Digital Image & Video Processing

Lecture 9
Image Segmentation

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9. Image Segmentation

9.1. Problem Statement

9.2. Method

9.3. Applications

9.1. Problem Statement

Let us suppose that an image domain I must be segmented in N different regions $R_1, R_2, \ldots, R_N$.

It is necessary to determine a segmentation rule is a logical predicate of the form $P(R)$ having the following properties:

$$I = \bigcup_{i=1}^{N} R_i$$

$$R_i \bigcap R_j = \varnothing, \quad i \neq j$$

$$P(R_i) = True, \quad i = 1,2,\ldots,N$$

$$P(R_i \bigcup R_j) = False, \quad i \neq j$$

9.2. Method

9.2.1. Region growing method

Principle

Geometrical proximity + homogeneity -> connected image regions.

9.2. Method

9.2.1. Region growing method

Method

- Starting from some pixels (seeds) representing distinct iamge regions and to grow them, until they cover the entire image.

- In order to implement region growing, we need determine:

. Seeds

. A rule describing a growth mechanism.

. A rule checking the homogeneity of the regions after each growth step..

9.2. Method

9.2.1. Region growing method

Method

. **Seeds**

Based on the histogram, choose the seed points corresponding to the histogram peaks.

9.2. Method

9.2.1. Region growing method

Method

. A rule describing a growth mechanism

Growing based on 8-neighborhood.

9.2. Method

9.2.1. Region growing method

Method

. A rule checking the homogeneity of the regions after each growth step.

At each step k, for each region $R_i^{(k)}, i = 1,2,\ldots,N$

We check if there are unclassified pixels in the 8-neighbourhood of each pixel of the region border.

If $P(R_i^{(k)} \bigcup \{b_i^{(k)}(x,y)\}) = True$ assigning $b_i^{(k)}(x,y)$ to region $R_i^{(k)}$.

9.2. Method

9.2.1. Region growing method

Method

. A rule checking the homogeneity of the regions after each growth step.

$$| f(x,y) - m(R_i^{(k)}) | < T$$

$$m(R_i^{(k)}) = (1/N(R_i^{(k)})) \sum_{(k,l)\in R_i^{(k)}} f(k,l)$$

$$\sigma(R_i^{(k)}) = \left[(1/N(R_i^{(k)})) \sum_{(k,l)\in R_i^{(k)}} (f(k,l) - m(R_i^{(k)}))^2 \right]^{1/2}$$

9.2. Method

9.2.1. Region growing method

Method

. A rule checking the homogeneity of the regions after each growth step.

$$m(R_i^{(k+1)}) = (1/(N(R_i^{(k)})+1))[f(x,y) + N(R_i^{(k)})m(R_i^{(k)})]$$

$$\sigma(R_i^{(k+1)}) = \begin{bmatrix} (1/(N(R_i^{(k)})+1))[N(R_i^{(k)})\sigma^2(R_i^{(k)}) + \\ (N(R_i^{(k)})/(N(R_i^{(k)})+1))(f(x,y) - m(R_i^{(k)}))] \end{bmatrix}^{1/2}$$

9.2. Method

9.2.1. Region growing method

Method

. A region merging rule.

$$| m(R_i^{(k+1)}) - m(R_{i'}^{(k+1)}) | < k\sigma(R_i^{(k+1)})$$

$$| m(R_i^{(k+1)}) - m(R_{i'}^{(k+1)}) | < k\sigma(R_{i'}^{(k+1)})$$

9.2. Method

9.2.2. K-means method

Principle

Unsupervised Clustering homogeneity regions -> Image Regions.

9.2. Method

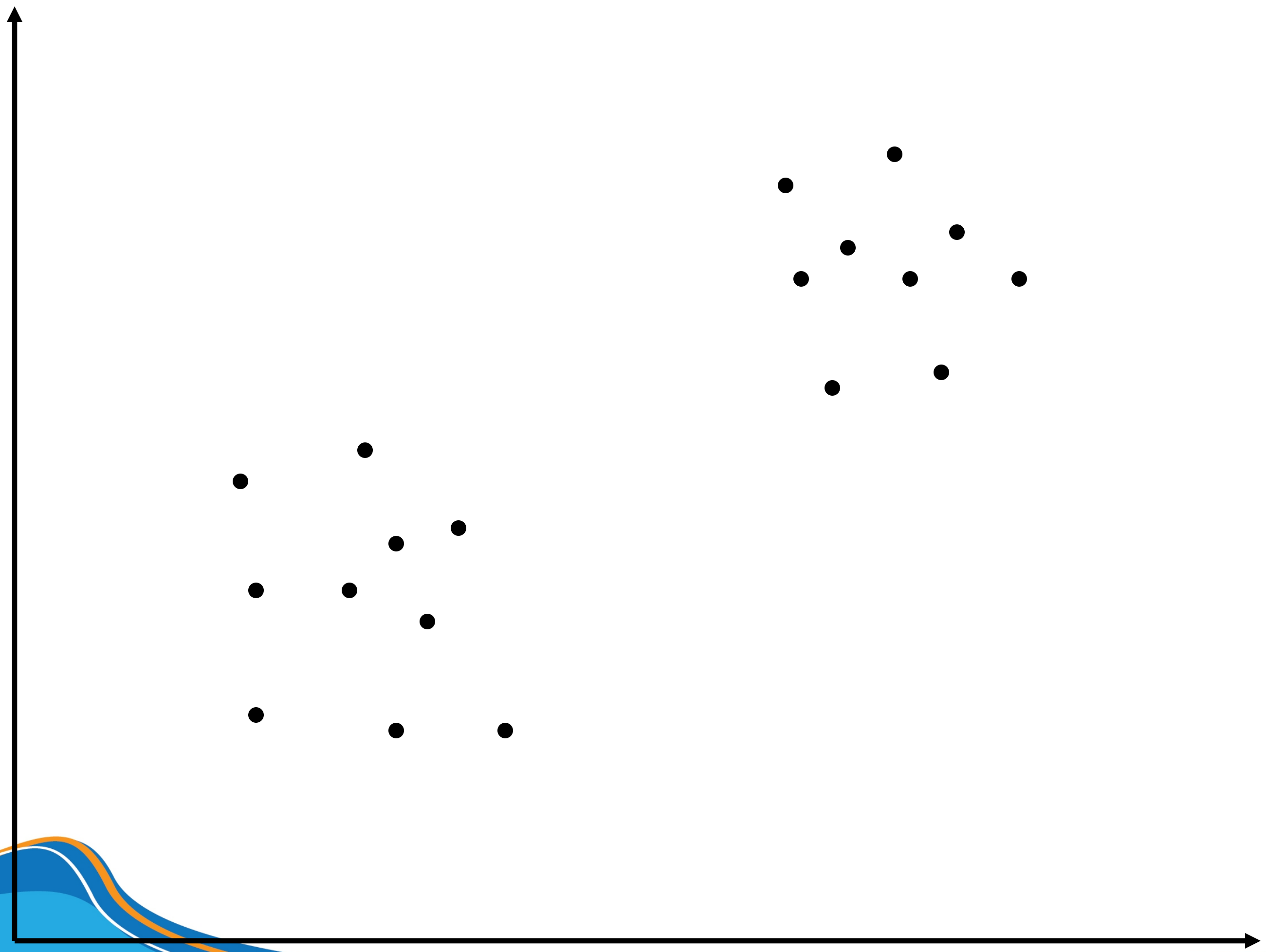
9.2.2. K-means method

Method

1. Partition the data points into K clusters randomly. Find the centroids of each cluster.
2. For each data point:
    - Calculate the distance from the data point to each cluster.
    - Assign the data point to the closest cluster.
3. Recompute the centroid of each cluster.
4. Repeat steps 2 and 3 until there is no further change in the assignment of data points (or in the centroids).

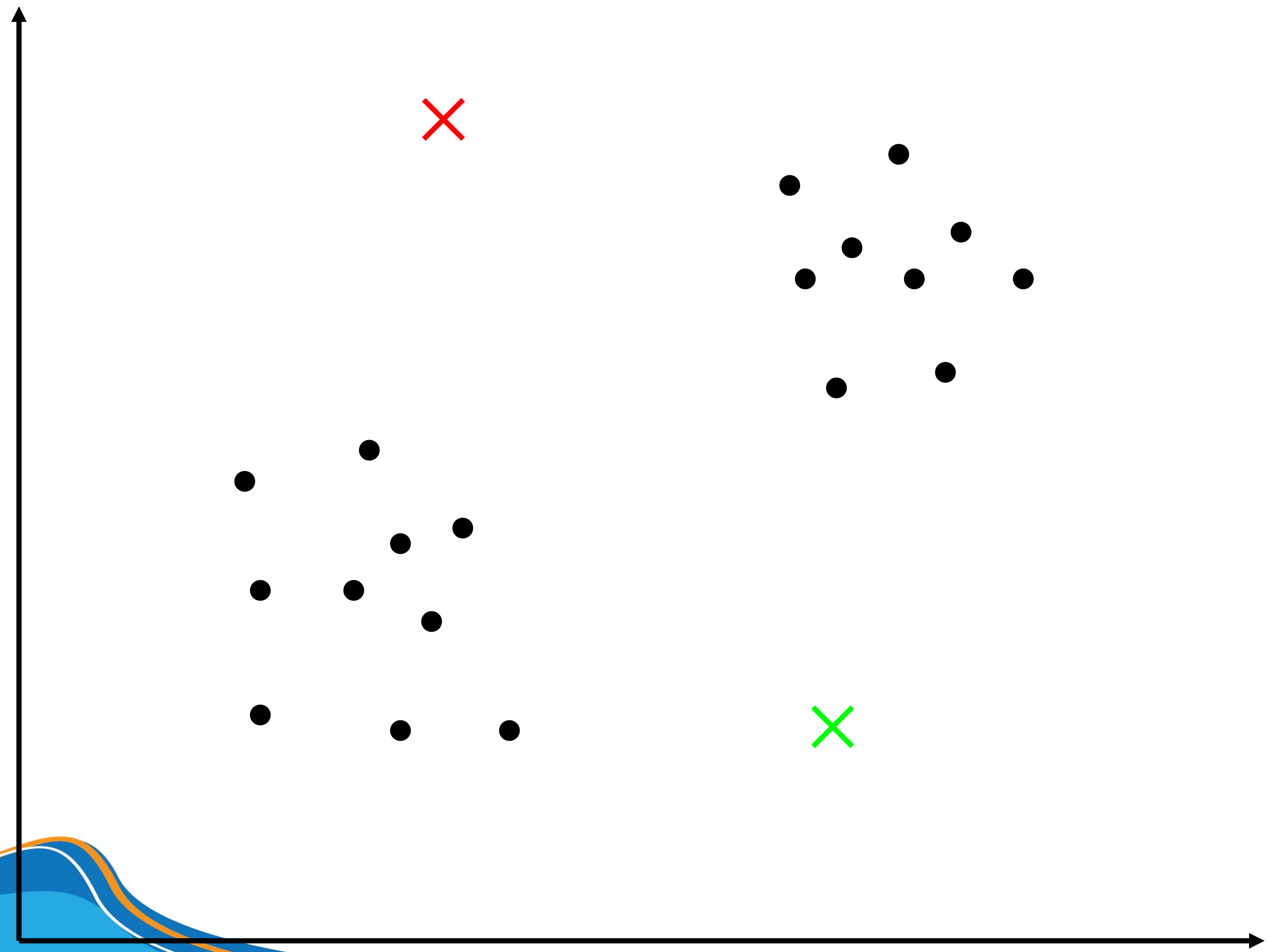
9.2. Method

9.2.2. K-means method



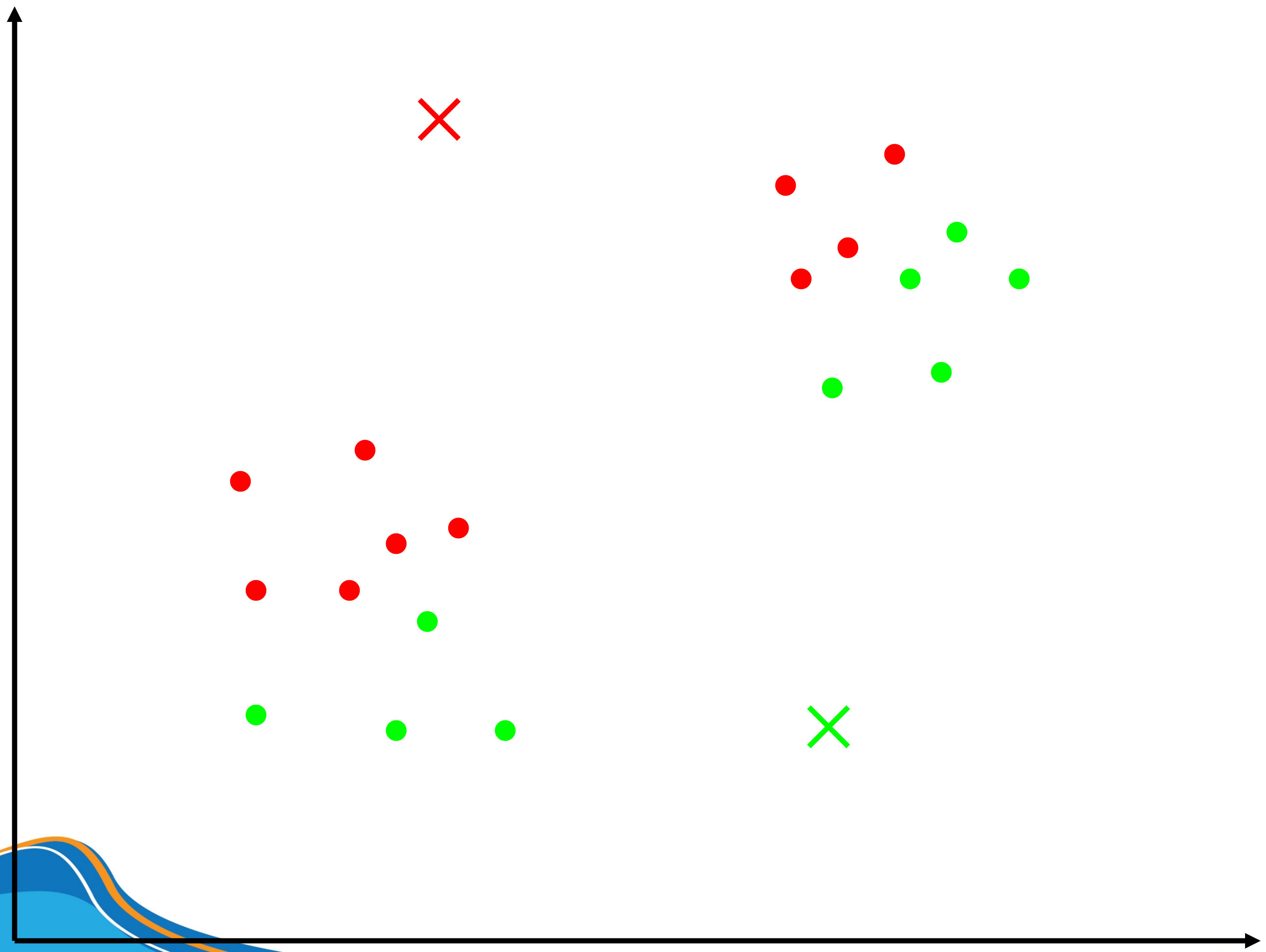
9.2. Method

9.2.2. K-means method



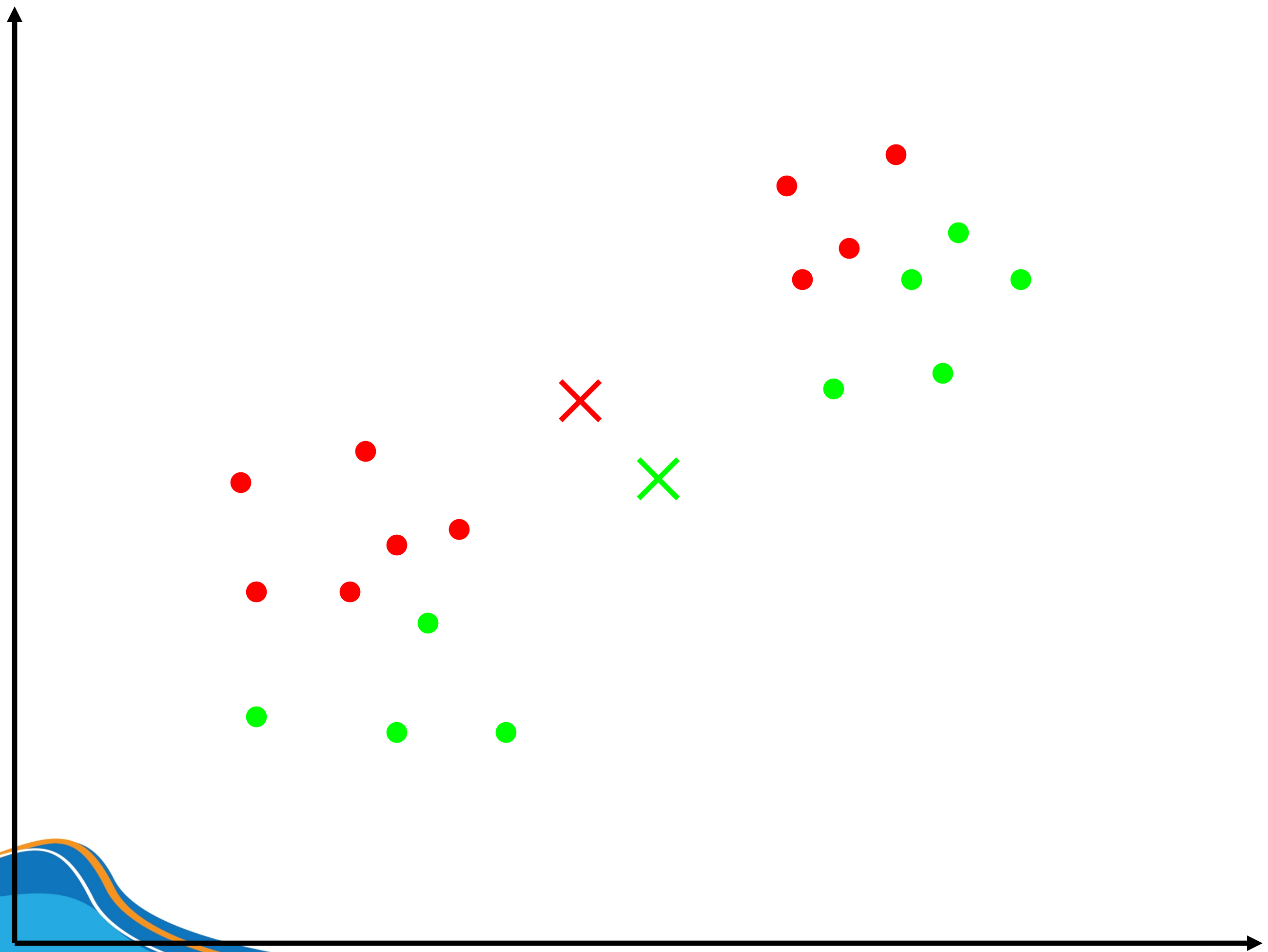
9.2. Method

9.2.2. K-means method



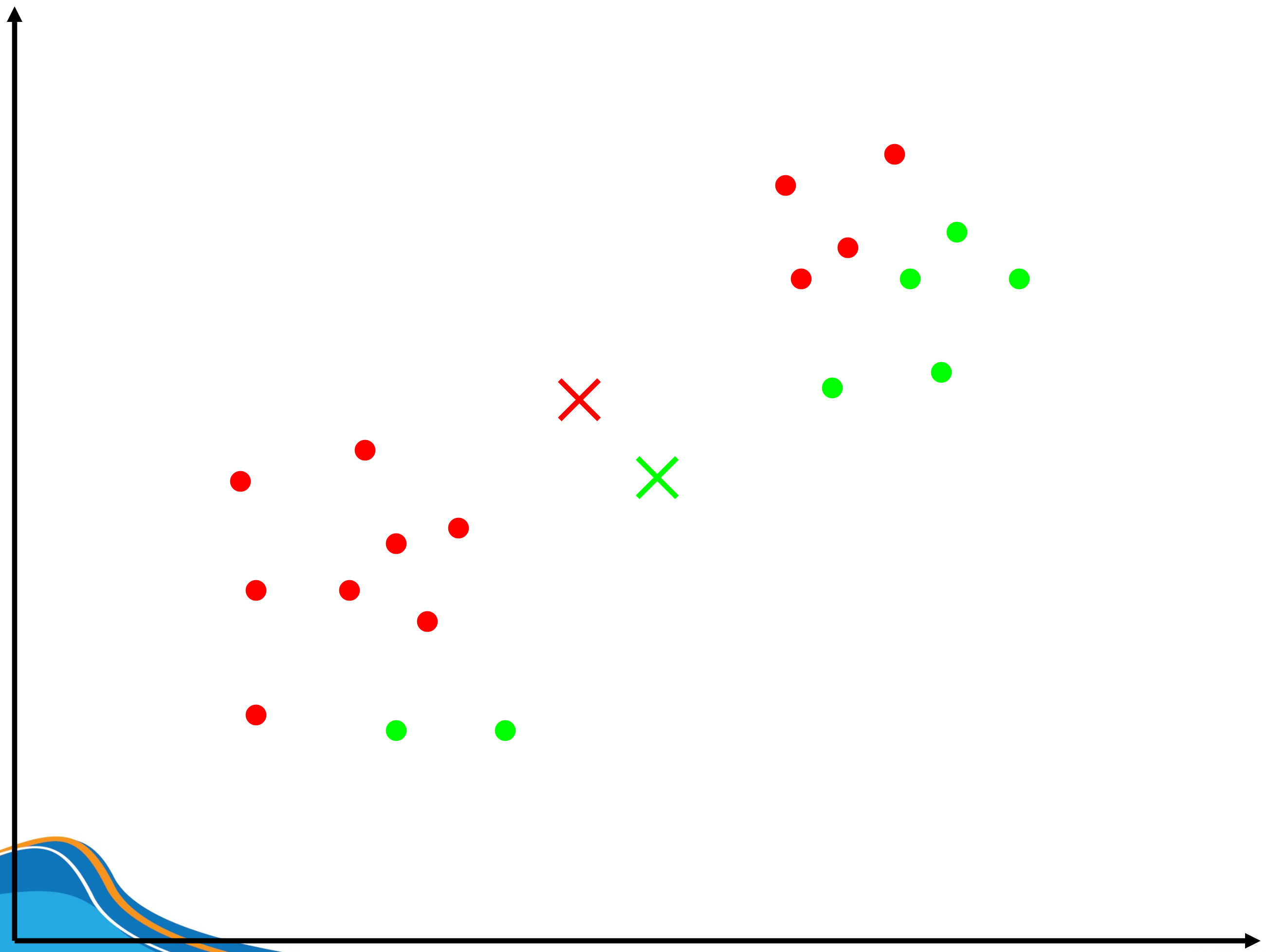
9.2. Method

9.2.2. K-means method



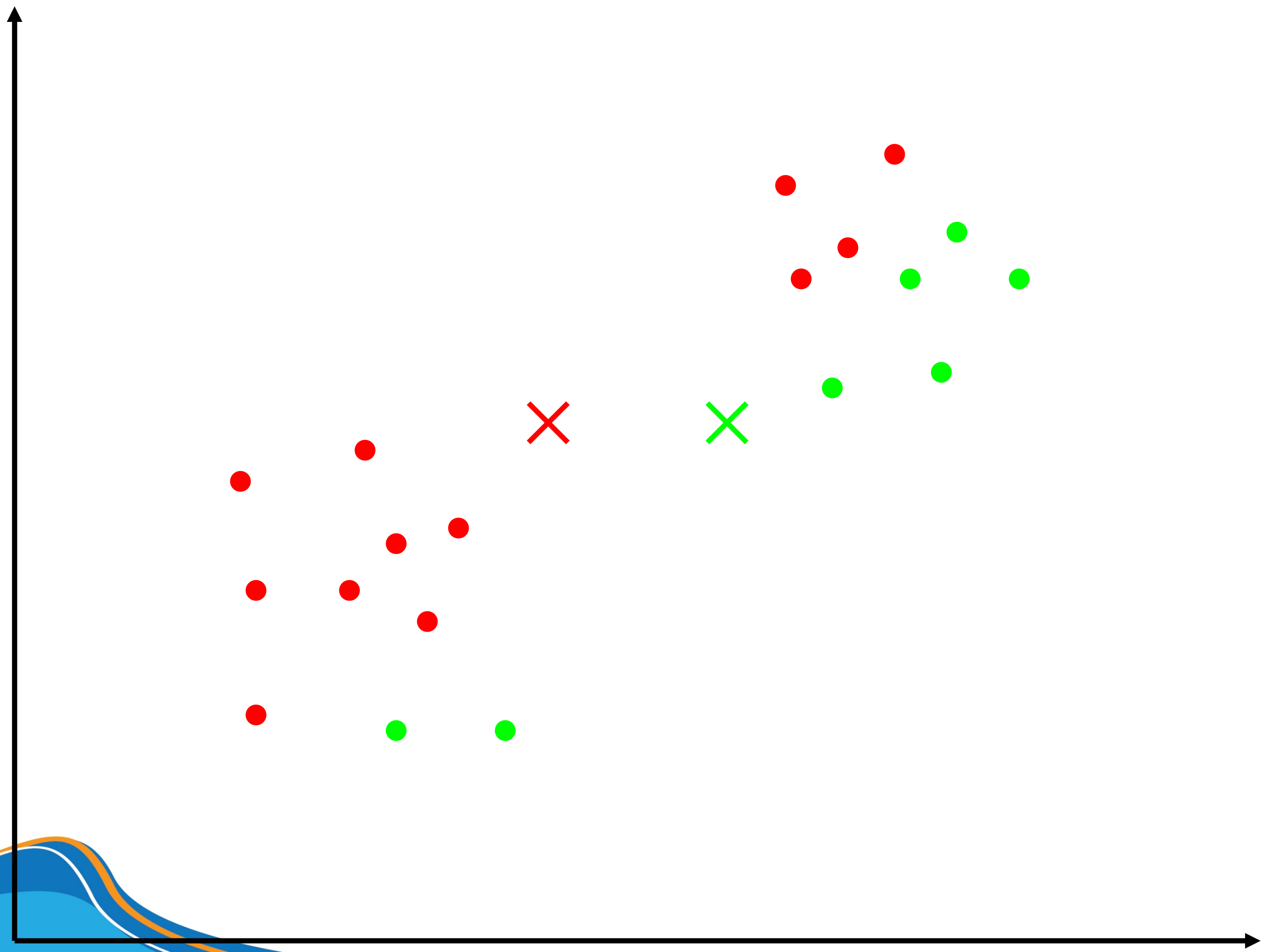
9.2. Method

9.2.2. K-means method



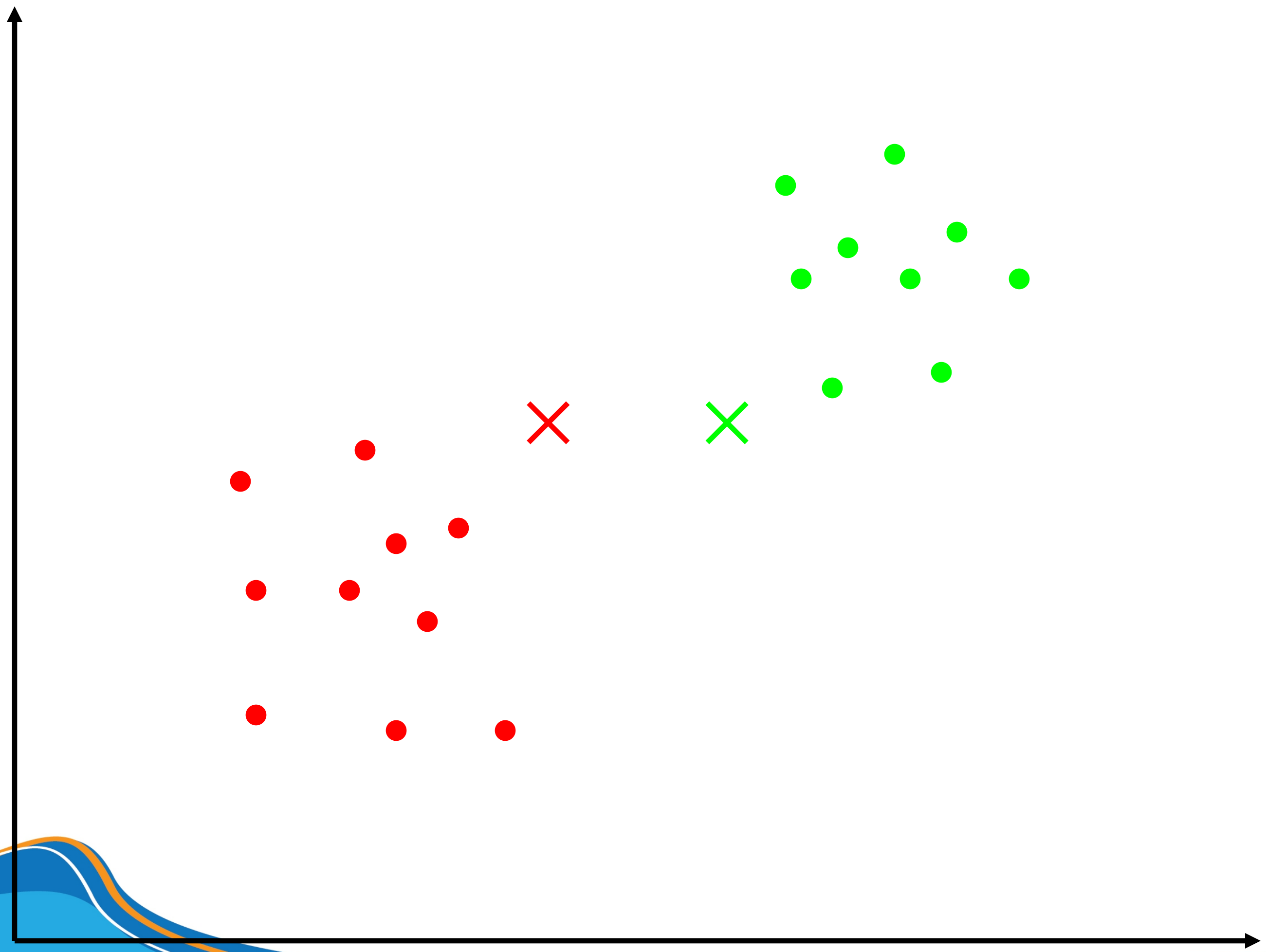
9.2. Method

9.2.2. K-means method



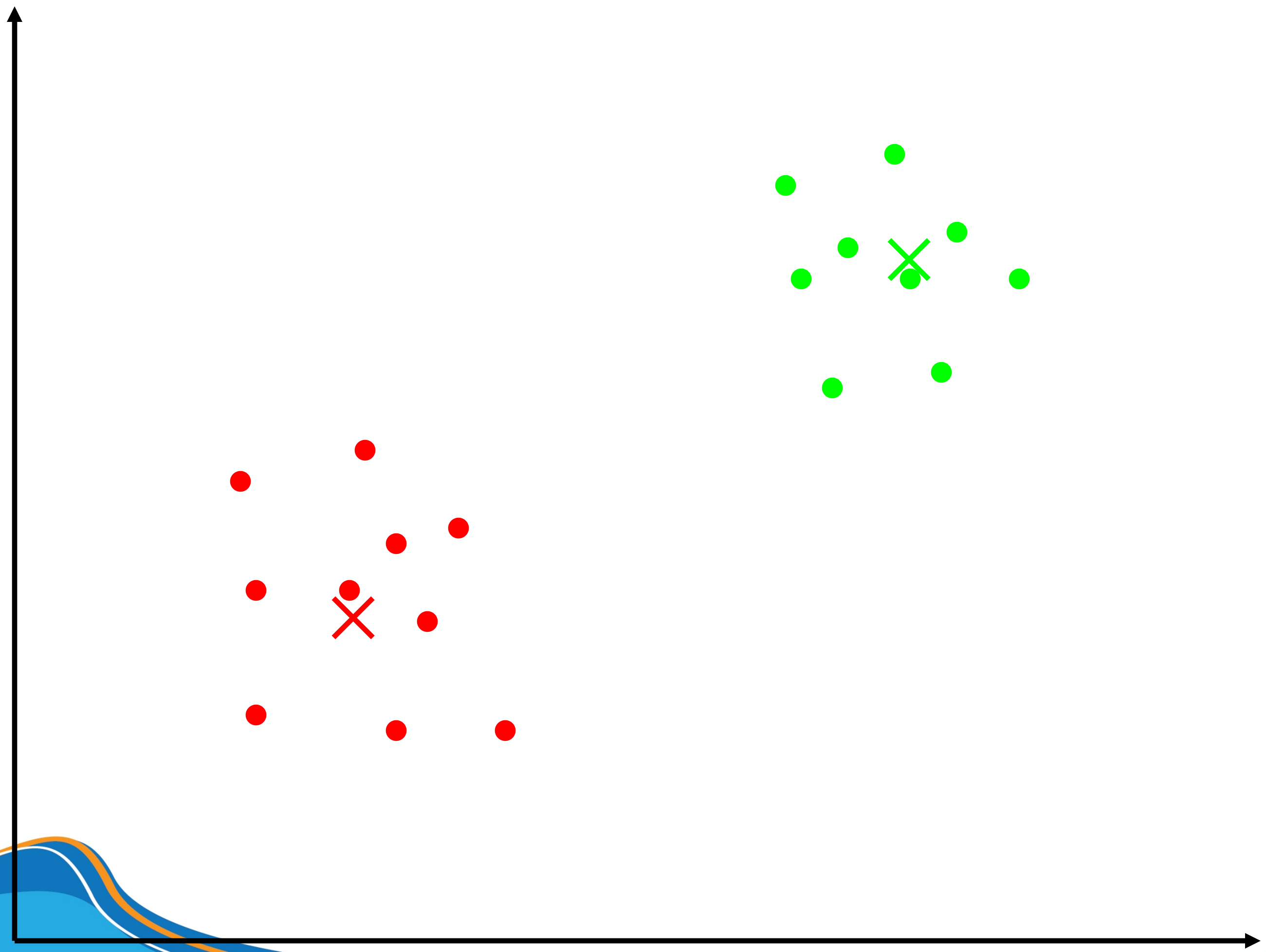
9.2. Method

9.2.2. K-means method



9.2. Method

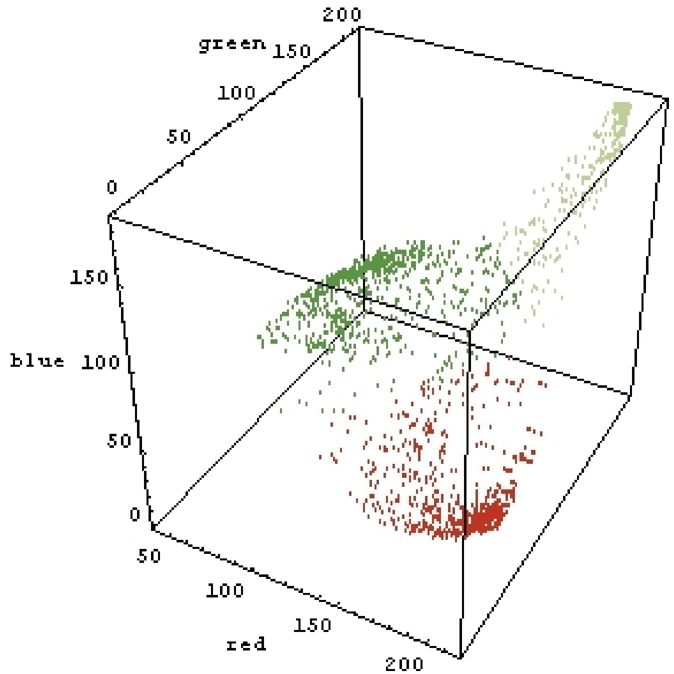
9.2.2. K-means method



9.2. Method

9.2.2. K-means method

- RGB vector



K-means clustering minimizes

$$\sum_{i \in \text{clusters}} \left\{ \sum_{j \in \text{elements of i'th cluster}} \left\| x_j - \mu_i \right\|^2 \right\}$$

9.2. Method

9.2.2. K-means method

- Example

Original

K=5

K=11

9.2. Method

9.2.2. K-means method

Algorithm

$Function\ \ K-means()$

$Initialize\ k$ prototypes $(w_1,...,w_k)$ such that $w_j = i_l,\ \mathrm{j} \in \{1,...,\mathrm{k}\}, \mathrm{l} \in \{1,...,\mathrm{n}\}$

Each cluster $\mathrm{C_j}$ is associated with prototype w_j

Repeat

For each input vector i_l , where $\mathrm{l} \in \{1,...,\mathrm{n}\}$,

do

Assign i_l to cluster $\mathrm{C_{j*}}$ with nearest prototype w_{j*}

For each cluster $\mathrm{C_j}$, where $\mathrm{j} \in \{1,...,\mathrm{k}\}$, do

Update the prototype w_j to the centroid of all samples

currently in $\mathrm{C_j}$, so that $w_j = \sum_{i_l \in \mathrm{C_j}} i_l / |\mathrm{C_j}|$

Computer the error function :

$$E = \sum_{j=1}^{k} \sum_{i_l \in \mathrm{C_j}} | i_l - w_j |^2$$

Until E does not change significantly or cluster membership

no longer changes