

# Image Gradients

Computational Photography (CSCI 3240U)

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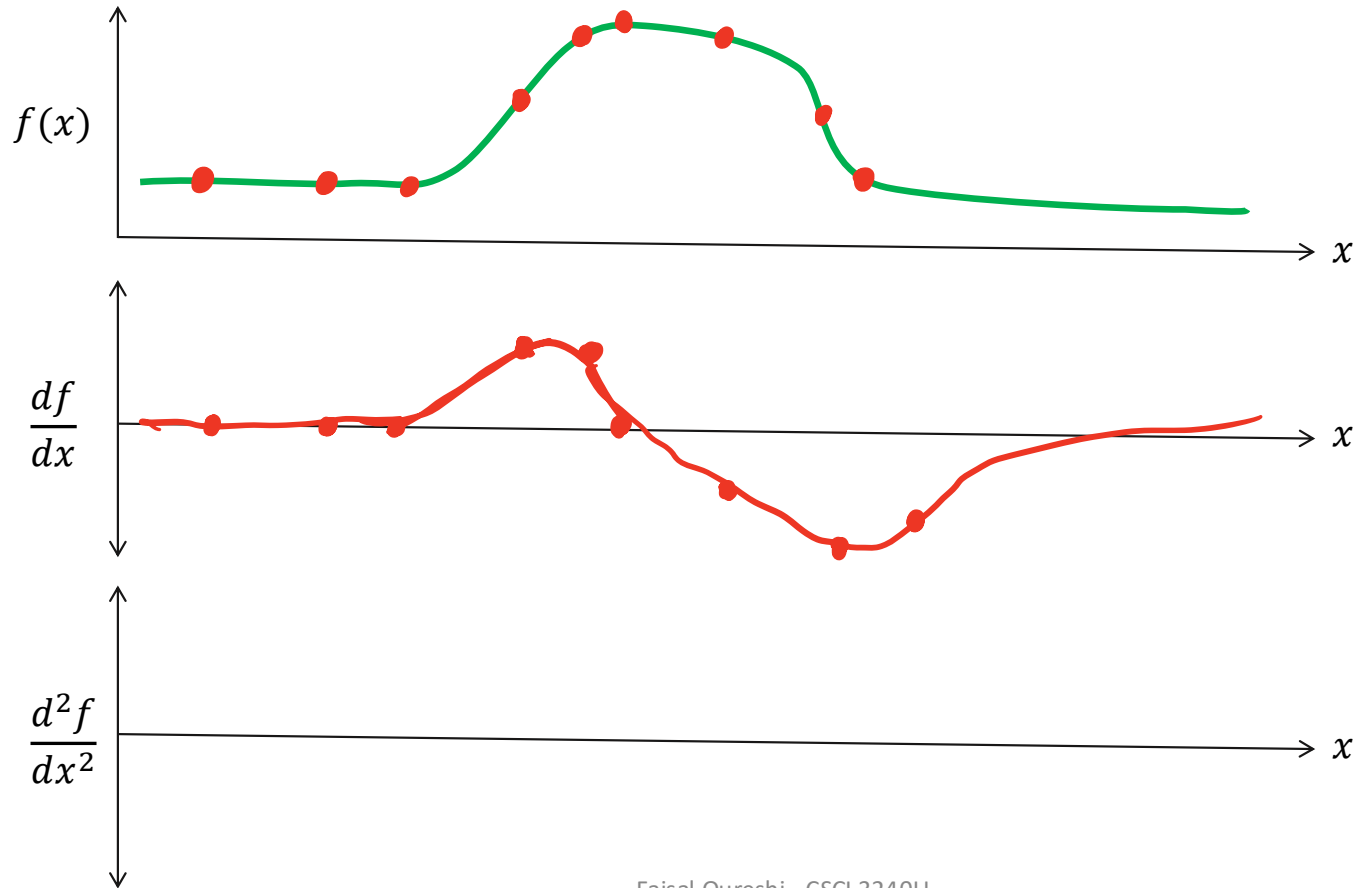
<http://vclab.science.ontariotechu.ca>



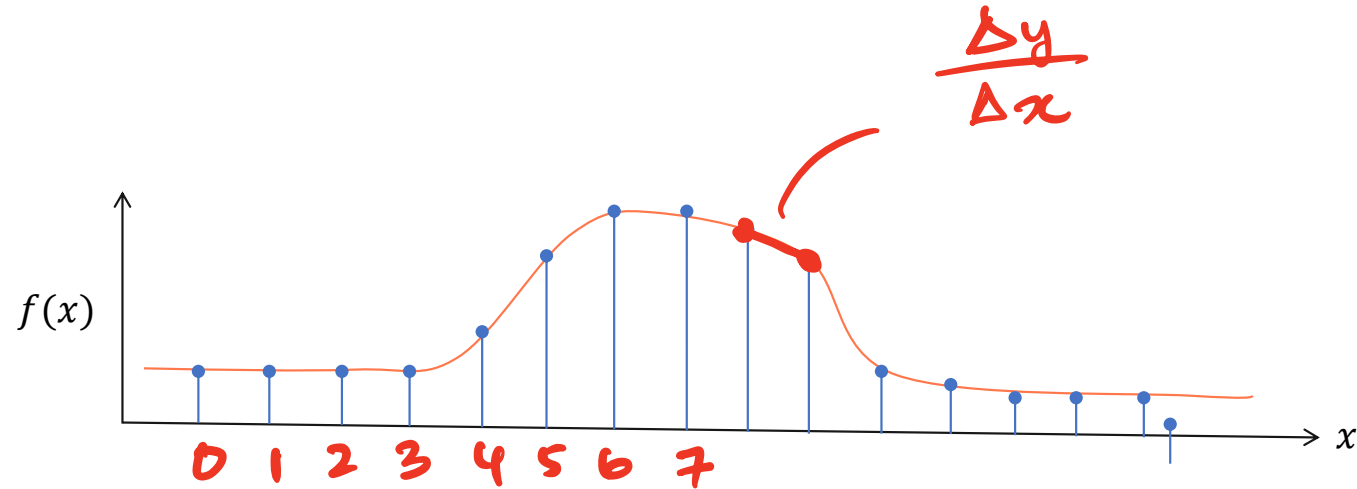
# Today's lecture

- Why do we care about image gradients?
- Computing image gradients
- Sobel filters
- Gradient magnitude and directions
- Visualizing image gradients

Derivative:  $\frac{df}{dx} = \lim_{\epsilon \rightarrow 0} \frac{f(x+\epsilon) - f(x)}{\epsilon}$



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**Finite-difference approximation**

$$\frac{df}{dx} \approx \frac{\Delta f}{\Delta x} = \frac{f(x+1) - f(x)}{(x+1) - x} = f(x+1) - f(x)$$

$\downarrow$   
SLOPE

# Use finite difference approximation to compute image derivatives

$$\frac{df}{dx} \approx \frac{\Delta f}{\Delta x} = \frac{f(x+1) - f(x)}{(x+1) - x} = f(x+1) - f(x)$$

$f =$

<b>1</b>	<b>1</b>	<b>9</b>	<b>8</b>	<b>6</b>	<b>0</b>	<b>0</b>
0	1	2	3	4	5	6

$f' =$

<b>0</b>	<b>8</b>	<b>-</b>				
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$f'' =$

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# Use finite difference approximation to compute image derivatives

$$\frac{df}{dx} \approx \frac{\Delta f}{\Delta x} = \frac{f(x+1) - f(x)}{(x+1) - x} = f(x+1) - f(x)$$

$f =$

1	1	9	8	6	0	0
0	1	2	3	4	5	6

$\begin{bmatrix} -1 & 1 \end{bmatrix}$

$f' =$

0	8	-1	-2	-6	0	?
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$f * [1, -1] =$

<del>0</del>						
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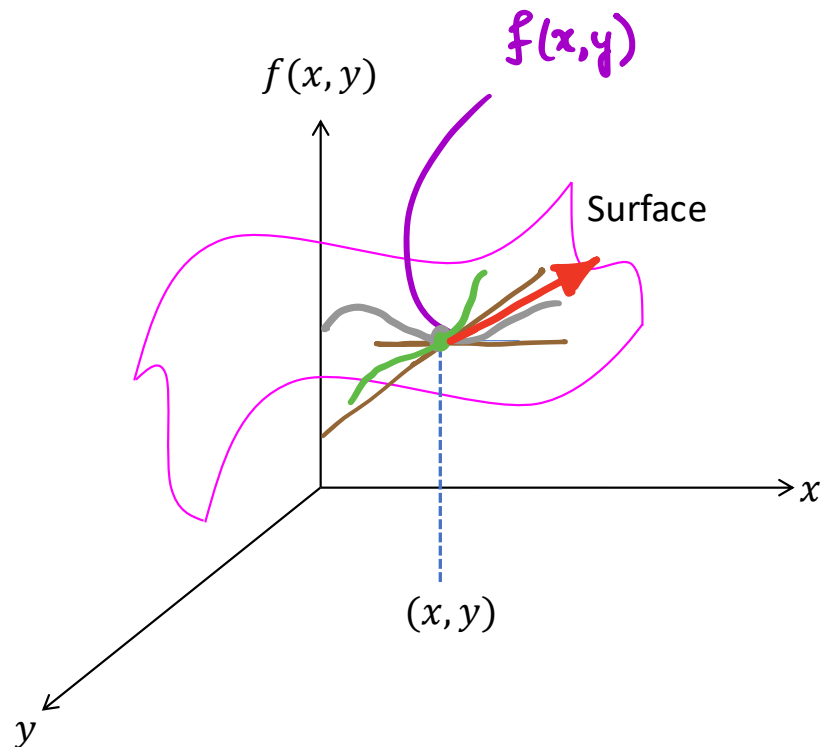
convolution (linear filtering)

# Partial derivatives

$$\begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$



GRADIENT



# How to compute image derivatives?

- Option 1: reconstruct a continuous function  $f(x, y)$ , then compute partial derivatives as  $f$

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

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



# How to compute image derivatives?

- Option 2: use finite differences to take a discrete derivative as

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

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

①  $\frac{\partial f}{\partial x}$       ②  $\frac{\partial f}{\partial y}$

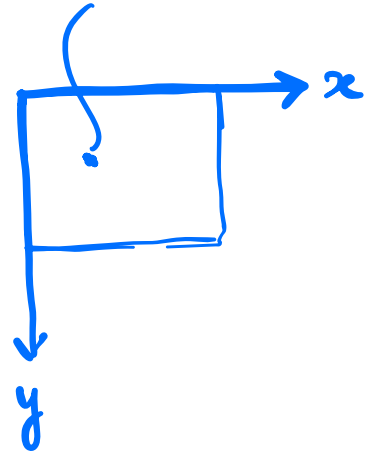
- We can achieve this using *convolution*

$$H_x = \begin{bmatrix} \text{white} & \text{black} \end{bmatrix}$$

$[+1, -1]$  ①

$$H_y = \begin{bmatrix} \text{white} \\ \text{black} \end{bmatrix}$$

$\begin{bmatrix} 1 \\ -1 \end{bmatrix}$  ②



# Image derivatives in $x$ and $y$ directions

Image

	0	1	2	3	4
0	1	1	9	8	1
1	8	8	8	8	8
2	1	3	5	8	1
3	5	3	2	8	6

$f =$

$f(x,y) \rightarrow \text{intensity}$

Pixel Locations

$$\text{GRADIENT}(0,0) = \begin{bmatrix} 0 \\ 7 \end{bmatrix}$$

Derivative along  $x$

$$f_x = f * [1, -1] =$$

$$\frac{\partial f}{\partial x}$$

0	8	-1		

Boundary Conditions

Derivative along  $y$

$$f_y = f * [1, -1]^T =$$

$$\frac{\partial f}{\partial y}$$

7				
-7				
4				
/	/	/	/	/

Image gradient:  $\nabla f$  =  $\left[ \frac{\partial f(x,y)}{\partial x}, \frac{\partial f(x,y)}{\partial y} \right]$

$f_x =$

0	8	-1	-7	<span style="border: 2px solid red; padding: 2px;">?</span>
0	0	0	0	
<span style="border: 2px solid red; padding: 2px;">2</span>	2	3	<span style="border: 2px solid red; padding: 2px;">-7</span>	
-2	-1	6	-2	

$f_y =$

7	7	-1	0	<span style="border: 2px solid red; padding: 2px;">7</span>
-7	-5	-3	0	7
<span style="border: 2px solid red; padding: 2px;">4</span>	0	-3	<span style="border: 2px solid red; padding: 2px;">0</span>	5

What is gradient at pixel location (0,2)? ~~(1,1)~~

$$\begin{bmatrix} 2 \\ 4 \end{bmatrix}$$

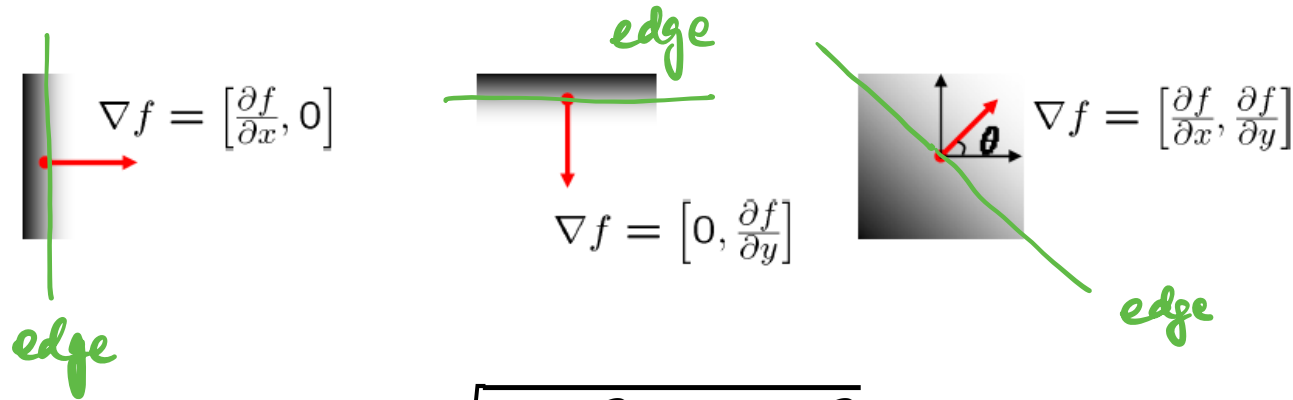
(3,2)?  $\begin{bmatrix} -7 \\ 0 \end{bmatrix}$

(4,0)? UNDEFINED

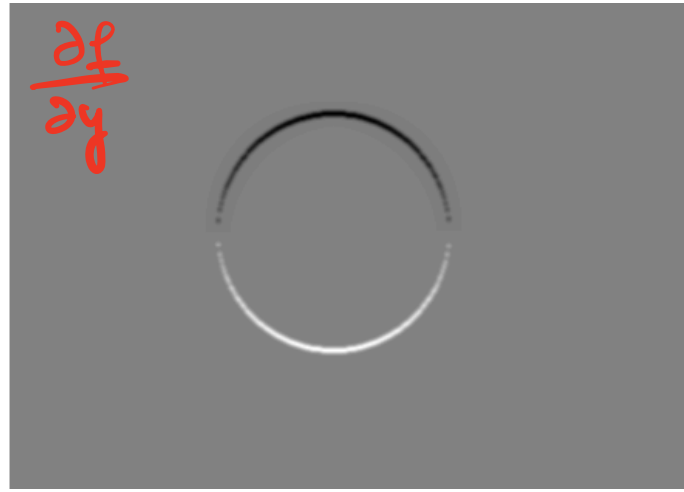
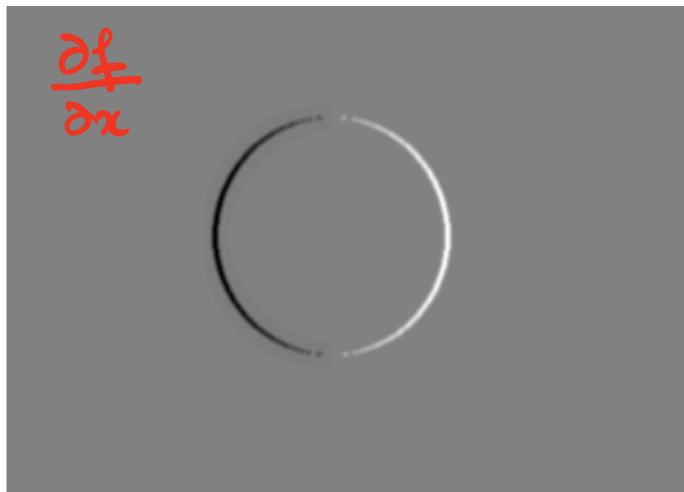
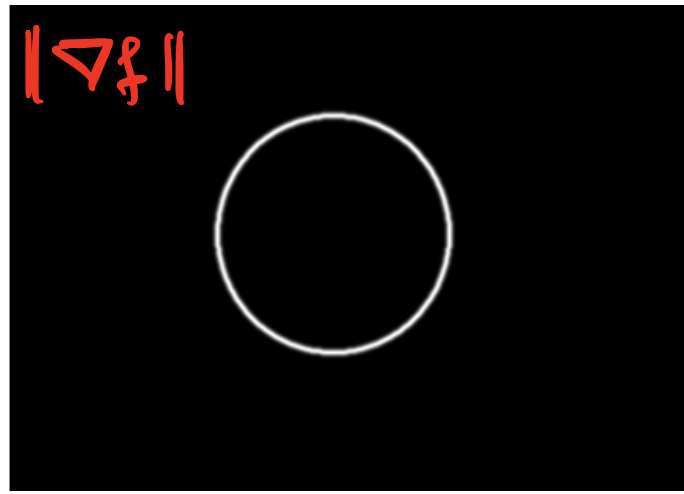
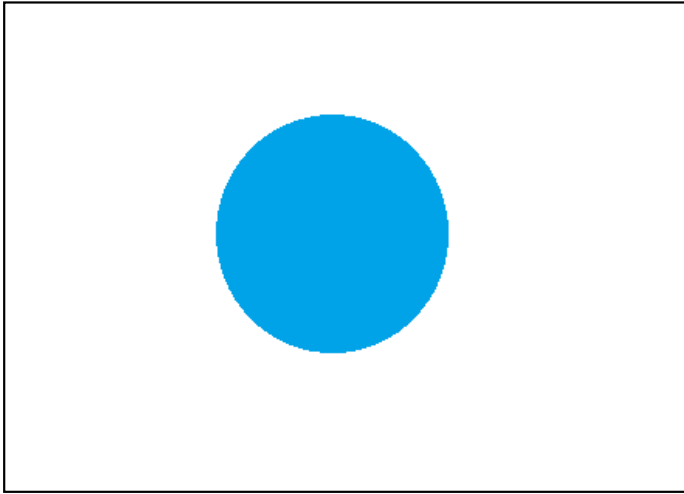
Image Gradient:  $\nabla f = \left[ \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right]$

$\nabla$  *nabla*  
 $\Delta$  *delta*

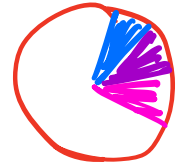
- The gradient of an image  $\nabla f$  points to the direction of most rapid change in intensity



- Gradient magnitude:  $\|\nabla f\| = \sqrt{\left( \frac{\partial f}{\partial x} \right)^2 + \left( \frac{\partial f}{\partial y} \right)^2}$
- Gradient direction:  $\theta = \tan^{-1} \left( \frac{\partial f / \partial y}{\partial f / \partial x} \right)$



# Gradient direction and magnitude

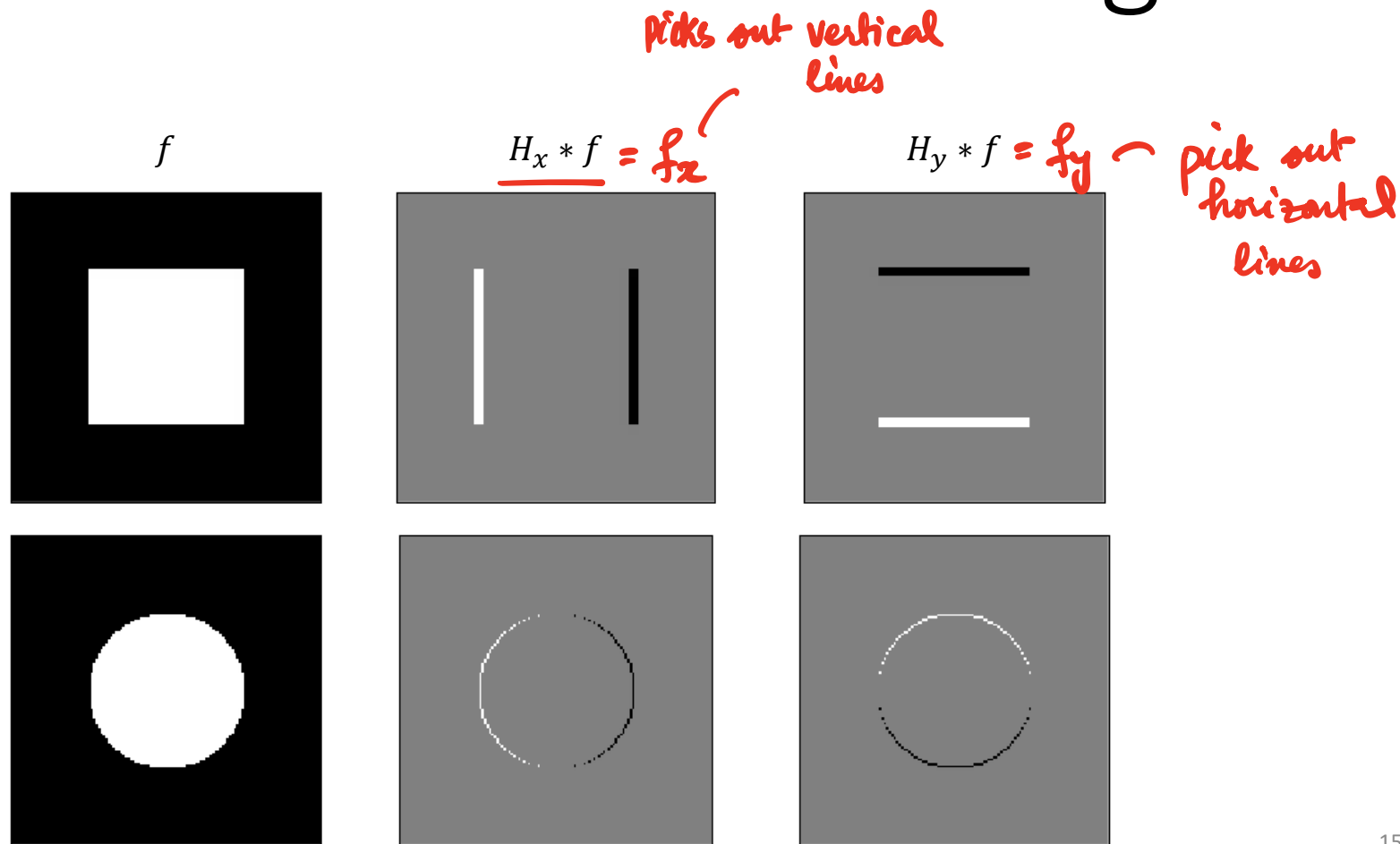


$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

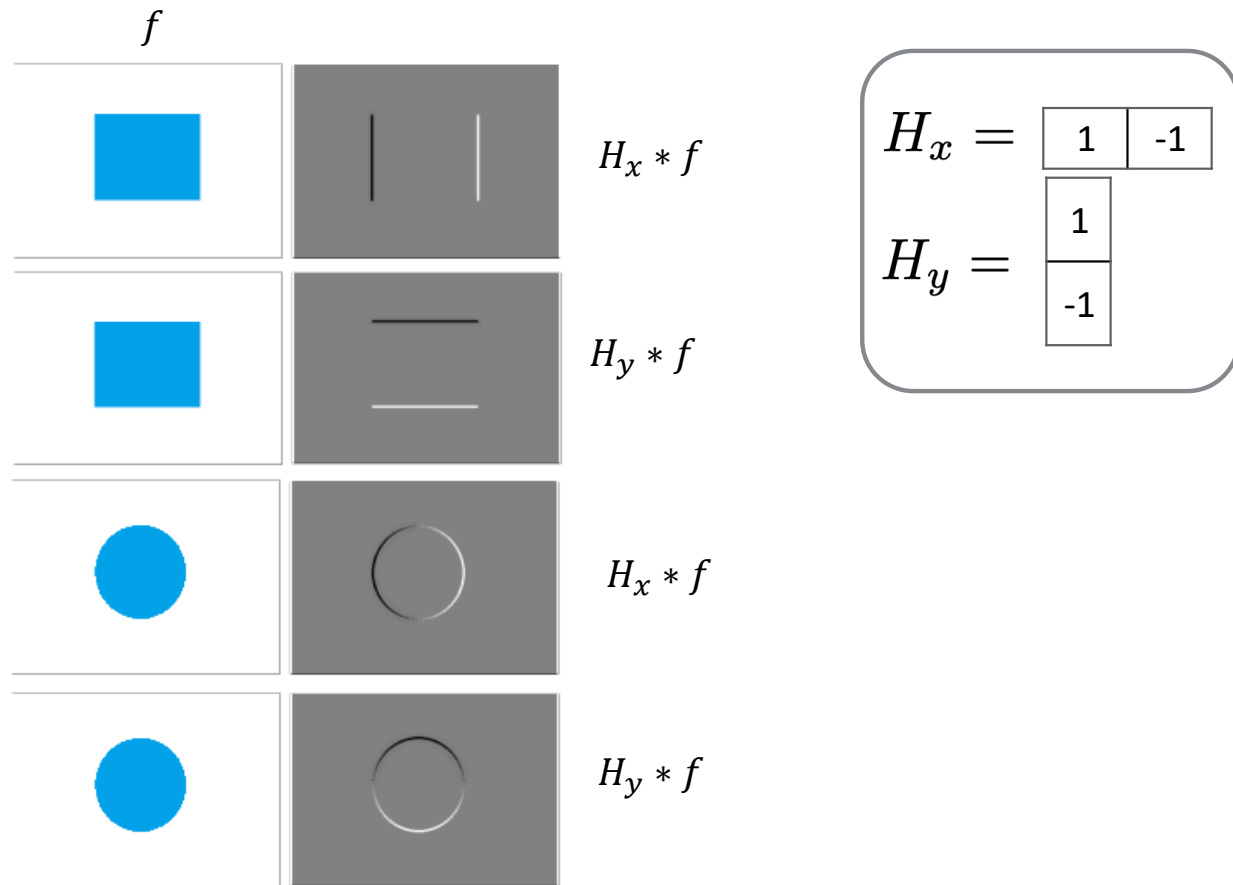
$$\theta = \tan^{-1}\left(\frac{\partial f / \partial y}{\partial f / \partial x}\right)$$



# Partial Derivative of an Image



# Partial Derivative of an Image





# Partial Derivatives of an Image



# Filters for computing image derivatives

## *Finite Difference Filters*

**Sobel**

$$H_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

$$H_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

**Prewitt**

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

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

**Roberts**

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

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

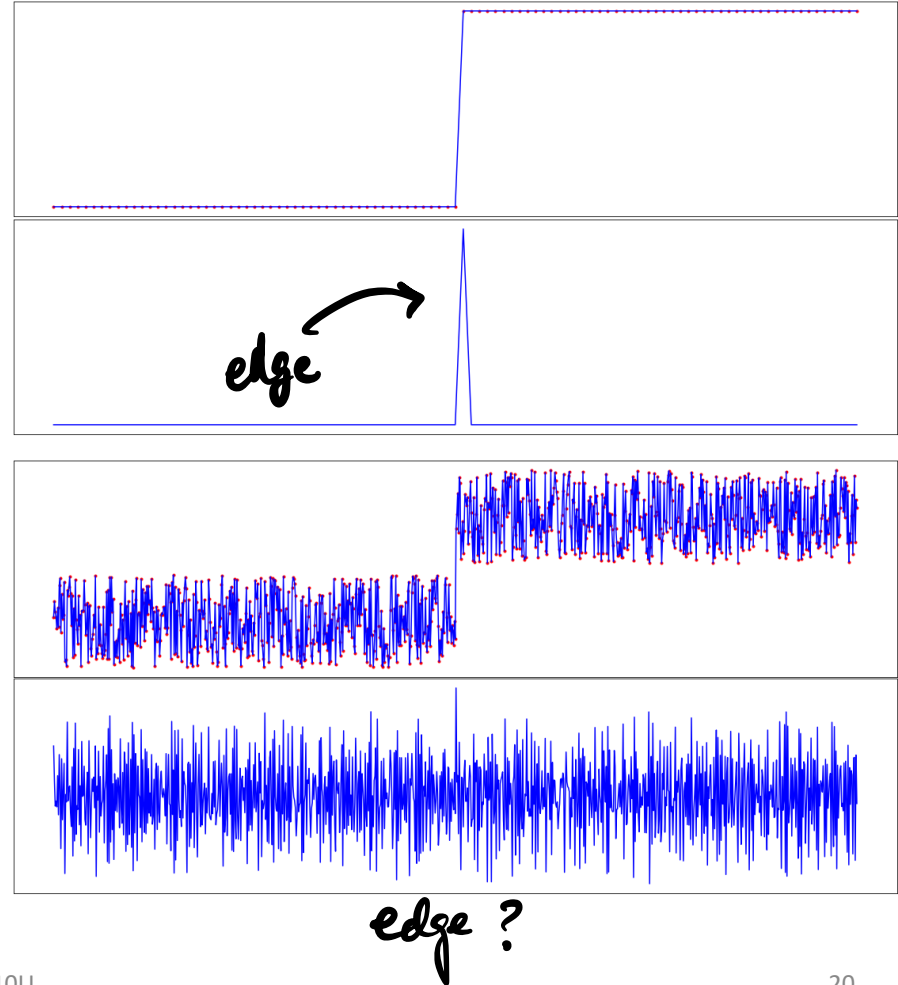
# Image noise and gradients

Clean signal  $f$

$$\frac{df}{dx}$$

Noisy signal  $g$

$$\frac{dg}{dx}$$



# Effects of Noise

- Gradient is highly sensitive to noise
- Difference filters (that we can use for gradient computation) respond strongly to noise
  - The larger the noise, the stronger the response
- How to handle it?
  - Smooth first. Get rid of high-frequency component.

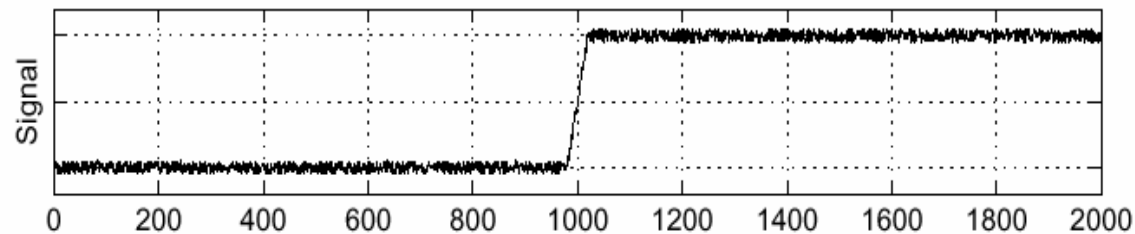
1. Average



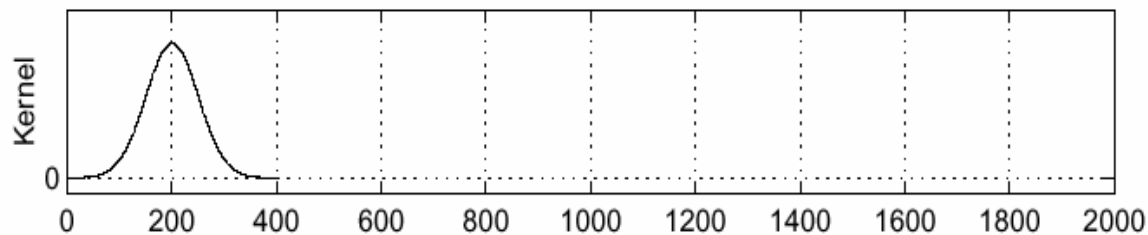
2. Gaussian

Sigma = 50

$f$

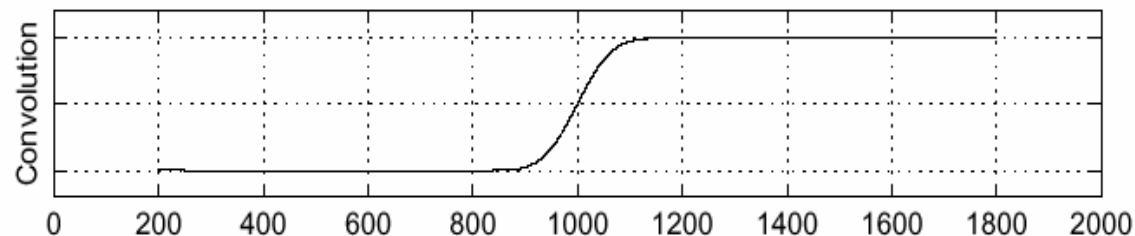


$g$



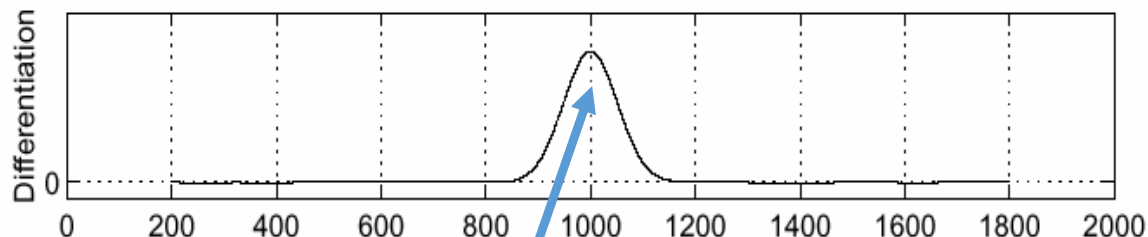
Smoothed  
Signal

$f * g$



Derivative

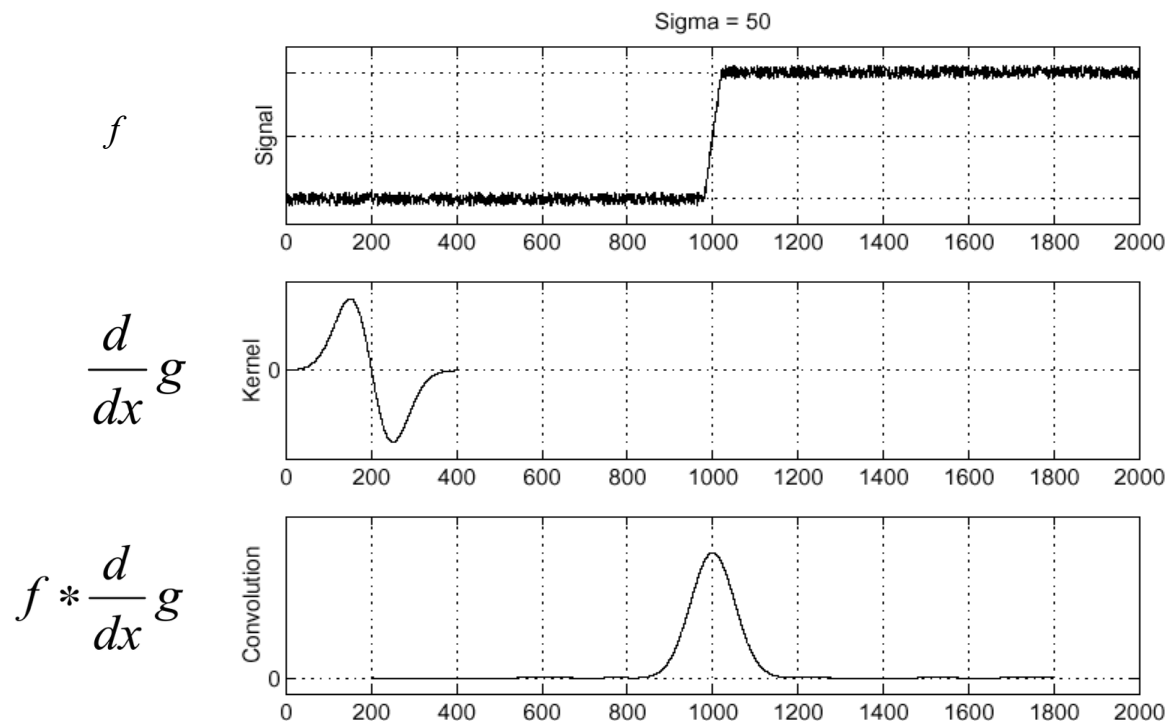
$\frac{d}{dx}(f * g)$



Peak corresponds to edge

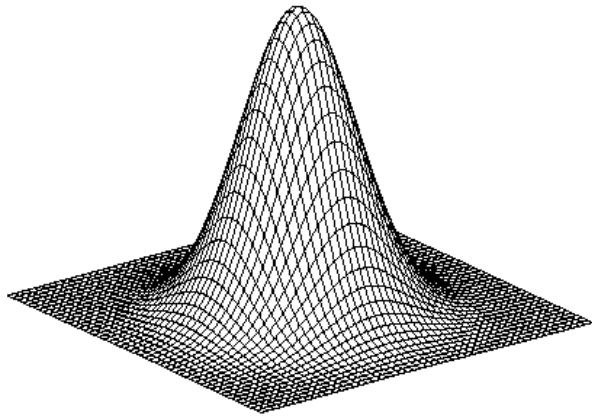
# Differentiation via Convolution

- Convolution is associative:  $\frac{d}{dx}(f * g) = f * \frac{d}{dx}g$



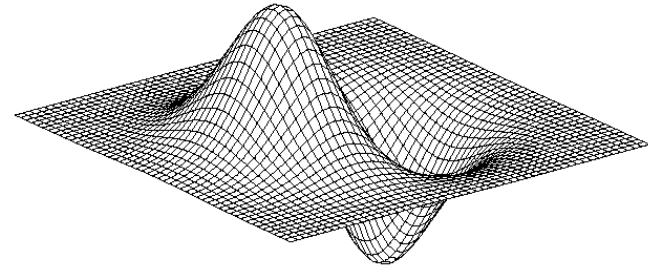
We saved one  
convolutional operation

# Derivative of Gaussian filter



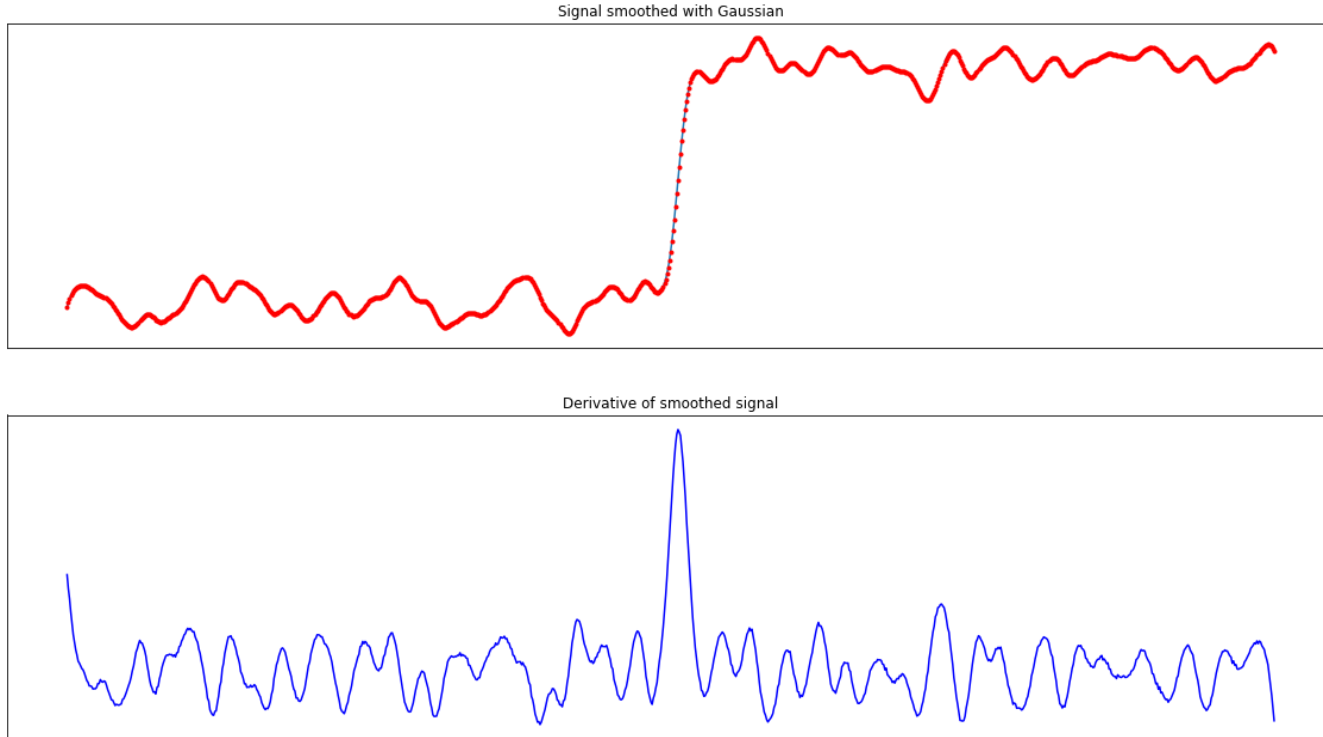
2D

$$* [1, -1] =$$

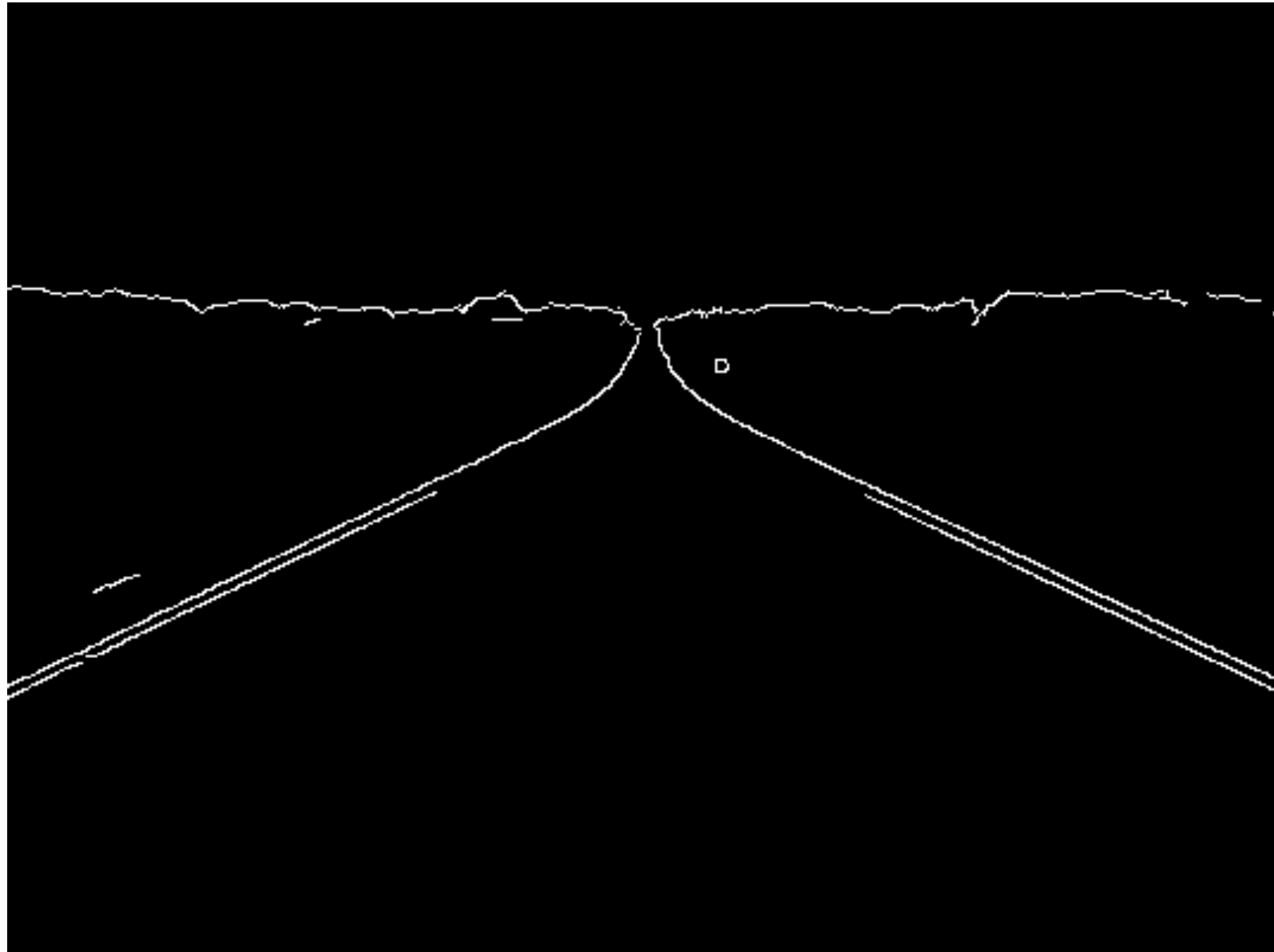


2D

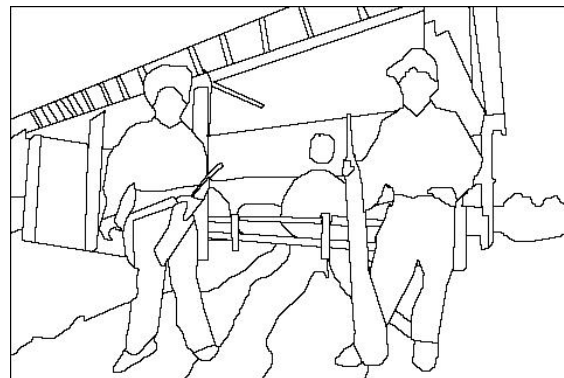
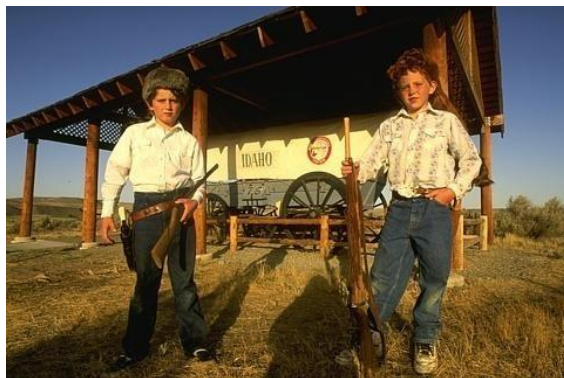
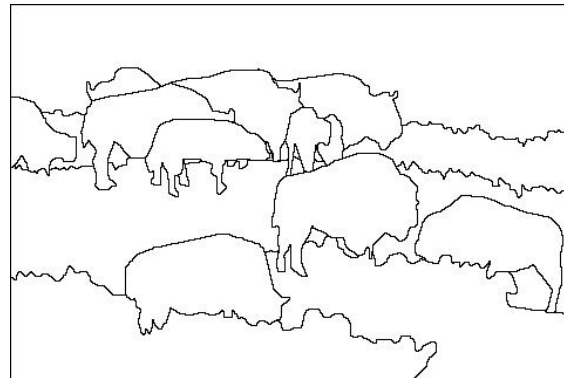
# Image noise and gradients







# Edge Detection



# Edge Detection

- Identify sudden changes (discontinuities) in an image
- Most semantic and shape information seen in an image can be encoded using the edges
- Edges are more compact than pixels

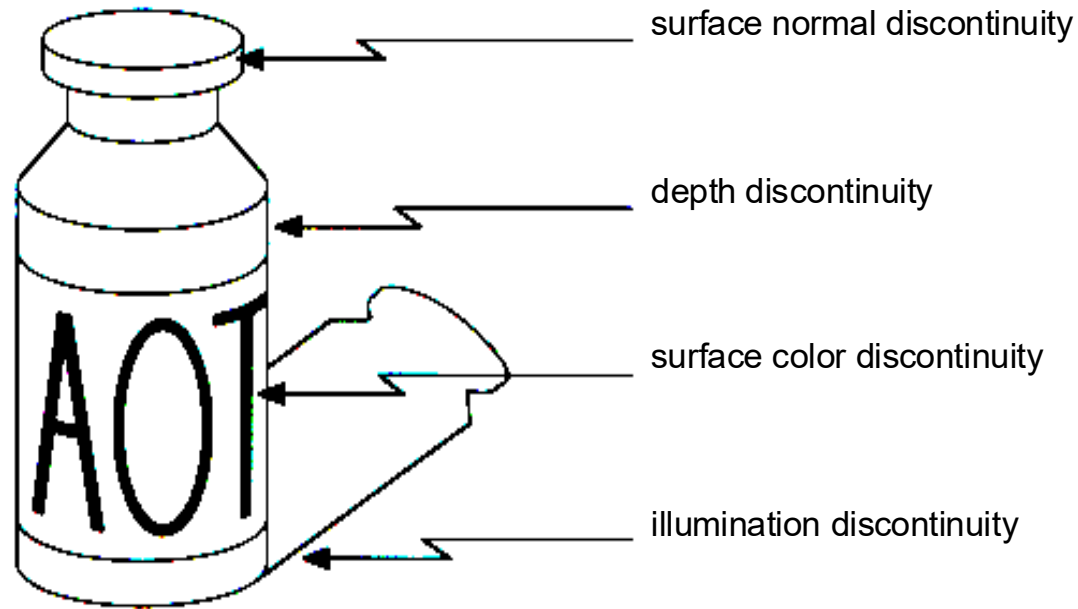


An artist's line drawing

[Source: D. Lowe]

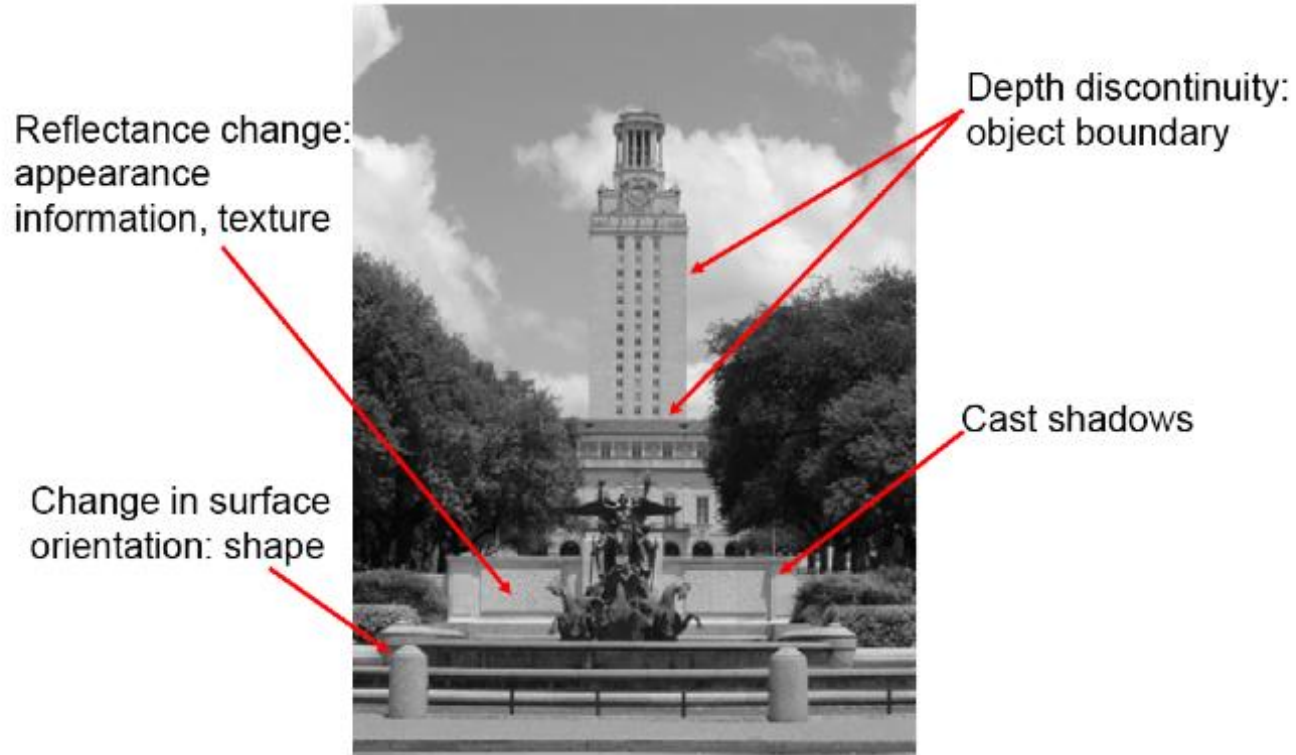
# Origin of Edges

- Edges are caused by



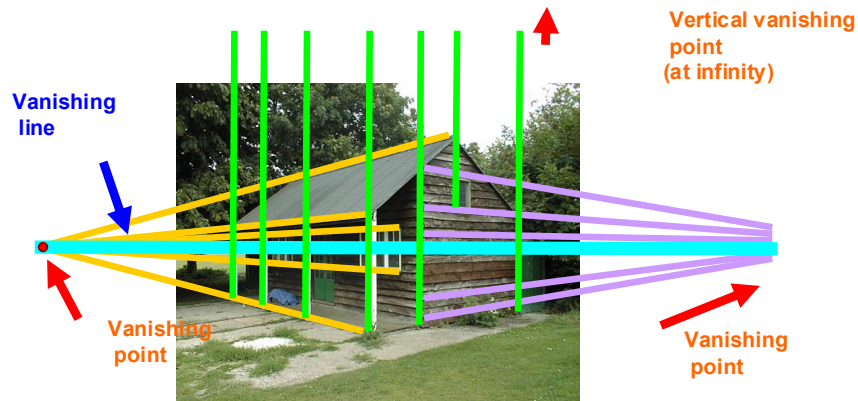
[Source: Steve Seitz]

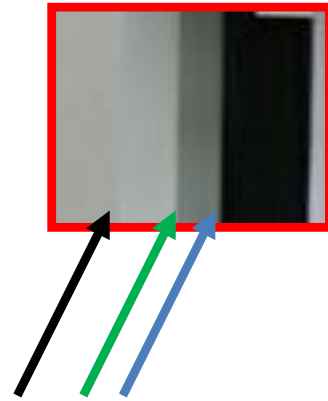
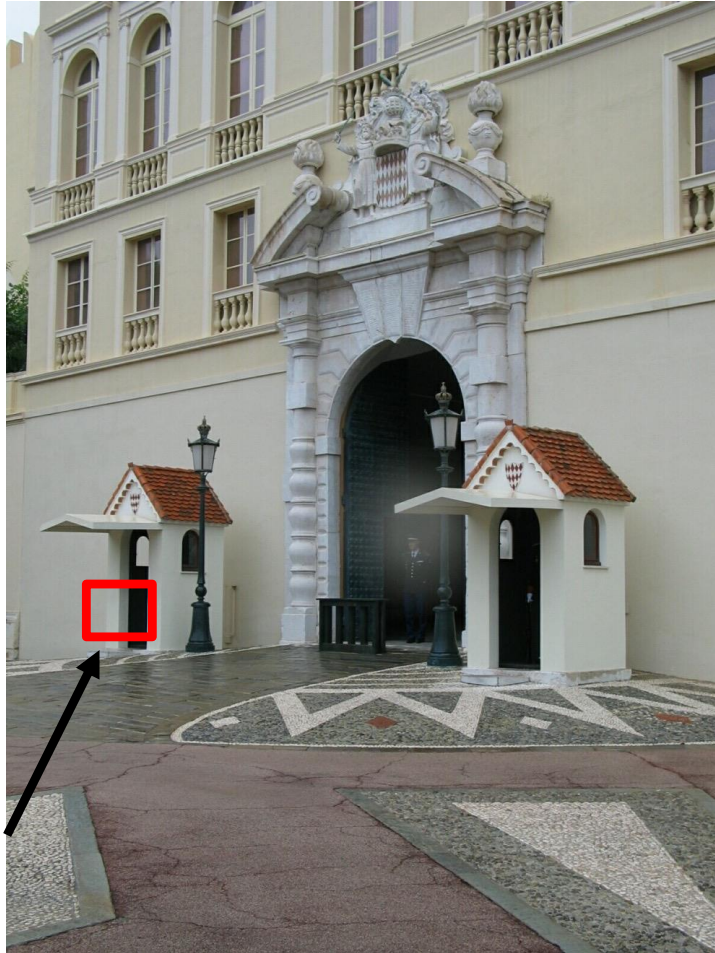
# What causes edges?



# Why edge detection?

- Extract information
- Recognize objects
- Understand scene
- Reconstruct 3D from images
  - Recover viewpoint and geometry





[Source: Steve Seitz]





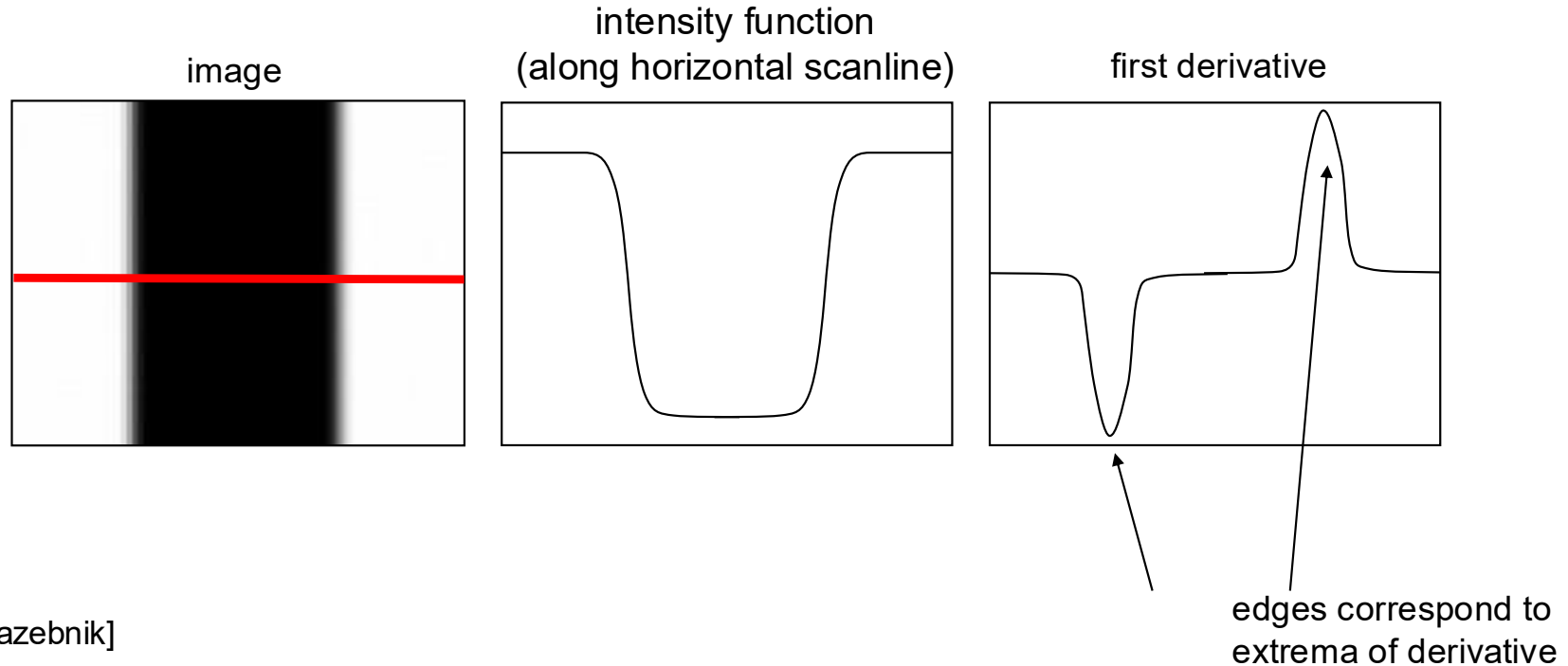




[Source: Steve Seitz]

# Characterizing Edges

- An edge is a place of rapid change in intensity



# Summary

- Image gradients
- Finite-difference approximation filters
- Gradient magnitude and direction
- Image noise and gradients
- Edges and their importance