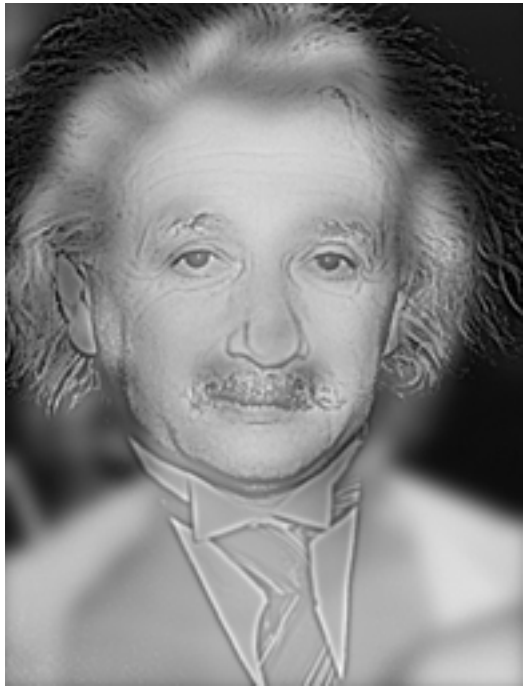
CSC 589 Introduction to Computer Vision

Lecture 2 linear filtering



Instructor: Bei Xiao

Wednesday , Jan 23, 2019

Announcement

- First homework out: Image Processing with Numpy/Scipy.
- Due, Wed, January 30th.
- Office hour: Tuesday, Friday, 2:30pm-3:30pm

Today’s class

- What is an image?
- Point Process
- Neighborhood operation
- Convolution

Choices of Python Image libraries

- Level 1 (basic): Numpy, treating image as matrix
- Level 2 (Scipy): an image I/O (scipy.misc.imread), scipy.ndimage package that has convolution, filters, etc.
- Level 3 (sckit-image): equivalent to MATLAB image processing toolbox, but better. Many built-in stuff, so not suitable for conceptual learning in the beginning.
- High-level (OpenCV): it is not suitable for teaching but suitable for development. Very different from actual Python. We might use it for some projects later in the course.

Choices of Python libraries

- Level 1 (basic): Numpy, treating image as matrix
- Level 2 (Scipy): an image I/O (scipy.misc.imread), scipy.ndimage package
- Level 3 (sckit-image): equivalent to MATLAB image processing toolbox, but better. We will use it when we need to.
- High-level (OpenCV): it is not suitable for teaching but suitable for development. We might use it for some projects later in the course.

The higher level library you use, the less control you have!

To start, we will use the basic level libraries!

- Level 1 (basic): Numpy, basic numerical Python, treating image as matrix
- Level 2 (Scipy): an image I/O (scipy.misc.imread), scipy.ndimage package

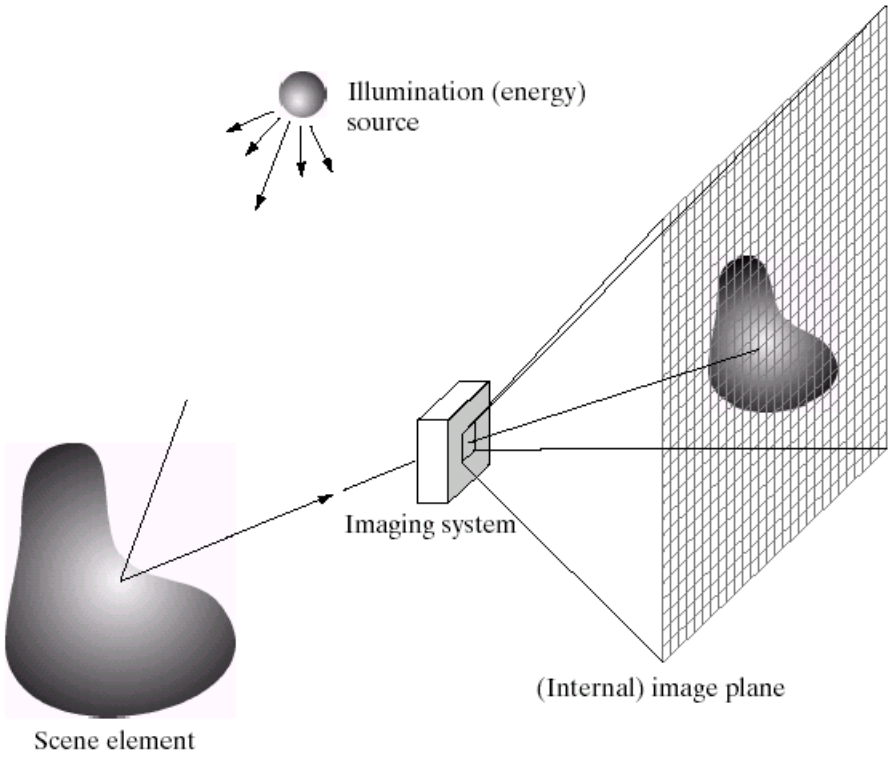
- We will write our own functions!

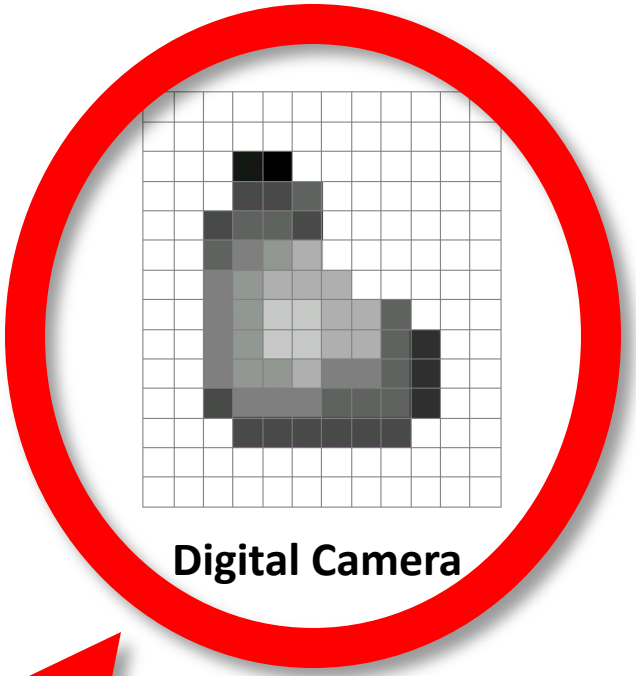
What is an image?

A useful tutorial

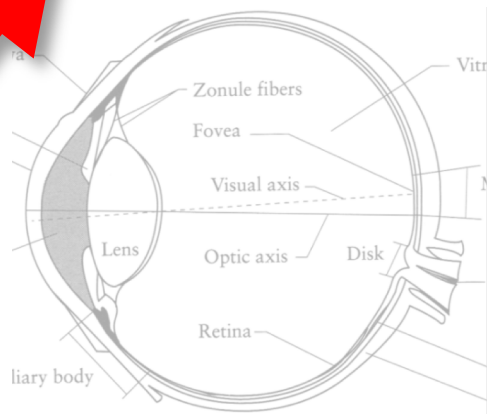
Computer vision for dummies

What is an image?





We'll focus on these in this class

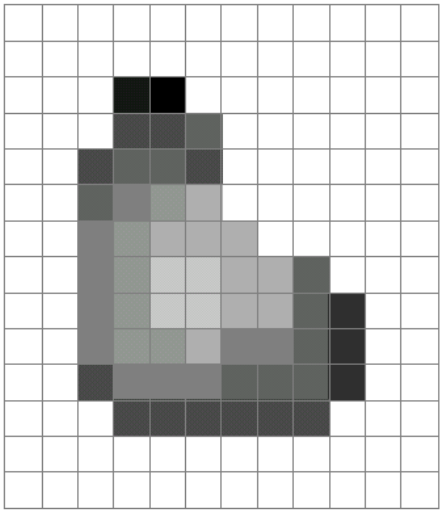


(More on this process later)

Source: A. Efros

What is an image?

- A grid (matrix) of intensity values



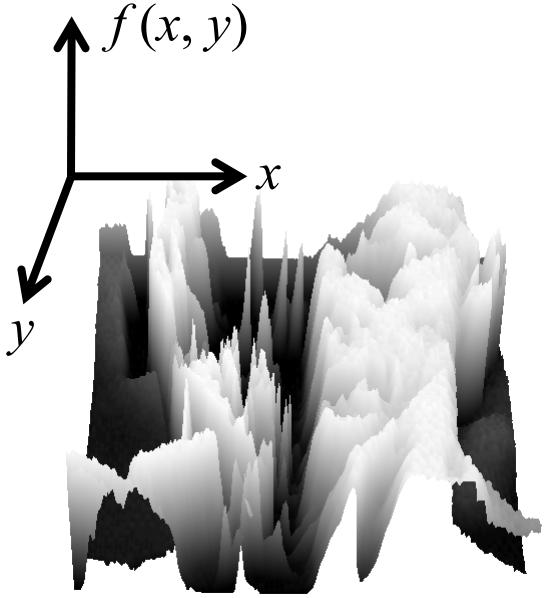
=

255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	20	0	255	255	255	255	255	255	255
255	255	255	75	75	75	255	255	255	255	255	255
255	255	75	95	95	75	255	255	255	255	255	255
255	255	96	127	145	175	255	255	255	255	255	255
255	255	127	145	175	175	175	255	255	255	255	255
255	255	127	145	200	200	175	175	95	255	255	255
255	255	127	145	200	200	175	175	95	47	255	255
255	255	127	145	145	175	127	127	95	47	255	255
255	255	74	127	127	127	95	95	95	47	255	255
255	255	255	74	74	74	74	74	74	255	255	255
255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255	255	255	255	255

(common to use one byte per value: 0 = black, 255 = white)

What is an image?

- We can think of a (grayscale) image as a **function**, f, from R^2 to R:
  - $f(x,y)$ gives the **intensity** at position (x,y)



  - A **digital** image is a discrete (**sampled**, **quantized**) version of this function

Slide credit: James Hays

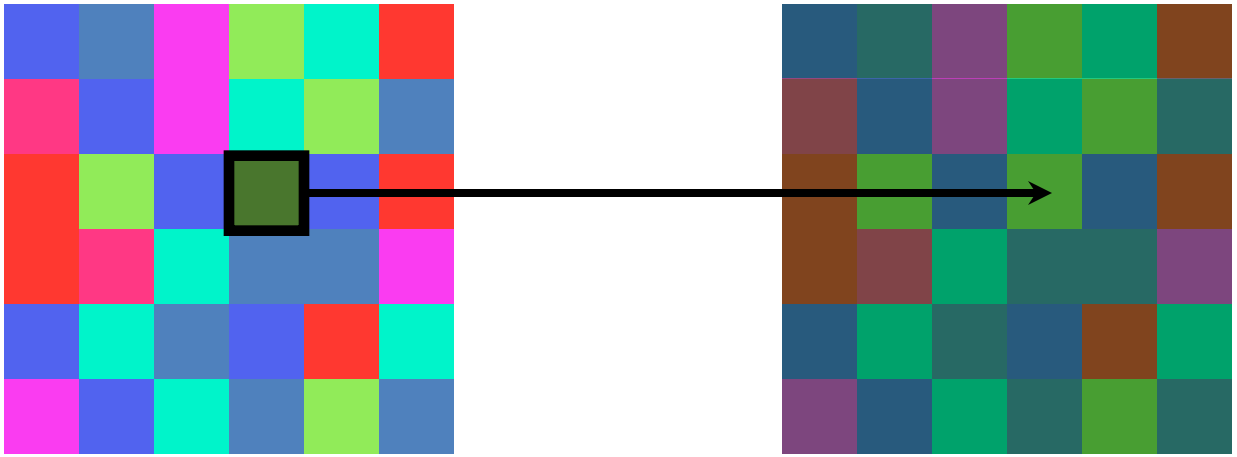
Image Processing

- Define a new image *g* in terms of an existing image *f*
  - We can transform either the domain or the range of *f*
- Range transformation:

$$g(x, y) = t(f(x, y))$$

What kinds of operations can this perform?

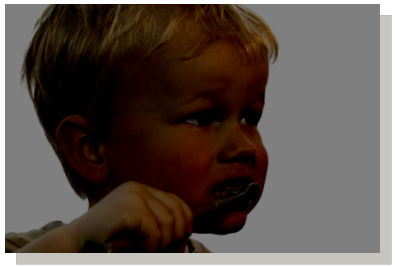
Point Operations



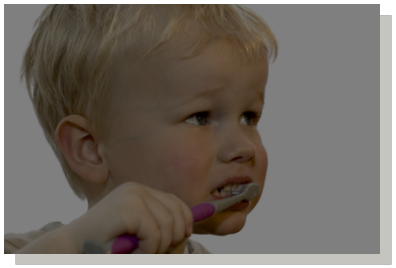
Point Processing

Original

Darken

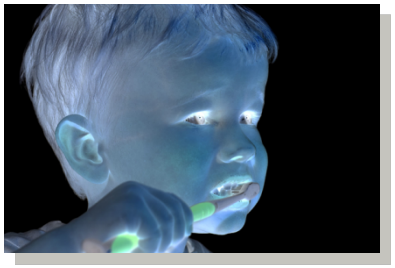


Lower Contrast

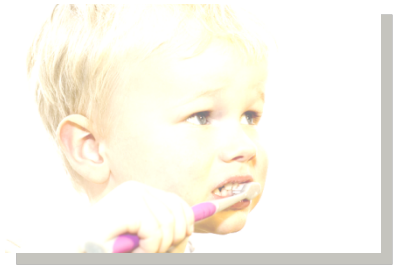


Nonlinear Lower Contrast

Invert

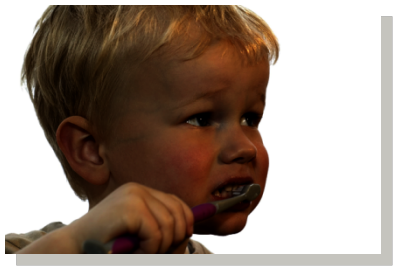


Lighten



Raise Contrast

Nonlinear Raise Contrast



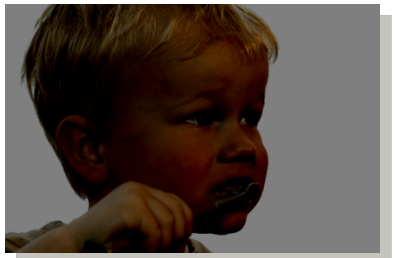
Slide source: S. Narasimhan

Point Processing

Original

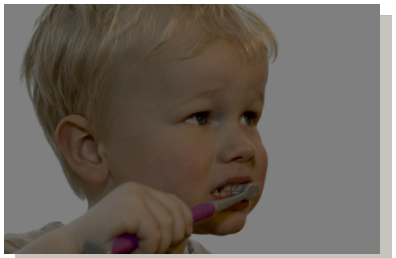
`x`

Darken



`x - 128`

Lower Contrast

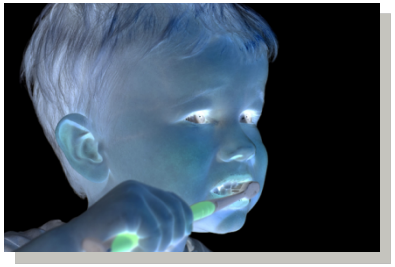


`x / 2`

Nonlinear Lower Contrast

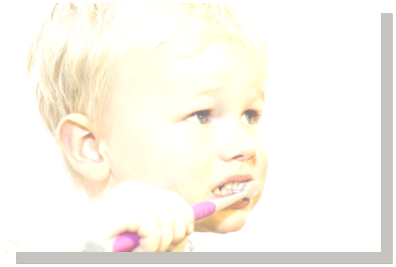
`((x / 255.0) ^ 0.33) * 255.0`

Invert



`255 - x`

Lighten

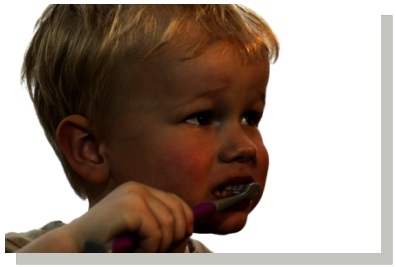


`x + 128`

Raise Contrast

`x * 2`

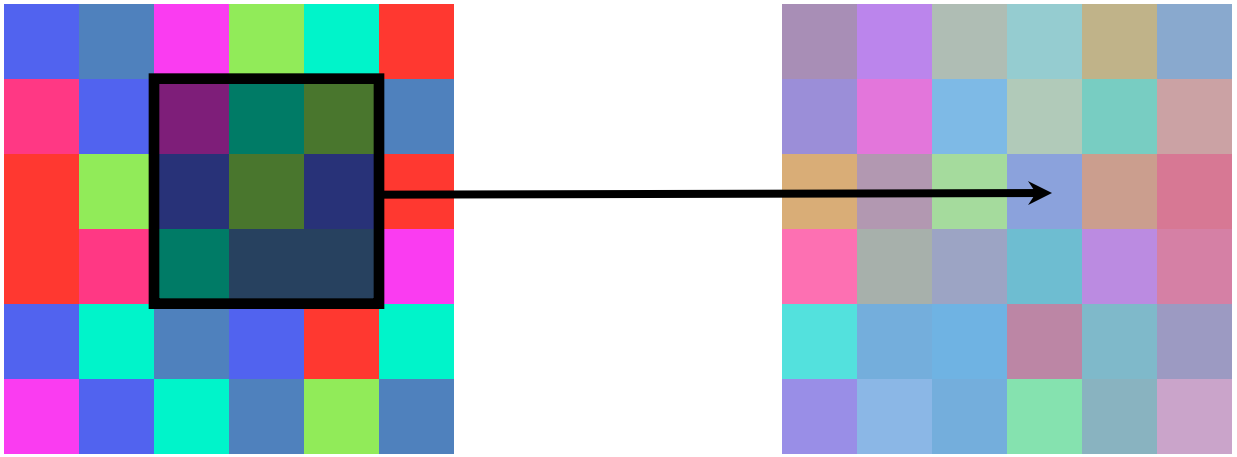
Nonlinear Raise Contrast



`((x / 255.0) ^2) * 255.0`

Slide source: S. Narasimhan

Neighborhood Operations



Slide source: S. Narasimhan

Neighborhood operations

Image

Edge detection

Blur

Slide source: S. Narasimhan

Neighborhood operations

Image

Edge detection

Blur

Slide source: S. Narasimhan

3×3 Neighborhood

5×5 Neighborhood

7×7 Neighborhood

Let’s represent this more generally

0	3	0	0
0	6	1	16
0	0	2	46
0	0	2	43

Slide source: Matthew Tappen

Let’s represent this more generally

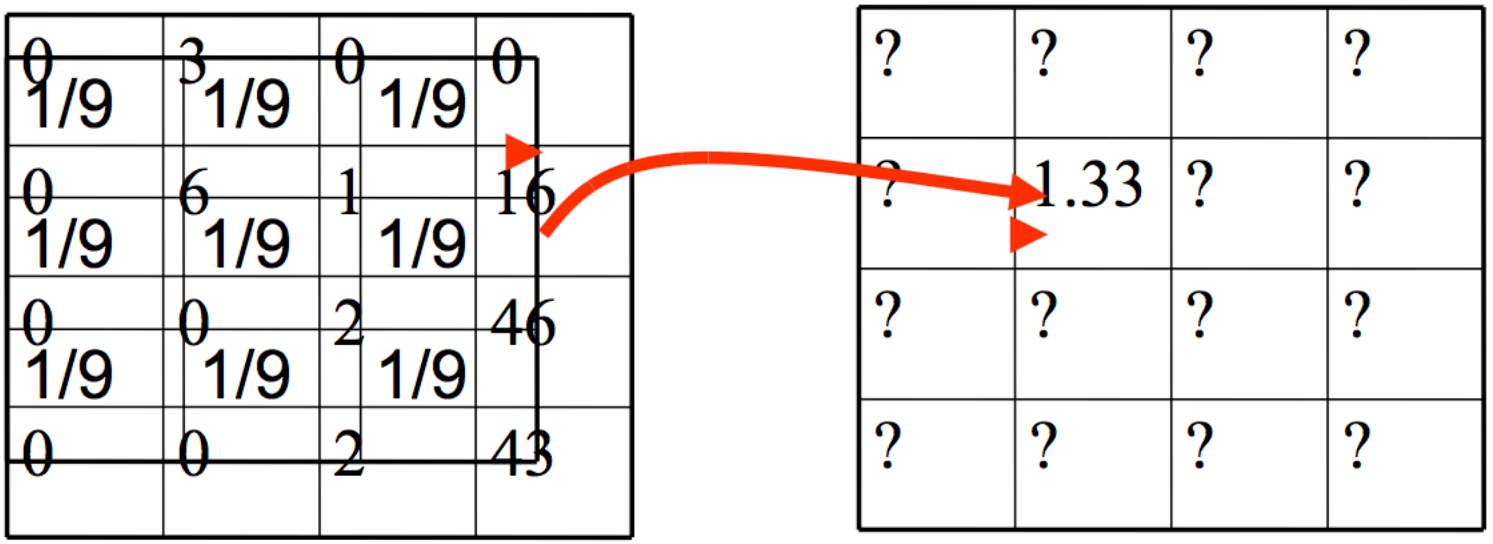
Normalized box filter (3×3)

0	3	0	0
0	6	1	16
0	0	2	46
0	0	2	43

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Slide source: Matthew Tappen

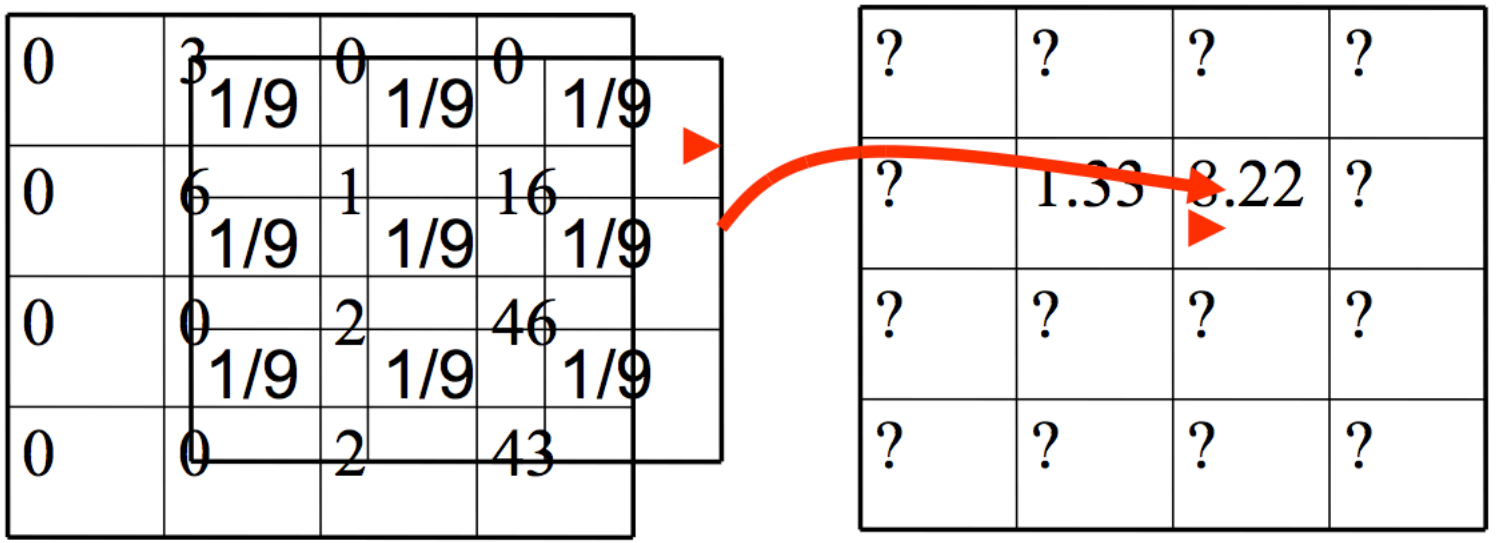
Let’s represent this more generally



- Multiply corresponding numbers and add

Slide source: Matthew Tappen

Let’s represent this more generally

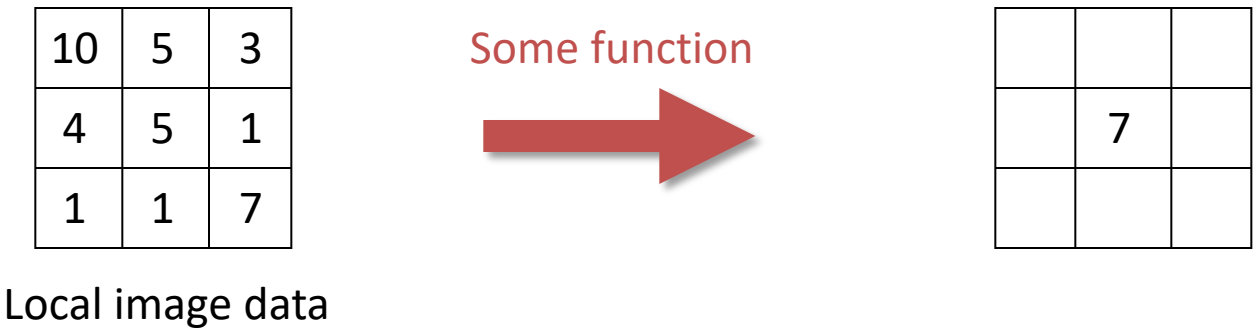


- Multiply corresponding numbers and add
- Template moves across the image
- Think of it as a sliding window

Slide source: Matthew Tappen

Image Filtering

- Modify the pixels in an image based on some function of a local neighborhood of each pixel

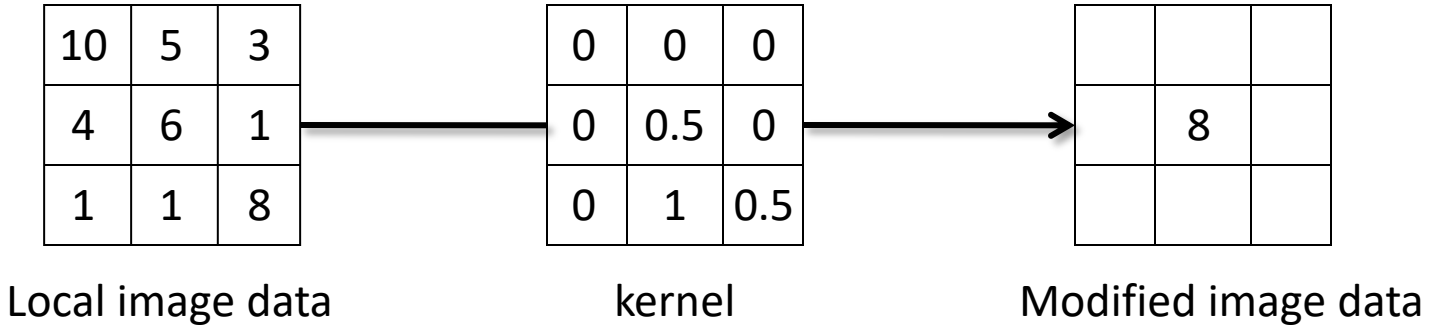


Local image data

Source: L. Zhang

Linear filtering

- One simple version of filtering: linear filtering (cross-correlation, convolution)
  - Replace each pixel by a linear combination (a weighted sum) of its neighbors
- The prescription for the linear combination is called the “kernel” (or “mask”, “filter”)



Source: L. Zhang

This is called convolution

- Mathematically expressed as

$$R(i,j) = \sum_{m=-N}^{N} \sum_{n=-N}^{N} I(m,n)K(i-m,j-n)$$

Resulting Image

Input Image

Convolution Kernel

https://en.wikipedia.org/wiki/Convolution
https://dsp.stackexchange.com/questions/2654/what-is-the-difference-between-convolution-and-cross-correlation

Slide source: Matthew Tappen

Notation

- Also denoted as
- R = I * K
- We “convolve” I with K

  -Not convolute!

$$R(i,j) = \sum_{m=-N}^{N} \sum_{n=-N}^{N} I(m,n)K(i-m,j-n)$$

Resulting Image

Input Image

Convolution Kernel

Slide source: Matthew Tappen

Filtering vs. Convolution

- 2d filtering
  - `h=filter2(g,f);` or
    `h=imfilter(f,g);`

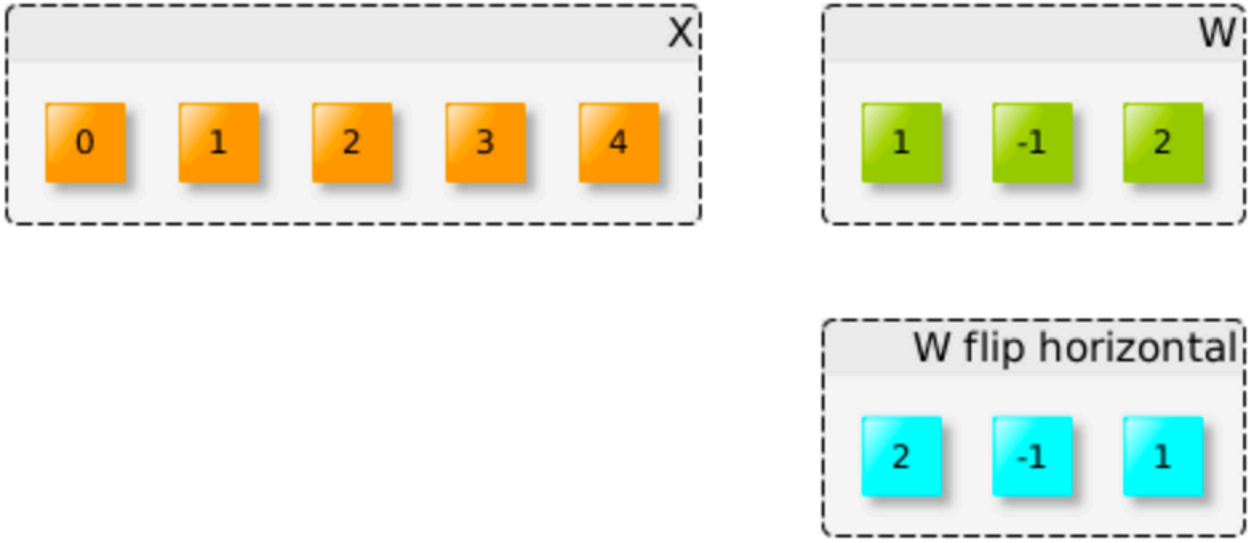
$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

- 2d convolution (must flip kernel)
  - `h=conv2(g,f);`

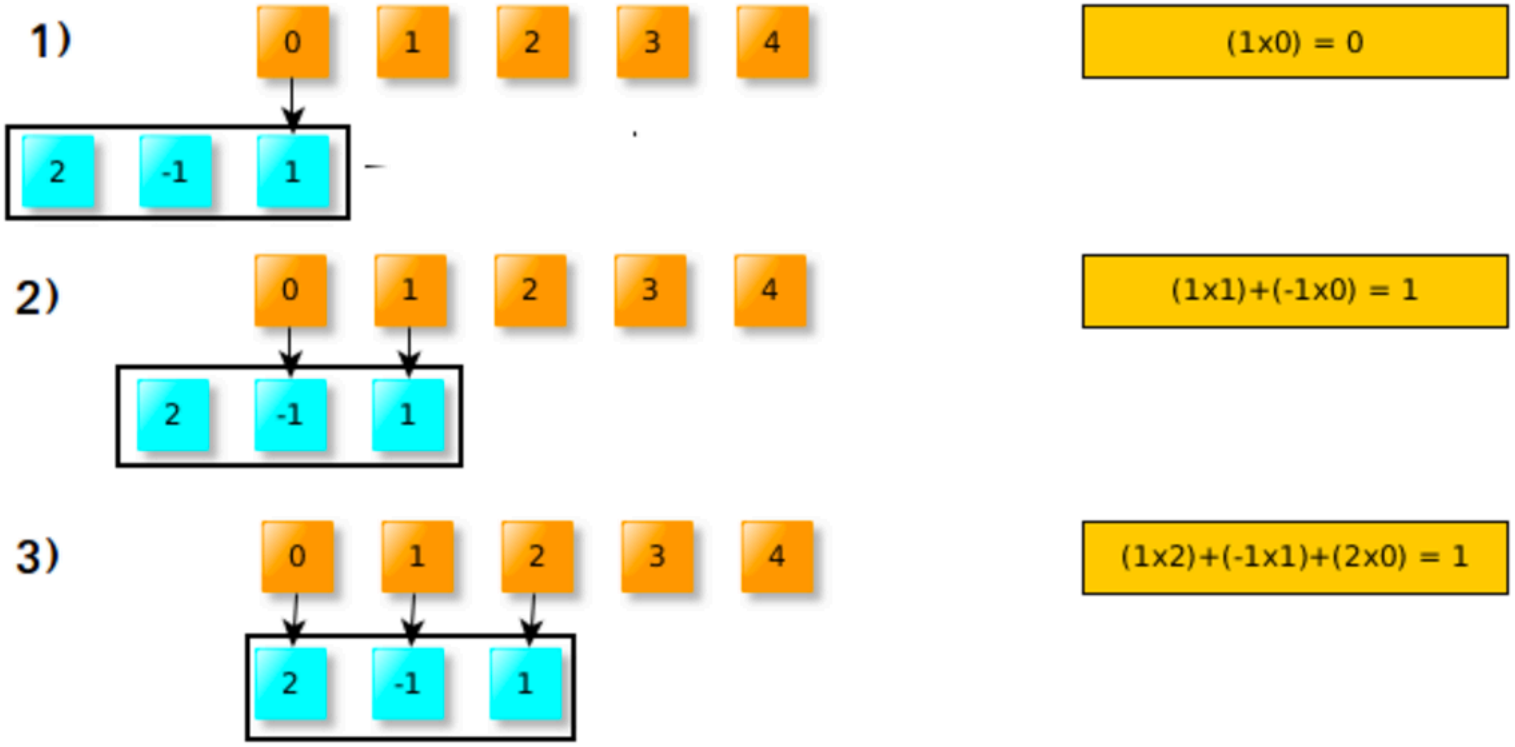
$$h[m,n] = \sum_{k,l} g[k,l]\, f[m-k, n-l]$$

We use Filter and Convolution interchangeable when the image is SYMMETRIC.

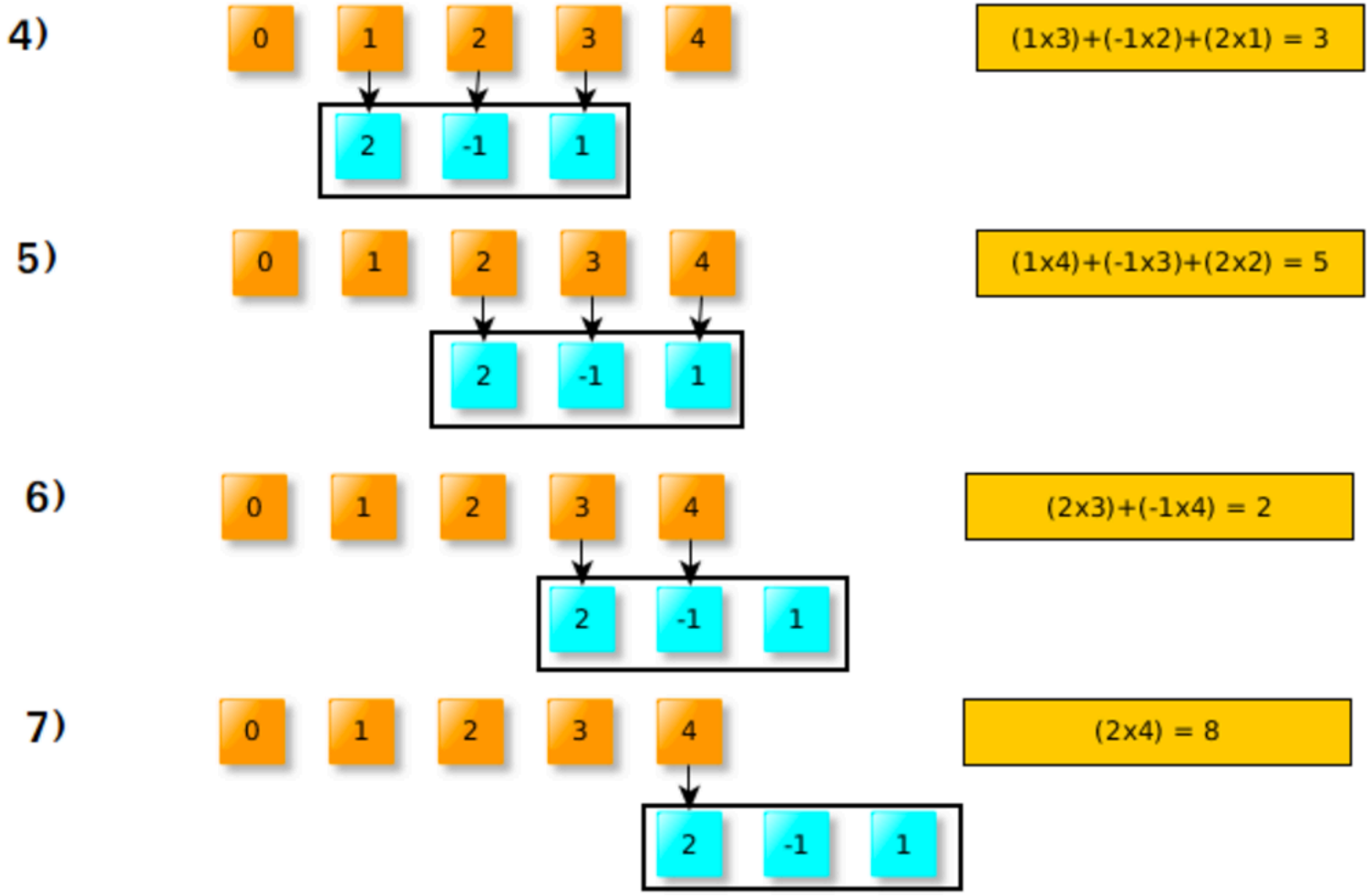
Short tutorial on convolution

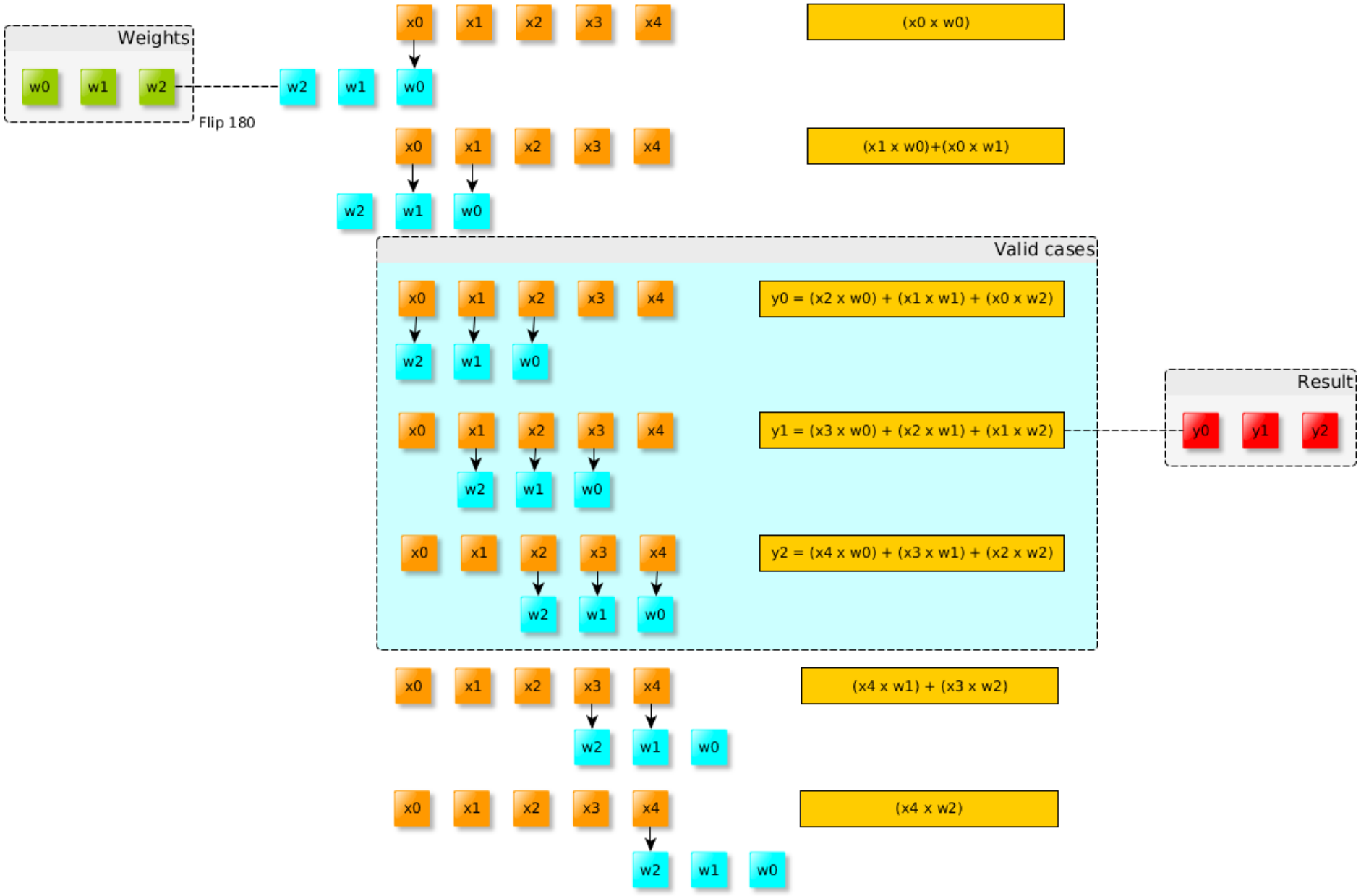


Doing by hand



Doing by hand

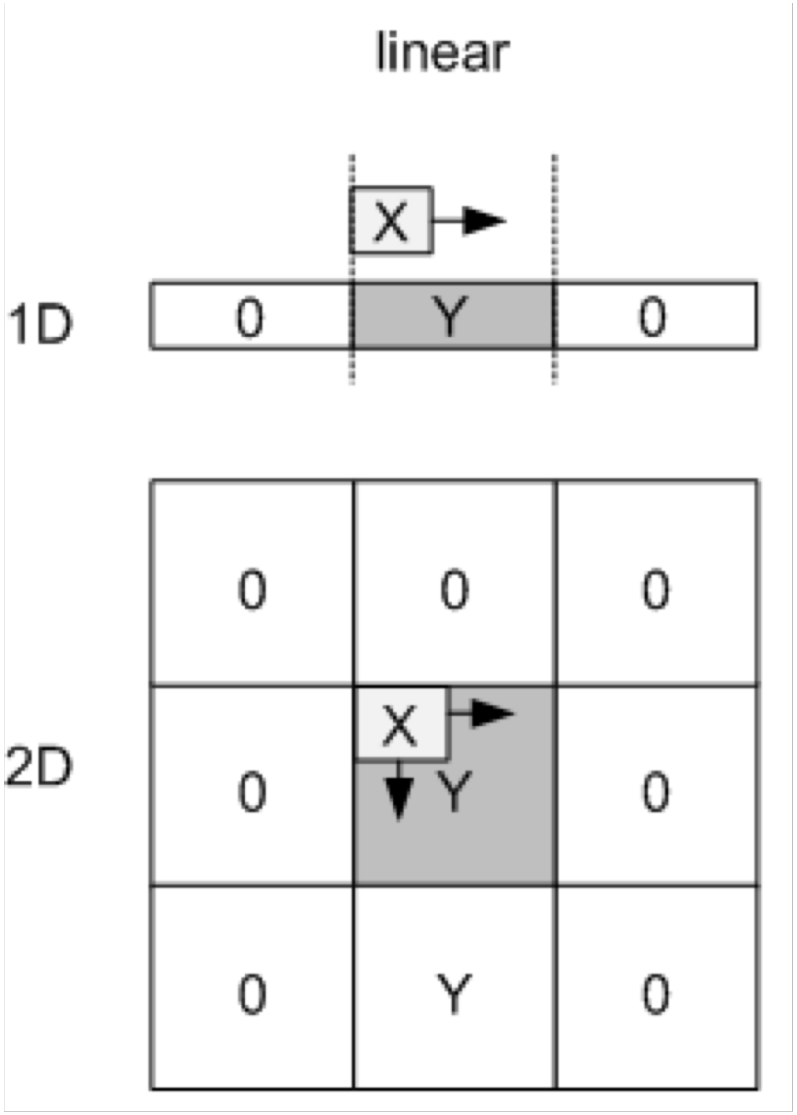



Weights
w0
w1
w2
Flip 180
x0
x1
x2
x3
x4
(x0 x w0)
(x1 x w0)+(x0 x w1)
Valid cases
y0 = (x2 x w0) + (x1 x w1) + (x0 x w2)
y1 = (x3 x w0) + (x2 x w1) + (x1 x w2)
y2 = (x4 x w0) + (x3 x w1) + (x2 x w2)
Result
y0
y1
y2
(x4 x w1) + (x3 x w2)
(x4 x w2)

in Python

```
import numpy as np
x = np.array([0,1,2,3,4])
w = np.array([1,-1,2])

res = np.convolve(x,w, ‘valid’)
print res
```

Input Padding



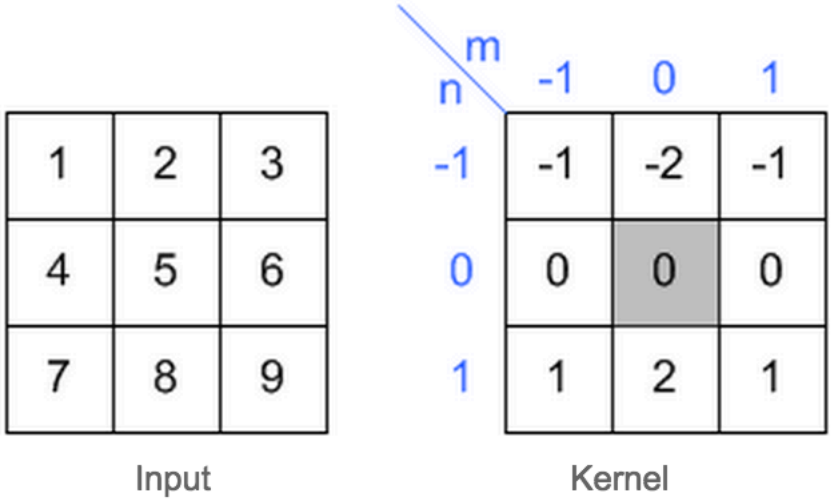
2D convolution

$*$

1	0	-1
2	0	-2
1	0	-1

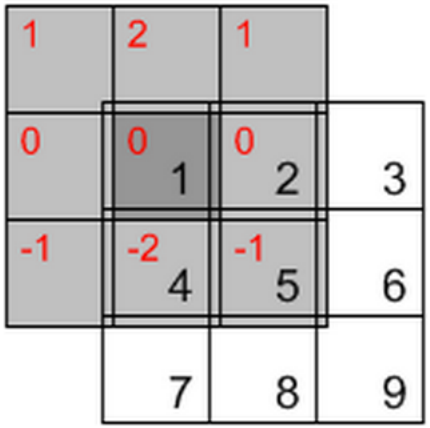
Let’s take out paper and pen

- What is the result of the following convolution?



Let’s take out a paper and a pen

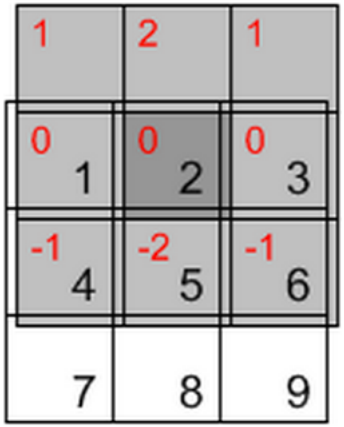
- What is the result of the following convolution?



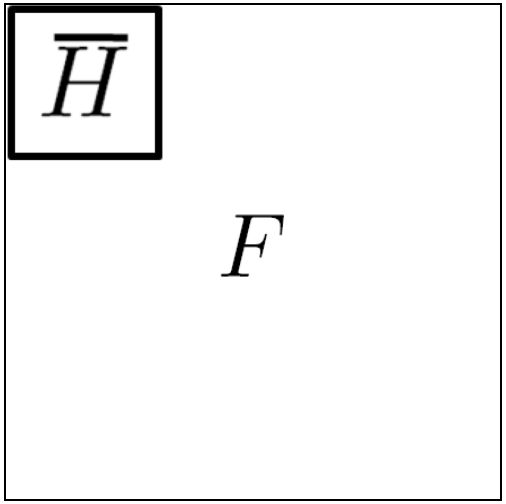
1*0 + 2*0 + 1*0+
0*0 + 1*0 + 2*0+
(-1)*0 + (-2)*4 +(-1)*5 = -13

Let’s take out a paper and a pen

- What is the result of the following convolution?

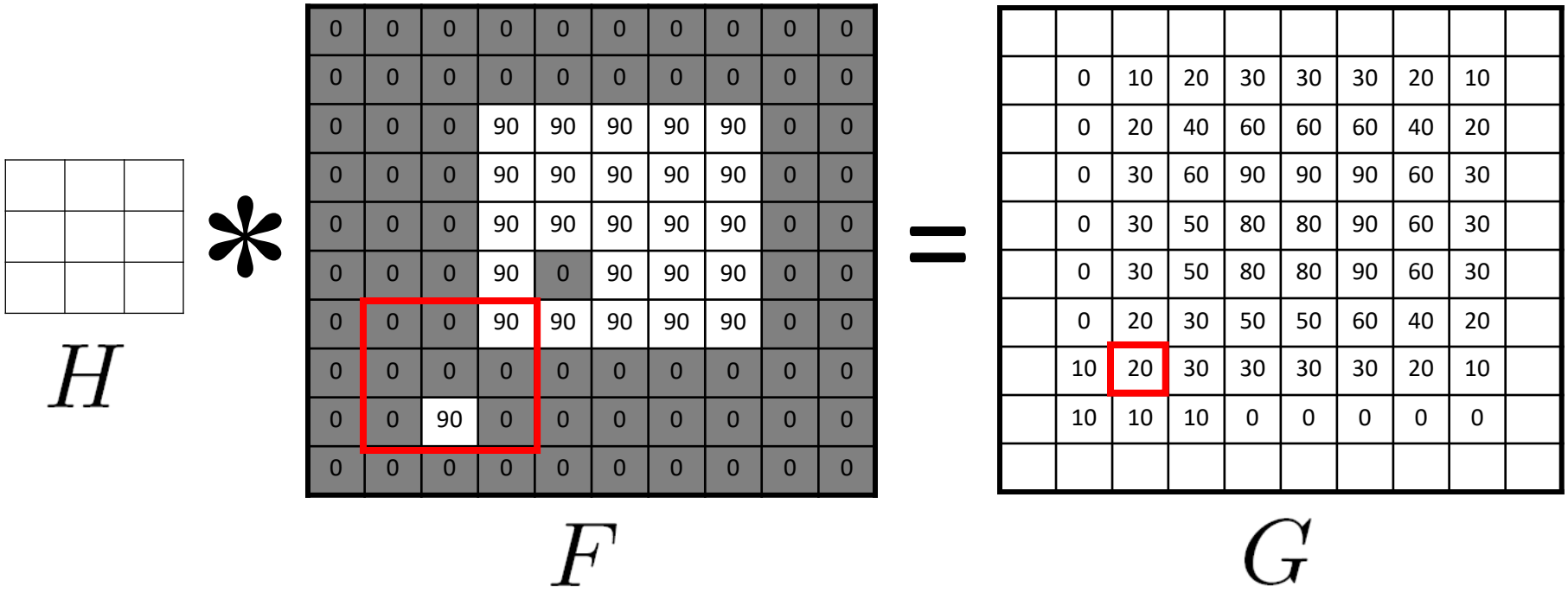


Convolution

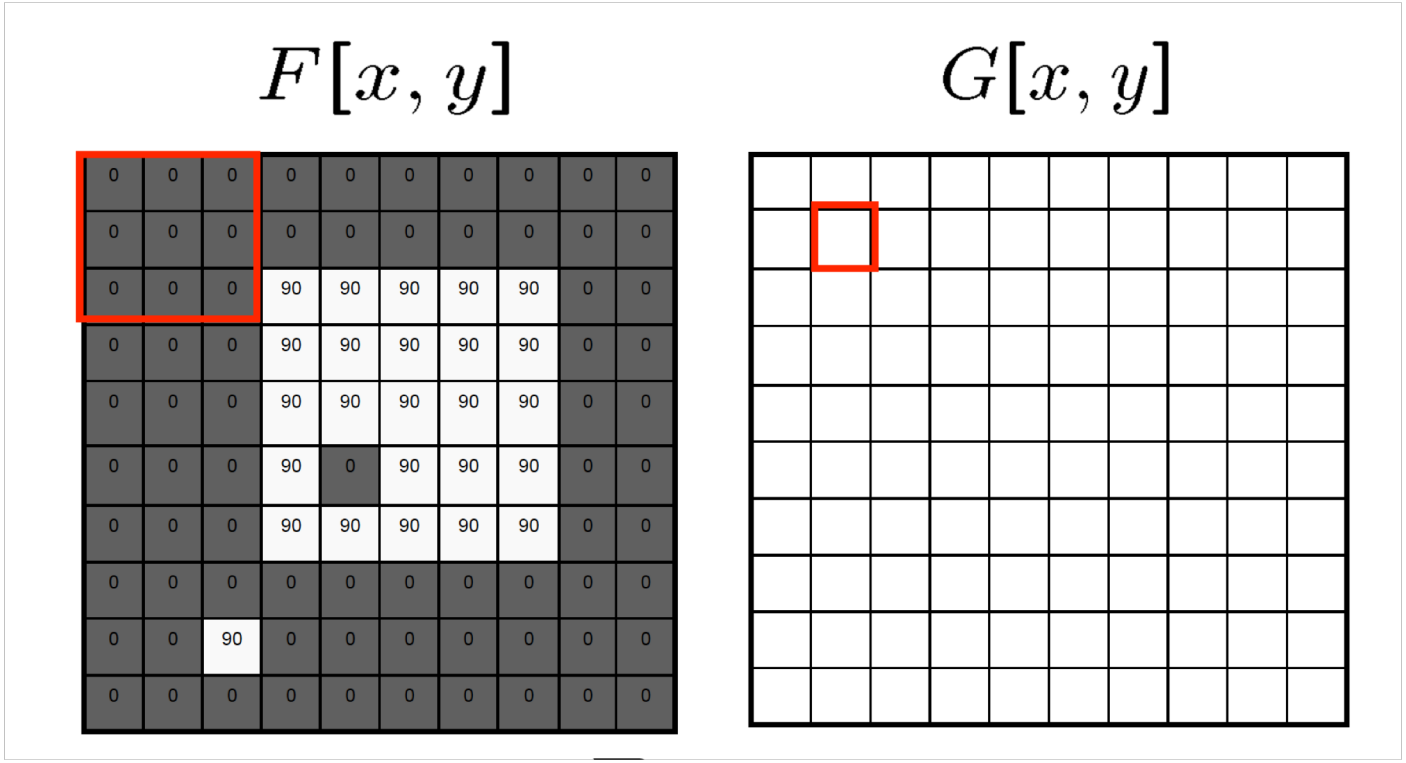


Adapted from F. Durand

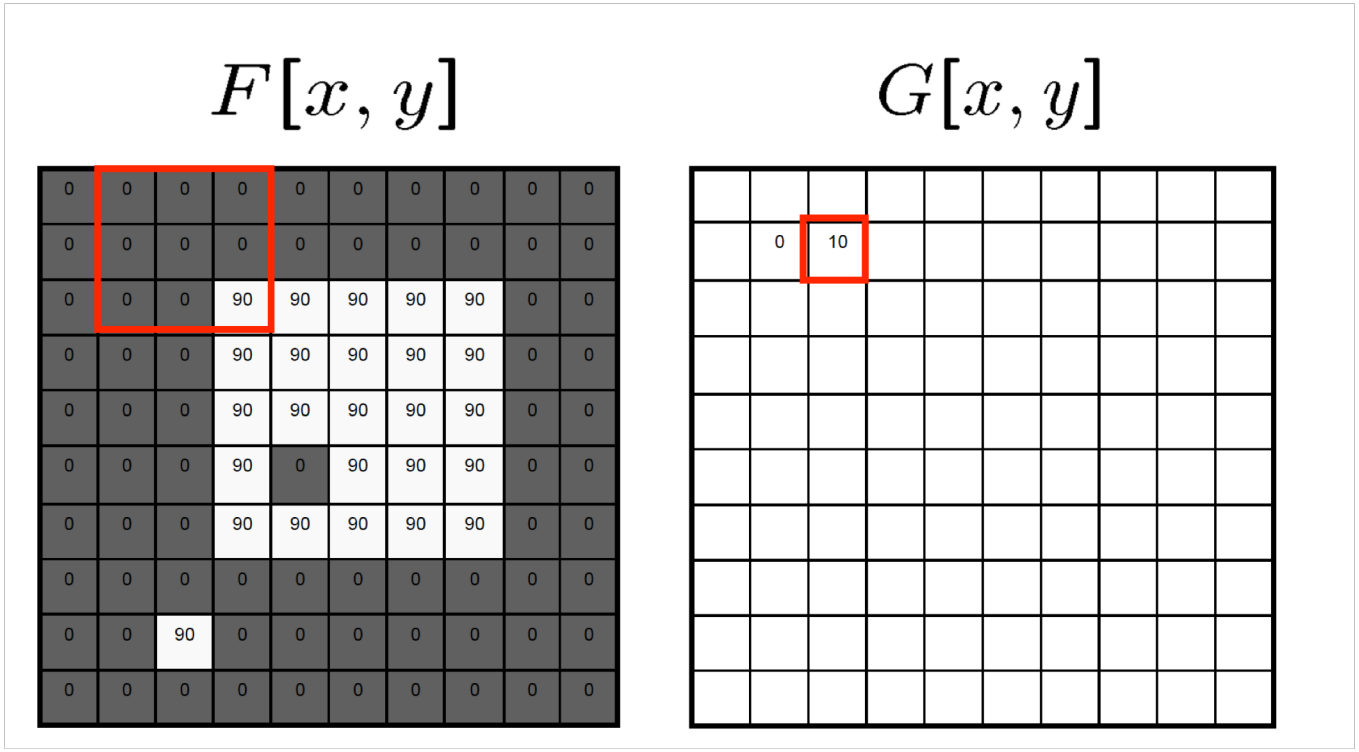
Mean filtering



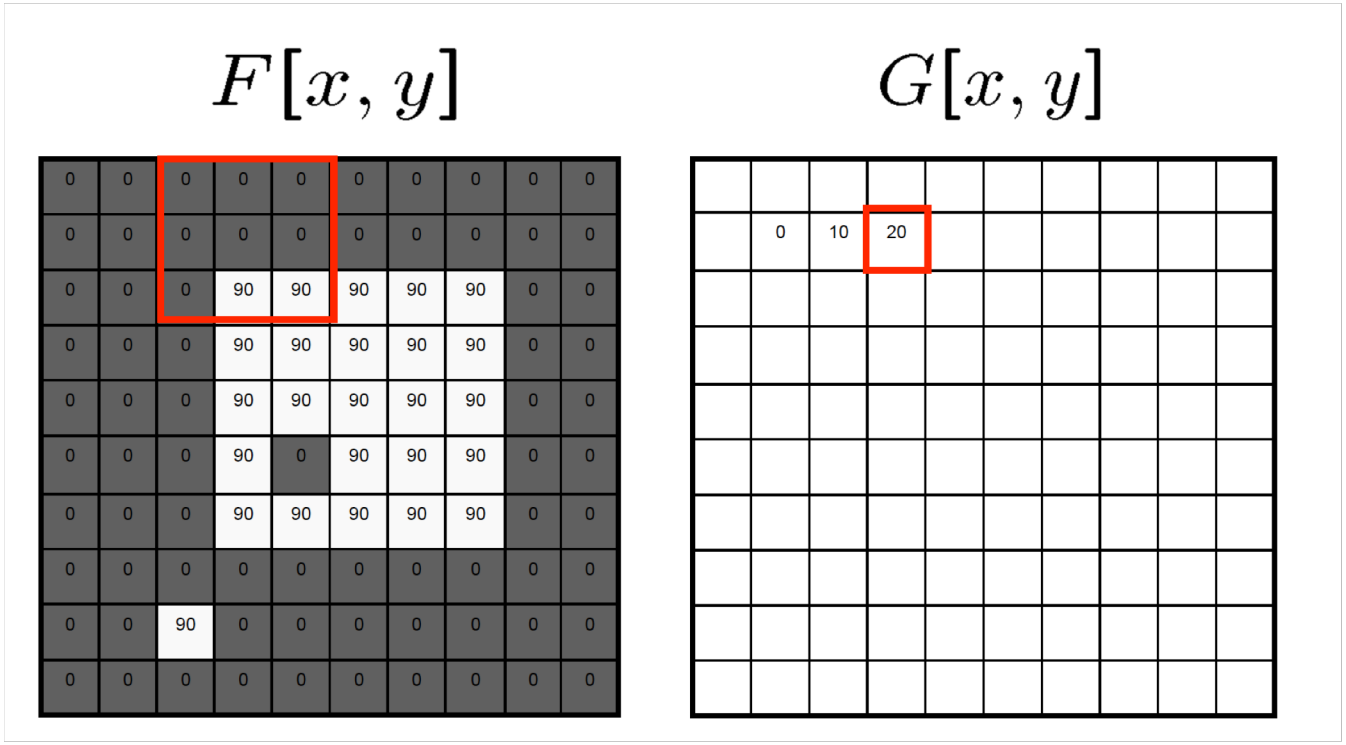
Mean filtering/Moving average



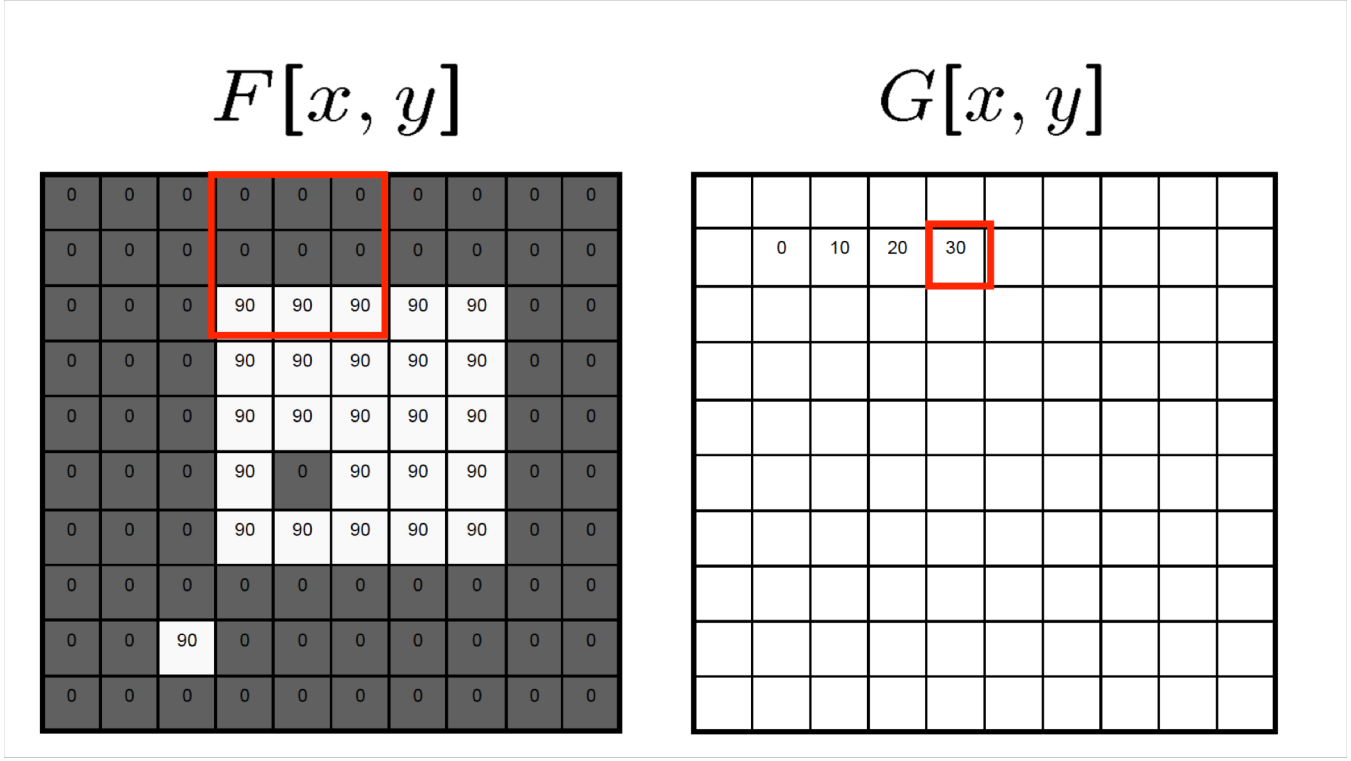
Mean filtering/Moving average



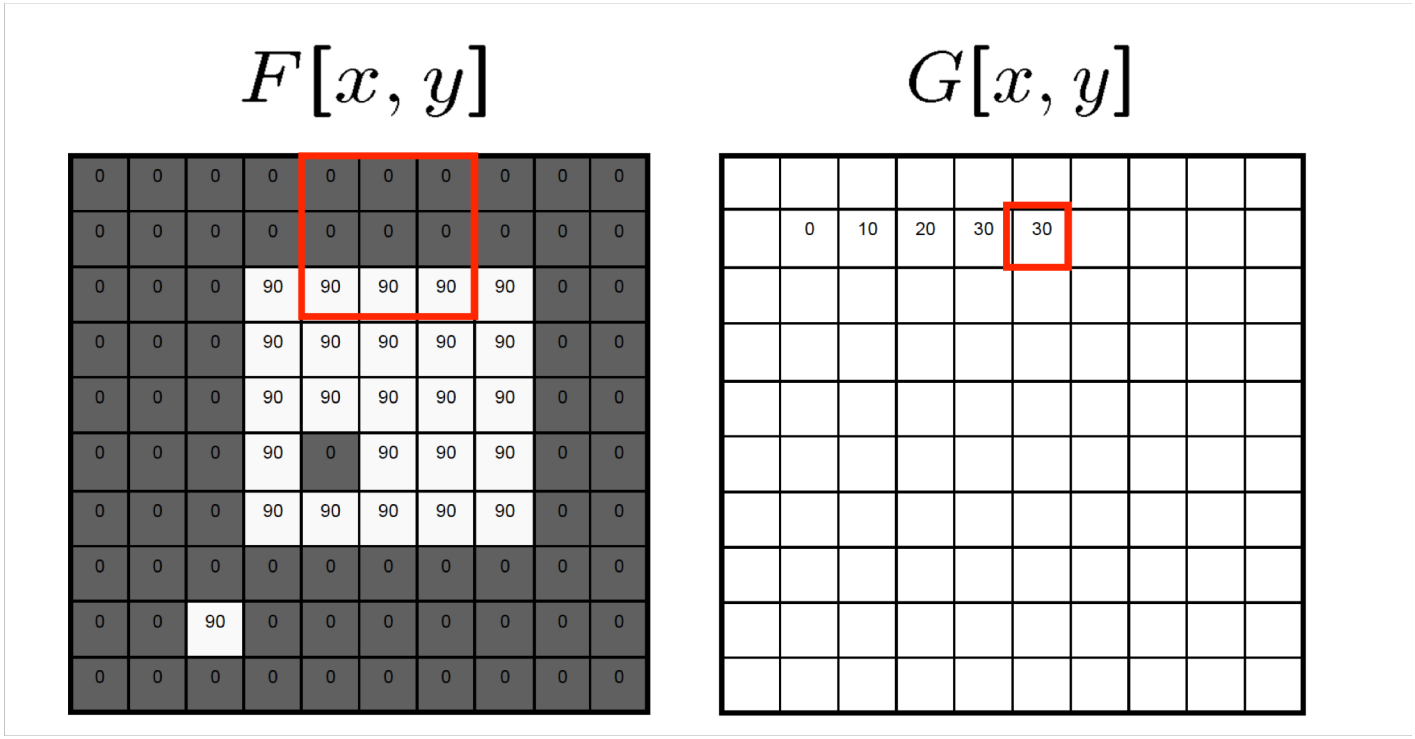
Mean filtering/Moving average



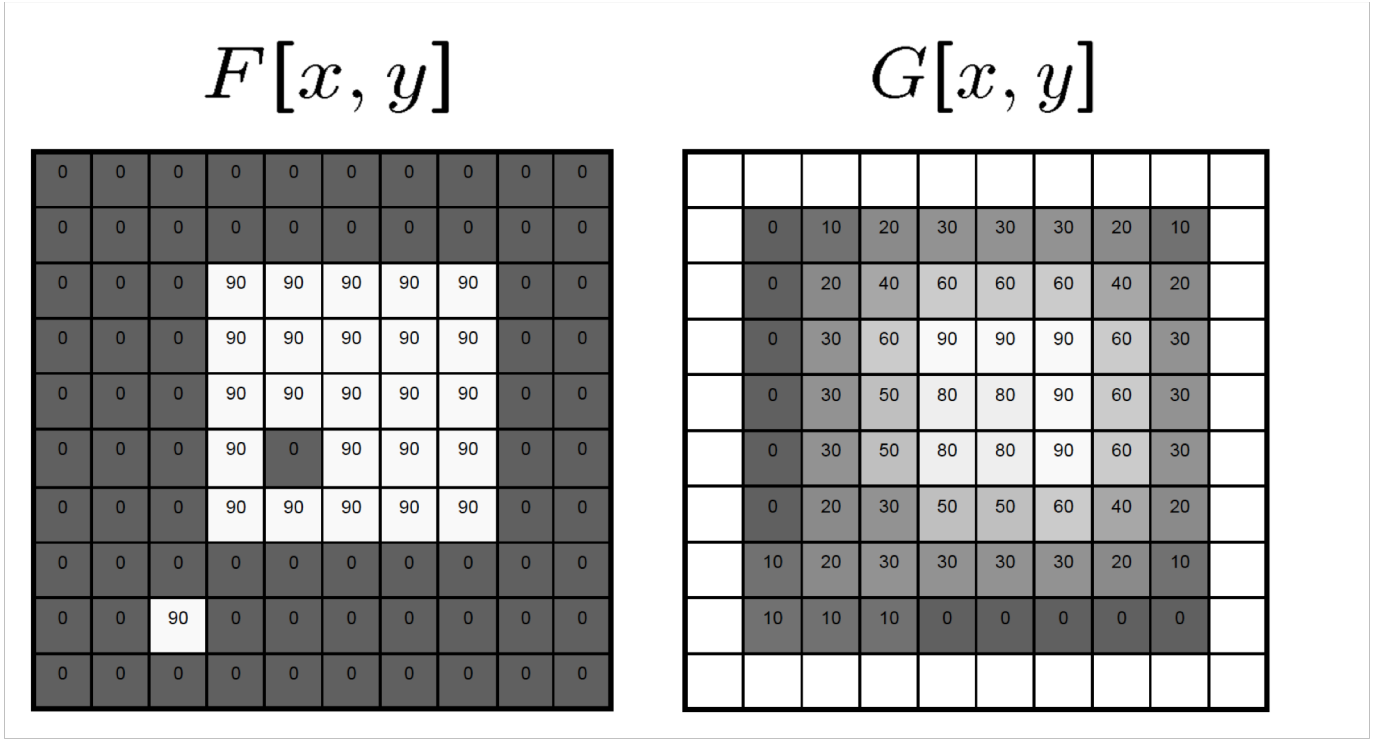
Mean filtering/Moving average



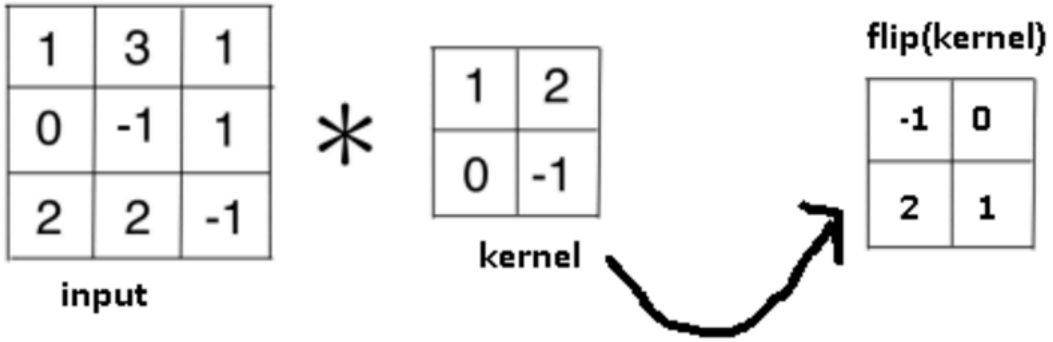
Mean filtering/Moving average



Mean filtering/Moving average



Let’s take out a paper and a pen



Let’s take out a paper and a pen

Multiply the window element by element with flip(kernel), then sum the results

1	3	1
0	-1	1
2	2	-1

=> 1(-1)+3(0)+0(2)-1(1) = -2

1	3	1
0	-1	1
2	2	-1

=> 3(-1)+1(0)-1(2)+1(1) = -4

1	3	1
0	-1	1
2	2	-1

=> 0(-1)-1(0)+2(2)+2(1) = 6

1	3	1
0	-1	1
2	2	-1

=> -1(-1)+1(0)+2(2)-1(1) = 4

result(valid)

-2	-4
6	4

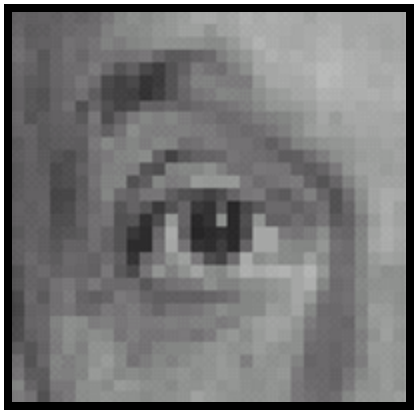
Check it with Python?

```
import numpy as np
from scipy import signal

# use np.array

# use signal.convolve2d
```

Rules of a image filter

- It's size has to be uneven, so that it has a center, for example, 3×3, 5×5, 7×7
- It doesn't have to, but the sum of all elements of the filter should be 1 if you want the result image to have the same brightness as the original
- If the sum of the element of is larger than 1, the result will be a brighter image, if it is smaller than 1, the resulting image will be darker.

Practice with linear filters

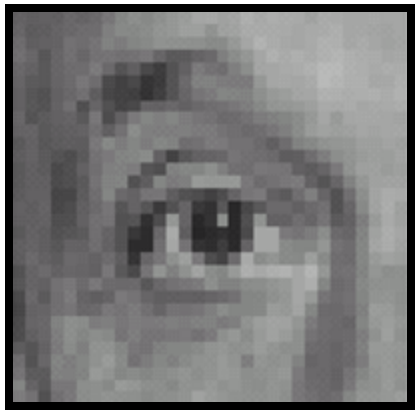


Original

$*$

0	0	0
0	1	0
0	0	0

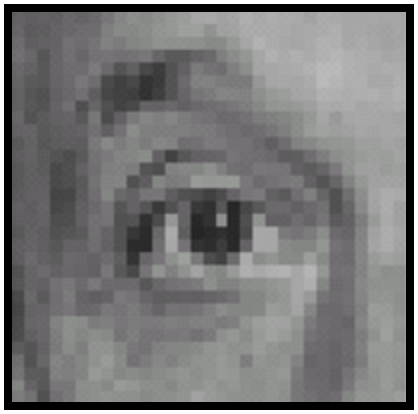
$=$



Filtered
(no change)

Source: D. Lowe

Linear filters: examples

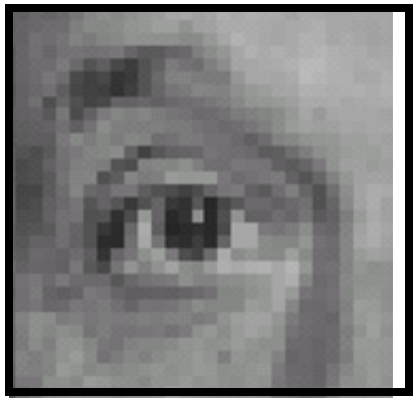


Original

$*$

0	0	0
1	0	0
0	0	0

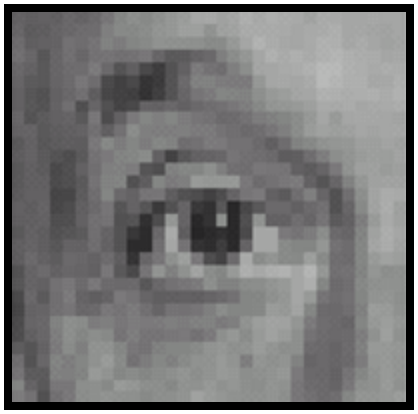
$=$



Shifted left
By 1 pixel

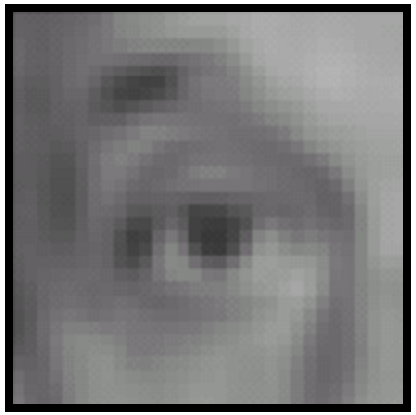
Source: D. Lowe

Linear filters: examples



Original

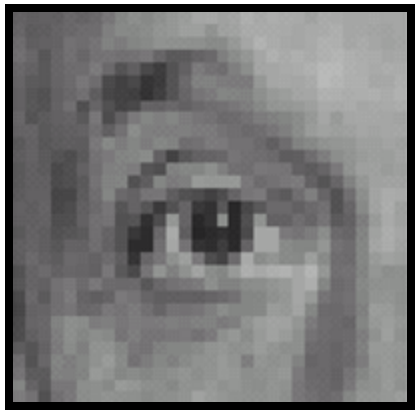
$$*\ \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix} =$$



Blur (with a mean filter)

Source: D. Lowe

Linear filters: examples



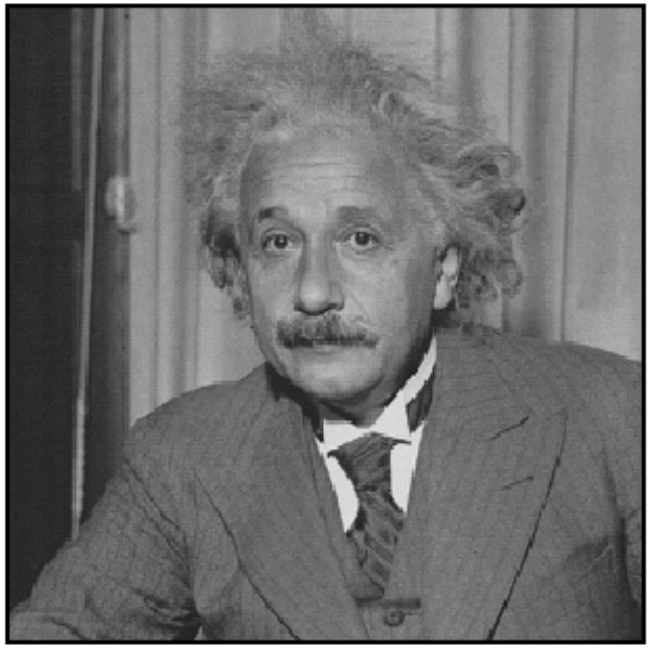
Original

$$* \left(\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \right) =$$

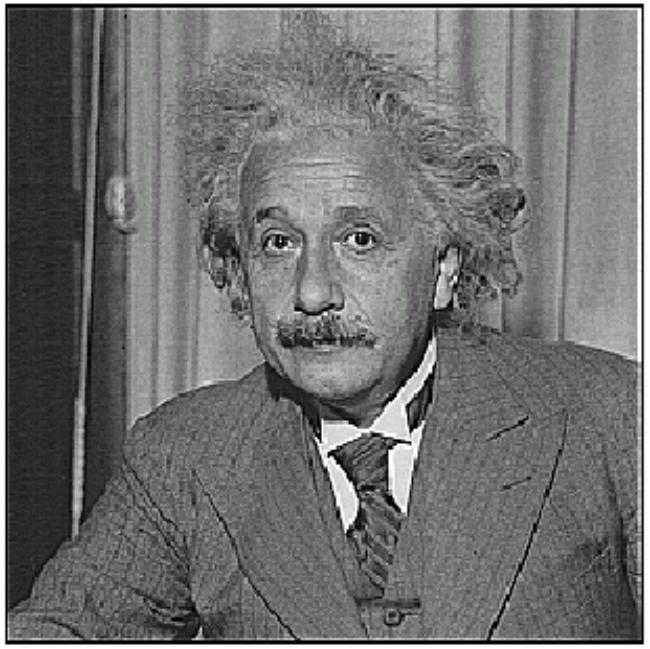
Sharpening filter
(accentuates edges)

Source: D. Lowe

Sharpening



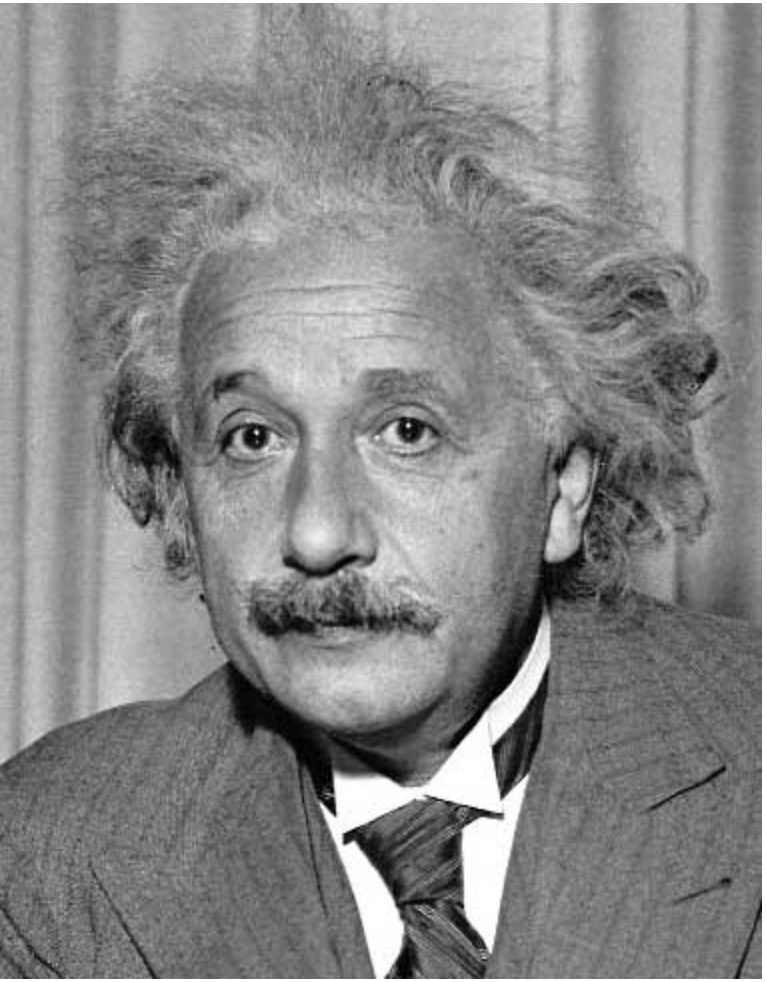
before



after

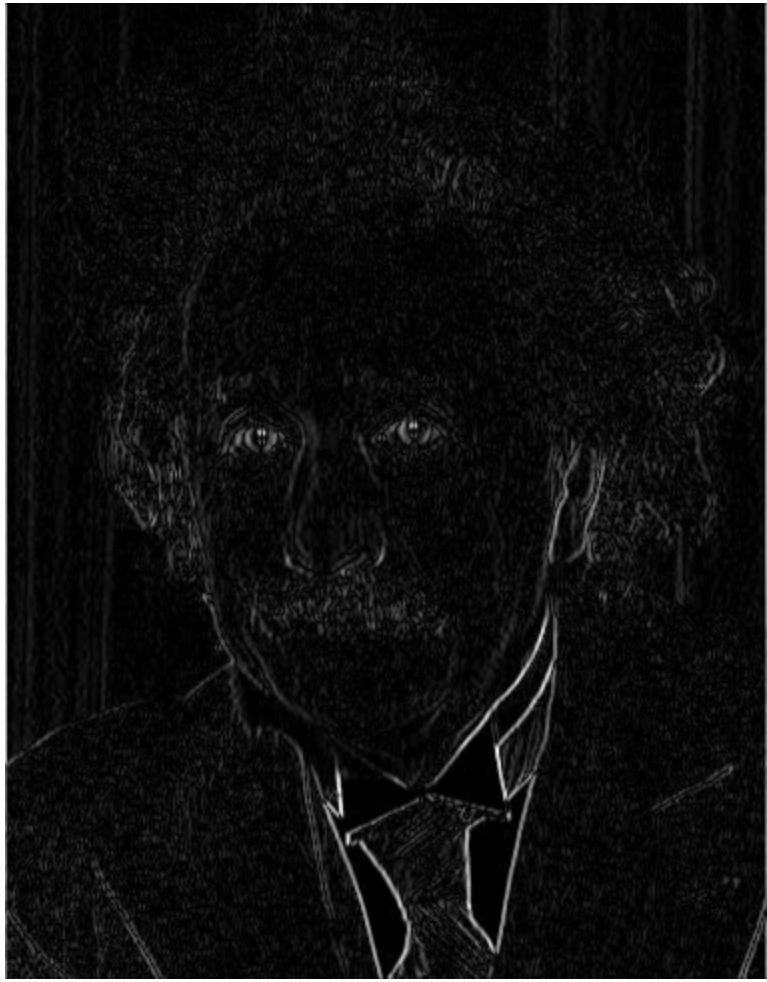
Source: D. Lowe

Other filters



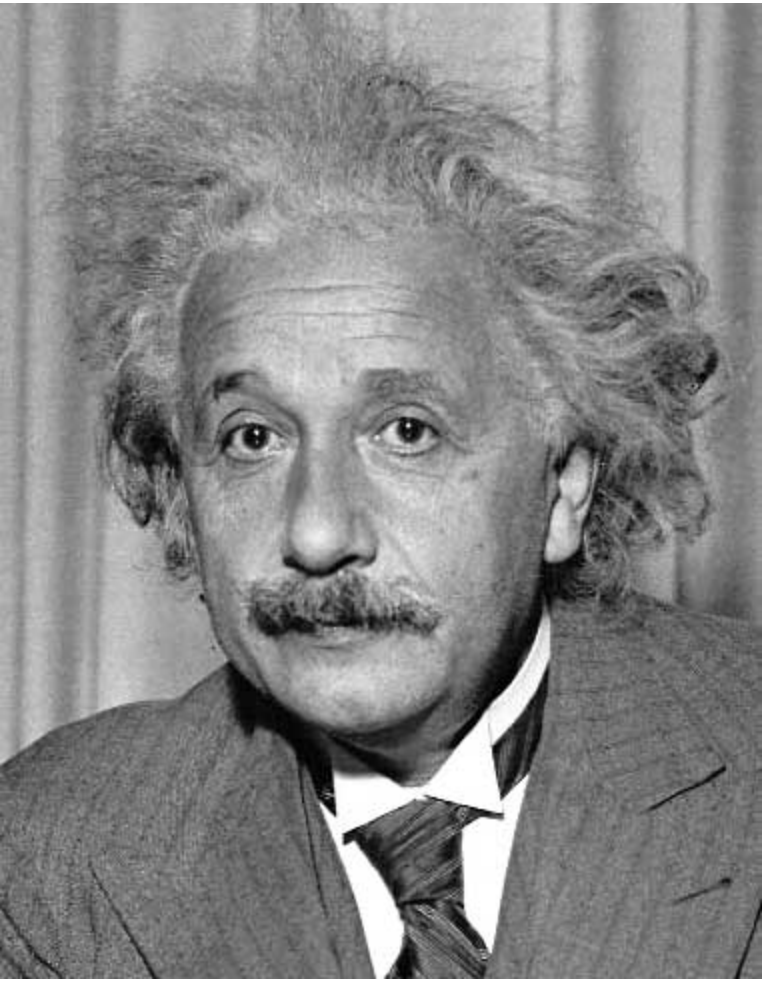
1	0	-1
2	0	-2
1	0	-1

Sobel



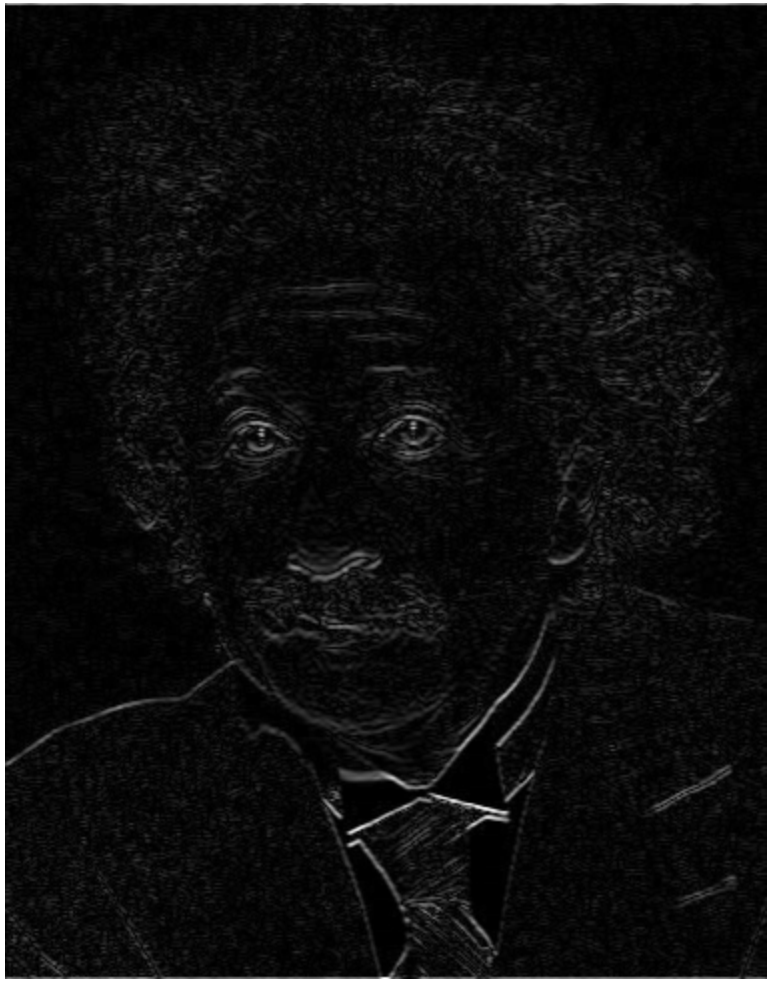
Vertical Edge
(absolute value)

Other filters



1	2	1
0	0	0
-1	-2	-1

Sobel



Horizontal Edge
(absolute value)

Practice with linear filters

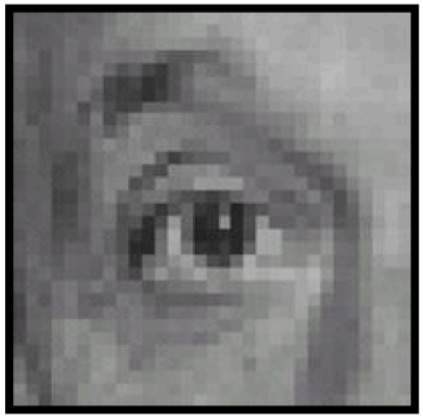
Original

0	0	0
0	1	0
0	0	0

Filtered
(no change)

Source: D. Lowe

Practice with linear filters



Original

0	0	0
0	0	1
0	0	0

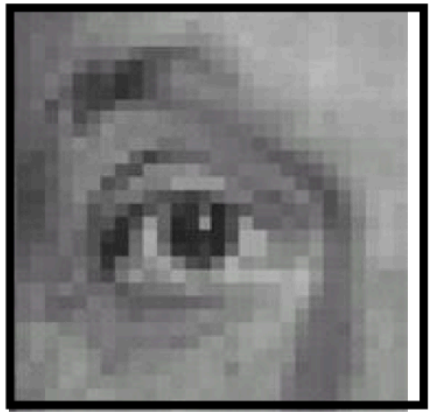
?

Source: D. Lowe

Practice with linear filters

Original

0	0	0
0	0	1
0	0	0



Shifted left
By 1 pixel

Practice with linear filters

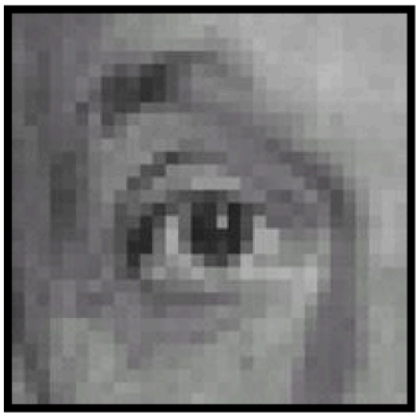
Original

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad ?$$

(Note that filter sums to 1)

Source: D. Lowe

Practice with linear filters



Original

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Sharpening filter

- Accentuates differences with local average

Source: D. Lowe

Exercise

- Find out why the sharper filter works by manually convolve a 5x5 matrix with the kernel.

Using Python to test all the linear filter operations on images.

Image Sharpening

- Take this image and blur it

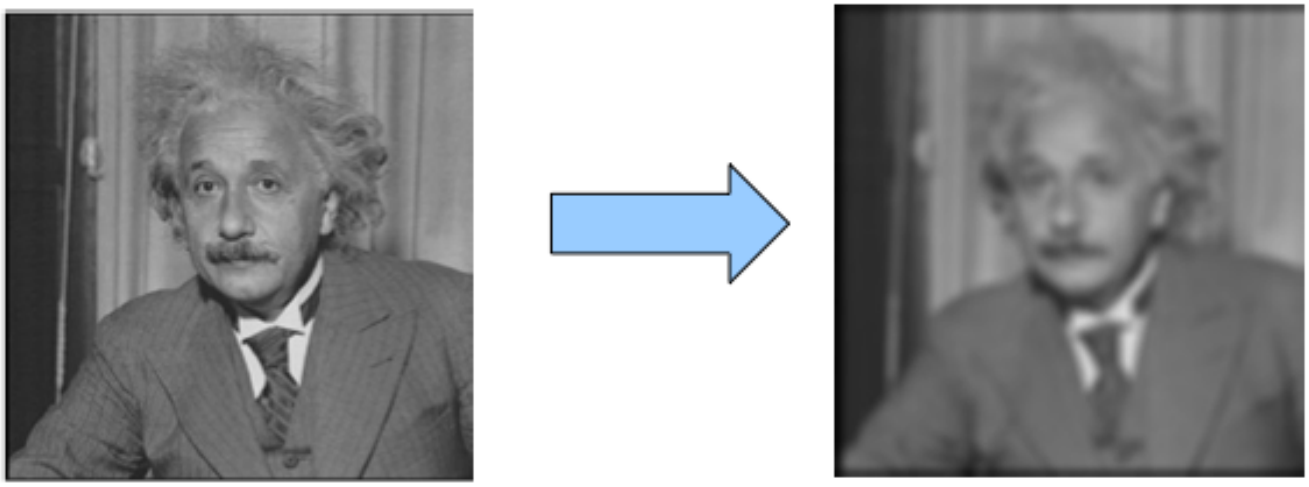
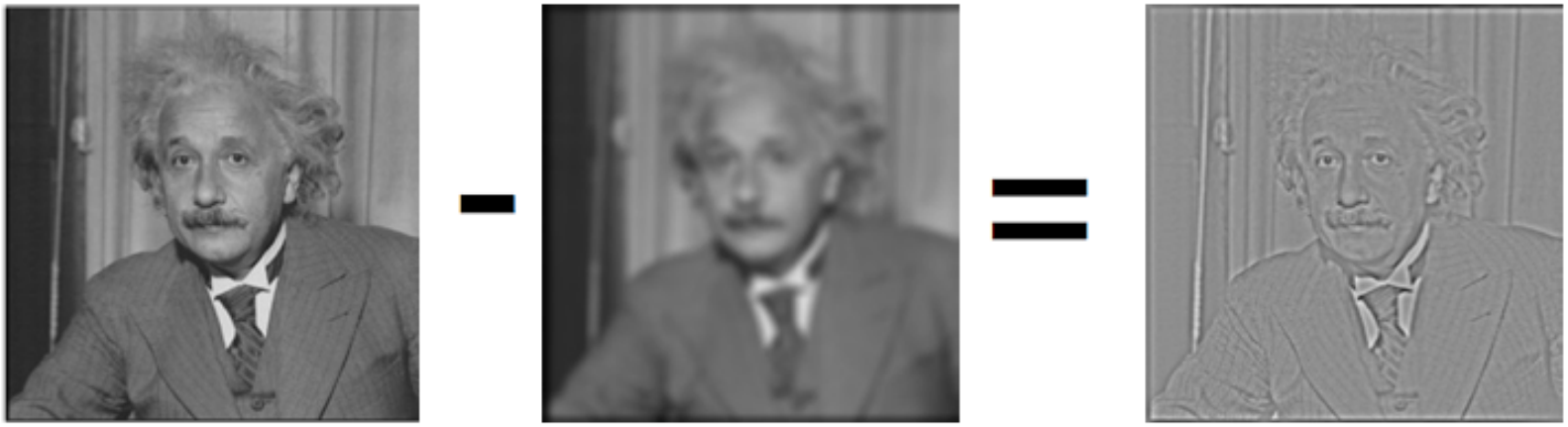


Image Sharpening

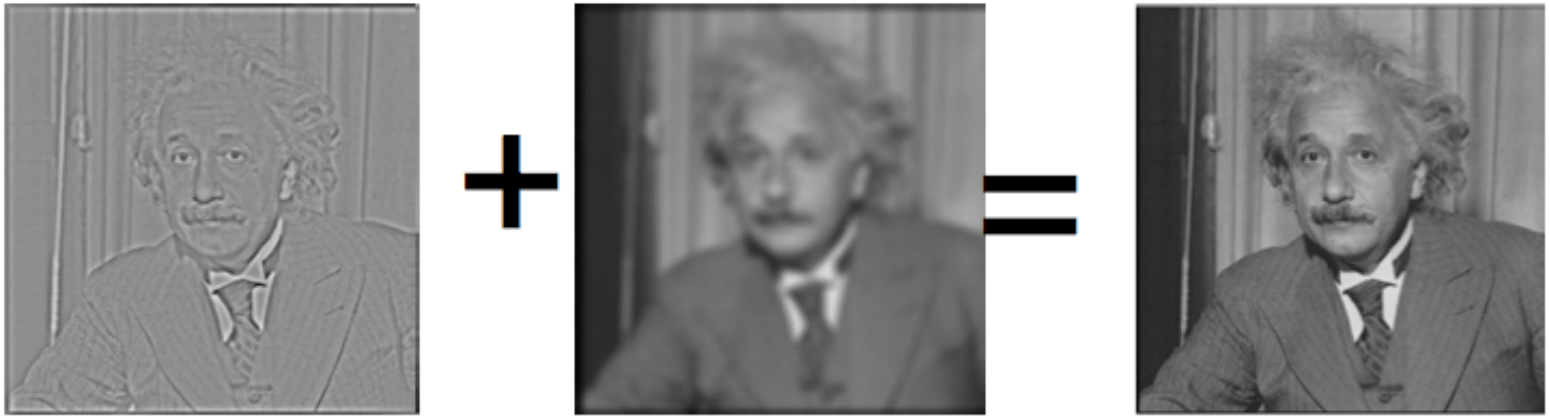
- What do we get if we subtract this two?



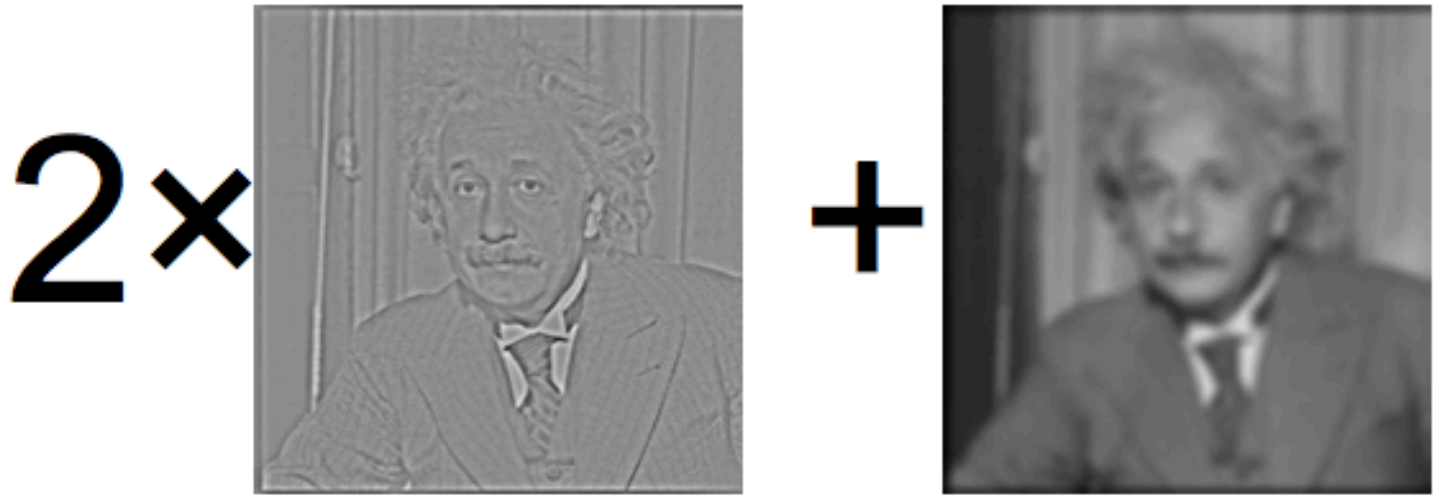
This is the left-over sharp stuff!

Let’s make the image sharper?

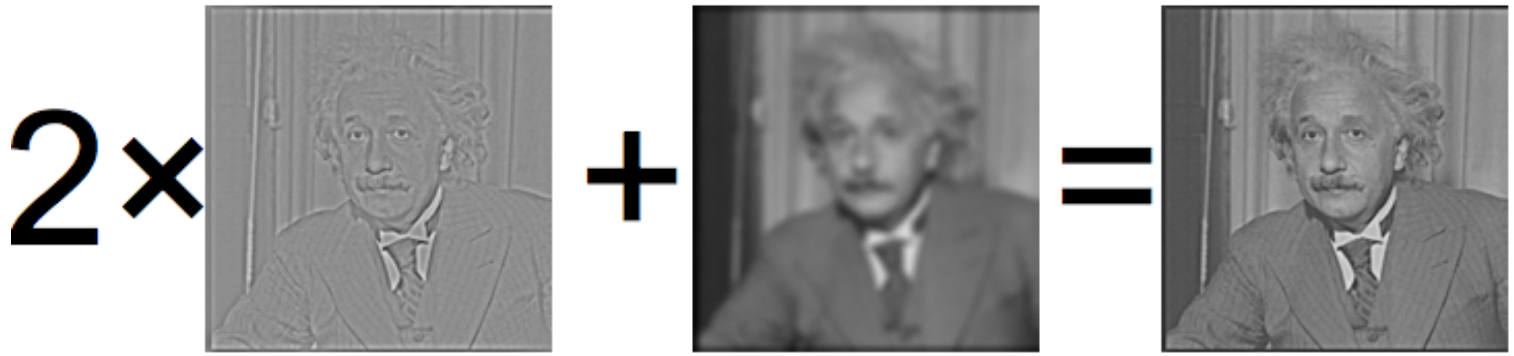
- We know: “sharp stuff + blurred = original”



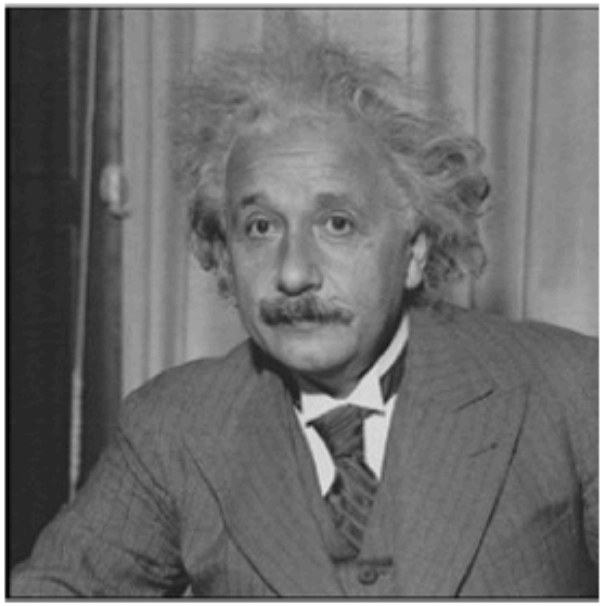
Let’s boost the sharp stuff a little

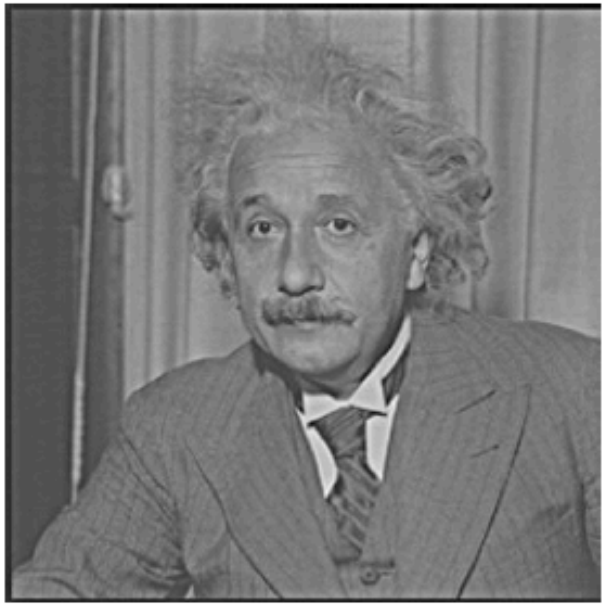


Let’s boost the sharp stuff a little



Side by Side





With Python

```
baby = misc.imread('Kaila.jpg',flatten=1)

## blur
blurred = ndimage.gaussian_filter(baby, 3)
## this is actually the original
filter_blurred= ndimage.gaussian_filter(blurred,1)
alpha = 30
## sharpen
sharpened = blurred + alpha * (blurred - filter_blurred)
```

Now look at the computation

- Operations
  - 1 convolution
  - 1 subtraction over the whole image
- As an equation:

$$\mathcal{I} * f + 2\left(\mathcal{I} - \mathcal{I} * f\right)$$

Blur: Convolve with mean filter

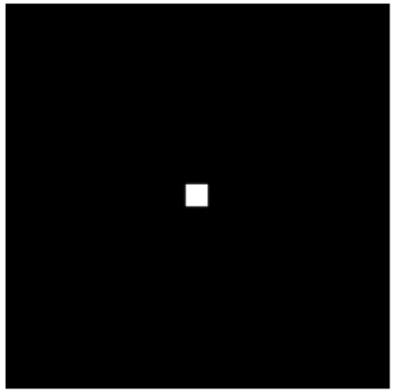
Sharpen: original - Convolve with mean filter

Rewrite this

$$\mathcal{I} * f + 2\left(\mathcal{I} - \mathcal{I} * f\right)$$

$$\mathcal{I} * f + 2\left(\mathcal{I} * \delta - \mathcal{I} * f\right)$$

This is an identity filter or unit impulse



Rewrite this

$$\mathcal{I} * f + 2\left(\mathcal{I} - \mathcal{I} * f\right)$$

$$\mathcal{I} * f + 2\left(\mathcal{I} * \delta - \mathcal{I} * f\right)$$

$$\mathcal{I} * \left(f + 2\delta - 2f\right)$$

Now look at the computation

$$\mathcal{I} * (f + 2\delta - 2f)$$

- Can pre-compute new filter
- Operations

  1 convolution

Photoshop: Unsharp Masking

- http://en.wikipedia.org/wiki/Unsharp_masking

Source image (left) and the sharpened image (right).

Unsharp Masking (Scikit)

```
from skimage import filter
from skimage import img_as_float
import matplotlib.pyplot as plt


unsharp_strength = 0.8
blur_size = 8  # Standard deviation in pixels.

# Convert to float so that negatives don't cause problems
image = img_as_float(data.camera())
blurred = filter.gaussian_filter(image, blur_size)
highpass = image - unsharp_strength * blurred
sharp = image + highpass


fig, axes = plt.subplots(ncols=2)
axes[0].imshow(image, vmin=0, vmax=1)
axes[1].imshow(sharp, vmin=0, vmax=1)
```

Your Convolution filter toolbox

- 90% of the filtering that you will do will be either
- Smoothing (or Blurring)
- High-Pass Filtering (will explain later)
- Most common filters:
- Smoothing: Gaussian
- High Pass Filtering: Derivative of Gaussian

Python image convolution demo

scipy.ndimage.filters.convolve, specifically for images

scipy.signal.convolve2d, general 2D convolution

Lecture 2 Lab

- Please download Lecture2_inclass exercise and finish the problem sets.

- The problem set is due next class. No submission is required but the instructor will check your solutions and code.

Next class (Next Wed)

- More on image processing, contrast enhancement, image histograms, Gaussian Filter.
- Take-home reading: Szeliski, Chapter 3.1-3.2