

Machine Learning I

60629A

Summary
Unsupervised Learning
– Week #7

1. Unsupervised

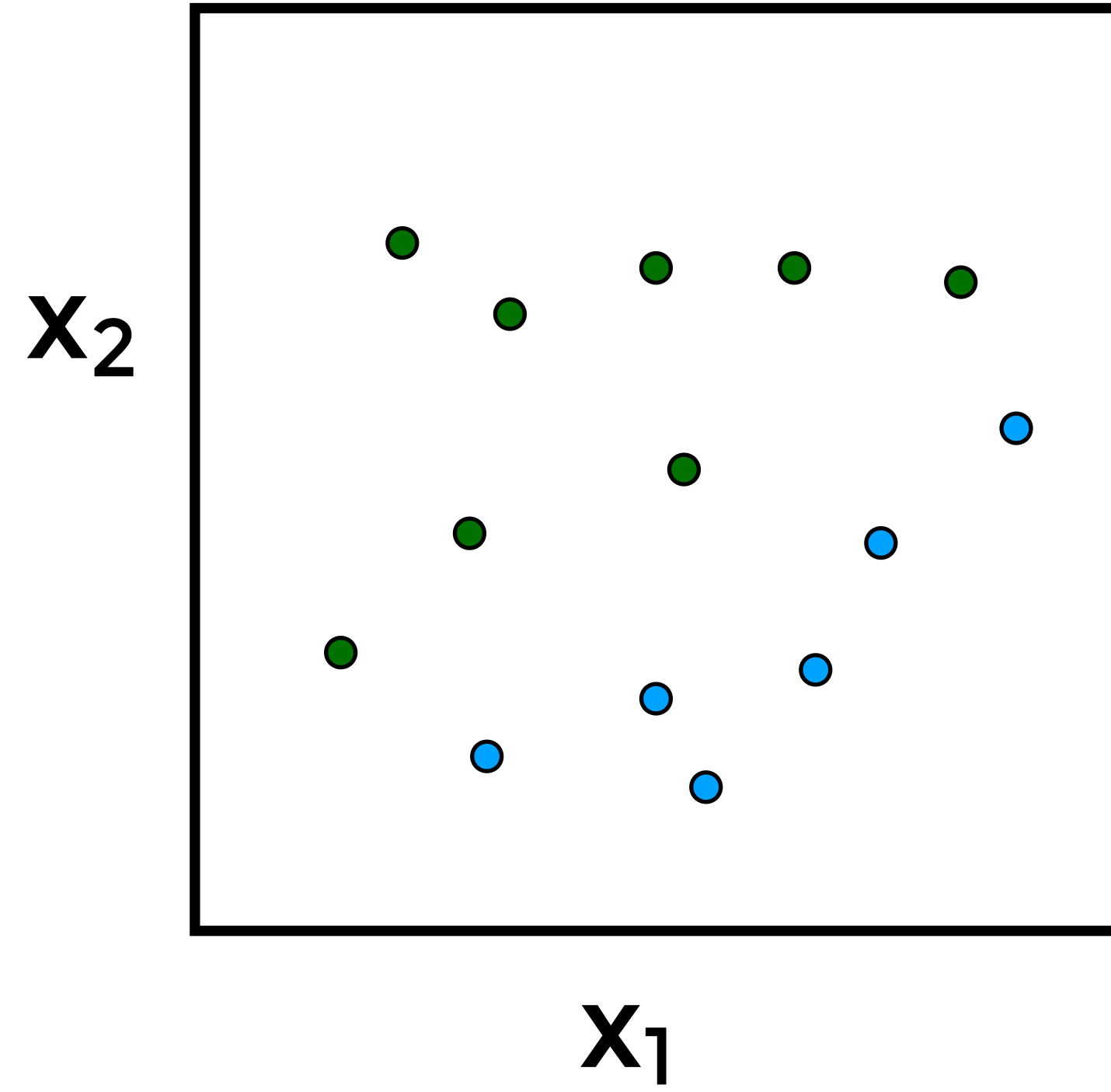
$$\{\mathbf{x}_i\}_{i=0}^n$$

- Experience examples alone
- Learn “useful properties of the structure of the data”
 - E.g., clustering, density modeling ($p(\mathbf{x})$), PCA, FA.

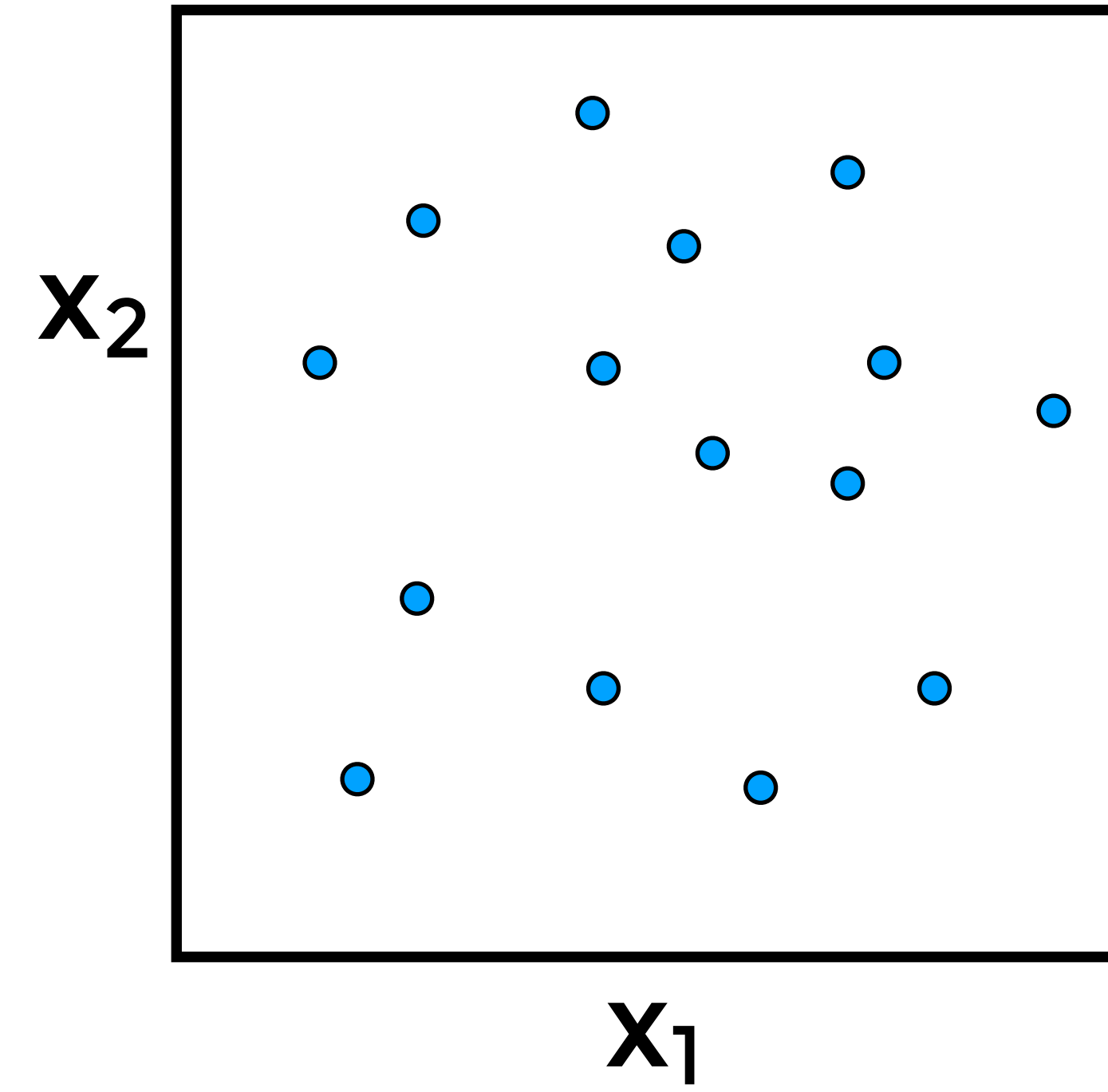
Different tasks

- Finding patterns
 - Clustering $f : X \rightarrow \{1, 2, \dots, K\}$ (K clusters)
 - Dimensionality reduction $f : X^p \rightarrow X^k, k \ll p$
 - Density modelling $f : X \rightarrow [0, 1]$
 - ...

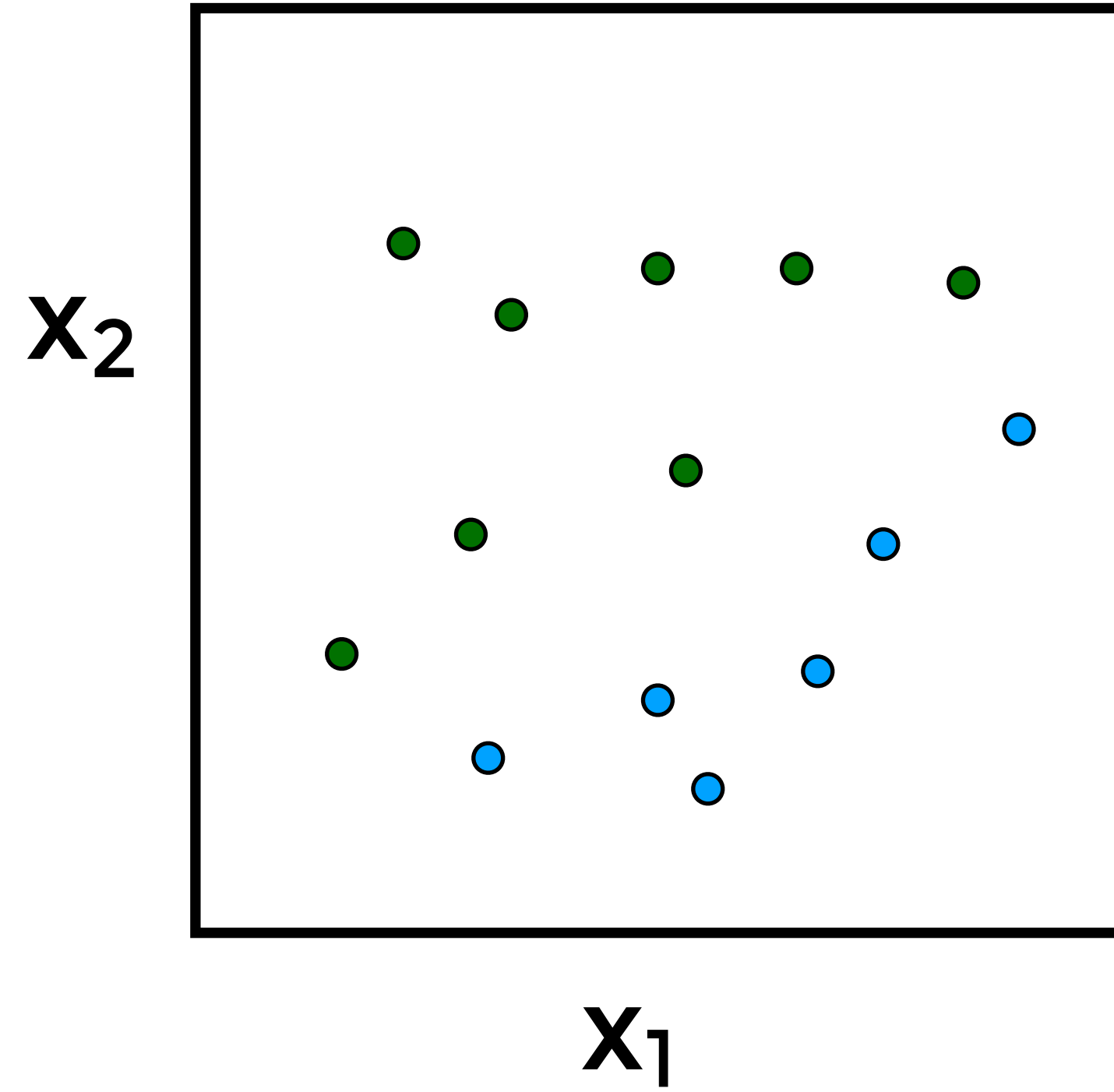
Supervised



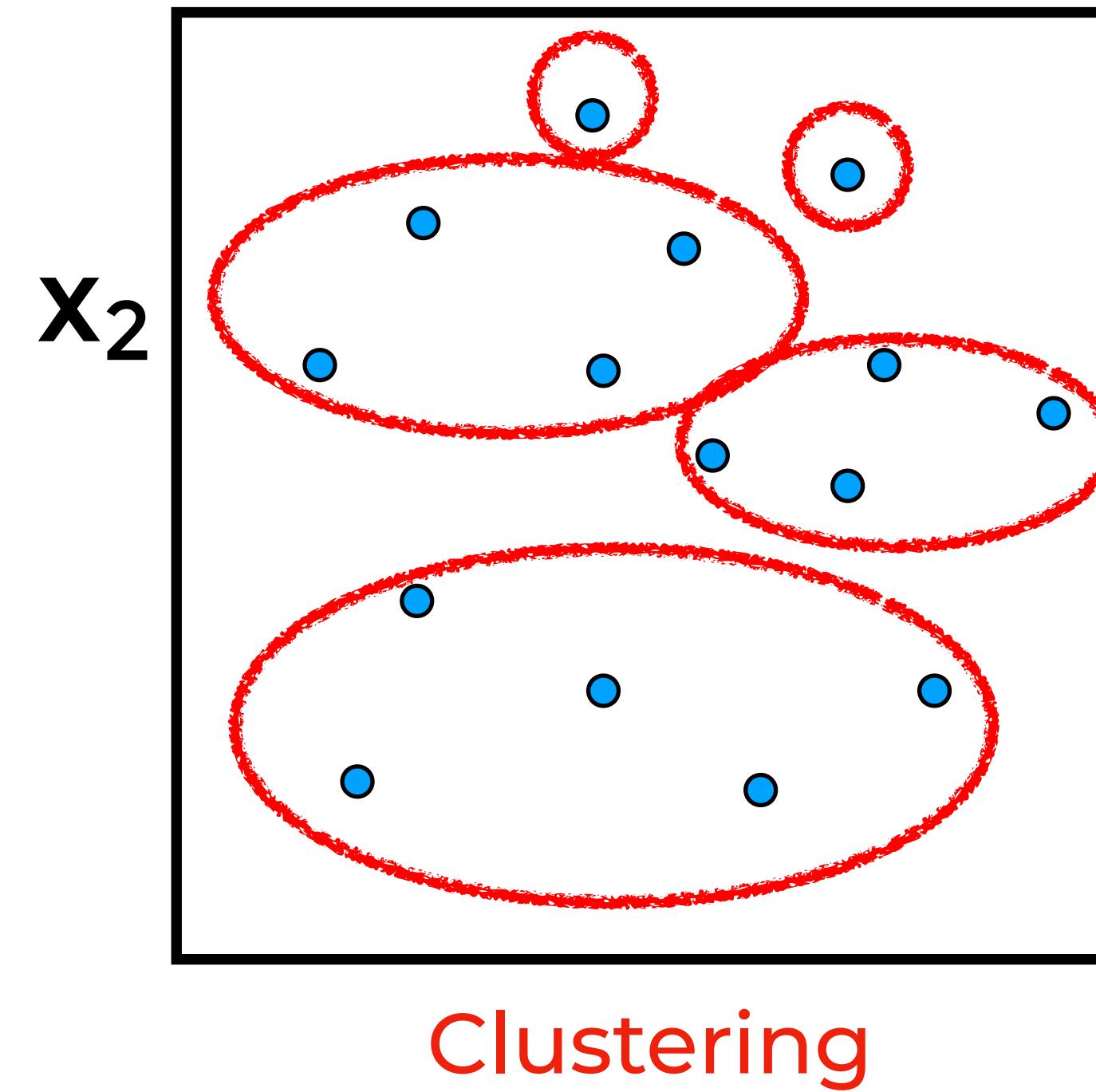
Unsupervised



Supervised

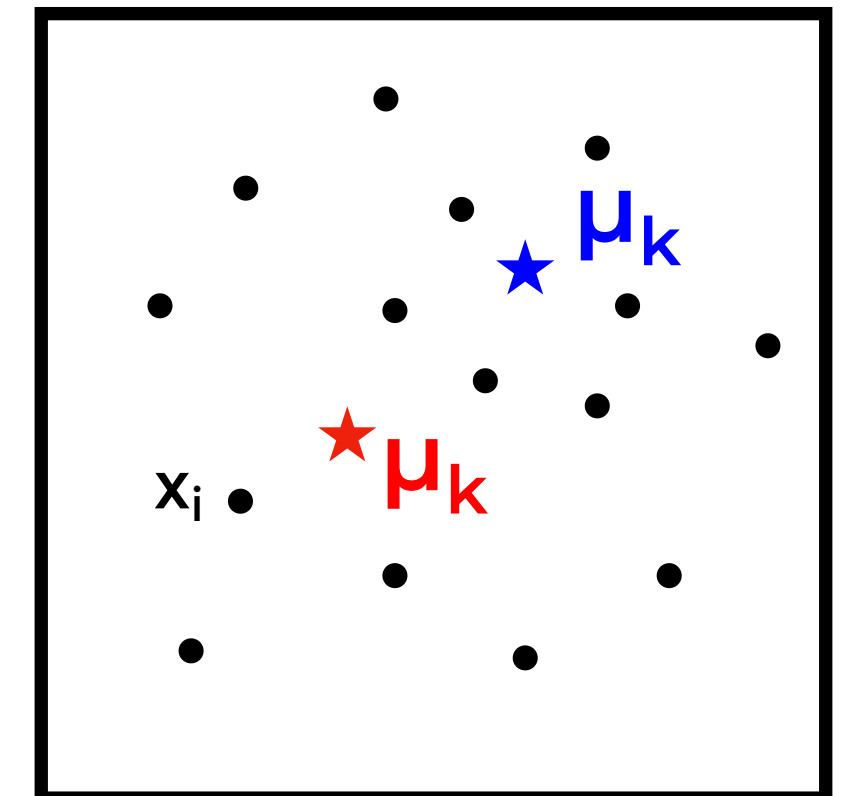


Unsupervised



K-means clustering

- A particular clustering model (and accompanying algorithm)
 - There are K clusters. Each point belongs to a cluster. Clusters have centers: μ
- Objective: Find cluster centers μ_k that minimize the within cluster distance

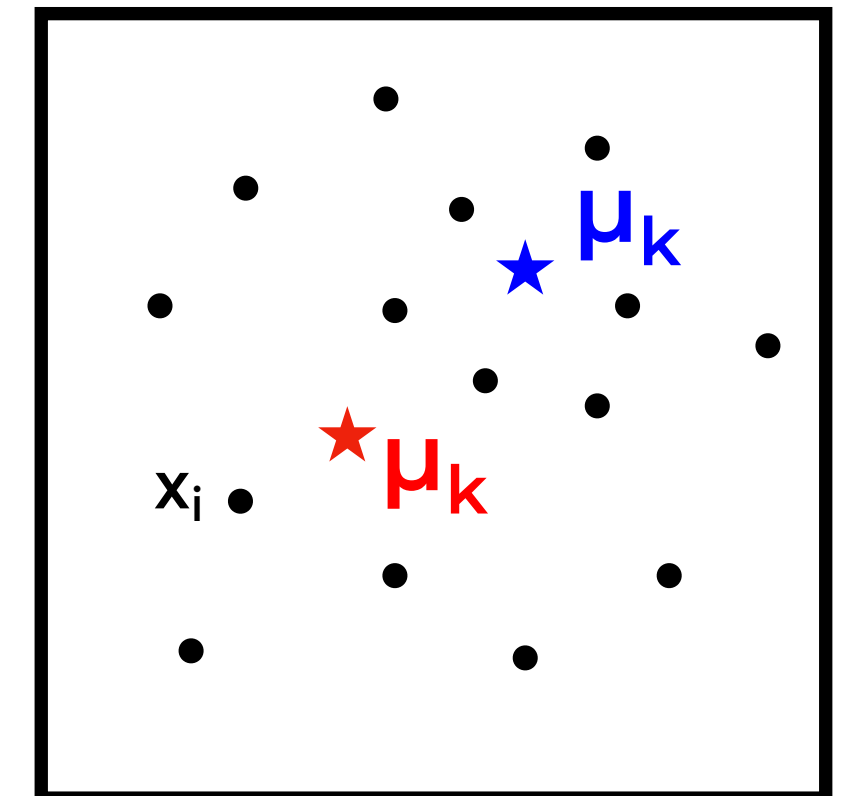


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$$\text{Objective} := \sum_{i=1}^N \sum_{k=1}^K r_{ik} \|x_i - \mu_k\|^2$$

$$r = \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix}_{N \times 2}$$



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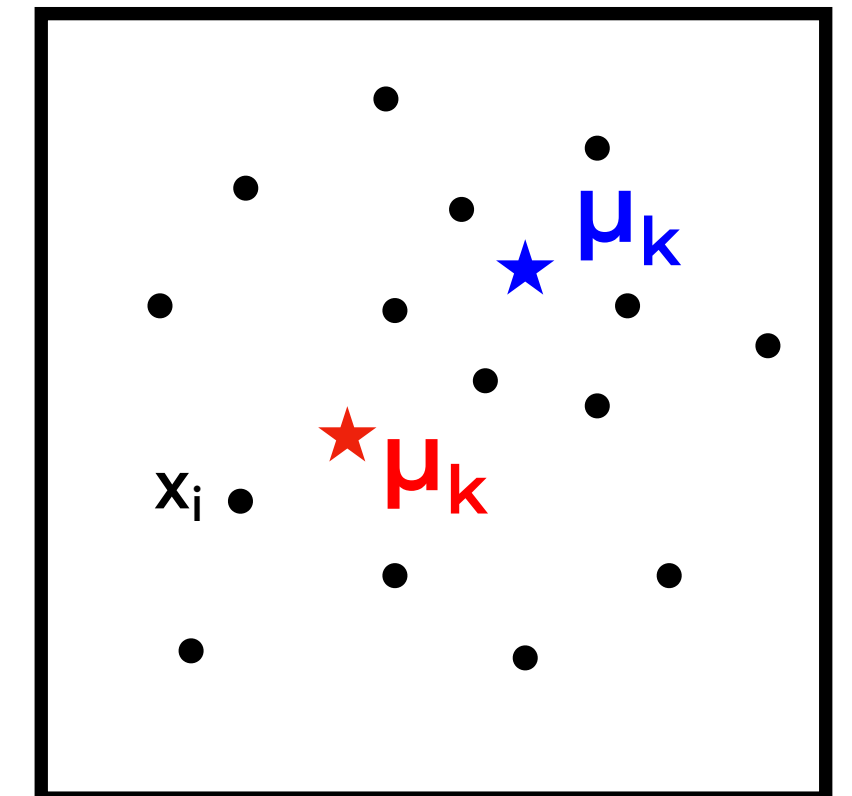
- Algorithm to minimize the objective:

- Initialize the cluster centers
- Until convergence:

1. Update responsibilities: r

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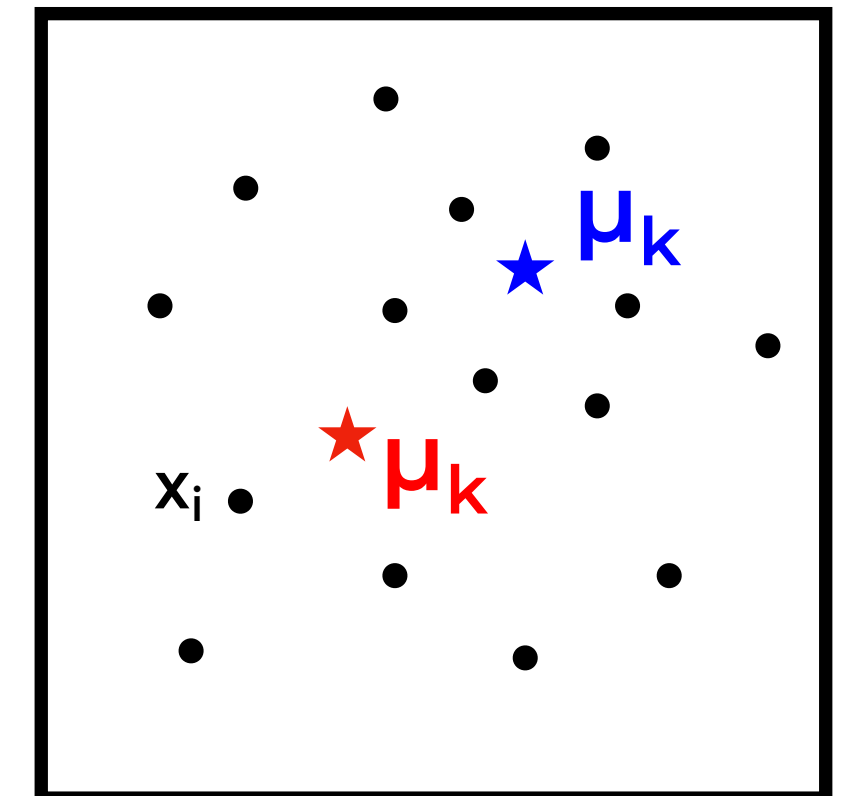
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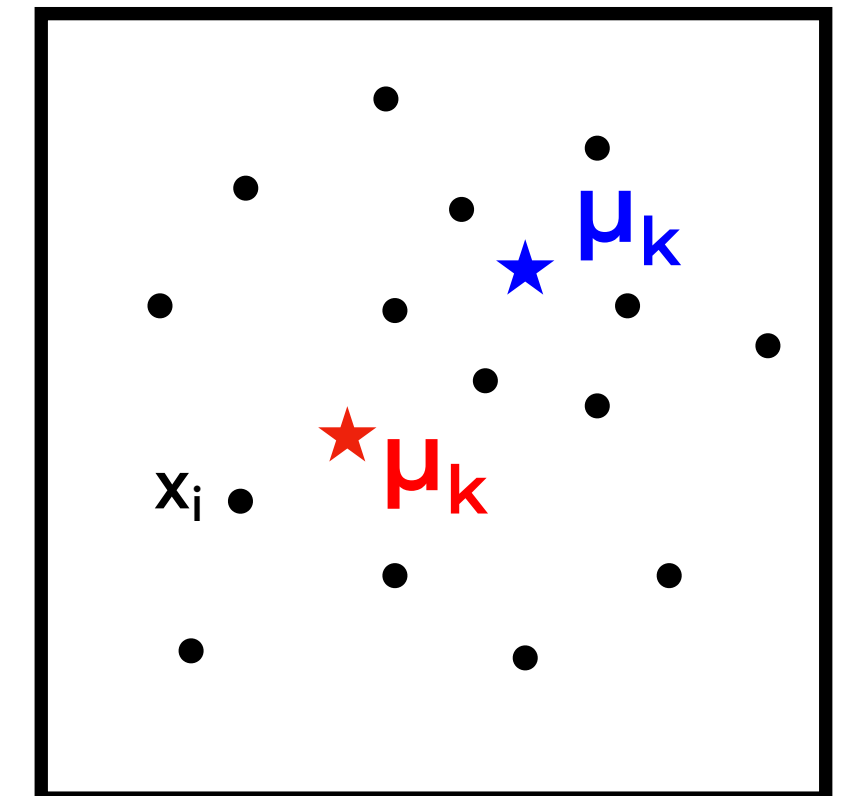
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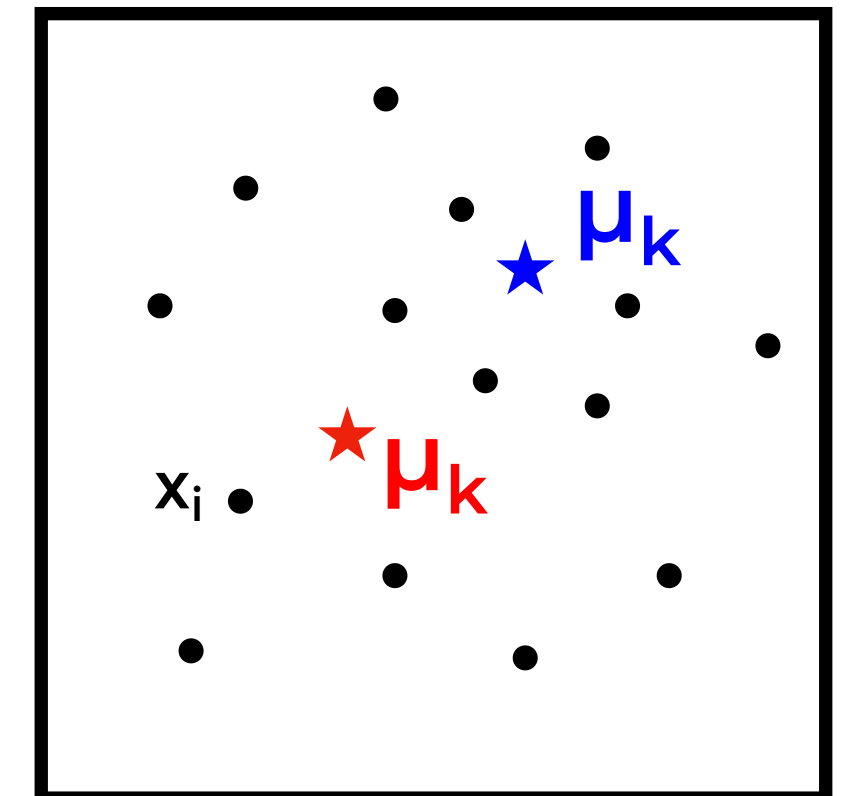
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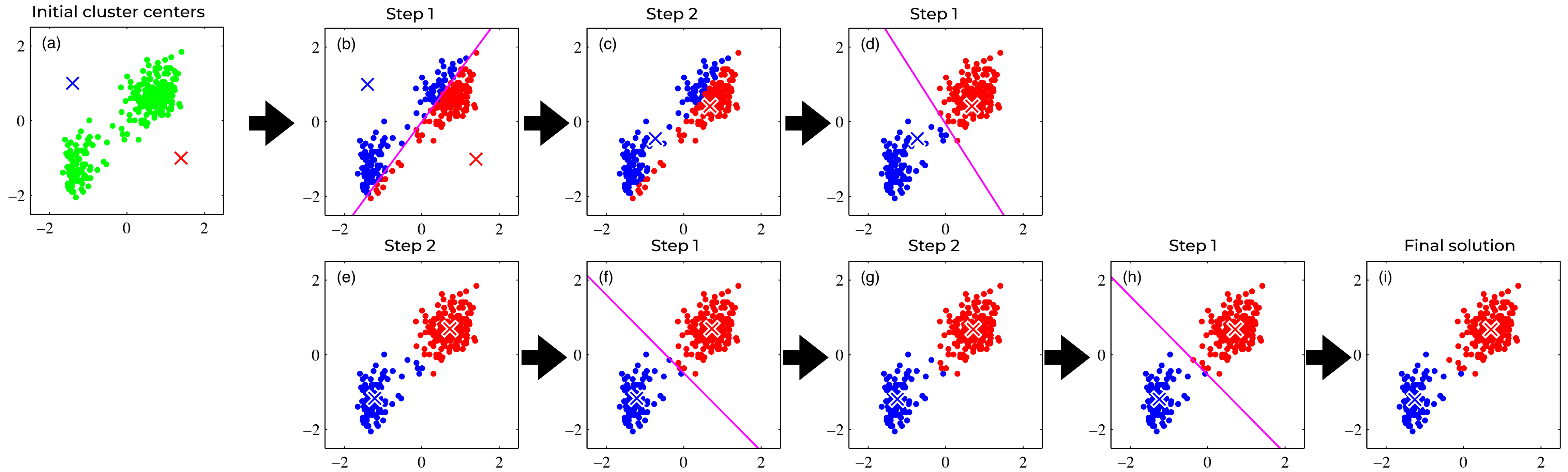
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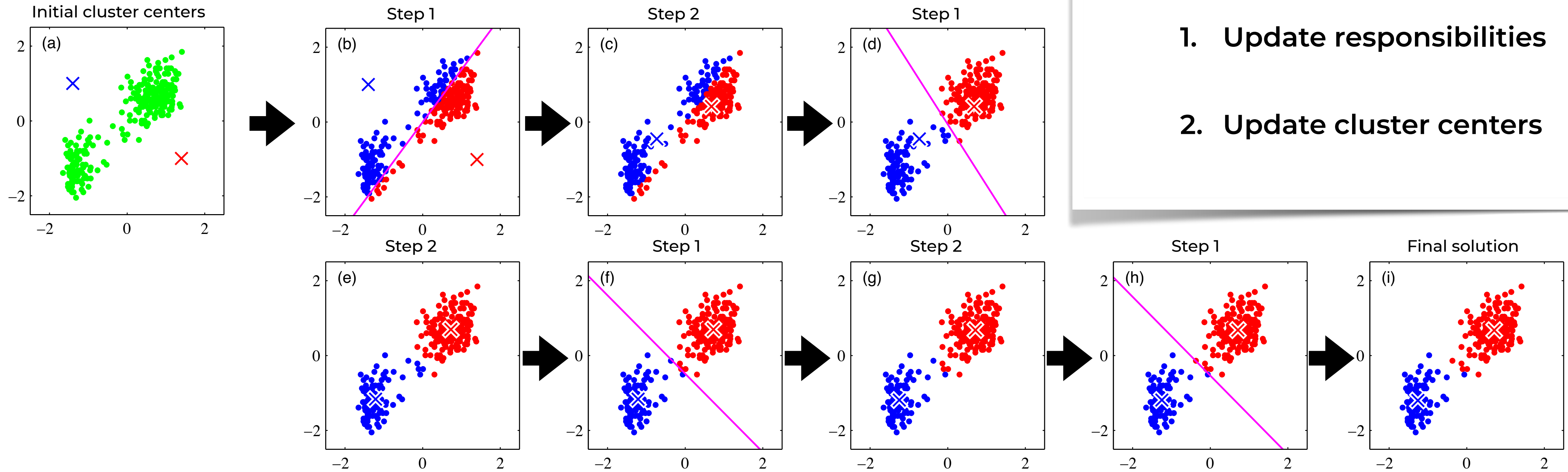
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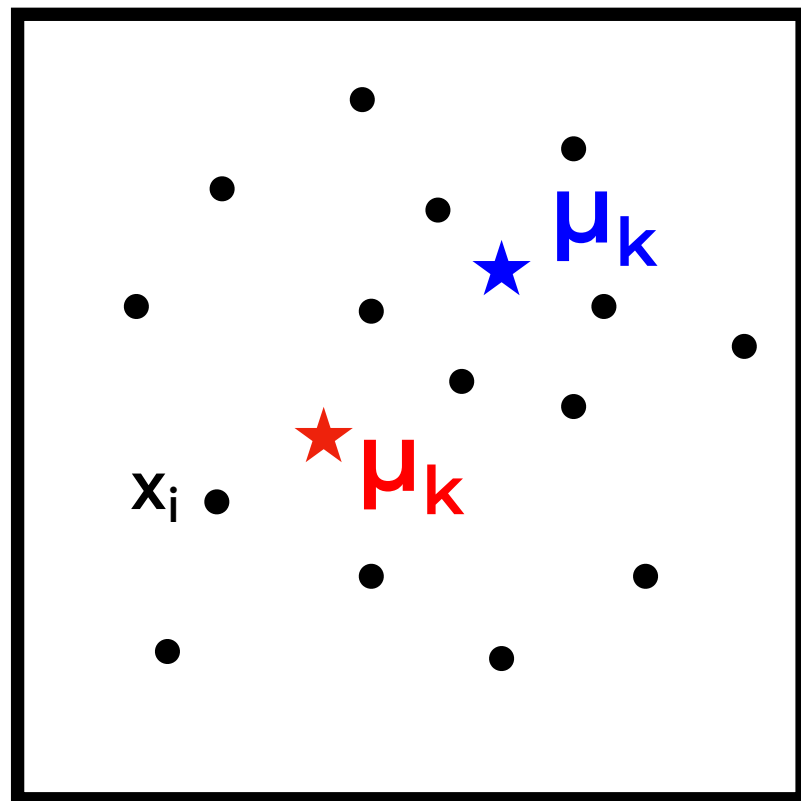
Algorithm

- Initialize the cluster centers
- Until convergence:
 1. Update responsibilities
 2. Update cluster centers



A probabilistic approach to k-means clustering

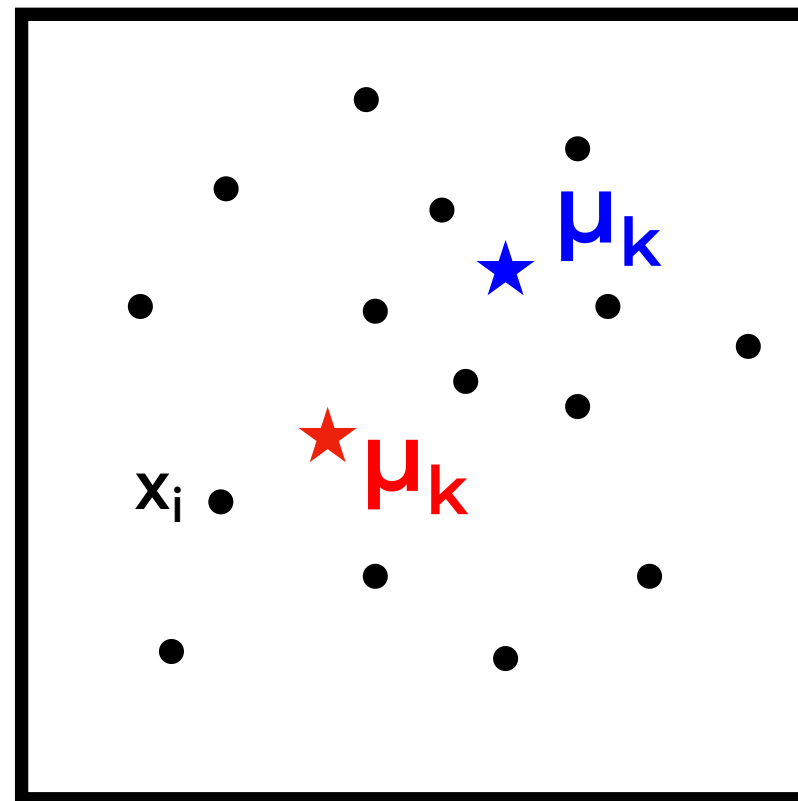
K-means Clustering



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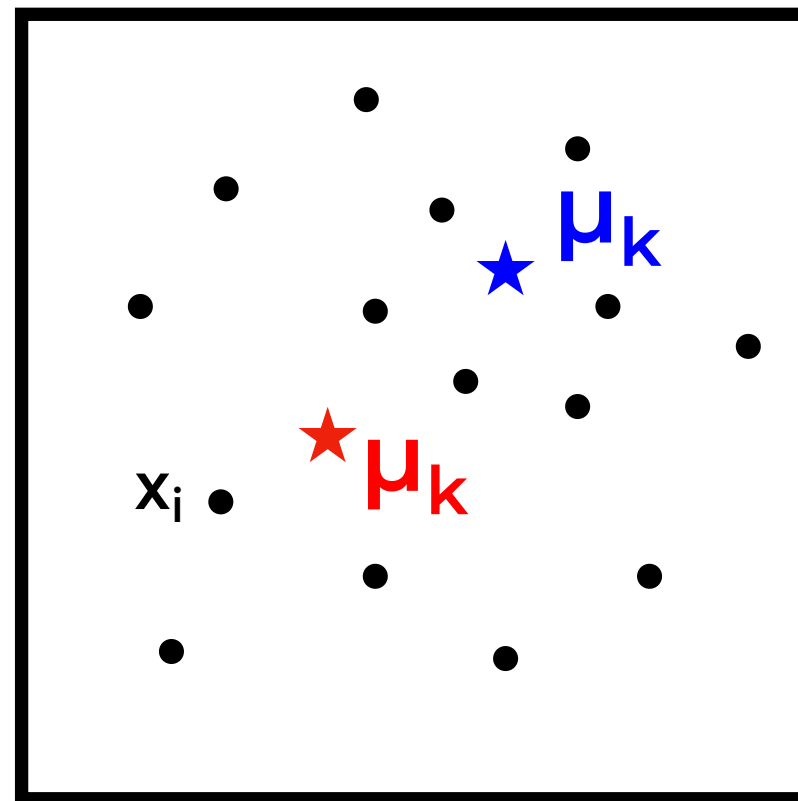
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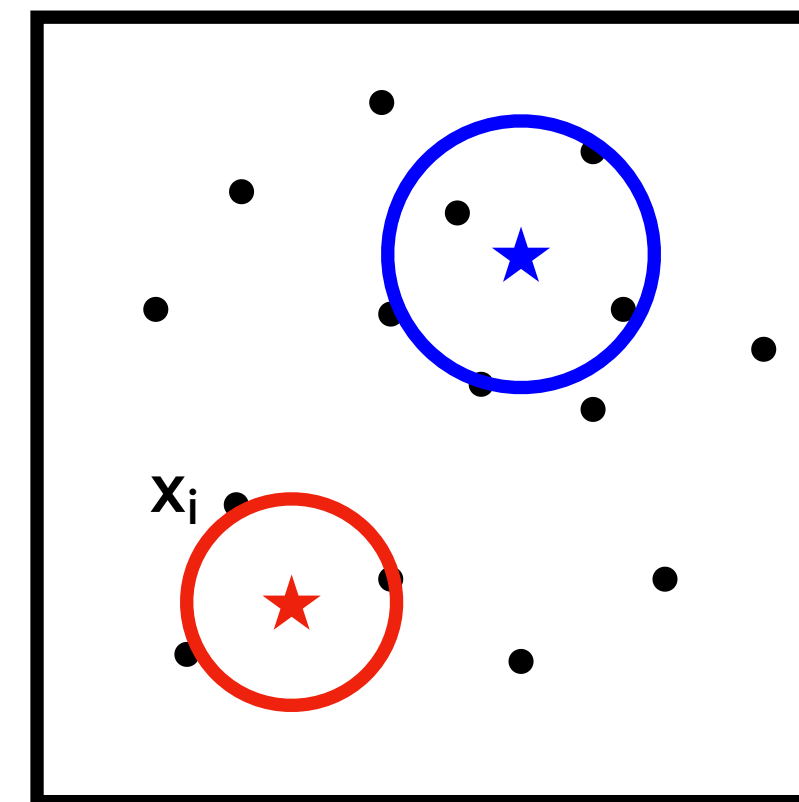
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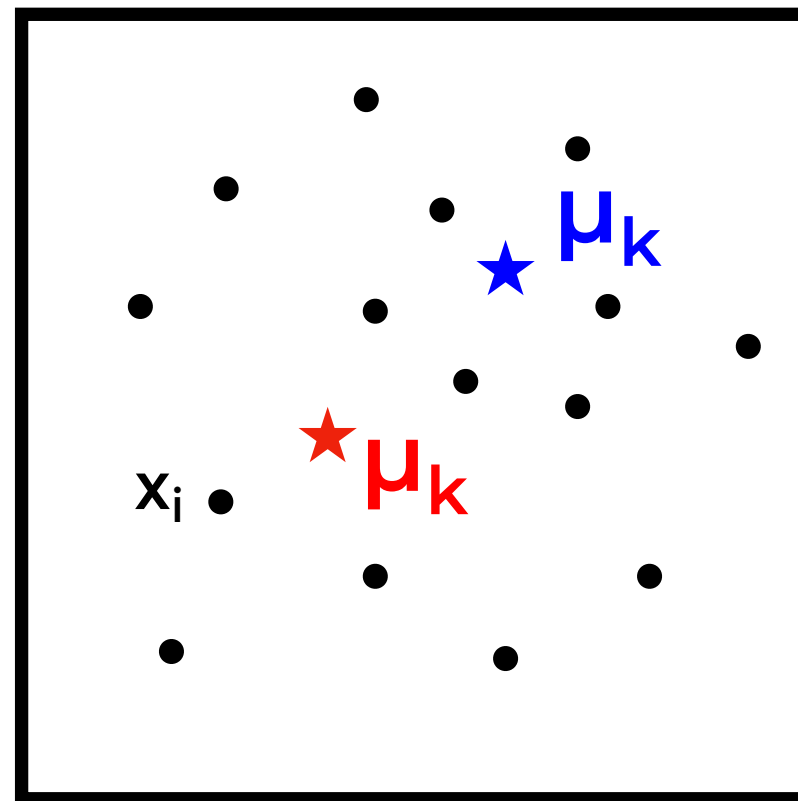
Soft K-means Clustering



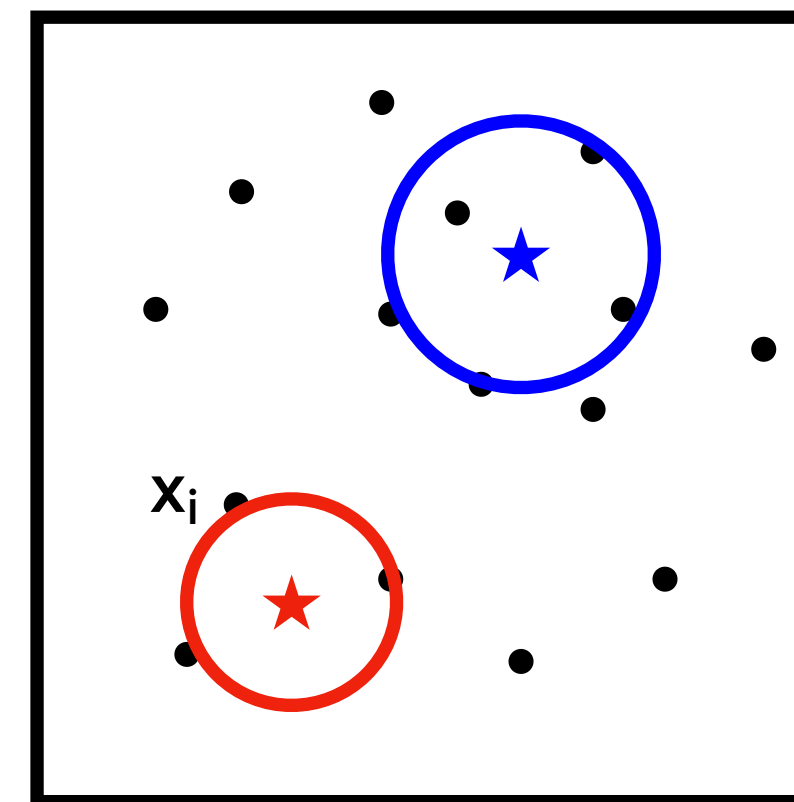
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K-means Clustering



Soft K-means Clustering

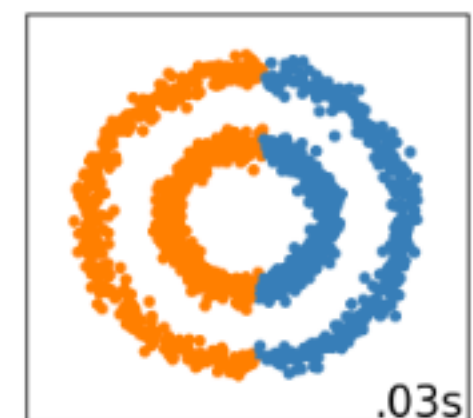


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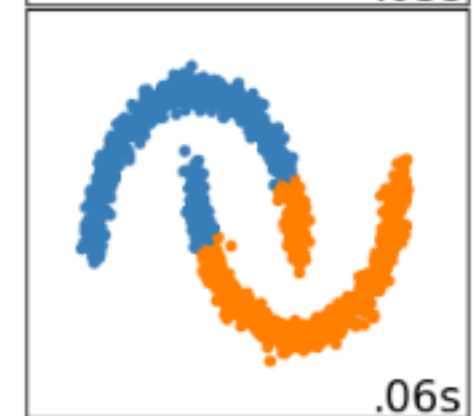
Responsibility center

- Responsibilities are continuous [0, 1]
- Each cluster has a responsibility: π_k
- Each cluster models data using a Gaussian: $\mathcal{N}(\mathbf{x}_i | \mu_k, \Sigma_k)$

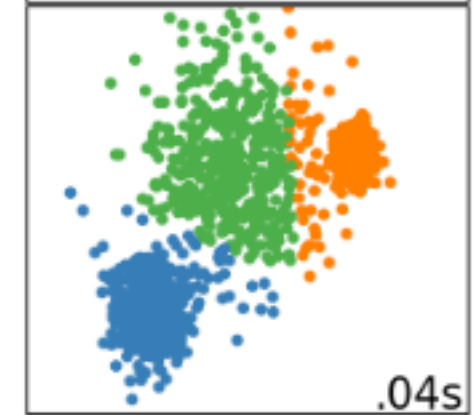
K-means



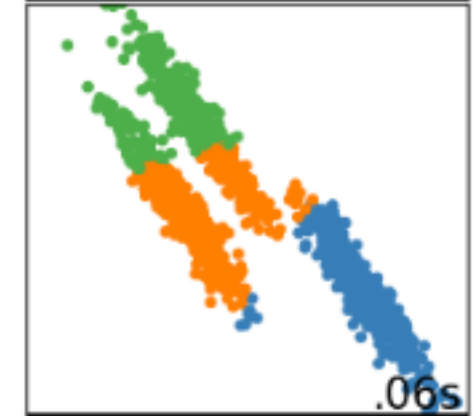
Similar



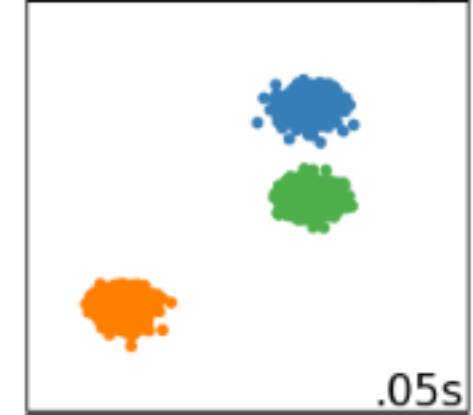
Similar



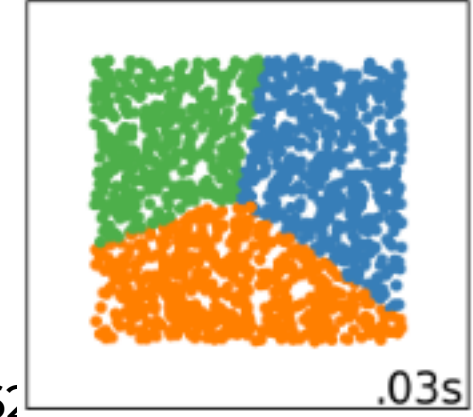
GMM better



GMM better

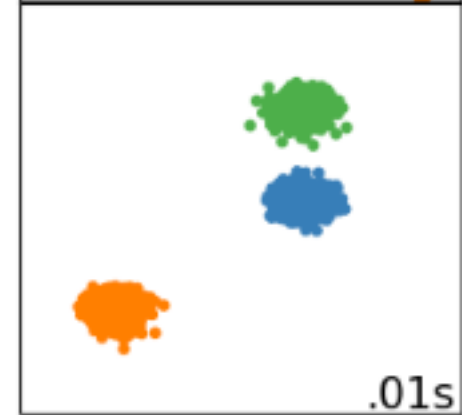
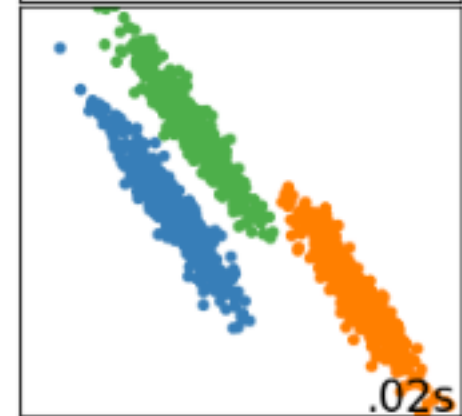
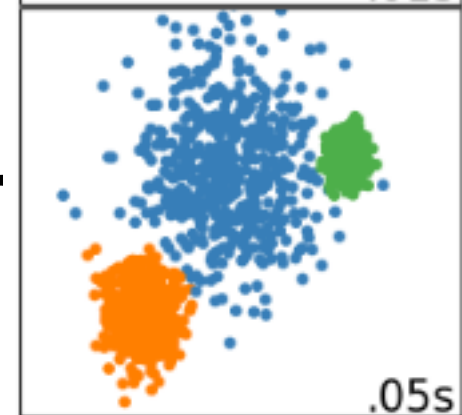
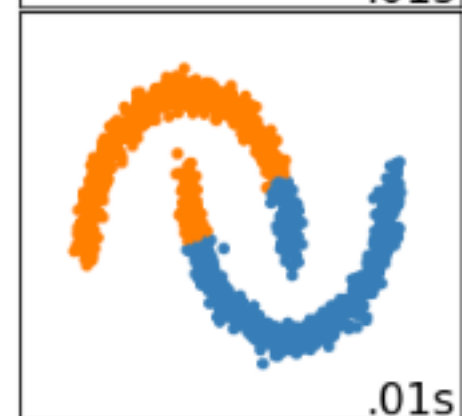


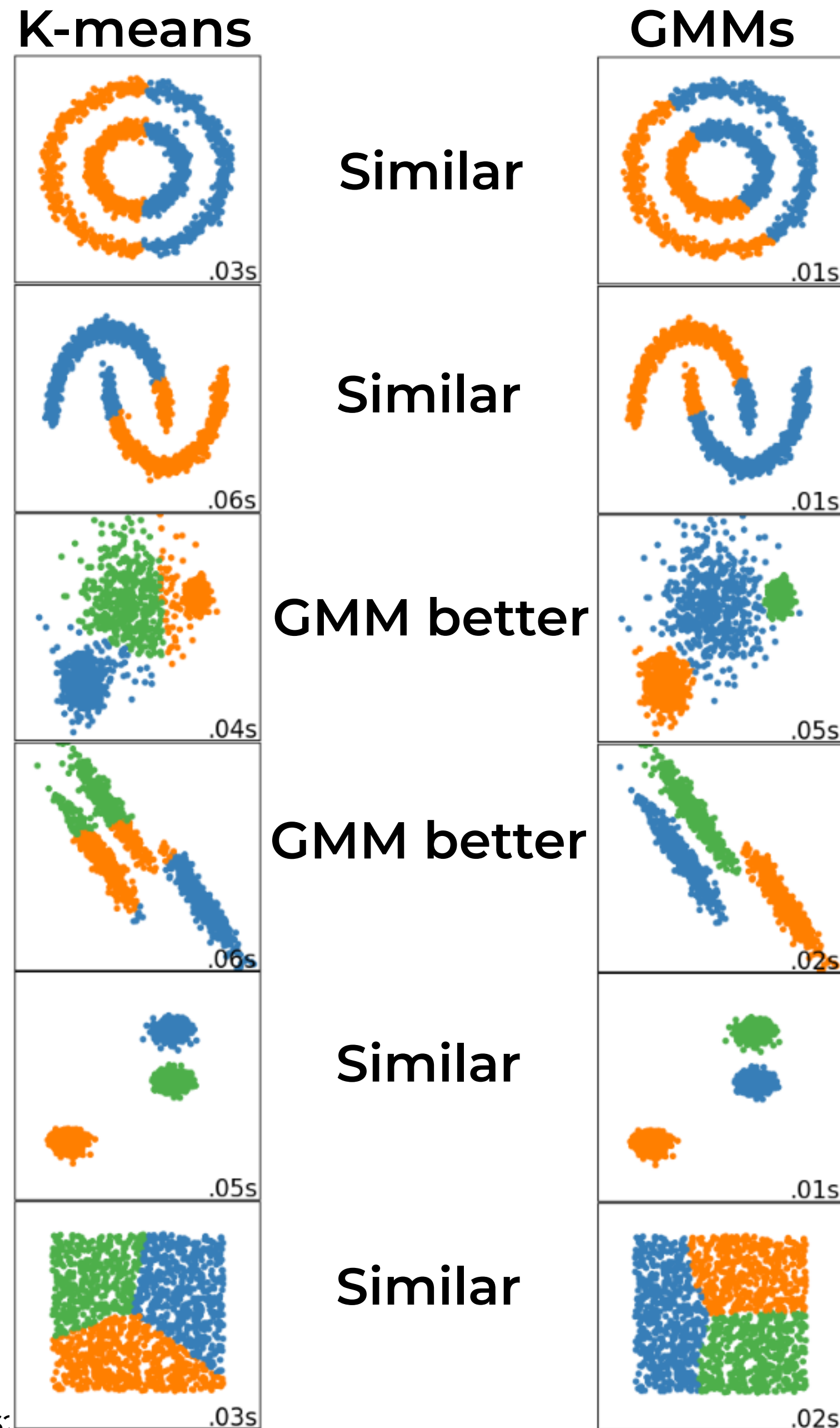
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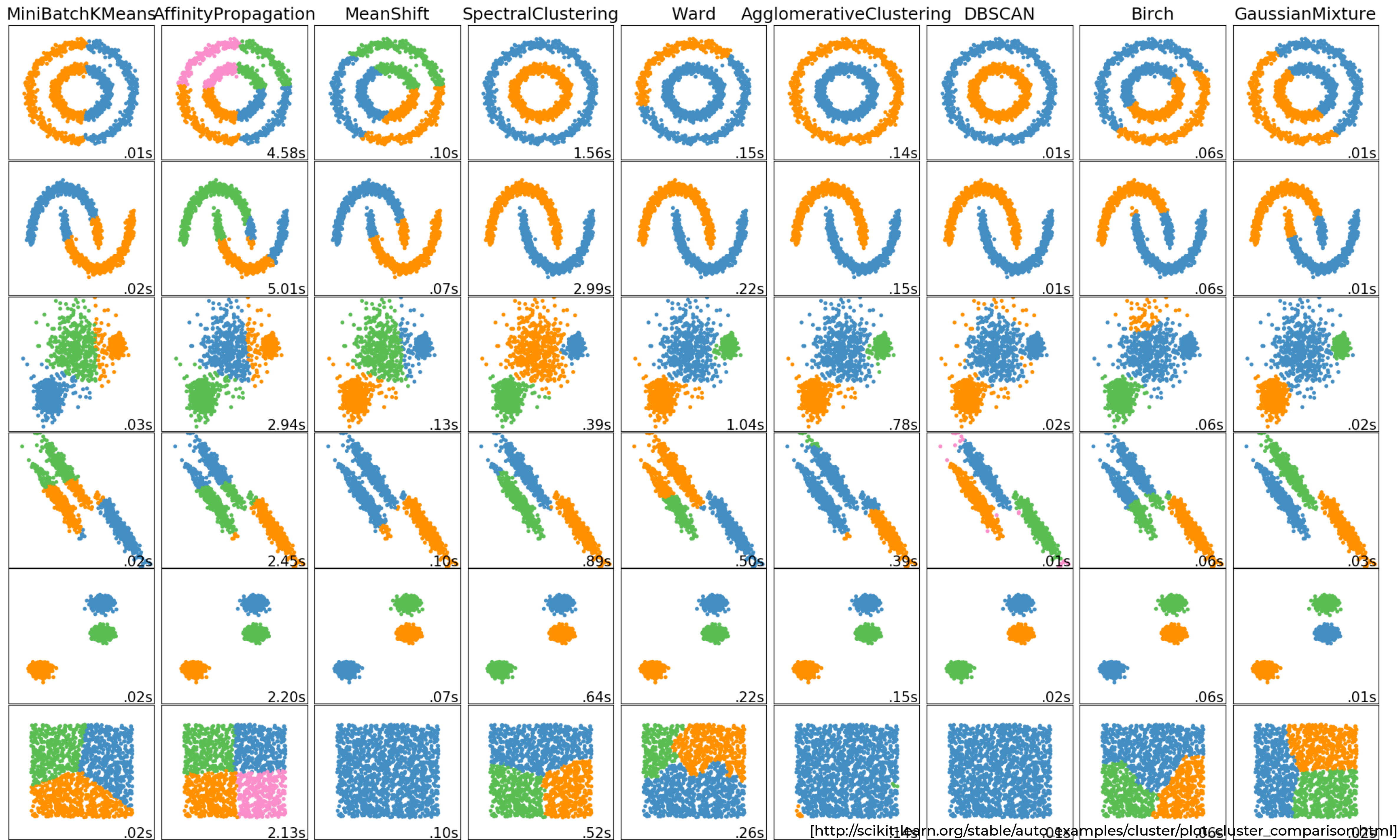
GMMs





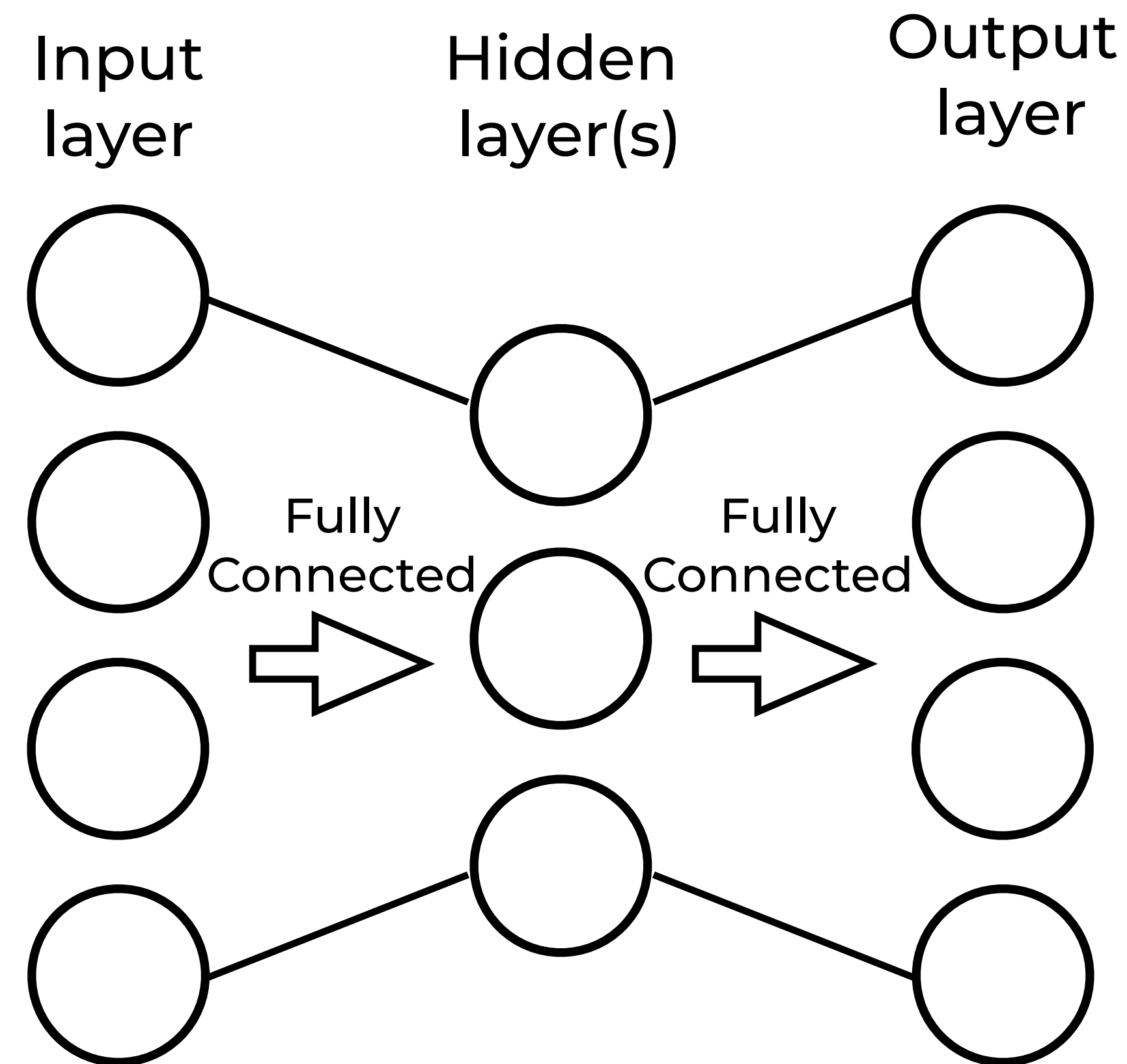
Comparing K-means to GMMs

- GMMs learns covariance matrix
 - Per cluster variance
 - Covariance terms
- GMMs has many more parameters
 - Covariance matrix (MxM)



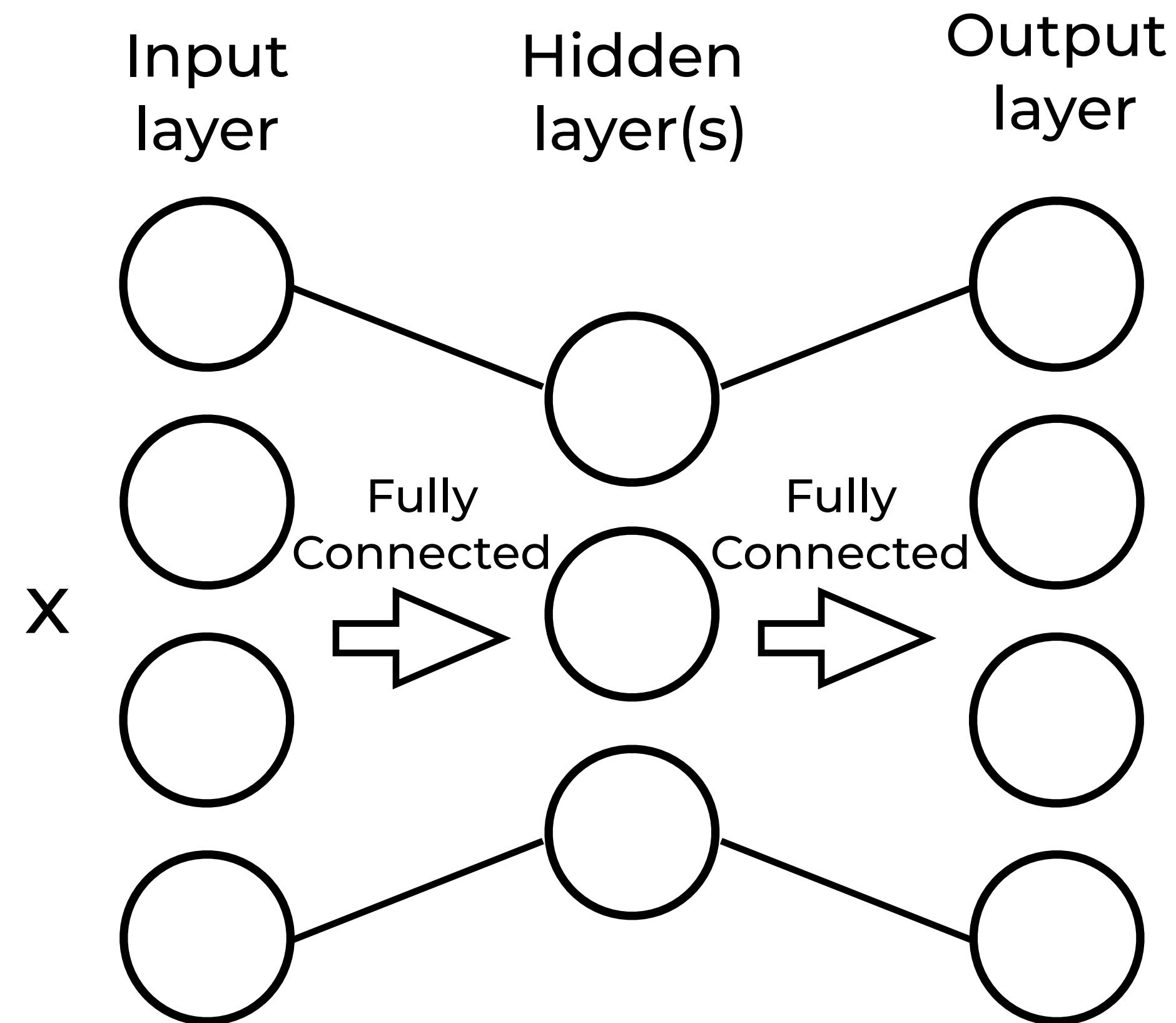
Autoencoders

- A neural network architecture for unsupervised learning



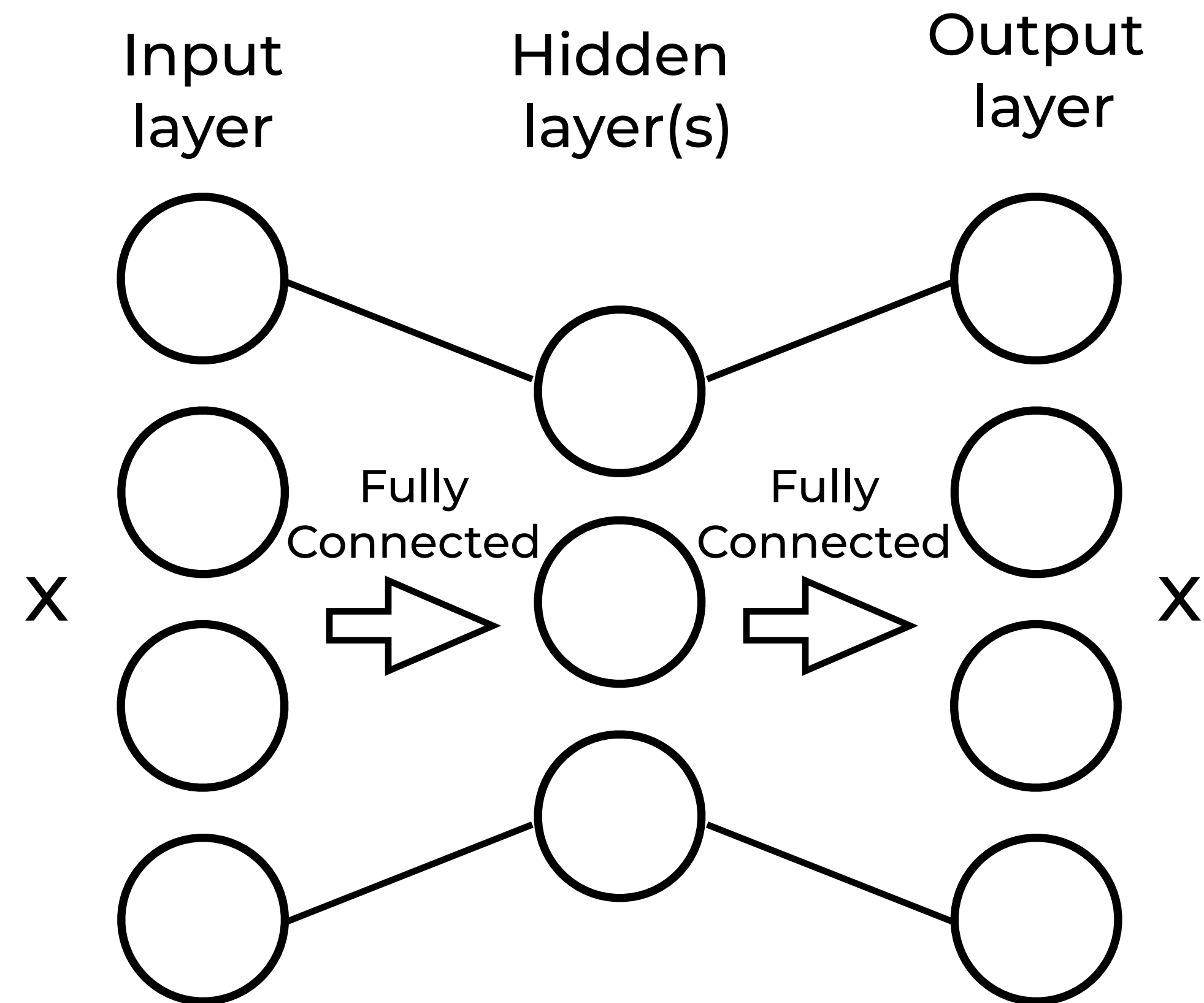
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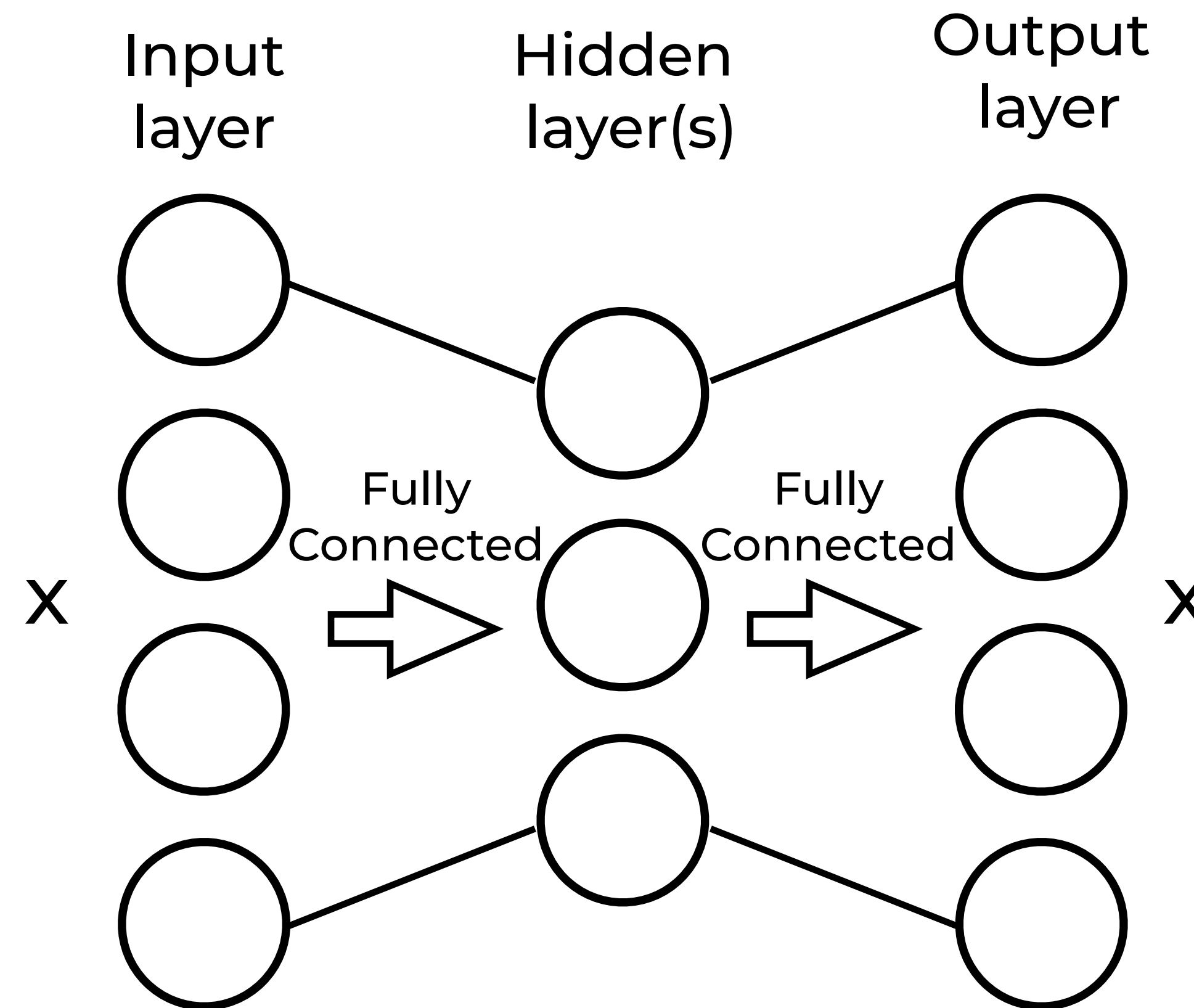
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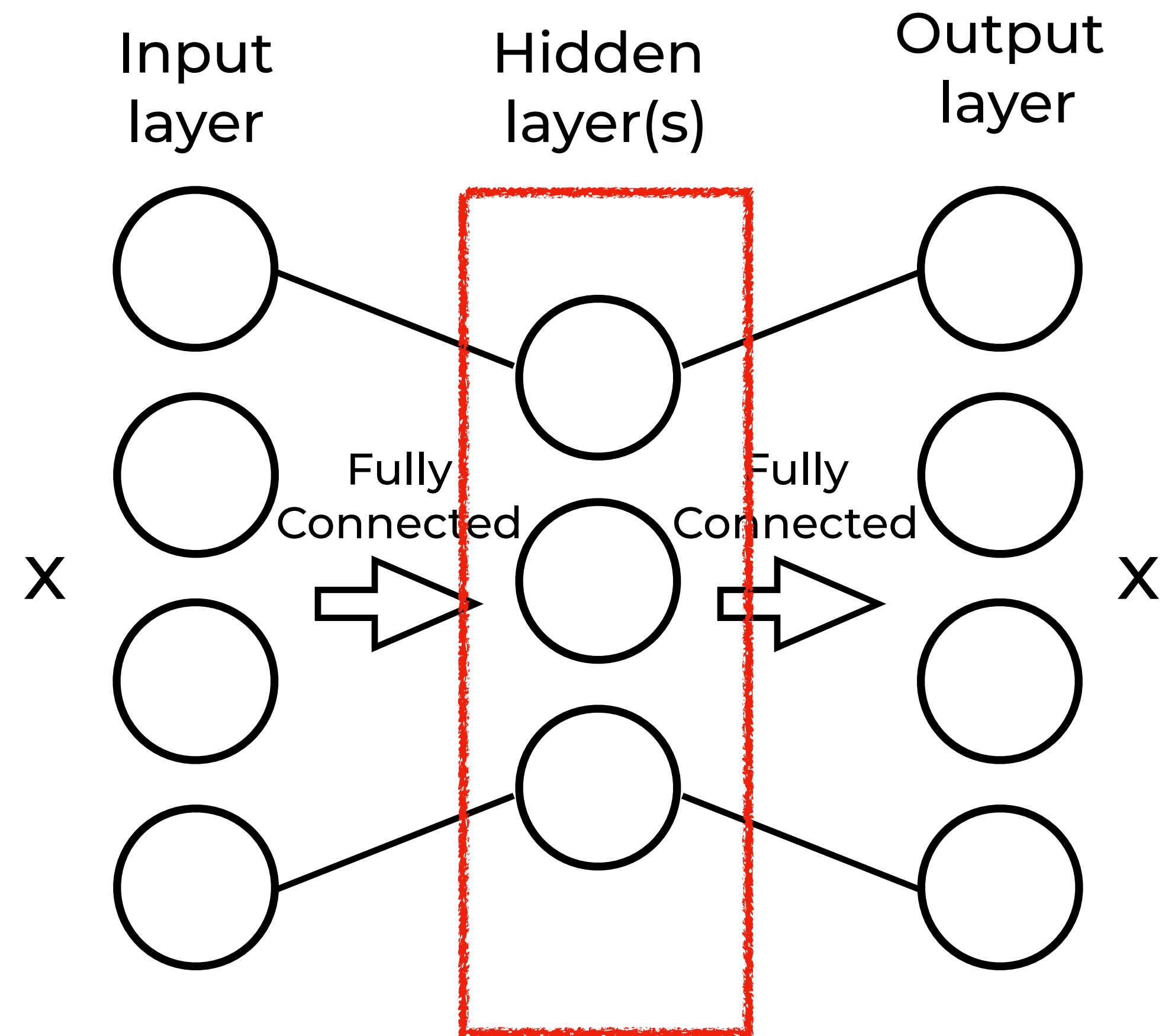
Objective:

How well the network predicts X ?

$$\begin{aligned} \text{Loss} &:= \sum_{i=1}^N (x_i - \hat{x}_i)^2 \\ &= \sum_{i=1}^N (x_i - f_2(f_1(x)))^2 \end{aligned}$$

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Lower dimensional representation

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