

# CSC 589 Introduction to Computer Vision

## Lecture 14 Boundary Detection

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# Edge detection

- **Goal:** Identify sudden changes (discontinuities) in an image
  - Intuitively, most semantic and shape information from the image can be encoded in the edges
  - More compact than pixels
- **Ideal:** artist's line drawing (but artist is also using object-level knowledge)



Source: D. Lowe

# Canny Edge Operator

1. **Noise reduction:** Filter image with x, y derivatives of Gaussian
2. **Intensity gradients:** Find magnitude and orientation of gradient
3. **Non-maximum suppression:**
  - Thin multi-pixel wide “ridges” down to single pixel width
4. **Thresholding and linking (hysteresis):**
  - Define two thresholds: low and high
  - Use the high threshold to start edge curves and the low threshold to continue them
  - Python: `cv2.Canny(img, lo, hi)`,
  - `skimage.filter.canny`
  - `canny(img, sigma)`

# Original image



# Gradient magnitude



(a) Smoothed



(b) Gradient magnitudes

# Gradient magnitude

Sobel Filter on x and y directions

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

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

$$|G| = \sqrt{G_x^2 + G_y^2}$$

$$|G| = |G_x| + |G_y|$$

# Non-maximum suppression



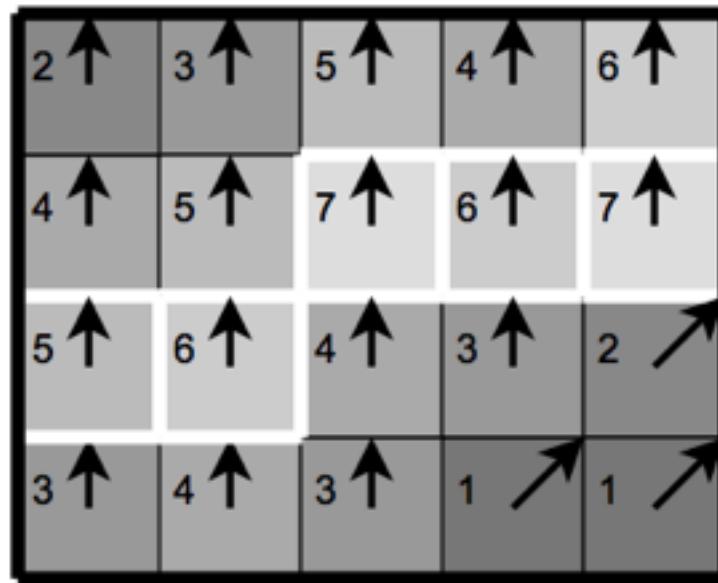
(a) Gradient values



(b) Edges after non-maximum suppression

<http://www.cse.iitd.ernet.in/~pkalra/csl783/canny.pdf>

# Non-maximum suppression

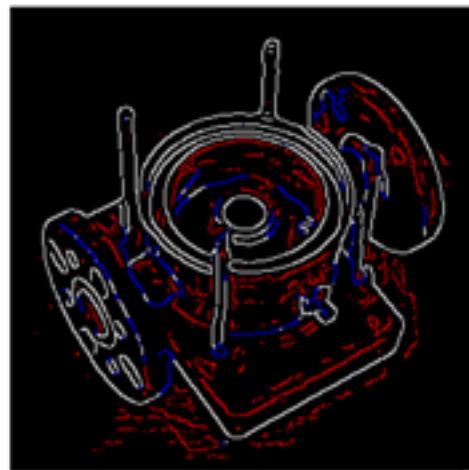


<http://www.cse.iitd.ernet.in/~pkalra/csl783/canny.pdf>

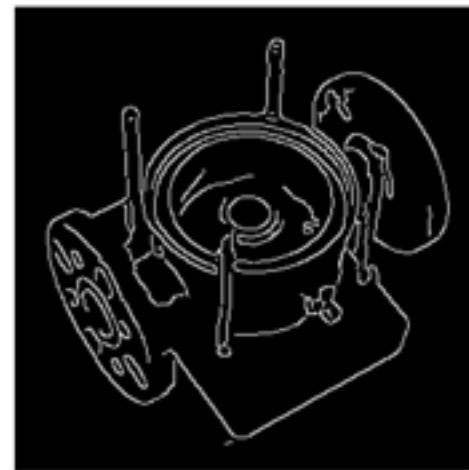
# Hysteresis



(a) Double thresholding



(b) Edge tracking by hysteresis

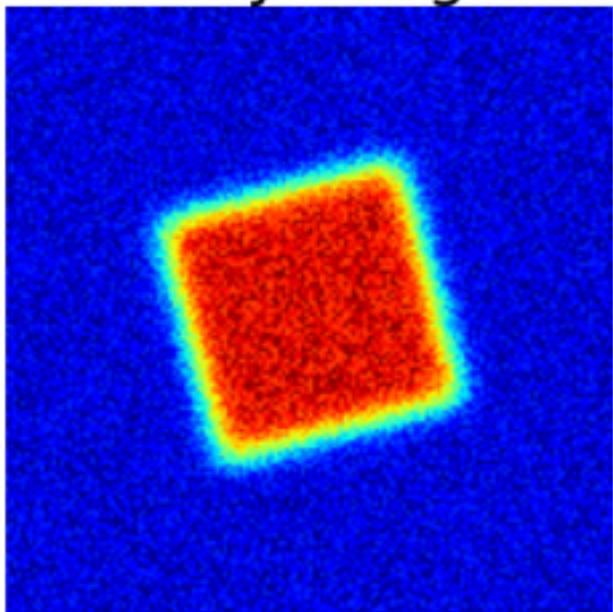


(c) Final output

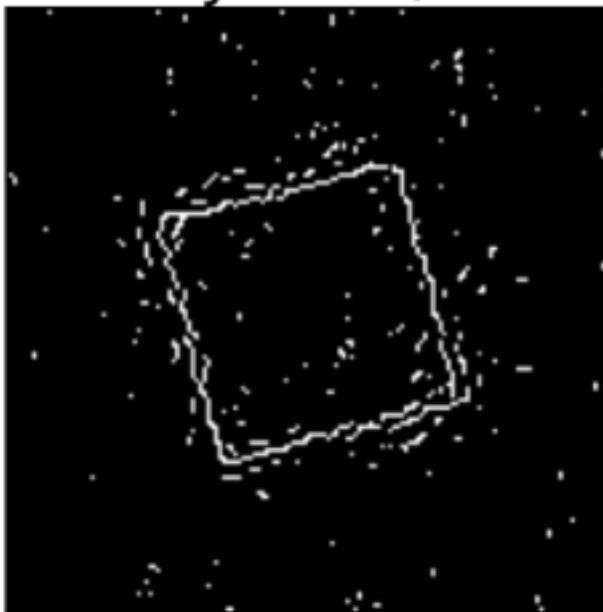
<http://www.cse.iitd.ernet.in/~pkalra/csl783/canny.pdf>

# Canny Edge Detector

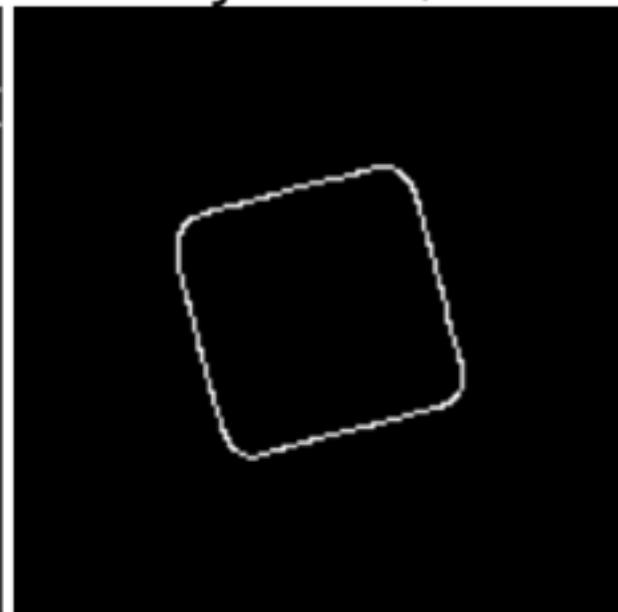
noisy image



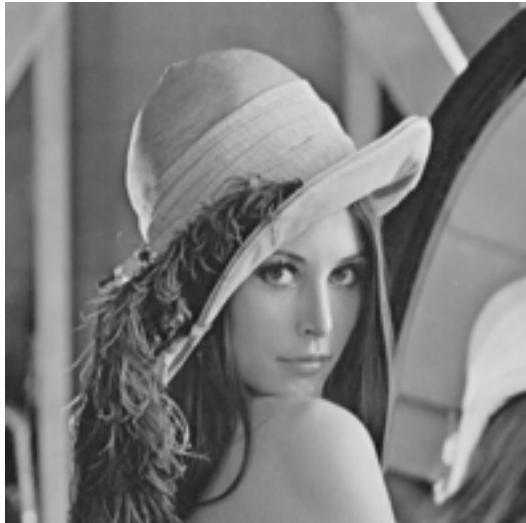
Canny filter,  $\sigma=1$



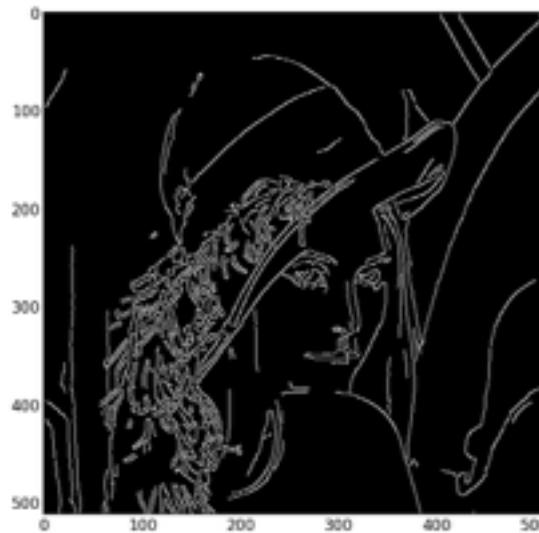
Canny filter,  $\sigma=3$



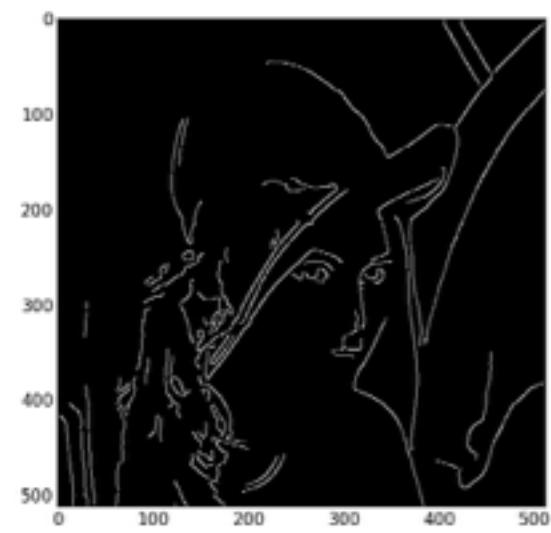
# Effect of $\sigma$ (Gaussian kernel spread/size)



original



Canny with  $\sigma = 1$

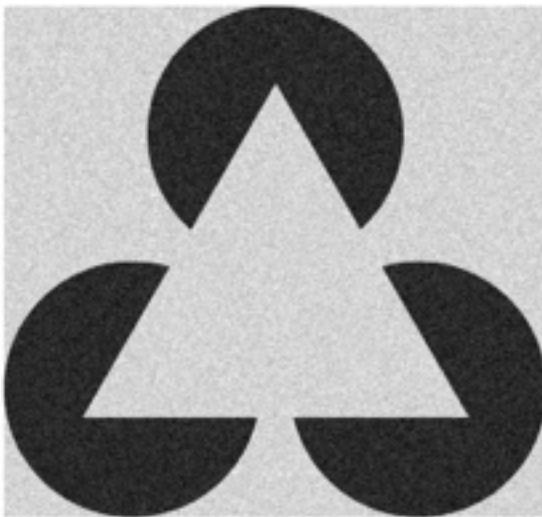


Canny with  $\sigma = 2$

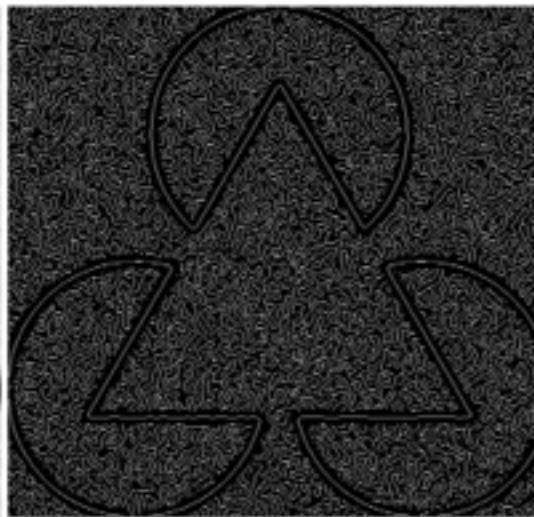
The choice of  $\sigma$  depends on desired behavior

- large  $\sigma$  detects large scale edges
- small  $\sigma$  detects fine features

Quiz: which image (b), (c), and (d) is the result of applying canny edge detector? Explain your answer.



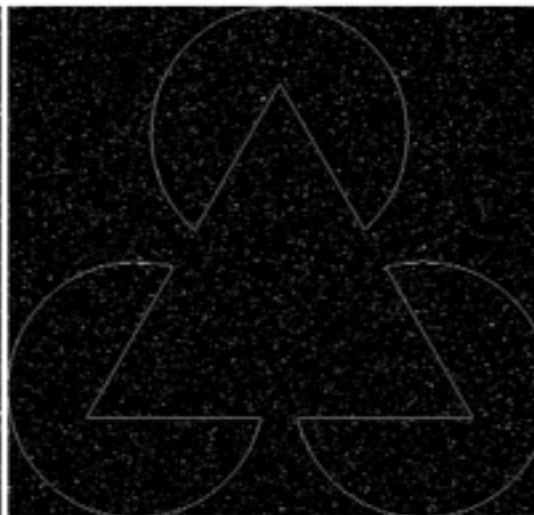
(a) Original Image



(b)



(c)



(d)

# What is difference between Boundary and edges?

Boundary: High-level object information. Whether a pixel belongs to an object or not.

Edges: Low-level information, sudden change in intensity values.

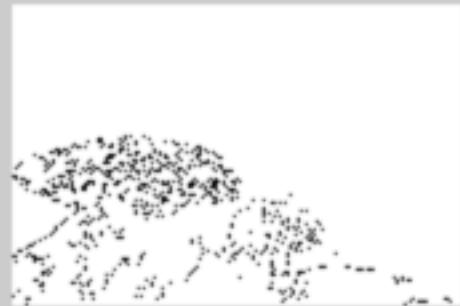
Input Image



Crispy Boundary



Canny

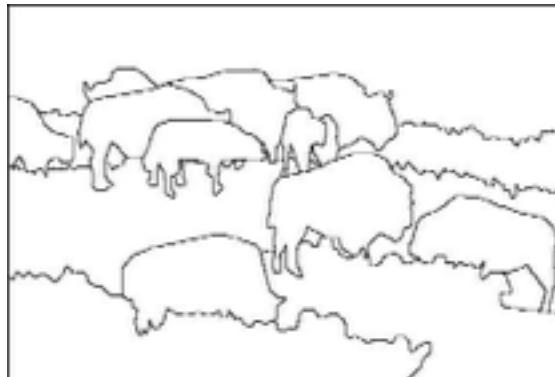


# Where do humans see boundaries?

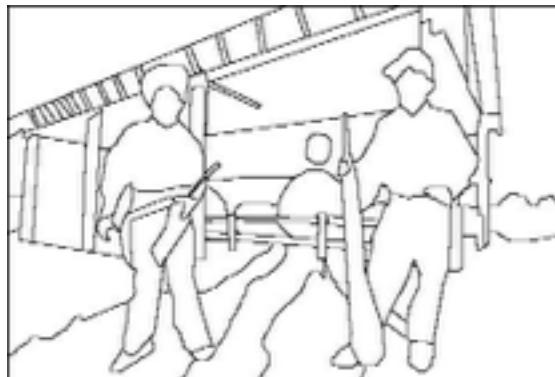
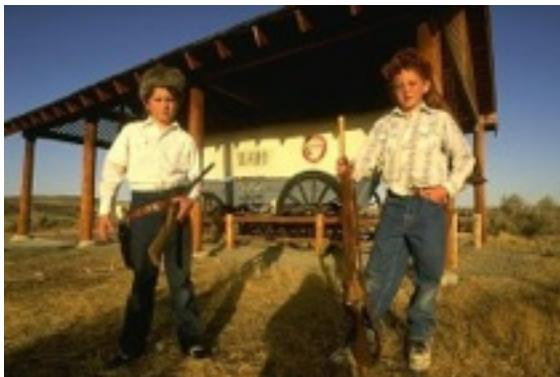
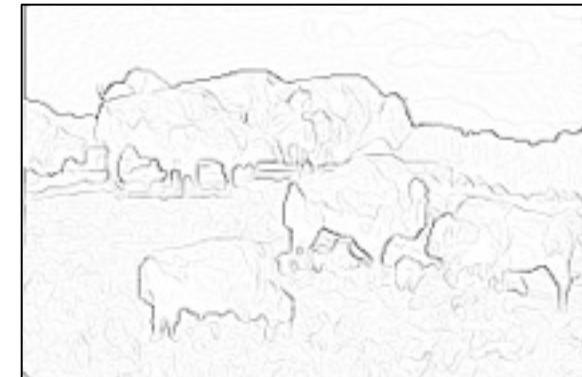
image



human segmentation



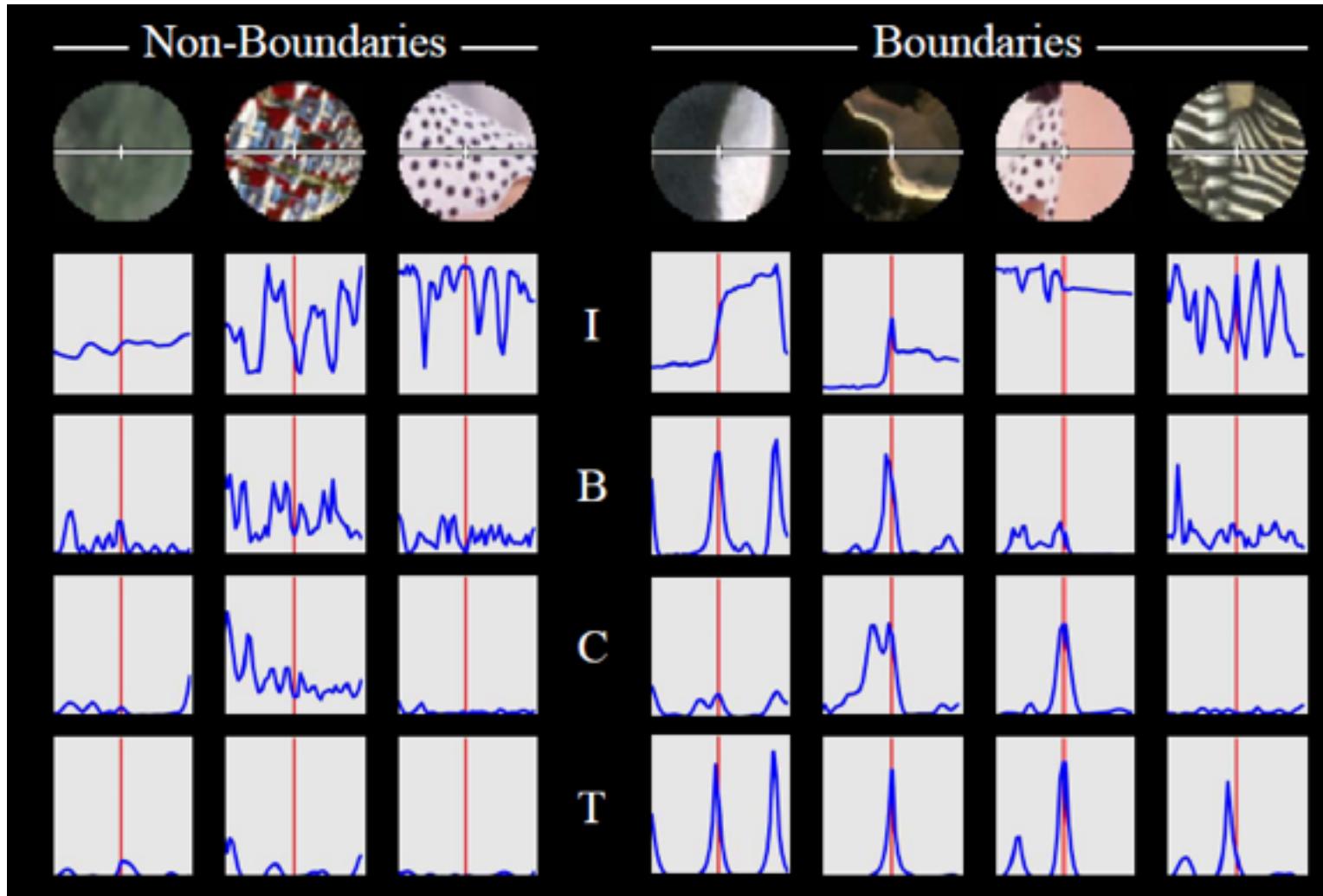
gradient magnitude



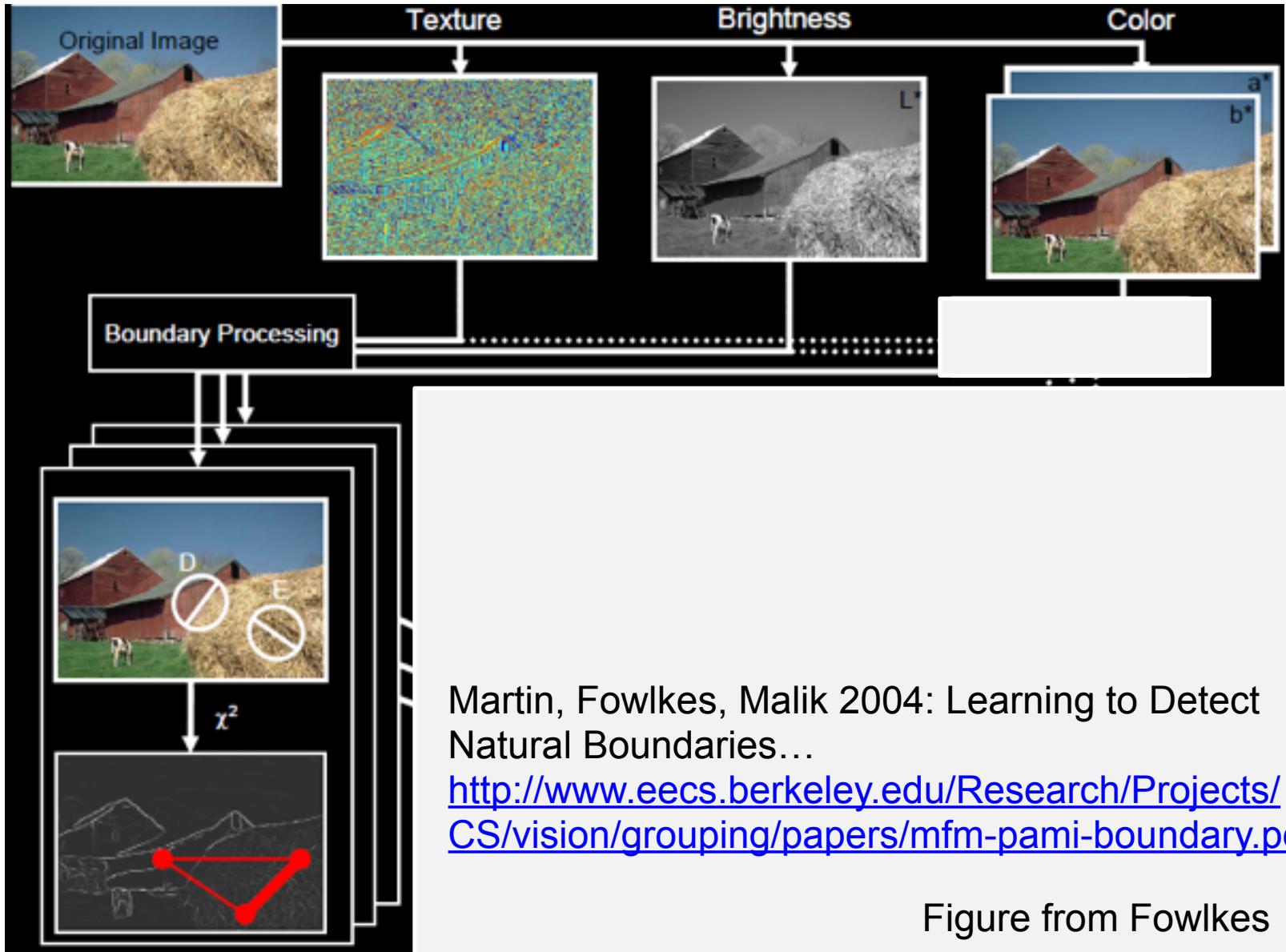
- Berkeley segmentation database:

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

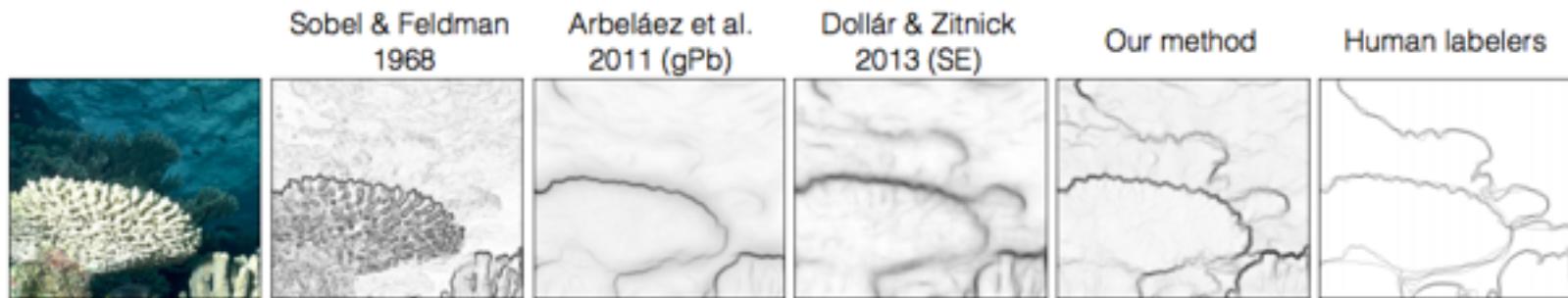
# Look for changes in texture, color, brightness



# pB boundary detector



# Edge detection vs. boundary detection



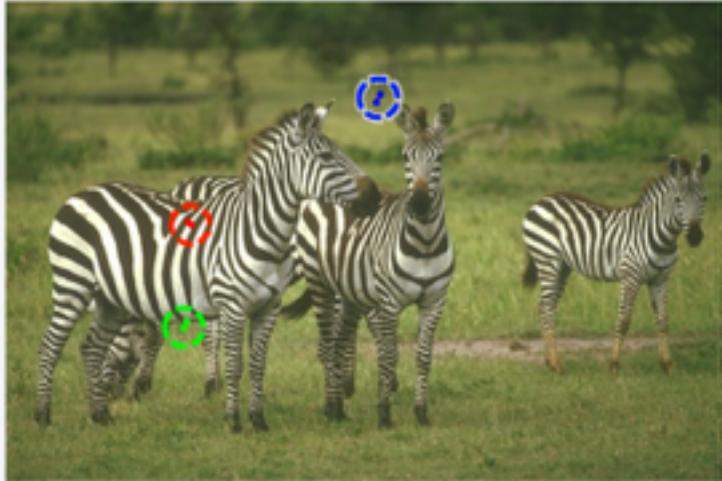
1. Classical methods use local derivative filters with fixed scales and only a few orientations. Tend to emphasize small and unimportant edges.
2. Contemporary methods use multiple scales, multiple features from image patches (color, textures, intensity). Using statistical methods (give each pixel a probability of being a boundary) to learn boundaries.
3. Isola et al. (2014) uses mutual information between pixels to detect boundary.



**Key observation:** *Pixels belonging to the same object have higher statistical association than pixels belonging to different objects.*

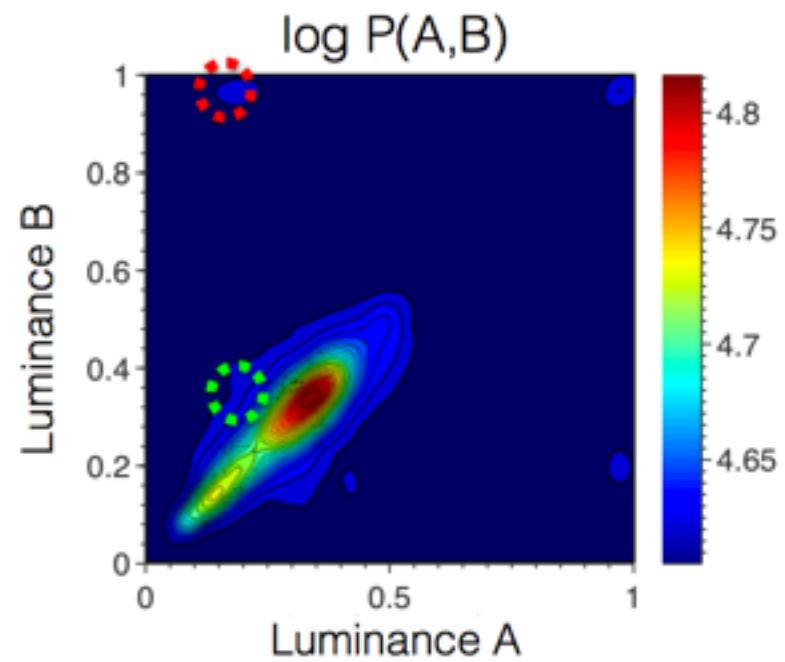
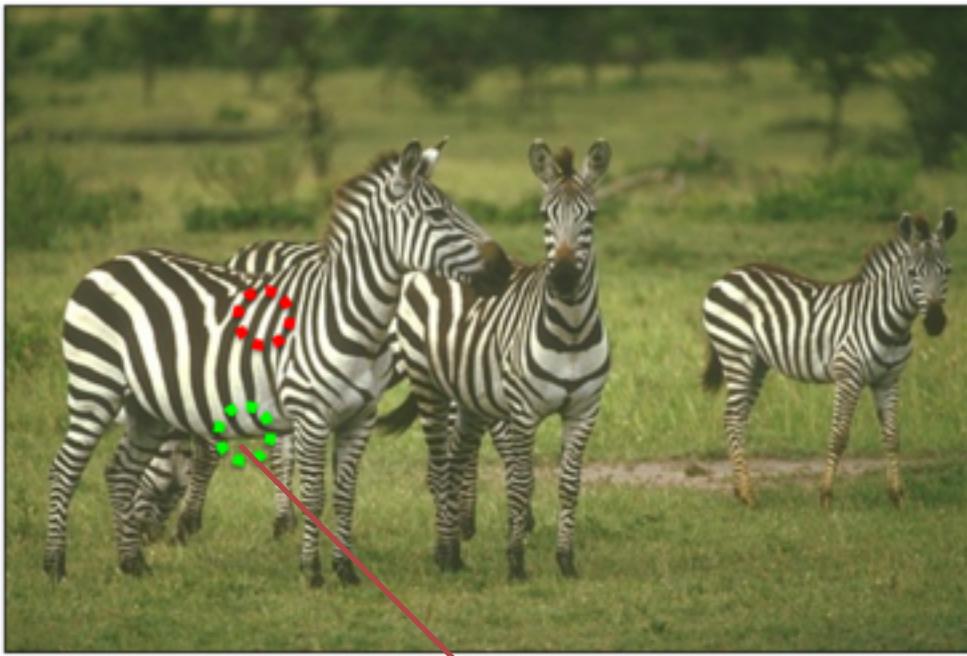
Slide courtesy from Philip Isola

# Point-wise mutual information reveals object structure



Above, black-next-to-white occurs over and over again. This pattern shows up in the image's statistics as a *suspicious coincidence* — these colors must be part of the same object!

How do we distinguish the red and the green patches?



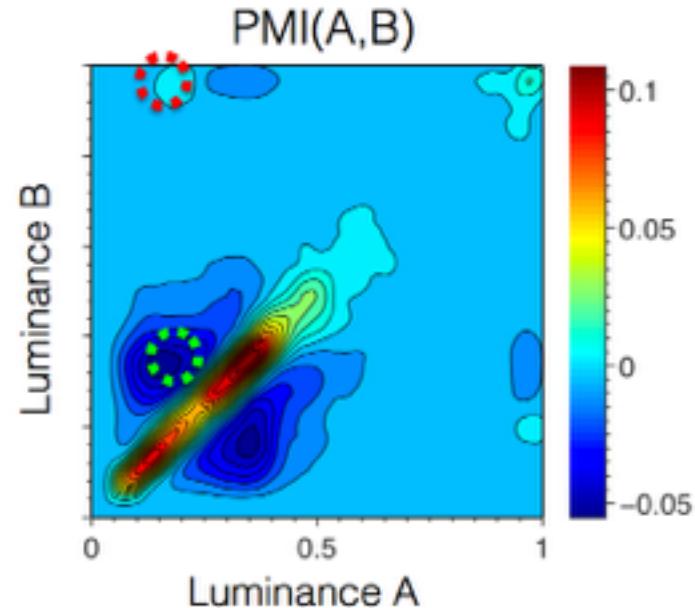
Object Boundary

A: Green pixel

B: Black pixel

$P(A, B) = \text{how often each color } A \text{ occurs next to each color } B$   
*within this image.*

[http://en.wikipedia.org/wiki/Mutual\\_information](http://en.wikipedia.org/wiki/Mutual_information)



## Pointwise mutual information (PMI)

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

Use PMI as affinity measure for affinity-based pixel grouping.

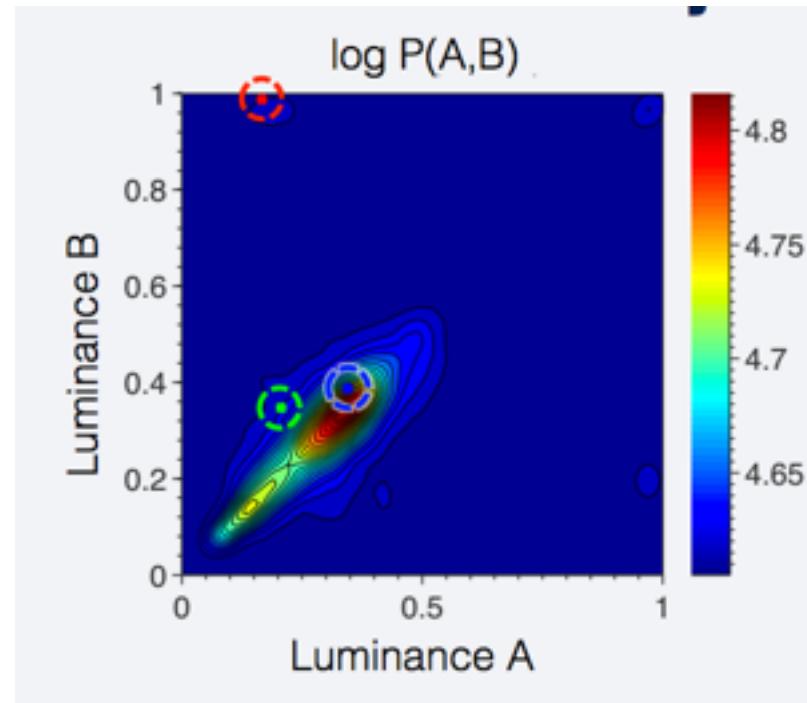
How much more likely is observing A given that we saw B in the same local region, compared to the base rate of observing A in the image.

# Joint distribution of two pixels



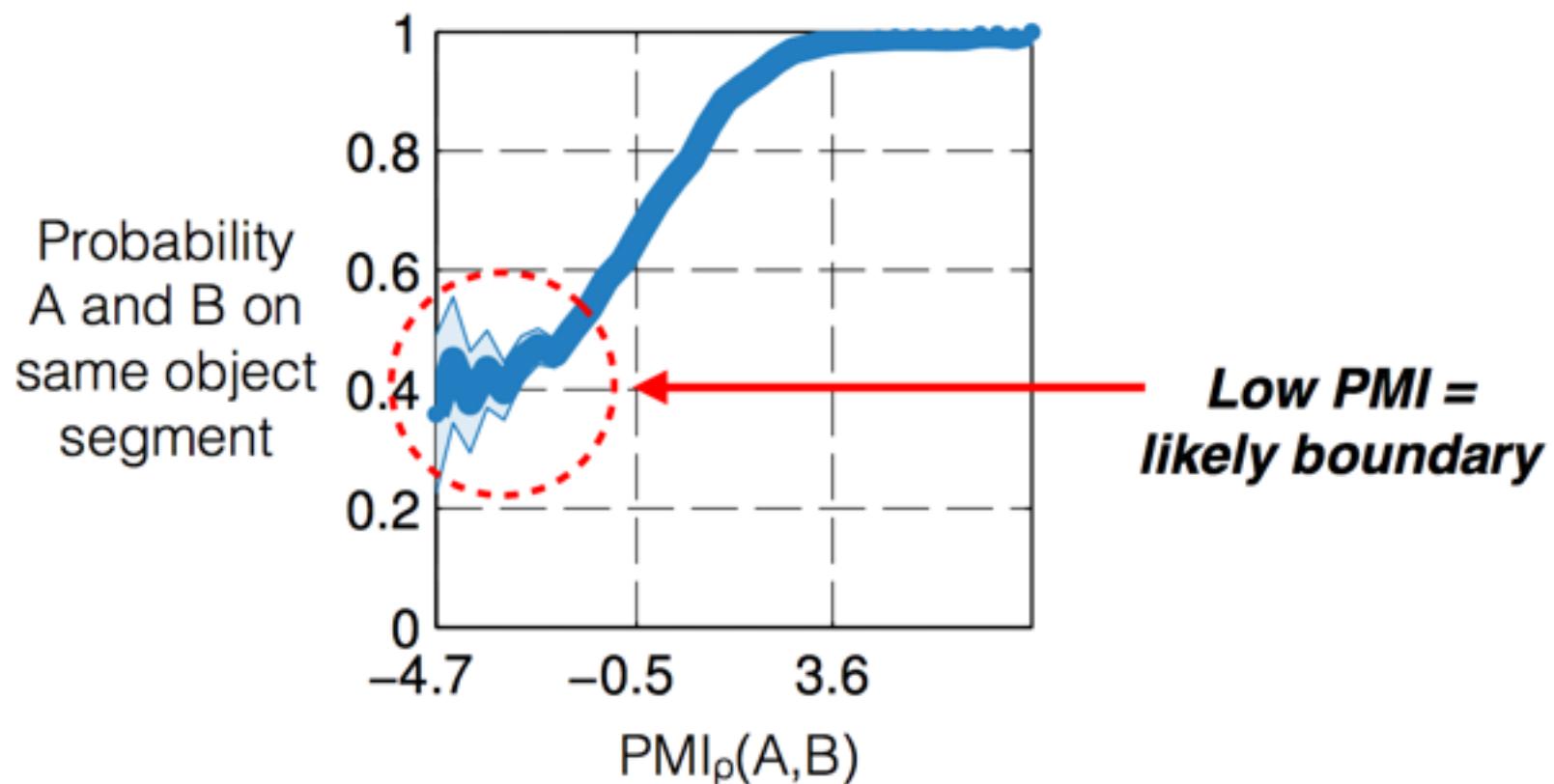
Above, black-next-to-white occurs over and over again. This pattern shows up in the image's statistics as a *suspicious coincidence* — these colors must be part of the same object!

$$P(A, B) = \frac{1}{Z} \sum_{d=d_0}^{\infty} w(d)p(A, B; d),$$



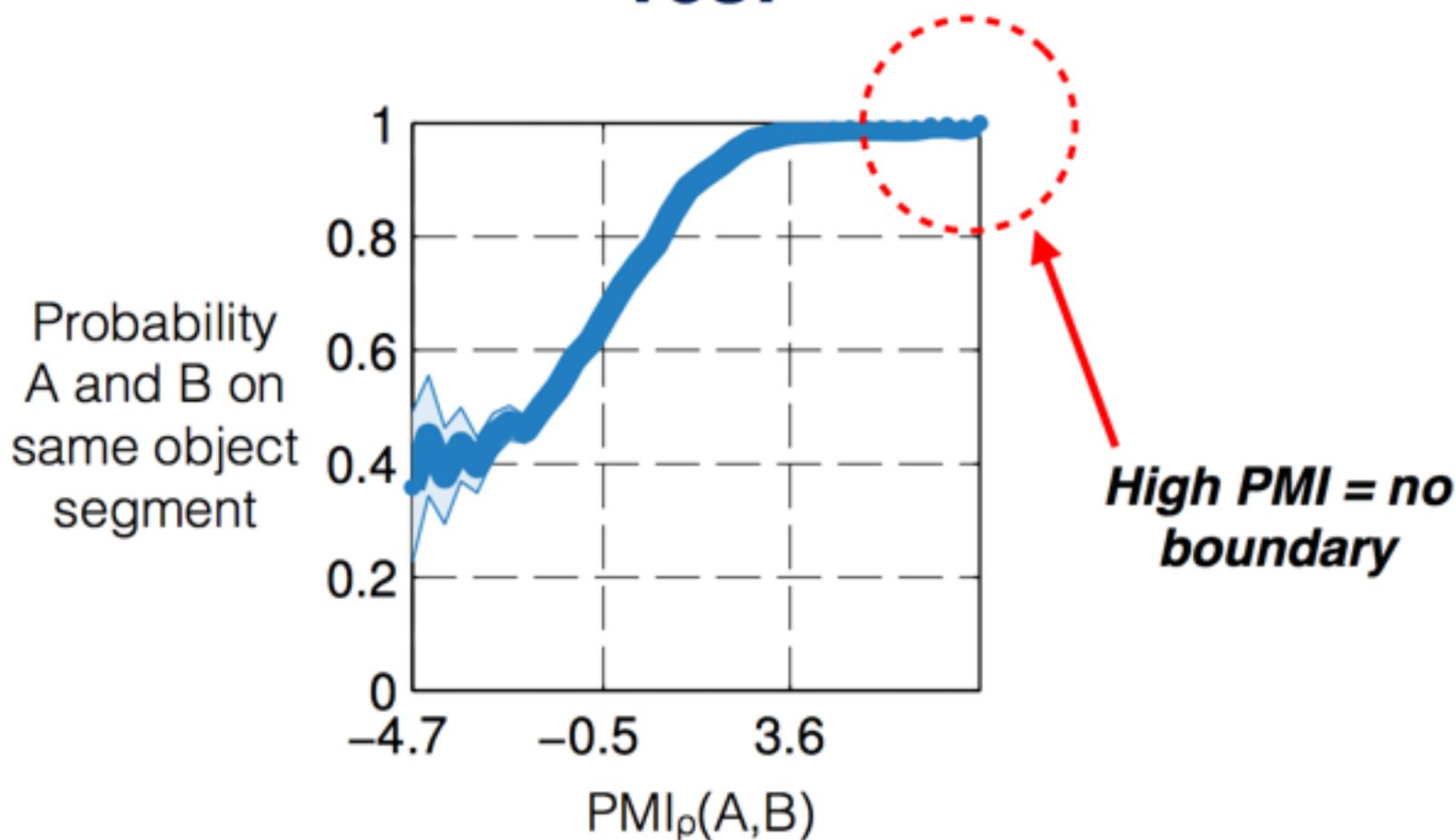
We measure how often each color A occurs next to each color B *within the image*.

# Is PMI informative about object boundaries?

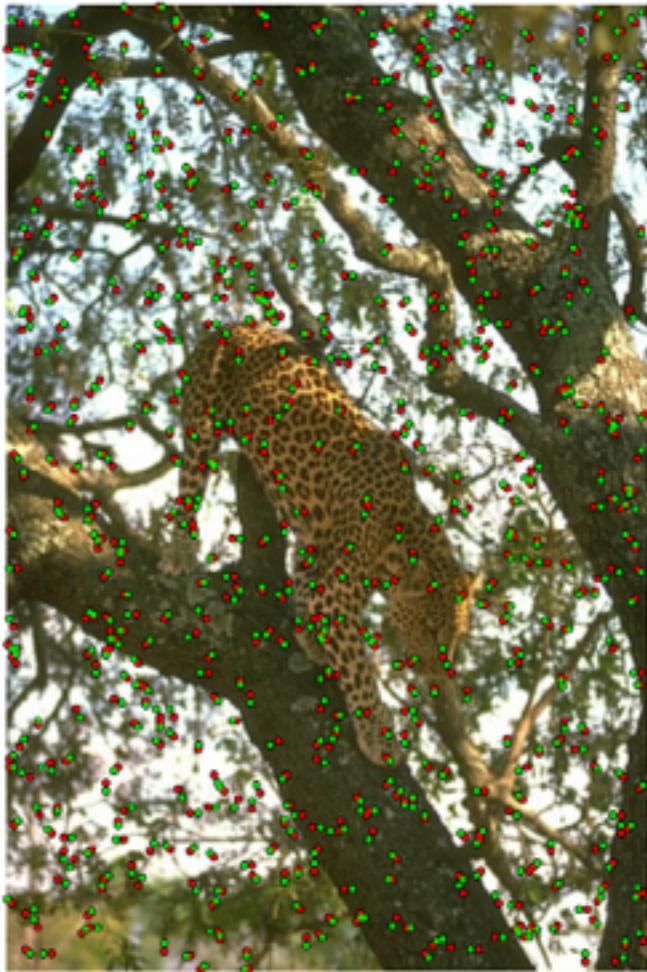


# Is PMI informative about object boundaries?

**Yes!**



## Step 1: Estimate feature co-occurrence distribution $P(A, B)$

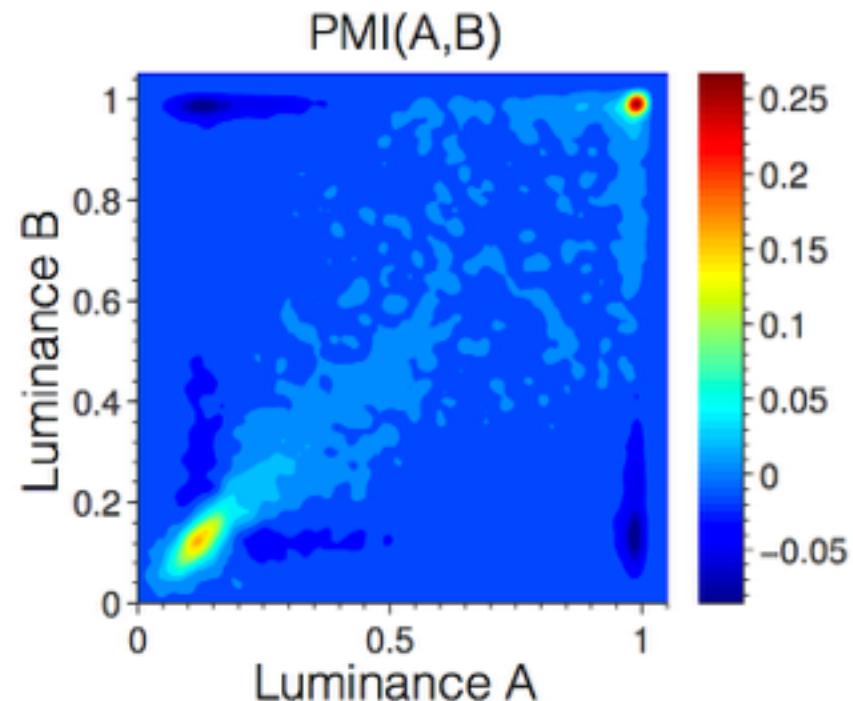
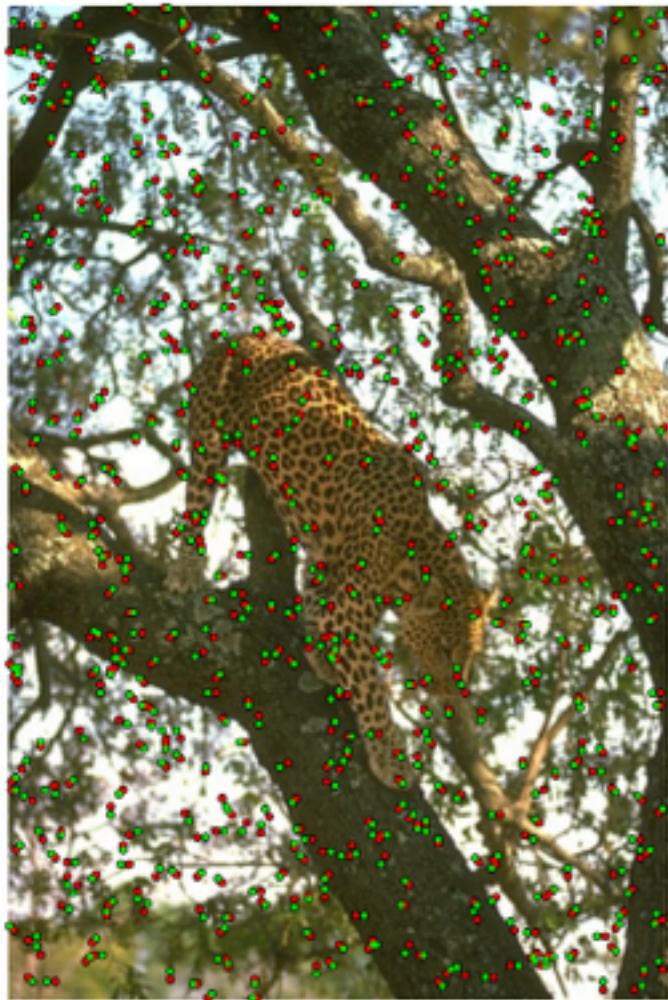


Samples



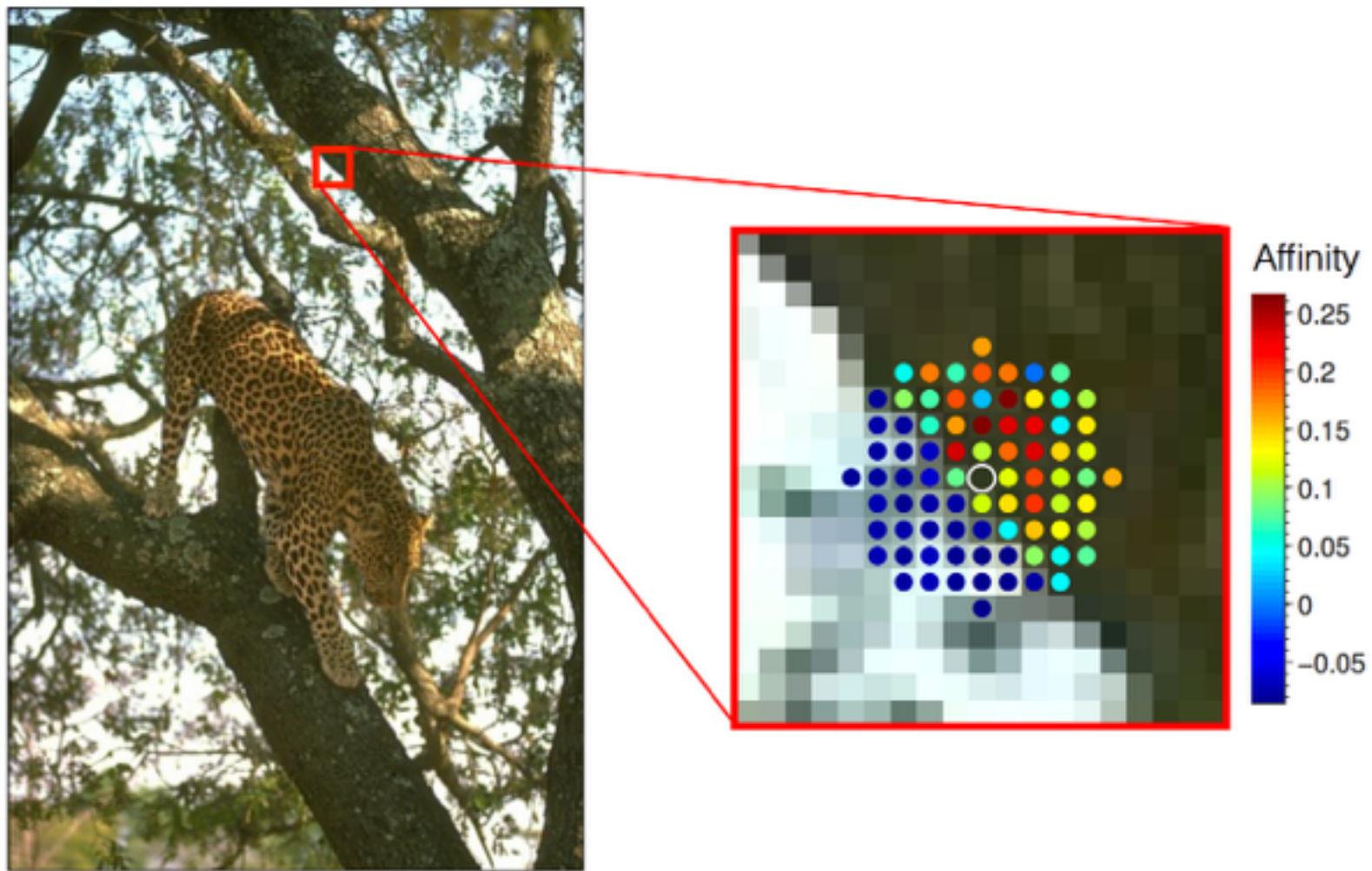
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## Step 2: Derive PMI(A,B) from feature co-occurrence distribution

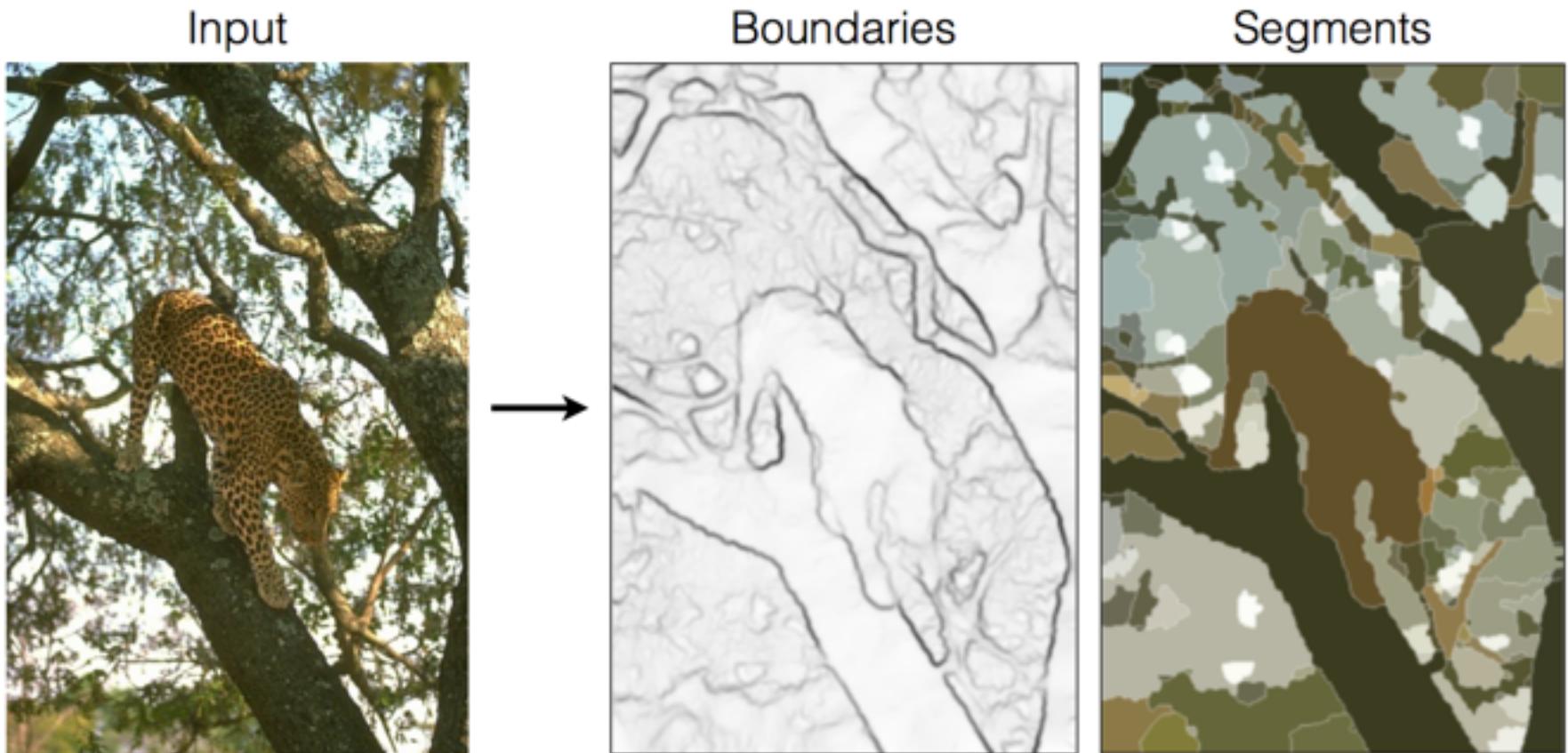


$$\text{PMI}_\rho(A, B) = \log \frac{P(A, B)^\rho}{P(A)P(B)}$$

Step 3: Use PMI as affinity between each pair of nearby pixels



## Step 4: Group pixels based on affinity (spectral clustering)



# Works on diverse stimuli

Cellphone photo



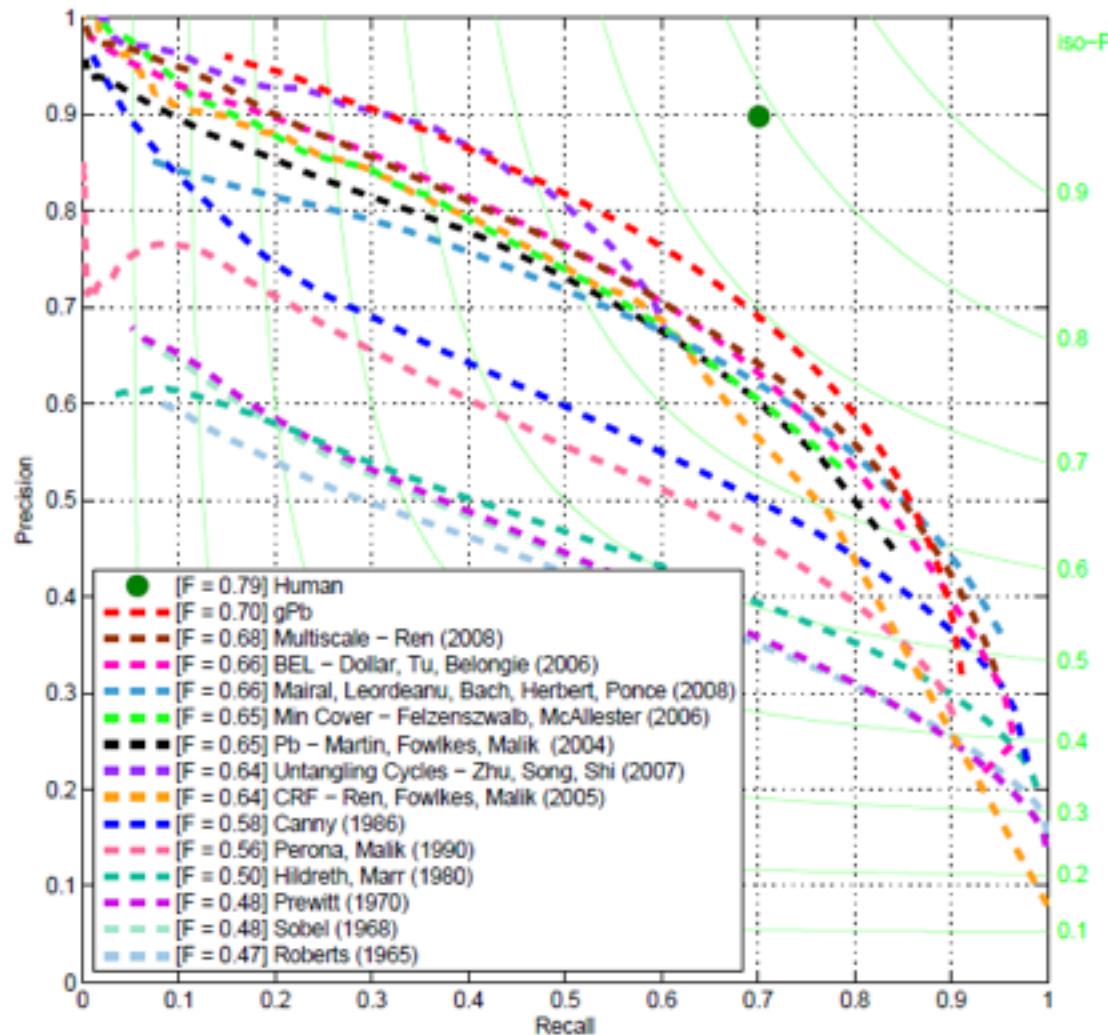
Satellite imagery



Art



# 45 years of boundary detection



# State of edge detection

- Local edge detection works well
  - But many false positives from illumination and texture edges
- Some methods to take into account longer contours, but could probably do better
- Few methods that actually “learn” from data. For example, Sketch Tokens, will do so.
- Poor use of object and high-level information

# Questions

# Take-home reading and demo code

- Szeliski Chapter 4.2 Edges
- Original PB paper:
- <http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/papers/mfm-pami-boundary.pdf>
- Crispy Boundary Paper and code:
  - <http://web.mit.edu/phillipi/pmi-boundaries/>
- Edge detection with Skimage:
  - [http://scikit-image.org/docs/dev/user\\_guide/tutorial\\_segmentation.html](http://scikit-image.org/docs/dev/user_guide/tutorial_segmentation.html)