CS 1674: Intro to Computer Vision

Grouping: Edges, Lines, Circles, Segments

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Plan for this lecture

- Edges
  - Extract gradients and threshold
- Lines and circles
  - Find which edge points are collinear or belong to another shape e.g. circle
  - Automatically detect and ignore outliers
- Segments
  - Find which pixels form a consistent region
  - Clustering (e.g. K-means)

Edge detection

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

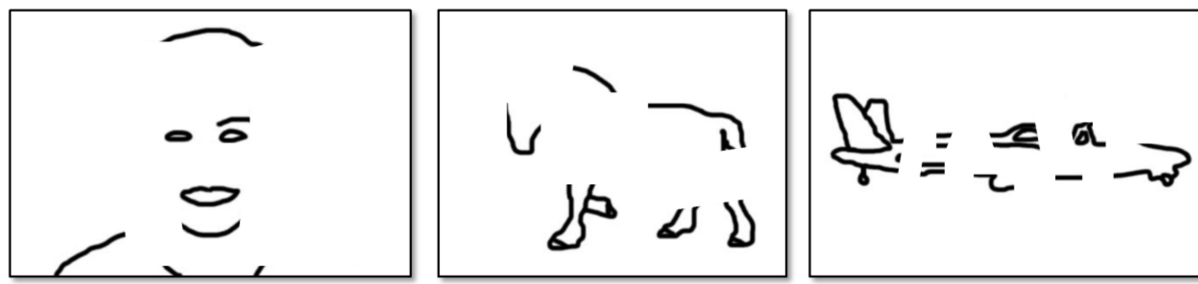


Figure from J. Shotton et al., PAMI 2007

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

Source: K. Grauman

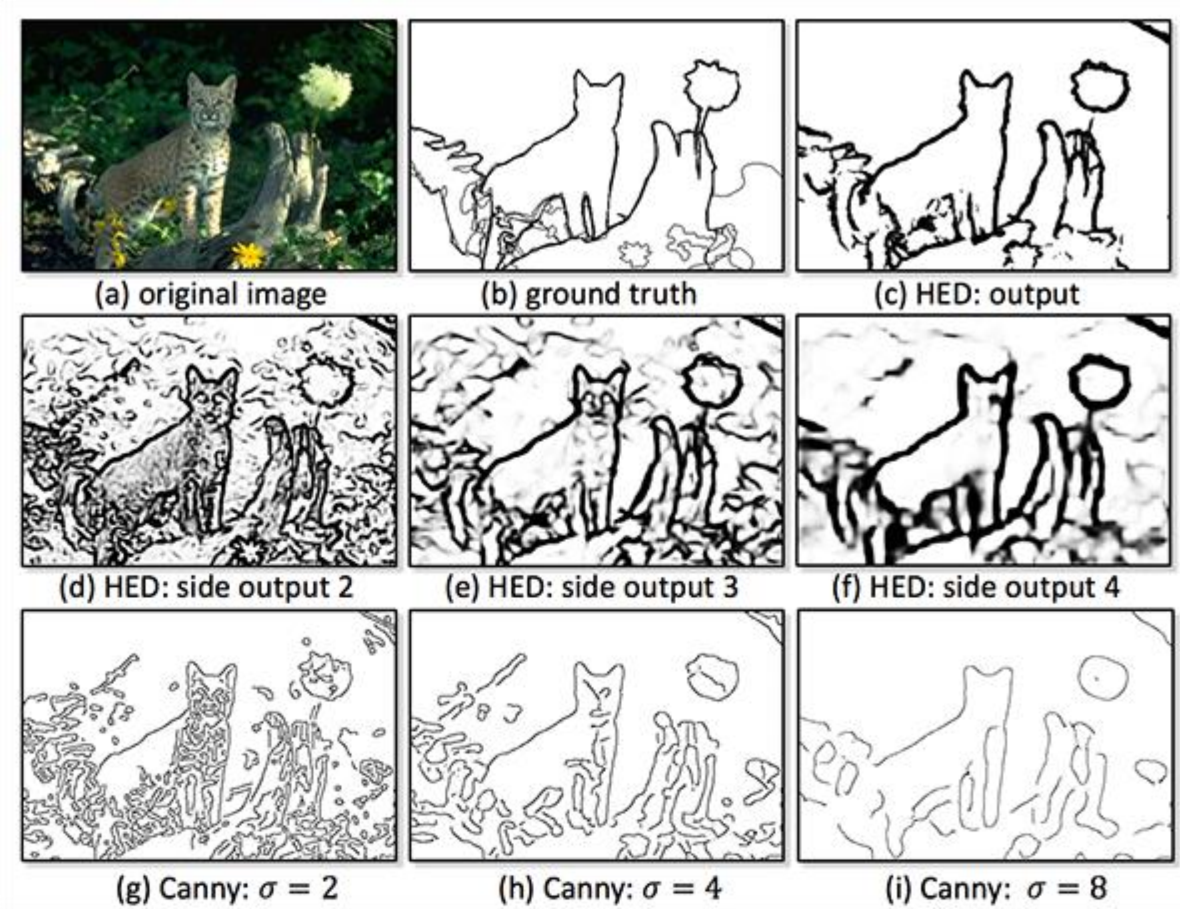
Designing an edge detector

- Criteria for a good edge detector
  - **Good categorization (edge vs not edge)**
    - find all real edges, ignoring noise or other artifacts
  - **Good localization**
    - detect edges as close as possible to the true edges
    - return one point only for each true edge point (true edges = the edges humans drew on an image)

- Cues of edge detection
  - Bottom-up: Differences in color, intensity, or texture across the boundary
  - Top-down: Continuity and closure, high-level knowledge

Adapted from L. Fei-Fei

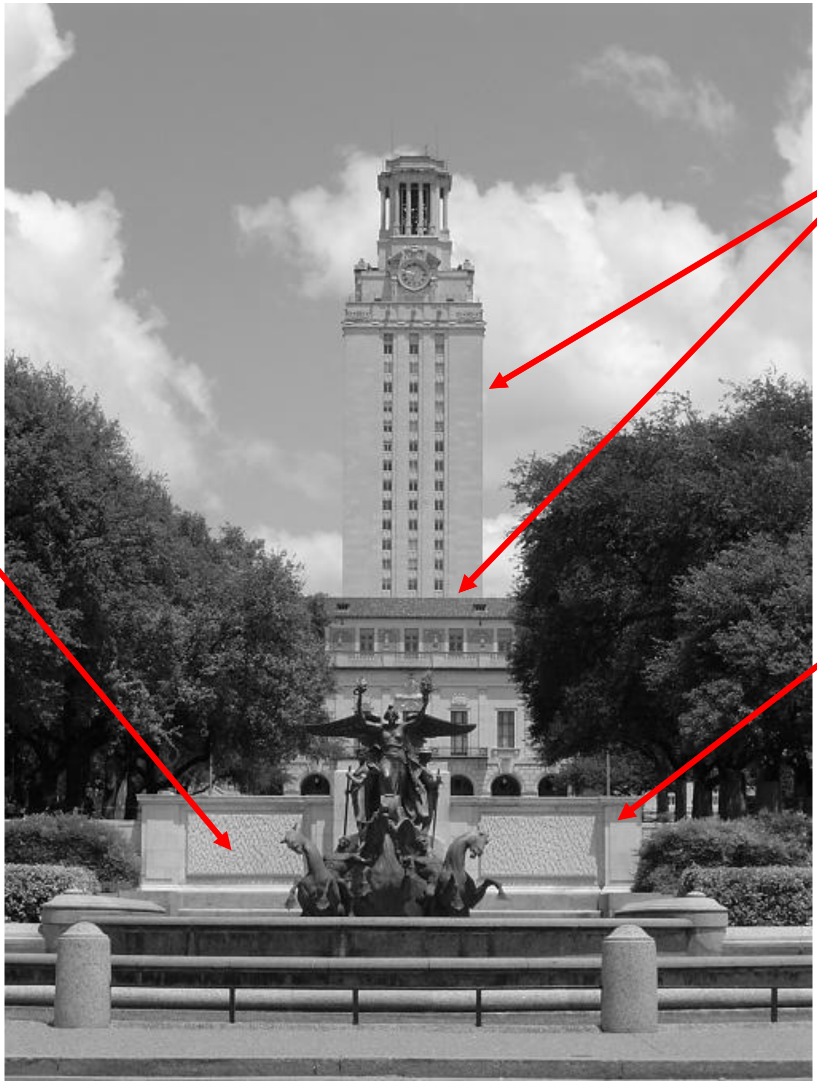
Examples of edge detection results



Xie and Tu, *Holistically-Nested Edge Detection*, ICCV 2015

What causes an edge?

Reflectance change: appearance information, texture



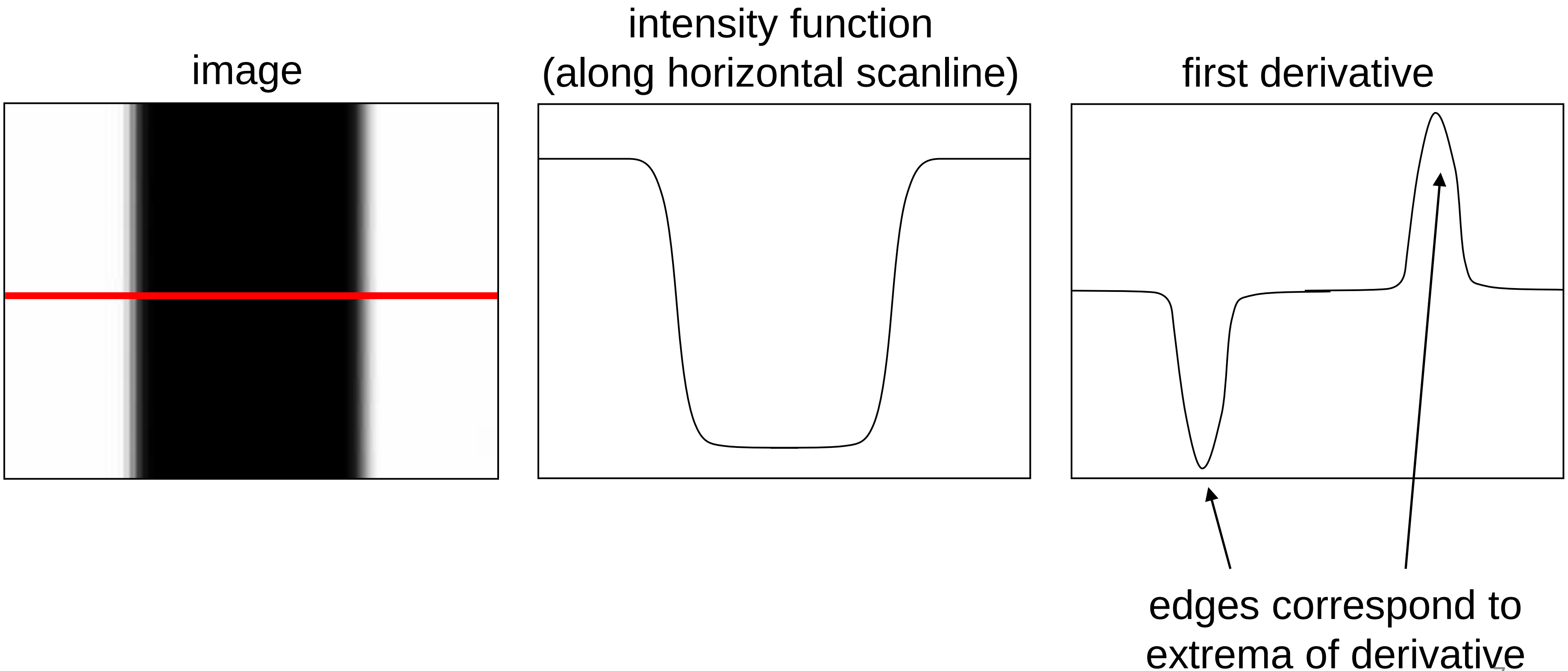
Depth discontinuity: object boundary

Cast shadows

Adapted from K. Grauman

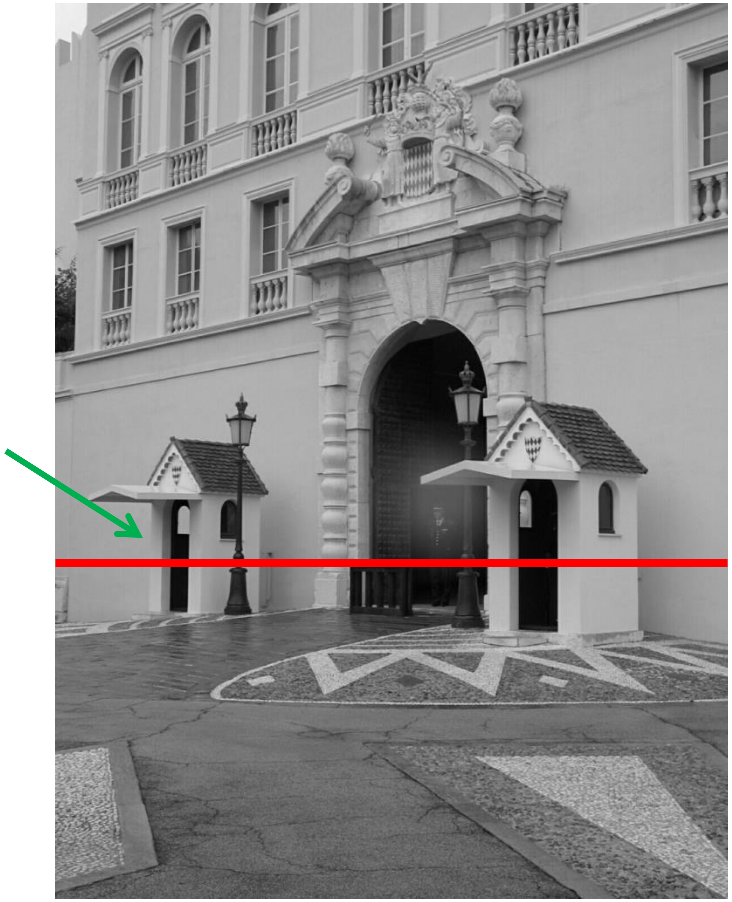
Characterizing edges

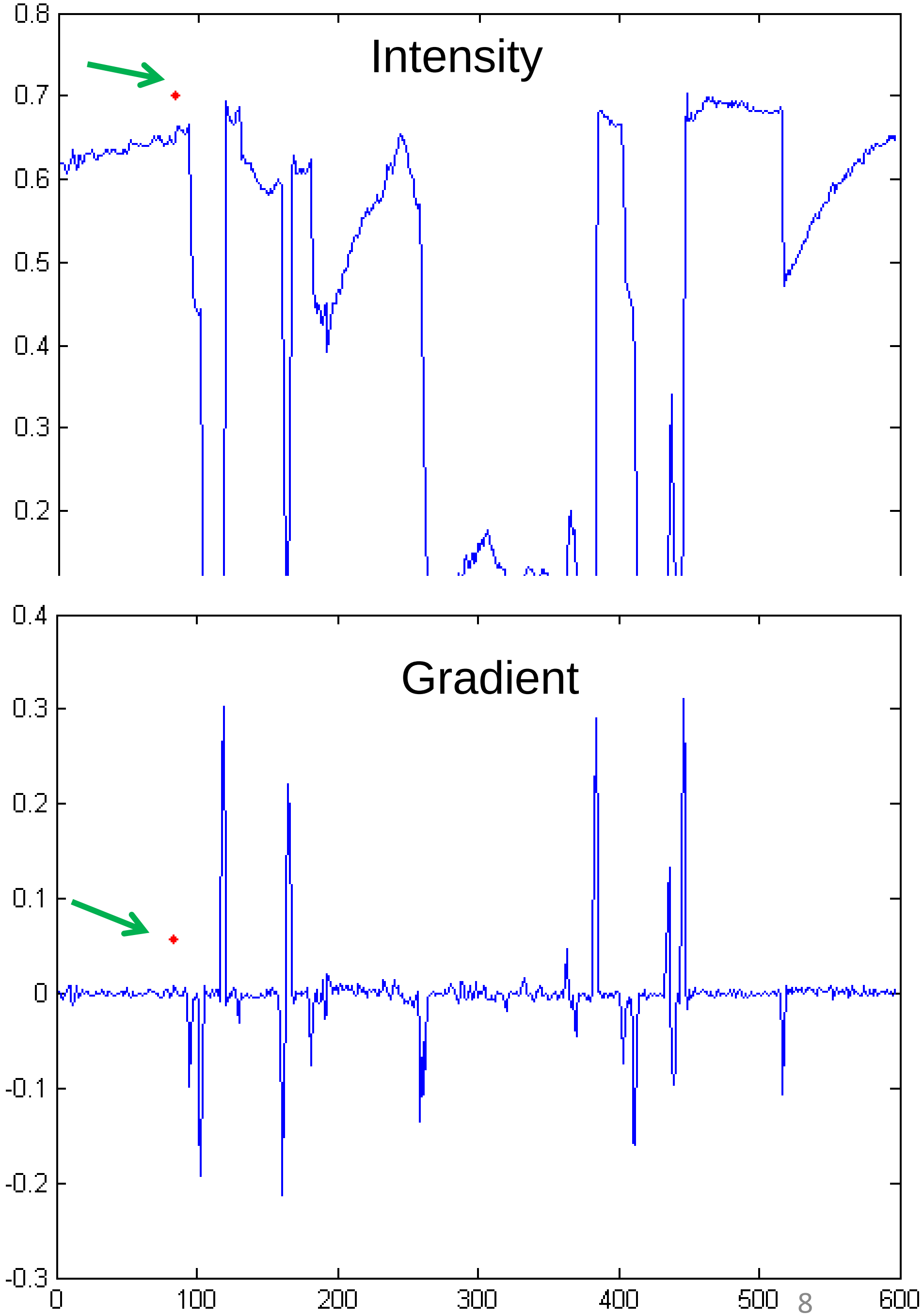
- An edge is a place of rapid change in the image intensity function



Source: L. Lazebnik

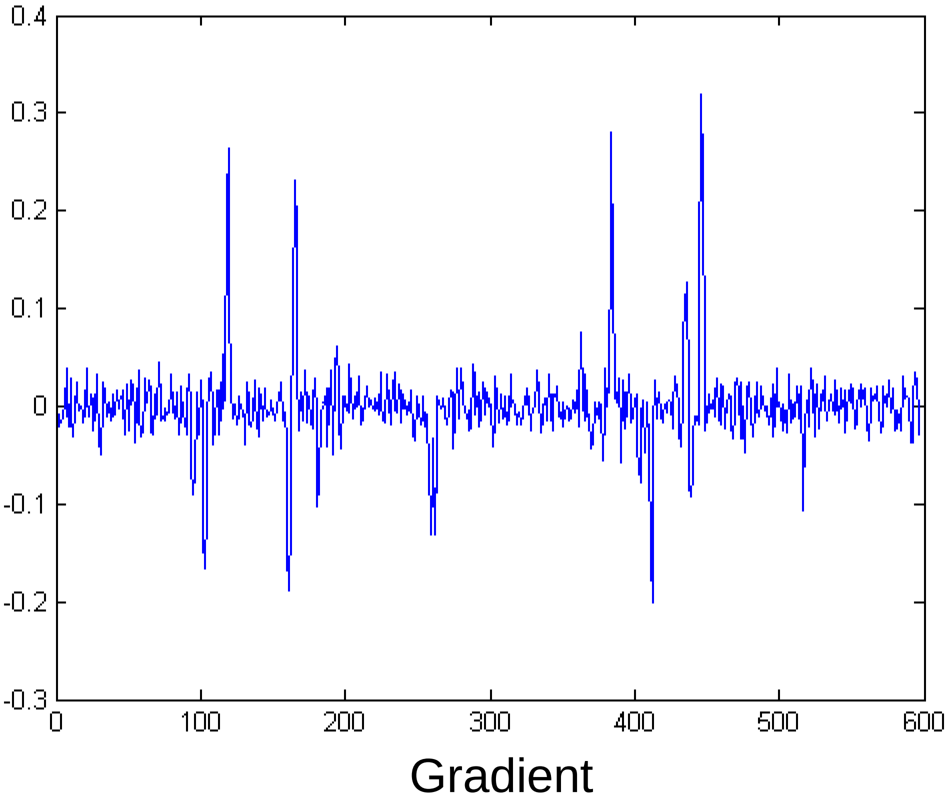
Intensity profile





Source: D. Hoiem

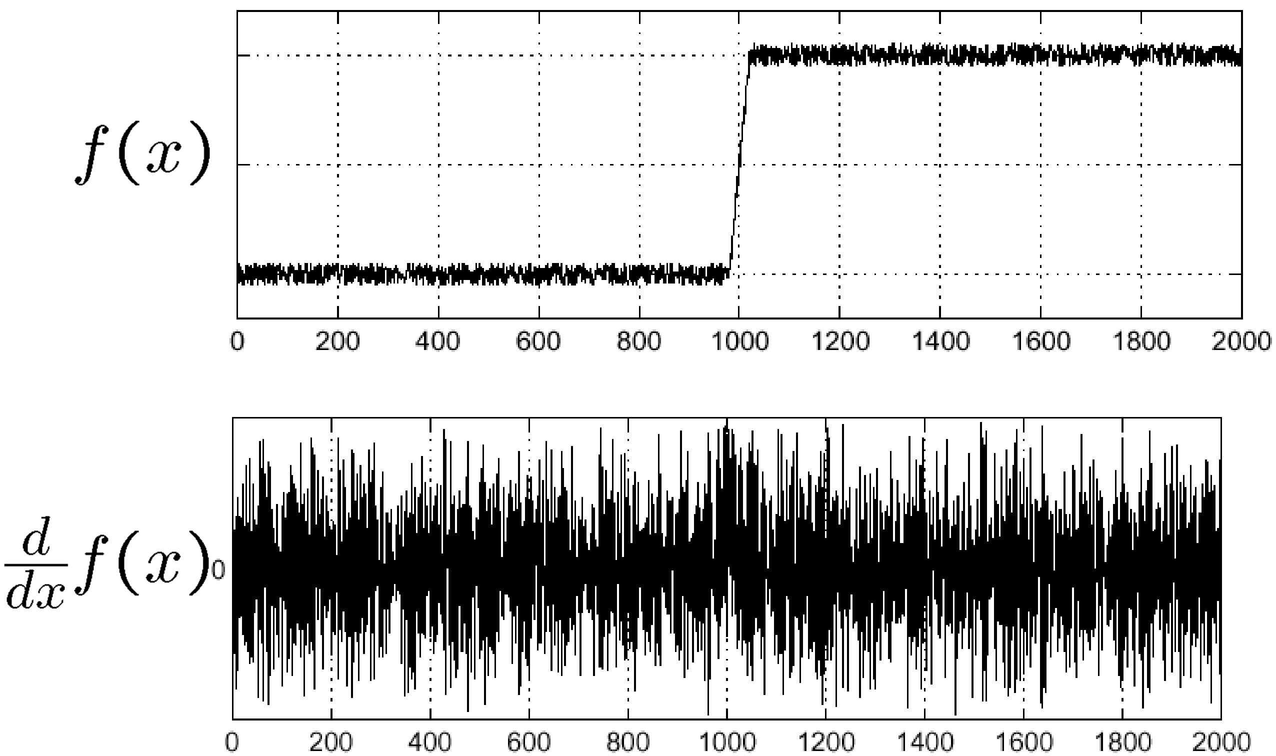
With a little Gaussian noise



Source: D. Hoiem

Effects of noise

- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal

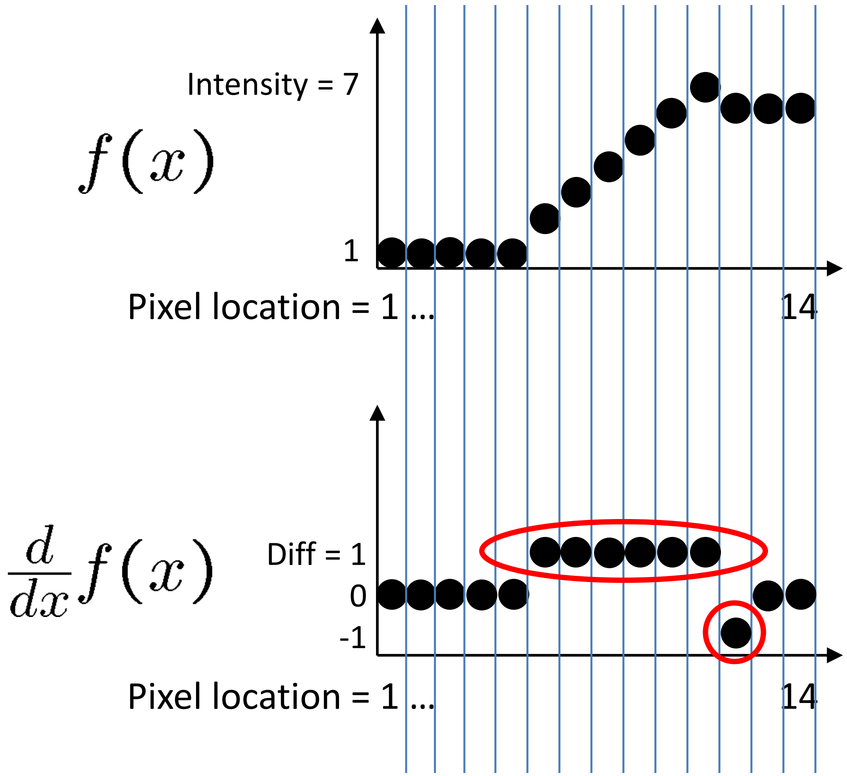


Where is the edge?

Source: S. Seitz

Without noise

- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal



$$= \frac{\Delta f(a)}{\Delta a} = \frac{f(a+h)-f(a)}{(a+h)-(a)} = \frac{f(a+h)-f(a)}{h}$$

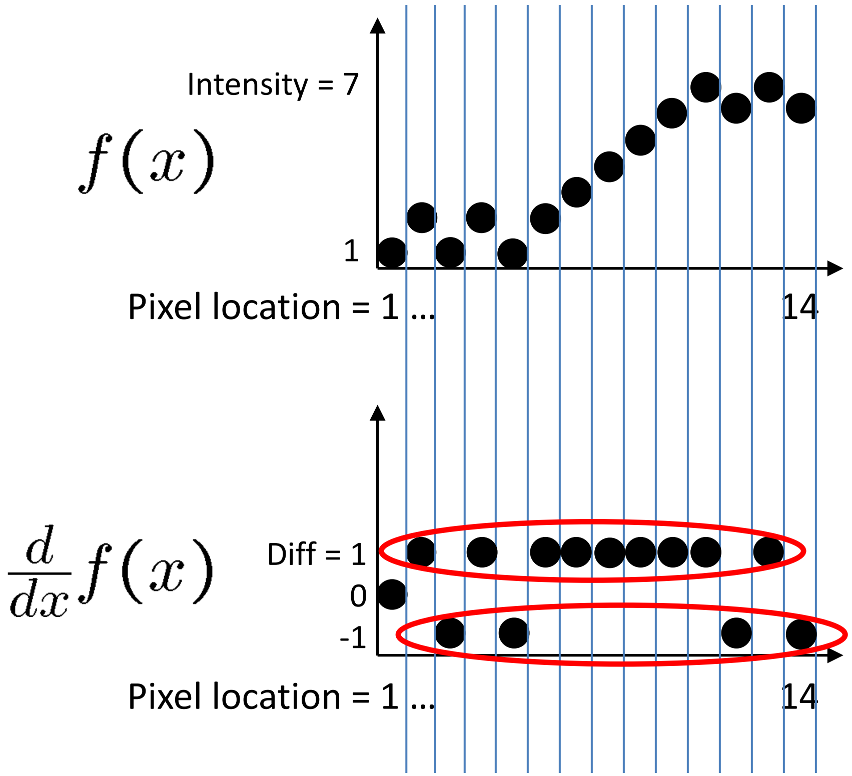
= f(x+1) – f(x)

Where is the edge?

https://en.wikipedia.org/wiki/Derivative

With noise

- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal



$$= \frac{\Delta f(a)}{\Delta a} = \frac{f(a+h) - f(a)}{(a+h) - (a)} = \frac{f(a+h) - f(a)}{h}$$

= f(x+1) – f(x)

Where is the edge?

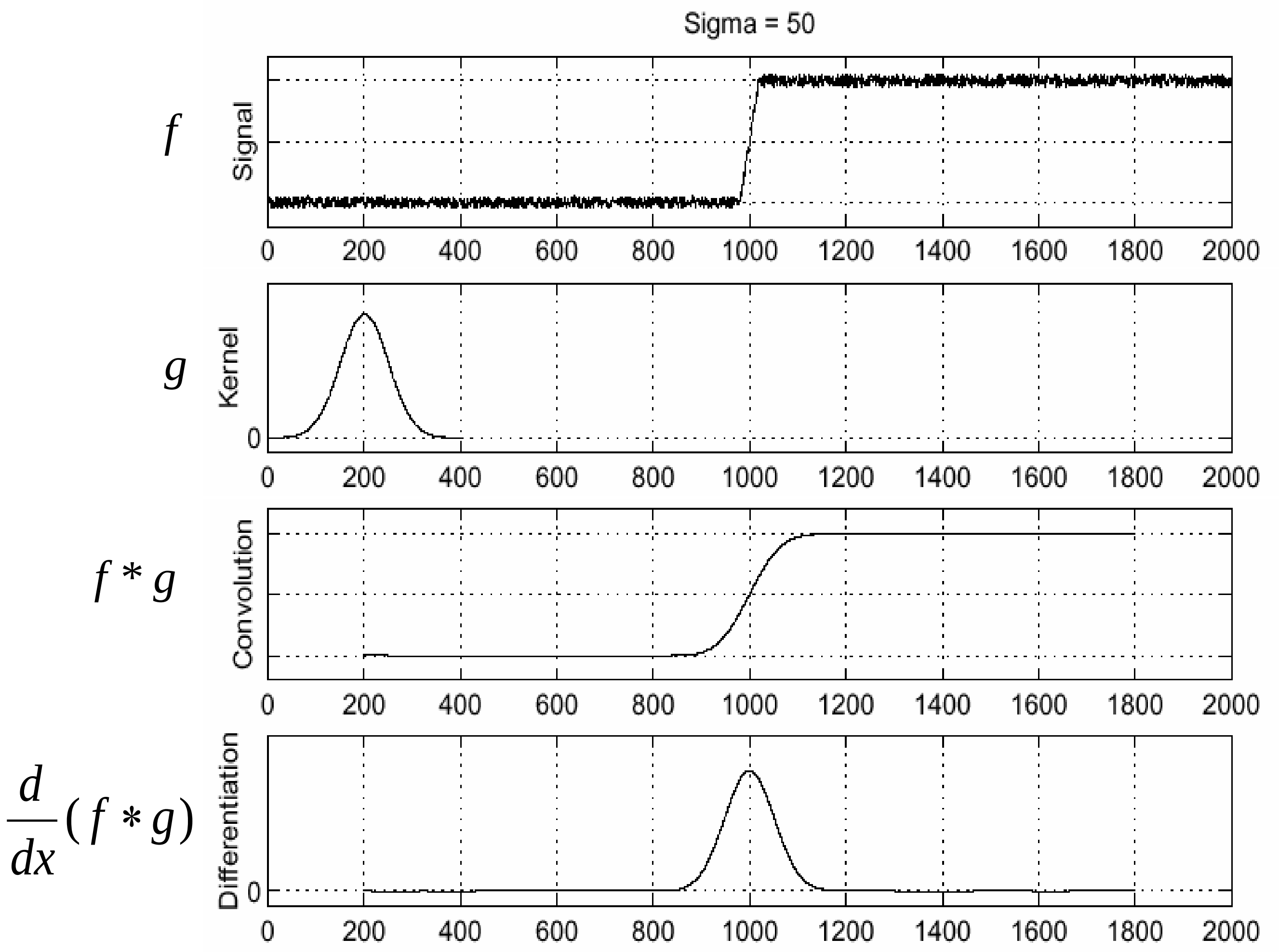
https://en.wikipedia.org/wiki/Derivative

Effects of noise

- Difference filters respond strongly to noise
  – Image noise results in pixels that look very different from their neighbors
  – Generally, the larger the noise the stronger the response
- What can we do about it?

Source: D. Forsyth

Solution: smooth first

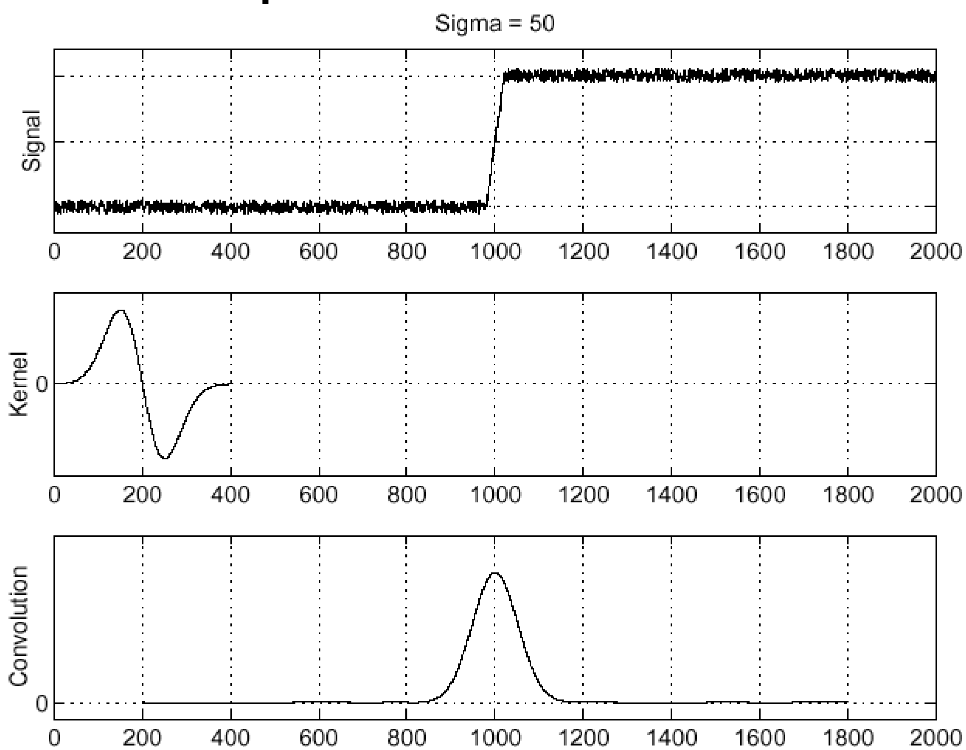


- To find edges, look for peaks in $\frac{d}{dx}(f * g)$

Source: S. Seitz

Derivative theorem of convolution

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



f — Image with edge

$\frac{d}{dx} g$ — Derivative of Gaussian

$f * \frac{d}{dx} g$ — Edge = max of derivative

Source: S. Seitz

Canny edge detector

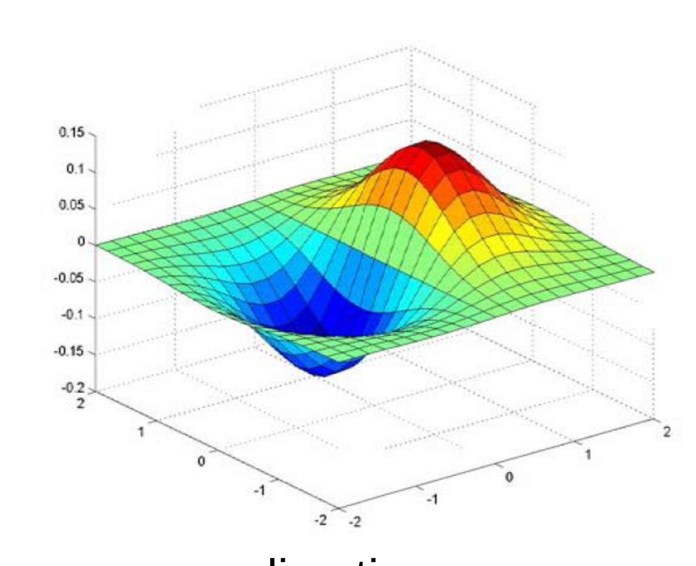
- Filter image with derivative of Gaussian
- Find magnitude and orientation of gradient
- Threshold: Determine which local maxima from filter output are actually edges
- **Non-maximum suppression**:
  - Thin wide “ridges” down to single pixel width
- **Linking and thresholding** (**hysteresis**):
  - Define two thresholds: low and high
  - Use the high threshold to start edge curves and the low threshold to continue them

Adapted from K. Grauman, D. Lowe, L. Fei-Fei

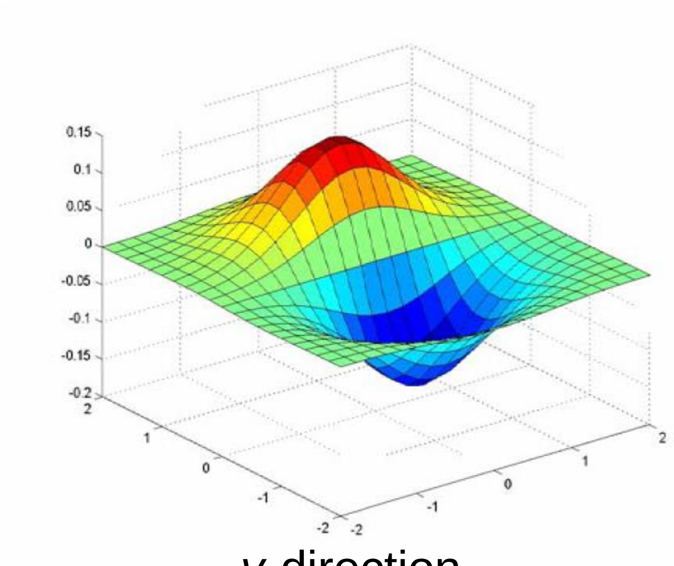
Example

input image ("Lena")

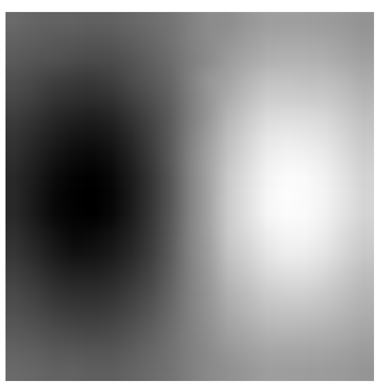
Derivative of Gaussian filter

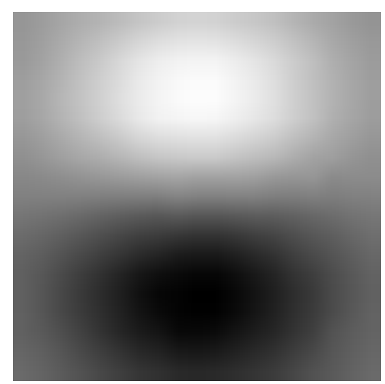


x-direction



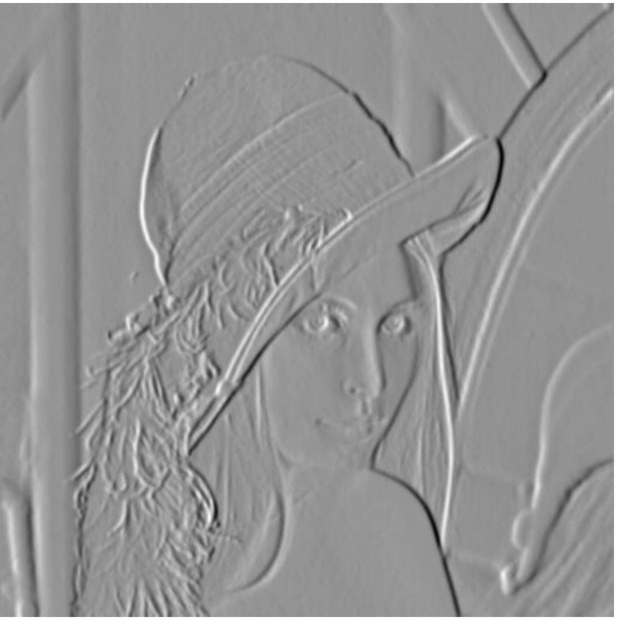
y-direction





Source: L. Lazebnik

Compute Gradients



X-Derivative of Gaussian

Y-Derivative of Gaussian

Gradient Magnitude

Source: D. Hoiem

Thresholding

- Choose a threshold value t
- Set any pixels less than t to 0 (off)
- Set any pixels greater than or equal to t to 1 (on)

Source: K. Grauman

The Canny edge detector

norm of the gradient (magnitude)

Source: K. Grauman

The Canny edge detector

thresholding

Source: K. Grauman

Another example: Gradient magnitudes

K. Grauman

Thresholding gradient with a lower threshold

Source: K. Grauman

Thresholding gradient with a higher threshold

Source: K. Grauman

Effect of σ of Gaussian kernel

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 edges

Source: S. Seitz

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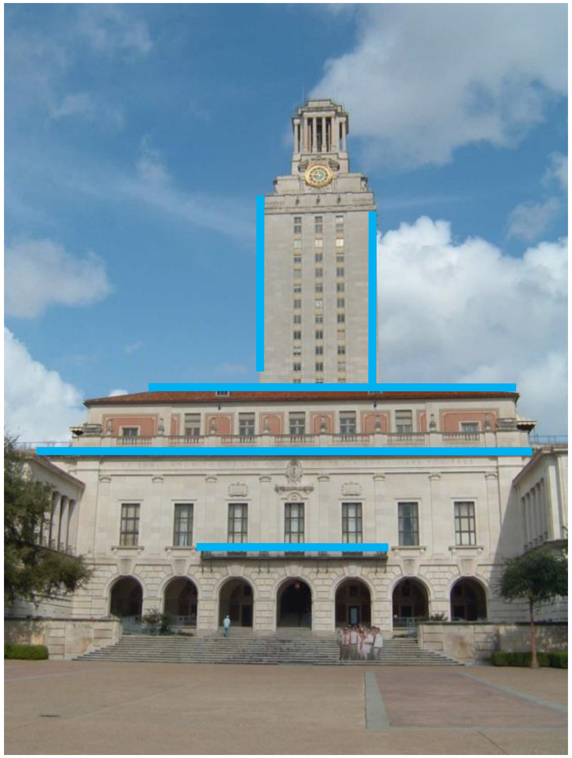
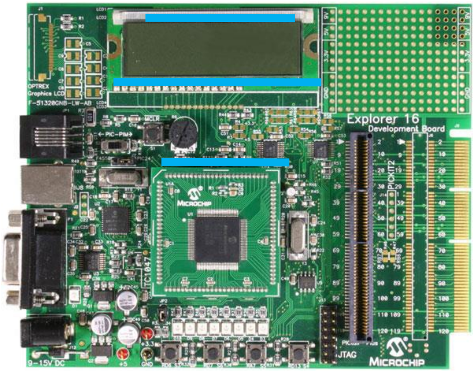
Line detection (fitting)

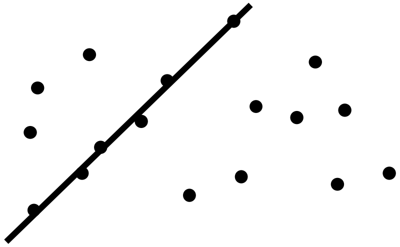
- Why fit lines?
  Many objects characterized by presence of straight lines

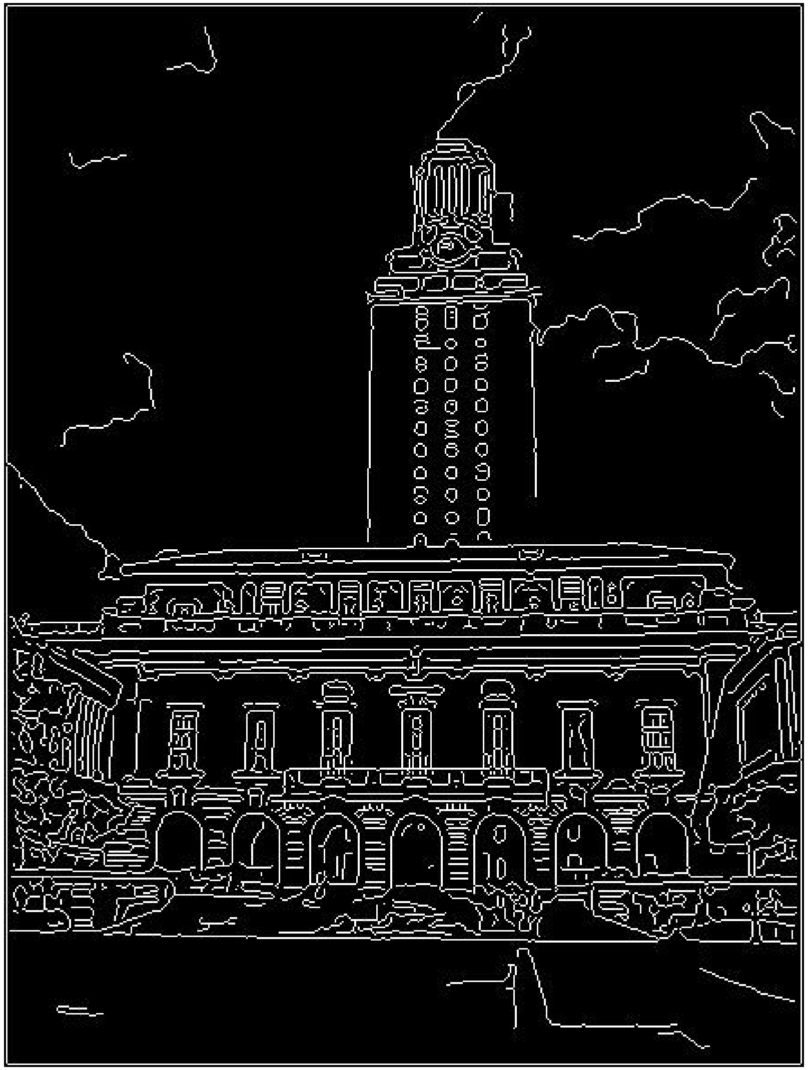



- Why aren't we done just by running edge detection?

Kristen Grauman

Difficulty of line fitting



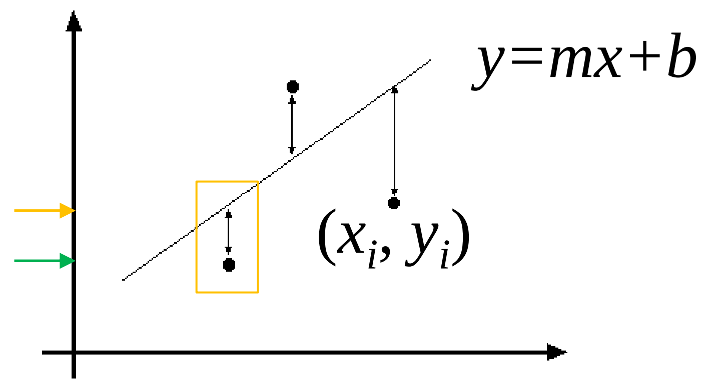


- **Noise** in measured edge points, orientations:
  - e.g. edges not collinear where they should be
  - how to detect true underlying parameters?
- **Extra** edge points (clutter):
  - which points go with which line, if any?
- Only some parts of each line detected, and some parts are **missing:**
  - how to find a line that bridges missing evidence?

Adapted from Kristen Grauman

Least squares line fitting

- Data: $(x_1, y_1), \ldots, (x_n, y_n)$
- Line equation: $y_i = m\,x_i + b$



- Find (m, b) to minimize

$$E = \sum_{i=1}^{n} (mx_i + b - y_i)^2$$

where line you found tells you point is along y axis ($mx_i + b$)

where point really is along y axis (y_i)

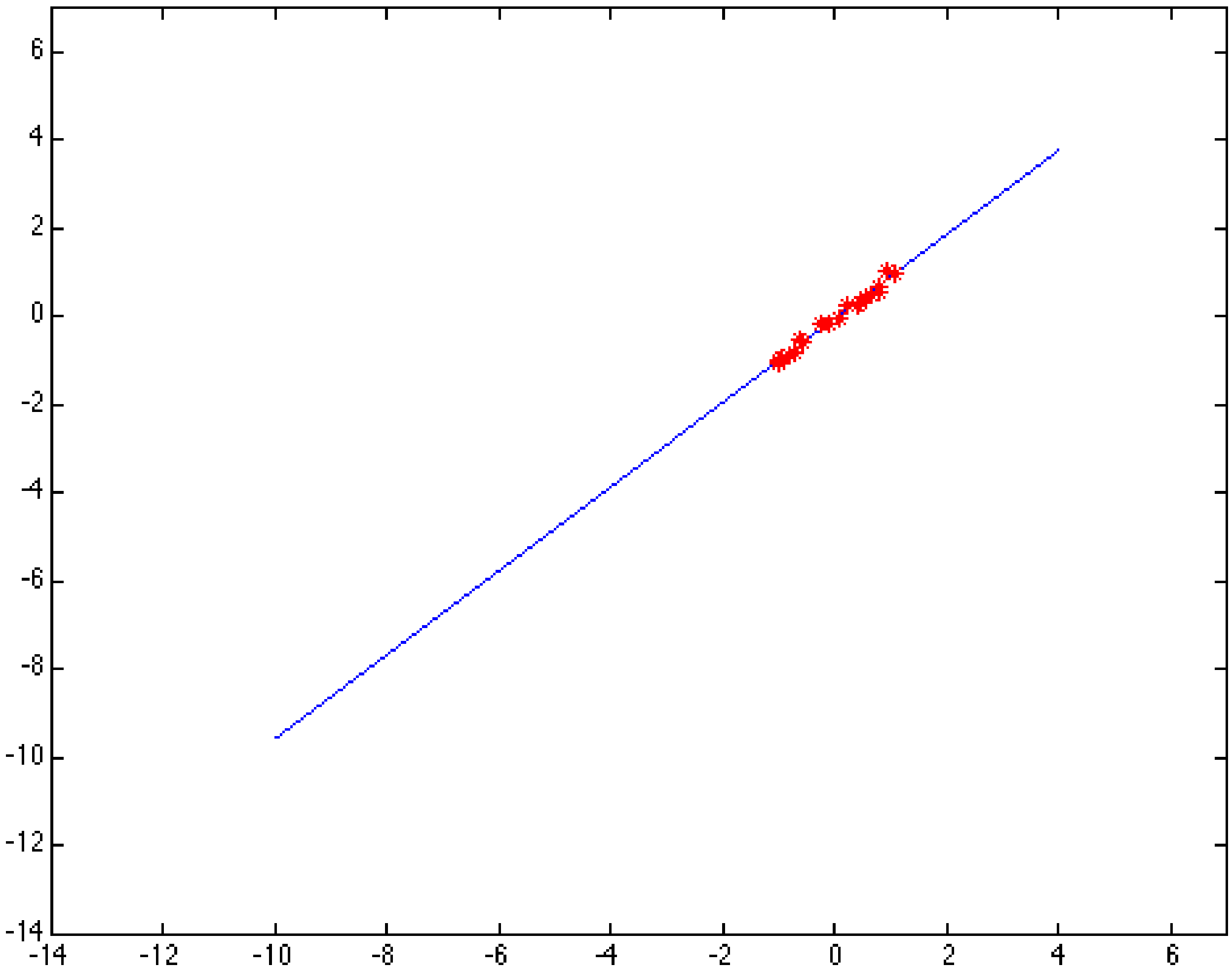
You want to find a single line that “explains” all of the points in your data, but data may be noisy!

$$E = \sum_{i=1}^{n} \left(\begin{bmatrix} x_i & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} - y_i \right)^2 = \left\| \begin{bmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} - \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \right\|^2 = \|\mathbf{Ap} - \mathbf{y}\|^2$$

Matlab: `p = A \ y;` or `p = pinv(A)*y;`

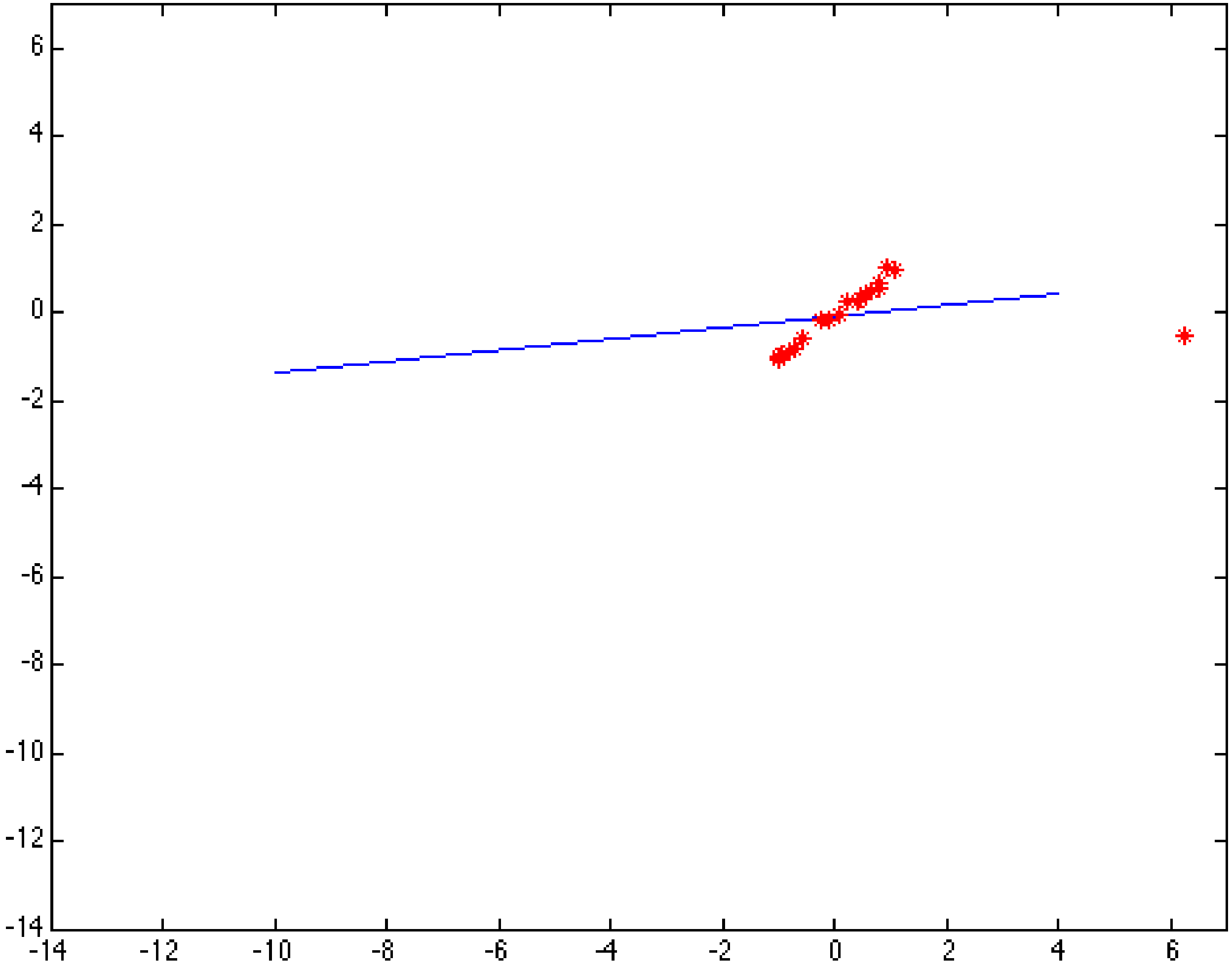
Adapted from Svetlana Lazebnik

Outliers affect least squares fit



Kristen Grauman

Outliers affect least squares fit



Kristen Grauman

Dealing with outliers: Voting

- **Voting** is a general technique where we let the features *vote for all models that are compatible with it*.
  - Cycle through features, cast votes for model parameters.
  - Look for model parameters that receive *a lot of votes*.
- Noise & clutter features?
  - They will cast votes too, *but* typically their votes should be inconsistent with the majority of “good” features.
- Common techniques
  - Hough transform
  - RANSAC

Adapted from Kristen Grauman

Finding lines in an image: Hough space

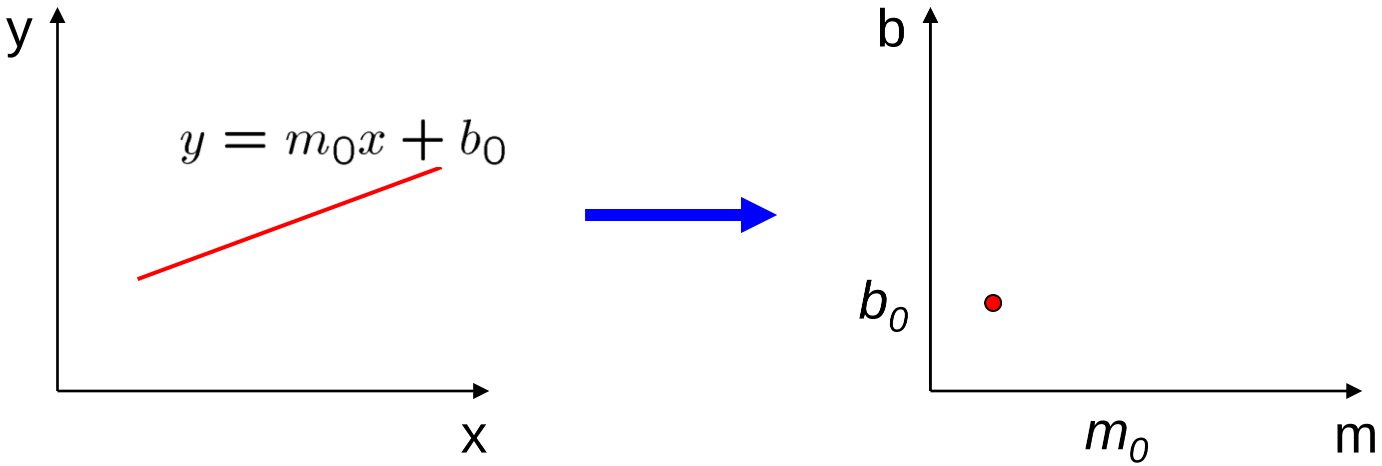
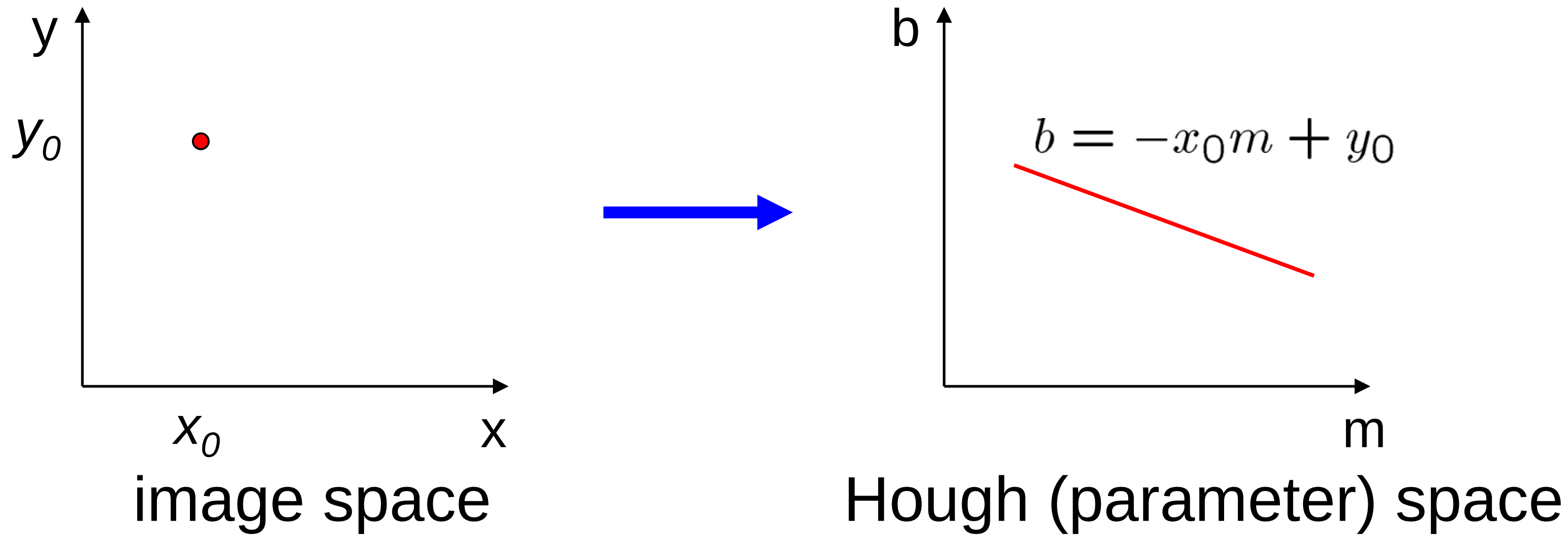


image space — Hough (parameter) space

Connection between image (x,y) and Hough (m,b) spaces

$y = m_0 x + b_0$
- A line in the image corresponds to a point in Hough space

Finding lines in an image: Hough space

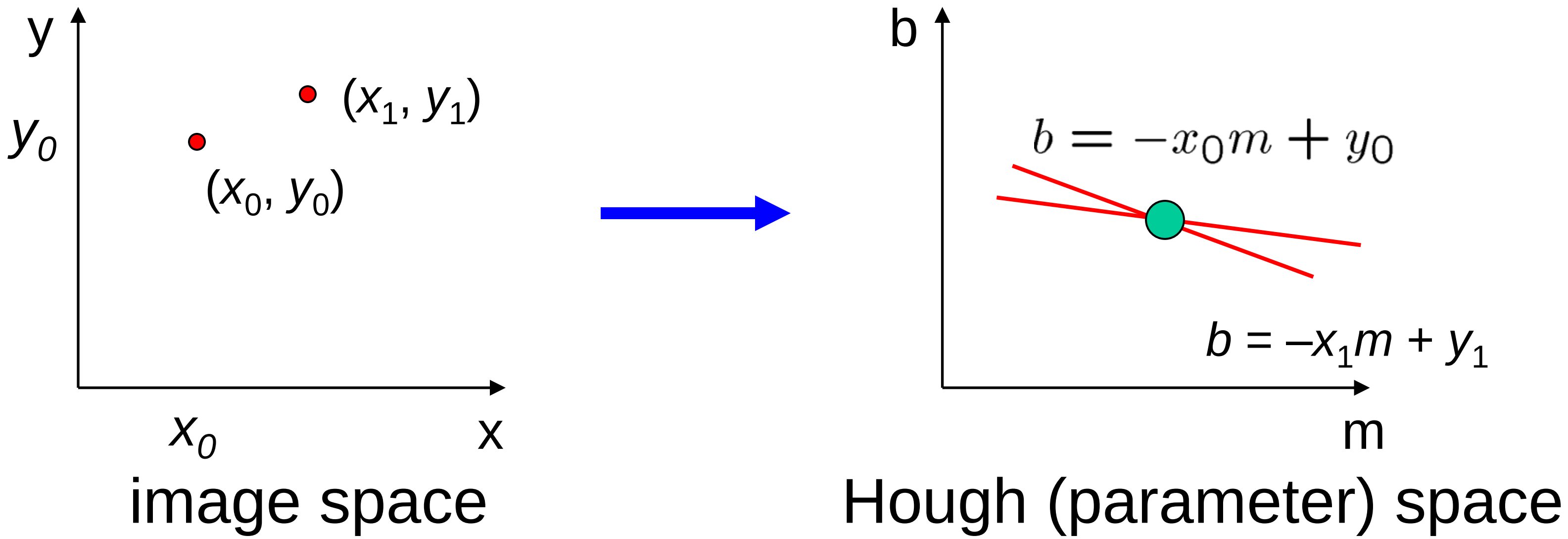


Connection between image (x,y) and Hough (m,b) spaces

- $y = m_0 x + b_0$ A line in the image corresponds to a point in Hough space
- What does a point (x_0, y_0) in the image space map to?
  - Answer: the solutions of $b = -x_0 m + y_0$
  - This is a line in Hough space
  - Given a pair of points (x,y), find all (m,b) such that y = mx + b

Adapted from Steve Seitz

Finding lines in an image: Hough space

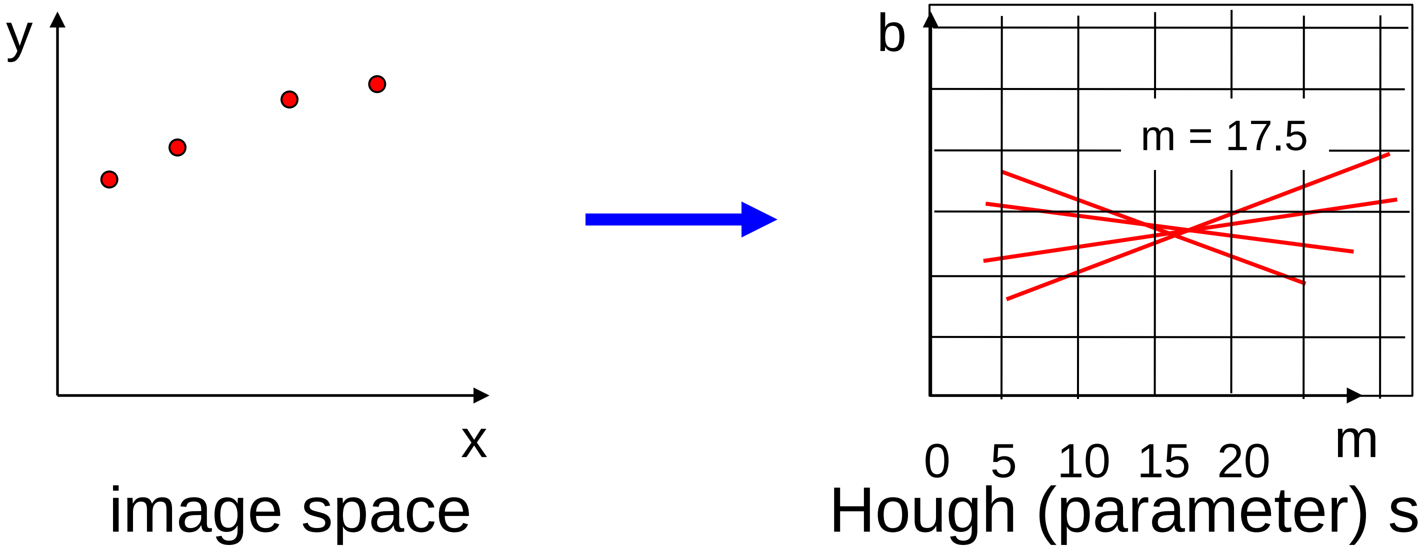


What are the line parameters for the line that contains both (x_0, y_0) and (x_1, y_1)?

- It is the intersection of the lines $b = -x_0 m + y_0$ and $b = -x_1 m + y_1$

Steve Seitz

Finding lines in an image: Hough space

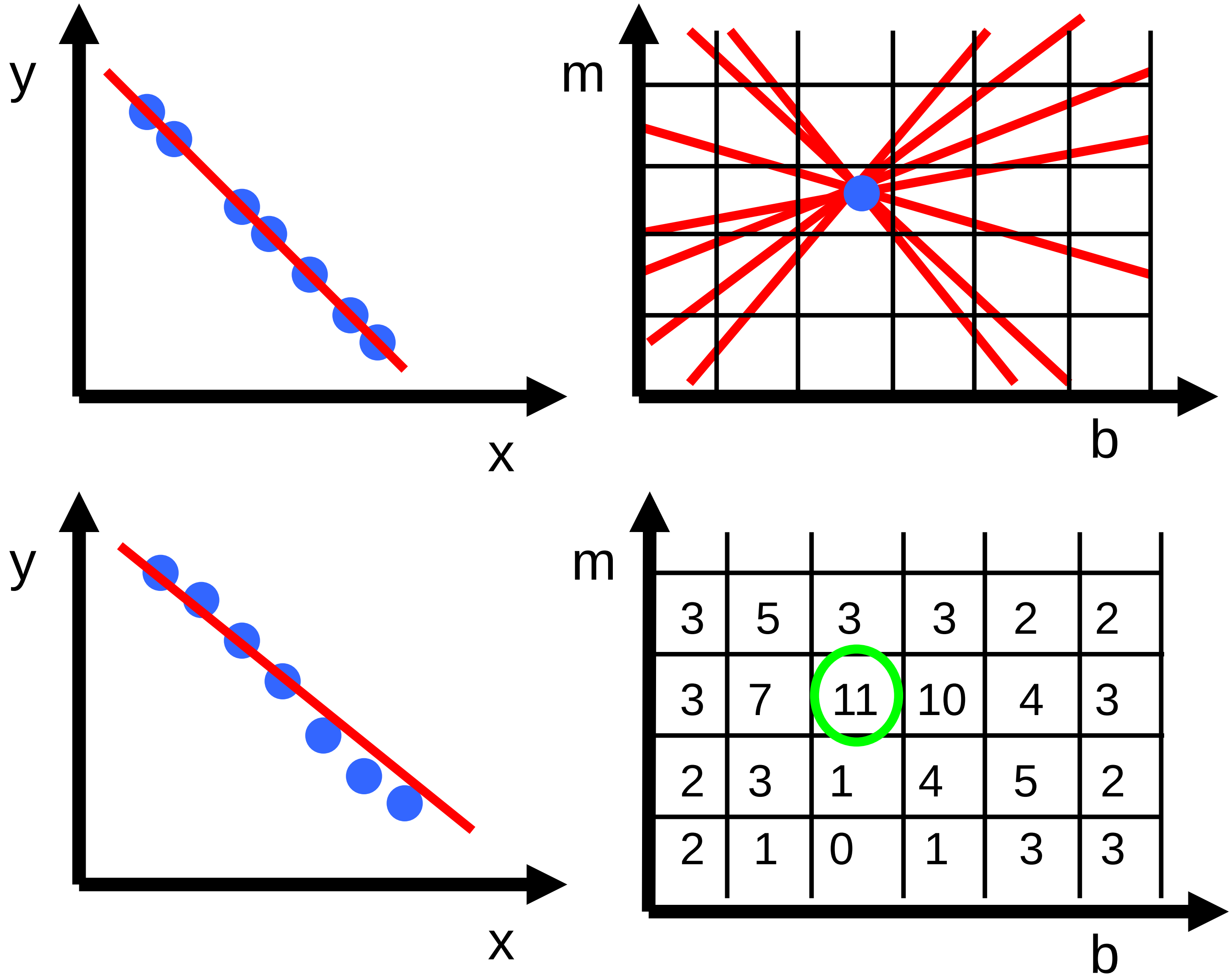


How can we use this to find the most likely parameters (m,b) for the most prominent line in the image space?

- 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.

Steve Seitz

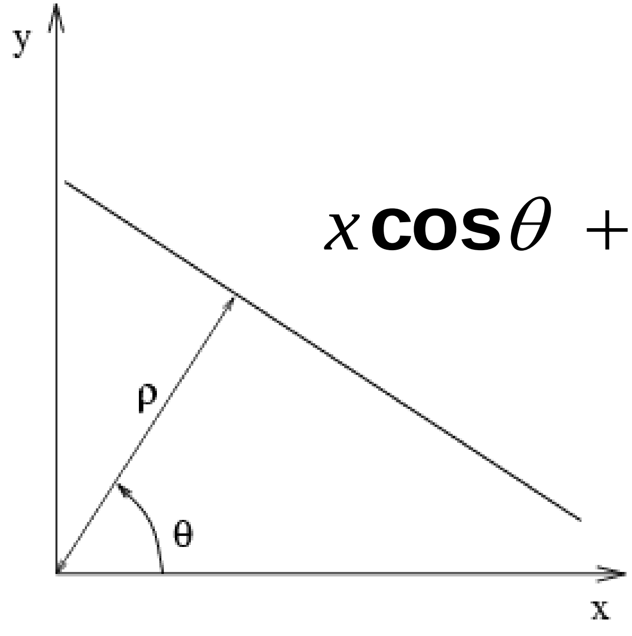
Finding lines in an image: Hough space



Adapted from Silvio Savarese

Parameter space representation

- Problems with the (m, b) space:
  - Unbounded parameter domains
  - Vertical lines require infinite m
- Alternative: *polar representation*



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

Each point (x,y) will add a sinusoid in the (θ,ρ) parameter space

Svetlana Lazebnik

Parameter space representation

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  - Unbounded parameter domains
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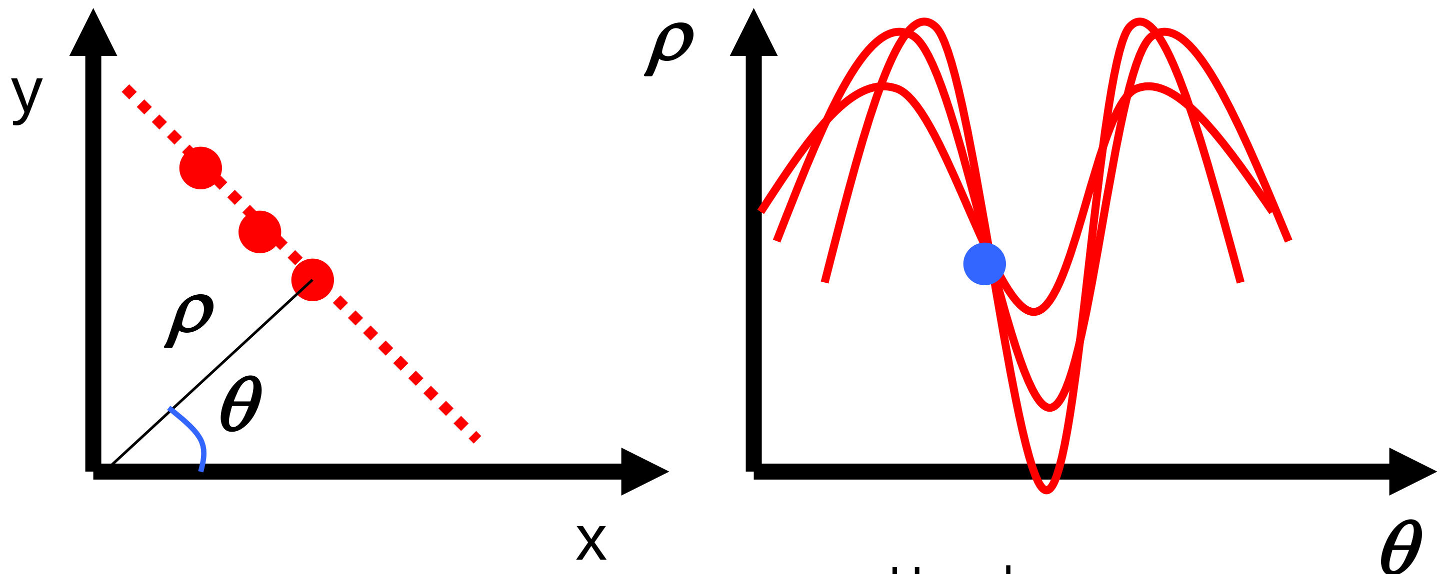


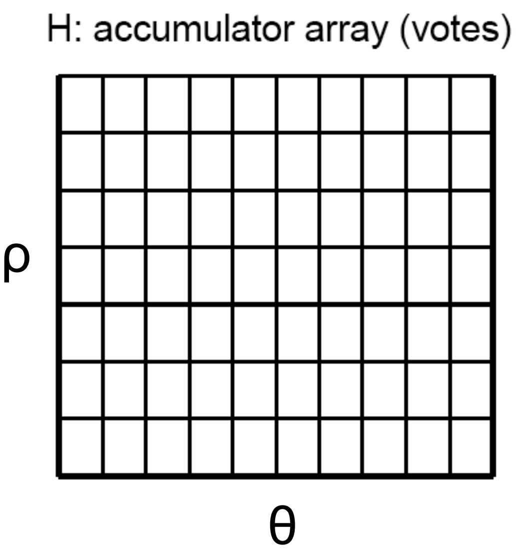
Hough space

Each point (x,y) will add a sinusoid in the (θ,ρ) parameter space

Svetlana Lazebnik

Algorithm outline: Hough transform

- Initialize accumulator H to all zeros

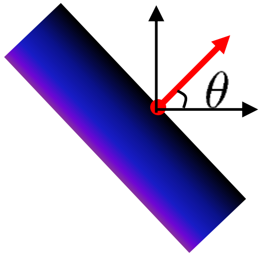


- For each edge point (x,y) in the image
    - For $\theta = 0$ to 180
        - $\rho = x \cos \theta + y \sin \theta$
        - $H(\theta, \rho) = H(\theta, \rho) + 1$
    - end
- end
- Find the value(s) of (θ^*, ρ^*) where $H(\theta, \rho)$ is a local maximum
    - The detected line in the image is given by $\rho^* = x \cos \theta^* + y \sin \theta^*$

Svetlana Lazebnik

Incorporating image gradients

- Recall: when we detect an edge point, we also know its gradient direction
- But this means that the line is uniquely determined!



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

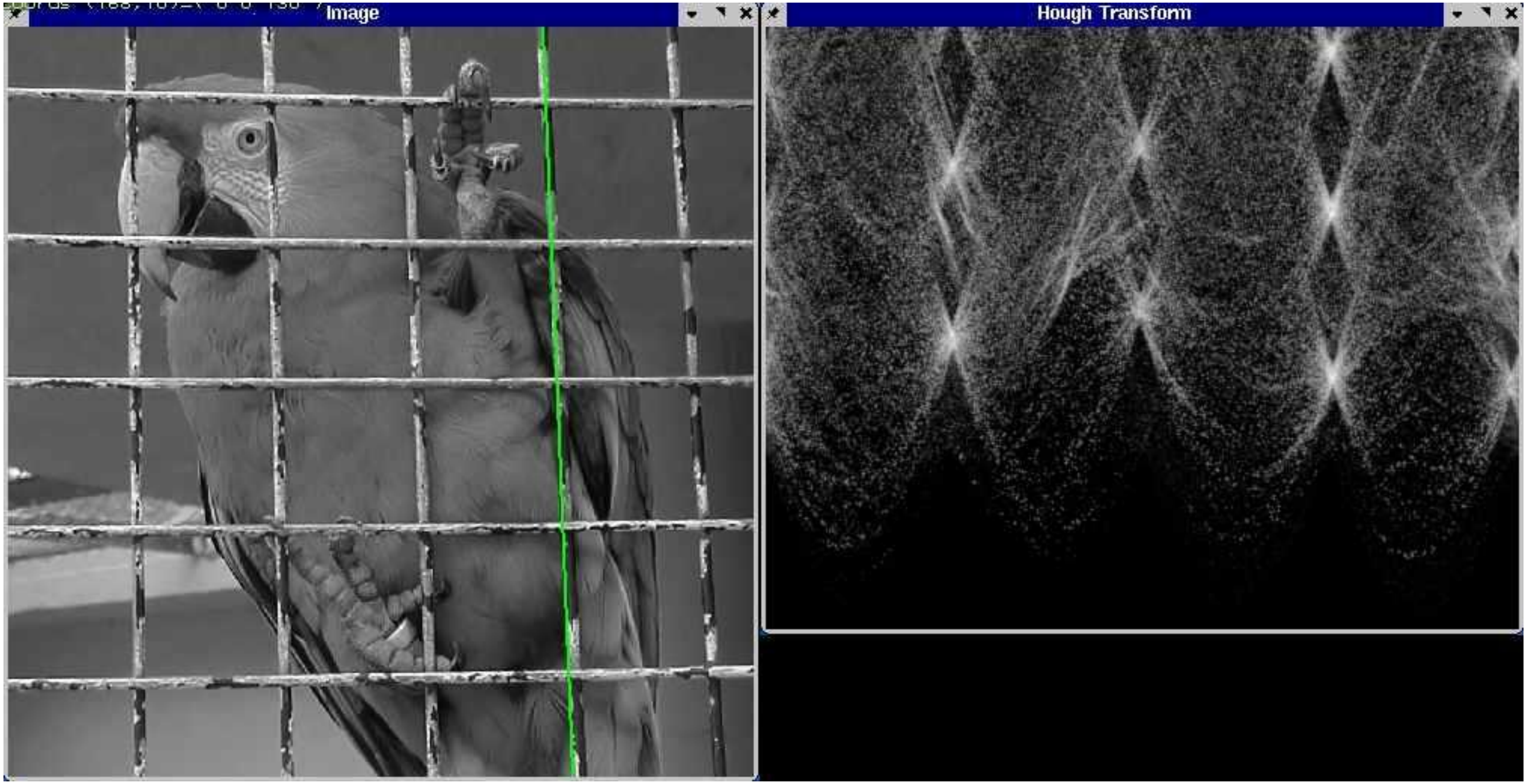
$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

- Modified Hough transform:

For each edge point (x,y) in the image
    θ = gradient orientation at (x,y)
    ρ = x cos θ + y sin θ
    H(θ, ρ) = H(θ, ρ) + 1
end

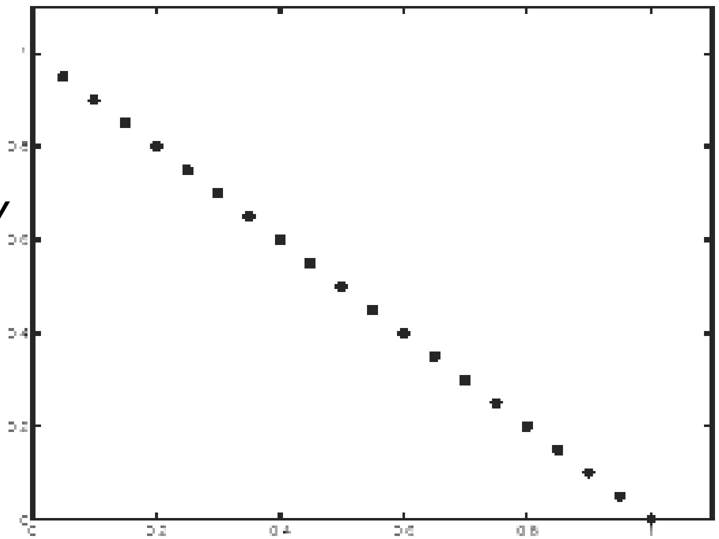
Svetlana Lazebnik

Hough transform example



Derek Hoiem

Impact of noise on Hough



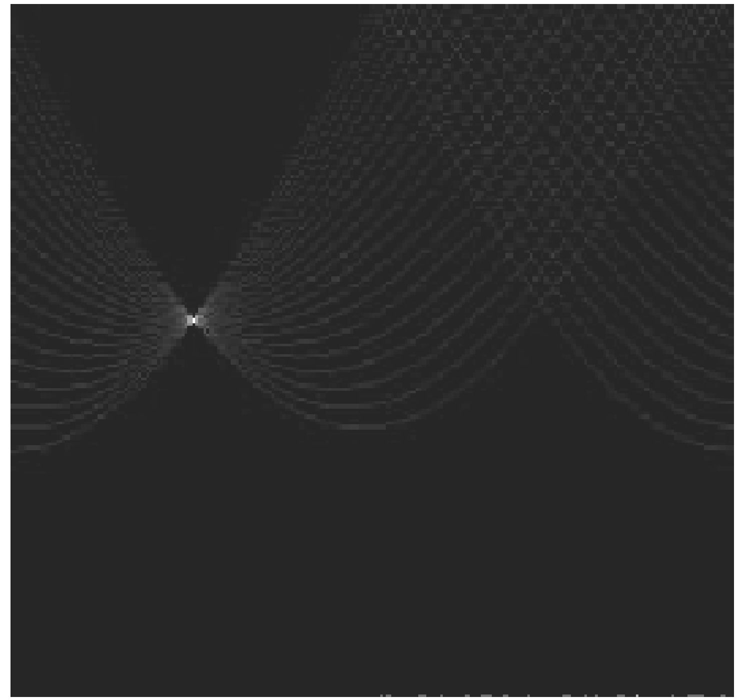
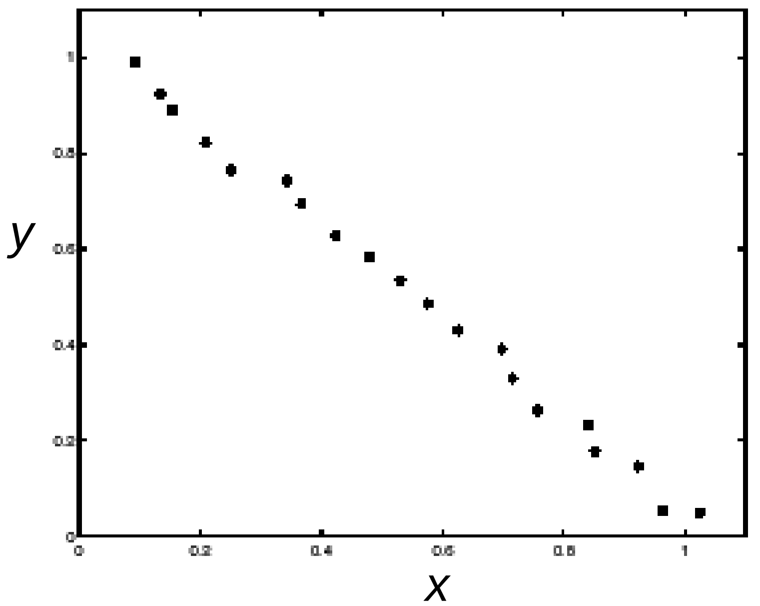


Image space edge coordinates

Votes

Kristen Grauman

Impact of noise on Hough



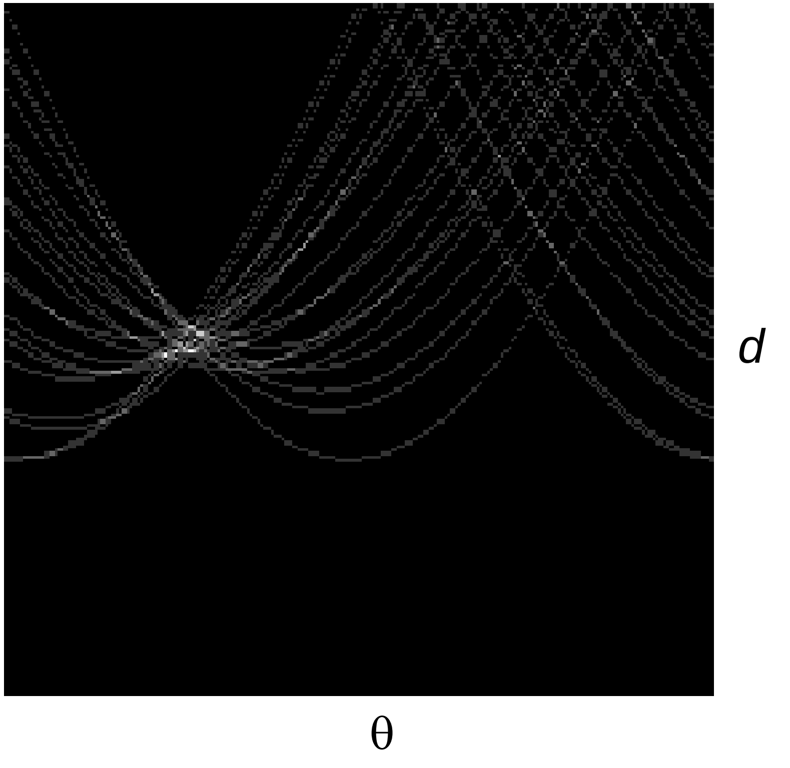


Image space edge coordinates

Votes

What difficulty does this present for an implementation?

Kristen Grauman

Voting: practical tips

- Minimize irrelevant tokens first (reduce noise)
- Choose a good grid / discretization

Too coarse ? Too fine

  - **Too coarse:** large votes obtained when too many different lines correspond to a single bucket
  - **Too fine:** miss lines because points that are not exactly collinear cast votes for different buckets

- Vote for neighbors (smoothing in accumulator array)
- Use direction of edge to reduce parameters by 1
- To read back which points voted for “winning” peaks, keep tags on the votes

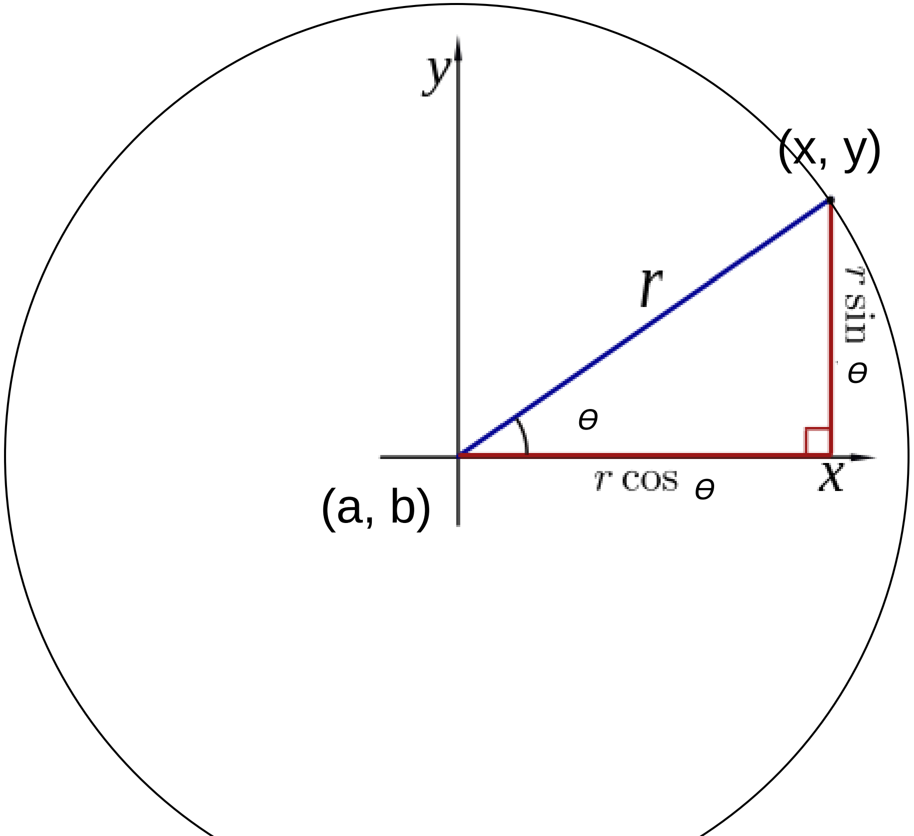
Kristen Grauman

Hough transform for circles

- A circle with radius *r* and center (*a, b*) can be described as:

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

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



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

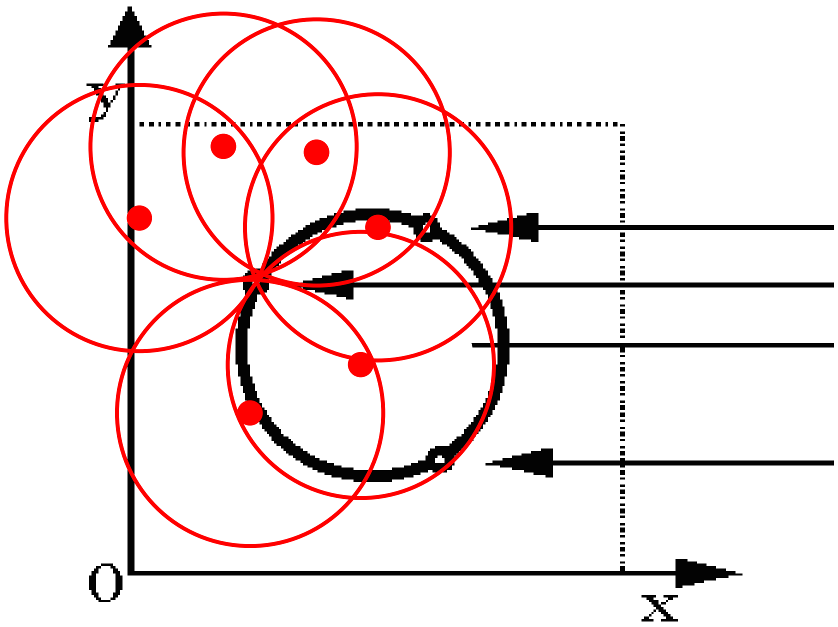
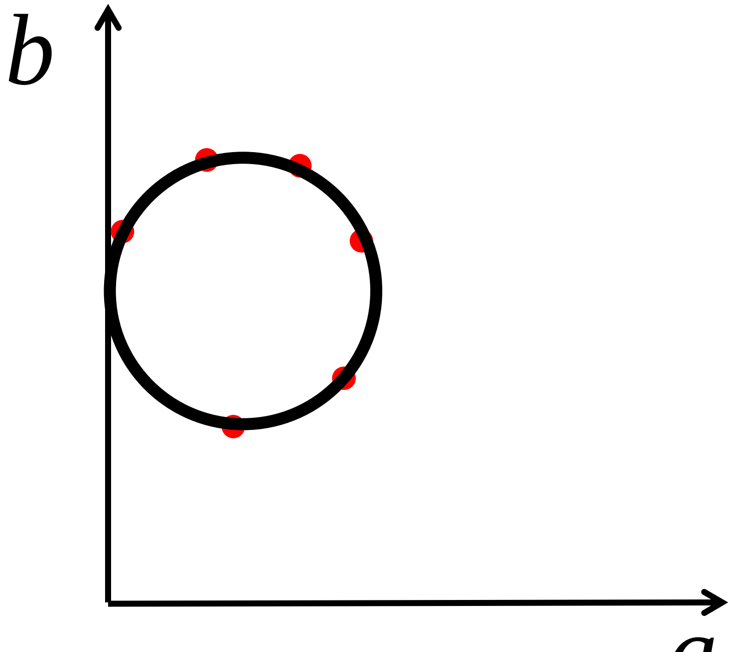


Image space



Hough space

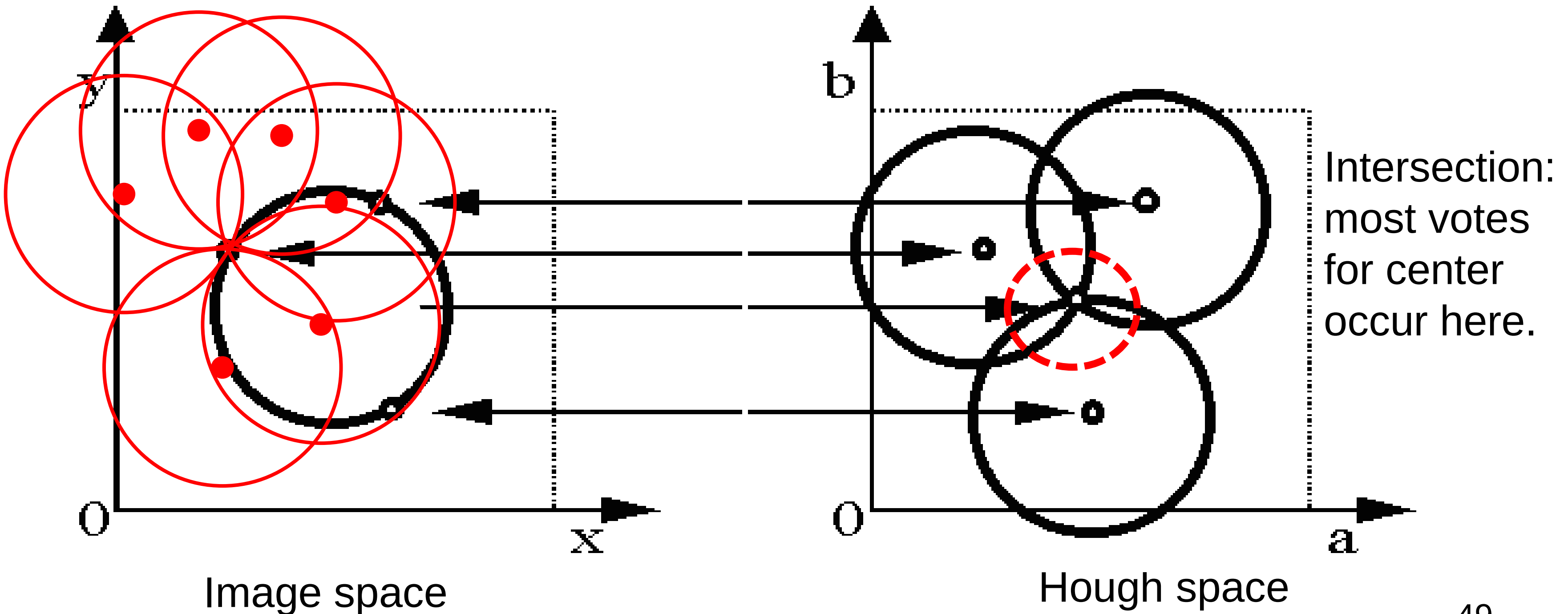
Kristen Grauman

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



Kristen Grauman

Hough transform for circles

$x = a + r\cos(\theta)$
$y = b + r\sin(\theta)$

For every edge pixel (x,y) :

  For each possible radius value r:

    For each possible gradient direction θ:

    // or use estimated gradient at (x,y)

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

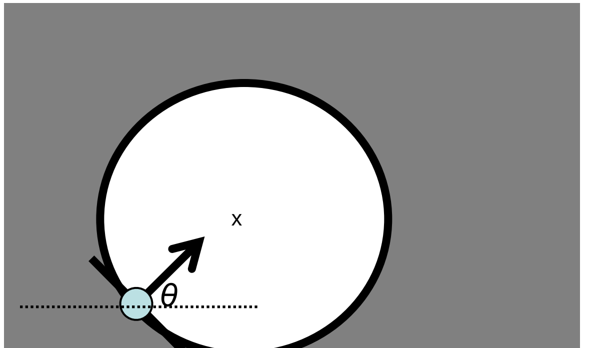
      $b = y - r\sin(\theta)$ // row

      $H[a,b,r]$ += 1

    end

  end

end

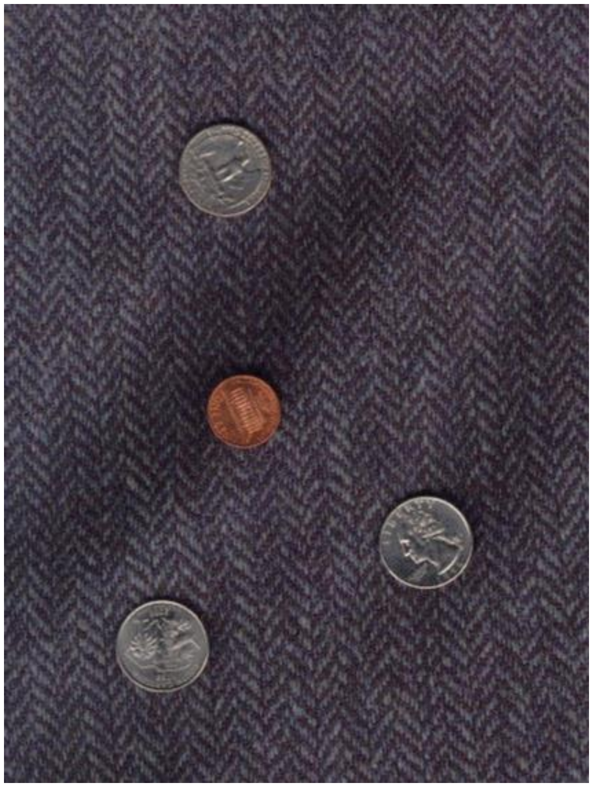


Your homework!

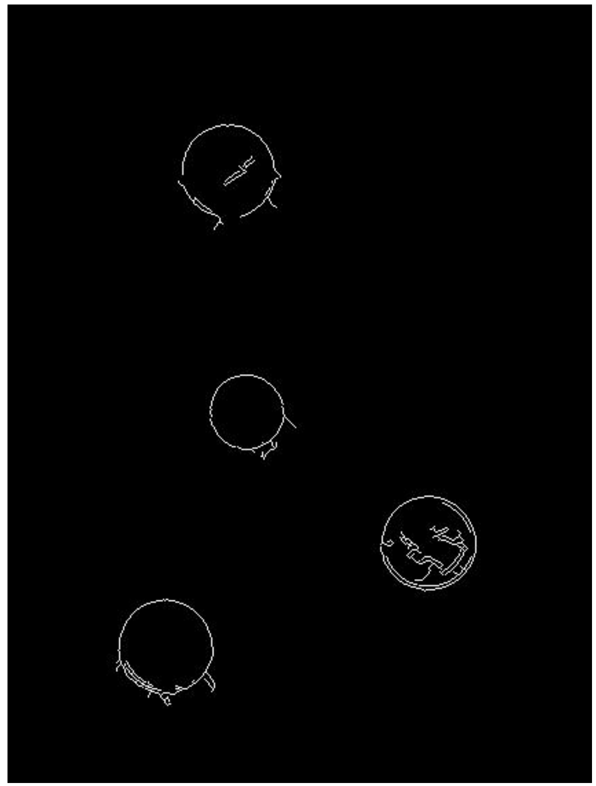
Modified from Kristen Grauman

Example: detecting circles with Hough

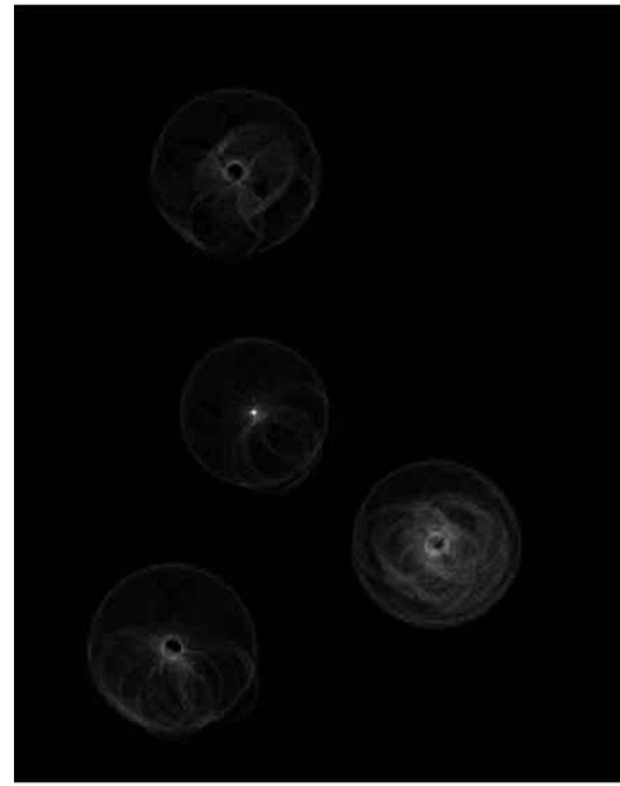
Original



Edges



Votes: Penny

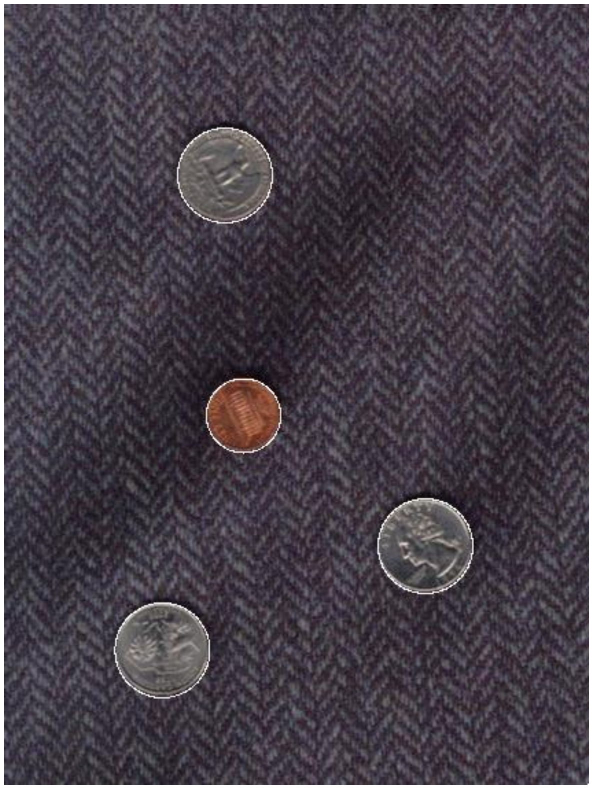


Note: a different Hough transform (with separate accumulators) was used for each circle radius (quarters vs. penny).

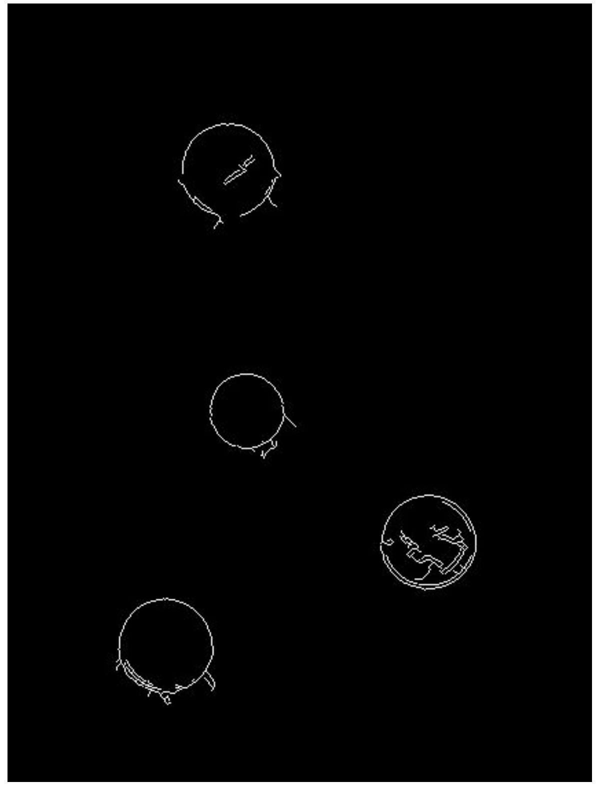
Kristen Grauman, images from Vivek Kwatra

Example: detecting circles with Hough

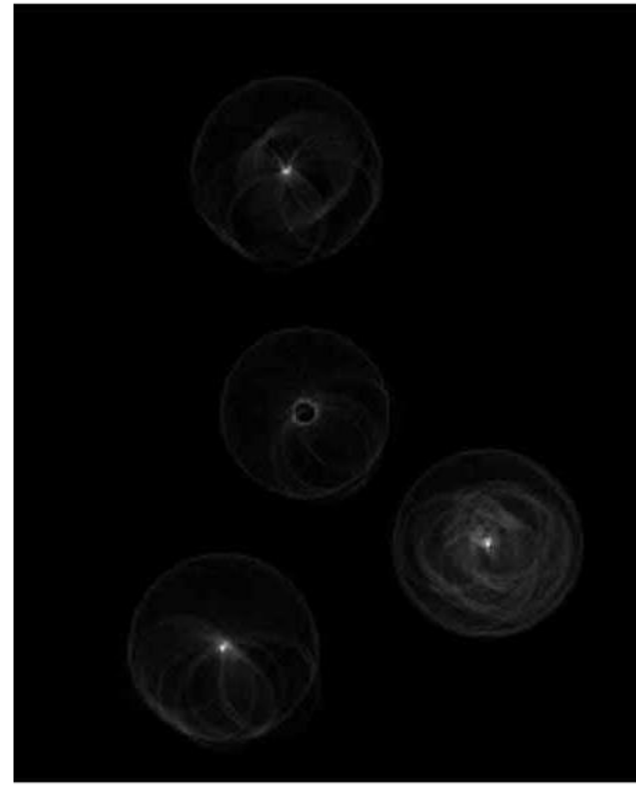
Combined detections
Original



Edges



Votes: Quarter



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

Kristen Grauman, images from Vivek Kwatra

Hough transform: pros and cons

Pros

- All points are processed independently, so can cope with occlusion, gaps
- 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

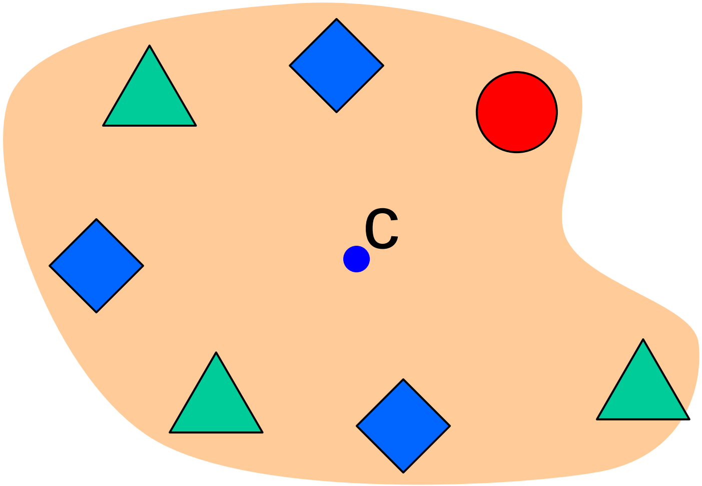
- Complexity of search time for maxima increases exponentially with the number of model parameters
  - If 3 parameters and 10 choices for each, search is $O(10^3)$
- Quantization: can be tricky to pick a good grid size

Adapted from Kristen Grauman

Generalized Hough transform

- We want to find a template defined by its reference point (center) and several distinct types of landmark points in stable spatial configuration

Template

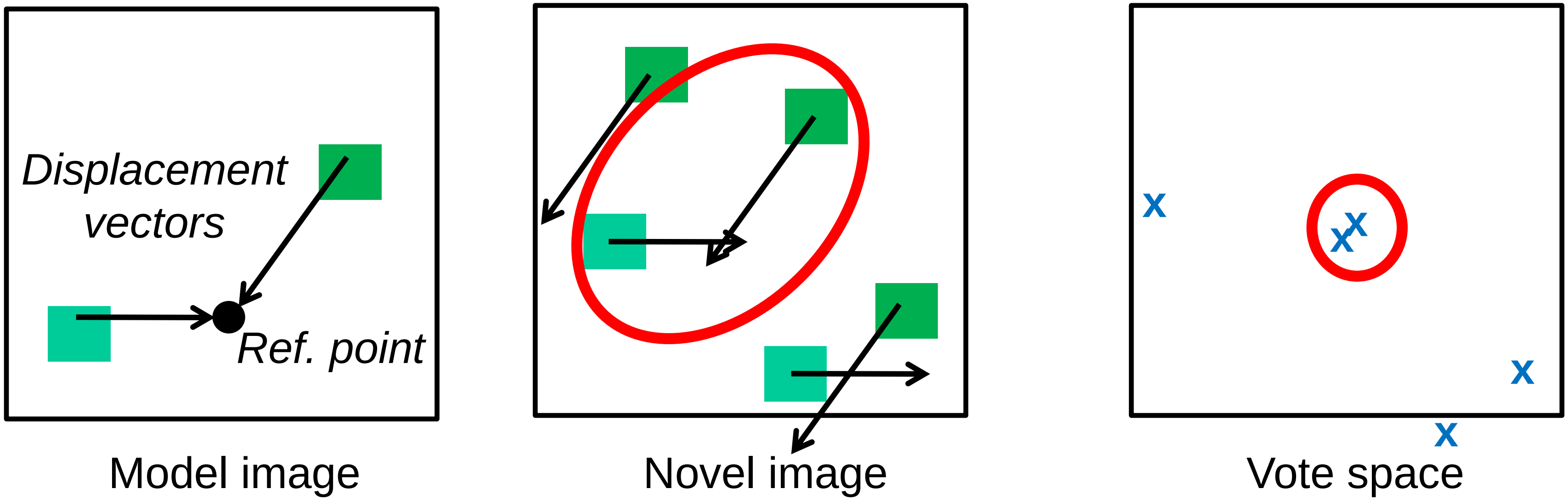


Triangle, circle, diamond: some *type* of visual token, e.g. feature or edge point

Adapted from Svetlana Lazebnik

Generalized Hough transform

Intuition:

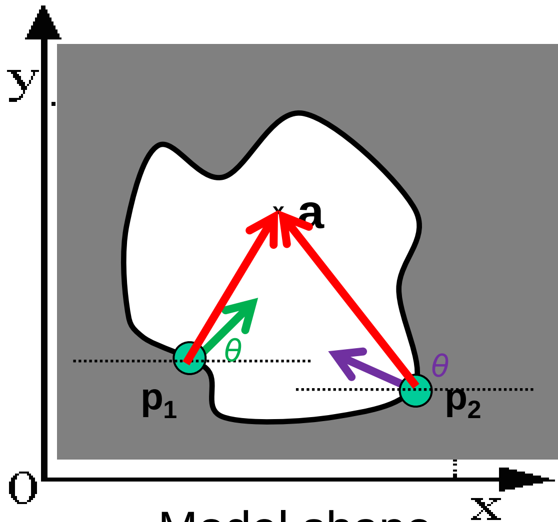


Now suppose those colors encode gradient directions…

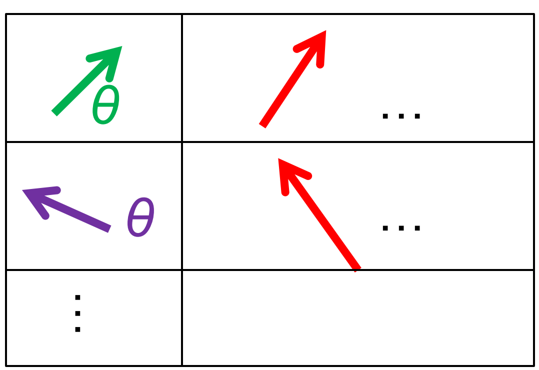
Adapted from Kristen Grauman

Generalized Hough transform

Define a model shape by its boundary points and a reference point.



Model shape



Offline procedure:

At each boundary point, compute displacement vector: $\mathbf{r} = \mathbf{a} - \mathbf{p}_i$.

Store these vectors in a table indexed by gradient orientation θ.

Kristen Grauman

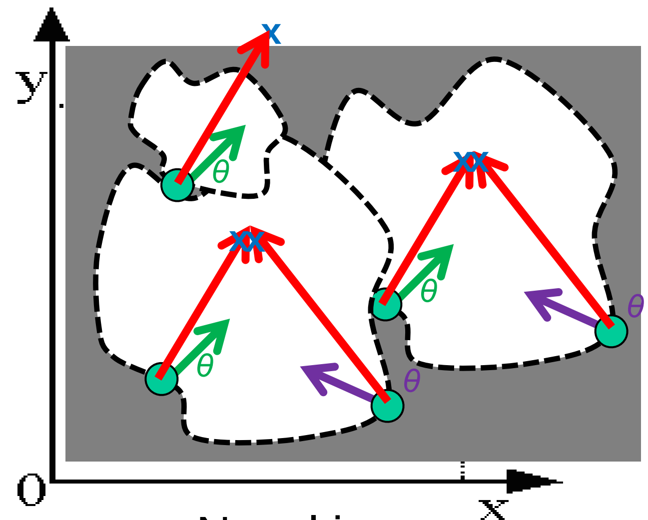
[Dana H. Ballard, Generalizing the Hough Transform to Detect Arbitrary Shapes, 1980]

Generalized Hough transform

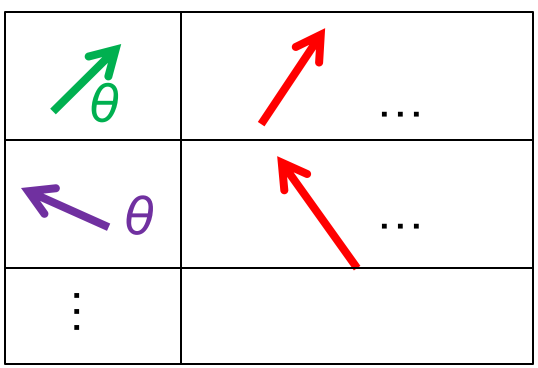
Detection procedure:

For each edge point:

- Use its gradient orientation θ to index into stored table
- Use retrieved **r** vectors to vote for reference point



Novel image



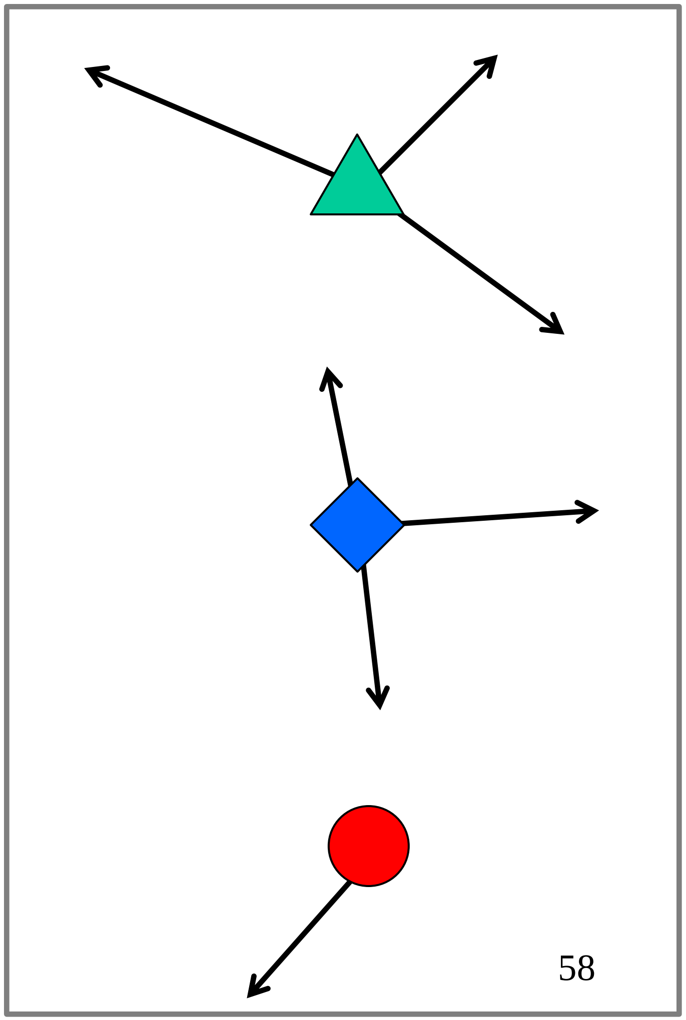
Assuming translation is the only transformation here, i.e., orientation and scale are fixed.

Kristen Grauman

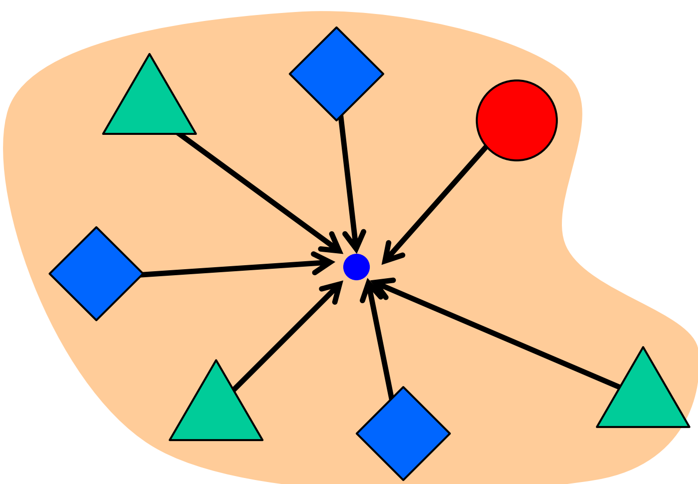
Generalized Hough transform

- Template representation
  - For each type of landmark point, store all possible displacement vectors towards the center

Model



Template

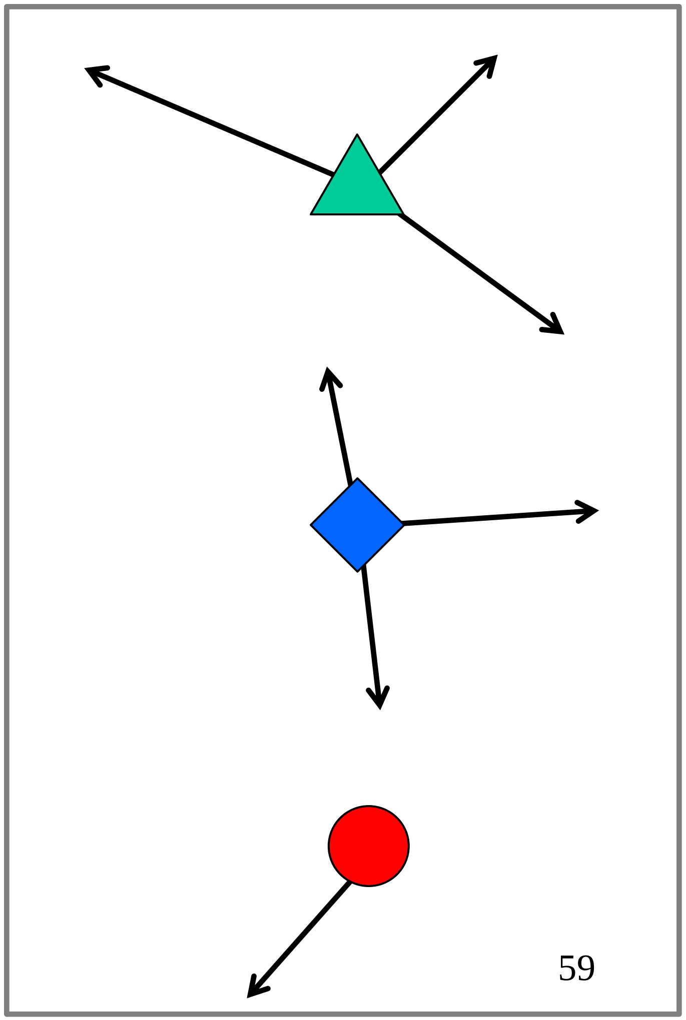


Svetlana Lazebnik

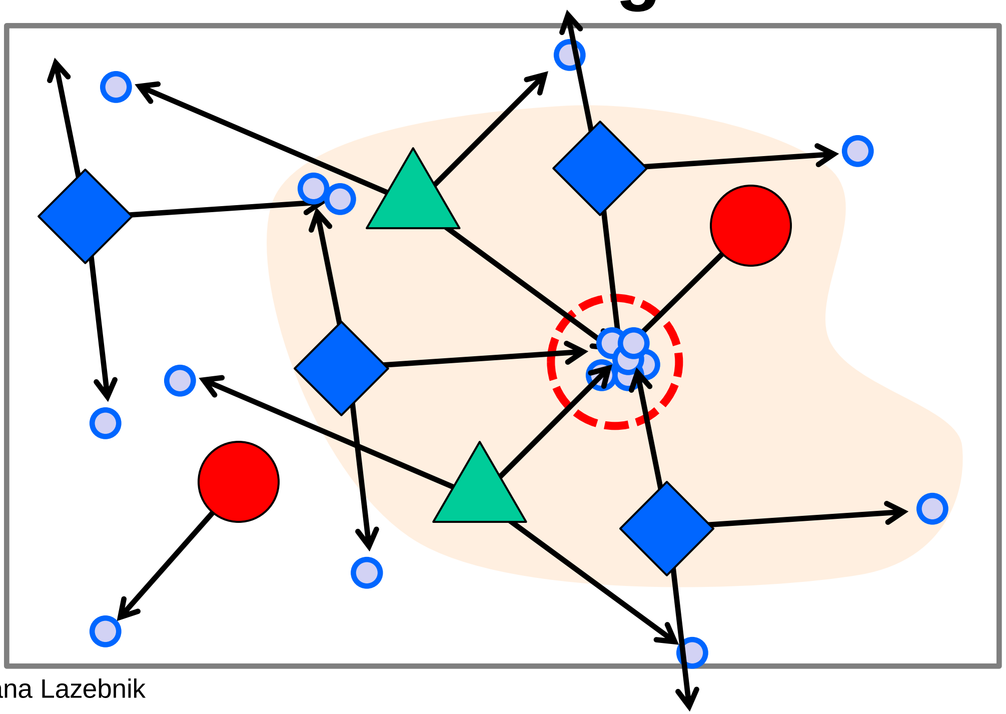
Generalized Hough transform

- Detecting the template
  - For each feature in a new image, look up that feature type in the model and vote for the possible center locations associated with that type in the model

Model



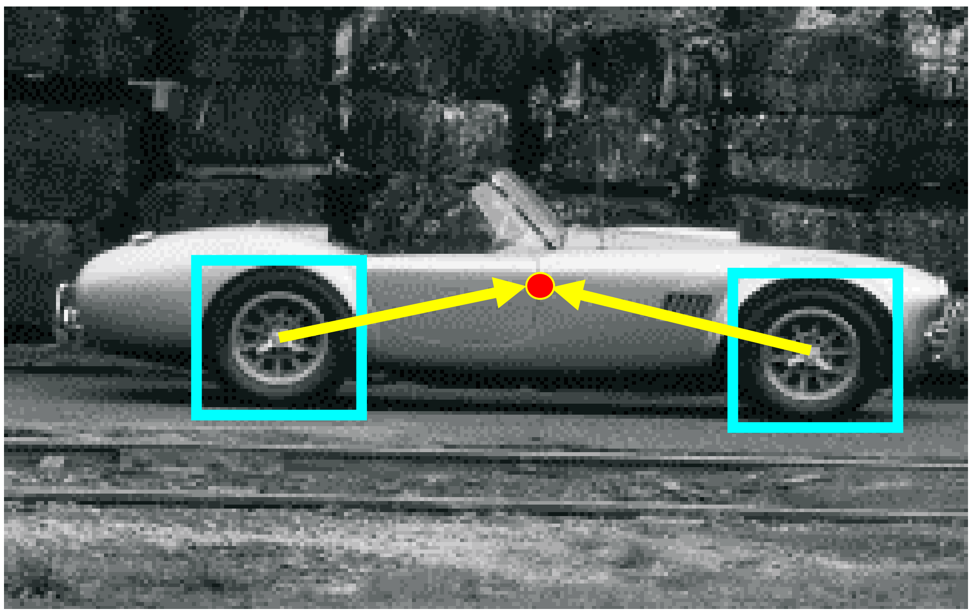
Test image



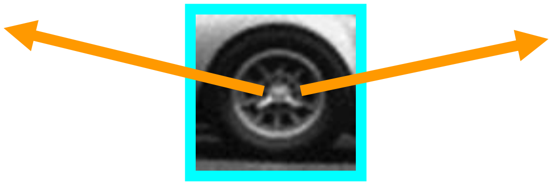
Svetlana Lazebnik

Hough for object detection

- Index displacements by "visual codeword"



training image



"visual codeword" with displacement vectors

B. Leibe, A. Leonardis, and B. Schiele, [Combined Object Categorization and Segmentation with an Implicit Shape Model](), ECCV Workshop on Statistical Learning in Computer Vision 2004

RANSAC

- RANdom Sample Consensus
- **Approach**: we want to avoid the impact of outliers, so let's look for "inliers", and use those only.
- **Intuition**: if an outlier is chosen to compute the current fit, then the resulting line won't have much support from rest of the points.

Kristen Grauman

RANSAC: General form

- RANSAC loop:

1. Randomly select a *seed group* of ***s*** points on which to base model estimate (e.g. ***s***=2 for a line)
2. Fit model to these ***s*** points
3. Find *inliers* to this model (i.e., points whose distance from the line is less than ***t***)
4. Repeat ***N*** times

- Keep the model with the largest number of inliers

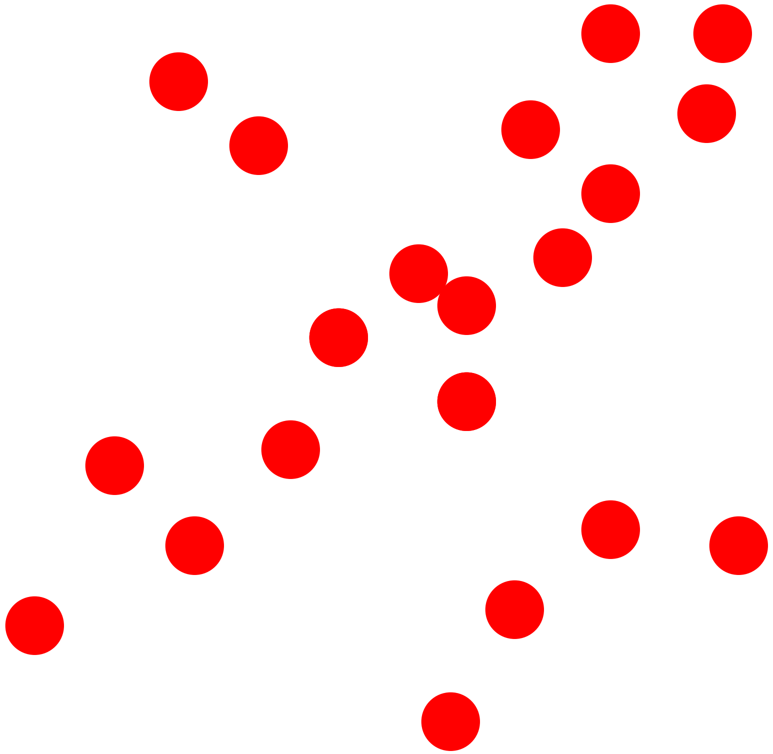
Adapted from Kristen Grauman and Svetlana Lazebnik

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in '81.

Line fitting example



Algorithm:

1. **Sample** (randomly) the number of points required to fit the model
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

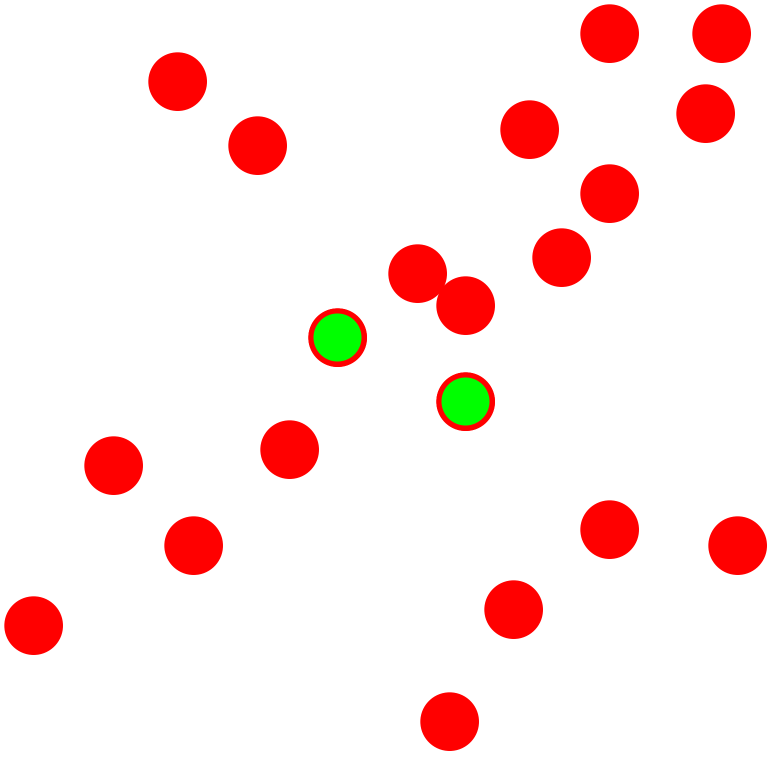
Repeat 1-3 until the best model is found with high confidence

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in '81.

Line fitting example



Algorithm:

1. **Sample** (randomly) the number of points required to fit the model (#=2)
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

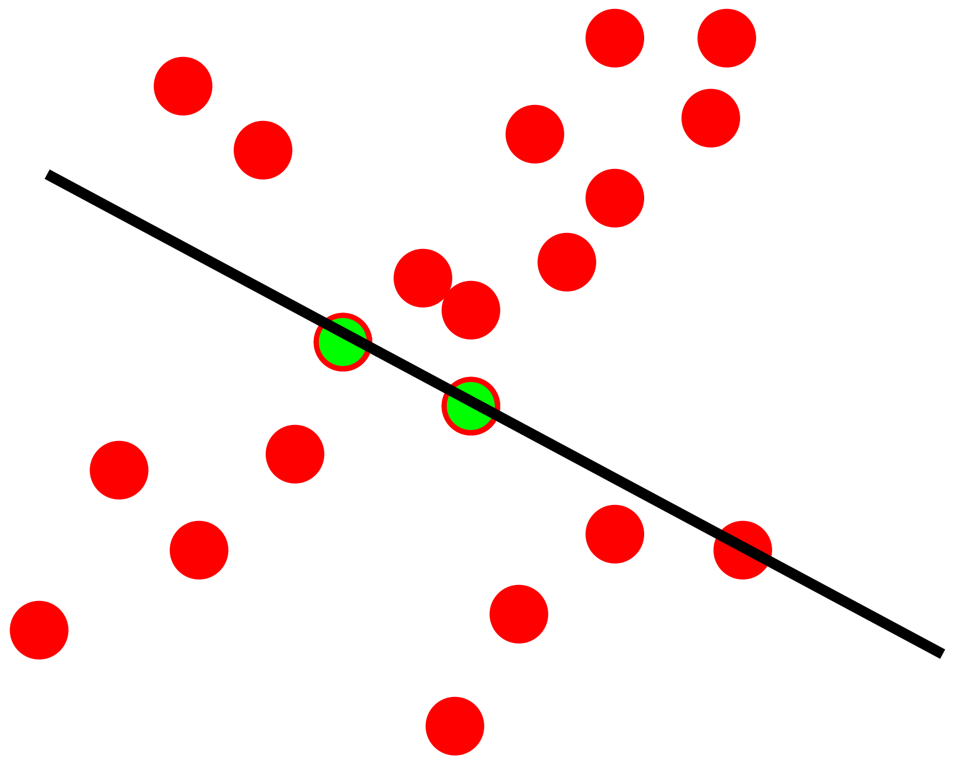
Silvio Savarese

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in '81.

Line fitting example



Algorithm:

1. **Sample** (randomly) the number of points required to fit the model (#=2)
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

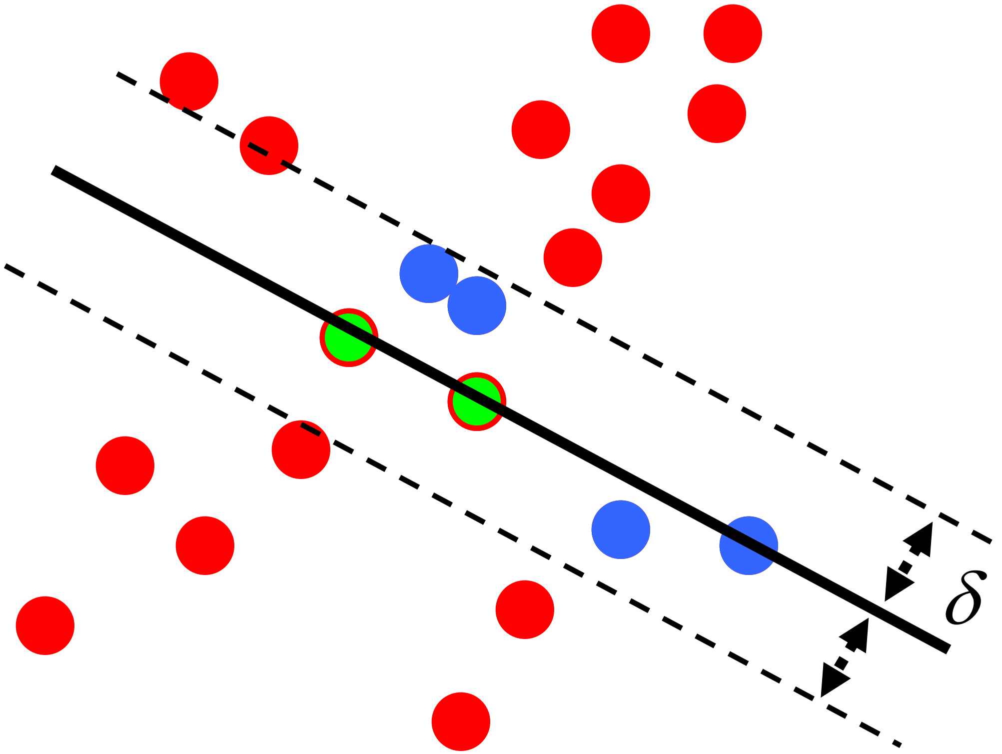
Silvio Savarese

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in '81.

Line fitting example



$$N_I = 6$$

Algorithm:

1. **Sample** (randomly) the number of points required to fit the model (#=2)
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

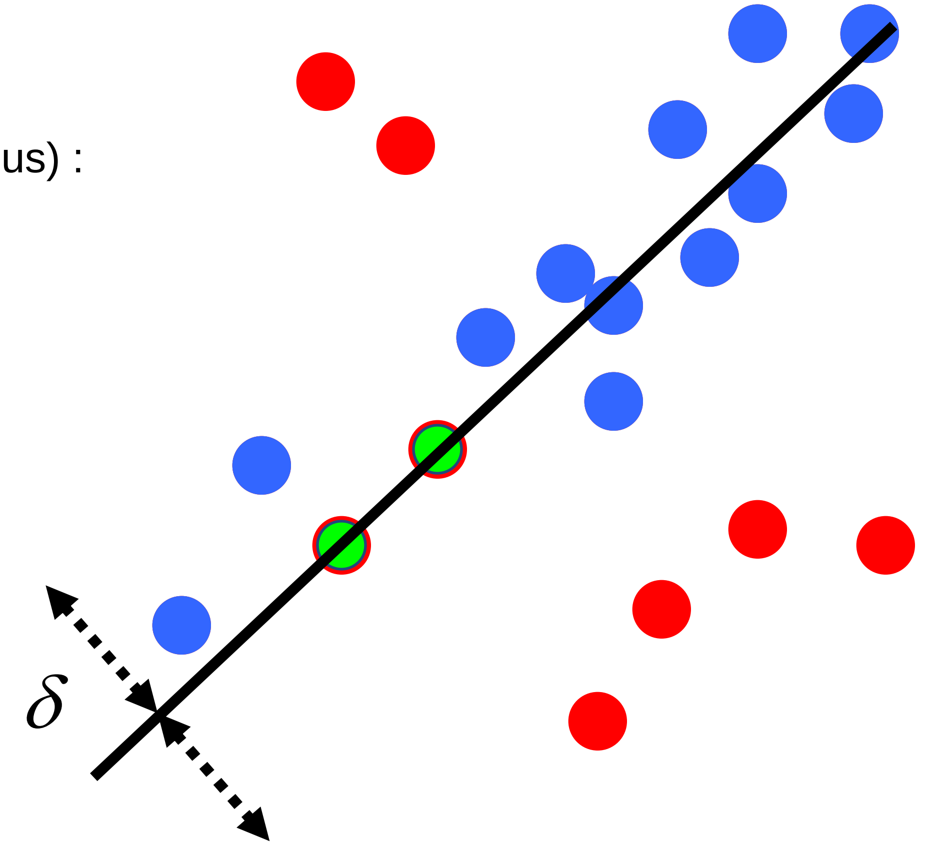
Repeat 1-3 until the best model is found with high confidence

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in ‘81.

Line fitting example



$N_I = 14$

Algorithm:

1. **Sample** (randomly) the number of points required to fit the model (#=2)
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Silvio Savarese

How to choose parameters?

- Number of samples *N*
  - Choose *N* so that, with probability *p*, at least one random sample is free from outliers (e.g. *p*=0.99) (outlier ratio: *e*)
- Number of sampled points *s*
  - Minimum number needed to fit the model
- Distance threshold δ
  - Choose δ so that a good point with noise is likely (e.g., prob=0.95) within threshold
  - E.g. for zero-mean Gaussian noise with std. dev. σ: $\delta^2 = 3.84\sigma^2$

$$N = \log(1-p)/\log\left(1-(1-e)^s\right)$$

Explanation in Szeliski 8.1.4

	proportion of outliers *e*						
s	5%	10%	20%	25%	30%	40%	50%
2	2	3	5	6	7	11	17
3	3	4	7	9	11	19	35
4	3	5	9	13	17	34	72
5	4	6	12	17	26	57	146
6	4	7	16	24	37	97	293
7	4	8	20	33	54	163	588
8	5	9	26	44	78	272	1177

Marc Pollefeys and Derek Hoiem

RANSAC pros and cons

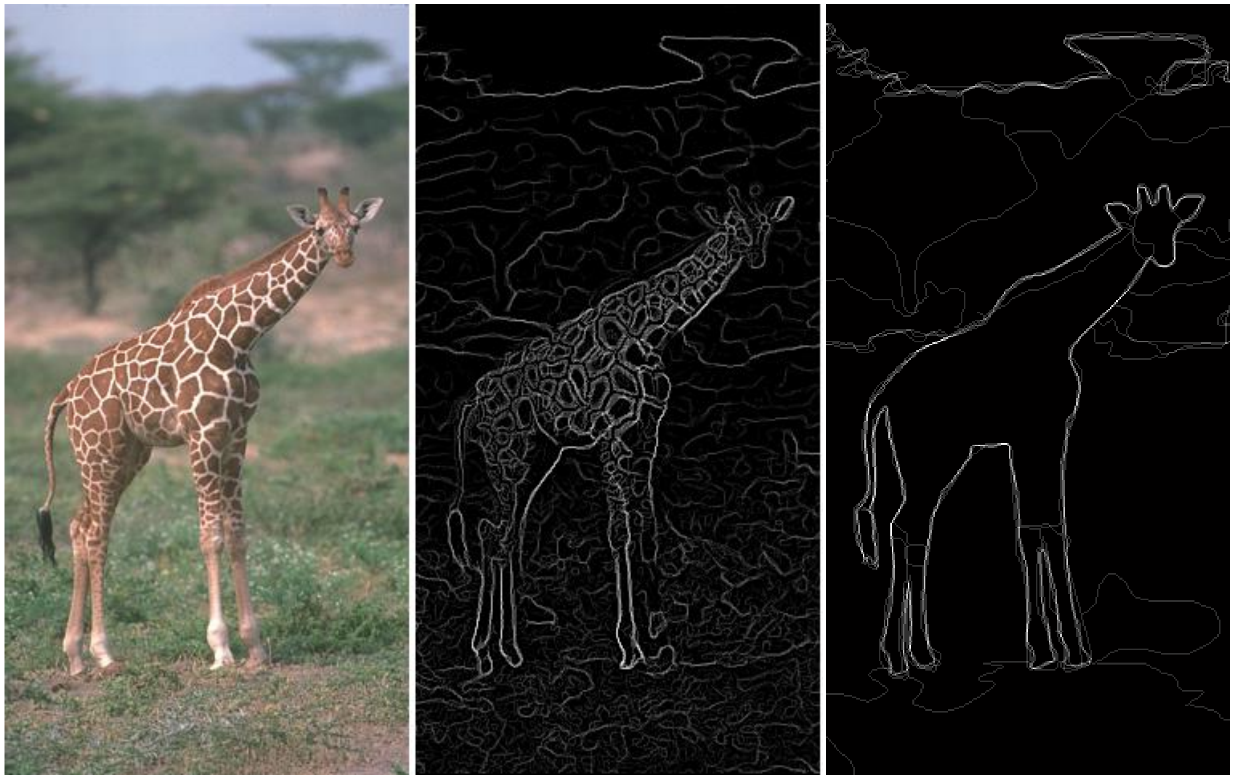
- Pros
  - Applicable to many different problems, e.g. image stitching, relating two views
  - Often works well in practice
- Cons
  - Lots of parameters to tune (see previous slide)
  - Doesn't work well for low inlier ratios (too many iterations, or can fail completely)

Adapted from Svetlana Lazebnik

Plan for today

- Edges
  - Extract gradients and threshold
- Lines and circles
  - Find which edge points are collinear or belong to another shape e.g. circle
  - Automatically detect and ignore outliers
- Segments
  - Find which pixels form a consistent region
  - Clustering (e.g. K-means)

Edges vs Segments



- Edges: More low-level; don't need to be closed
- Segments: Ideally one segment for each semantic group/object; should include closed contours

Figure adapted from J. Hays

The goals of segmentation

- Separate image into coherent “objects”

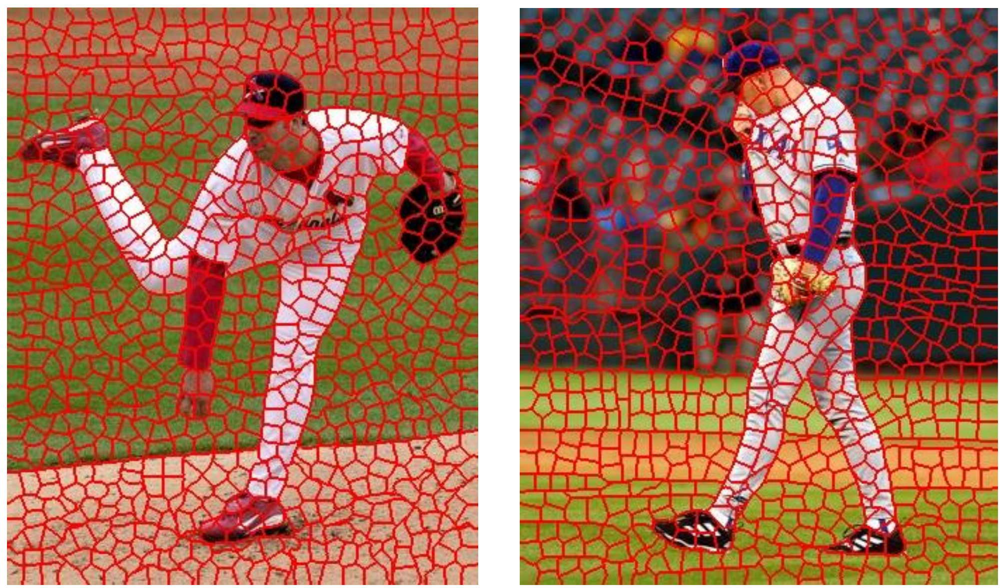
image | human segmentation

Source: L. Lazebnik

The goals of segmentation

- Separate image into coherent "objects"
- Group together similar-looking pixels for efficiency of further processing

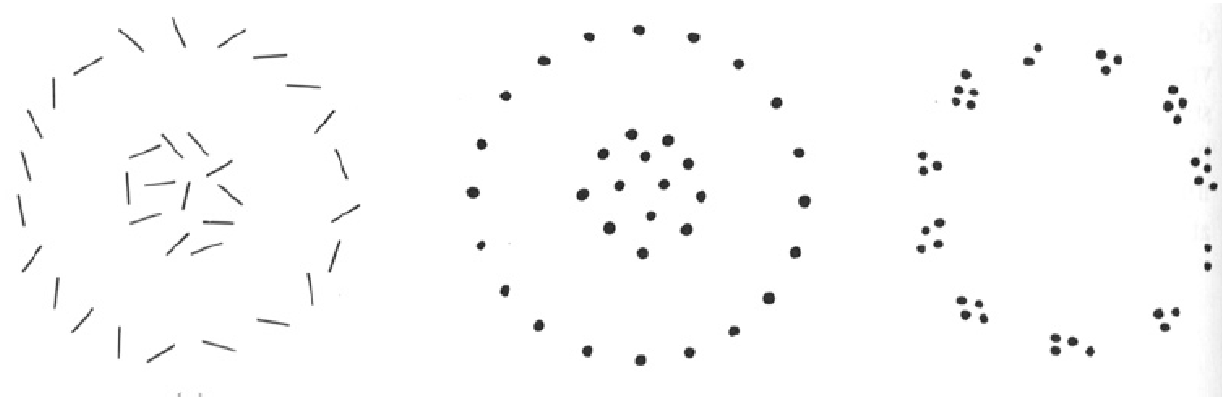
"superpixels"

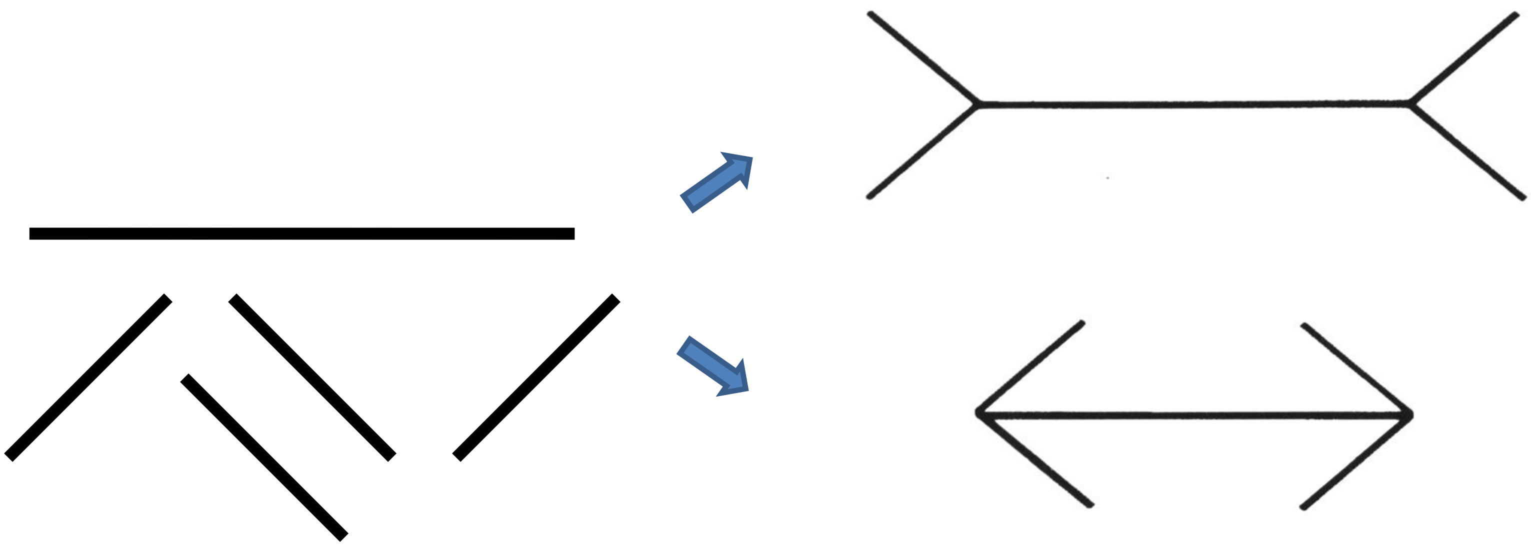


X. Ren and J. Malik. **Learning a classification model for segmentation.** ICCV 2003.

Source: L. Lazebnik

We perceive the interpretation





The Muller-Lyer illusion

Adapted from K. Grauman, D. Hoiem

Similarity

Slide: K. Grauman

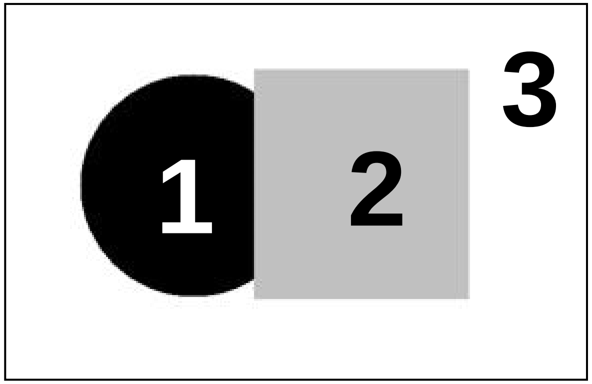
Proximity

Slide: K. Grauman

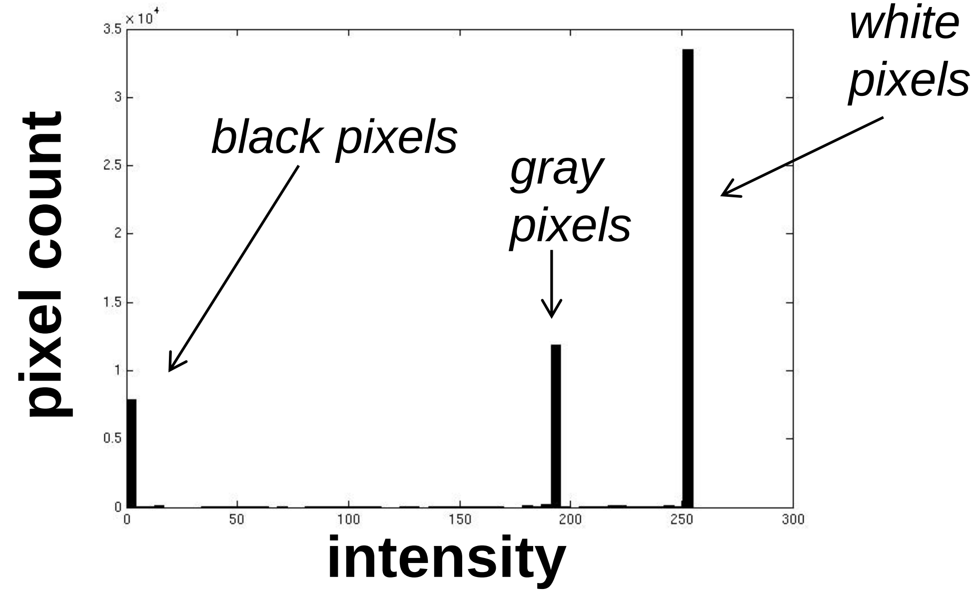
Common fate

Slide: K. Grauman

Image segmentation: toy example

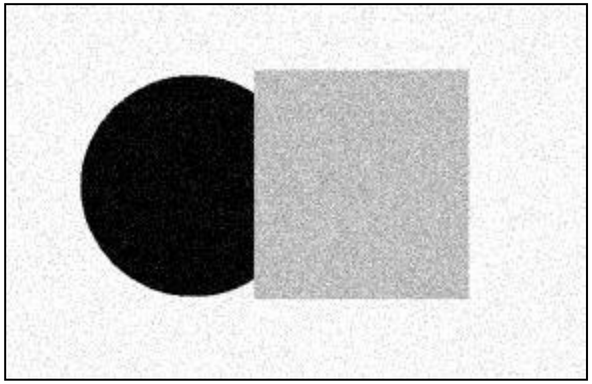


input image

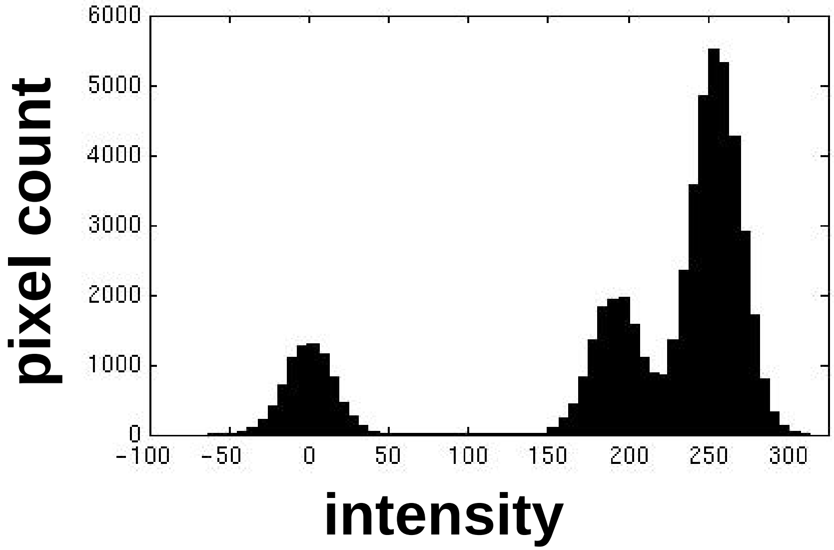


- These intensities define the three groups.
- We could label every pixel in the image according to which of these primary intensities it is.
  - i.e., *segment* the image based on the intensity feature.
- What if the image isn't quite so simple?

Source: K. Grauman

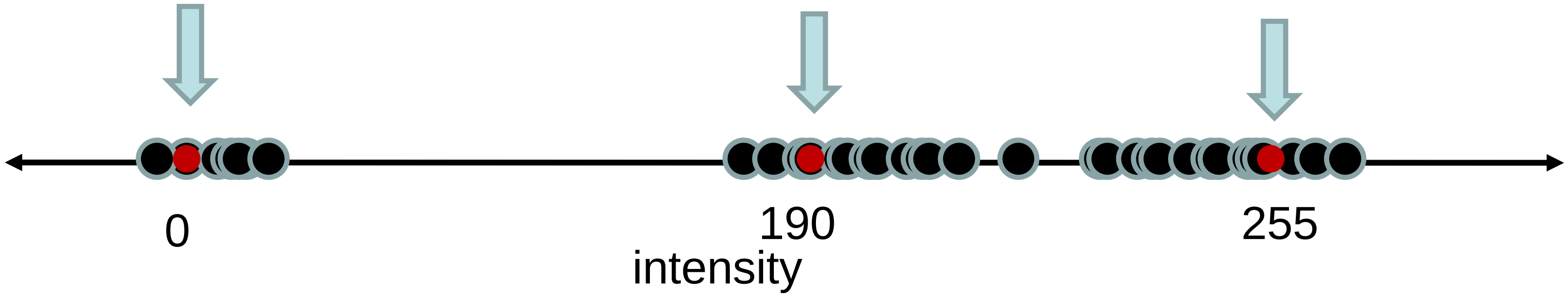


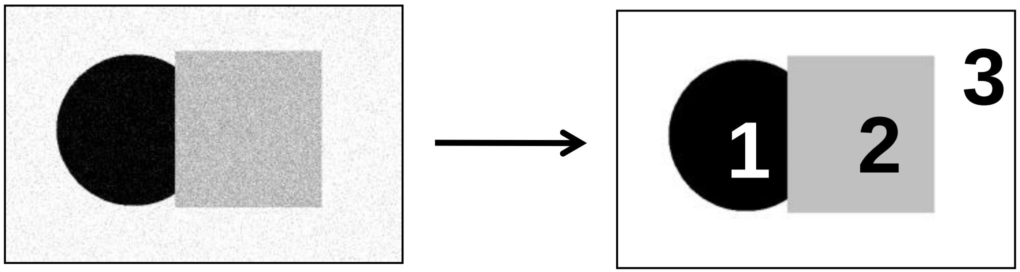
input image



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

Source: K. Grauman





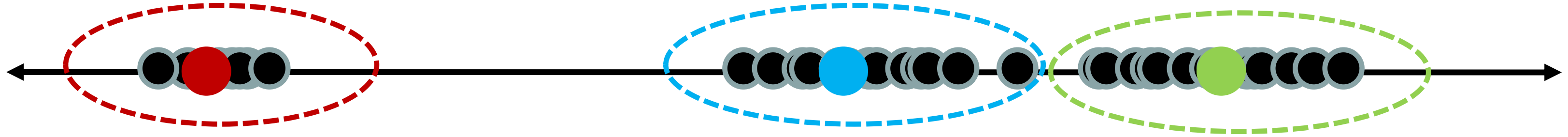
- Goal: choose three “centers” as the representative intensities, and label every pixel according to which of these centers it is nearest to.
- Best cluster centers are those that minimize *sum of squared differences* (SSD) between all points and their nearest cluster center c_i:

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

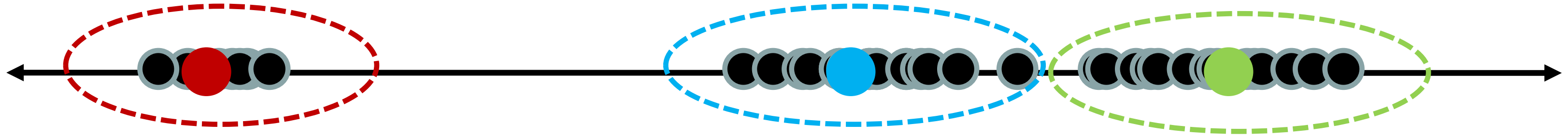
Source: K. Grauman

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.



Source: K. Grauman

K-means clustering

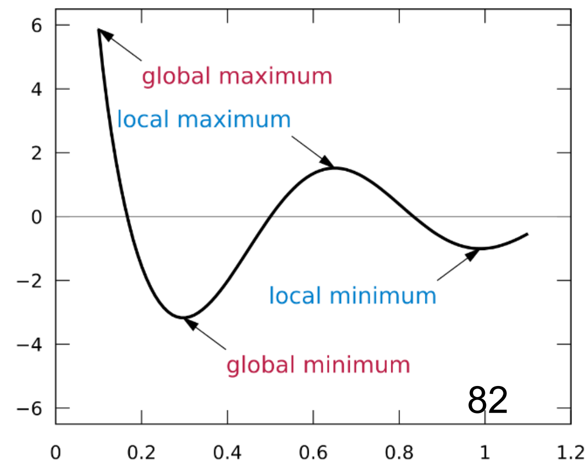
- Basic idea: randomly initialize the *k* cluster centers, and iterate between the two steps we just saw.

1. *Randomly* initialize the cluster centers, $c_1, ..., c_K$
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” of objective:

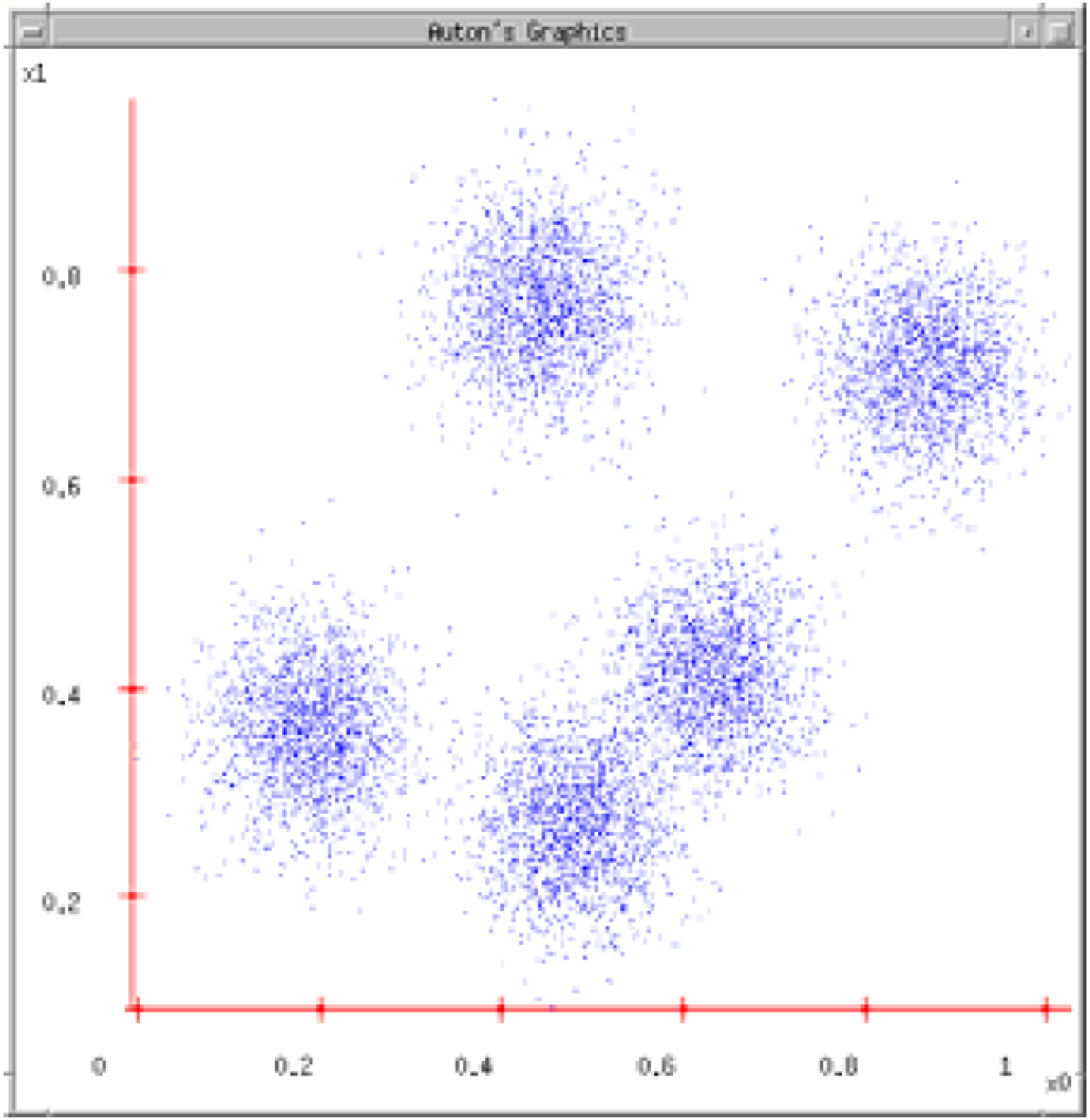
$$\sum_{\text{clusters } i} \sum_{\text{points p in cluster } i} ||p - c_i||^2$$



Slide: Steve Seitz, image: Wikipedia

K-means

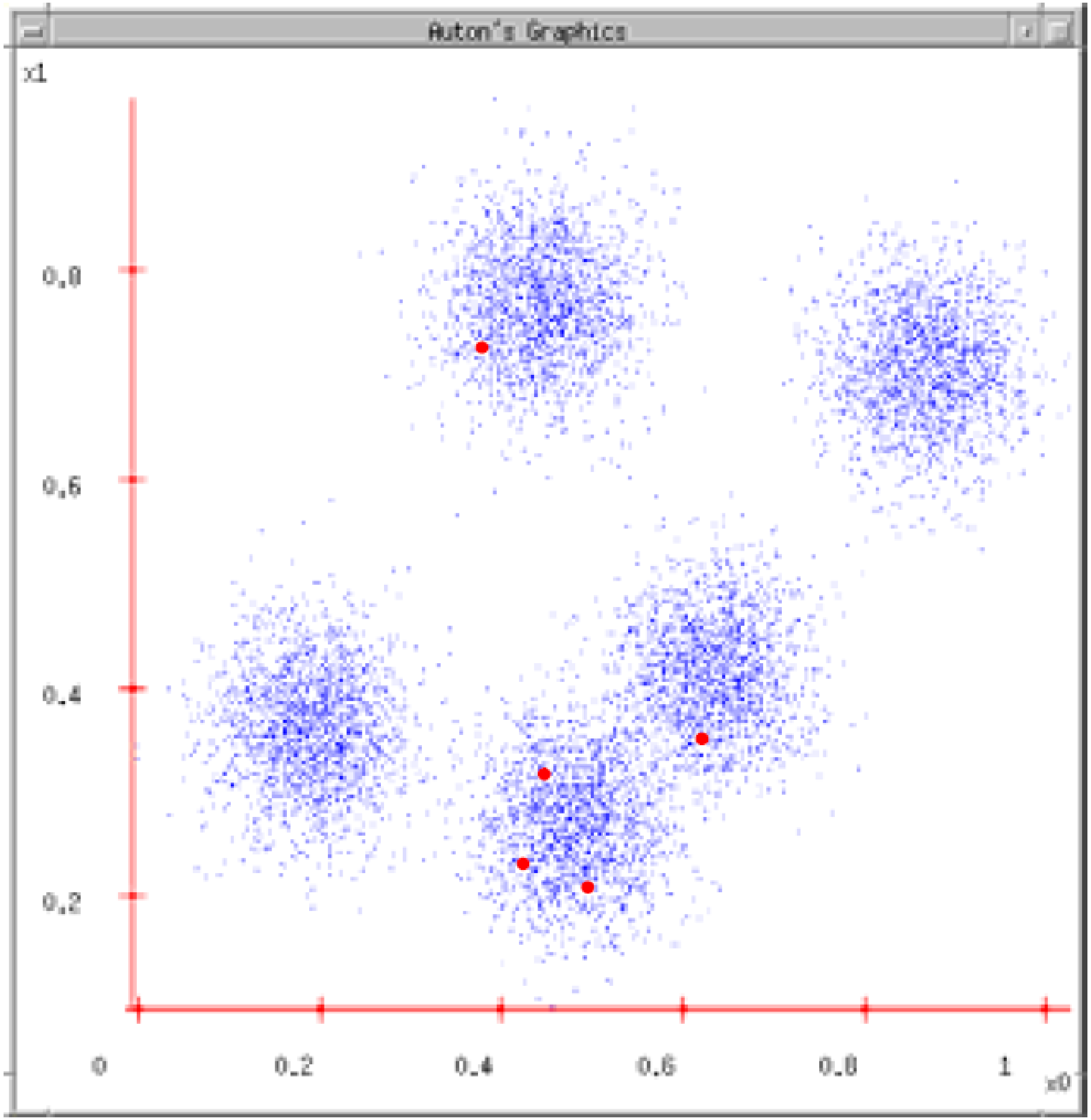
1. Ask user how many clusters they'd like. *(e.g. k=5)*



Source: A. Moore

K-means

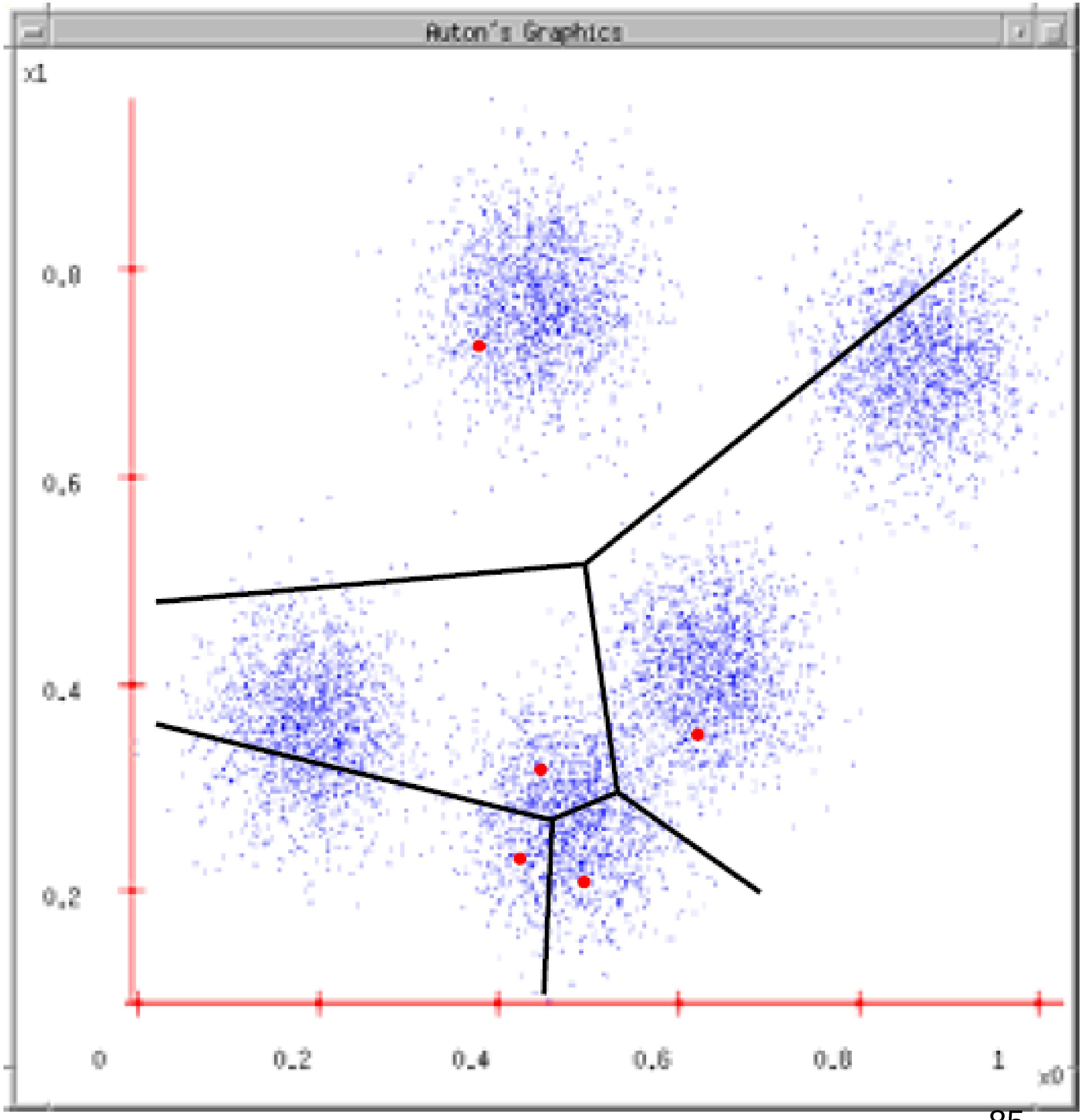
1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations



Source: A. Moore

K-means

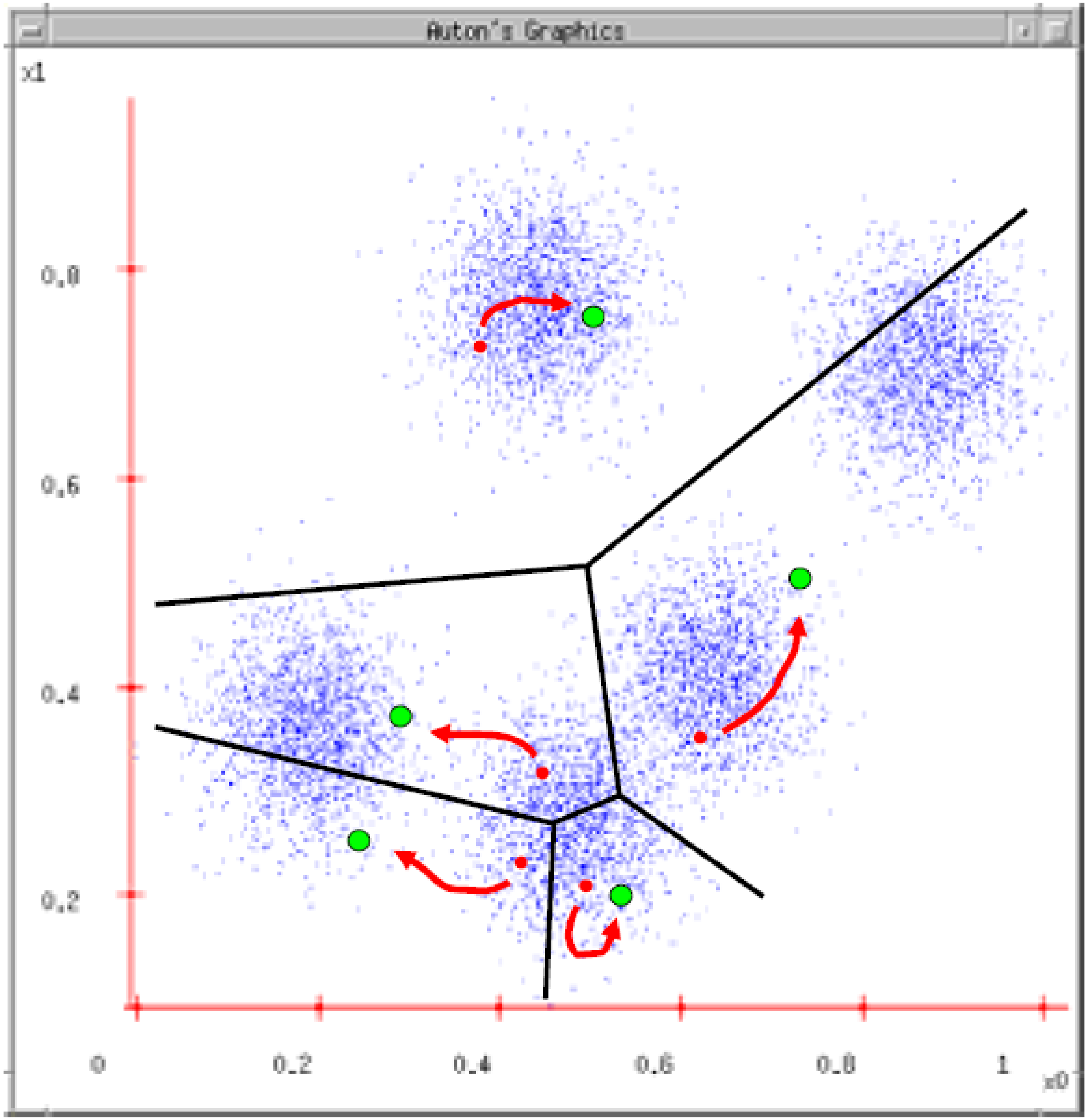
1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to. (Thus each Center "owns" a set of datapoints)



Source: A. Moore

K-means

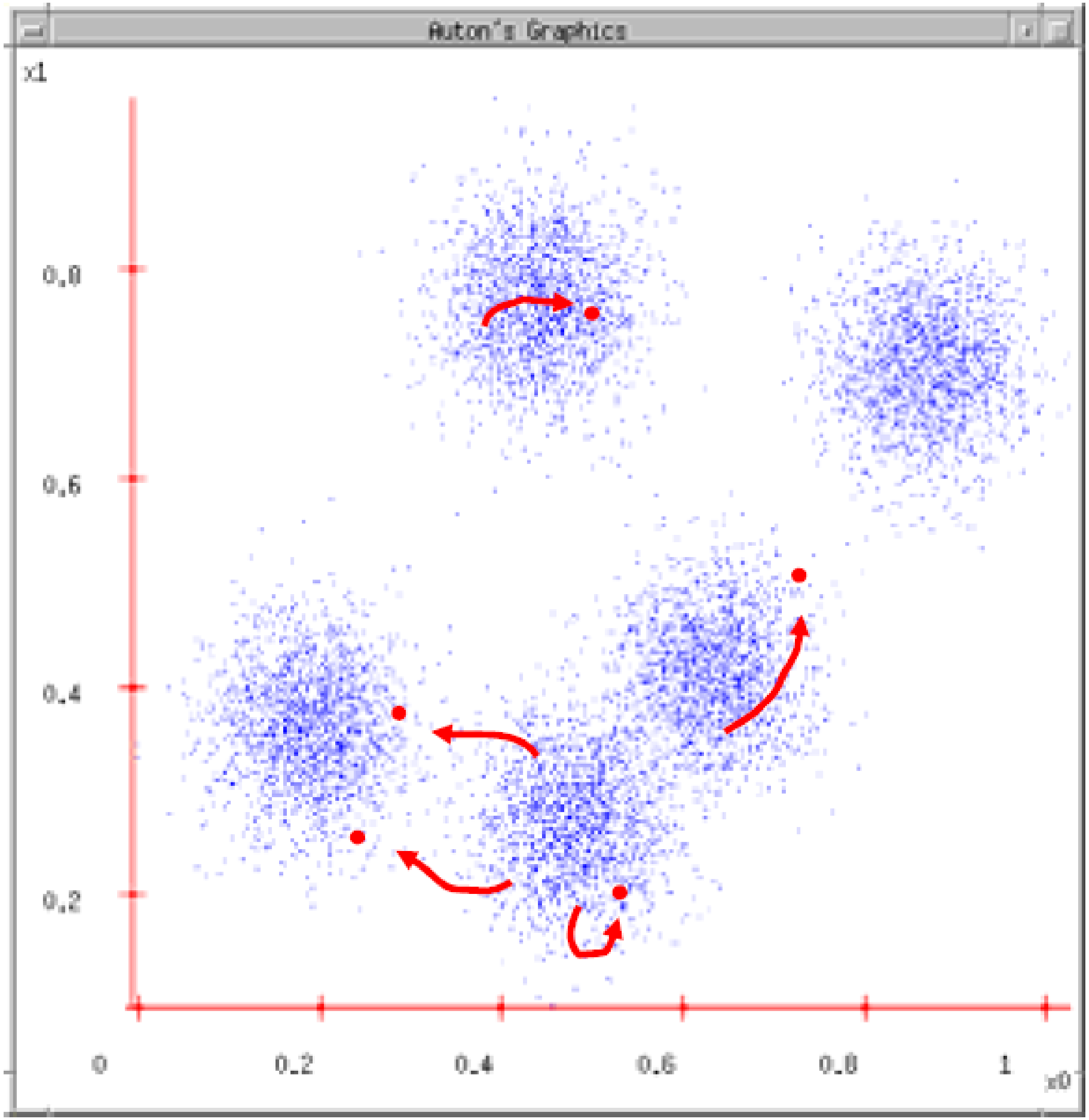
1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns



Source: A. Moore

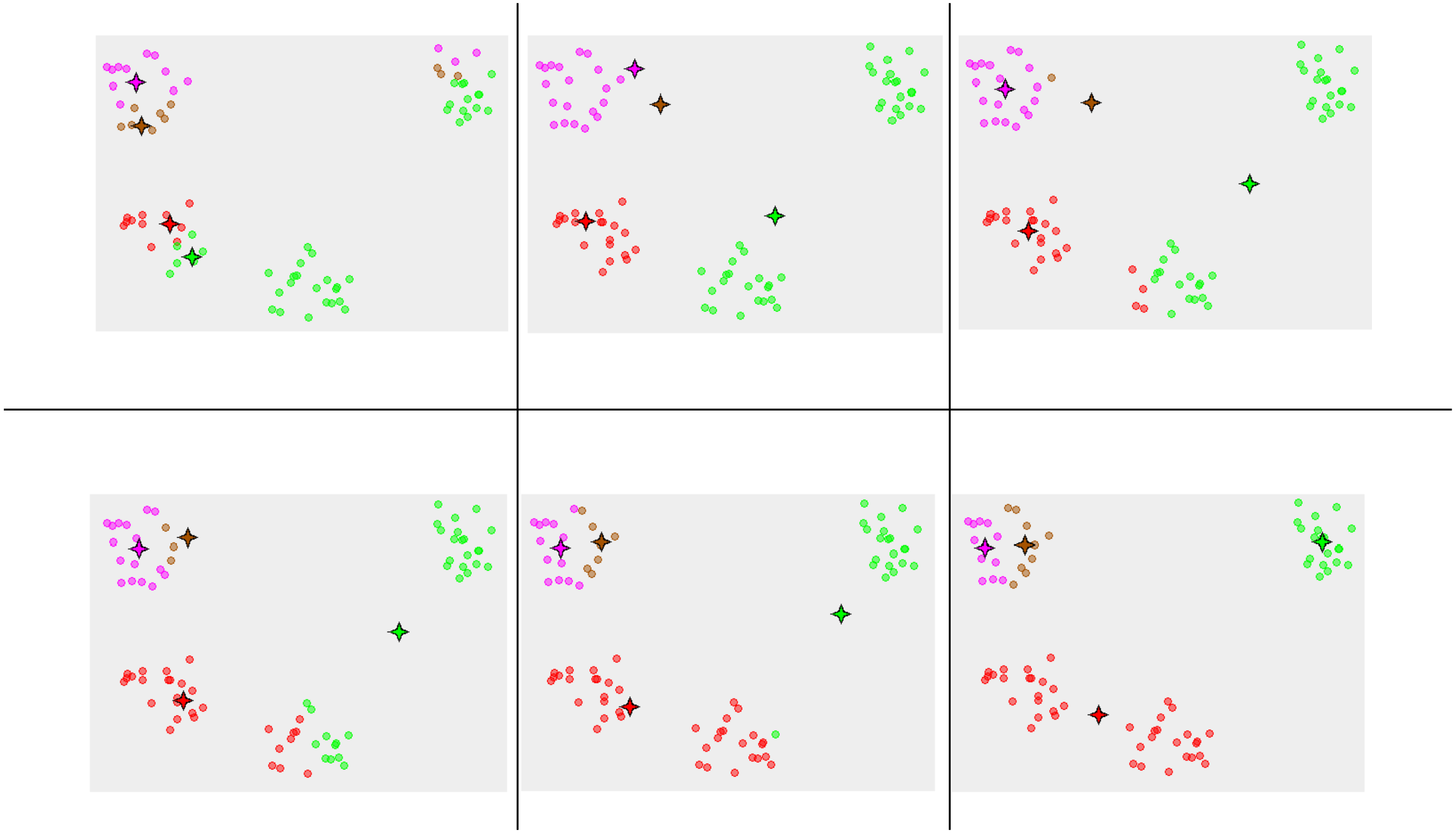
K-means

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!



Source: A. Moore

K-means converges to a local minimum



How can I try to fix this problem?

Adapted from James Hays

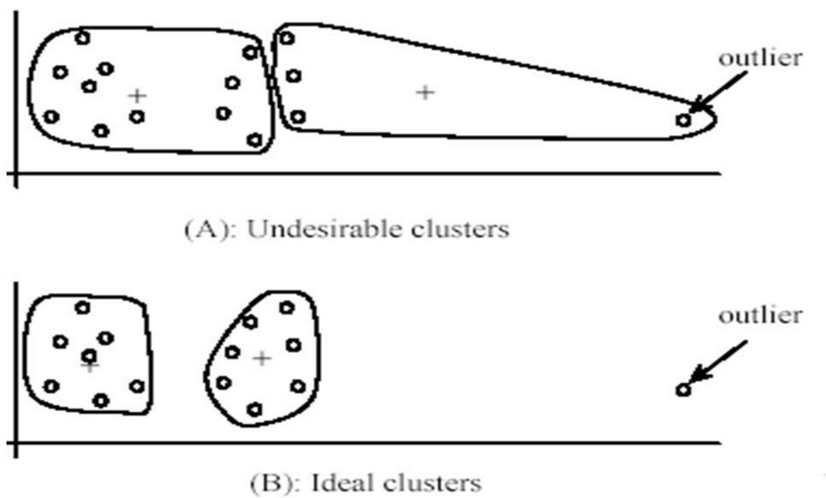
K-means: pros and cons

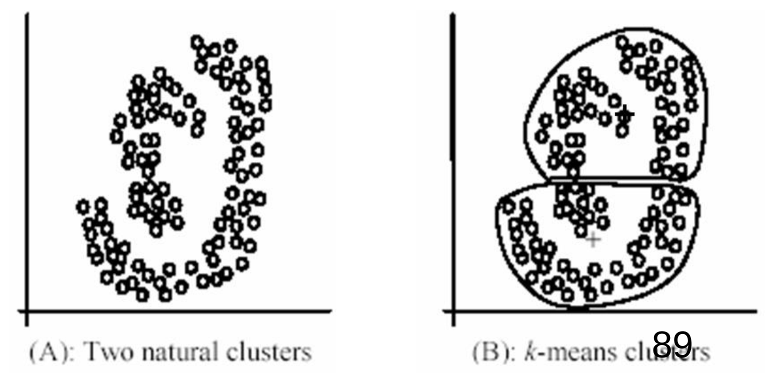
<u>Pros</u>

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

<u>Cons/issues</u>

- Setting k?
  - One way: silhouette coefficient
- Sensitive to initial centers
  - Use heuristics or output of another method
- Sensitive to outliers
- Detects spherical clusters

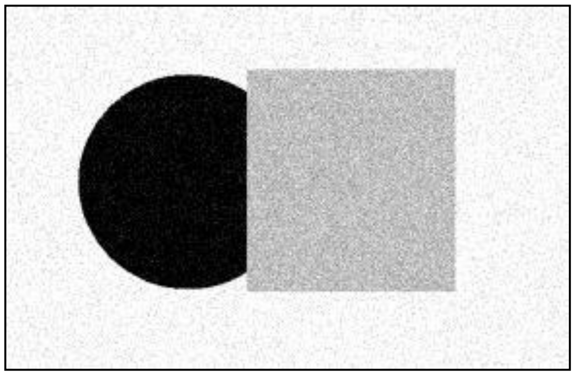




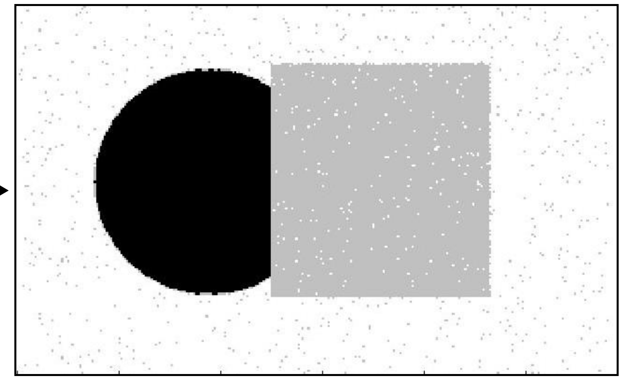
Adapted from K. Grauman

Aside: Smoothing cluster assignments

- Assigning a cluster label per pixel may yield outliers:



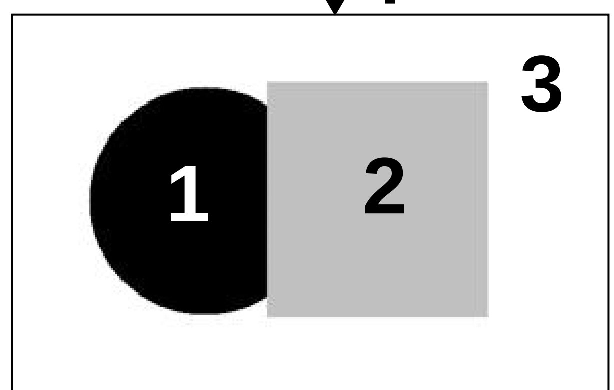
original



labeled by cluster center's intensity

?

- How to ensure they are spatially smooth?



Source: K. Grauman

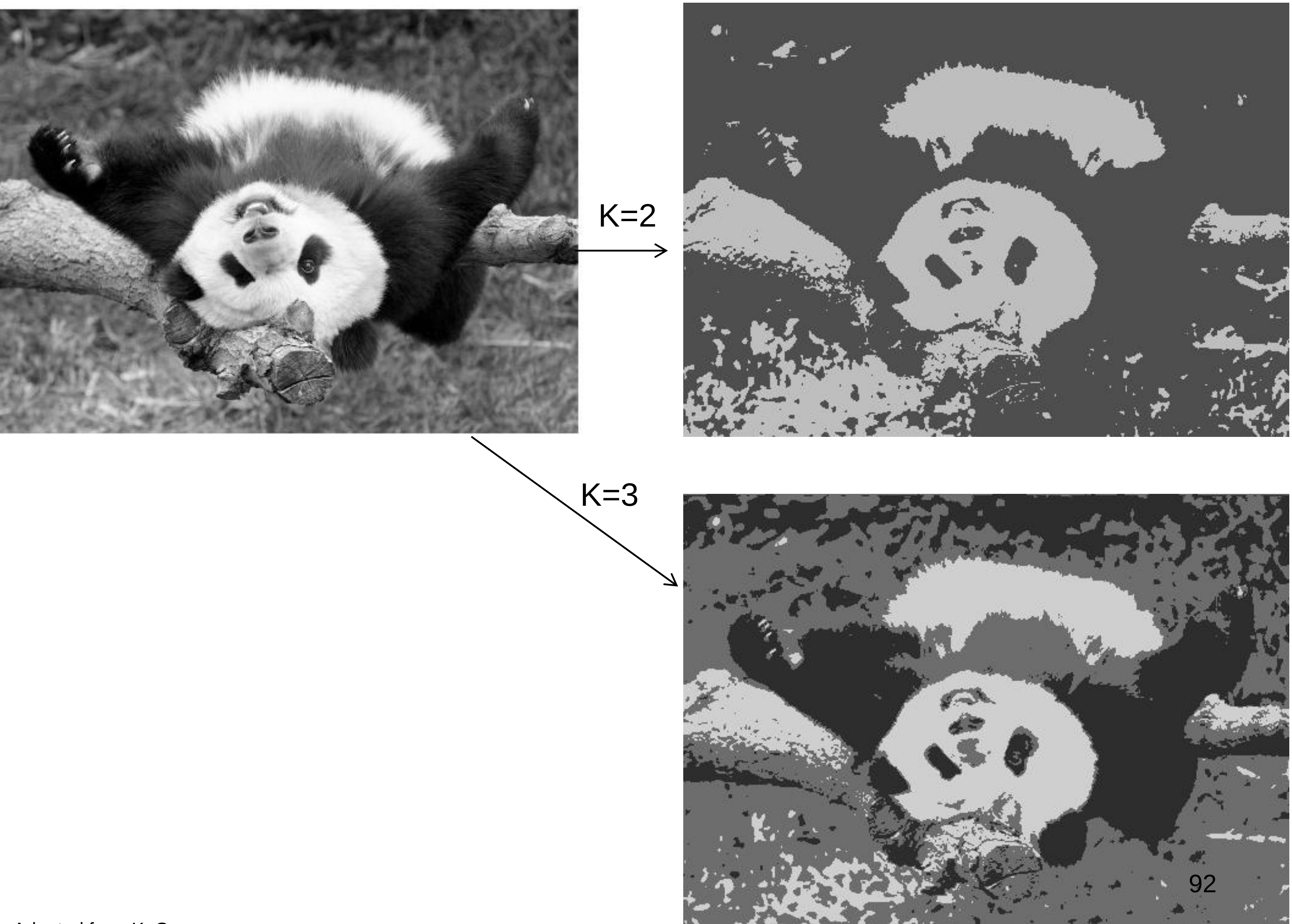
Segmentation as clustering

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

Grouping pixels based on **intensity** similarity

Feature space: intensity value (1-d)

Source: K. Grauman



Adapted from K. 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

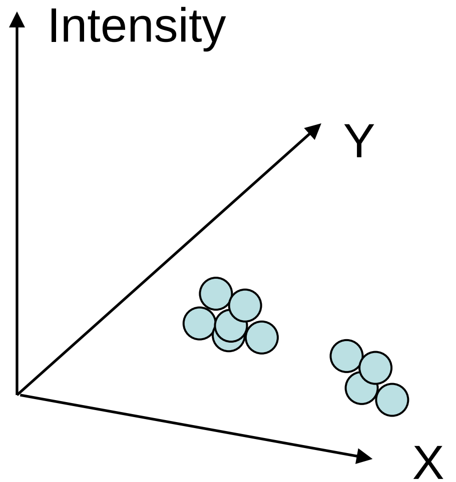
Clusters based on intensity similarity don’t have to be spatially coherent.

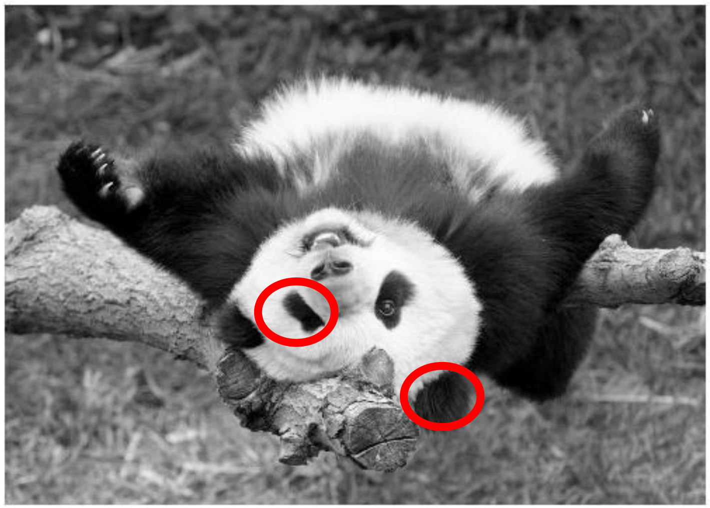
Source: K. Grauman

Segmentation as clustering

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

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





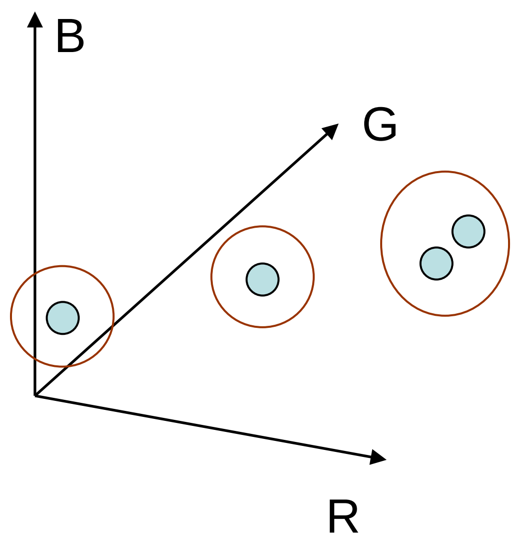
Both regions are black, but if we also include **position (x,y),** then we could group the two into distinct segments; way to encode both similarity & proximity.

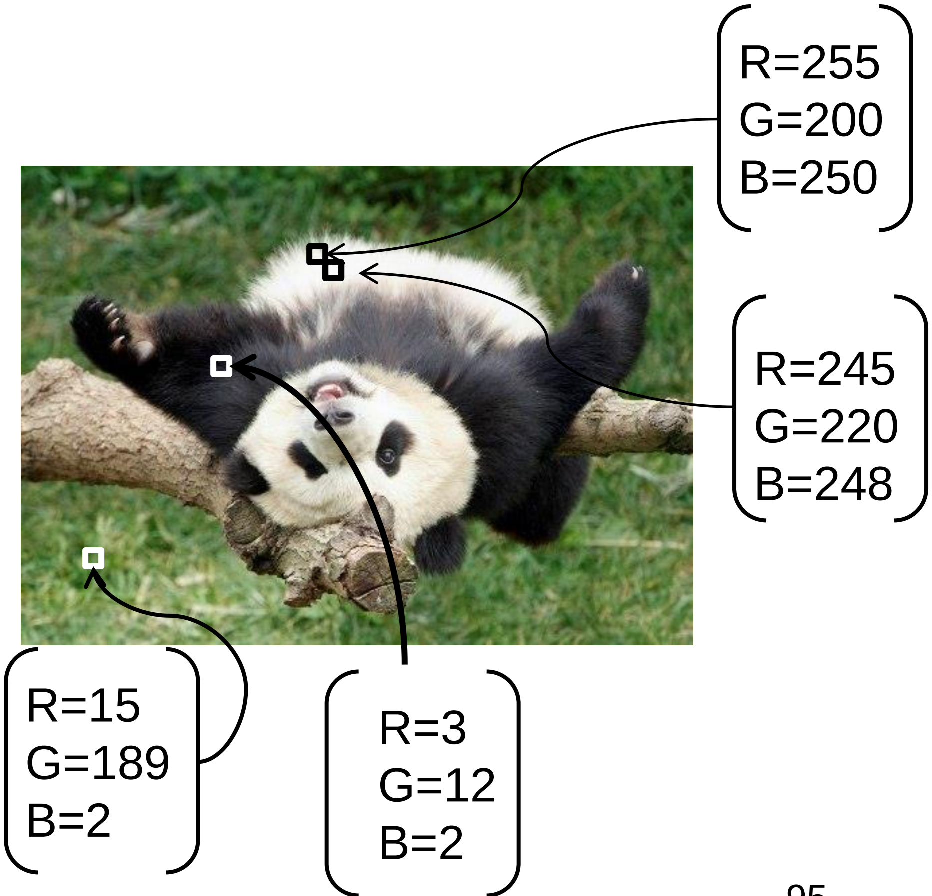
Source: K. Grauman

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)

Adapted from K. Grauman

Segmentation as clustering

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

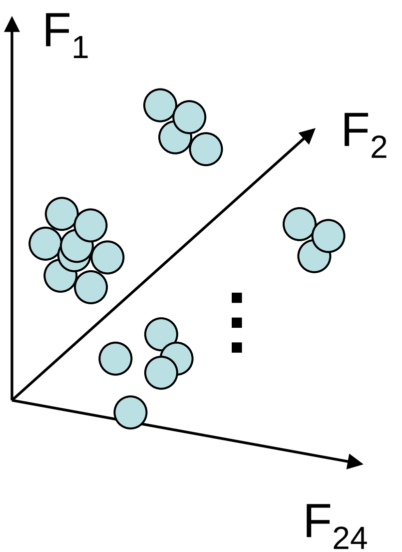


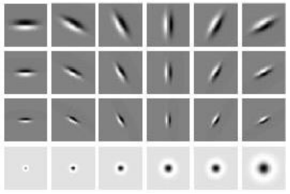
Source: L. Lazebnik

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)

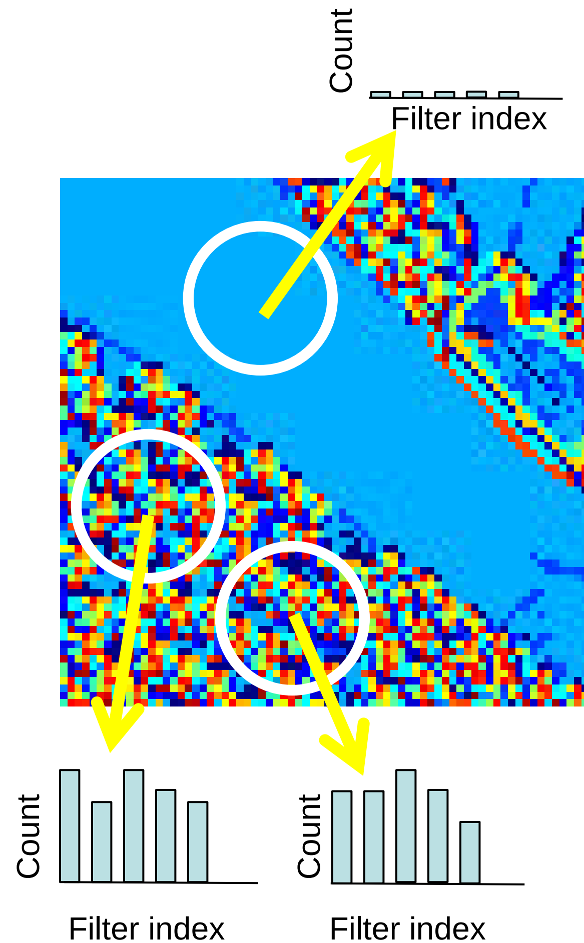
Source: K. Grauman

Segmentation w/ texture features

- Describe texture in a window as histogram over filter bank responses (simplified version, better: use “textons”)

Image

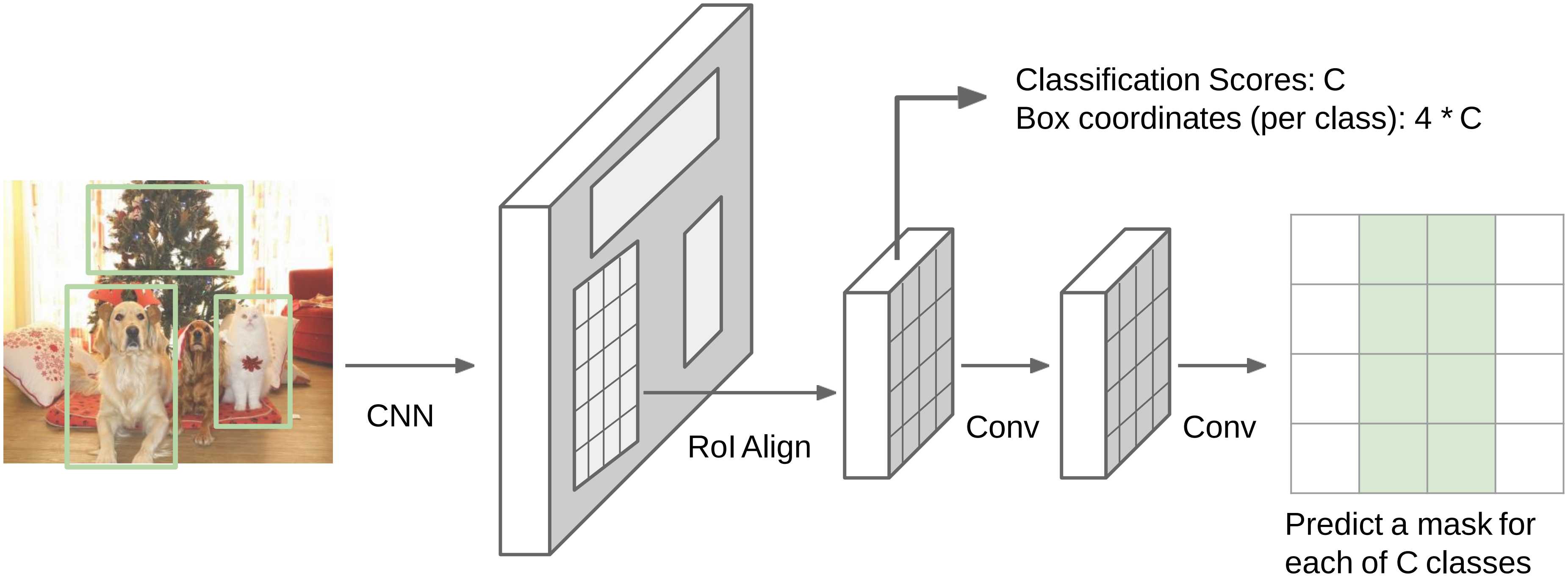
Texton map

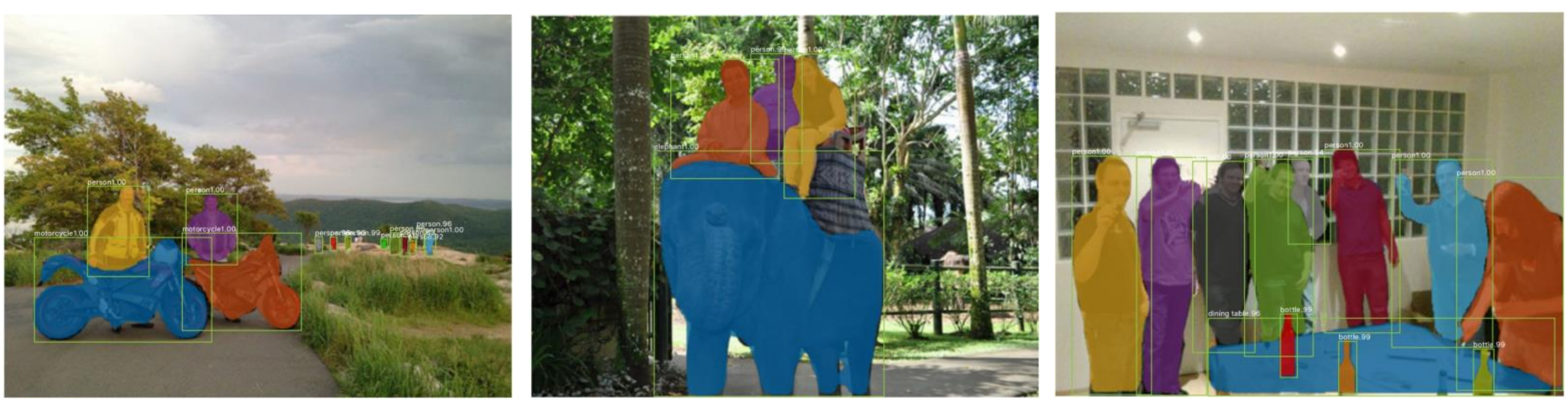


Malik, Belongie, Leung and Shi, IJCV 2001

Adapted from L. Lazebnik

State-of-the-art
(instance) segmentation: Mask R-CNN





He et al, "[Mask R-CNN]", ICCV 2017; slide adapted from Justin Johnson

Summary: classic approaches

- Edges: threshold gradient magnitude
- Lines: edge points vote for parameters of line, circle, etc. (works for general objects)
- Segments: use clustering (e.g. K-means) to group pixels by intensity, texture, etc.