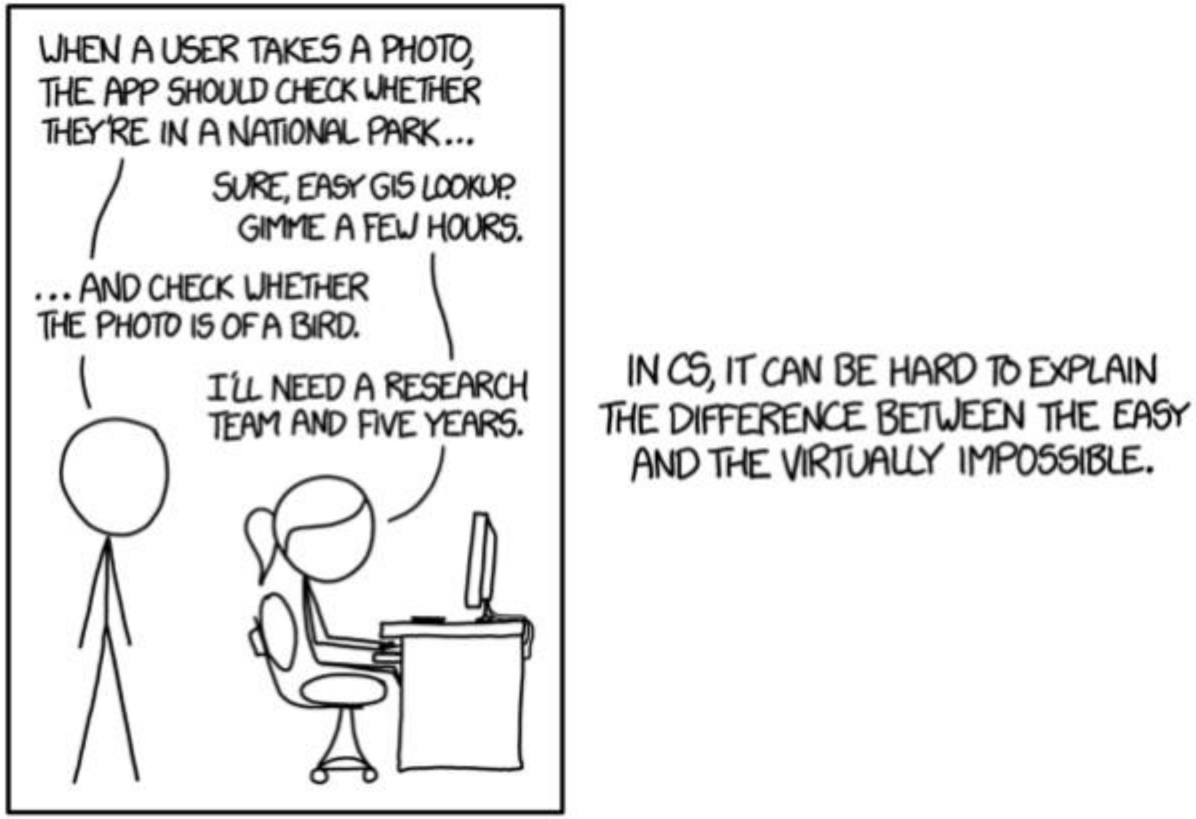
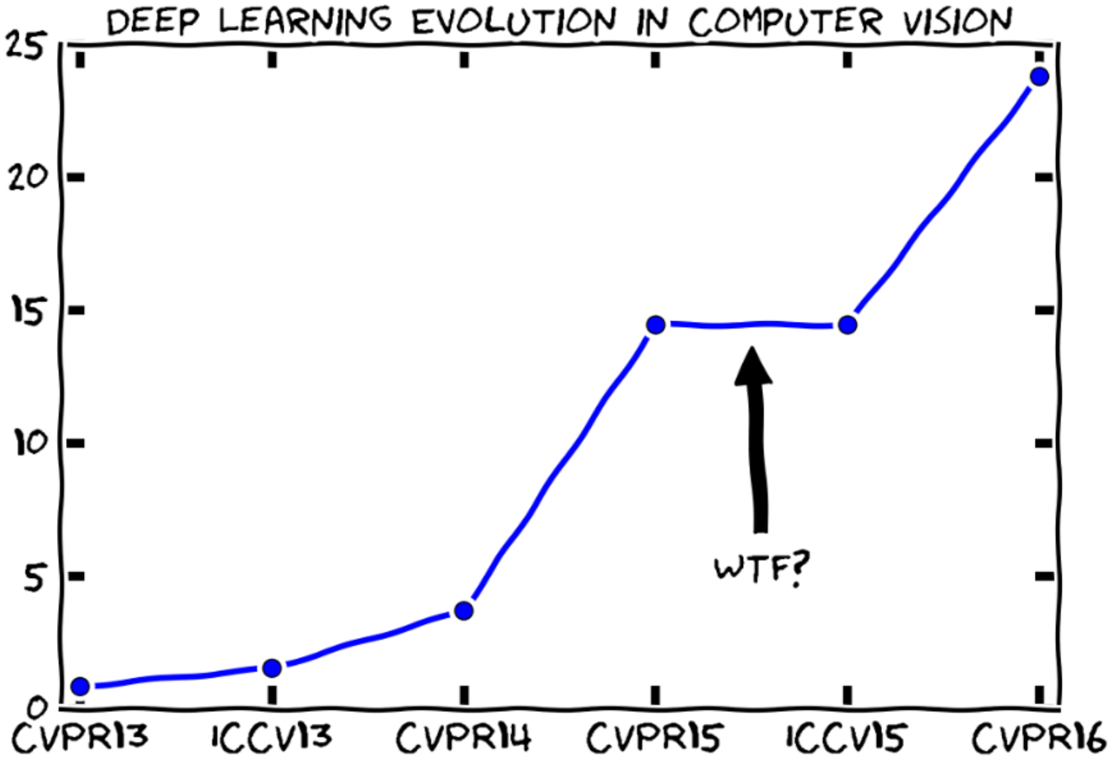
Image data



Xkcd, 2015

Image data

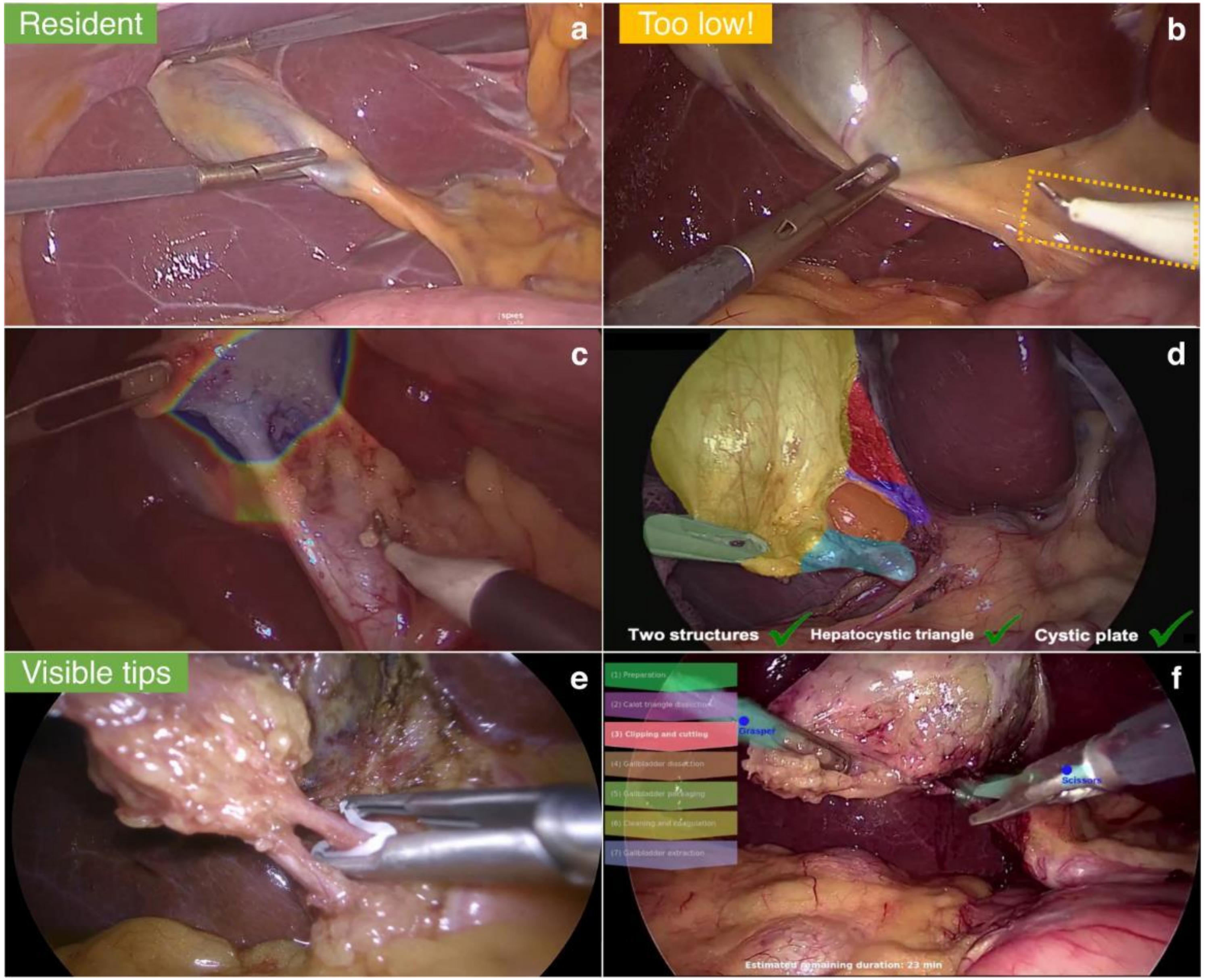


Xkcd

Computer vision

Derive meaningful information from digital images, videos and other visual inputs.

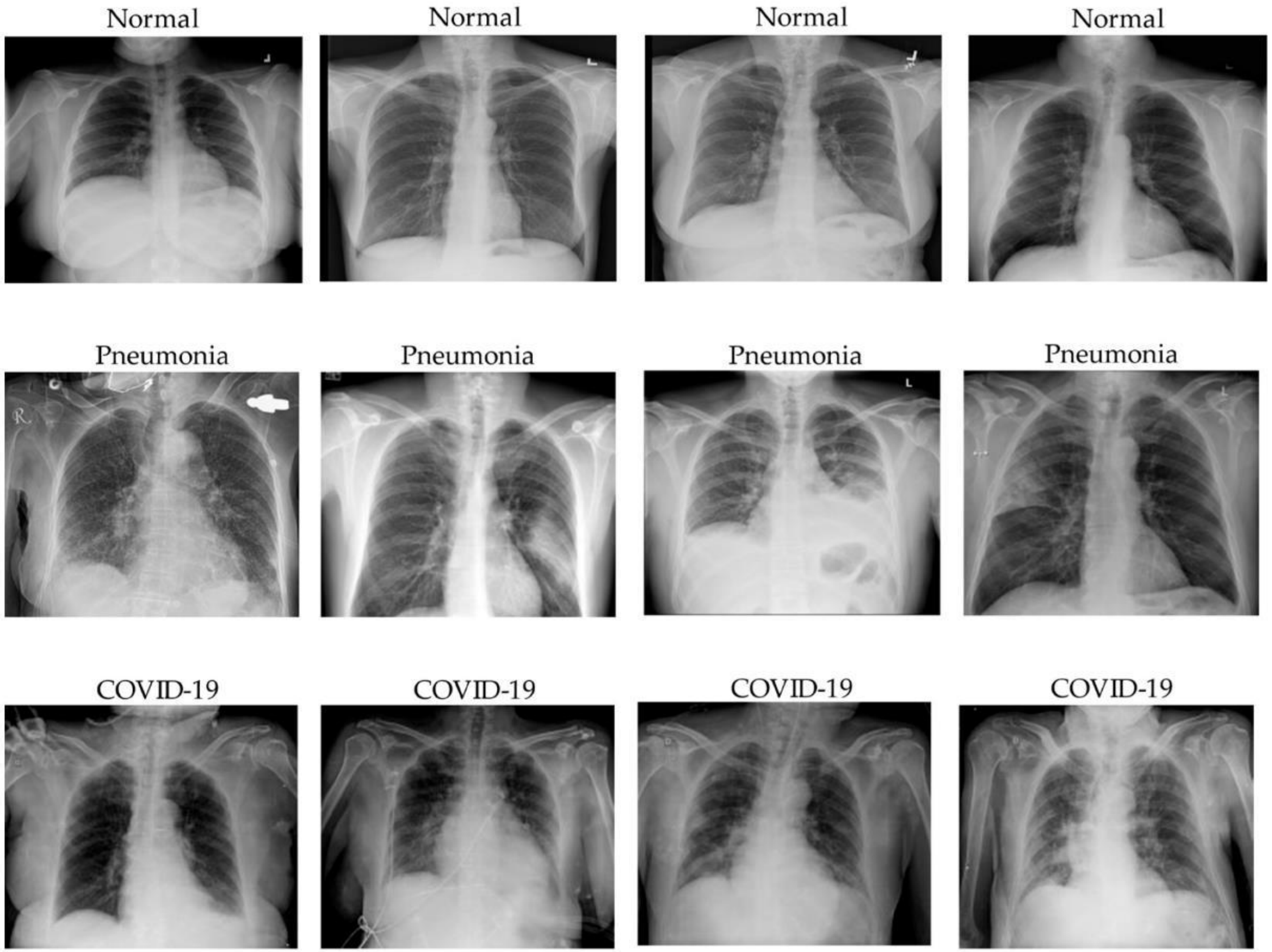
Take actions or make recommendations based on that information.



Mascagni, P., Alapatt, D., Sestini, L. et al. Computer vision in surgery: from potential to clinical value. npj Digit. Med. 5, 163 (2022)

Computer vision

Classification: predict the class(es) an image or video belongs to.

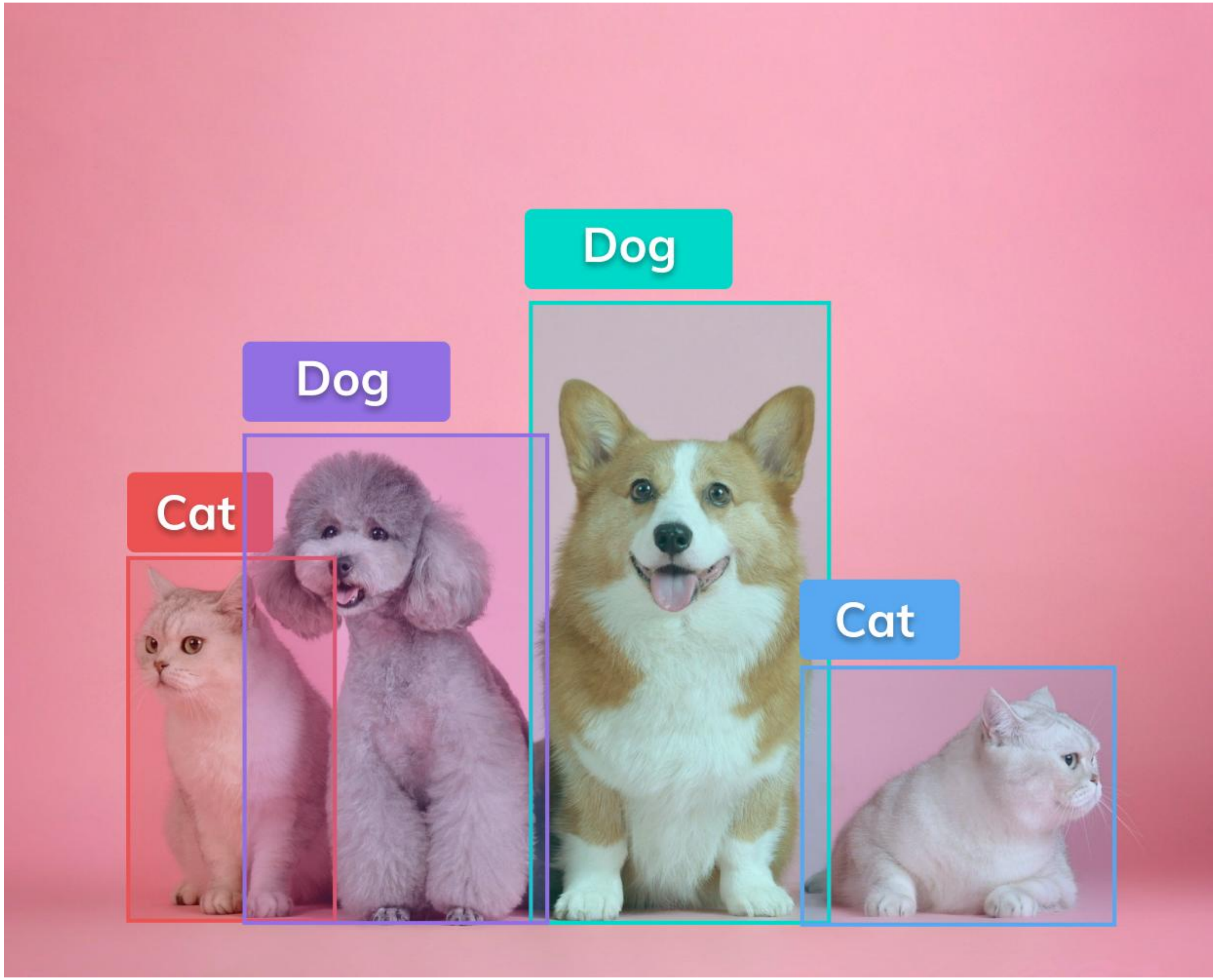


Le Dinh, T, et al. COVID-19 Chest X-ray Classification and Severity Assessment Using Convolutional and Transformer Neural Networks. Appl. Sci. 2022, 12, 4861

Computer vision

Classification: predict the class(es) an image or video belongs to.

Object detection: identify a certain class of image and then detect and tabulate their appearance in an image or video.



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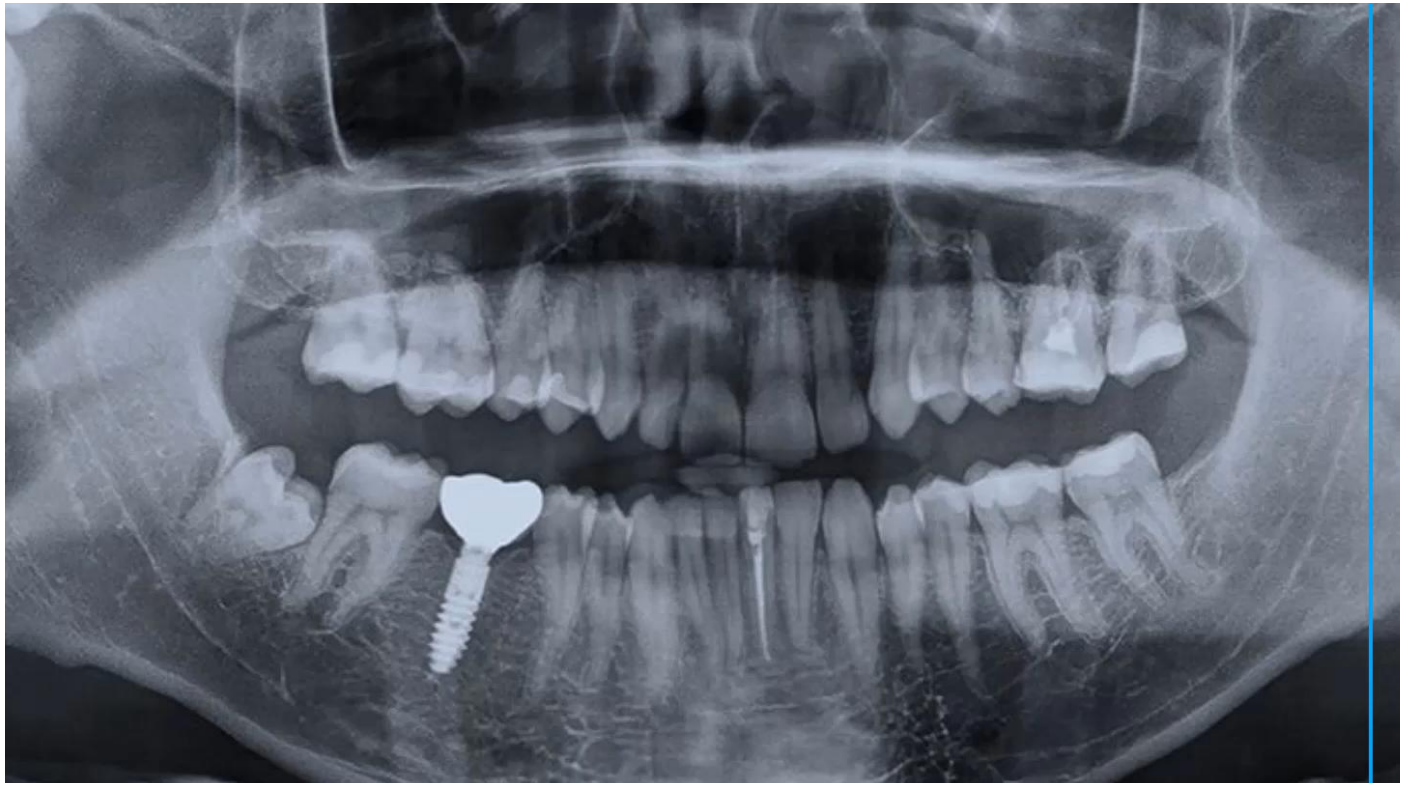

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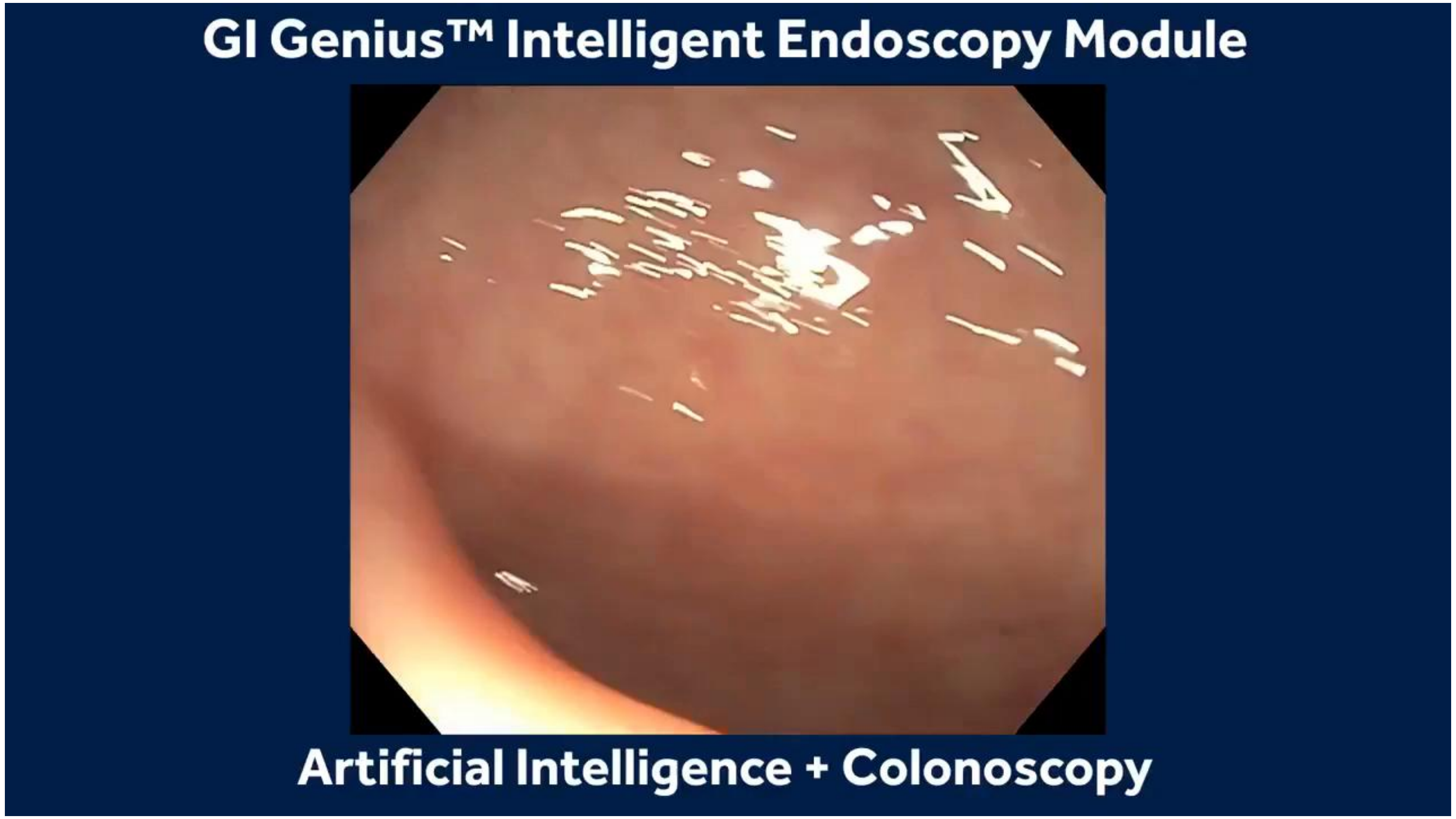

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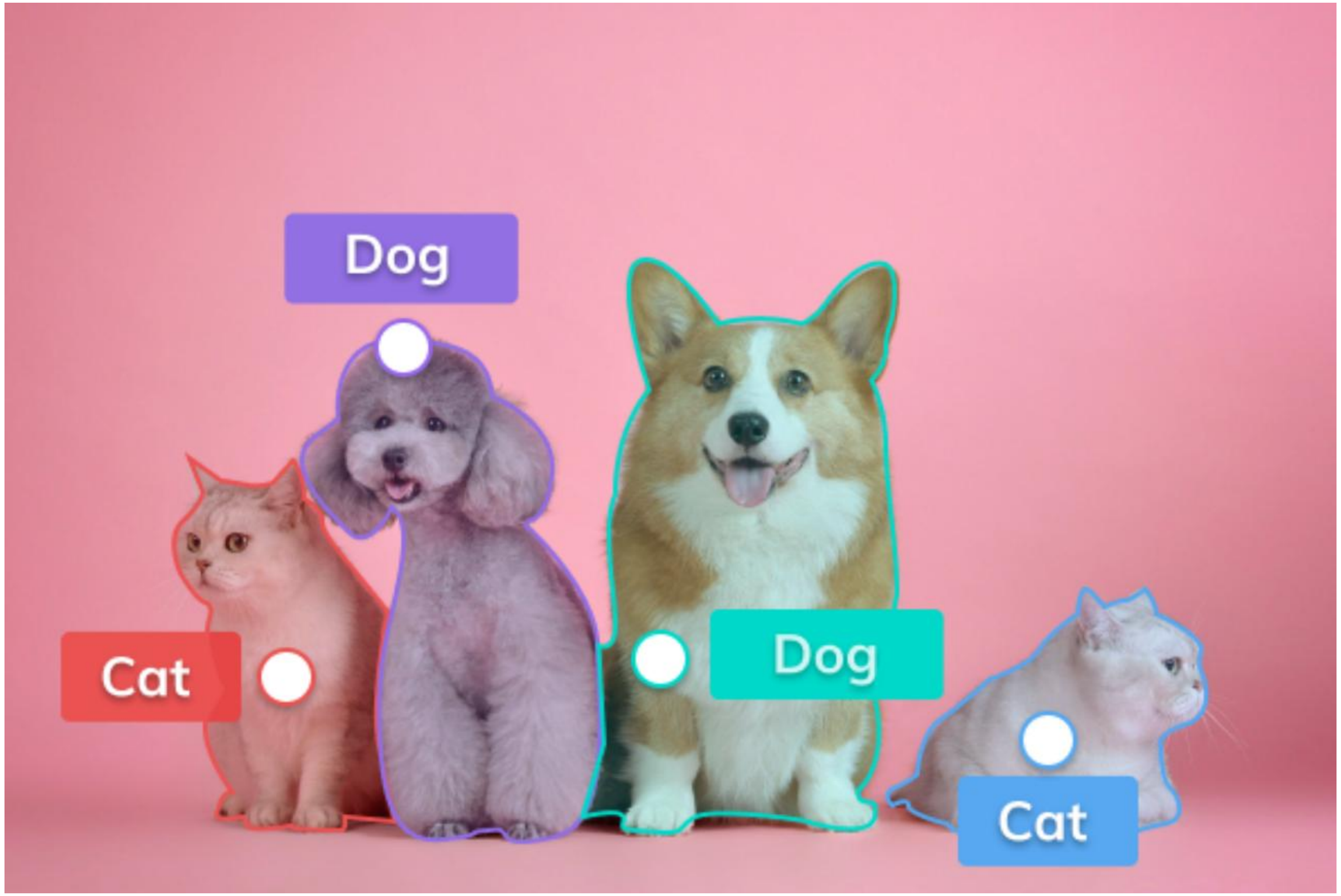
Segmentation: the process of partitioning a digital image into multiple image segments (regions).



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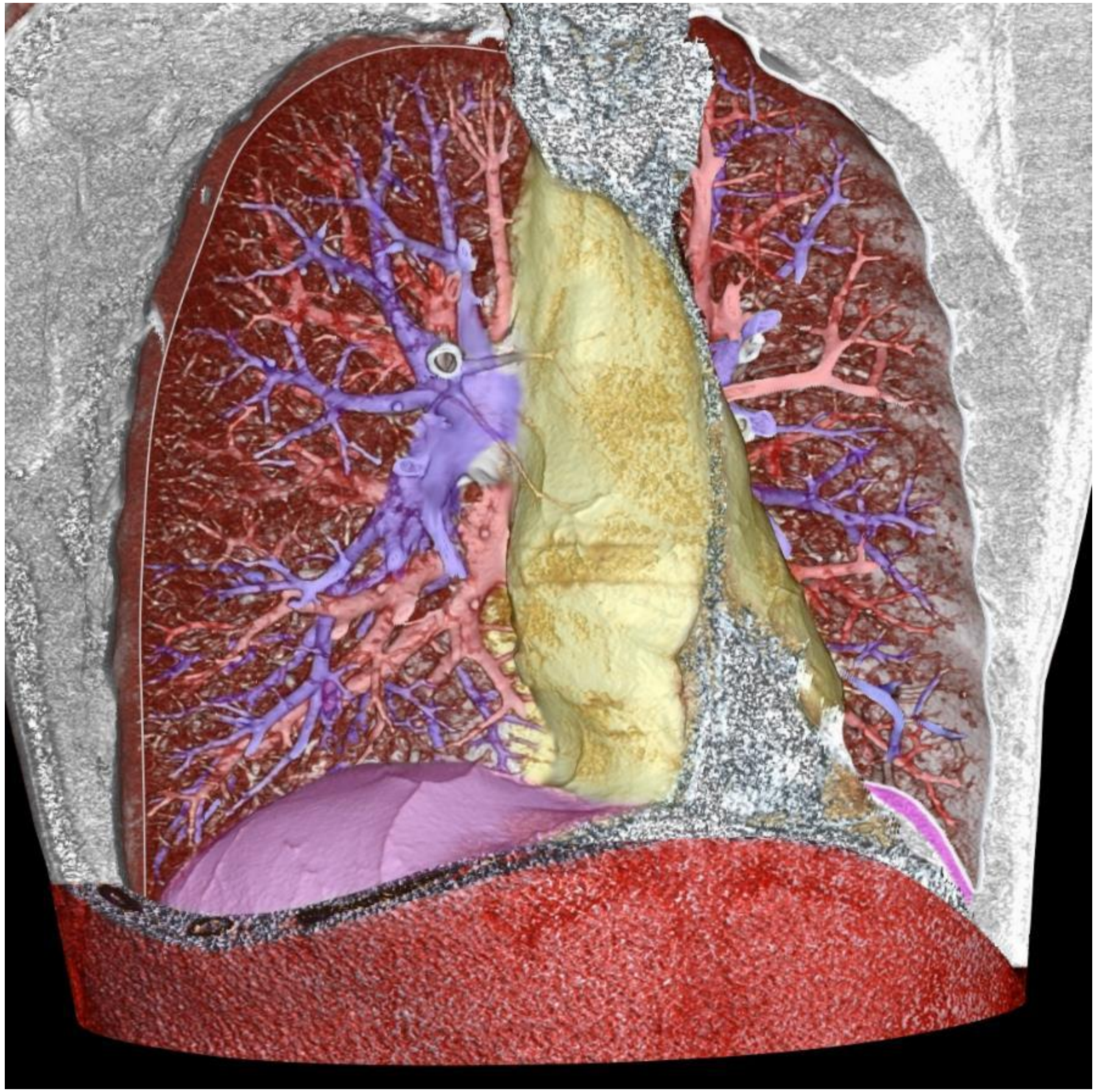

pulmonary arteries: blue; pulmonary veins (and also the abdominal wall): red; the mediastinum: yellow; the diaphragm: violet

Computer vision

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Segmentation: the process of partitioning a digital image into multiple image segments (regions).

Object tracking: follow the movement of an object in a video.

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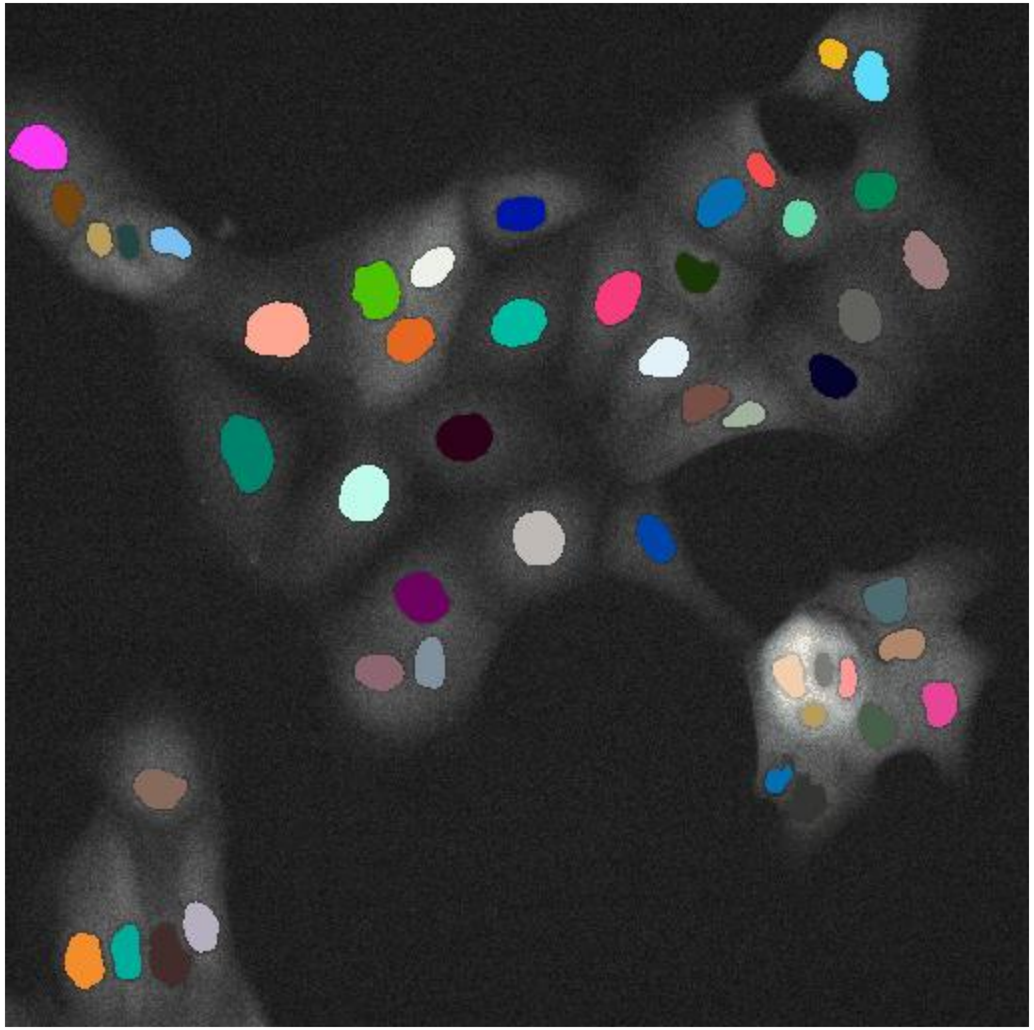

https://imaging.cs.msu.ru/en/research/cell-tracking

Computer vision

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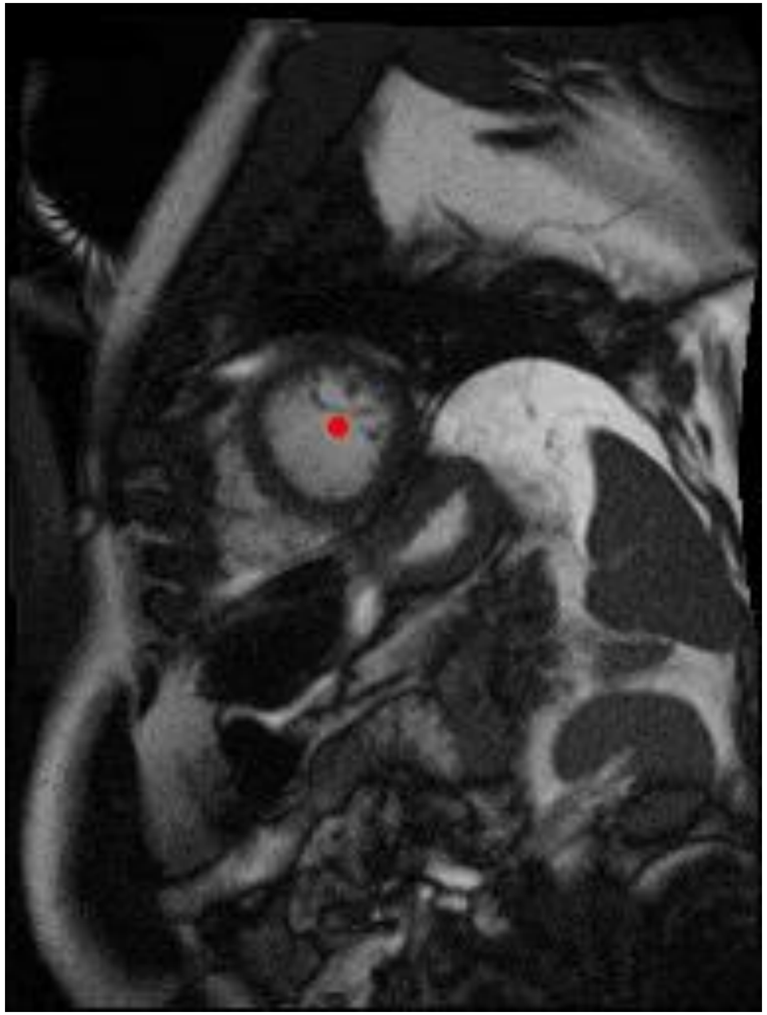

kaggle.com/second-annual-data-science-bowl (2015)

What computers see

206	205	247	245	244	253	247	245	136	151	255	255	255	255	255	255	234	207	231	255	254	254	255	255	254	255	252	255	255	254	255	247
244	161	137	244	254	255	254	255	118	103	209	228	155	153	236	193	74	52	66	173	255	254	254	255	255	255	254	255	254	253	244	184
192	154	75	200	249	255	255	255	110	98	84	61	35	44	89	53	44	45	43	54	140	213	253	255	255	255	255	245	187	186	176	223
90	109	98	143	223	255	255	252	117	75	41	35	31	24	25	38	45	44	44	46	81	118	148	234	252	254	255	248	231	248	255	254
67	69	107	196	236	255	255	255	104	25	34	35	29	20	25	34	32	30	32	34	53	85	100	142	231	242	247	249	255	255	255	255
55	51	45	134	218	251	255	232	51	12	28	33	24	24	46	75	82	78	71	66	58	53	67	90	136	228	208	158	253	246	249	255
79	58	56	75	224	255	255	118	11	27	74	99	91	106	140	162	173	173	173	172	158	137	92	46	78	187	217	206	254	222	233	255
38	43	47	52	147	255	229	56	41	81	129	145	160	169	169	172	178	179	178	179	177	177	172	110	31	82	209	238	255	244	249	255
40	40	33	36	90	245	171	32	65	110	139	145	151	162	171	174	178	179	182	184	187	183	173	162	71	45	167	255	254	255	254	255
37	44	44	31	69	250	158	36	70	129	143	142	153	162	171	175	177	178	182	191	194	188	180	170	120	51	137	255	254	250	254	255
34	45	51	64	116	237	181	53	116	138	140	143	154	164	176	178	174	177	183	186	185	185	183	178	140	66	141	254	252	225	249	255
34	36	52	74	71	188	156	63	131	134	144	155	160	161	173	179	178	179	189	193	190	185	187	182	156	93	148	250	254	214	247	255
32	38	52	54	159	250	126	57	129	138	138	140	151	156	166	168	171	178	180	187	186	185	185	183	180	102	136	242	255	255	254	254
36	32	72	129	212	228	115	65	121	104	102	104	94	103	134	158	170	162	125	106	121	143	155	190	191	104	134	230	253	253	255	251
61	82	116	107	179	247	124	60	101	90	111	119	103	81	94	147	191	178	126	98	123	153	147	161	200	92	100	222	207	167	227	215
144	178	167	231	210	232	170	67	115	88	76	62	83	85	88	139	192	190	135	80	53	99	141	165	201	97	79	192	245	235	248	249
127	145	149	195	204	213	197	95	133	122	117	133	126	108	110	139	191	197	167	129	127	148	147	171	188	110	121	228	233	180	215	212
87	112	100	79	85	82	65	75	142	148	151	153	138	125	120	149	191	190	193	175	174	193	198	190	208	127	163	239	219	149	198	196
63	83	109	134	129	106	39	78	132	142	155	159	139	111	124	164	195	200	186	192	191	195	200	202	200	143	217	253	249	242	238	234
69	78	78	113	97	74	43	106	127	140	152	155	125	97	112	150	185	194	174	183	196	198	202	208	209	166	247	254	255	254	254	254
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82	76	92	79	54	58	37	47	90	121	132	116	89	78	111	146	163	149	122	124	180	197	197	198	178	149	146	152	155	157	159	168
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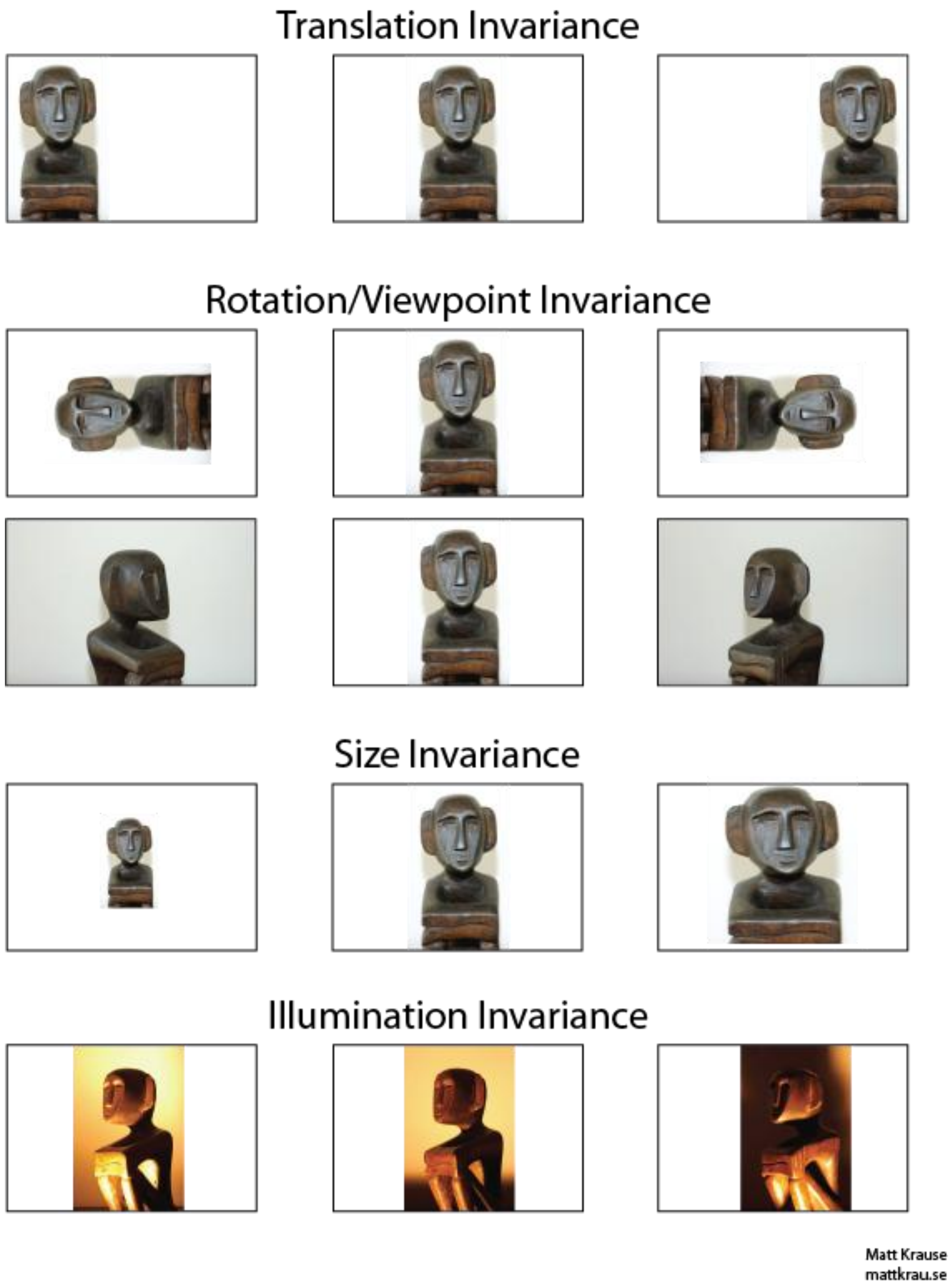
117	124	127	133	135	105	21	28	37	88	115	121	128	128	141	142	168	202	212	153	164	186	180	168	154	146	144	149	151	151	147	144
119	118	118	125	128	111	21	29	28	58	100	118	131	140	151	159	186	201	205	192	180	168	149	166	119	144	147	143	140	141	144	148
117	119	125	130	139	106	18	29	44	58	70	102	133	147	168	197	212	215	210	195	177	152	133	195	57	59	126	151	145	143	142	141
115	123	126	134	145	102	27	54	52	38	45	69	105	135	175	189	193	216	206	166	139	111	164	203	74	5	121	151	142	142	143	146
101	108	123	121	132	105	44	40	31	35	57	44	58	101	147	144	138	163	145	94	90	145	196	187	84	48	165	160	142	144	142	145
98	97	97	98	104	76	34	33	30	48	41	49	51	58	74	53	55	66	63	89	150	188	209	156	62	108	140	149	125	133	131	131
102	102	97	88	73	35	30	23	42	50	65	41	90	60	59	51	57	82	123	157	187	206	169	62	98	151	106	101	154	135	130	129

https://setosa.io/ev/image-kernels/

Invariances

Invariance means that we can recognize an object as an object, even when its appearance varies in some way.



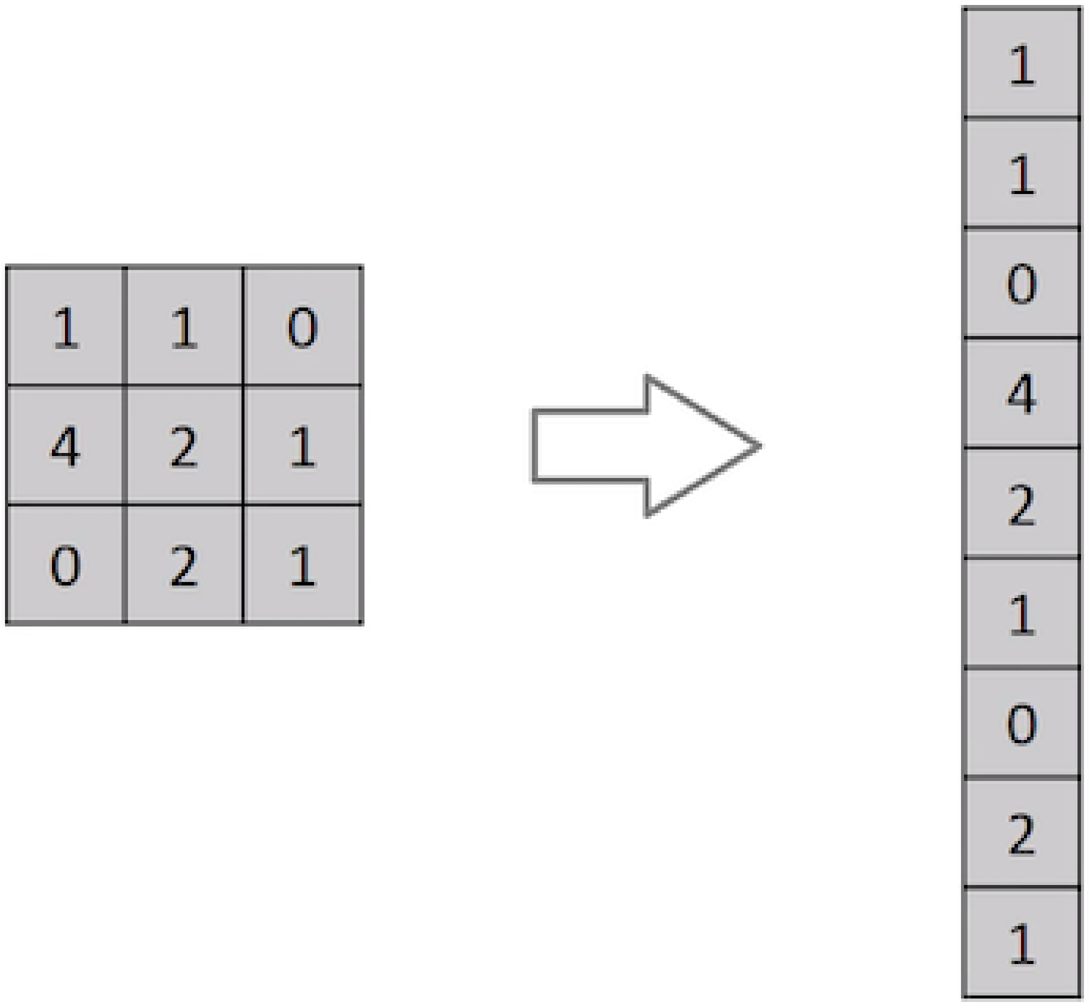
Flatten

We could just represent each pixel as a feature.

This would mean that we **flatten** the 2D matrix to a 1D feature vector.

The learning algorithm then needs to learn the 2D **spatial correlations** from the 1D representation.

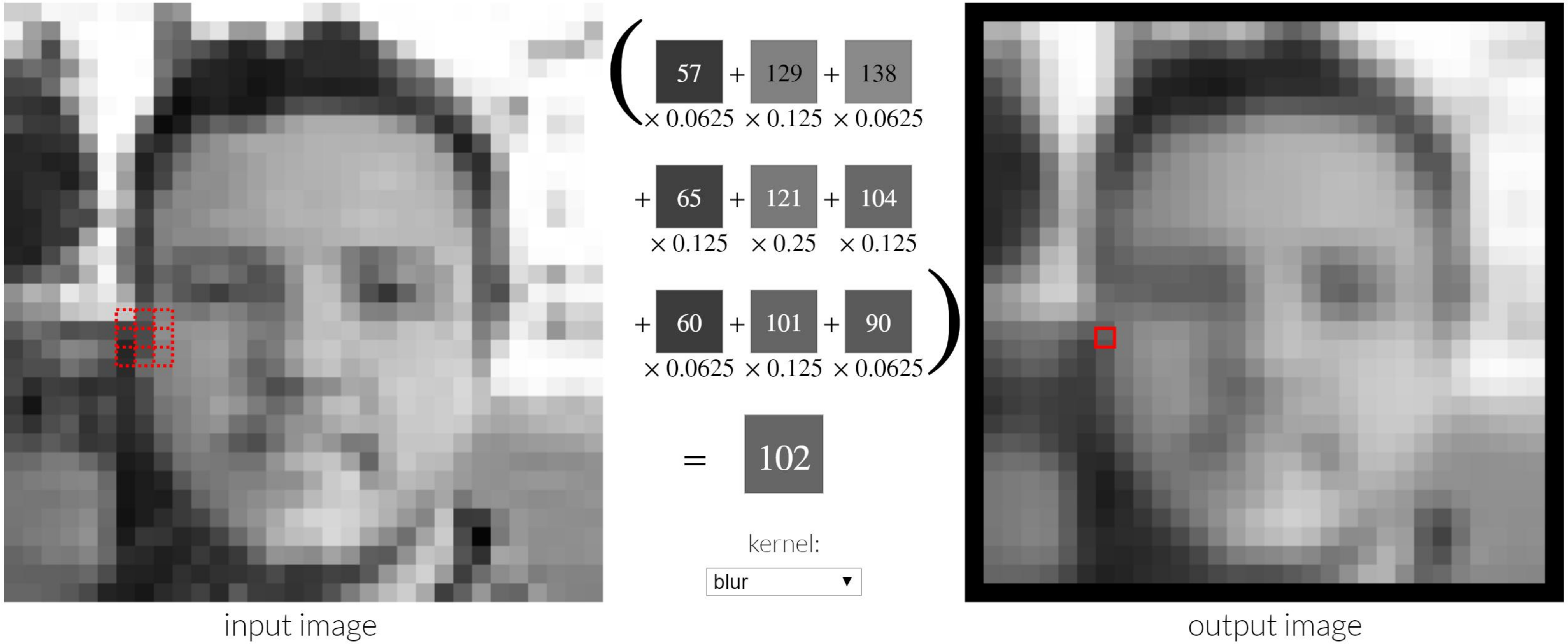
And what with the invariances?



Convolutional filter

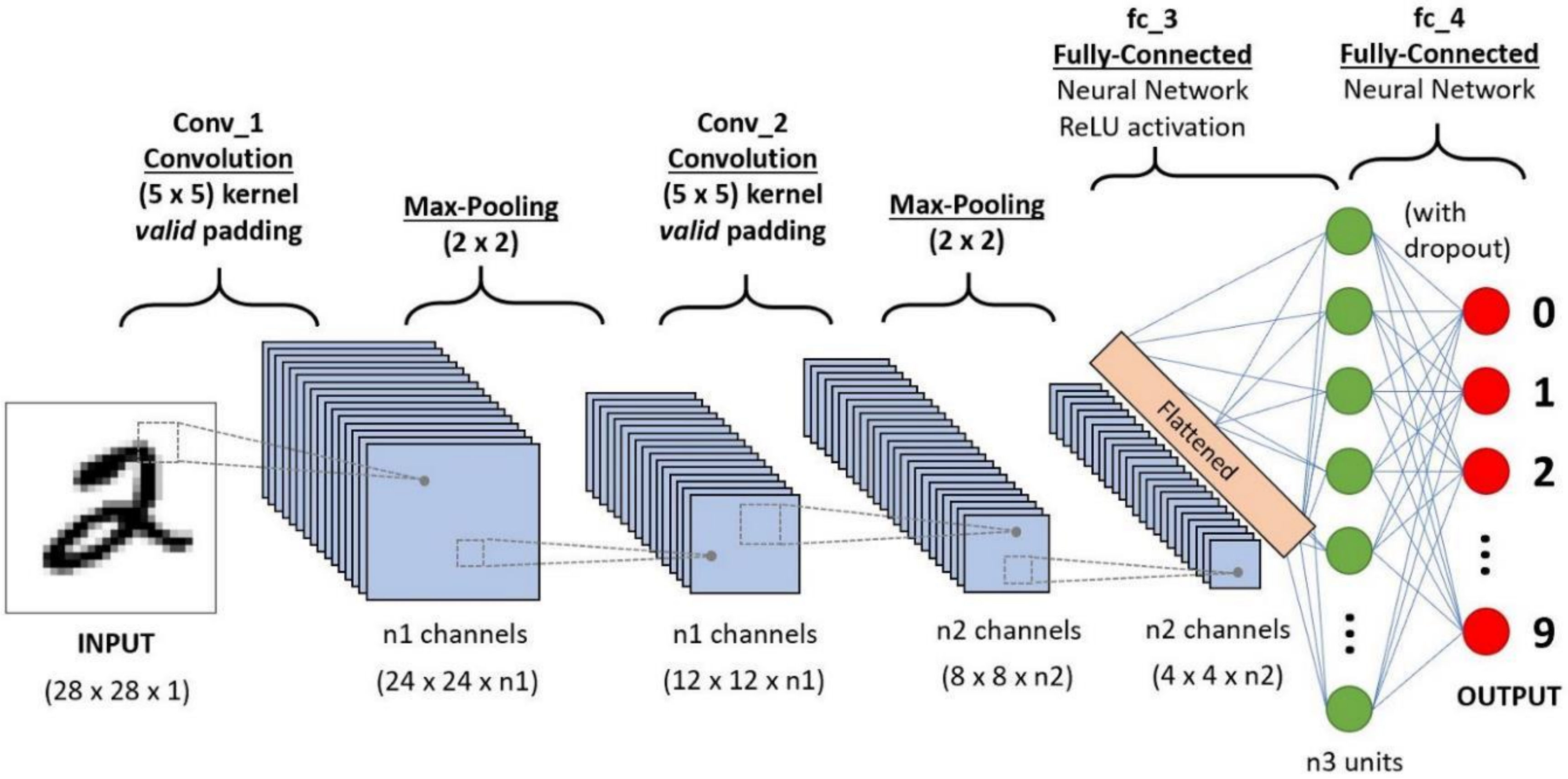
Convolutional filters are small matrices that "slide" over an image.

They provides a measure for how close a patch or a region in the image resembles a **feature**.



Convolutional neural networks (CNN)

A **convolutional neural network (CNN)** module stacks modules that consist of
- **feature maps** (or **channels**) that each learn a relevant convolutional filter with specific dimensions, and
- a **pooling layer** that allows for the location invariance of the learned features.

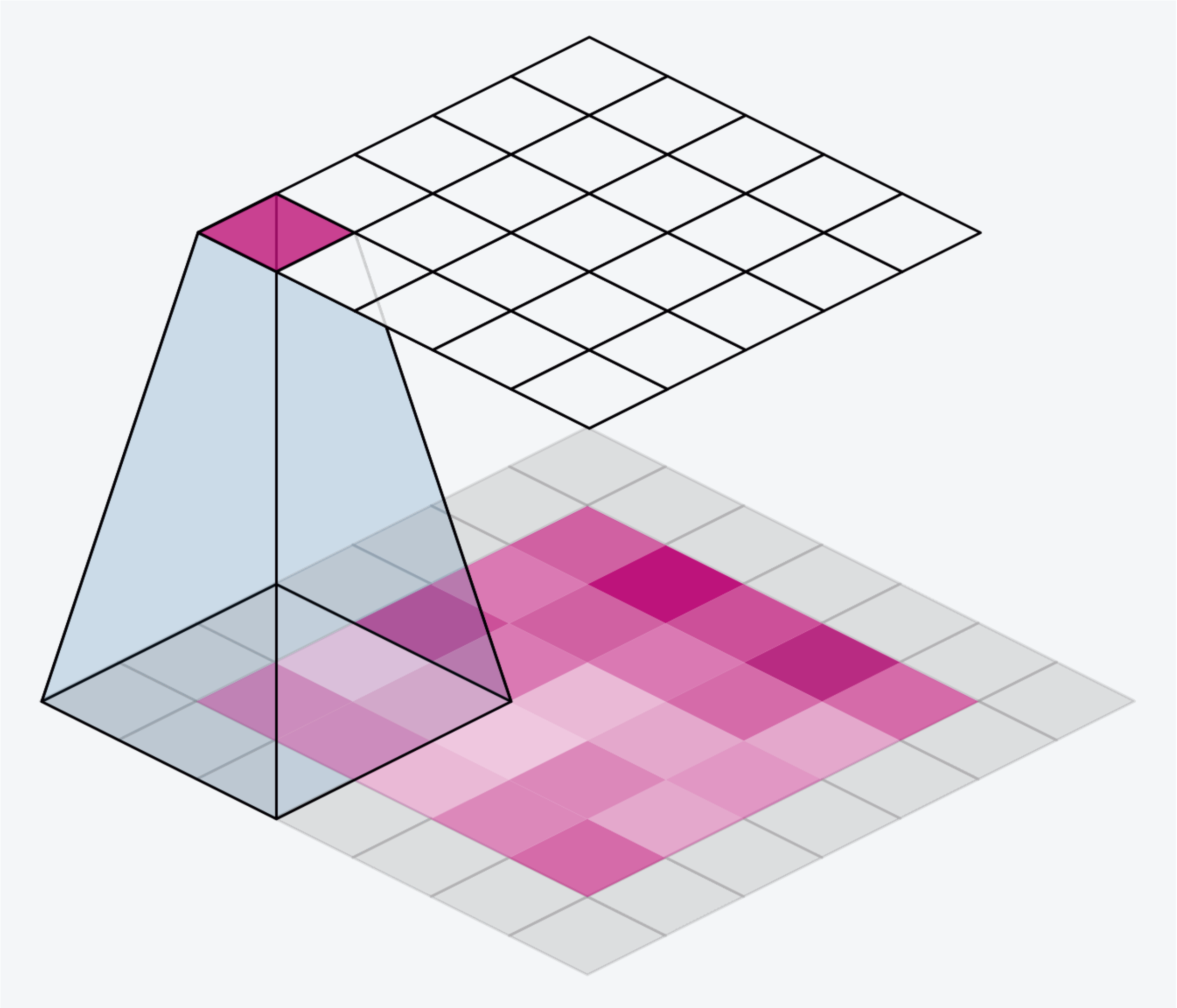


Feature map

Each neuron looks at a different (overlapping) part in the image and performs a convolution.

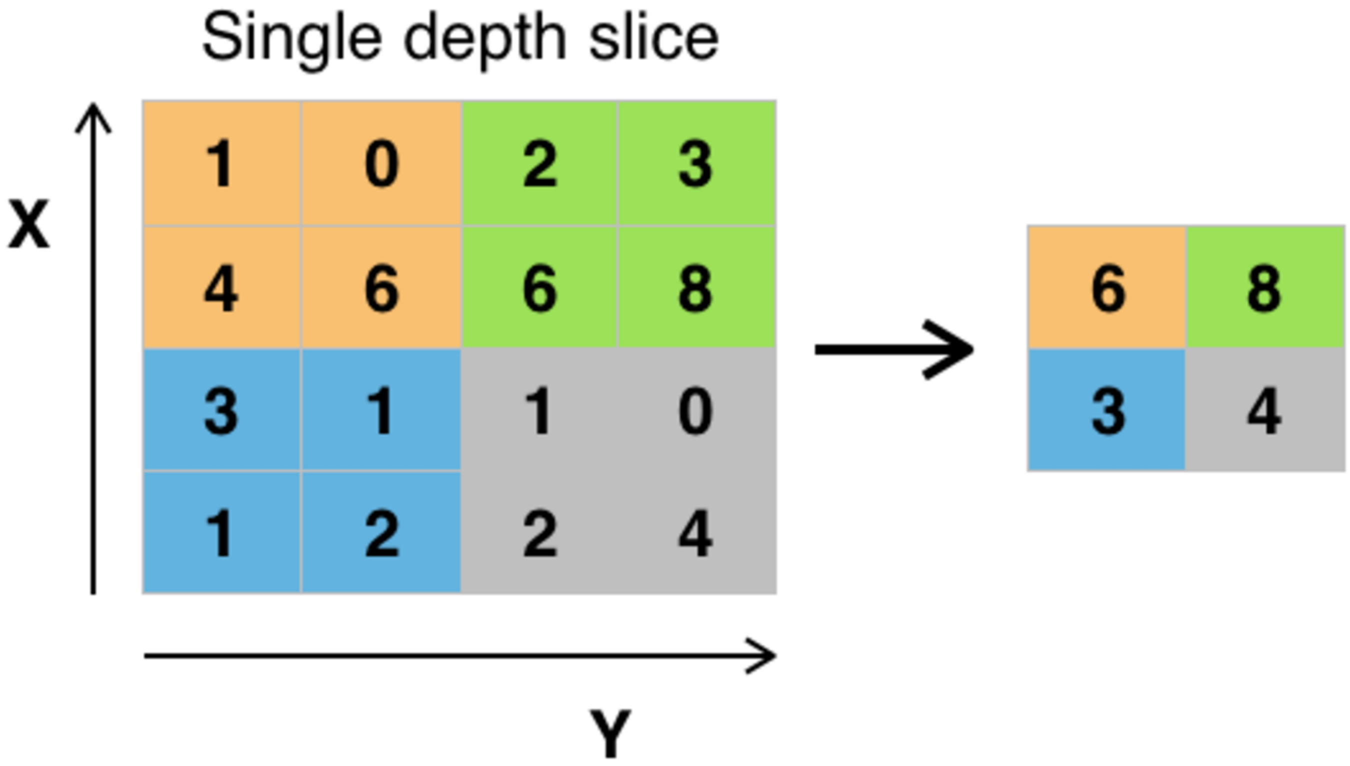
The convolution is defined by the modelparameters that are learned from the data.

So, in each feature maps, the modelparameters for each neuron have the same value, i.e. they are shared. The only difference is in what part of the image the neuron looks at.



Pooling

Maximum pooling, or max pooling, is a pooling operation that calculates the maximum, or largest, value in each patch of each feature map.



Example of Maxpool with a 2x2 filter and a stride of 2

Invariances: data augmentation

CNNs are

translation invariant,

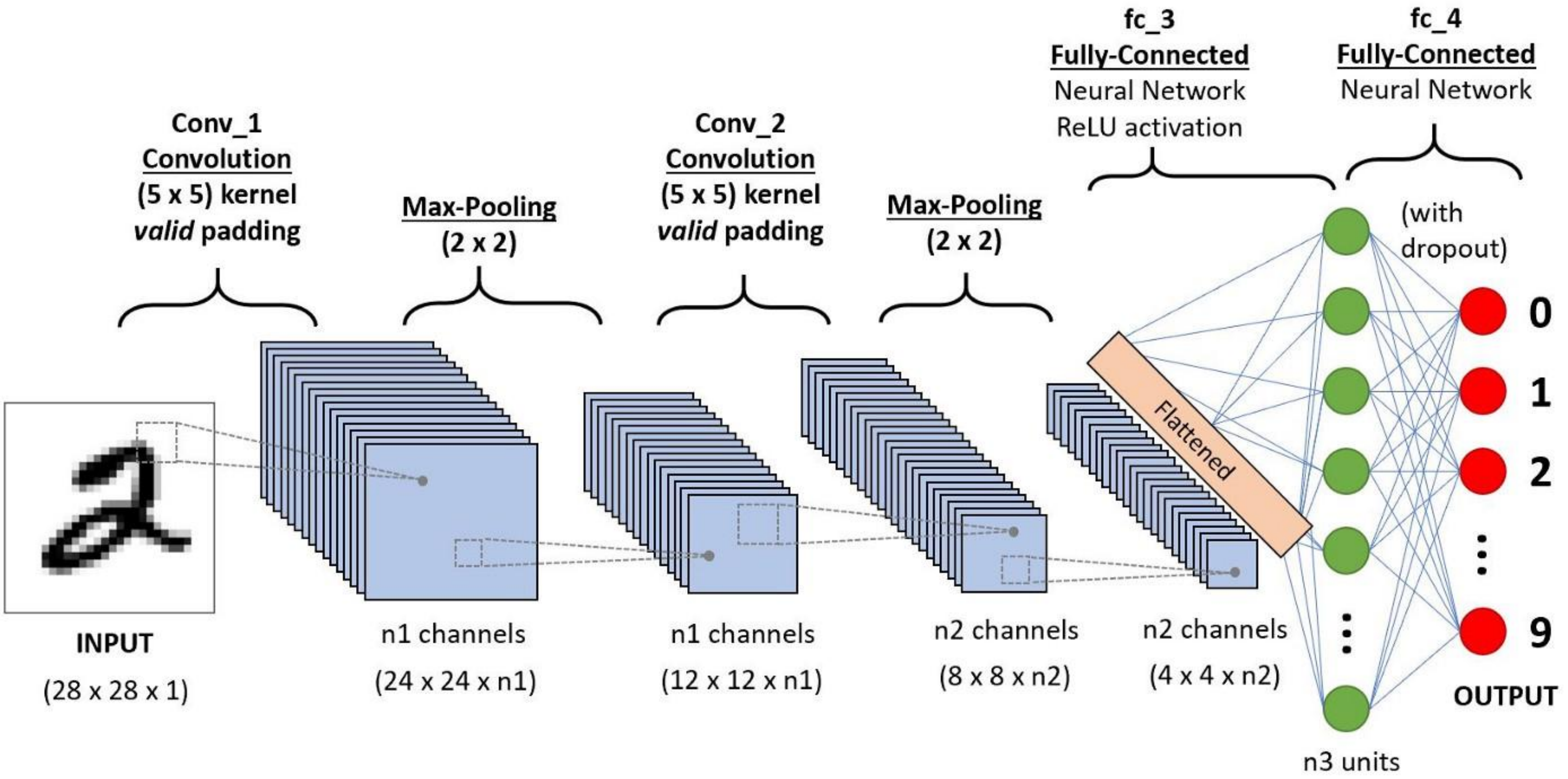
scale invariant to some degree (learned from data, not in filters),

not rotation invariant (learned from data),

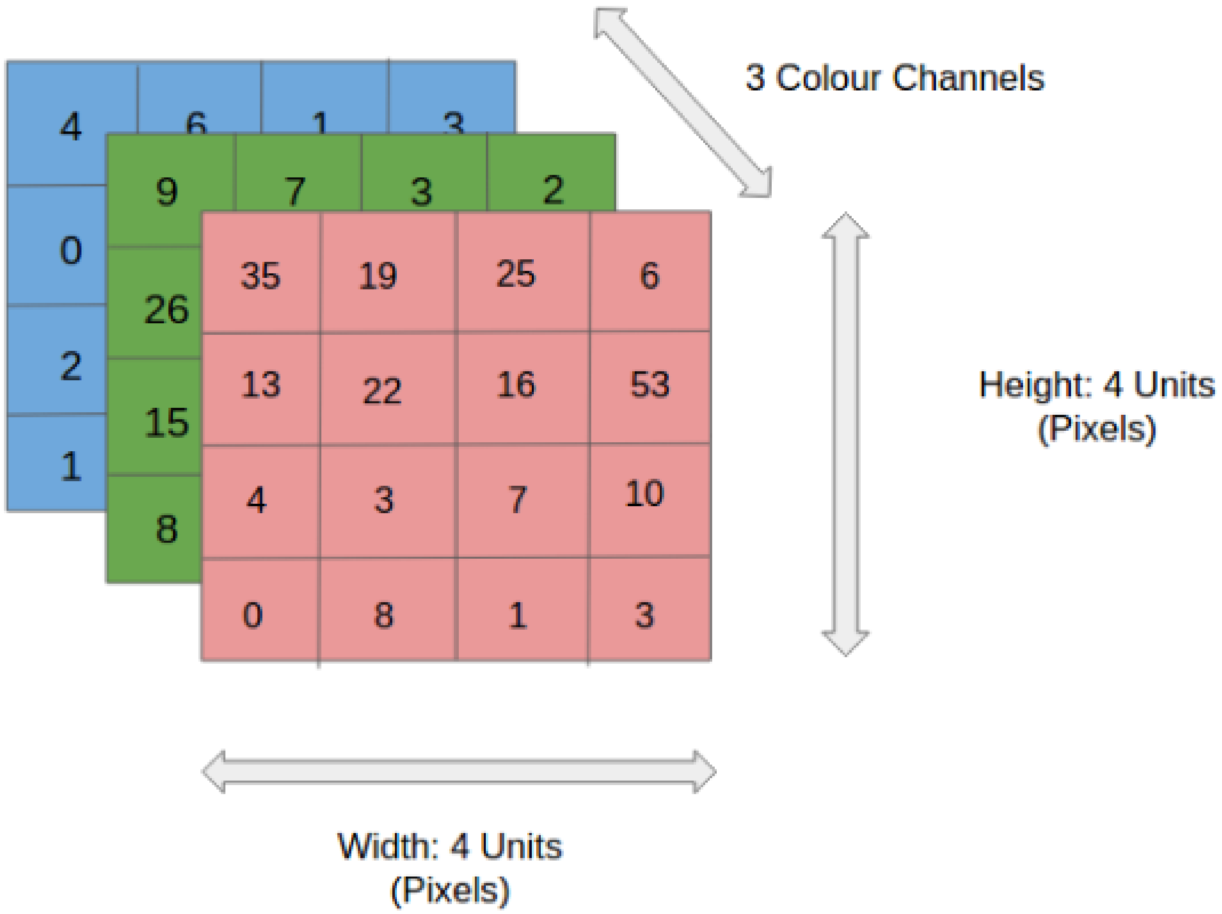
not illumination invariant (learned from data).

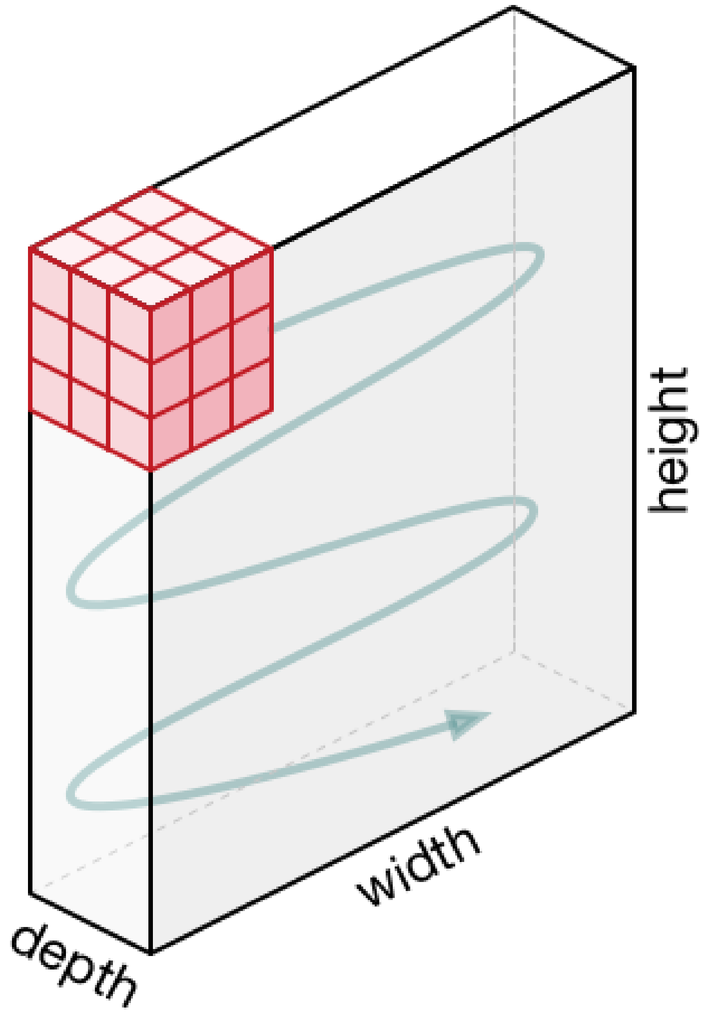
We can generate artificial data, by rotating, scaling, illuminating training images. A process called **data augmentation**. This is a form of model **regularization**.

CNN


Conv_1
Convolution
(5 x 5) kernel
valid padding
Max-Pooling
(2 x 2)
Conv_2
Convolution
(5 x 5) kernel
valid padding
Max-Pooling
(2 x 2)
fc_3
Fully-Connected
Neural Network
ReLU activation
fc_4
Fully-Connected
Neural Network
(with dropout)
Flattened
0
1
2
9
INPUT
(28 x 28 x 1)
n1 channels
(24 x 24 x n1)
n1 channels
(12 x 12 x n1)
n2 channels
(8 x 8 x n2)
n2 channels
(4 x 4 x n2)
n3 units
OUTPUT

CNN: channels





Neural network

mnist_pytorch.ipynb

ImageNet

ImageNet is a large-scale visual database designed for use in visual object recognition research, containing millions of labeled images across thousands of categories.

It was introduced by Fei-Fei Li and her team in 2009 and played a crucial role in advancing deep learning, particularly in convolutional neural networks (CNNs).

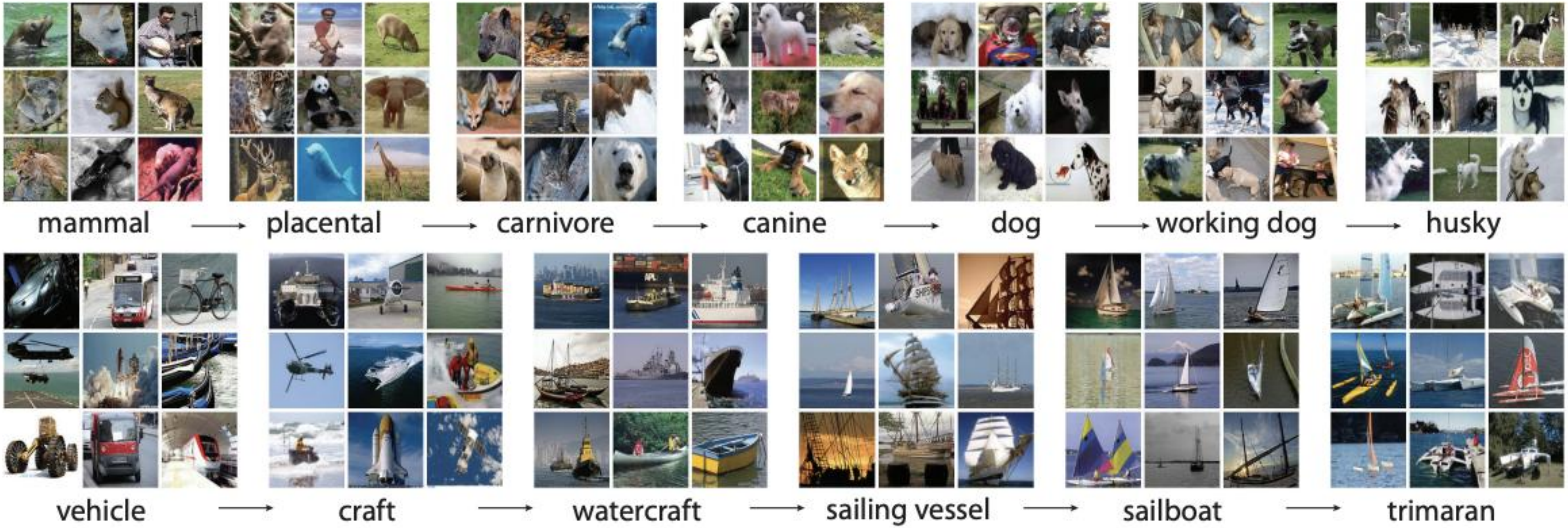
The ImageNet Large Scale Visual Recognition Challenge (ILSVRC), held annually from 2010 to 2017, drove major breakthroughs in AI and computer vision, with models like AlexNet, VGG, ResNet, and EfficientNet achieving state-of-the-art performance.

Despite its influence, ImageNet has limitations, including dataset bias, ethical concerns related to labeling, and challenges in real-world generalization beyond the controlled dataset.

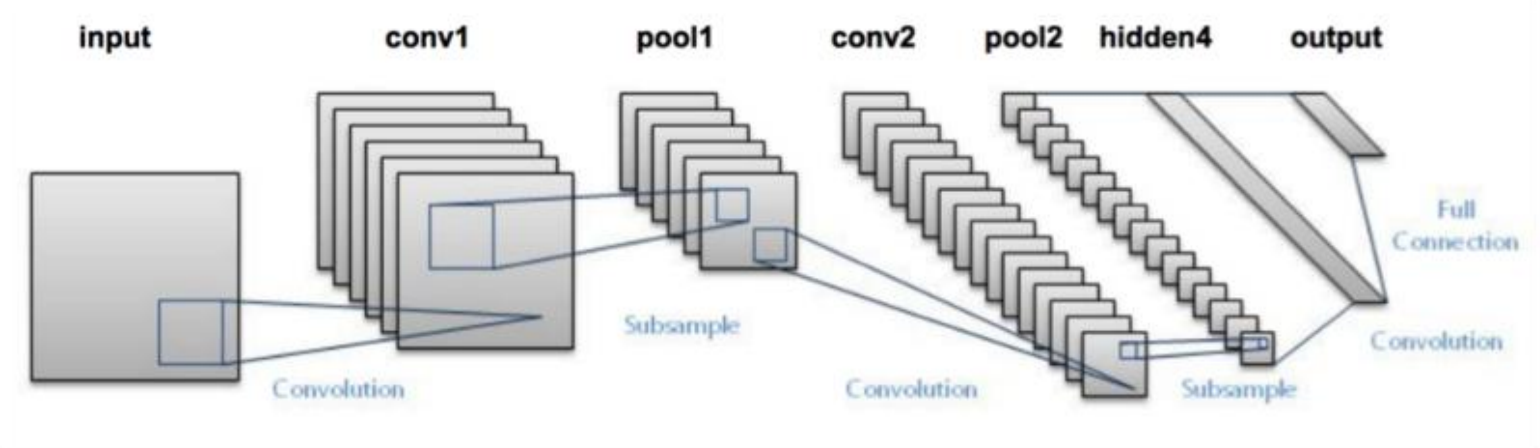
Data is everything: ImageNet

J. Deng et al., "ImageNet: A large-scale hierarchical image database," 2009 IEEE Conference on Computer Vision and Pattern Recognition

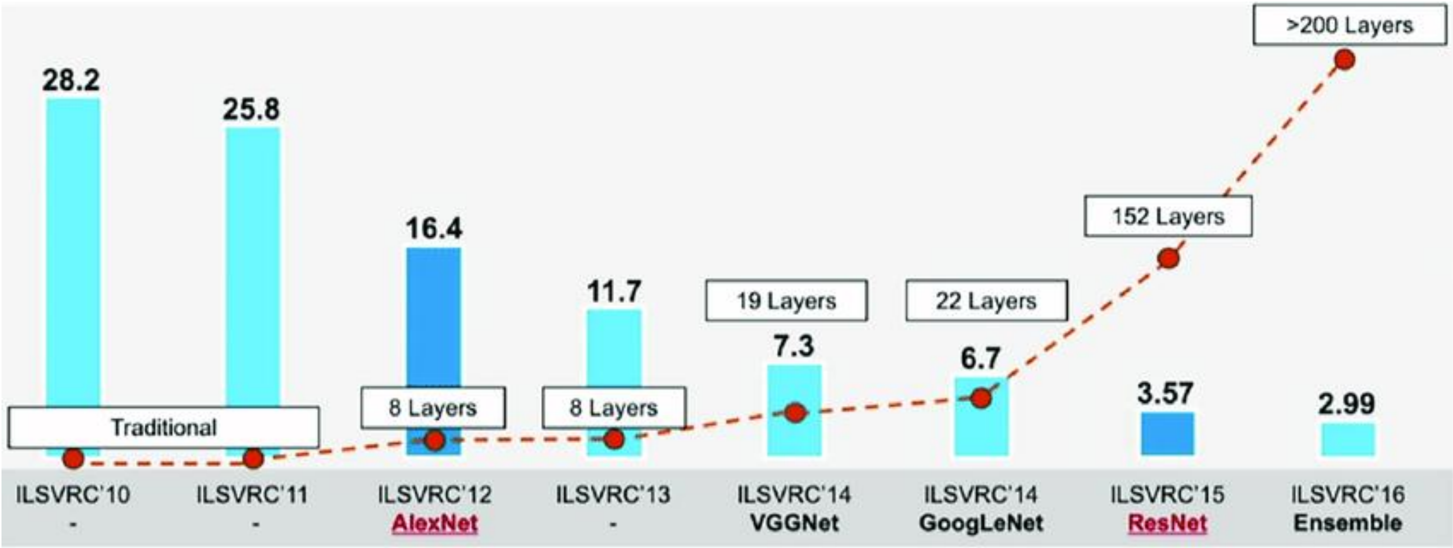
Data is everything: ImageNet



ImageNet: computer vision is solved

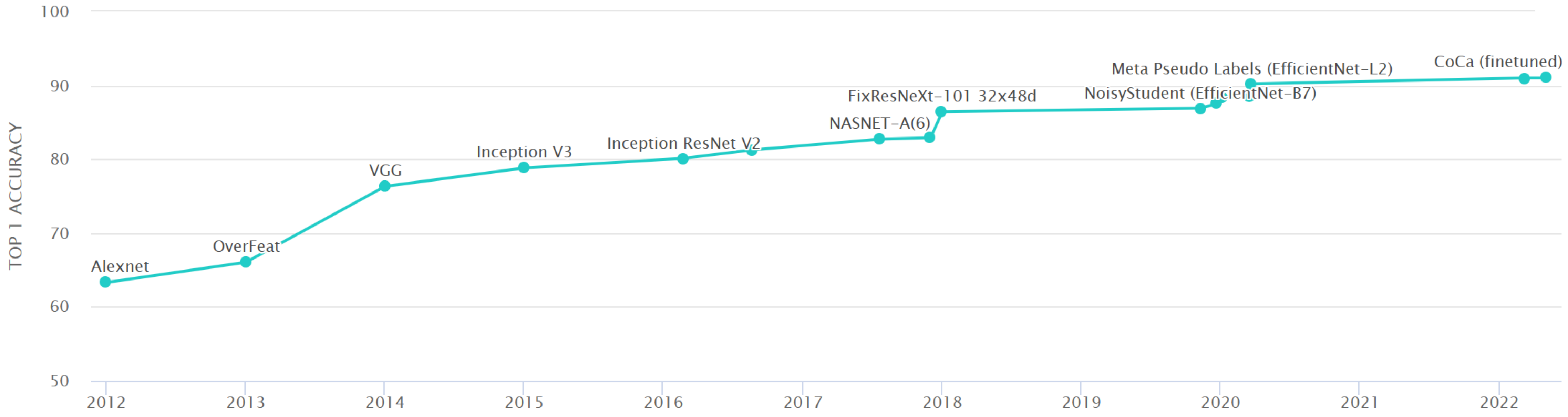


LeNet-5 (1998)



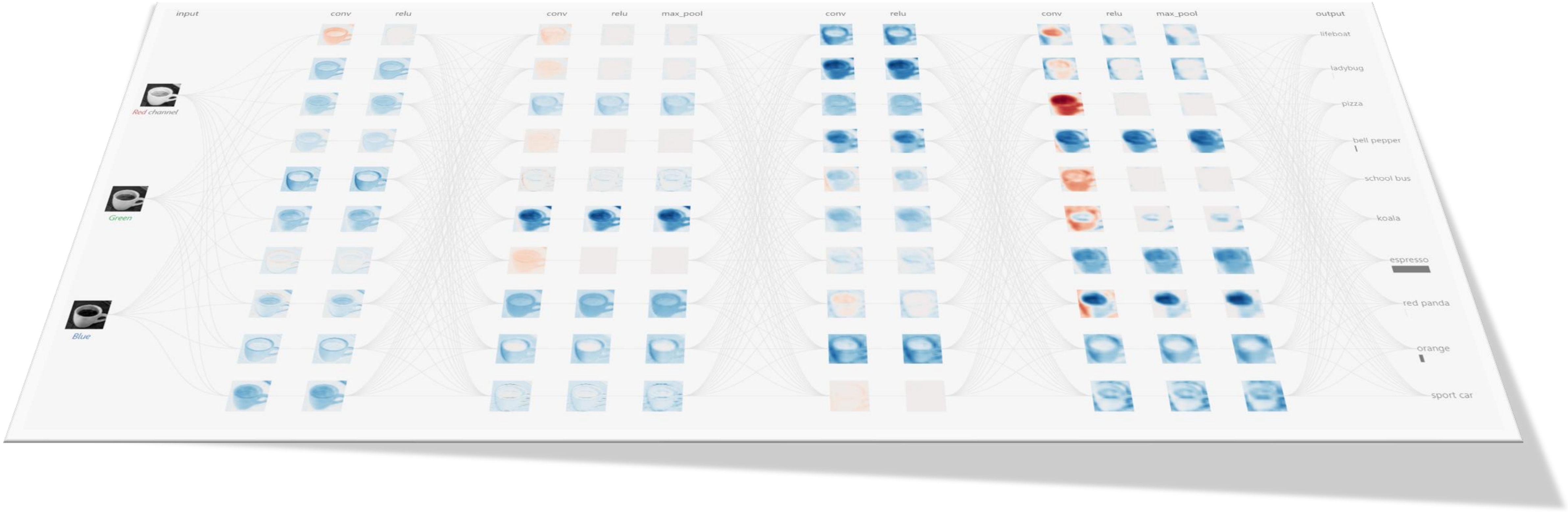
ImageNet Large Scale Visual Recognition Challenge: https://www.image-net.org/challenges/LSVRC/

ImageNet: computer vision is solved



https://paperswithcode.com/sota/image-classification-on-imagenet

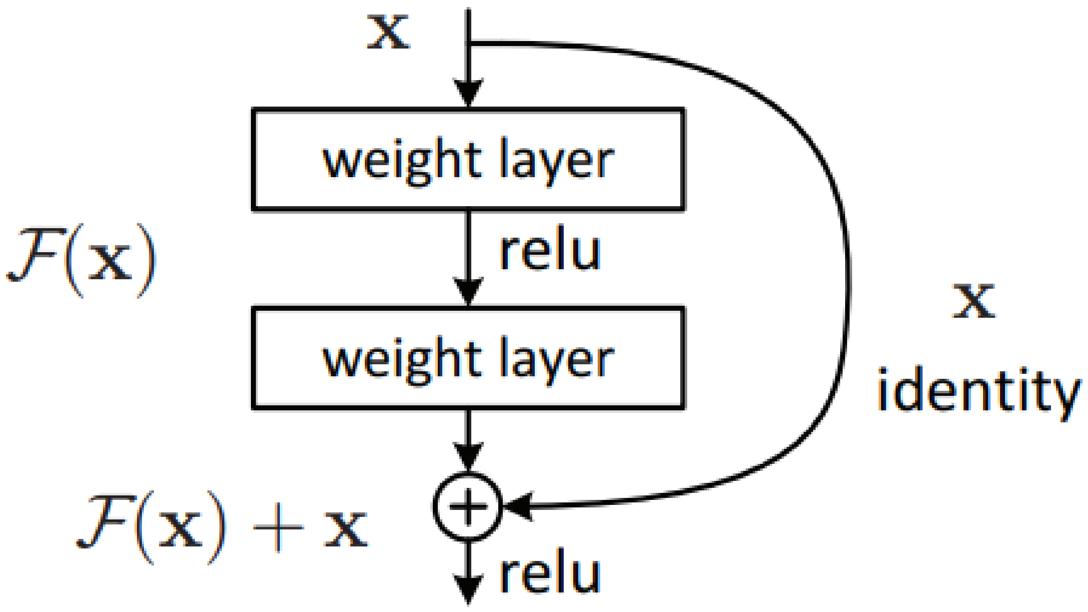
What computers see



https://poloclub.github.io/cnn-explainer/

ResNet (Residual Network)

ResNet introduces **skip connections**, allowing gradients to bypass certain layers, solving the vanishing gradient problem and enabling the training of very deep networks.



He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. CVPR, 770-778.

ResNet (Residual Network)

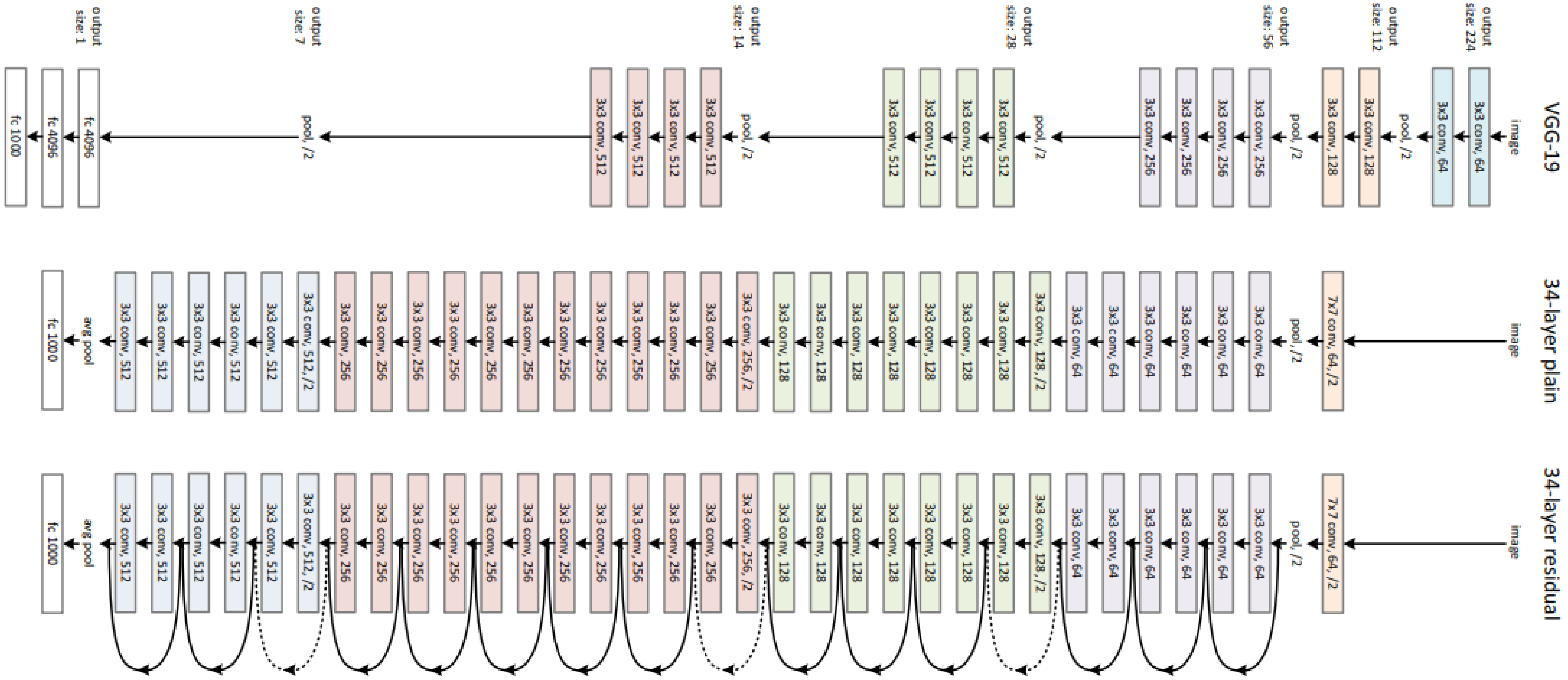
ResNet introduces **skip connections**, allowing gradients to bypass certain layers, solving the vanishing gradient problem and enabling the training of very deep networks.

Instead of learning the full transformation, ResNet learns the **residual (difference) between input and output**, making optimization easier and improving convergence.

ResNet enables training of networks with **hundreds or even thousands of layers**, significantly improving performance in image recognition tasks without degradation.

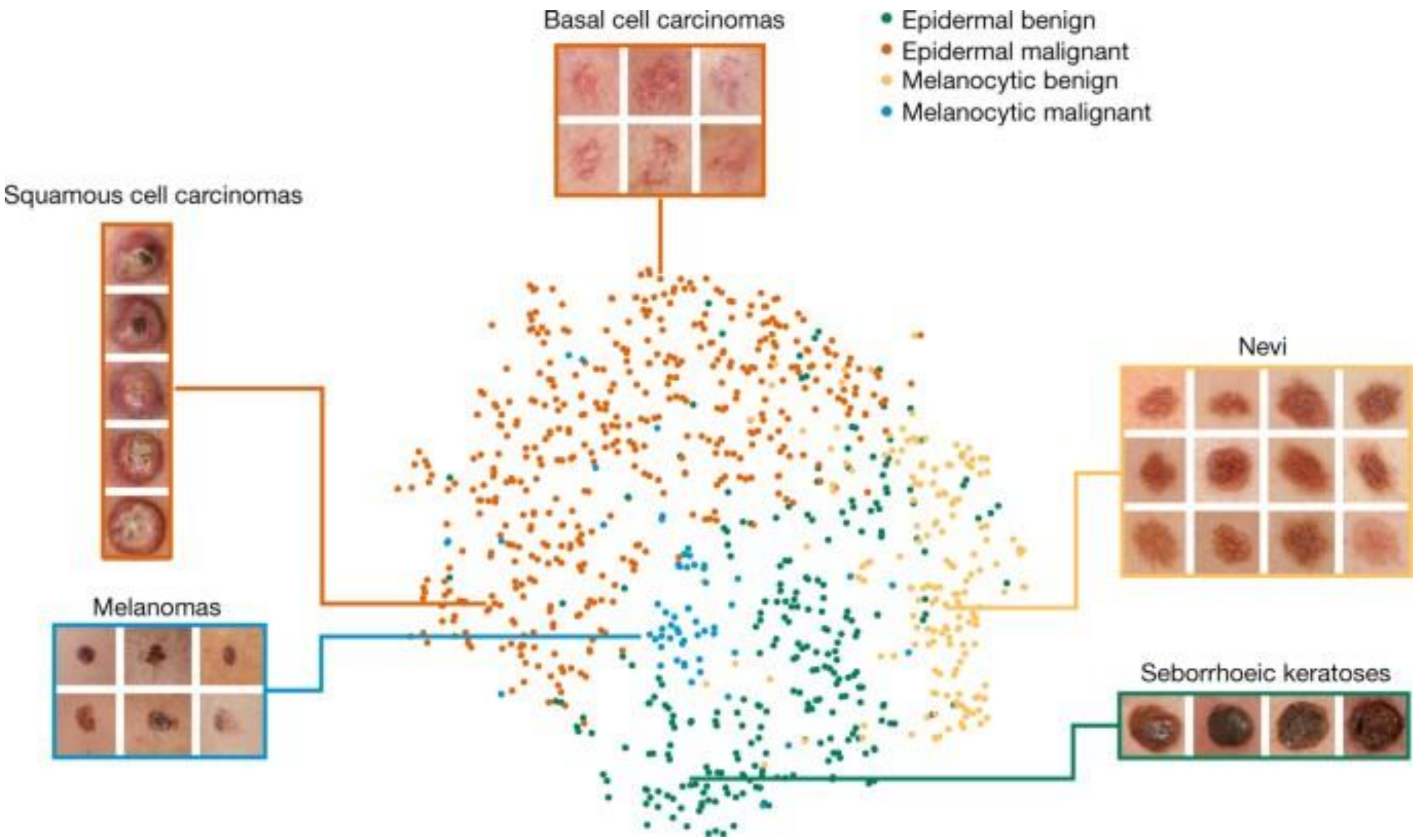
He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. CVPR, 770-778.

ResNet (Residual Network)

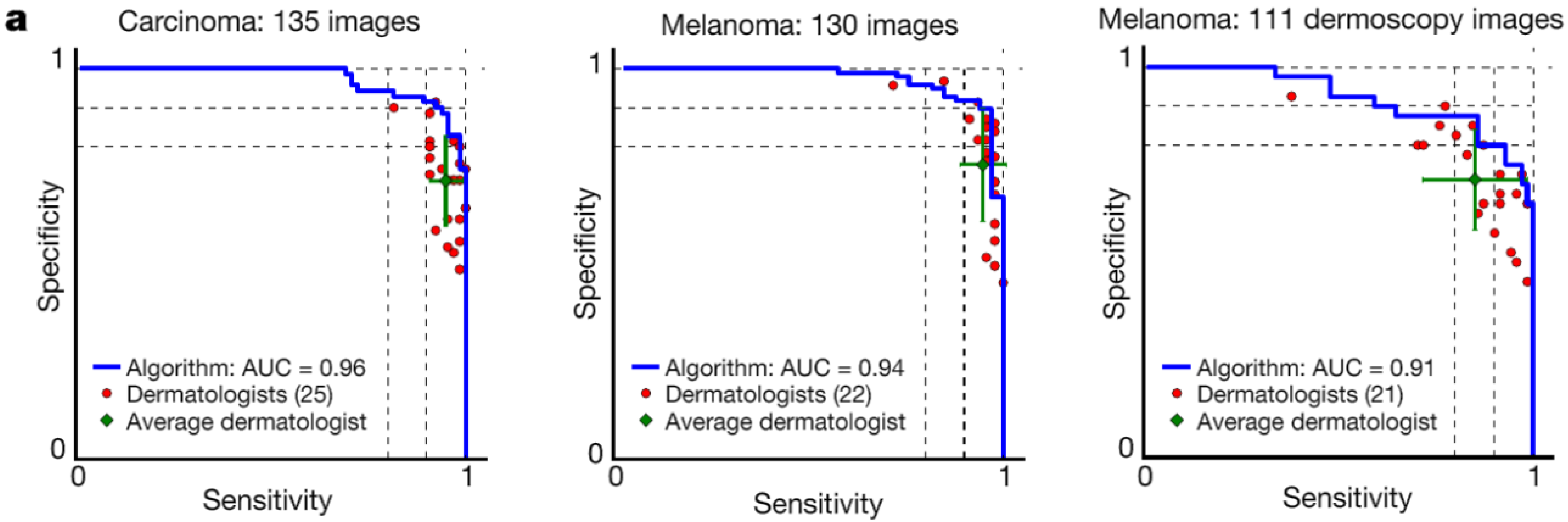


He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. CVPR, 770-778.

Remember this?



Thrun et al., Dermatologist-level classification of skin cancer with deep neural networks, Nature (2017)



keratinocyte carcinomas: 65
benign seborrheic keratoses: 75

malignant melanomas: 33
benign nevi: 97

malignant melanomas: 71
benign nevi: 40

Thrun et al., Dermatologist-level classification of skin cancer with deep neural networks, Nature (2017)