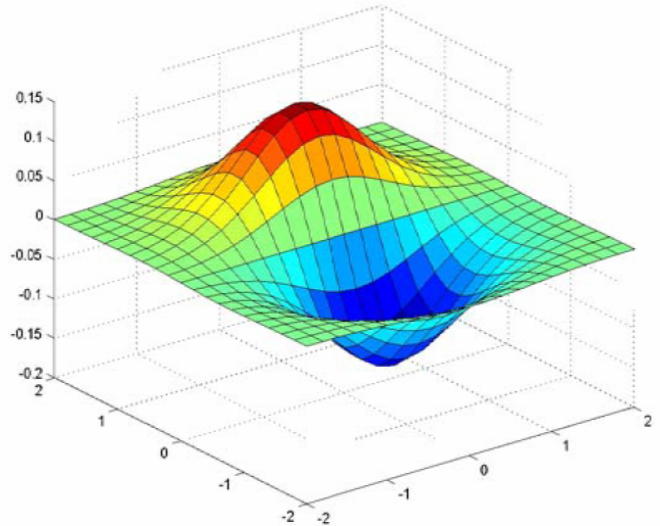
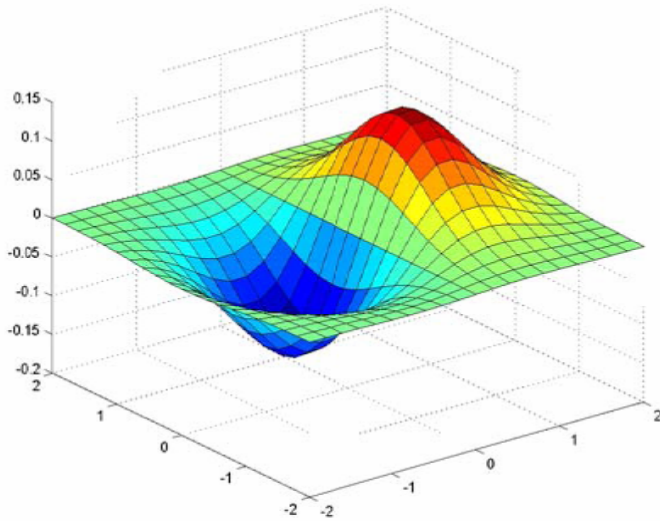


# CSCI 497P/597P: Computer Vision



Lecture 4: Gradients and Edge Detection

# Announcements

- Week 1 Feedback survey is out on Canvas - fill it out by Friday night.
  - It's worth 1 homework point.
  - It's quick: 4 multiple choice questions with an optional comments field.

# Goals

- Understand the limitations of linear filtering
- Know how to compute **image derivatives** using convolution filters
- Understand how the **Sobel filter** works to detect edges.

# Filtering, so far

- Filtering:  
output pixel depends on input neighborhood
- Linear filtering:  
output pixel is a weighted average of input neighborhood  
(must always use the same weights to be linear)
- Cross-correlation is a kind of linear filtering:  
output pixel = weighted average(neighborhood)
- Convolution: cross-correlation, but first flip the kernel horizontally and vertically

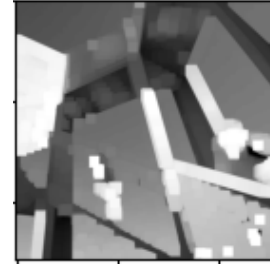
# Limitations:

## What *can't* convolution do?

Problem #1 (= #5 from last lecture) - discuss in groups.

- Maximum filter?

no!



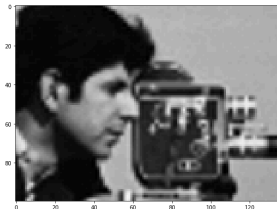
- Threshold?

no!



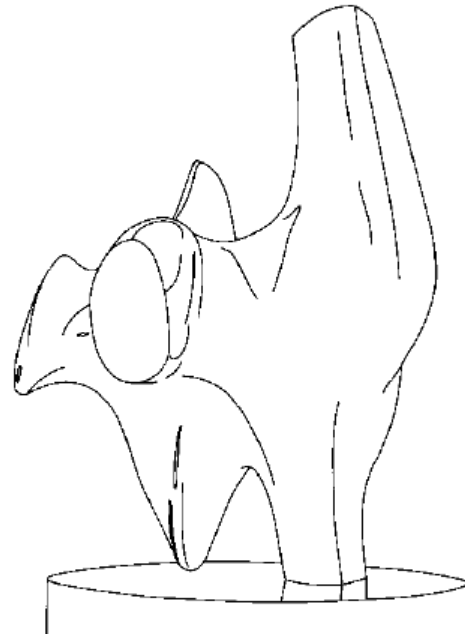
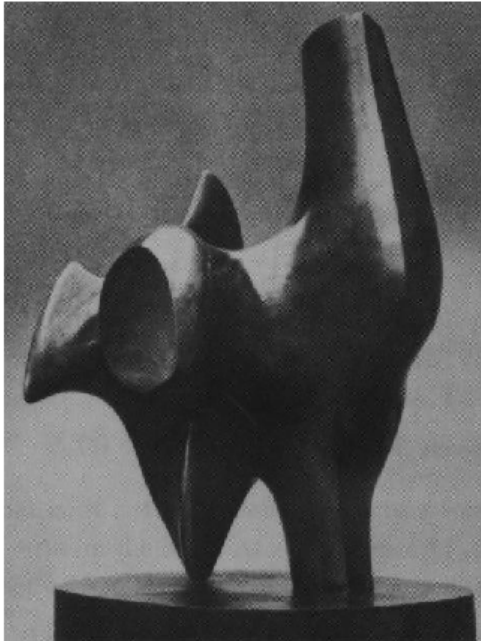
- $y$  partial derivative?

yes!

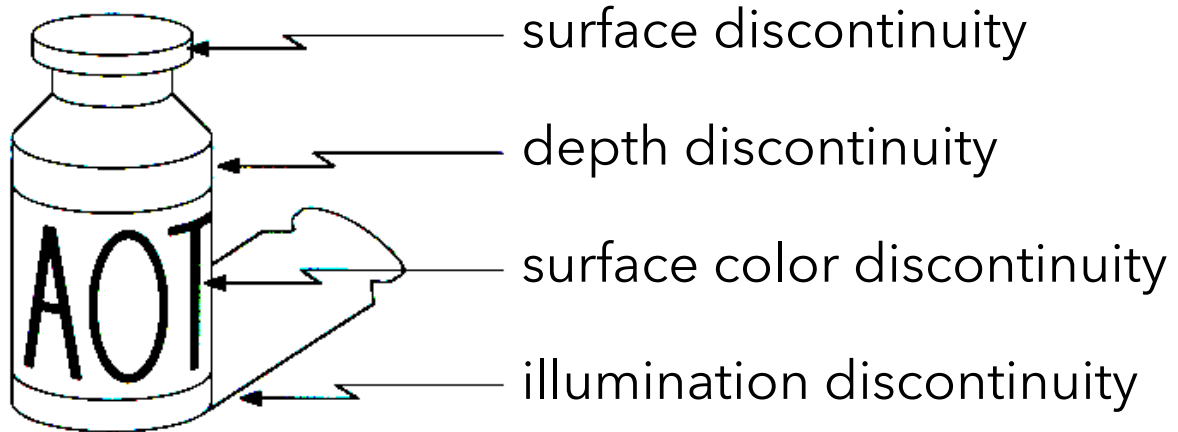


# Calculus!?

Edge detection: a classic vision problem.



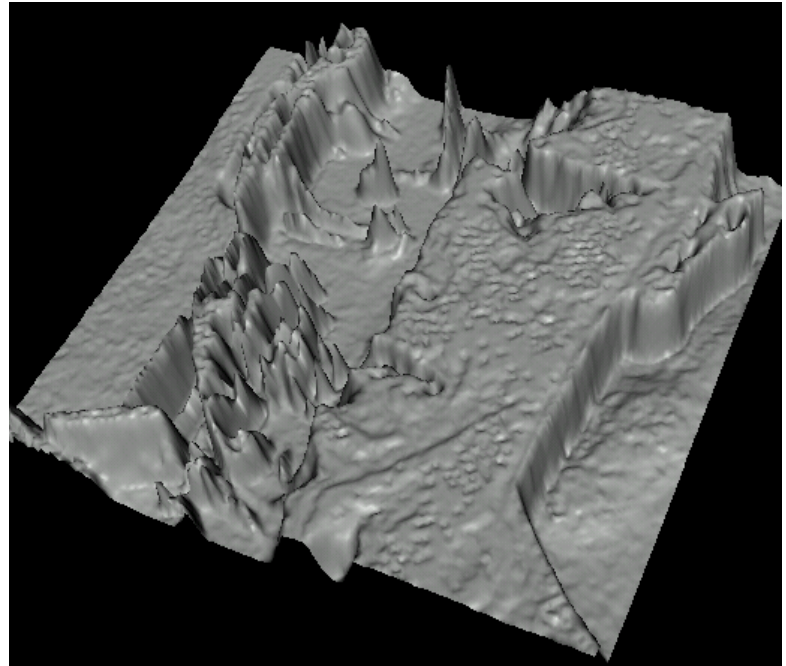
# What is an edge?



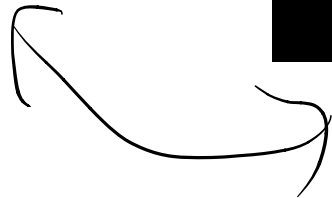
# How do we find them?



$f(x,y)$  as brightness

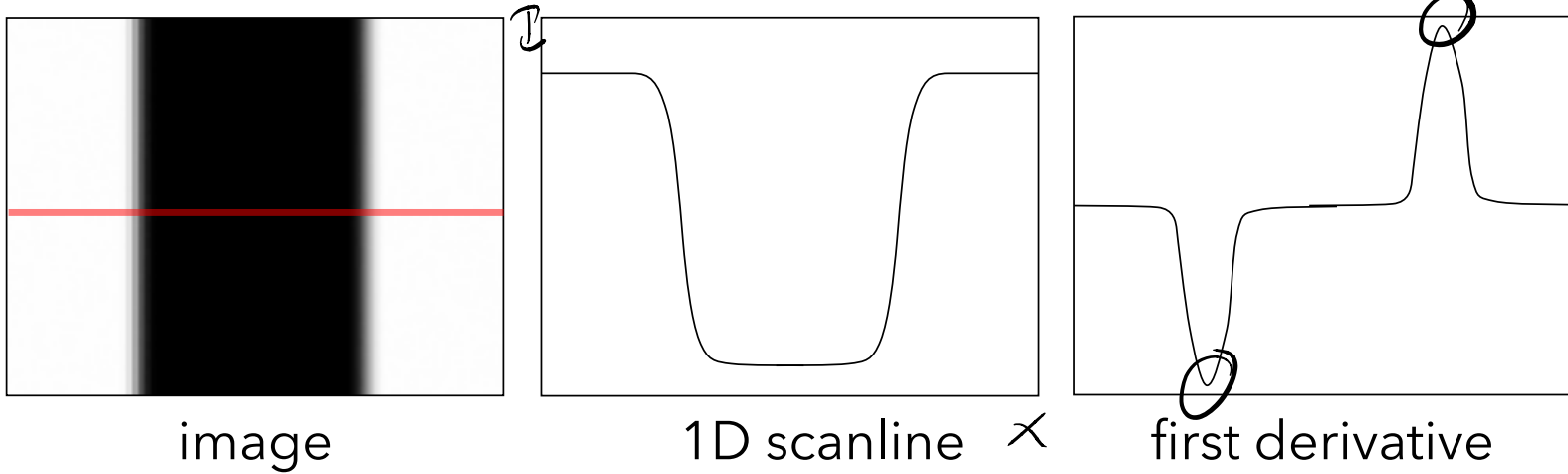


$f(x,y)$  as height





# Characterizing edges



# Multivariable Calculus!?

Partial derivative with respect to  $x$ : pretend all other variables are constants and differentiate.

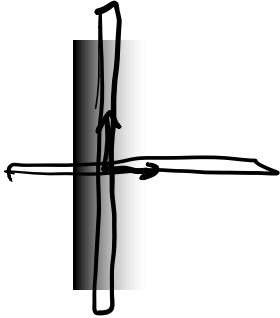
$$f(x, y) = x^2 + 2y$$
$$\frac{\partial f}{\partial x} = 2x \qquad \frac{\partial f}{\partial y} = 2$$

Gradient: the vector of all partial derivatives

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

# Image Derivatives

Images are 2D - have x and y **partial derivatives**

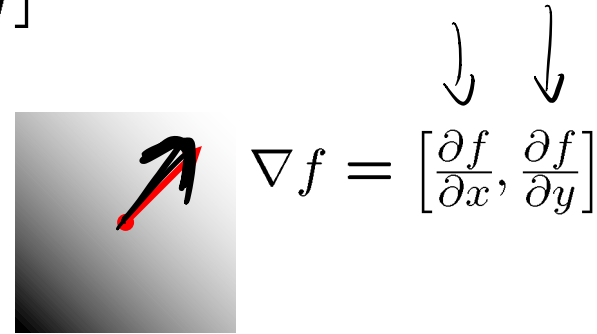
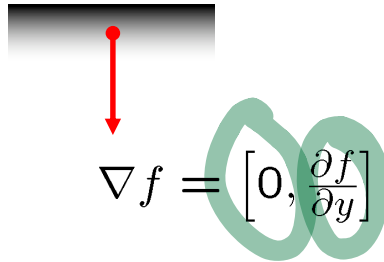
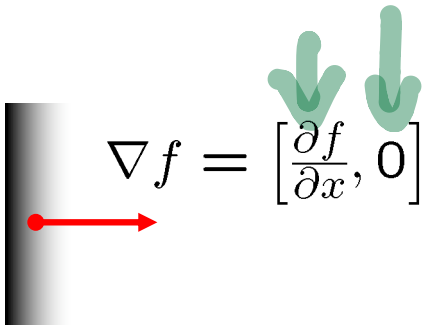


The **image gradient** is the vector of partial derivatives:

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

# Image Gradient as Edge Detector

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



What is the edge **strength**?

$$\|\nabla f\|$$

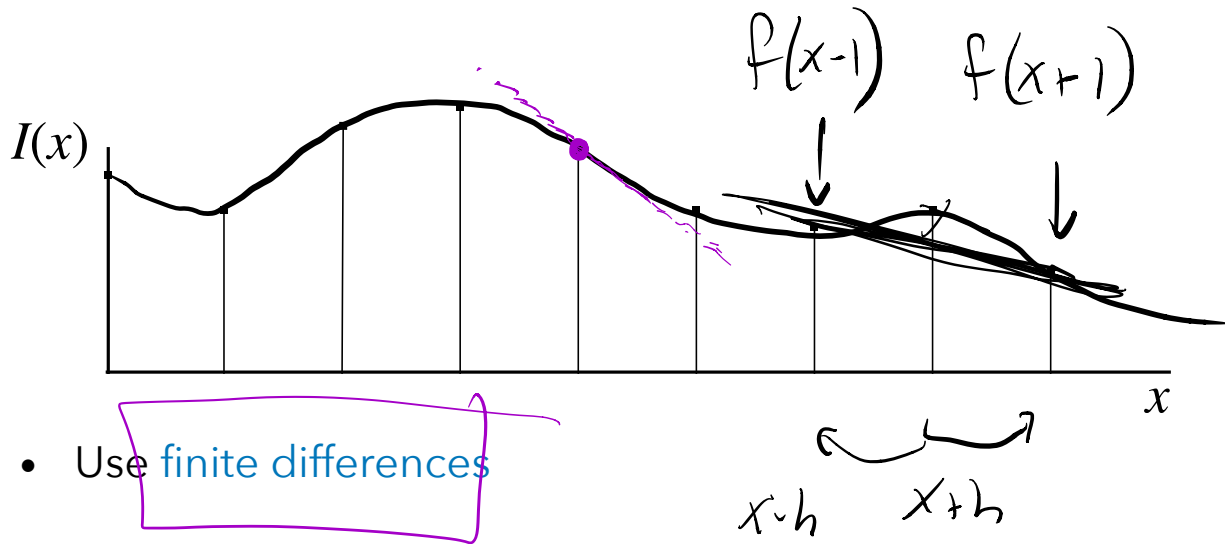
What is the edge **direction**?

$$\tan^{-1} \left( \frac{\partial f / \partial y}{\partial f / \partial x} \right)$$

in practice:  $\text{atan2}(y, x)$

# Image Derivatives

- How do we differentiate a discrete (sampled) image?
  - Reconstruct a continuous function and compute the derivative



- Use finite differences

# Derivative Filters

- How do we differentiate a discrete digital image?
  - Use finite differences

## Candidate derivative filters:

**Example image:**

0	0	1
0	0	1
0	1	1

not centered

0	0	0
1	-1	0
0	0	0

0	1	0
0	-1	0
0	0	0

centered

0	0	0
1	0	-1
0	0	0

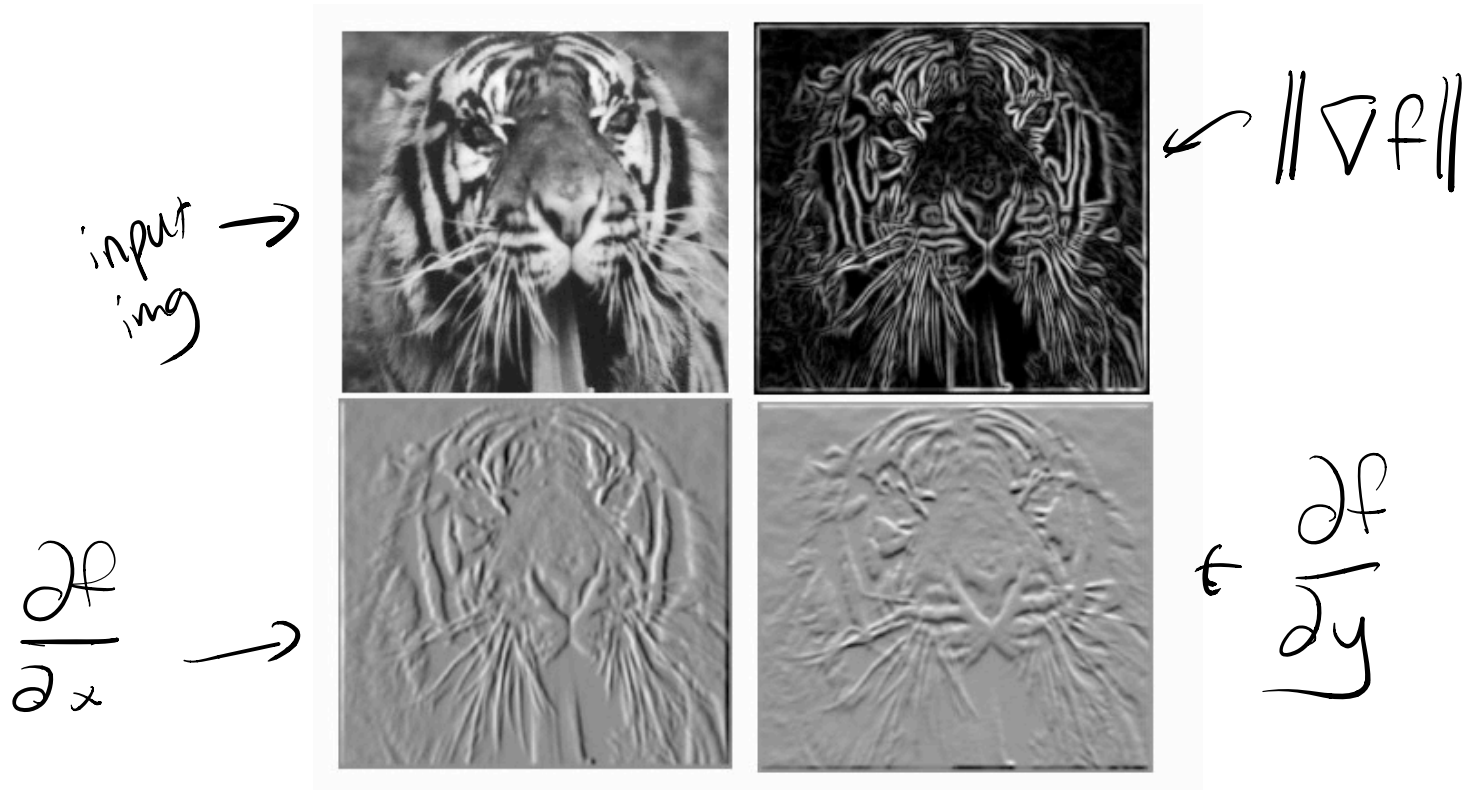
0	-1	0
0	0	0
0	1	0

# Problems 2-3: Compute a Derivative

- Same groupwork routine as usual.
- If your group has a question or is stuck, @mention me in your group's text channel.

$$\begin{bmatrix} -1 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix} \quad (1) \quad \begin{bmatrix} 0 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$

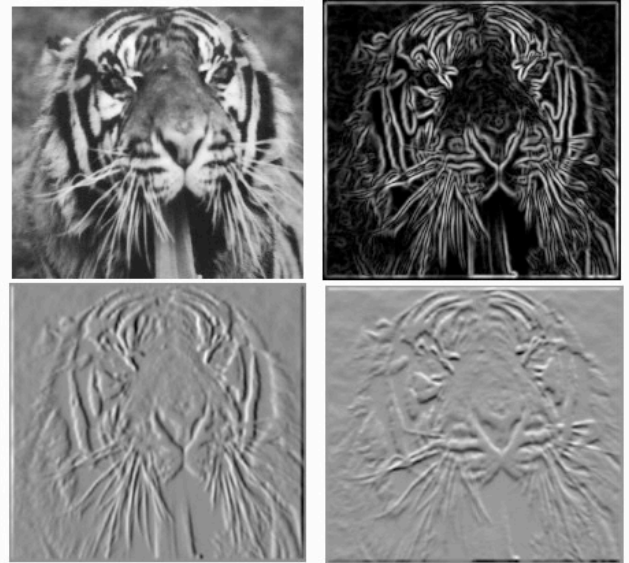
# Image Gradient: Visually



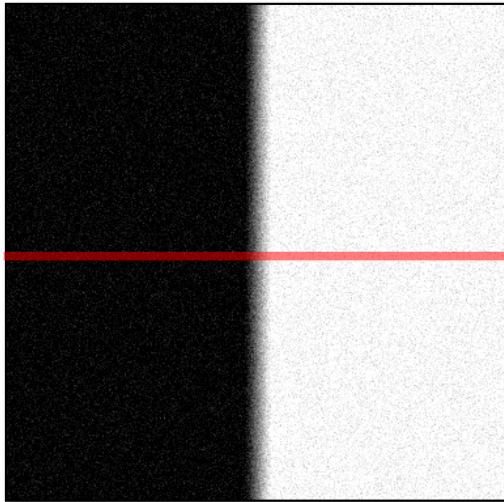


# Aside: why are the derivatives grayish, not blackish?

- Images are nonnegative
- Derivatives can be negative!
- Scale and shift derivative values to display in the range 0-255
- Gray is zero, darker is negative, lighter is positive

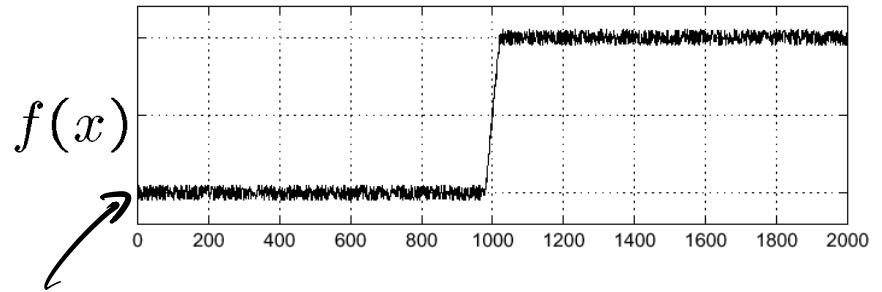


# Images (still) aren't perfect

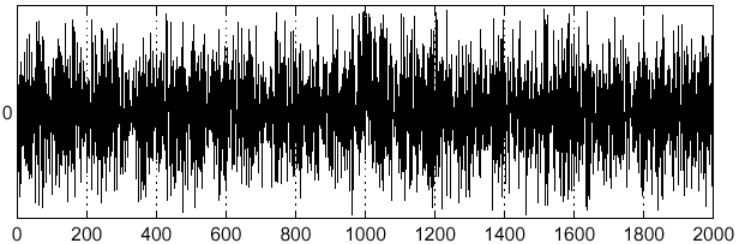


Noisy image

scanline

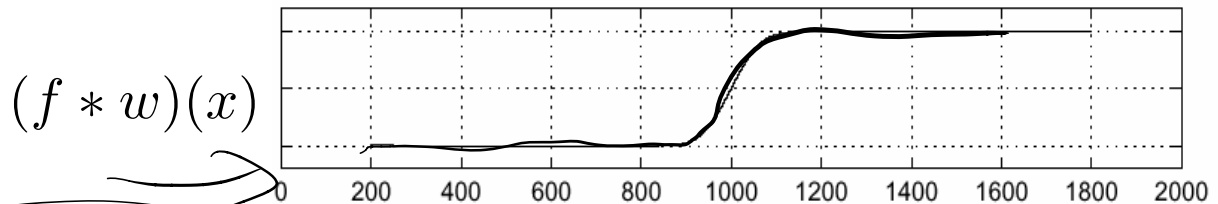
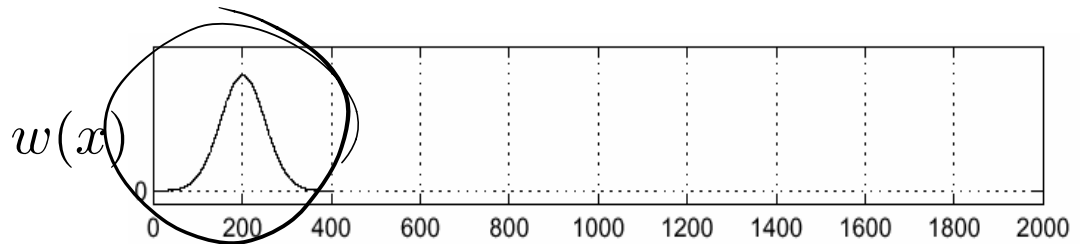
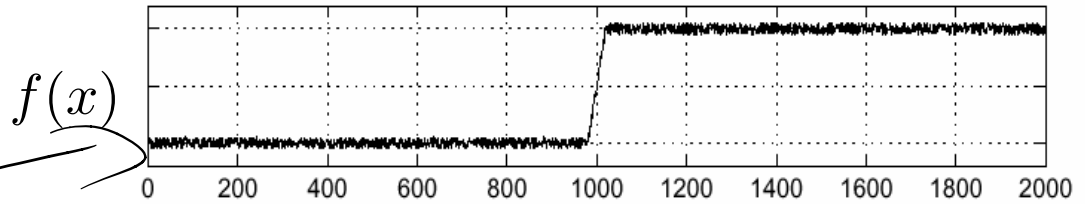


$$\frac{d}{dx} f(x)$$

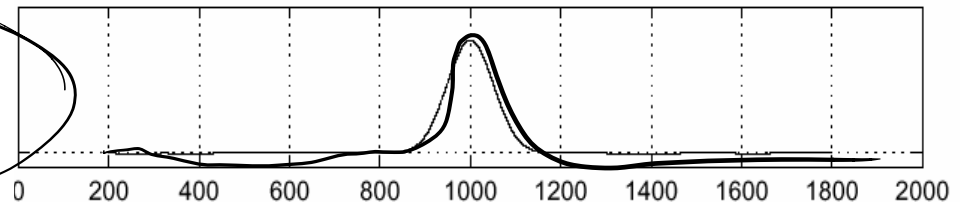


Can you find the edge?

# A solution: smooth it first



$\frac{d}{dx}(f * w)(x)$



# An Edge Detection Filter

- Blur, then take the derivative:

$$f * \frac{1}{16} \begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline 2 & 4 & 2 \\ \hline 1 & 2 & 1 \\ \hline \end{array} * \begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline -1 & 0 & 1 \\ \hline 0 & 0 & 0 \\ \hline \end{array}$$

# An Edge Detection Filter

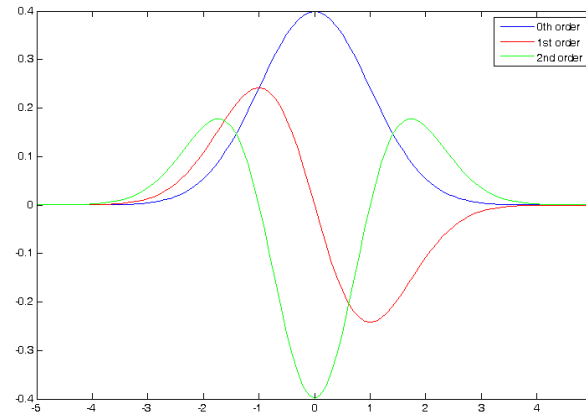
- Blur, then take the derivative:

$$f * \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} * \begin{bmatrix} 0 & 0 & 0 \\ -1 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

Or, do the composition in the continuous domain then build a discrete approximation:

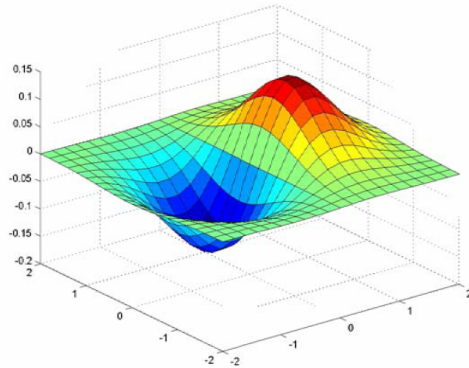
$$G_{\sigma}(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

$$G'_{\sigma}(x) = \frac{d}{dx} G_{\sigma}(x) = -\frac{x}{\sigma} \left( \frac{x}{\sigma} \right) G_{\sigma}(x)$$

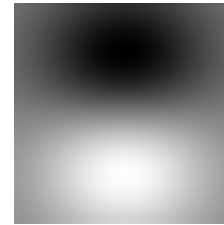
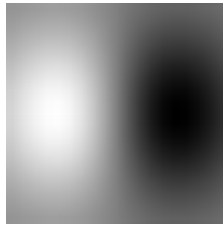
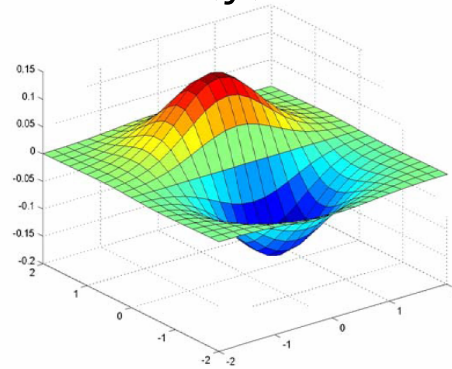


# Derivative-of-Gaussian Filter

(x)



(y)



**Sobel filter:** a 3x3 approximation of the DoG:

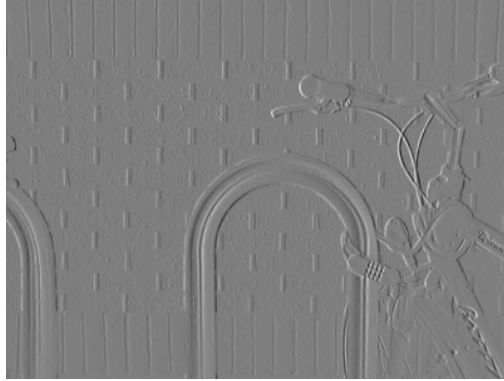
$$\frac{1}{8} \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

$$\frac{1}{8} \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

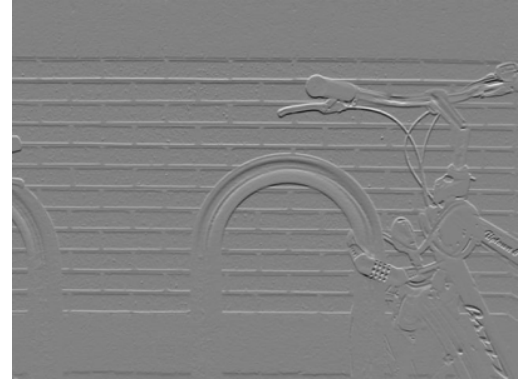
# Sobel filter: example



input

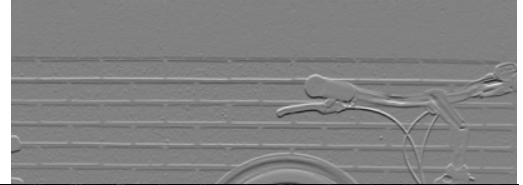


x sobel filtered



y sobel filtered

# Sobel filter: example



magnitude of  
sobel gradient



# Edge Detection

- Fancier edge detectors exist, to try to:
  - more precisely localize the edges (sub-pixel)
  - detect only "salient" edges

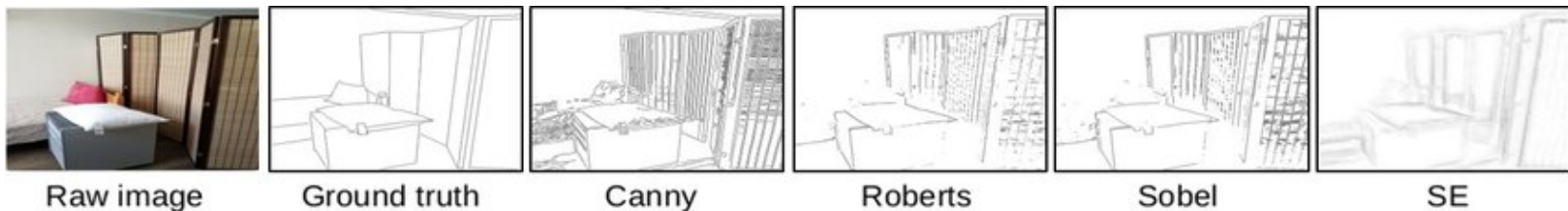


Figure source: Sun et al.: Structural Edge Detection: A Dataset and Benchmark

Questions?

# Problem 4

- Derive the Sobel filter for yourself.