

# Machine Learning Course - CS-433 K-Means Clustering

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## Clustering

Clusters are groups of points whose inter-point distances are small compared to the distances outside the cluster.

The goal is to find "prototype" points  $\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \dots, \boldsymbol{\mu}_K$  and cluster assignments  $z_n \in \{1, 2, \dots, K\}$  for all  $n = 1, 2, \dots, N$  data vectors  $\mathbf{x}_n \in \mathbb{R}^D$ .

## K-means clustering

Assume  $K$  is known.

$$\min_{\mathbf{z}, \boldsymbol{\mu}} \mathcal{L}(\mathbf{z}, \boldsymbol{\mu}) = \sum_{n=1}^N \sum_{k=1}^K z_{nk} \|\mathbf{x}_n - \boldsymbol{\mu}_k\|_2^2$$

s.t.  $\boldsymbol{\mu}_k \in \mathbb{R}^D, z_{nk} \in \{0, 1\}, \sum_{k=1}^K z_{nk} = 1$ ,  
where  $\mathbf{z}_n = [z_{n1}, z_{n2}, \dots, z_{nK}]^\top$

$$\mathbf{z} = [\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_N]^\top$$

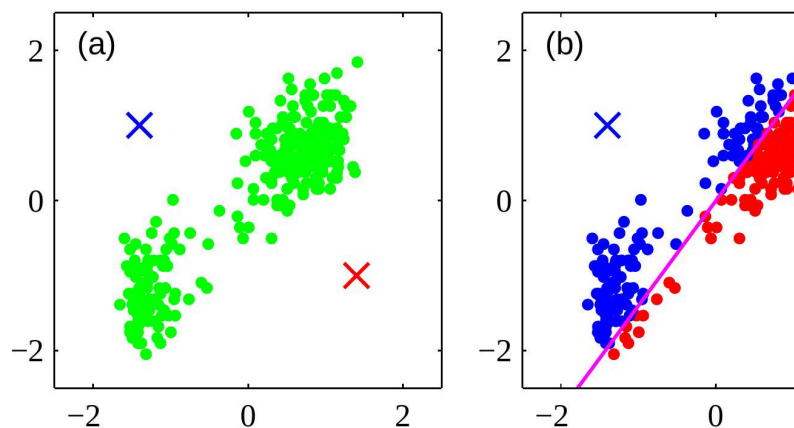
$$\boldsymbol{\mu} = [\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \dots, \boldsymbol{\mu}_K]^\top$$

Is this optimization problem easy?

Algorithm: Initialize  $\boldsymbol{\mu}_k \forall k$ ,

then iterate:

1. For all  $n$ , compute  $\mathbf{z}_n$  given  $\boldsymbol{\mu}$ .
2. For all  $k$ , compute  $\boldsymbol{\mu}_k$  given  $\mathbf{z}$ .



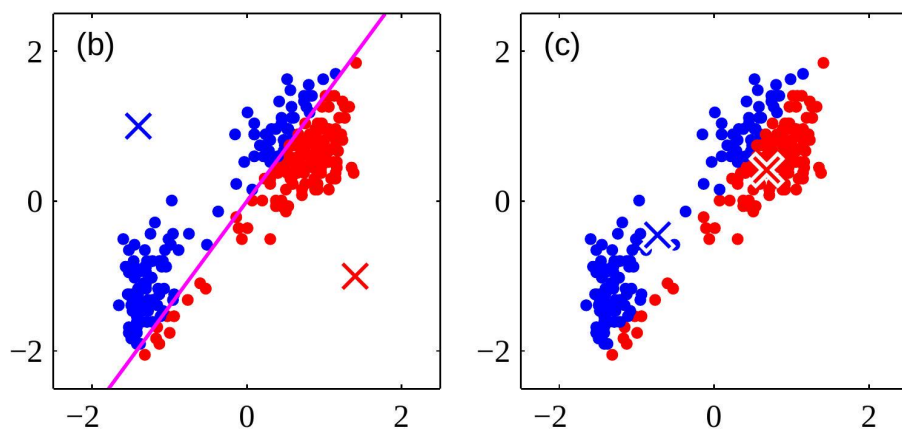
Step 1: For all  $n$ , compute  $\mathbf{z}_n$  given  $\boldsymbol{\mu}$ .

$$z_{nk} = \begin{cases} 1 & \text{if } k = \arg \min_{j=1,2,\dots,K} \|\mathbf{x}_n - \boldsymbol{\mu}_j\|_2^2 \\ 0 & \text{otherwise} \end{cases}$$

Step 2: For all  $k$ , compute  $\boldsymbol{\mu}_k$  given  $\mathbf{z}$ .

Take derivative w.r.t.  $\boldsymbol{\mu}_k$  to get:

$$\boldsymbol{\mu}_k = \frac{\sum_{n=1}^N z_{nk} \mathbf{x}_n}{\sum_{n=1}^N z_{nk}}$$



Hence, the name 'K-means'.

## Summary of K-means

Initialize  $\boldsymbol{\mu}_k \forall k$ , then iterate:

1. For all  $n$ , compute  $\mathbf{z}_n$  given  $\boldsymbol{\mu}$ .

$$z_{nk} = \begin{cases} 1 & \text{if } k = \arg \min_j \|\mathbf{x}_n - \boldsymbol{\mu}_j\|_2^2 \\ 0 & \text{otherwise} \end{cases}$$

2. For all  $k$ , compute  $\boldsymbol{\mu}_k$  given  $\mathbf{z}$ .

$$\boldsymbol{\mu}_k = \frac{\sum_{n=1}^N z_{nk} \mathbf{x}_n}{\sum_{n=1}^N z_{nk}}$$

Convergence to a local optimum is assured since each step decreases the cost (see Bishop, Exercise 9.1).

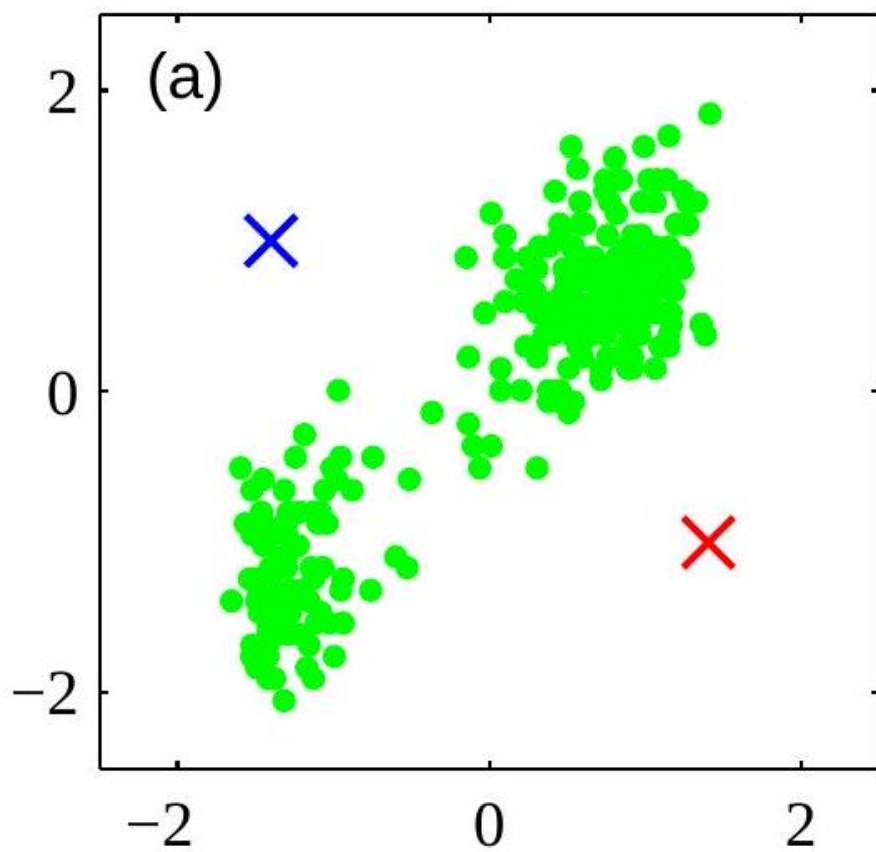
## Coordinate descent

K-means is a coordinate descent algorithm, where, to find  $\min_{\mathbf{z}, \boldsymbol{\mu}} \mathcal{L}(\mathbf{z}, \boldsymbol{\mu})$ , we start with some  $\boldsymbol{\mu}^{(0)}$  and repeat the following:

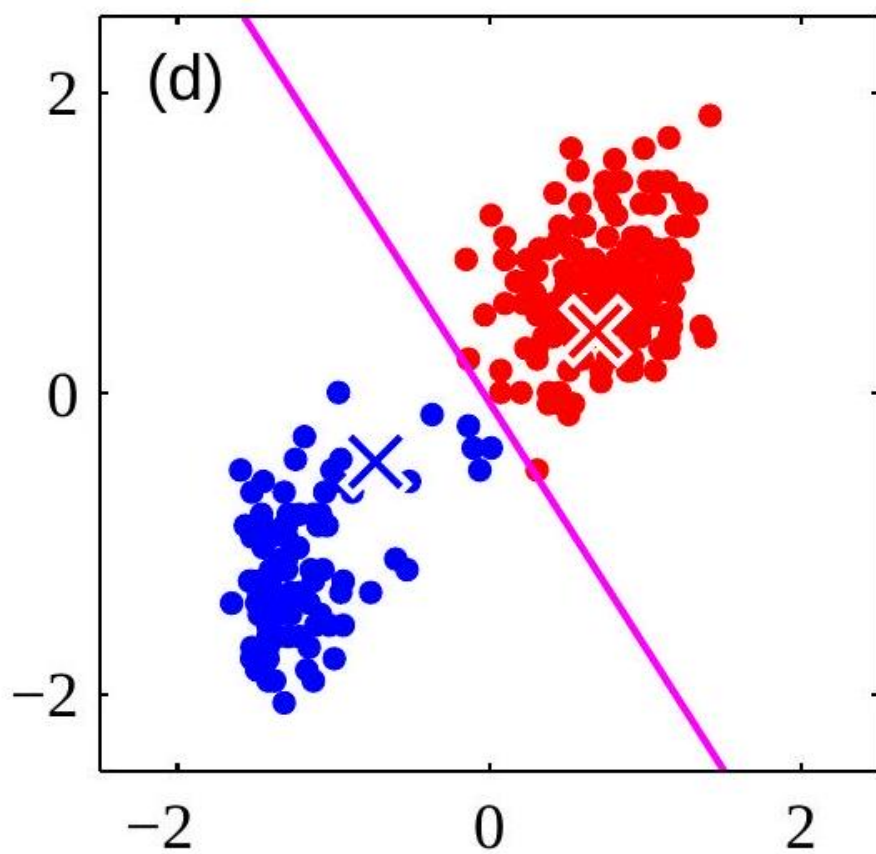
$$\begin{aligned}\mathbf{z}^{(t+1)} &:= \arg \min_{\mathbf{z}} \mathcal{L}(\mathbf{z}, \boldsymbol{\mu}^{(t)}) \\ \boldsymbol{\mu}^{(t+1)} &:= \arg \min_{\boldsymbol{\mu}} \mathcal{L}(\mathbf{z}^{(t+1)}, \boldsymbol{\mu})\end{aligned}$$

## Examples

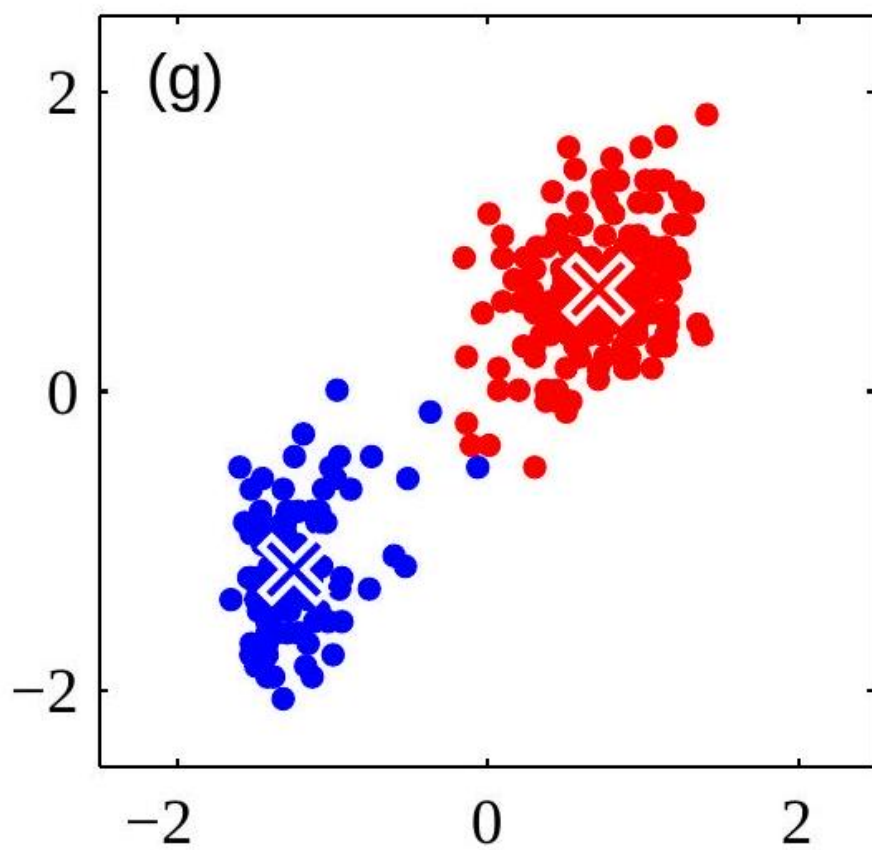
K-means for the "old-faithful" dataset (Bishop's Figure 9.1)



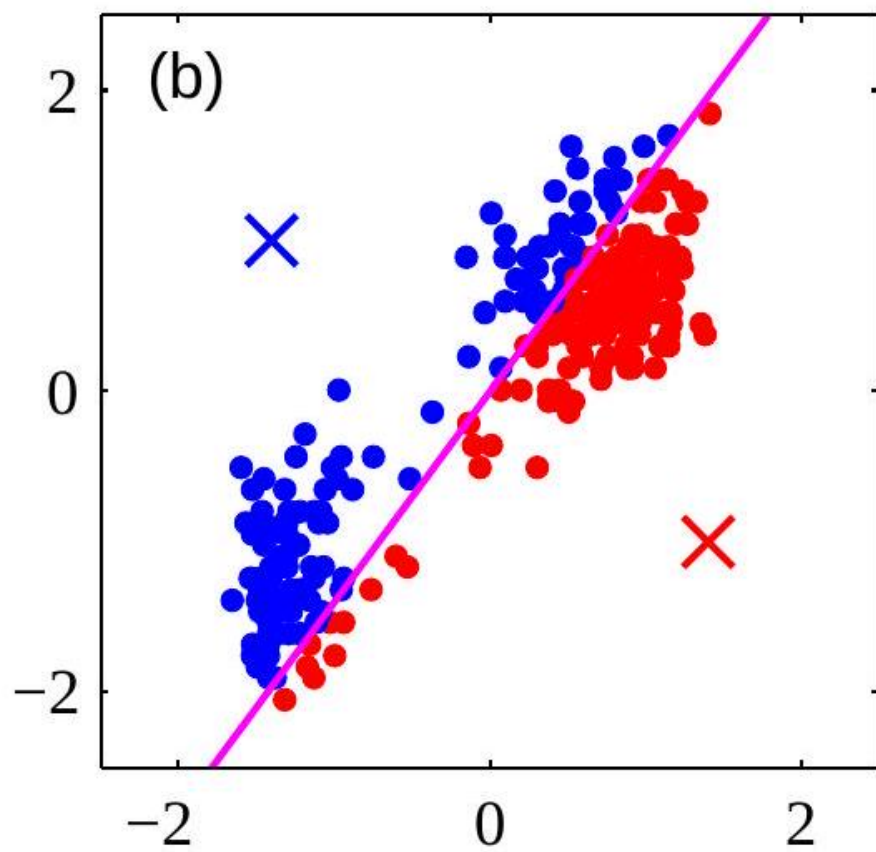
(e) Iteration 0



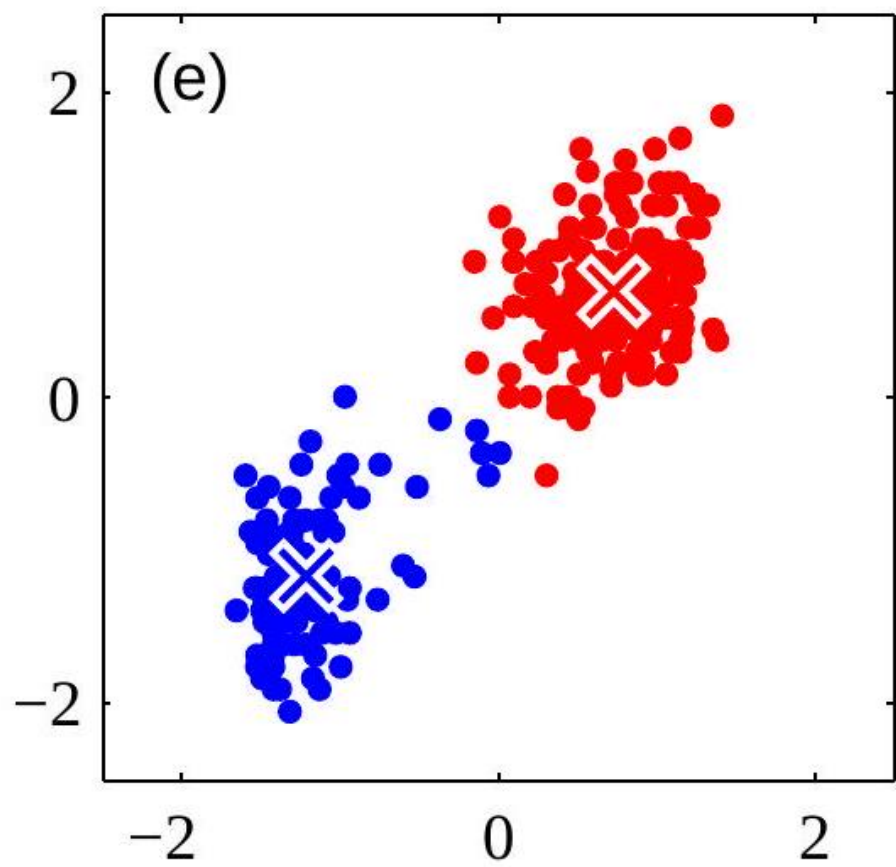
(h) Iteration 2



(k) Iteration 3

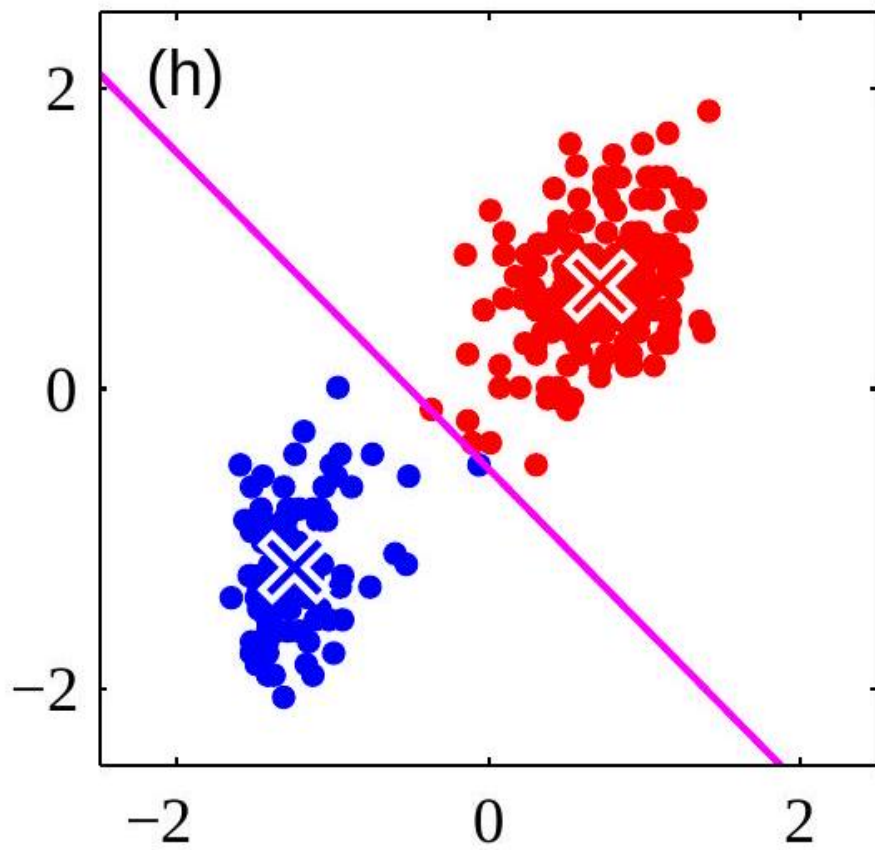


(f) Iteration 1

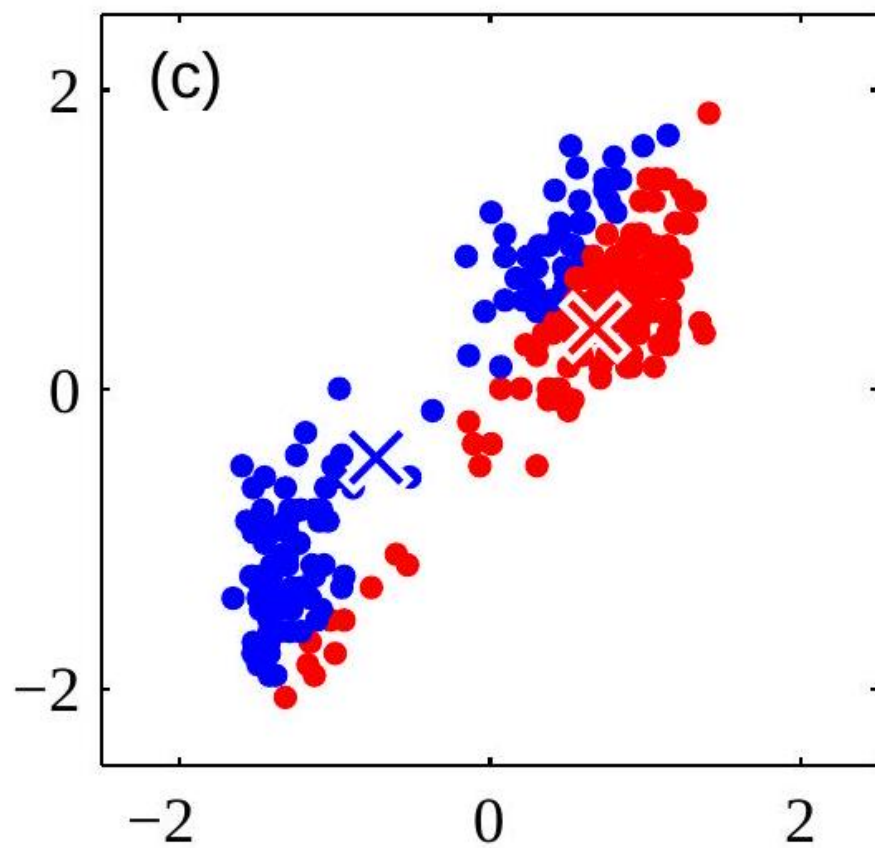


(i) Iteration 2

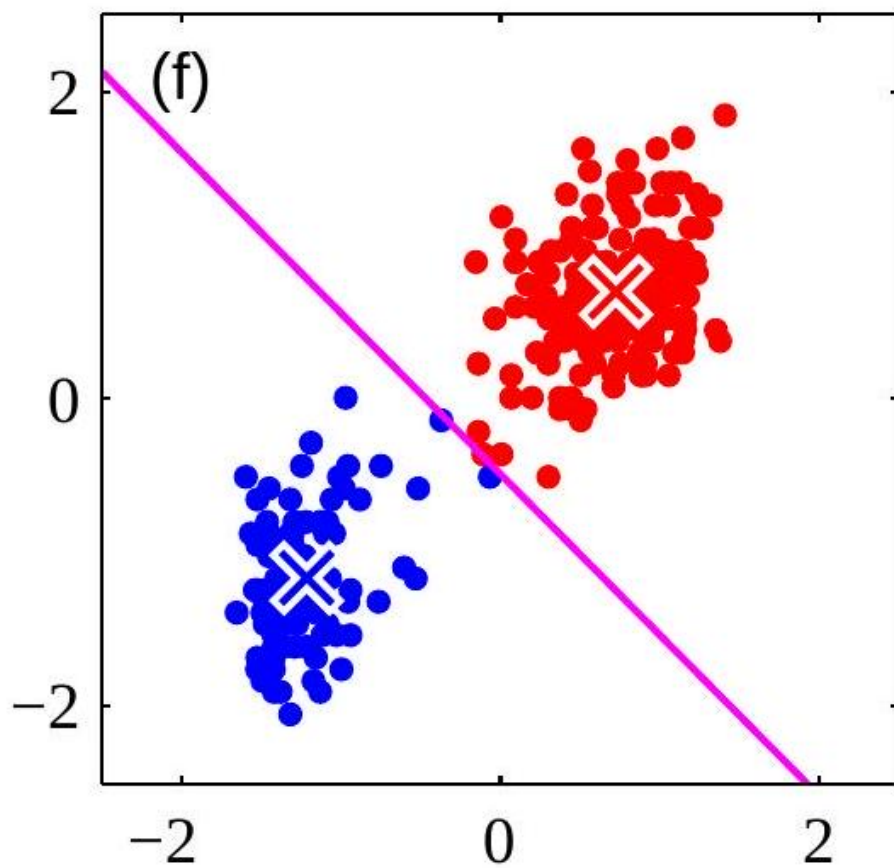




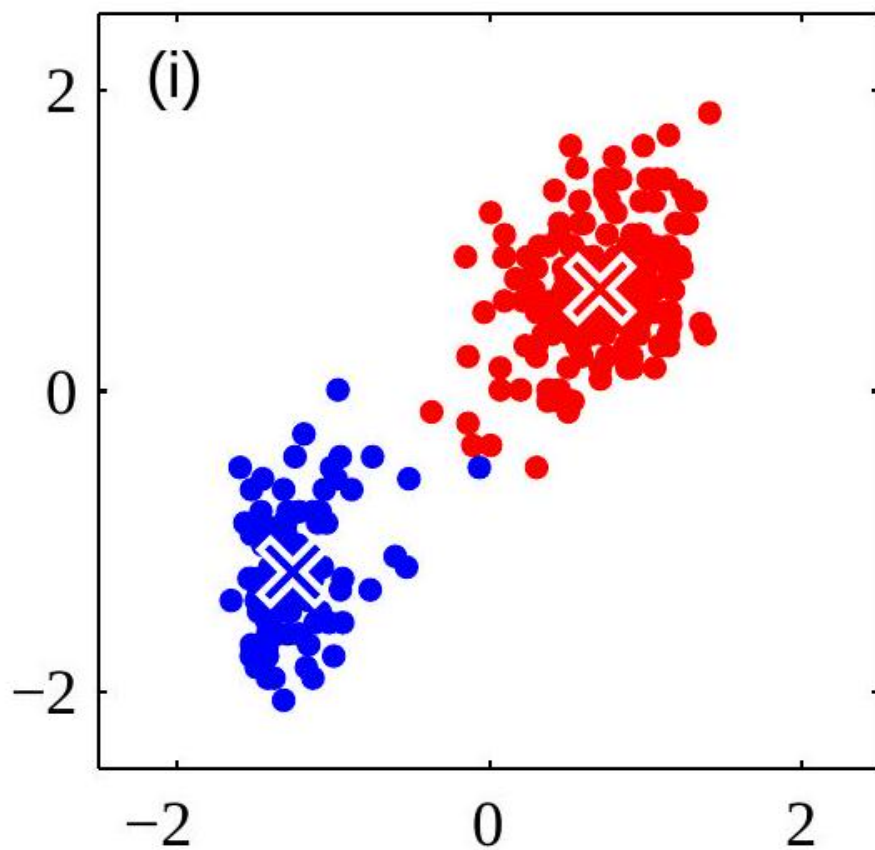
(l) Iteration 4



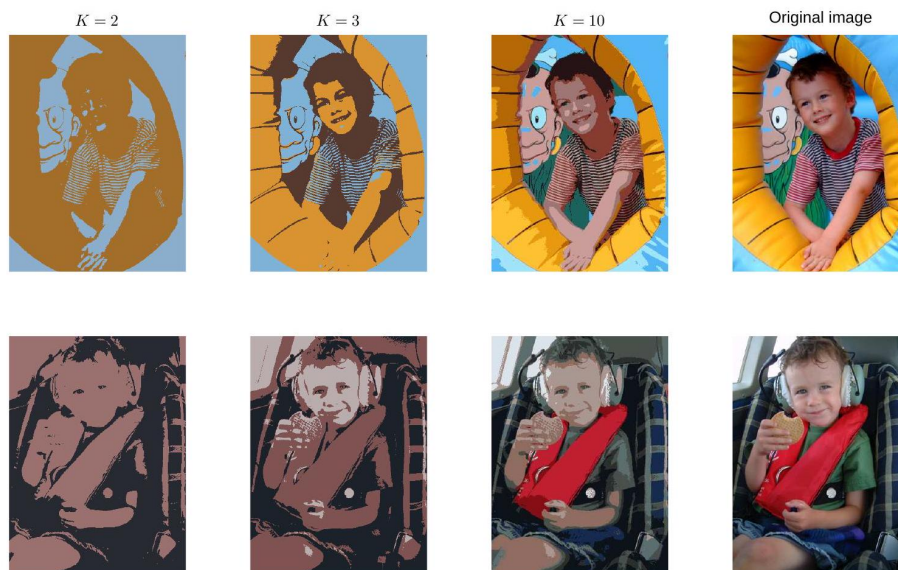
(g) Iteration 1



(j) Iteration 3



(m) Iteration 4  
Data compression for images (this is also known as vector quantization).



## Probabilistic model for K-means

### K-means as a Matrix Factorization

Recall the objective

$$\begin{aligned} \min_{\mathbf{z}, \boldsymbol{\mu}} \mathcal{L}(\mathbf{z}, \boldsymbol{\mu}) &= \sum_{n=1}^N \sum_{k=1}^K z_{nk} \|\mathbf{x}_n - \boldsymbol{\mu}_k\|_2^2 \\ &= \|\mathbf{X}^\top - \mathbf{M}\mathbf{Z}^\top\|_{\text{Frob}}^2 \\ \text{s.t. } \boldsymbol{\mu}_k &\in \mathbb{R}^D, \end{aligned}$$

$$z_{nk} \in \{0, 1\}, \sum_{k=1}^K z_{nk} = 1$$

### Issues with K-means

1. Computation can be heavy for large  $N, D$  and  $K$ .
2. Clusters are forced to be spherical (e.g. cannot be elliptical).
3. Each example can belong to only one cluster ("hard" cluster assignments).