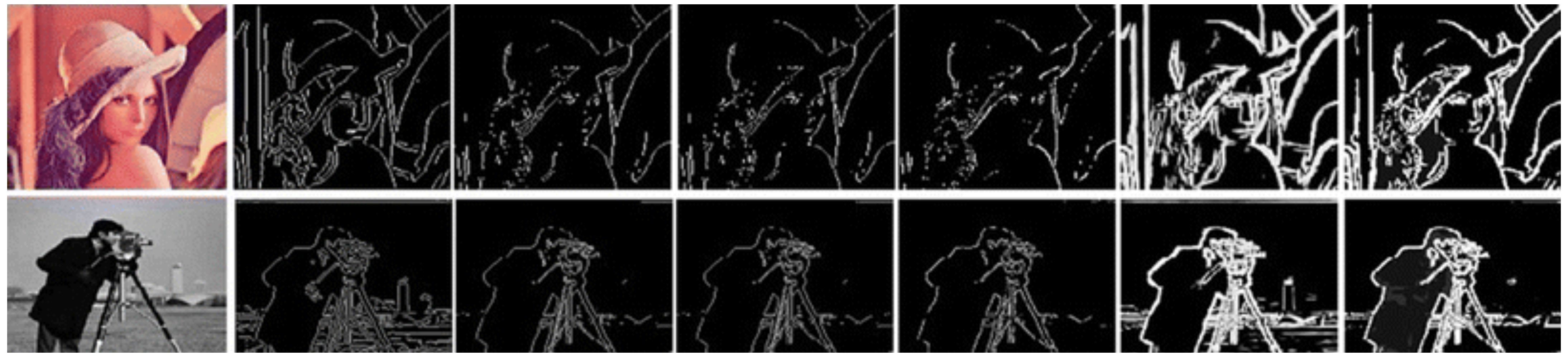
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 10: Edge Detection

(unless otherwise stated slides are taken or adopted from **Bob Woodham, Jim Little** and **Fred Tung**)

Menu for Today (**September 26, 2018**)

Topics:

— Estimating Derivatives

— Edge Detection

— iClicker Quiz

Redings:

— **Today's** Lecture: Forsyth & Ponce (2nd ed.) 5.1 - 5.2

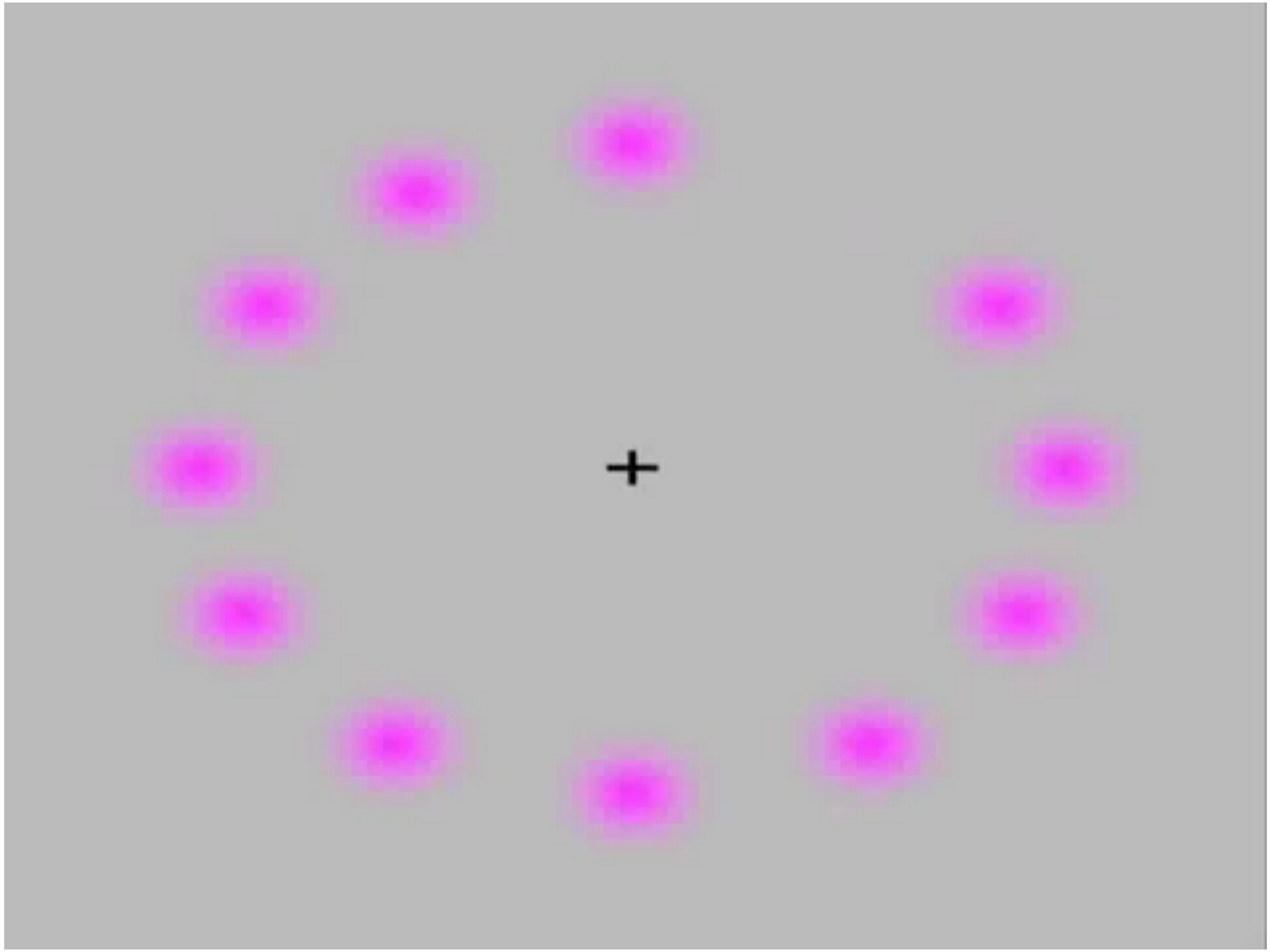
— **Next** Lecture: Forsyth & Ponce (2nd ed.) 5.3.0 - 5.3.1

Reminders:

— **Assignment 2**: Face Detection in a Scaled Representation is **out**

Today's "**fun**" Example: Rainbow Illusion

Today's "**fun**" Example: Lilac Chaser (a.k.a. Pac-Man) Illusion



Lecture 9: Re-cap

Template matching as (normalized) correlation

Template matching is **not robust** to changes in
— 2D spatial scale and 2D orientation
— 3D pose and viewing direction
— illumination

Scaled representations facilitate:
— template matching at multiple scales
— efficient search for image-to-image correspondences
— image analysis at multiple levels of detail

A **Gaussian pyramid** reduces artifacts introduced when sub-sampling to coarser scales

Lecture 9: Re-cap

A (**discrete**) approximation is

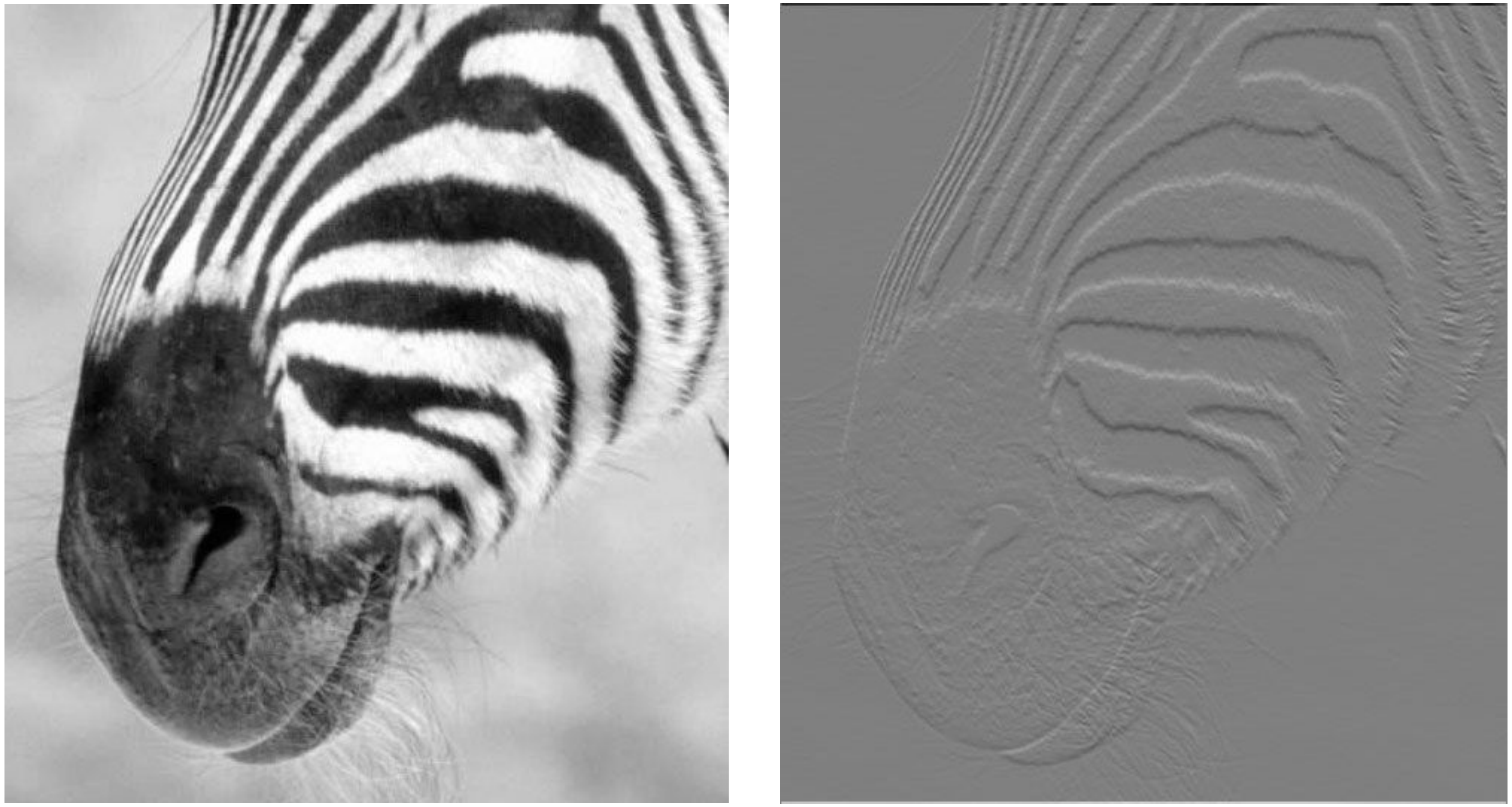
$$\frac{\partial f}{\partial x} \approx \frac{F(X+1, y) - F(x, y)}{\Delta x}$$

- “First forward difference”
- Can be implemented as a **convolution**
- Sensitive to **noise**: typically smooth the image prior to derivative estimation.

$$\begin{array}{|c|c|}\hline -1 & 1 \\ \hline \end{array} \qquad \begin{array}{|c|}\hline -1 \\ \hline 1 \\ \hline \end{array}$$

Lecture 9: Re-cap

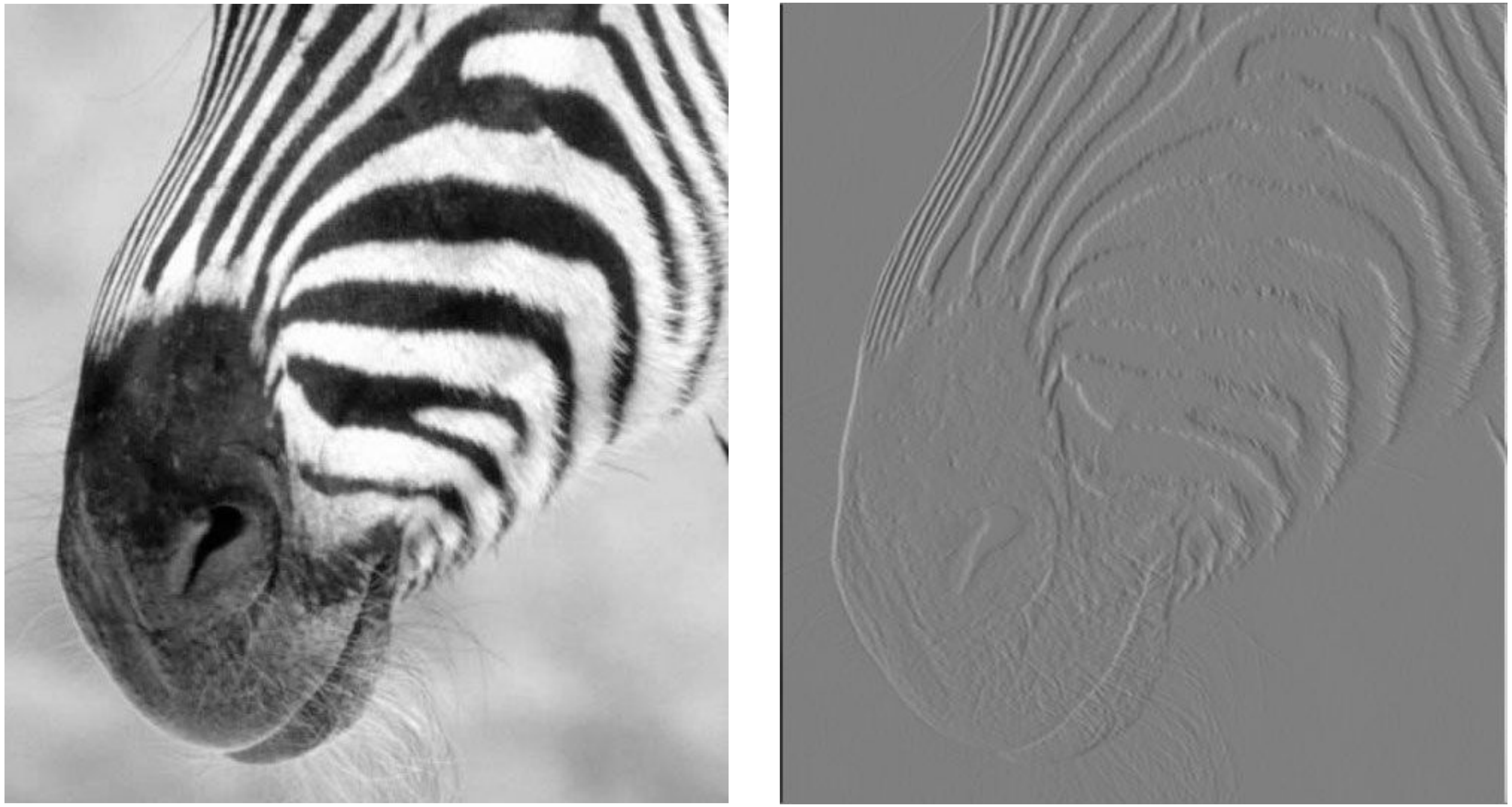
Derivative in Y (i.e., vertical) direction



Forsyth & Ponce (1st ed.) Figure 7.4 (top left & top middle)

Lecture 9: Re-cap

Derivative in X (i.e., horizontal) direction



Forsyth & Ponce (1st ed.) Figure 7.4 (top left & top right)

A Sort **Exercise**

Use the "first forward difference" to compute the image derivatives in X and Y directions.

(Compute two arrays, one of $\frac{\partial f}{\partial x}$ values and one of $\frac{\partial f}{\partial y}$ values.)

1	1	0.6	0.3	0	0
1	1	0.6	0.3	0	0
0	0	0	0	0	0
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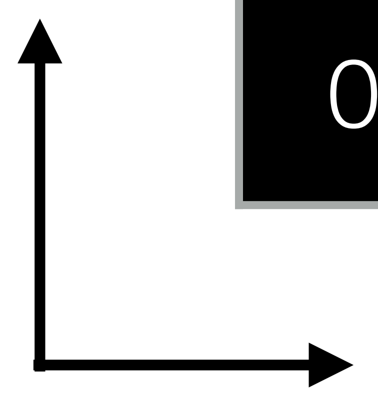

A Sort **Exercise**: Derivative in X Direction

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0	0	0	0	0	0
0	$\boxed{0}$	$\boxed{0}$	0	0	0

0					

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0	0				

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0					
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1	1	0.6	0.3	0	0
0	0	0	0	0	0
0	0	0	0	0	0

0	-0.4				
0	0	0	0	0	
0	0	0	0	0	

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1	1	0.6	0.3	0	0
1	1	0.6	0.3	0	0
0	0	0	0	0	0
0	0	0	0	0	0

0	-0.4	-0.3	-0.3	0	
0	-0.4	-0.3	-0.3	0	
0	0	0	0	0	
0	0	0	0	0	

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0	0	0	0	0	0
0	0	0	0	0	0

1					
0	0	0	0	0	0

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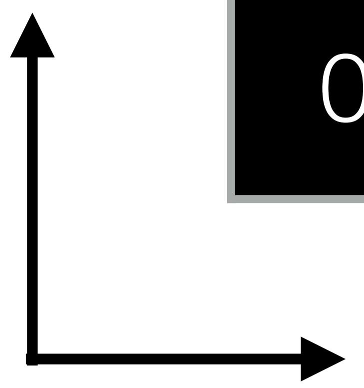
0	0	0	0	0	0
0	0	0	0	0	0



0	0	0	0	0	0
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0	0	0	0	0	0

Estimating **Derivatives**

Question: Why, in general, should the weights of a filter used for differentiation sum to 0?

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Answer: Think of a constant image, $I(X, Y) = k$. The derivative is 0. Therefore, the weights of any filter used for differentiation need to sum to 0.

Estimating **Derivatives**

Question: Why, in general, should the weights of a filter used for differentiation sum to 0?

Answer: Think of a constant image, $I(X, Y) = k$. The derivative is 0. Therefore, the weights of any filter used for differentiation need to sum to 0.

$$\sum_{i=1}^{N} f_i \cdot k = k \sum_{i=1}^{N} f_i = 0 \implies \sum_{i=1}^{N} f_i = 0$$

Edge Detection

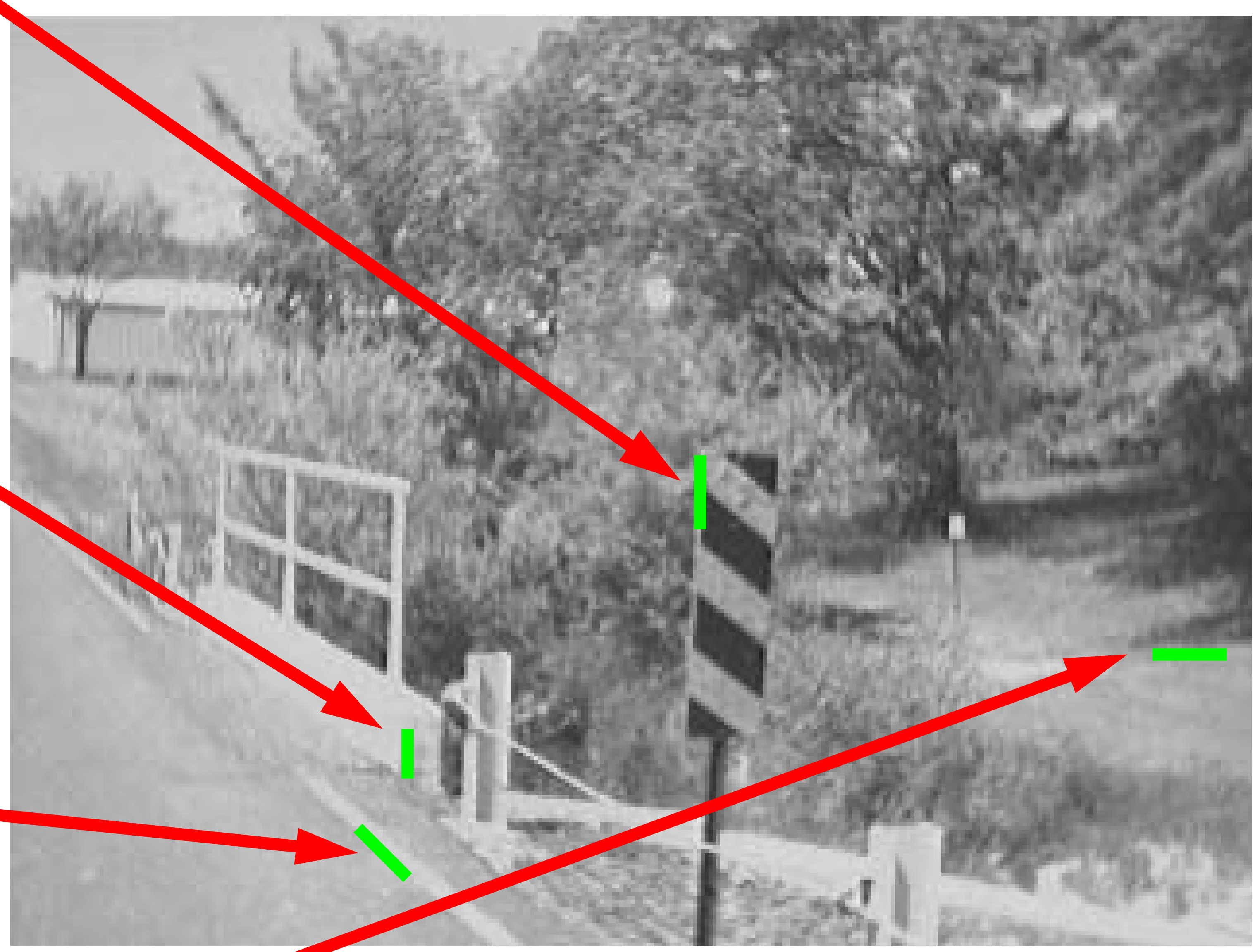
Goal: Identify sudden changes in image intensity

This is where most shape information is encoded

Example: artist's line drawing (but artist also is using object-level knowledge)

What Causes **Edges**?

- Depth discontinuity
- Surface orientation discontinuity
- Reflectance discontinuity (i.e., change in surface material properties)
- Illumination discontinuity (e.g., shadow)



Slide Credit: Christopher Rasmussen

Smoothing and Differentiation

Edge: a location with high gradient (derivative)

Need smoothing to reduce noise prior to taking derivative

Need two derivatives, in x and y direction

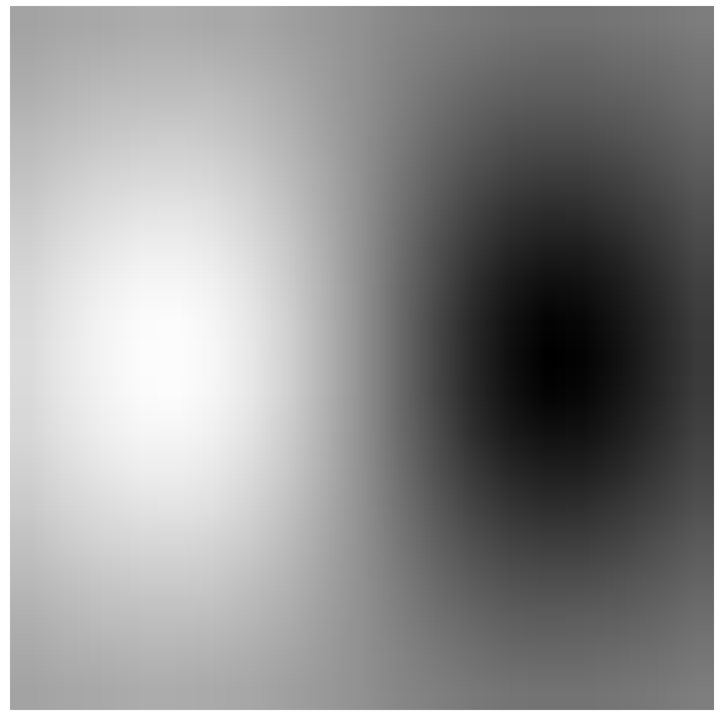
We can use **derivative of Gaussian** filters

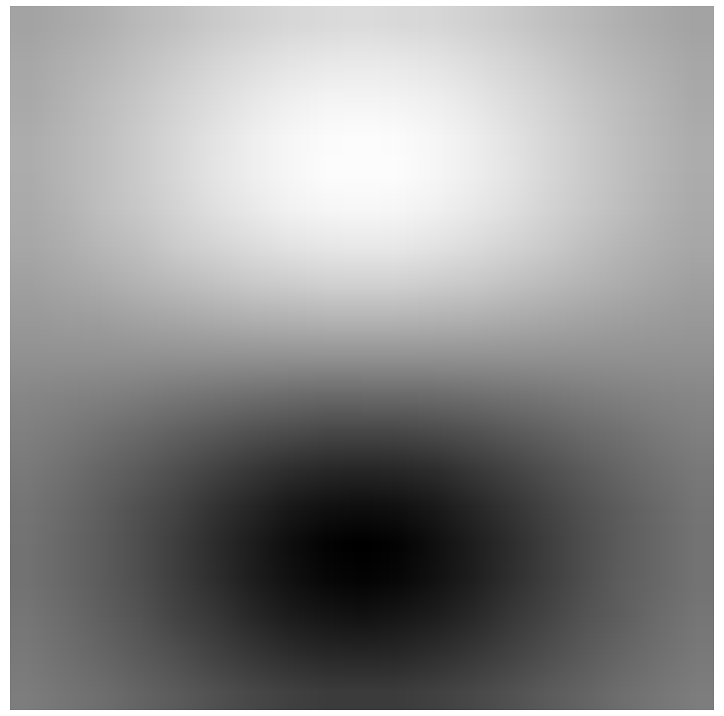
— because differentiation is convolution, and

— convolution is associative

Let $\otimes$ denote convolution

$$D \otimes (G \otimes I(X,Y)) = (D \otimes G) \otimes I(X,Y)$$

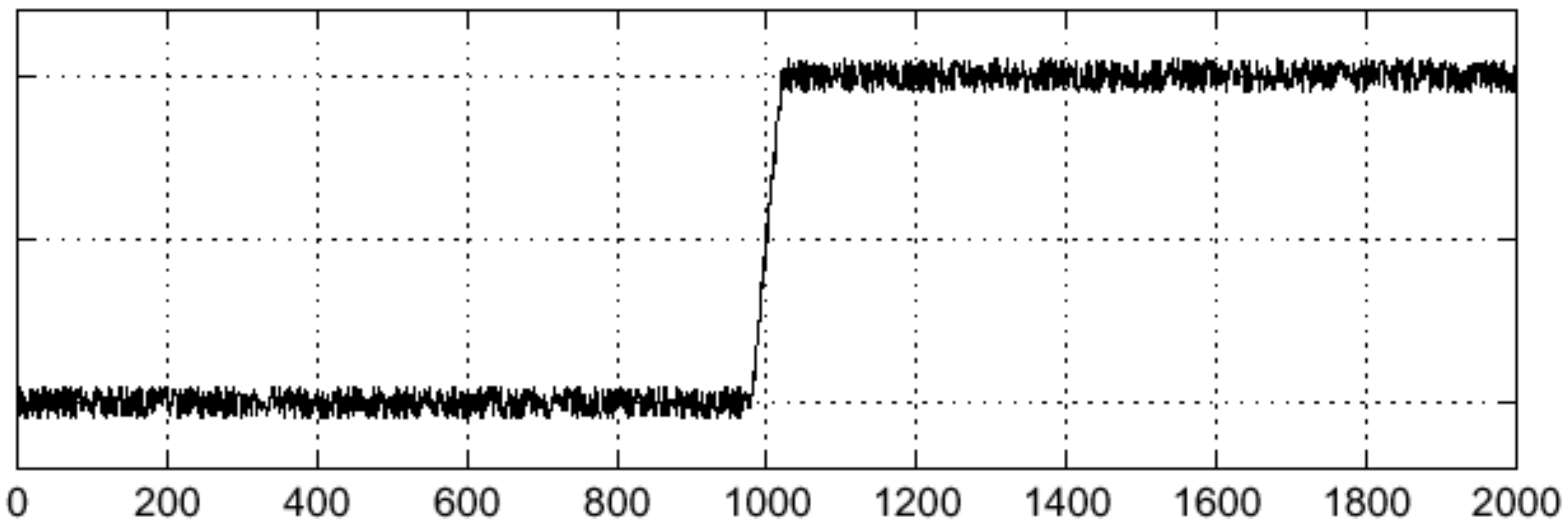




1D **Example**

Lets consider a row of pixels in an image:

$$I(X, 245)$$

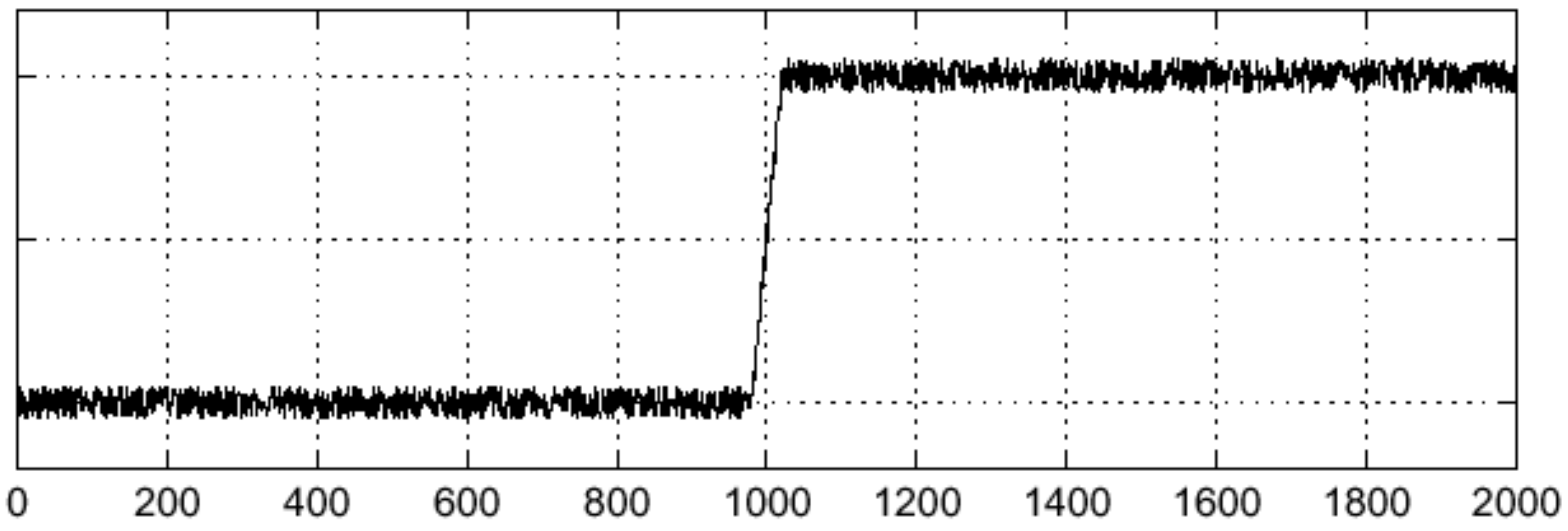


Where is the edge?

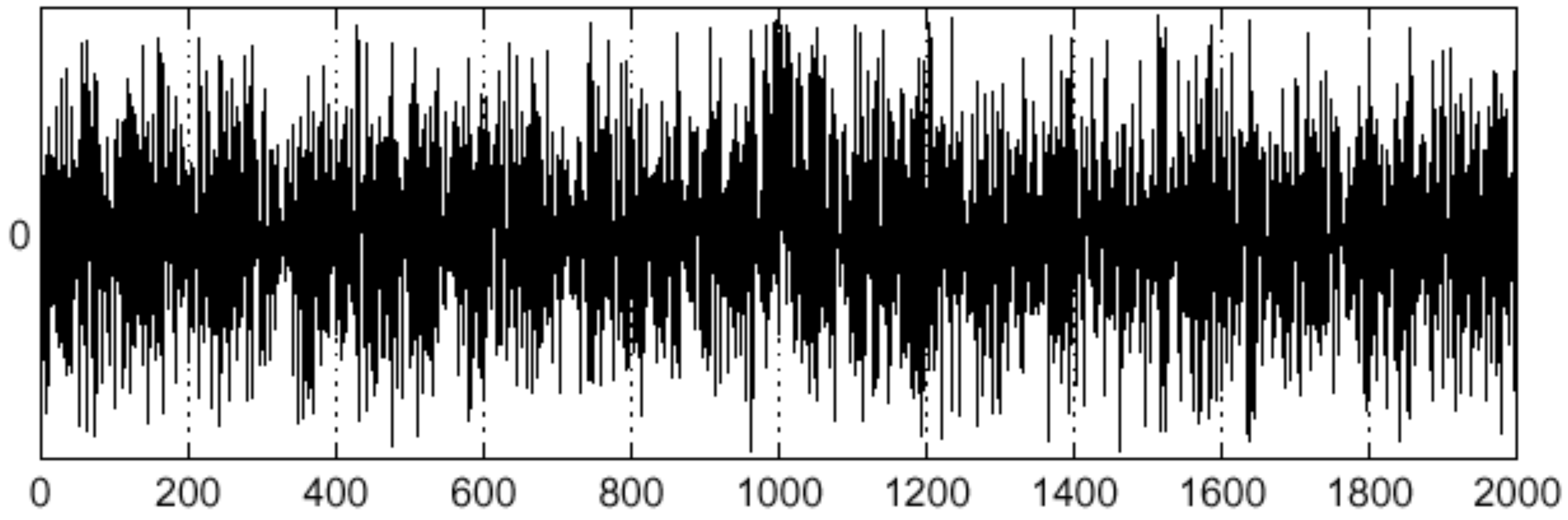
1D **Example**: Derivative

Lets consider a row of pixels in an image:

$$I(X, 245)$$



$$\frac{\partial I(X, 245)}{\partial x}$$



Where is the edge?

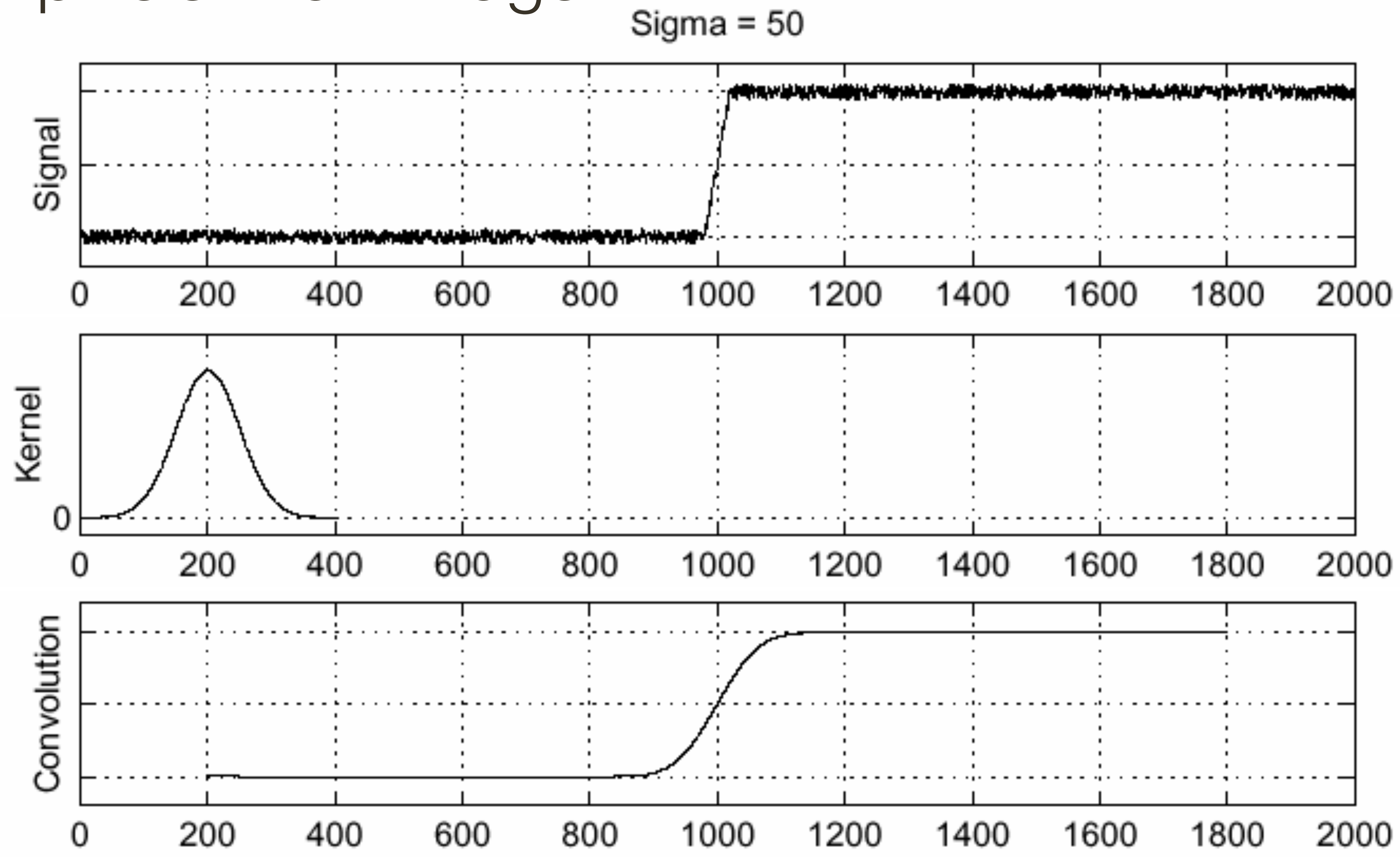
1D **Example**: Smoothing + Derivative

Lets consider a row of pixels in an image:

$$I(X, 245)$$

$$G$$

$$G \otimes I(X, Y)$$



1D **Example**: Smoothing + Derivative

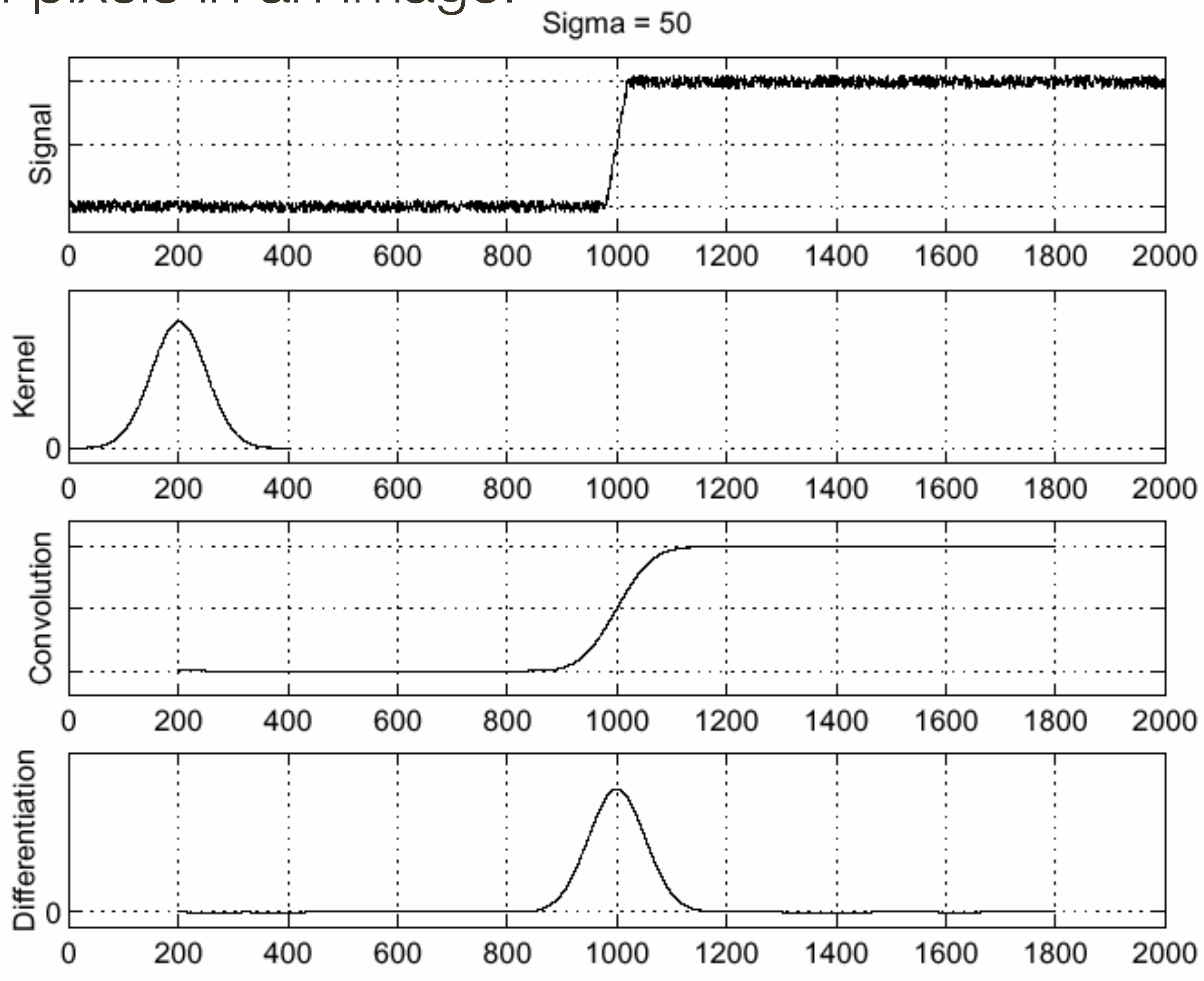
Lets consider a row of pixels in an image:

$$I(X, 245)$$

$$G$$

$$G \otimes I(X, Y)$$

$$\frac{\partial G \otimes I(X, Y)}{\partial x}$$



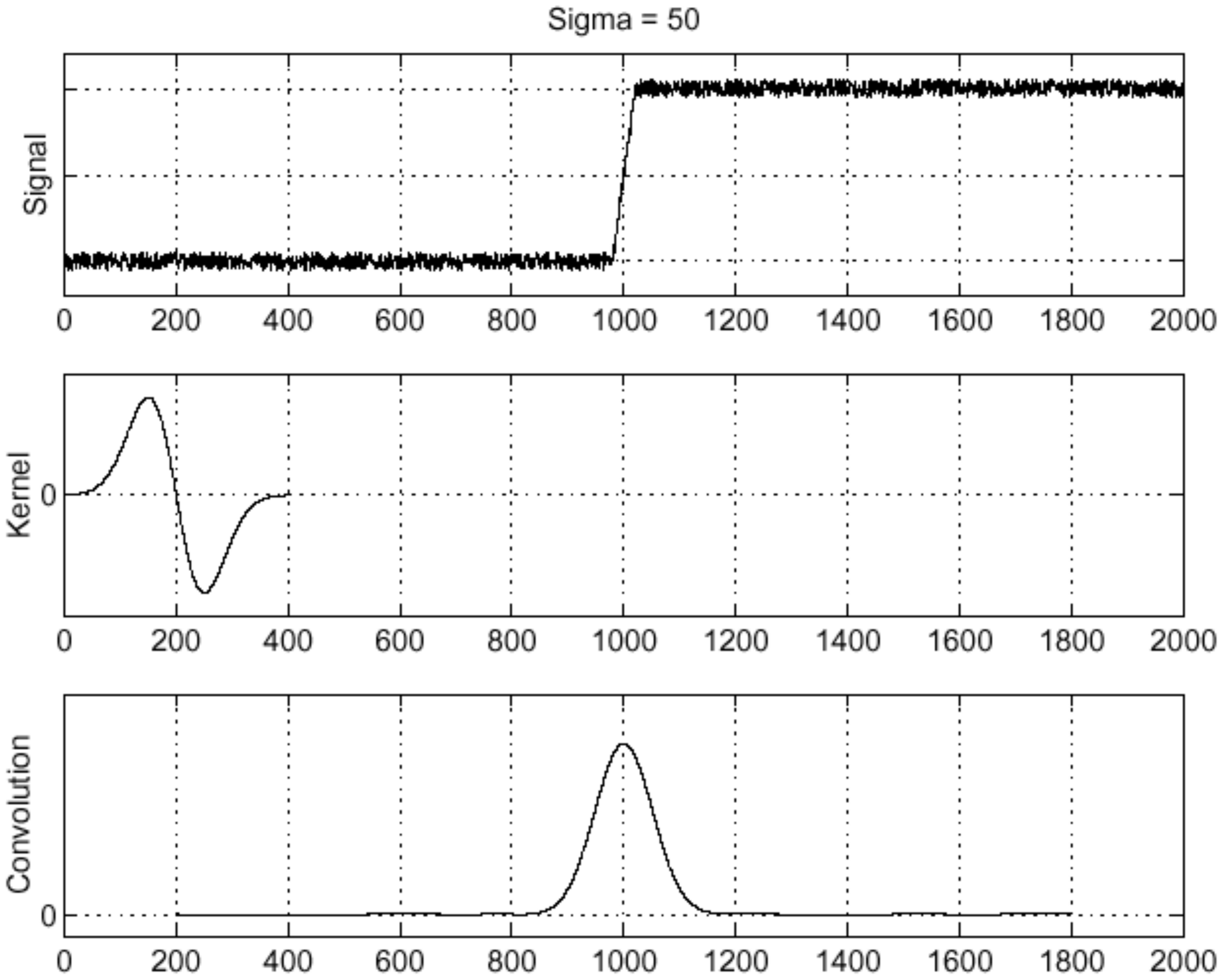
1D **Example**: Smoothing + Derivative (efficient)

Lets consider a row of pixels in an image:

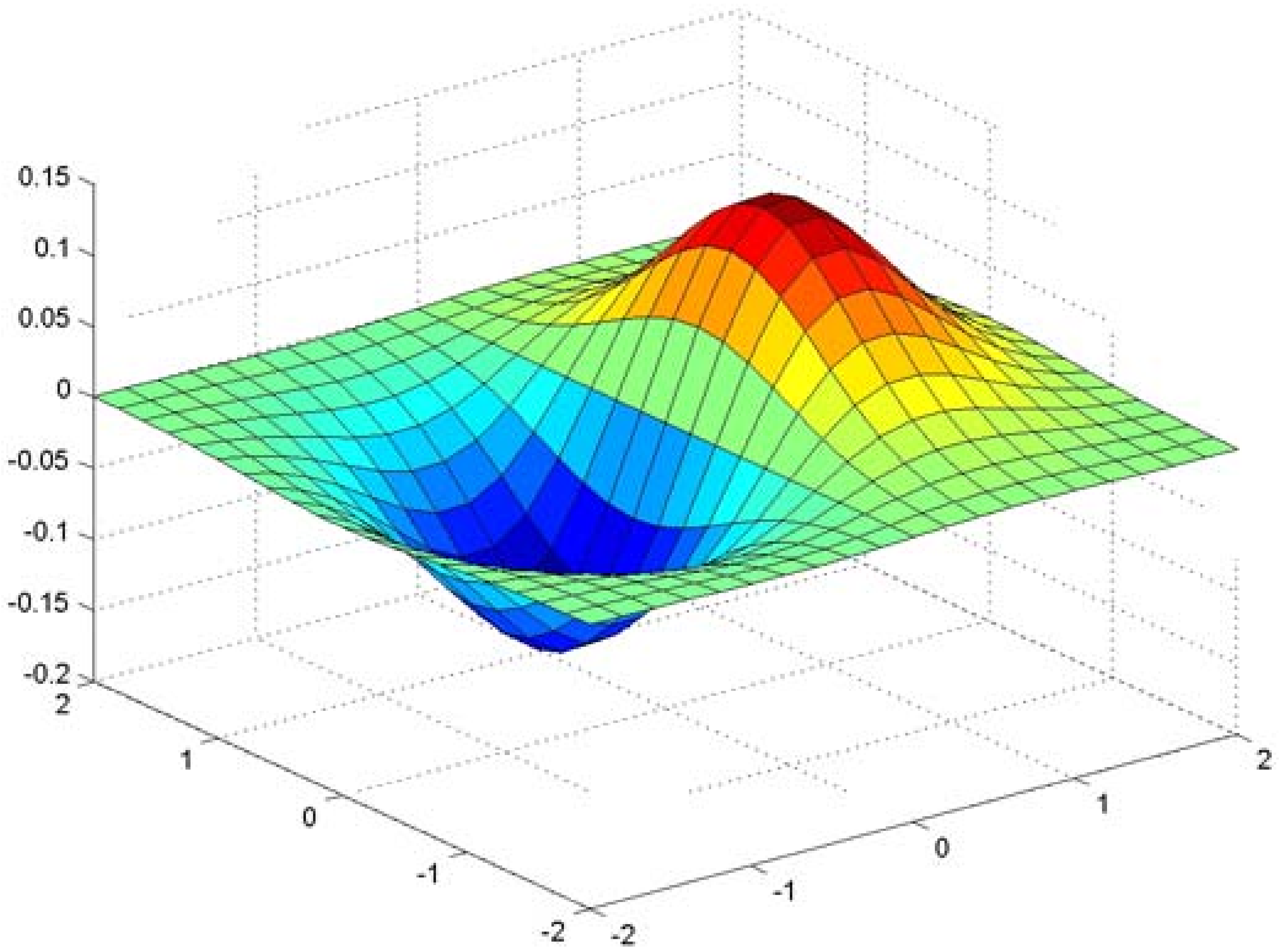
$$I(X, 245)$$

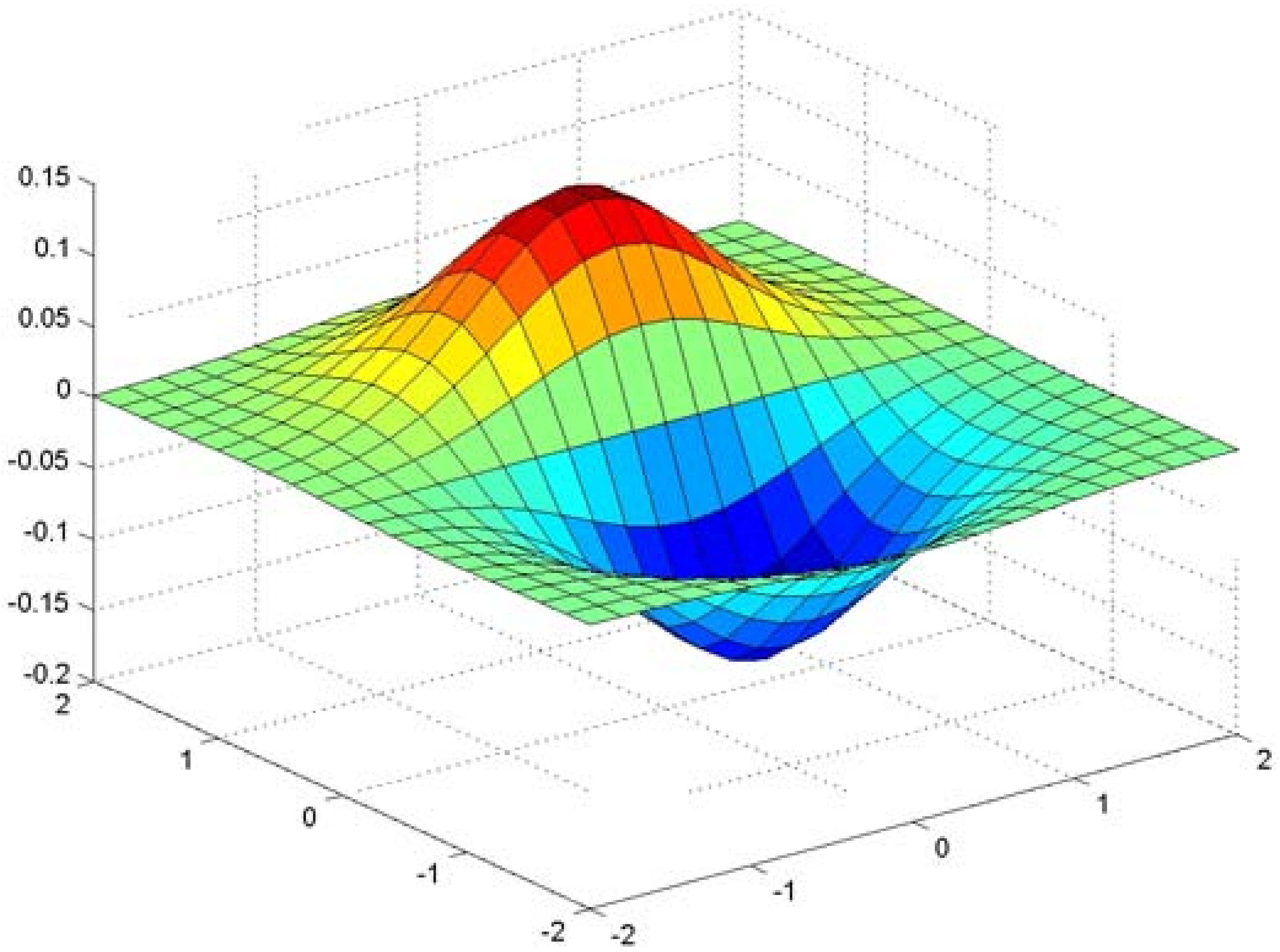
$$\frac{\partial G}{\partial x}$$

$$\frac{\partial G}{\partial x} \otimes I(X, Y)$$



Partial **Derivatives** of **Gaussian**





$$\frac{\partial}{\partial x} G_\sigma$$

$$\frac{\partial}{\partial y} G_\sigma$$

Slide Credit: Christopher Rasmussen

Gradient **Magnitude**

Let $I(X, Y)$ be a (digital) image

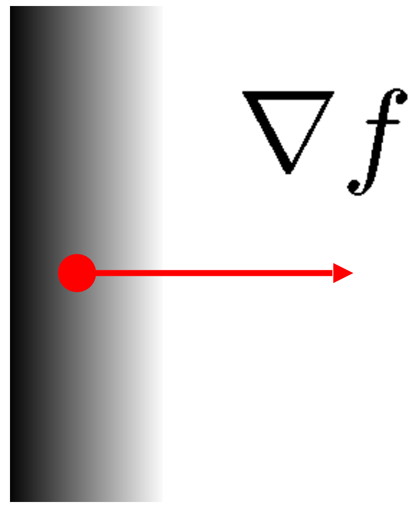
Let $I_x(X, Y)$ and $I_y(X, Y)$ be estimates of the partial derivatives in the x and y directions, respectively.

Call these estimates I_x and I_y (for short) The vector $[I_x, I_y]$ is the **gradient**

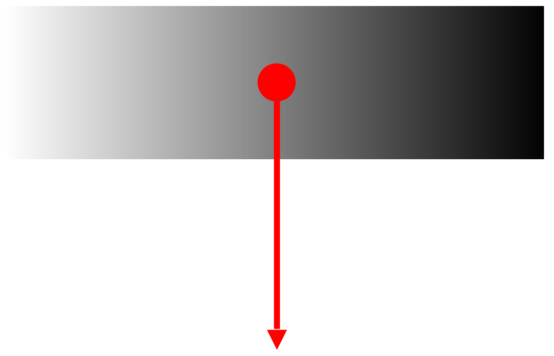
The scalar $\sqrt{I_x^2 + I_y^2}$ is the **gradient magnitude**

Image **Gradient**

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



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



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

Image **Gradient**

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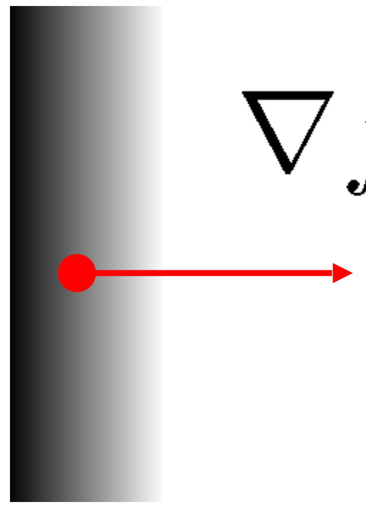

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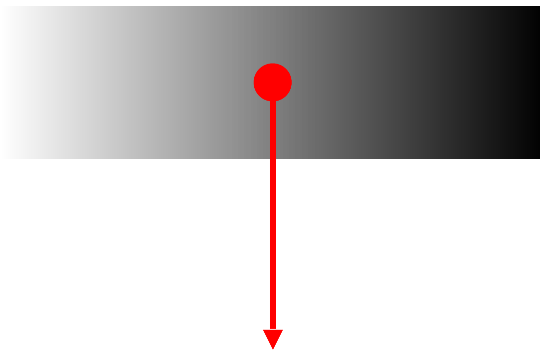

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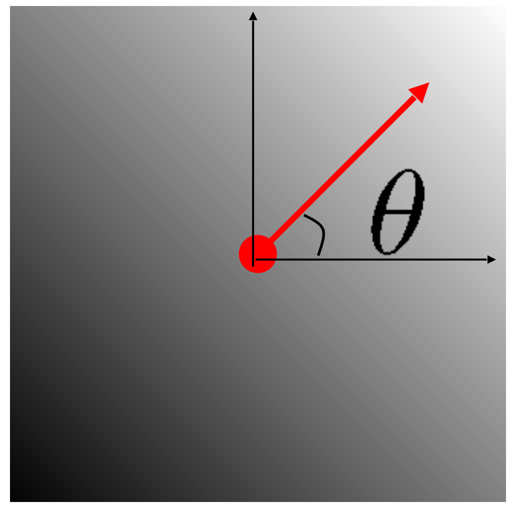
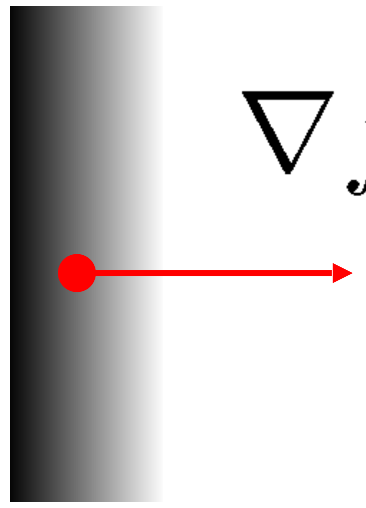


$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

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

Image **Gradient**

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



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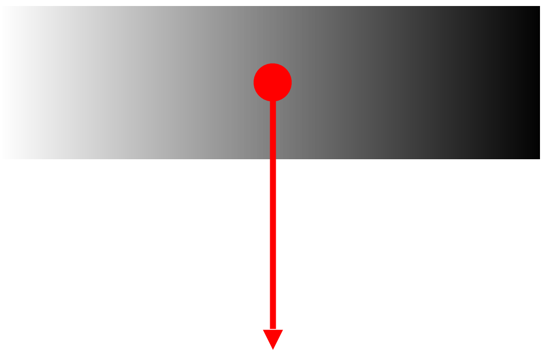

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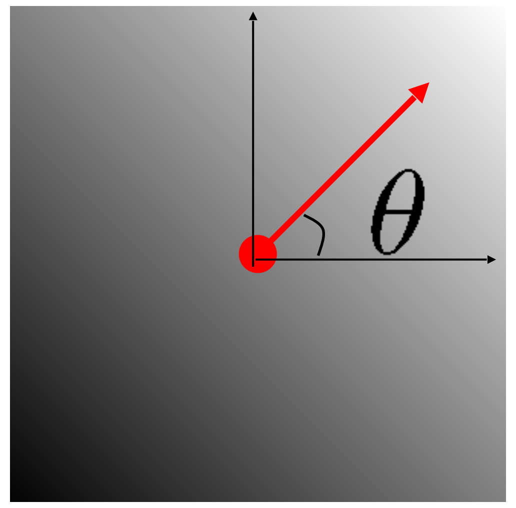


$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

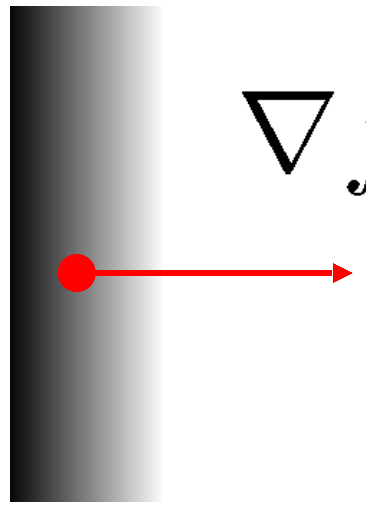
The gradient points in the direction of most rapid **increase of intensity**:

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

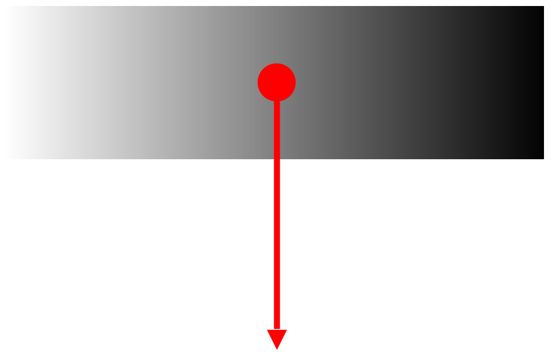
(how is this related to the direction of the edge?)

Image **Gradient**

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



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



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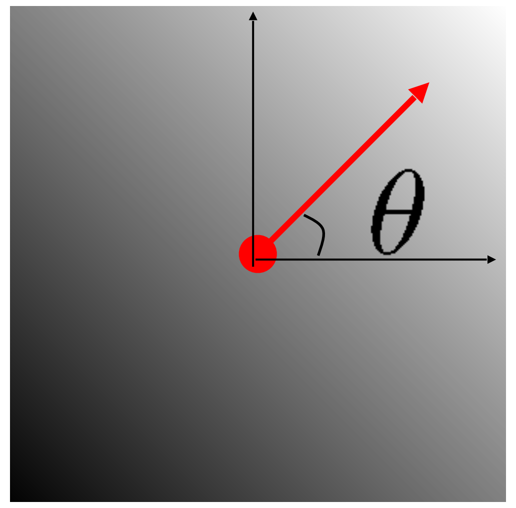

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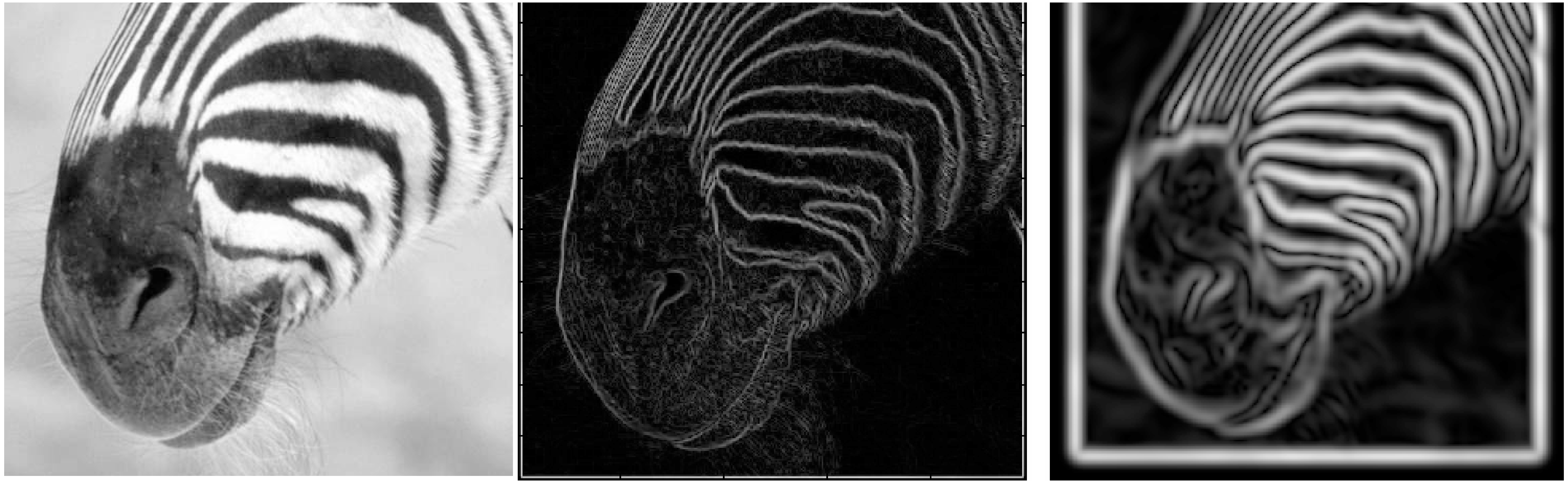
The **gradient direction** is given by: $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$

(how is this related to the direction of the edge?)

The edge strength is given by the **gradient magnitude**: $\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$

Gradient **Magnitude**



$\sigma = 1$ $\sigma = 2$

Forsyth & Ponce (2nd ed.) Figure 5.4

Increased **smoothing**:

— eliminates noise edges

— makes edges smoother and thicker

— removes fine detail

Sobel Edge Detector

1. Use **central differencing** to compute gradient image (instead of first forward differencing). This is more accurate.

2. **Threshold** to obtain edges

Original Image

Sobel Gradient

Sobel Edges

Thresholds are brittle, we can do better!

Please get your **iClickers** — Quiz