NANJING UNIVERSITY

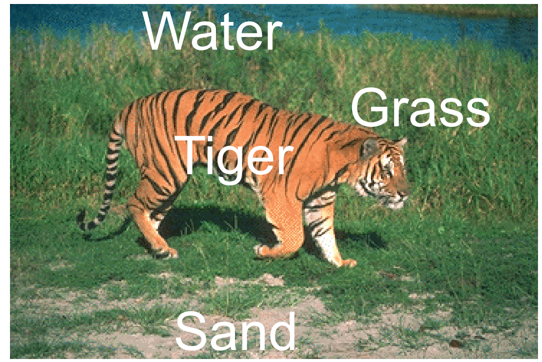
计算机视觉表征与识别
Chapter 6: Segmentation and Grouping

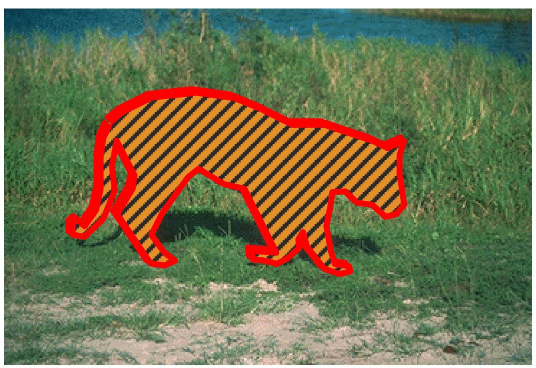
王利民

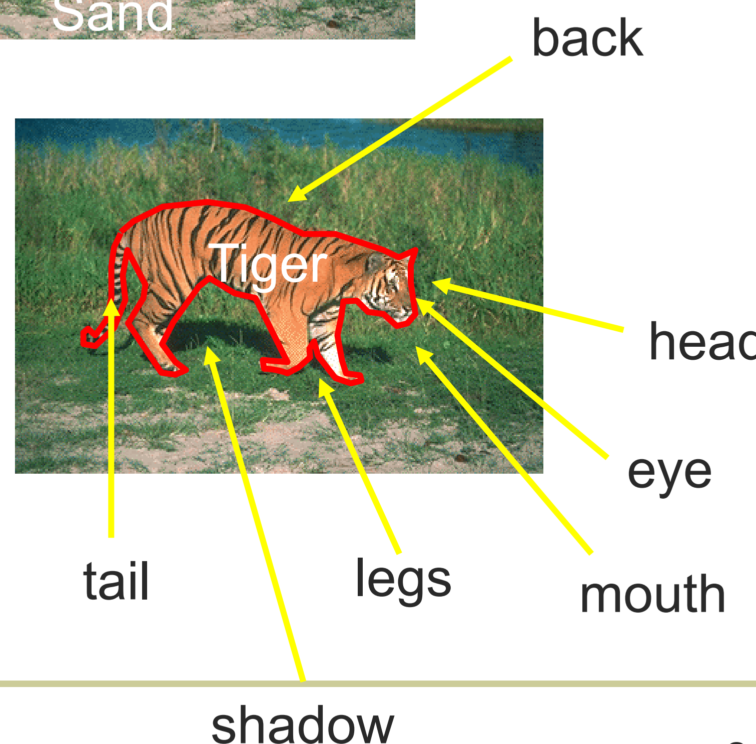
媒体计算课题组

http://mcg.nju.edu.cn/

From Pixels to Perception







Mid-level operations of Segmentation and Grouping

Edge detection

- **Goal**: map image from 2d array of pixels to a set of curves or line segments or contours.

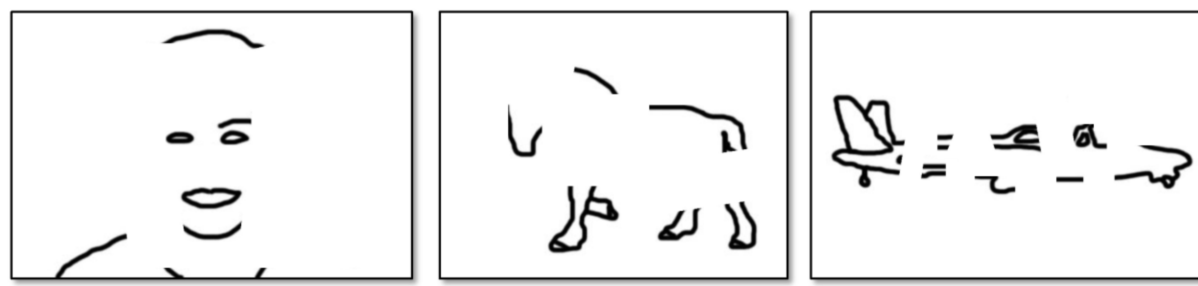


Figure from J. Shotton et al., PAMI 2007

- **Main idea**: look for strong gradients, post-process

Issues

- No precise problem formulation
- Much harder than it seems to be
- Edge detectors usually work by detecting “big changes” in image intensity
- Boundary is contour in the image plane that represents a change in pixel ownership from object or surface to another.

Gradients -> edges

Primary edge detection steps:

1. Smoothing: suppress noise
2. Edge enhancement: filter for contrast
3. Edge localization

   Determine which local maxima from filter output are actually edges vs. noise

   Thresholding and thinning

Canny edge detector

- Filter image with derivative of Gaussian
- Find magnitude and orientation of gradient
- **Non-maximum suppression**:
  - Thin wide "ridges" down to single pixel width
- **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
- MATLAB: `edge(image, 'canny');`
- `>>help edge`

Source: D. Lowe, 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

Low-level edges vs. perceived contours

image **human segmentation** **gradient magnitude**

- Berkeley segmentation database:
  http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

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

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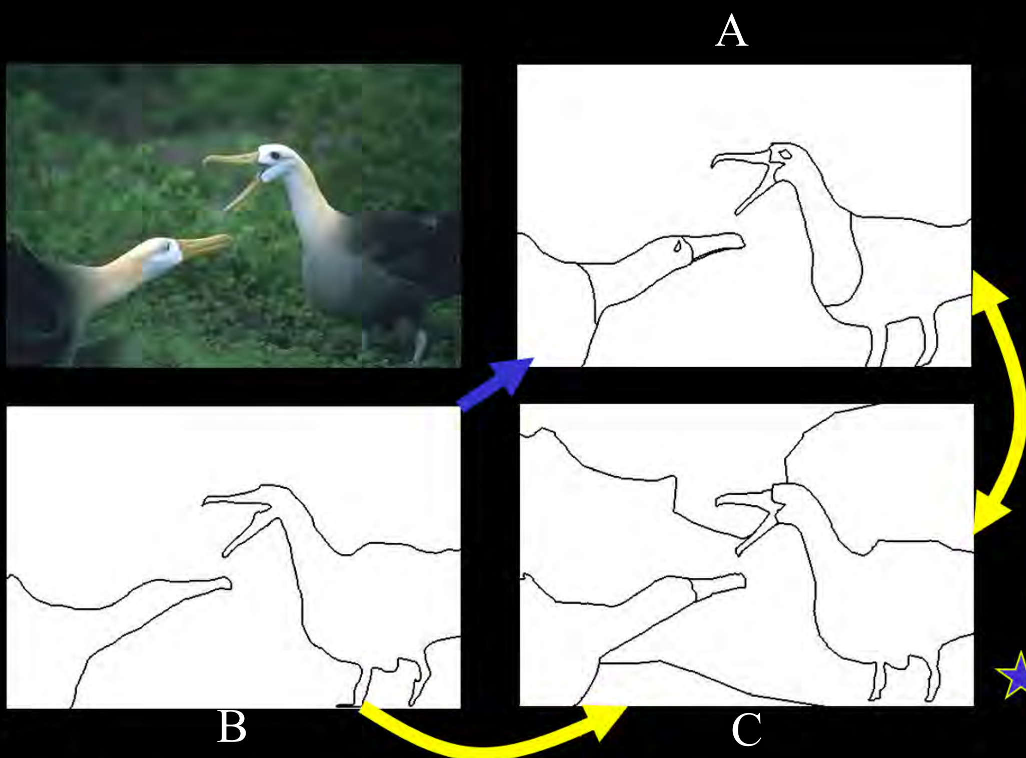
This paper presents a database containing 'ground truth' segmentations produced by humans for images of a wide variety of natural scenes. We define an error measure which quantifies the consistency between segmentations of differing granularities and find that different human segmentations of the same image are highly consistent. Use of this dataset is demonstrated in two applications: (1) evaluating the performance of segmentation algorithms and (2) measuring probability distributions associated with Gestalt grouping factors as well as statistics of image region properties.

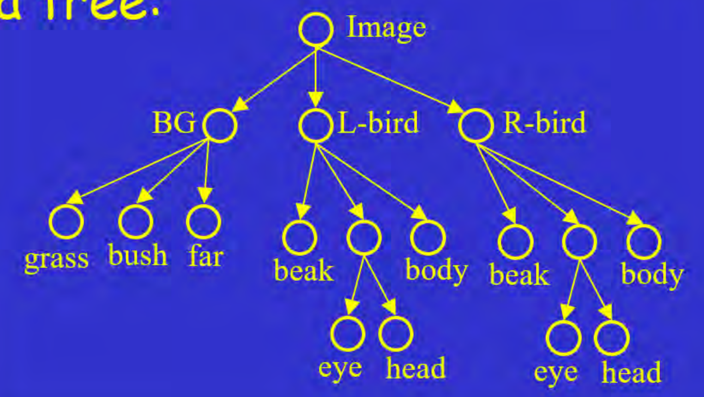
[A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics]()

D Martin, C Fowlkes, D Tal… - Proceedings Eighth IEEE …, 2001 - ieeexplore.ieee.org

Consistency



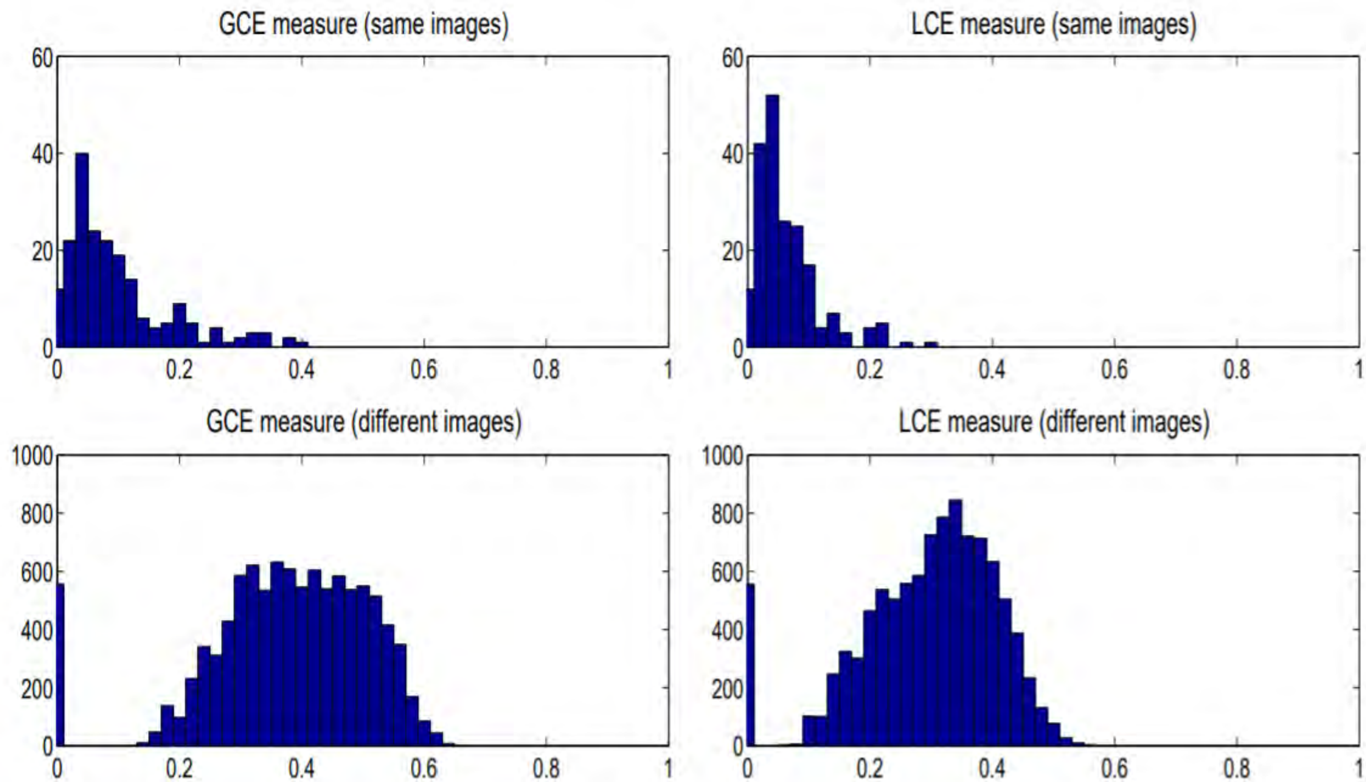
Perceptual organization forms a tree:



- A,C are refinements of B
- A,C are mutual refinements
- A,B,C represent the same percept
  - <u>Attention</u> accounts for differences

★ Two segmentations are consistent when they can be explained by the same segmentation tree (i.e. they could be derived from a single perceptual organization).

Error Measure Validation



Learning to Detect Natural Image Boundaries Using Local Brightness, Color, and Texture Cues

David R. Martin, *Member, IEEE*, Charless C. Fowlkes, and Jitendra Malik, *Member, IEEE*

Abstract—The goal of this work is to accurately detect and localize boundaries in natural scenes using local image measurements. We formulate features that respond to characteristic changes in brightness, color, and texture associated with natural boundaries. In order to combine the information from these features in an optimal way, we train a classifier using human labeled images as ground truth. The output of this classifier provides the posterior probability of a boundary at each image location and orientation. We present precision-recall curves showing that the resulting detector significantly outperforms existing approaches. Our two main results are 1) that cue combination can be performed adequately with a simple linear model and 2) that a proper, explicit treatment of texture is required to detect boundaries in natural images.

Index Terms—Texture, supervised learning, cue combination, natural images, ground truth segmentation data set, boundary detection, boundary localization.

Dataflow

Image

Boundary Cues

Brightness

Color

Texture

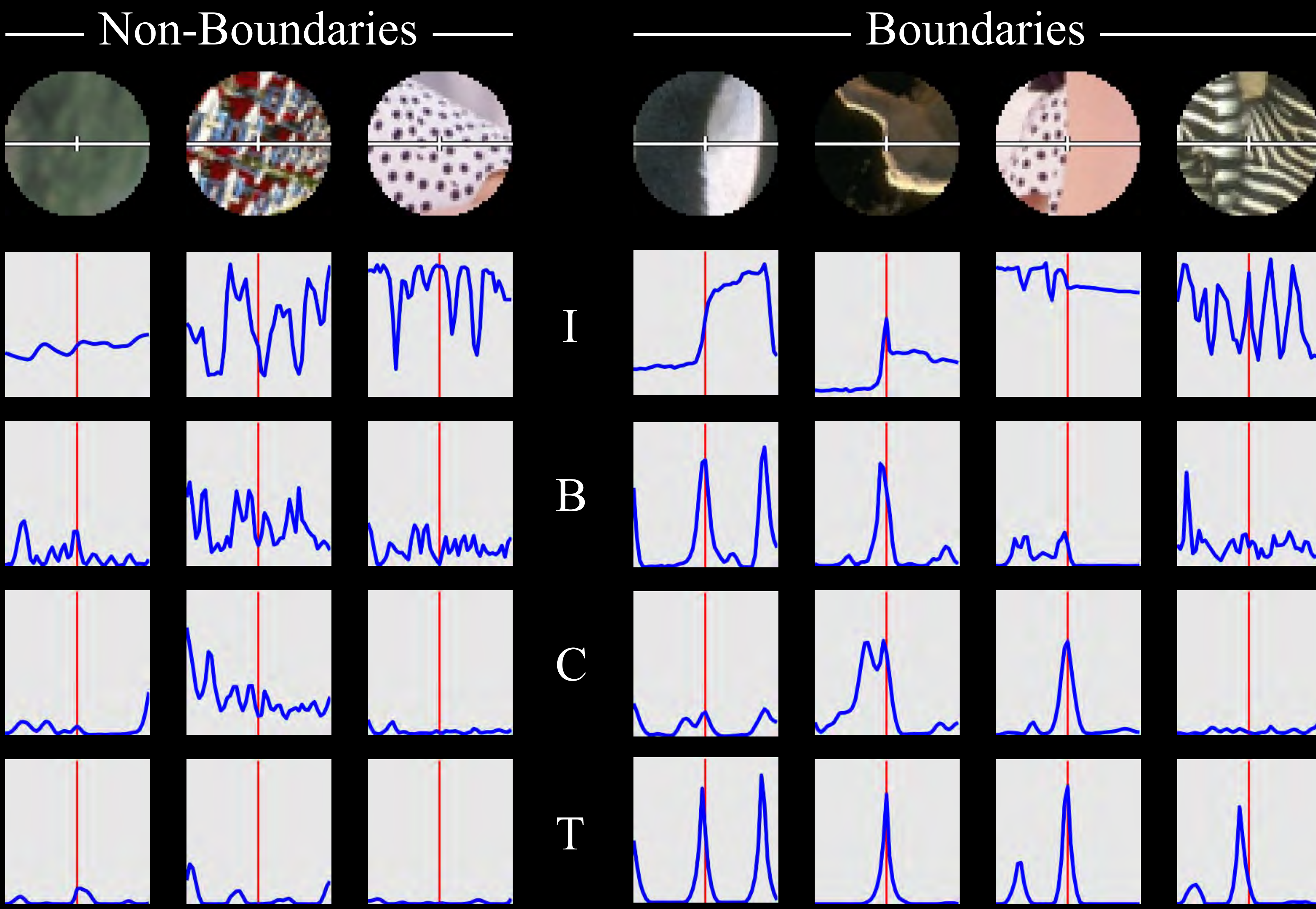
Cue Combination

Model

P_b

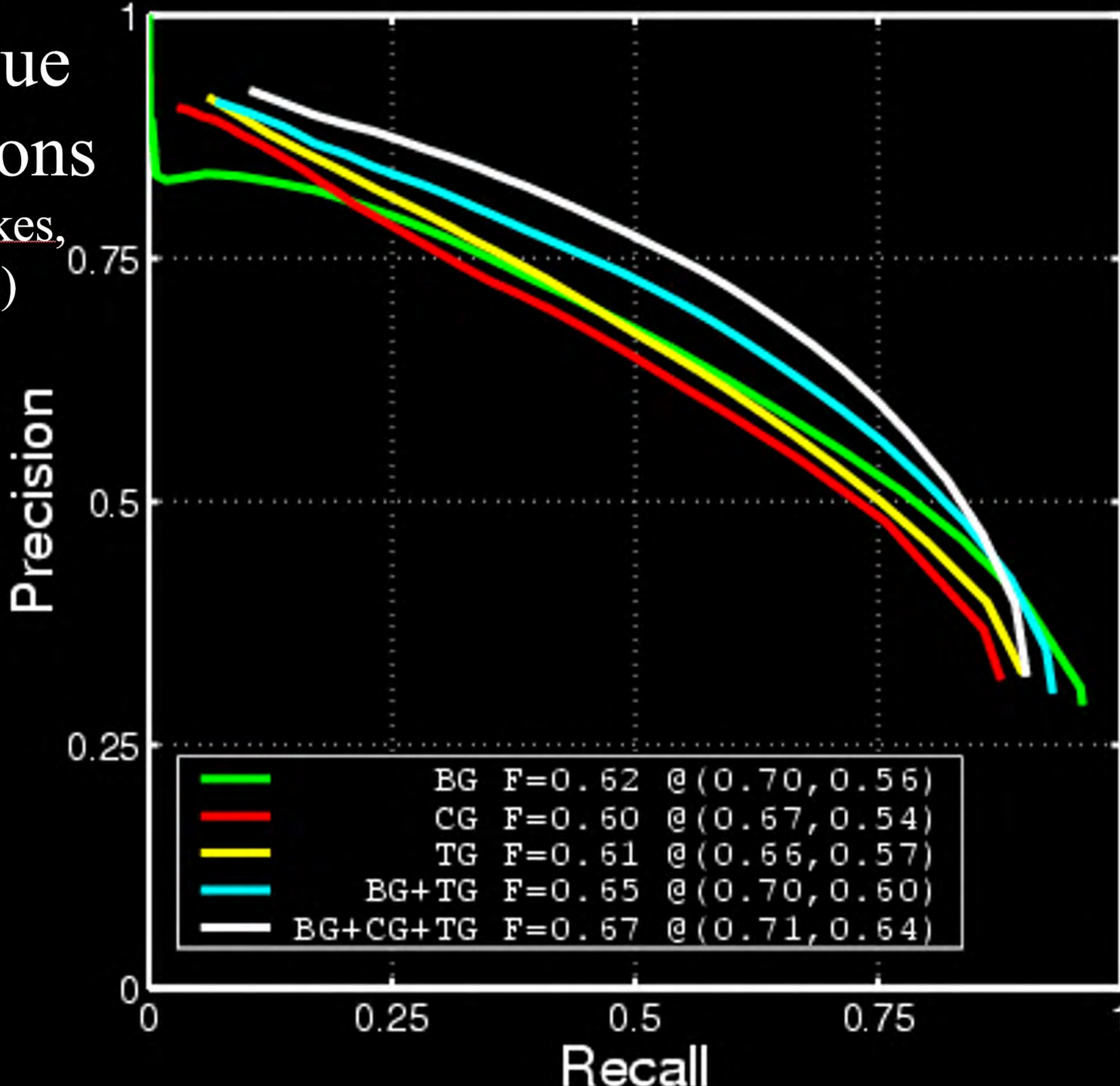
<u>Challenges</u>: texture cue, cue combination

<u>Goal</u>: learn the posterior probability of a boundary $P_b(x,y,\theta)$ from <u>local</u> information only


Non-Boundaries
Boundaries
I
B
C
T

Various Cue Combinations

(Martin, Fowlkes, Malik, 2004)



Findings

1. A simple linear model is sufficient for cue combination
   – All cues weighted approximately equally in logistic
2. Proper texture edge model is not optional for complex natural images
   – Texture suppression is not sufficient!
3. Significant improvement over state-of-the-art in boundary detection
   – $P_b(x,y,\theta)$ useful for higher-level processing
4. Empirical approach critical for both cue calibration and cue combination

Contour Detection and Hierarchical Image Segmentation

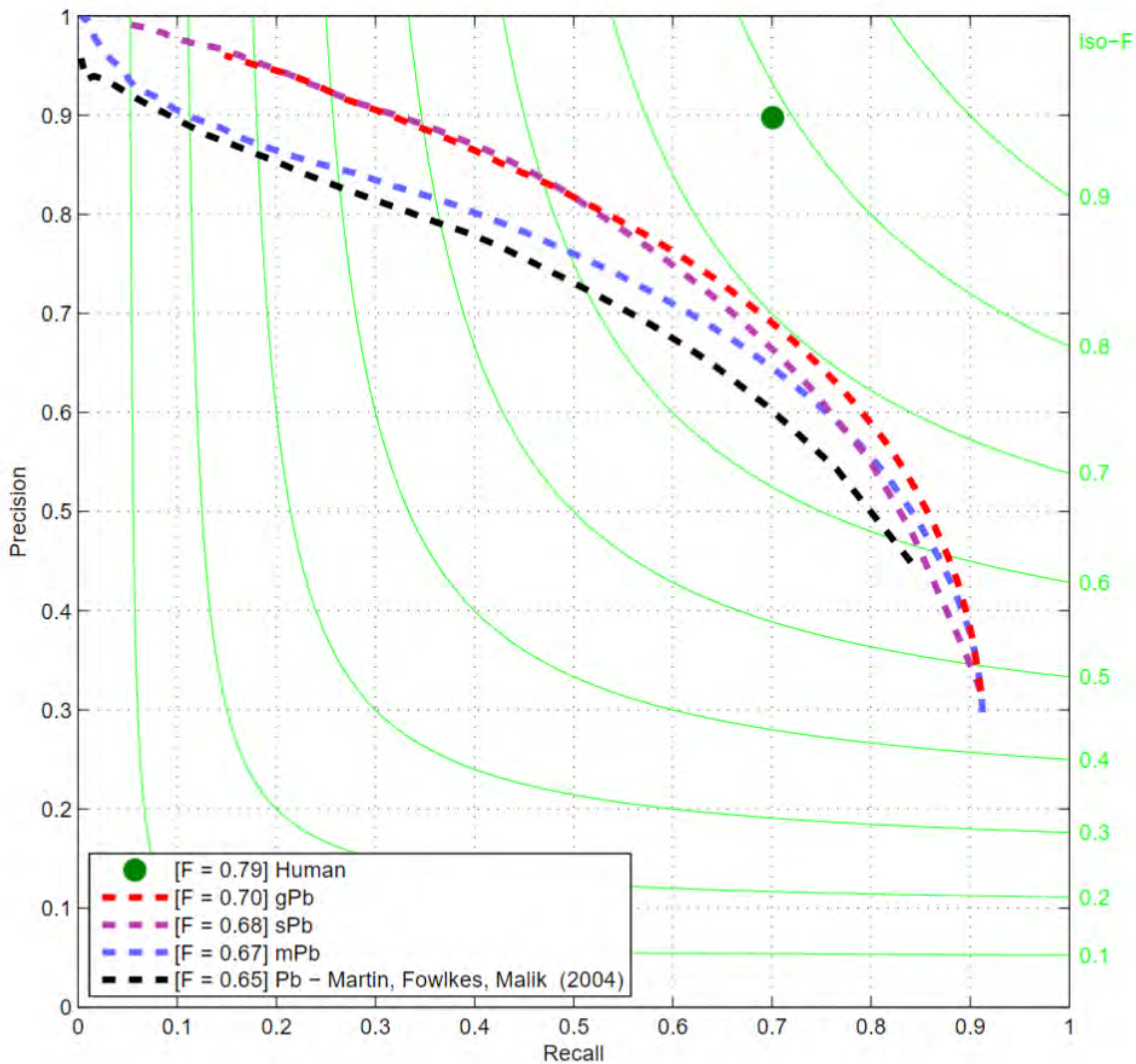
Pablo Arbeláez, *Member, IEEE,* Michael Maire, *Member, IEEE,*
Charless Fowlkes, *Member, IEEE,* and Jitendra Malik, *Fellow, IEEE.*

Abstract—This paper investigates two fundamental problems in computer vision: contour detection and image segmentation. We present state-of-the-art algorithms for both of these tasks. Our contour detector combines multiple local cues into a globalization framework based on spectral clustering. Our segmentation algorithm consists of generic machinery for transforming the output of any contour detector into a hierarchical region tree. In this manner, we reduce the problem of image segmentation to that of contour detection. Extensive experimental evaluation demonstrates that both our contour detection and segmentation methods significantly outperform competing algorithms. The automatically generated hierarchical segmentations can be interactively refined by user-specified annotations. Computation at multiple image resolutions provides a means of coupling our system to recognition applications.

Spectral Pb

Fig. 7. **Spectral Pb.** ***Left:*** Image. ***Middle Left:*** The thinned non-max suppressed multiscale Pb signal defines a sparse affinity matrix connecting pixels within a fixed radius. Pixels i and j have a low affinity as a strong boundary separates them, whereas i and k have high affinity. ***Middle:*** First four generalized eigenvectors resulting from spectral clustering. ***Middle Right:*** Partitioning the image by running K-means clustering on the eigenvectors erroneously breaks smooth regions. ***Right:*** Instead, we compute gradients of the eigenvectors, transforming them back into a contour signal.

$$sPb(x, y, \theta) = \sum_{k=1}^{n} \frac{1}{\sqrt{\lambda_k}} \cdot \nabla_\theta \mathbf{v_k}(x, y)$$


Precision
Recall
iso-F
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
[F = 0.79] Human
[F = 0.70] gPb
[F = 0.68] sPb
[F = 0.67] mPb
[F = 0.65] Pb − Martin, Fowlkes, Malik (2004)

Fast Edge Detection Using Structured Forests

Piotr Dollár and C. Lawrence Zitnick

Abstract—Edge detection is a critical component of many vision systems, including object detectors and image segmentation algorithms. Patches of edges exhibit well-known forms of local structure, such as straight lines or T-junctions. In this paper we take advantage of the structure present in local image patches to learn both an accurate and computationally efficient edge detector. We formulate the problem of predicting local edge masks in a structured learning framework applied to random decision forests. Our novel approach to learning decision trees robustly maps the structured labels to a discrete space on which standard information gain measures may be evaluated. The result is an approach that obtains realtime performance that is orders of magnitude faster than many competing state-of-the-art approaches, while also achieving state-of-the-art edge detection results on the BSDS500 Segmentation dataset and NYU Depth dataset. Finally, we show the potential of our approach as a general purpose edge detector by showing our learned edge models generalize well across datasets.

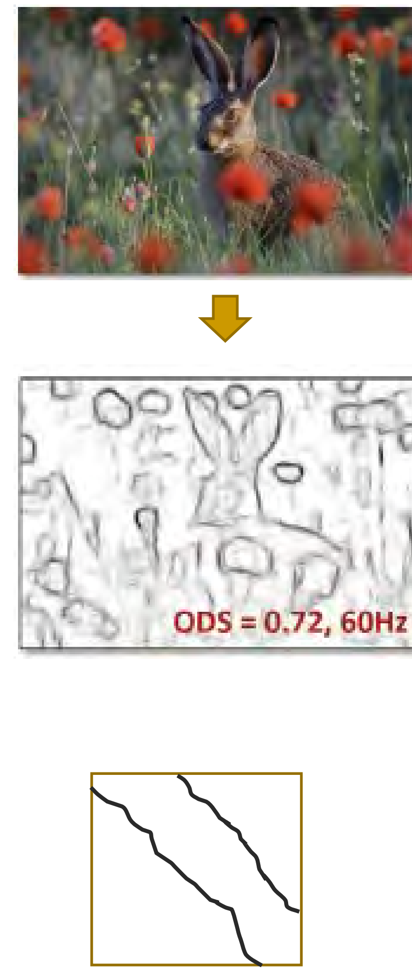
Index Terms—Edge detection, segmentation, structured random forests, real-time systems, visual features

Edge Detection with Structured Random Forests

- Goal: quickly predict whether each pixel is an edge

- Insights
  - Predictions can be learned from training data
  - Predictions for nearby pixels should not be independent

- Solution
  - Train structured random forests to split data into patches with similar boundaries based on features
  - Predict boundaries at patch level, rather than pixel level, and aggregate (average votes)

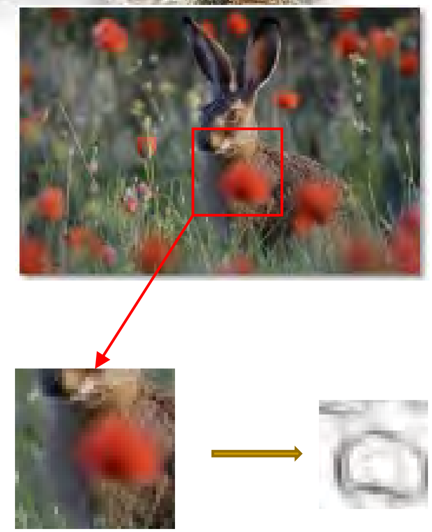


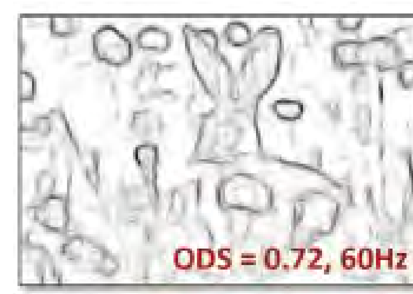
Boundaries in patch

http://research.microsoft.com/pubs/202540/DollarICCV13edges.pdf

Edge Detection with Structured Random Forests

- Algorithm
  1. Extract overlapping 32x32 patches at three scales
  2. Features are pixel values and pairwise differences in feature maps (LUV color, gradient magnitude, oriented gradient)
  3. Predict T boundary maps in the central 16x16 region using T trained decision trees
  4. Average predictions for each pixel across all patches





General Information Gain

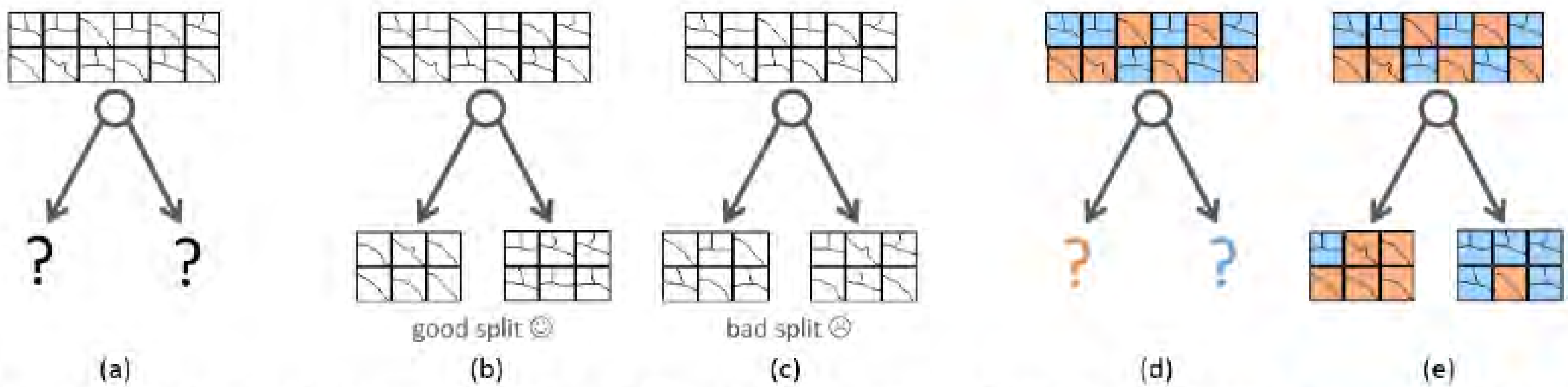
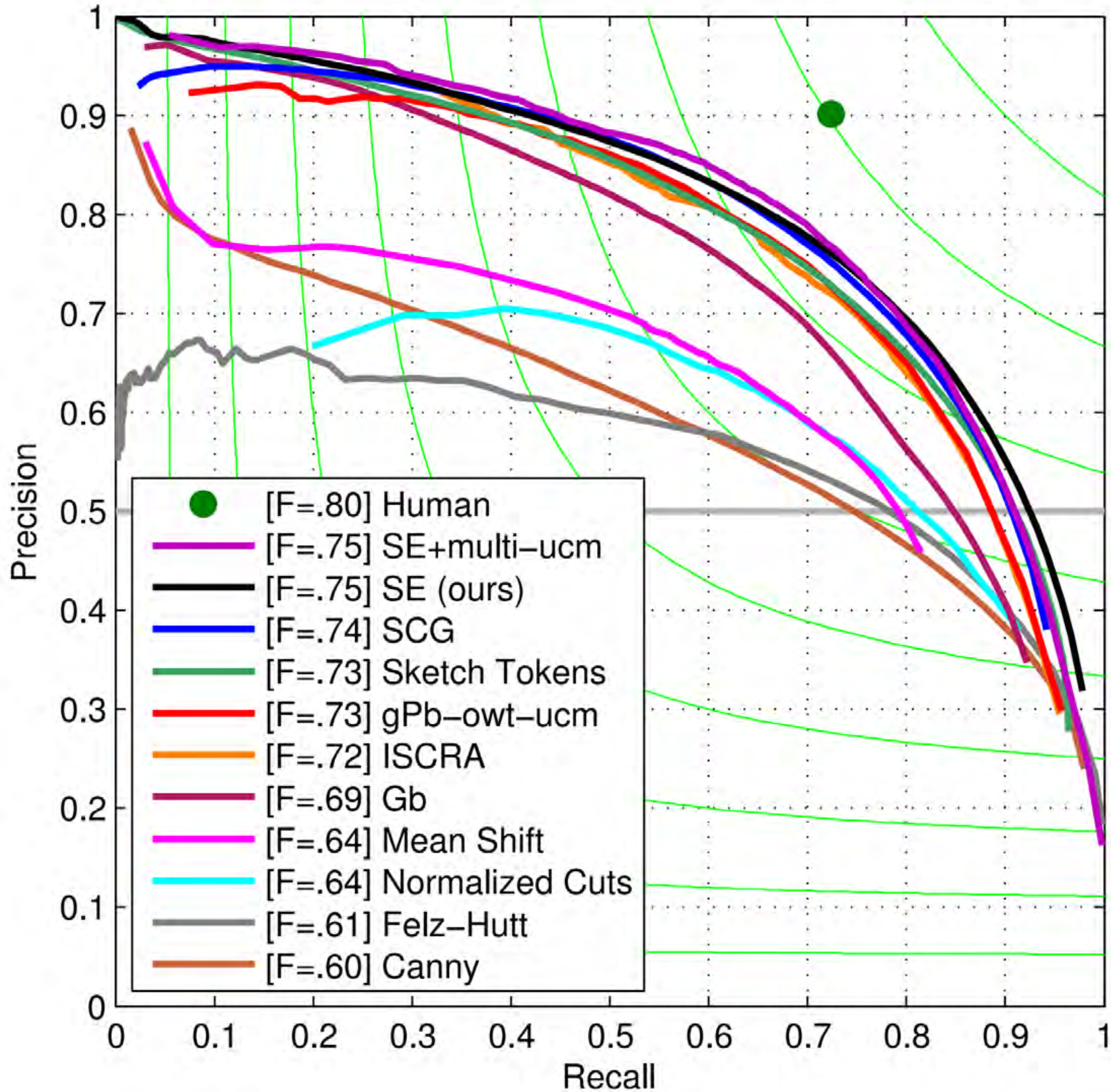


Fig. 2. Illustration of the decision tree node splits: (a) Given a set of structured labels such as segments, a splitting function must be determined. Intuitively a good split (b) groups similar segments, whereas a bad split (c) does not. In practice we cluster the structured labels into two classes (d). Given the class labels, a standard splitting criterion, such as Gini impurity, may be used (e).

Our key assumption is that for many structured output spaces, including for structured learning of edge detection, we can define a mapping of the form:

$$\Pi : \mathcal{Y} \rightarrow \mathcal{Z} \tag{4}$$

We map a set of structured labels $y \in \mathcal{Y}$ into a discrete set of labels $c \in \mathcal{C}$, where $\mathcal{C} = \{1, \ldots, k\}$, such that labels with similar z are assigned to the same discrete label c, see


Precision
Recall
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
[F=.80] Human
[F=.75] SE+multi–ucm
[F=.75] SE (ours)
[F=.74] SCG
[F=.73] Sketch Tokens
[F=.73] gPb–owt–ucm
[F=.72] ISCRA
[F=.69] Gb
[F=.64] Mean Shift
[F=.64] Normalized Cuts
[F=.61] Felz–Hutt
[F=.60] Canny

Holistically-Nested Edge Detection

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Holistically nested edge detection

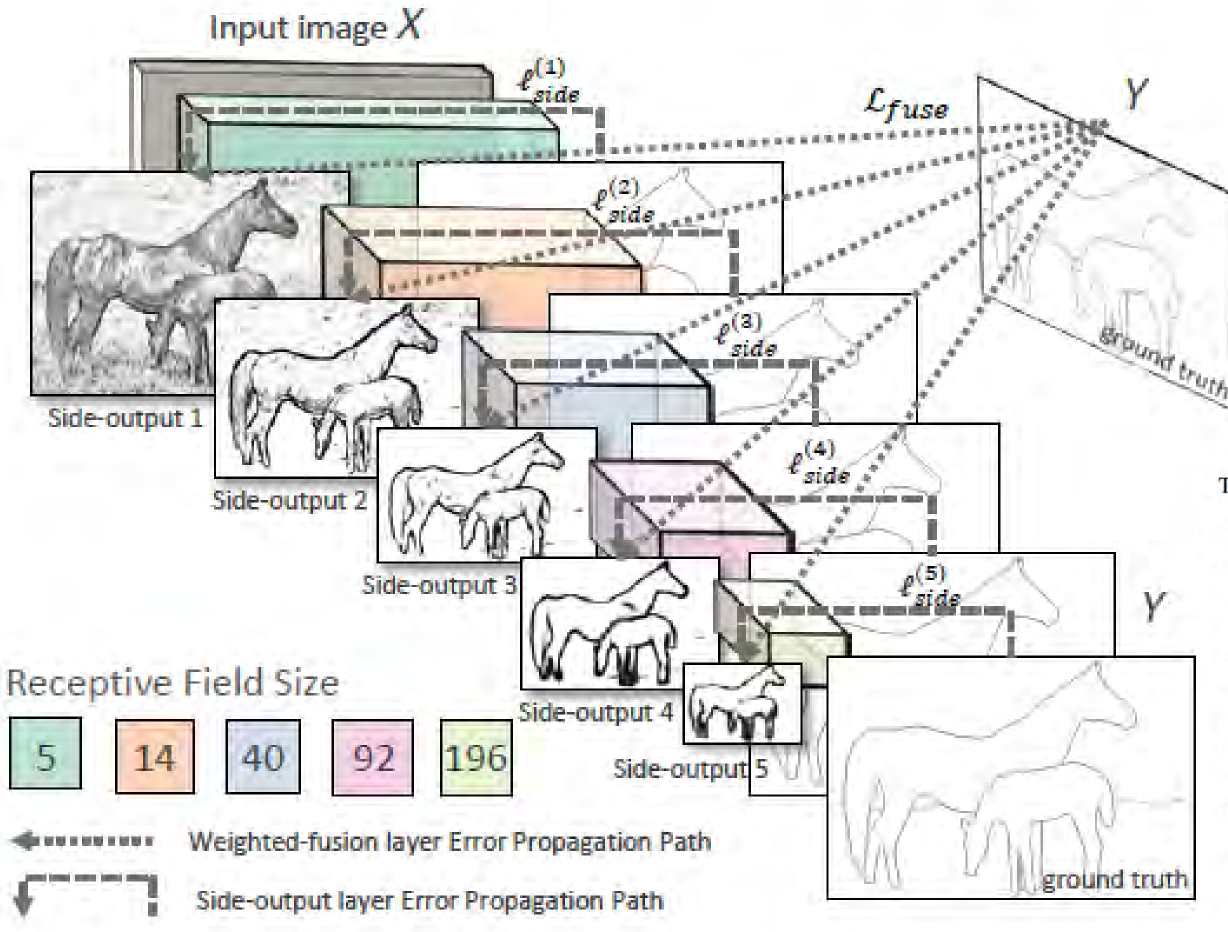


Table 4. Results on BSDS500. ∗BSDS300 results,†GPU time

	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

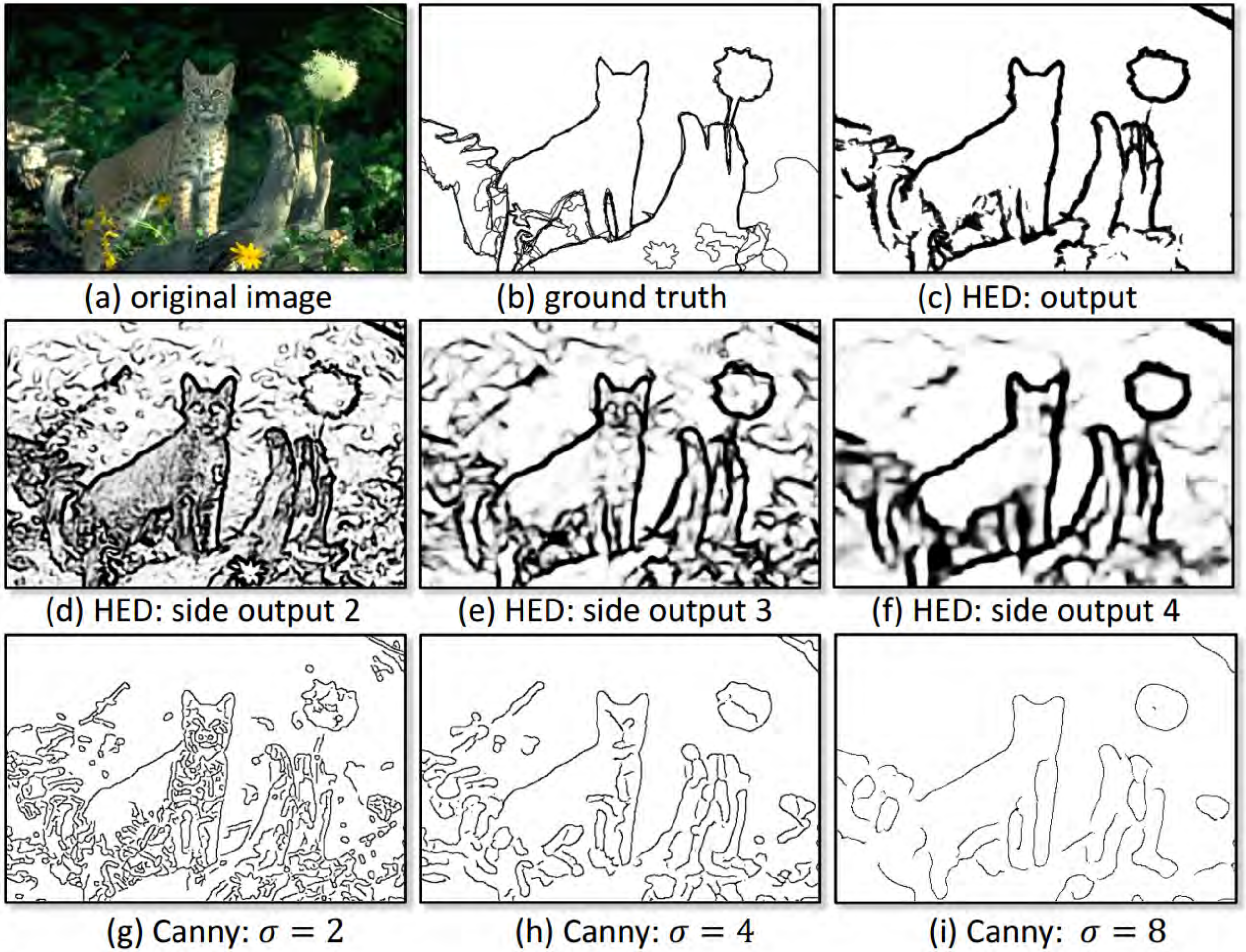
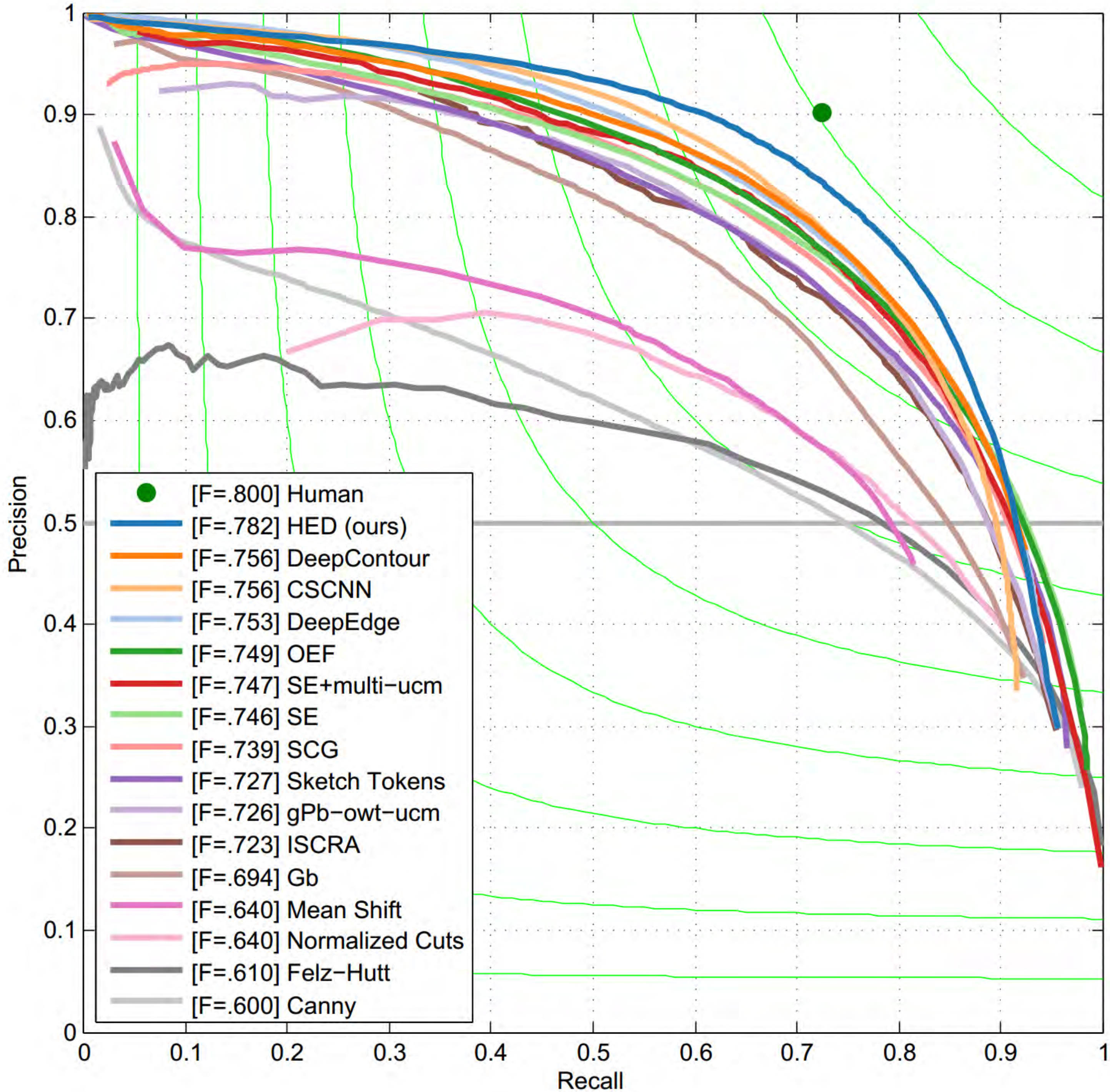


Figure 1. Illustration of the proposed HED algorithm. In the first row: (a) shows an example test image in the BSD500 dataset [28]; (b) shows its corresponding edges as annotated by human subjects; (c) displays the HED results. In the second row: (d), (e), and (f), respectively, show side edge responses from layers 2, 3, and 4 of our convolutional neural networks. In the third row: (g), (h), and (i), respectively, show edge responses from the Canny detector [4] at the scales $\sigma = 2.0$, $\sigma = 4.0$, and $\sigma = 8.0$. HED shows a clear advantage in consistency over Canny.



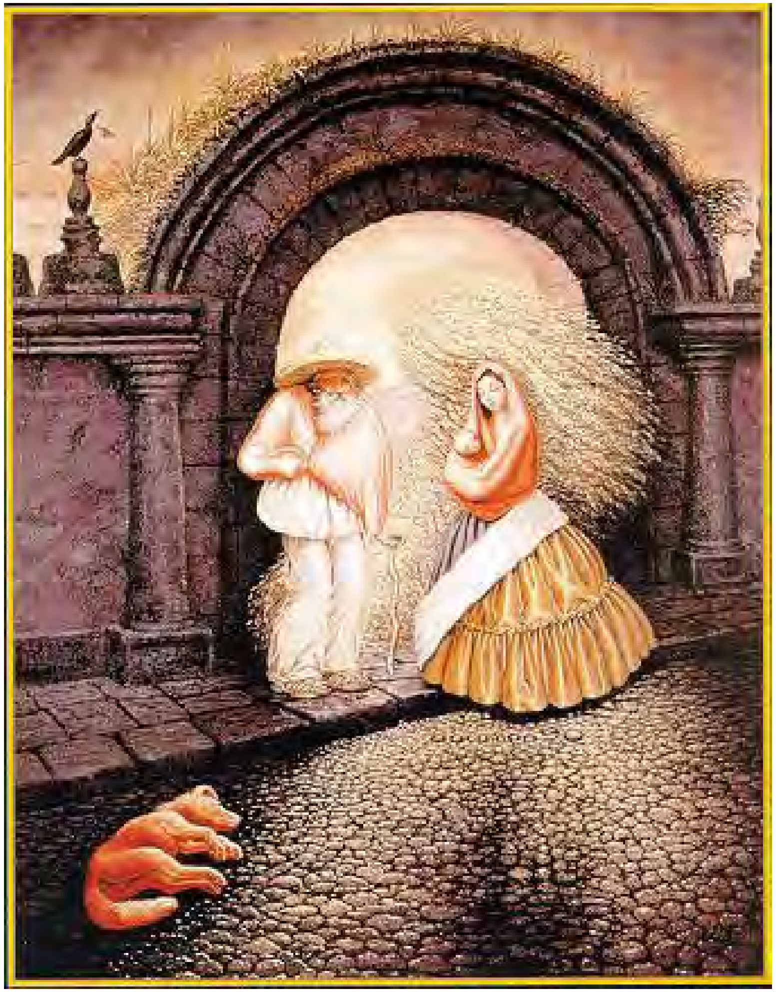
[F=.800] Human
[F=.782] HED (ours)
[F=.756] DeepContour
[F=.756] CSCNN
[F=.753] DeepEdge
[F=.749] OEF
[F=.747] SE+multi−ucm
[F=.746] SE
[F=.739] SCG
[F=.727] Sketch Tokens
[F=.726] gPb−owt−ucm
[F=.723] ISCRA
[F=.694] Gb
[F=.640] Mean Shift
[F=.640] Normalized Cuts
[F=.610] Felz−Hutt
[F=.600] Canny
Precision
Recall
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

State of edge detection

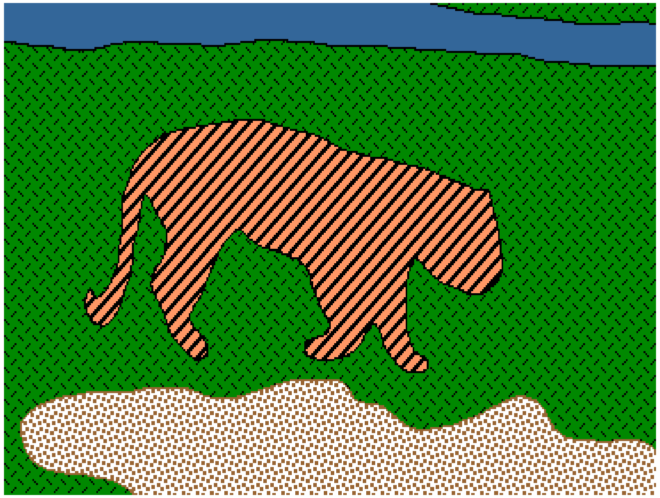
- Local edge detection is mostly solved
  - Intensity gradient, color, texture
  - HED on BSDS 500 is near human performance
- Some room for improvement by taking advantage of higher-level knowledge (e.g., objects)
- Still hard to produce all objects within a small number of regions

Today's Class

- **What are grouping problems in vision**?
- Inspiration from human perception
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Mode finding and mean shift: k-means, GMM, mean-shift
- Graph-based segmentation: Normalized Cut
- Oversegmentation
  - Watershed algorithm, Felzenszwalb and Huttenlocher graph-based
- Multiple segmentation



From Images to Objects



"I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees." --Max Wertheimer

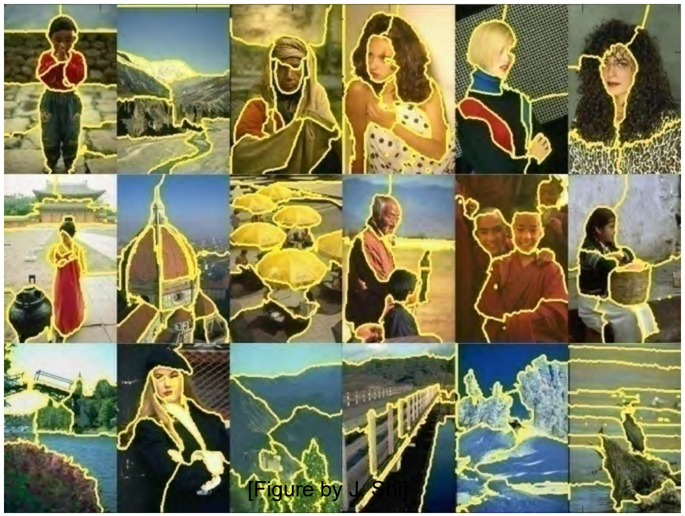
Grouping in vision

- Goals:
  - Gather features that belong together
  - **Obtain an intermediate representation that compactly describes key image or video parts**

Grouping in vision

- Goals:
  - Gather features that belong together
  - **Obtain an intermediate representation that compactly describes key image (video) parts**
- Top down vs. bottom up segmentation
  - Top down: pixels belong together because they are from the same object
  - Bottom up: pixels belong together because they look similar
- Hard to measure success
  - What is interesting depends on the app.

Examples of grouping in vision



[Figure by J. Shi]

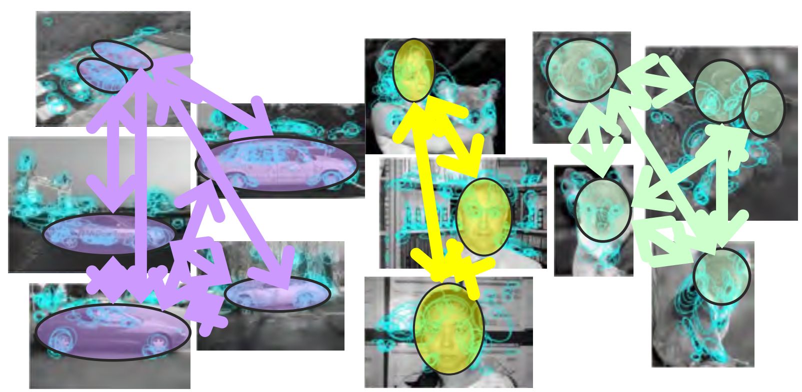
Determine image regions

[http://poseidon.csd.auth.gr/LAB_RESEARCH/Latest/imgs/SpeakDepVidIndex_img2.jpg]

Group video frames into shots

[Figure by Wang & Suter]

Figure-ground



[Figure by Grauman & Darrell]

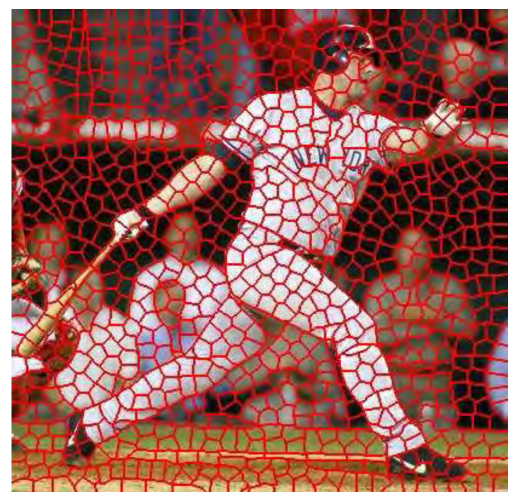
Object-level grouping

Image segmentation

Goal: Group pixels into meaningful or perceptually similar regions

Segmentation for efficiency: “superpixels”

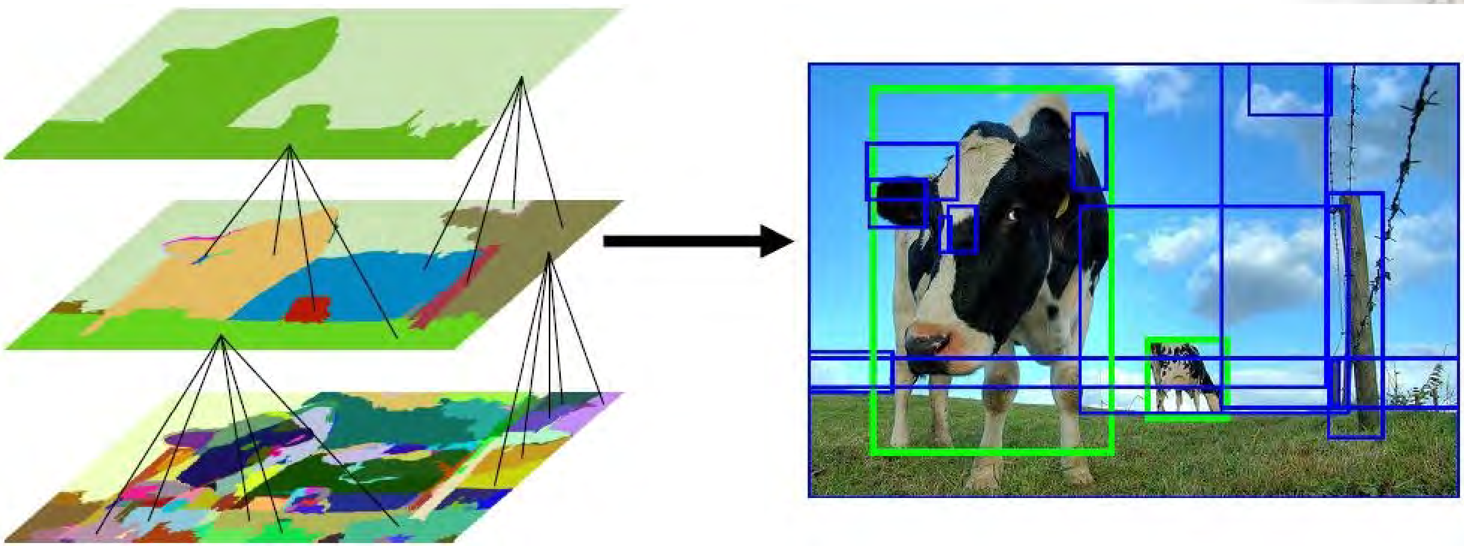
[Felzenszwalb and Huttenlocher 2004]



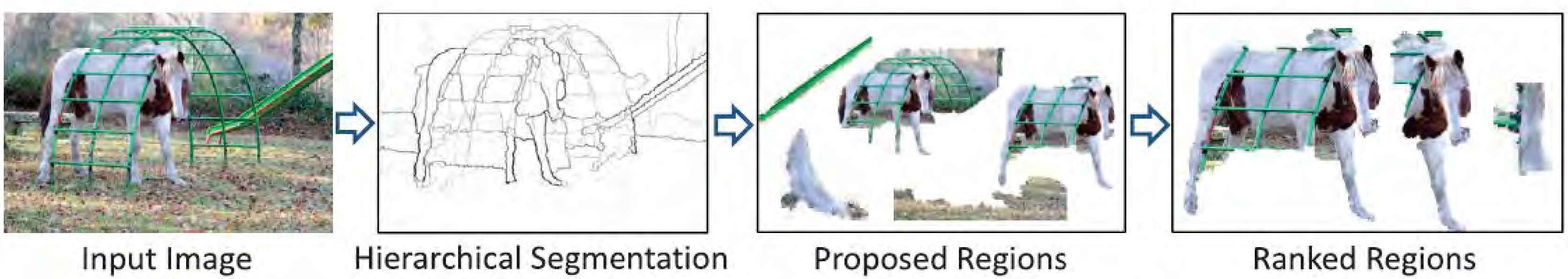
[Shi and Malik 2001]

Segmentation for feature support

Segmentation for object proposals



“Selective Search” [Sande, Uijlings et al. ICCV 2011, IJCV 2013]

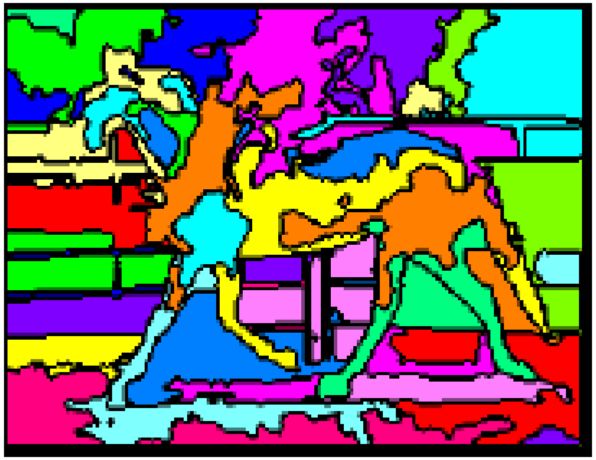


[Endres Hoiem ECCV 2010, IJCV 2014]

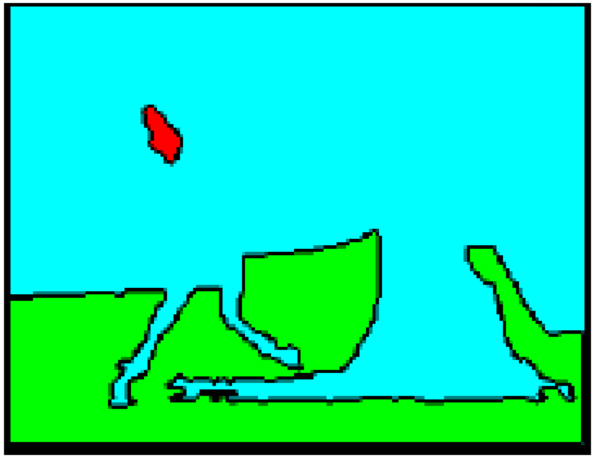
Segmentation as a result

Rother et al. 2004

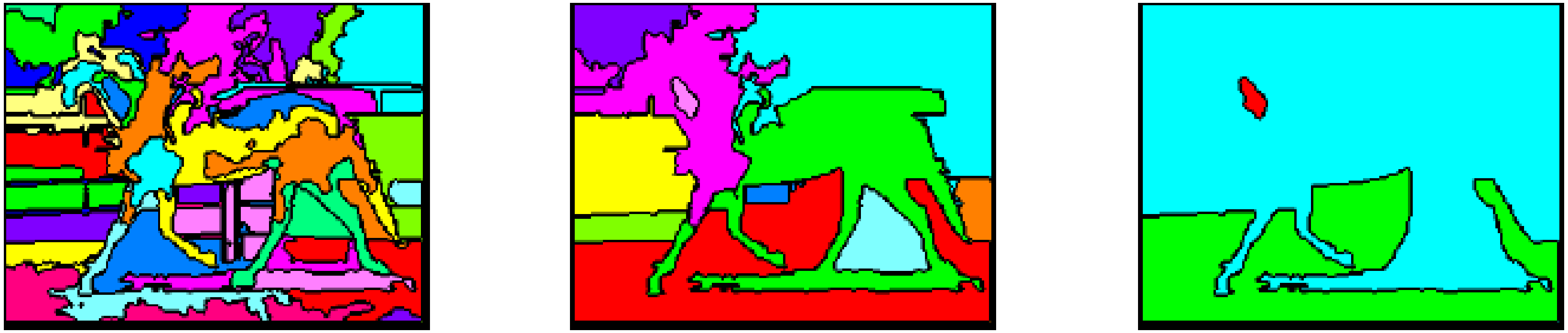
Types of segmentations



Oversegmentation



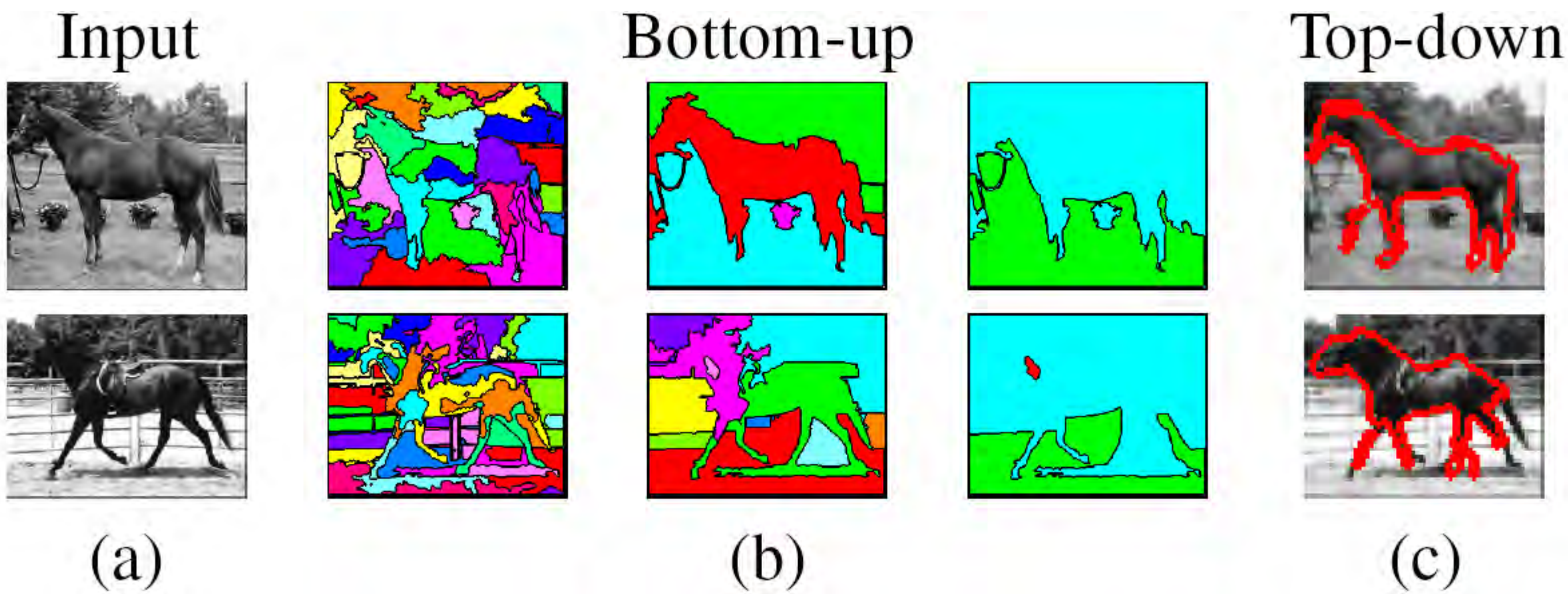
Undersegmentation



Multiple Segmentations

Major processes for segmentation

- **Bottom-up:** group tokens with similar features
- **Top-down:** group tokens that likely belong to the same object



Today's Class

- What are grouping problems in vision?
- **Inspiration from human perception**
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Mode finding and mean shift: k-means, GMM, mean-shift
- Graph-based segmentation: Normalized Cut
- Oversegmentation
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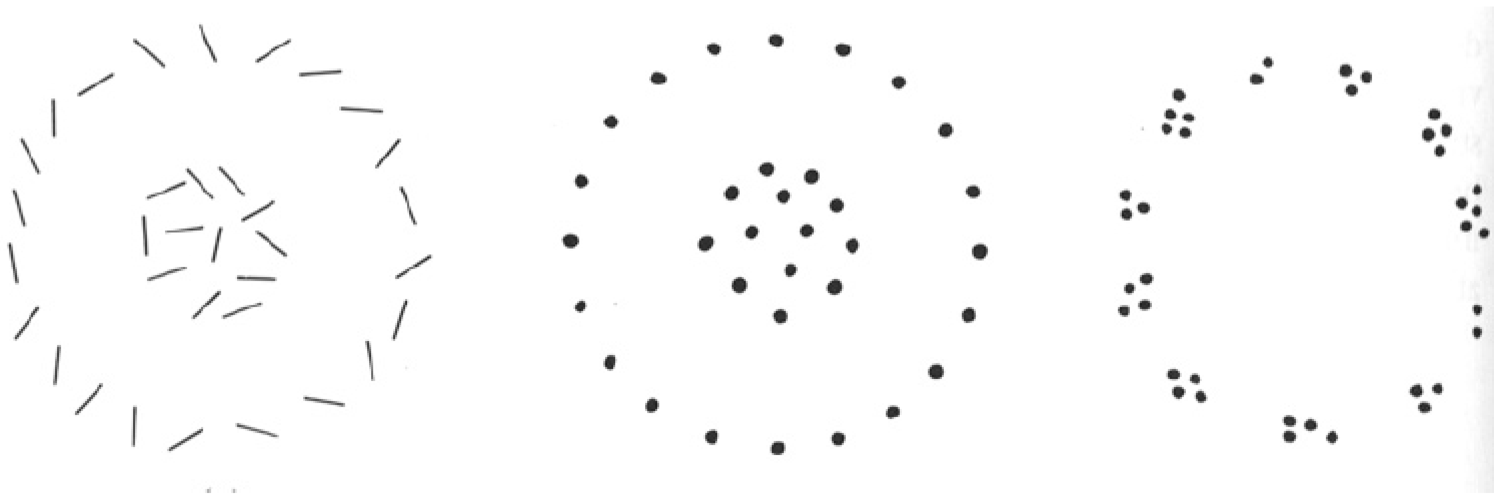


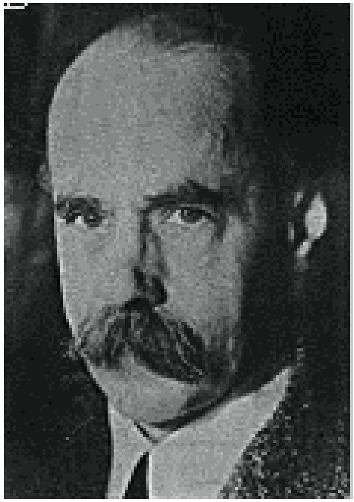
What are meta-cues for grouping?

Gestalt Theory

- Gestalt: whole or group
  - Whole is greater than sum of its parts
  - Relationships among parts can yield new properties/features
- Psychologists identified series of factors that predispose set of elements to be grouped (by human visual system)

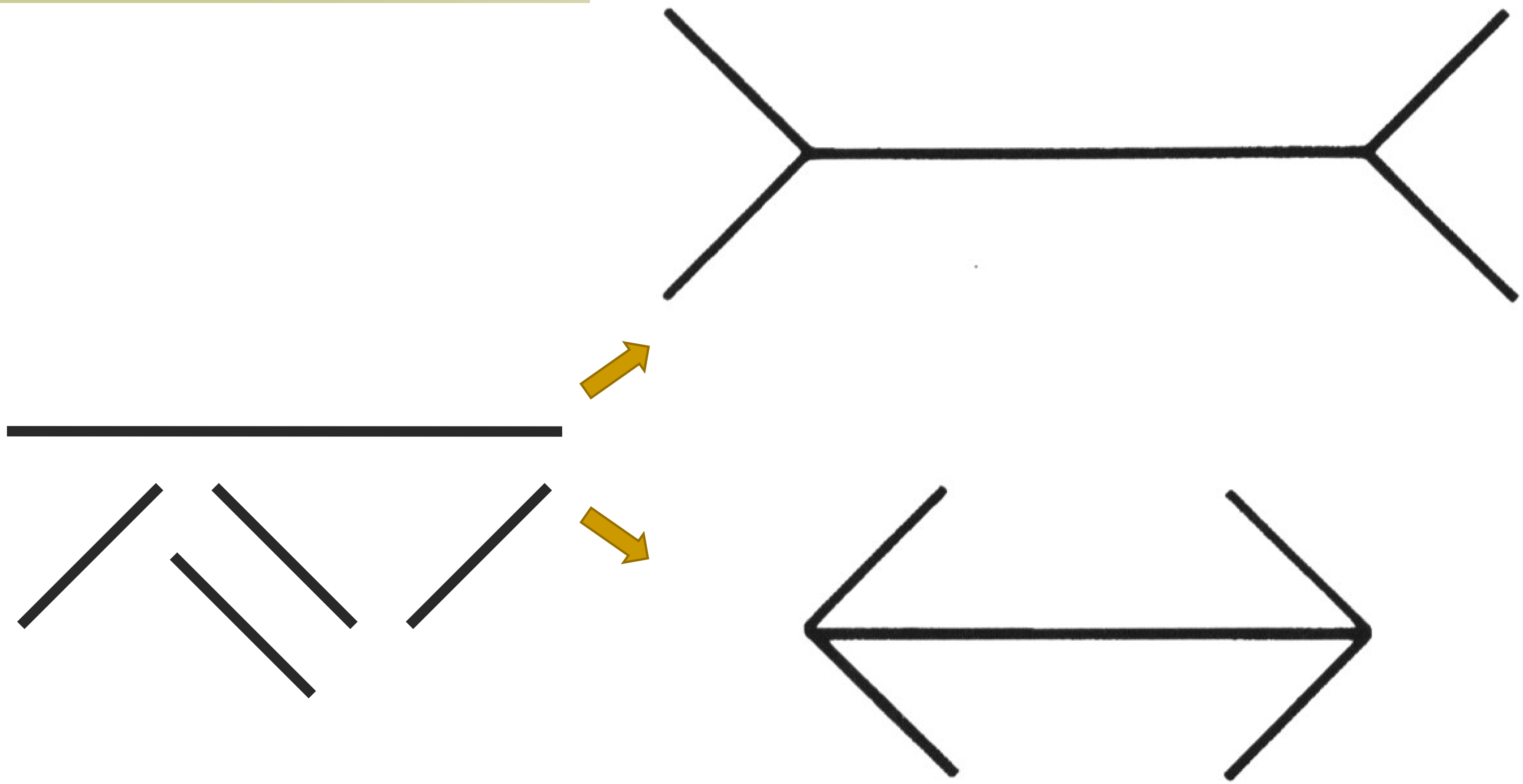
"I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees."

Max Wertheimer (1880-1943)



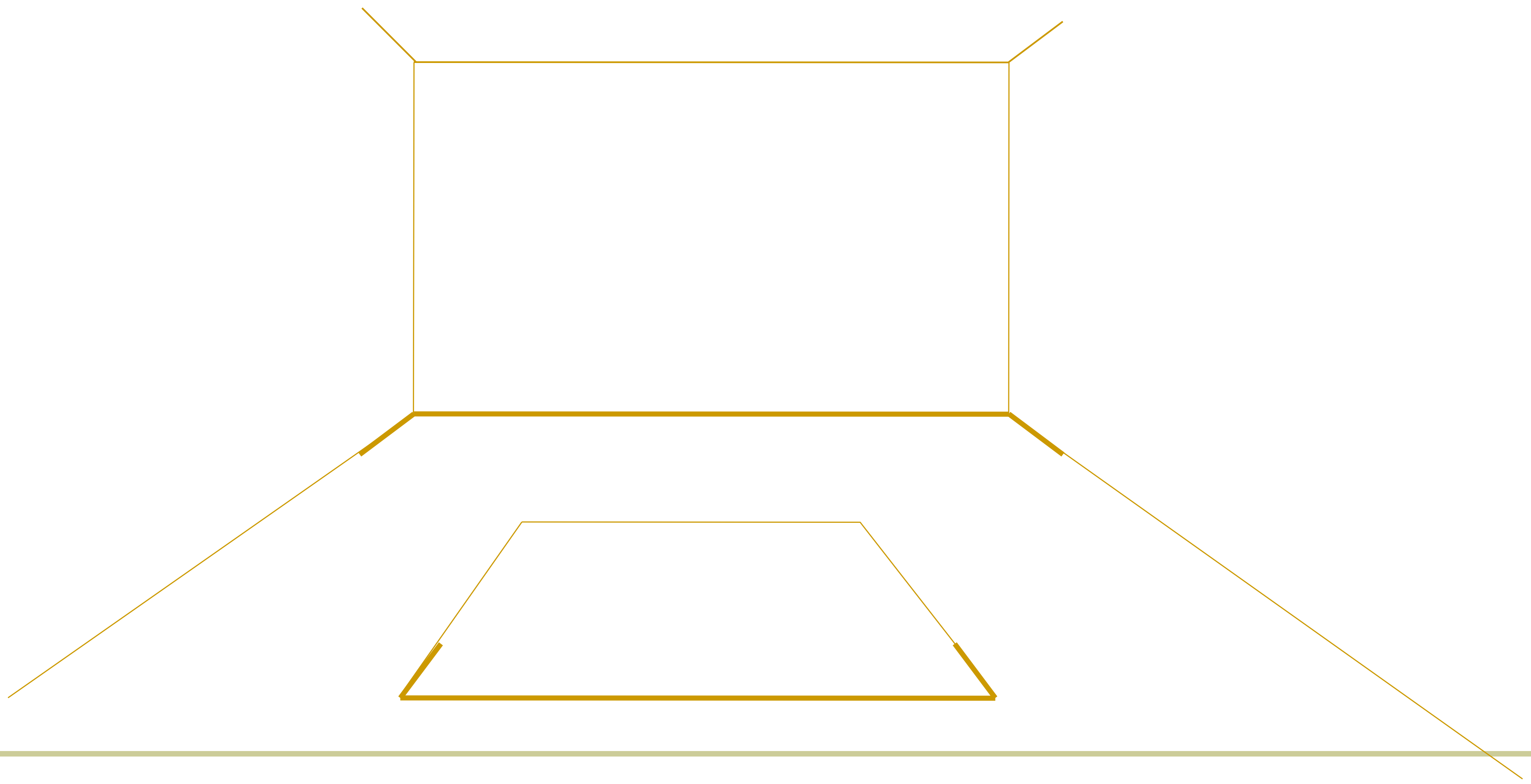
Untersuchungen zur Lehre von der Gestalt, *Psychologische Forschung*, Vol. 4, pp. 301-350, 1923
http://psy.ed.asu.edu/~classics/Wertheimer/Forms/forms.htm

Gestaltism

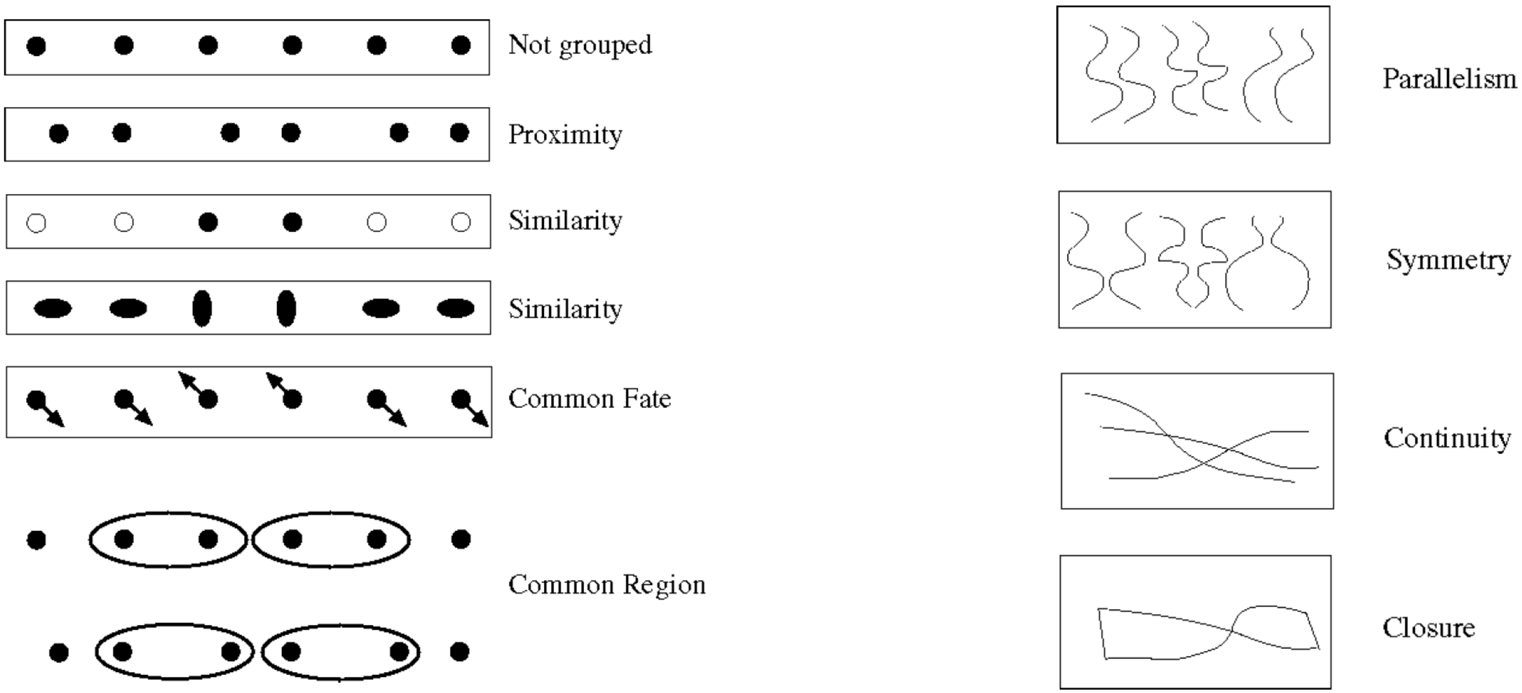


The Muller-Lyer illusion

We perceive the interpretation, not the senses

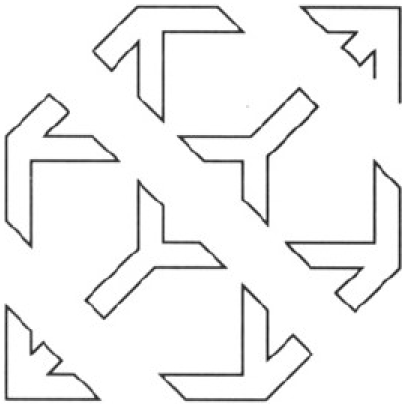


Gestalt Factors

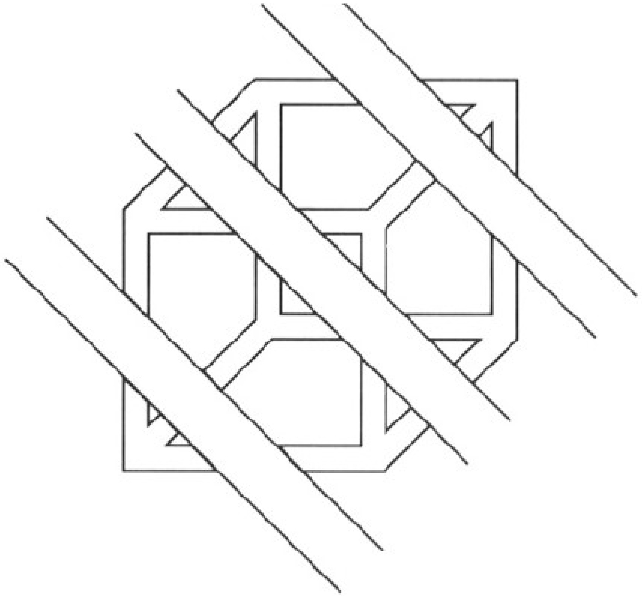


- These factors make intuitive sense, but are very difficult to translate into algorithms.

Continuity through Occlusion Cues



Continuity through Occlusion Cues



Continuity, explanation by occlusion

Continuity through Occlusion Cues

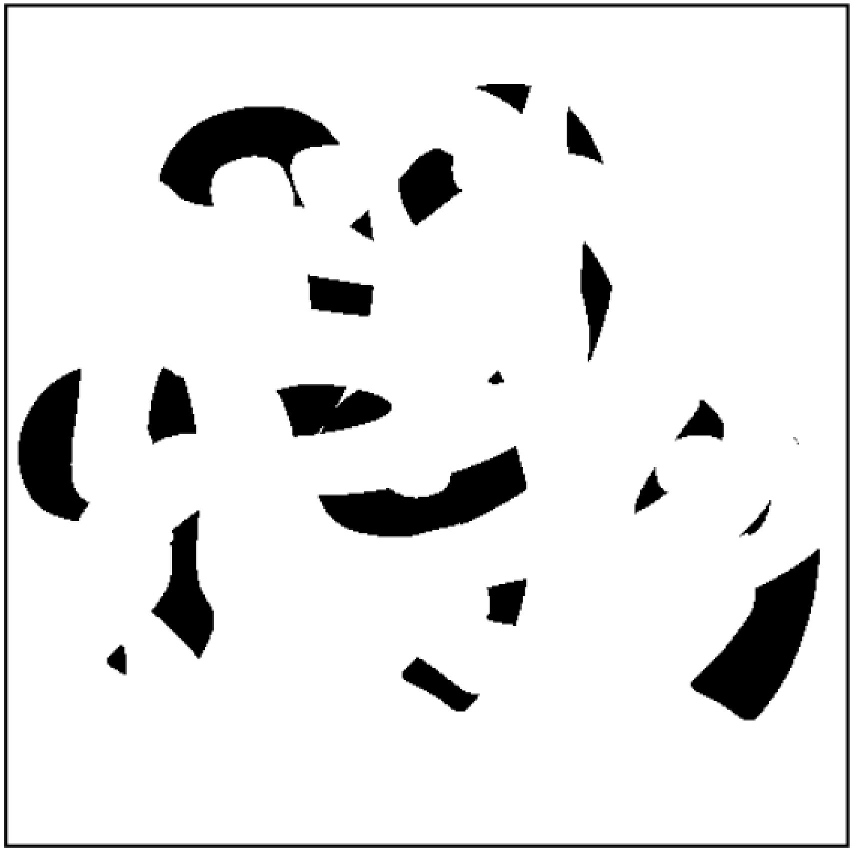
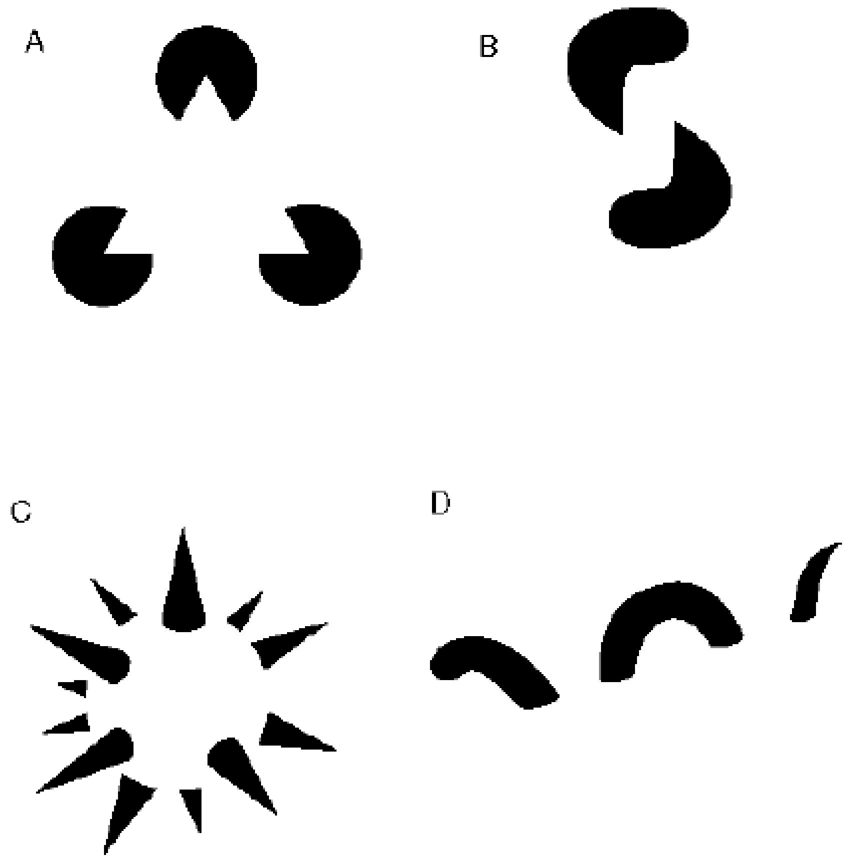


Image source: Forsyth & Ponce

Continuity through Occlusion Cues

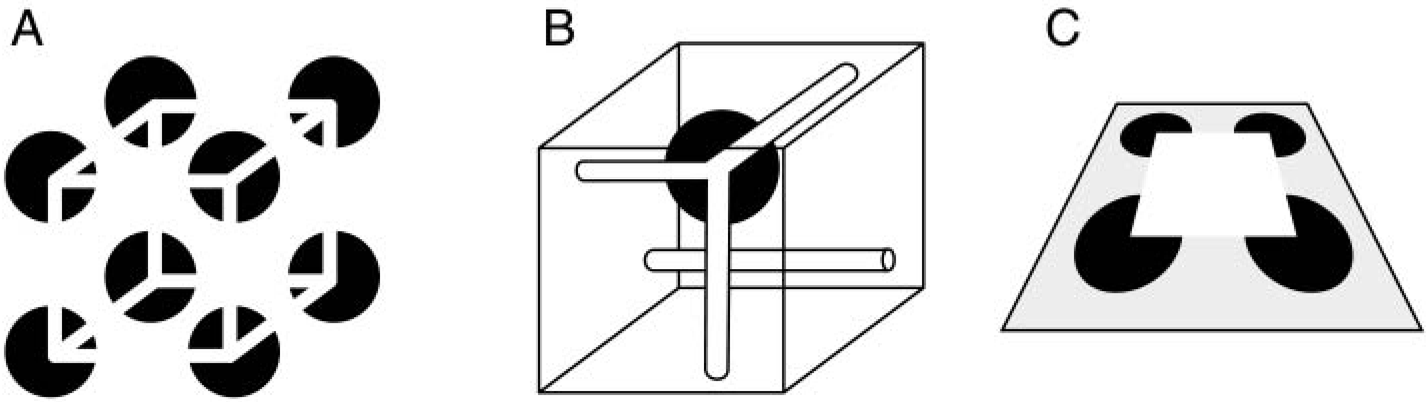
Image source: Forsyth & Ponce

Grouping by invisible completion



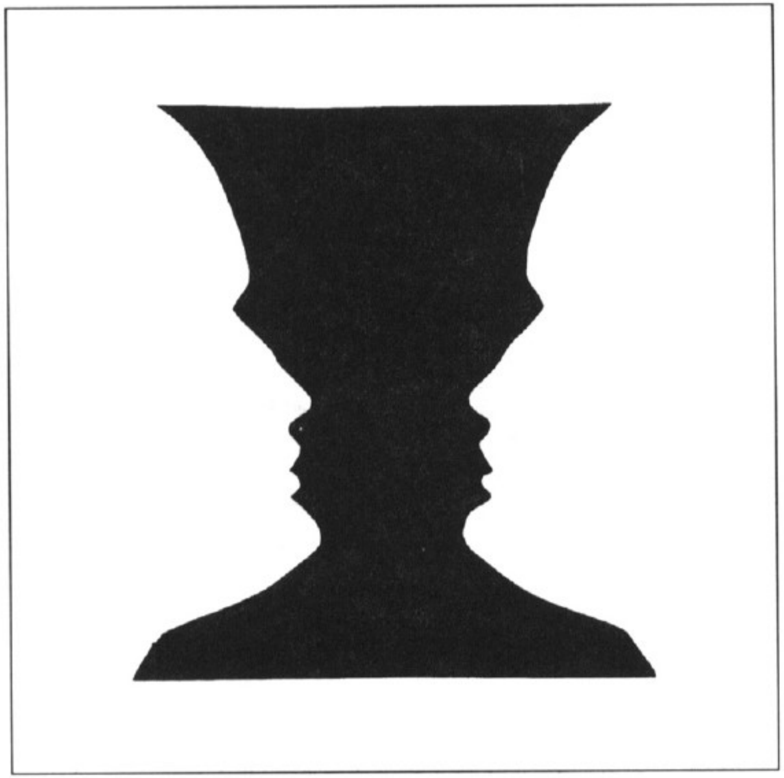
From Steve Lehar: The Constructive Aspect of Visual Perception

Grouping involves global interpretation



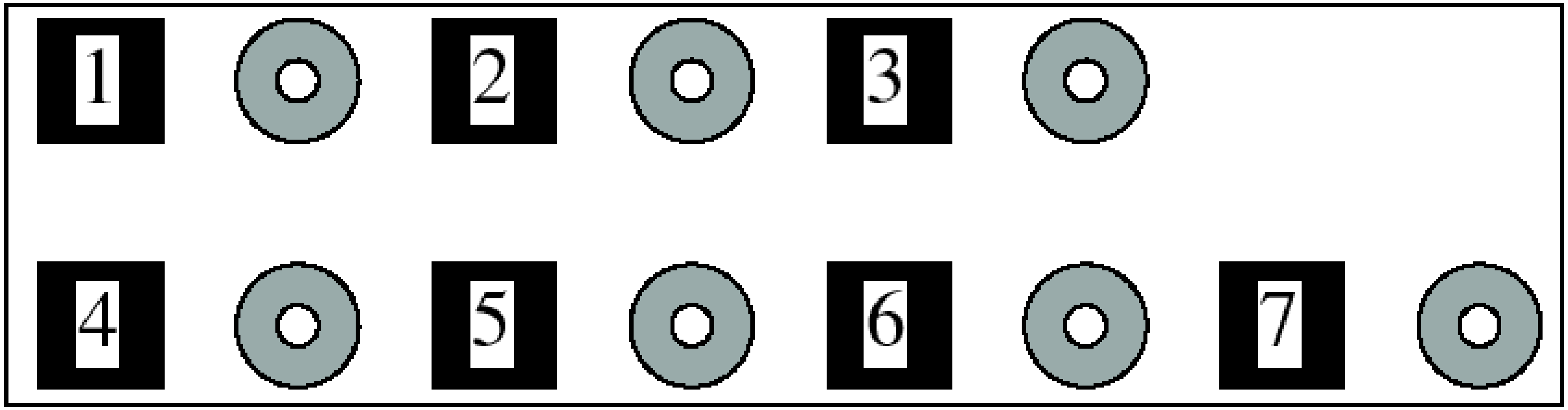
From Steve Lehar: The Constructive Aspect of Visual Perception

Figure-Ground Discrimination



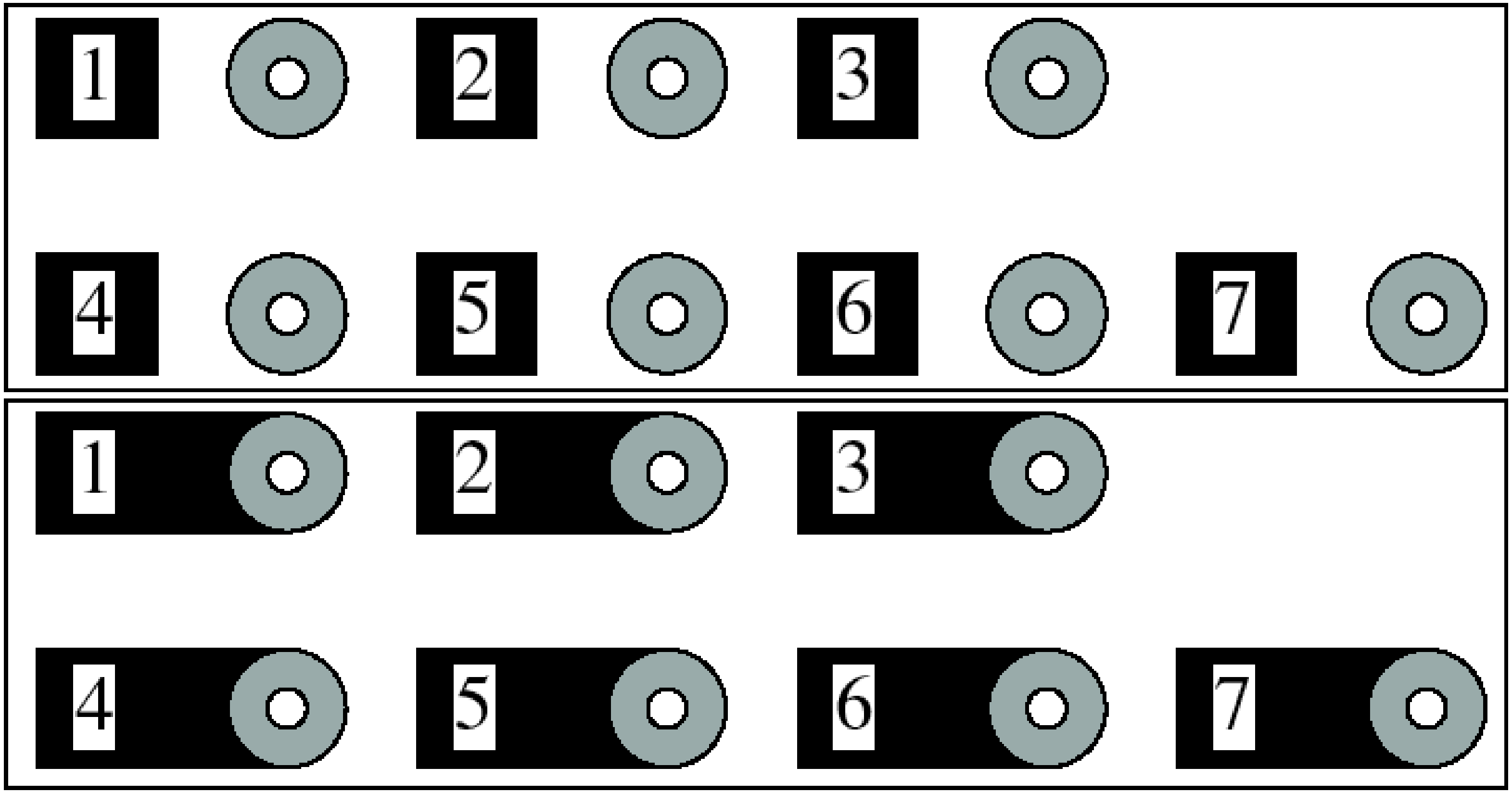
The Ultimate Gestalt?

Grouping phenomena in real life



Forsyth & Ponce, Figure 14.7

Grouping phenomena in real life



Forsyth & Ponce, Figure 14.7

Gestalt cues

- Good intuition and basic principles for grouping
- Basis for many ideas in segmentation and occlusion reasoning
- Some (e.g., symmetry) are difficult to implement in practice

Today's Class

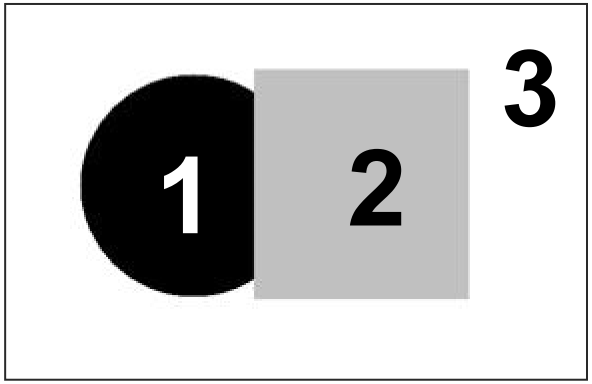
- What are grouping problems in vision?
- Inspiration from human perception
  - Gestalt properties
- **Bottom-up segmentation via clustering**
  - Mode finding and mean shift: k-means, GMM, mean-shift
- Graph-based segmentation: Normalized Cut
- Oversegmentation
  - Watershed algorithm, Felzenszwalb and Huttenlocher graph-based
- Multiple segmentation

Clustering

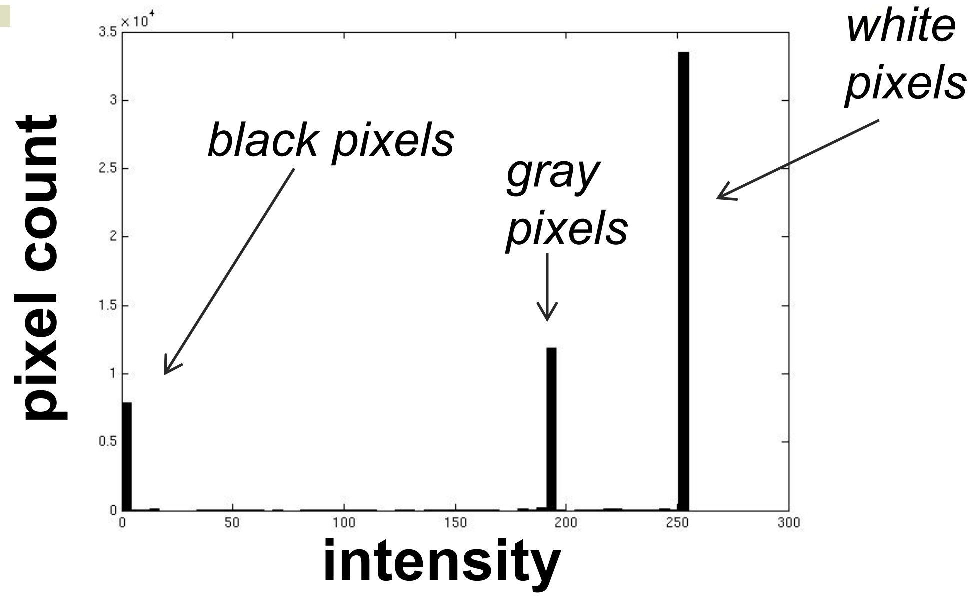
- Clustering algorithms:
  - Unsupervised learning
  - Detect patterns in unlabeled data
    - E.g. group emails or search results
    - E.g. find categories of customers
    - E.g. group pixels into regions
  - Useful when don’t know what you’re looking for
  - Requires data, but no labels

Slide credit: Dan I

Image segmentation: toy example

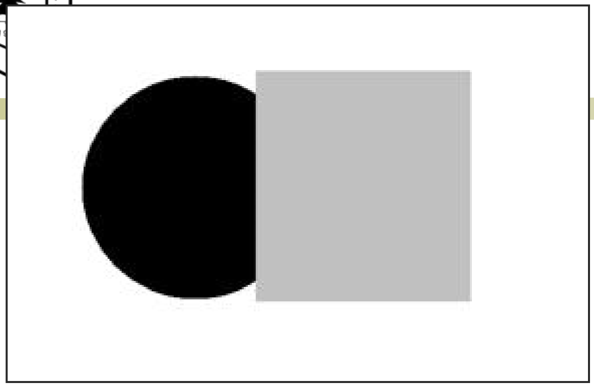


input image

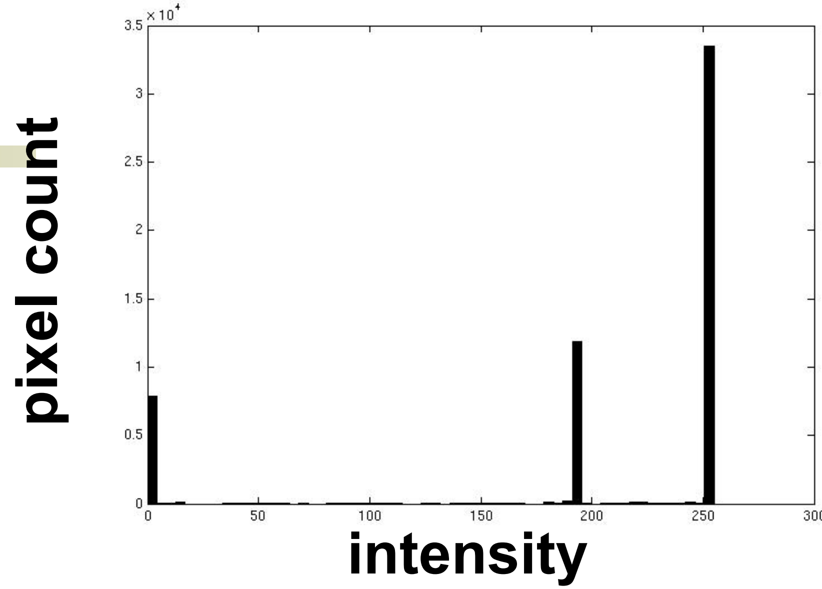


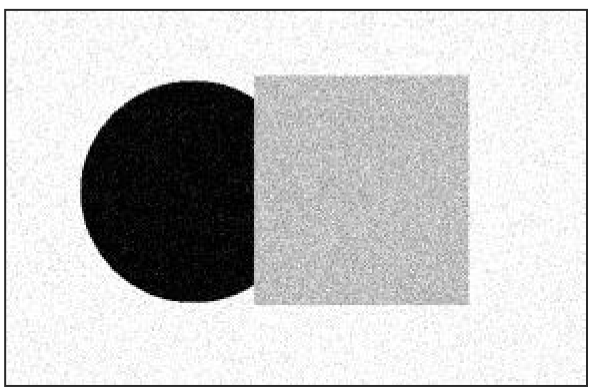
- These intensities define the three groups.
- We could label every pixel in the image according to which of these primary intensities it is.
  - i.e., *segment* the image based on the intensity feature.
- What if the image isn't quite so simple?

Slide credit: Kristen Grauman

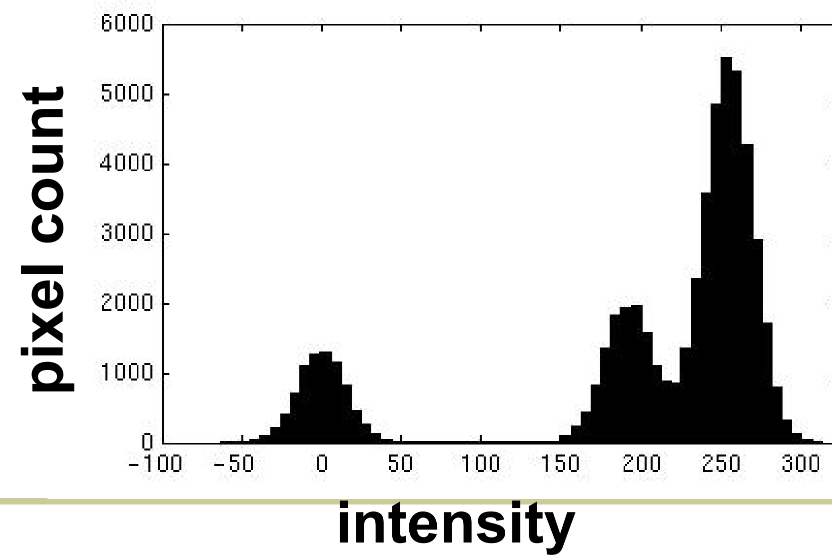


input image

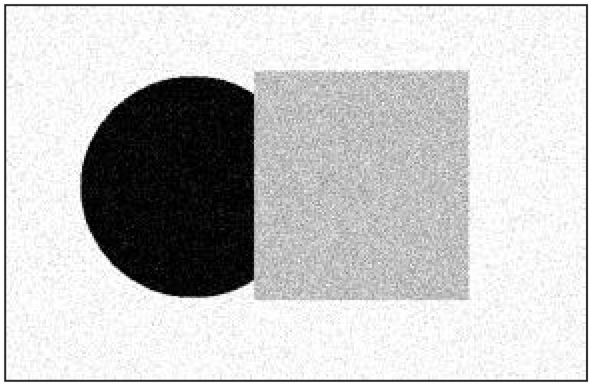




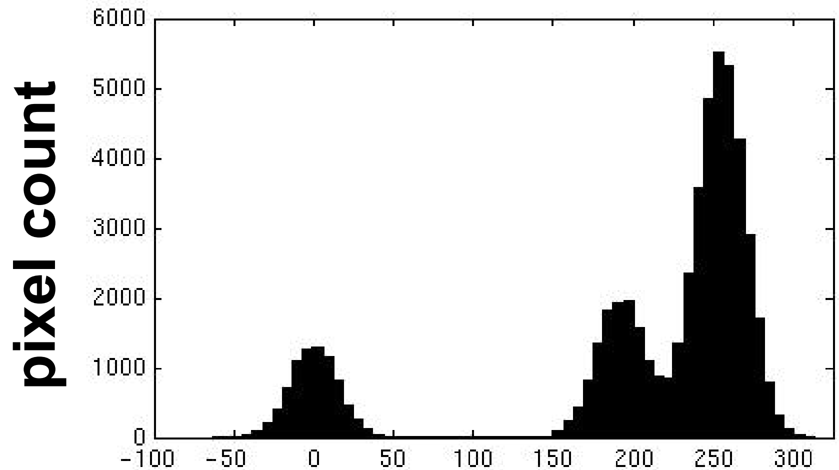
input image



Slide credit: Kristen Grauman

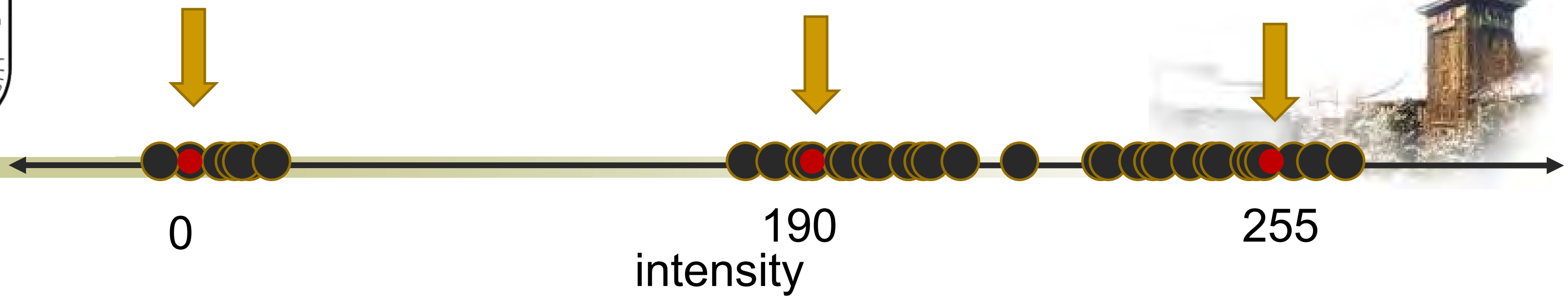


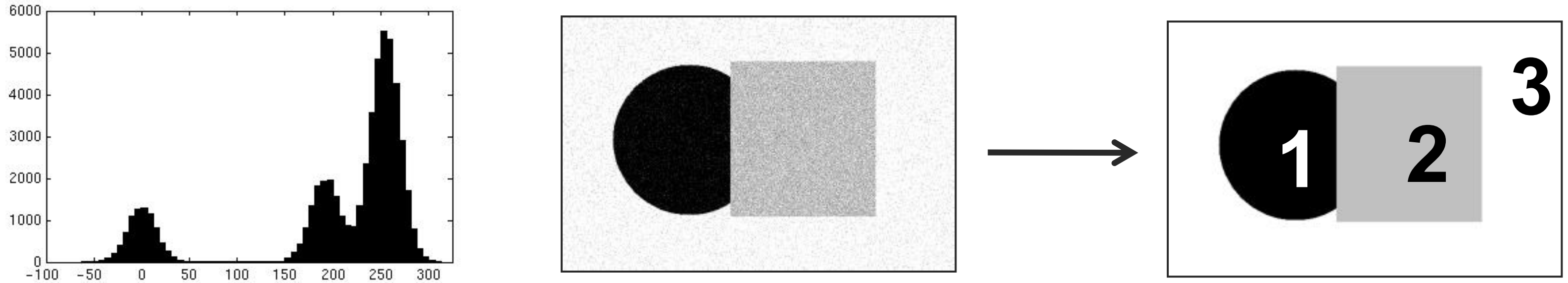
input image



intensity

- Now how to determine the three main intensities that define our groups?
- We need to ***cluster.***





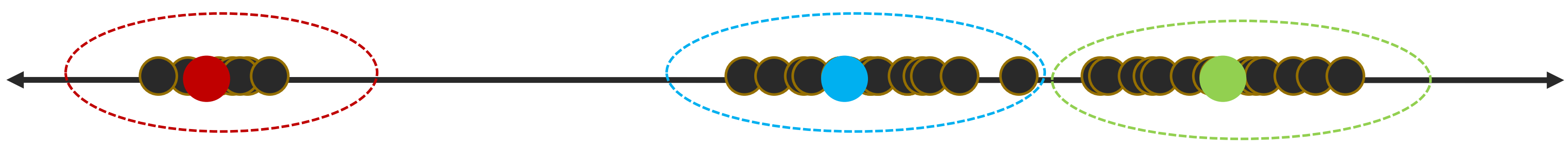
- Goal: choose three "centers" as the representative intensities, and label every pixel according to which of these centers it is nearest to.
- Best cluster centers are those that minimize SSD between all points and their nearest cluster center c_i:

$$\sum_{\text{clusters } i} \; \sum_{\text{points p in cluster } i} ||p - c_i||^2$$

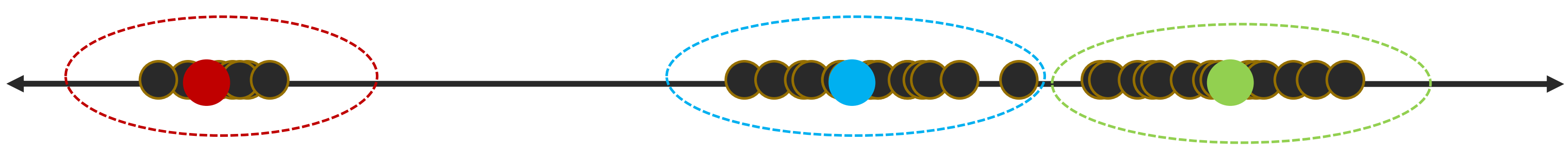
Slide credit: Kristen Grauman

Clustering

- With this objective, it is a “chicken and egg” problem:
  - If we knew the **cluster centers**, we could allocate points to groups by assigning each to its closest center.



  - If we knew the **group memberships**, we could get the centers by computing the mean per group.



Slide credit: Kristen Grauman

K-means clustering

- Basic idea: randomly initialize the *k* cluster centers, and iterate between the two steps we just saw.

  1. Randomly initialize the cluster centers, $c_1, \ldots, c_K$
  2. Given cluster centers, determine points in each cluster
     - For each point p, find the closest c_i. Put p into cluster i
  3. Given points in each cluster, solve for c_i
     - Set c_i to be the mean of points in cluster i
  4. If c_i have changed, repeat Step 2

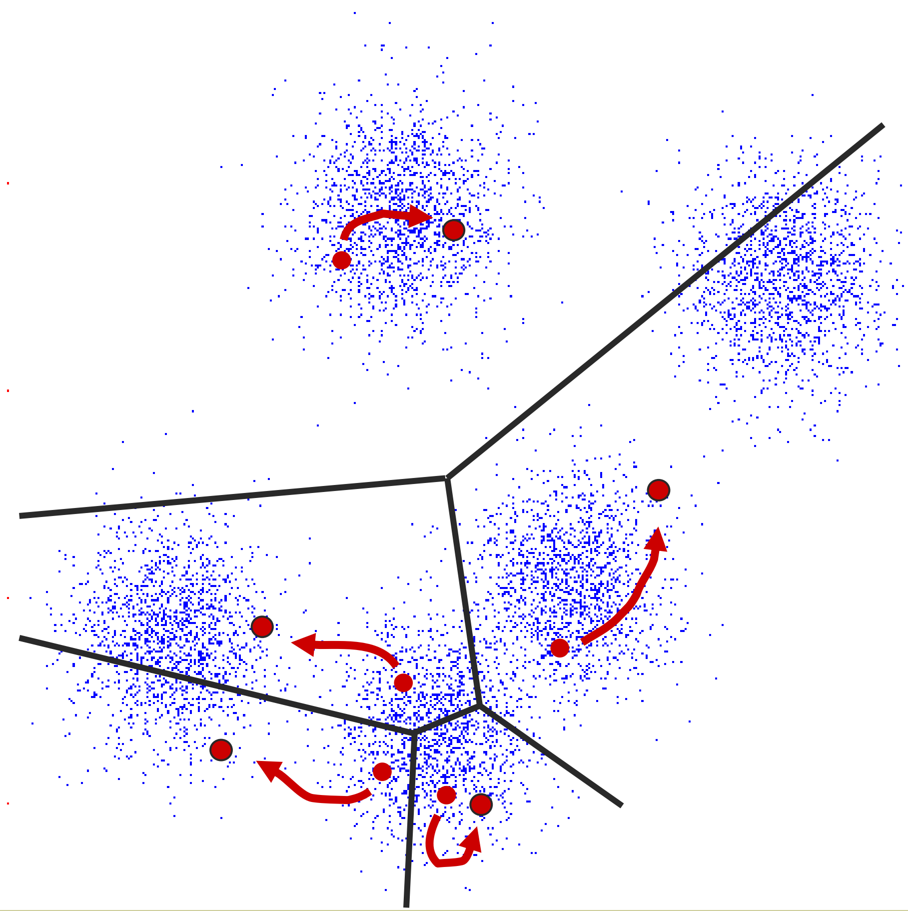
Properties

- Will always converge to *some* solution
- Can be a "local minimum"
  - does not always find the global minimum of objective function:

$$\sum_{\text{clusters } i} \quad \sum_{\text{points p in cluster } i} ||p - c_i||^2$$

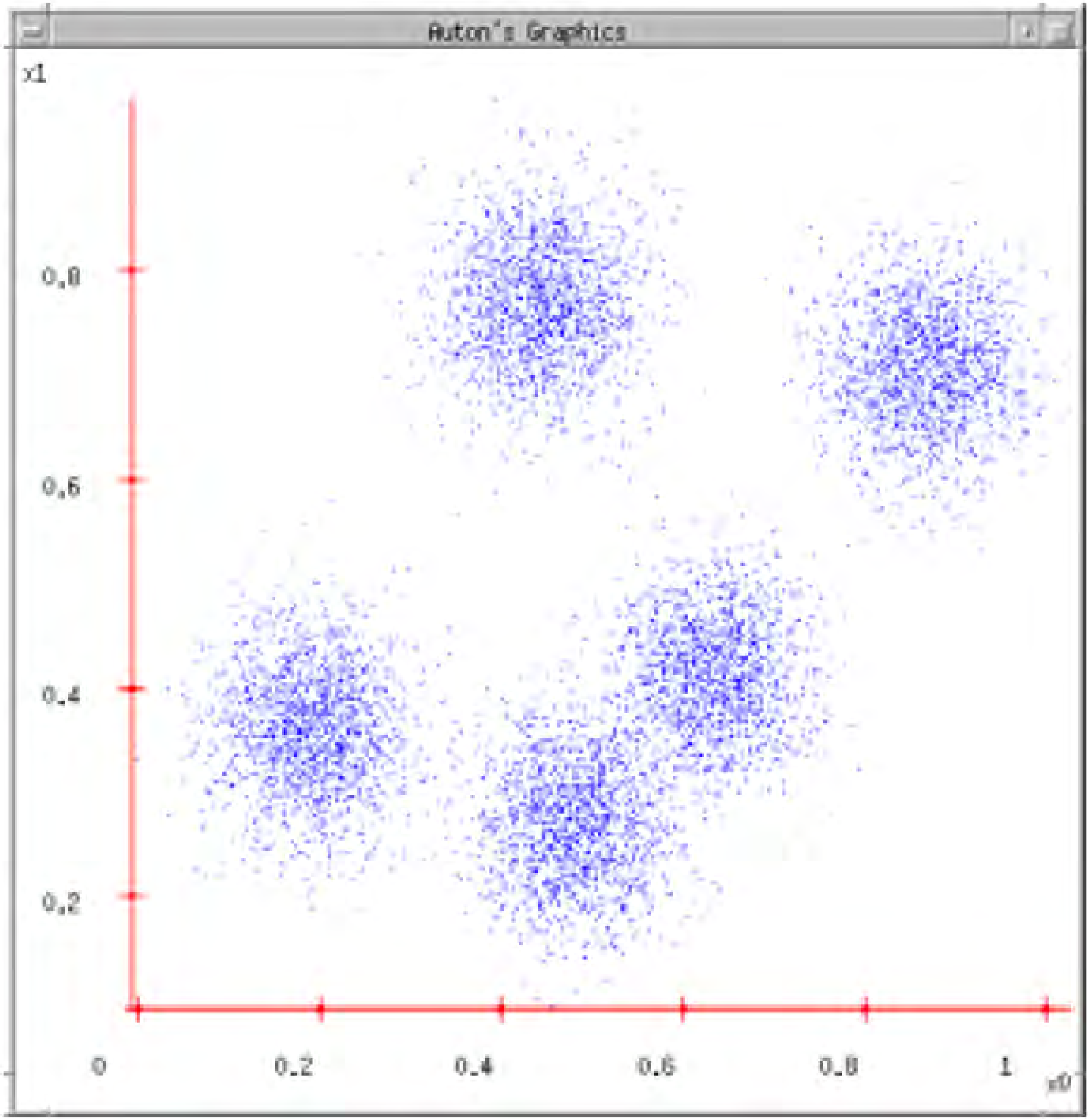
K-Means

- An iterative clustering algorithm
  - Pick K random points as cluster centers (means)
  - Alternate:
    - Assign data instances to closest mean
    - Assign each mean to the average of its assigned points
  - Stop when no points' assignments change



K-means

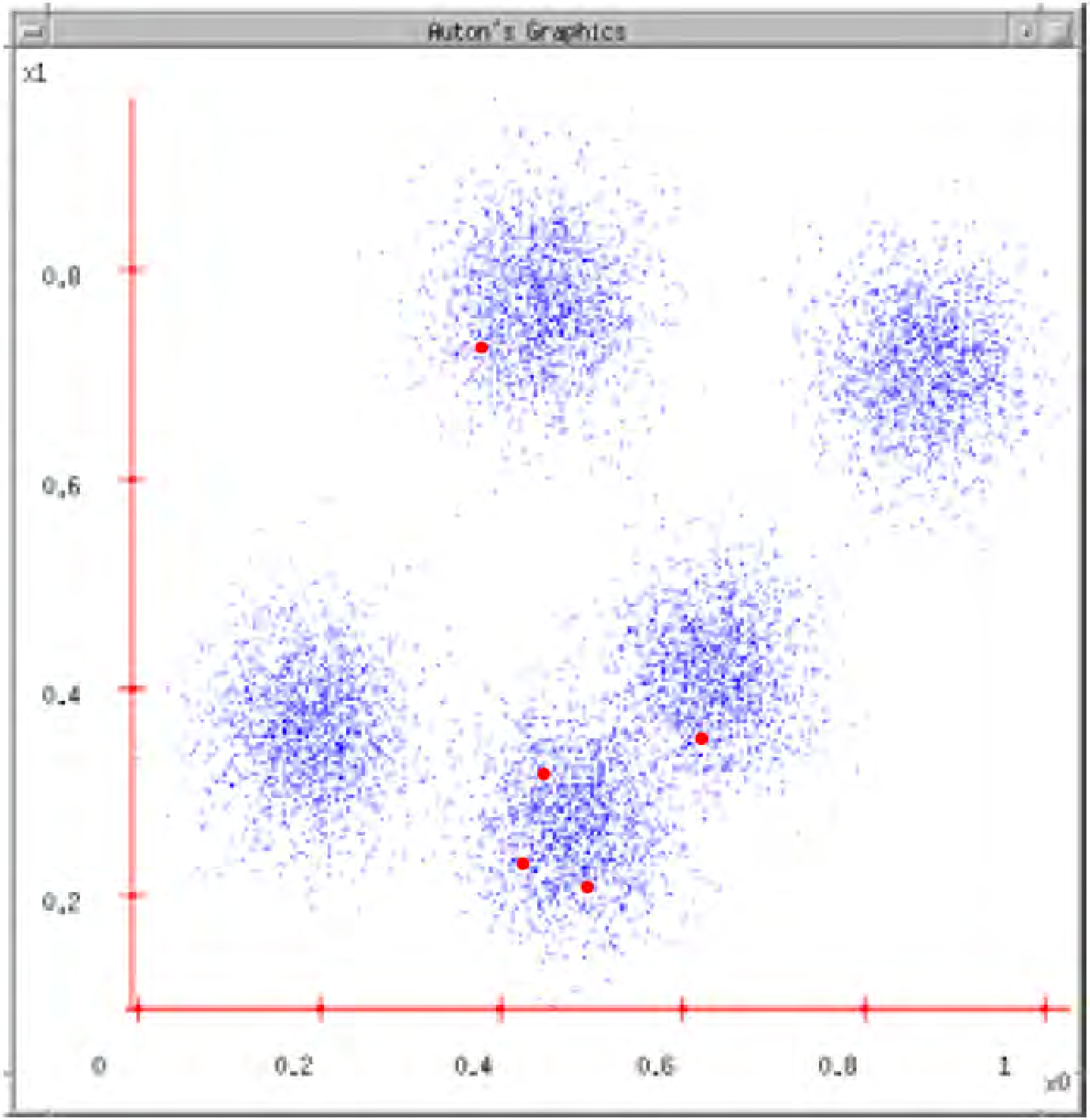
1. Ask user how many clusters they'd like. *(e.g. k=5)*



Slide credit Andrew Moore

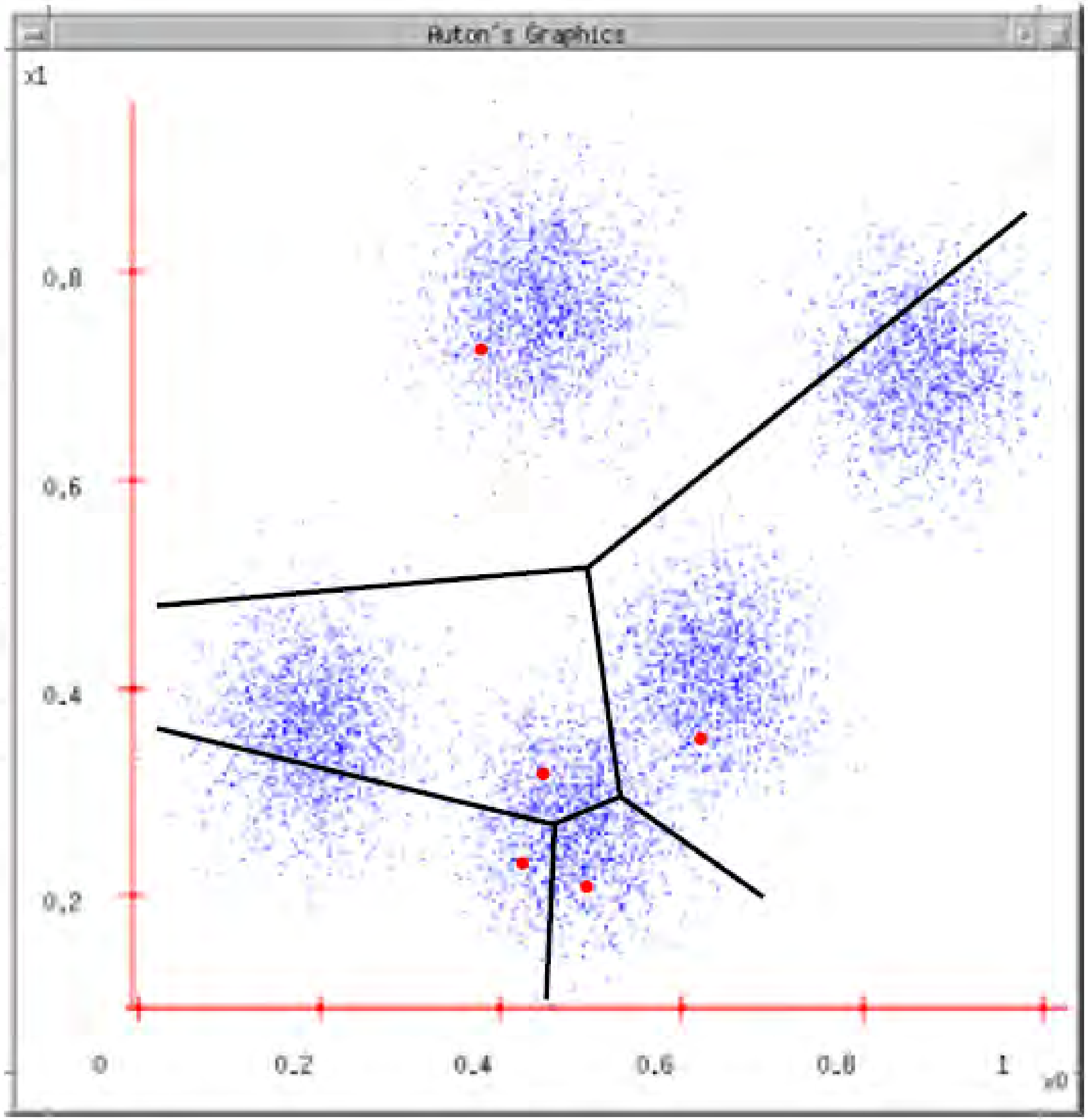
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations



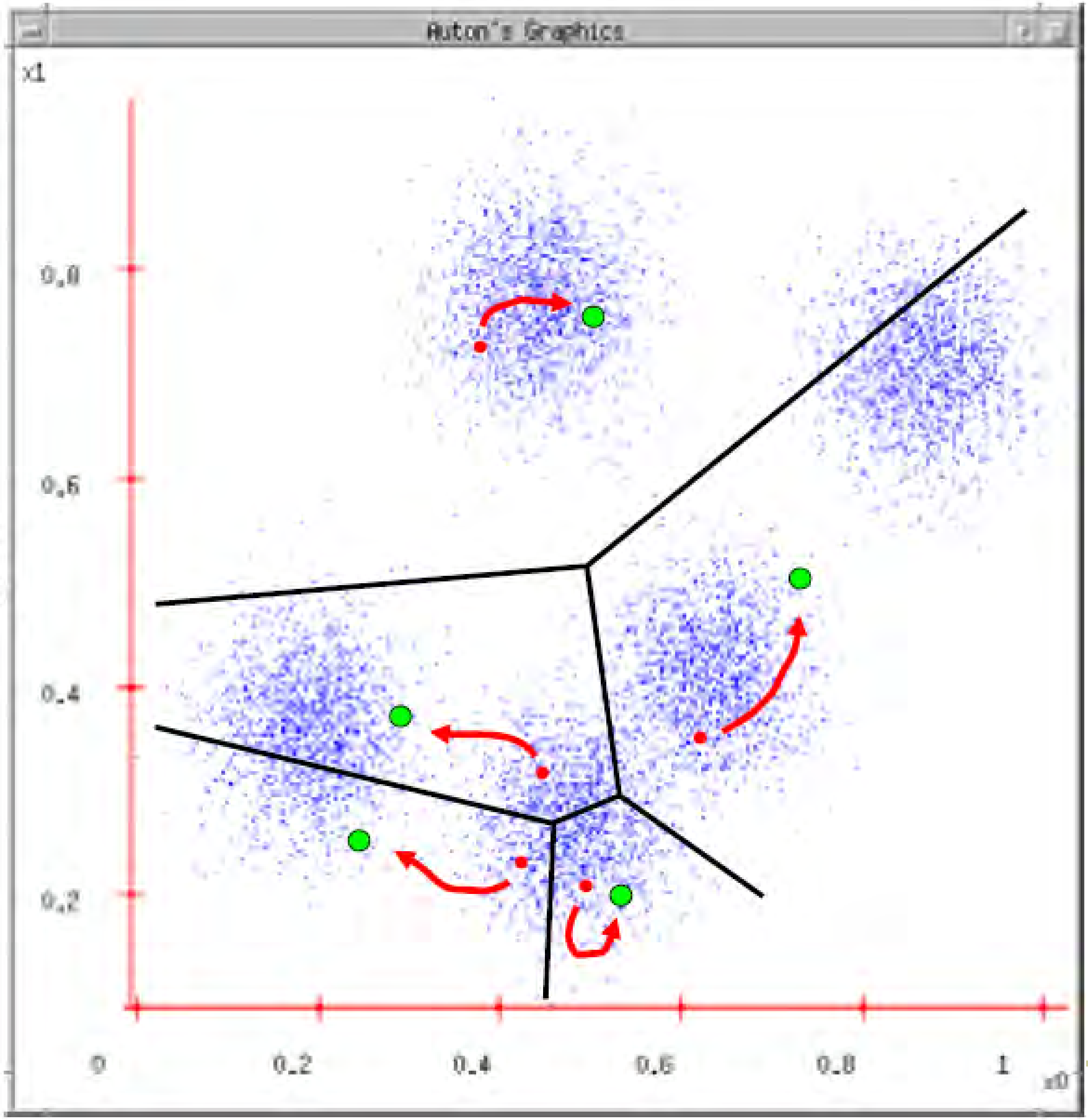
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to. (Thus each Center "owns" a set of datapoints)



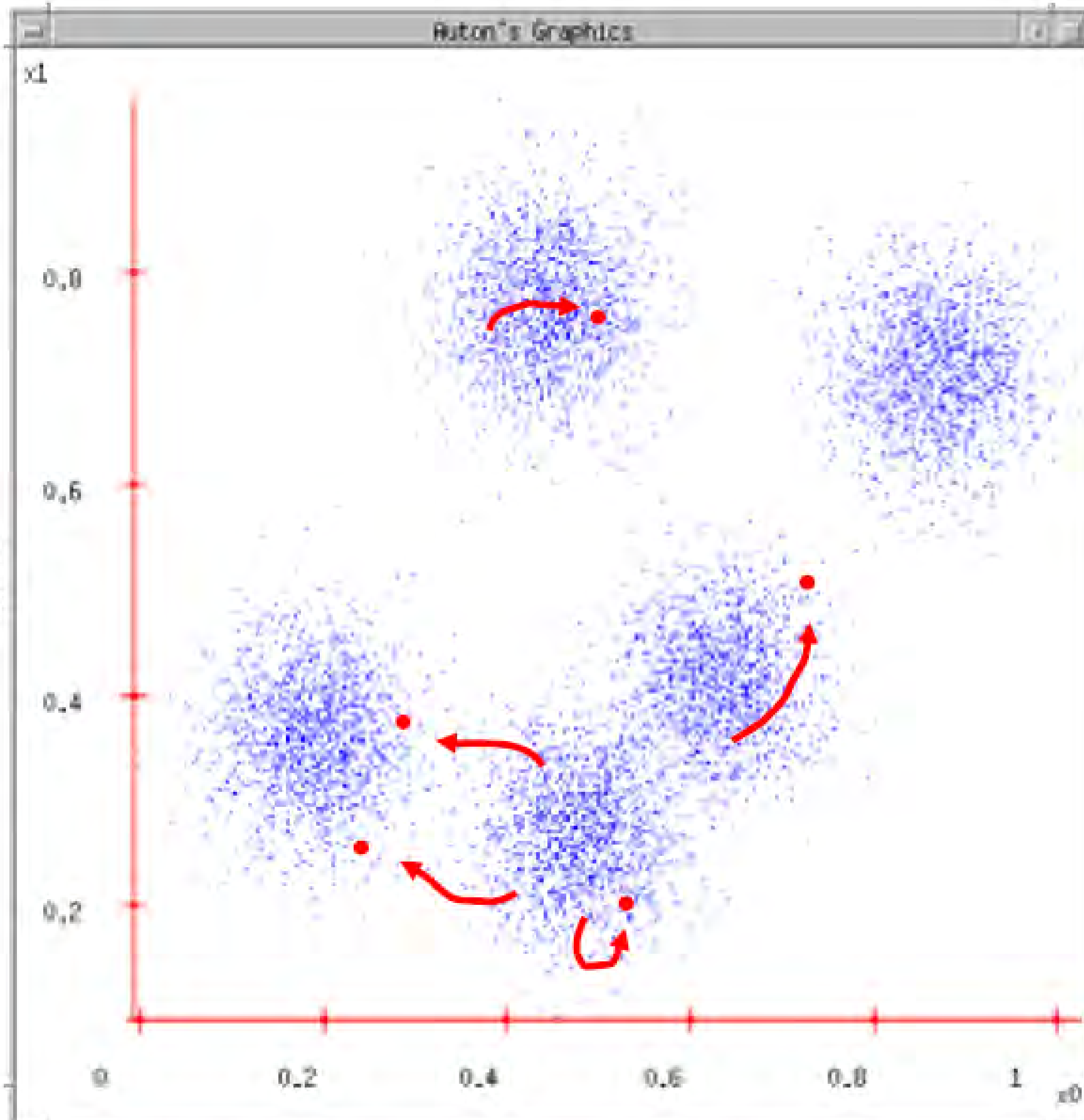
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns



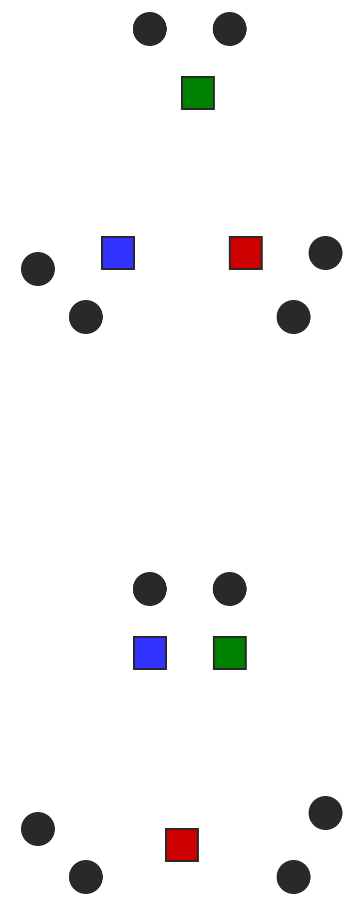
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns…
5. …and jumps there
6. …Repeat until terminated!

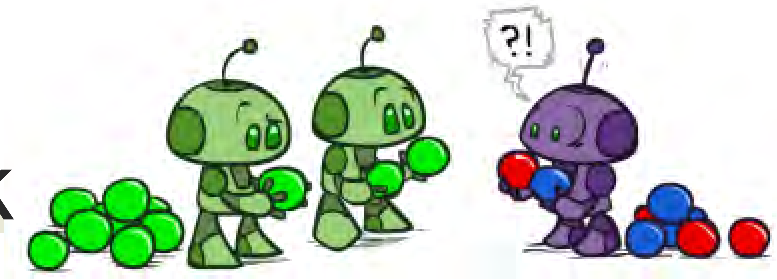


Initialization

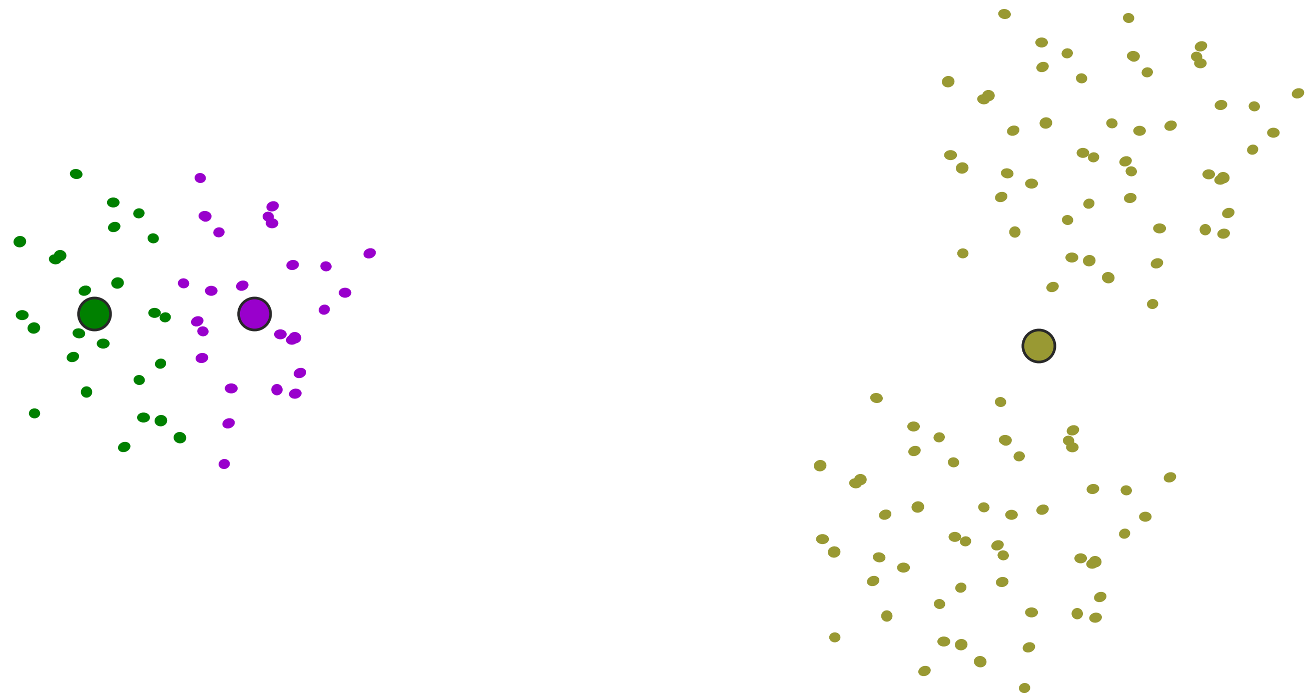
- K-means is non-deterministic
  - Requires initial means
  - It does matter what you pick!
  - What can go wrong?
  - Various schemes for preventing this kind of thing



K-Means Getting Stuck



- A local optimum:



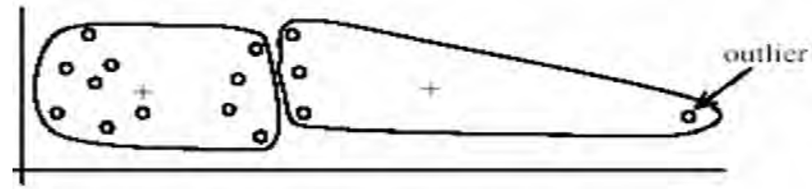
K-means: pros and cons

Pros

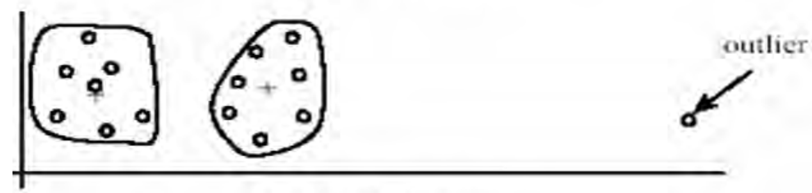
- Simple, fast to compute
- Converges to local minimum of within-cluster squared error

Cons/issues

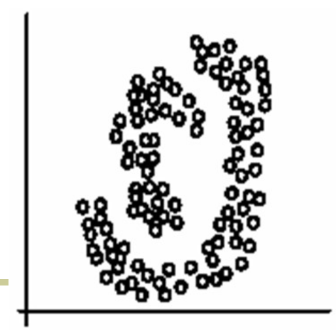
- Setting k?
- Sensitive to initial centers
- Sensitive to outliers
- Detects spherical clusters
- Assuming means can be computed



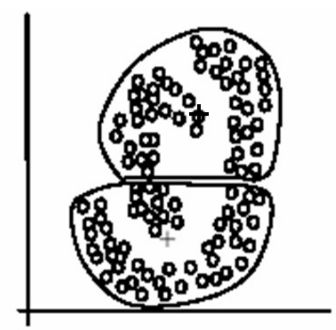
(A): Undesirable clusters



(B): Ideal clusters



(A): Two natural clusters



(B): *k*-means clusters

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity** similarity

Feature space: intensity value (1-d)

K=2

K=3

quantization of the feature space;
segmentation label map

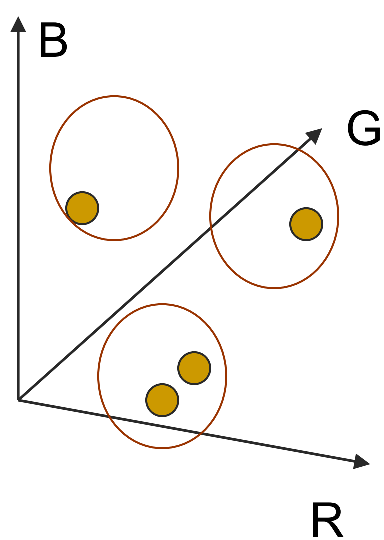
```
img_as_col = double(im(:));
cluster_membs = kmeans(img_as_col, K);

labelim = zeros(size(im));
for i=1:k
   inds = find(cluster_membs==i);
   meanval = mean(img_as_column(inds));
   labelim(inds) = meanval;
end
```

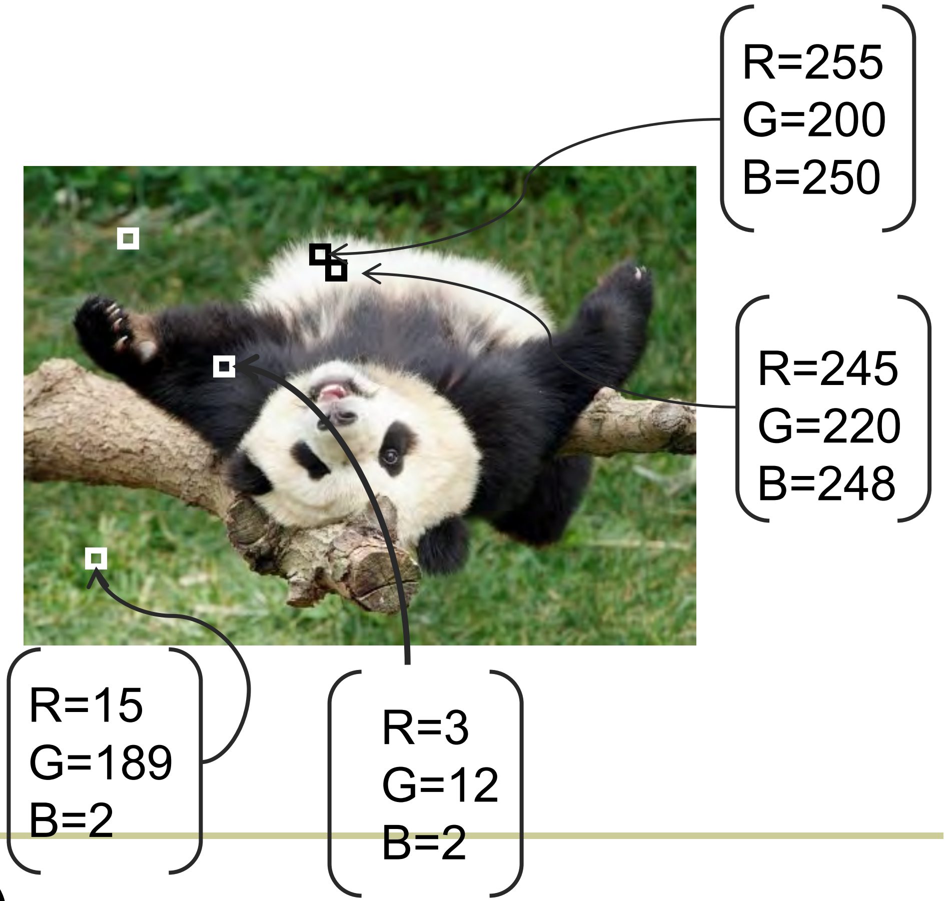
Slide credit: Kristen Grauman

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **color** similarity





Feature space: color value (3-d)

Slide credit: Kristen Grauman

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

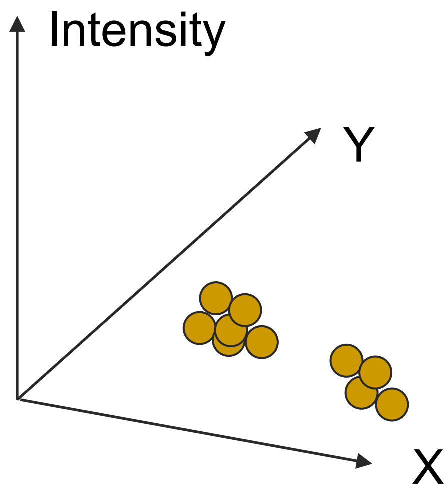
Grouping pixels based on **intensity** similarity

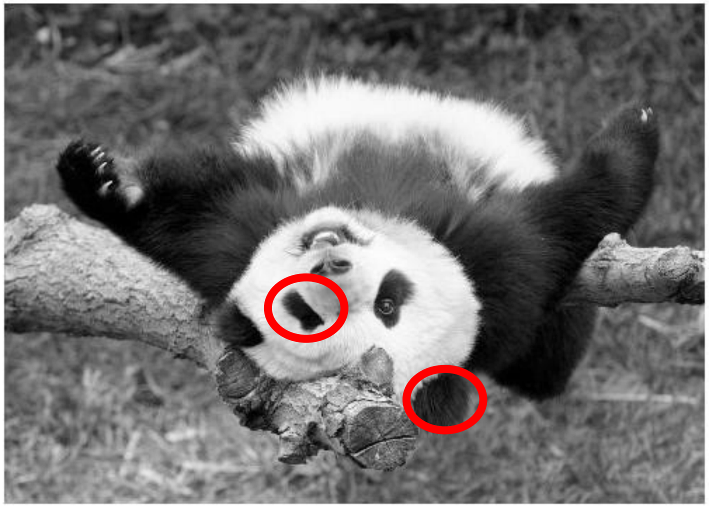
Clusters based on intensity similarity don’t have to be spatially coherent.

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity+position** similarity





Both regions are black, but if we also include **position (x,y),** then we could group the two into distinct segments; way to encode both similarity & proximity.

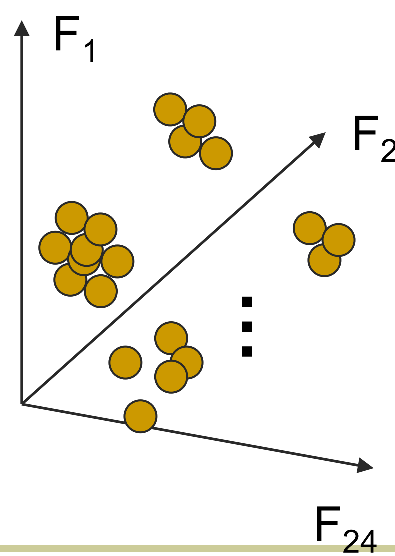
Segmentation as clustering

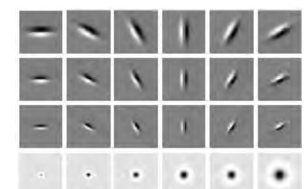
- Color, brightness, position alone are not enough to distinguish all regions…

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **texture** similarity





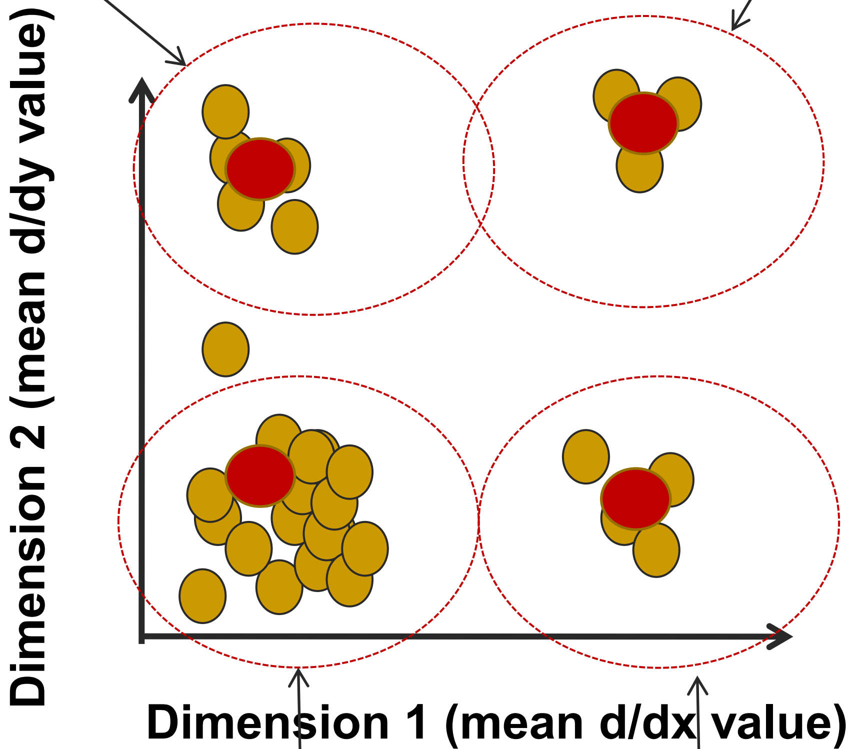
Filter bank of 24 filters

Feature space: filter bank responses (e.g., 24-d)

Recall: texture representation example

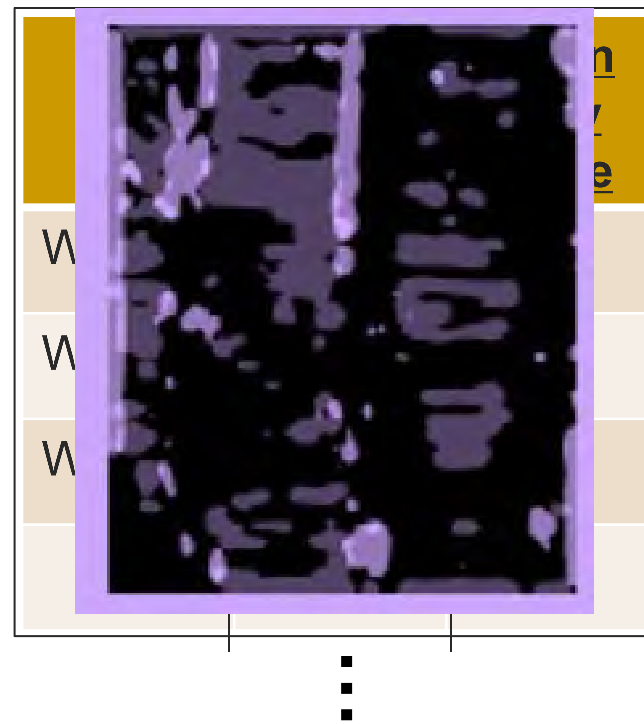
Windows with primarily horizontal edges

Both



Windows with small gradient in both directions

Windows with primarily vertical edges



statistics to summarize patterns in small windows

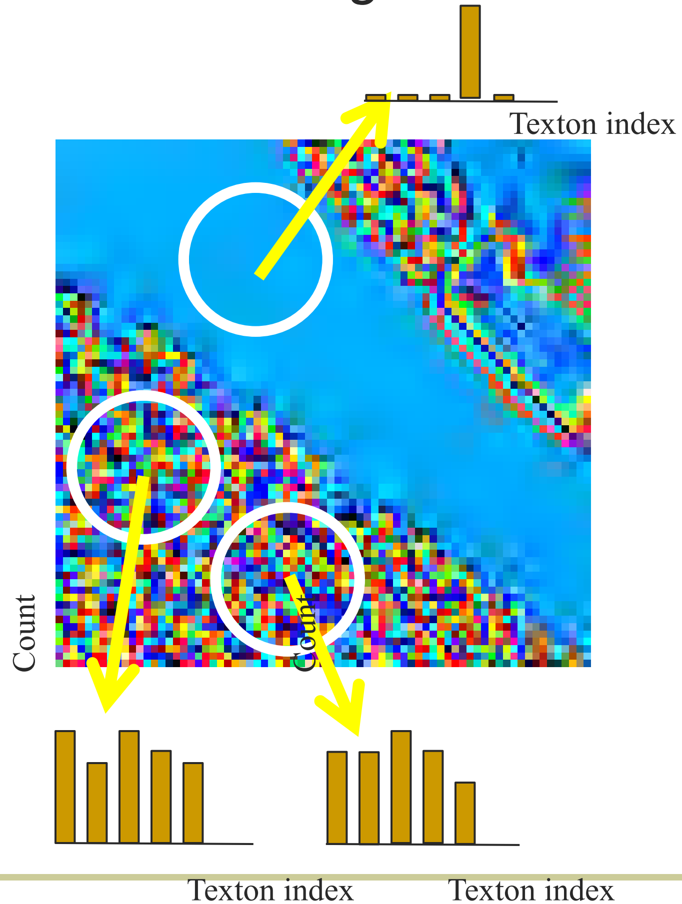
Slide credit: Kristen Grauman

Segmentation with texture features

- Find “textons” by **clustering** vectors of filter bank outputs
- Describe texture in a window based on *texton histogram*

Image

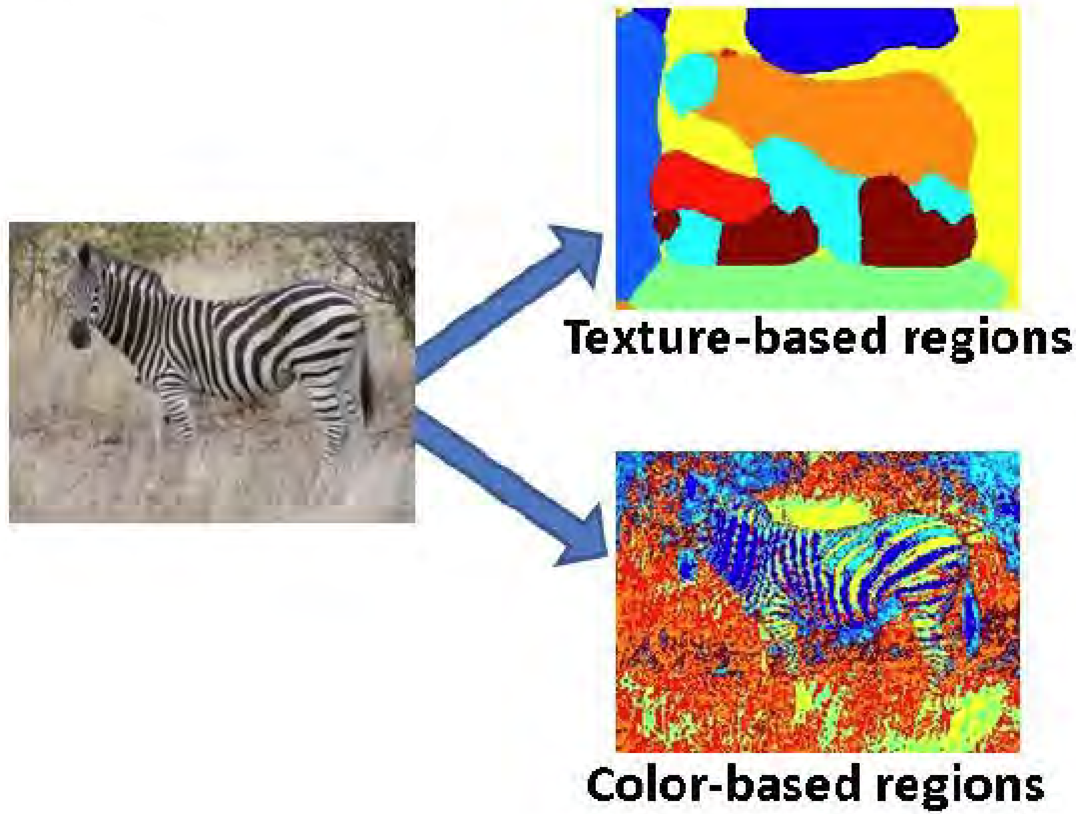
Texton map



Malik, Belongie, Leung and Shi. IJCV 2001.

Adapted from Lana Lazebnik

Image segmentation example



Slide credit: Kristen Grauman

Probabilistic clustering

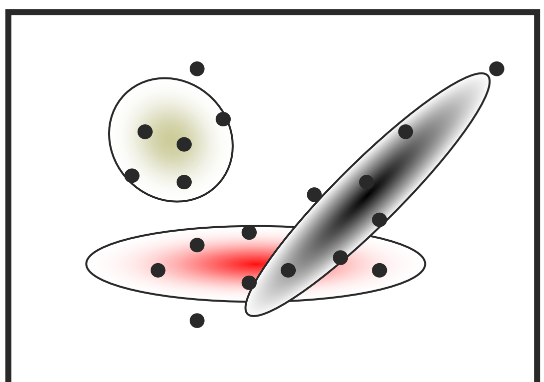
Basic questions

- what's the probability that a point **x** is in cluster m?
- what's the shape of each cluster?

K-means doesn't answer these questions

Probabilistic clustering (basic idea)

- Treat each cluster as a Gaussian density function



Mixture of Gaussians

mixture component

component model parameters

component prior

$$p\left(x_n \mid \boldsymbol{\mu}, \boldsymbol{\sigma}^2, \boldsymbol{\pi}\right) = \sum_m p\left(x_n, z_n = m \mid \mu_m, \sigma_m{}^2, \pi_m\right)$$

$$p\left(x_n, z_n = m \mid \boldsymbol{\mu}, \boldsymbol{\sigma}^2, \boldsymbol{\pi}\right) = p\left(x_n, z_n = m \mid \mu_m, \sigma_m{}^2, \pi_m\right)$$

$$= p\left(x_n \mid \mu_m, \sigma_m{}^2\right) p\left(z_n = m \mid \pi_m\right)$$

$$= \frac{1}{\sqrt{2\pi\sigma_m{}^2}} \exp\left(-\frac{\left(x_n - \mu_m\right)^2}{2\sigma_m{}^2}\right) \cdot \pi_m$$

Mixture of Gaussians

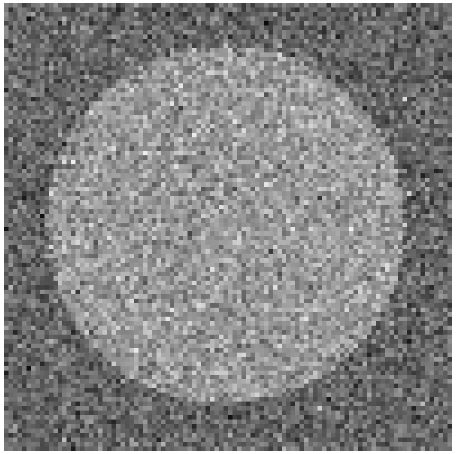
With enough components, can represent any probability density function

- Widely used as general purpose pdf estimator

Segmentation with Mixture of Gaussians

Pixels come from one of several Gaussian components

- We don’t know which pixels come from which components
- We don’t know the parameters for the components



Simple solution

1. Initialize parameters

2. Compute the probability of each hidden variable given the current parameters

3. Compute new parameters for each model, weighted by likelihood of hidden variables

4. Repeat 2-3 until convergence

Mixture of Gaussians: Simple Solution

1. Initialize parameters
2. Compute likelihood of hidden variables for current parameters

$$\alpha_{nm} = p(z_n = m \mid x_n, \boldsymbol{\mu}^{(t)}, \boldsymbol{\sigma}^{2(t)}, \boldsymbol{\pi}^{(t)})$$

3. Estimate new parameters for each model, weighted by likelihood

$$\hat{\mu}_m^{(t+1)} = \frac{1}{\sum_n \alpha_{nm}} \sum_n \alpha_{nm} x_n \qquad \hat{\sigma}_m^{2(t+1)} = \frac{1}{\sum_n \alpha_{nm}} \sum_n \alpha_{nm} \left(x_n - \hat{\mu}_m\right)^2 \qquad \hat{\pi}_m^{(t+1)} = \frac{\sum_n \alpha_{nm}}{N}$$

Expectation Maximization (EM)

Goal: $\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \log\left(\sum_{\mathbf{z}} p(\mathbf{x}, \mathbf{z} \mid \theta)\right)$

Log of sums is intractable

Jensen's Inequality

$$f\left(\mathrm{E}[X]\right) \geq \mathrm{E}\left[f(X)\right]$$

for concave functions f(x)

(so we maximize the lower bound!)

Expectation Maximization (EM) Algorithm

Goal: $\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \log\left(\sum_{\mathbf{z}} p(\mathbf{x}, \mathbf{z} \mid \theta) \right)$

1. E-step: compute

$$\mathrm{E}_{z|x,\theta^{(t)}}\left[\log\left(p(\mathbf{x},\mathbf{z} \mid \theta)\right)\right] = \sum_{\mathbf{z}} \log\left(p(\mathbf{x},\mathbf{z} \mid \theta)\right) p\left(\mathbf{z} \mid \mathbf{x}, \theta^{(t)}\right)$$

2. M-step: solve

$$\theta^{(t+1)} = \underset{\theta}{\operatorname{argmax}} \sum_{\mathbf{z}} \log\left(p(\mathbf{x},\mathbf{z} \mid \theta)\right) p\left(\mathbf{z} \mid \mathbf{x}, \theta^{(t)}\right)$$

Expectation Maximization (EM) Algorithm

Goal: $\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \log\left(\sum_{\mathbf{z}} p(\mathbf{x},\mathbf{z}|\theta)\right) = \log\left(\sum_{\mathbf{z}} q(\mathbf{z}) \frac{p(\mathbf{x},\mathbf{z}|\theta)}{q(\mathbf{z})}\right)$

log of expectation

$$\boxed{f(\mathrm{E}[X]) \geq \mathrm{E}[f(X)]}$$

1. E-step: compute

$$\mathrm{E}_{z|x,\theta^{(t)}}[\log(p(\mathbf{x},\mathbf{z}\mid\theta))] = \sum_{\mathbf{z}} \log(p(\mathbf{x},\mathbf{z}\mid\theta))p\left(\mathbf{z}\mid\mathbf{x},\theta^{(t)}\right)$$

expectation of log

2. M-step: solve

$$\theta^{(t+1)} = \underset{\theta}{\operatorname{argmax}} \sum_{\mathbf{z}} \log(p(\mathbf{x},\mathbf{z}\mid\theta))p\left(\mathbf{z}\mid\mathbf{x},\theta^{(t)}\right)$$

EM for Mixture of Gaussians

1. E-step: $\mathrm{E}_{z|x,\theta^{(t)}}\left[\log\left(p\left(\mathbf{x},\mathbf{z}\mid\theta\right)\right)\right]=\sum_{\mathbf{z}}\log\left(p\left(\mathbf{x},\mathbf{z}\mid\theta\right)\right)p\left(\mathbf{z}\mid\mathbf{x},\theta^{(t)}\right)$

2. M-step: $\theta^{(t+1)}=\underset{\theta}{\operatorname{argmax}}\sum_{\mathbf{z}}\log\left(p\left(\mathbf{x},\mathbf{z}\mid\theta\right)\right)p\left(\mathbf{z}\mid\mathbf{x},\theta^{(t)}\right)$

$$p\left(x_n\mid\boldsymbol{\mu},\boldsymbol{\sigma}^2,\boldsymbol{\pi}\right)=\sum_m p\left(x_n,z_n=m\mid\mu_m,\sigma_m{}^2,\pi_m\right)=\sum_m\frac{1}{\sqrt{2\pi\sigma_m{}^2}}\exp\left(-\frac{\left(x_n-\mu_m\right)^2}{\sigma_m{}^2}\right)\cdot\pi_m$$

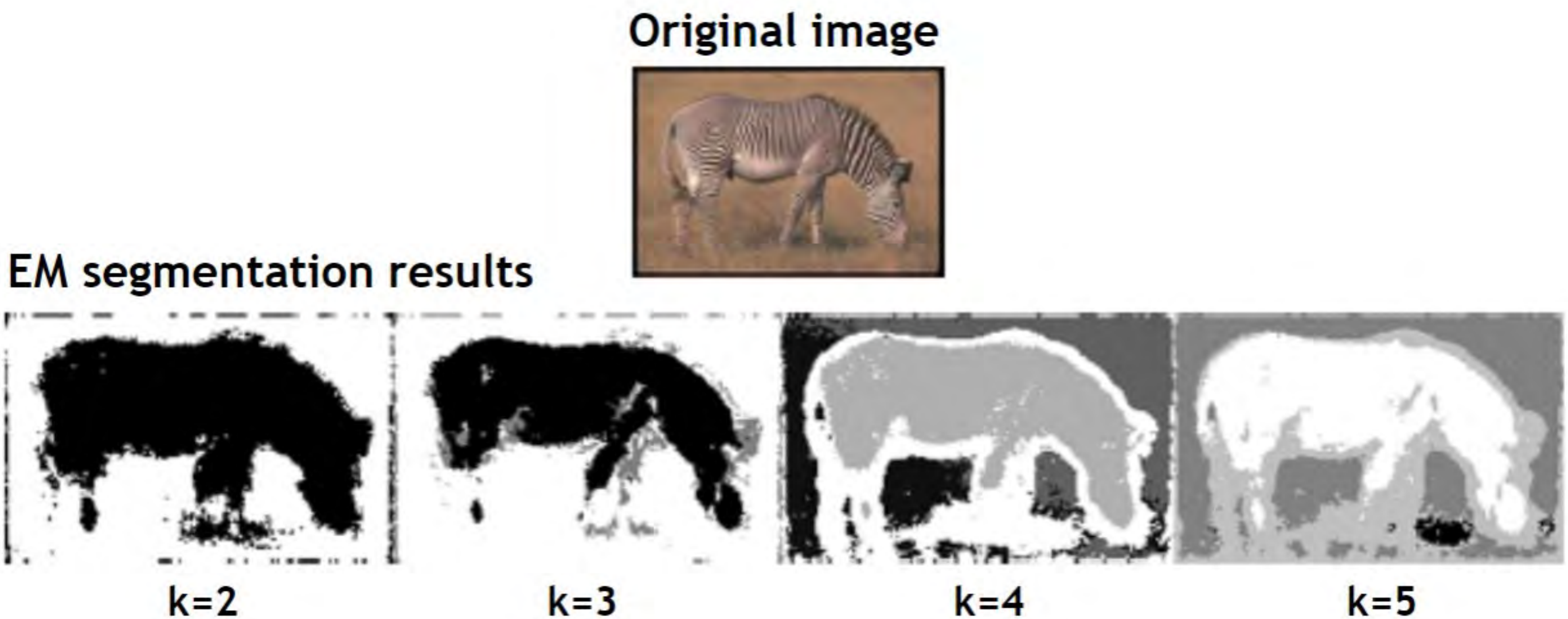
$$\alpha_{nm}=p(z_n=m\mid x_n,\boldsymbol{\mu}^{(t)},\boldsymbol{\sigma}^{2(t)},\boldsymbol{\pi}^{(t)})$$

$$\hat{\mu}_m{}^{(t+1)}=\frac{1}{\sum_n\alpha_{nm}}\sum_n\alpha_{nm}x_n \qquad \hat{\sigma}_m{}^{2(t+1)}=\frac{1}{\sum_n\alpha_{nm}}\sum_n\alpha_{nm}\left(x_n-\hat{\mu}_m\right)^2 \qquad \hat{\pi}_m{}^{(t+1)}=\frac{\sum_n\alpha_{nm}}{N}$$

Application of EM

- **Turns out this is useful for all sorts of problems**
  - Any clustering problem
  - Any model estimation problem
  - Missing data problems
  - Finding outliers
  - Segmentation problems
    - Segmentation based on color
    - Segmentation based on motion
    - Foreground/background separation
  - …

Segmentation with EM

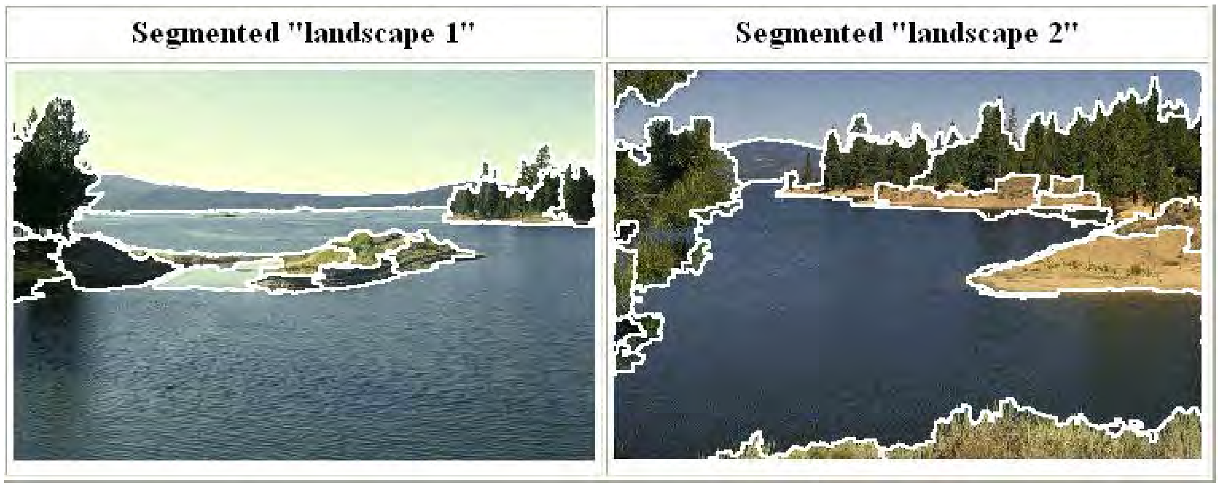


Summary of GMM

- **Pros**
  - Probabilistic interpretation
  - Soft assignments between data points and clusters
  - Generative model, can predict novel data points
  - Relatively compact storage
- **Cons**
  - Local minima
    - k-means is NP-hard even with k=2
  - Initialization
    - Often a good idea to start with some k-means iterations.
  - Need to know number of components
    - Solutions: model selection (AIC, BIC), Dirichlet process mixture
  - Need to choose generative model
  - Numerical problems are often a nuisance

Mean-Shift Segmentation

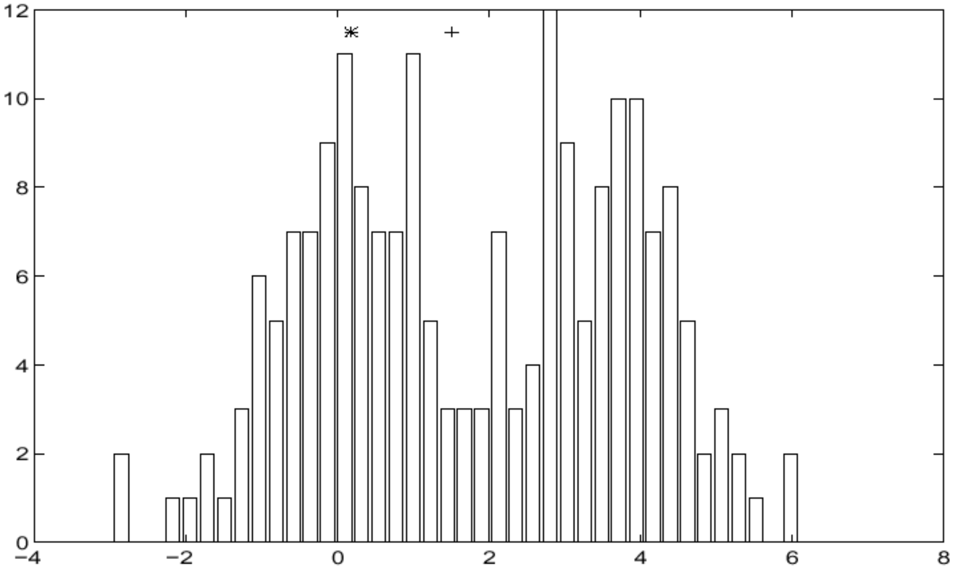
- An advanced and versatile technique for clustering-based segmentation



http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

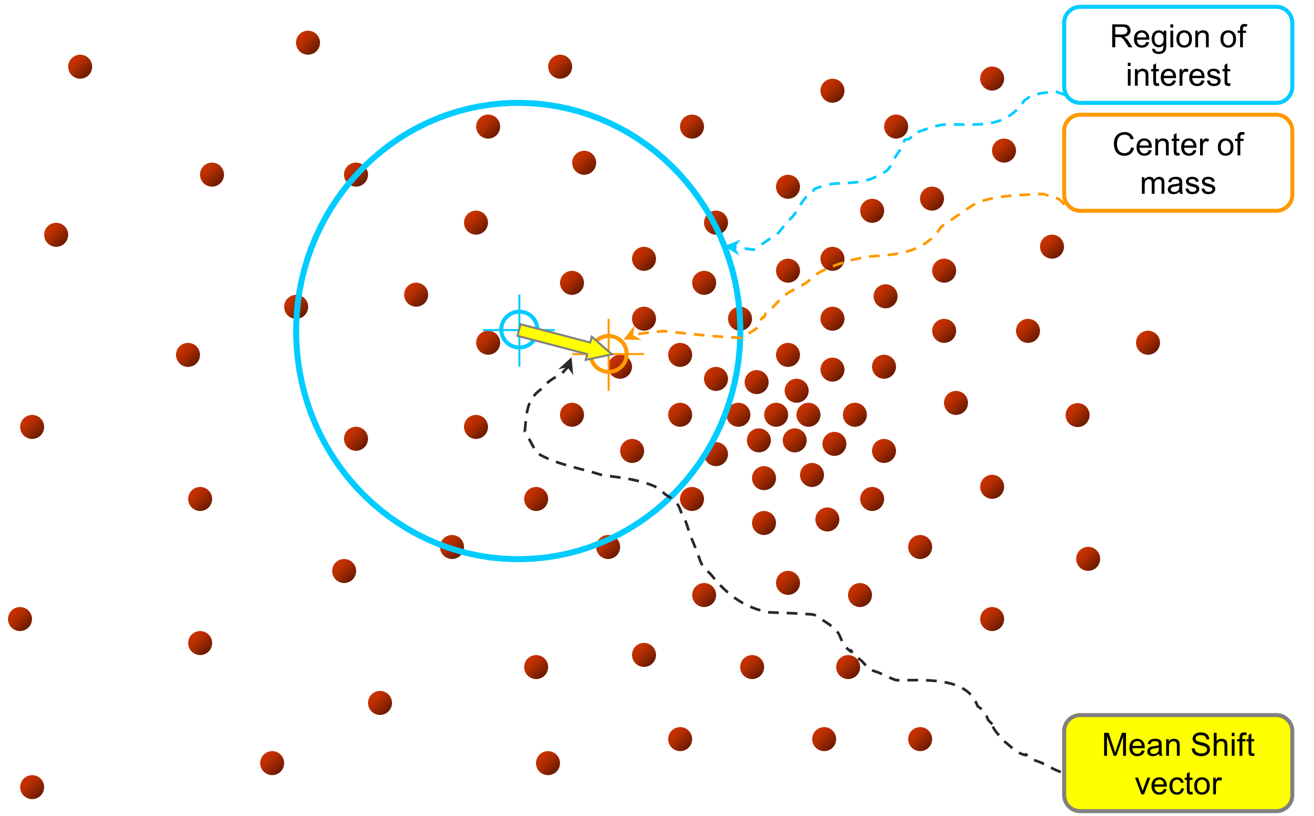
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Mean-Shift Algorithm



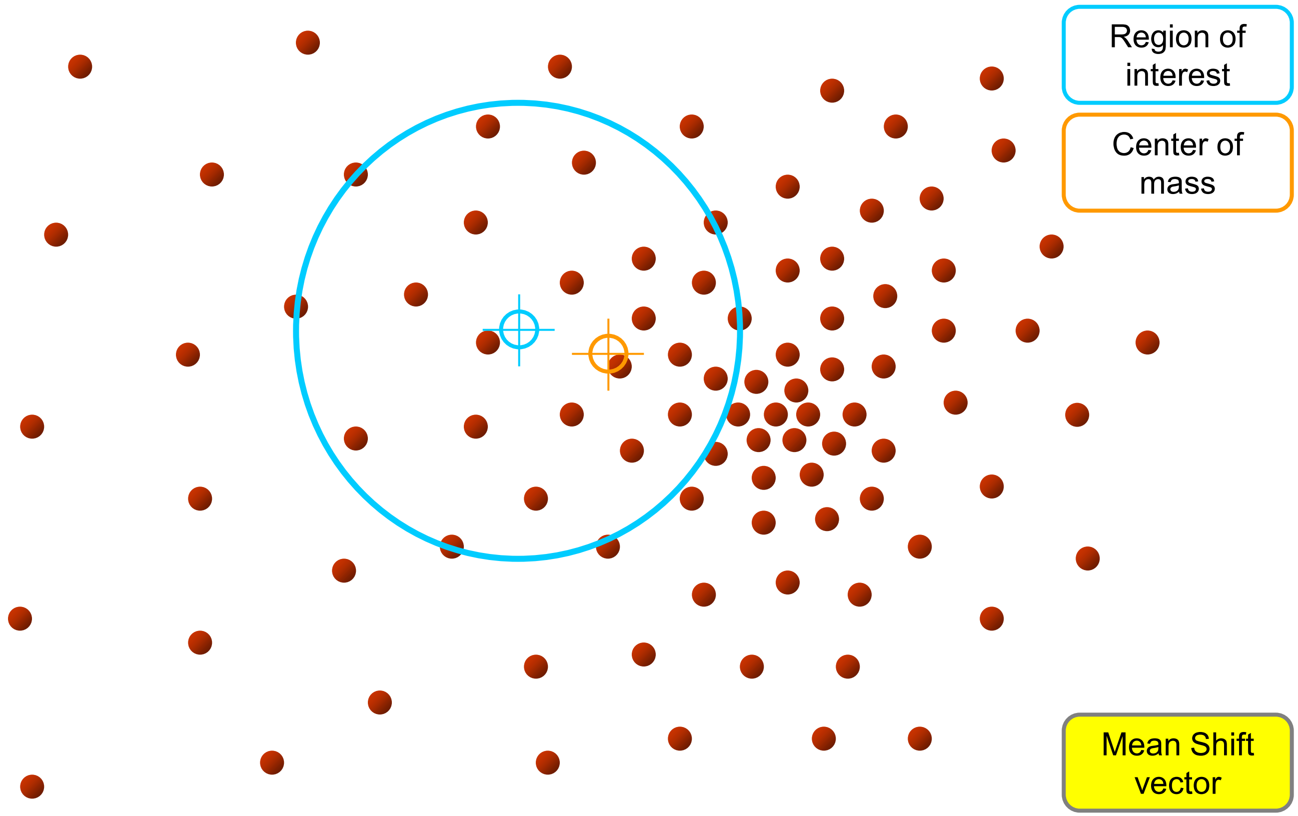
- Iterative Mode Search
  1. Initialize random seed, and window W
  2. Calculate center of gravity (the "mean") of W: $\sum_{x \in W} x H(x)$
  3. Shift the search window to the mean
  4. Repeat Step 2 until convergence

Mean-Shift



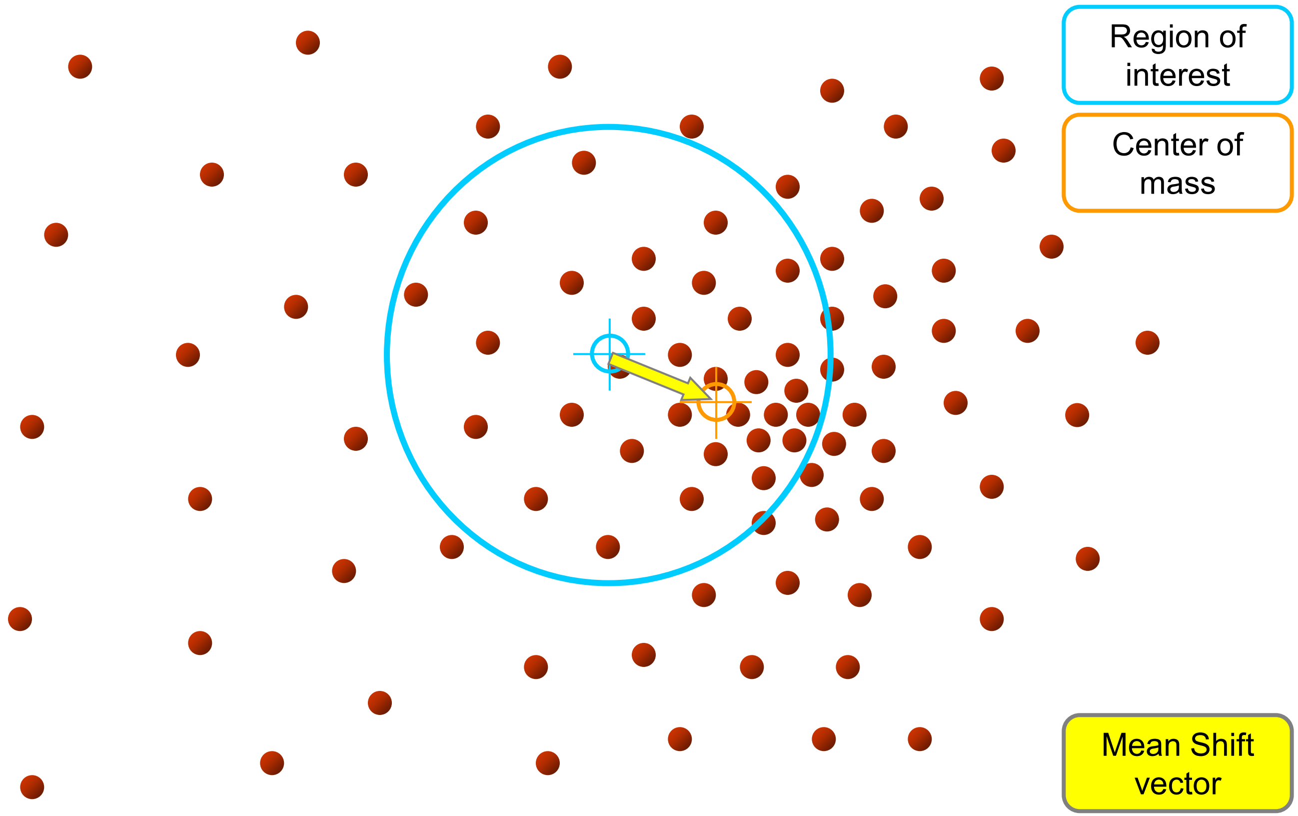
Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



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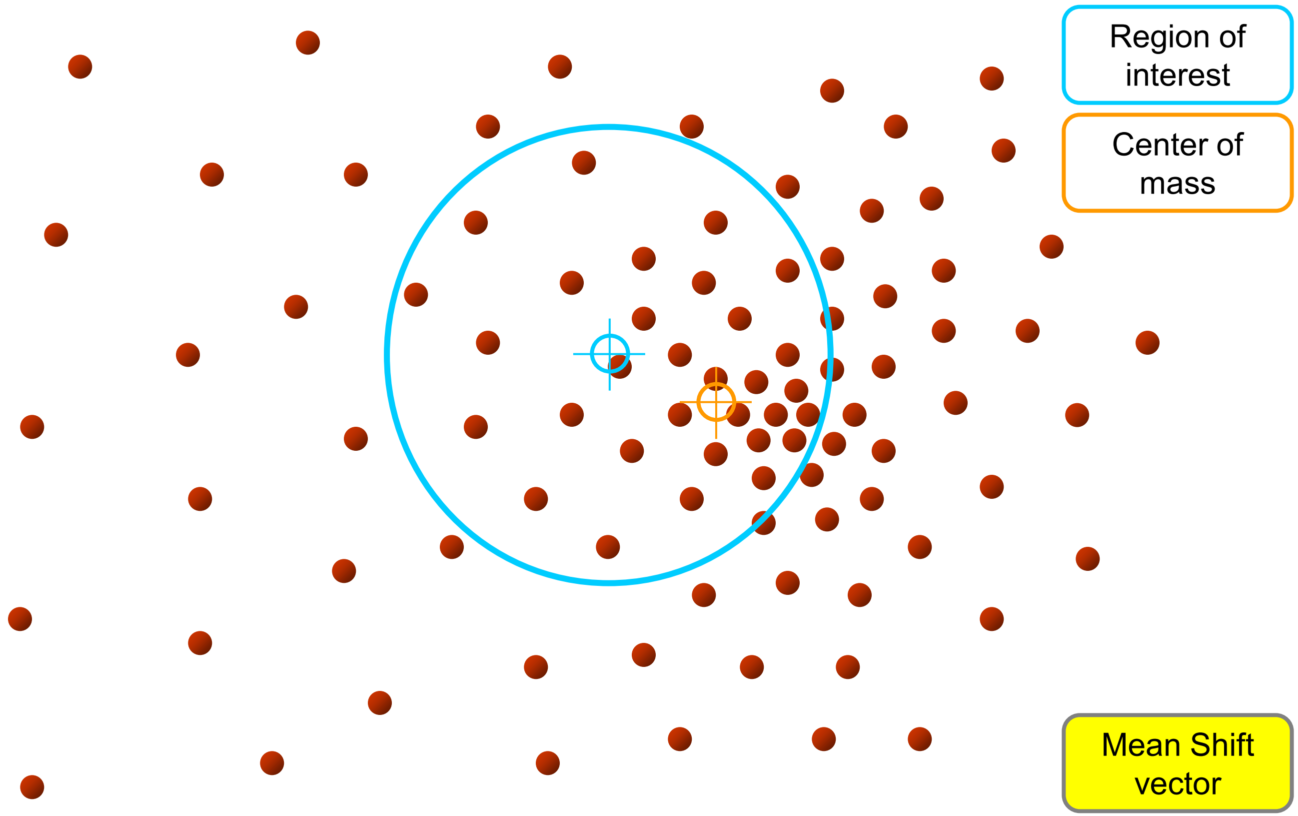
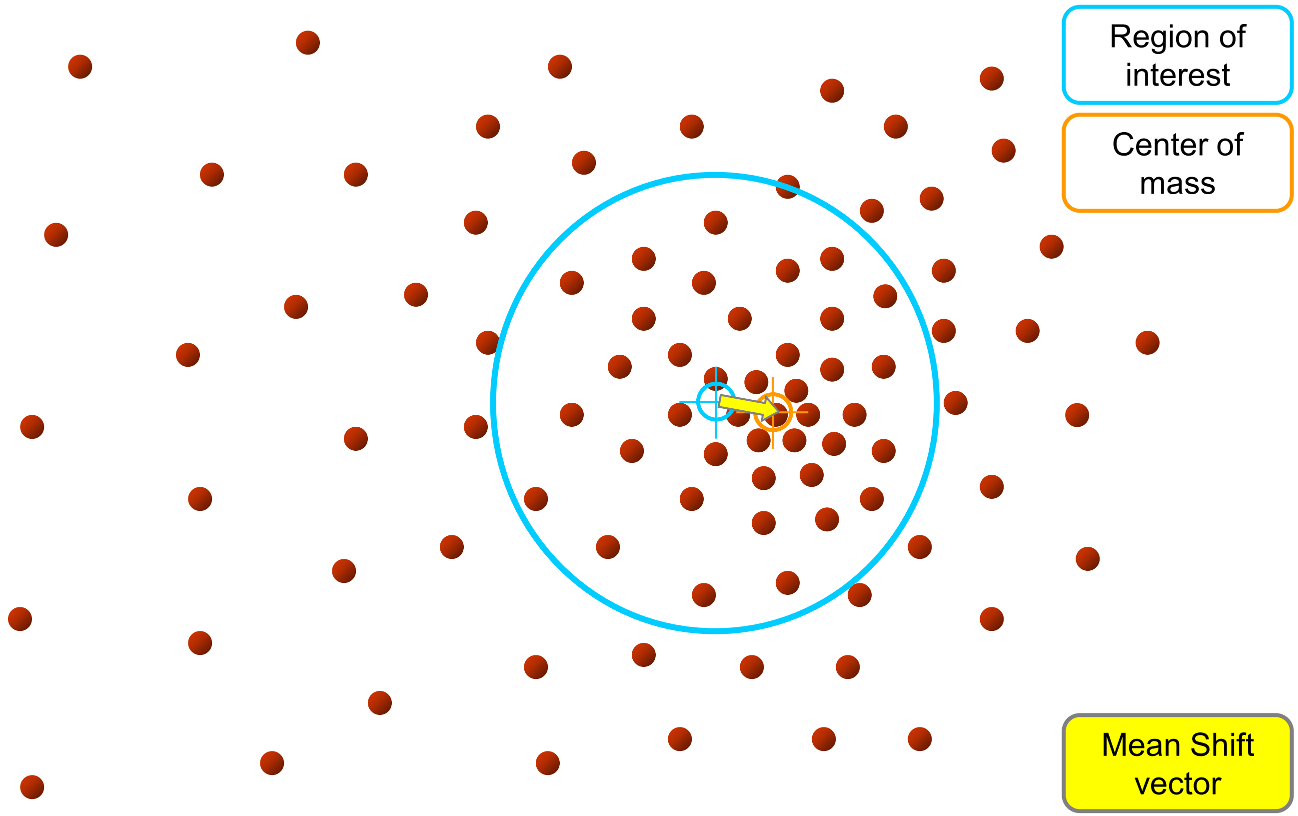
Mean-Shift



Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



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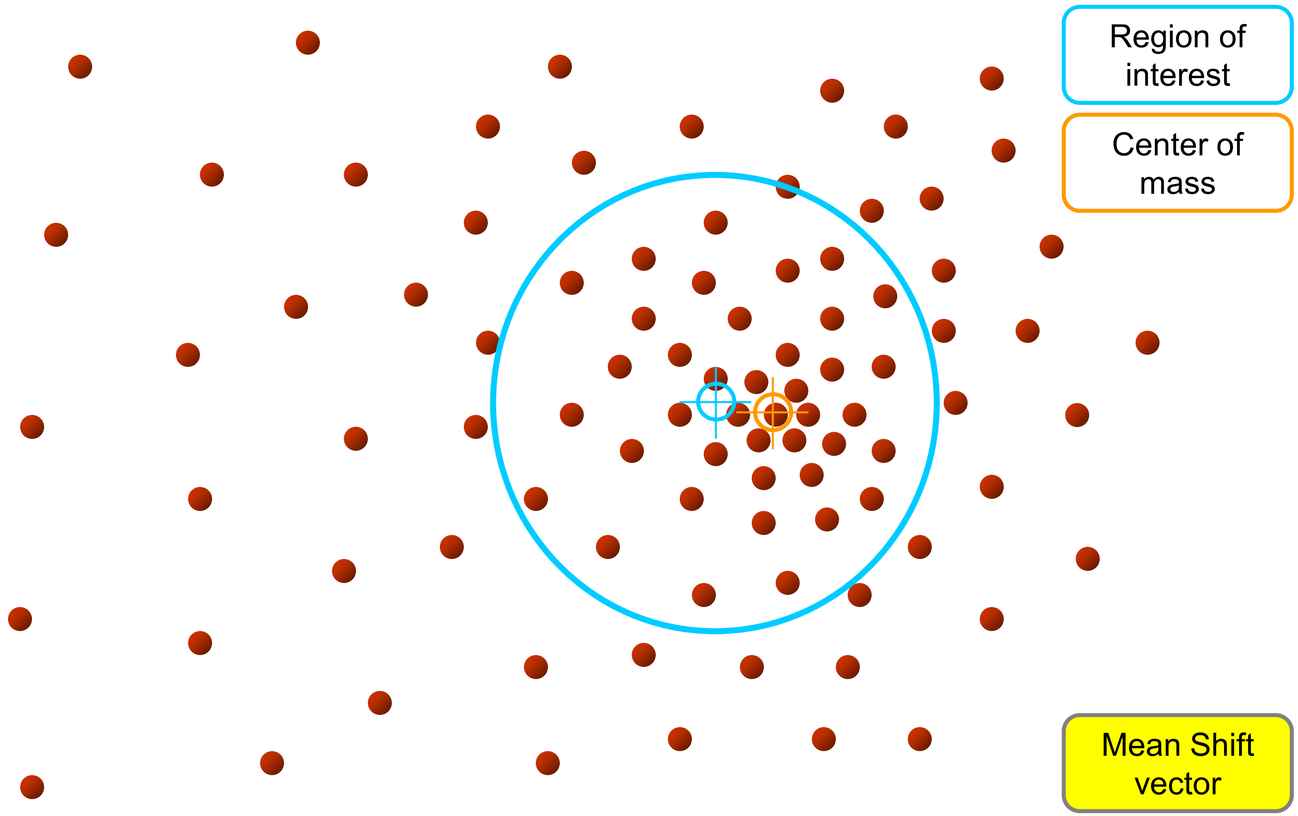
Mean-Shift



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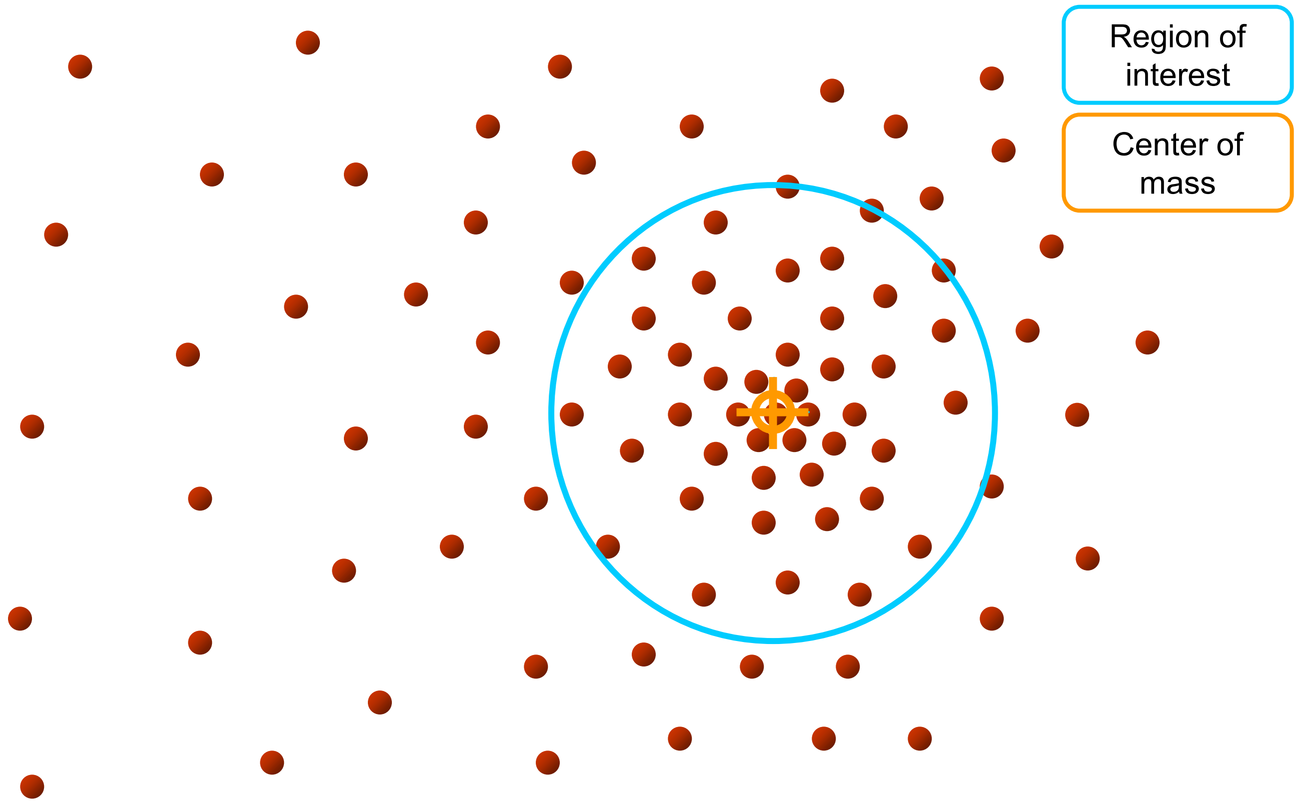
Mean-Shift



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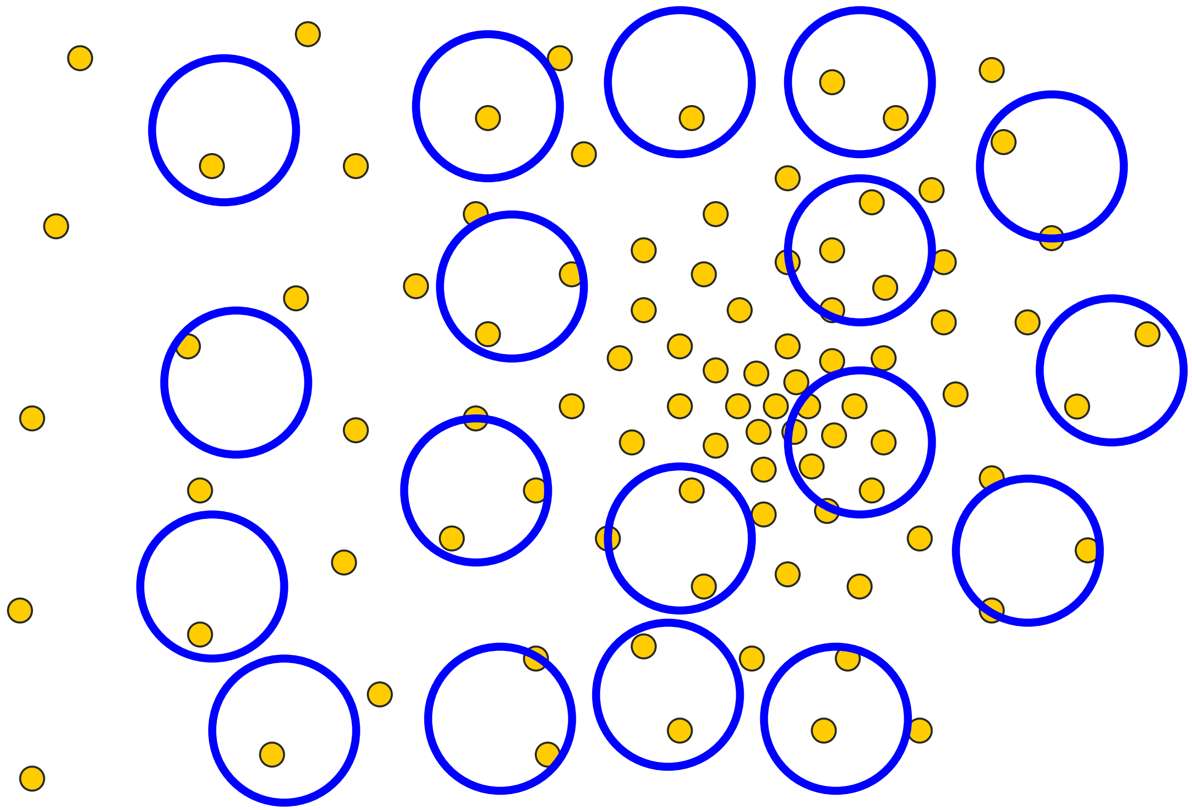
Real Modality Analysis

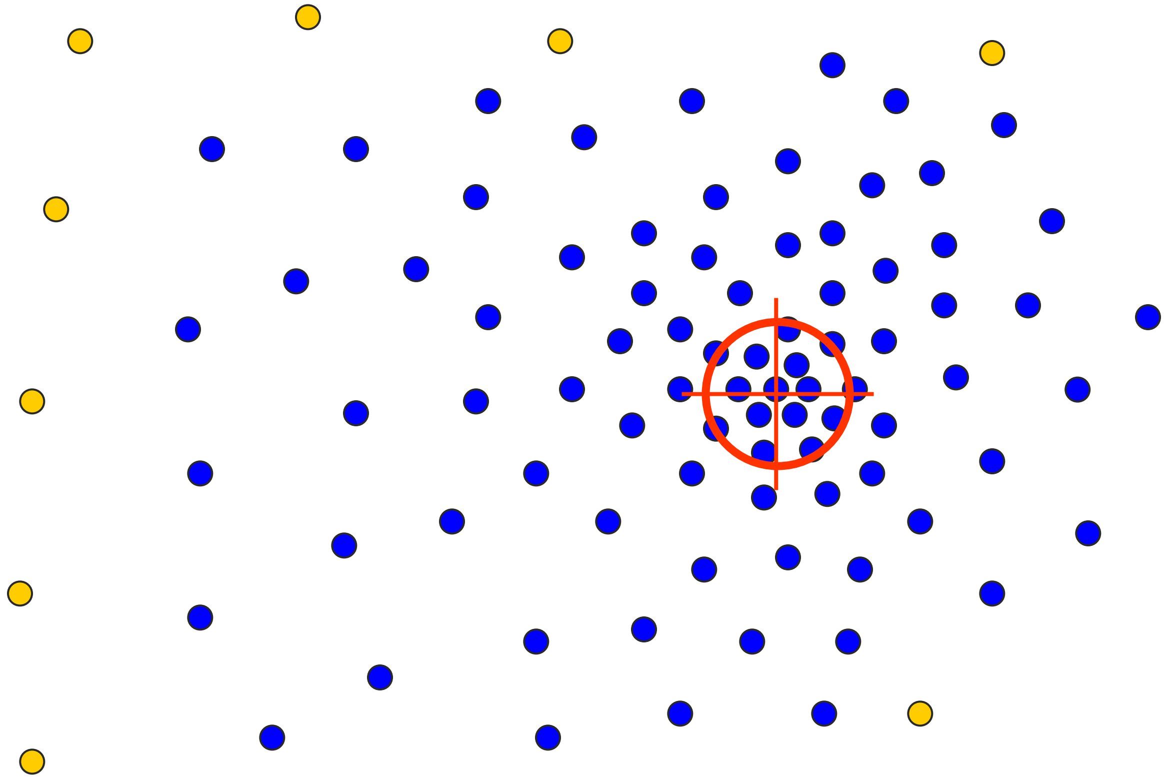


Tessellate the space with windows

Run the procedure in parallel

Slide by Y. Ukrainitz & B. Sarel

Real Modality Analysis

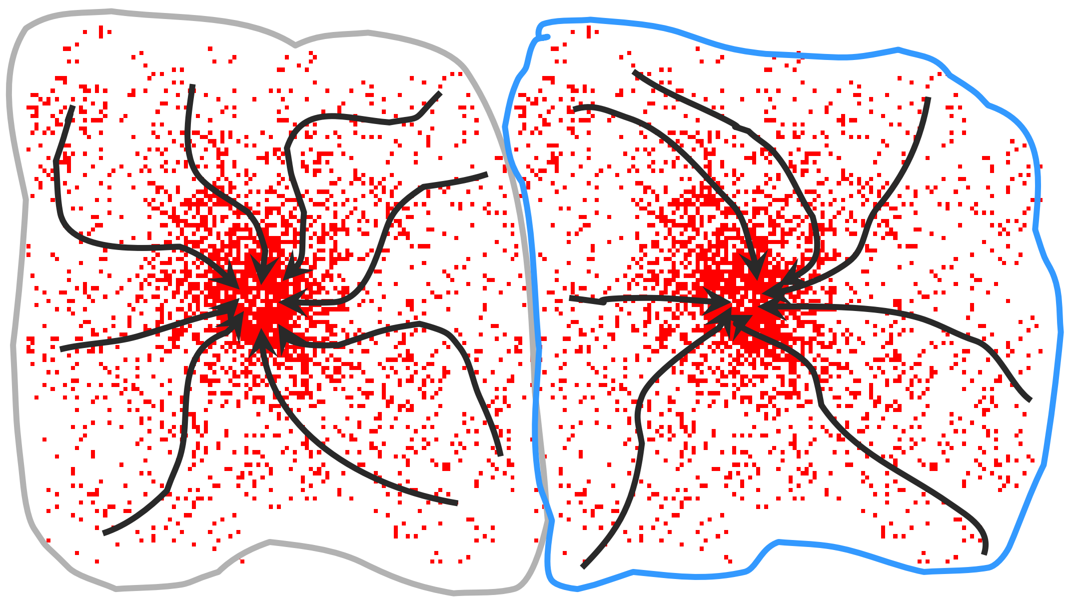


The blue data points were traversed by the windows towards the mode.

Slide by Y. Ukrainitz & B. Sarel

Attraction basin

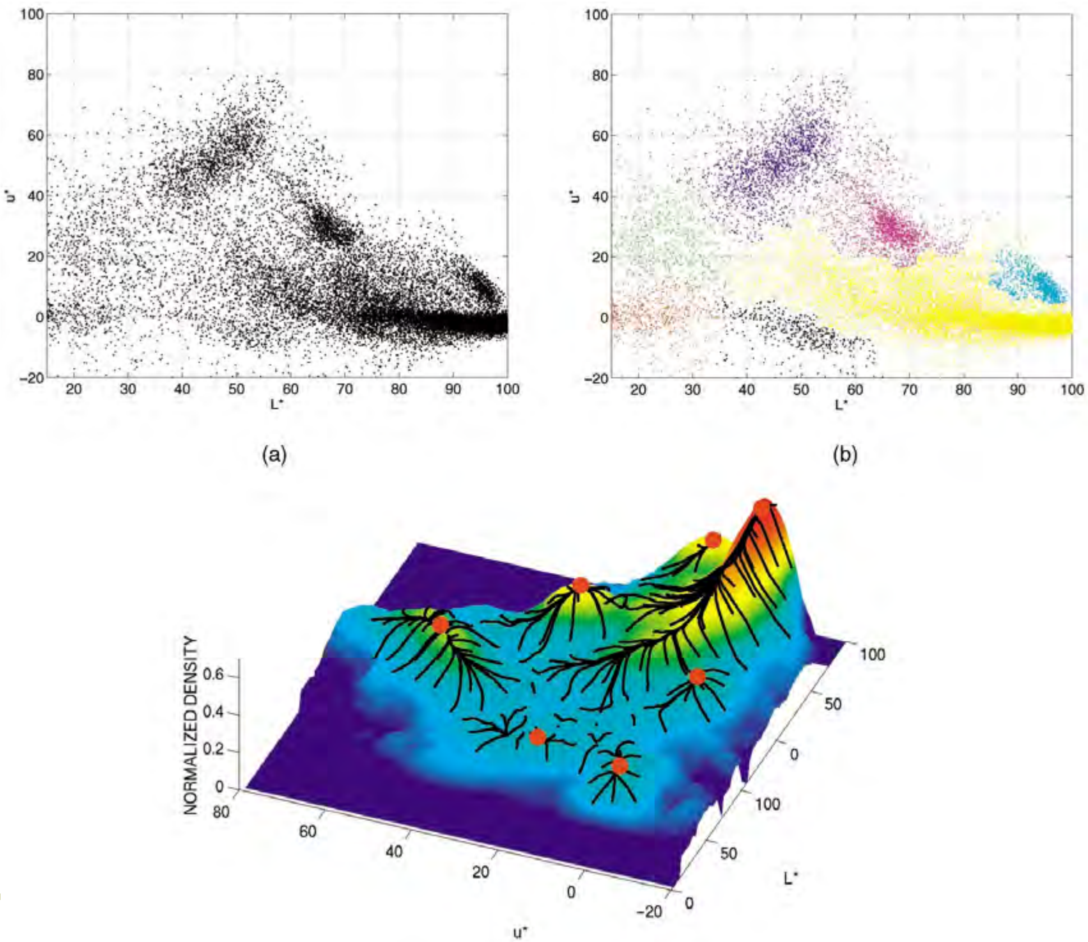
- Attraction basin: the region for which all trajectories lead to the same mode
- Cluster: all data points in the attraction basin of a mode



Slide by Y. Ukrainitz & B. Sarel

Mean shift algorithm

- Try to find *modes* of this non-parametric density



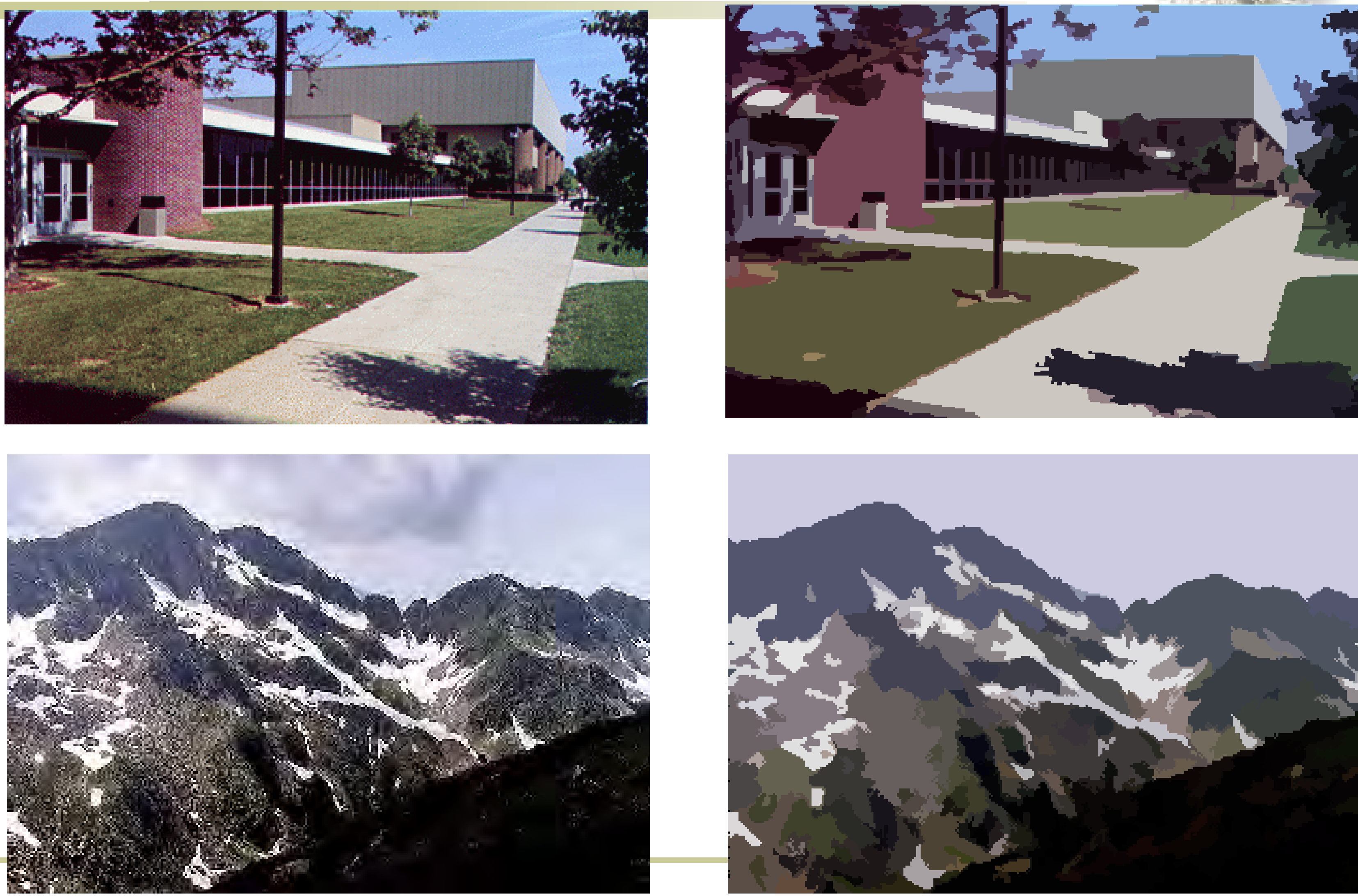
Mean shift clustering

- The mean shift algorithm seeks *modes* of the given set of points
  1. Choose kernel and bandwidth
  2. For each point:
     a) Center a window on that point
     b) Compute the mean of the data in the search window
     c) Center the search window at the new mean location
     d) Repeat (b,c) until convergence
  3. Assign points that lead to nearby modes to the same cluster

Segmentation by Mean Shift

- Compute features for each pixel (color, gradients, texture, etc); also store each pixel's position
- Set kernel size for features K_f and position K_s
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge modes that are within width of K_f and K_s

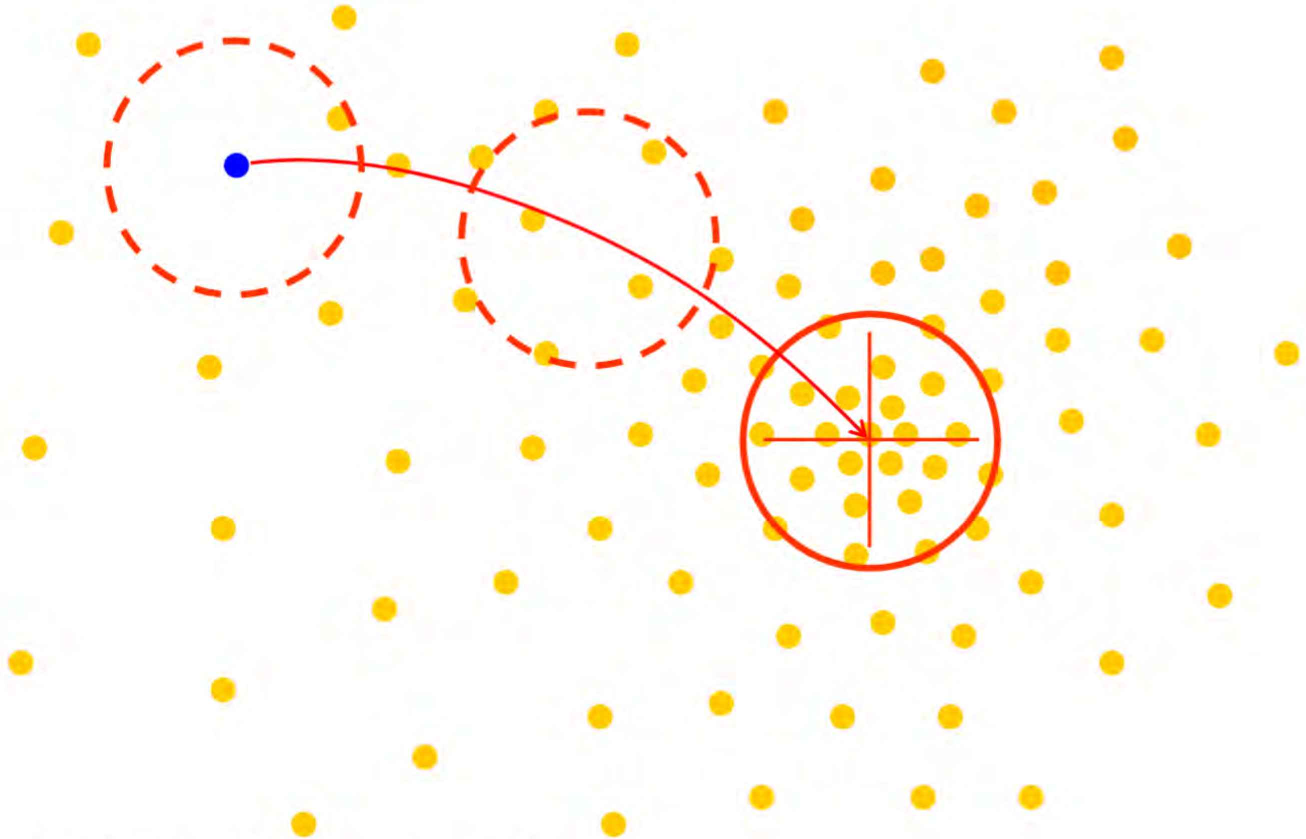
Mean shift segmentation results



http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

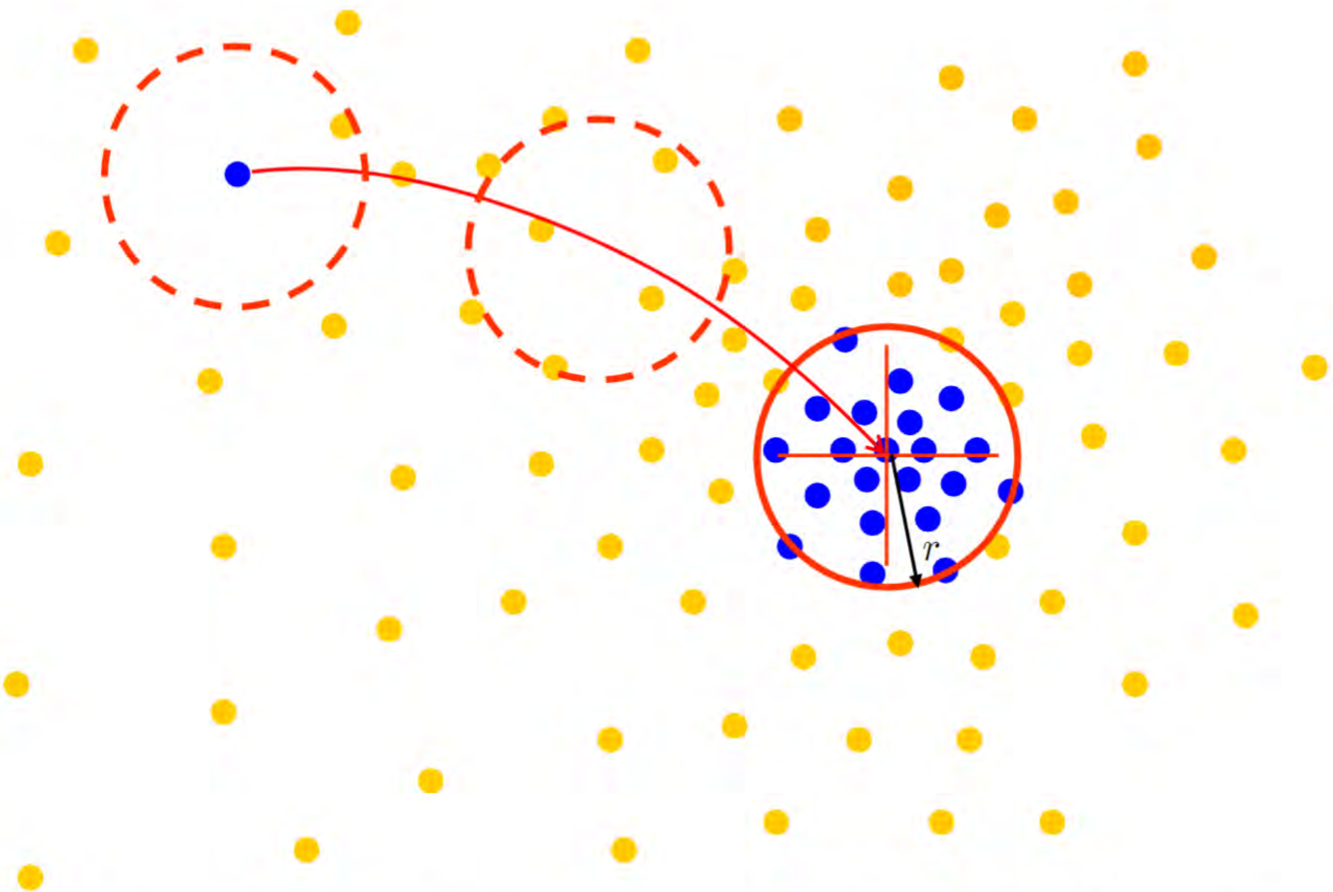
http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

Problem: Computational Complexity



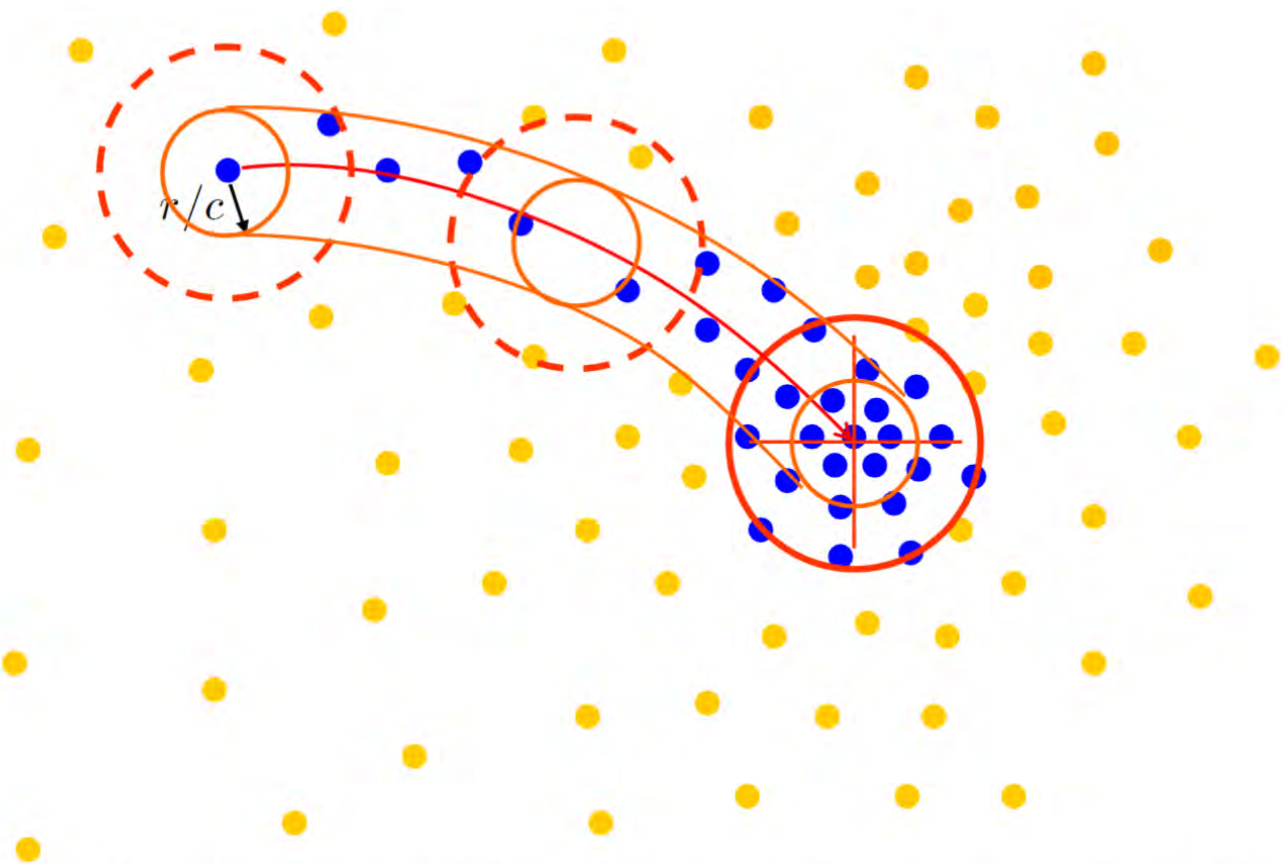
- Need to shift many windows…
- Many computations will be redundant.

Speed Up



1. Assign all points within radius r of end point to the mode.

Speed Up



2. Assign all points within radius r/c of the search path to the mode.

Mean-shift: other issues

- Speedups
  - Binned estimation – replace points within some “bin” by point at center with mass
  - Fast search of neighbors – e.g., k-d tree or approximate NN
  - Update all windows in each iteration (faster convergence)

- Other tricks
  - Use kNN to determine window sizes adaptively

- Lots of theoretical support

  D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Technical Details

Given n data points $\mathbf{x}_i \in \mathbb{R}^d$, the multivariate kernel density estimate using a radially symmetric kernel[1] (e.g., Epanechnikov and Gaussian kernels), $K(\mathbf{x})$, is given by,

$$\hat{f}_K = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{\mathbf{x} - \mathbf{x}_i}{h}\right), \tag{1}$$

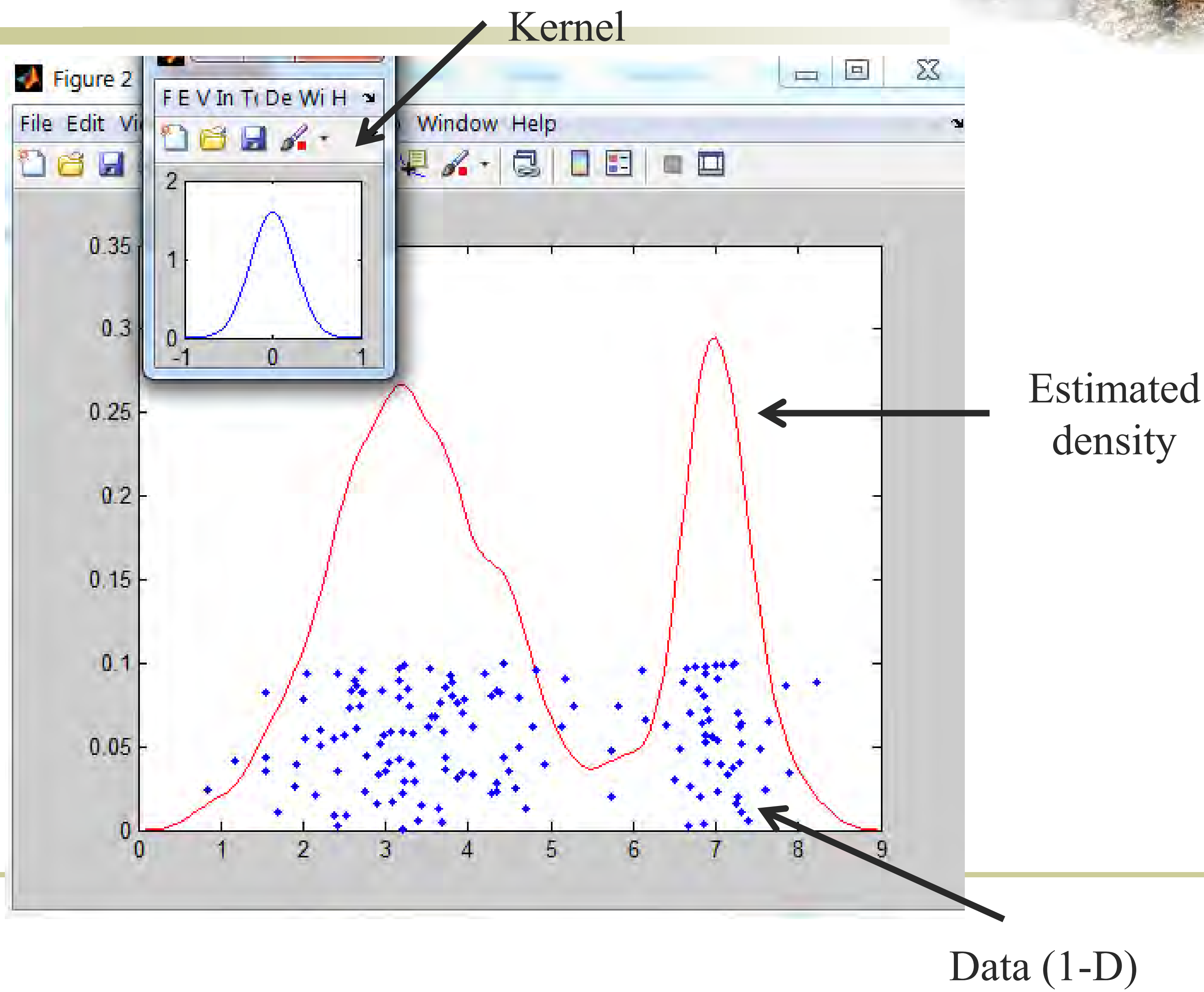
where h (termed the *bandwidth* parameter) defines the radius of kernel. The radially symmetric kernel is defined as,

$$K(\mathbf{x}) = c_k k(\|\mathbf{x}\|^2), \tag{2}$$

where c_k represents a normalization constant.

Comaniciu & Meer, 2002

Kernel density estimation



Other Kernels

A kernel is a function that satisfies the following requirements :

1. $\int_{R^d} \phi(x) = 1$

2. $\phi(x) \geq 0$

Some examples of kernels include :

1. Rectangular $\phi(x) = \begin{cases} 1 & a \leq x \leq b \\ 0 & else \end{cases}$

2. Gaussian $\phi(x) = e^{-\frac{x^2}{2\sigma^2}}$

3. Epanechnikov $\phi(x) = \begin{cases} \frac{3}{4}(1 - x^2) & if\ |x| \leq 1 \\ 0 & else \end{cases}$

source

Technical Details

Taking the derivative of: $$\hat{f}_K = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{\mathbf{x} - \mathbf{x}_i}{h}\right)$$

$$\nabla \hat{f}(\mathbf{x}) = \underbrace{\frac{2c_{k,d}}{nh^{d+2}} \left[\sum_{i=1}^{n} g\left(\left\|\frac{\mathbf{x} - \mathbf{x}_i}{h}\right\|^2\right)\right]}_{\text{term 1}} \underbrace{\left[\frac{\sum_{i=1}^{n} \mathbf{x}_i g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)} - \mathbf{x}\right]}_{\text{term 2}}, \qquad (3)$$

where $g(x) = -k'(x)$ denotes the derivative of the selected kernel profile.

- Term1: this is proportional to the density estimate at x (similar to equation 1 from two slides ago).
- Term2: this is the mean-shift vector that points towards the direction of maximum density.

Comaniciu & Meer, 2002

Technical Details

Finally, the mean shift procedure from a given point x_t is:

1. Computer the mean shift vector **m**:

$$\left[\frac{\sum_{i=1}^{n} \mathbf{x}_i g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{\mathbf{x}-\mathbf{x}_i}{h}\right\|^2\right)} - \mathbf{x}\right]$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{m}(\mathbf{x}_i^t).$$

2. Translate the density window:

$$\nabla f(\mathbf{x}_i) = 0.$$

3. Iterate steps 1 and 2 until convergence.

Comaniciu & Meer, 2002

Mean shift pros and cons

- Pros
  - Good general-purpose segmentation
  - Flexible in number and shape of regions
  - Robust to outliers
  - General mode-finding algorithm (useful for other problems such as finding most common surface normals)
- Cons
  - Have to choose kernel size in advance
  - Not suitable for high-dimensional features
- When to use it
  - Oversegmentation
  - Multiple segmentations
  - Tracking, clustering, filtering applications
    - D. Comaniciu, V. Ramesh, P. Meer: Real-Time Tracking of Non-Rigid Objects using Mean Shift, *Best Paper Award*, IEEE Conf. Computer Vision and Pattern Recognition (CVPR'00), Hilton Head Island, South Carolina, Vol. 2, 142-149, 2000

Mean-shift reading

- Nicely written mean-shift explanation (with math)

http://saravananthirumuruganathan.wordpress.com/2010/04/01/introduction-to-mean-shift-algorithm/

  - Includes .m code for mean-shift clustering

- Mean-shift paper by Comaniciu and Meer

http://www.caip.rutgers.edu/~comanici/Papers/MsRobustApproach.pdf

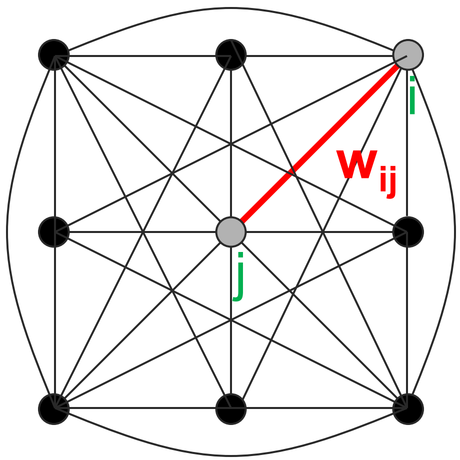
- Adaptive mean shift in higher dimensions

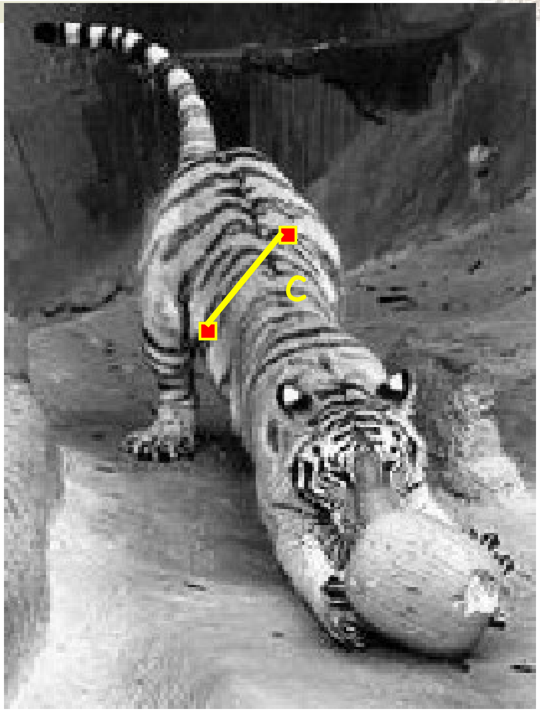
http://mis.hevra.haifa.ac.il/~ishimshoni/papers/chap9.pdf

Today's Class

- What are grouping problems in vision?
- Inspiration from human perception
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Mode finding and mean shift: k-means, GMM, mean-shift
- **Graph-based segmentation: Normalized Cut**
- Oversegmentation
  - Watershed algorithm, Felzenszwalb and Huttenlocher graph-based
- Multiple segmentation

Images as graphs





- *Fully-connected* graph
  - node for every pixel
  - link between *every* pair of pixels, **i,j**
  - similarity $\mathbf{w_{ij}}$ for each link

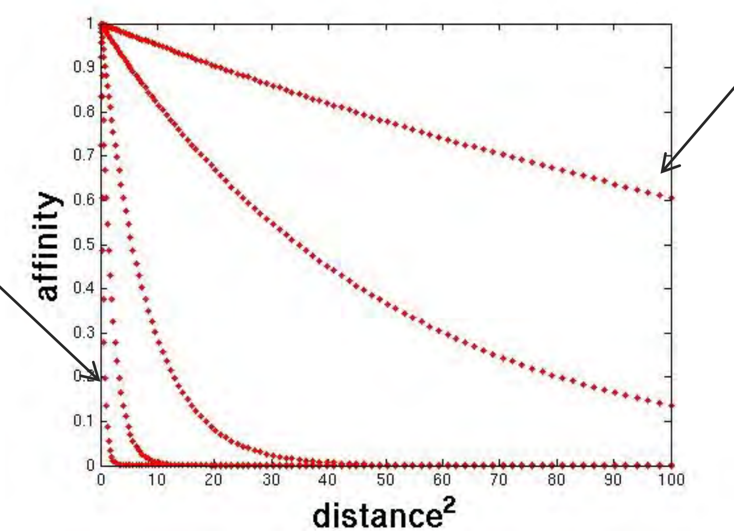
Source: Seitz

Measuring affinity

- One possibility:

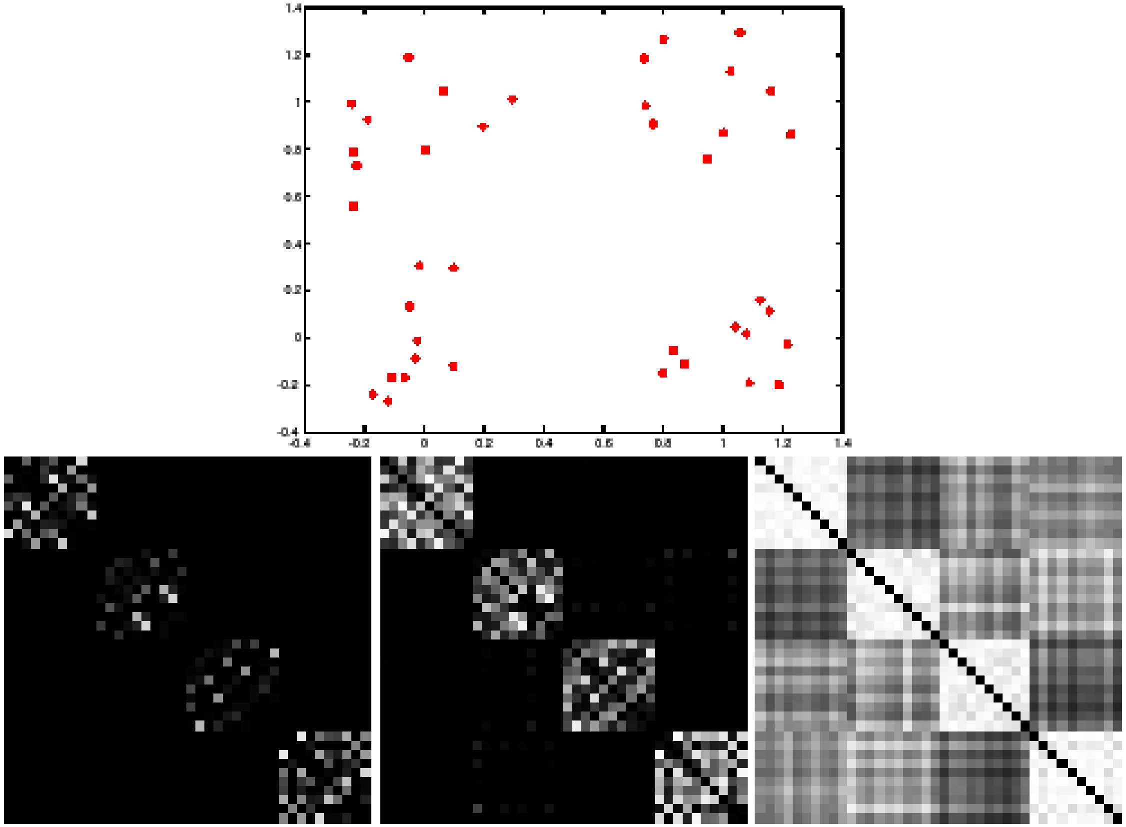
$$aff(x,y) = \exp\left\{ -\left(\frac{1}{2\sigma_d^2} \right) \left(\|x - y\|^2 \right) \right\}$$

Small sigma: group only nearby points



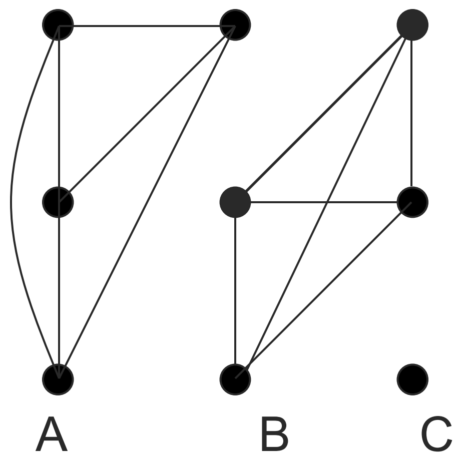
Large sigma: group distant points

Similarity matrix



Increasing sigma

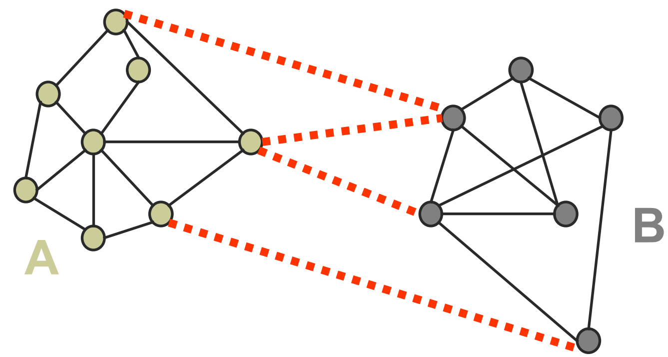
Segmentation by Graph Cuts



- Break Graph into Segments
  - Delete links that cross between segments
  - Easiest to break links that have low cost (low similarity)
    - similar pixels should be in the same segments
    - dissimilar pixels should be in different segments

Source: Seitz

Cuts in a graph



- Link Cut
  - set of links whose removal makes a graph disconnected
  - cost of a cut:

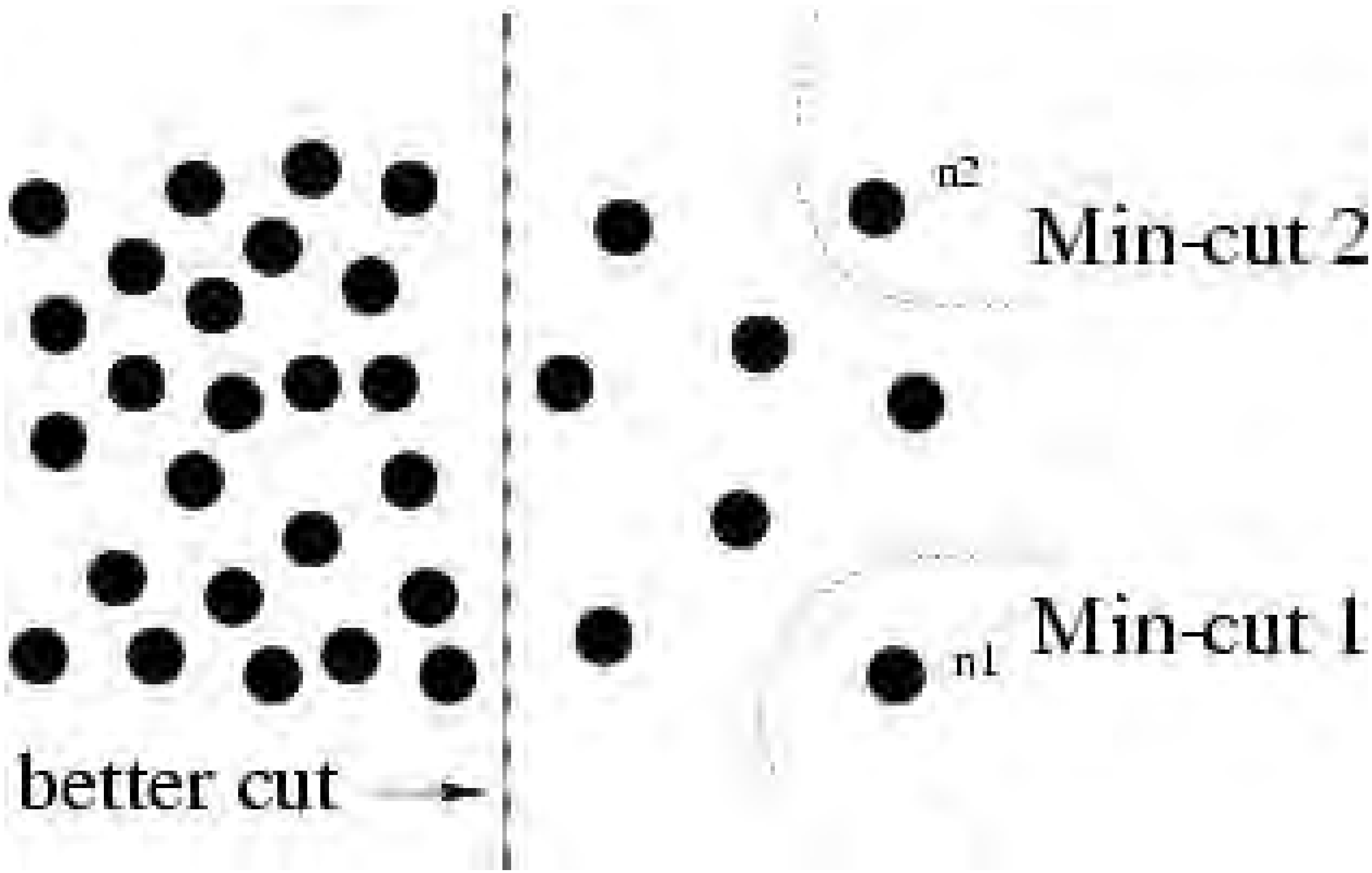
$$cut(A,B) = \sum_{p \in A, q \in B} c_{p,q}$$

One idea: Find minimum cut

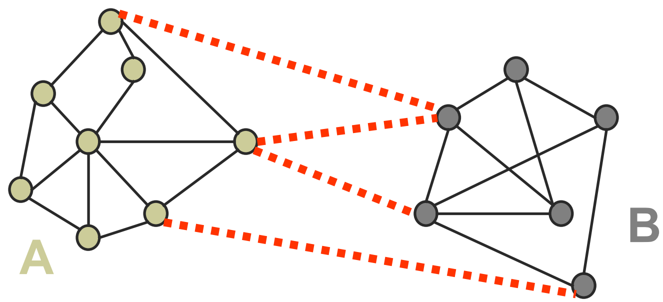
- gives you a segmentation
- fast algorithms exist for doing this

Source: Seitz

But min cut is not always the best cut...



Normalized Cuts in a graph



Normalized Cut

- a cut penalizes large segments
- fix by normalizing for size of segments

$$Ncut(A,B) = \frac{cut(A,B)}{volume(A)} + \frac{cut(A,B)}{volume(B)}$$

- volume(A) = sum of costs of all edges that touch A

Source: Seitz

Solving the Normalized Cut problem

- Exact discrete solution to Ncut is NP-hard even on regular grid [Papadimitriou’ 97]
- We first transform to

$$min_x Ncut(\boldsymbol{x}) = min_{\boldsymbol{y}} \frac{\boldsymbol{y}^T(\mathbf{D}-\mathbf{W})\boldsymbol{y}}{\boldsymbol{y}^T\mathbf{D}\boldsymbol{y}}$$

with the condition $y(i) \in \{1, -b\}$ and $y^T\mathbf{D}\mathbf{1} = 0$

- Drawing on spectral graph theory, good approximation can be obtained by solving a generalized eigenvalue problem.

$$(\mathbf{D}-\mathbf{W})\boldsymbol{y} = \lambda\mathbf{D}\boldsymbol{y}.$$

Recursive normalized cuts

1. Given an image or image sequence, set up a weighted graph: G=(V, E)
   1. Vertex for each pixel
   2. Edge weight for nearby pairs of pixels

2. Solve for eigenvectors with the smallest eigenvalues: $(D - W)y = \lambda Dy$
   1. Use the eigenvector with the second smallest eigenvalue to bipartition the graph
   2. Note: this is an approximation

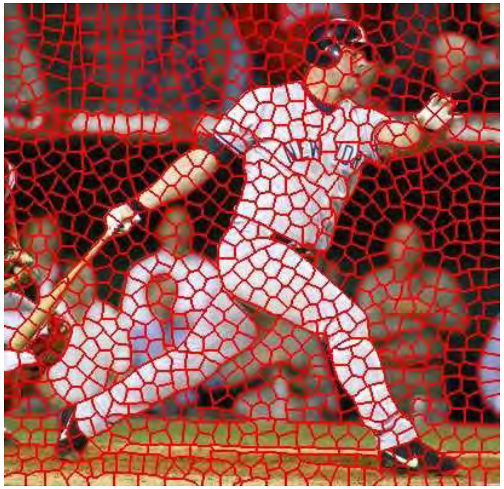
3. Recursively repartition the segmented parts if necessary

Details: [http://www.cs.berkeley.edu/~malik/papers/SM-n**cut**.pdf](http://www.cs.berkeley.edu/~malik/papers/SM-ncut.pdf)

Normalized cuts results

Normalized cuts: Pro and con

- Pros
  - Generic framework, can be used with many different features and affinity formulations
  - Provides regular segments
- Cons
  - Need to chose number of segments
  - High storage requirement and time complexity
  - Bias towards partitioning into equal segments
- Usage
  - Use for oversegmentation when you want regular segments



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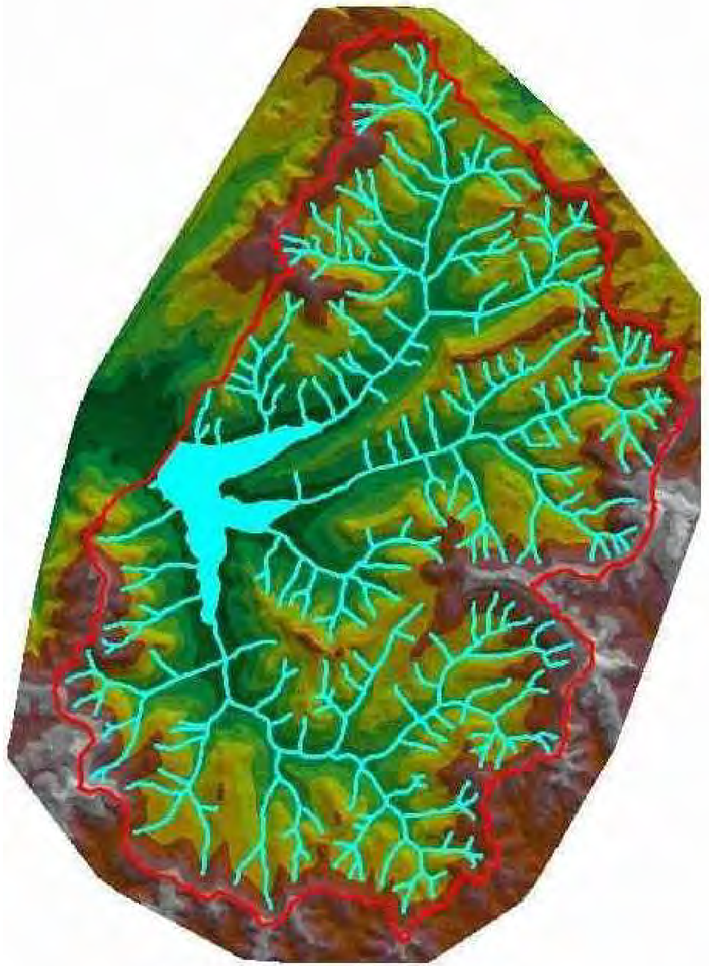
- Bottom-up segmentation via clustering
  - Mode finding and mean shift: k-means, GMM, mean-shift
- Graph-based segmentation: Normalized Cut
- **Oversegmentation**
  - Watershed algorithm, Felzenszwalb and Huttenlocher graph-based etc.
- Multiple segmentation

Superpixel algorithms

- Goal is to divide the image into a large number of regions, such that each regions lie within object boundaries

- Examples
  - Watershed
  - Felzenszwalb and Huttenlocher graph-based
  - Turbopixels
  - SLIC

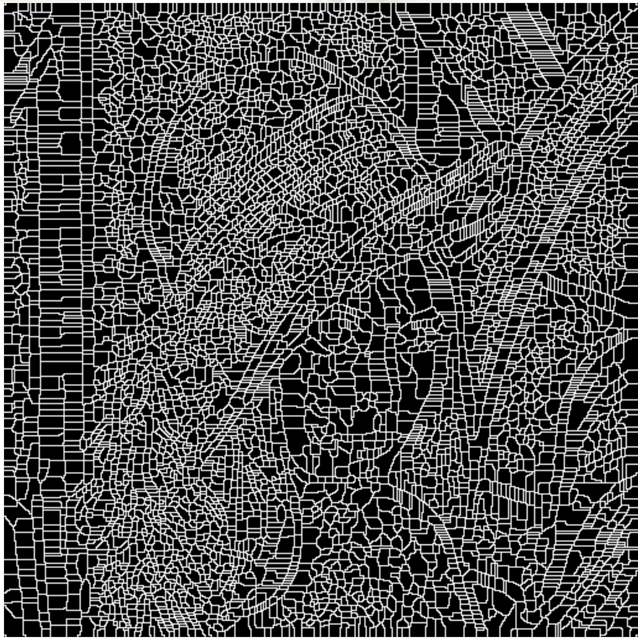
Watershed algorithm



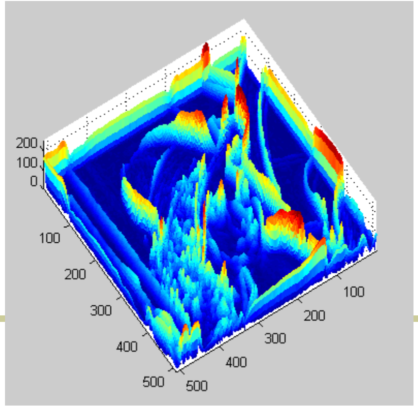
Watershed segmentation

Image

Gradient



Watershed boundaries



Meyer's watershed segmentation

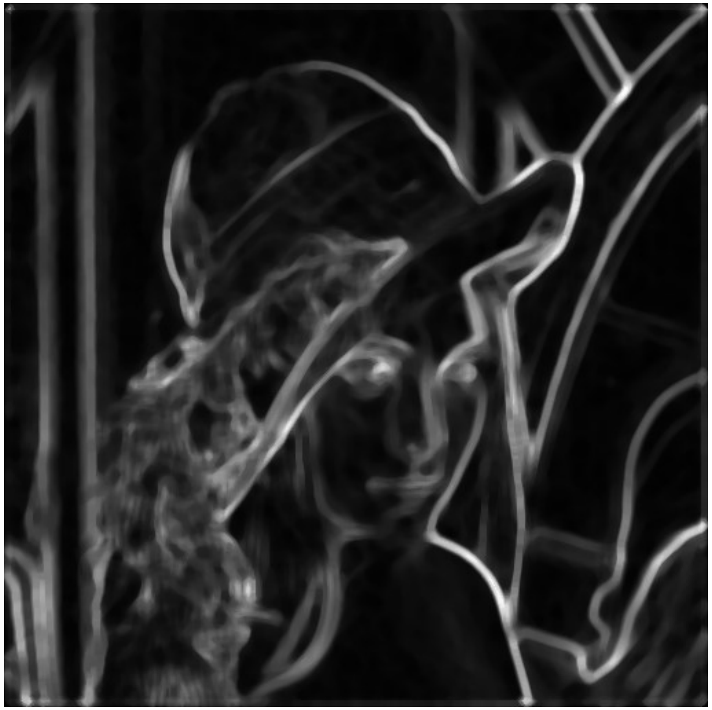
1. Choose local minima as region seeds
2. Add neighbors to priority queue, sorted by value
3. Take top priority pixel from queue
    1. If all labeled neighbors have same label, assign that label to pixel
    2. Add all non-marked neighbors to queue
4. Repeat step 3 until finished (all remaining pixels in queue are on the boundary)

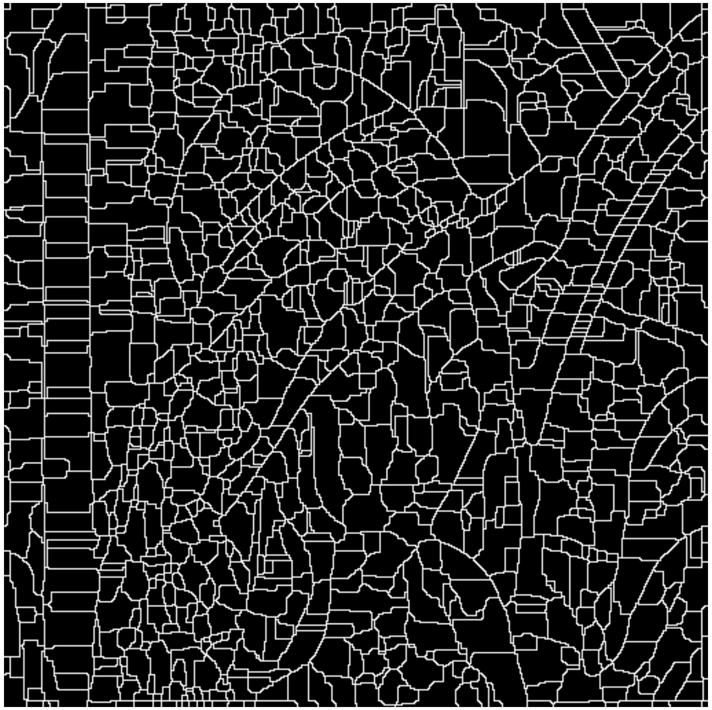
Matlab: seg = watershed(bnd_im)

Meyer 1991

Simple trick

- Use Gaussian or median filter to reduce number of regions





Watershed usage

- Use as a starting point for hierarchical segmentation
  - Ultrametric contour map (Arbelaez 2006)

- Works with any soft boundaries
  - Pb (w/o non-max suppression)
  - Canny (w/o non-max suppression)
  - Etc.

Watershed usage

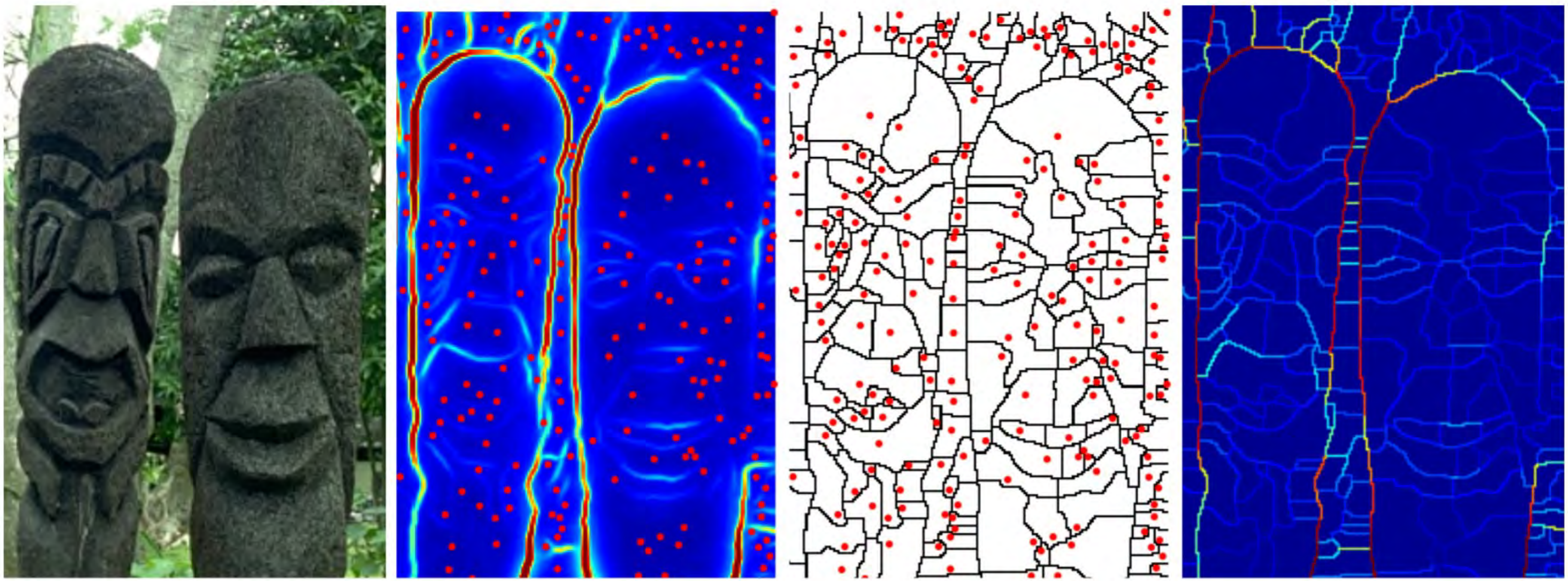


Fig. 11. **Watershed Transform.** ***Left:*** Image. ***Middle Left:*** Boundary strength $E(x, y)$. We regard $E(x, y)$ as a topographic surface and flood it from its local minima. ***Middle Right:*** This process partitions the image into catchment basins $\mathcal{P}_0$ and arcs $\mathcal{K}_0$. There is exactly one basin per local minimum and the arcs coincide with the locations where the floods originating from distinct minima meet. Local minima are marked with red dots. ***Right:*** Each arc weighted by the mean value of $E(x, y)$ along it. This weighting scheme produces artifacts, such as the strong horizontal contours in the small gap between the two statues.

Watershed pros and cons

- Pros
  - Fast (< 1 sec for 512x512 image)
  - Preserves boundaries
- Cons
  - Only as good as the soft boundaries (which may be slow to compute)
  - Not easy to get variety of regions for multiple segmentations
- Usage
  - Good algorithm for superpixels, hierarchical segmentation

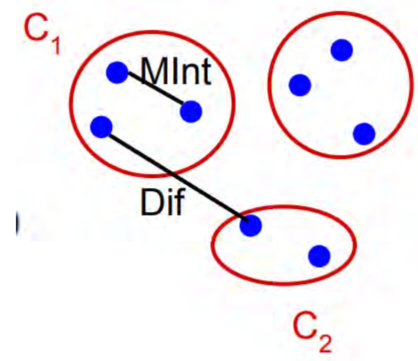
Graph-Based Segmentation

http://www.cs.brown.edu/~pff/segment/, by Felzenszwalb and Huttenlocher

+ Good for thin regions
+ Fast
+ Easy to control coarseness of segmentations
+ Can include both large and small regions
- Often creates regions with strange shapes
- Sometimes makes very large errors

Predicate for segmentation

- Predicate D determines whether there is a boundary for segmentation.

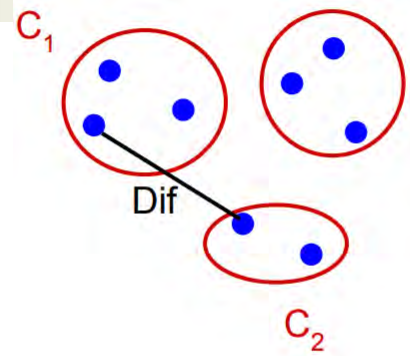


$$Merge(C_1, C_2) = \begin{cases} True & \text{if } dif(C_1, C_2) < in(C_1, C_2) \\ False & otherwise \end{cases}$$

Where

- dif(C1 , C2) is the difference between two clusters.
- in(C1 , C2) is the internal different in the clusters C1 and C2

Predicate for Segmentation



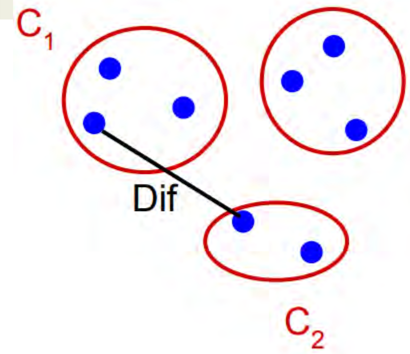
- Predicate D determines whether there is a boundary for segmentation.

$$Merge(C_1, C_2) = \begin{cases} True & if\ dif(C_1, C_2) < in(C_1, C_2) \\ False & otherwise \end{cases}$$

$$dif(C_1, C_2) = \min_{v_i \in C_1, v_j \in C_2, (C_1, C_2) \in E} w(v_i, v_j)$$

The different between two components is the minimum weight edge that connects a node vi in clusters C1 to node vj in C2

Predicate for Segmentation



- Predicate D determines whether there is a boundary for segme

$$Merge(C_1, C_2) = \begin{cases} True & if\ dif(C_1, C_2) < in(C_1, C_2) \\ False & otherwise \end{cases}$$

$$dif(C_1, C_2) = \min_{v_i \in C_1, v_j \in C_2, (C_1, C_2) \in E} w(v_i, v_j)$$

$$in(C_1, C_2) = \min_{C \in \{C_1, C_2\}} \left[\max_{v_i, v_j \in C} \left[w(v_i, v_j) + \frac{k}{|C|} \right] \right]$$

In(C1, C2) is to the maximum weight edge that connects two nodes in the same component.

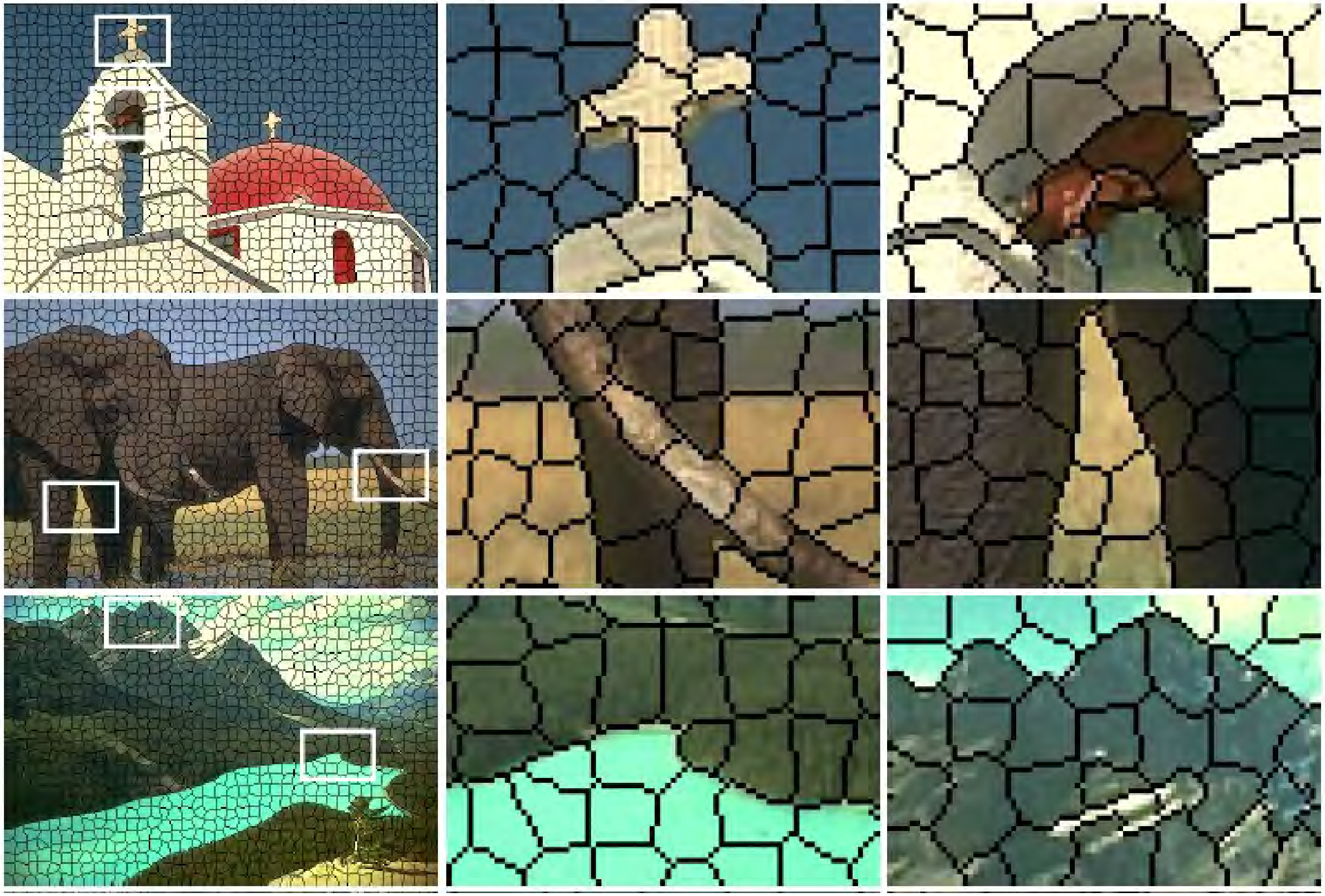
Predicate for Segmentation

- k/|C| sets the threshold by which the components need to be different from the internal nodes in a component.
- Properties of constant k:
  - If k is large, it causes a preference of larger objects.
  - k does not set a minimum size for components.

Turbo Pixels: Levinstein et al. 2009

http://www.cs.toronto.edu/~kyros/pubs/09.pami.turbopixels.pdf

Tries to preserve boundaries like watershed but to produce more regular regions



Turbo Pixels: Levinstein et al. 2009

http://www.cs.toronto.edu/~kyros/pubs/09.pami.turbopixels.pdf

Tries to preserve boundaries like watershed but to produce more regular regions

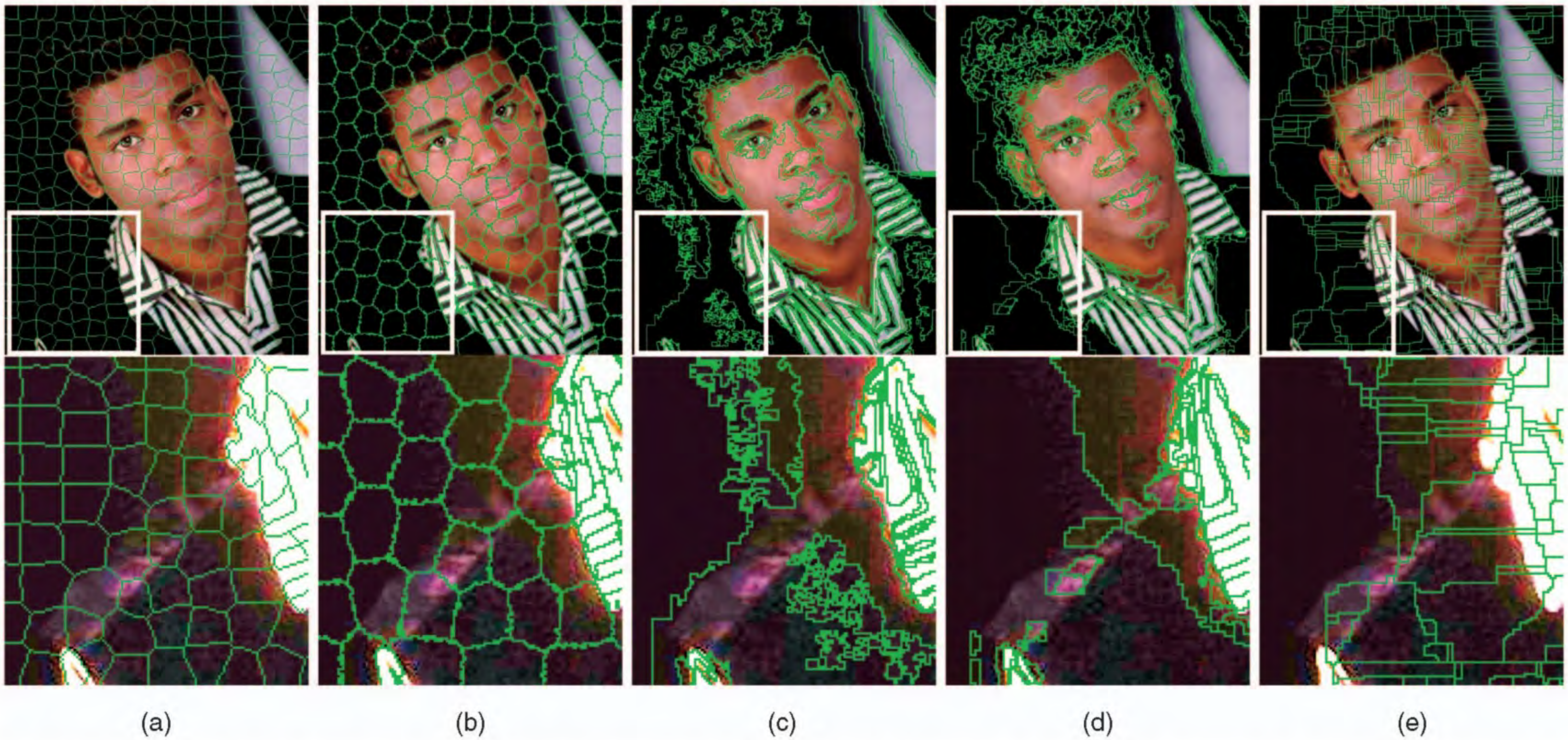


Fig. 1. Oversegmentations obtained with five algorithms: (a) TurboPixels, (b) N-Cuts [27], (c) Local variation [6], (d) Mean shift [3], and (e) Watershed [7]. Each segmentation has (approximately) the same number of segments. The second row zooms in on the regions of interest defined by the white boxes.

SLIC (Achanta et al. PAMI 2012)

http://infoscience.epfl.ch/record/177415/files/Superpixel_PAMI2011-2.pdf

1. Initialize cluster centers on pixel grid in steps S
   - Features: Lab color, x-y position
2. Move centers to position in 3x3 window with smallest gradient
3. Compare each pixel to cluster center within 2S pixel distance and assign to nearest
4. Recompute cluster centers as mean color/position of pixels belonging to each cluster
5. Stop when residual error is small

\+ Fast 0.36s for 320x240
\+ Regular superpixels
\+ Superpixels fit boundaries
\- May miss thin objects
\- Large number of superpixels

SLIC (Achanta et al. PAMI 2012)

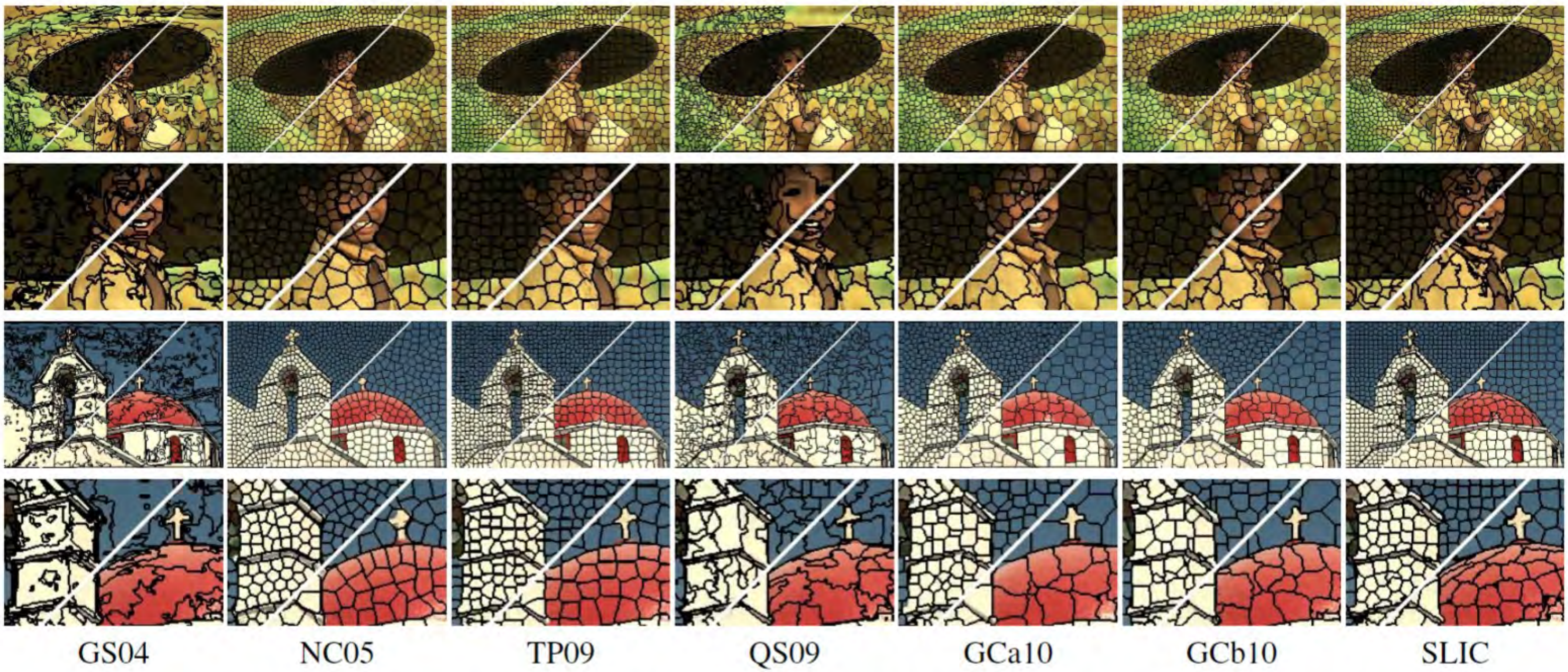


Fig. 7: Visual comparison of superpixels produced by various methods. The average superpixel size in the upper left of each image is 100 pixels, and 300 in the lower right. Alternating rows show each segmented image followed by a detail of the center of each image.

SLIC (Achanta et al. PAMI 2012)

TABLE I: Summary of existing superpixel algorithms. The ability of a superpixel method to adhere to boundaries found in the Berkeley data set [20] is measured and ranked according to two standard metrics: under-segmentation error and boundary recall (for ~500 superpixels). We also report the average time required to segment images using an Intel Dual Core 2.26 GHz processor with 2GB RAM, and the class-averaged segmentation accuracy obtained on the MSRC data set using the method described in [11]. Bold entries indicate best performance in each category. Ability to specify the amount of superpixels, control their compactness, and ability to generate supervoxels is also provided.

	Graph-based					Gradient-ascent-based				
	GS04 [8]	NC05 [23]	SL08 [21]	GCa10[b] [26]	GCb10[b] [26]	WS91 [28]	MS02 [4]	TP09[b] [15]	QS09 [25]	SLIC
Adherence to boundaries										
Under-segmentation error (rank)	0.23	0.22	-	0.22	0.22	-	-	0.24	0.20	**0.19**
Boundary recall (rank)	**0.84**	0.68	-	0.69	0.70	-	-	0.61	0.79	0.82
Segmentation speed										
320×240 image	1.08s[a]	178.15s	-	5.30s	4.12s	-	-	8.10s	4.66s	**0.36s**
2048×1536 image	90.95s[a]	N/A[c]	-	315s	235s	-	-	800s	181s	**14.94s**
Segmentation accuracy (using [11] on MSRC)	74.6%	75.9%	-	-	73.2%	-	-	62.0%	75.1%	**76.9%**
Control over amount of superpixels	No	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes
Control over superpixel compactness	No	No	No	No[d]	No[d]	No	No	No	No	Yes
Supervoxel extension	No	No	No	Yes	Yes	Yes	No	No	No	Yes

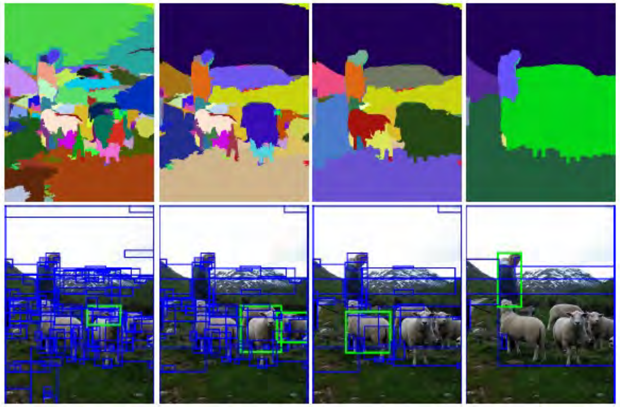
[a]Reported time includes parameter search. [b]Considers intensity only, ignores color. [c] NC05 failed to segment 2048 × 1536 images, producing "out of memory" errors.
[d]Constant-intensity (GCa10) or compact (GCb10) superpixels can be selected.

Today’s Class

- What are grouping problems in vision?
- Inspiration from human perception
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Mode finding and mean shift: k-means, GMM, mean-shift
- Graph-based segmentation: Normalized Cut
- Oversegmentation
  - Watershed algorithm, Felzenszwalb and Huttenlocher graph-based etc.
- **Multiple segmentation**

Multiple segmentations

- When creating regions for pixel classification or object detection, don't commit to one partitioning
- Strategies:
  - Hierarchical segmentation
    - Occlusion boundaries hierarchy: Hoiem et al. IJCV 2011 (uses trained classifier to merge)
    - Pb+watershed hierarchy: Arbeleaz et al. CVPR 2009
    - Selective search: FH + agglomerative clustering
  - Vary segmentation parameters
    - E.g., multiple graph-based segmentations or mean-shift segmentations
  - Region proposals
    - Propose seed superpixel, try to segment out object that contains it (Endres Hoiem ECCV 2010, Carreira Sminchisescu CVPR 2010)



Pb+watershed hierarchy

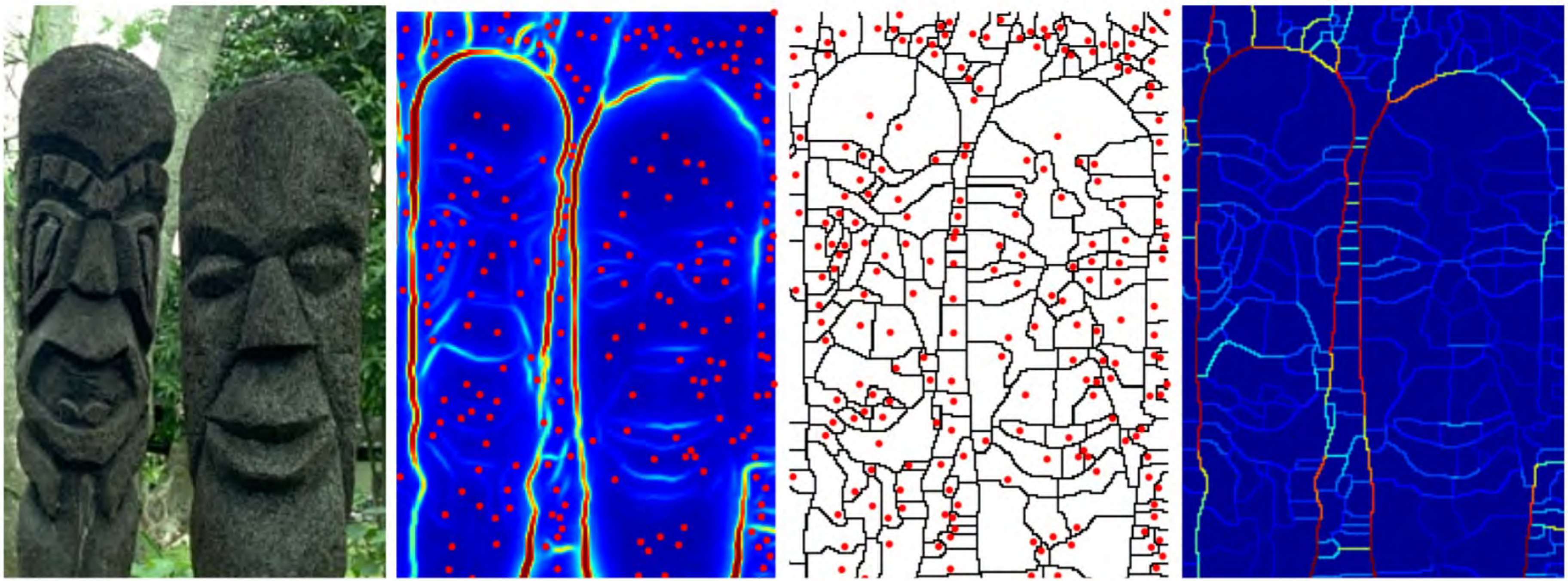


Fig. 11. **Watershed Transform.** ***Left:*** Image. ***Middle Left:*** Boundary strength $E(x, y)$. We regard $E(x, y)$ as a topographic surface and flood it from its local minima. ***Middle Right:*** This process partitions the image into catchment basins $\mathcal{P}_0$ and arcs $\mathcal{K}_0$. There is exactly one basin per local minimum and the arcs coincide with the locations where the floods originating from distinct minima meet. Local minima are marked with red dots. ***Right:*** Each arc weighted by the mean value of $E(x, y)$ along it. This weighting scheme produces artifacts, such as the strong horizontal contours in the small gap between the two statues.

Pb+watershed hierarchy

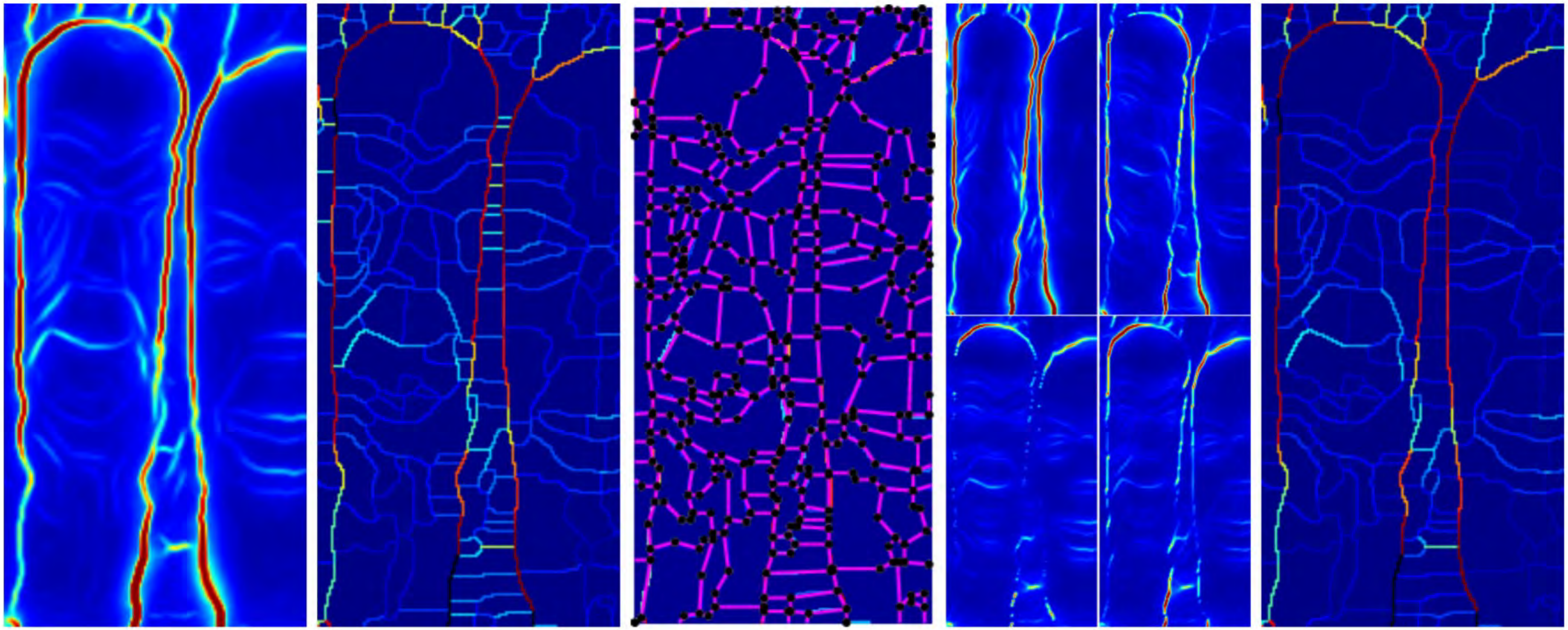


Fig. 12. **Oriented Watershed Transform.** ***Left:*** Input boundary signal $E(x, y) = \max_\theta E(x, y, \theta)$. ***Middle Left:*** Watershed arcs computed from $E(x, y)$. Note that thin regions give rise to artifacts. ***Middle:*** Watershed arcs with an approximating straight line segment subdivision overlaid. We compute this subdivision in a scale-invariant manner by recursively breaking an arc at the point maximally distant from the straight line segment connecting its endpoints, as shown in Figure 13. Subdivision terminates when the distance from the line segment to every point on the arc is less than a fixed fraction of the segment length. ***Middle Right:*** Oriented boundary strength $E(x, y, \theta)$ for four orientations θ. In practice, we sample eight orientations. ***Right:*** Watershed arcs reweighted according to E at the orientation of their associated line segments. Artifacts, such as the horizontal contours breaking the long skinny regions, are suppressed as their orientations do not agree with the underlying $E(x, y, \theta)$ signal.

Pb+watershed hierarchy

1) Select minimum weight contour:
   $C^* = \operatorname{argmin}_{C \in \mathcal{K}_0} W(C)$.
2) Let $R_1, R_2 \in \mathcal{P}_0$ be the regions separated by C^*.
3) Set $R = R_1 \cup R_2$, and update:
   $\mathcal{P}_0 \leftarrow \mathcal{P}_0 \backslash \{R_1, R_2\} \cup \{R\}$ and $\mathcal{K}_0 \leftarrow \mathcal{K}_0 \backslash \{C^*\}$.
4) Stop if $\mathcal{K}_0$ is empty.
   Otherwise, update weights $W(\mathcal{K}_0)$ and repeat.

Pb+watershed hierarchy: Arbeleaz et al. CVPR 2009

Pb+watershed hierarchy

Fig. 14. **Hierarchical segmentation from contours.** ***Far Left:*** Image. ***Left:*** Maximal response of contour detector gPb over orientations. ***Middle Left:*** Weighted contours resulting from the Oriented Watershed Transform - Ultrametric Contour Map (OWT-UCM) algorithm using gPb as input. This single weighted image encodes the entire hierarchical segmentation. By construction, applying any threshold to it is guaranteed to yield a set of closed contours (the ones with weights above the threshold), which in turn define a segmentation. Moreover, the segmentations are nested. Increasing the threshold is equivalent to removing contours and merging the regions they separated. ***Middle Right:*** The initial oversegmentation corresponding to the finest level of the UCM, with regions represented by their mean color. ***Right and Far Right:*** Contours and corresponding segmentation obtained by thresholding the UCM at level 0.5.

Pb+watershed hierarchy

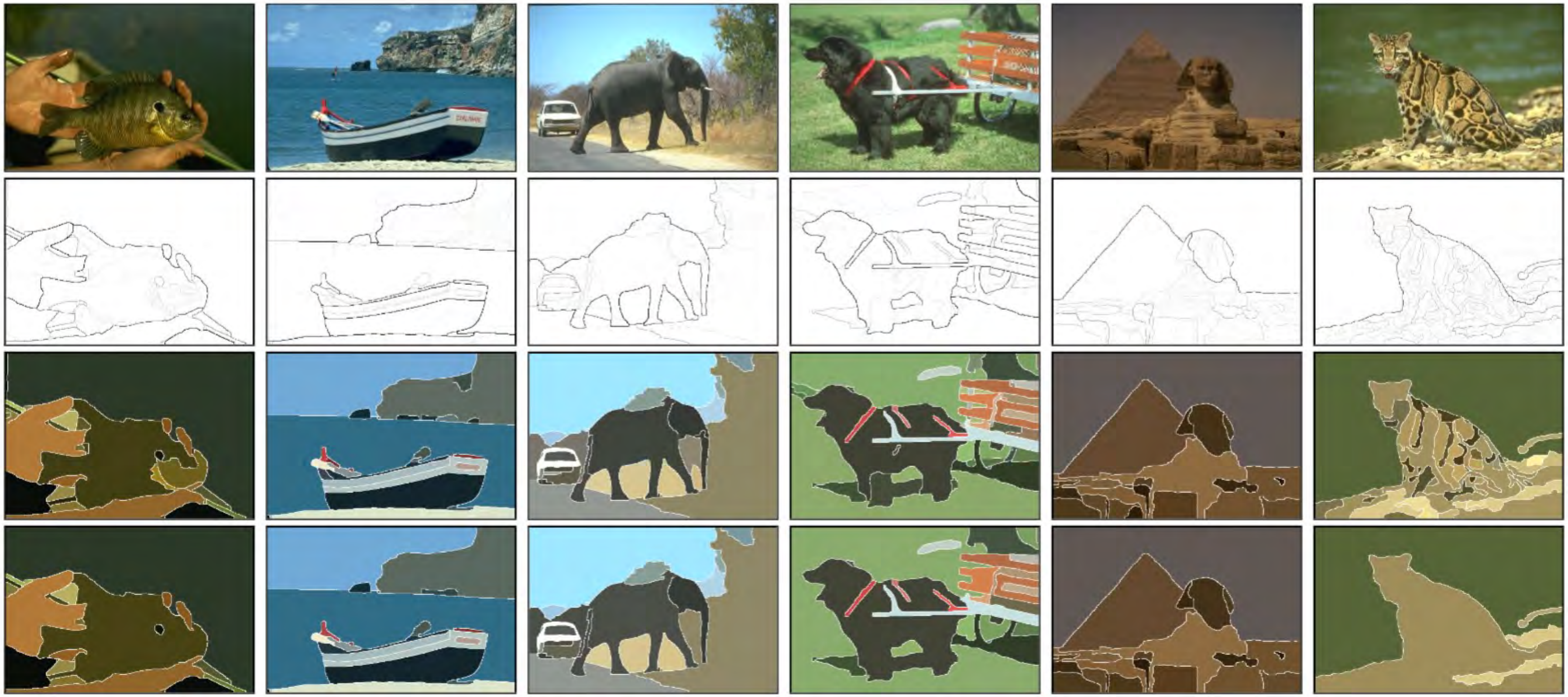


Fig. 16. **Additional hierarchical segmentation results on the BSDS500.** ***From Top to Bottom:*** Image, UCM produced by gPb-owt-ucm, and ODS and OIS segmentations. All images are from the test set.

Benchmark

	BSDS300			BSDS500		
	ODS	OIS	AP	ODS	OIS	AP
Human	0.79	0.79	–	0.80	0.80	–
gPb-owt-ucm	**0.71**	**0.74**	**0.73**	**0.73**	**0.76**	**0.73**
[34] Mean Shift	0.63	0.66	0.54	0.64	0.68	0.56
[33] NCuts	0.62	0.66	0.43	0.64	0.68	0.45
Canny-owt-ucm	0.58	0.63	0.58	0.60	0.64	0.58
[32] Felz-Hutt	0.58	0.62	0.53	0.61	0.64	0.56
[31] SWA	0.56	0.59	0.54	–	–	–
Quad-Tree	0.37	0.39	0.26	0.38	0.39	0.26
gPb	0.70	0.72	0.66	0.71	0.74	0.65
Canny	0.58	0.62	0.58	0.60	0.63	0.58

TABLE 1. **Boundary benchmarks on the BSDS.** Results for seven different segmentation methods (upper table) and two contour detectors (lower table) are given. Shown are the F-measures when choosing an optimal scale for the entire dataset (ODS) or per image (OIS), as well as the average precision (AP). Figures 1, 2, and 17 show the full precision-recall curves for these algorithms. Note that the boundary benchmark has the largest discriminative power among the evaluation criteria, clearly separating the Quad-Tree from all the data-driven methods.

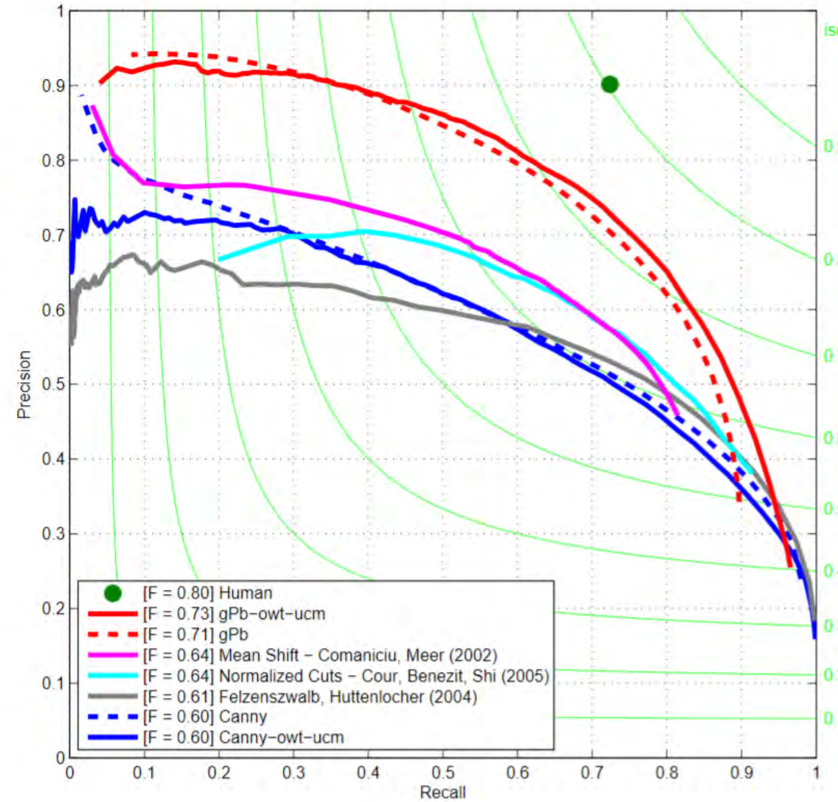


Fig. 17. **Boundary benchmark on the BSDS500.** Co
paring boundaries to human ground-truth allows us
evaluate contour detectors [3], [22] (dotted lines) and se
mentation algorithms [4], [32], [33], [34] (solid lines) in t
same framework. Performance is consistent when goi
from the BSDS300 (Figures 1 and 2) to the BSDS5
(above). Furthermore, the **OWT-UCM algorithm p
serves contour detector quality**. For both gPb a
Canny, comparing the resulting segment boundaries
the original contours shows that our OWT-UCM algorit
constructs hierarchical segmentations from contours wi
out losing performance on the boundary benchmark.

Benchmark

	BSDS300						
	Covering			PRI		VI	
	ODS	OIS	Best	ODS	OIS	ODS	OIS
Human	0.73	0.73	–	0.87	0.87	1.16	1.16
gPb-owt-ucm	**0.59**	**0.65**	**0.75**	**0.81**	**0.85**	**1.65**	**1.47**
[34] Mean Shift	0.54	0.58	0.66	0.78	0.80	1.83	1.63
[32] Felz-Hutt	0.51	0.58	0.68	0.77	0.82	2.15	1.79
Canny-owt-ucm	0.48	0.56	0.66	0.77	0.82	2.11	1.81
[33] NCuts	0.44	0.53	0.66	0.75	0.79	2.18	1.84
[31] SWA	0.47	0.55	0.66	0.75	0.80	2.06	1.75
[29] Total Var.	0.57	–	–	0.78	–	1.81	–
[70] T+B Encode	0.54	–	–	0.78	–	1.86	–
[30] Av. Diss.	0.47	–	–	0.76	–	2.62	–
[30] ChanVese	0.49	–	–	0.75	–	2.54	–
Quad-Tree	0.33	0.39	0.47	0.71	0.75	2.34	2.22

	BSDS500						
	Covering			PRI		VI	
	ODS	OIS	Best	ODS	OIS	ODS	OIS
Human	0.72	0.72	–	0.88	0.88	1.17	1.17
gPb-owt-ucm	**0.59**	**0.65**	**0.74**	**0.83**	**0.86**	**1.69**	**1.48**
[34] Mean Shift	0.54	0.58	0.66	0.79	0.81	1.85	1.64
[32] Felz-Hutt	0.52	0.57	0.69	0.80	0.82	2.21	1.87
Canny-owt-ucm	0.49	0.55	0.66	0.79	0.83	2.19	1.89
[33] NCuts	0.45	0.53	0.67	0.78	0.80	2.23	1.89
Quad-Tree	0.32	0.37	0.46	0.73	0.74	2.46	2.32

TABLE 2. **Region benchmarks on the BSDS.** For each segmentation method, the leftmost three columns report the score of the covering of ground-truth segments according to optimal dataset scale (ODS), optimal image scale (OIS), or Best covering criteria. The rightmost four columns compare the segmentation methods against ground-truth using the Probabilistic Rand Index (PRI) and Variation of Information (VI) benchmarks, respectively. Among the region benchmarks, the covering criterion has the largest dynamic range, followed by PRI and VI.

Summary

- What are grouping problems in vision?
- Inspiration from human perception
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Mode finding and mean shift: k-means, GMM, mean-shift
- Graph-based segmentation: Normalized Cut
- Oversegmentation
  - Watershed algorithm, Felzenszwalb and Huttenlocher graph-based
- Multiple segmentation

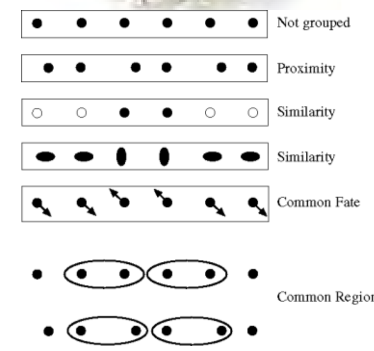
Choices in segmentation algorithms

- Oversegmentation
  - Watershed + Pb
  - Felzenszwalb and Huttenlocher 2004
    http://www.cs.brown.edu/~pff/segment/
  - SLIC ← good recent option
  - Turbopixels
  - Mean-shift

- Larger regions
  - Hierarchical segmentation (e.g., from Pb)
  - Normalized cuts
  - Mean-shift
  - Seed + graph cuts

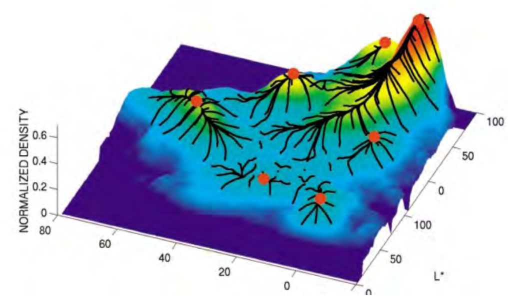
Things to remember

- Gestalt cues and principles of organization



- Uses of segmentation
  - Efficiency
  - Better features
  - Propose object regions
  - Want the segmented object

- Mean-shift segmentation
  - Good general-purpose segmentation method
  - Generally useful clustering, tracking technique



- Normalized cuts
  - Produces regular regions
  - Slow but good for oversegmentation

- Watershed segmentation
  - Good for hierarchical segmentation
  - Use in combination with boundary prediction