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Segmentation and Clustering (part 1)

Segmentation Lectures (parts 1, 2, 3 and 4)

- **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
- **Graph theoretic segmentation**
  - Normalised cuts

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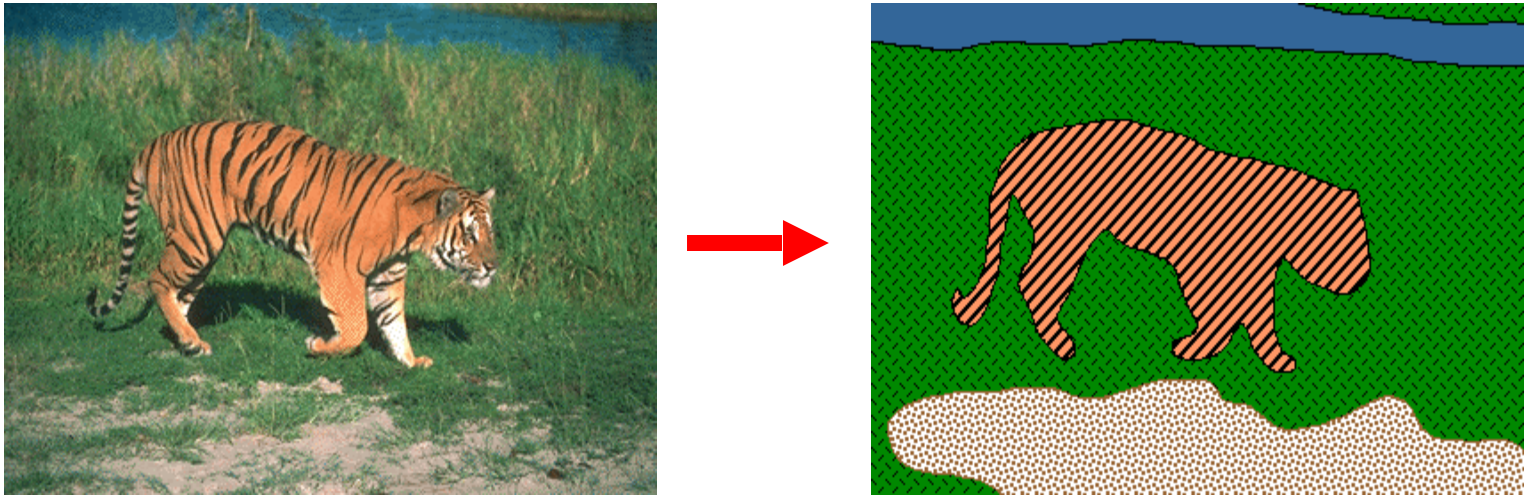
This lecture:

- **Segmentation and grouping**
  - Gestalt principles
  - Image segmentation
- **Segmentation as clustering**
  - k-Means
  - Feature spaces

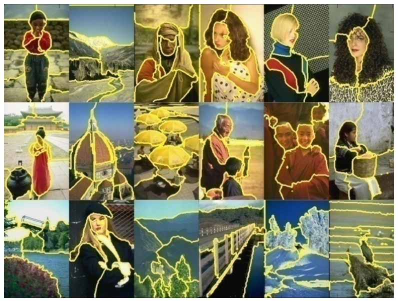
Grouping in vision

- **Goal:** Gather features that belong together



- Obtain an intermediate representation that compactly describes key image or video parts

Examples of Grouping in Computer Vision



Determining image regions

Grouping video frames into shots

Figure-ground

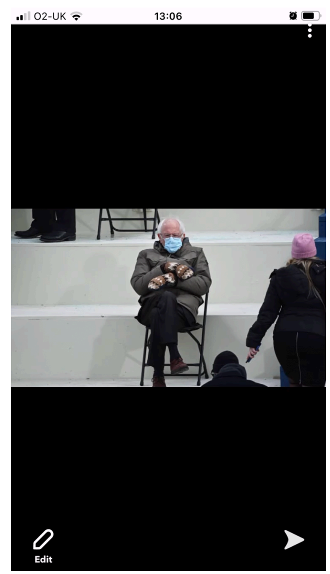


Image Segmentation

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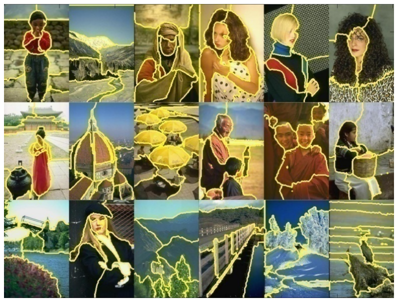

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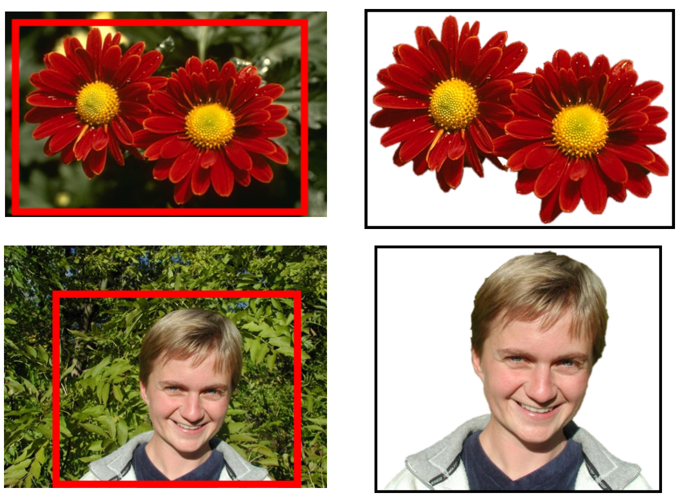

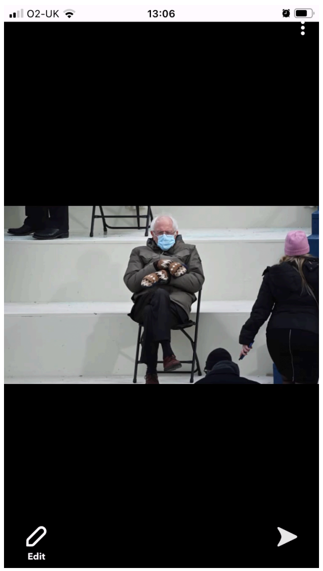

Image Segmentation

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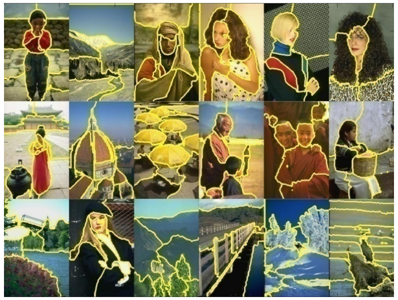

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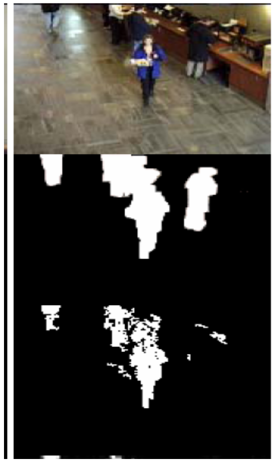

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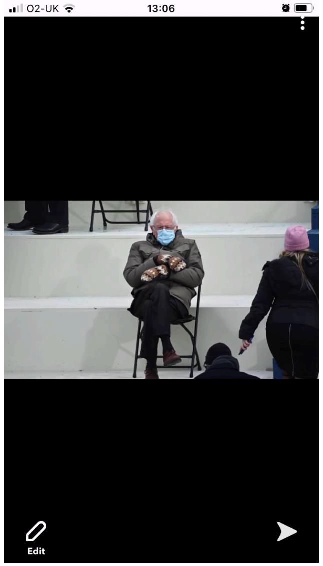


Image Segmentation

Basic ideas of grouping in human vision

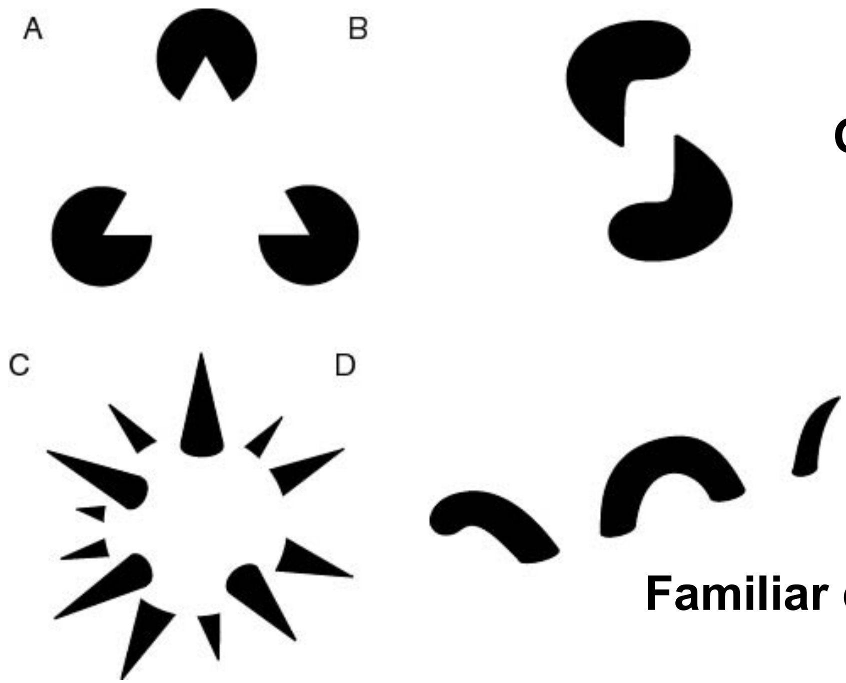
- We want to group together pixels that “belong together”
- Psychologists also thought of studying this (Gestalt school)

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



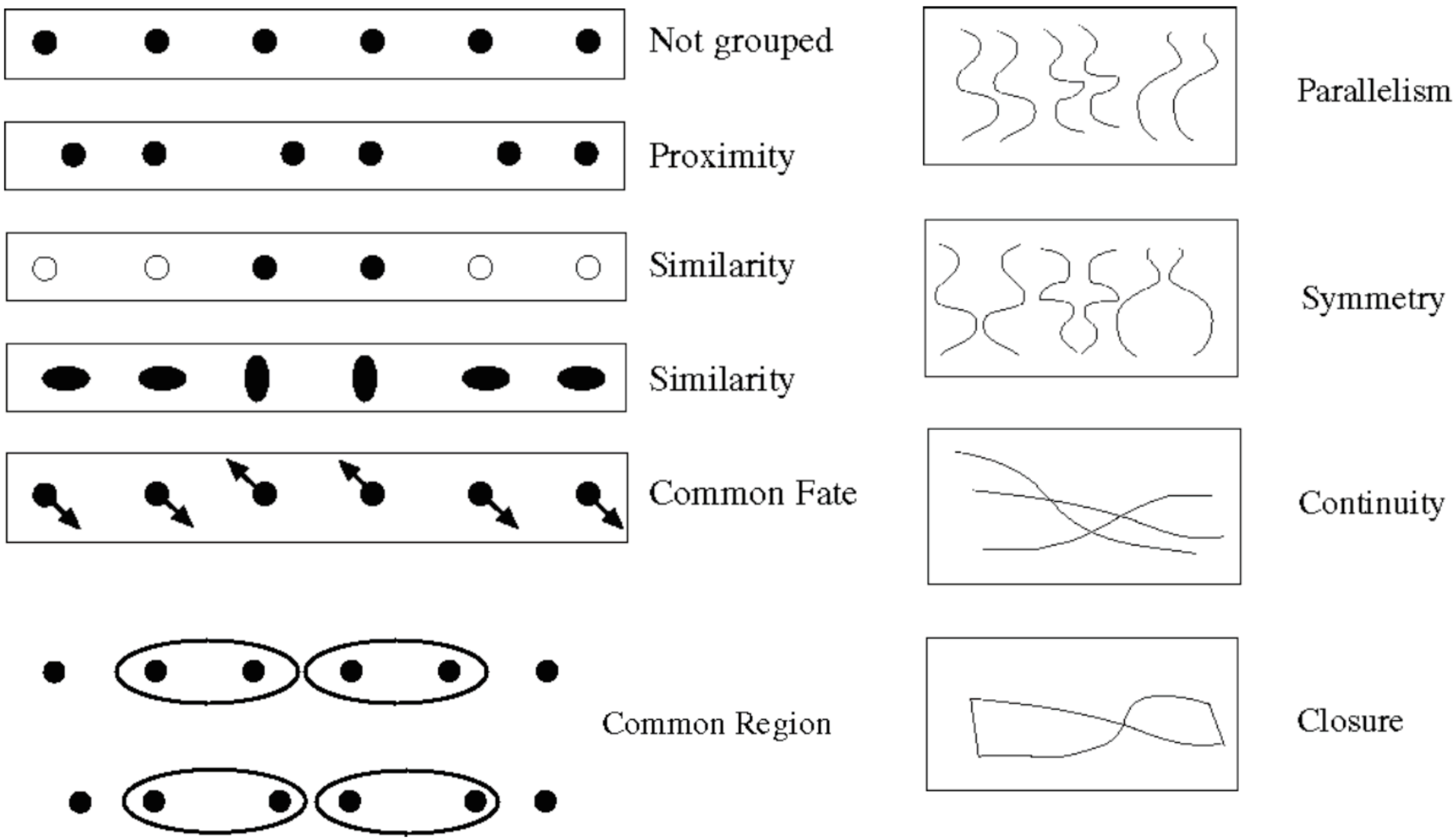
Familiar configuration

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

Image source: Steve Lehar

The University of Manchester

Gestalt Factors



Gestalt

- Psychologists identified series of factors that predispose set of elements to be grouped (by the human visual system)
- Inspiring observations/explanations; challenge remains how to best map to algorithms.

Grouping in computer vision

- **Goals:**
  - Gather features that belong together
  - Obtain an intermediate representation that compactly describes key image (video) parts
- **Top down vs. bottom up segmentation**

Slide credit: Kristen Grauman

Grouping in computer vision

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  - Top down: pixels belong together because they are from the same object

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Grouping in computer vision

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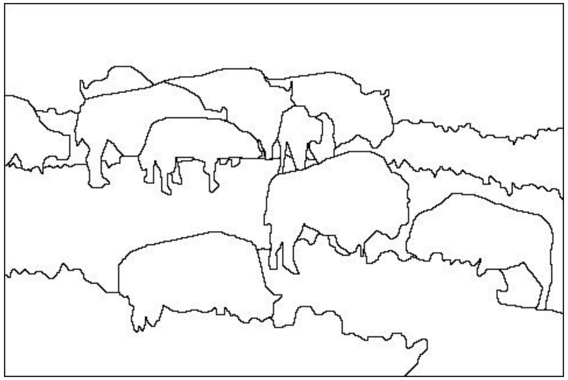
  - Obtain an intermediate representation that compactly describes key image (video) parts
- **Top down vs. bottom up segmentation**
  - Top down: pixels belong together because they are from the same object
  - Bottom up: pixels belong together because they look 'similar'
- **Hard to measure success**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

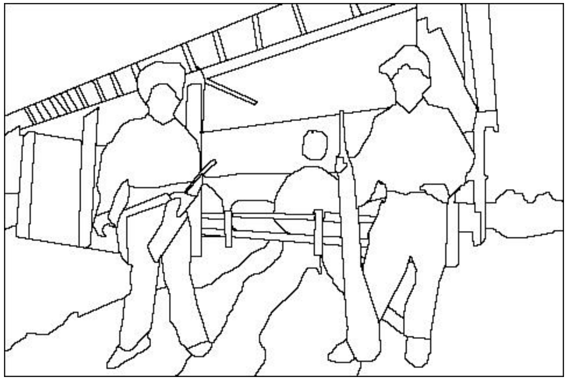
Slide credit: Kristen Grauman

The Goals of Segmentation

- Separate image into coherent “objects”

Image | **Human segmentation**





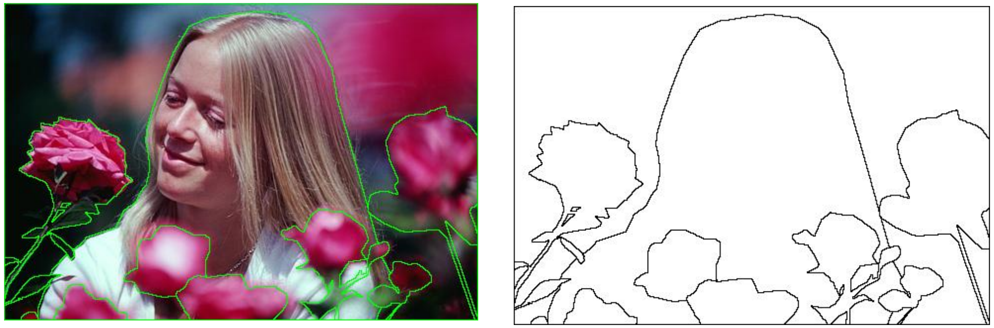
Berkeley Segmentation dataset

The Goals of Segmentation

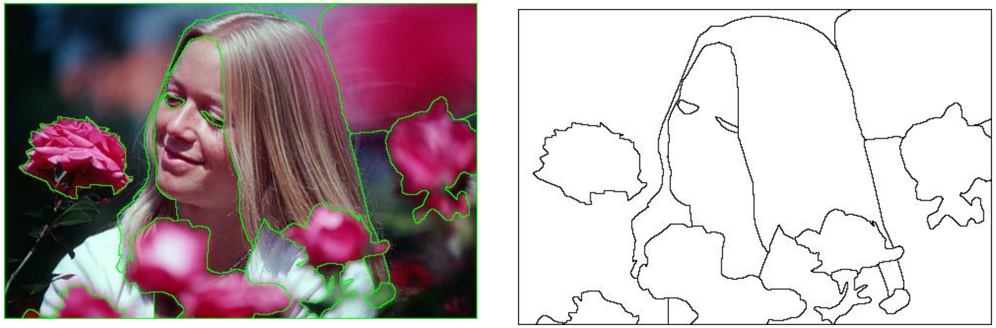
Original Image

Human segmentation

User 1



User 2



User 3

Berkeley Segmentation dataset

The Goals of Segmentation

- Group together similar-looking pixels for efficiency of further processing

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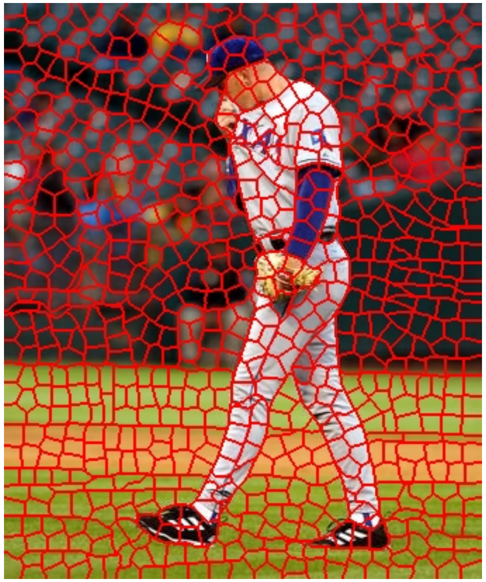

X. Ren and J. Malik. [Learning a classification model for segmentation.] ICCV 2003.

Today's Lecture

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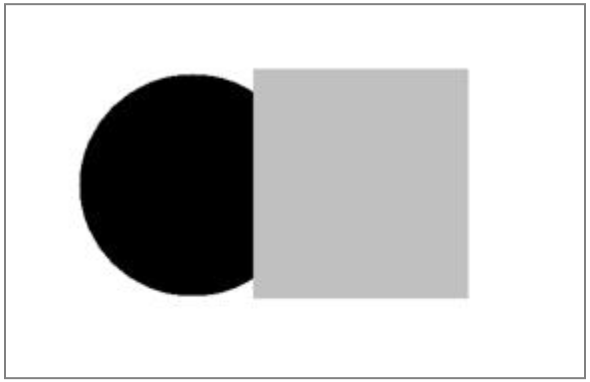
  - Gestalt principles
  - Image segmentation
- **Segmentation as clustering**
  - k-Means
  - Feature spaces

Image Segmentation: Toy Example



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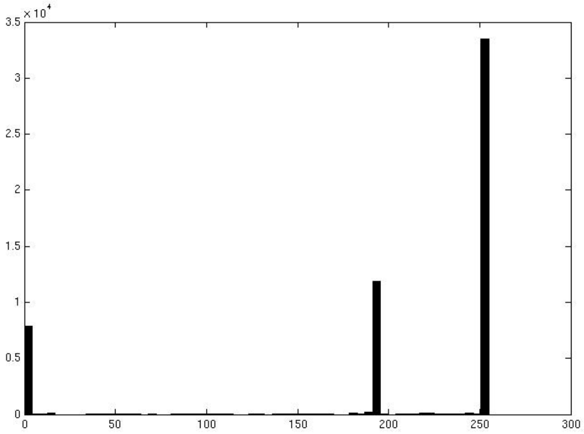

intensity

Slide credit: Kristen Grauman

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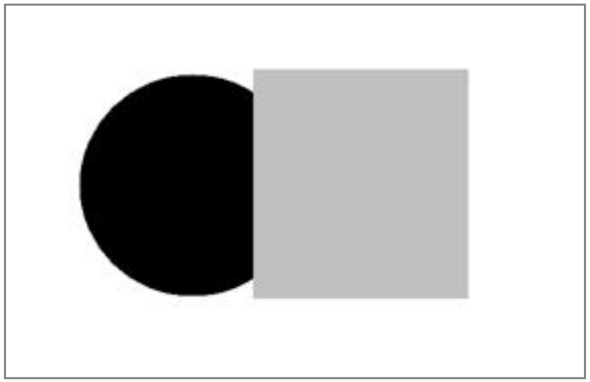

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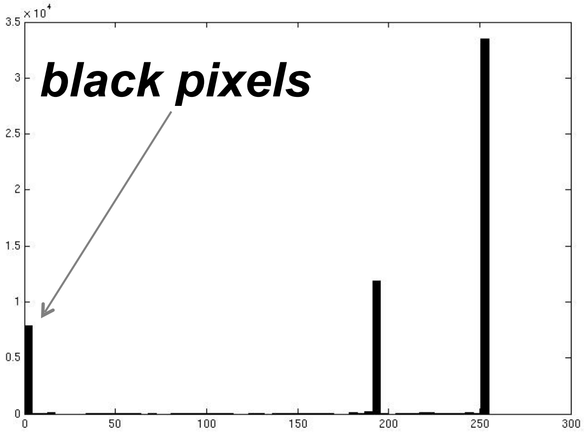

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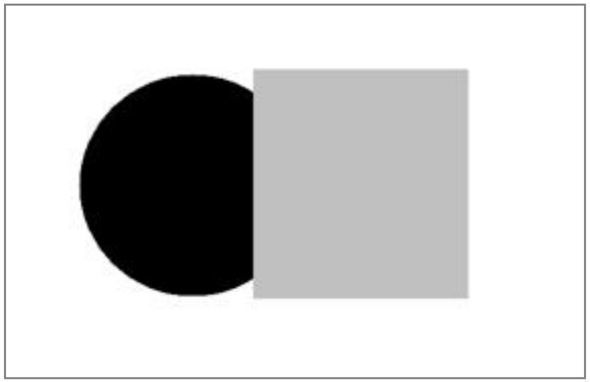

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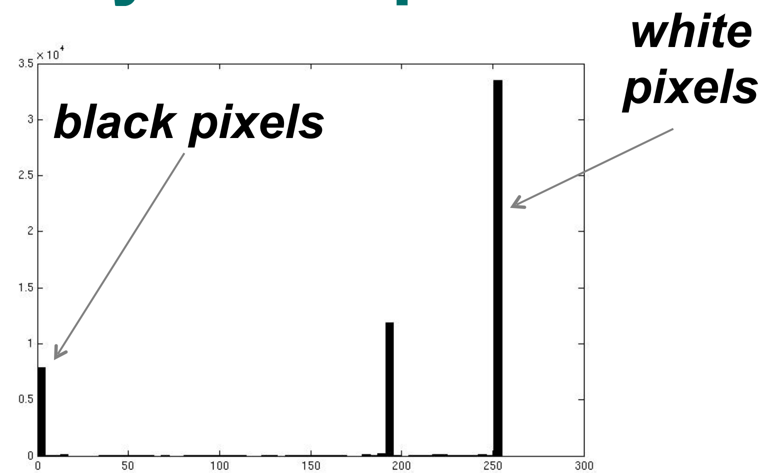

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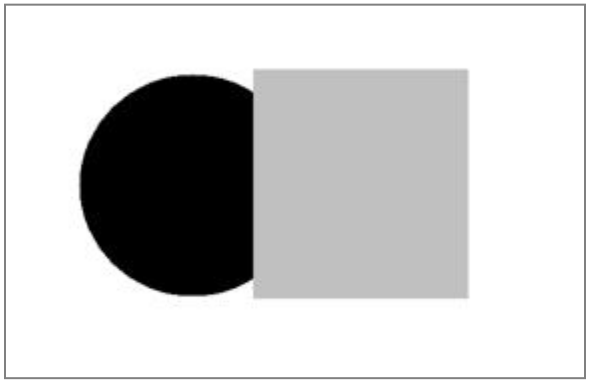

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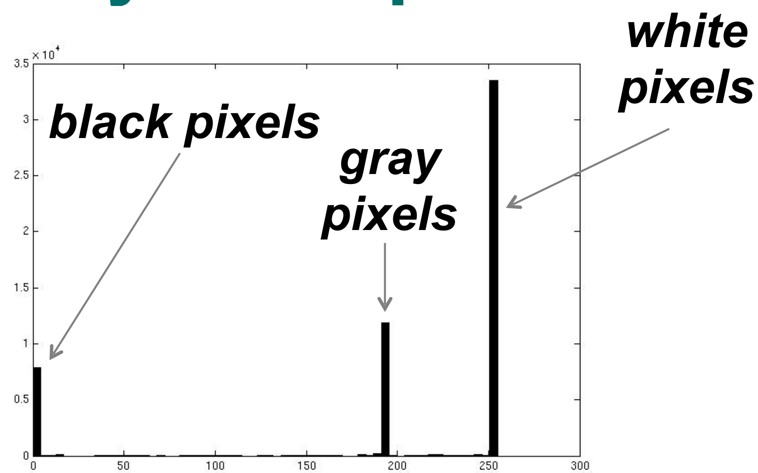

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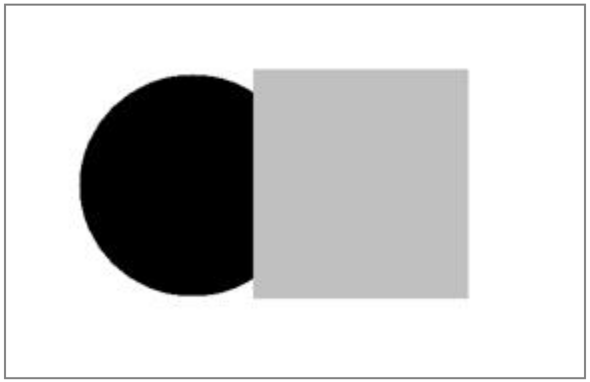

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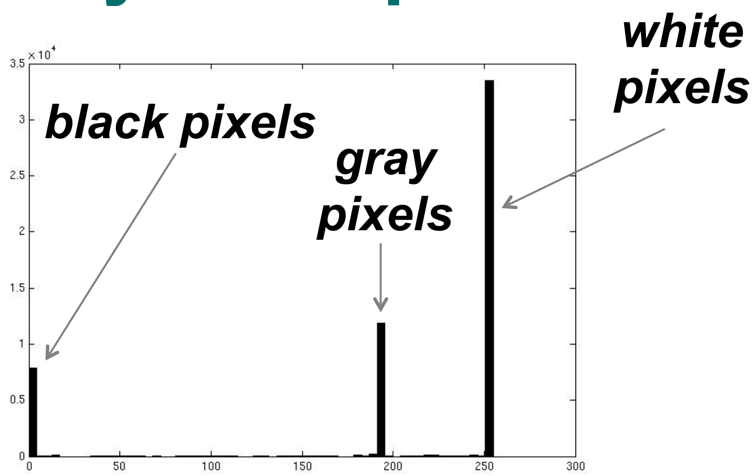

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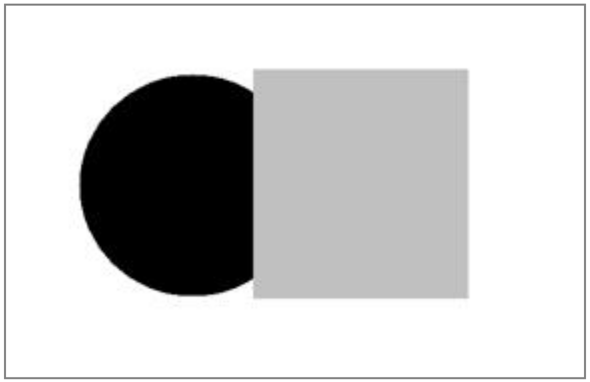

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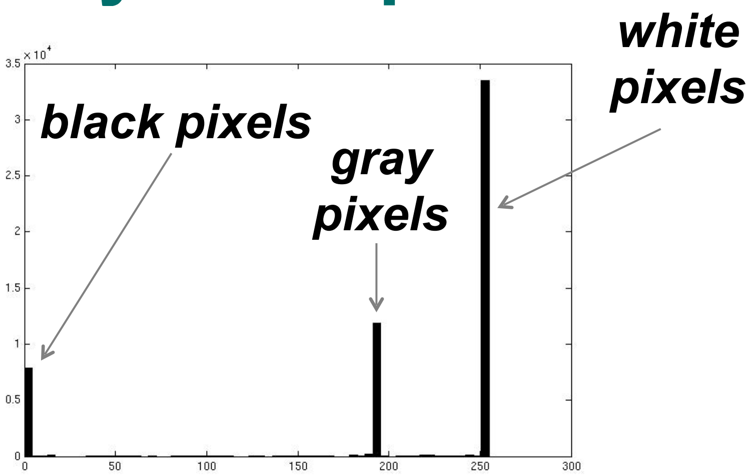

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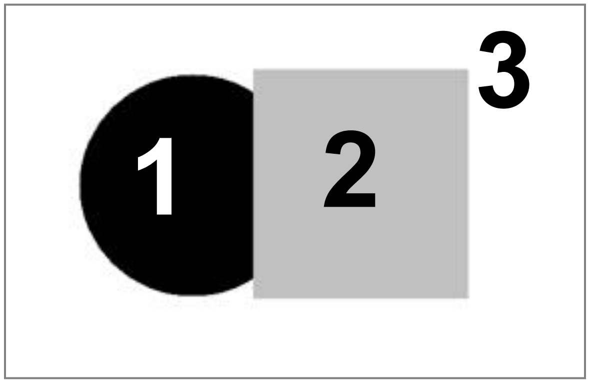

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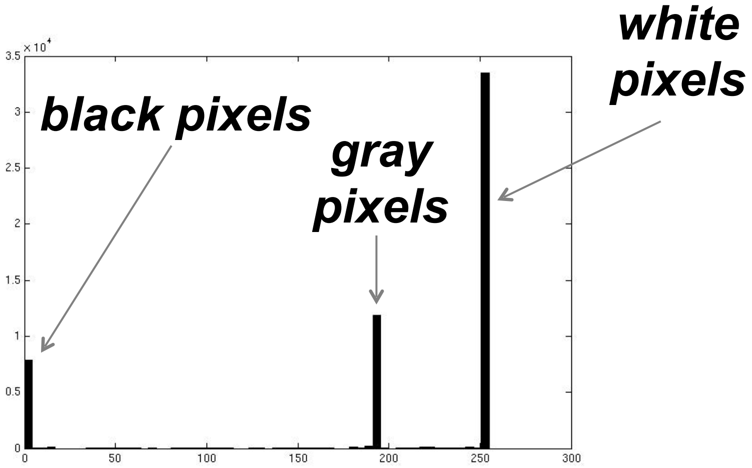

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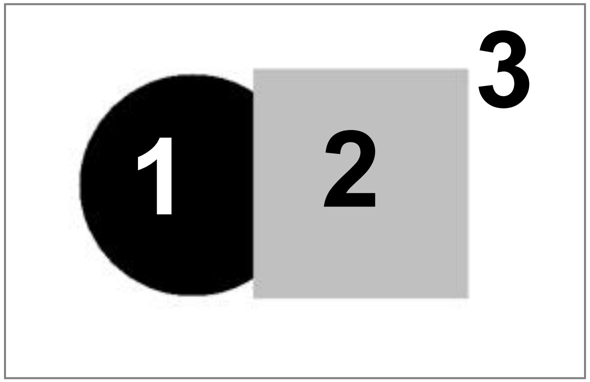

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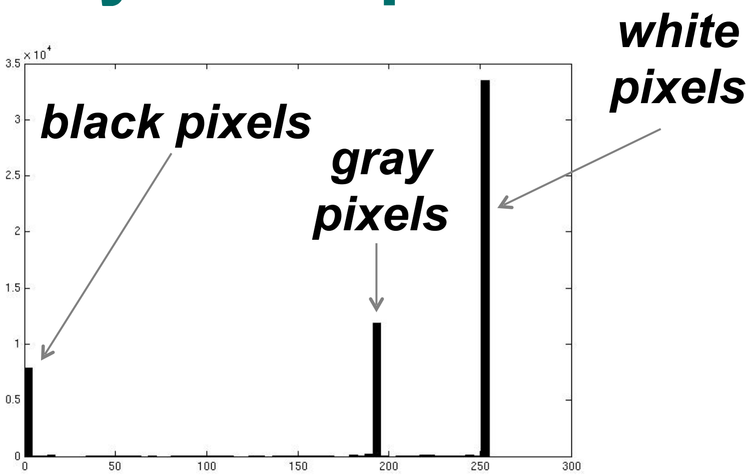

intensity

- These intensities define the three groups.

Slide credit: Kristen Grauman

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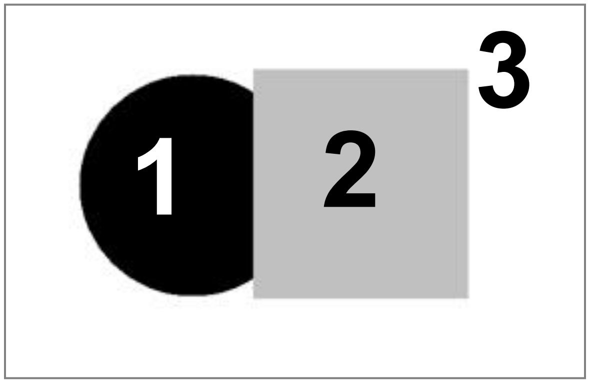

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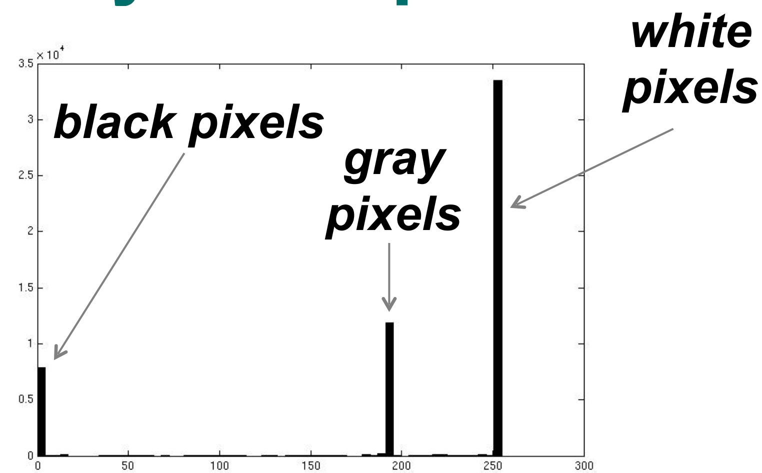

intensity

- 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.

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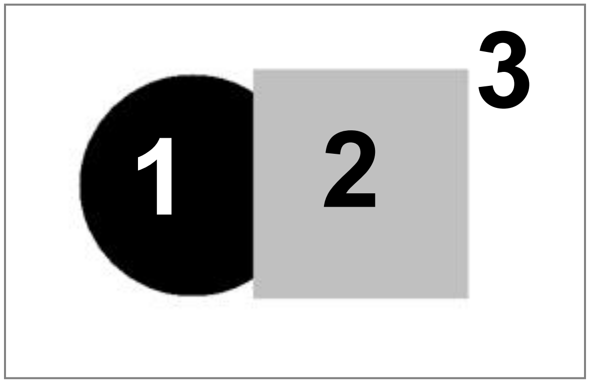

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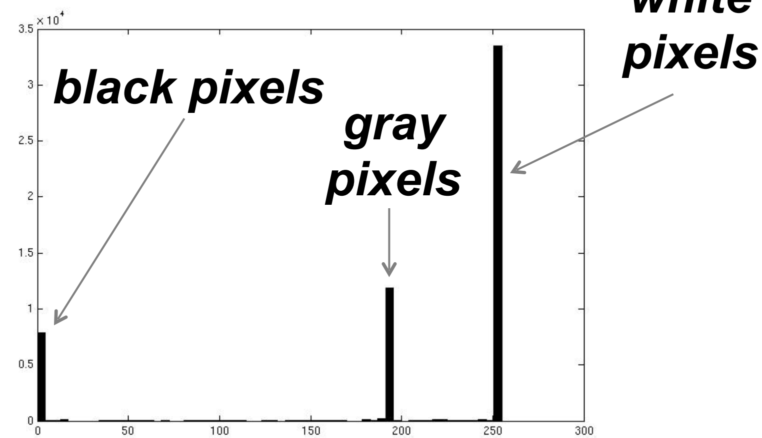
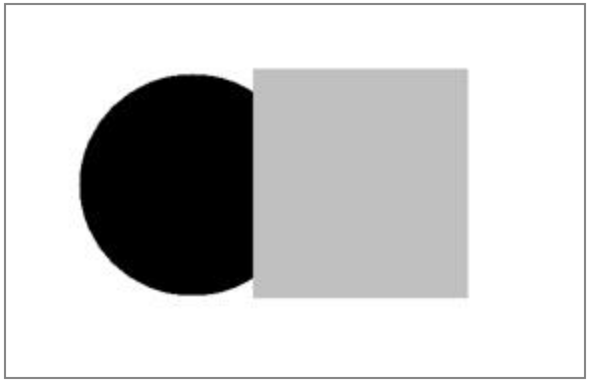


intensity

- **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?**

Slide credit: Kristen Grauman



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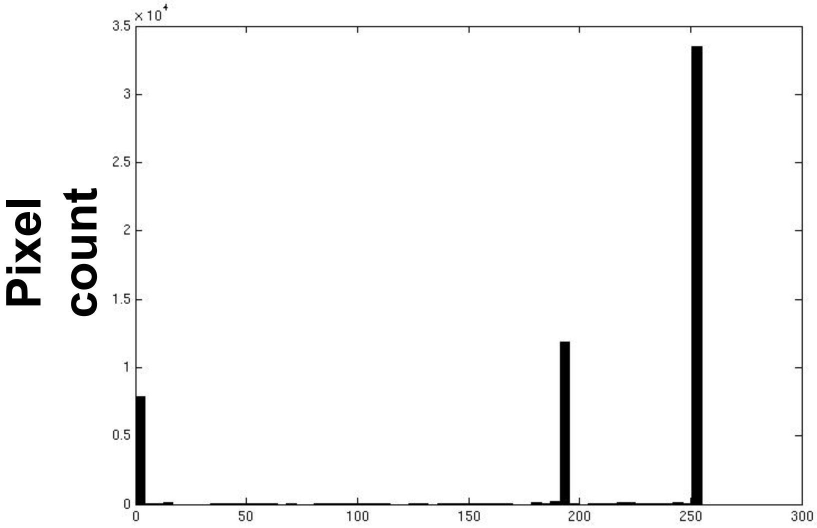

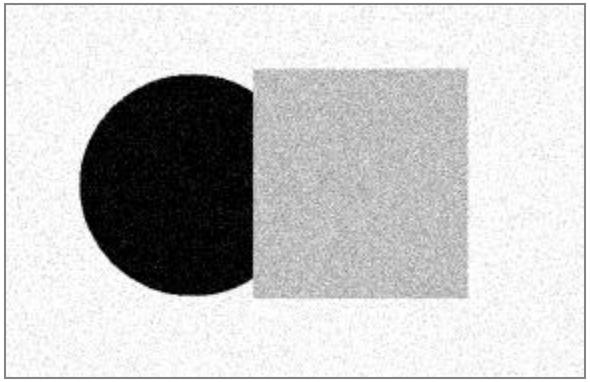

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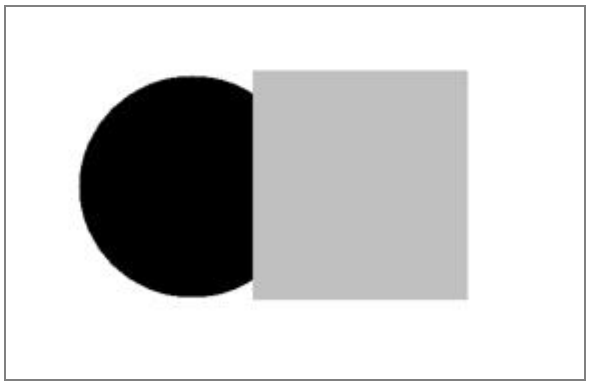

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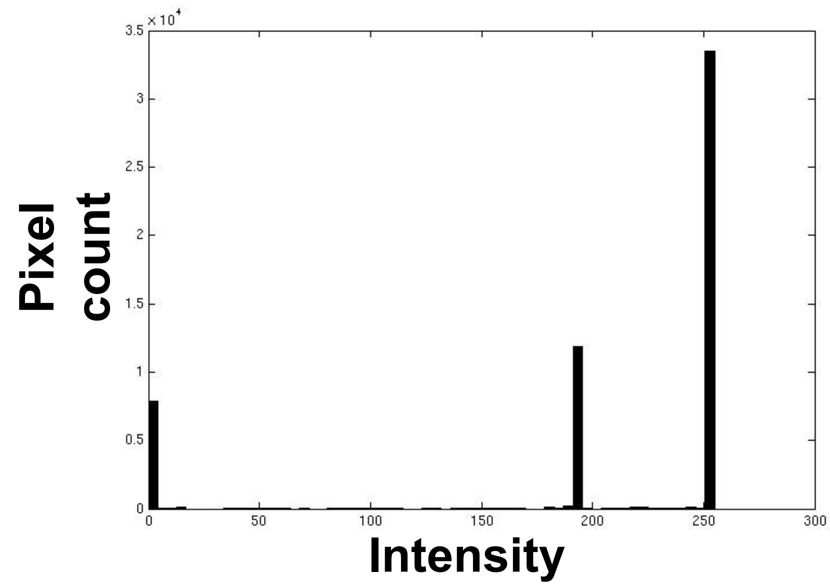

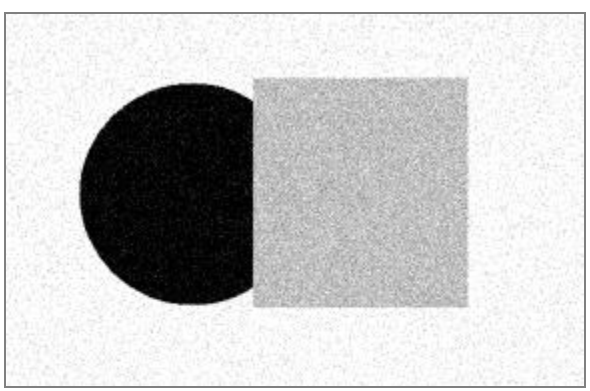

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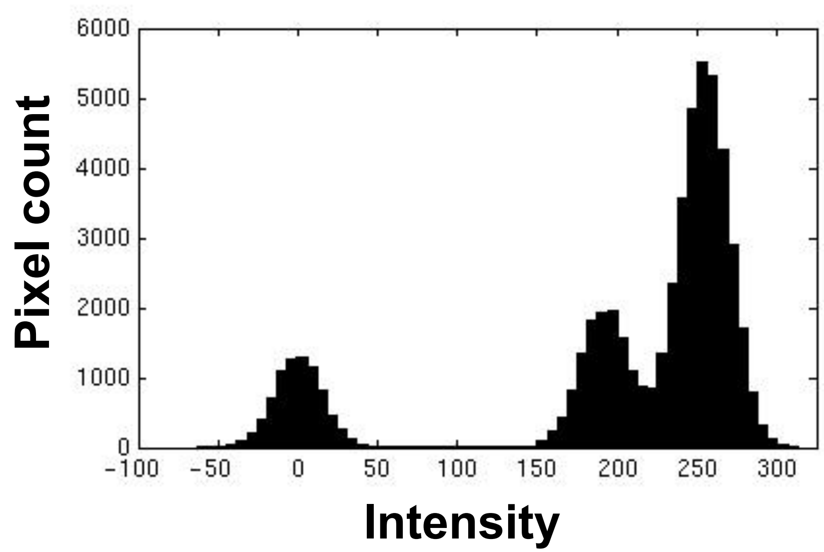

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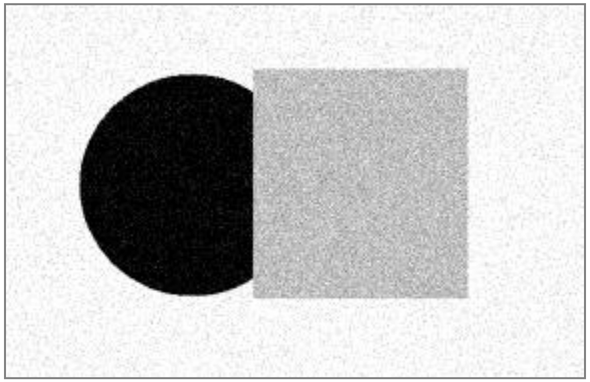

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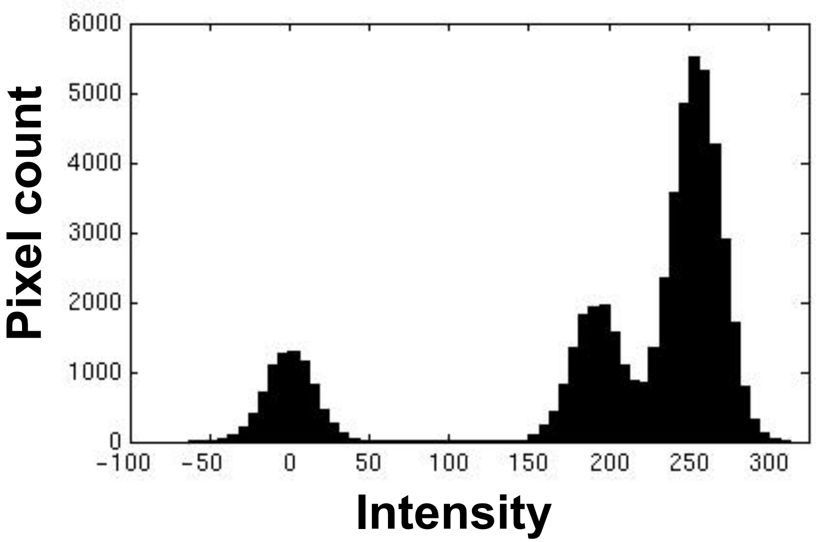
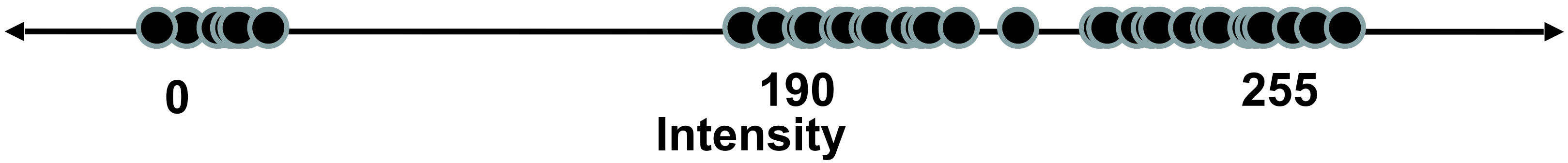


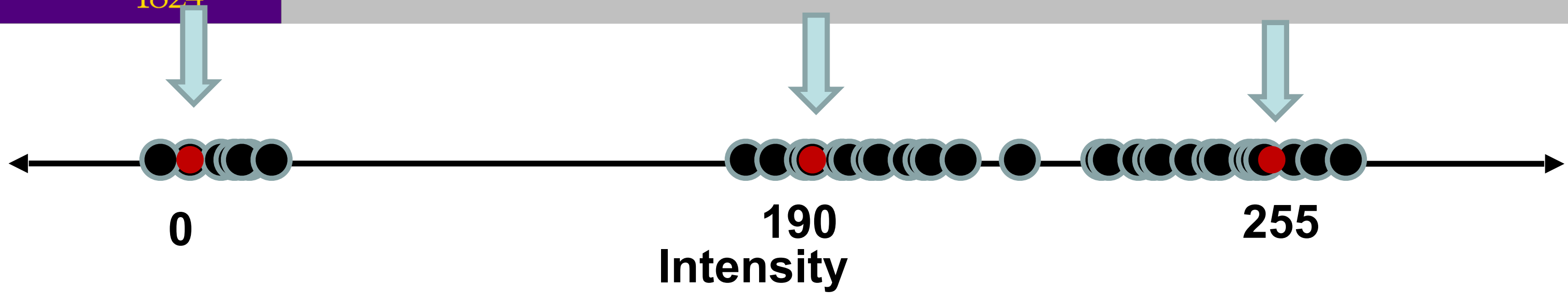
- Now how to determine the three main intensities that define our groups?
- We need to cluster

Slide credit: Kristen 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 SSD between all points and their nearest cluster center c_i:

Slide credit: Kristen Grauman



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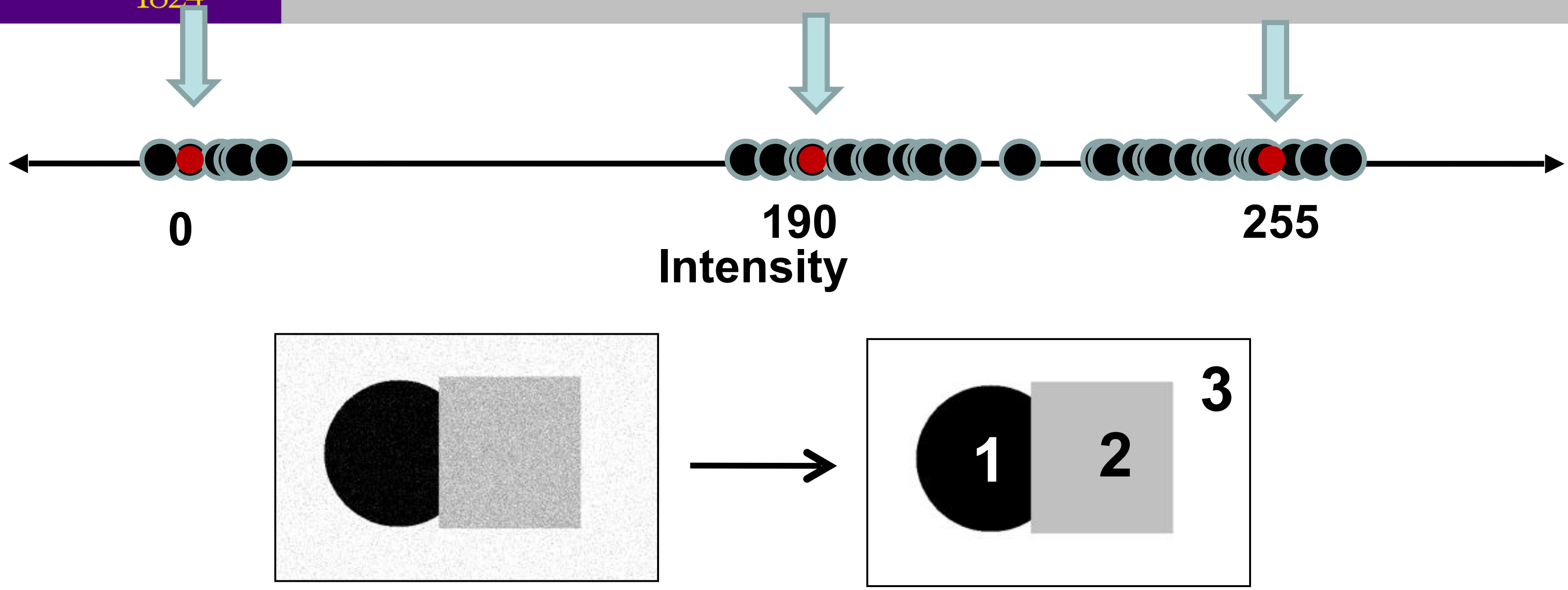

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$$\sum_{\text{clusters } i} \sum_{\text{points p in cluster } i} ||p - c_i||^2$$

Slide credit: Kristen Grauman

Clustering

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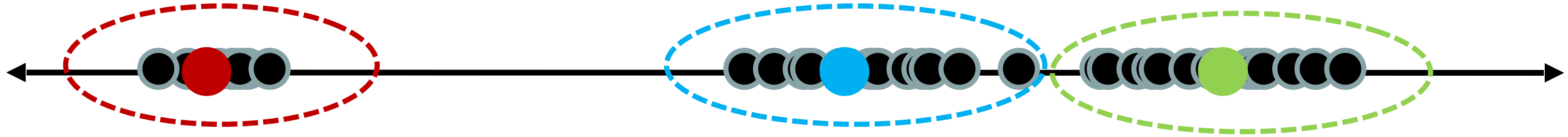
Clustering



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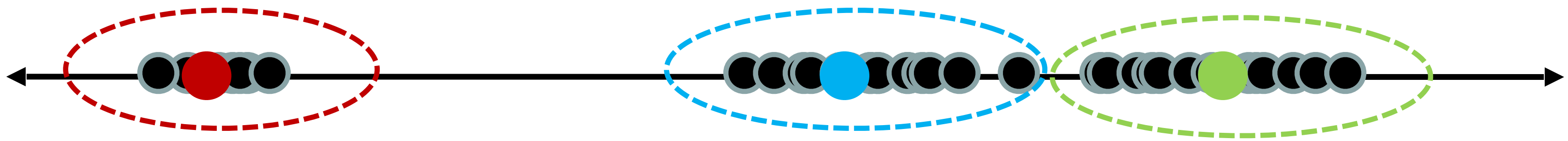
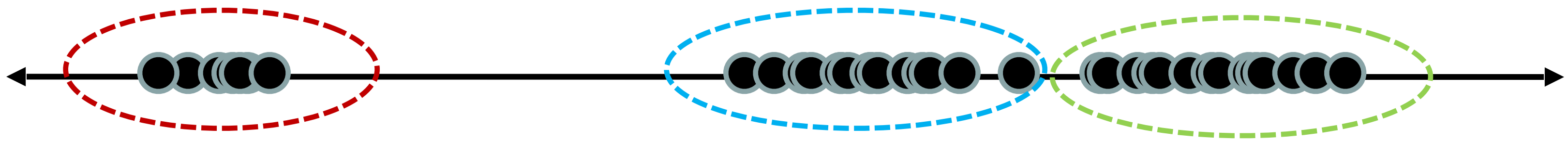
Clustering

- **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.



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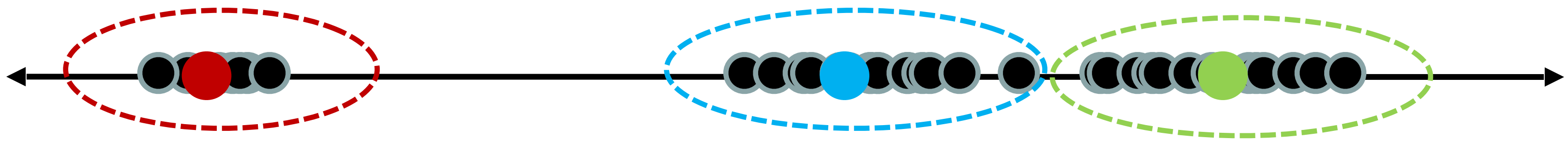

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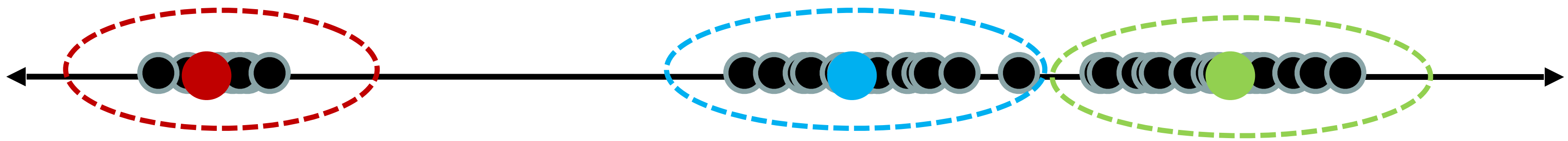

Slide credit: Kristen Grauman

K-Means Clustering

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     - For each point p, find the closest c_i. Put p into cluster i

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

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

Feature Space

Slide credit: Kristen Grauman

Feature Space

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

- Grouping pixels based on intensity similarity

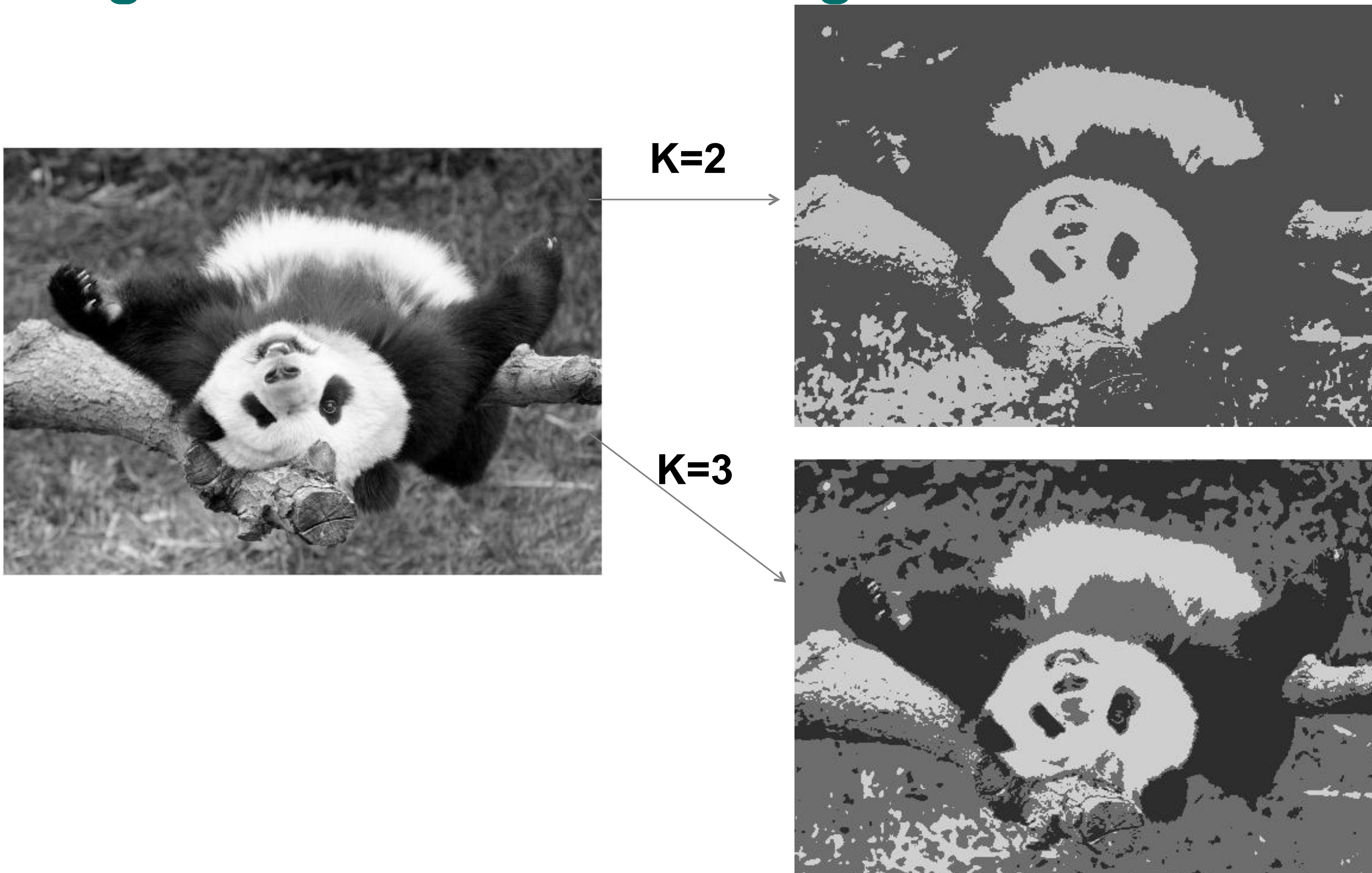
- Feature space: intensity value (1D)

Slide credit: Kristen Grauman

Segmentation as Clustering

K=2

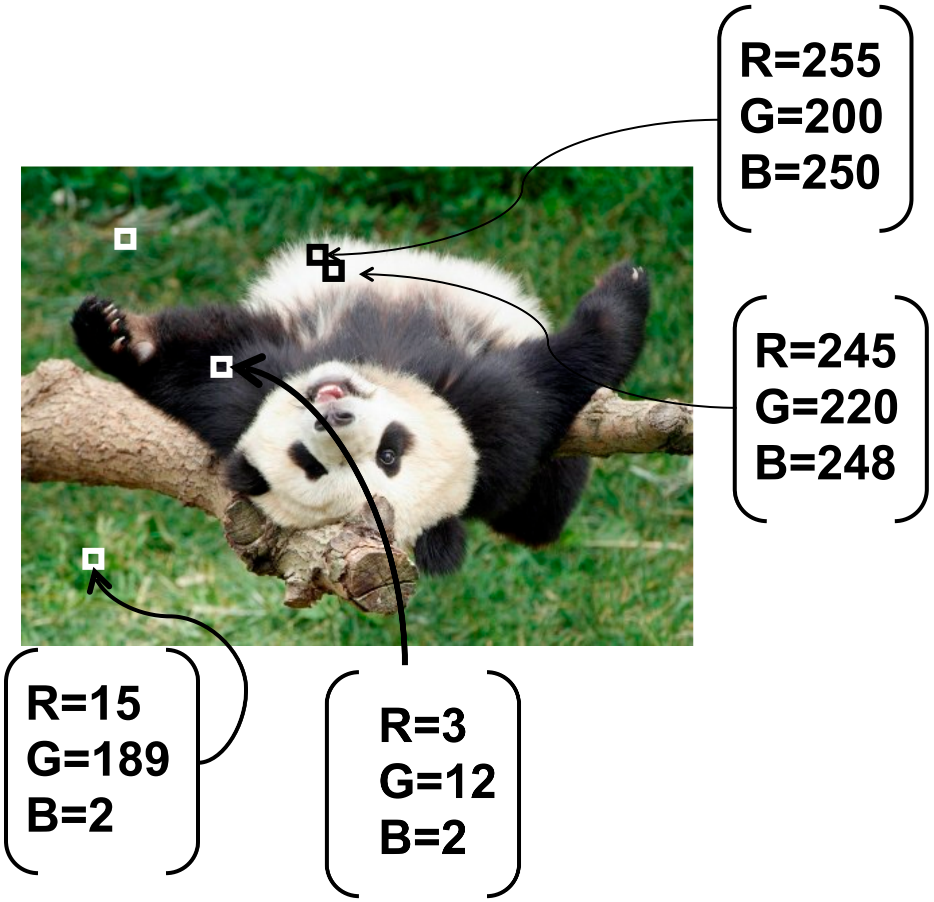
Segmentation as Clustering



Feature Space

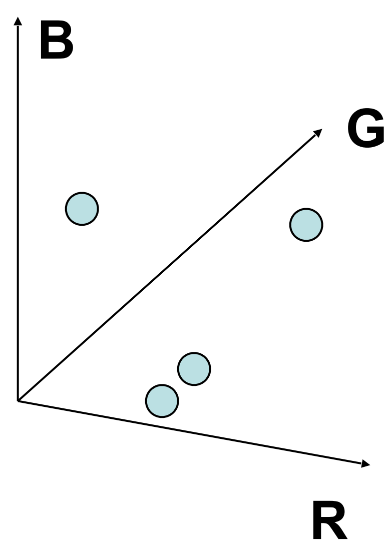
Slide credit: Kristen Grauman

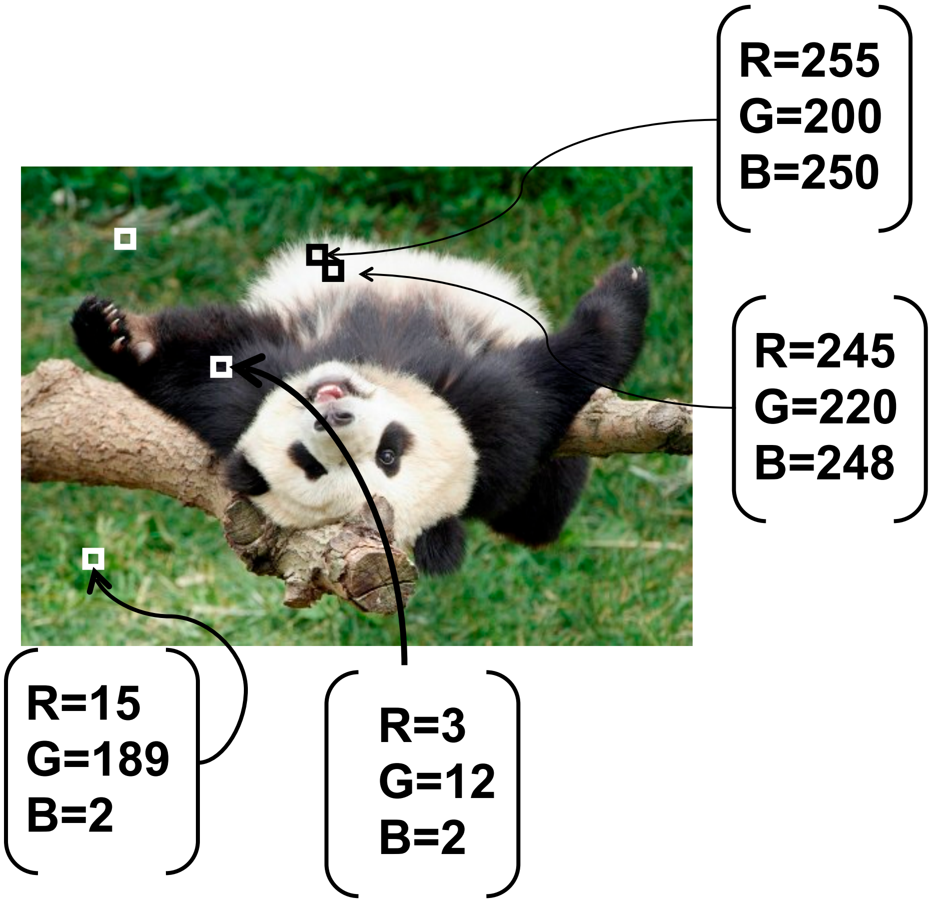
Feature Space



Slide credit: Kristen Grauman

Feature Space





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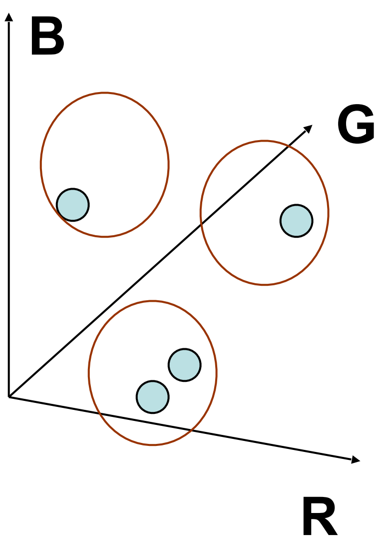
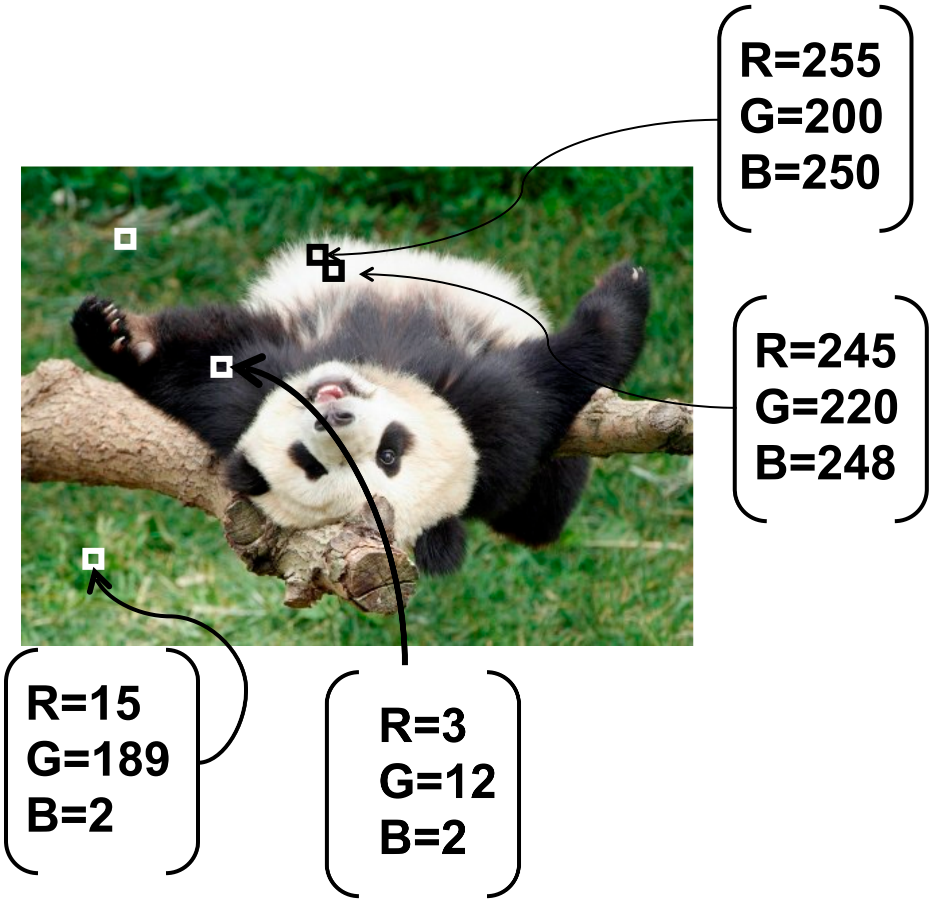
Feature Space



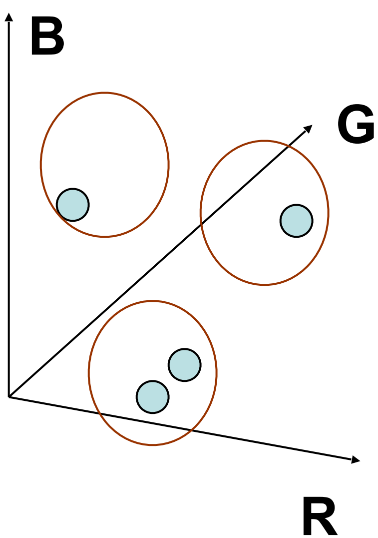


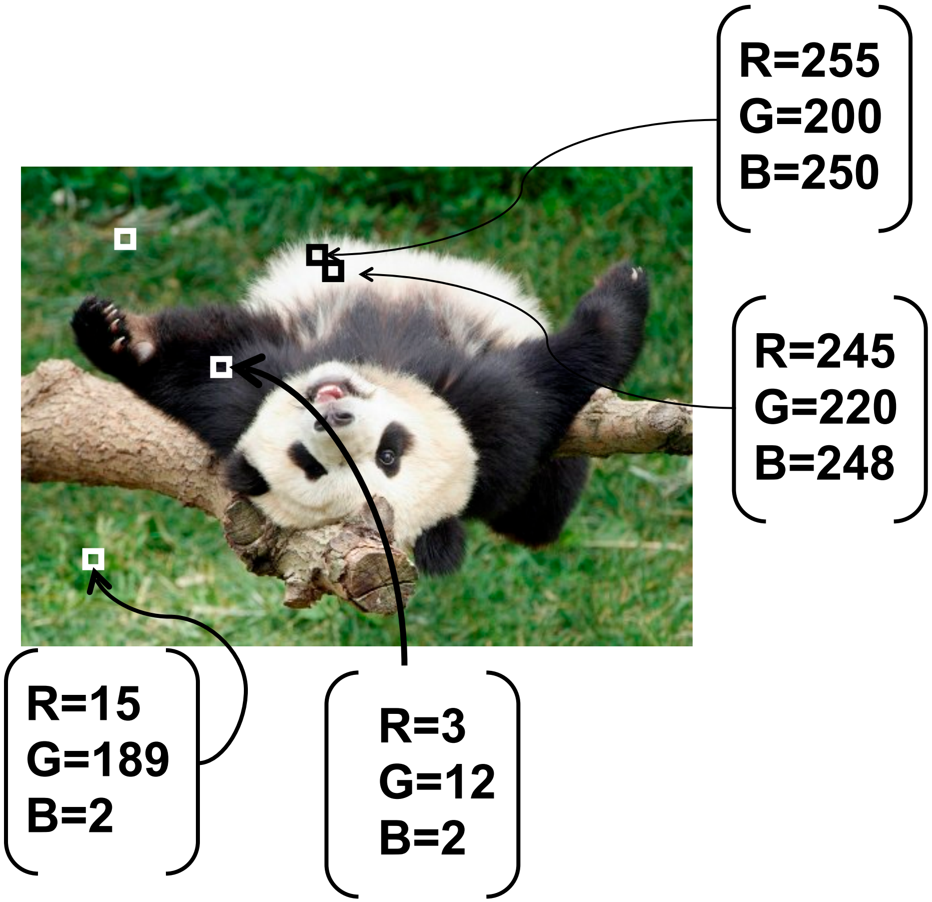
Slide credit: Kristen Grauman

Feature Space

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

- **Grouping pixels based on colour similarity**





- **Feature space: colour value (3D)**

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
		

We can cluster (r,g,b,x,y) values to enforce more spatial coherence

⇒ **Way to encode both *similarity* and *proximity*.**

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  - Simple, fast to compute
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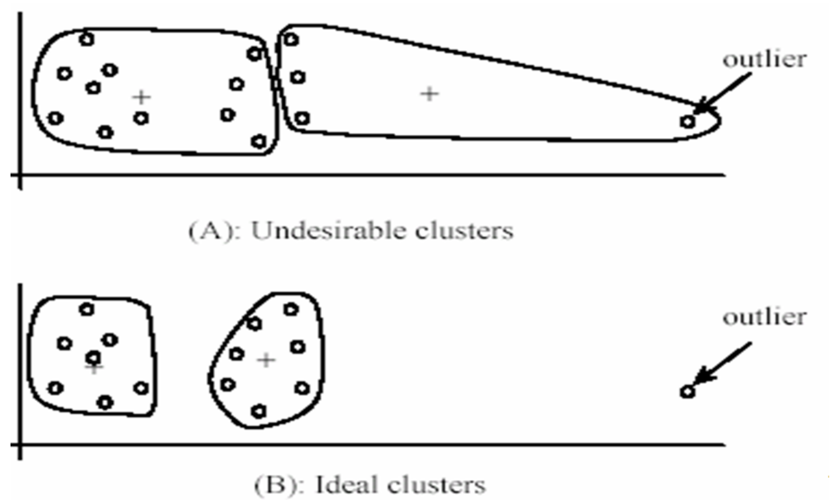
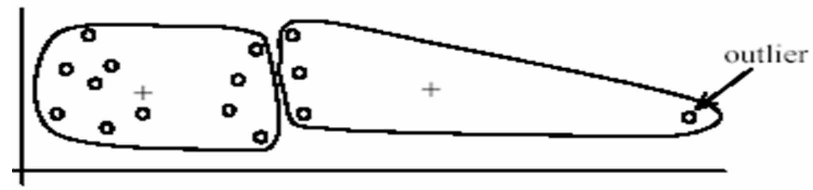


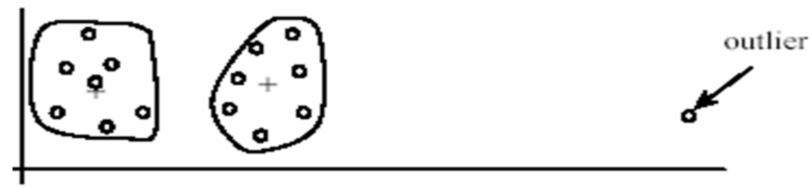
Summary K-Means

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

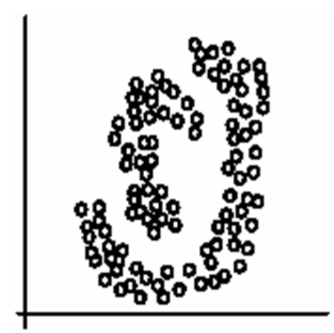
- **Cons/issues**
  - Setting k?
  - Sensitive to initial centers
  - Sensitive to outliers
  - Detects spherical clusters only



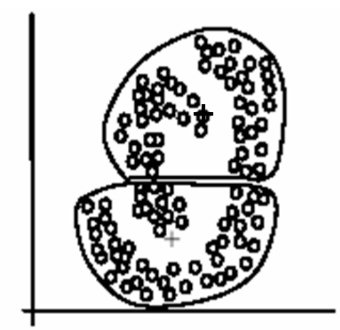
(A): Undesirable clusters



(B): Ideal clusters



(A): Two natural clusters



(B): *k*-means clusters

Next Lecture

- **Segmentation and grouping**
  - Gestalt principles
  - Image segmentation
- **Segmentation as clustering**
  - k-Means
  - Feature spaces
- **Probabilistic clustering**
  - Gaussian and Multivariate Gaussian distributions
  - Mixture of Gaussians
  - Expectation-Maximization (EM)
- **Model-free clustering**
  - Mean-Shift clustering
- **Graph theoretic segmentation**
  - Normalised cuts