Department of Computer Science
University of Bristol

COMS30030 - Image Processing and Computer Vision

Week 03

Segmentation Basics

Majid Mirmehdi | majid@cs.bris.ac.uk

Examples of Image Segmentation

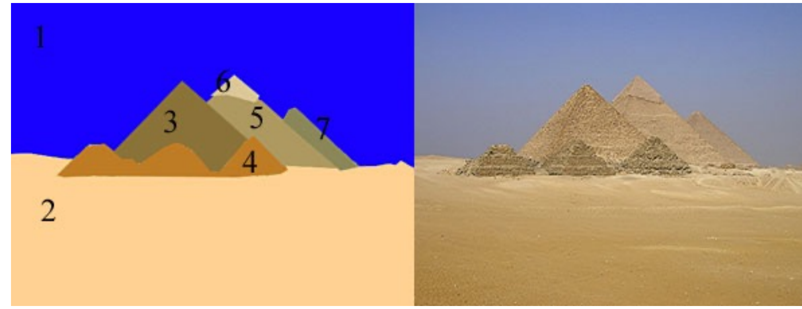
- **Image Segmentation ...**

  ... is the process of spatial subsectioning of a (digital) image into multiple partitions of pixels (i.e. segments or regions) according to given criteria.

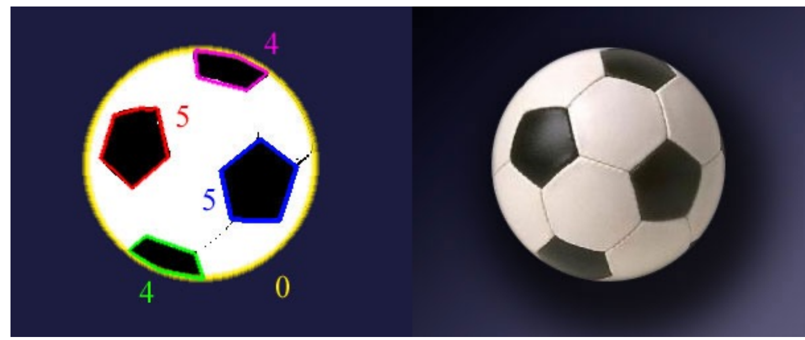
Example: segmentation of an image into locally coherent regions

Motivation: Why Segment Images?

- **Image Simplification**
  - an image may contain millions of pixels but only a few regions

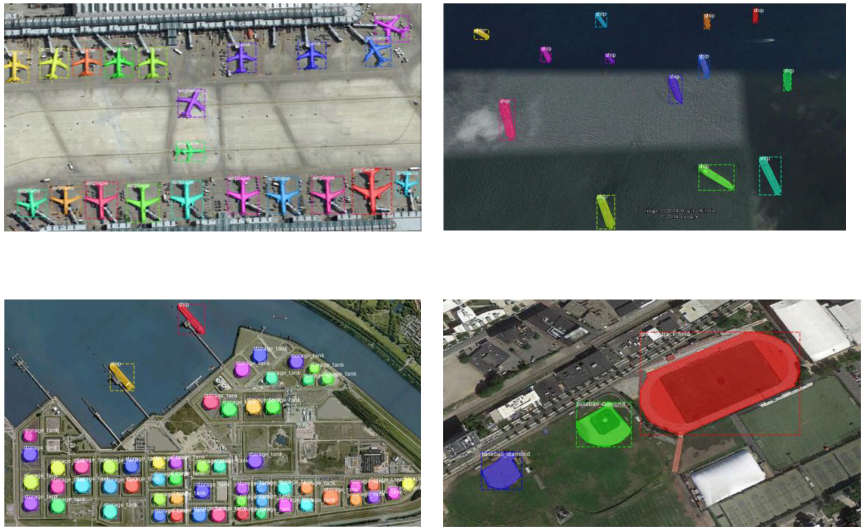


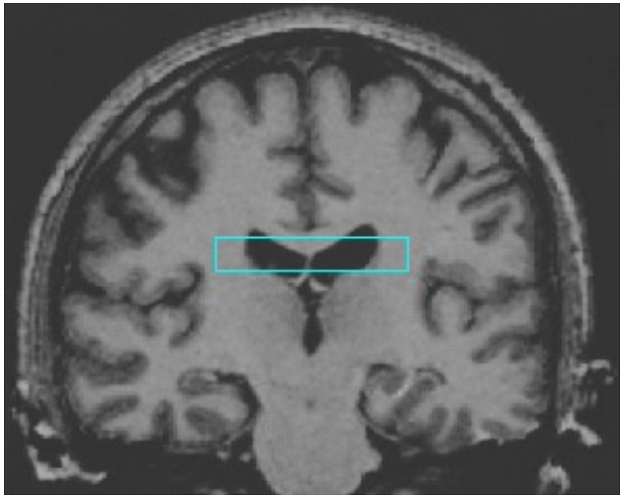
- **Higher-level Object Description**
  - regions tend to belong to the same class of object
  - regions may provide object properties (e.g. shape, colour, ...)



- **Input for Content Classifiers**
  - region descriptions can be input data for higher level classifiers, e.g. Bayesian Classifiers or Neural Networks.

Why Segment Images?



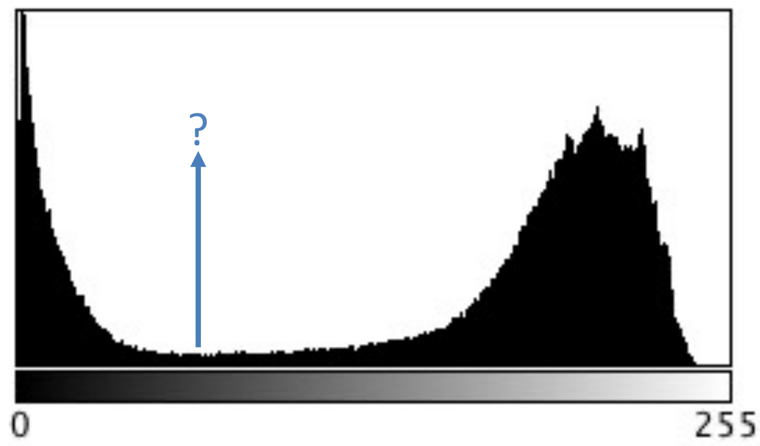


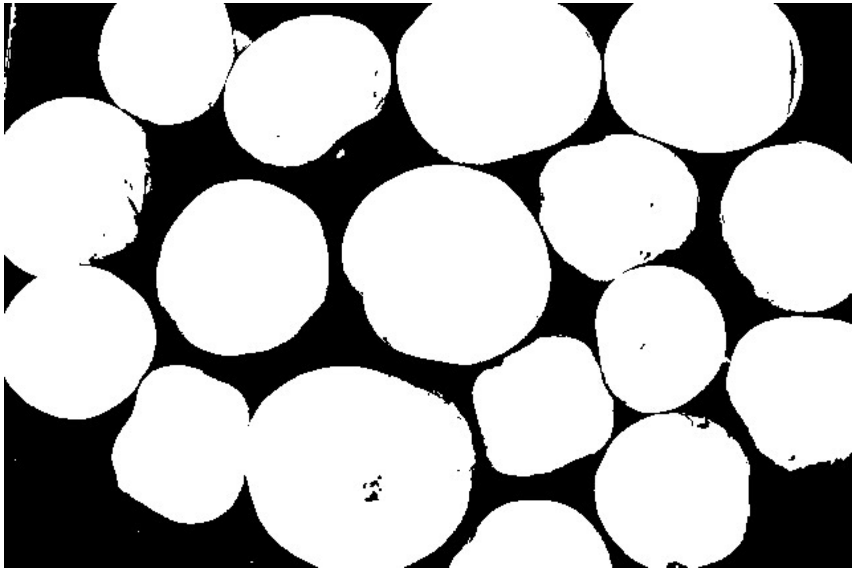
Examples from https://medium.com/cogitotech and Alberto Pretto

Image Segmentation

Perfect segmentation is difficult to achieve:

- a pixel may straddle the "real" boundary of objects such that it partially belongs to two or more objects
- effects of noise, non-uniform illumination, occlusions etc. give rise to the problem of *over-segmentation* and *under-segmentation*





Images from craftofcoding.wordpress.com

Example of Over-Segmentation

Original image

Over-segmentation

Over-segmentation: pixels belonging to the same region [object] are classified as belonging to different regions [objects]

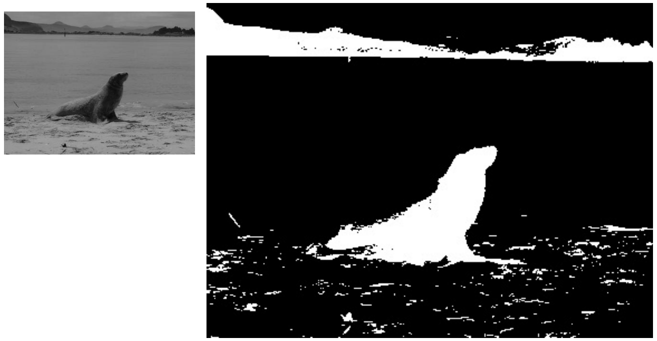
Example of Under-Segmentation

Original image

Under-segmentation

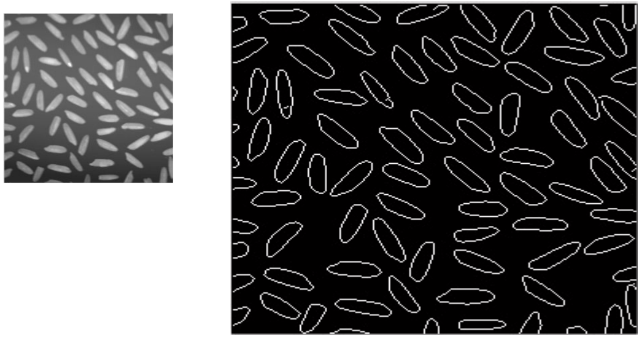
Under-segmentation: pixels belonging to different regions [objects] are classified as belonging to the same region [object]

Concepts of Segmentation I



Thresholding Methods

- pixels are categorized based on intensity
- only useful when sufficient contrast exists



Edge-based Methods

- region boundaries are constructed from edgemaps

Region-based Methods

- region growing from seed pixels
- region splitting and merging for efficient spatial encoding

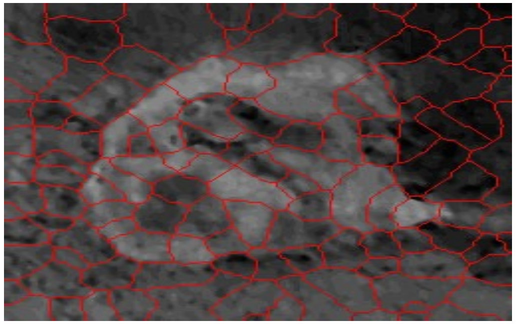
Concepts of Segmentation II

Clustering and Statistical Methods

- global, often histogram based image partitioning, e.g. *K*-means, Gaussian Mixture Model

Topographic Methods **(out of scope in this unit)**

- stepwise simplifications that take spatially wider (topographical) image configurations into account e.g. watershed transform, variational based methods



Thresholding Example

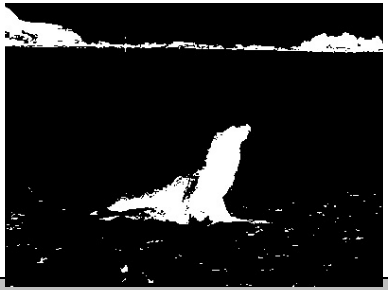
- If the image contains a dark object on a light background
  - choose a threshold value, *T*
  - for each pixel
    - if the brightness at that pixel is less than *T,* it is a pixel of interest
    - otherwise it is part of the background

- The value of the threshold is very important
  - if too high → background pixels classified as foreground
  - If too low → foreground pixels classified as background

T = 128

T = 96

T = 64



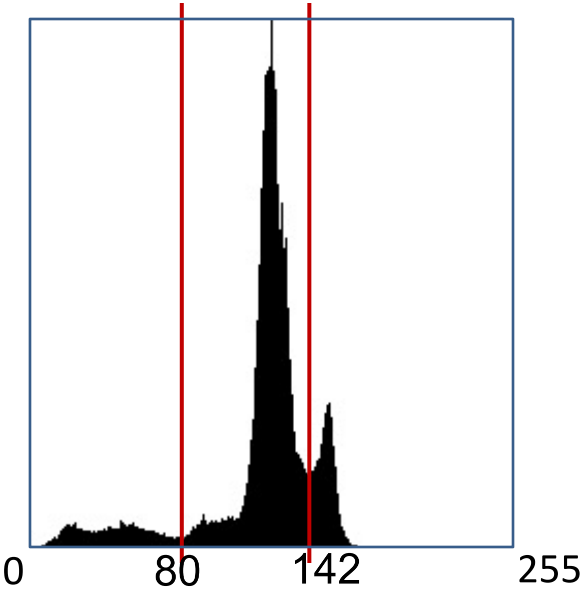
Using Histograms to Stipulate Regions

To find a threshold, we can use an image histogram:

- count how many pixels in the image have each value
- for simple images it shows peaks and valleys around regions of the image

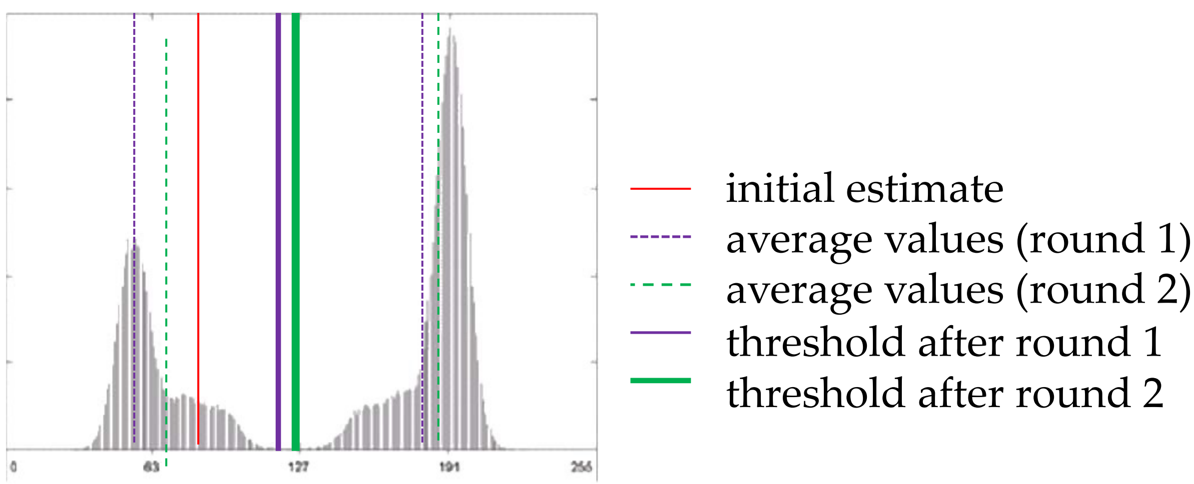
The seal image shows three regions

- one below T_1 = 80
- one above T_2 = 142
- one between the two thresholds



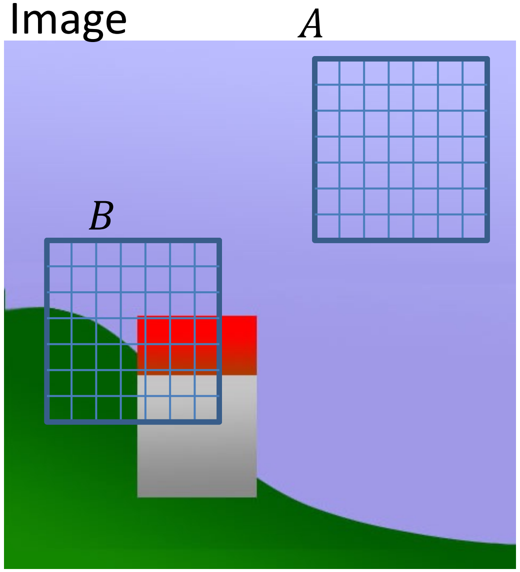
Threshold Selection Algorithm

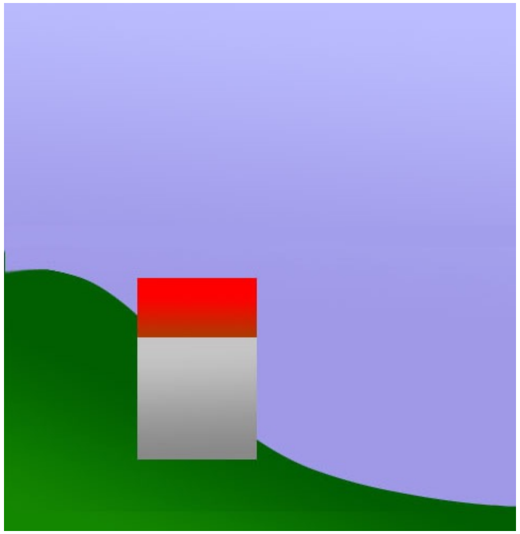
1. Select an initial estimate for the threshold T
2. Segment the image using T.
   This will produce two groups of pixels: G_1 consisting of all pixels with grey levels $>T$ and G_2 consisting of pixels with grey values $\leq T$.
3. Compute the average grey level values m_1 and m_2 for the pixels in regions G_1 and G_2.
4. Compute a new threshold value: $T = (m_1 + m_2)/2$
5. Repeat steps *(2.)* through *(4.)* until convergence



Split & Merge Segmentation – Divide & Conquer

Image





Segmentation Result

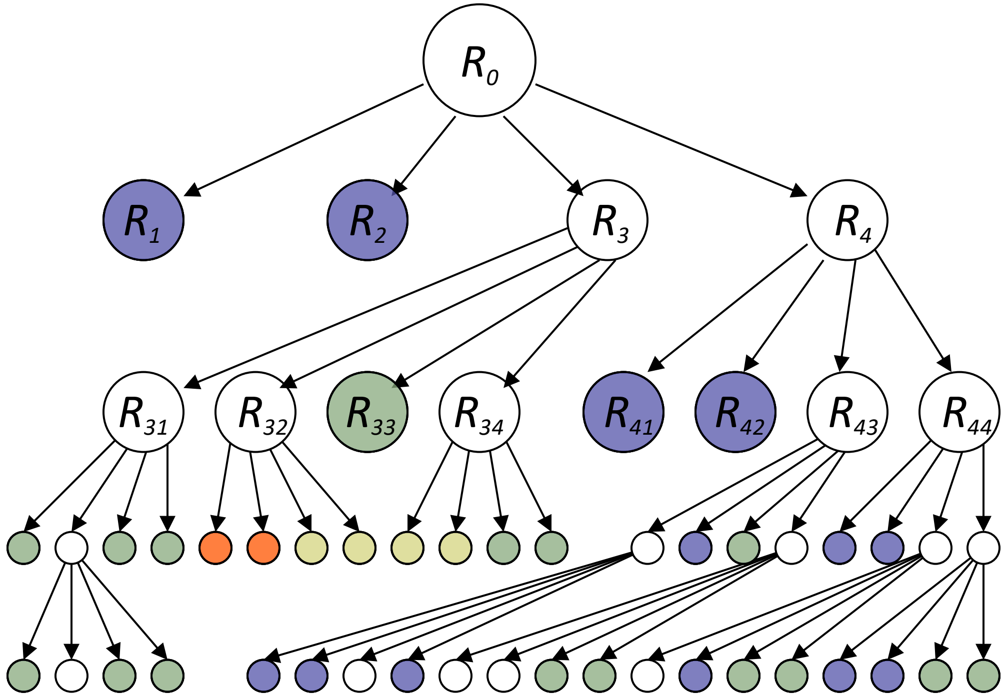
<u>Homogenity function *H*</u>

$H(Region\ A) = 1$ (homogeneous)

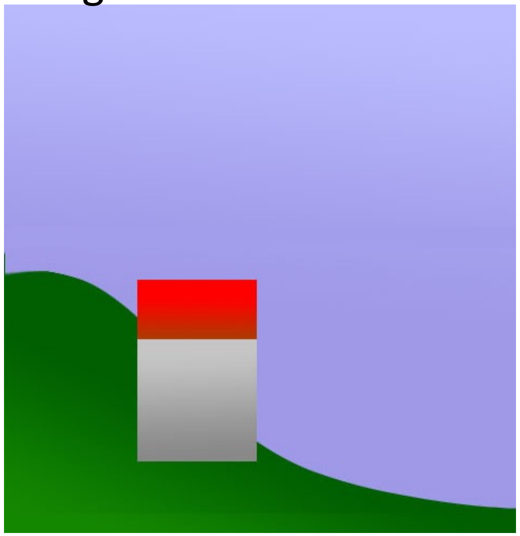
$H(Region\ B) = 0$ (inhomogeneous)

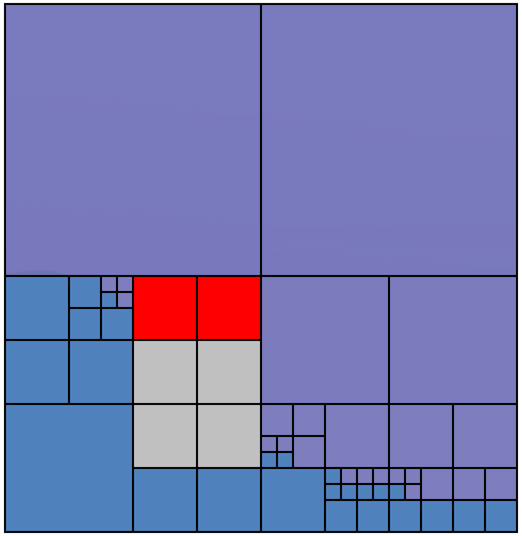
Split & Merge Segmentation – Divide & Conquer

1. Start with R_0 that represents the entire image
2. If $H(R_i) = 0$ (inhomogeneous) then {split area into 4 blocks (quadtree splitting) and process each area with step (2.)}
3. Merge all subregions that pairwise satisfy $H(R_i \cup R_j) = 1$ (homogenous)



Image





Segmentation Result

Split & Merge – Summary

Conceptual Summary:

- Iteratively decompose an image into regions of a maximally sized selected shape (e.g. rectangle) that do not satisfy a homogeneity condition. (split step)
- Then merge regions that together satisfy a homogeneity condition. (merge step)

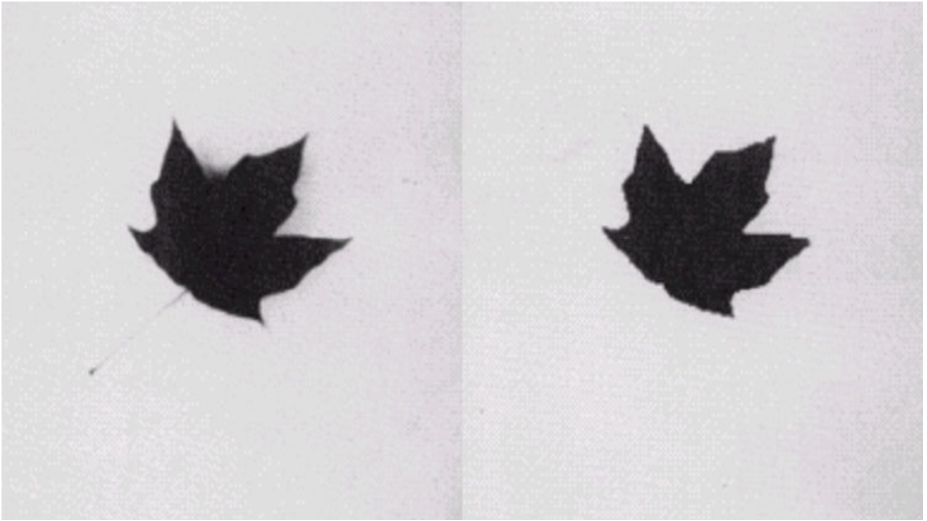
Some Comments:

- Using quadtrees, the results of split and merge tend to be *blocky*.
- Can have an adaptive homogeneity condition that, for instance, changes depending on the region size.

Example *H*

- $H(R_i)=1$ if at least 80% of the pixels in R_i have the property $|z_j - m_i| < 2\sigma_i$ where z_j is the grey level of the j^{th} pixel in R_i , m_i is the mean grey level of the region and σ_i is the standard deviation of the grey levels in R_i

- If $H(R_i)=1$ then set all the pixels in R_i to value m_i

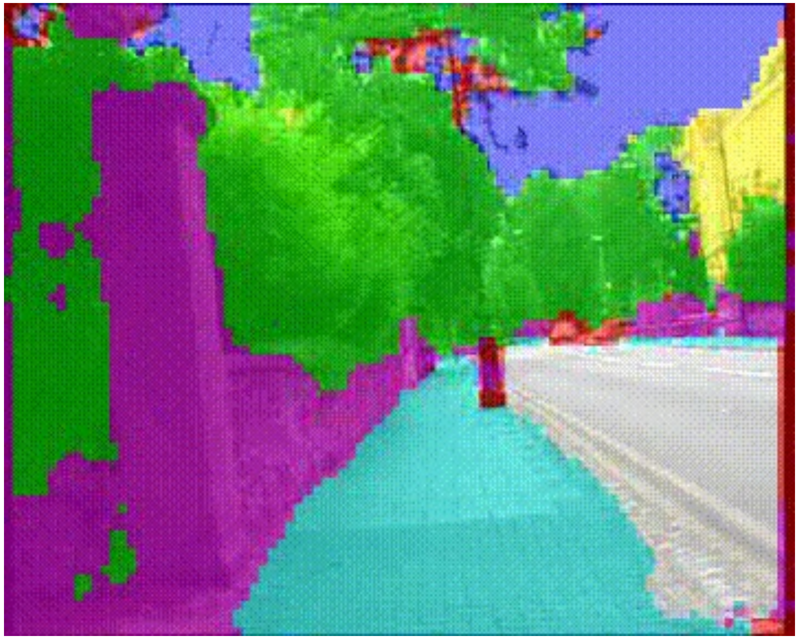


Original Result

Split & Merge – Bristol Video Scene Segmentation

Original Video

Segmentation Result

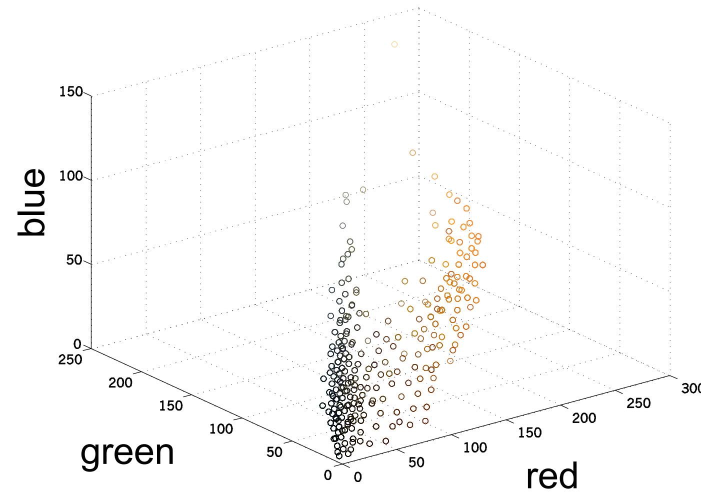


- Images are segmented using a Split-And-Merge technique. (Note the blocky nature of the regions!)
- Regions are then labelled by a Neural Network to associate the segments with semantics (colouration).
- This project dates back to around 20 years ago!

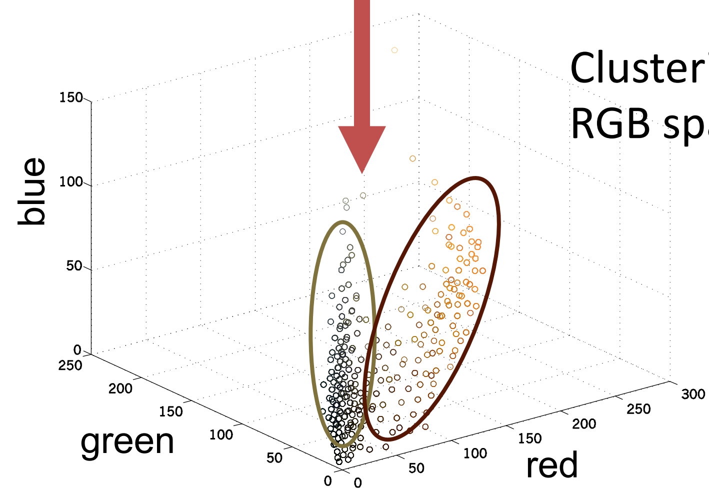
Clustering for image segmentation

map to 3D

RGB space

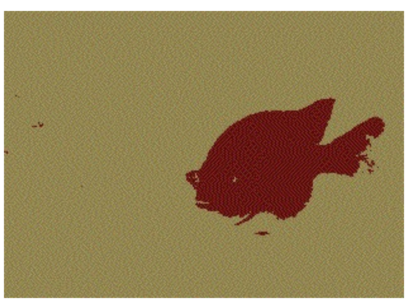


Clustering in RGB space



map back to

pixel space



K-means clustering – theoretical view

- It minimises the following objective function:

$$\Theta(clusters, data) = \sum_{j \in clusters} \left[\sum_{i \in j^{th} cluster} \left\| \mathbf{x}_i - \boldsymbol{\mu}_j \right\|^2 \right]$$

K-means clustering

function KMeans(*Features*, *K*)

randomly initialise K vectors $\mu_1 \ldots \mu_K$;

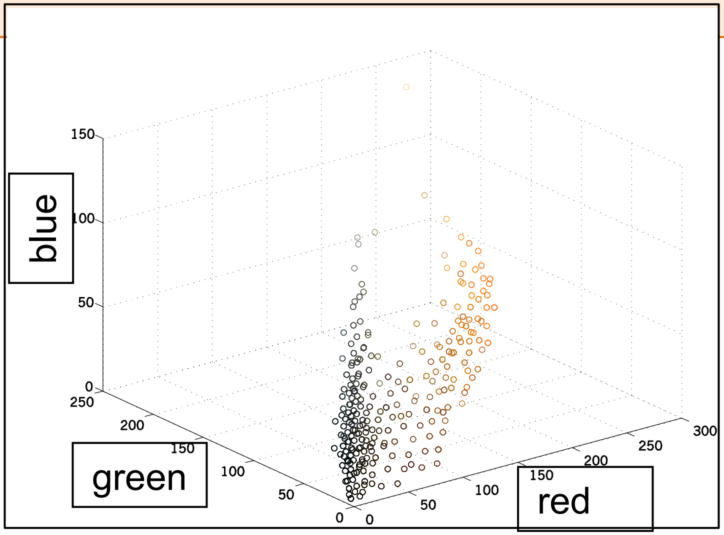
repeat

assign each $x \in$ *Features* to the nearest μ_j

recompute each μ_j as the mean of the features assigned to it

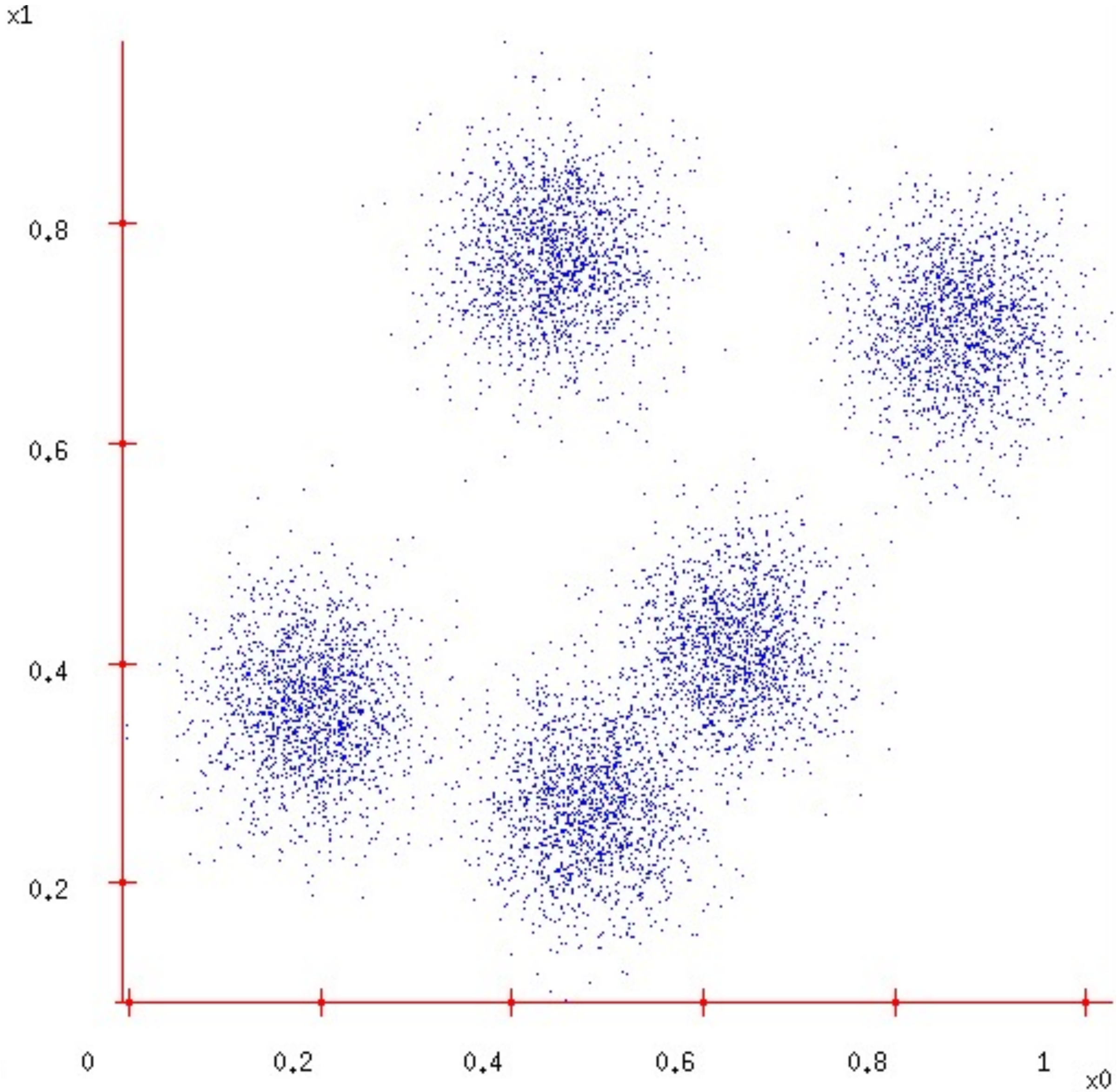
until no change in $\mu_1 \ldots \mu_K$

return $\mu_1 \ldots \mu_K$



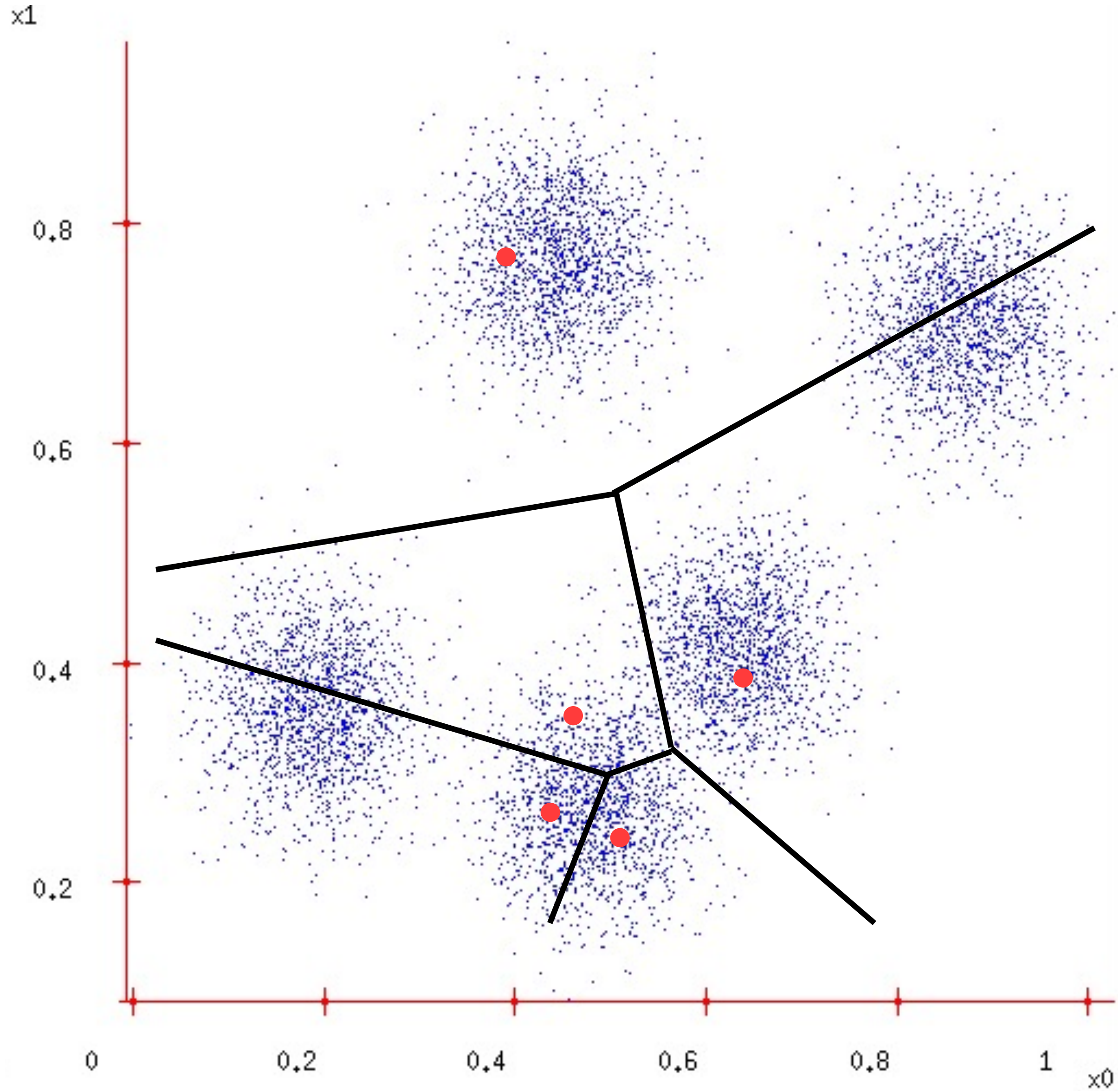
K-means clustering

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



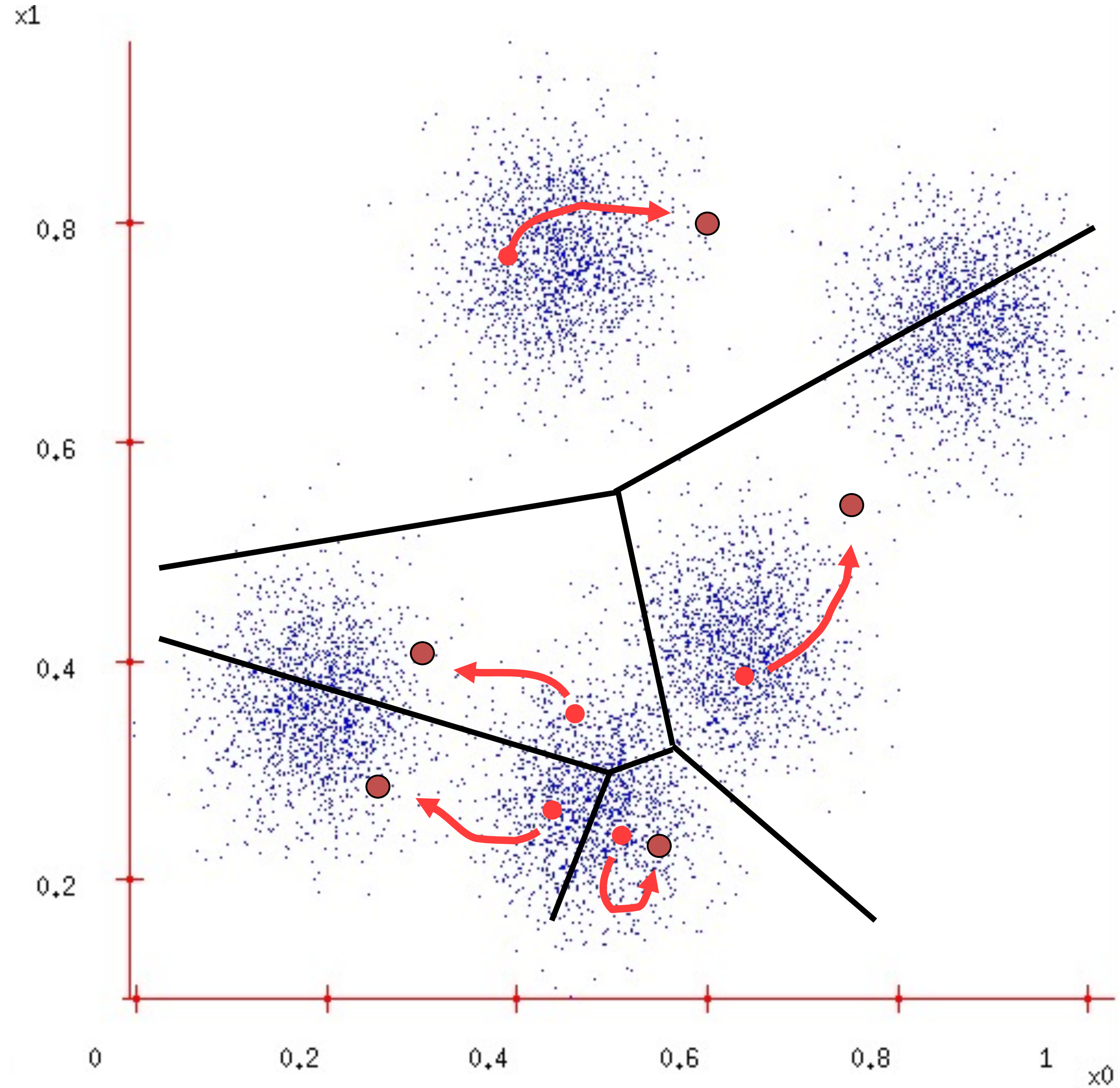
K-means clustering

1. Ask user how many clusters they'd like (e.g., *K*=5)
2. Randomly guess *K* cluster centre locations ($\boldsymbol{\mu}_1 \; \ldots \; \boldsymbol{\mu}_K$)
3. Each datapoint finds out which centre it's closest to (thus each centre "owns" a set of datapoints)



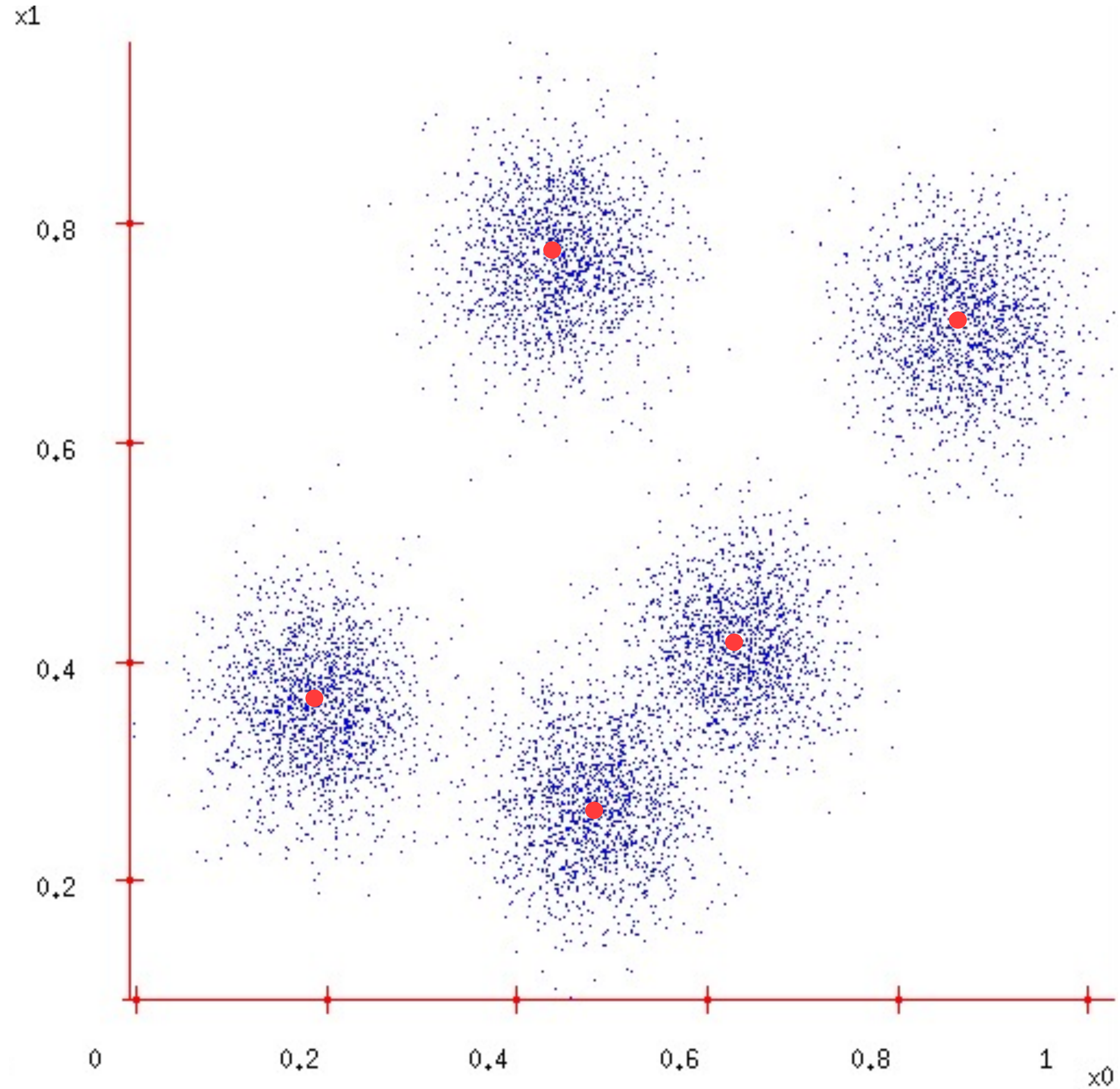
K-means clustering

1. Ask user how many clusters they'd like (e.g., K=5)
2. Randomly guess K cluster centre locations ($\mathbf{\mu}_1 \ \ldots \ \mathbf{\mu}_K$)
3. Each datapoint finds out which centre it's closest to
4. Each centre finds the centroid of the points it owns…
5. …and jumps there



K-means clustering

1. Ask user how many clusters they'd like (e.g., K=5)
2. Randomly guess K cluster centre locations ($\boldsymbol{\mu}_1$ … $\boldsymbol{\mu}_K$)
3. Each datapoint finds out which centre it's closest to
4. Each centre finds the centroid of the points it owns…
5. …and jumps there
6. Repeat from 3 until terminated!



Reflection on the K-means Algorithm

- **What does it do?**
  - *K*-means attempts to find a configuration $\mu_1 \dots \mu_K$ that minimises within-cluster scatter: total squared distance between point x_i and centroid μ_j in j^{th} cluster:

$$\sum_i \left\| \mathbf{x}_i - \boldsymbol{\mu}_j \right\|^2$$

  - This is equivalent to maximising the between-cluster scatter (total squared distance between each cluster centroid and the global centroid of all points)

- **Does it work?**

1. The algorithm terminates.
2. It finds a local optimum from which no further improvement is possible by making local changes.
3. It does not necessarily find a global optimum.

Next week

POSTPONED TO WEEK 5!

DETAILS TO FOLLOW...

Toby Perrett will continue the video lectures on the Basics of Object Detection, including:

- – Haar features
- – Integral Images
- – Viola Jones method for face detection