

CS4495/6495

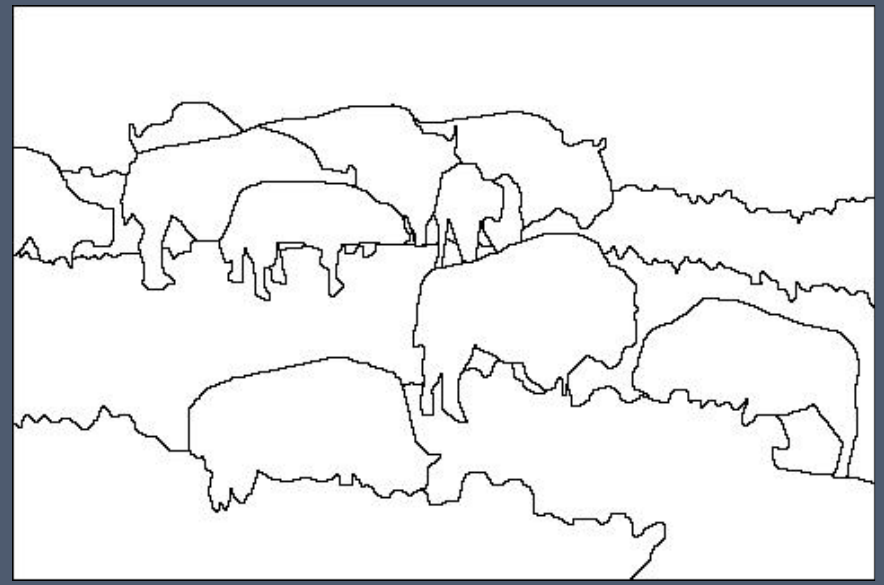
Introduction to Computer Vision

9A-L2 *Segmentation*



Slides by Tucker Hermans

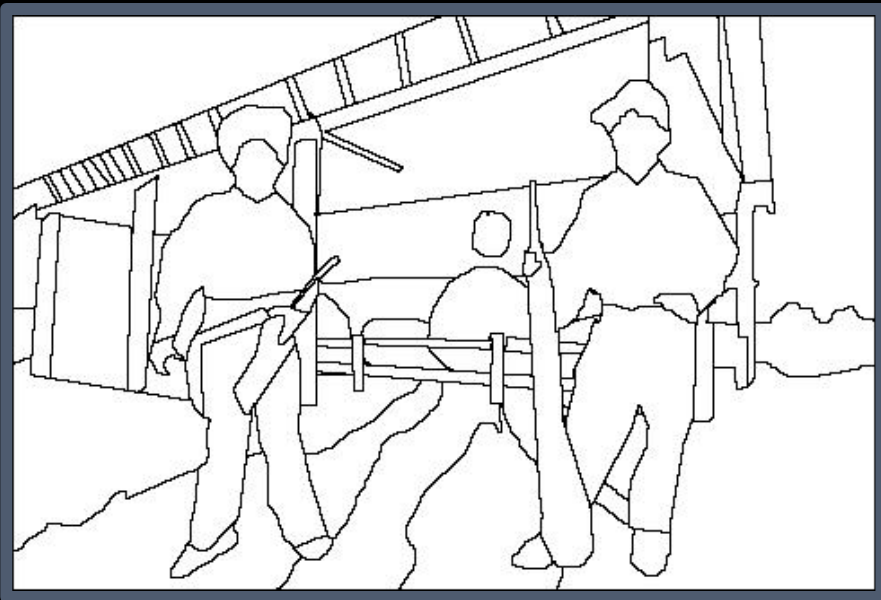
Segmentation of Coherent Regions



Berkeley segmentation database:

www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

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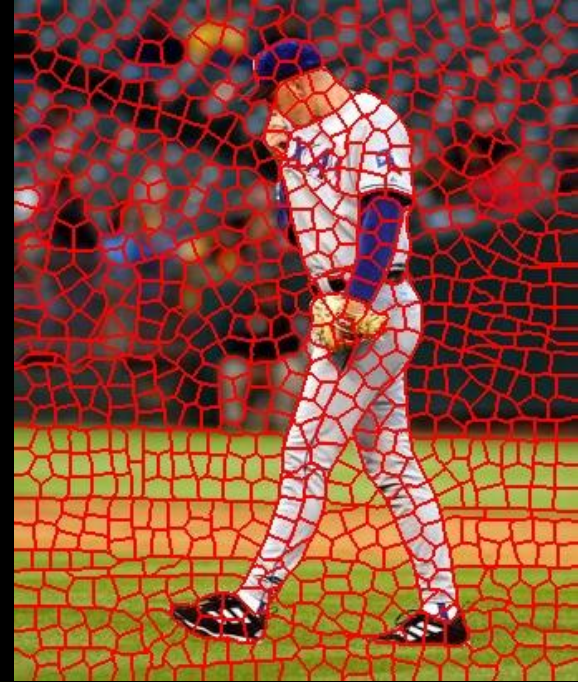
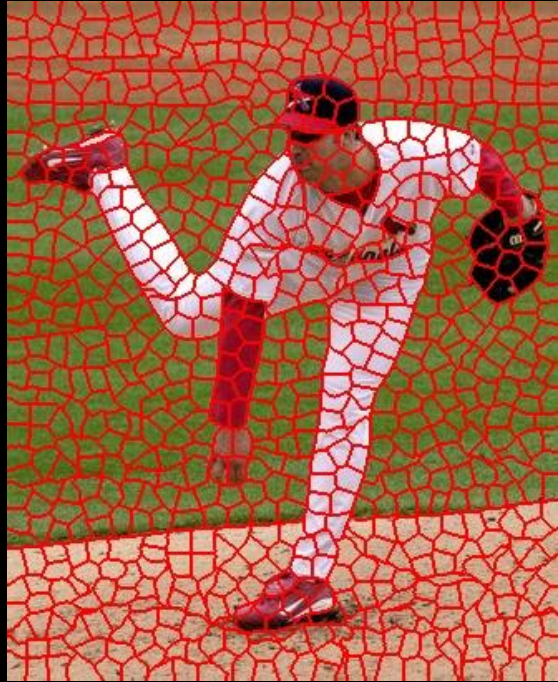
Figure-Ground Segmentation

- Separate the foreground object (figure) from the background (ground)



Grouping of Similar Neighbors

“Superpixels”

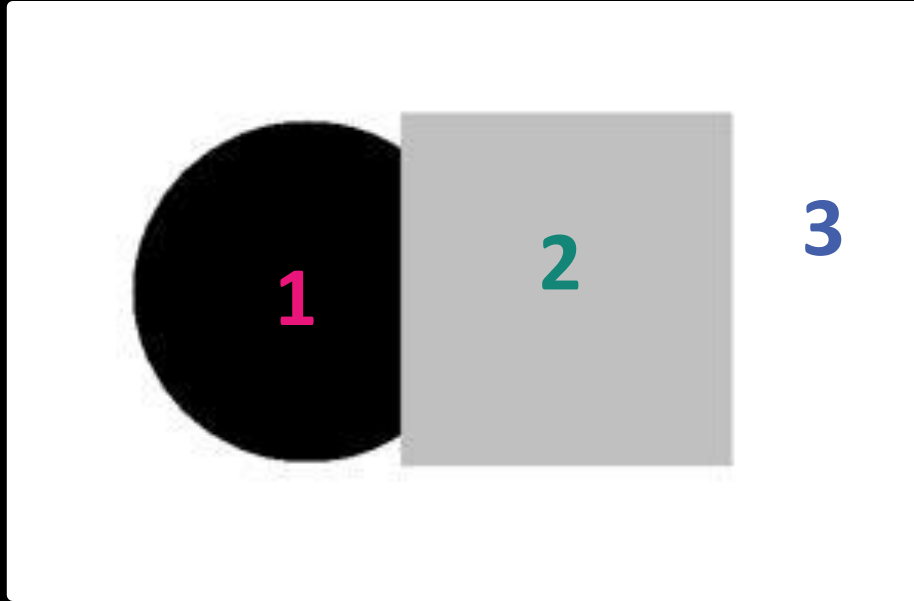


Slide by Svetlana Lazebnik

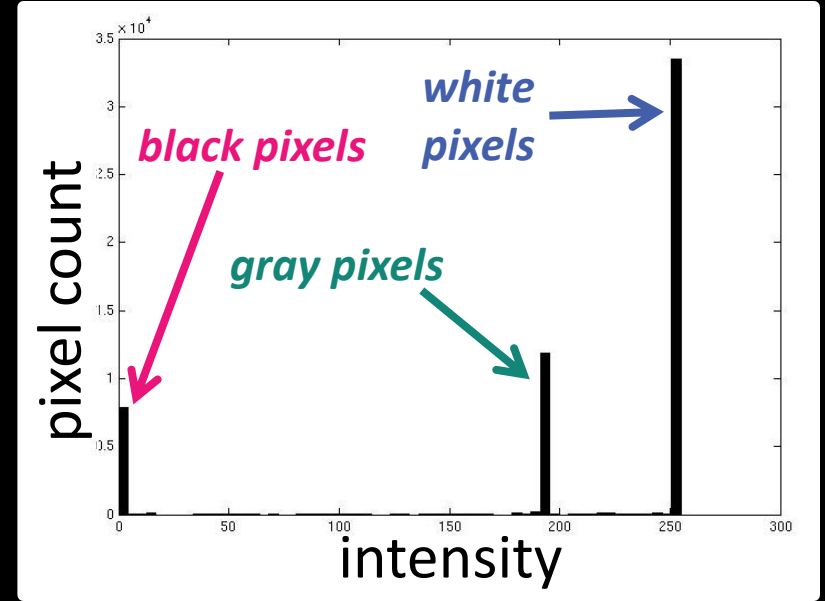
Extensions Beyond Single Images



Image segmentation: Toy example

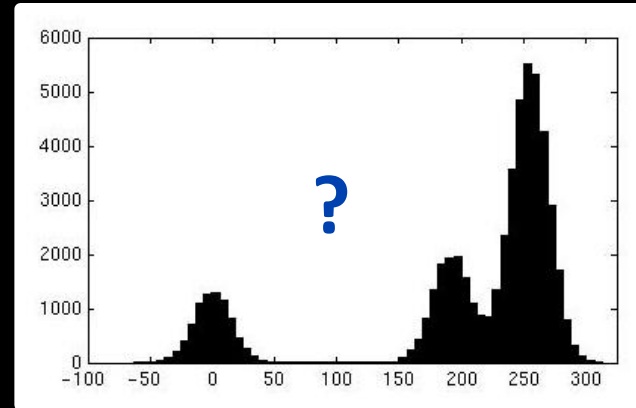
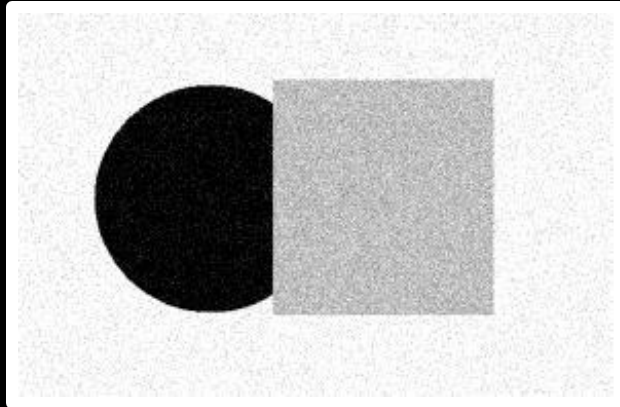
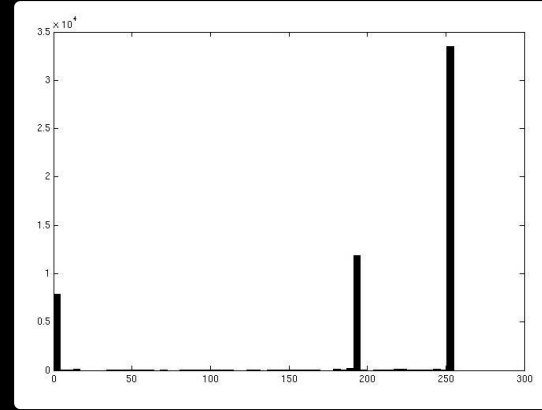
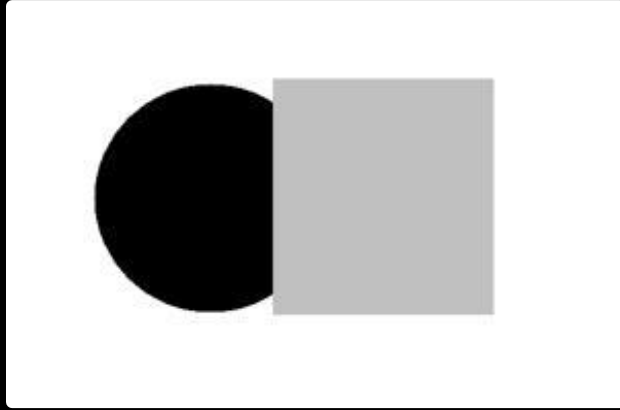


Input image

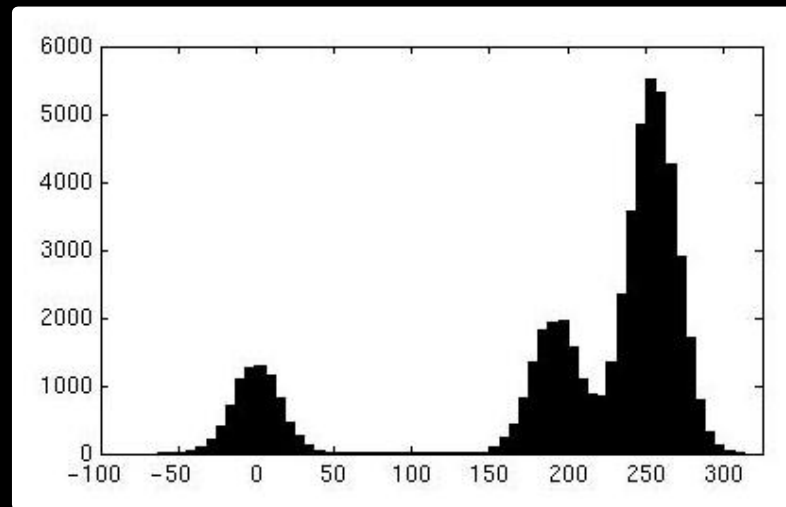
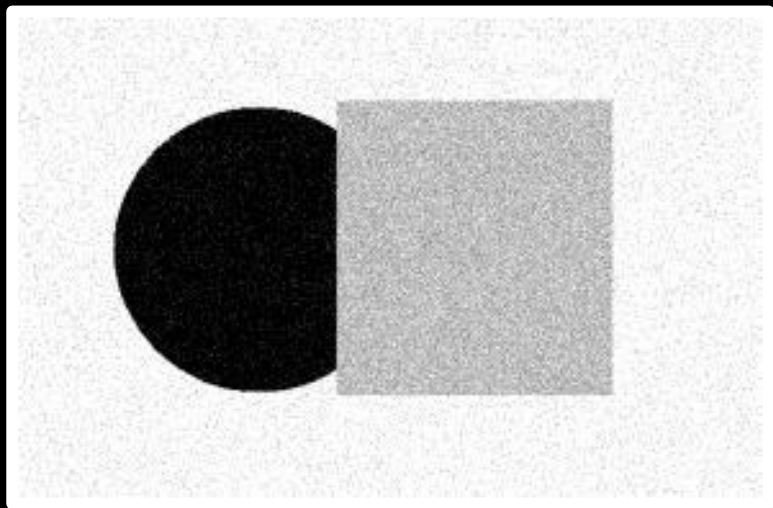


Intensity histogram

Noisy Images



Noisy Images



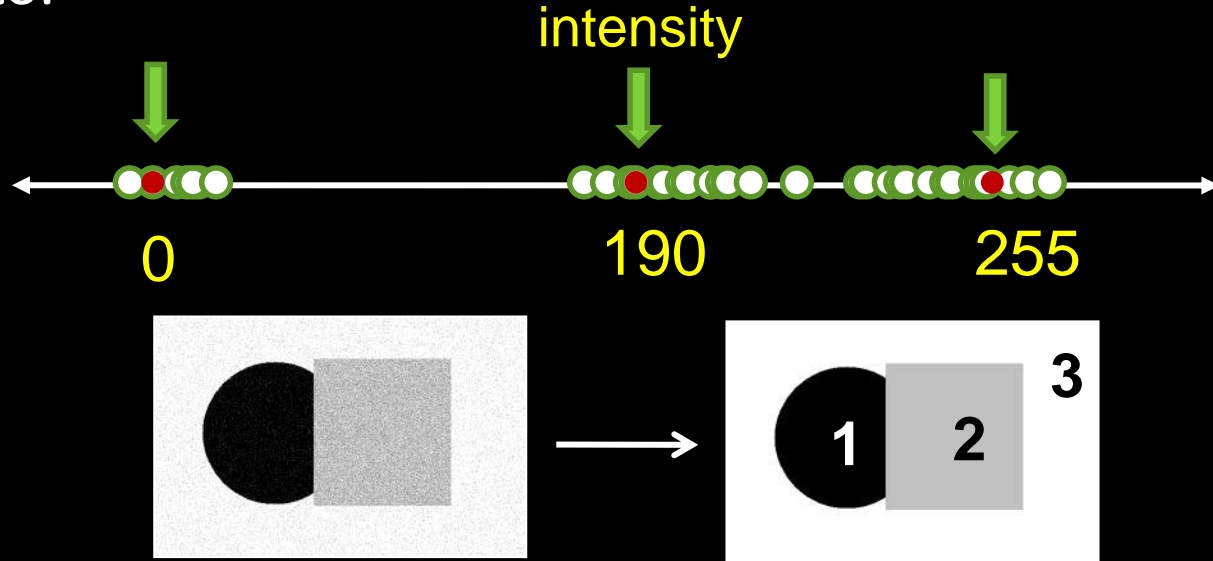
How to determine the three main intensities that define our groups?

- We need to *cluster*.

Kristen Grauman

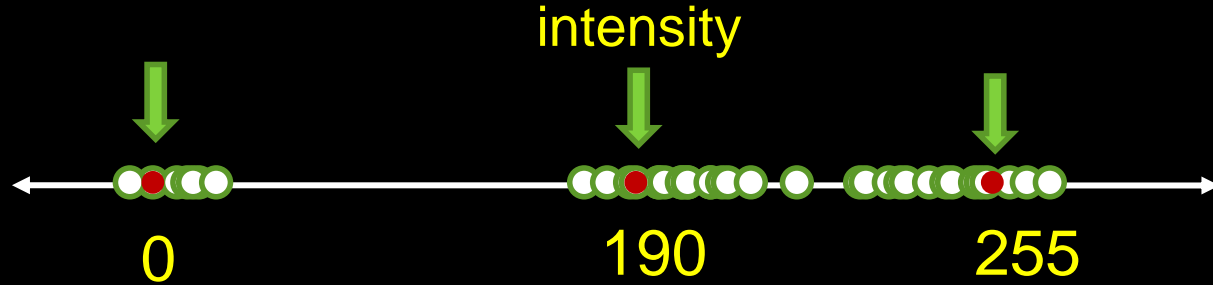
Clustering

- Goal: choose three “centers” as the **representative** intensities, and label every pixel according to which of these centers it is nearest to.



Clustering

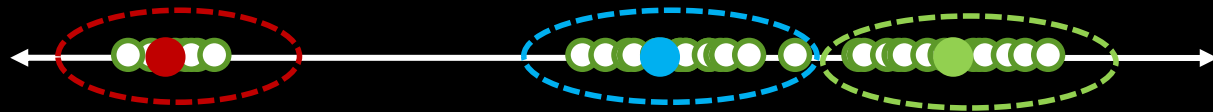
- Best cluster centers are those that **minimize SSD** between all points and their nearest cluster center c_i :



$$SSD = \sum_{\text{cluster } C_i} \sum_{p \in C_i} \|p_j - c_i\|$$

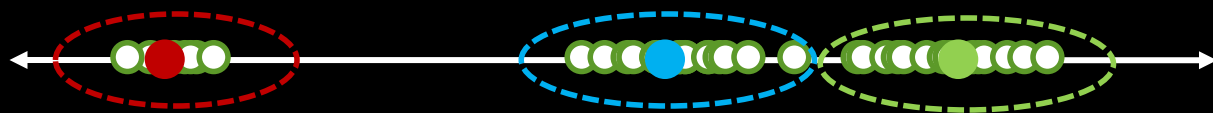
Clustering

- With this objective, it is a “chicken and egg” problem:
 - Q: If we knew c_i 's, how would we determine which points to associate with each **cluster center**?
 - A: for each point p , choose **closest** c_i




Clustering

- With this objective, it is a “chicken and egg” problem:
 - Q: If we knew the **cluster memberships**, how do we get the centers?
 - A: choose c_i to be the **mean** of all points in the cluster

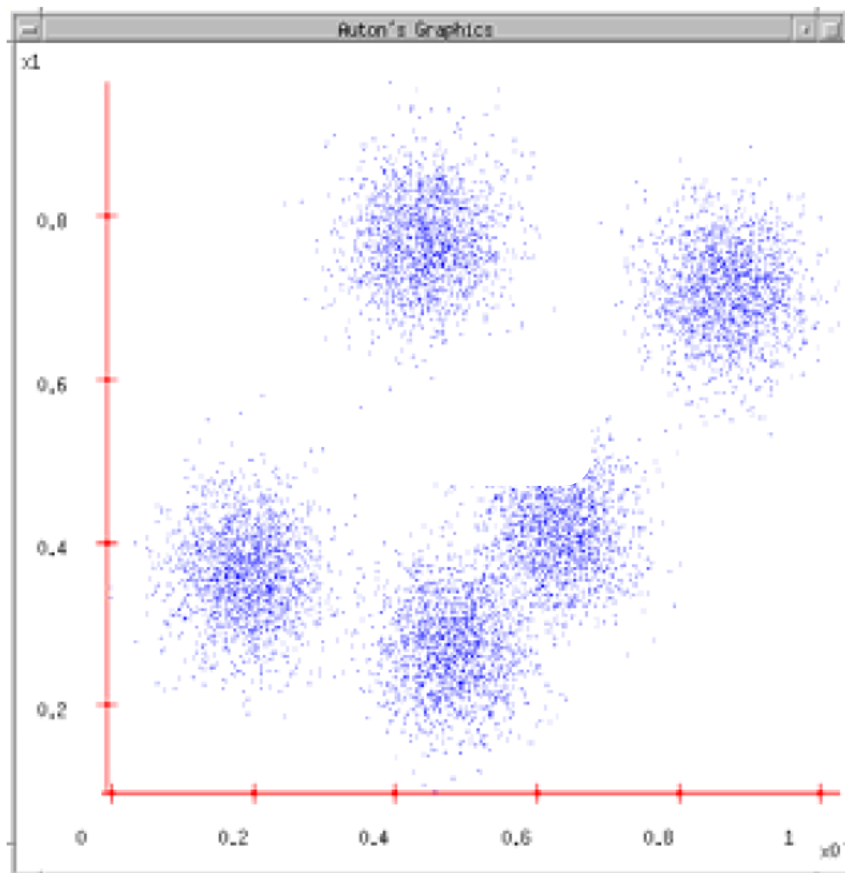


K-means clustering: Algorithm

1. Randomly initialize cluster centers c_1, \dots, c_K
 2. 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 any c_i has changed, repeat Step 2
- 

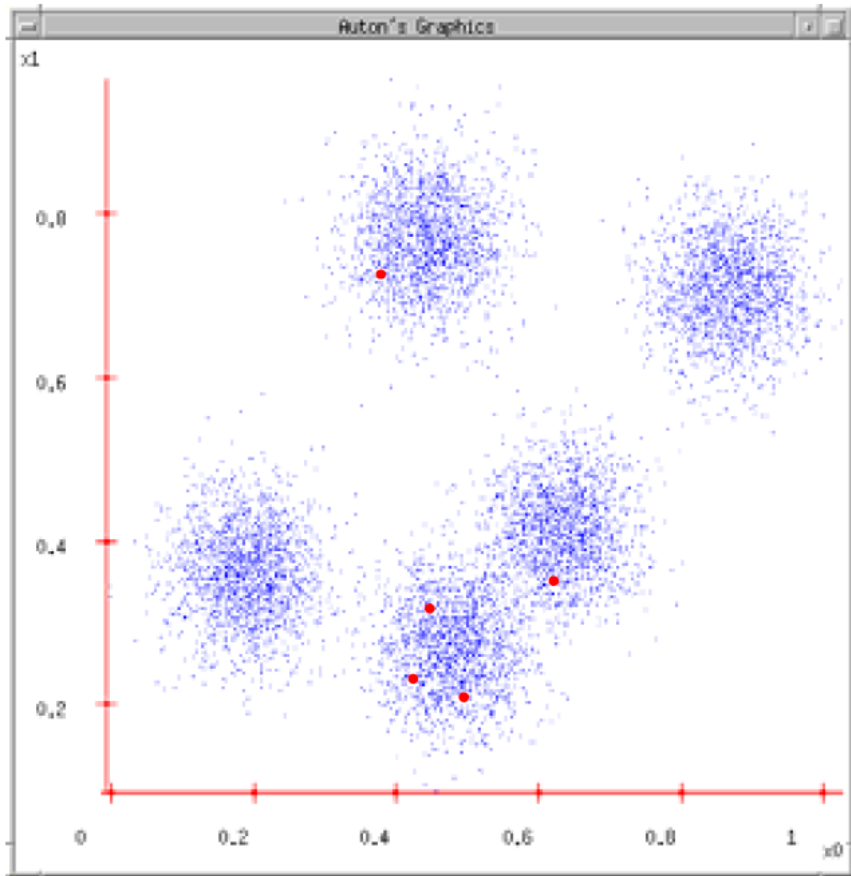
K-means

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



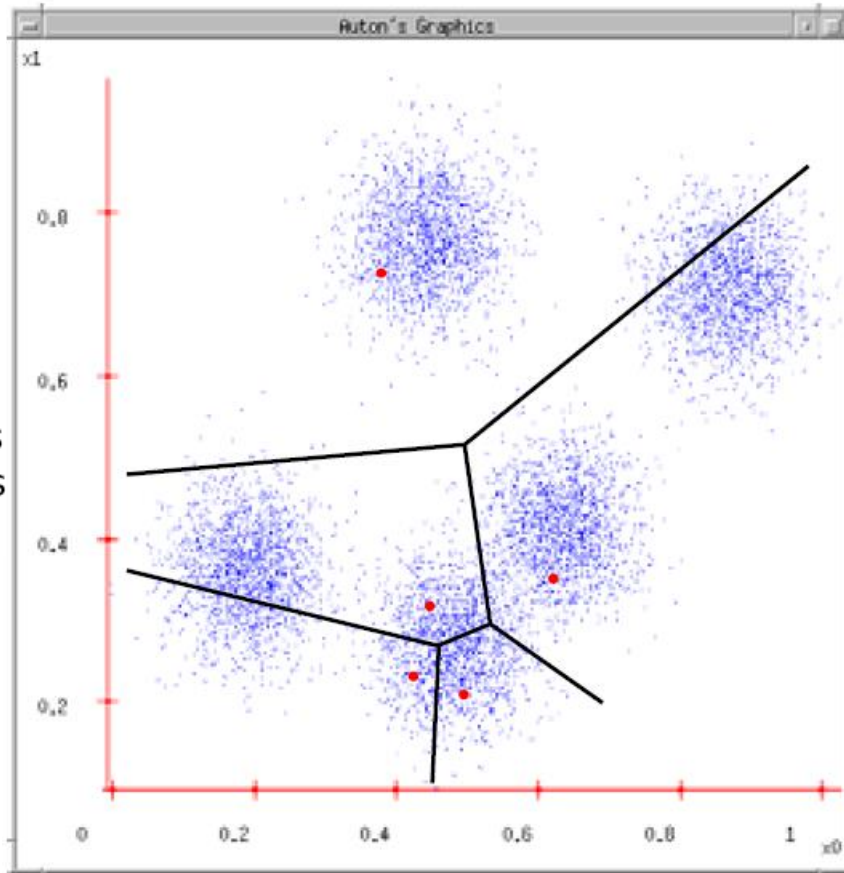
K-means

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



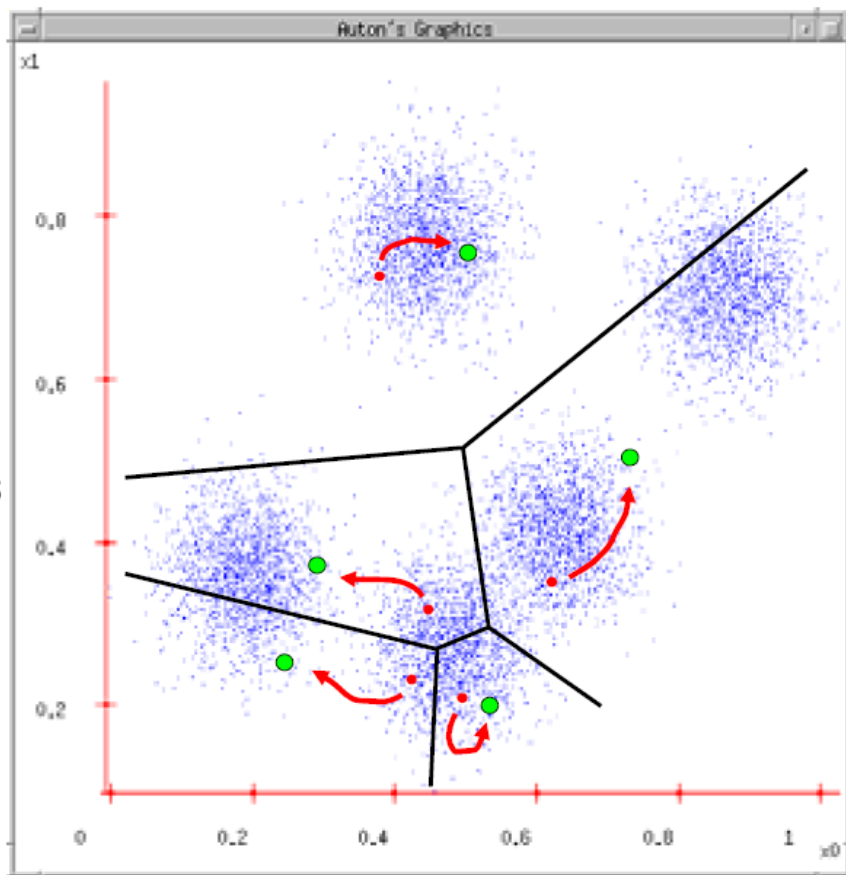
K-means

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



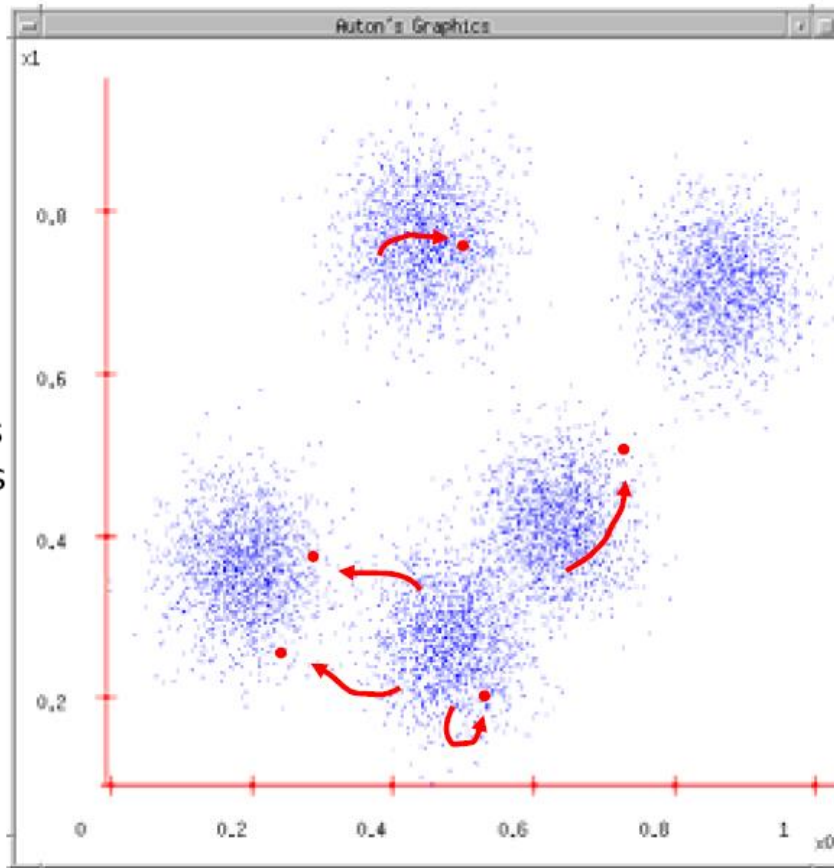
K-means

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



K-means

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



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)



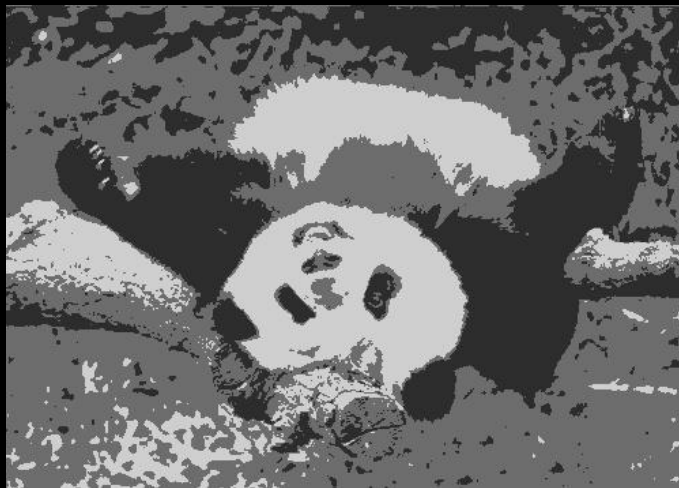
Number of Clusters



K=2



K=3

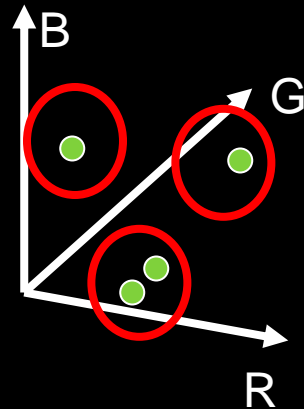


Can be thought of as *quantization* of the feature space; segmentation label map

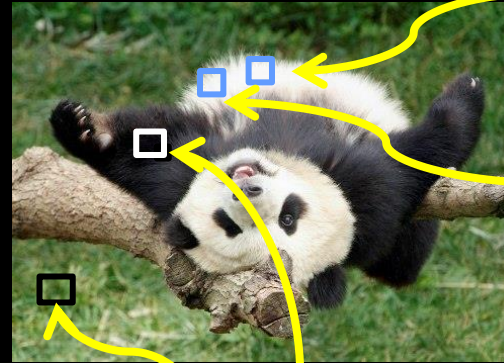
Segmentation as clustering

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)



$\begin{pmatrix} R=255 \\ G=200 \\ B=250 \end{pmatrix}$

$\begin{pmatrix} R=245 \\ G=220 \\ B=248 \end{pmatrix}$

$\begin{pmatrix} R=15 \\ G=189 \\ B=2 \end{pmatrix}$

$\begin{pmatrix} R=3 \\ G=12 \\ B=2 \end{pmatrix}$

Segmentation as clustering

K-means clustering based on intensity or color is essentially vector quantization of the image attributes

Image



Intensity-based clusters



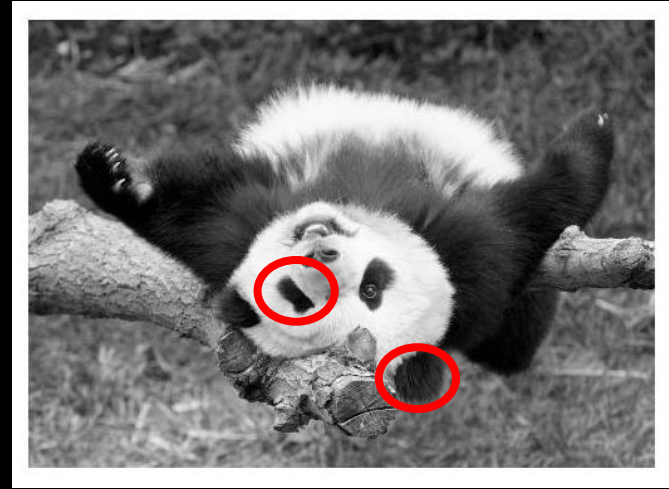
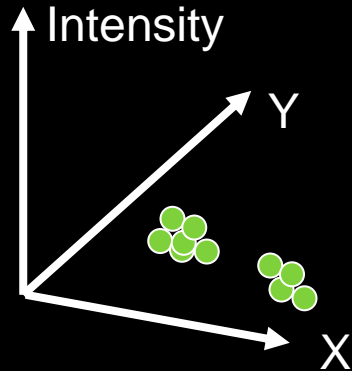
Color-based clusters



Segmentation as clustering

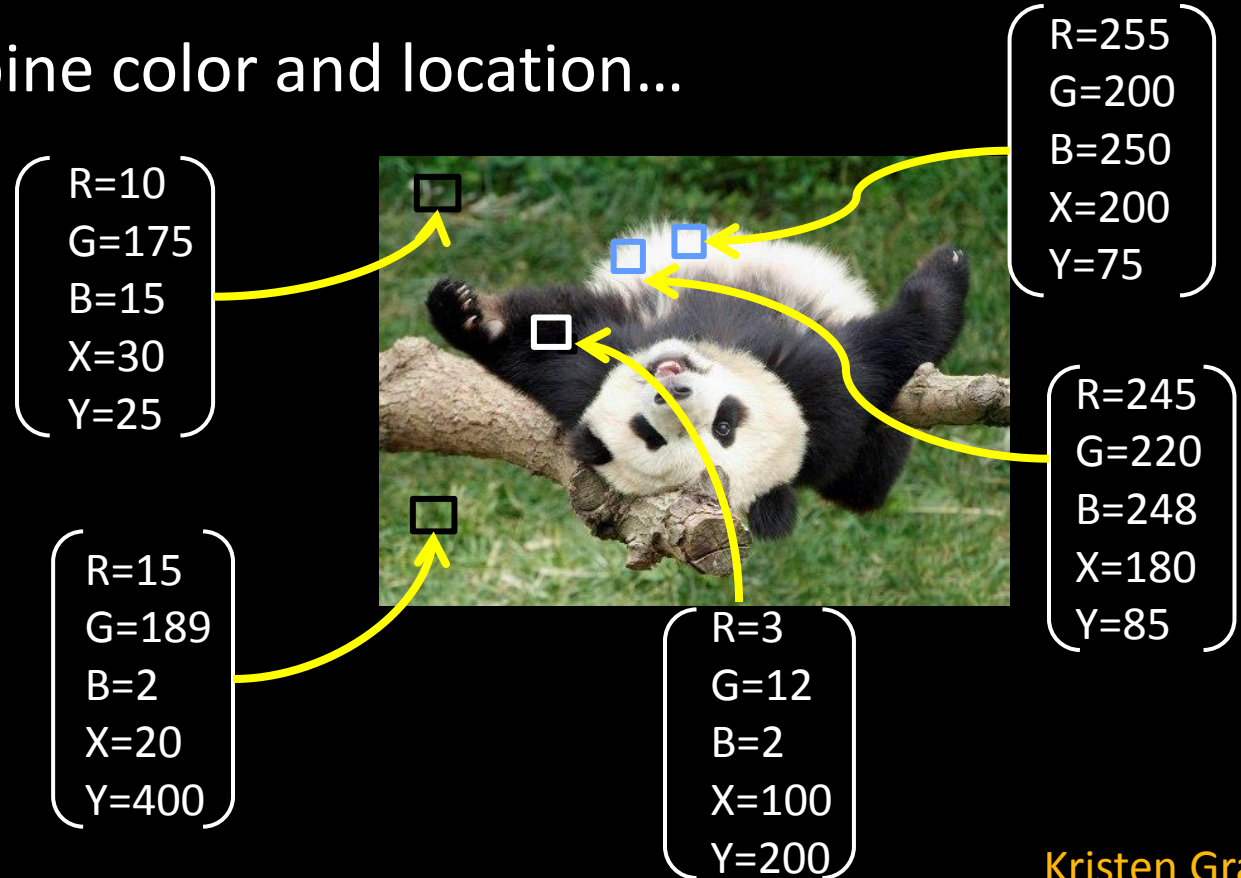
Depending on what we choose as the *feature space*, we can group pixels in different ways.

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



Segmentation as clustering

- Can combine color and location...



K-Means for segmentation

- Pros
 - Very simple method
 - Converges to a local minimum of the error function

K-Means for segmentation

- Cons
 - Memory-intensive
 - Need to pick K
 - Sensitive to initialization
 - Sensitive to outliers
 - Only finds “spherical” clusters

