Lecture 11:

Convolution and Image Classification & Segmentation

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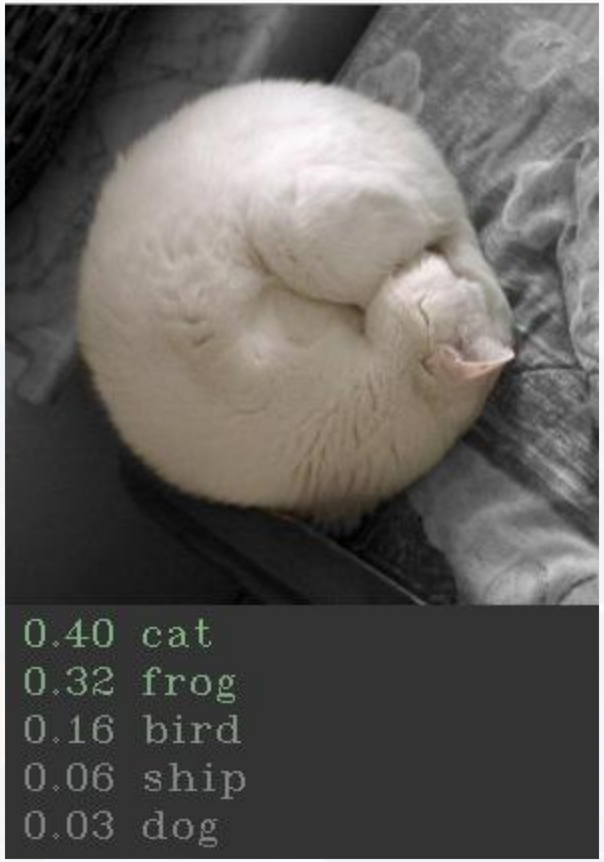
Bayesian Data Analysis and Machine Learning for Physical Sciences

Course Map



Outline

The Problem

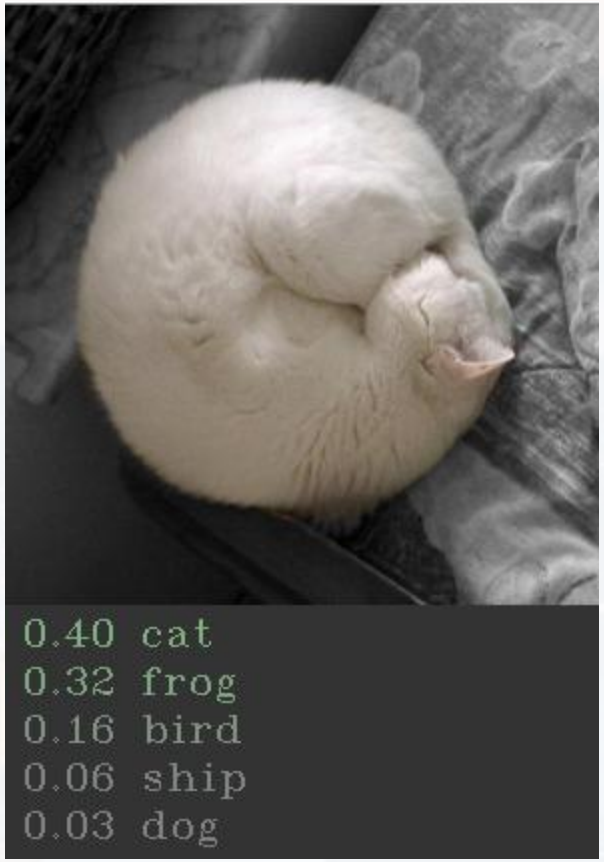
Convolution

CNN Architectures

Data Preparation & Training

Example

- LeNet numpy only
- LeNet TensorFlow
- sequences as images
- segmentation



Outline

The Problem **part I**

Convolution

CNN Architectures

Data Preparation & Training

Example **part II**

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- LeNet TensorFlow
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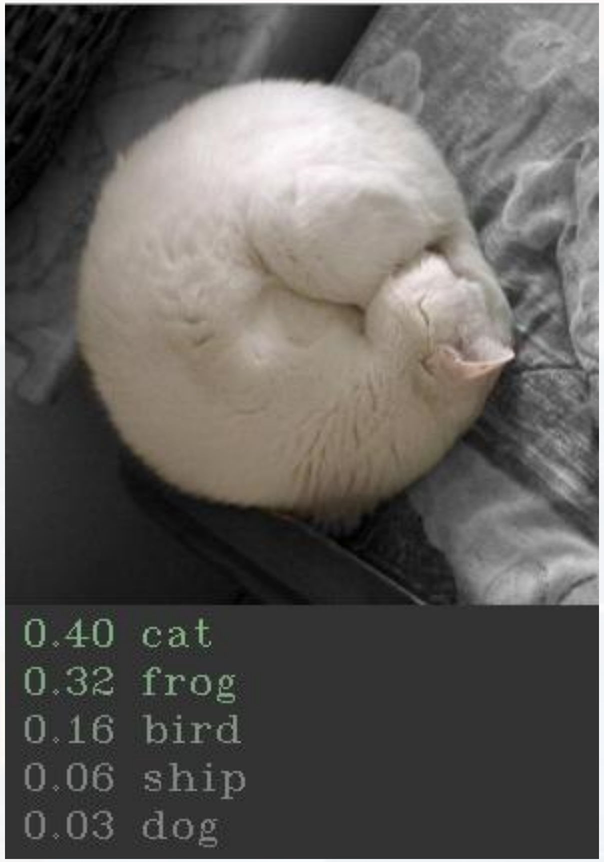
- segmentation



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Convolution and Image Classification & Segmentation

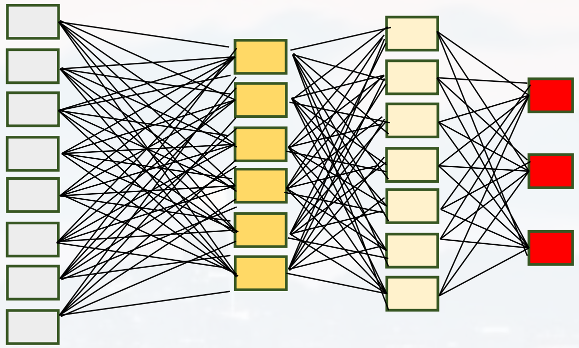
The Problem

so far:

data features

data points

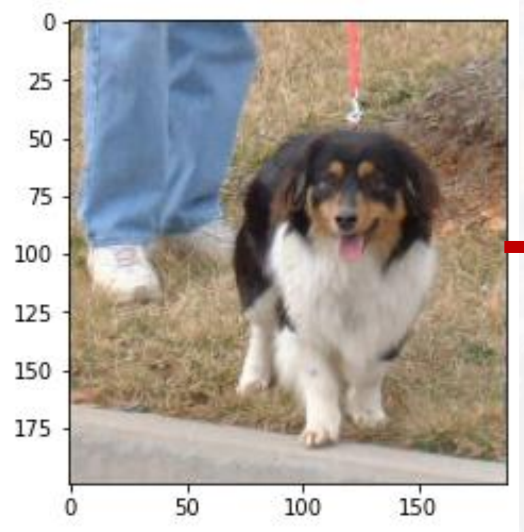
```
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
```



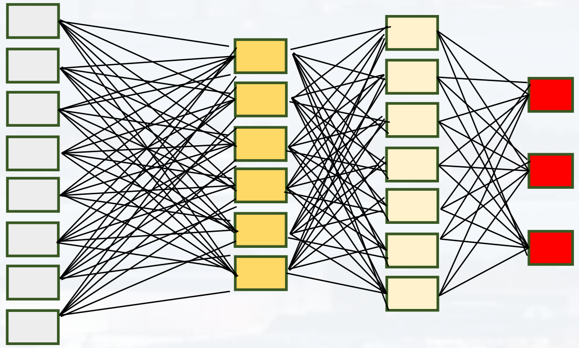
data points are **not related**,
no spatial information

row = data point

now:



?



data points are **related**,
lots of spatial information

Convolution and Image Classification & Segmentation

so far:

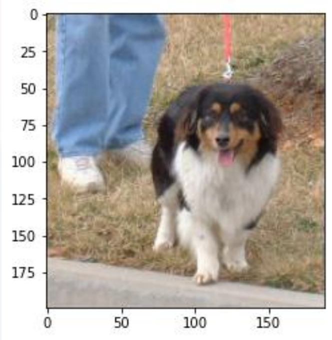
data features

data points

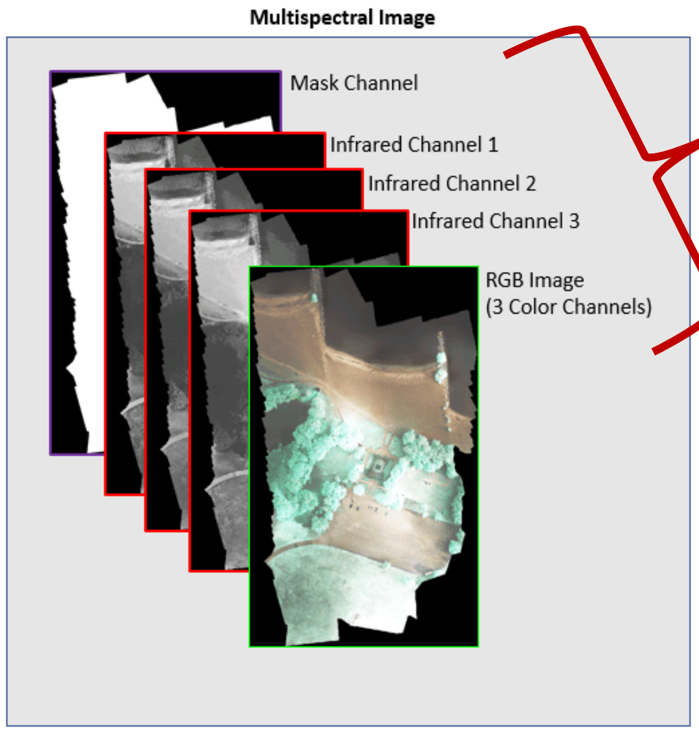
```
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
```

row = data point

now:



matrix = data point



matrices can have n color channels

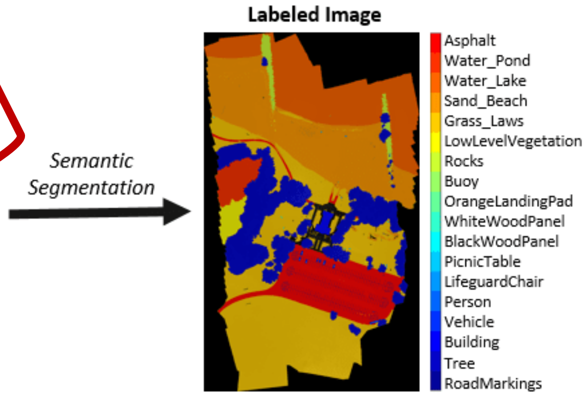
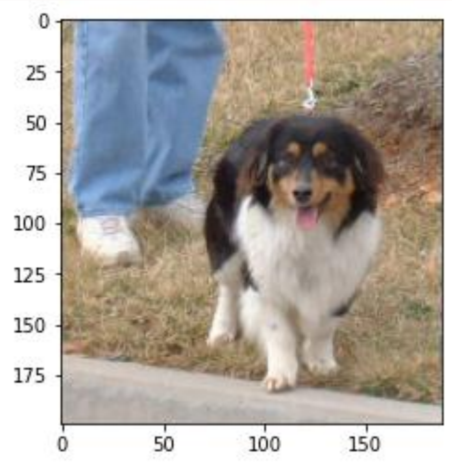


image curtesy: Mathworks

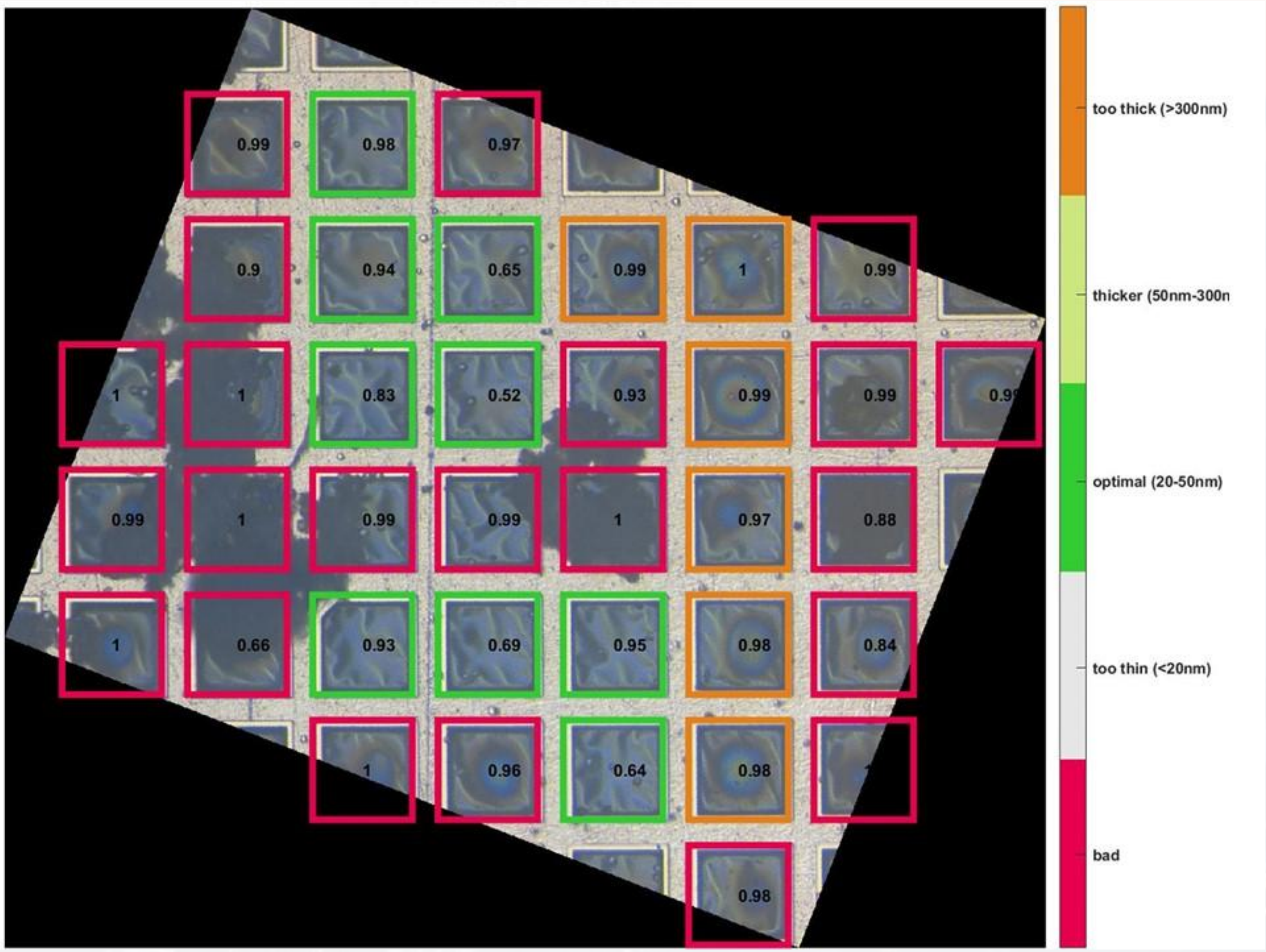
Convolution and Image Classification & Segmentation

1) classification: between different images



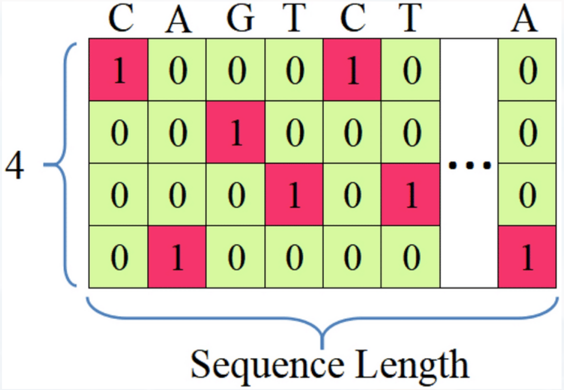
different pixel within images aka **2) segmentation**

segmentation *for* classification

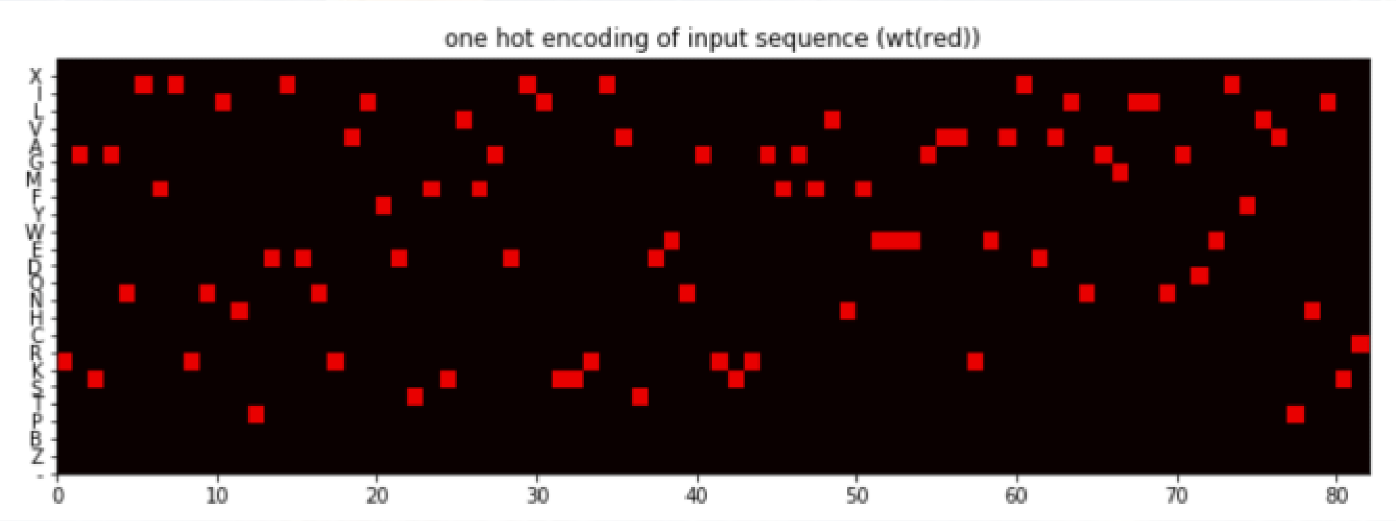


see here

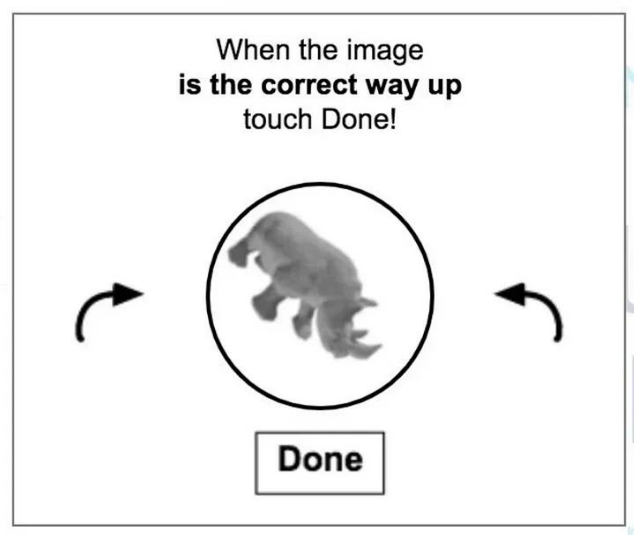
motif finding / sequence analysis



one – hot encoded NT or AA sequences can be interpreted as b/w images!

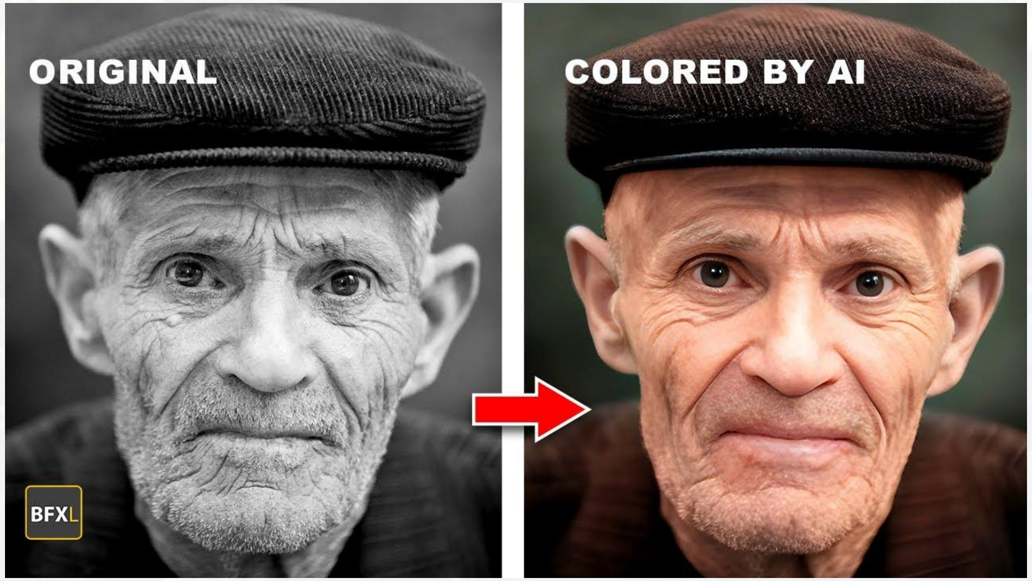


3) regression:



turning images the right way

4) generation



source: TopviewAI

before we had CNNs: k-means for segmentation & classification:

```
rows, cols, channels  = Image.shape
x_flat                = Image.reshape(rows * cols, channels)
```

```
kmeans                = KMeans(n_clusters = k)
pxl_labels            = kmeans.fit_predict(x_flat
colors                = kmeans.cluster_centers_
```

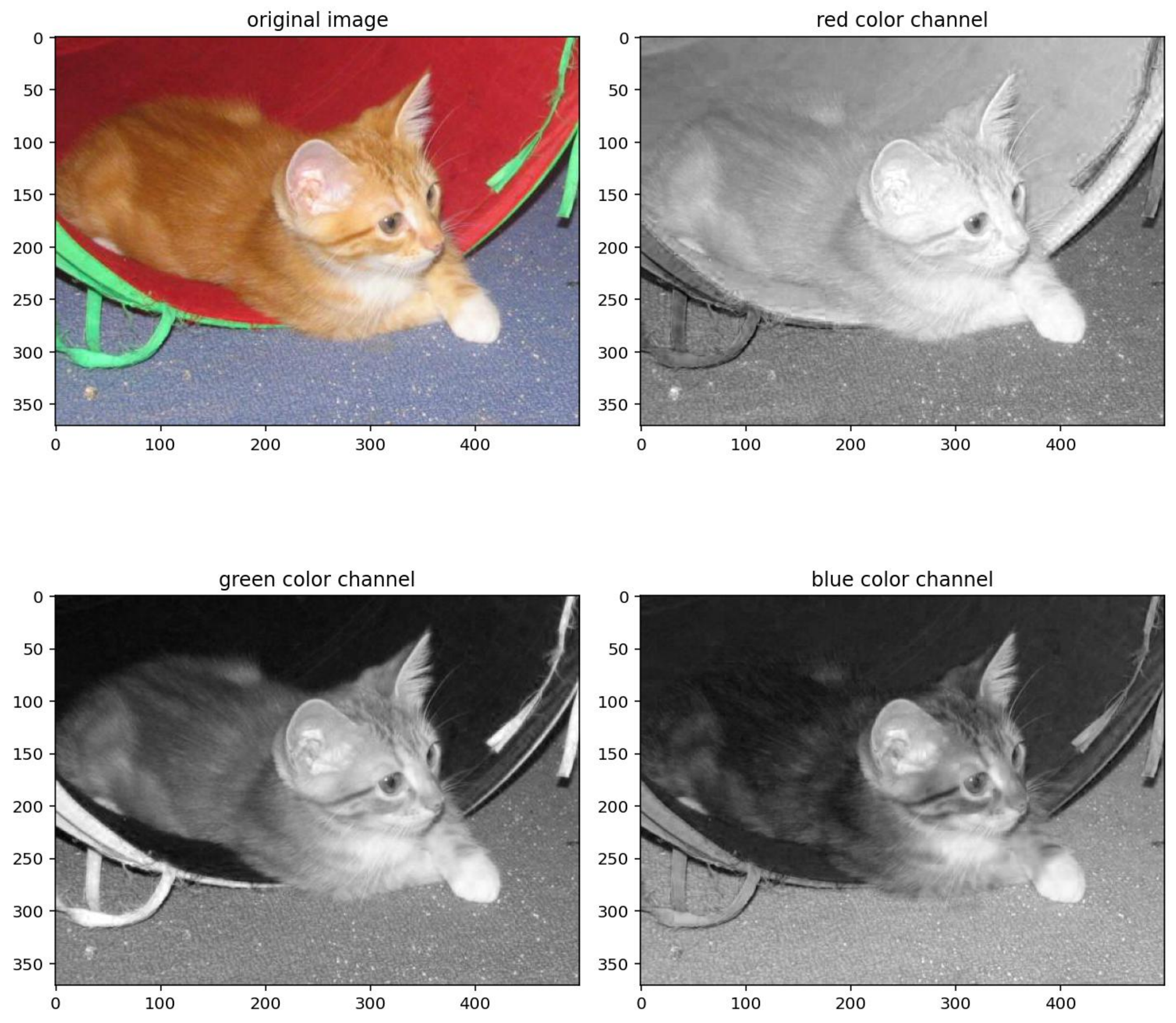
turning image into table
(spatial information is lost!)

- labels are assigned according to cluster in **color space** (RGB, HSV etc)
- cluster means are mean colors

see `KMeansSegmentation.py`

Convolution and Image Classification & Segmentation

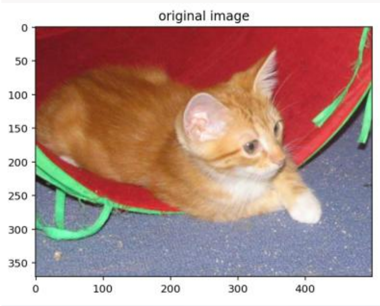
see `KMeansSegmentation.py`



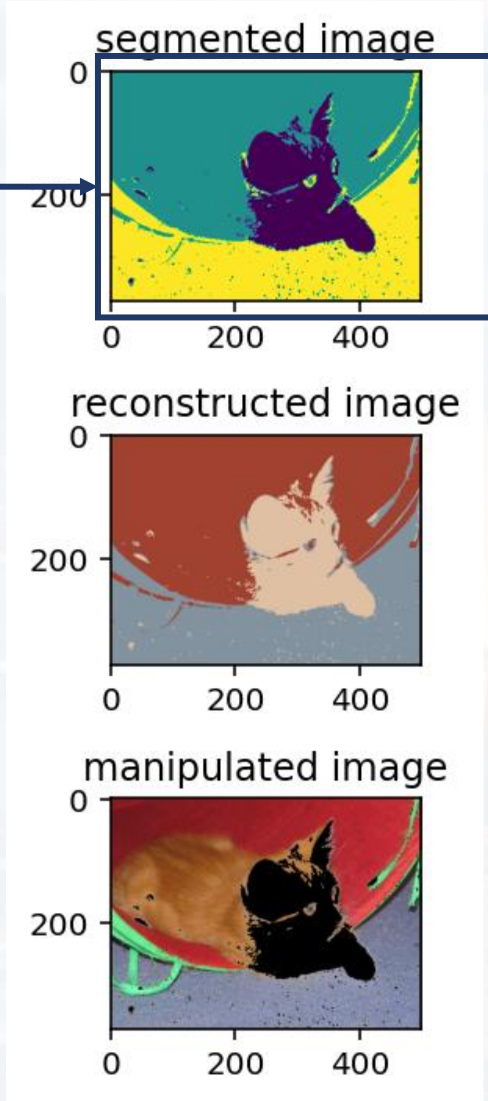

```
K = KMeansSegmentation()
```

Convolution and Image Classification & Segmentation

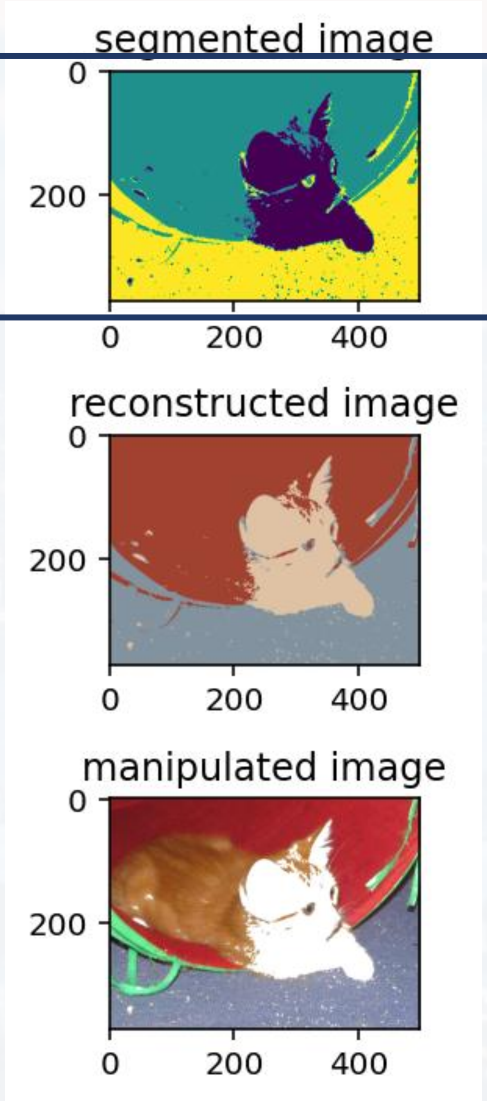
The Problem



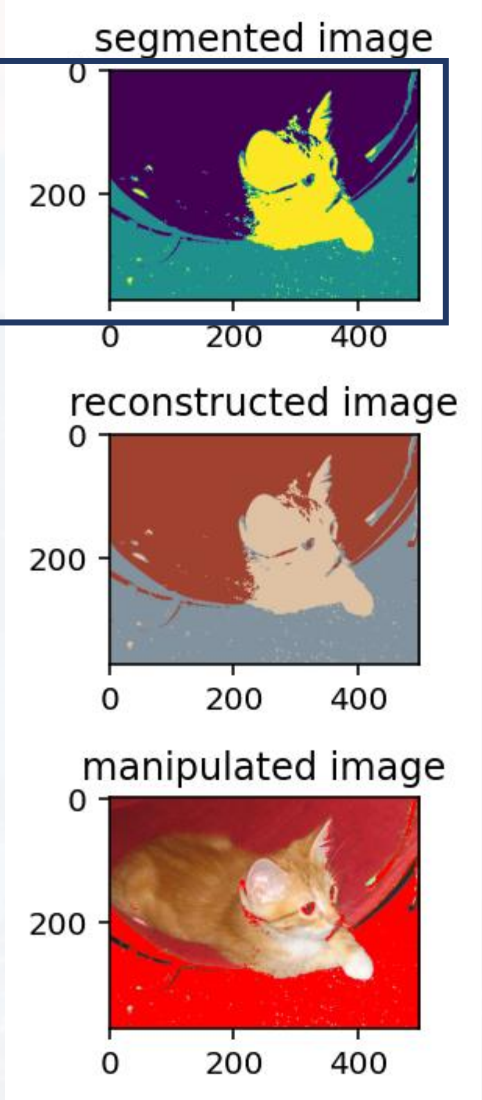

```
K.Segment()
```




```
K.Segment(values\
 = [255, 255, 255])
```




```
K.Segment(values\
= [255, 0, 0], label = 1)
```

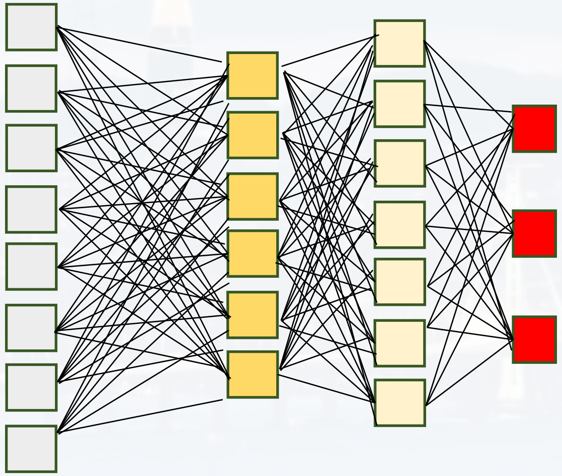


labels can swap **(k-means is unsupervised)**

Convolution and Image Classification & Segmentation

task: find a way to keep both: **color** and **spatial** information and link the image to our ANN

→ ? →



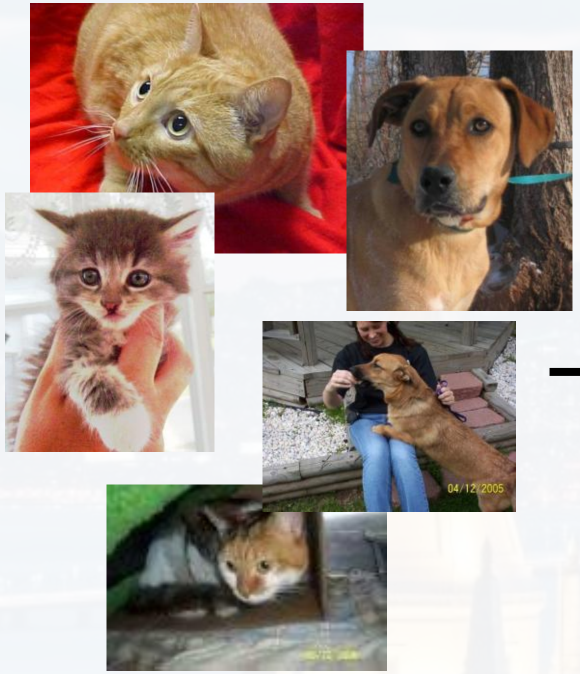
→ output: turning angle

input: image,
aka numerical matrix

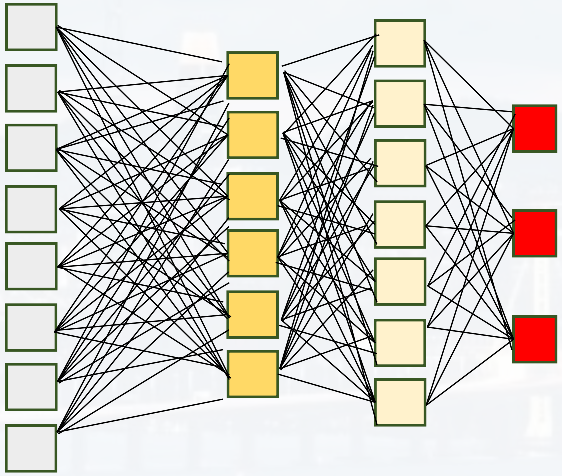
our ANN

→ regression

task: find a way to keep both: color and spatial information and link the image to our ANN



→ ? →



→

output:
- cat
- dog
- cat
- cat
- dog

input: image,
aka numerical matrix

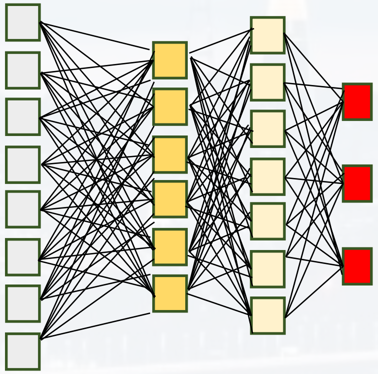
our ANN

→ classification

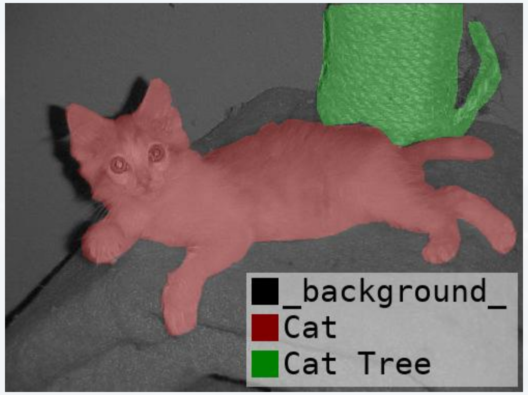
The Problem

task: find a way to keep both: color and spatial information and link the image to our ANN

→ ? →



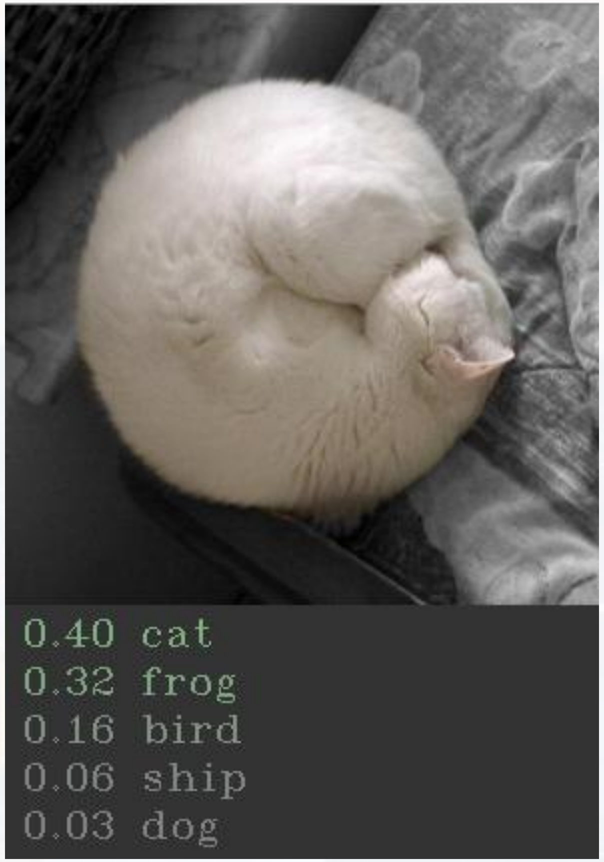
→ ? →



input: image,
aka numerical matrix

our ANN

segmented image



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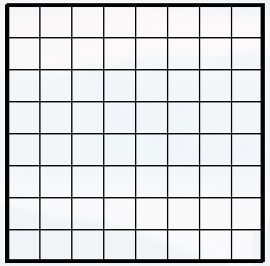
Convolution and Image Classification & Segmentation

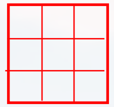
goal:
- maintaining the spatial information → convolution
- learning which features are important → training the convolution filter

$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta)\,\boldsymbol{g(x-\zeta)}\,d\zeta$$

image ***f*** and filter ***g***

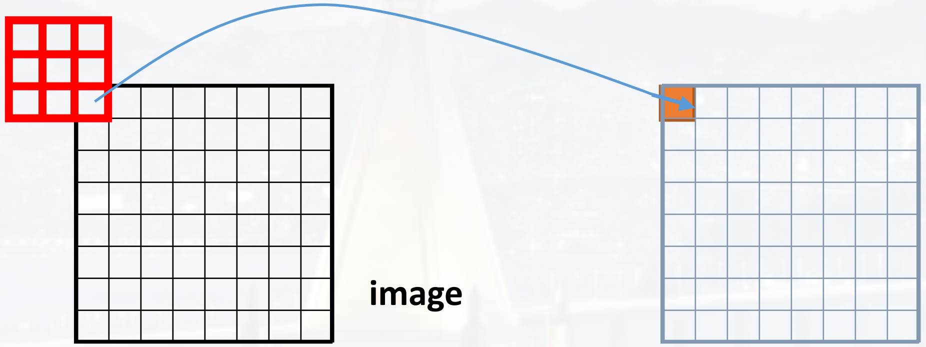


image

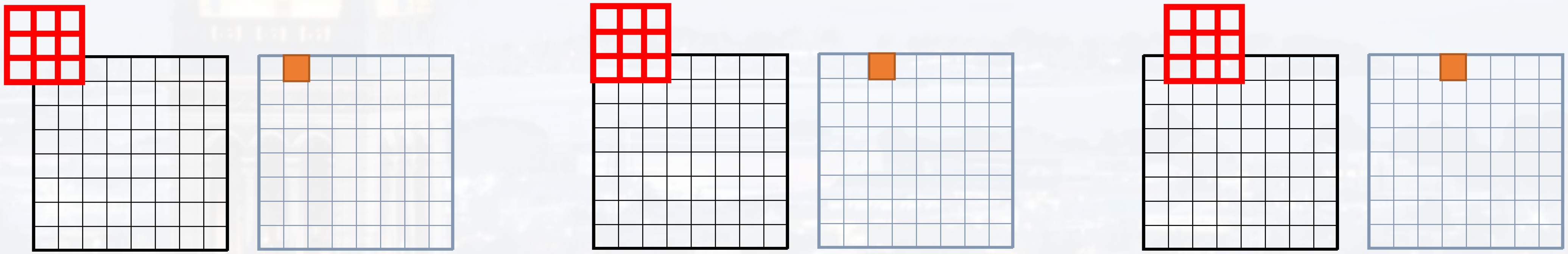


filter
(aka kernel)

convolved image



1) multiplying matrix values pixelwise
2) summing up products
3) → value for new matrix



Convolution and Image Classification & Segmentation

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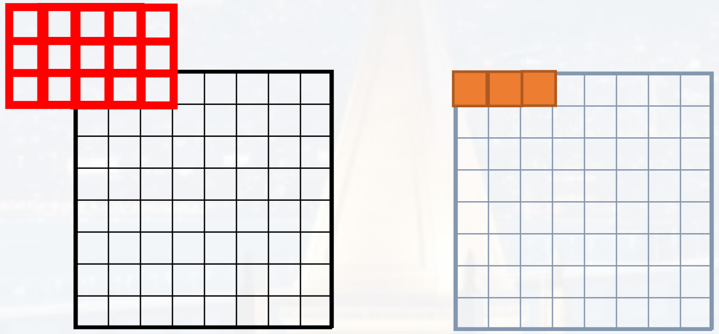
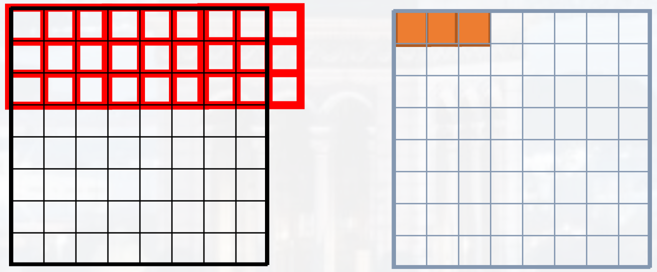
image ***f*** and filter ***g***

different techniques:



padding = 2; stride length = 1



padding = 0; stride length = 3

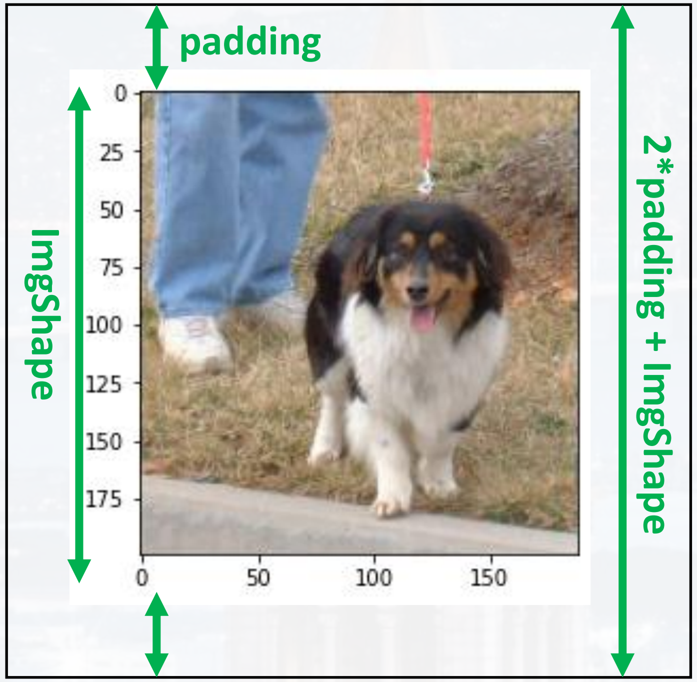
N: number of rows/columns

$$N_{out} = \frac{(N_{in} - N_{filt} + 2 * padding)}{stride\ length} + 1$$

goal: - maintaining the spatial information → convolution
- learning which features are important → training the convolution filter

$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta)\, g(x - \zeta)\, d\zeta$$

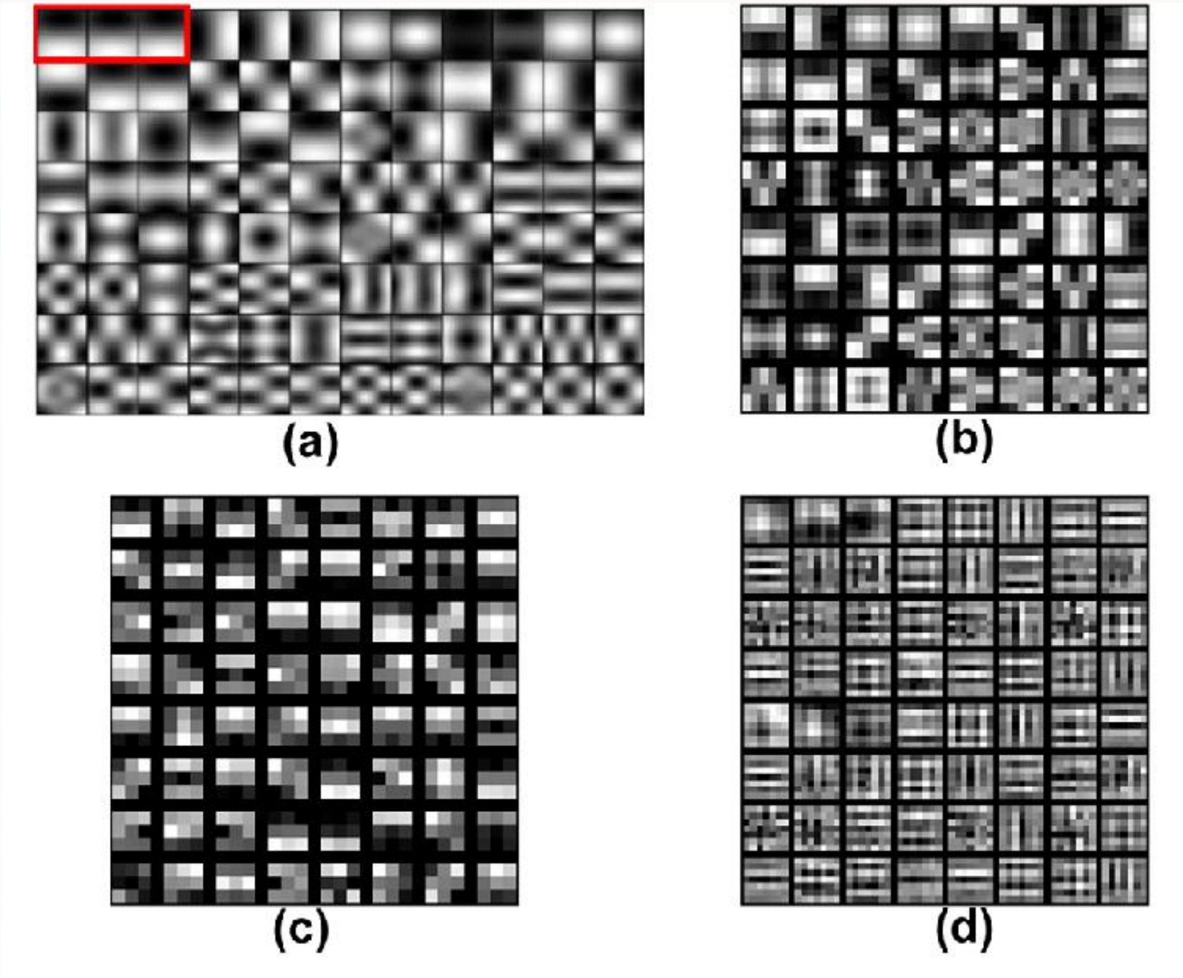
image f and filter g



N: number of rows/columns

$$N_{out} = \frac{(N_{in} - N_{filt} + 2 * padding)}{stride\ length} + 1$$

filters:

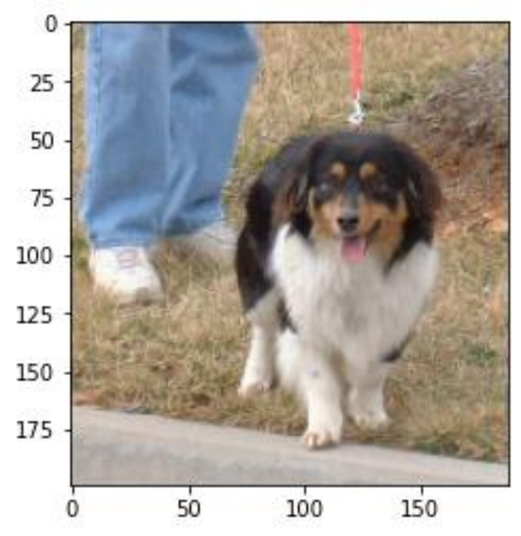


DOI:10.1016/j.actbio.2017.09.025

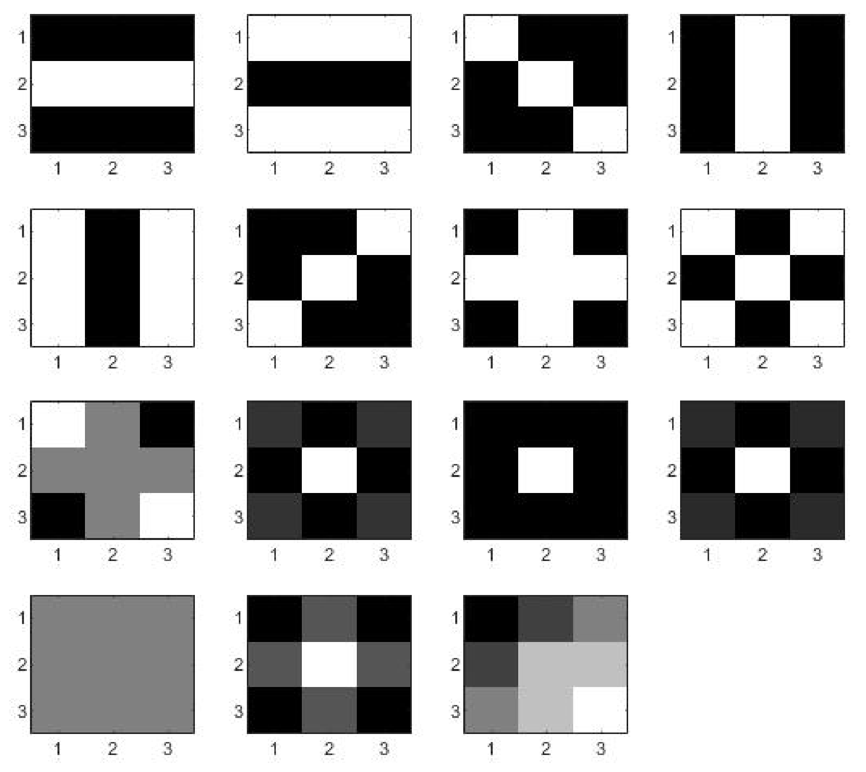
Convolution and Image Classification & Segmentation

see `Convolution.ipynb` for visualizing the impact of different convolution filter on the image

image



filter



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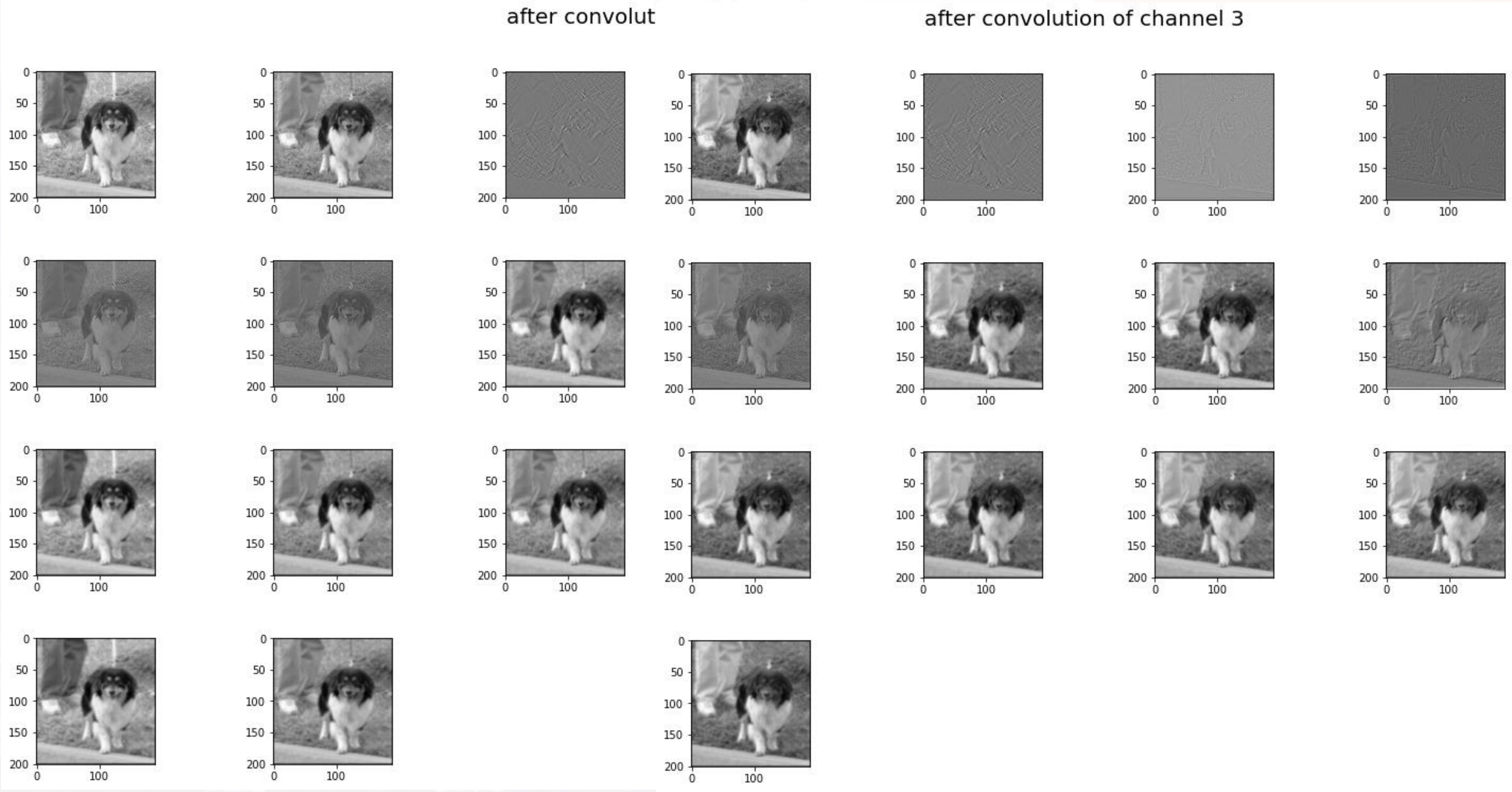


Convolution and Image Classification & Segmentation

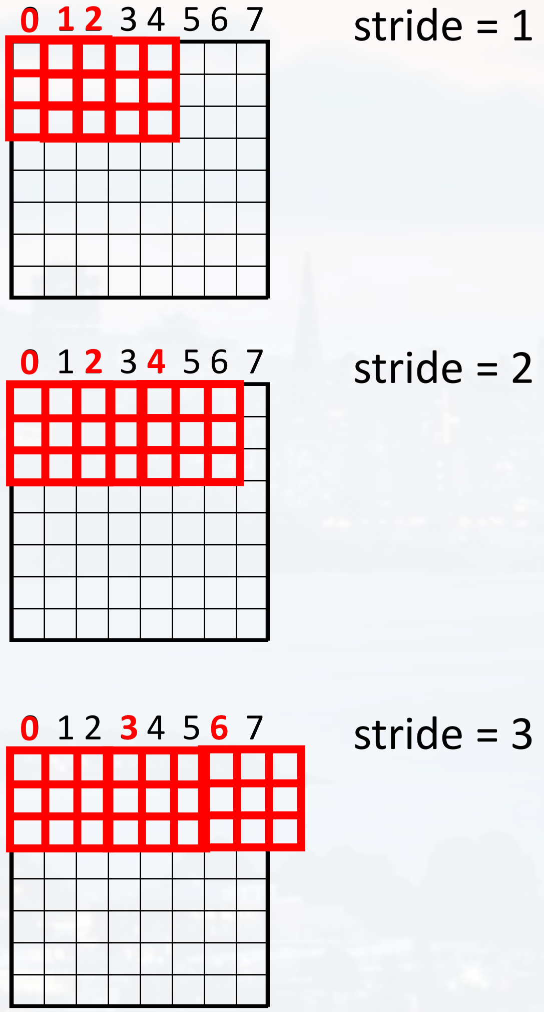

```python
def ConvSelfMade(*Image, K, padding = 0, stride = 1):
...


for c in range(numChans):# loop over channels
        for y in range(yOutput):# loop over y axis of output
            for x in range(xOutput):# loop over x axis of output

                # finding corners of the current "slice"
                y_start = y*stride
                y_end   = y*stride + yK
                x_start = x*stride
                x_end   = x*stride + xK

                #selecting the current part of the image
                current_slice = imagePadded[x_start:x_end,\
                                y_start:y_end, c]

                #the actual convolution part
                s             = np.multiply(current_slice, K)
                output[x,y,c] = np.sum(s)
```



Convolution and Image Classification & Segmentation

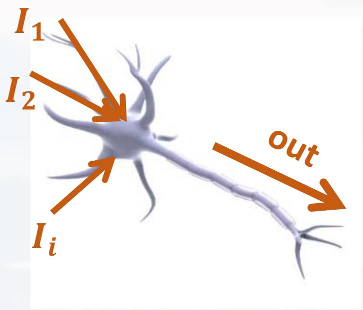
CNN:

- kernel act like **neurons with weights**
- start with random values for all kernels

→ the ANN **learns the filter values**

→ that's how the ANN learns which features are important

$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta)\boldsymbol{g(x-\zeta)}d\zeta$$



$$net = \sum_i I_i \cdot w_i + b$$

inputs are pixel values

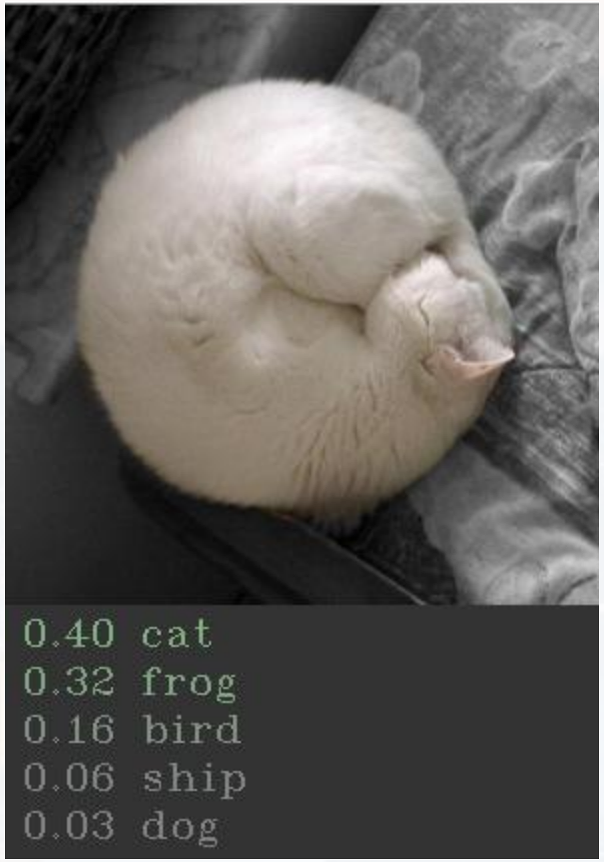
kernel weights

$$\sum_i I_i\, \boldsymbol{w_i} + \boldsymbol{b}$$

can be interpreted as a neuron!

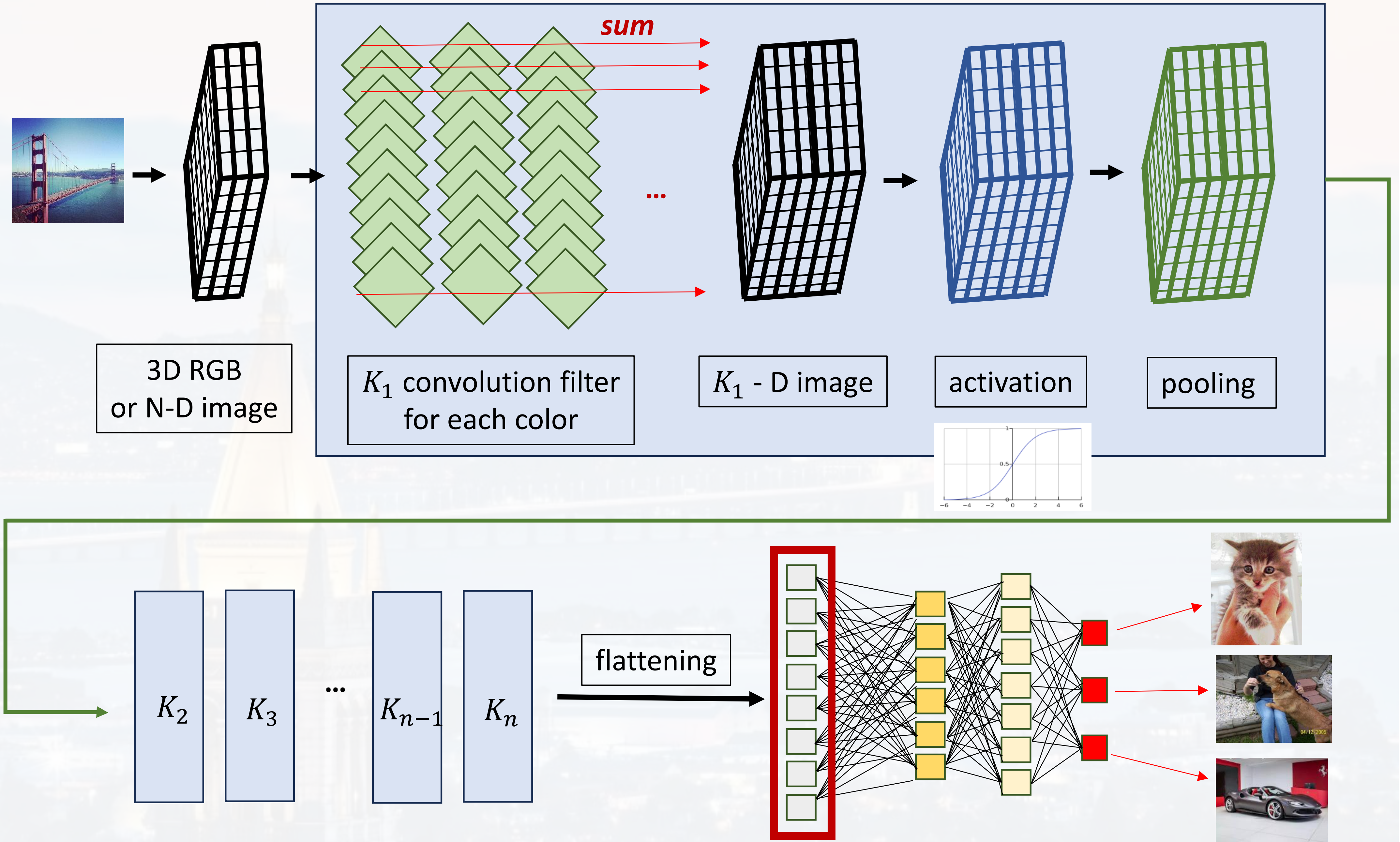
i. e. a filter of shape NxN

has $N^2 + 1$ learnables (N^2 weights + bias)



Outline

classification



classification

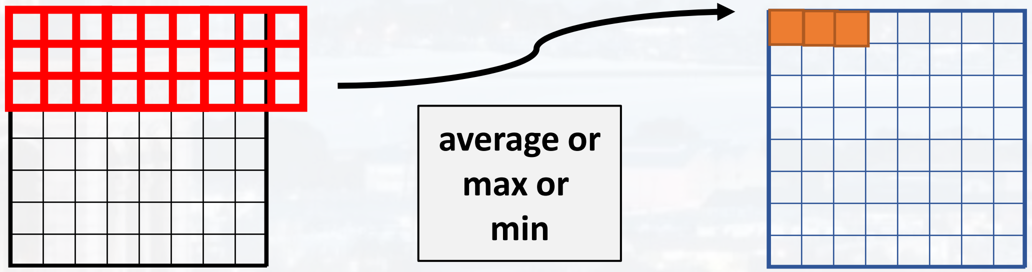
pooling:

there are three different main pooling methods

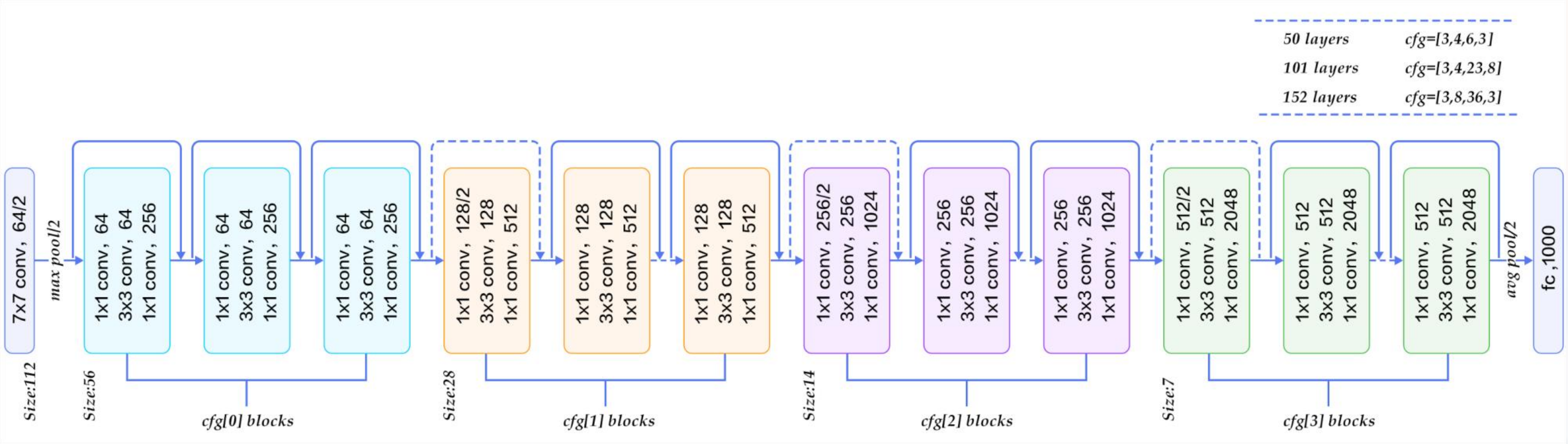
→ **average pool:** **blurs the image**, reduces edges (not what we want here)

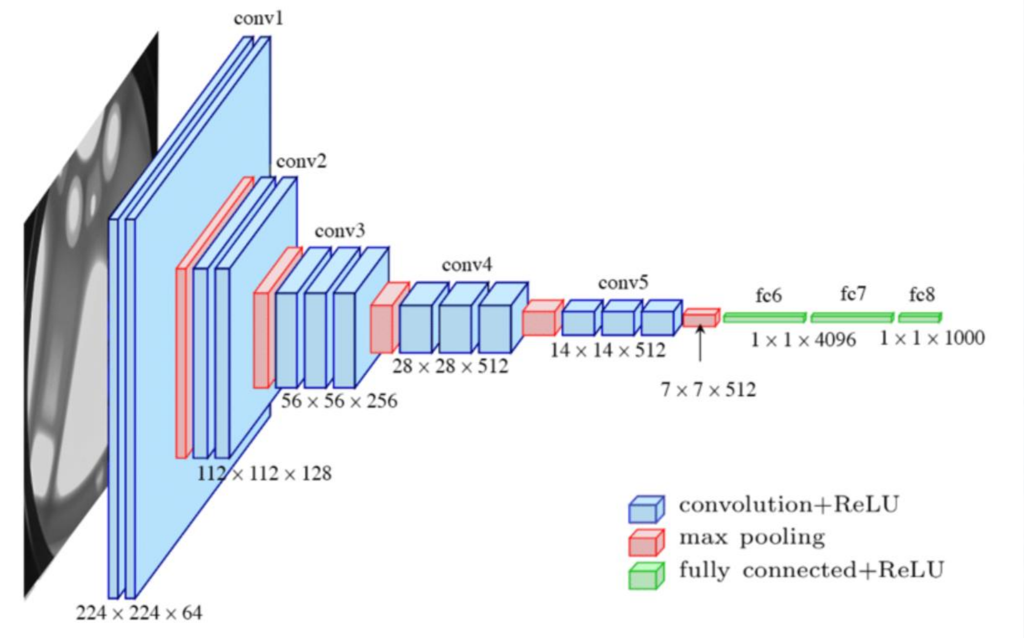
→ **max pool:** **reduces dark background** (those pixel values are usually low) and **enhances brighter foreground objects** (exactly what we need here)

→ **min pool:** does the opposite of max pool



classification



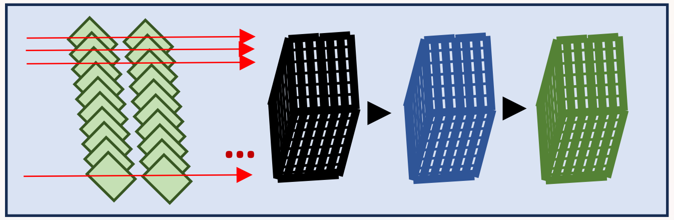


convolution process down-samples the image

- network focuses on important features
- reduces computational cost

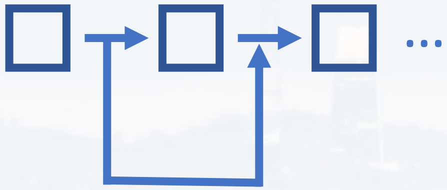
CNN Architectures

classification

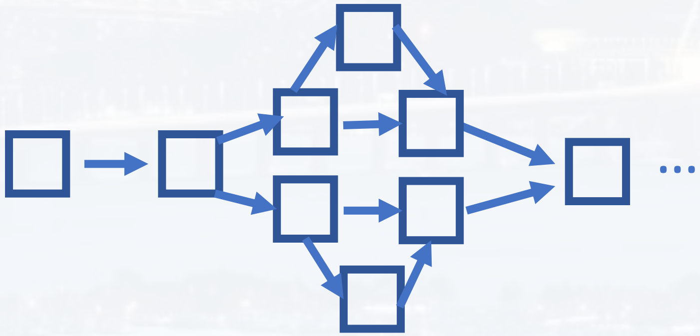


sequential CNNs

Residual**Net**



Inception Net



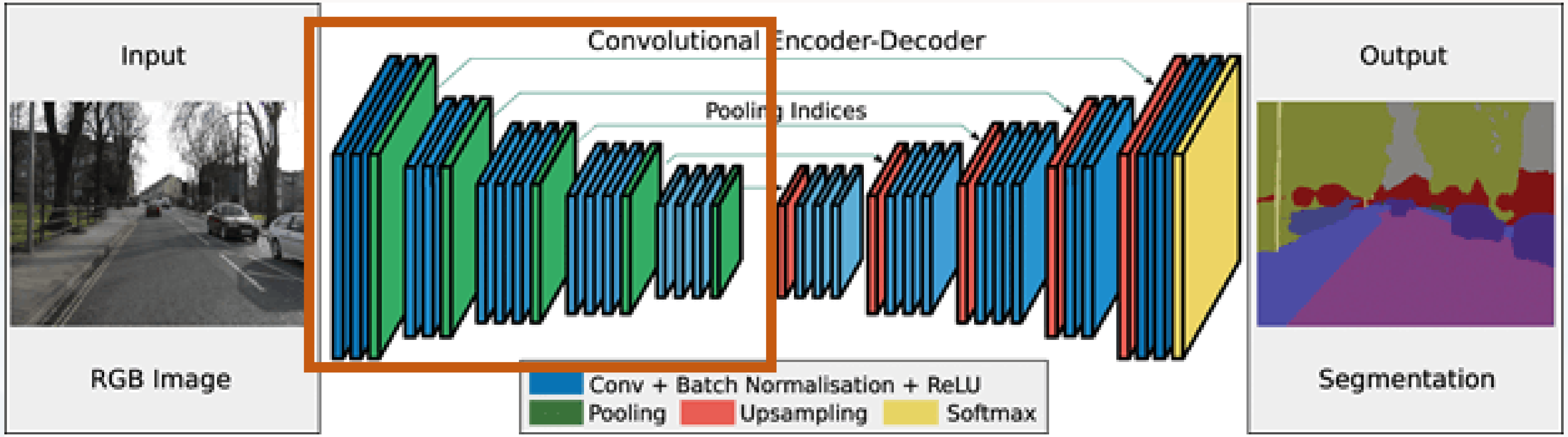
many others…

classification

common pretrained classification CNNs

Network	Depth	Size	Parameters (Millions)	rel computation time	Image Input Size
nasnetlarge	*	360 MB	88,9	45	331-by-331
darknet19	19	72.5 MB	21	5,5	256-by-256
densenet201	201	77 MB	20	22	224-by-224
resnet50	50	96 MB	25,6	3,5	224-by-224
resnet101	101	167 MB	44,6	5	224-by-224
inceptionv3	48	89 MB	23,9	8	299-by-299
resnet18	18	44 MB	11,7	1,8	224-by-224
xception	71	85 MB	22,9	12	299-by-299
darknet53	53	145 MB	41	10	256-by-256
inceptionresnetv2	164	209 MB	55,9	14	299-by-299
shufflenet	50	6.3 MB	1,4	1,5	224-by-224
googlenet	22	27 MB	7	2	224-by-224
mobilenetv2	53	13 MB	3,5	4	224-by-224
alexnet	8	227 MB	61	1,2	227-by-227
nasnetmobile	*	20 MB	5,3	5	224-by-224
squeezenet	18	4.6 MB	1,24	1	227-by-227
vgg16	16	515 MB	138	6,5	224-by-224
vgg19	19	535 MB	144	8,5	224-by-224

segmentation

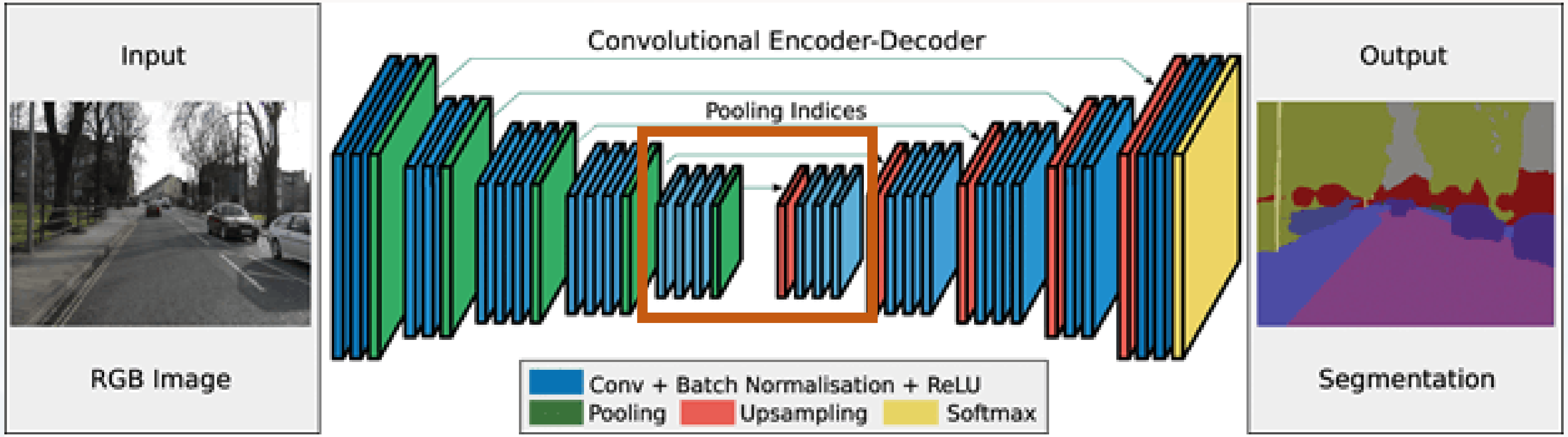


Vijay Badrinarayanan et. al 2017 "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation"

1) down-sampling as before (= **encoder**)

Convolution and Image Classification & Segmentation

segmentation



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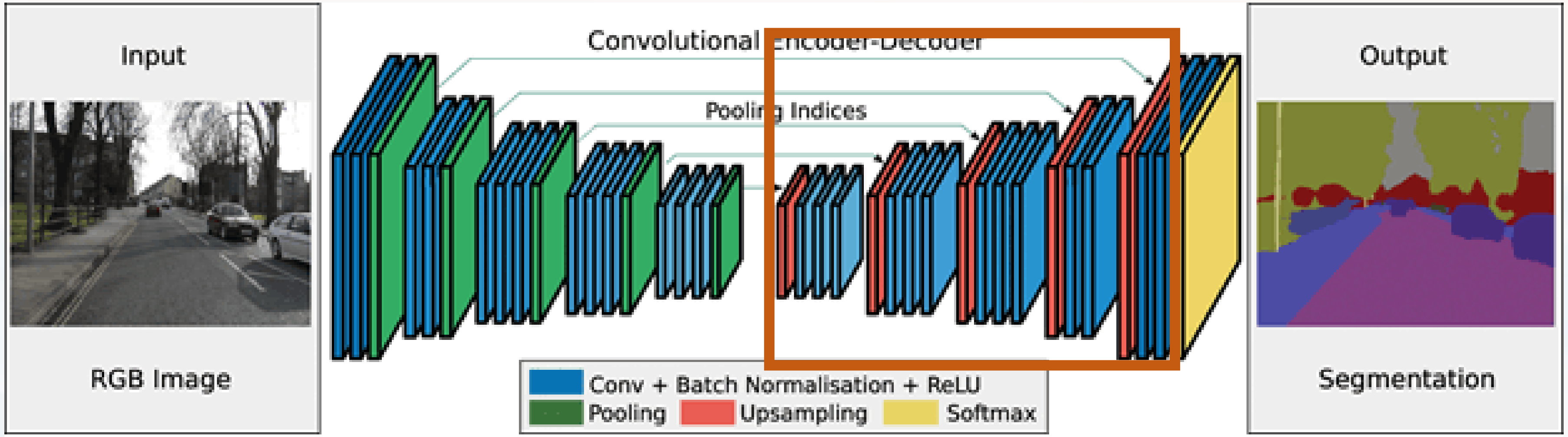
1) down-sampling as before (= **encoder**)

2) down to bottle neck

segmentation



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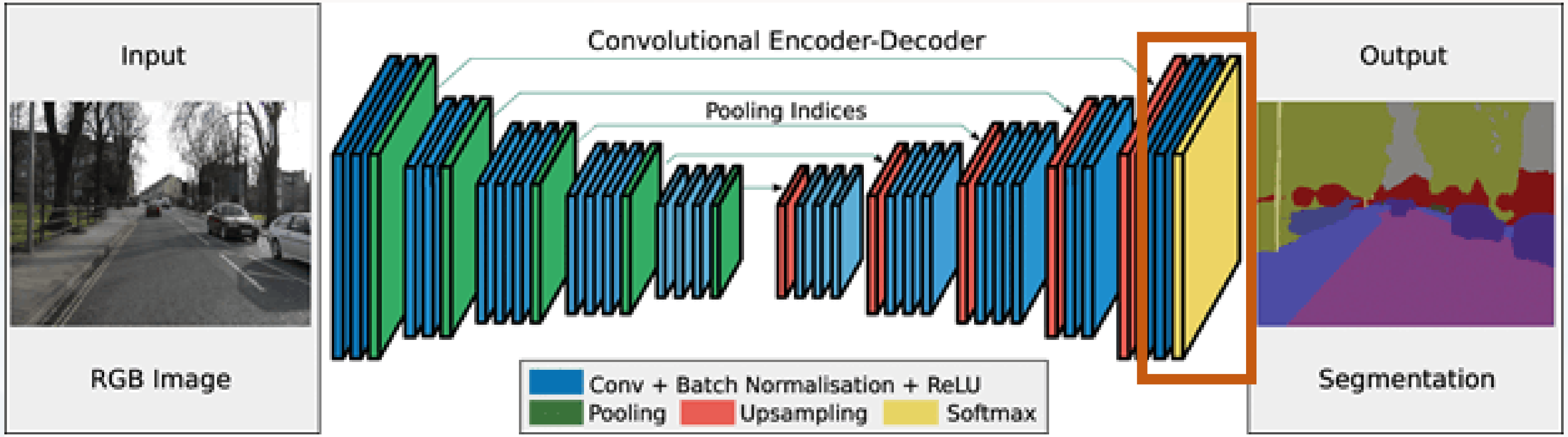
1) down-sampling as before (= **encoder**)

2) down to bottle neck

3) up-sampling (= **decoder**; how: see later) in order to generate output image of the same size as input image, where number of channels = number of pixel classes

segmentation



Vijay Badrinarayanan et. al 2017 "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation"

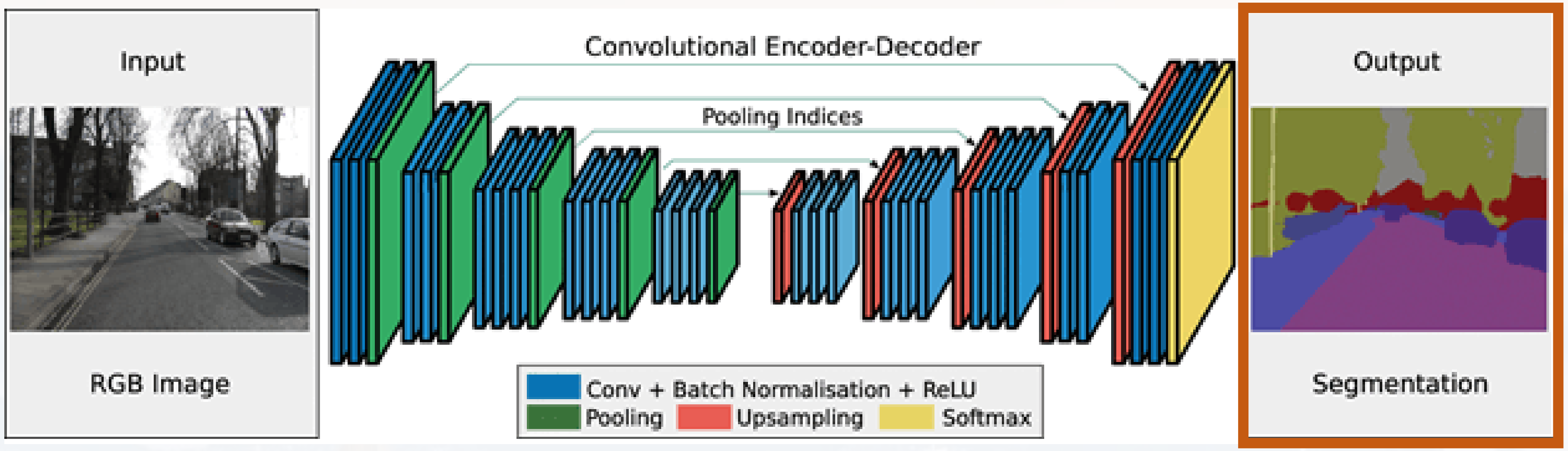
1) down-sampling as before (= **encoder**)

2) down to bottle neck

3) up-sampling (= **decoder;** how: see later) in order to generate output image of the same size as input image, where number of channels = number of pixel classes

4) softmax, in order to turn output of last layer into probabilities

segmentation



Vijay Badrinarayanan et. al 2017 "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation"

1) down-sampling as before (= encoder)

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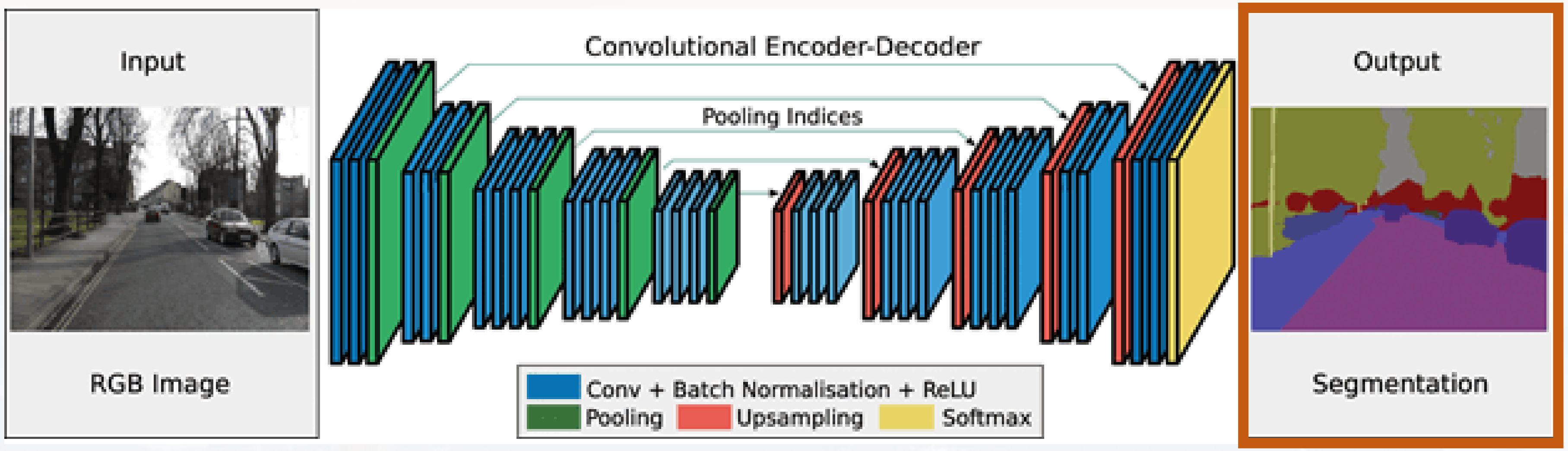
3) up-sampling (= **decoder;** how: see later) in order to generate output image of the same size as input image, where number of channels = number of pixel classes

4) softmax, in order to turn output of last layer into probabilities

5) generates segmentation mask from highest probabilities

= (arbitrary) colors are class labels and correspond to pixel class segmentation



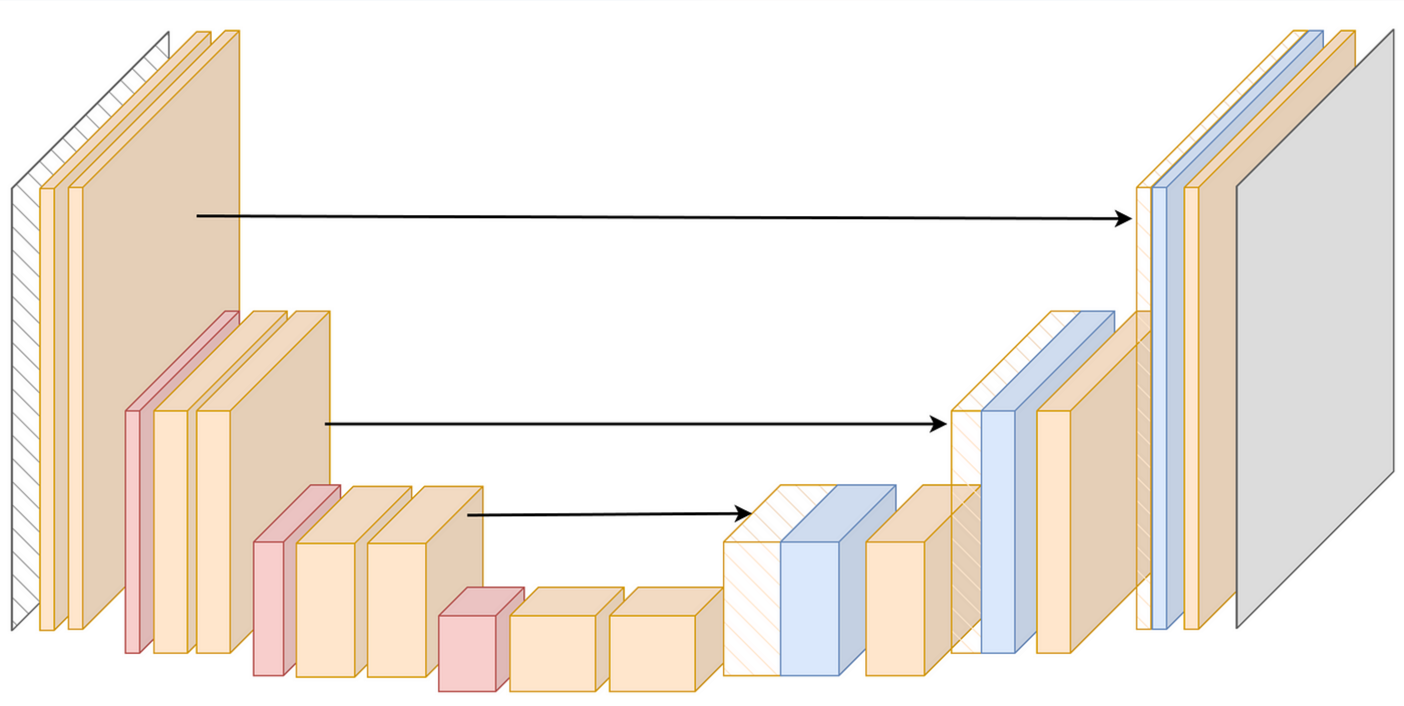
Vijay Badrinarayanan et. al 2017 “SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation”

depending on the architecture, the decoder has **different learning mechanisms**

- standard: up-sampling = inverse convolution: weights and biases are learnables
- U-Net: skips connections and concatenates decoder layer with corresponding encoder layer information
- transformer encoder: use attention (see later)

segmentation

U-net segmentation CNN



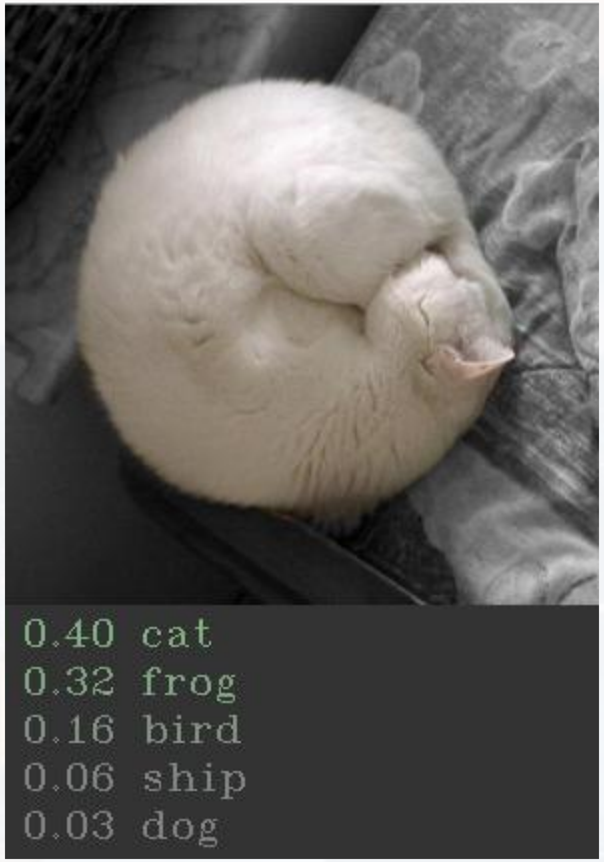
https://towardsdatascience.com/u-net-explained-understanding-its-image-segmentation-architecture-56e4842e313a

segmentation

common pretrained segmentation CNNs

note: the input size is usually 5 – 10 times larger than compared to a classification CNN!

Type	Names
VGG	'vgg16' 'vgg19'
ResNet	'resnet18' 'resnet34' 'resnet50' 'resnet101' 'resnet152'
SE-ResNet	'seresnet18' 'seresnet34' 'seresnet50' 'seresnet101' 'seresnet152'
ResNeXt	'resnext50' 'resnext101'
SE-ResNeXt	'seresnext50' 'seresnext101'
SENet154	'senet154'
DenseNet	'densenet121' 'densenet169' 'densenet201'
Inception	'inceptionv3' 'inceptionresnetv2'
MobileNet	'mobilenet' 'mobilenetv2'
EfficientNet	'efficientnetb0' 'efficientnetb1' 'efficientnetb2' 'efficientnetb3' 'efficientnetb4' 'efficientnetb5' efficientnetb6' efficientnetb7'

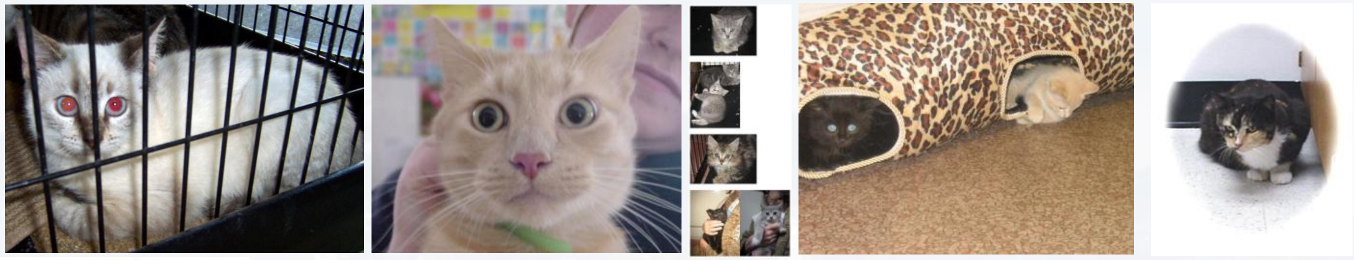


Outline

data acquisition

1) classes should be **well balanced**

2) dataset should be **diverse**



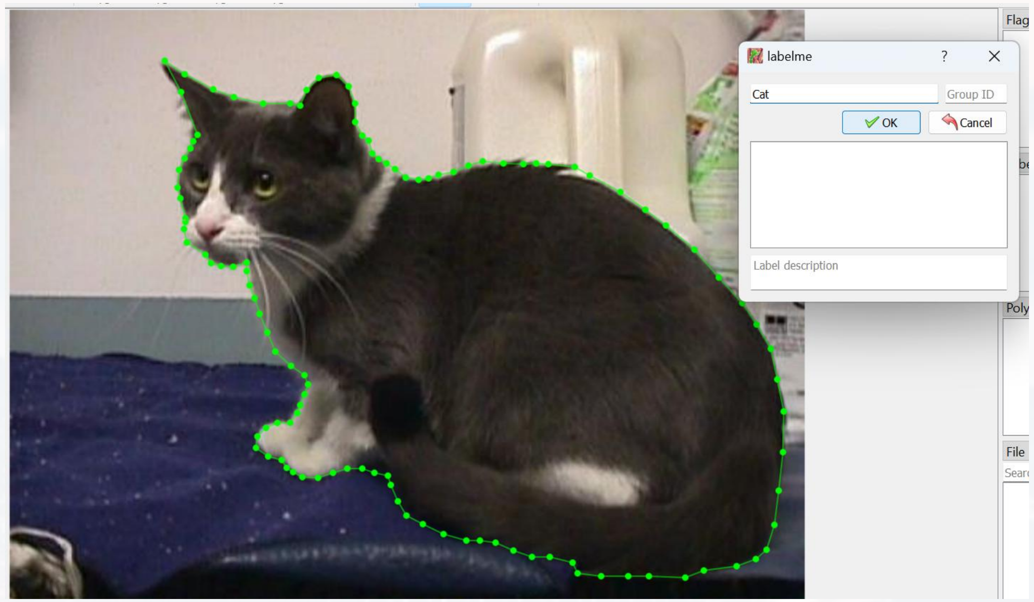
example Cryo-EM:

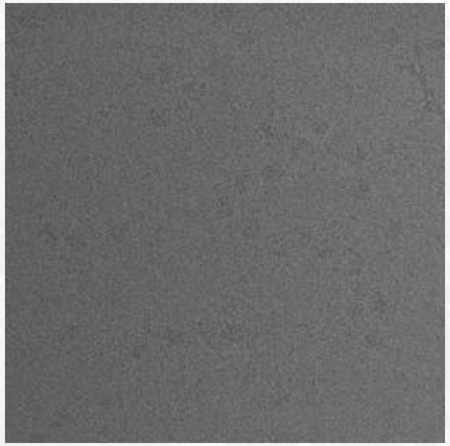
all grids (Cu, Au, …)
all cameras
all grid manufacturers
all resolutions

3) **augmentation:** blurred, skewed, fragmented, stretched, turned etc
tip: write your own augmentation routine!

data labeling

be as accurate as possible!





micrograph Cryo-EM image

→ good, medium and bad based on ice crystals

→ Undergrad, Grad, PostDoc, Senior Scientist

data preprocessing

scaling:

Image Input Size
331-by-331
256-by-256
224-by-224
224-by-224

All images have to be scaled to the input size of the CNN!

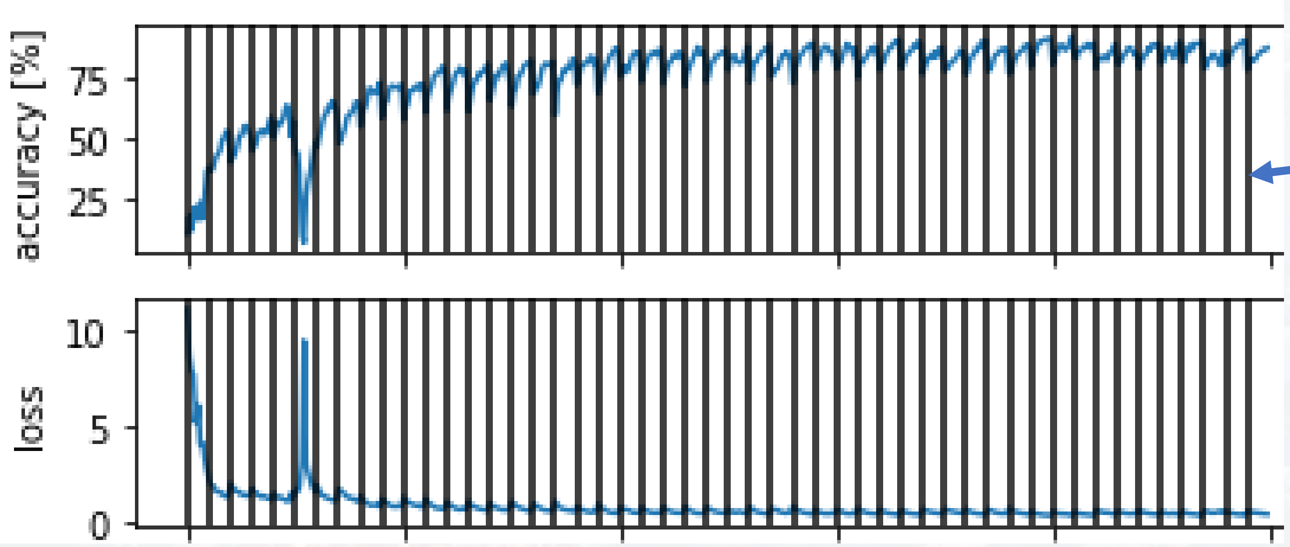
normalization: images can be

- logical (values are zero **or** one)
- gray scale (2D) → adding two more "color channels"
- 8bit (range 255), 16bit (range 512) etc

training

normalization: complex CNNs have many layers for normalization/re-centering/re-scaling
→ **batch normalization**

the training set is huge
→ loading only a few images at the time (**batches**)
→ the larger the batch, the better
→ run only **a few iterations** per batch (avoiding local minima)
→ check **training loss vs evaluation loss**



each line marks a new batch

epochs

training

check out:

[Training MLP]

[Training CNN 2D]

[Training CNN 3D]

End of Part I