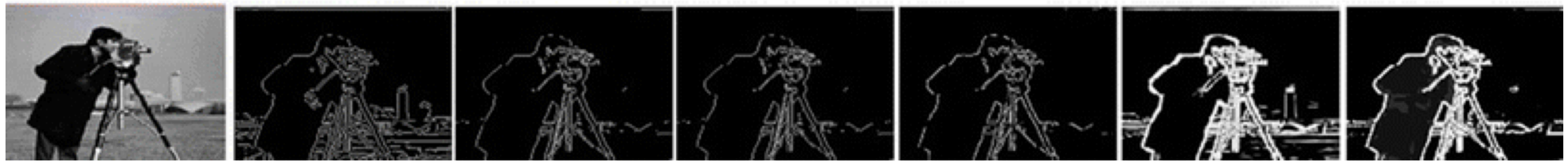
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 9: 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**
- **Quiz 2**

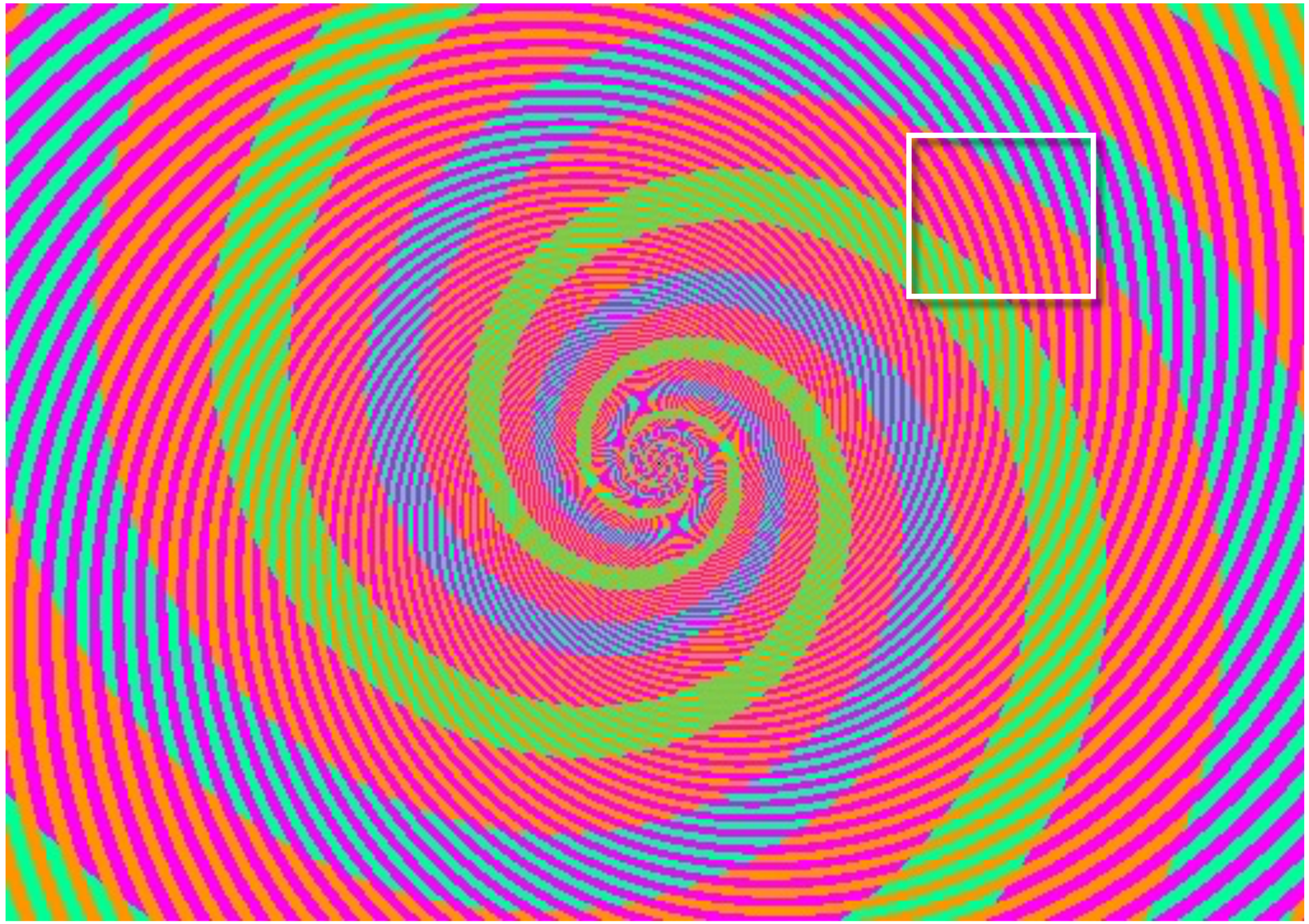
Readings:

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

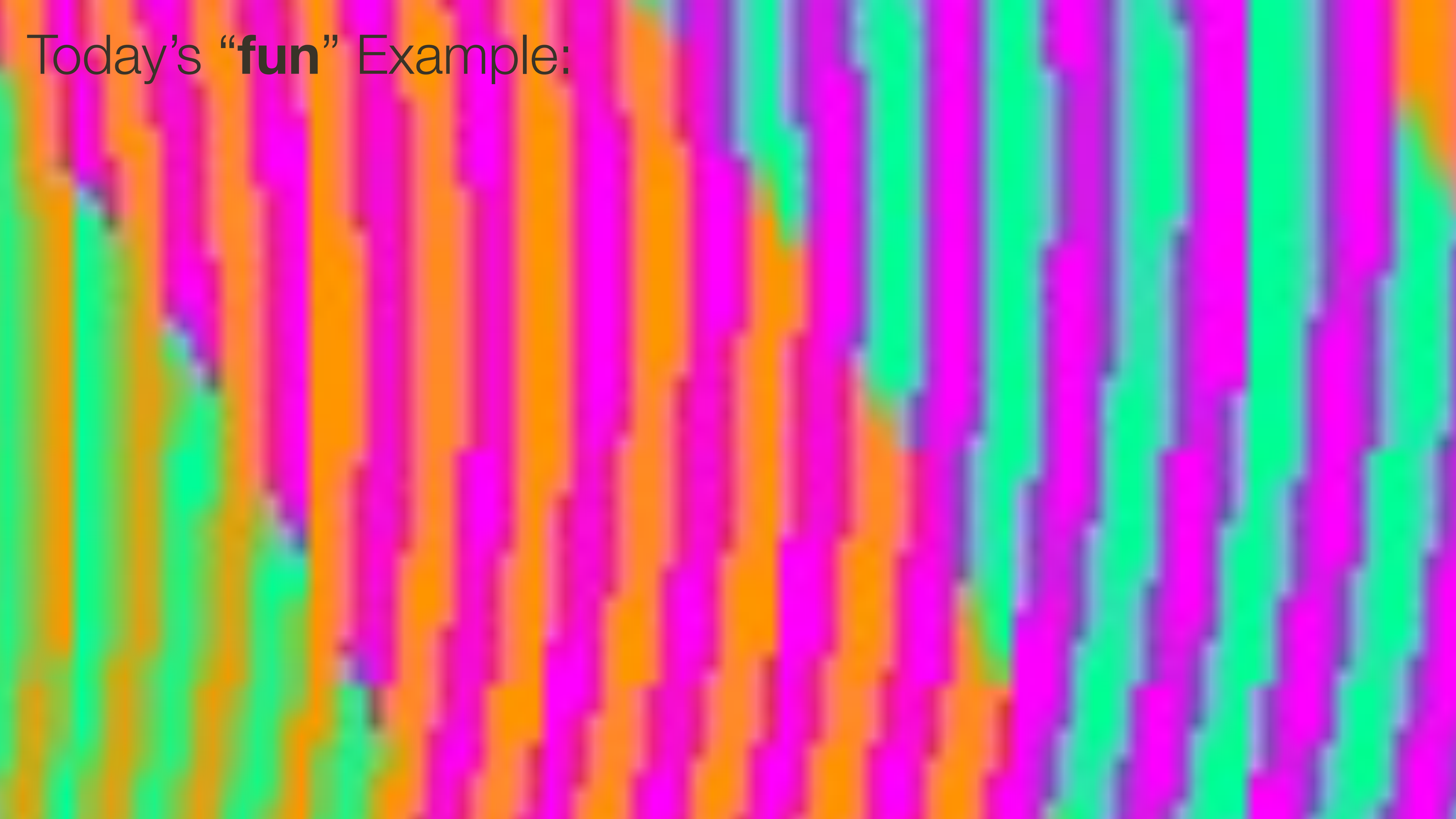
Reminders:

- **Assignment 2**: Scaled Representations, Face Detection and Image Blending (due **Oct 12** 23:59)

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



Today’s “**fun**” Example:



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

Edge Detection

- One of the first algorithms in Computer Vision

Edge Detection

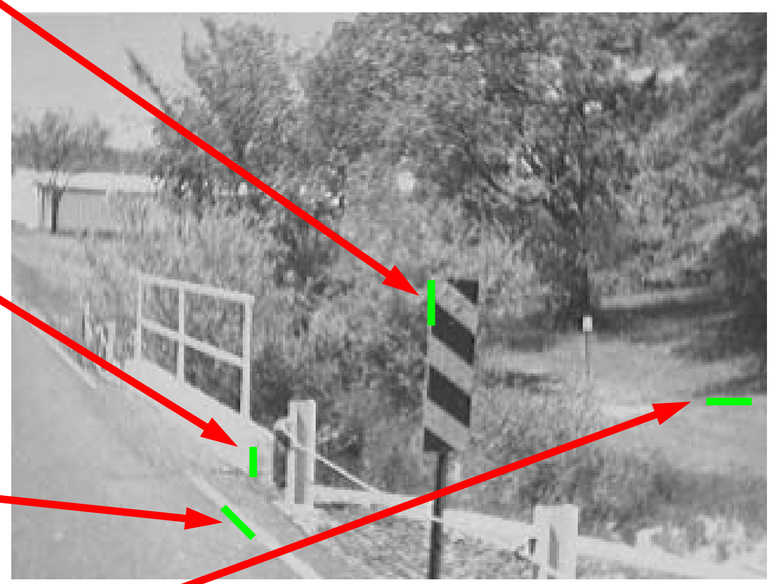
Goal: Identify sudden changes in image intensity

This is where most shape information is encoded

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

What Causes **Edges**?

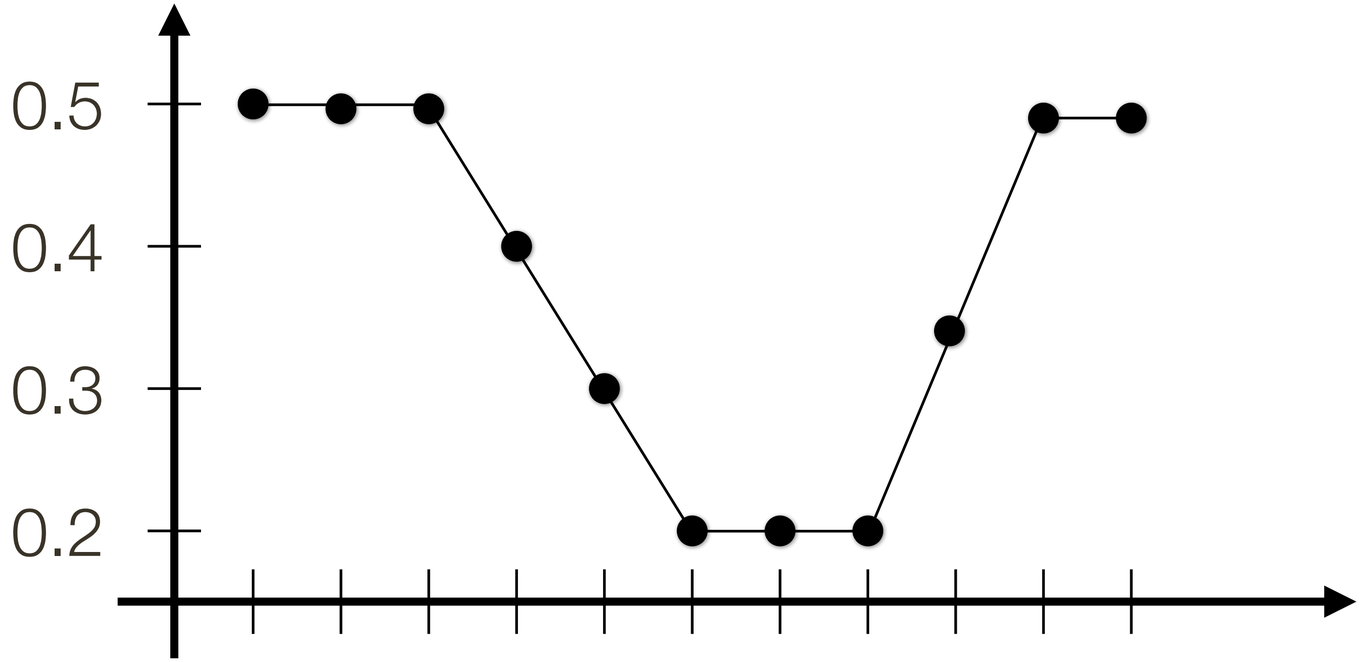
- Depth discontinuity
- Surface orientation discontinuity
- Reflectance discontinuity (i.e., change in surface material properties)
- Illumination discontinuity (e.g., shadow)



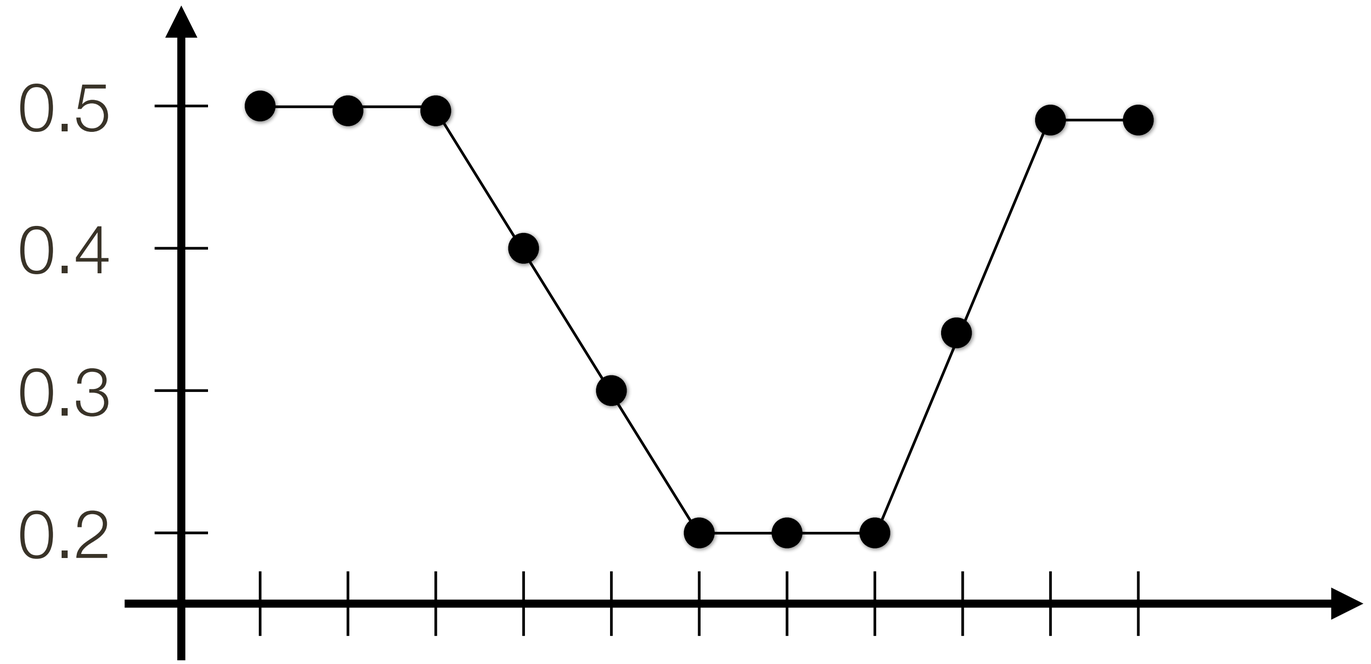
Slide Credit: Christopher Rasmussen

Derivative Definition

Example 1D

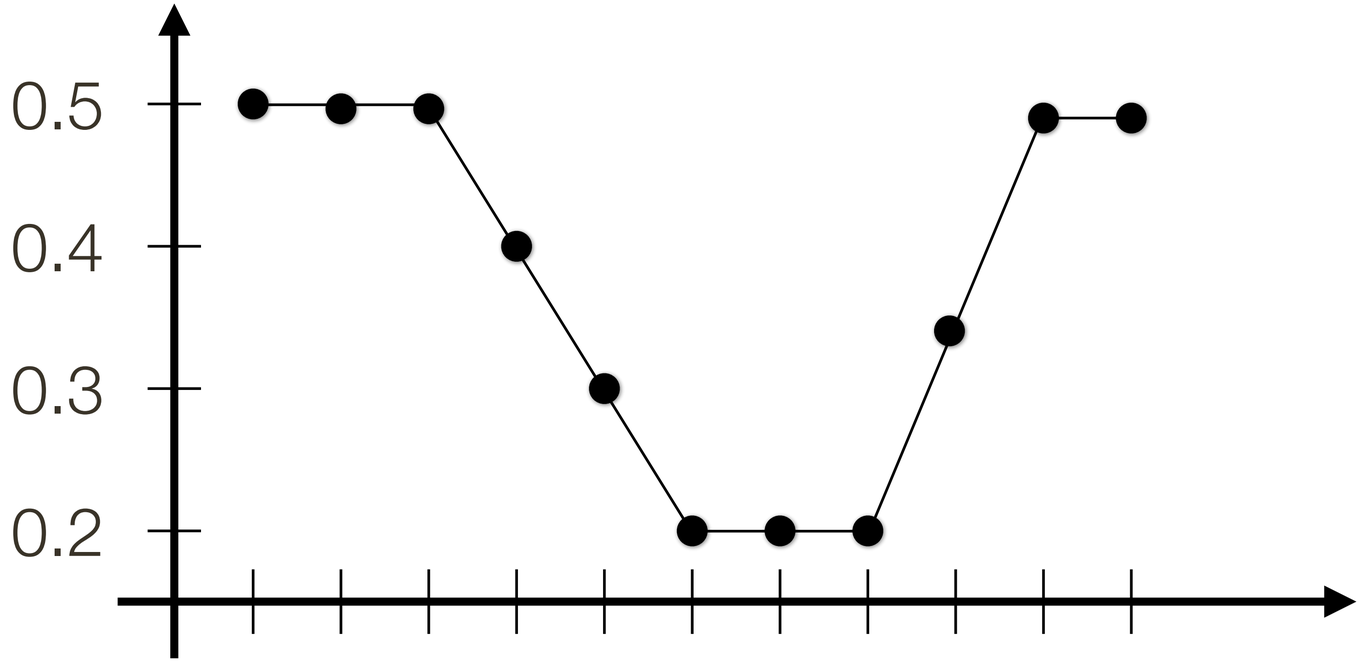


Example 1D



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

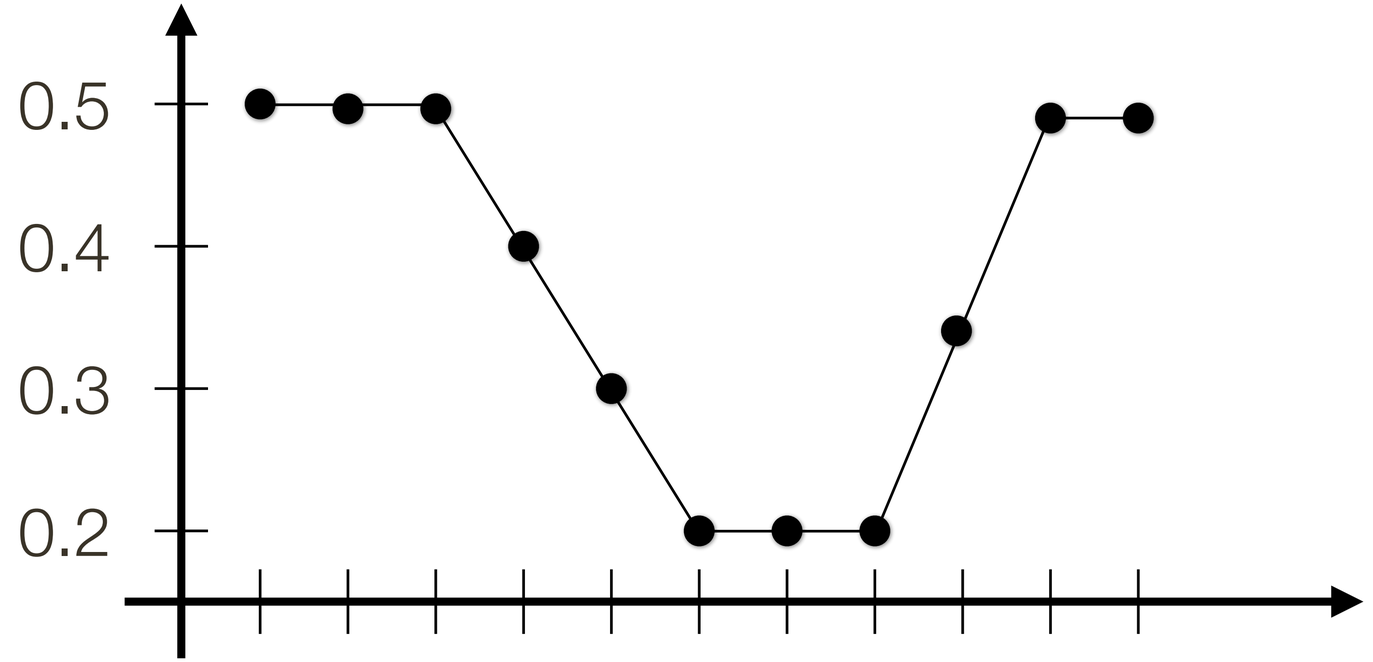
Example 1D



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

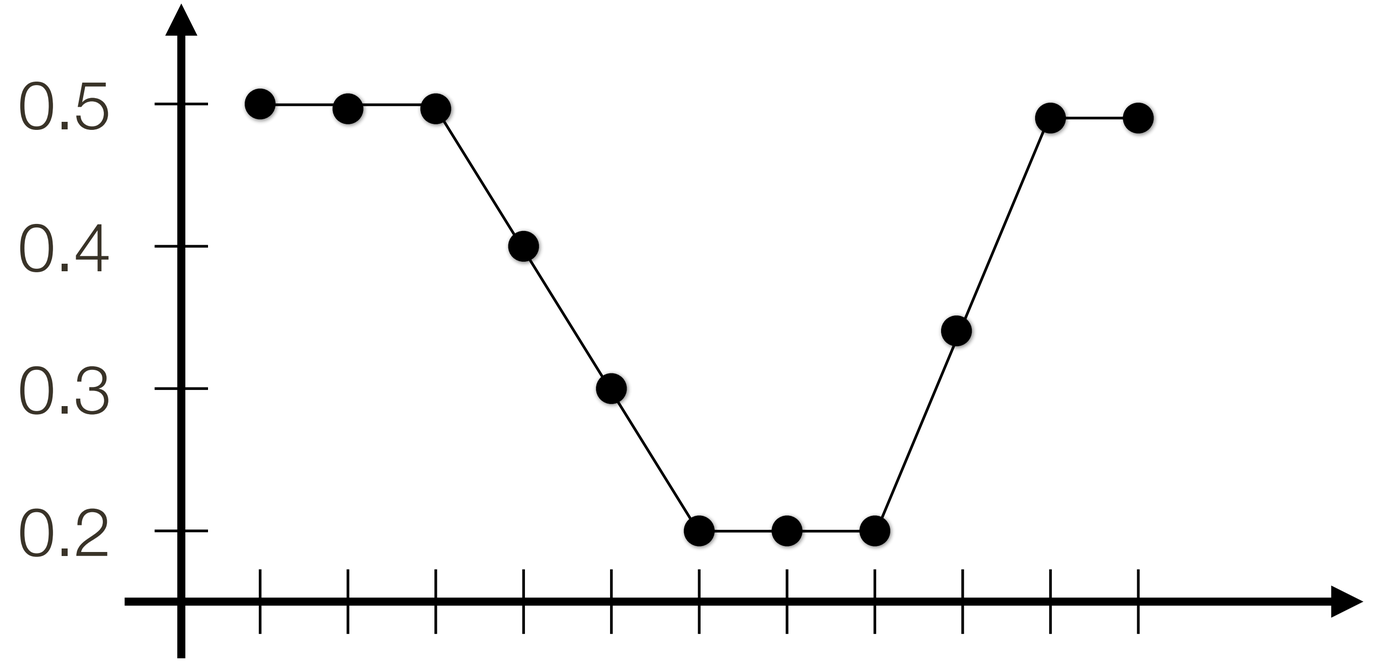
Derivative

Example 1D



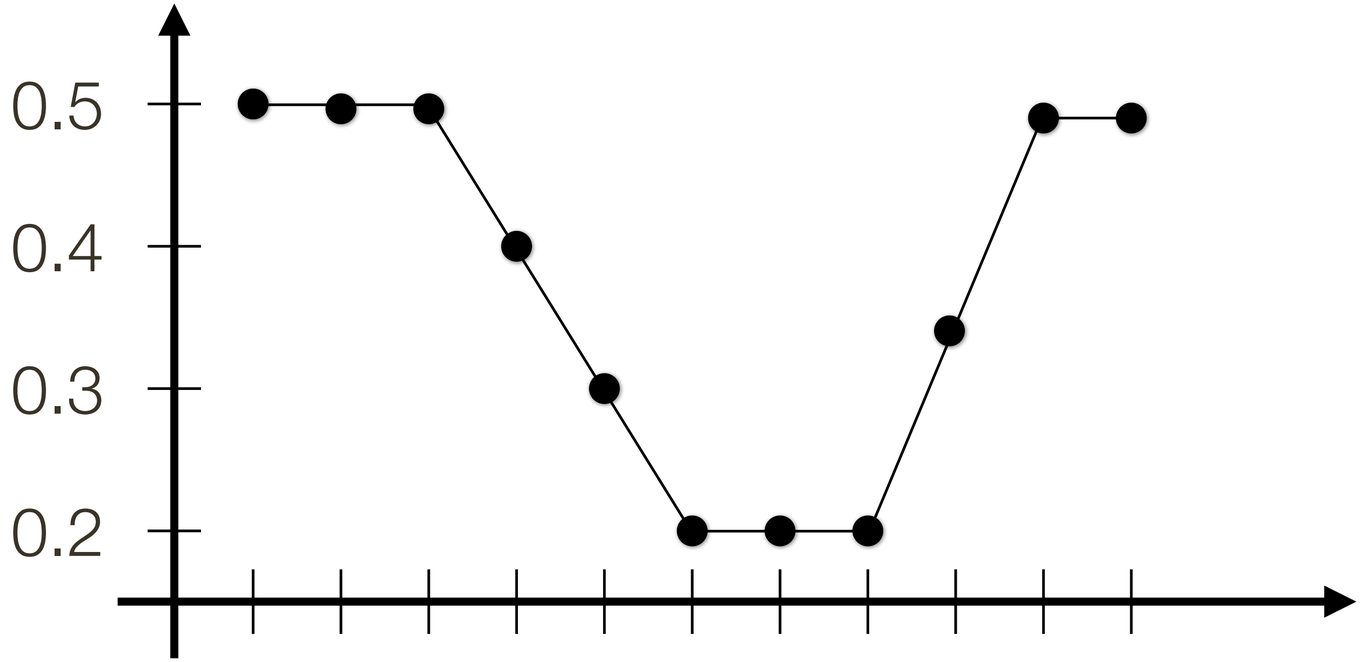
Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5
Derivative	0.0										

Example 1D



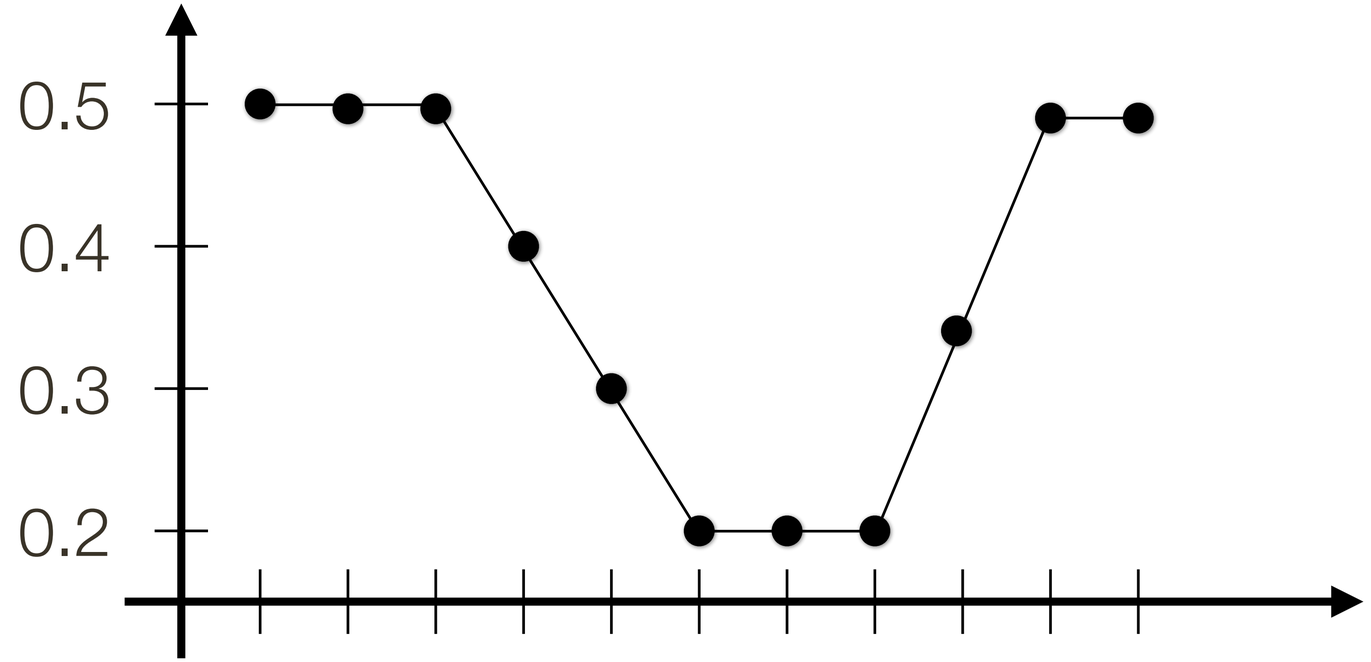
Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5
Derivative	0.0										

Example 1D



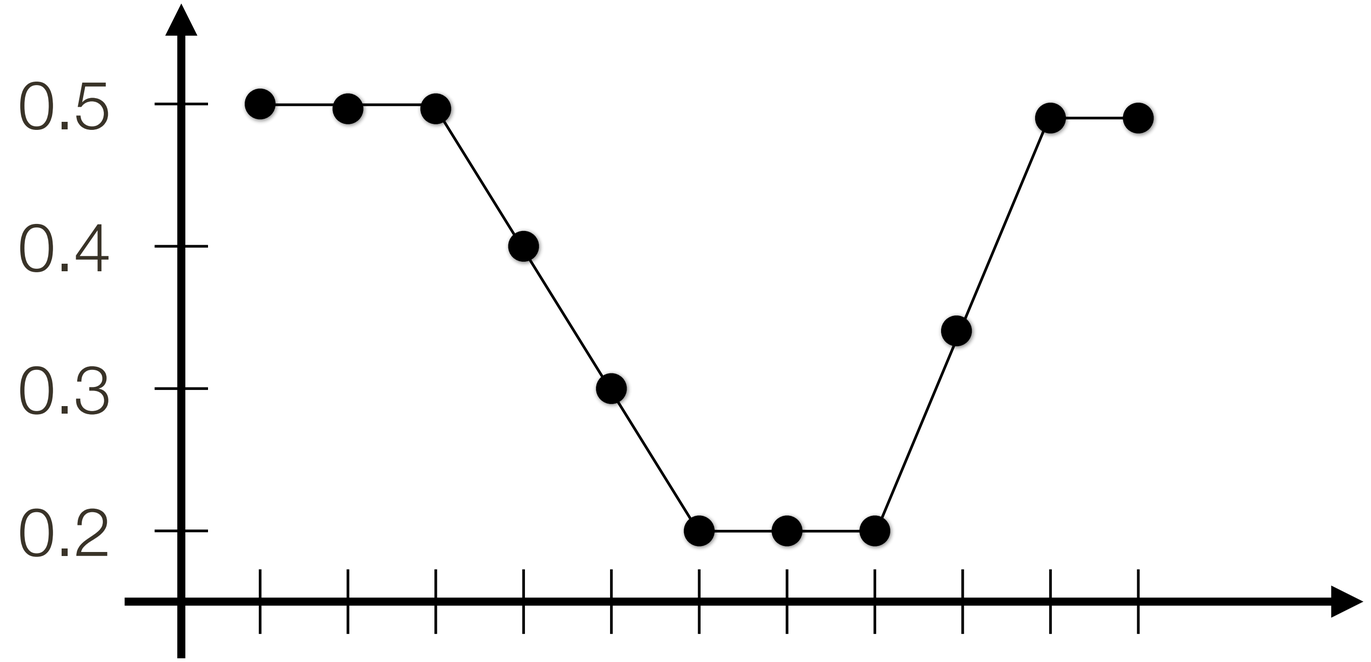
Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5
Derivative	0.0	0.0									

Example 1D



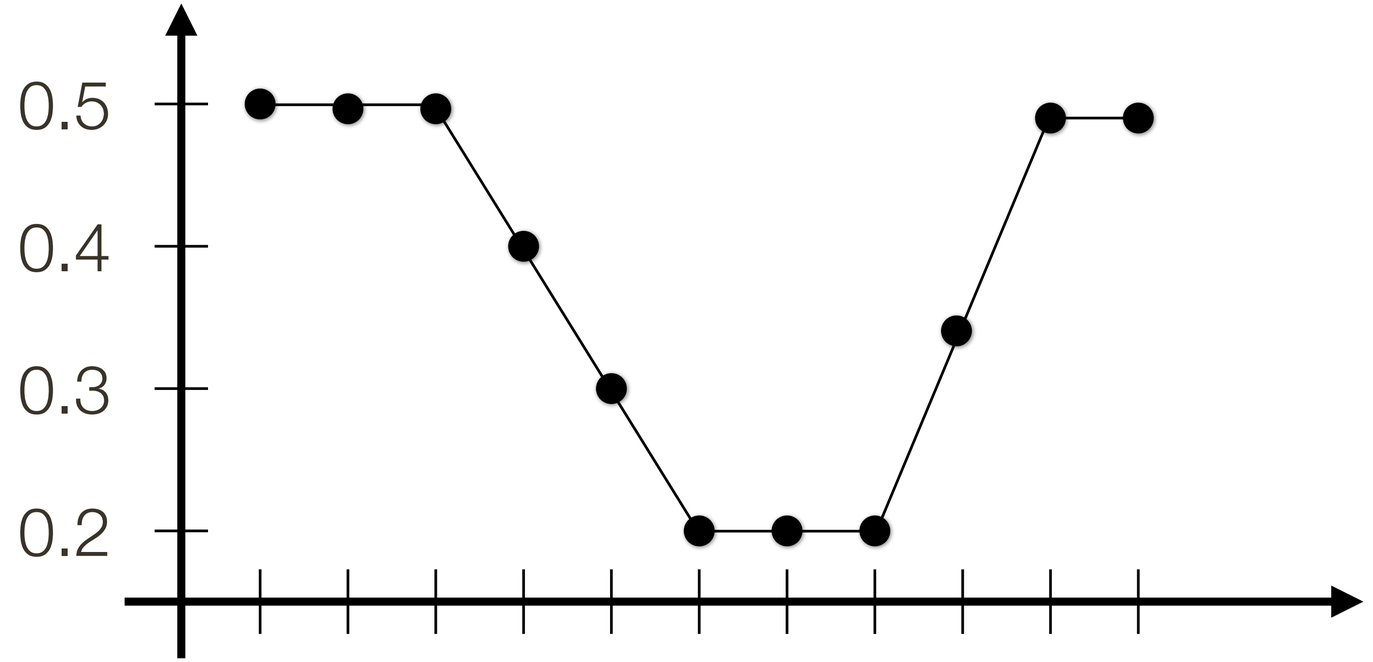
Signal	0.5	0.5	0.5	0.4	0.3	0.2	0.2	0.2	0.35	0.5	0.5
Derivative	0.0	0.0									

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								

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

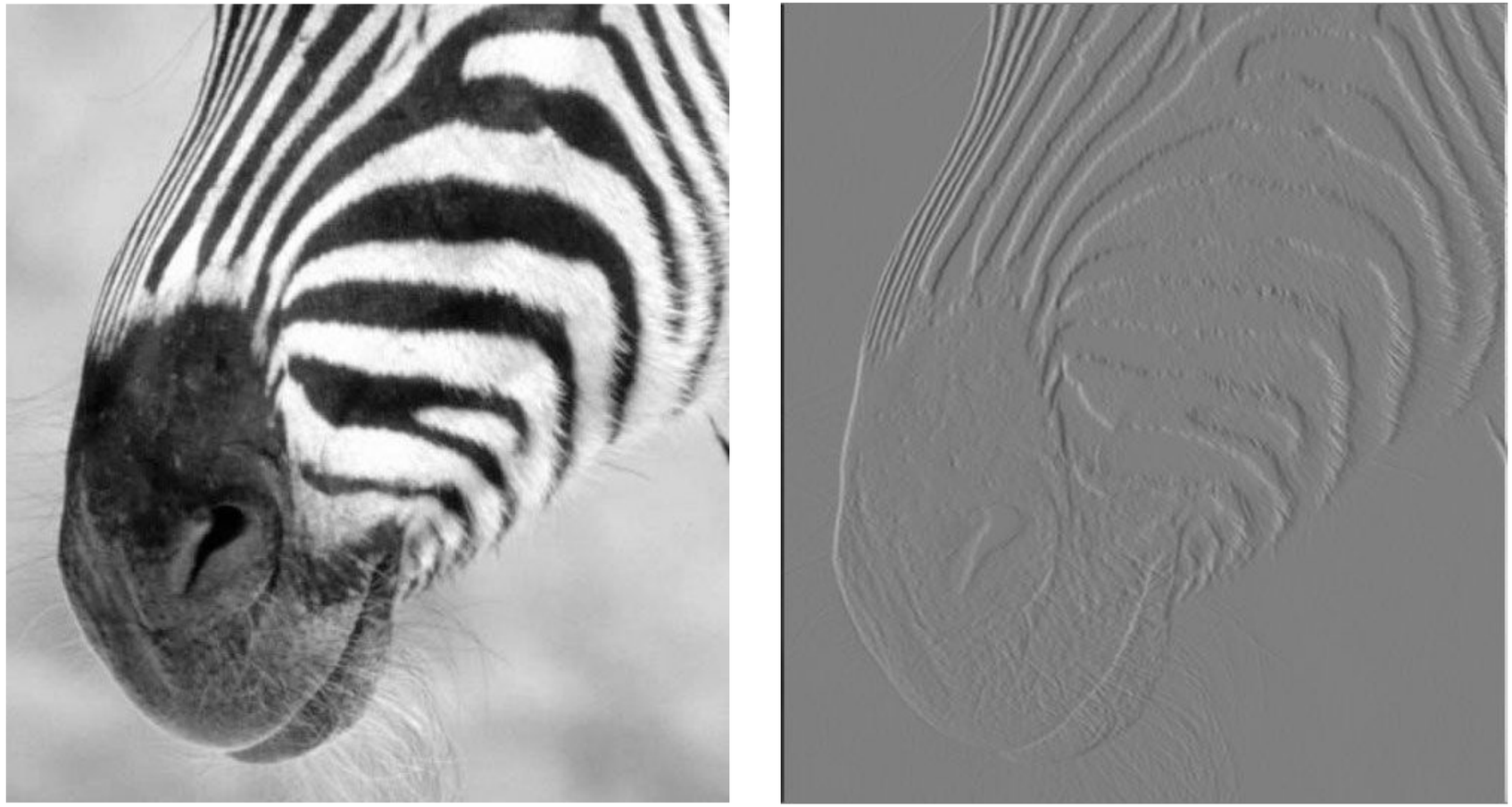
Estimating **Derivatives**

Derivative in Y (i.e., vertical) direction (**Note:** visualized by adding 0.5/128)

Forsyth & Ponce (1st ed.) Figure 7.4

Estimating **Derivatives**

Derivative in X (i.e., horizontal) direction (**Note:** visualized by adding 0.5/128)



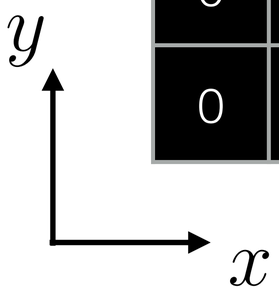
Forsyth & Ponce (1st ed.) Figure 7.4

Example: 2D Derivatives

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

9.2 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



Estimating **Derivatives**

Q: Why should the weights of a filter used for differentiation sum to 0?

Estimating **Derivatives**

Q: Why should the weights of a filter used for differentiation sum to 0?

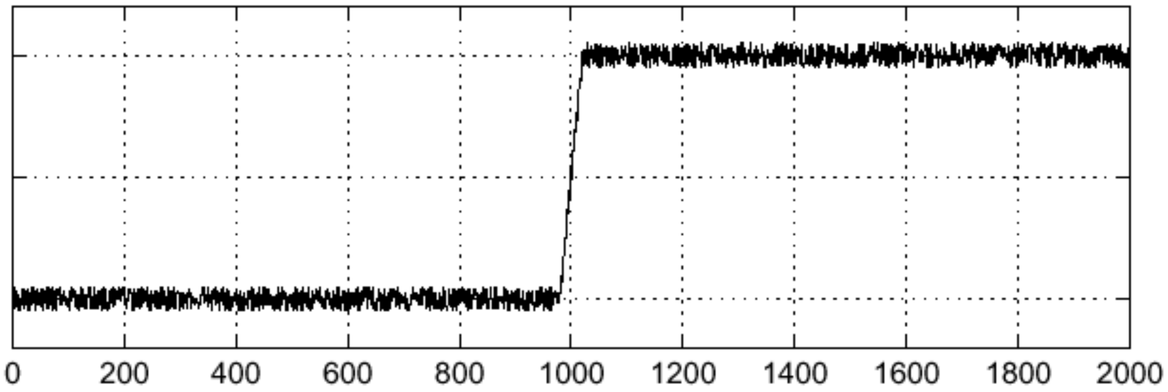
e.g. a constant image, $I(X,Y) = k$ has derivative = 0. Therefore, the weights of any filter used for differentiation need to sum to 0.

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

Edge Detection: 1D **Example**

Lets consider a row of pixels in an image:

$I(X, 245)$

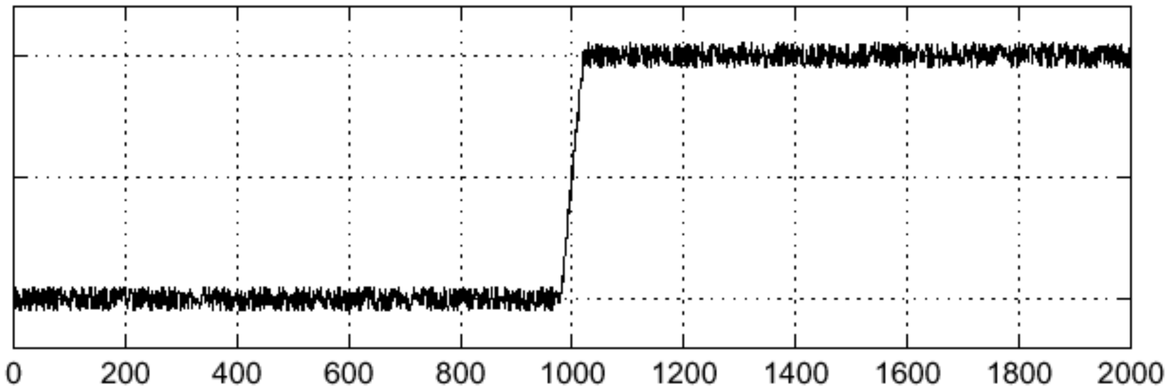


Where is the edge?

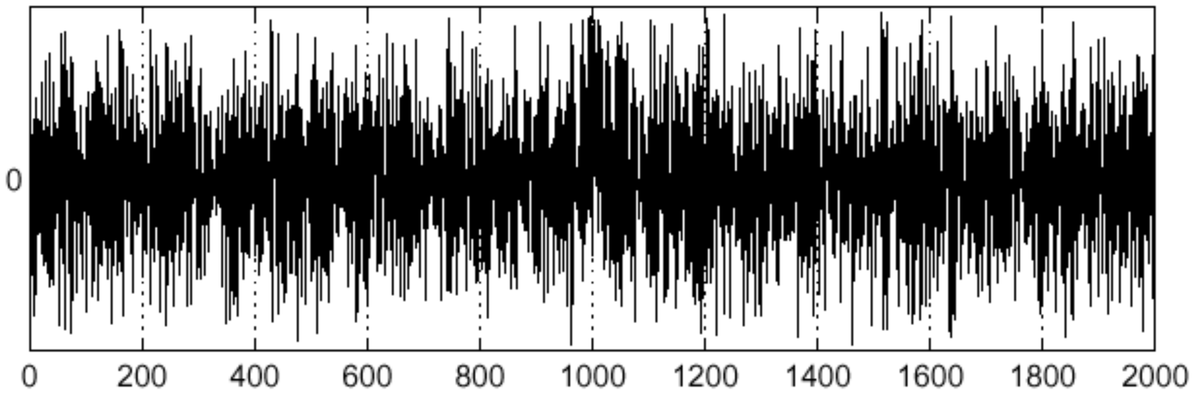
Edge Detection: 1D **Example**

Lets consider a row of pixels in an image:

$I(X, 245)$



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



Where is the edge?

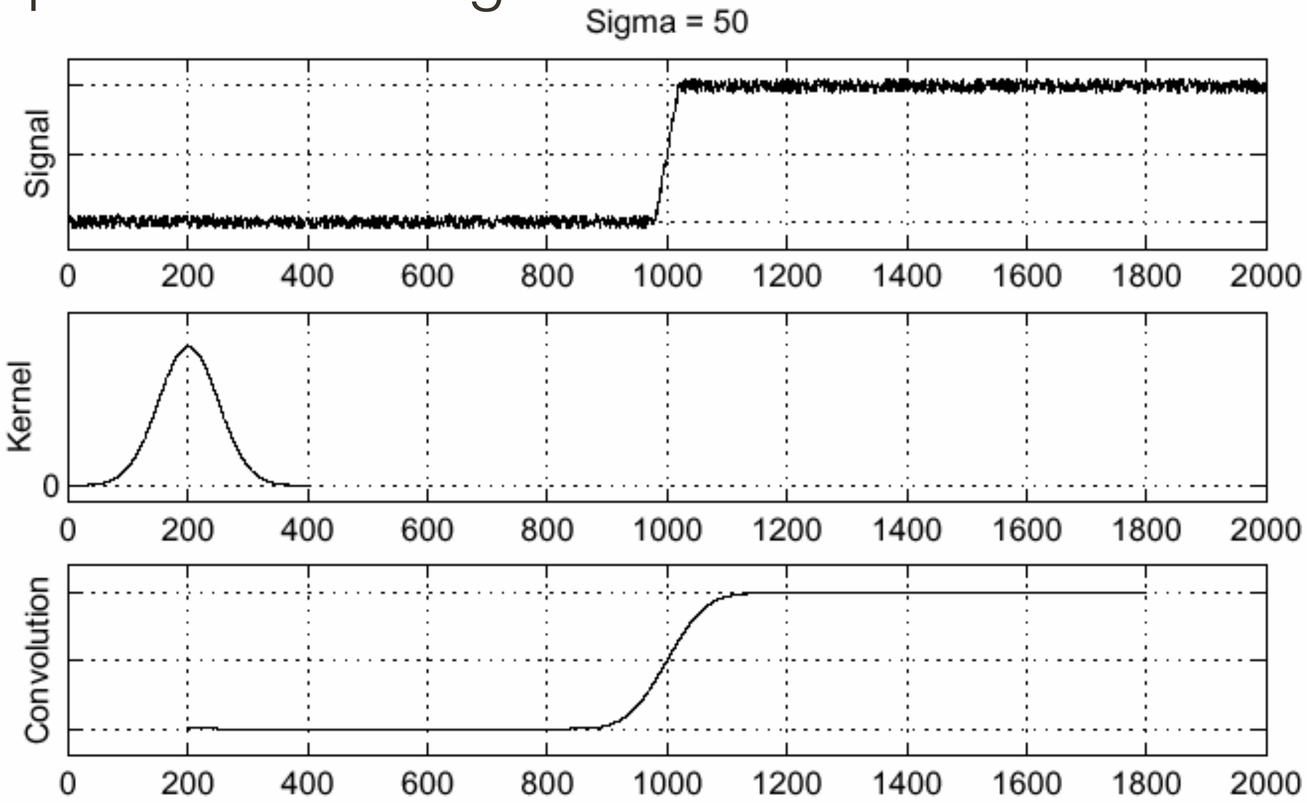
1D **Example**: Smoothing + Derivative

Lets consider a row of pixels in an image:

$I(X, 245)$

G

$G \otimes I(X, Y)$



1D **Example**: Smoothing + Derivative

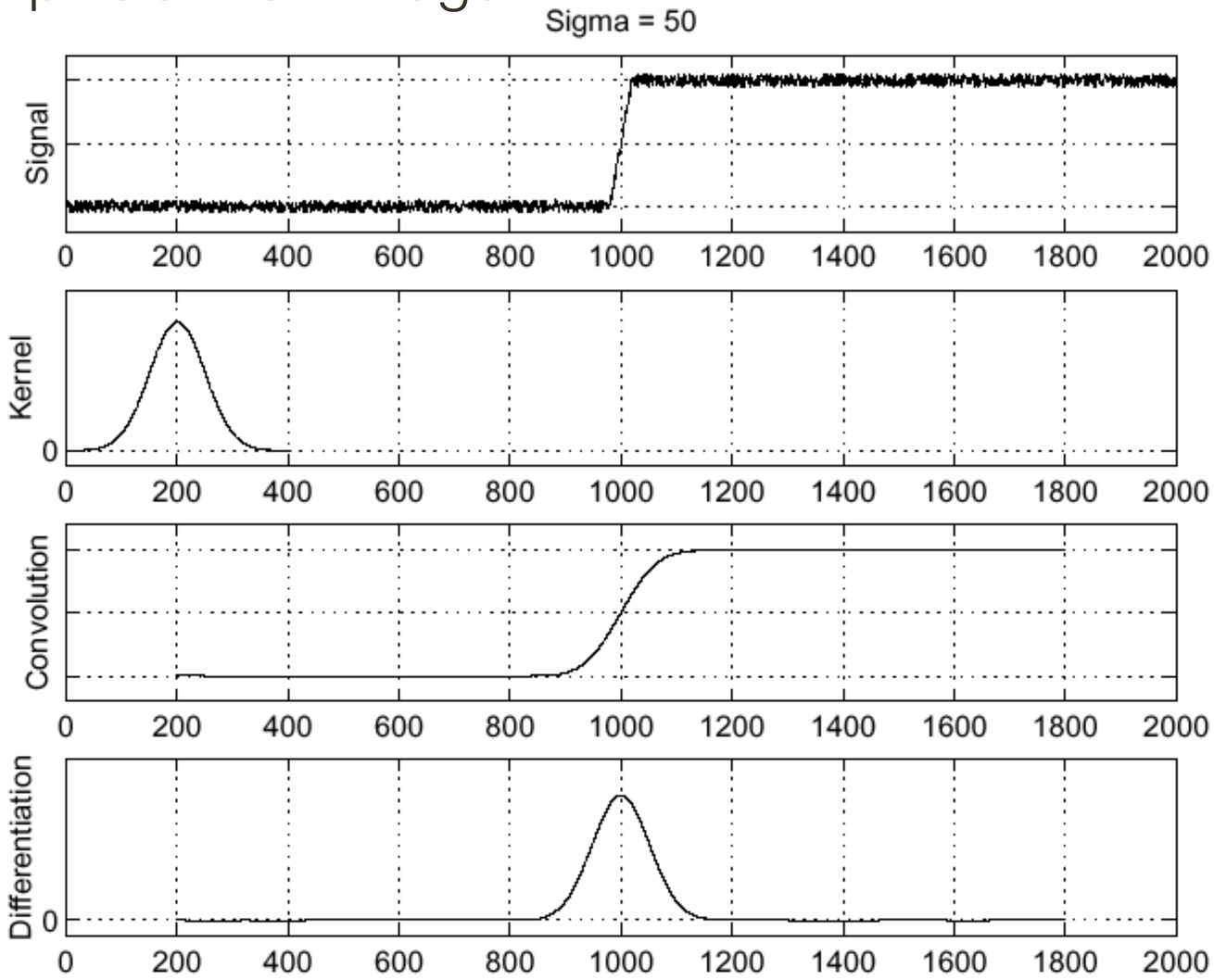
Lets consider a row of pixels in an image:

$I(X, 245)$

G

$G \otimes I(X, Y)$

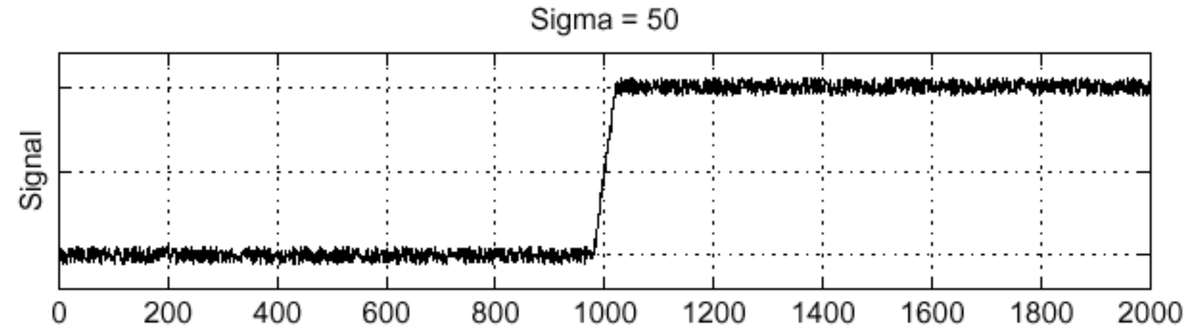
$$\frac{\partial G \otimes I(X, Y)}{\partial x}$$



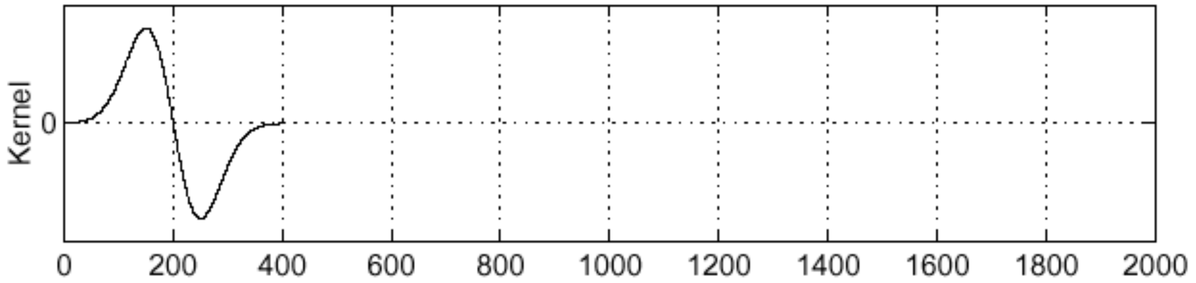
1D **Example**: Smoothing + Derivative

Lets consider a row of pixels in an image:

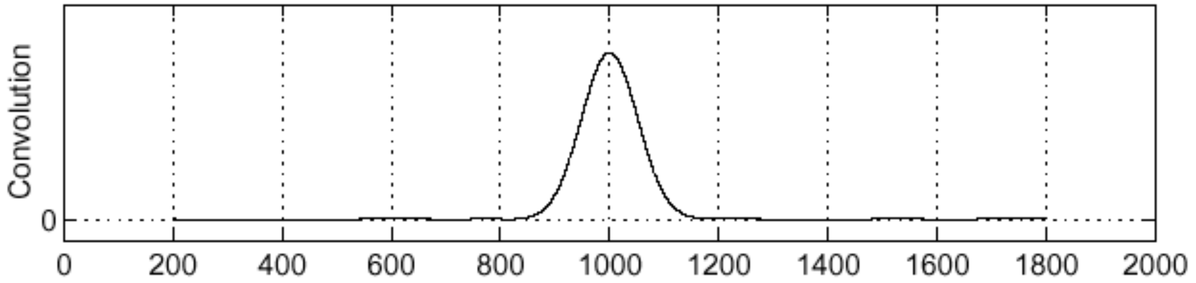
$I(X, 245)$



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



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



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

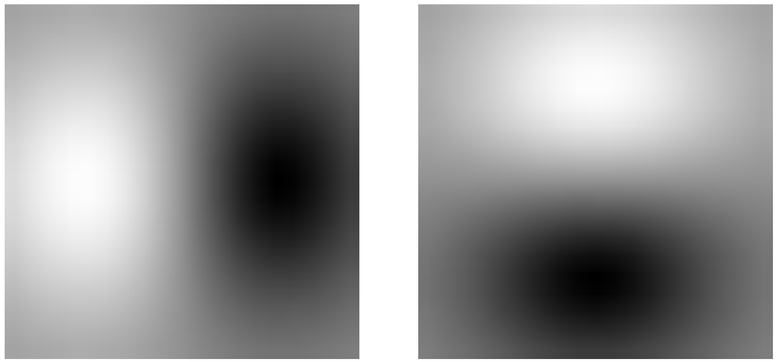
We can use **derivative of Gaussian** filters

— because differentiation is convolution, and

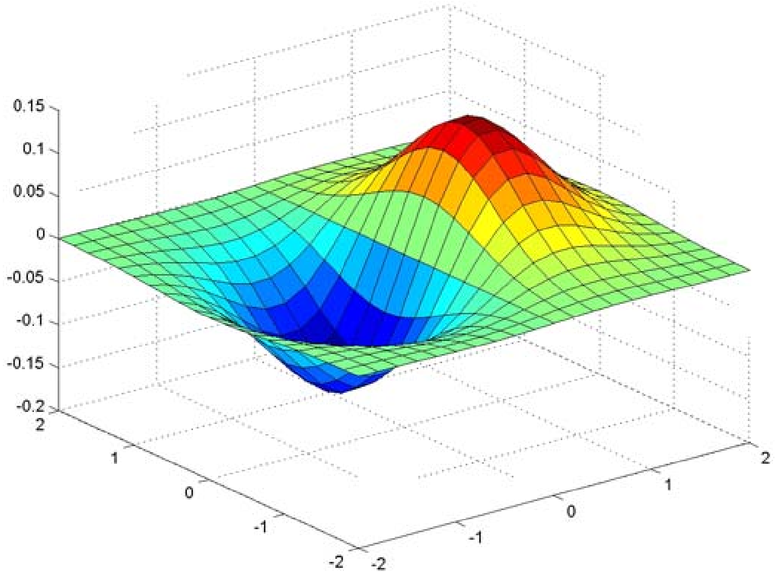
— convolution is associative

Let $\otimes$ denote convolution

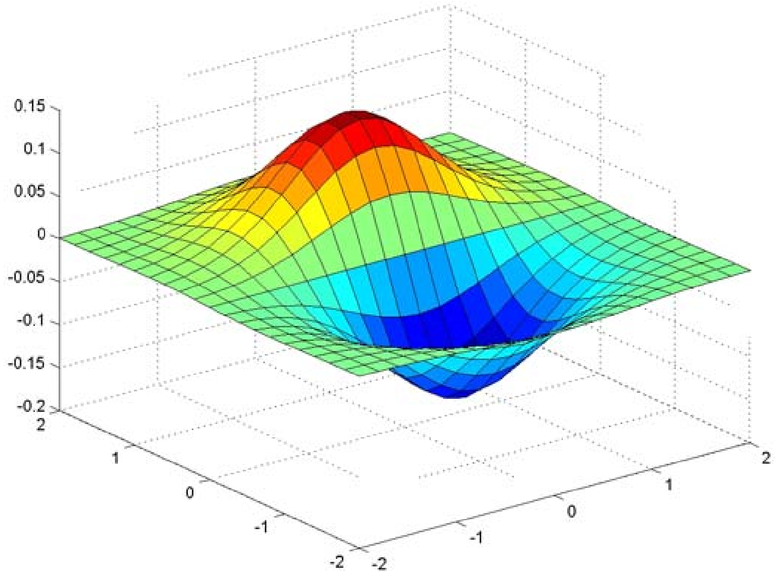
$$D \otimes (G \otimes I(X,Y)) = (D \otimes G) \otimes I(X,Y)$$



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



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



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

Slide Credit: Christopher Rasmussen

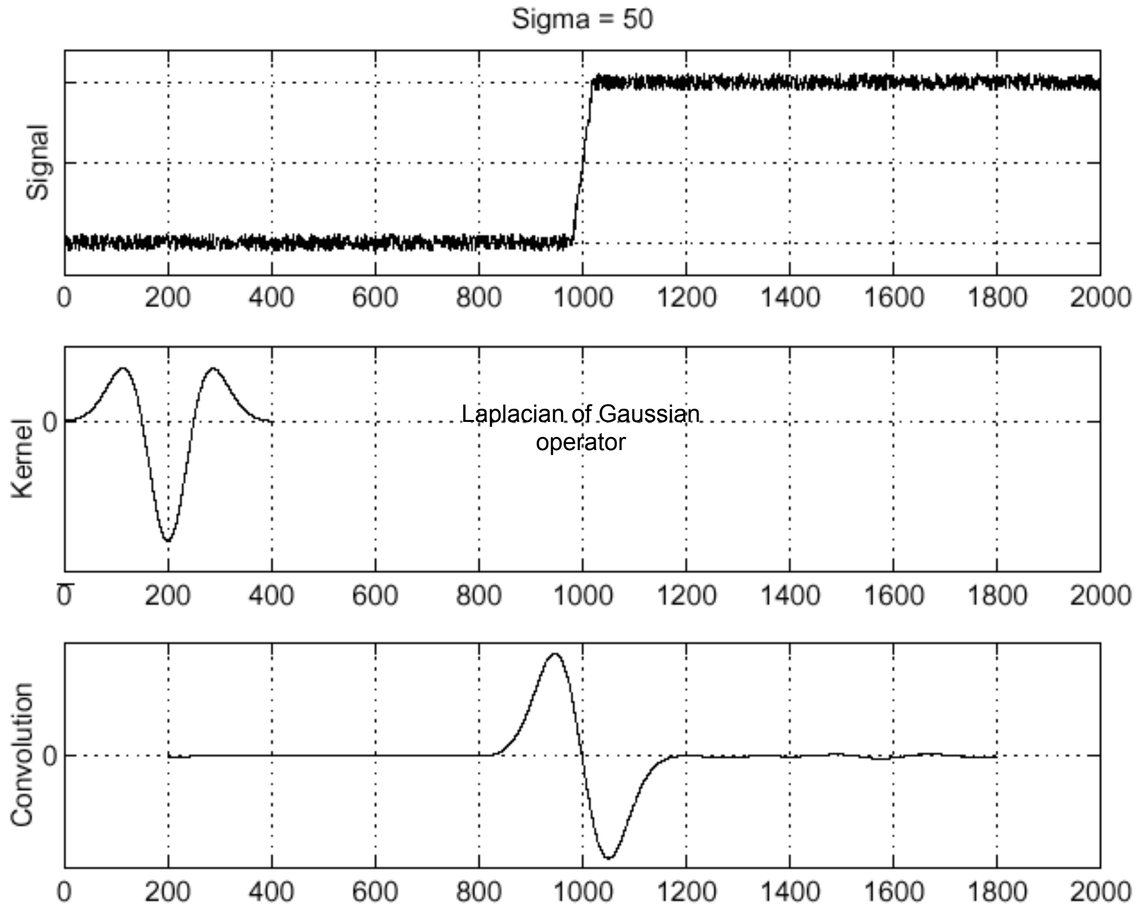
1D **Example**: Continued

Lets consider a row of pixels in an image:

$I(X, 245)$

$\nabla^2 G$

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



Zero-crossings of bottom graph

Derivative Approximations: Forward, Backward, Centred

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

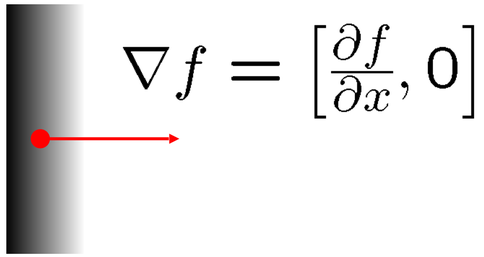
Thresholds are brittle, we can do better!

2D Image **Gradient**

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

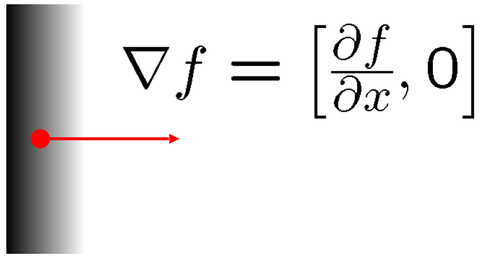
2D Image **Gradient**

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



2D Image **Gradient**

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

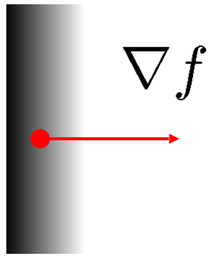


$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$

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

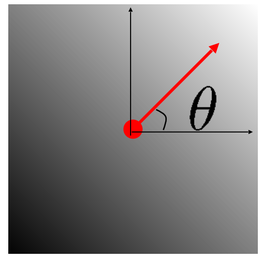
2D Image **Gradient**

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



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

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

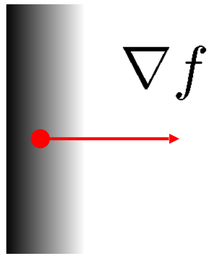


$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

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

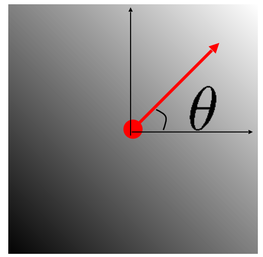
2D Image **Gradient**

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



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

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



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

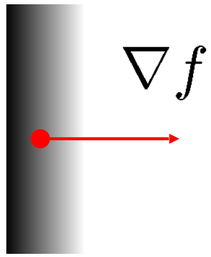
The gradient points in the direction of most rapid **increase of intensity**:

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?)

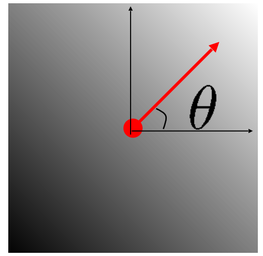
2D Image **Gradient**

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**:

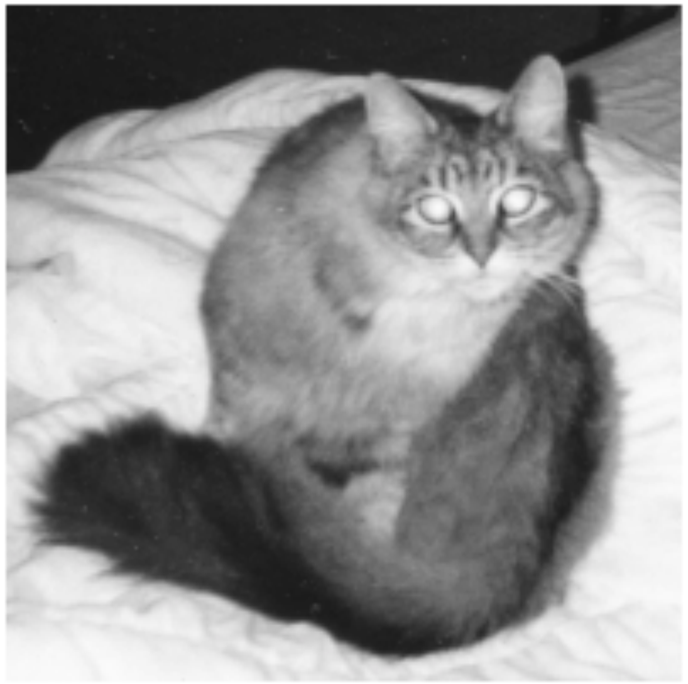
The **gradient direction** is given by: $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$

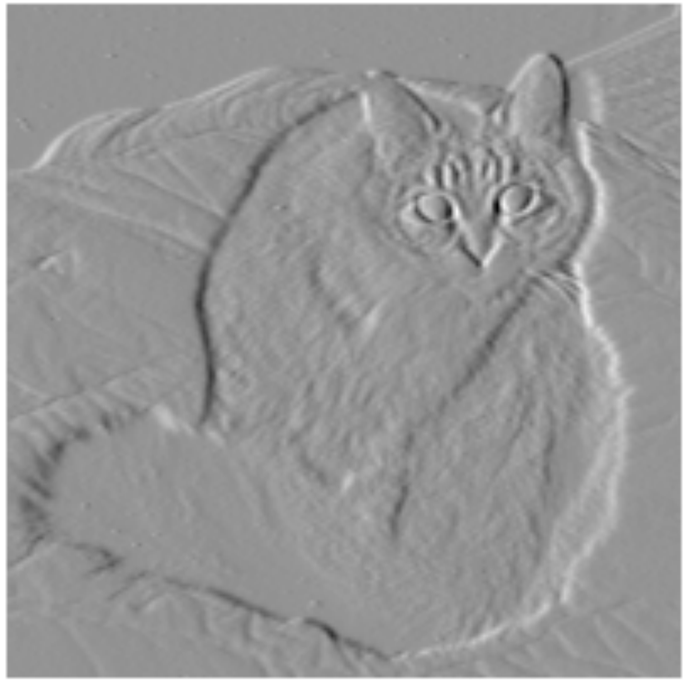
(how is this related to the direction of the edge?)

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

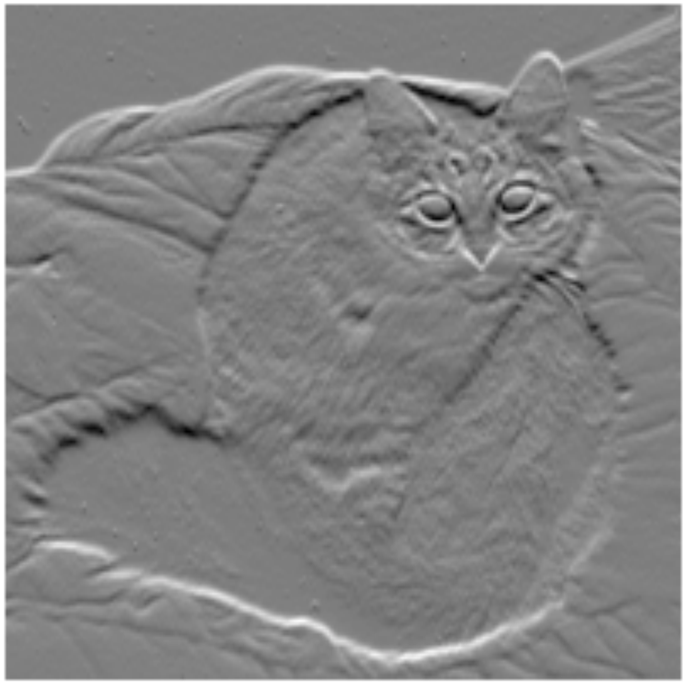
2D Edge Detection

- Smooth image and convolve with [-1 1]





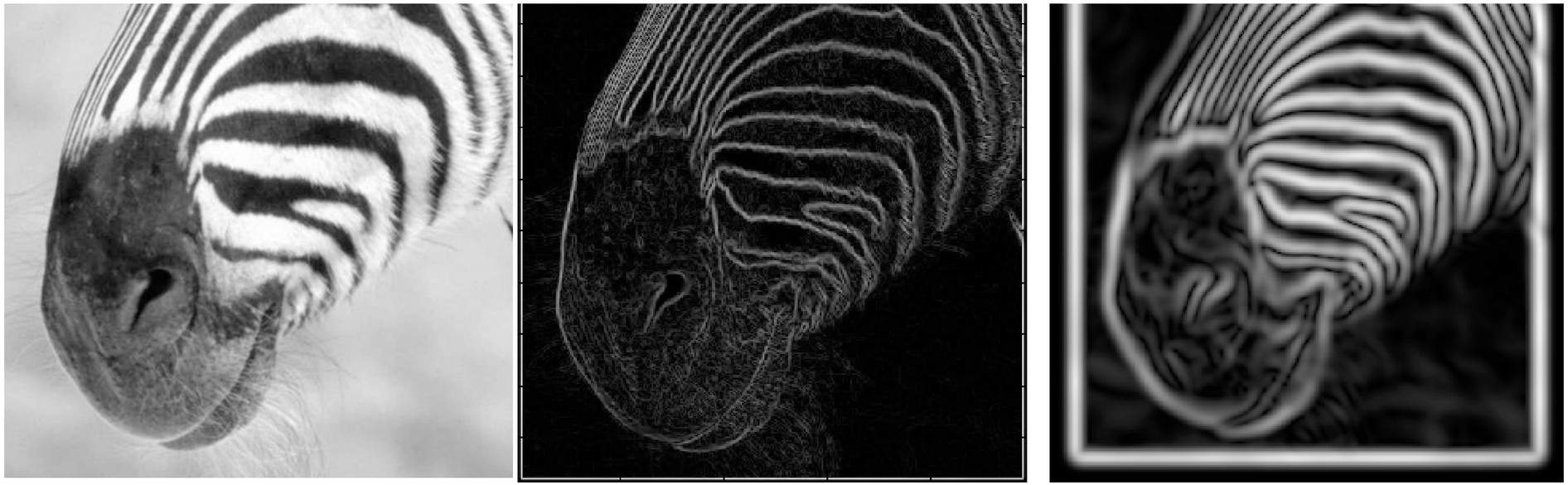
g_x



g_y

2D gradient: $\nabla I = \begin{bmatrix} g_x \\ g_y \end{bmatrix}$

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

Canny Edge Detector

A “**local extrema of a first derivative operator**” approach

Design Criteria:

1. good detection
    - low error rate for omissions (missed edges)
    - low error rate for commissions (false positive)
2. good localization
3. one (single) response to a given edge
    - (i.e., eliminate multiple responses to a single edge)

Canny Edge Detector

Steps:

1. Apply **directional derivatives** of Gaussian

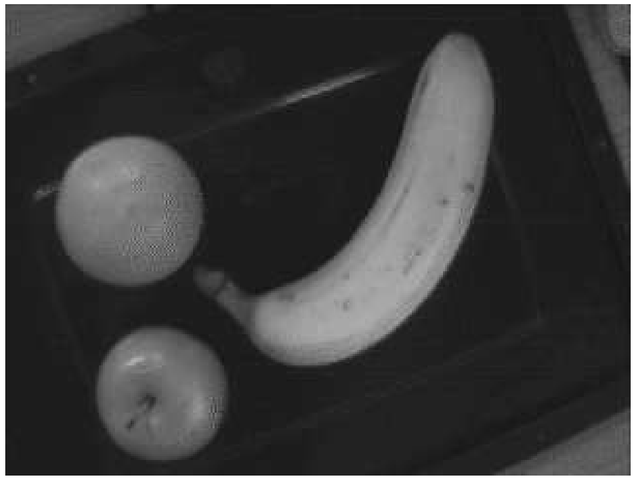
2. Compute **gradient magnitude** and **gradient direction**

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

2D Edge Detection

- Look at the magnitude of the smoothed gradient $|\nabla I|$



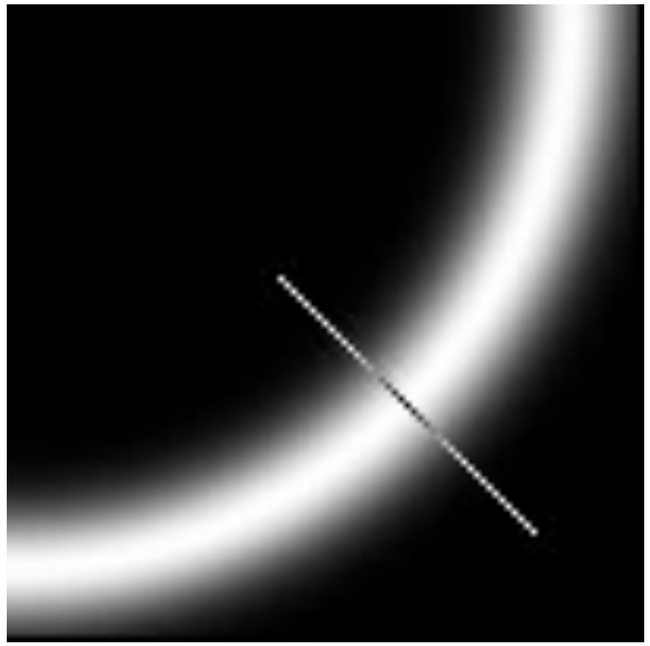
$$|\nabla I| = \sqrt{g_x^2 + g_y^2}$$

- Non-maximal suppression (keep points where $|\nabla I|$ is a maximum in directions $\pm\nabla I$)

[Canny 1986]

Non-maxima Suppression

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

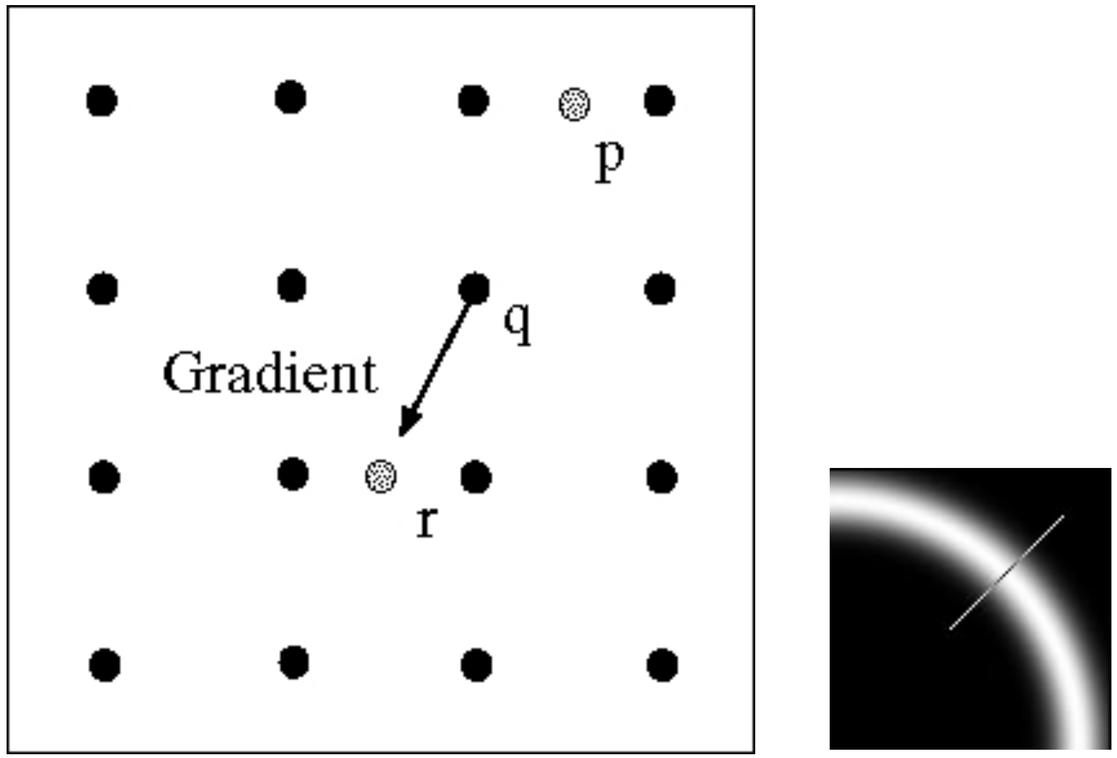


- Non-maximal suppression (keep points where $|\nabla I|$ is a maximum in directions $\pm\nabla I$)

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

Non-maxima Suppression

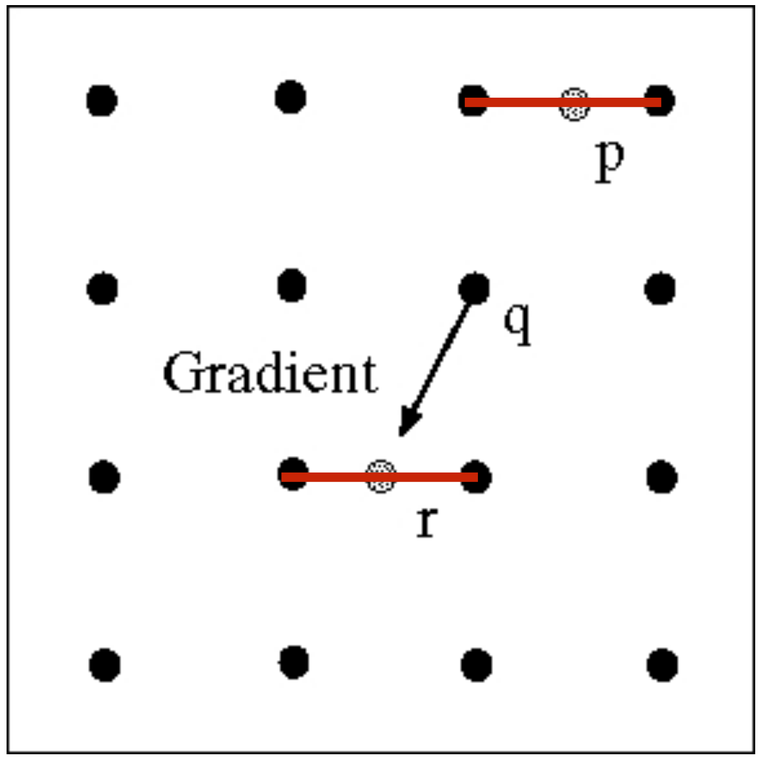
Value at *q* must be larger than interpolated values at *p* and *r*



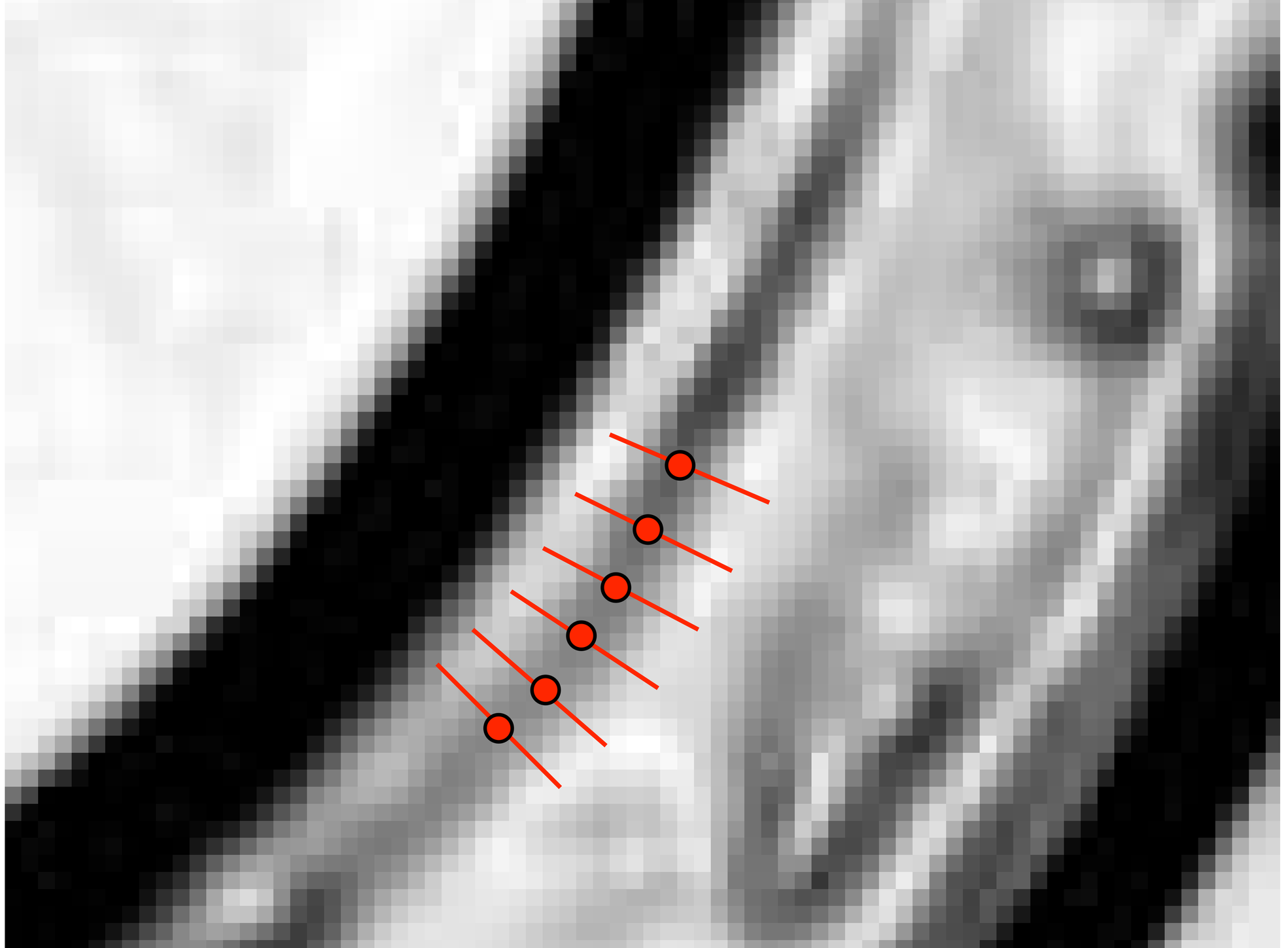
Forsyth & Ponce (2nd ed.) Figure 5.5 left

Non-maxima Suppression

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

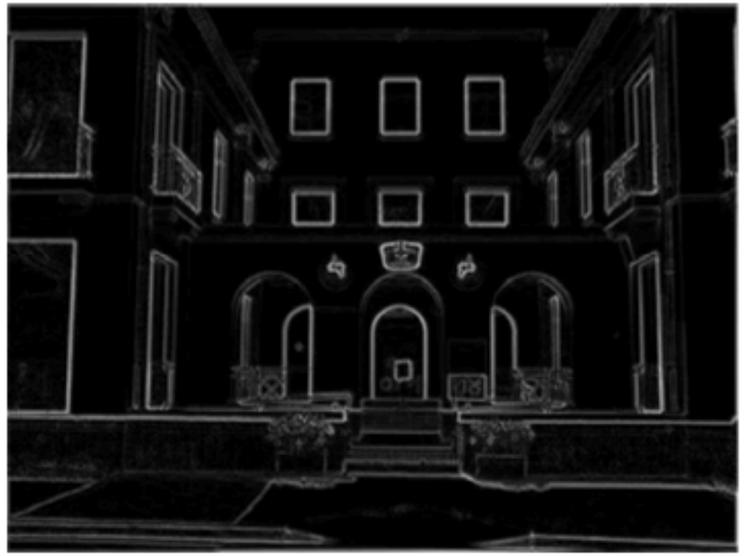


Forsyth & Ponce (2nd ed.) Figure 5.5 left

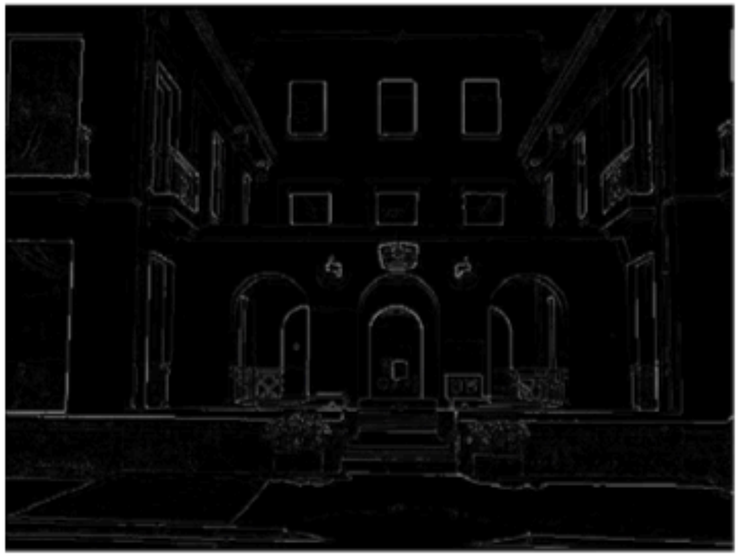


Example: Non-maxima Suppression

Original Image



Gradient Magnitude

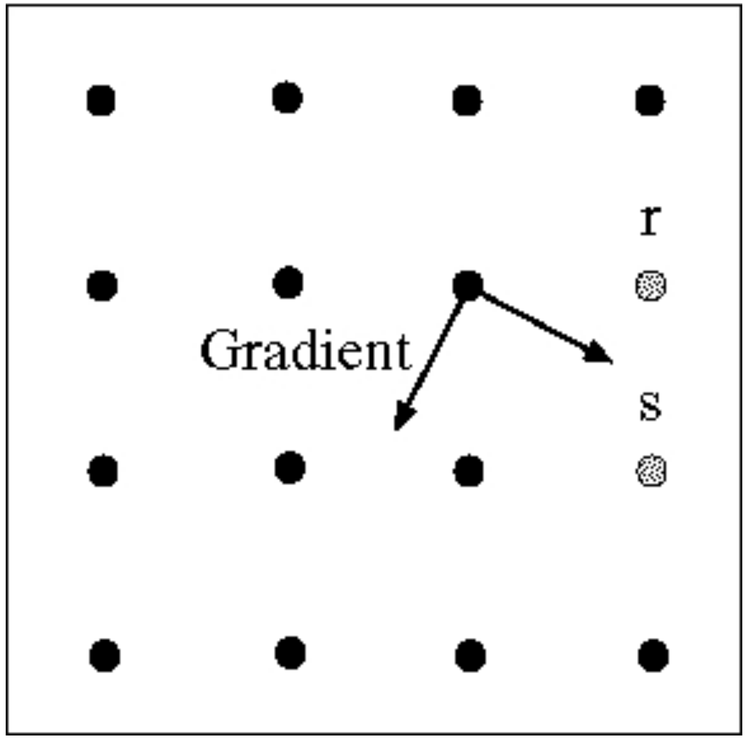


courtesy of G. Loy

Non-maxima Suppression

Slide Credit: Christopher Rasmussen

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 $\mathbf{k}_{low}$

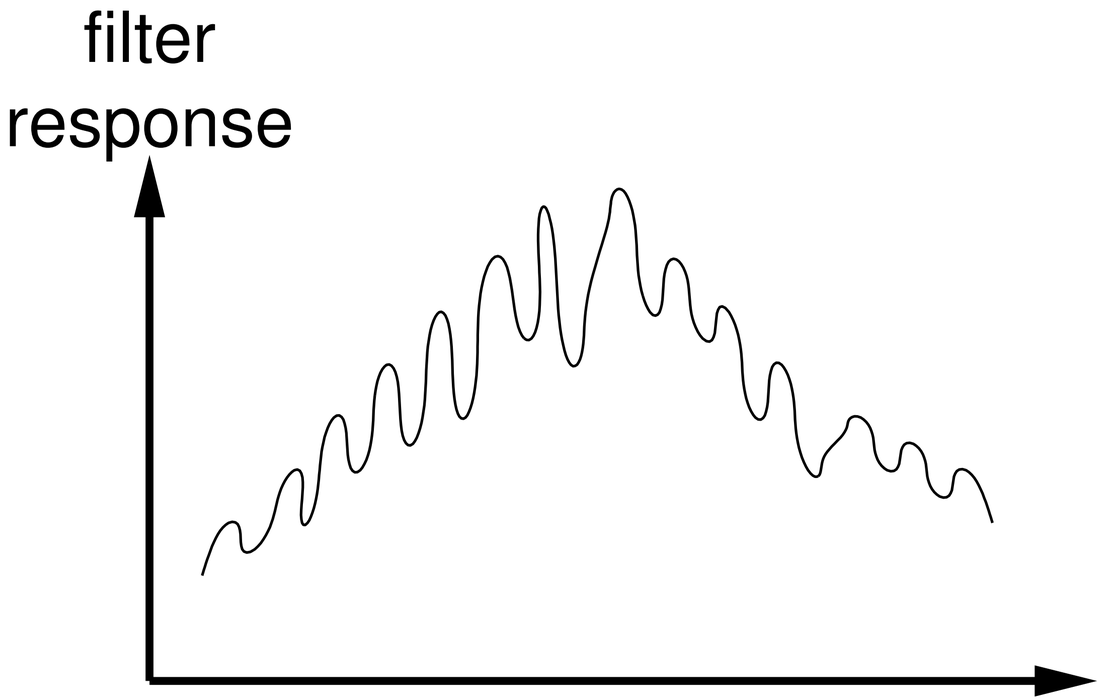
— Use khigh to find strong edges to start edge chain

— Use klow to find weak edges which continue edge chain

Typical ratio of thresholds is (roughly):

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

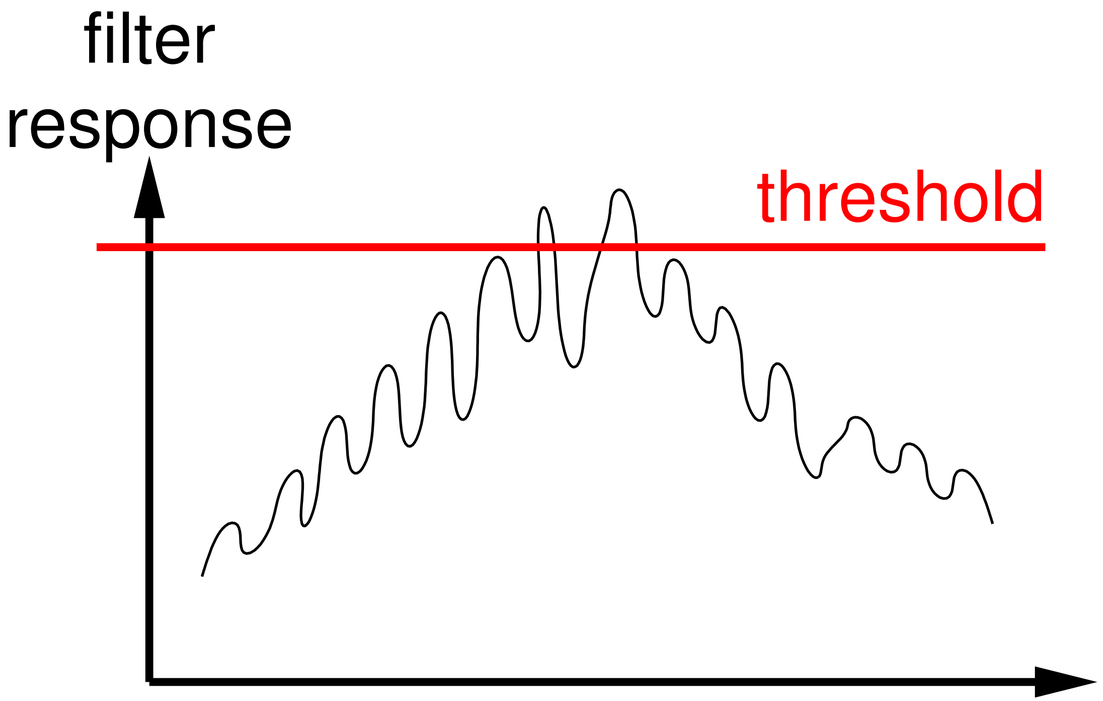
Example: Edge Detection



Question: How many edges are there?

Question: What is the position of each edge?

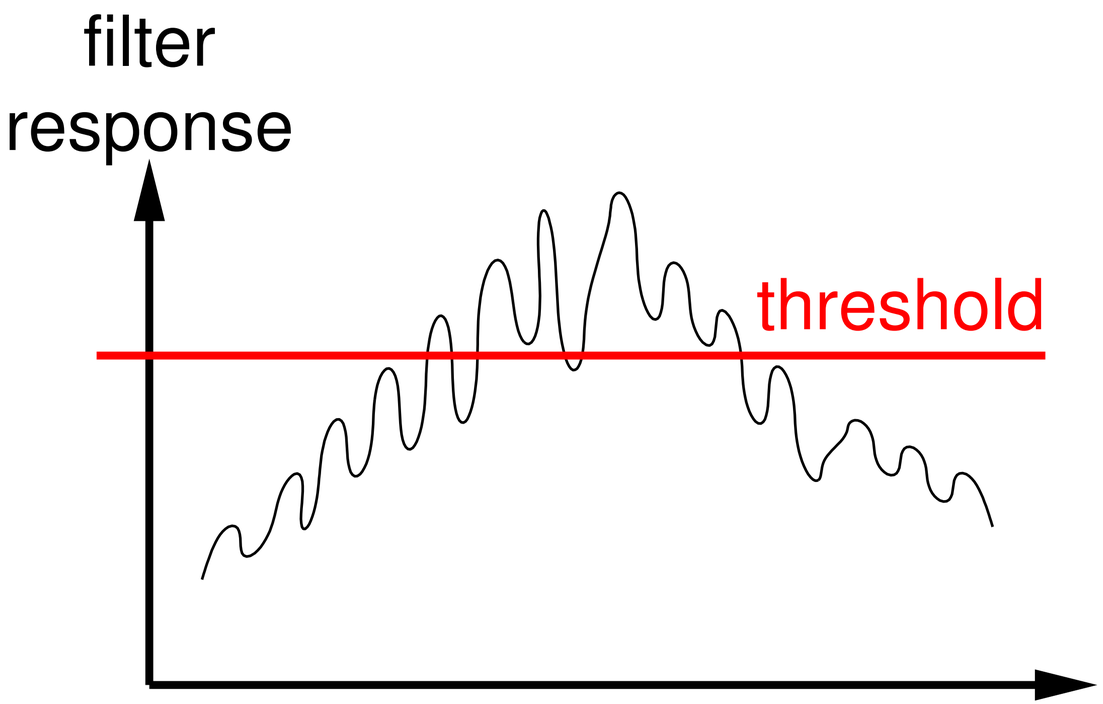
Example: Edge Detection



Question: How many edges are there?

Question: What is the position of each edge?

Example: Edge Detection



Question: How many edges are there?

Question: What is the position of each edge?

Canny Edge Detector

Original
Image

Strong +
connected
Weak Edges

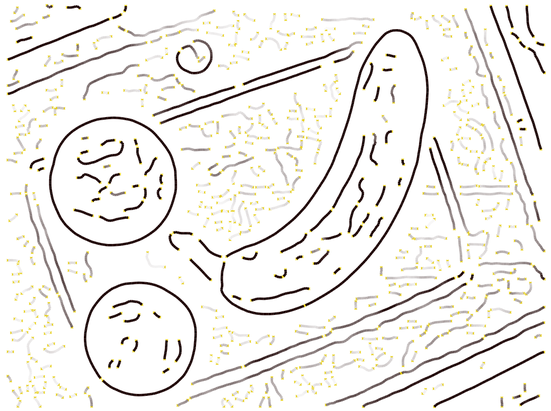
Strong
Edges

Weak
Edges

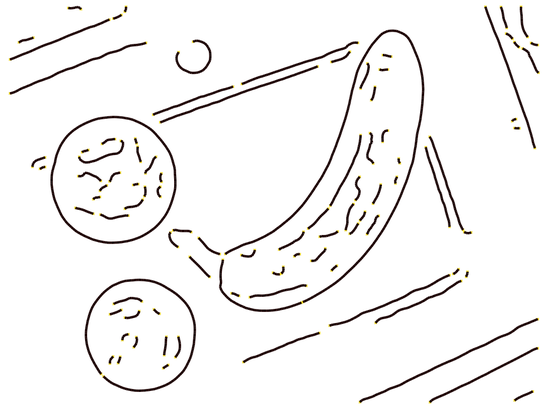
courtesy of G. Loy

2D Edge Detection

- Threshold the gradient magnitude with two thresholds: T_{high} and T_{low}
- Edges start at edge locations with gradient magnitude > T_{high}
- Continue tracing edge until gradient magnitude falls below T_{low}



Non-MS



Thresholded

[Canny 1986]

Example

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

Example

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

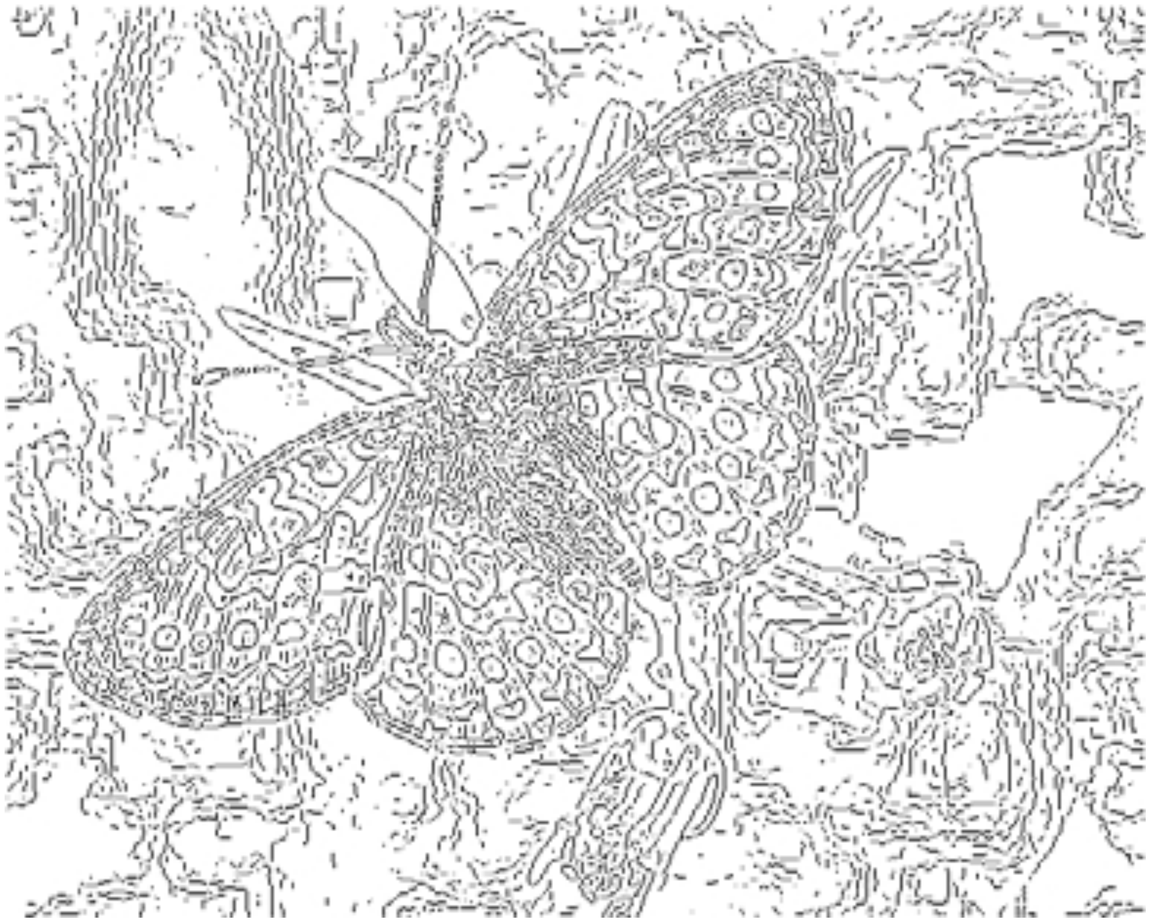


Figure 8.13 bottom left

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

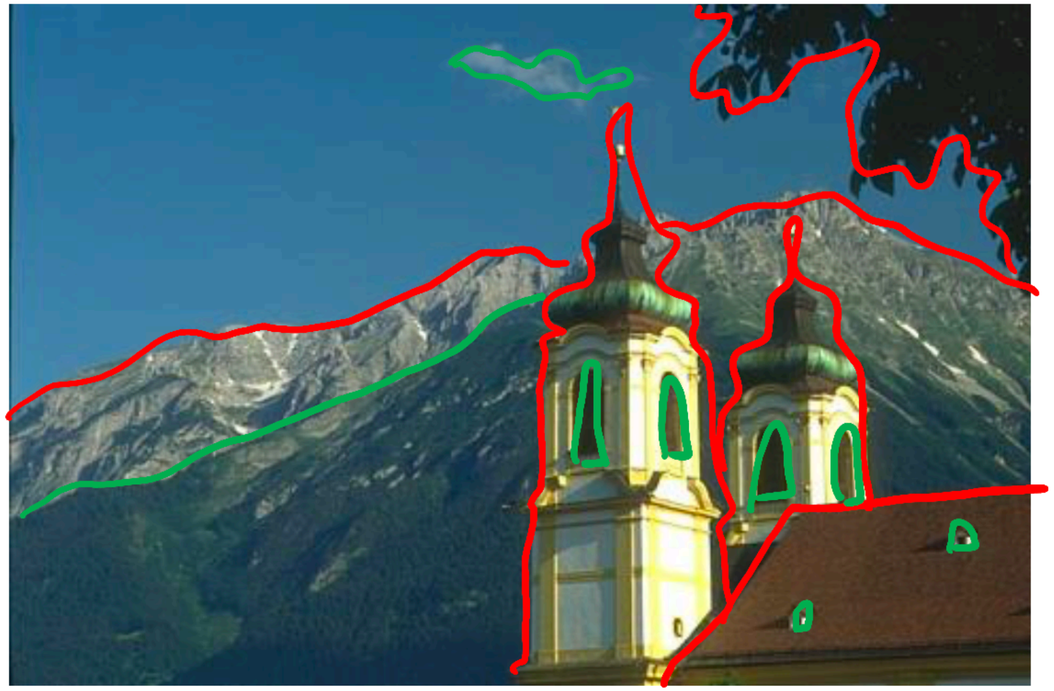
Fine scale ($\sigma = 4$), low threshold

How do humans perceive **boundaries**?

Edges are a property of the 2D image.

It is interesting to ask: How closely do image edges correspond to boundaries that humans perceive to be salient or significant?

How do humans perceive **boundaries**?



"Divide the image into some number of segments, where the segments represent 'things' or 'parts of things' in the scene. The number of segments is up to you, as it depends on the image. Something between 2 and 30 is likely to be appropriate. It is important that all of the segments have approximately equal importance."

(Martin et al. 2004)

How do humans perceive **boundaries**?

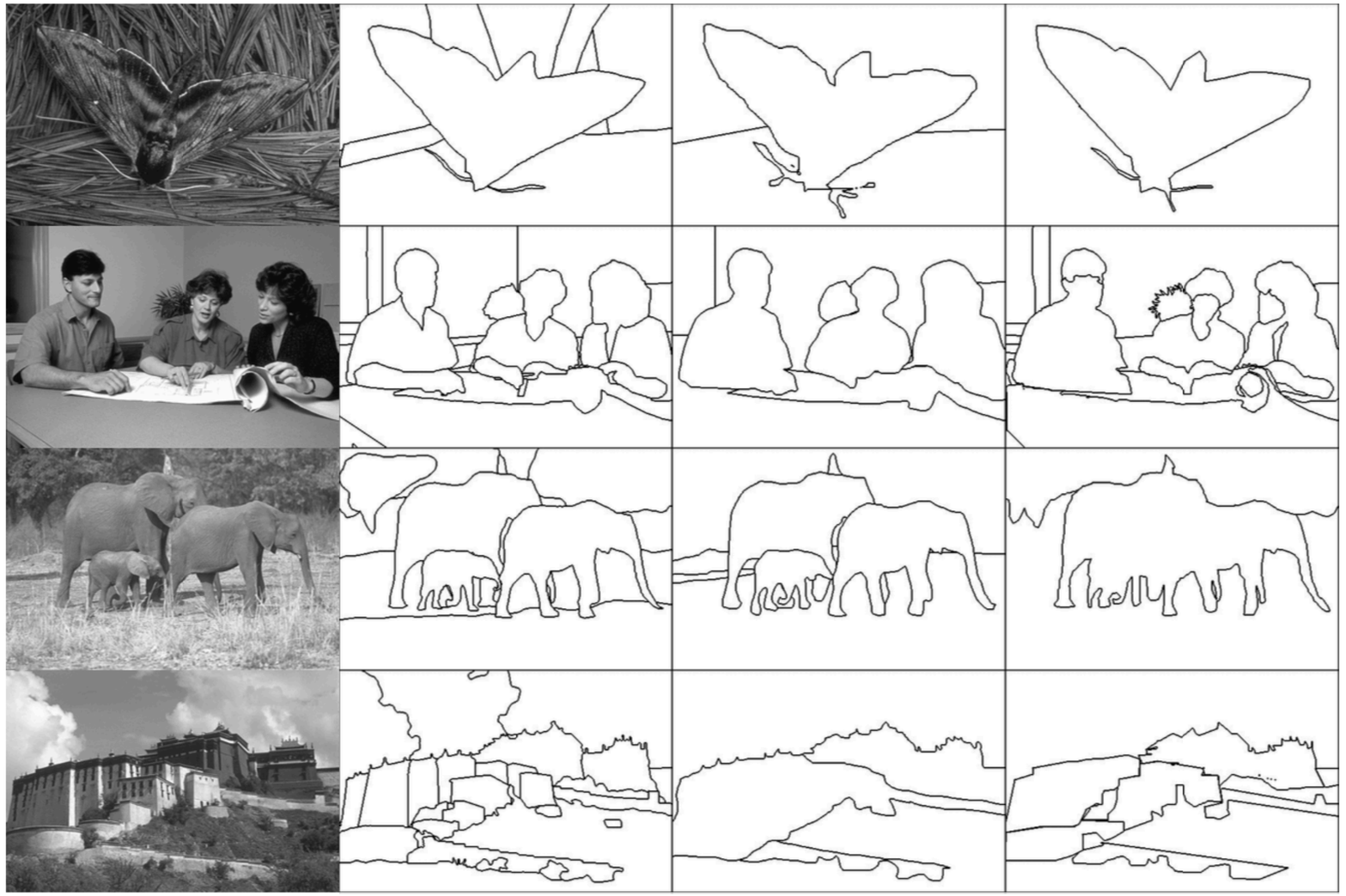


Figure Credit: Martin et al. 2001

How do humans perceive **boundaries**?

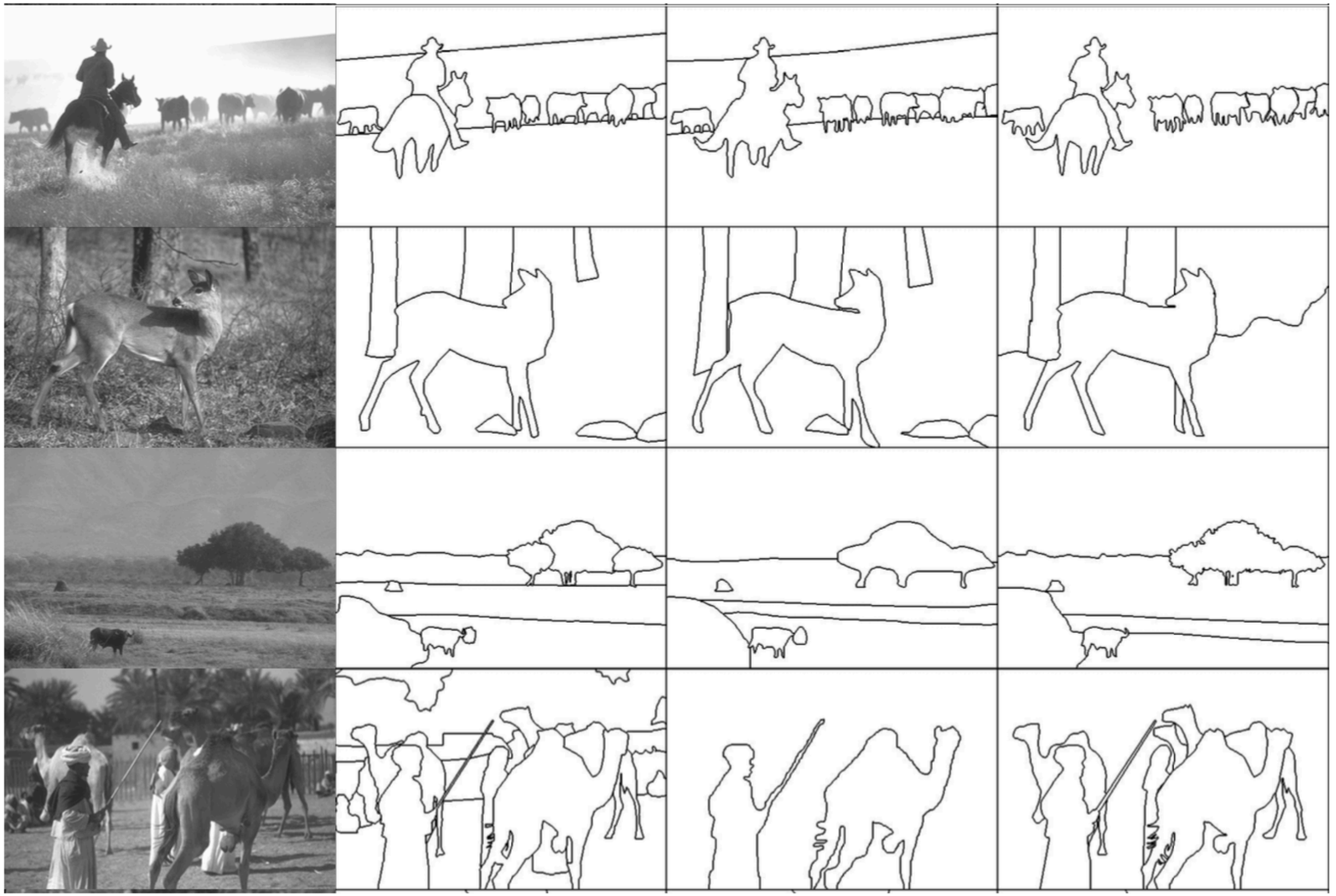
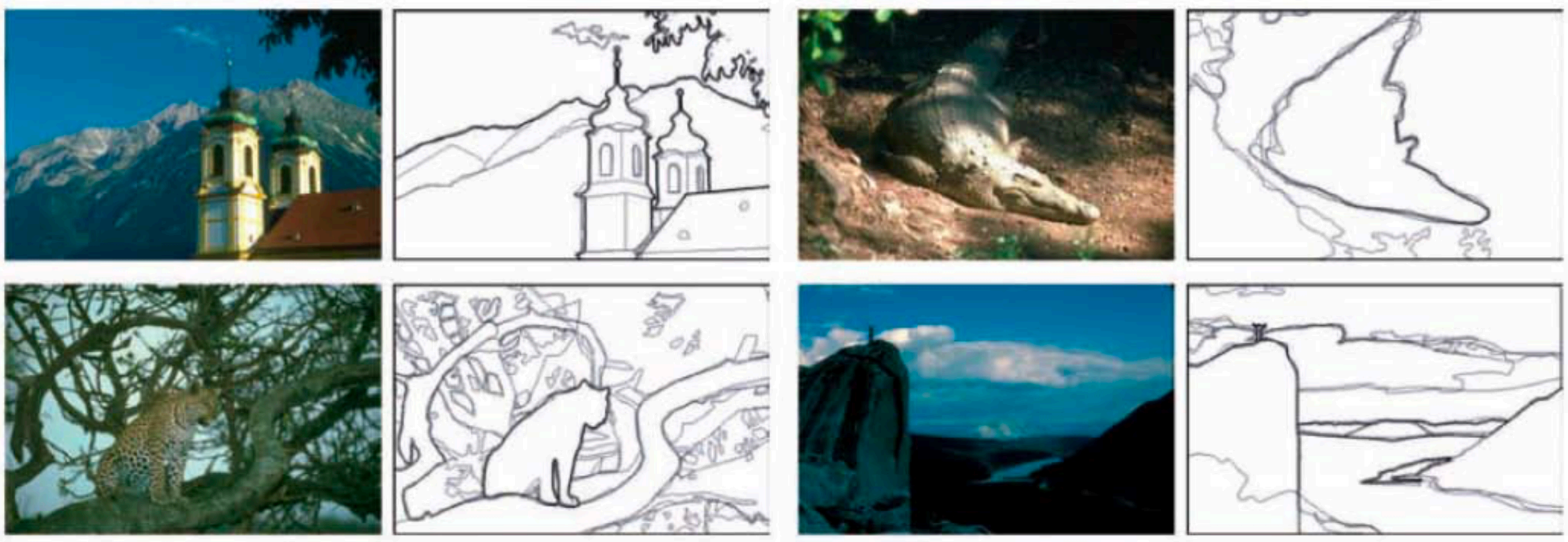


Figure Credit: Martin et al. 2001

How do humans perceive **boundaries**?



Each image shows multiple (4-8) human-marked boundaries. Pixels are darker where more humans marked a boundary.

Figure Credit: Szeliski Fig. 4.31. **Original**: Martin et al. 2004

Boundary Detection

We can formulate **boundary detection** as a high-level recognition task

— Try to learn, from sample human-annotated images, which visual features or cues are predictive of a salient/significant boundary

Many boundary detectors output a **probability or confidence** that a pixel is on a boundary

Summary

Physical properties of a 3D scene cause “**edges**” in an image:

— depth discontinuity

— surface orientation discontinuity

— reflectance discontinuity

— illumination boundaries

Basic approaches to **edge detection**:

—Smooth image to a desired scale and extract image gradients

—local extrema of a first derivative operator → **Canny**

Many algorithms consider “**boundary detection**” as a high-level recognition task and output a probability or confidence that a pixel is on a human-perceived boundary

Menu for Today

Topics:

- Edge **Detection**
- **Canny** Edge Detector
- Image **Boundaries**
- **Quiz 2**

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 **Oct 12** 23:59)

Next: Please get your **iClickers** —

Quiz 2: **6** questions