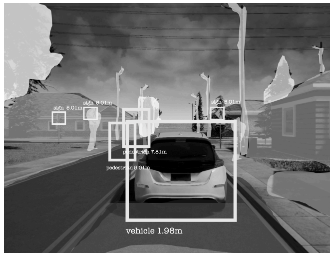
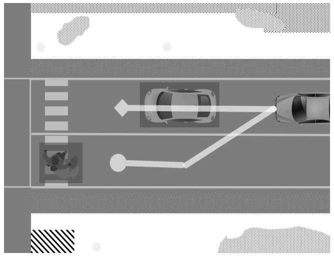
# Principles of Safe Autonomy
# Lecture 3: Perception and Vision

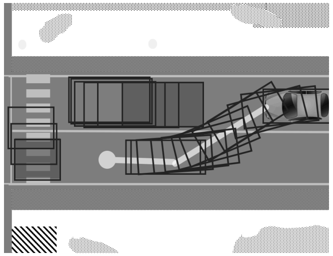
Sayan Mitra
slides from Svetlana Lazebnik

# GEM platform

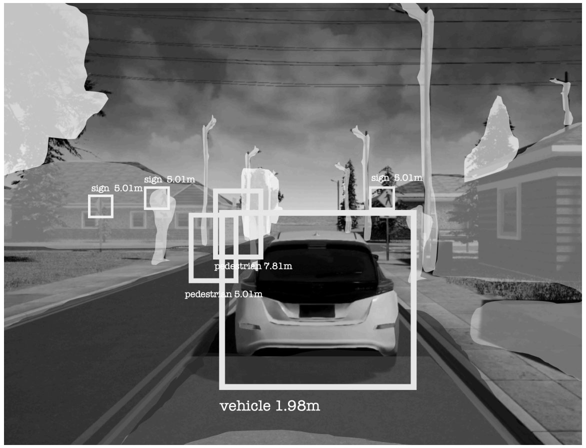

# Autonomy pipeline





| **Sensing** | **Perception** | **Decisions and planning** | **Control** |
|---|---|---|---|
| Physics-based models of camera, LIDAR, RADAR, GPS, etc. | Programs for object detection, lane tracking, scene understanding, etc. | Programs and multi-agent models of pedestrians, cars, etc. | Dynamical models of engine, powertrain, steering, tires, etc. |

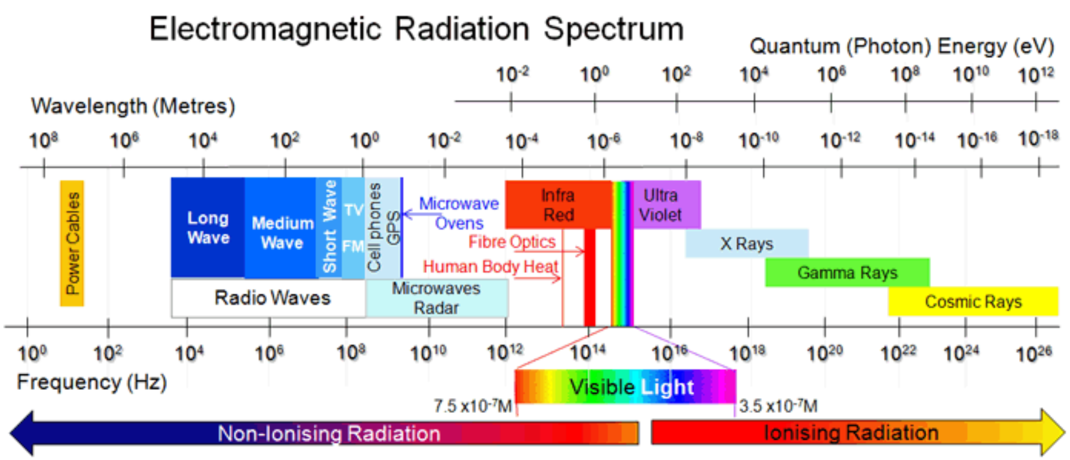



**Perception**

Programs for object detection, lane tracking, scene understanding, etc.

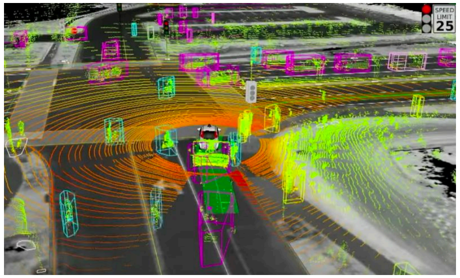
# Perception: EM to objects

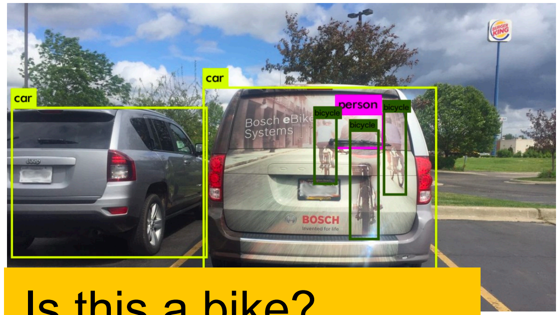
Problem: Process electromagnetic radiation from the environment to construct a *model* of the world, so that the constructed model is close to the real world




Challenging for computers: millions of years of evolution

Ill-defined problem: impossibility of defining meaning “car”, “bicycle”, etc.

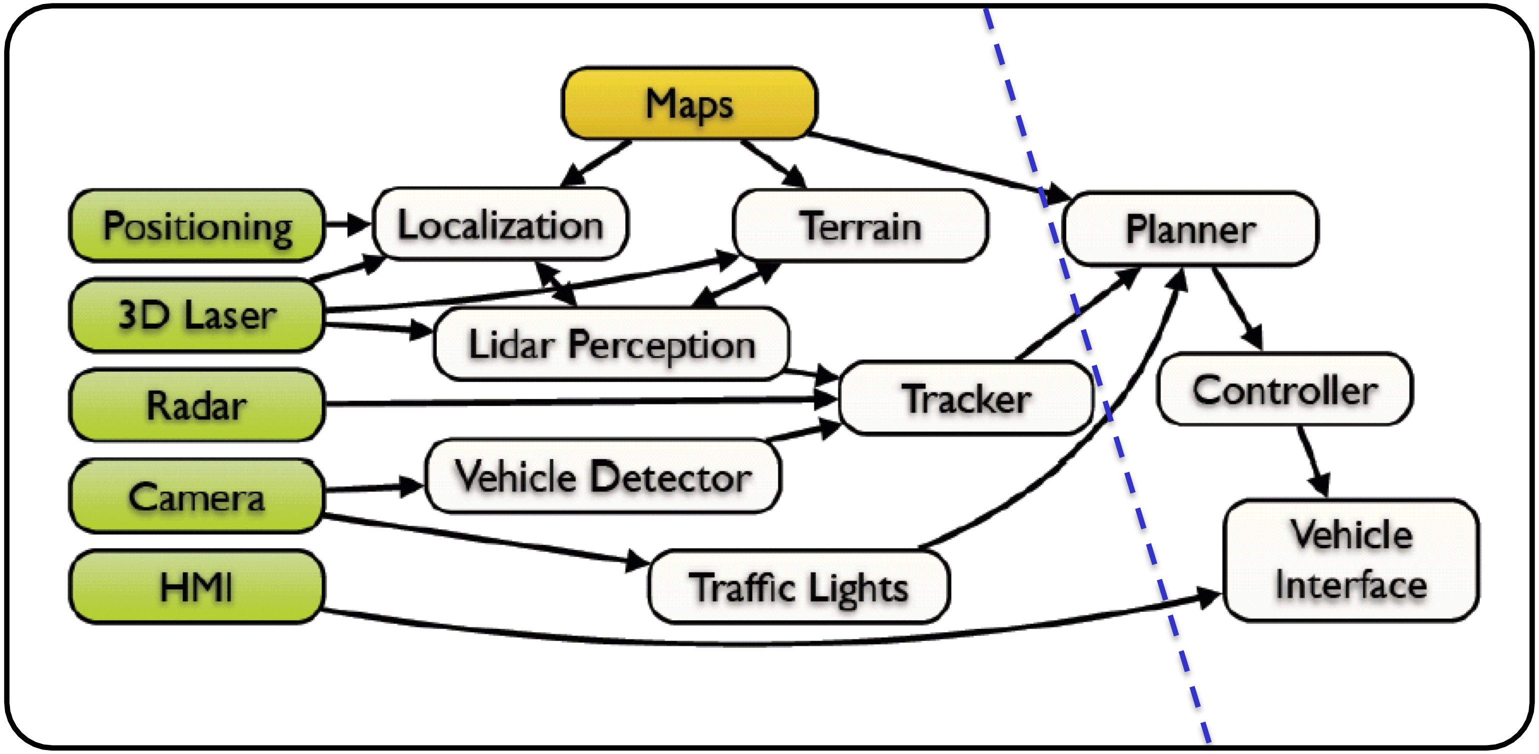



Is this a bike?

Is this a car?

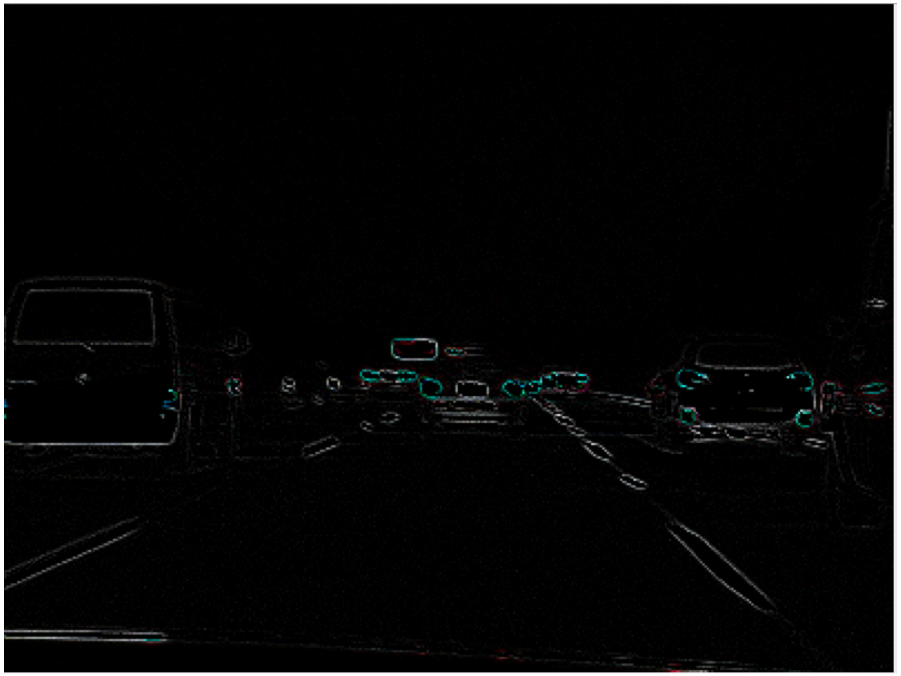
# A practical perception pipeline in an AV has many pieces




This architecture from a slide from M. James of Toyota Research Institute, North America

# Outline

- Linear filtering
- Edge detection
- Assumptions in simple safety model (read)



# Motivation: Image denoising

- How can we reduce noise in a photograph?

# Image representation

Images are represented as 2D arrays of pixels. Each pixel is represented by (array of) value(s) representing its color.

```
# read an image
img = cv2.imread('images/noguchi02.jpg')

# show image format (basically a 3-d array of pixel color info, in BGR format)
print(img)
```

```
[
  [[72 99 143]  [76 103 147]  [78 106 147]  ...,
  [[74 101 145]  [77 104 148]  [77 105 146]  ...,
  [[76 103 147]  [77 104 148]  [76 104 145]  ...,
  ...,
  [[39 78 130]  [39 78 130]  [40 79 131]  ...,  [
  [[32 71 123]  [32 71 123]  [32 71 123]  ...,  [
  [[39 78 130]  [39 78 130]  [39 78 130]  ...,  [
]
```

Where [72 99 143] is the blue, green, and red values of that pixel.

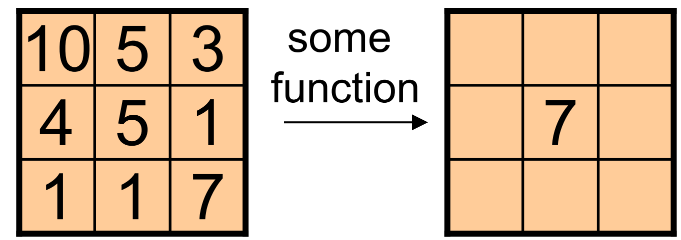
We will work with grayscale images

Denote by img[i,j] (or f[i,j]) the value of the i,j-th pixel

# What is filtering?

Modify the pixels in an image based on some function of a local neighborhood of the pixels.

Scaling: img’ = k*img




Shifting right by s: img’[k] = img[k-s]; img’[0]…img’[s-1] is undefined

Simplest: Linear filtering

replace each pixel by a linear combination of neighbors

# Moving average

- Let's replace each pixel with a *weighted* average of its neighborhood
- The weights are called the *filter kernel*
- What are the weights for the average of a 3x3 neighborhood?

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

"box filter"

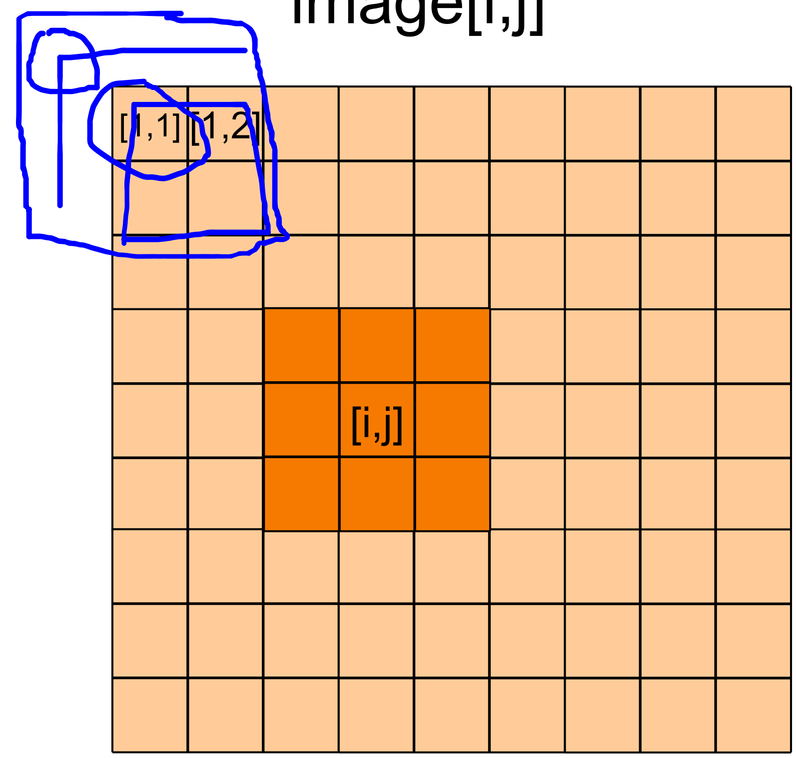
Source: D. Lowe

# Convolution

convolution mask g[,]

| | | |
|---|---|---|
| 1,1 | 1,2 | 1,3 |
| 2,1 | 2,2 | 2,3 |
| 3,1 | 3,2 | 3,3 |

image[i,j]




Output or convolved image

f = g * img

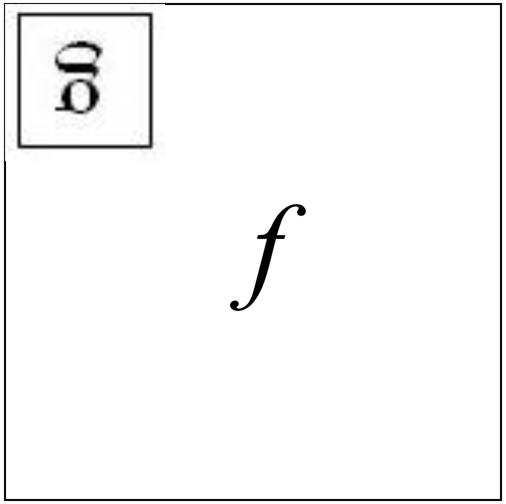
f[i,j] = g[1,1] img[i-1,j-1] + g[1,2] img[i-1,j] + g[1,3] img[i-1,j+1]
+ g[2,1] img[i,j-1] + g[2,2] img[i,j] + g[2,3] img[i,j+1]
+ g[3,1] img[i+1,j-1] + g[3,2] img[i+1,j] + g[3,3] img[i+1,j+1]

# Defining convolution

- Let *f* be the image and *g* be the kernel. The output of convolving *f* with *g* is denoted *f* * *g*.

$$(f*g)[m,n]=\sum_{k,l} f[m-k,n-l]\,g[k,l]$$

Convention: kernel is “flipped”



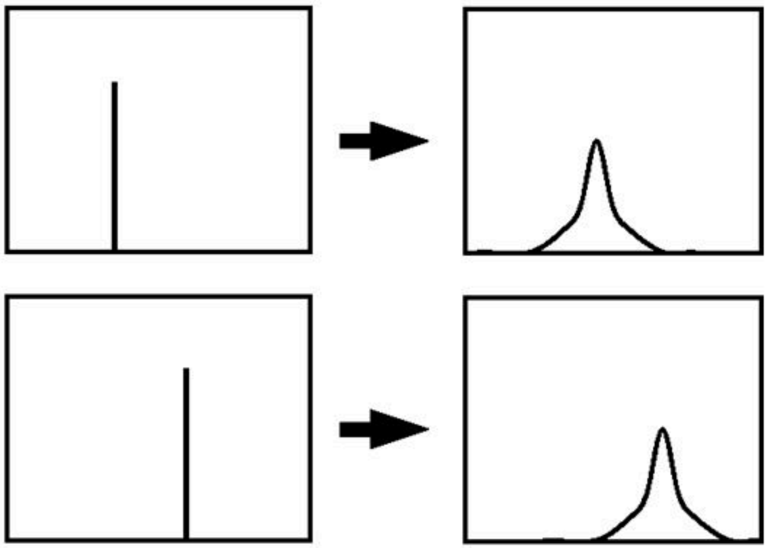
# For analysis we will work with 1D images

- Let *f* be the image and *g* be the kernel. The output of convolving *f* with *g* is denoted *f * g*.

$$(f * g)[\underline{m}] = \Sigma_k f[m-k]g[k]$$

# Key properties: Prove the first two

- **Shift invariance:** same behavior regardless of pixel location: filter(shift($f$)) = shift(filter($f$))



- **Linearity:** filter($f_1$ + $f_2$) = filter($f_1$) + filter($f_2$)

- **Theoretical result:** any linear shift-invariant operator can be represented as a convolution

# Properties in more detail

- Commutative: $a * b = b * a$
  - Conceptually no difference between filter and signal
- Associative: $a * (b * c) = (a * b) * c$
  - Often apply several filters one after another: $(((a * b_1) * b_2) * b_3)$
  - This is equivalent to applying one filter: $a * (b_1 * b_2 * b_3)$
- Distributes over addition: $a * (b + c) = (a * b) + (a * c)$
- Scalars factor out: $ka * b = a * kb = k\,(a * b)$
- Identity: unit impulse $e = [\ldots, 0, 0, 1, 0, 0, \ldots]$, $a * e = a$

# openCV: filter2D

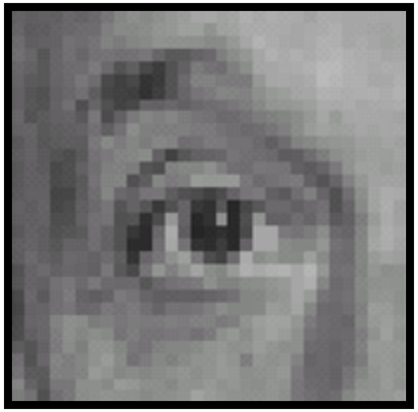
Output image same size as input

Multi-channel: each channel is processed independently

→ Extrapolation of border

Examples

# Practice with linear filters



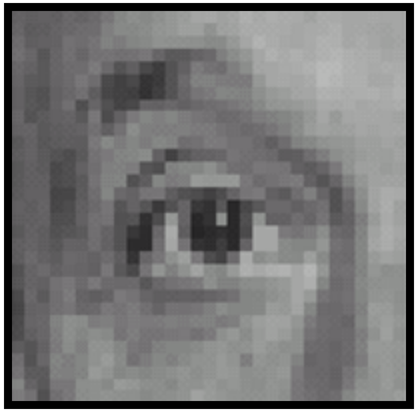
Original

| | | |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 1 | 0 |
| 0 | 0 | 0 |

?

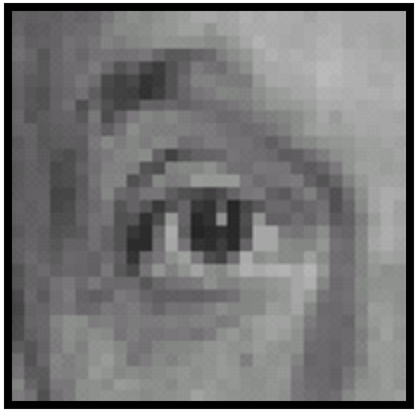
Source: D. Lowe

# Practice with linear filters



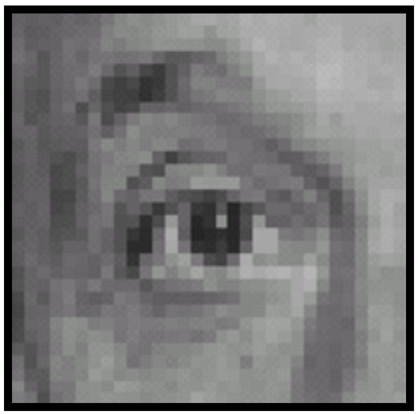
Original

| | | |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 1 | 0 |
| 0 | 0 | 0 |



Filtered
(no change)

# Practice with linear filters



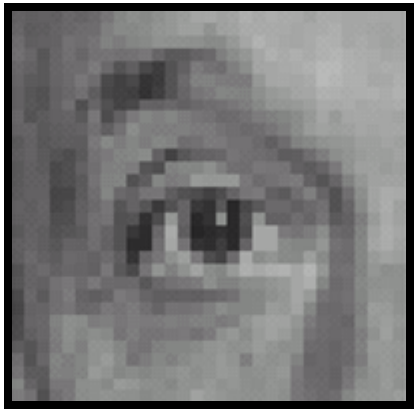
Original

| | | |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 0 | 1 |
| 0 | 0 | 0 |

?

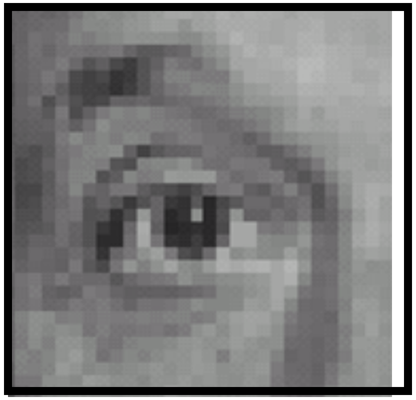
Source: D. Lowe

# Practice with linear filters



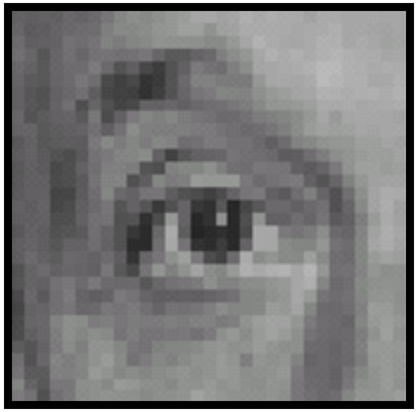
Original

| | | |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 0 | 1 |
| 0 | 0 | 0 |



Shifted *left*
By 1 pixel

# Practice with linear filters



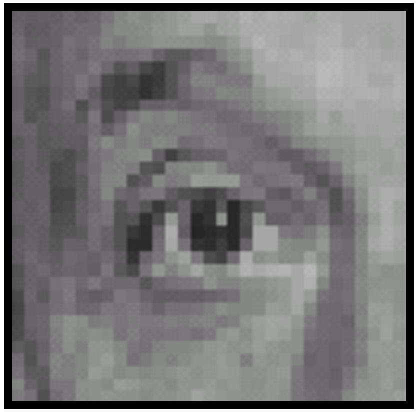
Original

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

?

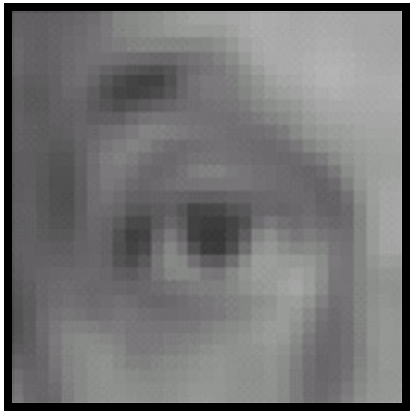
Source: D. Lowe

# Practice with linear filters



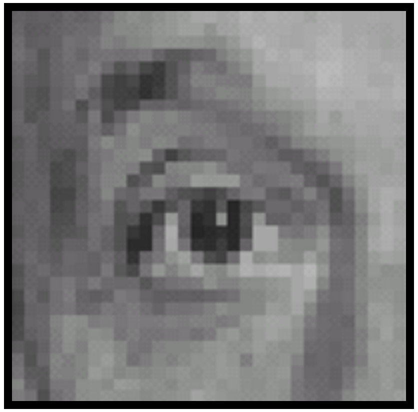
Original

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



Blur (with a box filter)

# Practice with linear filters

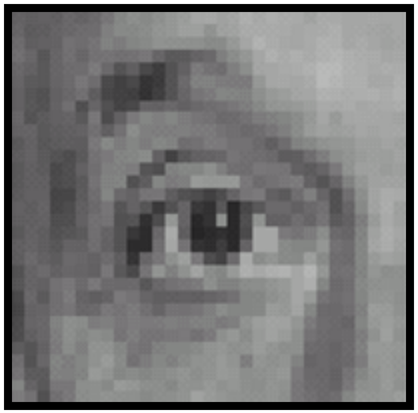


Original

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

(Note that filter sums to 1)

# Practice with linear filters



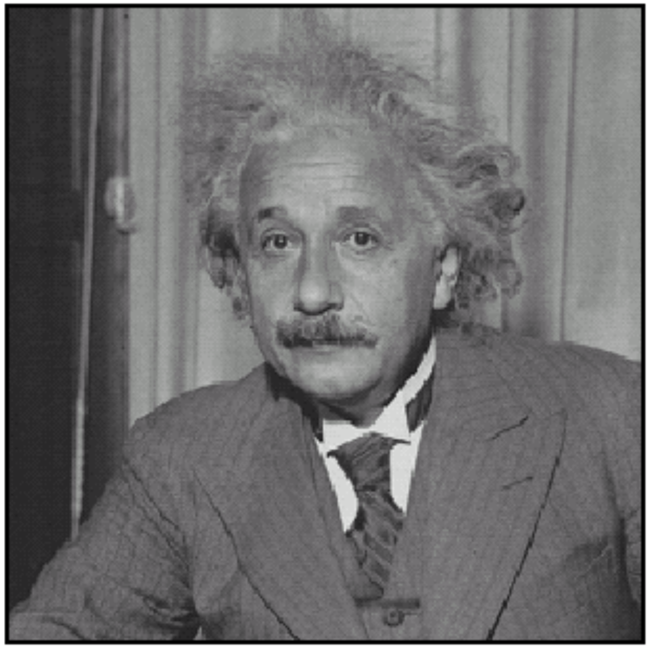
Original

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

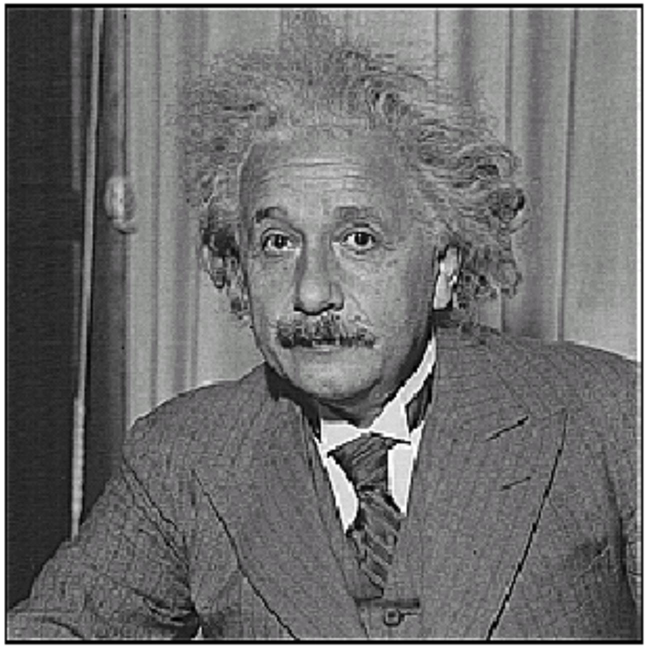
**Sharpening filter**

- Accentuates differences with local average

# Sharpening



before



after

Source: D. Lowe

# Sharpening

## What does blurring take away?


–


=

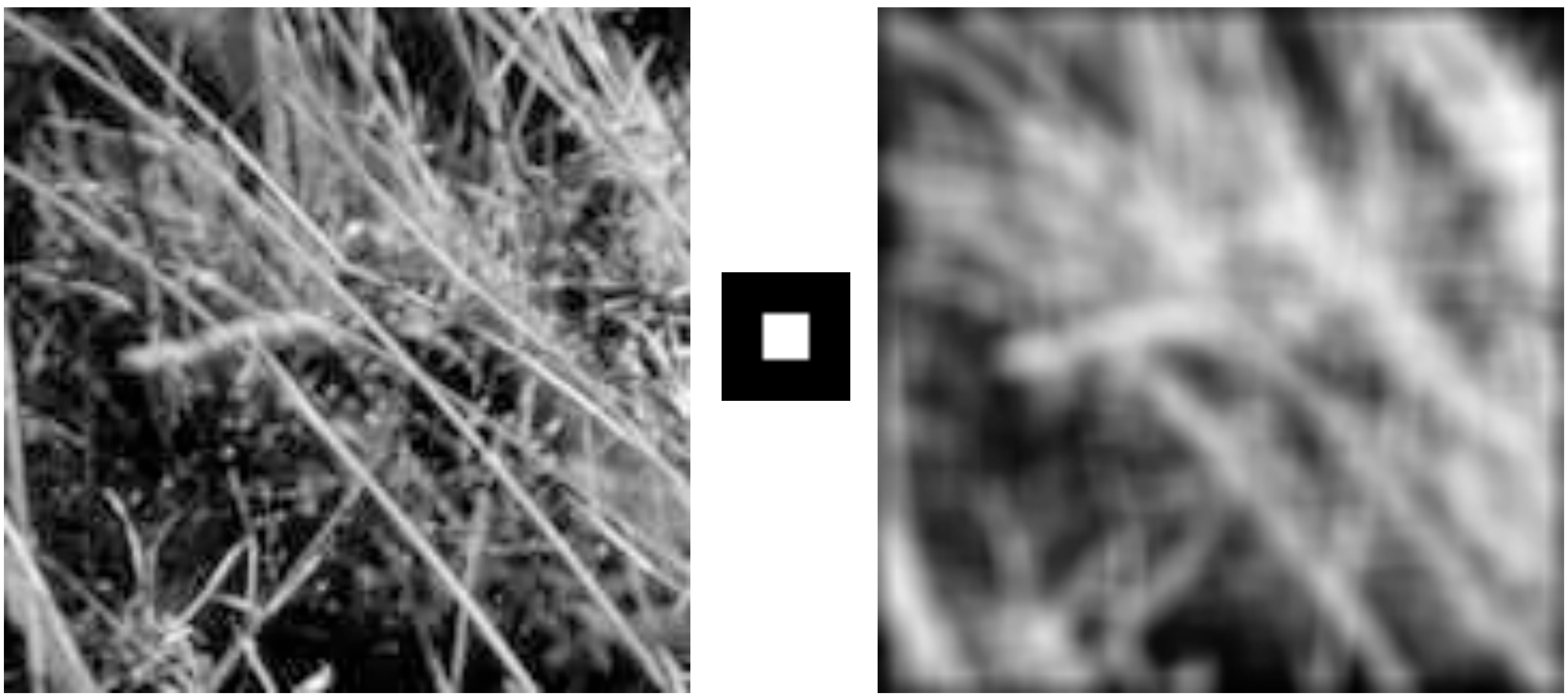

## Let’s add it back:


+


=

# Smoothing with box filter revisited

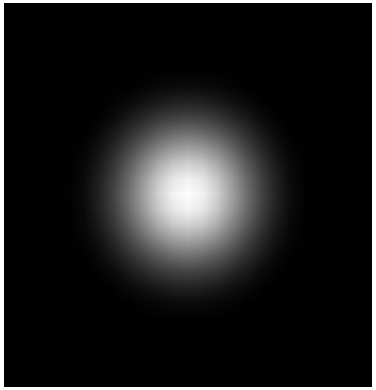
- What's wrong with this picture?
- What's the solution?



Source: D. Forsyth

# Smoothing with box filter revisited

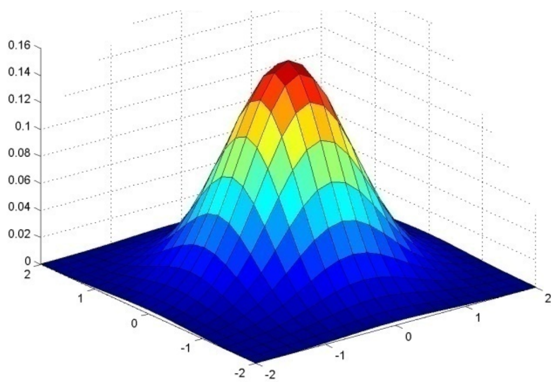
- What's wrong with this picture?
- What's the solution?
  - To eliminate edge effects, weight contribution of neighborhood pixels according to their closeness to the center

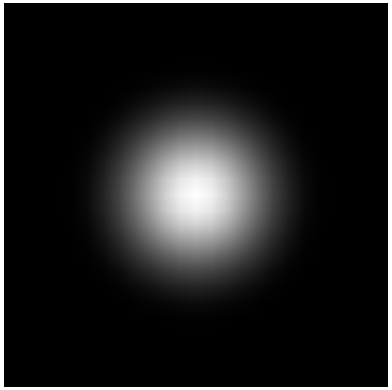


"fuzzy blob"

# Gaussian Kernel

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



| | | | | |
|---|---|---|---|---|
| 0.003 | 0.013 | 0.022 | 0.013 | 0.003 |
| 0.013 | 0.059 | 0.097 | 0.059 | 0.013 |
| 0.022 | 0.097 | 0.159 | 0.097 | 0.022 |
| 0.013 | 0.059 | 0.097 | 0.059 | 0.013 |
| 0.003 | 0.013 | 0.022 | 0.013 | 0.003 |

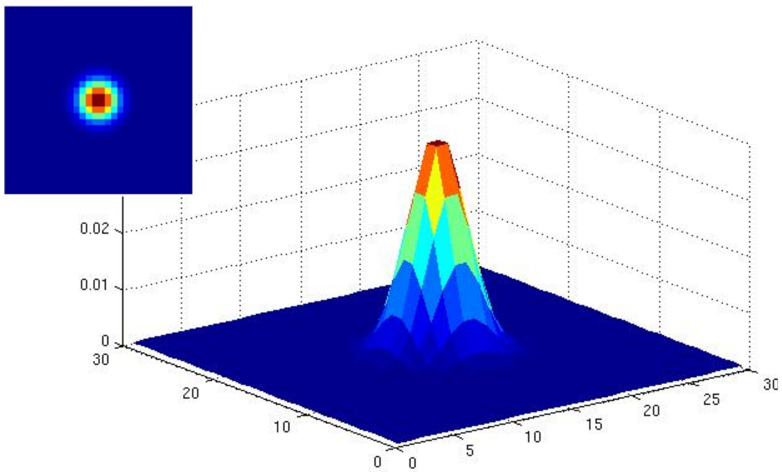
5 x 5, $\sigma$ = 1

Constant factor at front makes volume sum to 1 (can be ignored when computing the filter values, as we should renormalize weights to sum to 1 in any case)

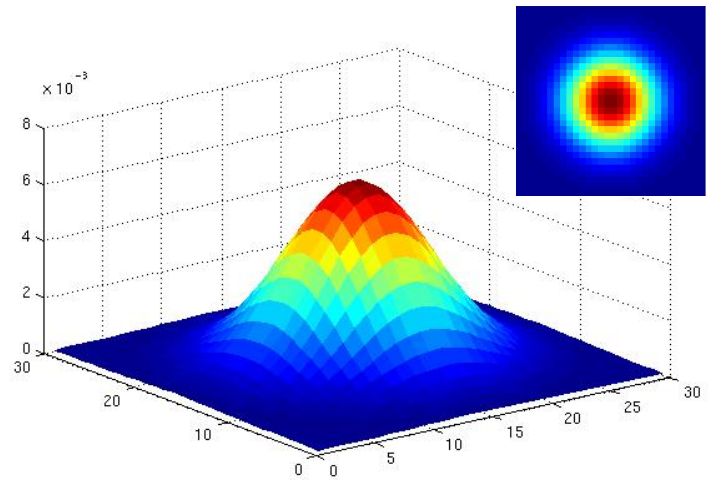
Source: C. Rasmussen

# Gaussian Kernel

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




σ = 2 with 30 x 30 kernel



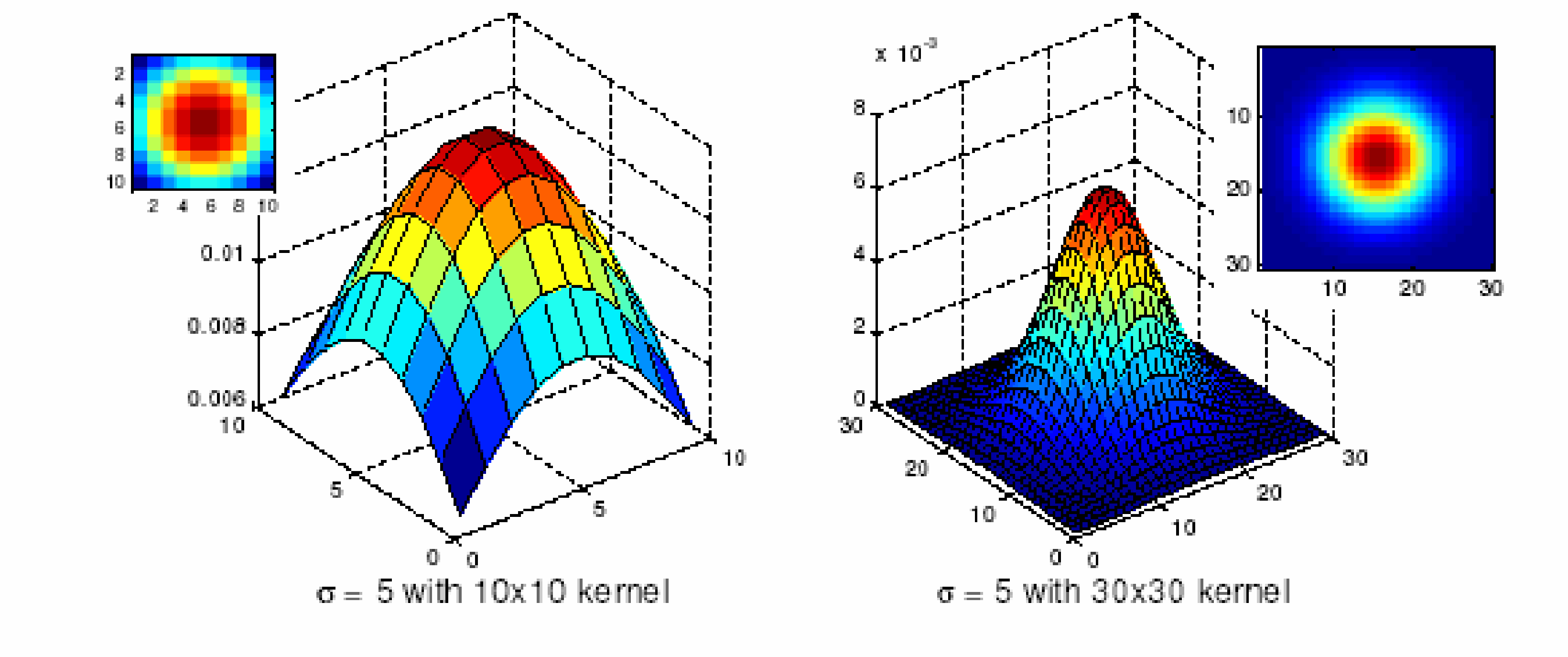

σ = 5 with 30 x 30 kernel

Standard deviation $\sigma$: determines extent of smoothing

Source: K. Grauman

# Choosing kernel width

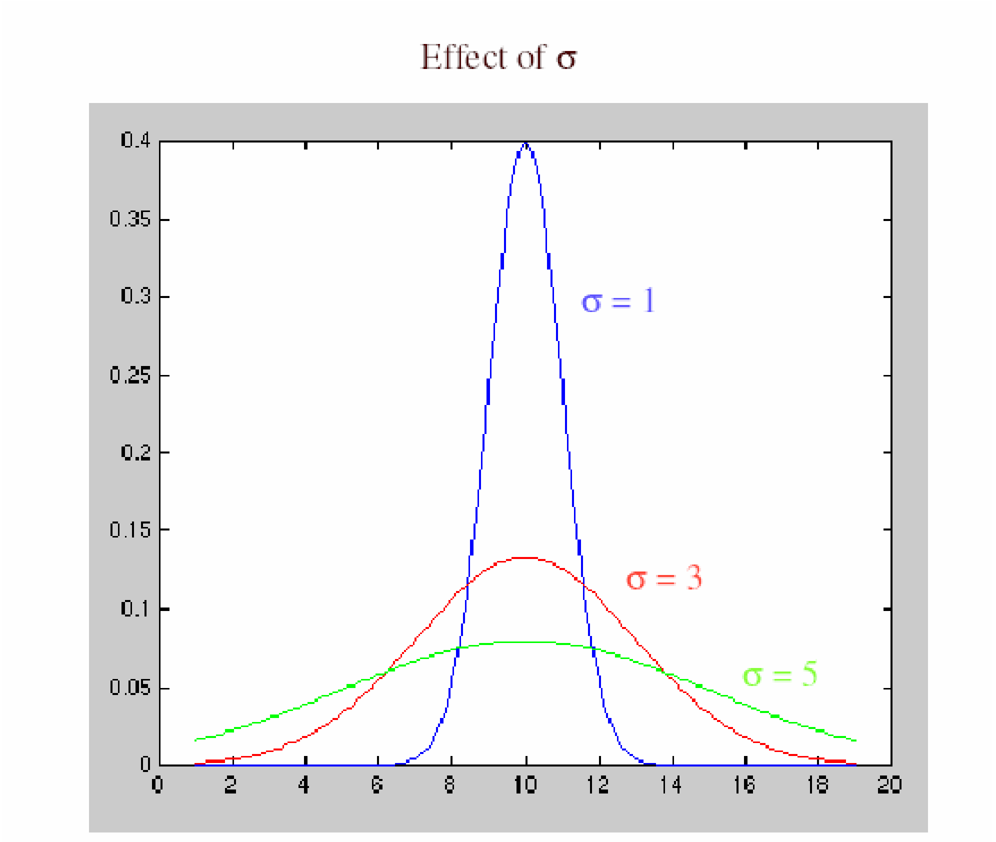
The Gaussian function has infinite support, but discrete filters use finite kernels



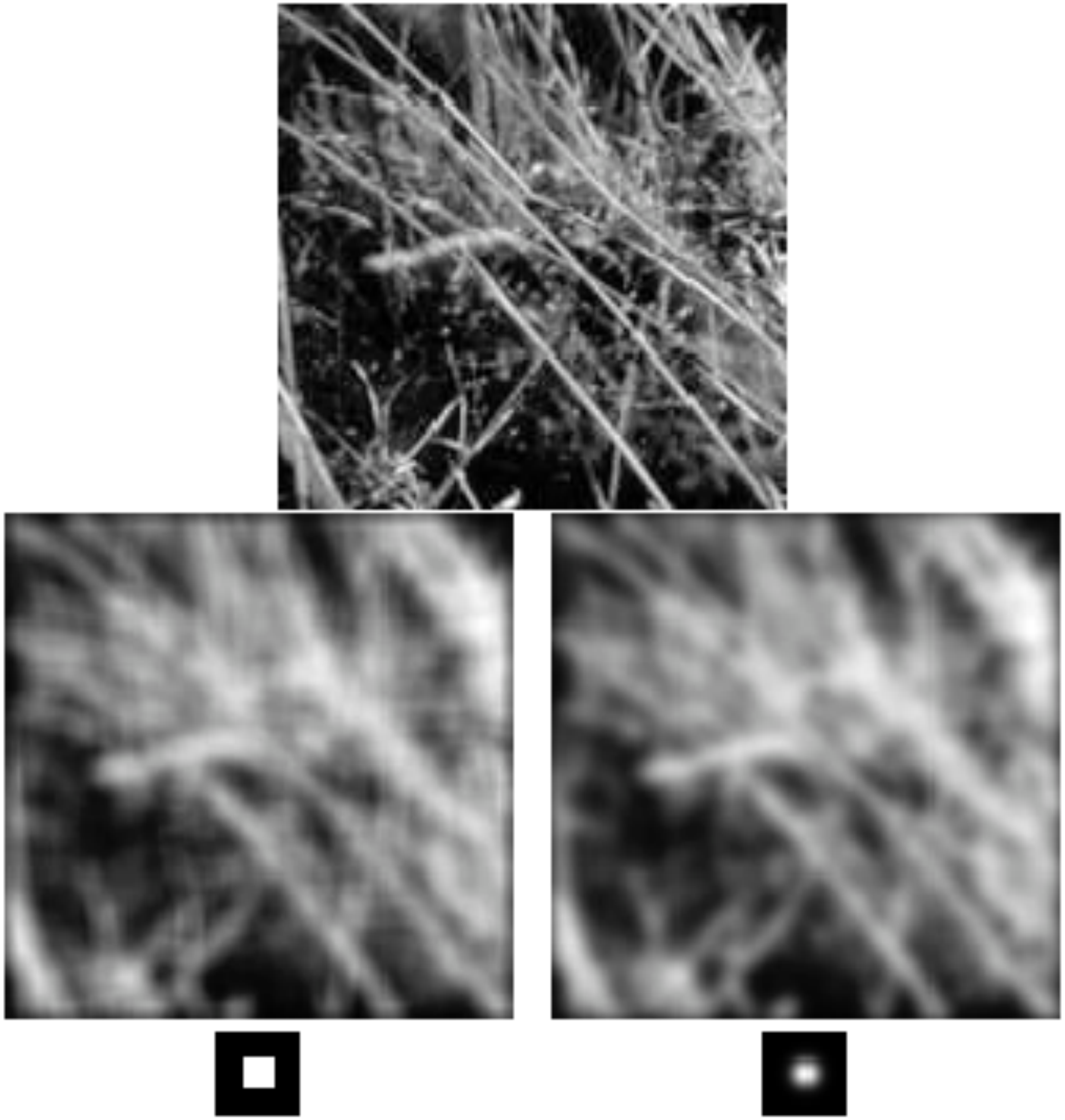

Source: K. Grauman

# Choosing kernel width

Rule of thumb: set filter half-width to about $3\sigma$



# Gaussian vs. box filtering



# Gaussian filters

- Remove high-frequency components from the image (*low-pass filter*)
- Convolution with self is another Gaussian
  - So can smooth with small-$\sigma$ kernel, repeat, and get same result as larger-$\sigma$ kernel would have
  - Convolving two times with Gaussian kernel with std. dev. $\sigma$ is same as convolving once with kernel with std. dev. $\sigma\sqrt{2}$
- *Separable* kernel
  - Factors into product of two 1D Gaussians
  - Discrete example:

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

$m \times 1$

$K = m \times m$

$I = n \times n$

$n^2 m^2$ $n^2 m \times 2$

Source: K. Grauman

# Separability of the Gaussian filter

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

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

The 2D Gaussian can be expressed as the product of two functions, one a function of $x$ and the other a function of $y$

In this case, the two functions are the (identical) 1D Gaussian

Source: D. Lowe

# Why is separability useful?

- Separability means that a 2D convolution can be reduced to two 1D convolutions (one along rows and one along columns)
- What is the complexity of filtering an $n \times n$ image with an $m \times m$ kernel?
  - $O(n^2 m^2)$
- What if the kernel is separable?
  - $O(n^2 m)$

# Noise


Original


Salt and pepper noise


Impulse noise


Gaussian noise

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

Source: S. Seitz

# Reducing salt-and-pepper noise

3x3

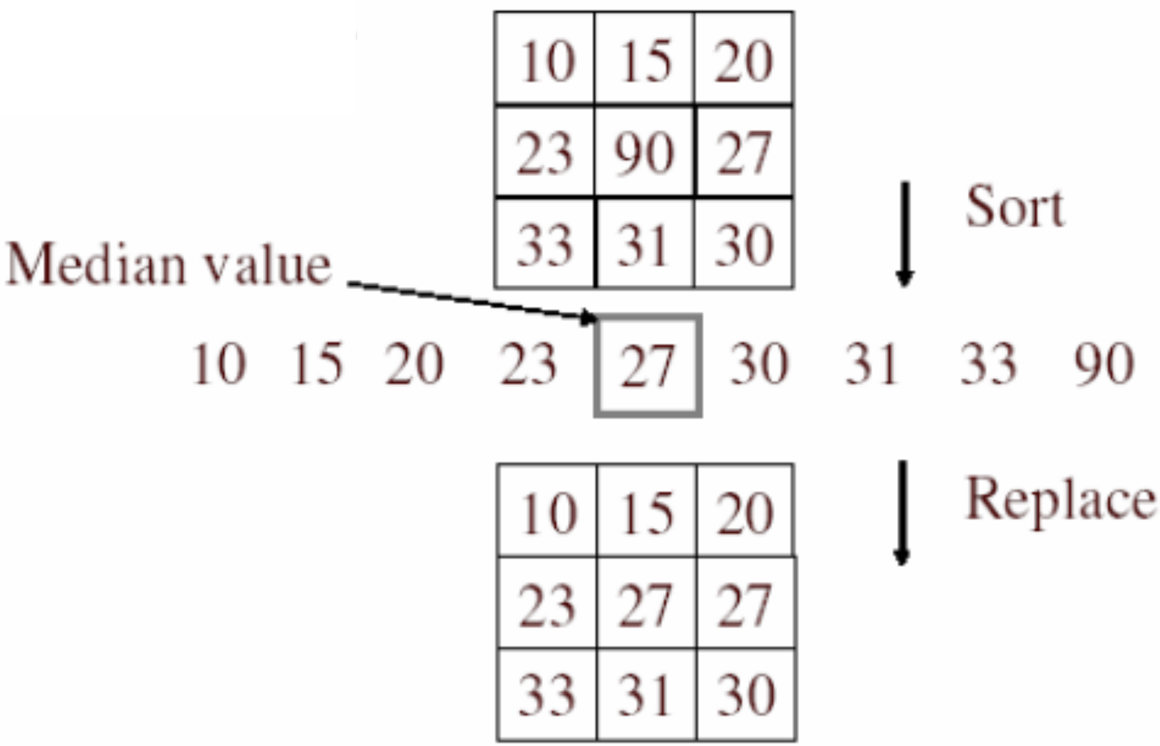
5x5

7x7

What’s wrong with the results?

# Alternative idea: Median filtering

- A **median filter** operates over a window by selecting the median intensity in the window




- Is median filtering linear?

Source: K. Grauman

# Median filter

- Is median filtering linear?
- Let's try filtering

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 2 \\ 2 & 2 & 2 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

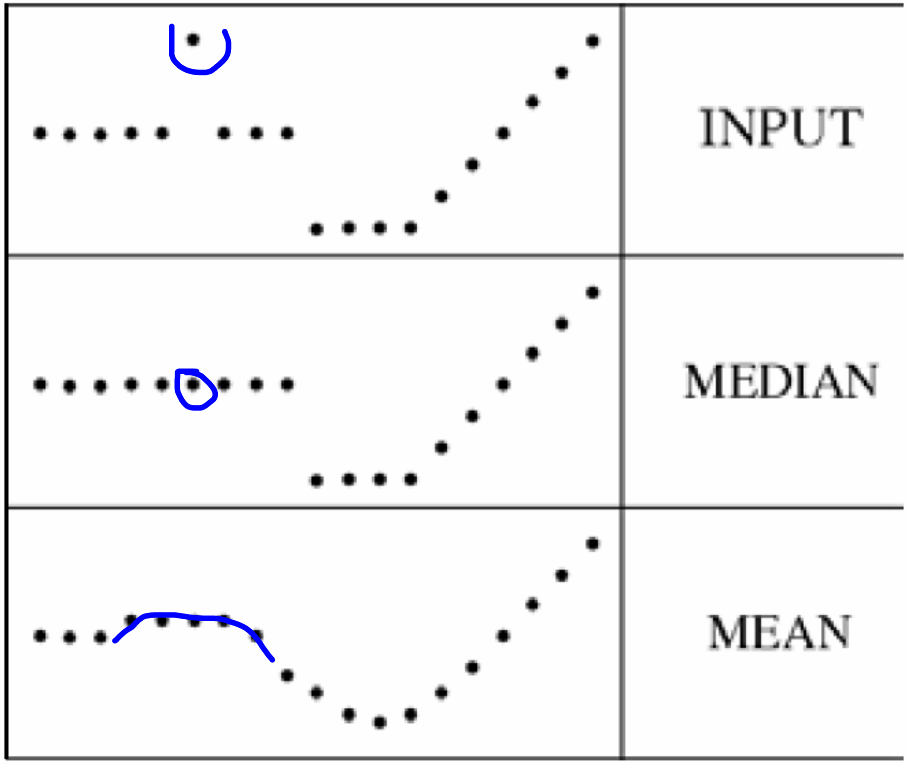
→ 1

$$\begin{matrix} 1 & 1 & 1 \\ 1 & 2 & 2 \\ 2 & 2 & 2 \end{matrix} \xrightarrow{f} 2$$

# Median filter

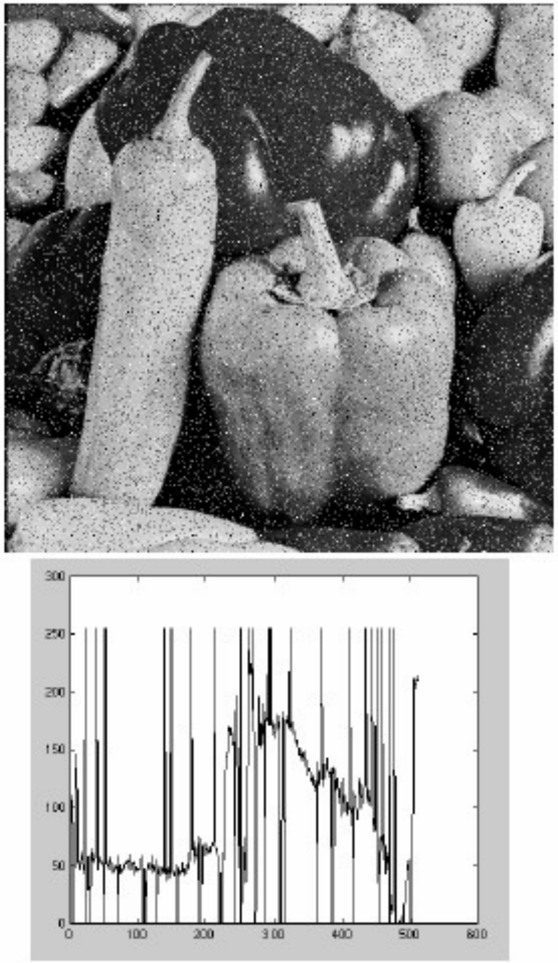
- What advantage does median filtering have over Gaussian filtering?
  - Robustness to outliers

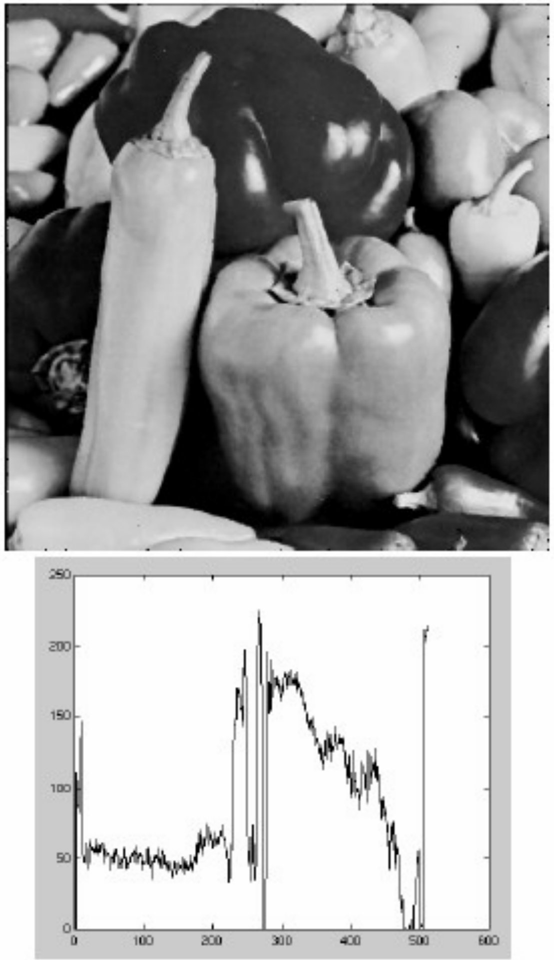
filters have width 5 :



# Median filter

Salt-and-pepper noise — Median filtered




open cv: cv2.medianBlur (input, output,ksize)

Source: M. Hebert

# Gaussian vs. median filtering

3x3 | 5x5 | 7x7

Gaussian

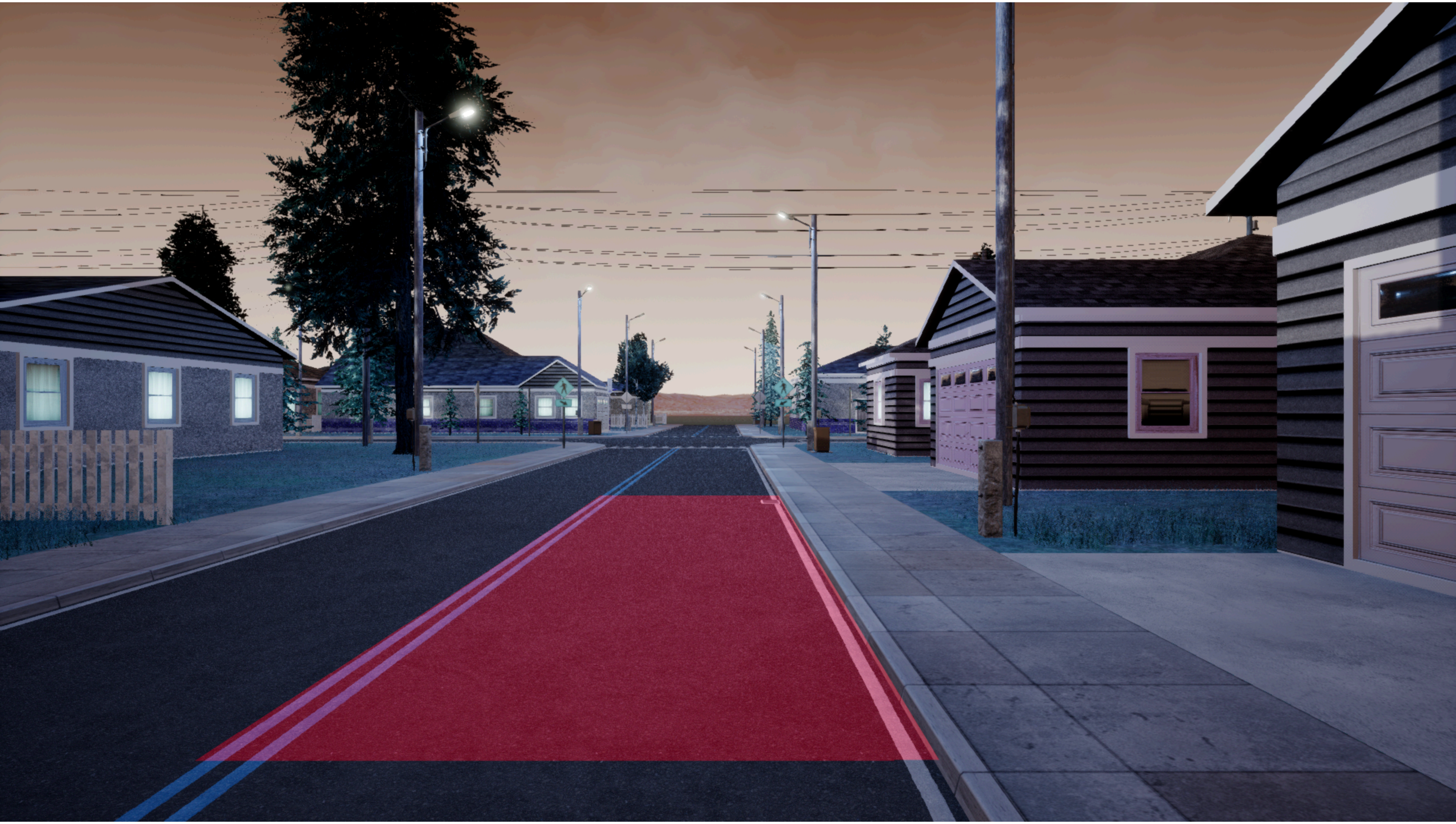
Median

# Review: Image filtering

- Convolution
- Box vs. Gaussian filter
- Separability
- Median filter

# Edge detection

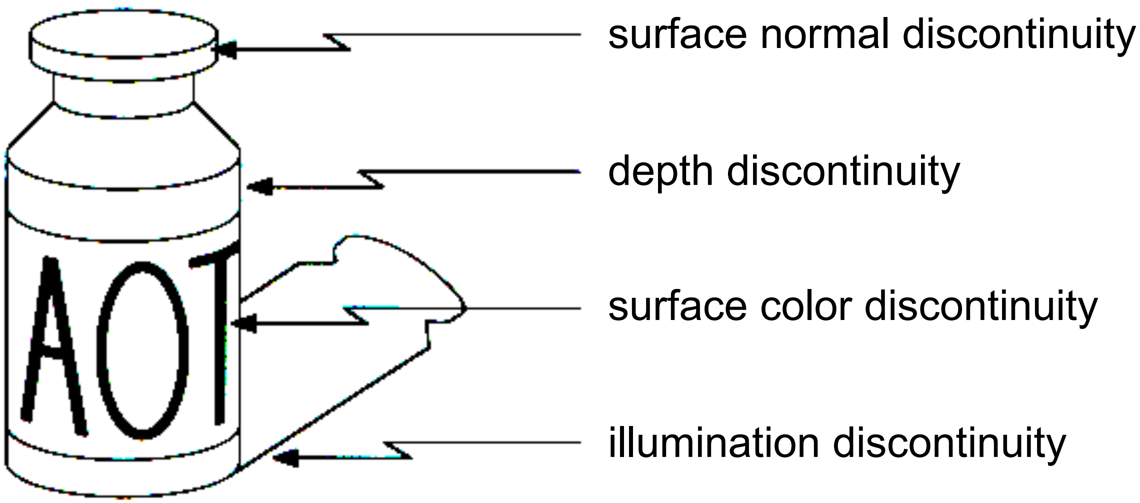
[Winter in Kraków photographed by Marcin Ryczek](#)




I AM SO
TEMPTED...

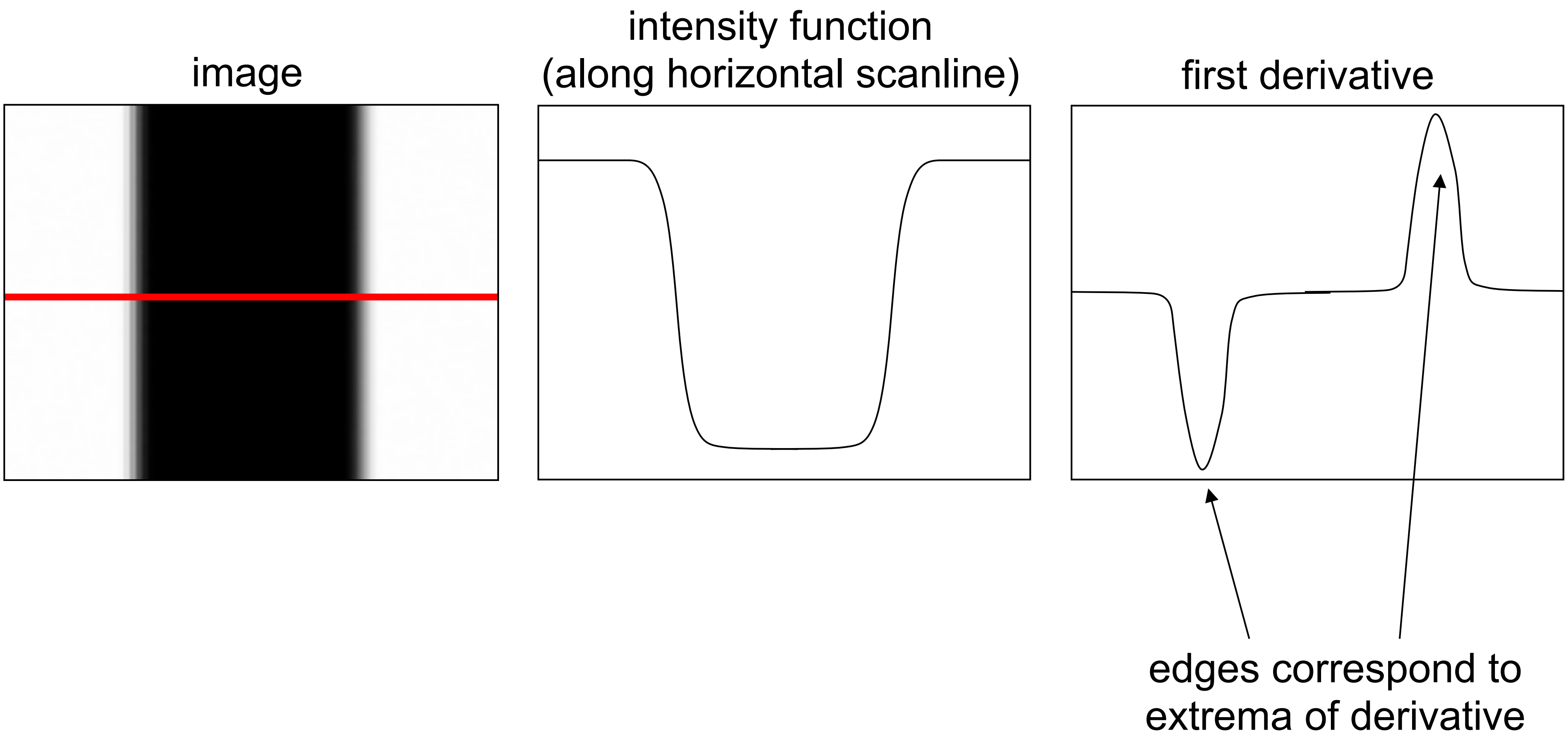
# Edge detection

- **Goal:** Identify sudden changes (discontinuities) in an image
- Intuitively, edges carry most of the semantic and shape information from the image
  - E.g., Lanes, traffic signs, cars



# Edge detection

- An edge is a place of rapid change in the image intensity function



# Derivatives with convolution

For 2D function f(x,y), the partial derivative w.r.t *x* is:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{\varepsilon \to 0} \frac{f(x+\varepsilon, y) - f(x,y)}{\varepsilon}$$

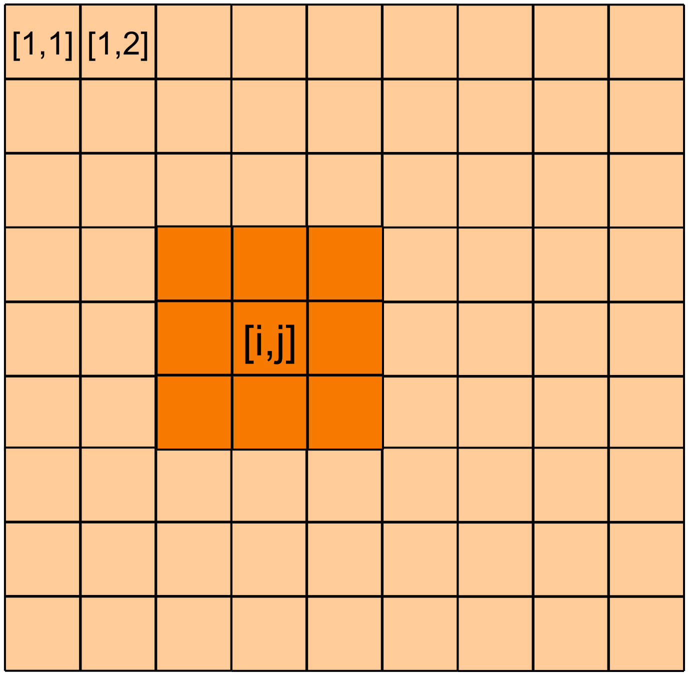
For discrete data, we can approximate using finite differences:

$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x+1, y) - f(x,y)}{1}$$

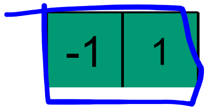
To implement the above as convolution, what would be the associated filter?

# Convolution

image[i,j]




convolution mask g[,]




Output or convolved image

f = g * img

f[i,j] = -1.img[i,j-1] + 1. img[i,j]

# Partial derivatives of an image

$$\frac{\partial f(x,y)}{\partial x}$$

| | |
|---|---|
| -1 | 1 |

$$\frac{\partial f(x,y)}{\partial y}$$

| |
|---|
| -1 |
| 1 |

| |
|---|
| 1 |
| -1 |

Which shows changes with respect to x?

# Finite difference filters

Other approximations of derivative filters exist:

**Prewitt:** $M_x =$

| | | |
|---|---|---|
| -1 | 0 | 1 |
| -1 | 0 | 1 |
| -1 | 0 | 1 |

; $M_y =$

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 0 | 0 | 0 |
| -1 | -1 | -1 |

**Sobel:** $M_x =$

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

; $M_y =$

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

**Roberts:** $M_x =$

| | |
|---|---|
| 0 | 1 |
| -1 | 0 |

; $M_y =$

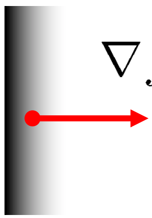
| | |
|---|---|
| 1 | 0 |
| 0 | -1 |

Source: K. Grauman

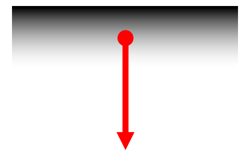
Kahoot!

# Image gradient

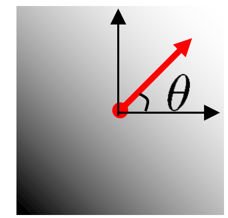
The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$



$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$




$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

The gradient points in the direction of most rapid increase in intensity

- How does this direction relate to the direction of the edge?

The gradient direction is given by $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$

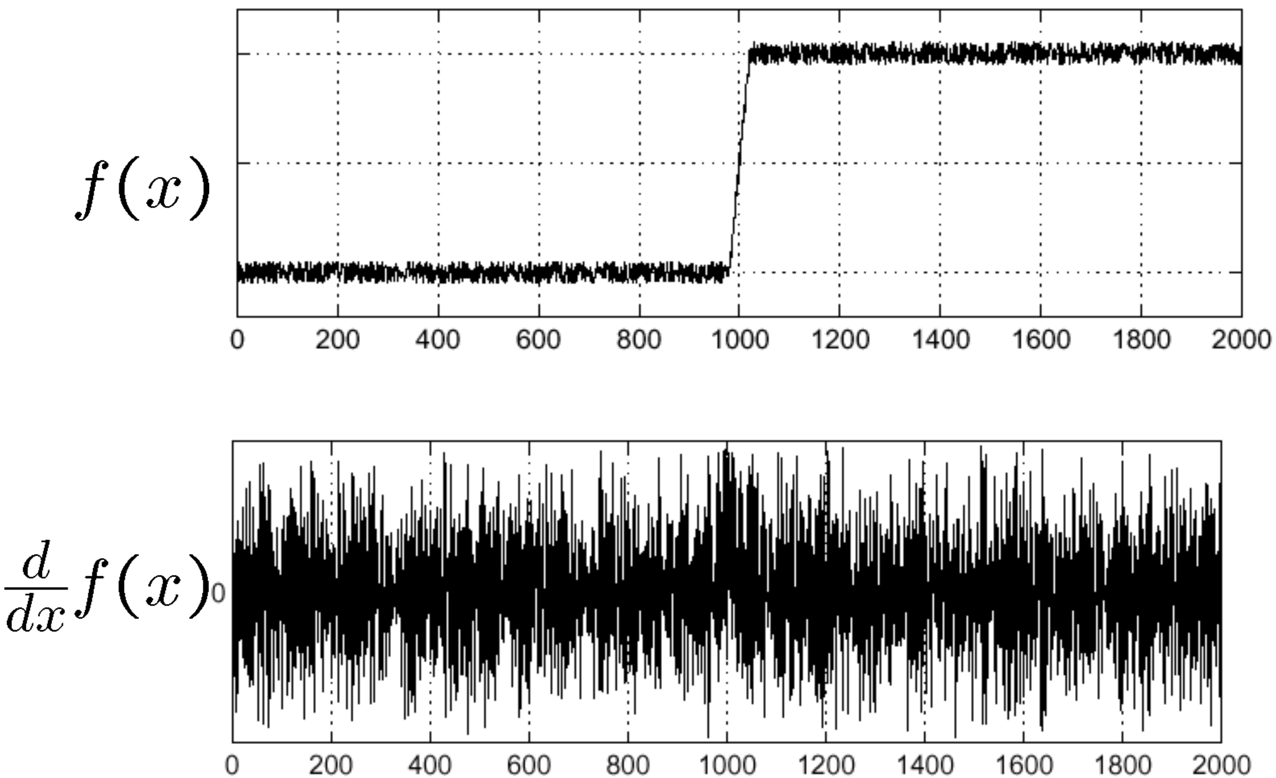
The edge strength is given by the gradient magnitude (norm)

$$||\nabla f|| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Source: Steve Seitz

# Effects of noise

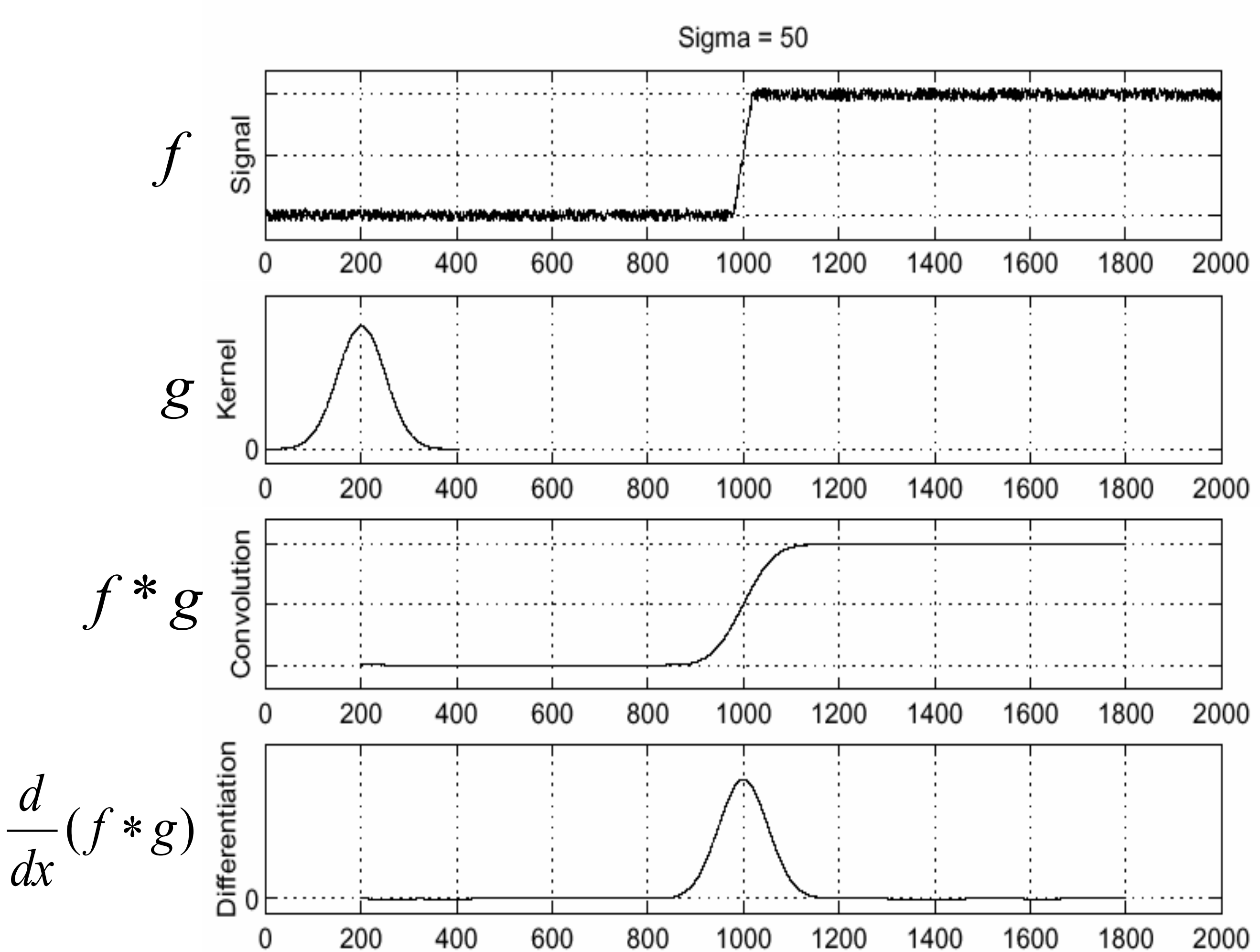
Consider a single row or column of the image




Where is the edge?

Source: S. Seitz

# Solution: smooth first




- To find edges, look for peaks in $\frac{d}{dx}(f * g)$

Source: S. Seitz

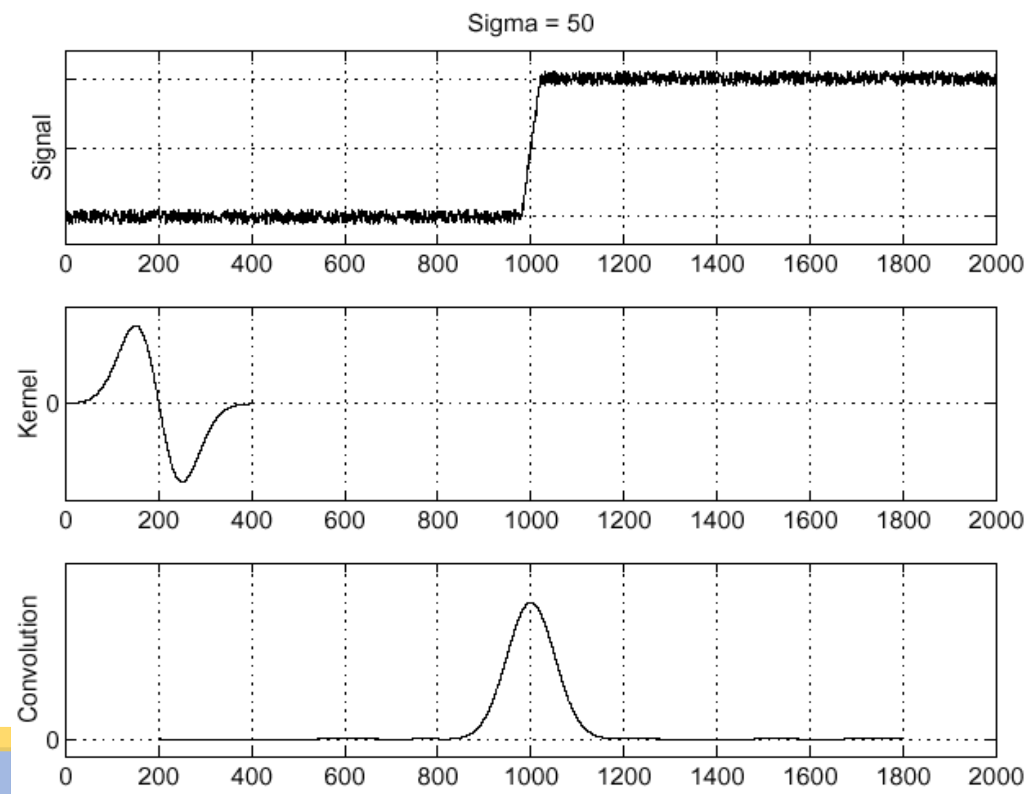
# Derivative theorem of convolution

- Differentiation is convolution, and convolution is associative: $$\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$$
- This saves us one operation:

$f$

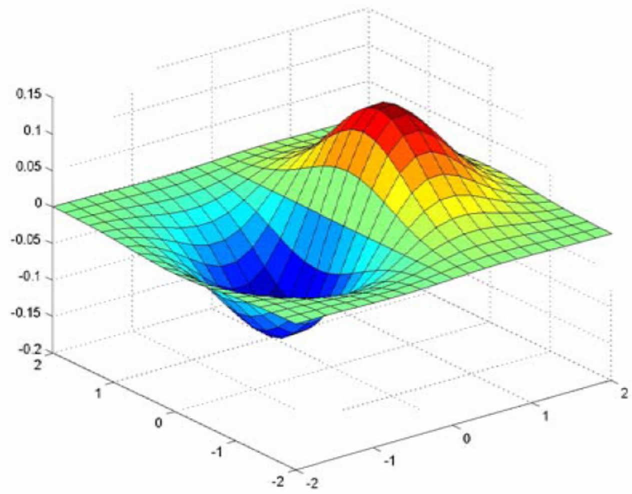
$\frac{d}{dx} g$

$f * \frac{d}{dx} g$

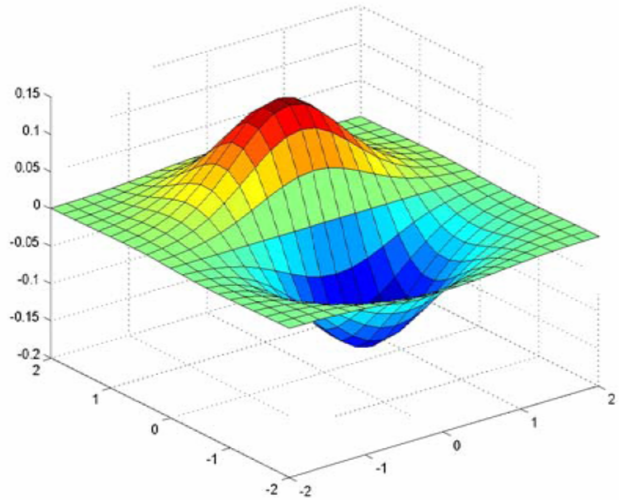



Source: S. Seitz

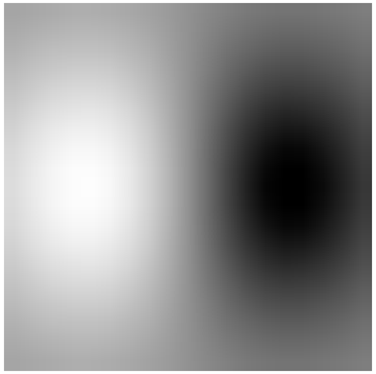
# Derivative of Gaussian filters

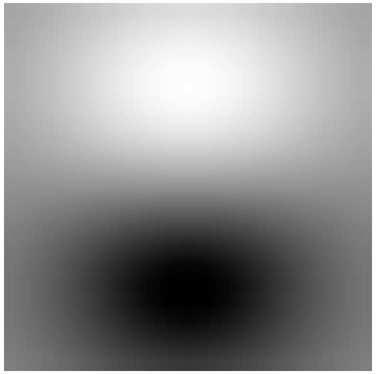



*x*-direction



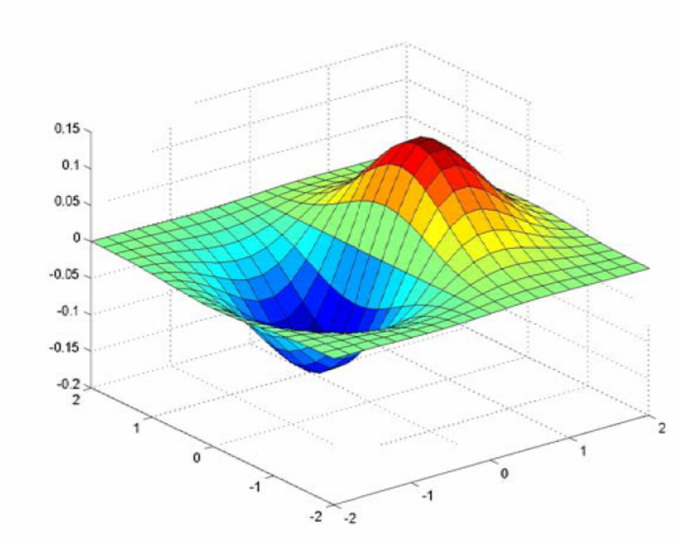

*y*-direction



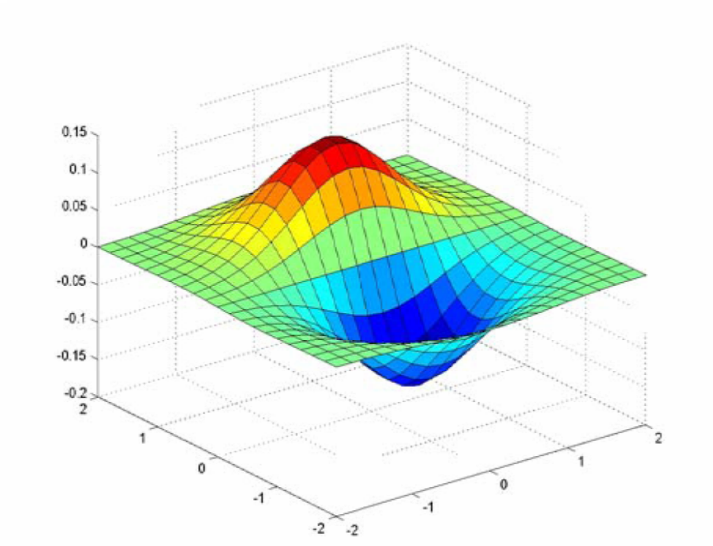


Which one finds horizontal/vertical edges?

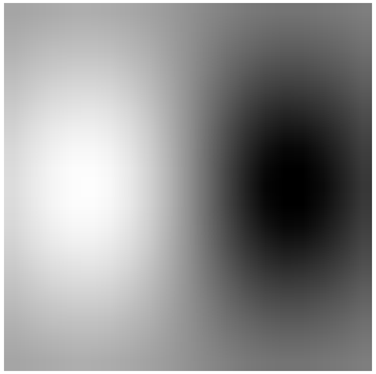
# Derivative of Gaussian filters

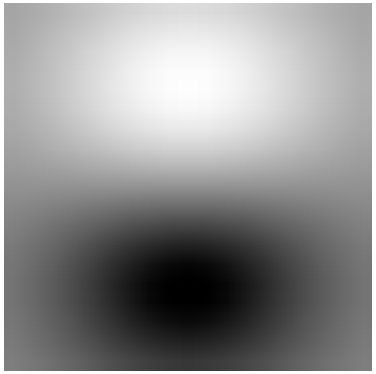



*x*-direction




*y*-direction





Are these filters separable?

# Recall: Separability of the Gaussian filter

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

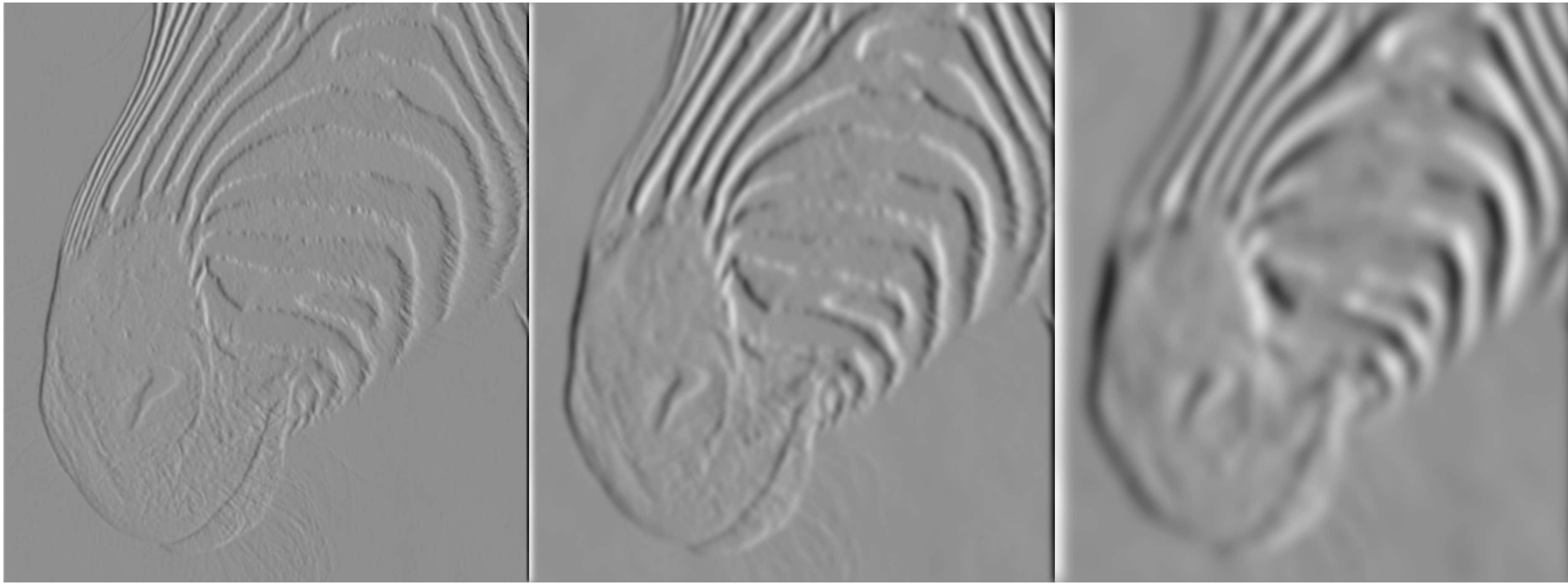
$$= \left(\frac{1}{\sqrt{2\pi}\sigma} \exp^{-\frac{x^2}{2\sigma^2}}\right) \left(\frac{1}{\sqrt{2\pi}\sigma} \exp^{-\frac{y^2}{2\sigma^2}}\right)$$

The 2D Gaussian can be expressed as the product of two functions, one a function of $x$ and the other a function of $y$

In this case, the two functions are the (identical) 1D Gaussian

Source: D. Lowe

# Scale of Gaussian derivative filter



1 pixel　　3 pixels　　7 pixels

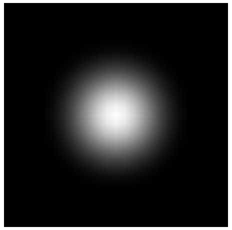
Smoothed derivative removes noise, but blurs edge

Also finds edges at different “scales”

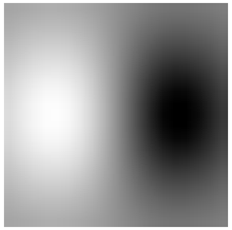
Source: D. Forsyth

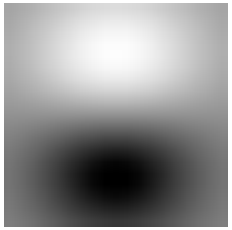
# Review: Smoothing vs. derivative filters

## Smoothing filters



- Gaussian: remove "high-frequency" components; "low-pass" filter
- Can the values of a smoothing filter be negative?
- What should the values sum to?
  - **One:** constant regions are not affected by the filter



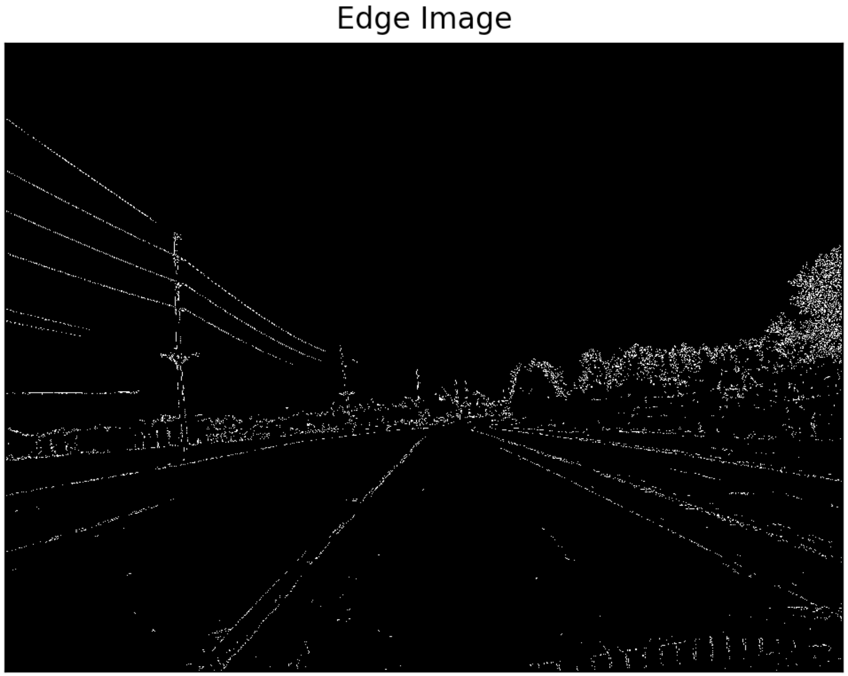


## Derivative filters

- Derivatives of Gaussian
- Can the values of a derivative filter be negative?
- What should the values sum to?
  - **Zero:** no response in constant regions

# Building an edge detector

original image



final output

norm of the gradient $\|\nabla f\| = \sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2}$

# Building an edge detector

How to turn these thick regions of the gradient into curves?

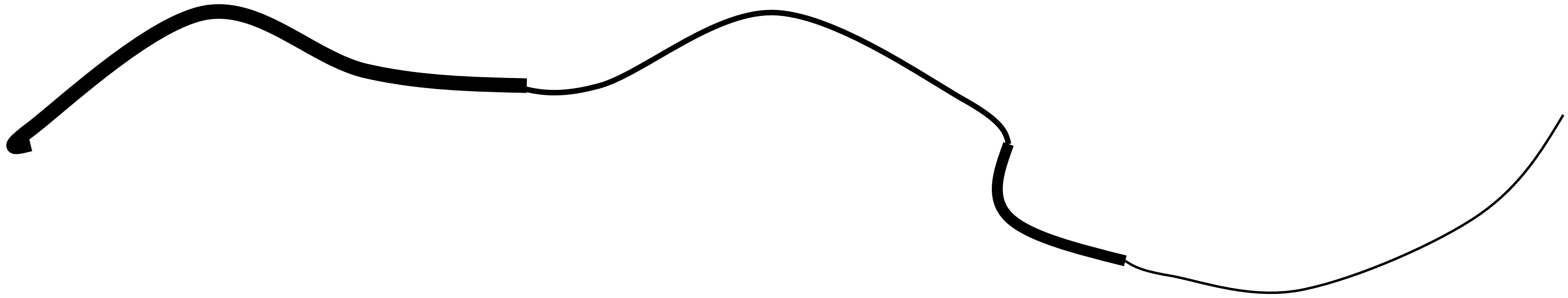
Thresholded norm of the gradient

# Non-maximum suppression

Another problem: pixels along this edge didn't survive thresholding

# Hysteresis thresholding

Use a high threshold to start edge curves, and a low threshold to continue them.



Source: Steve Seitz

# Hysteresis thresholding

**original image**

**high threshold (strong edges)**

**low threshold (weak edges)**

**hysteresis threshold**

Source: L. Fei-Fei

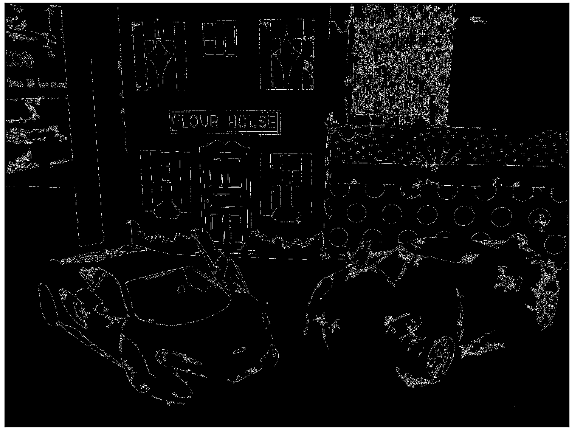
# Recap: Canny edge detector

1. Compute x and y gradient images
2. Find magnitude and orientation of gradient
3. **Non-maximum suppression**:
   - Thin wide “ridges” down to single pixel width
4. **Linking and thresholding** (**hysteresis**):
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves and the low threshold to continue them

opencv: `canny(image,th1,th2)`

Original Image


Edge Image



J. Canny, A Computational Approach To Edge Detection, IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679-714, 1986.

# Summary

- Convolution as translation invariant linear operations on signals and images
- Definition of convolution and its properties (associativity, commutativity, etc.)
- Artifacts of of hard-edge kernels
- Gaussian kernel, its definition and properties (separability)
- Median filter, sharpening
- Derivatives as convolution (Sobel, etc.)

# Sharpening

What does blurring take away?


–


=


Let’s add it back:


+


=

# Unsharp mask filter

$$f + \alpha(f - f * g) = (1+\alpha)f - \alpha f * g = f * ((1+\alpha)e - g)$$

image

blurred image

unit impulse (identity)