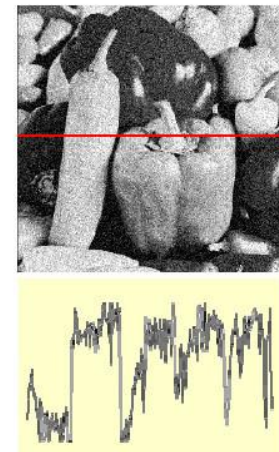
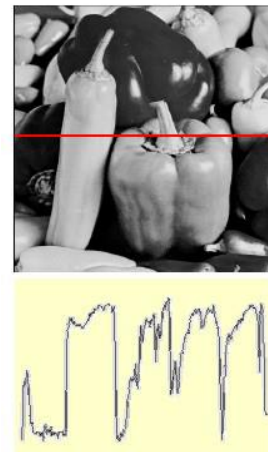


CS 4495 Computer Vision

Linear Filtering 1: Filters, Convolution, Smoothing

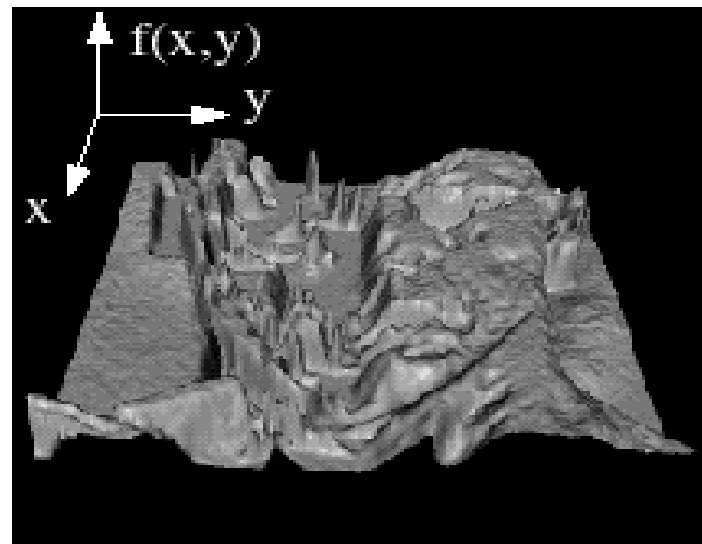
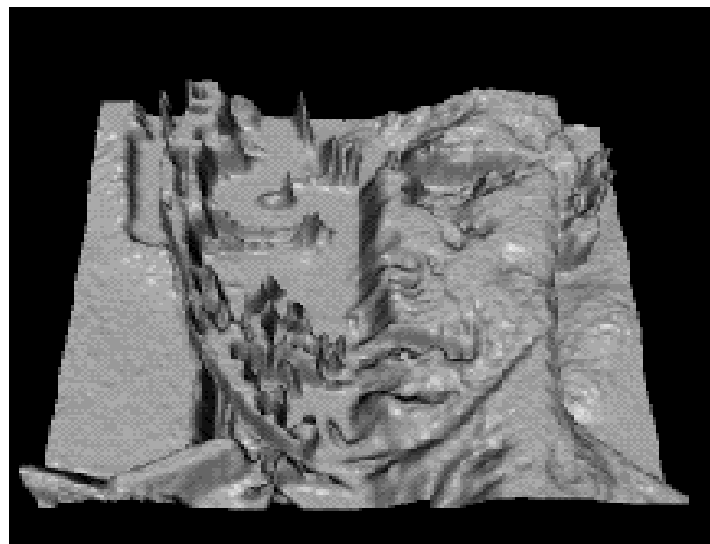
Aaron Bobick
School of Interactive Computing



Linear outline

- Images are really functions $I(x, y)$ where the vector can be any dimension but typical are 1, 3, and 4. (When 4?) Or thought of as a multi-dimensional *signal* as a function of spatial location.
- **Image processing** is (mostly) computing new functions of image functions. Many involve **linear operators**.
- Very useful linear operator is *convolution / correlation* - what most people call filtering – because the new value is determined by local values.
- With convolution can do things like noise reduction, smoothing, and edge finding (last one is next time).

Images as functions



Images as functions

- We can think of an image as a function, f or I , from \mathbb{R}^2 to \mathbb{R} :

$f(x, y)$ gives the *intensity* or value at position (x, y)

Realistically, we expect the image only to be defined over a rectangle, with a finite range:

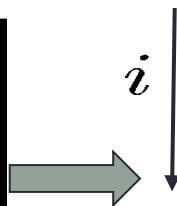
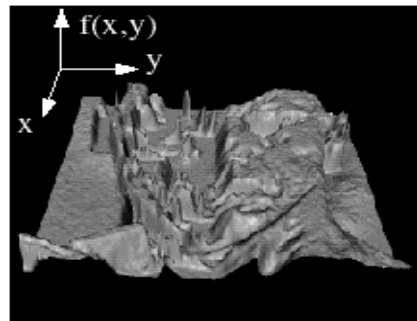
$$f: [a, b] \times [c, d] \rightarrow [0, 1.0] \text{ (why sometimes 255???)}$$

- A color image is just three functions “pasted” together. We can write this as a “vector-valued” function:

$$f(x, y) = \begin{bmatrix} r(x, y) \\ g(x, y) \\ b(x, y) \end{bmatrix}$$

Digital images

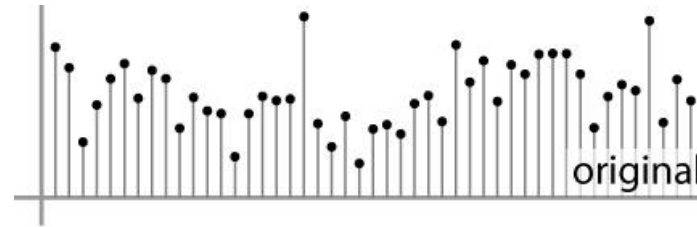
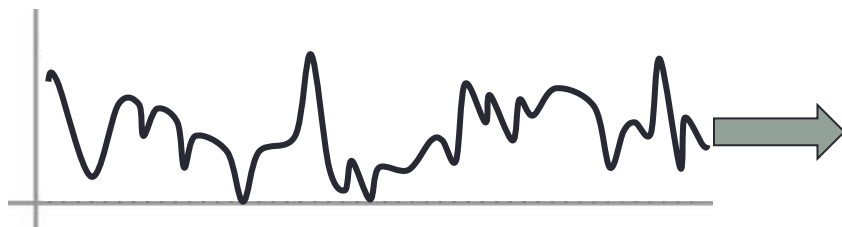
- In computer vision we typically operate on **digital (discrete)** images:
 - **Sample** the 2D space on a regular grid
 - **Quantize** each sample (round to “nearest integer”)
- Image thus represented as a matrix of integer values.



j →

62	79	23	119	120	105	4	0
10	10	9	62	12	78	34	0
10	58	197	46	46	0	0	48
176	135	5	188	191	68	0	49
2	1	1	29	26	37	0	77
0	89	144	147	187	102	62	208
255	252	0	166	123	62	0	31
166	63	127	17	1	0	99	30

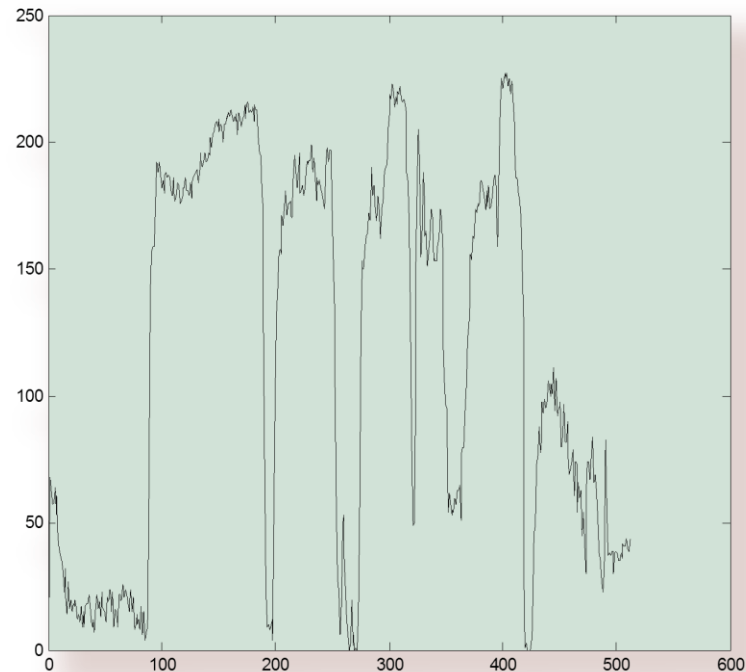
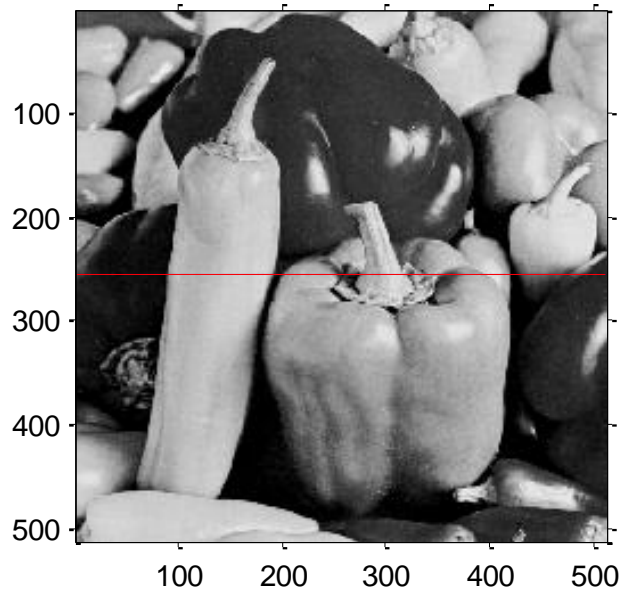
2D



1D

Matlab – images are matrices

```
>> im = imread('peppers.png'); % semicolon or many numbers  
>> imgreen = im(:, :, 2);  
>> imshow(imgreen)  
>> line([1 512], [256 256], 'color', 'r')  
>> plot(imgreen(256, :));
```



Noise in images

- Noise as an example of images really being functions
- Noise is just another function that is combined with the original function to get a new – guess what – function

$$\vec{I}'(x, y) = \vec{I}(x, y) + \vec{\eta}(x, y)$$

- In images noise looks, well, noisy.

Common types of noise

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



Original



Salt and pepper noise

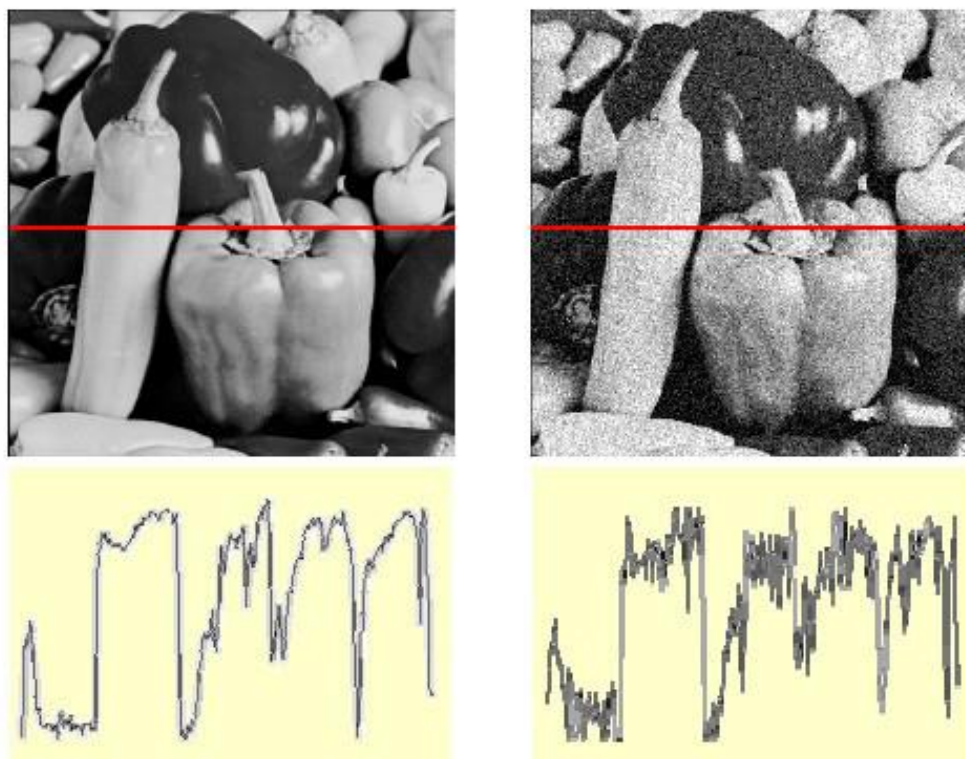


Impulse noise



Gaussian noise

Gaussian noise



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

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

```
>> noise = randn(size(im)).*sigma;
```

```
>> output = im + noise;
```

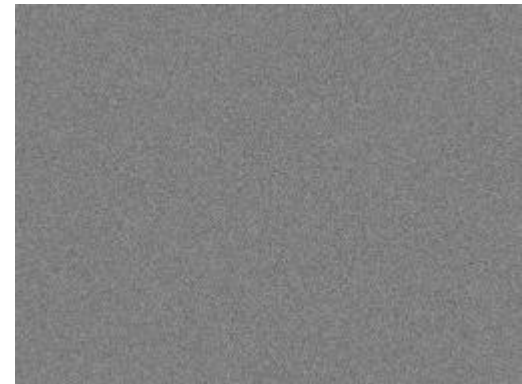
Effect of σ on Gaussian noise

**Image shows
the noise
values
themselves.**

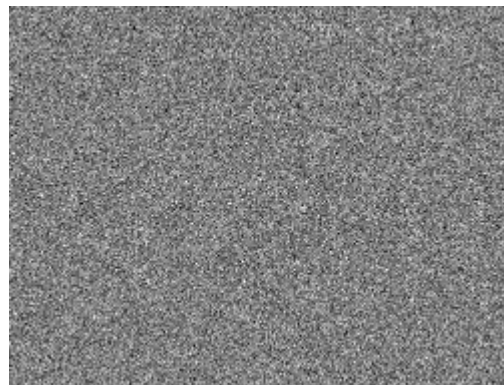
```
noise = randn(size(im)).*sigma;
```



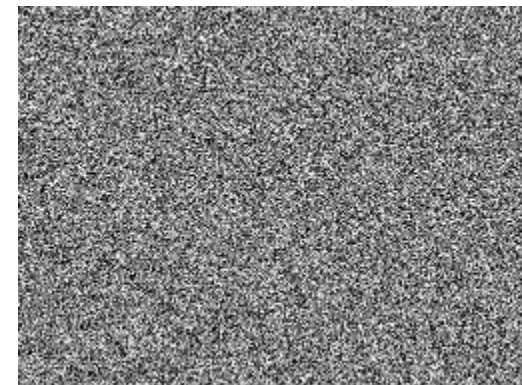
Sigma = 2



Sigma = 8



Sigma = 32



Sigma = 64

BE VERY CAREFUL!!!

- In previous slides, I did not say (at least wasn't supposed to say) what the range of the image was. A σ of 1.0 would be tiny if the range is [0 255] but huge if [0.0 1.0].
- Matlab can do either and you need to be very careful. If in doubt convert to double.
- Even more difficult can be displaying the image. Things like:
 - `imshow(I, [LOW HIGH])`
display the image from [low high]

Don't worry – you'll get used to these hassles... see problem set PS0.

Back to our program...

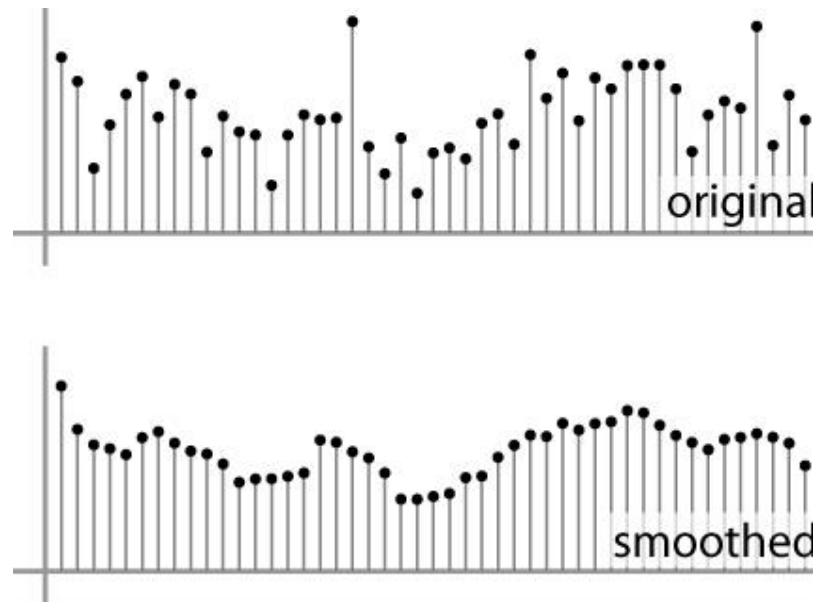
Suppose want to remove the noise...

First attempt at a solution

- Let's replace each pixel with an average of all the values in its neighborhood
- Assumptions:
 - Expect pixels to be like their neighbors
 - Expect noise processes to be independent from pixel to pixel

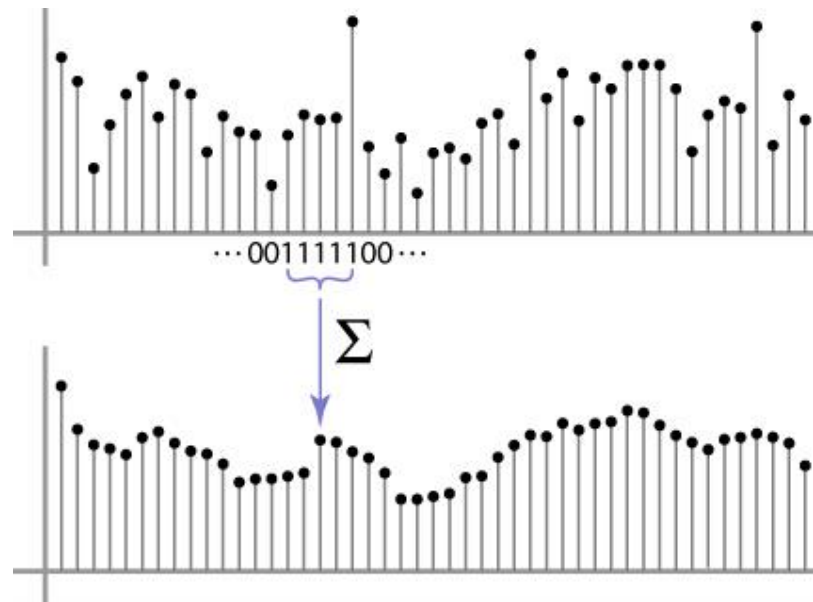
First attempt at a solution

- Let's replace each pixel with an average of all the values in its neighborhood
- Moving average in 1D:



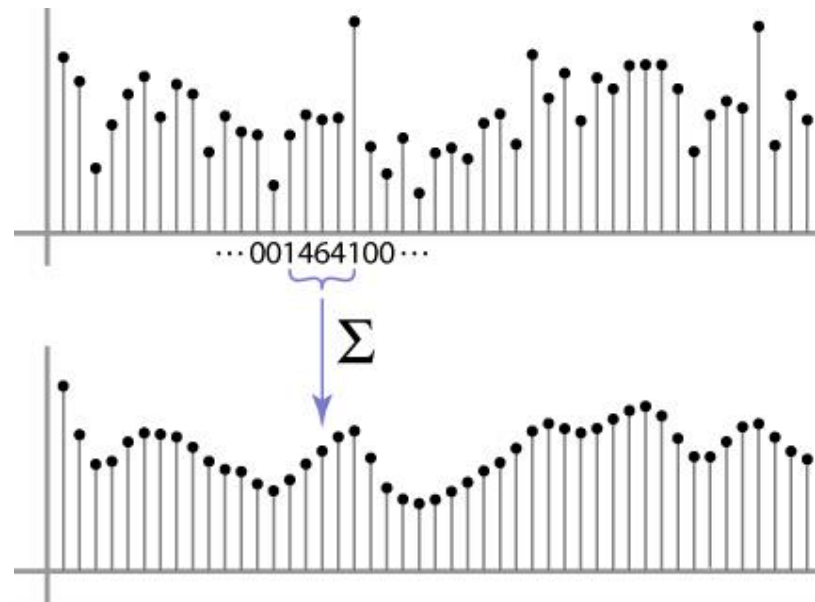
Weighted Moving Average

- Can add weights to our moving average
- *Weights* $[1, 1, 1, 1, 1] / 5$



Weighted Moving Average

- Non-uniform weights [1, 4, 6, 4, 1] / 16



Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0								

Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10							

Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20						

Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20	30					

Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20	30	30				

Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

Correlation filtering

Say the averaging window size is $2k+1 \times 2k+1$:

$$G[i, j] = \underbrace{\frac{1}{(2k+1)^2}}_{\text{Attribute uniform weight to each pixel}} \underbrace{\sum_{u=-k}^k \sum_{v=-k}^k F[i+u, j+v]}_{\text{Loop over all pixels in neighborhood around image pixel } F[i,j]}$$

Attribute uniform weight to each pixel *Loop over all pixels in neighborhood around image pixel $F[i,j]$*

Now generalize to allow **different weights** depending on neighboring pixel's relative position:

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k \underbrace{H[u, v]}_{\text{Non-uniform weights}} F[i+u, j+v]$$

Correlation filtering

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

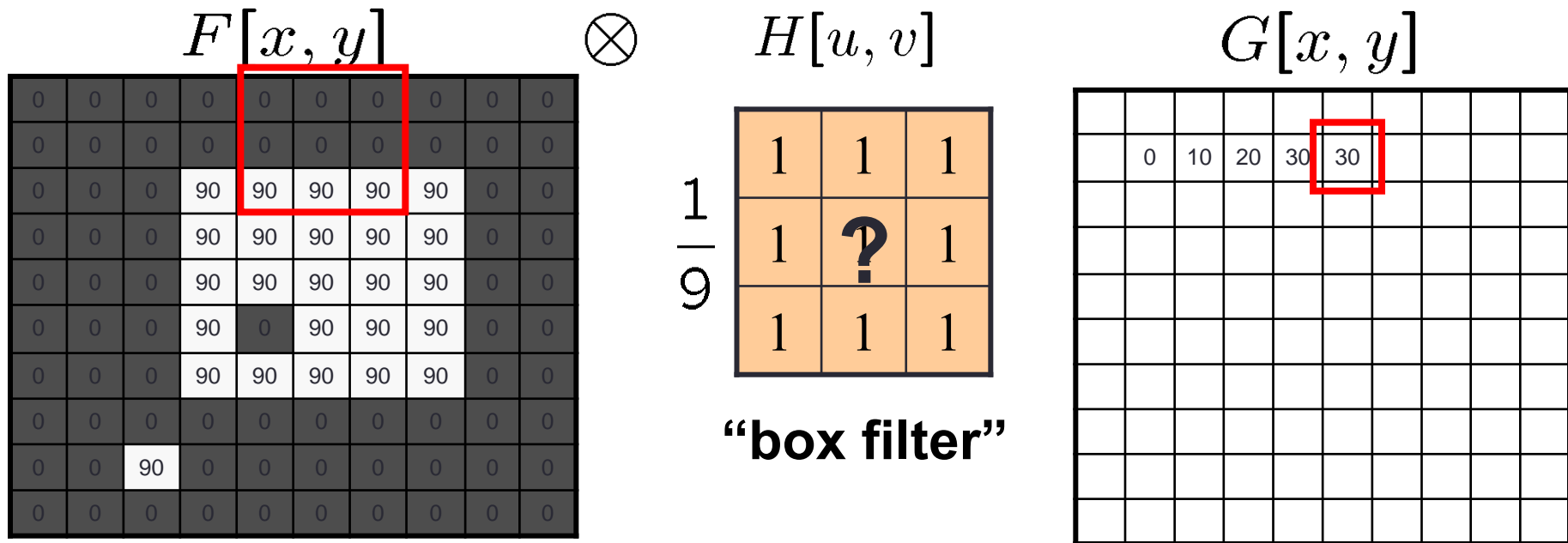
This is called **cross-correlation**, denoted $G = H \otimes F$

Filtering an image: replace each pixel with a linear combination of its neighbors.

The filter “**kernel**” or “**mask**” $H[u, v]$ is the prescription for the weights in the linear combination.

Averaging filter

- What values belong in the kernel H for the moving average example?



$$G = H \otimes F$$

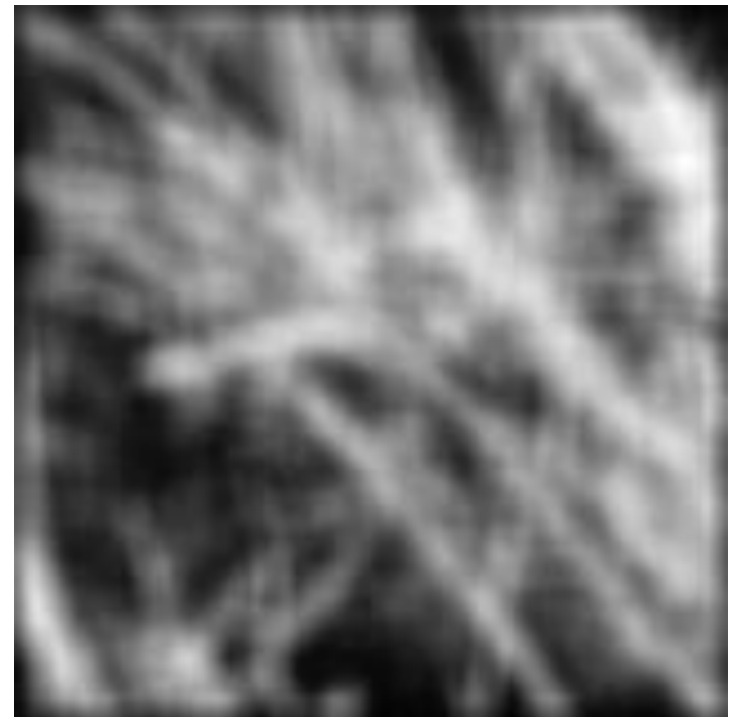
Smoothing by averaging



depicts box filter:
white = high value, black = low value



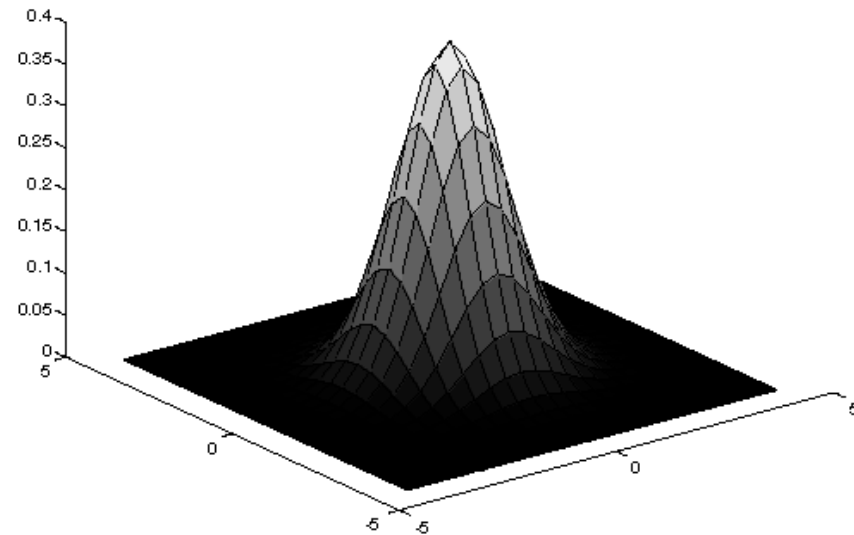
original



filtered

Squares aren't smooth...

- Smoothing with an average actually doesn't compare at all well with a defocussed lens
- Most obvious difference is that a single point of light viewed in a defocussed lens looks like a fuzzy blob; but the averaging process would give a little square.
- More about “impulse” responses later...



Gaussian filter

- What if we want nearest neighboring pixels to have the most influence on the output?

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$F[x, y]$

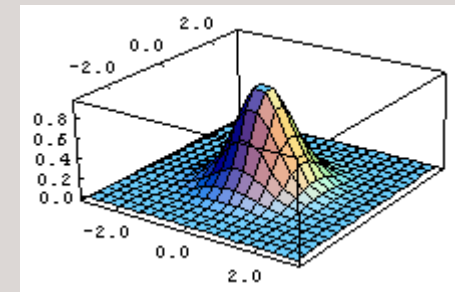
$\frac{1}{16}$

1	2	1
2	4	2
1	2	1

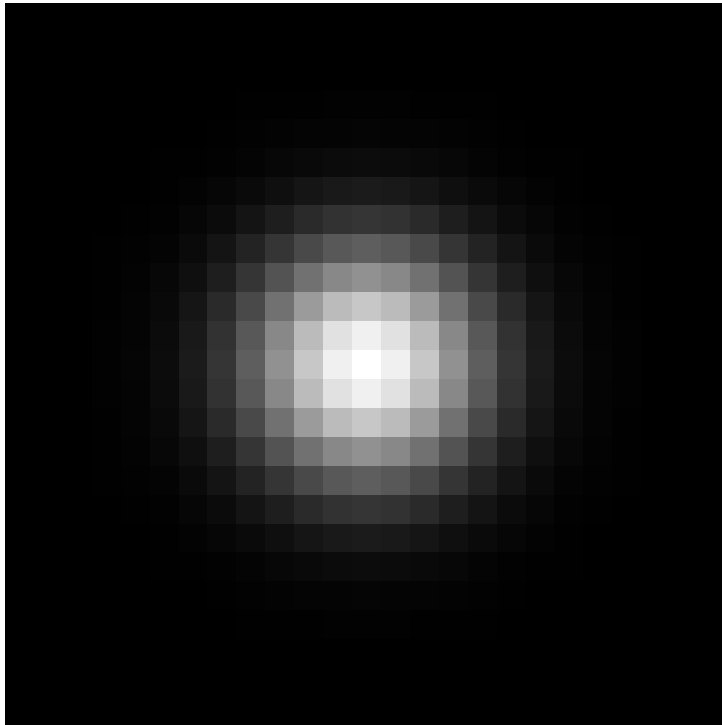
$H[u, v]$

This kernel is an approximation of a Gaussian function:

$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$



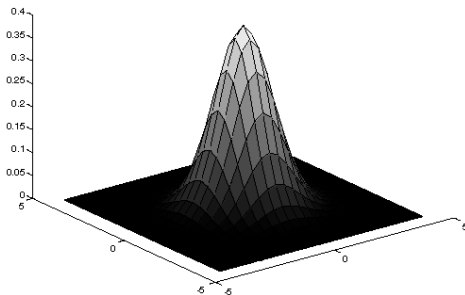
An Isotropic Gaussian



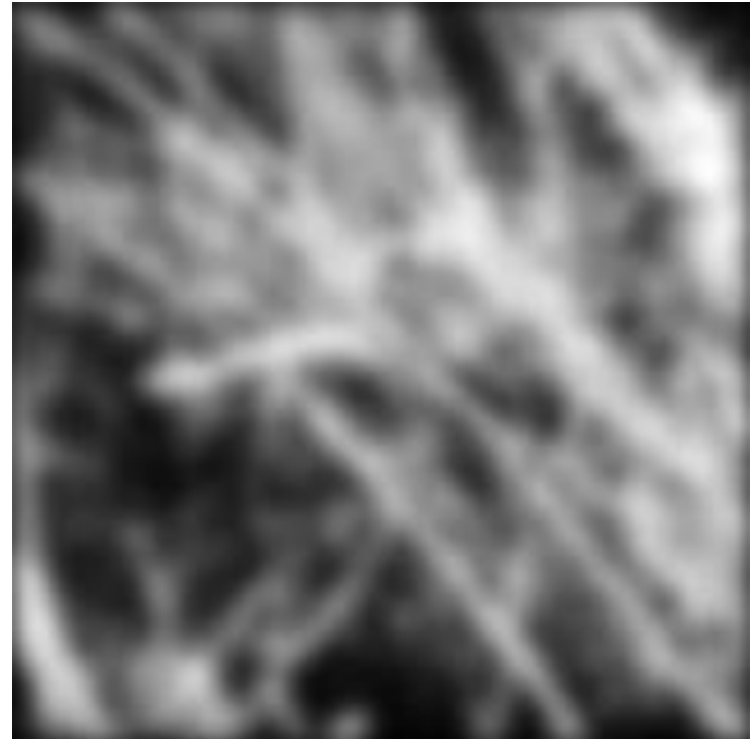
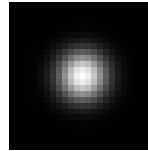
The picture shows a smoothing kernel proportional to

$$\exp\left(-\frac{(x^2 + y^2)}{2\sigma^2}\right)$$

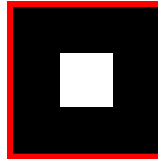
(which is a reasonable model of a circularly symmetric fuzzy blob)



Smoothing with a Gaussian

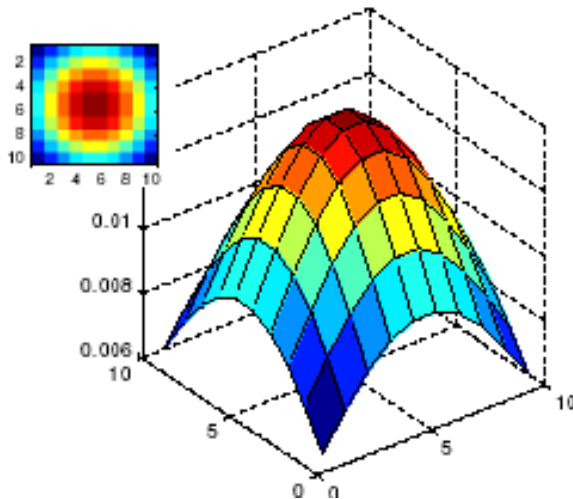


Smoothing with not a Gaussian

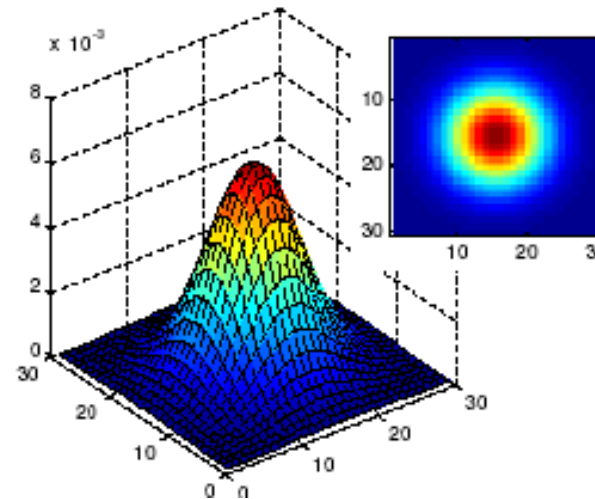


Gaussian filters

- What parameters matter here?
- **Size** of kernel or mask
 - Note, Gaussian function has infinite support, but discrete filters use finite kernels



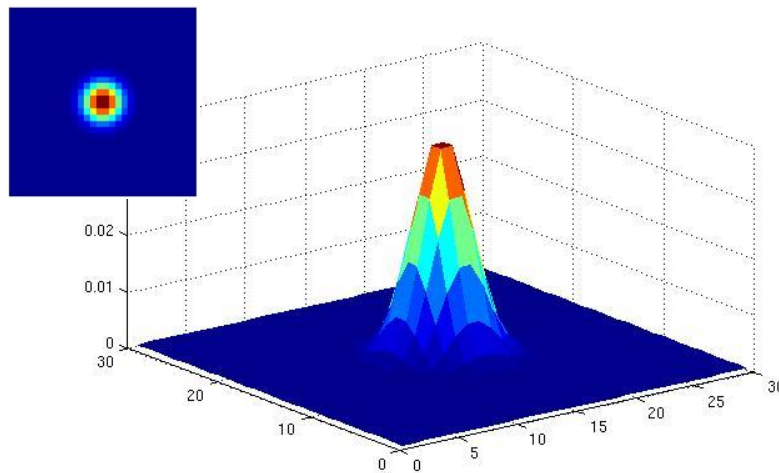
$\sigma = 5$ with
10 x 10
kernel



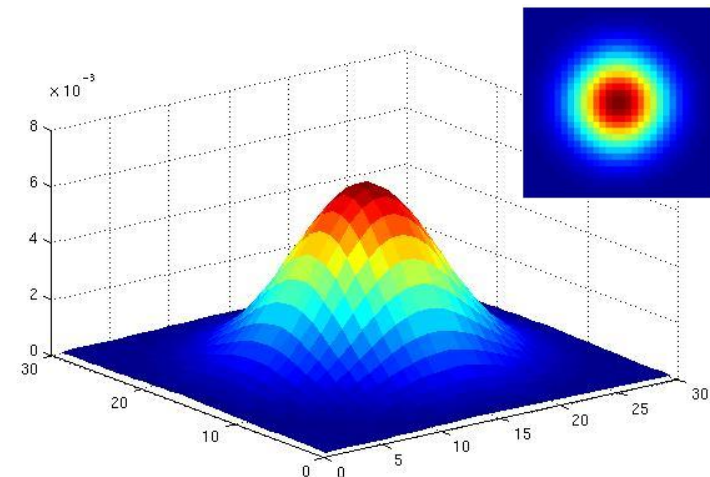
$\sigma = 5$ with
30 x 30
kernel

Gaussian filters

- What parameters matter here?
- **Variance** of Gaussian: determines extent of smoothing



$\sigma = 2$ with
 30×30
kernel

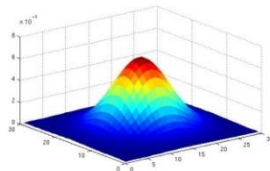


$\sigma = 5$ with
 30×30
kernel

Matlab

```
>> hsize = 10;  
>> sigma = 5;  
>> h = fspecial('gaussian', hsize, sigma);
```

```
>> mesh(h);
```



```
>> imagesc(h);
```



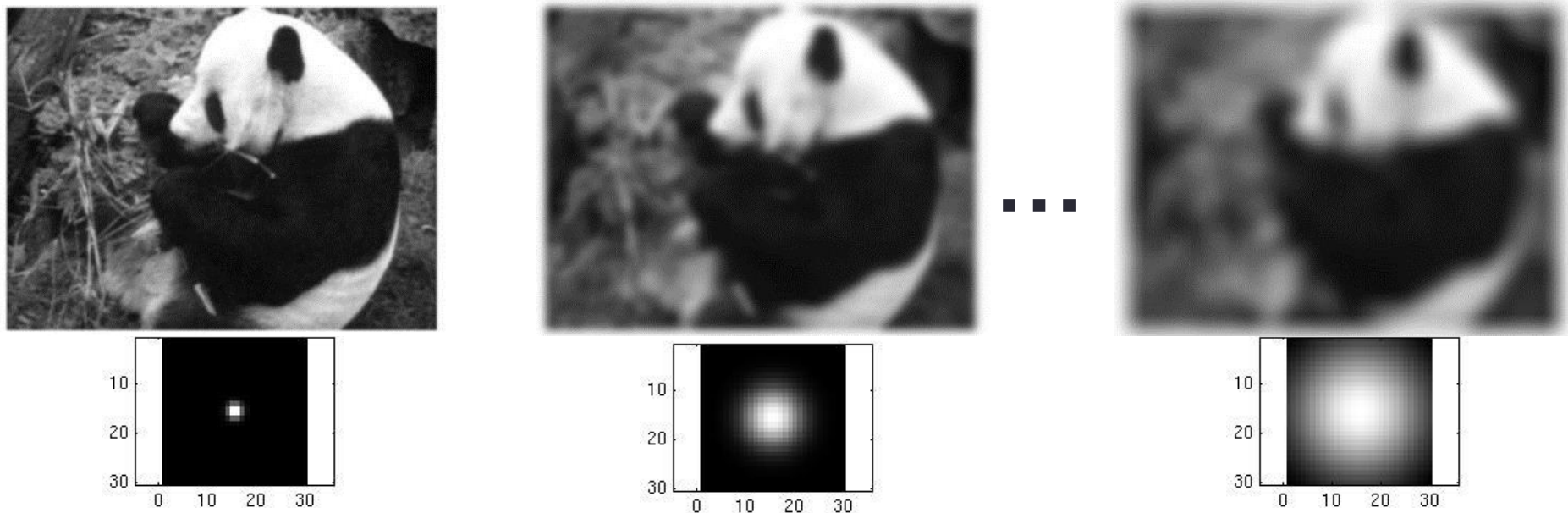
```
>> outim = imfilter(im, h);  
>> imshow(outim);
```



outim
K. Grauman

Smoothing with a Gaussian

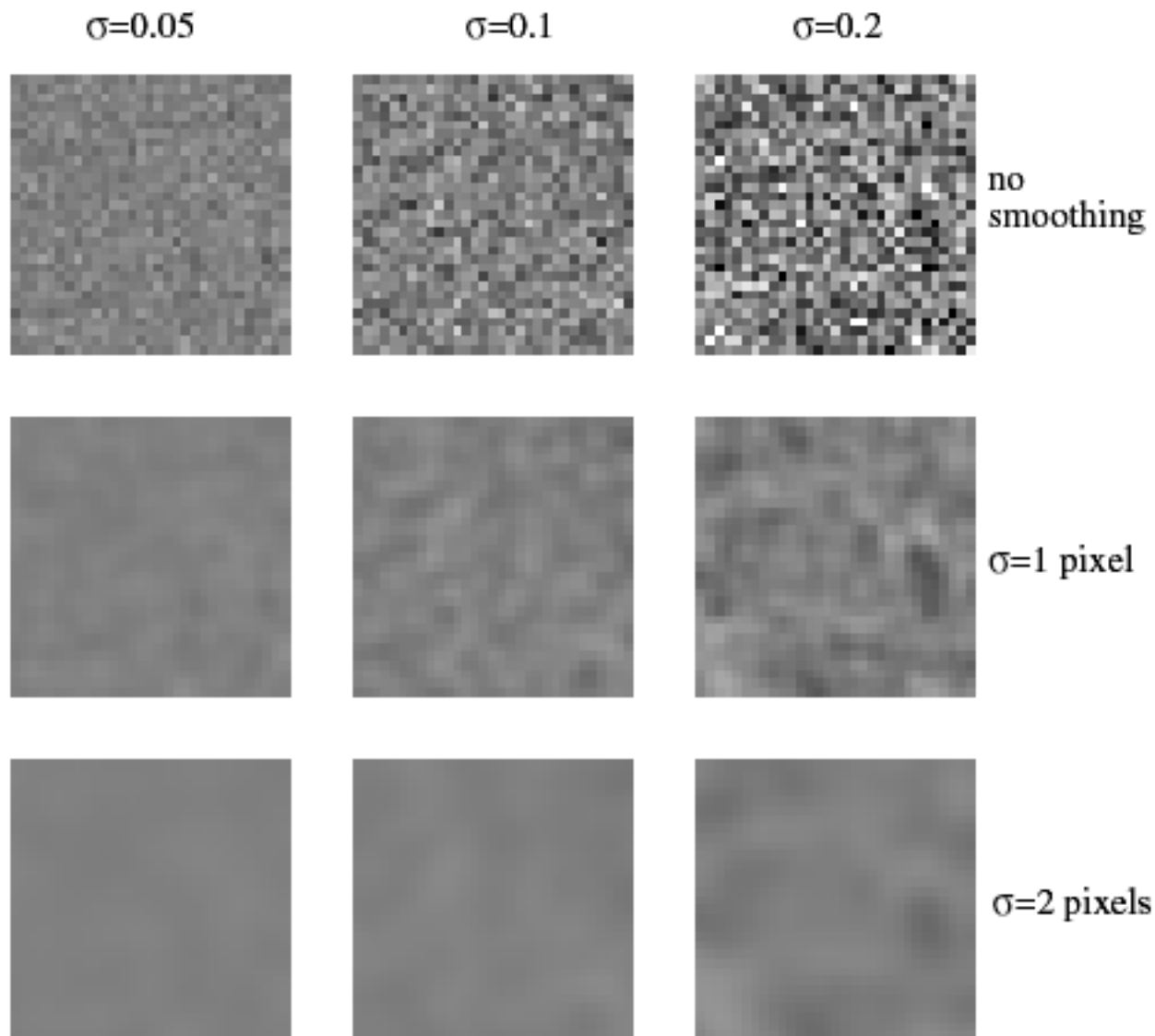
Parameter σ is the “scale” / “width” / “spread” of the Gaussian kernel, and controls the amount of smoothing.



```
for sigma=1:3:10
    h = fspecial('gaussian', fsize, sigma);
    out = imfilter(im, h);
    imshow(out);
    pause;
end
```

Keeping the two Gaussians straight...

More Gaussian noise (like earlier) $\sigma \rightarrow$



Wider Gaussian smoothing kernel $\sigma \rightarrow$

And now some linear intuition...

An operator H (or system) is *linear* if two properties hold (f_1 and f_2 are some functions, a is a constant):

- **Superposition** (things sum):

$$H(f_1 + f_2) = H(f_1) + H(f_2) \quad (\text{looks like distributive law})$$

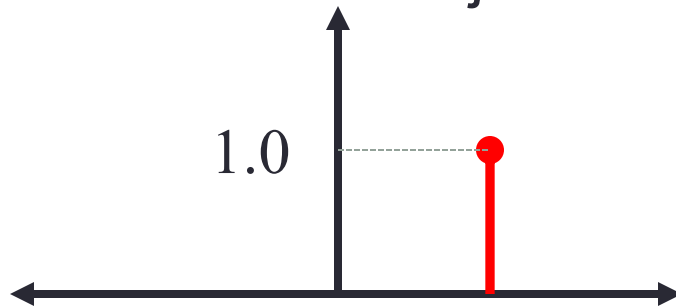
- **Scaling** (constant scales):

$$H(a \cdot f_1) = a \cdot H(f_1)$$

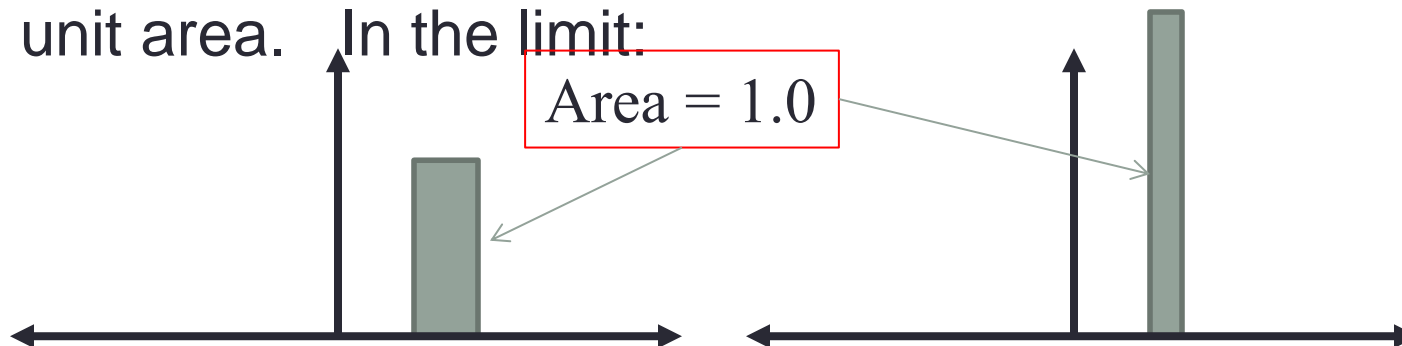
*Because it is sums and multiplies, the
“filtering” operation we were doing are linear.*

An impulse function...

- In the discrete world, and *impulse* is a very easy signal to understand: it's just a value of 1 at a single location.

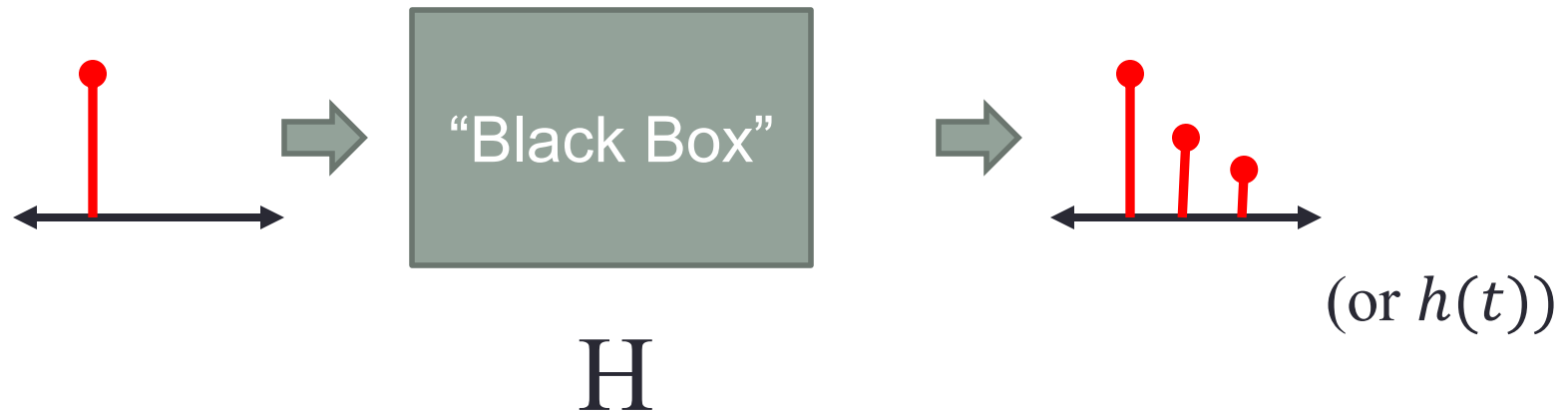


- In the continuous world, an impulse is an idealized function that is very narrow and very tall so that it has a unit area. In the limit:



An impulse response

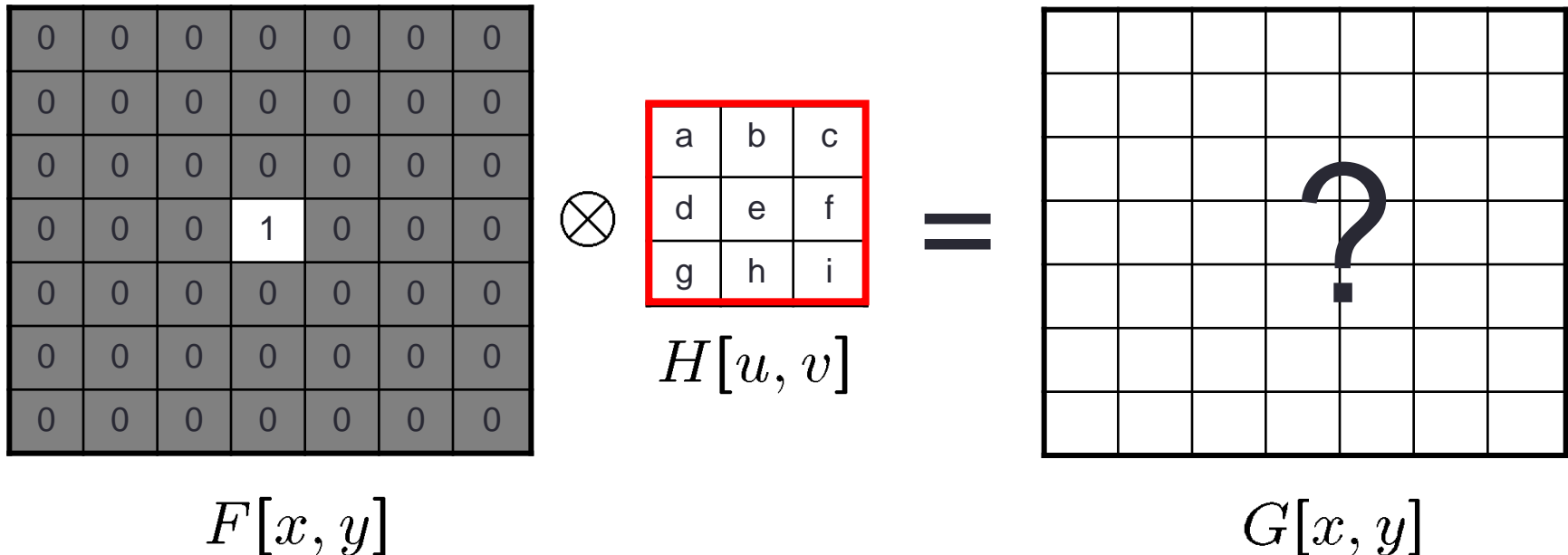
- If I have an unknown system and I “put in” an impulse, the response is called the impulse response. (Duh?)



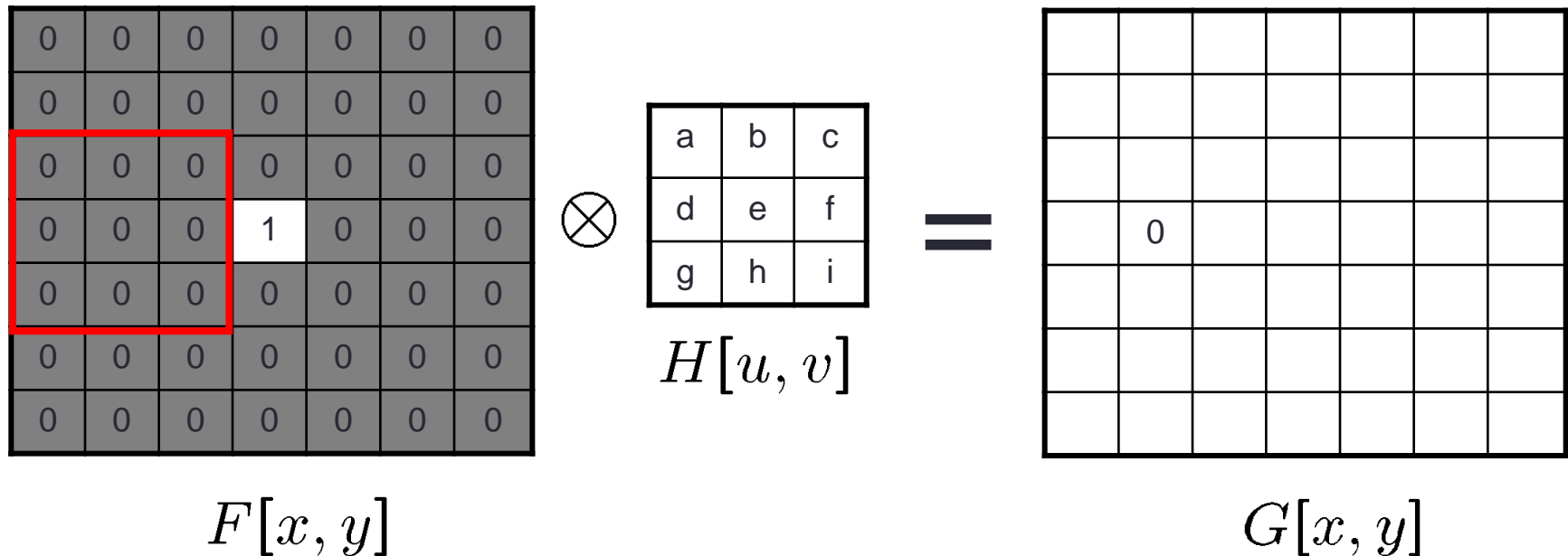
- So if the black box is linear you can describe H by $h(x)$. Why?

Filtering an impulse signal

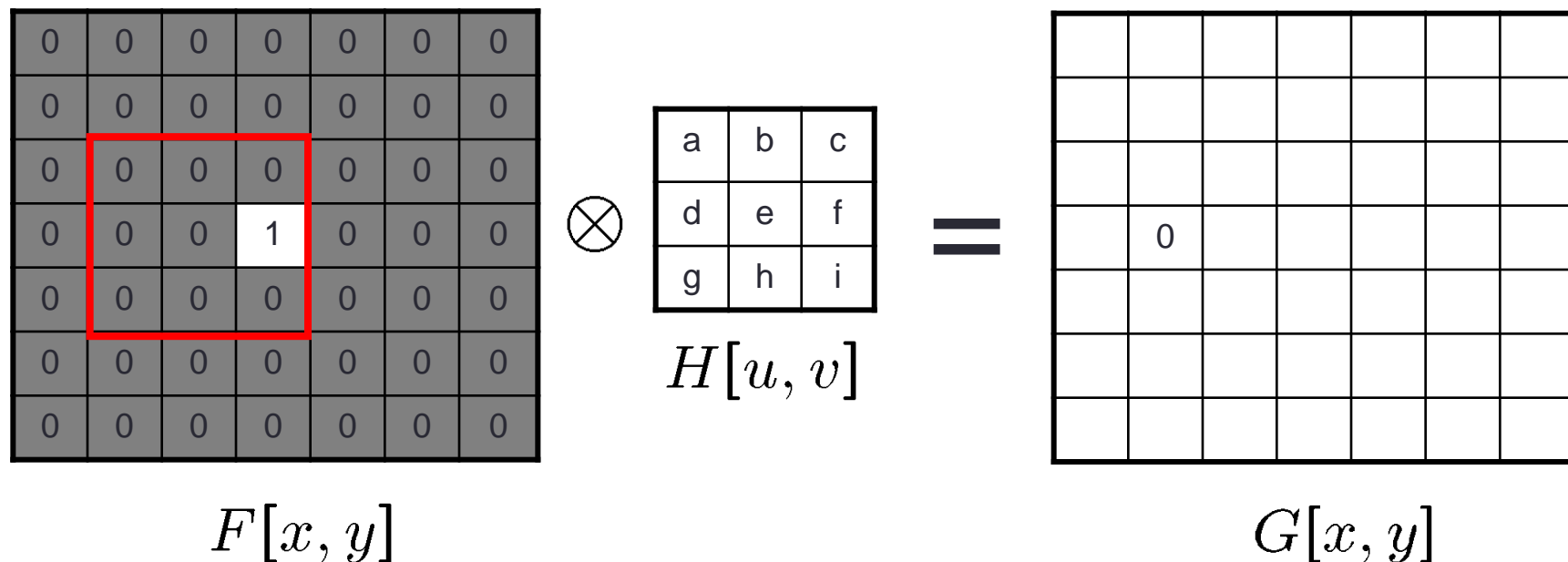
What is the result of filtering the impulse signal (image) F with the arbitrary kernel H ?



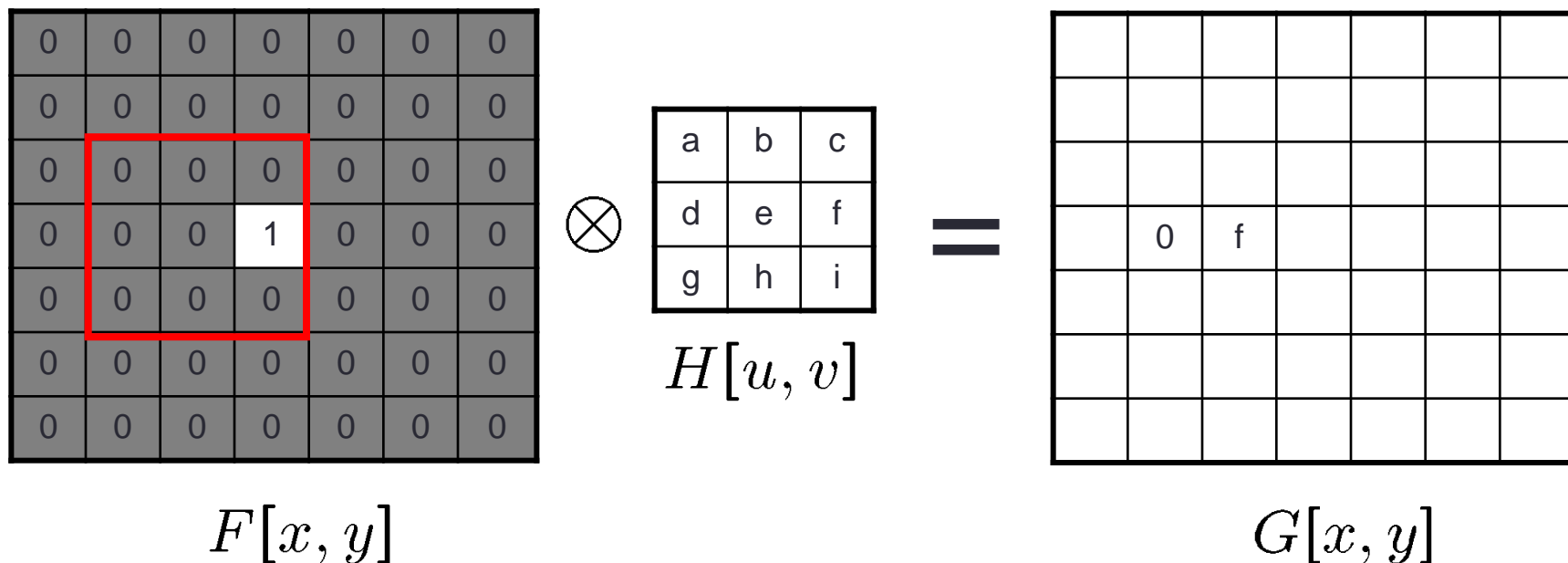
Filtering an impulse signal



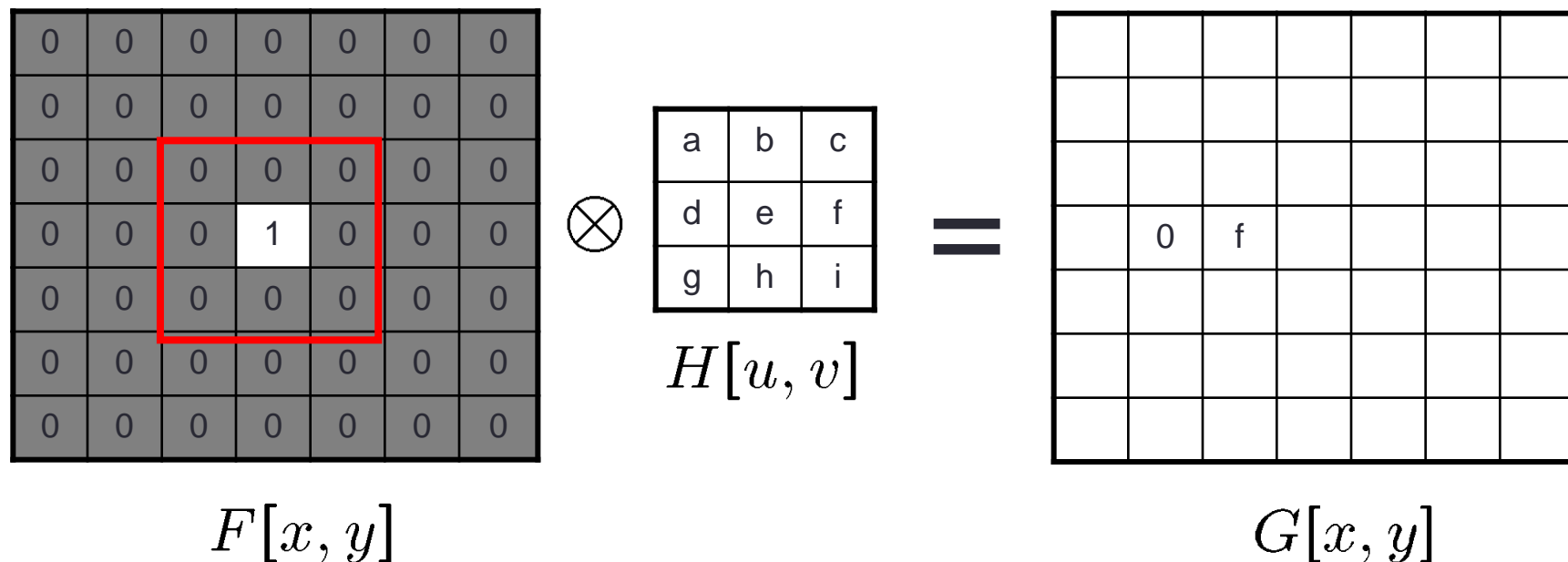
Filtering an impulse signal



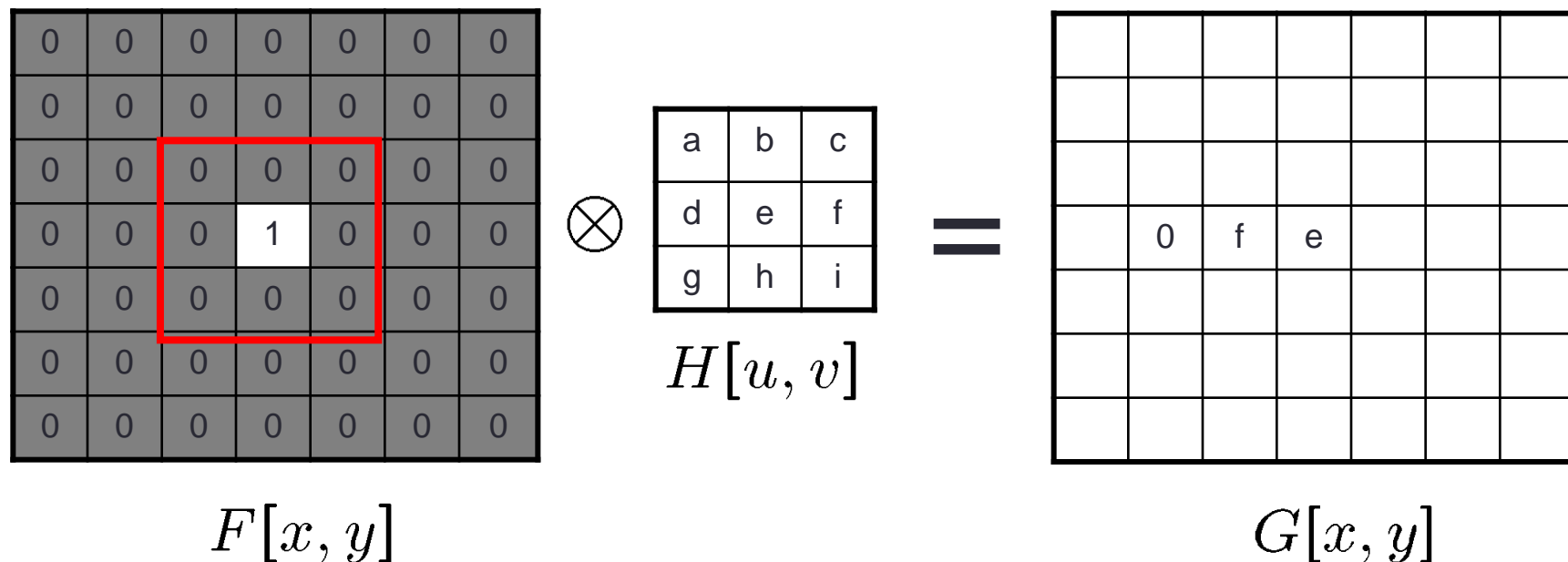
Filtering an impulse signal



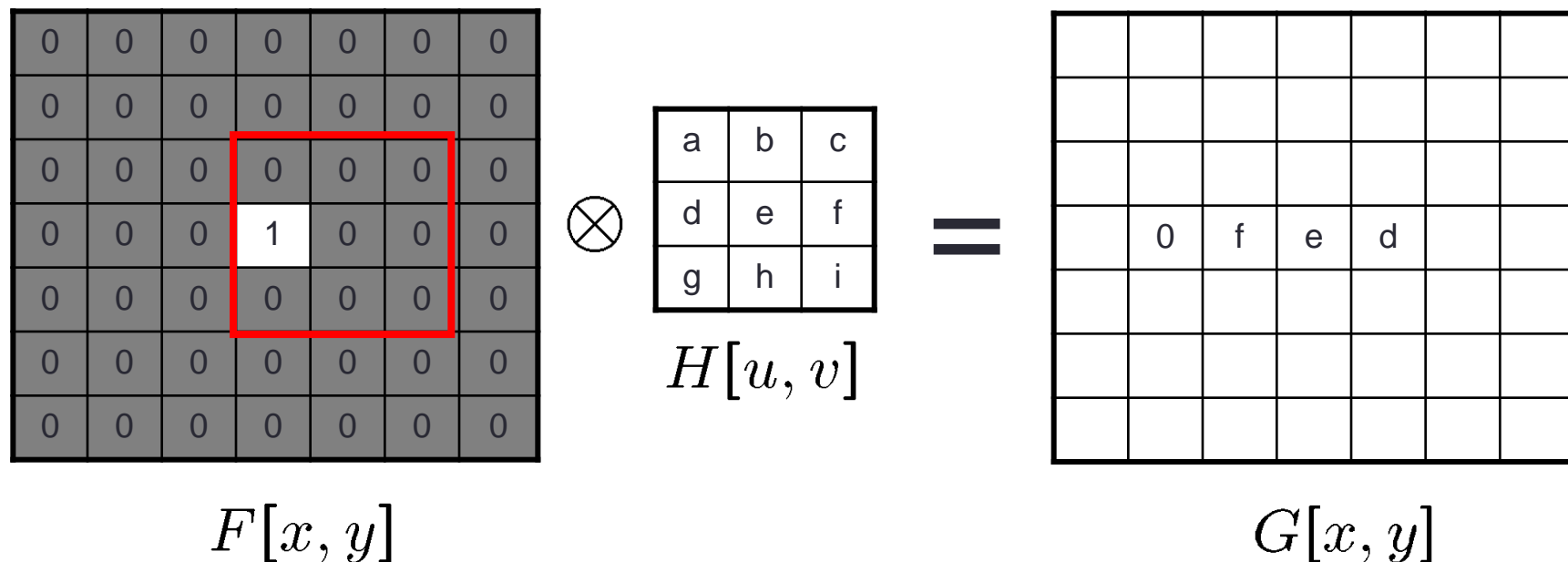
Filtering an impulse signal



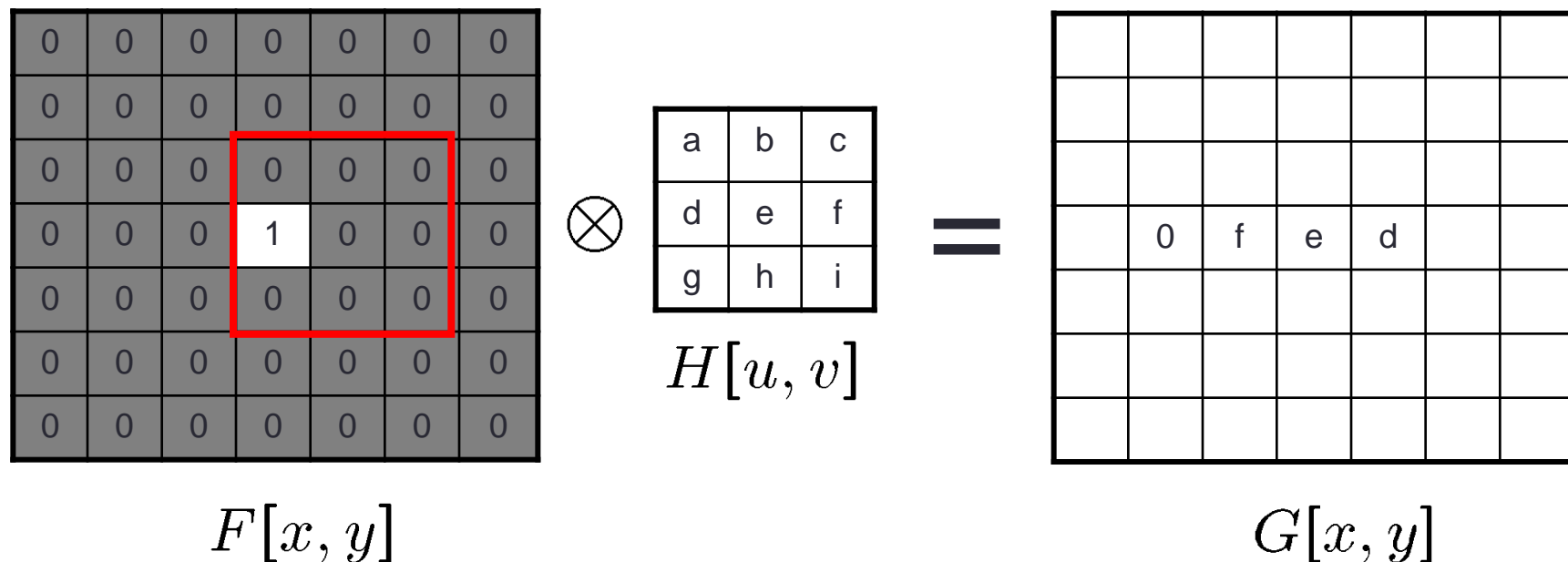
Filtering an impulse signal



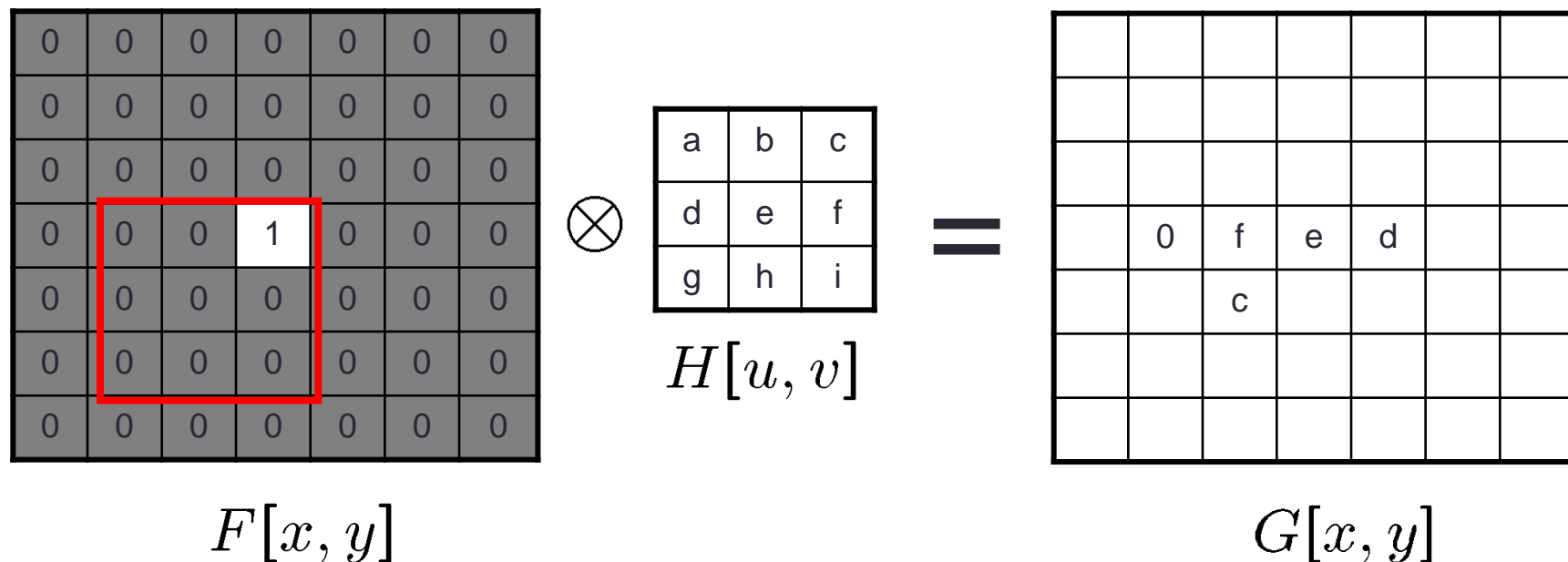
Filtering an impulse signal



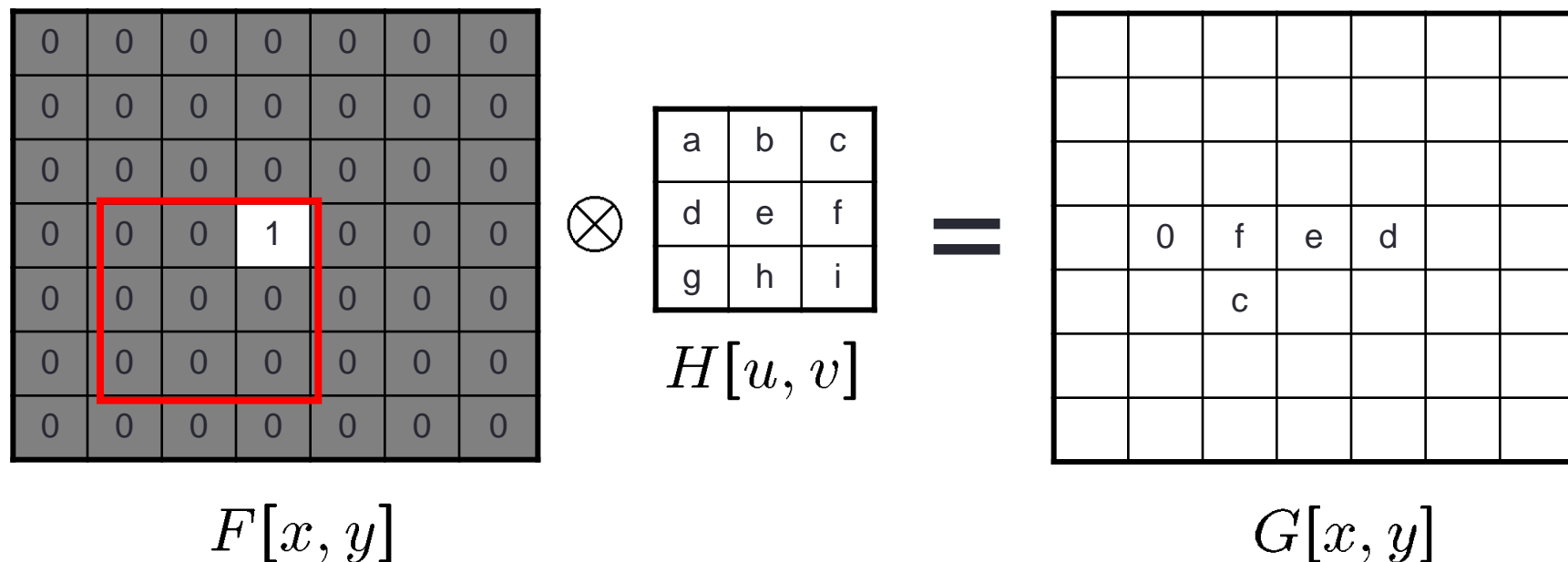
Filtering an impulse signal



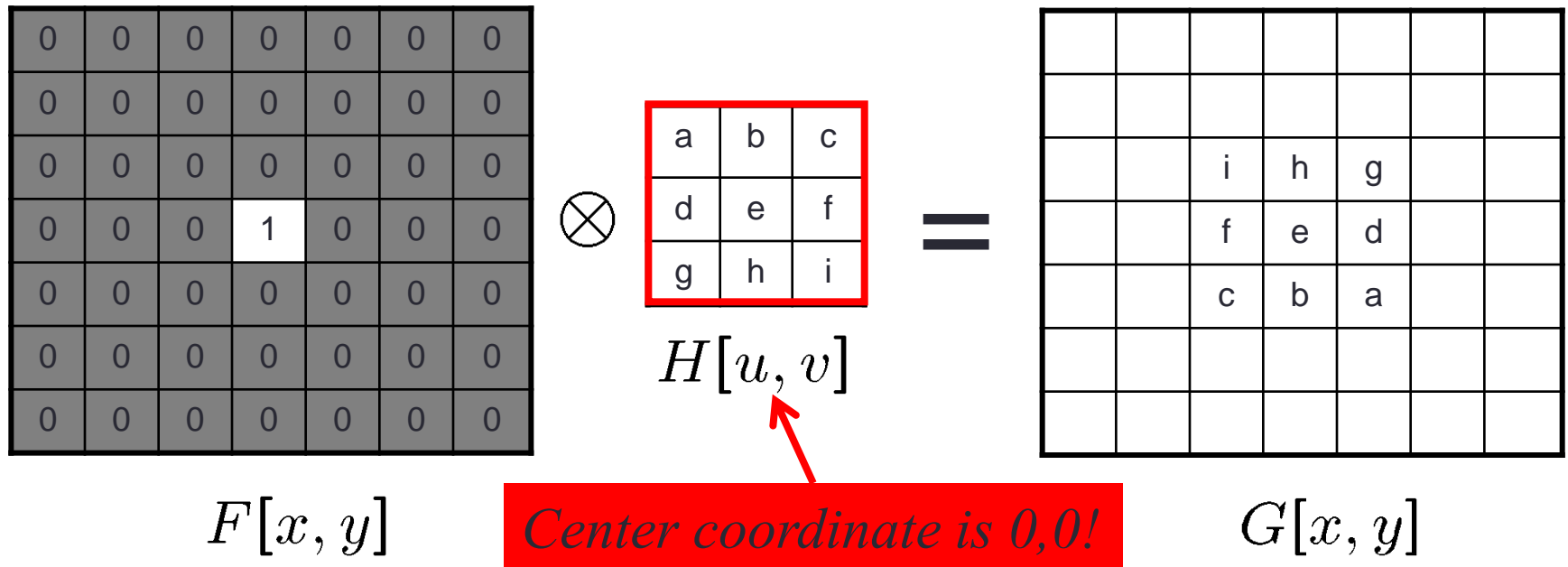
Filtering an impulse signal



Filtering an impulse signal



“Filtering” an impulse signal



If you just “filter” meaning slide the kernel over the image you get a **reversed** response.

Convolution

- Convolution:

- Flip where the filter is applied in both dimensions (bottom to top, right to left)
- Then apply cross-correlation

Centered at zero!

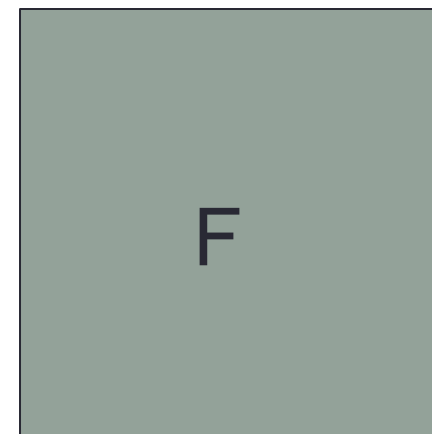


$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H * F$$



*Notation for
convolution
operator*



One more thing...

- **Shift invariant:**
 - Operator behaves the same everywhere, i.e. the value of the output depends on the pattern in the image neighborhood, not the position of the neighborhood.

Properties of convolution

- Linear & shift invariant

- Commutative:

$$f * g = g * f$$

- Associative

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

- Identity:

$$\text{unit impulse } e = [\dots, 0, 0, 1, 0, 0, \dots]. \quad f * e = f$$

- Differentiation: $\frac{\partial}{\partial x} (f * g) = \frac{\partial f}{\partial x} * g$



We'll use
this later!

Convolution vs. correlation

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

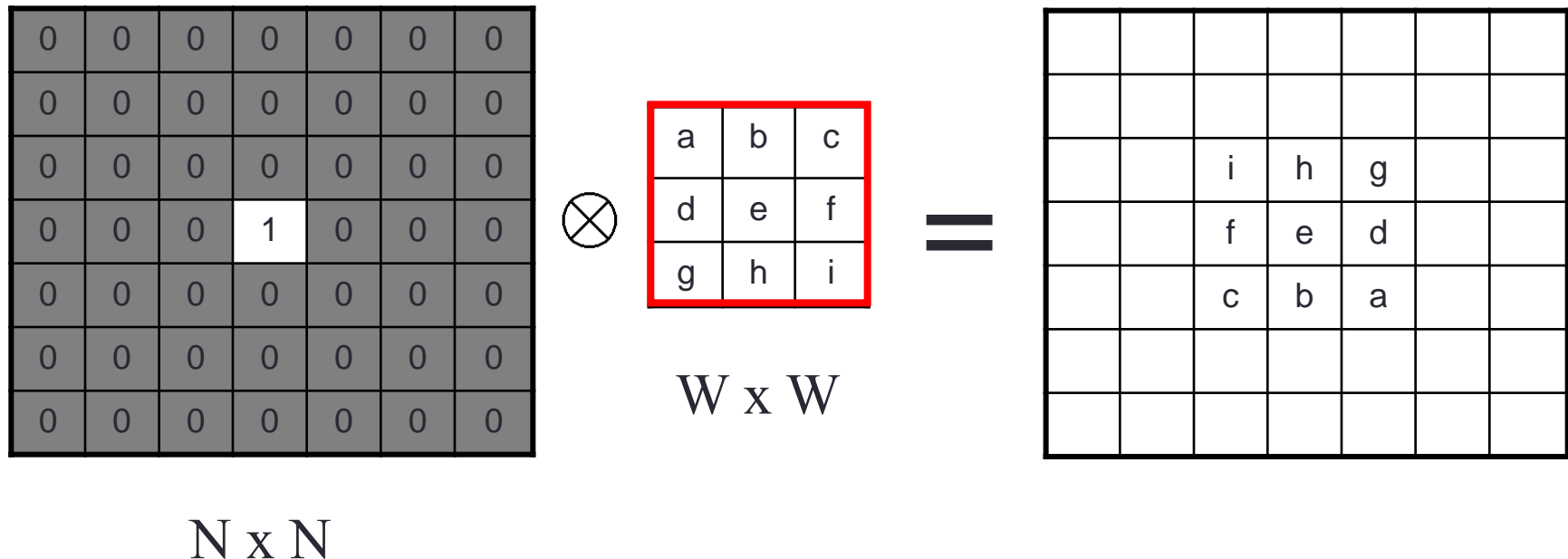
$$G = H \otimes F$$

For a Gaussian or box filter, how will the outputs differ?

If the input is an impulse signal, how will the outputs differ?

Computational Complexity

- If an image is $N \times N$ and a kernel (filter) is $W \times W$, how many multiplies do you need to compute a convolution?



- You need $N \times N \times W \times W = N^2 W^2$
 - which can get big (ish)

Separability

- In some cases, filter is separable, meaning you can get the square kernel by convolving a single column vector by some row vector:

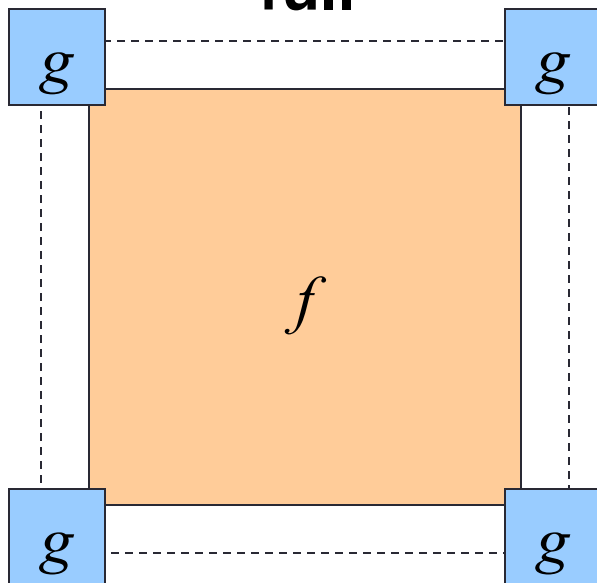
$$\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

- To apply to an image you:
 - Convolve all rows
 - Convolve all resulting columns
- This used to be *very* important – instead of $N \times N \times W \times W$ it's $N \times N \times W \times 2$
 - So if your Kernel is a 31x31 filter you save a factor of 15

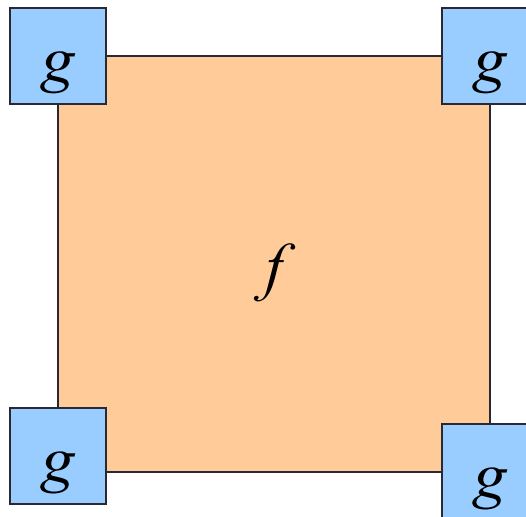
Boundary issues

- What is the size of the output?
- Old 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*

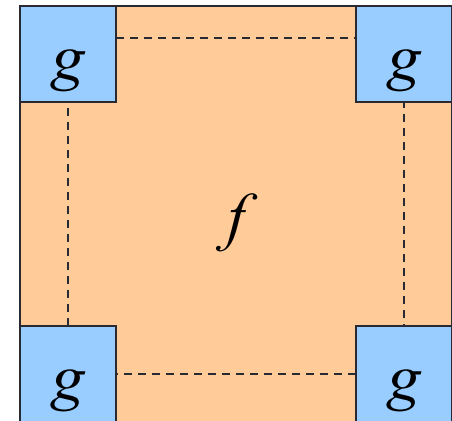
full



same

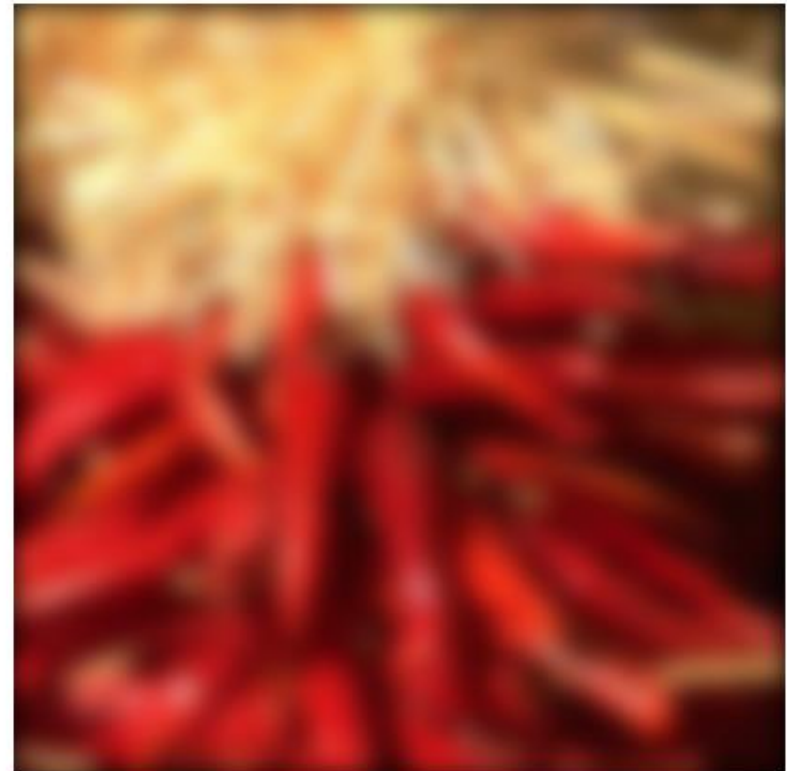


valid



Boundary issues

- What about near the edge?
 - the filter window falls off the edge of the image
 - need to extrapolate
 - methods:
 - **clip filter (black)**



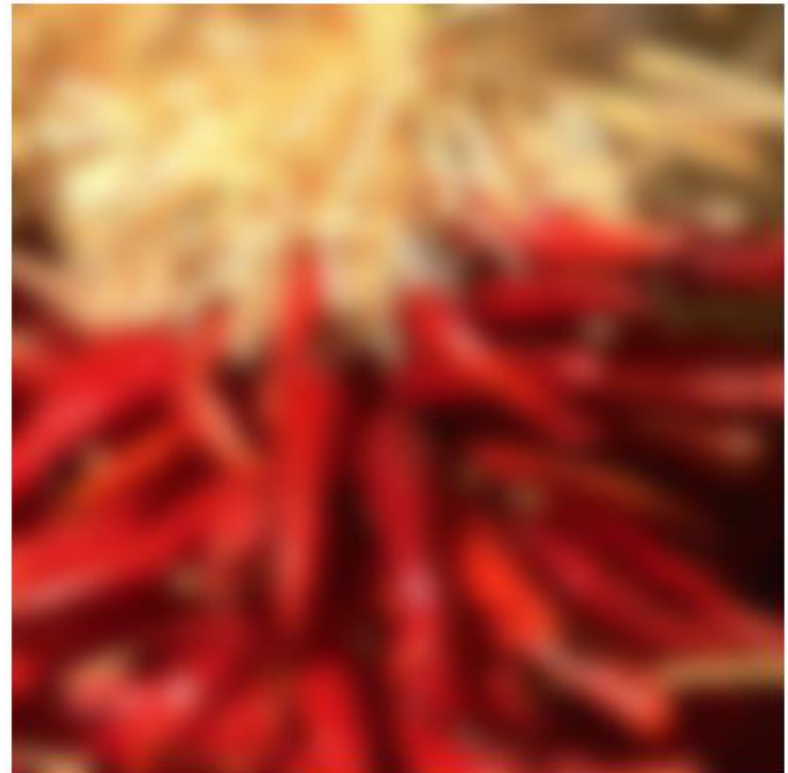
Boundary issues

- What about near the edge?
 - the filter window falls off the edge of the image
 - need to extrapolate
 - methods:
 - clip filter (black)
 - **wrap around**



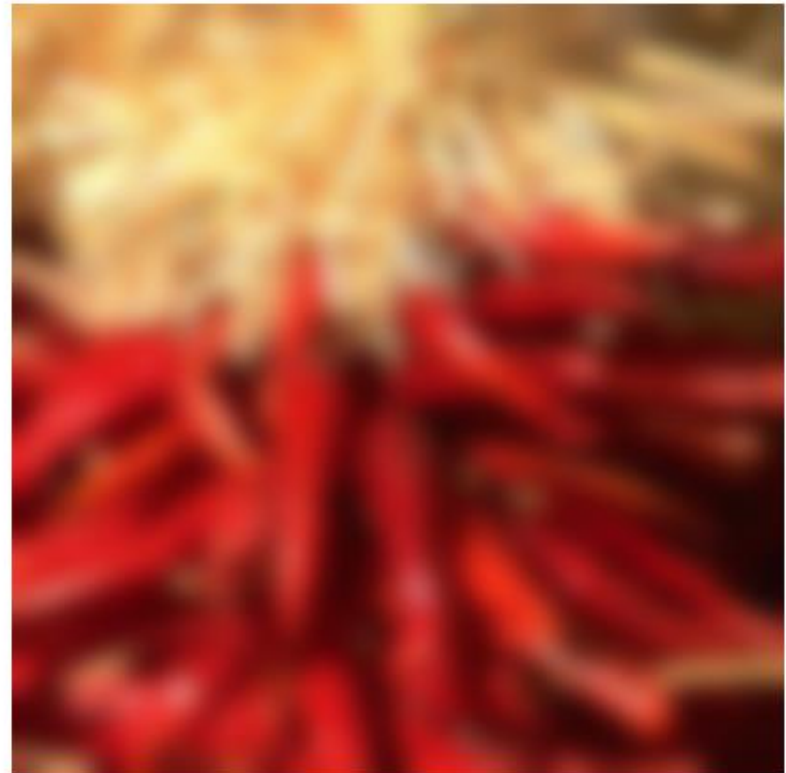
Boundary issues

- 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**



Boundary issues

- 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**



Boundary issues

- What about near the edge?
 - the filter window falls off the edge of the image
 - need to extrapolate
 - methods (new 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')`

Predict the filtered outputs



$$\begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 0 & 1 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array} = ?$$



$$\begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 0 & 0 & 1 \\ \hline 0 & 0 & 0 \\ \hline \end{array} = ?$$



$$\begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 0 & 2 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array} - \frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array} = ?$$

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

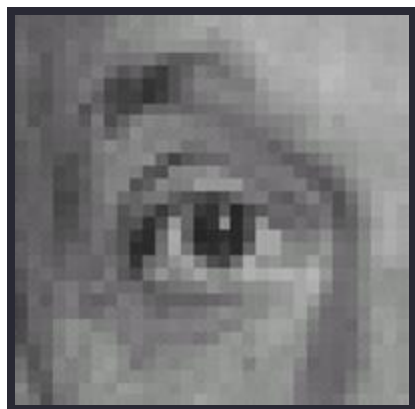


Original

0	0	0
0	0	1
0	0	0

?

Practice with linear filters



Original

0	0	0
0	0	1
0	0	0



Center coordinate is 0,0!



**Shifted left
by 1 pixel
with
correlation**

Practice with linear filters



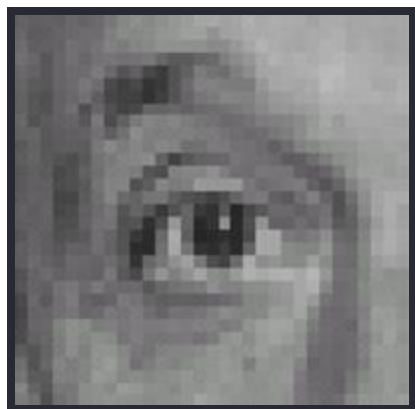
Original

 $\frac{1}{9}$

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

?

Practice with linear filters



Original

0	0	0
0	2	0
0	0	0

–

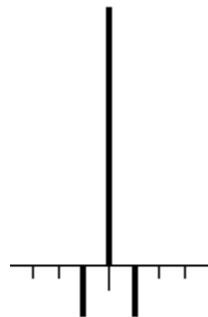
$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

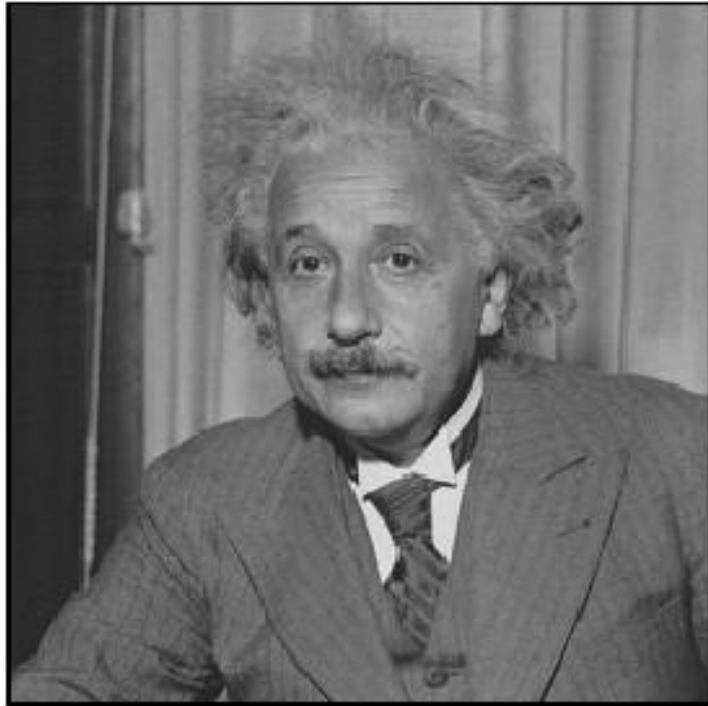


Sharpening filter

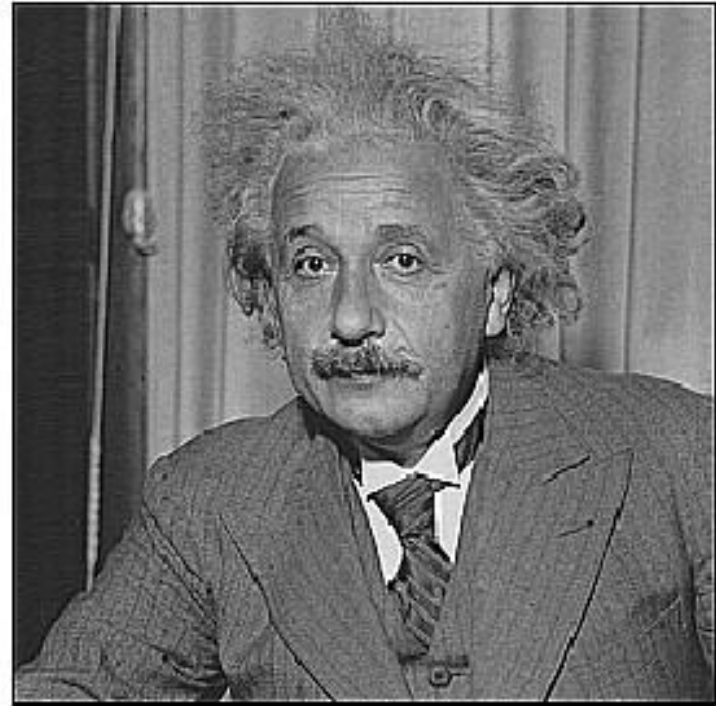
**- Accentuates differences
with local average**



Filtering examples: sharpening



before



after

Effect of smoothing filters

5x5

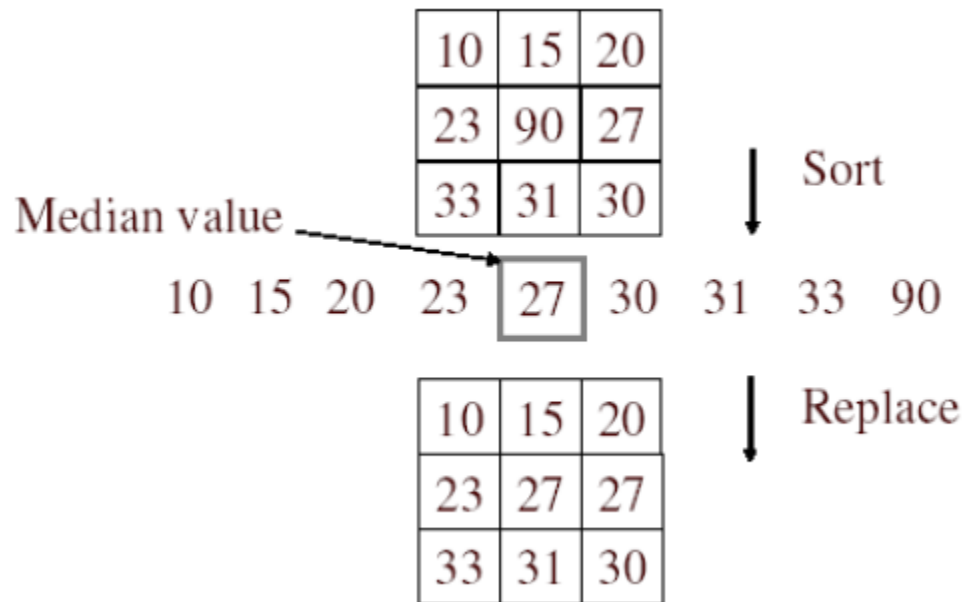


Additive Gaussian noise



Salt and pepper noise

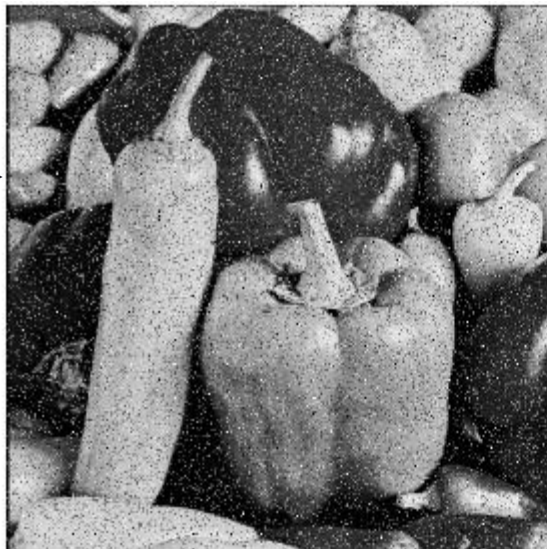
Median filter



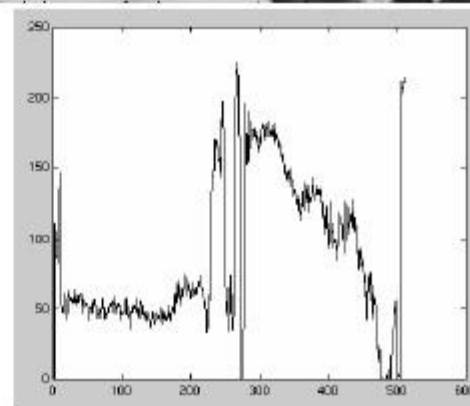
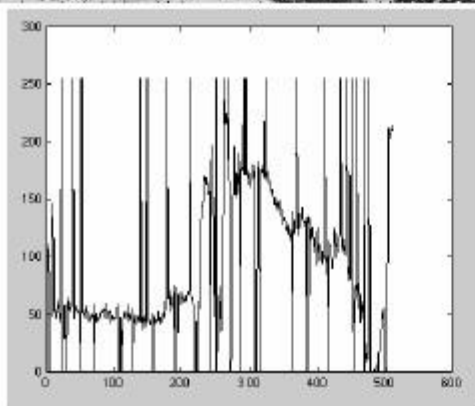
- No new pixel values introduced
- Removes spikes: good for impulse, salt & pepper noise
- Linear?

Median filter

**Salt and
pepper
noise** →



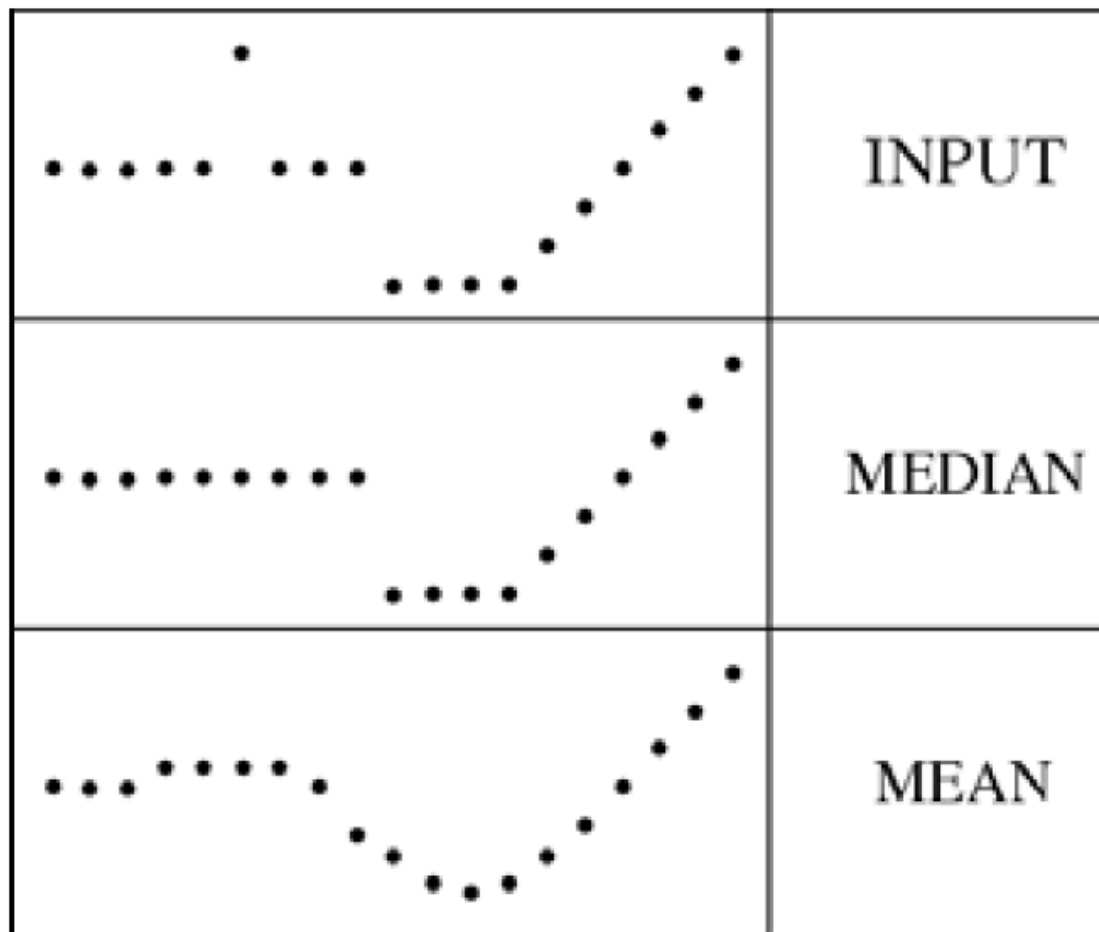
← **Median
filtered**



**Plots of a row of the
image**

Median filter

- Median filter is edge preserving



Exercise

- Design a kernel for:
 - Horizontal derivative
 - Vertical derivative
 - Second derivative
- What If:
 - H is the max/min operator?
 - We use an affine operator?

To do:

- Matlab tutorial code on *Tools* page (CS 4495)
- Problem set 0 available; due 11:59pm Fri Jan 17th
- Problem set 1 – Filtering, Edges, Hough – will be handed out Jan 15th (Wed) and is due Sun Sept 26th, 11:59pm.

Homework For Tuesday Jan 14th

- Read slide set for Tuesday and Wednesday
- Prepare 3 questions
 - Option 1: on things that you don't understand
 - Option 2: on things that you think would make good exam questions
- Prepare 3 applications
 - Things that you think the notions from the class have been used in
 - Things that you think could be done with the tools from the class
- Do it individually
- Write them down and cut them into 6 strips: 1 per questions/applications and distribute them.
- **BRING ENOUGH LAPTOPS** to access the class.