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Convolutional Neural Networks basics

and an example with classification

(LENS ML School 2021; Emmanouela Rantsiou)

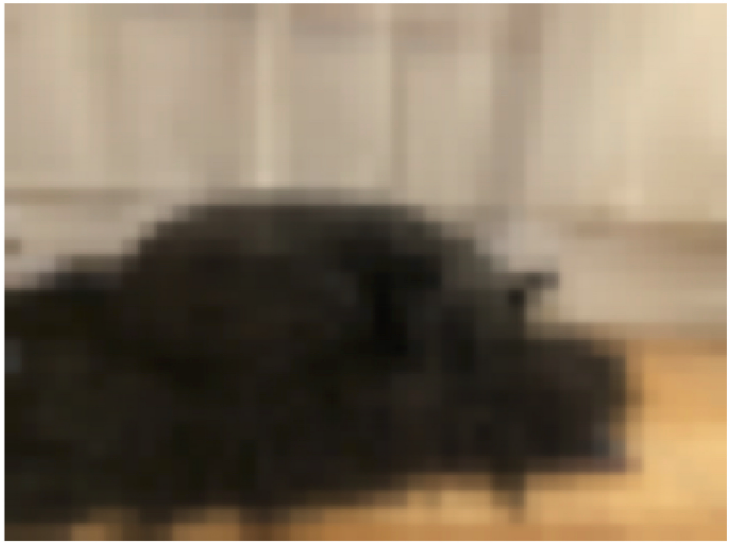
Convolutional Neural Networks (CNN, ConvNet)

- a class of artificial Neural Networks
- widely used in computer vision*
- learn hierarchy of features

*Computer vision is an essential, complex, wide-spread, and ever developing part of AI. Computer vision tasks include:

- Image Classification
- Classification with localization
- Object detection
- Image captioning
- action classification
- Semantic segmentation
- Instance segmentation
- Neural Style Transfer

Why CNNs?



- Need not to be restricted to small input images.
- Image of 1300 X 1300px --> Input on a layer of a FC (Dense) network with e.g. 1000 hidden units $\rightarrow$ parameters (weights) to calculate : (1000,1300x1300) = 1.69E9 parameters (x3 for a color image) $\rightarrow$ Computationally expensive and data hungry.

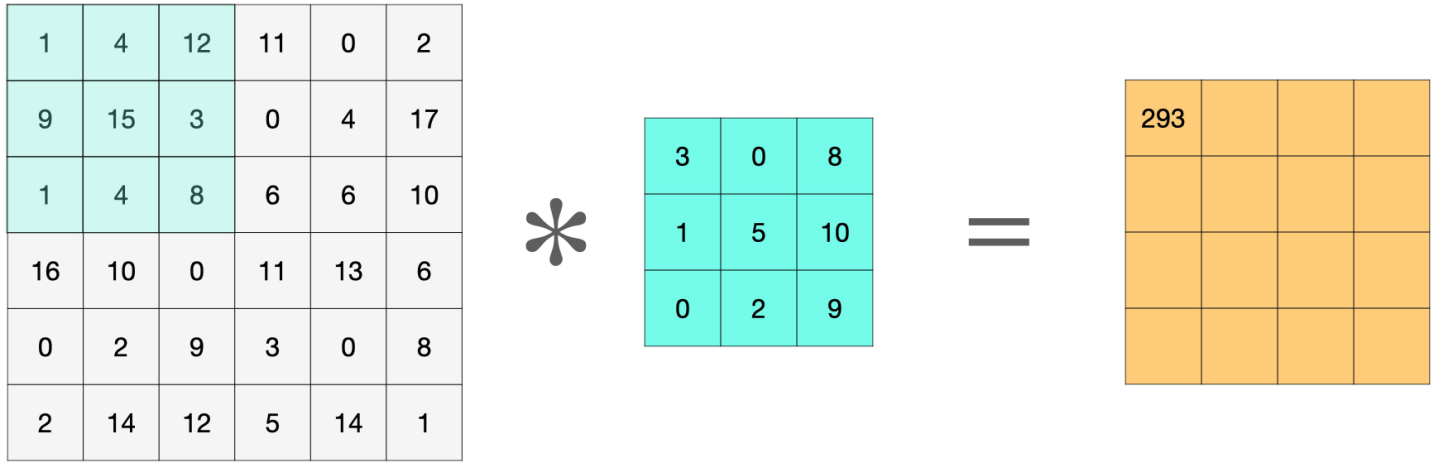
Convolution Operation

IMAGE

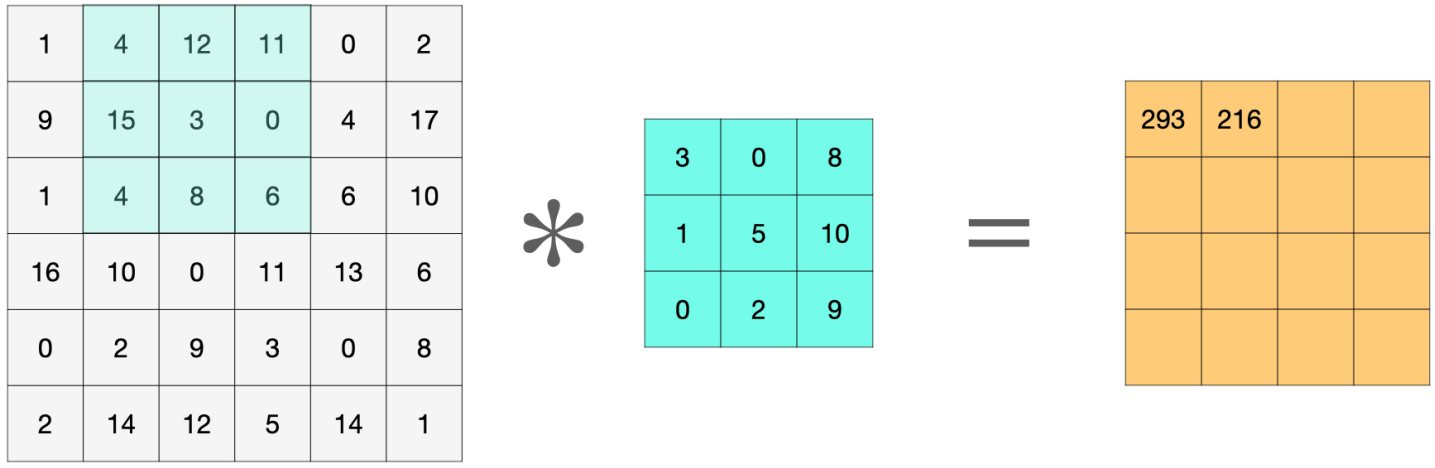
1	4	12	11	0	2
9	15	3	0	4	17
1	4	8	6	6	10
16	10	0	11	13	6
0	2	9	3	0	8
2	14	12	5	14	1

Convolution Kernel (Filter)

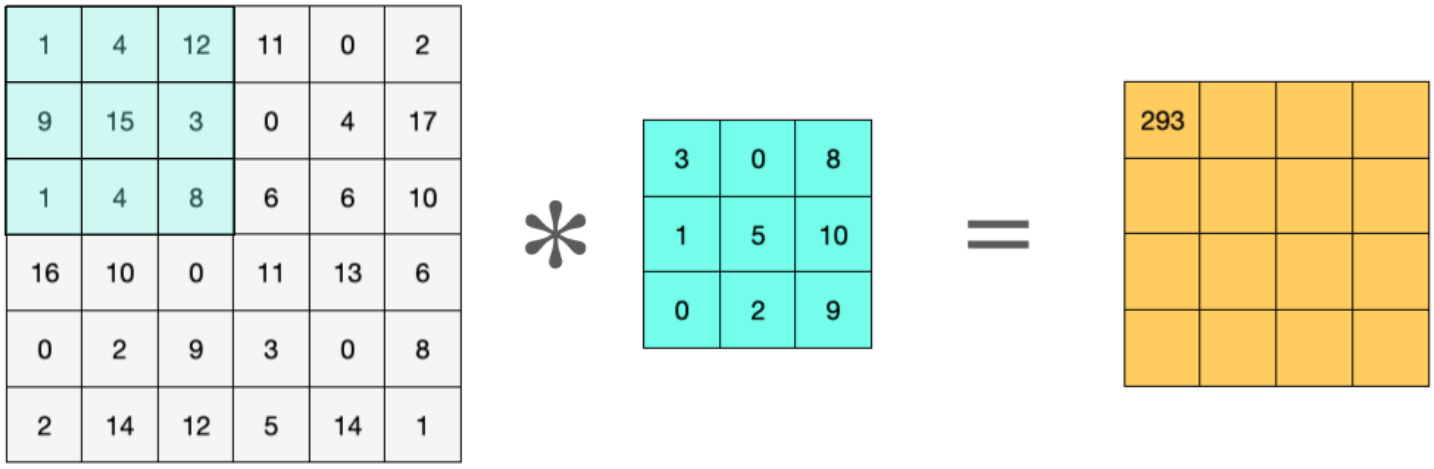
3	0	8
1	5	10
0	2	9



$$1 \times 3 + 4 \times 0 + 12 \times 8 + 9 \times 1 + 15 \times 5 + 3 \times 10 + 1 \times 0 + 4 \times 2 + 8 \times 9 = 293$$



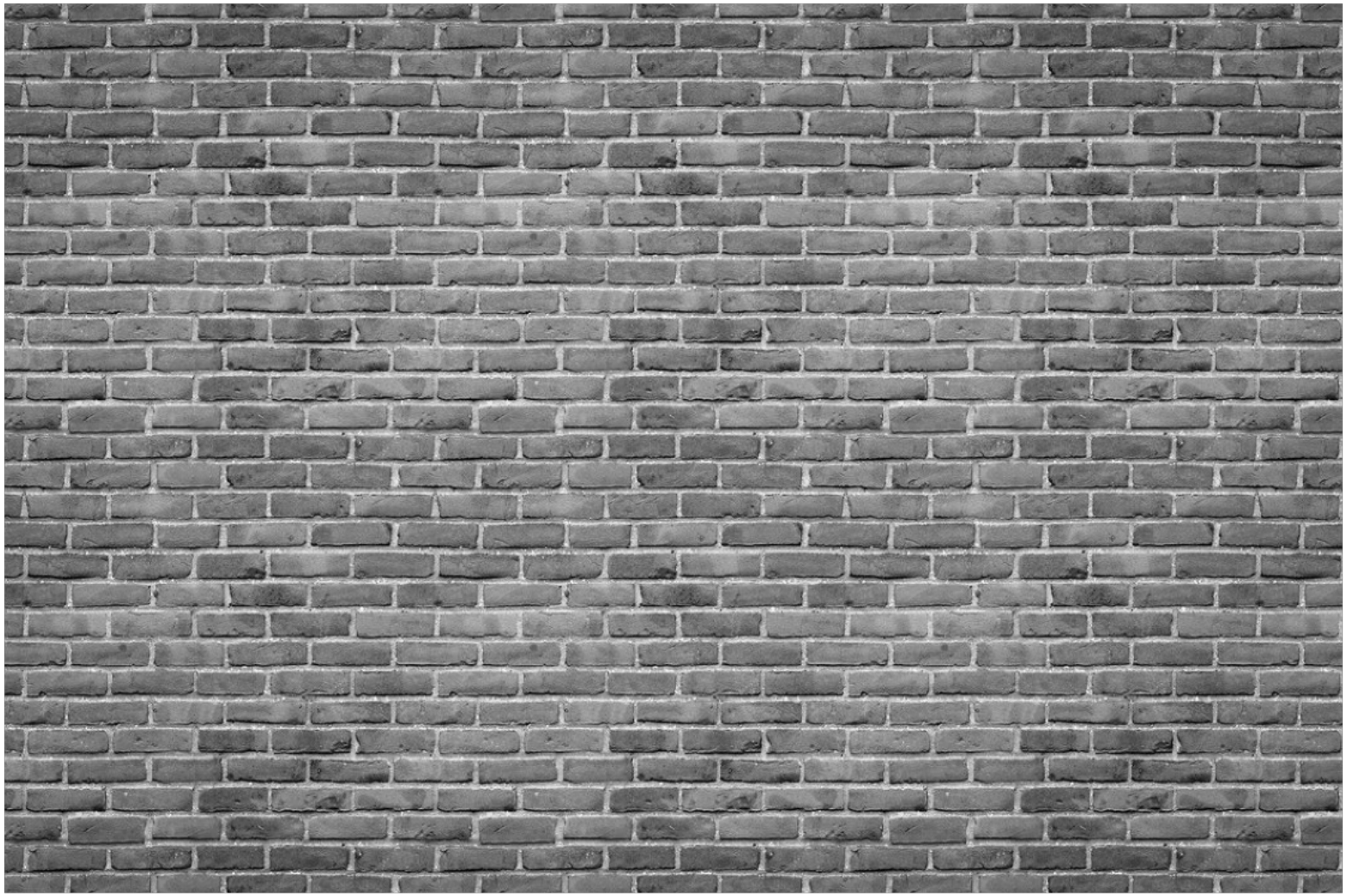
$$4 \times 3 + 12 \times 0 + 11 \times 8 + 15 \times 1 + 3 \times 5 + 0 \times 10 + 4 \times 0 + 8 \times 2 + 6 \times 9 = 216$$


1 4 12 11 0 2
9 15 3 0 4 17
1 4 8 6 6 10
16 10 0 11 13 6
0 2 9 3 0 8
2 14 12 5 14 1
*
3 0 8
1 5 10
0 2 9
=
293

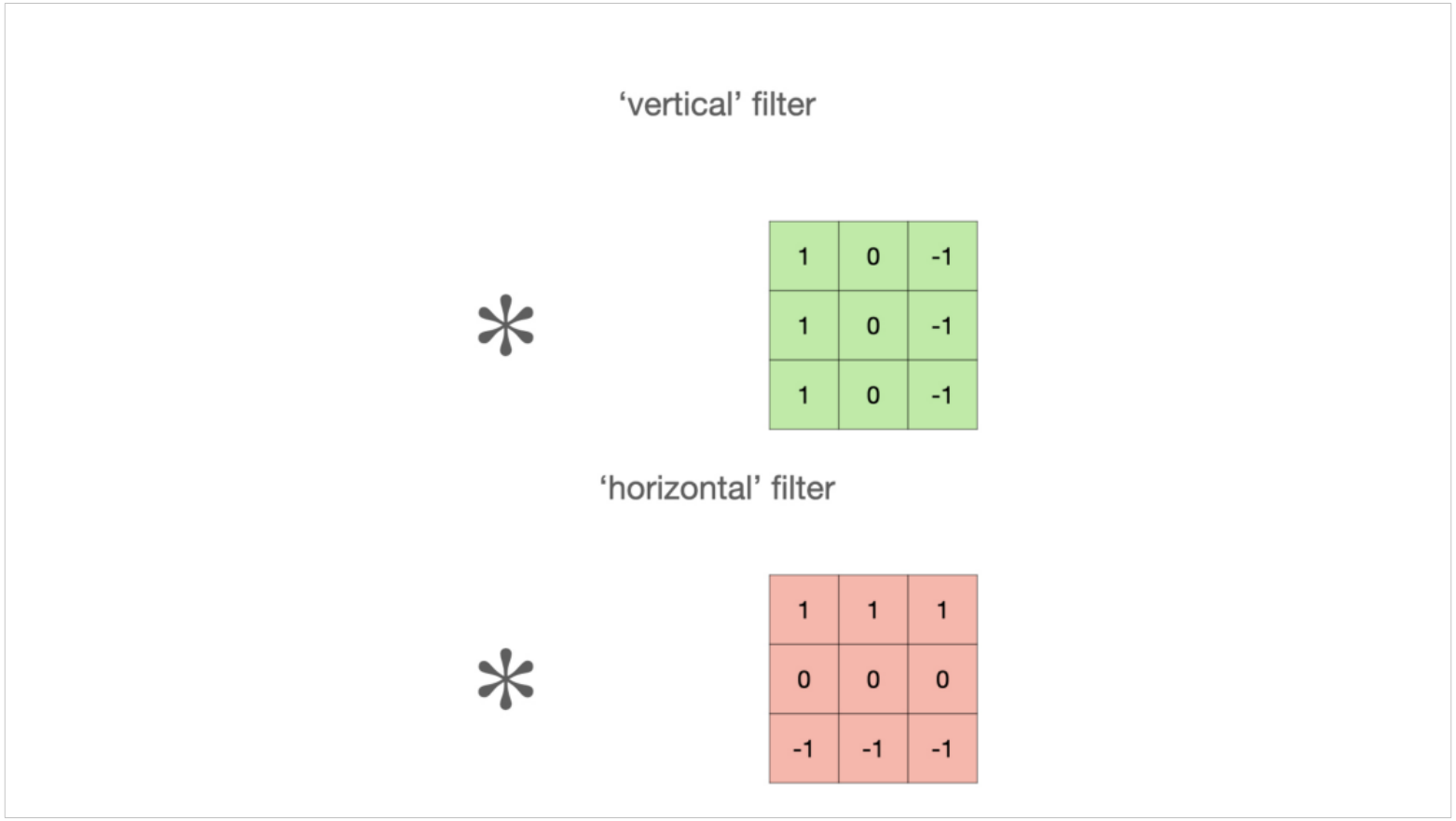
Example with edges filters

(edge detectors)

In [17]:
```
image = PIL.Image.open('brick2.jpeg').convert('L')
brick = asarray(image)
plt.figure(figsize=(20,20))
plt.imshow(brick,cmap='gray')
plt.axis('off')
plt.show()
```

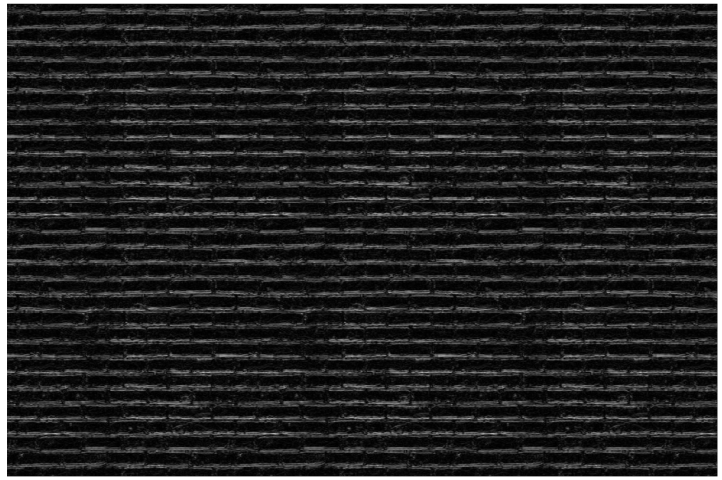


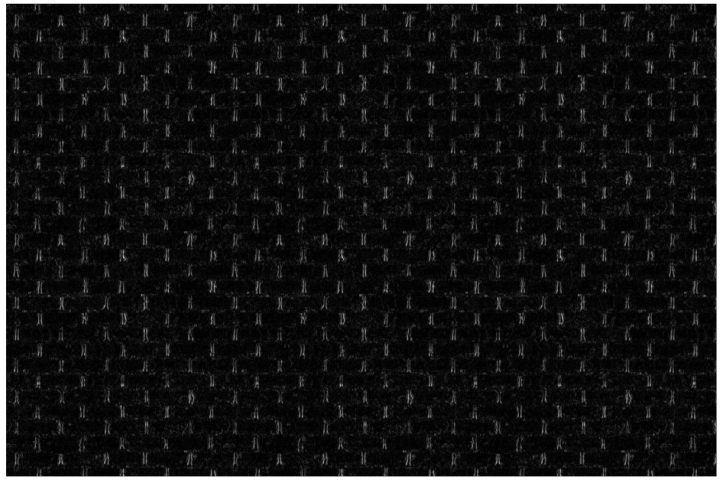
In [18]:
```
image = plt.imread('filters_conv.jpeg')
plt.figure(figsize = (20,20))
plt.imshow(image)
plt.axis('off')
plt.show()
```



In [14]:
```
out_conv_h=signal.convolve2d(brick,filter_h,mode='valid')
out_conv_v=signal.convolve2d(brick,filter_v,mode='valid')
f, axarr = plt.subplots(1,2,figsize = (50,50))
axarr[0].imshow(np.absolute(out_conv_h),cmap='gray')
axarr[0].set_axis_off()
axarr[1].imshow(np.absolute(out_conv_v),cmap='gray')
axarr[1].set_axis_off()

plt.show()
```



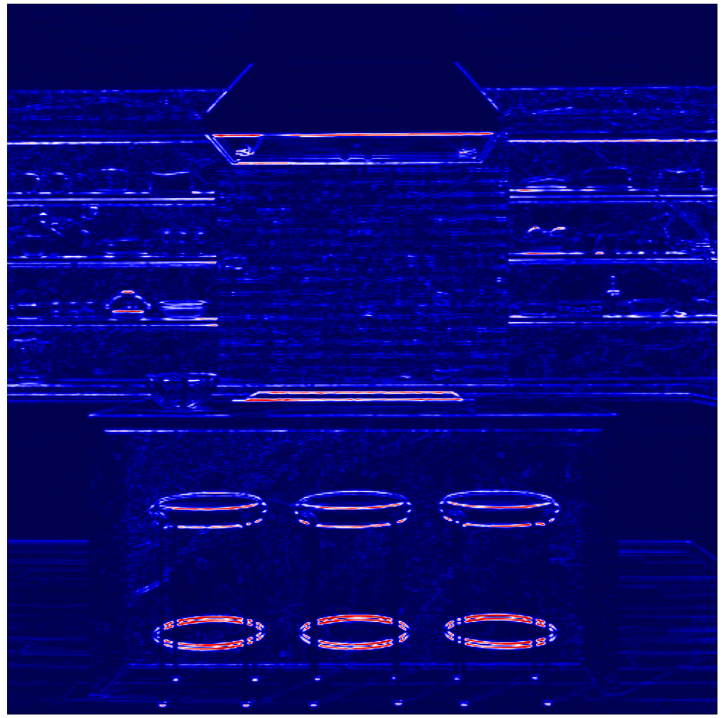


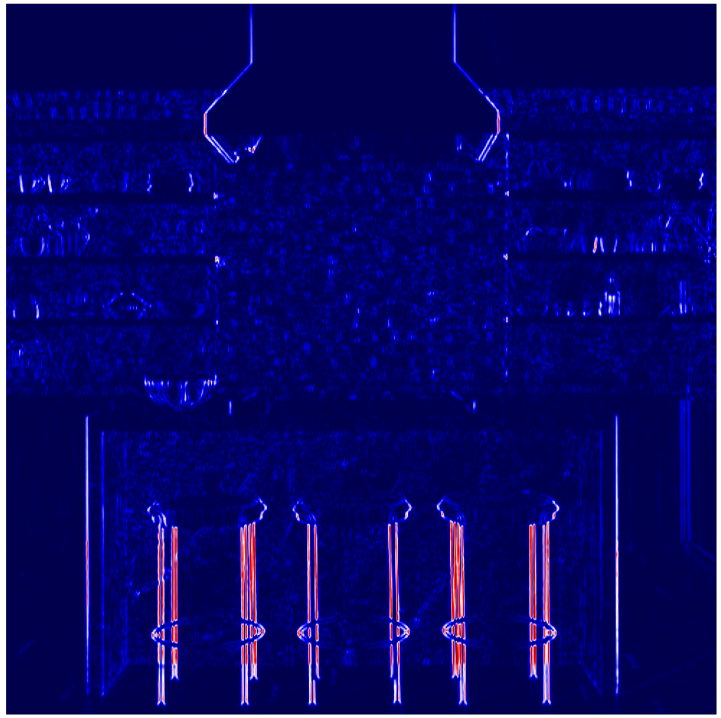
In [10]:
```
image = PIL.Image.open('brick.jpeg')
brick = asarray(image)
plt.figure(figsize=(10,10))
plt.imshow(brick)
plt.axis('off')
plt.show()
```

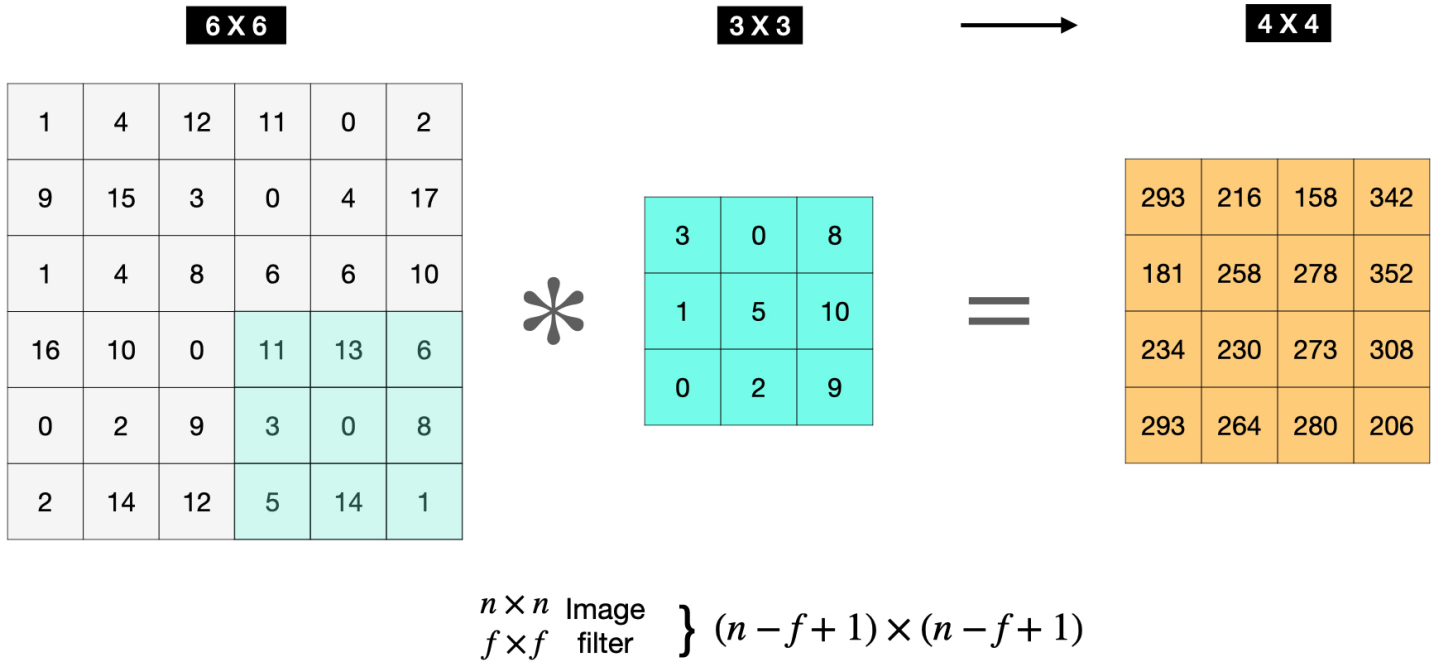
In [11]:

```
out_corr_v=signal.correlate(brick,filter_v_3d,mode='valid')
out_corr_h=signal.correlate(brick,filter_h_3d,mode='valid')

f, axarr = plt.subplots(1,2,figsize = (50,50))
axarr[0].imshow(np.absolute(out_corr_h),cmap='seismic')
axarr[0].set_axis_off()
axarr[1].imshow(np.absolute(out_corr_v),cmap='seismic')
axarr[1].set_axis_off()
plt.show()
```



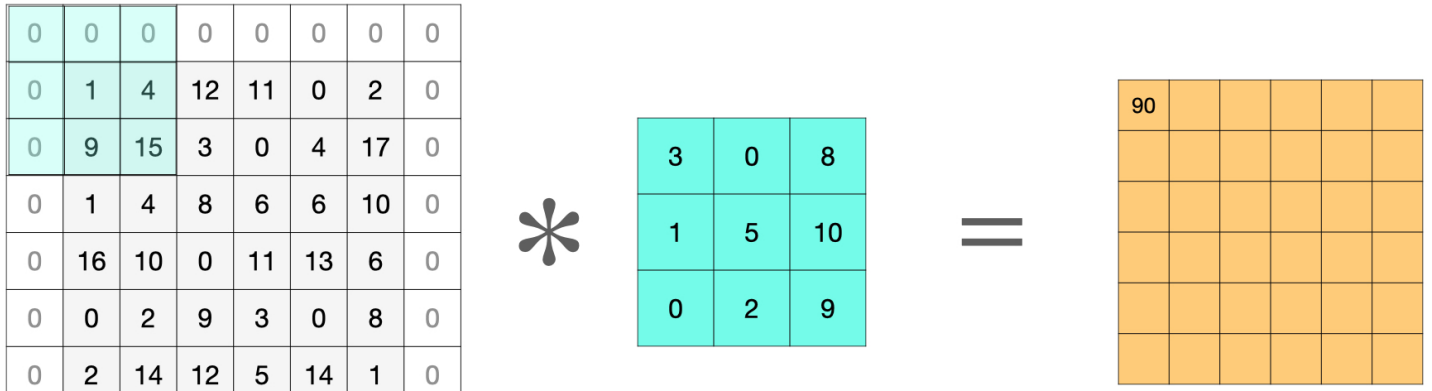




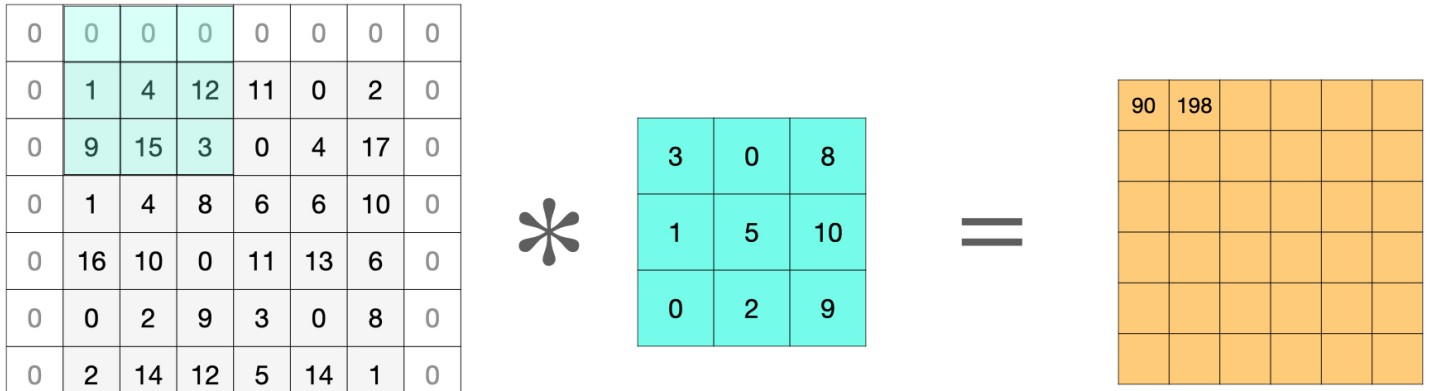
$n \times n$ Image
$f \times f$ filter
$\}$ $(n-f+1) \times (n-f+1)$

Padding

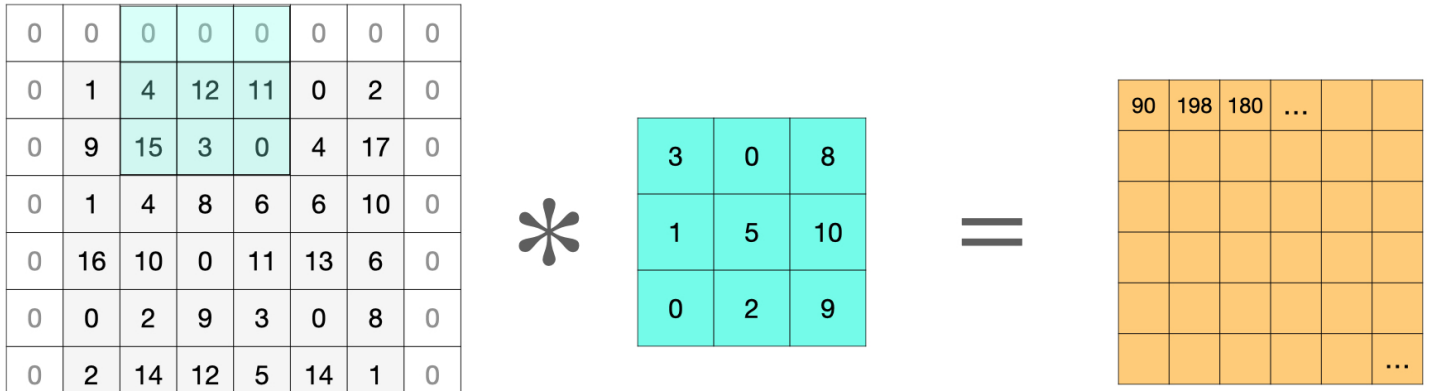
Padding


0 0 0 0 0 0 0 0
0 1 4 12 11 0 2 0
0 9 15 3 0 4 17 0
0 1 4 8 6 6 10 0
0 16 10 0 11 13 6 0
0 0 2 9 3 0 8 0
0 2 14 12 5 14 1 0
0 0 0 0 0 0 0 0
*
3 0 8
1 5 10
0 2 9
=
90

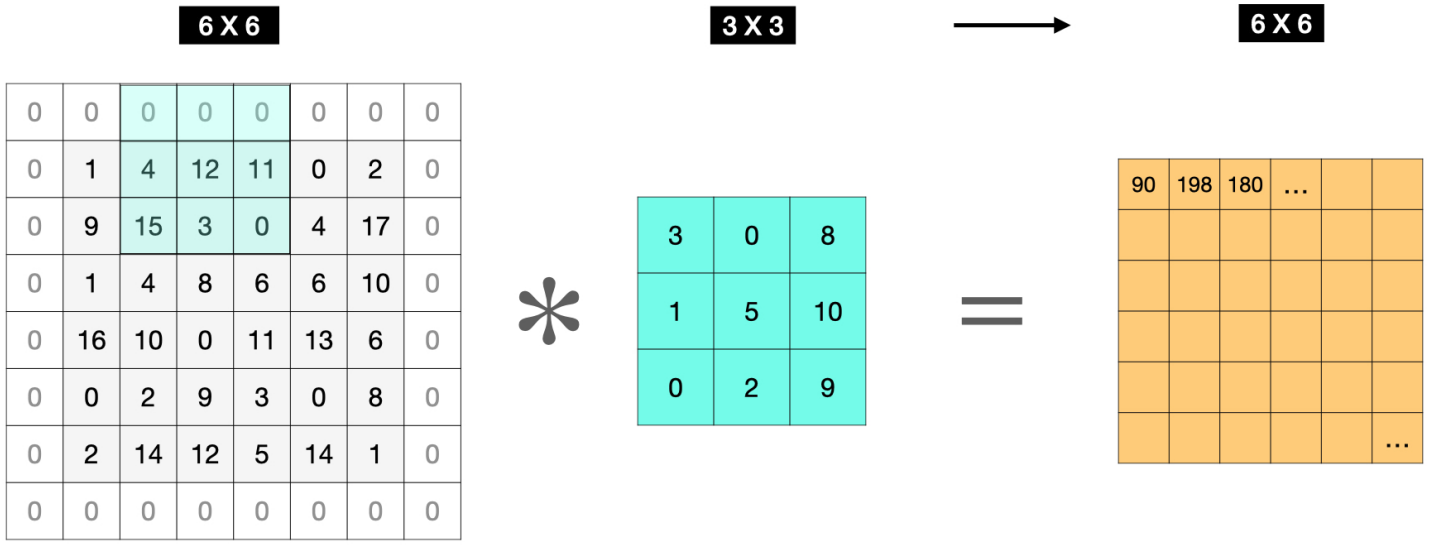
Padding


0 0 0 0 0 0 0 0
0 1 4 12 11 0 2 0
0 9 15 3 0 4 17 0
0 1 4 8 6 6 10 0
0 16 10 0 11 13 6 0
0 0 2 9 3 0 8 0
0 2 14 12 5 14 1 0
0 0 0 0 0 0 0 0
*
3 0 8
1 5 10
0 2 9
=
90 198

Padding


0 0 0 0 0 0 0 0
0 1 4 12 11 0 2 0
0 9 15 3 0 4 17 0
0 1 4 8 6 6 10 0
0 16 10 0 11 13 6 0
0 0 2 9 3 0 8 0
0 2 14 12 5 14 1 0
0 0 0 0 0 0 0 0
*
3 0 8
1 5 10
0 2 9
=
90 198 180 ...
...

Padding



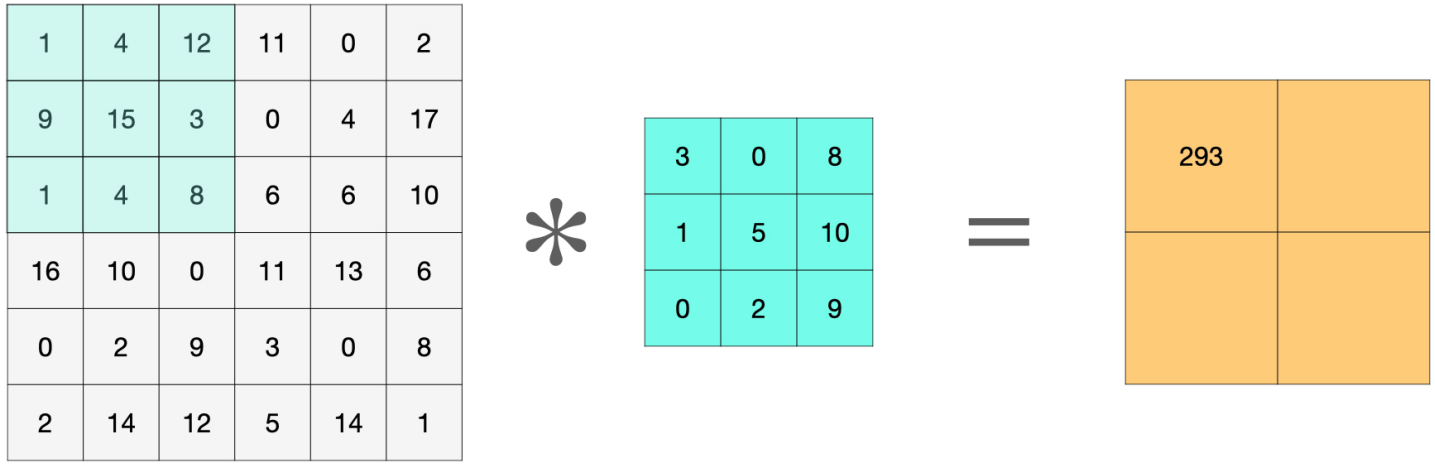
$n \times n$
$f \times f$
$p = 1$
Image
filter
padding

$$(n + 2p) - f + 1 \times (n + 2p) - f + 1$$

Valid convolution: no padding / p=0
Same convolution: output size = input size

Strided Convolutions

Strided Convolutions



Strided Convolutions

Stride = 2

1	4	12	11	0	2
9	15	3	0	4	17
1	4	8	6	6	10
16	10	0	11	13	6
0	2	9	3	0	8
2	14	12	5	14	1

$*$

3	0	8
1	5	10
0	2	9

$=$

293	158

Strided Convolutions

Stride = 2

1	4	12	11	0	2
9	15	3	0	4	17
1	4	8	6	6	10
16	10	0	11	13	6
0	2	9	3	0	8
2	14	12	5	14	1

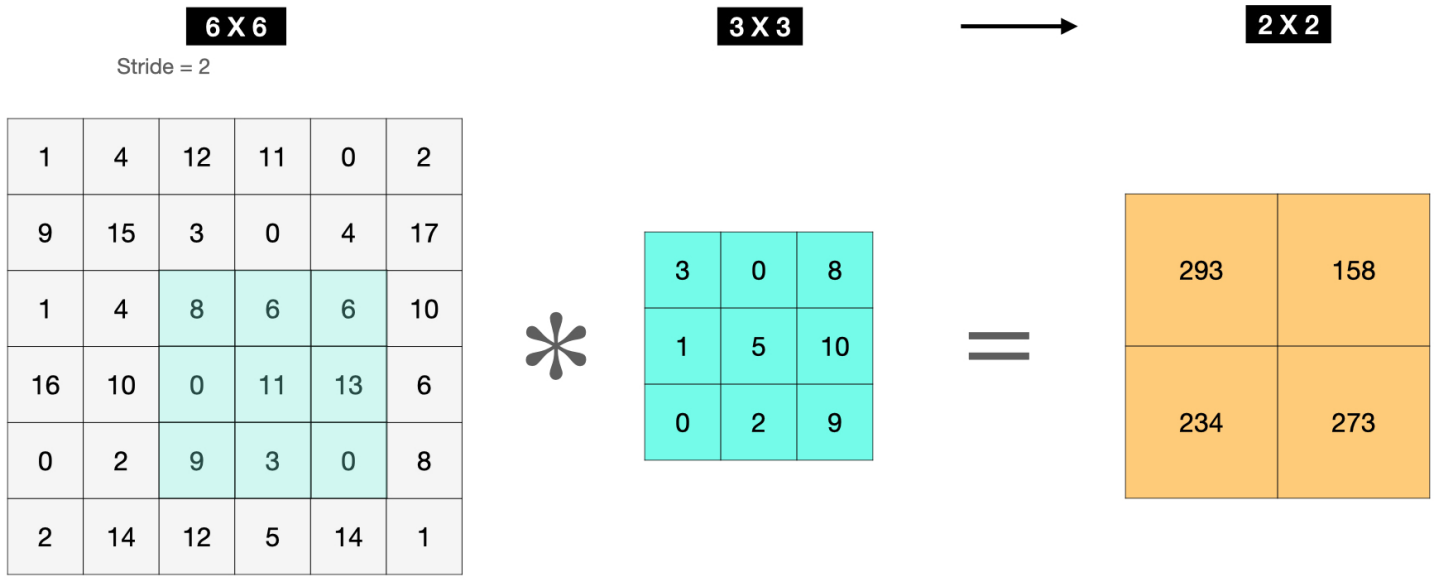
$*$

3	0	8
1	5	10
0	2	9

$=$

293	158
234	

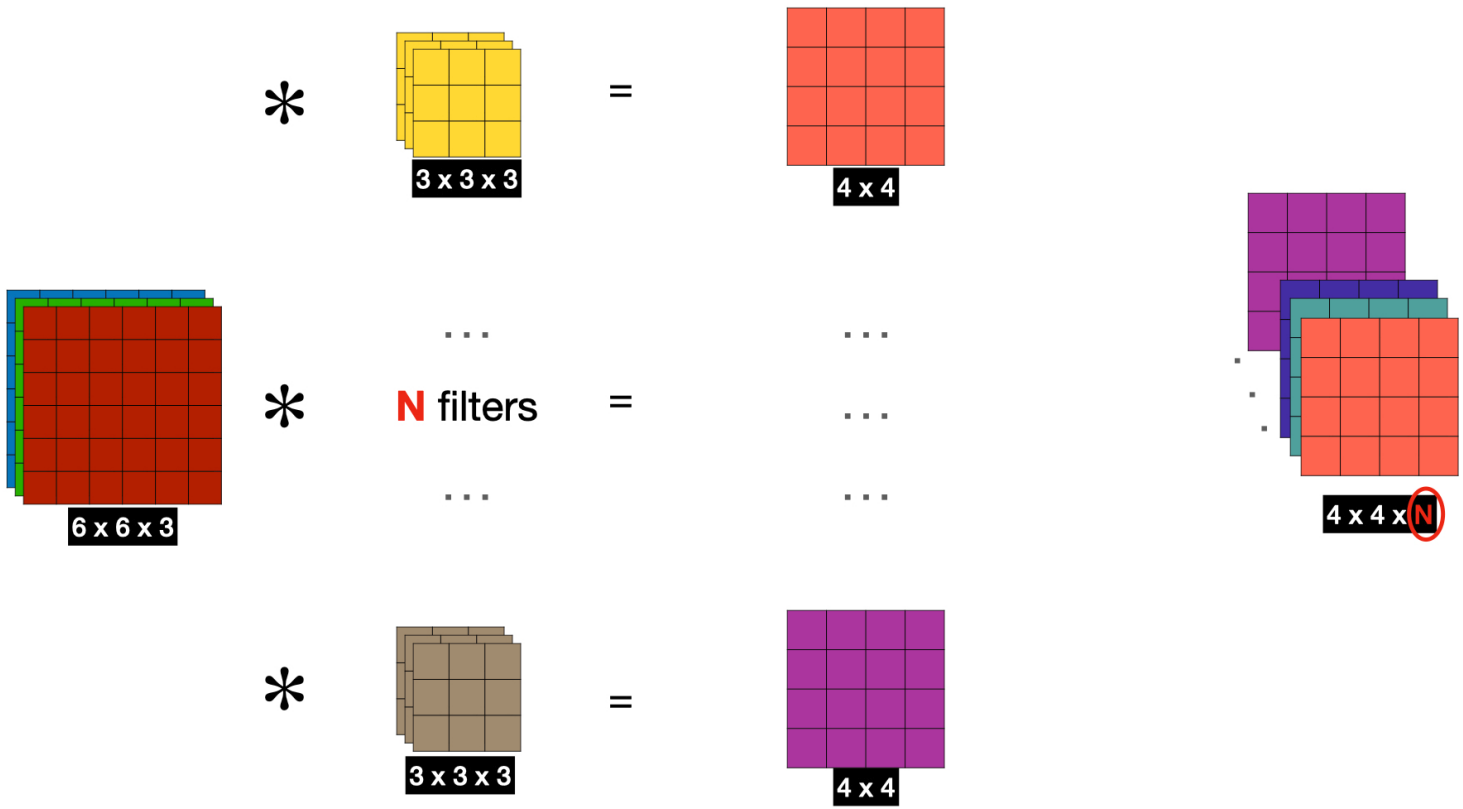
Strided Convolutions

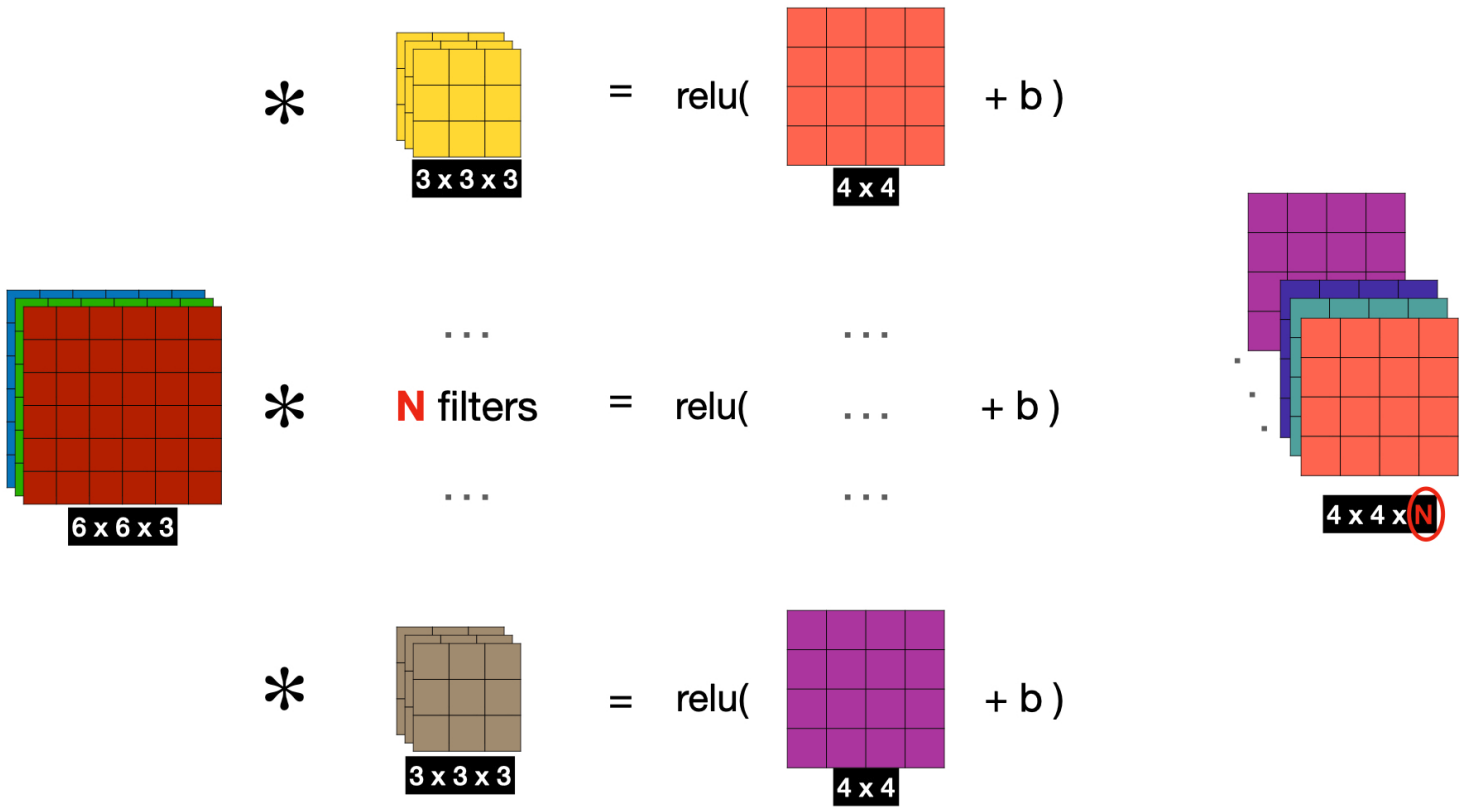


$n \times n$ Image
$f \times f$ filter
p padding
s stride

$$\lfloor \frac{n+2p-f}{s} + 1 \times \frac{n+2p-f}{s} + 1 \rfloor$$

Convolutions on volumes (RGB images)


3 x 3 x 3
4 x 4
6 x 6 x 3
N filters
4 x 4 x N
3 x 3 x 3
4 x 4

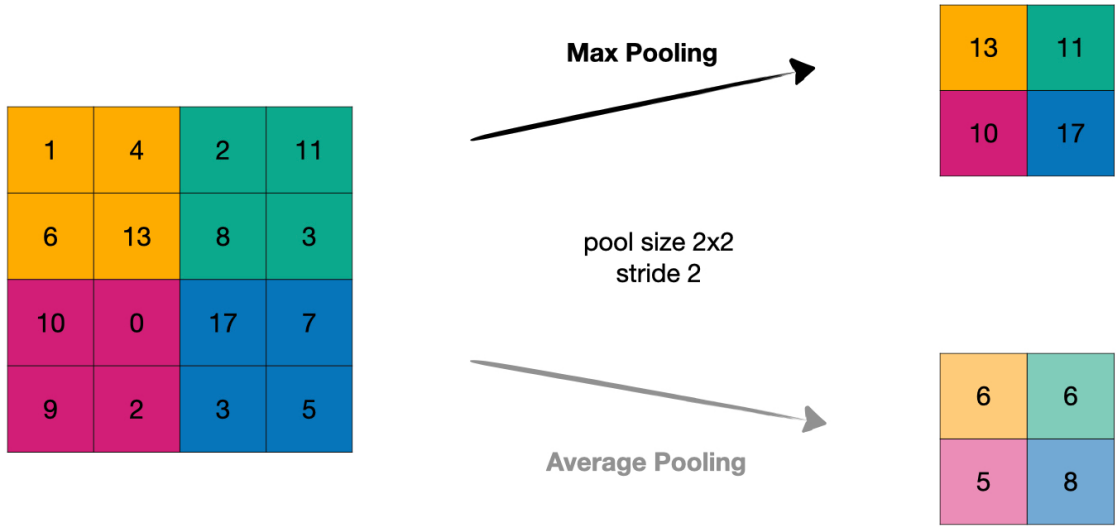

*
3 x 3 x 3
=
relu(
+ b)
4 x 4
6 x 6 x 3
. . .
N filters
. . .
. . .
. . .
. . .
4 x 4 x N
*
3 x 3 x 3
=
relu(
+ b)
4 x 4

Layers in ConvNets

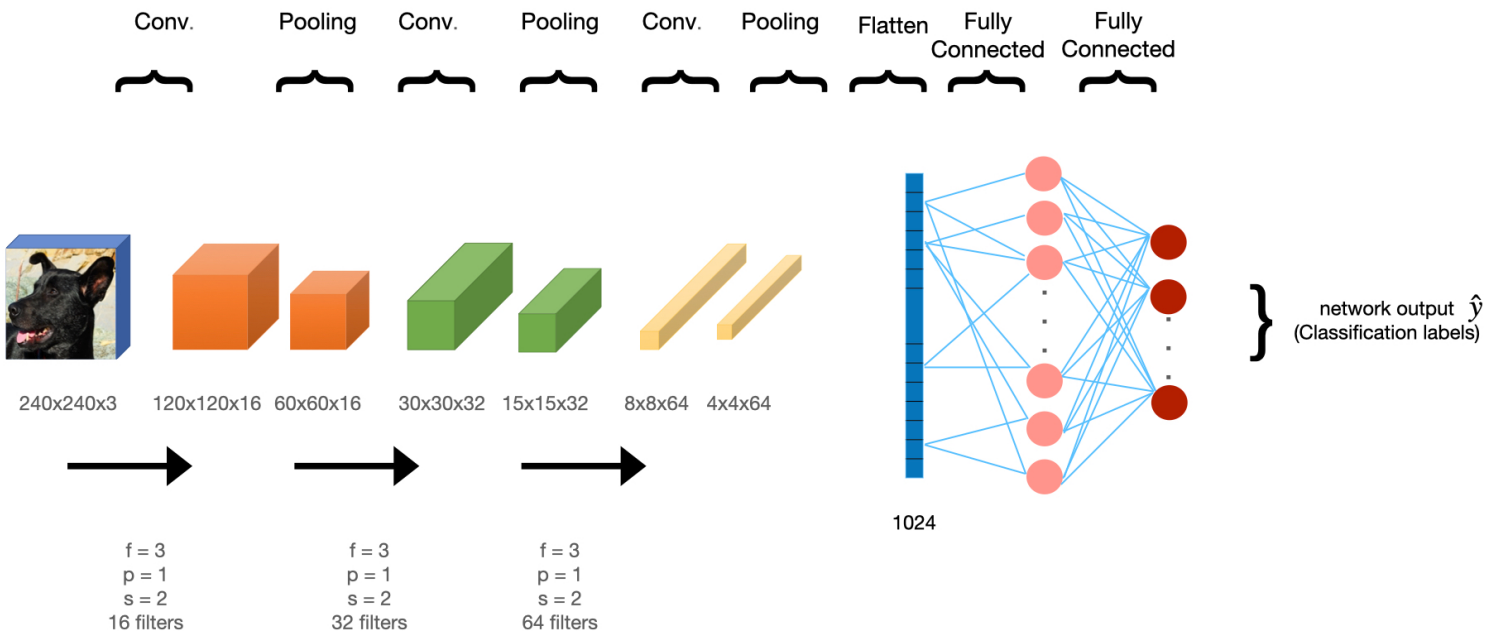
The building blocks (i.e. most commonly used types of layers in CNNs)

- Convolutional layers
- Pooling layers
    - Max Pooling
    - Average Pooling
    - Global Pooling
- Dense (Fully Connected) layers

Pooling


1
4
2
11
6
13
8
3
10
0
17
7
9
2
3
5
Max Pooling
pool size 2x2
stride 2
Average Pooling
13
11
10
17
6
6
5
8

Schematic Description of a ConvNet


Conv.
Pooling
Conv.
Pooling
Conv.
Pooling
Flatten
Fully Connected
Fully Connected
240x240x3
120x120x16
60x60x16
30x30x32
15x15x32
8x8x64
4x4x64
f = 3
p = 1
s = 2
16 filters
f = 3
p = 1
s = 2
32 filters
f = 3
p = 1
s = 2
64 filters
1024
network output $\hat{y}$
(Classification labels)

CNNs in Tensorflow

In [5]:

```
import tensorflow
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras import models

model = models.Sequential()
model.add(layers.Conv2D(8, (3, 3), activation='relu', input_shape=(80,80,3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(16, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(64,activation='relu'))
model.add(layers.Dense(4, activation='softmax'))
```

Hands-on

- Simple classification example using a ConvNet

Classification/Regression

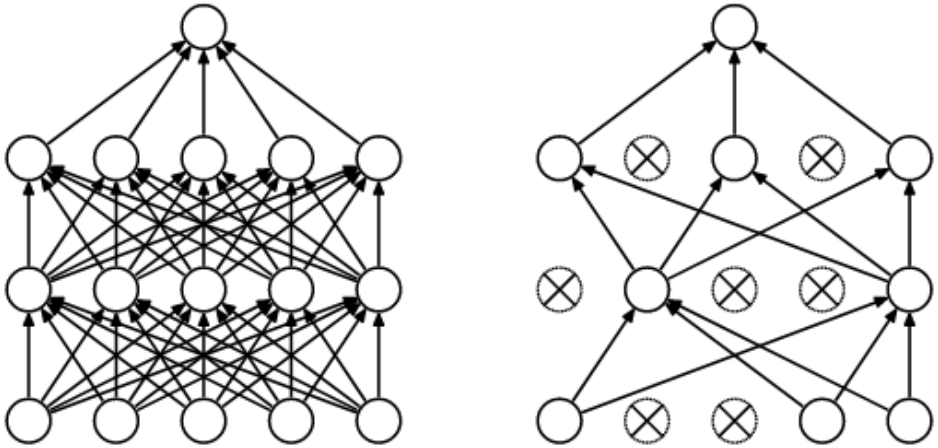
- Regression:
    - output is a prediction on a quantity which takes continuous values
- Classification:
    - output is a prediction on a class, i.e. discrete labels
        - binary classification
        - multi-class classification
            - single-label classification
            - multi-label classification

steps

1. Data
    - set of 8 different classes of images: airplane, car, cat, dog, flower, fruit, motorbike, person
    - create the relevant datasets
2. CNN model
    - build the CNN model, train it with the given data, check performance
    - we will observe overfitting
3. Improve previous CNN model: i.e. avoid overfitting
    - Dropout (interfere in the model architecture)
    - Augmentation (interfere with the data)
4. Transfer learning
    - Do not use own CNN model, but borrow a pretrained one. Use it on our given data.

Dropout

Dropout: A Simple Way to Prevent Neural Networks from Overfitting, JMLR (2014) http://jmlr.org/papers/v15/srivastava14a.html (http://jmlr.org/papers/v15/srivastava14a.html)



(a) Standard Neural Net (b) After applying dropout.

Figure 1: Dropout Neural Net Model. **Left**: A standard neural net with 2 hidden layers. **Right**: An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.

Augmentation

Augmenting the training dataset, by applying transformations to existing data (images in this case): flip, rotate, shear, shift, zoom, color distortion, etc.

Transfer Learning