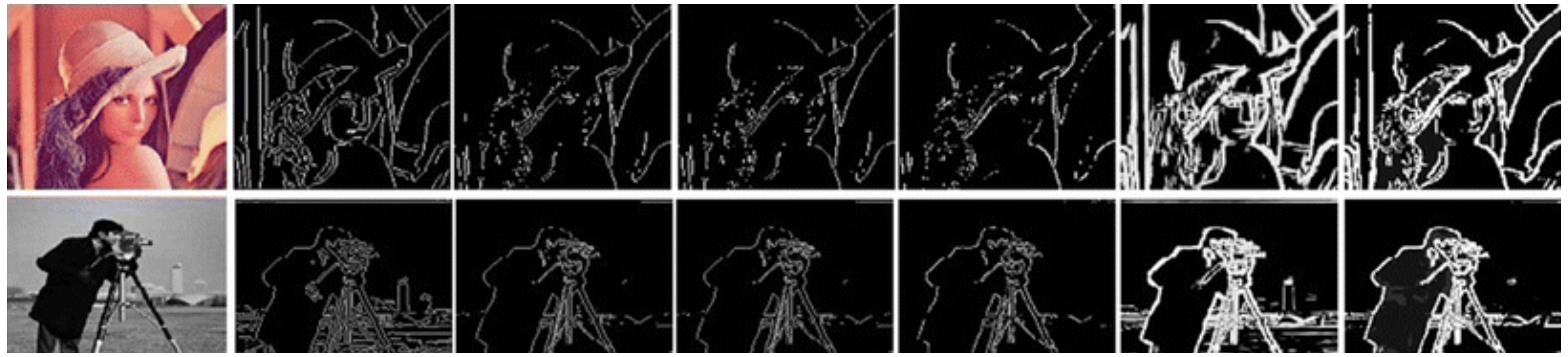
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 7: Edge Detection

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

Edge Detection

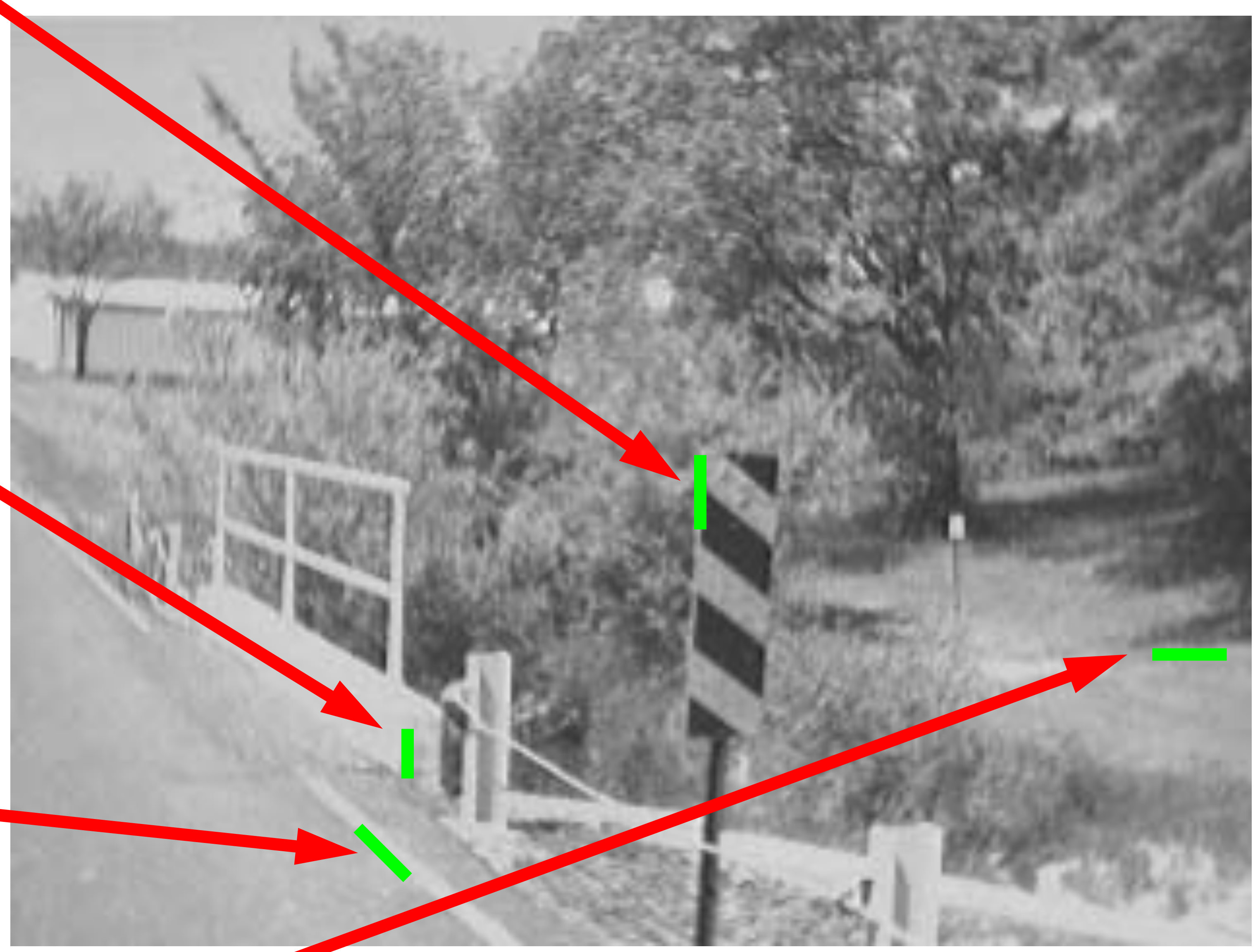
Goal: Identify sudden changes in image intensity

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)

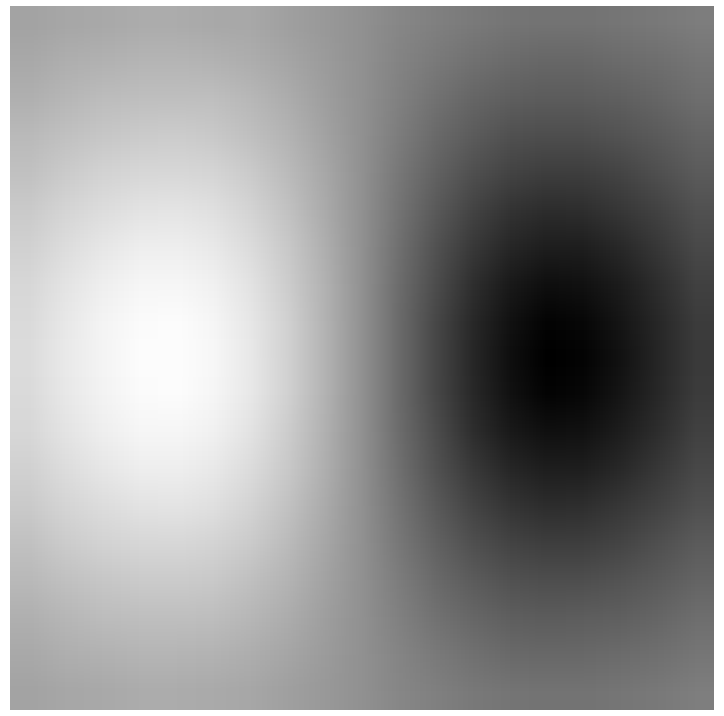
Need smoothing to reduce noise prior to taking derivative

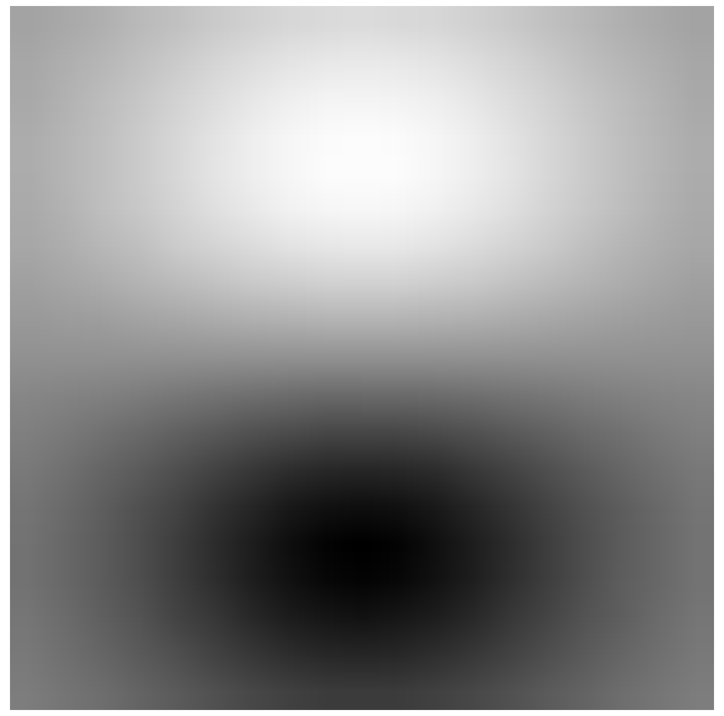
Need two derivatives, in x and y direction

We can use **derivative of Gaussian** filters
— because differentiation is convolution, and
— convolution is associative

Let $\otimes$ denote convolution

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

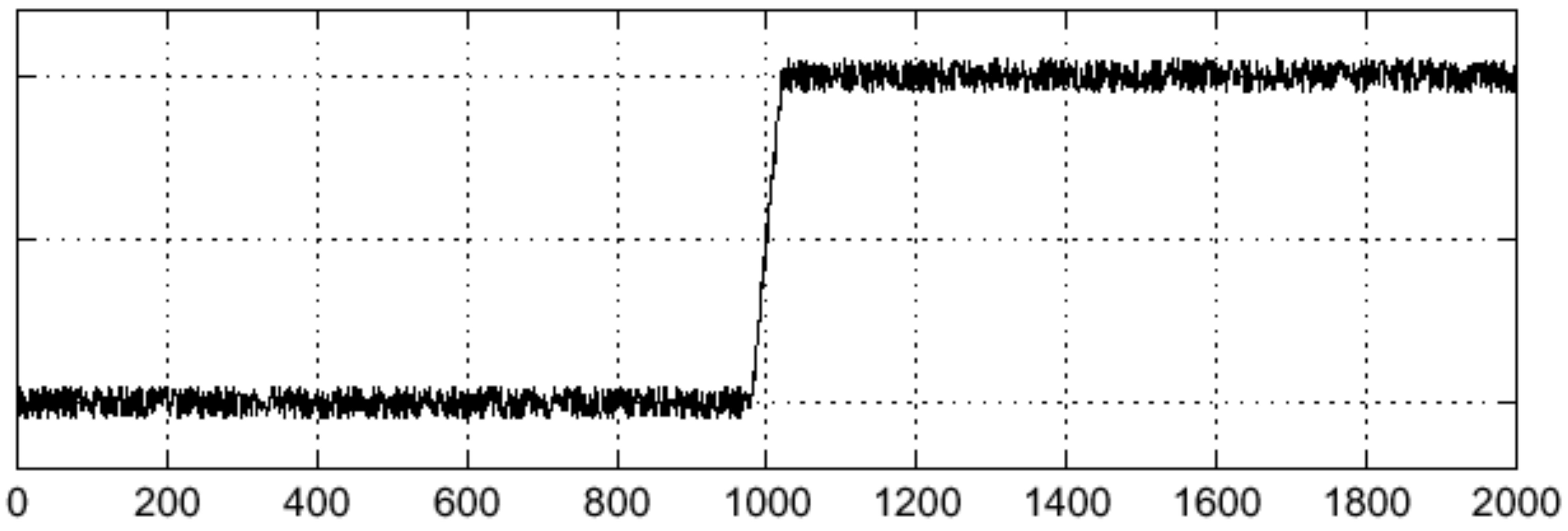




1D **Example**

Lets consider a row of pixels in an image:

$I(X, 245)$

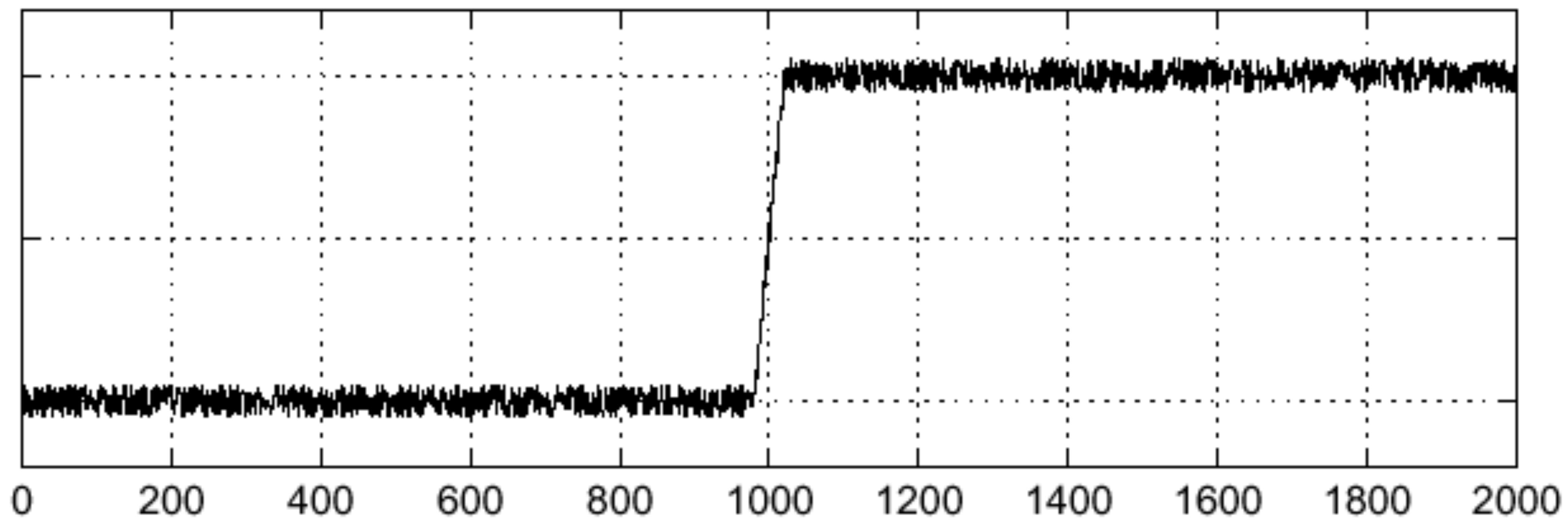


Where is the edge?

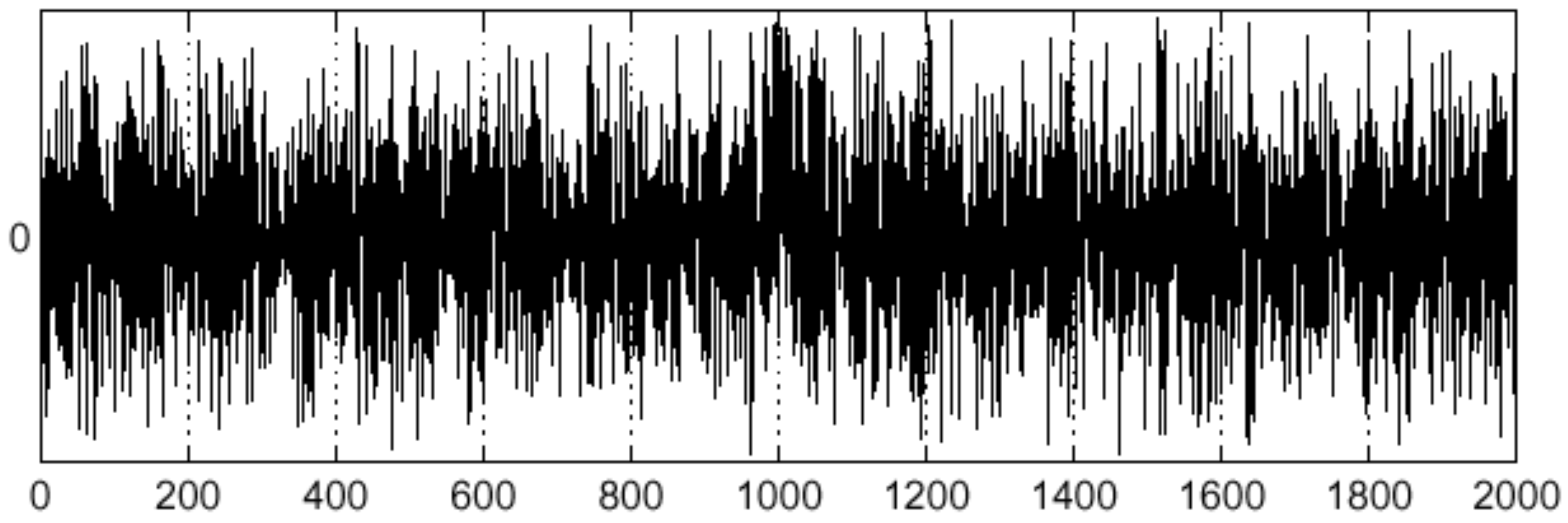
1D **Example**: Derivative

Lets consider a row of pixels in an image:

$$I(X, 245)$$



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



Where is the edge?

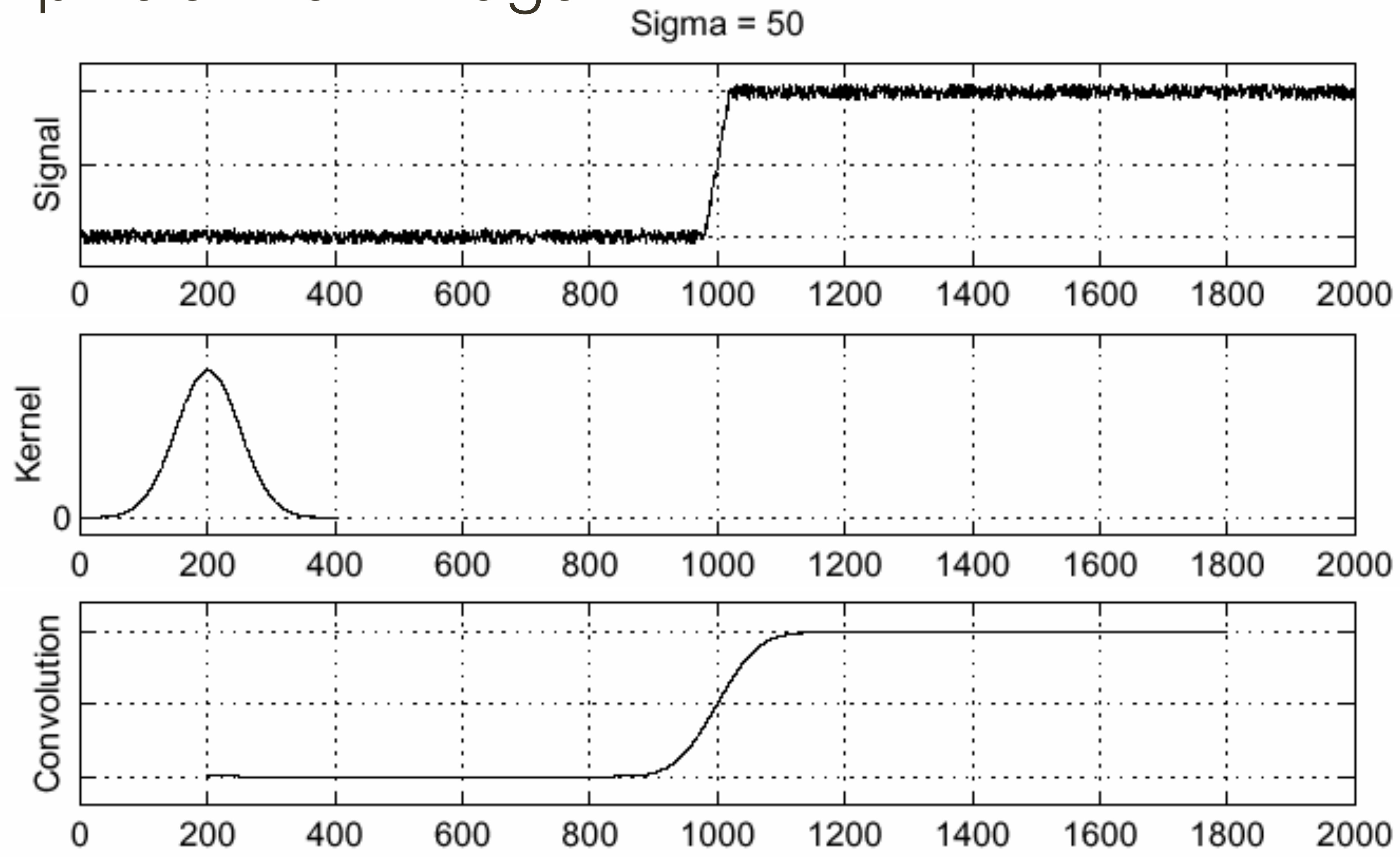
1D **Example**: Smoothing + Derivative

Lets consider a row of pixels in an image:

$I(X, 245)$

G

$G \otimes I(X, Y)$



1D **Example**: Smoothing + Derivative

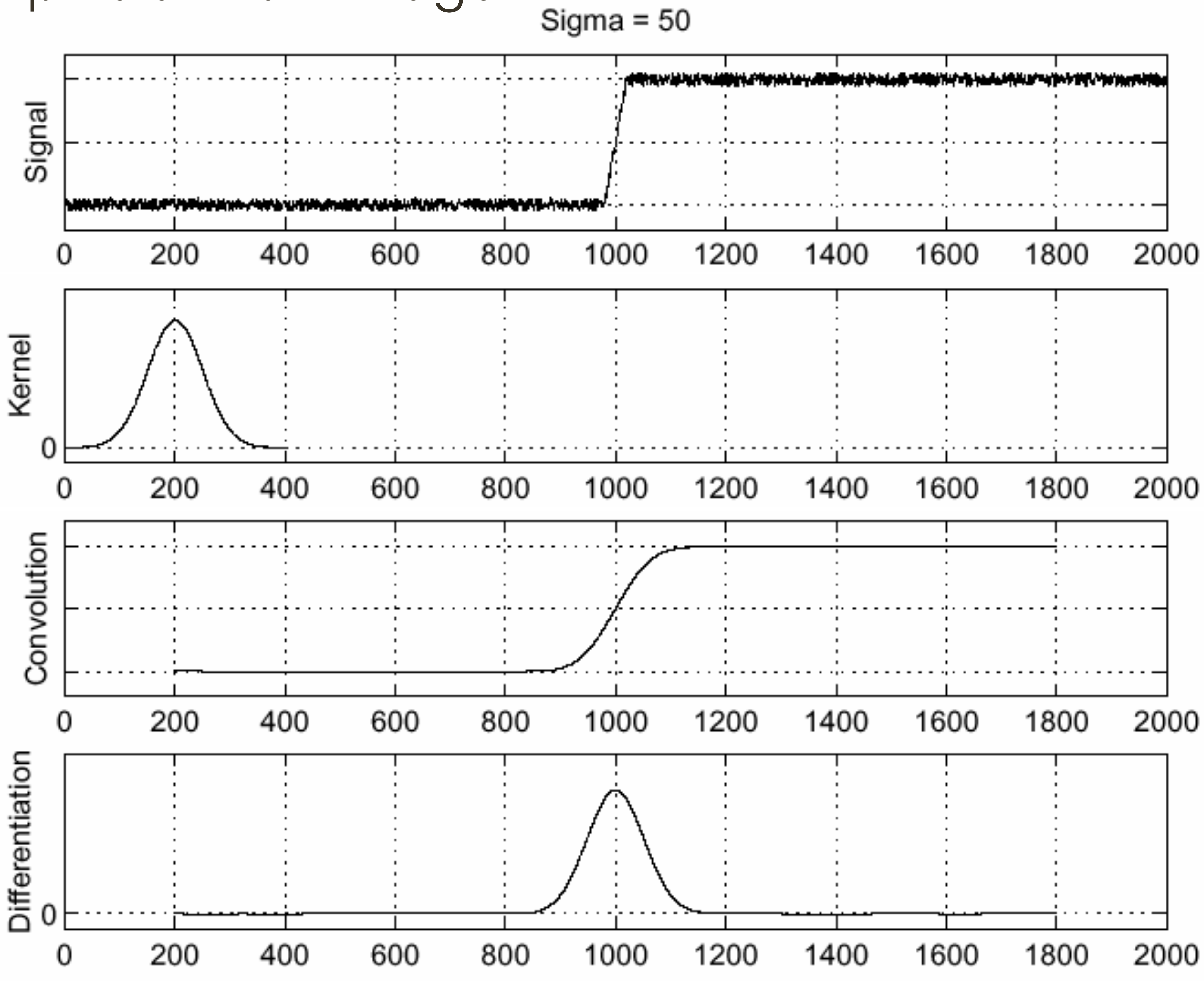
Lets consider a row of pixels in an image:

$$I(X, 245)$$

$$G$$

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

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



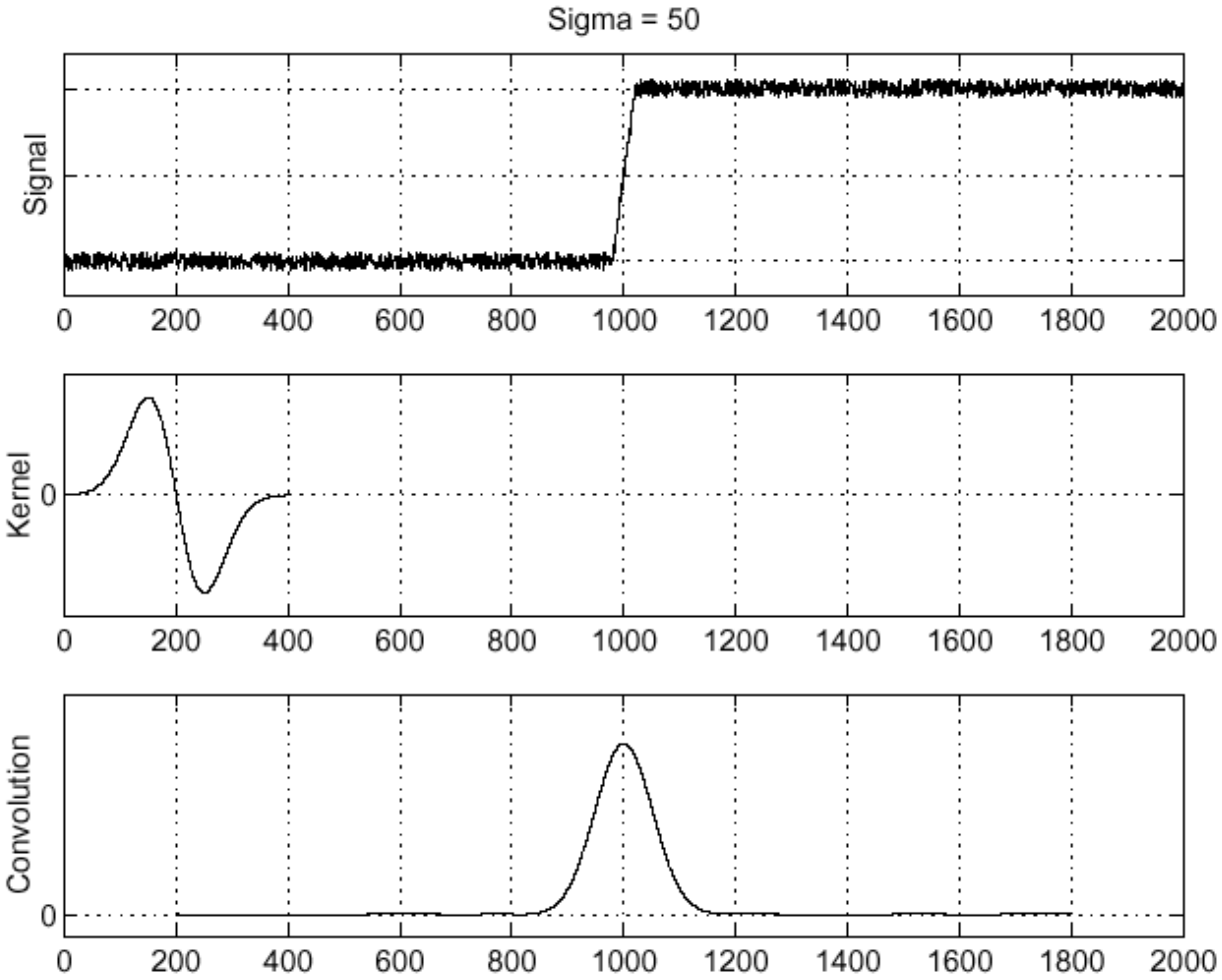
1D **Example**: Smoothing + Derivative (efficient)

Lets consider a row of pixels in an image:

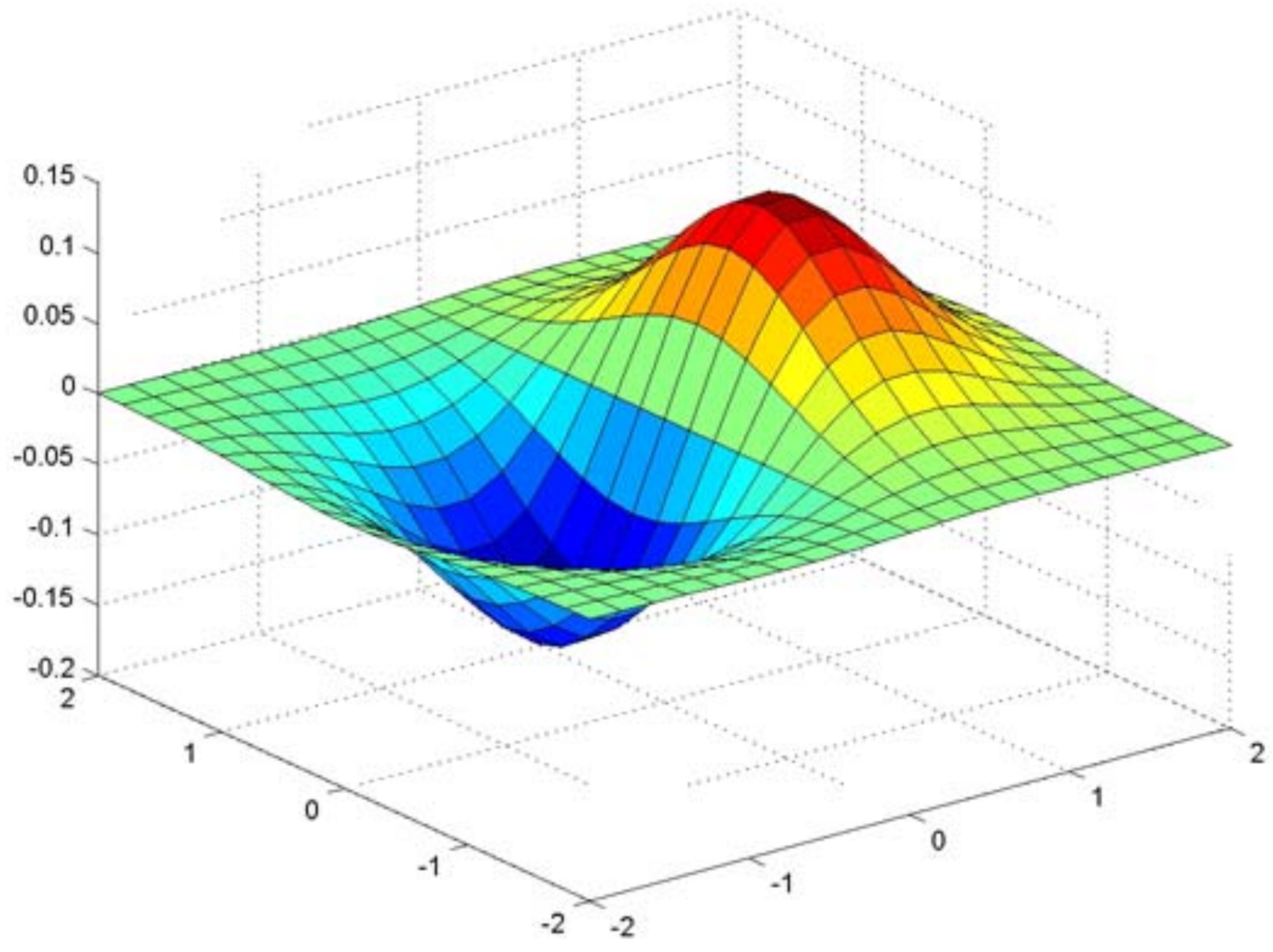
$$I(X, 245)$$

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

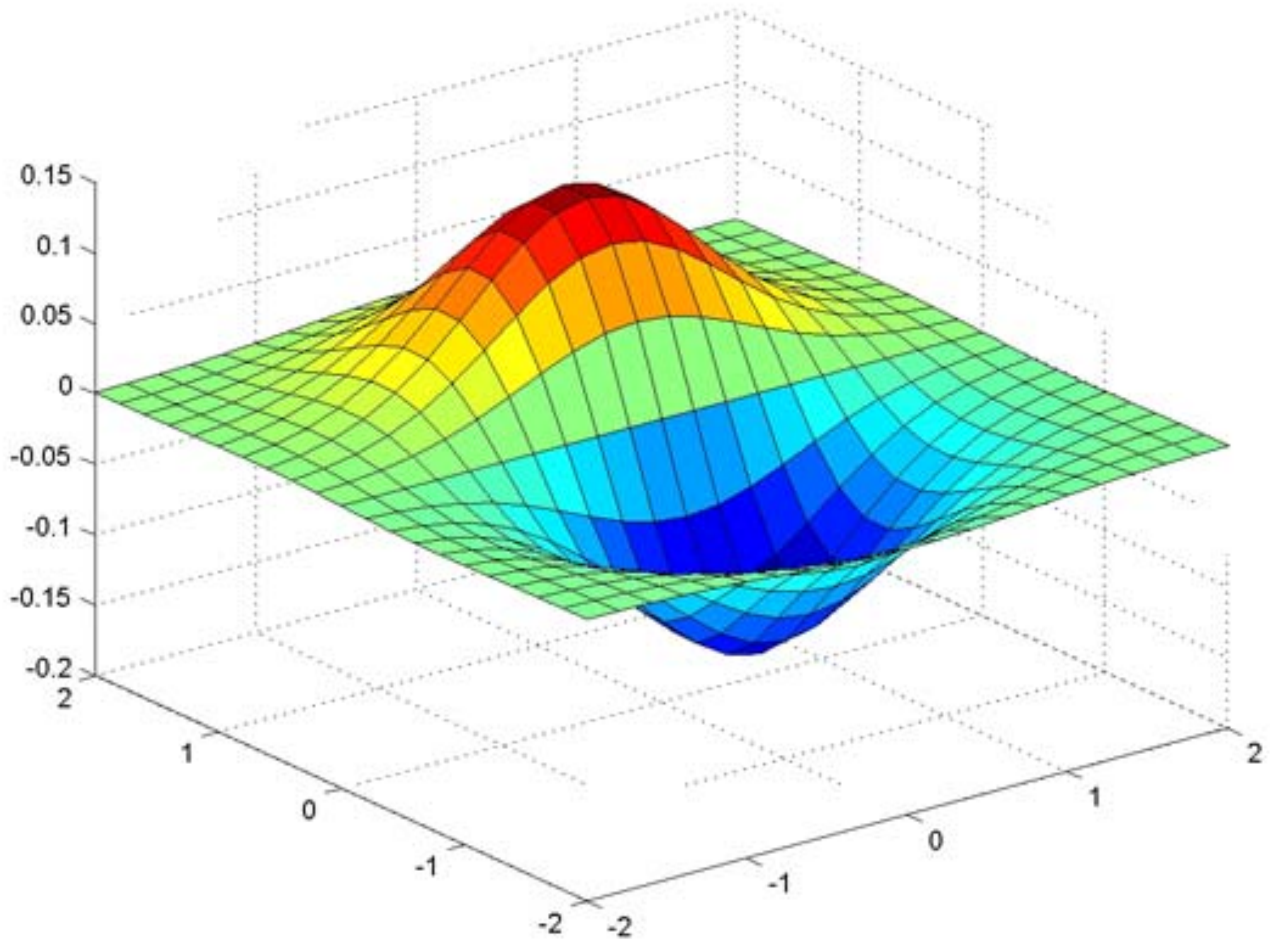
$$\frac{\partial G}{\partial x} \otimes I(X, Y)$$



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

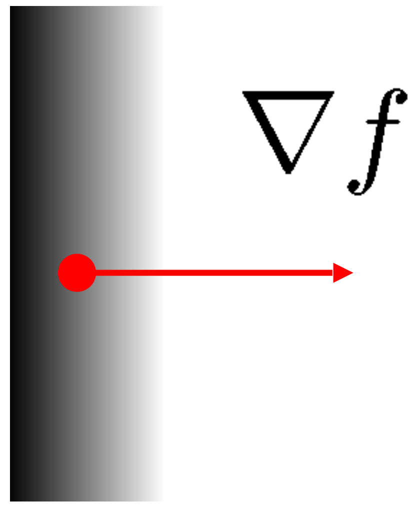
Let $I_x(X, Y)$ and $I_y(X, Y)$ be estimates of the partial derivatives in the x and y directions, respectively.

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

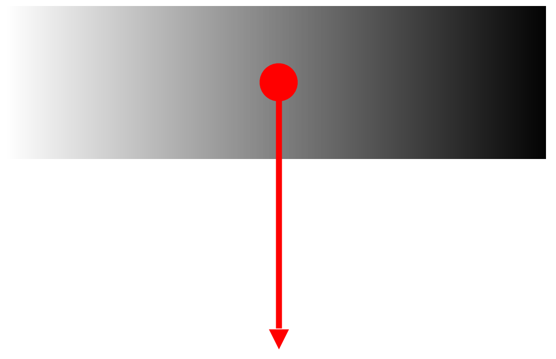
The scalar $\sqrt{I_x^2 + I_y^2}$ is the **gradient magnitude**

Image **Gradient**

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



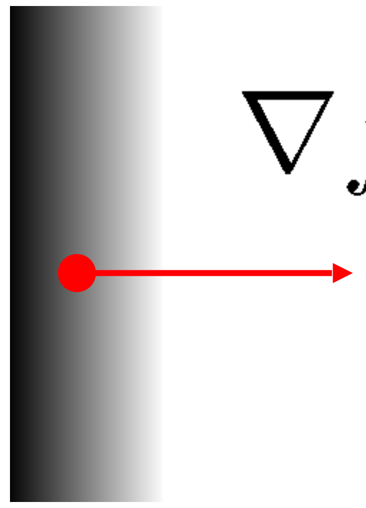
$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$



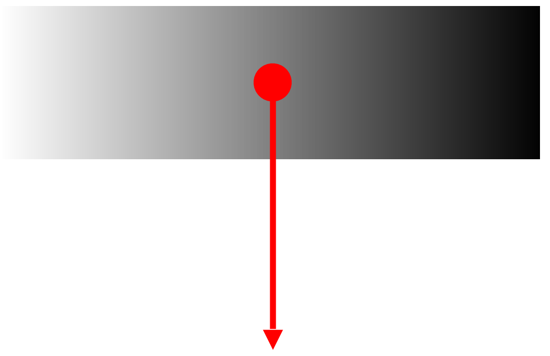
$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$

Image **Gradient**

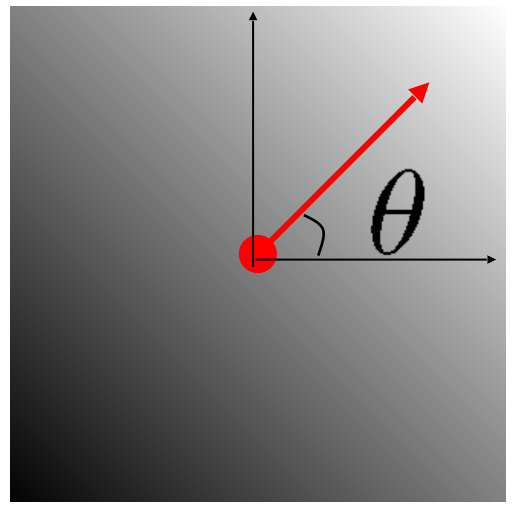
The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



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



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

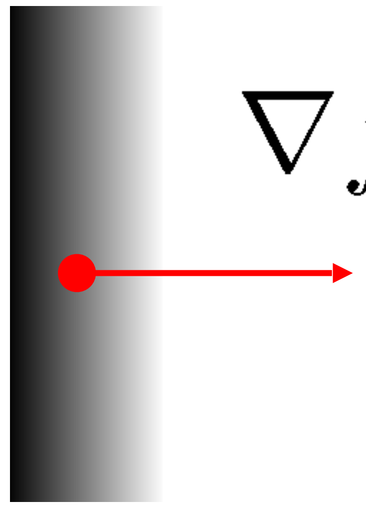


$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

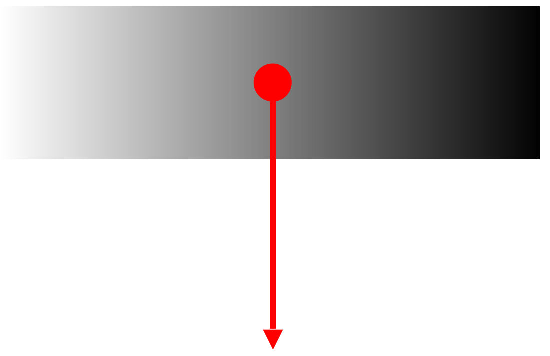
The gradient points in the direction of most rapid **increase of intensity**:

Image **Gradient**

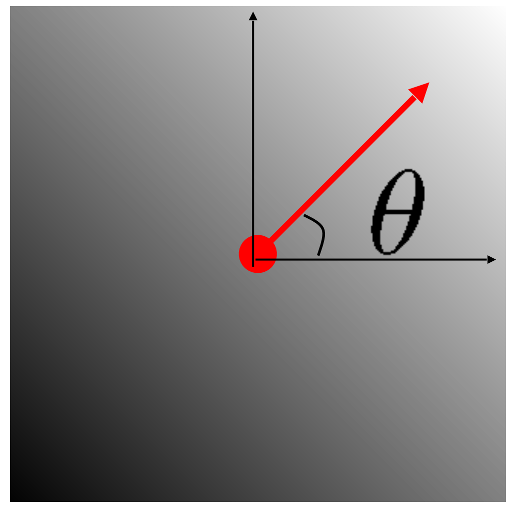
The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



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



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



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

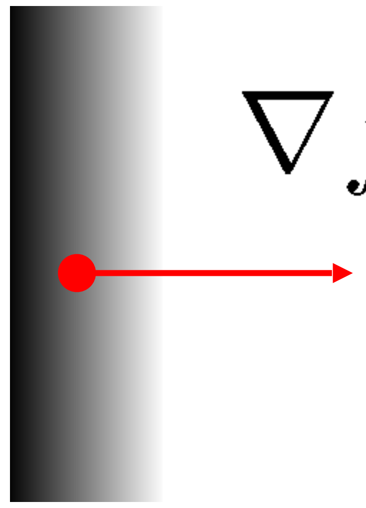
The gradient points in the direction of most rapid **increase of intensity**:

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

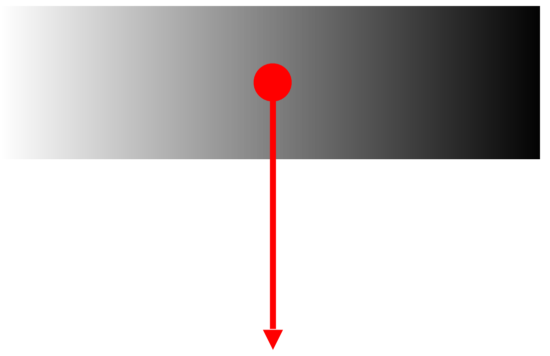
(how is this related to the direction of the edge?)

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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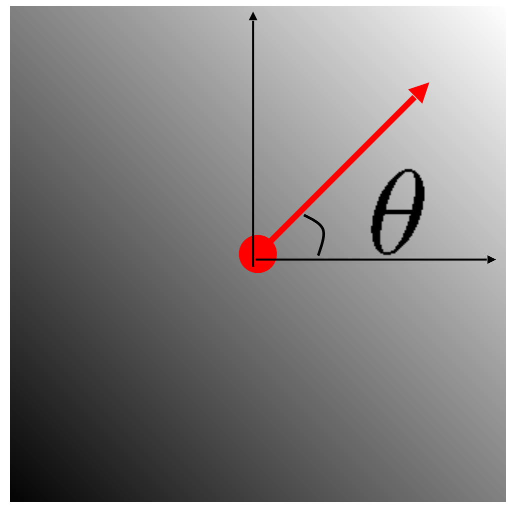


$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

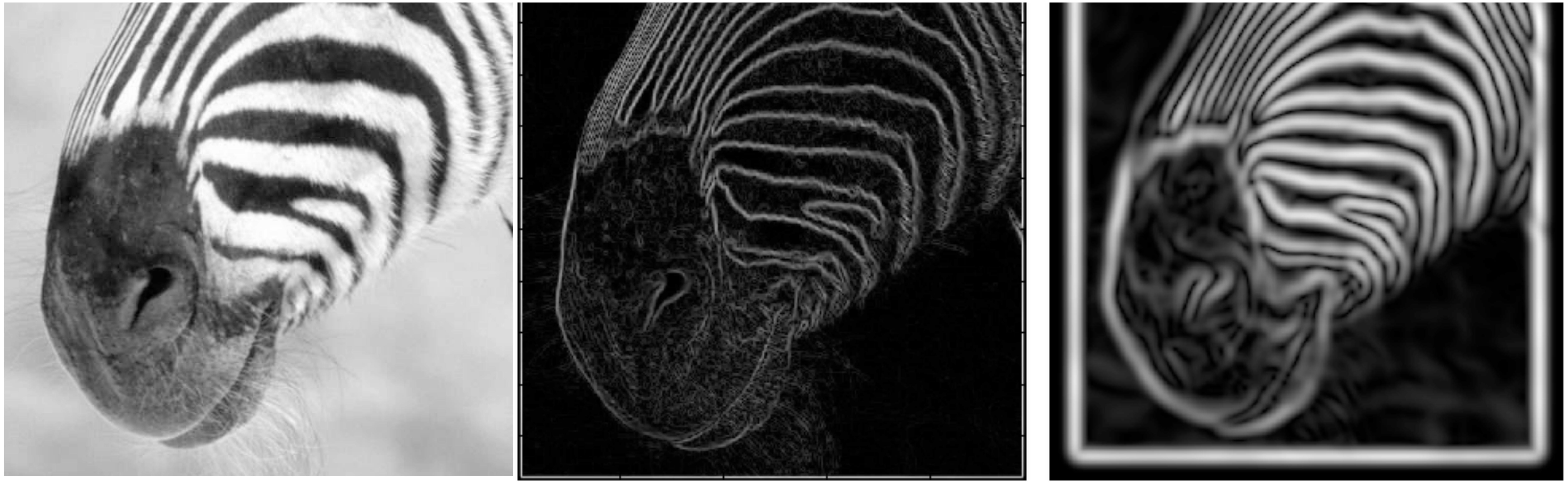
The gradient points in the direction of most rapid **increase of intensity**:

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?)

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!