

# Image filtering

Olac Fuentes

Computer Science Department  
University of Texas at El Paso

# Image filtering

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

10	5	3
4	5	1
1	1	7

Local image data

Some function



	7	

Modified image data

# Image filtering

Why?

- Reduce noise
- Make important information more salient
- Find simple patterns

# Cross-correlation

Let  $F$  be the image,  $H$  be the kernel (of size  $2k+1 \times 2k+1$ ), and  $G$  be the output image

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

This is called a **cross-correlation** operation:

$$G = H \otimes F$$

# Convolution

- Same as cross-correlation, except that the kernel is “flipped” (horizontally and vertically)

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

This is called a **convolution** operation:

$$G = H * F$$

- Convolution is **commutative** and **associative**

# Cross-correlation

```
def correlate2d(image, filt):  
    # For convolution, we would need to do filt = filt[::-1,::-1]  
  
    r,c = filt.shape  
  
    result = np.zeros((image.shape[0]-r + 1, image.shape[1]-c + 1))  
  
    for i in range(result.shape[0]):  
        for j in range(result.shape[1]):  
            result[i,j] = np.sum(image[i:i+r, j:j+c]*filt) # Dot product of region and filter  
  
    return result
```

# Cross-correlation

In practice, we will use the much more efficient implementation provided by Scipy

```
from scipy import signal  
image_f = signal.correlate2d(image, f, mode='valid')
```

This code will produce the same results as the one in the previous slide

By changing the mode parameter, we can obtain slightly different results

mode = 'same' returns an array of the same size as *image*. To do this it 'pads' *image* with extra rows and columns (with value 0, by default)

# Cross-correlation

## scipy.signal.correlate2d

scipy.signal.correlate2d(*in1*, *in2*, *mode*='full', *boundary*='fill', *fillvalue*=0)

[\[source\]](#)

Cross-correlate two 2-dimensional arrays.

Cross correlate *in1* and *in2* with output size determined by *mode*, and boundary conditions determined by *boundary* and *fillvalue*.

Parameters:

*in1* : *array\_like*

First input.

*in2* : *array\_like*

Second input. Should have the same number of dimensions as *in1*.

*mode* : str {'full', 'valid', 'same'}, optional

A string indicating the size of the output:

**full**

The output is the full discrete linear cross-correlation of the inputs. (Default)

**valid**

The output consists only of those elements that do not rely on the zero-padding. In 'valid' mode, either *in1* or *in2* must be at least as large as the other in every dimension.

**same**

The output is the same size as *in1*, centered with respect to the 'full' output.

# Cross-correlation

$$\begin{matrix} -1 & 1 \\ -1 & 1 \end{matrix} \otimes \begin{matrix} 3 & 4 & 5 & 6 & 0 \\ 2 & 1 & 6 & 1 & 3 \\ 5 & 4 & 5 & 4 & 5 \\ 3 & 7 & 7 & 4 & 2 \\ 6 & 4 & 8 & 6 & 3 \end{matrix} = \begin{matrix} 0 & & & \\ & & & \\ & & & \\ & & & \\ & & & \end{matrix}$$

# Cross-correlation

$$\begin{matrix} -1 & 1 \\ -1 & 1 \end{matrix} \otimes \begin{matrix} 3 & 4 & 5 & 6 & 0 \\ 2 & 1 & 6 & 1 & 3 \\ 5 & 4 & 5 & 4 & 5 \\ 3 & 7 & 7 & 4 & 2 \\ 6 & 4 & 8 & 6 & 3 \end{matrix} = \begin{matrix} 0 & 6 & & \\ & & & \\ & & & \\ & & & \end{matrix}$$

# Cross-correlation

$$\begin{matrix} -1 & 1 \\ -1 & 1 \end{matrix} \otimes \begin{matrix} 3 & 4 & 5 & 6 & 0 \\ 2 & 1 & 6 & 1 & 3 \\ 5 & 4 & 5 & 4 & 5 \\ 3 & 7 & 7 & 4 & 2 \\ 6 & 4 & 8 & 6 & 3 \end{matrix} = \begin{matrix} 0 & 6 & -4 & \\ & & & \\ & & & \\ & & & \end{matrix}$$

# Cross-correlation

$$\begin{matrix} -1 & 1 \\ -1 & 1 \end{matrix} \otimes \begin{matrix} 3 & 4 & 5 & 6 & 0 \\ 2 & 1 & 6 & 1 & 3 \\ 5 & 4 & 5 & 4 & 5 \\ 3 & 7 & 7 & 4 & 2 \\ 6 & 4 & 8 & 6 & 3 \end{matrix} = \begin{matrix} 0 & 6 & -4 & -4 \\ & & & \\ & & & \\ & & & \end{matrix}$$

# Cross-correlation

$$\begin{matrix} -1 & 1 \\ -1 & 1 \end{matrix} \otimes \begin{matrix} 3 & 4 & 5 & 6 & 0 \\ 2 & 1 & 6 & 1 & 3 \\ 5 & 4 & 5 & 4 & 5 \\ 3 & 7 & 7 & 4 & 2 \\ 6 & 4 & 8 & 6 & 3 \end{matrix} = \begin{matrix} 0 & 6 & -4 & -4 \\ -2 & & & \\ & & & \\ & & & \end{matrix}$$

# Cross-correlation

$$\begin{matrix} -1 & 1 \\ -1 & 1 \end{matrix} \otimes \begin{matrix} 3 & 4 & 5 & 6 & 0 \\ 2 & 1 & 6 & 1 & 3 \\ 5 & 4 & 5 & 4 & 5 \\ 3 & 7 & 7 & 4 & 2 \\ 6 & 4 & 8 & 6 & 3 \end{matrix} = \begin{matrix} 0 & 6 & -4 & -4 \\ -2 & 6 & & \\ & & & \\ & & & \end{matrix}$$

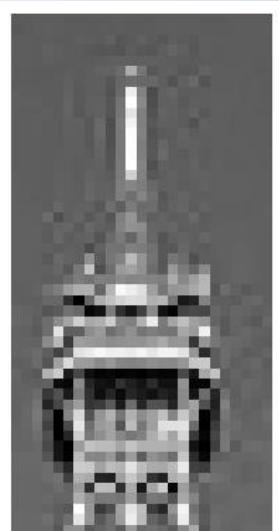
# Cross-correlation

$$\begin{array}{|c|c|} \hline -1 & 1 \\ \hline -1 & 1 \\ \hline \end{array} \otimes \begin{array}{|c|c|c|c|c|} \hline 3 & 4 & 5 & 6 & 0 \\ \hline 2 & 1 & 6 & 1 & 3 \\ \hline 5 & 4 & 5 & 4 & 5 \\ \hline 3 & 7 & 7 & 4 & 2 \\ \hline 6 & 4 & 8 & 6 & 3 \\ \hline \end{array} = \begin{array}{|c|c|c|c|} \hline 0 & 6 & -4 & -4 \\ \hline -2 & 6 & -6 & 3 \\ \hline 3 & 1 & -4 & -1 \\ \hline 2 & 4 & -5 & -5 \\ \hline \end{array}$$

# Cross-correlation



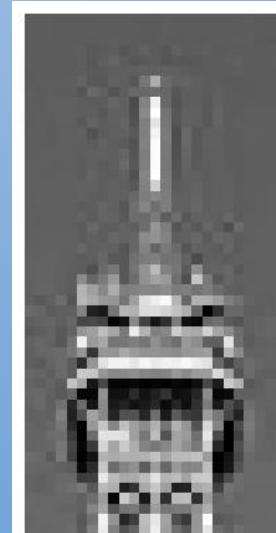
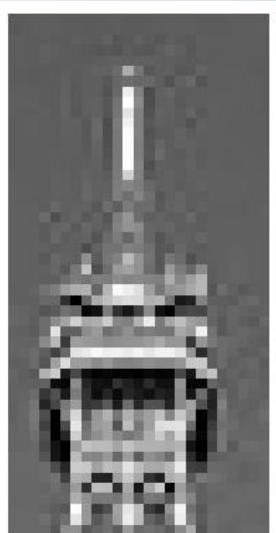
$$\otimes \begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 0 & 1 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array} =$$



# Cross-correlation



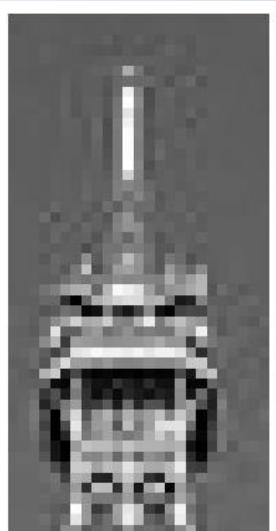
$$\begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 0 & 1 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array}$$

 $=$ 

# Cross-correlation



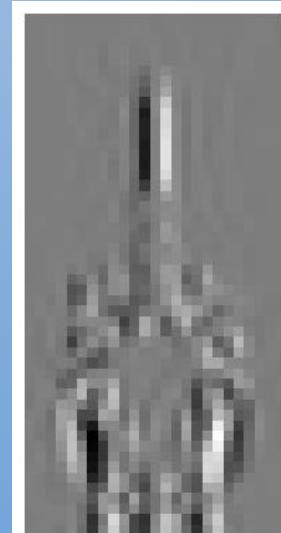
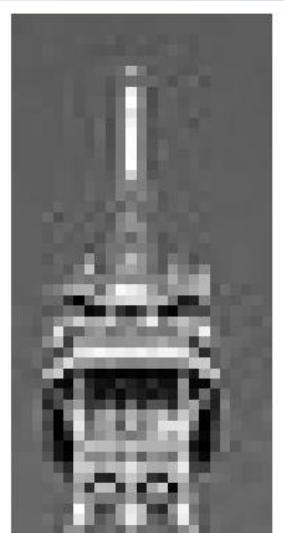
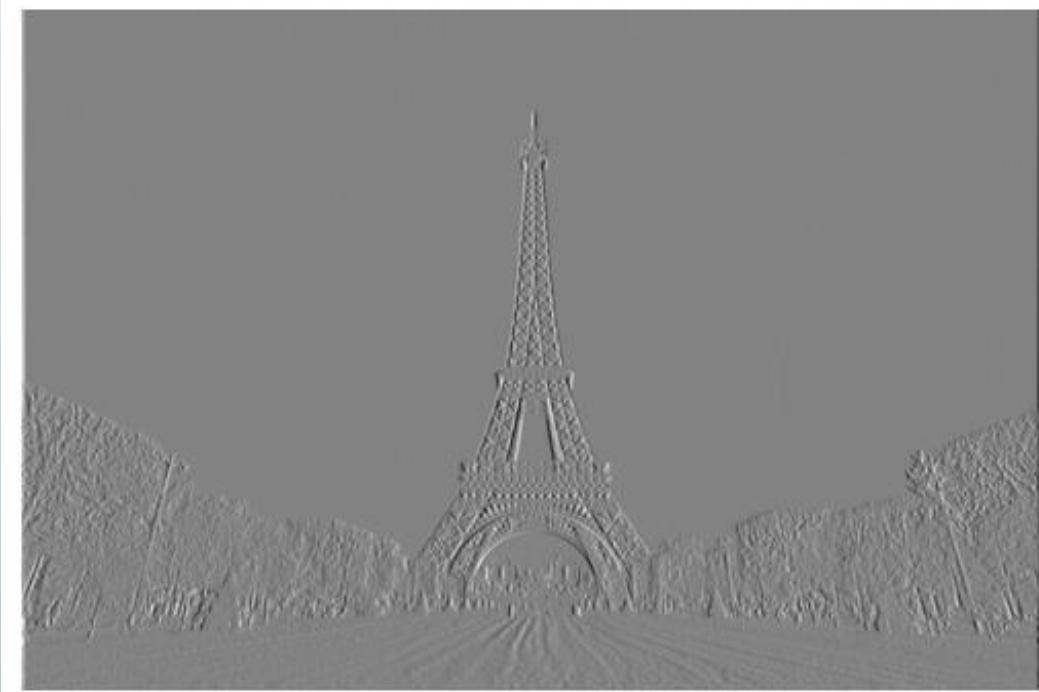
$$\otimes \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline \end{array} =$$



# Cross-correlation

 $\otimes$ 

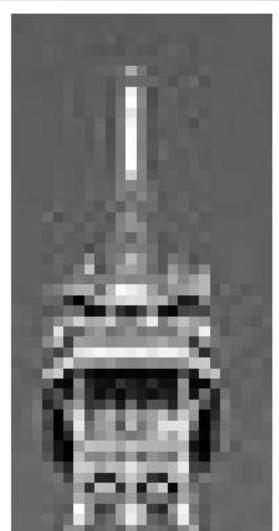
-1	0	1
-2	0	2
-1	0	1

 $=$ 

# Cross-correlation



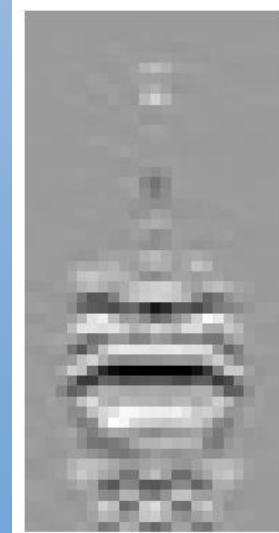
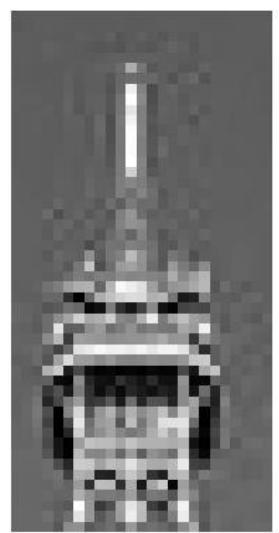
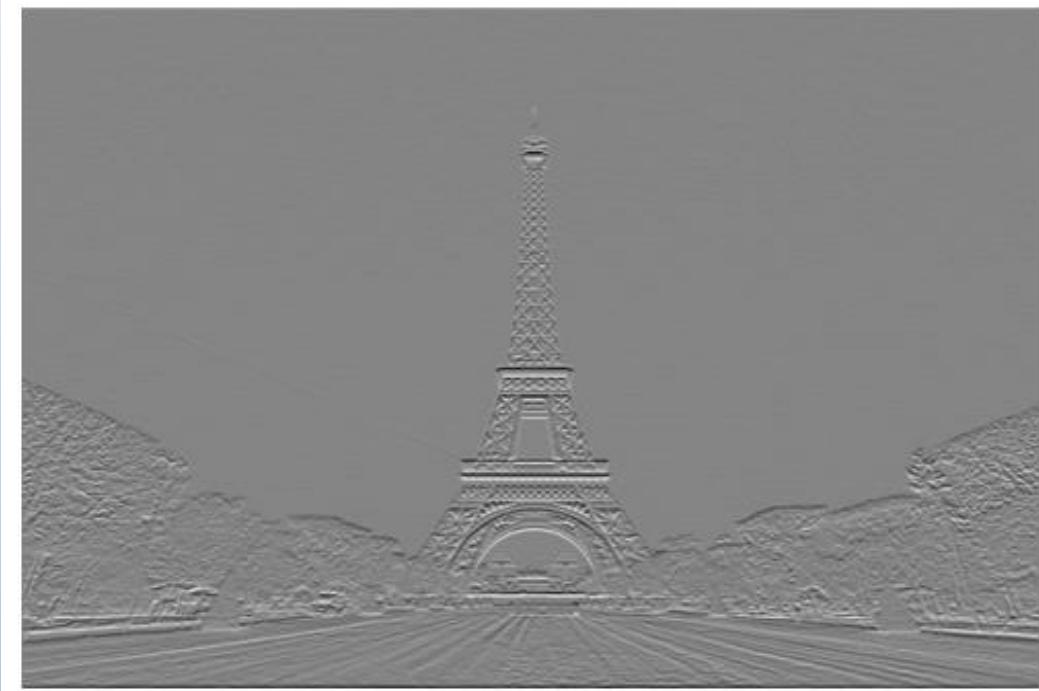
$$\otimes \quad \begin{array}{|c|c|c|} \hline -1 & -2 & -1 \\ \hline 0 & 0 & 0 \\ \hline 1 & 2 & 1 \\ \hline \end{array} =$$



# Cross-correlation

 $\otimes$ 

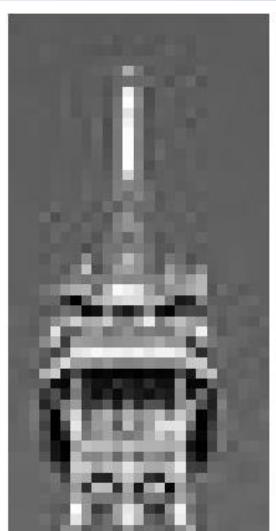
$$\begin{array}{|c|c|c|} \hline -1 & -2 & -1 \\ \hline 0 & 0 & 0 \\ \hline 1 & 2 & 1 \\ \hline \end{array}$$

 $=$ 

# Cross-correlation



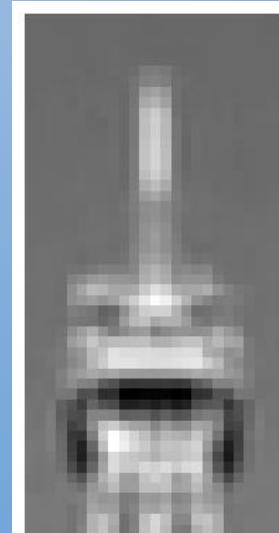
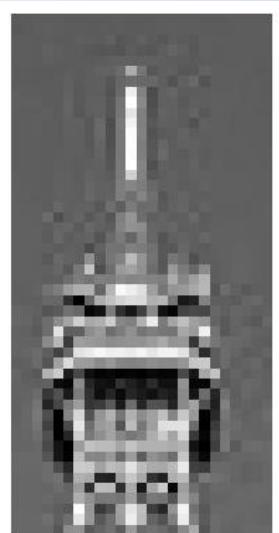
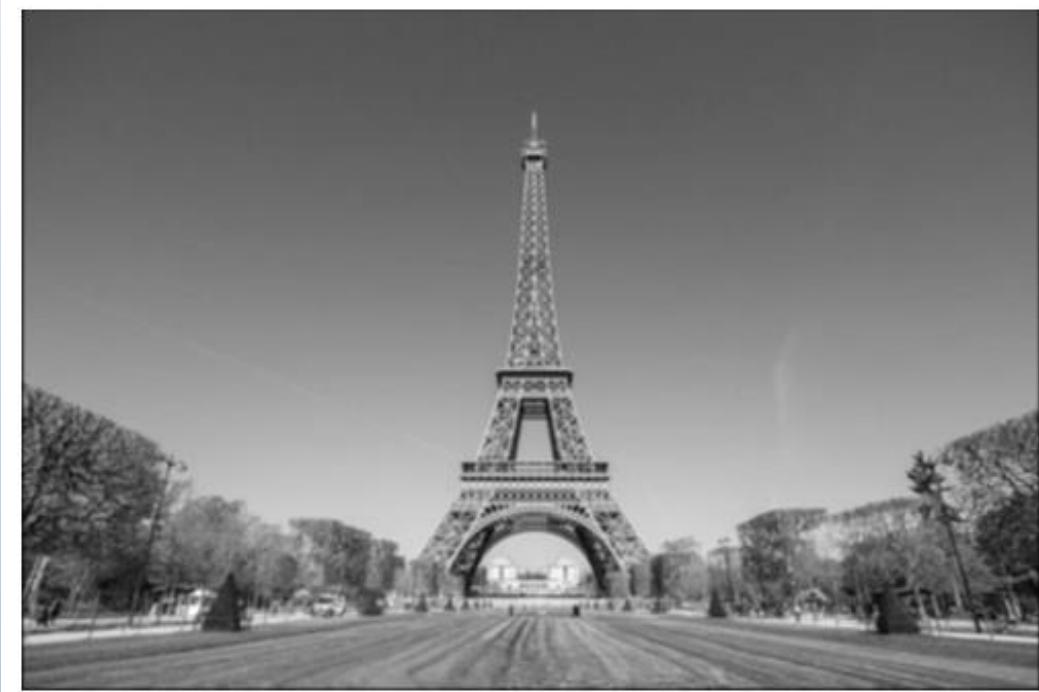
$$\otimes \begin{array}{|c|c|c|} \hline 1/9 & 1/9 & 1/9 \\ \hline 1/9 & 1/9 & 1/9 \\ \hline 1/9 & 1/9 & 1/9 \\ \hline \end{array} =$$



# Cross-correlation



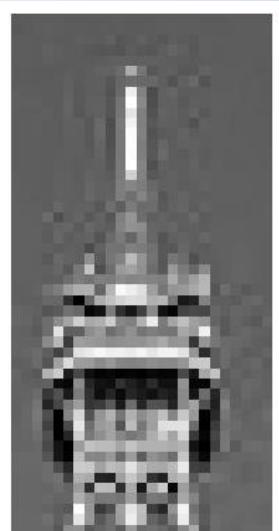
$$\begin{matrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{matrix}$$

 $=$ 

# Cross-correlation



$$\otimes \begin{array}{|c|c|c|} \hline -1/9 & -1/9 & -1/9 \\ \hline -1/9 & 17/9 & -1/9 \\ \hline -1/9 & -1/9 & -1/9 \\ \hline \end{array} =$$

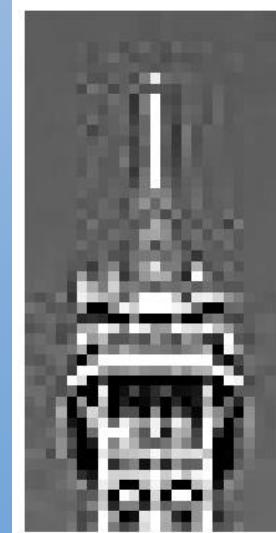
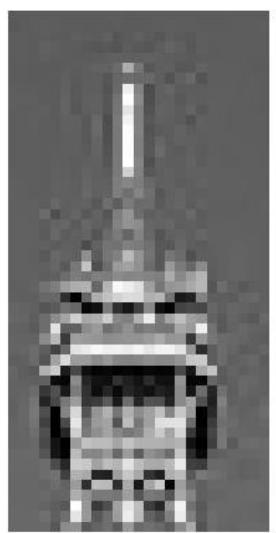


# Cross-correlation



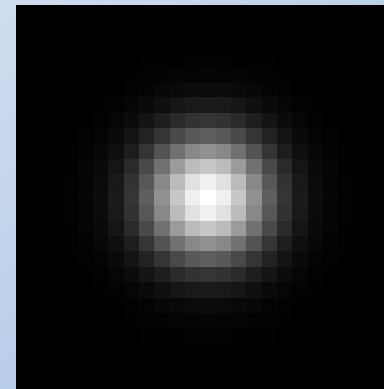
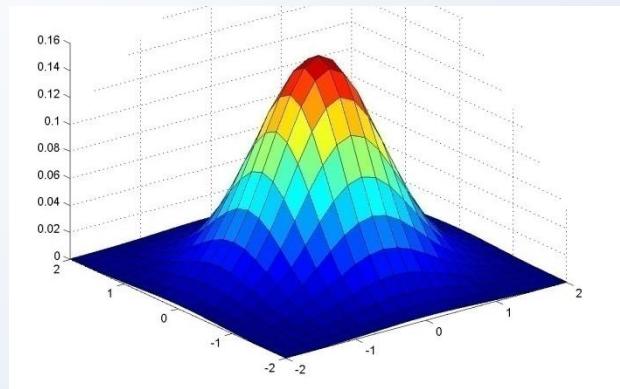
$$\begin{matrix} -1/9 & -1/9 & -1/9 \\ -1/9 & 17/9 & -1/9 \\ -1/9 & -1/9 & -1/9 \end{matrix}$$

=



# Gaussian Filters

Gaussian filters simulate natural blur in images



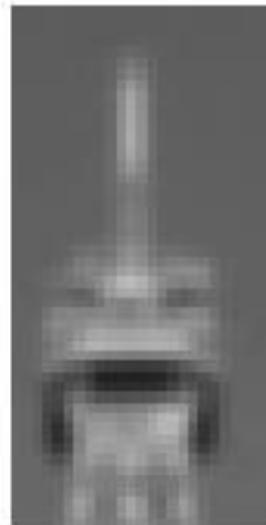
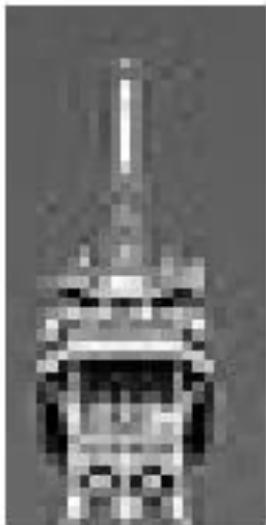
$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

# Cross-correlation

$\text{sigma} = 1e-10$

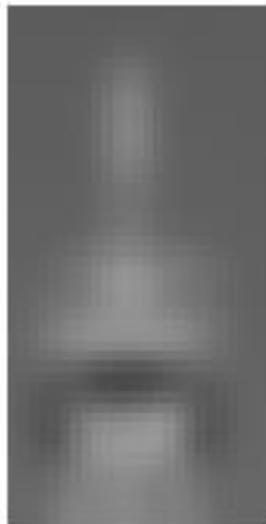


$\text{sigma} = 1$



# Cross-correlation

$\text{sigma} = 2$



$\text{sigma} = 4$



# Cross-correlation

sigma = 8



sigma = 16



# Gaussian filters for color images

We simply filter each channel separately

# Gaussian filters for color images

We simply filter each channel separately

$\sigma = 1e-10$



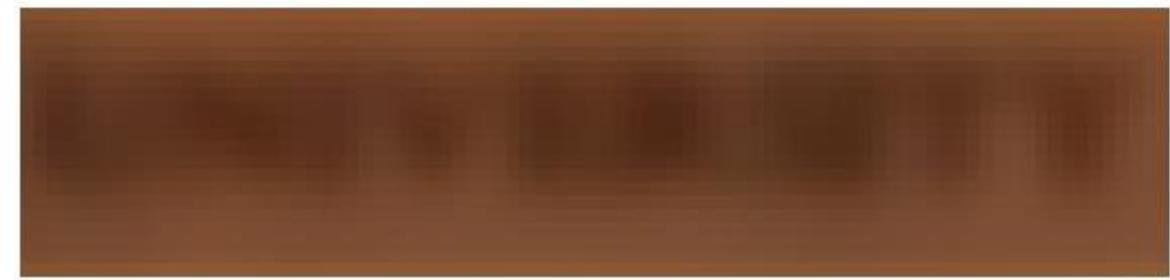
# Gaussian filters for color images

sigma = 1



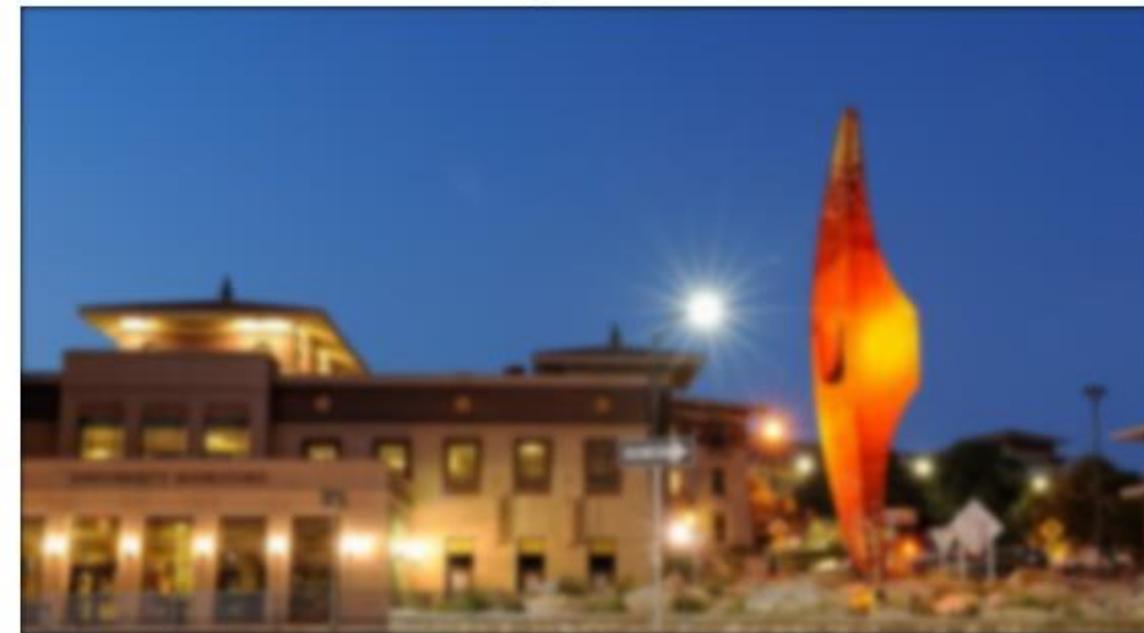
# Gaussian filters for color images

sigma = 2



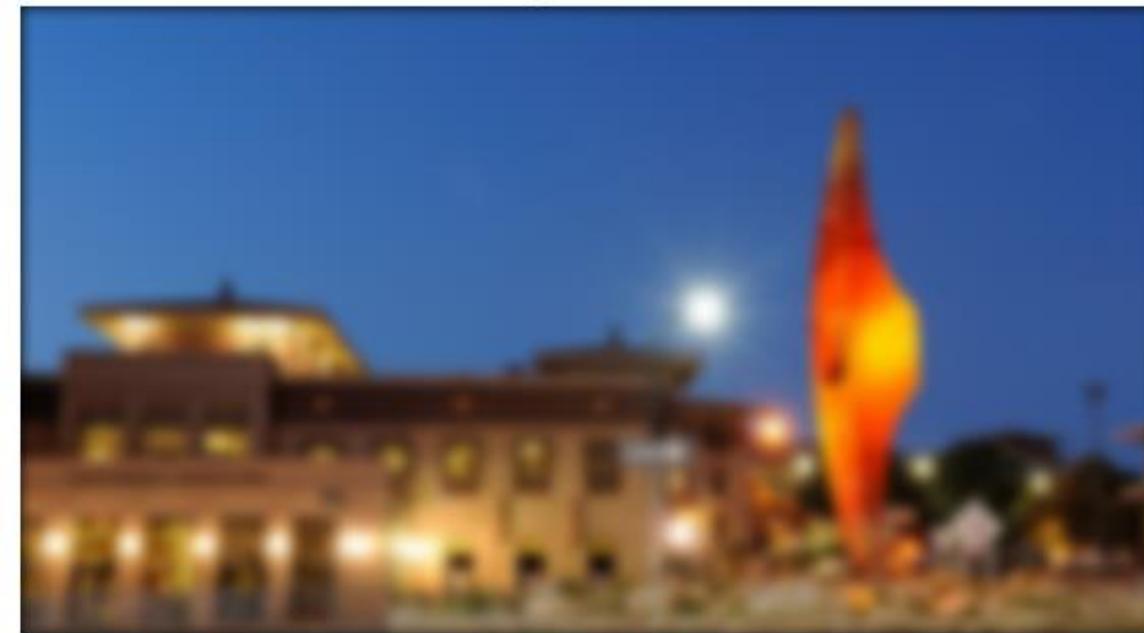
# Gaussian filters for color images

sigma = 3



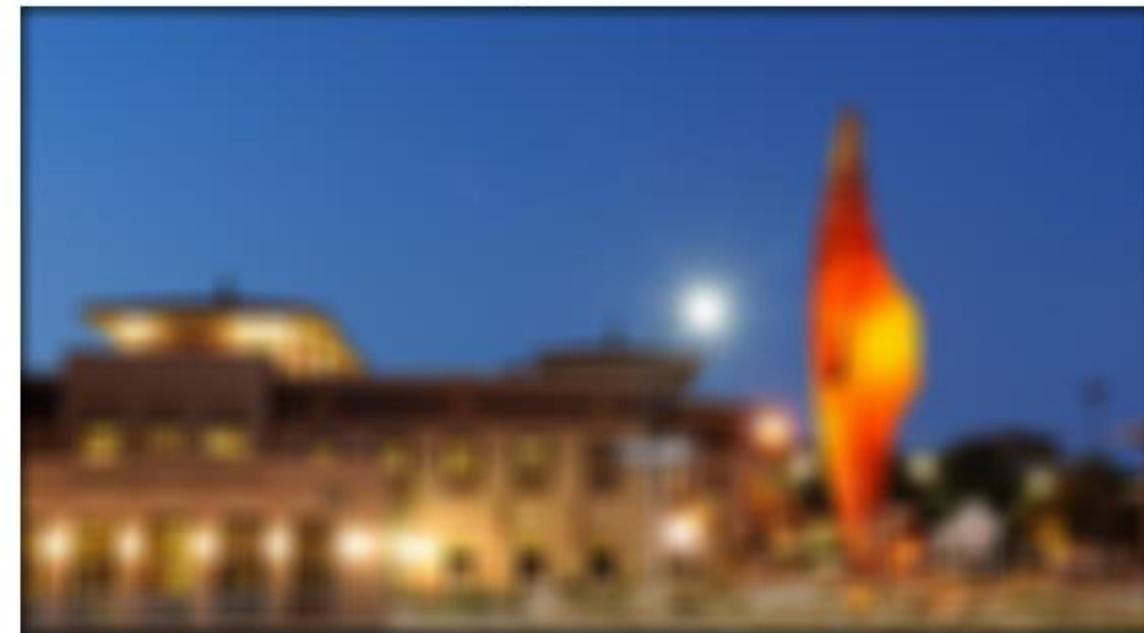
# Gaussian filters for color images

sigma = 6



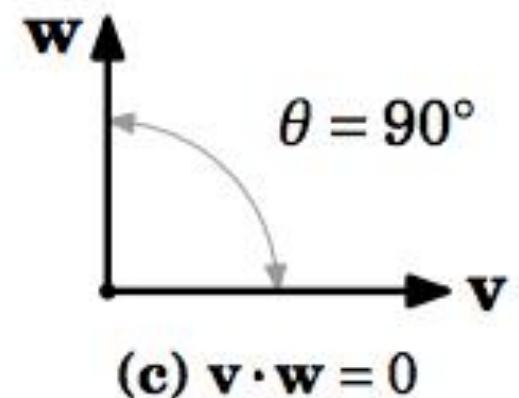
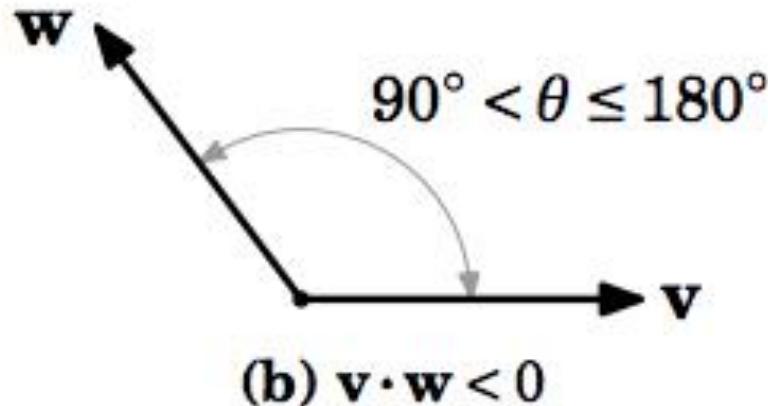
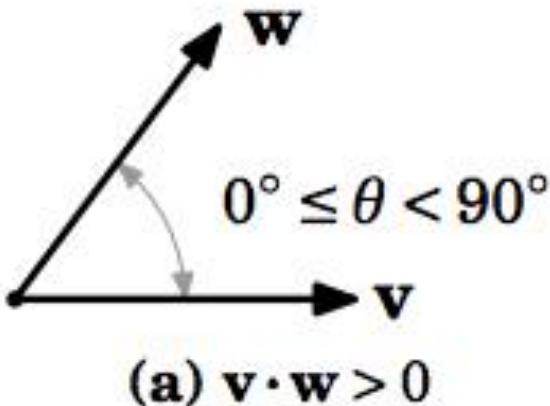
# Gaussian filters for color images

sigma = 12



# Pattern Matching

The similarity of two vectors can be measured by the angle they form:



$v$  and  $w$  are similar

$$\cos \theta > 0$$

$v$  and  $w$  are very different

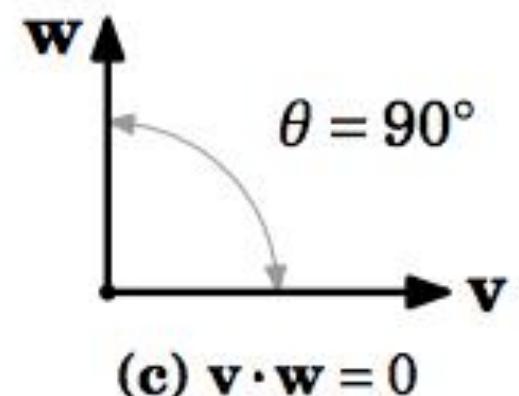
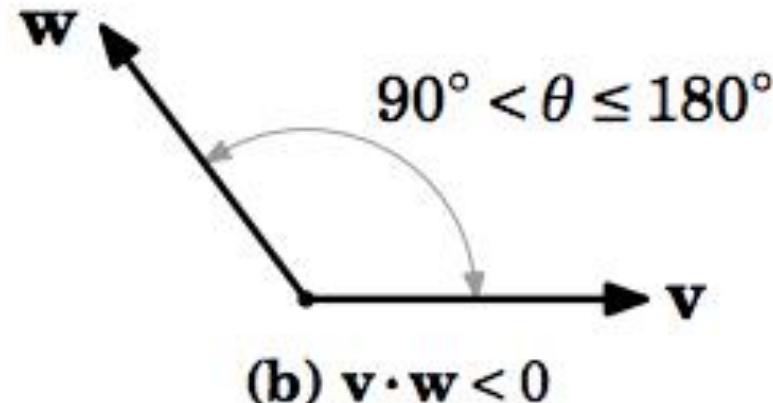
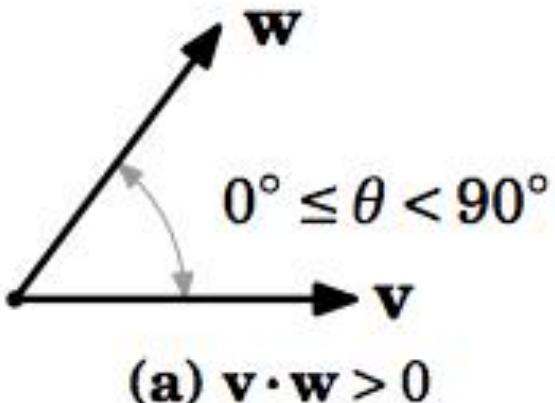
$$\cos \theta < 0$$

$v$  and  $w$  are somewhat different

$$\cos \theta = 0$$

# Pattern Matching

The similarity of two vectors can be measured by the angle they form:



$$\cos \theta = \frac{\mathbf{v} \cdot \mathbf{w}}{|\mathbf{v}| |\mathbf{w}|}$$

where:  $\mathbf{v} \cdot \mathbf{w} = \sum_{k=0}^{n-1} v_k w_k$

$$|\mathbf{v}| = \sqrt{\sum_{k=0}^{n-1} v_k^2}$$

# Pattern Matching

If we view an  $n$ -by- $n$  pattern as a vector in a space of  $n^2$  dimensions, the similarity of the pattern with every region in an image is given by the cosine of the angle that the pattern makes with every  $n$ -by- $n$  region in the image.



## Example

P:

-1	1
-1	1

(size: r-by-c)

I:

3	4	5	6	0
2	1	6	1	3
5	4	5	4	5
3	7	7	4	2
6	4	8	6	3

C:



$$\frac{[-1,1,-1,1] \cdot [3,4,2,1]}{|[-1,1,-1,1]| |[3,4,2,1]|}$$

$$\begin{aligned} C[i,j] &= \cos(P, I[i:i+r, j:j+c]) \\ &= \frac{P \cdot I[i:i+r, j:j+c]}{|P| |I[i:i+r, j:j+c]|} \end{aligned}$$

# Pattern Matching

P:

-1	1
-1	1

(size: r-by-c)

I:

3	4	5	6	0
2	1	6	1	3
5	4	5	4	5
3	7	7	4	2
6	4	8	6	3

C:


$$\begin{aligned} C[i,j] &= \cos(P, I[i:i+r, j:j+c]) \\ &= \frac{P \cdot I[i:i+r, j:j+c]}{|P| |I[i:i+r, j:j+c]|} \end{aligned}$$

$$C = P' \otimes I_{\text{mag}}$$

where  $I_{\text{mag}}[i,j] = |I[i:i+r, j:j+c]|$

$$\text{and } P' = \frac{P}{|P|}$$

# Pattern Matching

P:

-1	1
-1	1

(size: r-by-c)

I:

3	4	5	6	0
2	1	6	1	3
5	4	5	4	5
3	7	7	4	2
6	4	8	6	3

C:


$$C[i,j] = \cos(P, I[i:i+r, j:j+c])$$

$$= P \cdot I[i:i+r, j:j+c]$$

---


$$\frac{|P| |I[i:i+r, j:j+c]|}{|P| |I[i:i+r, j:j+c]|}$$

$$|P| = \sqrt{((-1)^2 + (1)^2 + (-1)^2 + (1)^2)} = \sqrt{4} = 2$$

$$P' = \begin{matrix} -0.5 & 0.5 \\ -0.5 & 0.5 \end{matrix}$$

$$I_{mag} = \begin{matrix} 5.48 & 8.83 & 9.9 & 6.78 \\ 6.78 & 8.83 & 8.83 & 7.14 \\ 9.95 & 11.79 & 10.3 & 7.81 \\ 10.49 & 13.34 & 12.85 & 8.06 \end{matrix}$$

$$P' \otimes I =$$

$$\begin{matrix} 0 & 3 & -2 & -2 \\ -1 & 3 & -3 & 1.5 \\ 1.5 & 0.5 & -2 & -0.5 \\ 1 & 2 & -2.5 & -2.5 \end{matrix}$$

$$C = \begin{matrix} 0.00 & 0.34 & -0.20 & -0.30 \\ -0.15 & 0.34 & -0.34 & 0.21 \\ 0.15 & 0.04 & -0.19 & -0.06 \\ 0.10 & 0.15 & -0.20 & -0.31 \end{matrix}$$

# Pattern Matching

P

I

C

