Edge Detection

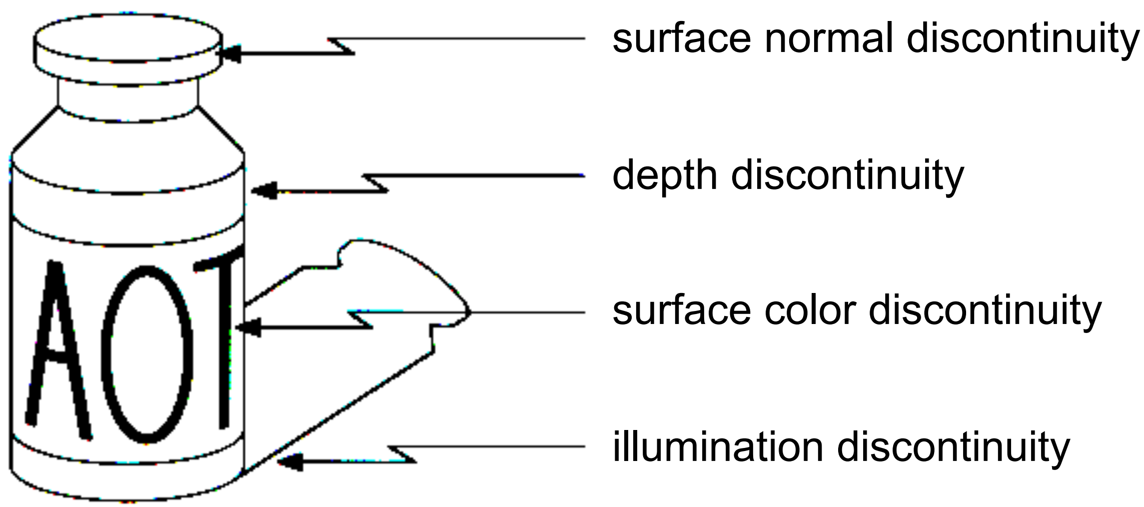
CS 543 / ECE 549 – Saurabh Gupta
Spring 2020, UIUC

http://saurabhg.web.illinois.edu/teaching/ece549/sp2020/

Many slides from S. Lazebnik.

Edge detection

- **Goal:** Identify sudden changes (discontinuities) in an image
- Intuitively, edges carry most of the semantic and shape information from the image

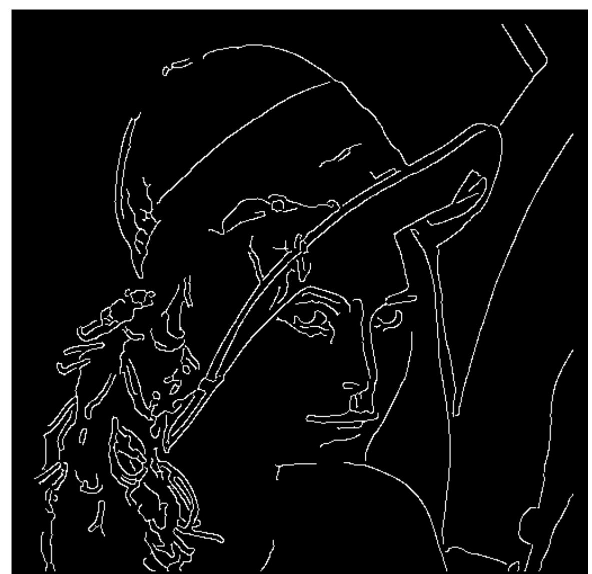


Sources: D. Lowe and S. Seitz

Edge detection

- **Ideal:** artist's line drawing

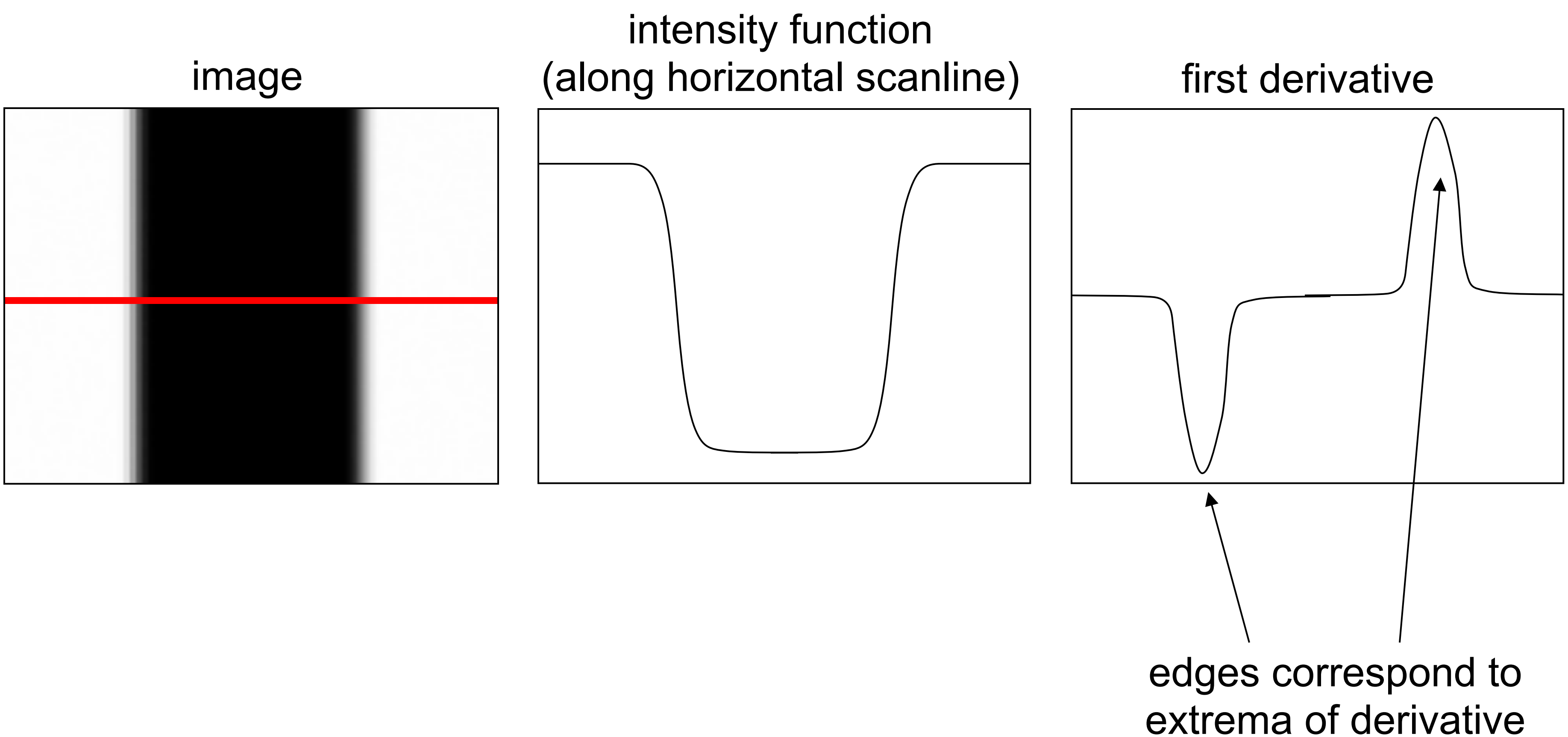
- **Reality:**



Source: L. Lazebnik

Edge detection

- An edge is a place of rapid change in the image intensity function



Derivatives with convolution

For 2D function f(x,y), the partial derivative is:

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

For discrete data, we can approximate using finite differences:

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

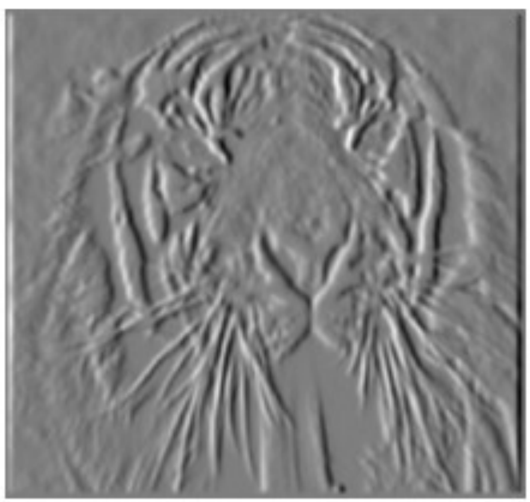
To implement the above as convolution, what would be the associated filter?

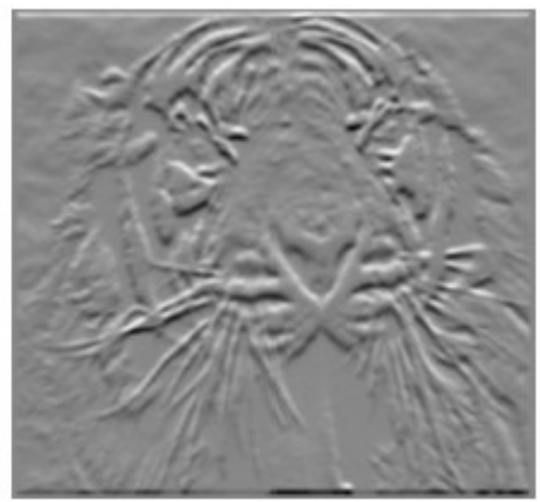
Source: K. Grauman

Partial derivatives of an image

$$\frac{\partial f(x,y)}{\partial x}$$

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





$$\frac{\partial f(x,y)}{\partial y}$$

$$\begin{bmatrix} -1 \\ 1 \end{bmatrix} \text{ or } \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Which shows changes with respect to x?

Source: L. Lazebnik

Finite difference filters

Other approximations of derivative filters exist:

Prewitt: $M_x =$

-1	0	1
-1	0	1
-1	0	1

; $M_y =$

1	1	1
0	0	0
-1	-1	-1

Sobel: $M_x =$

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

; $M_y =$

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

Roberts: $M_x =$

0	1
-1	0

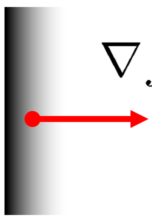
; $M_y =$

1	0
0	-1

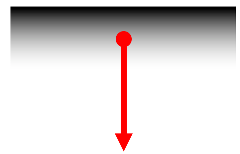
Source: K. Grauman

Image gradient

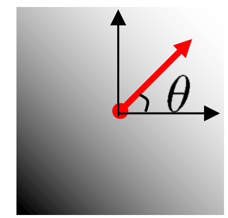
The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



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



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



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

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

- How does this direction relate to the direction of the edge?

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

The edge strength is given by the gradient magnitude

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

Source: Steve Seitz

Application: Gradient-domain image editing

- Goal: solve for pixel values in the target region to match gradients of the source region while keeping background pixels the same

sources/destinations

cloning

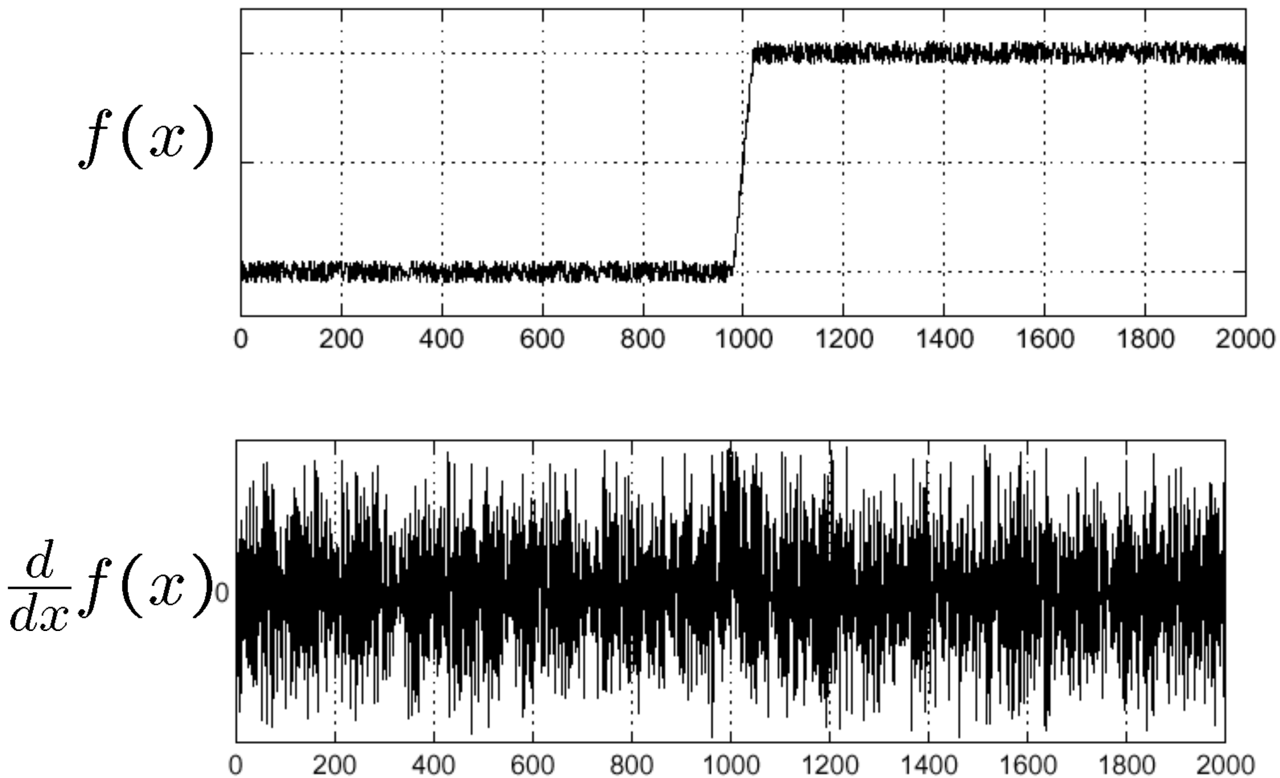
seamless cloning

P. Perez, M. Gangnet, A. Blake, [Poisson Image Editing](), SIGGRAPH 2003

Source: L. Lazebnik

Effects of noise

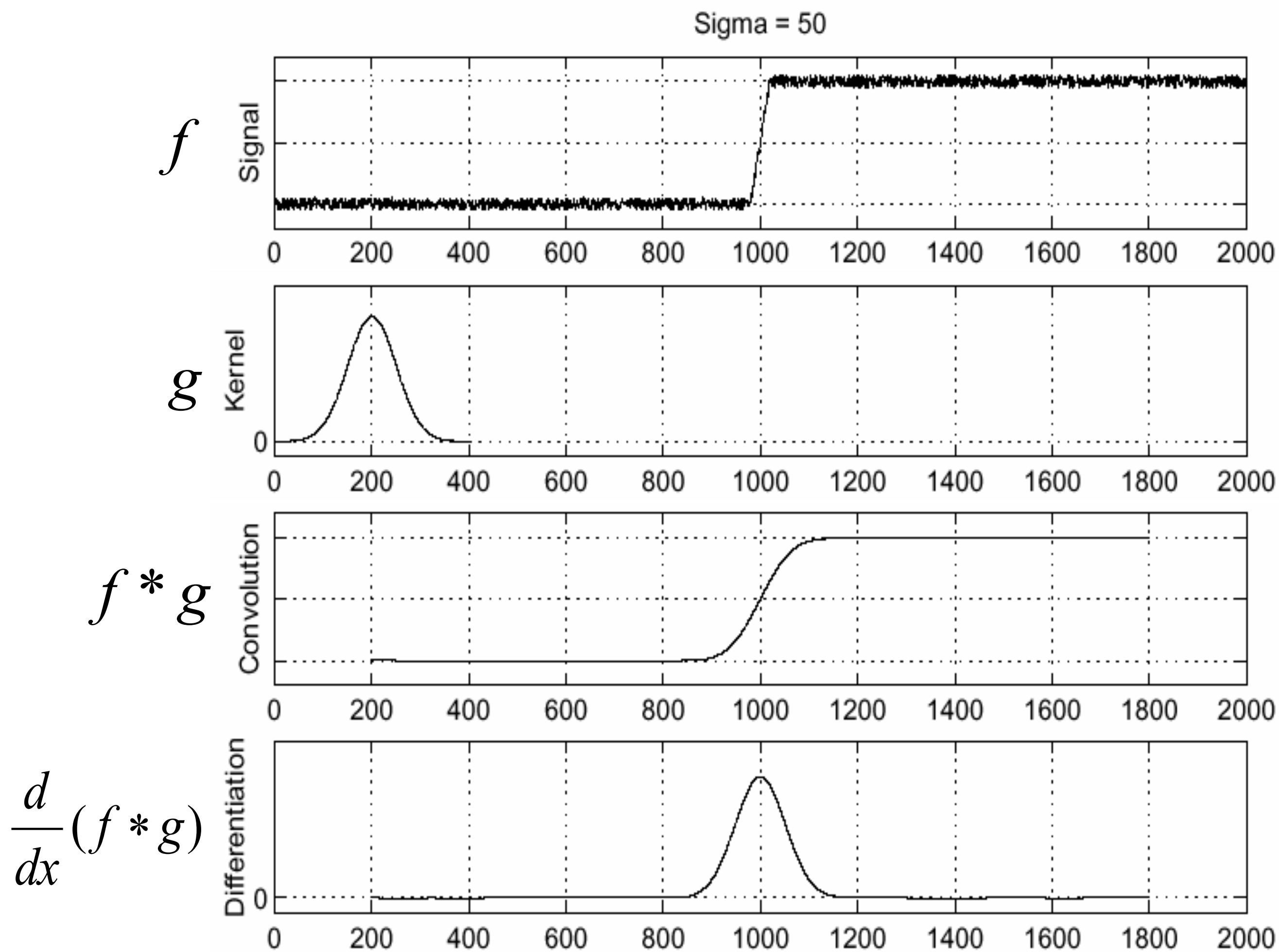
Consider a single row or column of the image



Where is the edge?

Source: S. Seitz

Solution: smooth first



- To find edges, look for peaks in $\frac{d}{dx}(f * g)$

Source: S. Seitz

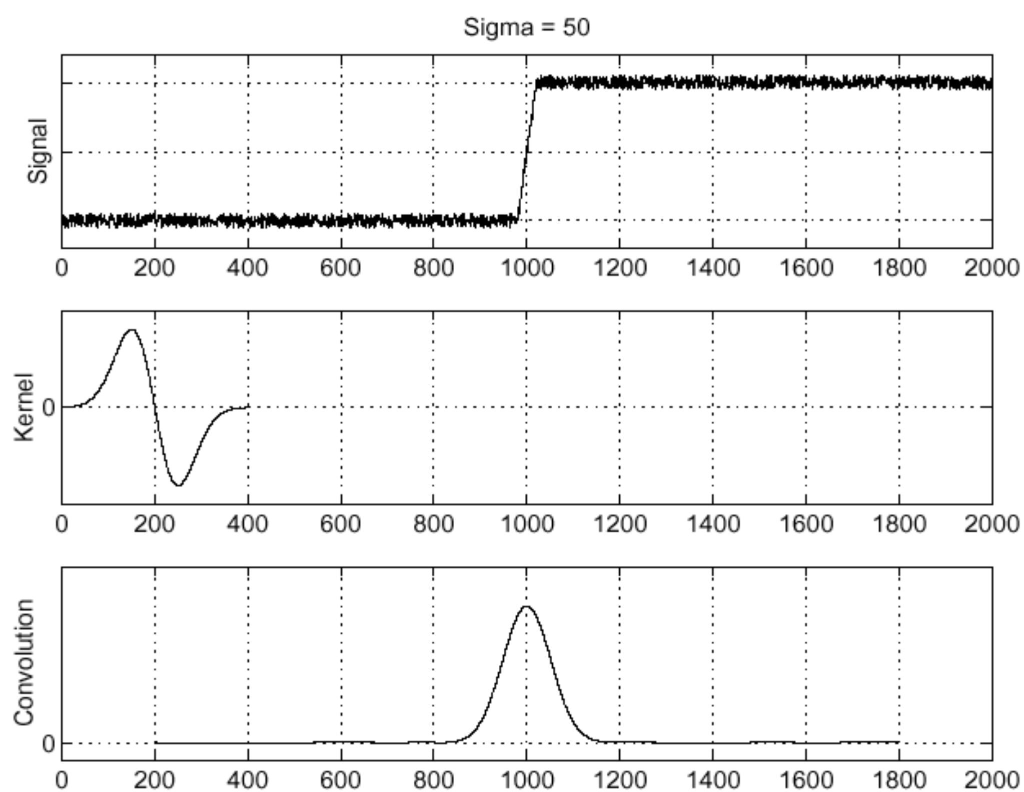
Derivative theorem of convolution

- Differentiation is convolution, and convolution is associative: $$\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$$
- This saves us one operation:

f

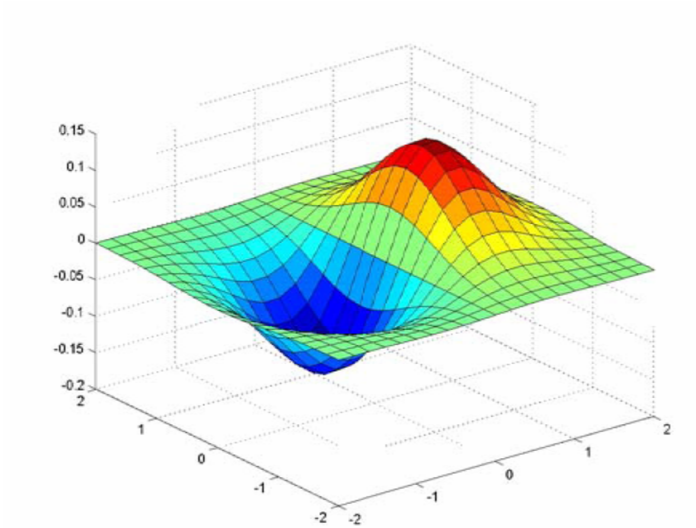
$\frac{d}{dx} g$

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

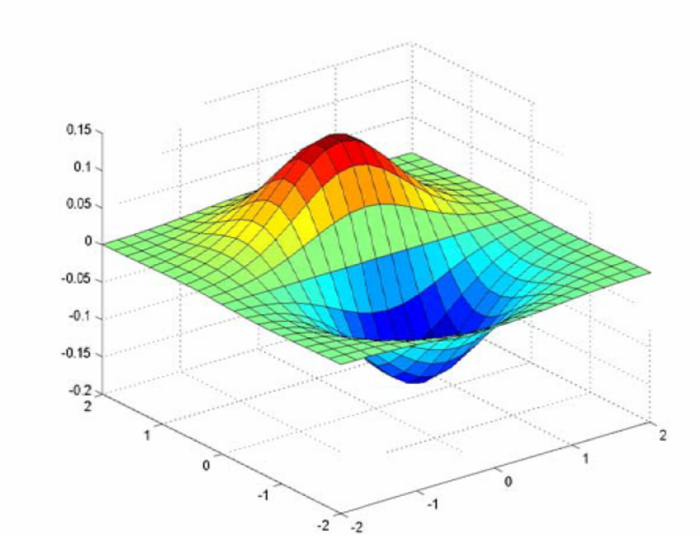


Source: S. Seitz

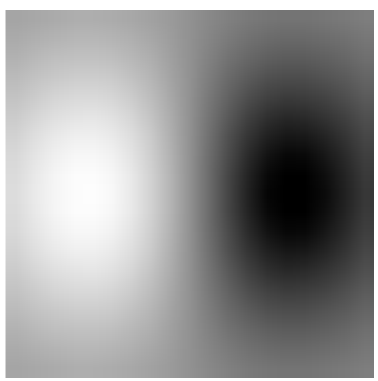
Derivative of Gaussian filters

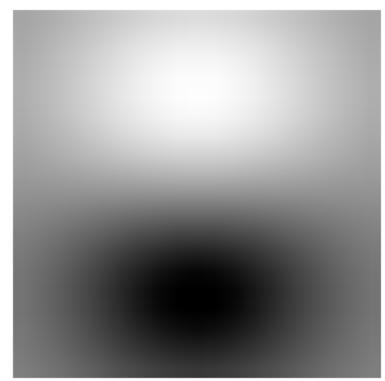


x-direction



y-direction

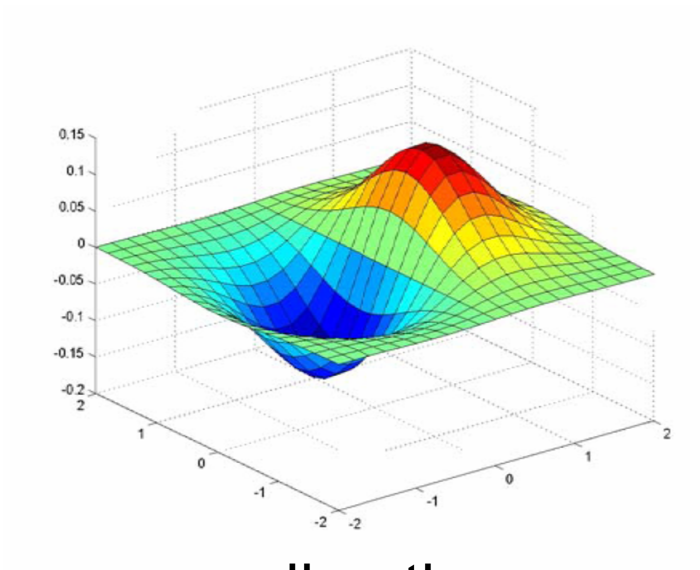




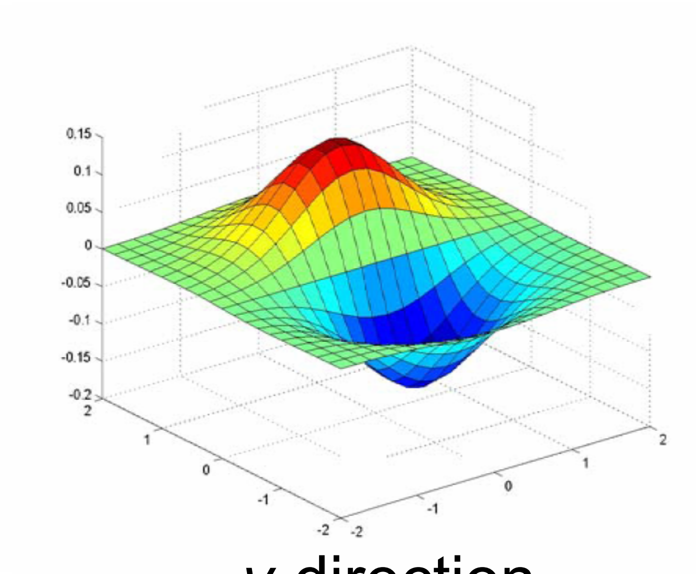
Which one finds horizontal/vertical edges?

Source: L. Lazebnik

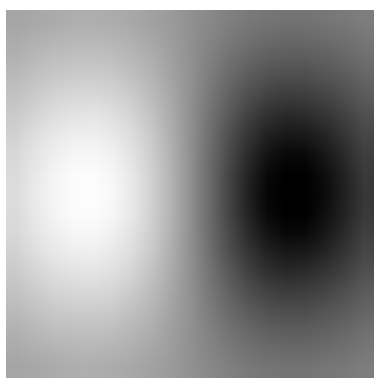
Derivative of Gaussian filters

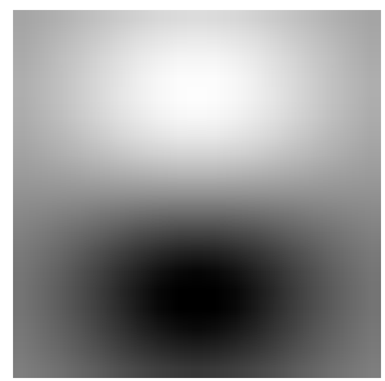


x-direction



y-direction





Are these filters separable?

Recall: Separability of the Gaussian filter

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{x^2 + y^2}{2\sigma^2}}$$

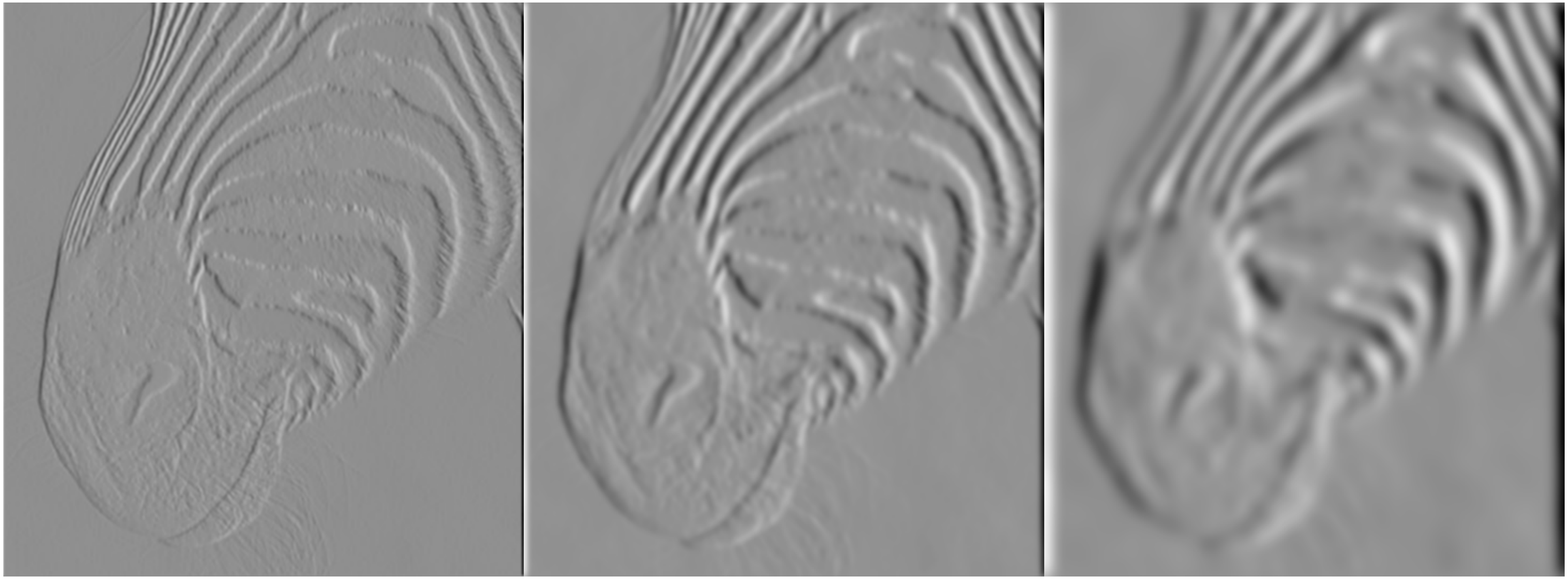
$$= \left(\frac{1}{\sqrt{2\pi}\sigma} \exp^{-\frac{x^2}{2\sigma^2}}\right) \left(\frac{1}{\sqrt{2\pi}\sigma} \exp^{-\frac{y^2}{2\sigma^2}}\right)$$

The 2D Gaussian can be expressed as the product of two functions, one a function of x and the other a function of y

In this case, the two functions are the (identical) 1D Gaussian

Source: D. Lowe

Scale of Gaussian derivative filter



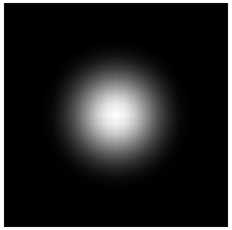
1 pixel 3 pixels 7 pixels

Smoothed derivative removes noise, but blurs edge. Also finds edges at different “scales”

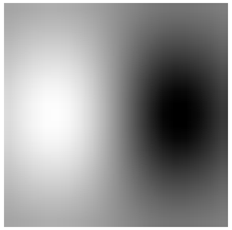
Source: D. Forsyth

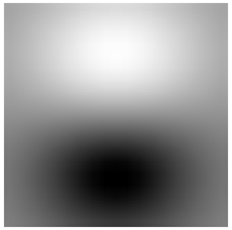
Review: Smoothing vs. derivative filters

Smoothing filters



- Gaussian: remove “high-frequency” components; “low-pass” filter
- Can the values of a smoothing filter be negative?
- What should the values sum to?
  - **One:** constant regions are not affected by the filter





Derivative filters

- Derivatives of Gaussian
- Can the values of a derivative filter be negative?
- What should the values sum to?
  - **Zero:** no response in constant regions

Source: L. Lazebnik

Building an edge detector

original image

final output

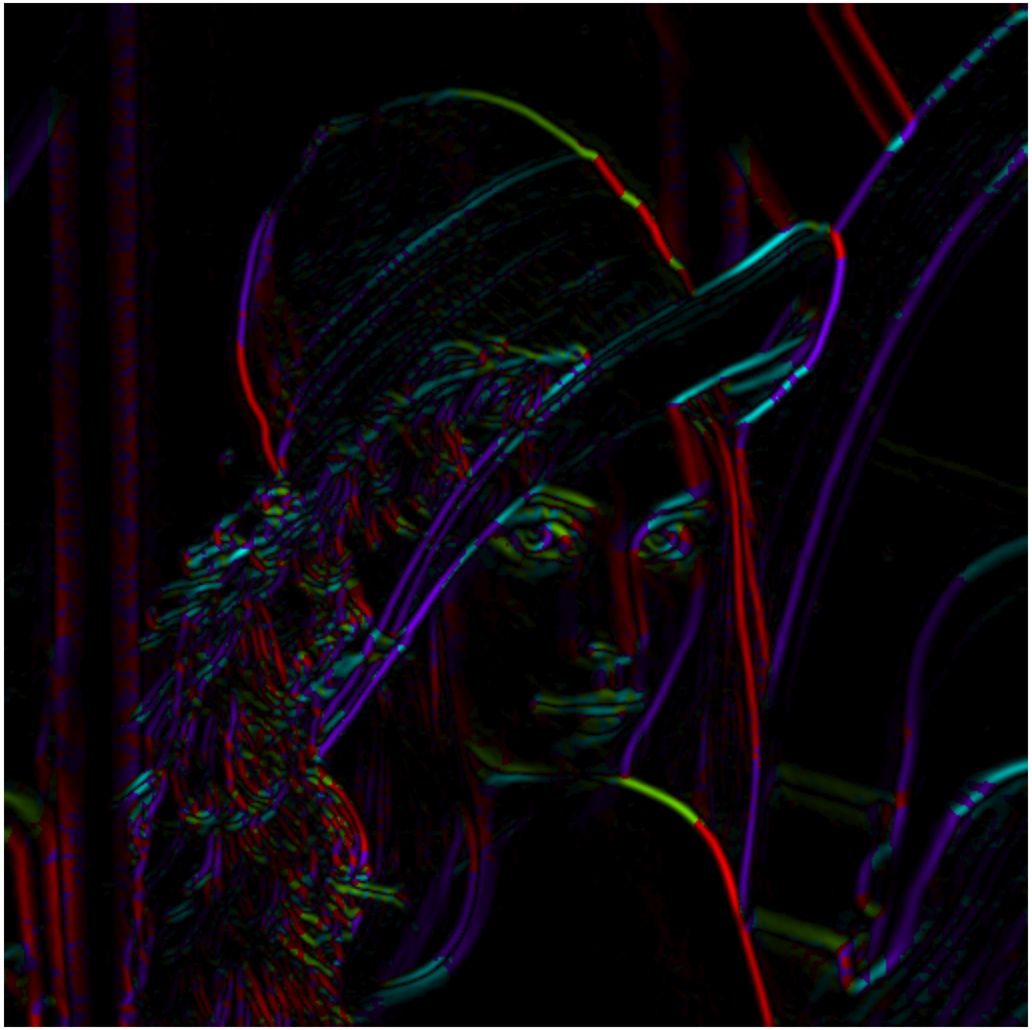
Source: L. Lazebnik

Building an edge detector

norm of the gradient

Source: L. Lazebnik

Building an edge detector



orientation of the gradient

theta = atan2(-gy, gx)

Source: D. Hoeim

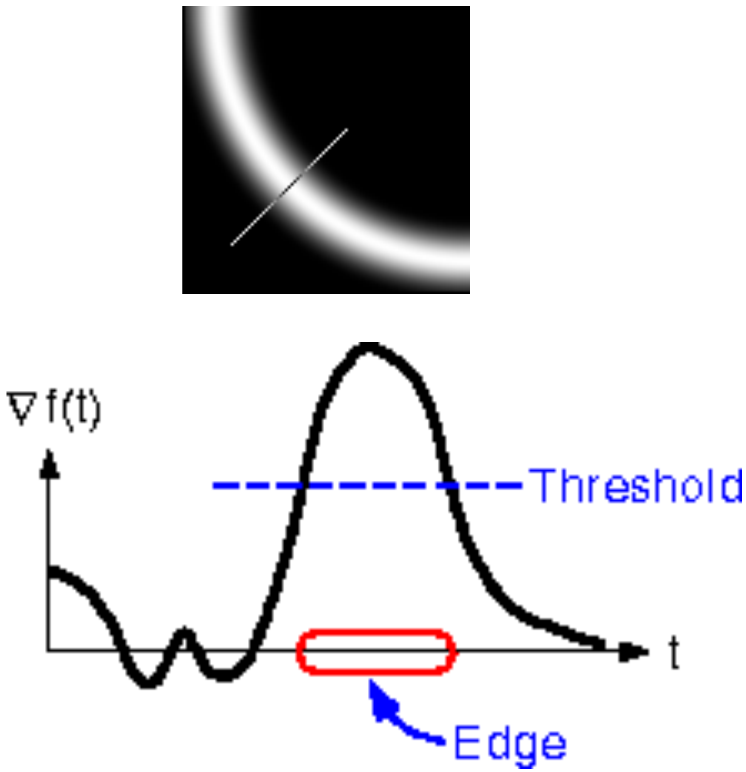
Building an edge detector

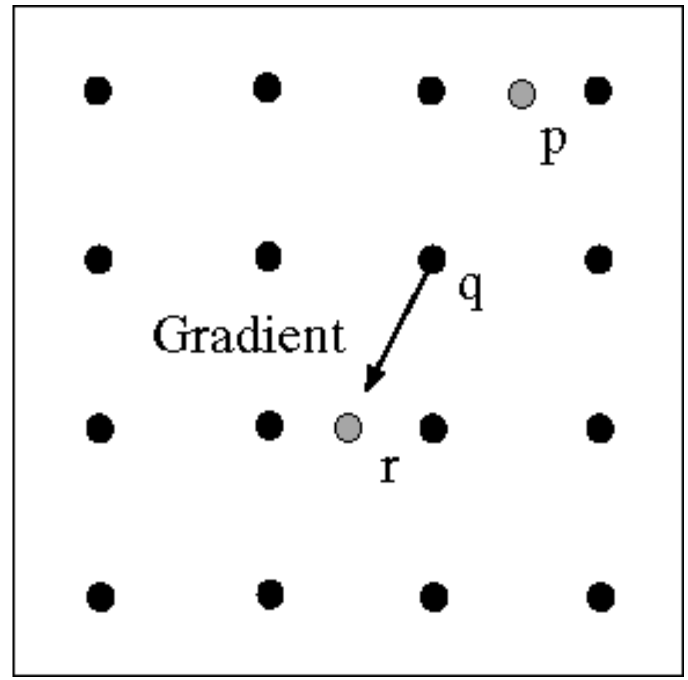
How to turn these thick regions of the gradient into curves?

Thresholded norm of the gradient

Source: L. Lazebnik

Non-maximum suppression



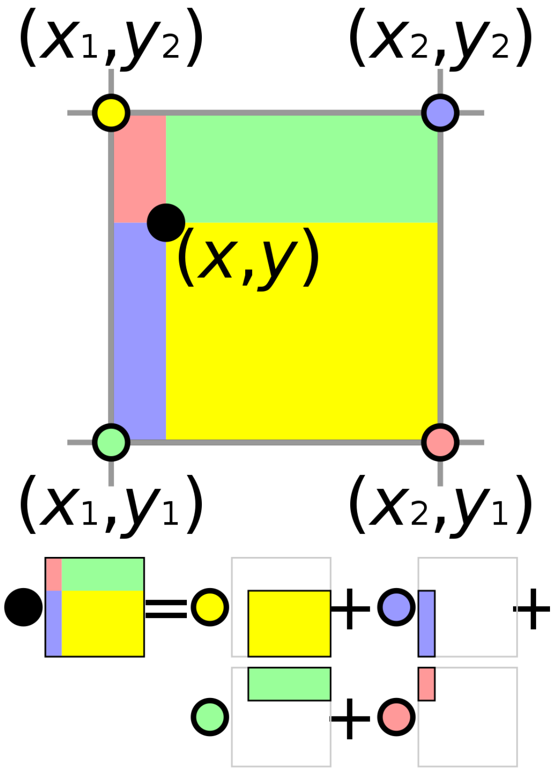


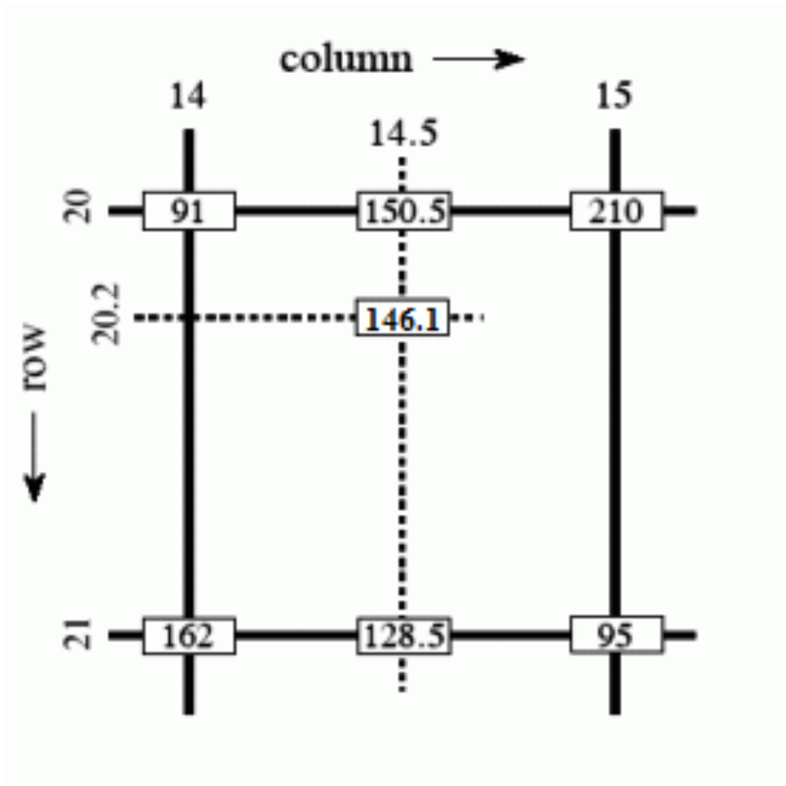
- For each location q above threshold, check that the gradient magnitude is higher than at neighbors p and r along the direction of the gradient
  - May need to interpolate to get the magnitudes at p and r

Source: L. Lazebnik

Bilinear Interpolation

$$f(x,y) \approx \begin{bmatrix} 1-x & x \end{bmatrix} \begin{bmatrix} f(0,0) & f(0,1) \\ f(1,0) & f(1,1) \end{bmatrix} \begin{bmatrix} 1-y \\ y \end{bmatrix}$$

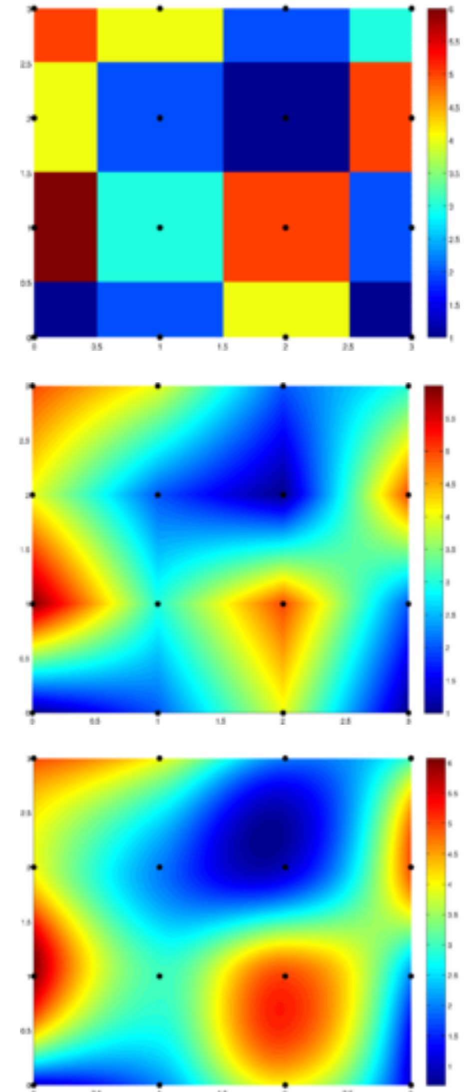




http://en.wikipedia.org/wiki/Bilinear_interpolation

Sidebar: Interpolation options

imx2 = imresize(im, 2, interpolation_type)



‘nearest’

- Copy value from nearest known
- Very fast but creates blocky edges

‘bilinear’

- Weighted average from four nearest known pixels
- Fast and reasonable results

‘bicubic’ (default)

- Non-linear smoothing over larger area
- Slower, visually appealing, may create negative pixel values

Source: D. Hoeim

Examples from http://en.wikipedia.org/wiki/Bicubic_interpolation

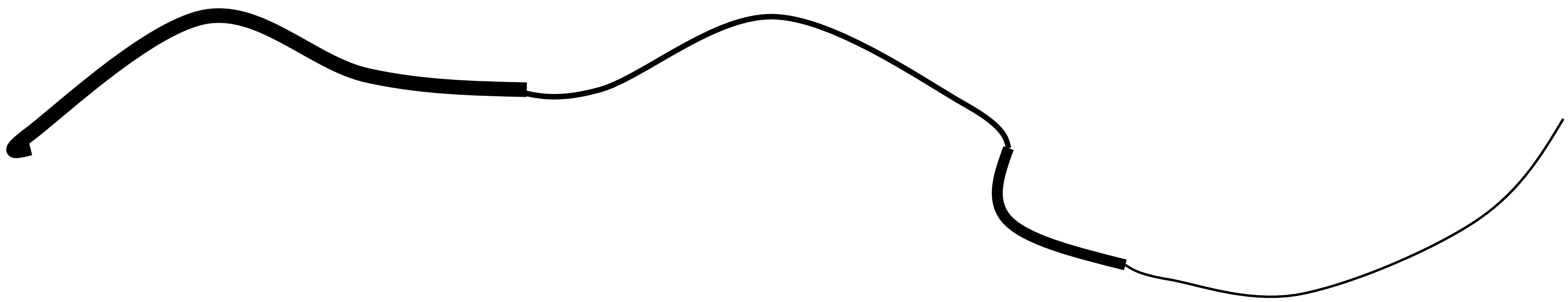
Non-maximum suppression

Another problem: pixels along this edge didn't survive the thresholding

Source: L. Lazebnik

Hysteresis thresholding

Use a high threshold to start edge curves, and a low threshold to continue them.



Source: Steve Seitz

Hysteresis thresholding

original image

high threshold (strong edges)

low threshold (weak edges)

hysteresis threshold

Source: L. Fei-Fei

Effect of σ (Gaussian kernel spread/size)

original

Canny with $\sigma = 1$

Canny with $\sigma = 2$

The choice of σ depends on desired behavior

- large σ detects large scale edges
- small σ detects fine features

Source: S. Seitz

Recap: Canny edge detector

1. Compute x and y gradient images
2. Find magnitude and orientation of gradient
3. **Non-maximum suppression**:
   - Thin wide “ridges” down to single pixel width
4. **Linking and thresholding** (**hysteresis**):
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves and the low threshold to continue them

J. Canny, A Computational Approach To Edge Detection, IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679-714, 1986.

Source: L. Lazebnik

Image gradients vs. meaningful contours

image | human segmentation | gradient magnitude

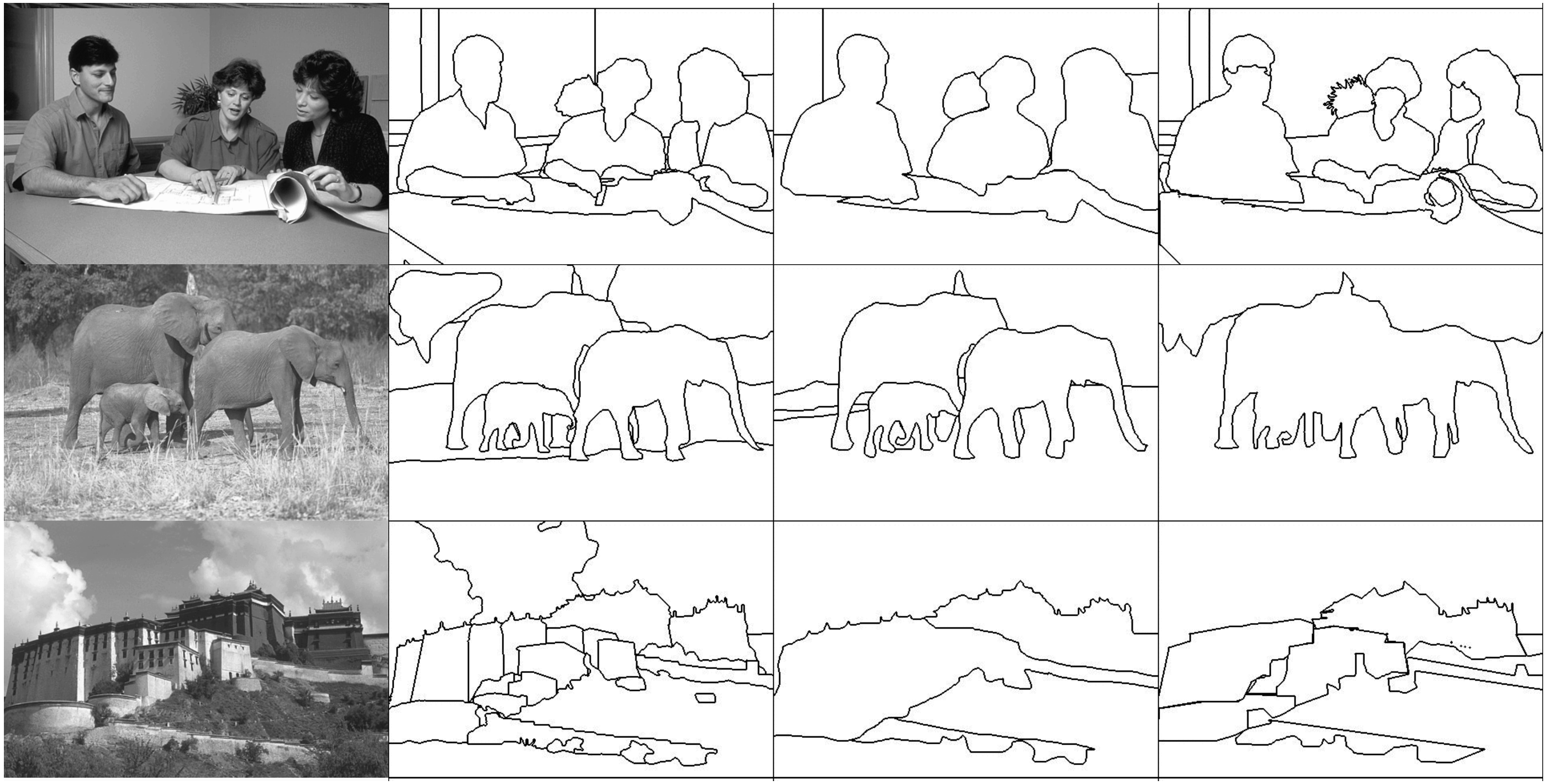
Berkeley segmentation database:

http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

Source: L. Lazebnik

Do humans consistently segment images?

Divide each image into pieces, where each piece represents a distinguished thing in the image. It is important that all of the pieces have approximately equal importance. The number of things in each image is up to you. Something between 2 and 20 should be reasonable for any of our images.



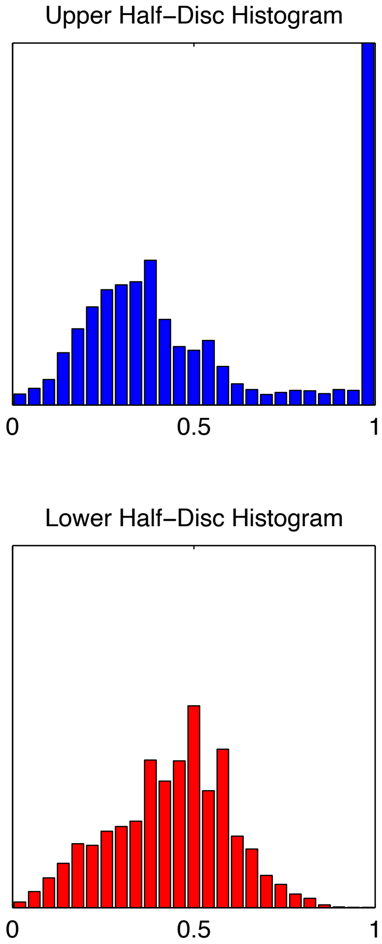
[A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics]

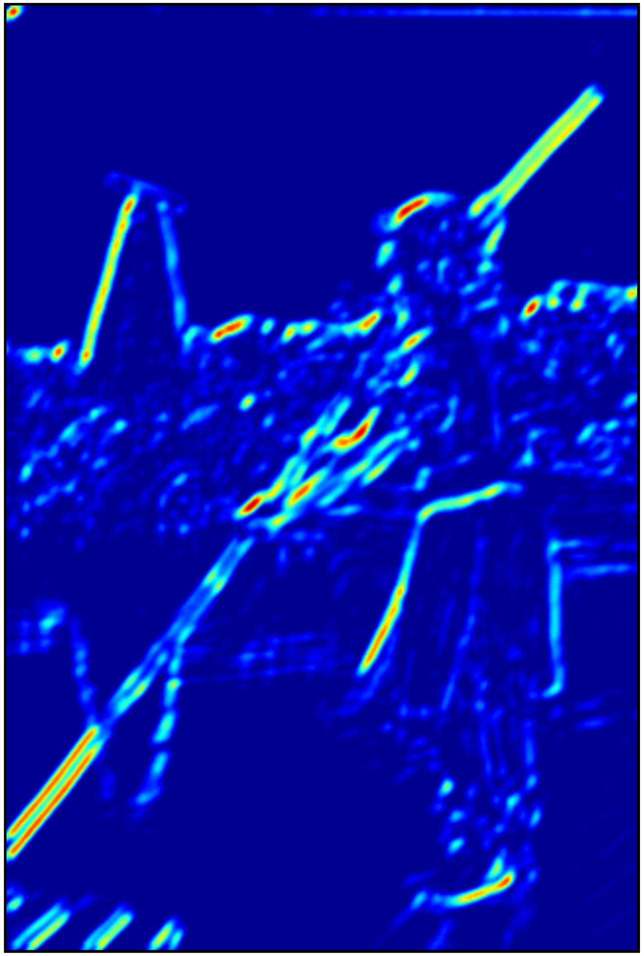
Aside: Datasets, Metrics and Benchmarks

- Standard image sets
- Standard metrics
- Possible to *quantitatively* compare different methods

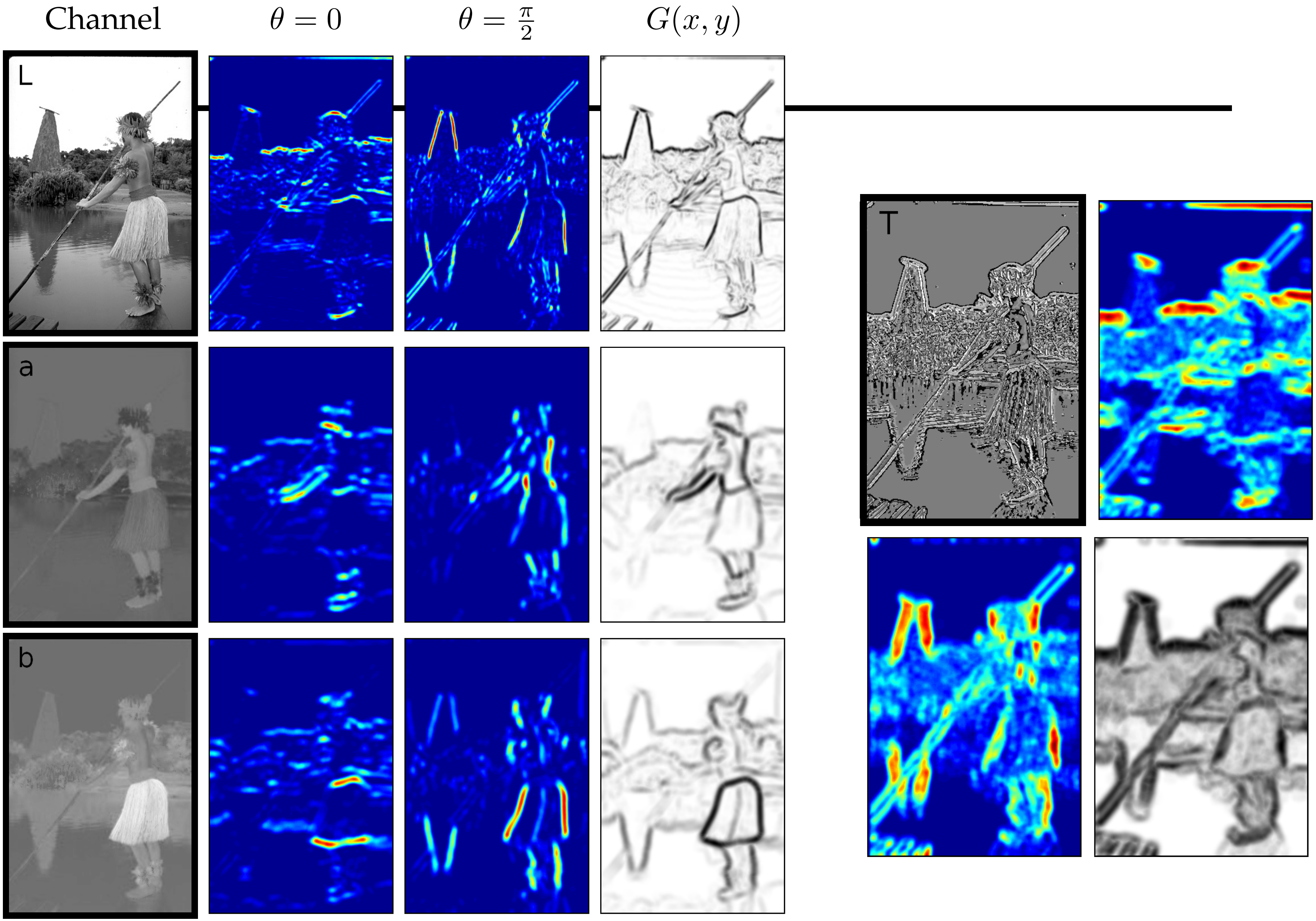
[A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics]

pB Boundary Detector



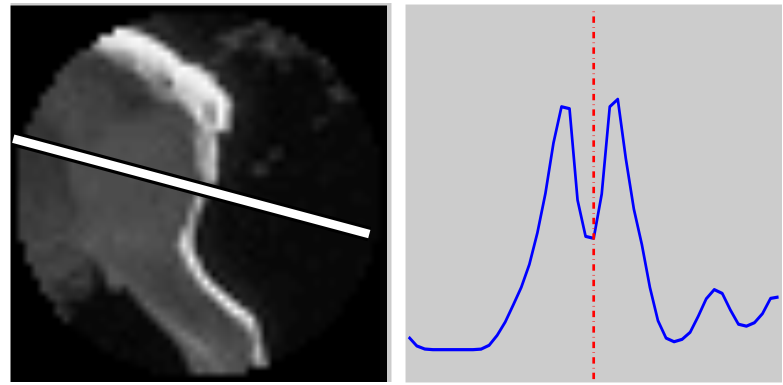


[Contour Detection and Hierarchical Image Segmentation]() P. Arbeláez. PAMI 2010.



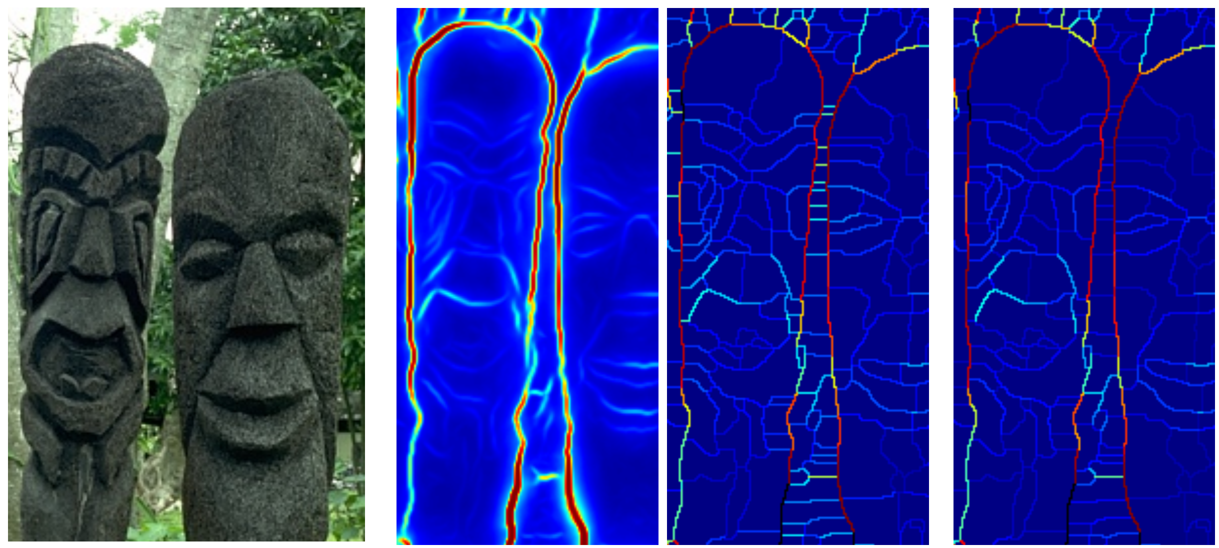
[Contour Detection and Hierarchical Image Segmentation](#) P. Arbeláez. PAMI 2010.

Lots of Tricks



"Bird Edge" Problem with Texture Gradients

Sky Breaking

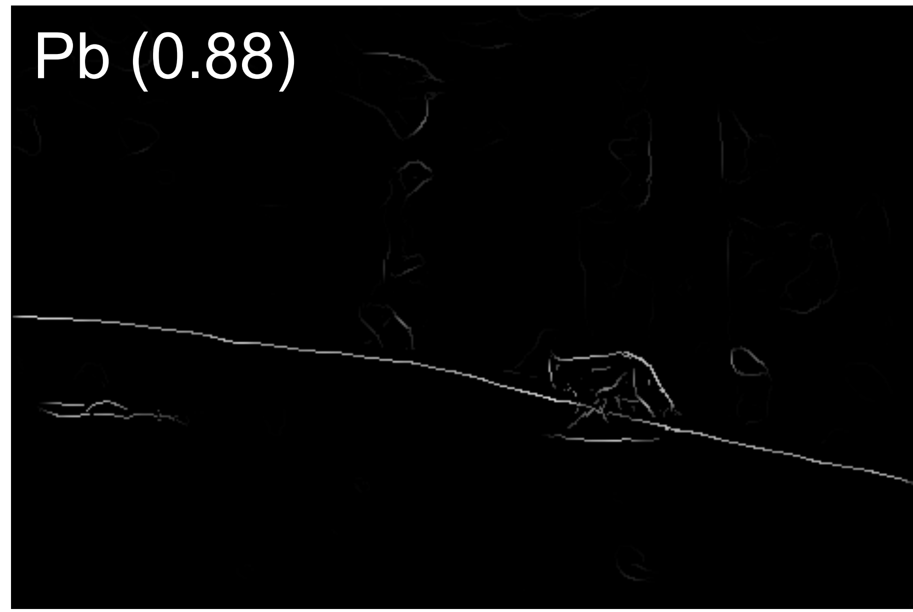


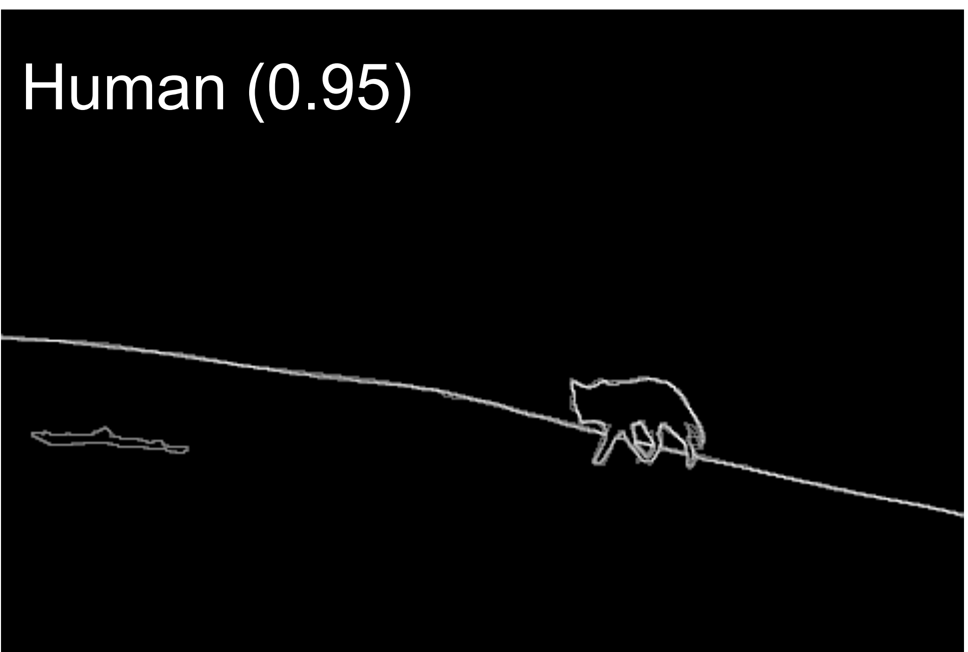
Information Leakage across Orientations

[Learning to Detect Natural Image Boundaries Using Brightness and Texture]

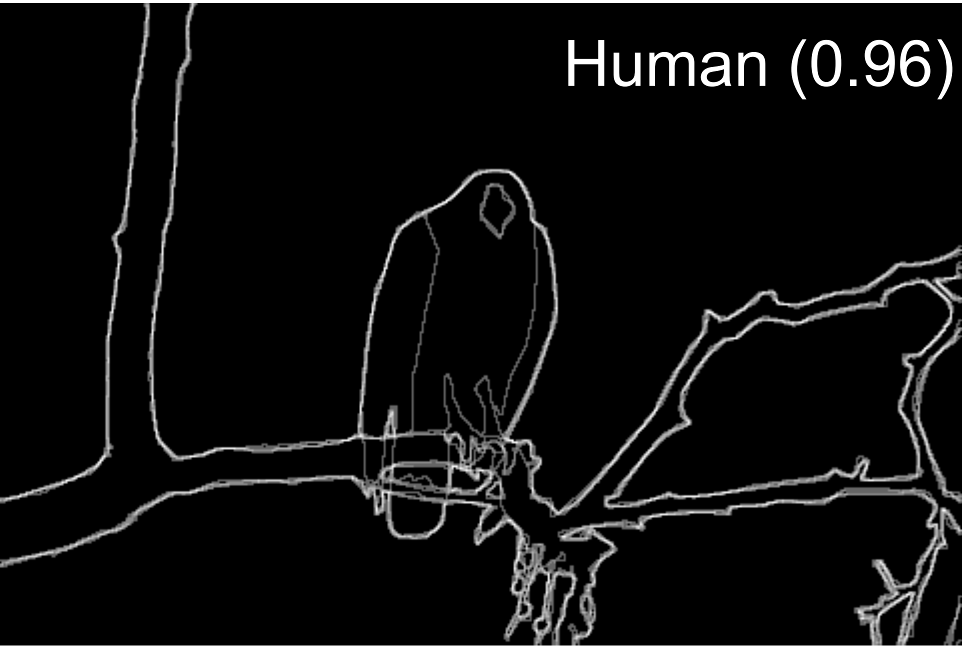
[Contour Detection and Hierarchical Image Segmentation]

Results

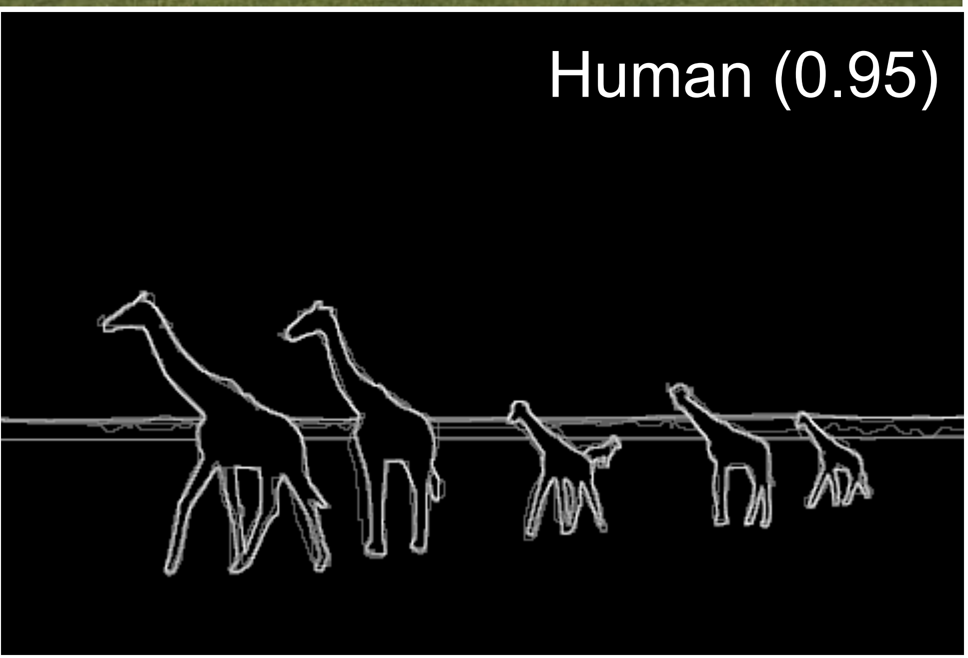


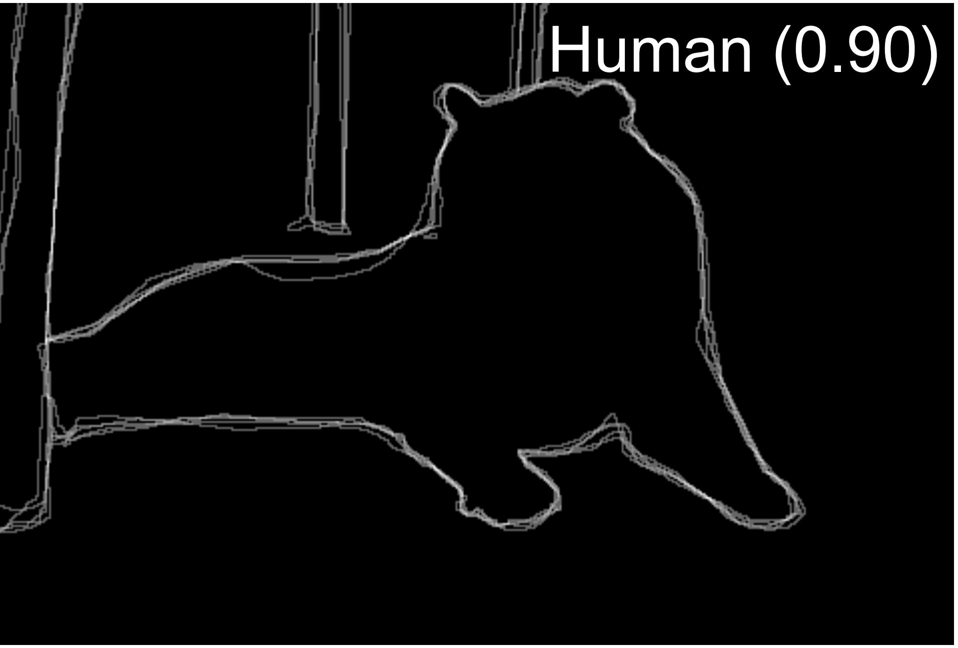


Results




Pb (0.63)

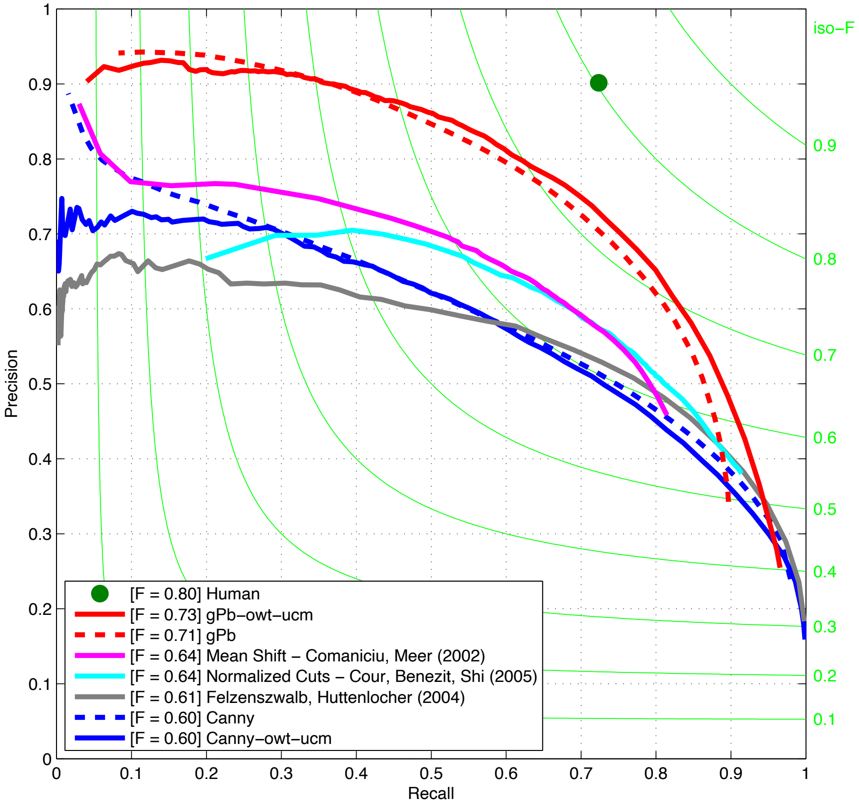

Human (0.95)



For more:
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/bench/html/108082-color.html

Empirical Research

	BSDS300		
	ODS	OIS	AP
Human	0.79	0.79	—
gPb-owt-ucm	**0.71**	**0.74**	**0.73**
[34] Mean Shift	0.63	0.66	0.54
[33] NCuts	0.62	0.66	0.43
Canny-owt-ucm	0.58	0.63	0.58
[32] Felz-Hutt	0.58	0.62	0.53
[31] SWA	0.56	0.59	0.54
Quad-Tree	0.37	0.39	0.26
gPb	0.70	0.72	0.66
Canny	0.58	0.62	0.58

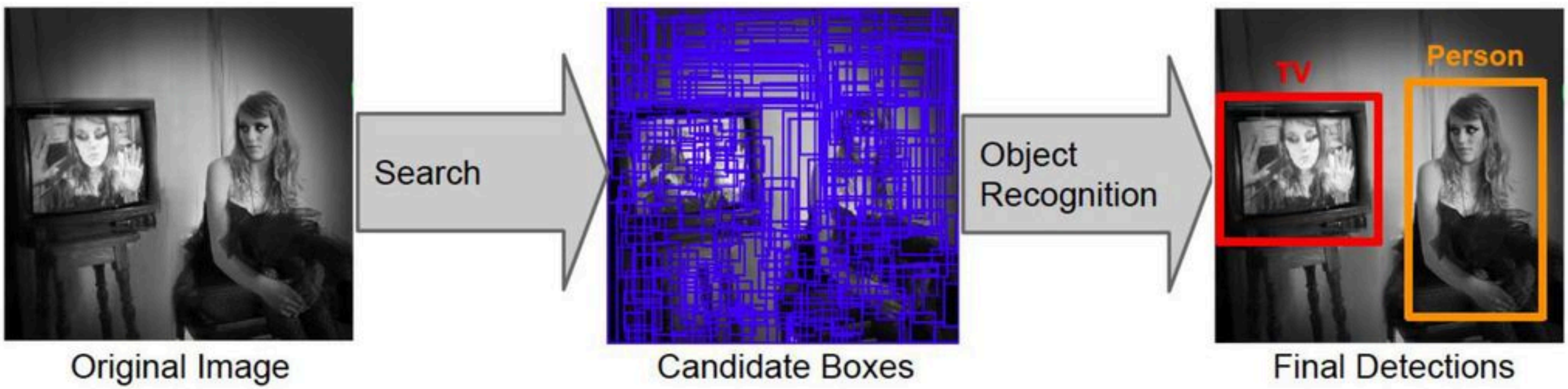


[Contour Detection and Hierarchical Image Segmentation]

Applications: Interactive Segmentation

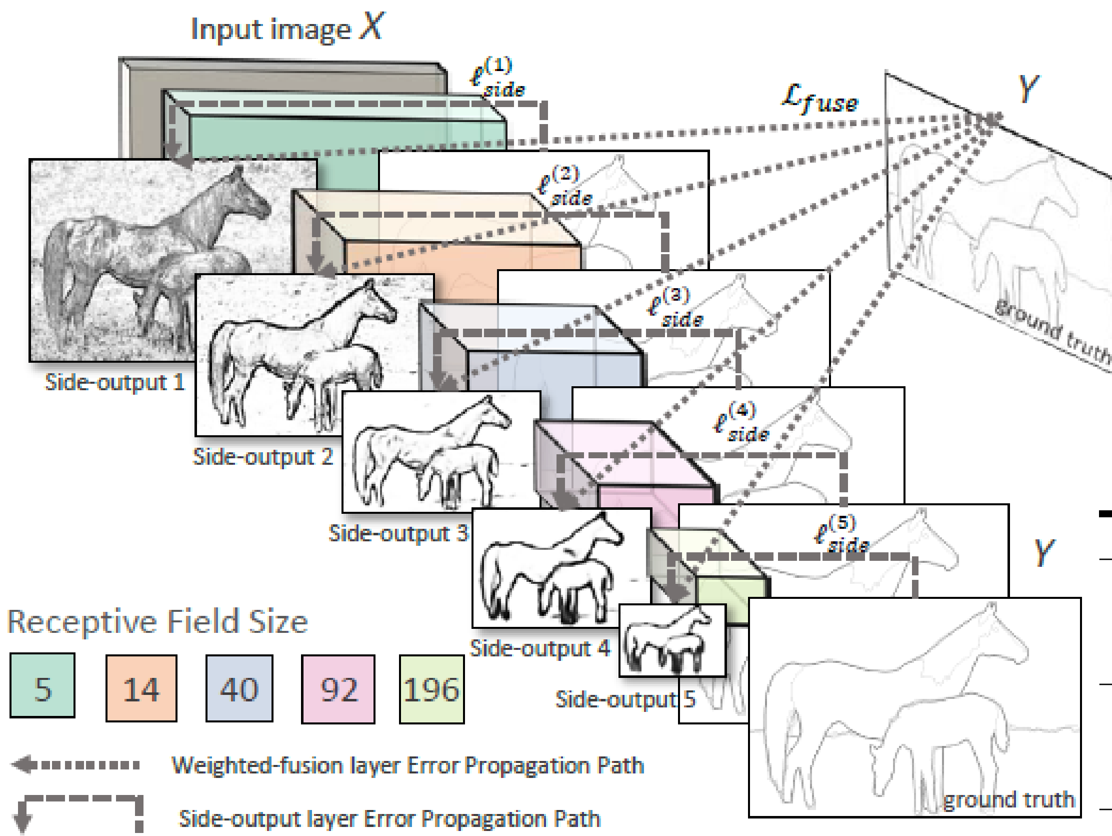
[Contour Detection and Hierarchical Image Segmentation. P. Arbeláez et al. PAMI 2010]

Applications: Pre-processing for Object Detection



J. Uijlings, K. van de Sande, T. Gevers, and A. Smeulders,
[Selective Search for Object Recognition](), IJCV 2013

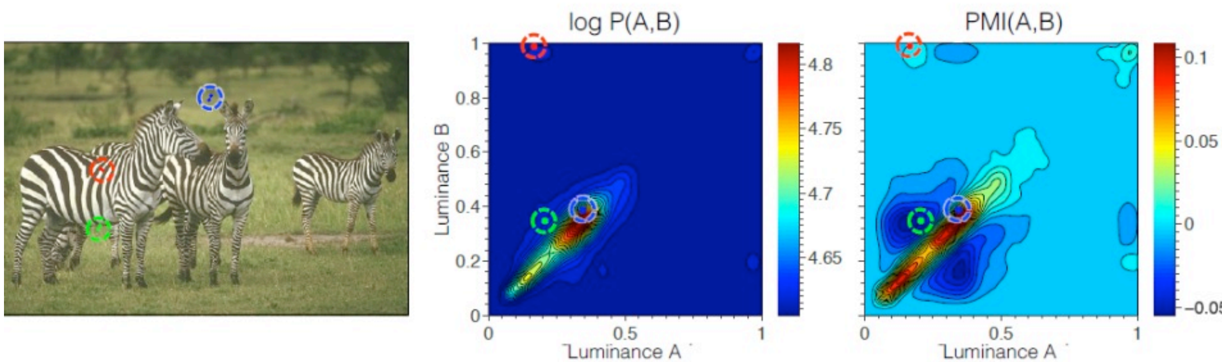
Holistically nested edge detection



	ODS	OIS	AP	FPS
Human	.80	.80	-	-
Canny	.600	.640	.580	15
Felz-Hutt [9]	.610	.640	.560	10
BEL [5]	.660∗	-	-	1/10
gPb-owt-ucm [1]	.726	.757	.696	1/240
Sketch Tokens [24]	.727	.746	.780	1
SCG [31]	.739	.758	.773	1/280
SE-Var [6]	.746	.767	.803	2.5
OEF [13]	.749	.772	.817	-
DeepNets [21]	.738	.759	.758	1/5†
N4-Fields [10]	.753	.769	.784	1/6†
DeepEdge [2]	.753	.772	.807	$1/10^3$†
CSCNN [19]	.756	.775	.798	-
DeepContour [34]	.756	.773	.797	1/30†
HED (ours)	**.782**	**.804**	**.833**	2.5†, 1/12

https://arxiv.org/pdf/1504.06375.pdf

Crisp Boundary Detection using Pointwise Mutual Information (Isola et al. ECCV 2014)



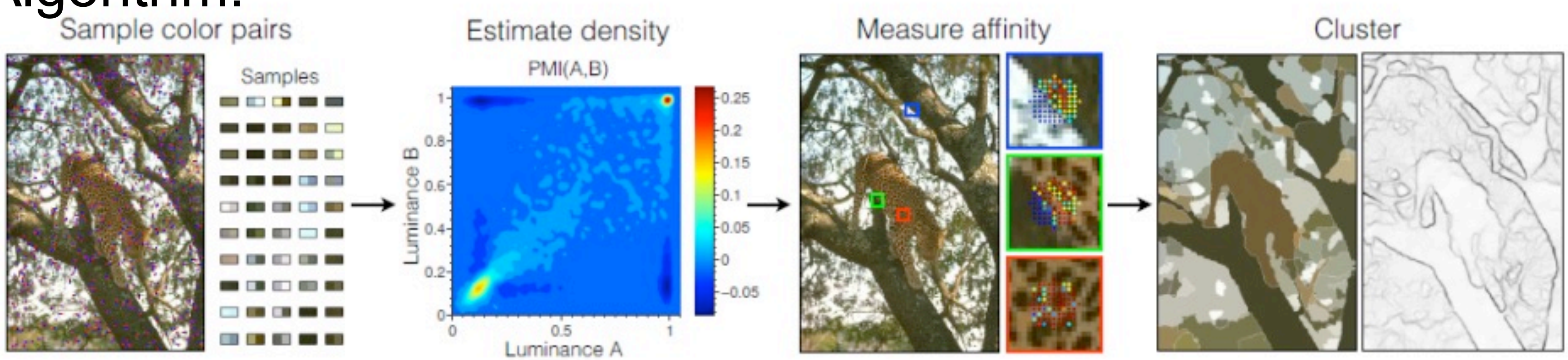
$$\mathrm{PMI}_\rho(A,B) = \log \frac{P(A,B)^\rho}{P(A)P(B)}$$

Pixel combinations that are unlikely to be together are edges

Algorithm:

Kernel density estimation

Spectral clustering



http://web.mit.edu/phillipi/www/publications/crisp_boundaries.pdf

Crisp Boundary Detection using Pointwise Mutual Information

Algorithm	ODS	OIS	AP
Canny [14]	0.60	0.63	0.58
Mean Shift [36]	0.64	0.68	0.56
NCuts [37]	0.64	0.68	0.45
Felz-Hutt [38]	0.61	0.64	0.56
gPb [1]	0.71	0.74	0.65
gPb-owt-ucm [1]	0.73	0.76	0.73
SCG [9]	**0.74**	0.76	0.77
Sketch Tokens [7]	0.73	0.75	0.78
SE [8]	**0.74**	0.76	0.78
Our method – SS, color only	0.72	0.75	0.77
Our method – SS	0.73	0.76	**0.79**
Our method – MS	**0.74**	**0.77**	0.78

State of edge detection

Local edge detection is mostly solved

- Intensity gradient, color, texture
- HED on BSDS 500 is near human performance

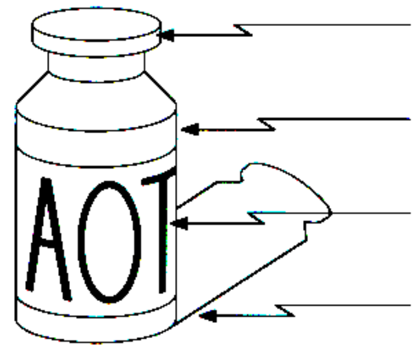
Some room for improvement by taking advantage of higher-level knowledge (e.g., objects)

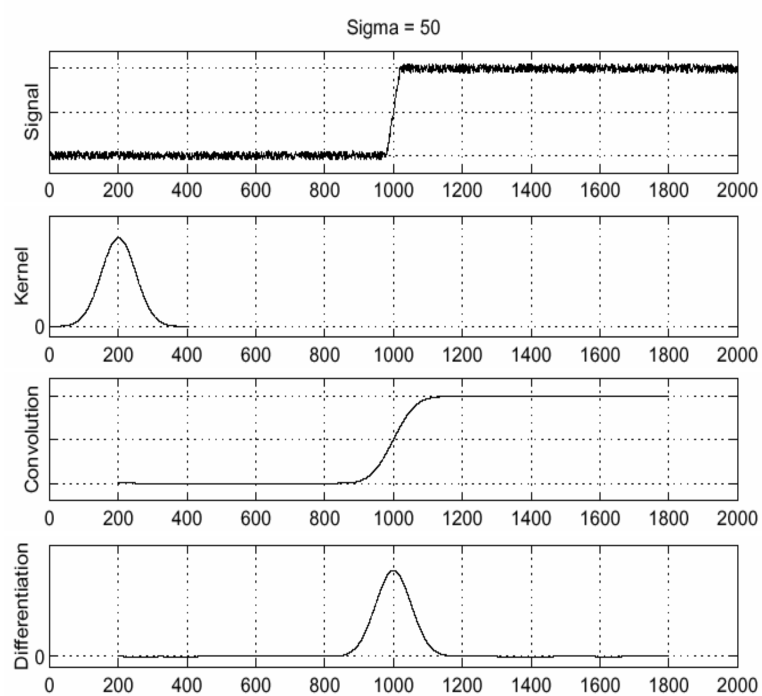
Still hard to produce all objects within a small number of regions

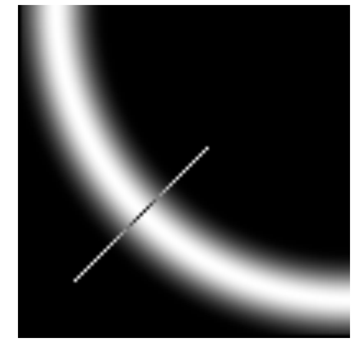
Are Edges an Input or an Output?

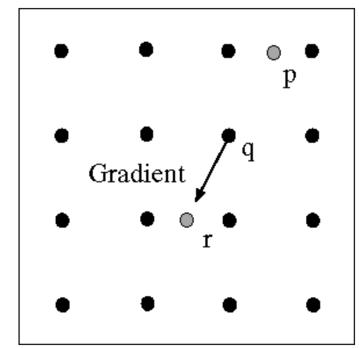
Source: Gregory, R. L. (1970). The Intelligent Eye. New York, NY: McGraw-Hill Paperbacks.

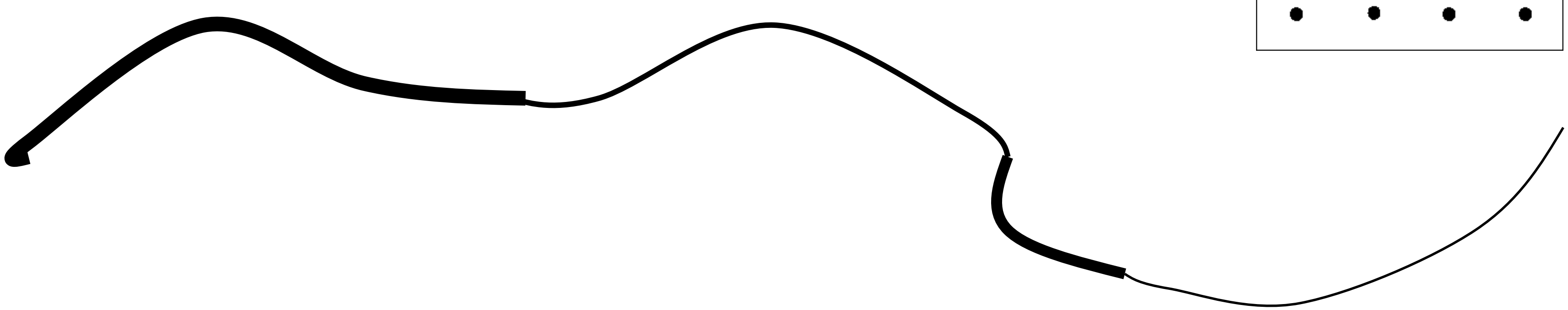
Recap


AOT

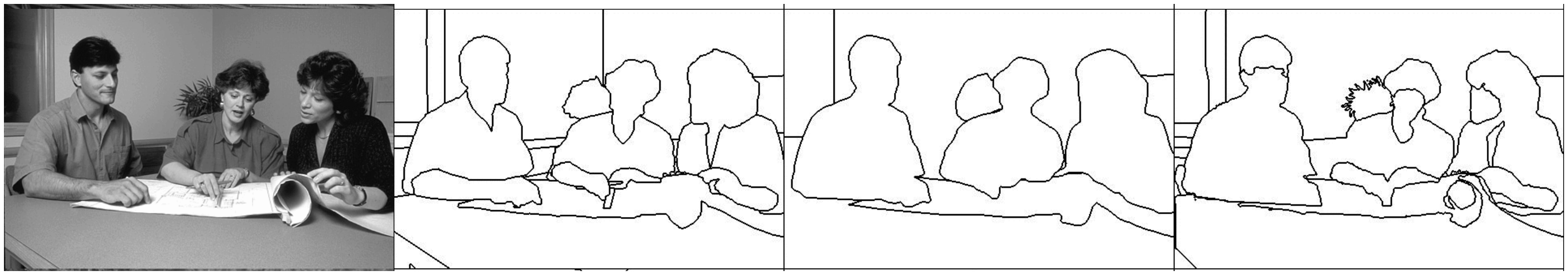

Sigma = 50
Signal
Kernel
Convolution
Differentiation
0
200
400
600
800
1000
1200
1400
1600
1800
2000

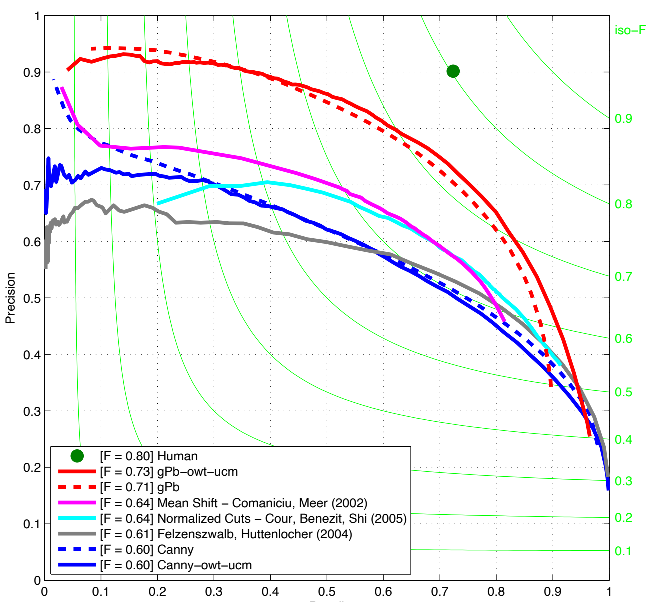



p
q
Gradient
r



Recap





	BSDS300		
	ODS	OIS	AP
Human	0.79	0.79	–
gPb-owt-ucm	**0.71**	**0.74**	**0.73**
[34] Mean Shift	0.63	0.66	0.54
[33] NCuts	0.62	0.66	0.43
Canny-owt-ucm	0.58	0.63	0.58
[32] Felz-Hutt	0.58	0.62	0.53
[31] SWA	0.56	0.59	0.54
Quad-Tree	0.37	0.39	0.26
gPb	0.70	0.72	0.66
Canny	0.58	0.62	0.58