

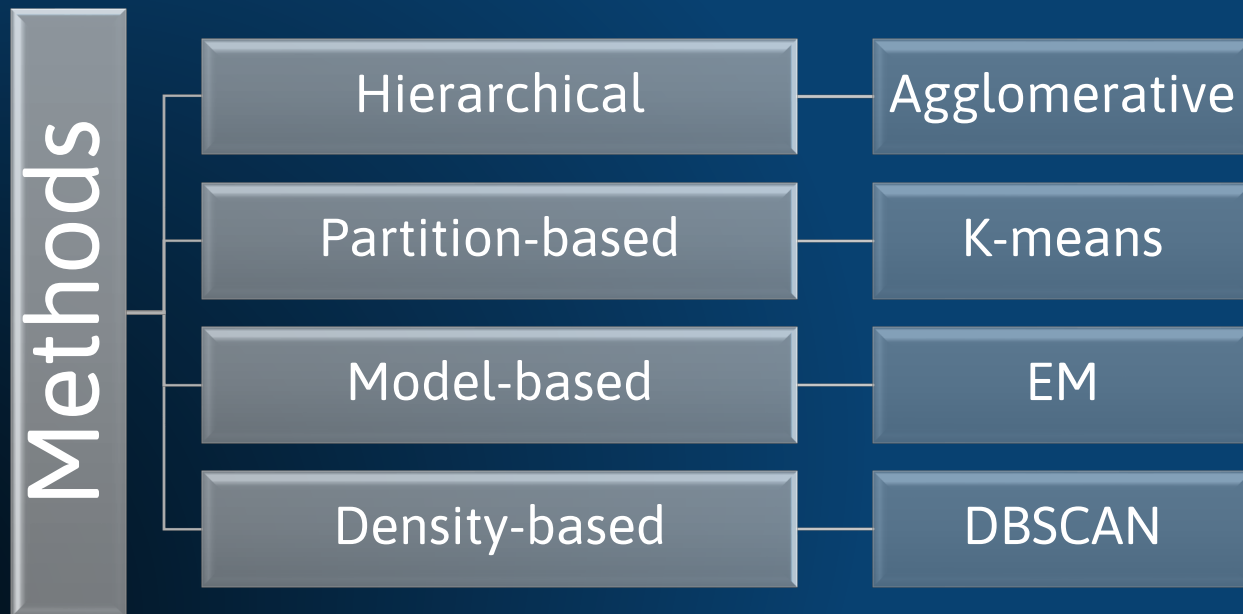
The background of the slide features a dark blue, almost black, field. On the left, a human hand is visible, with the index finger pointing towards the right. The hand is rendered in a realistic style with some lighting effects. Overlaid on the right side of the image is a complex, futuristic digital interface. This interface includes several concentric circles, some of which are filled with teal or light blue segments. There are also gear-like shapes, some of which are interlocking. The overall aesthetic is high-tech and digital, suggesting themes of data, technology, and algorithms.

Clustering Algorithms

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APPROACHES



Partitioning



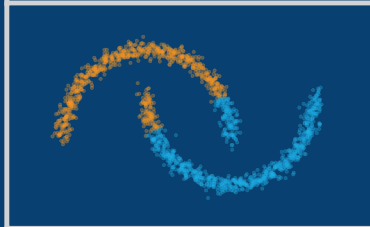
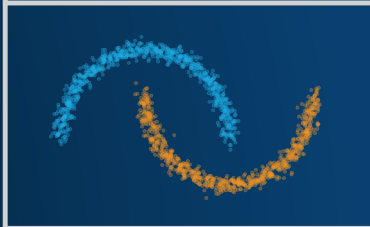
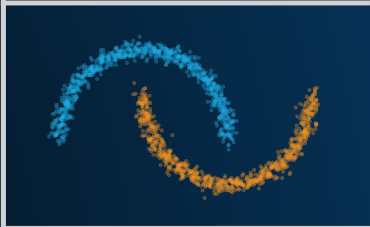
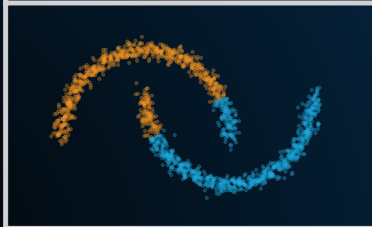
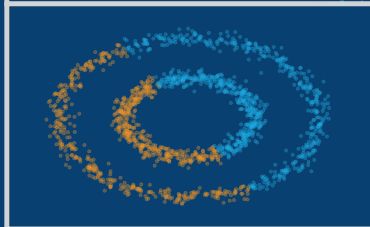
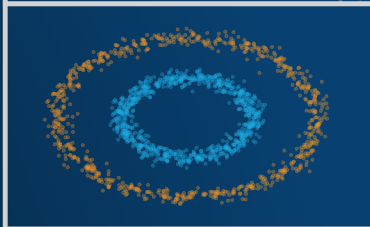
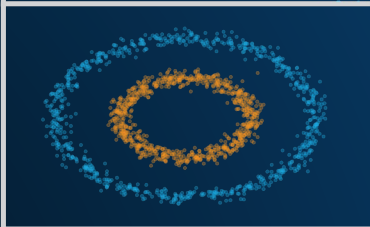
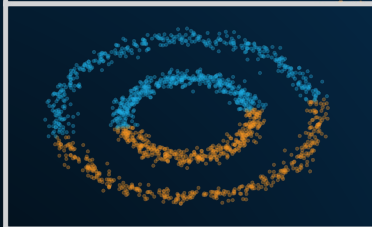
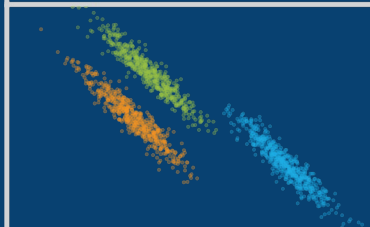
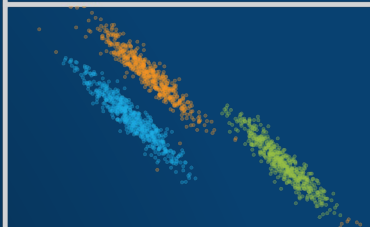
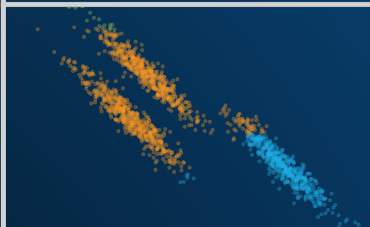
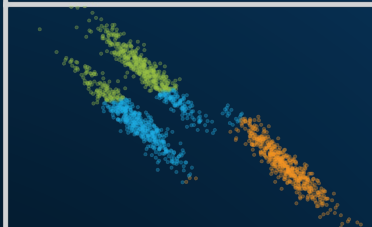
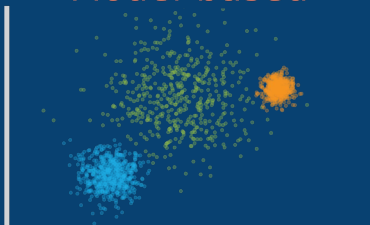
Hierarchical



Density



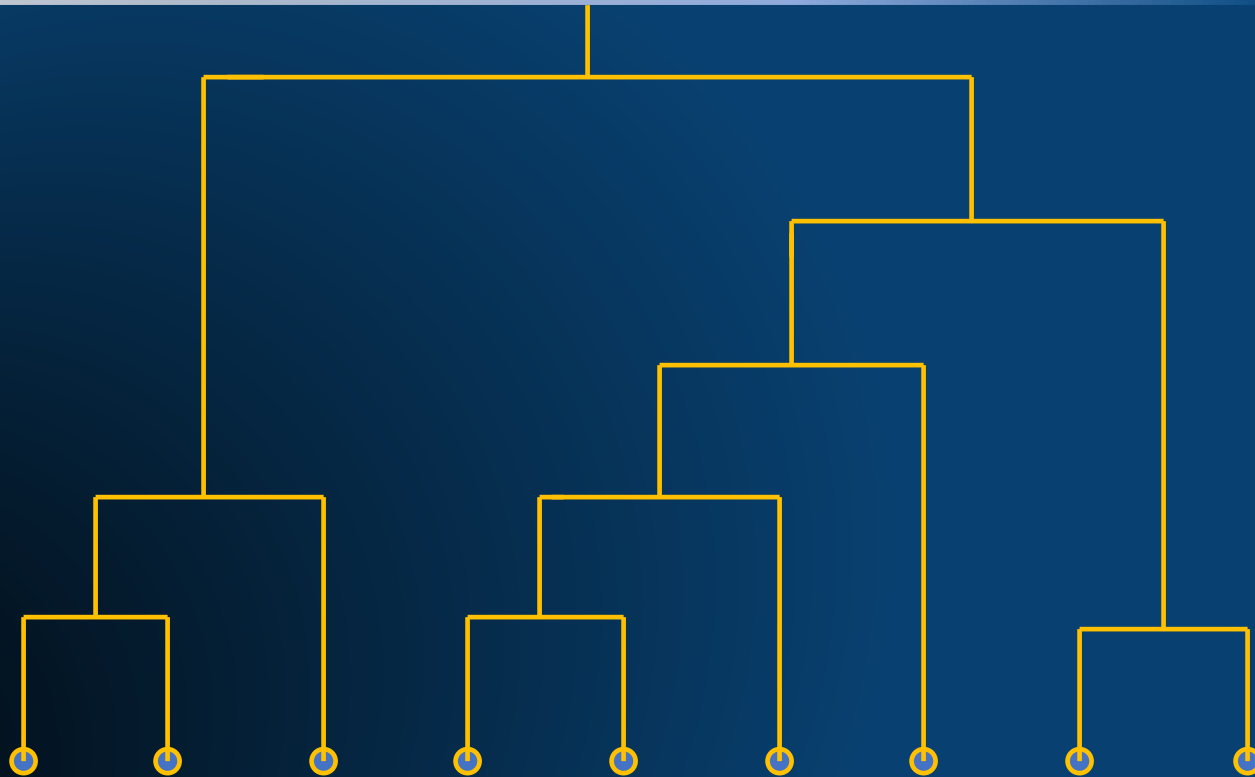
Model-based



Hierarchical Algorithms

Agglomerative

HIERARCHICAL METHODS

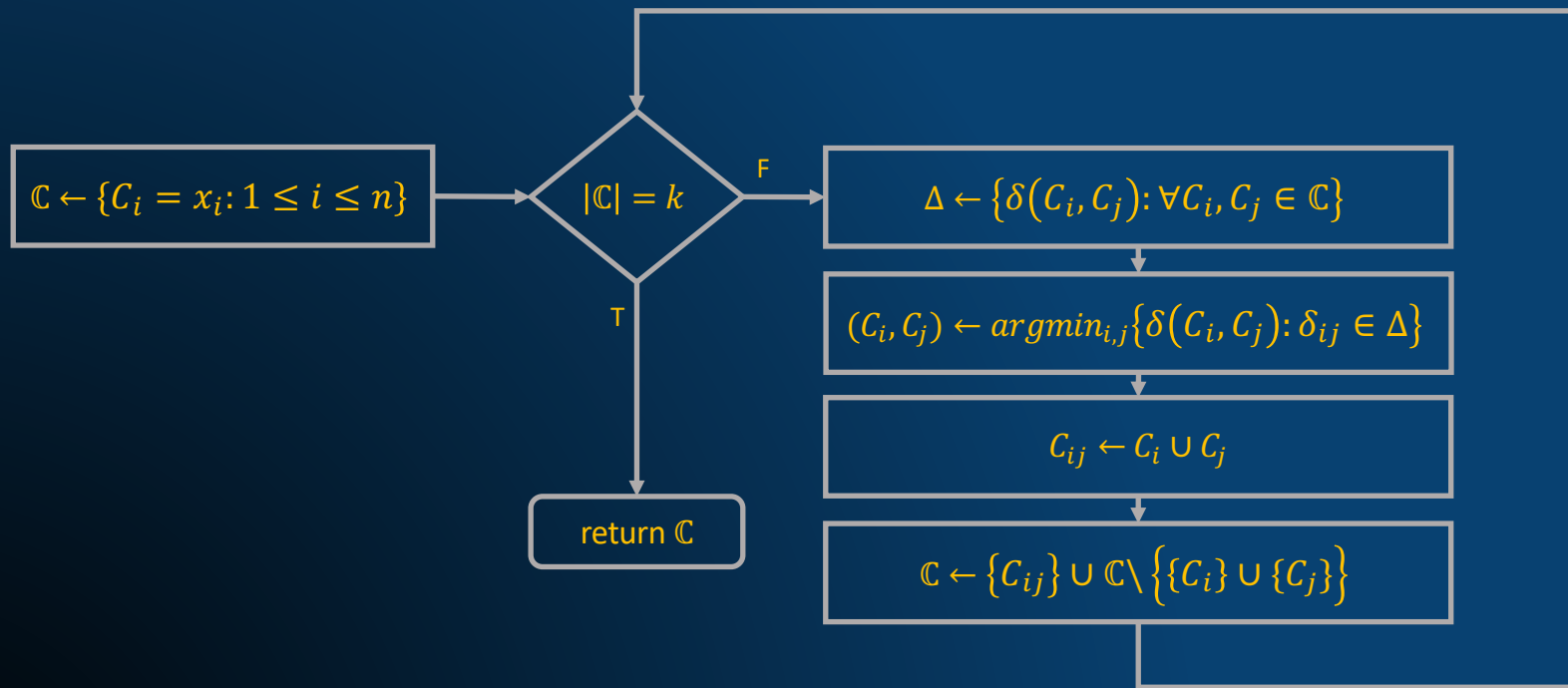


Agglomerative

Divisive

Input $D = \{x_1, \dots, x_n\}, k$

Output \mathbb{C}



Agglomerative Clustering (Dataset D , int k)



Put each record in a separate cluster

$\mathbb{C} \leftarrow \{C_i = x_i : x_i \in D\}$

while $|\mathbb{C}| \neq k$ **do**

Compute distance matrix

$\Delta \leftarrow \{\delta(C_i, C_j) : \forall C_i, C_j \in \mathbb{C}\}$

Find the closest pair of clusters

$(C_i, C_j) \leftarrow \operatorname{argmin}_{i,j} \{\delta(C_i, C_j) : \delta_{ij} \in \Delta\}$

Merge the clusters

$C_{ij} \leftarrow C_i \cup C_j$

Update the clustering partition

$\mathbb{C} \leftarrow \mathbb{C} \setminus \{\{C_i\} \cup \{C_j\}\} \cup \{C_{ij}\}$

return \mathbb{C}

Partition-Based Algorithms

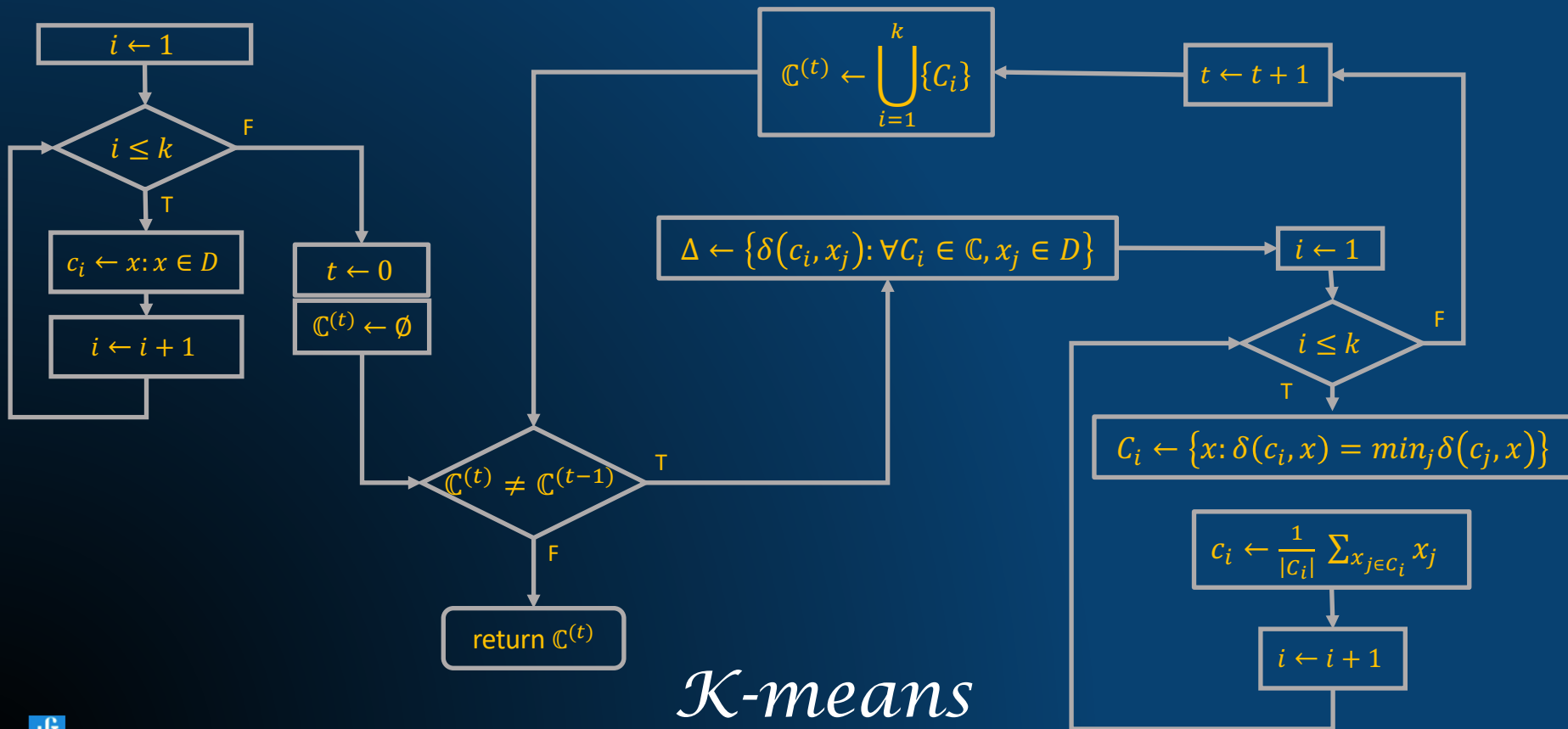
K-Means

PARTITION-BASED ALGORITHMS



Input $D = \{x_1, \dots, x_n\}, k, \xi$

Output \mathbb{C}



K-means

K-means Algorithm (Dataset D , int k , float ξ)

for each $i: 1 \leq i \leq k$ **do**

Choose a centroid for each cluster

$c_i \leftarrow \text{random}(x): x \in D$

$t \leftarrow 0$

$\mathbb{C}^{(0)} \leftarrow \emptyset$

do

$\Delta \leftarrow \{\delta(c_i, x_j): \forall C_i \in \mathbb{C}, x_j \in D\}$

Compute distance for each (record, centroid)

for each $i: 1 \leq i \leq k$ **do**

$C_i \leftarrow \{x: \delta(c_i, x) = \min_j \delta(c_j, x)\}$ *# Assign each record to the closest cluster*

$c_i \leftarrow \frac{1}{|C_i|} \sum_{x_j \in C_i} x_j$

Update the centroids

$\mathbb{C}^{(t)} \leftarrow \bigcup_{i=1}^k \{C_i\}$

until $\|\mathbb{C}^{(t)} - \mathbb{C}^{(t-1)}\| \leq \xi$

return \mathbb{C}

Model-based Algorithms

Expectation Maximization

MIXTURE MODELS

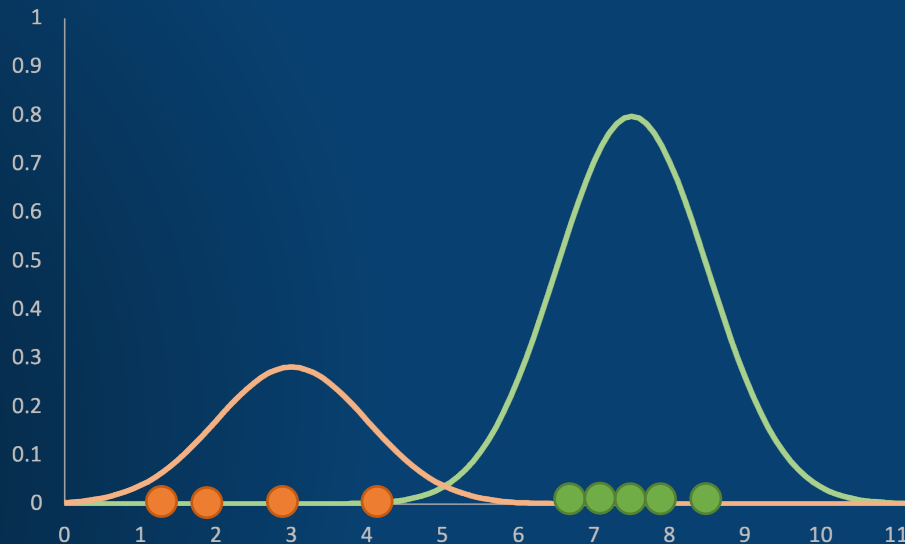


Mixture of models given by

$$P(x) = \sum_{i=1}^k P(C = i)P(x|C = i)$$

$$1 = \sum_{i=1}^k P(C = i)$$

Find a set C of k probabilistic clusters
where $P(D|C)$ is **maximized**

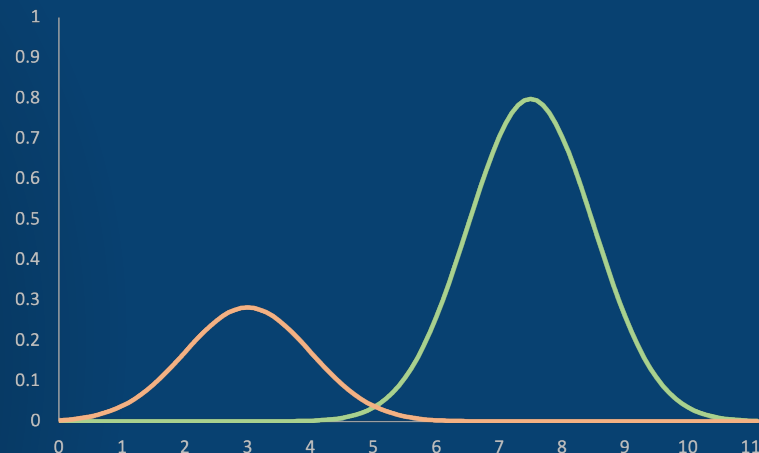


GAUSSIAN MIXTURE MODEL

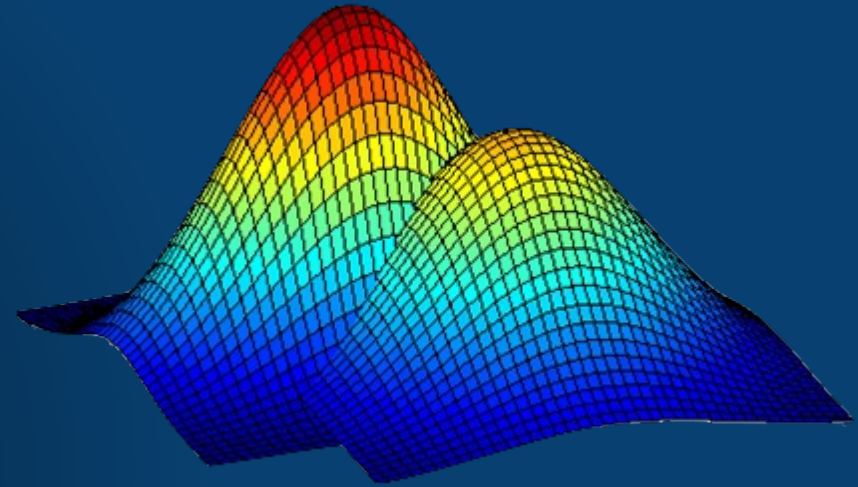


In \mathbb{R} :

$$C_i \sim \mathcal{N}(\mu_i, \sigma_i)$$
$$f_i(x) = f(x|\mu_i, \sigma_i) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu_i)^2}{2\sigma^2}}$$



GAUSSIAN MIXTURE MODEL



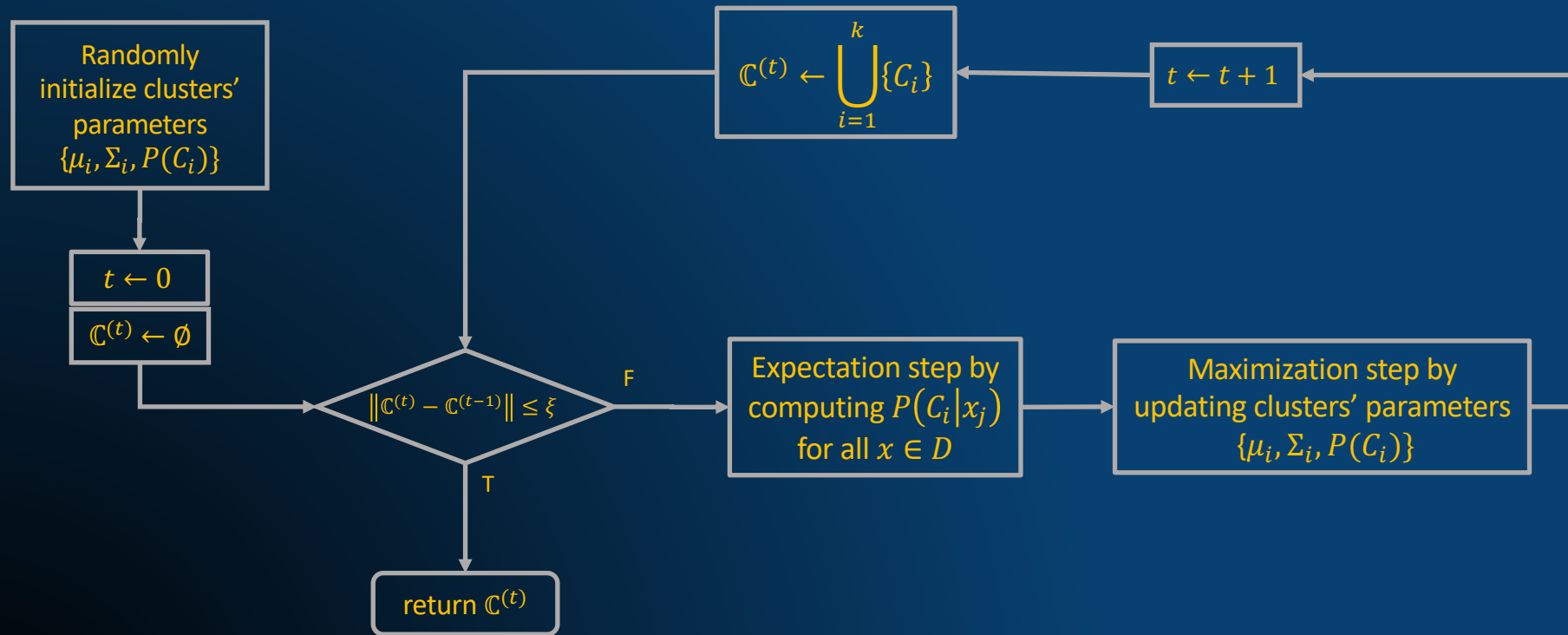
In \mathbb{R}^d :

$$C_i \sim \mathcal{N}(\mu_i, \Sigma_i)$$

$$f_i(x) = f(x|\mu_i, \Sigma_i) = \frac{1}{\sqrt{2\pi^d |\Sigma|}} e^{-\frac{(x-\mu_i)^T \Sigma_i^{-1} (x-\mu_i)}{2}}$$

Input $D = \{x_1, \dots, x_n\}, k, \xi$

Output \mathbb{C}



Expectation-Maximization

EM Algorithm (Dataset D, int k, float ξ)

$t \leftarrow 0$

for each $i: 1 \leq i \leq k$ **do**

Clusters initialization

$\mu_i^t \leftarrow \text{random}()$

$\Sigma_i^t \leftarrow \mathbb{I}$

$P^t(C_i) \leftarrow \frac{1}{k}$

do

$t \leftarrow t + 1$

for $i = 1 \dots k$ **and** $j = 1 \dots n$ **do**

Expectation step

$$w_{ij} \leftarrow \frac{f(x_j | \mu_i, \Sigma_i)^{P(C_i)}}{\sum_{a=1}^k f(x_j | \mu_a, \Sigma_a)^{P(C_a)}}$$

$w_{ij} = P(C_i | x_j)$

for $i = 1 \dots k$ **do**

Maximization step

$$\mu_i^t \leftarrow \frac{\sum_{j=1}^n w_{ij} x_j}{\sum_{j=1}^n w_{ij}}$$

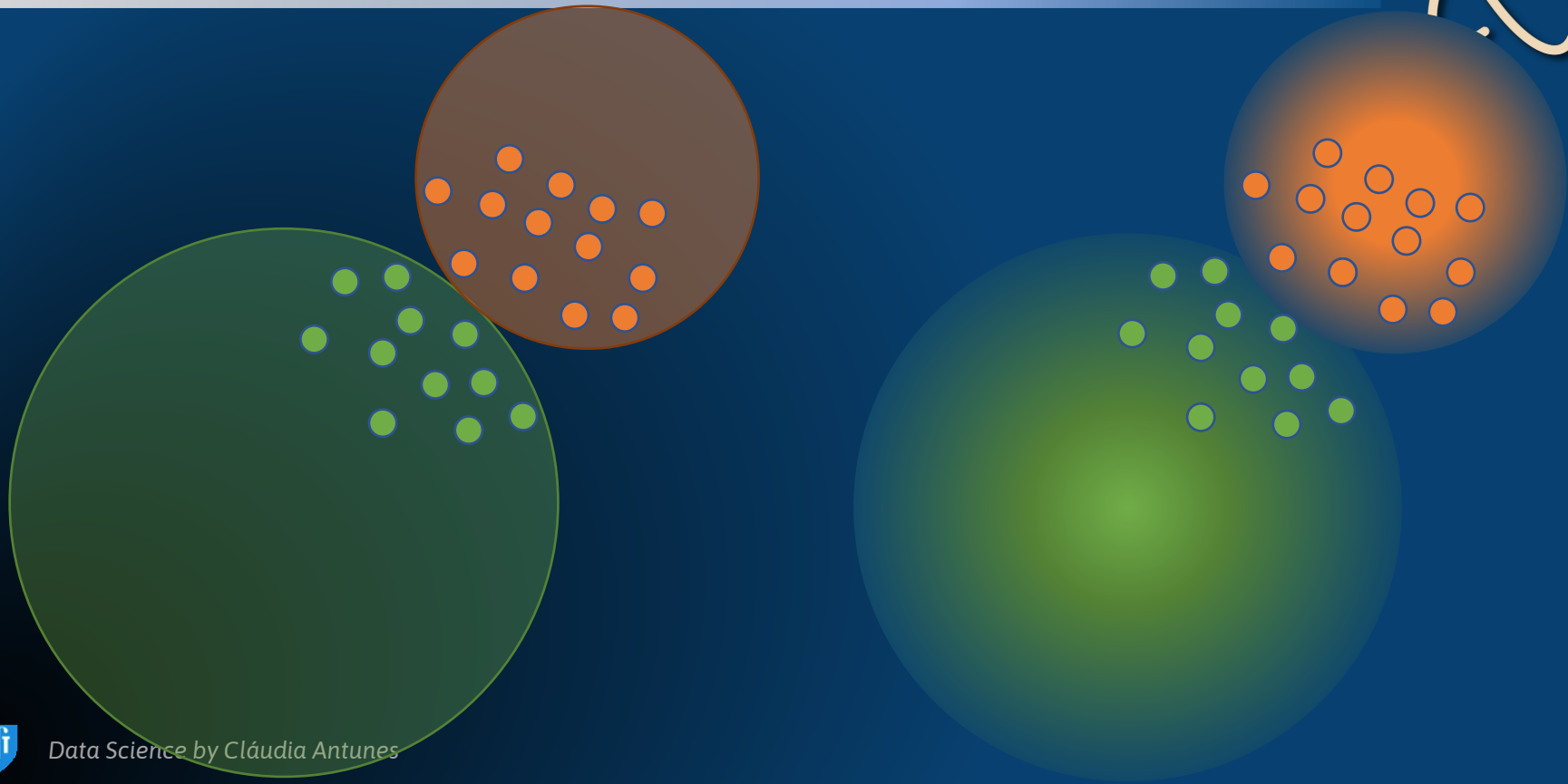
$$\Sigma_i^t \leftarrow \frac{\sum_{j=1}^n w_{ij} (x_j - \mu_i)(x_j - \mu_i)^T}{\sum_{j=1}^n w_{ij}}$$

$$P^t(C_i) \leftarrow \frac{\sum_{j=1}^n w_{ij}}{N}$$

until $\sum_{i=1}^k \|\mu_i^t - \mu_i^{t-1}\|^2 \leq \xi$

return $\cup_{i=1}^k \{C_i\}$

SOFT X HARD CLUSTERS



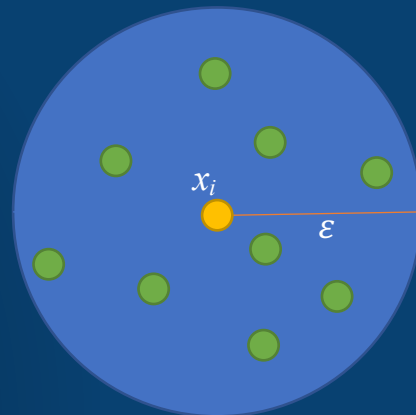
Density-based

DBSCAN

ε – neighborhood



$$x \in Core \leftrightarrow |N_\varepsilon(x)| \geq minpts$$



$$N_\varepsilon(x) \leftarrow \{x' : x' \in D \wedge \delta(x, x') \leq \varepsilon\}$$

ε – neighborhood

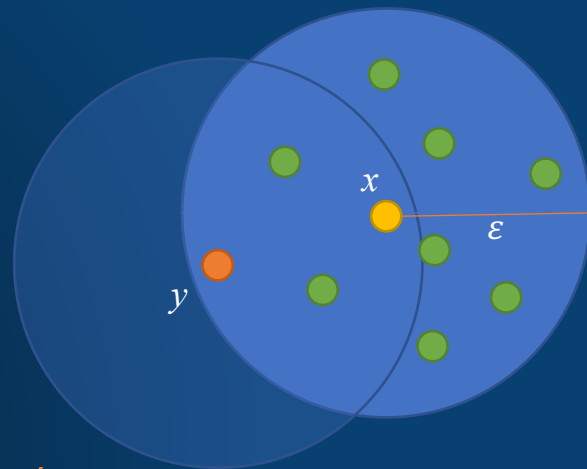


$$x \in Core \leftrightarrow |N_\varepsilon(x)| \geq minpts$$

$$y \in Border$$



$$\exists x \in Core: y \in N_\varepsilon(x) \wedge |N_\varepsilon(y)| < minpts$$

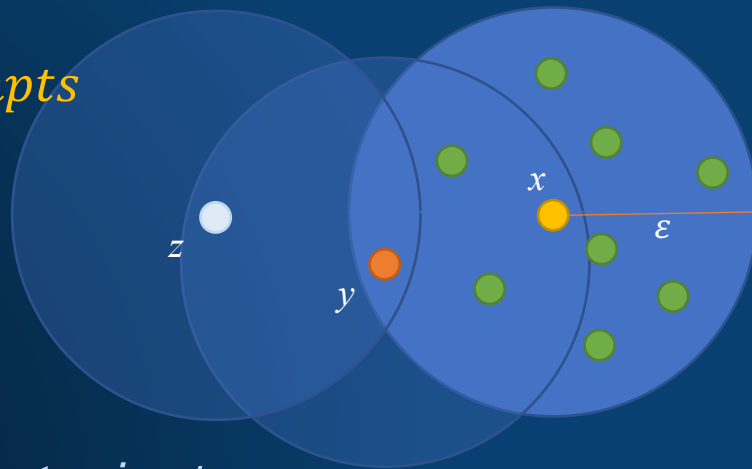


$$N_\varepsilon(x) \leftarrow \{x' : x' \in D \wedge \delta(x, x') \leq \varepsilon\}$$

ε – neighborhood



$$x \in \text{Core} \leftrightarrow |N_\varepsilon(x)| \geq \text{minpts}$$



$$z \in \text{Noise}$$



$$\nexists x \in \text{Core}: z \in N_\varepsilon(x) \wedge |N_\varepsilon(z)| < \text{minpts}$$

$$N_\varepsilon(x) \leftarrow \{x' : x' \in D \wedge \delta(x, x') \leq \varepsilon\}$$

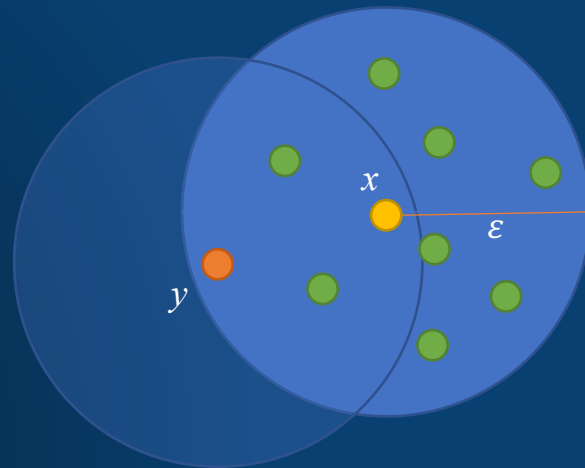
DIRECTLY DENSITY REACHABLE



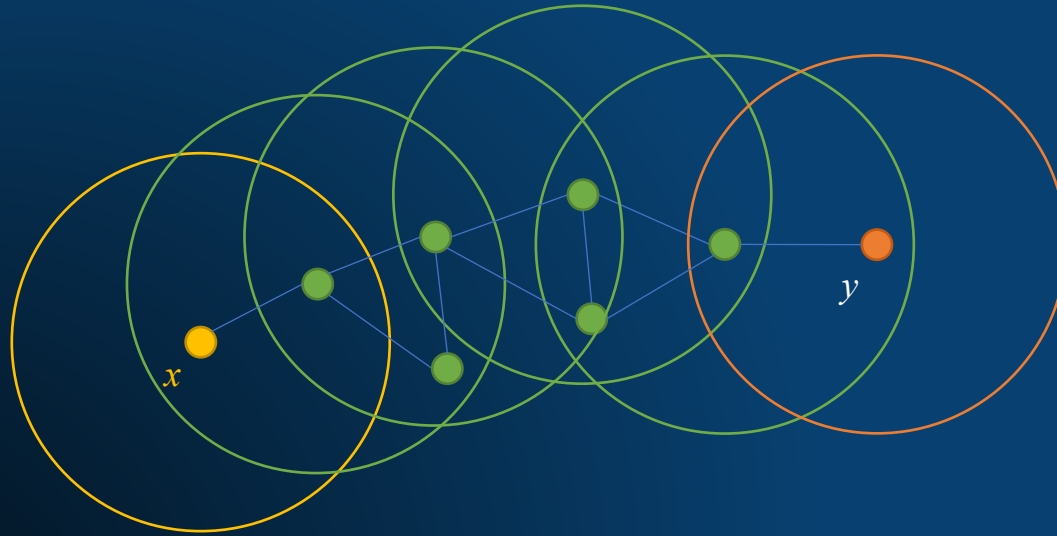
y is directly density reachable by x



$$y \in N_{\varepsilon}(x) \wedge x \in Core$$



DENSITY REACHABLE

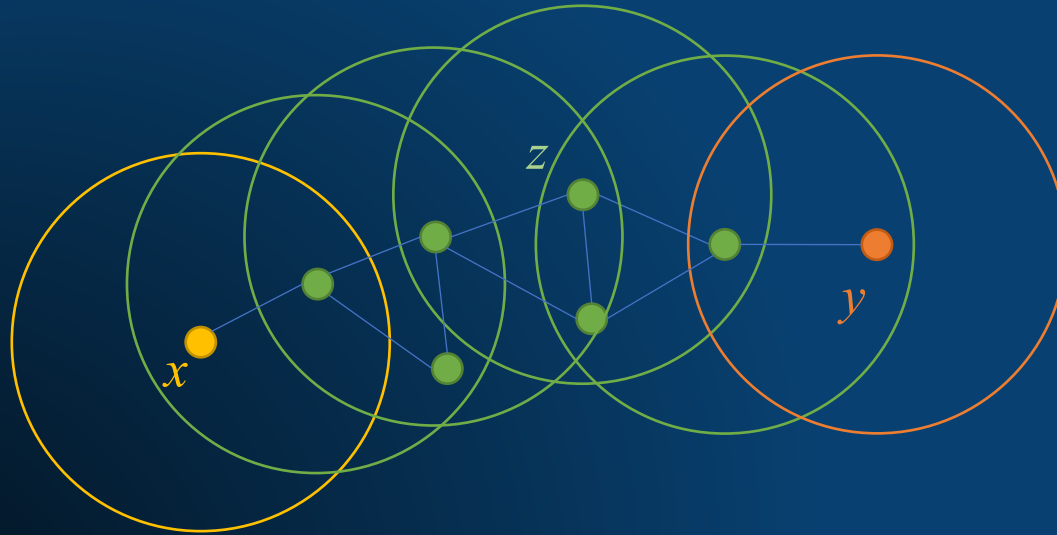


x is density reachable by y



$$\exists x_0 \dots x_m: x = x_0 \wedge y = x_m \wedge x_i \text{ is density reachable by } x_{i-1} \forall 0 \leq i \leq m$$

DENSITY CONNECTED

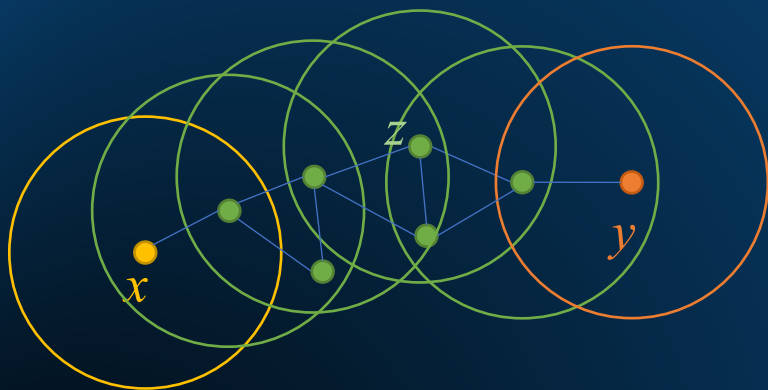


x is density connected to y



$\exists z \in \text{Core} \wedge x \text{ is density reachable by } z \wedge y \text{ is density reachable by } z$

DENSITY-BASED CLUSTER



A *density-based cluster* is a maximal set of density connected points.

DBSCAN Algorithm (Dataset D , float ε , int $minpts$)



$Core \leftarrow \emptyset$

for each $x_i \in D$ **do**

$N_\varepsilon(x_i) \leftarrow \{x' : x' \in D \wedge \delta(x_i, x') \leq \varepsilon\}$

$id(x_i) \leftarrow \emptyset$

if $|N_\varepsilon(x)| \geq minpts$ **then** $Core \leftarrow Core \cup \{x_i\}$

$k \leftarrow 0$

for each $x_i \in Core \wedge id(x_i) = \emptyset$ **do**

$k \leftarrow k + 1$

$id(x_i) \leftarrow k$

$DensityConnected(x_i, k)$

$\mathbb{C} \leftarrow \bigcup_{i=1}^k \{x : x \in D \wedge id(x) = i\}$

$Noise \leftarrow \{x : x \in D \wedge id(x) = \emptyset\}$

$Border \leftarrow D \setminus \{Core \cup Noise\}$

return $\mathbb{C}, Core, Border, Noise$

DensityConnected(x, k)

for each $y \in N_\varepsilon(x)$ **do**

$id(y) \leftarrow k$

if $|N_\varepsilon(x)|y \in Core$ **then**
 $DensityConnected(y, k)$



*Thank
you!*

