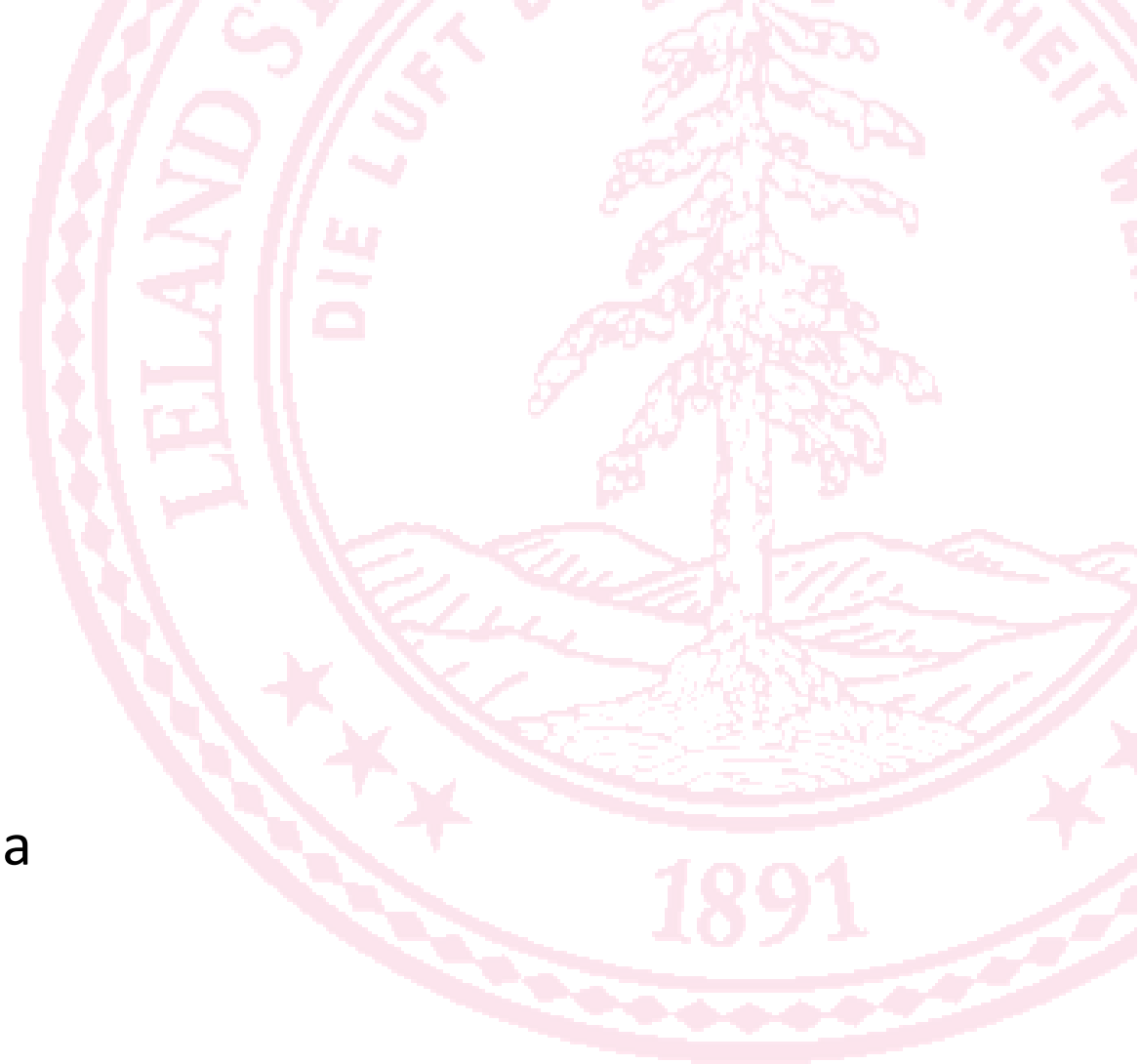

Lecture: Pixels and Filters

Juan Carlos Niebles and Ranjay Krishna

Stanford Vision Lab

What we will learn today?

- Image sampling and quantization
- Image histograms
- Images as functions
- Linear systems (filters)
- Convolution and correlation

Some background reading:
Forsyth and Ponce, Computer Vision, Chapter 7

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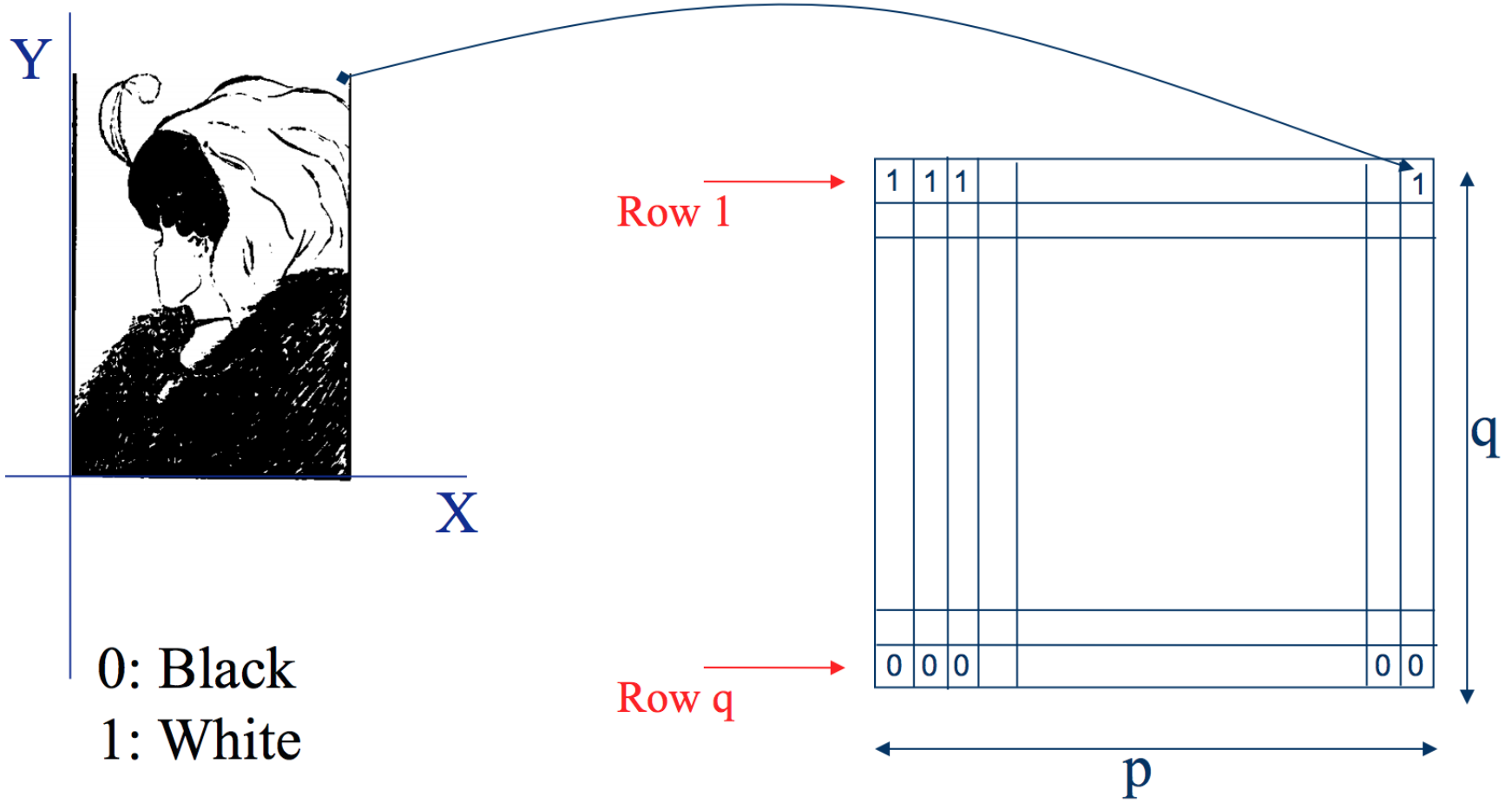
Types of Images

Binary

Gray Scale

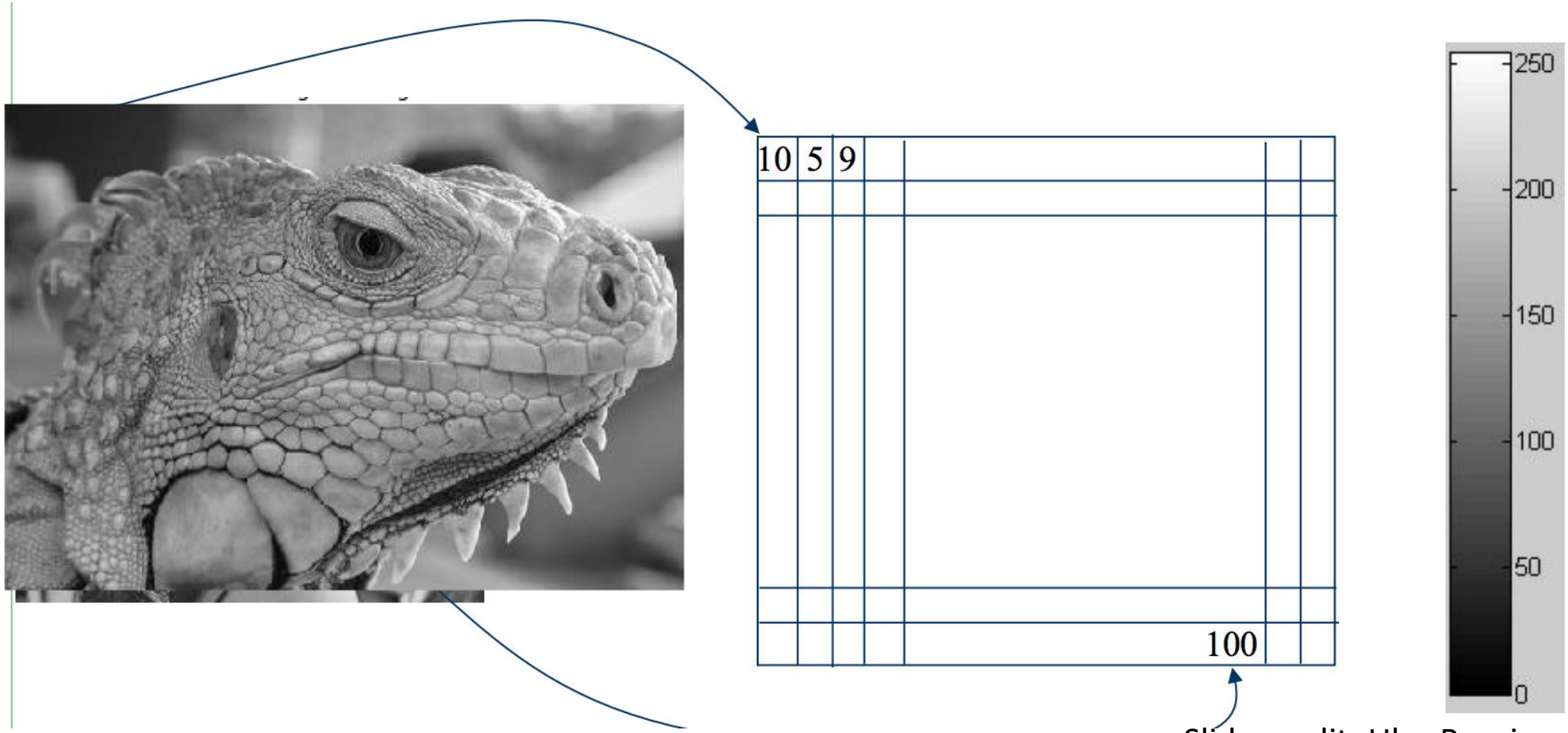
Color

Binary image representation



Slide credit: Ulas Bagci

Grayscale image representation



Slide credit: Ulas Bagci

Color Image - one channel

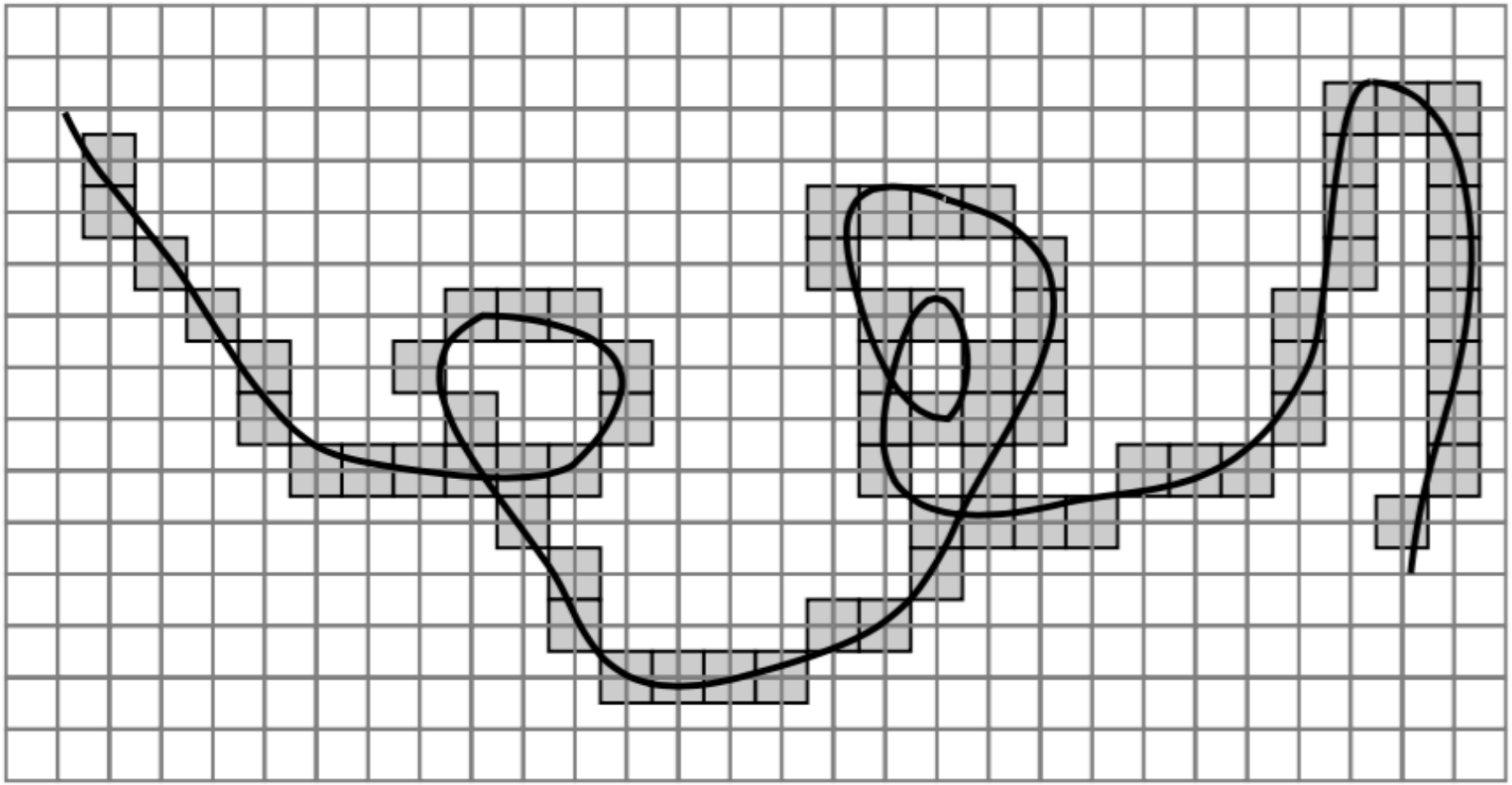
Color image representation

Slide credit: Ulas Bagci

Images are sampled

What happens when we zoom into the images we capture?

Errors due Sampling



Slide credit: Ulas Bagci

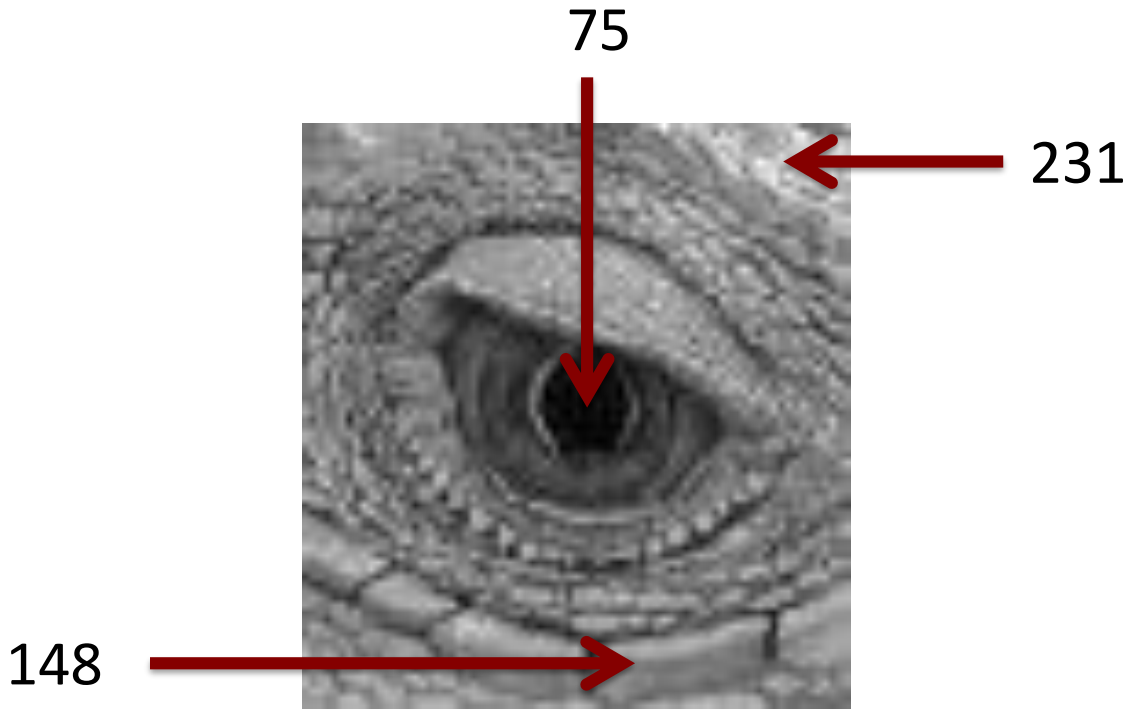
Resolution

is a **sampling** parameter, defined in dots per inch (DPI) or equivalent measures of spatial pixel density, and its standard value for recent screen technologies is 72 dpi

Slide credit: Ulas Bagci

Images are Sampled and Quantized

- An image contains discrete number of pixels
  - A simple example
  - Pixel value:
    - "grayscale"
      (or "intensity"): [0,255]



Images are Sampled and Quantized

- An image contains discrete number of pixels
  - A simple example
  - Pixel value:
    - “grayscale” (or “intensity”): [0,255]
    - “color”
      - RGB: [R, G, B]
      - Lab: [L, a, b]
      - HSV: [H, S, V]

[90, 0, 53]

[249, 215, 203]

[213, 60, 67]

With this loss of information (from sampling and quantization),

Can we still use images for useful tasks?

What we will learn today?

- Image sampling and quantization
- Image histograms
- Images as functions
- Linear systems (filters)
- Convolution and correlation

Some background reading:
Forsyth and Ponce, Computer Vision, Chapter 7

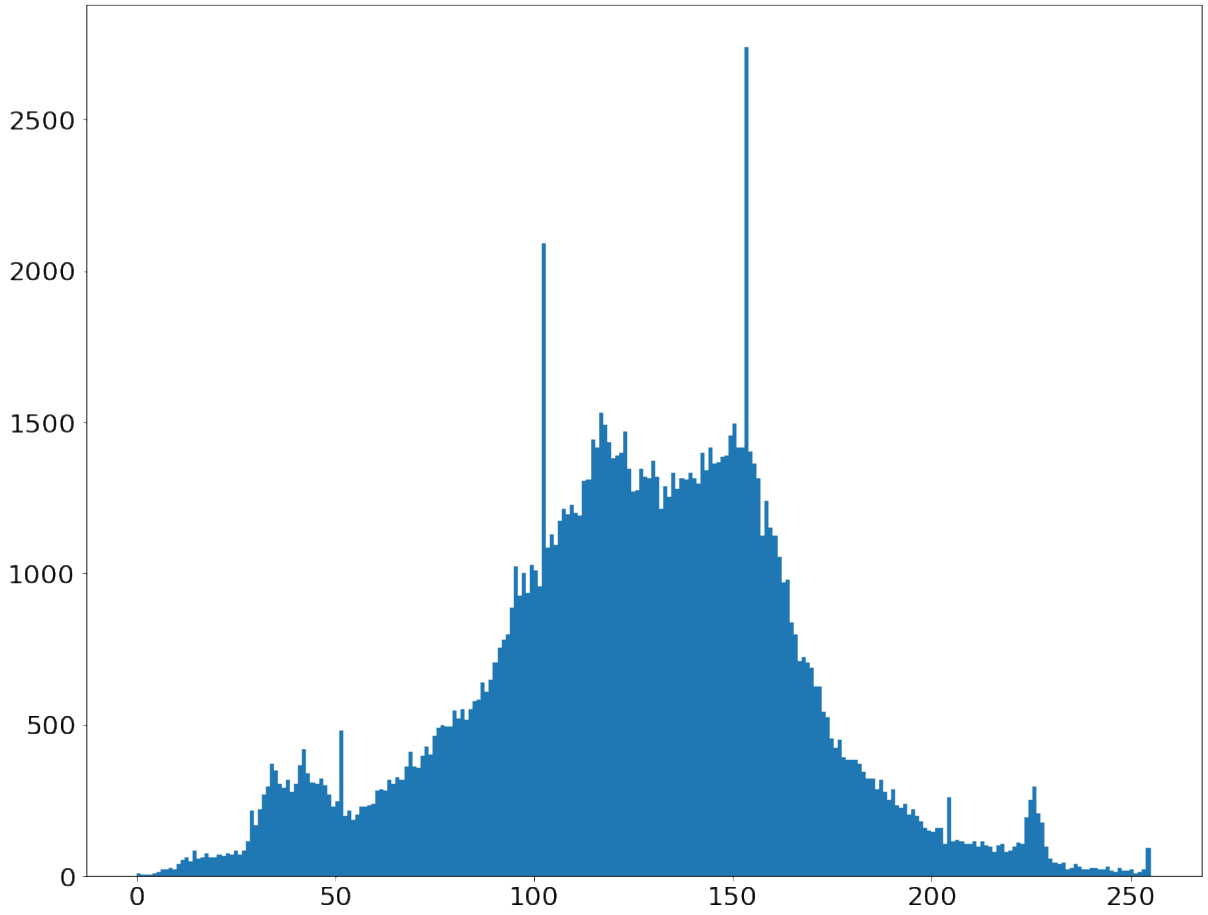
Histogram

- Histogram of an image provides the frequency of the brightness (intensity) value in the image.

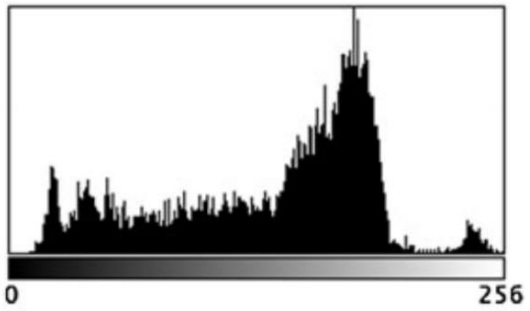
```
def histogram(im):
    h = np.zeros(255)
    for row in im.shape[0]:
        for col in im.shape[1]:
            val = im[row, col]
            h[val] += 1
```

Histogram

- Histogram captures the distribution of gray levels in the image.
- How frequently each gray level occurs in the image

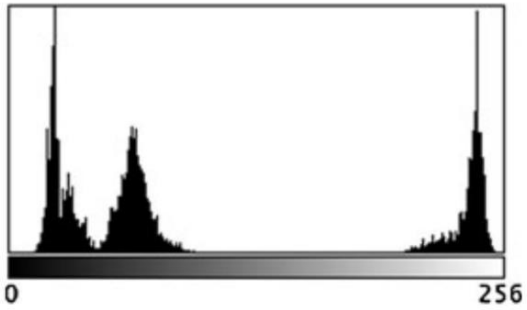


Histogram



Count: 10192
Mean: 133.711
StdDev: 55.391

Min: 9
Max: 255
Mode: 178 (180)

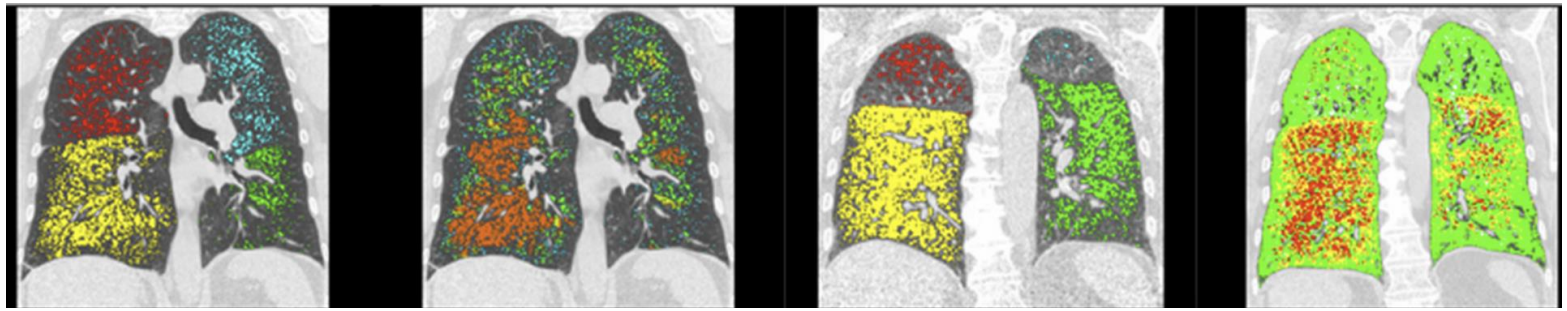


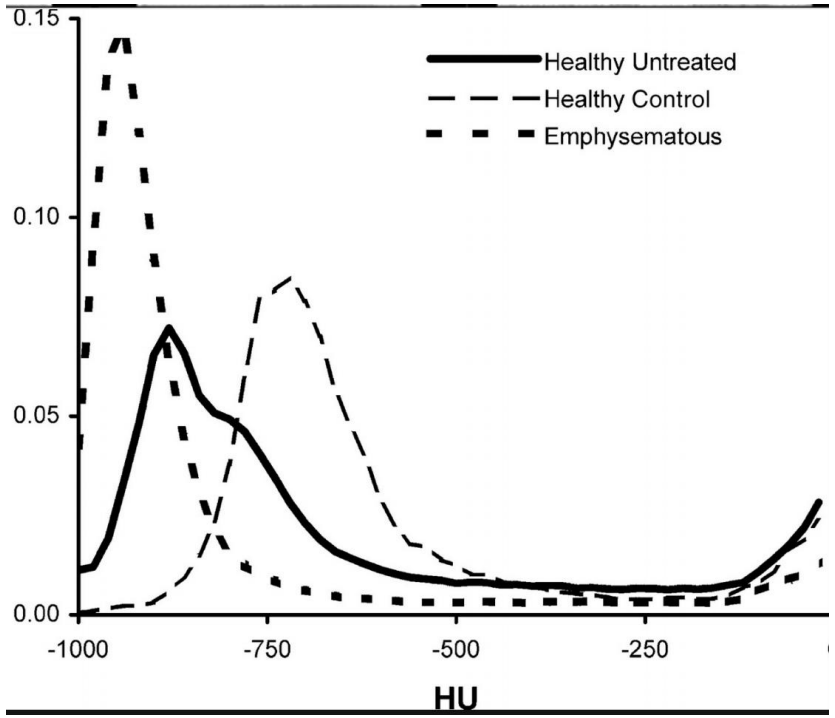
Count: 10192
Mean: 104.637
StdDev: 89.862

Min: 11
Max: 254
Mode: 23 (440)

Slide credit: Dr. Mubarak Shah

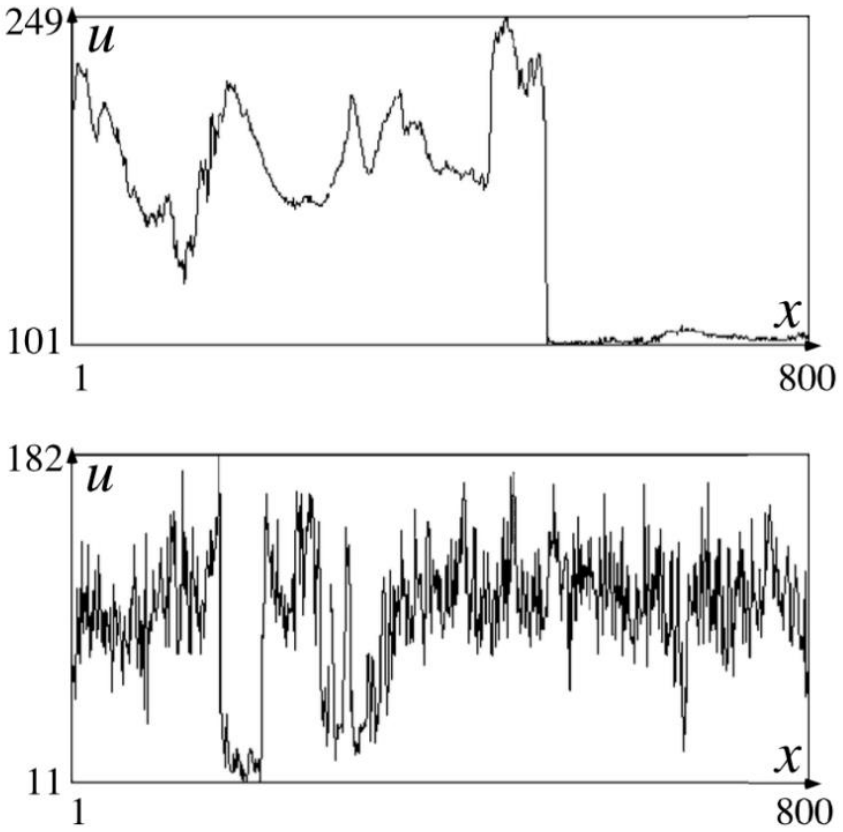
Histogram – use case





Slide credit: Dr. Mubarak Shah

Histogram – another use case



Slide credit: Dr. Mubarak Shah

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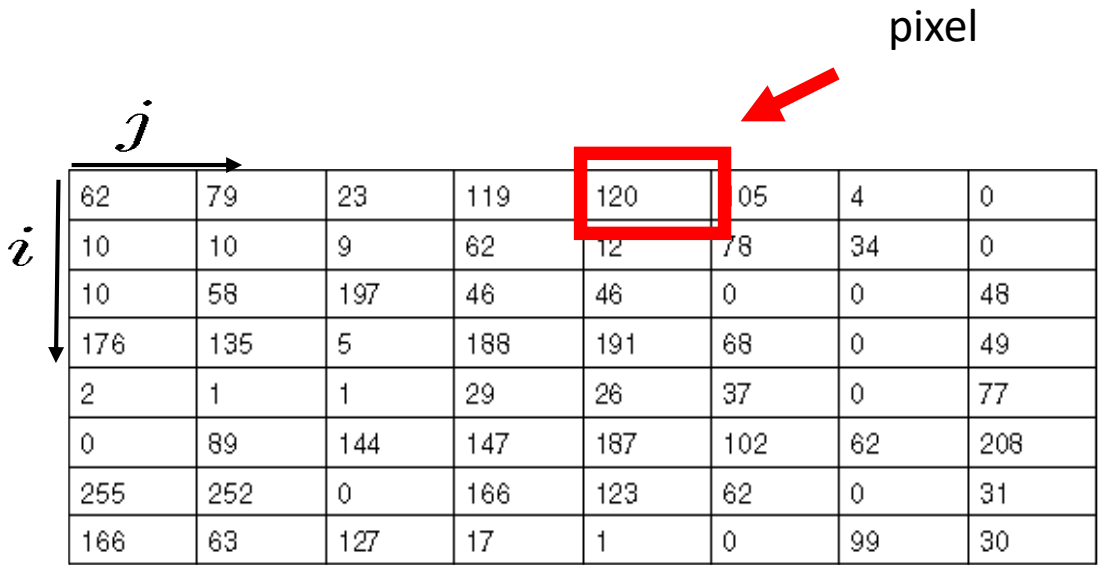
Images as discrete functions

- Images are usually **digital** (**discrete**):
  - **Sample** the 2D space on a regular grid

- Represented as a matrix of integer values



Images as coordinates

Cartesian coordinates

$$f[n,m] = \begin{bmatrix} \ddots & \vdots & \\ f[-1,-1] & f[0,-1] & f[1,-1] \\ \dots \quad f[-1,0] & \underline{f[0,0]} & f[1,0] \quad \dots \\ f[-1,1] & f[0,1] & f[1,1] \\ & \vdots & \ddots \end{bmatrix}$$

Notation for discrete functions

Images as coordinates

Cartesian coordinates

$$f[n,m] = \begin{bmatrix} \ddots & \vdots & \\ f[-1,-1] & f[0,-1] & f[1,-1] \\ \dots \quad f[-1,0] & \underline{f[0,0]} & f[1,0] \quad \dots \\ f[-1,1] & f[0,1] & f[1,1] \\ & \vdots & \ddots \end{bmatrix}$$

Notation for discrete functions

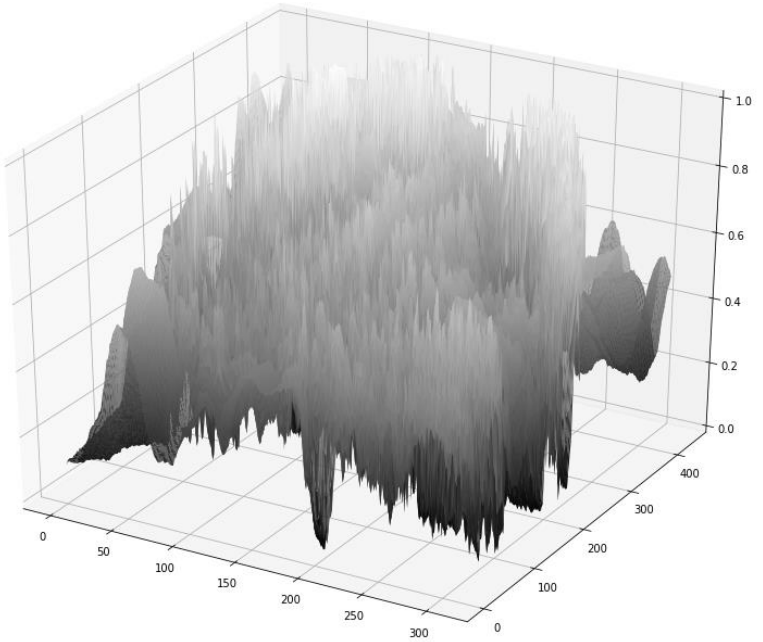
Images as functions

- **An Image** as a function f from R^2 to R^M:
  - $f(x, y)$ gives the **intensity** at position (x, y)
  - Defined over a rectangle, with a finite range:

$$f: [a,b] \times [c,d] \rightarrow [0,255]$$

Domain support

range



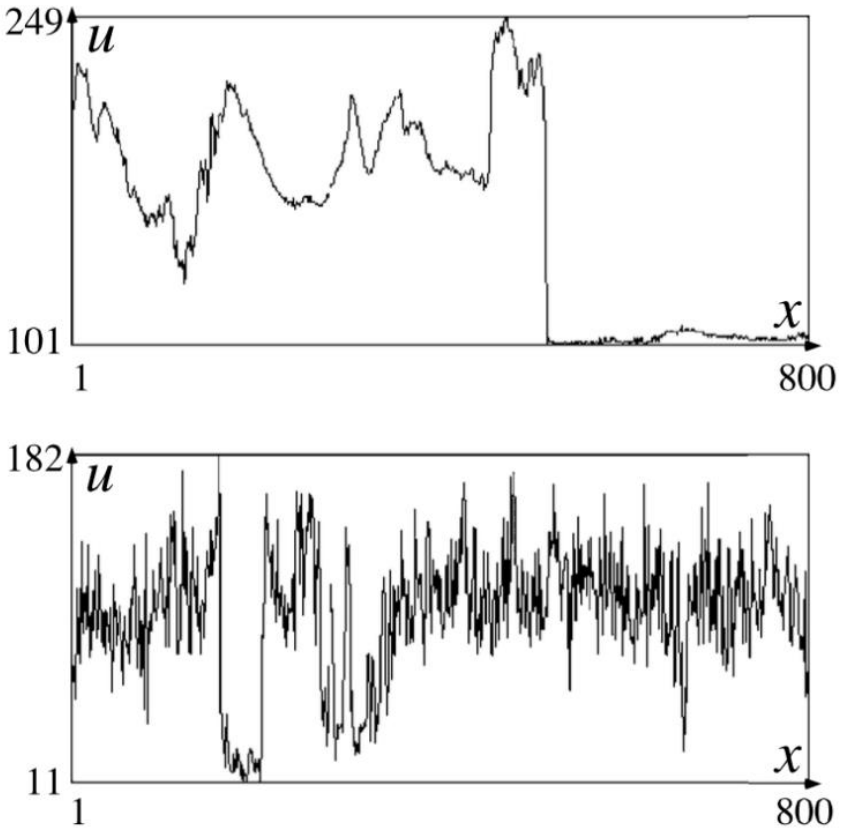
Images as functions

- **An Image** as a function f from R^2 to R^M:
  - $f(x, y)$ gives the **intensity** at position (x, y)
  - Defined over a rectangle, with a finite range:

$$f: \underbrace{[a,b] \times [c,d]}_{\text{Domain support}} \rightarrow \underbrace{[0,255]}_{\text{range}}$$

- A color image: $$f(x,y) = \begin{bmatrix} r(x,y) \\ g(x,y) \\ b(x,y) \end{bmatrix}$$

Histograms are a type of image function



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Some background reading:
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Systems and Filters

Filtering:

– Forming a new image whose pixel values are transformed from original pixel values

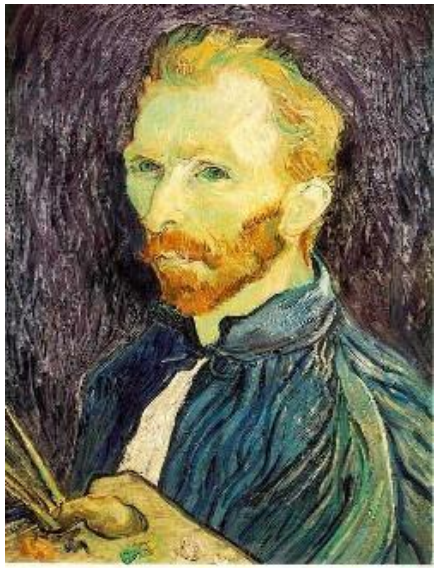
Goals:

- Goal is to extract useful information from images, or transform images into another domain where we can modify/enhance image properties
  - Features (edges, corners, blobs…)
  - super-resolution; in-painting; de-noising

De-noising

Salt and pepper noise

Super-resolution



In-painting

Bertamio et al

System and Filters

- we define a system as a unit that converts an input function f[n,m] into an output (or response) function g[n,m], where (n,m) are the independent variables.
  - In the case for images, (n,m) represents the **spatial position in the image.**

$$f[n,m] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow g[n,m]$$

Images as coordinates

Cartesian coordinates

$$f[n,m] = \begin{bmatrix} \ddots & \vdots & \\ f[-1,-1] & f[0,-1] & f[1,-1] \\ \dots \quad f[-1,0] & \underline{f[0,0]} & f[1,0] \quad \dots \\ f[-1,1] & f[0,1] & f[1,1] \\ & \vdots & \ddots \end{bmatrix}$$

Notation for discrete functions

2D discrete-space systems (filters)

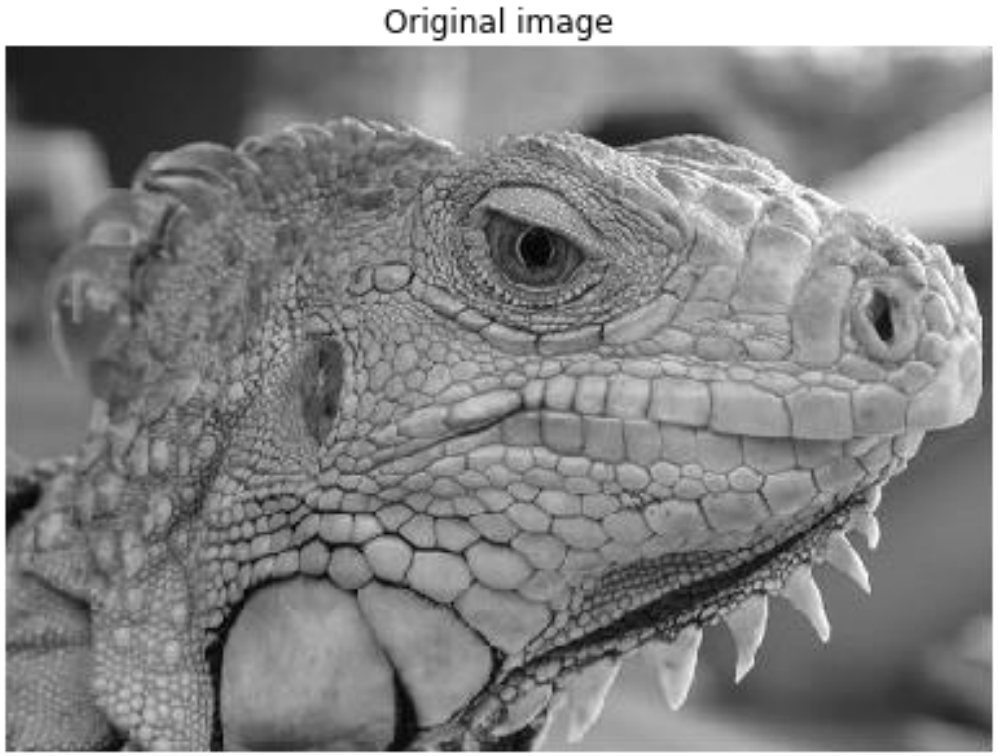
S is the **system operator**, defined as a mapping or assignment of a member of the set of possible outputs g[n,m] to each member of the set of possible inputs f[n,m].

$$f[n,m] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow g[n,m]$$

$$g = \mathcal{S}[f], \quad g[n,m] = \mathcal{S}\{f[n,m]\}$$

$$f[n,m] \xrightarrow{\mathcal{S}} g[n,m]$$

Filter example #1: Moving Average



Filter example #1: Moving Average

2D DS moving average over a 3 × 3 window of neighborhood

$$g[n,m] = \frac{1}{9} \sum_{k=n-1}^{n+1} \sum_{l=m-1}^{m+1} f[k,l]$$

$$= \frac{1}{9} \sum_{k=-1}^{1} \sum_{l=-1}^{1} f[n-k, m-l]$$

h

$\frac{1}{9}$

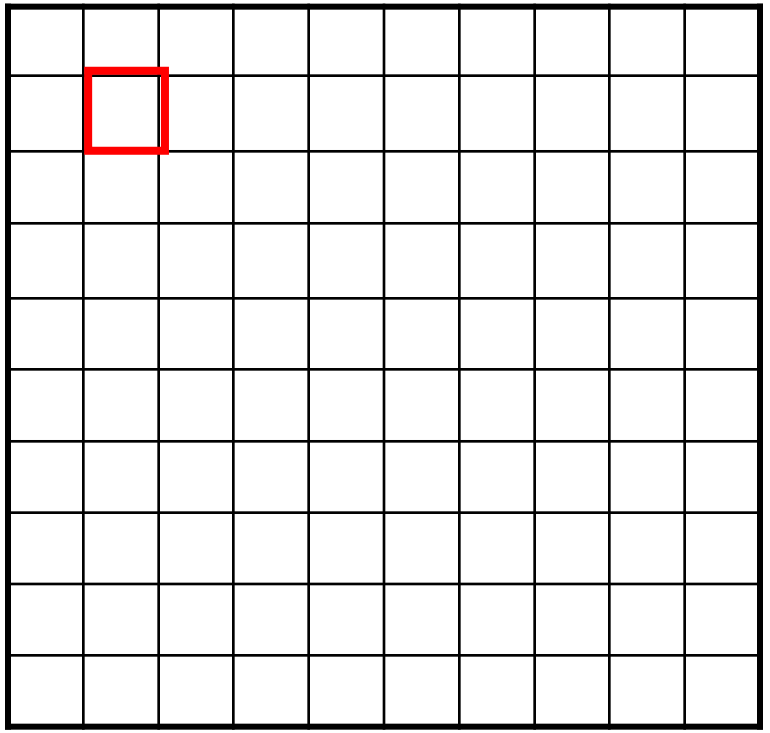
1	1	1
1	1	1
1	1	1

Filter example #1: Moving Average

$f[n, m]$

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

$g[n, m]$



Courtesy of S. Seitz

Filter example #1: Moving Average

$f[n, m]$

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

$g[n, m]$

	0	10							

Filter example #1: Moving Average

$f[n, m]$

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

$g[n, m]$

	0	10	20						

Filter example #1: Moving Average

$f[n, m]$

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

$g[n, m]$

	0	10	20	30					

Filter example #1: Moving Average

$f[n, m]$

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

$g[n, m]$

	0	10	20	30	30				

Filter example #1: Moving Average

$f[n, m]$

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

$g[n, m]$

	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	

Filter example #1: Moving Average

In summary:

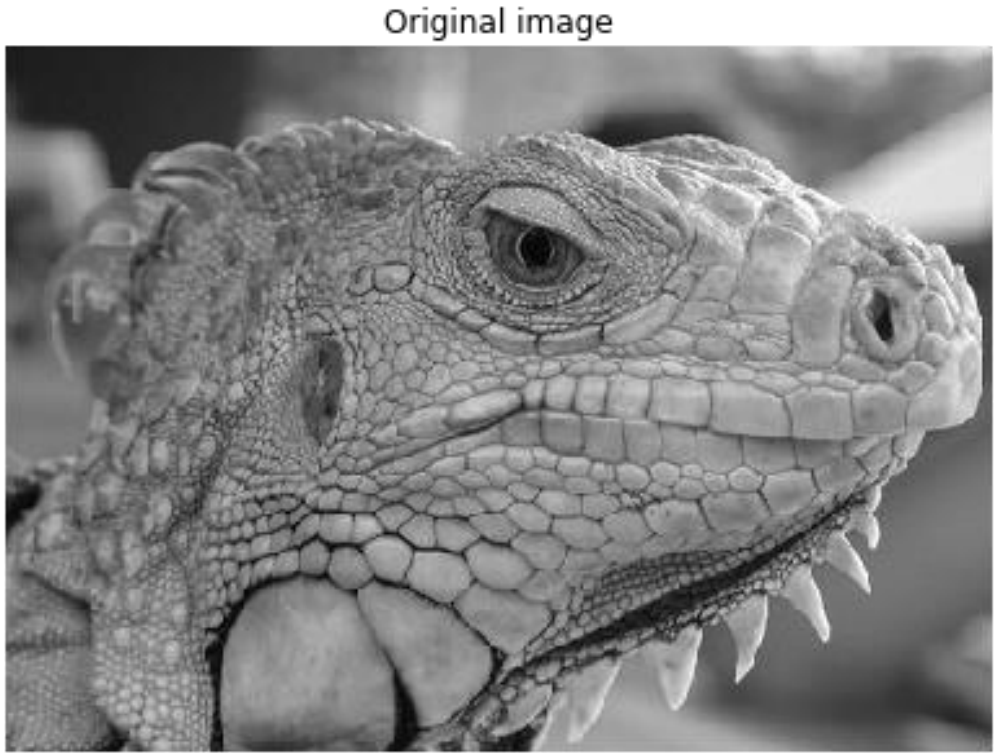
- This filter creates a new pixel with an average of its neighborhood.

- Achieve smoothing effect (remove sharp features)

$$h[\times,\times]$$

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

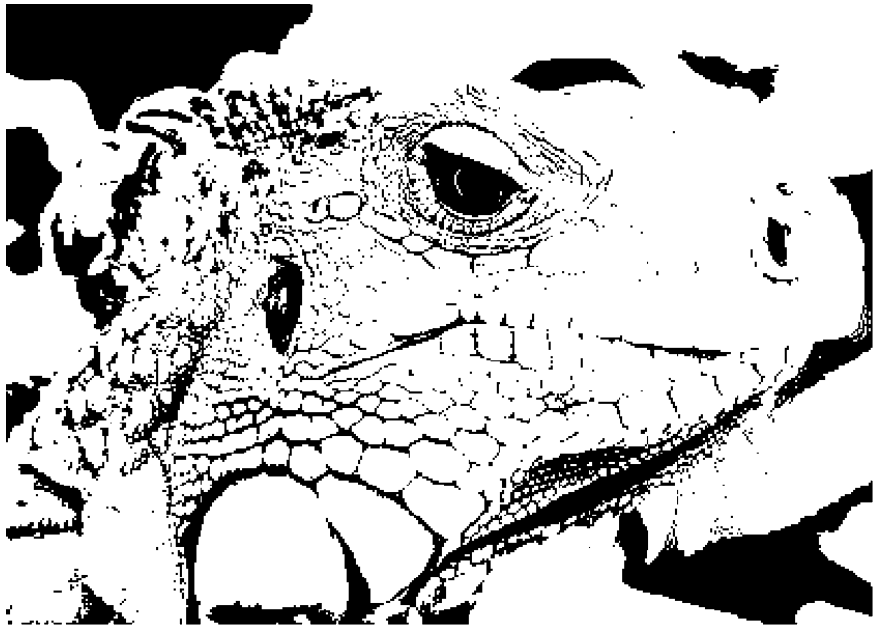
Filter example #1: Moving Average



Filter example #2: Image Segmentation

- Image segmentation based on a simple threshold:

$$g[n,m] = \begin{cases} 255, & f[n,m] > 100 \\ 0, & \text{otherwise.} \end{cases}$$



Example Properties of systems

- Amplitude properties:
  - Additivity

$$S[f_i[n,m] + f_j[n,m]] = S[f_i[n,m]] + S[f_j[n,m]]$$

  - Homogeneity

$$S[\alpha f_i[n,m]] = \alpha S[f_i[n,m]]]$$

  - Superposition

$$S[\alpha f_i[n,m] + \beta f_j[n,m]] = \alpha S[f_i[n,m]] + \beta S[f_j[n,m]]$$

  - Stability

$$|f[n,m]| \leq k \implies |g[n,m]| \leq ck$$

  - Invertibility

$$S^{-1}[S[f_i[n,m]]] = f[n,m]$$

Example Properties of linear systems

- Spatial properties
  - Causality

$$\text{for } n < n_0, m < m_0, \text{ if } f[n,m] = 0 \implies g[n,m] = 0$$

  - Shift invariance:

$$f[n - n_0, m - m_0] \xrightarrow{\mathcal{S}} g[n - n_0, m - m_0]$$

These properties have to be true for **Linear Systems**

- Amplitude properties:
  - Additivity

$$S[f_i[n,m] + f_j[n,m]] = S[f_i[n,m]] + S[f_j[n,m]]$$

  - Homogeneity

$$S[\alpha f_i[n,m]] = \alpha S[f_i[n,m]]]$$

  - Superposition

$$S[\alpha f_i[n,m] + \beta f_j[n,m]] = \alpha S[f_i[n,m]] + \beta S[f_j[n,m]]$$

These properties have to be true for **Linear SHIFT INVARIANT Systems**

- Amplitude properties:
  - Additivity

$$S[f_i[n,m] + f_j[n,m]] = S[f_i[n,m]] + S[f_j[n,m]]$$

  - Homogeneity

$$S[\alpha f_i[n,m]] = \alpha S[f_i[n,m]]]$$

  - Superposition

$$S[\alpha f_i[n,m] + \beta f_j[n,m]] = \alpha S[f_i[n,m]] + \beta S[f_j[n,m]]$$

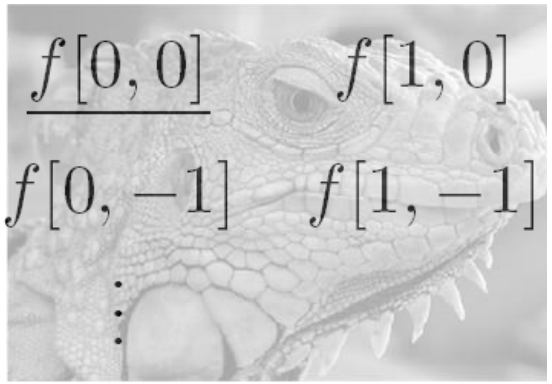
  - Shift invariance:

$$f[n - n_0, m - m_0] \xrightarrow{\mathcal{S}} g[n - n_0, m - m_0]$$

What does shifting an image look like?

Cartesian coordinates

$$f[n,m] = \begin{bmatrix} \ddots & & \vdots & & \\ & f[-1,1] & f[0,1] & f[1,1] & \\ \dots & f[-1,0] & \underline{f[0,0]} & f[1,0] & \dots \\ & f[-1,-1] & f[0,-1] & f[1,-1] & \\ & & \vdots & & \ddots \end{bmatrix}$$



Is the moving average system is shift invariant?

$$g[n,m] = \frac{1}{9} \sum_{k=n-1}^{n+1} \sum_{l=m-1}^{m+1} f[k,l]$$

f$[n,m]$

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$[n,m]$

	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	

Is the moving average system is shift invariant?

$$f[n,m] \xrightarrow{\mathcal{S}} g[n,m]$$

$$g[n,m] = \frac{1}{9}\sum_{k=n-1}^{n+1}\sum_{l=m-1}^{m+1} f[k,l] \quad = \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1} f[n-k,m-l]$$

Let $f[n-n_0, m-m_0]$ be a shifted input of $f[n,m]$

Now let's pass $f[n-n_0, m-m_0]$ through the system:

$$f[n-n_0,m-m_0] \xrightarrow{s} \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1} f[n-n_0-k, m-m_0-l]$$

$$= g[n-n_0, m-m_0]$$ Yes!

Is the moving average system is casual?

$$g[n,m] = \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1} f[n-k, m-l]$$

$\mathrm{f}[n,m]$

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

$\mathrm{g}[n,m]$

	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	

$$\text{for } n < n_0, m < m_0, \text{ if } f[n,m] = 0 \implies g[n,m] = 0$$

Linear Systems (filters)

$$f[n,m] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow g[n,m]$$

- Linear filtering:
  - Form a new image whose pixels are a weighted sum of original pixel values
  - Use the same set of weights at each point

- **S** is a linear system (function) iff it *S satisfies*

$$S[\,\alpha f_i[n,m] + \beta f_j[k,l]\,] \quad = \quad \alpha\, S[\,f_i[n,m]] \;+\; \beta\, S[\,f_j[k,l]\,]$$

superposition property

Linear Systems (filters)

$$f[n,m] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow g[n,m]$$

- Is the moving average a linear system?

- Is thresholding a linear system?
  - f1[n,m] + f2[n,m] > T
  - f1[n,m] < T
  - f2[n,m]<T

No!

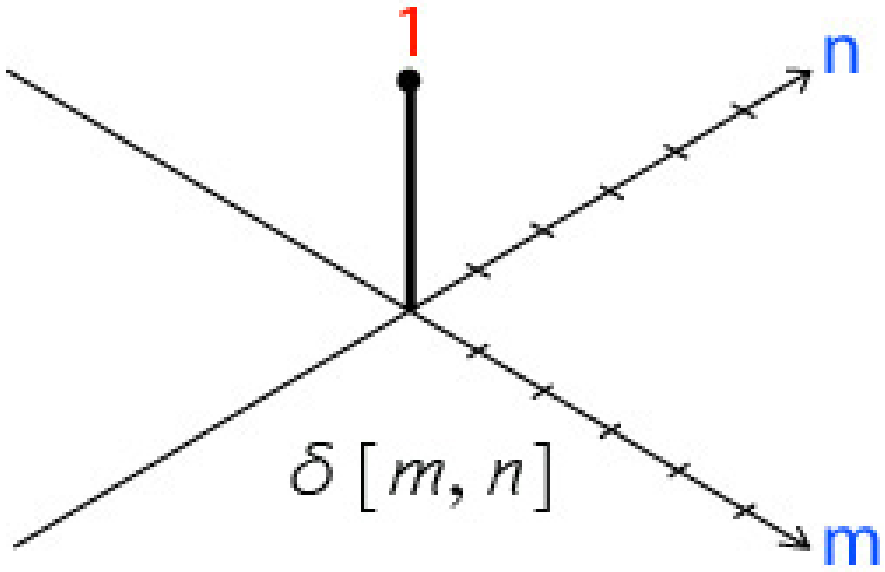
How do we characterize a linear shift invariant (LSI) system?

- Mathematically, how do you calculate g[n,m] from f[n,m]

$$f[n,m] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow g[n,m]$$

2D impulse function

- 1 at [0,0].
- 0 everywhere else

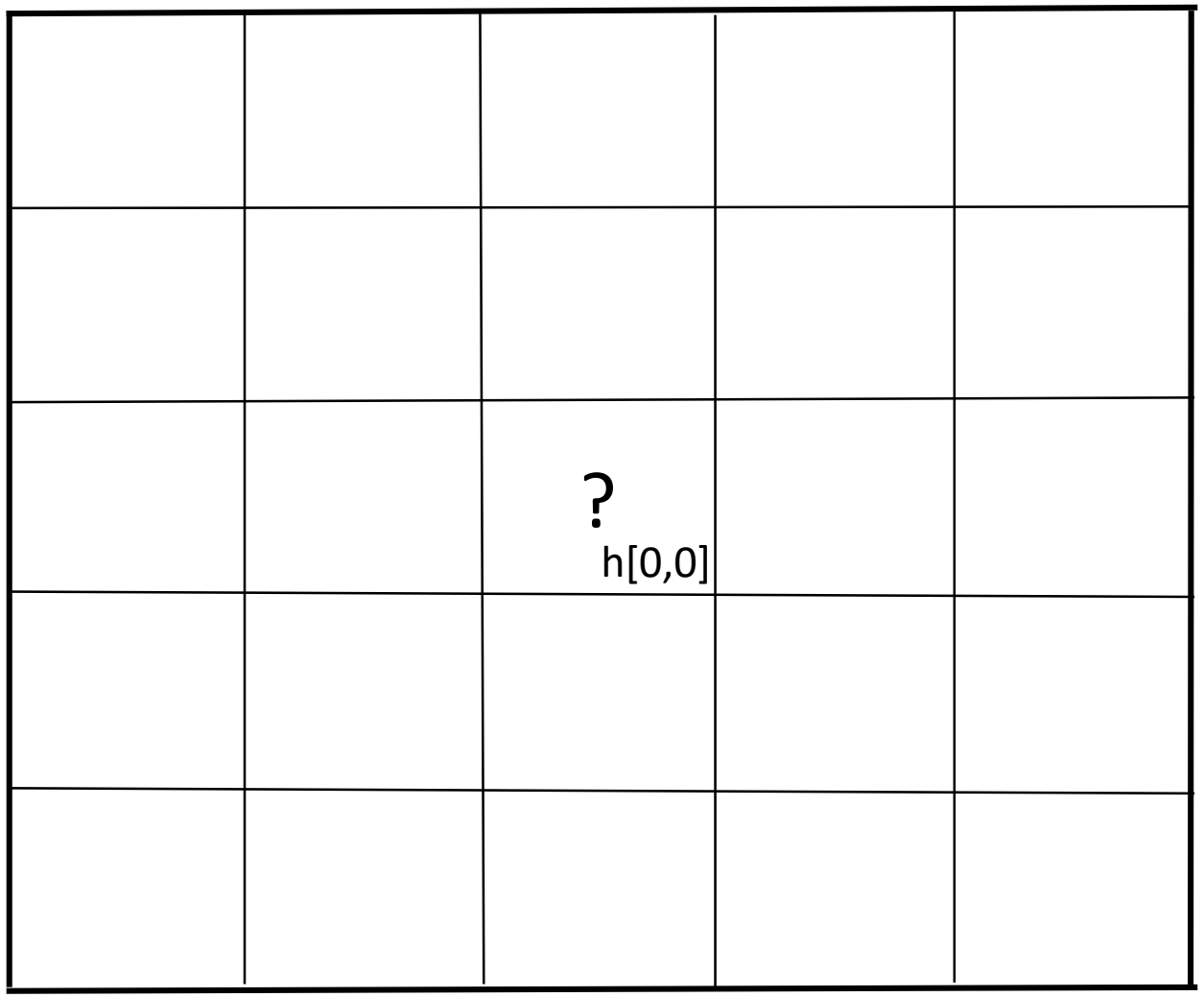


Impulse response to the moving filter

$$\delta_2 \xrightarrow{S} h[n,m]$$

$$= \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k,m-l]$$

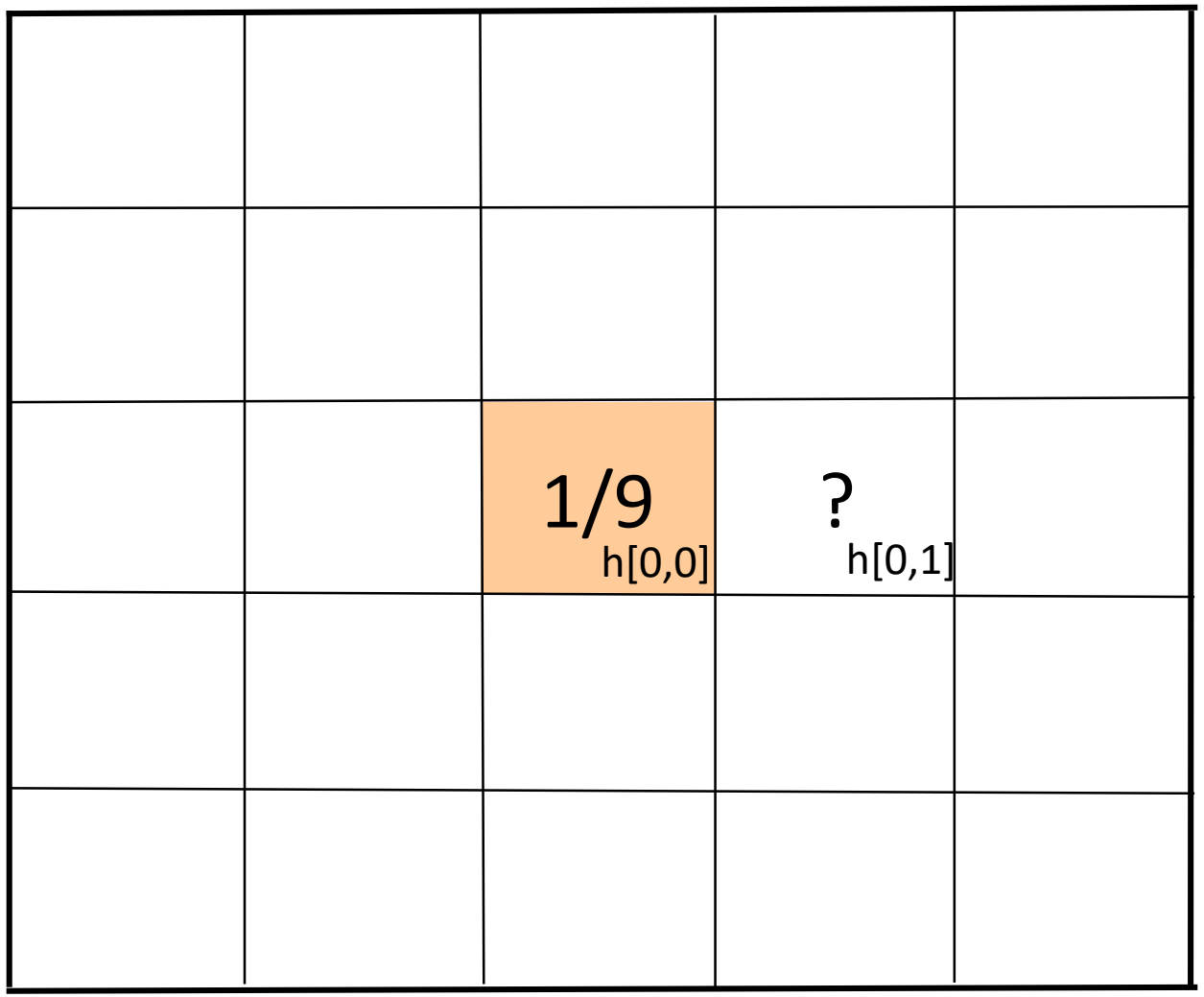
Impulse response to the moving filter



$$\delta_2 \xrightarrow{S} h[n,m]$$

$$= \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k,m-l]$$

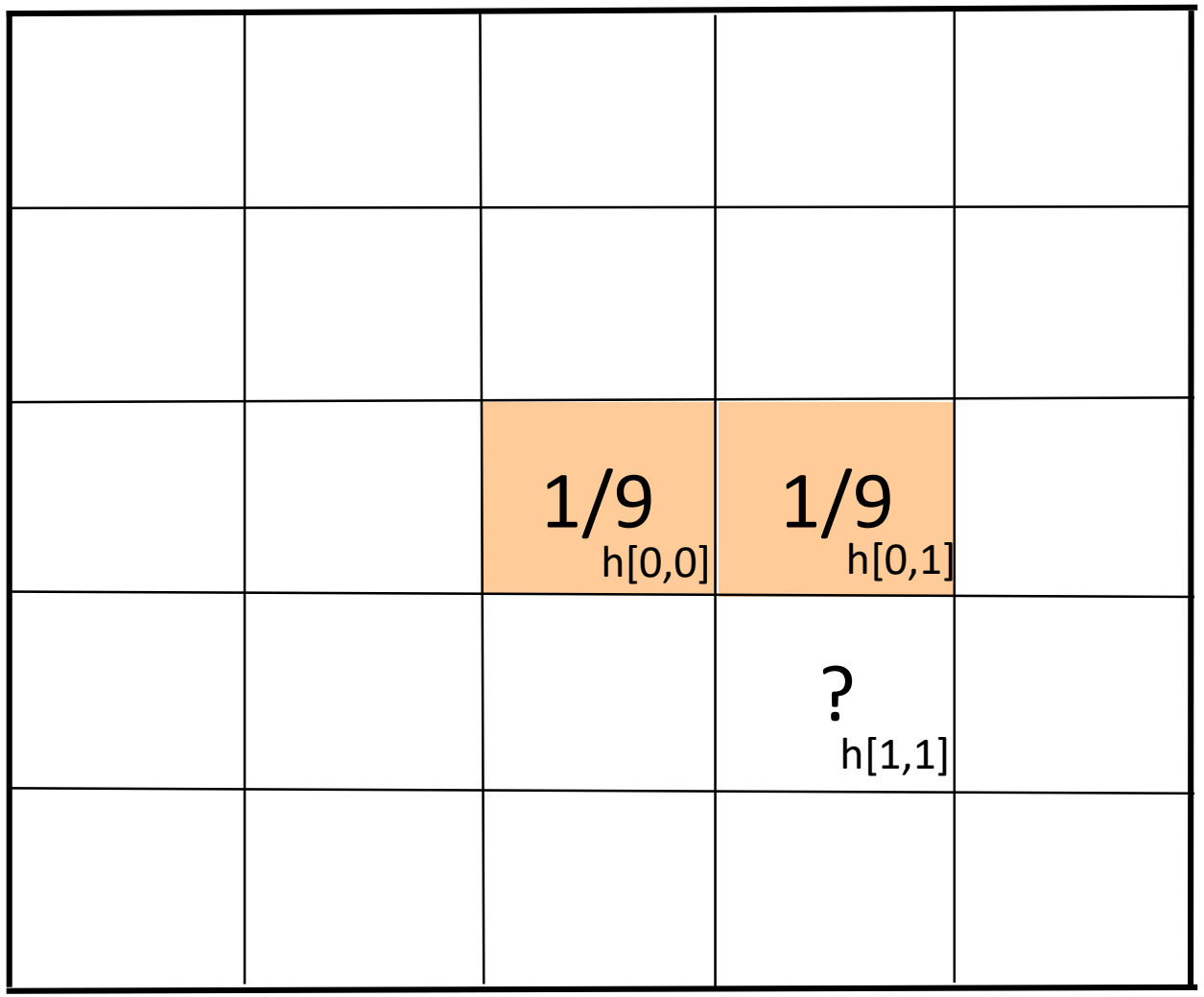
Impulse response to the moving filter



$$\delta_2 \xrightarrow{S} h[n,m]$$

$$= \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k,m-l]$$

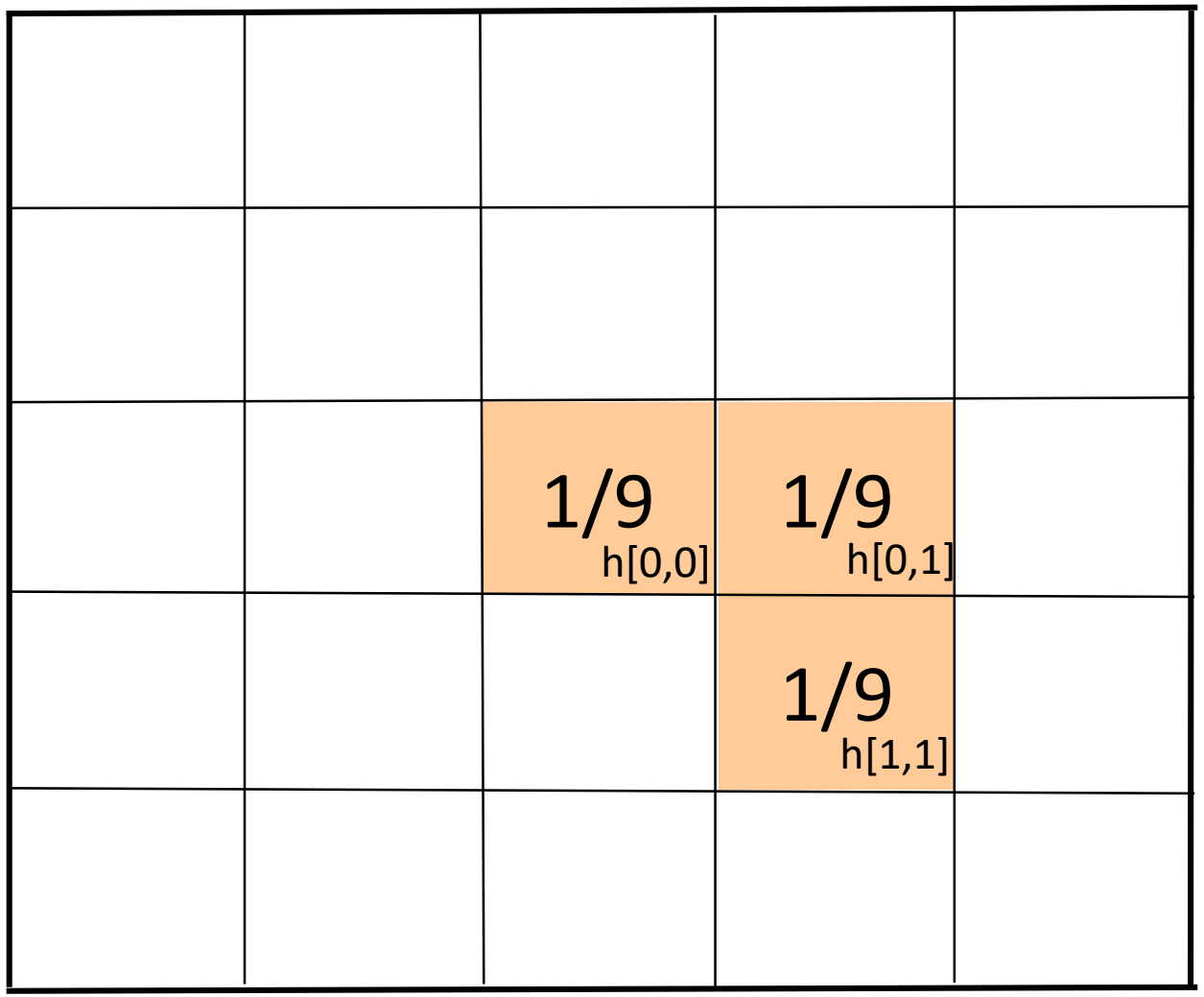
Impulse response to the moving filter



$$\delta_2 \xrightarrow{S} h[n,m]$$

$$= \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k,m-l]$$

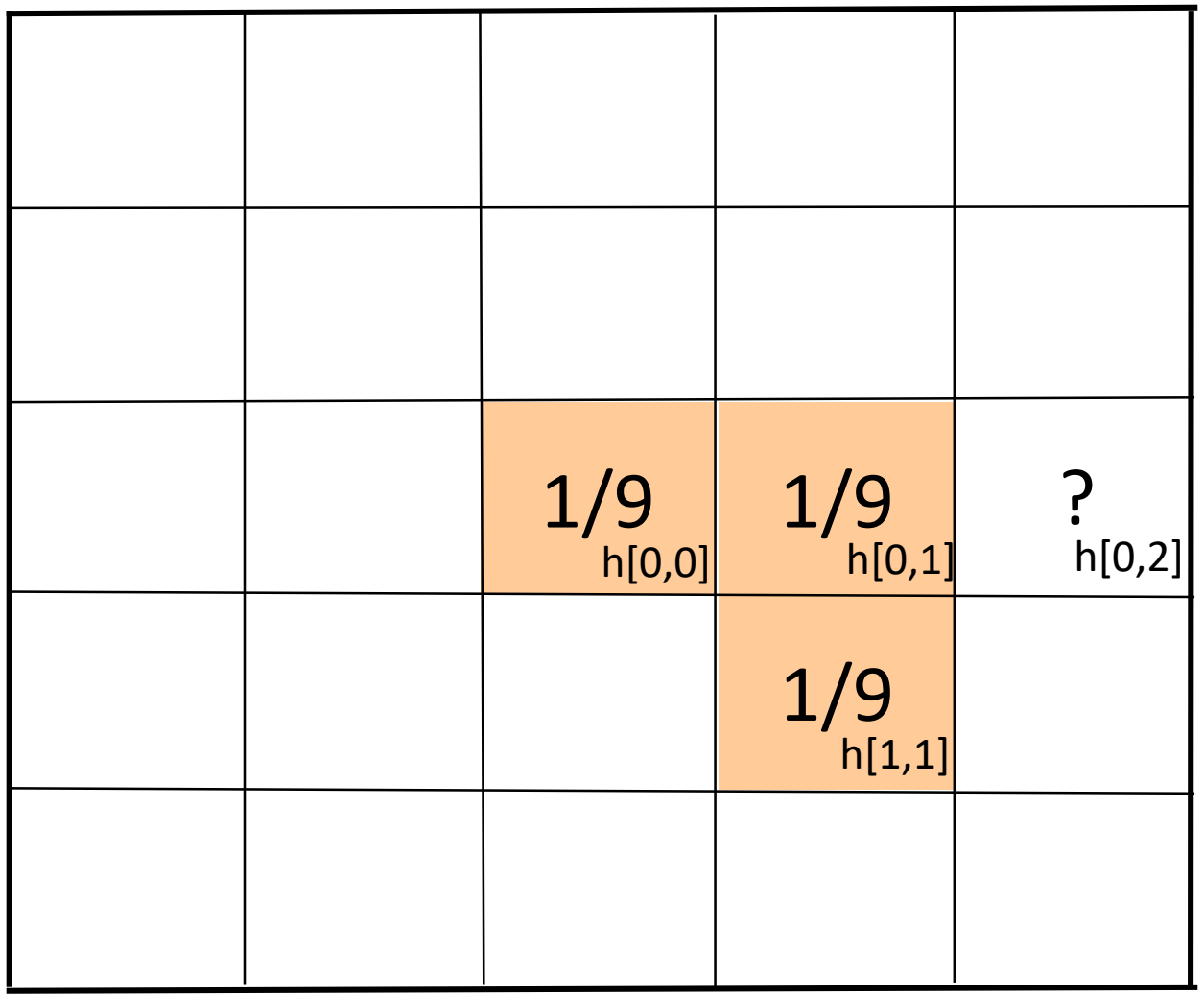
Impulse response to the moving filter



$$\delta_2 \xrightarrow{S} h[n,m]$$

$$= \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k,m-l]$$

Impulse response to the moving filter



$$\delta_2 \xrightarrow{S} h[n,m]$$

$$= \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k,m-l]$$

Impulse response to the moving filter

		1/9 h[0,0]	1/9 h[0,1]	0 h[0,2]
			1/9 h[1,1]	

$$\delta_2 \xrightarrow{S} h[n,m]$$

$$= \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k,m-l]$$

Impulse response to the moving filter

0	0	0	0	0
0	1/9 h[-1,-1]	1/9	1/9	0
0	1/9	1/9 h[0,0]	1/9 h[0,1]	0 h[0,2]
0	1/9	1/9	1/9 h[1,1]	0
0	0	0	0	0

$$\delta_2 \xrightarrow{S} g[n,m]$$

$$= \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k,m-l]$$

Impulse response of the 3 by 3 moving average filter

$$h[n,m] = \frac{1}{9}\sum_{k=-1}^{1}\sum_{l=-1}^{1}\delta_2[n-k, m-l]$$

$$= \begin{bmatrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{bmatrix}$$

h

$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

Any linear shift invariant system

- By passing an impulse into a linear system, we get it's impulse response.

- So, if we don't know what the linear system is doing, we can pass an impulse into it to get a filter $h[n, m]$ that tells us what the system is actually doing.

$$\delta_2[n, m] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow h[n, m]$$

- But how do we use $h[n, m]$ to calculate $\mathrm{g}[n, m]$ from $\mathrm{f}[n, m]$

$$f[n, m] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow g[n, m]$$

General linear shift invariant system

- Let's say our input f is a 3x3 image:

f[0,0]	f[0,1]	f[1,1]
f[1,0]	f[1,1]	f[1,2]
f[2,0]	f[2,1]	f[2,2]

We can rewrite $f[n,m]$ as a sum of delta functions:

$$f[n,m] = f[0,0] \times \delta_2[n-0, m-0] + f[0,1] \times \delta_2[n-0, m-1] + f[0,2] \times \delta_2[n-0, m-2] + \ldots$$

Or you can write it as: $$f[n,m] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l] \times \delta_2[n-k, m-l]$$

3 properties we need:

Now, we know what happens when we send a delta function through a LSI system:

$$\delta_2[n,m] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow h[n,m]$$

We also know that LSI systems shift the output if the input is shifted:

$$\delta_2[n-k,m-l] \rightarrow \boxed{\text{System } \mathcal{S}} \rightarrow h[n-k,m-l]$$

Finally, the superposition principle:

$$S[\,\alpha f_i[n,m] + \beta f_j[k,l]\,] = \alpha\, S[\,f_i[n,m]] + \beta\, S[\,f_j[k,l]\,]$$

We can generalize this superposition principle…

$$S[\,\alpha f_i[n,m] + \beta f_j[k,l]\,] \quad = \quad \alpha\, S[\,f_i[n,m]] \;+\; \beta\, S[\,f_j[k,l]\,]$$

… with our summation of deltas…

$$f[n,m] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l] \times \delta_2[n-k, m-l]$$

… as follows:

$$S\left[\sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l] \times \delta_2[n-k, m-l]\right]$$

$$= \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l] \times S[\delta_2[n-k, m-l]]$$

Linear shift invariant system

$$S\left[\sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty} f[k,l] \times \delta_2[n-k, m-l]\right]$$

$$= \sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty} f[k,l] \times S[\delta_2[n-k, m-l]]$$

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

Linear Shift Invariant systems

An LSI system is completely specified by its impulse response.

$$f[n,m] \rightarrow \boxed{\mathcal{S}\ \text{LSI}} \rightarrow \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l]\, h[n-k, m-l]$$

$$\delta_2[n,m] \rightarrow \boxed{\mathcal{S}} \rightarrow h[n,m]$$

Discrete convolution

$$f[n,m] * h[n,m]$$

What we will learn today?

- Image sampling and quantization
- Image histograms
- Images as functions
- Linear systems (filters)
- Convolution and correlation

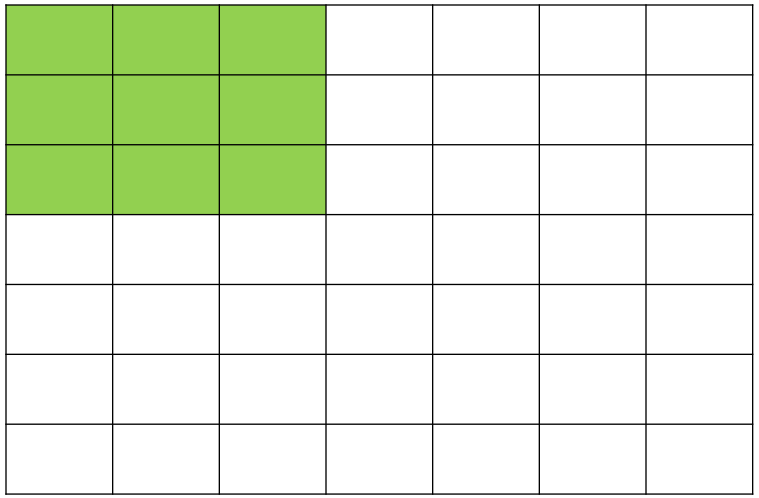
Some background reading:
Forsyth and Ponce, Computer Vision, Chapter 7

2D convolution

2D convolution is very similar to 1D.

- The main difference is that we now have to iterate over 2 axis instead of 1.

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



Assume we have a filter(h[,]) that is 3x3. and an image (f[,]) that is 7x7.

2D convolution

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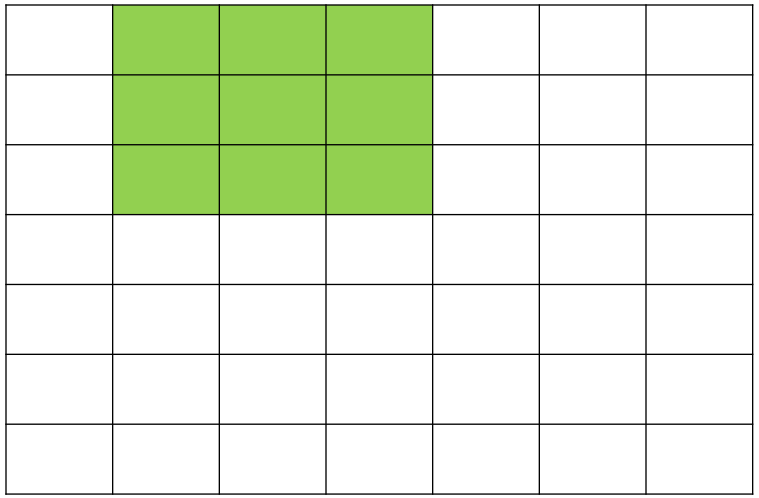
$$f[n,m] * h[n,m] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l]\, h[n-k, m-l]$$



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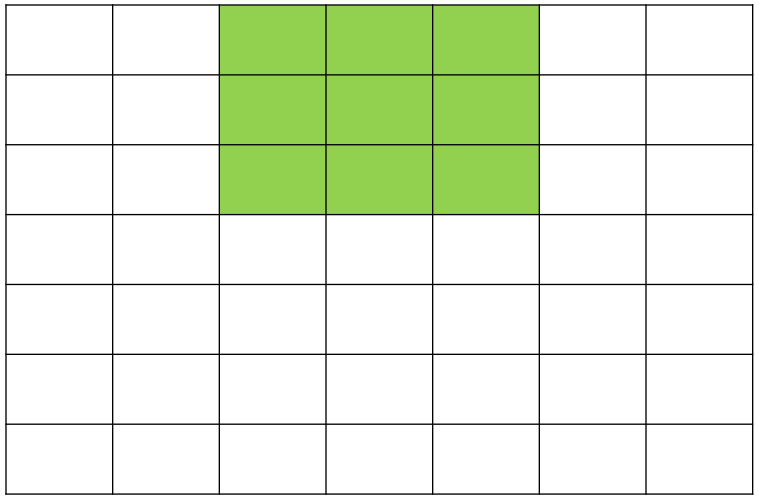
$$f[n,m] * h[n,m] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l]\, h[n-k, m-l]$$



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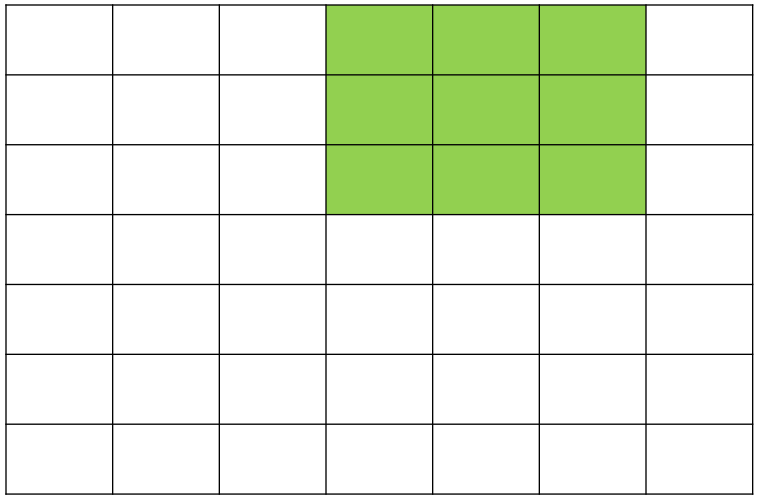

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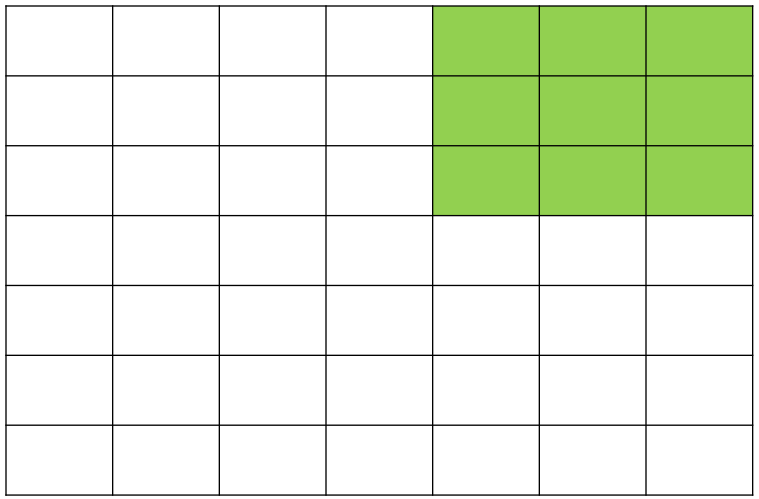
$$f[n,m] * h[n,m] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l]\, h[n-k, m-l]$$



Assume we have a filter(h[,]) that is 3x3. and an image (f[,]) that is 7x7.

2D convolution

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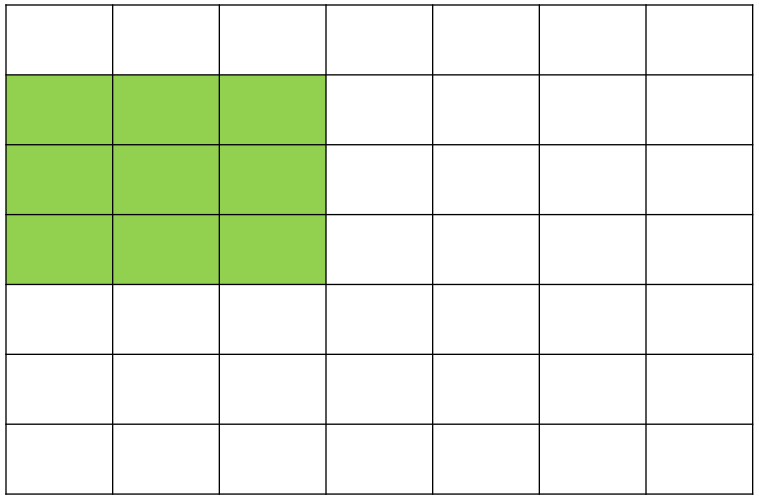
$$f[n,m] * h[n,m] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l]\, h[n-k, m-l]$$



Assume we have a filter(h[,]) that is 3x3. and an image (f[,]) that is 7x7.

Convolution

$$f * h = \sum_k \sum_l f(k,l)h(-k,-l)$$

f = Image

h = Kernel

h

h_1	h_2	h_3
h_4	h_5	h_6
h_7	h_8	h_9

$X - flip$

h_7	h_8	h_9
h_4	h_5	h_6
h_1	h_2	h_3

$Y - flip$

f

f_1	f_2	f_3
f_4	f_5	f_6
f_7	f_8	f_9

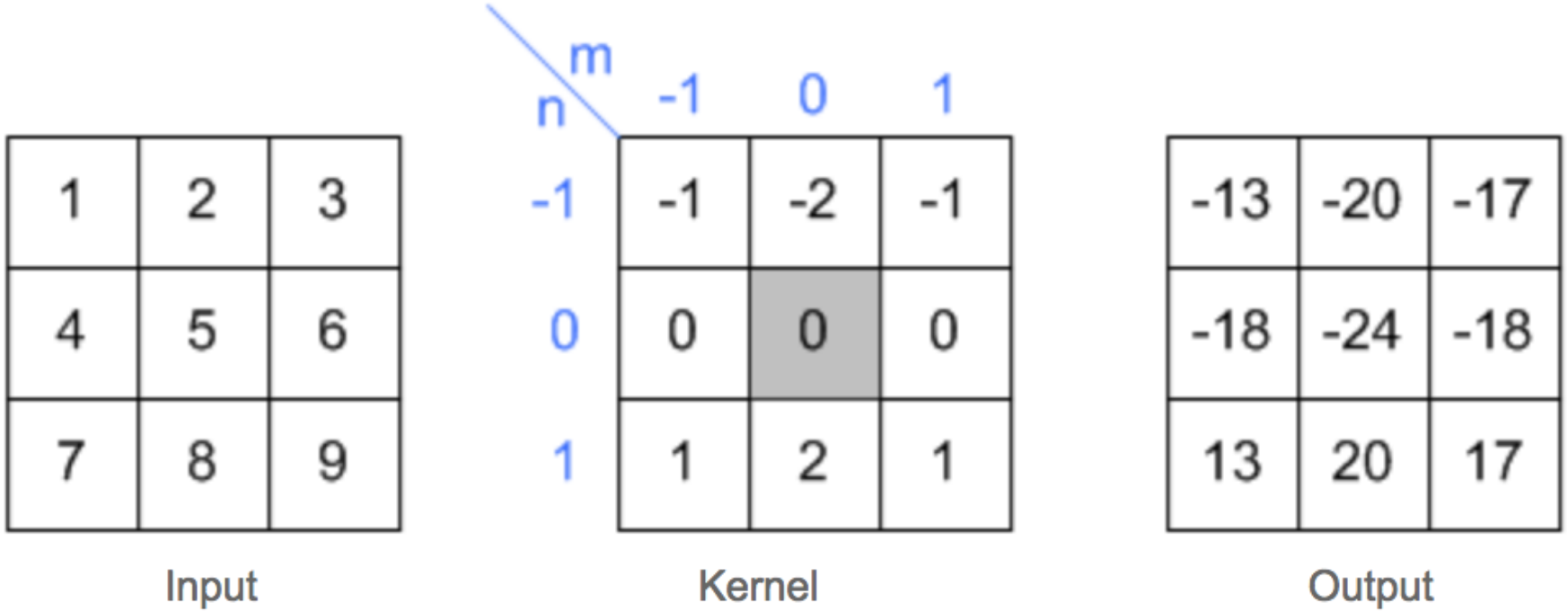
$*$

h_9	h_8	h_7
h_6	h_5	h_4
h_3	h_2	h_1

$$f * h = f_1h_9 + f_2h_8 + f_3h_7 + f_4h_6 + f_5h_5 + f_6h_4 + f_7h_3 + f_8h_2 + f_9h_1$$

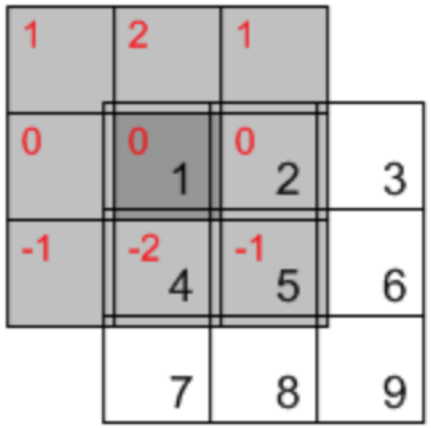
Slide credit: Ulas Bagci

2D convolution example



Slide credit: Song Ho Ahn

2D convolution example



$$
\begin{aligned}
&= x[-1,-1]\cdot h[1,1] + x[0,-1]\cdot h[0,1] + x[1,-1]\cdot h[-1,1] \\
&\quad + x[-1,0]\cdot h[1,0] + x[0,0]\cdot h[0,0] + x[1,0]\cdot h[-1,0] \\
&\quad + x[-1,1]\cdot h[1,-1] + x[0,1]\cdot h[0,-1] + x[1,1]\cdot h[-1,-1] \\
&= 0\cdot 1 + 0\cdot 2 + 0\cdot 1 + 0\cdot 0 + 1\cdot 0 + 2\cdot 0 + 0\cdot(-1) + 4\cdot(-2) + 5\cdot(-1) = -13
\end{aligned}
$$

-13	-20	-17
-18	-24	-18
13	20	17

Output

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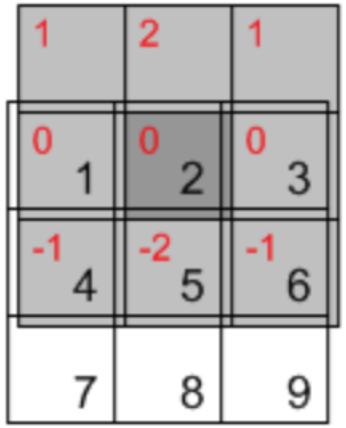
2D convolution example



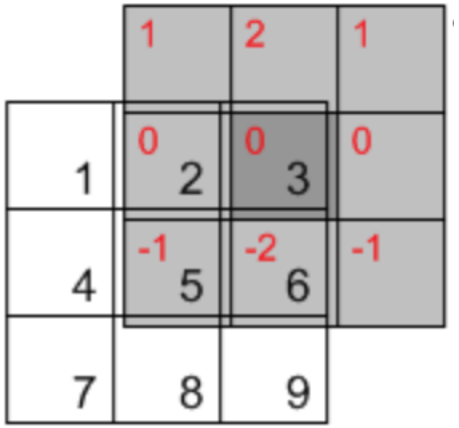
$$
\begin{aligned}
&= x[0,-1]\cdot h[1,1] + x[1,-1]\cdot h[0,1] + x[2,-1]\cdot h[-1,1] \\
&\quad + x[0,0]\cdot h[1,0] + x[1,0]\cdot h[0,0] + x[2,0]\cdot h[-1,0] \\
&\quad + x[0,1]\cdot h[1,-1] + x[1,1]\cdot h[0,-1] + x[2,1]\cdot h[-1,-1] \\
&= 0\cdot 1 + 0\cdot 2 + 0\cdot 1 + 1\cdot 0 + 2\cdot 0 + 3\cdot 0 + 4\cdot(-1) + 5\cdot(-2) + 6\cdot(-1) = -20
\end{aligned}
$$

-13	-20	-17
-18	-24	-18
13	20	17

Output

Slide credit: Song Ho Ahn

2D convolution example



$$
\begin{aligned}
&= x[1,-1]\cdot h[1,1] + x[2,-1]\cdot h[0,1] + x[3,-1]\cdot h[-1,1] \\
&\quad + x[1,0]\cdot h[1,0] + x[2,0]\cdot h[0,0] + x[3,0]\cdot h[-1,0] \\
&\quad + x[1,1]\cdot h[1,-1] + x[2,1]\cdot h[0,-1] + x[3,1]\cdot h[-1,-1] \\
&= 0\cdot 1 + 0\cdot 2 + 0\cdot 1 + 2\cdot 0 + 3\cdot 0 + 0\cdot 0 + 5\cdot(-1) + 6\cdot(-2) + 0\cdot(-1) = -17
\end{aligned}
$$

-13	-20	-17
-18	-24	-18
13	20	17

Output

Slide credit: Song Ho Ahn

2D convolution example

$$
\begin{aligned}
&= x[-1,0]\cdot h[1,1] + x[0,0]\cdot h[0,1] + x[1,0]\cdot h[-1,1] \\
&\quad + x[-1,1]\cdot h[1,0] + x[0,1]\cdot h[0,0] + x[1,1]\cdot h[-1,0] \\
&\quad + x[-1,2]\cdot h[1,-1] + x[0,2]\cdot h[0,-1] + x[1,2]\cdot h[-1,-1] \\
&= 0\cdot 1 + 1\cdot 2 + 2\cdot 1 + 0\cdot 0 + 4\cdot 0 + 5\cdot 0 + 0\cdot(-1) + 7\cdot(-2) + 8\cdot(-1) = -18
\end{aligned}
$$

-13	-20	-17
-18	-24	-18
13	20	17

Output

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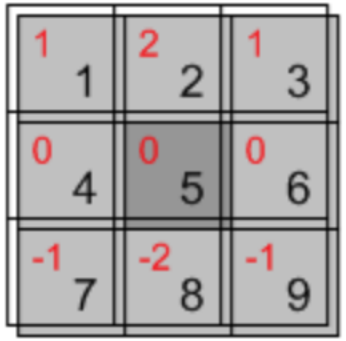
2D convolution example



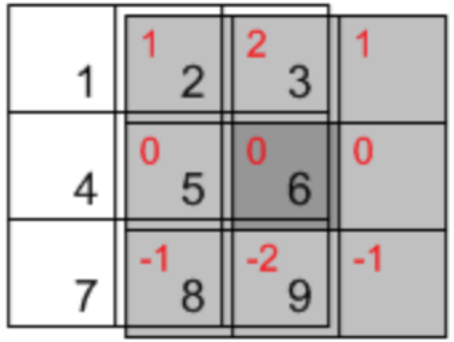
$$
\begin{aligned}
&= x[0,0]\cdot h[1,1] + x[1,0]\cdot h[0,1] + x[2,0]\cdot h[-1,1] \\
&\quad + x[0,1]\cdot h[1,0] + x[1,1]\cdot h[0,0] + x[2,1]\cdot h[-1,0] \\
&\quad + x[0,2]\cdot h[1,-1] + x[1,2]\cdot h[0,-1] + x[2,2]\cdot h[-1,-1] \\
&= 1\cdot 1 + 2\cdot 2 + 3\cdot 1 + 4\cdot 0 + 5\cdot 0 + 6\cdot 0 + 7\cdot(-1) + 8\cdot(-2) + 9\cdot(-1) = -24
\end{aligned}
$$

-13	-20	-17
-18	-24	-18
13	20	17

Output

Slide credit: Song Ho Ahn

2D convolution example



$$
\begin{aligned}
&= x[1,0]\cdot h[1,1] + x[2,0]\cdot h[0,1] + x[3,0]\cdot h[-1,1] \\
&\quad + x[1,1]\cdot h[1,0] + x[2,1]\cdot h[0,0] + x[3,1]\cdot h[-1,0] \\
&\quad + x[1,2]\cdot h[1,-1] + x[2,2]\cdot h[0,-1] + x[3,2]\cdot h[-1,-1] \\
&= 2\cdot 1 + 3\cdot 2 + 0\cdot 1 + 5\cdot 0 + 6\cdot 0 + 0\cdot 0 + 8\cdot(-1) + 9\cdot(-2) + 0\cdot(-1) = -18
\end{aligned}
$$

-13	-20	-17
-18	-24	-18
13	20	17

Output

Slide credit: Song Ho Ahn

Convolution in 2D - examples

Original

$$* \begin{bmatrix} \cdot 0 & \cdot 0 & \cdot 0 \\ \cdot 0 & \cdot 1 & \cdot 0 \\ \cdot 0 & \cdot 0 & \cdot 0 \end{bmatrix} = ?$$

Convolution in 2D - examples

Original

$*$

•0	•0	•0
•0	•1	•0
•0	•0	•0

$=$

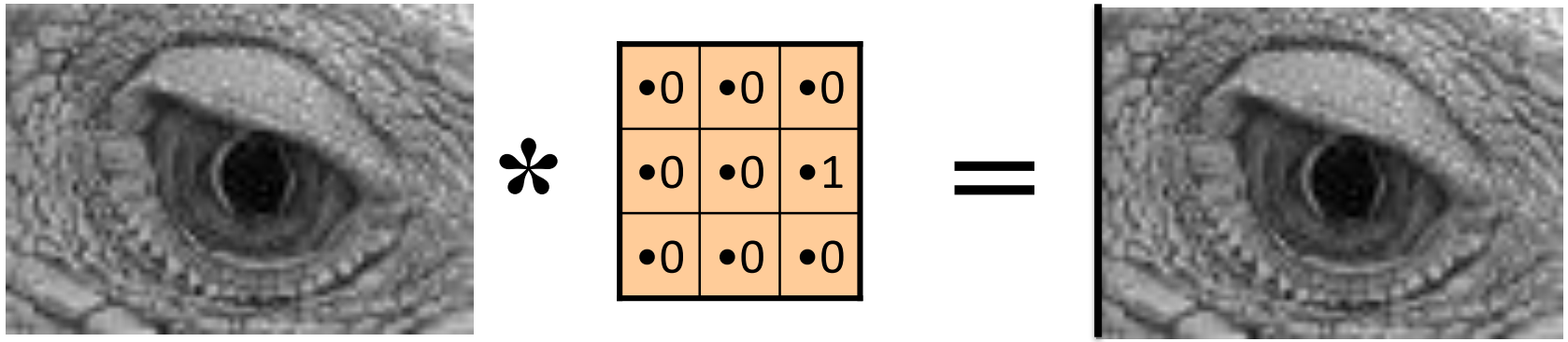
Filtered
(no change)

Convolution in 2D - examples

Original

$$*\begin{bmatrix} \bullet 0 & \bullet 0 & \bullet 0 \\ \bullet 0 & \bullet 0 & \bullet 1 \\ \bullet 0 & \bullet 0 & \bullet 0 \end{bmatrix} = ?$$

Convolution in 2D - examples



Original

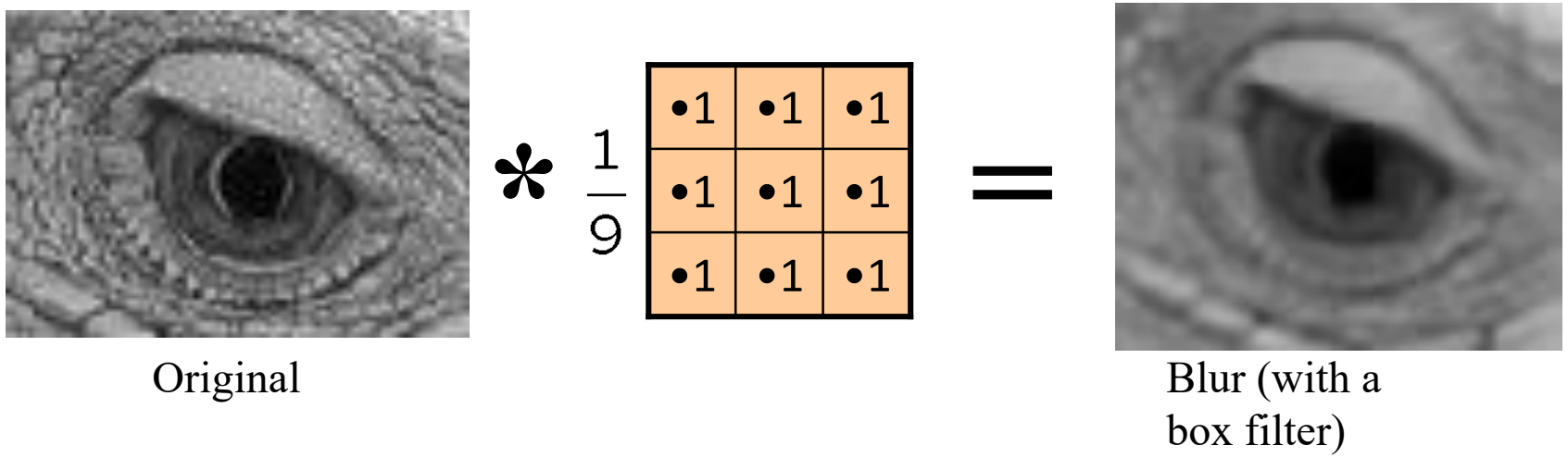
Shifted right
By 1 pixel

Convolution in 2D - examples

Original

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

Convolution in 2D - examples



Original

Blur (with a box filter)

Convolution in 2D - examples

Original

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

(Note that filter sums to 1)

"details of the image"

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

What does blurring take away?

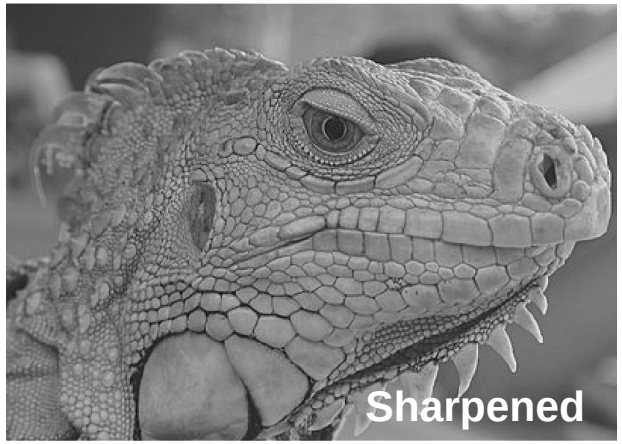
–

=

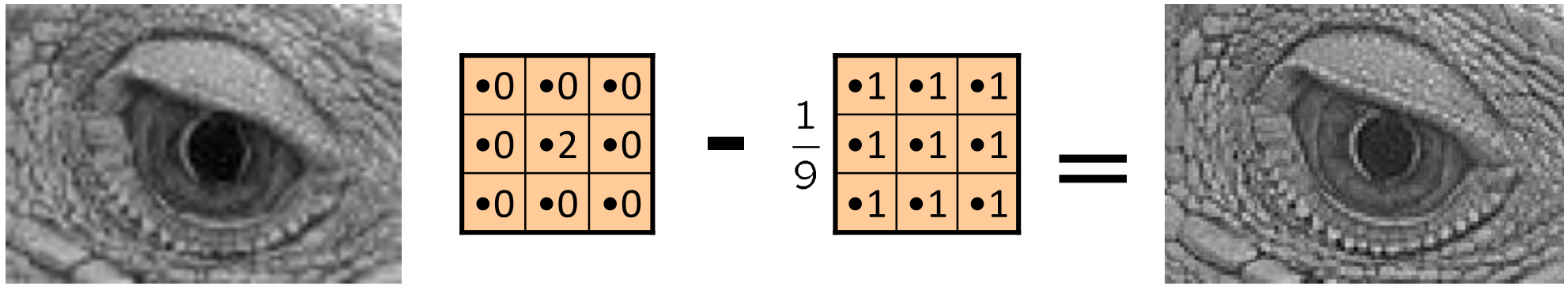
- Let's add it back:

+

=



Convolution in 2D – Sharpening filter

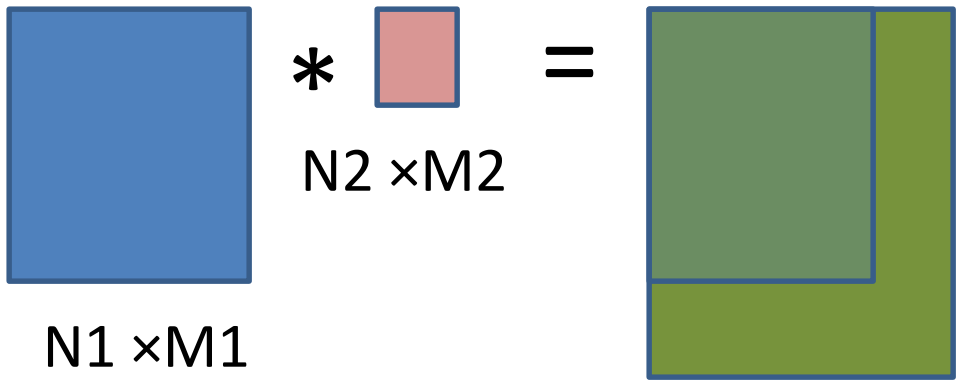


Original

Sharpening filter: Accentuates differences with local average

Image support and edge effect

- A computer will only convolve **finite support signals.**
  - That is: images that are zero for n,m outside some rectangular region
- numpy's convolution performs 2D DS convolution of finite-support signals.

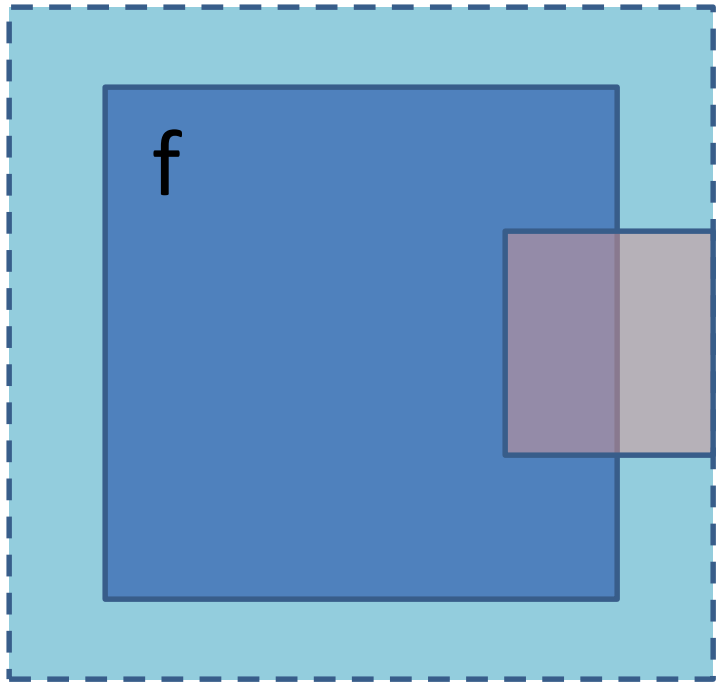


$(N1 + N2 - 1) \times (M1 + M2 - 1)$

Image support and edge effect

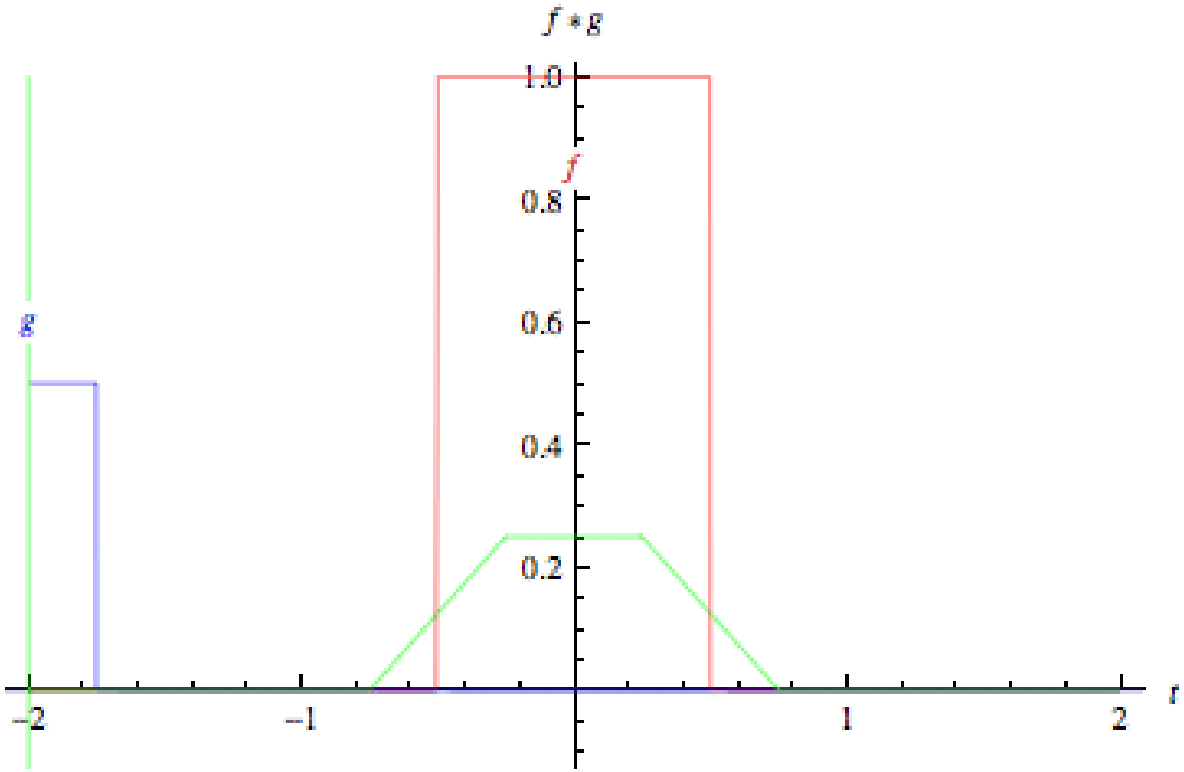
•A computer will only convolve **finite support signals.**

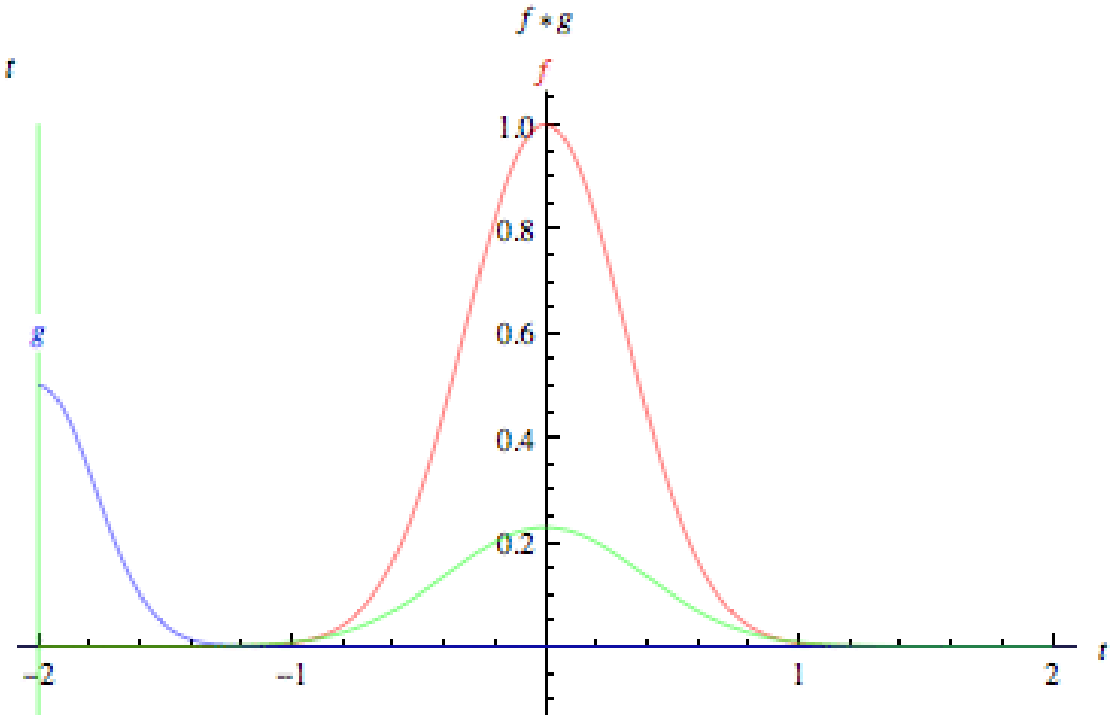
• What happens at the edge?



h

- zero “padding”
- edge value replication
- mirror extension
- more (beyond the scope of this class)





Slide credit: Wolfram Alpha

What we will learn today?

- Image sampling and quantization
- Image histograms
- Images as functions
- Linear systems (filters)
- Convolution and correlation

Some background reading:
Forsyth and Ponce, Computer Vision, Chapter 7

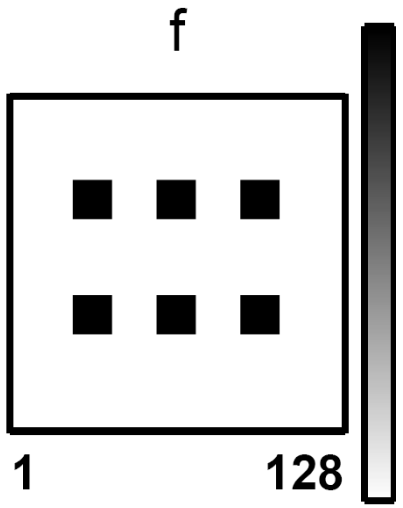
(Cross) correlation (symbol: $**$)

Cross correlation of two 2D signals f[n,m] and h[n,m]:

$$f[n,m] ** h[n,m] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[n,m] \times h[n+k, m+l]$$

Equivalent to a convolution without the flip

(Cross) correlation – example

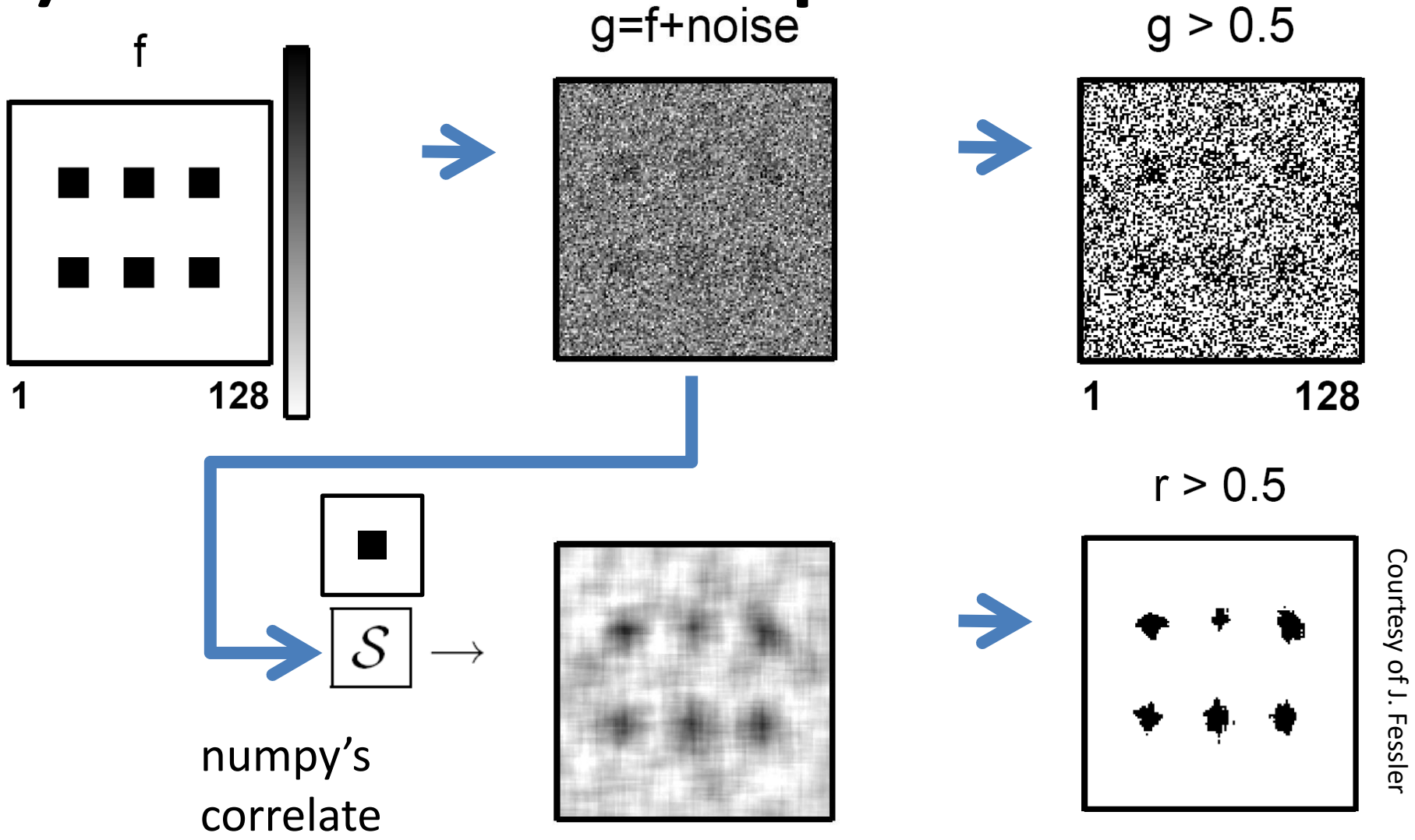


Courtesy of J. Fessler

(Cross) correlation – example

Courtesy of J. Fessler

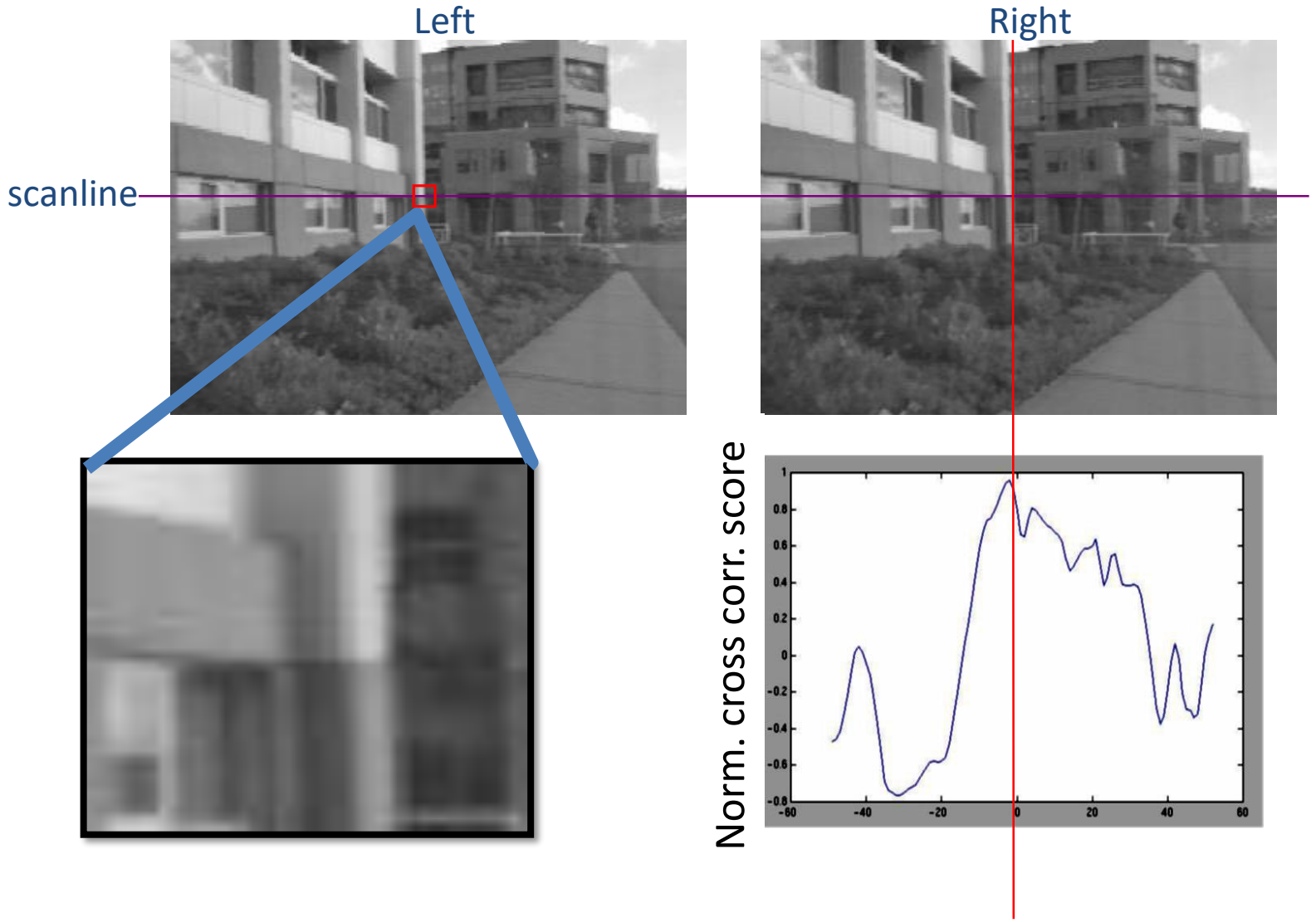
(Cross) correlation – example

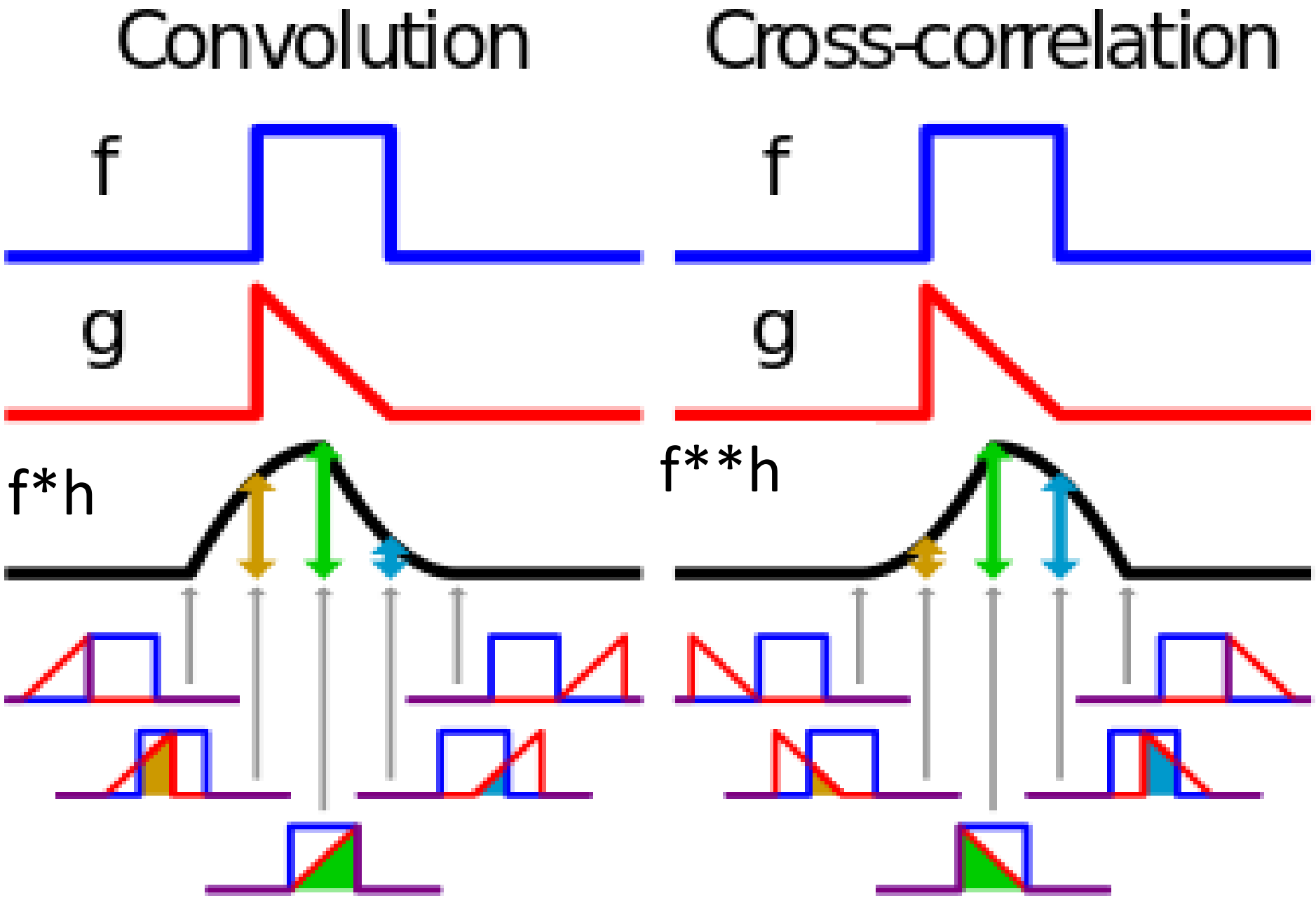


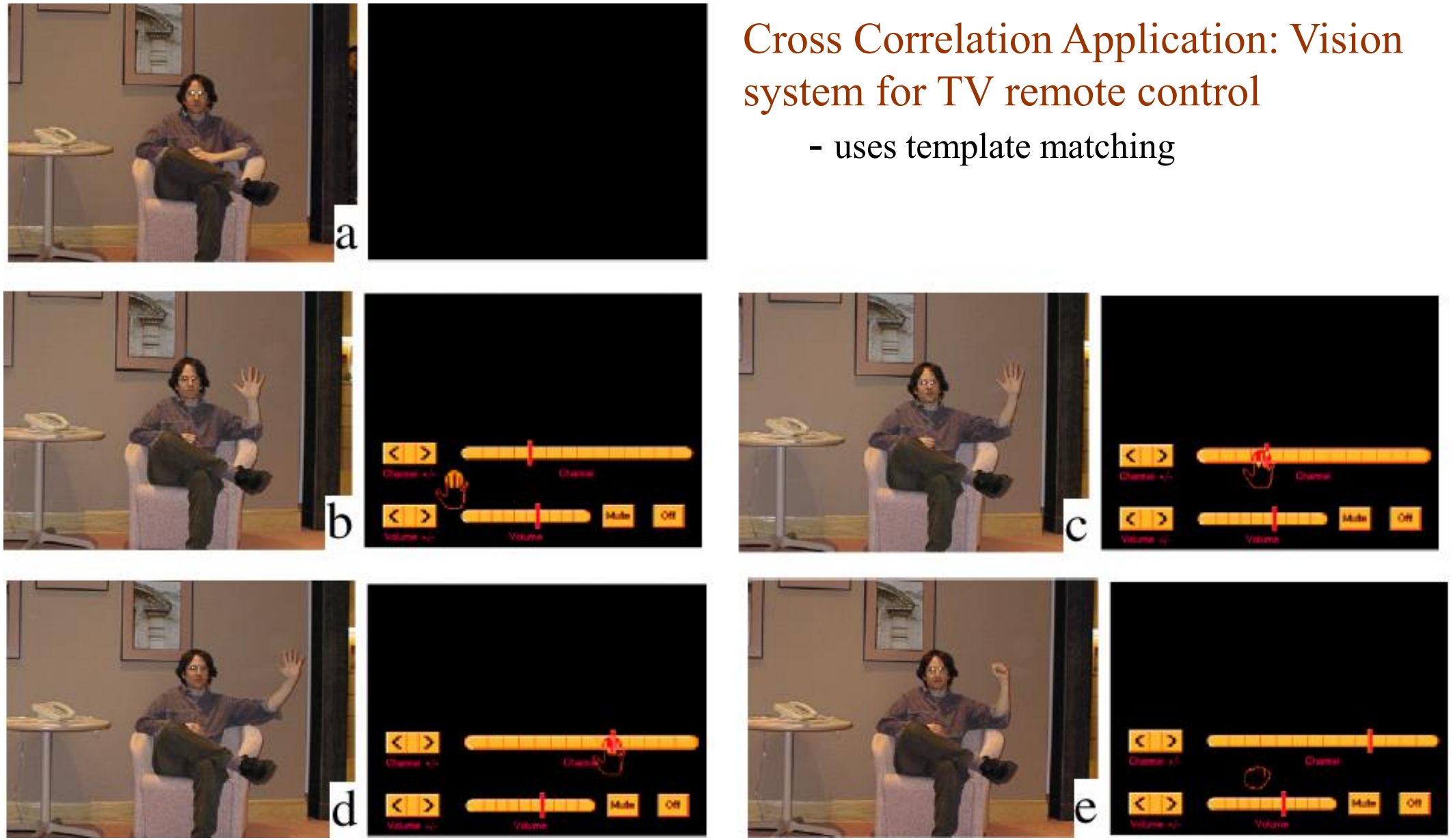
Courtesy of J. Fessler

Courtesy of J. Fessler

(Cross) correlation – example




Convolution
Cross-correlation
f
g
f*h
f
g
f**h



Cross Correlation Application: Vision system for TV remote control

- uses template matching

Figure from "Computer Vision for Interactive Computer Graphics," W.Freeman et al, IEEE Computer Graphics and Applications, 1998 copyright 1998, IEEE

Properties

- Commutative property:

$$f ** h = h ** f$$

- Associative property:

$$(f ** h_1) ** h_2 = f ** (h_1 ** h_2)$$

- Distributive property:

$$f ** (h_1 + h_2) = (f ** h_1) + (f ** h_2)$$

The order doesn't matter! $h_1 ** h_2 = h_2 ** h_1$

Properties

- Shift property:

$$f[n,m] ** \delta_2[n-n_0, m-m_0] = f[n-n_0, m-m_0]$$

- Shift-invariance:

$$\begin{aligned} g[n,m] &= f[n,m] ** h[n,m] \\ &\Longrightarrow f[n-l_1, m-l_1] ** h[n-l_2, m-l_2] \\ &= g[n-l_1-l_2, m-l_1-l_2] \end{aligned}$$

Convolution vs. (Cross) Correlation

- A **convolution** is an integral that expresses the amount of overlap of one function as it is shifted over another function.
  - convolution is a filtering operation

- **Correlation** compares the ***similarity*** *of* ***two*** *sets of* ***data.*** Correlation computes a measure of similarity of two input signals as they are shifted by one another. The correlation result reaches a maximum at the time when the two signals match best .
  - correlation is a measure of relatedness of two signals

What we have learned today?

- Image sampling and quantization
- Image histograms
- Images as functions
- Linear systems (filters)
- Convolution and correlation