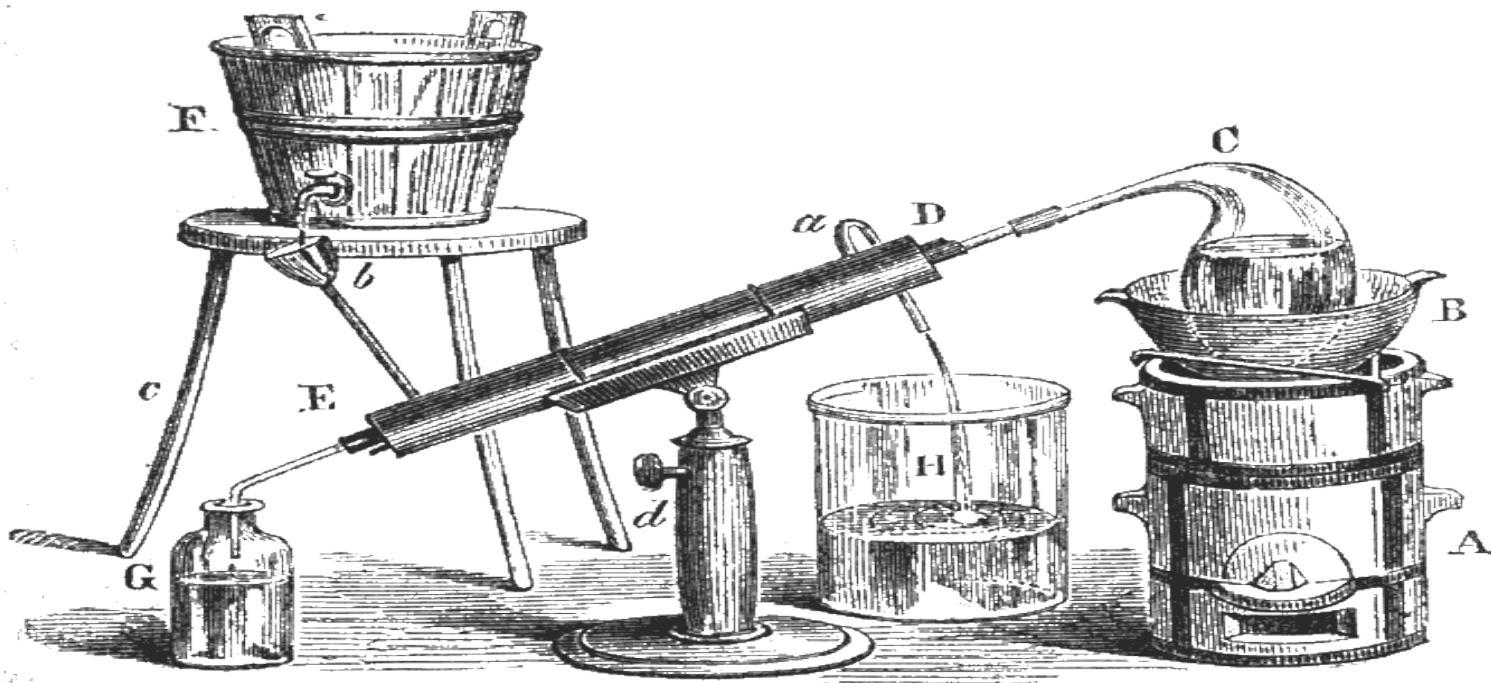


# Filtering

## Back to Basics



<http://nodewebstore.blogspot.com/>

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2015



# Previously

- Image Filtering
  - Examples
    - Low Pass
    - High Pass
    - Directional
    - Global
      - Normalization and Histogram Equalization
  - Relation to Image Enhancement
    - Spatial Domain
      - not so much the frequency domain

# Outline

- Filters and Convolutions
  - General Definitions
    - Working around the Edges
  - Low Pass Examples
  - High Pass Examples

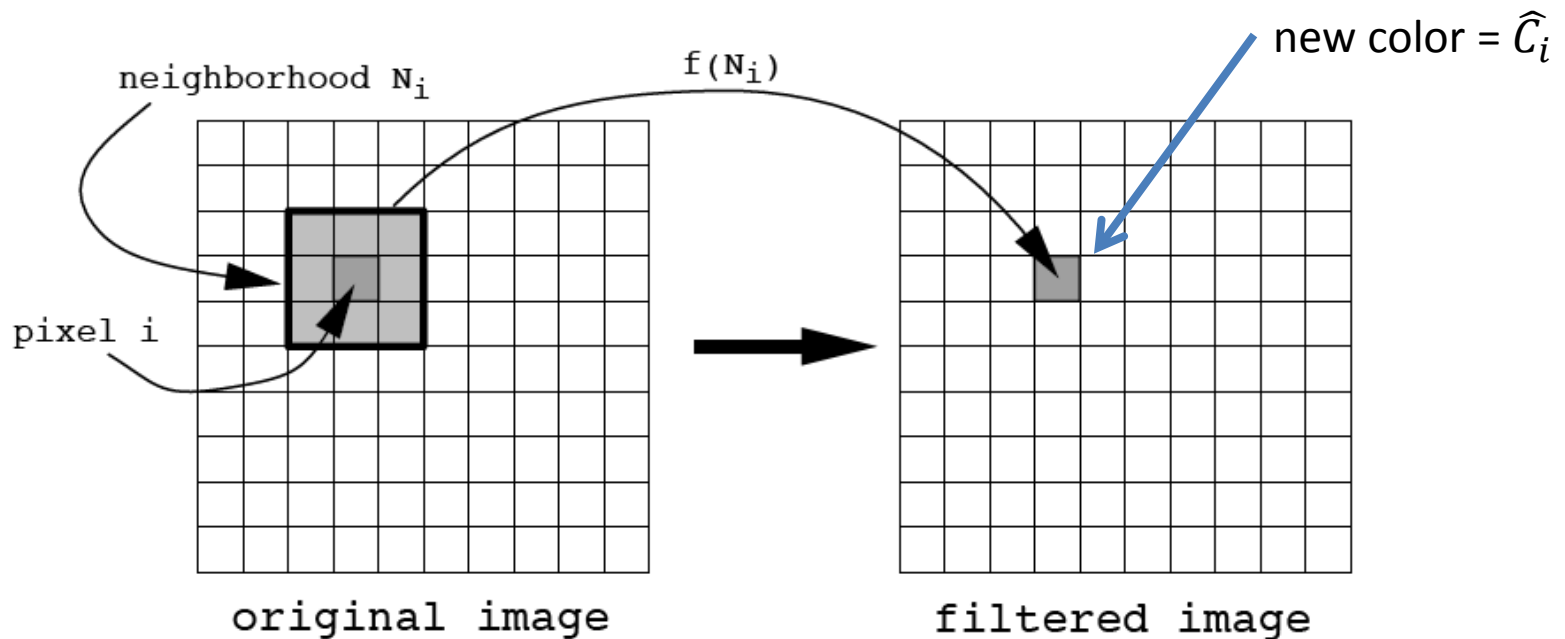
# Filtering

- Filtering
  - modify an image based on image color content without any intentional change in image geometry
    - resulting image essentially has the same size and shape as the original

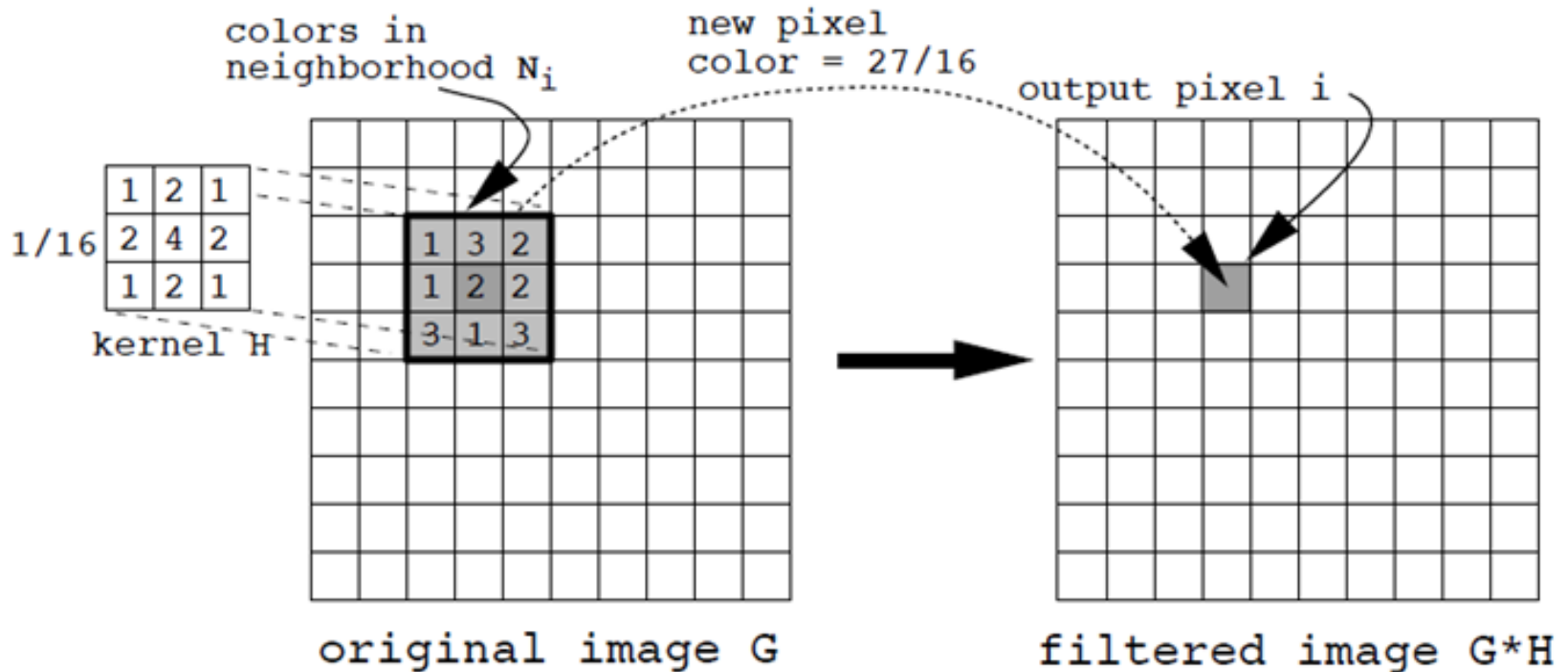
# Image Filtering Operation

- Image Filtering Operation
  - Let  $P_i$  be the single **input pixel** with index  $i$  and color  $C_i$ .
  - Let  $\widehat{P}_i$  be the corresponding **output pixel** with color  $\widehat{C}_i$ .
  - **A Filtering Operation**
    - associates each pixel,  $P_i$ , with a neighborhood set of pixels,  $N_i$ , and determines an output pixel color via a **filter function**,  $f$ , such that:

$$\widehat{C}_i = f(N_i)$$



# Convolution Filtering

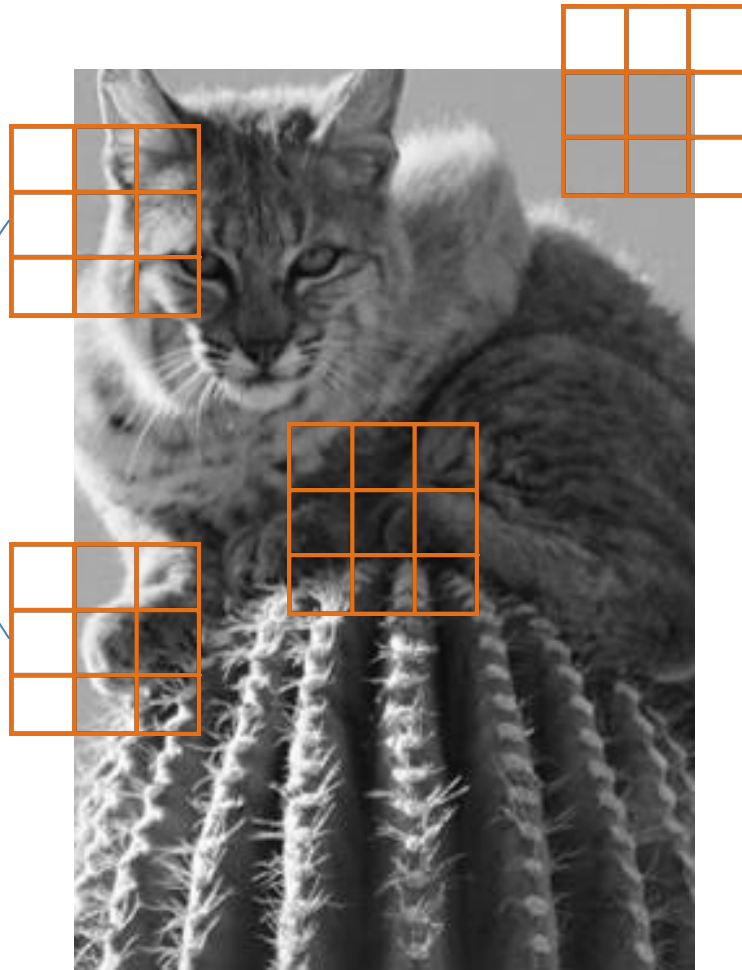


Effectively this is doing a weighted sum

$$\begin{aligned} \text{Weighted Sum} = & \left( (1*1) + (2*3) + (1*2) \right. \\ & + (2*1) + (4*2) + (2*2) \\ & \left. + (1*3) + (2*1) + (1*3) \right) * (1/16) = 27/16 \end{aligned}$$

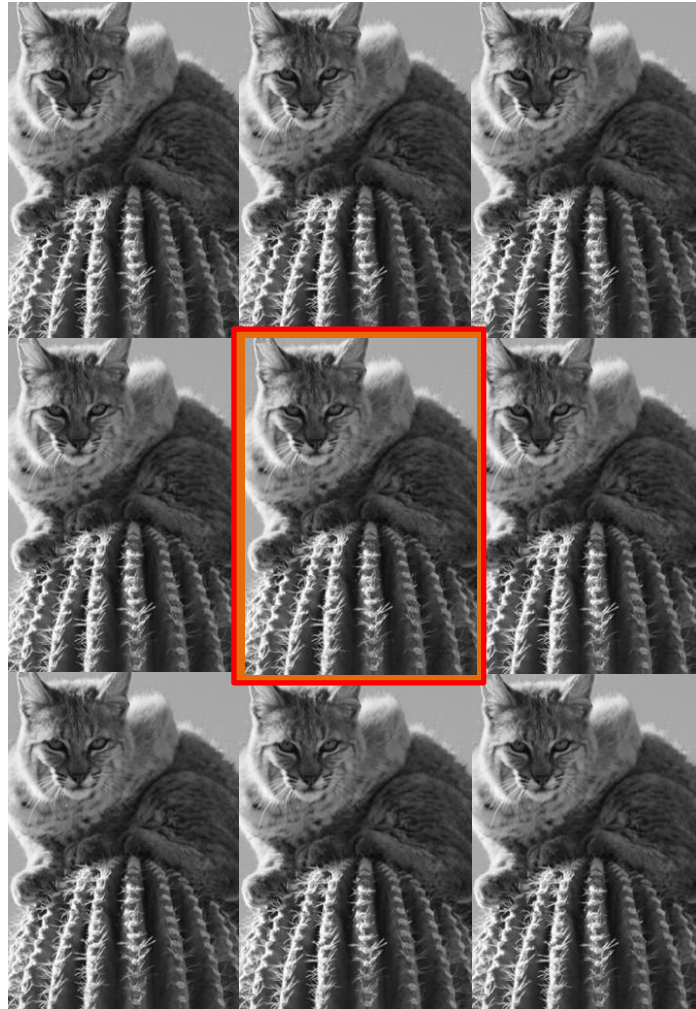
# Tricky Around the Edges

Neighborhood  
Needed  
for some pixels  
is out of the image



**Many options... let's look at a good choice**

# Expand the Input Image: Tiling



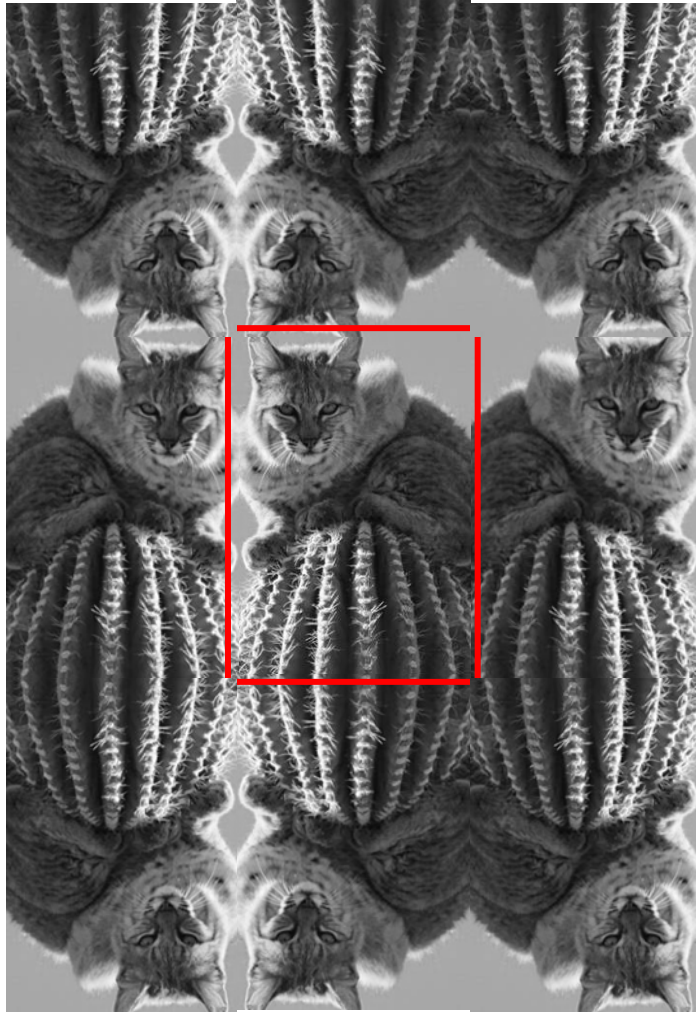
This orientation may have problems

Do the pixels at the edges  
“match” from one side to the other?

→ NO



# Expand the Input Image: Tiling



Flipping/Reflecting the image  
Then Tiling

Usually works  
and  
Is a GOOD Strategy

# Convolution in 1D

output image

$$\hat{G}[i] = (G * H)[i] = \sum_{j=i-n}^{i+n} G[j]H[i-j], \quad i \in [0, N-1]$$

input image

kernel

pixel at index  $i$

pixel at index  $j$

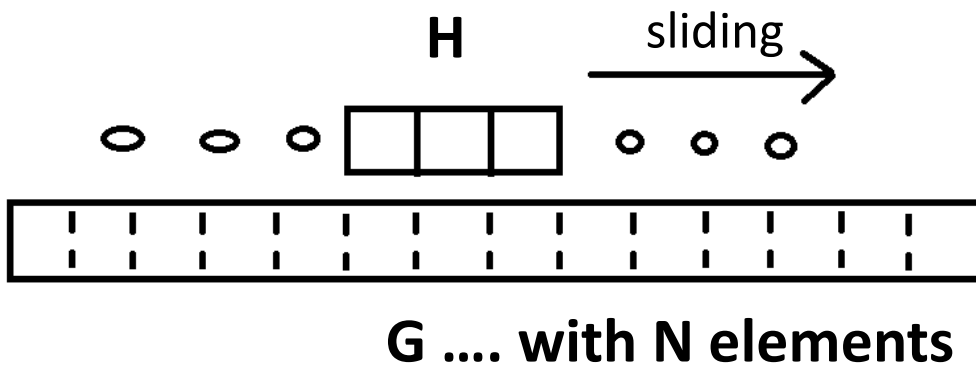
Weighted Sum

# Convolution in 1D

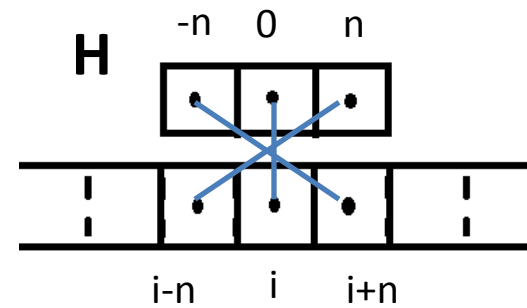
$$\hat{G}[i] = (G * H)[i] = \sum_{j=i-n}^{i+n} G[j]H[i-j], \quad i \in [0, N-1]$$

set  $j$  from  $(i-n)$  to  $(i+n)$   
 $H$  from  $n$  to  $-n$

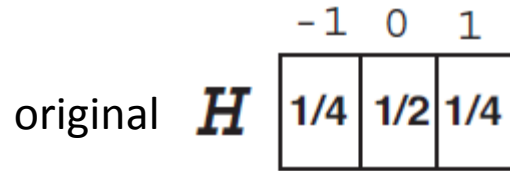
reflected or flipped



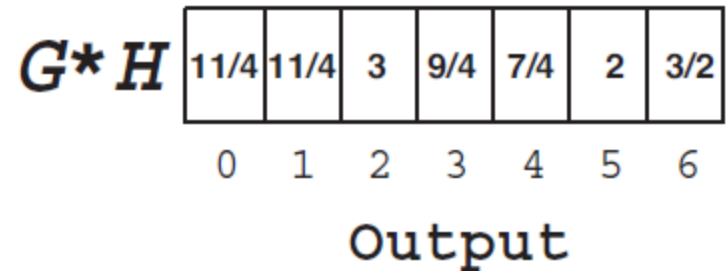
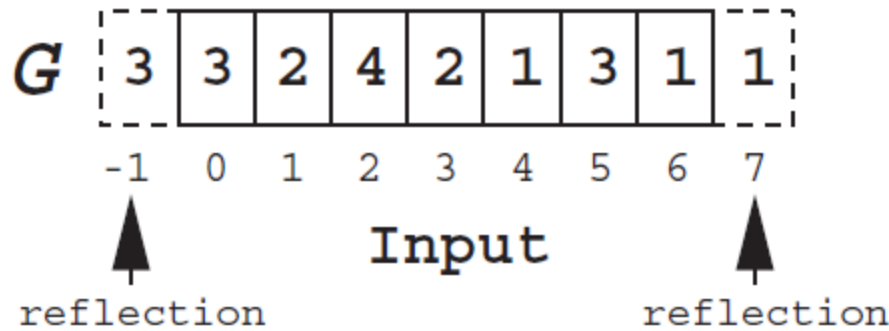
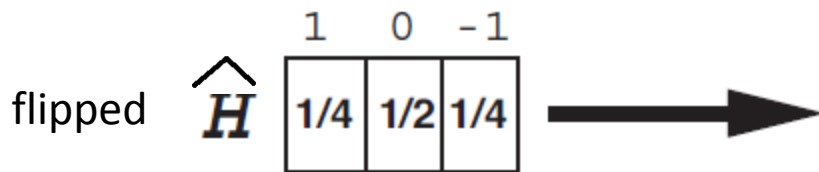
As drawn kernel  $H$  has a width,  $w = 3$  so  $n = 1$



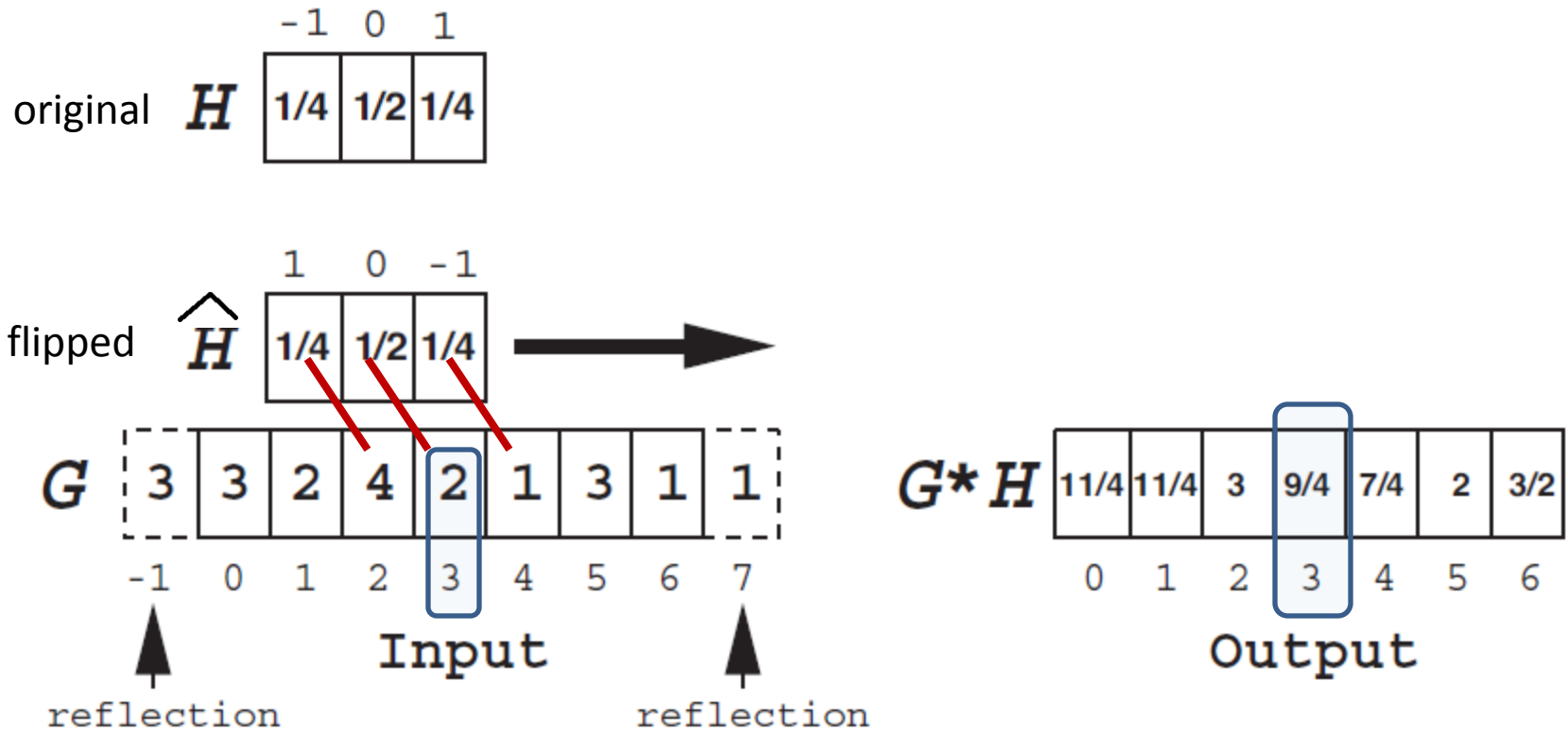
# 1D Example: Convolution $G * H$



width of  $H = 3$ , so  $n = 1$   
and  $N$  here is 7 pixels, indexed 0 to 6



# 1D Example: Convolution $G * H$



Example for  $i = 3$

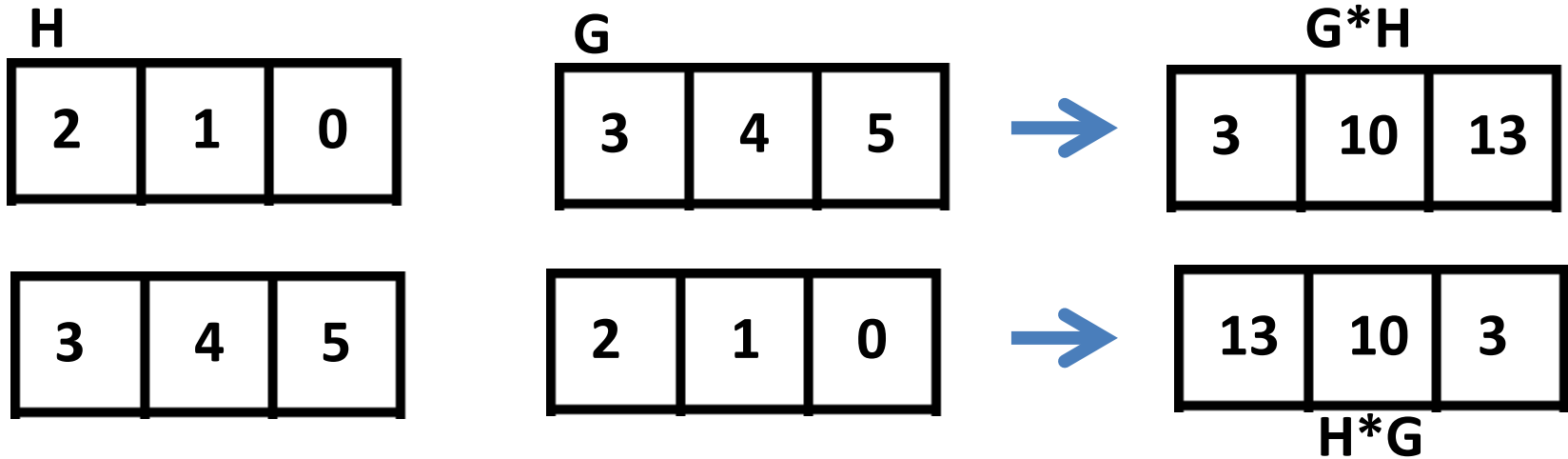
$$\sum_{j=3-1}^{3+1} G(j)H(3-j) = G(2)H(1) + G(3)H(0) + G(4)H(-1)$$

$$= (4 * 1/4) + (2 * 1/2) + (1 * 1/4)$$

$$= 9/4$$

# Why Flip the Kernel?

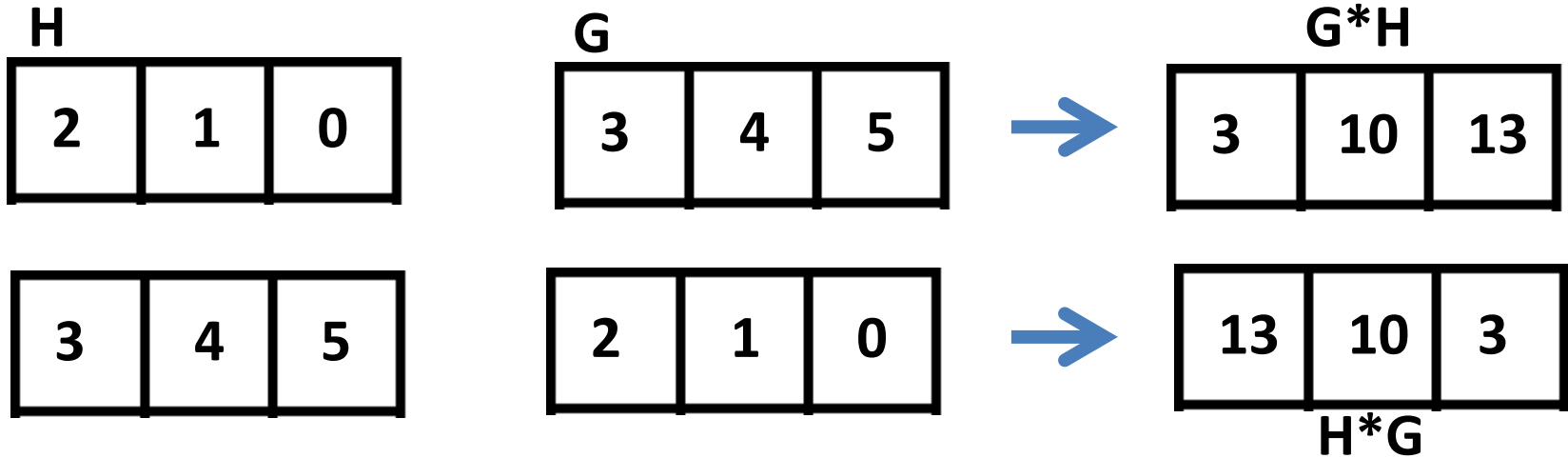
Example with **no flip**:



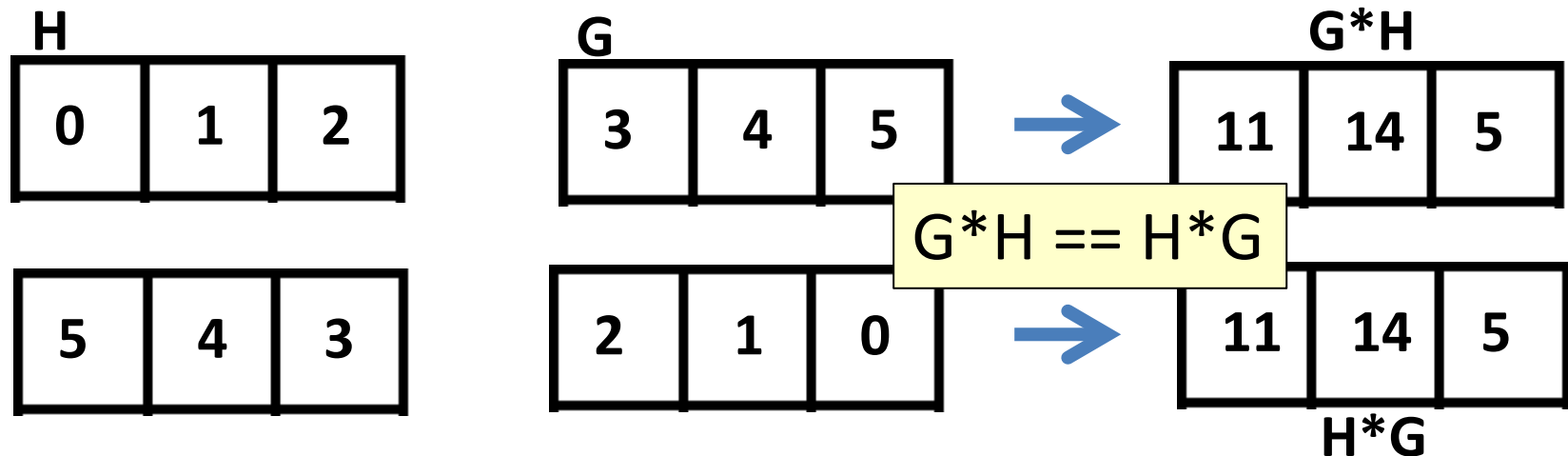
G\*H does NOT equal H\*G

# Why Flip the Kernel?

Example with **no flip**:



Example with **flipped kernel**:

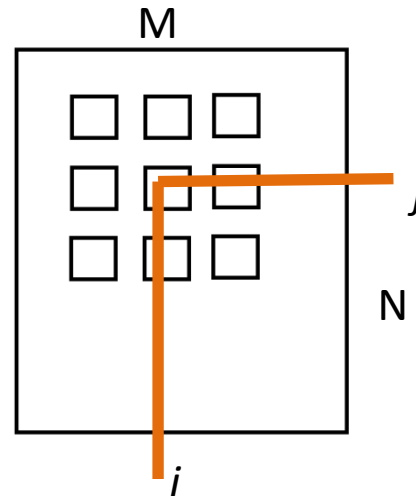
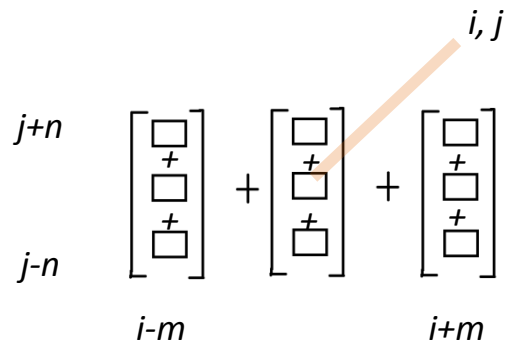


# Convolution: 1D to 2D

- Convolution extends to 2D in straightforward fashion
  - Assume kernel  $H$  is rectangular array of width,  $w=2n+1$  and height,  $h=2m+1$
  - Assume image  $G$  is of width  $M$  and height  $N$
  - Then...

$$\hat{G}[i, j] = (G * H)[i, j] = \sum_{l=i-m}^{i+m} \sum_{k=j-n}^{j+n} G[l, k] H[i-l, j-k], \quad i \in [0, M-1], \quad j \in [0, N-1]$$

$i$  is column  
 $j$  is row

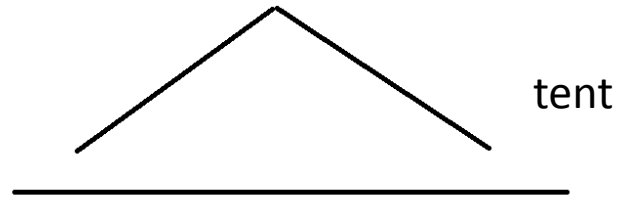
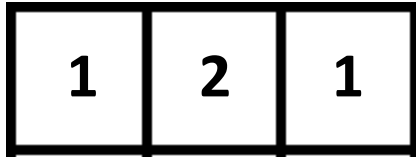


As drawn  
 $w = 3$  and  $h = 3$   
Thus  $n = 1$  and  $m = 1$



# 2D kernel from a 1D kernel

$$H_2 = H_1 H_1^t$$



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

2D kernel

that yields results  
similar to 1D kernel

# 2D Kernel Separability

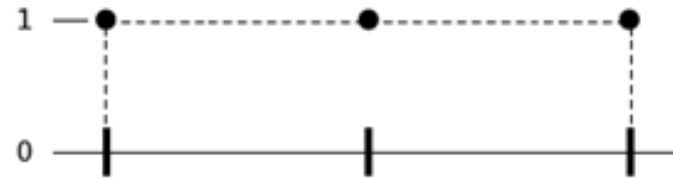
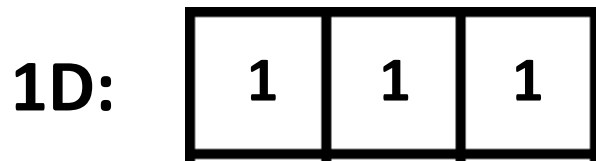
- 2D kernels can be separated
  - Apply filtering twice using the 1D filter
    - once “horizontally”
    - once “vertically”
  - Get same results as applying the 2D filter once
- Efficiency increase when  $W$  large
  - multiplications per pixel =  $2W < W^2$ 
    - e.g.  $2*3 < 3^2$  .

# Outline

- Filters and Convolutions
  - General Definitions
    - Working around the Edges
  - Low Pass Examples
  - High Pass Examples

# Low Pass Filters

- A filter that retains low frequencies and reduces high frequencies
  - Example: box, or pulse, kernel

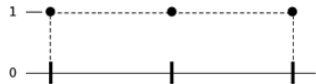


**2D:** 
$$\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} [1 \quad 1 \quad 1] = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

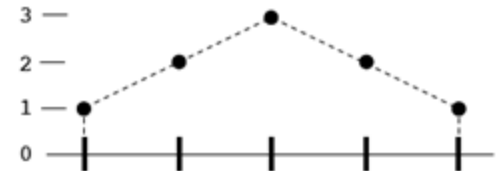
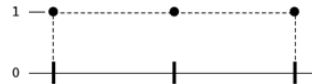
# Box \* Box = Tent

- Convolution of box kernel with itself
  - Gives a tent filter

$$0 \quad \boxed{1 \quad 1 \quad 1} \quad 0 * \quad \boxed{1 \quad 1 \quad 1} \quad = \quad \boxed{1 \quad 2 \quad 3 \quad 2 \quad 1}$$

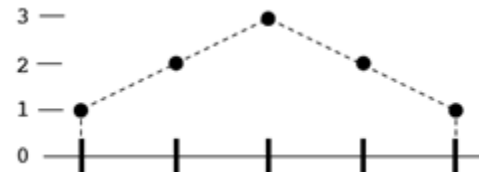
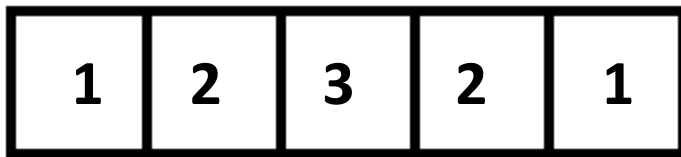


\*



# Low Pass Filter: 2D Tent

**1D:**



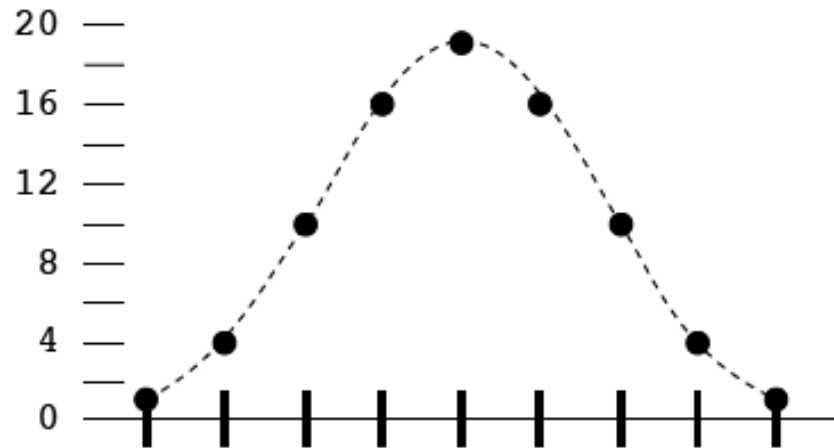
**2D:**

$$\begin{bmatrix} 1 \\ 2 \\ 3 \\ 2 \\ 1 \end{bmatrix} [1 \quad 2 \quad 3 \quad 2 \quad 1] = \begin{bmatrix} 1 & 2 & 3 & 2 & 1 \\ 2 & 4 & 6 & 4 & 2 \\ 3 & 6 & 9 & 6 & 3 \\ 2 & 4 & 6 & 4 & 2 \\ 1 & 2 & 3 & 2 & 1 \end{bmatrix}$$

# Tent \* Tent = Bell

- Convolution of tent kernel with itself
  - Gives a Bell filter

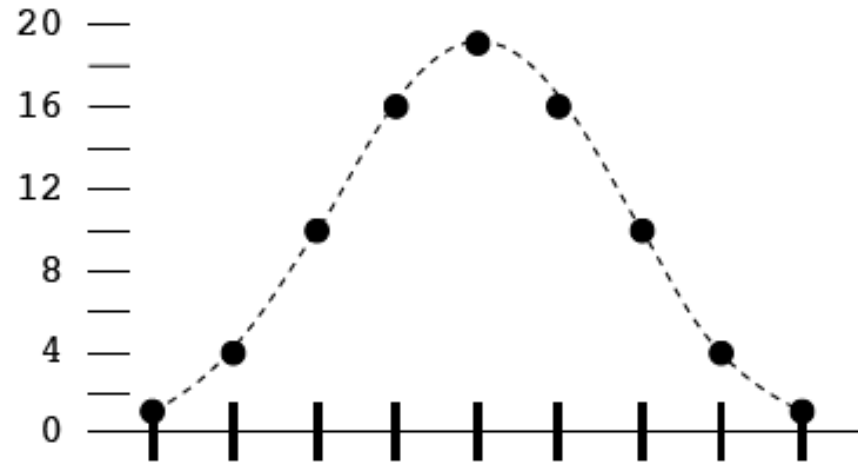
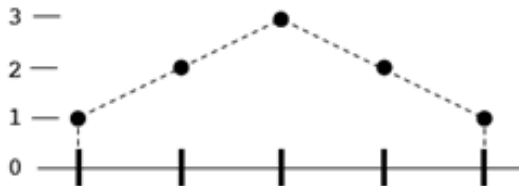
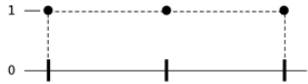
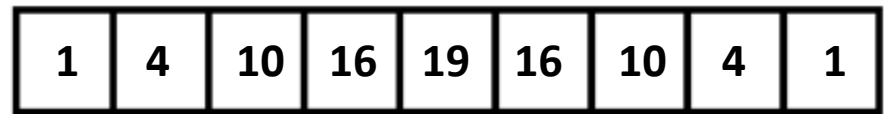
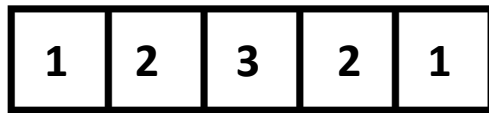
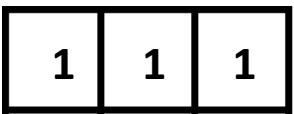
$$\begin{array}{cccccc} 0 & 0 & \boxed{1} & \boxed{2} & \boxed{3} & \boxed{2} & \boxed{1} & 0 & 0 & * & \boxed{1} & \boxed{2} & \boxed{3} & \boxed{2} & \boxed{1} \\ & & & & & & & & & & & & & & & = & \boxed{1} & \boxed{4} & \boxed{10} & \boxed{16} & \boxed{19} & \boxed{16} & \boxed{10} & \boxed{4} & \boxed{1} \end{array}$$



# Low Pass Filters

- The more convolutions with self
  - The better smoothing you achieve

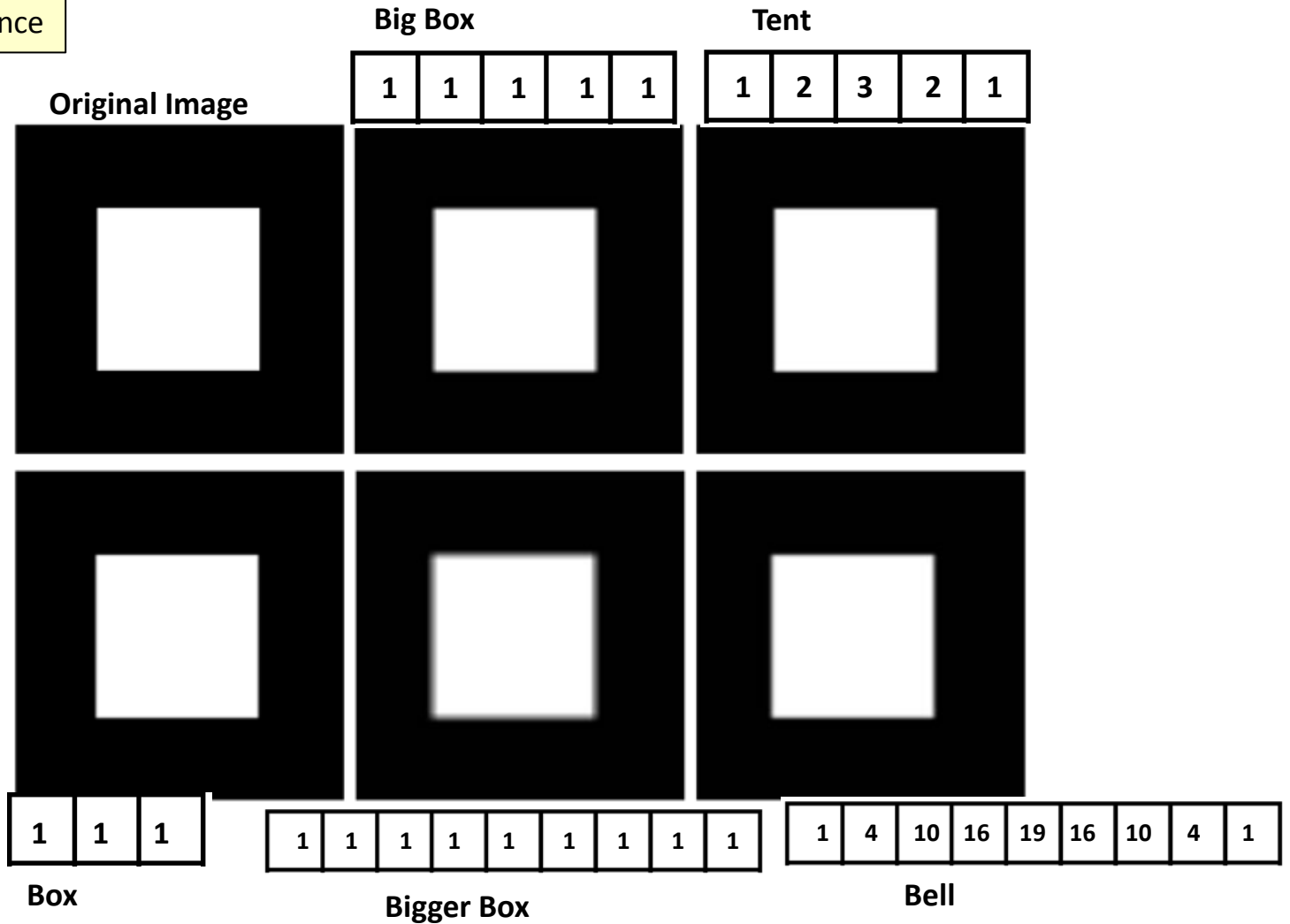
*continue  
towards Gaussian*





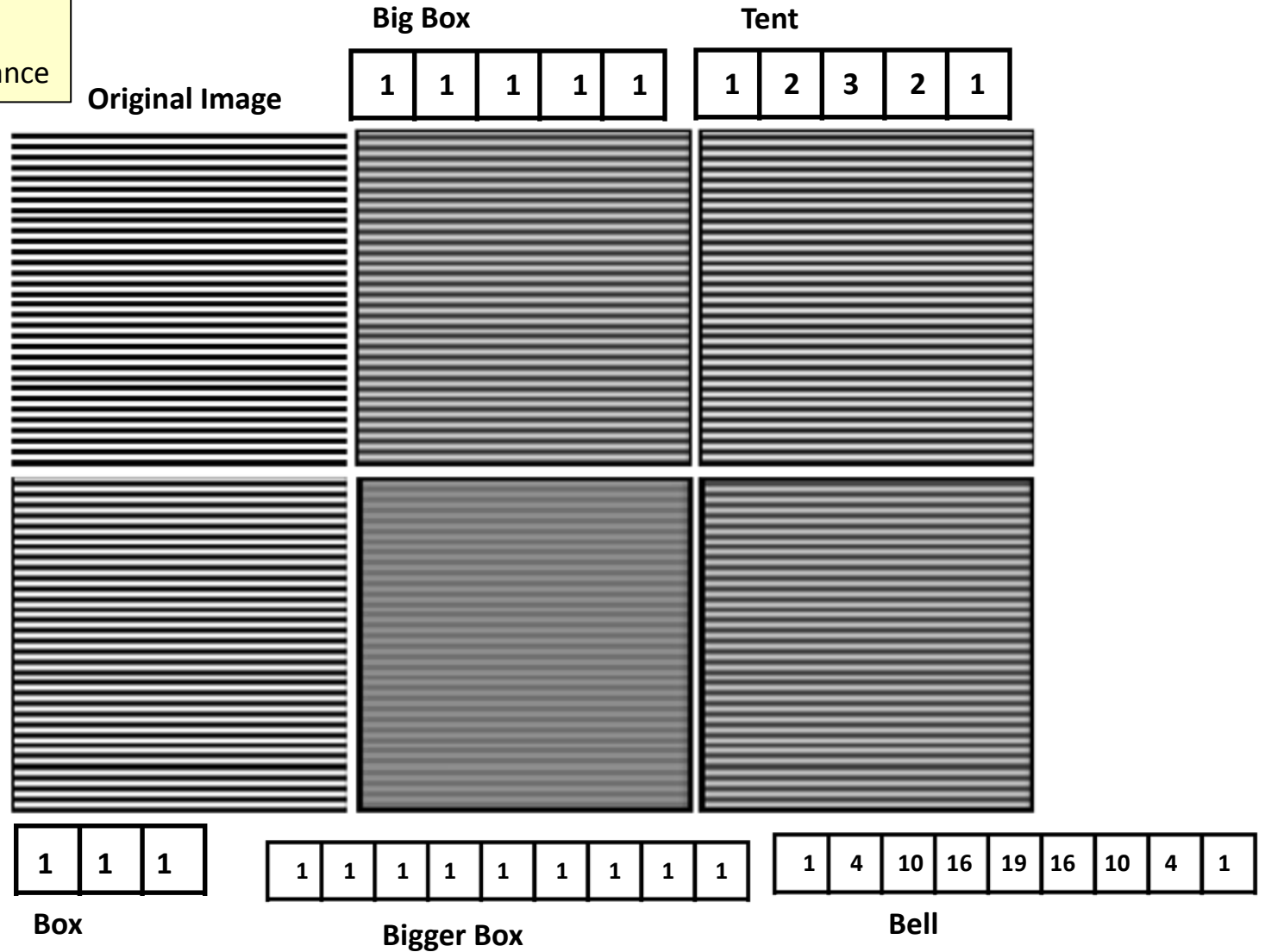
**Note:**  
 Tent and Bell  
 have better quality  
 than just a "bigger" box  
 They more cleanly  
 blur the edges...  
 ...less muddy in appearance

# Example Results



**Note:**  
Tent and Bell  
have better quality  
than just a "bigger" box  
They more cleanly  
blur the edges...  
...less muddy in appearance

# Example Results



# Outline

- Filters and Convolutions
  - General Definitions
    - Working around the Edges
  - Low Pass Examples
  - High Pass Examples

# High Pass Filters

- A filter that retains high frequencies and reduces low frequencies

Example:

1	1	1
1	-8	1
1	1	1

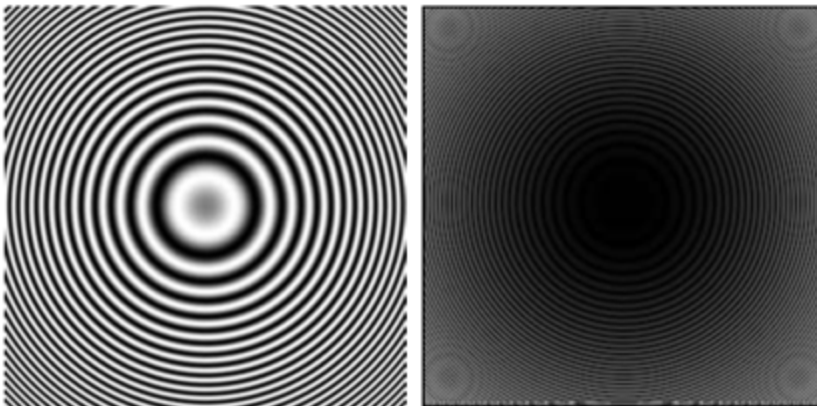
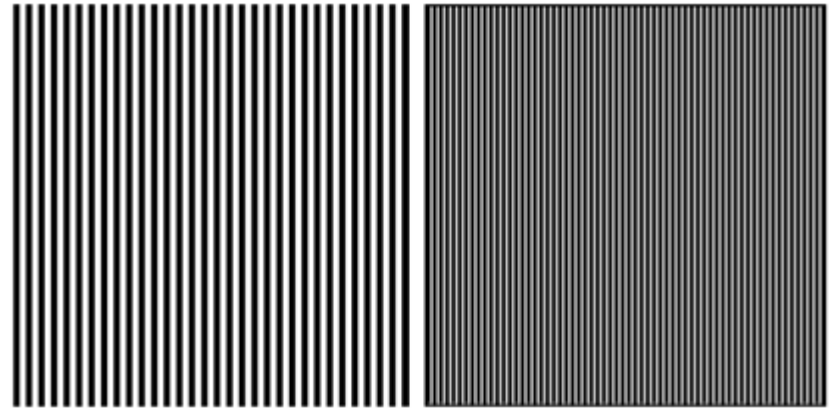
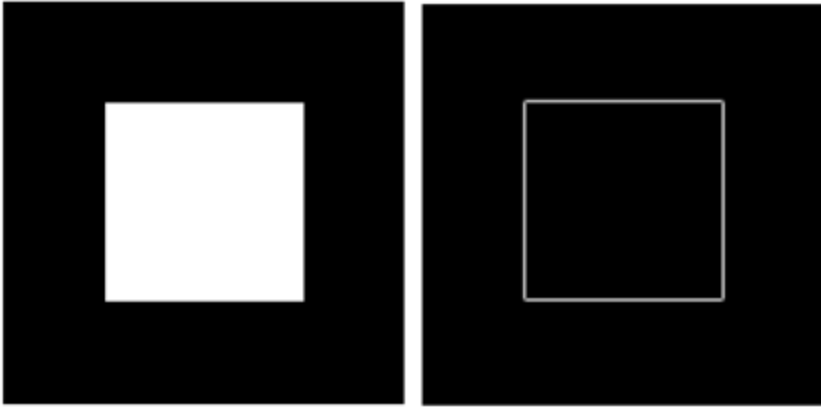
This example suppresses large areas of uniform or smoothly varying color  
It will emphasize edges (and other steep changes in color)

Why?

The sum of the kernel weights is zero

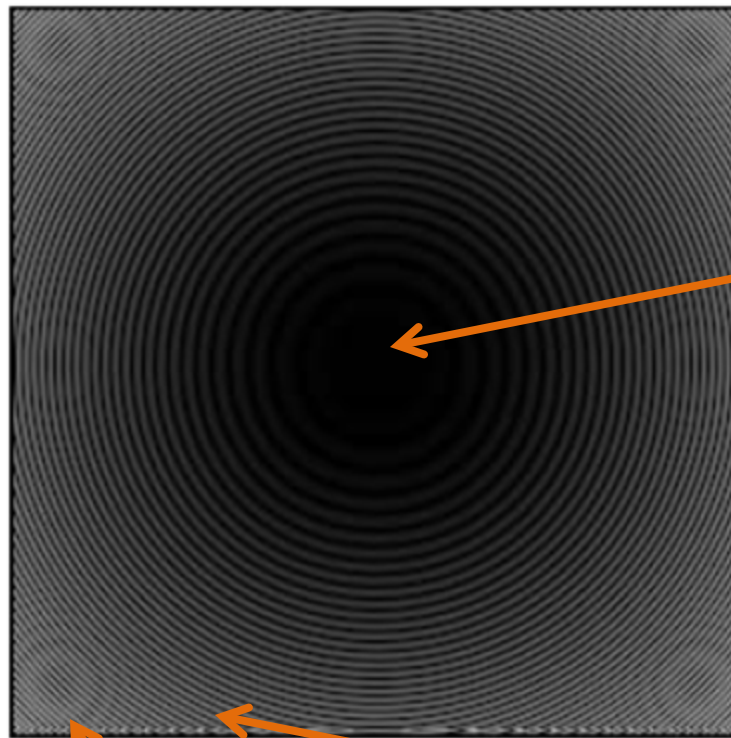
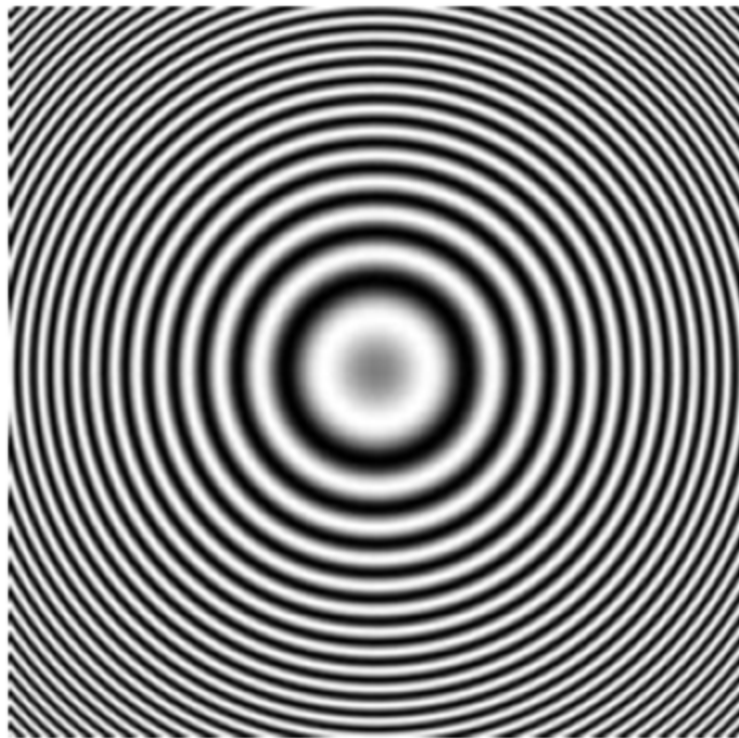
So an area of 'constant' color will result in a filtered output of zero

# Example Results



low frequency suppressed – yet high frequency remains

# High Pass: Examples Continue



low  
frequency  
removed

high frequency  
remains

Yes you are seeing smaller circles

Why? Remember Moire Patterns?  
Aliasing Artifacts?

# Summary

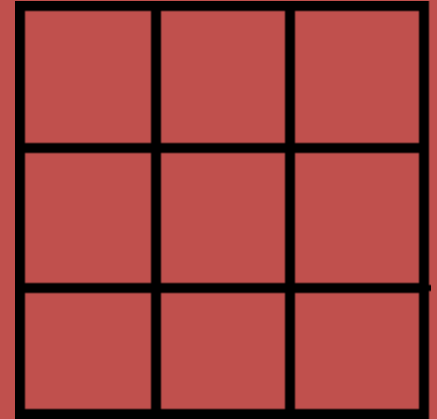
- More Details provided on
  - Filters and Convolutions
    - General Definitions
      - Working around the Edges
    - Low Pass Examples
    - High Pass Examples
- Should help in implementation and detailed understanding
- Go try doing these things! =)

# Questions?

- Beyond D2L
  - Examples and information can be found online at:
    - *<http://docdingle.com/teaching/cs.html>*
  
- *Continue to more stuff as needed*



# Extra Reference Stuff Follows



# Credits

- Much of the content derived/based on slides for use with the book:
  - *Digital Image Processing*, Gonzalez and Woods
- Some layout and presentation style derived/based on presentations by
  - Donald House, Texas A&M University, 1999
  - Bernd Girod, Stanford University, 2007
  - Shreekanth Mandayam, Rowan University, 2009
  - Igor Aizenberg, TAMUT, 2013
  - Xin Li, WVU, 2014
  - George Wolberg, City College of New York, 2015
  - Yao Wang and Zhu Liu, NYU-Poly, 2015
  - Sinisa Todorovic, Oregon State, 2015

