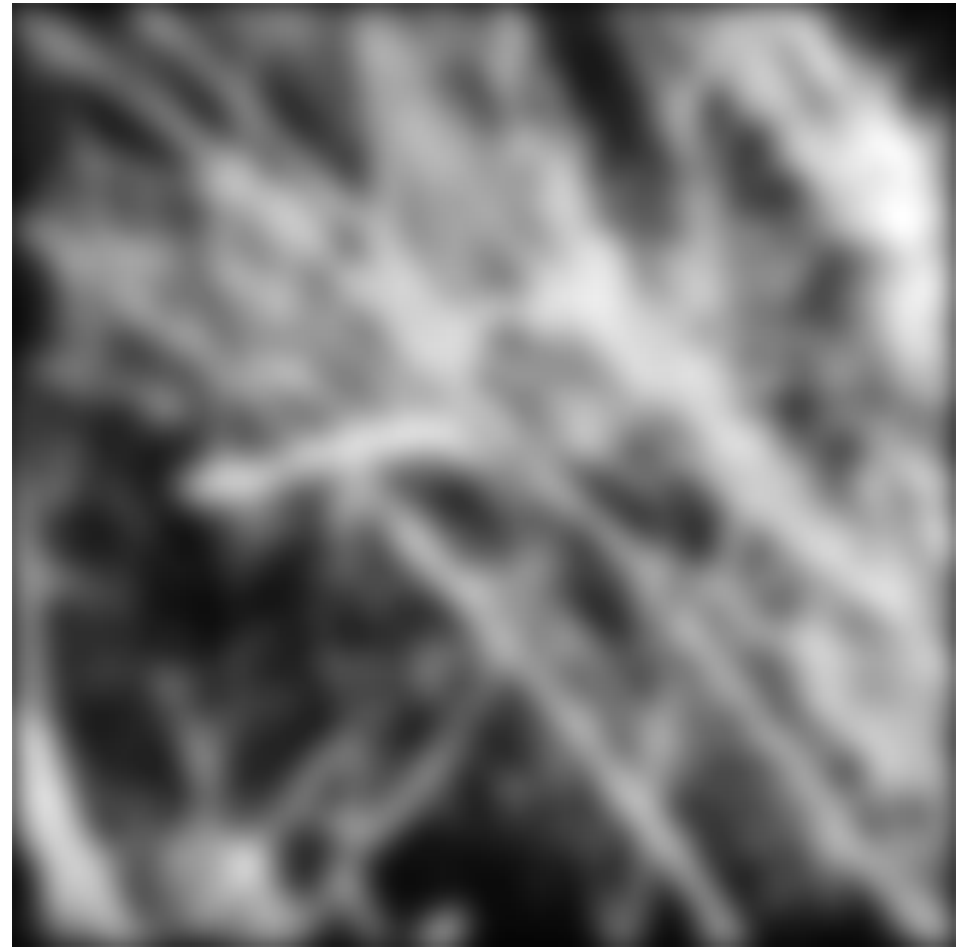


# Linear filtering

---



# Motivation: Image denoising

---

- How can we reduce noise in a photograph?



# Moving average

---

- Let's replace each pixel with a *weighted* average of its neighborhood
- The weights are called the *filter kernel*
- What are the weights for the average of a 3x3 neighborhood?

$$\frac{1}{9}$$

1	1	1
1	1	1
1	1	1

“box filter”

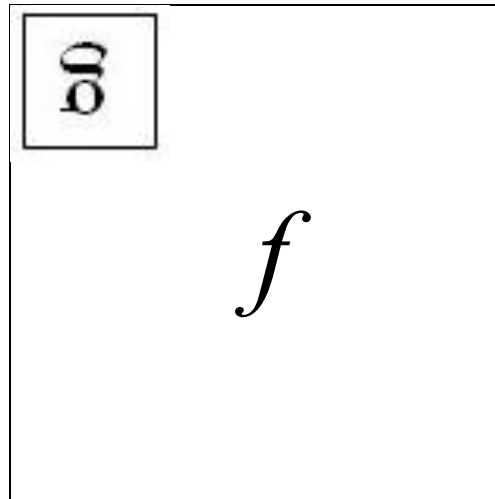
# Defining convolution

---

- Let  $f$  be the image and  $g$  be the kernel. The output of convolving  $f$  with  $g$  is denoted  $f * g$ .

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

Convention:  
kernel is “flipped”



- MATLAB functions: `conv2`, `filter2`, `imfilter`

# Key properties

---

- **Linearity:**  $\text{filter}(f_1 + f_2) = \text{filter}(f_1) + \text{filter}(f_2)$
- **Shift invariance:** same behavior regardless of pixel location:  $\text{filter}(\text{shift}(f)) = \text{shift}(\text{filter}(f))$
- Theoretical result: any linear shift-invariant operator can be represented as a convolution

# Properties in more detail

---

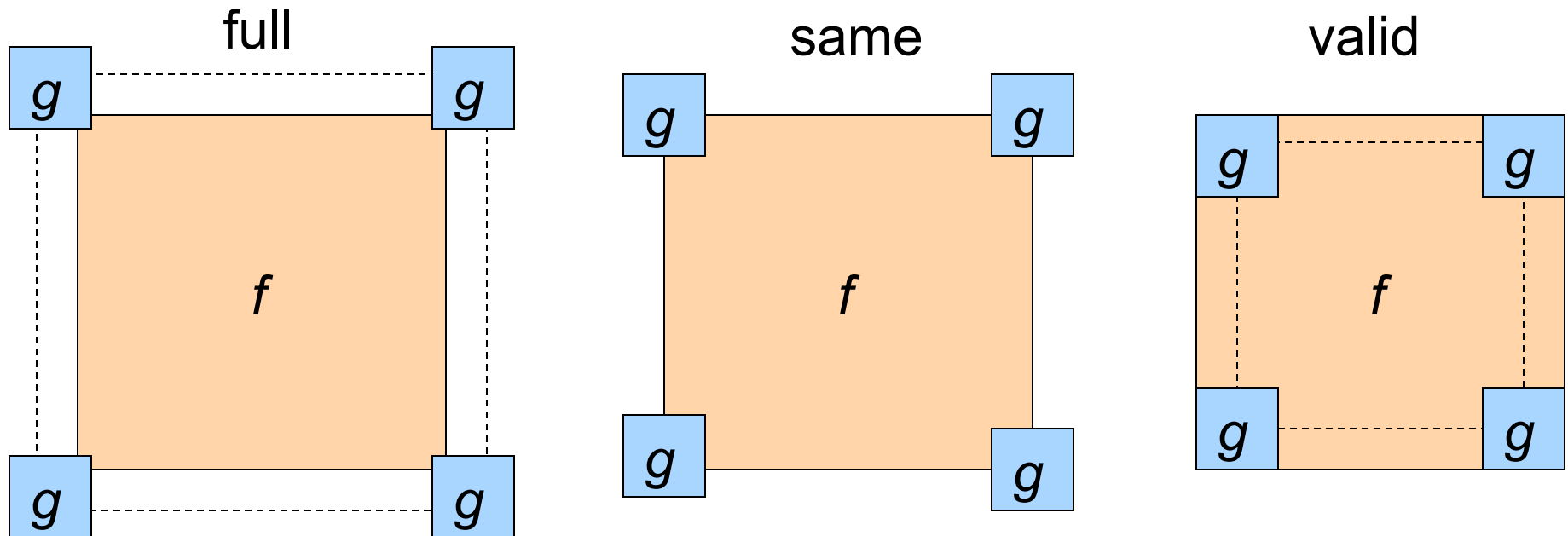
- Commutative:  $a * b = b * a$ 
  - Conceptually no difference between filter and signal
- Associative:  $a * (b * c) = (a * b) * c$ 
  - Often apply several filters one after another:  $((a * b_1) * b_2) * b_3$
  - This is equivalent to applying one filter:  $a * (b_1 * b_2 * b_3)$
- Distributes over addition:  $a * (b + c) = (a * b) + (a * c)$
- Scalars factor out:  $ka * b = a * kb = k(a * b)$
- Identity: unit impulse  $e = [\dots, 0, 0, 1, 0, 0, \dots]$ ,  
 $a * e = a$

# Annoying details

---

What is the size of the output?

- MATLAB: `filter2(g, f, shape)`
  - `shape = 'full'`: output size is sum of sizes of  $f$  and  $g$
  - `shape = 'same'`: output size is same as  $f$
  - `shape = 'valid'`: output size is difference of sizes of  $f$  and  $g$



# Annoying details

---

## What about near the edge?

- the filter window falls off the edge of the image
- need to extrapolate
- methods:
  - clip filter (black)
  - wrap around
  - copy edge
  - reflect across edge





# Annoying details

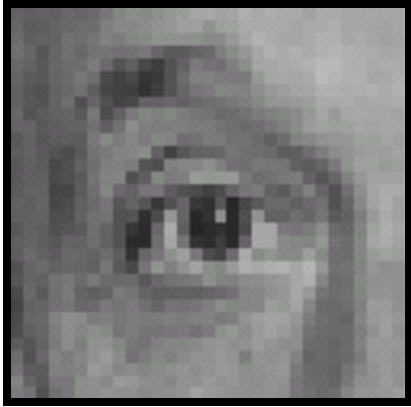
---

## What about near the edge?

- the filter window falls off the edge of the image
- need to extrapolate
- methods (MATLAB):
  - clip filter (black): `imfilter(f, g, 0)`
  - wrap around: `imfilter(f, g, 'circular')`
  - copy edge: `imfilter(f, g, 'replicate')`
  - reflect across edge: `imfilter(f, g, 'symmetric')`

# Practice with linear filters

---



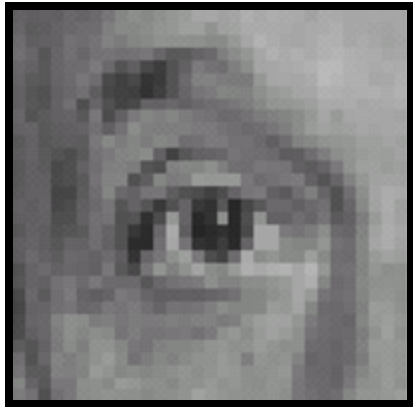
Original

0	0	0
0	1	0
0	0	0

?

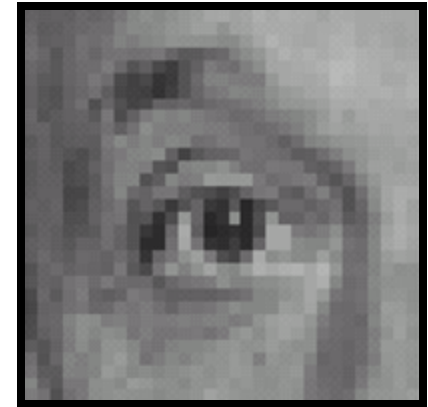
# Practice with linear filters

---



Original

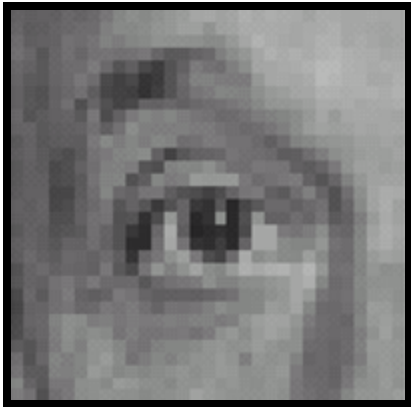
0	0	0
0	1	0
0	0	0



Filtered  
(no change)

# Practice with linear filters

---



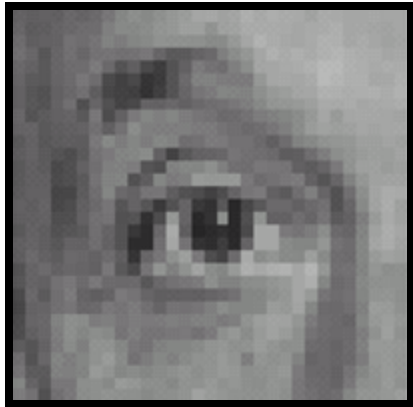
Original

0	0	0
0	0	1
0	0	0

?

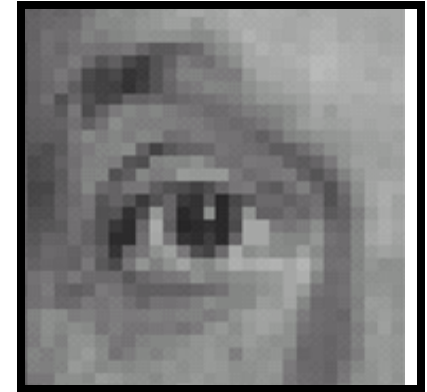
# Practice with linear filters

---



Original

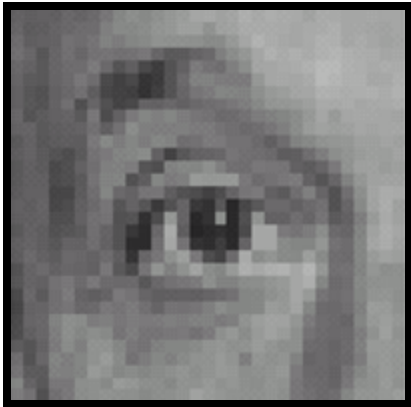
0	0	0
0	0	1
0	0	0



Shifted *left*  
By 1 pixel

# Practice with linear filters

---



Original

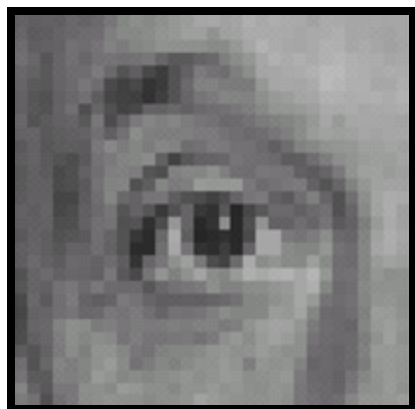
 $\frac{1}{9}$ 

1	1	1
1	1	1
1	1	1

?

# Practice with linear filters

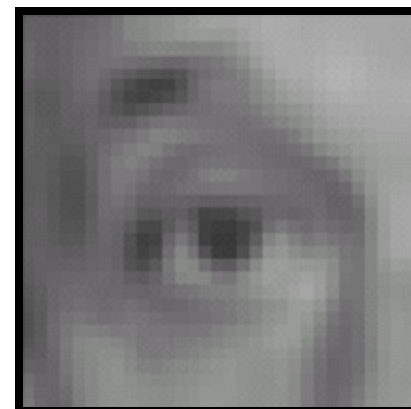
---



Original

 $\frac{1}{9}$ 

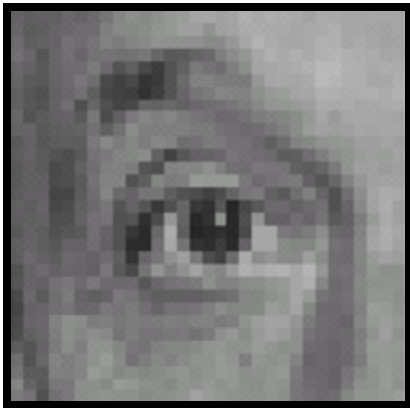
1	1	1
1	1	1
1	1	1



Blur (with a  
box filter)

# Practice with linear filters

---



Original

0	0	0
0	2	0
0	0	0

−

$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

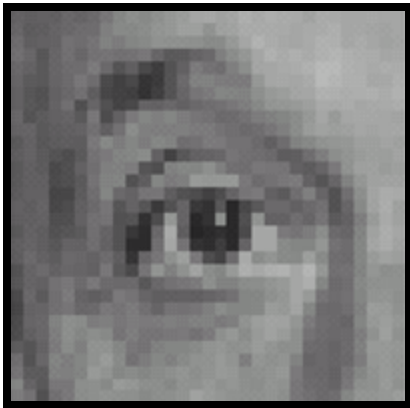
?

(Note that filter sums to 1)



# Practice with linear filters

---



Original

0	0	0
0	2	0
0	0	0

−

$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

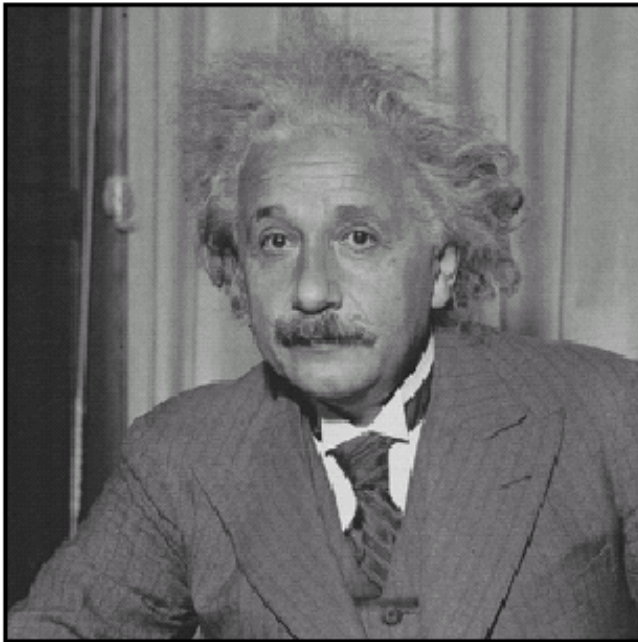


## Sharpening filter

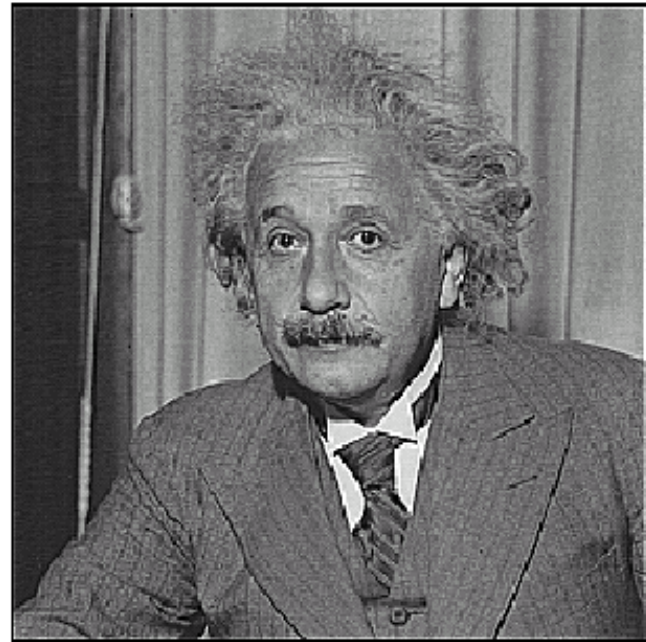
- Accentuates differences with local average

# Sharpening

---



**before**



**after**

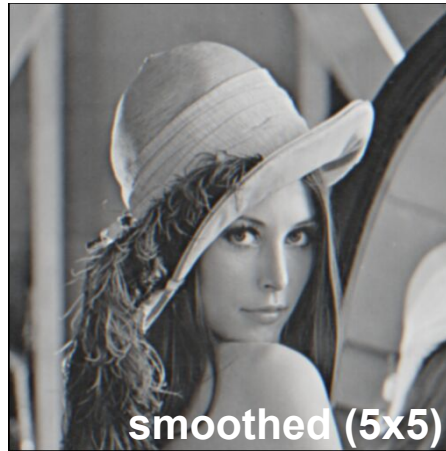
# Sharpening

---

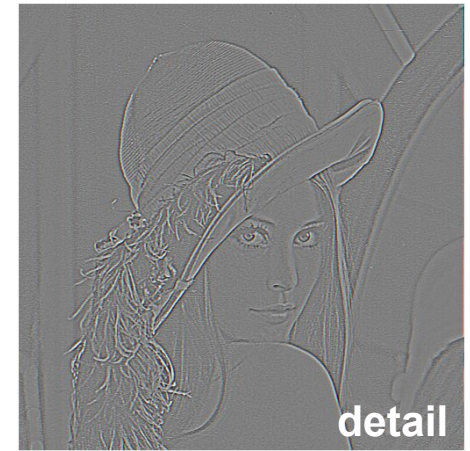
What does blurring take away?



−



=



Let's add it back:



+



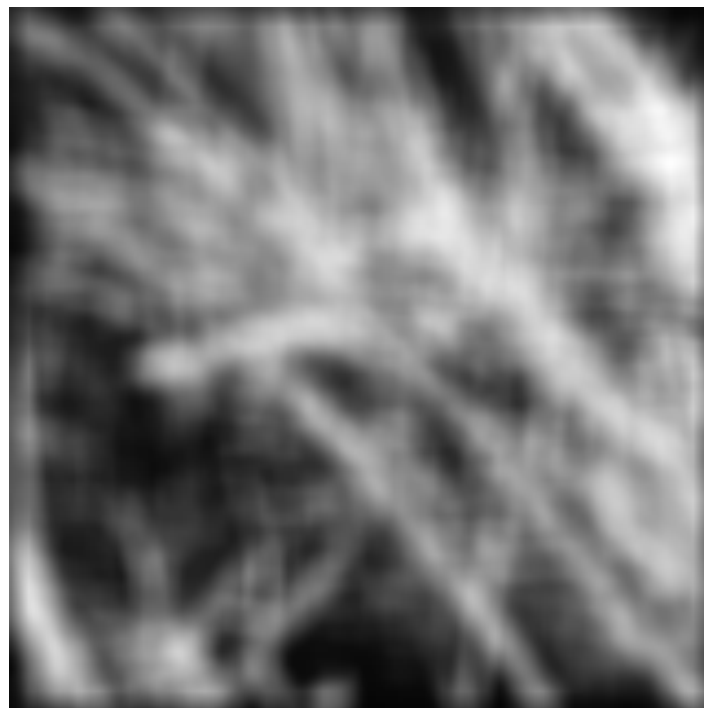
=



# Smoothing with box filter revisited

---

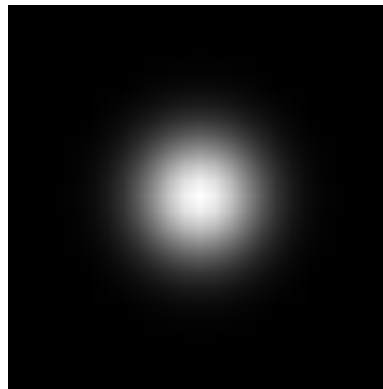
- What's wrong with this picture?
- What's the solution?



# Smoothing with box filter revisited

---

- What's wrong with this picture?
- What's the solution?
  - To eliminate edge effects, weight contribution of neighborhood pixels according to their closeness to the center

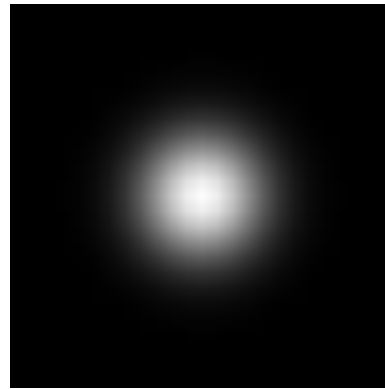
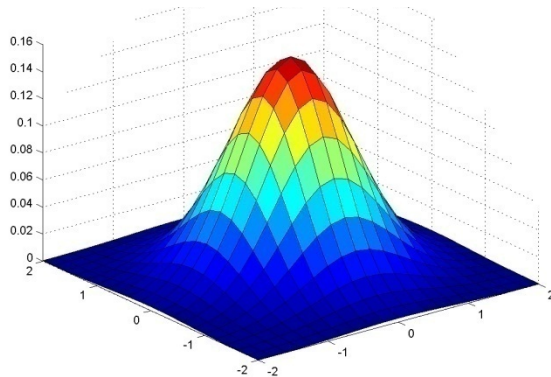


“fuzzy blob”

# Gaussian Kernel

---

$$G_{\sigma} = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$



0.003	0.013	0.022	0.013	0.003
0.013	0.059	0.097	0.059	0.013
0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

5 x 5,  $\sigma = 1$

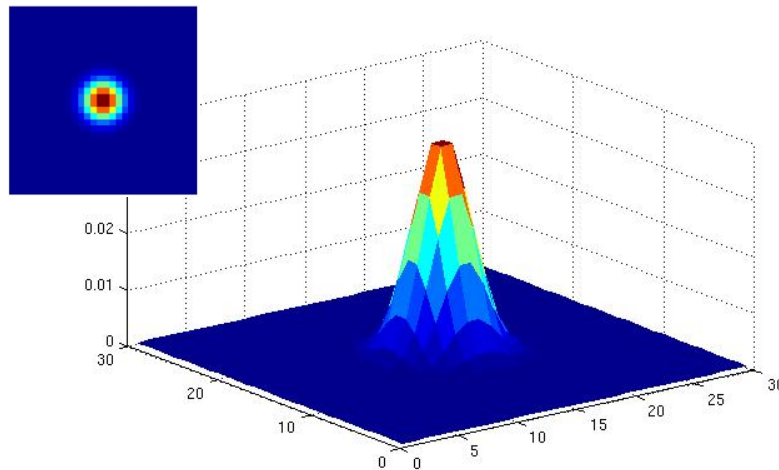
- Constant factor at front makes volume sum to 1 (can be ignored when computing the filter values, as we should renormalize weights to sum to 1 in any case)



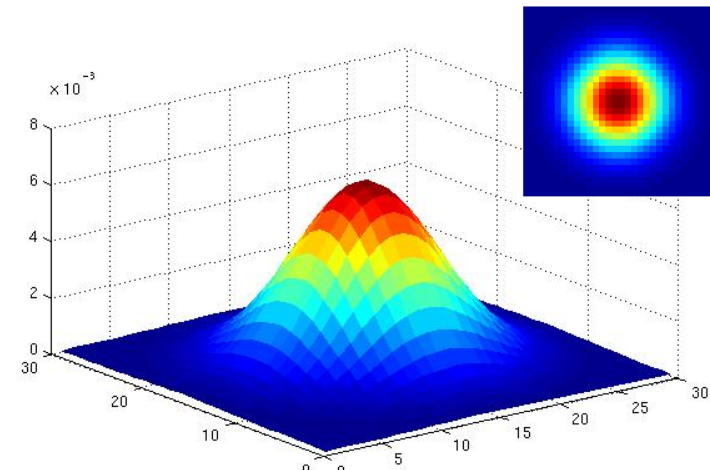
# Gaussian Kernel

---

$$G_{\sigma} = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$



$\sigma = 2$  with 30 x 30  
kernel

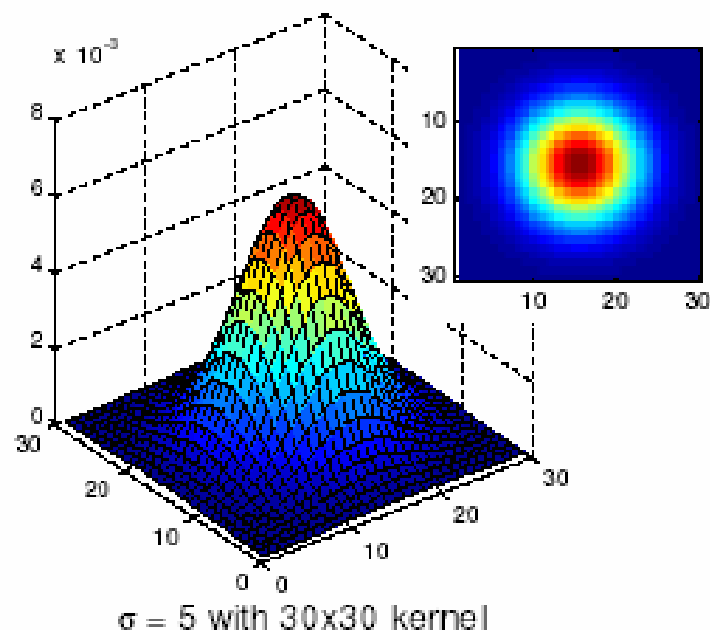
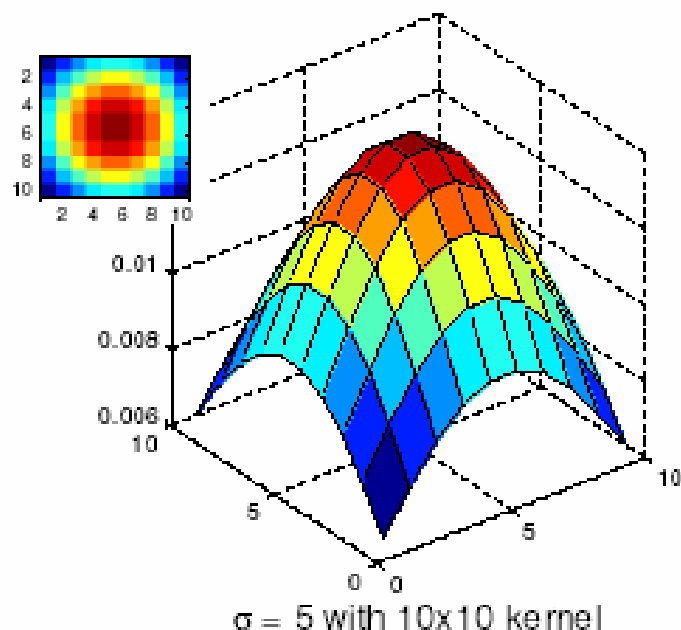


$\sigma = 5$  with 30 x 30  
kernel

- Standard deviation  $\sigma$ : determines extent of smoothing

# Choosing kernel width

- The Gaussian function has infinite support, but discrete filters use finite kernels

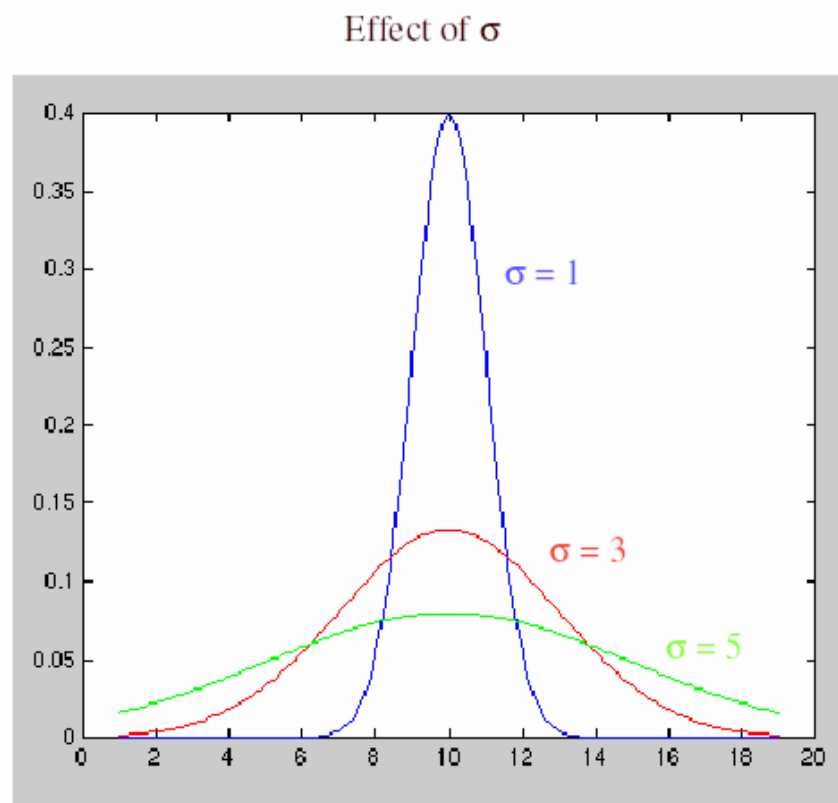




# Choosing kernel width

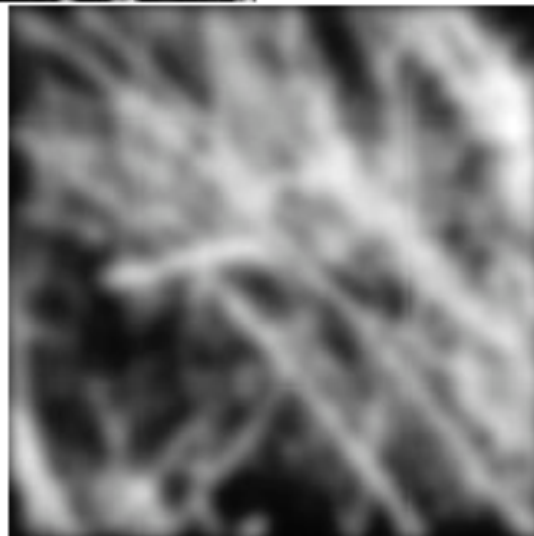
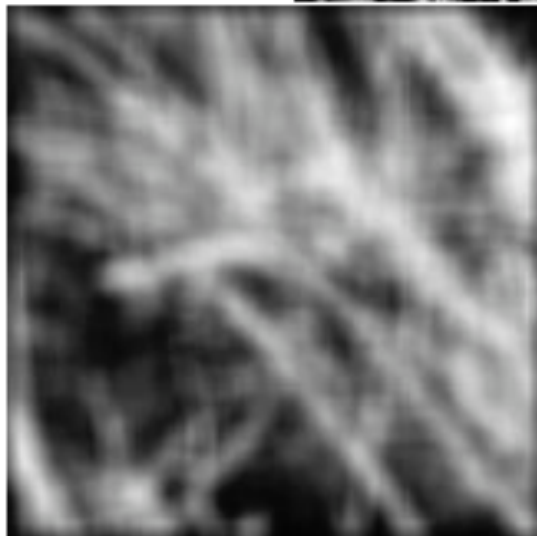
---

- Rule of thumb: set filter half-width to about  $3\sigma$



# Gaussian vs. box filtering

---



# Gaussian filters

---

- Remove high-frequency components from the image (*low-pass filter*)
- Convolution with self is another Gaussian
  - So can smooth with small- $\sigma$  kernel, repeat, and get same result as larger- $\sigma$  kernel would have
  - Convoluting two times with Gaussian kernel with std. dev.  $\sigma$  is same as convoluting once with kernel with std. dev.  $\sigma\sqrt{2}$
- *Separable* kernel
  - Factors into product of two 1D Gaussians
  - Discrete example:

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$$

# Separability of the Gaussian filter

---

$$\begin{aligned} G_{\sigma}(x, y) &= \frac{1}{2\pi\sigma^2} \exp^{-\frac{x^2 + y^2}{2\sigma^2}} \\ &= \left( \frac{1}{\sqrt{2\pi}\sigma} \exp^{-\frac{x^2}{2\sigma^2}} \right) \left( \frac{1}{\sqrt{2\pi}\sigma} \exp^{-\frac{y^2}{2\sigma^2}} \right) \end{aligned}$$

The 2D Gaussian can be expressed as the product of two functions, one a function of  $x$  and the other a function of  $y$

In this case, the two functions are the (identical) 1D Gaussian

# Why is separability useful?

---

- Separability means that a 2D convolution can be reduced to two 1D convolutions (one among rows and one among columns)
- What is the complexity of filtering an  $n \times n$  image with an  $m \times m$  kernel?
  - $O(n^2 m^2)$
- What if the kernel is separable?
  - $O(n^2 m)$

# Noise

---



Original



Salt and pepper noise



Impulse noise



Gaussian noise

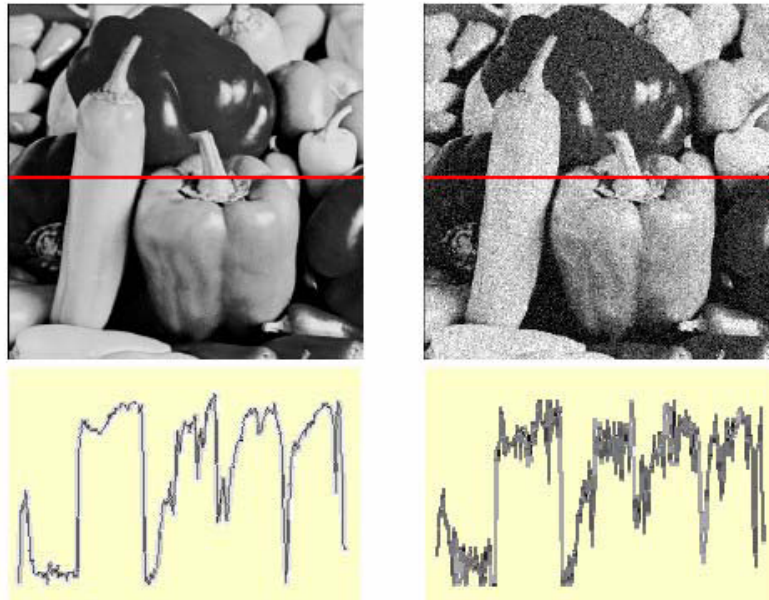
- **Salt and pepper noise:** contains random occurrences of black and white pixels
- **Impulse noise:** contains random occurrences of white pixels
- **Gaussian noise:** variations in intensity drawn from a Gaussian normal distribution

# Gaussian noise

---

- Mathematical model: sum of many independent factors
- Good for small standard deviations
- Assumption: independent, zero-mean noise

Image  
Noise

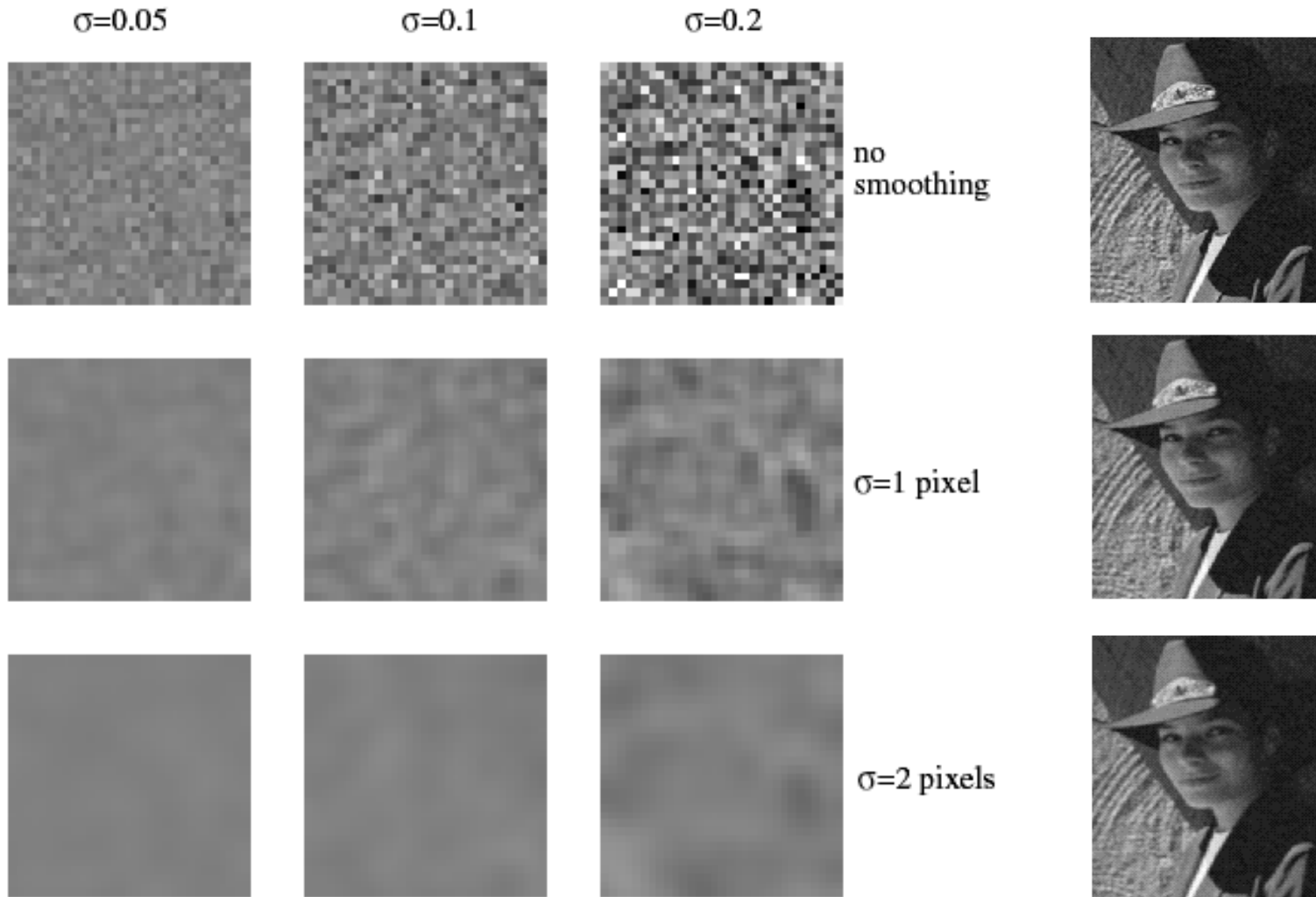


$$f(x, y) = \overbrace{\hat{f}(x, y)}^{\text{Ideal Image}} + \overbrace{\eta(x, y)}^{\text{Noise process}}$$

Gaussian i.i.d. ("white") noise:  
 $\eta(x, y) \sim \mathcal{N}(\mu, \sigma)$

# Reducing Gaussian noise

---



Smoothing with larger standard deviations suppresses noise, but also blurs the image



# Reducing salt-and-pepper noise

---

3x3



5x5



7x7

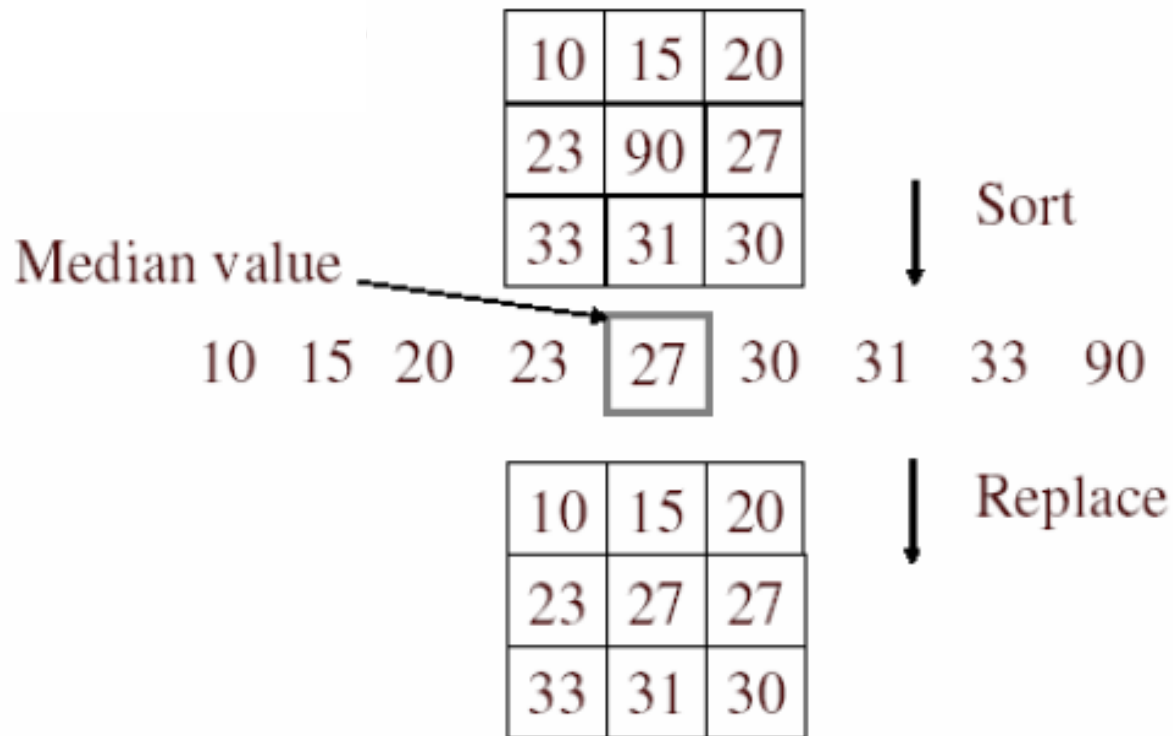


What's wrong with the results?

# Alternative idea: Median filtering

---

- A **median filter** operates over a window by selecting the median intensity in the window



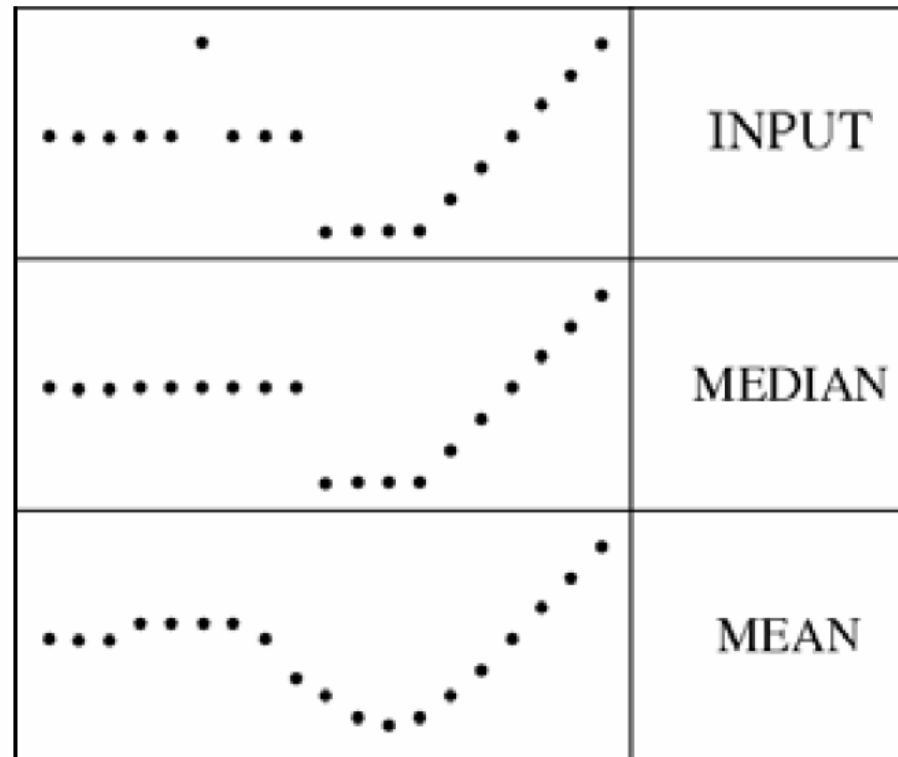
- Is median filtering linear?

# Median filter

---

- What advantage does median filtering have over Gaussian filtering?
  - Robustness to outliers

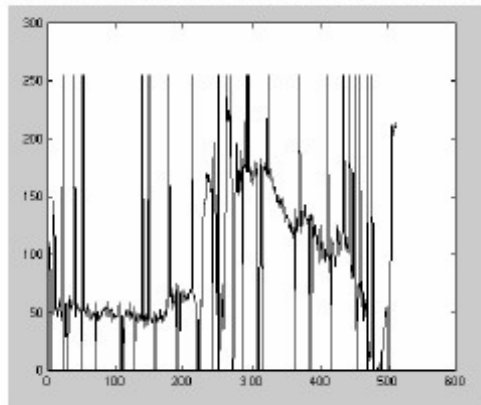
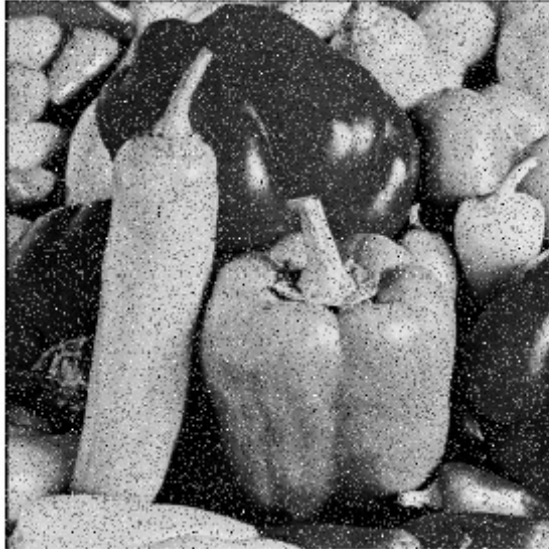
filters have width 5 :



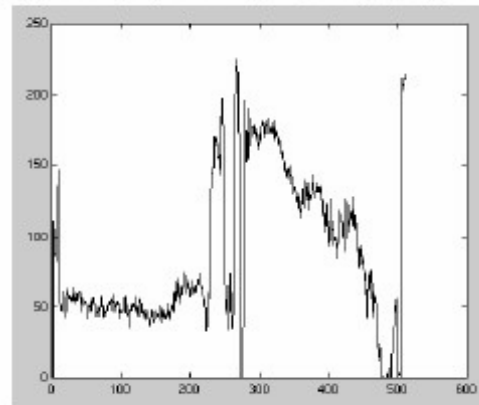
# Median filter

---

Salt-and-pepper noise



Median filtered



MATLAB: `medfilt2(image, [h w])`

# Gaussian vs. median filtering

---

3x3

5x5

7x7

Gaussian

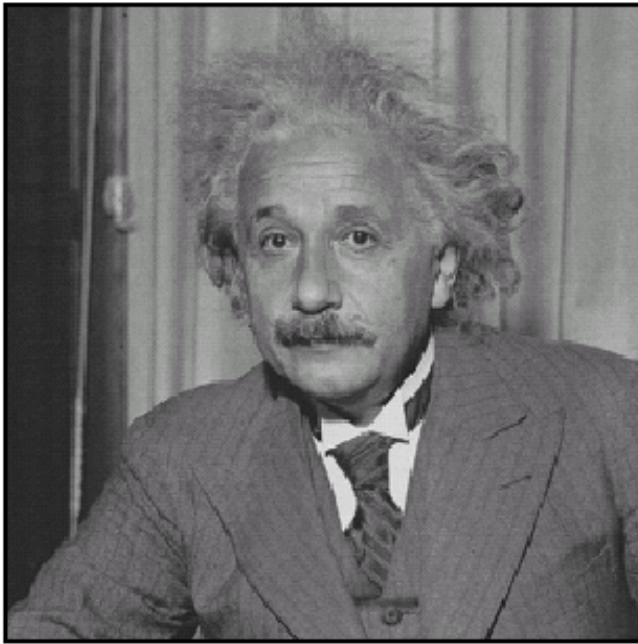


Median

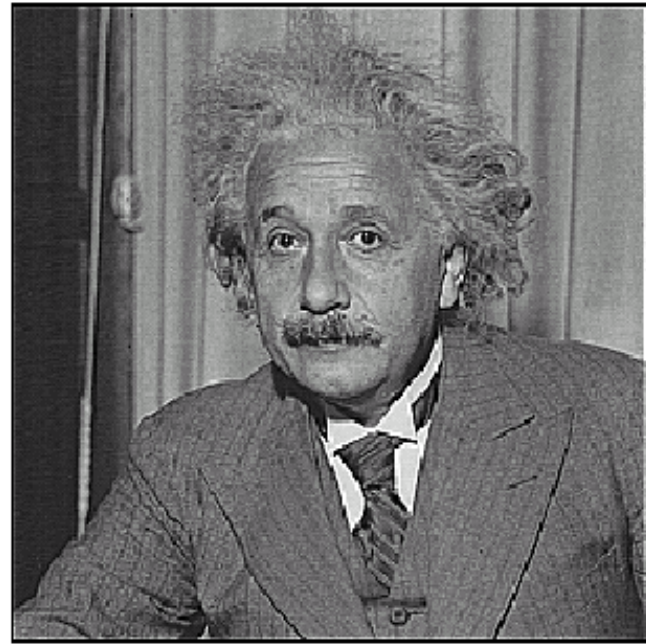


# Sharpening revisited

---



**before**



**after**



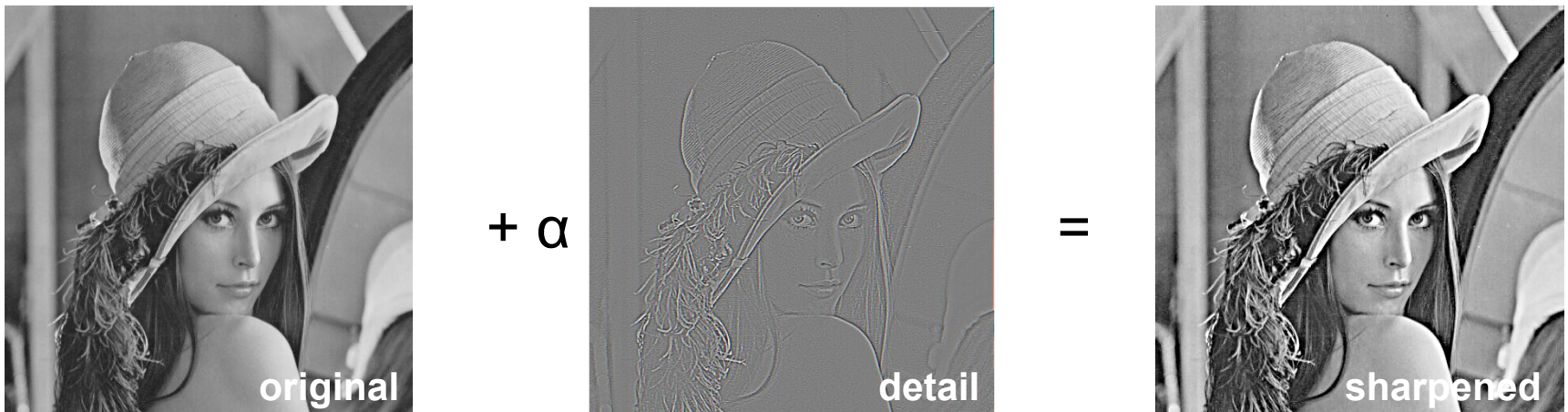
# Sharpening revisited

---

What does blurring take away?



Let's add it back:



# Unsharp mask filter

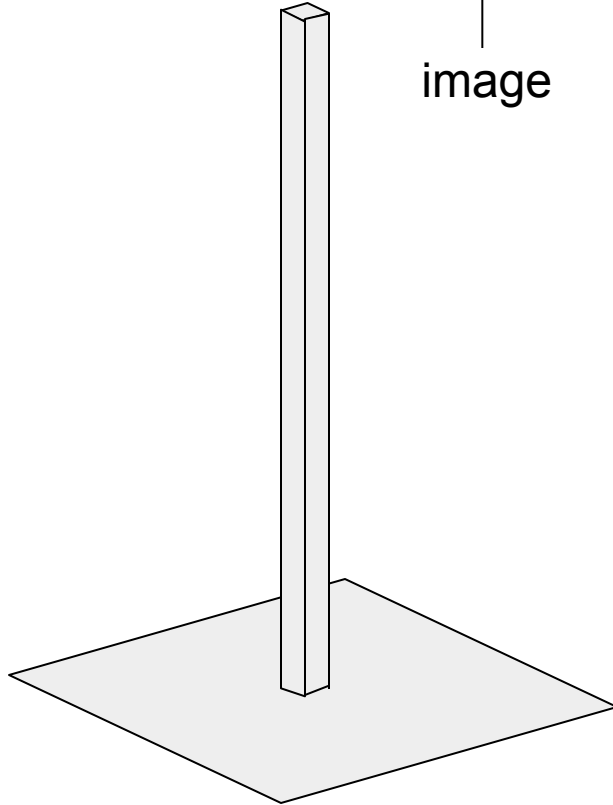
---

$$f + \alpha(f - f * g) = (1 + \alpha)f - \alpha f * g = f * ((1 + \alpha)e - g)$$

image

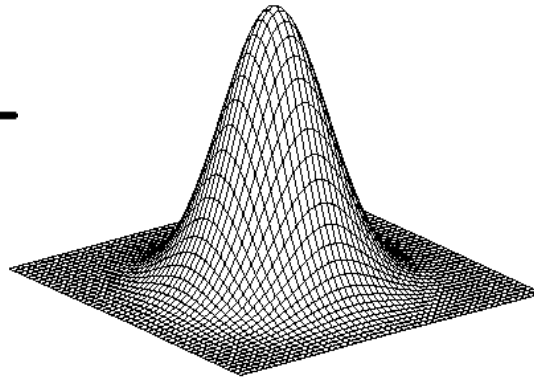
blurred  
image

unit impulse  
(identity)



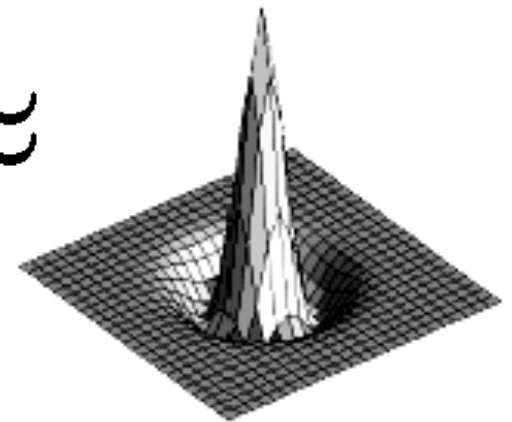
unit impulse

—



Gaussian

$\approx$



Laplacian of Gaussian