Master in Computer Vision Barcelona

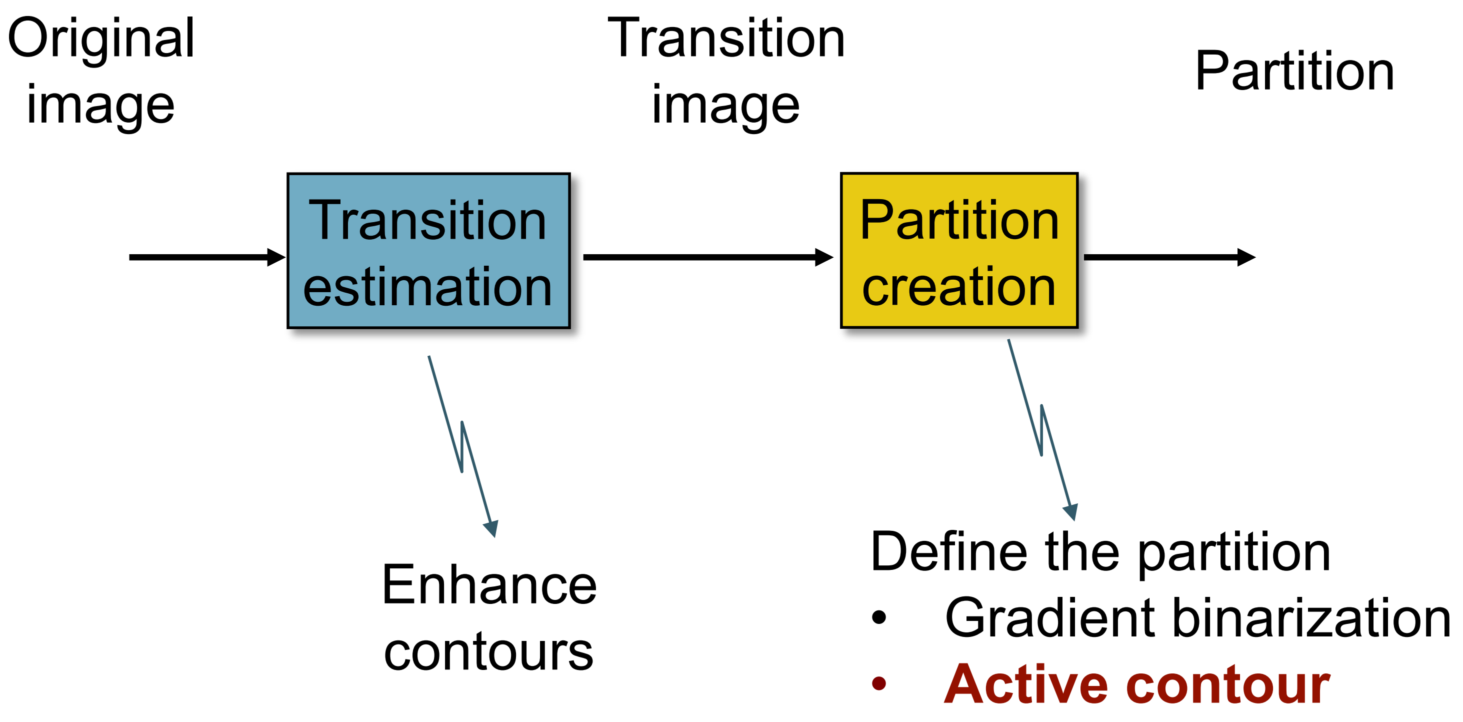
Module: Introduction to human and computer vision

Lecture 10: Grouping, segmentation and classification (II)

Lecturer: Ramon Morros

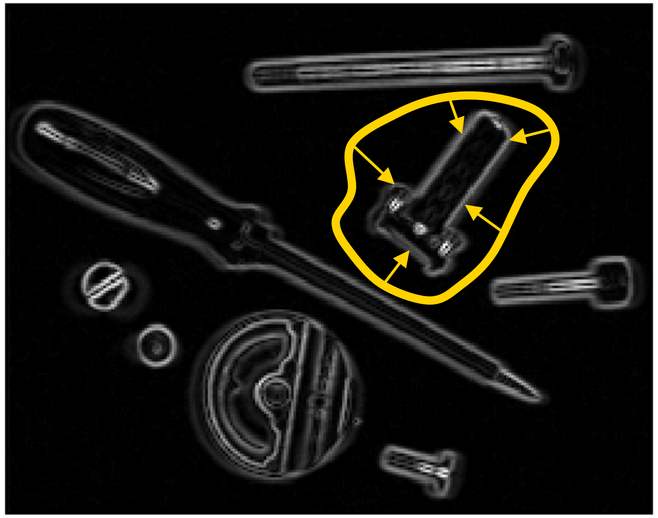
SEGMENTATION

Segmentation: Transition based



Transition based – Active contours

- Robust strategy: Active contours (Snakes)
  - **Evolution of a closed curve towards the points of high**



  - How to define the curve evolution?
  - How to implement it?
  - How to define the initial curve?

Transition based – Active contours

- Basic idea: Minimize the "length" of the curve
  - If s is the arc-length parametrization of the curve C:

$$\text{Length} = \oint ds$$

$$\text{Geodesic length} = \oint g(\nabla x)\, ds, \text{where g is function of } \nabla x$$

  - Assume g is low when the gradient is high and g∈[0,1], ex:

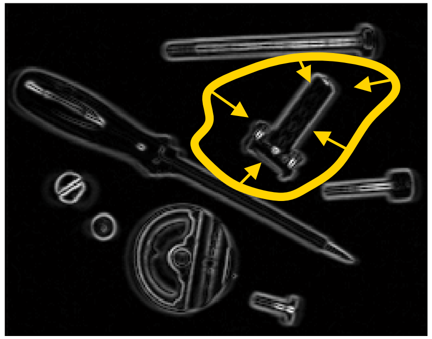
$$g(\nabla x) = \frac{1}{1+\|\nabla x\|^{p}}$$

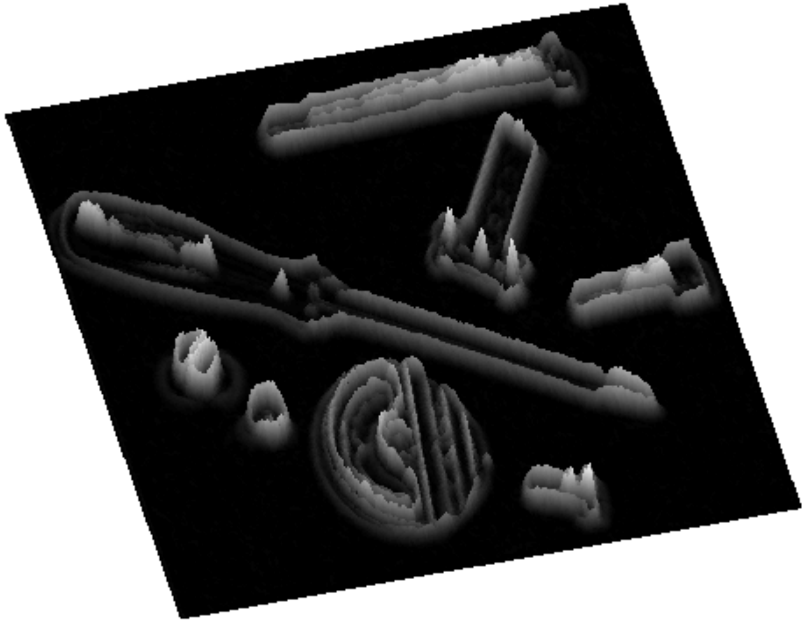
Transition based – Active contours

Find the curve $C(s)$ such that

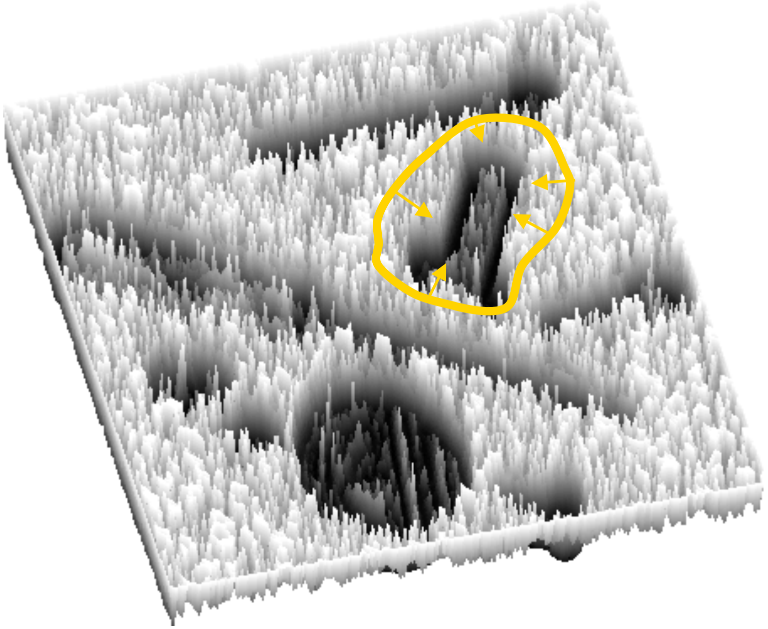
$\oint g(\nabla x)\,ds$ is minimum

Gradient: ∇x





3D view of ∇x



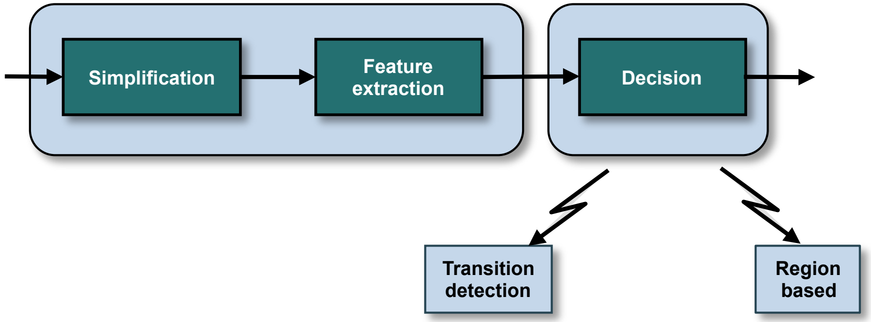
3D view of $g(\nabla x)$

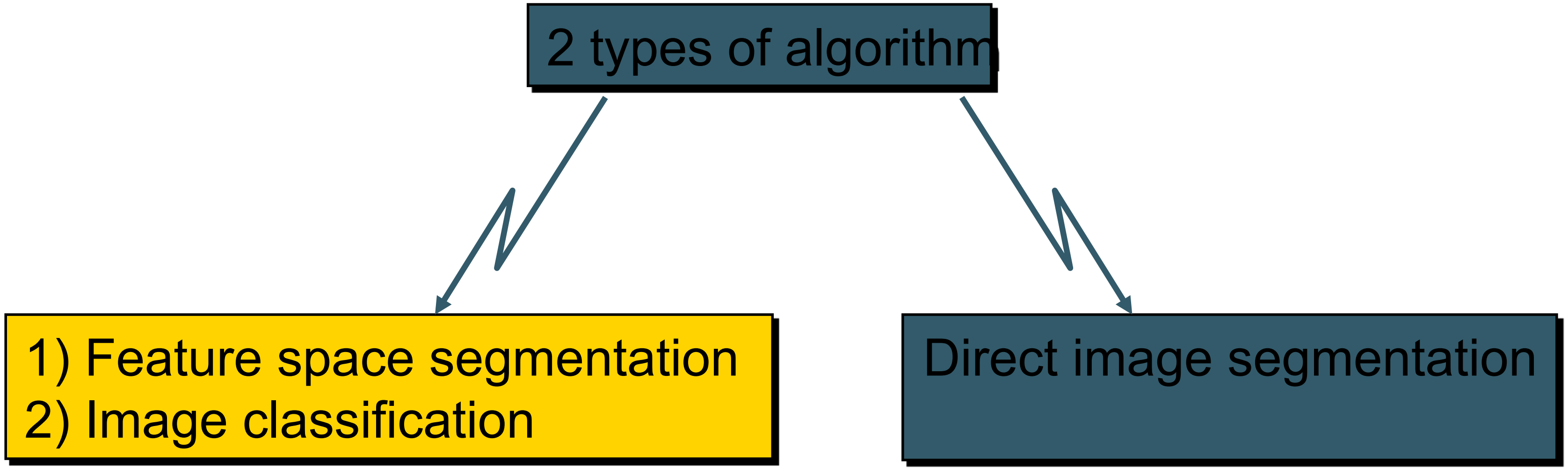
Segmentation: Transition based

- 3 main steps for segmentation:
  - Simplification, feature extraction and decision
  - Decision can be based on discontinuity (transition-based) or homogeneity (region-based)

- Transition-based segmentation:
  - Estimate transitions: gradient (may be linear or not)
  - Decision:
    - **Thresholding**: difficult because of threshold definition, noise and open contour
    - **Active contours**:
      - Curve evolution to minimize the length "weighted" by the gradient
      - Gradient descent leads to a combination of internal (smoothing) forces and external force (attraction to data)

Segmentation: Homogeneity based





Homogeneity based – Feature space segmentation

Approach:

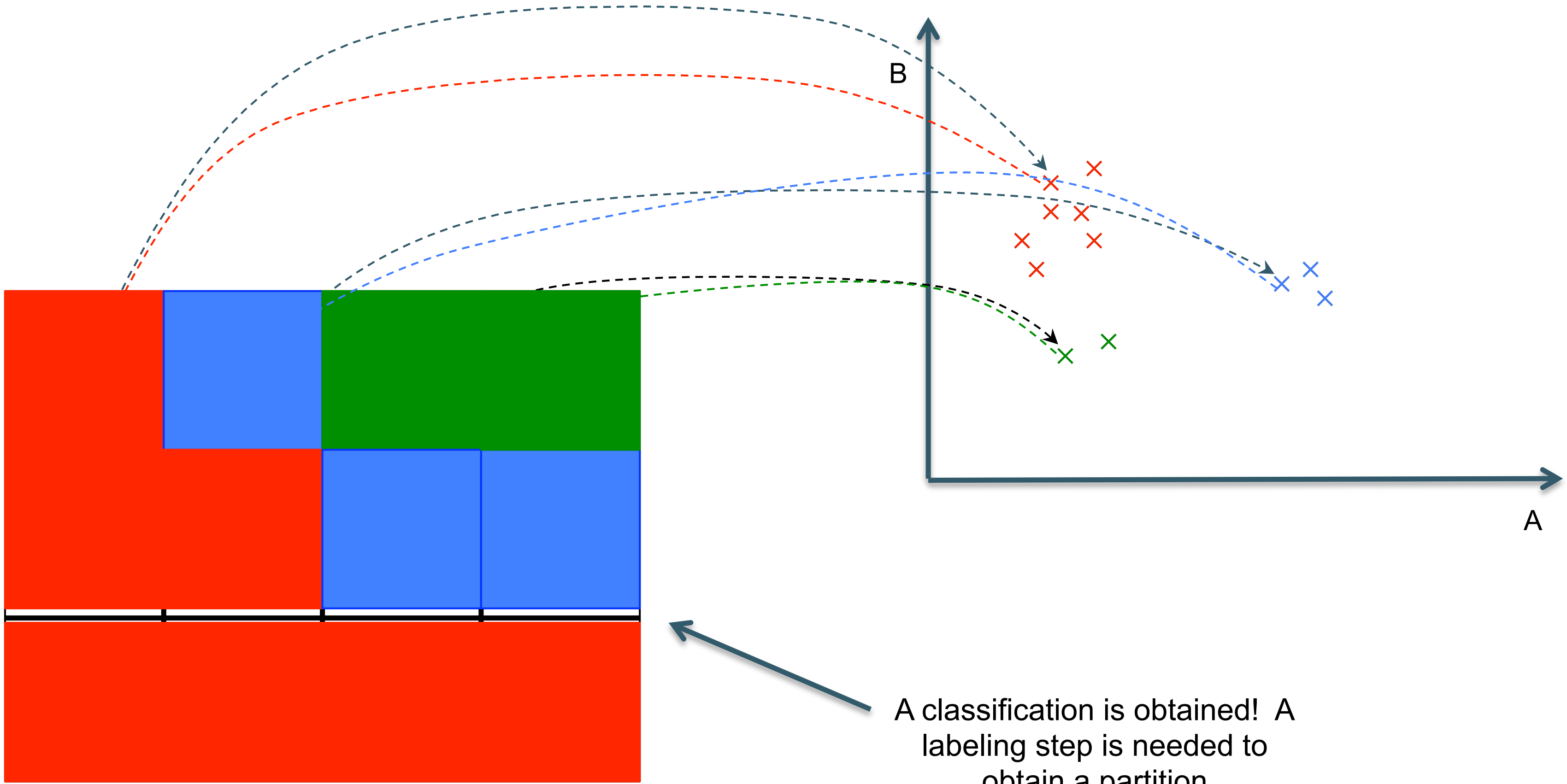
- Study the feature space
- Defines classes in the feature space
  (feature space segmentation)
- Region definition
  (image pixel classification)

Examples:

- Mono-dimensional feature space (gray level)
  - 2 classes
  - N classes
- Multidimensional feature space

Homogeneity based – Feature space segmentation

Example: bi-dimensional feature space

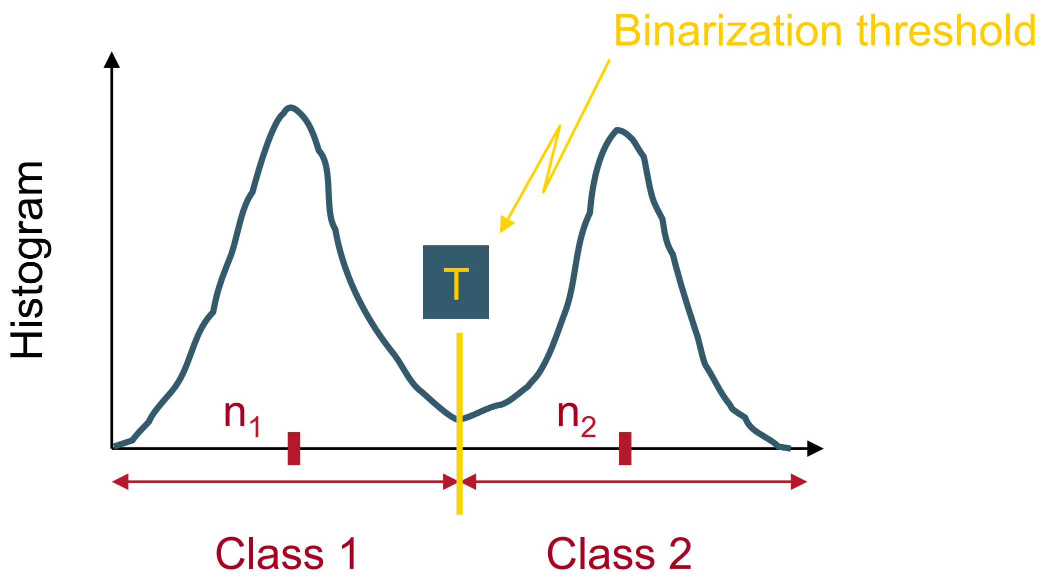


A classification is obtained! A labeling step is needed to obtain a partition

Homogeneity based – Feature space segmentation

Mono-dimensional feature space, 2 classes

- Study of the histogram (of gray level or a given feature)



- Image classification algorithm: Binarization

Homogeneity based – Feature space segmentation

Mono-dimensional feature space, 2 classes: threshold

- If the class centers n_1 y n_2 are known (e.g.: histogram maxima)

  - Criterion: Intra class minimum variance

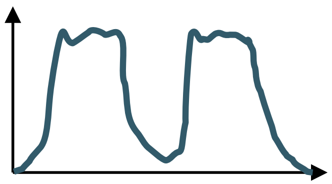
$$C = \underset{T}{Min}\Big[\sum_{0 \le n \le T} (n-n_1)^2 h(n) + \sum_{T < n \le M} (n-n_2)^2 h(n)\Big]$$

- If class centers are NOT known

➛ Iterative estimation

$\hat{n}_1, \hat{n}_2 \rightarrow$

Fixed n_1, n_2 ⇓ Optimum T	→ ←	Fixed T ⇓ Optimum n_1, n_2



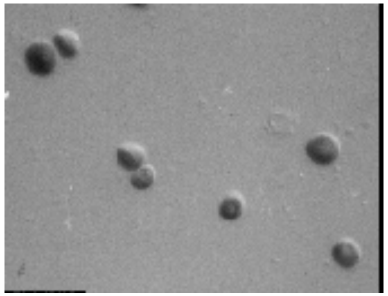
➛ Local minimum

$$n_1 = \sum_{0 \le n \le T} nh(n) / \sum_{0 \le n \le T} h(n)$$
$$n_2 = \sum_{T < n \le M} nh(n) / \sum_{T < n \le M} h(n)$$

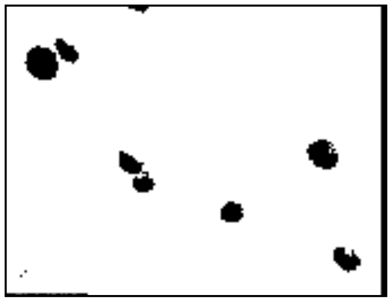
Mean of each class

Homogeneity based – Feature space segmentation

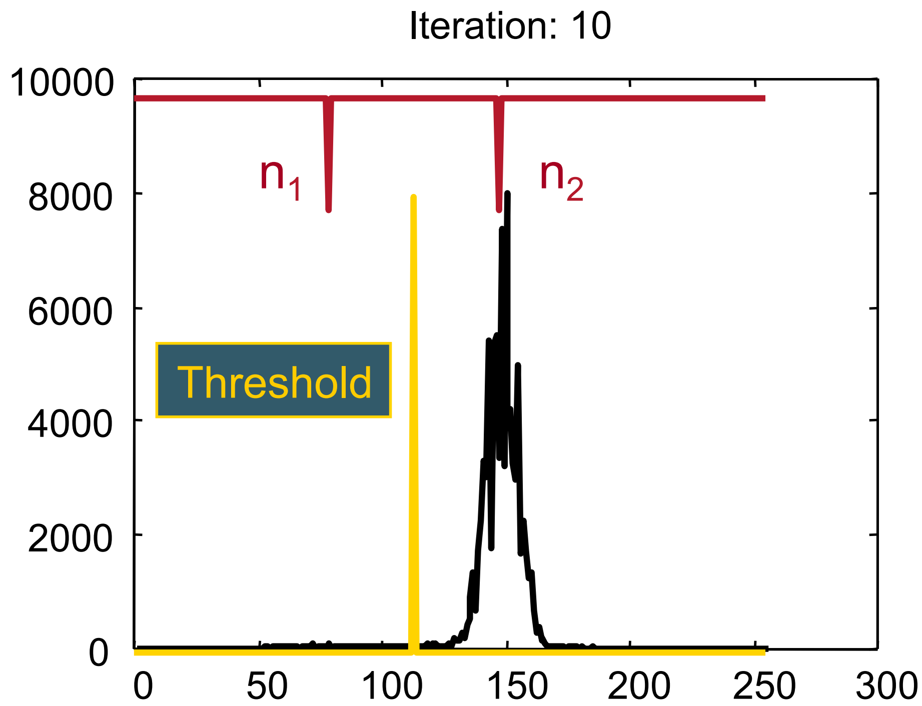
Mono-dimensional feature space, 2 classes: threshold



Original



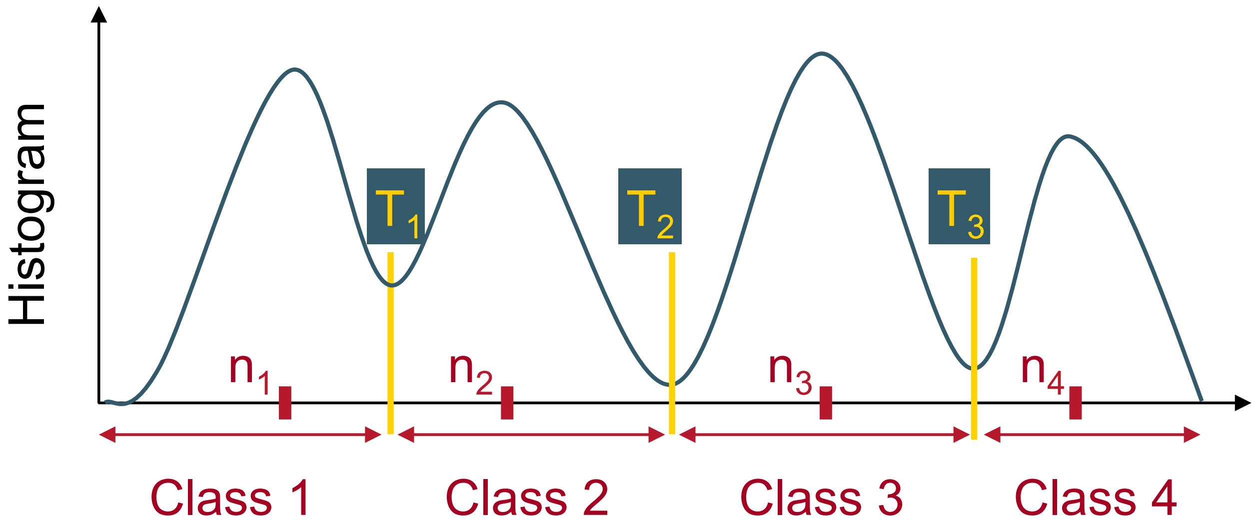
Binarized image



Homogeneity based – Feature space segmentation – K-Means

Mono-dimensional feature space, K classes

- ➢ Histogram analysis



- ➢ Classification algorithm: “K-means”

Homogeneity based – Feature space segmentation – K-Means

K-Means algorithm

$\hat{n}_1, \cdots, \hat{n}_K \rightarrow$

Fixed $n_1,\ldots,n_k$ $\Downarrow$ Optimum $T_1,\ldots, T_{k-1}$	$\rightleftarrows$	Fixed $T_1,\ldots, T_{k-1}$ $\Downarrow$ Optimum $n_1,\ldots,n_k$

- All T combinations (may be complex!)
- Euclidean distance

$$\left\| \begin{array}{l} T_1 = (n_1 + n_2)/2 \\ \cdots \\ T_{k-1} = (n_{k-2} + n_{k-1})/2 \end{array} \right.$$

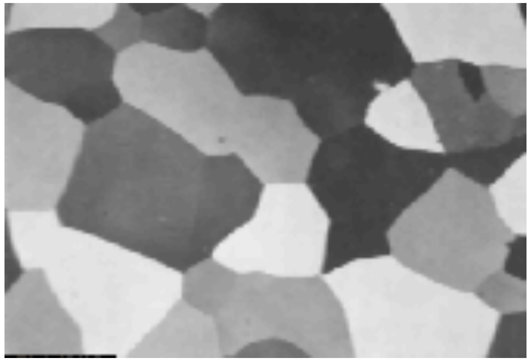
Individual class mean

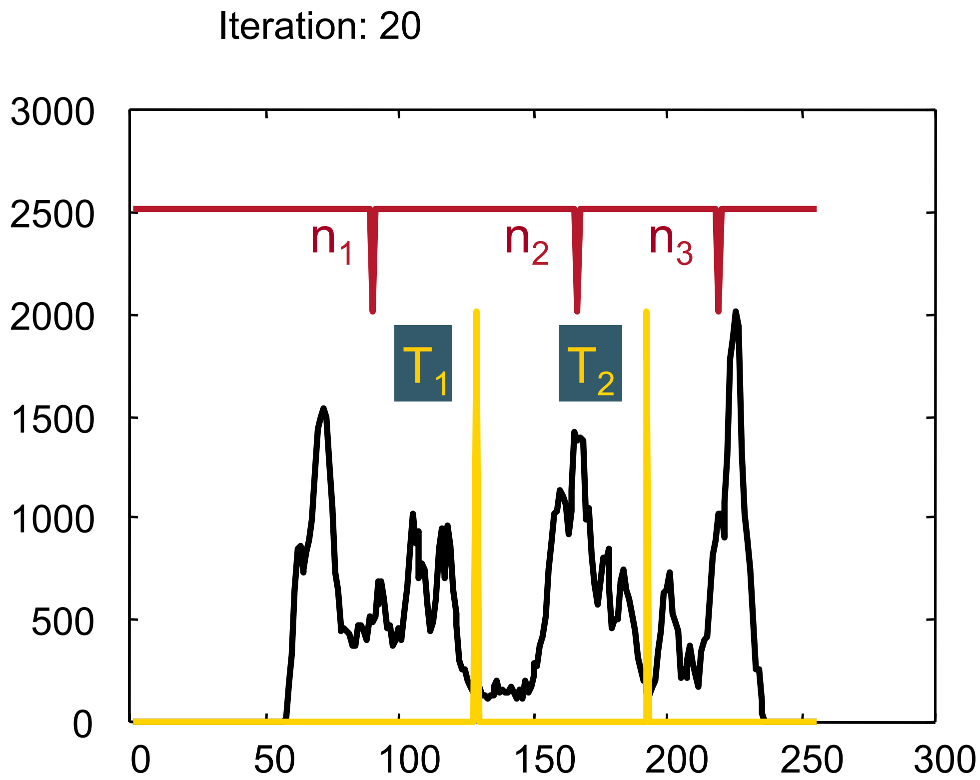
$$\left\| \begin{array}{l} n_1 = \sum_{0 \le n \le T_1} nh(n) / \sum_{0 \le n \le T_1} h(n) \\ \cdots \\ n_K = \sum_{T_{k-1} < n \le M} nh(n) / \sum_{T_{k-1} < n \le M} h(n) \end{array} \right.$$

➛ Local minimum

Homogeneity based – Feature space segmentation – K-Means

K-Means example : 3 classes

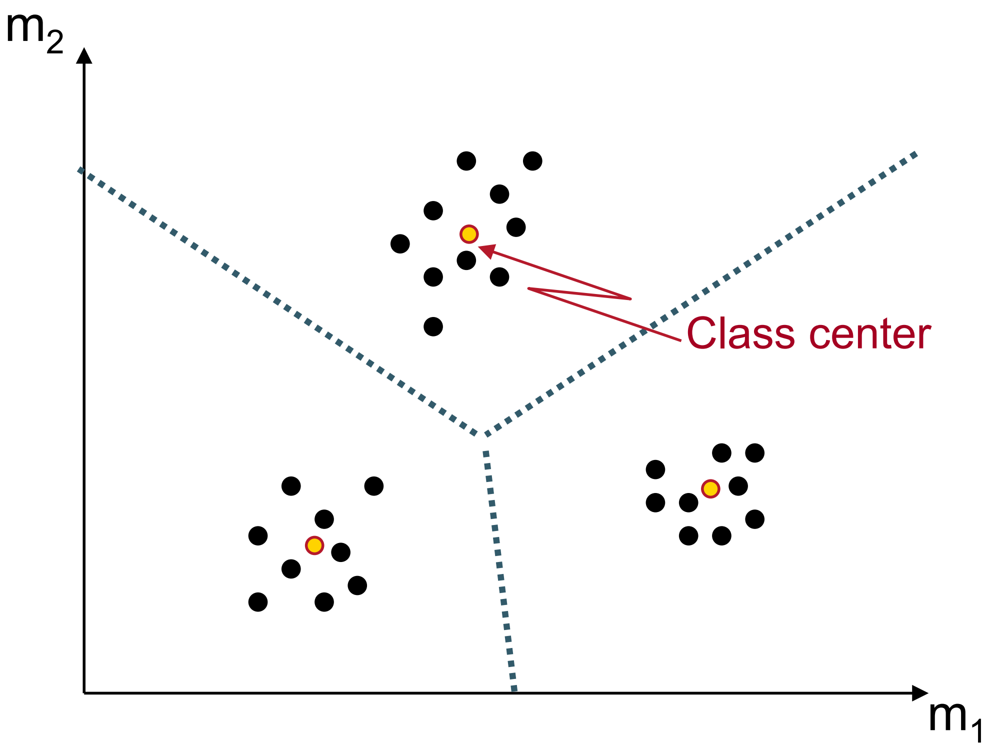




Homogeneity based – Feature space segmentation – K-Means

Multi-dimensional feature space, K classes

Dimension of the feature space:	2
Number of classes:	3



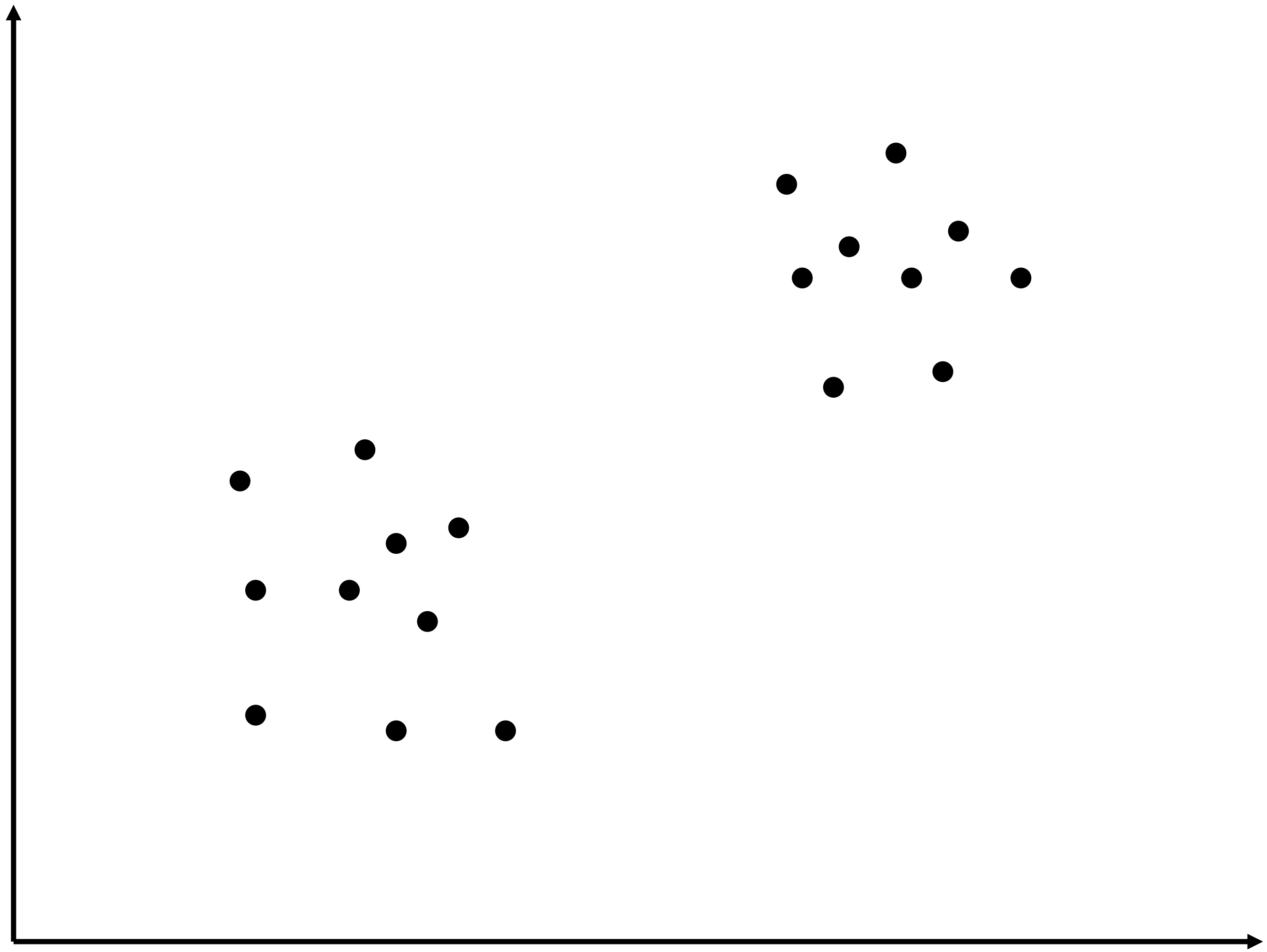
1. Initialize K classes. Compute the centers of each class
2. For each point:
   a. Compute the distances between the point and the class centers
   b. Assign the point to the closest class
3. Update the class centers
4. Repeat 2 & 3 until no change (in assignments or center values) is observed.

Max Lloyd algorithm

Complexity: O(n·k·d·i)
d: dimension, n: number of points, i: iterations

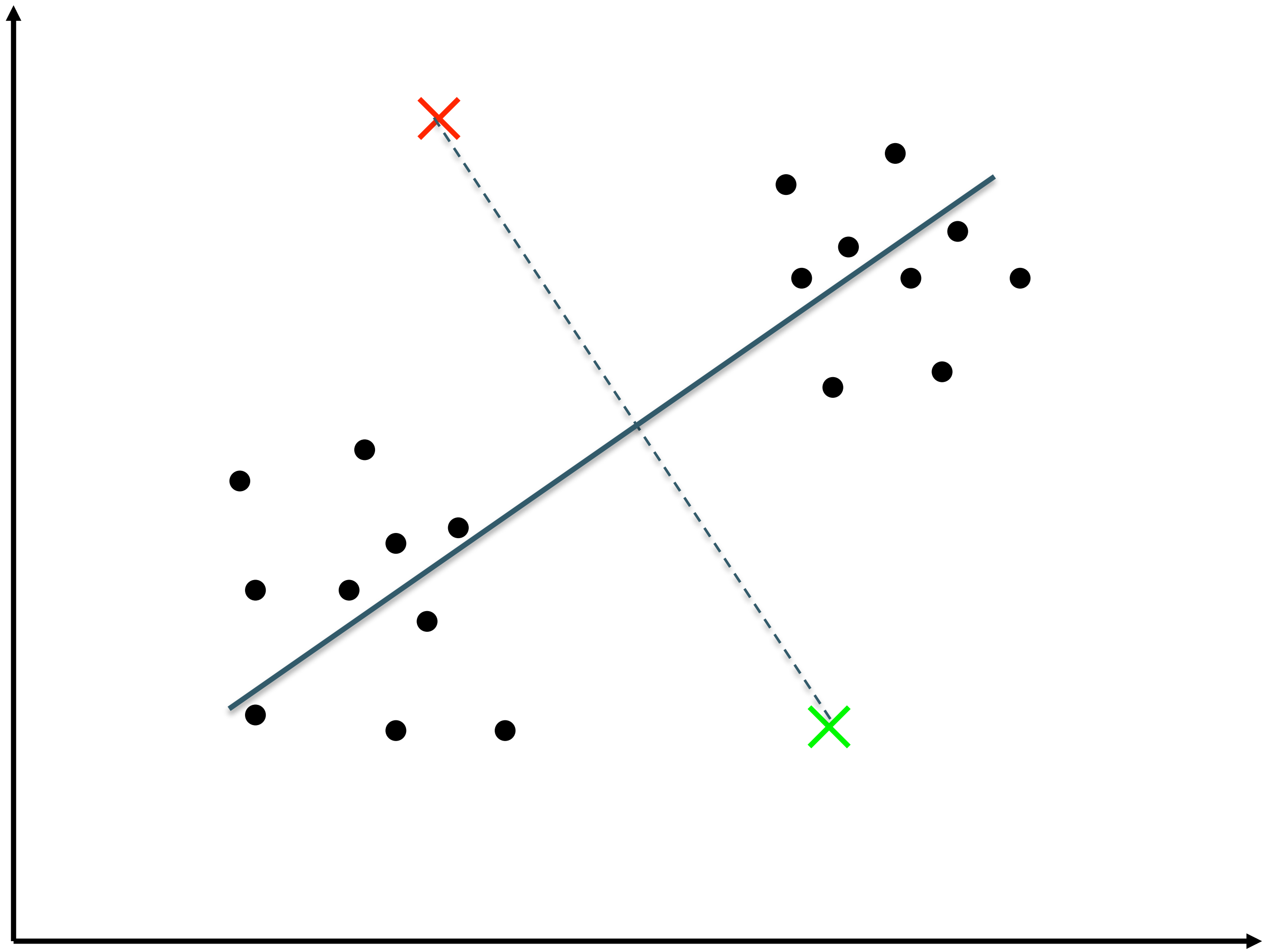
Homogeneity based – Feature space segmentation – K-Means

Example:



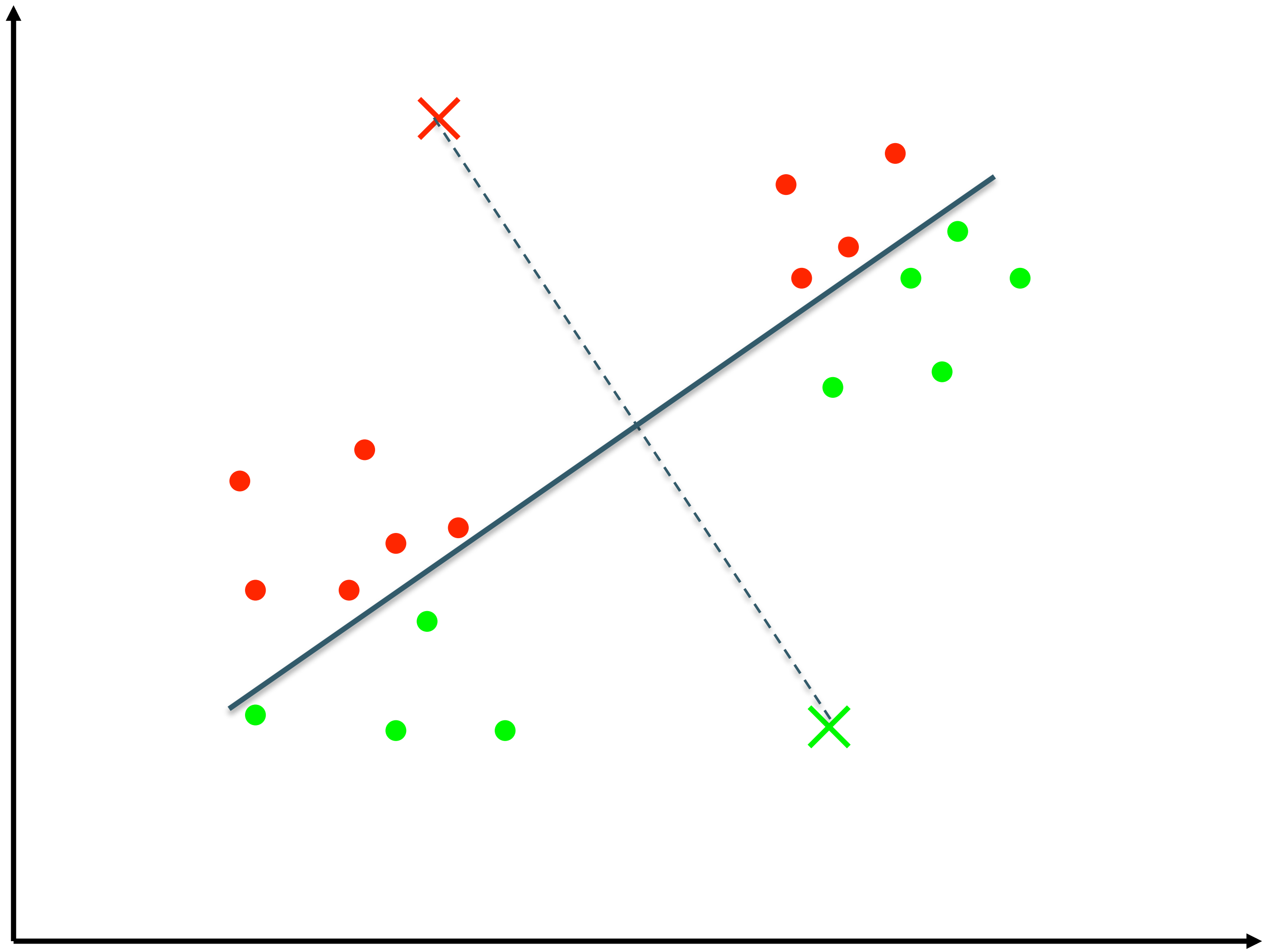
Homogeneity based – Feature space segmentation – K-Means

Example:



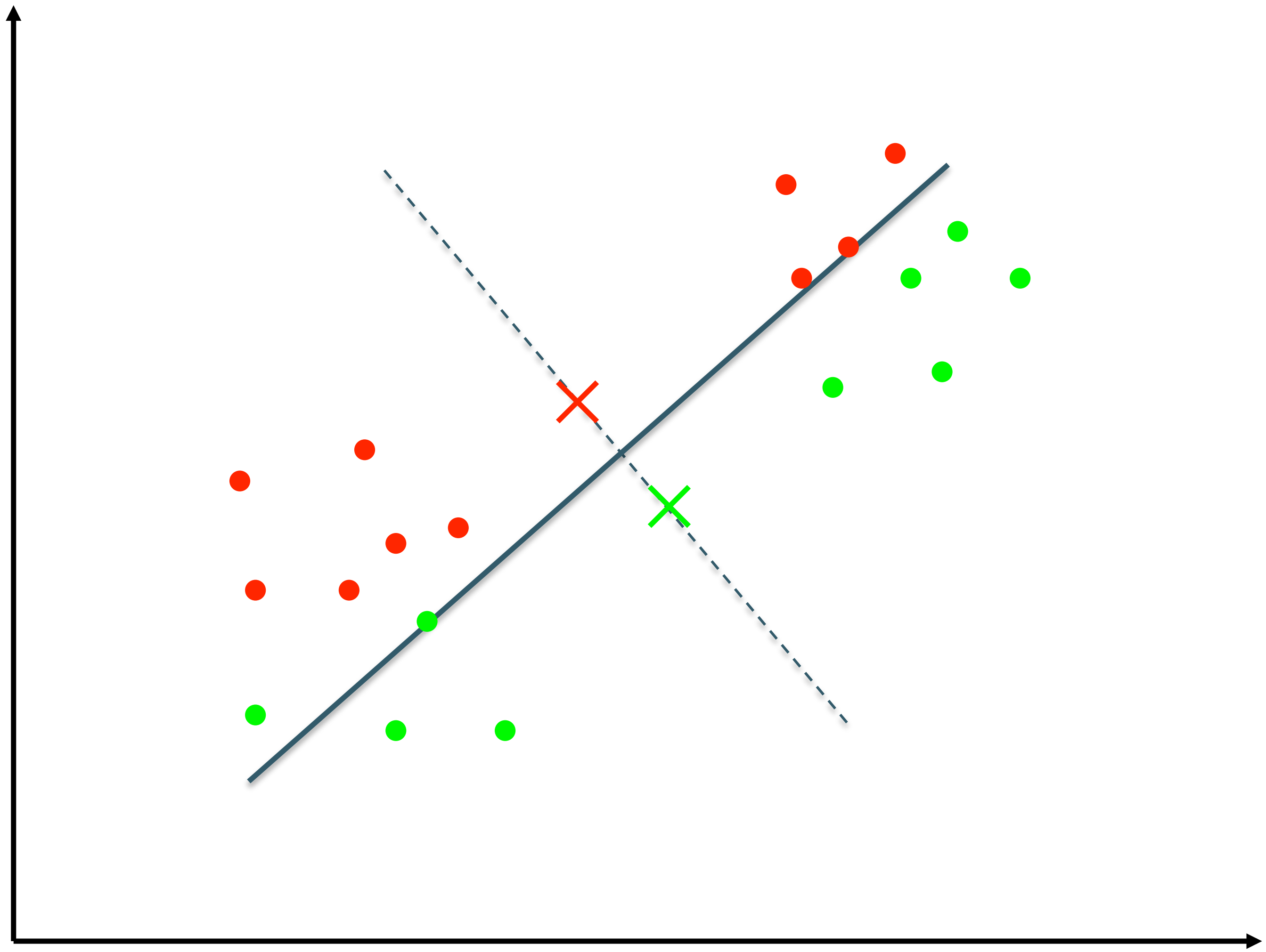
Homogeneity based – Feature space segmentation – K-Means

Example:



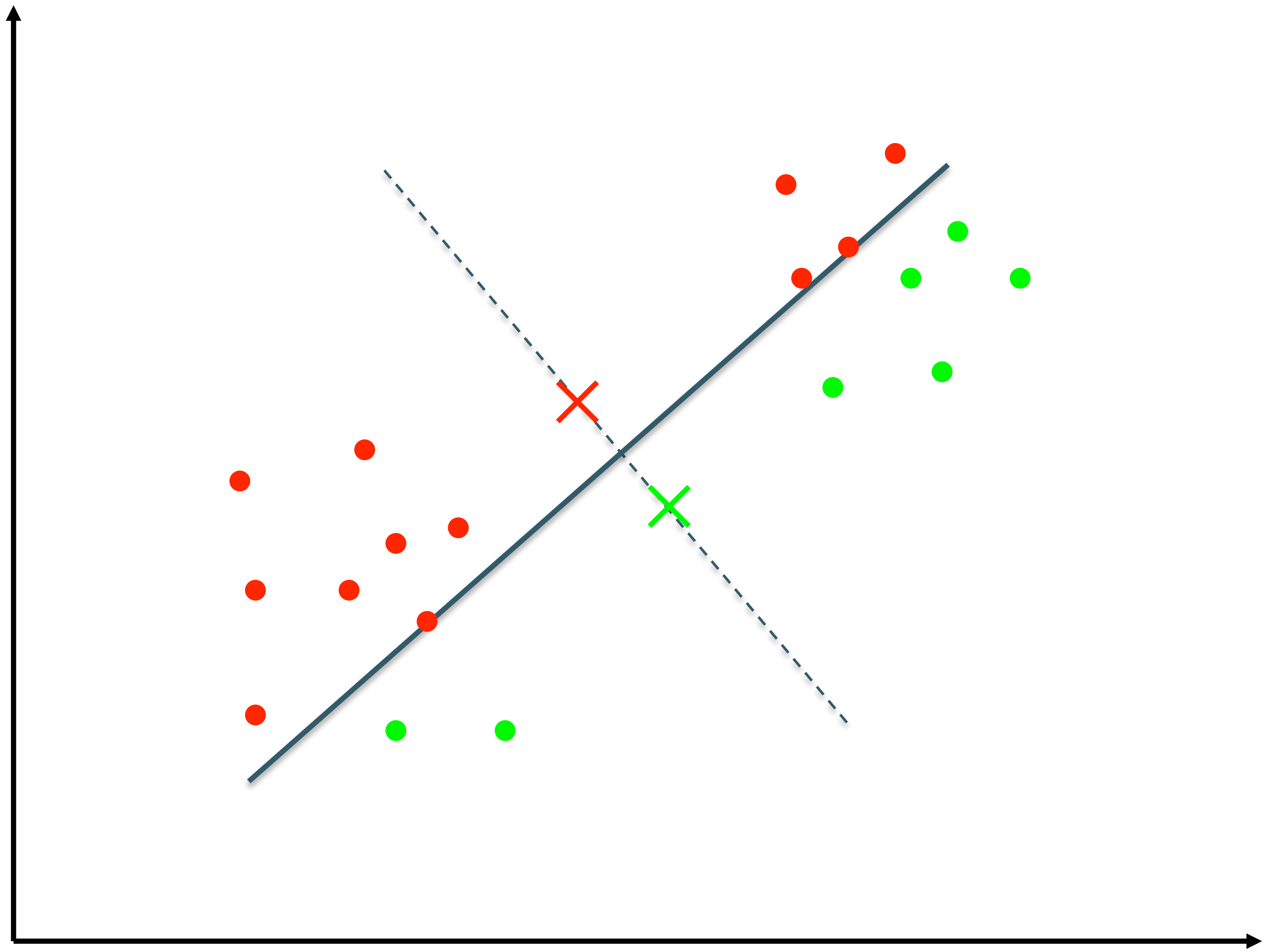
Homogeneity based – Feature space segmentation – K-Means

Example:



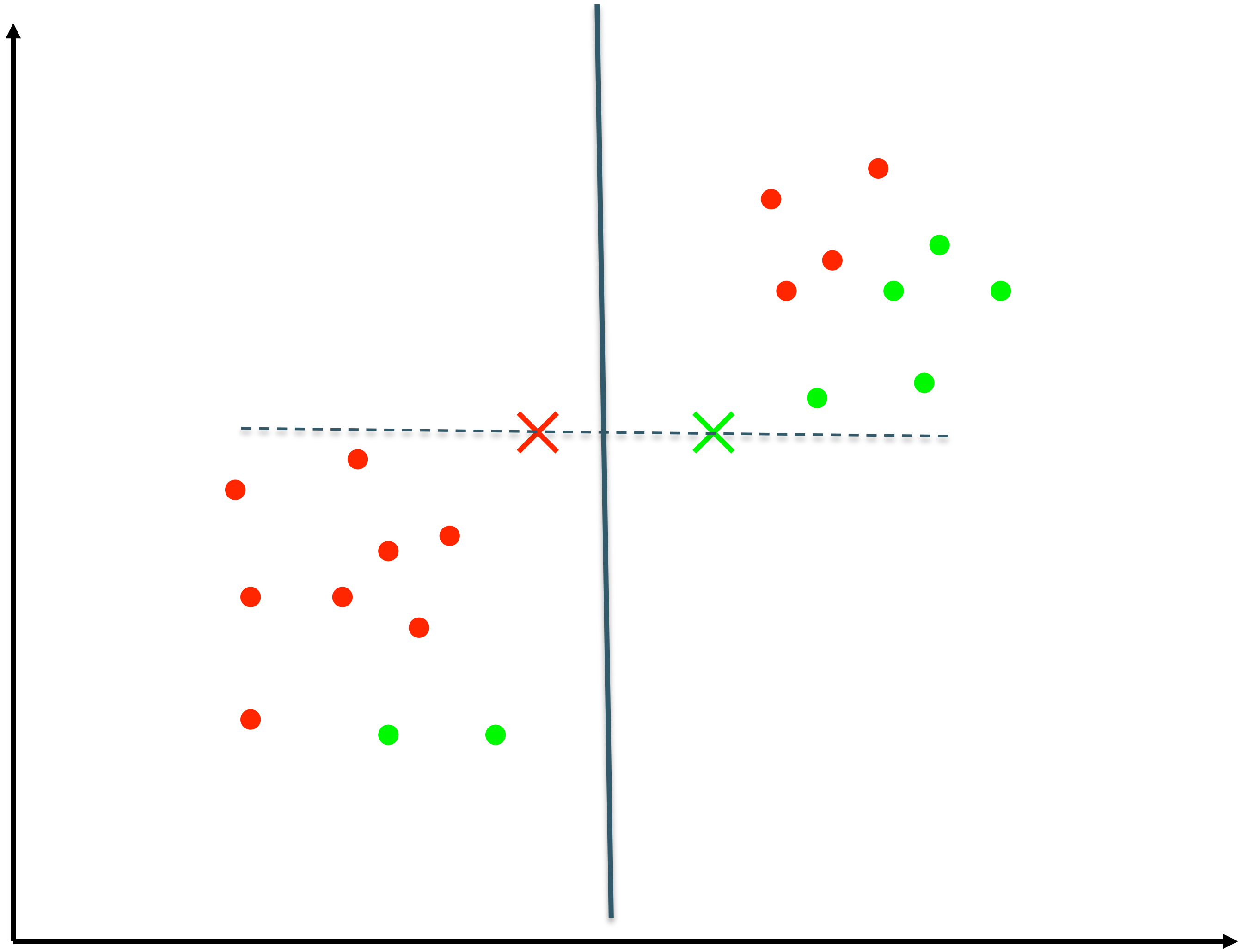
Homogeneity based – Feature space segmentation – K-Means

Example:



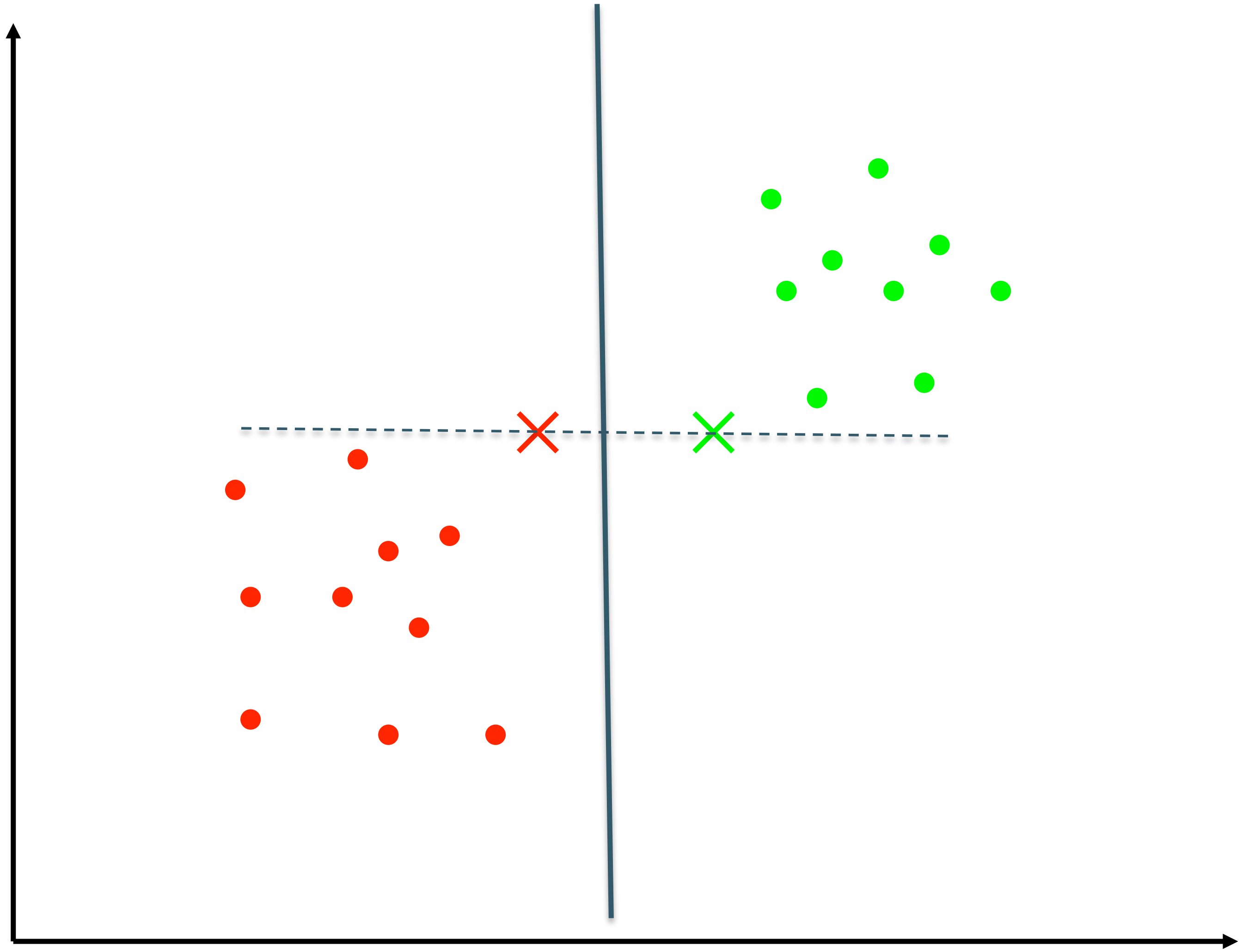
Homogeneity based – Feature space segmentation – K-Means

Example:



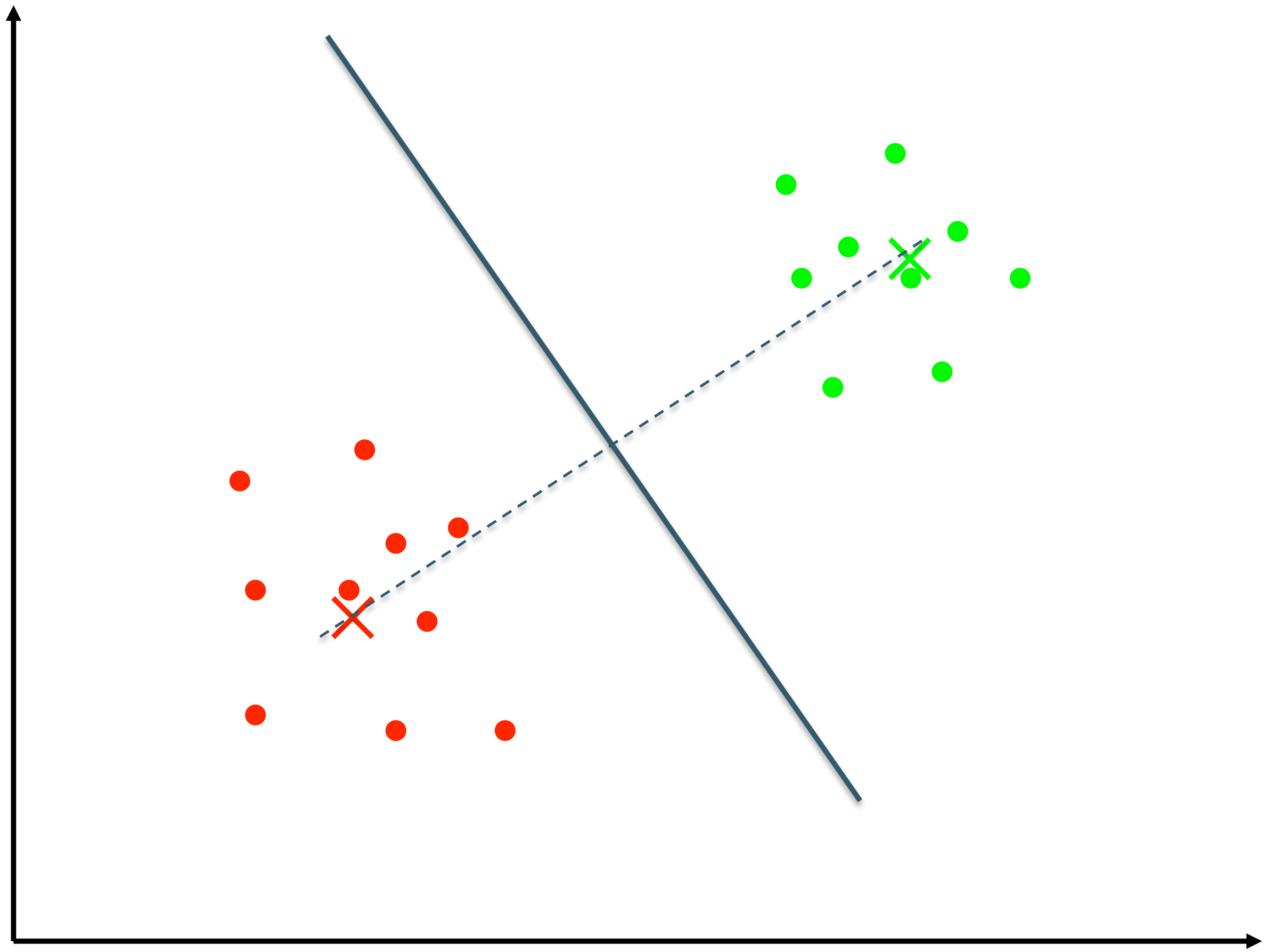
Homogeneity based – Feature space segmentation – K-Means

Example:



Homogeneity based – Feature space segmentation – K-Means

Example:



Homogeneity based – Feature space segmentation – K-Means

- Convergence is guaranteed … but may be to a local minimum → application optimized strategies can be added
- The straightforward implementation of such method may be too slow → there are proposed optimizations, especially for the classification step.
- Other distances are also possible (K-Medoids).
- Hard assignment of data points to clusters: small shift of a data point can flip it to a different cluster → can be solved by a soft assignment based on a probabilistic approach.

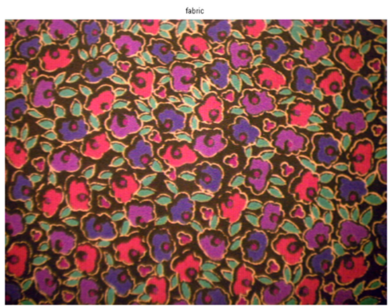
Gaussian Mixture Models

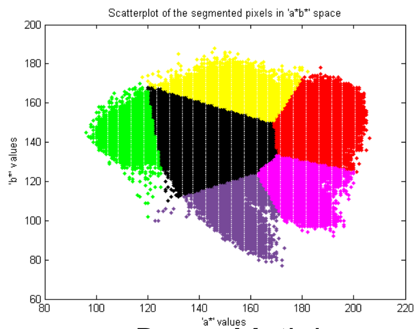
Slide credit: Dr. Antonio M. López (UAB)

Homogeneity based – Feature space segmentation – K-Means

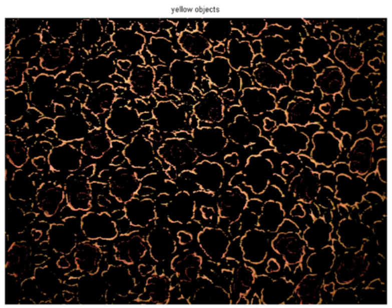
Example: Color segmentation

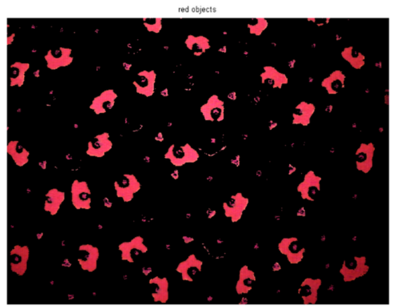
Goal: Segment the regions corresponding to the N dominant color of the image
Color space: CIE Lab

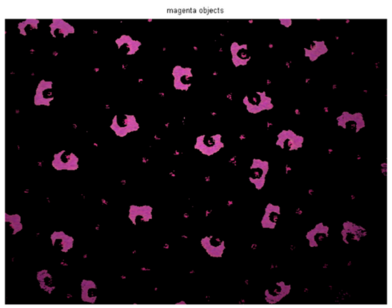


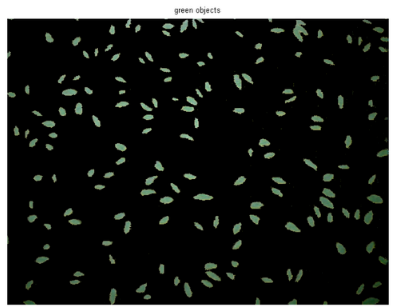


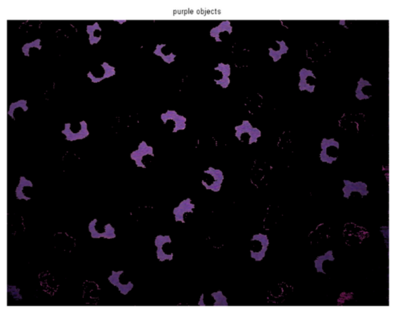
Demo Matlab (ipexfabric)







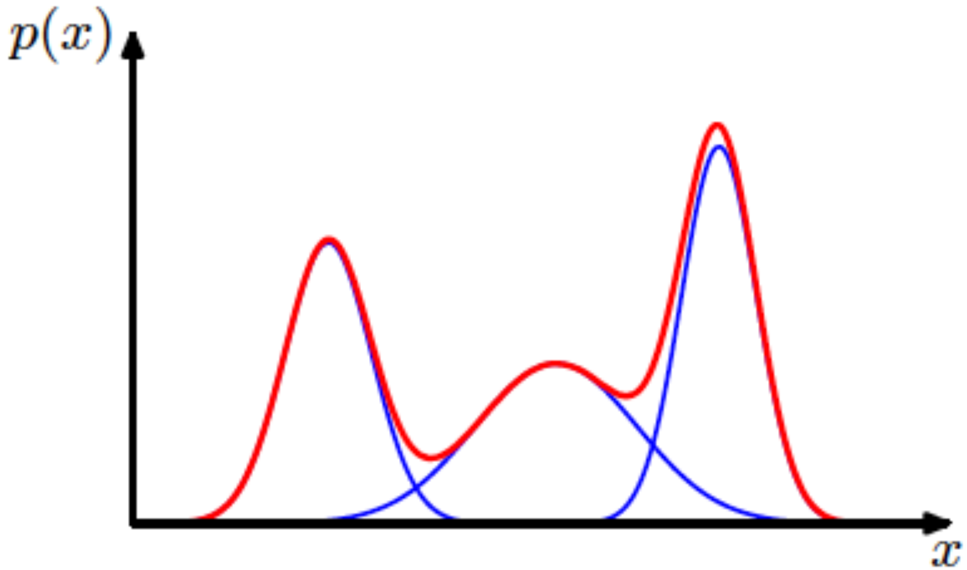




Homogeneity based – FS segmentation : Mixture Models

- In k-means, pixels are clustered using hard assignments
  - Each pixel goes to closest cluster center
  - A probabilistic approach, where each pixel helps estimating more than one cluster, may be more robust

→Probabilistic Mixture Model



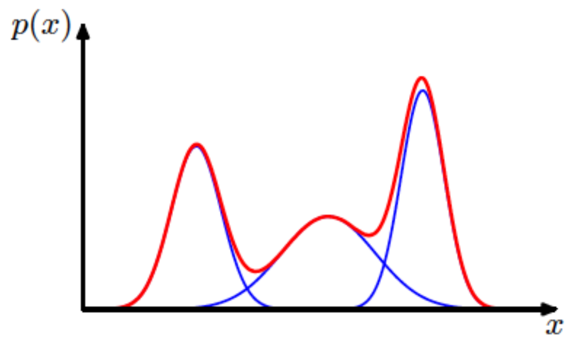
Homogeneity based – FS segmentation : Mixture Models

- Distributions can be approximated as a linear combination of basic densities

$$p(x) = \sum_{k=1}^{K} \pi_k p(x \mid k) = \sum_{k=1}^{K} P(k) p(x \mid k)$$

Mixing parameters

Densities



Where:

- **Mixing parameters**: can be seen as prior probabilities or normalized positive weights.
- **Densities** $p(x \mid k)$ are class-conditional densities, with *k* the discrete random variable of the class

Slide credit: Dr. Antonio M. López

Homogeneity based – FS segmentation : Mixture Models

- The $p(x \mid k)$ are, in fact, parametric densities: $p(x \mid \theta_k)$
- A widely used approach is to assume that all the $p(x \mid k)$ from the same family of densities
- In the limit, even smooth densities can be approximated
- Multivariate gaussians are a very popular choice

- Applications:
  - Probability density estimation
  - Clustering: every component is a cluster center

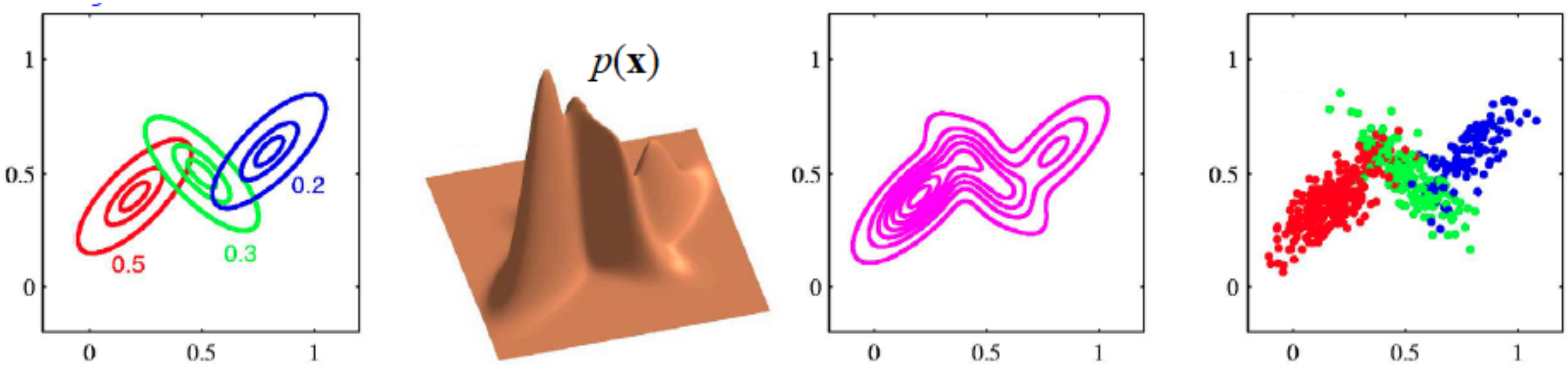
Homogeneity based – FS segmentation : GMM

Good choice for the components → Gaussians

$$\boxed{p(x \mid \theta) = \sum_{k=1}^{K} \pi_k p(x \mid \theta_k)} \qquad 0 \le \pi_k \le 1, \quad \sum_{k=1}^{K} \pi_k = 1$$

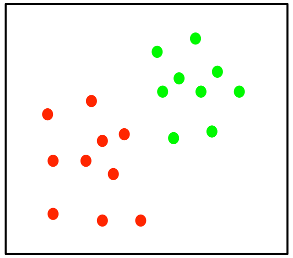
$$p(x \mid \theta_k) = N(x \mid \mu_k, \Sigma_k) \propto \exp\left(\frac{-(x-\mu_k)\Sigma_j^{-1}(x-\mu_k)}{2}\right)$$

Gaussians can be seen as oriented "blobs" in feature space



Homogeneity based – FS segmentation : GMM

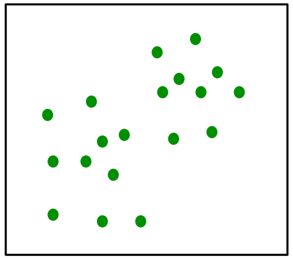
- Mixture parameter estimation:
  - Labeled data: we know which component generates each Gaussian → Easy!!



$$\pi_k = \frac{n_k}{N}, \quad \mu_k = \frac{1}{n_k}\sum_{i|l_i=k} x_i, \quad \Sigma_k = \frac{1}{n_k}\sum_{i|l_i=k}(x_i - \mu_k)(x_i - \mu_k)^T$$

Maximum Likelihood (ML) estimates

  - Unlabeled data: the assignments are not known
    - Guessed based on the current mixture distribution estimate
    - Soft assignments (posterior probabilities)



Homogeneity based – FS segmentation : GMM

- Maximum Likelihood Estimation

$$\theta^* = \underset{\theta}{\operatorname{argmax}}\{L(\theta \mid x)\} \quad where\ L(\theta \mid x) = P(x \mid \theta)$$

$$\theta^* = \underset{\theta}{\operatorname{argmax}}\{\log(L(\theta \mid x))\}$$ ← Analytically easier

Data set: $\{x_i\}$

$$p(x \mid \theta) = \prod_{i=1}^{N} p(x_i \mid \theta)$$

Incomplete data Log-Likelihood

$$\sum_i \log p(x_i \mid \theta) = \sum_i \log\left(\sum_k \pi_k \underbrace{p(x_i \mid \mu_k, \Sigma_k)}_{N(x \mid \mu_k, \Sigma_k)}\right)$$

- We do not know which component generates each gaussian → incomplete data or hidden variables

Homogeneity based – FS segmentation : GMM

- To maximize $\log(L(\theta \mid x))$, we can derive with respect to the parameters and equal to zero. We obtain:

$$\mu_k = \frac{1}{N_k} \sum_{i=1}^{N} \gamma_k(x_i) \cdot x_i$$

$$N_k = \sum_{i=1}^{N} \gamma_k(x_i) \cdot x$$

$$\Sigma_k = \frac{1}{N_k} \sum_{i=1}^{N} \gamma_k(x_i) \cdot (x_i - \mu_k) \cdot (x_i - \mu_k)^T$$

$$\pi_k = \frac{N_k}{N}$$

$$\gamma_k(x_i) = \frac{\pi_k N(x_i \mid \mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j N(x_i \mid \mu_j, \Sigma_j)}$$

Posterior probability of *k* given $\boldsymbol{x}_i$, or in other words, responsibility that the Gaussian *k* takes for explaining the observation $\boldsymbol{x}_i$.

Slide credit: Dr. Antonio M. López

Homogeneity based – FS segmentation : GMM

- $\gamma_k(x_i)$ represents the posterior prob. of *k* given x_i
  → responsibility that gaussian *k* takes for explaining observation x_i

$$p(x \mid k) \sim N(x \mid \mu_k, \Sigma_k)$$

$$p(k \mid x) = \frac{P(k)p(x \mid k)}{p(x)} = \frac{\pi_k N(x \mid \mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j N(x \mid \mu_j, \Sigma_j)} \Rightarrow \gamma_k(x_i) = p(k \mid x_i)$$

$$p(x) = \sum_{k=1}^{K} \pi_k p(x \mid \theta_k)$$

Slide credit: Dr. Antonio M. López

Homogeneity based – FS segmentation : GMM

Interpretation

$$\gamma_k(x_i) = \frac{\pi_k N(x_i \mid \mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j N(x_i \mid \mu_j, \Sigma_j)}$$

$$\mu_k = \frac{1}{N_k} \sum_{i=1}^{N} \gamma_k(x_i) \cdot x_i$$

Weighted mean of all the points in the data set

$$N_k = \sum_{i=1}^{N} \gamma_k(x_i)$$

Effective number of points assigned to cluster **k**

Covariance as weighted variances of the data wrt to each component estimated mean

$$\Sigma_k = \frac{1}{N_k} \sum_{i=1}^{N} \gamma_k(x_i) \cdot (x_i - \mu_k) \cdot (x_i - \mu_k)^T$$

$$\pi_k = \frac{N_k}{N}$$

Average responsibility that each component takes for explaining the data

Notice: if **K=1** then $\gamma_1(x_n) = 1$. This corresponds to the ML estimation of the parameters of a single Gaussian kernel.

Slide credit: Dr. Antonio M. López

Homogeneity based – FS segmentation : GMM

- If K>1, there is no closed form solution

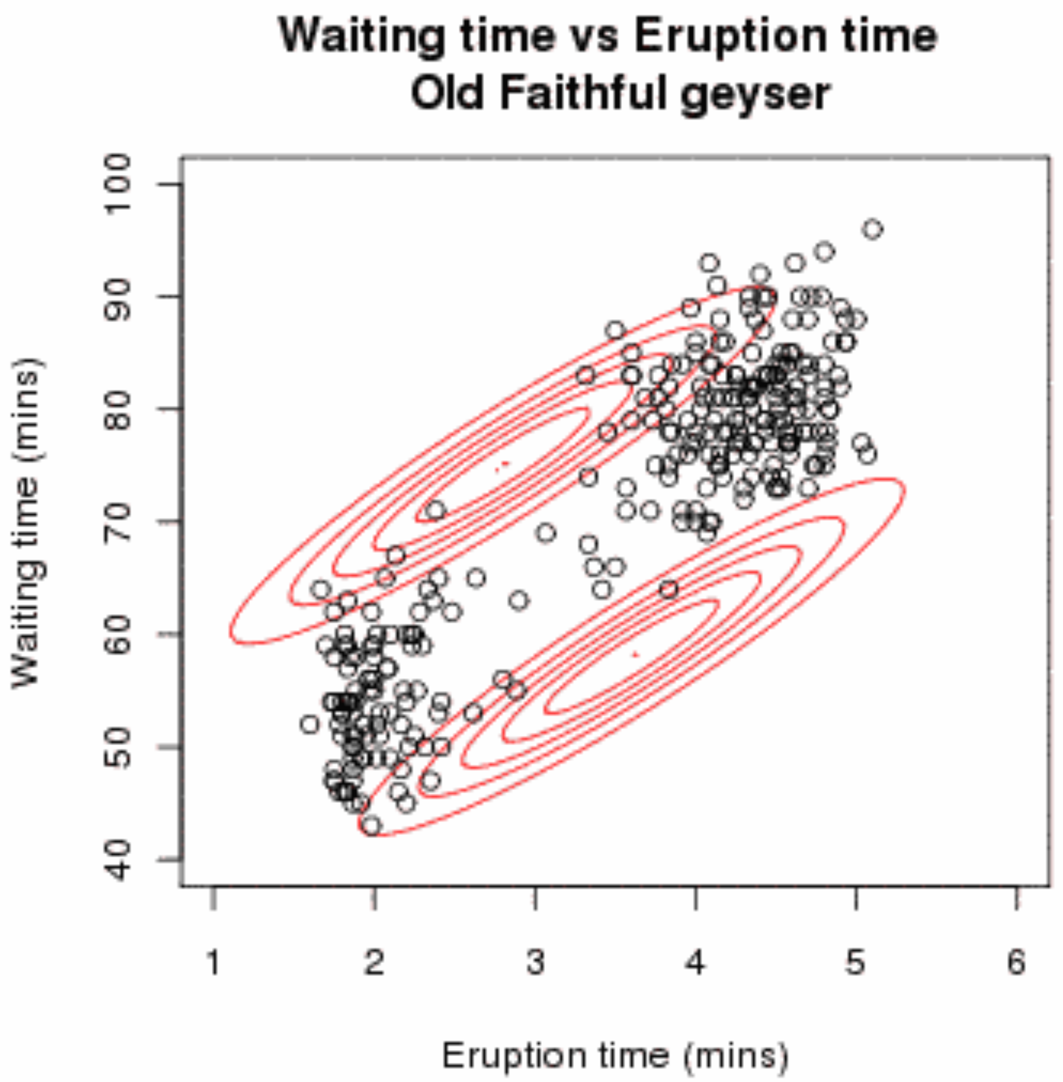
$$\{\pi_K, \mu_k, \Sigma_k\} \text{ depend on } \{\gamma_k\}$$
$$\{\gamma_k\} \text{ depend on } \{\pi_k, \mu_k, \Sigma_k\}$$

- Recursive procedure:
  1. Start: Given K, provide the initial parameters $\{\pi_k, \mu_k, \Sigma_k\}, \quad k = 1 \ldots K$
  2. Classify: given $\{\pi_k, \mu_k, \Sigma_k\}$ compute the $\{\gamma_k\}$
  3. Re-center: Given $\{\gamma_k\}$, compute the $\{\pi_k, \mu_k, \Sigma_k\}$
  4. Repeat 2-3 until convergence

→ This can be seen as Expectation Maximization (EM) framework!
Classification: **E**xpectation step
Re-centering: **M**aximization step (ML estimation)

Slide credit: Dr. Antonio M. López

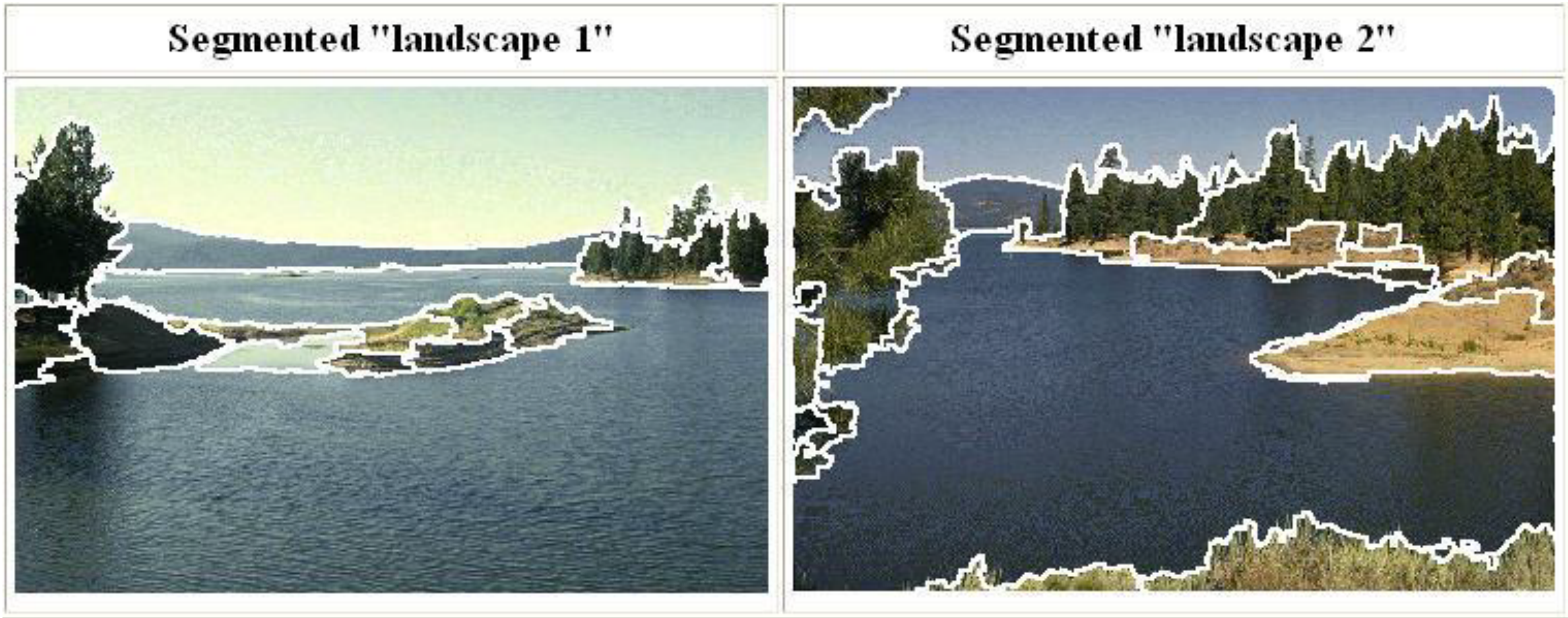
Homogeneity based – FS segmentation : GMM



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

Homogeneity based – FS segmentation : Mean shift

- Technique for clustering-based segmentation
- It seeks nodes (local maxima of density) in feature space

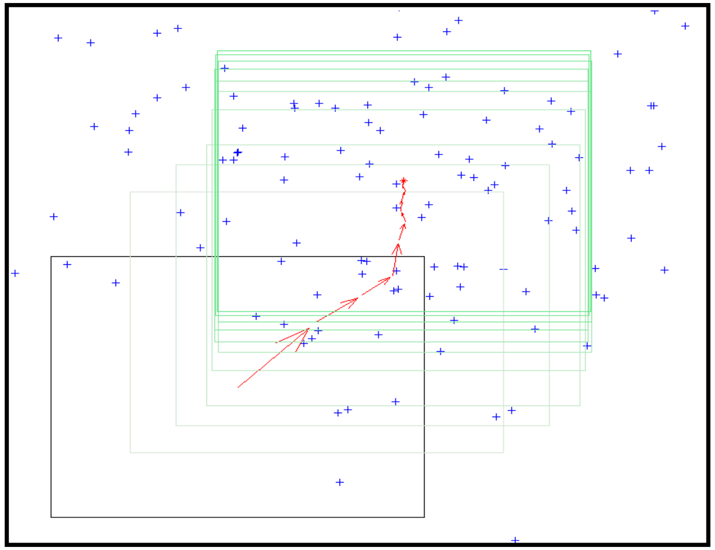


D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Homogeneity based – FS segmentation : Mean shift

Mean-shift

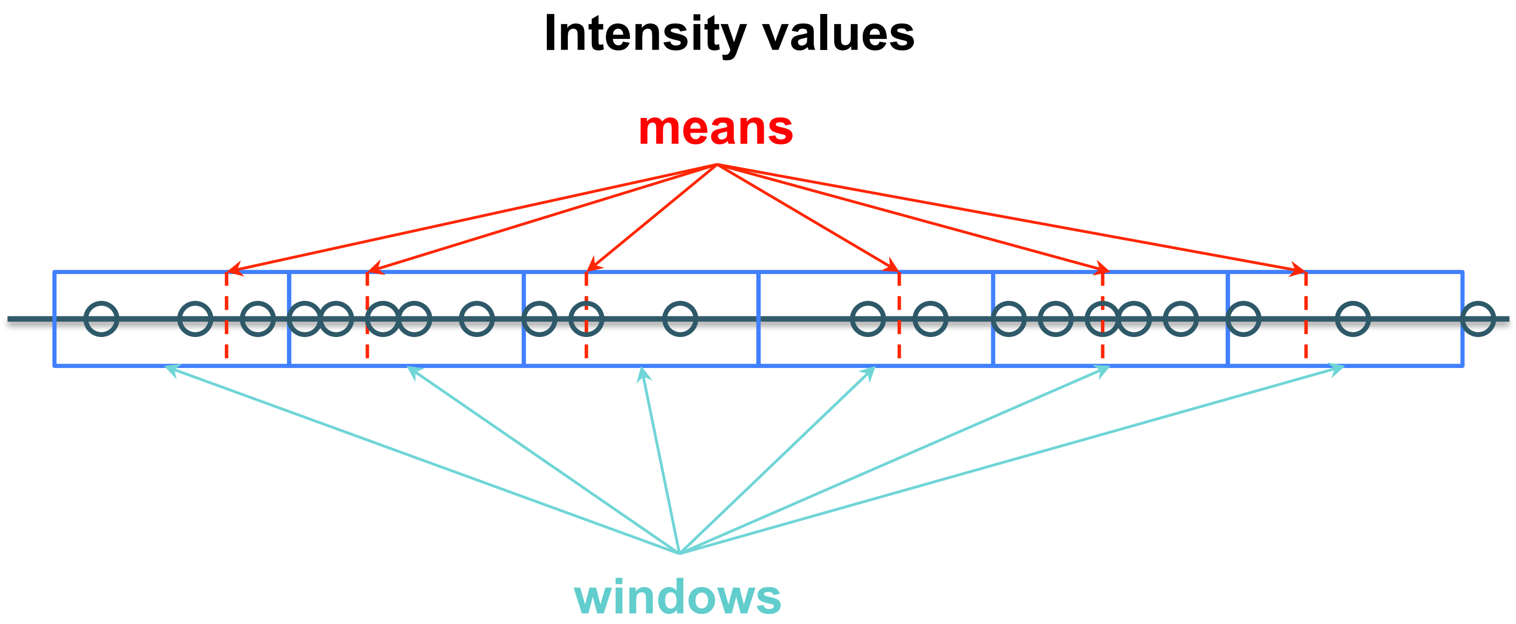
1. Select a search window size
2. Define a set of initial points for the search windows
3. Compute the mean location (centroid) of the data inside the window
4. Re-center the window at position computed in 3.
5. Iterate 3. and 4. until convergence



Slide credit: Gary Bradski & Sebastian Thrun

Homogeneity based – FS segmentation : Mean shift

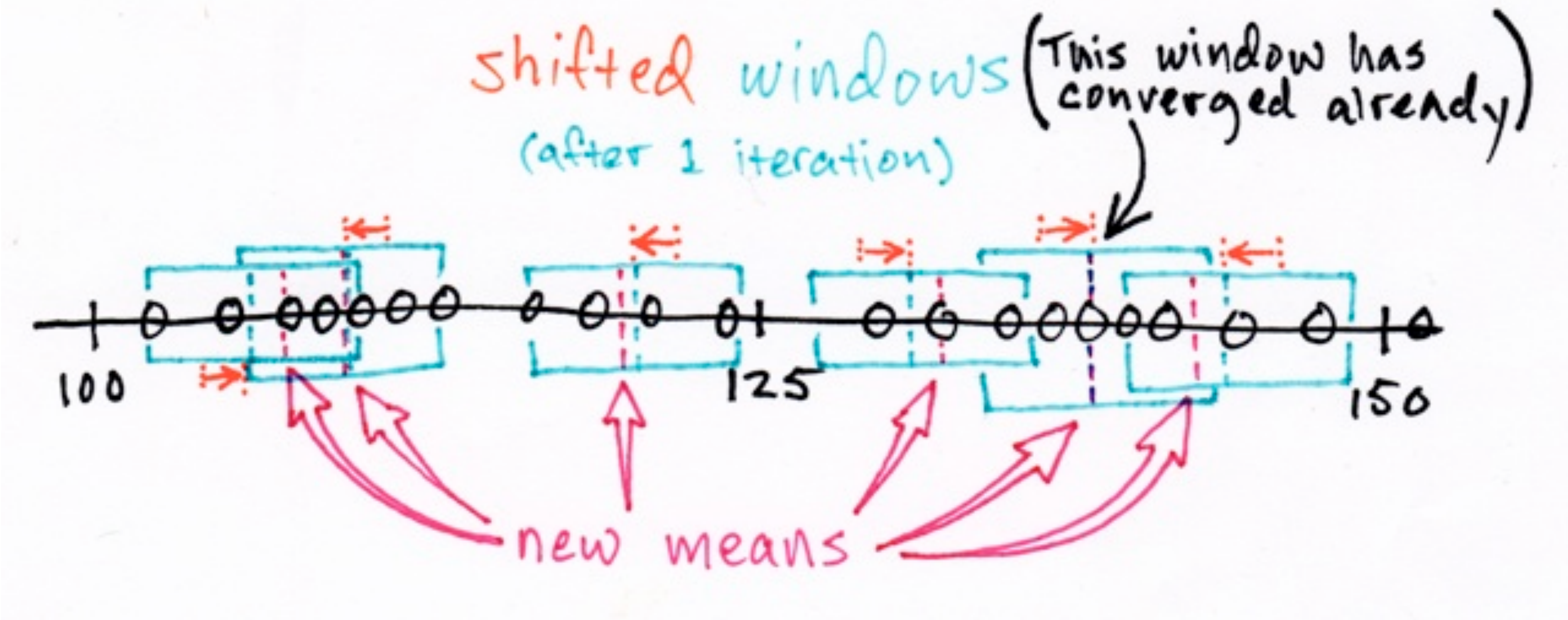
1D example



Source: Mike Laielli – benderseye.com

Homogeneity based – FS segmentation : Mean shift

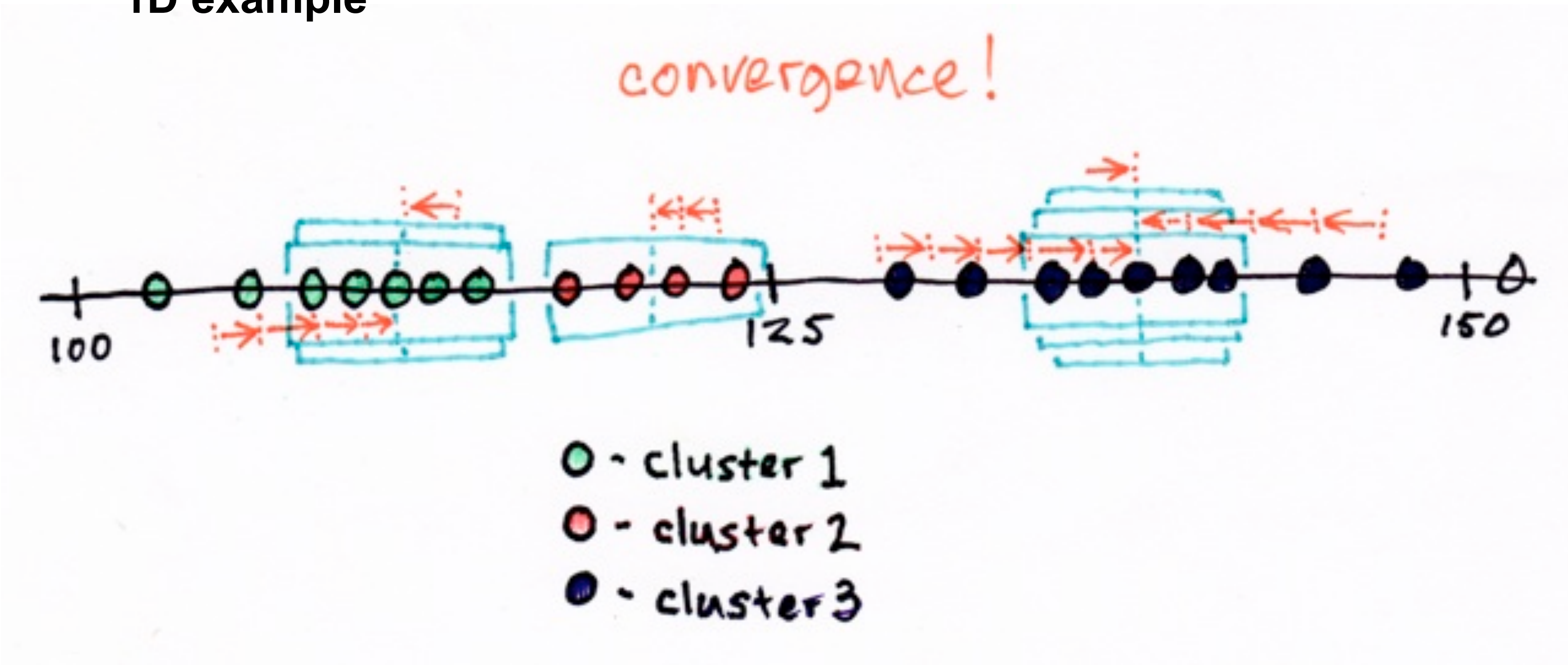
1D example



Source: Mike Laielli – benderseye.com

Homogeneity based – FS segmentation : Mean shift

1D example

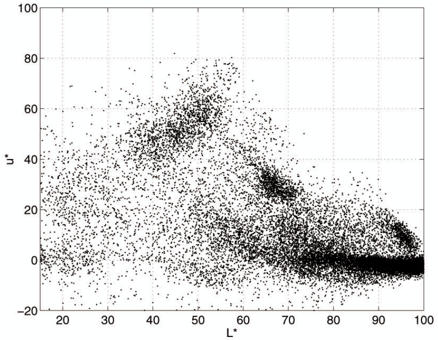


Source: Mike Laielli – benderseye.com

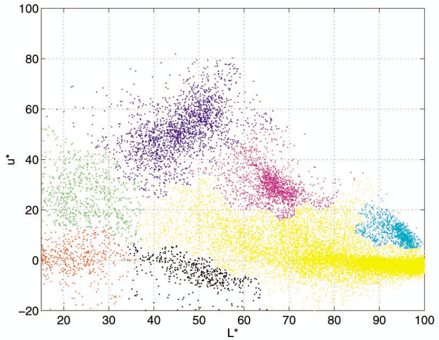
Homogeneity based – FS segmentation : Mean shift

Procedure:

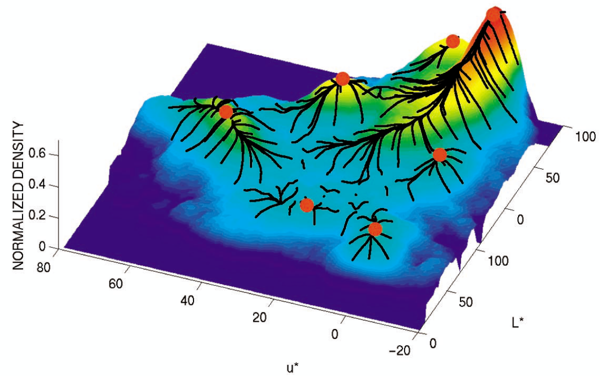
- Find features: (color, gradient, etc.)
- Select window size. Initialize windows at individual feature points
- Perform mean-shift for each window until convergence
- Merge windows that end near the same mode.



(a)



(b)



(c)

Homogeneity based – FS segmentation : Mean shift

Pros

- Does not assume spherical clusters
- Just a single parameter (window size)
- Finds variable number of modes
- Robust to outliers

Cons

- Output depends on window size
- Computationally expensive
- Does not scale well with dimension of feature space (curse of dimensionality)

$O(Tn^2)$

T: Number of iterations
N : number of points in the dataset

Segmentation - Feature Space segmentation : Conclusions

Strong point:

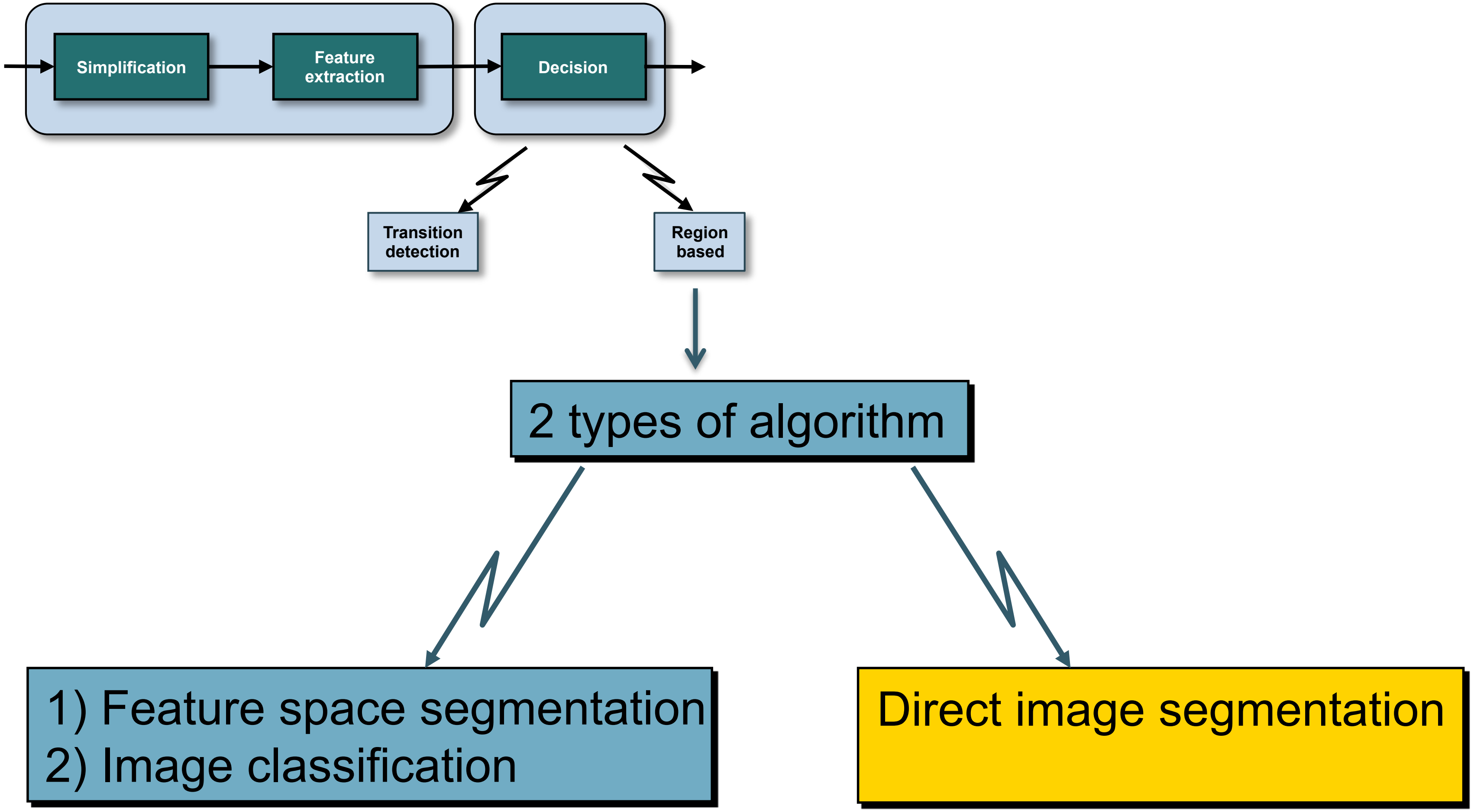
- Simple

Drawback:

- No control of the space connectivity

➢ May result on large number of **small isolated** regions

Segmentation: Homogeneity based

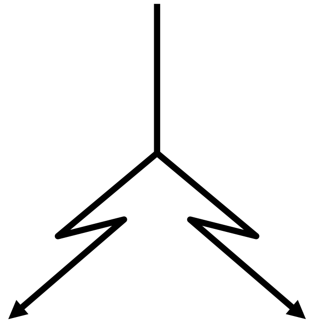


Region Splitting, merging, growing

Homogeneity based – Region splitting, merging & growing

Strategy:

- Create an initial partition
- Define an optimization criterion
- Optimize (modify) the partition (criterion minimization)



Split **Merge**

Regions

Create / remove regions
Shift contours

Homogeneity based

Segmentation: Create a partition of the image such that

$$\begin{cases} C(R_i) = \mathrm{T}rue, & \forall i \\ C(R_i \cup R_j) = \text{False}, & \forall i, j \end{cases}$$

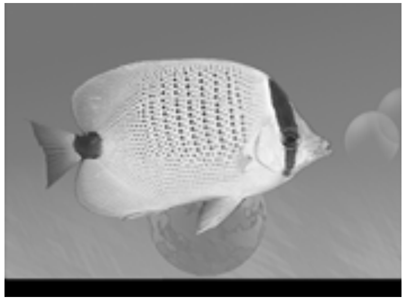
Regions should group pixels which are homogenous.

How to estimate the homogeneity?

- Define a region model
- Measure the variability of the pixels with respect to the model

Homogeneity based: region model

$x(i,j)$



R_n

$M_n(i,j)$

0 Order Polynomial (Mean)

$$M_n(i,j) = \sum_{i,j \in R_n} x(i,j)$$

1st order polynomial

$$M_n(i,j) = ai + bj + c$$

2nd order polynomial

$$M_n(i,j) = ai^2 + bj^2 + cij + di + ej + f$$

Homogeneity based: measure of variability

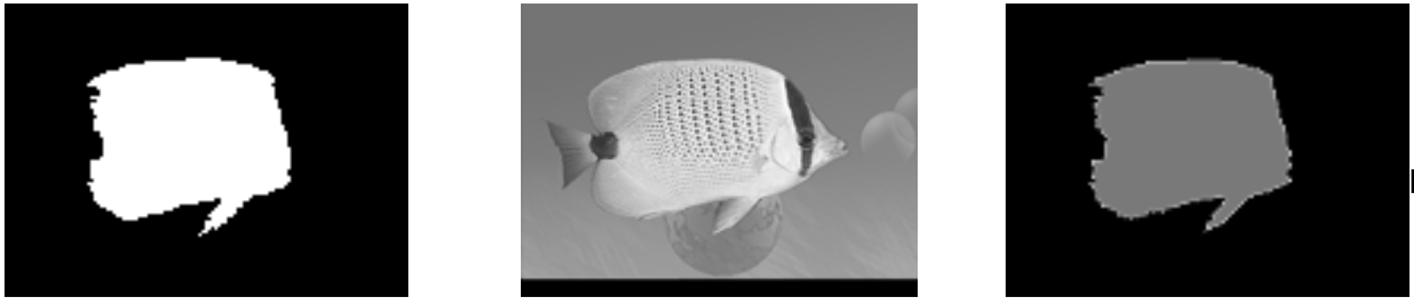
Classical example: Mean Squared Error

$$C_T = \frac{1}{N} \sum_{n} \sum_{i,j \in R_n} [x(i,j) - M_n(i,j)]^2$$

R_n: Region
i,j: Position
N: Pixel num.

Gray level (or color)

Region model:
- Constant (mean)
- Polynomial, ...



0 Order polynomial

But is this enough?

Segmentation: Homogeneity based

4 Examples:

- Split & Merge (top-down)
- Region merging (bottom-up)
- Region growing (seeds)
    - Watershed

Homogeneity based – Split & Merge

1) Initial partition: Image = 1 region (top-down)

2) Classical criterion, C: Mean squared error with respect to a 0, 1st or 2nd order model

---

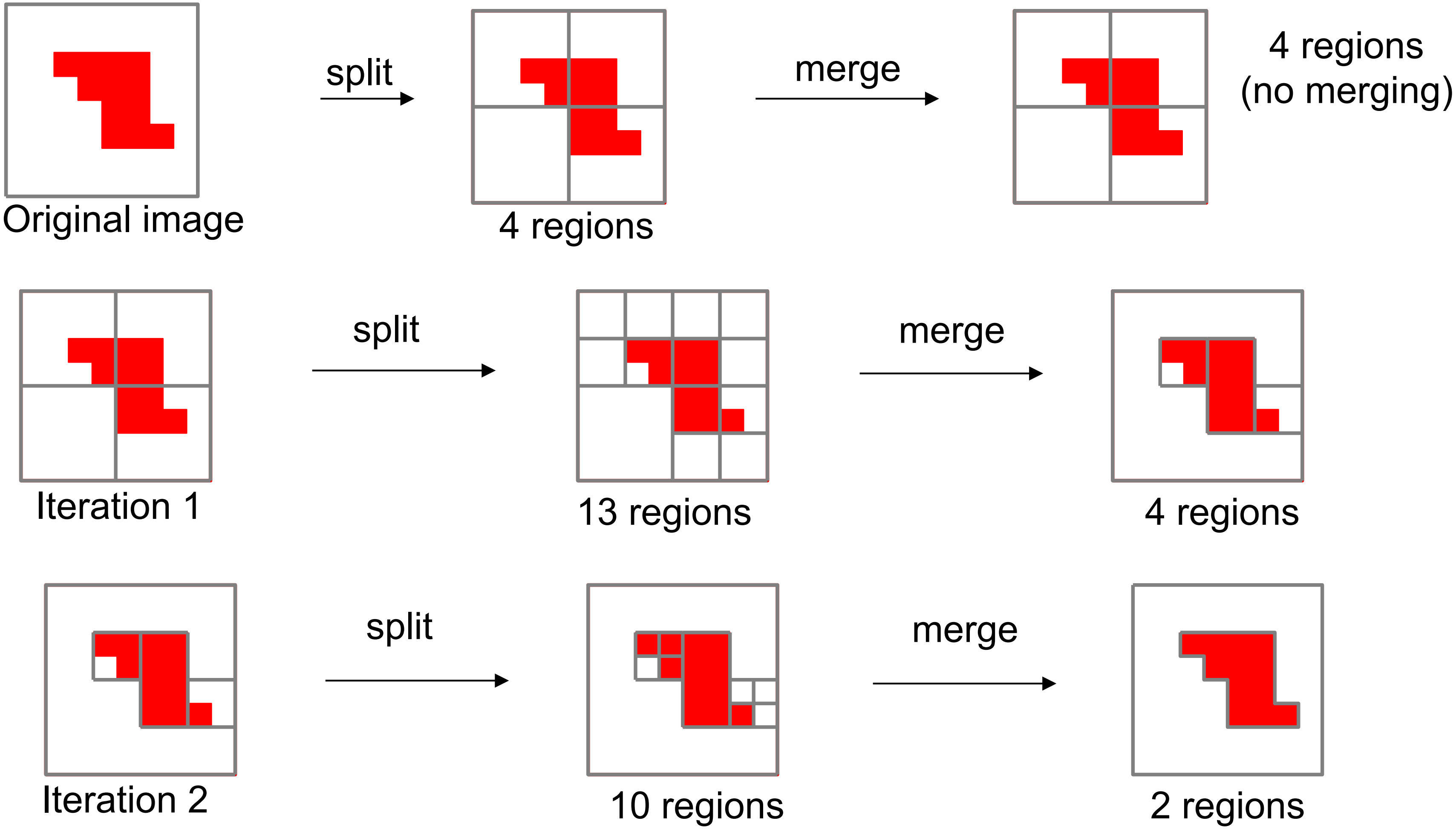
"Split":

If $C(R_i) > T_0$ ➛ Geometric splitting

"Merge":

If $C(R_i \cup R_j) < T_1$ ➛ Merge R_i and R_j

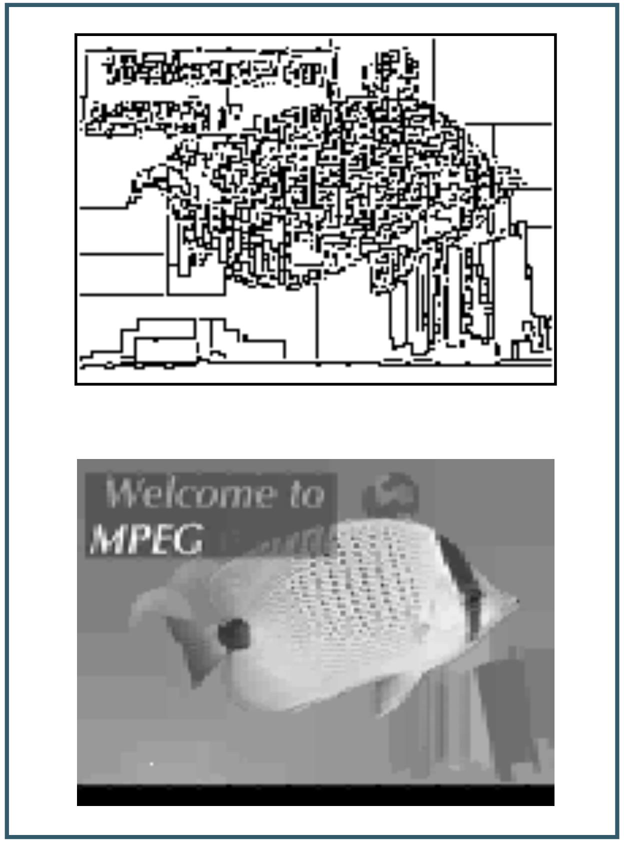
Homogeneity based – Split & Merge



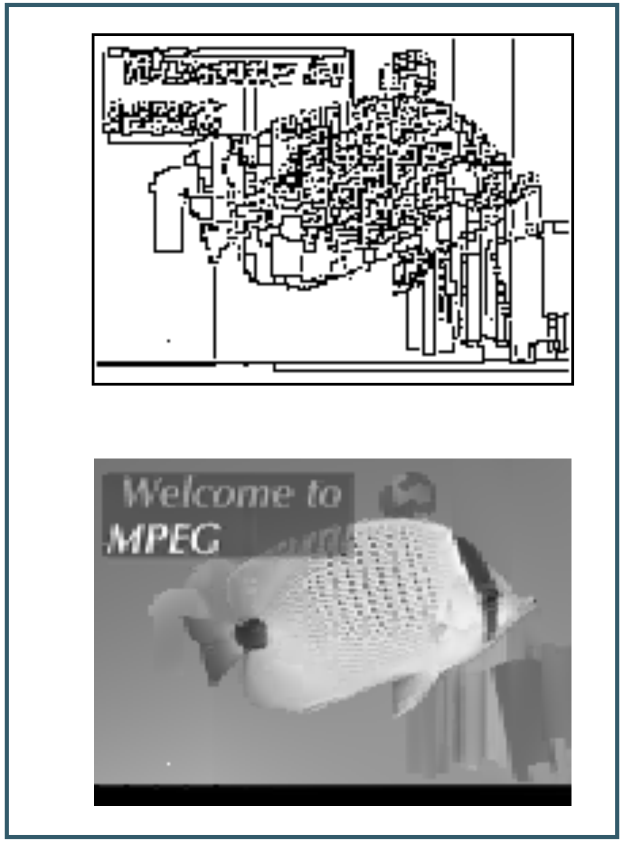
Split → If region is not homogeneous, split in 4
Merge → If neighboring regions are homogenous, Merge them

Homogeneity based – Split & Merge

0 order model



2nd order model



Split & Merge:

- Simple
- Simple initial partition
- Global view

- Pure geometrical split
- Contour are not always natural

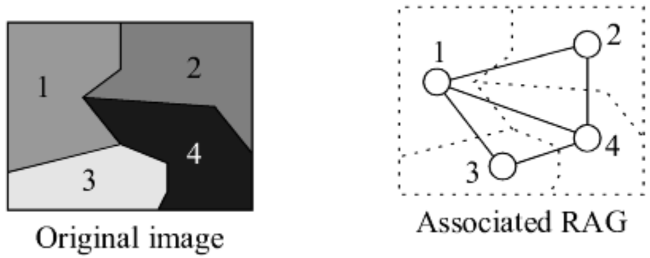
Segmentation: Homogeneity based

4 Examples:

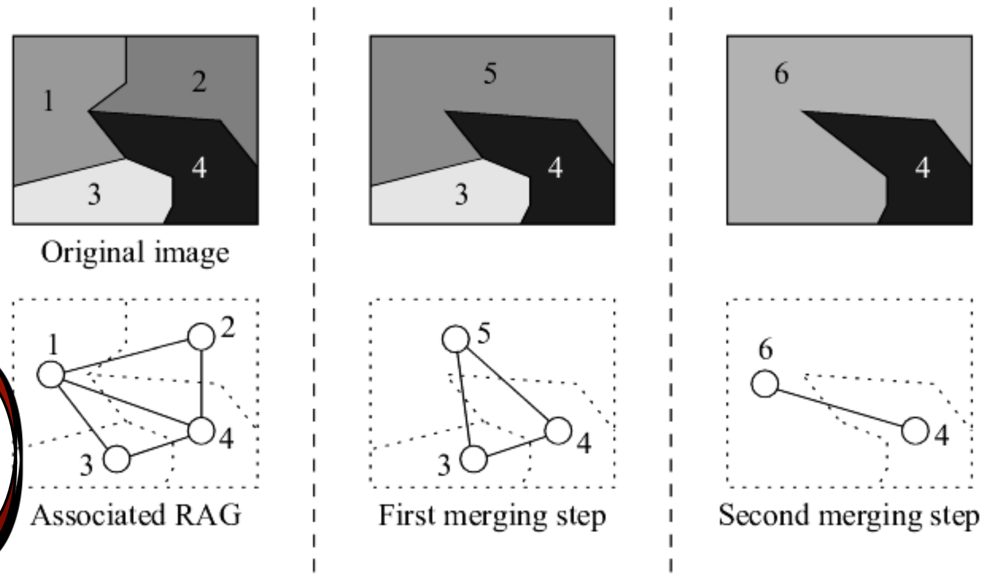
- Split & Merge (top-down)
- Region merging (bottom-up)
- Region growing (seeds)
    - Watershed

Homogeneity based – Region merging

- Region Adjacency Graph (RAG)
  - Node: regions of the image
  - Edge: Neighbor relationship



- Iterative merging process:
  - Define an initial partition and its RAG (nodes: regions, edges: neighboring region similarity)
  - Find the pair of most similar neighboring regions
  - Merge them
  - Update the edges



Homogeneity based – Region merging

- Initial partition:
  - Each pixel is an individual region or
  - Over-segmentation
- Similarity between regions:
  - Approximation of Mean Squared Error:

$$C_{color}(R_1,R_2) = N_{R1}\left\|M_{R1} - M_{R1\cup R2}\right\|_2^2 + N_{R2}\left\|M_{R2} - M_{R1\cup R2}\right\|_2^2$$

  - Contour length variation:

$$C(R_1,R_2) = \alpha C_{color}(R_1,R_2) + (1-\alpha)C_{cont}(R_1,R_2)$$
$$C_{cont}(R_1,R_2) \approx -\text{Length of common contour}$$

- Stopping criterion:
  - Given number of regions
  - PSNR resulting from modeling the regions of the partition

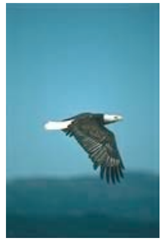
Individual pixels

R_1 R_2 $R_1 U R_2$

M_{R_1} M_{R_2} $M_{R_1 \cup R_2} = (M_{R_1} + M_{R_2})/2$

$$(M_{R_1} - M_{R_1 \cup R_2})^2 + (M_{R_2} - M_{R_1 \cup R_2})^2$$

Homogeneity based – Region merging



Region number (50)

22,00 dB [50 regions]

29,50 dB [50 regions]

22,13 dB [50 regions]

32,29 dB [50 regions]

PSNR (26dB)

[26 dB] 273 regions

[26 dB] 13 regions

[26 dB] 347 regions

[26 dB] 7 regions

Slide credit: Verónica Vilaplana

Segmentation: Homogeneity based

4 Examples:

- Split & Merge (top-down)
- Region merging (bottom-up)
- Region growing (seeds)
    - Watershed

Homogeneity based – Region growing

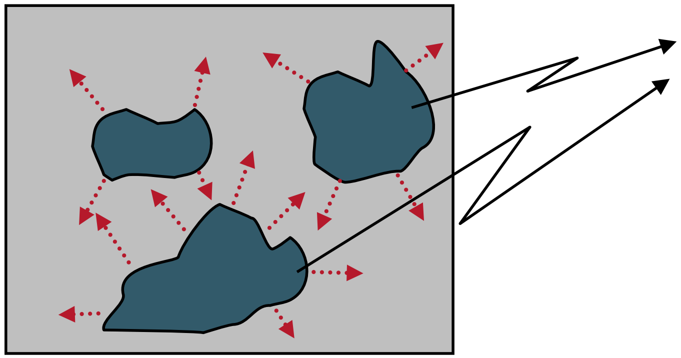
Basic strategy:

- Initial segmentation: Partial segmentation

$$\bigcup_i R_i \neq E$$

$$E \setminus \bigcup R_i = \text{Uncertainty zone}$$

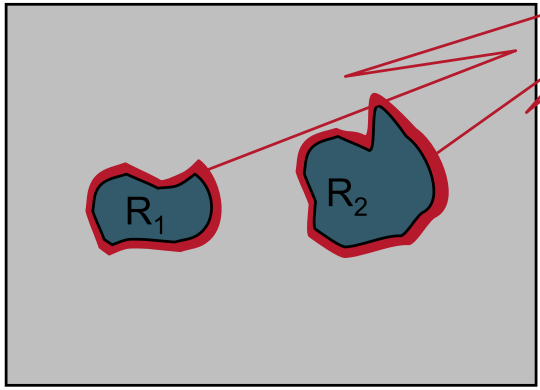
- Progressive elimination of the uncertainty zone



Initial regions:

- Regions interior
- “Safe” areas
- Application dependent

Homogeneity based – Region growing



Pixels from the uncertainty area that are connected to regions: $\{p_j^{R_i}\}$

Assign iteratively the "closest" pixel

$p_j^{R_i}$ is assigned to R_i if:

$$C\{R_1,\ldots,\{p_j^{R_i} \cup R_i\},\ldots,R_k\} < C\{R_1,\ldots,\{p_m^{R_n} \cup R_n\},\ldots,R_k\}$$

$$\forall (n,m) \neq (i,j)$$

⇒ Merging between regions and pixels from the uncertainty area

Homogeneity based – Region growing

Criterion: Local estimation of the variation of the criterion

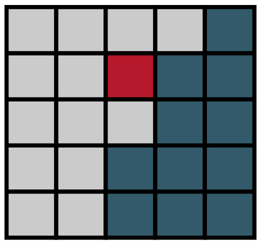
For each potential merging between p_0 and R_i, compute:

$$\Delta C = \alpha\,(p_0 - M_{R_i})^2 + (1-\alpha)\,\Delta contour$$

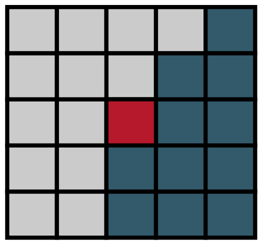
Pixel gray level

Region mean

Variation of the contour length



Δcontour = 3-1 = 2



Δcontour = 2-2 = 0

Homogeneity based – Region growing

Original image | Initial regions | $\alpha = 1$ contour=9800

$\alpha = 0.75$ cont.=8000 | $\alpha = 0.50$ cont.=6300 | $\alpha = 0$ cont.=3500

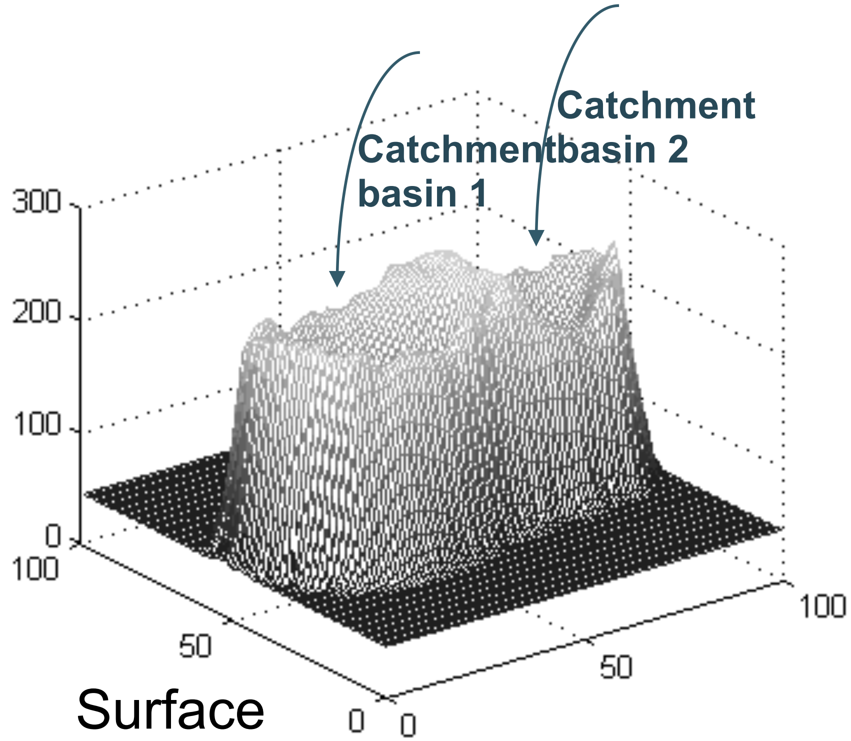
Homogeneity based – Region growing : Watershed

Watershed: Morphological approach to image segmentation through region growing

Image ➝ Topographic surface

Gray level ➝ Height

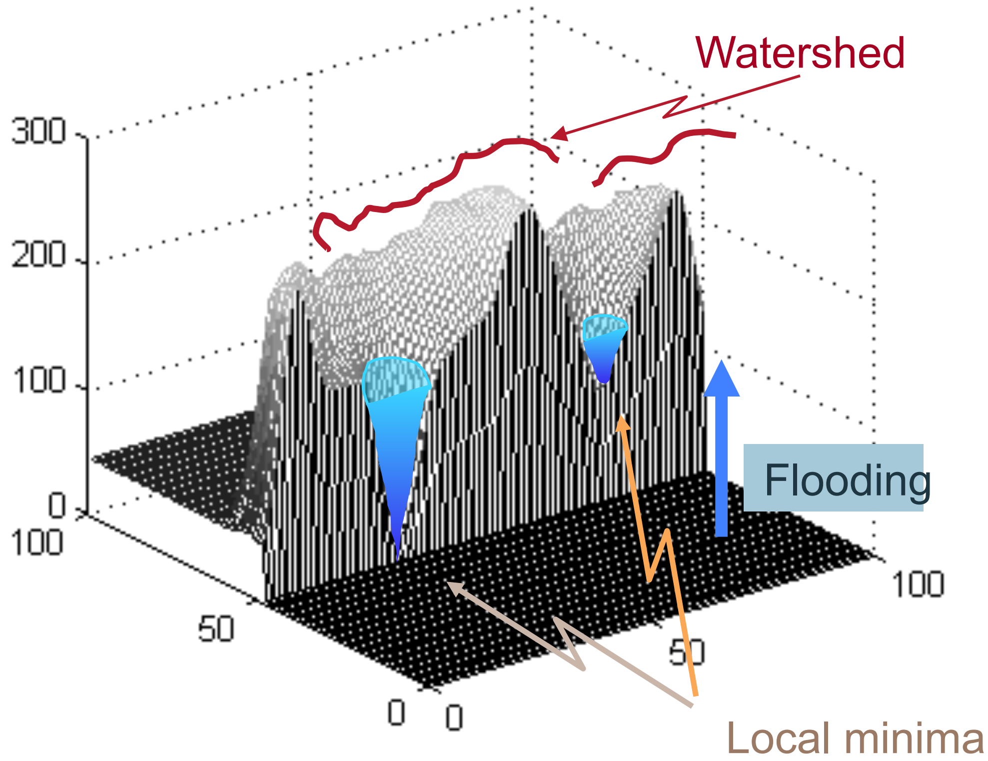
Original image



Surface

Homogeneity based – Region growing : Watershed

Watershed: locations where 2 (or more) catchment basins meet

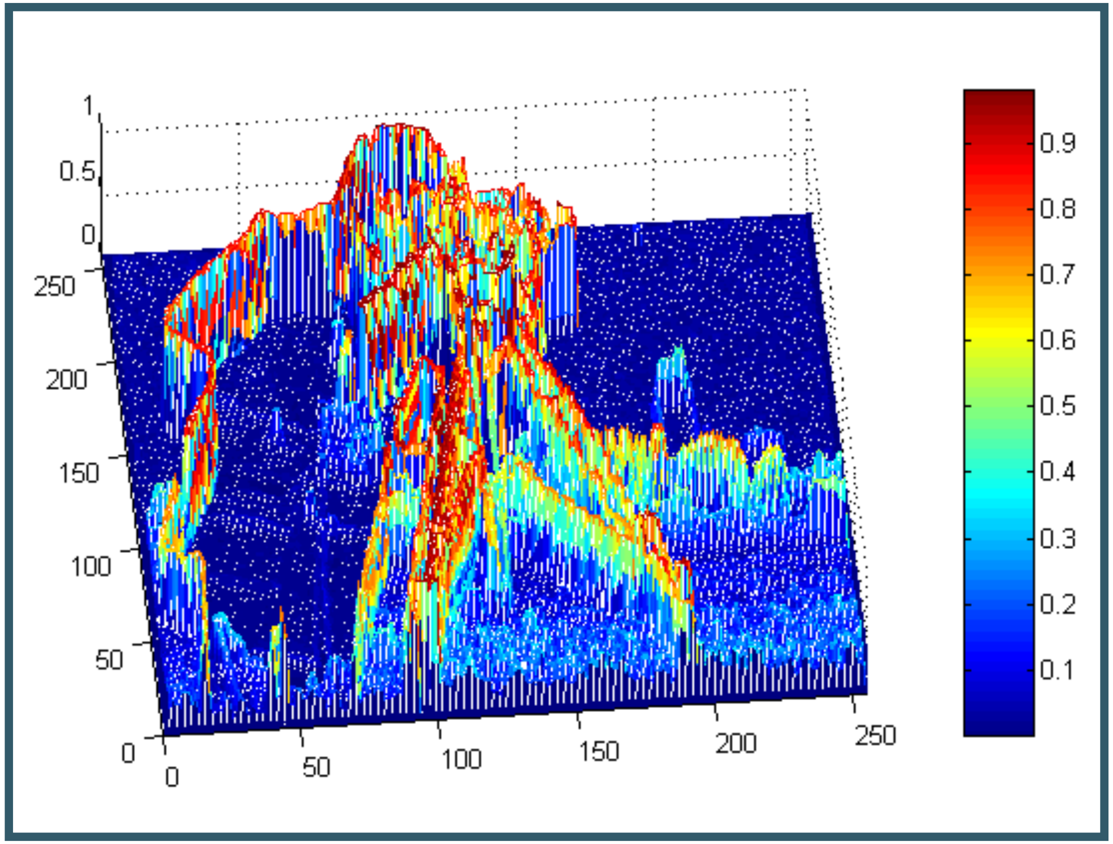


Each pixel is assigned to the catchment basin assigned to its minimum
➛ Flooding algorithm

Homogeneity based – Region growing : Watershed

Original image

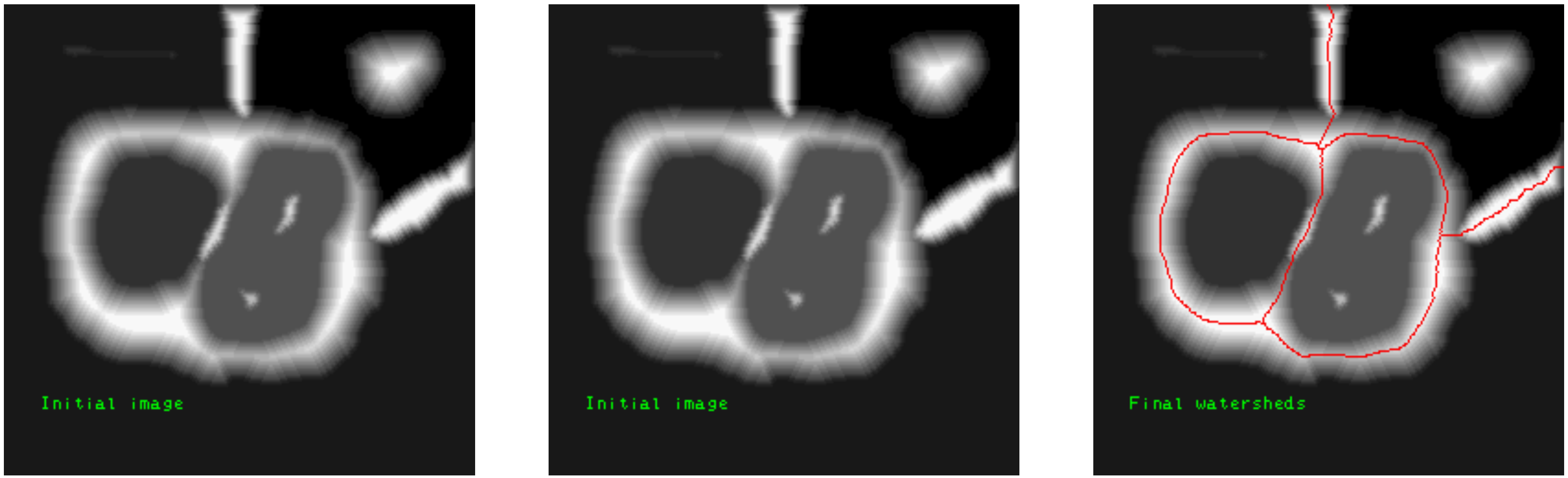
Gradient



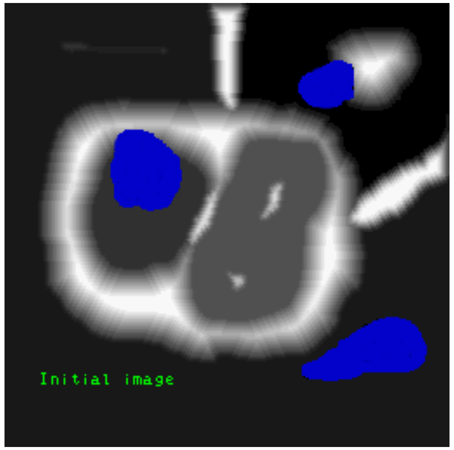
➛ image contours = watershed of gradient

Homogeneity based – Region growing : Watershed

- Initial regions: Local minima of the image
- Growing process: The pixel with the gray level that is the closest to the flooded level is assigned to its corresponding catchment basin.

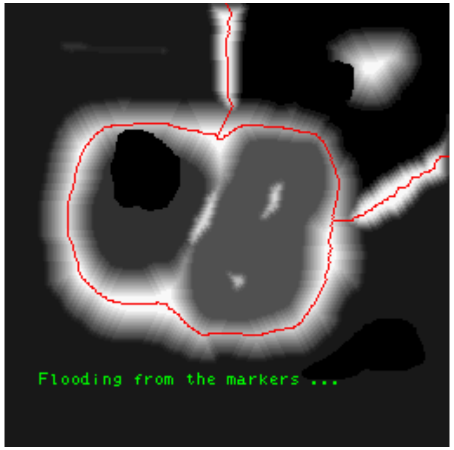


Homogeneity based – Region growing : Watershed



Original image with marker

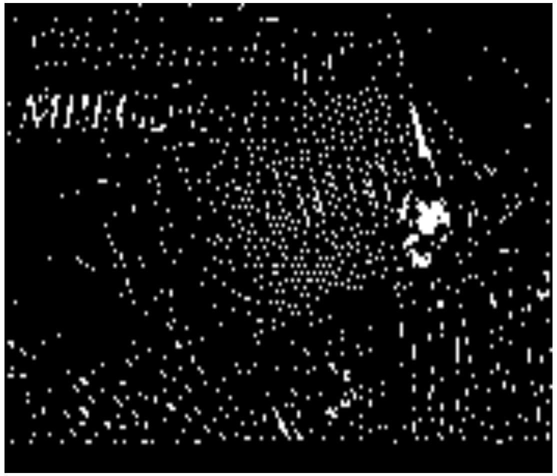
Segmentation



Markers: initial partition

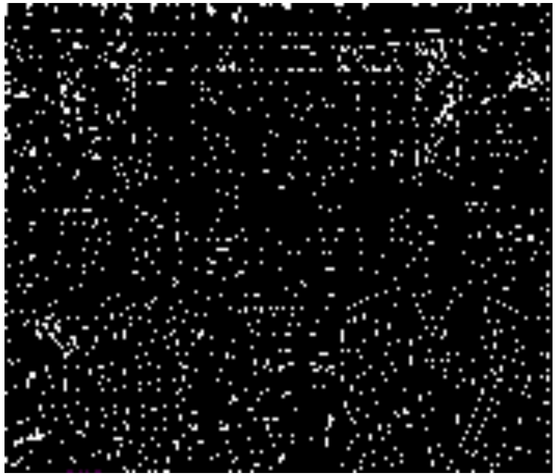
Homogeneity based – Region growing : Watershed

Original



703 max.

Maxima



1055 max.

Homogeneity based – Region growing

Advantages:

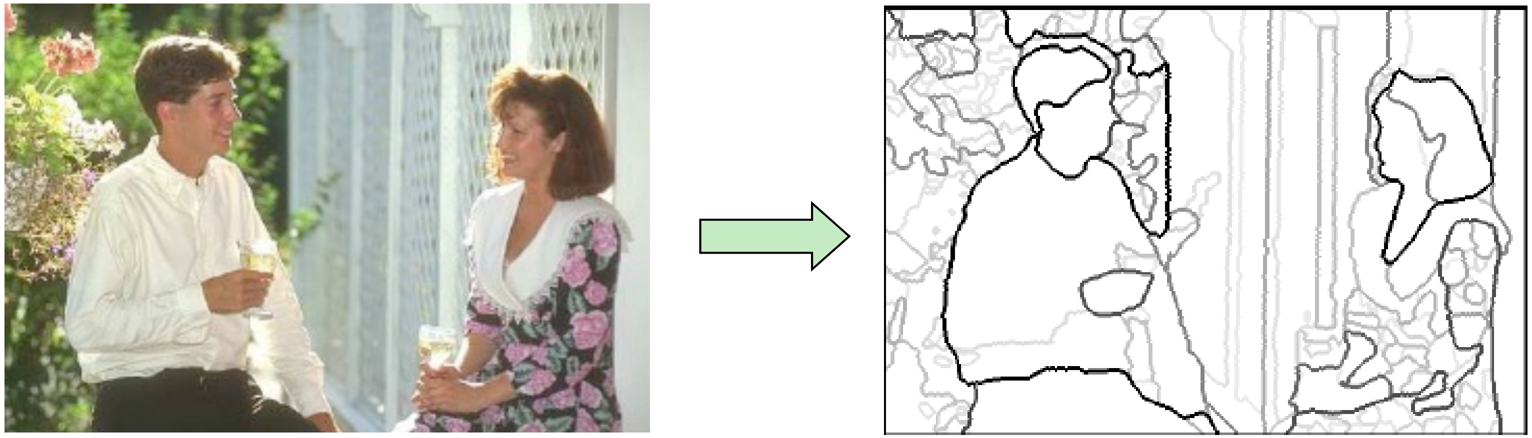
- Precise contours
- Control the region connectivity

Drawbacks:

- Need of a partial segmentation
  - Markers
  - Definition of a “safe” area

Mixed transition/homogeneity – gPb-OWT-UCM

- Ultrametric contour maps (UCM)
  - Transforms a contour map into a hierarchy of regions
  - Iterative merging using *Ultrametric* dissimilarities



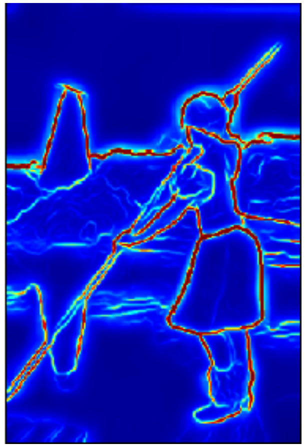
Mixed transition/homogeneity – gPb-OWT-UCM

Original image

gPb

- Local cues
- Global cues

Contour image



Oriented Watershed Transform

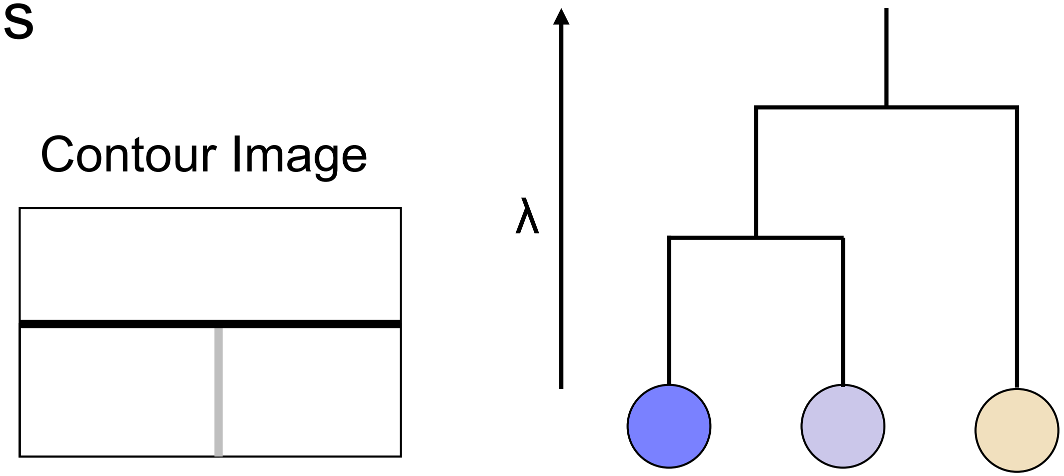
Iterative merging

P. Arbelaez, M. Maire, C. Fowlkes, J. Malik. **Contour Detection and Hierarchical image Segmentation**. IEEE Trans. on PAMI , 2011.

Source: Hsin-Min Cheng

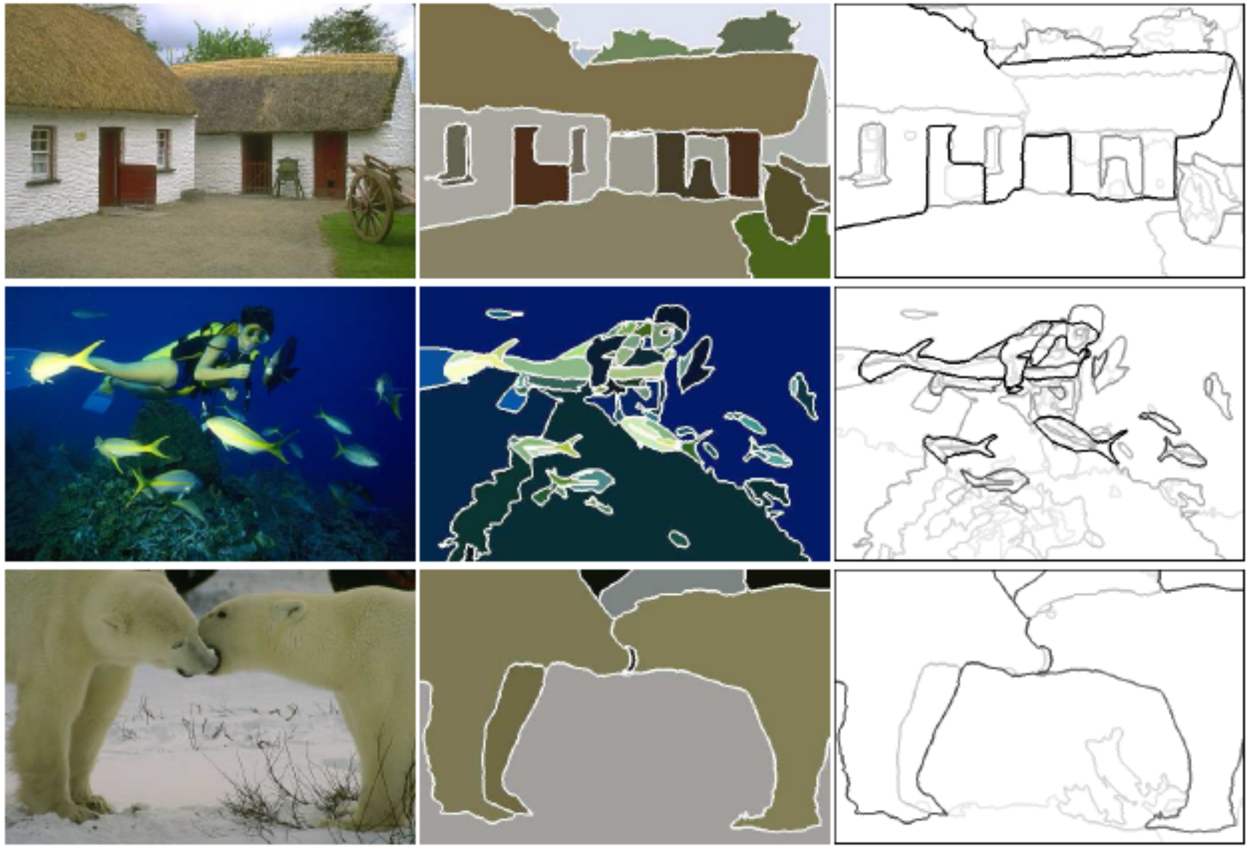
Mixed transition/homogeneity – gPb-OWS-UCM

- Defines a duality between closed, non-self-intersecting weighted contours and a hierarchy of regions
- The base level of this hierarchy respects even weak contours and is thus an over-segmentation of the image.
- Upper levels of the hierarchy respect only strong contours, resulting in an under-segmentation.
- Moving between levels offers a continuous trade-off between these extremes



Mixed transition/homogeneity – gPb-OWS-UCM

Results



Source: Pablo Arbeláez

Fast UCM implementation (MCG Pre-trained, Matlab/C++):
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/mcg/