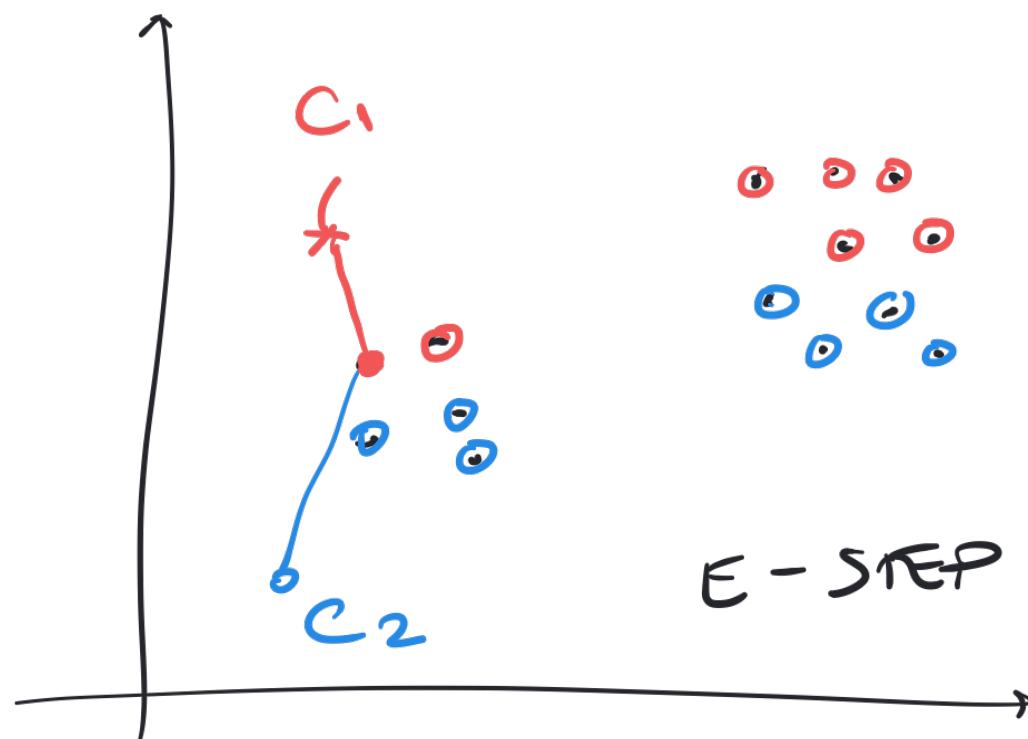


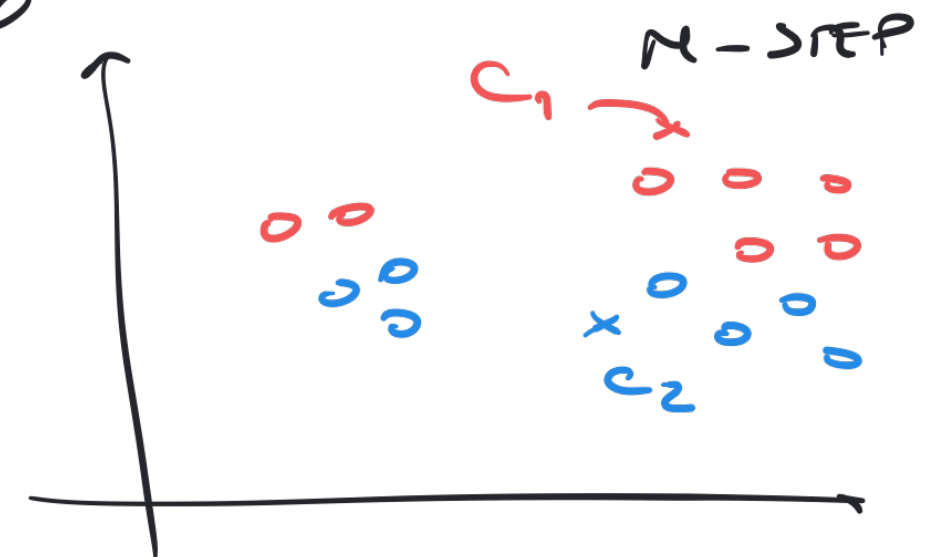
$K=2$



Clustering

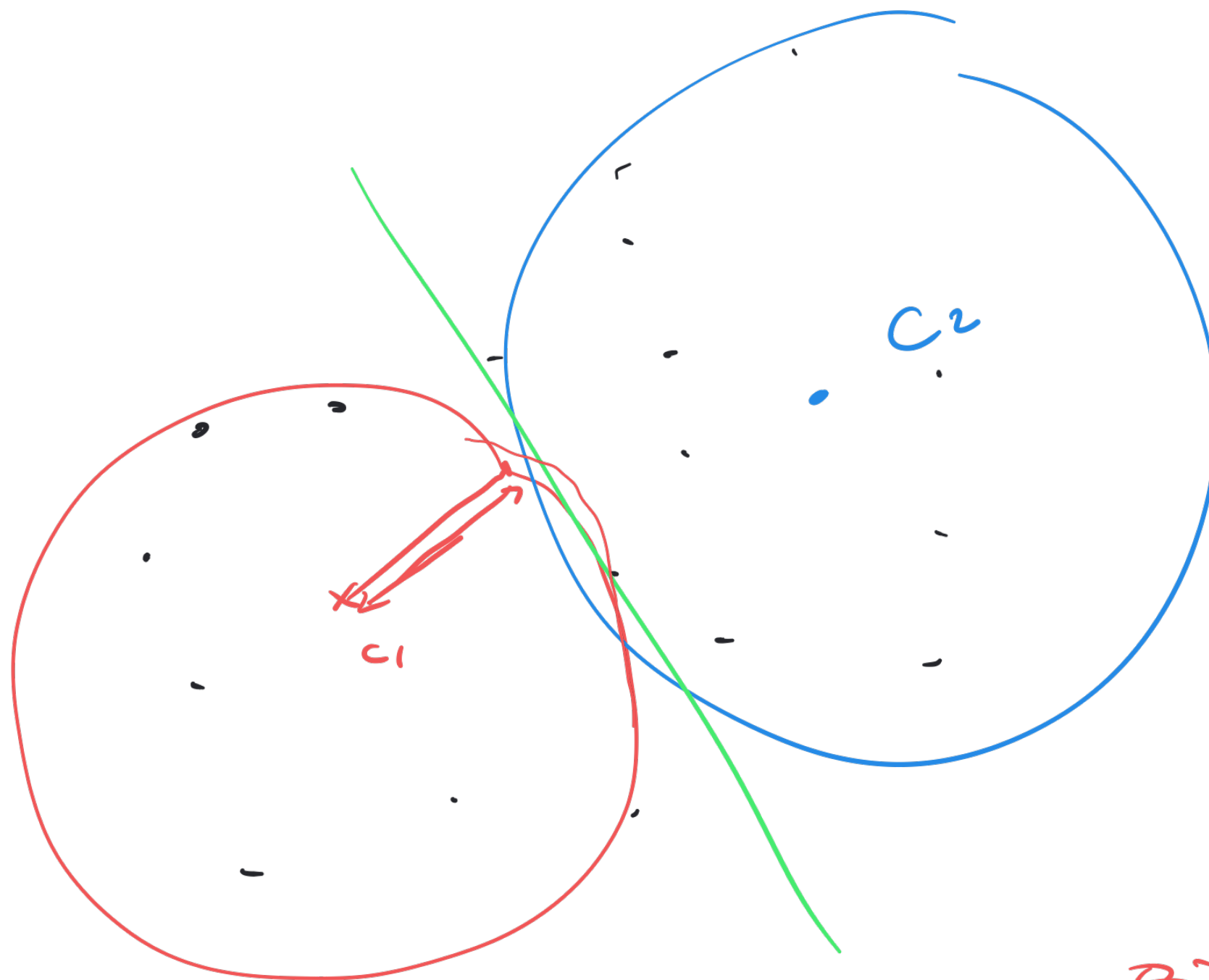
unsupervised learning

algorithm



K-Means Clustering

- K is the # of groups (hyperparameter)
- centroid-based clustering



when we use **Euclidean Distance** as similarity measure, clusters will be spherical / circular.

Other distance metrics:

- ① City-Block distance — measures dist. parallel to canonical axis
- ② Cosine distance — measures angle between samples.
- ③ Mahalanobis distance — introduces covariance

K-Means uses Alternating

Optimization which means

that its solution will depend

on initial conditions for C_K, μ_K .

Assignment in K-Means is known
as a **Hard Assignment**

So each point can only
belong to a single cluster

Membership Matrix : U , $N \times K$

$$U = \begin{matrix} & \begin{matrix} 1 & 2 & \dots & K \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ \vdots \\ N \end{matrix} & \begin{bmatrix} 0 & 1 & \dots & 0 \\ \hline & & & \end{bmatrix} \end{matrix}$$

$$\sum_{j=1}^K u_{ij} = 1, \forall i$$

Sparse
Matrix

$u_{ij} \equiv$ membership of point x_i
in cluster with centroid θ_j

$\theta_j \equiv$ centroid for cluster j

$d(x_i, \theta_j) \equiv$ distance between x_i and
 θ_j

e.g. Euclidean distance : $d(x_i, \theta_j) = \|x_i - \theta_j\|_2$
$$= \sqrt{\sum_{d=1}^D (x_{i(d)} - \theta_{j(d)})^2}$$

OBJECTIVE FUNCTION:

$$J(\theta, u) = \sum_{i=1}^N \sum_{j=1}^K u_{ij} \cdot d^2(x_i, \theta_j)$$

Constraints : $\sum_{j=1}^K u_{ij} = 1$ and $u_{ij} \in \{0, 1\}$

$$\arg \min_{\{\theta, u\}} J(\theta, u)$$