



Artificial Neural Networks in Python

From Scratch!

Part II



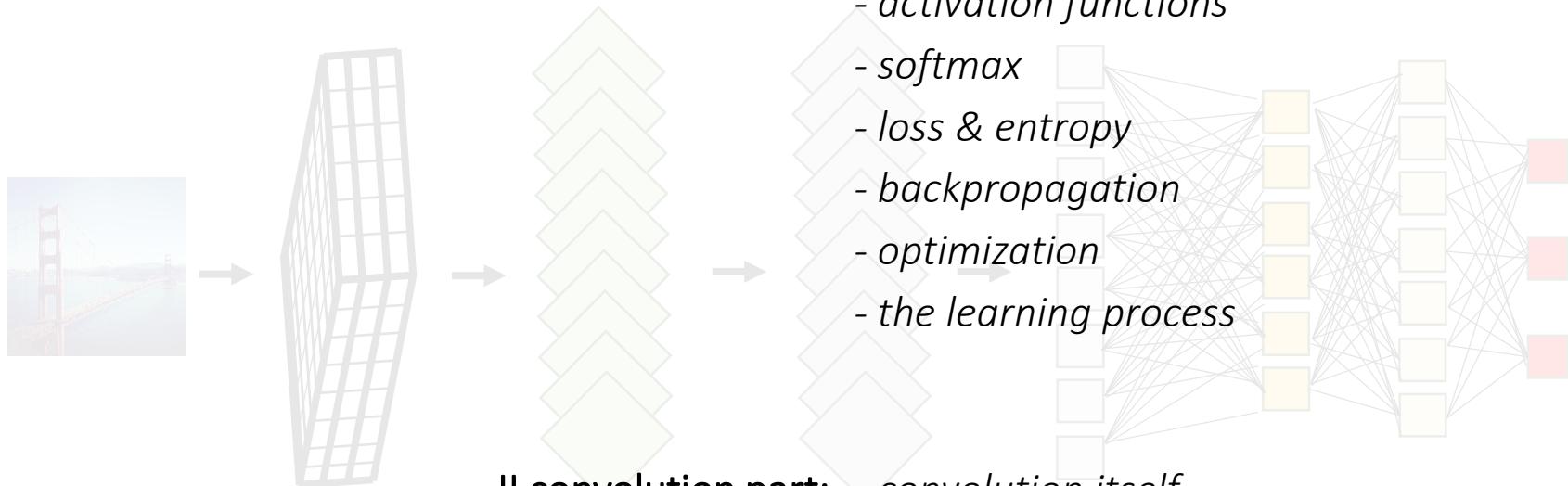
**) Yes, I know it's not Python,
but it's still funny :)*

outline

0 intro

I the core:

- *a single neuron*
- *layers of neurons*
- *activation functions*
- *softmax*
- *loss & entropy*
- *backpropagation*
- *optimization*
- *the learning process*



II convolution part:

- *convolution itself*
- *pooling*
- *sigmoid*
- *flattening*
- *backpropagation - again*
- *testing the CNN & final remarks*

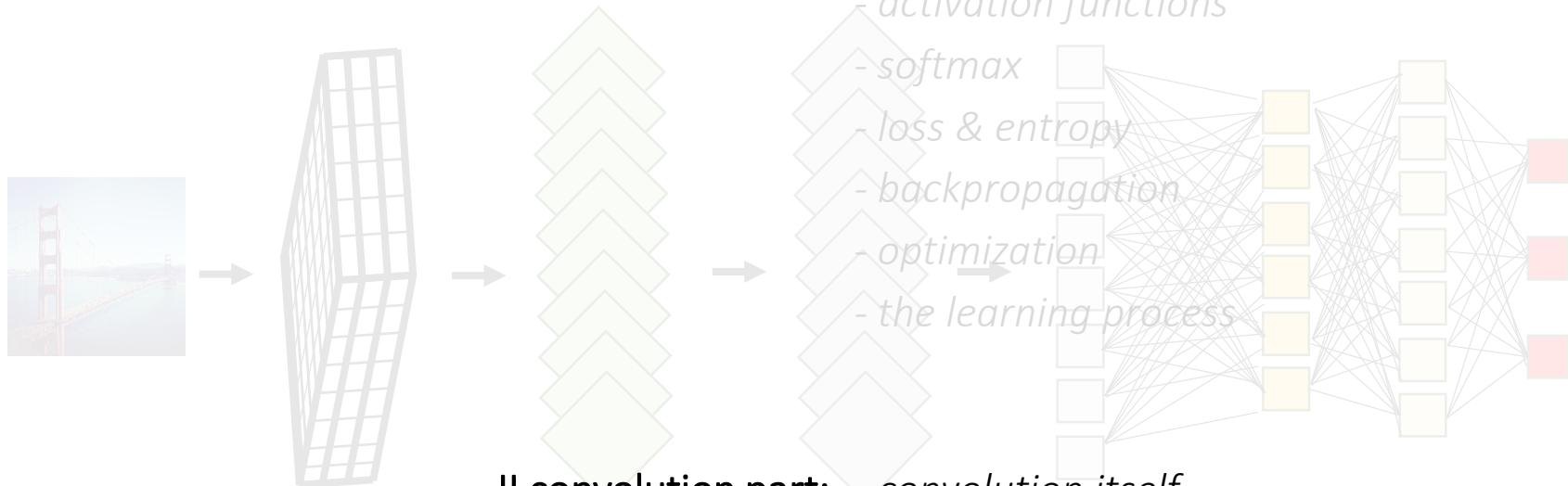


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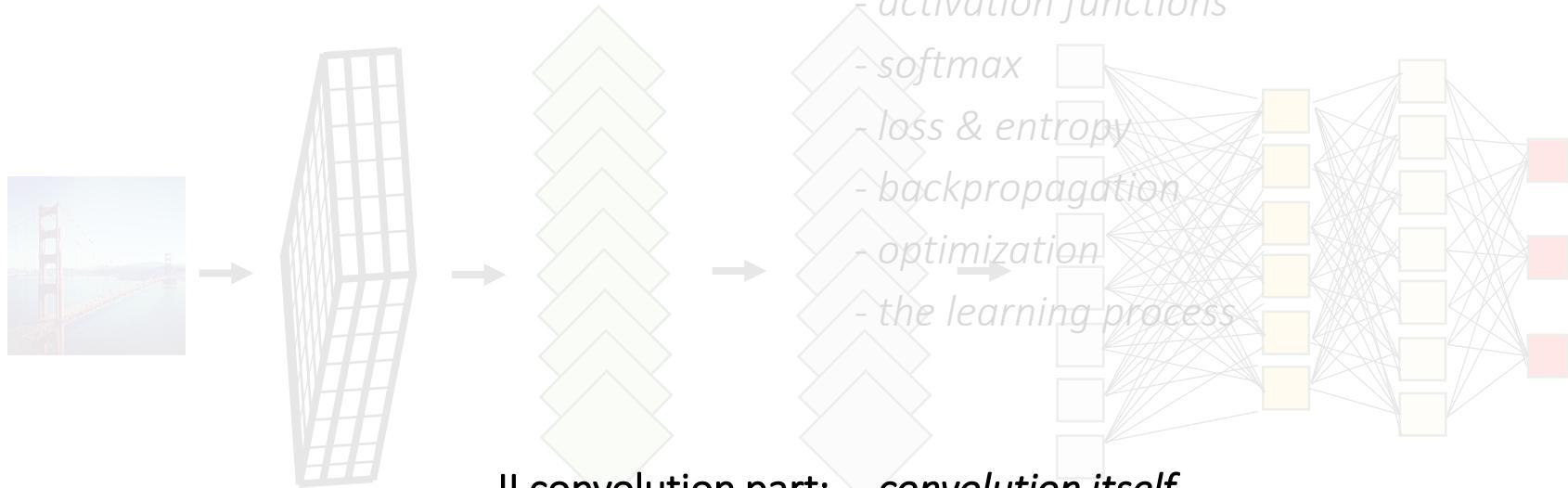


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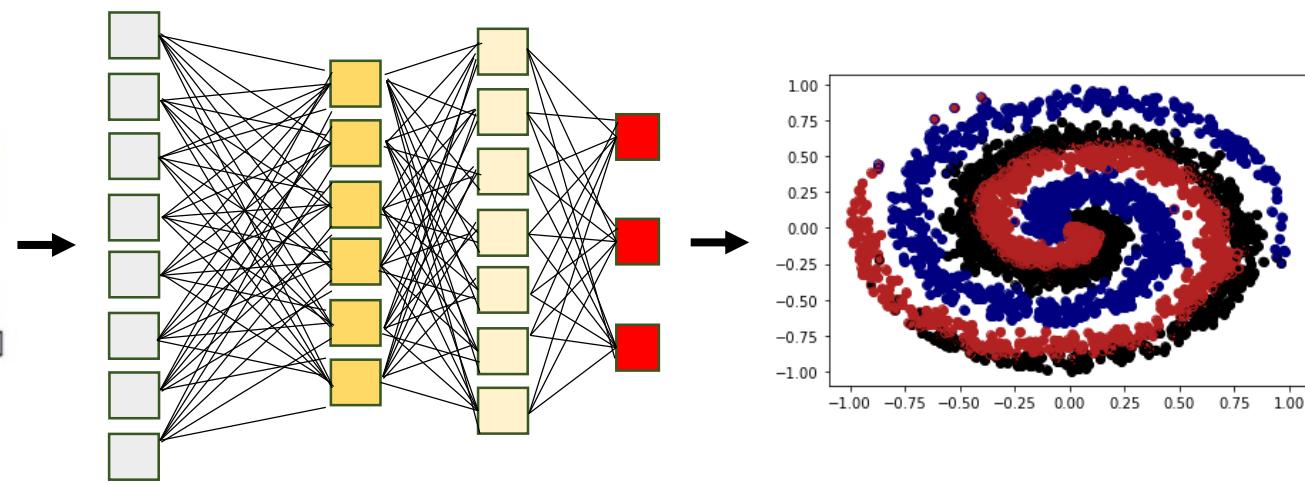
II convolution part:

- *convolution itself*
- *pooling*
- *sigmoid*
- *flattening*
- *backpropagation - again*
- *testing the CNN & final remarks*

What we have so far:

- an input layer for a matrix containing coordinates
- an activation layer
- a soft-max layer for calculating probabilities

```
In [6]: print(x)
[[-0.00000000e+00  0.00000000e+00]
 [ 7.94393385e-04  6.09050207e-04]
 [-5.63224823e-05  2.00120958e-03]
 ...
 [-9.27303549e-01 -3.68928357e-01]
 [-9.61714970e-01 -2.70376249e-01]
 [-9.38792891e-01  3.44482085e-01]]
```



input: numerical matrix

our ANN

output:

- blue dots
- red dots
- black dots

→ classification

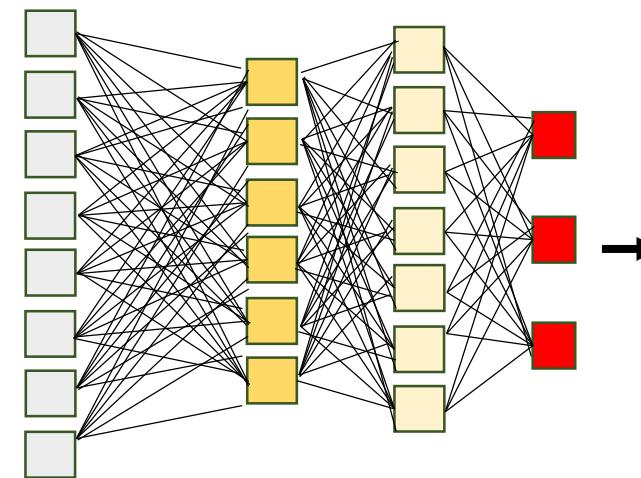


Basic building blocks of most ANNs:

- an input layer for a matrix containing coordinates
- an activation layer
- a soft-max layer for calculating probabilities



?



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

input: image,
aka numerical matrix

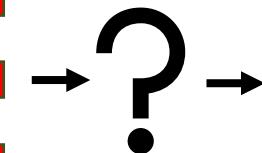
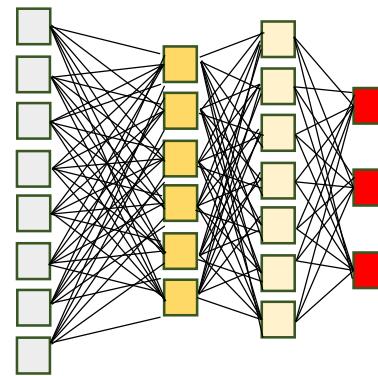
our ANN

→ classification



Basic building blocks of most ANNs:

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input: image,
aka numerical matrix

our ANN

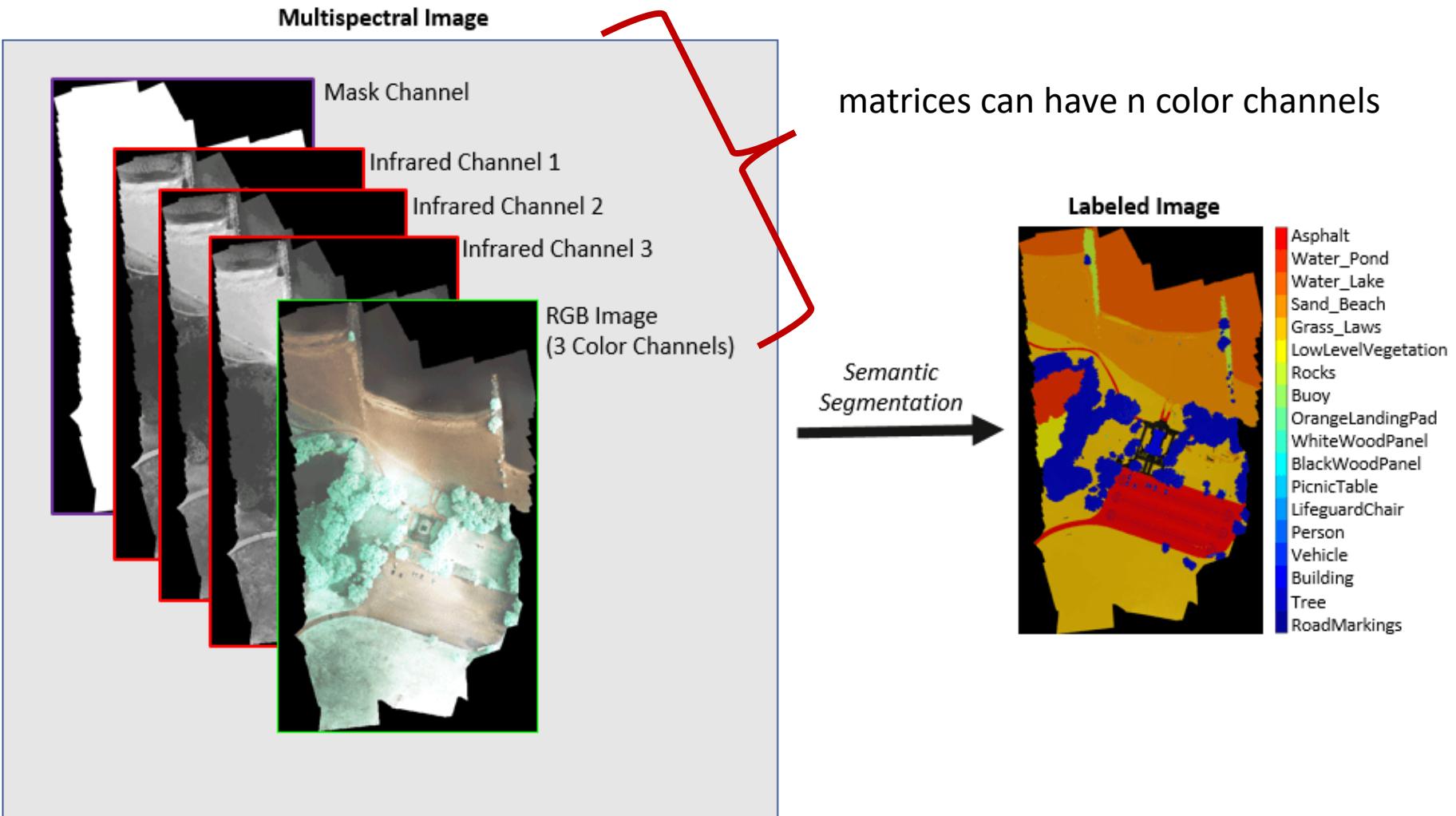
output: categorizing
each pixel
aka *Semantic Segmentation*

→ classification



Basic building blocks of most ANNs:

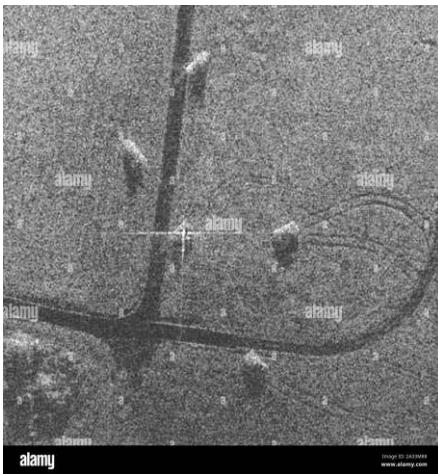
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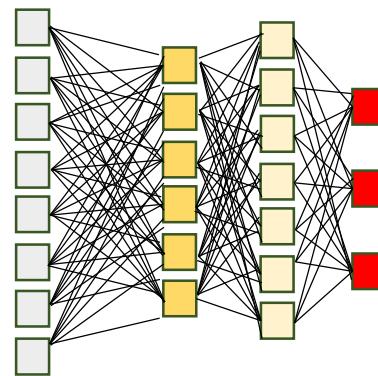


Basic building blocks of most ANNs:

- an input layer for a matrix containing coordinates
- an activation layer
- a soft-max layer for calculating probabilities



→ ? →



output: → ?

- are these enemy tanks; yes/no
- suitable shell is XYZ
- attack; yes/no

input: image,
aka numerical matrix

our ANN

→ autonomous
systems

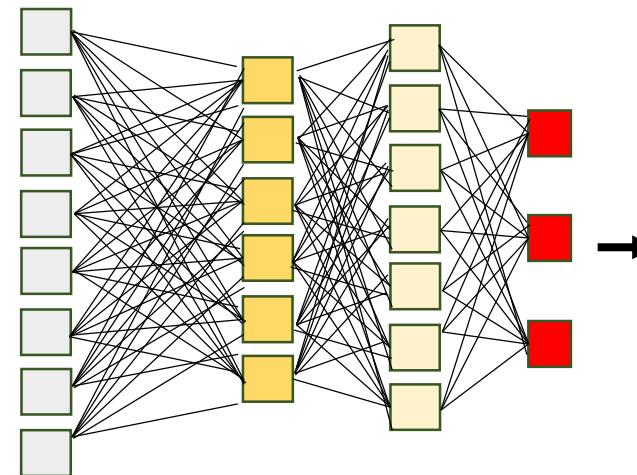


Basic building blocks of most ANNs:

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input: image,
aka numerical matrix



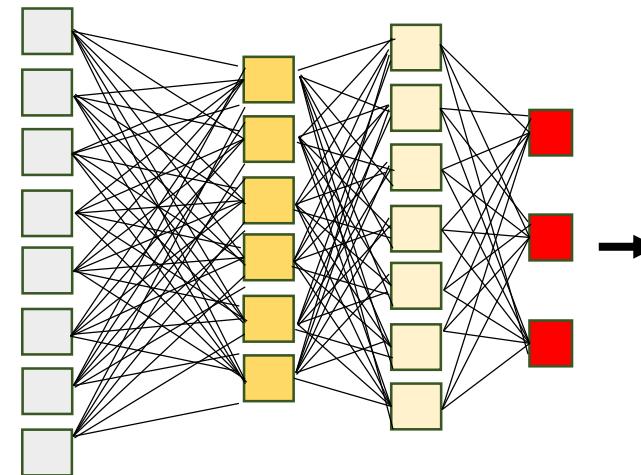
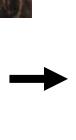
our ANN

output:
turning angle

→ regression



Our goal: creating an ANN that can tell cats from dogs



output:

- cat
- dog
- cat
- cat
- dog

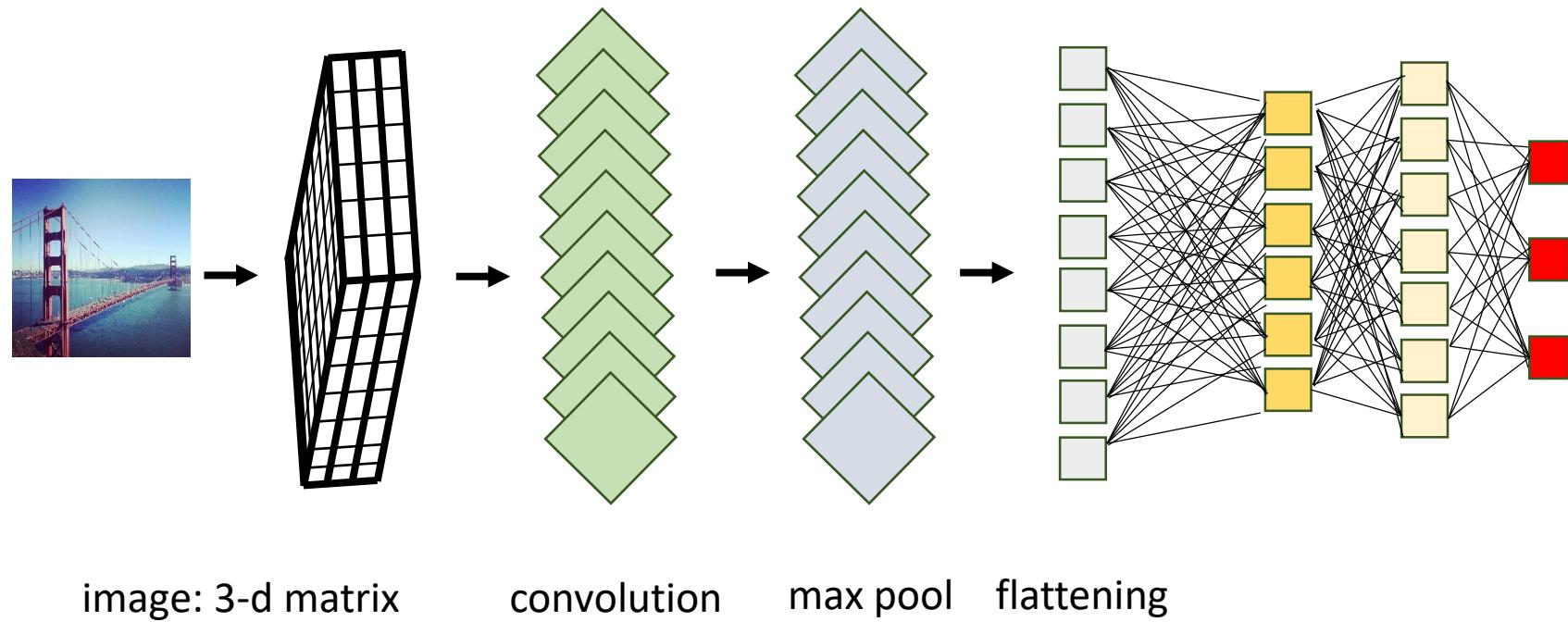
input: image,
aka numerical matrix

our ANN

→ classification

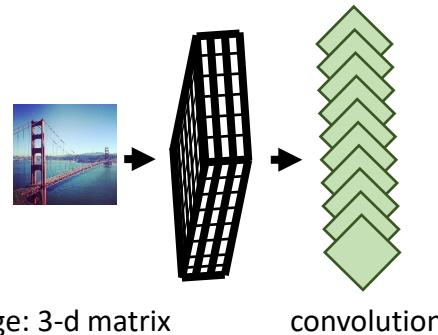


Our goal: creating an ANN that can tell cats from dogs





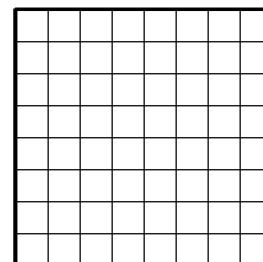
Our goal: creating an ANN that can tell cats from dogs



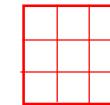
→ What is convolution and why do we need it?

What is convolution?

$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta) \mathbf{g}(x - \zeta) d\zeta \quad \text{image } \mathbf{f} \text{ and filter } \mathbf{g}$$



image



filter
(aka kernel)

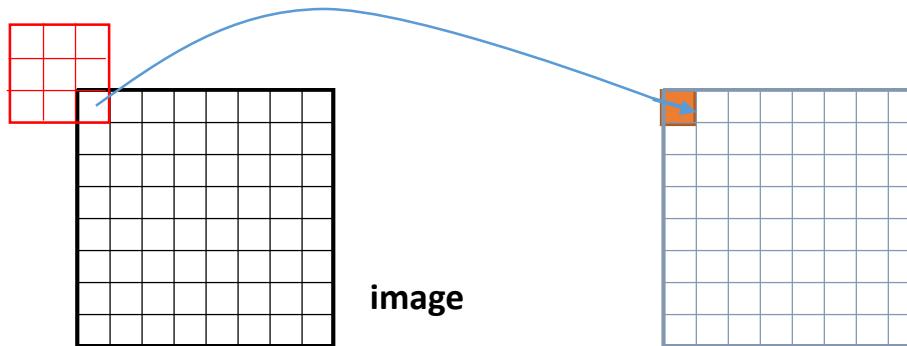


What is convolution?

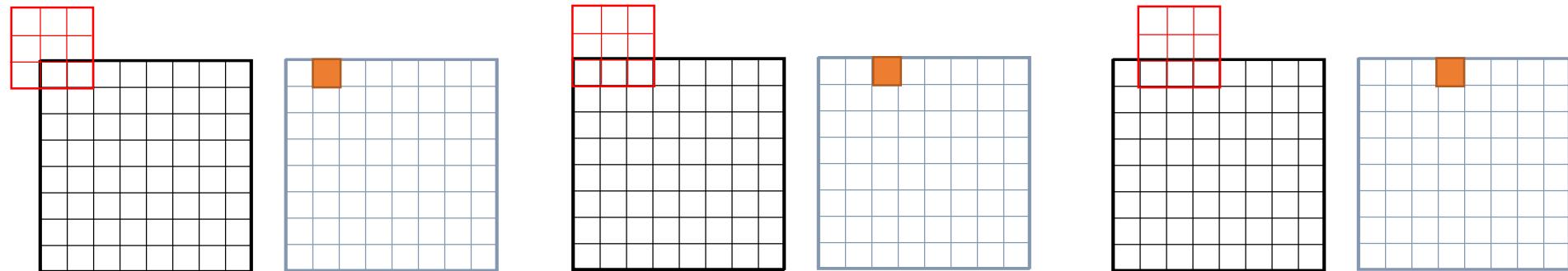
$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta) \mathbf{g}(x - \zeta) d\zeta$$

image f and filter g

filter
(aka kernel)



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





What is convolution?

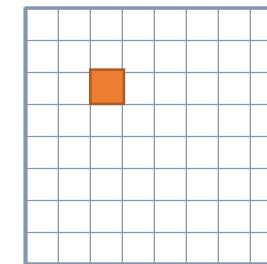
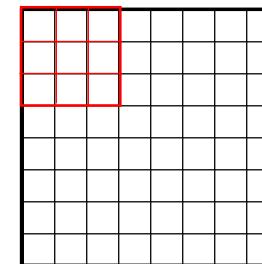
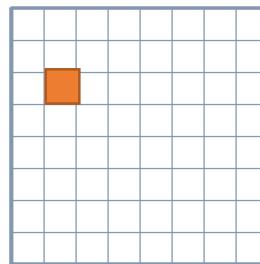
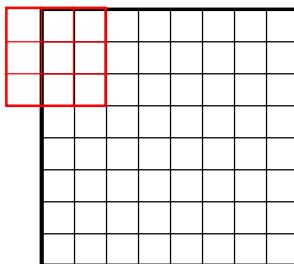
$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta) \mathbf{g}(x - \zeta) d\zeta \quad \text{image } \mathbf{f} \text{ and filter } \mathbf{g}$$

filter
(aka kernel)

image

convolved image

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



and so on...

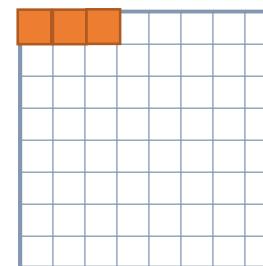
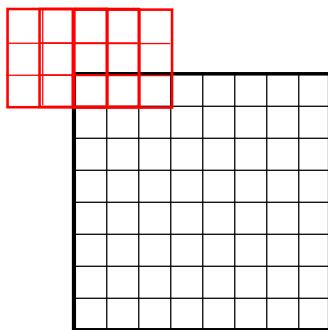


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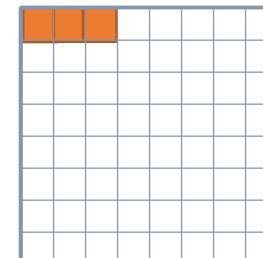
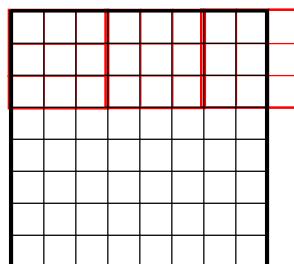
$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta) \mathbf{g}(x - \zeta) d\zeta \quad \text{image } \mathbf{f} \text{ and filter } \mathbf{g}$$

different techniques:

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



padding = 2; stride length = 1



padding = 0; stride length = 3

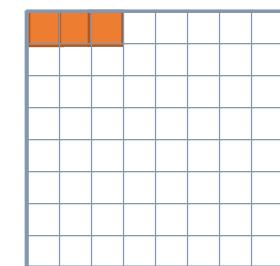
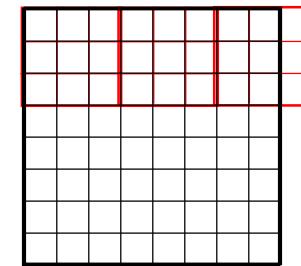
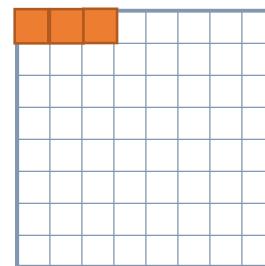
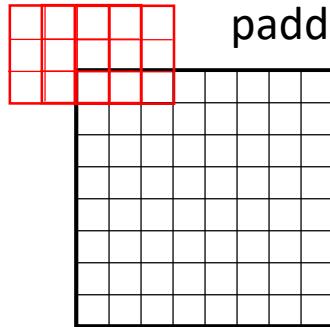


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different techniques:

- 1) multiplying matrix values pixelwise
- 2) summing up products
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the resulting image has the following size (N is the number of rows/columns):

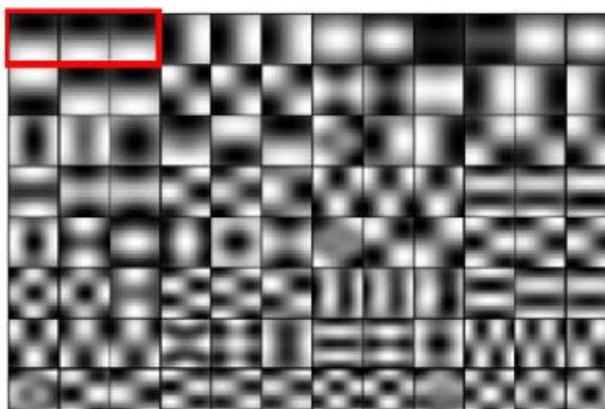
$$N_{out} = \frac{(N_{in} - N_{filt} + 2 * padding)}{\text{stride length}} + 1$$



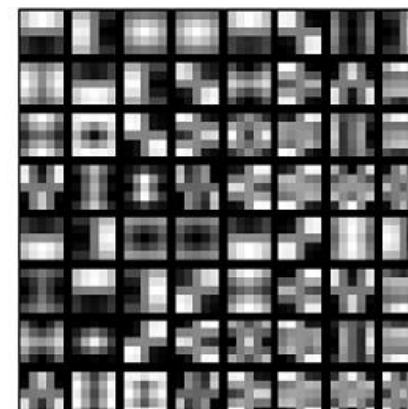
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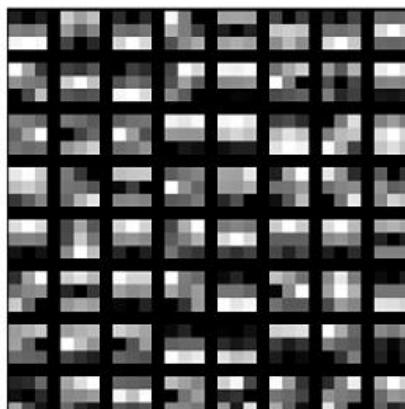
filters:



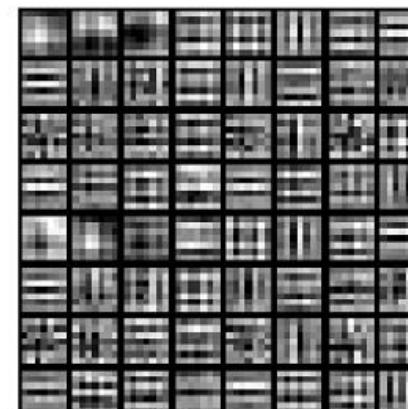
(a)



(b)



(c)



(d)

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



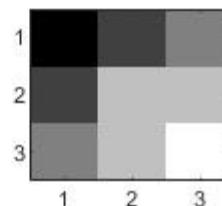
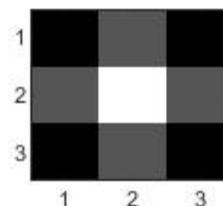
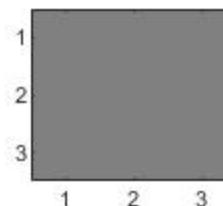
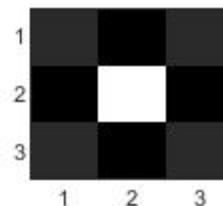
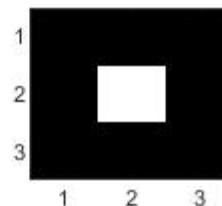
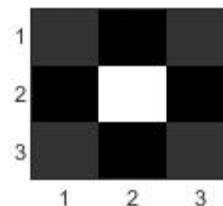
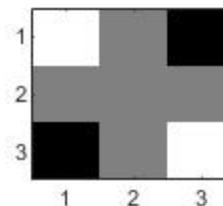
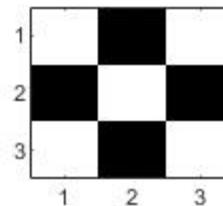
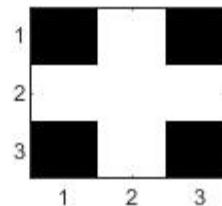
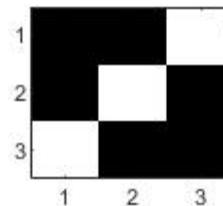
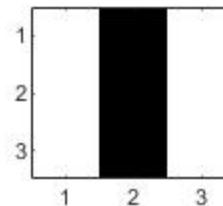
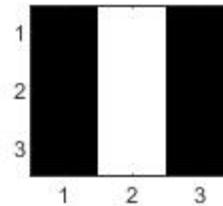
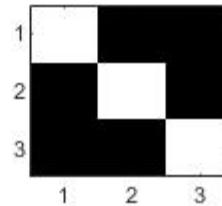
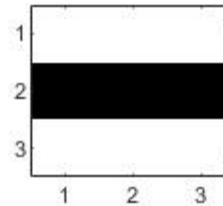
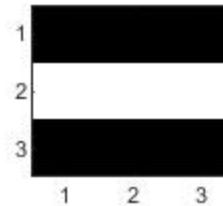
Why do we need it?

$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta) \mathbf{g}(x - \zeta) d\zeta \quad \text{image } \mathbf{f} \text{ and filter } \mathbf{g}$$

image \mathbf{f}



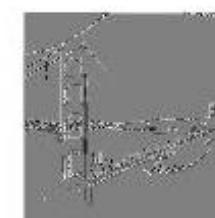
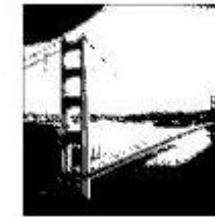
filter \mathbf{g}





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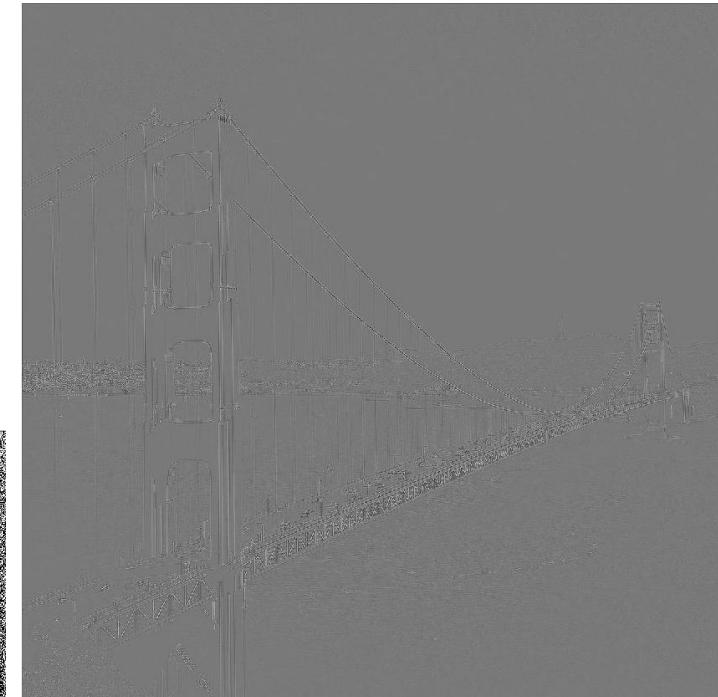
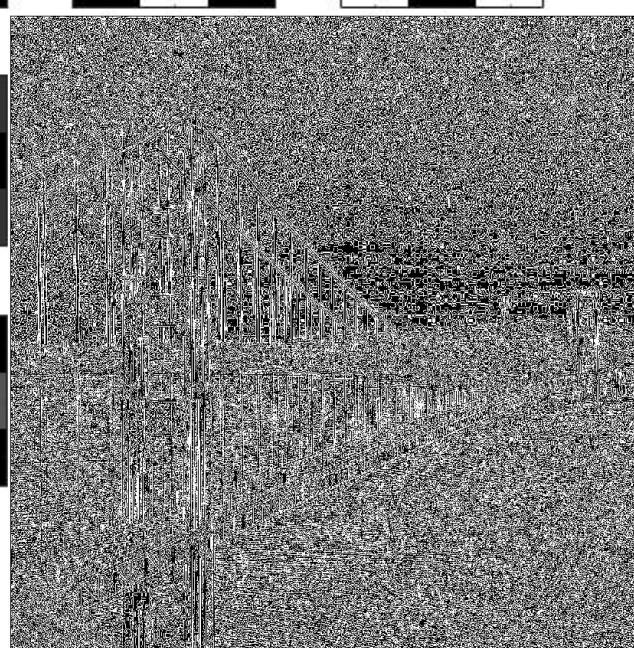
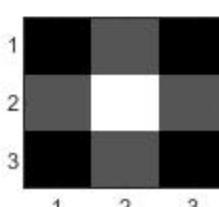
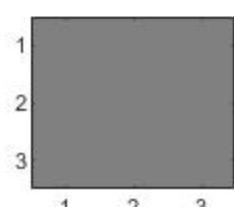
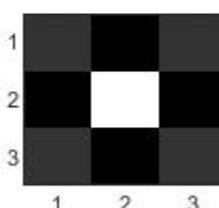
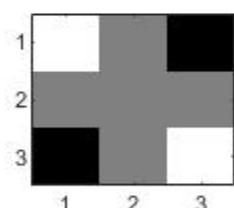
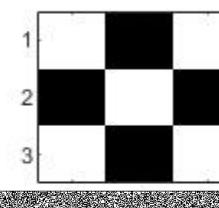
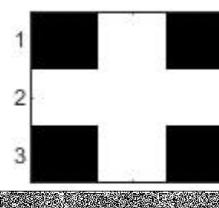
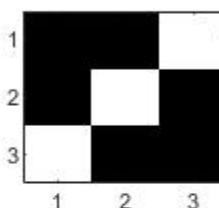
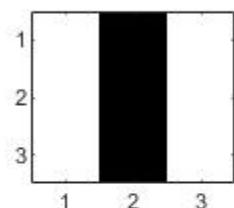
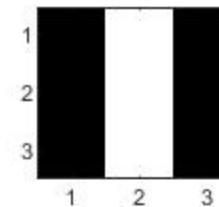
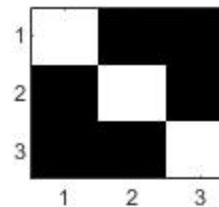
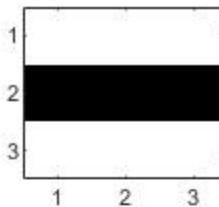
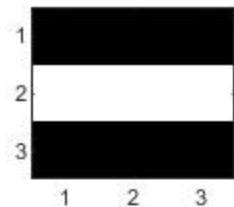


Why do we need it?

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

image f and filter \mathbf{g}

filter \mathbf{g}

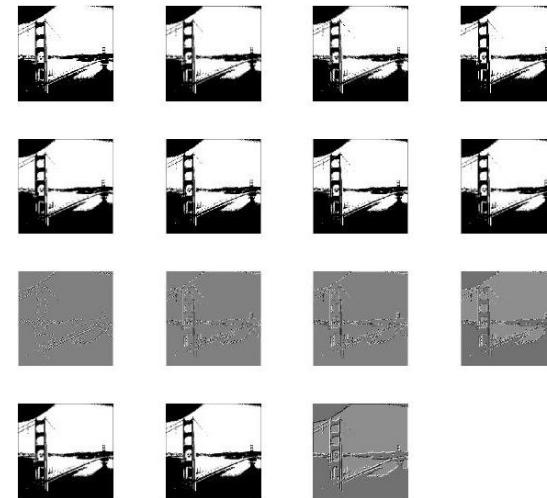
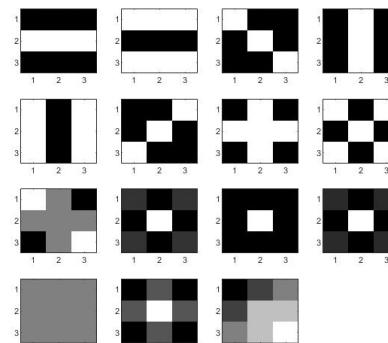




Why do we need it?

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

image f and filter g



idea:

- filtering relevant features
- Which features are relevant?

→ for classification

→ well, that's what the ANN learns

→ **learning filter weights**

Convolution is the main part → Convolutional Neural Network



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

This is all somewhat abstract → let us write a code, that

- 1) loads an image
- 2) loads different convolution filter (aka kernel)
- 3) shows the filtered image

I: reading & displaying images in python

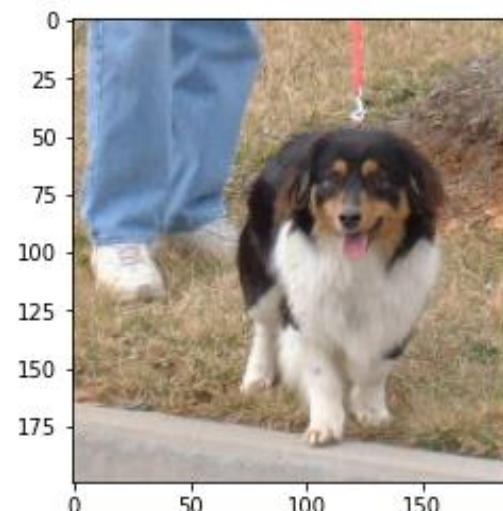
```
import matplotlib.pyplot as plt
```

```
I = plt.imread('C:/my_path/Dog/2.jpg')
```

Name	Type	Size	Value
I	Array of uint8	(199, 188, 3)	<pre>[[[190 161 129] [189 160 130]]]</pre>

```
plt.imshow(I)
```

the commands we are going to need are part of matplotlib



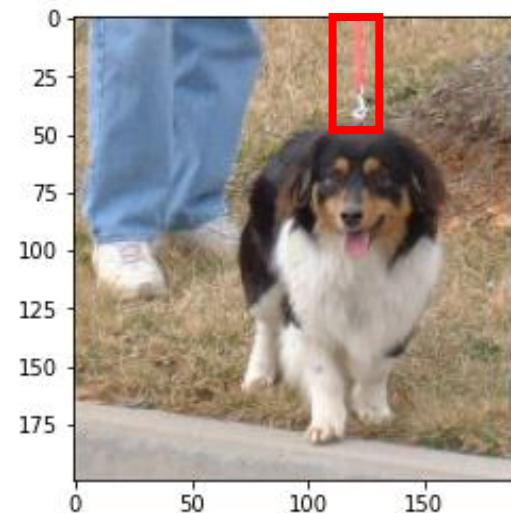


$$(f * g)(x) := \int_{\mathbb{R}^n} f(\zeta) g(x - \zeta) d\zeta$$

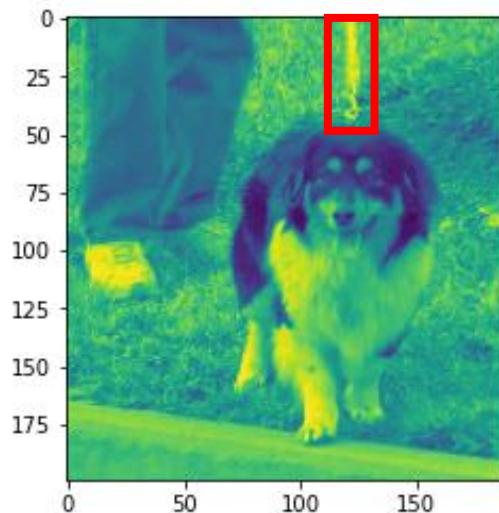
I: reading & displaying images in python

```
import matplotlib.pyplot as plt  
I = plt.imread('C:/my_path/Dog/2.jpg')
```

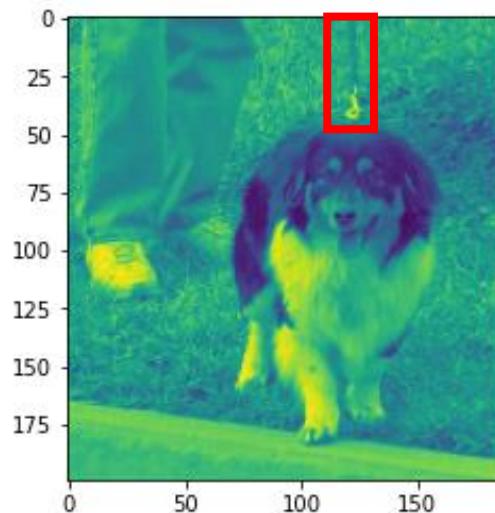
Name	Type	Size	Value
I	Array of uint8	(199, 188, 3)	[[[190 161 129] [189 160 130]]]



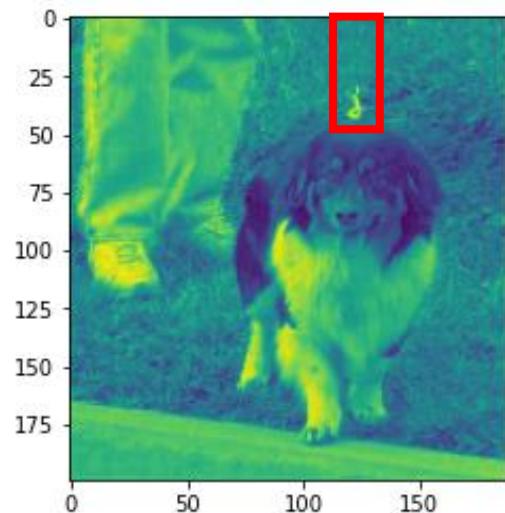
```
plt.imshow(I[:, :, 0])
```



```
plt.imshow(I[:, :, 1])
```



```
plt.imshow(I[:, :, 2])
```





I: reading & displaying images in python

```
import matplotlib.pyplot as plt
import numpy as np
from scipy.signal import convolve as Conv # N-Dim convolution

def My_Convolution(*Image):    #we want to read the image as an optional
                                #input argument

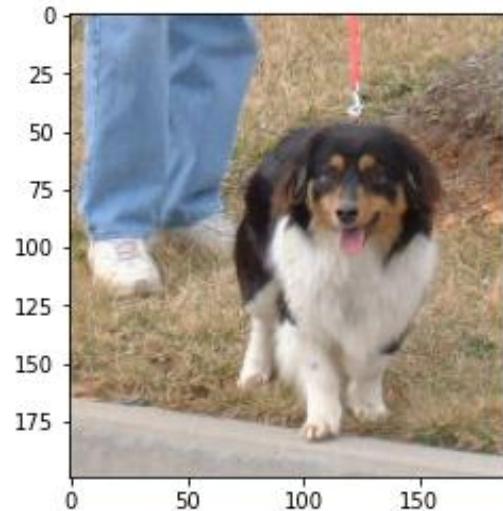
    #displaying the image
    if Image:
        for Image in Image:
            plt.imshow(Image)
    else:
        # read some default image
        Image = plt.imread('C:/my_path/Dog/2.jpg')
        plt.imshow(Image)
```



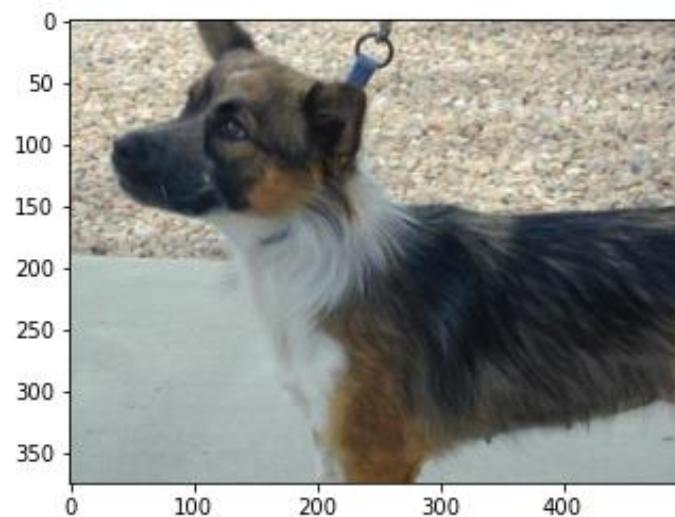
I: reading & displaying images in python

compile and run the code:

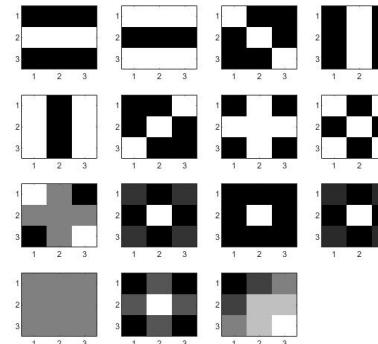
My_Convolution()



My_Convolution(I)



now it's time for the filters:





II: Convolution with different filter

```
def My_Convolution(*Image):
...
else:
    Image = plt.imread('C:/my_path/Dog/2.jpg')
    plt.imshow(Image)

#creating kernels
K1 = np.array([[0, 0, 0], [0, 1, 0], [0, 0, 0]])
#edges
K2 = np.array([[1, 0, -1], [0, 0, 0], [-1, 0, 1]])
K3 = np.array([[0, 1, 0], [1, -4, 1], [0, 1, 0]])
K4 = np.array([[-1, -1, -1], [-1, 8, -1], [-1, -1, -1]])
#sharpen
K5 = np.array([[0, -1, 0], [-1, 5, -1], [0, -1, 0]])
#blur
K6 = np.array([[1, 1, 1], [1, 1, 1], [1, 1, 1]])
K6 = K6/9
K7 = np.array([[1, 2, 1], [2, 4, 2], [1, 2, 1]])
```



II: Convolution with different filter

```
def My_Convolution(*Image):  
    ...  
    #creating kernels  
    K1 = np.array([[0, 0, 0], [0, 1, 0], [0, 0, 0]])  
    #edges  
    K2 = np.array([[1, 0, -1], [0, 0, 0], [-1, 0, 1]])  
    K3 = np.array([[0, 1, 0], [1, -4, 1], [0, 1, 0]])  
    K4 = np.array([[-1, -1, -1], [-1, 8, -1], [-1, -1, -1]])  
    #sharpen  
    K5 = np.array([[0, -1, 0], [-1, 5, -1], [0, -1, 0]])  
    #blur  
    K6 = np.array([[1, 1, 1], [1, 1, 1], [1, 1, 1]])  
    K6 = K6/9  
    K7 = np.array([[1, 2, 1], [2, 4, 2], [1, 2, 1]])  
  
    #skeewed  
    K8 = np.array([[-2, -1, 0], [-1, 1, 1], [0, 1, 2]])  
    #misc  
    K9 = np.array([[1, 0, 1], [0, 1, 0], [1, 0, 1]])  
    K10 = np.array([[1, 1, 1], [0, 0, 0], [1, 1, 1]])  
    K11 = np.array([[1, 0, 0], [0, 1, 0], [0, 0, 1]])  
    K12 = np.array([[0, 0, 1], [0, 1, 0], [1, 0, 0]])  
    K13 = np.array([[1, 0, 1], [1, 0, 1], [1, 0, 1]])
```



II: Convolution with different filter

```
def My_Convolution(*Image):  
    ...  
    #skewed  
    K8 = np.array([[-2, -1, 0], [-1, 1, 1], [0, 1, 2]])  
    #misc  
    K9 = np.array([[1, 0, 1], [0, 1, 0], [1, 0, 1]])  
    K10 = np.array([[1, 1, 1], [0, 0, 0], [1, 1, 1]])  
    K11 = np.array([[1, 0, 0], [0, 1, 0], [0, 0, 1]])  
    K12 = np.array([[0, 0, 1], [0, 1, 0], [1, 0, 0]])  
    K13 = np.array([[1, 0, 1], [1, 0, 1], [1, 0, 1]])
```

putting all filters into one matrix:

```
K = np.dstack((K1,K2,K3,K4,K5,K6,K7,K8,K9,K10,K11,K12,K13))
```

```
# some parameter we are going to need soon:  
NK = K.shape[2]  
NC = Image.shape[2]
```



II: Convolution with different filter

```
def My_Convolution(*Image):
```

```
...
```

```
NK = K.shape[2]  
NC = Image.shape[2]
```

```
PS = np.math.ceil(NK**0.5)
```

We want to display the filtered images for each filter and color channel

```
for i in range(NC):
```

```
    plt.figure(figsize = (15, 12))  
    plt.suptitle("after convolution of channel " + str(i+1),  
                fontsize = 20, y = 0.95)  
    plt.subplots_adjust(hspace = 0.5)
```

one figure for each channel

```
    for k in range(NK):
```

```
        plt.subplot(PS,PS,k+1)  
        Out = Conv(Image[:, :, i], K[:, :, k])  
        plt.imshow(Out, cmap = 'gray')
```

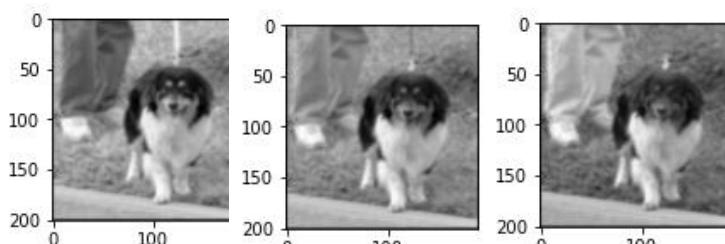
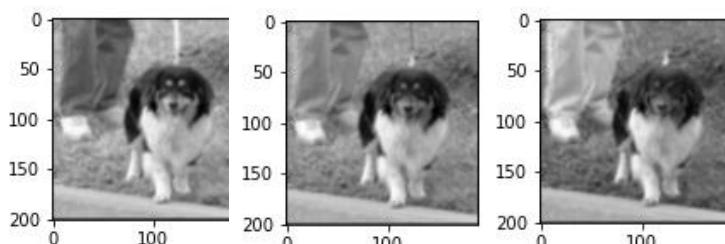
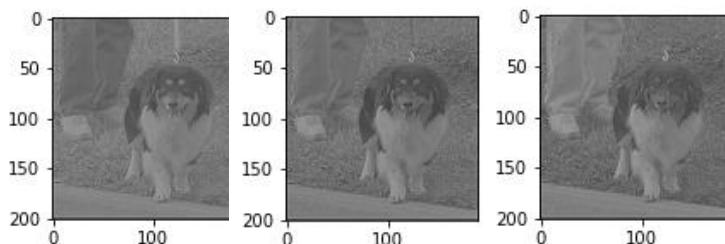
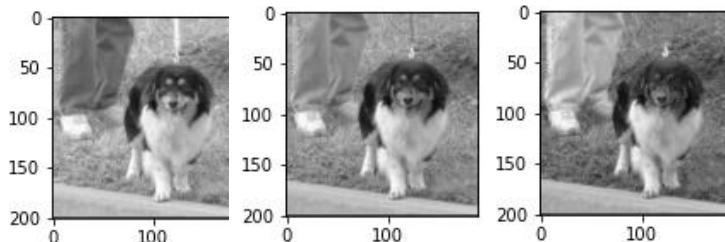
creating different subplots

```
    plt.show()
```

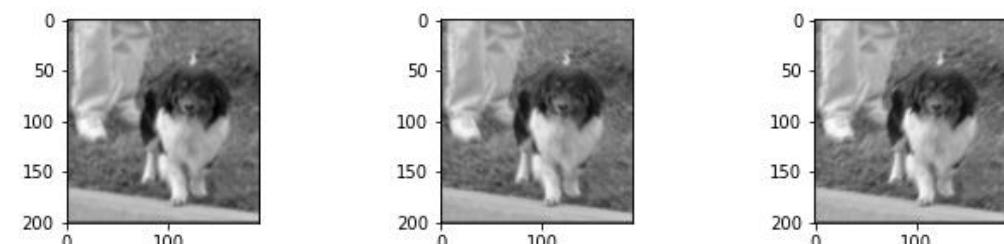
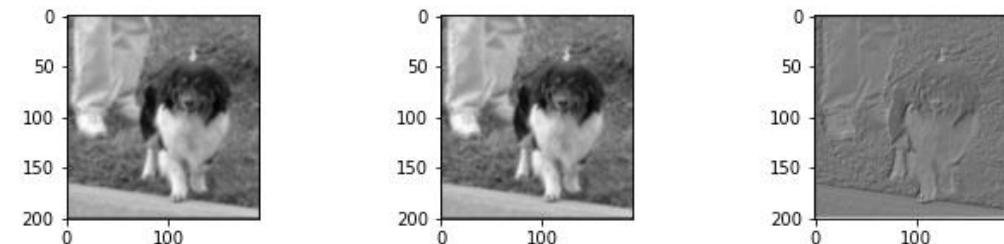
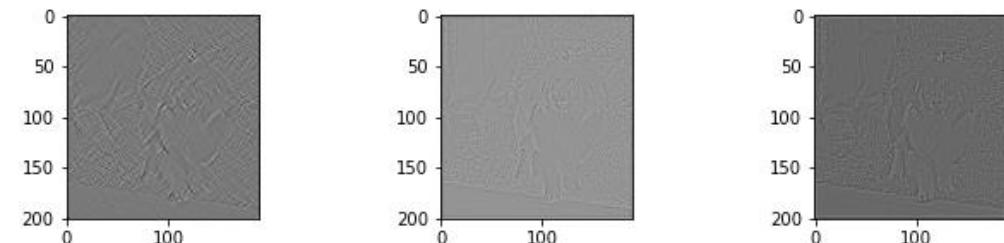
the actual convolution



II: Convolution with different filter



compile and run the code:
after convolution of channel 3





II: Convolution with different filter

This has worked perfectly, however, we would like to understand **convolution entirely**

- writing our own convolution routine
- input arguments: the image itself, stride length, padding
- output arguments: convolved image

aim: → once this code is working, we can copy/paste it into
 our ANN with slight modifications
 → especially for backpropagation it will become crucial
 to understand what we are doing (will be the most laborious part)

```
import numpy as np
import matplotlib.pyplot as plt
```

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



II: Convolution with different filter

```
import numpy as np
import matplotlib.pyplot as plt

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

    if Image:
        for Image in Image:
            plt.imshow(Image)
            plt.show()
    else:
        Image = plt.imread('C:/my_path/Dog/2.jpg')
        plt.imshow(Image)
        plt.show()
```

again, we'd like to keep the option of loading a default image



II: Convolution with different filter

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

```
    import numpy as np
    import matplotlib.pyplot as plt

    if Image:
        for Image in Image:
            plt.imshow(Image)
            plt.show()
    else:
        Image = plt.imread('C:/my_path/Dog/2.jpg')
        plt.imshow(Image)
        plt.show()
```

```
xImgShape = Image.shape[0]
yImgShape = Image.shape[1]
numChans = Image.shape[2]
```

```
xK = K.shape[0]
yK = K.shape[1]
```

#determining size of output image

```
xOutput = int(((xImgShape - xK + 2 * padding)/stride) + 1)
yOutput = int(((yImgShape - yK + 2 * padding)/stride) + 1)
```

determining sizes of image & kernel
third image dimension = number of color channels

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



II: Convolution with different filter

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

...

```
xImgShape = Image.shape[0]
yImgShape = Image.shape[1]
numChans = Image.shape[2]

xK = K.shape[0]
yK = K.shape[1]

#determining size of output image
xOutput = int(((xImgShape - xK + 2 * padding)/stride) + 1)
yOutput = int(((yImgShape - yK + 2 * padding)/stride) + 1)
```

Note: we don't use np.empty here, since it would lead to NaNs

```
#initializing empty output matrix
output = np.zeros((xOutput,yOutput,numChans))
```

```
imagePadded = np.zeros(((xImgShape + padding*2),
(yImgShape + padding*2), numChans))
```

```
imagePadded[int(padding):int(padding + xImgShape), \
int(padding):int(padding + yImgShape),:] = Image
```



II: Convolution with different filter

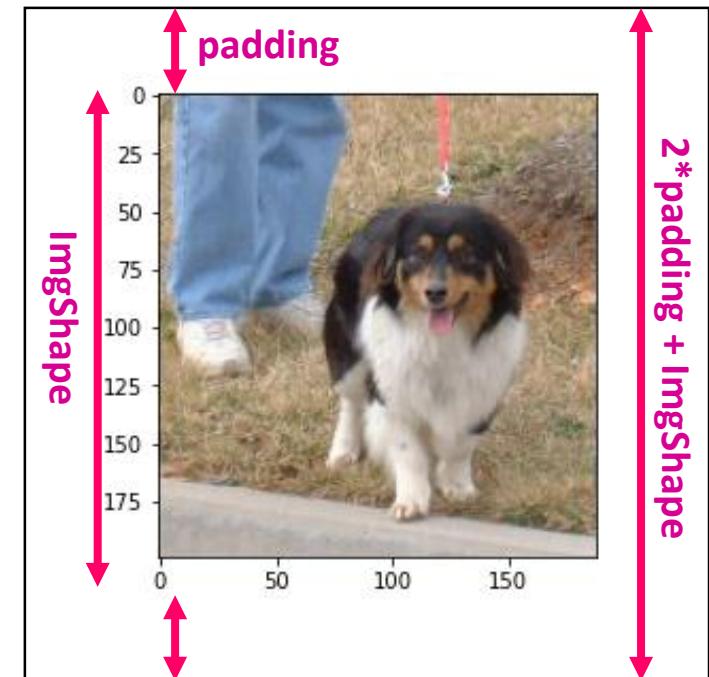
```
def ConvSelfMade(*Image, K, padding = 0, stride = 1):
```

...

```
#initializing empty output matrix  
output = np.zeros((xOutput,yOutput,numChans))
```

```
imagePadded = np.zeros(((xImgShape + padding*2),  
                      (yImgShape + padding*2), numChans))
```

```
imagePadded[int(padding):int(padding + xImgShape),\n            int(padding):int(padding + yImgShape),:] = Image
```





II: Convolution with different filter

```
def ConvSelfMade(*Image, K, padding = 0, stride = 1):  
    ...  
  
    imagePadded = Image  
  
    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,\n                                         y_start:y_end,c]  
  
                #the actual convolution part  
                s             = np.multiply(current_slice,K)  
                output[x,y,c] = np.sum(s)
```



II: Convolution with different filter

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

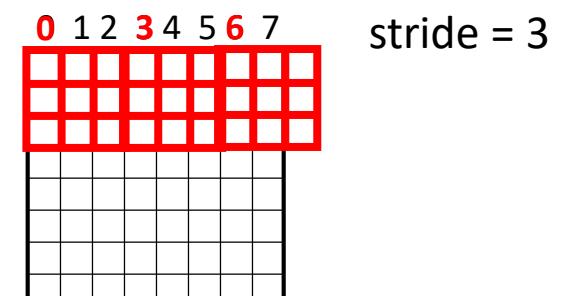
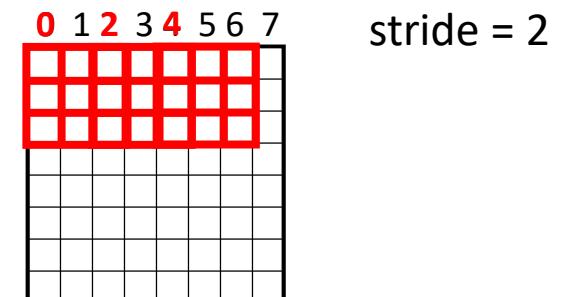
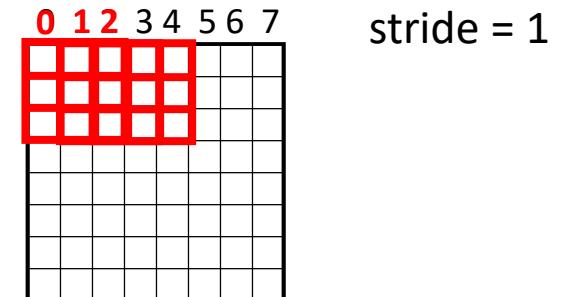
...

```
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,\n                                         y_start:y_end,c]

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





II: Convolution with different filter

```
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,\n                                y_start:y_end,c]

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

```
plt.imshow(output.sum(2), cmap = 'gray')
```

```
plt.title('after convolution with padding'\
          '=' + str(padding) + ' and stride=' + str(stride))
plt.show()
```

```
return(output)
```

finally, in ANNs,
the results are summed
over the color channels



II: Convolution with different filter

Let us now test the code with different settings for one **particular kernel**

```
kernel = np.array([[1, 0, -1], [0, 0, 0], [-1, 0, 1]])
```

```
ConvSelfMade(K = kernel, padding = 0, stride = 1)
```

```
ConvSelfMade(K = kernel, padding = 0, stride = 2)
```

```
ConvSelfMade(K = kernel, padding = 0, stride = 5)
```

```
ConvSelfMade(K = kernel, padding = 0, stride = 10)
```

```
ConvSelfMade(K = kernel, padding = 0, stride = 20)
```

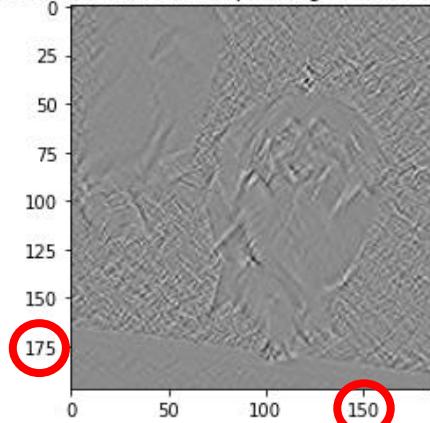
```
ConvSelfMade(K = kernel, padding = 30, stride = 1)
```



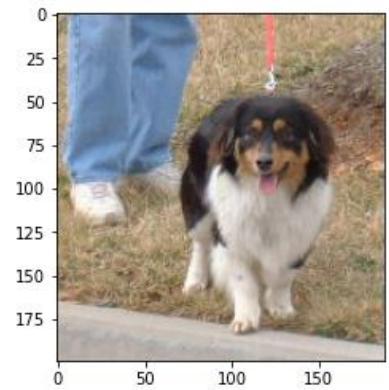
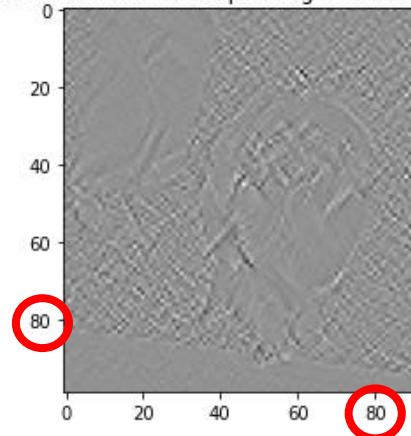
II: Convolution with different filter

Let us now test the code with different settings for one **particular kernel**

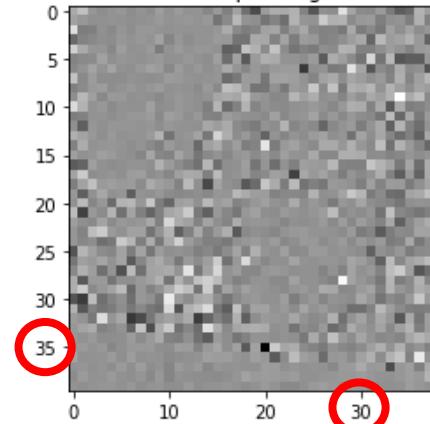
after convolution with padding=0 and stride=1



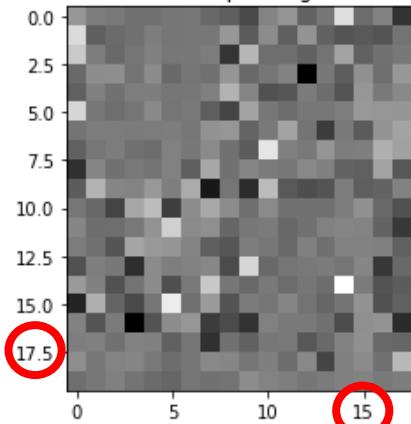
after convolution with padding=0 and stride=2



after convolution with padding=0 and stride=5

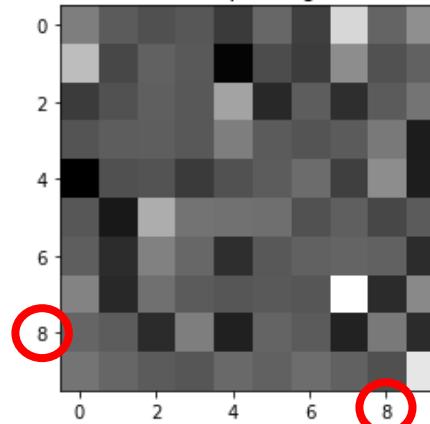


after convolution with padding=0 and stride=10



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

after convolution with padding=0 and stride=20

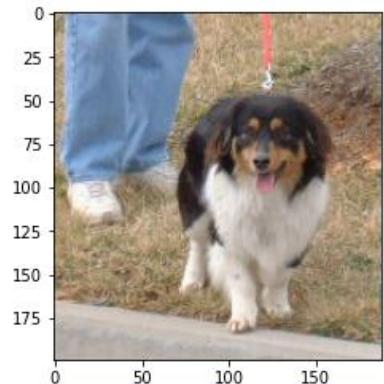
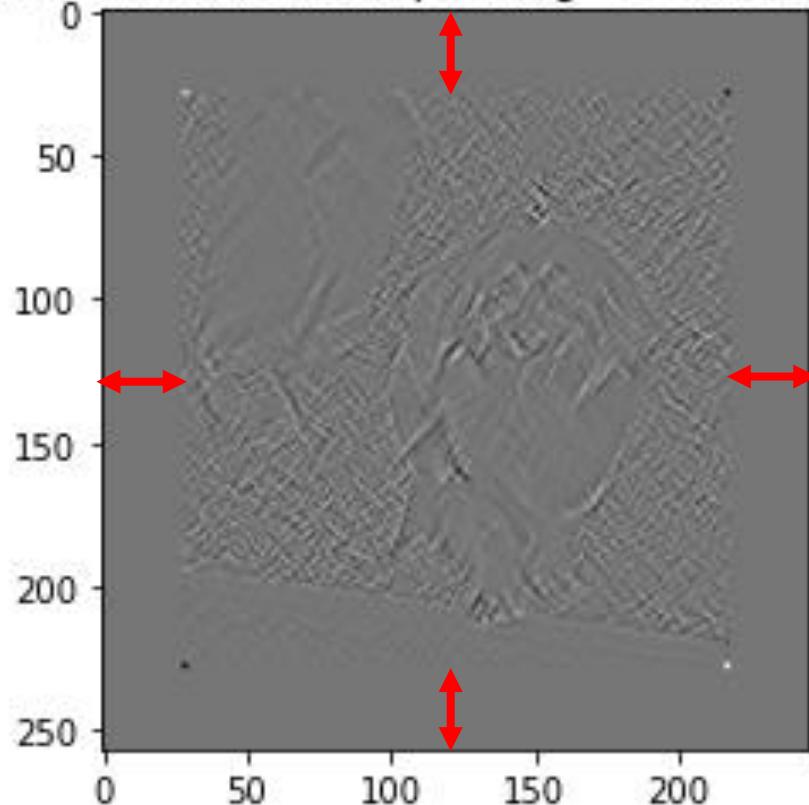




II: Convolution with different filter

Let us now test the code with different settings for one **particular kernel**

after convolution with padding=30 and stride=1



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



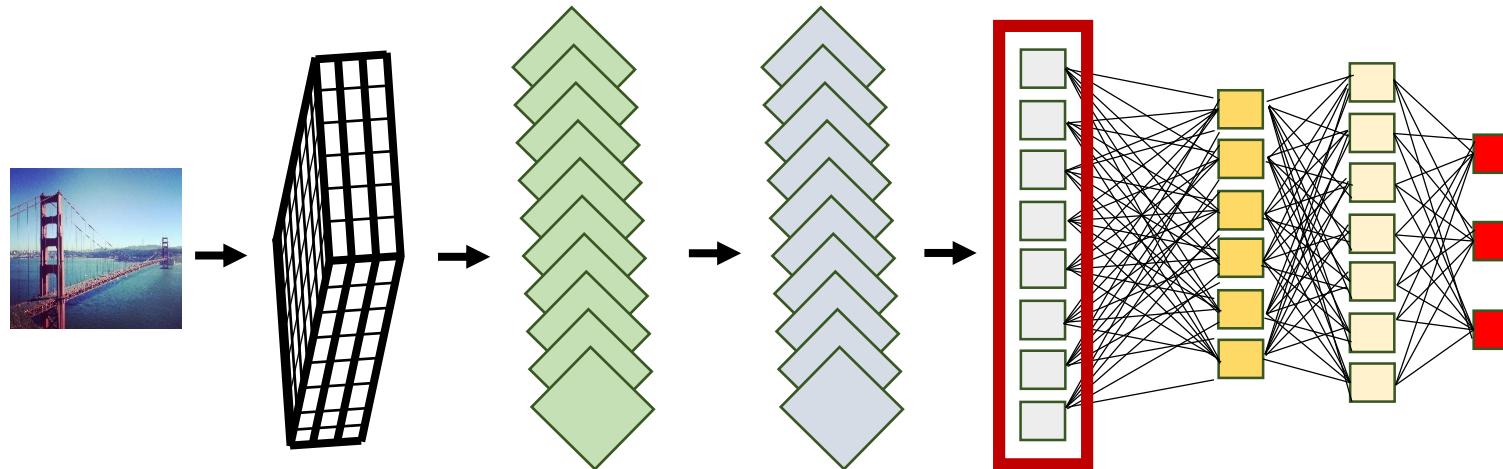
III: Loading a batch of images

We are almost ready for including the convolution part in our network!

An CNN needs **hundreds**, if not **thousands** of images as training sample

→ loading only **mini batches** of sizes 64, 128, 256... at once

Eventually, we have to **link our convolution part** somehow to the actual network...



...but the images have **different sizes** → **rescaling all images**

We have to do these things first!



III: Loading a batch of images

For this, we need to load a few more libraries:

→ go to our current ANN and add the following lines to the header:

```
import glob as gl      # for ls like in linux  
  
import random          # for picking mini batches randomly  
  
from PIL import Image  # for resizing images  
  
class Read_Scale_Imds:  
  
    def Read_Scale(self, minibatch_size, ANN_size):
```

as usual, we want to set up a class

input: 1) **minibatch_size (number)**
 → how many images does the CNN run at once

 2) **ANN_size (array of two numbers)**
 → pixel size to which all images have to be scaled



III: Loading a batch of images

```
import glob as gl      # for ls like in linux
import random          # for picking mini batches randomly
from PIL import Image   # for resizing images

class Read_Scale_Imds:

    def Read_Scale(self, minibatch_size, ANN_size):

        path_dogs = 'C:/my_path/Dog/*.jpg'
        path_cats = 'C:/my_path/Cat/*.jpg'
```

setting paths to data

```
Cats = gl.glob(path_cats)
Dogs = gl.glob(path_dogs)
```

equivalent to *ls* in linux

```
Ld = len(Dogs)
Lc = len(Cats)
D = np.zeros((Ld))
C = np.zeros((Lc)) + 1
```

creating a list of all
images and assigning
classes to training data:
dogs = 0
cats = 1

```
All_class = np.array(np.hstack((D,C)))
All_imds = np.hstack((Dogs,Cats))
```

putting both together



III: Loading a batch of images

```
import glob as gl      # for ls like in linux
import random          # for picking mini batches randomly
from PIL import Image   # for resizing images

class Read_Scale_Imds:

    def Read_Scale(self, minibatch_size, ANN_size):
        ...
        All_class = np.array(np.hstack((D,C)))
        All_imds  = np.hstack((Dogs,Cats))

        idx = random.sample(range(Ld+Lc), minibatch_size)

        classes = All_class[idx]
        imds     = All_imds[idx]

        xANN      = ANN_size[0]
        yANN      = ANN_size[1]
```

randomly selecting a
subsample as mini batch



III: Loading a batch of images

```
import glob as gl      # for ls like in linux
import random          # for picking mini batches randomly
from PIL import Image  # for resizing images

class Read_Scale_Imds:

    def Read_Scale(self, minibatch_size, ANN_size):
        ...
        All_class = np.array(np.hstack((D,C)))
        All_imds  = np.hstack((Dogs,Cats))

        idx = random.sample(range(Ld+Lc),
                           minibatch_size)

        classes = All_class[idx]
        imds     = All_imds[idx]

        xANN     = ANN_size[0]
        yANN     = ANN_size[1]

#size ANN x size ANN x RGB x minibatch matrix
ImdsMatrix = np.zeros((xANN, yANN, 3, minibatch_size))

for i in range(minibatch_size):

    I                  = Image.open(imds[i])
    Ire                = I.resize((xANN_size, yANN_size))
    Iar                = np.array(Ire) # better be save
    ImdsMatrix[:, :, :, i] = Iar
```

loading & resizing the images and
storing them in one big array



III: Loading a batch of images

```
import glob as gl      # for ls like in linux
import random          # for picking mini batches randomly
from PIL import Image  # for resizing images

class Read_Scale_Imds:

    def Read_Scale(self, minibatch_size, ANN_size):
        ...
        All_class = np.array(np.hstack((D,C)))
        All_imds  = np.hstack((Dogs,Cats))

        idx = random.sample(range(Ld+Lc), minibatch_size)

        classes = All_class[idx]
        imds     = All_imds[idx]

        xANN     = ANN_size[0]
        yANN     = ANN_size[1]

        #size ANN x size ANN x RGB x minibatch matrix
        ImdsMatrix = np.zeros((xANN, yANN, 3, minibatch_size))

        for i in range(minibatch_size):

            I           = Image.open(imds[i])
            Ire         = I.resize((xANN, yANN))
            Iar         = np.array(Ire) # better be save
            ImdsMatrix[:, :, :, i] = Iar

        ImdsMatrix.astype(np.uint8) # again, making sure,
                                  # that we have the correct type

    return(ImdsMatrix, classes)
```



III: Loading a batch of images

```
class Read_Scale_Imds:

    def Read_Scale(self, minibatch_size, ANN_size):
        path_dogs = 'C:/my_path/Dog/*.jpg'
        path_cats = 'C:/my_path/Cat/*.jpg'

        Cats = gl.glob(path_cats)
        Dogs = gl.glob(path_dogs)

        Ld = len(Dogs)
        Lc = len(Cats)
        D = np.zeros((Ld))
        C = np.zeros((Lc)) + 1

        All_class = np.array(np.hstack((D,C)))
        All_imds = np.hstack((Dogs,Cats))

        idx = random.sample(range(Ld+Lc), minibatch_size)

        classes = All_class[idx]
        imds = All_imds[idx]

        xANN = ANN_size[0]
        yANN = ANN_size[1]

        #size ANN x size ANN x RGB x minibatch matrix
        ImdsMatrix = np.zeros((xANN, yANN, 3,minibatch_size))

        for i in range(minibatch_size):

            I = Image.open(imds[i])
            Ire = I.resize((xANN, yANN))
            Iar = np.array(Ire) # better be save
            ImdsMatrix[:, :, :, i] = Iar

        ImdsMatrix.astype(np.uint8) # again, making sure,
                                    # that we have the correct type

    return(ImdsMatrix,classes)
```

We just need to add a tiny loop if some images are b/w

```
if len(Iar.shape) != 3:
    I3D = np.zeros((xANN, yANN, 3))
    I3D[:, :, 0] = Iar
    I3D[:, :, 1] = Iar
    I3D[:, :, 2] = Iar
    Iar = I3D
```

←

again, making sure,
that we have the correct type



III: Loading a batch of images

```
class Read_Scale_Imds:

    def Read_Scale(self, minibatch_size, ANN_size):
        ...
        All_class = np.array(np.hstack((D,C)))
        All_imds = np.hstack((Dogs,Cats))

        idx = random.sample(range(Ld+Lc), minibatch_size)

        classes = All_class[idx]
        imds = All_imds[idx]

        xANN = ANN_size[0]
        yANN = ANN_size[1]

        ImdsMatrix = np.zeros((xANN, yANN, 3, minibatch_size))

        for i in range(minibatch_size):

            I = Image.open(imds[i])
            Ire = I.resize((xANN, yANN))
            Iar = np.array(Ire) # better be save

            if len(Iar.shape) != 3:

                I3D = np.zeros((xANN, yANN, 3))
                I3D[:, :, 0] = Iar
                I3D[:, :, 1] = Iar
                I3D[:, :, 2] = Iar
                Iar = I3D

            ImdsMatrix[:, :, :, i] = Iar

        ImdsMatrix.astype(np.uint8) # again, making sure,
                                    # that we have the correct type
        return(ImdsMatrix, classes)
```

our complete code

→ check and test run the code



III: Loading a batch of images

→ check and test run the code

in the console:

```
from MyANN import *
```

```
WithKernelConv.py
  └── Read_Scale_Imds
      └── Read_Scale
  ├── Layer_Dense
  ├── Activation_ReLU
  ├── Activation_Softmax
  ├── Loss
  ├── Loss_CategoricalCrossEntropy
  ├── Activation_Softmax_Loss_CategoricalCrossentropy
  └── Optimizer_SGD
```

```
In [78]: MyANN.Read_Scale_Imds.Read_Scale(22,[128, 128])
```



IV: Including convolution part with kernels

```
class Create_Kernels:  
  
    def kernel_library():  
  
        #creating kernels  
        K1 = np.array([[0, 0, 0], [0, 1, 0], [0, 0, 0]])  
  
        #edges  
        K2 = np.array([[1, 0, -1], [0, 0, 0], [-1, 0, 1]])  
  
        ...  
  
        K = np.dstack((K1,K2,K3,K4,K5,K6,K7,K8,K9,K10,K11,K12,K13))  
  
    return(K)
```

→ go to the function My_Convolution.py

→ copy the part with the kernels, starting at
 K1 = np.array(...
 until
 K = np.dstack(...

→ paste it into the ANN



IV: Including convolution part with kernels

in the console:

```
from MyANN import *
```

The screenshot shows a file explorer window with the following structure:

- WithKernelConv.py (selected)
- Read_Scale_Imds
- Create_Kernels
 - kernel_library
- Layer_Dense
- Activation_ReLU
- Activation_Softmax
- Loss
- Loss_CategoricalCrossEntropy
- Activation_Softmax_Loss_CategoricalCrossentropy
- Optimizer_SGD

A red box highlights the 'Create_Kernels' folder and its 'kernel_library' sub-module.

Name	Type	Size	Value
Kout	Array of float64	(3, 3, 13)	[[[0. 1. 0. ... 1. 0. 1.] [0. 0. 1. ... 0. 0. 0.] [0. 0. 0. ... 0. 0. 0.]]]

```
Kout = MyANN.Create_Kernels.kernel_library()
```



IV: Including convolution part with kernels

we now want to integrate the convolution part itself:

the `__init__` part calls the kernels

→ the entries of the kernels are the *weights* (which will be learned) of the convolution part

```
class ConvLayer:
```

```
def __init__(self):
    #reading kernels from library
    K = Create_Kernels.kernel_library()

    #kernel sizes
    self.xKernShape = K.shape[0]
    self.yKernShape = K.shape[1]
    self.Kernnumber = K.shape[2]
```



IV: Including convolution part with kernels

`class ConvLayer:`

```
def __init__(self):
    #reading kernels from library
    K = Create_Kernels.kernel_library()

    #kernel sizes
    self.xKernShape = K.shape[0]
    self.yKernShape = K.shape[1]
    self.Kernnumber = K.shape[2]
```

we now want to integrate the convolution part itself:

`self.weights = K`

`self.biases = np.zeros((1, self.Kernnumber))`



IV: Including convolution part with kernels

`class ConvLayer:`

```
def __init__(self):
    #reading kernels from library
    K = Create_Kernels.kernel_library()

    #kernel sizes
    self.xKernShape = K.shape[0]
    self.yKernShape = K.shape[1]
    self.Kernnumber = K.shape[2]

    self.weights      = K
    self.biases       = np.zeros((1, self.Kernnumber))
```

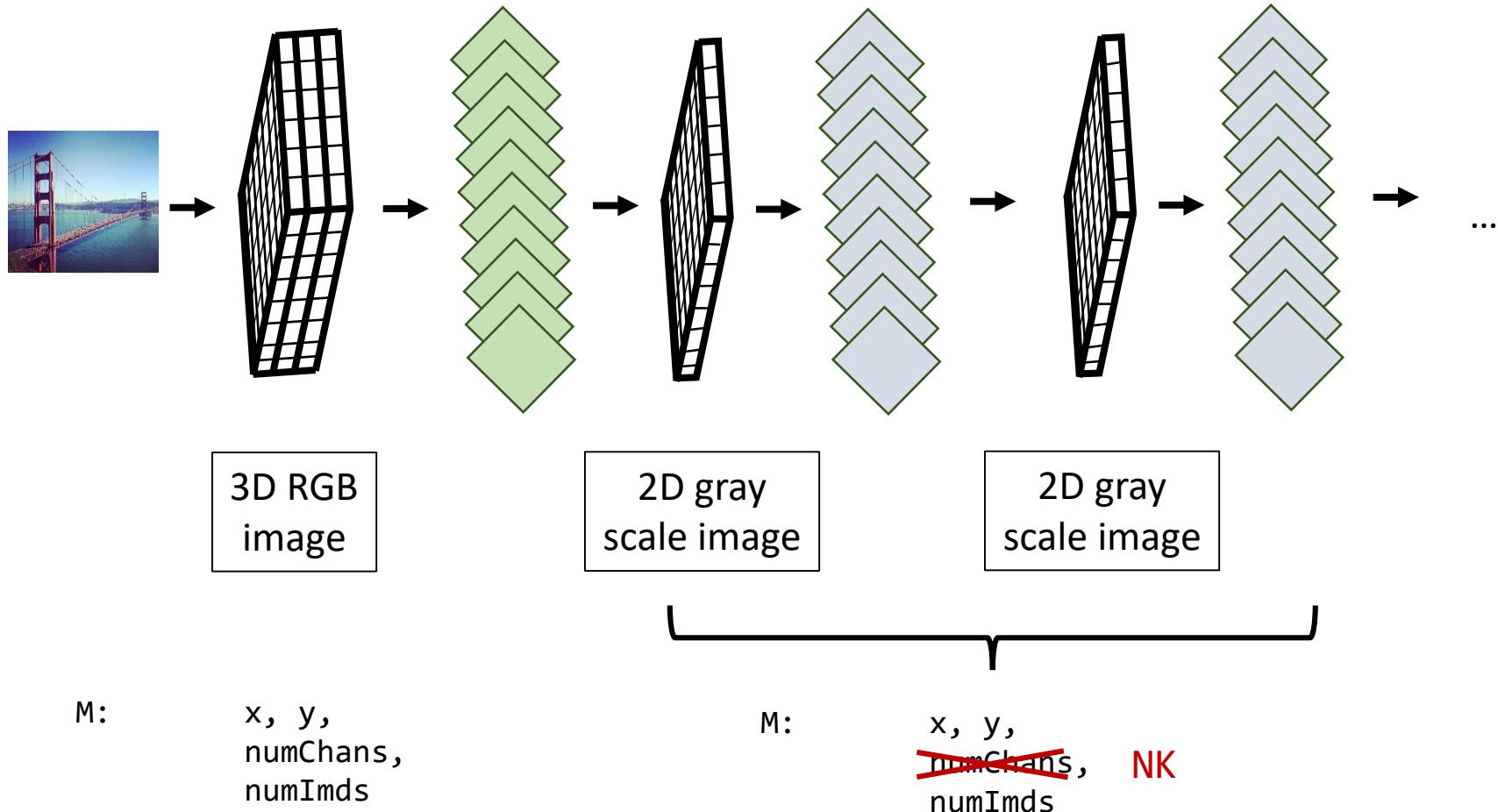
we now want to integrate the convolution part itself:

`def forward(self, M, padding = 0, stride = 1):`



IV: Including convolution part with kernels

typically, there are many convolution layers in a CNN



in our code: numChans refers to incoming matrix, Kernnumber to output matrix



IV: Including convolution part with kernels

```
class ConvLayer:
```

...

```
def forward(self, M, padding = 0, stride = 1):
```



we now want to integrate the convolution part itself:

M is the matrix containing the images,
according to Read_Scale_Imds

```
xImgShape = M.shape[0]
```

```
yImgShape = M.shape[1]
```

```
numChans = M.shape[2]
```

```
numImds = M.shape[3]
```

numChans refers to incoming matrix,
Kernnumber to output matrix

```
xK = self.xKernShape
```

```
yK = self.yKernShape
```

```
NK = self.Kernnumber
```

```
b = self.biases
```



IV: Including convolution part with kernels

```
class ConvLayer:
```

```
...
```

```
def forward(self, M, padding = 0, stride = 1):
```

```
xImgShape = M.shape[0]
yImgShape = M.shape[1]
numChans = M.shape[2]
numImds = M.shape[3]

xK = self.xKernShape
yK = self.yKernShape
NK = self.Kernnumber

b = self.biases
```

#storage for backprop, see later

```
self.padding = padding
self.stride = stride
```

we now want to integrate the convolution part itself:

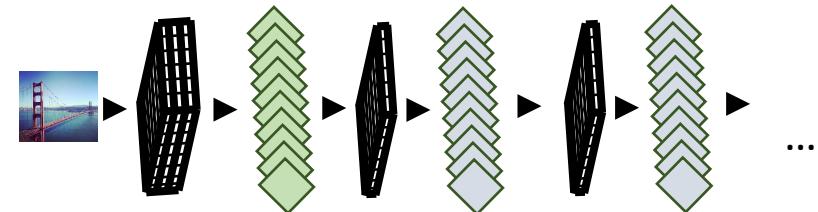
$$\text{recall: } N_{out} = \frac{(N_{in} - N_{filt} + 2 * padding)}{\text{stride length}} + 1$$

**copy/paste this part from
ConvSelfMade.py**

```
xOutput = int(((xImgShape - xK + 2 * padding)/stride) + 1)
yOutput = int(((yImgShape - yK + 2 * padding)/stride) + 1)
```



IV: Including convolution part with kernels



→ *in our code: numChans refers to incoming matrix, Kernnumber to output matrix*

→ go to the function **ConvSelfMade.py**

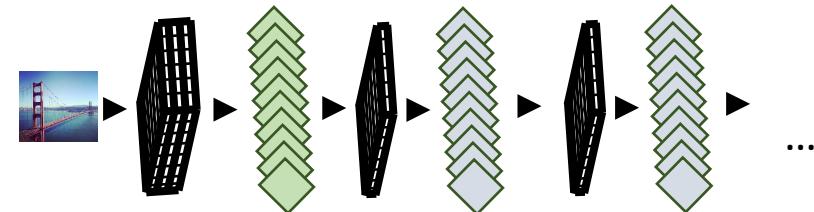
→ copy the convolution part, starting at

```
output = np.zeros( ...
    until
output[x,y,c] = np.sum(s)
```

→ paste it into the ANN



IV: Including convolution part with kernels



```
W = np.nan_to_num(self.weights)
```

```
output = np.zeros((xOutput,yOutput,numChans , NK, numImds))
```

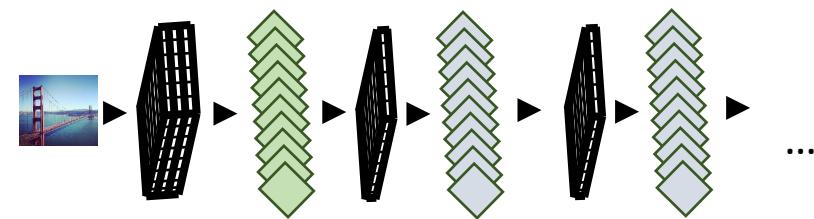
```
imagePadded = np.zeros(((xImgShape + padding*2).\  
 (yImgShape + padding*2),numChans , NK, numImds))
```

```
for k in range(NK):  
    imagePadded[int(padding):int(padding + xTmgShape), \  
    int(padding):int(padding + yImgShape),:,k,:,:] = M
```



IV: Including convolution part with kernels

...

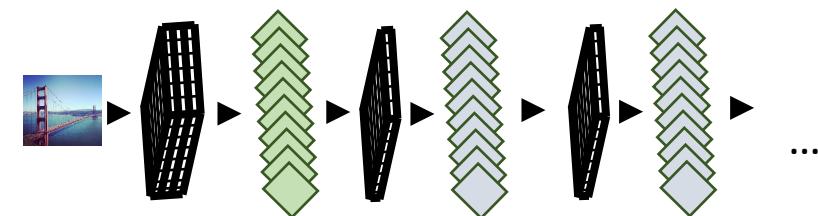


```
for i in range(numImds):# loop over number of images
    currentIm_pad = imagePadded[:, :, :, :, i]# select ith padded image
    for y in range(yOutput):# loop over vert axis of output
        for x in range(xOutput):# loop over hor axis of output
            for c in range(numChans):# loop over channels
                for k in range(NK): # loop over filter
                    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 = currentIm_pad[x_start:x_end,\n                                         y_start:y_end,c,k]
                    #the actual conv part
                    s             = np.multiply(current_slice, K)
                    output[x,y,c] = np.sum(s)
```



IV: Including convolution part with kernels

...



```
for i in range(numImds):# loop over number of images
    currentIm_pad = imagePadded[:,:,:,:,i]# select ith padded image
    for y in range(yOutput):# loop over vert axis of output
        for x in range(xOutput):# loop over hor axis of output
            for c in range(numChans):# loop over channels
                for k in range(NK): # loop over filter

                    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 = currentIm_pad[x_start:x_end,\n                                         y_start:y_end,c,k]

                    s             = np.multiply(current_slice, W[:, :, :, k])

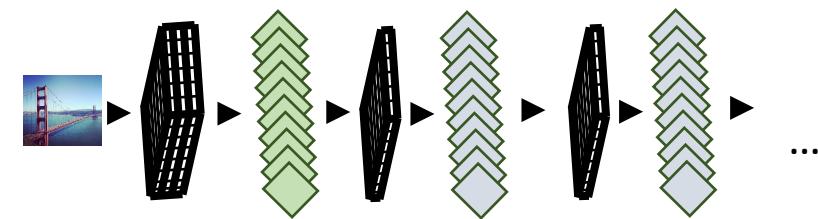
                    output[x, y, c, k, i] = np.sum(s) + b[0,k].astype(float)

#results are usually summed over channels...
output = output.sum(2)
```



IV: Including convolution part with kernels

...



```
for i in range(numImds):# loop over number of images
    currentIm_pad = imagePadded[:,:,:,:,i]# select ith padded image
    for y in range(yOutput):# loop over vert axis of output
        for x in range(xOutput):# loop over hor axis of output
            for c in range(numChans):# loop over channels
                for k in range(NK): # loop over filter

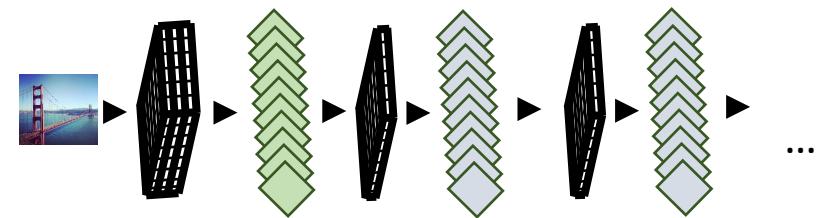
                    y_start = y*stride
                    y_end   = y*stride + yK
                    x_start = x*stride
                    x_end   = x*stride + xK

                    #selecting the current part of the image
                    current_slice      = currentIm_pad[x_start:x_end,\n                                         y_start:y_end,c,k]
                    s                  = np.multiply(current_slice, W[:, :, k])
                    output[x, y, c, k, i] = np.sum(s) + b[0,k].astype(float)

#results are usually summed over channels...
output = output.sum(2)
```



IV: Including convolution part with kernels



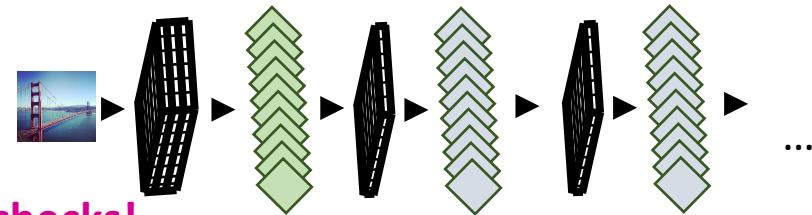
finally, we save the output
and M

```
self.output = np.nan_to_num(output)
self.input = M
self.impad = imagePadded
```

Let us run the code now and perform some sanity checks!



IV: Including convolution part with kernels



Let us run the code now and perform some sanity checks!

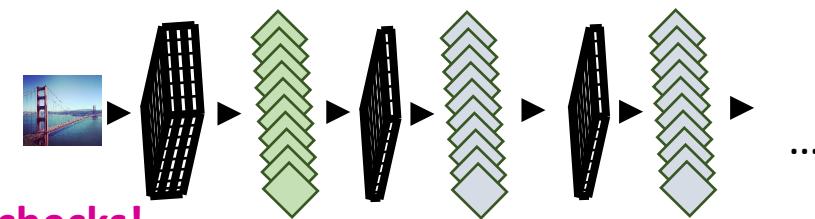
check the network structure →

```
WithKernelConv.py
├── Read_Scale_lmds
│   └── Read_Scale
├── Create_Kernels
│   └── kernel_library
├── ConvLayer
│   ├── __init__
│   └── forward
├── Layer_Dense
│   ├── __init__
│   ├── forward
│   └── backward
├── Activation_ReLU
│   ├── forward
│   └── backward
├── Activation_Softmax
│   ├── forward
│   └── backward
├── Loss
│   └── calculate
├── Loss_CategoricalCrossEntropy
│   ├── forward
│   └── backward
└── Activation_Softmax_Loss_CategoricalCrossEntropy
    ├── __init__
    ├── forward
    └── backward

```



IV: Including convolution part with kernels



Let us run the code now and perform some sanity checks!

```
from MyANN import *
import matplotlib.pyplot as plt

minibatch_size = 10
ANN_size        = [128,128]
```

calling 10 images randomly and
scaling them to part size (**here 128x128**)
= number of input neurons

→ returning batch of scaled images
and classes C

```
read_and_scale = Read_Scale_Imds(minibatch_size, ANN_size)
[M, C] = read_and_scale.Read_Scale()
```

```
Conv1 = My_ANN.ConvLayer()
Conv2 = My_ANN.ConvLayer()
Conv3 = My_ANN.ConvLayer()
```

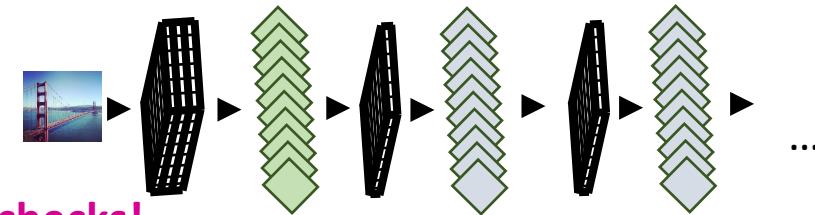
initializing convolution layers

```
Conv1.forward(M,2,1)
Conv2.forward(Conv1.output)
Conv3.forward(Conv2.output,0,3)
```

run convolution on all images



IV: Including convolution part with kernels



Let us run the code now and perform some sanity checks!

```
from MyANN import *
import matplotlib.pyplot as plt
minibatch_size = 10
ANN_size        = [128,128]

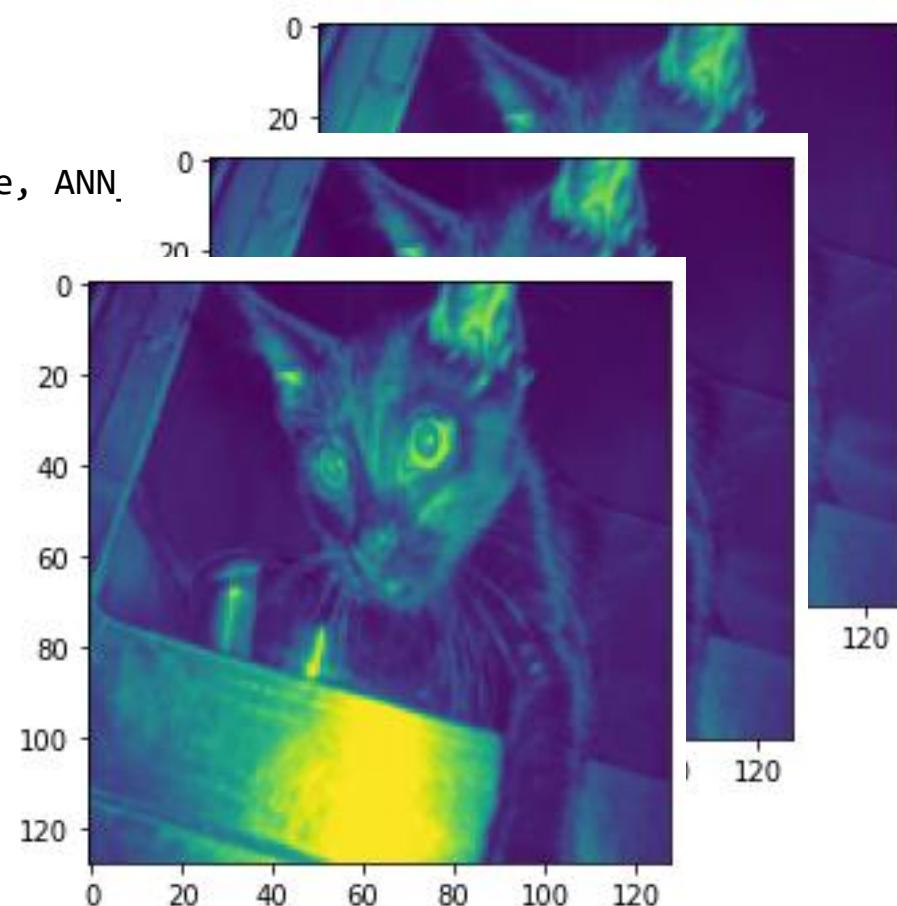
read_and_scale = Read_Scale_Imds(minibatch_size, ANN)
[M, C] = read_and_scale.Read_Scale()
```

```
Conv1 = My_Ann.ConvLayer()
Conv2 = My_Ann.ConvLayer()
Conv3 = My_Ann.ConvLayer()

Conv1.forward(M, 2, 1)
Conv2.forward(Conv1.output)
Conv3.forward(Conv2.out
```

original image (RGB)

```
plt.imshow(M[:, :, 0, 1])
plt.show()
plt.imshow(M[:, :, 1, 1])
plt.show()
plt.imshow(M[:, :, 2, 1])
plt.show()
```





IV: Including convolution part with kernels

```
from MyANN import *
import matplotlib.pyplot as plt

minibatch_size = 10
ANN_size        = [128, 128]

read_and_scale = Read_Scale_Imds(minibatch_size, ANN_size)
[M, C] = read_and_scale.Read_Scale()

Conv1 = My ANN.ConvLayer()
Conv2 = My ANN.ConvLayer()
Conv3 = My ANN.ConvLayer()

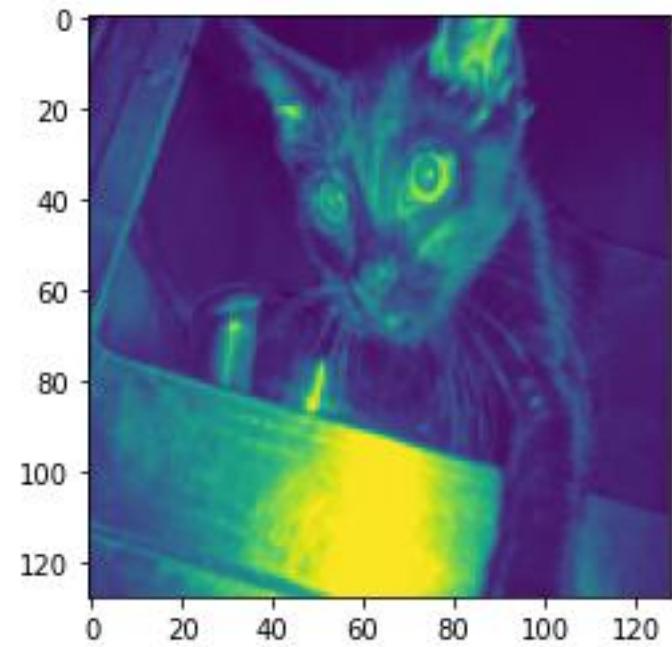
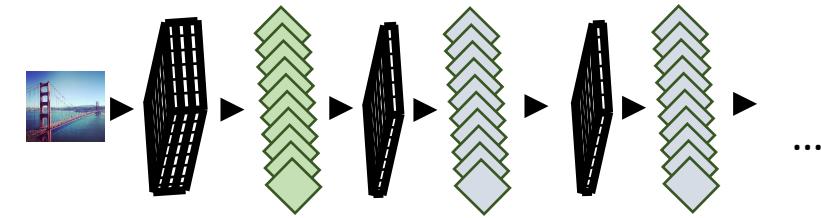
Conv1.forward(M, 2, 1)
Conv2.forward(Conv1.output)
Conv3.forward(Conv2.output, 0, 3)

plt.imshow(M[:, :, 0, 1])
plt.show()
plt.imshow(M[:, :, 1, 1])
plt.show()
plt.imshow(M[:, :, 2, 1])
plt.show()
```

In [1]: M.shape

Out[1]: (128, 128, 3, 10)

RGB



original image (RGB)



IV: Including convolution part with kernels

```
Conv1.forward(M[2,1])
```

```
Conv2.forward(Conv1.output)
```

```
Conv3.forward(Conv2.output, 0, 3)
```

```
plt.imshow(M[:, :, 0, 1])
```

```
plt.show()
```

```
plt.imshow(M[:, :, 1, 1])
```

```
plt.show()
```

```
plt.imshow(M[:, :, 2, 1])
```

```
plt.show()
```

```
In [1]: M.shape
```

```
Out[1]: (128, 128, 3, 10)
```

```
plt.imshow(Conv1.output[:, :, 1, 1])
```

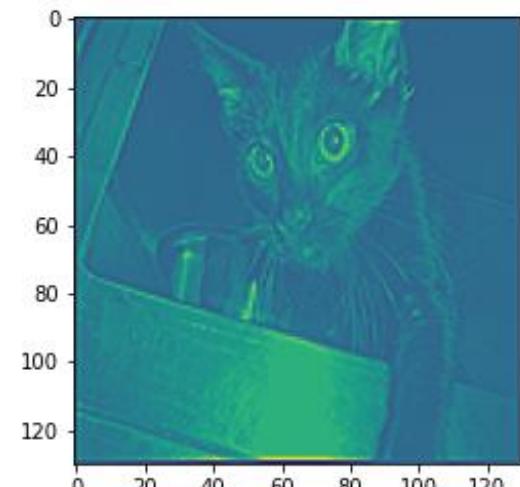
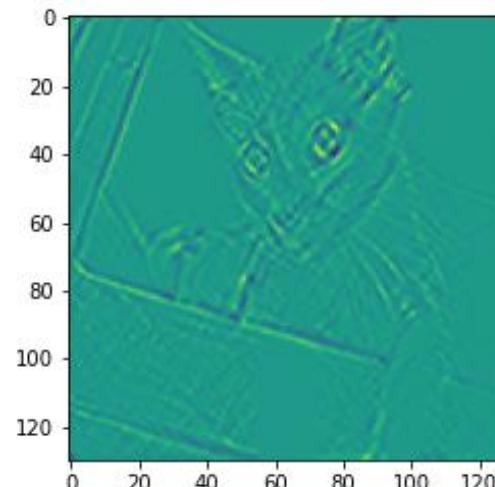
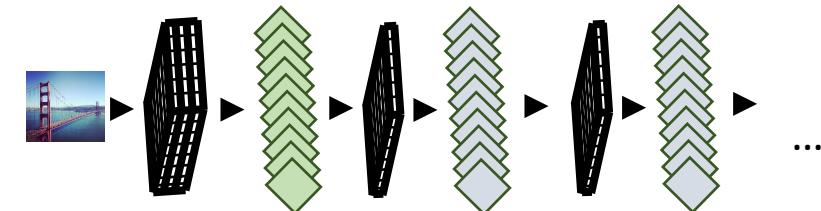
```
plt.show()
```

```
plt.imshow(Conv1.output[:, :, 4, 1])
```

```
plt.show()
```

```
In [2]: Conv1.output.shape
```

```
Out[2]: (130, 130, 13, 10)
```



after 1st convolution (filter 2 and 5)

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



IV: Including convolution part with kernels

```
Conv1.forward(M, 2, 1)
```

```
Conv2.forward(Conv1.output) padding = 0, stride = 1
```

```
Conv3.forward(Conv2.output, 0, 3)
```

```
plt.imshow(Conv1.output[:, :, 1, 1])
```

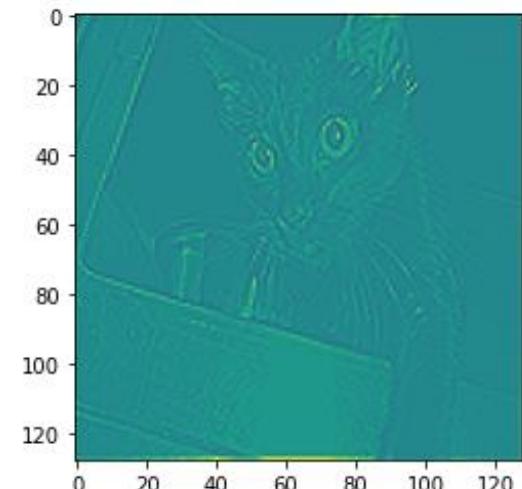
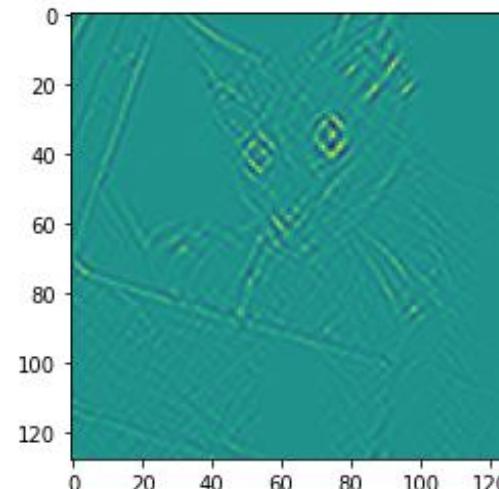
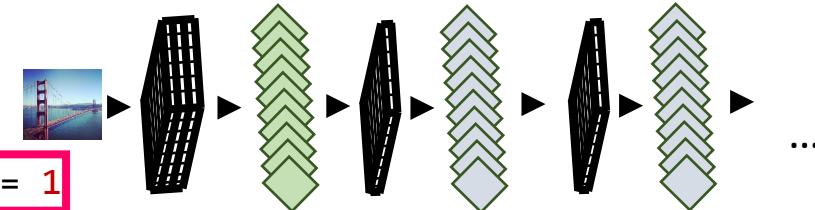
```
plt.show()
```

```
plt.imshow(Conv1.output[:, :, 4, 1])
```

```
plt.show()
```

In [2]: Conv1.output.shape

Out[2]: (130, 130, 13, 10)



after 2nd convolution (filter 2 and 5)

```
plt.imshow(Conv2.output[:, :, 1, 1])
```

```
plt.show()
```

```
plt.imshow(Conv2.output[:, :, 4, 1])
```

```
plt.show()
```

In [3]: Conv2.output.shape

Out[4]: (128, 128, 13, 10)

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



IV: Including convolution part with kernels

```
Conv1.forward(M, 2, 1)
```

```
Conv2.forward(Conv1.output)
```

```
Conv3.forward(Conv2.output, 0, 3)
```

```
plt.imshow(Conv2.output[:, :, 1, 1])
```

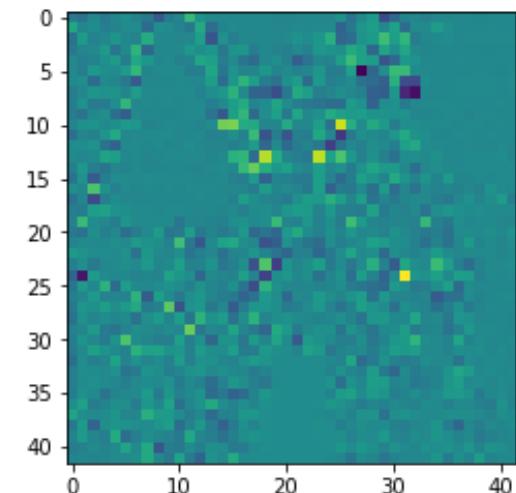
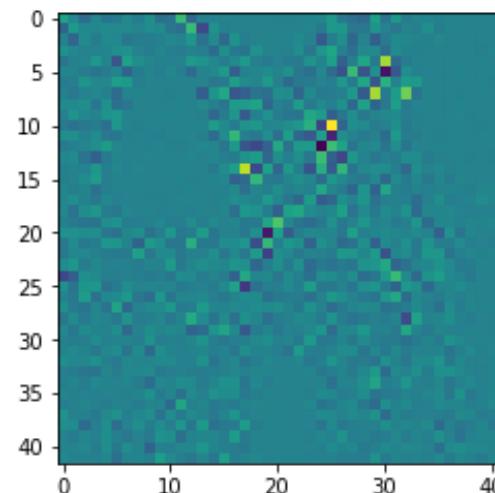
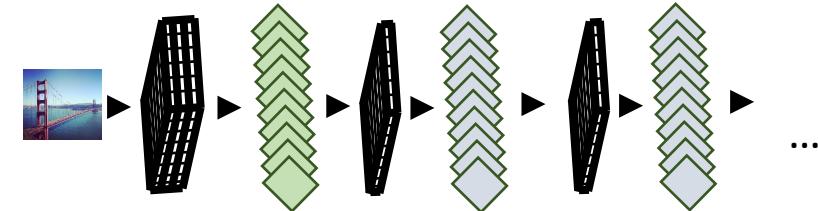
```
plt.show()
```

```
plt.imshow(Conv2.output[:, :, 4, 1])
```

```
plt.show()
```

In [3]: Conv2.output.shape

Out[4]: (128, 128, 13, 10)



after 3rd convolution (filter 2 and 5)

```
plt.imshow(Conv3.output[:, :, 1, 1])
```

```
plt.show()
```

```
plt.imshow(Conv3.output[:, :, 4, 1])
```

```
plt.show()
```

In [3]: Conv3.output.shape

Out[4]: (42, 42, 13, 10)

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

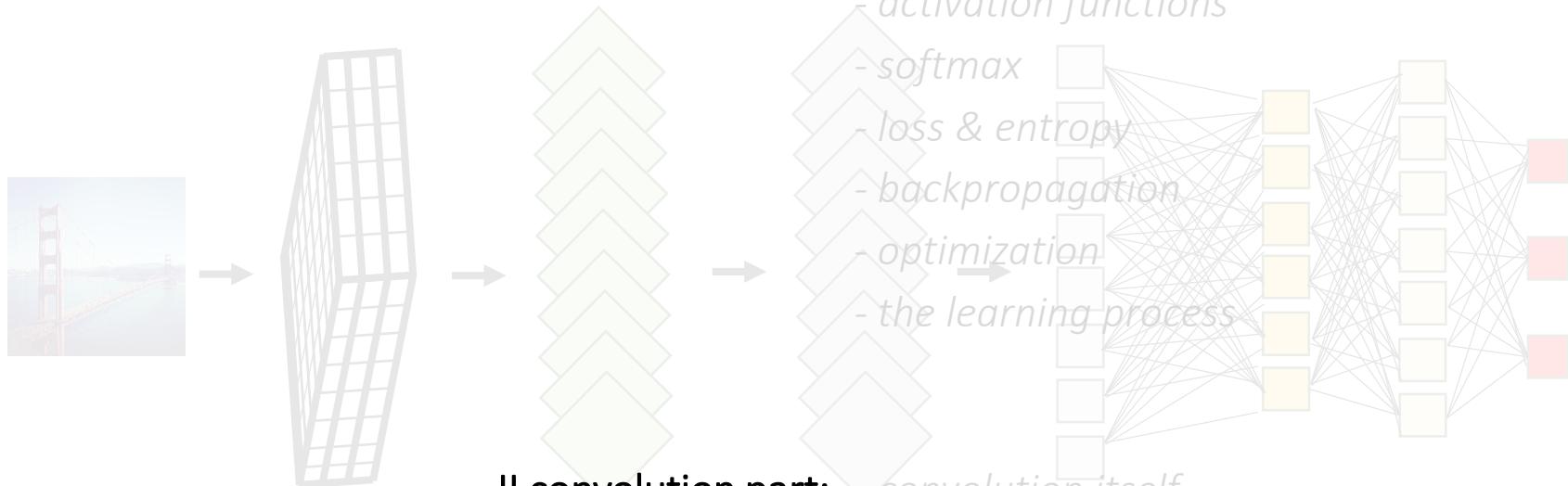


outline

0 intro

I the core:

- *a single neuron*
- *layers of neurons*
- *activation functions*
- *softmax*
- *loss & entropy*
- *backpropagation*
- *optimization*
- *the learning process*



II convolution part:

- *convolution itself*
- *pooling*
- *sigmoid*
- *flattening*
- *backpropagation - again*
- *testing the CNN & final remarks*



- often, a **pooling layer** is set after each convolution layer
(reduces variance and computation complexity)
- there are three different main pooling methods

→ **average pool:**

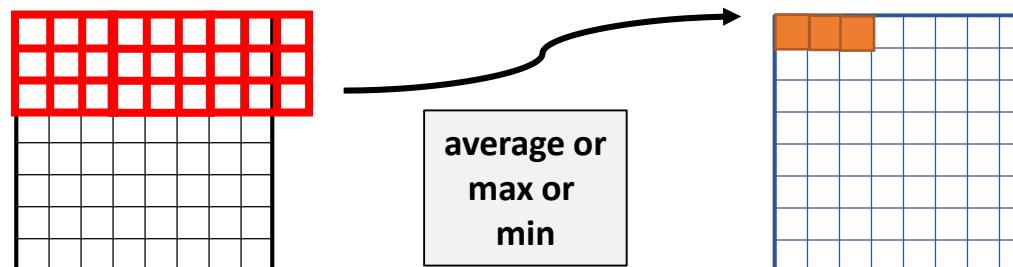
blurs the image, reduces edges
(not what we want here)

→ **max pool:**

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

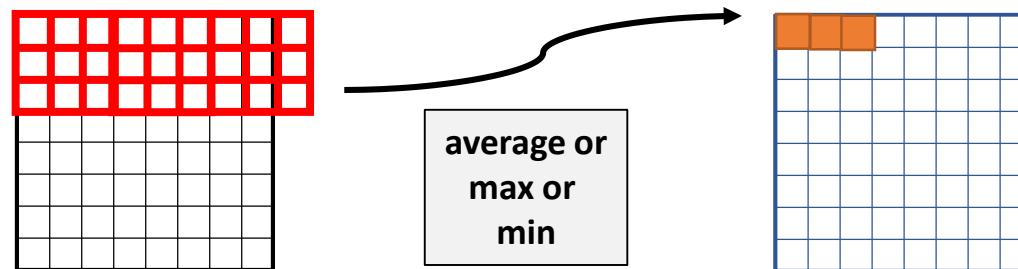
→ **min pool:**

does the opposite of max pool





- creating a max pool layer: essentially the same as a **convolution layer**
→ just take the max instead of multiplication



```
class Max_Pool:
```

padding doesn't make sense since
we want to get the max of a patch

```
def forward(self, M, stride = 1, KernShape = 2):
```

```
xImgShape      = M.shape[0]
yImgShape      = M.shape[1]
numChans       = M.shape[2] ←
numImds         = M.shape[3]
```

```
self.inputs = M
```

the max pool layer comes
after a convolution layer

→ numChans refers
to number of kernel



class Max_Pool:

```
def forward(self, M, stride = 1, KernShape = 2):  
  
    xImgShape    = M.shape[0]  
    yImgShape    = M.shape[1]  
    numChans     = M.shape[2]  
    numImds      = M.shape[3]  
    self.inputs = M
```

```
#maxpool usually over nxn matrix  
xK = KernShape  
yK = KernShape
```

we can copy the convolution part and paste it into the forward method

```
xOutput = int(((xImgShape - xK + ) / stride) + 1)  
yOutput = int(((yImgShape - yK + ) / stride) + 1)
```



class Max_Pool:

```
def forward(self, M, stride = 1, KernShape = 2):  
    ...  
  
    #maxpool usually over nxn matrix  
    xK = KernShape  
    yK = KernShape  
  
    xOutput = int(((xImgShape - xK) / stride) + 1)  
    yOutput = int(((yImgShape - yK) / stride) + 1)
```



```
class Max_Pool:
```

```
    def forward(self, M, stride = 1, KernShape = 2):
```

```
        ...
```

```
    imagePadded = M
```

we keep the name so that we don't need
to change anything in the subsequent loop

```
#output matrix after max pool
```

```
output = np.zeros((xOutput,yOutput,numChans,numImds))
```

creating mask for storing location of maximum → needed for backpropagation

```
imagePadded_copy = imagePadded.copy() *0
```



class Max_Pool:

```
def forward(self, M, stride = 1, KernShape = 2):
```

```
    ...
```

```
imagePadded = M
```

again, we can copy the convolution part and modify it slightly

```
output          = np.zeros((xOutput,yOutput,numChans,numImds))
imagePadded_copy = imagePadded.copy() *0
```

```
for i in range(numImds):# loop over number of images
    currentIm_pad = imagePadded[:, :, :, i]# select ith padded image
    for y in range(yOutput):# loop over vert axis of output
        for x in range(xOutput):# loop over hor axis of output
            for c in range(numChans):# loop over channels
```

```
                y_start = y*stride
                y_end   = y*stride + yK
                x_start = x*stride
                x_end   = x*stride + xK
```



class Max_Pool:

```
def forward(self, M, stride = 1, KernShape = 2):
```

```
    ...
```

```
    y_start = y*stride  
    y_end   = y*stride + yK  
    x_start = x*stride  
    x_end   = x*stride + xK
```

we are going to need the slicing vectors
a few more times and therefore
save them as new variable

```
sx      = slice(x_start,x_end)  
sy      = slice(y_start,y_end)
```

```
current_slice = currentIm_pad[sx,sy,c]
```

```
slice_max          = float(current_slice.max())  
output[x, y, c, i] = slice_max
```

actual max pool

```
imagePadded_copy[sx,sy,c,i] += np.equal(\  
    currentIm_pad[sx,sy,c], slice_max).astype(float)
```



class Max_Pool:

```
def forward(self, M, stride = 1, KernShape = 2):
```

```
    ...
```

```
slice_max          = float(current_slice.max())
output[x, y, c, i] = slice_max
```

```
imagePadded_copy[sx,sy,c,i] += np.equal(\n        currentIm_pad[sx,sy,c],slice_max).astype(float)
```

avoids deletion of ones if
stride < KernShape
→ has to be normalized to
ones and zeros afterwards

compares entries in a matrix to a value
→ returns matrix with ones (where
statement is true) and zeros otherwise



class Max_Pool:

```
def forward(self, M, stride = 1, KernShape = 2):
```

```
    ...
```

```
    slice_max      = float(current_slice.max())
    output[x, y, c, i] = slice_max
```

```
    imagePadded_copy[sx,sy,c,i] += np.equal(\n        currentIm_pad[sx,sy,c],slice_max).astype(float)
```

```
mask = imagePadded_copy
```

```
mask = np.matrix.round(mask/(mask + 1e-7))
```

has to be normalized to
ones and zeros afterwards

```
self.xKernShape = xK
self.yKernShape = yK
self.output     = output
self.mask       = mask
self.stride     = stride
```

saving some outputs
for backpropagation later
and sanity checks



testing the new layer:

```
WithKernelConvMaxpool.py
    Read_Scale_lmds
        Read_Scale
    Create_Kernels
        kernel_library
    ConvLayer
        __init__
        forward
    Max_Pool
        forward
    Layer_Dense
    Activation_ReLU
    Activation_Softmax
    Loss
    Loss_CategoricalCrossEntropy
    Activation_Softmax_Loss_CategoricalCrossentropy
    Optimizer_SGD
```



testing the new layer:

```
from MyANN import *
import matplotlib.pyplot as plt
```

loading the network,
reading the images

```
minibatch_size = 10
ANN_size       = [128,128]
```

```
read_and_scale = Read_Scale_Imds(minibatch_size, ANN_size)
[M, C] = read_and_scale.Read_Scale()
```

```
Conv1 = My_ANN.ConvLayer()
MP1  = My_ANN.Max_Pool()
```

initializing layers

```
Conv1.forward(M,2,1)
MP1.forward(Conv1.output,2,3)
```

running layers

```
MP1in  = MP1.inputs
MP1out = MP1.output
Mask   = MP1.mask
```

we want to compare the
original image (after
convolution) to the max
pooled image and the mask



testing the new layer:

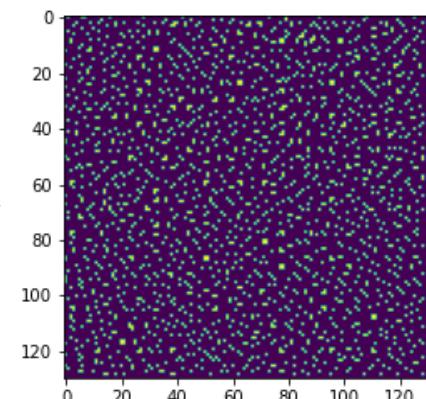
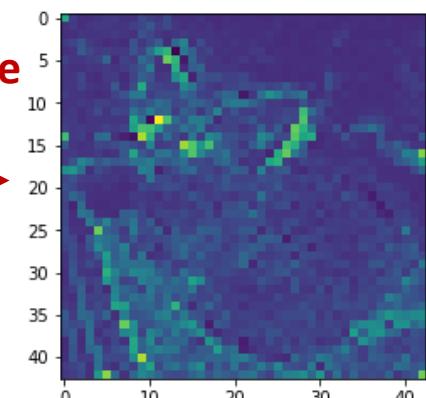
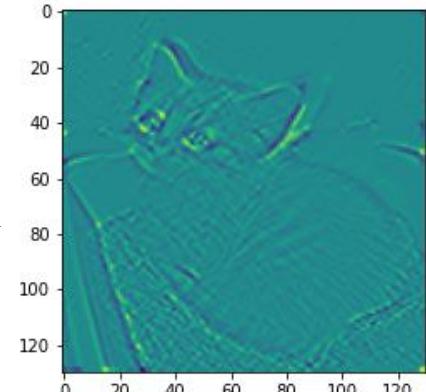
```
plt.imshow(MP1in[:, :, 1, 1])  
plt.show()  
plt.imshow(MP1out[:, :, 1, 1])  
plt.show()  
plt.imshow(Mask[:, :, 1, 1])  
plt.show()
```

```
I1 = MP1in[:, :, 1, 1]  
I2 = MP1out[:, :, 1, 1]  
I3 = Mask[:, :, 1, 1]
```

original image

max pool image

mask





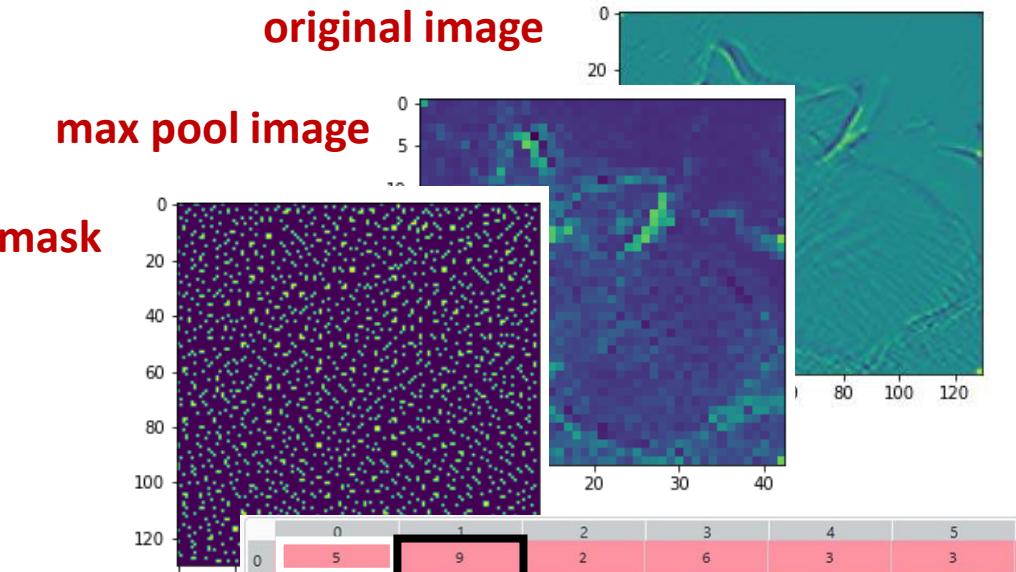
testing the new layer:

```
plt.imshow(MP1in[:, :, 1, 1])
plt.show()
plt.imshow(MP1out[:, :, 1, 1])
plt.show()
plt.imshow(Mask[:, :, 1, 1])
plt.show()
```

```
I1 = MP1in[:, :, 1, 1]
I2 = MP1out[:, :, 1, 1]
I3 = Mask[:, :, 1, 1]
```

I1 stride = 2

	0	1	2	3	4	5
0	5	0	-2	9	2	-6
1	2	0	1	9	2	-6
2	-4	1	5	-2	2	0
3	0	2	5	-3	-2	0
4	3	10	8	-8	-11	0
5	9	20	6	-17	-18	0
6	15	20	-2	-18	-17	-2
7	12	4	-17	-9	12	3
8	95	20	-82	-12	-14	-9



	0	1	2	3	4	5
0	5	9	2	6	3	3
1	10	8	2	3	54	54
2	20	8	12	12	133	133
3	95	12	12	12	123	123
4	191	1	-1	7	37	56
5	199	312	219	23	23	176
6	122	312	298	210	23	372
7	48	48	302	347	313	313
8	48	48	213	360	360	125

	0	1	2	3	4	5
0	1	0	0	1	1	0
1	0	0	0	1	1	0
2	0	0	1	0	1	0
3	0	0	0	0	0	0
4	0	1	1	0	0	0
5	0	1	0	0	0	0
6	0	1	0	0	0	0
7	0	0	0	0	1	0
8	1	0	0	0	0	0

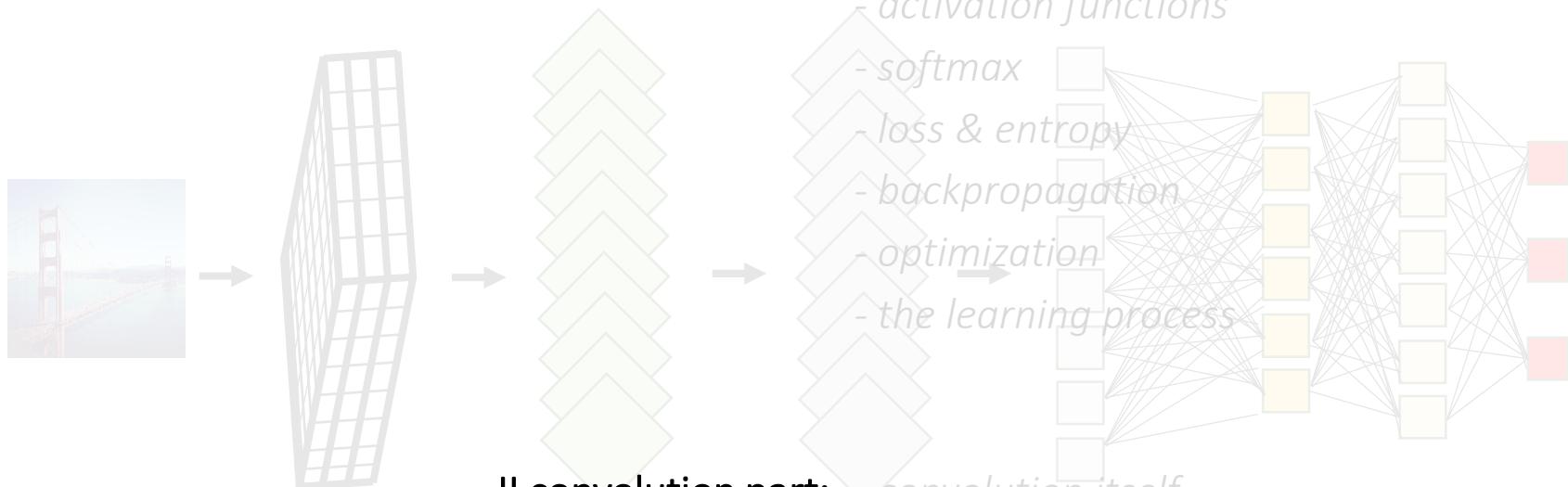


outline

0 intro

I the core:

- *a single neuron*
- *layers of neurons*
- *activation functions*
- *softmax*
- *loss & entropy*
- *backpropagation*
- *optimization*
- *the learning process*



II convolution part:

- *convolution itself*
- *pooling*
- ***sigmoid***
- *flattening*
- *backpropagation - again*
- *testing the CNN & final remarks*



CNNs have many convolution layers: → lots of multiplying/adding

subsequent max pool layers: → again, lots of increasing values

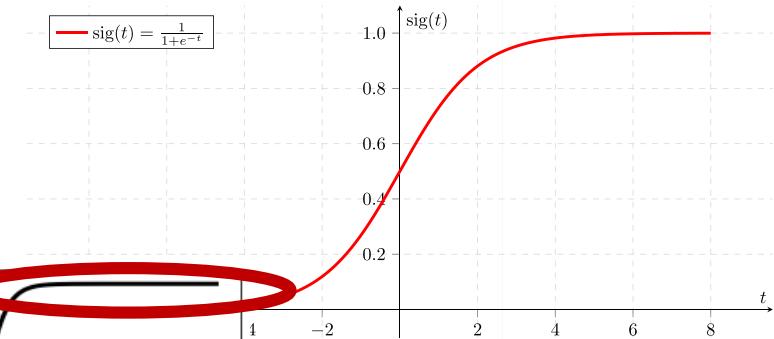
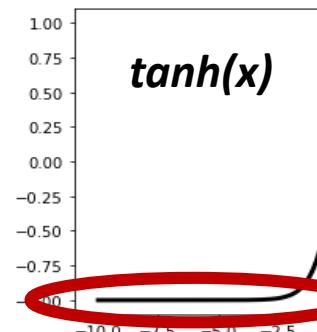
problem: values might increase and get out of control

solution: mapping small values to themselves, but large values to a limit

e.g.: $[-\infty; +\infty] \rightarrow [-1; +1]$ or $[0; +1]$

called “*compactification*”

- sigmoid
- atan
- tanh

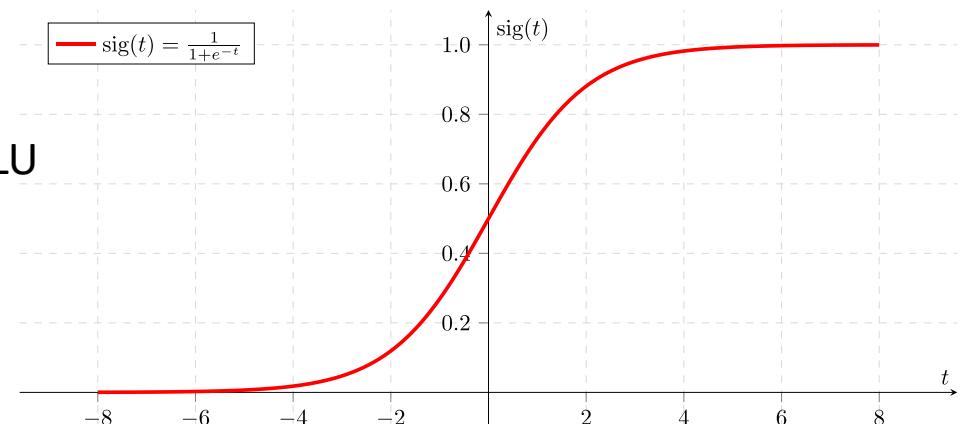


moreover, ReLUs tend to overfitting because of their fast convergence



But sigmoids have disadvantages too:

- 2x more computational time than a ReLU
- saturate easily, so that derivatives are zero → bad for backpropagation



At the end...depends on the ANN and a bit of **trial and error**

```
class Sigmoid:
```

```
    def forward(self, M):
```

```
        sigm      = np.clip(1/(1 + np.exp(-M)), 1e-7, 1 - 1e-7)
        self.output = sigm
        self.inputs = M
```

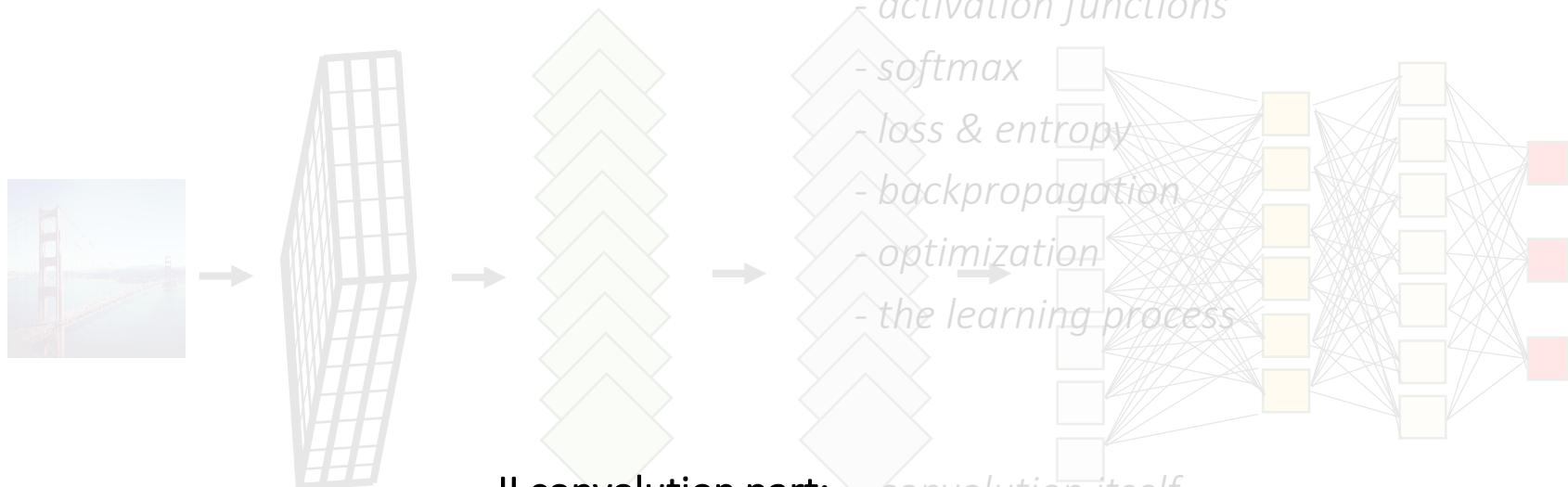


outline

0 intro

I the core:

- *a single neuron*
- *layers of neurons*
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- *softmax*
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- *backpropagation*
- *optimization*
- *the learning process*



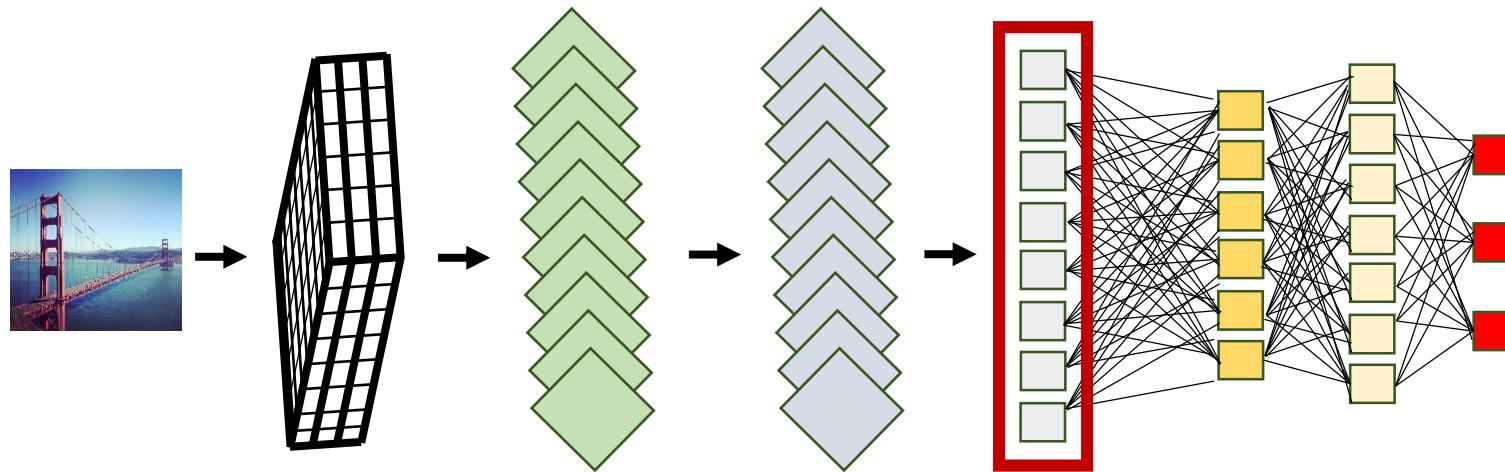
II convolution part:

- *convolution itself*
- *pooling*
- *sigmoid*
- flattening**
- *backpropagation - again*
- *testing the CNN & final remarks*



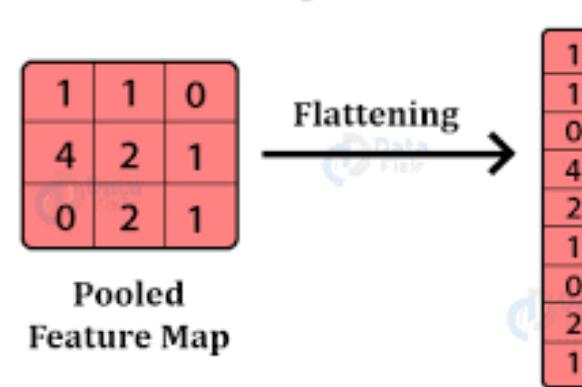
We are almost done with our CNN

→ linking the CNN part to the dense layer



Flatten Layer in Keras

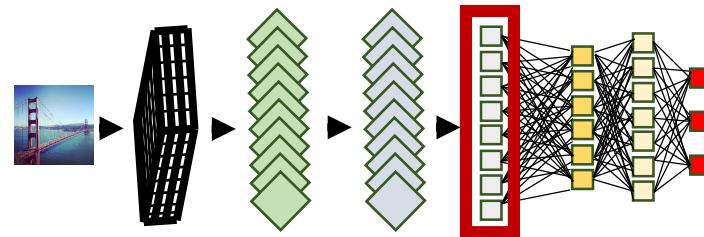
called **flattening**





We are almost done with our CNN

→ linking the CNN part to the dense layer



```
class Flat:
```

```
    def forward(self, M):
```

```
        self.inputs = M
```

```
        xImgShape = M.shape[0]
```

```
        yImgShape = M.shape[1]
```

```
        numChans = M.shape[2]
```

```
        numImds = M.shape[3]
```

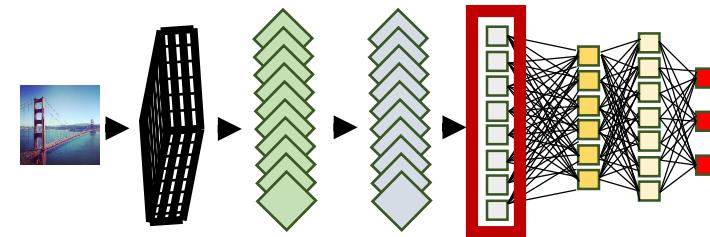
```
#turning each image into a vector of length L
```

```
L = xImgShape*yImgShape*numChans
```



We are almost done with our CNN

→ linking the CNN part to the dense layer



```
class Flat:
```

```
    def forward(self, M):
        self.inputs = M

        xImgShape  = M.shape[0]
        yImgShape  = M.shape[1]
        numChans   = M.shape[2]
        numImds    = M.shape[3]

        #turning each image into a vector of length L
        L = xImgShape*yImgShape*numChans

        output = np.zeros((numImds,L))

        for i in range(numImds):
            output[i,:] = M[:,:,:,:,i].reshape((1,L))

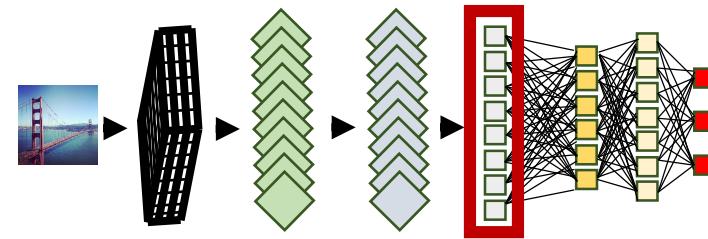
        self.output = output
```

making sure that every
image gets flattened
separately
→ using a (slow) **for** loop



We are almost done with our CNN

→ saving and checking the CNN



WithKernelConvMaxpoolSigmFlat.py

- > C Read_Scale_Imds
- > C Create_Kernels
- > C ConvLayer
- > C Max_Pool
- > C Sigmoid
- > C Flat

└ m forward

- > C Layer_Dense
- > C Activation_ReLU
- > C Activation_Softmax
- > C Loss
- > C Loss_CategoricalCrossEntropy
- > C Activation_Softmax_Loss_CategoricalCrossentropy
- > C Optimizer_SGD

our network is complete now

→ we still have to teach it
how to learn

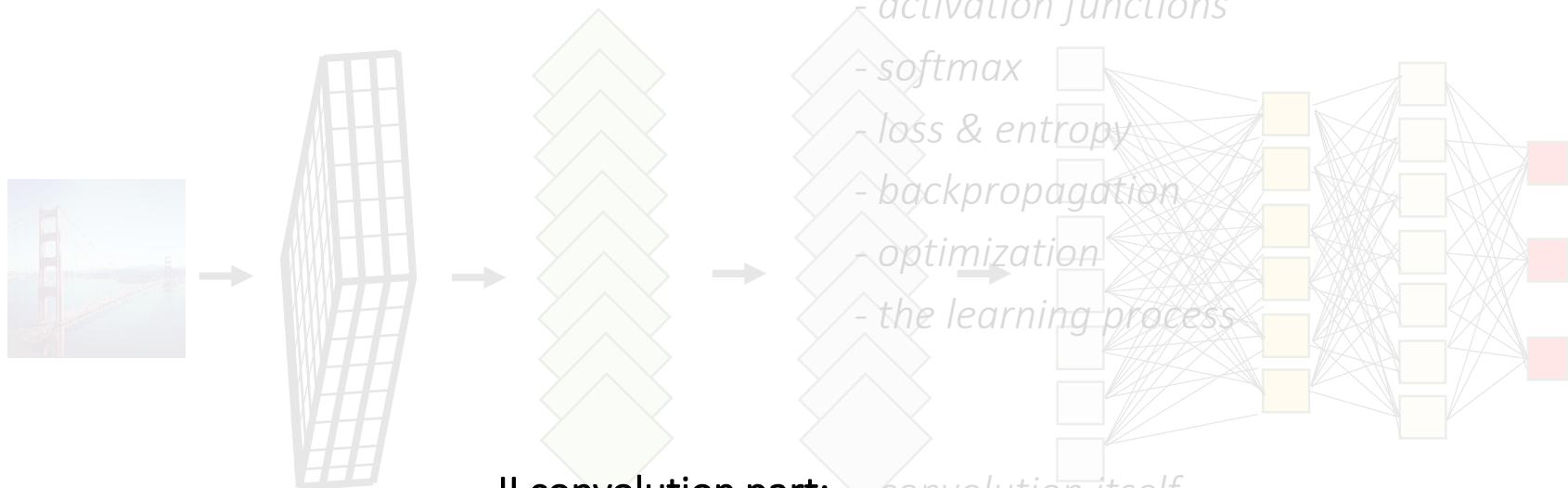


outline

0 intro

I the core:

- *a single neuron*
- *layers of neurons*
- *activation functions*
- *softmax*
- *loss & entropy*
- *backpropagation*
- *optimization*
- *the learning process*



II convolution part:

- *convolution itself*
- *pooling*
- *sigmoid*
- *flattening*
- *backpropagation - again***
- *testing the CNN & final remarks*



We have created all parts needed for a CNN

- next step: implement the entire backpropagation
- starting with the simplest layer first: **flattening**

the **flattening** layer only rearranges the data

- no derivatives are needed
- turning a vector from the dense layer into the matrix **M** again

```
class Flat:
```

```
    def forward(self, M):  
        ...
```

```
    def backward(self, dvalues):
```

recall: **dvalues** are the derivatives returned from the next lower layer



the **flattening** layer only rearranges the data

- no derivatives are needed
- turning a vector from the dense layer into the matrix **M** again

class Flat:

```
def forward(self, M):  
    ...
```

```
def backward(self, dvalues):
```

recall: **dvalues** are the derivatives returned from the next lower layer

```
[xImgShape, yImgShape, numChans, numImds] = \  
    np.shape(self.inputs)
```

```
dinputs = np.zeros((xImgShape, yImgShape, \  
    numChans, numImds))
```

```
for i in range(numImds):
```

```
dinputs[:, :, :, i] = \  
dvalues[i, :].reshape((xImgShape, yImgShape, \  
    numChans))
```

turning each vector **dvalues** back into an image



the **flattening** layer only rearranges the data

→ no derivatives are needed

→ turning a vector from the dense layer
into the matrix **M** again

```
class Flat:
```

```
    def forward(self, M):
```

```
        ...
```

```
    def backward(self, dvalues):
```

```
        [xImgShape, yImgShape, numChans, numImds] = \  
            np.shape(self.inputs)
```

```
        dinputs = np.zeros((xImgShape, yImgShape, \  
                            numChans, numImds))
```

```
        for i in range(numImds):  
            dinputs[:, :, :, i] = \  
                dvalues[i, :].reshape((xImgShape, yImgShape, \  
                                      numChans))
```

```
        self.dinputs = dinputs
```



checking, if the backward part is recovering the image:

```
from MyANN import *
import matplotlib.pyplot as plt
```

same as before

```
minibatch_size = 4
ANN_size       = [128,128]
```

```
read_and_scale = Read_Scale_Imds(minibatch_size, ANN_size)
[M, C] = read_and_scale.Read_Scale()
#initializing three convolution layer
Conv1 = ConvLayer()
MP1   = Max_Pool()
F     = Flat()
```

```
Conv1.forward(M,2,1)
MP1.forward(Conv1.output,5,5)
F.forward(MP1.output)
```

running the
layers



checking, if the backward part is recovering the image:

```
from MyANN import *
import matplotlib.pyplot as plt
```

same as before

```
minibatch_size = 4
```

```
ANN_size = [128, 128]
```

```
read_and_scale = Read_Scale_Imds(minibatch_size, ANN_size)
[M, C] = read_and_scale.Read_Scale()
```

```
#initializing layer
```

```
Conv1 = My ANN.ConvLayer()
```

```
MP1 = My ANN.Max_Pool()
```

```
F = My ANN.Flat()
```

```
Conv1.forward(M, 2, 1)
```

```
MP1.forward(Conv1.output, 5, 5)
```

```
F.forward(MP1.output)
```

running the
layers

```
F.backward(F.output)
```

```
MP1out = MP1.output
```

```
Test = F.dinputs
```

checking if **F.backward**
maintains the structure of M,
if returned as vector from
the dense layer



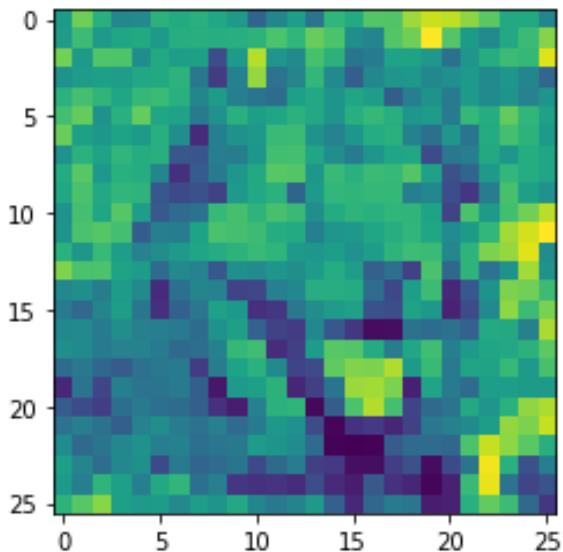
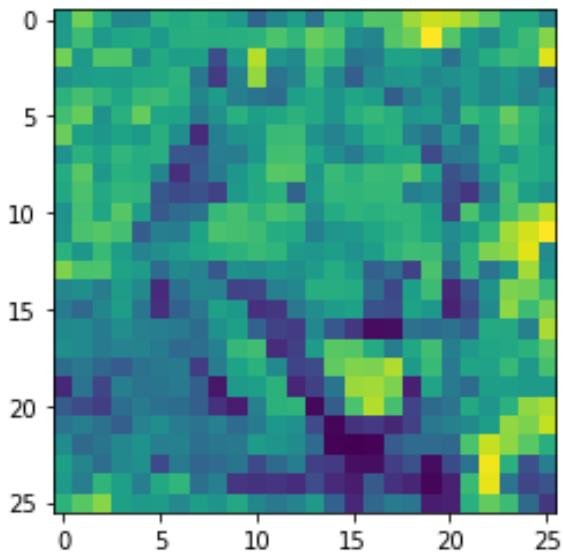
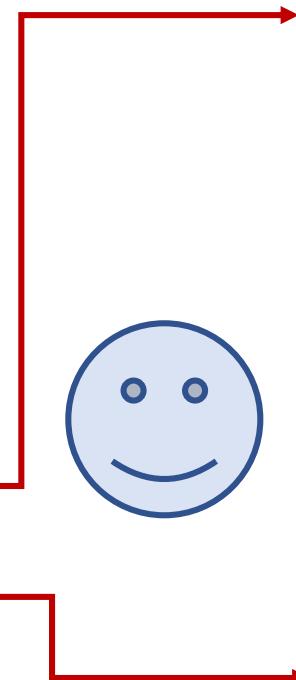
checking, if the backward part is recovering the image:

```
Conv1.forward(M, 2, 1)  
MP1.forward(Conv1.output, 5, 5)  
F.forward(MP1.output)
```

```
F.backward(F.output)
```

```
MP1out = MP1.output  
Test    = F.dinputs
```

```
plt.imshow(Test[:, :, 1, 0])  
plt.show()  
plt.imshow(MP1out[:, :, 1, 0])
```





We have created all parts needed for a CNN

- next step: implement the entire backpropagation
- continuing with the next layer: **sigmoid**

recall: we need to multiply the inner derivative with **dvalues**

inner derivative:

$$\begin{aligned}\frac{d}{dx} \sigma(x) &= \frac{d}{dx} \frac{1}{1+e^{-x}} = \frac{1}{(1+e^{-x})^2} e^{-x} \\&= \frac{1}{1+e^{-x}} \left(\frac{e^{-x}}{1+e^{-x}} \right) \\&= \frac{1}{1+e^{-x}} \left[\frac{e^{-x} + 1 - 1}{1+e^{-x}} \right] \\&= \frac{1}{1+e^{-x}} \left(\frac{e^{-x} + 1}{1+e^{-x}} - \frac{1}{1+e^{-x}} \right) \\&= \sigma(x) \left(\frac{e^{-x} + 1}{1+e^{-x}} - \sigma(x) \right) = \boxed{\sigma(x)(1 - \sigma(x))}\end{aligned}$$



inner derivative:

$$\frac{d}{dx} \sigma(x) = \sigma(x)(1 - \sigma(x))$$

```
class Sigmoid:
```

```
    ...
```

```
def backward(self, dvalues):
```

```
    sigm = self.output
```

```
    deriv = np.multiply(sigm, (1 - sigm))
```

```
    self.dinputs = np.multiply(deriv, dvalues)
```

recall: **dvalues** are the derivatives returned from the next lower layer



inner derivative:

$$\frac{d}{dx} \tanh(x) = 1 - \tanh(x)^2$$

```
class Tanh:
```

```
    def forward(self, M):
```

```
        tanh      = np.tanh(M)
        self.output = tanh
        self.inputs = M
```

```
    def backward(self, dvalues):
```

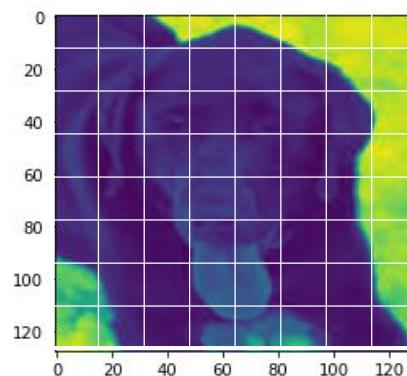
```
        deriv      = 1 - self.output**2
        deriv      = np.nan_to_num(deriv)
        self.dinputs = np.multiply(deriv, dvalues)
```



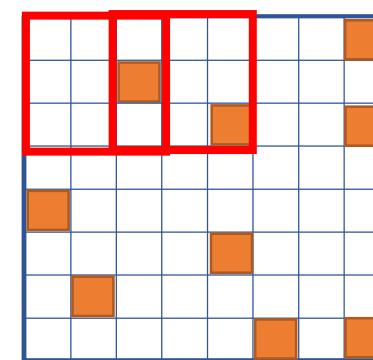
We have created all parts needed for a CNN

- next step: implement the entire backpropagation
- continuing with the next layer: **max pool**

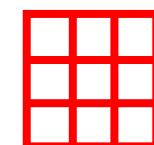
again, no derivatives, only need to multiply the **mask** with **dvalues**



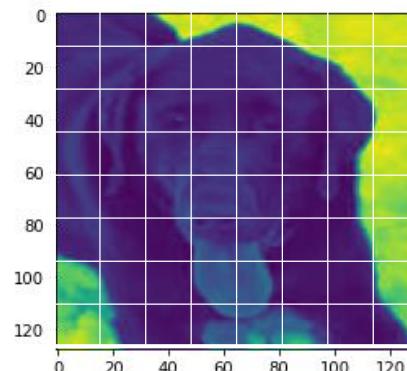
image



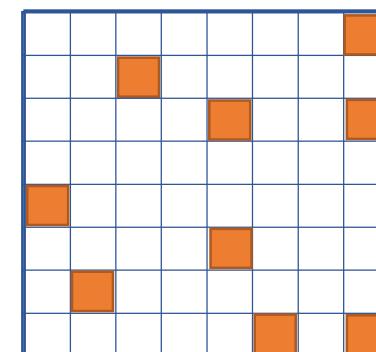
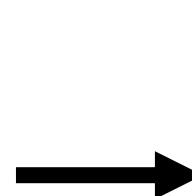
mask



max

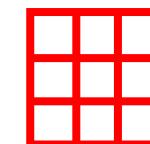


image

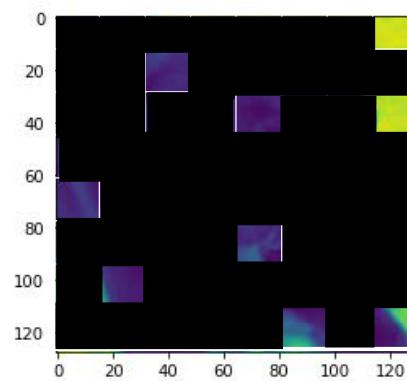


mask

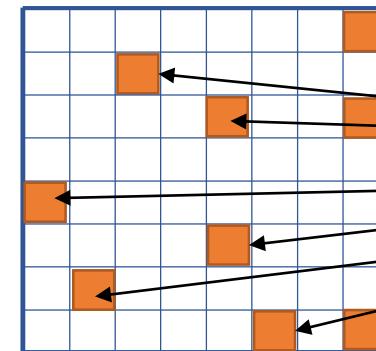
max pool



max

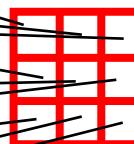


dinputs



mask

?



dvalues



Let us first go back to the **forward** part:

...

number of
maxima in
slice

number of slices/ windows

```
StoreMax = np.zeros((xK*yK, 2, xOutput*yOutput, numChan, numImds))
```

```
StoreNMax = np.zeros((xOutput*yOutput, numChan, numImds))
```

```
imagePadded_copy = imagePadded.copy() * 0  
  
for i in range(numImds):  
    currentIm_pad = imagePadded[:, :, :, i]  
    for c in range(numChan):
```

We need to know
how many maxima
are there in each
slice

We are going to need
the **location** of a pixel
if it was a maximum
(see later)



Let us first go back to the **forward** part:

```
imagePadded_copy = imagePadded.copy() * 0  
  
for i in range(numImds):  
    currentIm_pad = imagePadded[:, :, :, i]  
    for c in range(numChan):  
  
        ct = 0  
  
        for y in range(yOutput):  
            for x in range(xOutput):  
  
                ct += 1  
  
                y_start = y*stride  
                y_end    = y_start + yK  
                ...
```

We need to know
when (which slice) a
pixel value was a
maximum



Let us first go back to the **forward** part:

```
...  
current_slice      = currentIm_pad[sx,sy,c]  
slice_max          = float(current_slice.max())  
output[x, y, c, i] = slice_max
```

returns a tuple with indices of
up to $xK \cdot yK$ maxima

```
(xsm, ysm) = np.where(current_slice == slice_max)
```

storing indices of all
maxima

```
for ii, (xx, yy) in enumerate(zip(xsm, ysm)):  
    StoreMax[ii, 0, ct-1, c, i] = int(xx)  
    StoreMax[ii, 1, ct-1, c, i] = int(yy)
```

```
StoreNMax[ct-1, c, i]
```

```
= ii + 1
```

counting maxima per
slice/window

```
imagePadded_copy[sx, sy, c, i] += np.equal(\n        currentIm_pad[sx,sy,c], slice_max).astype(float)
```



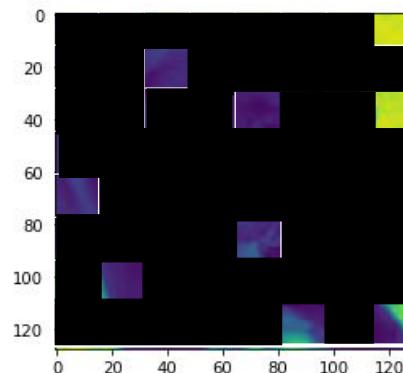
Let us first go back to the **forward** part:

outside the loops:

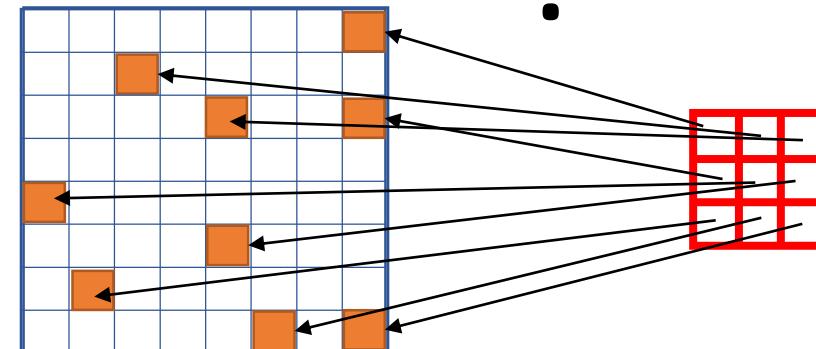
`mask` = `imagePadded_copy`

`self.xKernShape` = `xK`
`self.yKernShape` = `yK`
`self.output` = `output`
`self.mask` = `mask`
`self.stride` = `stride`

`self.StoreMax` = `StoreMax`
`self.StoreNMax` = `StoreNMax`



dinputs



mask

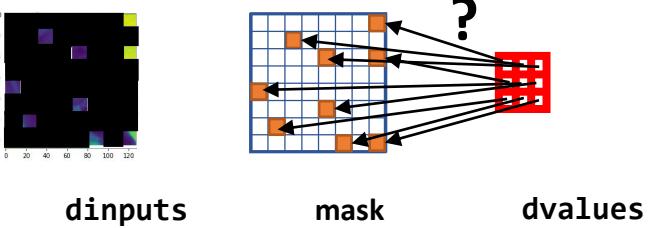
dvalues

We have the connection between **mask** coordinates and **dvalues** already from the **forward** part → **backward** part will be similar!

```
def backward(self, dvalues):  
    [xd, yd, numChan, numImds] = dvalues.shape  
  
    StoreMax  = self.StoreMax  
    StoreNMax = self.StoreNMax  
    stride     = self.stride  
  
    dinputs   = np.zeros(self.inputs.shape)
```



```
def backward(self, dvalues):  
  
    [xd, yd, numChan, numImds] = dvalues.shape  
  
    StoreMax = self.StoreMax  
    StoreNMax = self.StoreNMax  
    stride = self.stride  
  
    dinputs = np.zeros(self.inputs.shape)  
  
    for i in range(numImds):  
        for c in range(numChan):  
            ct = 0  
            for y in range(yd):  
                for x in range(xd):  
                    ct += 1  
  
                    y_start = y*stride  
                    x_start = x*stride
```



just copy/paste from **forward part**



```
def backward(self, dvalues):
```

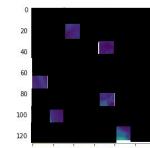
...

```
y_start = y*stride  
x_start = x*stride
```

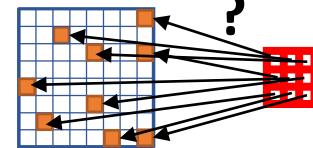
```
Nmax = int(StoreNMax[ct-1,c,i])
```

```
for ii in range(Nmax):  
    xm = int(StoreMax[ii,0,ct-1,c,i])  
    ym = int(StoreMax[ii,1,ct-1,c,i])
```

```
dinputs[x_start + xm, y_start + ym,c,i] = dvalues[x,y,c,i]
```



dinputs



mask

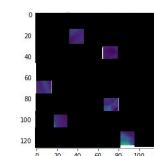
dvalues

outside the loops:

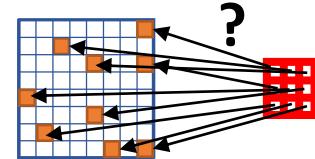
```
self.dinputs = dinputs
```



```
def backward(self, dvalues):  
  
    [xd, yd, numChan, numImds] = dvalues.shape  
  
    StoreMax = self.StoreMax  
    StoreNMax = self.StoreNMax  
    stride = self.stride  
  
    dinputs = np.zeros(self.inputs.shape)  
  
    for i in range(numImds):  
        for c in range(numChan):  
            ct = 0  
            for y in range(yd):  
                for x in range(xd):  
                    ct += 1  
  
                    Nmax = int(StoreNMax[ct-1,c,i])  
  
                    y_start = y*stride  
                    x_start = x*stride  
  
                    for ii in range(Nmax):  
                        xm = int(StoreMax[ii,0,ct-1,c,i])  
                        ym = int(StoreMax[ii,1,ct-1,c,i])  
  
                        dinputs[x_start + xm, y_start + ym, c, i] =\n                                         dvalues[x,y,c,i]  
  
    self.dinputs = dinputs
```



dinputs



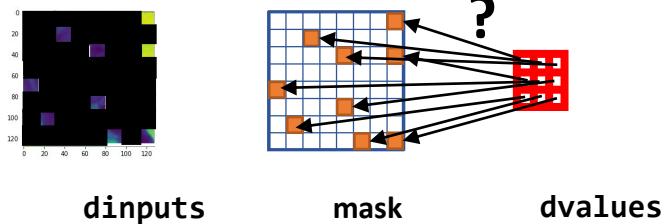
mask

dvalues

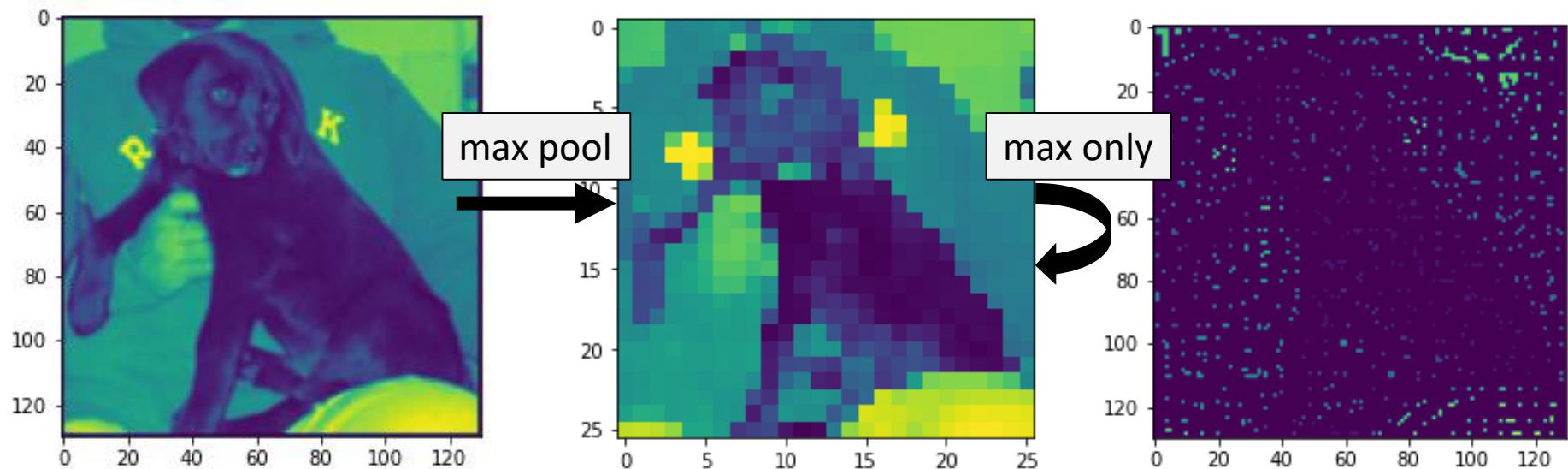


again: let's test the code!

note: we want to check if the **backward** part of the max pool layer assigns the **dvalues** correctly to the image coordinates

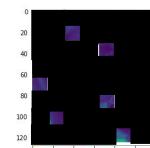


idea: We don't have actual **dvalues** yet → feeding the output of the max pool layer to its **backward** part
→ should return maxima of the input image (easy to check)

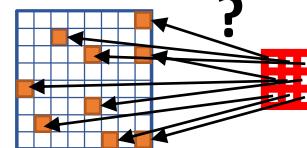




again: let's test the code!



dinputs



mask

dvalues

same as before

```
from MyANN import *
import matplotlib.pyplot as plt

minibatch_size = 4
ANN_size        = [128,128]

read_and_scale = Read_Scale_Imds(minibatch_size, ANN_size)
[M, C] = read_and_scale.Read_Scale()

#initializing layer
Conv1 = My_ANN.ConvLayer()
MP1   = My_ANN.Max_Pool()
```



again: let's test the code!

```
from MyANN import *
import matplotlib.pyplot as plt
```

```
minibatch_size = 4
```

```
ANN_size        = [128, 128]
```

```
read_and_scale = Read_Scale_Imds(minibatch_size, ANN_size)
[M, C] = read_and_scale.Read_Scale()
```

```
#initializing layer
```

```
Conv1 = My_ANN.ConvLayer()
MP1  = My_ANN.Max_Pool()
```

```
Conv1.forward(M, 2, 1)
```

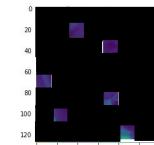
```
MP1.forward(Conv1.output, 3, 5)
```

```
MP1.backward(MP1.output)
```

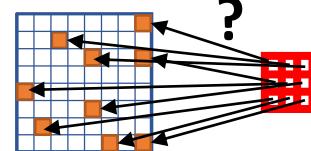
```
MP1in  = Conv1.output
```

```
MP1out = MP1.output
```

```
D      = MP1.dinputs
```



dinputs



mask

dvalues

take **stride** ≠ **KernShape**
in order to check
for a general case

feeding output to
backward part



again: let's test the code!

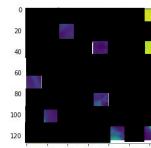
```
Conv1.forward(M, 2, 1)  
MP1.forward(Conv1.output, 3, 5)  
MP1.backward(MP1.output)
```

```
MP1in = Conv1.output  
MP1out = MP1.output  
D = MP1.dinputs
```

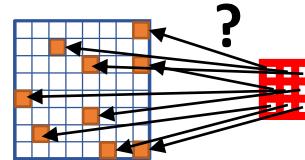
```
I1 = MP1in[:, :, 0, 0]  
I2 = MP1out[:, :, 0, 0]  
I3 = D[:, :, 0, 0]
```

```
plt.imshow(I1)  
plt.show()  
plt.imshow(I2)  
plt.show()  
plt.imshow(I3)
```

picking a random image



dinputs

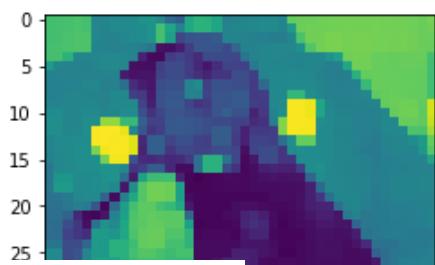


mask

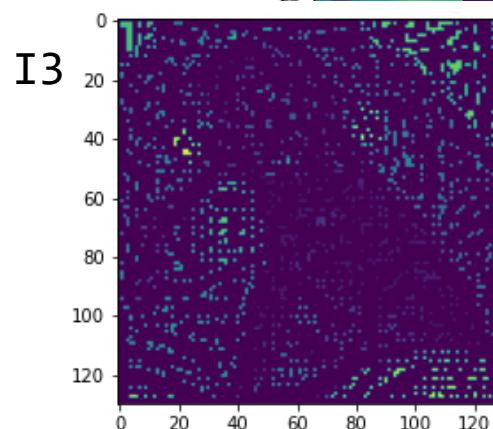
dvalues



I1



I2



I3





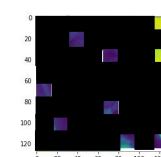
again: let's test the code!

```
I1 = MP1in[:, :, 0, 0]
I2 = MP1out[:, :, 0, 0]
I3 = D[:, :, 0, 0]
```

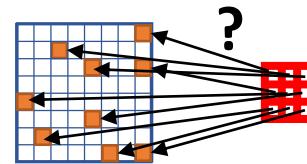
```
plt.imshow(I1)
plt.show()
plt.imshow(I2)
plt.show()
plt.imshow(I3)
```

I1 stride = 3; xK = yK = 5

	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	538	538	538	538	541	541
2	0	538	538	538	538	541	541
3	0	535	535	538	538	541	541
4	0	535	535	538	538	541	541
5	0	535	535	538	538	538	538
6	0	535	535	538	538	538	538
7	0	535	535	538	538	541	541
8	0	535	535	538	538	541	541
9	0	535	535	538	538	538	544



dinputs



mask



dvalues

I2

	0	1	2	3	4	5	6
0	538	544	545	551	543	357	364
1	538	544	547	550	544	369	361
2	538	544	548	554	554	369	361
3	544	547	548	554	554	361	358
4	544	544	499	364	362	368	375
5	424	363	355	355	350	363	375
6	352	354	358	358	356	356	357
7	352	353	354	359	368	368	350
8	353	353	362	362	360	359	356
9	357	356	367	367	366	365	356

I3

	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	538	538	538	538	0	0
2	0	538	538	538	538	0	0
3	0	0	0	0	538	538	0
4	0	0	0	0	538	538	0
5	0	0	0	538	538	0	0
6	0	0	0	538	538	0	0
7	0	0	0	538	538	0	0
8	0	0	0	538	538	0	0
9	0	0	0	538	538	0	544

and so on...

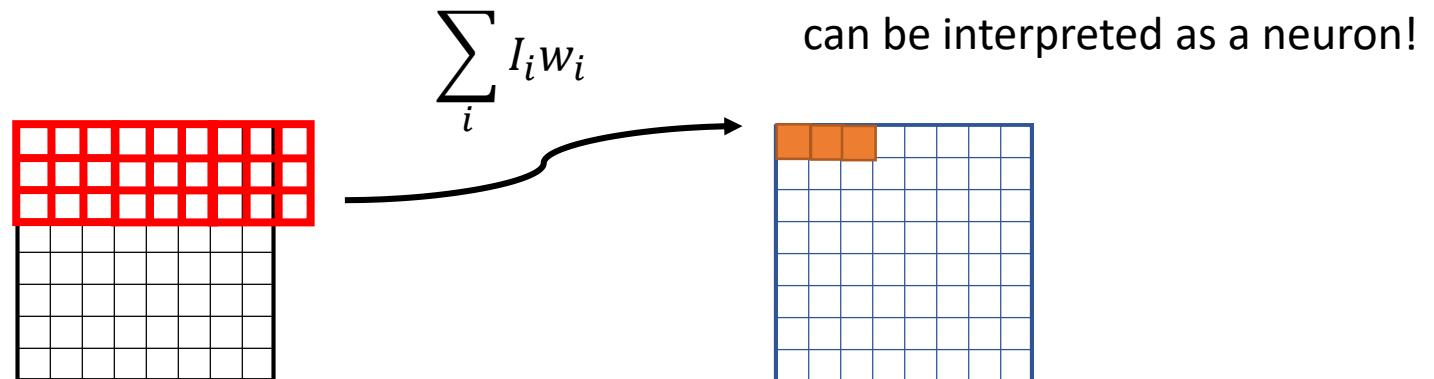


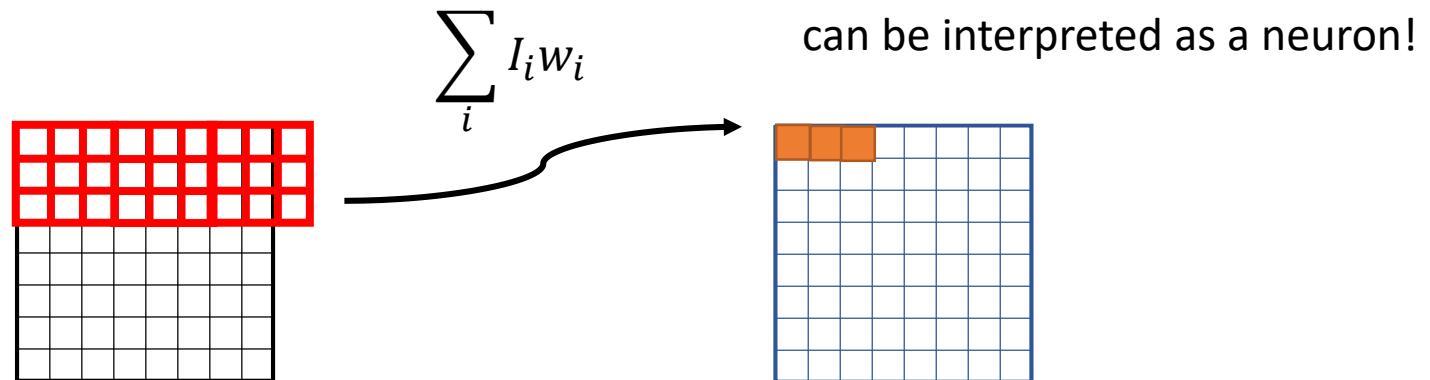
We have created all parts needed for a CNN

- next step: implement the entire backpropagation
- continuing with the next layer: **convolution!**

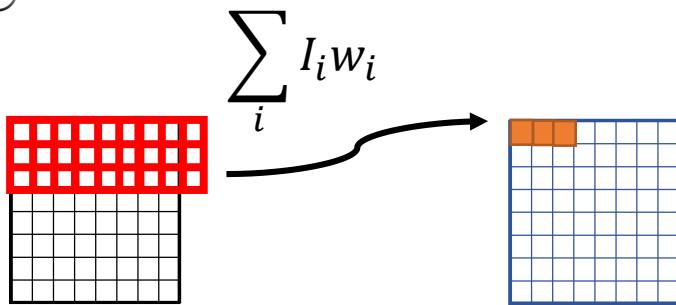
The **last** part is going to be the most tricky one!

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





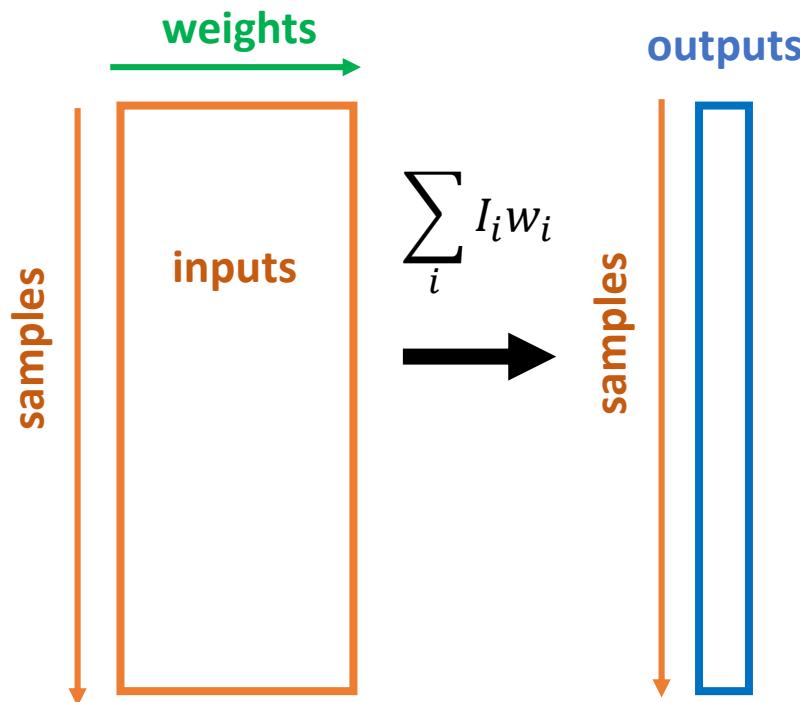
dweights	= -dvalues * inputs
dinputs	= -dvalues * weights
dbiases	= -dvalues



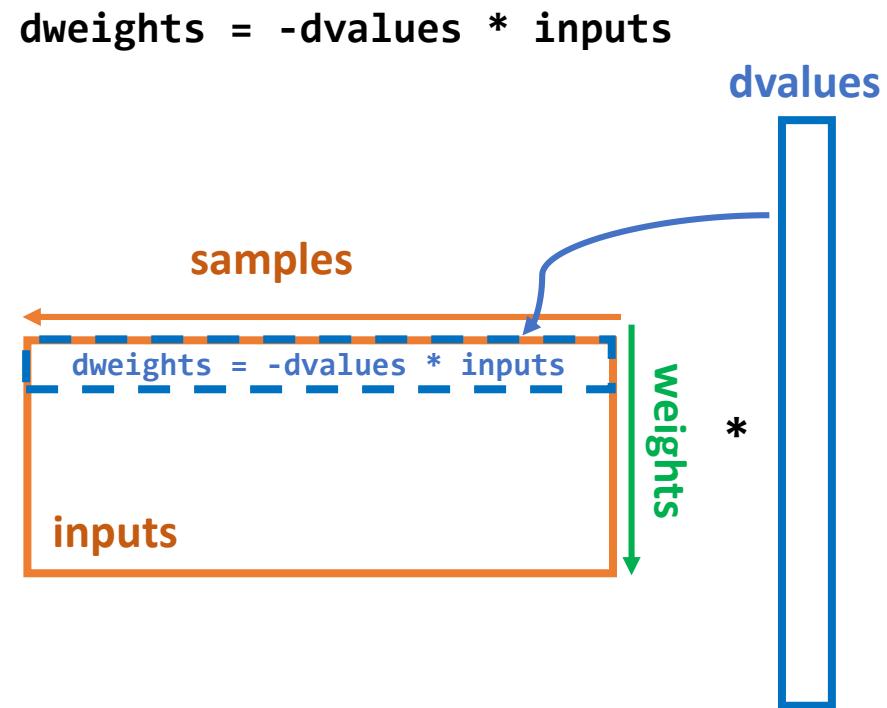
dweights	= -dvalues * inputs
dinputs	= -dvalues * weights
dbiases	= -dvalues

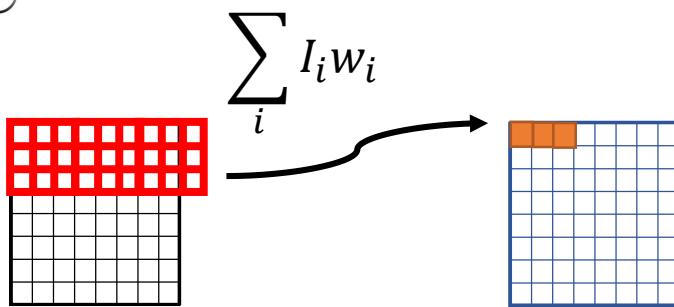
single neuron:

forward



backward



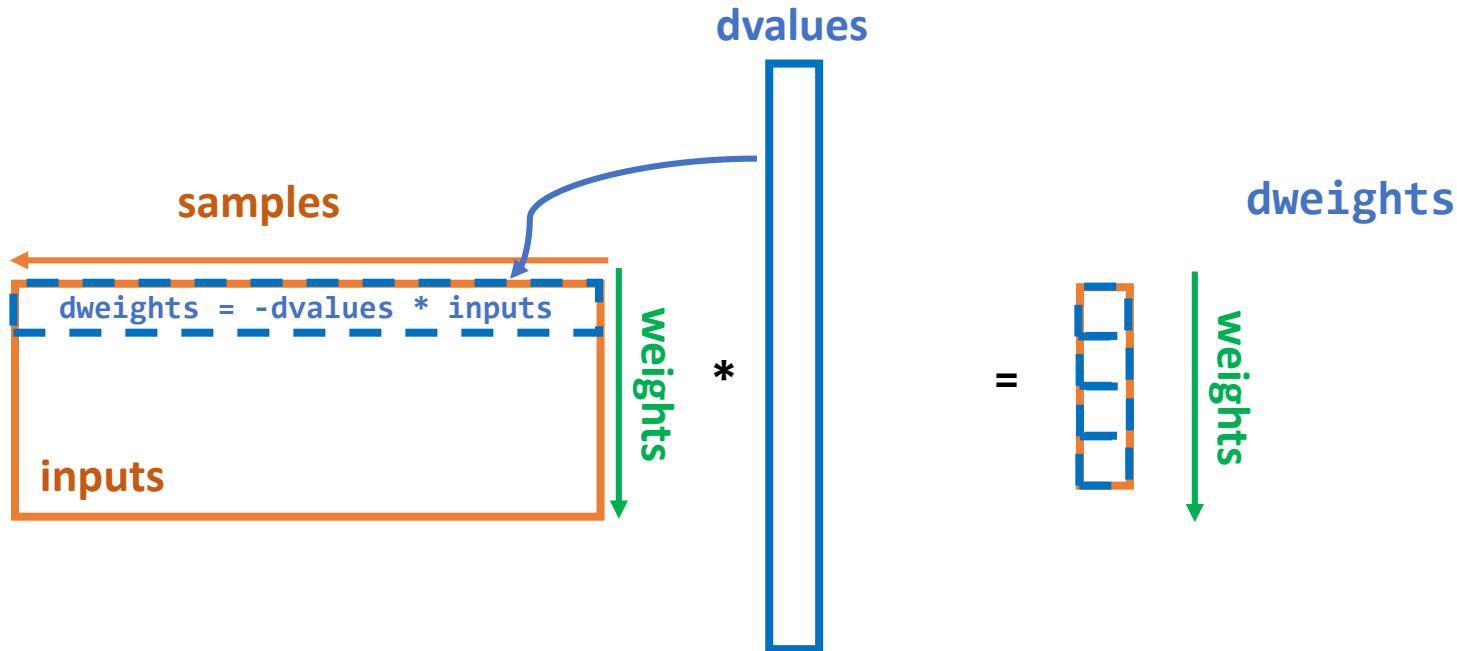


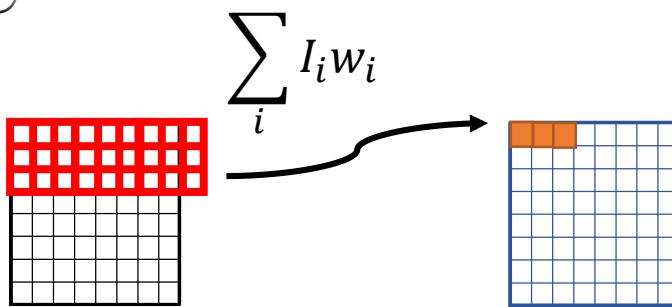
dweights	= -dvalues * inputs
dinputs	= -dvalues * weights
dbiases	= -dvalues

single neuron:

backward

dweights = -**dvalues** * **inputs**

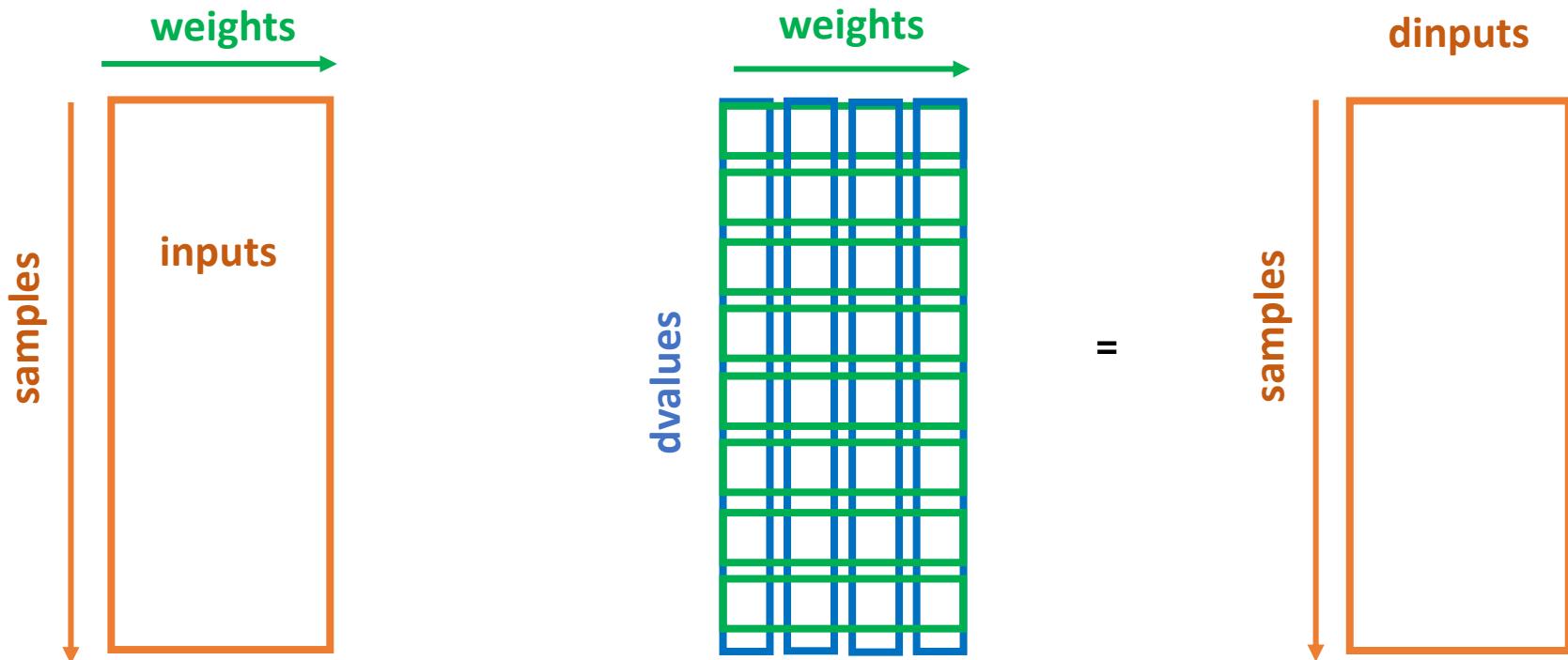


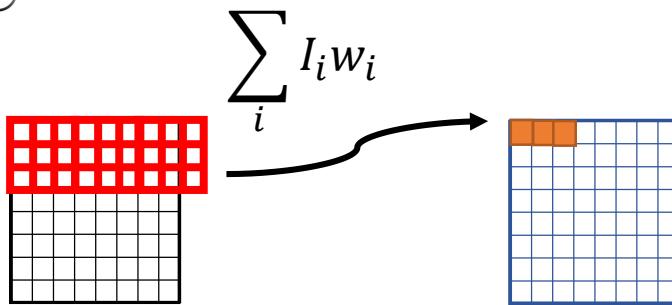


dweights	= -dvalues * inputs
dinputs	= -dvalues * weights
dbiases	= -dvalues

single neuron:

backward **dinputs** = -dvalues * weights (we don't need for first conv layer!)

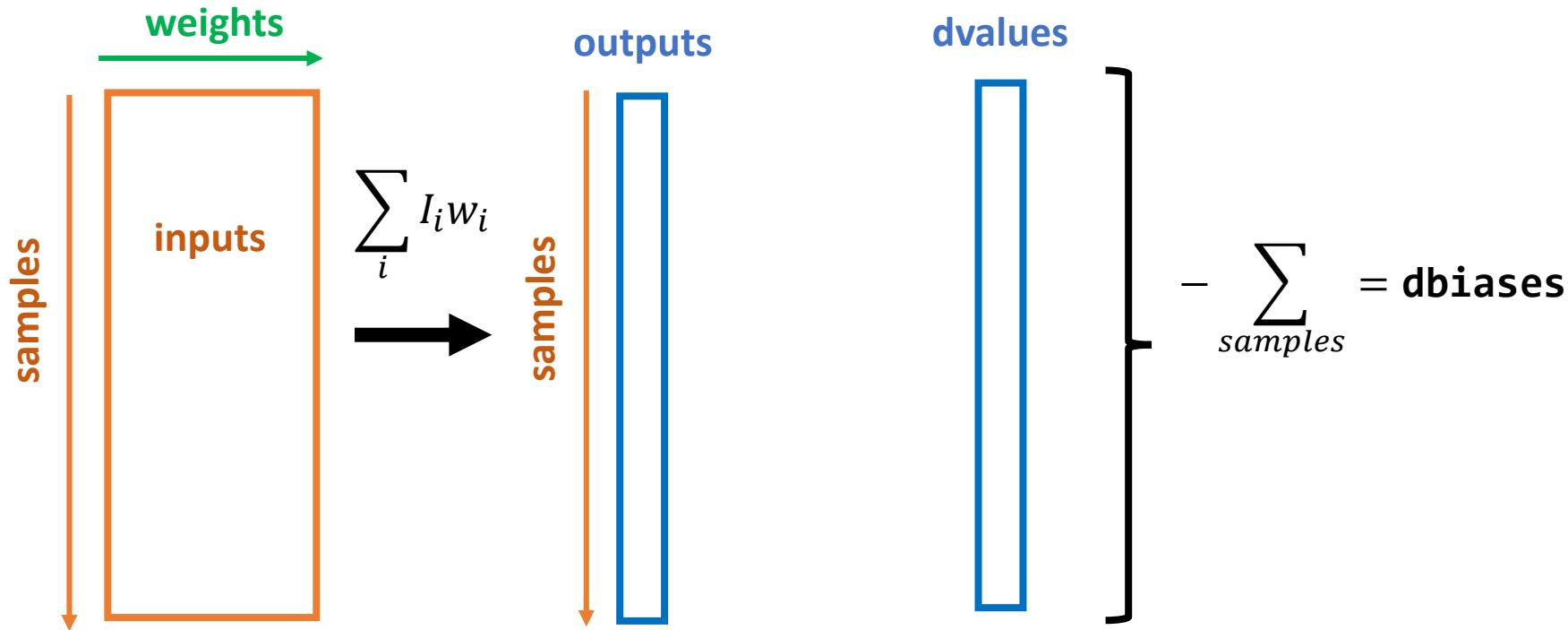




dweights	= -dvalues * inputs
dinputs	= -dvalues * weights
dbiases	= -dvalues

single neuron:

backward **dbiases** = -**dvalues**





class ConvLayer:

...

```
def backward(self, dvalues):
```

```
    biases      = self.biases  
    weights     = self.weights
```

```
    stride      = self.stride  
    padding     = self.padding
```

```
    xK          = self.xKernShape  
    yK          = self.yKernShape  
    NK          = self.Kernnumber
```

```
    imagePadded = self.impad
```

```
S = imagePadded.shape
```

As in the previous classes, we need some information from the **forward** part first



```
def backward(self, dvalues):
```

```
    ...
```

```
    xK      = self.xKernShape  
    yK      = self.yKernShape  
    NK     = self.Kernnumber
```

```
    imagePadded = self.impad
```

```
    S = imagePadded.shape
```

```
    dinputs     = np.zeros((S[0],S[1],S[2],S[4]))  
    dbiases     = np.zeros(biases.shape)  
    dweights    = np.zeros(weights.shape)
```

```
    xd          = dvalues.shape[0]  
    yd          = dvalues.shape[1]  
    numChans   = S[2]  
    numImds    = dvalues.shape[3]
```

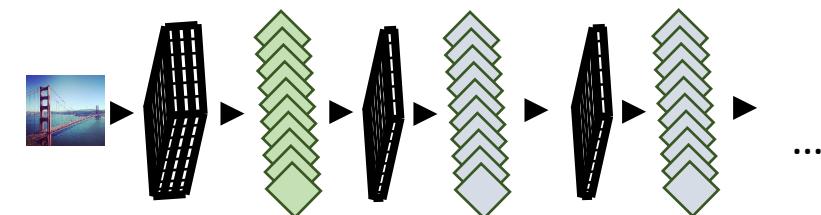
recall: the third index [2] refers to numChan (incoming matrix) and the fourth index [3] refers to Kernnumber (outcoming matrix)



```
def backward(self, dvalues):
```

```
    ...  
    xd      = dvalues.shape[0]  
    yd      = dvalues.shape[1]  
    numChans = S[2]  
    numImds  = dvalues.shape[3]  
  
    dinputs = np.zeros(imagePadded.shape)  
    dbiases  = np.zeros(biases.shape)
```

```
#defining matrix for dinputs: note: has do be de-padded at  
#the end; was the same input for all the k  
imagePadded = imagePadded[:, :, :, :, 0, :]
```



```
for i in range(numImds):  
    currentIm_pad = imagePadded[:, :, :, :, i]  
    for k in range(NK):  
        for c in range(numChans):  
            for y in range(yd):  
                for x in range(xd):
```

same structure
as for **forward** part



```
def backward(self, dvalues):
```

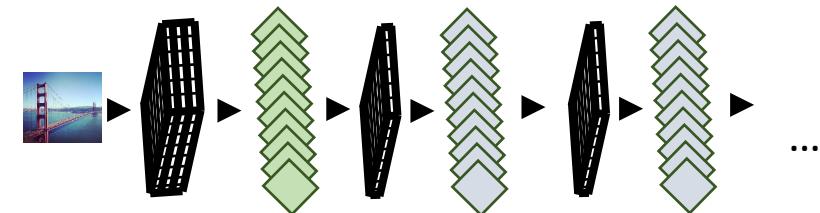
```
    ...
```

```
    for i in range(numImds):
        currentIm_pad = imagePadded[:, :, :, :, i]
        for k in range(NK):
            for c in range(numChans):
                for y in range(yd):
                    for x in range(xd):
```

```
                    y_start = y*stride
                    y_end   = y*stride + yK
                    x_start = x*stride
                    x_end   = x*stride + xK
```

```
                    sx      = slice(x_start,x_end)
                    sy      = slice(y_start,y_end)
```

```
                    current_slice = currentIm_pad[sx,sy,c]
```



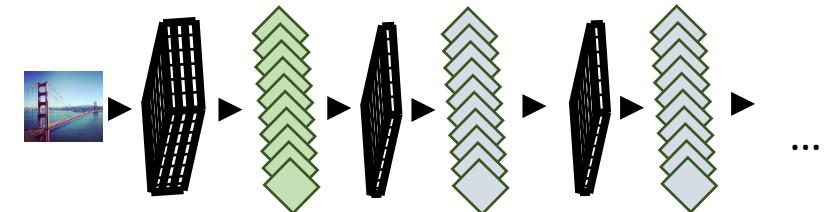
Again, same setup, as in
forward part



```
def backward(self, dvalues):
```

```
    ...
```

```
        for i in range(numImds):
            currentIm_pad = imagePadded[:, :, :, :, i]
            for k in range(NK):
                for c in range(numChans):
                    for y in range(yd):
                        for x in range(xd):
```



```
                y_start = y*stride
                y_end   = y*stride + yK
                x_start = x*stride
                x_end   = x*stride + xK
```

Again, same setup, as in
forward part

```
                sx      = slice(x_start,x_end)
                sy      = slice(y_start,y_end)
```

depending on **stride**,
some parts of the
padded image contributed
to different output pixel

```
current_slice = currentIm_pad[sx,sy,c]
```

```
dweights[:, :, k] += current_slice * \
                        dvalues[x, y, k, i]
```

```
dinputs[sx, sy, c, i] += weights[:, :, k]* \
                        dvalues[x, y, k, i]
```



```
def backward(self, dvalues):
```

```
    ...
```

```
    for i in range(numImds):
```

```
        currentIm_pad = imagePadded[:, :, :, :, i]
```

```
        for k in range(NK):
```

```
            for c in range(numChans):
```

```
                for y in range(yd):
```

```
                    for x in range(xd):
```

```
                        y_start = y*stride
```

```
                        y_end = y*stride + yK
```

```
                        x_start = x*stride
```

```
                        x_end = x*stride + xK
```

```
                        sx = slice(x_start,x_end)
```

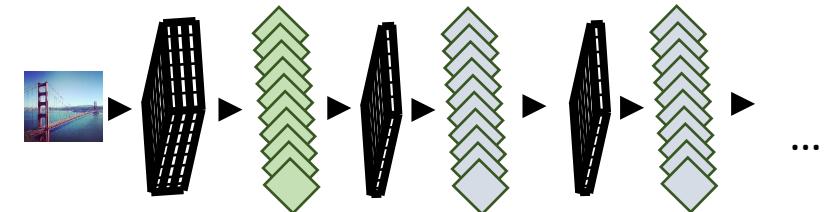
```
                        sy = slice(y_start,y_end)
```

```
                        current_slice = currentIm_pad[sx,sy,c]
```

```
                        dweights[:, :, k] += current_slice*dvalues[x,y,k,i]
```

```
                        dinputs[sx,sy,c,i] += weights[:, :, k]*dvalues[x,y,k,i]
```

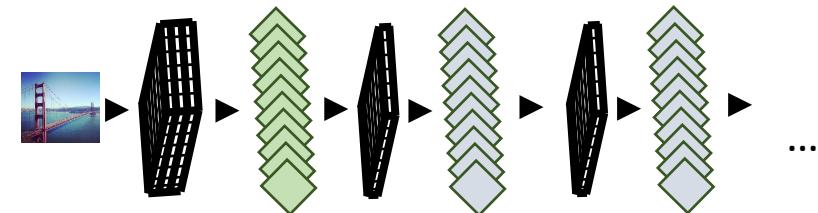
```
                        dbiases[0,k] += np.sum(np.sum(dvalues[:, :, k, i], axis=0), axis=0)
```





```
def backward(self, dvalues):
```

```
    ...
```



```
        y_start = y*stride  
        y_end   = y*stride + yK  
        x_start = x*stride  
        x_end   = x*stride + xK
```

```
        sx      = slice(x_start,x_end)  
        sy      = slice(y_start,y_end)
```

```
        current_slice = currentIm_pad[sx,sy,c]
```

```
        dweights[:, :, k] += current_slice*dvalues[x, y, k, i]  
        dinputs[sx, sy, c, i] += weights[:, :, k]*dvalues[x, y, k, i]
```

```
        dbiases[0,k] += np.sum(np.sum(dvalues[:, :, k, i], axis=0), axis=0)
```

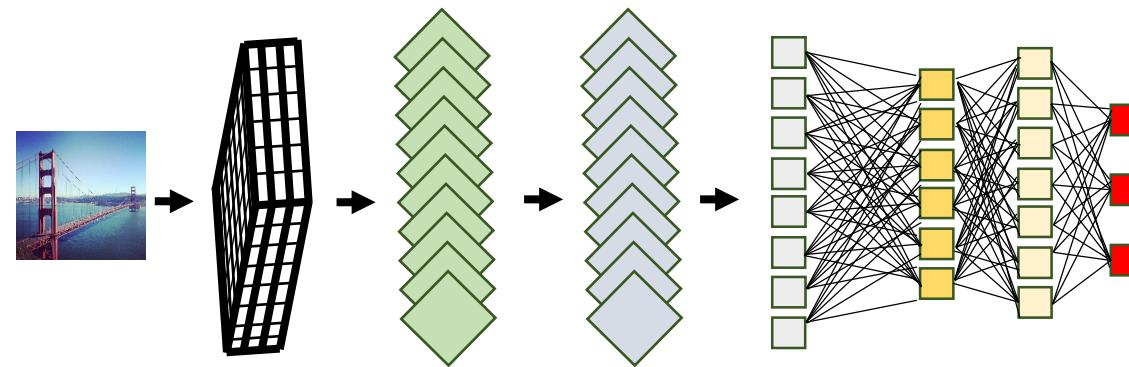
```
dinputs      = dinputs[padding:S[0]-padding, padding:S[1]-padding, :, :]  
self.dinputs = dinputs
```

```
self.dbiases = dbiases
```

```
self.dweights = dweights
```



Congratulations – we are done!



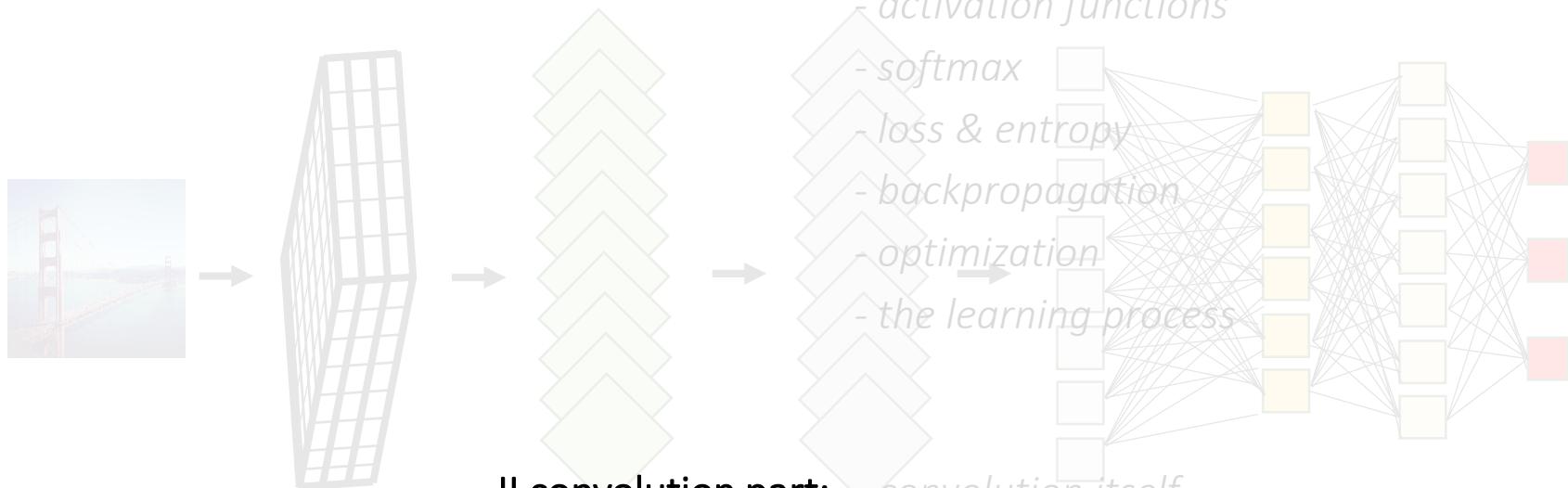


outline

0 intro

I the core:

- *a single neuron*
- *layers of neurons*
- *activation functions*
- *softmax*
- *loss & entropy*
- *backpropagation*
- *optimization*
- *the learning process*



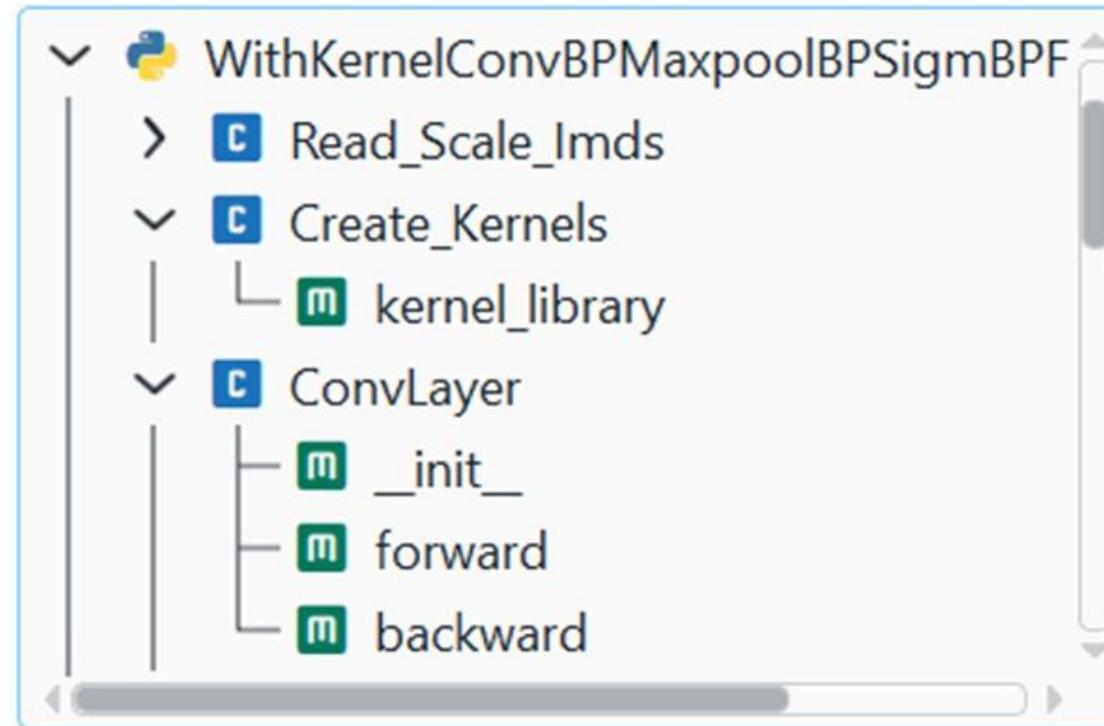
II convolution part:

- *convolution itself*
- *pooling*
- *sigmoid*
- *flattening*
- *backpropagation - again*
- *testing the CNN & final remarks*



We still haven't tested the backpropagation part of the convolution layer yet

- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message





- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

```
Conv1.forward(M,2,1)  
RL1.forward(Conv1.output)  
MP1.forward(RL1.output,4,4)
```

```
Conv2.forward(MP1.output,1,1)  
RL2.forward(Conv2.output)  
MP2.forward(RL2.output,1,4)
```

```
Conv3.forward(MP2.output,0,3)  
RL3.forward(Conv3.output)  
MP3.forward(RL3.output,2,2)
```

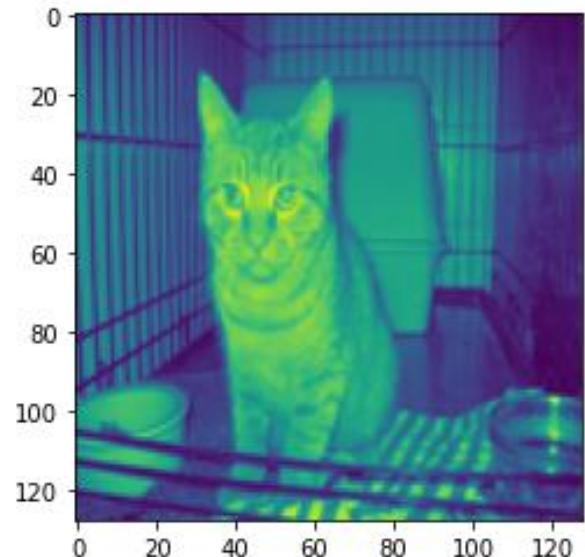
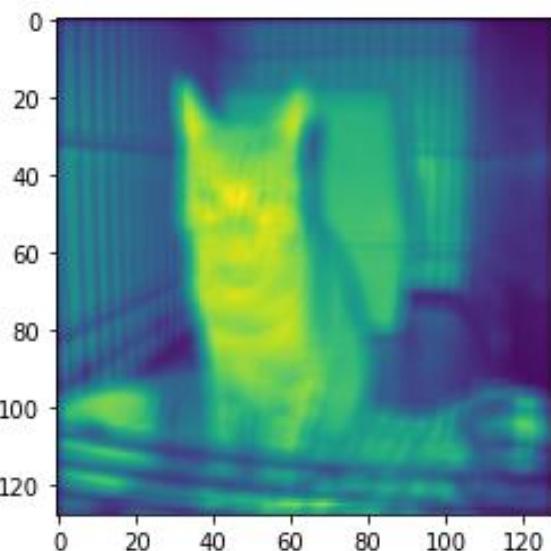


- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

Conv1.forward($M, 2, 1$)
RL1.forward(Conv1.output)
MP1.forward(RL1.output, $4, 4$)

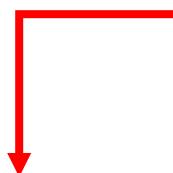
Conv2.forward(MP1.output, $1, 1$)
RL2.forward(Conv2.output)
MP2.forward(RL2.output, $1, 4$)

3.forward(MP2.output, $0, 3$)
Forward(Conv3.output)
Forward(RL3.output, $2, 2$)





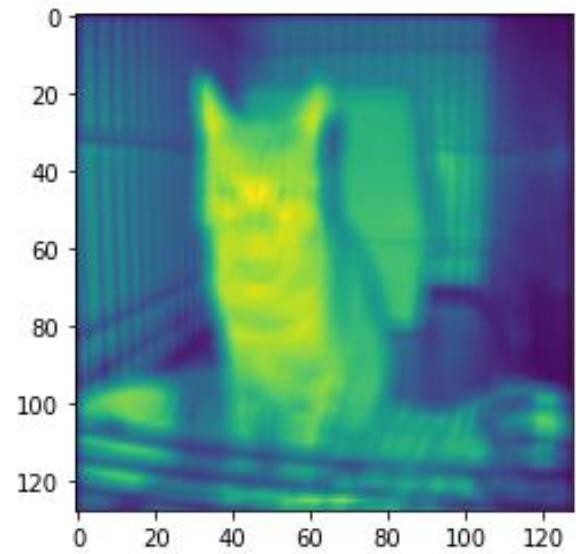
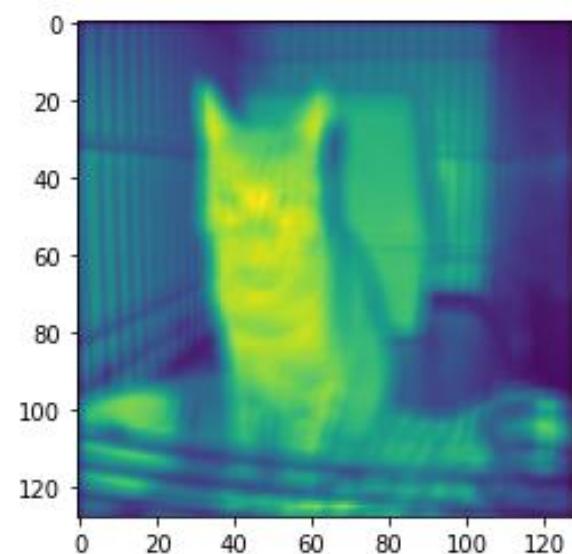
- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message



```
Conv1.forward(M, 2, 1)
RL1.forward(Conv1.output)
MP1.forward(RL1.output, 4, 4)

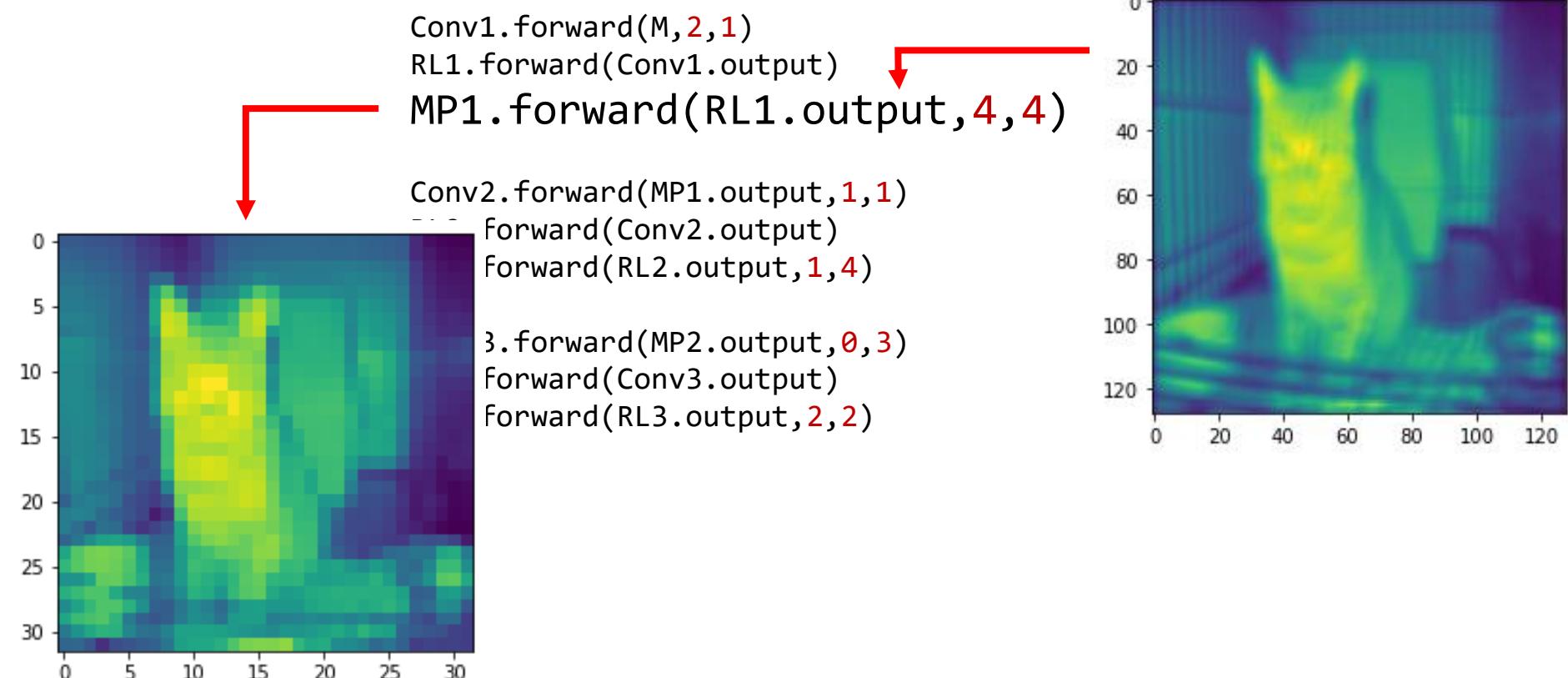
Conv2.forward(MP1.output, 1, 1)
RL2.forward(Conv2.output)
Forward(RL2.output, 1, 4)

b.forward(MP2.output, 0, 3)
Forward(Conv3.output)
Forward(RL3.output, 2, 2)
```





- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message



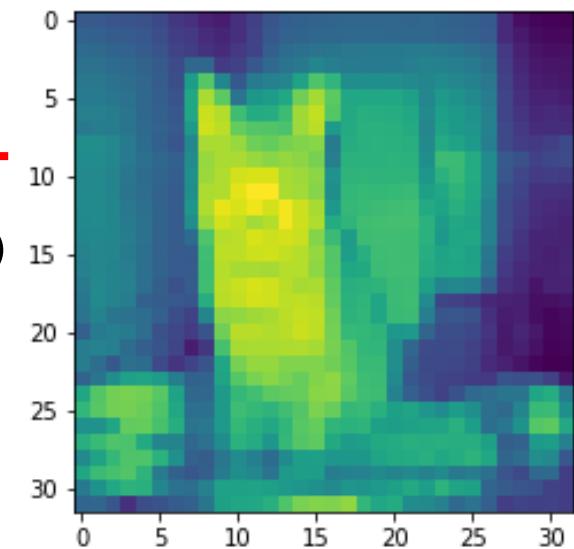
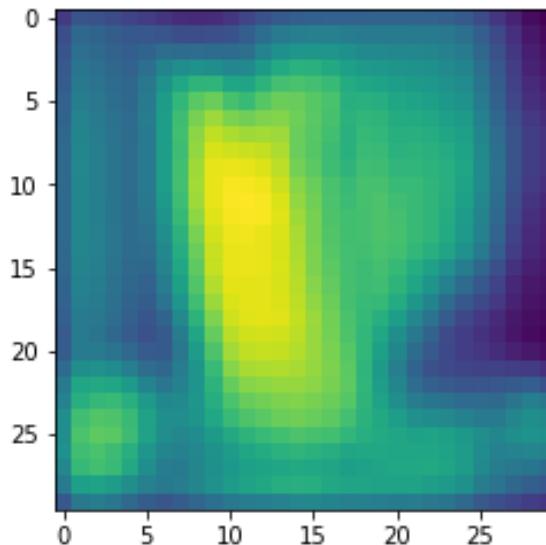


- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

```
Conv1.forward(M, 2, 1)
RL1.forward(Conv1.output)
MP1.forward(RL1.output, 4, 4)
```

```
Conv2.forward(MP1.output, 1, 1)
RL2.forward(Conv2.output)
MP2.forward(RL2.output, 1, 4)
```

```
.forward(MP2.output, 0, 3)
forward(Conv3.output)
forward(RL3.output, 2, 2)
```



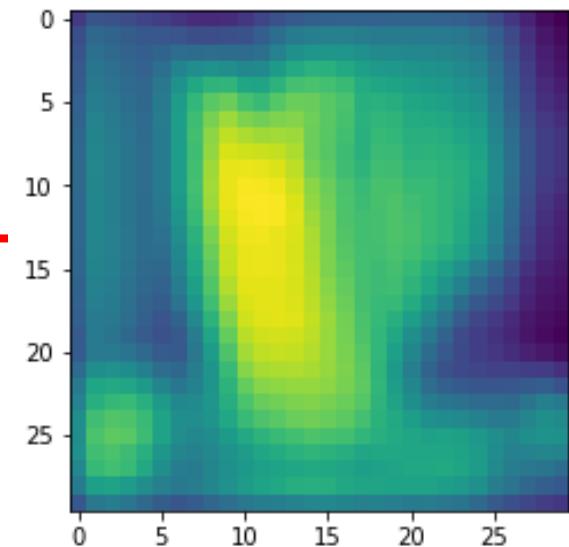
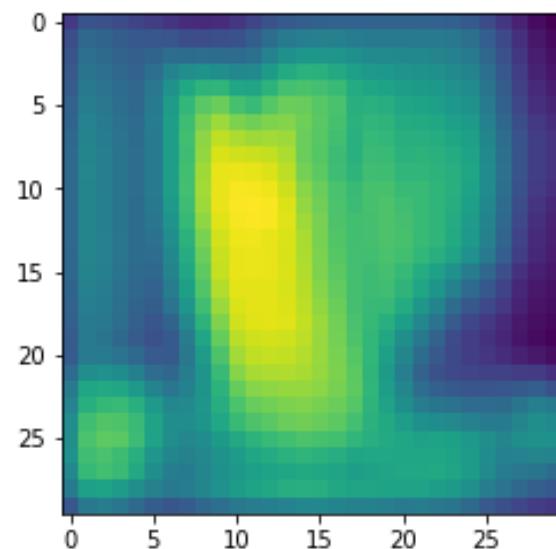


- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

```
Conv1.forward(M, 2, 1)  
RL1.forward(Conv1.output)  
MP1.forward(RL1.output, 4, 4)
```

```
Conv2.forward(MP1.output, 1, 1)  
RL2.forward(Conv2.output)  
MP2.forward(RL2.output, 1, 4)
```

```
Conv3.forward(MP2.output, 0, 3)  
forward(Conv3.output)  
forward(RL3.output, 2, 2)
```



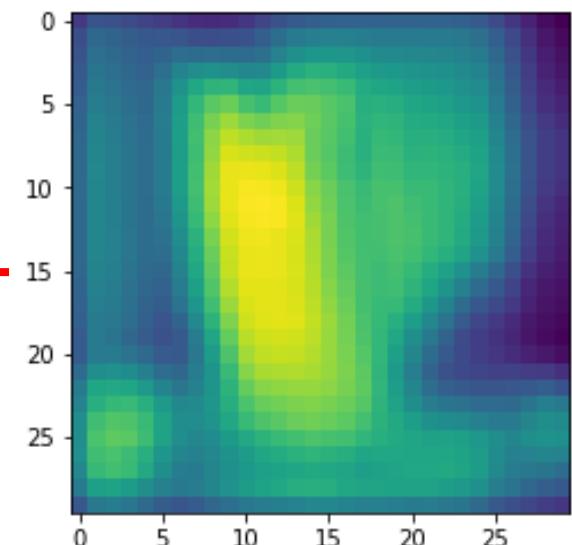
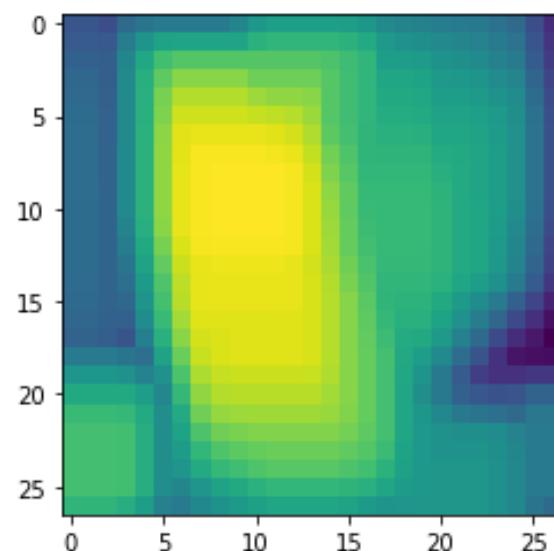


- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

```
Conv1.forward(M, 2, 1)  
RL1.forward(Conv1.output)  
MP1.forward(RL1.output, 4, 4)
```

```
Conv2.forward(MP1.output, 1, 1)  
RL2.forward(Conv2.output)  
MP2.forward(RL2.output, 1, 4)
```

```
Conv3.forward(MP2.output, 0, 3)  
forward(Conv3.output)  
forward(RL3.output, 2, 2)
```



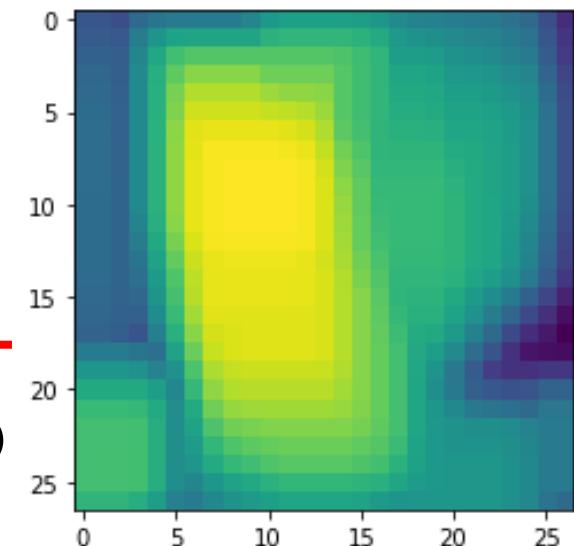
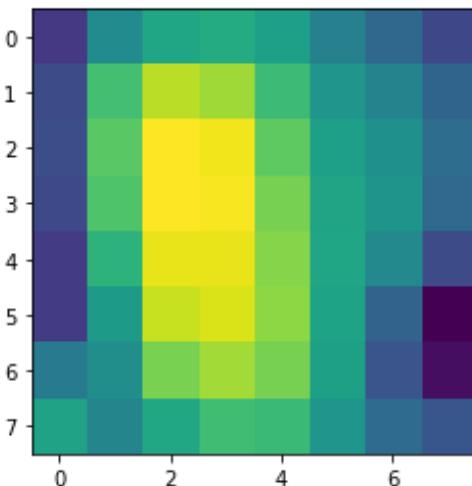


- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

```
Conv1.forward(M, 2, 1)  
RL1.forward(Conv1.output)  
MP1.forward(RL1.output, 4, 4)
```

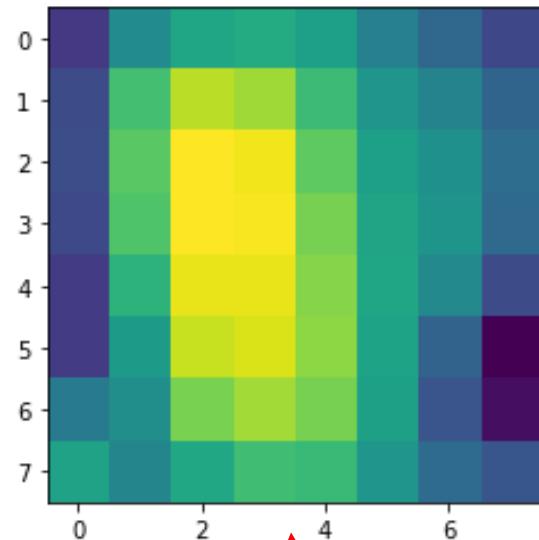
```
Conv2.forward(MP1.output, 1, 1)  
RL2.forward(Conv2.output)  
MP2.forward(RL2.output, 1, 4)
```

```
Conv3.forward(MP2.output, 0, 3)  
RL3.forward(Conv3.output)  
3.forward(RL3.output, 2, 2)
```





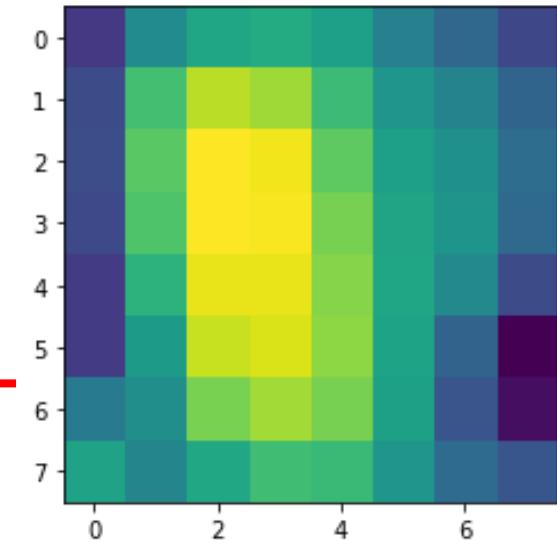
- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message



```
v1.forward(M, 2, 1)  
.forward(Conv1.output)  
.forward(RL1.output, 4, 4)
```

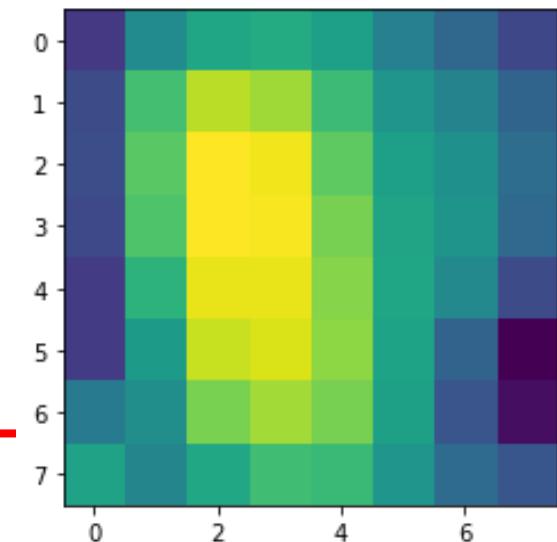
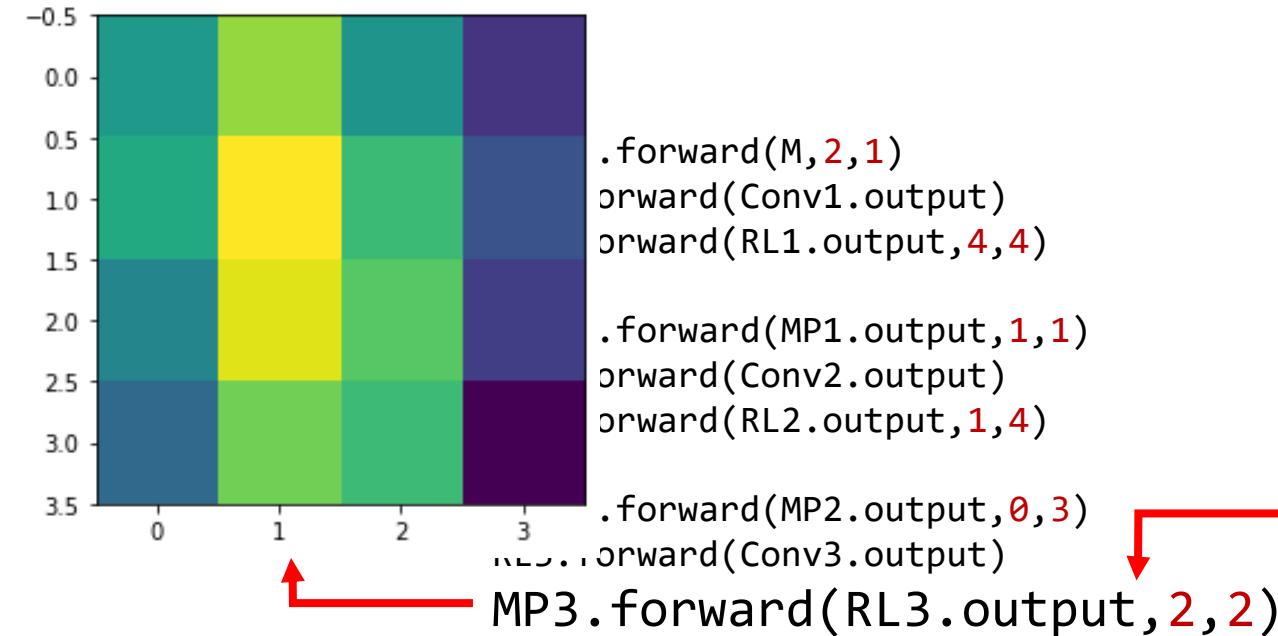
```
v2.forward(MP1.output, 1, 1)  
.forward(Conv2.output)  
.forward(RL2.output, 1, 4)
```

v3.forward(MP2.output, 0, 3)
RL3.forward(Conv3.output)
MP3.forward(RL3.output, 2, 2)





- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message





- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding **now back propagation!**
- if indices have gotten confused: you will receive an error message

```
MP3.backward(F.dinputs)
RL3.backward(MP3.dinputs)
Conv3.backward(MP3.dinputs)
```

```
MP2.backward(Conv3.dinputs)
RL2.backward(MP2.dinputs)
Conv2.backward(RL2.dinputs)
```

```
MP1.backward(Conv2.dinputs)
RL1.backward(MP1.dinputs)
Conv1.backward(RL1.dinputs)
```



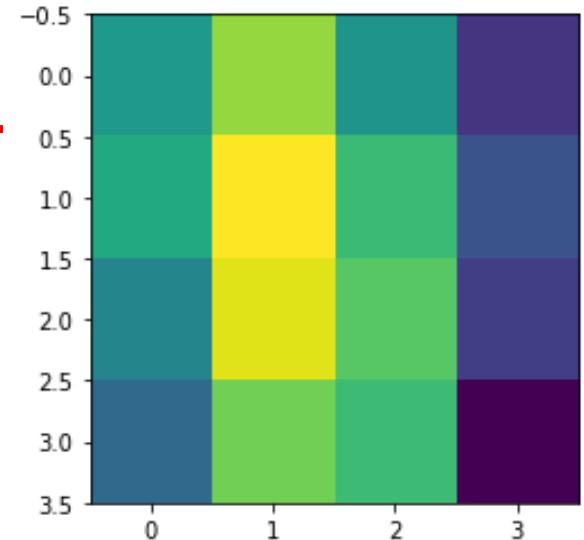
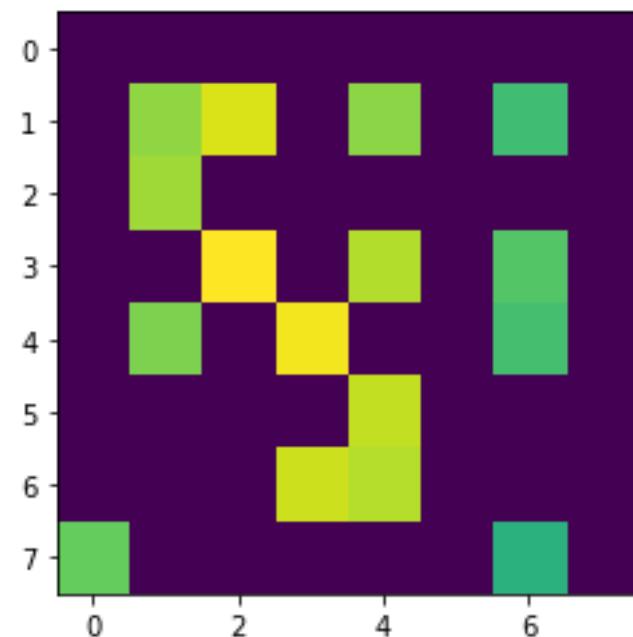
- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

now back propagation!

MP3.backward(F.dinputs)
RL3.backward(MP3.dinputs)
Conv3.backward(MP3.dinputs)

backward(Conv3.dinputs)
backward(MP2.dinputs)
backward(RL2.dinputs)

backward(Conv2.dinputs)
backward(MP1.dinputs)
backward(RL1.dinputs)





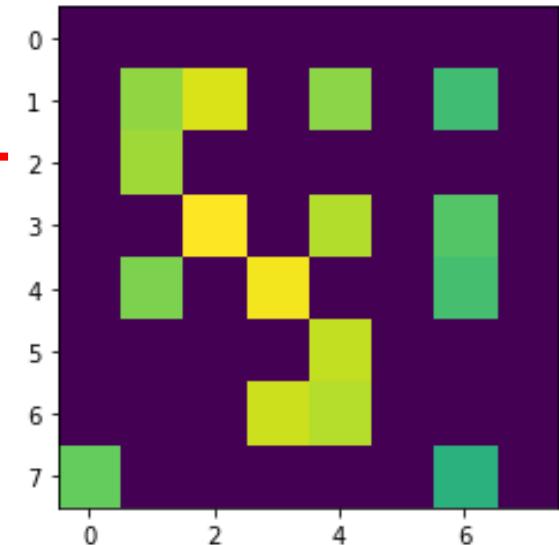
- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

now back propagation!

```
MP3.backward(F.dinputs)
RL3.backward(MP3.dinputs)
Conv3.backward(MP3.dinputs)

MP2.backward(Conv3.dinputs)
    .backward(MP2.dinputs)
v2.backward(RL2.dinputs)

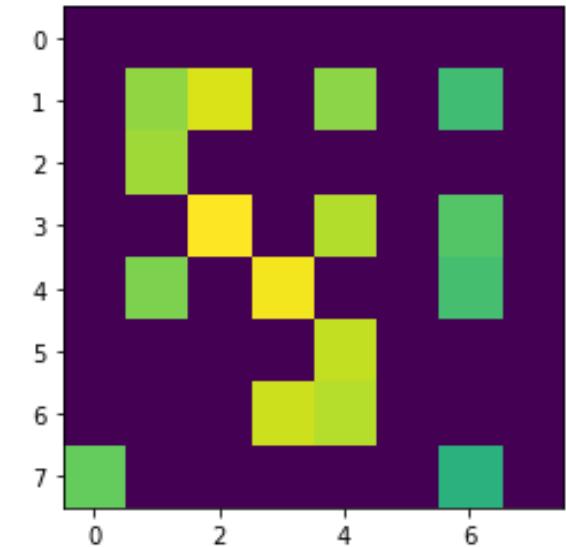
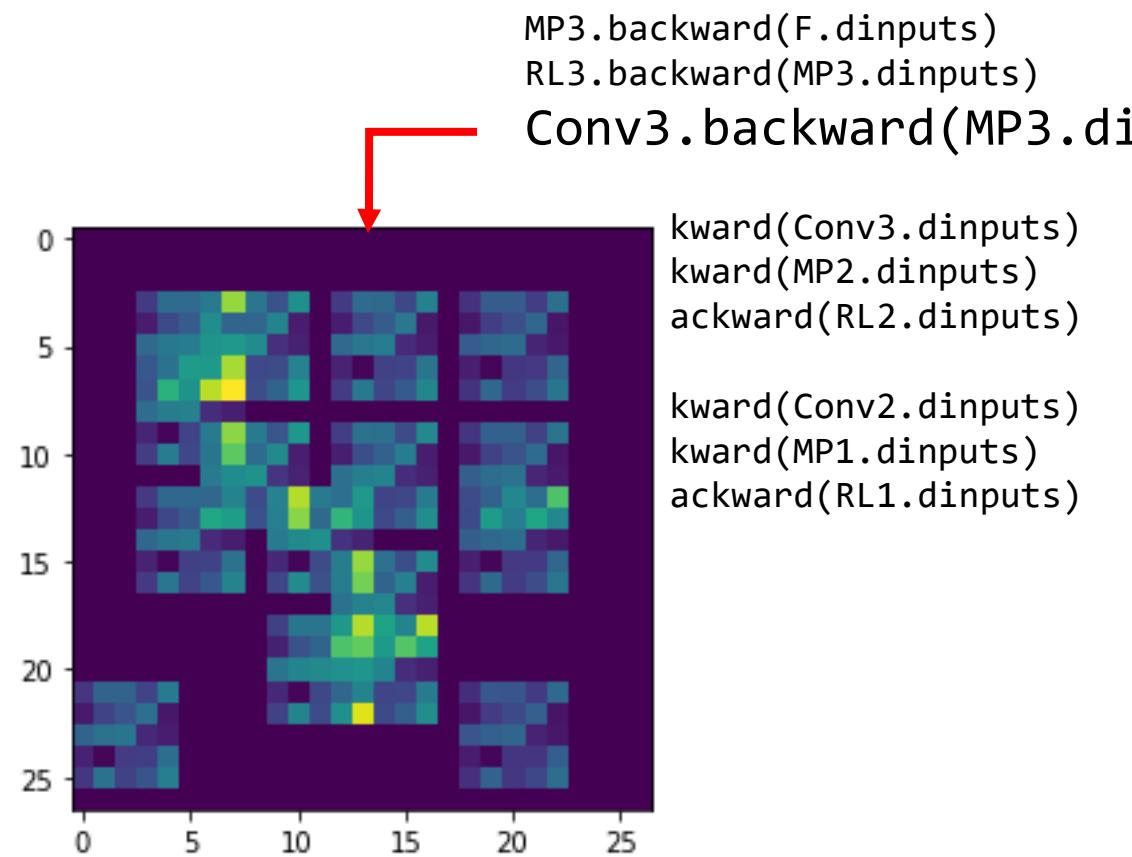
    .backward(Conv2.dinputs)
    .backward(MP1.dinputs)
v1.backward(RL1.dinputs)
```





- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

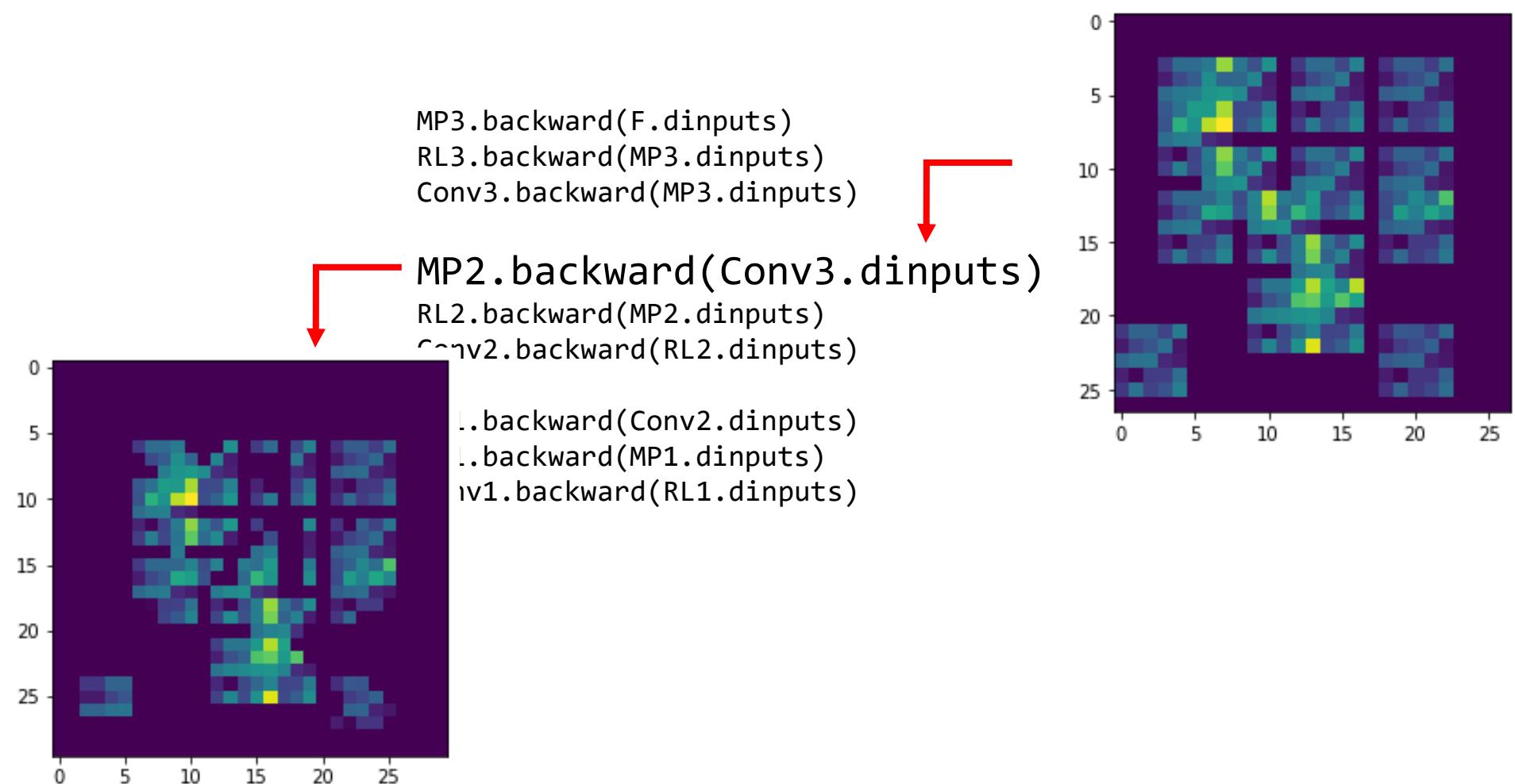
now back propagation!





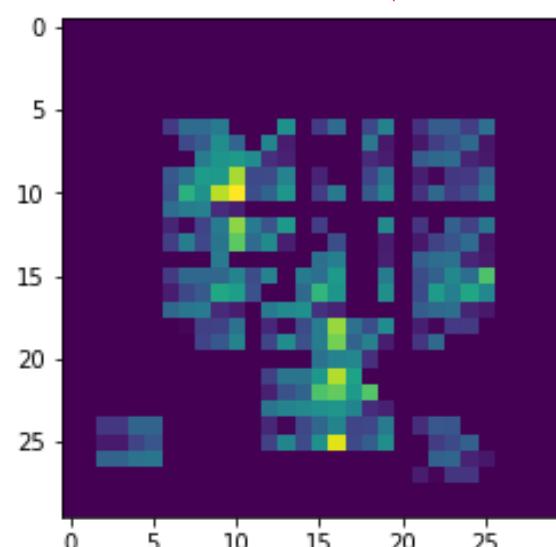
- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

now back propagation!





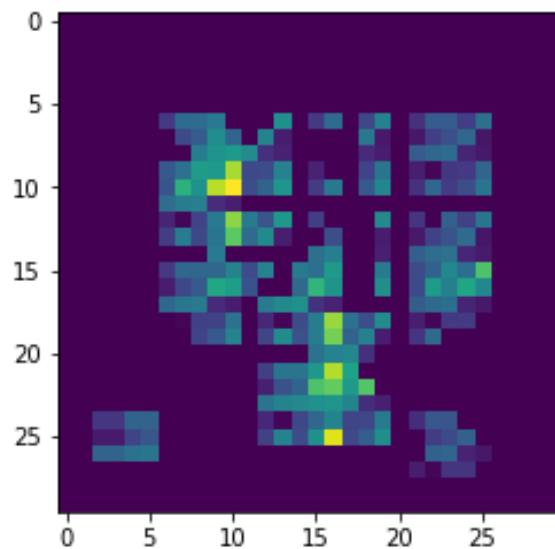
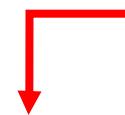
- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding **now back propagation!**
- if indices have gotten confused: you will receive an error message



```
MP3.backward(F.dinputs)
RL3.backward(MP3.dinputs)
Conv3.backward(MP3.dinputs)
```

```
MP2.backward(Conv3.dinputs)
RL2.backward(MP2.dinputs)
rv2.backward(RL2.dinputs)
```

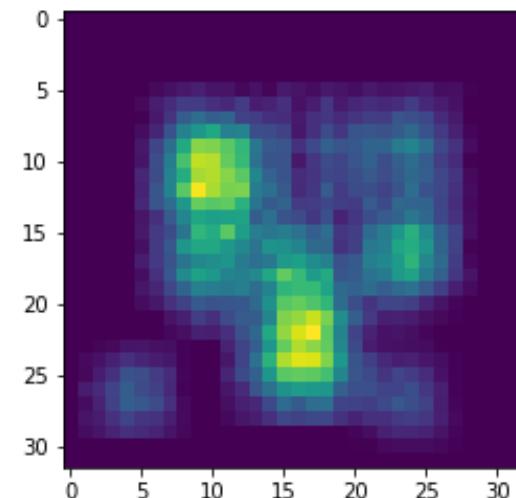
```
L.backward(Conv2.dinputs)
L.backward(MP1.dinputs)
rv1.backward(RL1.dinputs)
```





- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

now back propagation!

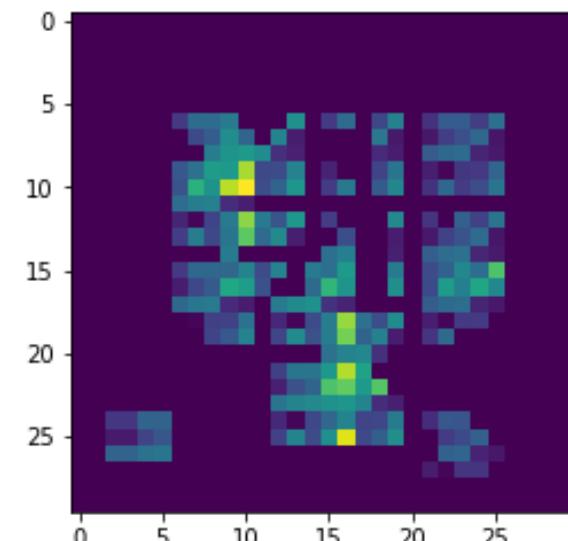


MP3.backward(F.dinputs)
RL3.backward(MP3.dinputs)
Conv3.backward(MP3.dinputs)

MP2.backward(Conv3.dinputs)
RL2.backward(MP2.dinputs)

Conv2.backward(RL2.dinputs)

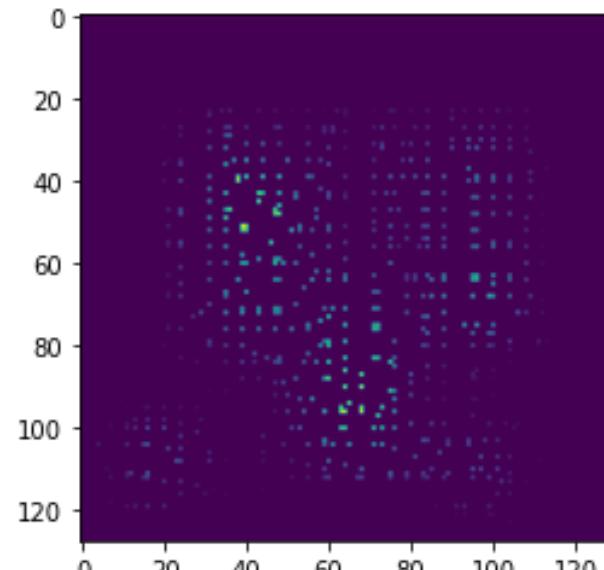
MP1.backward(Conv2.dinputs)
RL1.backward(MP1.dinputs)
Conv1.backward(RL1.dinputs)





- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

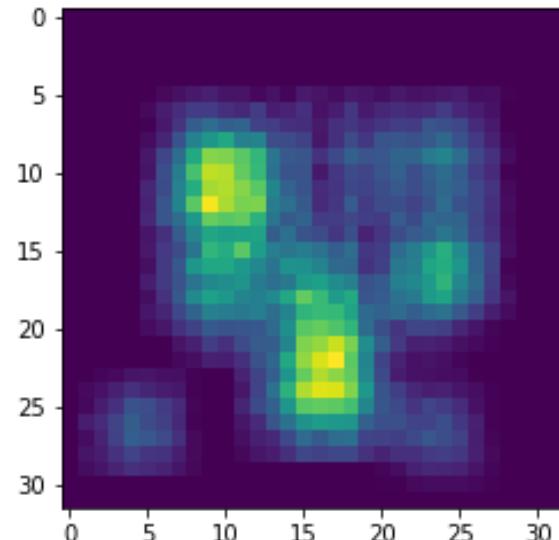
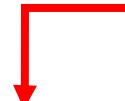
now back propagation!



```
backward(F.dinputs)
backward(MP3.dinputs)
!.backward(MP3.dinputs)

backward(Conv3.dinputs)
backward(MP2.dinputs)
!.backward(RL2.dinputs)

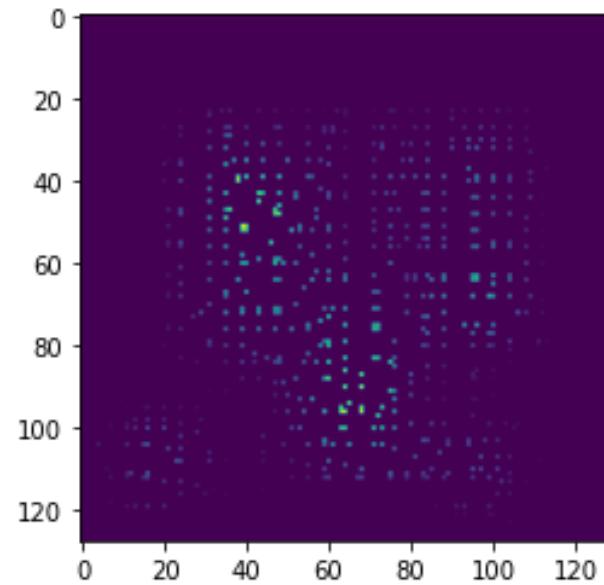
MP1.backward(Conv2.dinputs)
RL1.backward(MP1.dinputs)
Conv1.backward(RL1.dinputs)
```





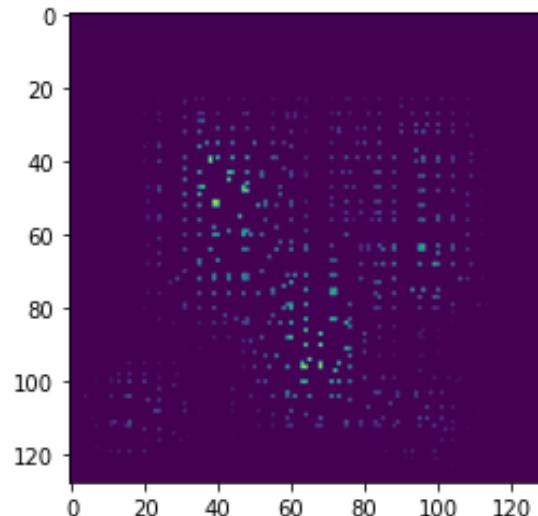
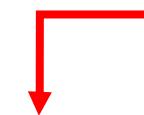
- best way: just run a few convolution layers + backpropagation subsequently
- choose different values for stride/padding
- if indices have gotten confused: you will receive an error message

now back propagation!



```
MP1.backward(F.dinputs)
MP1.backward(MP3.dinputs)
MP1.backward(MP3.dinputs)

Conv1.backward(RL1.dinputs)
Conv1.backward(RL1.dinputs)
RL1.backward(MP1.dinputs)
```

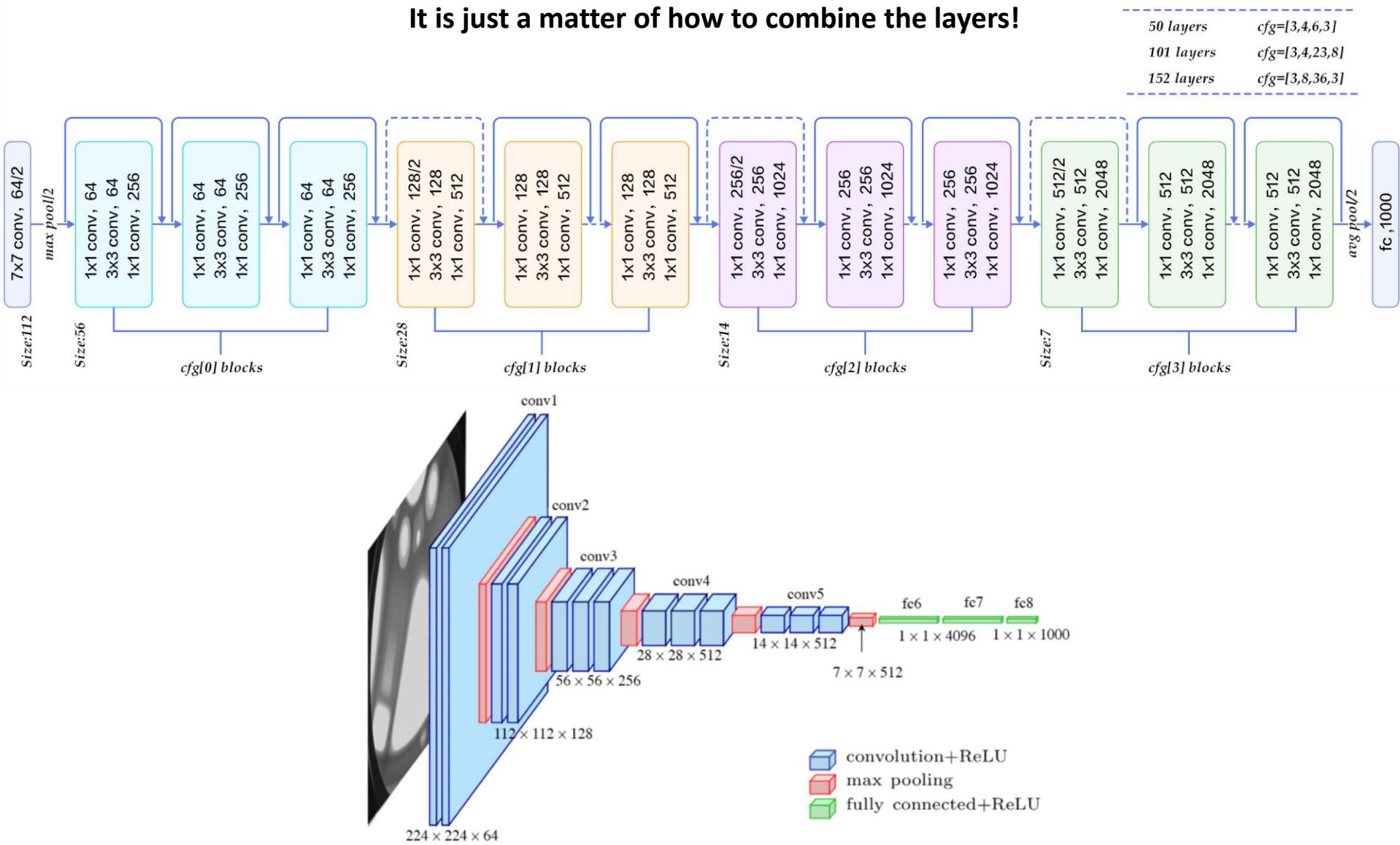


It all seems to work!



We now have the ingredients to build any common CNN!

It is just a matter of how to combine the layers!





- LeNet:
- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998
 - one of the 1st CNN that was able to categorize images
 - MNIST data set

A 10x10 grid of handwritten digits, likely from the MNIST dataset. The digits are arranged in a 10x10 pattern. Some digits are slightly blurred or distorted. The digits represent the numbers 0 through 9.

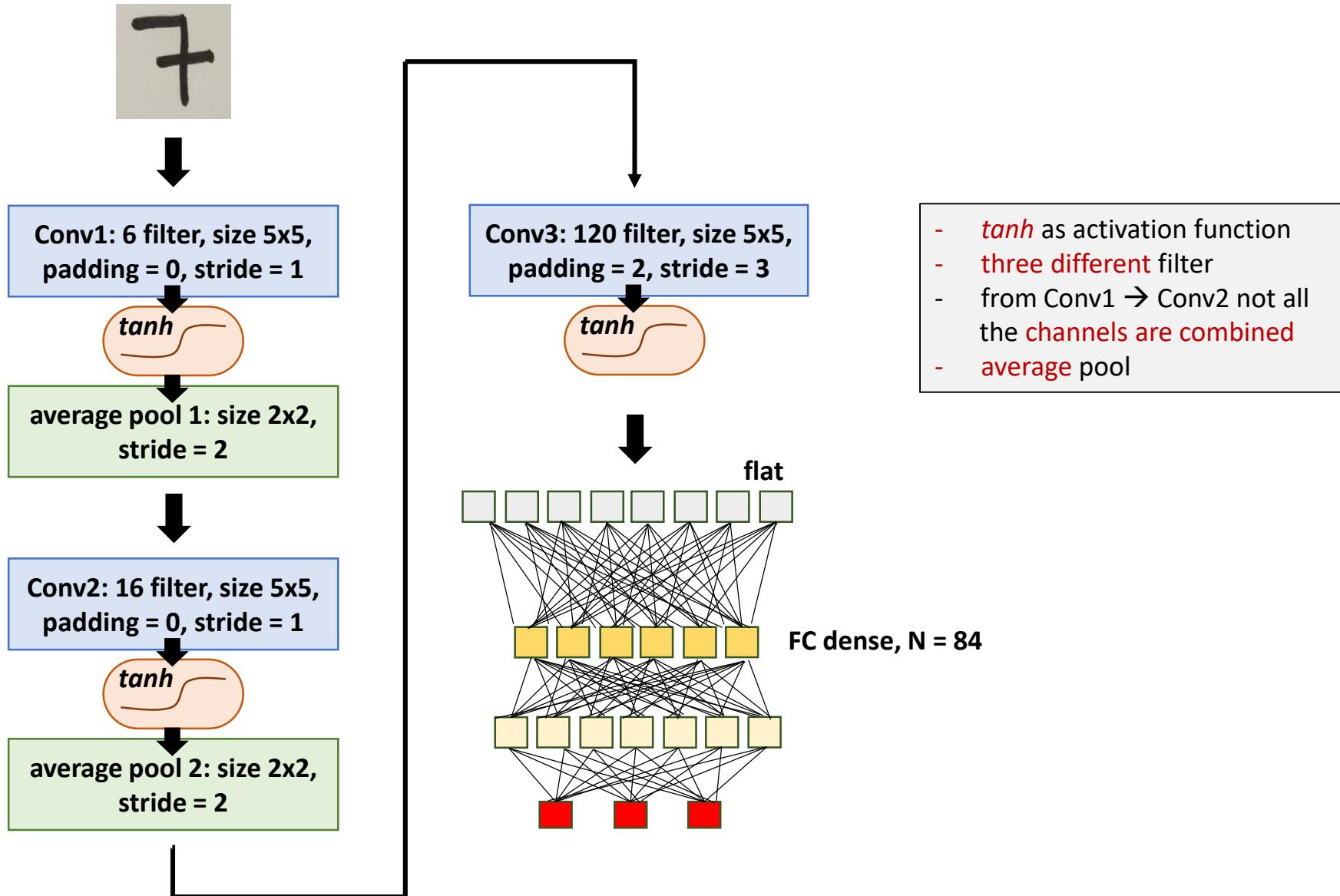
0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1
2	2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3	3	3
4	4	4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5	5	5
6	6	6	6	6	6	6	6	6	6
7	7	7	7	7	7	7	7	7	7
8	8	8	8	8	8	8	8	8	8
9	9	9	9	9	9	9	9	9	9

- only **seven layers** in total
- modern CNNs (google, ResNet etc have **100 or more** layers)

→ since we have limited computational resources and
our CNN is not optimized regarding speed → let us built LeNet and see how that works

LeNet:

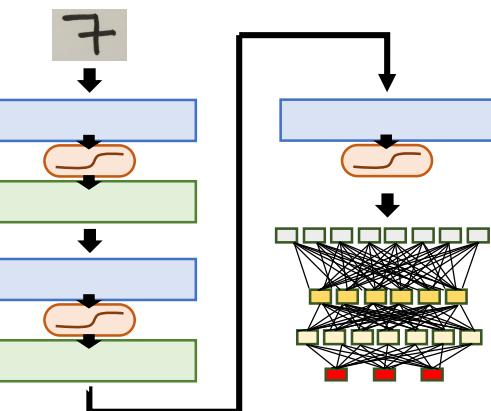
- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

- *tanh* as activation function
- three different filter
- from Conv1 → Conv2 not all the channels are combined
- average pool



here:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	X			X	X	X			X	X	X	X		X	X	
1	X	X			X	X	X			X	X	X	X		X	
2	X	X	X			X	X	X			X		X	X	X	
3		X	X	X		X	X	X	X		X		X	X		
4			X	X	X		X	X	X	X	X	X		X		
5				X	X	X		X	X	X	X	X	X		X	

creating a filter matrix:

```

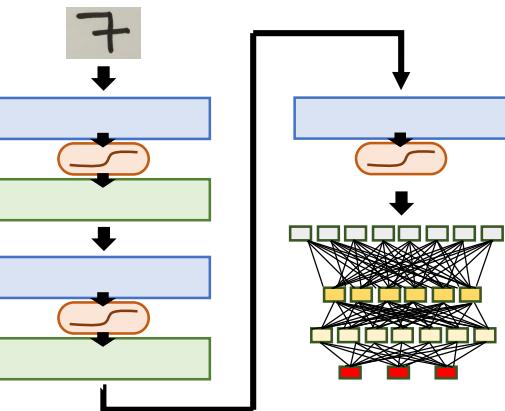
if numChans == 6 & NK == 16:
    filt = np.array([[1,0,0,0,1,1,1,0,0,1,1,1,1,0,1,1], \
                    [1,1,0,0,0,1,1,1,0,0,1,1,1,1,0,1], \
                    [1,1,1,0,0,0,1,1,1,0,0,1,0,1,1,1], \
                    [0,1,1,1,0,0,1,1,1,1,0,0,1,0,1,1], \
                    [0,0,1,1,1,0,0,1,1,1,1,0,1,1,0,1], \
                    [0,0,0,1,1,1,0,0,1,1,1,1,0,1,1,1]])
else:
    filt = np.ones([numChans,NK])
self.filt = filt

```

LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

- *tanh* as activation function
- three different filter
- from Conv1 → Conv2 not all the channels are combined
- average pool



	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	X				X	X	X			X	X	X	X		X	X
1	X	X				X	X	X			X	X	X	X		X
2	X	X	X				X	X	X		X		X	X	X	X
3	X	X	X				X	X	X	X		X		X	X	X
4		X	X	X				X	X	X	X	X	X		X	X
5		X	X	X				X	X	X	X	X	X		X	X

```
filt = np.array([[1,0,0,0,1,1,1,0,0,1,1,1,1,0,1,1], \
[1,1,0,0,0,1,1,1,0,0,1,1,1,1,0,1], \
[1,1,1,0,0,0,1,1,1,0,0,1,0,1,1,1], \
[0,1,1,1,0,0,1,1,1,1,0,0,1,0,1,1], \
[0,0,1,1,1,0,0,1,1,1,1,0,1,1,0,1], \
[0,0,0,1,1,1,0,0,1,1,1,1,0,1,1,1]])
```

creating a filter matrix:

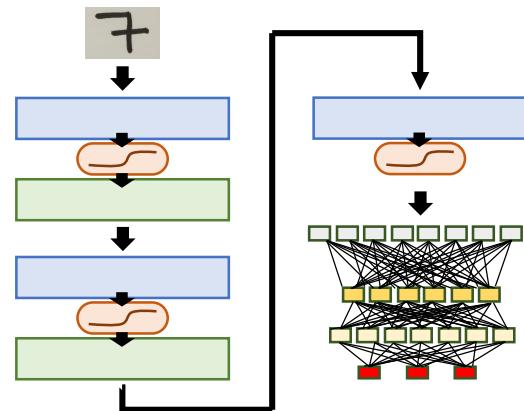
→ performing operations in forward and backward part only,

```
if filt[c,k] == 1:
```

LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

- *tanh* as activation function
- three different filter numbers
- from Conv1 → Conv2 not all the channels are combined
- **average pool**



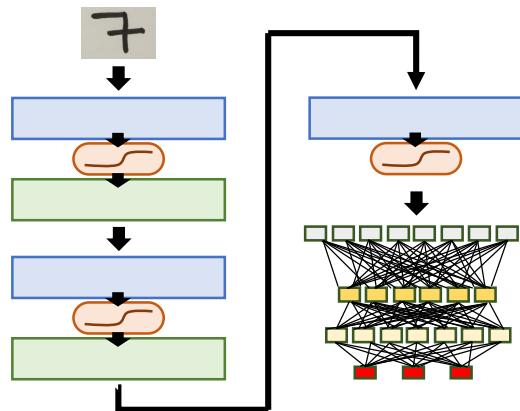
like max pool, only a few differences:

```
def forward(self, ...):  
    ...  
  
    #actual average pool  
    slice_mean      = float(current_slice.mean())  
    output[x, y, c, i] = slice_mean  
  
    ...
```

LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

- *tanh* as activation function
- three different filter numbers
- from Conv1 → Conv2 not all the channels are combined
- **average pool**



like max pool, only a few differences:

```
def backward(self, ...):
```

```
    Ones      = Ones/xK/yK
```

```
...
```

normalization from
the derivative of the average

```
    dinputs[sx,sy,c,i] += Ones[sx,sy,c,i]*dvalues[x,y,c,i]
```

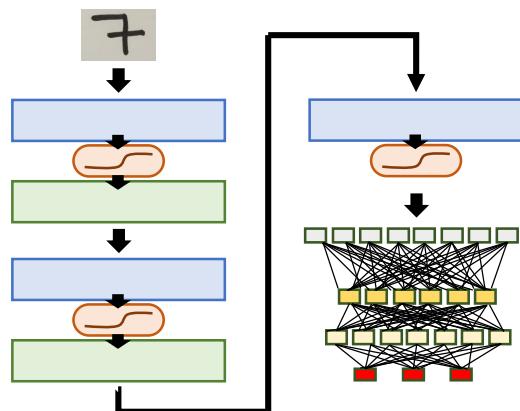
```
...
```

LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

The MNIST data set:

0 0 0 0 0 0 0 0 0 0 0 0 0 0
1 1 1 1 1 1 1 1 1 1 1 1 1 1
2 2 2 2 2 2 2 2 2 2 2 2 2 2
3 3 3 3 3 3 3 3 3 3 3 3 3 3
4 4 4 4 4 4 4 4 4 4 4 4 4 4
5 5 5 5 5 5 5 5 5 5 5 5 5 5
6 6 6 6 6 6 6 6 6 6 6 6 6 6
7 7 7 7 7 7 7 7 7 7 7 7 7 7
8 8 8 8 8 8 8 8 8 8 8 8 8 8
9 9 9 9 9 9 9 9 9 9 9 9 9 9



```
#pip install keras  
#pip install tensorflow
```

```
from keras.datasets import mnist
```

```
(train_x, train_y), (test_x, test_y) = mnist.load_data()
```



already a sparse vector

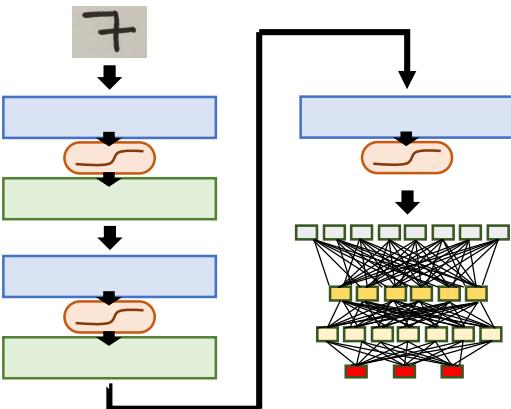
LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

The MNIST data set:

```
#pip install keras  
#pip install tensorflow
```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4
5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5
6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6
7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7
8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8
9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9

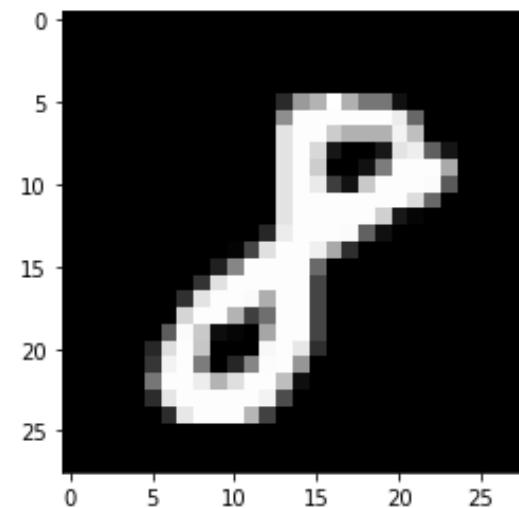
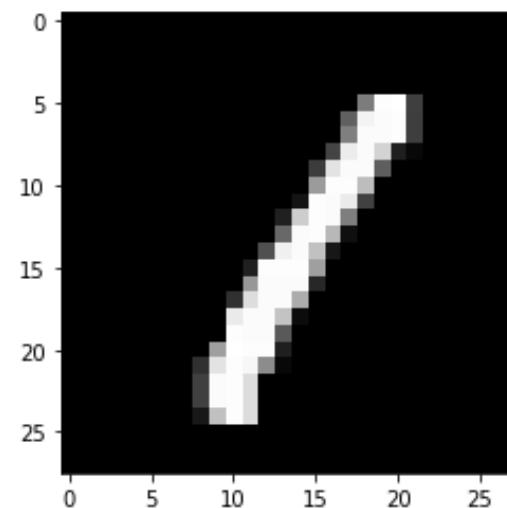
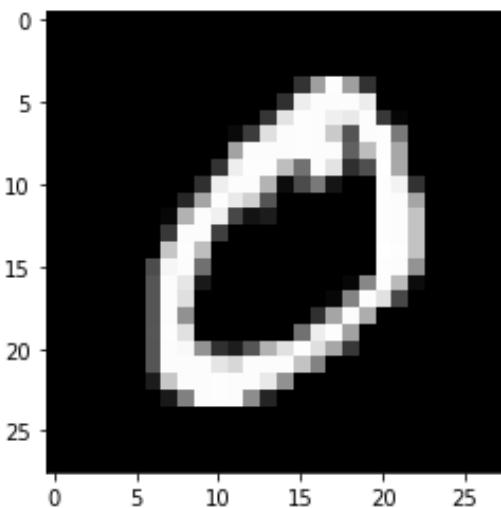


```
from keras.datasets import mnist
```

```
(train_x, train_y), (test_x, test_y) = mnist.load_data()
```



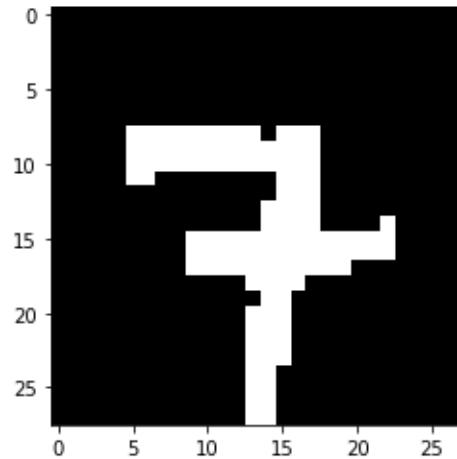
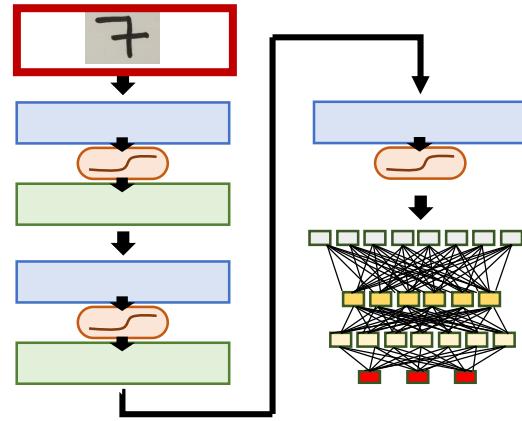
```
plt.imshow(train_x[1,:,:], cmap = 'gray')
```





LeNet:

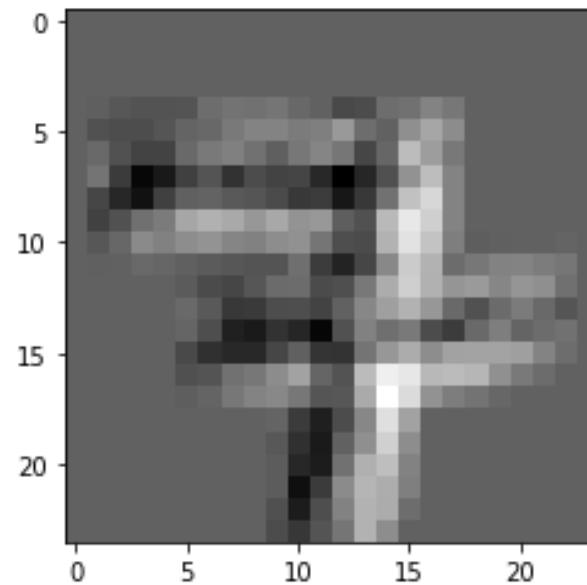
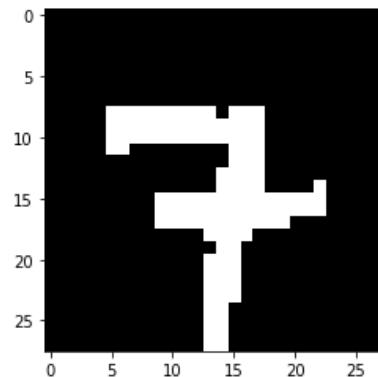
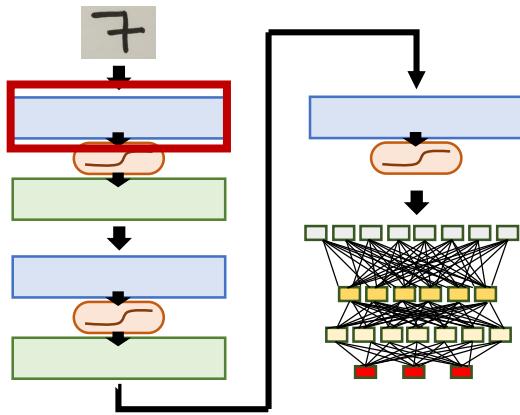
- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998





LeNet:

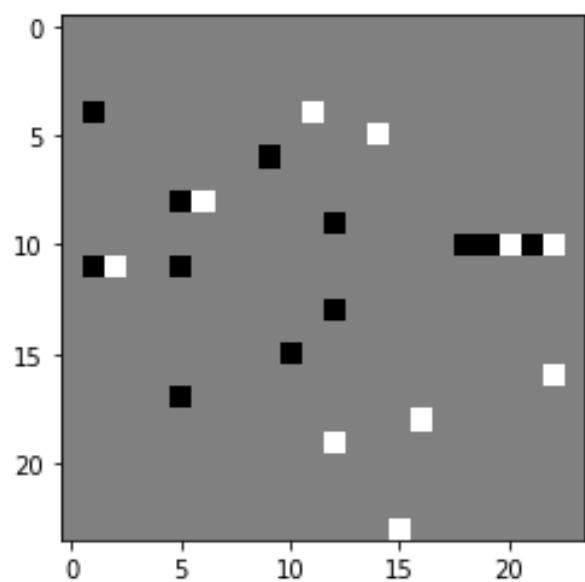
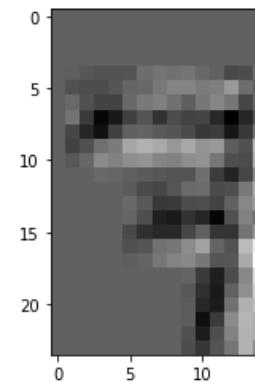
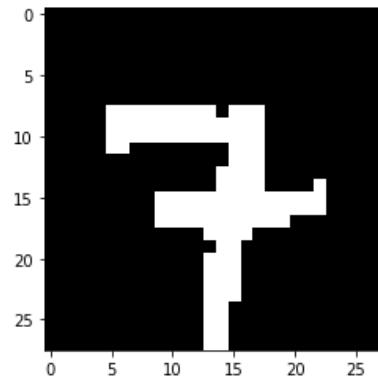
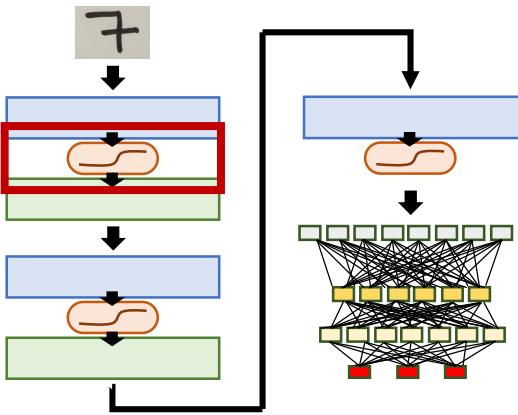
- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998





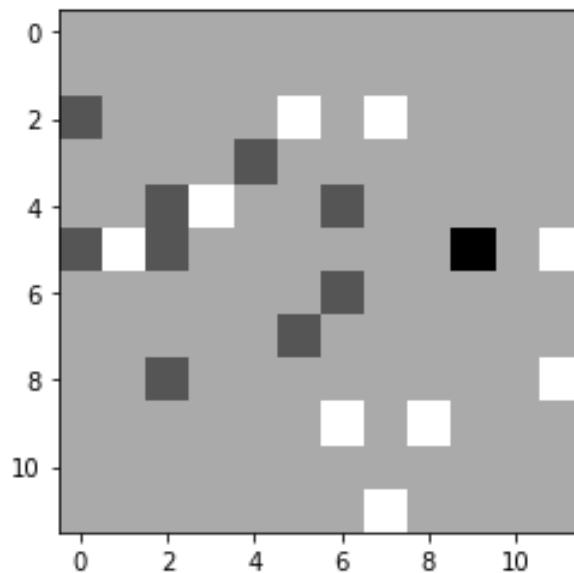
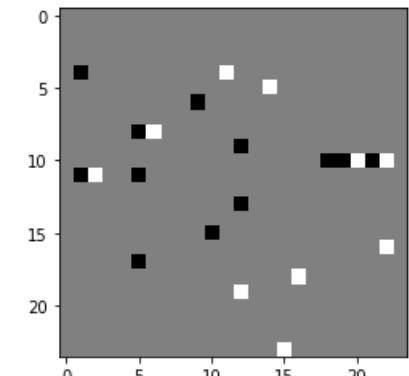
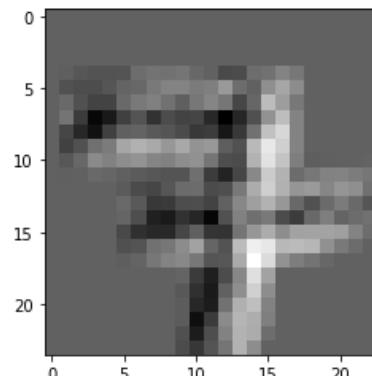
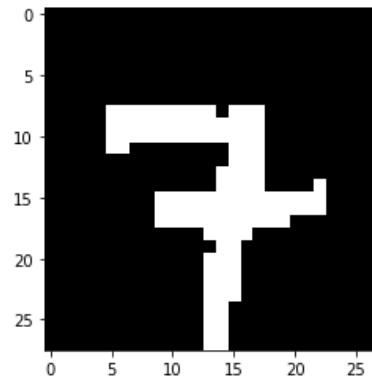
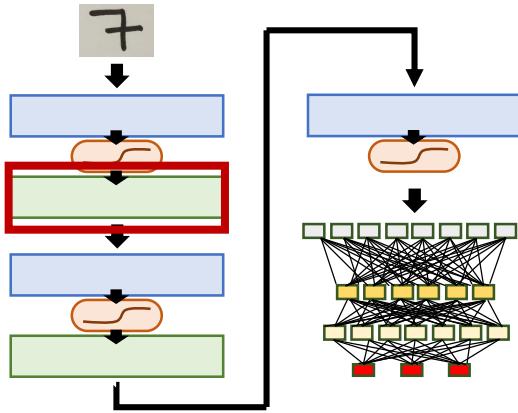
LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



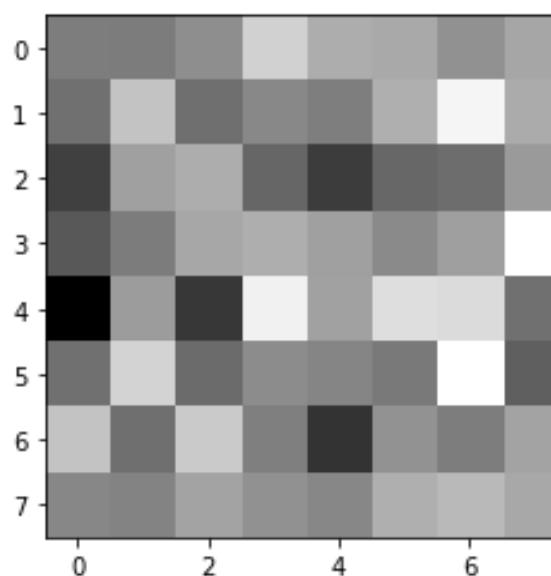
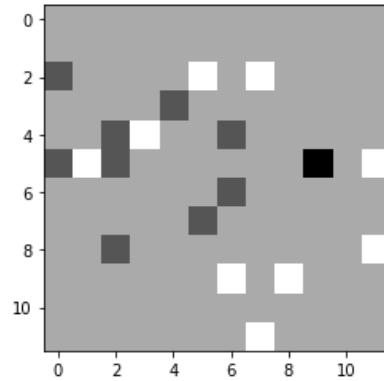
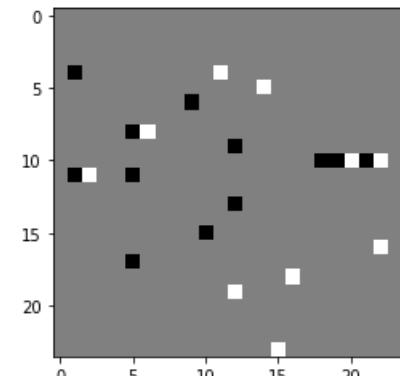
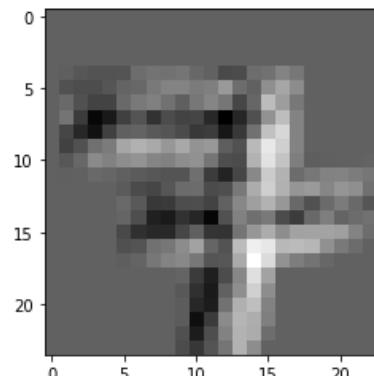
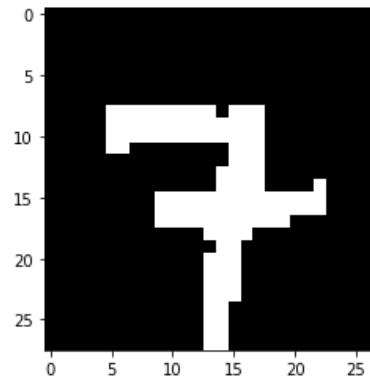
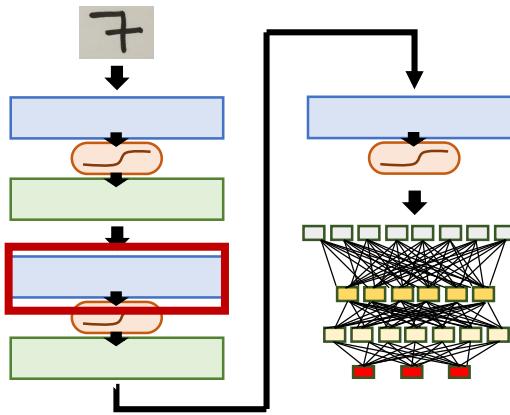
LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



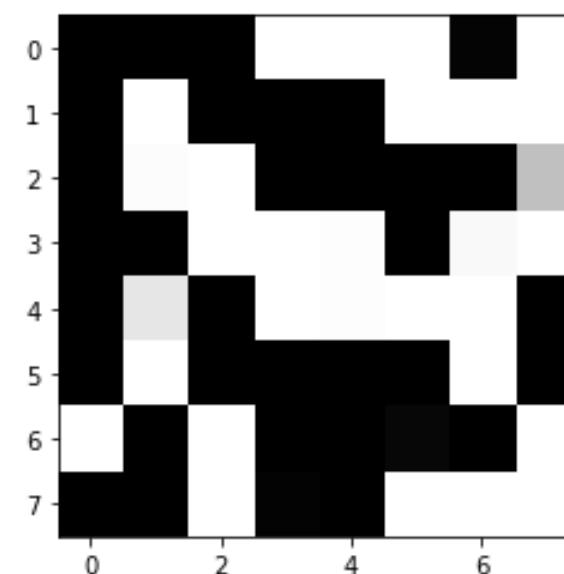
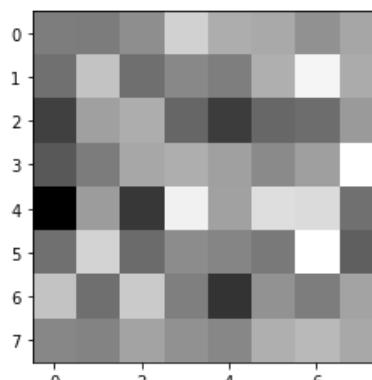
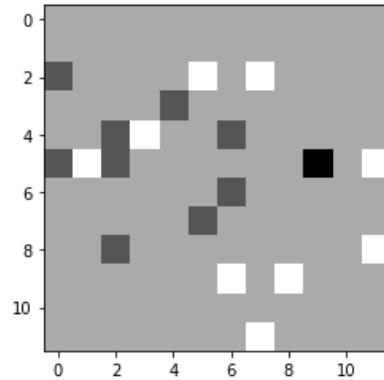
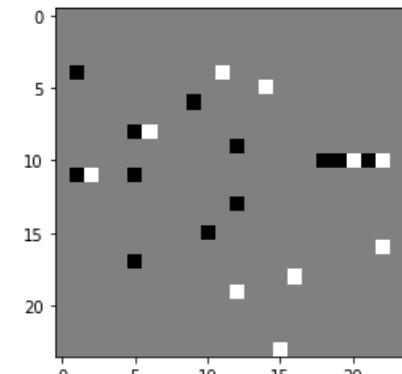
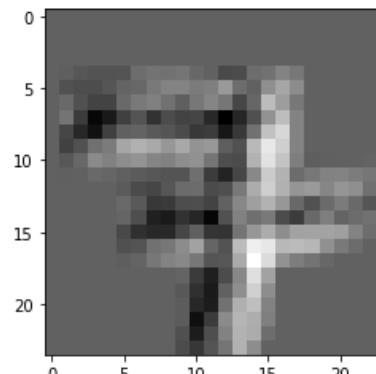
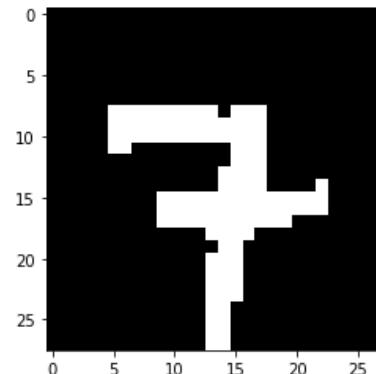
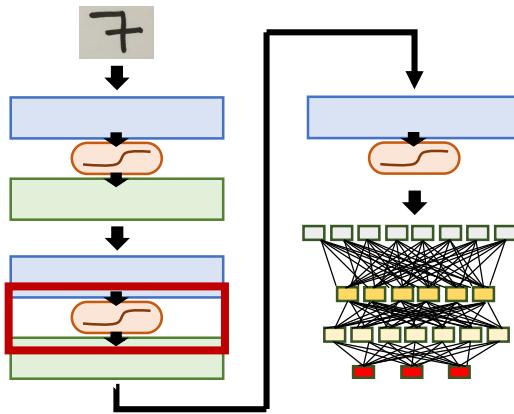
LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



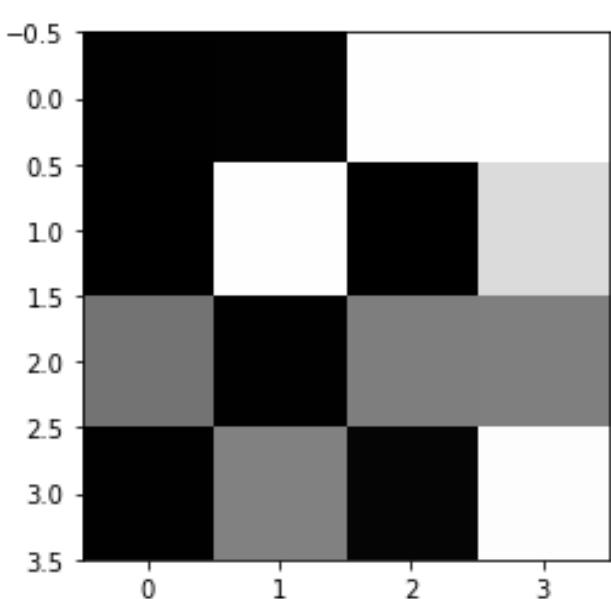
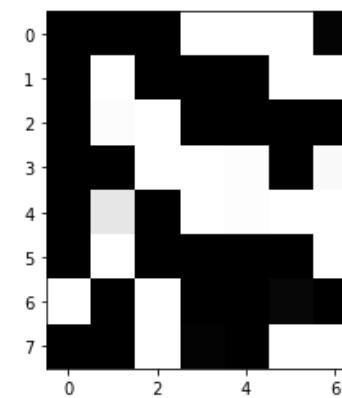
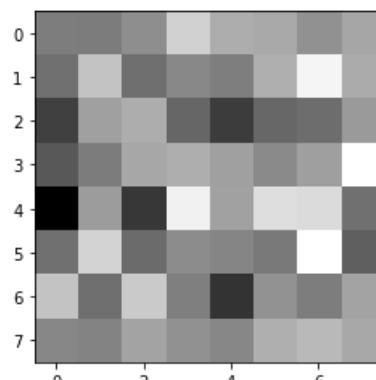
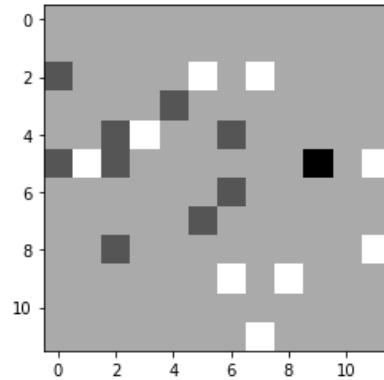
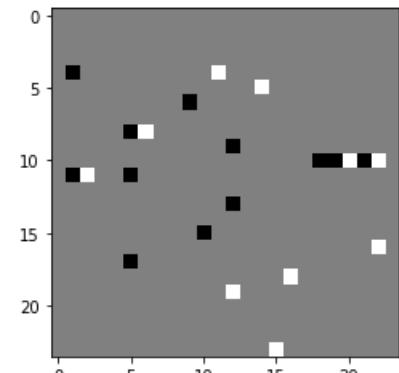
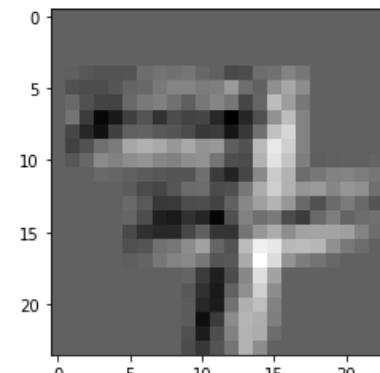
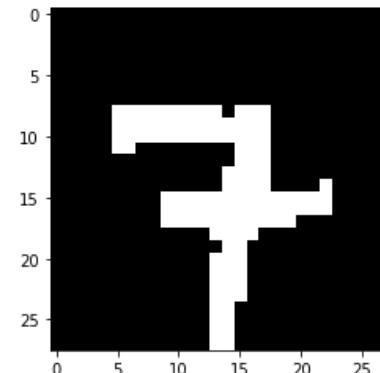
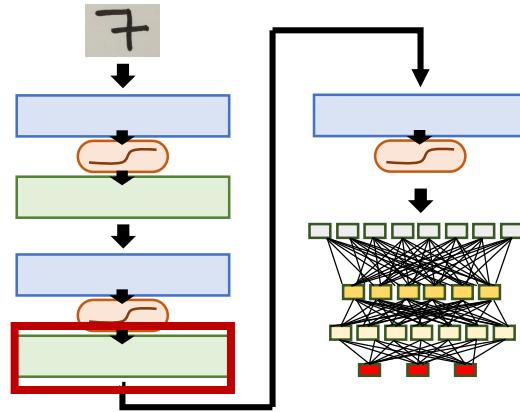
LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



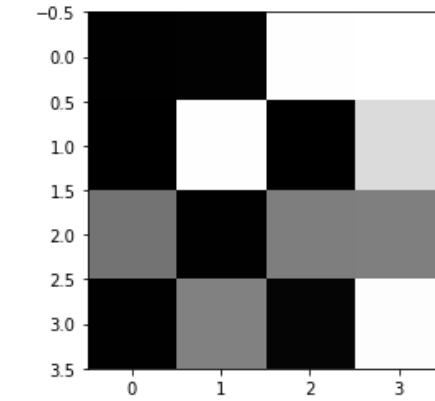
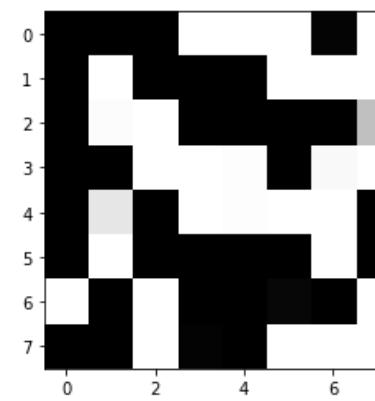
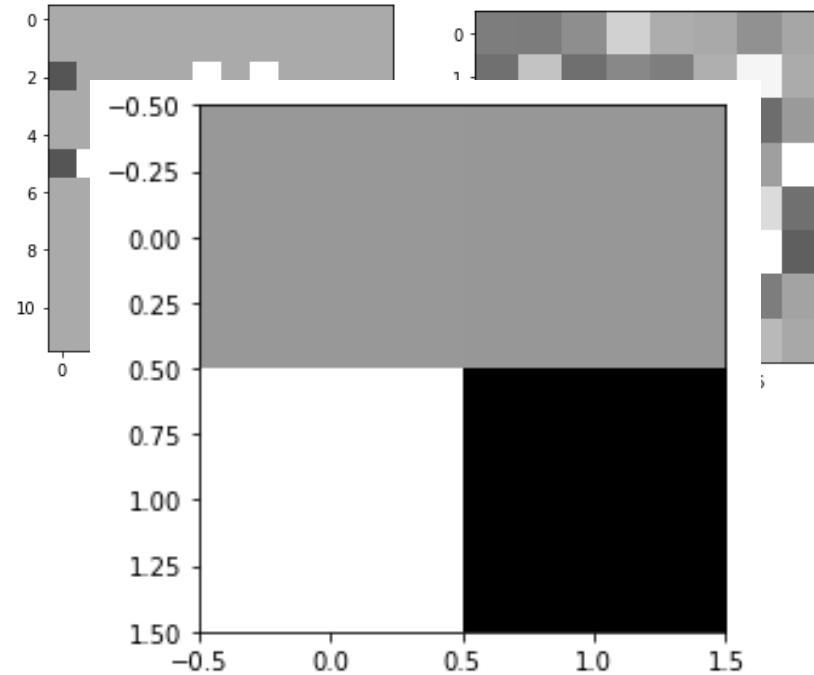
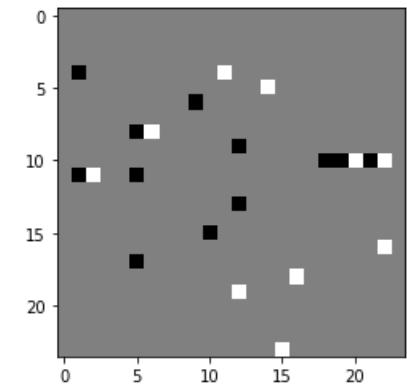
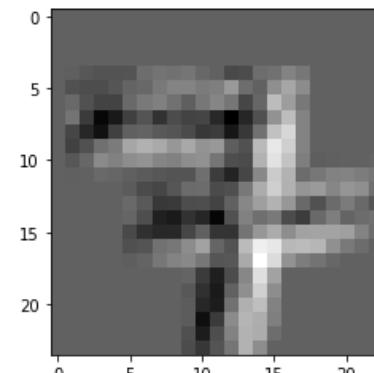
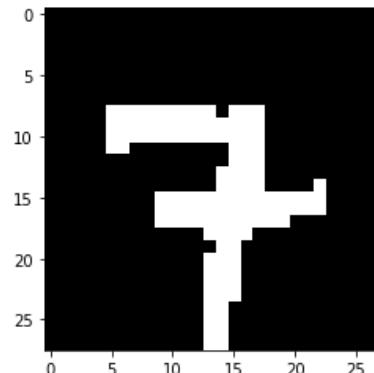
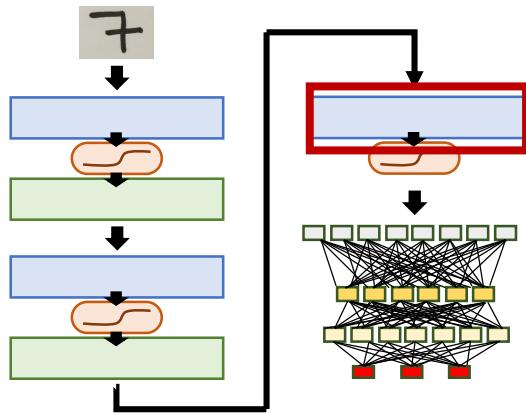
LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



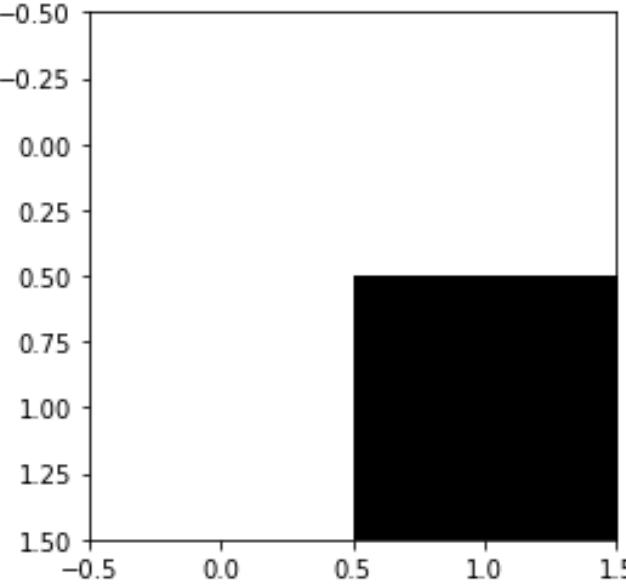
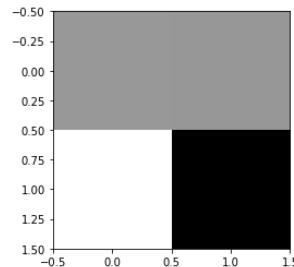
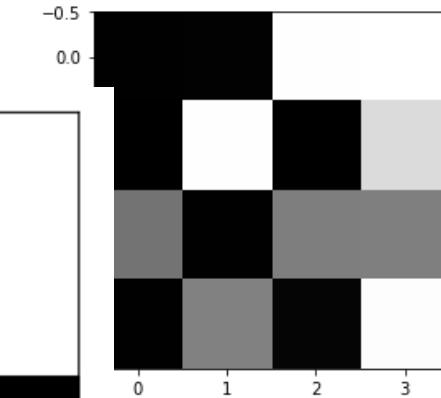
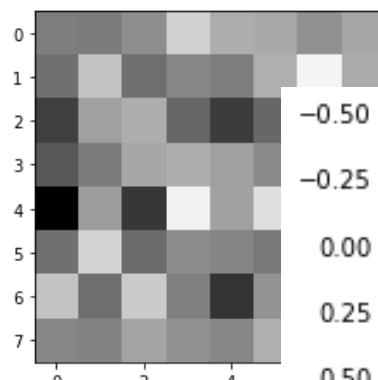
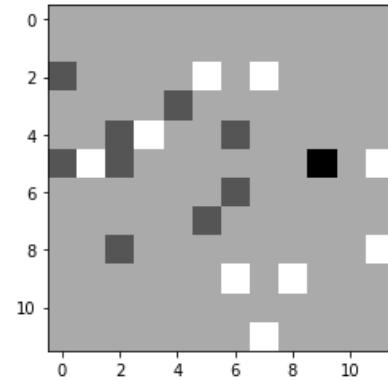
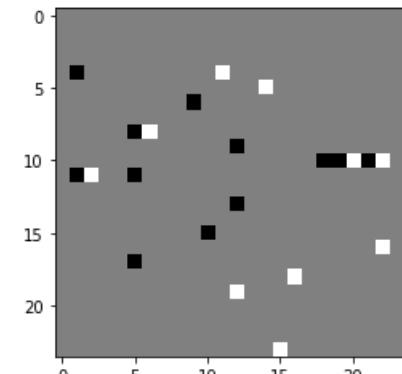
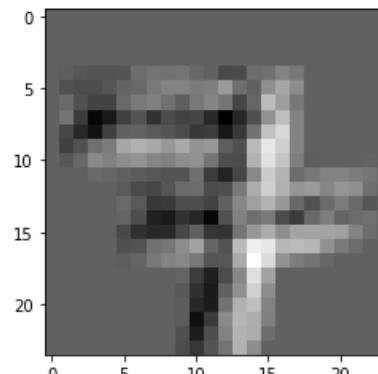
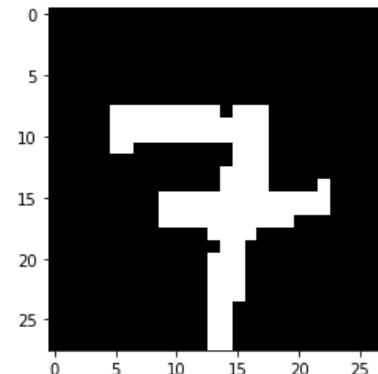
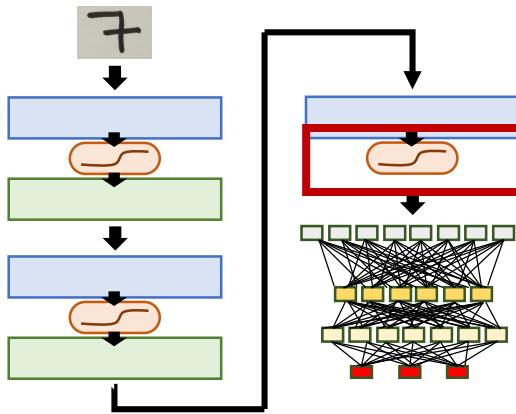
LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



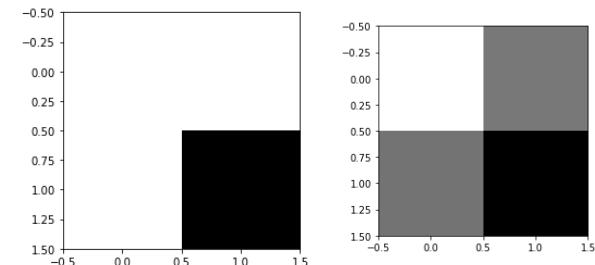
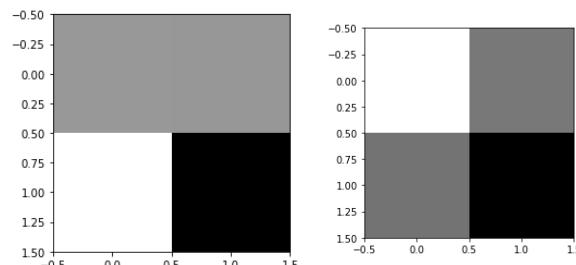
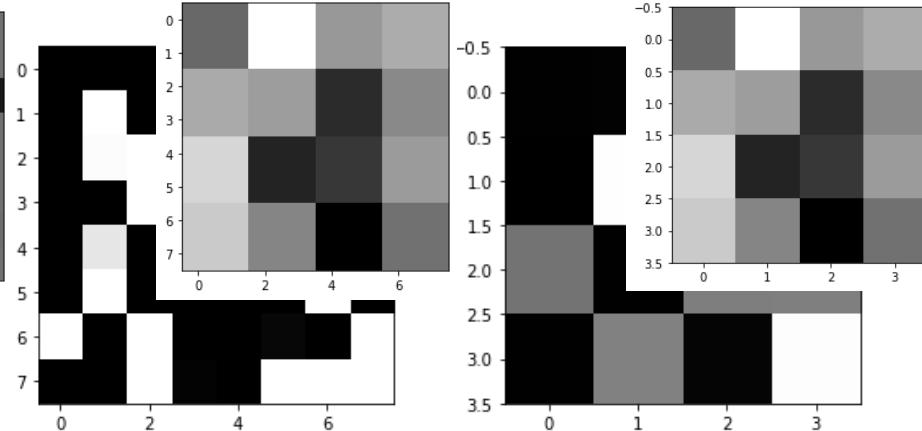
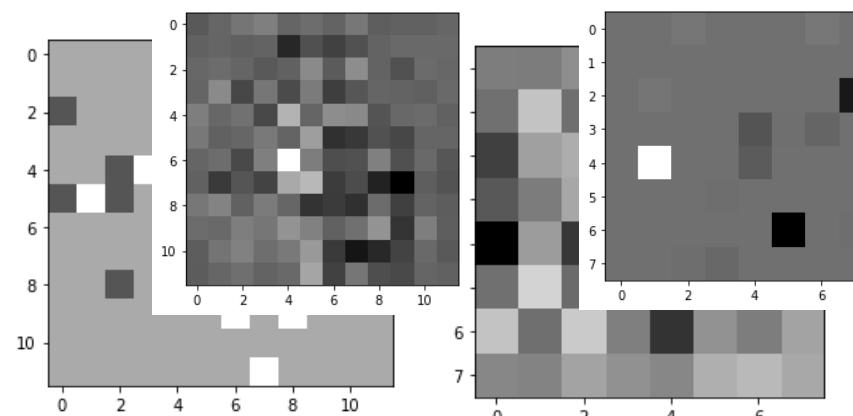
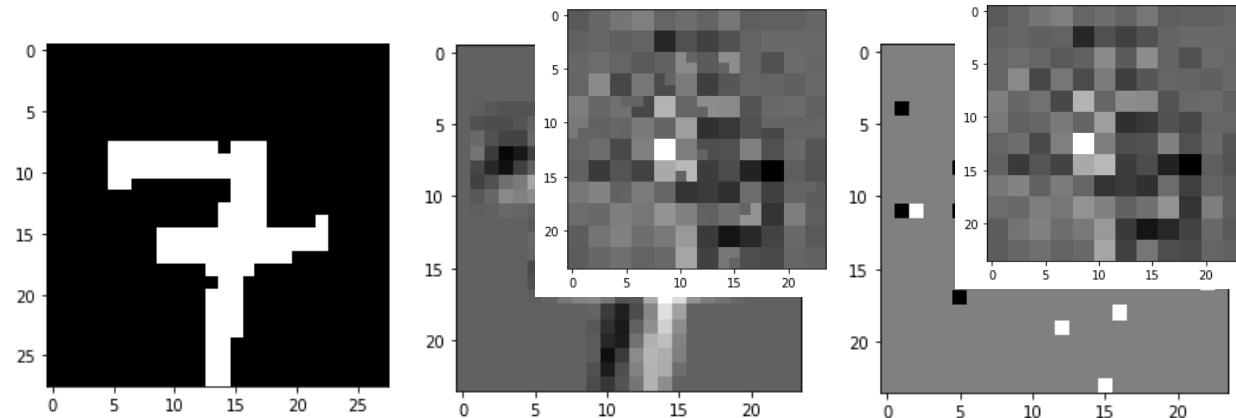
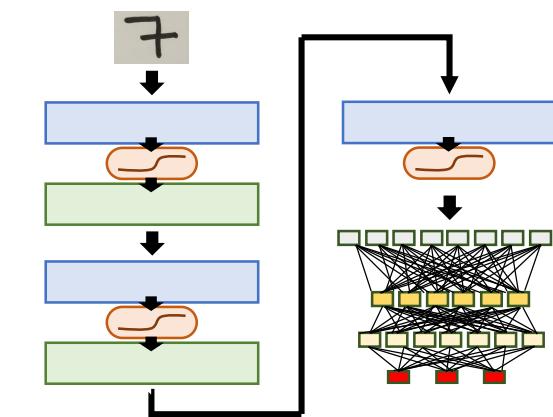
LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

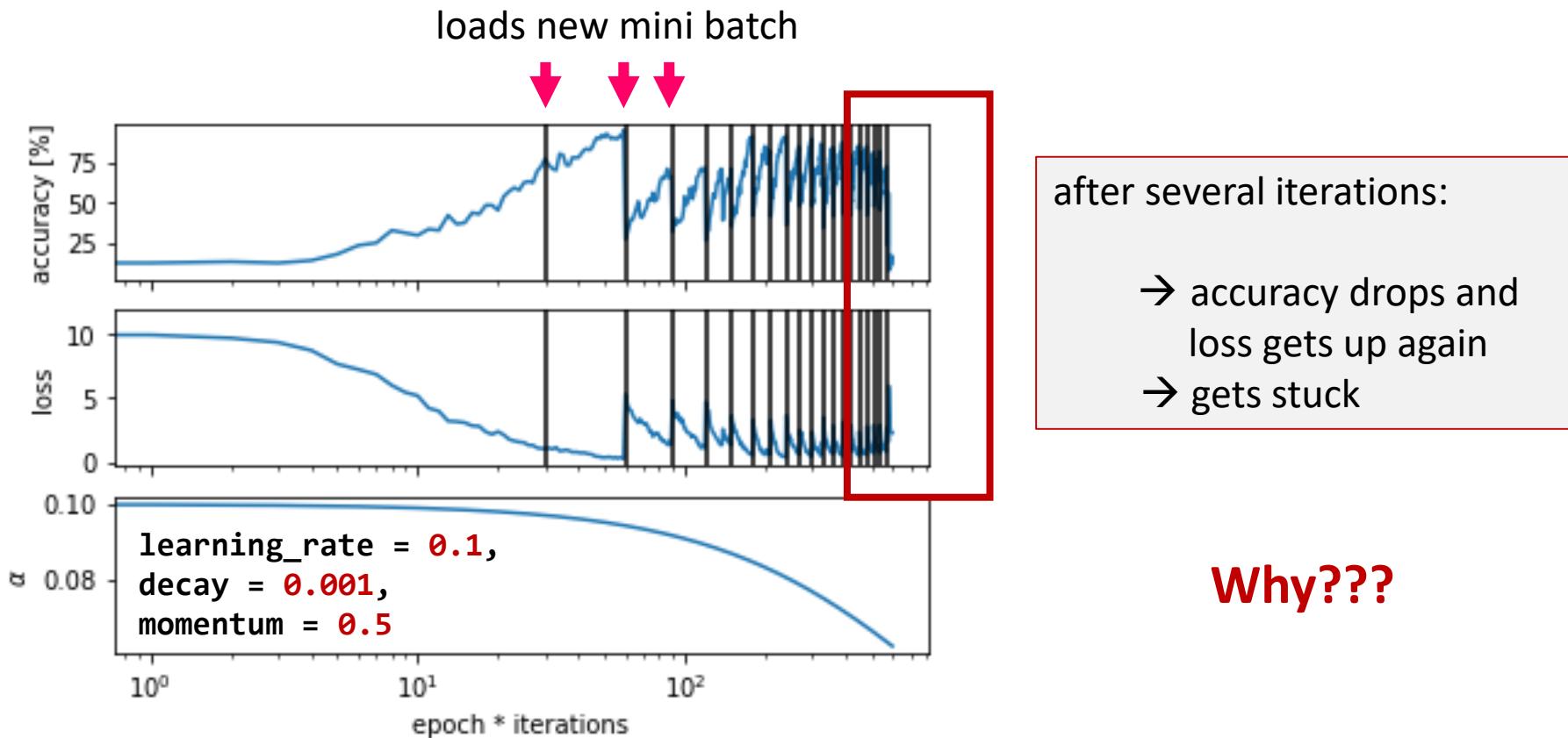
now back propagation!



LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

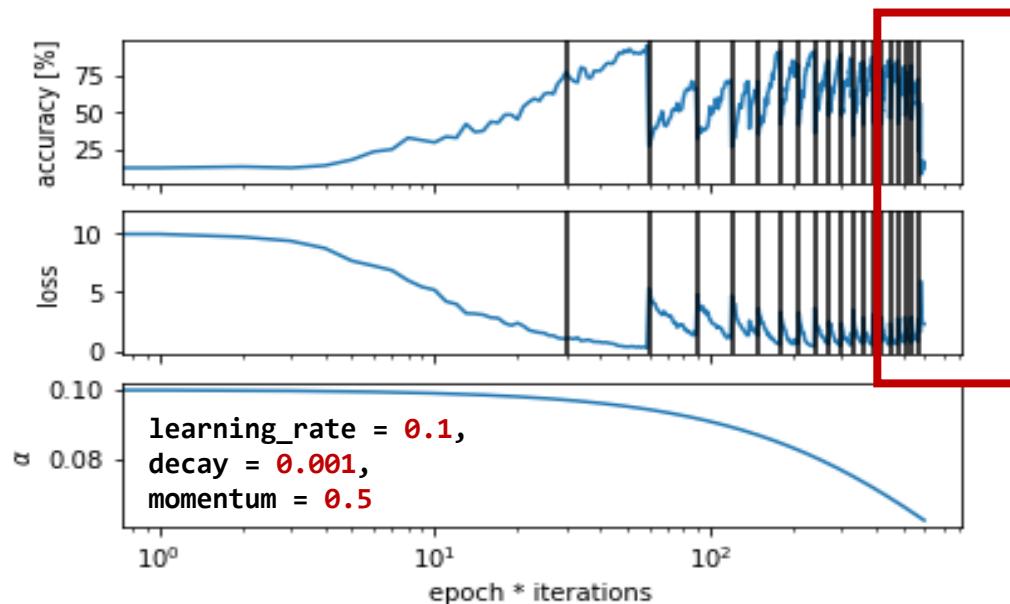
The function MyLeNet runs LeNet (MyANN) with the MNIST data set

```
LeNet = MyLeNet()  
LeNet.RunTraining()
```



LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998



Weights are exploding!

→ penalizing large weights
→ L1 & L2 regularization

```
W = np.load('weightsC1.npy')
```

```
W[:, :, 0]
```

	0	1	2	3	4	5
0	-15923.3	-16647.4	-16277.1	-16993.1	-15715.7	-15390.1
1	9795.1	8468.91	9110.83	8205.6	9852.06	11061
2	37956.4	36572.6	37324.2	37008.4	37485.4	38515.2
3	39686.6	39131	39087.4	39614.6	39421.7	39876.7
4	25465.3	26270.1	25232.4	25836.7	25590.5	25270.9

LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

Weights are exploding!

- penalizing large weights
- L1 & L2 regularization

adding a **linear (L1)** and/or
a **quadratic (L2)** term here



$$\rho_{i+1} = \rho_i + \mu \cdot \mu_i - \alpha \cdot \text{grad}(E)_{\rho_i} + 2 \cdot l_2 \rho_i$$

$$\mu_{i+1} = \mu \cdot \mu_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

- derivative (gradient!)
of L2 term $l_2 \rho_i^2$

- new hyper parameter l_2

Hence, for every learnable (`__init__` part of convolution and dense layer), we add:

```
L2 = 1e-2
self.weights_L2 = L2
self.biases_L2 = L2
```

LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

Weights are exploding!

- penalizing large weights
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$$\rho_{i+1} = \rho_i + \mu \cdot \mu_i - \alpha \cdot \text{grad}(E)_{\rho_i} + \boxed{2 \cdot l_2 \rho_i}$$

- derivative (gradient!)
of L2 term $l_2 \rho_i^2$

$$\mu_{i+1} = \mu \cdot \mu_i - \alpha \cdot \text{grad}(E)_{\rho_i}$$

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Hence, for every learnable (__init__ part of convolution and dense layer), we add:

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L2 = 1e-2  
self.weights_L2 = L2  
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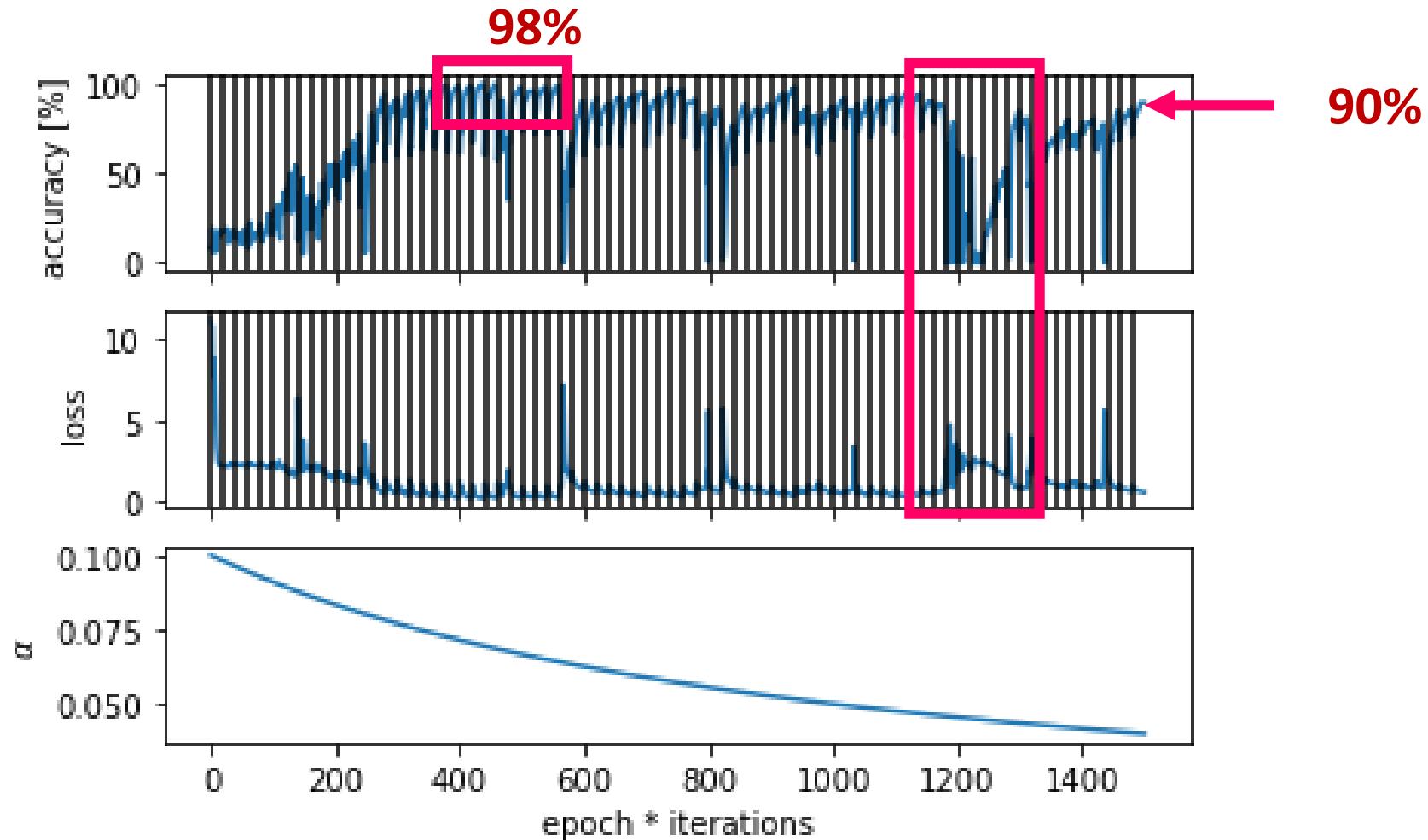
thus, for every **backpropagation** part of the convolution and dense layer, we add:

```
self.dbiases = dbiases + 2* self.biases_L2 * self.biases  
self.dweights = dweights + 2* self.weights_L2 * self.weights
```

LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

run the function `MyLeNet` again, but this time with L2

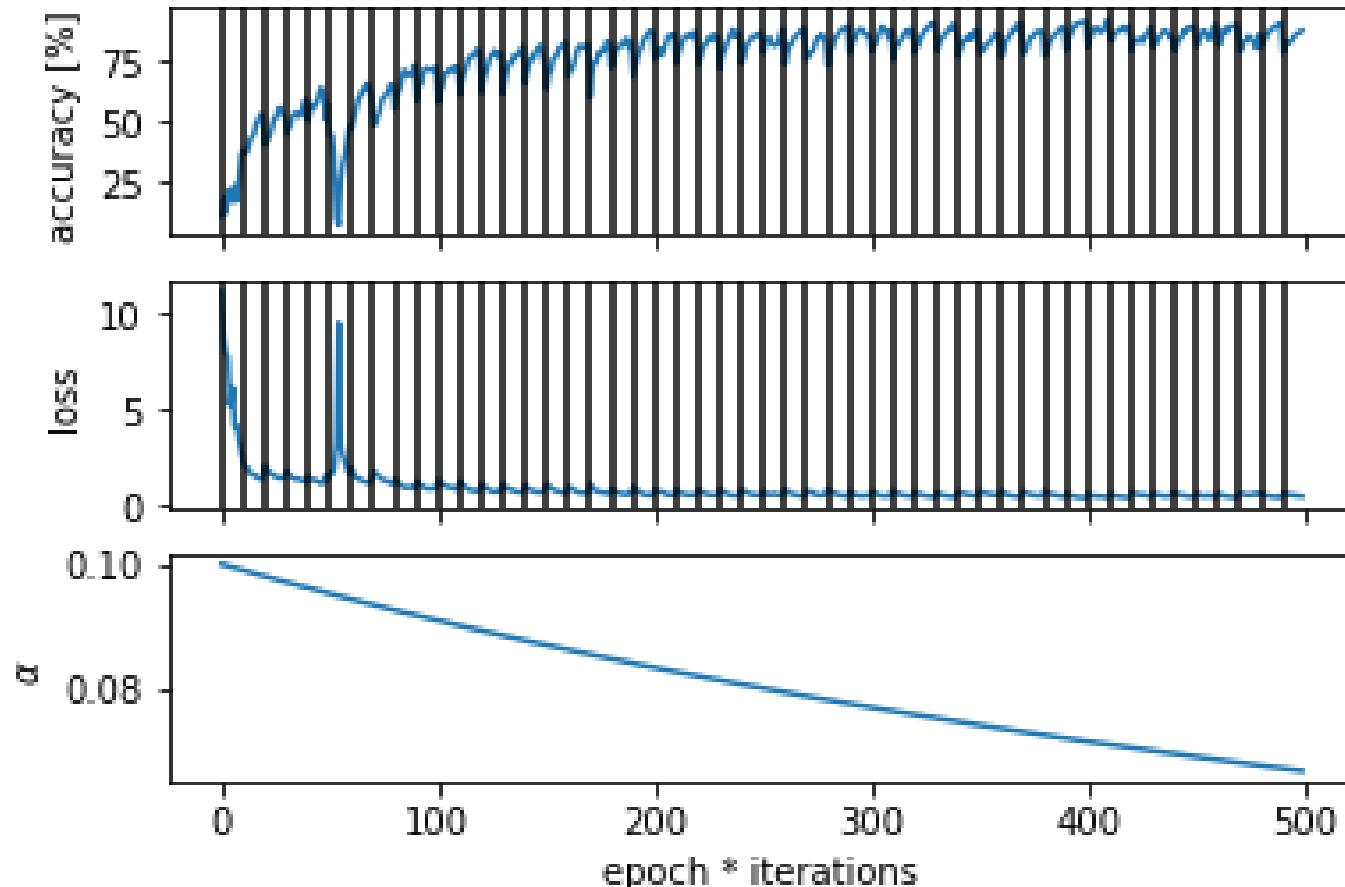


LeNet:

- Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

run the function `MyLeNet` again, but this time with L2

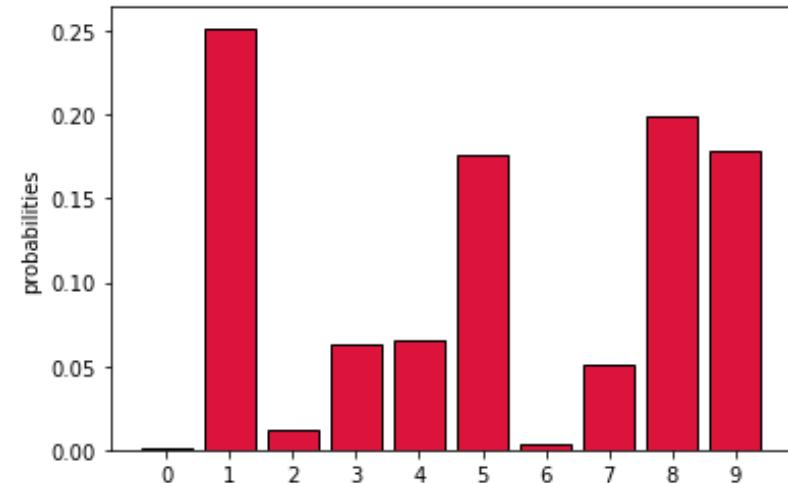
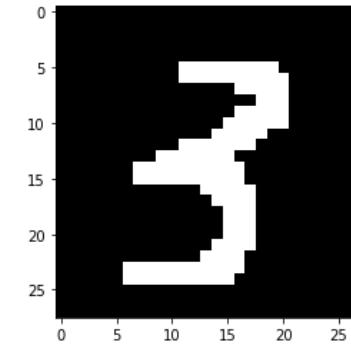
`minibatch_size = 512, iterations = 10, epochs = 50`





LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

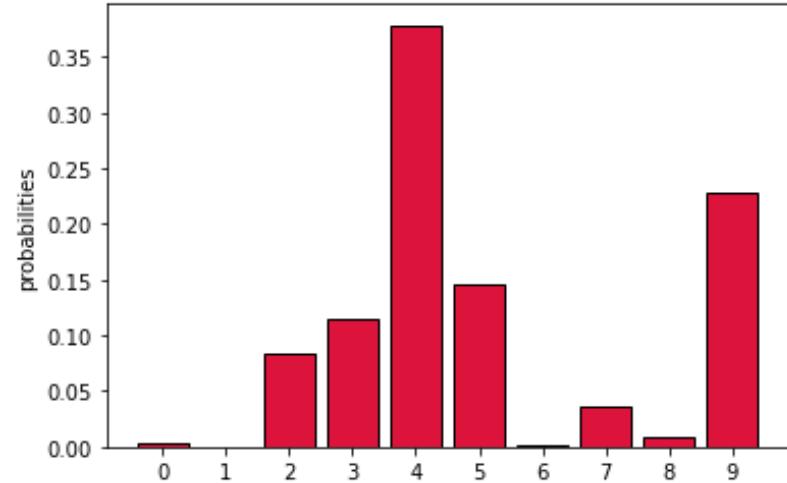
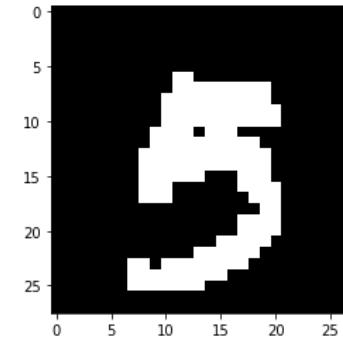
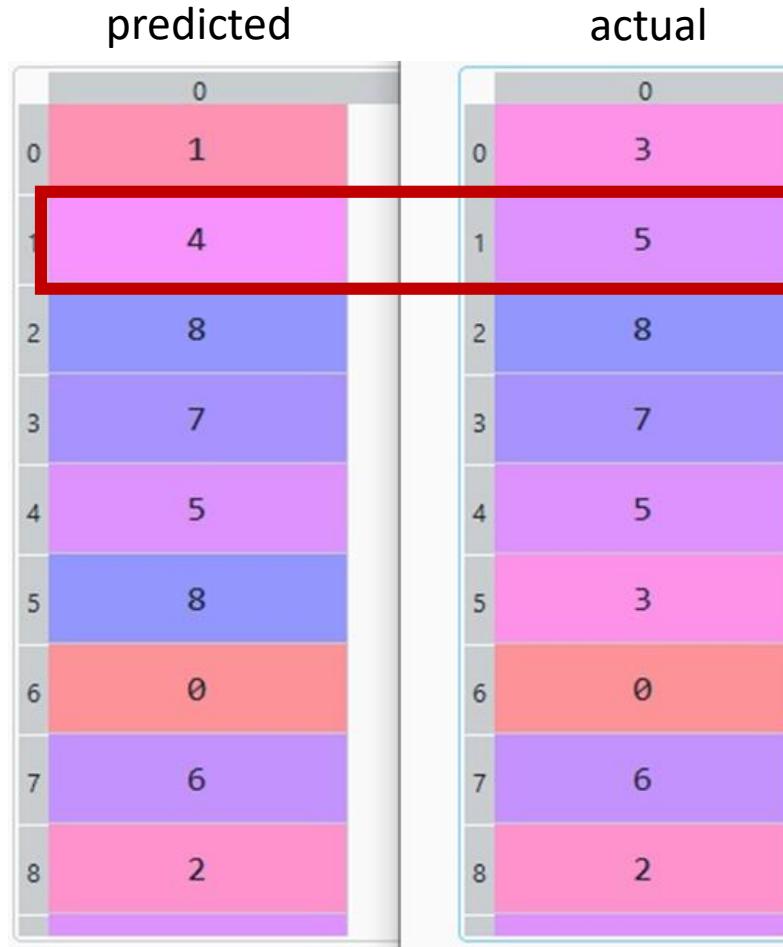
Now, we can apply/evaluate the ANN EvaluateMyLeNet($N = 50$)





LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

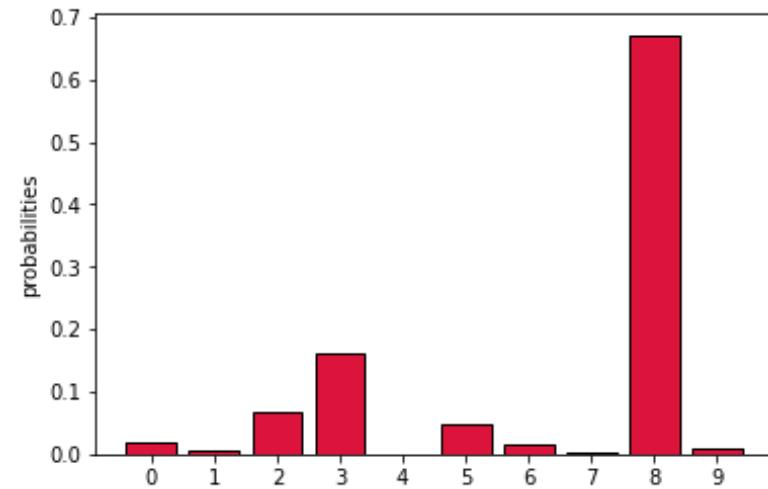
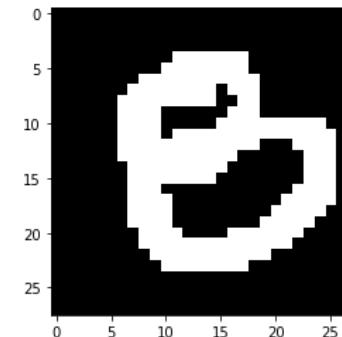
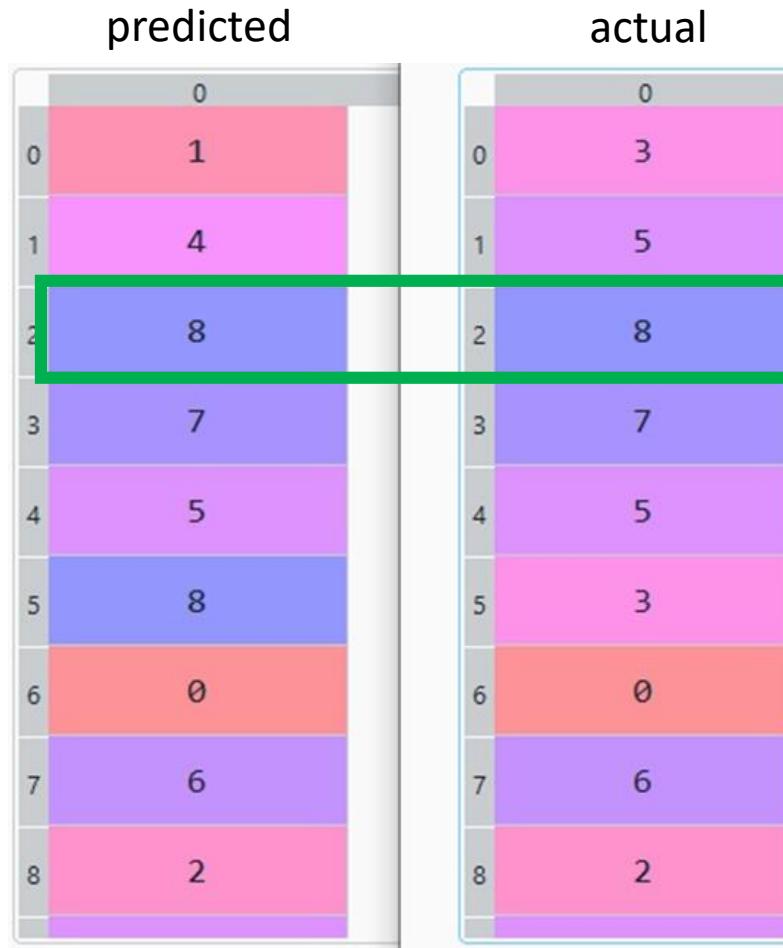
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LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

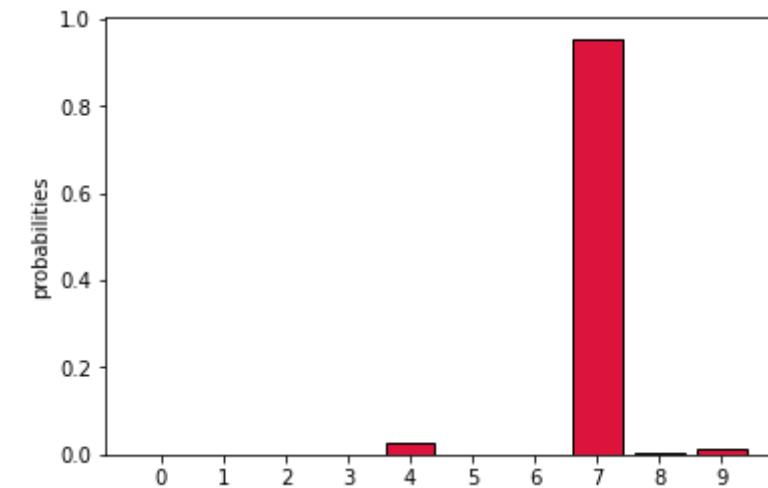
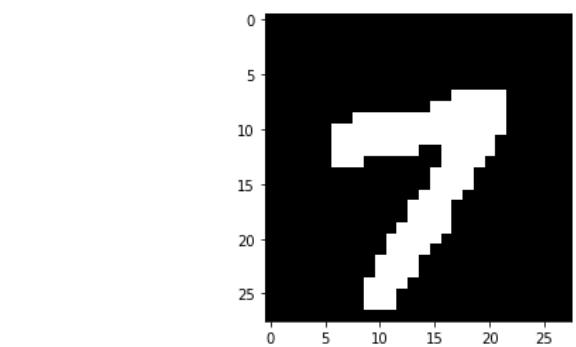
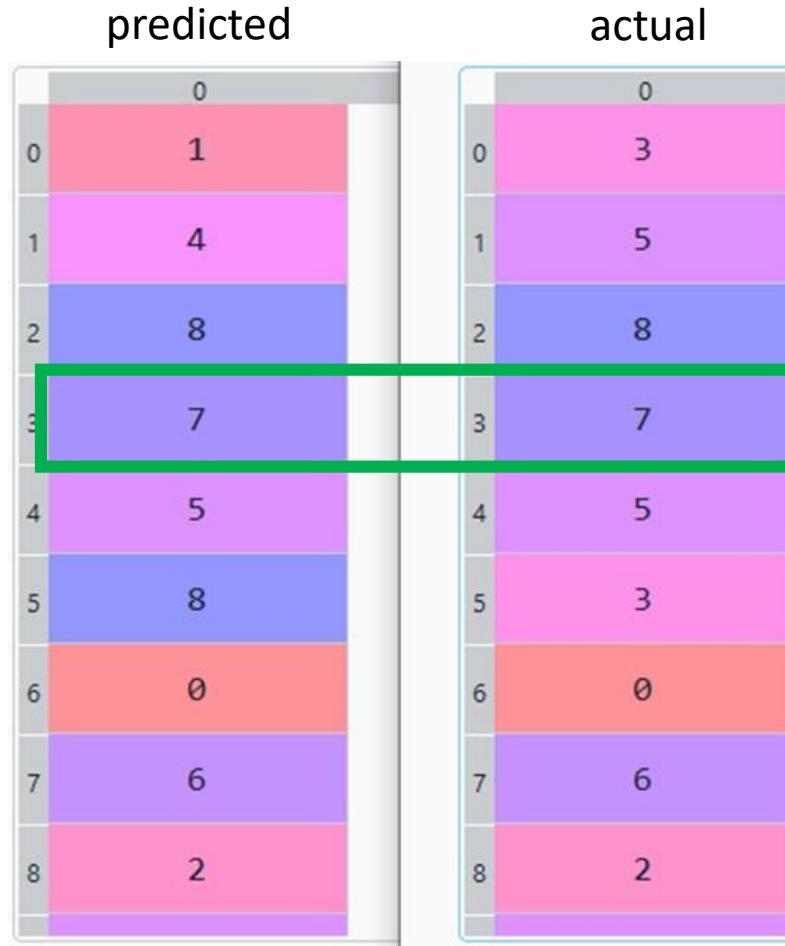
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LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

Now, we can apply/evaluate the ANN EvaluateMyLeNet($N = 50$)





LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

Now, we can apply/evaluate the ANN EvaluateMyLeNet($N = 50$)

	predicted	actual
0	1	3
1	4	5
2	8	8
3	7	7
4	5	5
5	8	3
6	0	0
7	6	6
8	2	2

and so on...

**homework: train the ANN with
the pet pics and evaluate the results!**



LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

let us compare our code to the **actual tensorflow version** of LeNet:

→ explore the file LeNetTF.py

creates LeNet as class

```
LeNetTF.py
├── # run the module like eg.
└── MyLeNet
    ├── __init__.py
    └── CallData
        └── CallMNIST.py
└── Model
    ├── Run.py
    └── Eval.py
```

```
class MyLeNet(Sequential):
    def __init__(self, input_shape, nb_classes):
        super().__init__()

        self.add(Conv2D(6, kernel_size=(5, 5), strides=(1, 1), activation='tanh', input_shape=input_shape, padding="same"))
        self.add(AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))
        self.add(Conv2D(16, kernel_size=(5, 5), strides=(1, 1), activation='tanh', padding='valid'))
        self.add(AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))
        self.add(Conv2D(120, kernel_size=(5, 5), strides=(3, 3), activation='tanh', padding='valid'))
        self.add(Flatten())
        self.add(Dense(84, activation='tanh'))
        self.add(Dense(nb_classes, activation='softmax'))

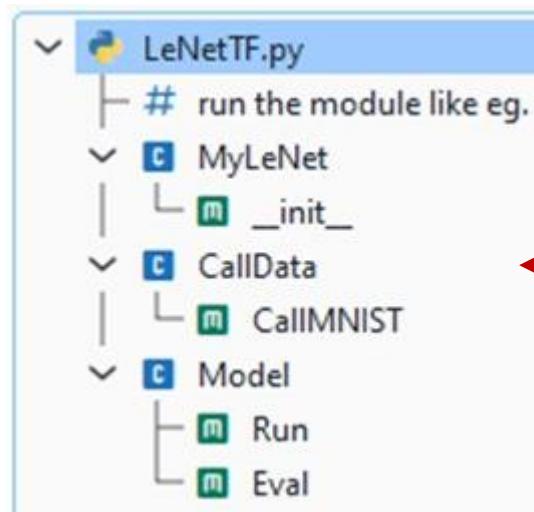
        sgd = tf.keras.optimizers.SGD(learning_rate=0.01, momentum=0.9,
                                     nesterov=True)
        self.compile(optimizer=sgd,
                     loss='categorical_crossentropy',
                     metrics=['accuracy'])
```



LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

let us compare our code to the **actual tensorflow version** of LeNet:

→ explore the file LeNetTF.py



← just calls and preprocesses the data set

note these two lines:

```
Train_y = to_categorical(Train_y, num_classes)
Test_y = to_categorical(Test_y, num_classes)
```

without that Tensor Flow will create a confusing error message
when using categorical cross entropy for optimization

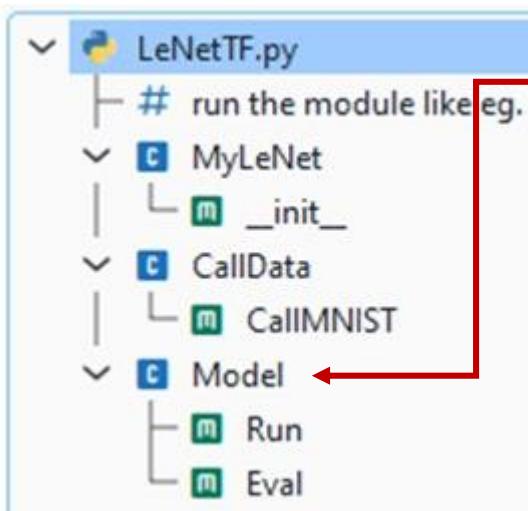
*shapes (none, 1) and (none, 10) are
incompatible categorical_crossentropy*



LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

let us compare our code to the **actual tensorflow version** of LeNet:

→ explore the file LeNetTF.py



we only need to run this part:

Run: trains the model

Eval: evaluates the model

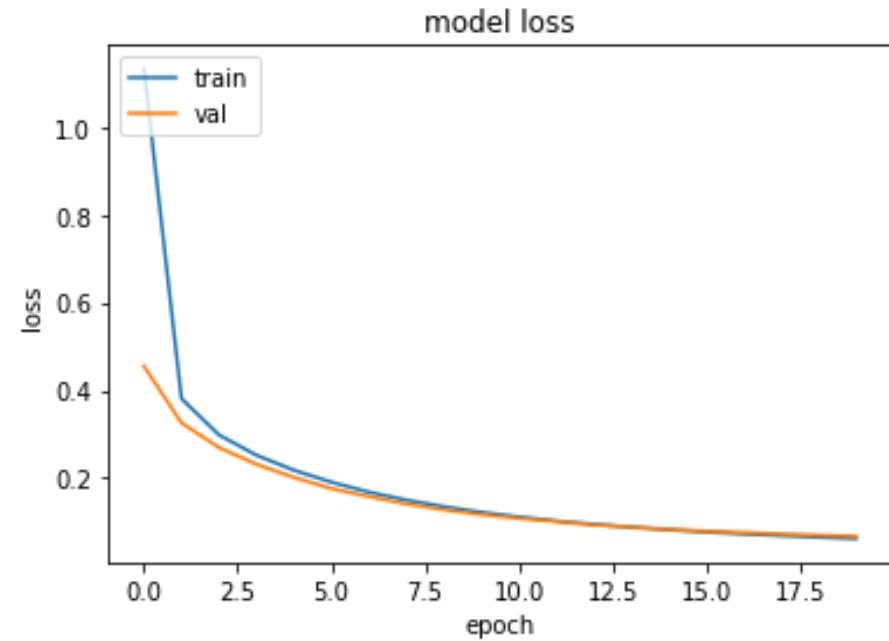
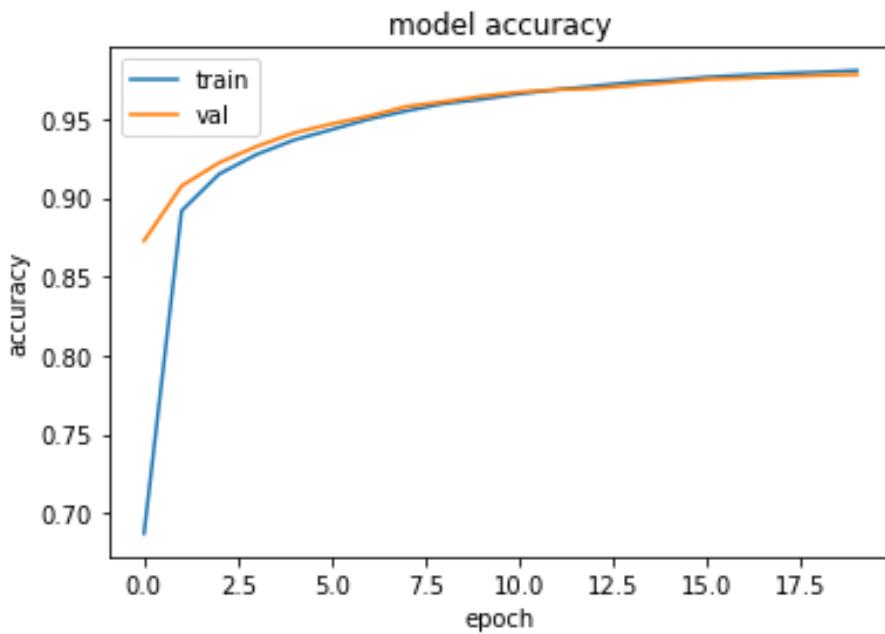
run the model with e.g.

```
import LeNetTF as L
M = L.Model()
M.Run(20)
M.Eval()
```



LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

```
import LeNetTF as L  
M = L.Model()  
M.Run(20)  
M.Eval()
```



It is 100 times faster than our code!!



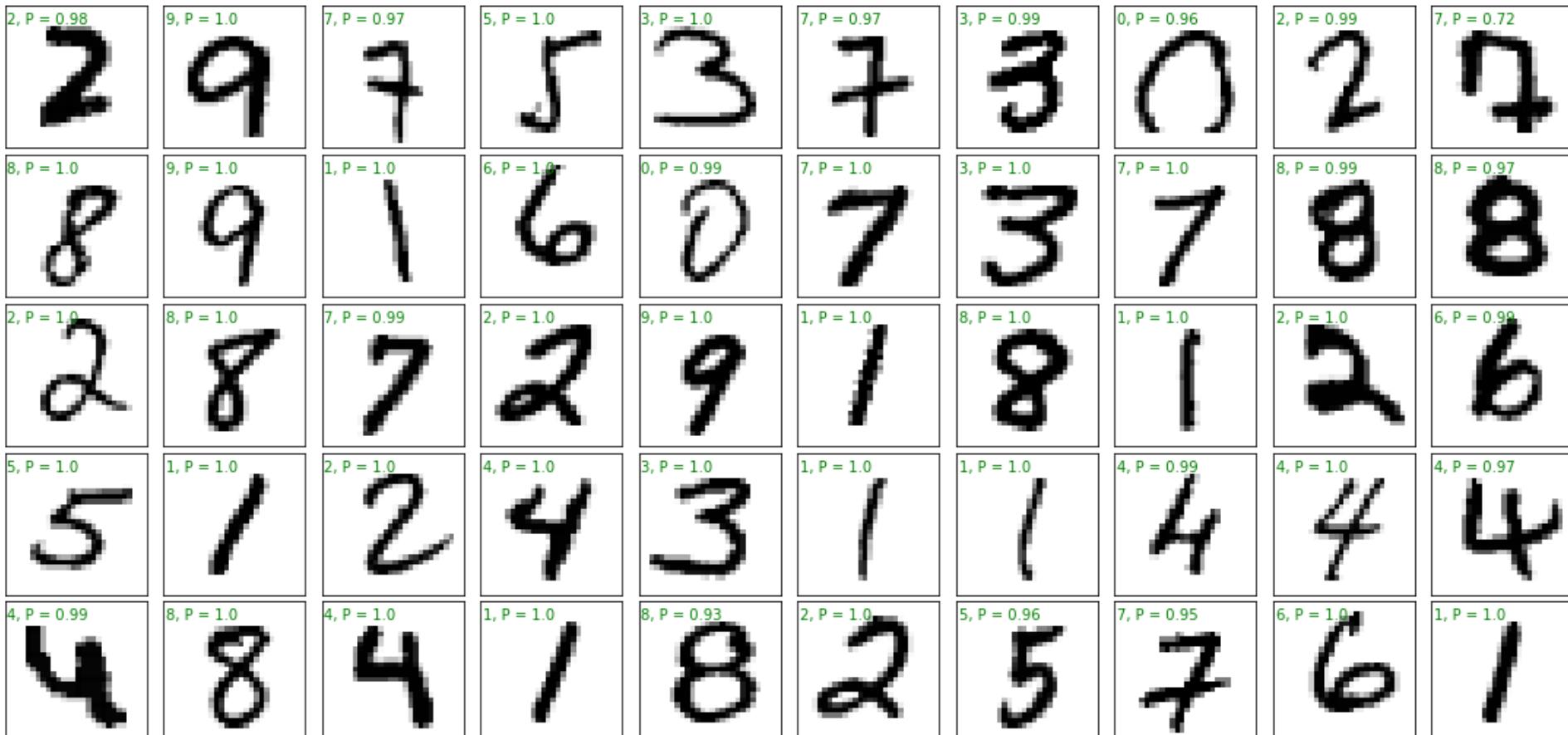
LeNet: - Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, 1998

```
import LeNetTF as L
```

```
M = L.Model()
```

```
M.Run(20)
```

```
M.Eval()
```





modern CNNs have an inception architecture

- different filter sizes per layer
- pooled in next layer(s)

segmentation CNNs

- labels *within* each image
- we could use our backpropagation part as decoder (with some slight modifications)

What influences training performance:

- **training params:** learning rate, decay, momentum, L2
- **initialization:** `0.1*np.random.rand` vs `10*np.random.rand`
- **architecture:** number of layers, filter, pooling
- **sample:** minibatch size, number of iterations



modern CNNs have an inception architecture

- different filter sizes per layer
- pooled in next layer(s)

segmentation CNNs

- labels *within* each image
- we could use our backpropagation part as decoder (with some slight modifications)

Golden Rules of training:

- **diversity:** all kinds of weird angles, blurred, frequency of classes
- **augmentation:** turning/stretching/blurring/random cut out
- **batch effects:** too specific vs too general → pre processing
- **labeling:** as accurate as possible, experience!
- **amount:** the more data the better



Artificial Neuronal Networks in Python

From Scratch!

Part II

Thank you very much for your attention!