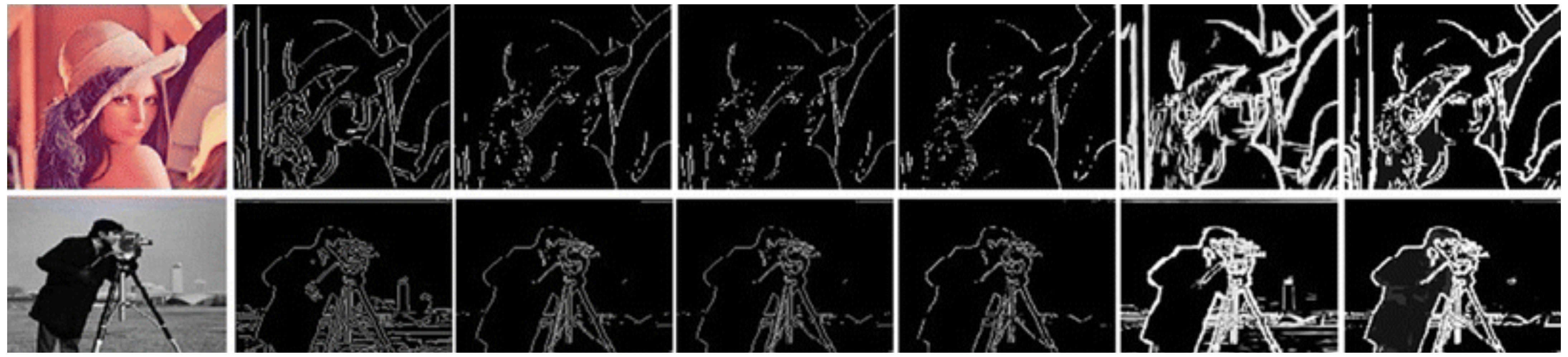
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 8: Edge Detection

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

Menu for Today

Topics:

— Edge **Detection**
— **Canny** Edge Detector
— Image **Boundaries**

Readings:

— **Today's** Lecture: Szeliski 7.1-7.2, Forsyth & Ponce 5.1 - 5.2

Reminders:

— **Assignment 2**: Scaled Representations, Face Detection and Image Blending (due Monday **Feb 13** 23:59)

— **Midterm**: **February 27th 3:30pm** in class

Today's "**fun**" Example: Colour Constancy

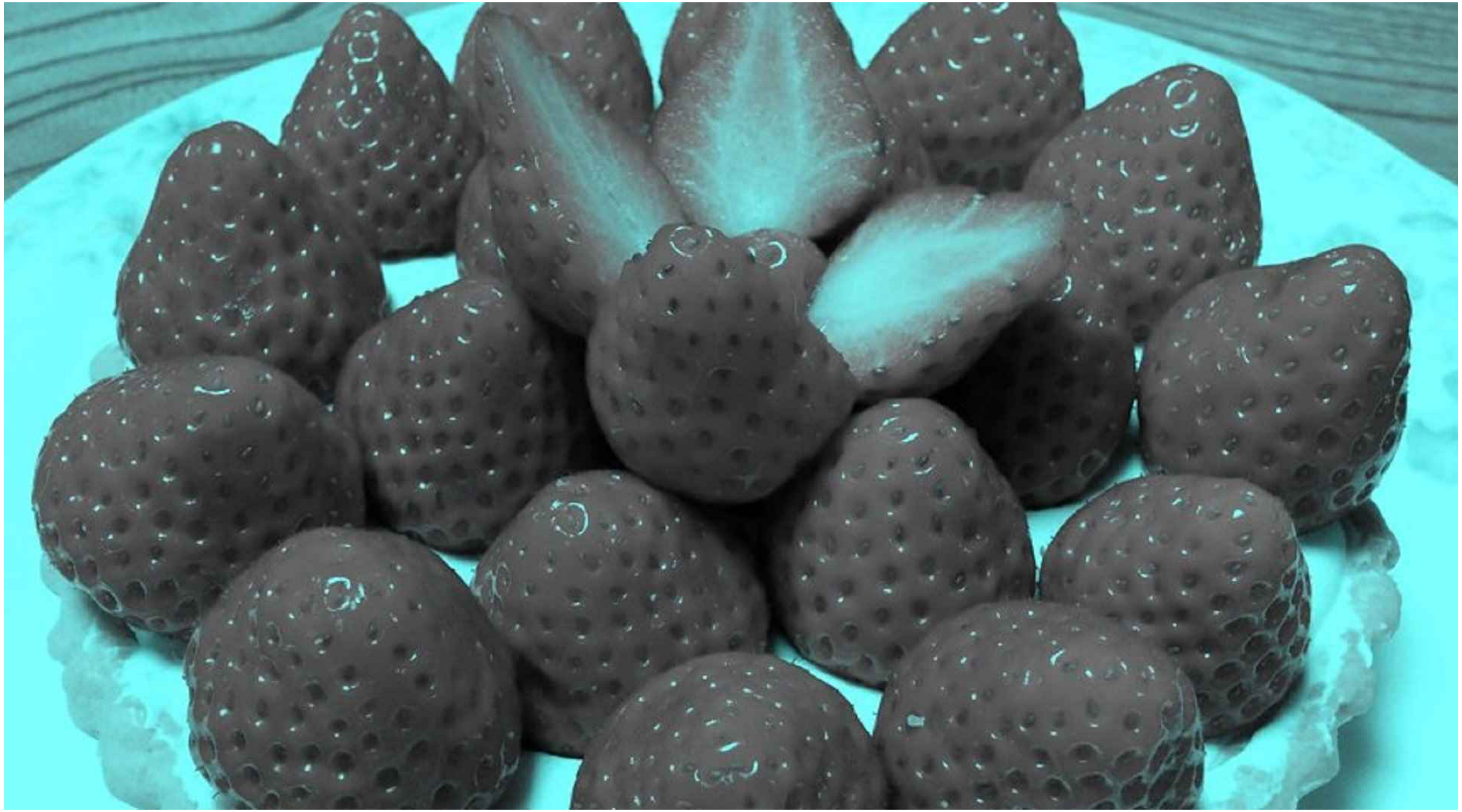
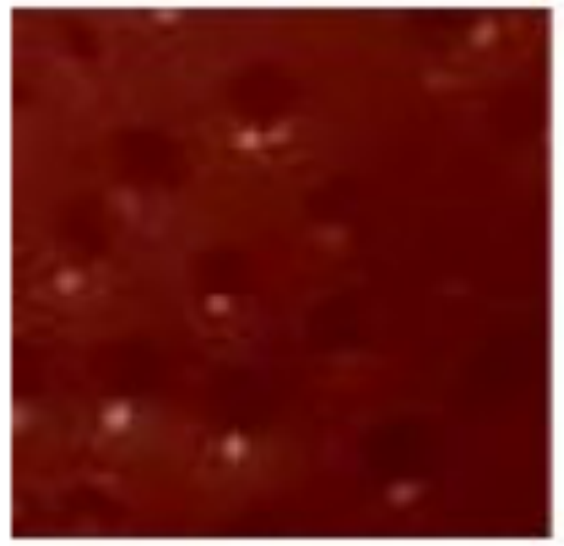


Image Credit: Akiyosha Kitoaka

Today's "**fun**" Example: Colour Constancy



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Today's "**fun**" Example: Colour Constancy

— Some people see a white and gold dress.

— Some people see a blue and black dress.

— Some people see one interpretation and then switch to the other

https://www.nytimes.com/interactive/2015/02/28/science/white-or-blue-dress.html

Today's "**fun**" Example: Colour Constancy

- Some people see a white and gold dress.
- Some people see a blue and black dress.
- Some people see one interpretation and then switch to the other

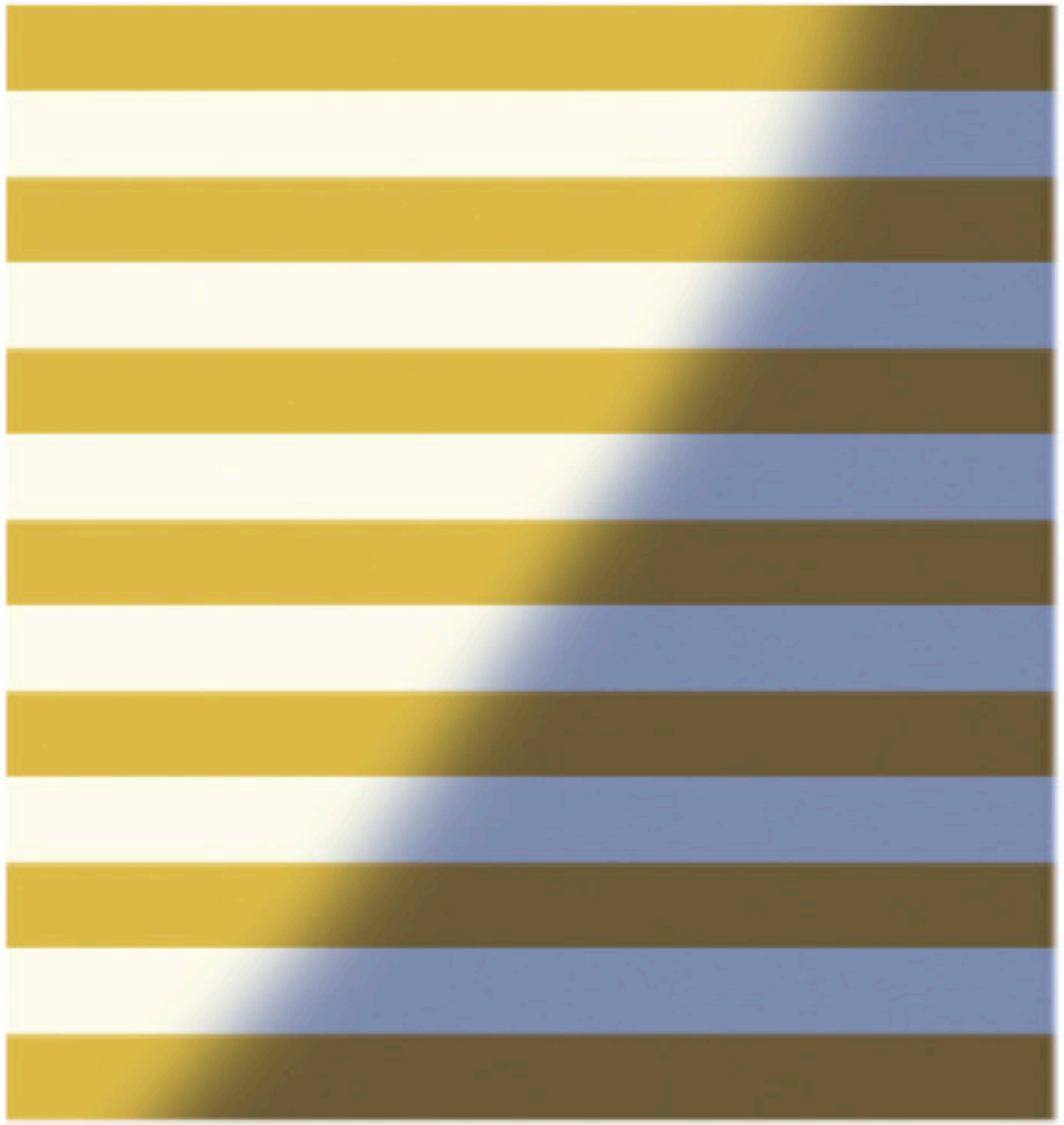
Two pieces of the dress | Average colors | The basic pattern of the dress

https://www.nytimes.com/interactive/2015/02/28/science/white-or-blue-dress.html

Today's "**fun**" Example: Colour Constancy

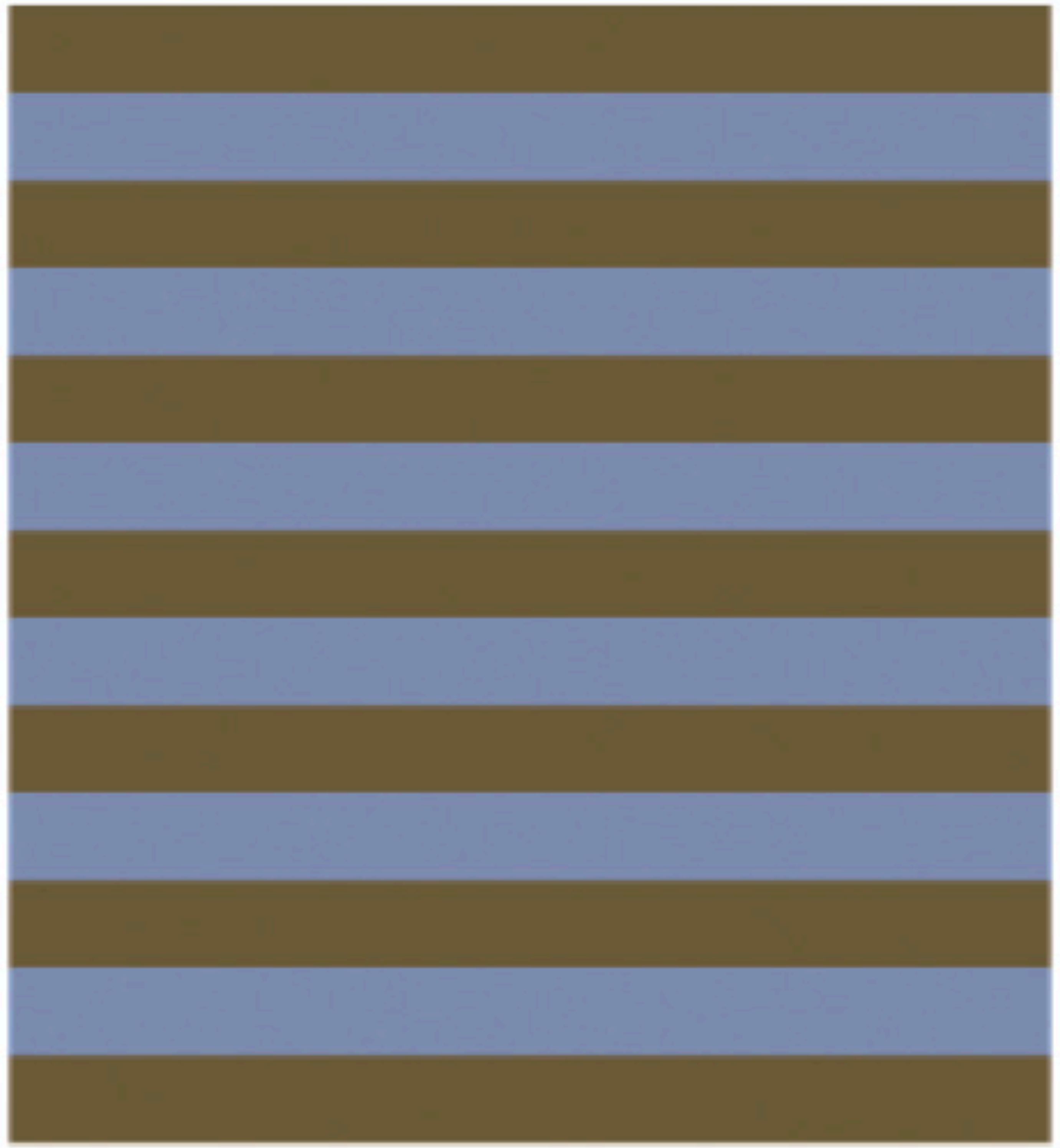
IS THE DRESS IN SHADOW?

If you think the dress is in shadow, your brain may remove the blue cast and perceive the dress as being white and gold.



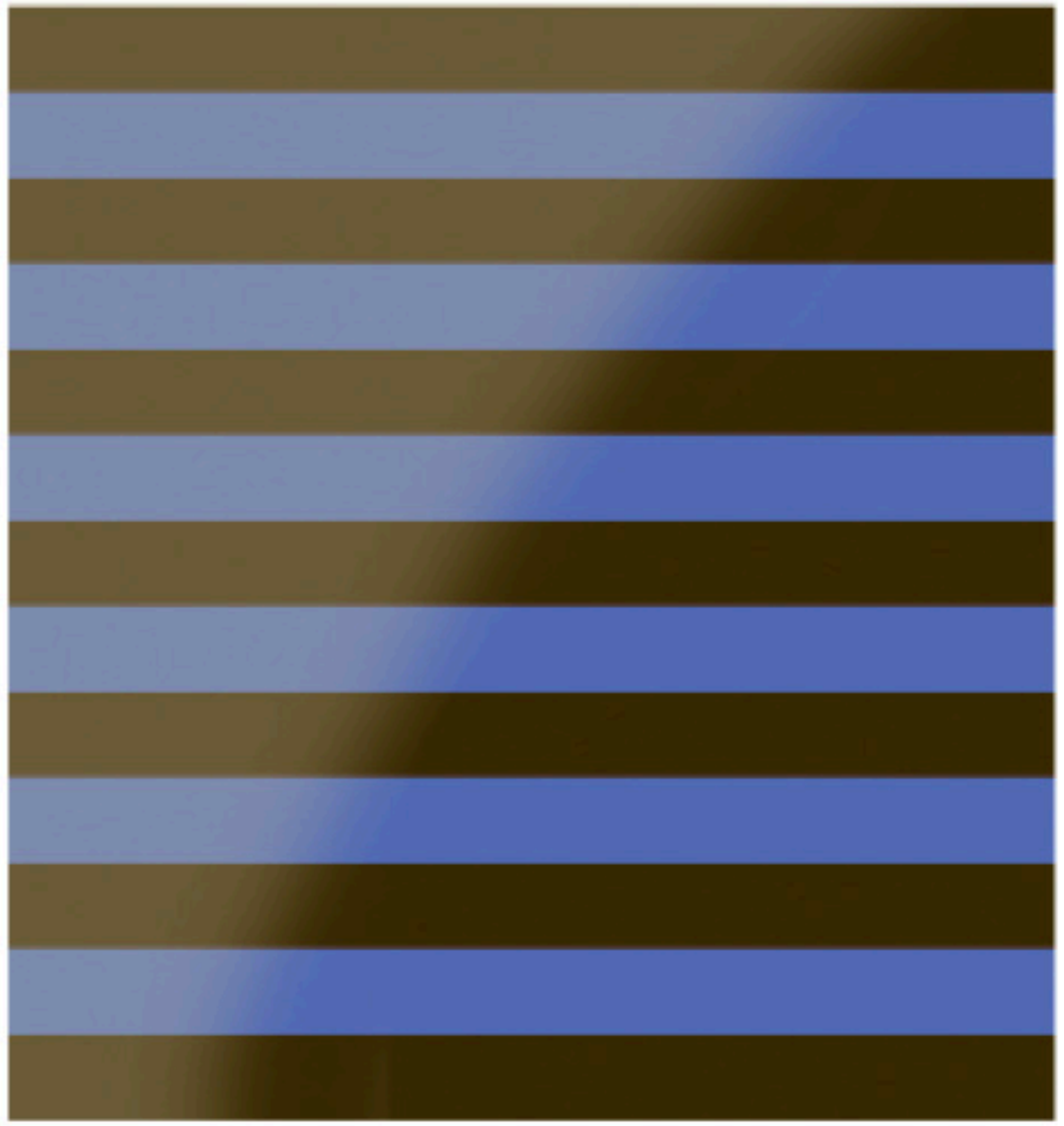
THE DRESS IN THE PHOTO

If the photograph showed more of the room, or if skin tones were visible, there might have been more clues about the ambient light.



IS THE DRESS IN BRIGHT LIGHT?

If you think the dress is being washed out by bright light, your brain may perceive the dress as a darker blue and black.



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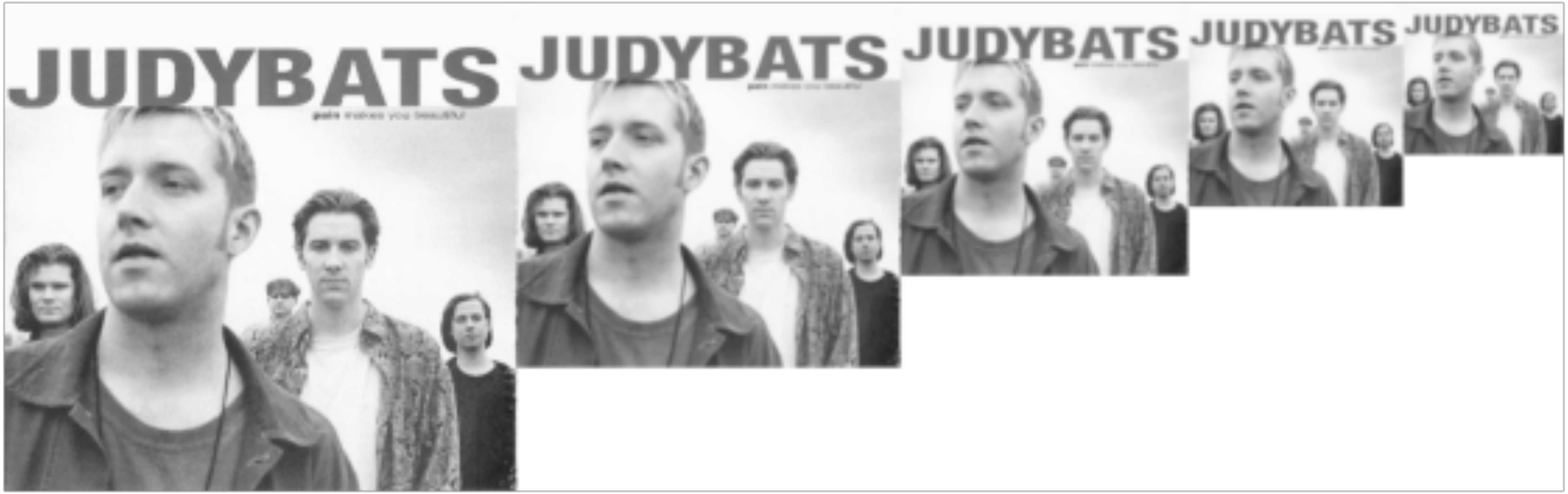
Lecture 8: Re-cap **Multi-Scale** Template Matching

Correlation with a **fixed-sized image** only detects faces at **specific scales**



= Template

Lecture 8: Re-cap **Multi-Scale** Template Matching

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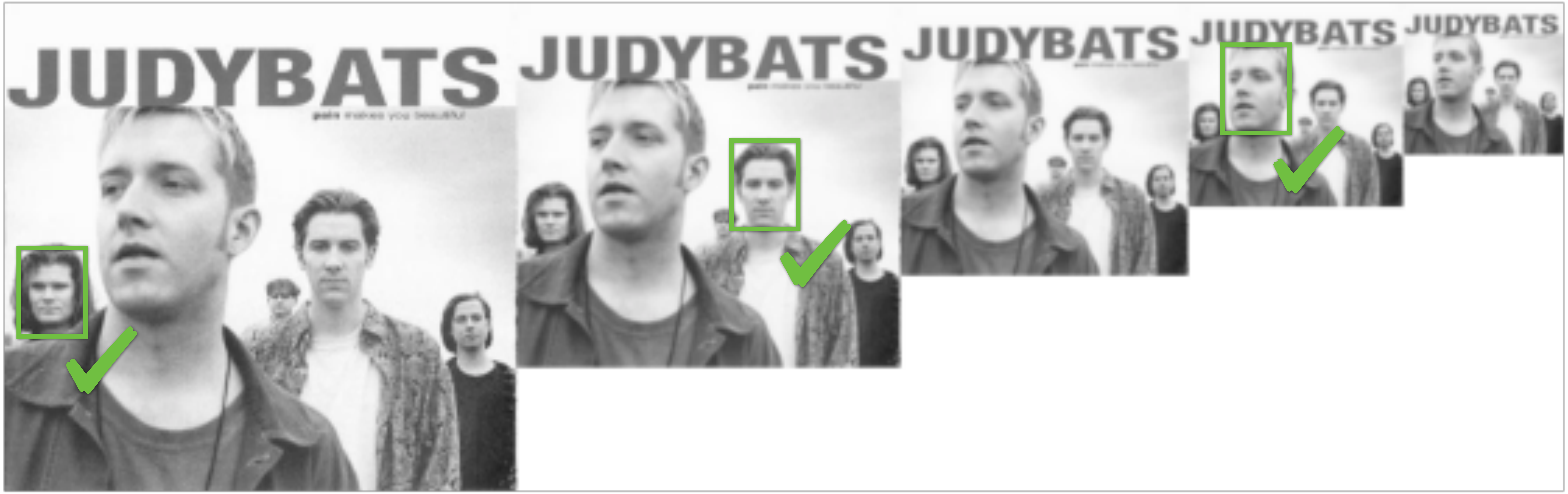


 = Template

Lecture 8: Re-cap **Scaled Representations**

Gaussian Pyramid

— Each level represents a **low-pass** filtered image at a different scale

— Generated by successive Gaussian blurring and downsampling

— Useful for image resizing, sampling

Laplacian Pyramid

— Each level is a **band-pass** image at a different scale

— Generated by differences between successive levels of a Gaussian Pyramid

— Used for pyramid blending, feature extraction etc.

From Template Matching to **Local Feature Detection**

We'll now shift from global template matching to **local feature detection**

Consider the problem of finding images of an elephant using a template

From Template Matching to **Local Feature Detection**

We’ll now shift from global template matching to **local feature detection**

Consider the problem of finding images of an elephant using a template

An elephant looks different from different viewpoints

— from above (as in an aerial photograph or satellite image)

— head on

— sideways (i.e., in profile)

— rear on

What happens if parts of an elephant are obscured from view by trees, rocks, other elephants?

From Template Matching to **Local Feature Detection**

— Move from global template matching to **local template matching**

— Local template matching also called local **feature detection**

— Obvious local features to detect are **edges** and **corners**

Edge Detection

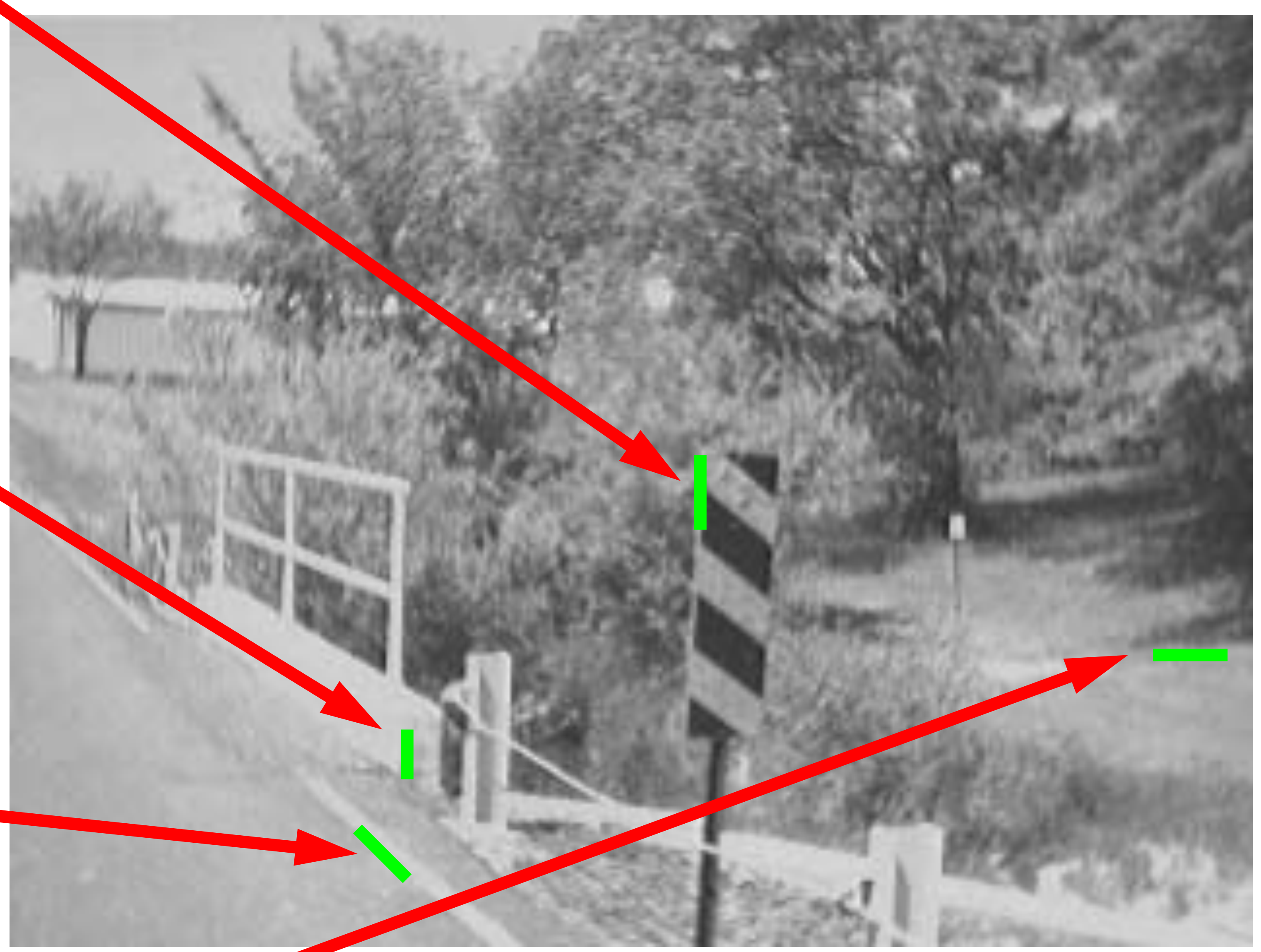
Goal: Identify sudden changes in image intensity

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

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)

Estimating **Derivatives**

Recall, for a 2D (continuous) function, f(x,y)

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

Differentiation is linear and shift invariant, and therefore can be implemented as a convolution

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A (discrete) approximation is

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

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-1	1

Estimating **Derivatives**

A (**discrete**) approximation is

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

"**forward** difference" implemented as

correlation

-1	1

from **left**

convolution

1	-1

Estimating **Derivatives**

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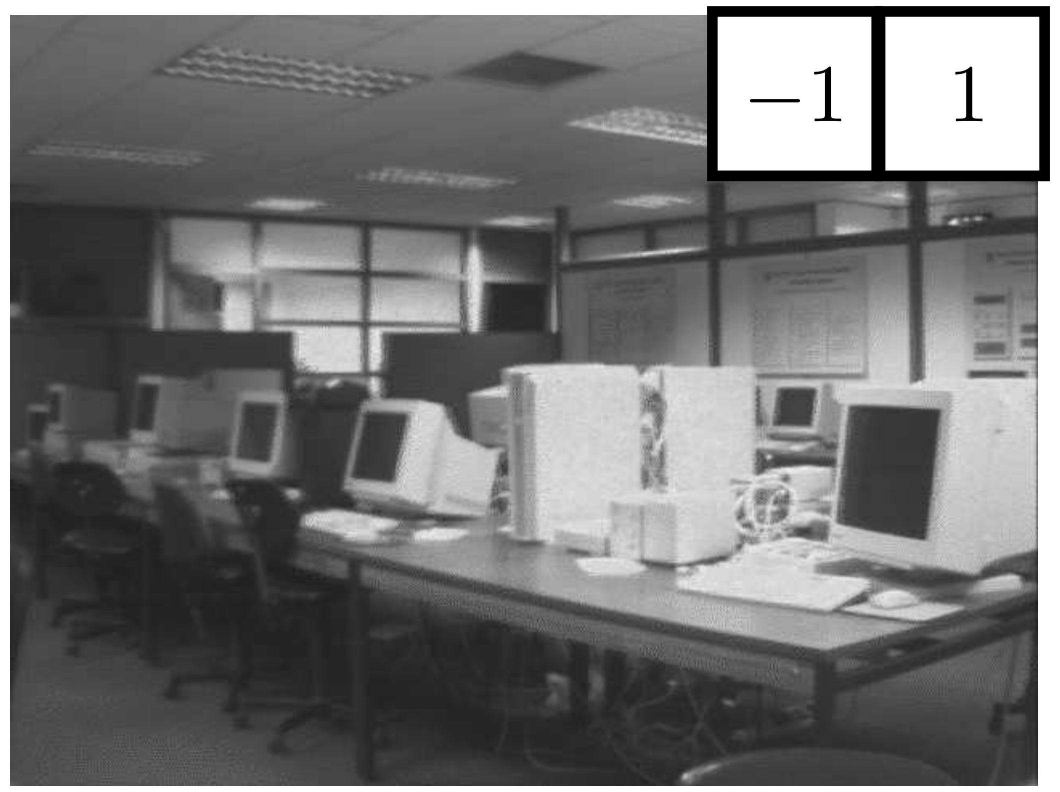
from **right**	

Estimating **Derivatives**



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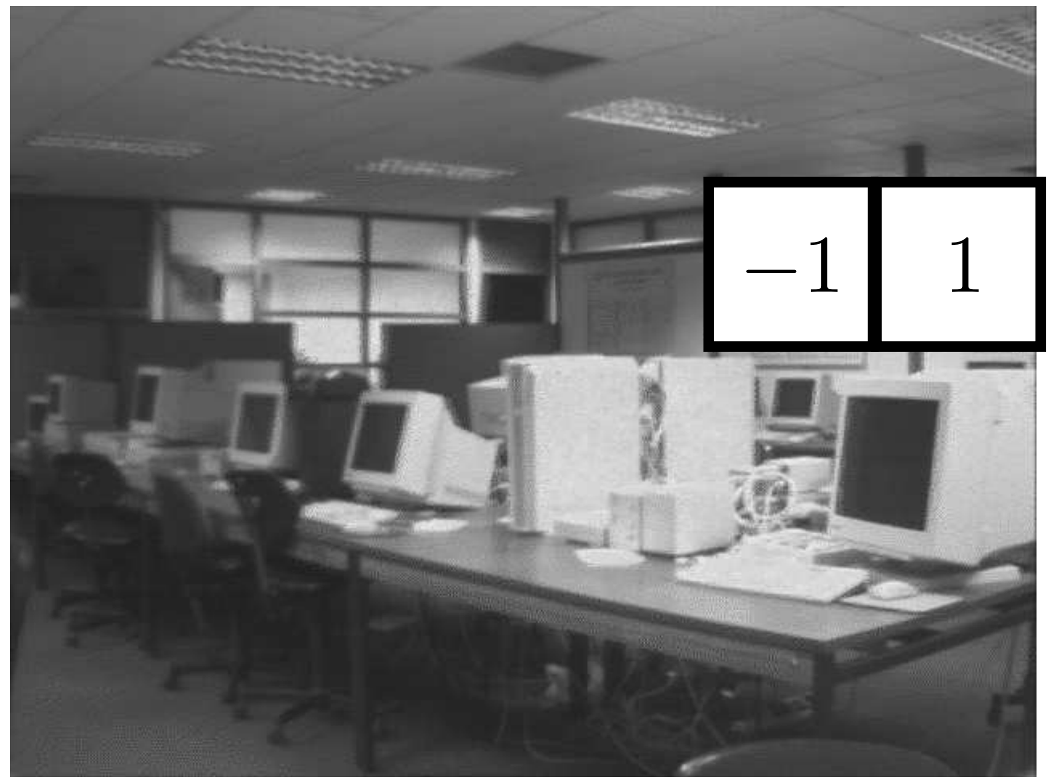
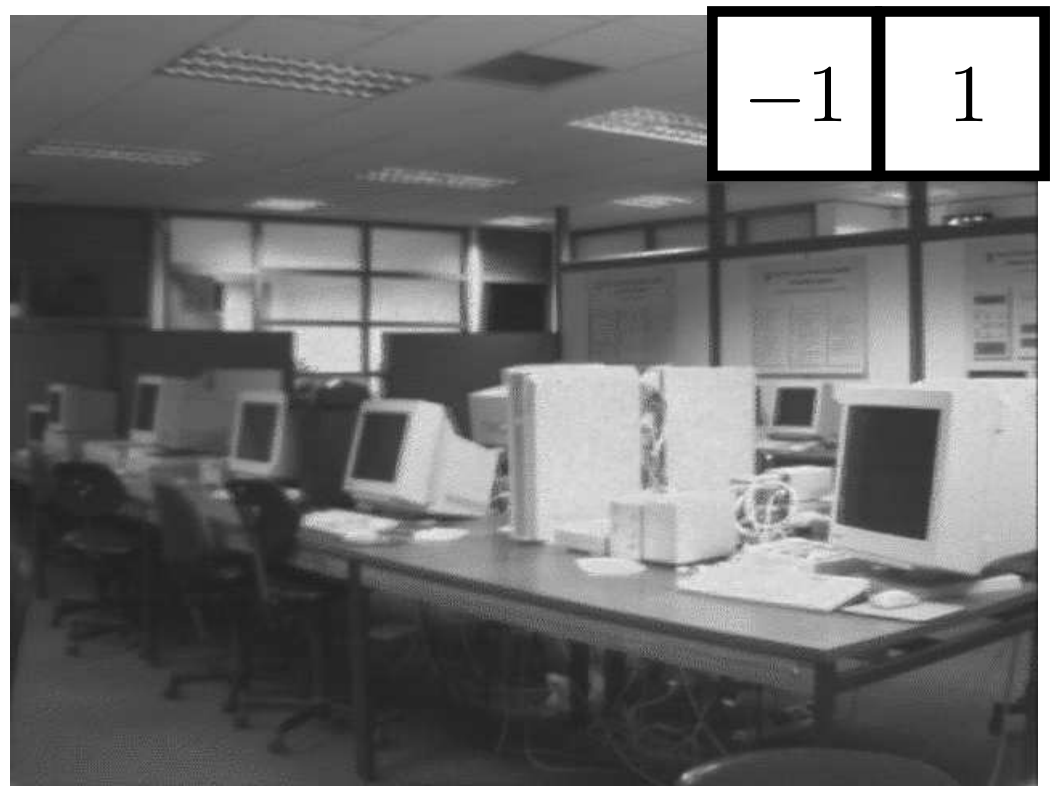
Estimating **Derivatives**





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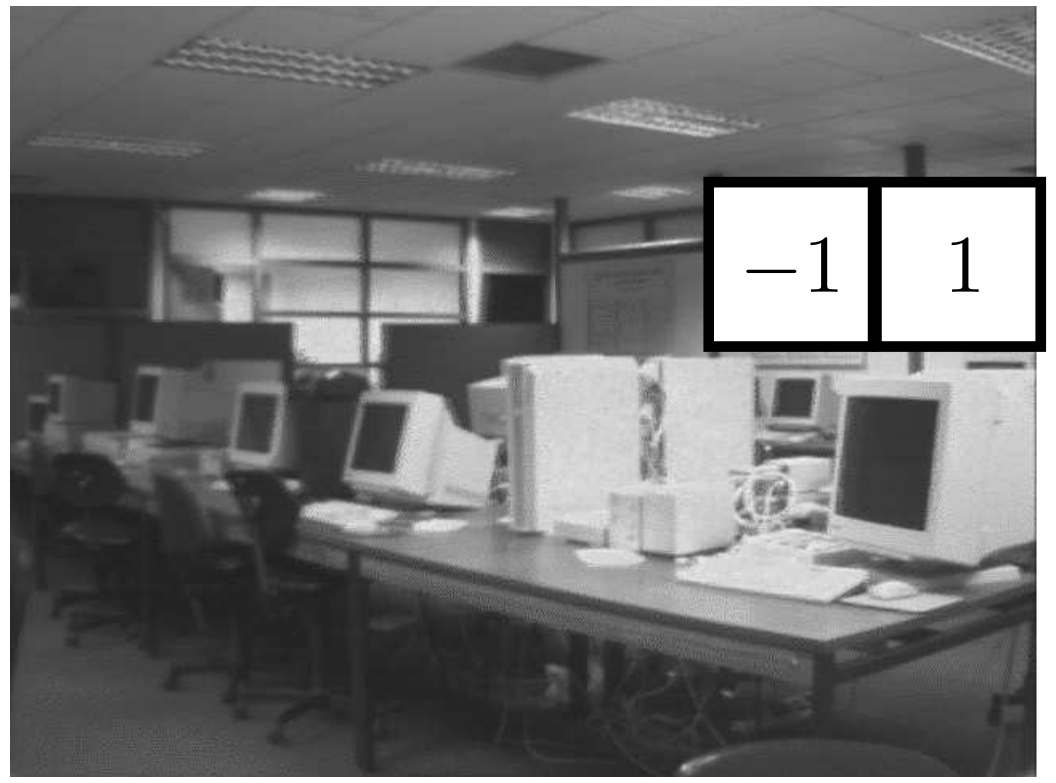

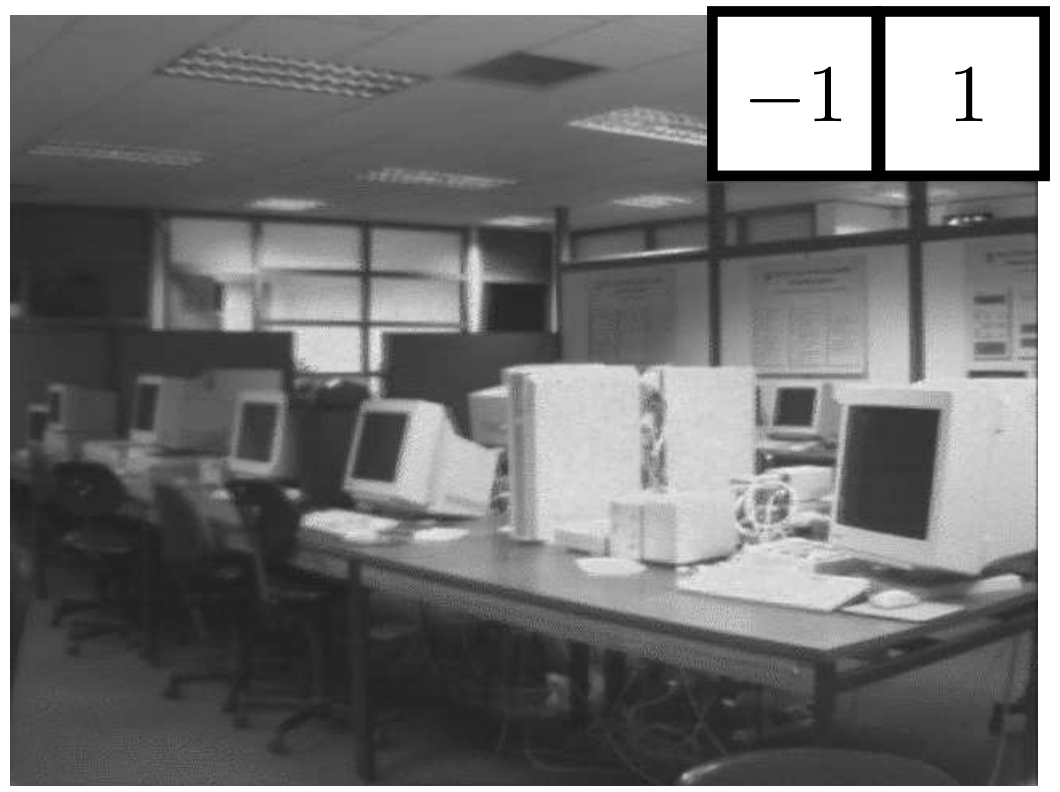

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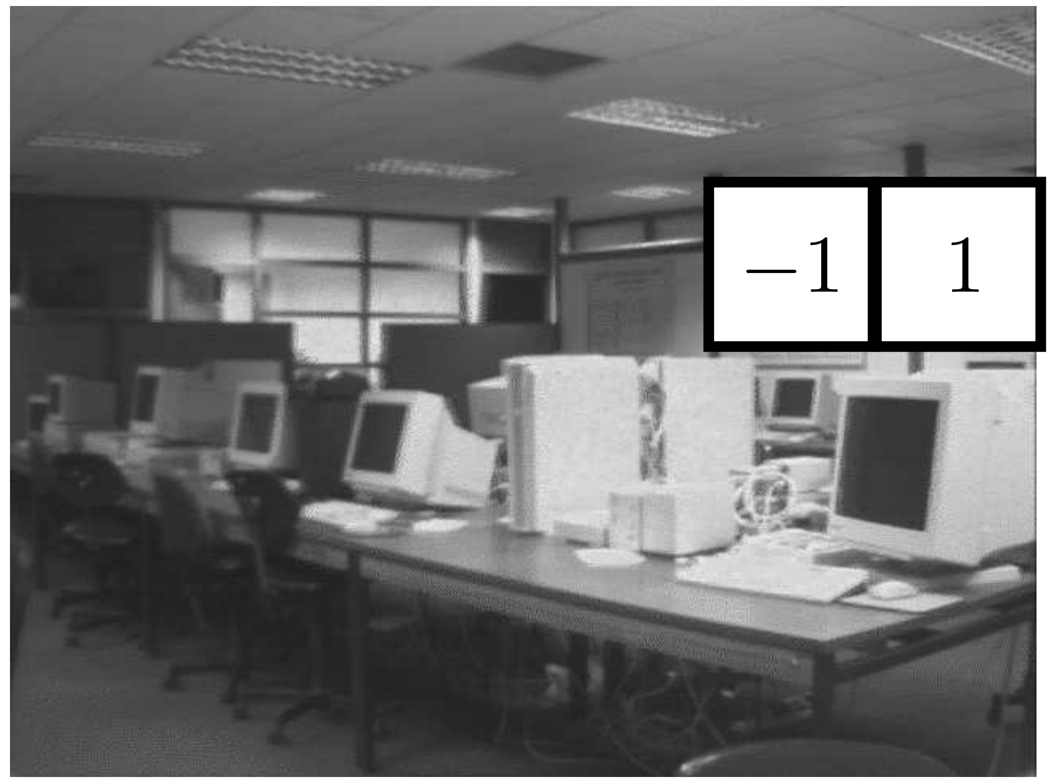
Estimating **Derivatives**



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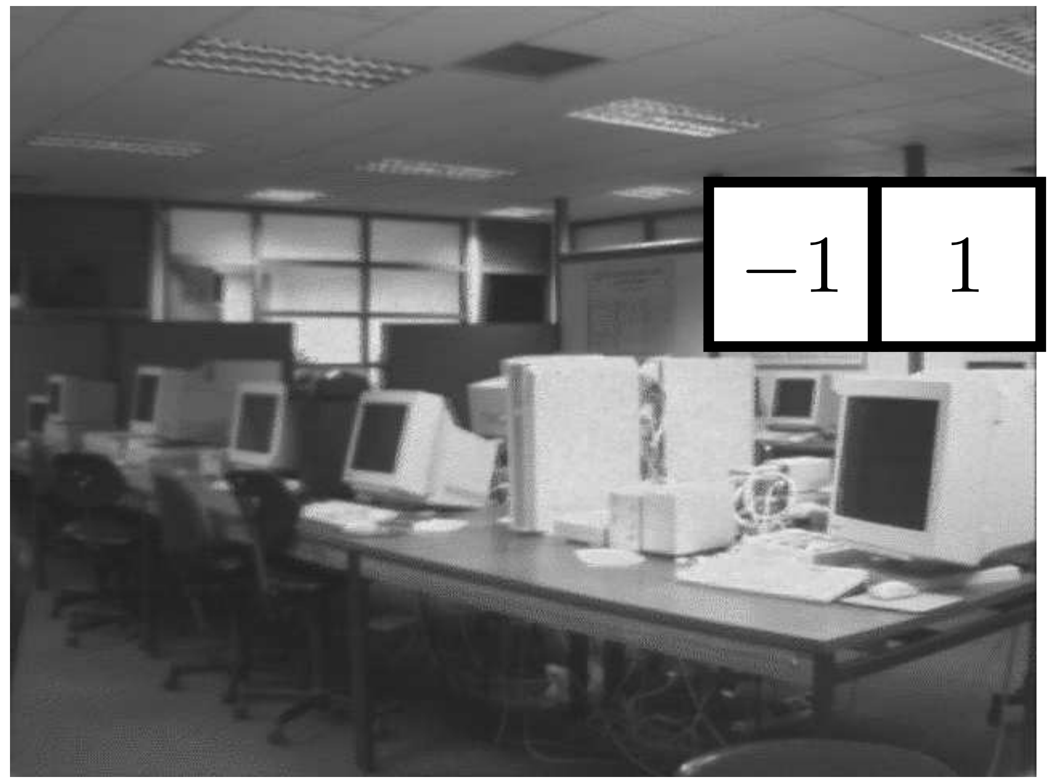

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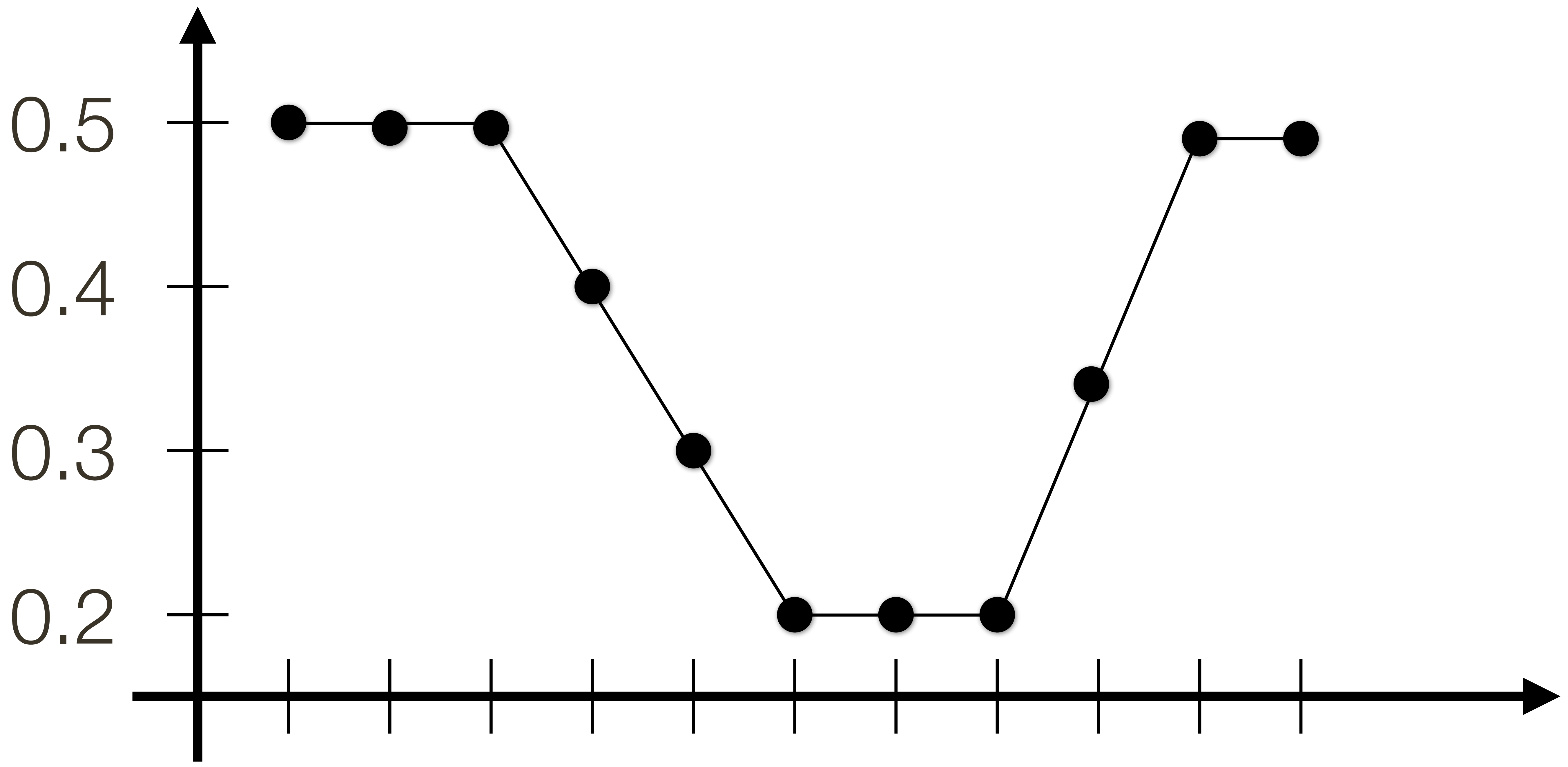
Estimating **Derivatives**

A similar definition (and approximation) holds for $\frac{\partial f}{\partial y}$

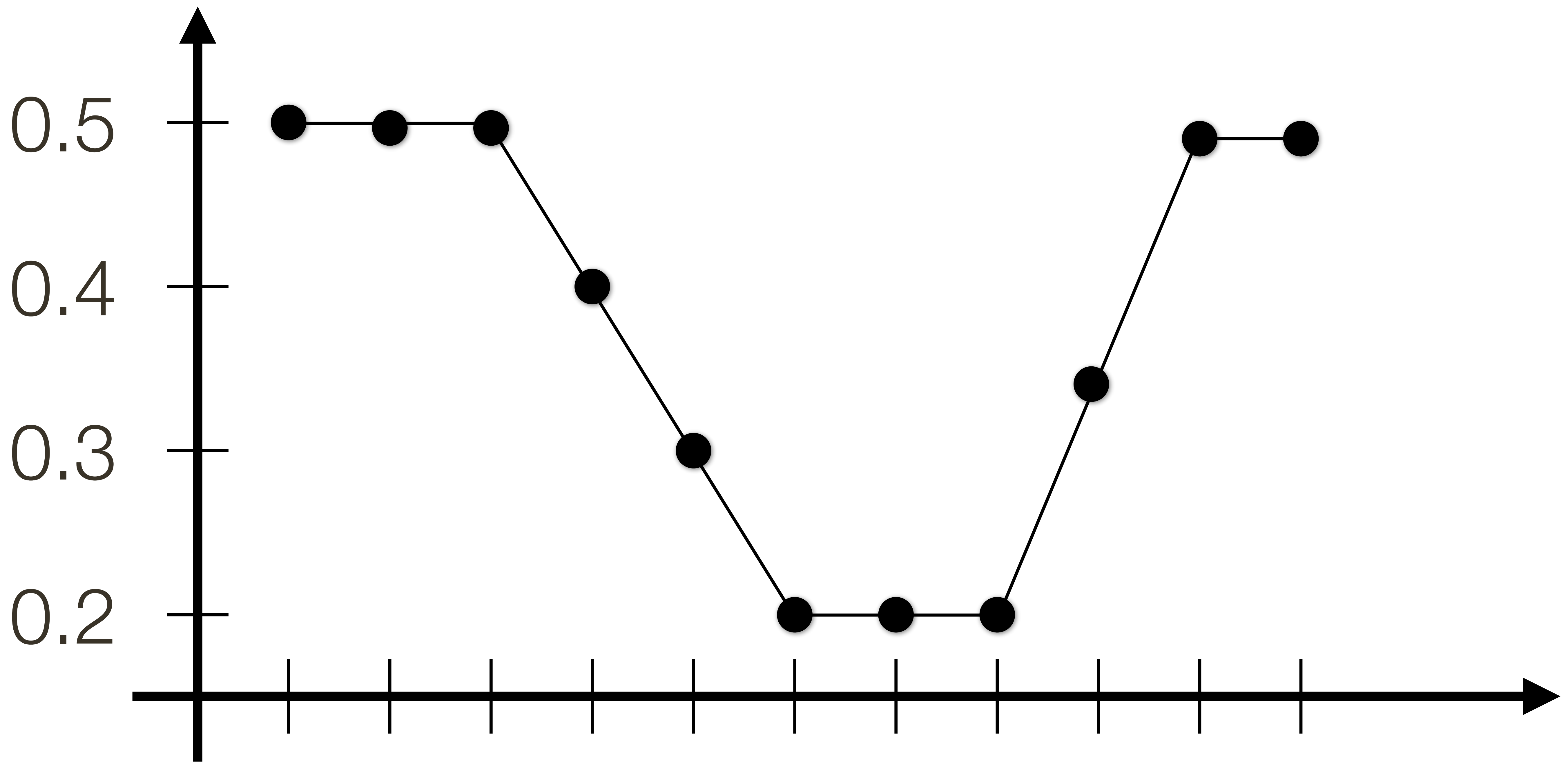
Image **noise** tends to result in pixels not looking exactly like their neighbours, so simple “finite differences” are sensitive to noise.

The usual way to deal with this problem is to **smooth** the image prior to derivative estimation.

Example 1D

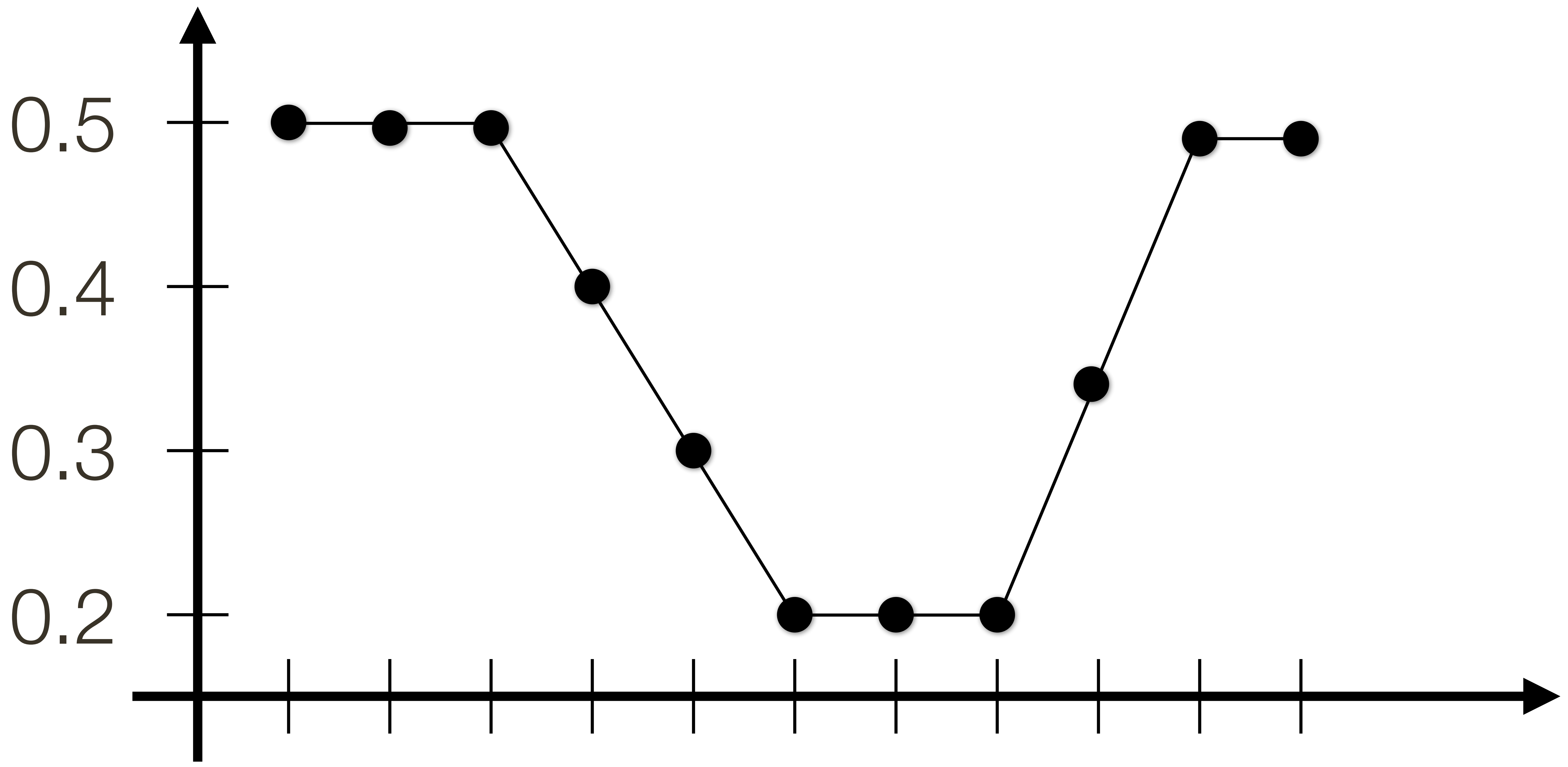


Example 1D



Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5

Example 1D



Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5
Derivative											

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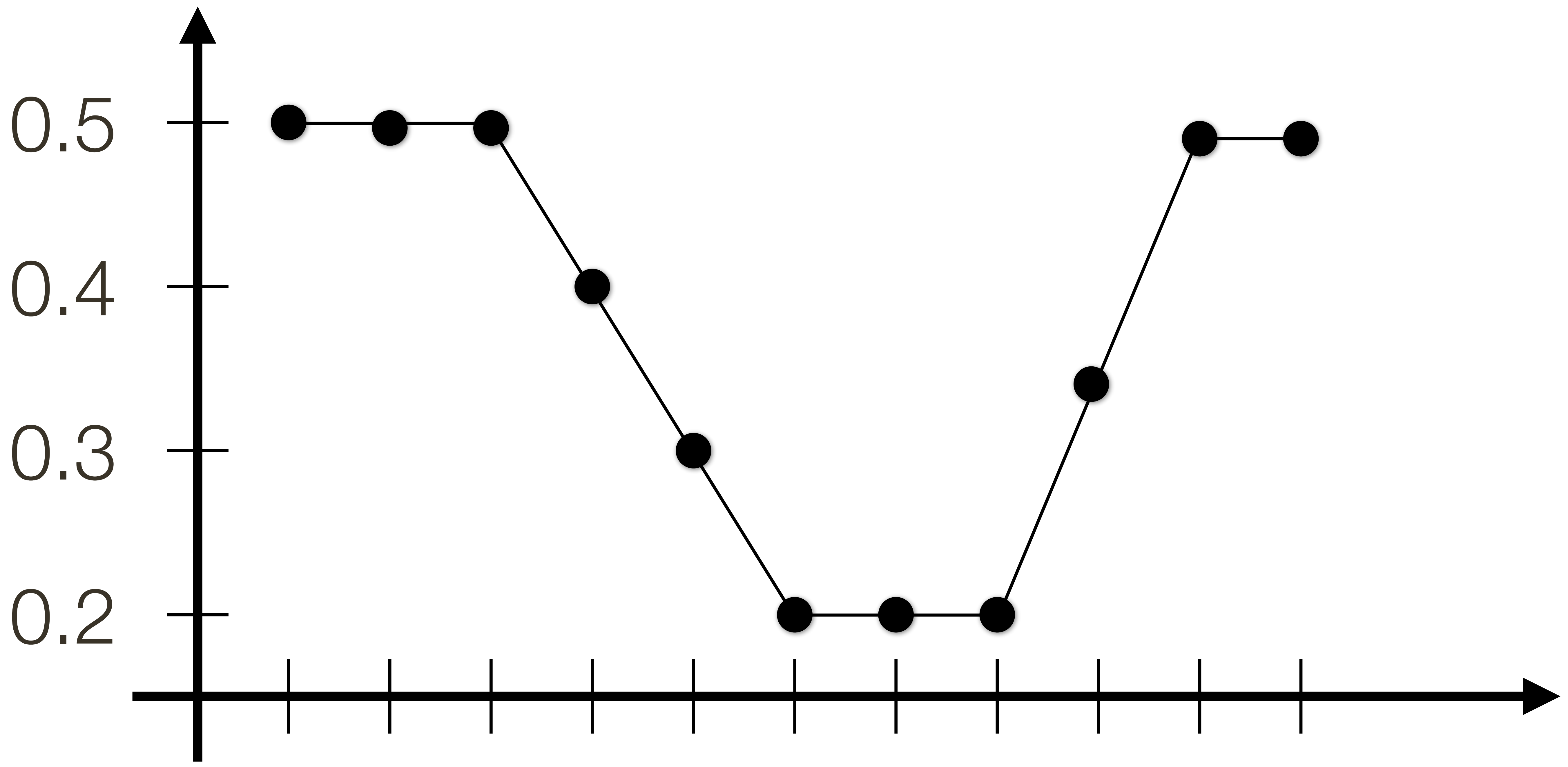
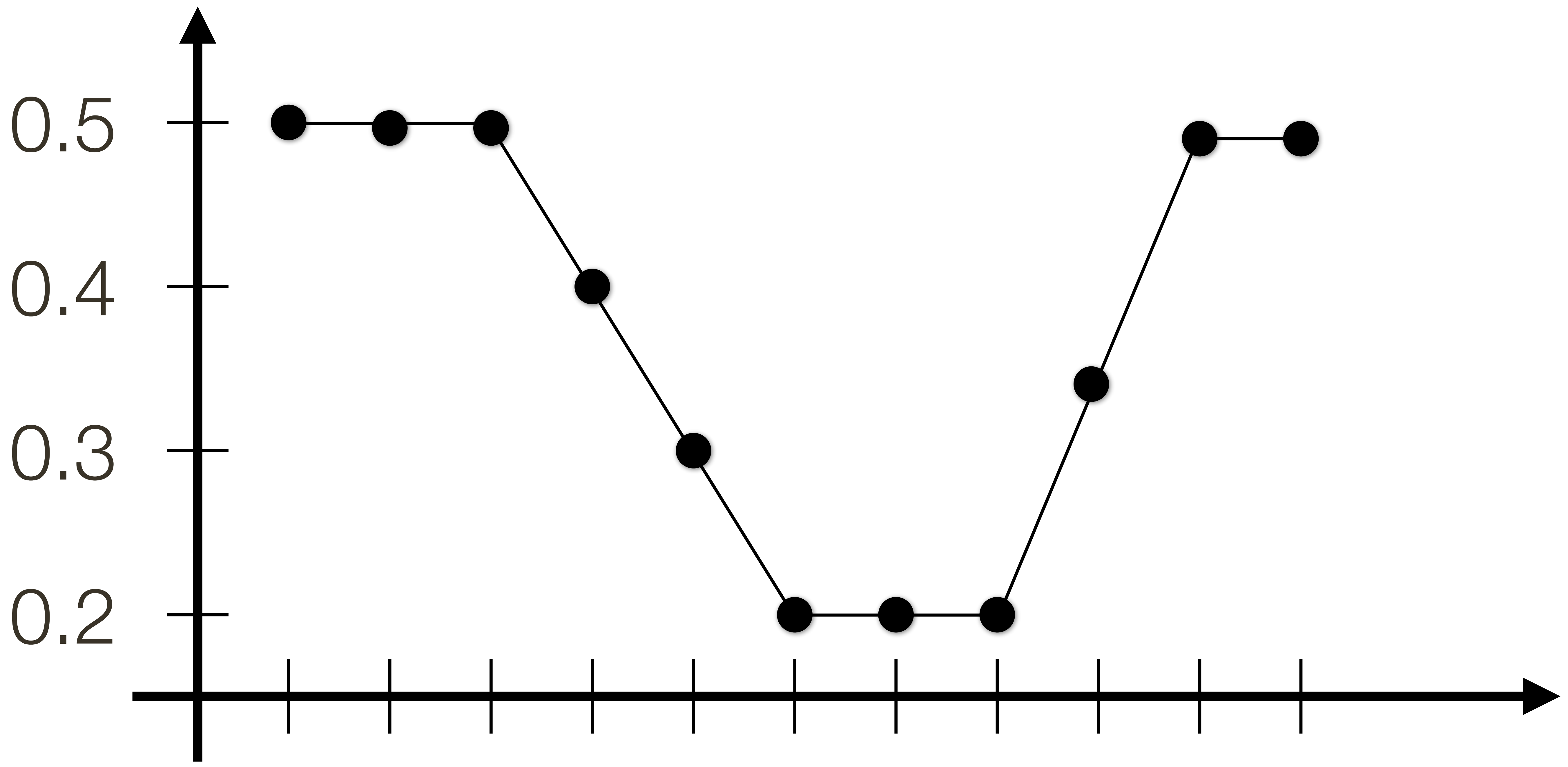


Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5
Derivative	0.0										

Example 1D



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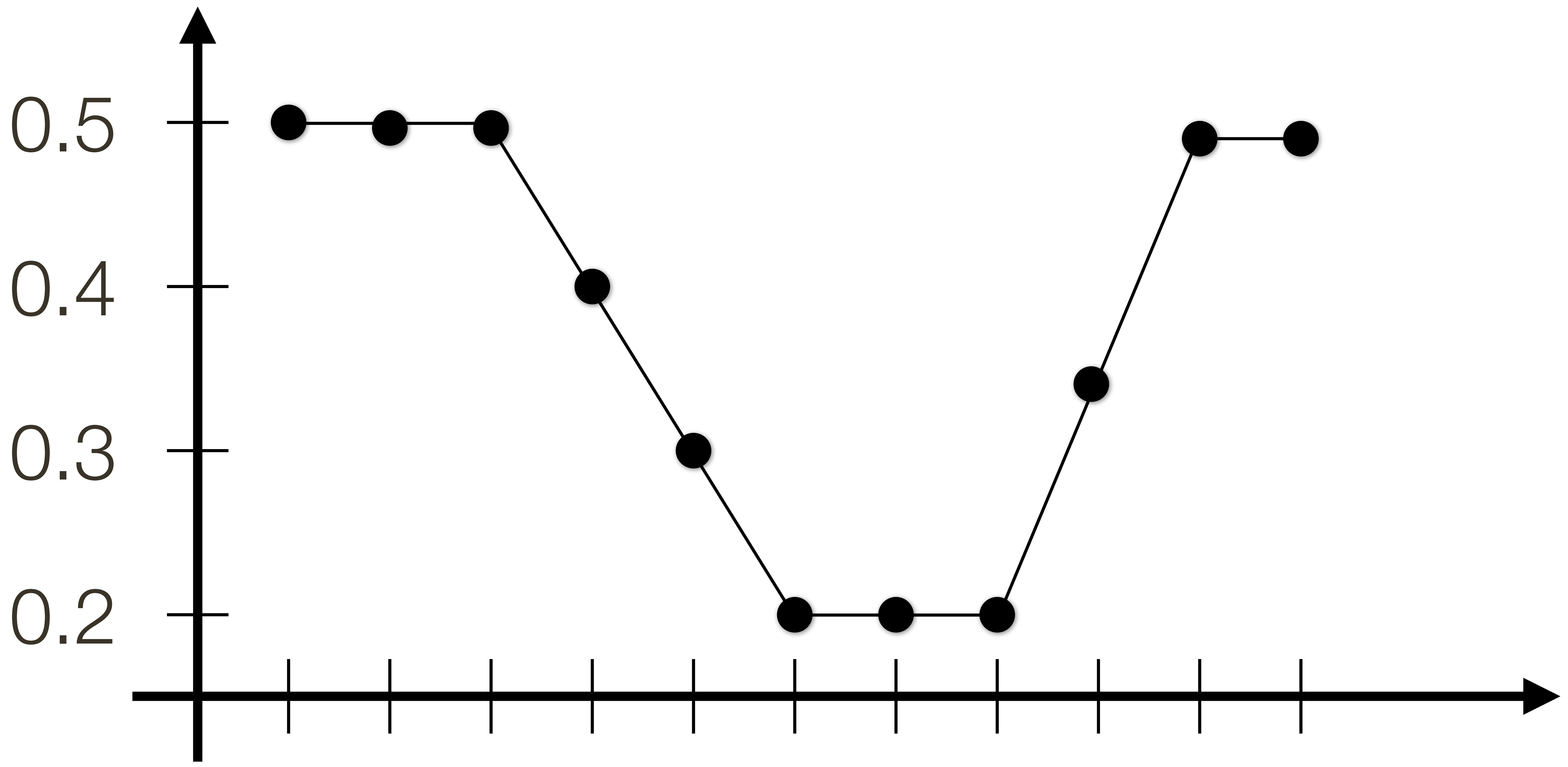

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Derivative	0.0	0.0									

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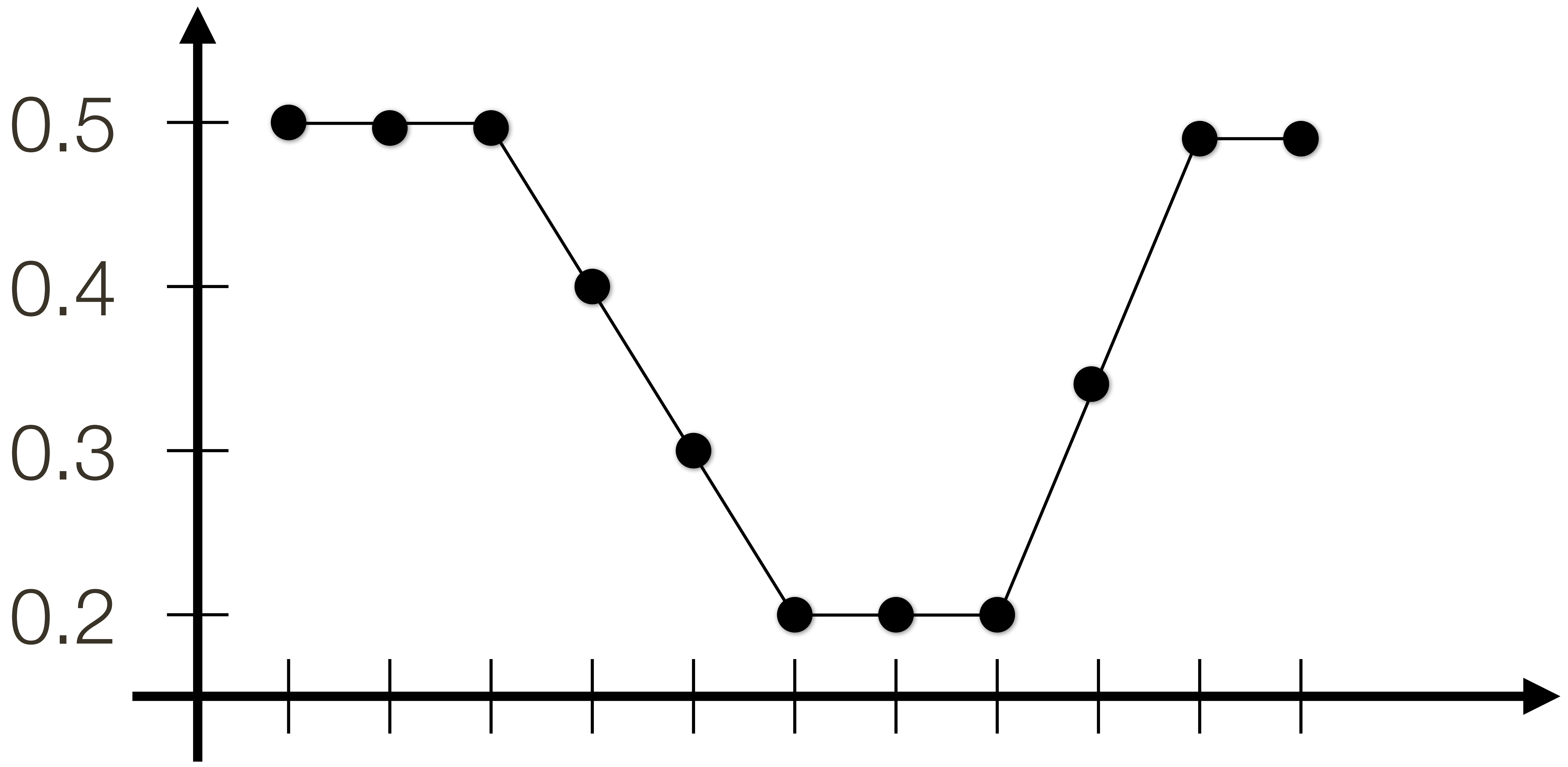

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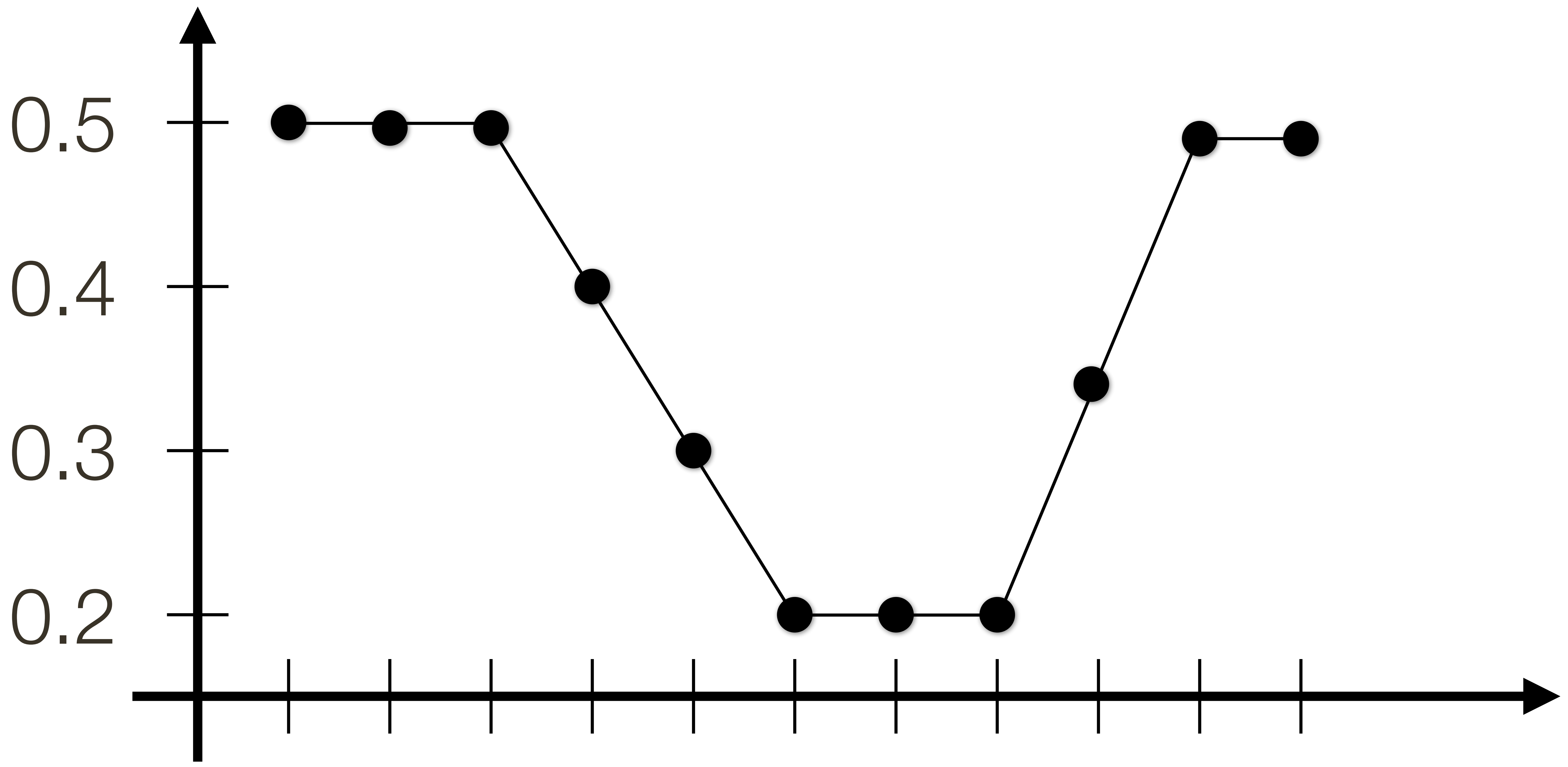
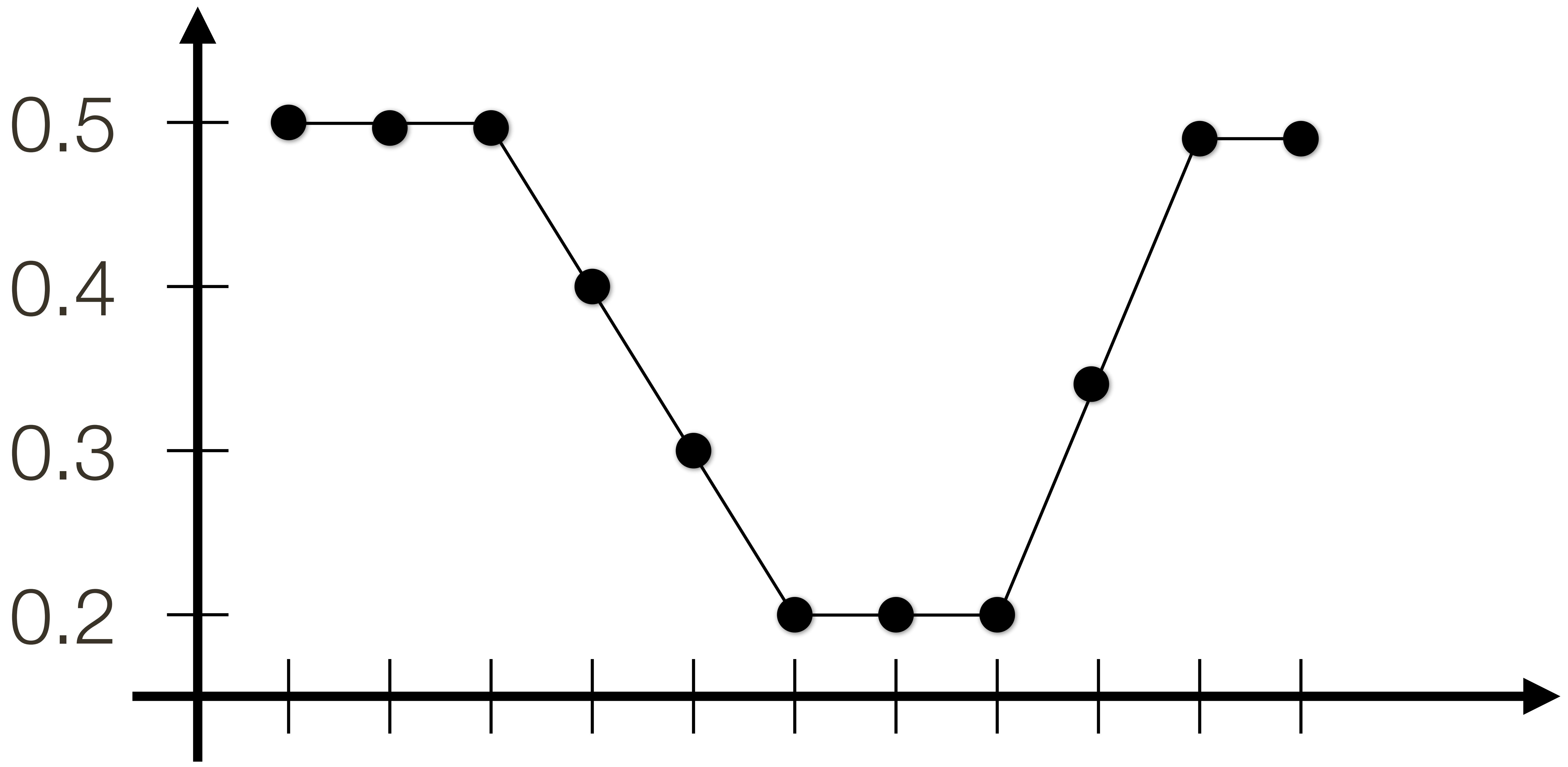


Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5
Derivative	0.0	0.0	-0.1								

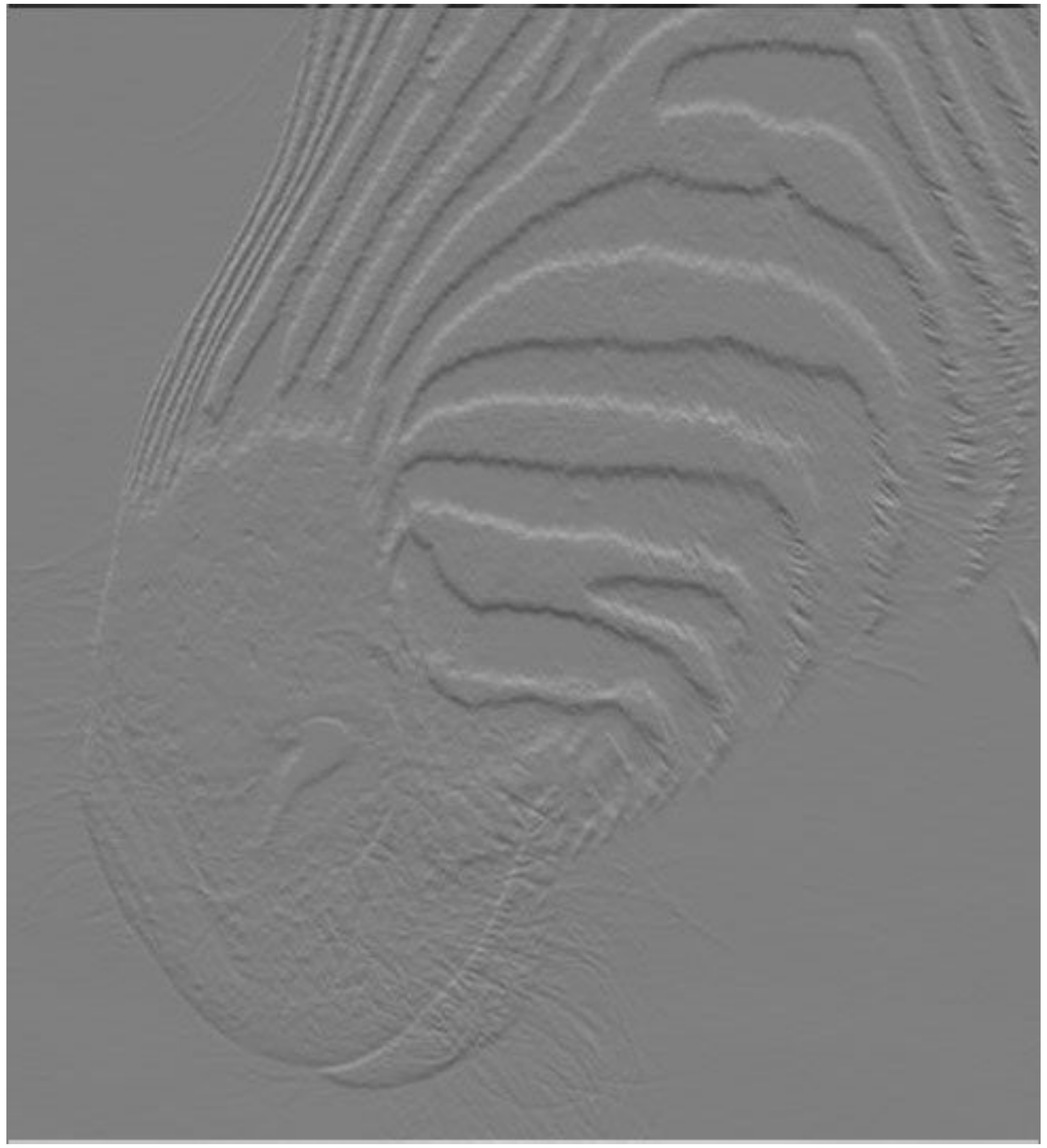
Example 1D



Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5
Derivative	0.0	0.0	-0.1	-0.1	-0.1	0.0	0.0	0.15	0.15	0.0	X

Estimating **Derivatives**

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



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

Estimating **Derivatives**

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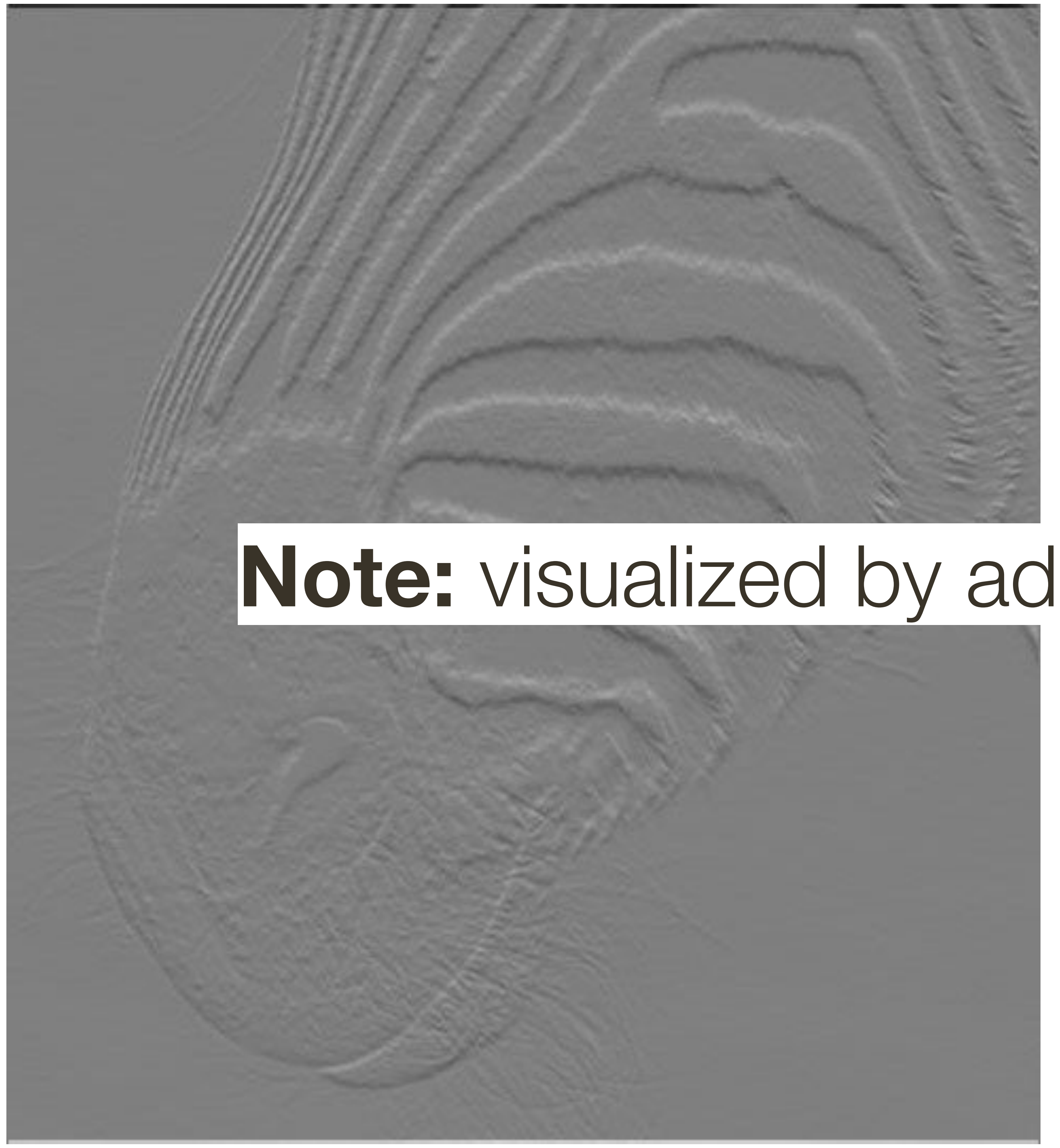
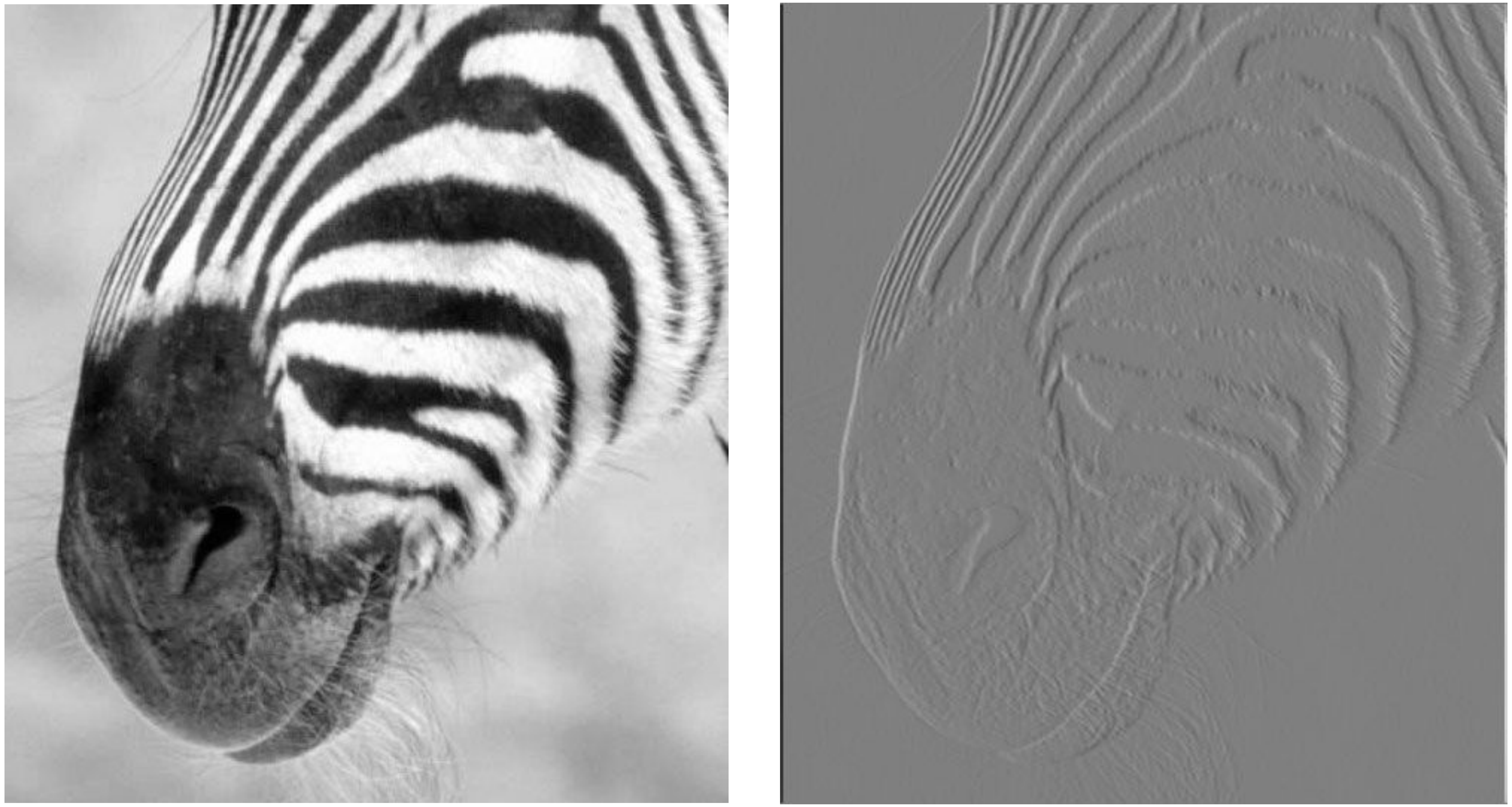


Note: visualized by adding 0.5/128

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

Estimating **Derivatives**

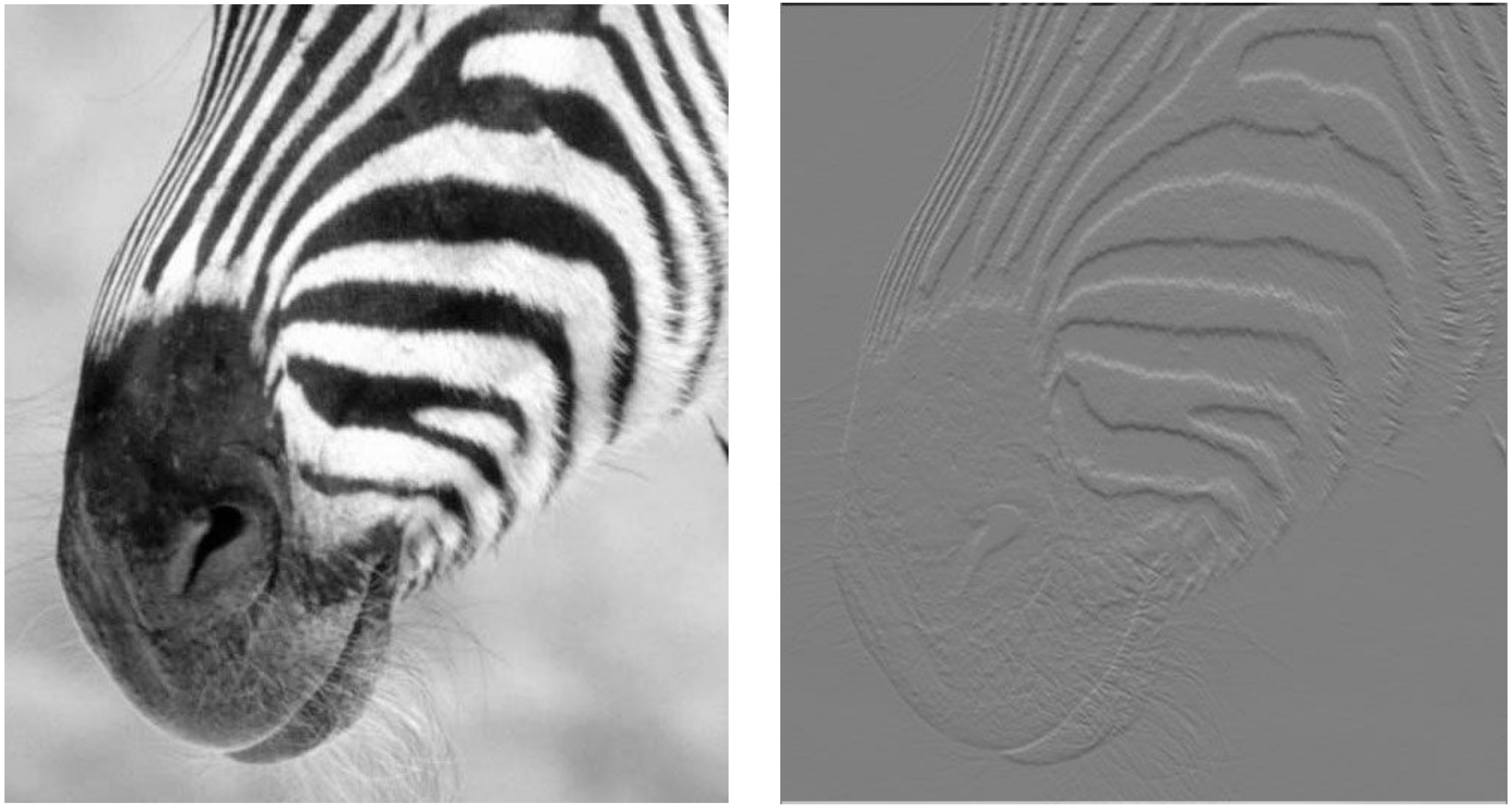
Derivative in X (i.e., horizontal) direction



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

Estimating **Derivatives**

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



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

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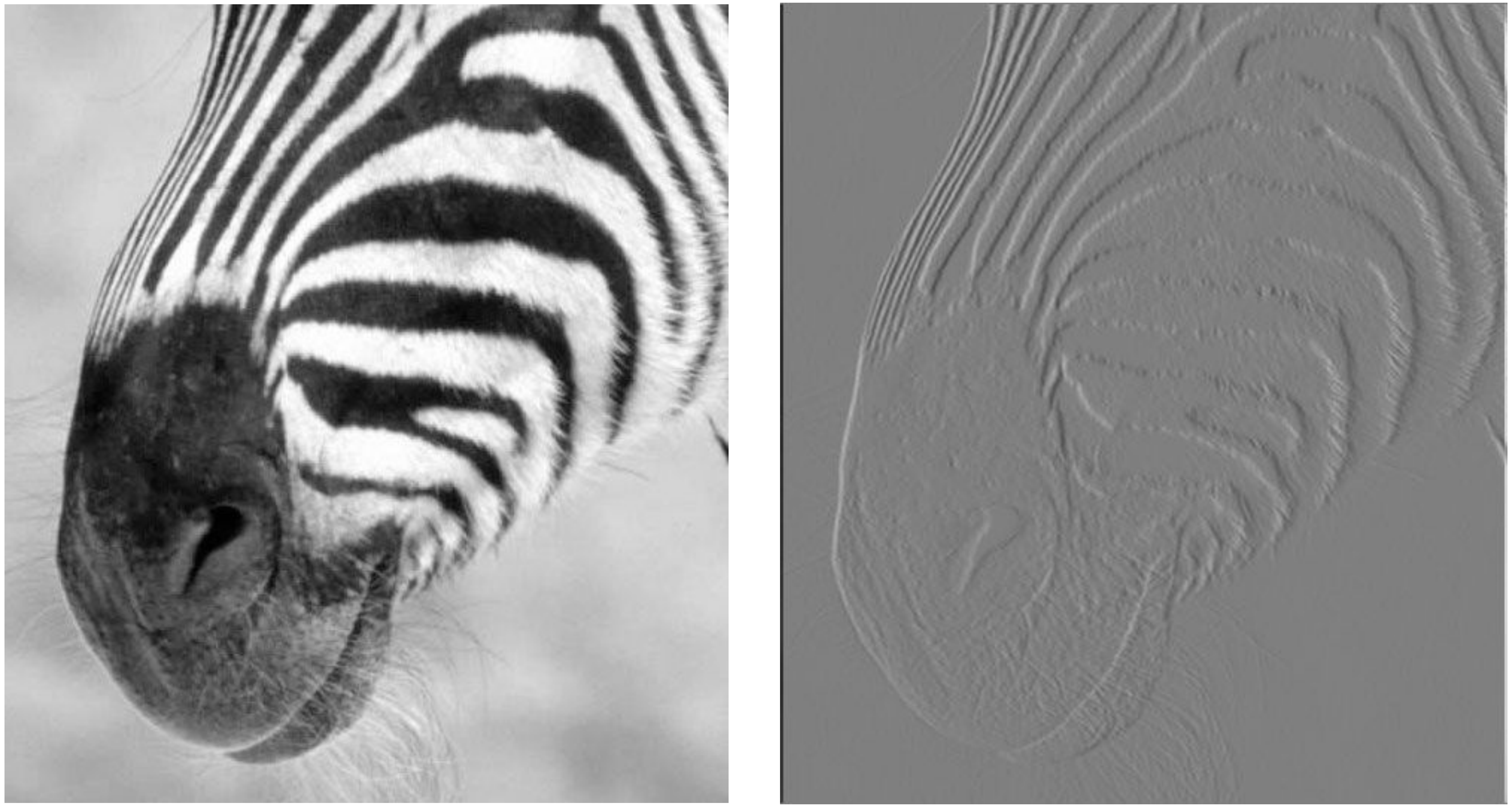
Derivative in X (i.e., horizontal) direction



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
0	0	0	0	0	0

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

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0					

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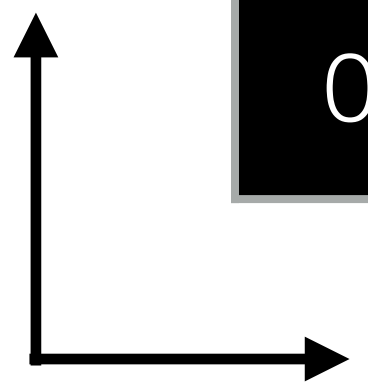

0	0				

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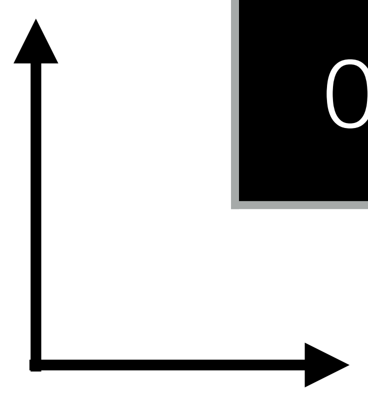

0					
0	0	0	0	0	
0	0	0	0	0	

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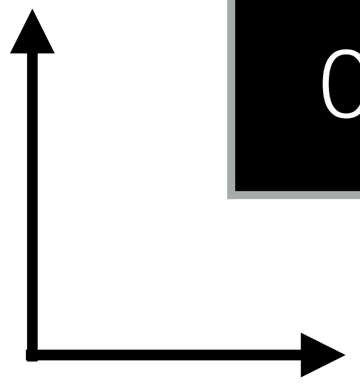

0	-0.4				
0	0	0	0	0	
0	0	0	0	0	

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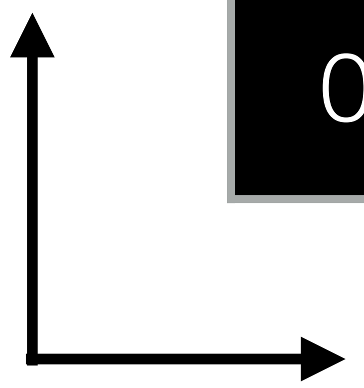

0	-0.4	-0.3	-0.3	0	
0	-0.4	-0.3	-0.3	0	
0	0	0	0	0	
0	0	0	0	0	

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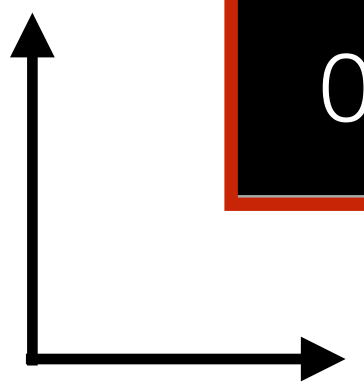
0	0	0	0	0	0
0	0	0	0	0	0



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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					

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

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

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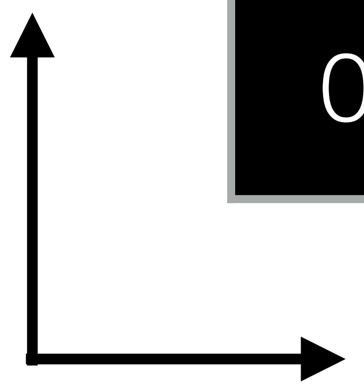

0	0	0	0	0	0

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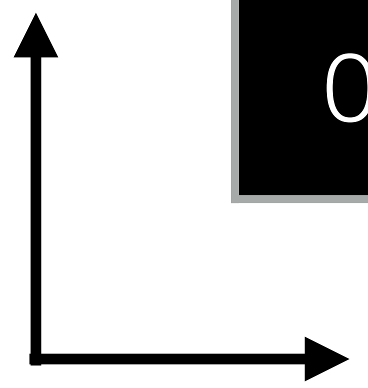

0	0	0	0	0	0
1	1	0.6	0.3	0	0
0	0	0	0	0	0

Estimating **Derivatives**

-1	1

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

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

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

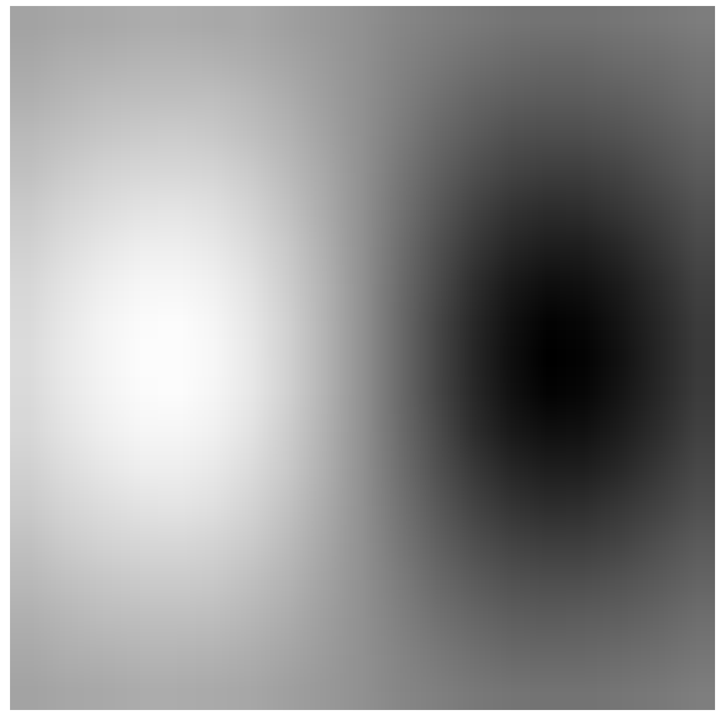
We can use **derivative of Gaussian** filters

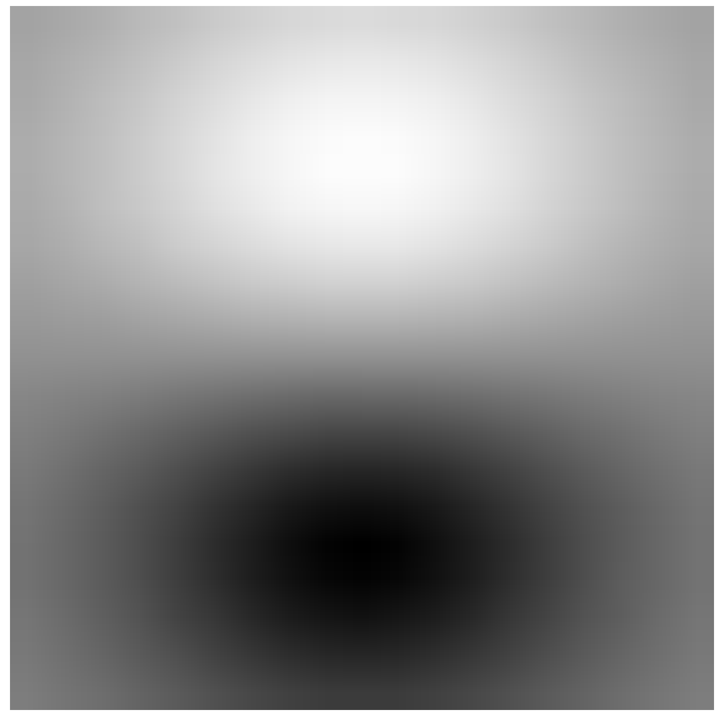
— because differentiation is convolution, and

— convolution is associative

Let $\otimes$ denote convolution

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

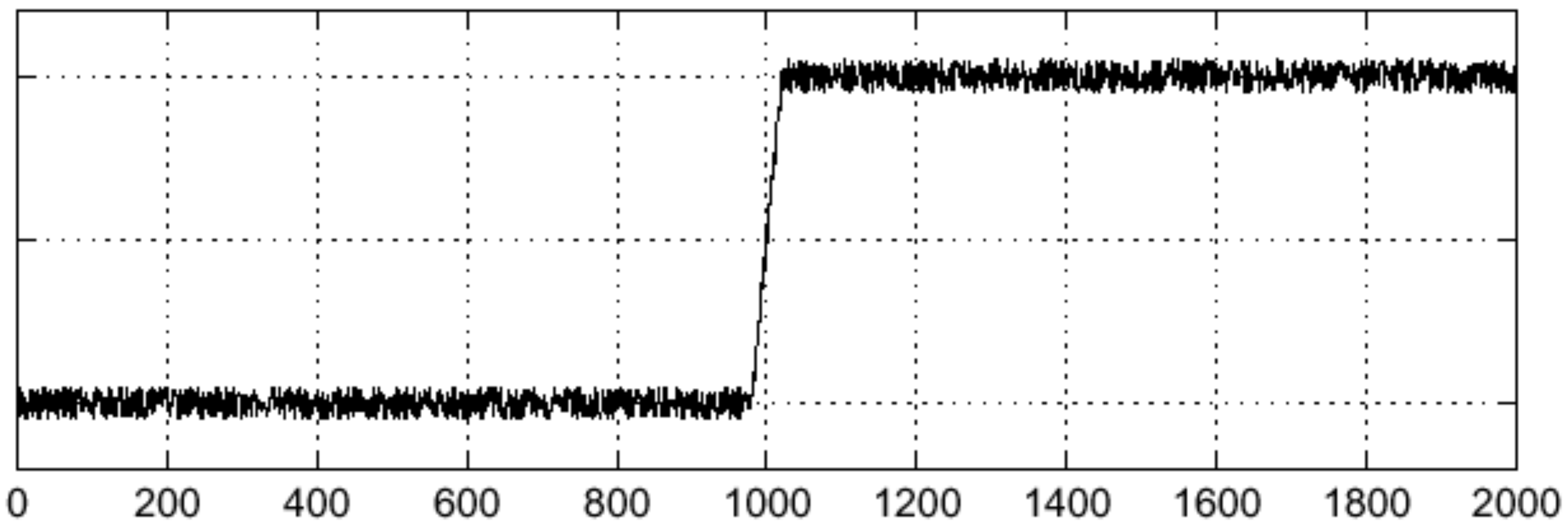




1D **Example**

Lets consider a row of pixels in an image:

$I(X, 245)$

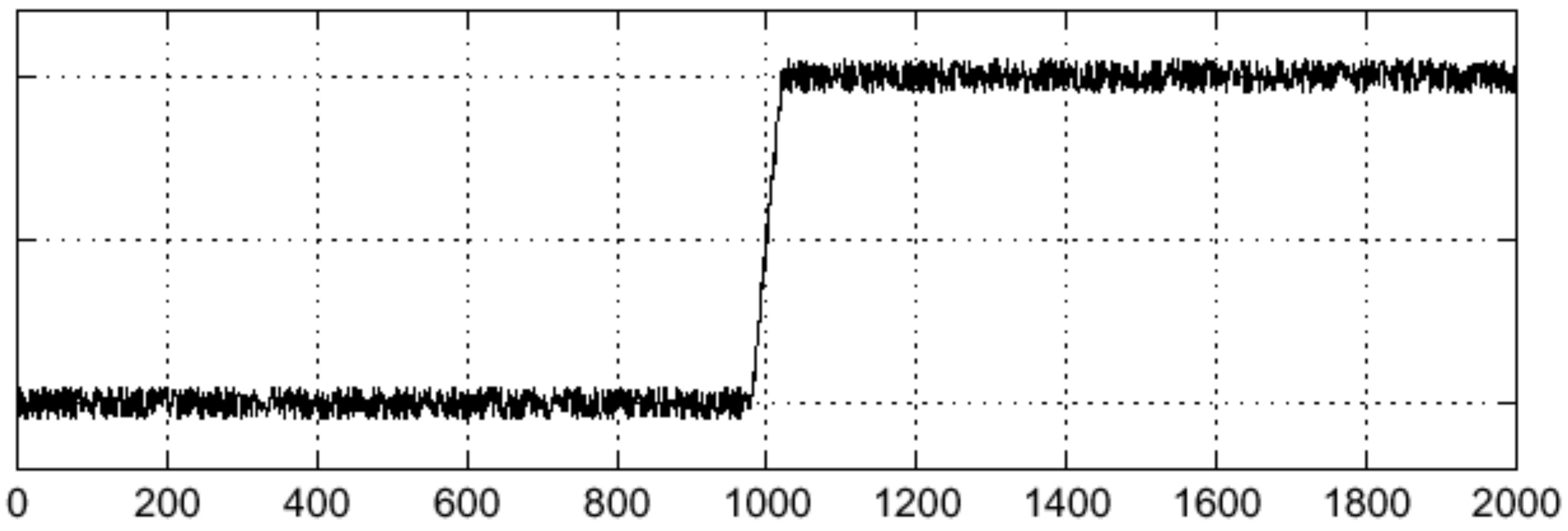


Where is the edge?

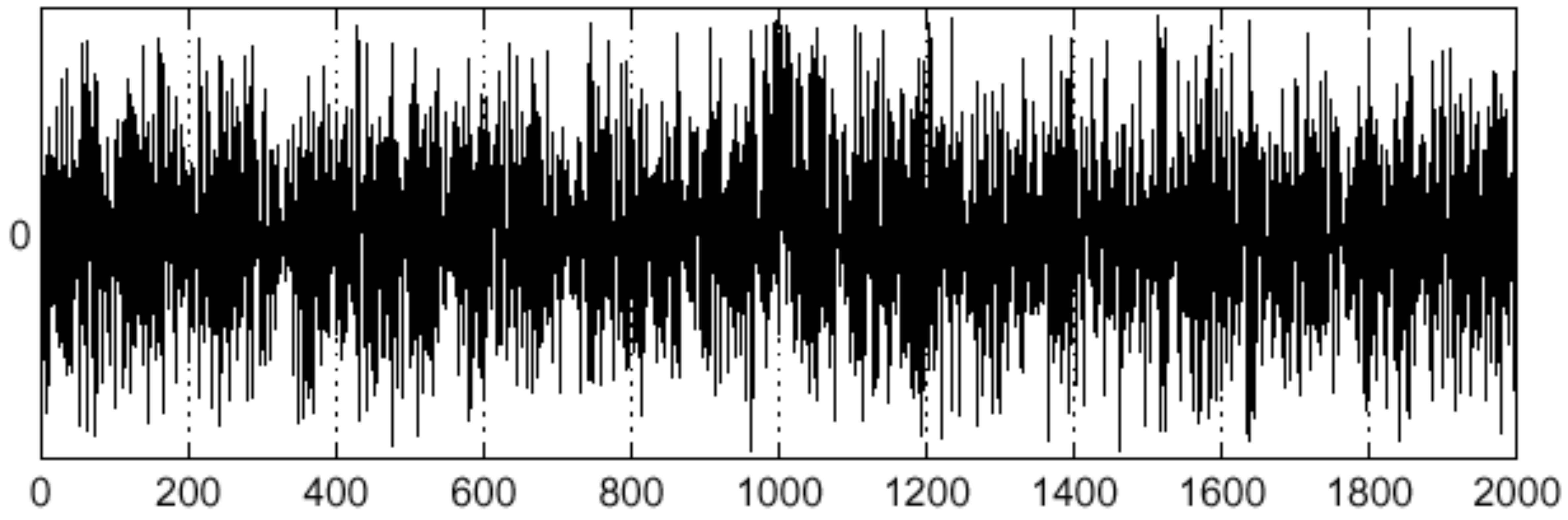
1D **Example**: Derivative

Lets consider a row of pixels in an image:

$$I(X, 245)$$



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



Where is the edge?

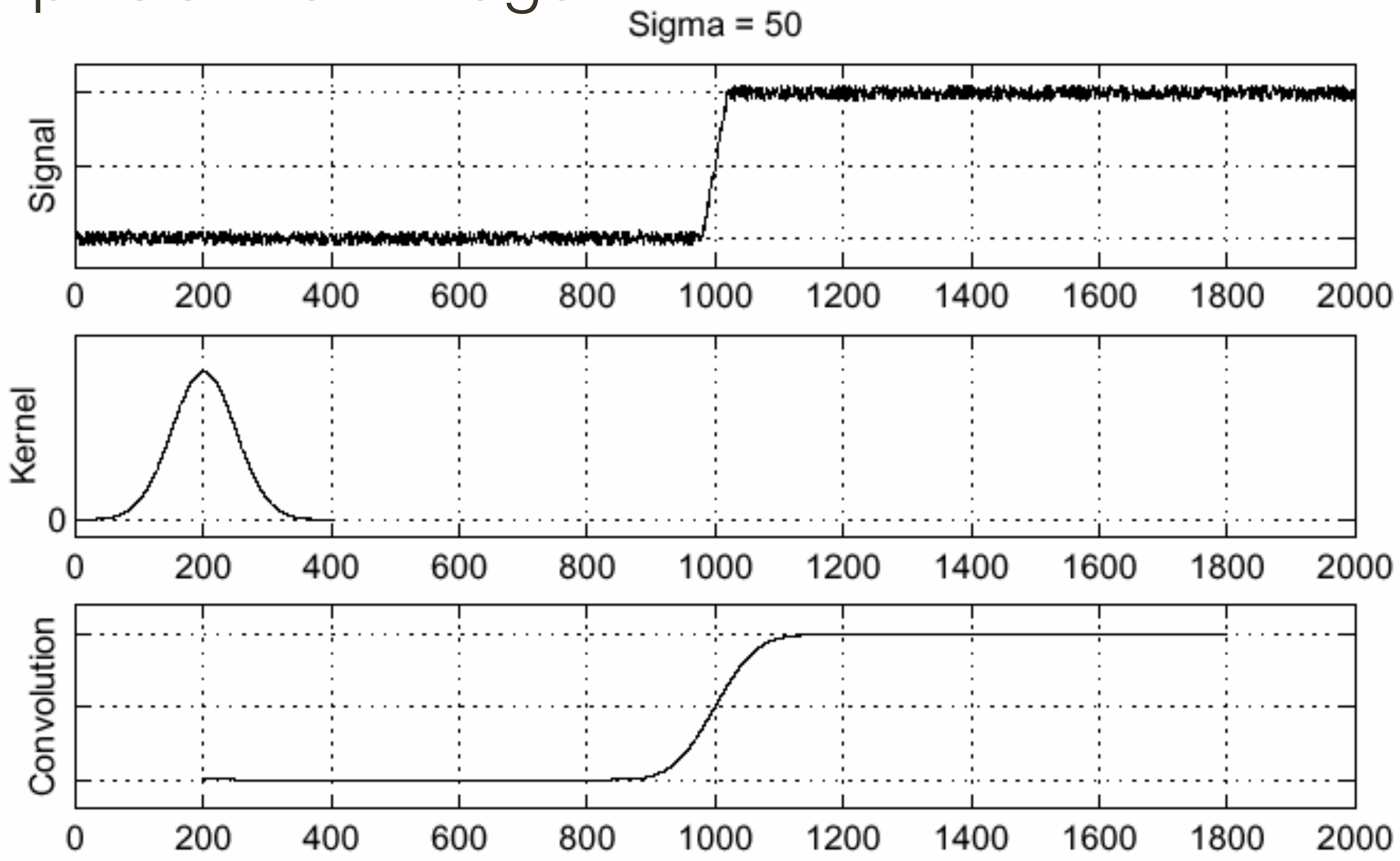
1D **Example**: Smoothing + Derivative

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:

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$$G$$

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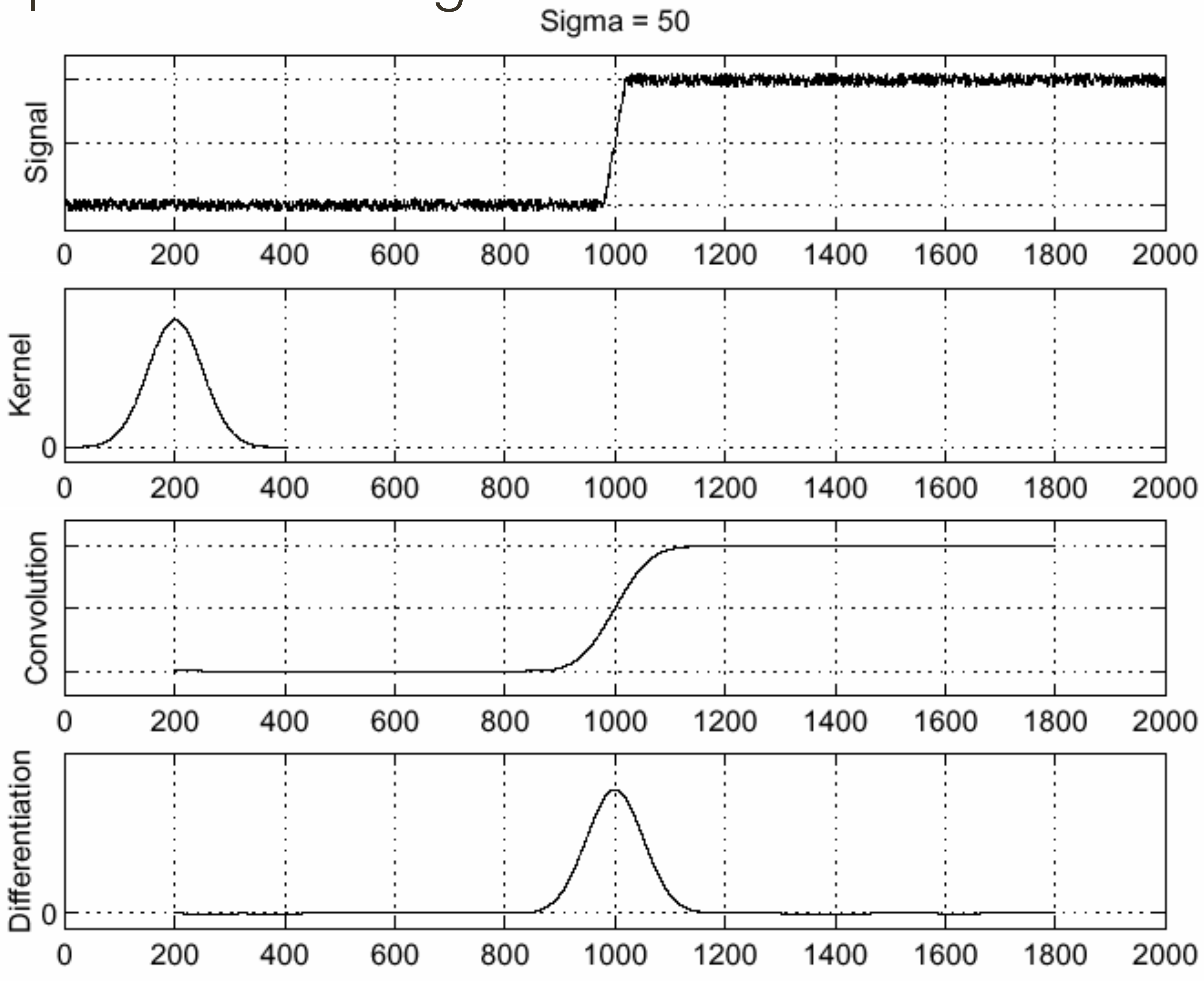
$$\frac{\partial G \otimes I(X,Y)}{\partial x}$$



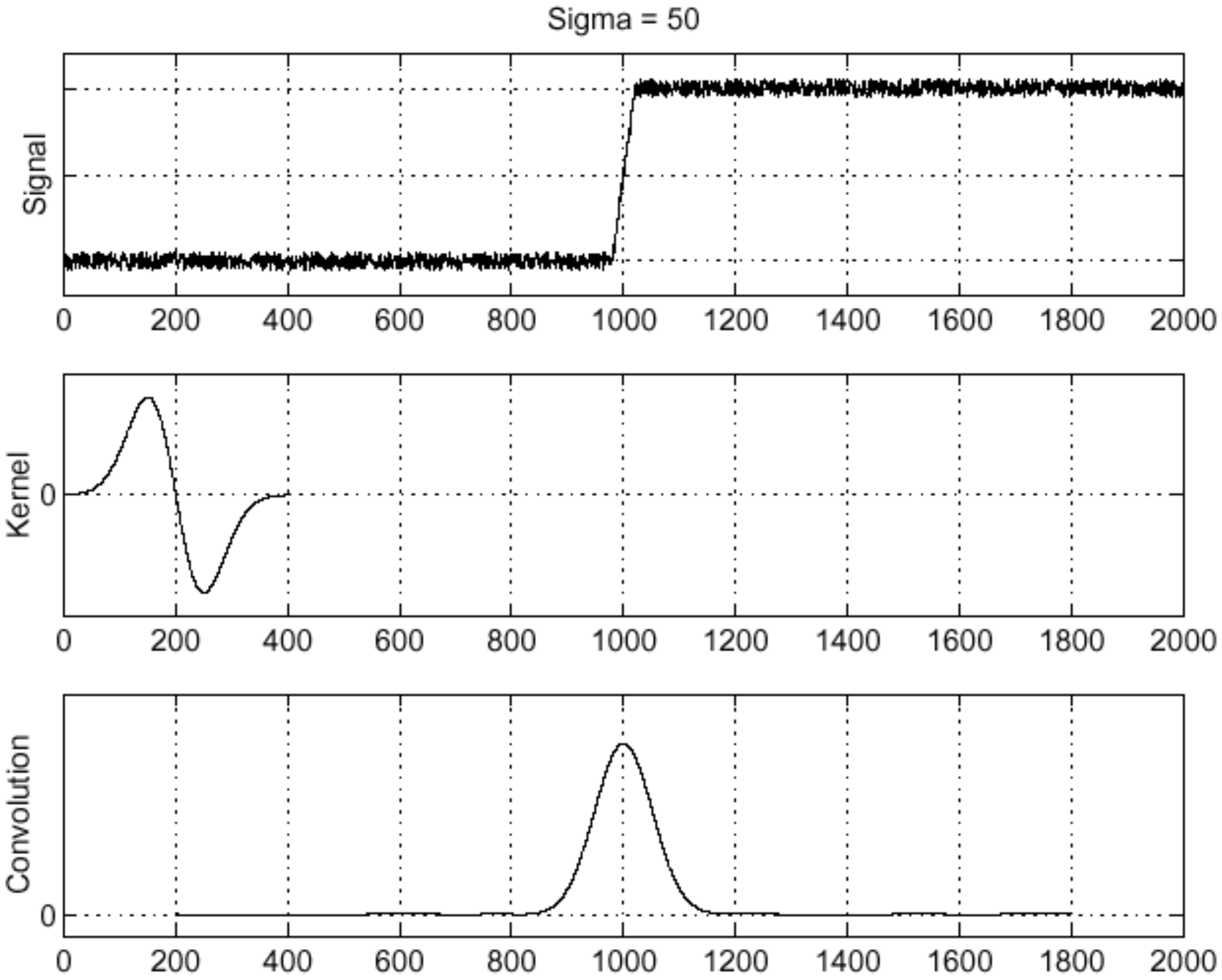
1D **Example**: Smoothing + Derivative (efficient)

Lets consider a row of pixels in an image:

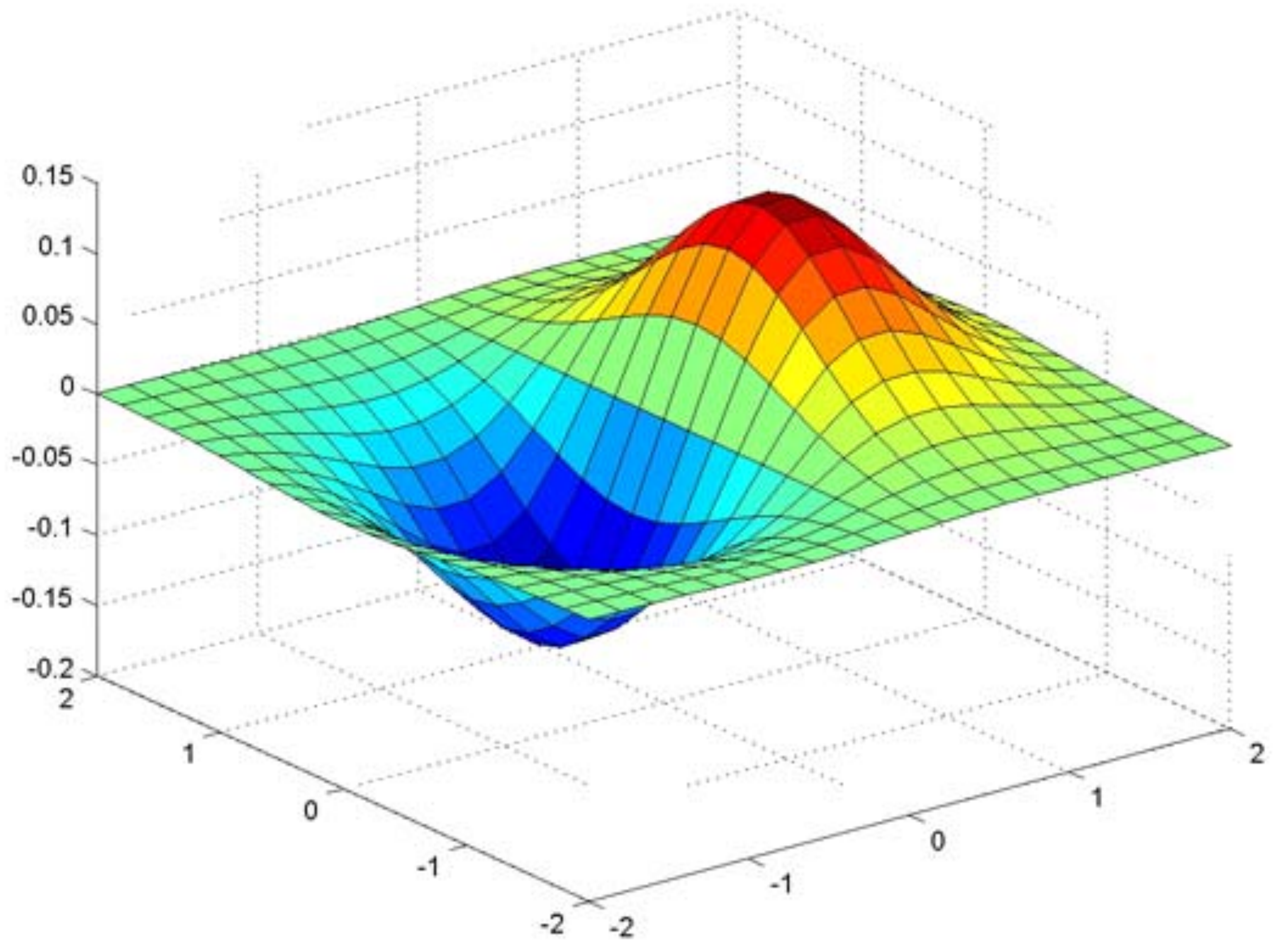
$$I(X, 245)$$

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

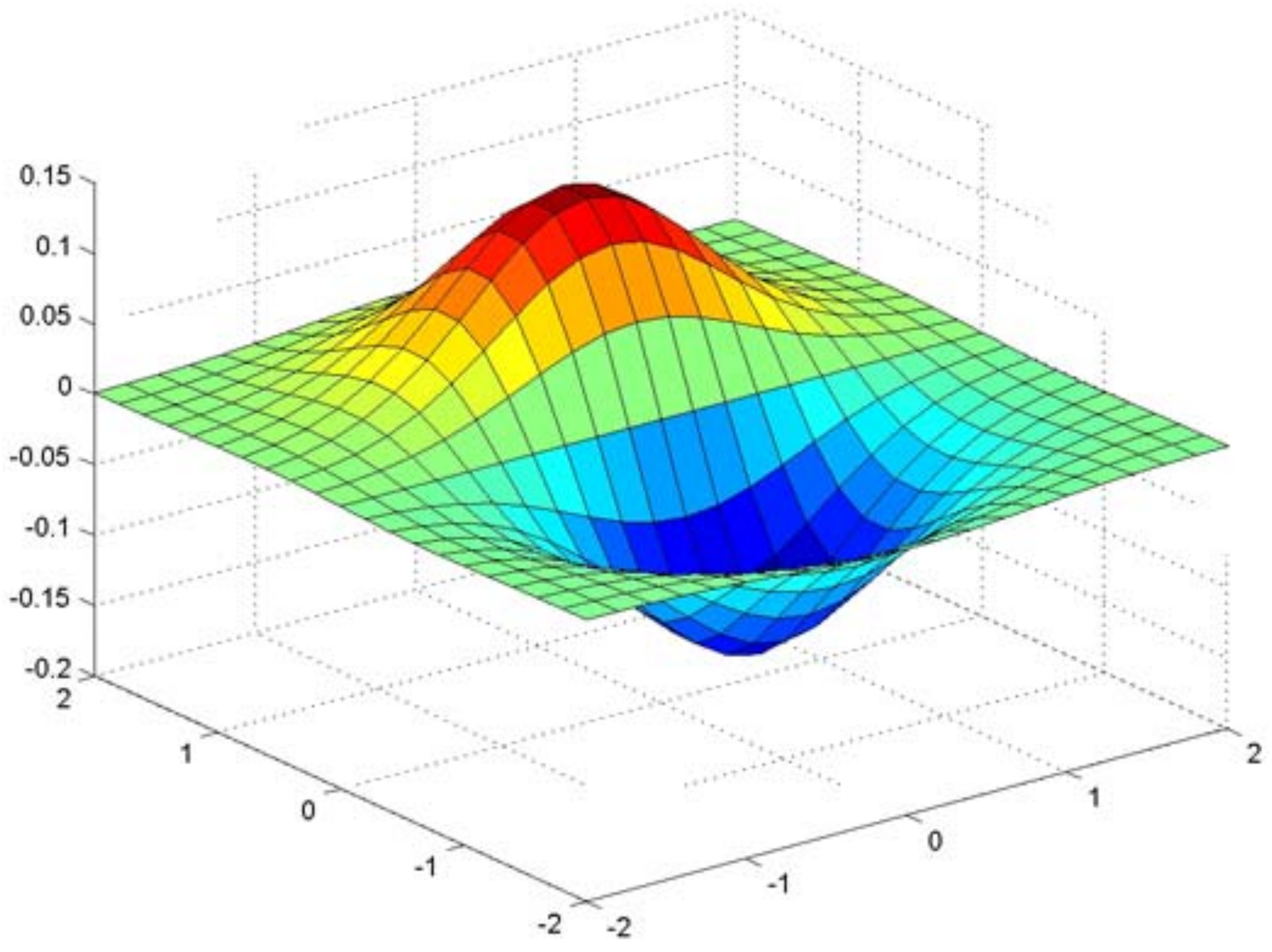
$$\frac{\partial G}{\partial x} \otimes I(X, Y)$$



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

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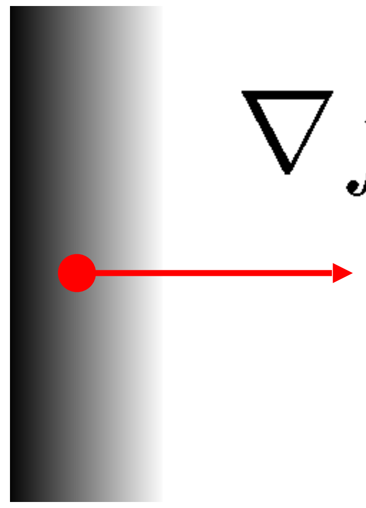
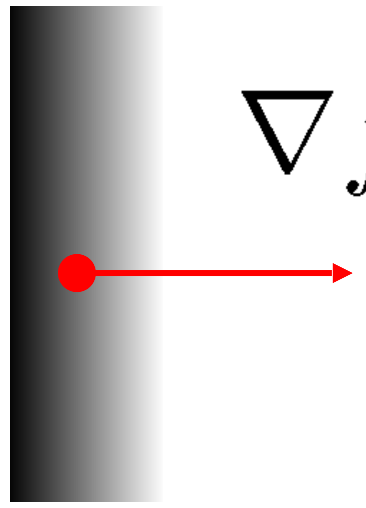


$$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$$

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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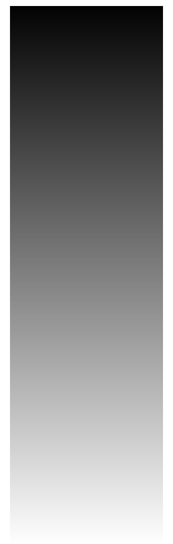

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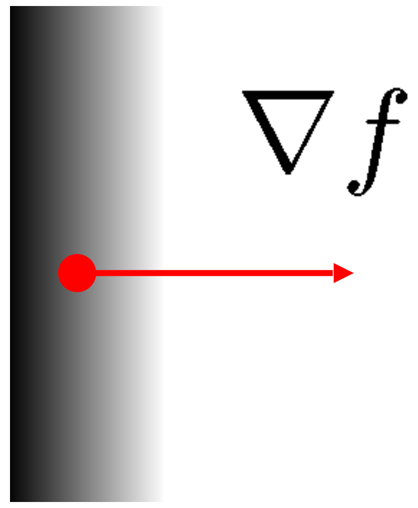

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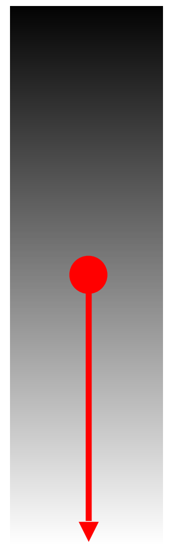

$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$

Image **Gradient**

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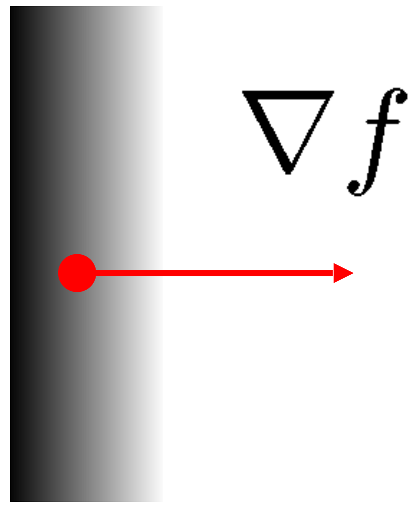

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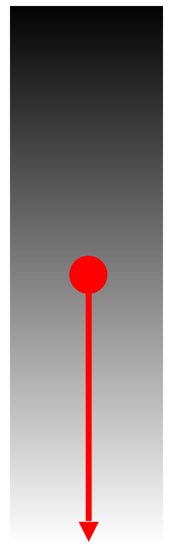

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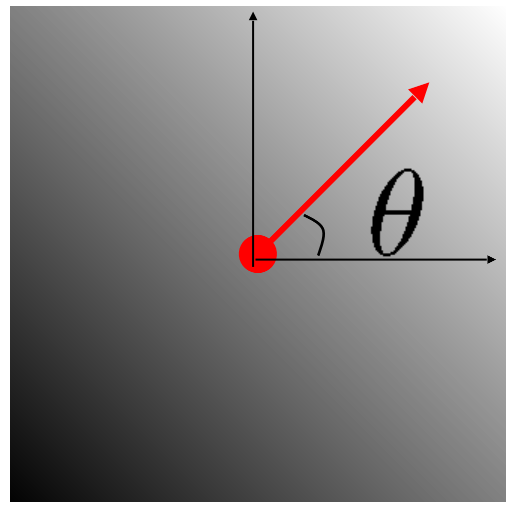
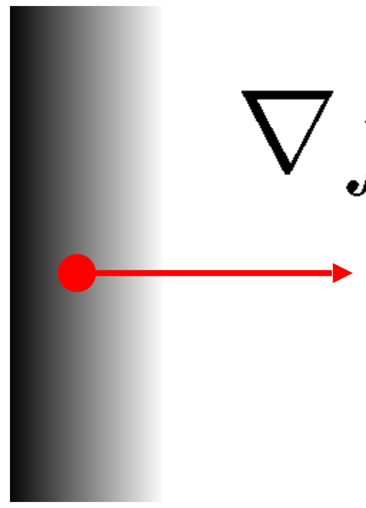


$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

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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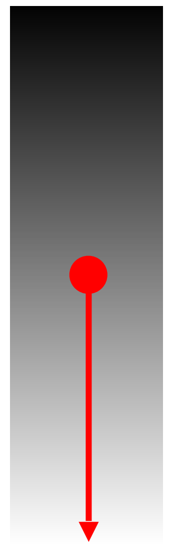

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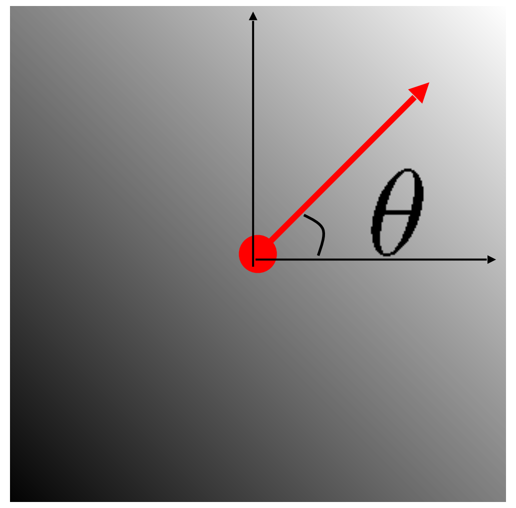

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The gradient points in the direction of most rapid **increase of intensity**:

The **gradient direction** is given by:

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

Image **Gradient**

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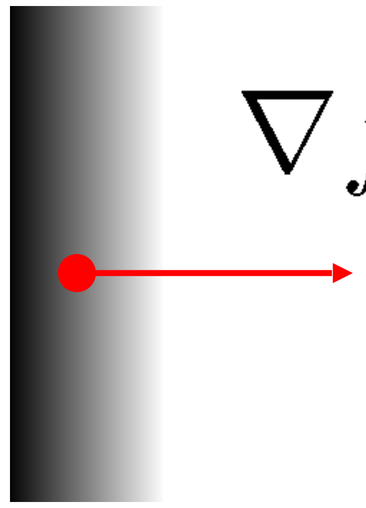

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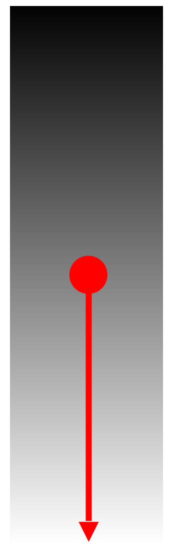

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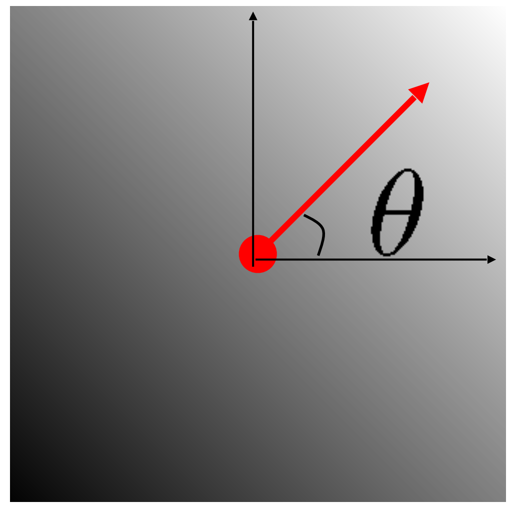

$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

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

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

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Image **Gradient**

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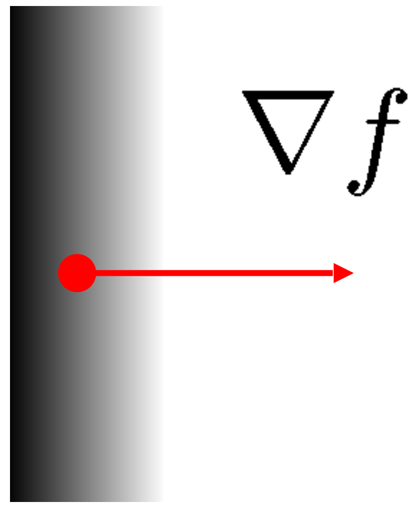

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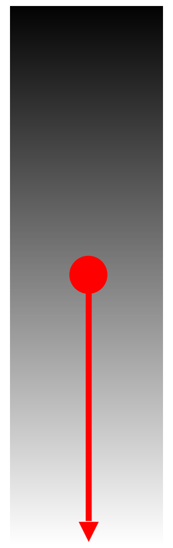

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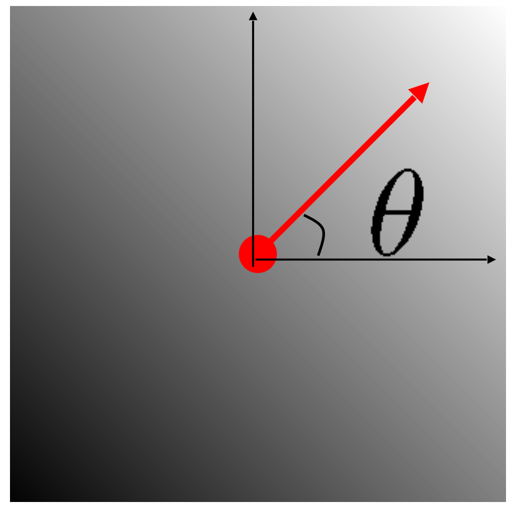


$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

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

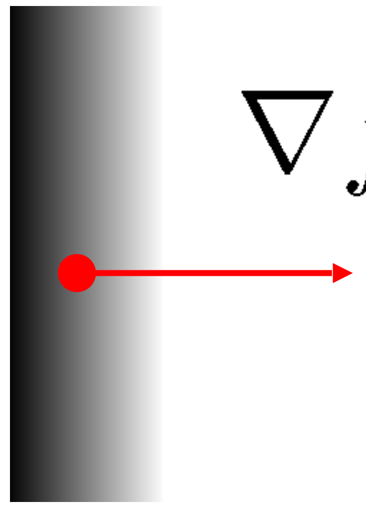
The **gradient direction** is given by:

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

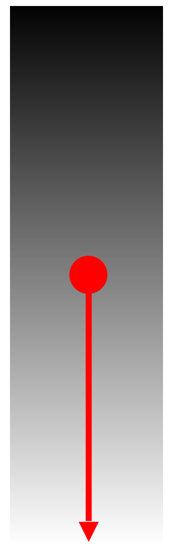
The edge strength is given by the **gradient magnitude**:

Image **Gradient**

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



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



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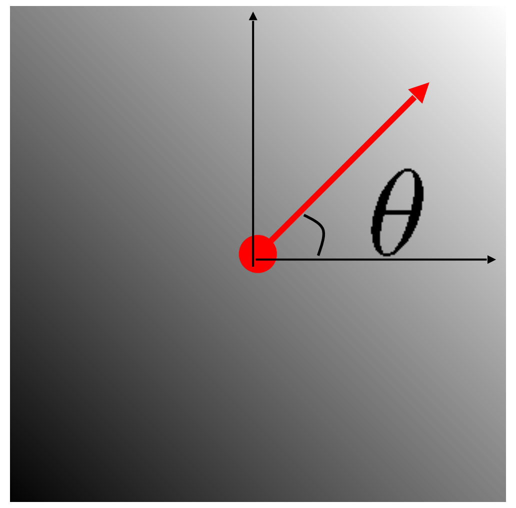

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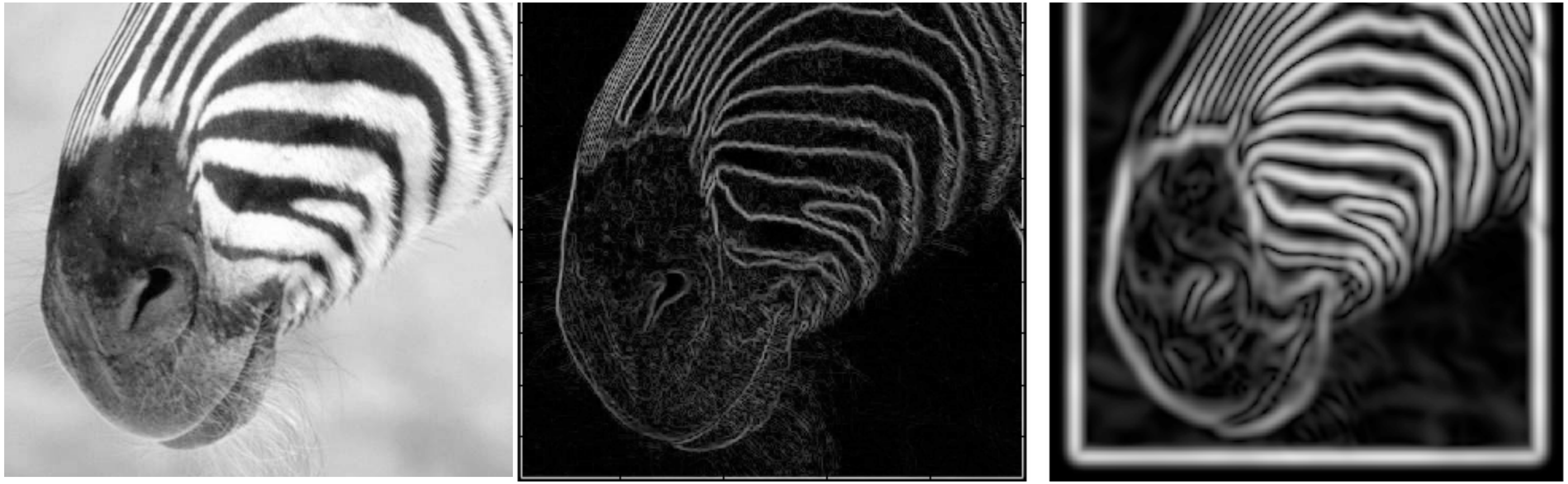
The **gradient direction** is given by: $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$

(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.

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

2. **Threshold** to obtain edges

Original Image

Sobel Gradient

Sobel Edges

Sobel Edge Detector

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

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2. **Threshold** to obtain edges

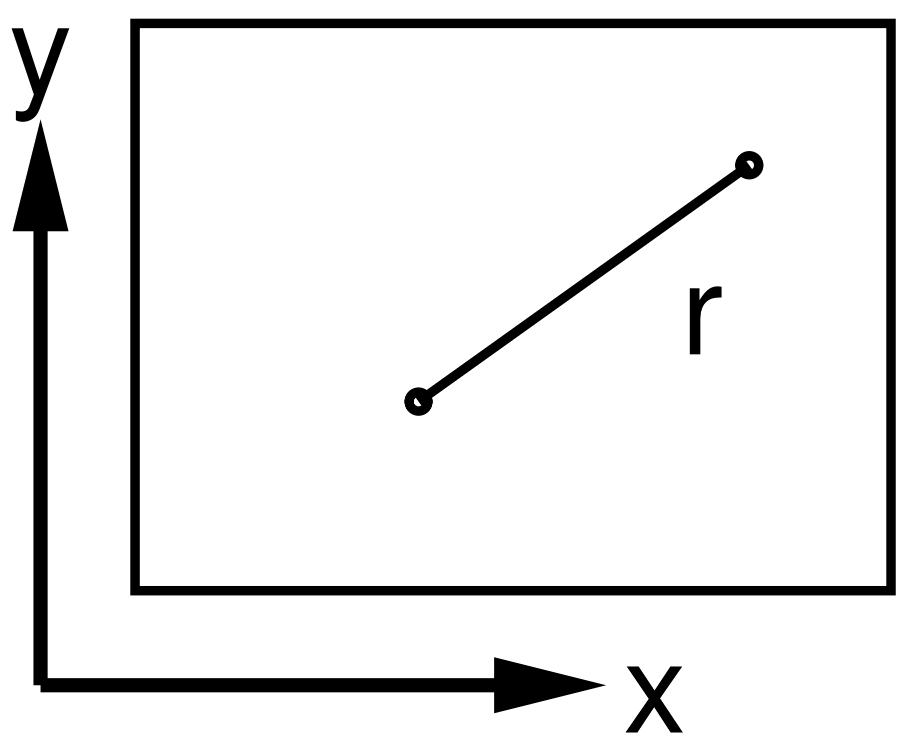
Original Image

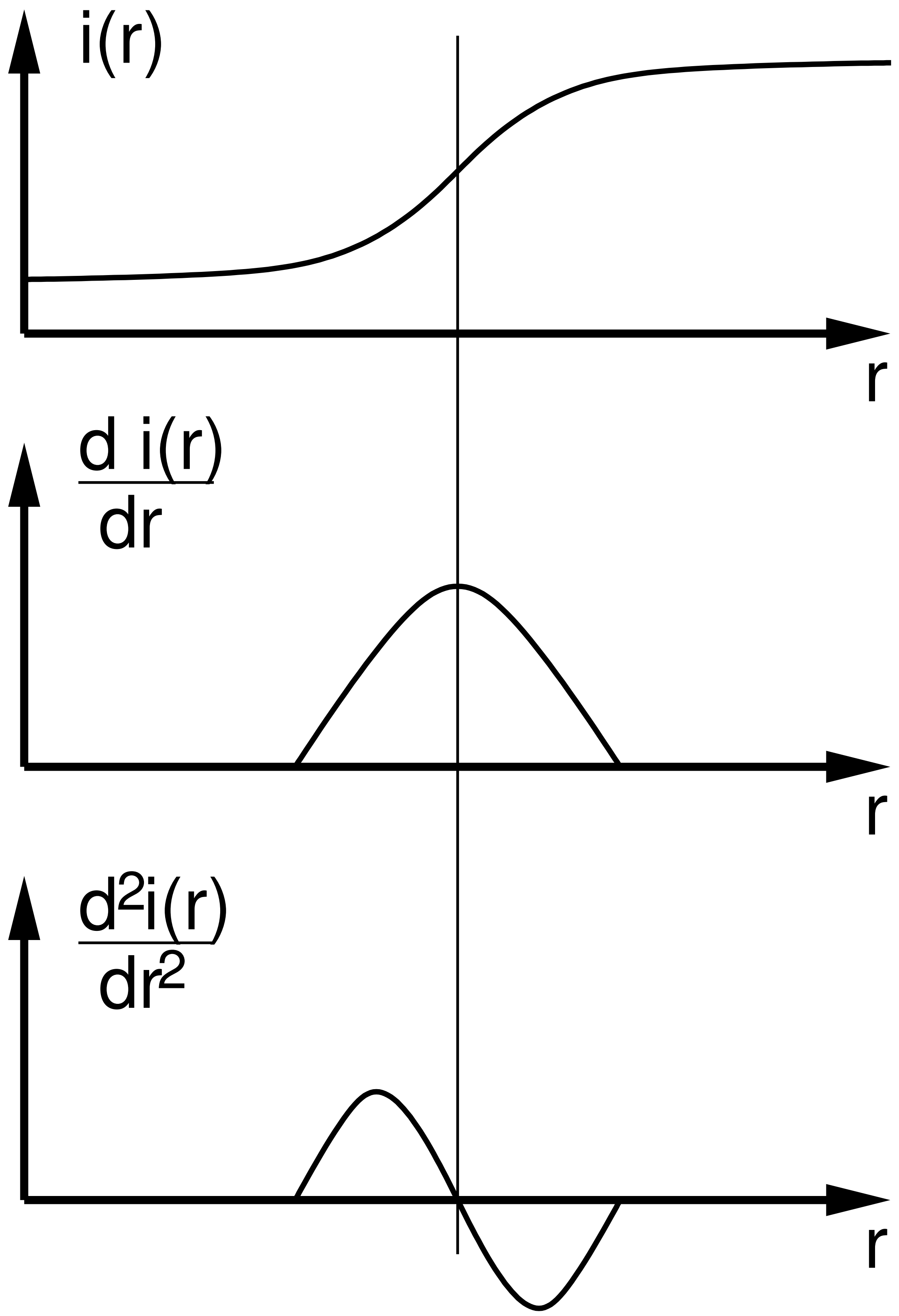
Sobel Gradient

Sobel Edges

Thresholds are brittle, we can do better!

Two Generic Approaches for **Edge** Detection





Two generic approaches to **edge point detection**:

— (significant) local extrema of a first derivative operator

— zero crossings of a second derivative operator

Marr / Hildreth **Laplacian of Gaussian**

A “**zero crossings** of a second derivative operator” approach

Design Criteria:

1. localization in space

2. localization in frequency

3. rotationally invariant

Marr / Hildreth **Laplacian of Gaussian**

A “**zero crossings** of a second derivative operator” approach

Steps:

1. Gaussian for smoothing

2. Laplacian (∇^2) for differentiation where

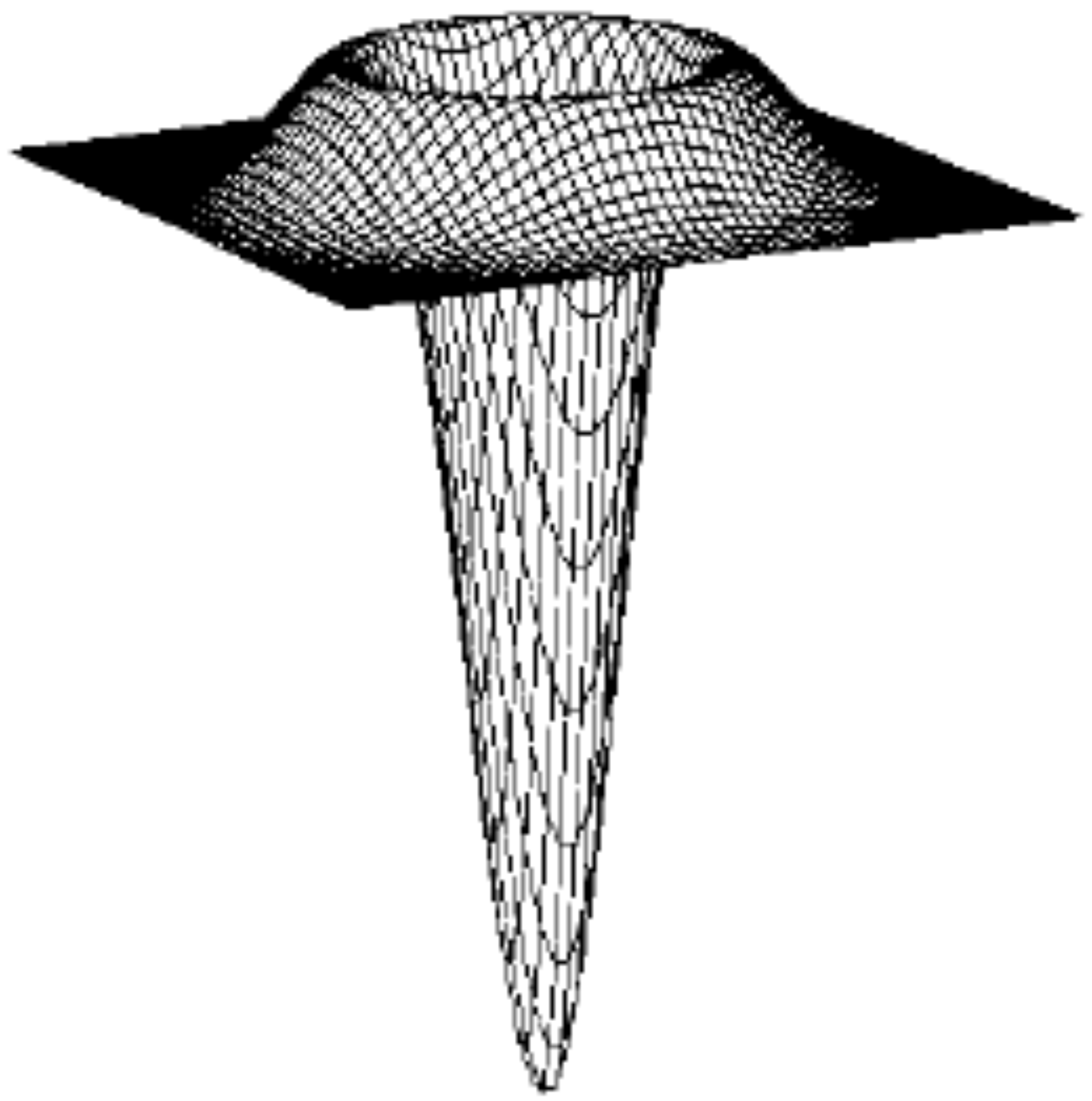
$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}$$

3. Locate zero-crossings in the Laplacian of the Gaussian ($\nabla^2 G$) where

$$\nabla^2 G(x,y) = \frac{-1}{2\pi\sigma^4}\left[2 - \frac{x^2+y^2}{\sigma^2}\right]\exp^{-\frac{x^2+y^2}{2\sigma^2}}$$

Marr / Hildreth **Laplacian of Gaussian**

Here's a 3D plot of the Laplacian of the Gaussian ($\nabla^2 G$)



. . . with its characteristic "Mexican hat" shape

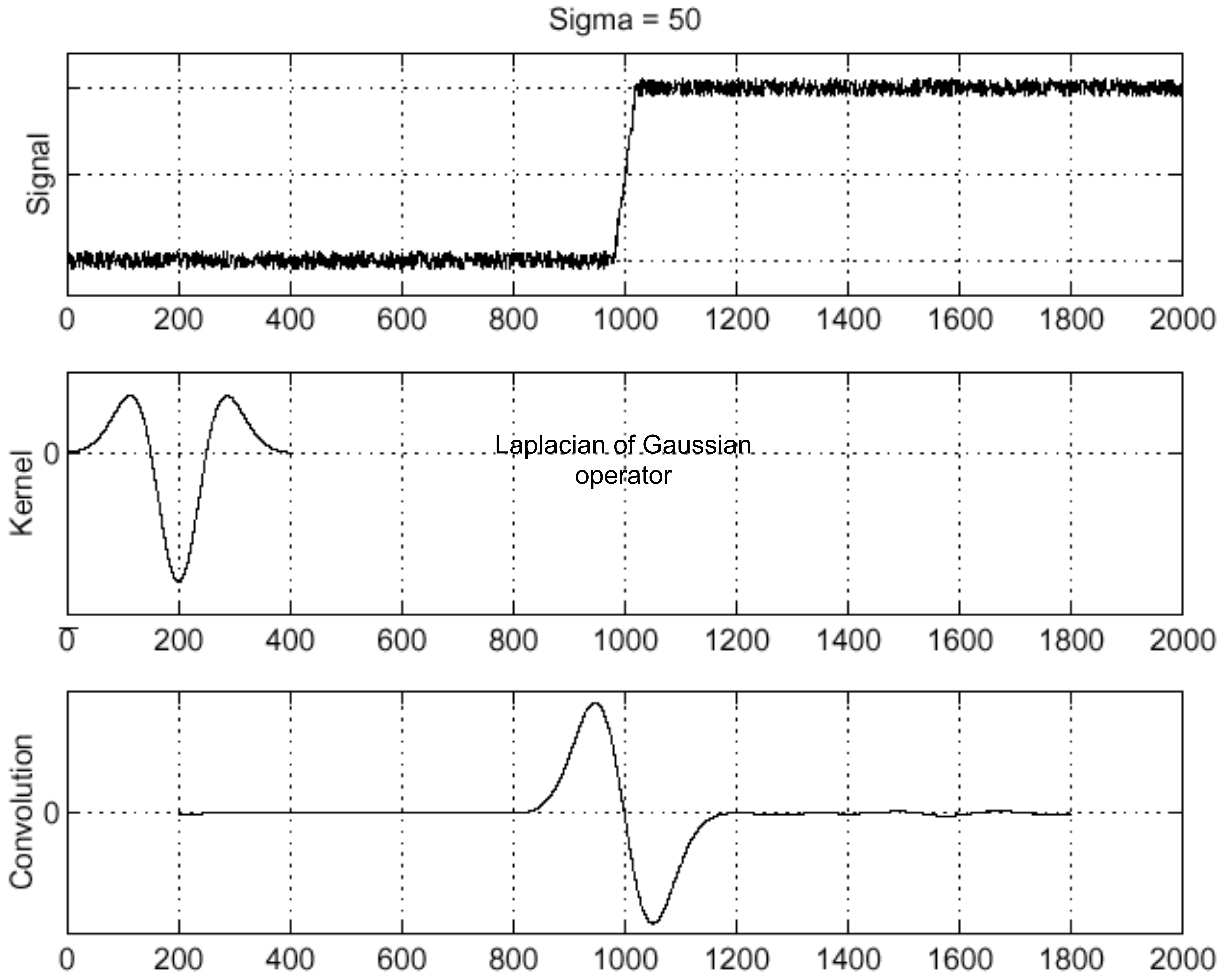
1D **Example**: Continued

Lets consider a row of pixels in an image:

$$I(X, 245)$$

$$\nabla^2 G$$

$$\nabla^2 G \otimes I(X, Y)$$



Where is the edge?

Zero-crossings of bottom graph

Marr / Hildreth **Laplacian of Gaussian**

5 x 5 LoG filter

0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0

17 x 17 LoG filter

0	0	0	0	0	0	-1	-1	**-1**	-1	-1	0	0	0	0	0
0	0	0	0	-1	-1	-1	-1	**-1**	-1	-1	-1	-1	0	0	0
0	0	-1	-1	-1	-2	-3	-3	**-3**	-3	-3	-2	-1	-1	-1	0
0	0	-1	-1	-2	-3	-3	-3	**-3**	-3	-3	-3	-2	-1	-1	0
0	-1	-1	-2	-3	-3	-3	-2	**-3**	-2	-3	-3	-3	-2	-1	-1
0	-1	-2	-3	-3	-3	0	2	**4**	2	0	-3	-3	-3	-2	-1
-1	-1	-3	-3	-3	0	4	10	**12**	10	4	0	-3	-3	-3	-1
-1	-1	-3	-3	-2	2	10	18	**21**	18	10	2	-2	-3	-3	-1
-1	**-1**	**-3**	**-3**	**-3**	**4**	**12**	**21**	**24**	**21**	**12**	**4**	**-3**	**-3**	**-3**	**-1**
-1	-1	-3	-3	-2	2	10	18	**21**	18	10	2	-2	-3	-3	-1
-1	-1	-3	-3	-3	0	4	10	**12**	10	4	0	-3	-3	-3	-1
0	-1	-2	-3	-3	-3	0	2	**4**	2	0	-3	-3	-3	-2	-1
0	-1	-1	-2	-3	-3	-3	-2	**-3**	-2	-3	-3	-3	-2	-1	-1
0	-1	-1	-2	-3	-3	-3	-2	**-3**	-2	-3	-3	-3	-2	-1	-1
0	0	-1	-1	-1	-2	-3	-3	**-3**	-3	-3	-2	-1	-1	-1	0
0	0	0	0	-1	-1	-1	-1	**-1**	-1	-1	-1	-1	0	0	0

Scale (σ)

Image From: A. Campilho

Marr / Hildreth **Laplacian of Gaussian**

Image From: A. Campilho

Assignment 1: High Frequency Image

original

-

smoothed
(5x5 Gaussian)

=

original - smoothed
(scaled by 4, offset +128)

Assignment 1: High Frequency Image

original

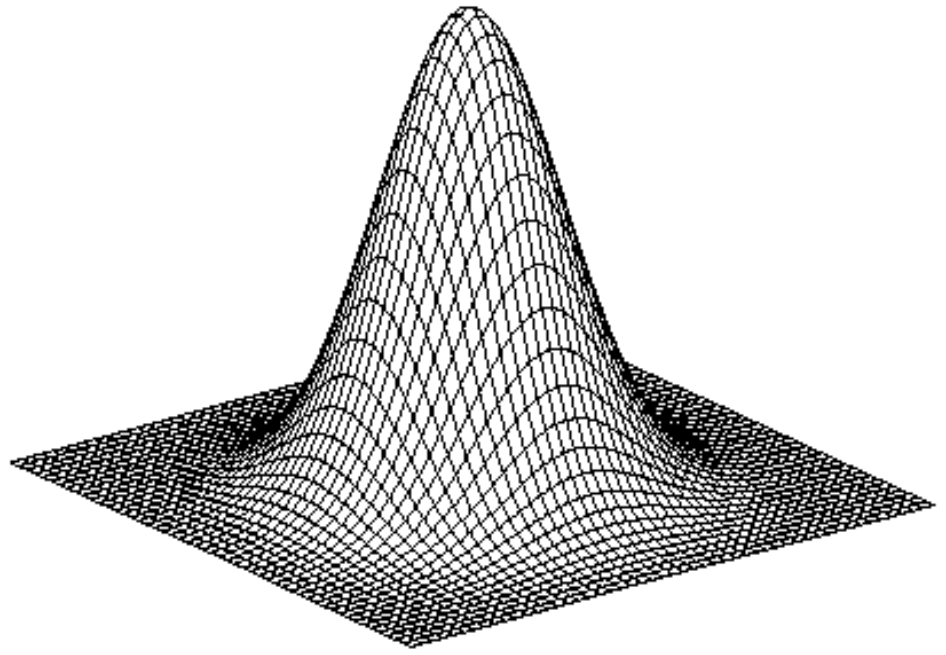
-

smoothed
(5x5 Gaussian)

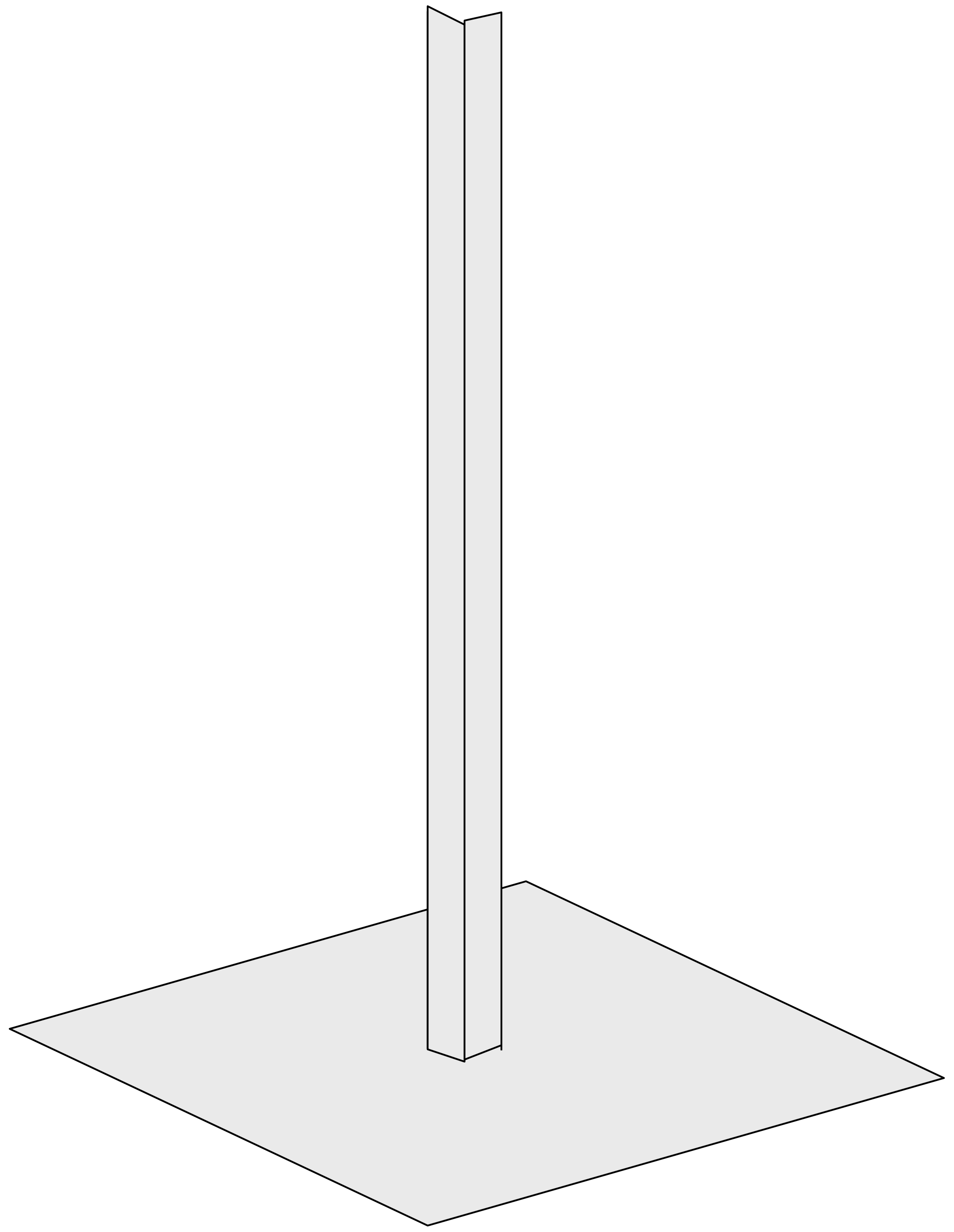
=

smoothed - original
(scaled by 4, offset +128)

Assignment 1: High Frequency Image

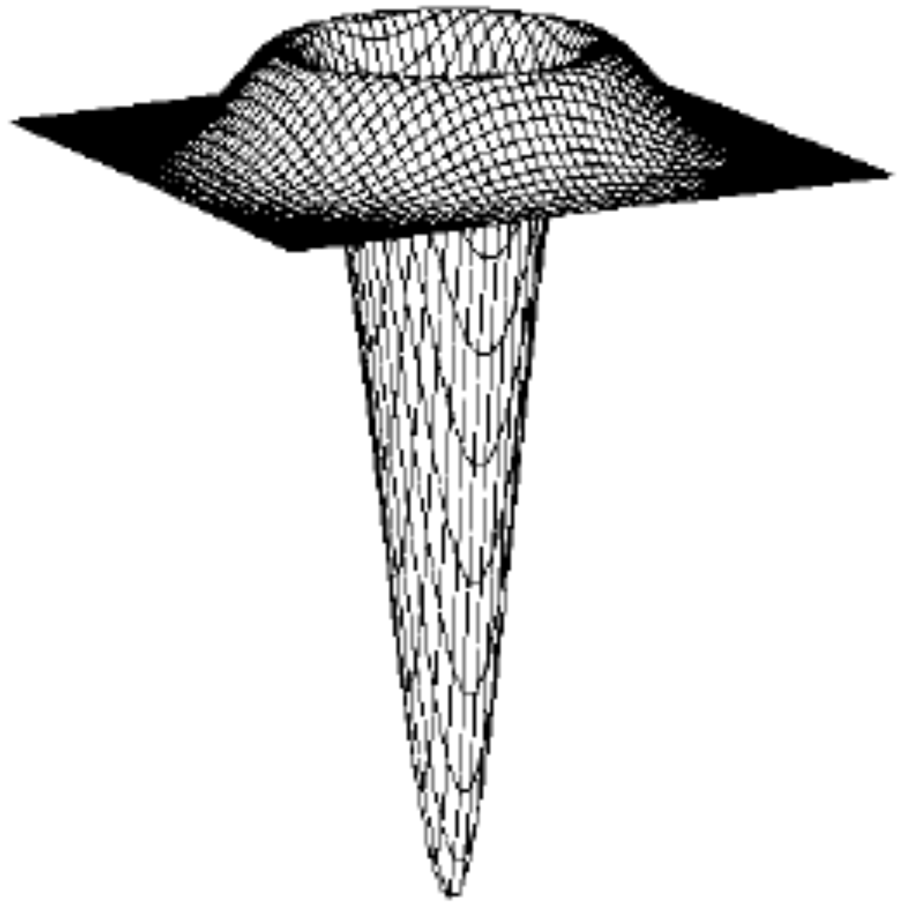


Gaussian

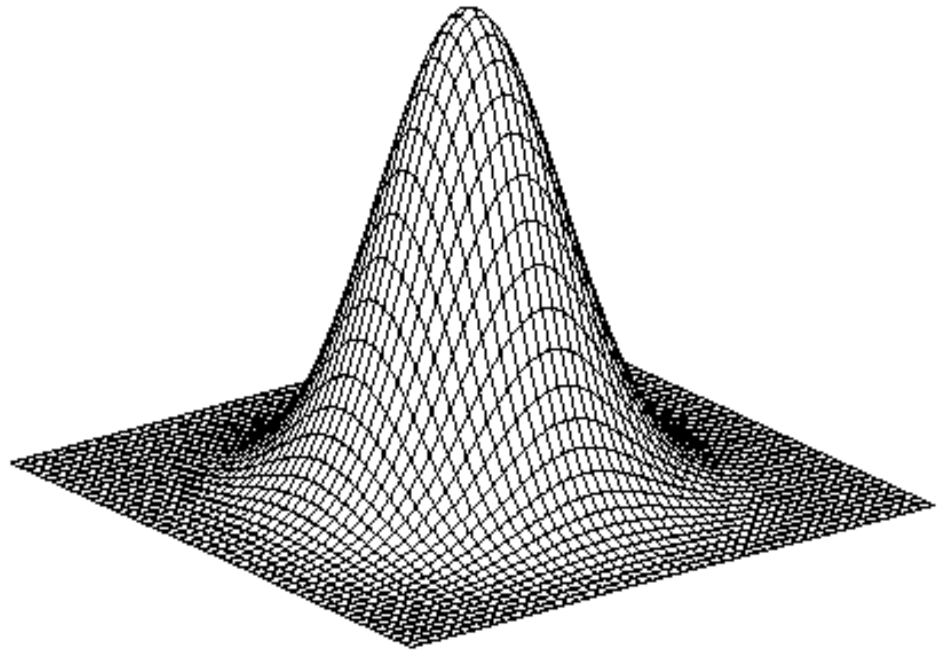


delta function

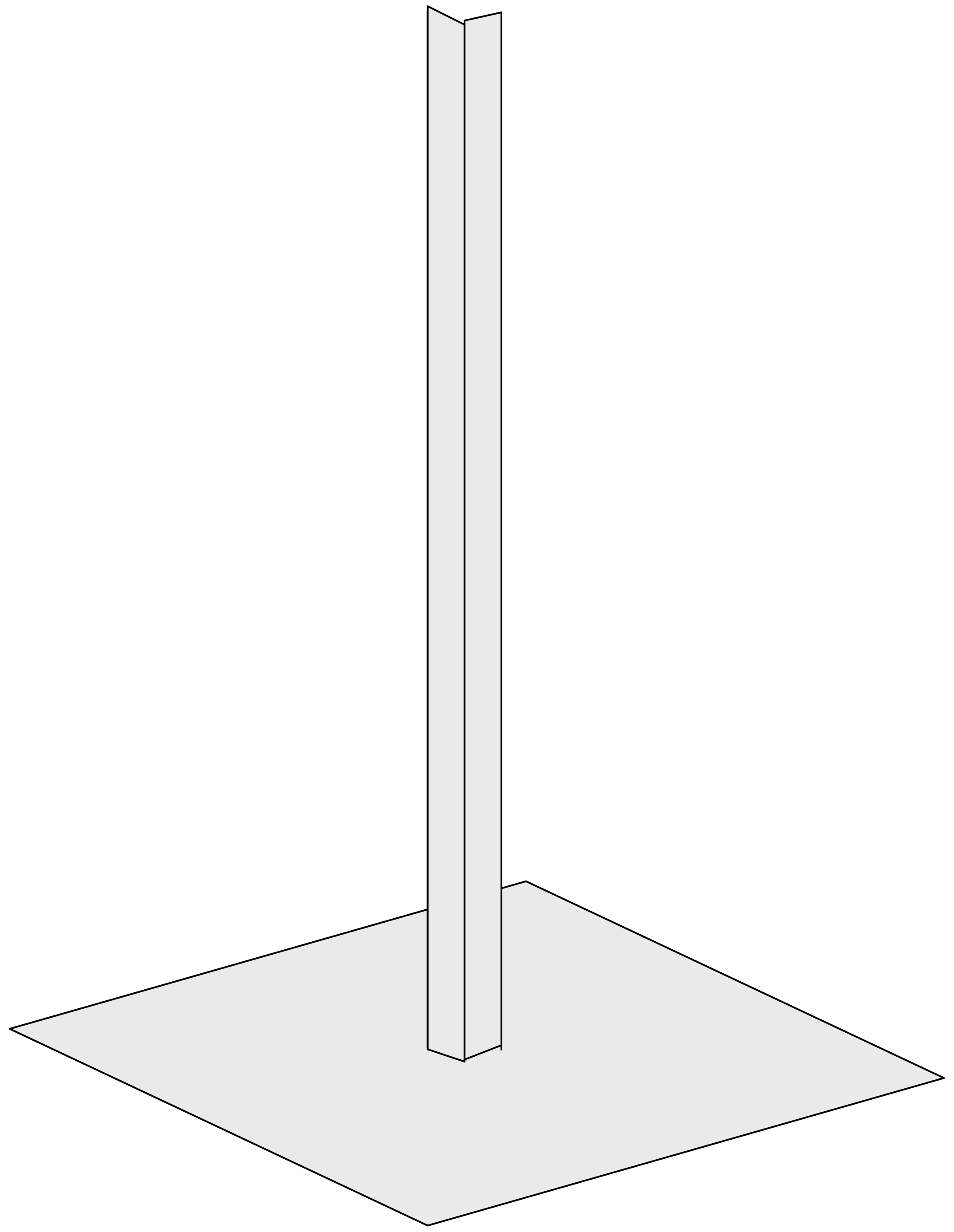
Laplacian of Gaussian



Assignment 1: High Frequency Image

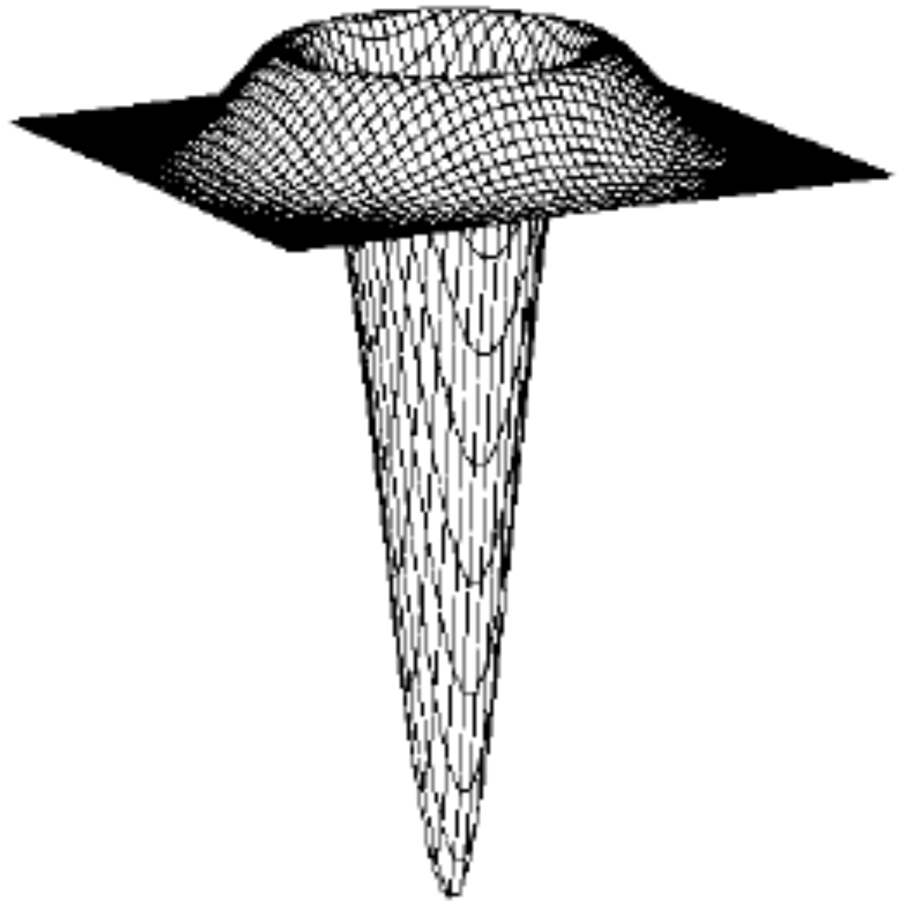


Gaussian



delta function

Laplacian of Gaussian



Comparing **Edge** Detectors

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Good detection: minimize probability of false positives/negatives (spurious/missing) edges

Good localization: found edges should be as close to true image edge as possible

Single response: minimize the number of edge pixels around a single edge

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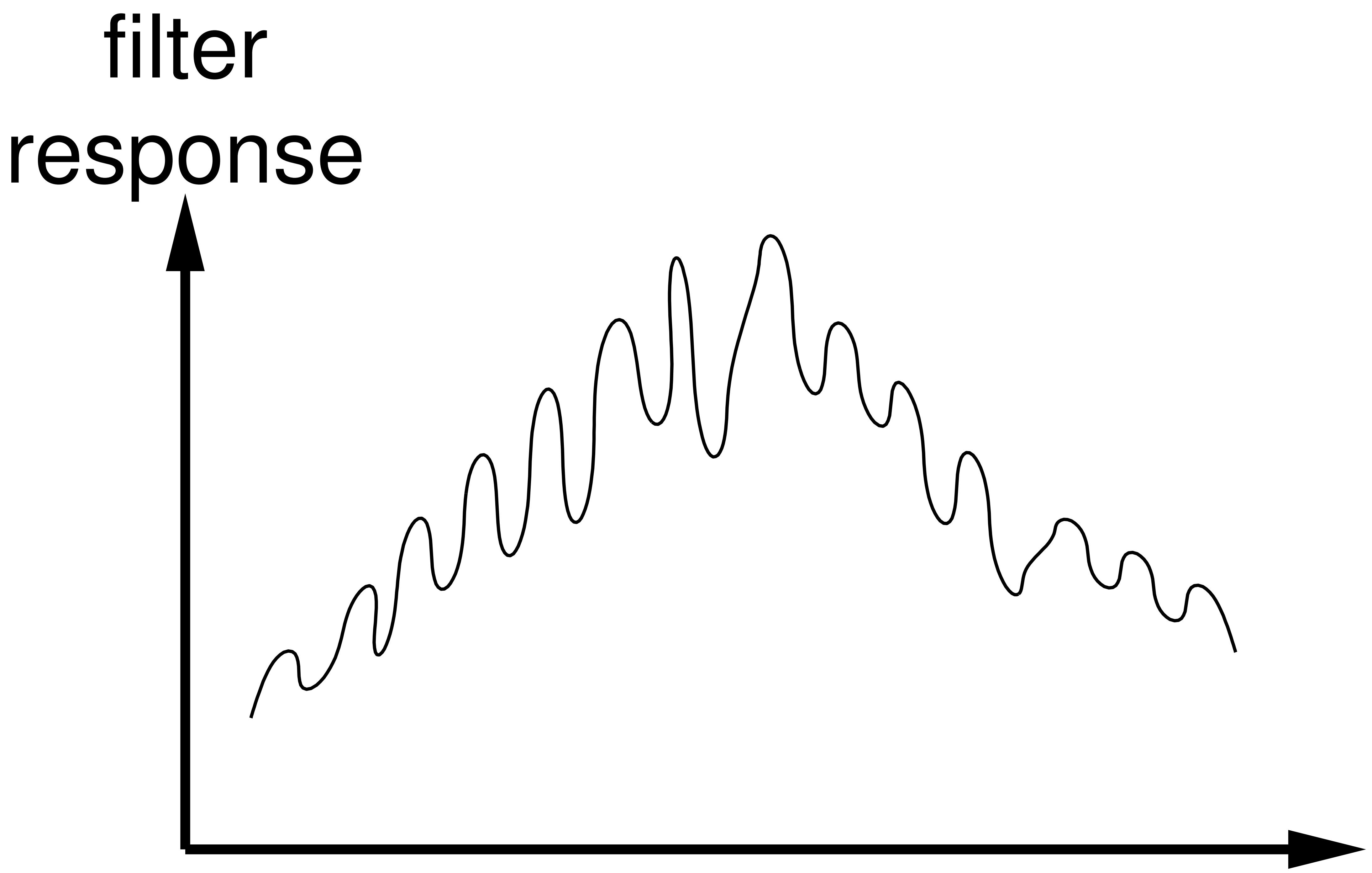
	Approach	Detection	Localization	Single Resp	Limitations
Sobel	Gradient Magnitude Threshold	Good	Poor	Poor	Results in Thick Edges
Marr / Hildreth	Zero-crossings of 2nd Derivative (LoG)	Good	Good	Good	Smooths Corners
Canny	Local extrema of 1st Derivative	Best	Good	Good	

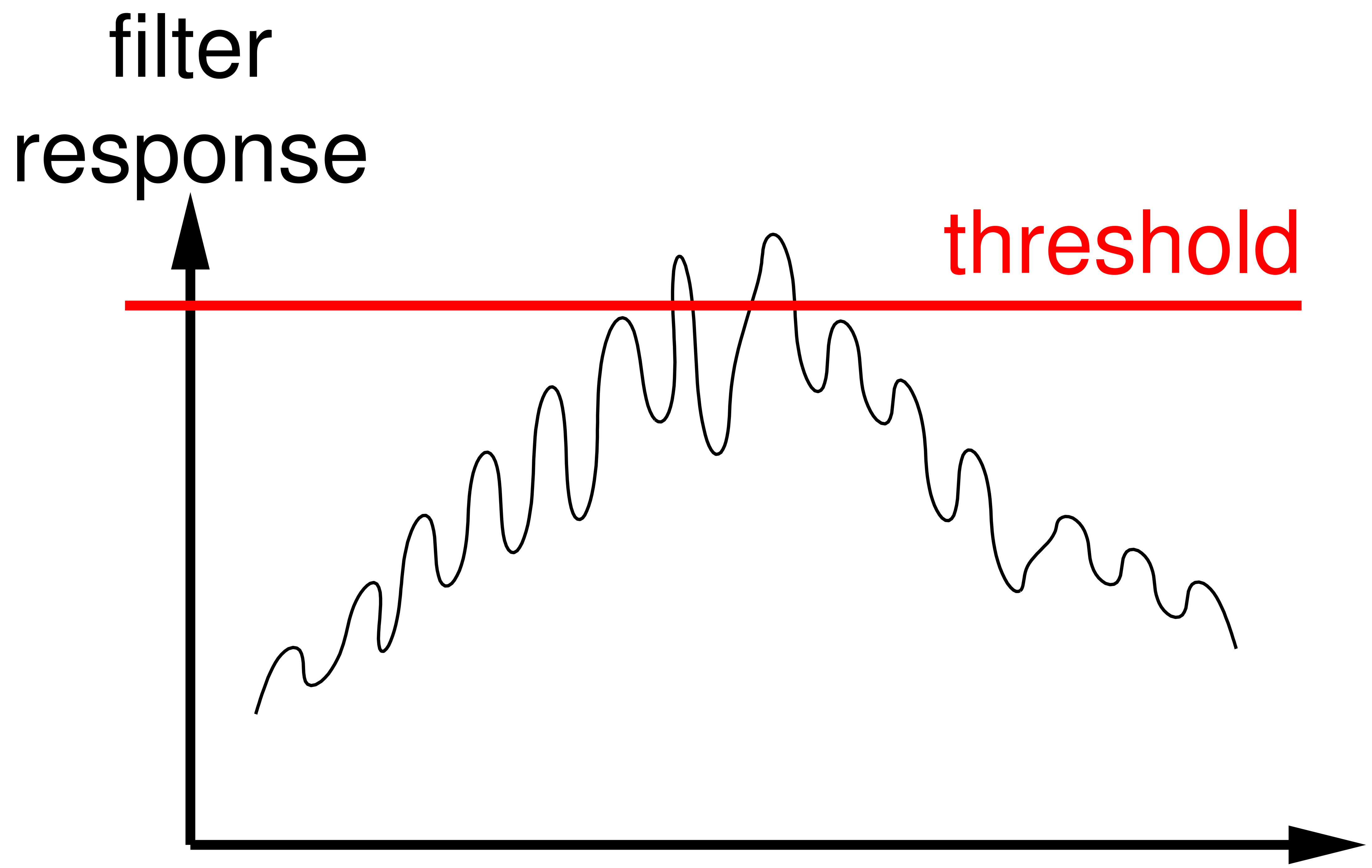
Example: Edge Detection



Question: How many edges are there?

Question: What is the position of each edge?

Example: Edge Detection



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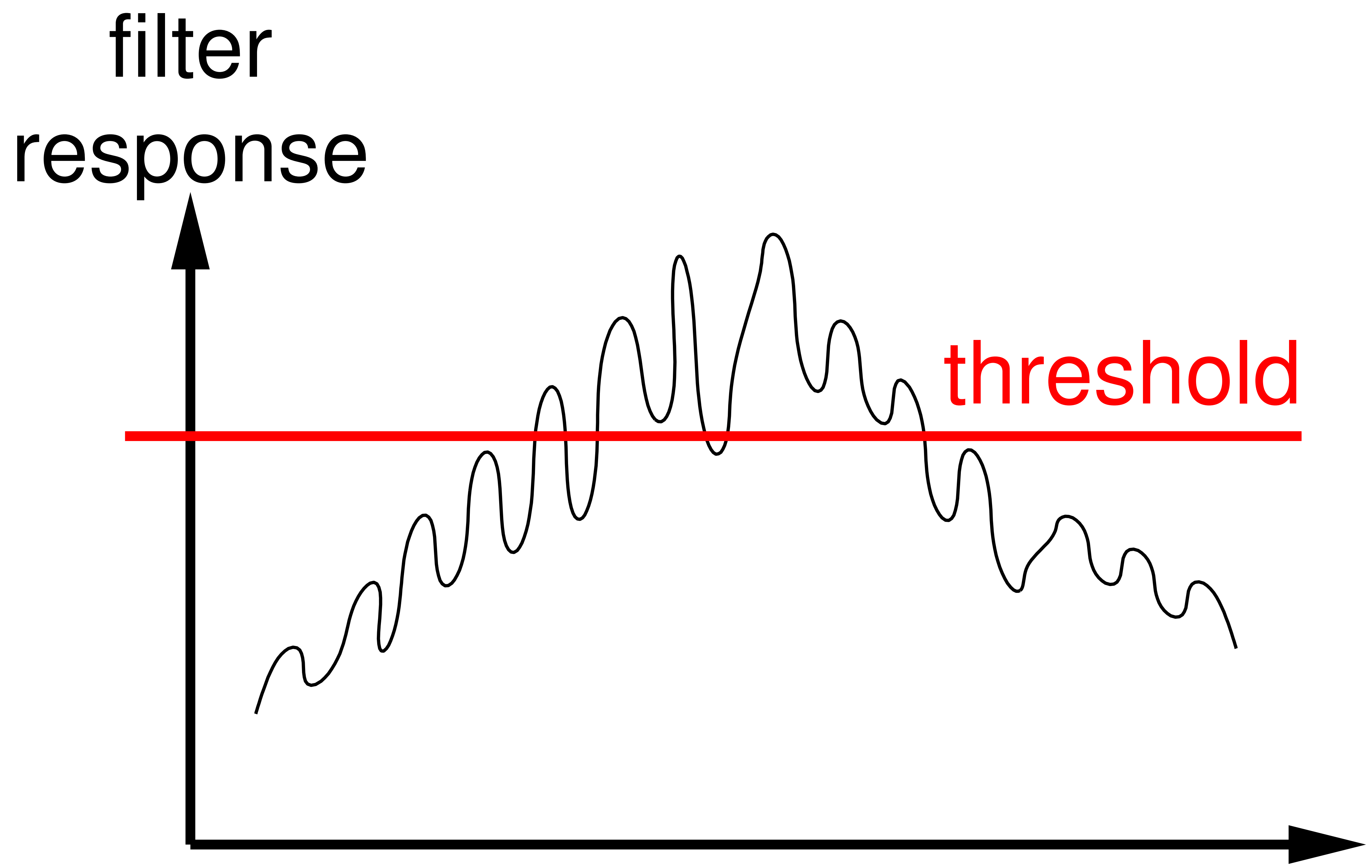
Example: Edge Detection



Question: How many edges are there?

Question: What is the position of each edge?

Canny Edge Detector

Steps:

1. Apply **directional derivatives** of Gaussian

2. Compute **gradient magnitude** and **gradient direction**

3. **Non-maximum** suppression
   — thin multi-pixel wide “ridges” down to single pixel width

4. **Linking** and thresholding
   — Low, high edge-strength thresholds
   — Accept all edges over low threshold that are connected to edge over high threshold

Non-maxima Suppression

Idea: suppress near-by similar detections to obtain one "true" result

Non-maxima Suppression

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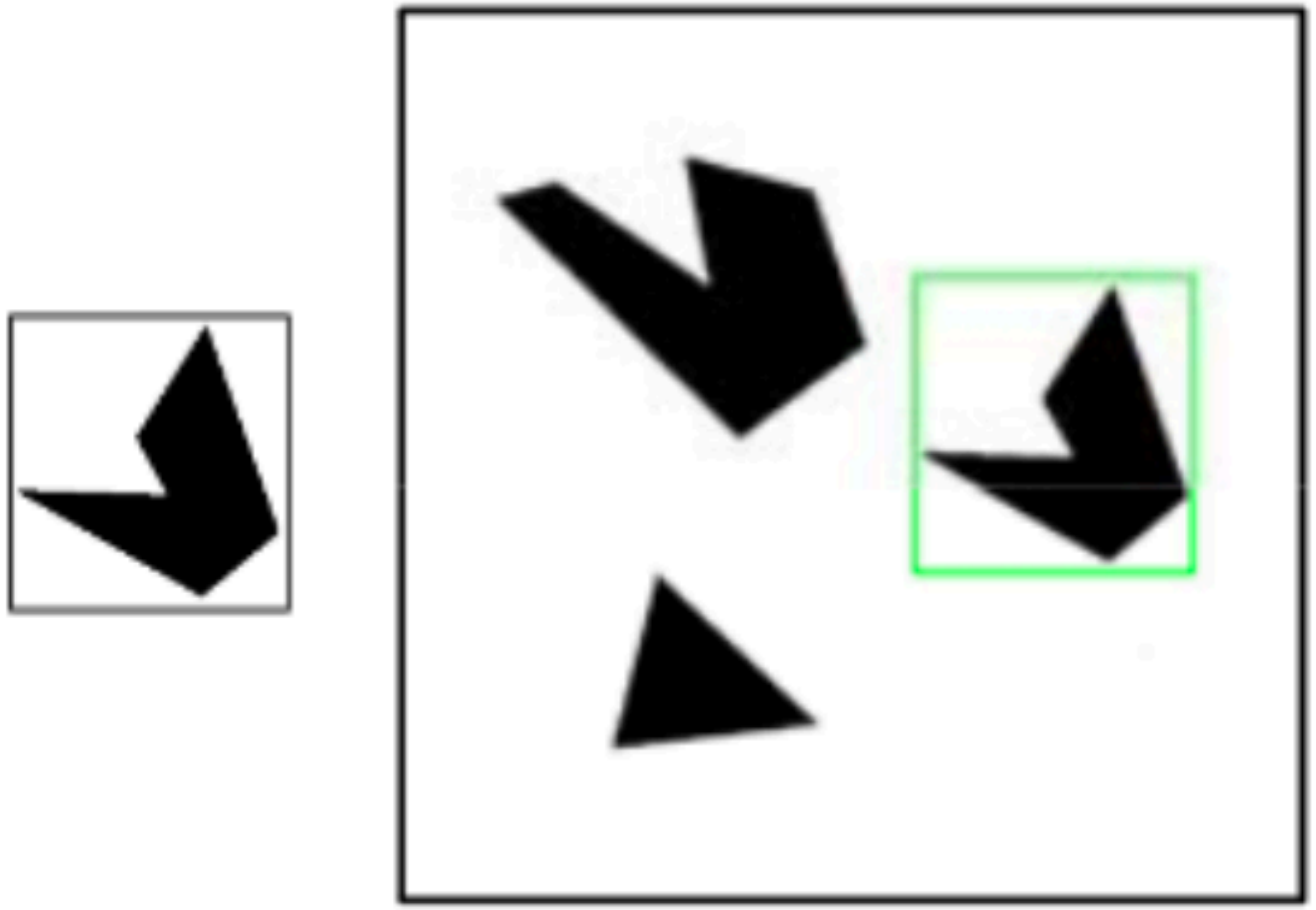
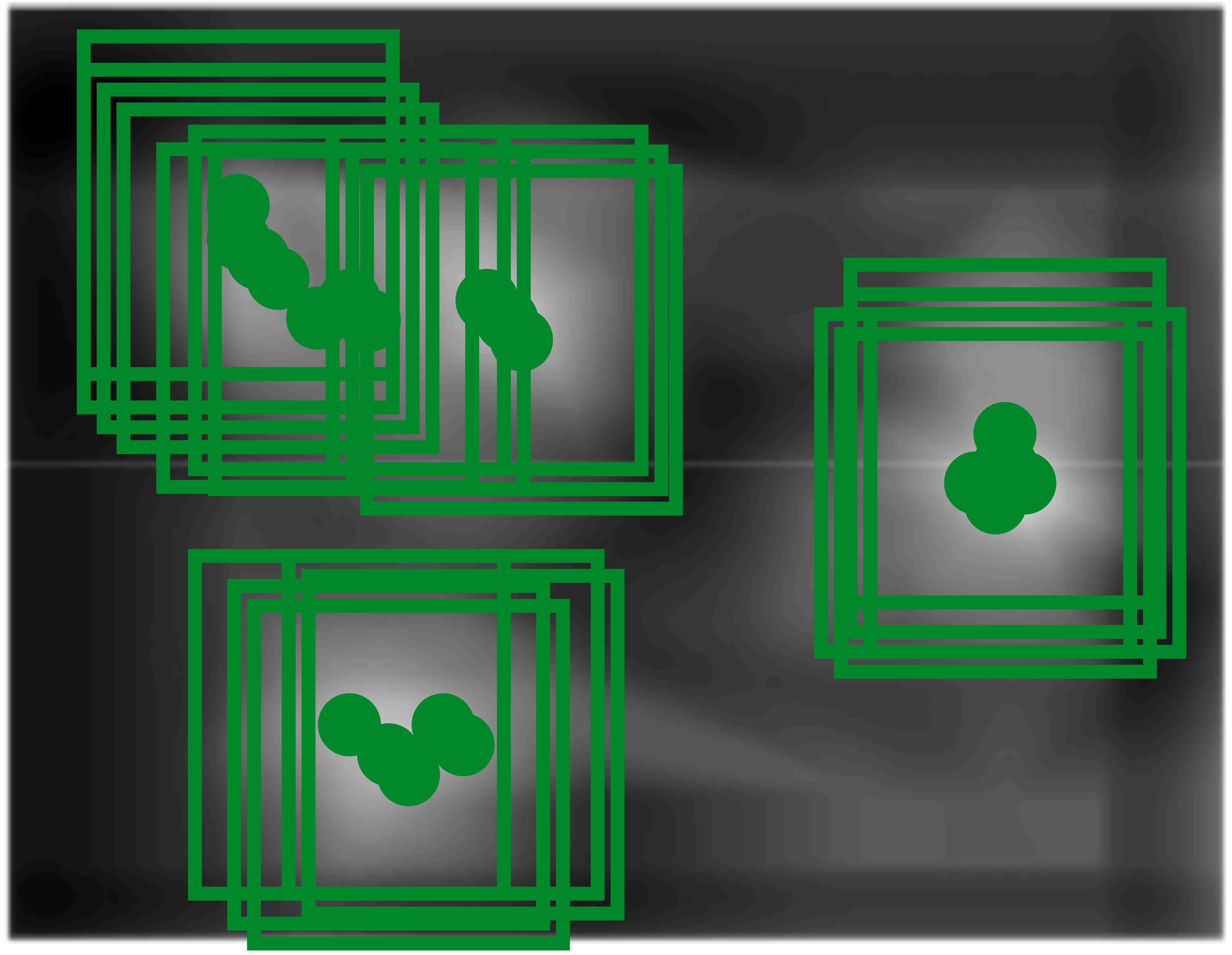


Detected template

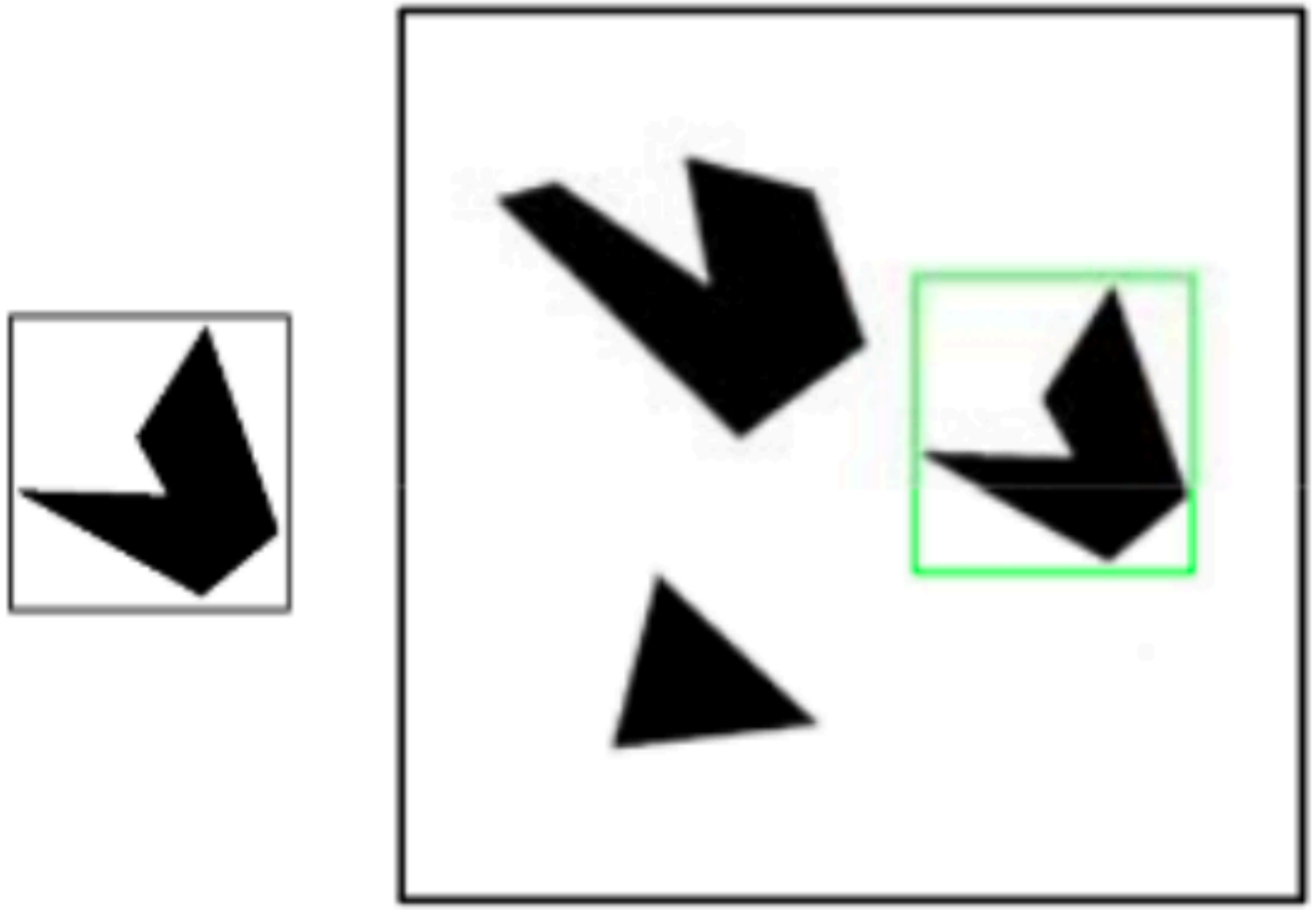


Correlation map

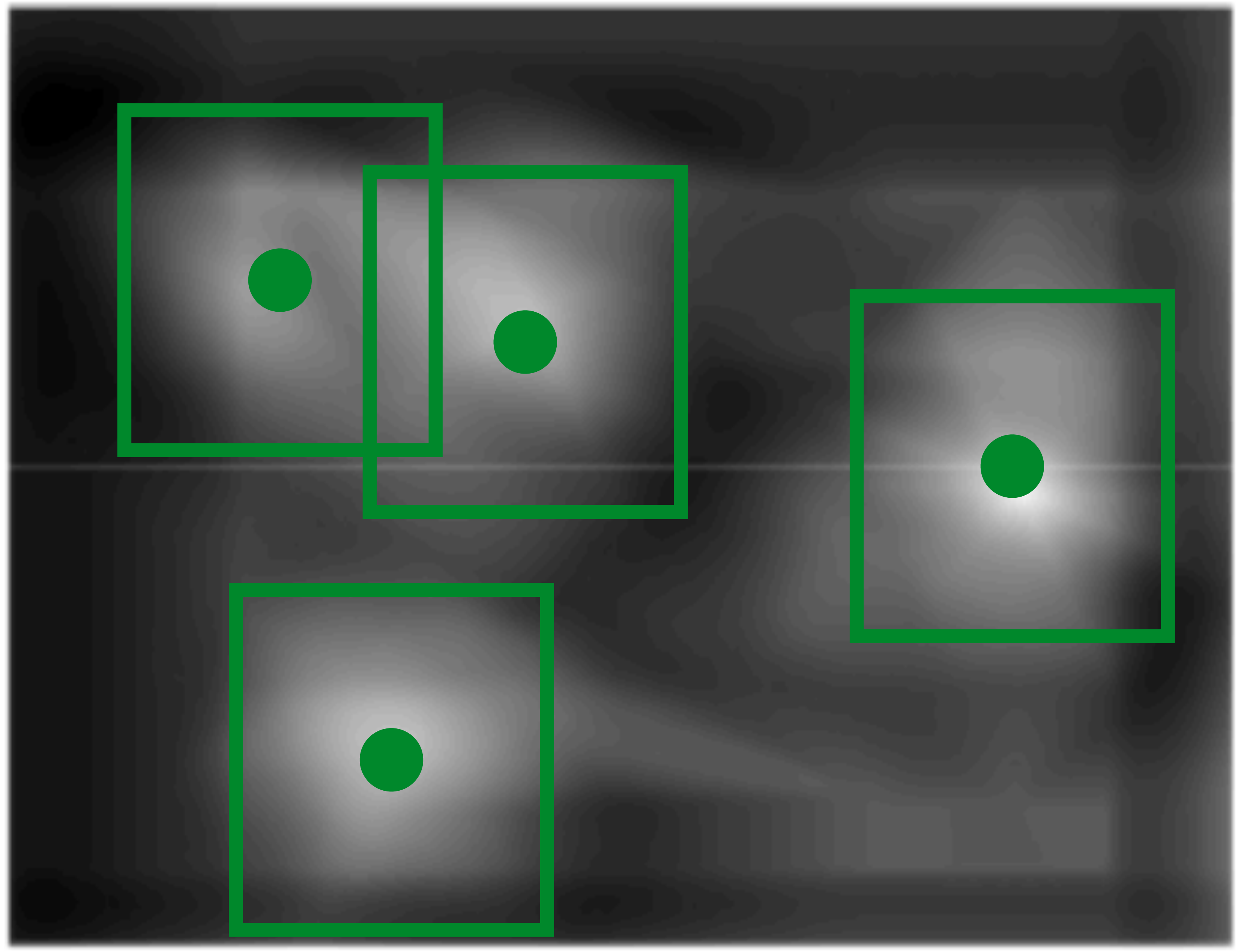
Slide Credit: Kristen Grauman

Non-maxima Suppression

Idea: suppress near-by similar detections to obtain one “true” result



Detected template



Correlation map

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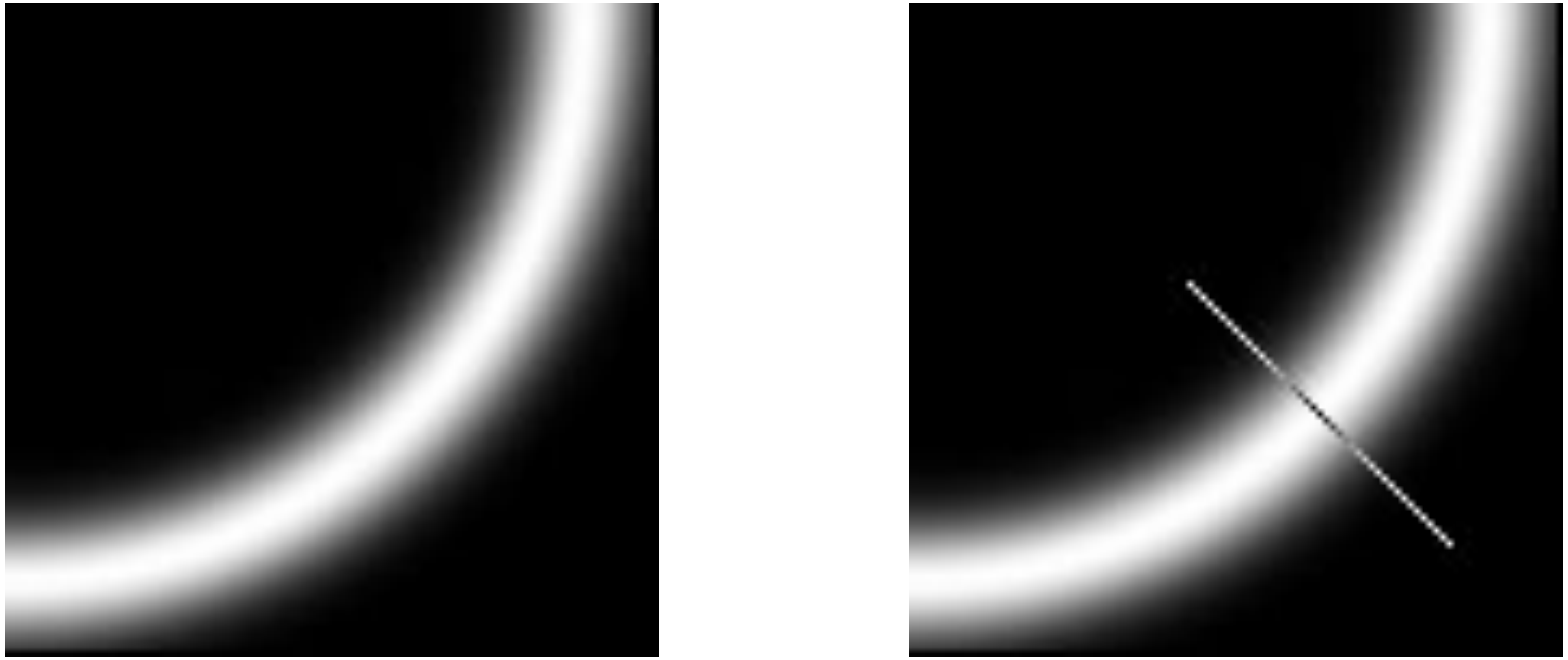
Non-maxima Suppression

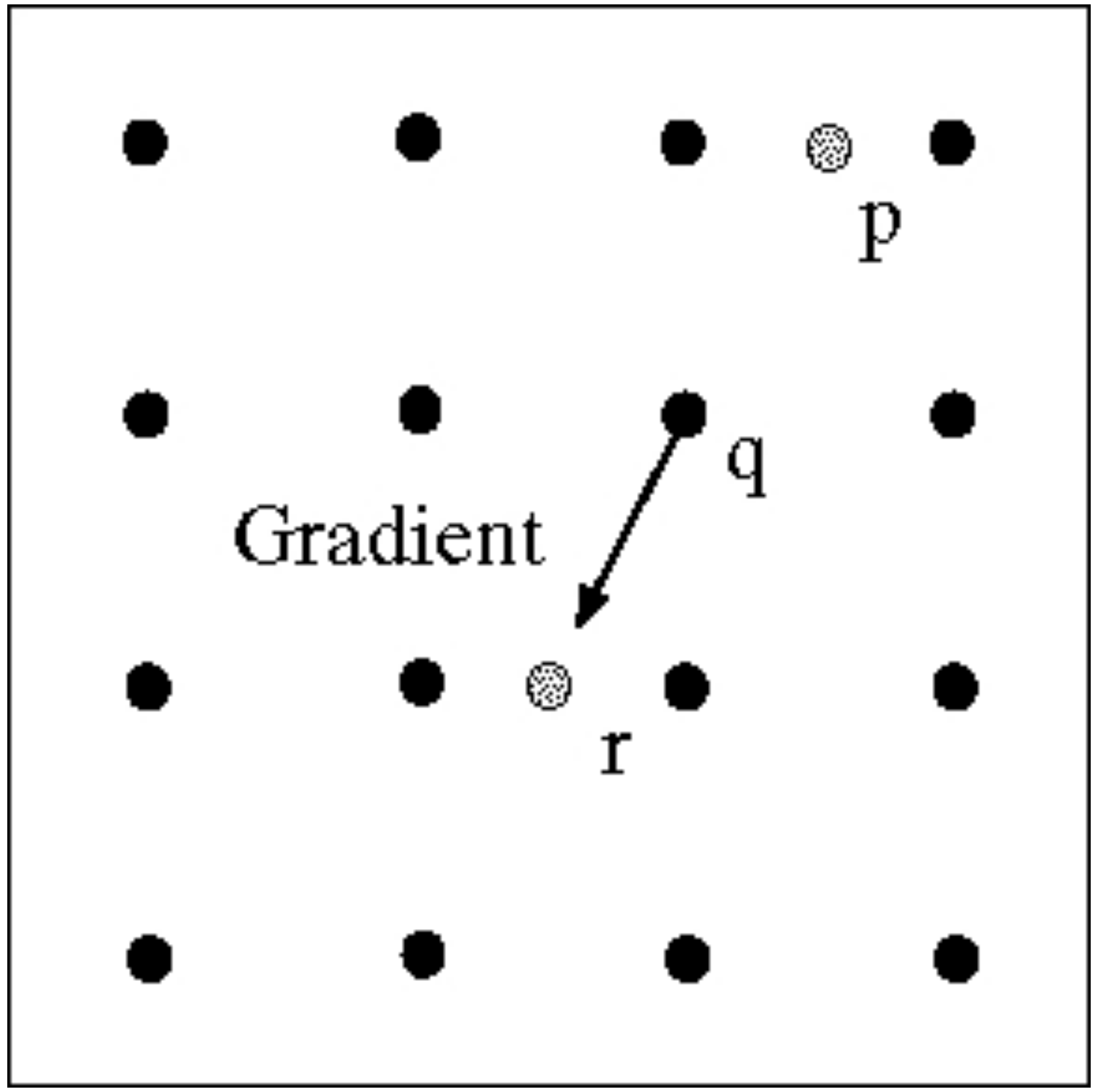


Forsyth & Ponce (1st ed.) Figure 8.11

Select the image **maximum point** across the width of the edge

Non-maxima Suppression

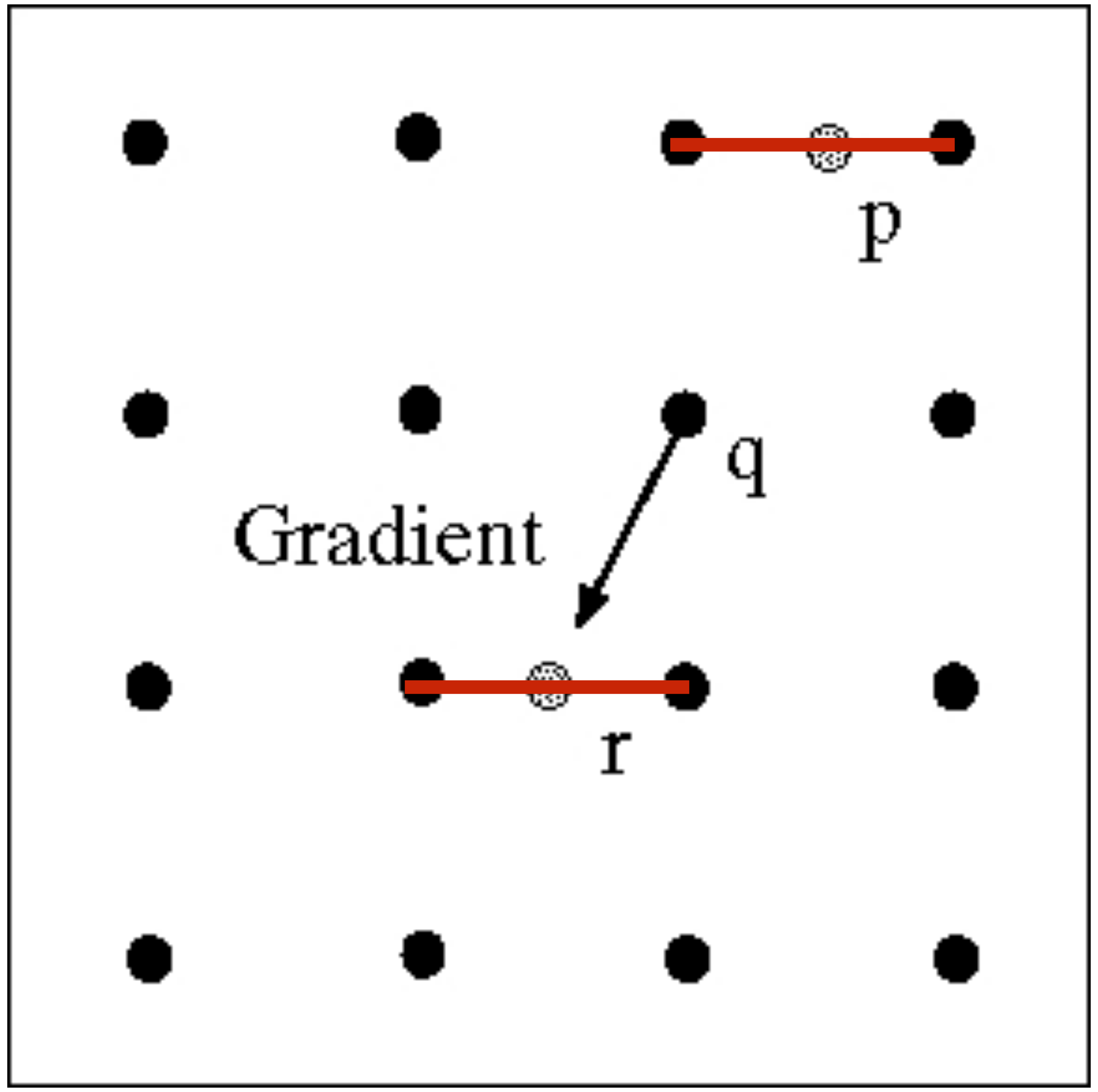
Value at *q* must be larger than interpolated values at *p* and *r*



Forsyth & Ponce (2nd ed.) Figure 5.5 left

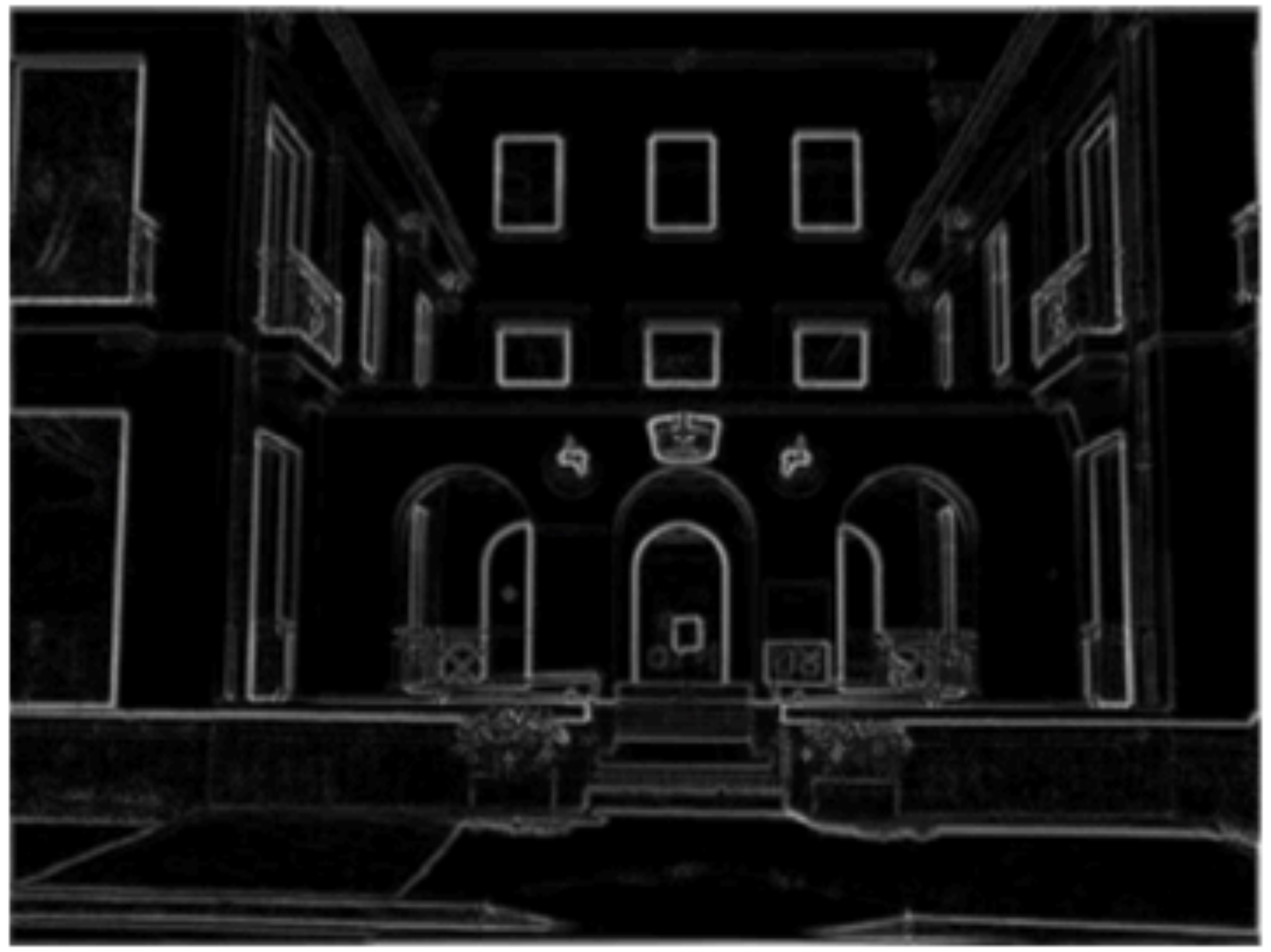
Non-maxima Suppression

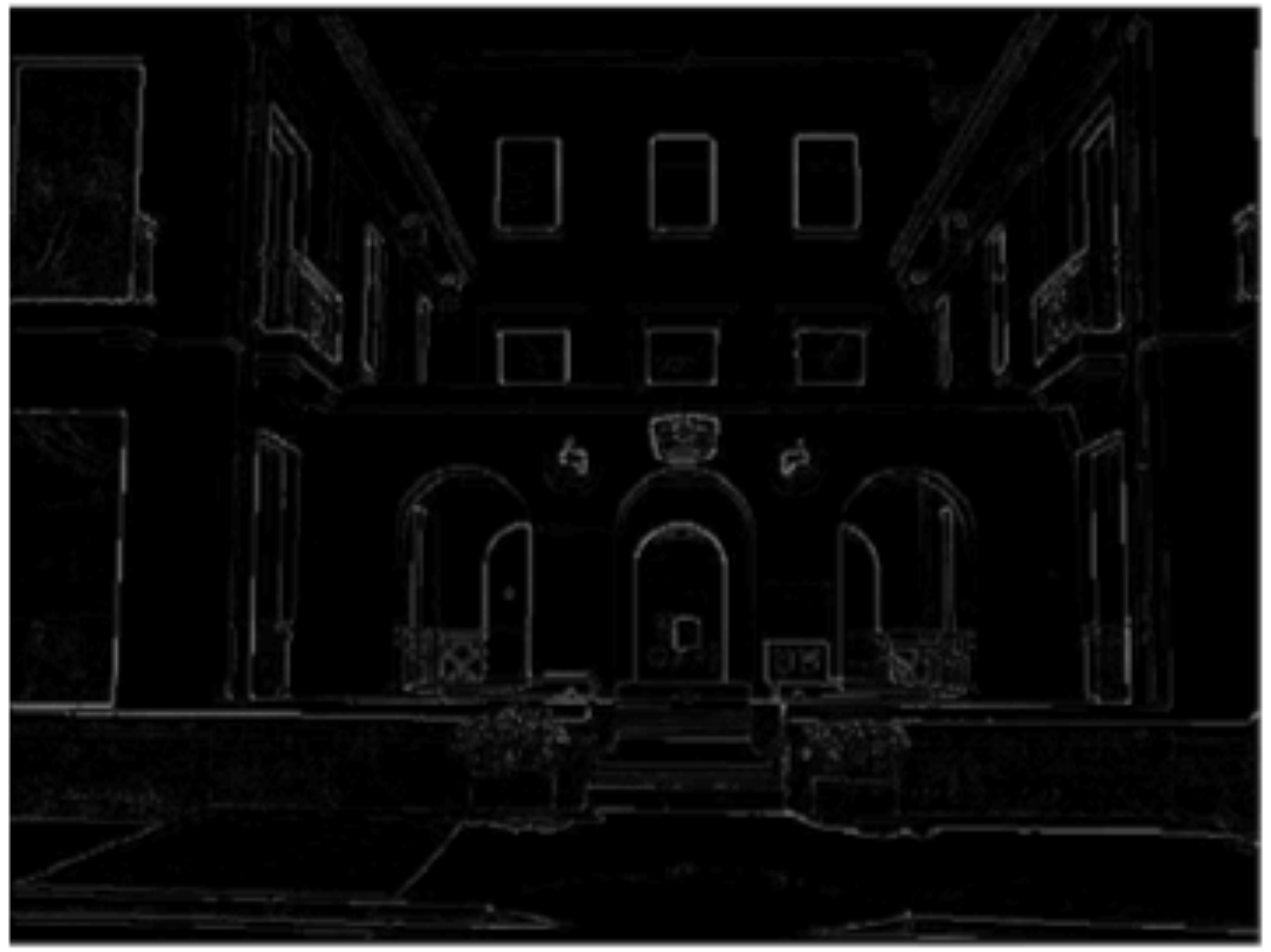
Value at *q* must be larger than interpolated values at *p* and *r*



Forsyth & Ponce (2nd ed.) Figure 5.5 left

Example: Non-maxima Suppression





courtesy of G. Loy

Original Image

Gradient Magnitude

Non-maxima Suppression

Slide Credit: Christopher Rasmussen

Example

Forsyth & Ponce (1st ed.) Figure 8.13 top

Example

Forsyth & Ponce (1st ed.) Figure 8.13 top

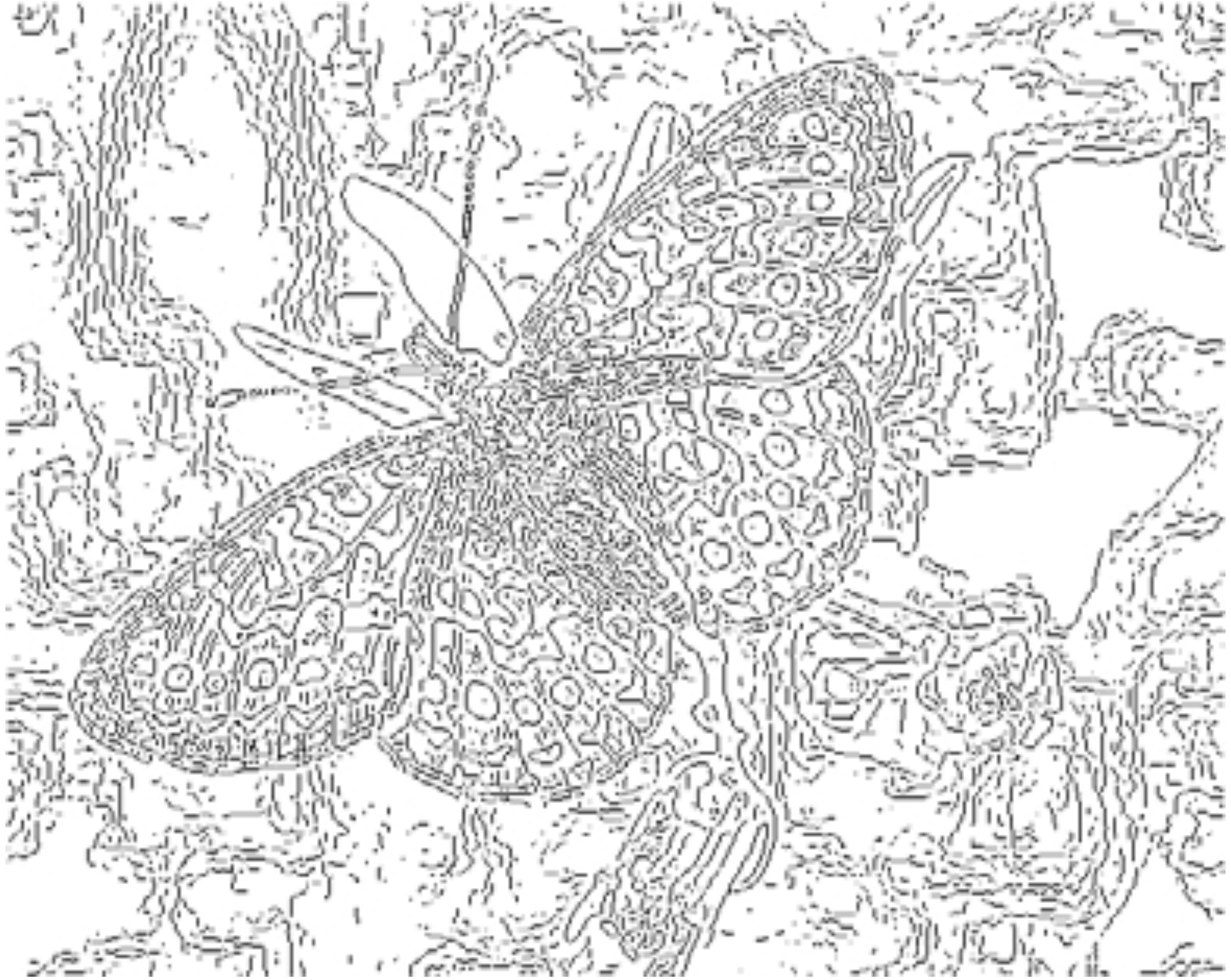


Figure 8.13 bottom left

Fine scale ($\sigma = 1$), high threshold

Example

Forsyth & Ponce (1st ed.) Figure 8.13 top

Figure 8.13 bottom middle

Fine scale ($\sigma = 4$), high threshold

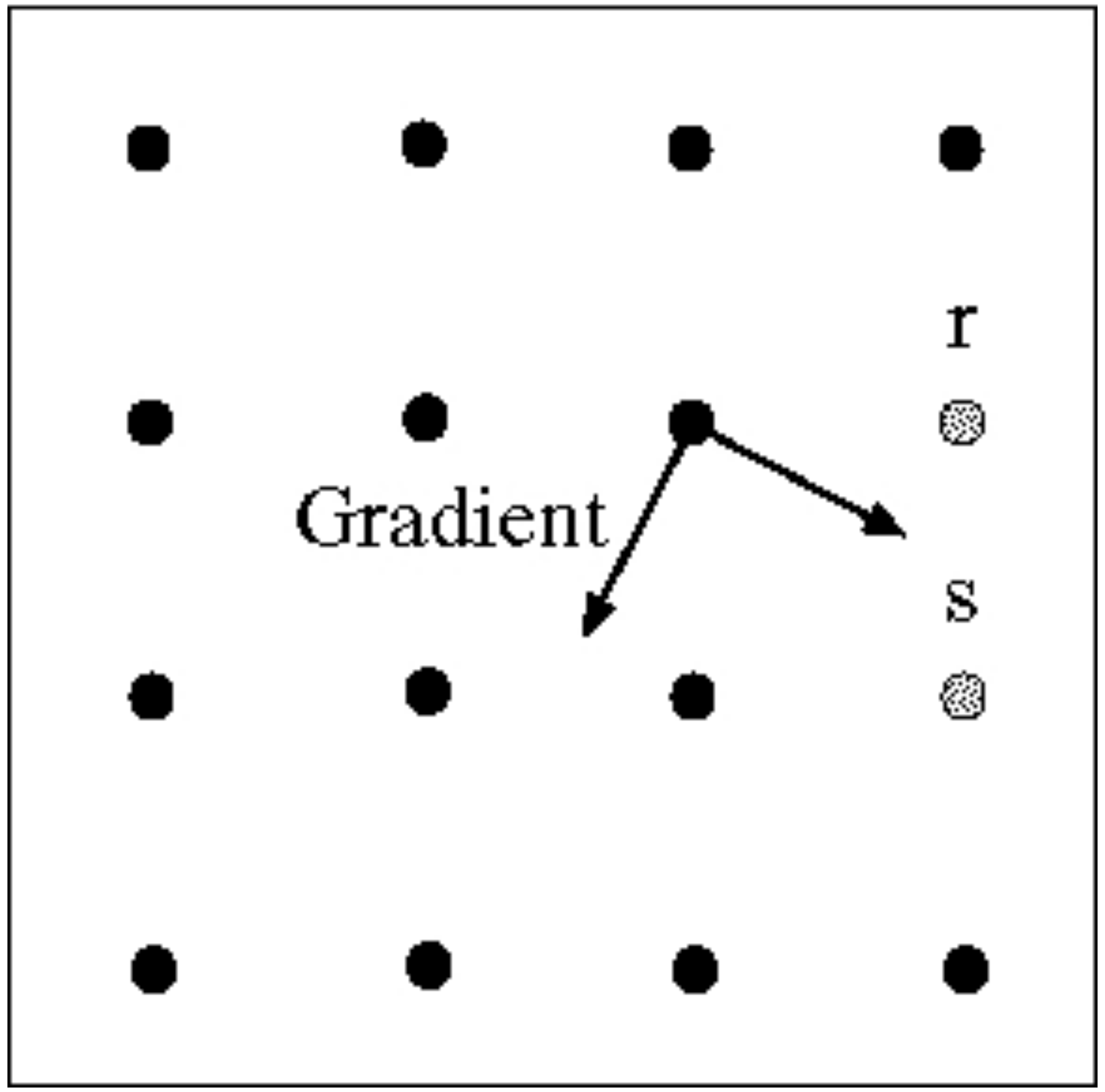
Example

Forsyth & Ponce (1st ed.) Figure 8.13 top

Figure 8.13 bottom right

Fine scale ($\sigma = 4$), low threshold

Linking Edge Points



Forsyth & Ponce (2nd ed.) Figure 5.5 right

Assume the marked point is an **edge point**. Take the normal to the gradient at that point and use this to predict continuation points (either *r* or *s*)

Edge **Hysteresis**

One way to deal with broken edge chains is to use hysteresis

Hysteresis: A lag or momentum factor

Idea: Maintain two thresholds $\mathbf{k}_{high}$ and $\mathbf{k}_{low}$

— Use khigh to find strong edges to start edge chain

— Use klow to find weak edges which continue edge chain

Typical ratio of thresholds is (roughly):

$$\frac{\mathbf{k}_{high}}{\mathbf{k}_{low}} = 2$$

Canny Edge Detector

Original Image

Strong + connected **Weak** Edges

Strong Edges

Weak Edges

courtesy of G. Loy