

# Computer Vision in Python

## Day 1, Part 2/4

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# About this lecture

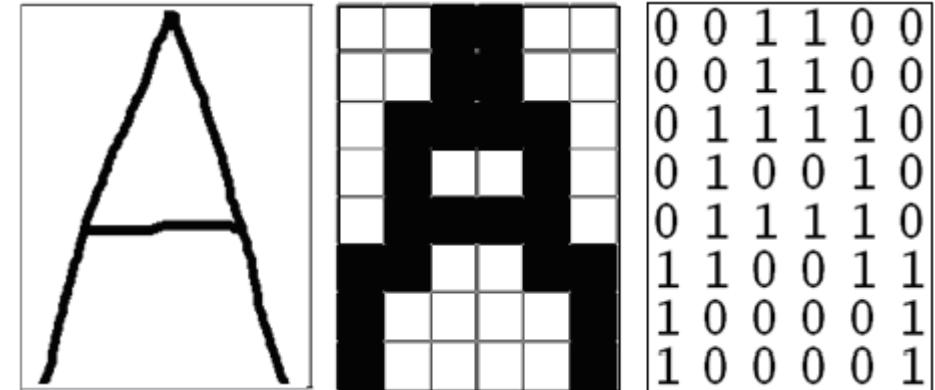
1. What are **images** and how is this datatype represented?
2. What is a **pixel** and how can **its information be interpreted?**
3. What is the **spatial dependence** property of pixels?
4. What is the **homophily** property of pixels?
5. Why is the **linear processing operation failing** on images?
6. What is the **convolution** operation?
7. How can we perform **image processing using convolutions?**
8. What is **padding** in convolutions?

# About this lecture

9. What is **stride** in convolution?
10. What is **dilation** in convolution?
11. How does convolution apply to **higher dimensional images**?

# How to encode an image

- Both **grayscale** and **RGB** (Red Green Blue) **images** can be represented as **matrices** or **tensors**.



- Typically, our sample images in the MNIST dataset were 2D matrices of shape  $28 \times 28$ .

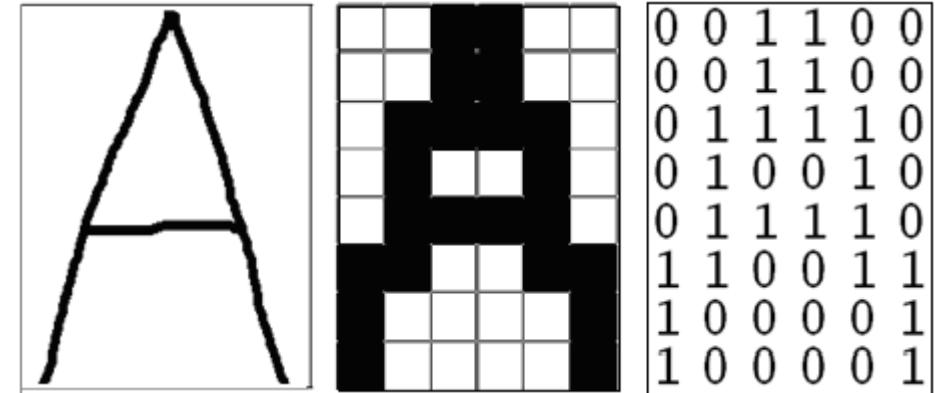
	165	187	209	58	7	
14	125	233	201	98	159	
253	144	120	251	41	147	204
67	100	32	241	23	165	30
209	118	124	27	59	201	79
210	236	105	169	19	218	156
35	178	199	197	4	14	218
115	104	34	111	19	196	
32	69	231	203	74		

# How to encode an image

**Definition (encoding a **grayscale** image):**

**Grayscale** images can be represented as a **2D matrix** of shape *height*  $\times$  *width*, where each element is an 8-bit integer.

- Each **element** of the matrix represents the **intensity of light** at that pixel.
- The intensity of light can be represented as a single number between 0 and 255, where **0** represents no light (**black**) and **255** represents maximum light intensity (**white**). Sometimes normalized to [0, 1].



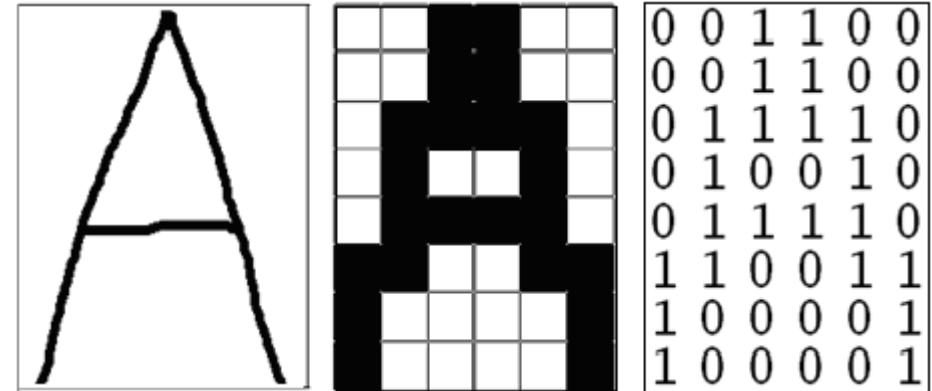
	165	187	209	58	7	
	14	125	233	201	98	159
253	144	120	251	41	147	204
67	100	32	241	23	165	30
209	118	124	27	59	201	79
210	236	105	169	19	218	156
35	178	199	197	4	14	218
115	104	34	111	19	196	
32	69	231	203	74		

# How to encode an image

**Definition (encoding a **RGB** image):**

**RGB images** are more complex because each pixel has three values representing the intensity of light for each color **channel** (red, green, and blue).

- An RGB image is represented as a **3D tensor** of shape  $height \times width \times 3$ .
- Each element in the tensor would be an integer representing the intensity of the corresponding color channel.



165	187	209	58	7	
14	125	233	201	98	159
253	144	120	251	41	147
67	100	32	241	23	165
209	118	124	27	59	201
210	236	105	169	19	218
35	178	199	197	4	14
115	104	34	111	19	218
32	69	231	203	74	196

# How to encode an image

- Combining the red, green and blue values allows to generate any color. Try it!

<https://www.rapidtables.com/convert/color/rgb-to-hex.html>

Red color (R)

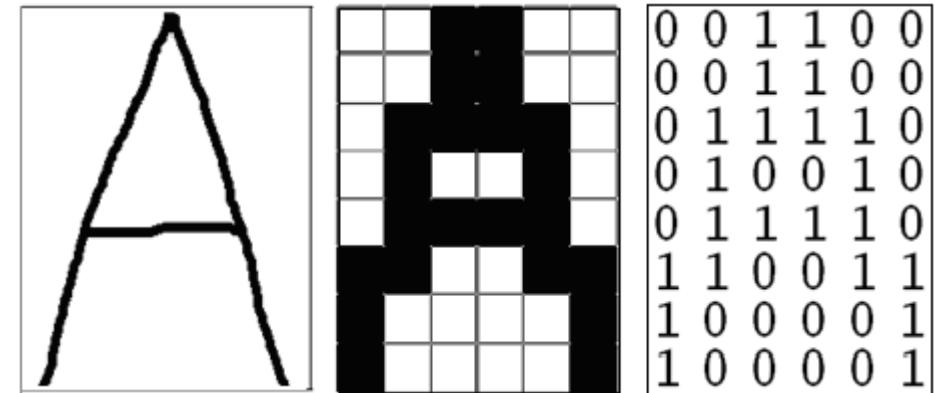
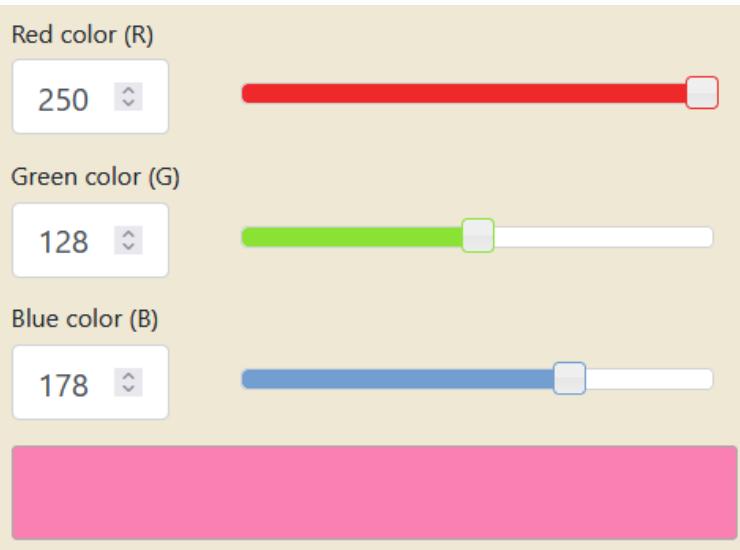
250

Green color (G)

128

Blue color (B)

178

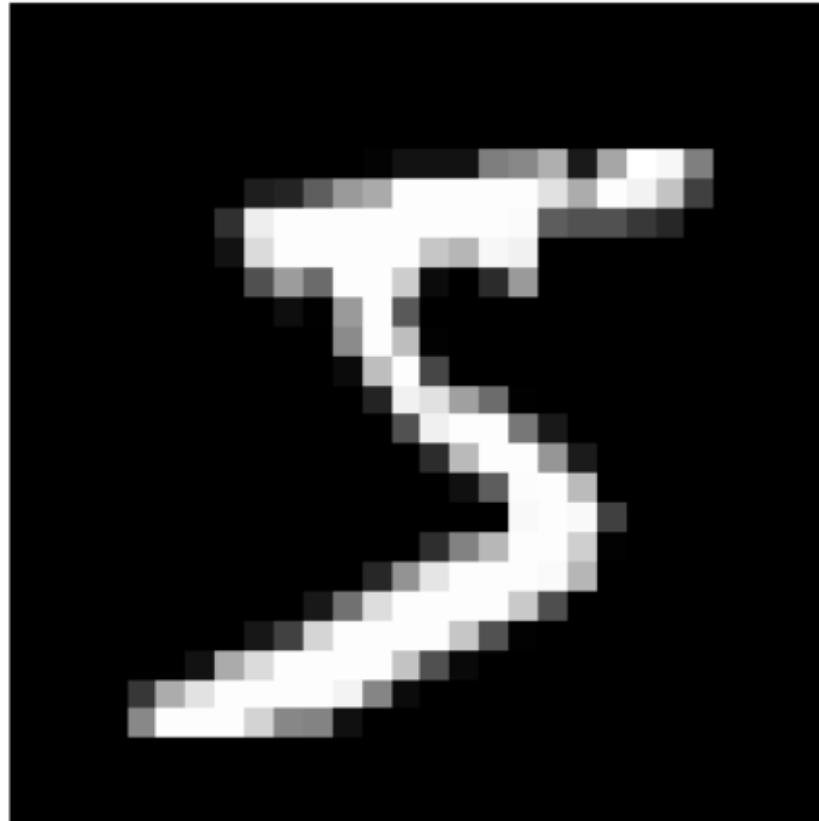


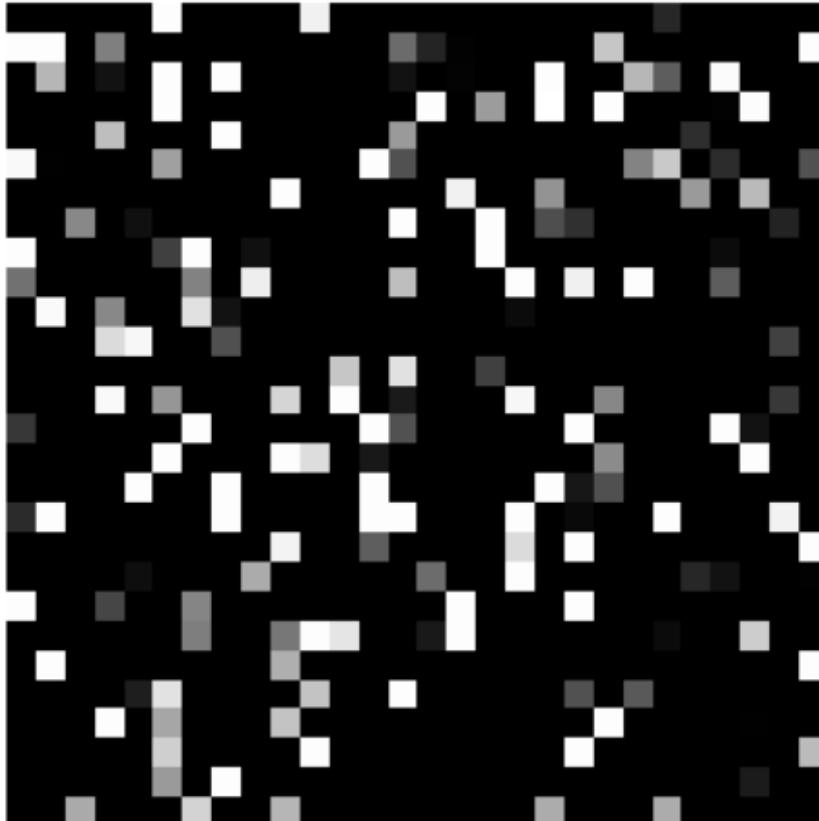
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# The problem with images

- Earlier, we played with apartment price prediction using surface (as the first input feature) and distance to MRT (as second input feature).
- If I were to swap both input features (distance to MRT becomes first feature, and surface becomes second feature), a human would still be able to understand the information in inputs and predict prices.
- **But problem in the case of images:**  
What happens if I randomly shuffle the pixels in all input images?
- If we shuffled pixels, a human would not be able to tell the number in the image... Would this mean that we lost information about what is inside the image? Or, in other words, that the structure matters?

# The problem with images

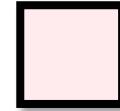
- Earlier we played with convolution and padding using `same` (as the first feature).  


Original (label=5)
- If we were to use `valid` padding, we would still be able to get the first feature.  


Pixel-shuffled
- **But pixels are not independent!** What if we change the order?  
What if we change the order?  
What if we change the order?  
What if we change the order?
- If we change the order of pixels, the interpretation of the number inside the image changes. Or, in other words, that the **structure** matters?

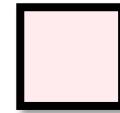
# The problem with images: another example

- Each element in a Greyscale matrix or RGB matrix corresponds to a pixel, representing something in the image.
- The problem, however, is that **it is often impossible to guess the meaning of a given pixel, by looking at this pixel alone.**



# The problem with images: another example

→ **Can you guess what this pixel represents and what object it belongs to?**

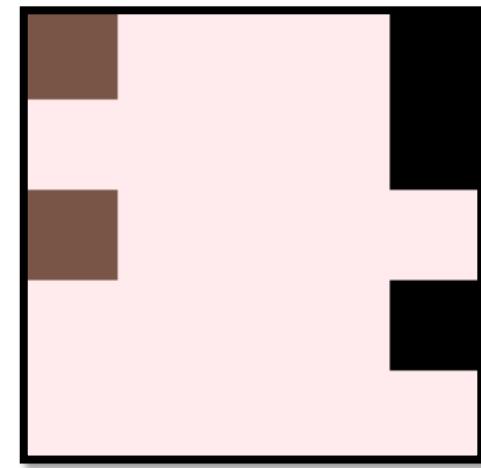


1. Flower petal
2. Piece of clothing
3. Skin of a human person
4. Feather of a bird

# The problem with images: another example

→ What if I show you some neighbouring pixels now?

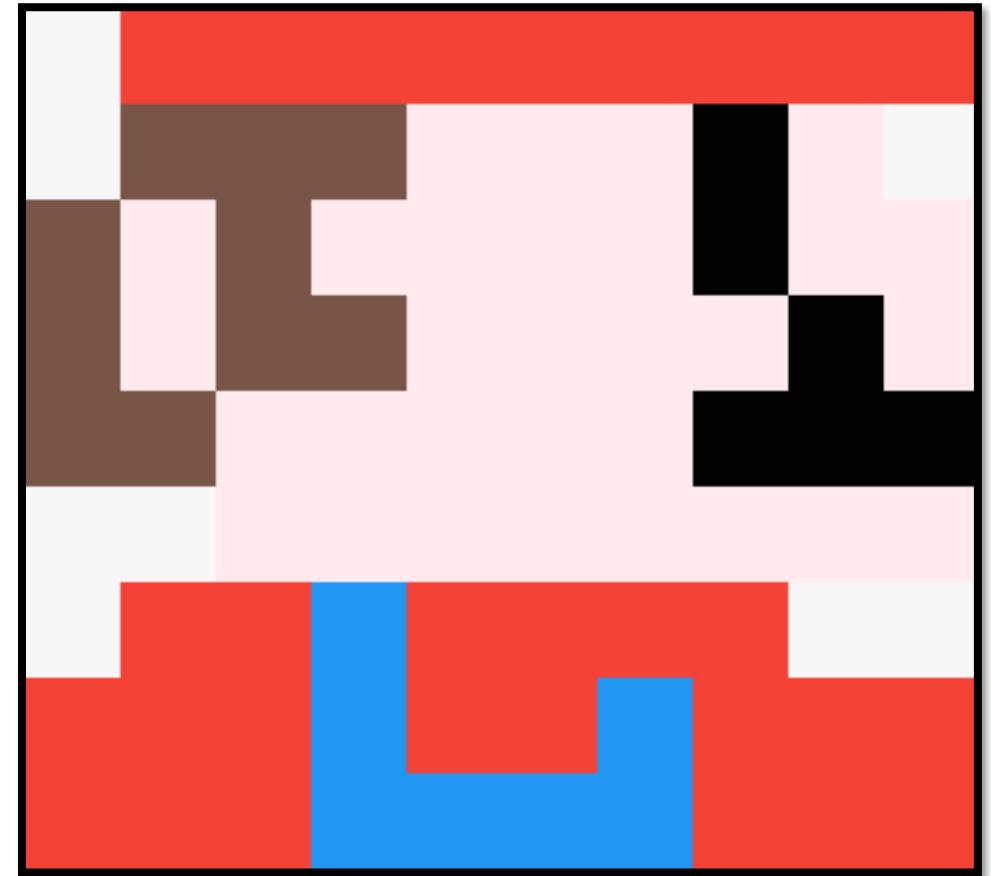
1. Flower petal
2. Piece of clothing
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4. Feather of a bird



# The problem with images: another example

→ What if I show you MORE neighbouring pixels now?

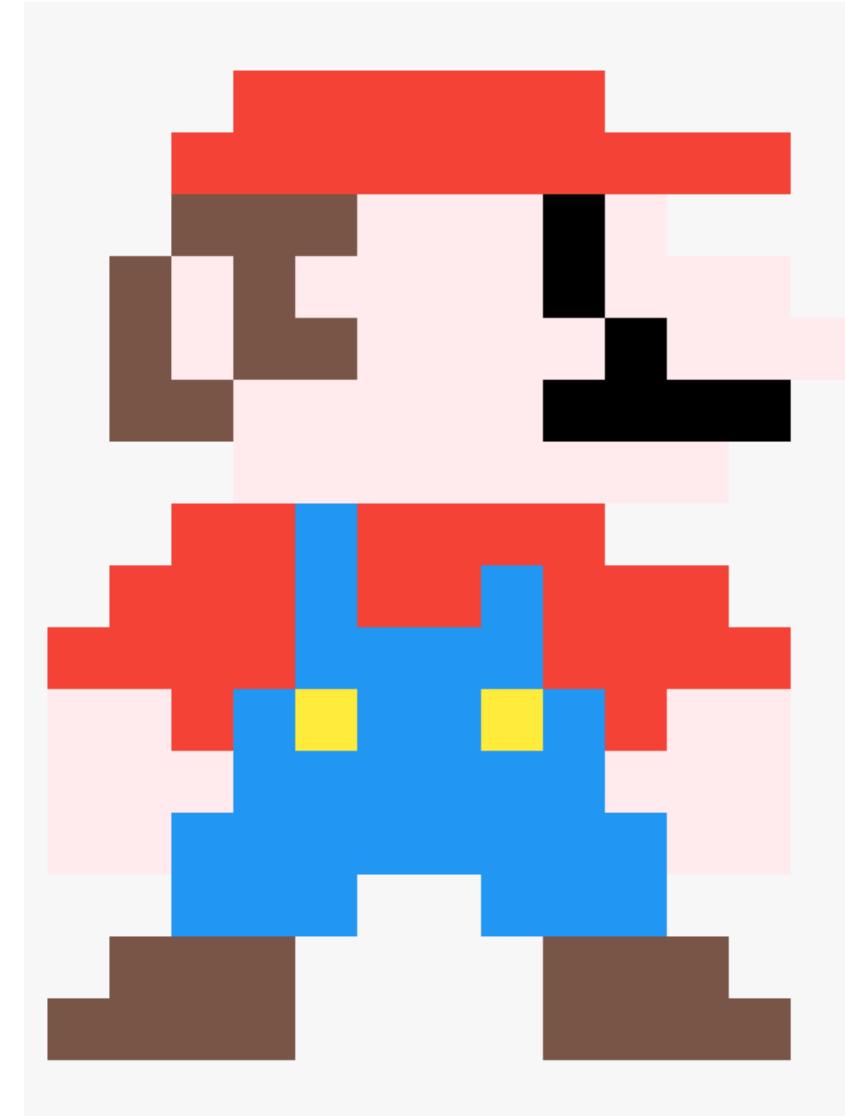
1. Flower petal
2. Piece of clothing
3. Skin of a human person
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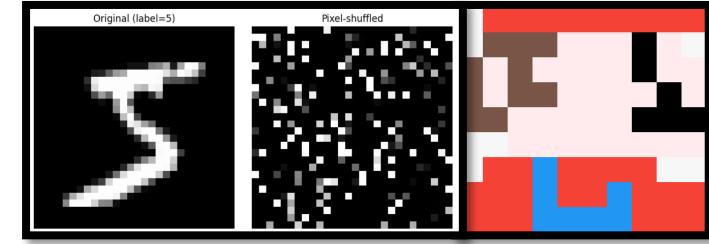
# The problem with images: another example

→ What if I show you MORE neighbouring pixels now?

1. Flower petal
2. Piece of clothing
- 3. Skin of a human person**
4. Feather of a bird



# The spatial dependence property



**Definition (the **spatial dependence** property of pixels):**

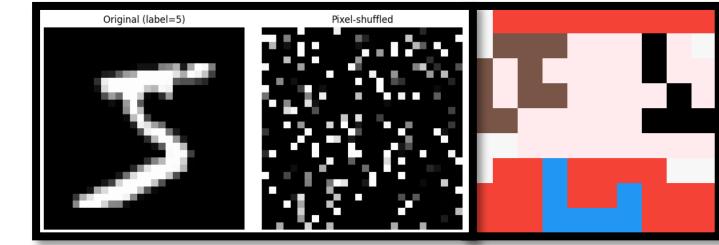
The **spatial dependence** property of pixels states that **the meaning or interpretation of a single pixel in an image can often only be understood in the context of the pixels around it.**

This is because the information in a single pixel is often not enough to describe the complete picture, or even just the pixel itself.

**The structure of the image (i.e. the relationship between a given pixel and its neighbouring pixels) is necessary to provide a full understanding of this particular pixel, or even the image as a whole.**

Images have “structure” and this structure contains information, which is something we observed in the Mario pixel art example.

# The homophily property



**Definition (the **homophily** property of pixels):**

**Homophily** in images refers to the phenomenon where **pixels that are close to each other in the image tend to have similar properties** (such as color, texture, or intensity).

For example, pixels that are close to each other and have a similar blue color can often be grouped together and be considered part of the sky region. Identifying parts of the image where the homophily property breaks (i.e. drastic changes in pixel color) is how we recognize objects in the image.

This property is a **key factor in image processing and computer vision** algorithms, as it provides a way to segment images into meaningful regions and perform tasks like object recognition and image classification.

Note: The whole point of camouflage is to make it difficult to separate pixels from objects of interest and background, by having objects use similar colors as their backgrounds (i.e. homophily!)



and perform tasks like object recognition and image classification.

# The problem with Linear processing

So far, we have only used Linear operations in our neural networks, even when playing with images, as in the MNIST dataset.

- We would flatten the image, assembling all pixels in a 1D vector, **essentially losing the “structure” or spatial information of the image.**
- Then, Linear processing layers would simply **process pixels independently**, applying individual coefficients to each pixel separately.

$$Z = \sum_i \sum_j w_{i,j} x_{i,j} + b$$

With  $x_{i,j}$  the pixel value at location  $(i, j)$ ,  $w_{i,j}$  the weight coefficient for the Linear layer assigned to this pixel, and  $b$  the bias.

# The problem with Linear processing

Linear layers are not great at processing images because they do not take into account the **spatial dependence of pixels**.

- Pixels in images are typically related to each other in a spatial manner, i.e. the meaning of a pixel depends on the neighbour pixels.
- Unfortunately, linear models would assume each pixel is independent of the others and process them independently, which is not correct.
- As a result, linear layers can miss important spatial relationships between pixels. This can, in turn, result in poor image representation and interpretation.

→ Need for a more specific processing operation for images, to use in place of the Linear one!

# Introducing convolution!

## Definition (**convolution**):

**Convolution** is a **mathematical operation** that is widely used in image processing, computer vision, and deep learning.

It involves applying a small matrix called a **convolution kernel** or **filter**  $K$ , over a given image  $X$ , element-wise multiplying each overlapping set of values in the image with the kernel, and then summing the results.

The result of this operation is a new image  $Y$ , where each output pixel represents the sum of the product of the corresponding input pixel and the filter.

$$Y = f(X, K)$$

# Introducing convolution!

Let us consider

- A grayscale image, defined as a 2D matrix  $X$  of size  $h \times w$ , with pixel values  $(X_{i,j}) \in [0, 255]$ .
- A convolution kernel  $K$  of size  $k \times k$ , with values  $(K_{i,j}) \in \mathbb{R}$ .

**First, let us discuss sizes...**

The convolution operation defined as  $Y = f(X, K)$ , produces an image  $Y$  of size  $h' \times w'$ ,

- With  $h' = h - k + 1$ ,
- And  $w' = w - k + 1$ .

**Note:** we often use a kernel defined as a square matrix, with odd sizes (i.e.  $3 \times 3$ ,  $5 \times 5$ , etc.). The operation, however, remains valid for other kernel sizes (but some notations showed in next slide would have to be adjusted).

# Introducing convolution!

**Second**, the pixel values  $y_{i,j}$  for image  $Y$  are calculated using the convolution operation, defining  $Y_{i,j}$ ,  
 $\forall i \in [1, h'], j \in [1, w']$  as:

$$Y_{i,j} = \frac{1}{k^2} \sum_{m=1}^k \sum_{n=1}^k X_{i+m-1, j+n-1} K_{m,n}$$

This operation might seem complicated, but is easily visualised!

 $X$ 

1	2	4	2	1
4	7	3	2	1
4	5	2	3	1
2	1	7	8	4
3	2	4	7	8

X is 5 by 5

K is 3 by 3

Y is therefore  
3 by 3. $(5-3+1 = 3)$  $K$ 

1	0	1
0	2	1
1	0	1

 $Y$ 

...	...	...
...	...	...
...	...	...

# Introducing convolution!

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$$Y_{i,j} = \frac{1}{k^2} \sum_{m=1}^k \sum_{n=1}^k X_{i+m-1, j+n-1} K_{m,n}$$

This operation is a weighted average of a pixel and its neighbouring pixels!

 $X$ 

1	2	4	2	1
4	7	3	2	1
4	5	2	3	1
2	1	7	8	4
3	2	4	7	8

 $K$ 

1	0	1
0	2	1
1	0	1

 $Y$ 

$\frac{28}{9}$	...	...
...	...	...
...	...	...

$$\begin{aligned}
 & 1 \times 1 \\
 & + 2 \times 0 \\
 & + 4 \times 1 \\
 & + 4 \times 0 \\
 & + 7 \times 2 \\
 & + 3 \times 1 \\
 & + 4 \times 1 \\
 & + 5 \times 0 \\
 & + 2 \times 1 \\
 & = 28
 \end{aligned}$$

# Introducing convolution!

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 $X$ 

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4	7	3	2	1
4	5	2	3	1
2	1	7	8	4
3	2	4	7	8

 $K$ 

1	0	1
0	2	1
1	0	1

 $Y$ 

$\frac{28}{9}$	...	...
...	...	...
...	$\frac{39}{9}$	...

$$\begin{aligned}
 & 5 \times 1 \\
 & + 2 \times 0 \\
 & + 3 \times 1 \\
 & + 1 \times 0 \\
 & + 7 \times 2 \\
 & + 8 \times 1 \\
 & + 2 \times 1 \\
 & + 4 \times 0 \\
 & + 7 \times 1 \\
 & = 39
 \end{aligned}$$

# Introducing convolution!

**Second**, the pixel values  $y_{i,j}$  for image  $Y$  are calculated using the convolution operation, defining  $Y_{i,j}$ ,  
 $\forall i \in [1, h'], j \in [1, w']$  as:

$$Y_{i,j} = \cancel{\frac{1}{k^2}} \sum_{m=1}^k \sum_{n=1}^k X_{i+m-1, j+n-1} K_{m,n}$$

**Note:** Sometimes, the **normalization term** is removed and we may instead **normalize the kernel** (ensuring elements in kernel matrix sum up to 1), or not.

 $X$ 

1	2	4	2	1
4	7	3	2	1
4	5	2	3	1
2	1	7	8	4
3	2	4	7	8

 $K$ 

1	0	1
0	2	1
1	0	1

 $Y$ 

$\frac{28}{9}$	...	...
...	...	...
...	$\frac{39}{9}$	...

$$\begin{aligned}
 & 5 \times 1 \\
 & + 2 \times 0 \\
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$$Y_{i,j} = \frac{1}{k^2} \sum_{m=1}^k \sum_{n=1}^k X_{i+m-1, j+n-1} K_{m,n}$$

→ At the end of the day, convolution is just another type of matrix multiplication!

 $X$ 

1	2	4	2	1
4	7	3	2	1
4	5	2	3	1
2	1	7	8	4
3	2	4	7	8

 $K$ 

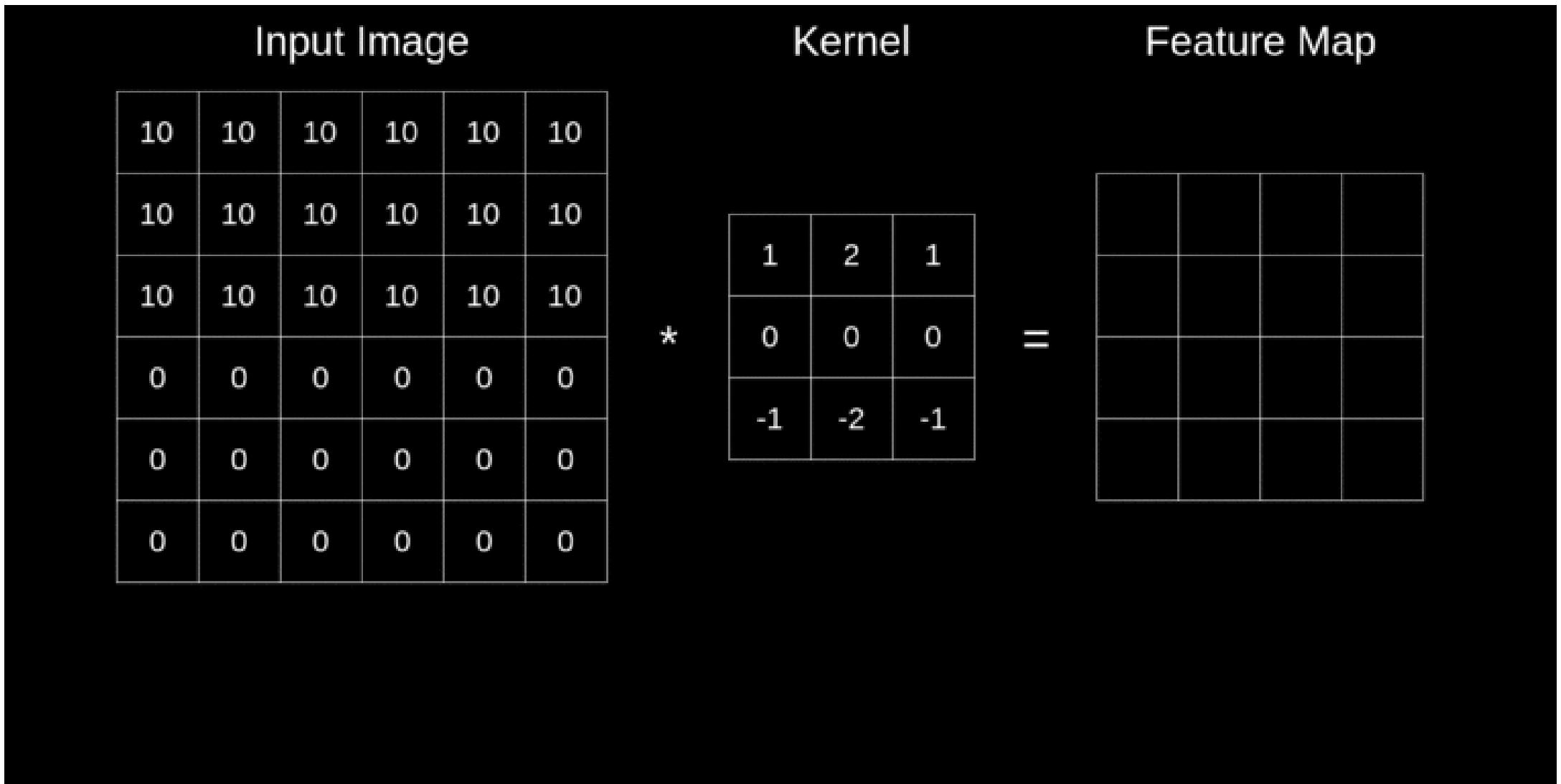
1	0	1
0	2	1
1	0	1

 $Y$ 

$\frac{28}{9}$	...	...
...	...	...
...	$\frac{39}{9}$	...

$$\begin{aligned}
 & 5 \times 1 \\
 & + 2 \times 0 \\
 & + 3 \times 1 \\
 & + 1 \times 0 \\
 & + 7 \times 2 \\
 & + 8 \times 1 \\
 & + 2 \times 1 \\
 & + 4 \times 0 \\
 & + 7 \times 1 \\
 & = 39
 \end{aligned}$$

# An animated visualisation of Convolution



# Convolution and Image Processing courses

**Convolution** is a **key mathematical operation** that is widely used in computer vision and image processing to apply a wide range of **transformations on an image** (enhancing contrast, blurring, edge detection, Instagram filters, etc).

- If **Computer Vision** is a direction that interests you, I would strongly advise to take a course on Image Processing (with implementations in OpenCV, Photoshop, etc.) during your continued learning.
- For instance: <https://www.udemy.com/course/digital-image-processing-from-ground-up-in-python/>

# Testing convolution on images

Let us try the convolution operation on images to see their effect.

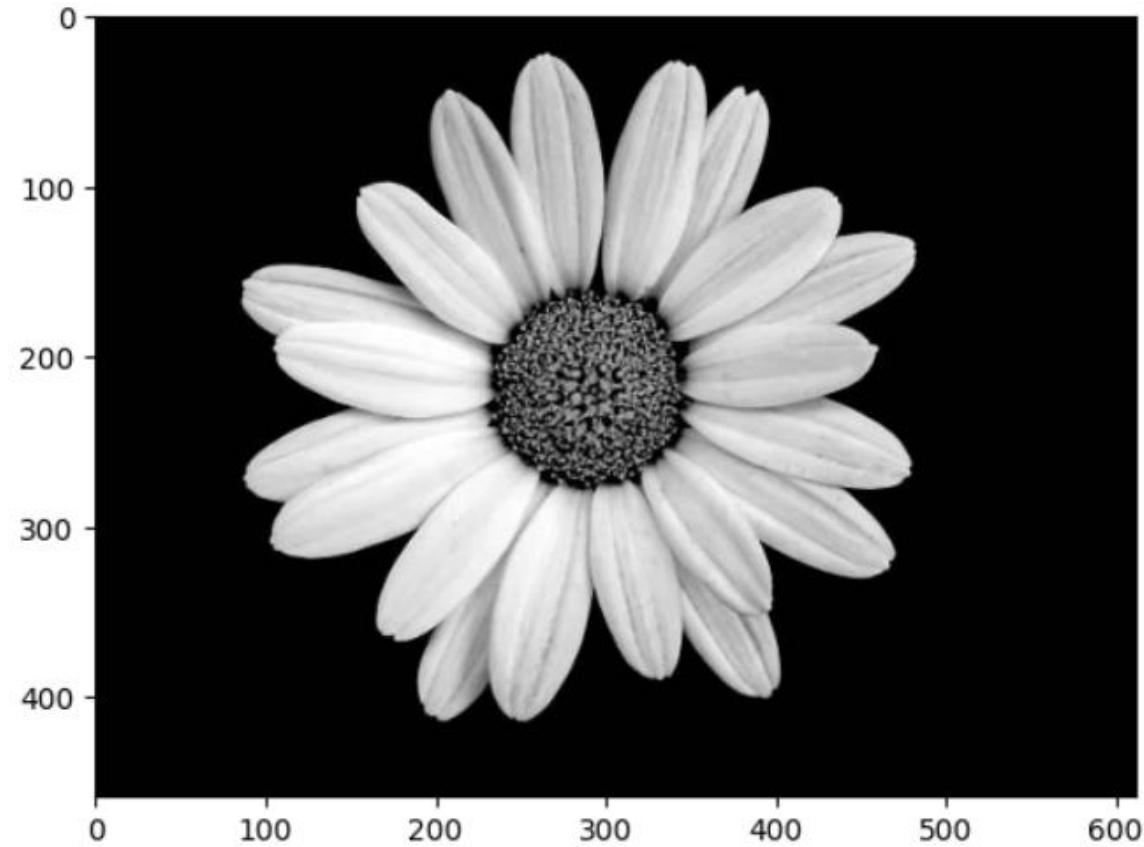
- First, we need a **greyscale image**.

Restricted

```
1 # Open the image and convert it to grayscale
2 im = Image.open('flower.jpg').convert('L')
3
4 # Convert the image to a NumPy array
5 im_array = np.array(im)
6
7 # Print the shape of the array
8 print(im_array.shape)
```

(459, 612)

```
1 # Display image in matplotlib
2 plt.imshow(im_array, cmap = 'gray')
3 plt.show()
```



Restricted

# Testing convolution on images

Let us try the convolution operation on images to see their effect.

- First, we need a greyscale image.
- Second, we need a **convolution function**.

Restricted

```
# Our convolution function
def convolution(image, kernel):
    # Flip the kernel (optional)
    kernel = np.flipud(np.fliplr(kernel))

    # Get the dimensions of the image and kernel
    image_rows, image_cols = image.shape
    kernel_rows, kernel_cols = kernel.shape

    # Convolve using Numpy
    output = correlate(image, kernel, mode = 'valid')

    # Note that this is equivalent to this
    ...
    # Loop through the image, applying the convolution
    output = np.zeros_like(image)
    for x in range(image_rows - kernel_rows + 1):
        for y in range(image_cols - kernel_cols + 1):
            output[x, y] = (kernel * image[x:x+kernel_rows, y:y+kernel_cols]).sum()
    ...
    return output
```

Restricted

# Testing convolution on images

## What is the purpose of flipping the kernel?

Optional, but in short, flipping the kernel has mathematical and practical advantages that make it a common practice in deep learning.

(It has to do with commutativity, signal processing, the Fourier Transform and the convolution theorem, 100% out-of-scope).

Restricted

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            output[x, y] = (kernel * image[x:x+kernel_rows, y:y+kernel_cols]).sum()
    ...

    return output
```

<https://stackoverflow.com/questions/45152473/why-is-the-convolutional-filter-flipped-in-convolutional-neural-networks>

Restricted

# Testing convolution on images

Let us try the convolution operation on images to see their effect.

- First, we need a greyscale image.
- Second, we need a **convolution function**.
- The magic for the transformation then happens when deciding **which kernel to use**.

Restricted

```
# Our convolution function
def convolution(image, kernel):
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    ...
    return output
```

Restricted

# Testing convolution on images

**Definition (the blur kernel):**

The **blur kernel** is a matrix with constant values, summing up to 1.

For instance, a  $5 \times 5$  **blur kernel** is defined as:

$$K = \frac{1}{25} \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{pmatrix}$$

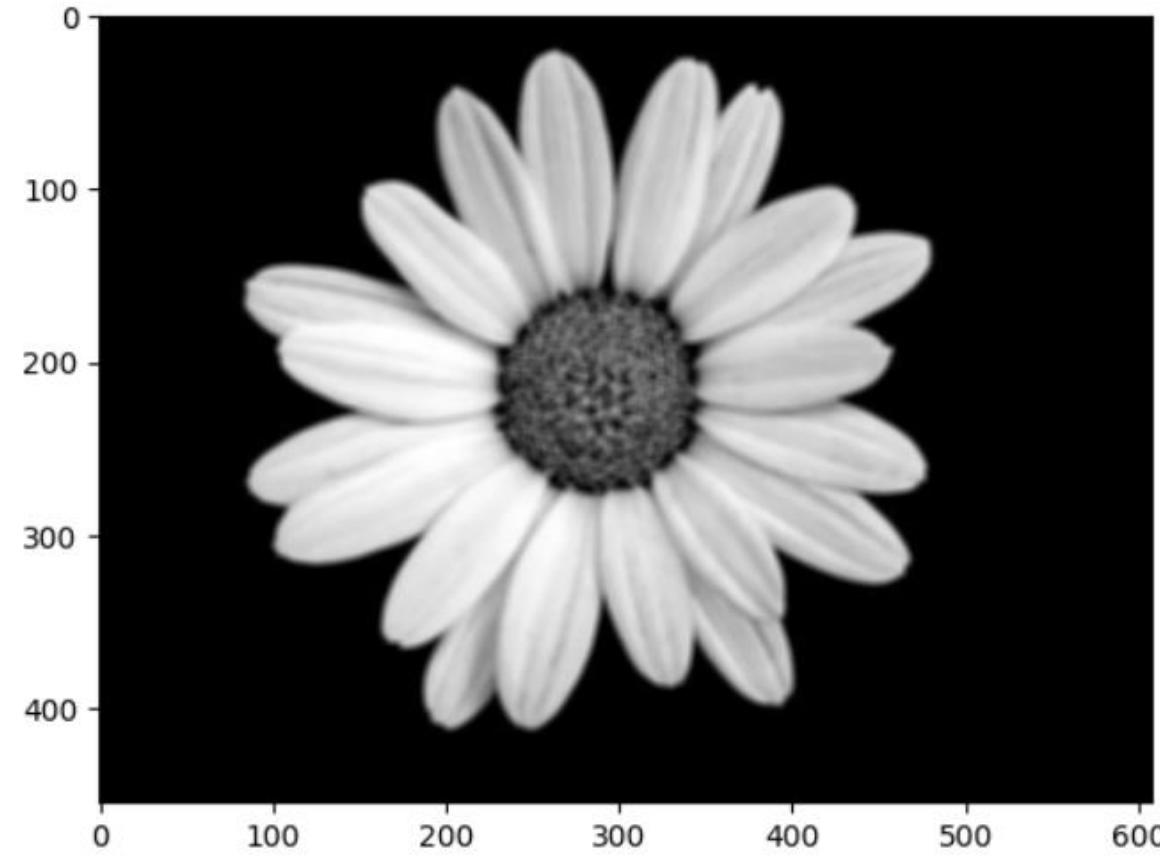
Its effect is to **transform the image into a more blurred version of it.**

Restricted

```
1 # Blur kernel
2 kernel = np.array([[1, 1, 1, 1, 1],
3                     [1, 1, 1, 1, 1],
4                     [1, 1, 1, 1, 1],
5                     [1, 1, 1, 1, 1],
6                     [1, 1, 1, 1, 1]])/25
7 image_conv = convolution(im_array, kernel)
8 print(image_conv.shape)
```

(455, 608)

```
1 # Display image in matplotlib
2 plt.imshow(image_conv, cmap = 'gray')
3 plt.show()
```



Restricted

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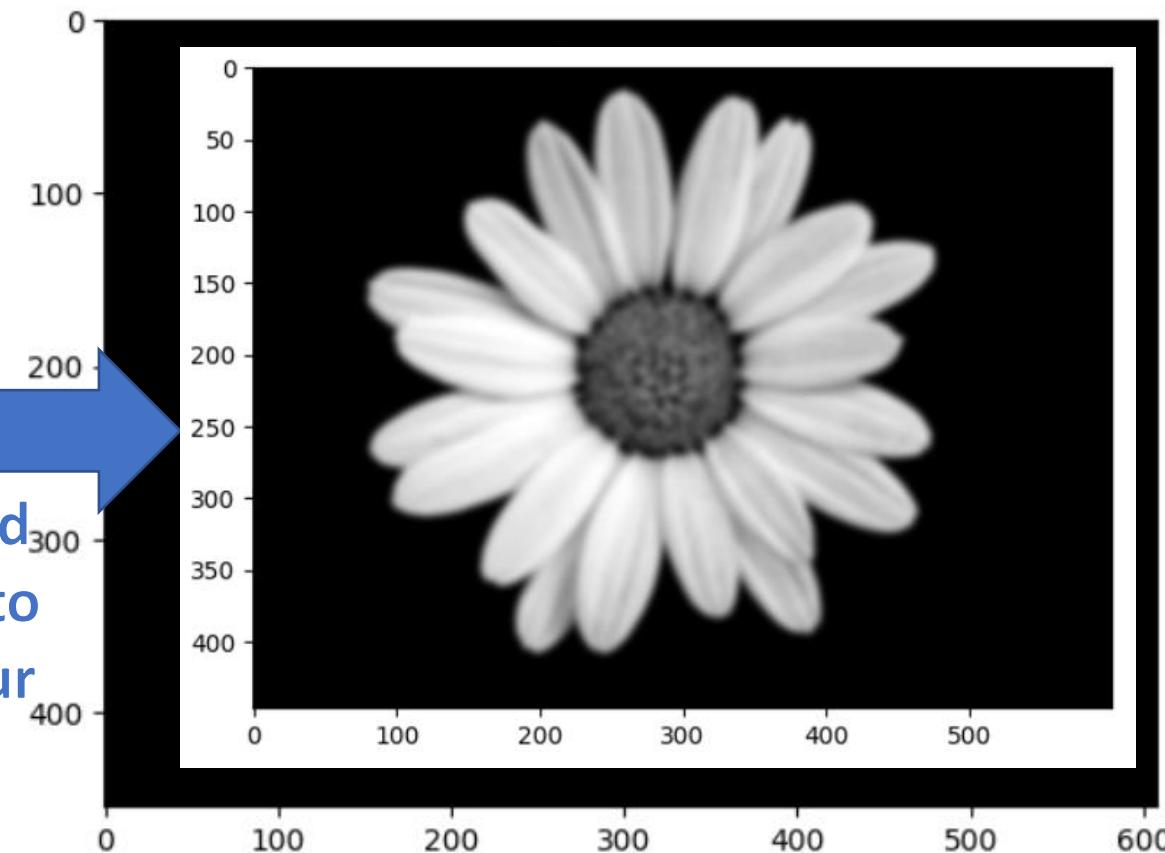
Can be repeated  
multiple times to  
increase the blur  
effect!

Restricted

```
1 # Blur kernel
2 kernel = np.array([[1, 1, 1, 1, 1],
3 [1, 1, 1, 1, 1],
4 [1, 1, 1, 1, 1],
5 [1, 1, 1, 1, 1],
6 [1, 1, 1, 1, 1]])/25
7 image_conv = convolution(im_array, kernel)
8 print(image_conv.shape)
```

(455, 608)

```
1 # Display image in matplotlib
2 plt.imshow(image_conv, cmap = 'gray')
3 plt.show()
```



Restricted

# Testing convolution on images

**Definition (the edge detection kernel):**

We can also perform **edge detection**, using, for instance the **3 × 3 Prewitt horizontal kernel**, defined as:

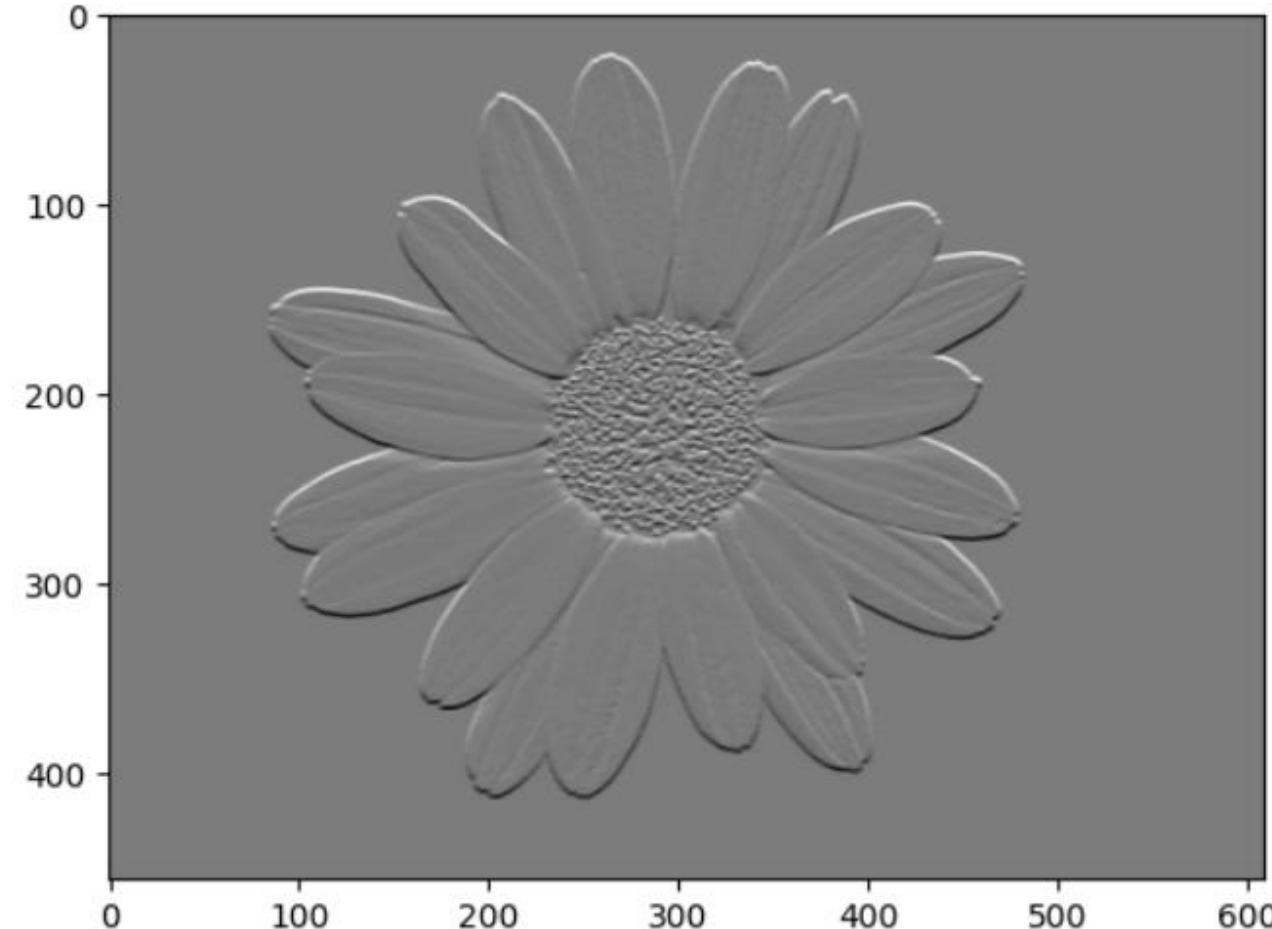
$$K = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{pmatrix}$$

This kernel highlights the horizontal edges in the image.

```
Re
1 # Trying one kernel (Prewitt kernel for horizontal edges)
2 kernel1 = np.array([[1, 1, 1],[0, 0, 0],[-1, -1, -1]])
3 image_conv1 = convolution(im_array, kernel1)
4 print(image_conv1.shape)
```

(457, 610)

```
1 # Display image in matplotlib
2 plt.imshow(image_conv1, cmap = 'gray')
3 plt.show()
```



# Testing convolution on images

**Definition (the edge detection kernel):**

This kernel produces

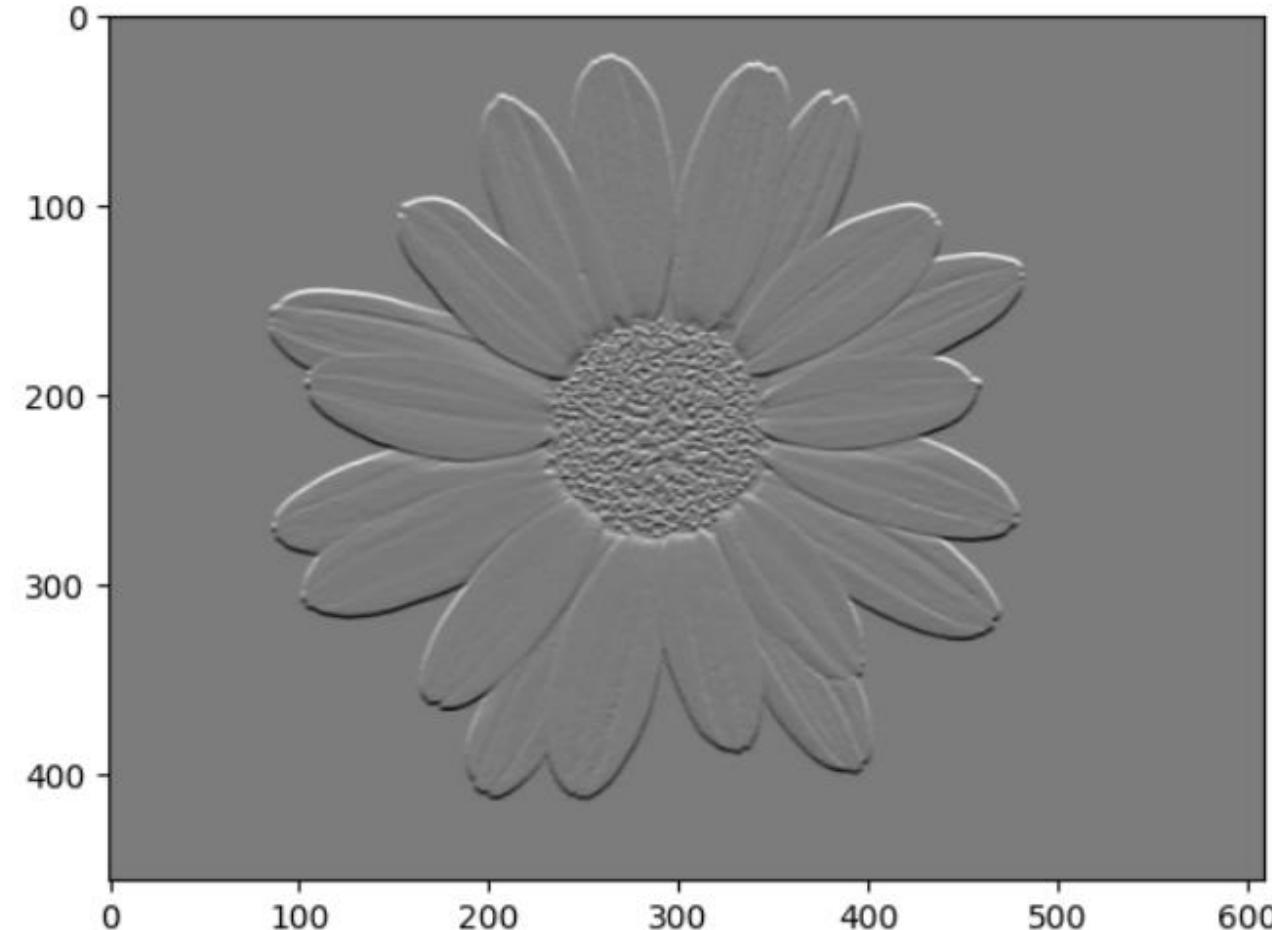
- a value close to zero when all pixels are similar,
- and a non-zero value if there is a drastic change of values in the pixel and its neighbouring pixels.

Typically, it detects scenarios where the **homophily property does not hold** (i.e. an edge!).

```
Re
1 # Trying one kernel (Prewitt kernel for horizontal edges)
2 kernel1 = np.array([[1, 1, 1],[0, 0, 0],[-1, -1, -1]])
3 image_conv1 = convolution(im_array, kernel1)
4 print(image_conv1.shape)
```

(457, 610)

```
1 # Display image in matplotlib
2 plt.imshow(image_conv1, cmap = 'gray')
3 plt.show()
```



```
1 # Open the image and convert it to grayscale
2 im = Image.open('flower.jpg').convert('L')
3
4 # Convert the image to a NumPy array
5 im_array = np.array(im)
6
7 # Print the shape of the array
8 print(im_array.shape)
```

(459, 612)

```
1 # Display image in matplotlib
2 plt.imshow(im_array, cmap = 'gray')
3 plt.show()
```

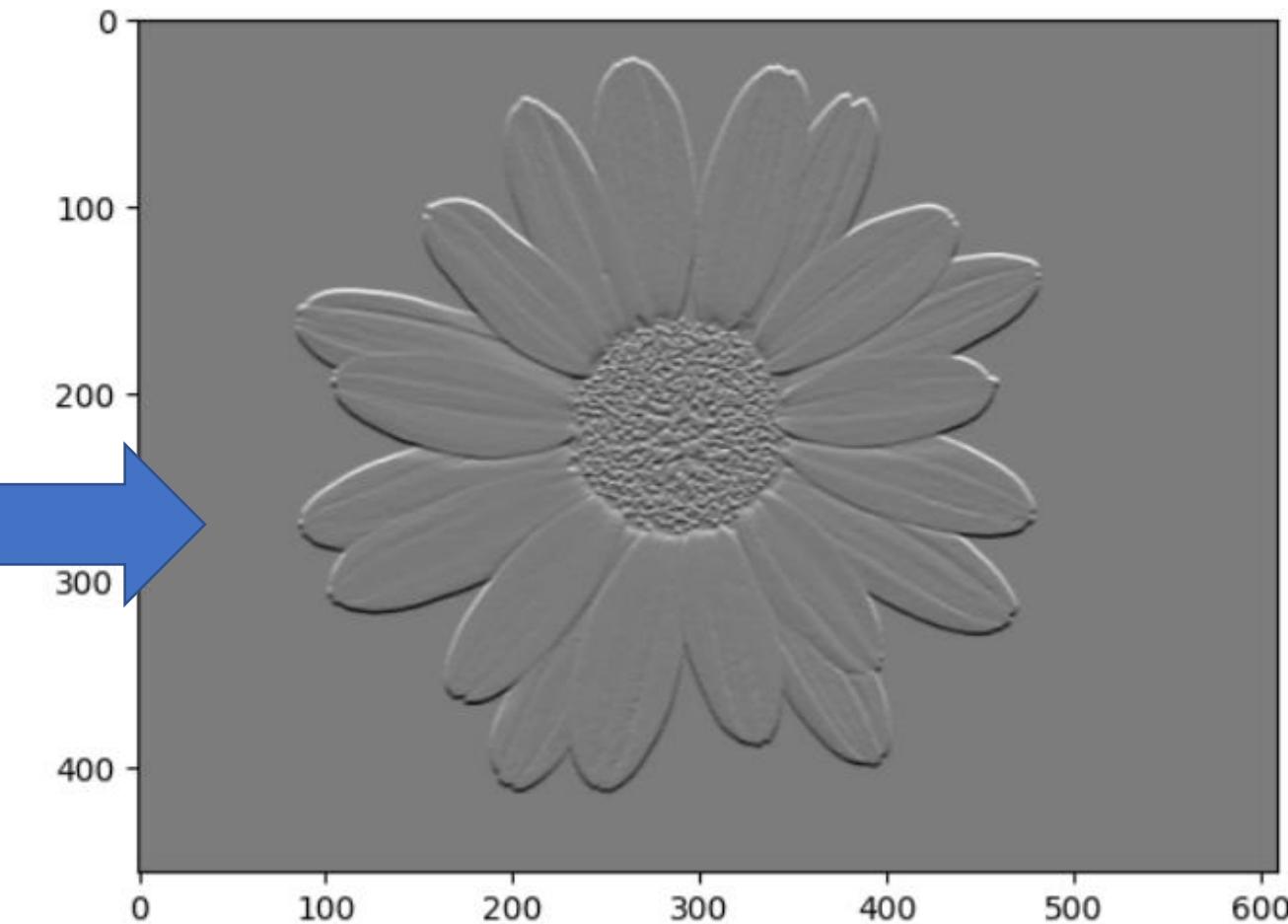


Re

```
1 # Trying one kernel (Prewitt kernel for horizontal edges)
2 kernel1 = np.array([[1, 1, 1],[0, 0, 0],[-1, -1, -1]])
3 image_conv1 = convolution(im_array, kernel1)
4 print(image_conv1.shape)
```

(457, 610)

```
1 # Display image in matplotlib
2 plt.imshow(image_conv1, cmap = 'gray')
3 plt.show()
```



Re

# Testing convolution on images

**Definition (the sharpen, or contrast enhancer kernel):**

We can also perform **contrast enhancement** (or **sharpening**), using, the following  $3 \times 3$  **sharpen kernel**, defined as:

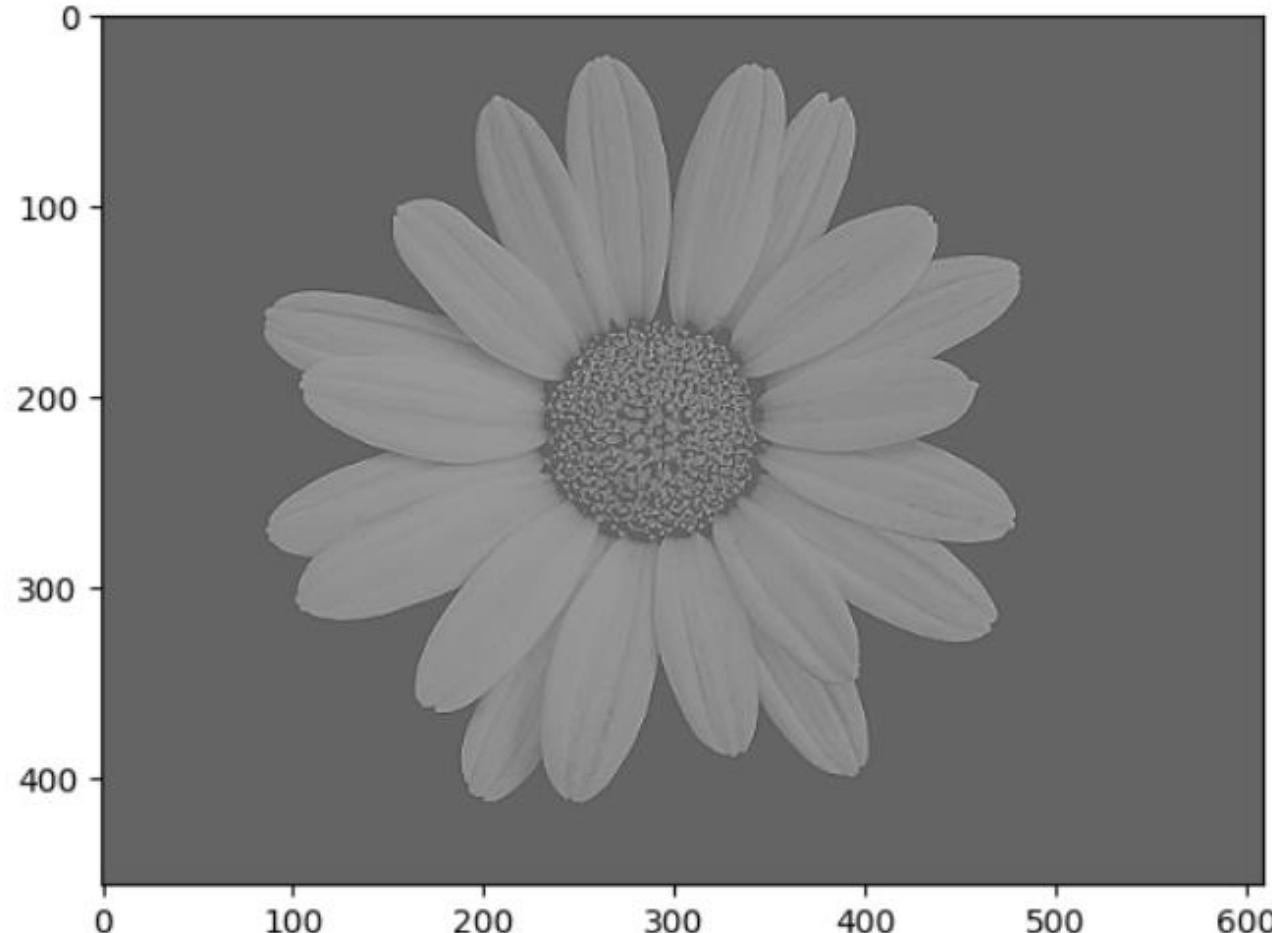
$$K = \begin{pmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{pmatrix}$$

This kernel typically enhances the edges and high-frequency details

```
1 # Sharpen (= improve contrast)
2 kernel5 = np.array([[0, -1, 0], [-1, 5, -1], [0, -1, 0]])
3 image_conv5 = convolution(im_array, kernel5)
4 print(image_conv5.shape)
```

(457, 610)

```
1 # Display image in matplotlib
2 plt.imshow(image_conv5, cmap = 'gray')
3 plt.show()
```



```
1 # Open the image and convert it to grayscale
2 im = Image.open('flower.jpg').convert('L')
3
4 # Convert the image to a NumPy array
5 im_array = np.array(im)
6
7 # Print the shape of the array
8 print(im_array.shape)
```

(459, 612)

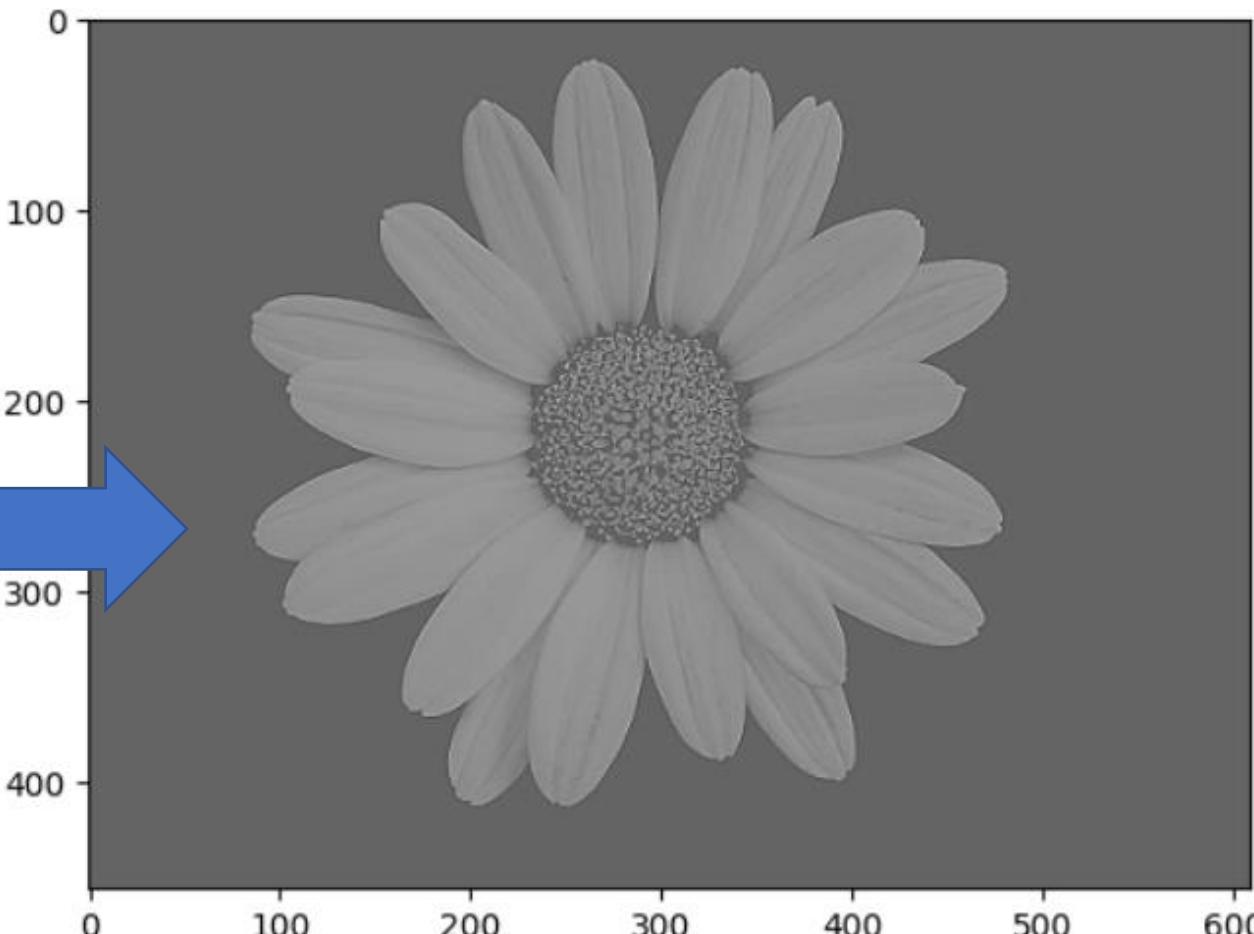
```
1 # Display image in matplotlib
2 plt.imshow(im_array, cmap = 'gray')
3 plt.show()
```



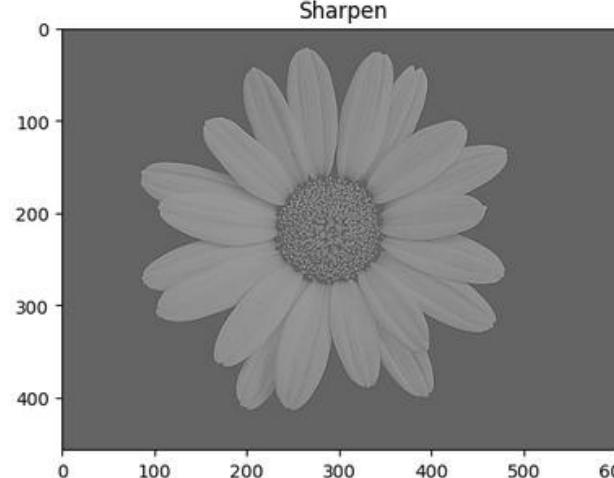
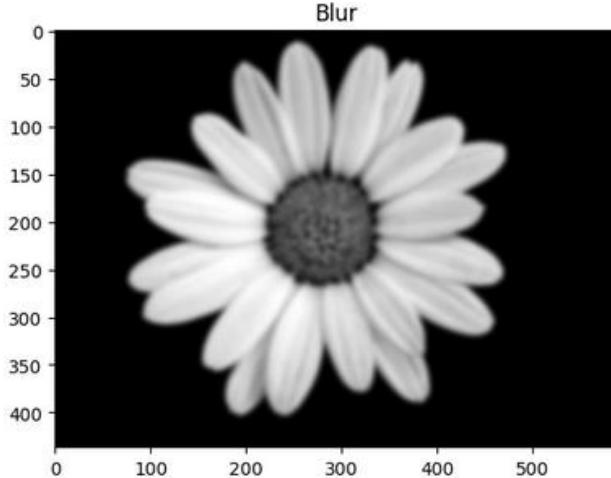
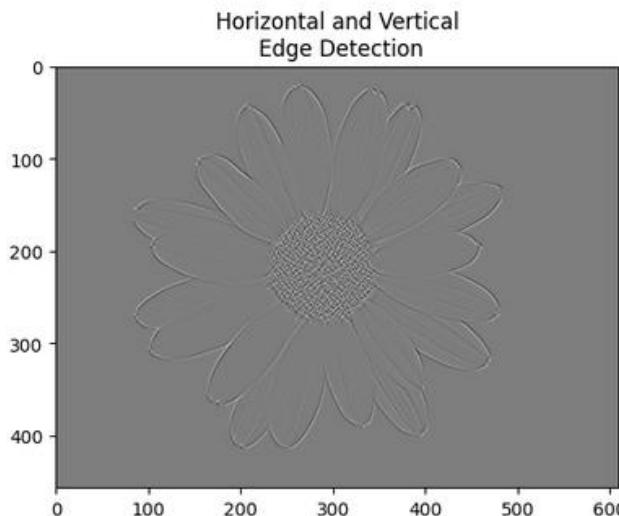
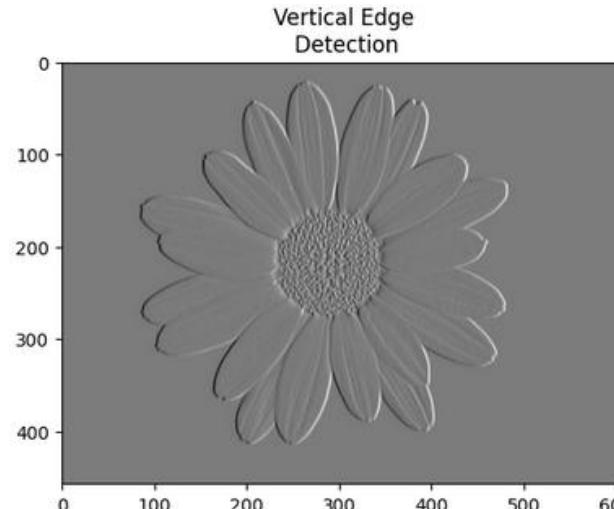
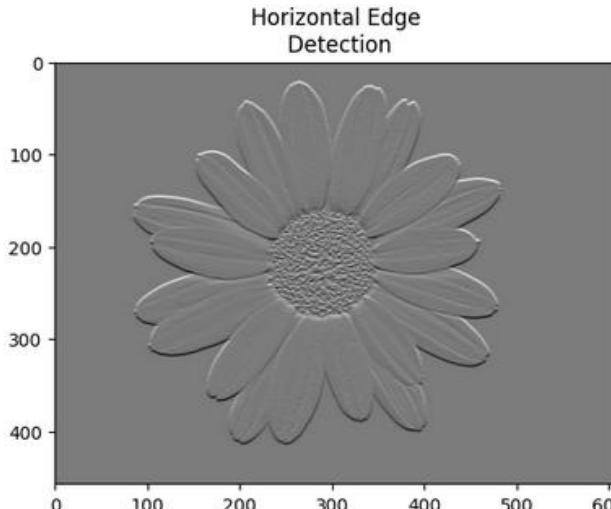
```
1 # Sharpen (= improve contrast)
2 kernel5 = np.array([[0, -1, 0], [-1, 5, -1], [0, -1, 0]])
3 image_conv5 = convolution(im_array, kernel5)
4 print(image_conv5.shape)
```

(457, 610)

```
1 # Display image in matplotlib
2 plt.imshow(image_conv5, cmap = 'gray')
3 plt.show()
```



# Many transformation kernels exist



# More on convolution kernels and their effects



# Downsizing

**Remember:** The convolution operation defined as  $Y = f(X, K)$ , produces an image  $Y$  of size  $h' \times w'$ ,

- With  $h' = h - k + 1$ ,
- And  $w' = w - k + 1$ .

A typical problem with the convolution operation we defined earlier is that it produces a new image  $Y$  whose size/resolution has been reduced.

This has to do with the kernel being used, which sums several pixels together, but only produces one pixel as a result.

This effect is even increased with the size of the kernel being used.

# Adding some padding

**Definition (**padding** in convolution):**

A typical way to address this issue consists of **padding** the image.

**Padding** consists of adding some extra pixels on the outer part of the original image  $X$ .

**Padding** artificially increases the size of the original image  $X$ , so that the convolution produces an image  $Y$  matching the size of  $X$ .

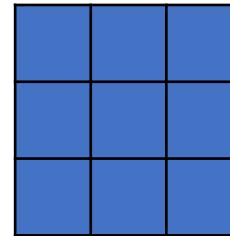
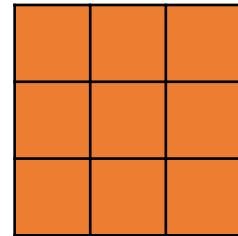
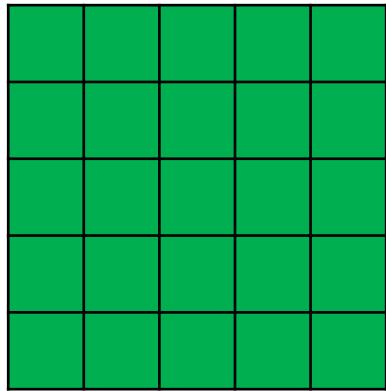
Three possible patterns for padding exist:

- Valid/Same padding,
- Zero padding,
- Other types of padding...

This is typically used to maintain the spatial dimensions of the input image and prevent the spatial dimensions of the output from getting too small.

# Adding some padding

**Valid padding:** default configuration, no padding is applied to the input data. The convolution operation is only performed only on the valid parts of the input and the output size is then smaller than the input size.



$$Y = f(X, K)$$

$X$

$K$

$Y$

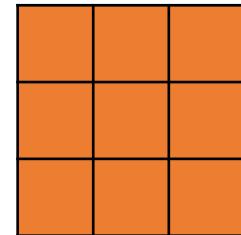
# Adding some padding

**Same padding:** The number of elements added to the image (i.e. **padding size  $p$** ) is defined so that image  $Y$  has the same size as  $X$ .

**Zero padding:** added pixels can simply be set to have the value 0.

0	0	0	0	0	0	0
0						0
0						0
0						0
0						0
0						0
0	0	0	0	0	0	0

$X$



$K$



$$Y = f(X, K)$$

0	0	0	0	0	0	0
0						0
0						0
0						0
0						0
0						0
0	0	0	0	0	0	0

$Y$

# Adding some padding

**When using a padding with size  $p$ ,** the convolution operation defined as  $Y = f(X, K)$ , produces an image  $Y$  of size  $h' \times w'$ ,

- With  $h' = h + 2p - k + 1$ ,
- And  $w' = w + 2p - k + 1$ .

**Same padding:** to ensure the image  $Y$  has the same dimension as  $X$ , we need to use a padding size  $p = \frac{k-1}{2}$ .

It is therefore adjusted to the kernel size  $k$ .

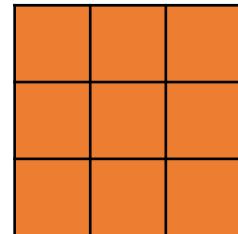
If we are not interested in  $Y$  having the same size as  $X$ , we are free to use any padding size.

# Adding some padding

**Interpolation padding:** instead of zeros, added pixels have the value of the closest pixel. Can also “zoom in” the original image and resize it to the expected number of pixels we want for image  $X$  after padding.

1	1	5	5	2	4	4
1	1	5	5	2	4	4
2	2	4	5	2	2	2
3	3	1	1	1	1	1
4	4	4	7	2	3	3
5	5	0	0	3	1	1
5	5	0	0	0	1	1

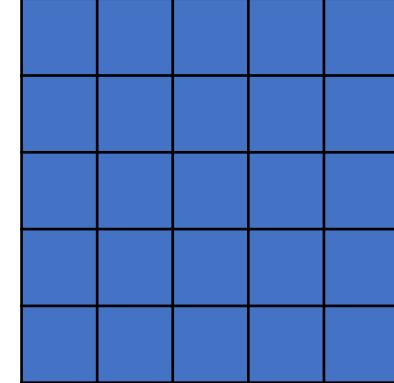
$\textcolor{green}{X}$



$\textcolor{brown}{K}$



$$Y = f(X, K)$$



$\textcolor{blue}{Y}$

# Adding some padding

Padding is simply implemented using the `pad()` function.

It adds a layer of zeroes to the matrix `image`, of size *padding* on top, bottom, right and left side of the image matrix.

```
def convolution_with_padding(image, kernel, padding = 0):
    # Flip the kernel (optional)
    kernel = np.flipud(np.fliplr(kernel))

    # Get the dimensions of the image and kernel
    image_rows, image_cols = image.shape
    kernel_rows, kernel_cols = kernel.shape

    # Add padding to the image
    image = np.pad(image, ((padding, padding), (padding, padding)), 'constant')

    # Set the output image to the correct size
    output_rows = image_rows - kernel_rows + 1
    output_cols = image_cols - kernel_cols + 1
    output = np.zeros((output_rows, output_cols))

    # Convolve using Numpy
    output = correlate(image, kernel, mode = 'valid')

return output
```

0	0	0	0	0	0	0	0
0							0
0							0
0							0
0							0
0							0
0							0
0	0	0	0	0	0	0	0

# Adding some padding

- When using no padding, the resulting image is downsized.
- When using **same padding**, i.e.

$$p = \frac{k-1}{2} = \frac{5-1}{2} = 2,$$

**the resulting image has the same size as the original one.**

```

1 # Blur (no padding)
2 kernel = np.array([[1, 1, 1, 1, 1],
3                     [1, 1, 1, 1, 1],
4                     [1, 1, 1, 1, 1],
5                     [1, 1, 1, 1, 1],
6                     [1, 1, 1, 1, 1]])/25
7 image_conv = convolution_basic(im_array, kernel)
8 # Print the shape of the array
9 print(im_array.shape)
10 print(image_conv.shape)
```

(459, 612)  
(455, 608)

```

1 # Blur (same padding)
2 kernel = np.array([[1, 1, 1, 1, 1],
3                     [1, 1, 1, 1, 1],
4                     [1, 1, 1, 1, 1],
5                     [1, 1, 1, 1, 1],
6                     [1, 1, 1, 1, 1]])/25
7 image_conv_pad = convolution_with_padding(im_array, kernel, padding = 2)
8 # Print the shape of the array
9 print(im_array.shape)
10 print(image_conv_pad.shape)
```

(459, 612)  
(459, 612)

# Adding a stride

## **Definition (**stride** in convolution):**

The purpose of **stride** in convolution is to **control the movement or step size of the convolution filter as it slides over the input image**.

A larger stride results in a smaller output feature map, while a smaller stride results in a larger output feature map.

Stride can also be used to reduce the spatial dimensions of the feature map, which can help to reduce the number of parameters and computation in the network.

**Note:** Using a stride with a size  $s$  that is not 1, will drastically reduce the size of the output image, so beware!

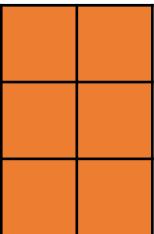
# Adding a stride

Below, we demonstrate **what a stride of size  $s = 2$  does** (no padding).

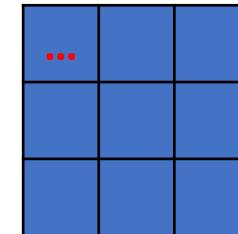
First, use the convolution as before, next elements to be used are “two steps” away from the first position, and so on.

1	1	5	5	2	4	4
1	1	5	5	2	4	4
2	2	4	5	2	2	2
3	3	1	1	1	1	1
4	4	4	7	2	3	3
5	5	0	0	3	1	1
5	5	0	0	0	1	1

$X$



$K$



$$Y = f(X, K)$$

$Y$

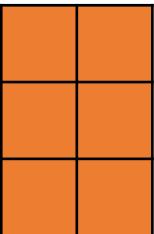
# Adding a stride

Below, we demonstrate **what a stride of size  $s = 2$  does** (no padding).

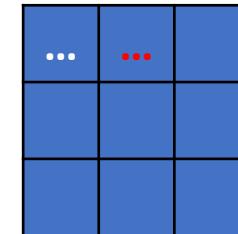
First, use the convolution as before, next elements to be used are “two steps” away from the first position, and so on.

1	1	5	5	2	4	4
1	1	5	5	2	4	4
2	2	4	5	2	2	2
3	3	1	1	1	1	1
4	4	4	7	2	3	3
5	5	0	0	3	1	1
5	5	0	0	0	1	1

$X$



$K$



$$Y = f(X, K)$$

$Y$

# Adding a stride

- Stride is easily implemented by using a slicing in the result of the correlation.
- This is not the most optimized way to do it, however!
- *(We do not care so much, as we will use the PyTorch version of convolution after this!)*

```
def convolution_with_stride_and_padding(image, kernel, stride = 1, padding = 0):  
    # Flip the kernel (optional)  
    kernel = np.flipud(np.fliplr(kernel))  
  
    # Get the dimensions of the image and kernel  
    image_rows, image_cols = image.shape  
    kernel_rows, kernel_cols = kernel.shape  
  
    # Add padding to the image  
    image = np.pad(image, ((padding, padding), (padding, padding)), 'constant')  
  
    # Set the output image to the correct size  
    output_rows = (image_rows - kernel_rows) // stride + 1  
    output_cols = (image_cols - kernel_cols) // stride + 1  
    output = np.zeros((output_rows, output_cols))  
  
    # Convolve using Numpy  
    # (not the most optimal way to implement it but good enough!)  
    output = correlate(image, kernel, mode = 'valid')[::stride, ::stride]  
  
    return output
```

# The (final) magic formula for convolution

**Magic formula for convolution:**  
let us consider

- An input image, defined as a 3D tensor  $X$  of size  $h \times w \times c$ , with  $h$  the height,  $w$  the weight and  $c$  the number of channels.
- A convolution kernel  $K$  of size  $k \times k$ .
- A padding of size  $p$ , a stride of size  $s$ .

The resulting image  $Y$  will have a size  $h' \times w' \times c$ , with:

$$h' = \left\lfloor \frac{h + 2p - k}{s} + 1 \right\rfloor$$

And

$$w' = \left\lfloor \frac{w + 2p - k}{s} + 1 \right\rfloor$$

**Note:** the floor function  $\lfloor \dots \rfloor$  is used in case the division result is an integer.

# Adding a stride

```

1 # Blur (with stride and padding)
2 kernel = np.array([[1, 1, 1, 1, 1],
3                     [1, 1, 1, 1, 1],
4                     [1, 1, 1, 1, 1],
5                     [1, 1, 1, 1, 1],
6                     [1, 1, 1, 1, 1]])/25
7 image_conv_pad_stride = convolution_with_stride_and_padding(im_array, \
8                                                               kernel, \
9                                                               stride = 2, \
10                                                              padding = 2)
11 # Print the shape of the array
12 print(im_array.shape)
13 print(image_conv_pad_stride.shape)

```

(459, 612)

(230, 306)

$$h' = \left\lceil \frac{h + 2p - k}{s} + 1 \right\rceil$$

$$h' = \left\lceil \frac{459 + 2 \times 2 - 5}{2} + 1 \right\rceil = 230$$

# Adding a dilation

**Definition (**dilation in convolution**):**

Dilation in image convolution determines **the spacing between the values of the original image multiplying the kernel**.

By default, the value for dilation is  $d = 1$ .

With a dilation greater than 1, the pixel values of the original image multiplying the kernel are **spread apart by a specified number of pixels**.

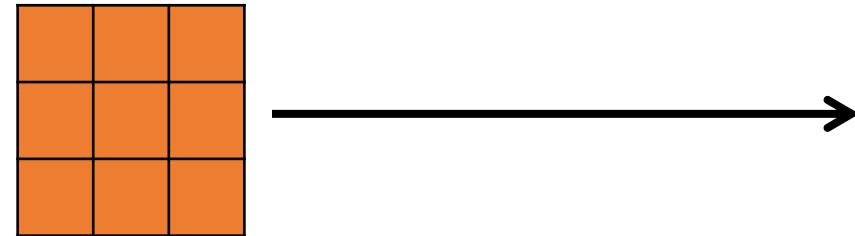
This is a very niche feature of the convolution operation. It is easier to visualise it than explain it.

*(We leave its implementation as practice to the reader.)*

# Adding a dilation

Below, we demonstrate **what a dilation of size  $d = 2$  does**. Our convolution uses a stride with default value set to 1, padding is also set to its default value 0. Elements being computed together are then “2 steps away” from each other.

1	1	5	5	2	4	4
1	1	5	5	2	4	4
2	2	4	5	2	2	2
3	3	1	1	1	1	1
4	4	4	7	2	3	3
5	5	0	0	3	1	1
5	5	0	0	0	1	1

**X****K****Y**

$$Y = f(X, K)$$

# The (final) magic formula for convolution

## Magic formula for convolution version 2.0: let us consider

- An input image, defined as a 3D tensor  $X$  of size  $h \times w \times c$ , with  $h$  the height,  $w$  the weight and  $c$  the number of channels.
- A convolution kernel  $K$  of size  $k \times k$ .
- A padding of size  $p$ , a stride of size  $s$ , and a dilation of size  $d$ .

The resulting image  $Y$  will have a size  $h' \times w' \times c$ , with:

$$h' = \left\lfloor \frac{h + 2p - d(k - 1) - 1}{s} + 1 \right\rfloor$$

And

$$w' = \left\lfloor \frac{w + 2p - d(k - 1) - 1}{s} + 1 \right\rfloor$$

**Note:** the floor function  $\lfloor \dots \rfloor$  is used in case the division result is an integer.

# Implementing a custom Conv in PyTorch (with stride and padding, no dilation)

```
def convolution_with_stride_and_padding_torch(image, kernel, stride = 1, padding = 0):
    # Convert image and kernel to PyTorch tensors
    image = torch.from_numpy(image)
    kernel = torch.from_numpy(kernel)

    # Flip the kernel (optional)
    kernel = torch.flip(torch.flip(kernel, [0]), [1])

    # Add padding to the image
    image = torch.nn.functional.pad(image, (padding, padding, padding, padding))

    # Set the output image to the correct size
    output_rows = (image.shape[0] - kernel.shape[0]) // stride + 1
    output_cols = (image.shape[1] - kernel.shape[1]) // stride + 1
    output = torch.zeros((output_rows, output_cols))

    # Convolve using PyTorch
    for i in range(0, output_rows, stride):
        for j in range(0, output_cols, stride):
            output[i, j] = (kernel * image[i:i + kernel.shape[0], j:j + kernel.shape[1]]).sum()

    return output
```

# Implementing a custom Conv in PyTorch (with stride and padding, no dilation)

The PyTorch and the Numpy implementations are indeed equivalent.

```
1 # Blur
2 kernel = np.array([[1, 1, 1, 1, 1],
3                     [1, 1, 1, 1, 1],
4                     [1, 1, 1, 1, 1],
5                     [1, 1, 1, 1, 1],
6                     [1, 1, 1, 1, 1]])/25
7
8 # Numpy and torch implementations comparison
9 image_conv_pad_stride = convolution_with_stride_and_padding(im_array, kernel, stride = 2, padding = 2)
10 image_conv_pad_stride_torch = convolution_with_stride_and_padding_torch(im_array, kernel, stride = 2, padding = 2)
11 # Print the shape of the array
12 print(im_array.shape)
13 print(image_conv_pad_stride.shape)
14 print(image_conv_pad_stride_torch.shape)
```

```
(459, 612)
(230, 306)
torch.Size([230, 306])
```

# The Conv2d in PyTorch

PyTorch has a Conv2d function implementing said convolution.

We will rely on it from now on.

```
1 def convolution_batch_torch_conv2d(images, kernel, stride = 1, padding = 0):
2
3     # Convert kernel to PyTorch tensor, if needed
4     kernel = torch.from_numpy(kernel)
5     kernel = kernel.view(1, 1, kernel.shape[0], kernel.shape[1])
6     kernel = kernel.float()
7
8     # Flip the kernel (optional)
9     kernel = torch.flip(torch.flip(kernel, [2]), [3])
10
11    # Create a convolutional layer
12    conv = torch.nn.Conv2d(in_channels = images.shape[1], \
13                          out_channels = 1, \
14                          kernel_size = kernel.shape[2:], \
15                          stride = stride, \
16                          padding = padding)
17
18    # Assign the kernel to the layer
19    conv.weight = torch.nn.Parameter(kernel)
20    conv.bias = torch.nn.Parameter(torch.tensor([0.0]))
21
22    # Perform convolution
23    output = conv(images)
24
25    return output
```

# The Conv2d in PyTorch

Note, however that this layer has **two trainable parameters**:

- **Weight** (which is our kernel, whose values will be decided later during training).
- **Bias** (which was not there before?)

```
1 def convolution_batch_torch_conv2d(images, kernel, stride = 1, padding = 0):  
2  
3     # Convert kernel to PyTorch tensor, if needed  
4     kernel = torch.from_numpy(kernel)  
5     kernel = kernel.view(1, 1, kernel.shape[0], kernel.shape[1])  
6     kernel = kernel.float()  
7  
8     # Flip the kernel (optional)  
9     kernel = torch.flip(torch.flip(kernel, [2]), [3])  
10  
11    # Create a convolutional layer  
12    conv = torch.nn.Conv2d(in_channels = images.shape[1], \  
13                          out_channels = 1, \  
14                          kernel_size = kernel.shape[2:], \  
15                          stride = stride, \  
16                          padding = padding)  
17  
18    # Assign the kernel to the layer  
19    conv.weight = torch.nn.Parameter(kernel)  
20    conv.bias = torch.nn.Parameter(torch.tensor([0.0]))  
21  
22    # Perform convolution  
23    output = conv(images)  
24  
25    return output
```

# The Conv2d in PyTorch

Note, however that this layer has **two trainable parameters**:

- **Weight** (which is our kernel, whose values will be decided later during training).
- **Bias** (which was not there before?)

Bias is simply added to our convolution operation, following the intuition of the  $WX + b$  operation from earlier.

$$Y_{i,j} = \frac{1}{k^2} \sum_{m=1}^k \sum_{n=1}^k X_{i+m-1, j+n-1} K_{m,n} + b$$

# Let us call it a break for now

We will continue on the next lecture with our PyTorch implementation of the convolution operation and our first Convolutional Neural Network.