CAP 5415 – Computer Vision

Marshall Tappen
Fall 2010

Lecture 1

Welcome!

- About Me
  -
  - Interested in Machine Vision and Machine Learning
  - Happy to chat with you at almost any time
    - May want to e-mail me first
  - Office Hours:
    - Tuesday-Thursday before class

Grading

- Problem Sets – 50%
- 3 Solo Problem Sets – 50%
  - You may not collaborate on these

Doing the problems

- Finishing the problem sets will require access to an interpreted environment
  - MATLAB
  - Octave
  - Numerical Python
- NO COMPILED LANGUAGES!!!!!
  - No C/C++
  - No Java
  - No x86 Assembler
- My Compiled Languages Rant

Environments

- MATLAB
  - Pro:Well-established package. You can find many tutorials on the net.
  - Con: Not free. If your lab does not already have it, talk to me about getting access.
- Octave
  - Free MATLAB look-alike
  - Pro: Should be able to handle anything you will do in this class
  - Con: “Should be”. I'm not sure about support in Windows

Environments

- Numerical Python
  - All the capabilities of MATLAB
  - Free!
  - Real programming language
  - Used for lots of stuff besides numerical computing
  - Cons: Documentation is a bit sparse and can be outdated
    - I can get you started – I am working on a tutorial

Math

- We will use it
- We will be talking about mathematical models of images and image formation
- This class is not about proving theorems
- My goal is to have you build intuitions about the models
- Try and visualize the computation that each equation is expressing
- Basic Calculus and Basic Linear Algebra should be sufficient

Course Text

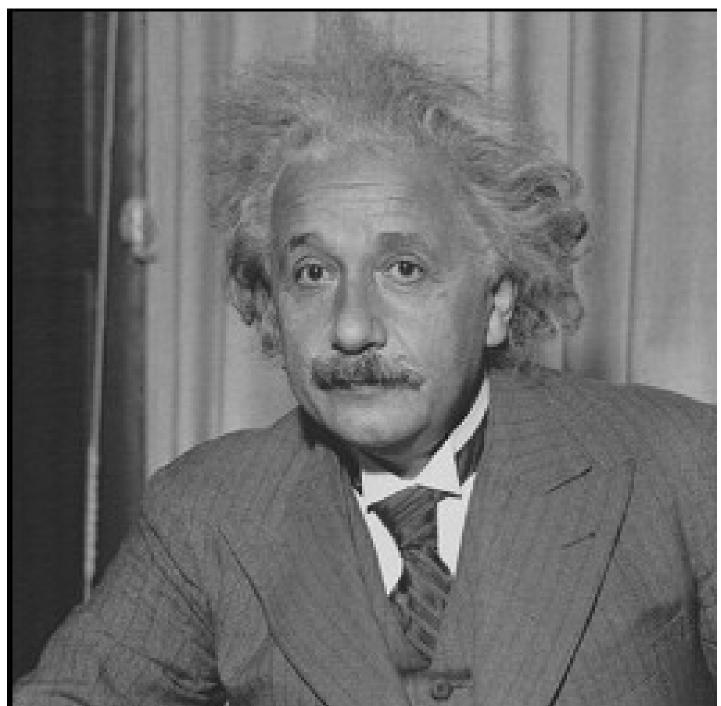
- We will use Szeliski Book – Free this year!
- Not required – more of a reference

Course Structure

- This year, we will be covering pattern recognition more deeply than in previous years
- Machine learning is critical to modern computer vision
- You need to understand it well
- Important Foundational Topics:
  - Image Processing
  - Optimization
  - Machine Learning
  - Geometry

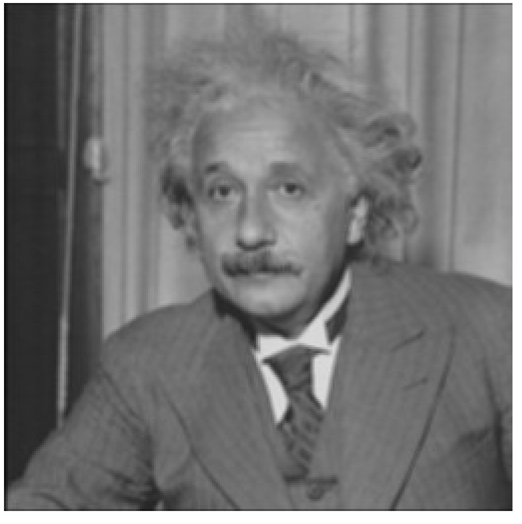
Image Processing

- For now, we won't worry about the physical aspects of getting images
- View image as an array of continuous values

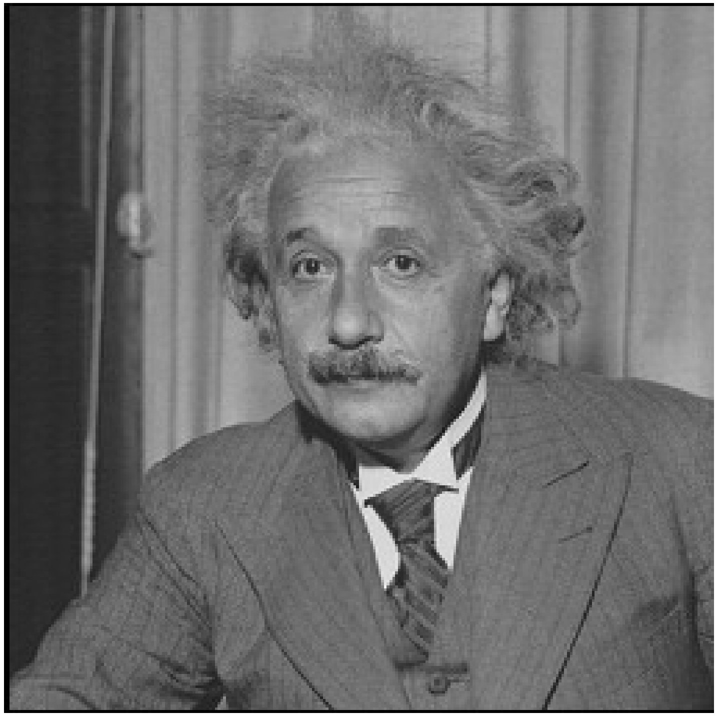


Simple Modification

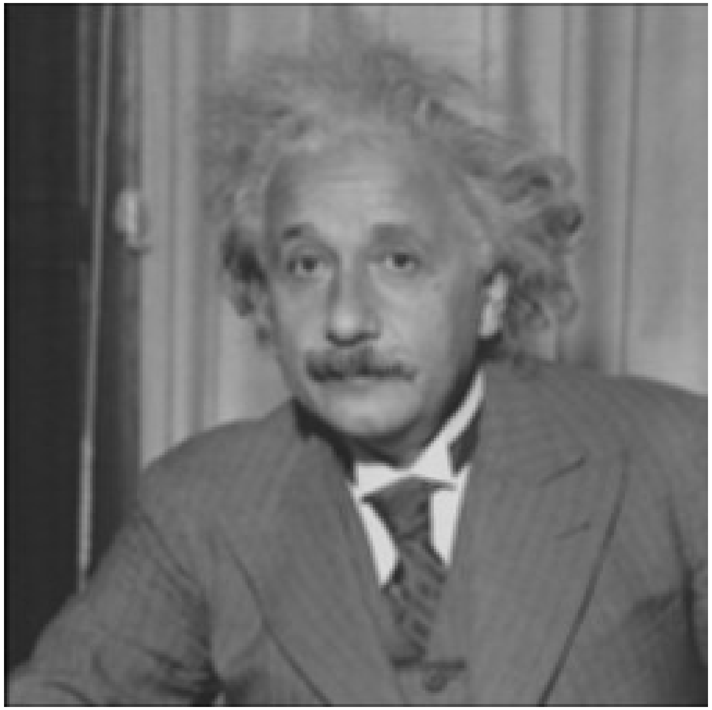
- What if we wanted to blur this image?
- We could take a local average
  - Replace each pixel with the mean of an NxN pixel neighborhood surrounding that pixel.



3x3 Neighborhood

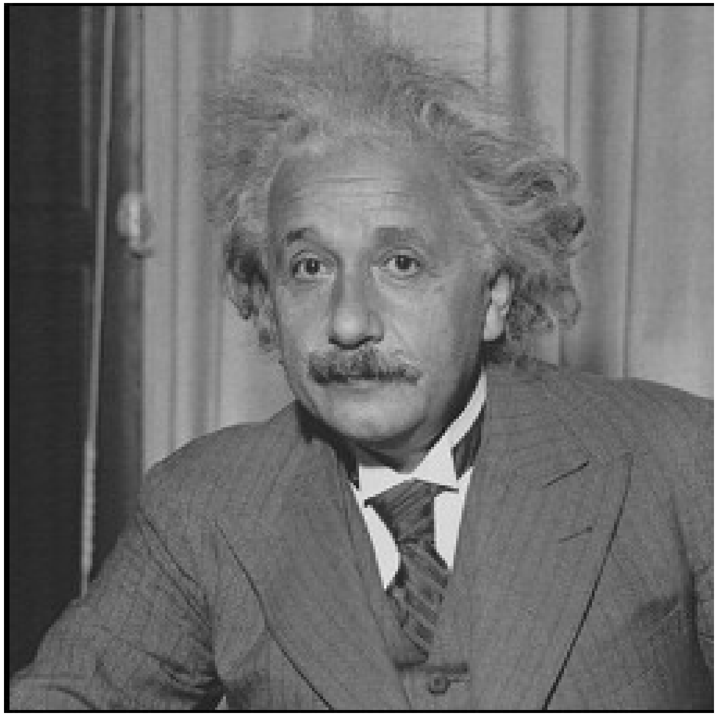


Original

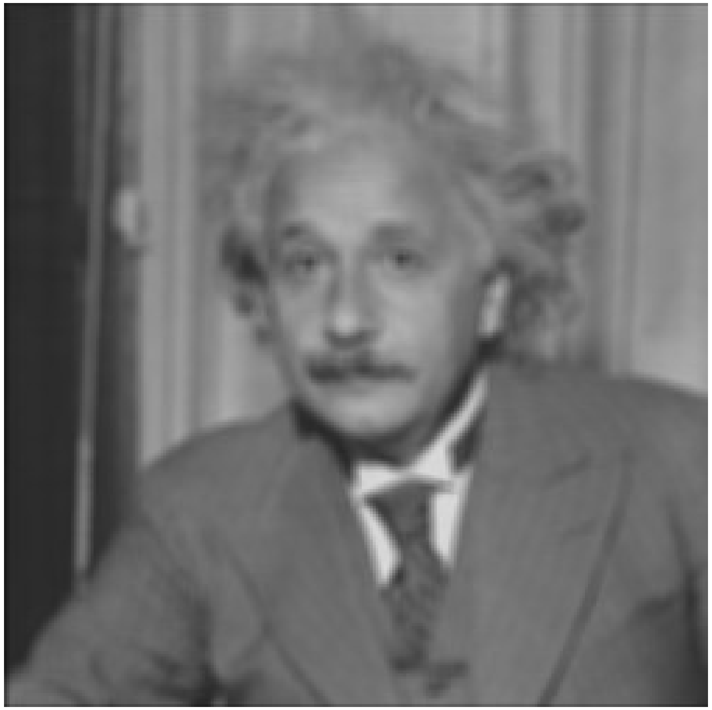


Averaged

5x5 Neighborhood

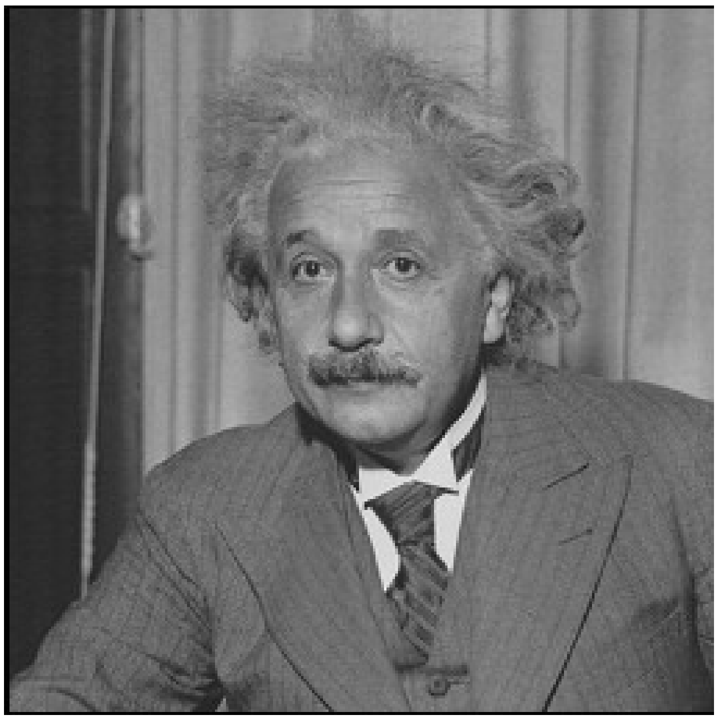


Original

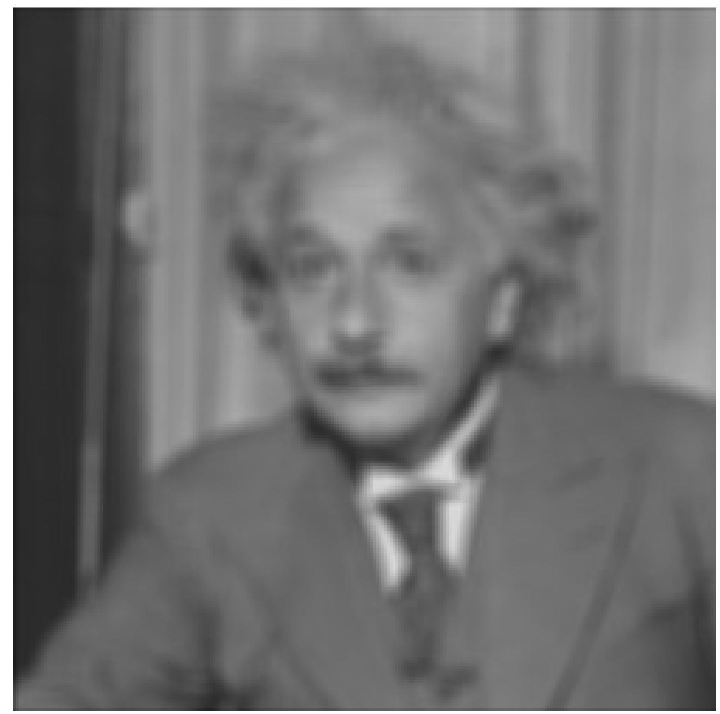


Averaged

7x7 Neighborhood

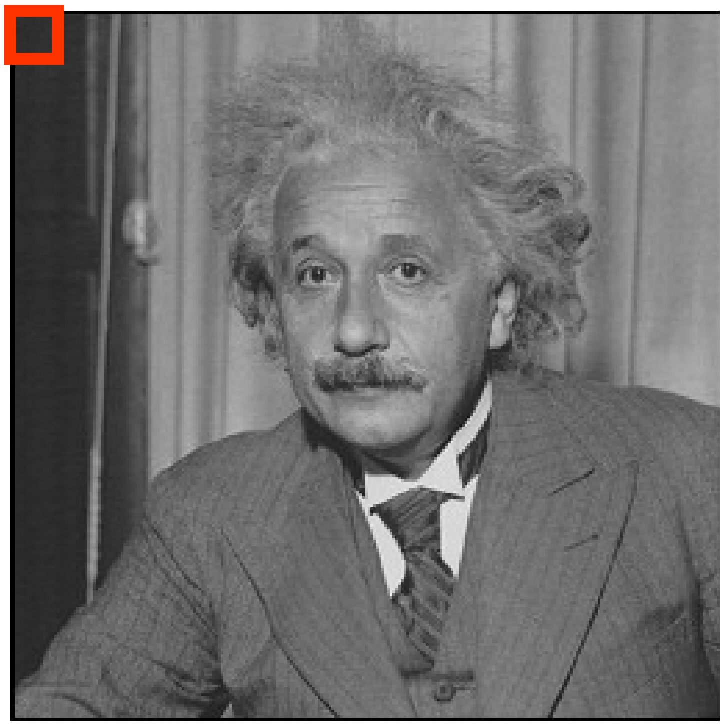


Original



Averaged

Let's represent this more generally



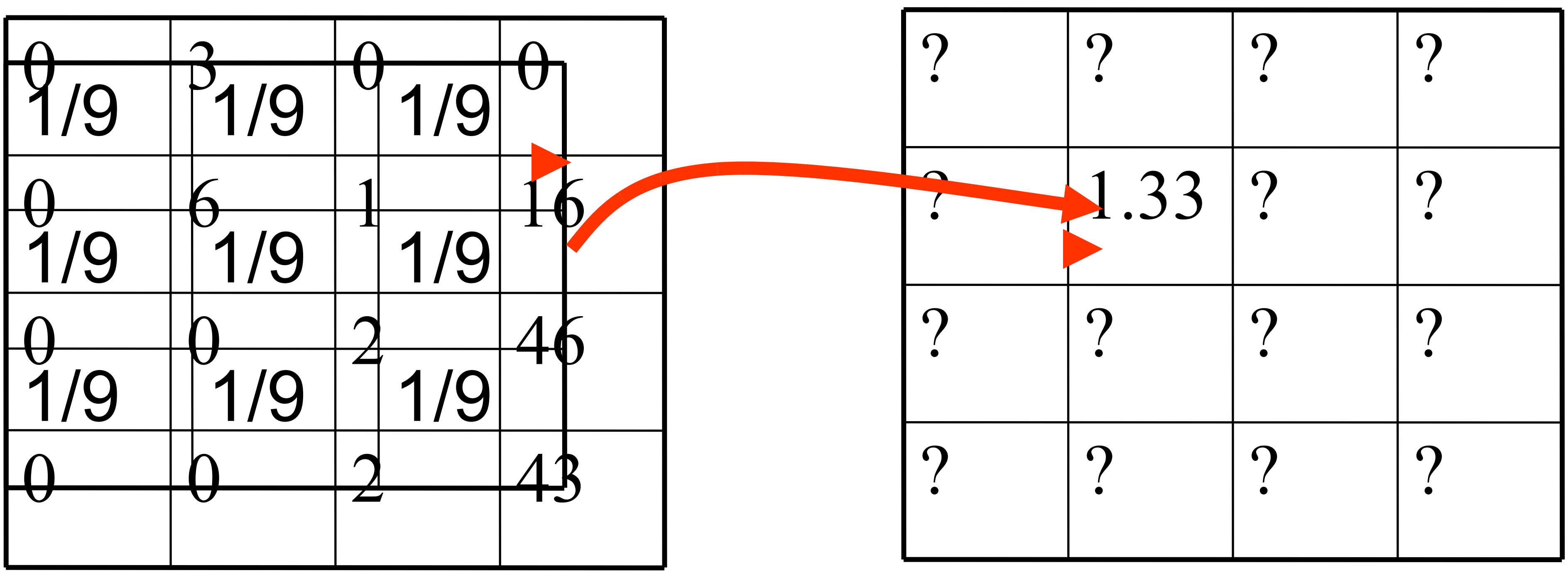
0	3	0	0
0	6	1	16
0	0	2	46
0	0	2	43

Let's represent this more generally

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

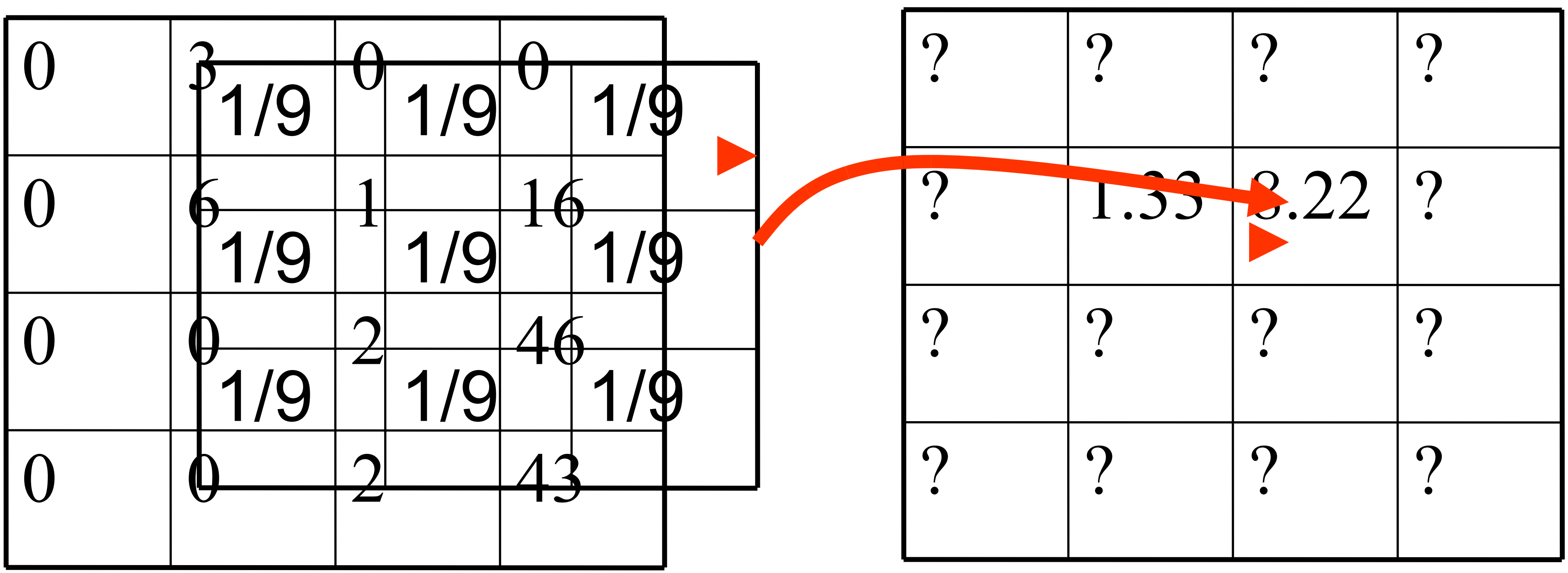
1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Let's represent this more generally



- Multiply corresponding numbers and add

Let's represent this more generally



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

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

Take out a piece of paper

- Let's say *i*= 10 and *j=10*
- Which location in *K* is multiplied by *I*(5,5)?
- *I*(5,4)

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

Resulting Image

Input Image

Convolution Kernel

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

Sliding Template View

- Take the template *K*

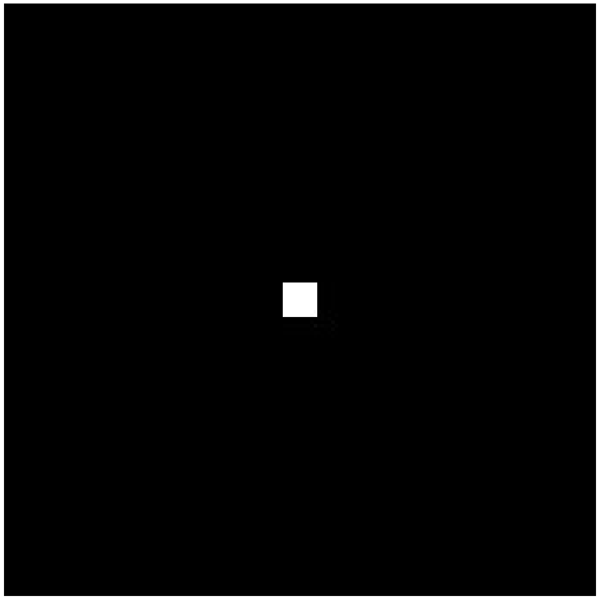
1	2	3
4	5	6
7	8	9

- Flip it

9	8	7
6	5	4
3	2	1

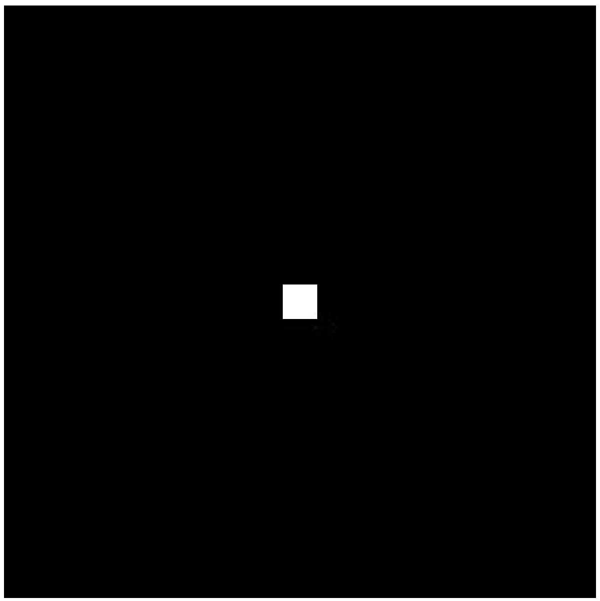
- Slide across image

Predict the Image

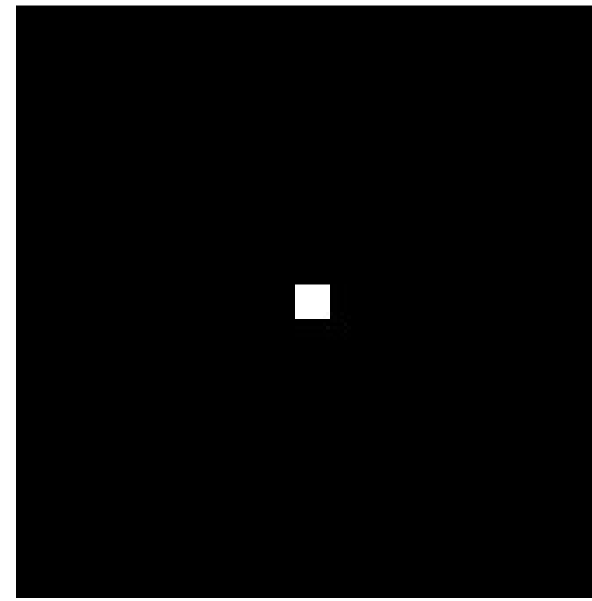


0	0	0
0	1	0
0	0	0

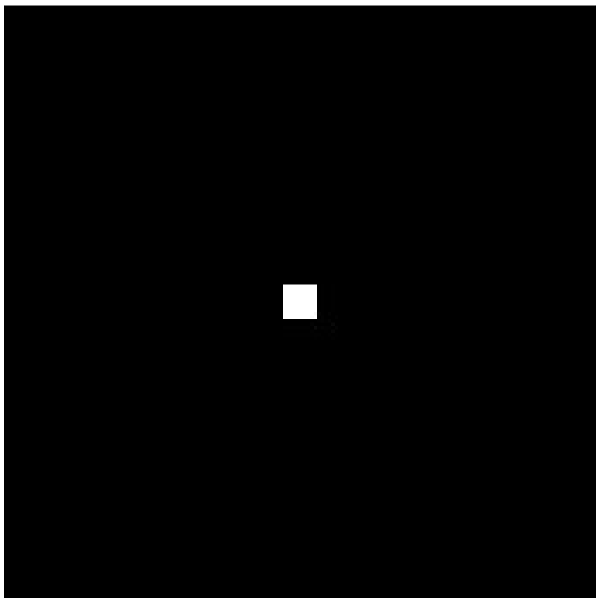
Predict the Image



0	0	0
0	1	0
0	0	0

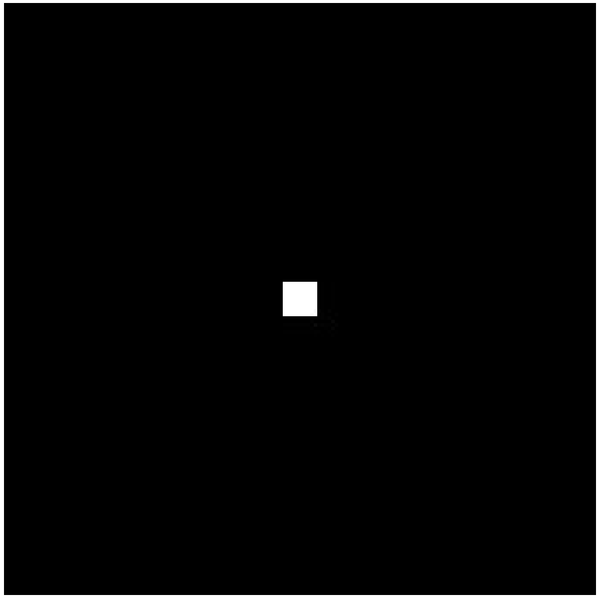


Predict the Image

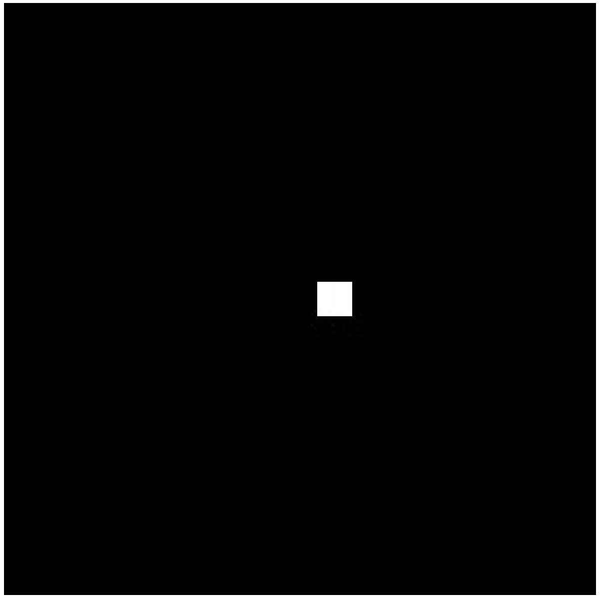


0	0	0
0	0	1
0	0	0

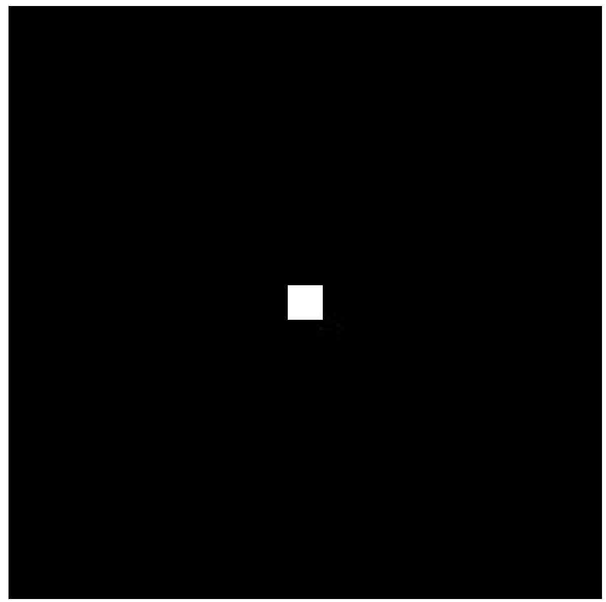
Predict the Image



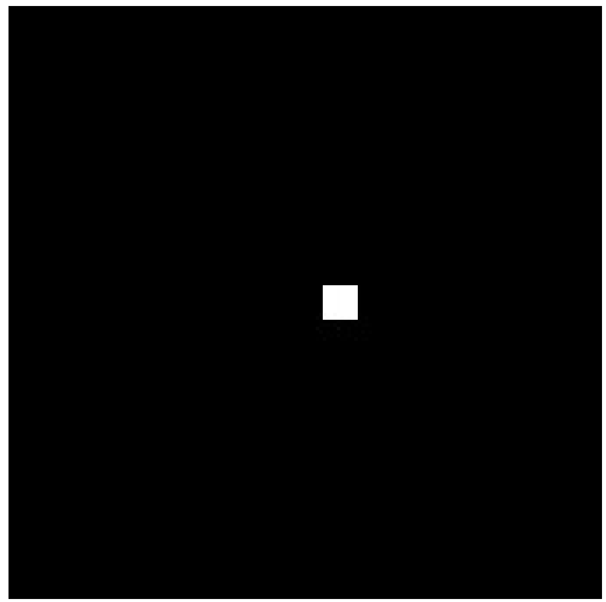
0	0	0
0	0	1
0	0	0



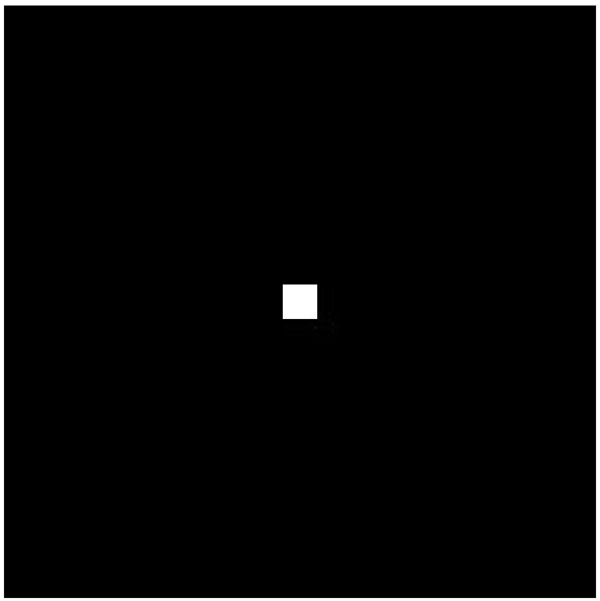
Predict the Image



Predict the Image

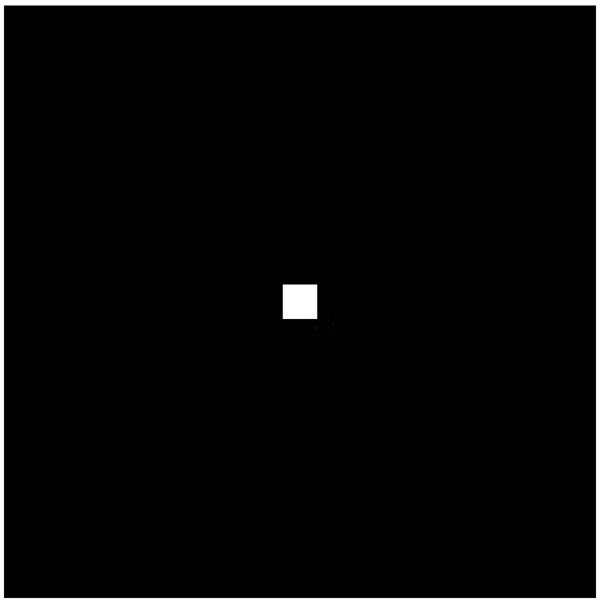


Predict the Image

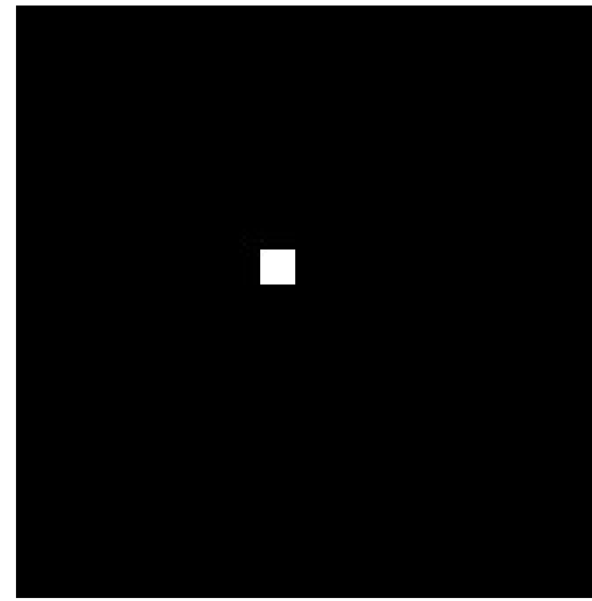


1	0	0
0	0	0
0	0	0

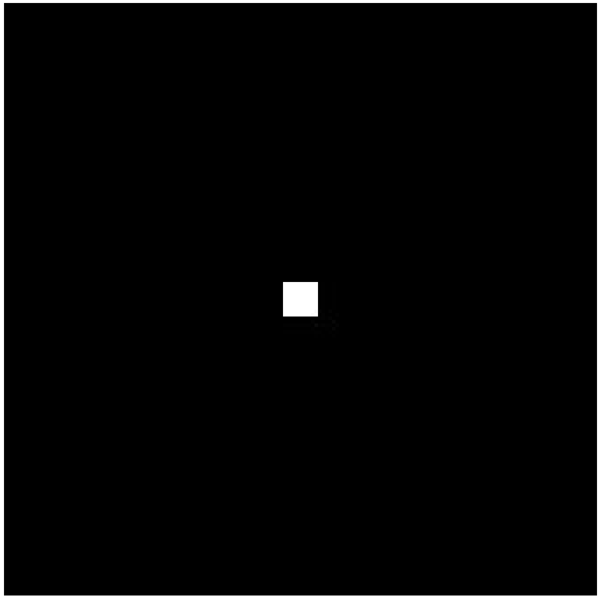
Predict the Image



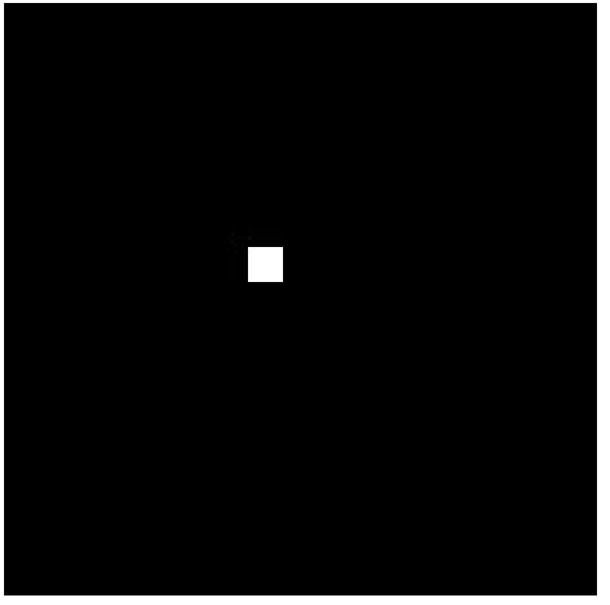
1	0	0
0	0	0
0	0	0



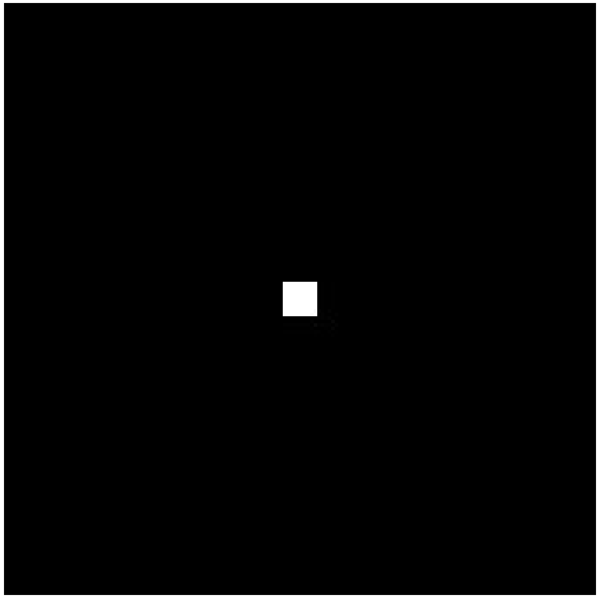
Predict the Image



Predict the Image

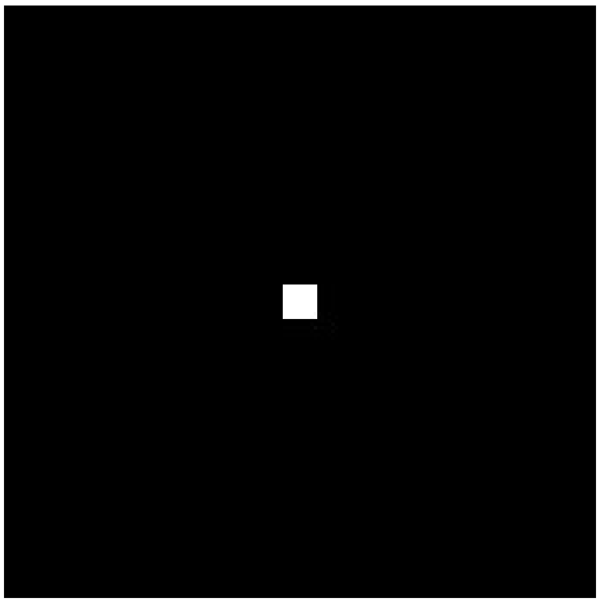


Predict the Image

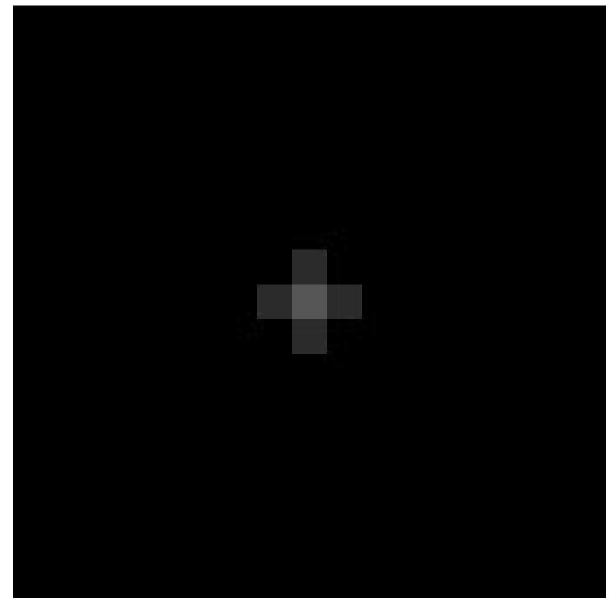


0	1	0
1	2	1
0	1	0

Predict the Image



0	1	0
1	2	1
0	1	0



Predict the kernel

- What if I wanted to compute

  $R(i,j) = I(i+1,j) - I(i,j)$

  at every pixel?
- What would the kernel be?
- This is one discrete approximation to the derivative

What’s the problem with this derivative?

[1 -1 0]

- Where’s the center of the derivative?

- An alternative
  - [-1 0 1]

Your Convolution filter toolbox

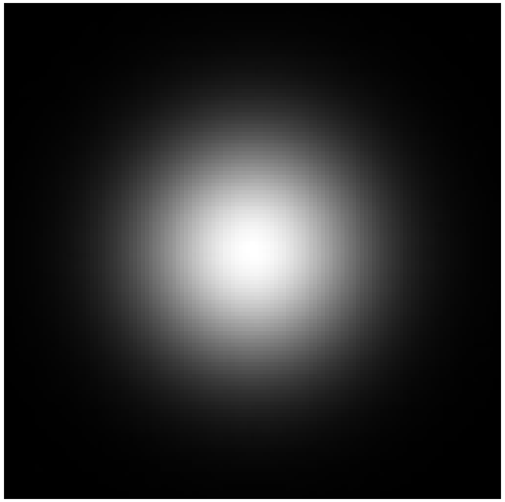
- In my experience, 90% of the filtering that you will do will be either
  - Smoothing (or Blurring)
  - High-Pass Filtering (I’ll explain this later)
- Most common filters:
  - Smoothing: Gaussian
  - High Pass Filtering: Derivative of Gaussian

Gaussian Filter

- Let's assume that a (2*k*+1) x (2*k*+ 1) filter is parameterized from –*k* to +*k*
- The Gaussian filter has the form

$$K(i,j) = \frac{1}{Z}\exp\left(-\frac{i^2+j^2}{2\sigma^2}\right)$$

- And looks like

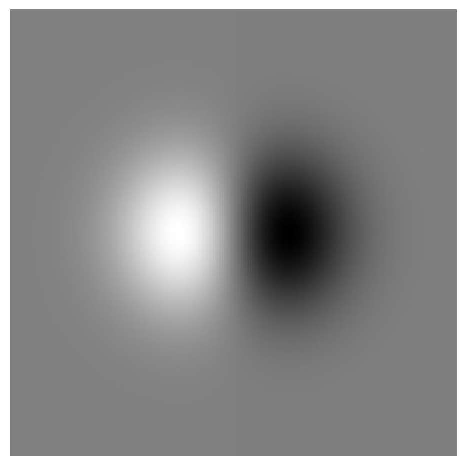


Derivative of Gaussian Filter

- Take the derivative of the filter with respect to *i*:

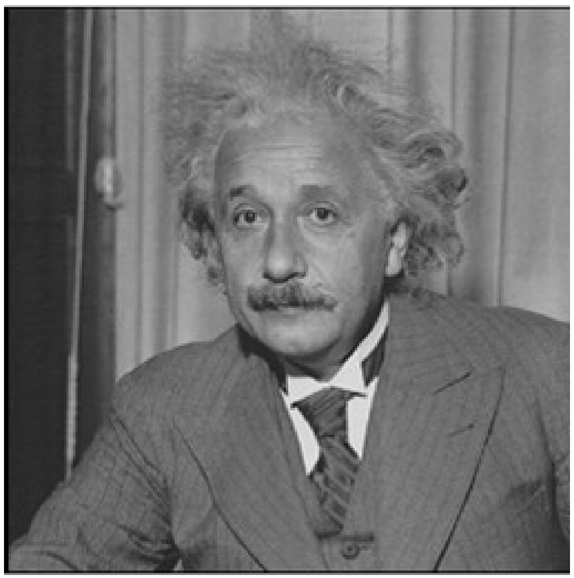
$$\frac{\partial K(i,j)}{\partial i} = \frac{-i}{\sigma^2 Z} \exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right)$$

- Filter looks like:



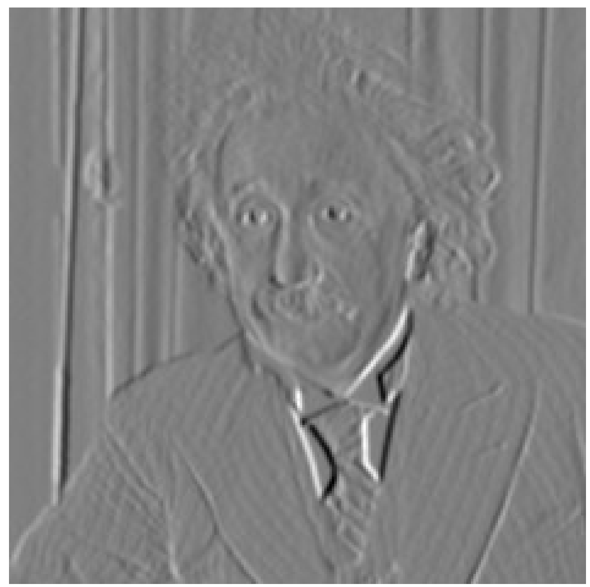
- Basically blur then take the derivative

Effect of Changing σ



Input

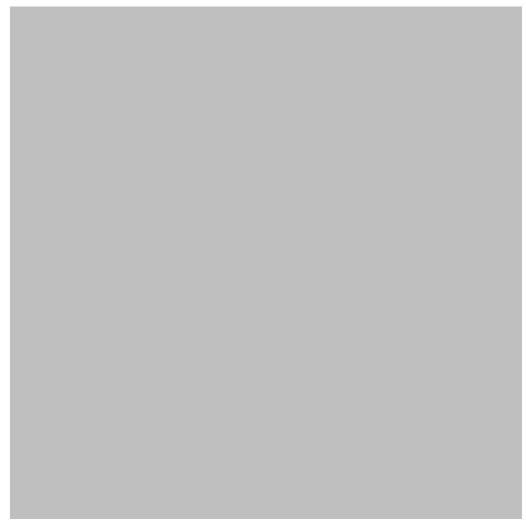
- With σ set to 1



- With σ set to 3

Practical Aspects of Computing Convolutions

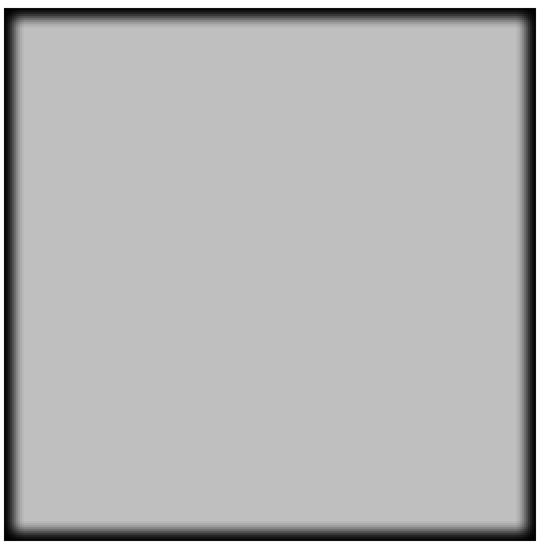
- Let's blur this flat, gray image:



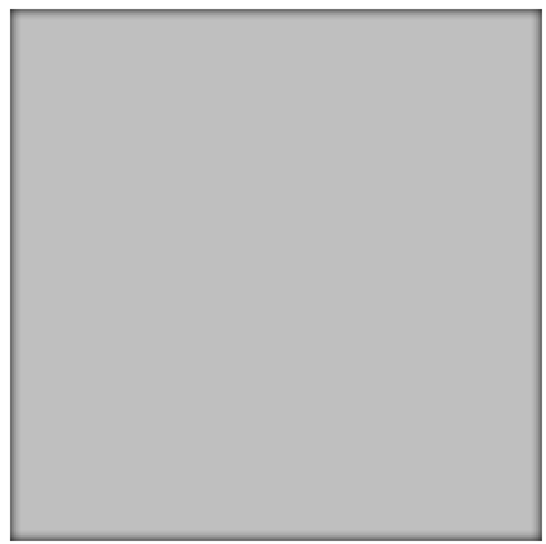
- What should it look like?

Practical Aspects of Computing Convolutions

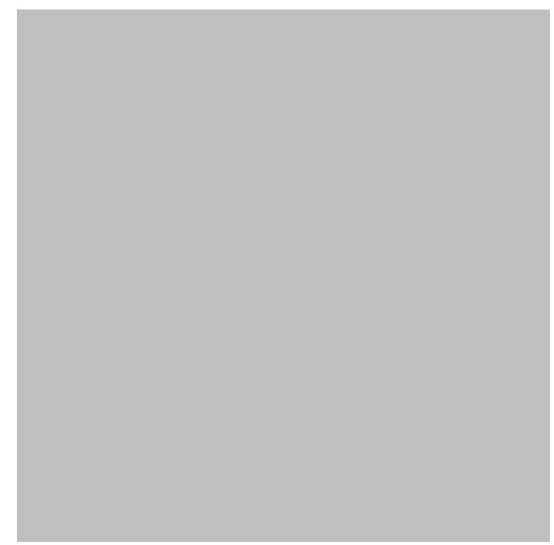
- Depending on how you do the convolution in MATLAB, you could end up with 3 different images



266x266 Image



256x256 Image



246x246 Image

Border Handling

- Lets go back to the sliding template view
- What if I wanted to compute an average right here?

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

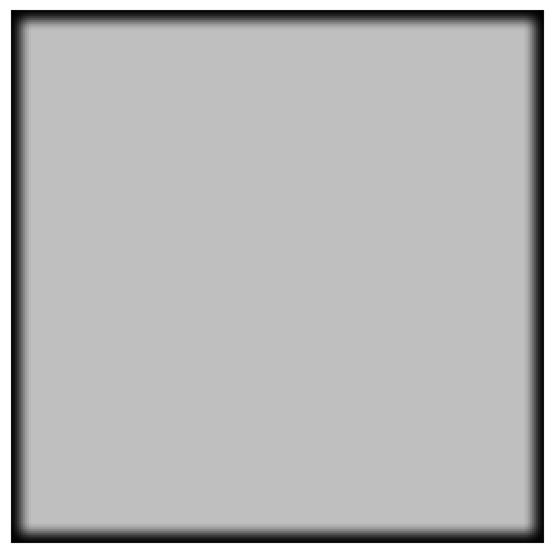
Border Handling

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

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

Practical Aspects of Computing Convolutions

- Filled in borders with zeros, computed everywhere the kernel touches
- Called “full” in MATLAB



266x266 Image

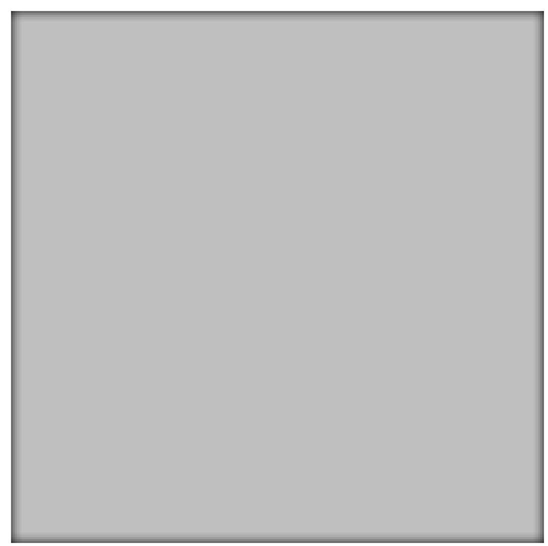
Border Handling

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

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

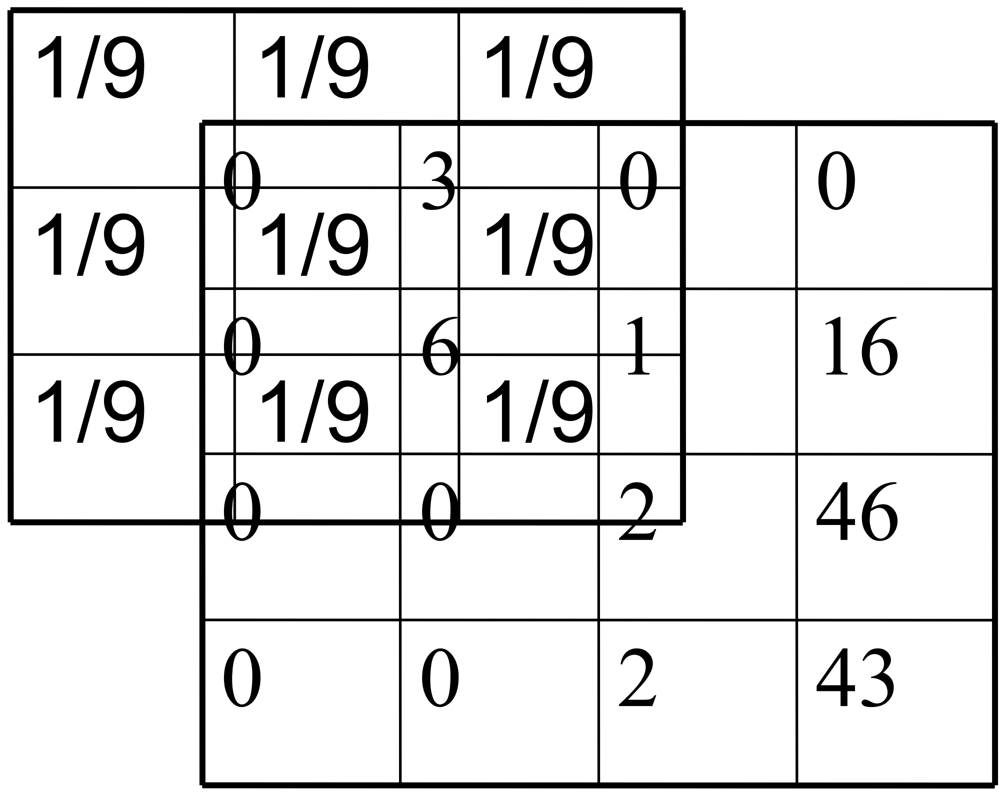
Practical Aspects of Computing Convolutions

- Fill in border with zeros, only compute at "original pixels"
- Called "same" in MATLAB



256x256 Image

Border Handling



Practical Aspects of Computing Convolutions

- Only compute at places where the kernel fits in the image

246x246 Image

There are other options

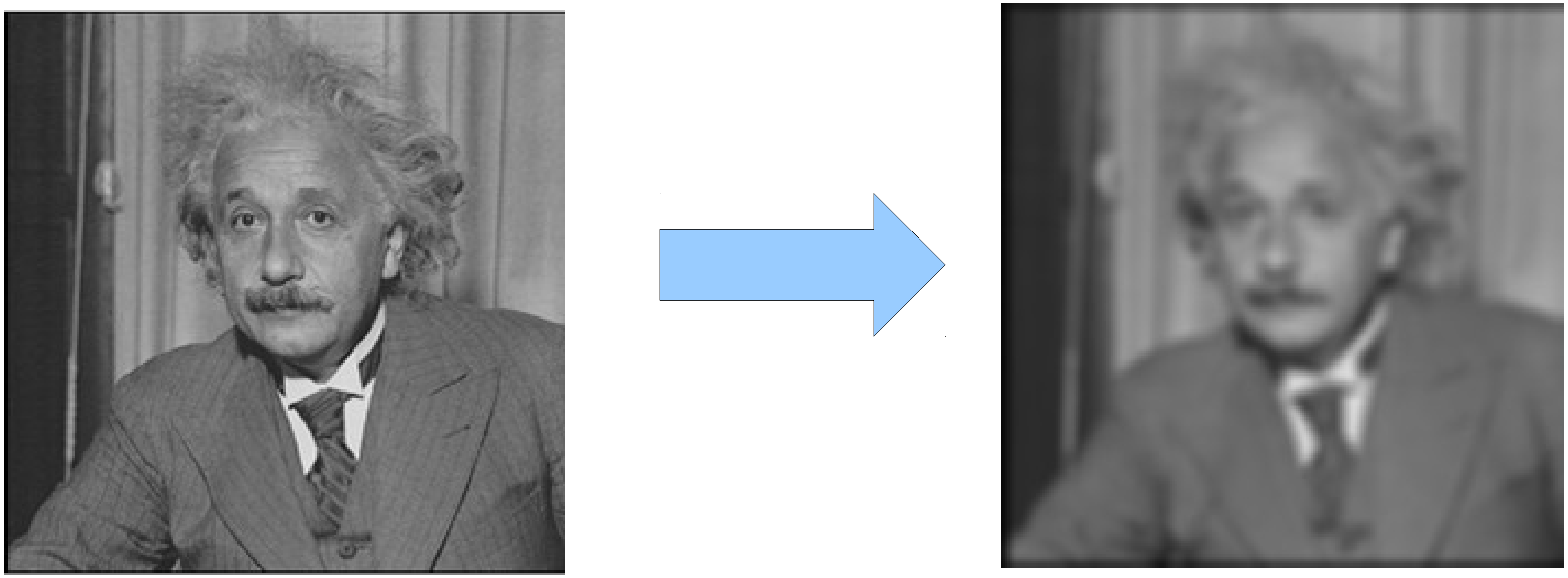
- The first two methods that I described fill missing values in by substituting zero
- Can fill in values with different methods
  - Reflect image along border
  - Pull values from other side
- Not supported in MATLAB's convolution
  - Eero Simoncelli has a package that supports that kind of convolution

Going Non-Linear

- Convolution is a linear operation
  - What does that mean?
- A simple *non-linear* operation is the median filter
  - Will explore that filter in the first problem set.

Practical Use of These Properties – Image Sharpening

- Take this image and blur it



Basic Convolution Properties

$$f(x) * ((g(x) * h(x)) = (f(x) * g(x)) * h(x)$$

$$(\alpha f(x)) * g(x) = \alpha\,(f(x) * g(x))$$

$$f(x) * g(x) = g(x) * f(x)$$

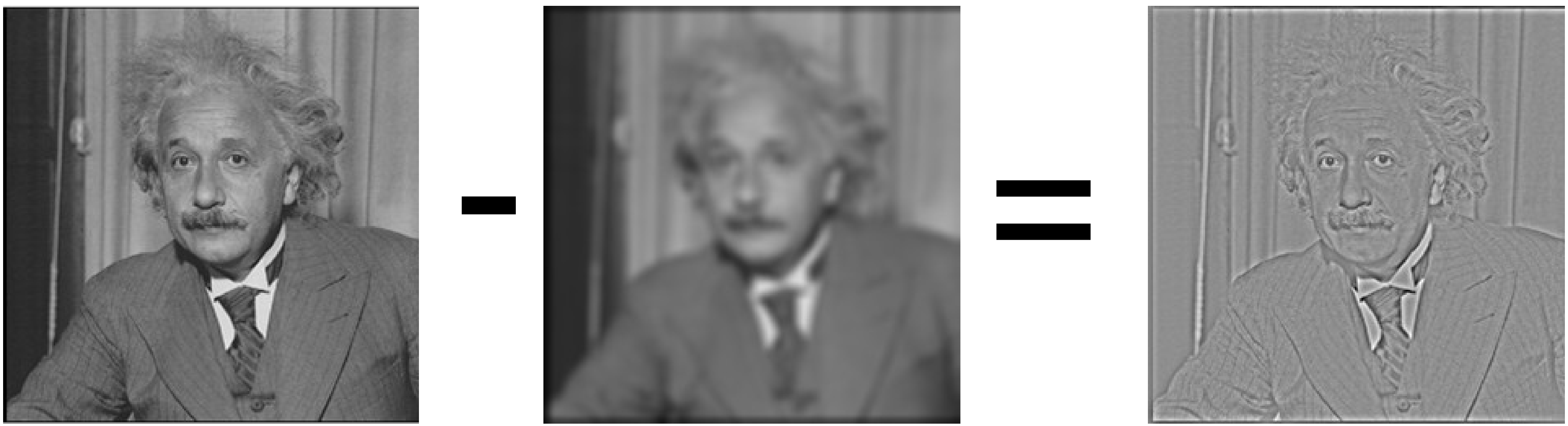
$$f(x) * (g(x) + h(x)) = f(x) * g(x) + f(x) * h(x)$$

- Can derive all of these with the definition of convolution
- Comes from linearity of convolution

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

Practical Use of These Properties – Image Sharpening

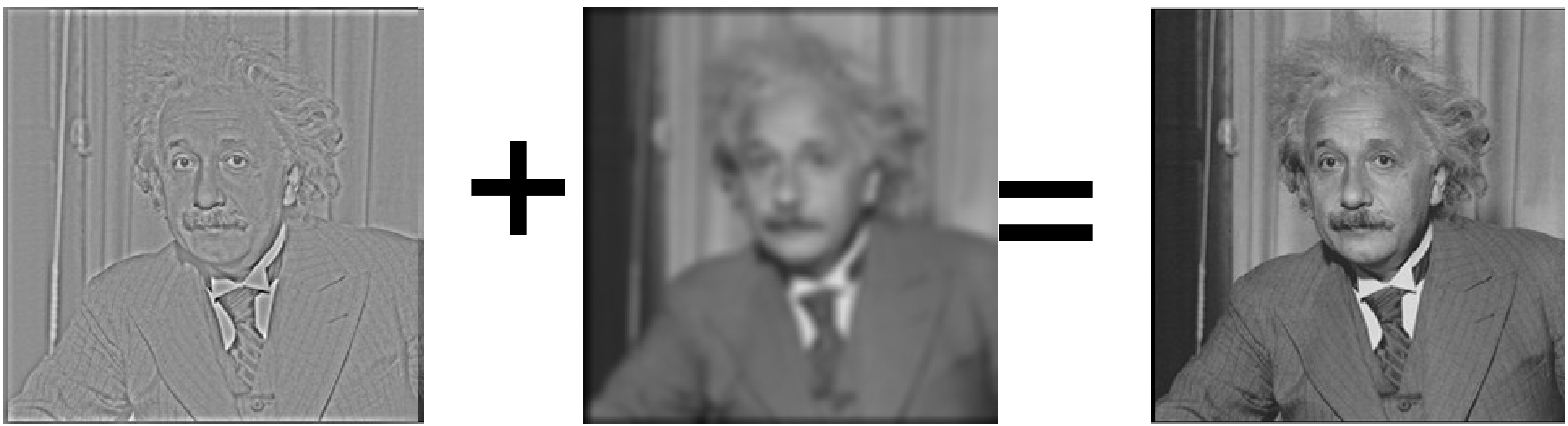
- What do we get if we subtract the two?



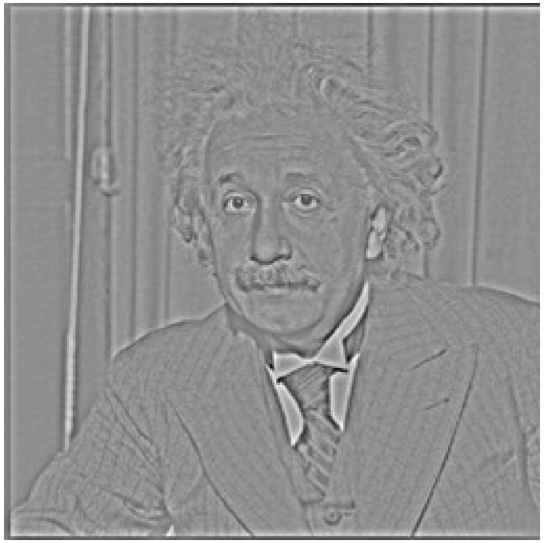
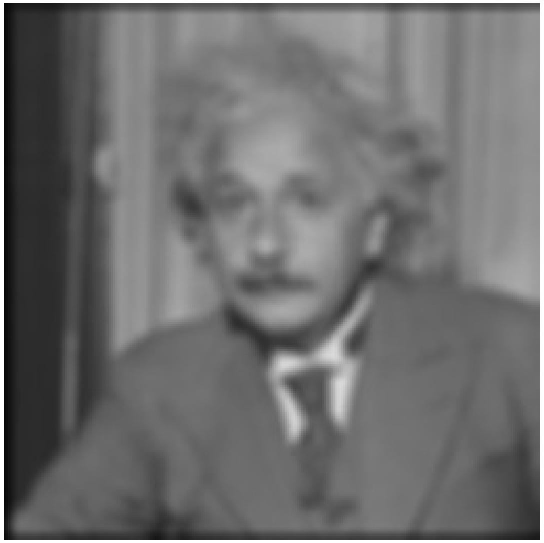
- This is the leftover “sharp-stuff”

Let's make the image sharper

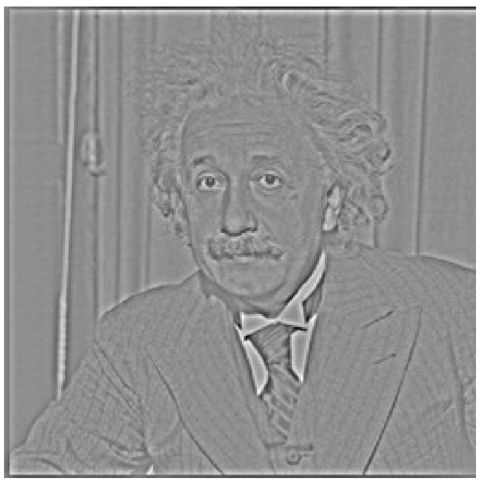
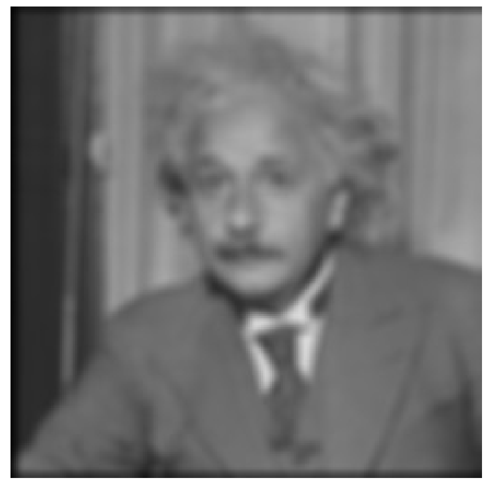
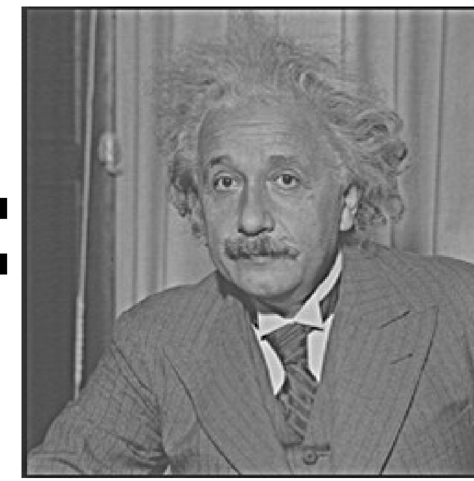
- We know



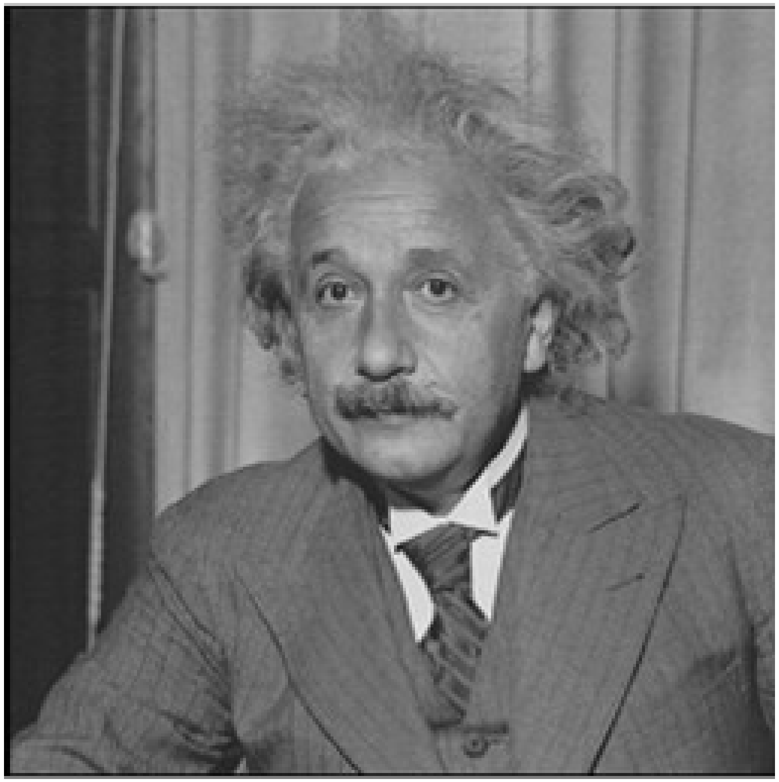
Let's boost the sharp stuff a little

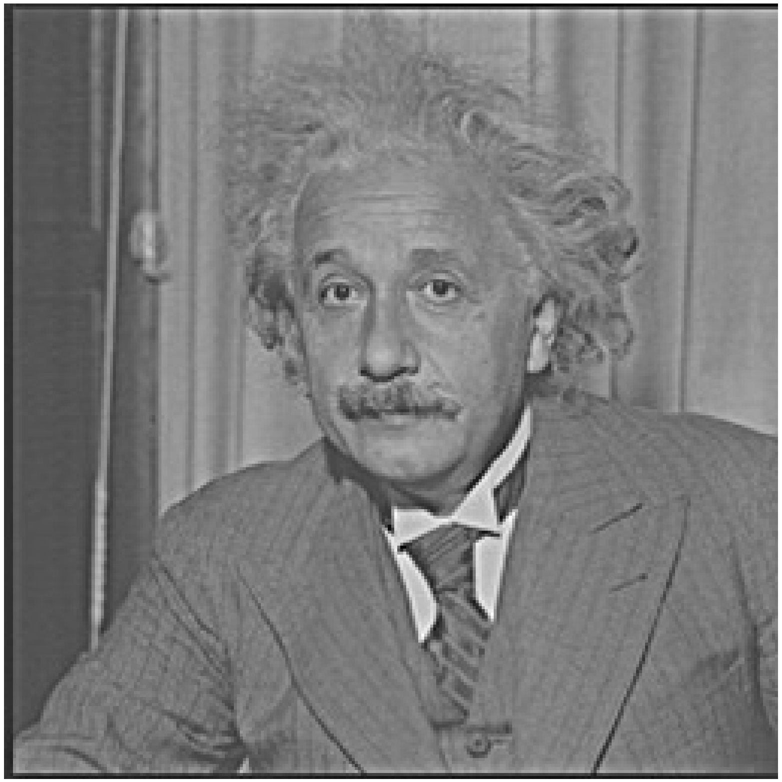
$2\times$  $+$ 

Let's boost the sharp stuff a little

2×

+

=


Side-by Side





Now look at the computation

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

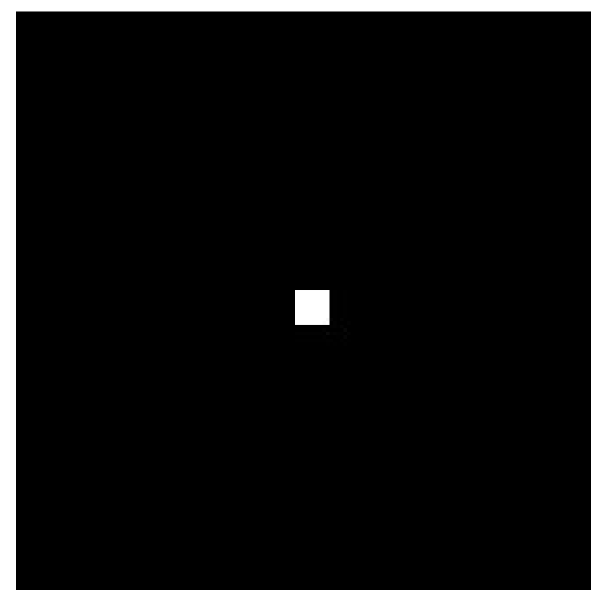
$$\mathcal{I} * f + 2\left(\mathcal{I} - \mathcal{I} * f\right)$$

Rewrite this

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

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

This is an identity filter or unit impulse



Basic Convolution Properties

$$f(x) * ((g(x) * h(x)) = (f(x) * g(x)) * h(x)$$
$$(\alpha f(x)) * g(x) = \alpha\,(f(x) * g(x))$$
$$f(x) * g(x) = g(x) * f(x)$$
$$f(x) * (g(x) + h(x)) = f(x) * g(x) + f(x) * h(x)$$

- Can derive all of these with the definition of convolution
- Comes from linearity of convolution

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

Rewrite this

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

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

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

Now look at the computation

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

- Can pre-compute new filter
- Operations
  - 1 convolution