Lecture 21
Unsupervised Clustering

ECEN5283 Computer Vision

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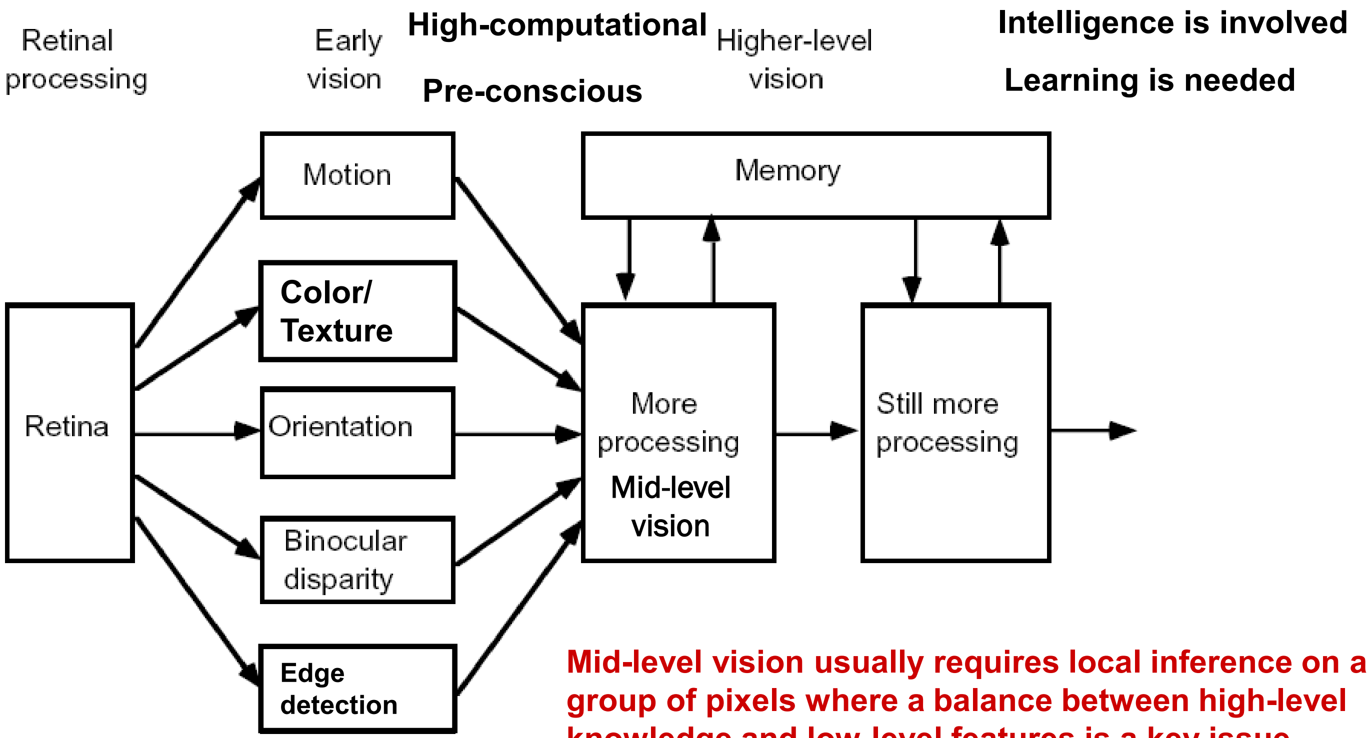
Goals

To review a few issues related to mid-level vision and unsupervised clustering.

To introduce the K-means clustering method.

Parallel pathways in early vision



Mid-level vision usually requires local inference on a group of pixels where a balance between high-level knowledge and low-level features is a key issue.

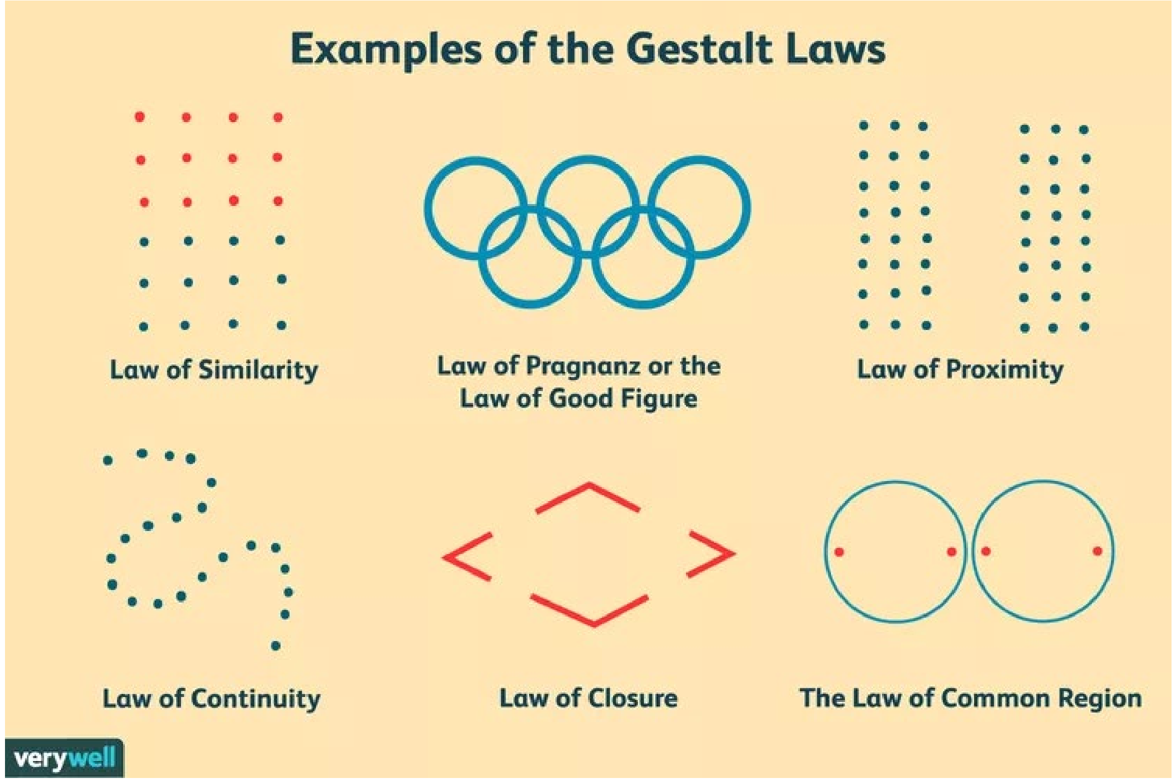
Fig.1.1
A generic diagram for visual processing. In this approach, early vision consists of a set of parallel pathways, each analyzing some particular aspect of the visual stimulus.

Mid-level Vision

The classical computer vision literature distinguishes between low-level, mid-level, and high-level vision processes.

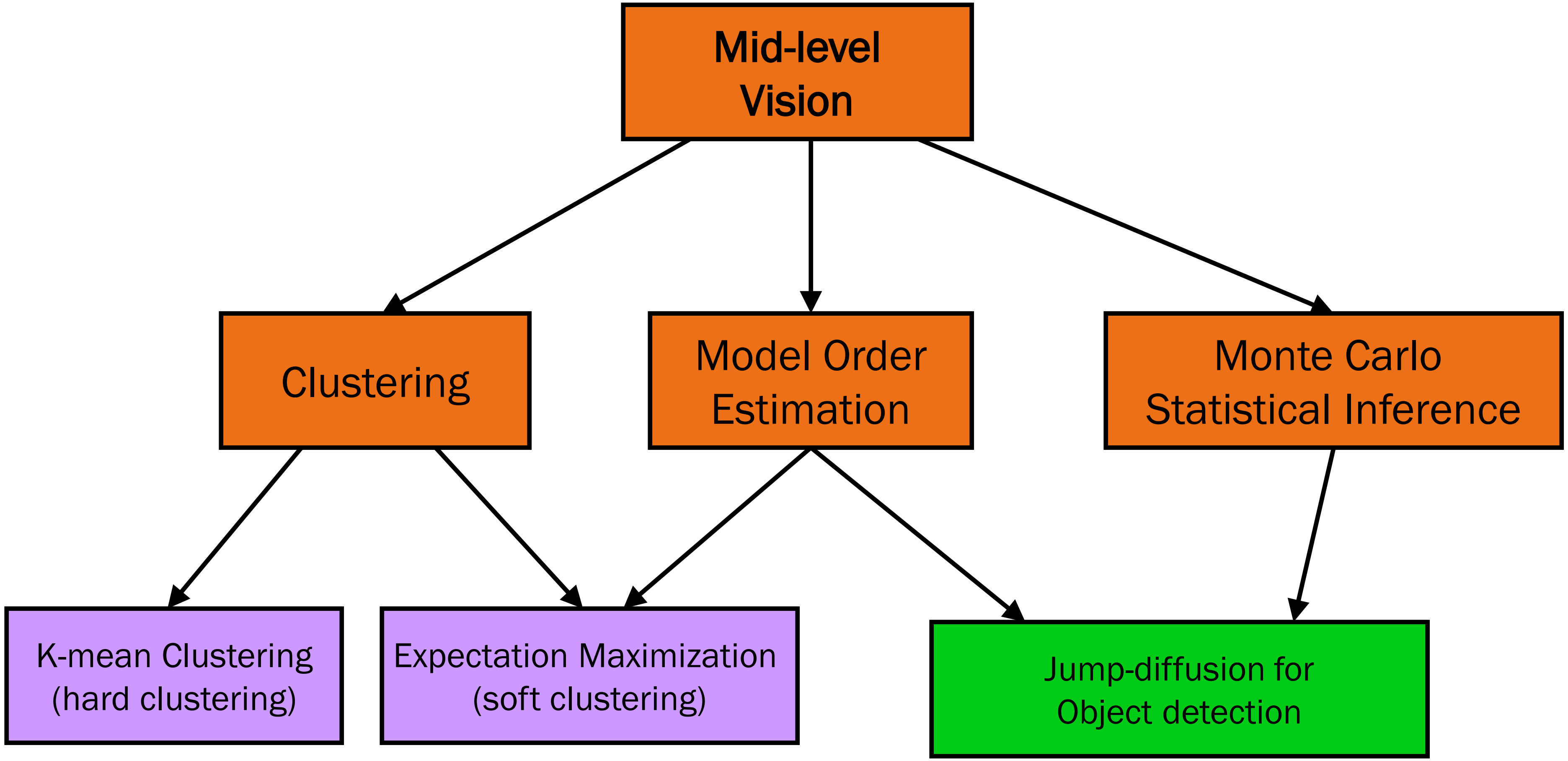
The ideas on mid-level vision are due to the Gestalt psychologists, who suggested that the underlying processes are grouping mechanisms to separate figure from ground.

However, the current learning approaches do not explicitly involve these intermediate representation.



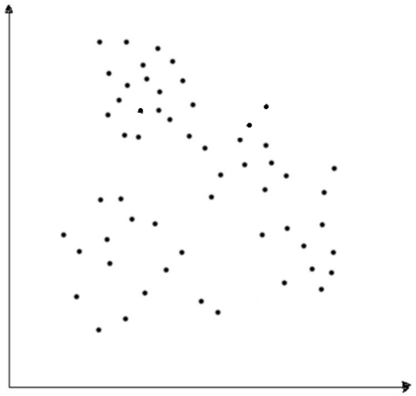
https://www.verywellmind.com/gestalt-laws-of-perceptual-organization-2795835

Overview of Mid-level Vision

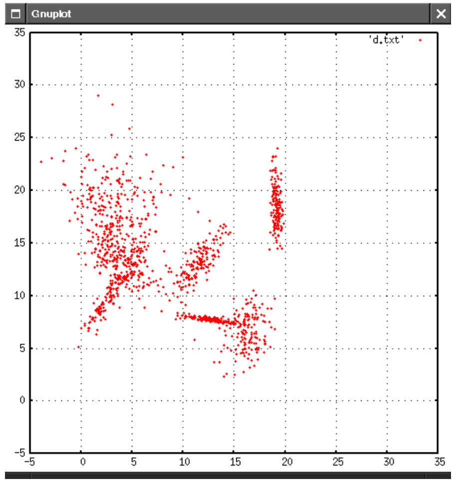


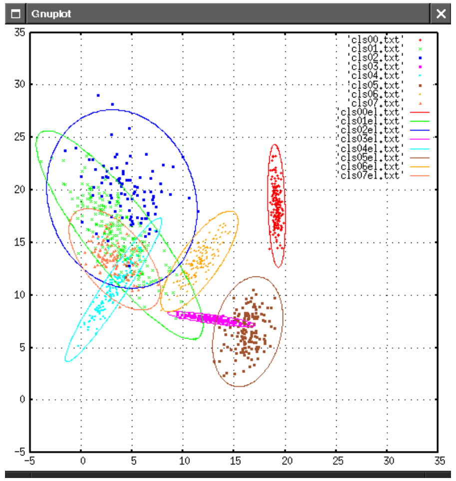
Hard and Soft Clustering

A hard clustering method (K-means) provides is a deterministic classification rule.



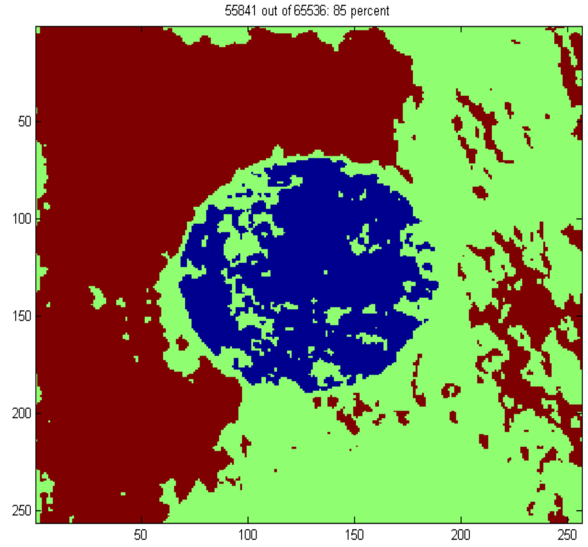
A soft clustering method (EM) computes the probability of each sample belonging to each class label during the iteration.

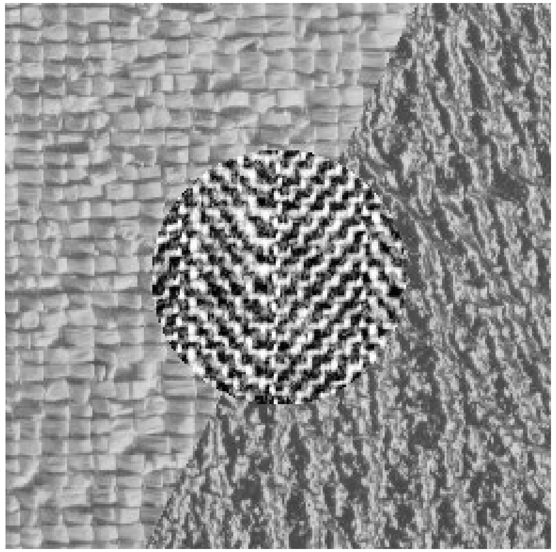


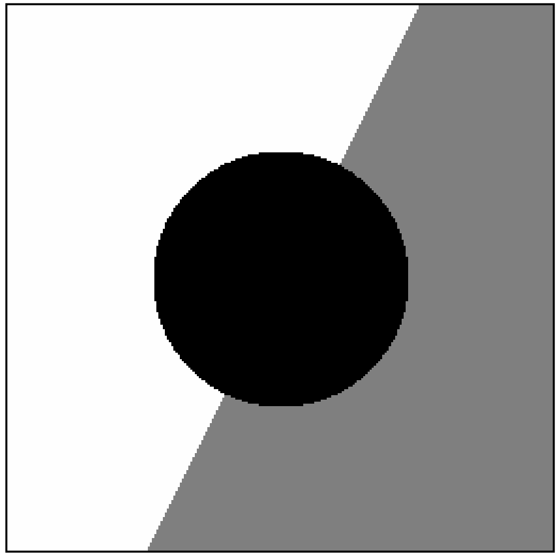


Project 4. Image Segmentation

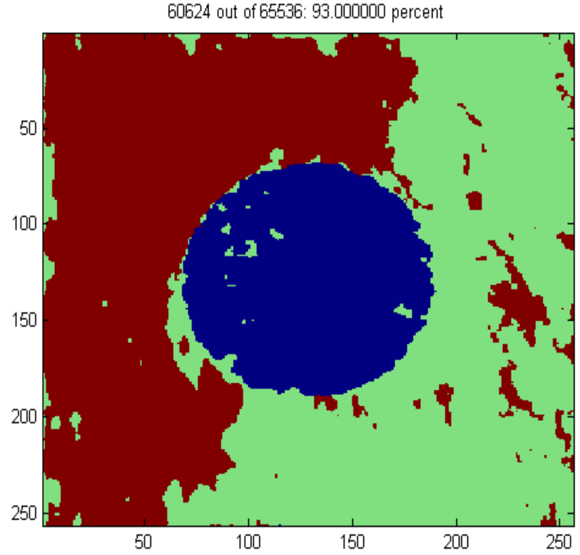
Hard-clustering





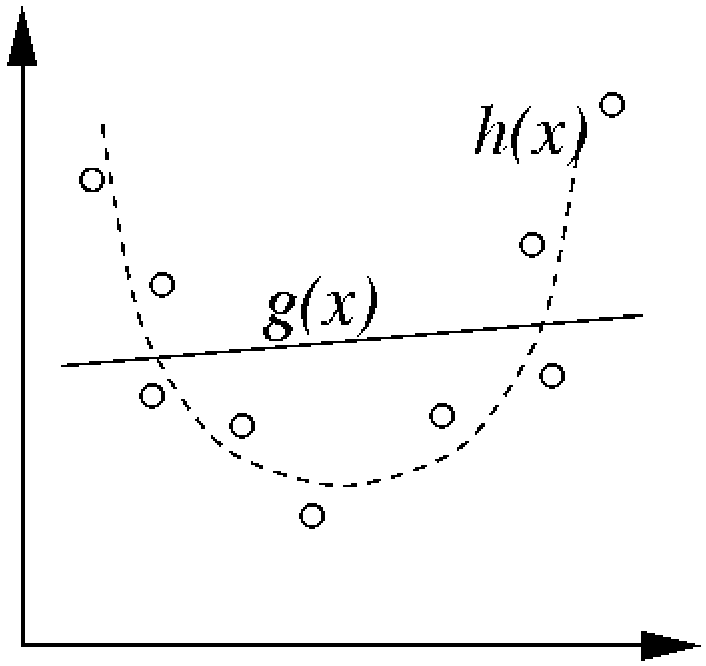


Soft-clustering

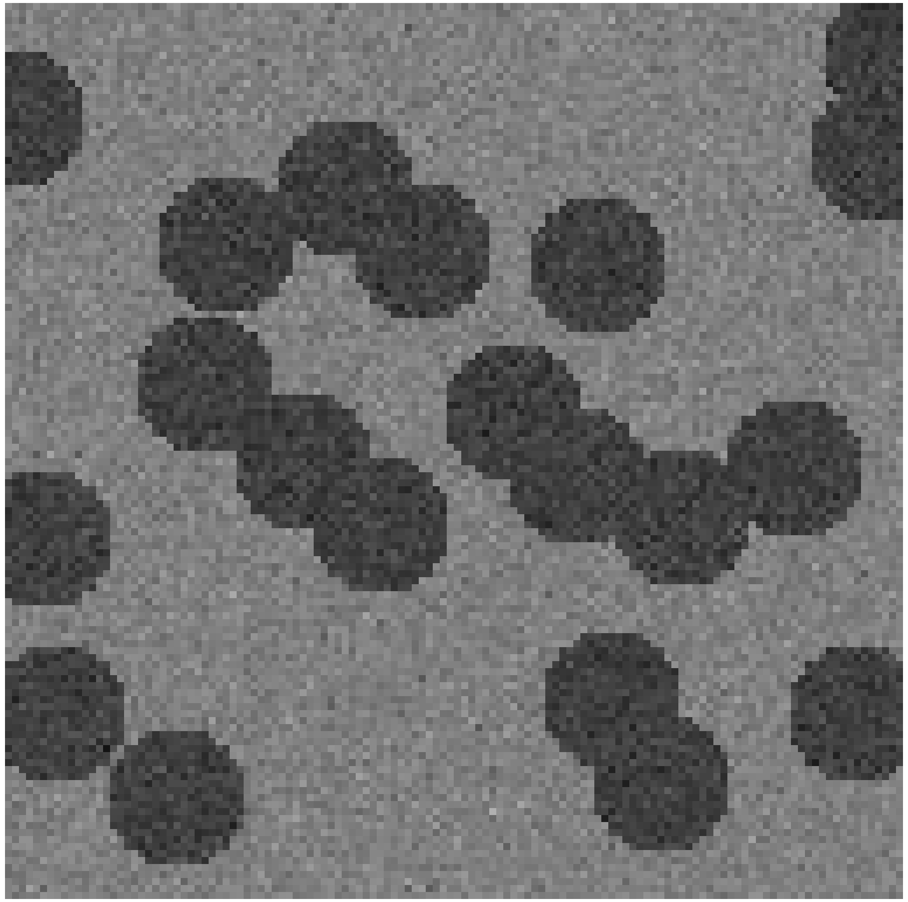


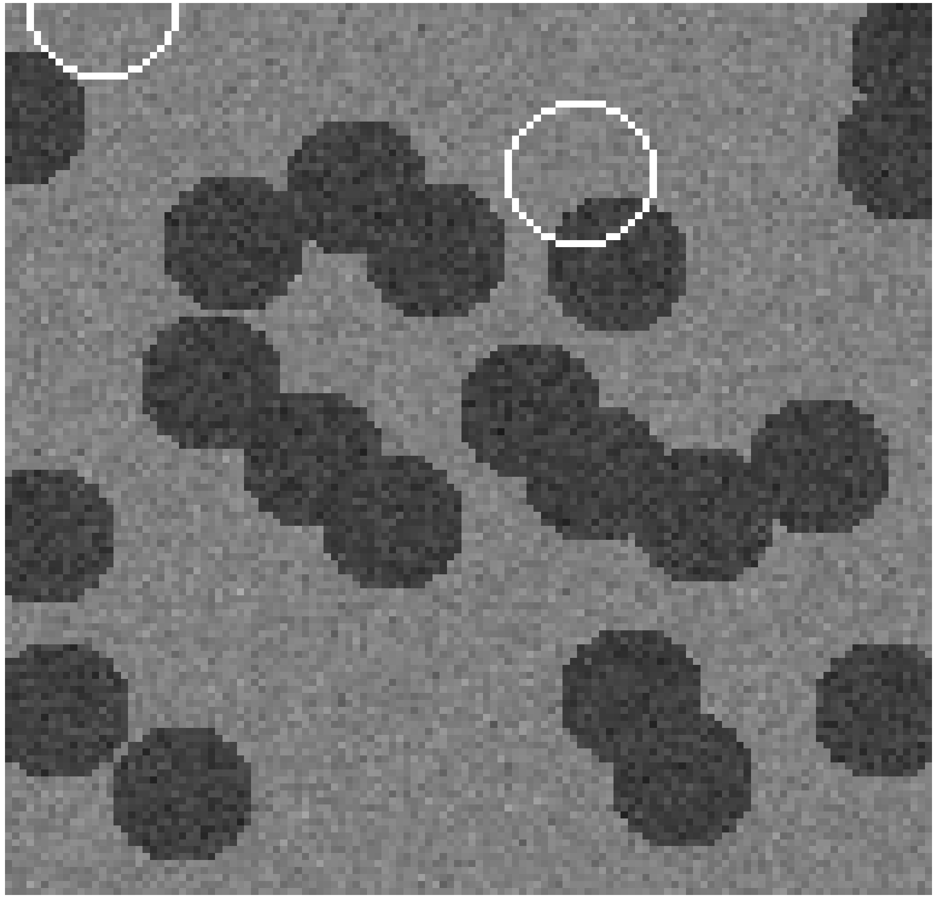
Model Order Estimation

We try to avoid both under-fitting and over-fitting problems and obtain an appropriate model.



Project 5.
Object Detection and Counting





K-means Clustering

Goal: Given the number of classes k, we want to optimize an objective function.

Objective:

- We want to segment data points in the feature space, then **y** represent the feature vector, and **c** is the center of a cluster.
- We assume that elements are close to center of their cluster, yielding the objective function (intra-class divergence)

$$\Phi(\text{clusters,data}) = \sum_{i \in \text{clusters}} \left\{ \sum_{j \in i^{th} \text{ cluster}} \left| \mathbf{y}_j - \mathbf{c}_i \right|^2 \right\}$$

Two activities:

- Assume the cluster centers are known, allocate each data point to the closest cluster center.
- Assume the allocation is known, compute a new set of cluster centers (means).

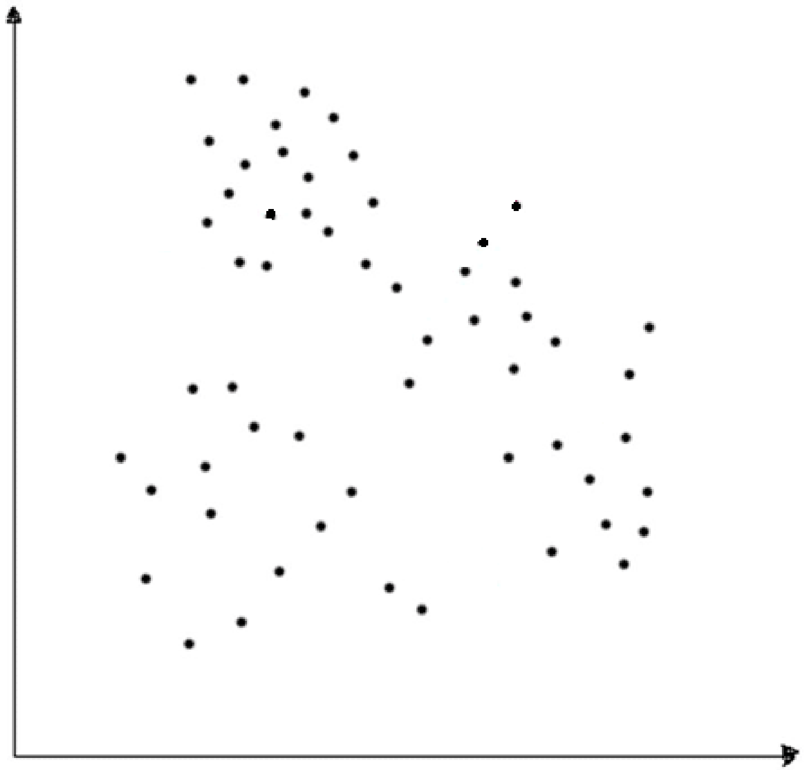
K-means Algorithm

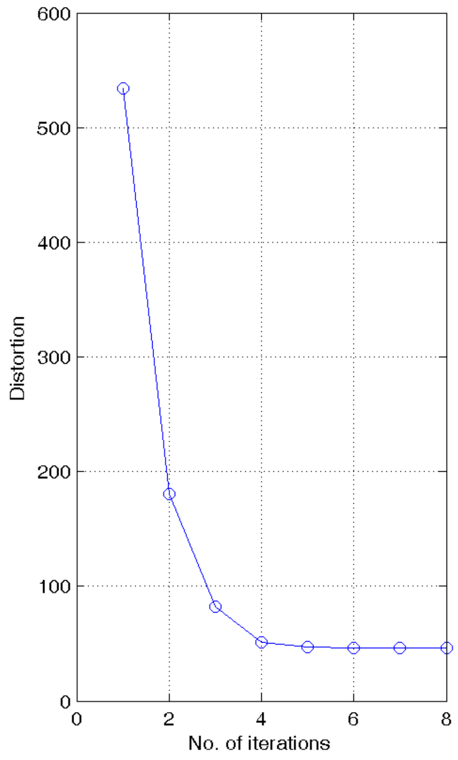
Form K-means clusters from a set of n-dimensional vectors.

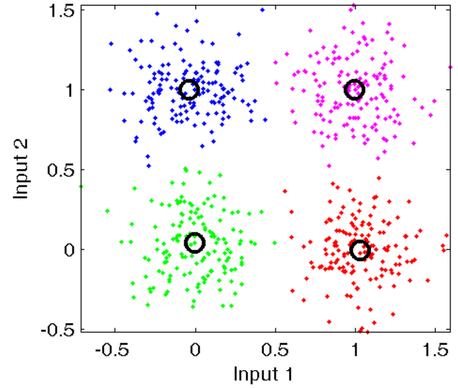
- Set *Nc* =1 (iteration number).
- Choose randomly a set of K means, $\{\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_k\}$.
- For each vector y, compute $D(\mathbf{y}, \mathbf{c}_k)$ for each $k = 1,2, \ldots, K$, and assign y to the cluster with the nearest distance.
- Increment *Nc* by 1 and update the means based on new class labels to get a new set of centers $\{\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_k\}$
- Repeat until no change to $\{\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_k\}$ or the objective function has insignificant change, or *Nc=Nmax*

This process eventually converges to a local minimum of the objective function.

K-means Clustering Examples







K-means Clustering for Color Quantization

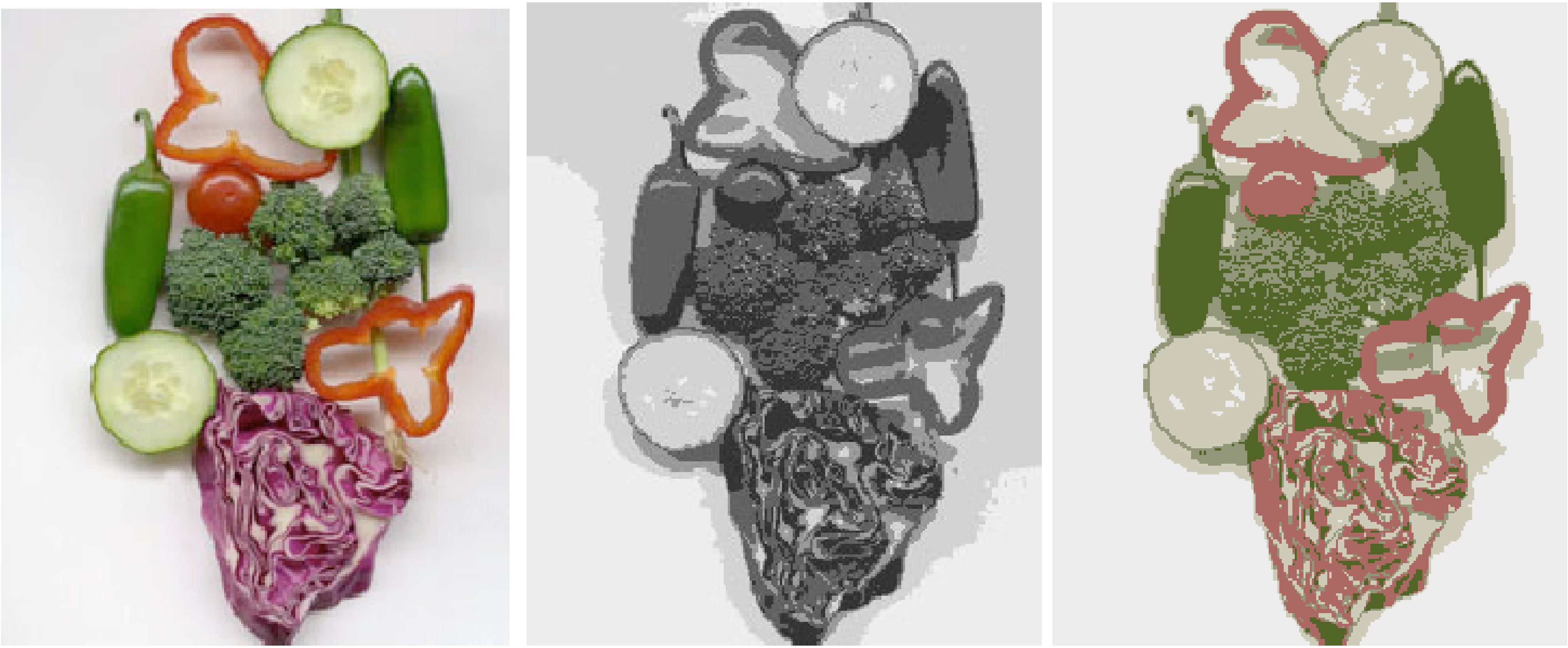


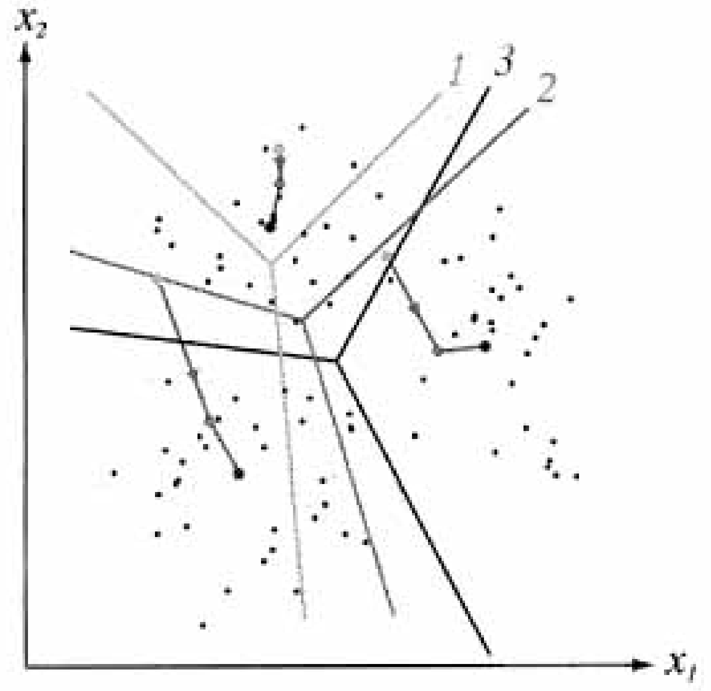
Figure 16.13. On the left, an image of mixed vegetables, which is segmented using k-means to produce the images at center and on the right. We have replaced each pixel with the mean value of its cluster; the result is somewhat like an adaptive requantization, as one would expect. In the center, a segmentation obtained using only the intensity information. At the right, a segmentation obtained using colour information. Each segmentation assumes five clusters.

Why K-means Converge?

Whenever an assignment is changed, the sum squared distances of data-points from their assigned cluster centers is reduced.

Whenever a cluster center is moved the sum squared distances of the data-points from their currently assigned cluster centers is reduced.

If the assignments do not change in the assignment step, we have converged.



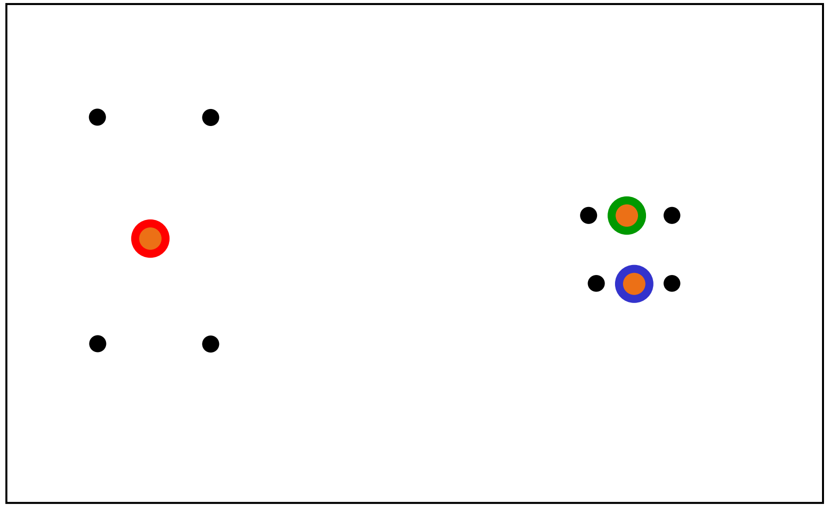
Why K-means can be stuck at a local minima?

There is nothing to prevent k-means getting stuck at local minima.

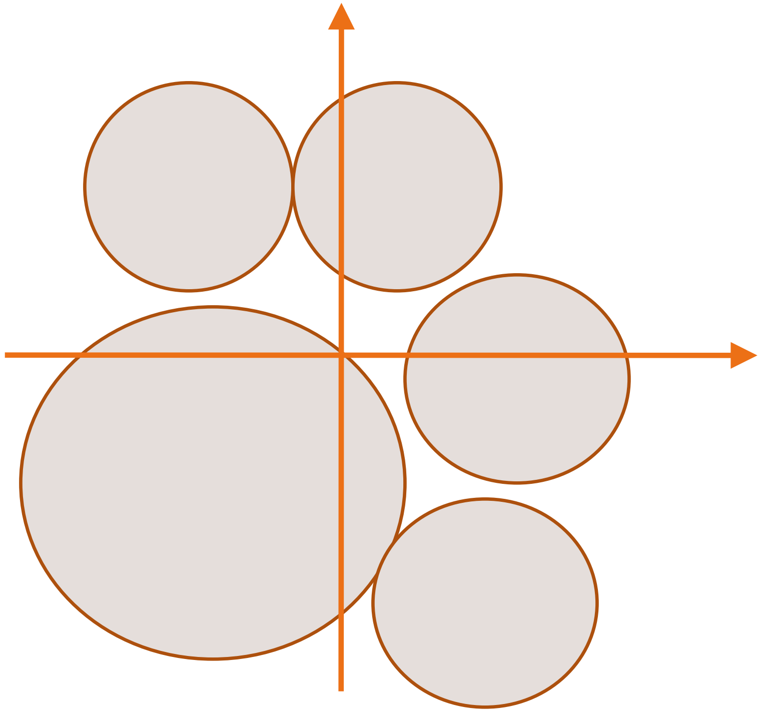
We could try many random starting points

We could try non-local split-and-merge moves: simultaneously merge two nearby clusters and split a big cluster into two.

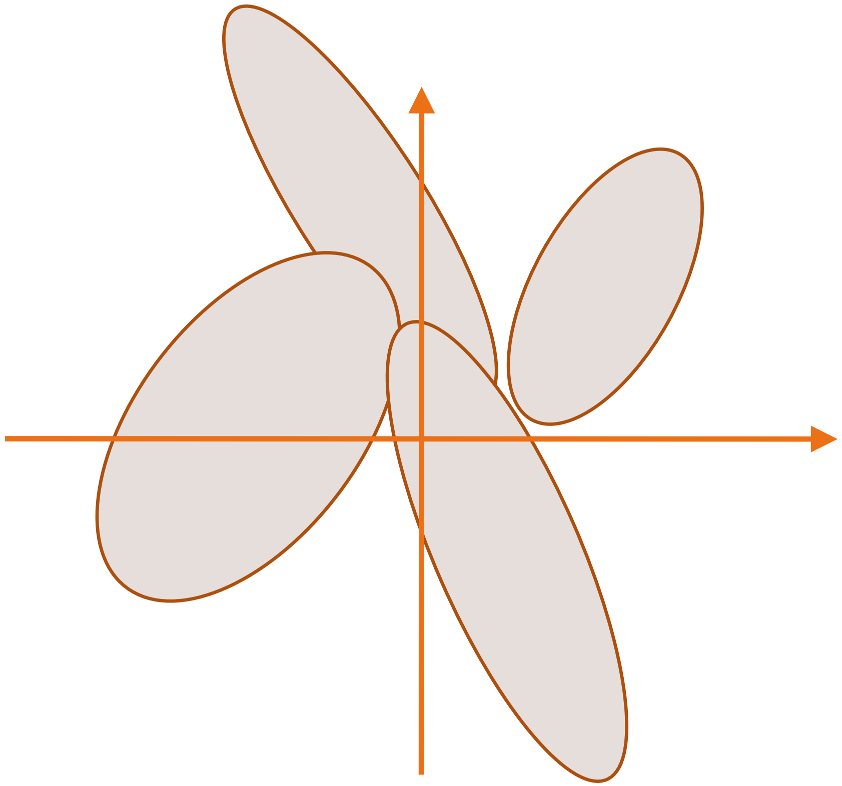
A bad local optimum



Underlying Assumption of K-means



All feature distributions are isotropic and equally probable



K-mean does not work well for the case of non-isotropic feature distributions