Computer Vision – Lecture 6

Segmentation

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Course Outline

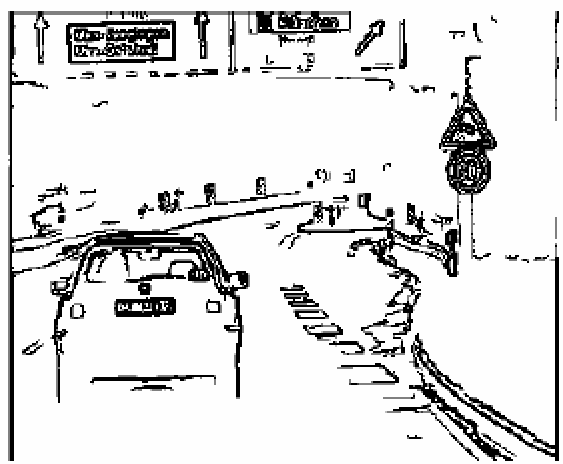
- Image Processing Basics
  - Structure Extraction
- Segmentation
  - Segmentation as Clustering
  - Graph-theoretic Segmentation
- Recognition
  - Global Representations
  - Subspace representations
- Local Features & Matching
- Object Categorization
- 3D Reconstruction
- Motion and Tracking

Recap: Chamfer Matching

- **Chamfer Distance**
  - Average distance to nearest feature

$$D_{chamfer}(T, I) \equiv \frac{1}{|T|} \sum_{t \in T} d_I(t)$$

  - This can be computed efficiently by correlating the edge template with the distance-transformed image



Edge image

Distance transform image

[D. Gavrila, DAGM'99]

Recap: Hough Transform

see Exercise 3.1!

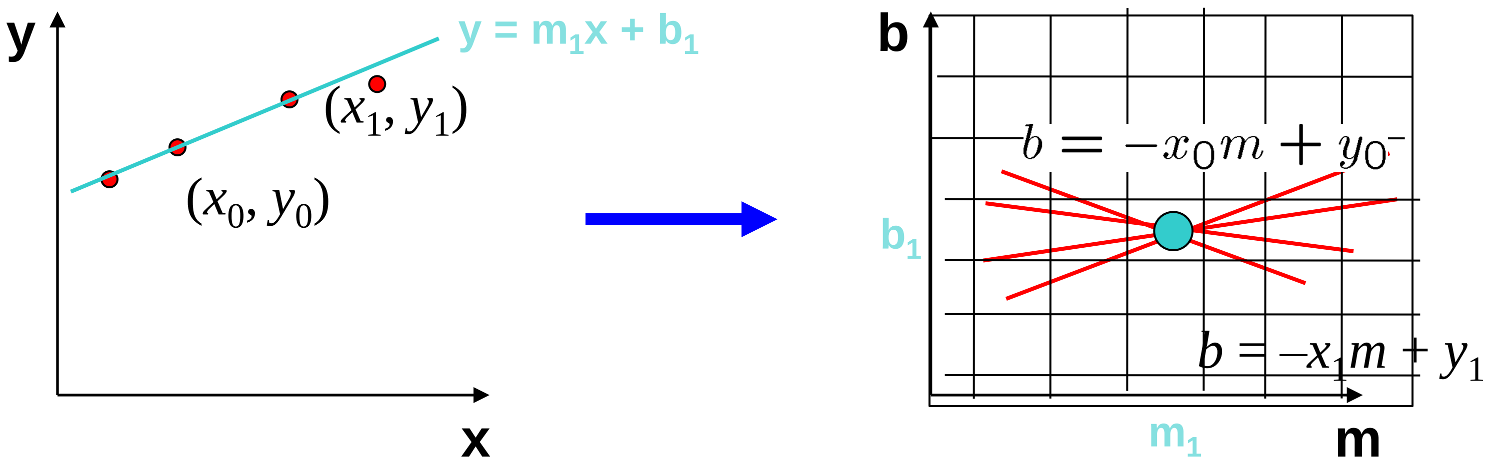


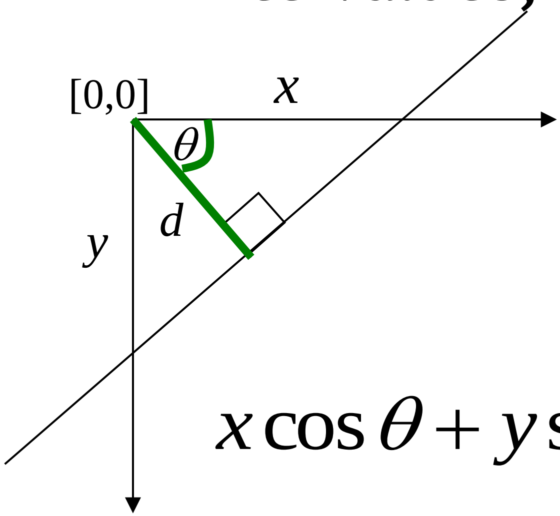
Image space Hough (parameter) space

- **How can we use this to find the most likely parameters (m,b) for the most prominent line in the image space?**
  - **Let each edge point in image space *vote* for a set of possible parameters in Hough space**
  - **Accumulate votes in discrete set of bins; parameters with the most votes indicate line in image space.**

Slide credit: Steve Seitz

Recap: Hough Transf. Polar Parametrization

- Usual (m,b) parameter space problematic: can take on infinite values, undefined for vertical lines.

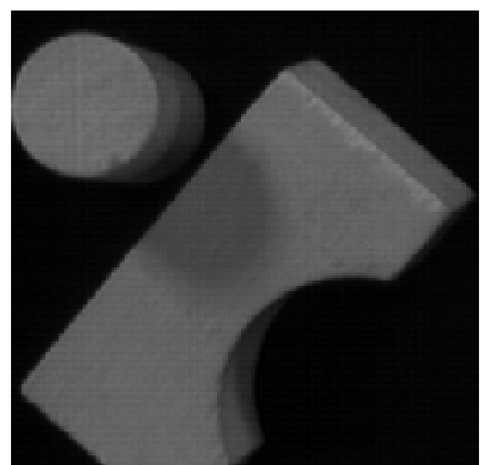


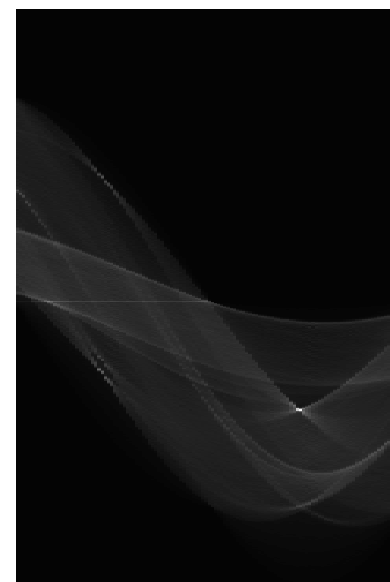
$$x\cos\theta + y\sin\theta = d$$

d : perpendicular distance from line to origin

θ : angle the perpendicular makes with the x-axis

- Point in image space
$\Rightarrow$ sinusoid segment in Hough space





Slide credit: Steve Seitz

Hough Transform for Circles

- **Circle: center (a,b) and radius r**

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

- **For a fixed radius r, unknown gradient direction**

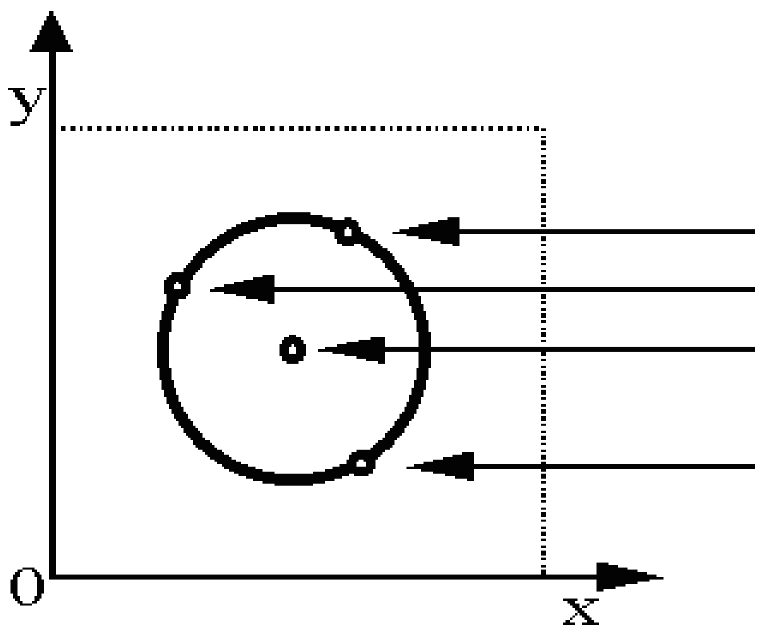
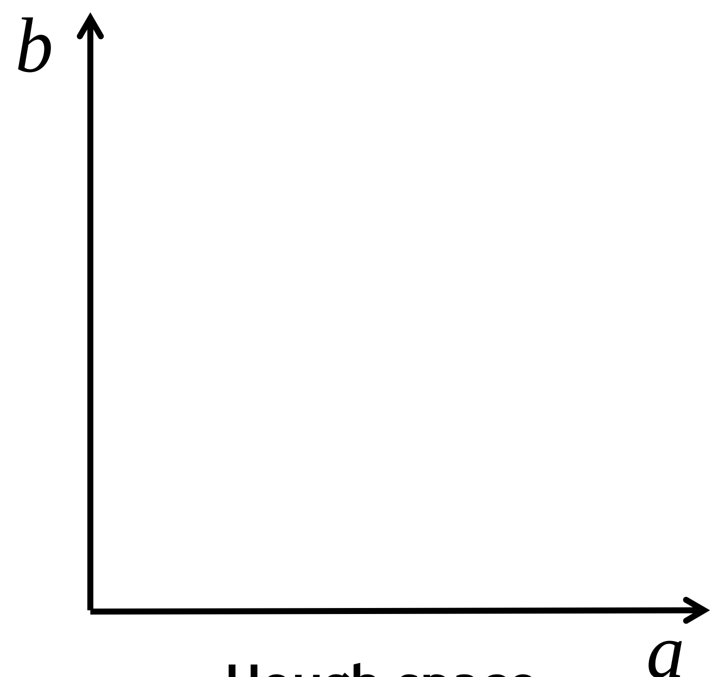


Image space



Hough space

Hough Transform for Circles

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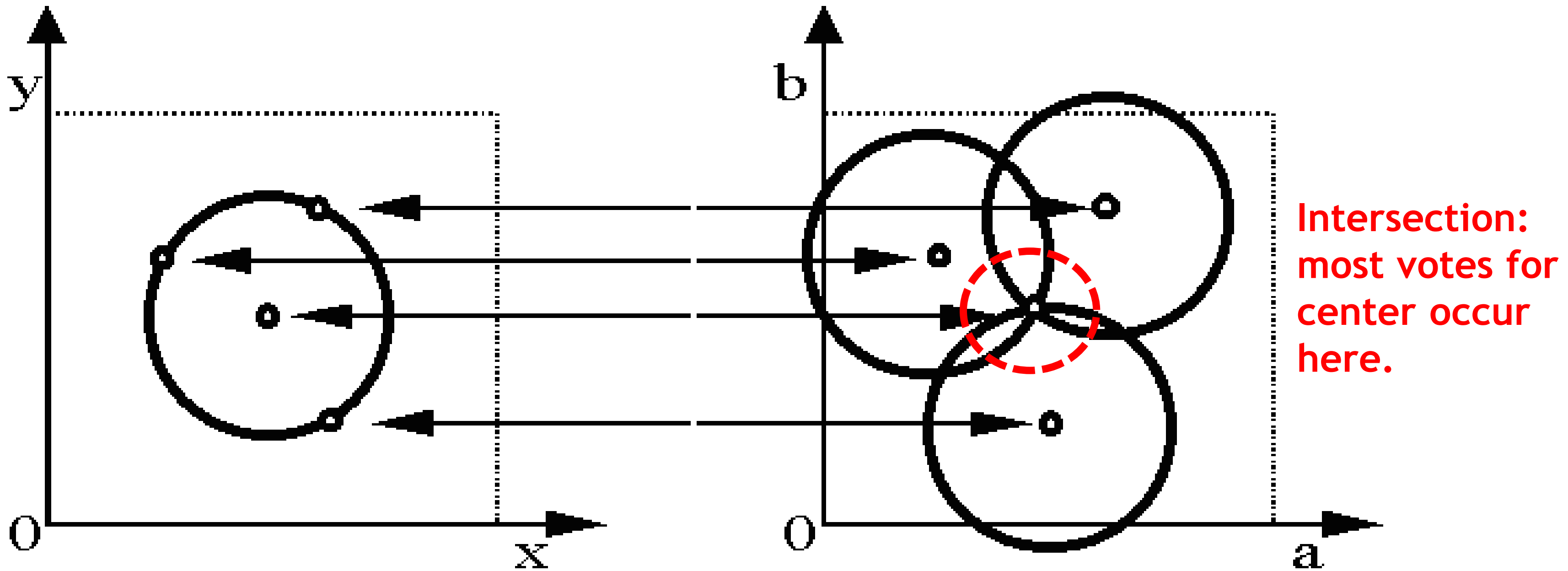

Image space **Hough space**

Hough Transform for Circles

- **Circle: center (a,b) and radius r**

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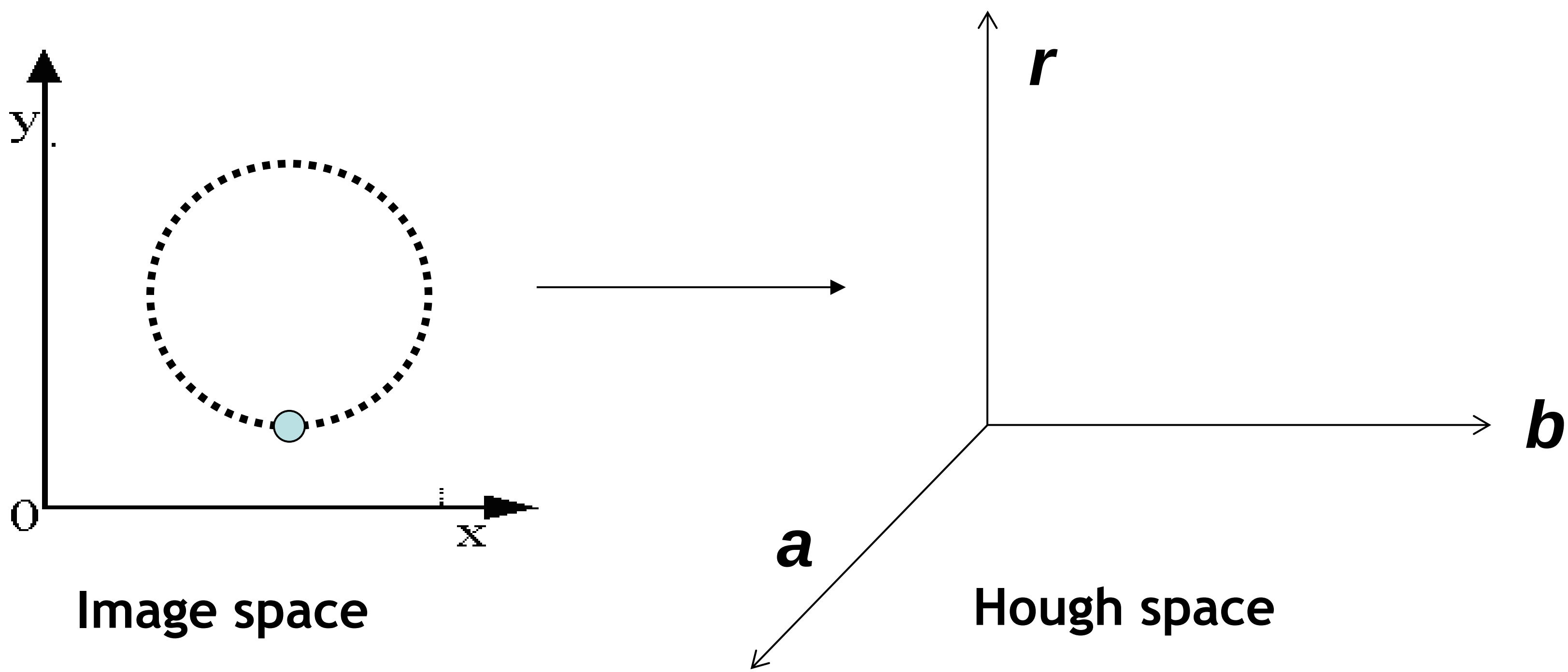

Hough Transform for Circles

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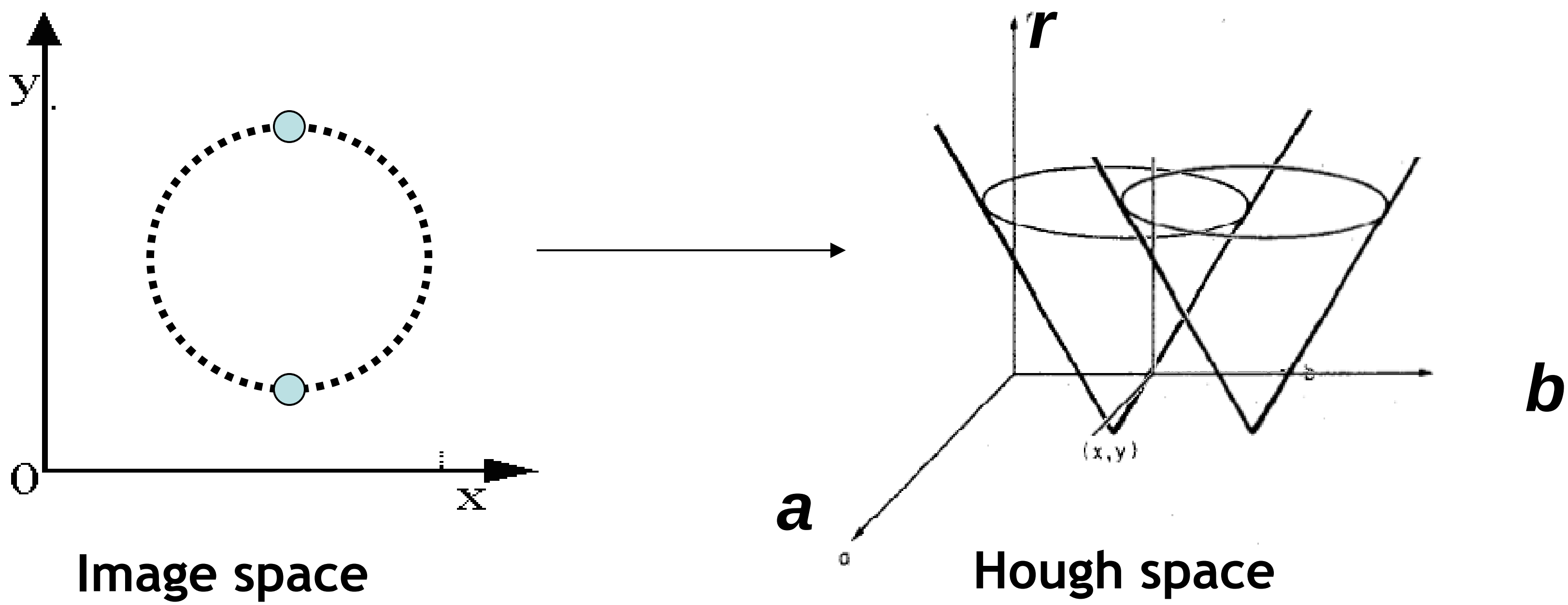


Hough Transform for Circles

- **Circle: center (a,b) and radius r**

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

- **For an unknown radius r, *known* gradient direction**

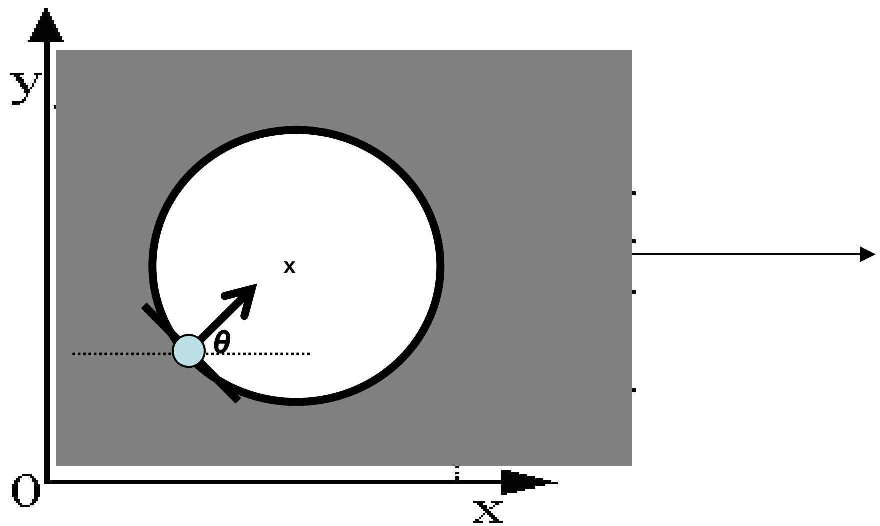
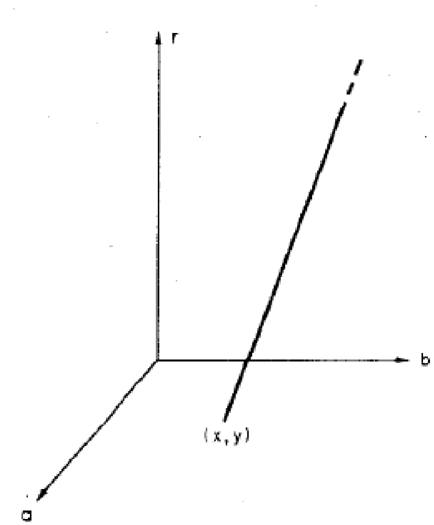


Image space



Hough space

Hough Transform for Circles

For every edge pixel (x,y) :

For each possible radius value r:

For each possible gradient direction θ:
// or use estimated gradient

$$a = x - r\cos(\theta)$$

$$b = y + r\sin(\theta)$$

$$H[a,b,r] \mathrel{+}= 1$$

end

end

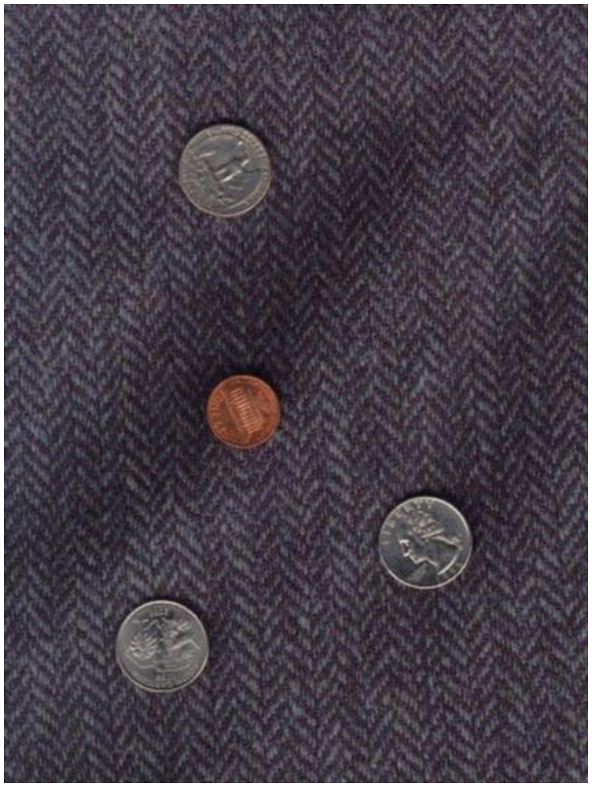
Slide credit: Kristen Grauman

Example: Detecting Circles with Hough

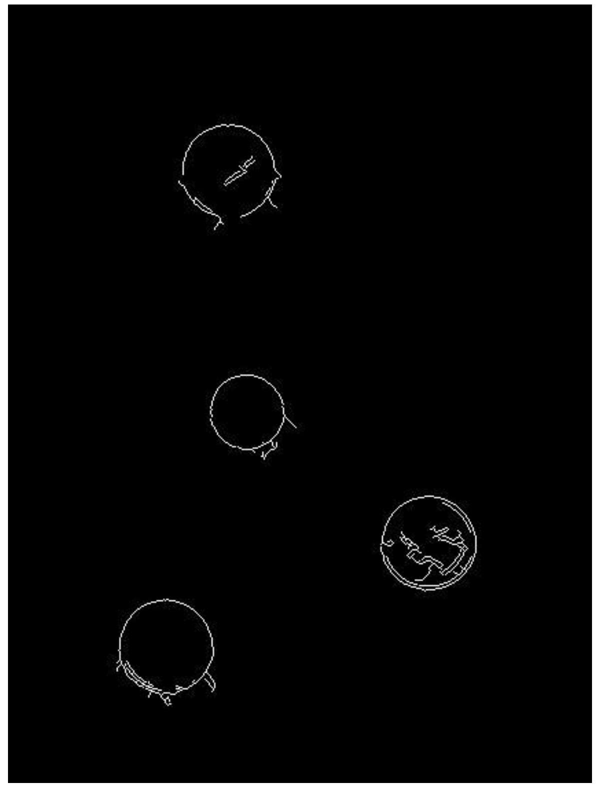
Crosshair indicates results of Hough transform, bounding box found via motion differencing.

Example: Detecting Circles with Hough

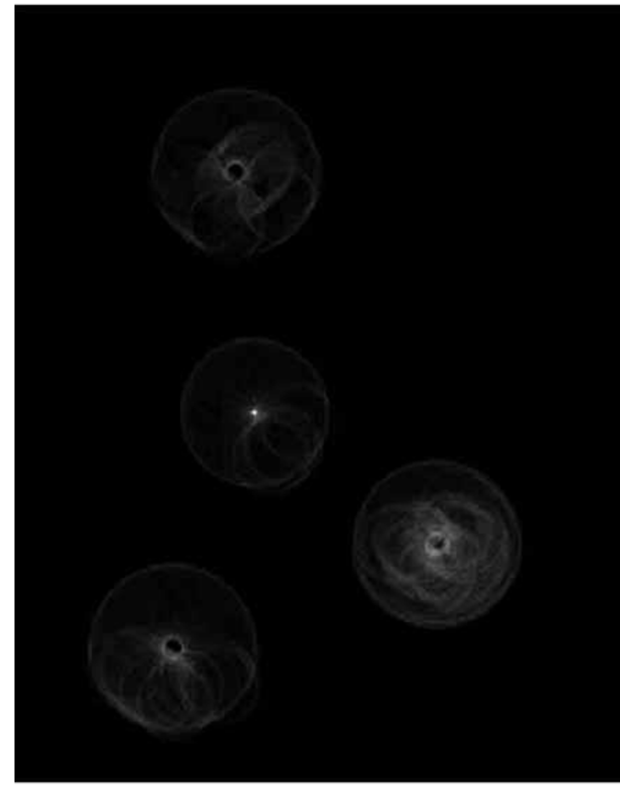
Original



Edges



Votes: Penny



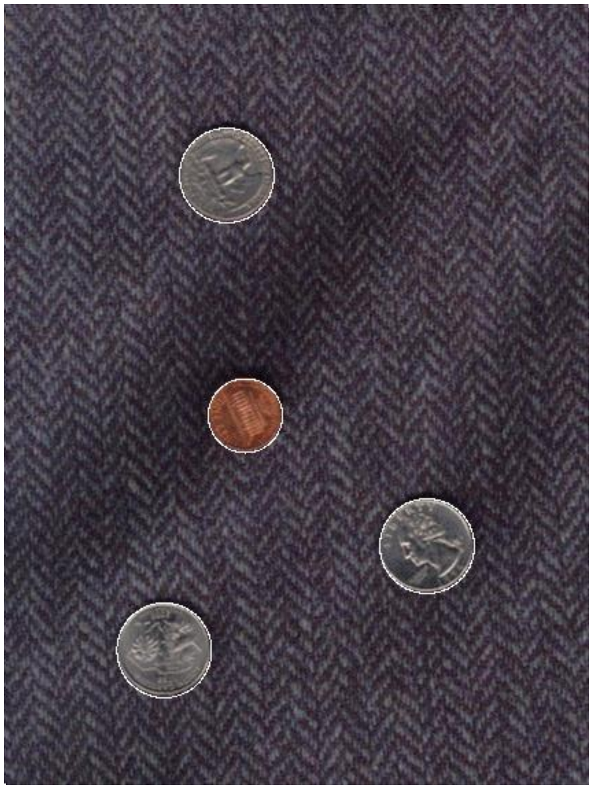
Note: a different Hough transform (with separate accumulators) was used for each circle radius (quarters vs. penny).

Coin finding sample images from: Vivek Kwatra

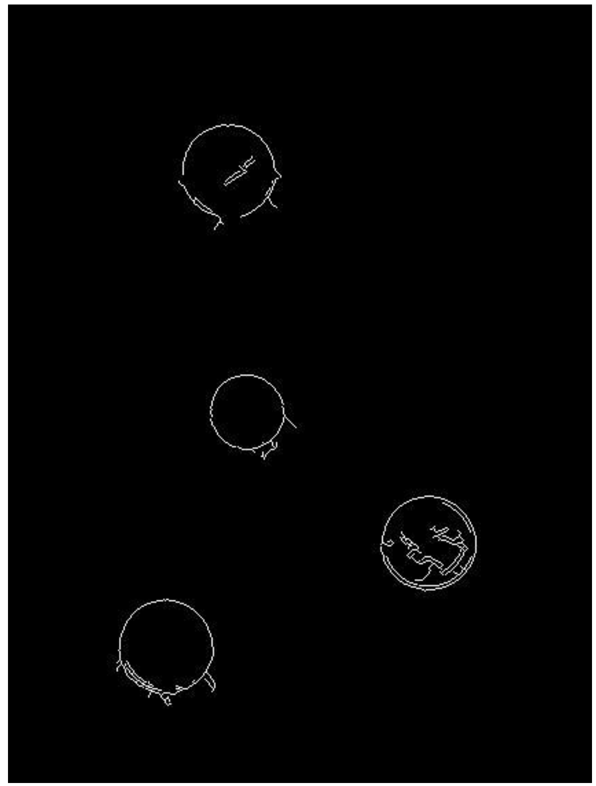
Example: Detecting Circles with Hough

Original

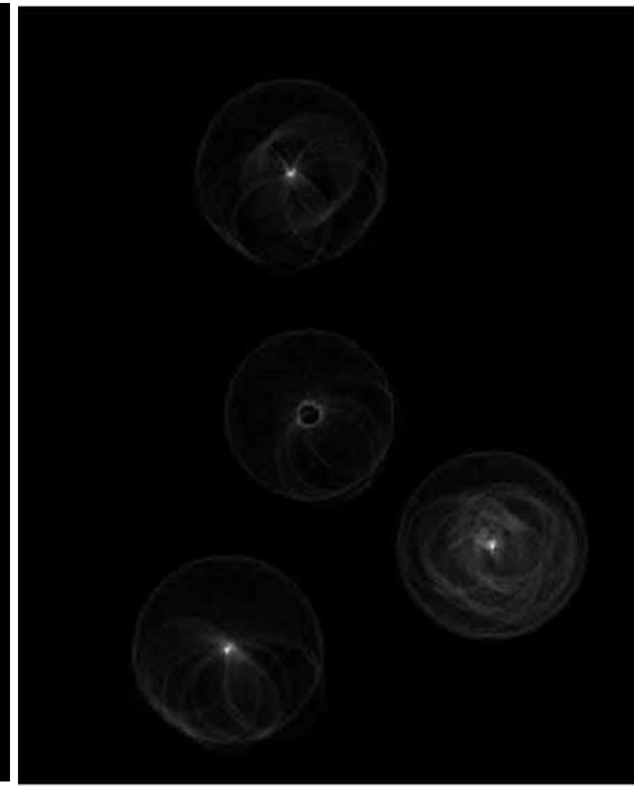
Combined detections



Edges



Votes: Quarter



Coin finding sample images from: Vivek Kwatra

Voting: Practical Tips

- Minimize irrelevant tokens first (take edge points with significant gradient magnitude)
- Choose a good grid / discretization
  - Too coarse: large votes obtained when too many different lines correspond to a single bucket
  - Too fine: miss lines because some points that are not exactly collinear cast votes for different buckets
- Vote for neighbors, also (smoothing in accumulator array)
- Utilize direction of edge to reduce free parameters by 1
- To read back which points voted for “winning” peaks, keep tags on the votes.

Hough Transform: Pros and Cons

Pros

- All points are processed independently, so can cope with occlusion
- Some robustness to noise: noise points unlikely to contribute consistently to any single bin
- Can detect multiple instances of a model in a single pass

Cons

- Complexity of search time increases exponentially with the number of model parameters
- Non-target shapes can produce spurious peaks in parameter space
- Quantization: hard to pick a good grid size

Generalized Hough Transform

- **What if we want to detect arbitrary shapes defined by boundary points and a reference point?**

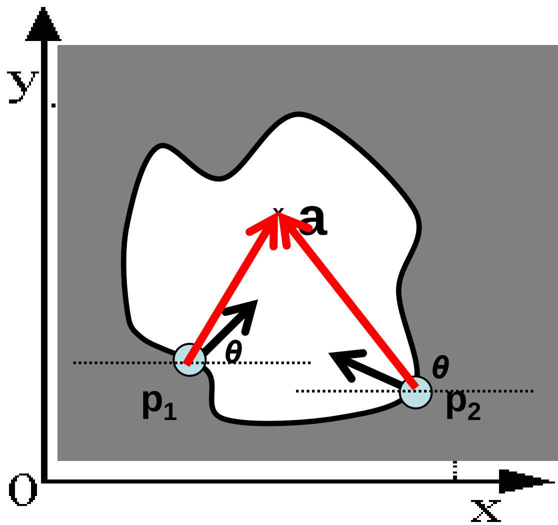


Image space

At each boundary point, compute displacement vector: $r = a - p_i$.

For a given model shape: store these vectors in a table indexed by gradient orientation θ.

[Dana H. Ballard, Generalizing the Hough Transform to Detect Arbitrary Shapes, 1980]

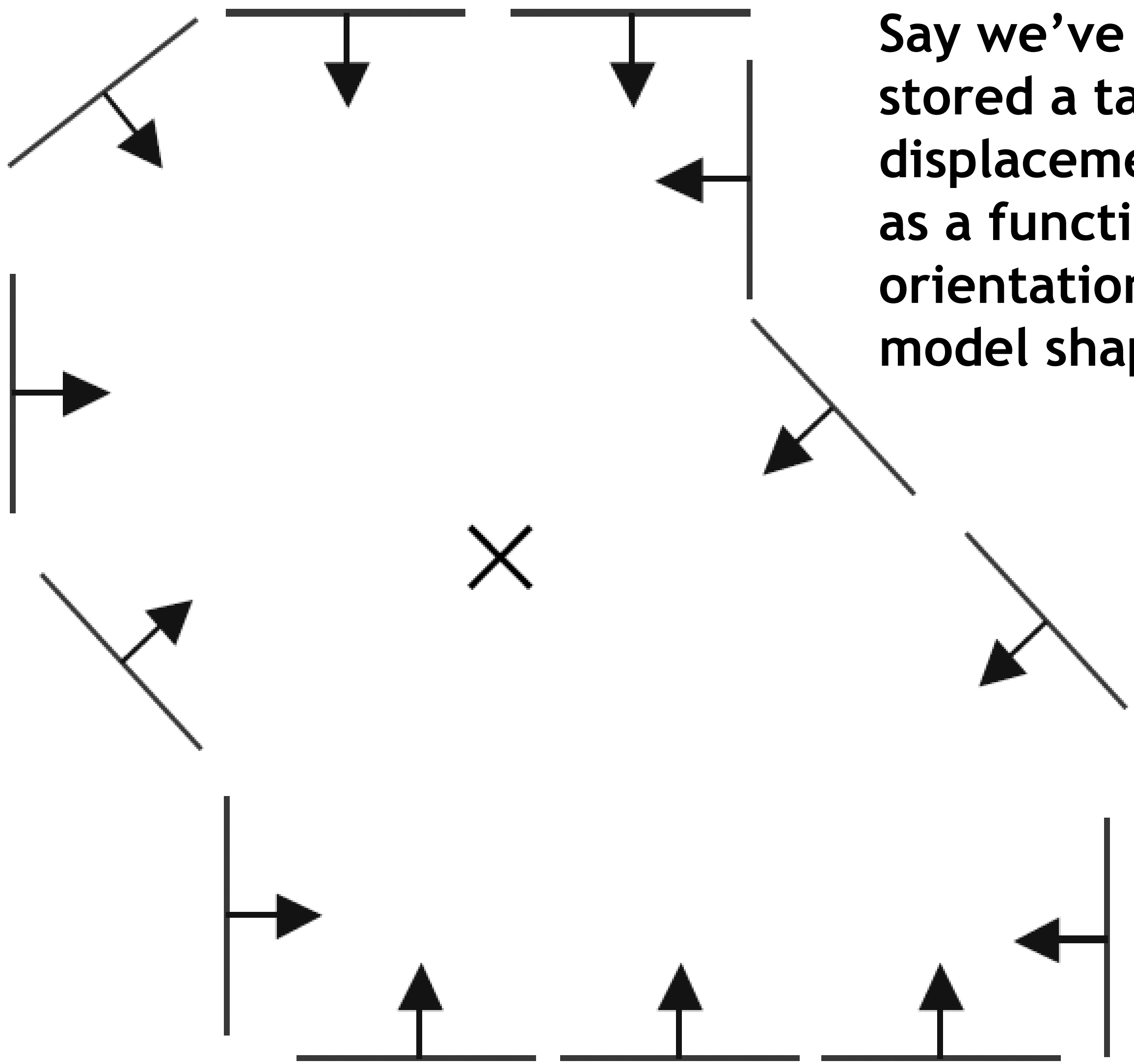
Generalized Hough Transform

To *detect* the model shape in a new image:

- For each edge point
  - Index into table with its gradient orientation θ
  - Use retrieved r vectors to vote for position of reference point
- Peak in this Hough space is reference point with most supporting edges

Assuming translation is the only transformation here, i.e., orientation and scale are fixed.

Example: Generalized Hough Transform

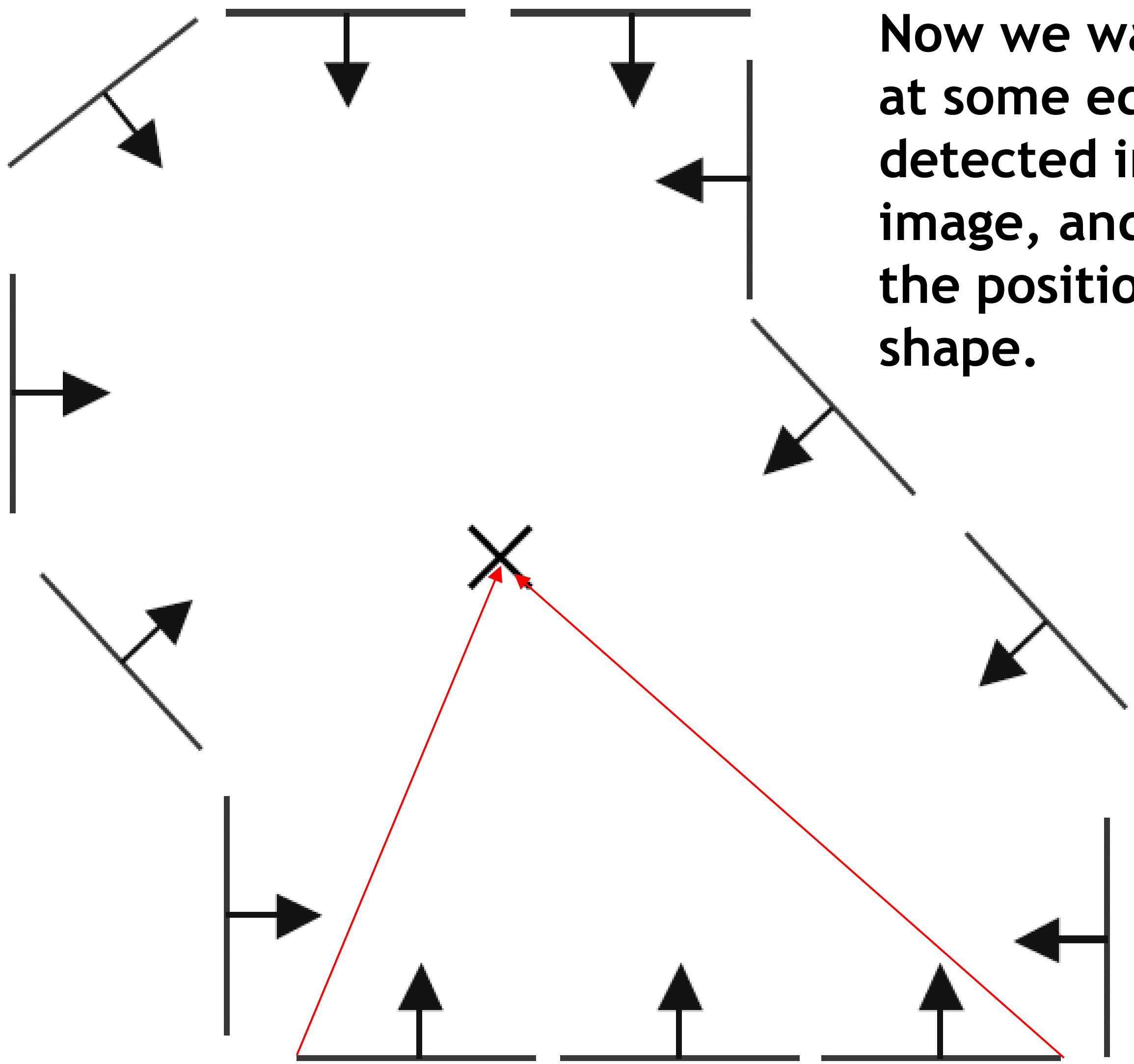


Model shape

Say we've already stored a table of displacement vectors as a function of edge orientation for this model shape.

Slide credit: Svetlana Lazebnik

Example: Generalized Hough Transform

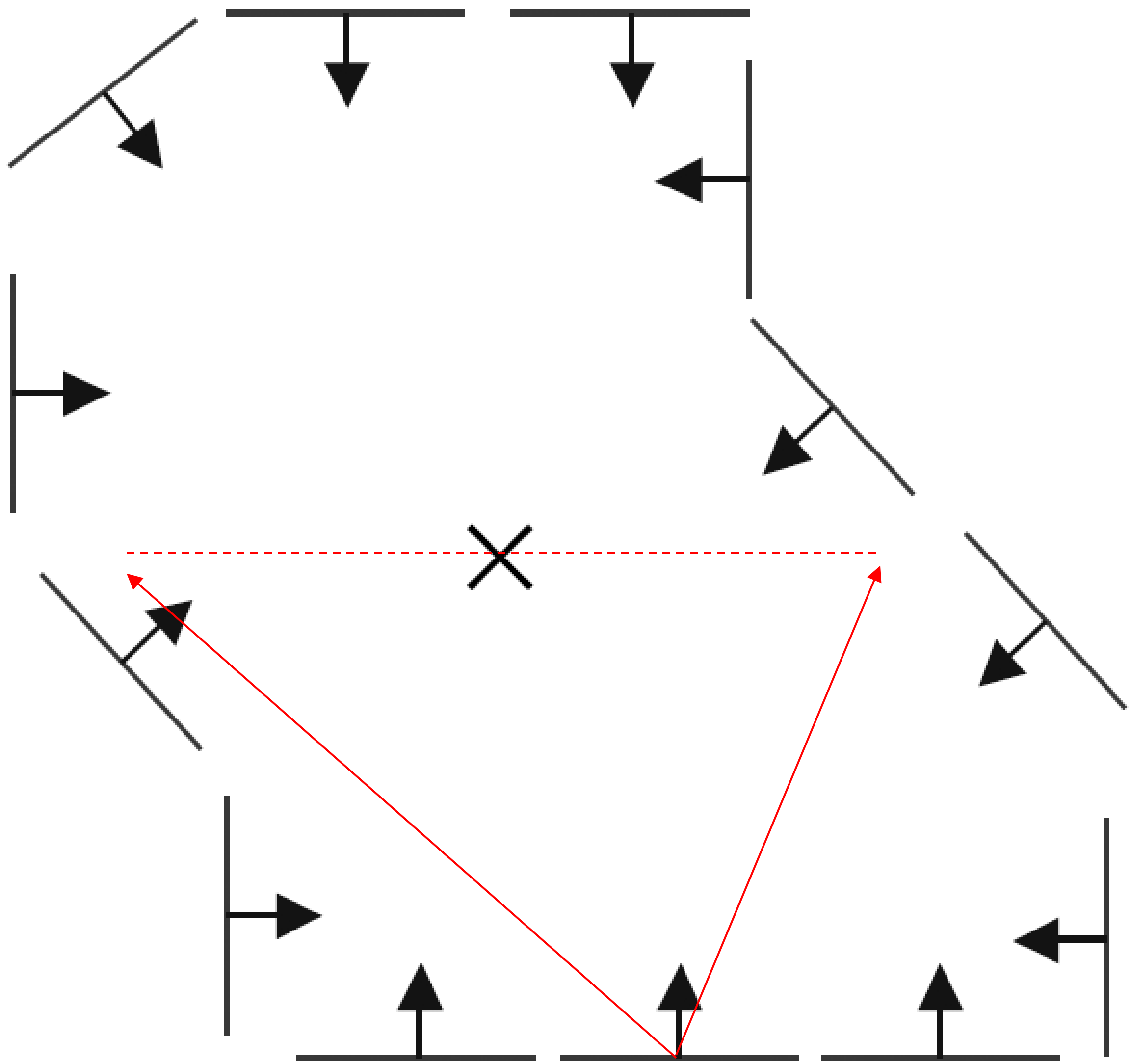


Now we want to look at some edge points detected in a *new* image, and vote on the position of that shape.

Displacement vectors for model points

Slide credit: Svetlana Lazebnik

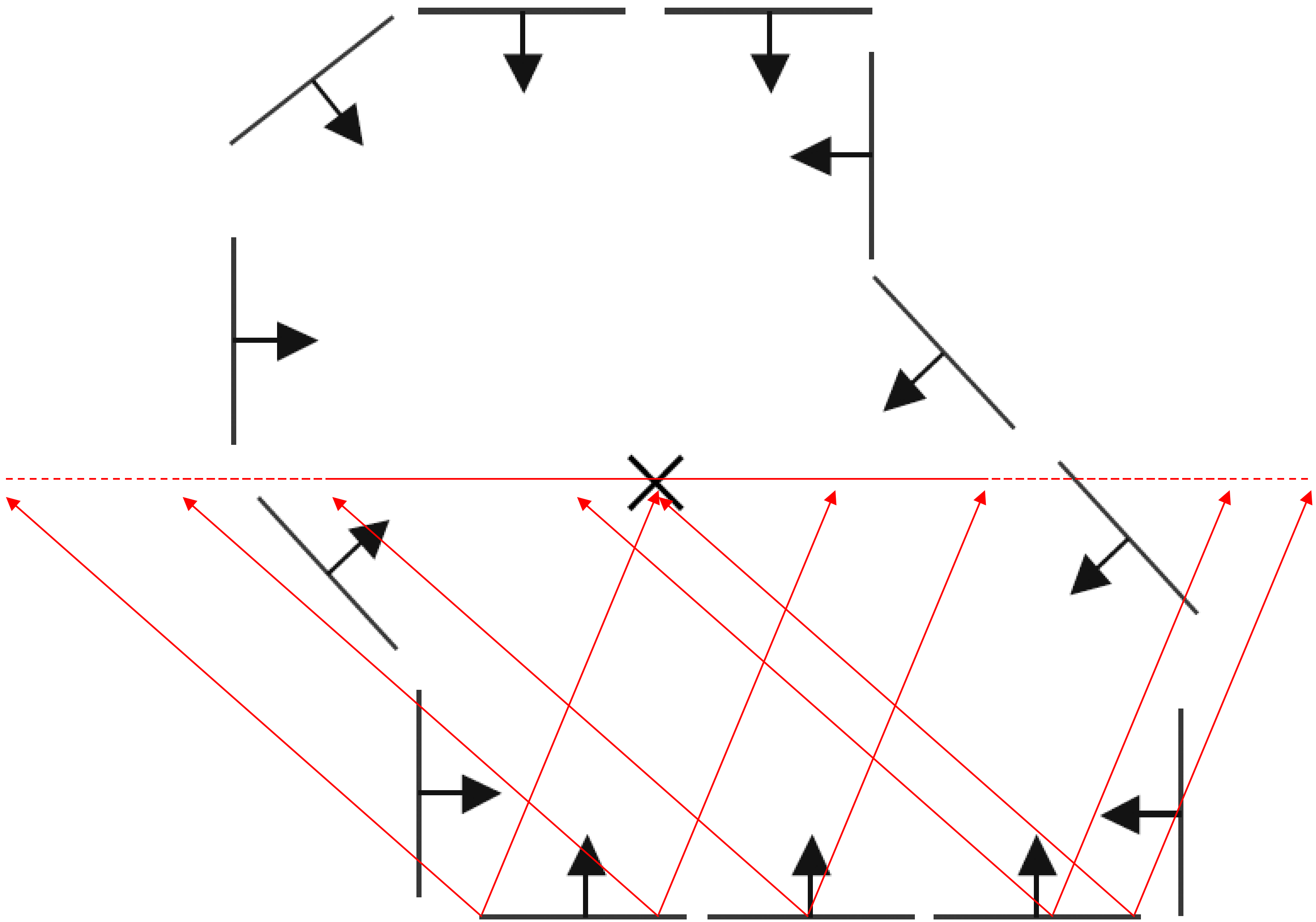
Example: Generalized Hough Transform



Range of voting locations for test point

Slide credit: Svetlana Lazebnik

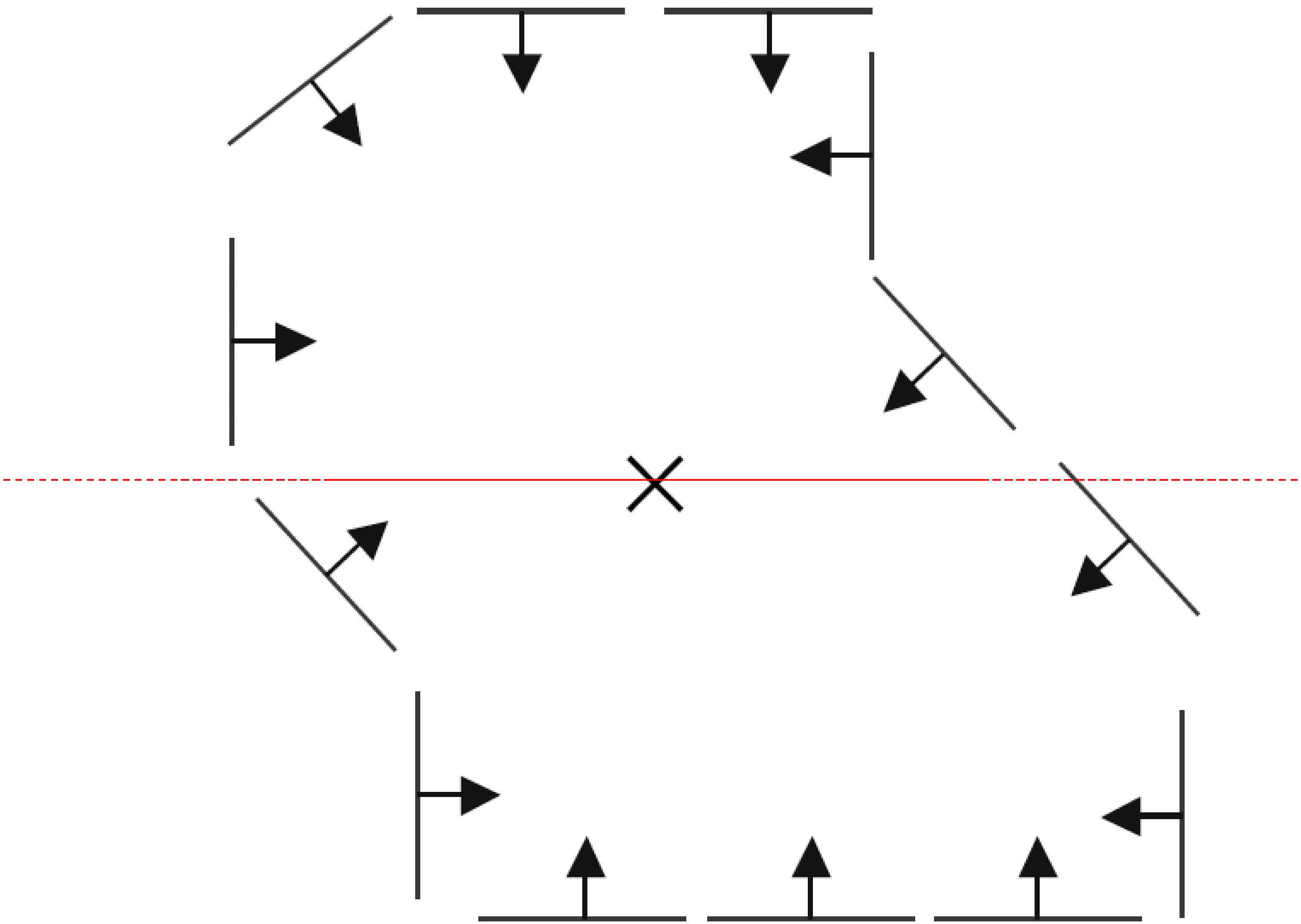
Example: Generalized Hough Transform



Range of voting locations for test point

Slide credit: Svetlana Lazebnik

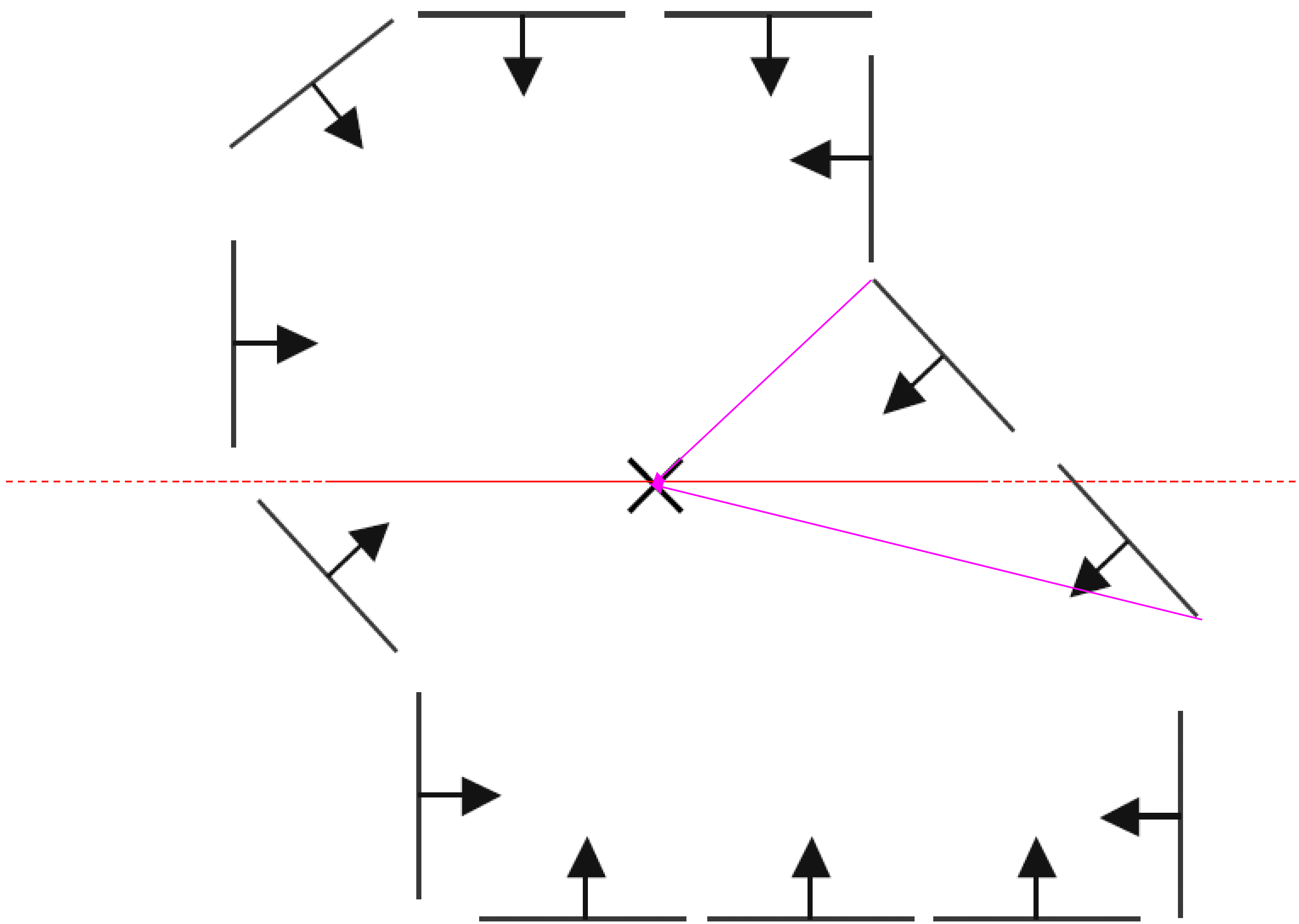
Example: Generalized Hough Transform



Votes for points with $\theta = \uparrow$

Slide credit: Svetlana Lazebnik

Example: Generalized Hough Transform



Displacement vectors for model points

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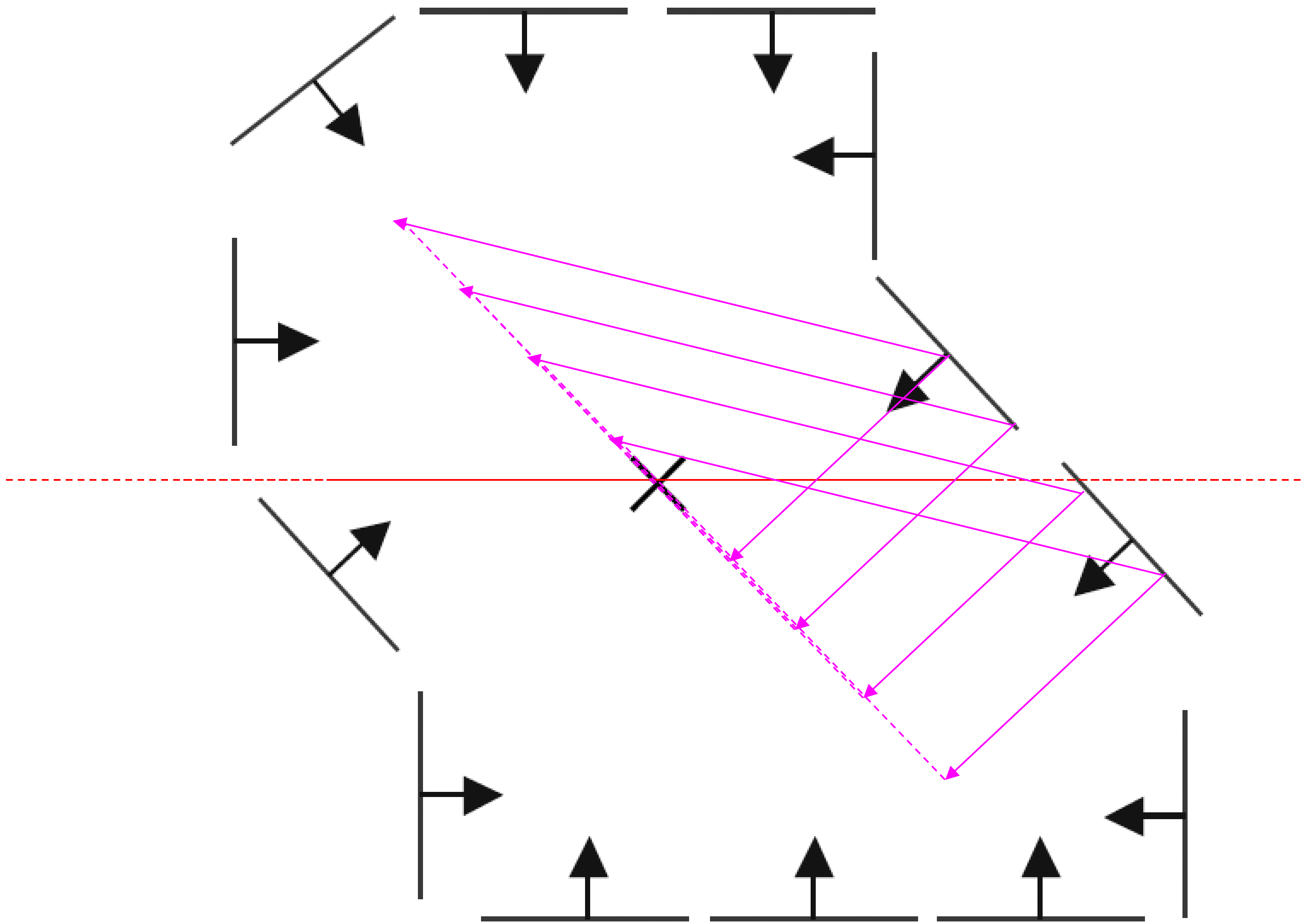
Example: Generalized Hough Transform



Range of voting locations for test point

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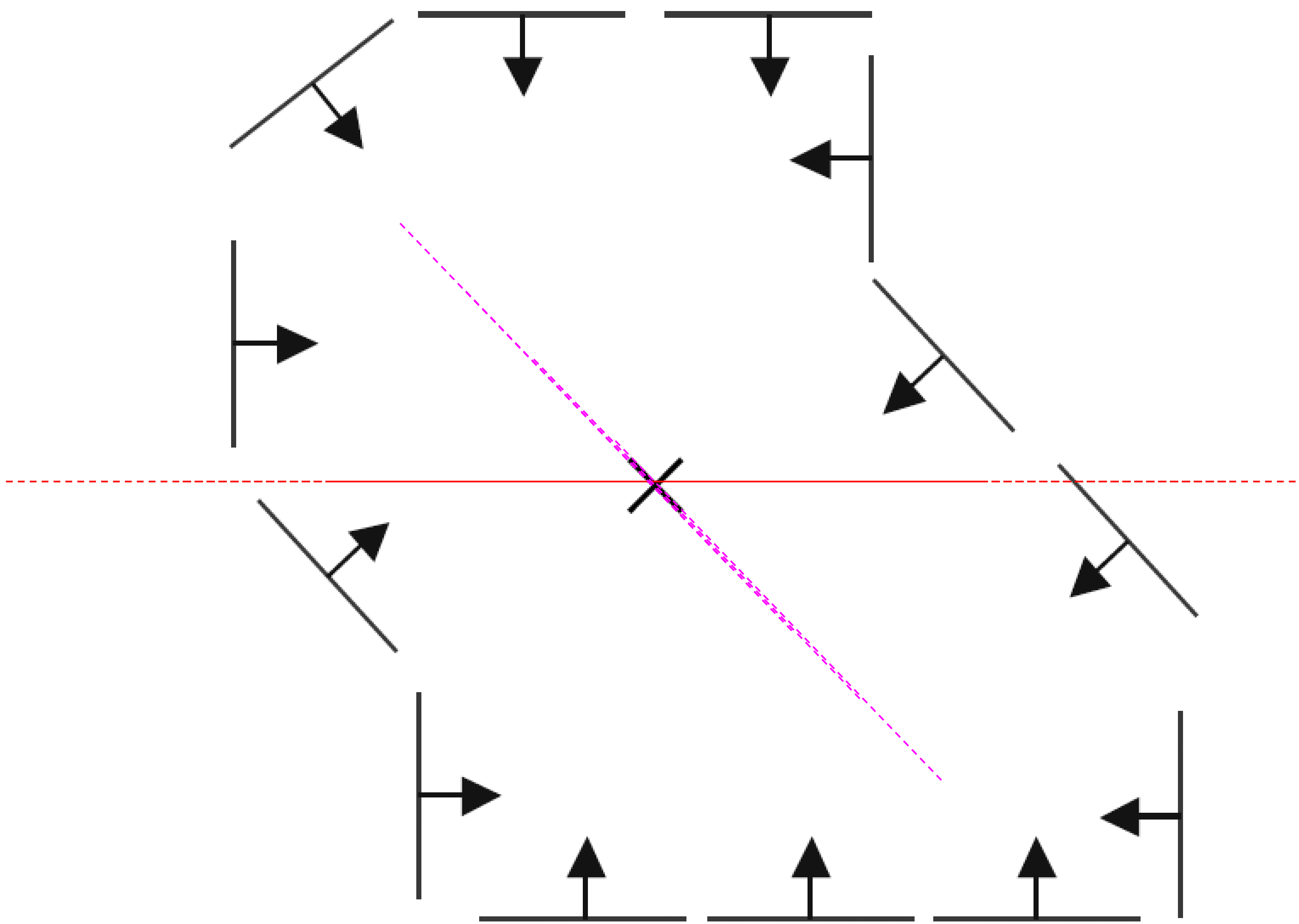
Example: Generalized Hough Transform

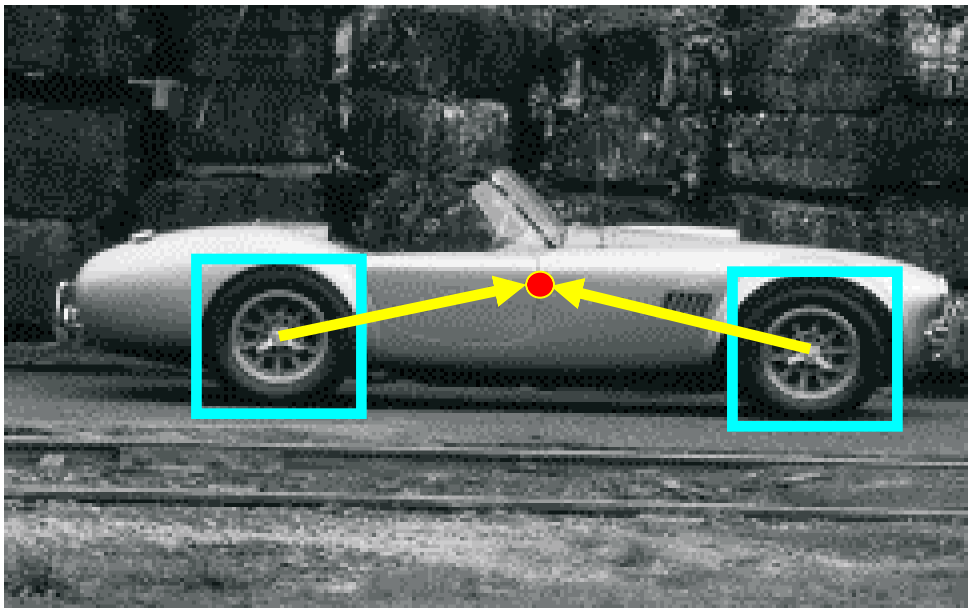


Votes for points with θ =

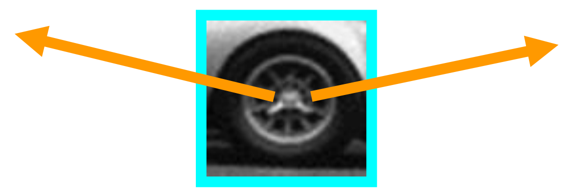
Slide credit: Svetlana Lazebnik

Application in Recognition

- Instead of indexing displacements by gradient orientation, index by "visual codeword".



Training image



Visual codeword with displacement vectors

B. Leibe, A. Leonardis, and B. Schiele, [Robust Object Detection with Interleaved Categorization and Segmentation](), International Journal of Computer Vision, Vol. 77(1-3), 2008.

Application in Recognition

- Instead of indexing displacements by gradient orientation, index by “visual codeword”.

Test image

- We’ll hear more about this in later lectures…

Topics of This Lecture

- Segmentation and grouping
  - Gestalt principles
  - Image Segmentation
- Segmentation as clustering
  - k-Means
  - Feature spaces
- Probabilistic clustering
  - Mixture of Gaussians, EM
- Model-free clustering
  - Mean-Shift clustering

Examples of Grouping in Vision

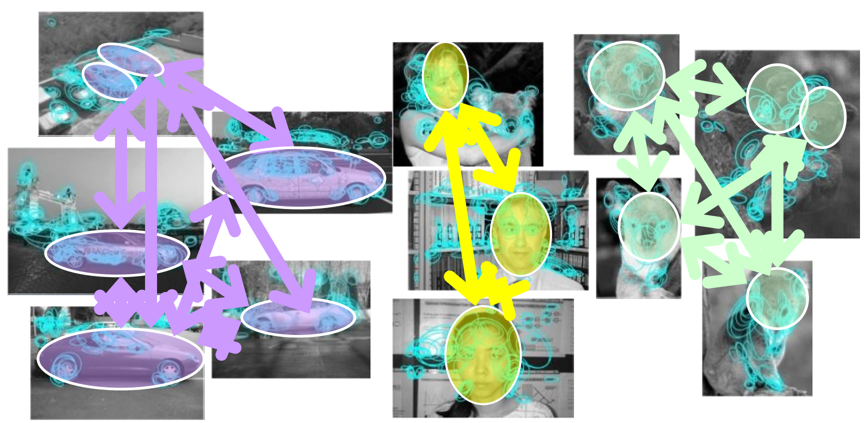
Determining image regions

Grouping video frames into shots

Figure-ground

What things should be grouped?

What cues indicate groups?



Object-level grouping

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Similarity

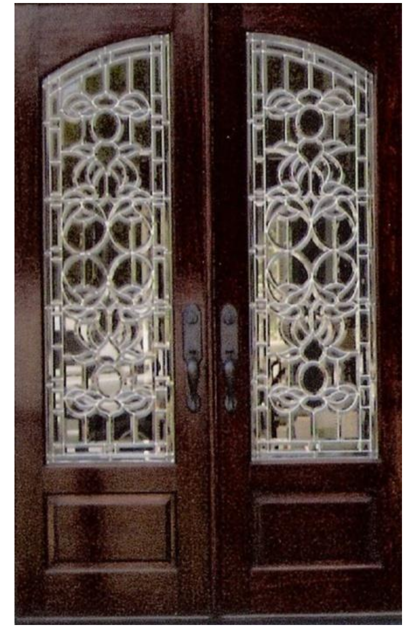
Slide credit: Kristen Grauman

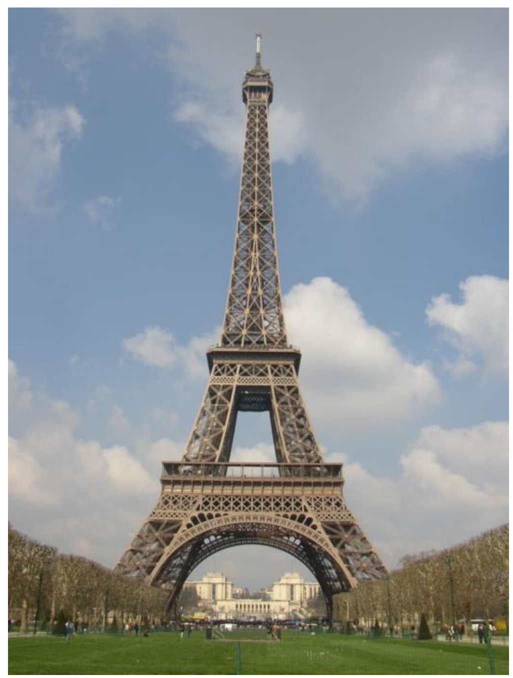
http://chicagoist.com/attachments/chicagoist_alicia/GEESE.jpg, http://wwwdelivery.superstock.com/WI/223/1532/PreviewComp/SuperStock_1532R-0831.jpg

Proximity

Slide credit: Kristen Grauman
http://www.capital.edu/Resources/Images/outside6_035.jpg

Symmetry





Slide credit: Kristen Grauman
http://seedmagazine.com/news/2006/10/beauty_is_in_the_processingtim.php

Common Fate

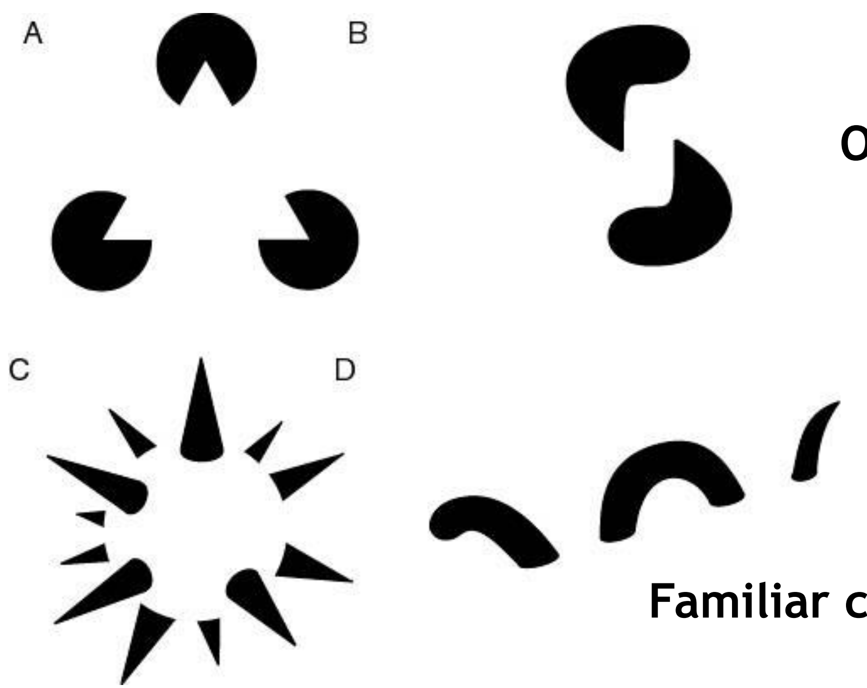
Image credit: Arthus-Bertrand (via F. Durand)

The Gestalt School

- Grouping is key to visual perception
- Elements in a collection can have properties that result from relationships
  - “The whole is greater than the sum of its parts”

Illusory/subjective contours

Occlusion



Familiar configuration

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

Slide credit: Svetlana Lazebnik

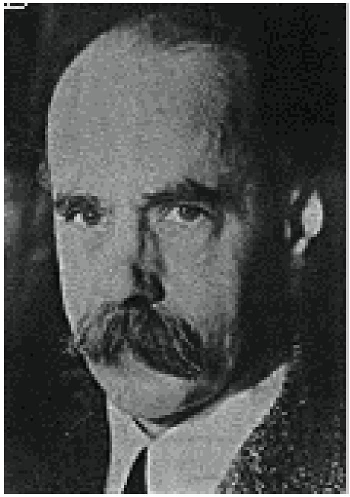
Image source: Steve Lehar

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)

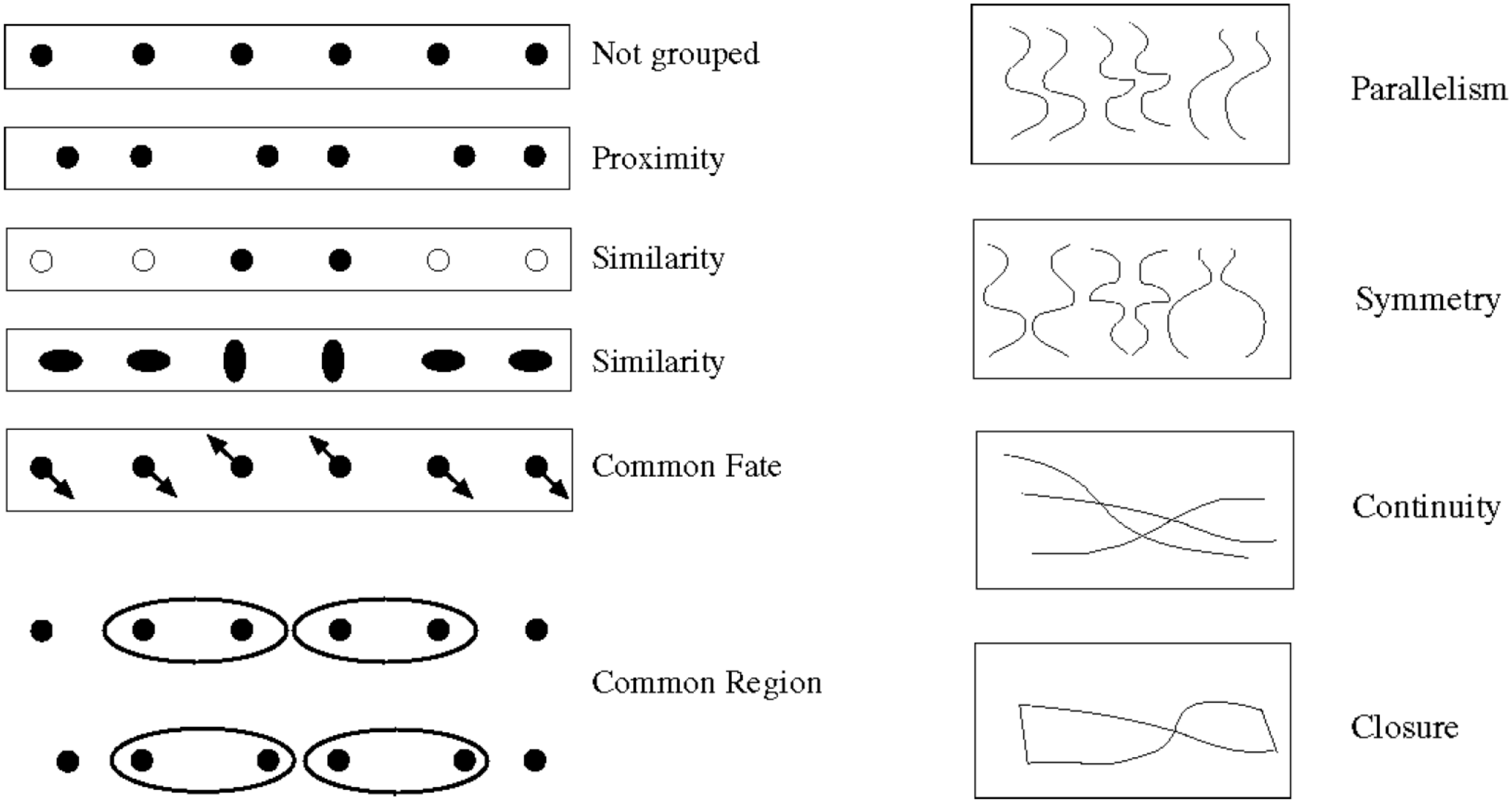
"I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees."

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

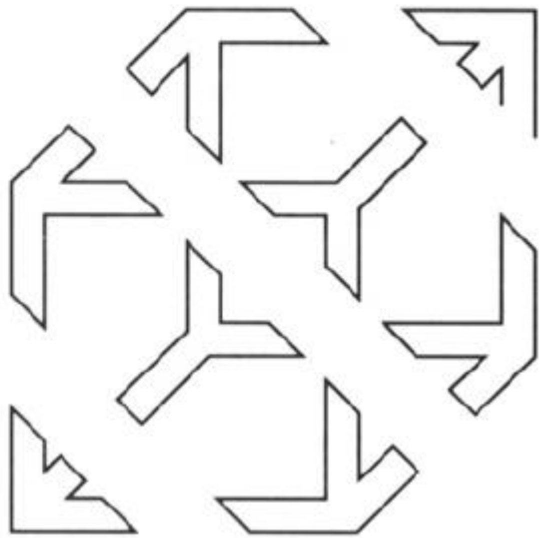
Gestalt Factors



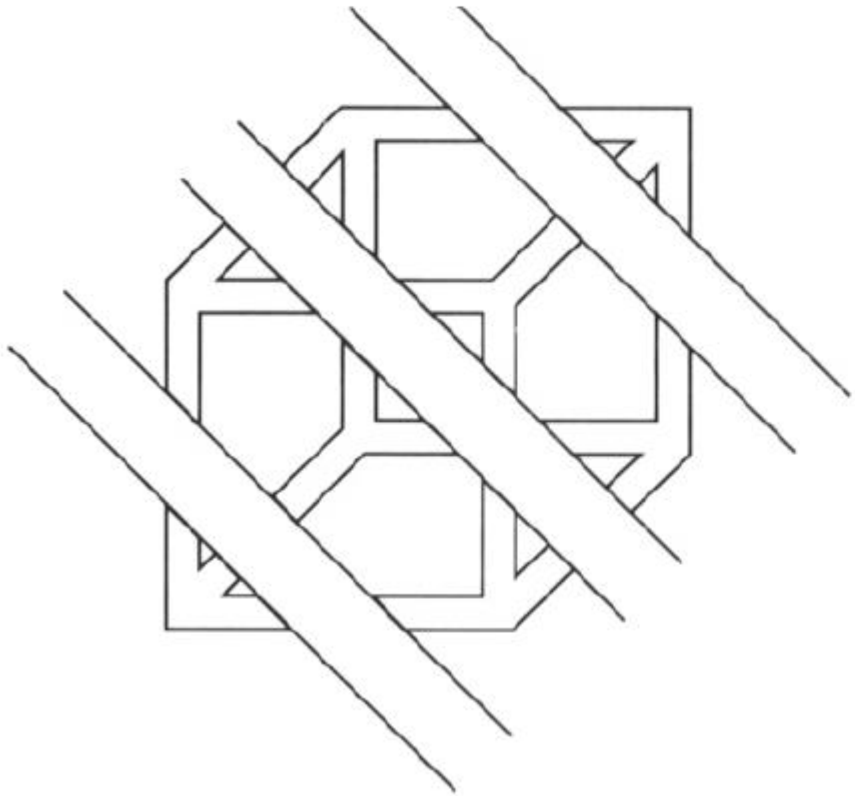
- **These factors make intuitive sense, but are very difficult to translate into algorithms.**

Image source: Forsyth & Ponce

Continuity through Occlusion Cues



Continuity through Occlusion Cues



Continuity, explanation by occlusion

Continuity through Occlusion Cues

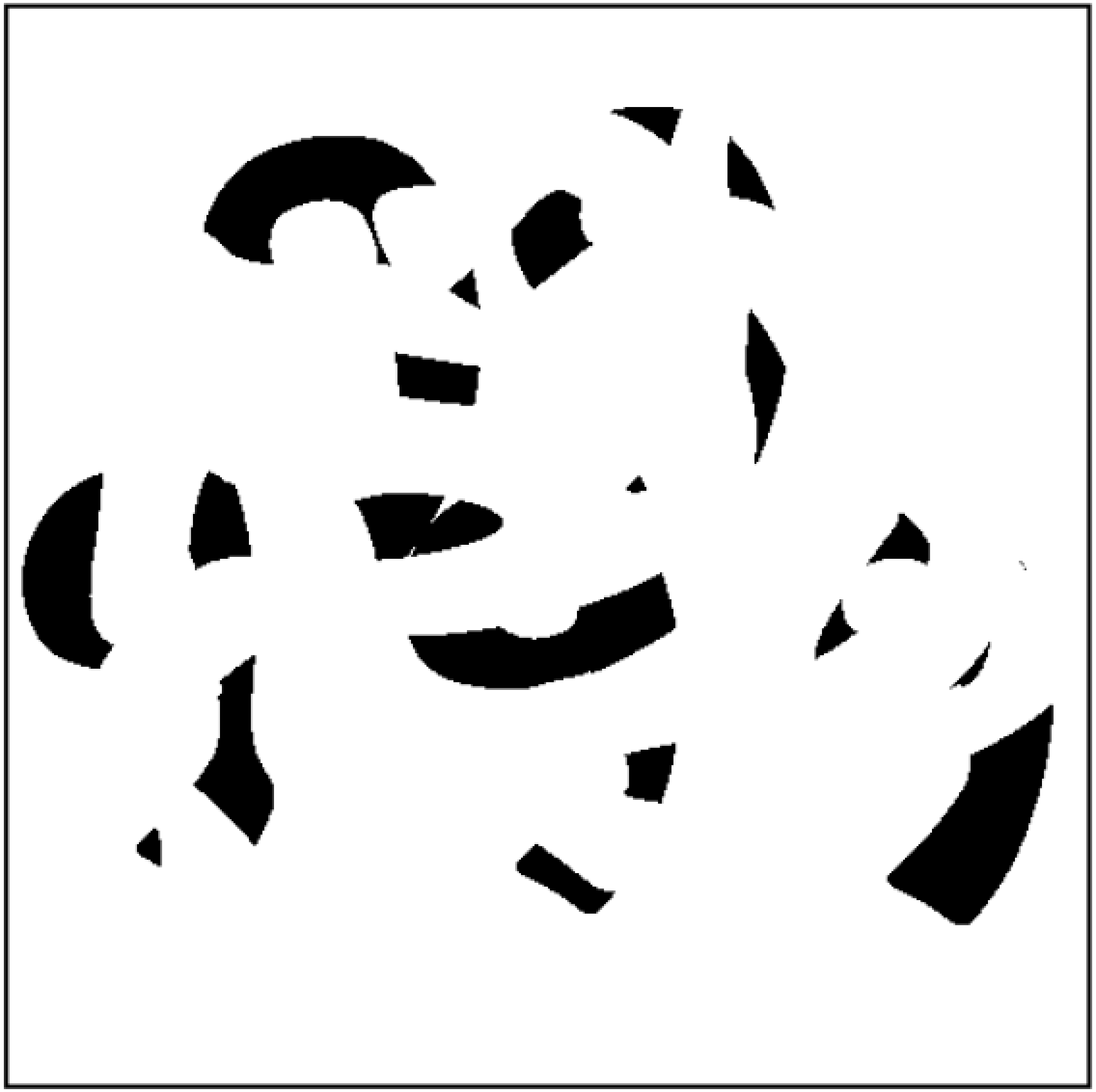


Image source: Forsyth & Ponce

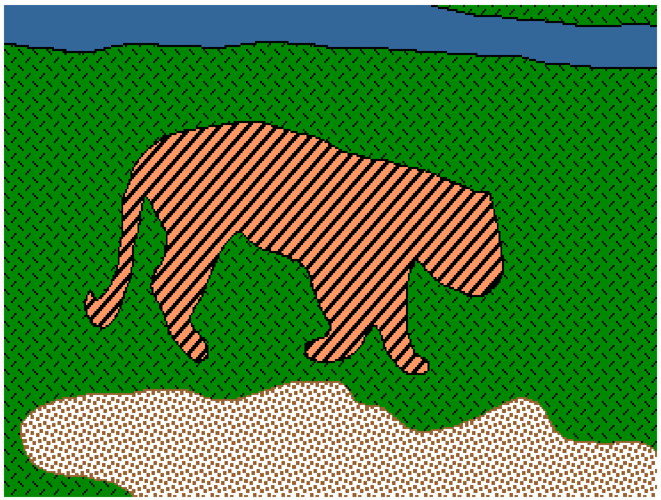
Continuity through Occlusion Cues

Image source: Forsyth & Ponce

The Ultimate Gestalt?

Image Segmentation

- **Goal: identify groups of pixels that go together**



Slide credit: Steve Seitz, Kristen Grauman

The Goals of Segmentation

- Separate image into coherent “objects”

Image **Human segmentation**

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  - Feature spaces
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  - Mixture of Gaussians, EM
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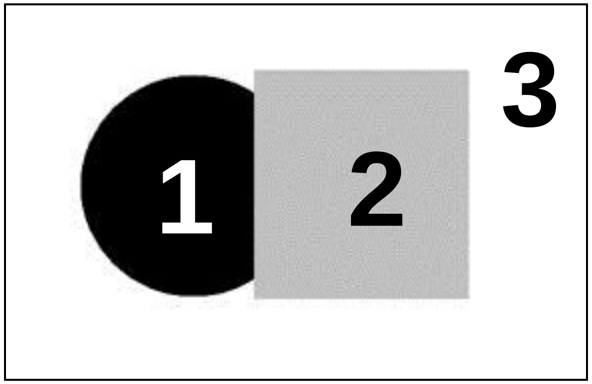
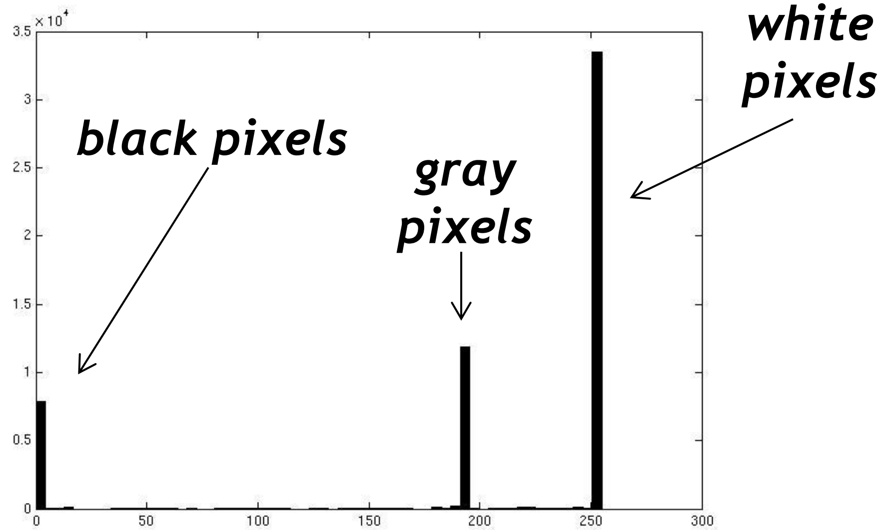
  - Mean-Shift clustering

Image Segmentation: Toy Example

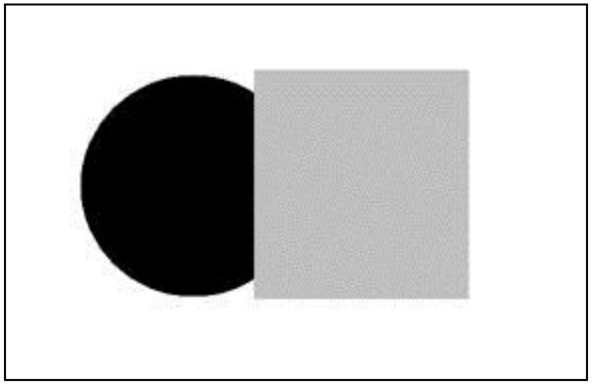


input image

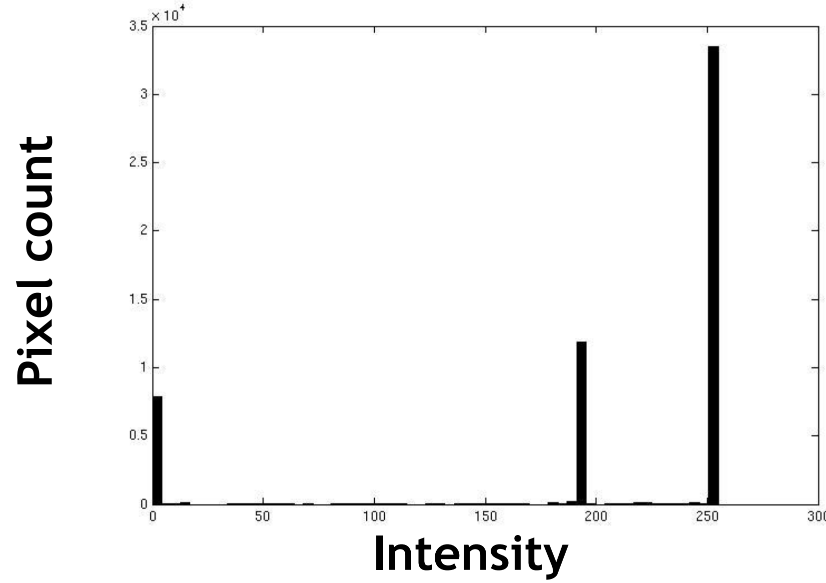


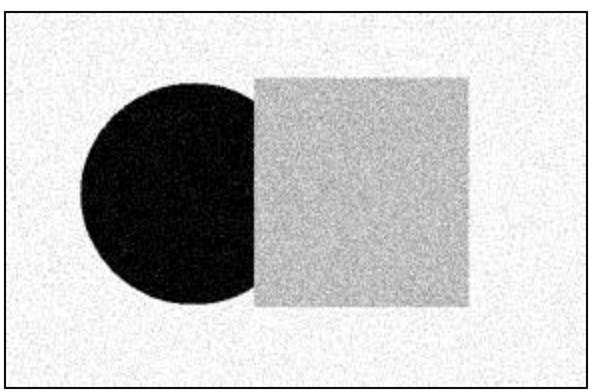
intensity

- 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?

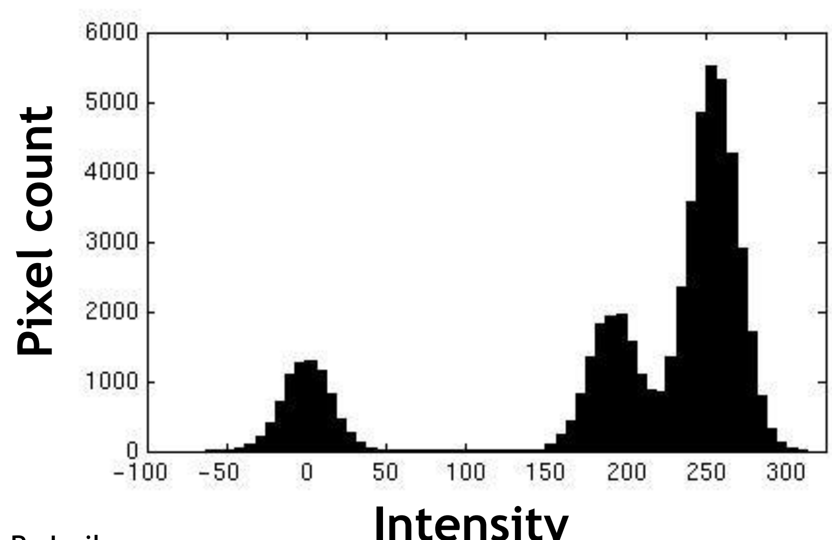


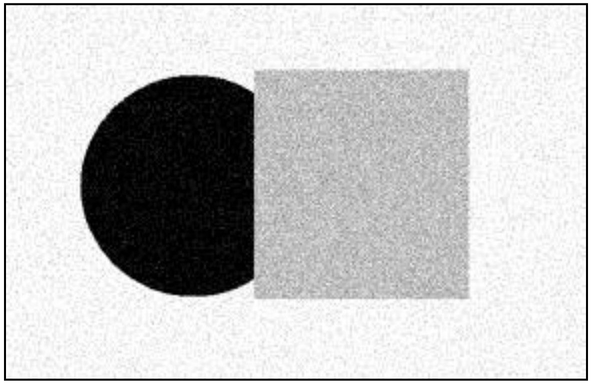
Input image



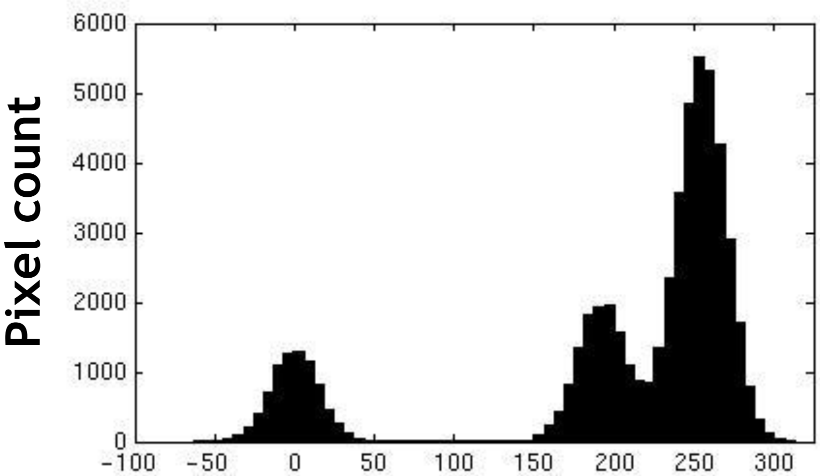


Input image

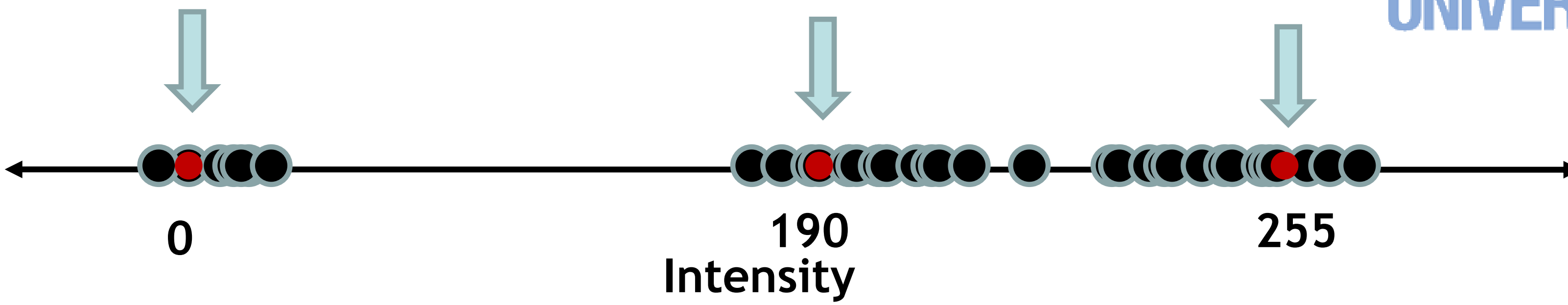


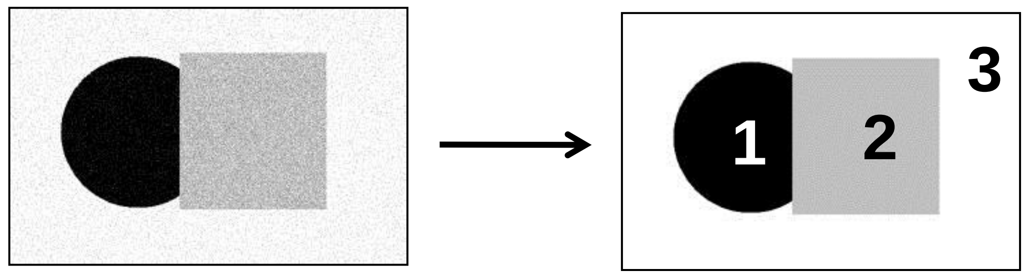


Input image



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



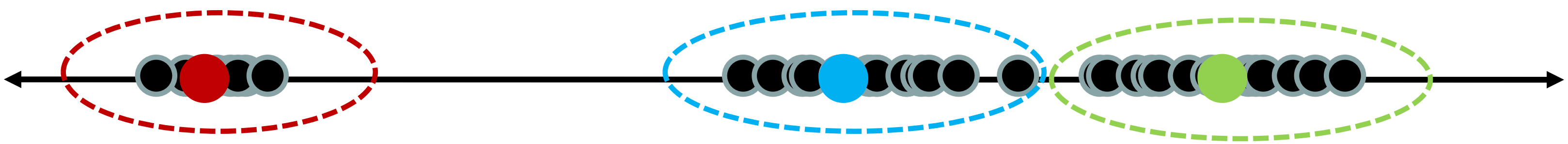


- Goal: choose three “centers” as the representative intensities, and label every pixel according to which of these centers it is nearest to.
- Best cluster centers are those that minimize SSD between all points and their nearest cluster center c_i:

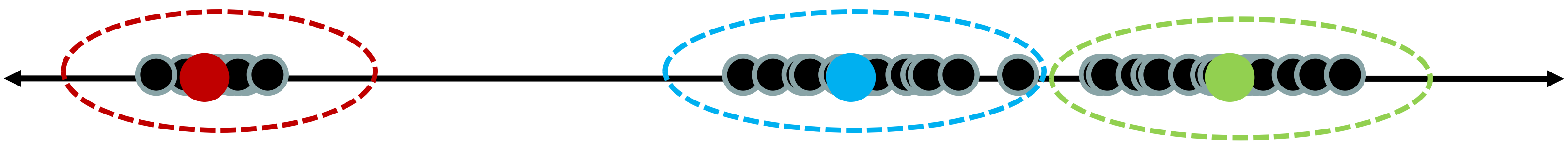
$$\sum_{\text{clusters } i} \; \sum_{\text{points p in cluster } i} ||p - c_i||^2$$

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:

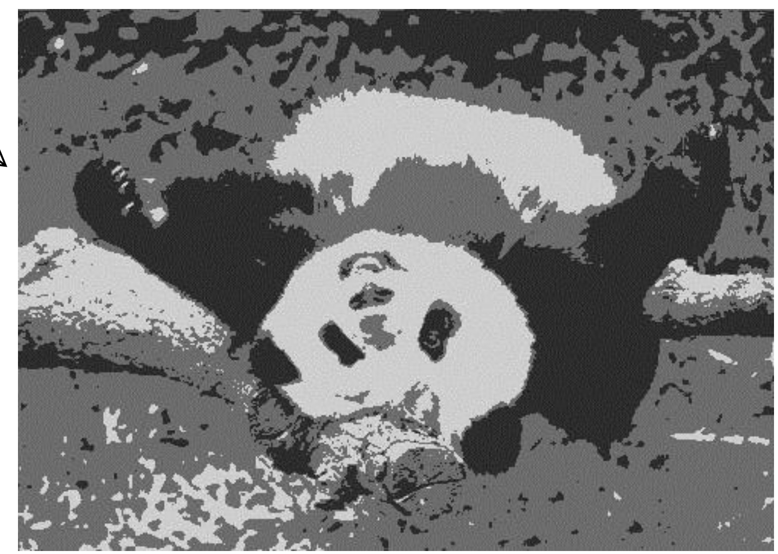
$$\sum_{\text{clusters } i} \sum_{\text{points p in cluster } i} ||p - c_i||^2$$

Slide credit: Steve Seitz

Segmentation as Clustering

K=2

K=3



```
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
```

K-Means Clustering

- **Java demo:**

http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/AppletKM.html

K-Means++

- Can we prevent arbitrarily bad local minima?

1. Randomly choose first center.
2. Pick new center with prob. proportional to $||p - c_i||^2$
   - (Contribution of *p* to total error)
3. Repeat until *k* centers.

- Expected error = *O*(log *k*) * optimal

Arthur & Vassilvitskii 2007

Feature Space

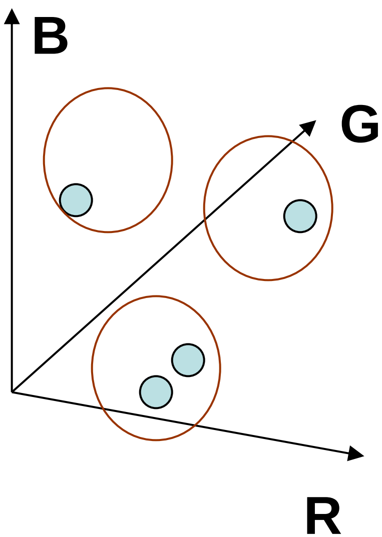
- Depending on what we choose as the *feature space*, we can group pixels in different ways.

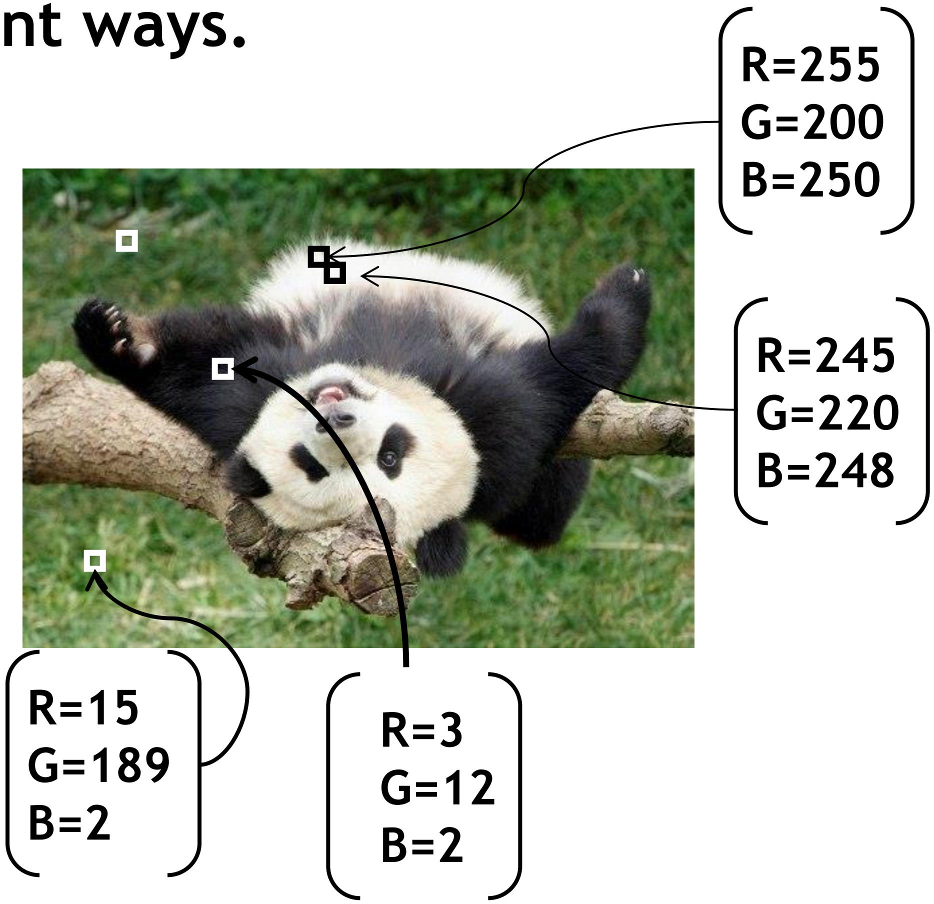
- Grouping pixels based on intensity similarity

- Feature space: intensity value (1D)

Feature Space

- Depending on what we choose as the *feature space*, we can group pixels in different ways.
- Grouping pixels based on color similarity



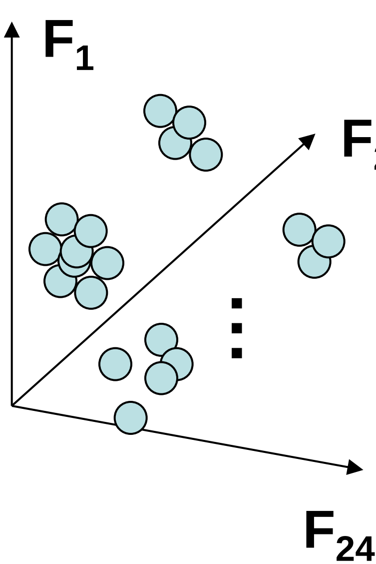


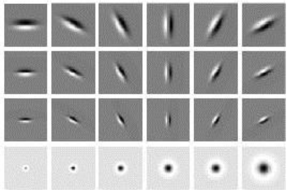
- Feature space: color value (3D)

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





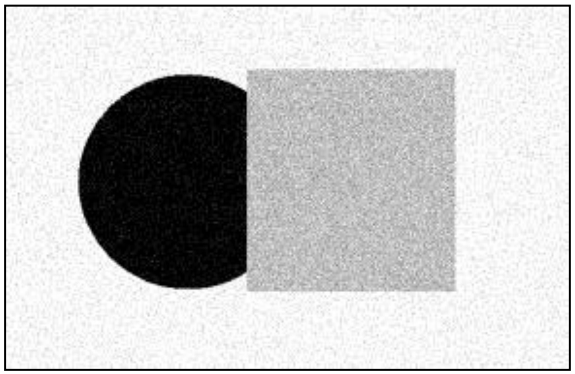
Filter bank of 24 filters

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

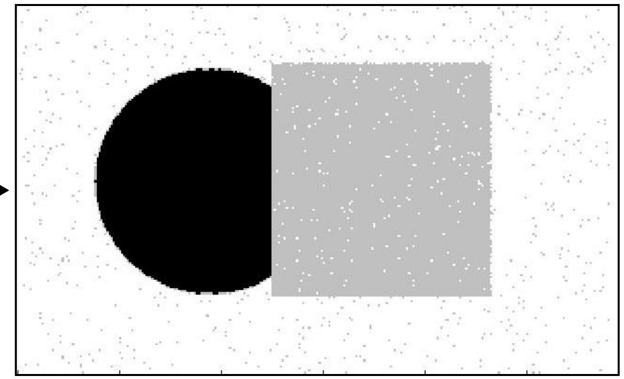
Slide credit: Kristen Grauman

Smoothing Out Cluster Assignments

- Assigning a cluster label per pixel may yield outliers:

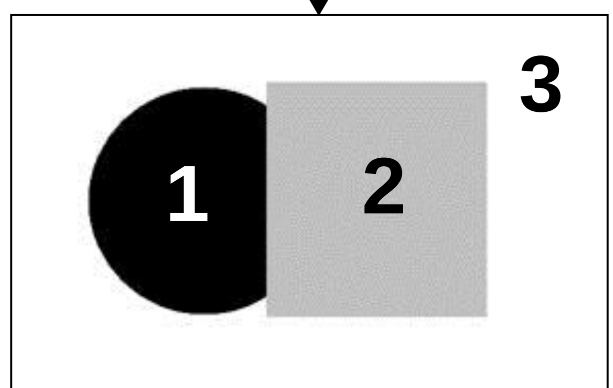


Original



Labeled by cluster center's intensity

?

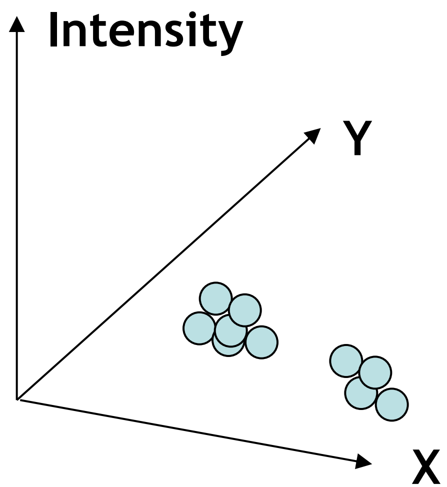


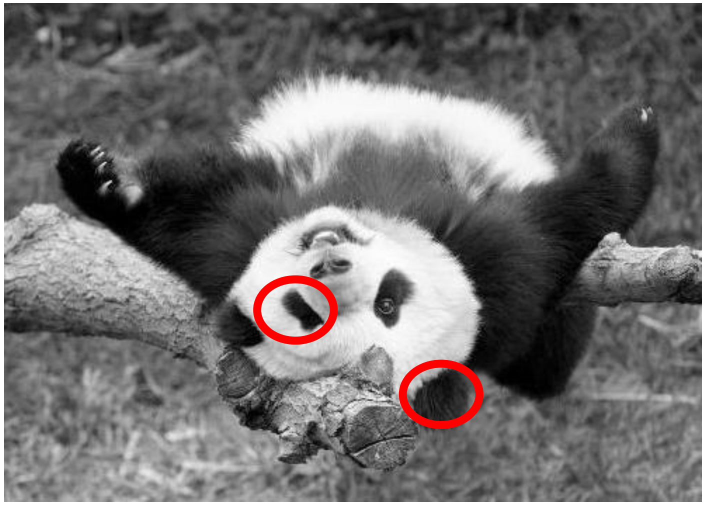
- How can we ensure they are spatially smooth?

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





⇒ Simple way to encode both *similarity* and *proximity*.

Slide credit: Kristen Grauman

K-Means Clustering Results

- K-means clustering based on intensity or color is essentially vector quantization of the image attributes
  - Clusters don't have to be spatially coherent

Image

Intensity-based clusters

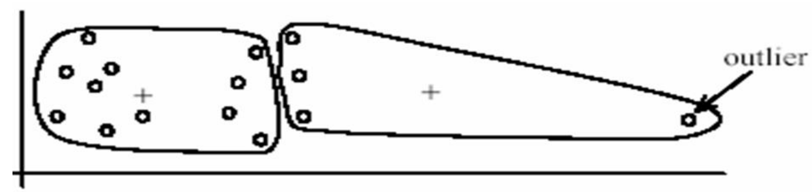
Color-based clusters

K-Means Clustering Results

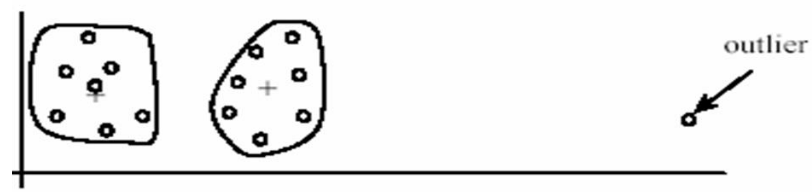
- K-means clustering based on intensity or color is essentially vector quantization of the image attributes
  - Clusters don't have to be spatially coherent
- Clustering based on (r,g,b,x,y) values enforces more spatial coherence

Summary K-Means

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

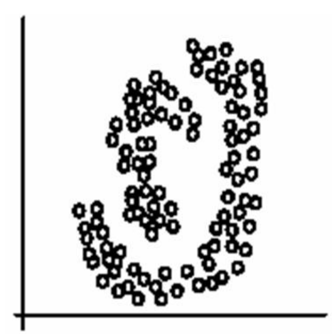


(A): Undesirable clusters

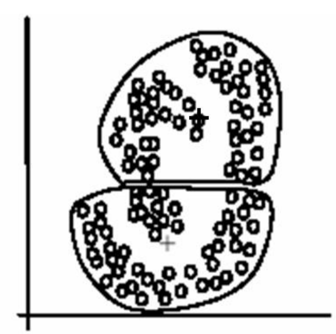


(B): Ideal clusters

- **Cons/issues**
  - Setting k?
  - Sensitive to initial centers
  - Sensitive to outliers
  - Detects spherical clusters only
  - Assuming means can be computed



(A): Two natural clusters



(B): *k*-means clusters

Topics of This Lecture

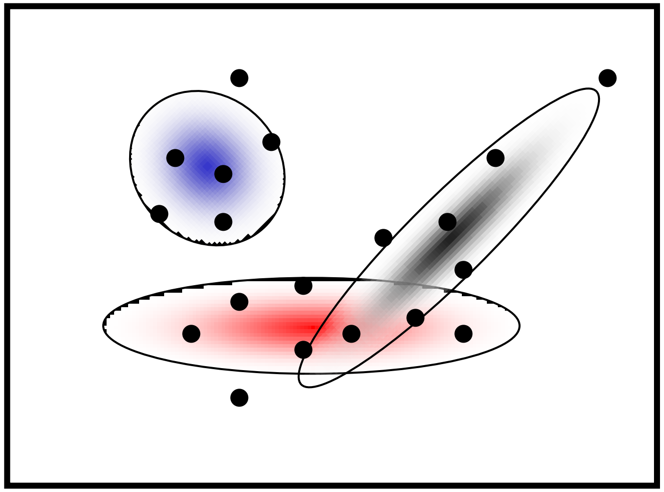
- Segmentation and grouping
  - Gestalt principles
  - Image Segmentation
- Segmentation as clustering
  - k-Means
  - Feature spaces
- **Probabilistic clustering**
  - **Mixture of Gaussians, EM**
- Model-free clustering
  - Mean-Shift clustering

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.

- Basic idea
  - Instead of treating the data as a bunch of points, assume that they are all generated by sampling a continuous function.
  - This function is called a generative model.
  - Defined by a vector of parameters θ

Mixture of Gaussians



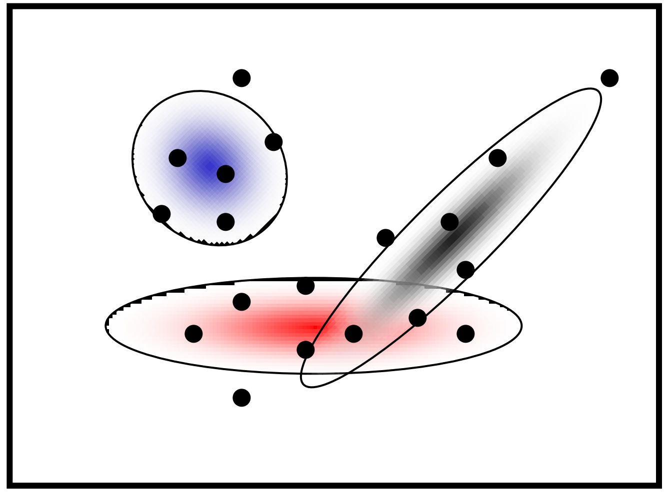
- **One generative model is a mixture of Gaussians (MoG)**
  - K **Gaussian blobs with means** $\boldsymbol{\mu}_j$, **cov. matrices** $\boldsymbol{\Sigma}_j$, **dim.** D

$$p(\mathbf{x}|\theta_j) = \frac{1}{(2\pi)^{D/2}|\boldsymbol{\Sigma}_j|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_j)^{\mathrm{T}}\boldsymbol{\Sigma}_j^{-1}(\mathbf{x}-\boldsymbol{\mu}_j)\right\}$$

  - **Blob** j **is selected with probability** π_j
  - **The likelihood of observing** $\mathbf{x}$ **is a weighted mixture of Gaussians**

$$p(\mathbf{x}|\theta) = \sum_{j=1}^{K} \pi_j p(\mathbf{x}|\theta_j) \qquad \theta = (\pi_1, \boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1, \ldots, \pi_M, \boldsymbol{\mu}_M, \boldsymbol{\Sigma}_M)$$

Expectation Maximization (EM)



- **Goal**
  - Find blob parameters θ that maximize the likelihood function:

$$p(data|\theta) = \prod_{n=1}^{N} p(\mathbf{x}_n|\theta)$$

- **Approach:**
  1. E-step: given current guess of blobs, compute ownership of each point
  2. M-step: given ownership probabilities, update blobs to maximize likelihood function
  3. Repeat until convergence

see lecture Machine Learning!

EM Algorithm

- Expectation-Maximization (EM) Algorithm
  - **E-Step**: softly assign samples to mixture components

$$\gamma_j(\mathbf{x}_n) \leftarrow \frac{\pi_j \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}{\sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)} \qquad \forall j = 1, \ldots, K, \quad n = 1, \ldots, N$$

  - **M-Step**: re-estimate the parameters (separately for each mixture component) based on the soft assignments

$$\hat{N}_j \leftarrow \sum_{n=1}^{N} \gamma_j(\mathbf{x}_n)$$ = soft number of samples labeled j

$$\hat{\pi}_j^{\text{new}} \leftarrow \frac{\hat{N}_j}{N}$$

$$\hat{\boldsymbol{\mu}}_j^{\text{new}} \leftarrow \frac{1}{\hat{N}_j} \sum_{n=1}^{N} \gamma_j(\mathbf{x}_n)\mathbf{x}_n$$

$$\hat{\boldsymbol{\Sigma}}_j^{\text{new}} \leftarrow \frac{1}{\hat{N}_j} \sum_{n=1}^{N} \gamma_j(\mathbf{x}_n)(\mathbf{x}_n - \hat{\boldsymbol{\mu}}_j^{\text{new}})(\mathbf{x}_n - \hat{\boldsymbol{\mu}}_j^{\text{new}})^{\mathrm{T}}$$

Applications of EM

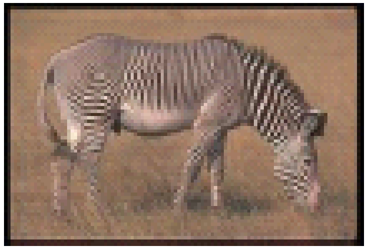
- Turns out this is useful for all sorts of problems
  - Any clustering problem
  - Any model estimation problem
  - Missing data problems
  - Finding outliers
  - Segmentation problems
    - Segmentation based on color
    - Segmentation based on motion
    - Foreground/background separation
  - ...

- EM demo
  - http://lcn.epfl.ch/tutorial/english/gaussian/html/index.html

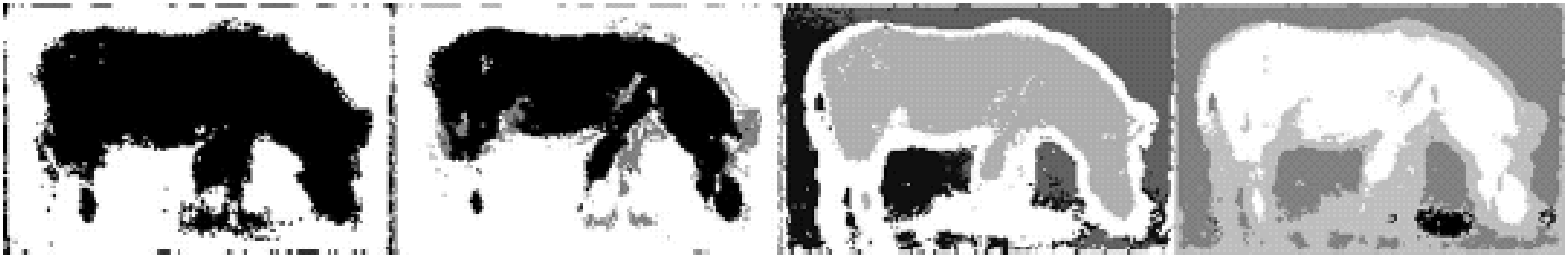
Slide credit: Steve Seitz

Segmentation with EM

Original image



EM segmentation results



k=2 k=3 k=4 k=5

Image source: Serge Belongie

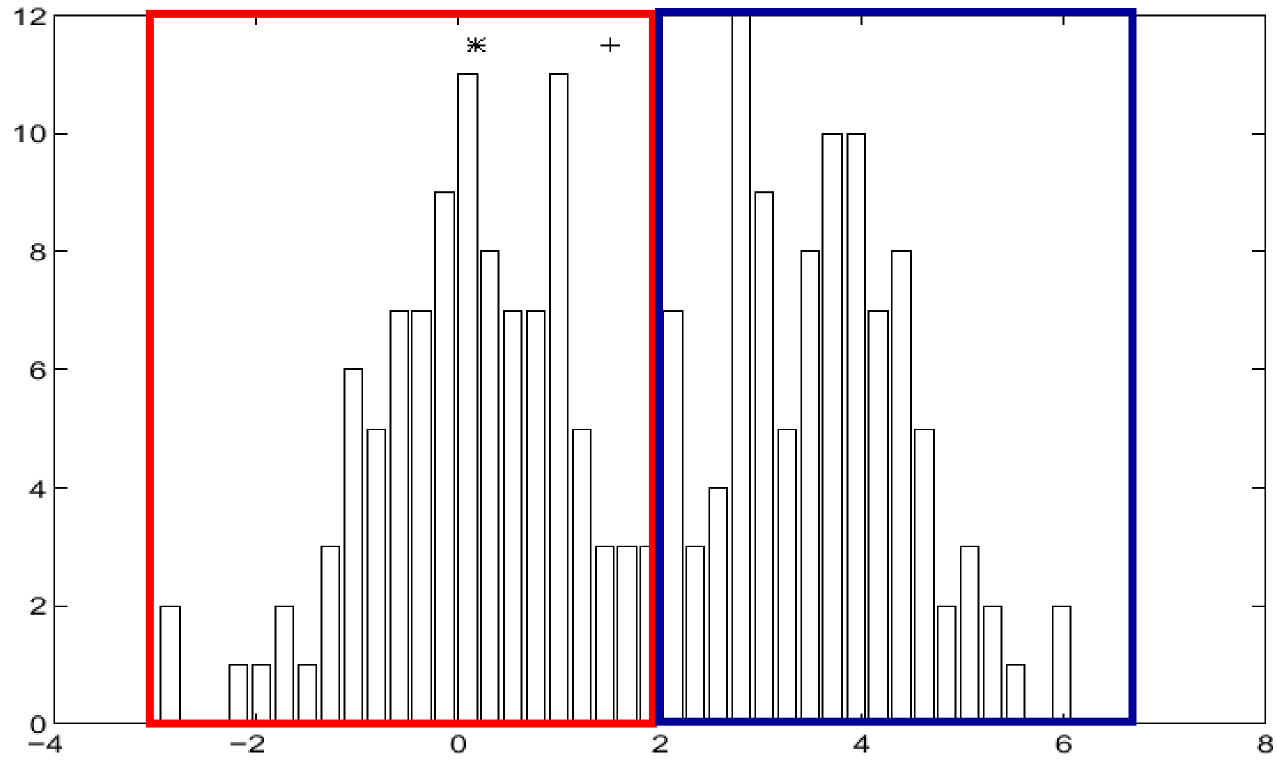
Summary: Mixtures of Gaussians, EM

- **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

Topics of This Lecture

- Segmentation and grouping
  - Gestalt principles
  - Image segmentation
- Segmentation as clustering
  - k-Means
  - Feature spaces
- Probabilistic clustering
  - Mixture of Gaussians, EM
- **Model-free clustering**
  - **Mean-Shift clustering**

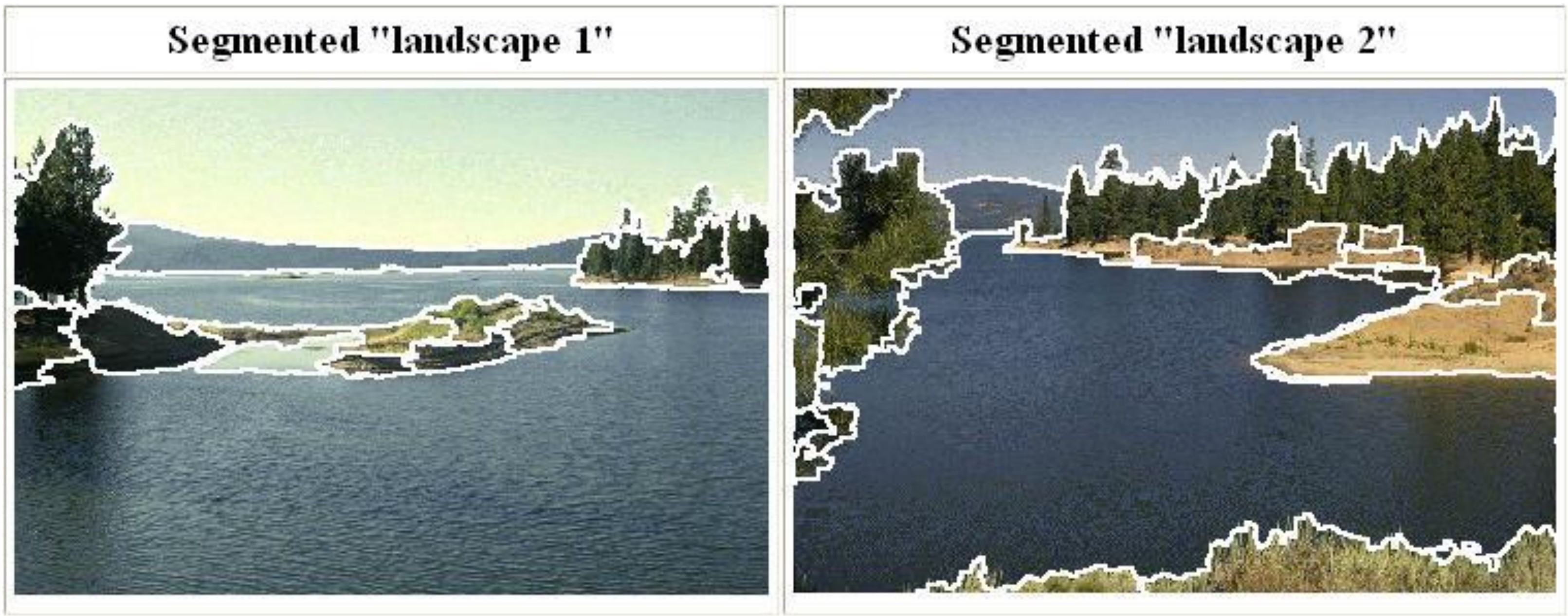
Finding Modes in a Histogram



- How many modes are there?
  - *Mode* = local maximum of the density of a given distribution
  - Easy to see, hard to compute

Mean-Shift Segmentation

- An advanced and versatile technique for clustering-based segmentation

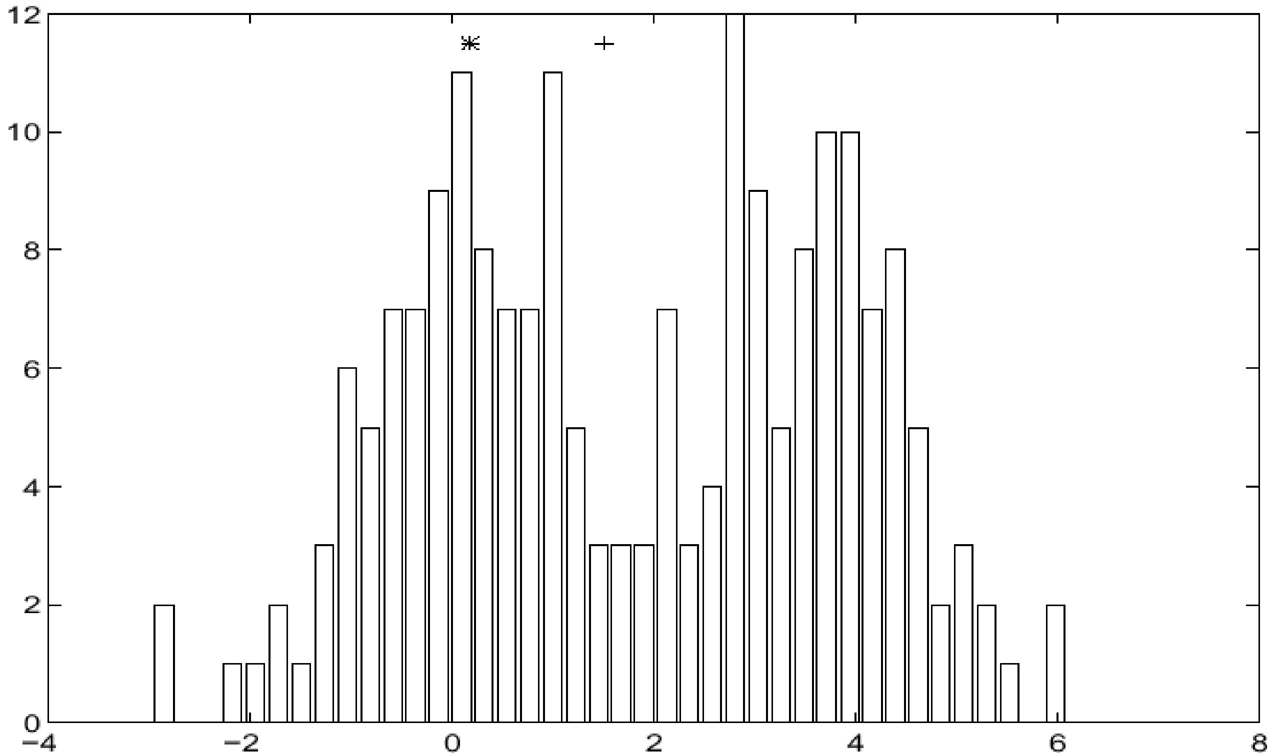


http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

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

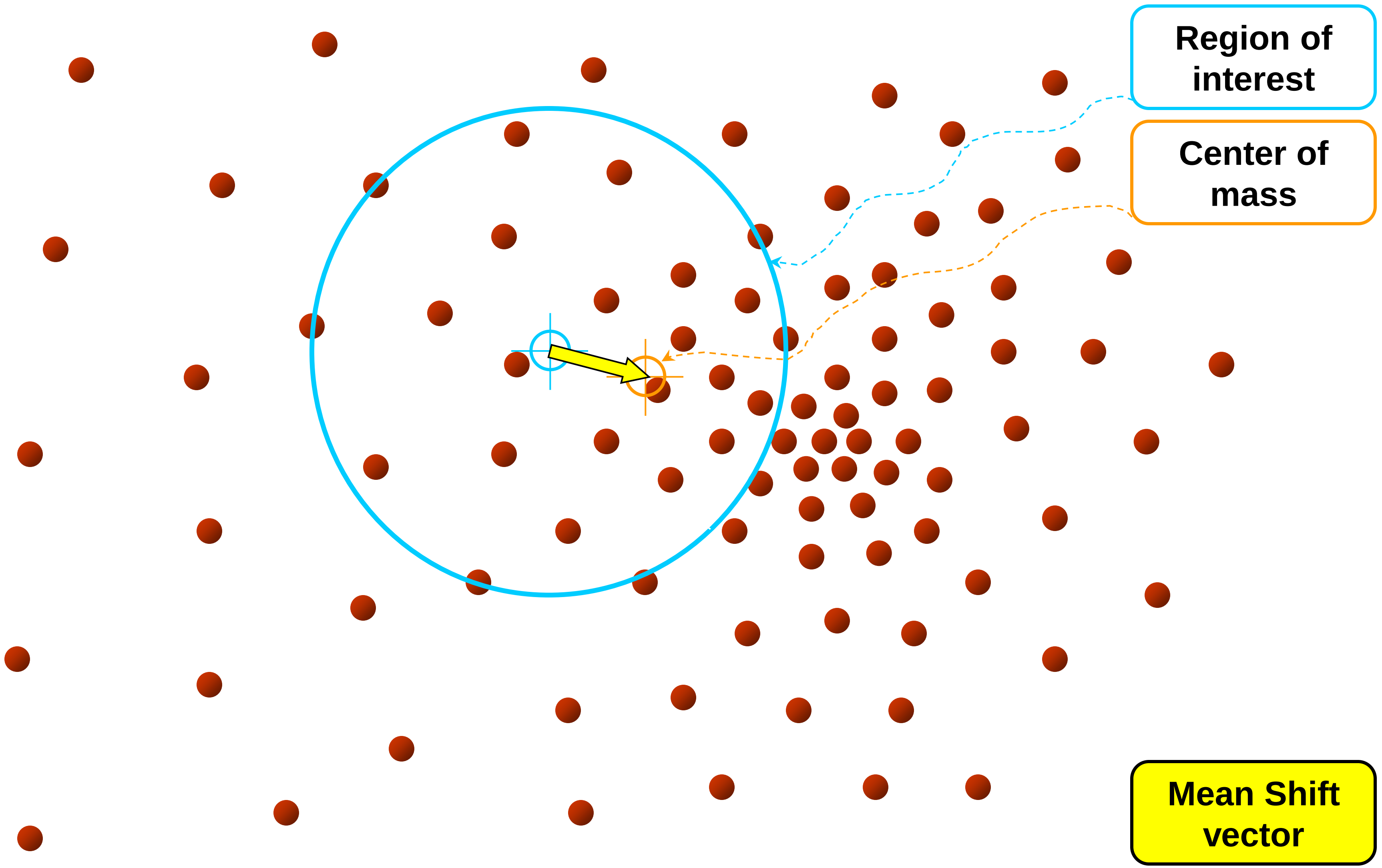
Slide credit: Svetlana Lazebnik

Mean-Shift Algorithm



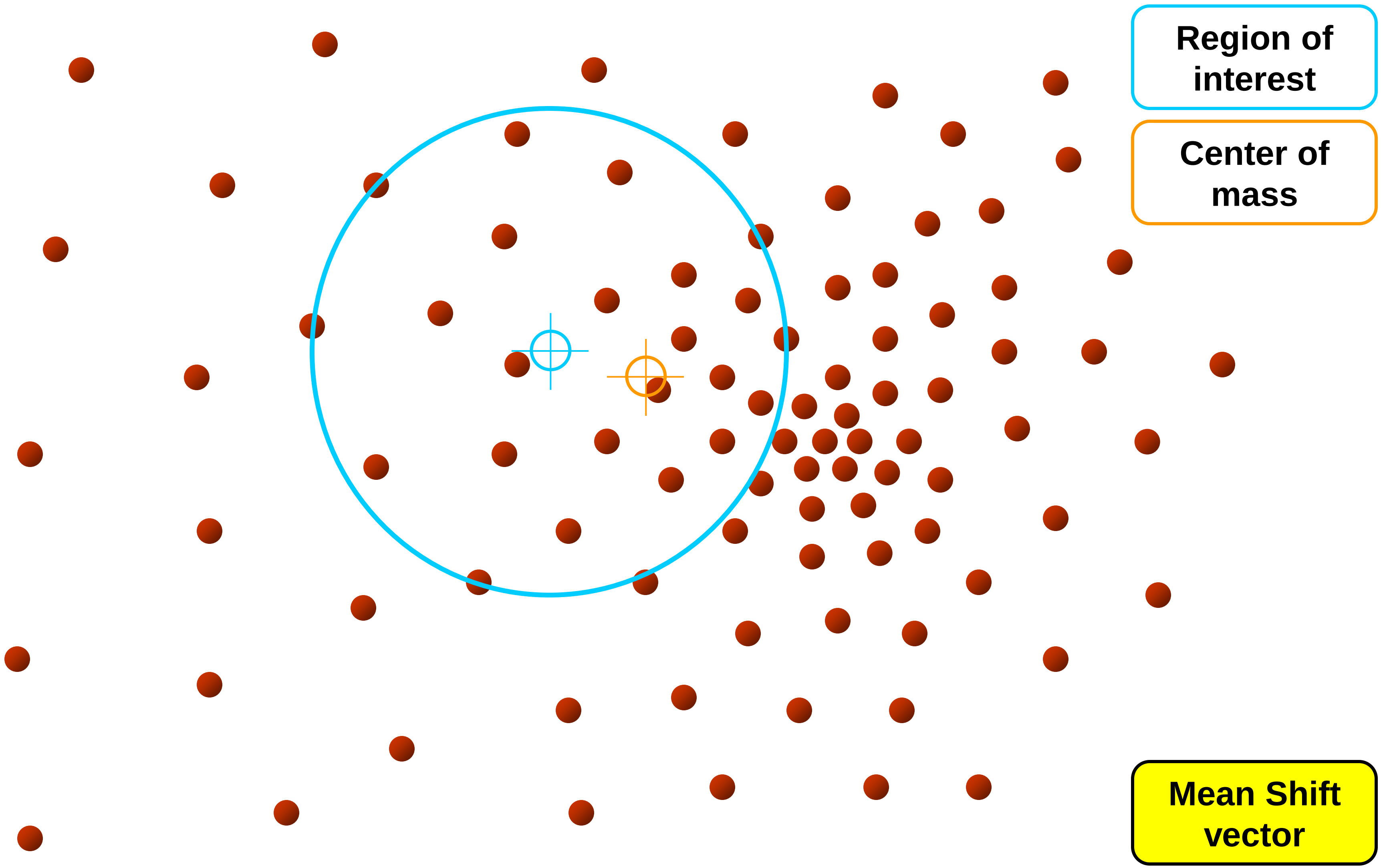
- **Iterative Mode Search**
  1. Initialize random seed, and window W
  2. Calculate center of gravity (the "mean") of W: $\sum_{x \in W} x H(x)$
  3. Shift the search window to the mean
  4. Repeat Step 2 until convergence

Mean-Shift



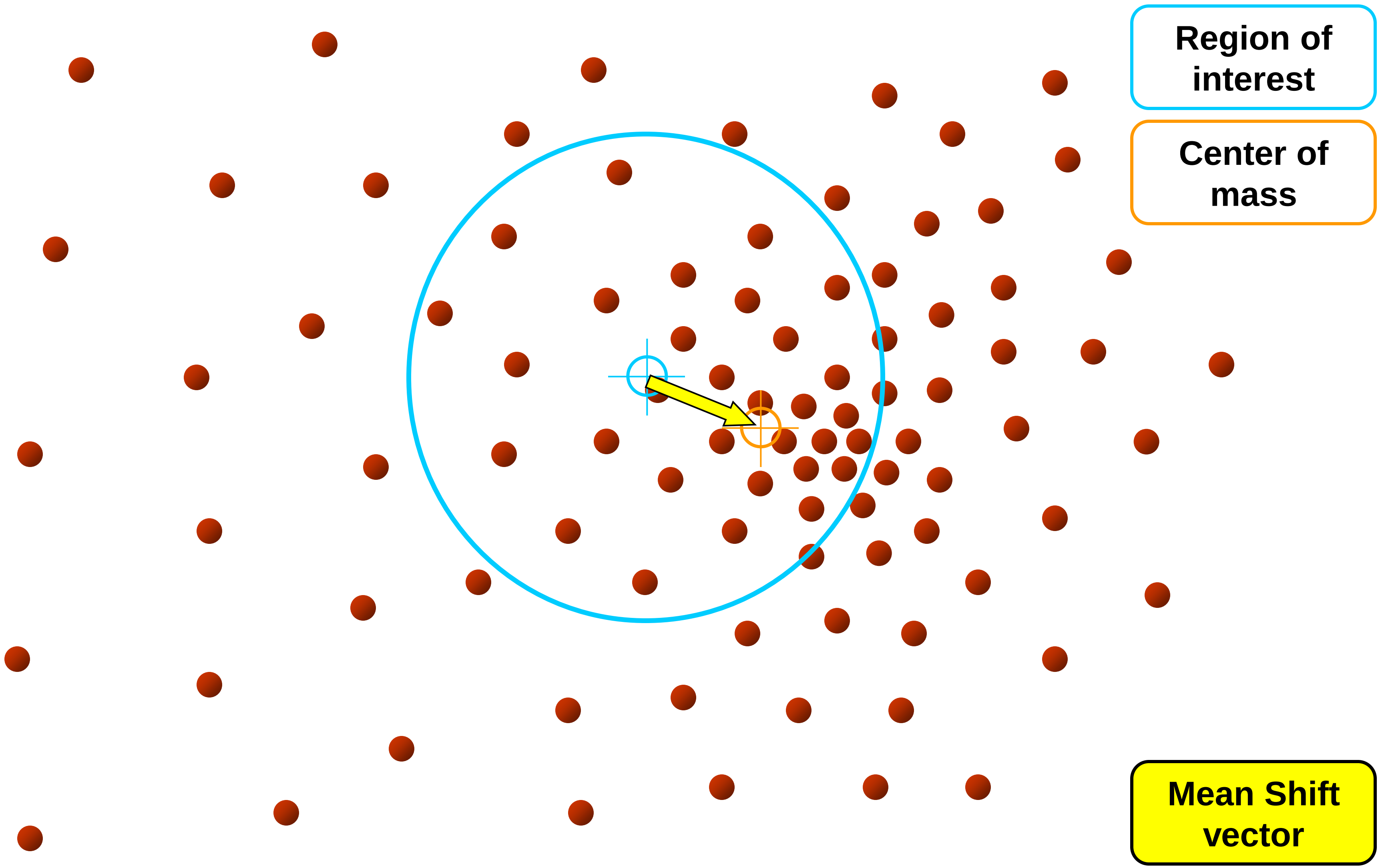
Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



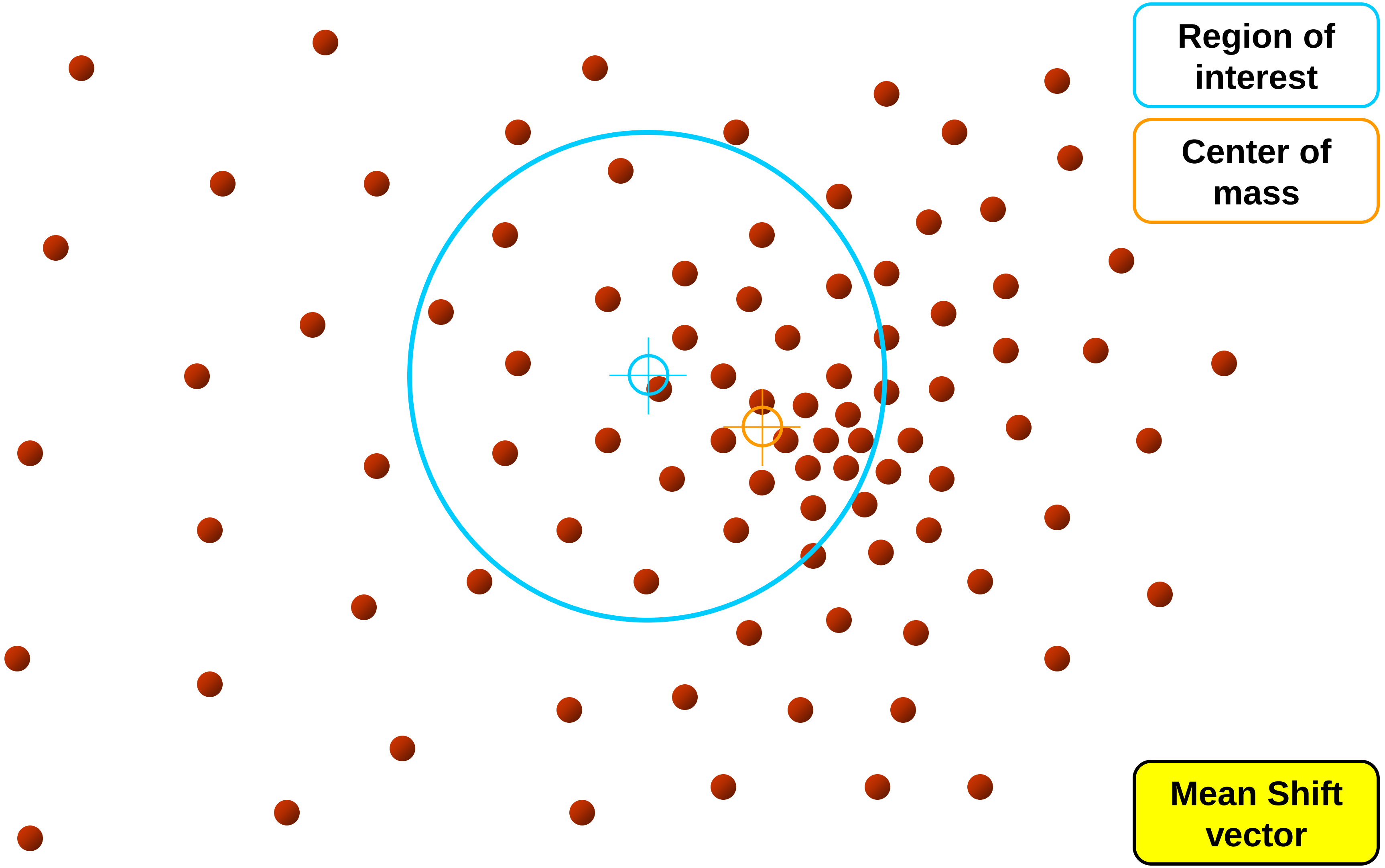
Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



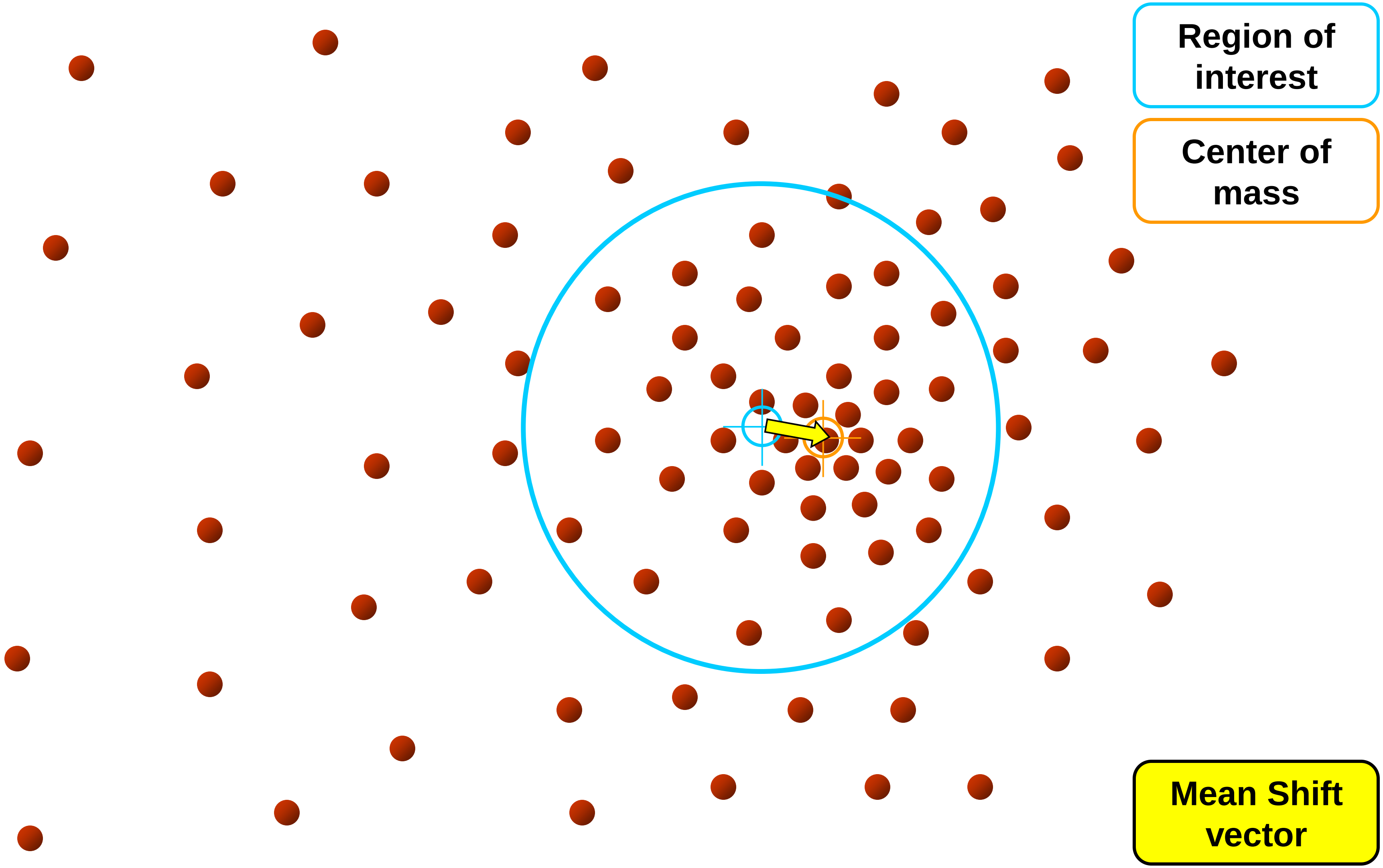
Slide by Y. Ukrainitz & B. Sarel

Mean-Shift

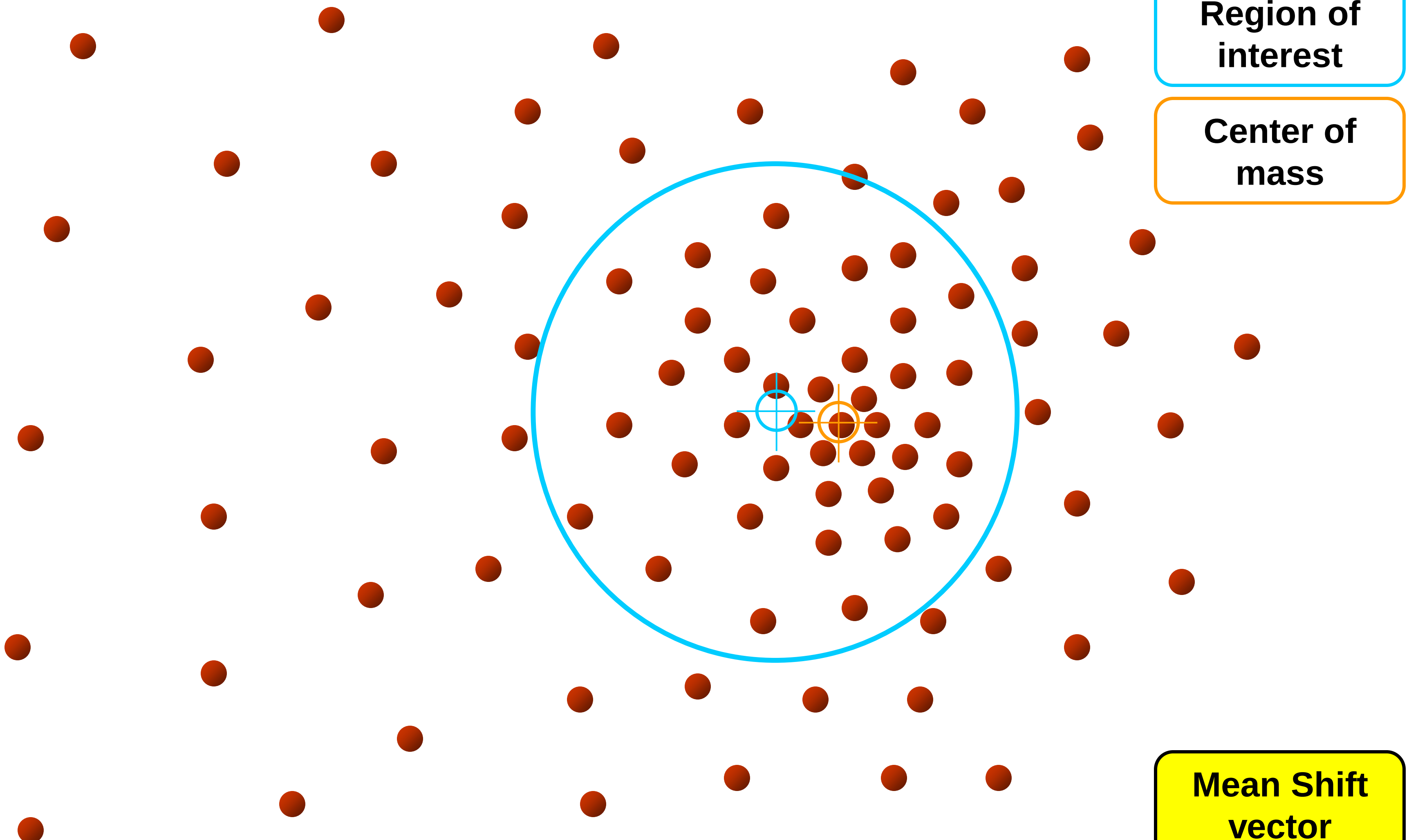


Slide by Y. Ukrainitz & B. Sarel

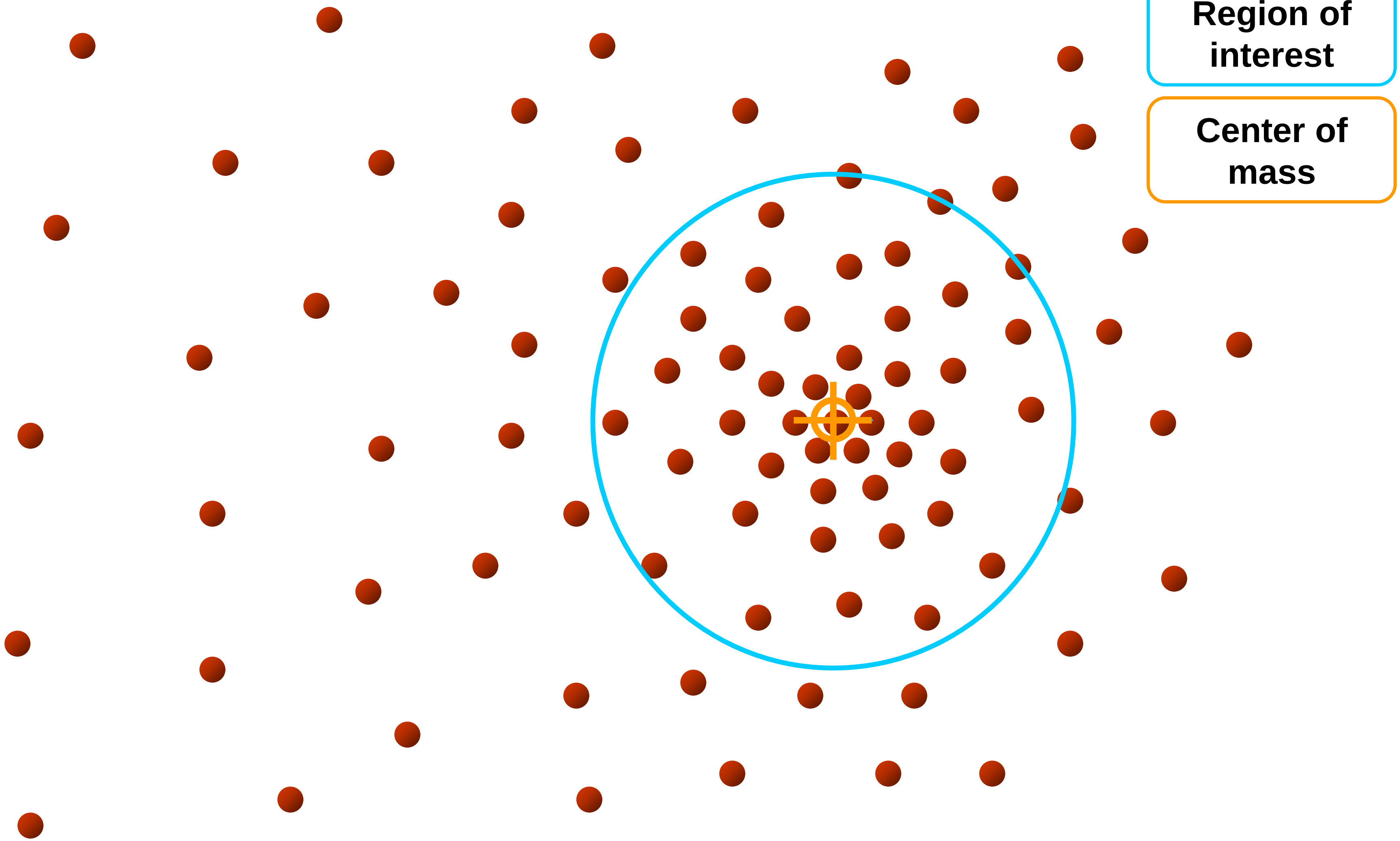
Mean-Shift



Mean-Shift

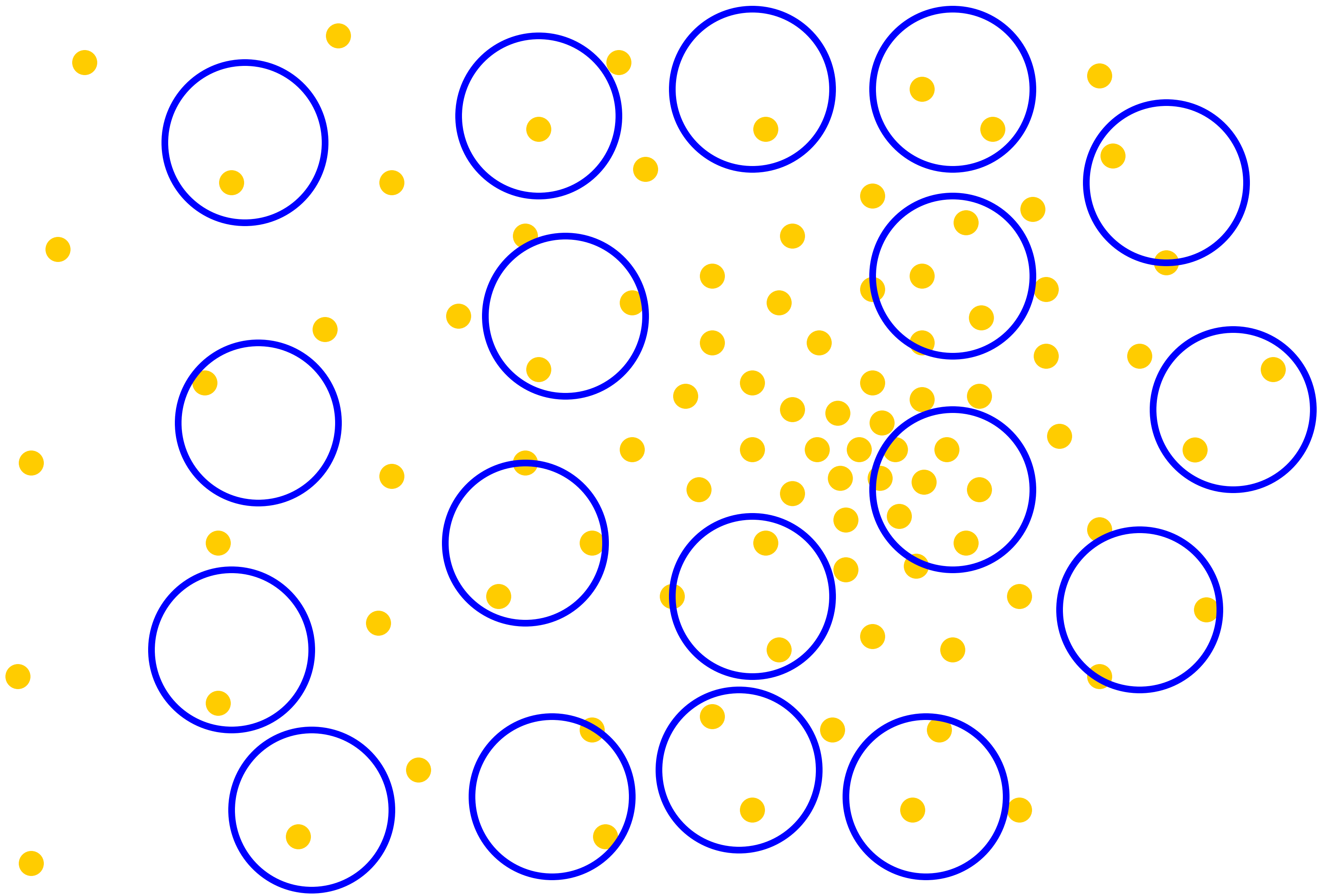


Mean-Shift



Slide by Y. Ukrainitz & B. Sarel

Real Modality Analysis

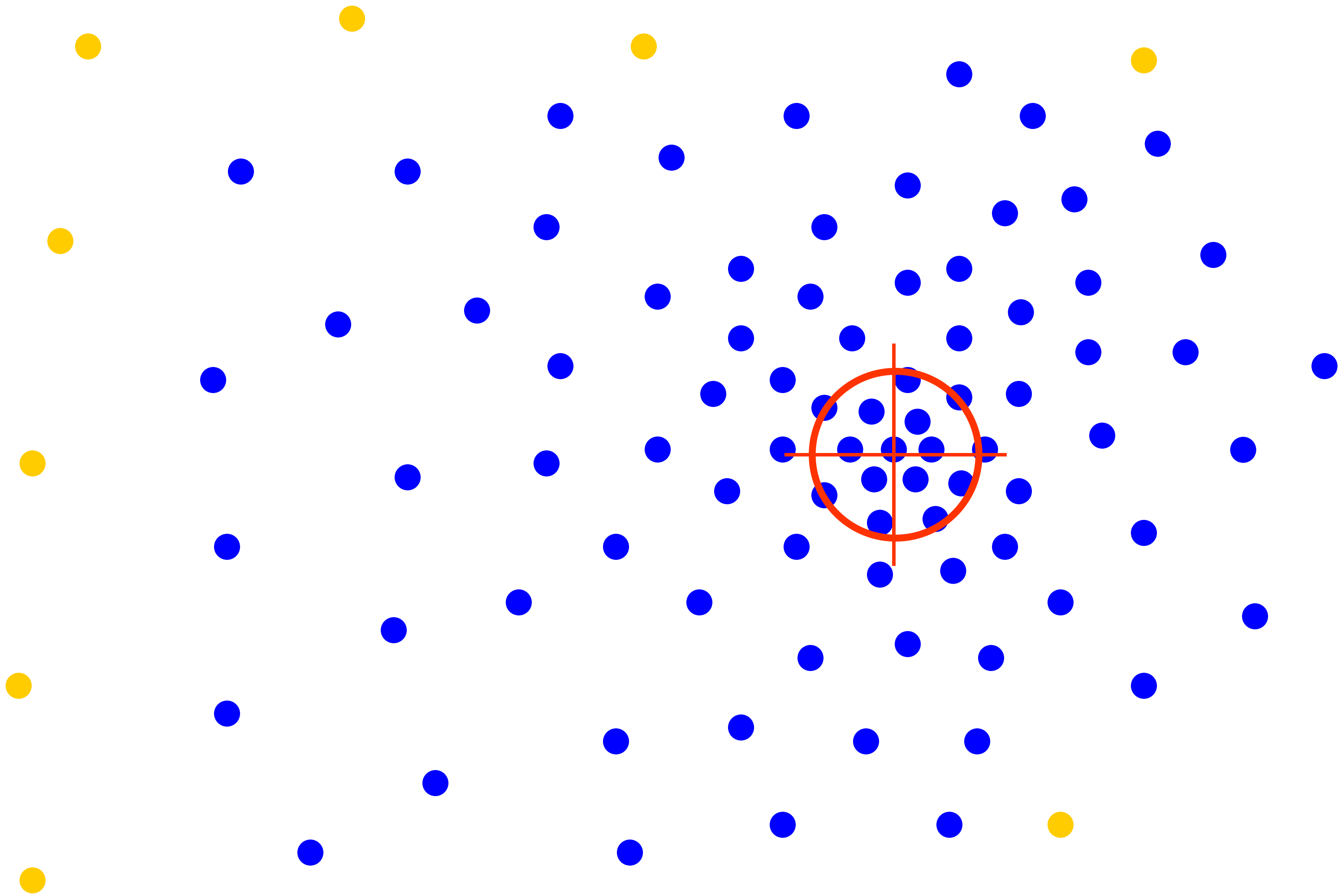


Tessellate the space with windows

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.

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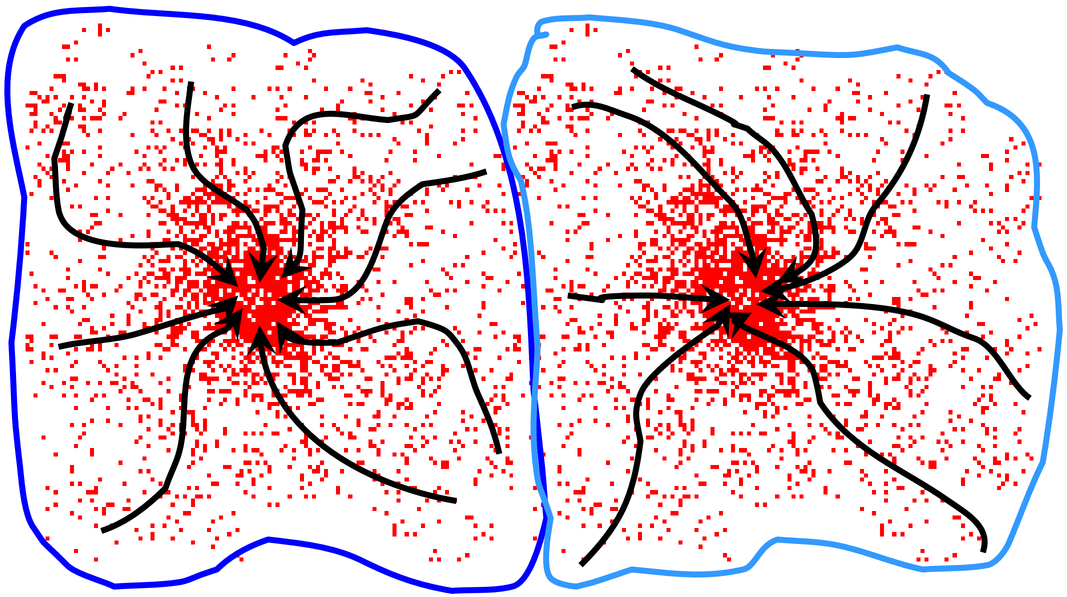
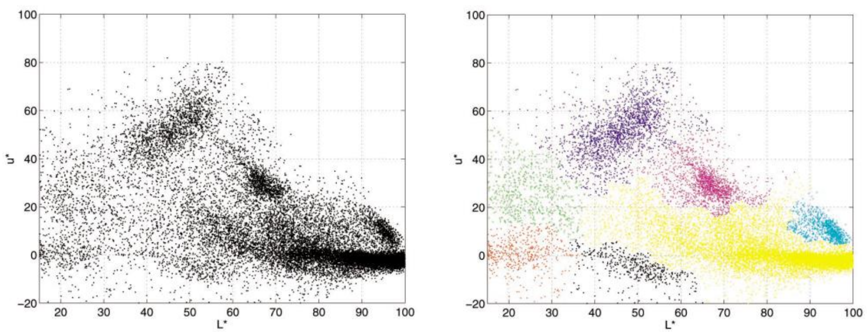
Mean-Shift Clustering

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

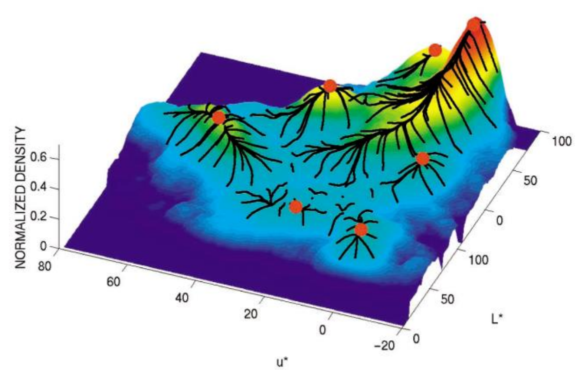


Mean-Shift Clustering/Segmentation

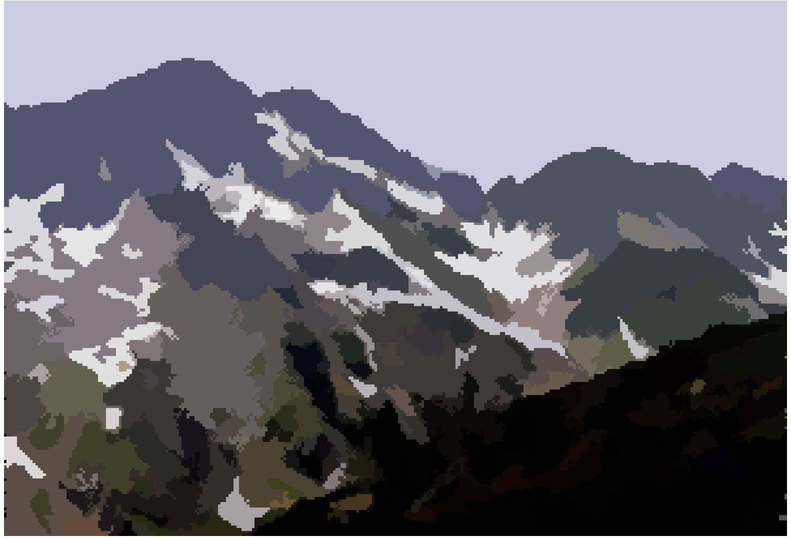
- Find features (color, gradients, texture, etc)
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge windows that end up near the same "peak" or mode



(a) (b)



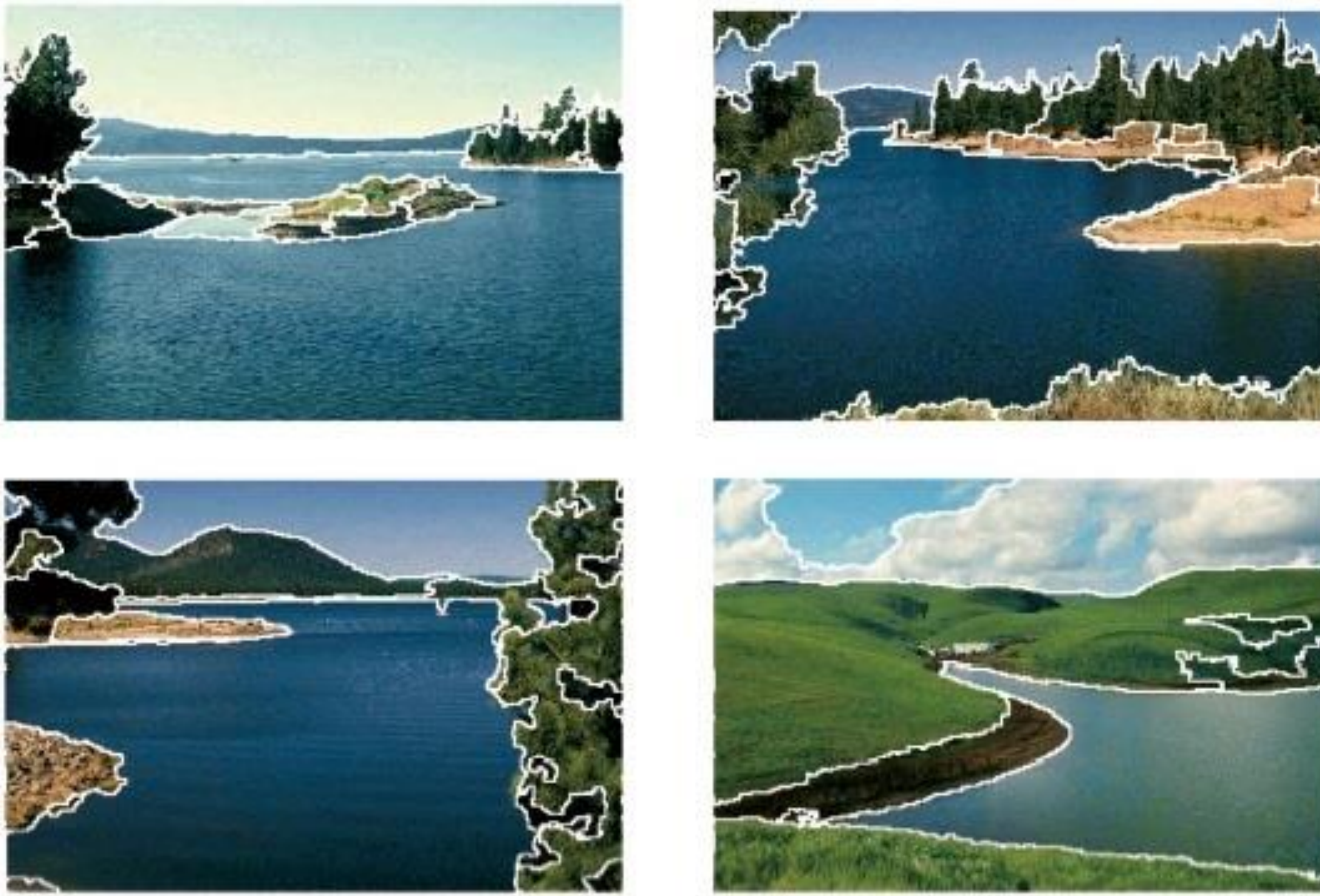
Mean-Shift Segmentation Results



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

Slide credit: Svetlana Lazebnik

More Results

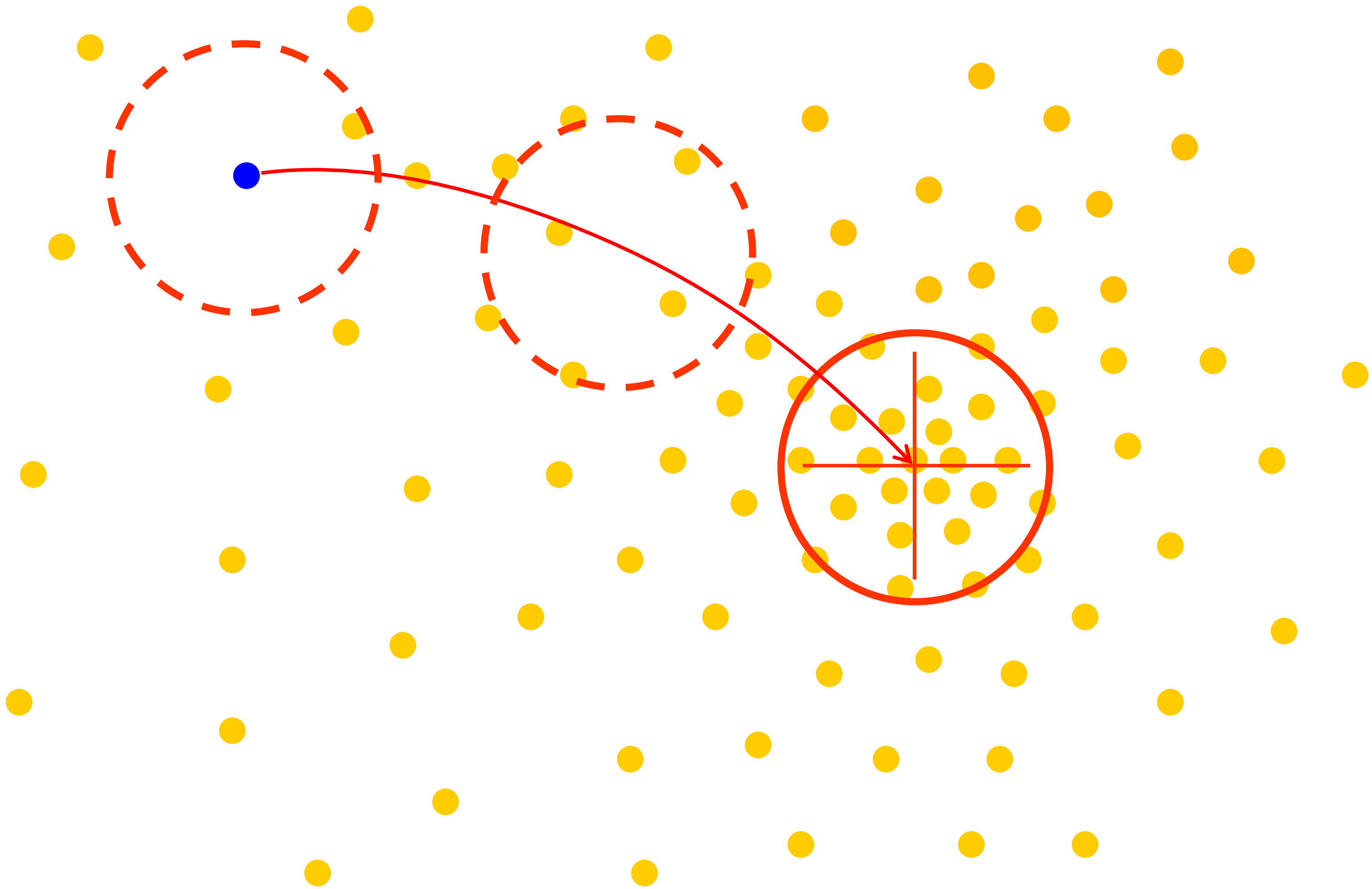


Slide credit: Svetlana Lazebnik

More Results

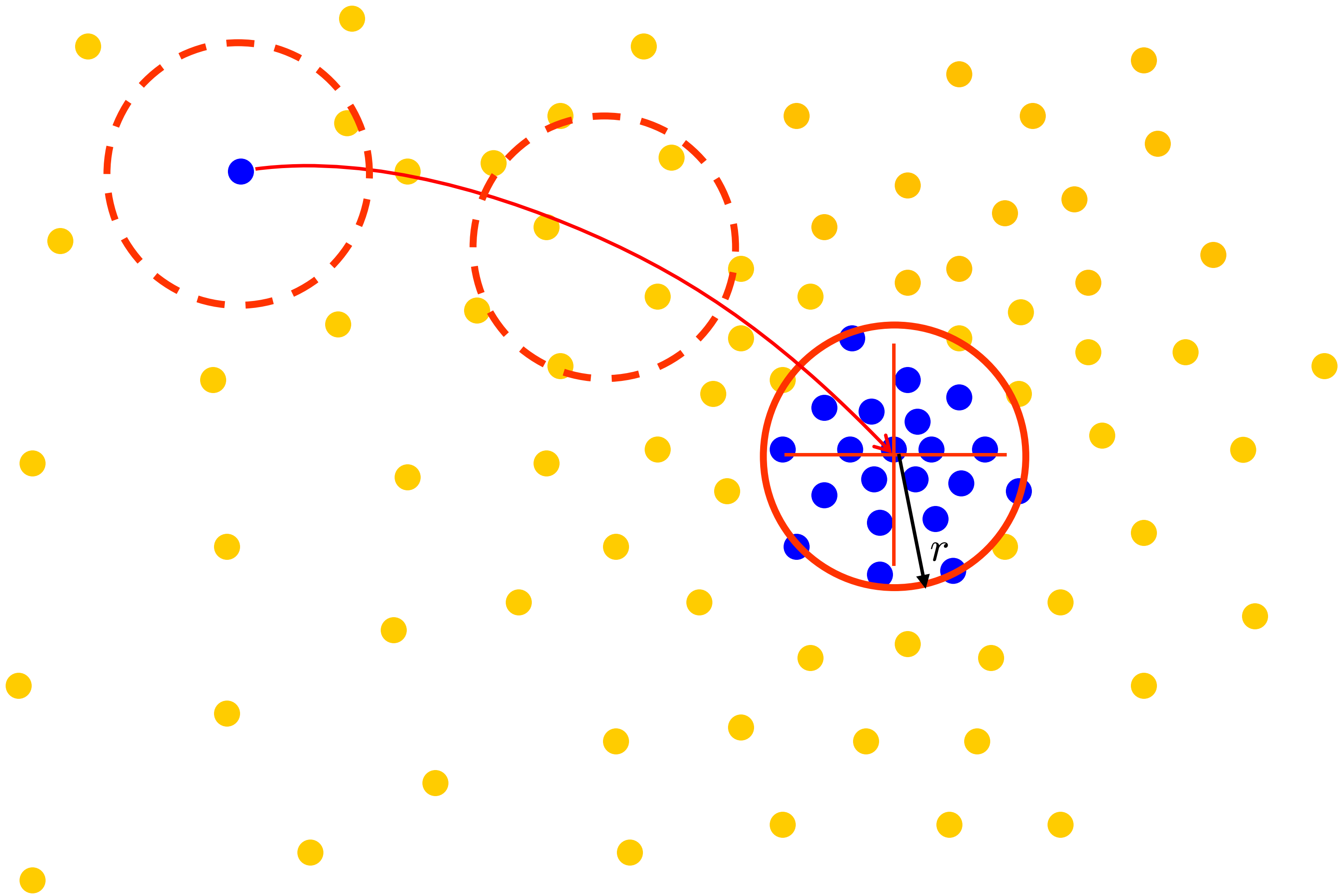
Slide credit: Svetlana Lazebnik

Problem: Computational Complexity



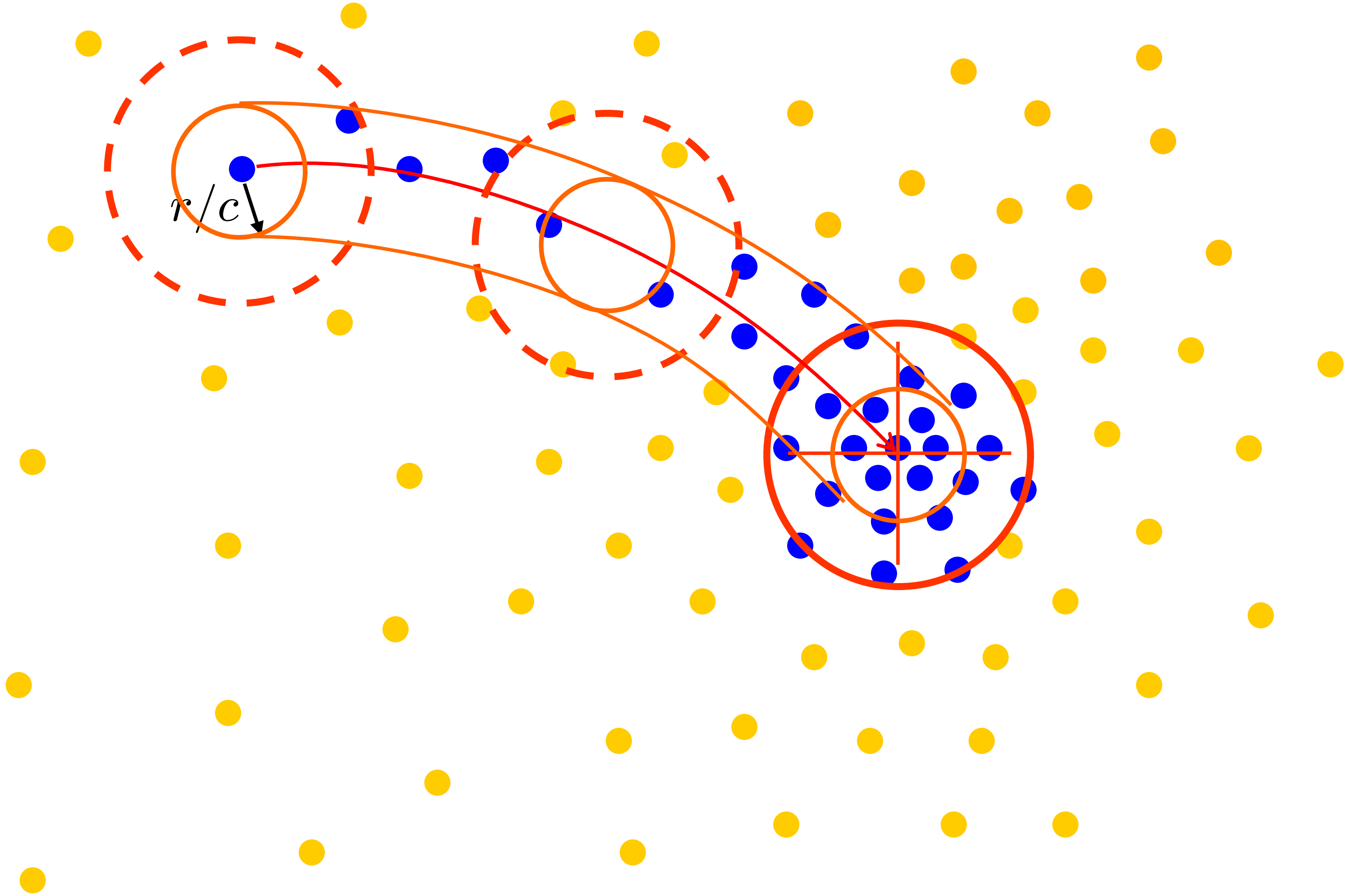
- Need to shift many windows…
- Many computations will be redundant.

Speedups: Basin of Attraction



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

Speedups



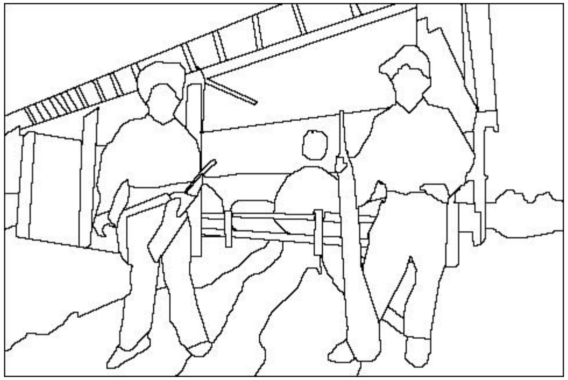
2. **Assign all points within radius r/c of the search path to the mode.**

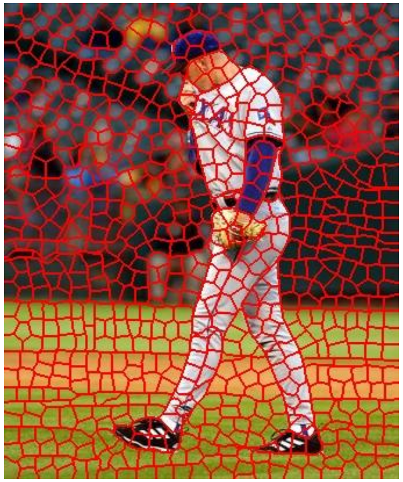
Summary Mean-Shift

- **Pros**
  - General, application-independent tool
  - Model-free, does not assume any prior shape (spherical, elliptical, etc.) on data clusters
  - Just a single parameter (window size h)
    - h has a physical meaning (unlike k-means)
  - Finds variable number of modes
  - Robust to outliers
- **Cons**
  - Output depends on window size
  - Window size (bandwidth) selection is not trivial
  - Computationally (relatively) expensive (~2s/image)
  - Does not scale well with dimension of feature space

Segmentation: Caveats

- We've looked at *bottom-up* ways to segment an image into regions, yet finding meaningful segments is intertwined with the recognition problem.
- Often want to avoid making hard decisions too soon
- Difficult to evaluate; when is a segmentation successful?





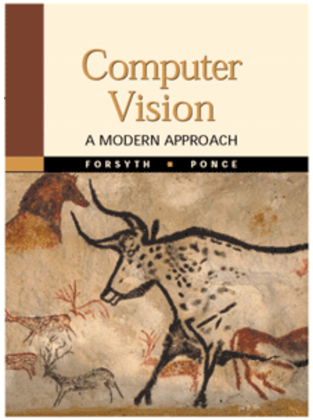
Slide credit: Kristen Grauman

Generic Clustering

- We have focused on ways to group pixels into image segments based on their appearance
  - Find groups; "quantize" feature space
- In general, we can use clustering techniques to find groups of similar "tokens", provided we know how to compare the tokens.
  - *E.g.*, segment an image into the types of motions present
  - *E.g.*, segment a video into the types of scenes (shots) present

References and Further Reading

- Background information on segmentation by clustering can be found in Chapter 14 of
  - D. Forsyth, J. Ponce, *Computer Vision – A Modern Approach*. Prentice Hall, 2003



- More on the EM algorithm can be found in Chapter 16.1.2.

- Try the k-means and EM demos at
  - http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/AppletKM.html
  - http://lcn.epfl.ch/tutorial/english/gaussian/html/index.html