# Image Processing


COS 426, Spring 2014
Tom Funkhouser

# Image Processing

Goal: read an image, process it, write the result

input.jpg

output.jpg

```
imgpro input.jpg output.jpg -histogram_equalization
```

# Image Processing Operations

- Luminance
  - Brightness
  - Contrast.
  - Gamma
  - Histogram equalization
- Color
  - Black & white
  - Saturation
  - White balance
- Linear filtering
  - Blur & sharpen
  - Edge detect
  - Convolution
- Non-linear filtering
  - Median
  - Bilateral filter
- Dithering
  - Quantization
  - Ordered dither
  - Floyd-Steinberg

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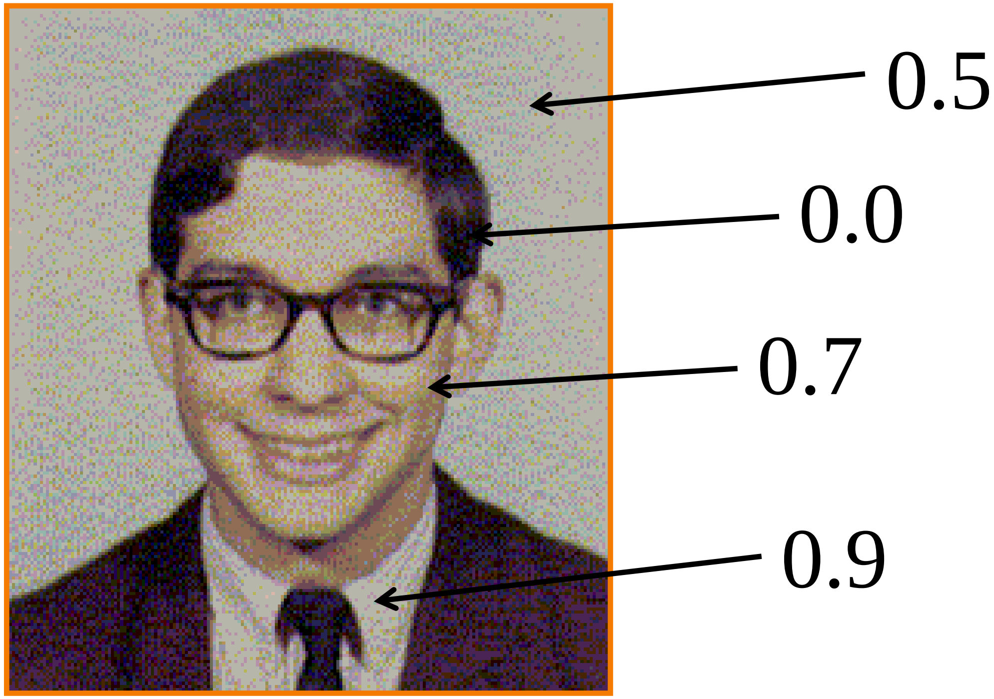
# What is Luminance?

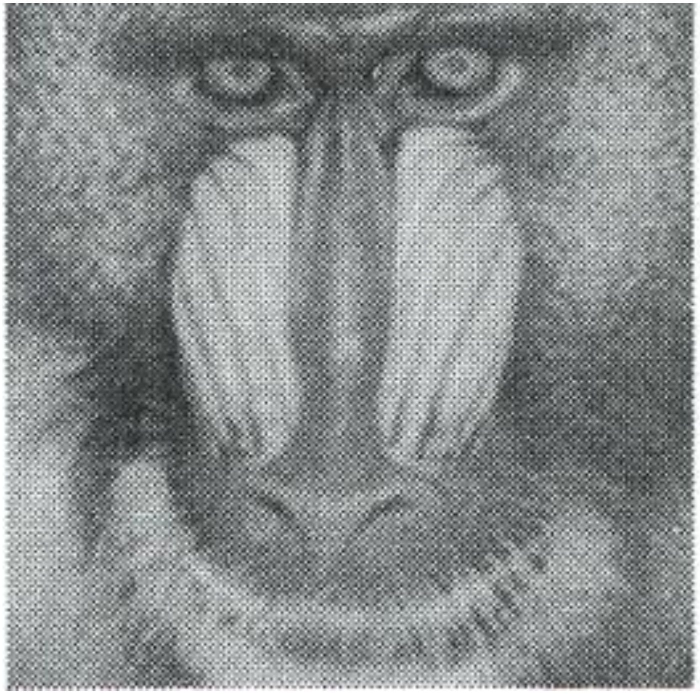
Measures perceived “gray-level” of pixel

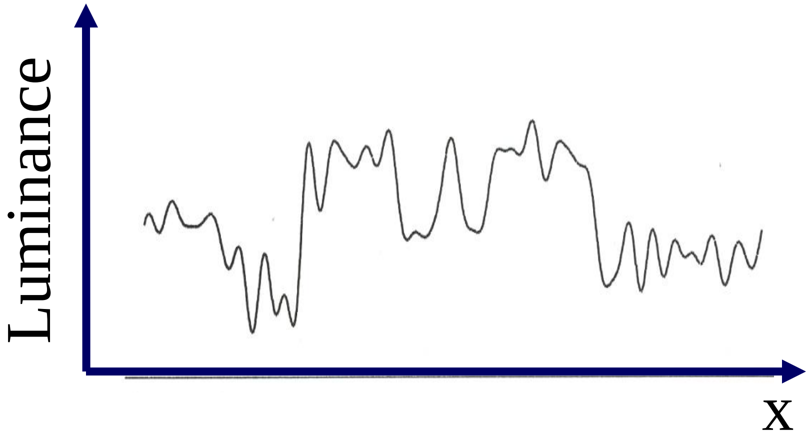
L = 0.30*red + 0.59*green + 0.11*blue



# Luminance

Measures perceived “gray-level” of pixel



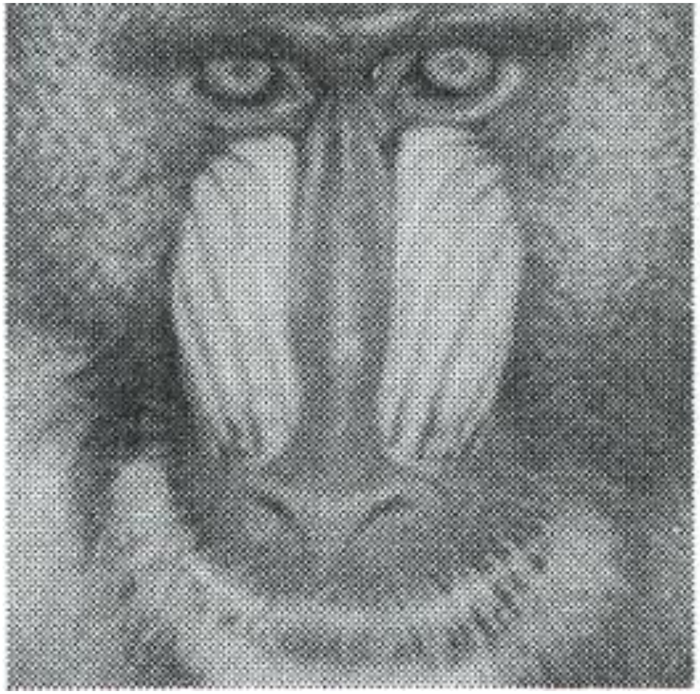


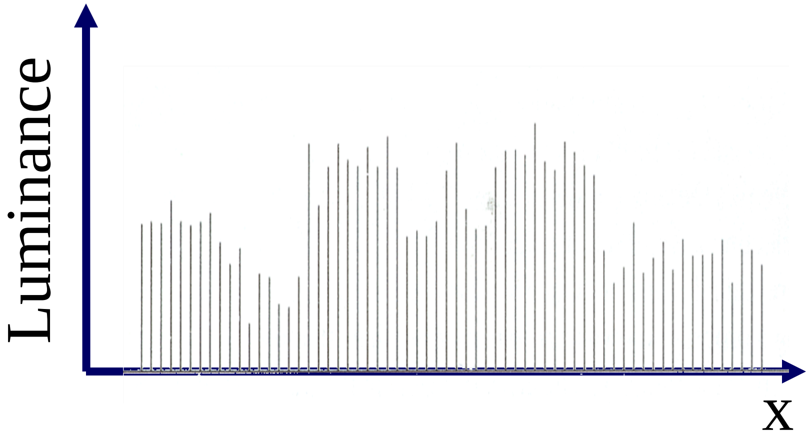

Values of luminance for positions on one horizontal scanline

Figure 19.9 FvDFH

# Luminance

Measures perceived “gray-level” of pixel



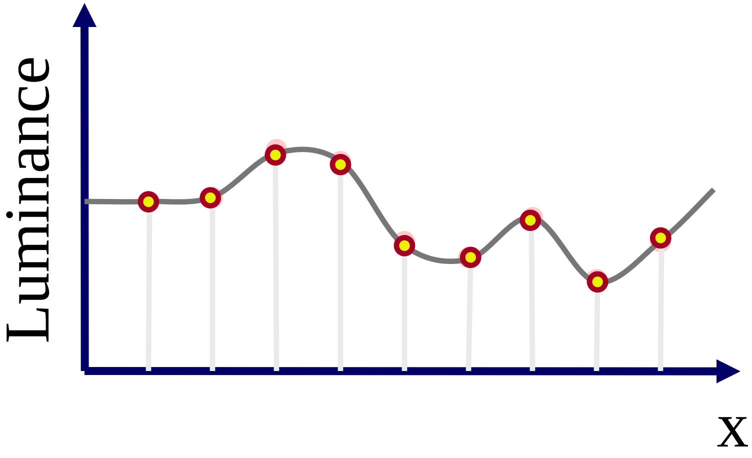



Samples of luminance for pixels on one horizontal scanline

Figure 19.9 FvDFH

# Adjusting Brightness

- What must be done to the RGB values to make this image brighter?

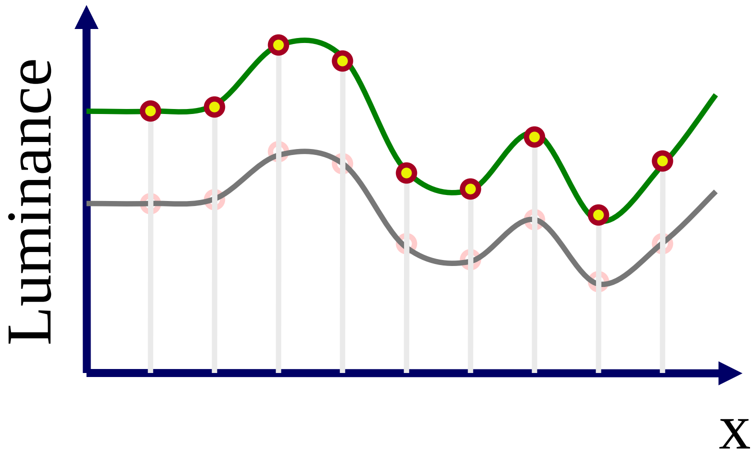


# Adjusting Brightness

- Method 1: Convert to HSV, scale V, convert back
- Method 2: Scale R, G, and B directly
  - Multiply each of red, green, and blue by a factor
  - Must clamp to [0..1] … always

Original

Brighter

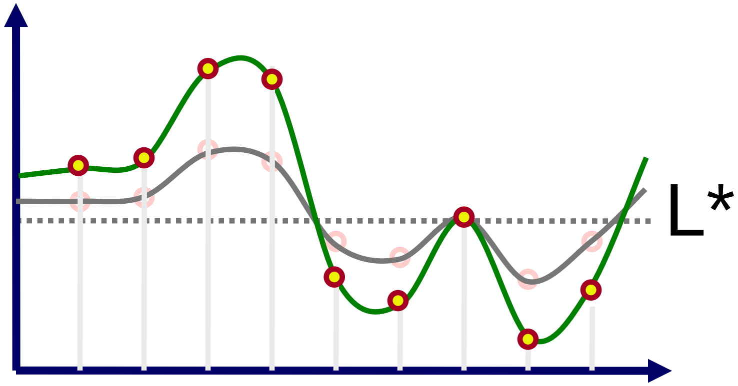


# Adjusting Contrast

- Compute one mean luminance L* for whole image
  Scale deviation from L* for each pixel component

Original

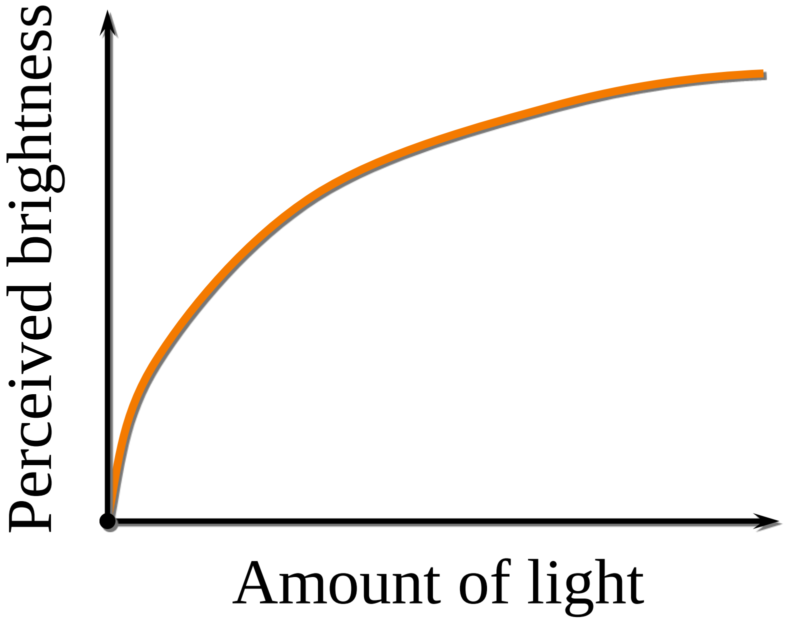
More Contrast



# Adjusting Gamma

Apply non-linear function to account for difference between brightness and perceived brightness of display

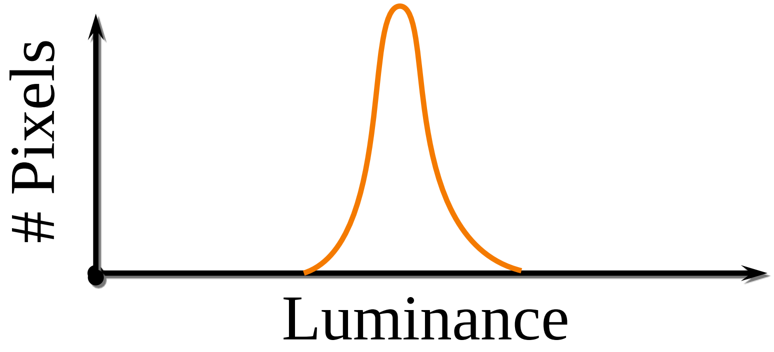
$$I_{out} = I_{in}^{\gamma}$$




$\gamma$ depends on camera and monitor

# Histogram Equalization

Change distribution of luminance values to cover full range [0-1]




# Image Processing Operations

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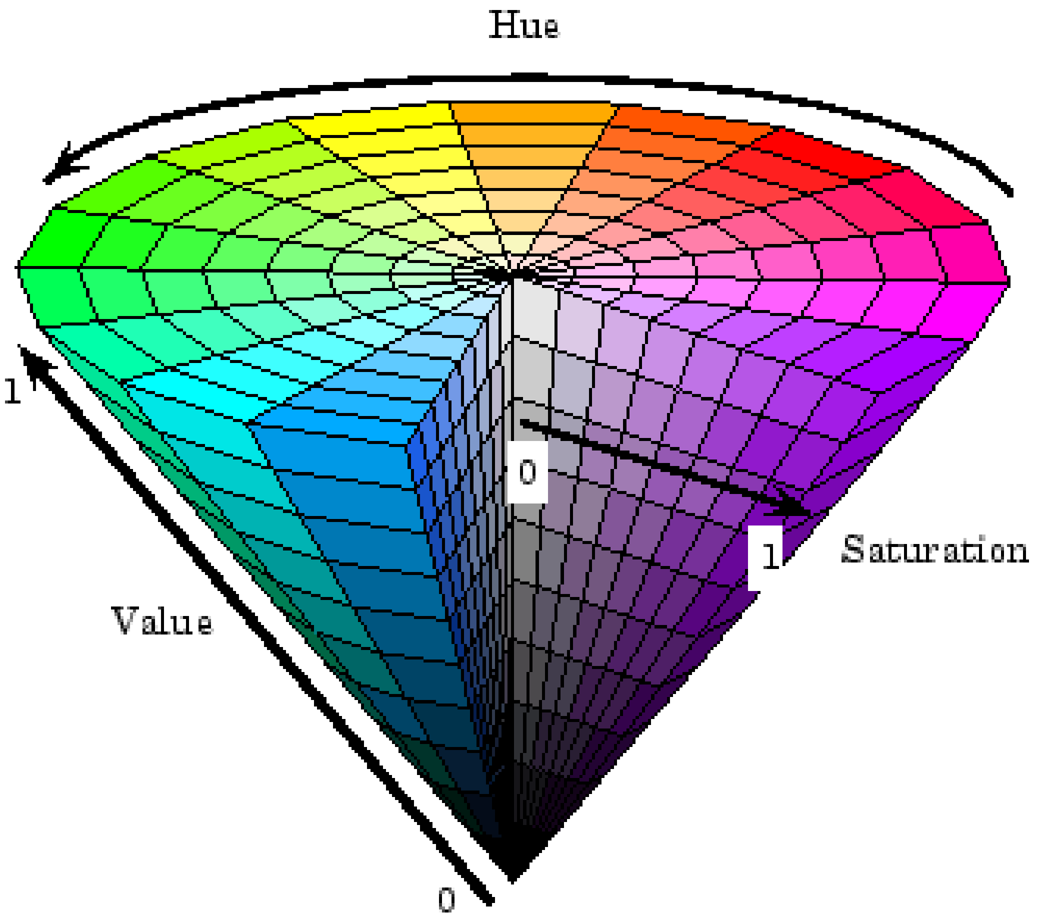
  - Floyd-Steinberg

# Color processing

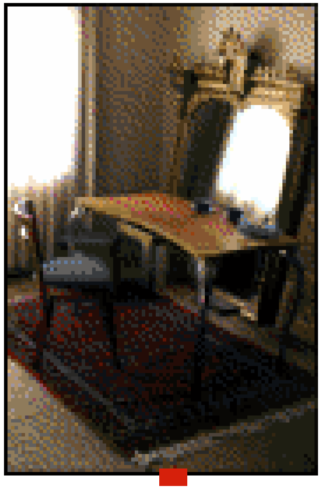
- Color models
  - RGB
  - CMY
  - HSV
  - XYZ
  - La*b*
  - Etc.




HSV Color Model

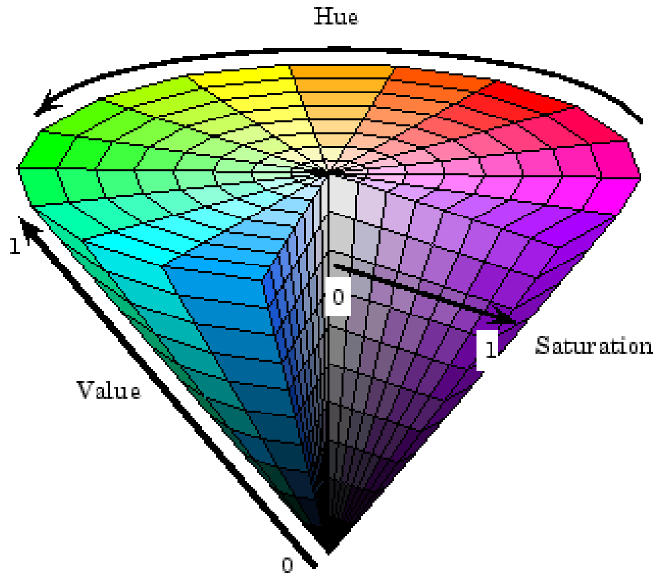
# Black & White

Convert from color to gray-levels



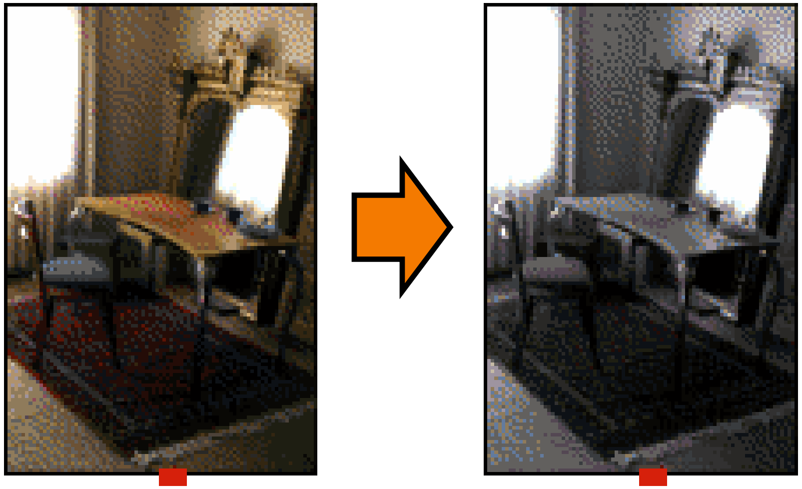
Original

Black & White
(actually gray levels)



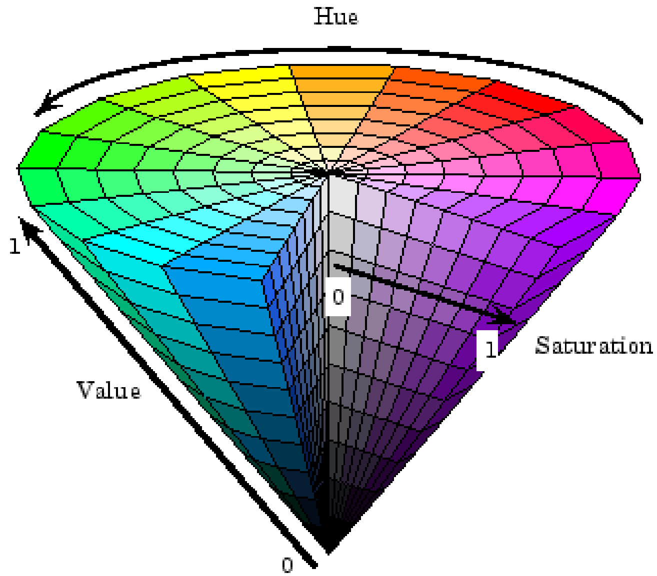
# Black & White

Convert from color to gray-levels



Original

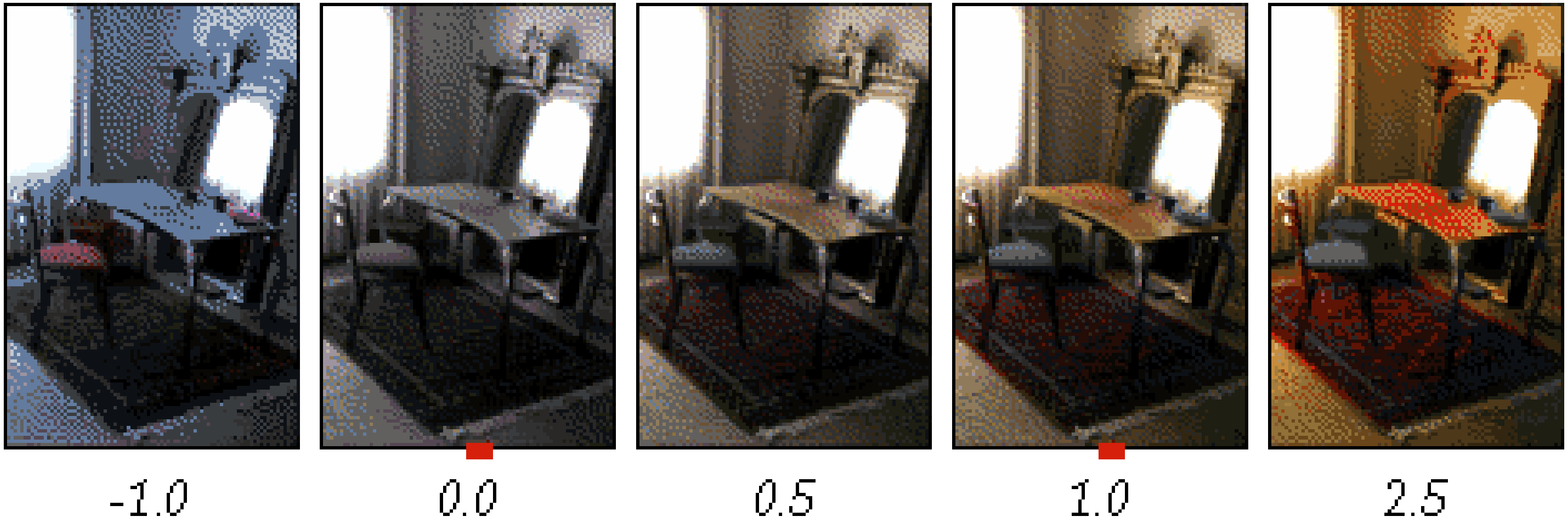
Black & White
(actually gray levels)

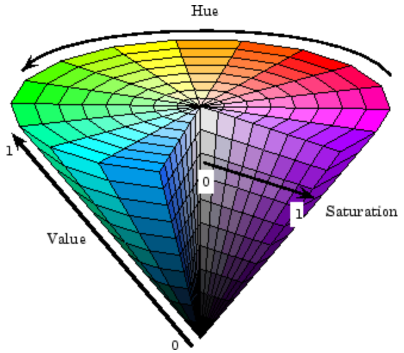



Method 1: Convert to HSV, set S=0, convert back to RGB
Method 2: Set RGB of every pixel to (L,L,L)

# Adjusting Saturation

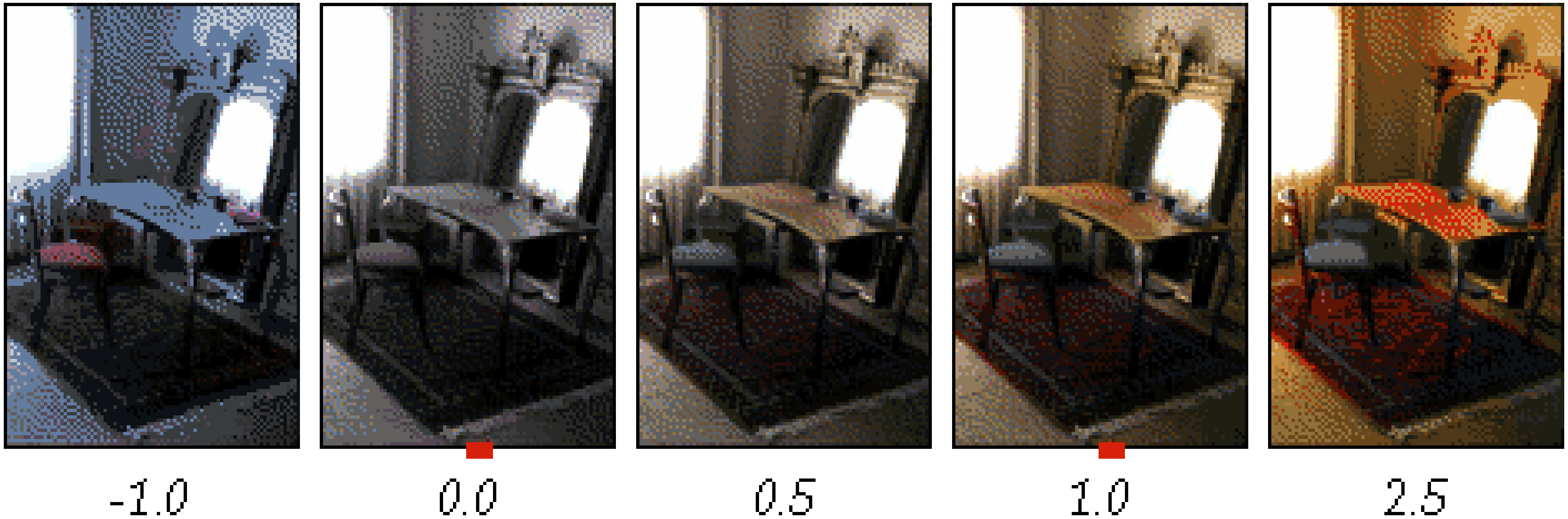
Increase/decrease color saturation of every pixel

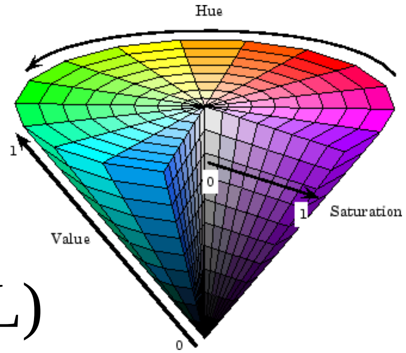


# Adjusting Saturation

Increase/decrease color saturation of every pixel



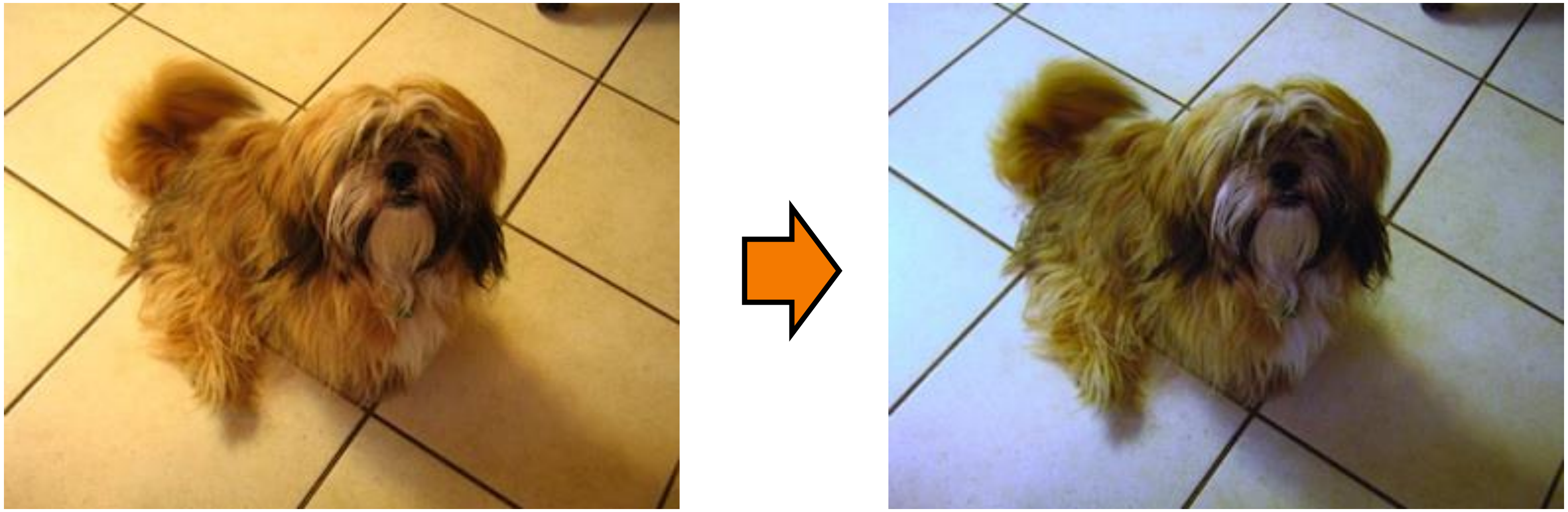




Method 1: Convert to HSV, scale S, convert back

Method 2: Set each pixel to factor * (R-L, G-L, B-L)

# White Balance

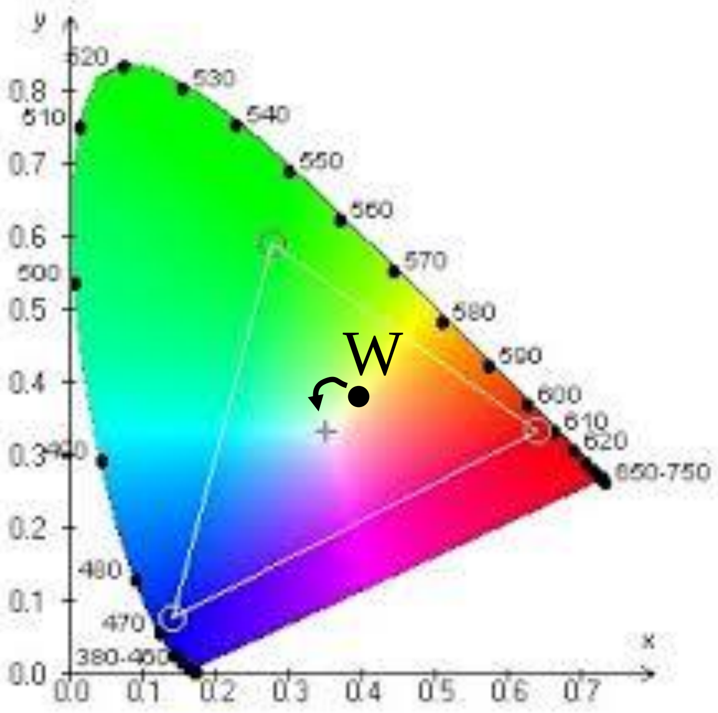
Adjust colors so that a given RGB value is mapped to a neutral color



# White Balance

Conceptually:

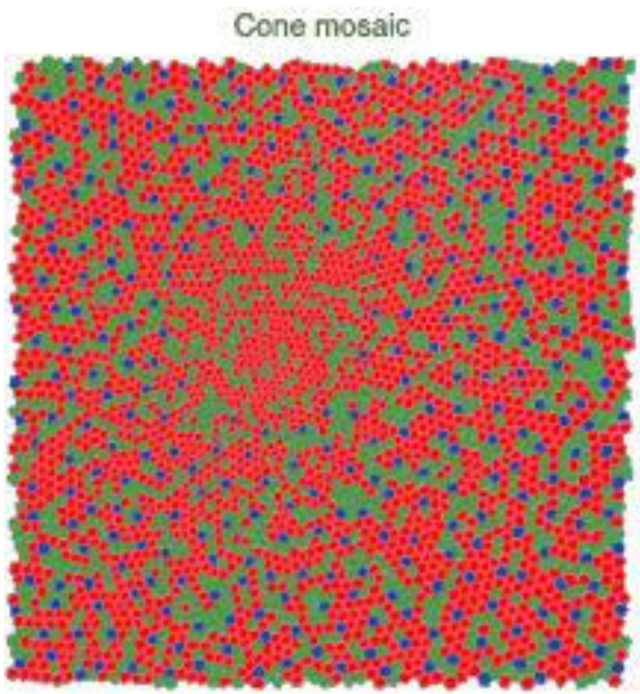
- Provide an RGB value W that should be mapped to white
- Perform transformation of color space

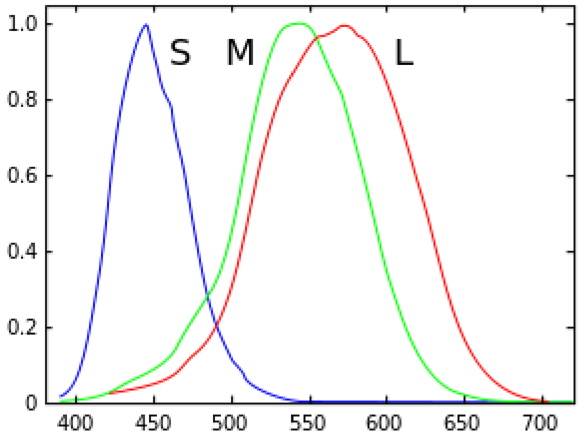


# White Balance

Von Kries method: adjust colors in LMS color space

- LMS primaries represent the responses of the three different types of cones in our eyes



# White Balance

For each pixel RGB:

1) Convert to XYZ color space

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9502 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

2) Convert to LMS color space

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.40024 & 0.7076 & -0.08081 \\ -0.2263 & 1.16532 & 0.0457 \\ 0 & 0 & 0.91822 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

3) Divide by $L_W M_W S_W$

4) Convert back to RGB

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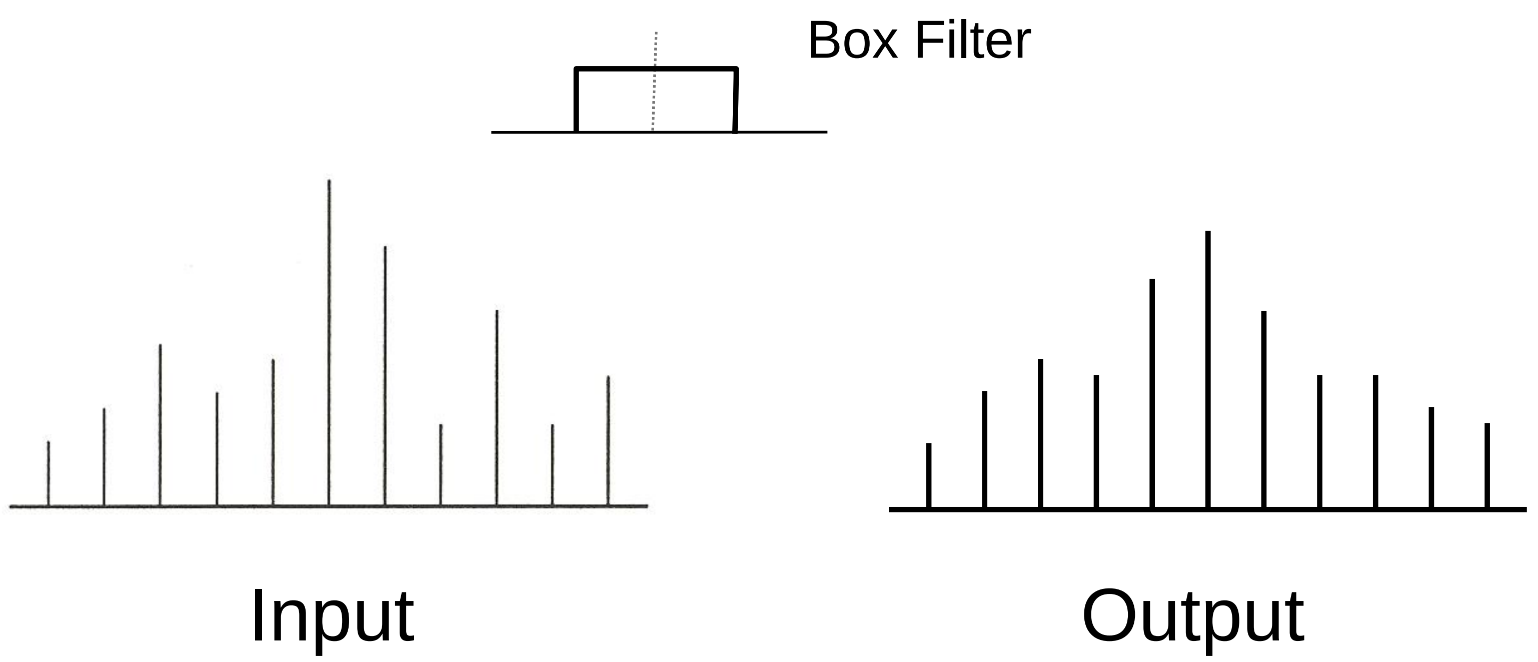
# Blur

What is the basic operation for each pixel when blurring an image?

# Basic Operation: Convolution

Output value is weighted sum of values in neighborhood of input image

- Pattern of weights is the “filter” or “kernel”



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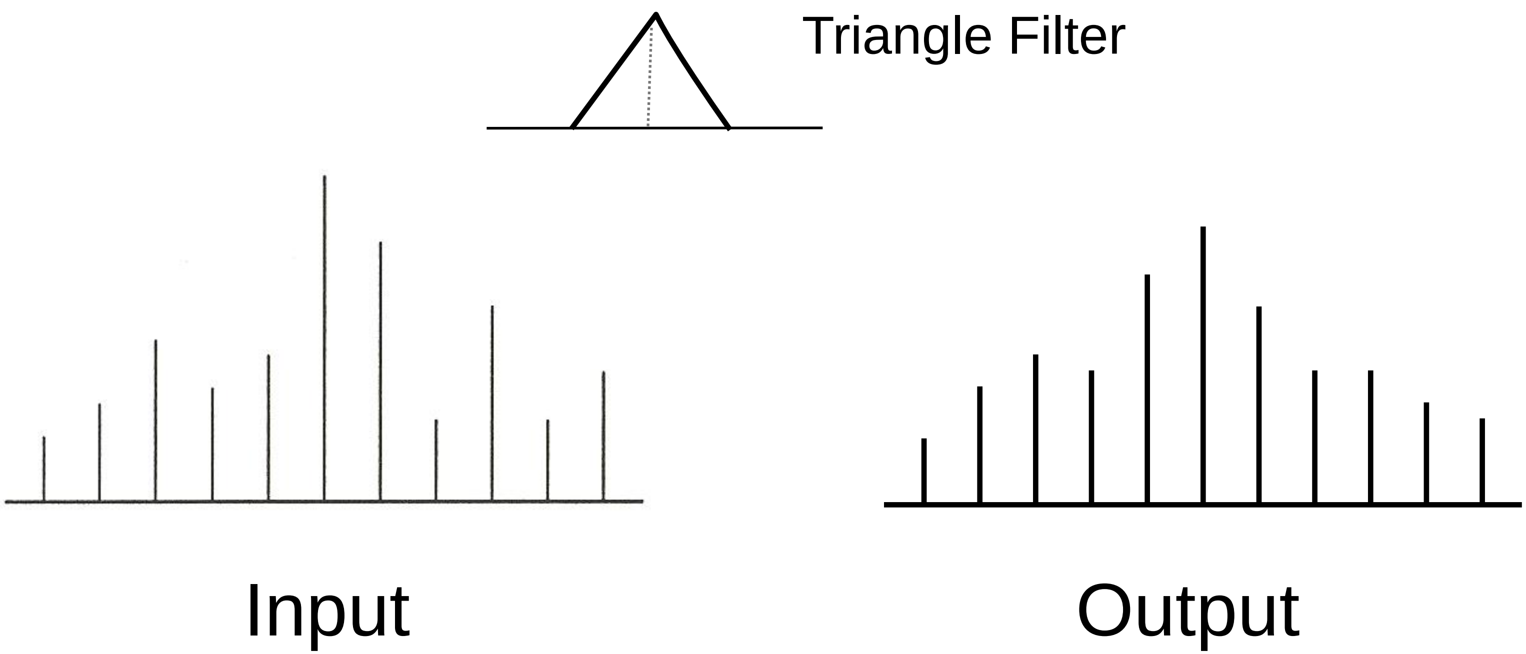

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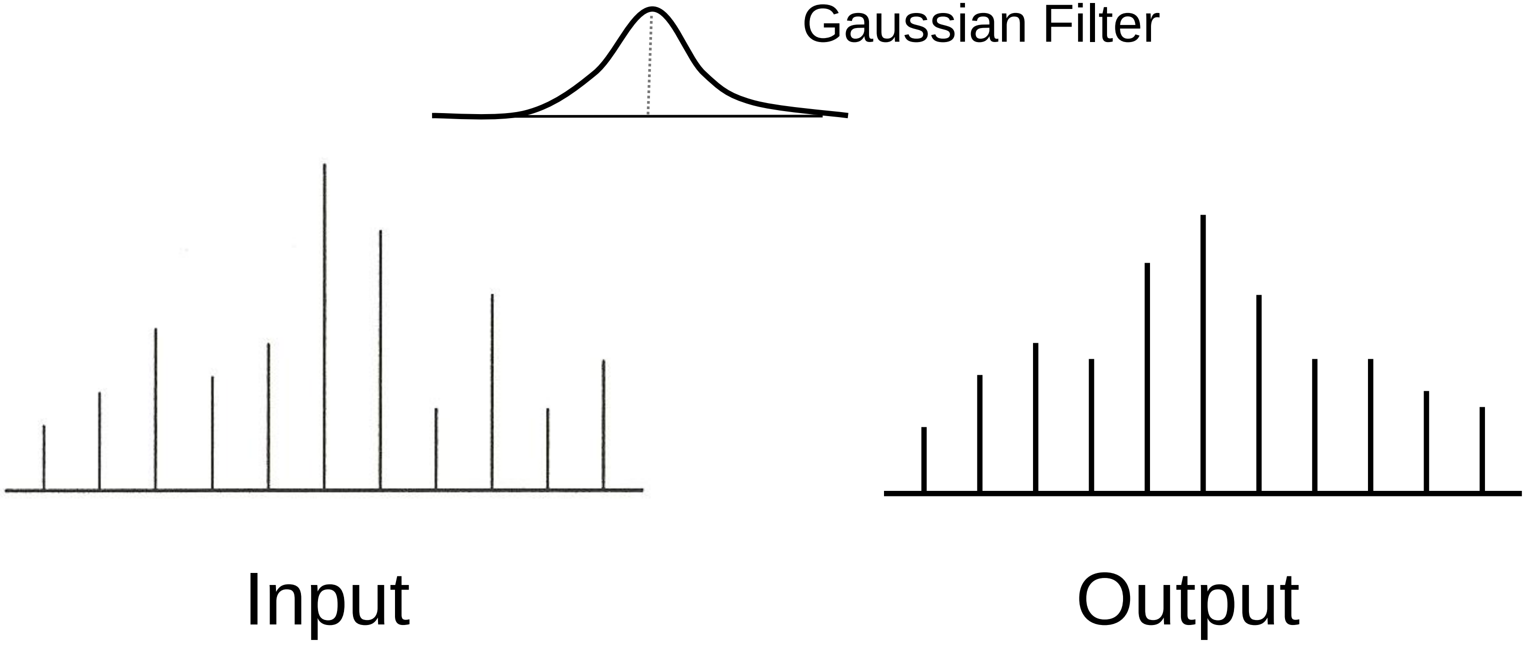
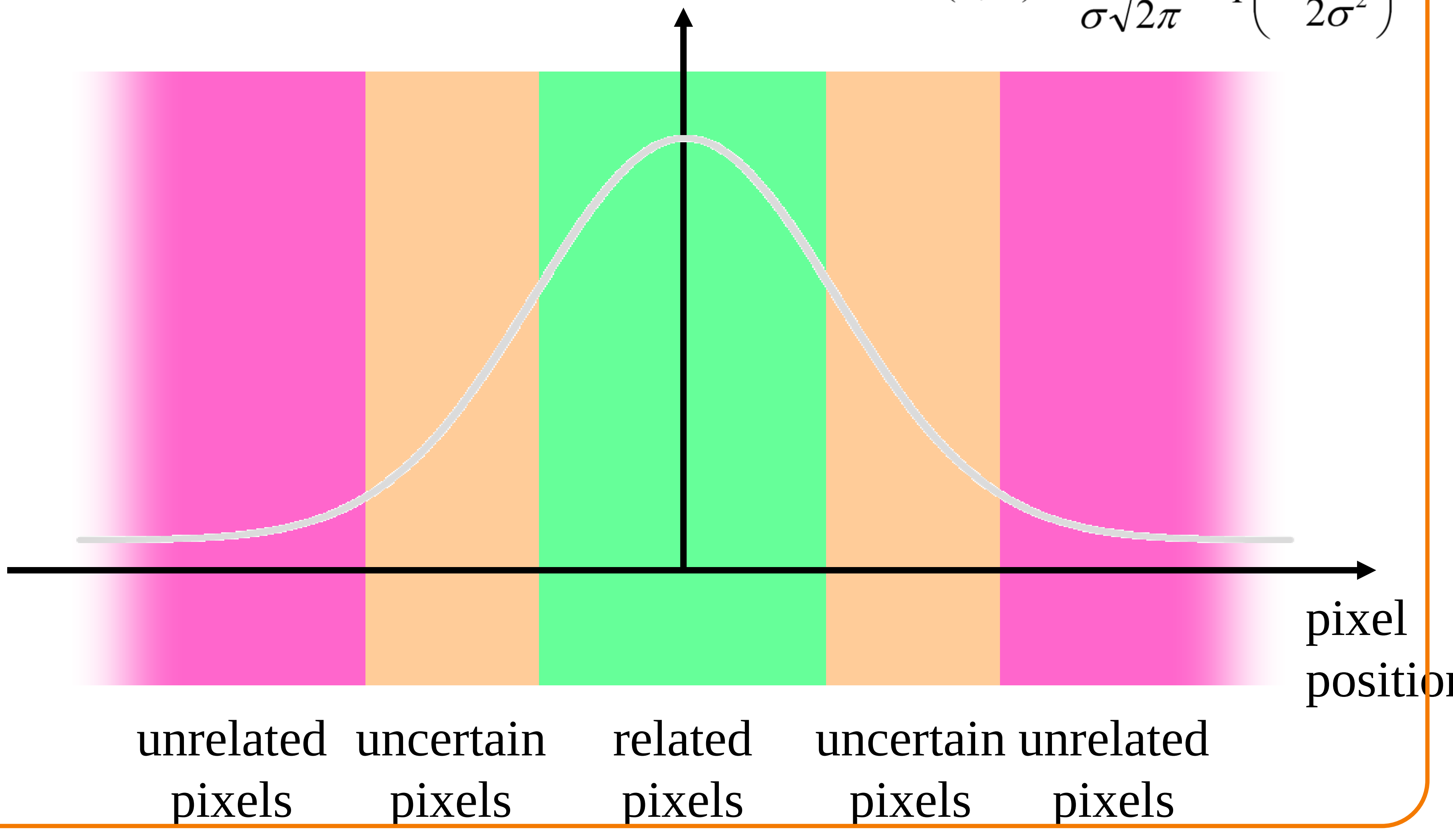


# Convolution with a Gaussian Filter

$$G(x,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left( -\frac{x^2}{2\sigma^2} \right)$$



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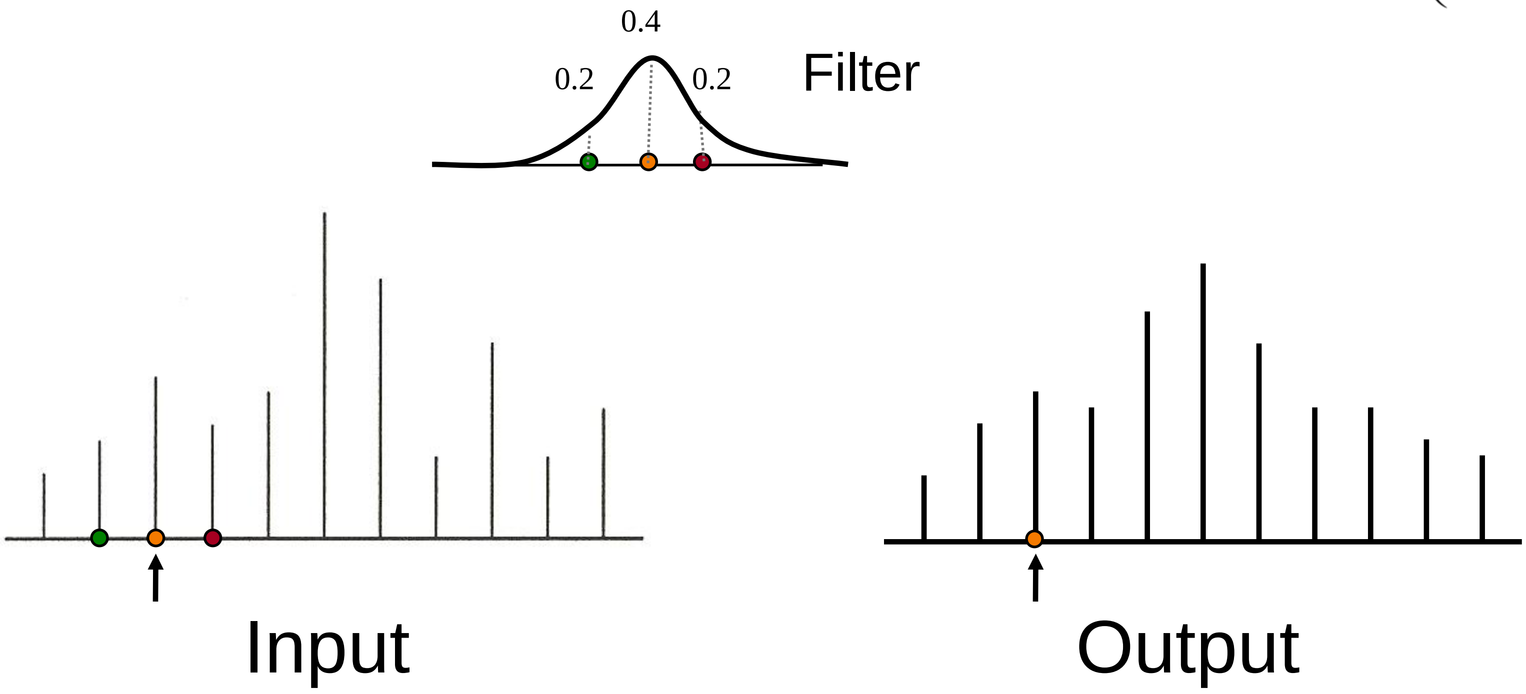

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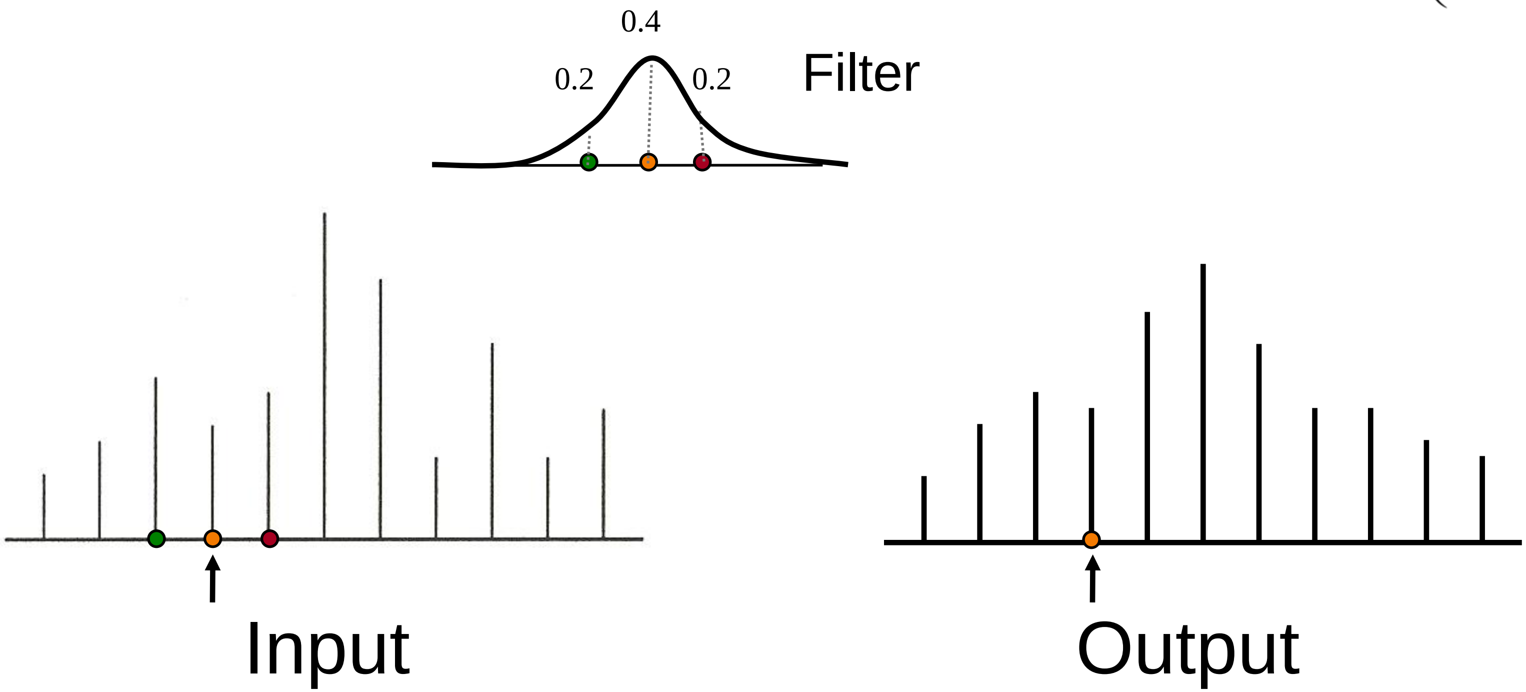

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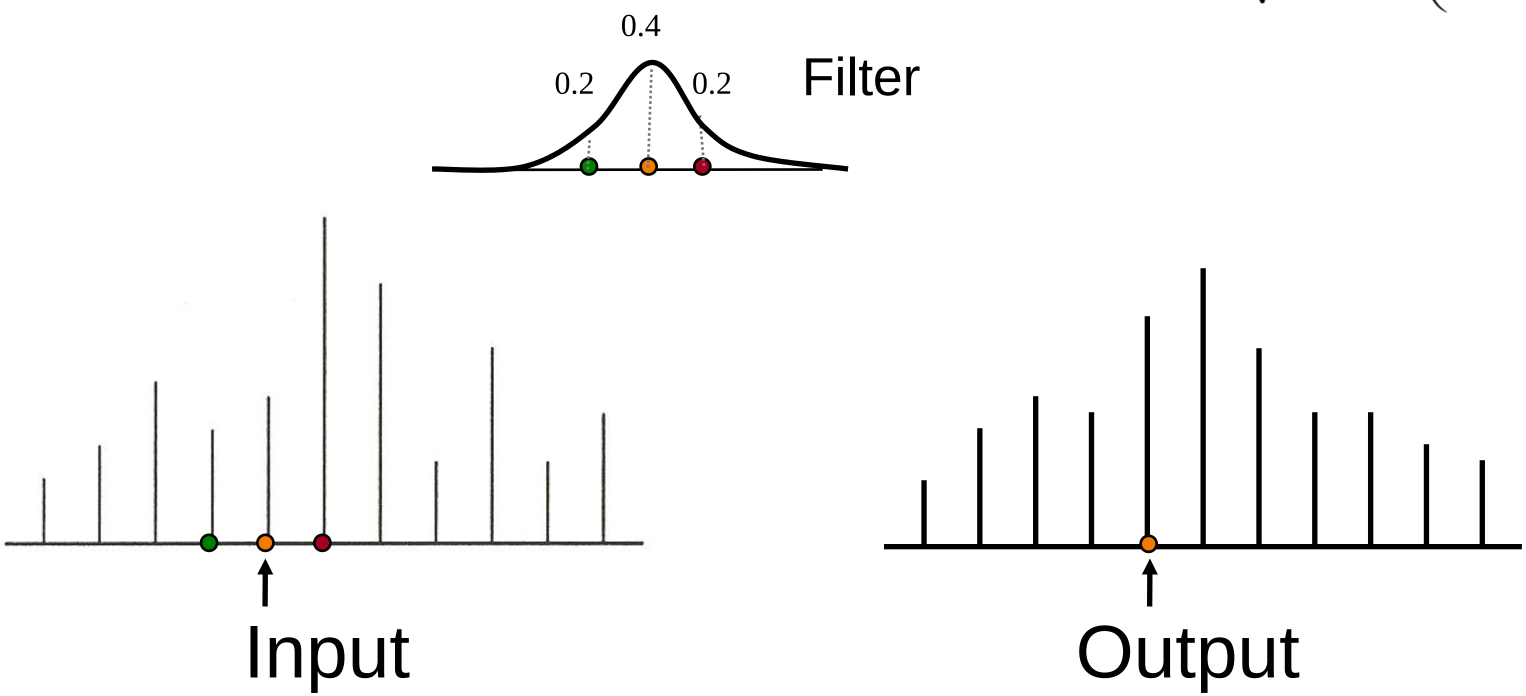

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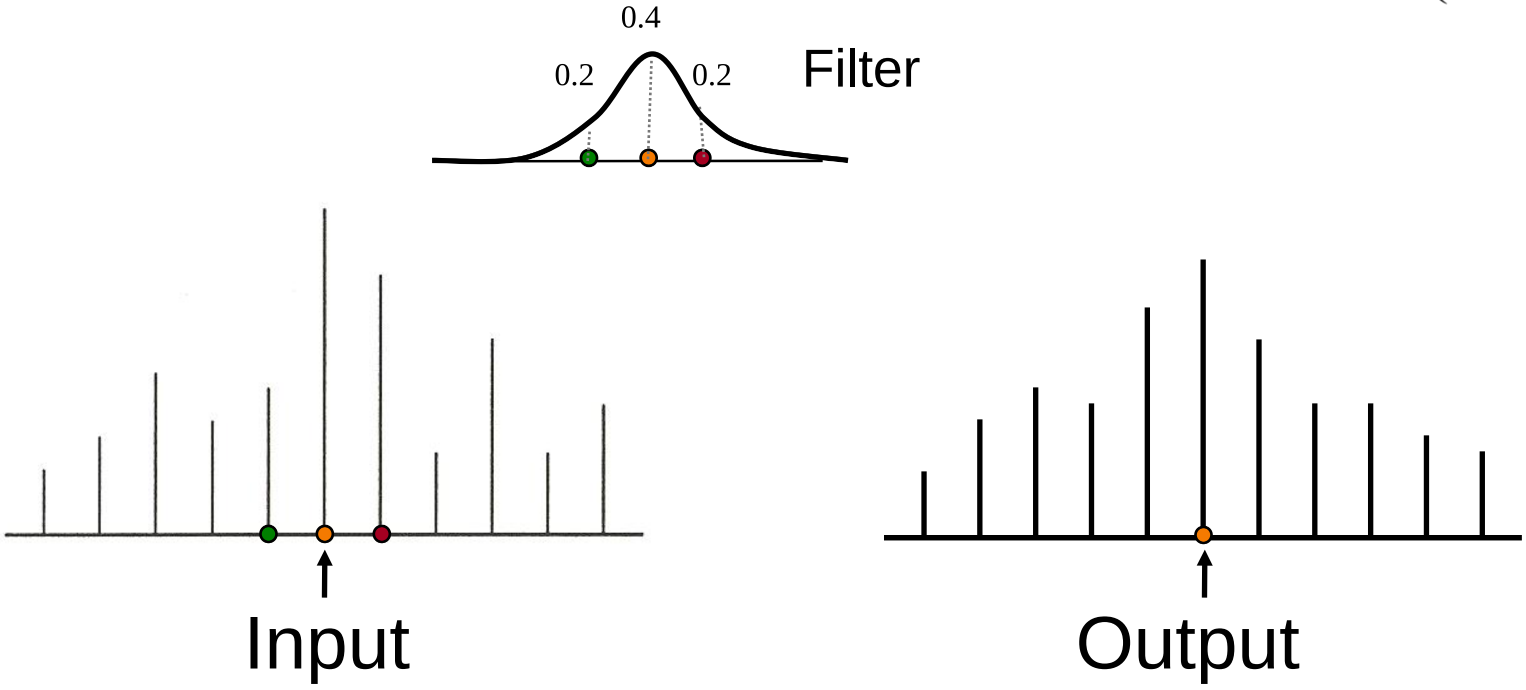

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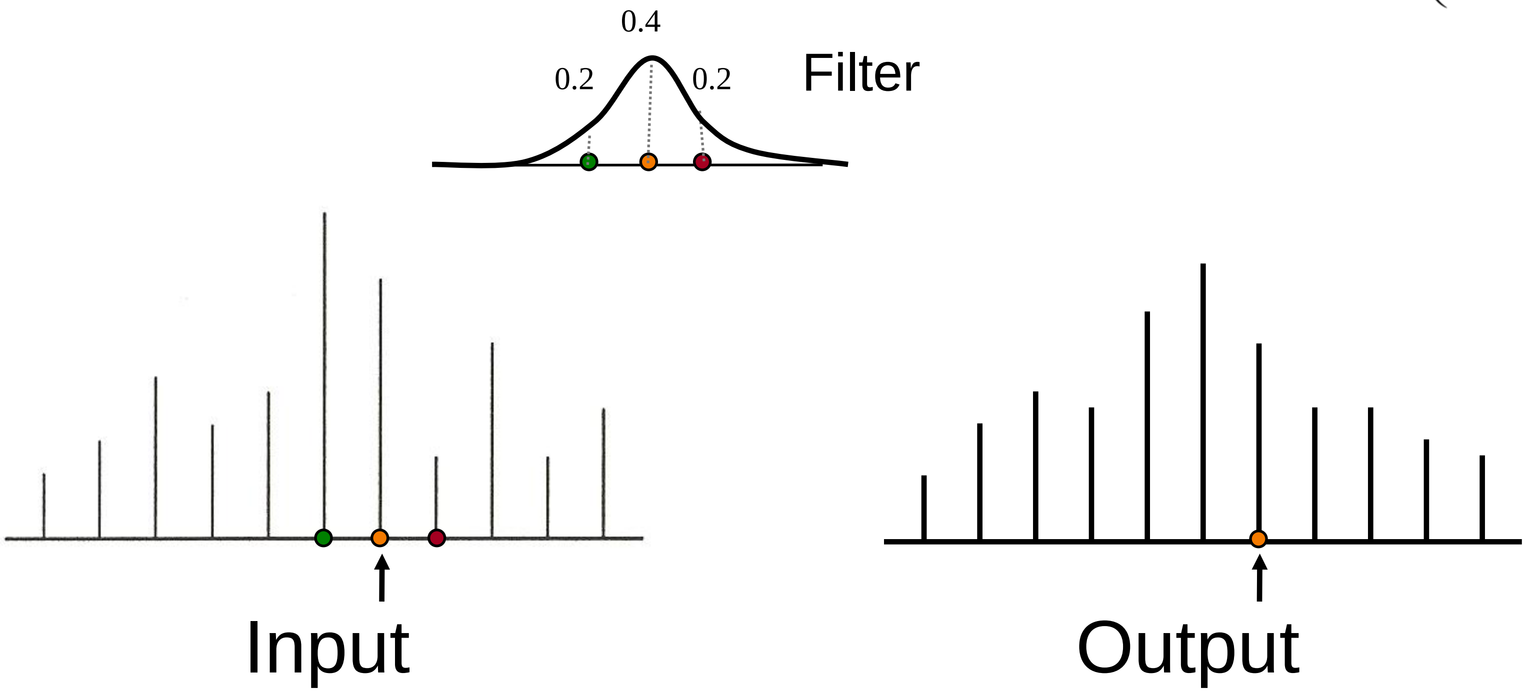
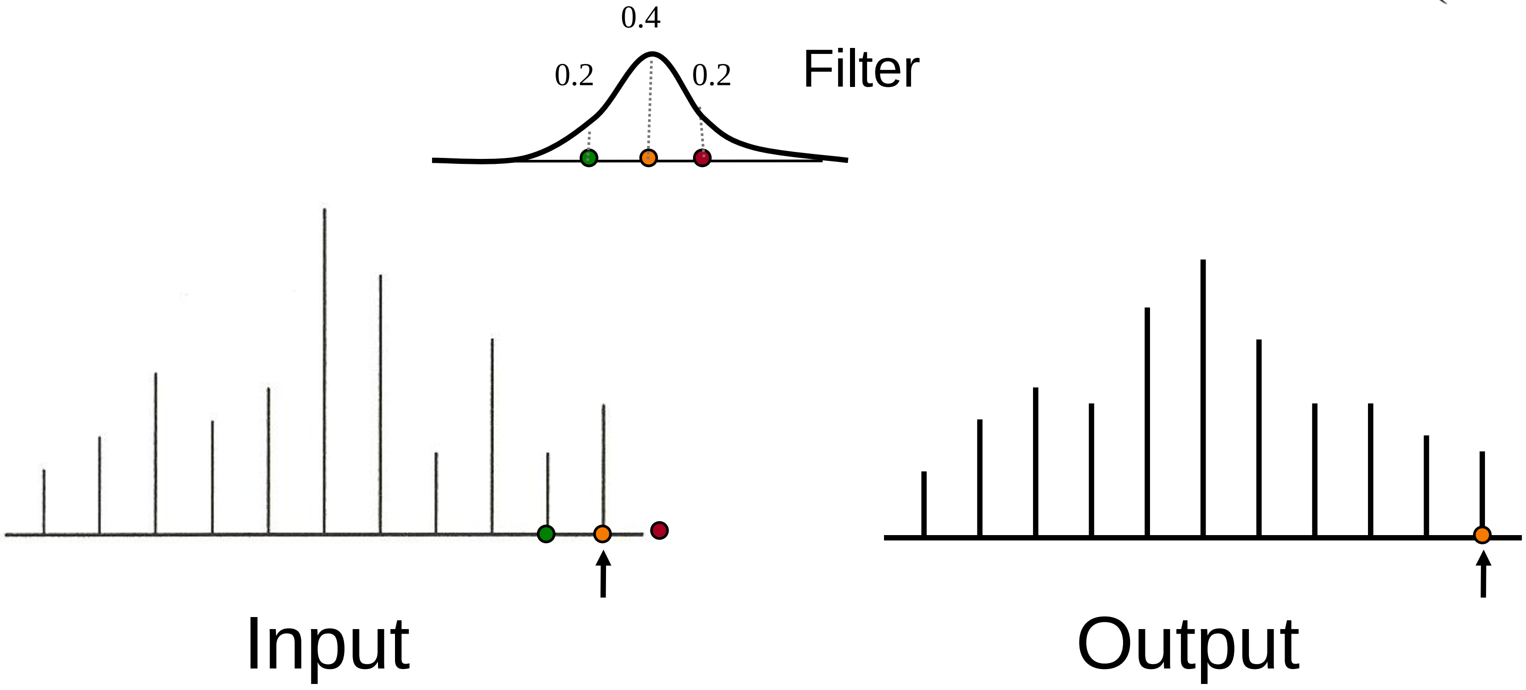


# Convolution with a Gaussian Filter

What if filter extends beyond boundary?

$$G(x,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right)$$



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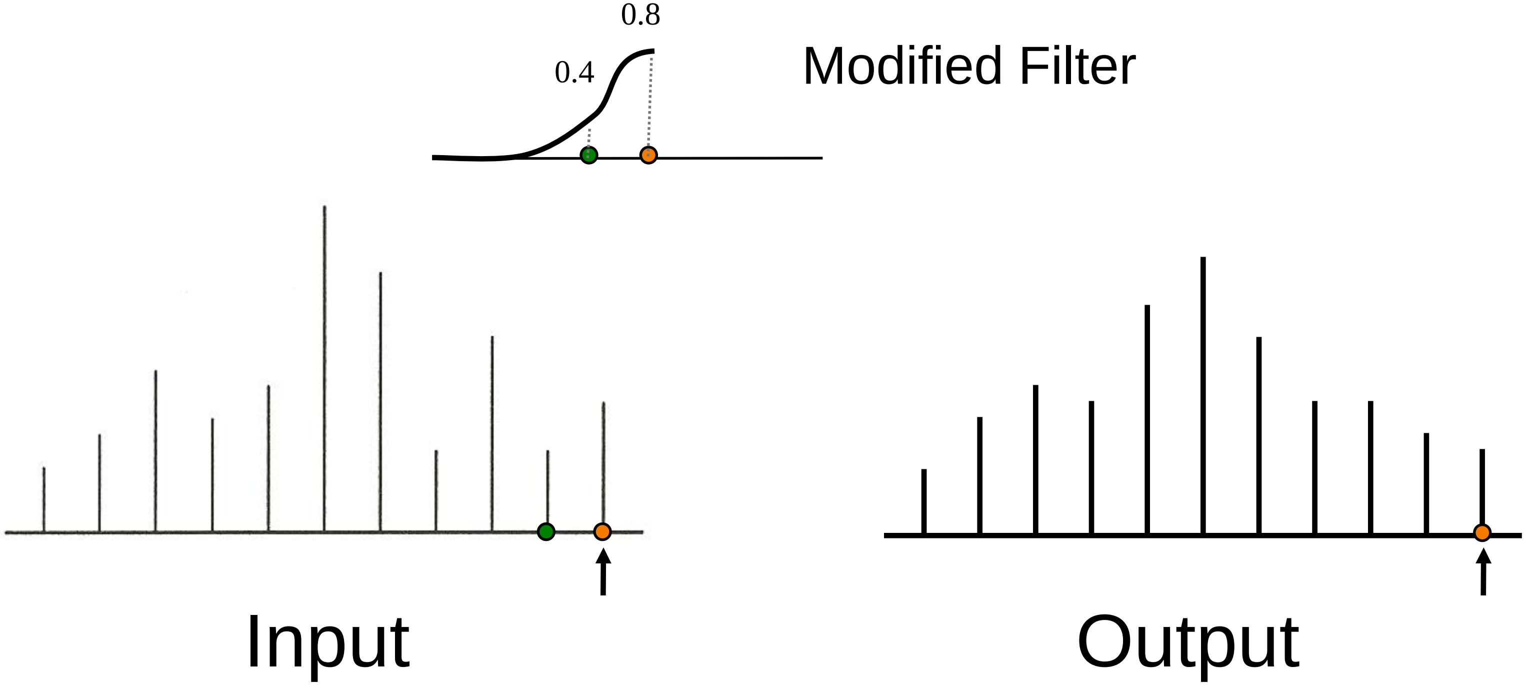


# Convolution with a Gaussian Filter

Output contains samples from smoothed input

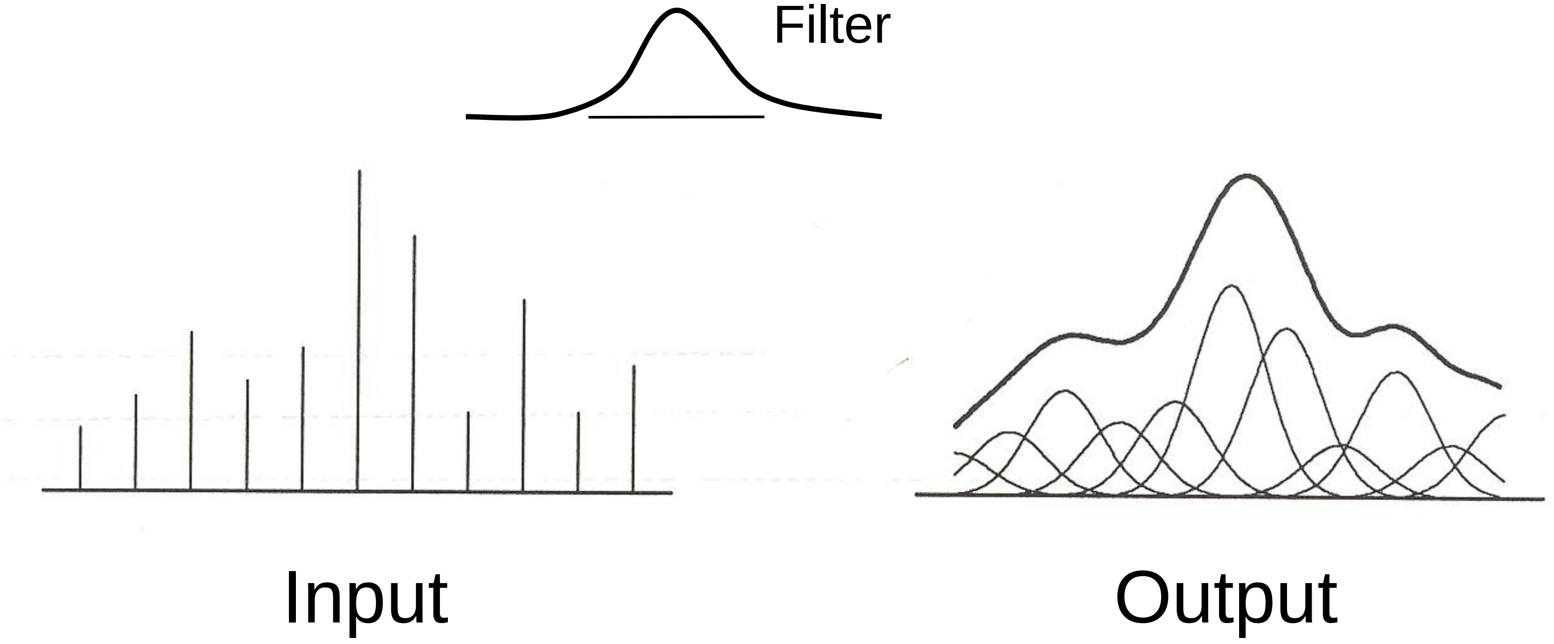
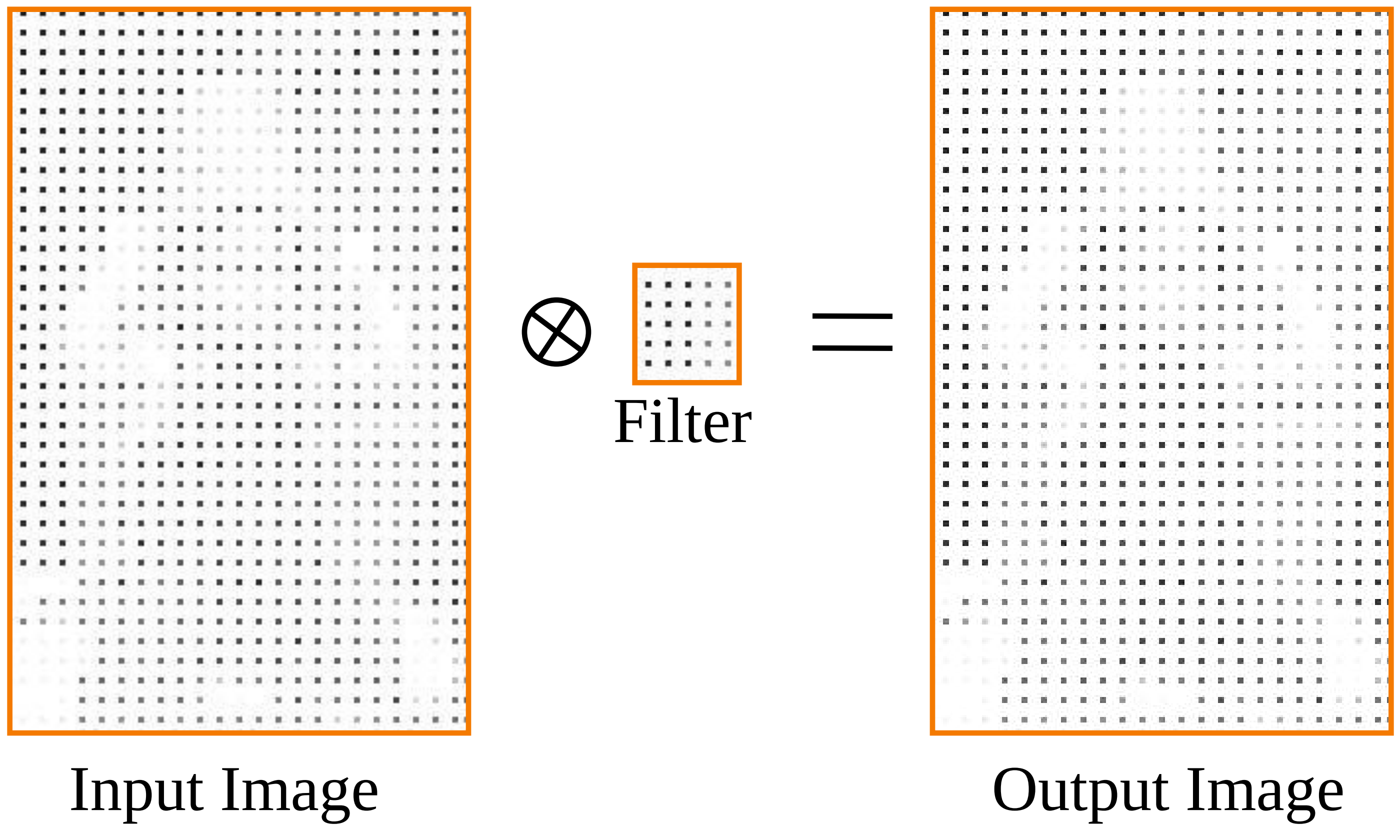



Figure 2.4 Wolberg

# Linear Filtering

## 2D Convolution

- Each output pixel is a linear combination of input pixels in 2D neighborhood with weights prescribed by a filter




# Linear Filtering

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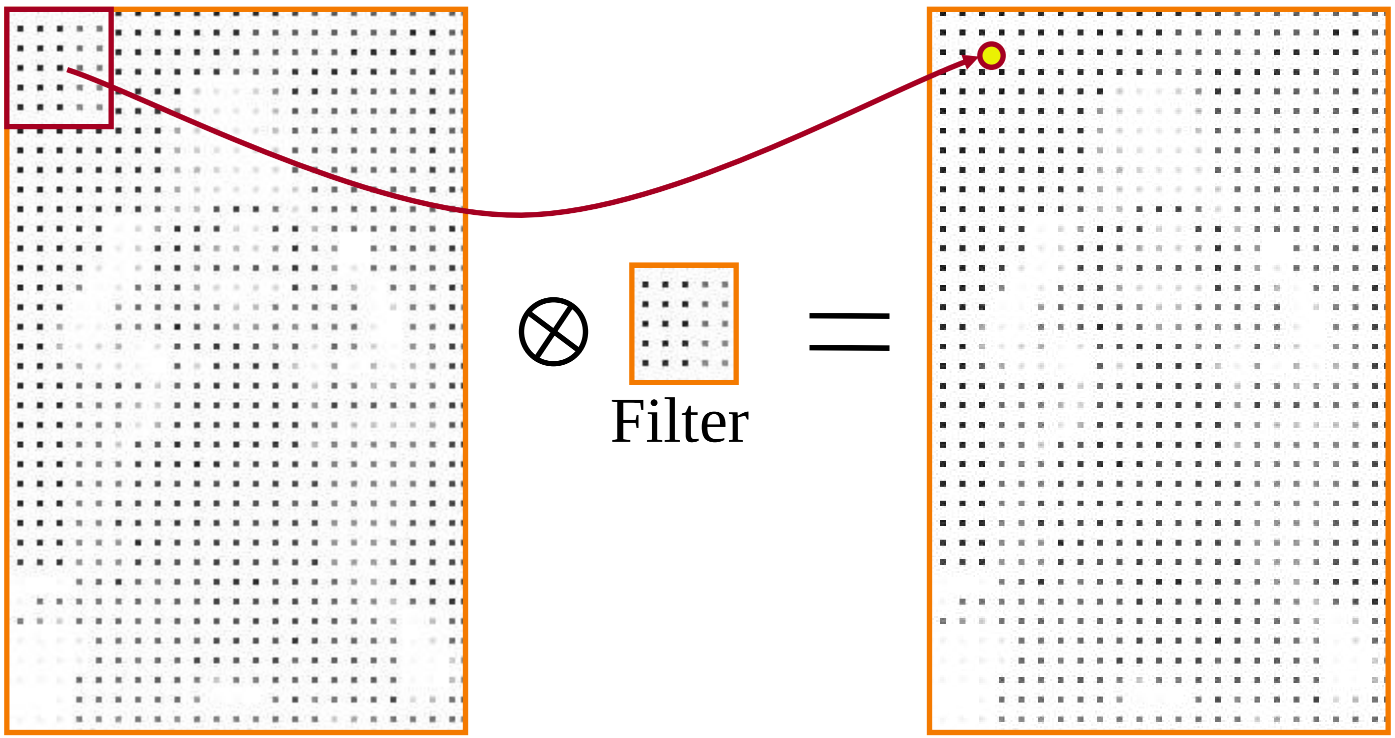


Input Image

Output Image

# Linear Filtering

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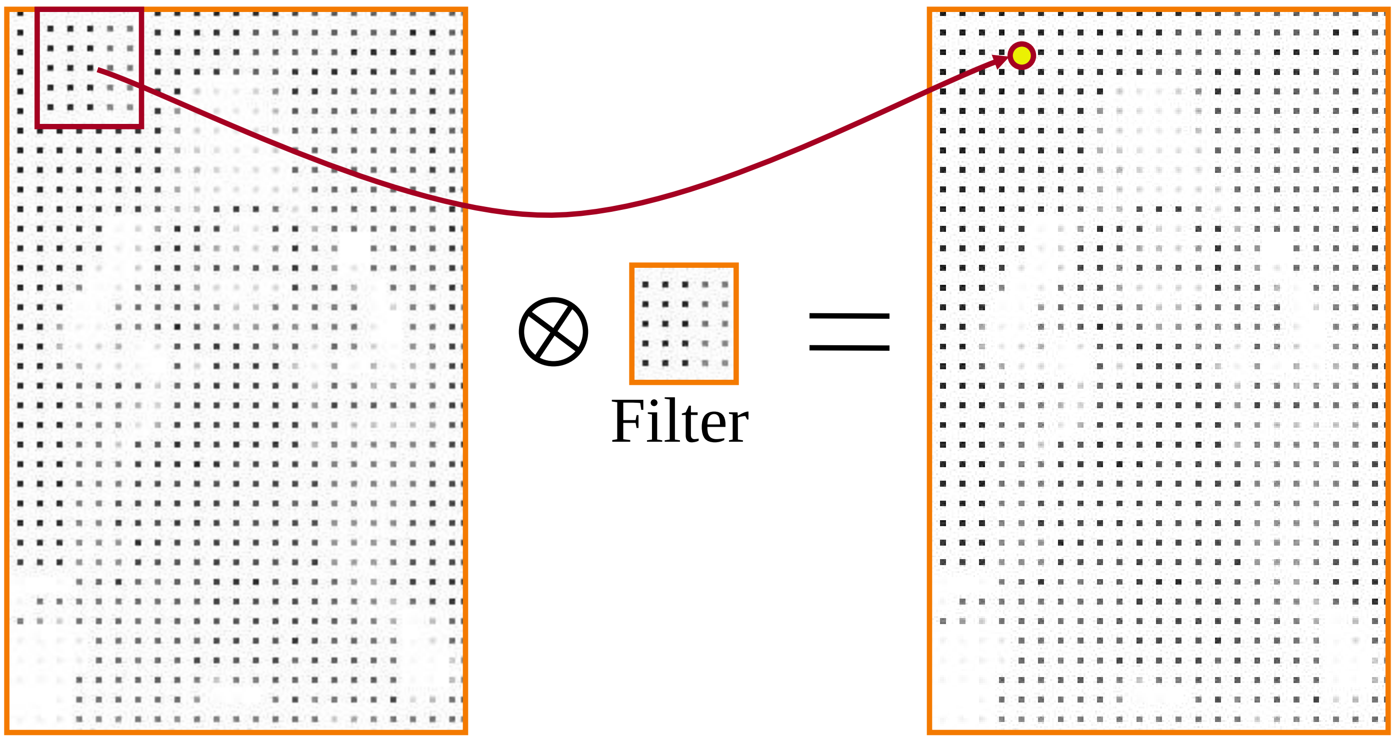


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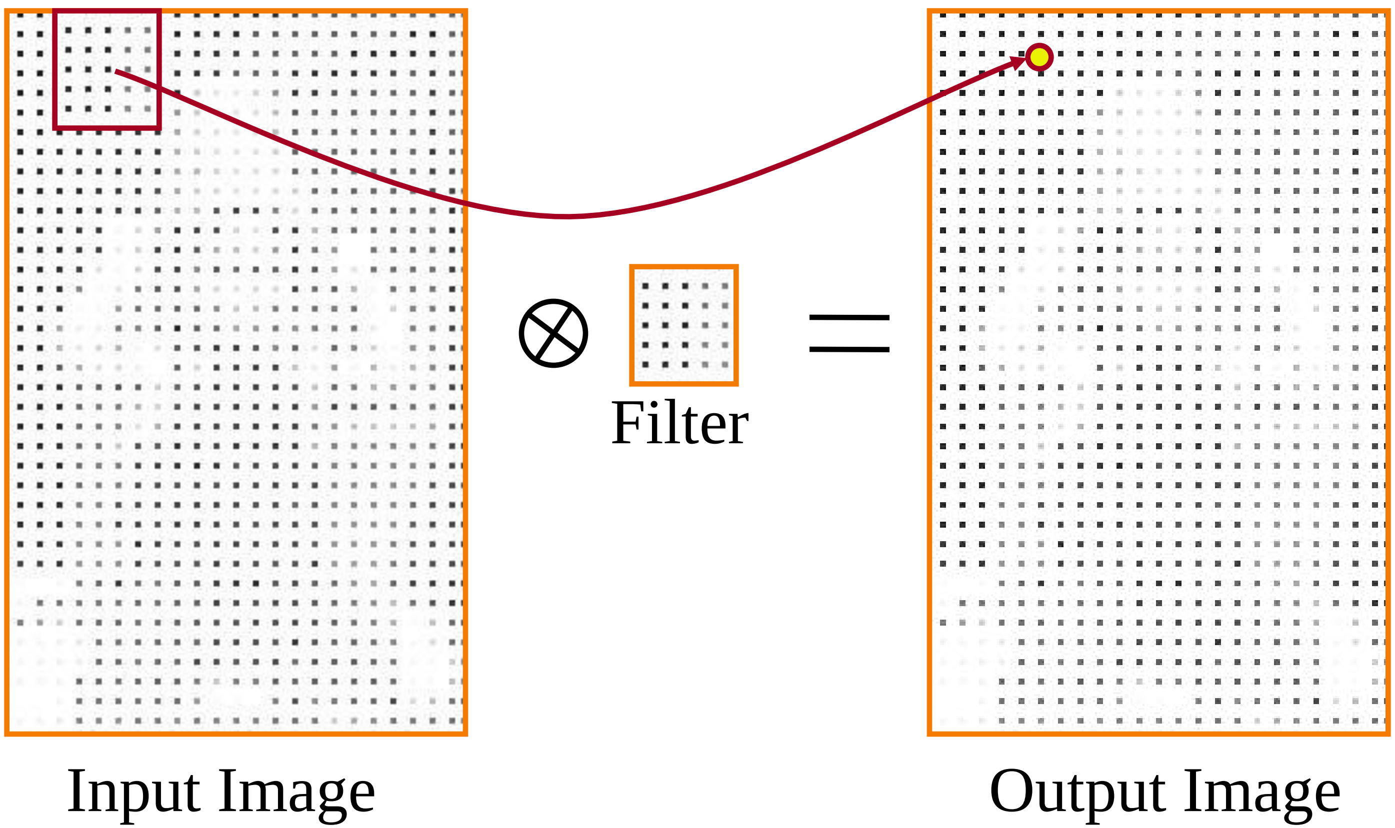


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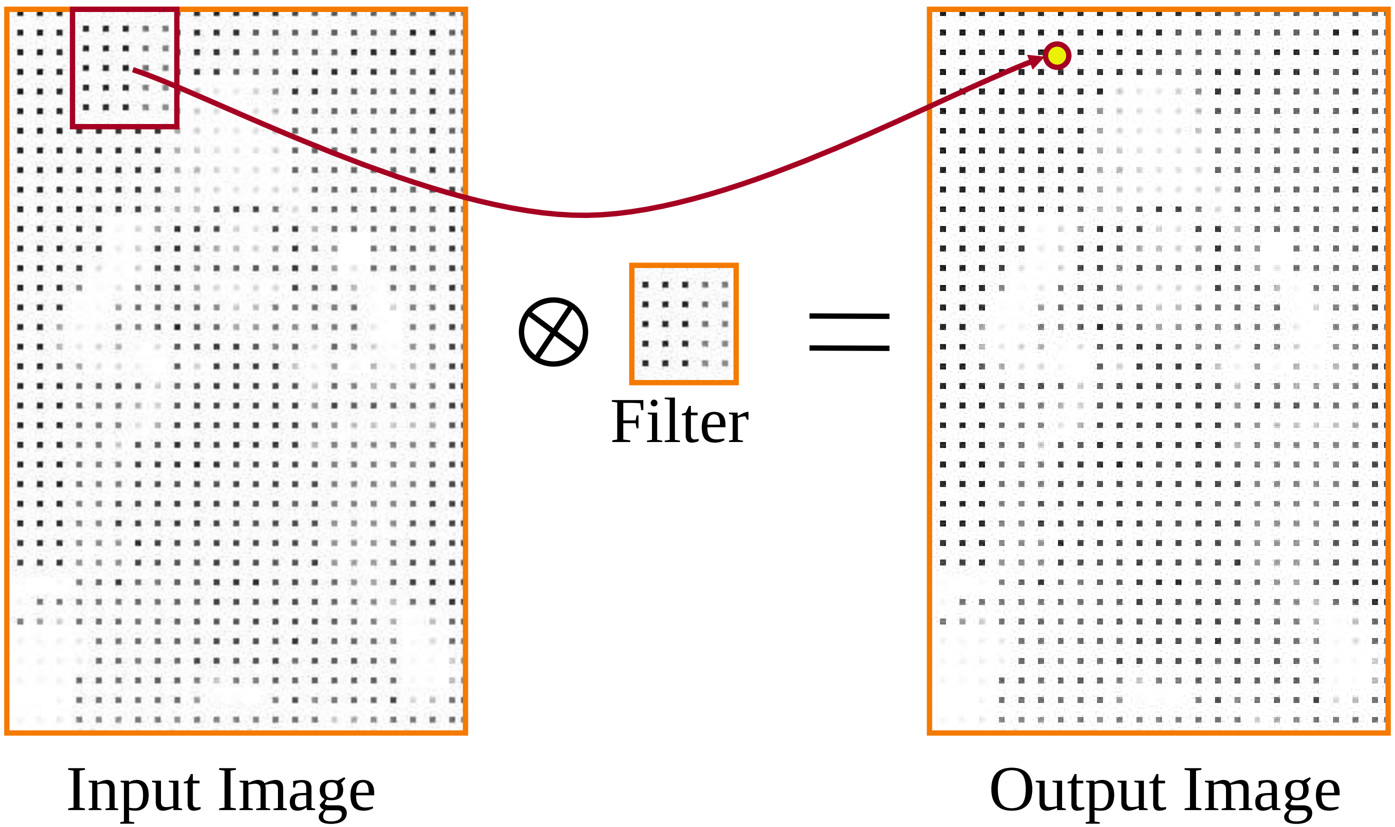
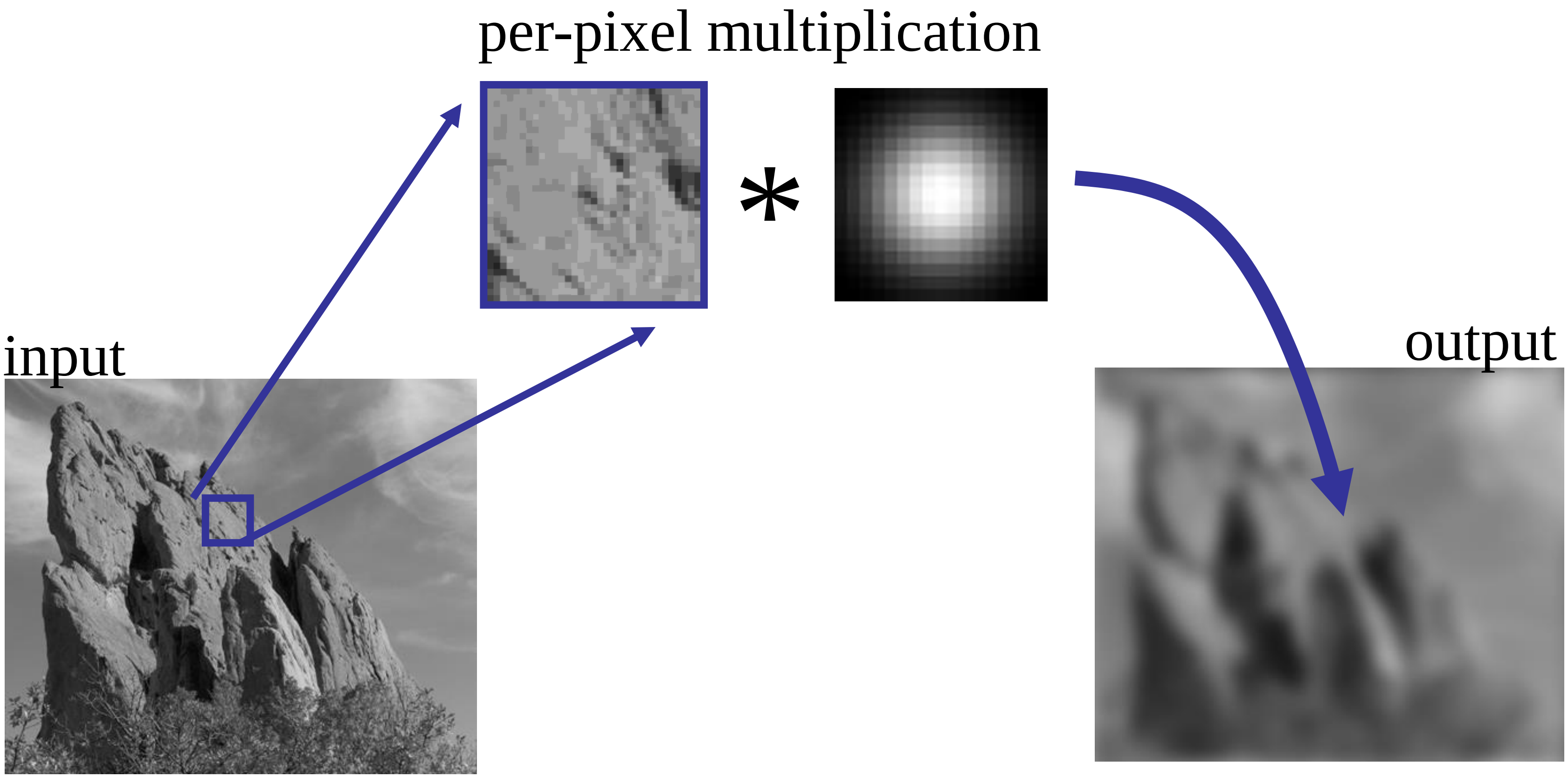



# Gaussian Blur

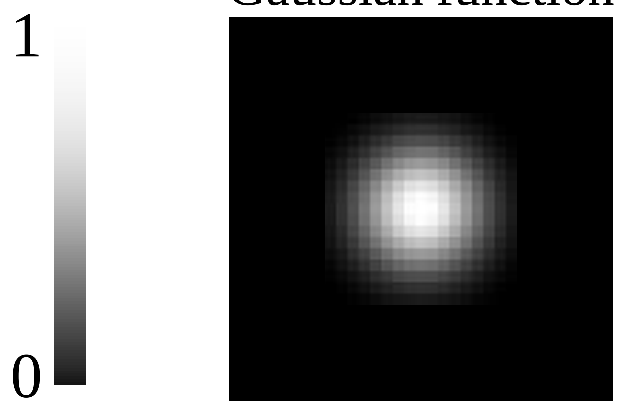


# Gaussian Blur

Output value is weighted sum of values in neighborhood of input image

$$Blur(I_{\mathbf{p}},\sigma)=\sum_{\mathbf{q}\in S} G(\|\mathbf{p}-\mathbf{q}\|,\sigma)\, I_{\mathbf{q}}$$

normalized Gaussian function




input


Gaussian blur

# Linear Filtering

- Many interesting linear filters
  - Blur
  - Edge detect
  - Sharpen
  - Emboss
  - etc.

Filter = ?

# Blur

## Convolve with a 2D Gaussian filter

Original

Blur

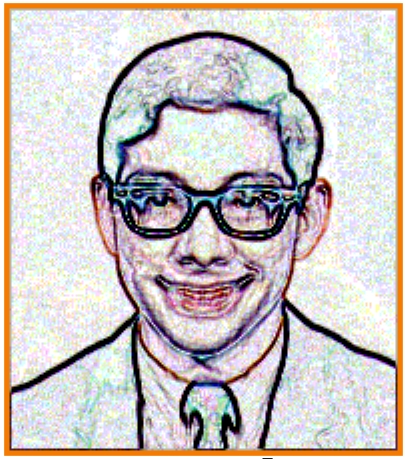
$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

$$\text{Filter} = \begin{bmatrix} 1/16 & 2/16 & 1/16 \\ 2/16 & 4/16 & 2/16 \\ 1/16 & 2/16 & 1/16 \end{bmatrix}$$

# Edge Detection

Convolve with a 2D Laplacian filter that finds differences between neighbor pixels

Original



Detect edges

$$\text{Filter} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & +8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

# Sharpen

Sum detected edges with original image

Original

Sharpened

$$\text{Filter} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & +9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

# Emboss

Convolve with a filter that highlights gradients in particular directions

Original

Embossed

$$\text{Filter} = \begin{bmatrix} -1 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$$

# Side Note: Separable Filters

Some filters are separable (e.g., Gaussian)

- First, apply 1-D convolution across every row
- Then, apply 1-D convolution across every column
- Big impact on performance

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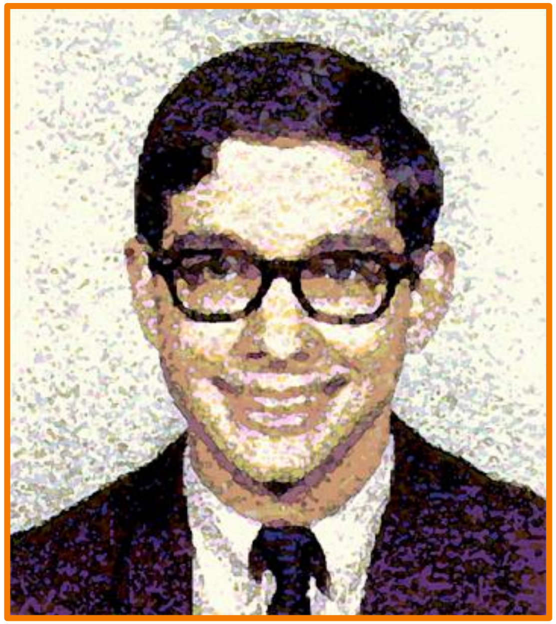
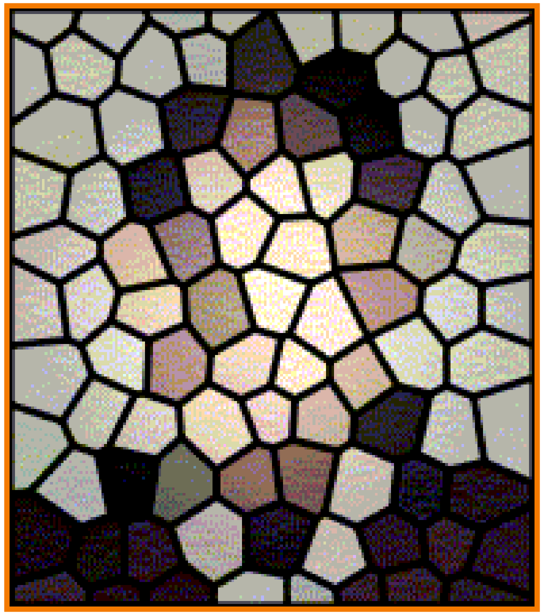
# Non-Linear Filtering

Each output pixel is a non-linear function of input pixels in neighborhood (filter depends on input)

Original



Paint



Stained Glass

# Median Filter

Each output pixel is median of input pixels in neighborhood

original image

1px median filter

3px median filter

10px median filter

# Bilateral Filter

Gaussian blur uses same filter for all pixels

- Blurs across edges as much as other areas

Original

Gaussian Blur

# Bilateral Filter

Gaussian blur uses same filter for all pixels

Prefer a filter that preserves edges (adapts to content)

Original

Bilateral Filter

# Bilateral Filter

Combine Gaussian filtering in both spatial domain and color domain

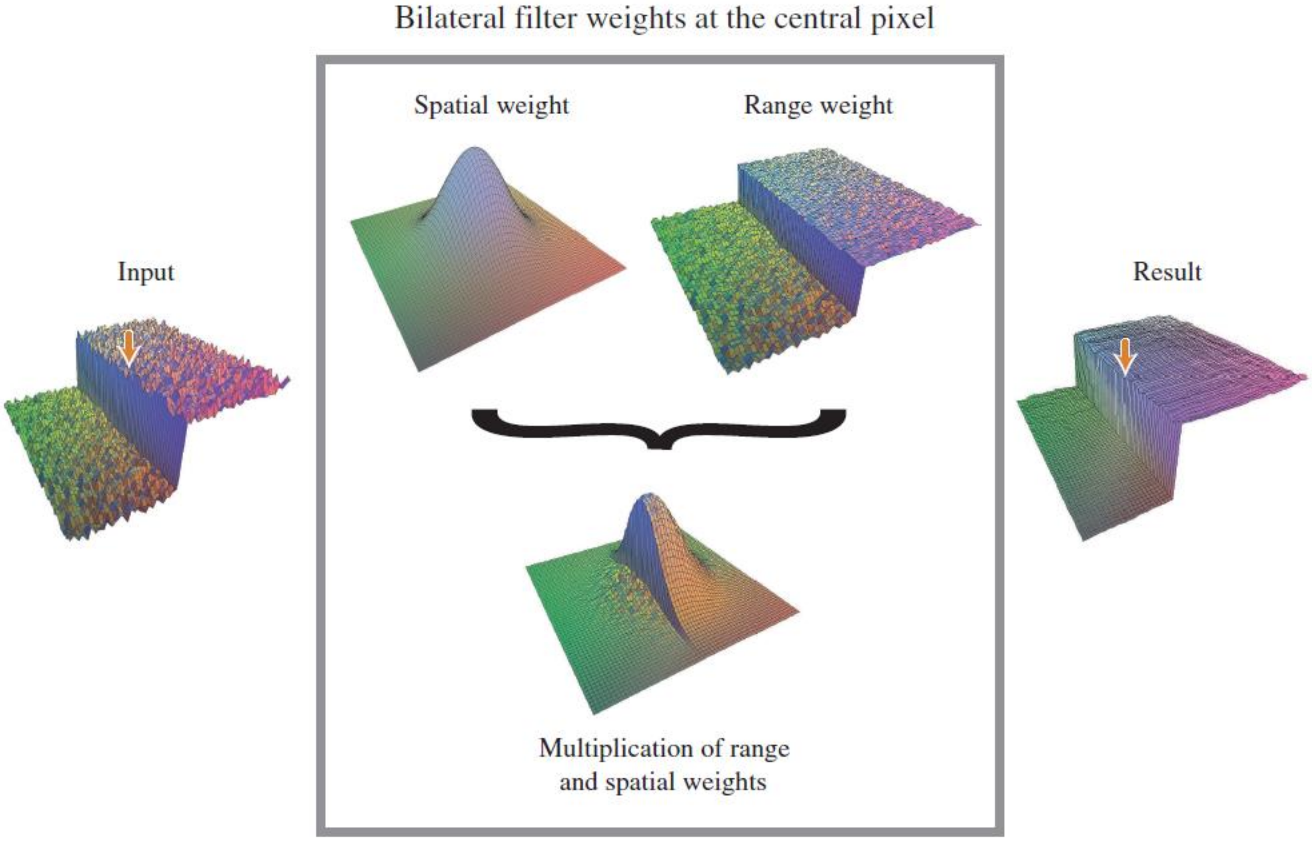
$$Bilateral[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}\left(\| \mathbf{p} - \mathbf{q} \|\right) G_{\sigma_r}\left(| I_{\mathbf{p}} - I_{\mathbf{q}} |\right) I_{\mathbf{q}}$$

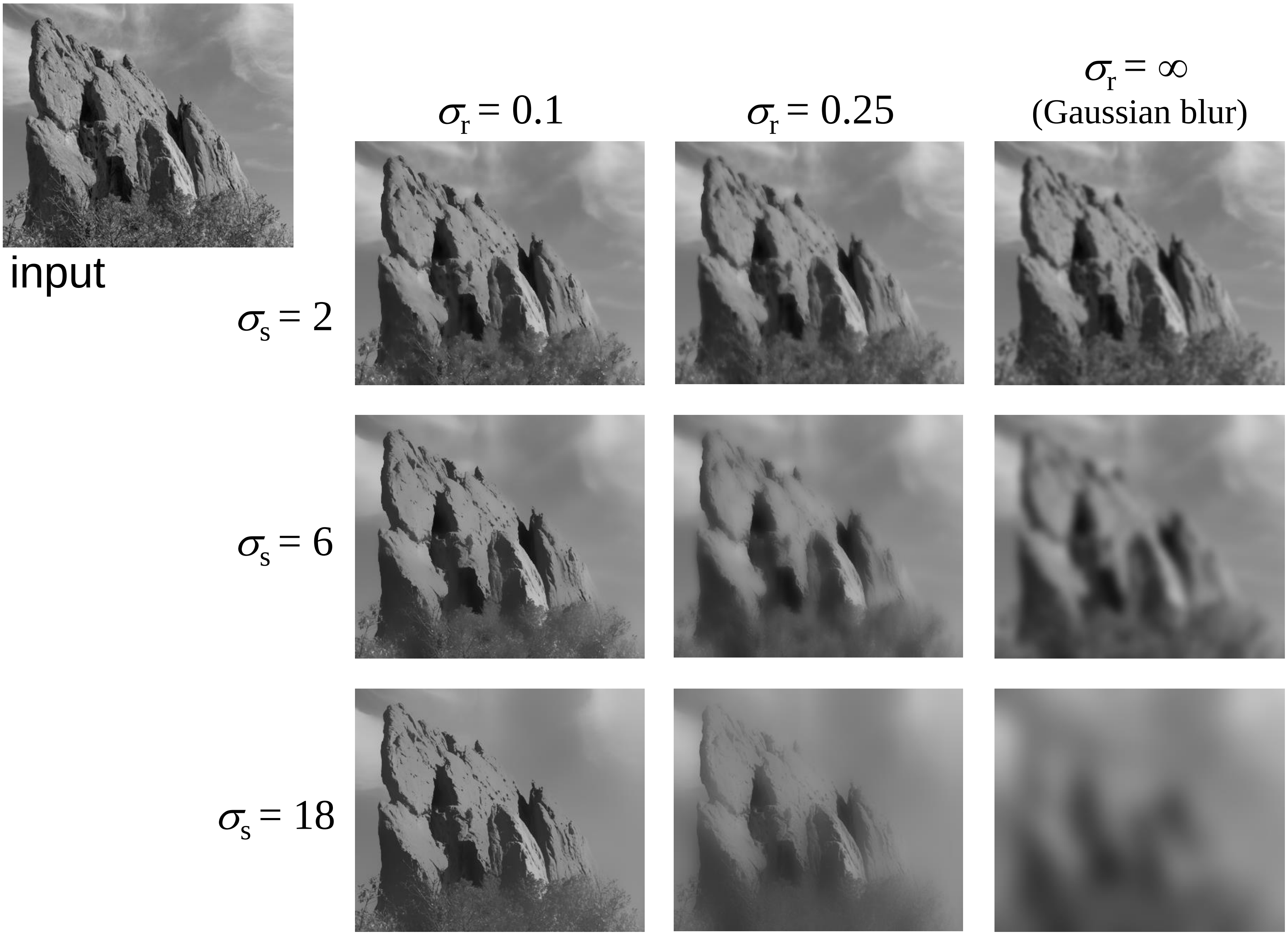
Spatial Proximity Weight

Color Proximity Weight

# Bilateral Filtering

Combine Gaussian filtering in both spatial domain and color domain




input
$\sigma_r = 0.1$
$\sigma_r = 0.25$
$\sigma_r = \infty$
(Gaussian blur)
$\sigma_s = 2$
$\sigma_s = 6$
$\sigma_s = 18$

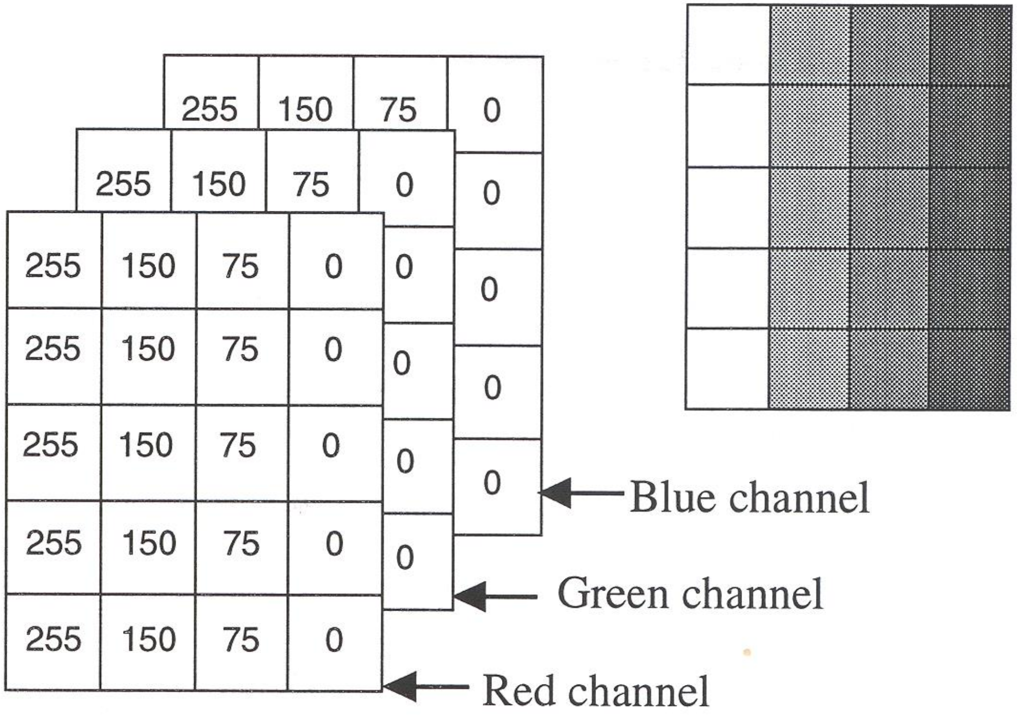
# Image Processing Operations

- Luminance
  - Brightness
  - Contrast.
  - Gamma
  - Histogram equalization
- Color
  - Black & white
  - Saturation
  - White balance
- Linear filtering
  - Blur & sharpen
  - Edge detect
  - Convolution
- Non-linear filtering
  - Median
  - Bilateral filter
- Dithering
  - Quantization
  - Ordered dither
  - Floyd-Steinberg

# Quantization

Reduce intensity resolution

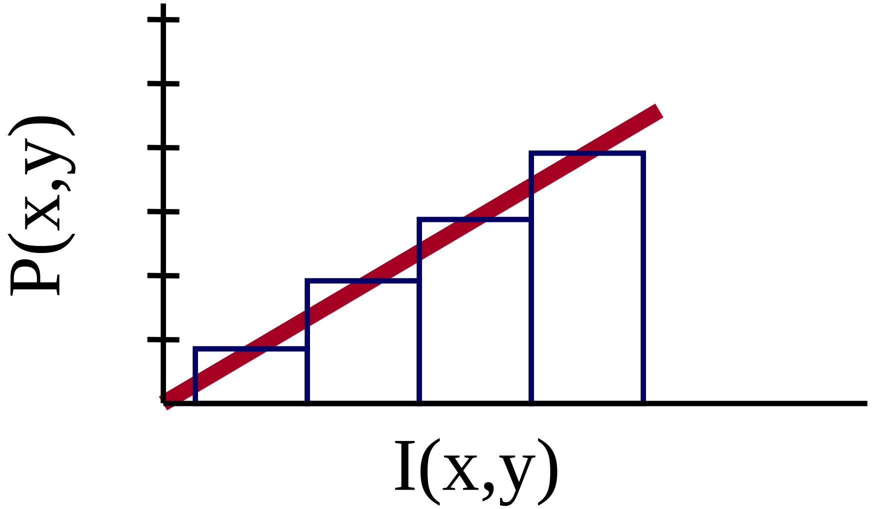
- Frame buffers have limited number of bits per pixel
- Physical devices have limited dynamic range



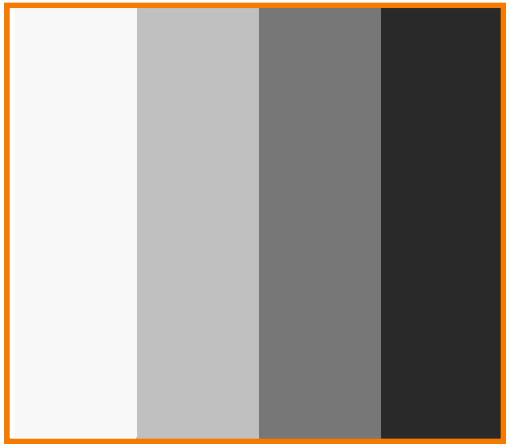
# Uniform Quantization

$P(x, y) = \text{round}( I(x, y) )$

where round() chooses nearest value that can be represented.




I(x,y)

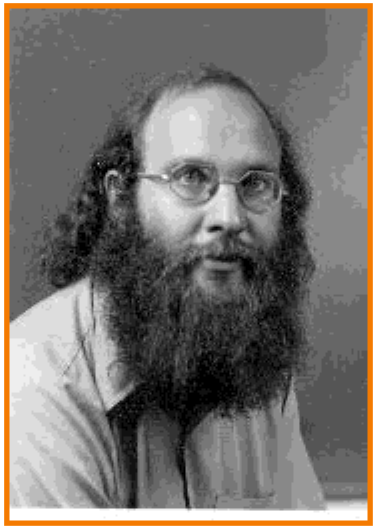


P(x,y)
(2 bits per pixel)

# Uniform Quantization

Images with decreasing bits per pixel:

8 bits



4 bits

2 bits

1 bit

Notice contouring.

# Reducing Effects of Quantization

- Intensity resolution / spatial resolution tradeoff

- Dithering
  - Random dither
  - Ordered dither
  - Error diffusion dither

- Halftoning
  - Classical halftoning

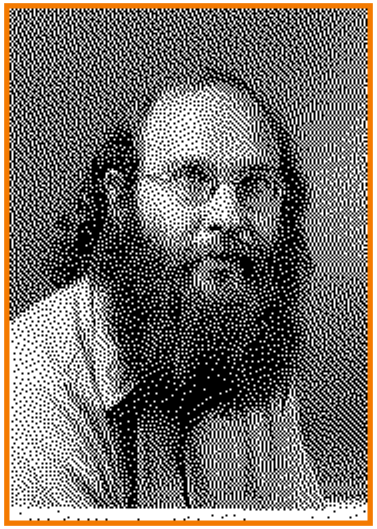
# Dithering

Distribute errors among pixels

- Exploit spatial integration in our eye
- Display greater range of perceptible intensities

Original
(8 bits)

Uniform
Quantization
(1 bit)

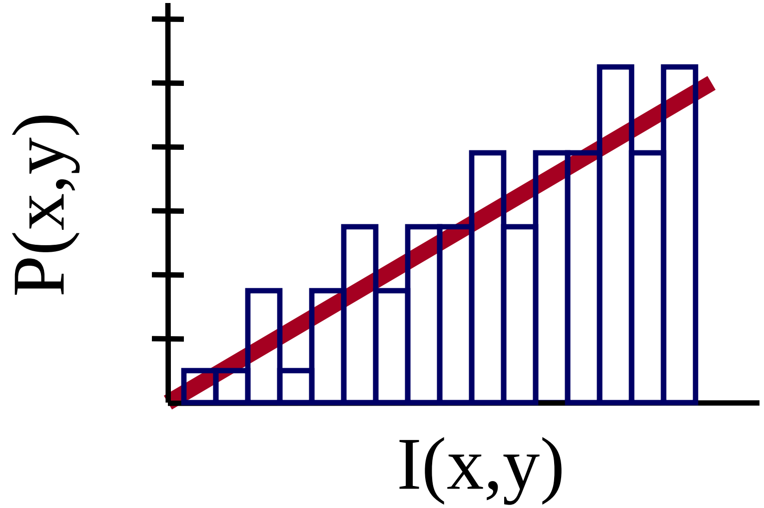


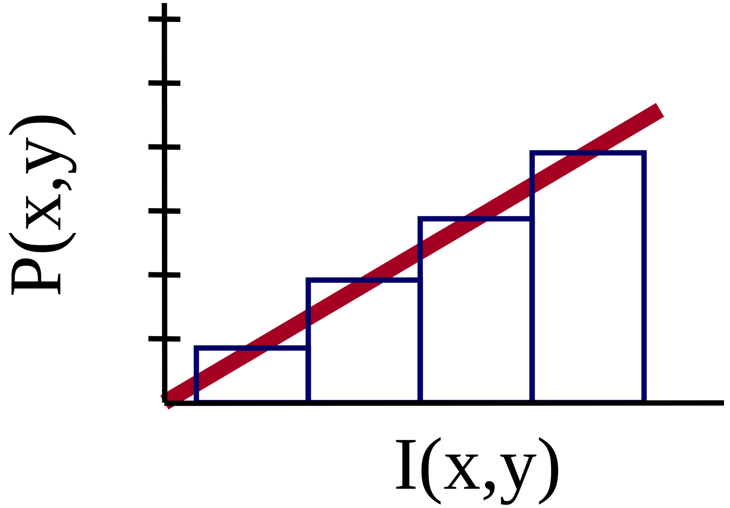
Floyd-Steinberg
Dither
(1 bit)

# Random Dither

Randomize quantization errors

- Errors appear as noise




$$P(x, y) = \mathrm{round}\big(I(x, y) + \mathrm{noise}(x,y)\big)$$

# Random Dither

Original
(8 bits)

Uniform
Quantization
(1 bit)

Random
Dither
(1 bit)

# Ordered Dither

Pseudo-random quantization errors

- Matrix stores pattern of threshholds

i = x mod n

j = y mod n

e = I(x,y) - trunc(I(x,y))

threshold = (D(i,j)+1)/(n²+1)

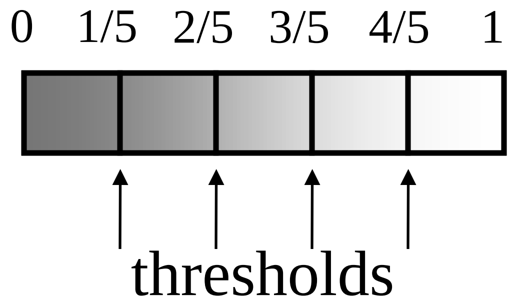
if (e > threshold)

  P(x,y) = ceil(I(x, y))

else

  P(x,y) = floor(I(x,y))

$$D_2 = \begin{bmatrix} 3 & 1 \\ 0 & 2 \end{bmatrix}$$



# Ordered Dither

Bayer's ordered dither matrices

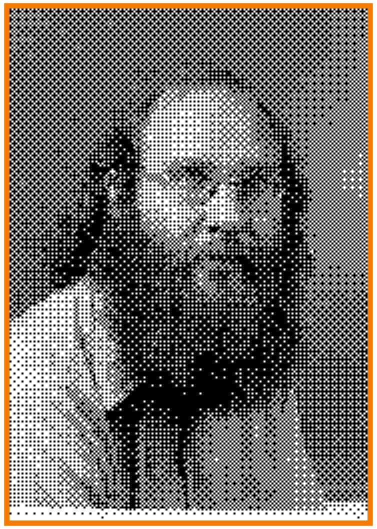
$$D_n = \begin{bmatrix} 4D_{n/2} + D_2(1,1)U_{n/2} & 4D_{n/2} + D_2(1,2)U_{n/2} \\ 4D_{n/2} + D_2(2,1)U_{n/2} & 4D_{n/2} + D_2(2,2)U_{n/2} \end{bmatrix}$$

$$D_2 = \begin{bmatrix} 3 & 1 \\ 0 & 2 \end{bmatrix} \qquad D_4 = \left[\begin{array}{cc|cc} 15 & 7 & 13 & 5 \\ 3 & 11 & 1 & 9 \\ \hline 12 & 4 & 14 & 6 \\ 0 & 8 & 2 & 10 \end{array}\right]$$

# Ordered Dither

Original
(8 bits)

Random
Dither
(1 bit)

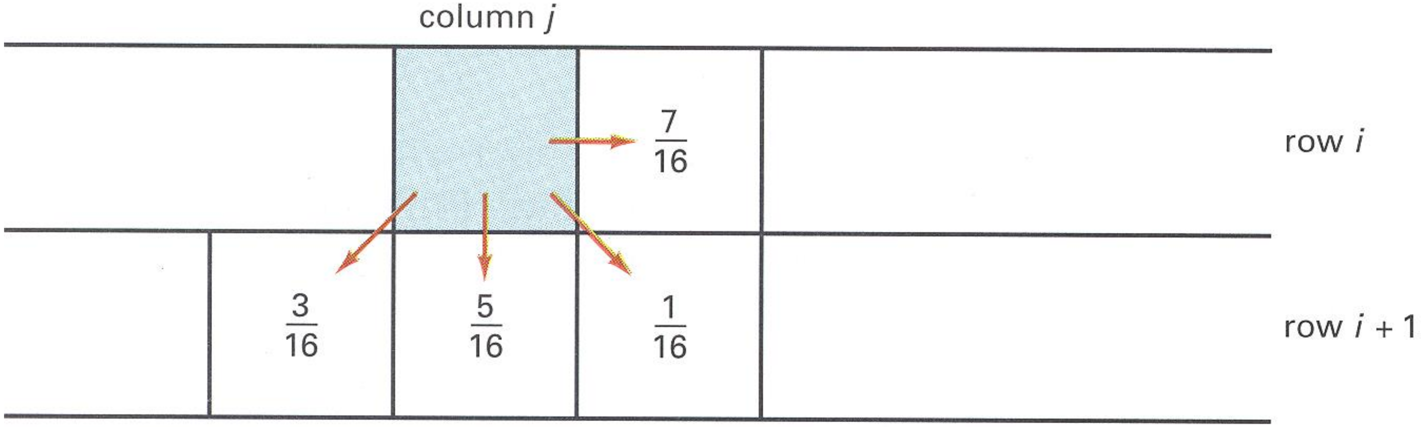


Ordered
Dither
(1 bit)

# Error Diffusion Dither

Spread quantization error over neighbor pixels

- Error dispersed to pixels right and below
- Floyd-Steinberg weights:



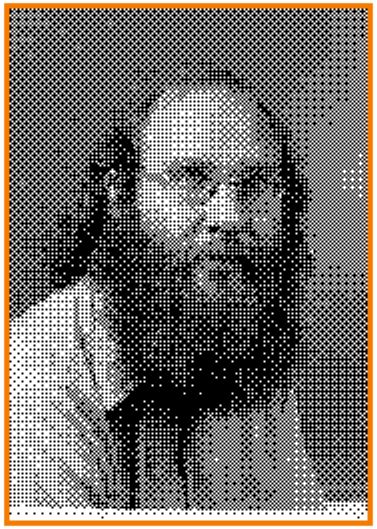

$$3/16 + 5/16 + 1/16 + 7/16 = 1.0$$

Figure 14.42 from H&B

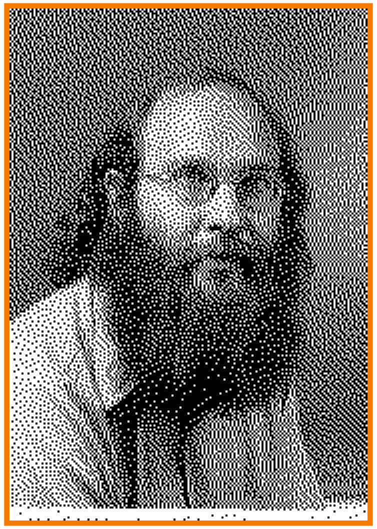
# Error Diffusion Dither

Original
(8 bits)

Random
Dither
(1 bit)



Ordered
Dither
(1 bit)



Floyd-Steinberg
Dither
(1 bit)

# Summary

- Color transformations
  - Different color spaces useful for different operations
- Filtering
  - Compute new values for image pixels based on function of old values in neighborhood
- Dithering
  - Reduce visual artifacts due to quantization
  - Distribute errors among pixels
    Exploit spatial integration in our eye