



# Latent models, EM and GMM

*Creative Machine Learning - Course 06*

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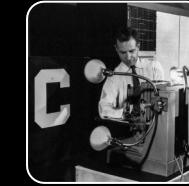


# Brief history of AI

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1943 - Neuron

First model by McCulloch & Pitts (purely theoretical)



1957 - Perceptron

Actual **learning machine** built by Frank Rosenblatt

Learns character recognition analogically



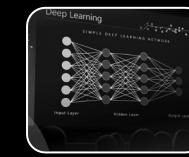
1986 - Backpropagation

First to learn neural networks efficiently (*G. Hinton*)



1989 - Convolutional NN

Mimicking the vision system in cats (*Y. LeCun*)



*This lesson*

2012 - Deep learning

Layerwise training to have deeper architectures

Swoop all state-of-art in classification competitions



*Lesson #6*

2015 - Generative model

First wave of interest in generating data

Led to current model craze (VAEs, GANs, Diffusion)

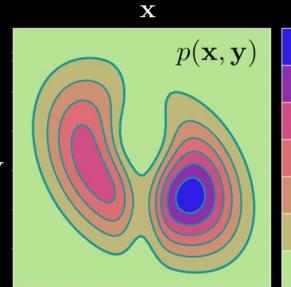
2012 onwards    *Deep learning era*



# Brief history of AI

Pre-requisites for understanding generative models

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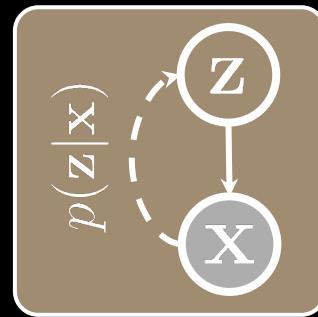
Probability theory

*Random variables, distributions, independence*

Bayesian inference

*Bayes' theorem, likelihood, conjugate priors*

3

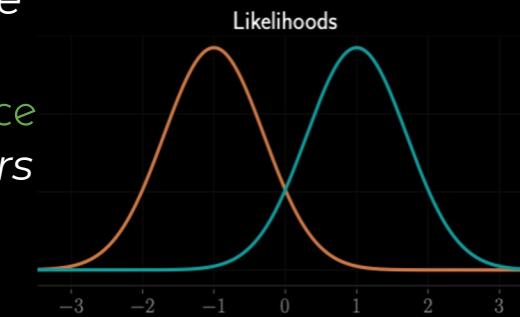


Latent models

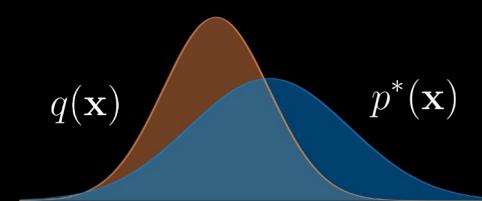
*Latent variables, probability graphs*

Approximate inference

*Latent variables, probability graphs*



2



4

Lesson #6

2015 - Generative model

First wave of interest in generating data

Led to current model craze (VAEs, GANs, Diffusion)



2012 onwards Deep learning era

# Supervised learning

Typical machine learning tasks

Until now, we mostly dealt with **supervised** problems

- *Classification, regression*
- *Implies that we have labels*

Based on *labeled* data, assign class to *unlabeled* data

- *Multiple approaches to solve this task*
- *We have also seen the probabilistic formulation*

Probabilistic formulation

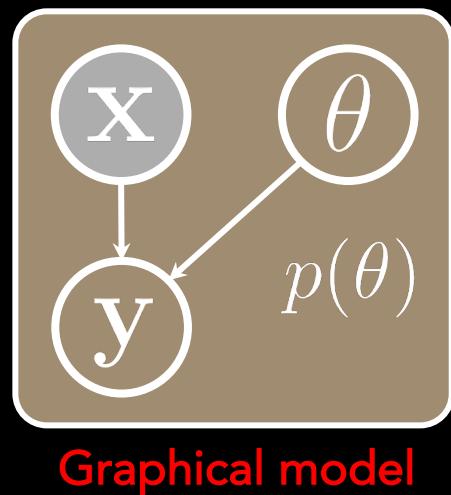
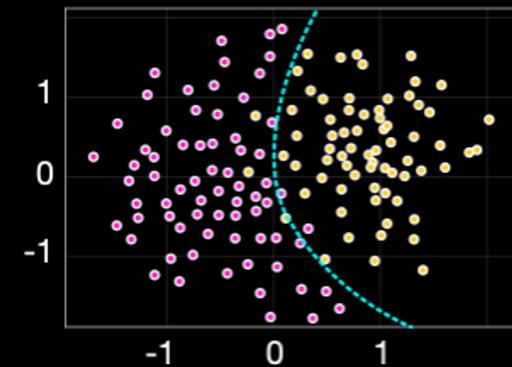
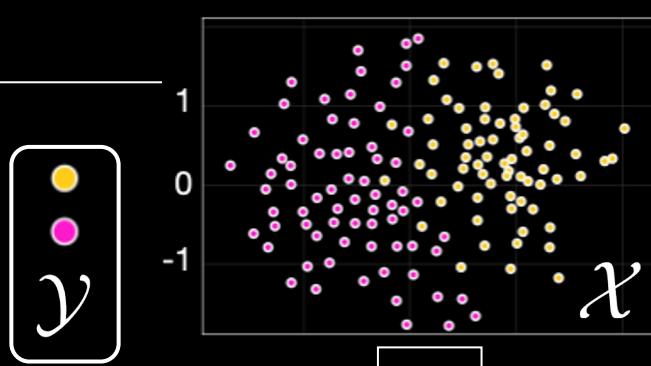
We have data  $\mathbf{x} \in \mathbb{R}^n$  and labels  $\mathbf{y} \in \mathbb{R}^m$

Supervised learning tries to model  $p(\mathbf{y}|\mathbf{x})$

We define a parametric model  $p_\theta(\mathbf{y}|\mathbf{x})$

Optimization might be seen as solving for

$$p(\mathbf{y}|\mathbf{x}) = \int p(\mathbf{y}|\mathbf{x}, \theta) d\theta$$



# Unsupervised learning

Laying out the framework

In some cases, we might only have access to  $\mathbf{x} \in \mathbb{R}^n$

- No labels are available (**costly, ill-defined**)
- Structure still exists in any data
- As humans we perceive it easily

How to learn from this ?

Here we can clearly see four clusters

This is a form of unsupervised structure

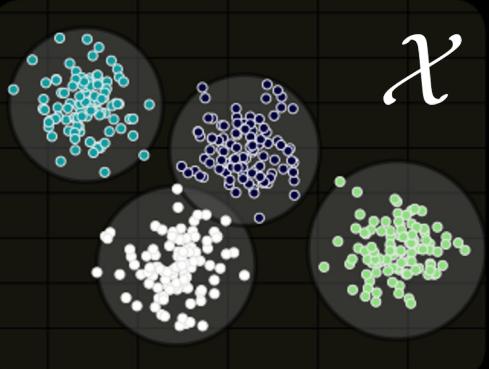
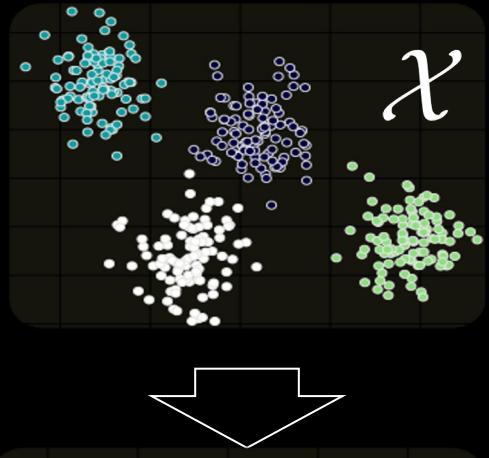
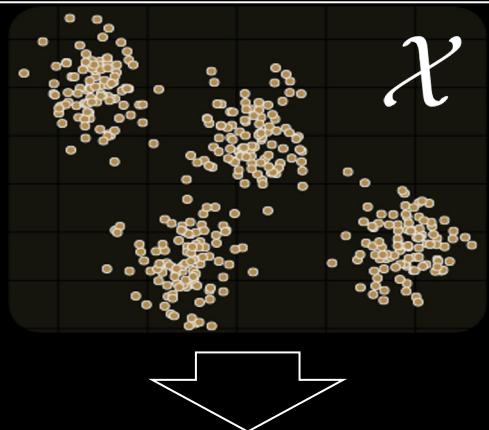
Unsupervised clustering

Aim to model the entire data distribution  $\mathbf{x} \sim p(\mathbf{x})$

How to choose the *form* of the distribution ?

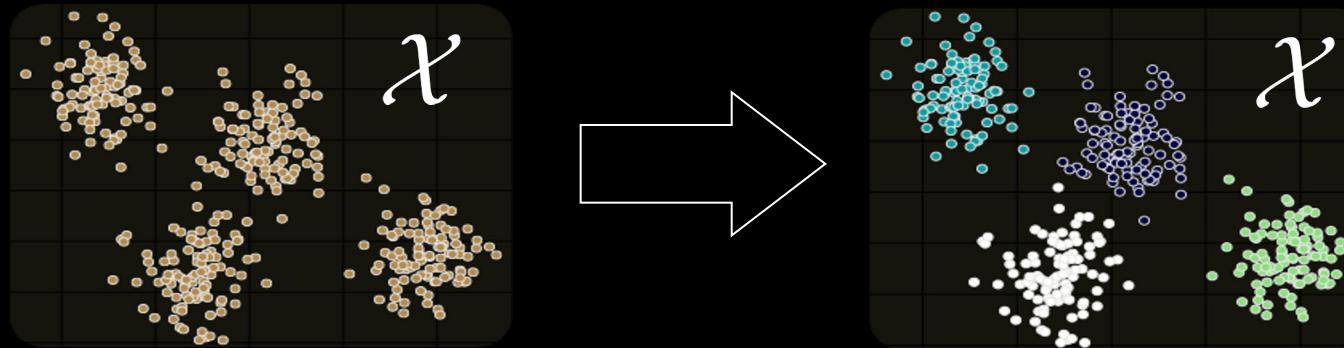
How to *optimize* it directly ?

Seems to be missing information



# Unsupervised learning

We need to **add information** to our problem, but only have  $\mathbf{x} \in \mathbb{R}^n$



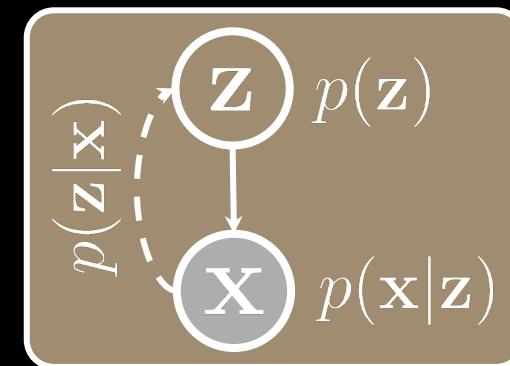
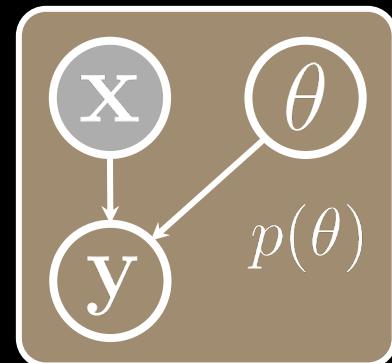
Structure is clearly defined  
by the **cluster identity**

Introducing the need for **latent variables**  $\mathbf{z} \in \mathbb{R}^z$

Allows to clearly define the *hidden information*

Can be seen as the **hidden factors that generated the data**

Supervised



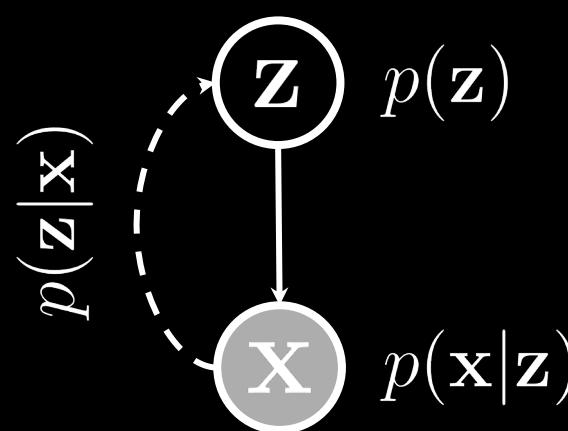
Latent  
(unsupervised)

# Latent variables

We are interested in the **generative problem**  $\mathbf{x} \sim p(\mathbf{x})$

This problem is highly complex (distribution)

So we introduce **latent variables**  $\mathbf{z} \in \mathbb{R}^z \ll \mathbb{R}^x$



*Happy, female*



*Neutral, male*



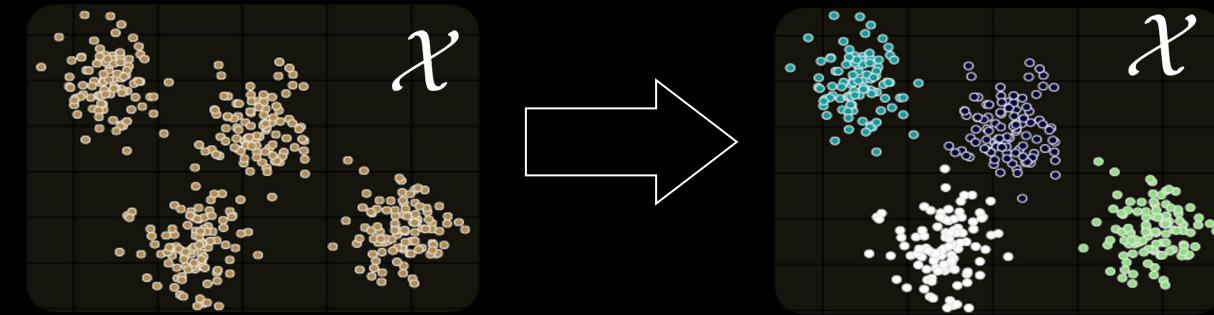
$$p(\mathbf{x}) = \int_{\mathbb{R}} p(\mathbf{x}|\mathbf{z})p(\mathbf{z})d\mathbf{z}$$

## Understanding latent variables

- Variables that led to generate the data
- Hidden variation factors in the data structure
- Variables that simplify our optimization task

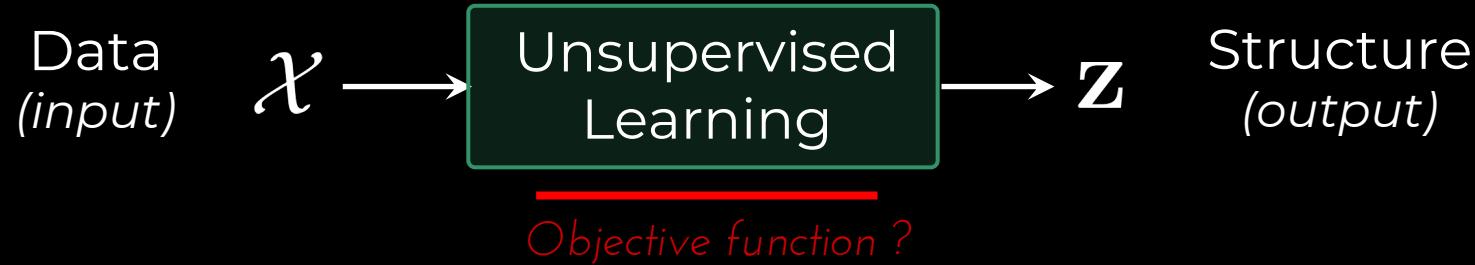
# Defining clustering

Clustering tasks



Goal

- Attach label to each data points (“*unsupervised classification*”)
- Aim to assign same label to data points that are “close”
- Clustering implicitly relies on a distance metric



First approach

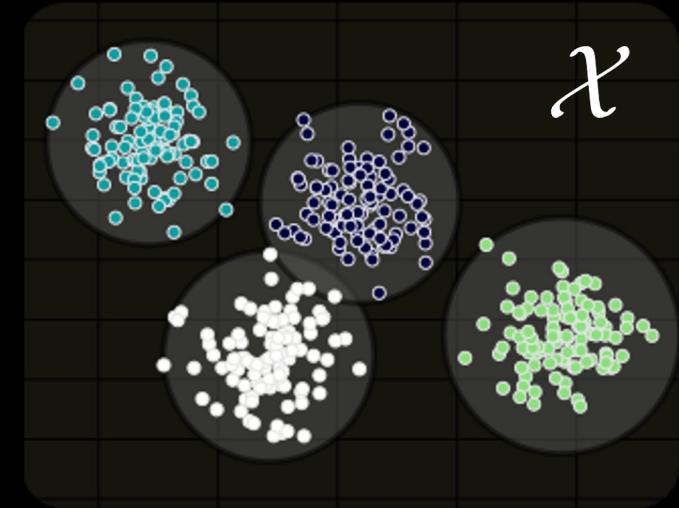
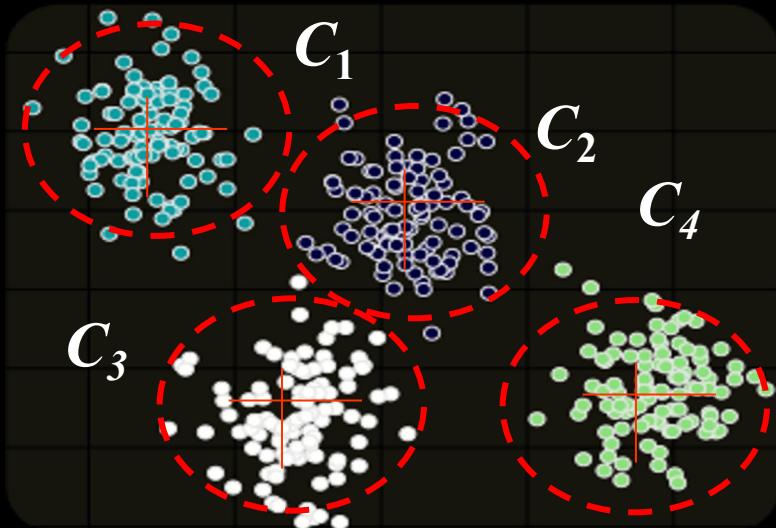
- Address this in a *non-probabilistic* way
- How can we cluster a given set of points ?

# Clustering intuition

What defines a **good** clustering ?

Evaluate the within-clusters distance (centroid-based)

$$\operatorname{argmin}_{C_j, m_{i,j}} \left[ \sum_j \sum_i (\mathbf{x}_i - \mathbf{c}_j)^2 \right]$$



How to optimize ?

Fixed *memberships*  $m_{i,j}$

We could *infer* *centroids*

$$\mathbf{c}_j = \frac{\sum_{i=1}^n m_{i,j} \mathbf{x}_i}{\sum_{i=1}^n m_{i,j}}$$

Fixed centroids  $\mathbf{c}_j$

We could infer the memberships

$$m_{i,j} = \operatorname{argmin}_k (\mathbf{x}_i - \mathbf{c}_j)^2$$

# Implementing clustering

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Summarizing our observations

Obviously, memberships  $m_{i,j}$  and centroids  $\mathbf{c}_j$  are correlated

It seems that we have an alternating problem definition

1. Knowing the memberships  $m_{i,j}$

We compute centroids

$$\mathbf{c}_j = \frac{\sum_{i=1}^n m_{i,j} \mathbf{x}_i}{\sum_{i=1}^n m_{i,j}}$$

2. Knowing the centroids  $\mathbf{c}_j$

We compute memberships

$$m_{i,j} = \underset{k}{\operatorname{argmin}} (\mathbf{x}_i - \mathbf{c}_j)^2$$

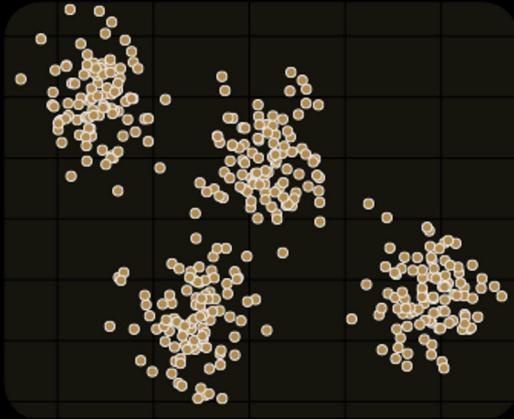
This can be solved by an iterative algorithm

- Starts from *random cluster centroids initialization*
- Alternates between the two types of updates

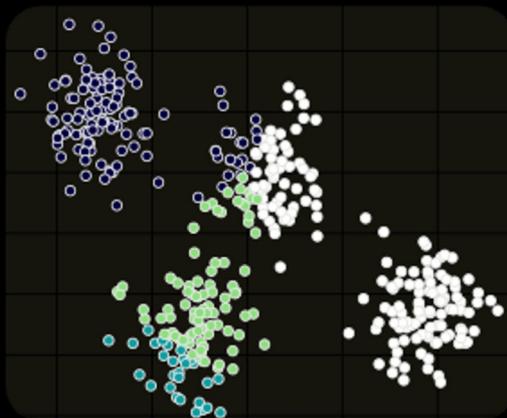
Seminal K-Means clustering algorithm

# K-Means for clustering

Detailing the K-Means algorithm

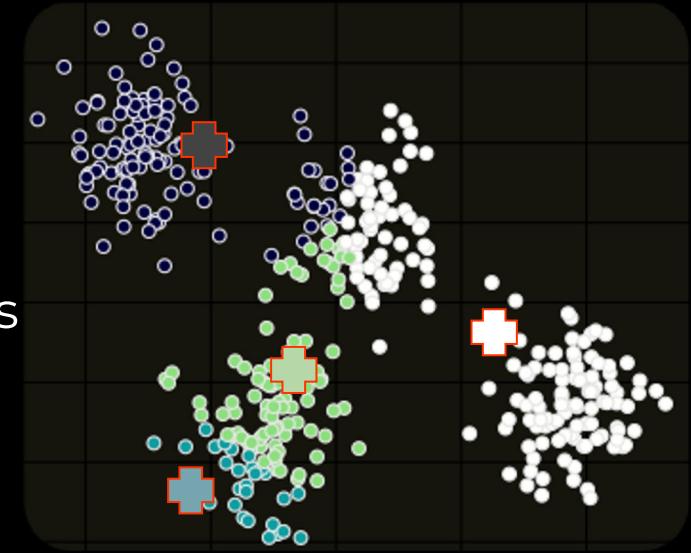


Alternate updates



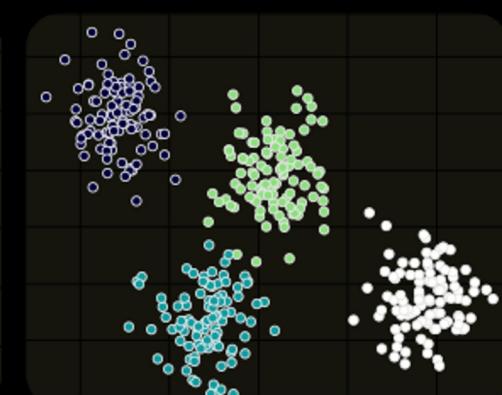
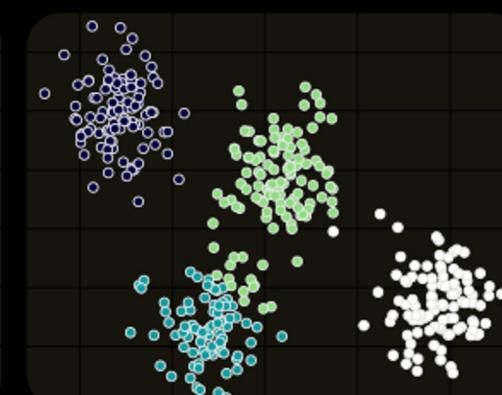
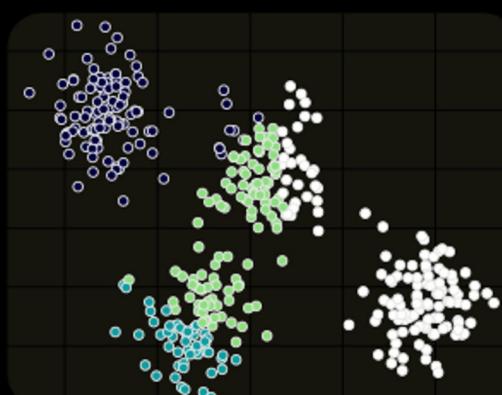
Initialization

1. Random init of cluster centers
2. Compute membership
3. Assign to points



Then perform loop of alternating updates

1. Re-compute the centroid of each cluster
2. Determine membership of all the datapoints



# Details of the K-Means algorithm

## Issues in the algorithm

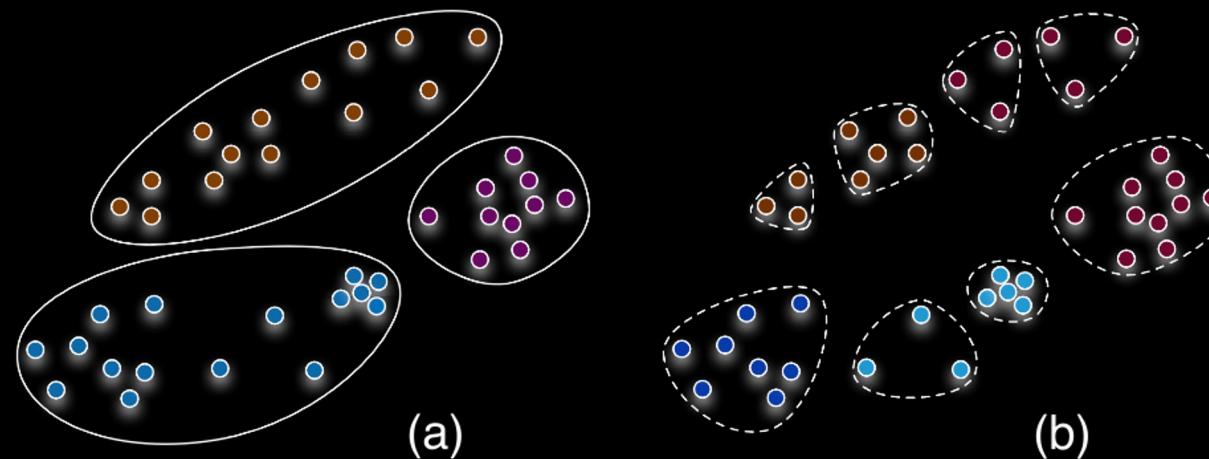
How do we define the *stopping criterion* ?

1. *Iterations number or thresholding*
2. *Measure of cluster quality* -----

$$\mathcal{L}_K = \sum_{n=1}^N \sum_{k=1}^K \| x_n - \mathbf{c}_k \|^2$$

How do we choose the number of clusters

1. *Even with the right number, will we find a good optima?*
2. **Problem** = Any subset of points is a valid clustering



# Hard or soft clustering

Problems with deterministic clustering

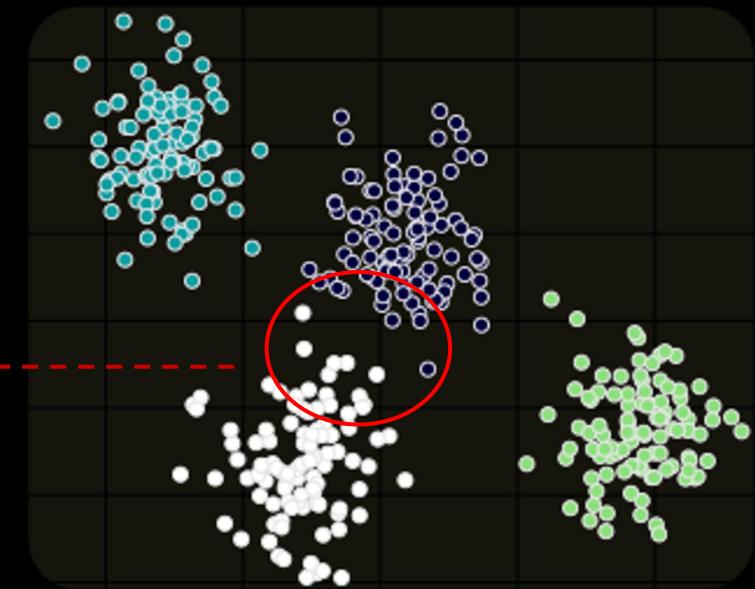
K-Means assign single memberships

*Each point belongs to **one** cluster*

For some examples this is inadequate

K-Means is a form of hard (crisp) clustering

*Membership is an indicator function*



Would seem more flexible to define **probabilities** of membership

Given datapoints  $\mathbf{X}_i$ , cluster index  $C_k$  and centroid positions  $\mathbf{C}_k$

Aim to define

Membership probabilities  $p(\mathbf{x}_i|C_k)$   
Cluster parameters probability  $p_\theta(C_k|\mathbf{x}_i)$

# Probabilistic clustering: centroids

Looping back to the Bayesian framework

- All parameters are probabilities
- We can safely rely on the Bayes rule to have

$$p(C_k | \mathbf{x}_i) = \frac{p(\mathbf{x}_i | C_k)p(C_k)}{\sum_{l=1}^k p(\mathbf{x}_i | C_l)p(C_l)}$$

$\mathbf{x}_i$  Datapoints  
 $C_k$  Cluster index  
 $\mathbf{c}_k$  Centroid positions

Need to assign weights to each cluster

- Weights may not be equal
- Similar to **prior probabilities**  $p(C_k) = \frac{1}{m} \sum_{i=1}^m p(C_k | \mathbf{x}_i)$

Then we can infer centroid positions as

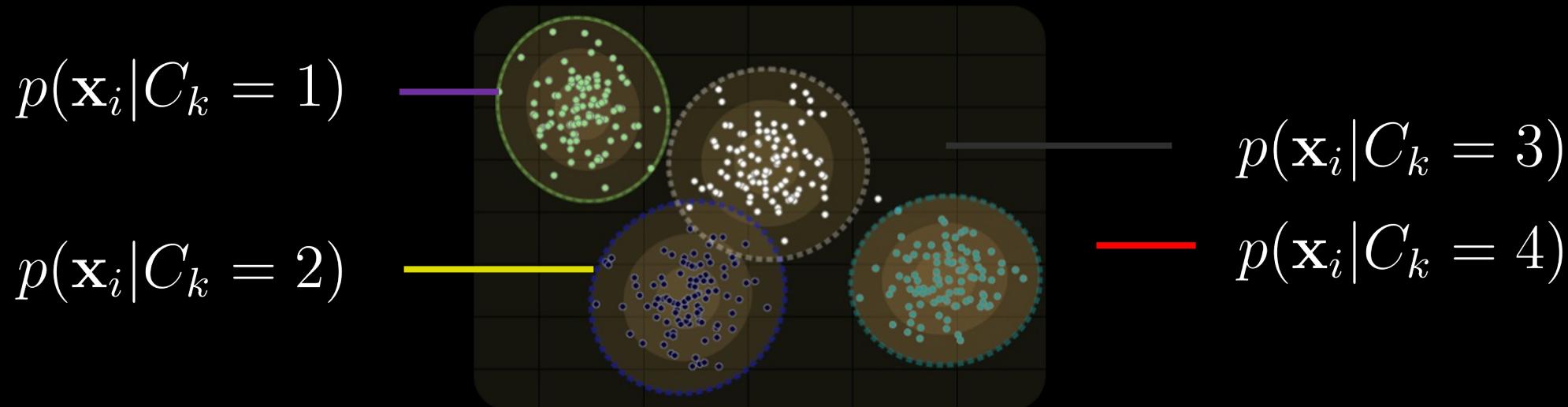
$$\mathbf{c}_k = \frac{\sum_{i=1}^m \mathbf{x}_i p(C_k | \mathbf{x}_i)}{\sum_{i=1}^m p(C_k | \mathbf{x}_i)}$$

# Probabilistic interpretation of clustering

Formal definition of the problem

| We can *define one Gaussian distribution per cluster*

| For each cluster we have  $p(\mathbf{x}_i|C_k) = \mathcal{N}(\mu_k, \Sigma_k)$



| However note that the *full density is multi-modal*

| Each mode represents a sub-population

| – Unimodal Gaussian for each group  $p(\mathbf{x}_i) = \sum_k p(\mathbf{x}_i|C_k) p(C_k)$

**Mixing coefficients**

$$p(\mathbf{x}_i) = \sum_k p(\mathbf{x}_i|C_k) p(C_k)$$

Unimodal

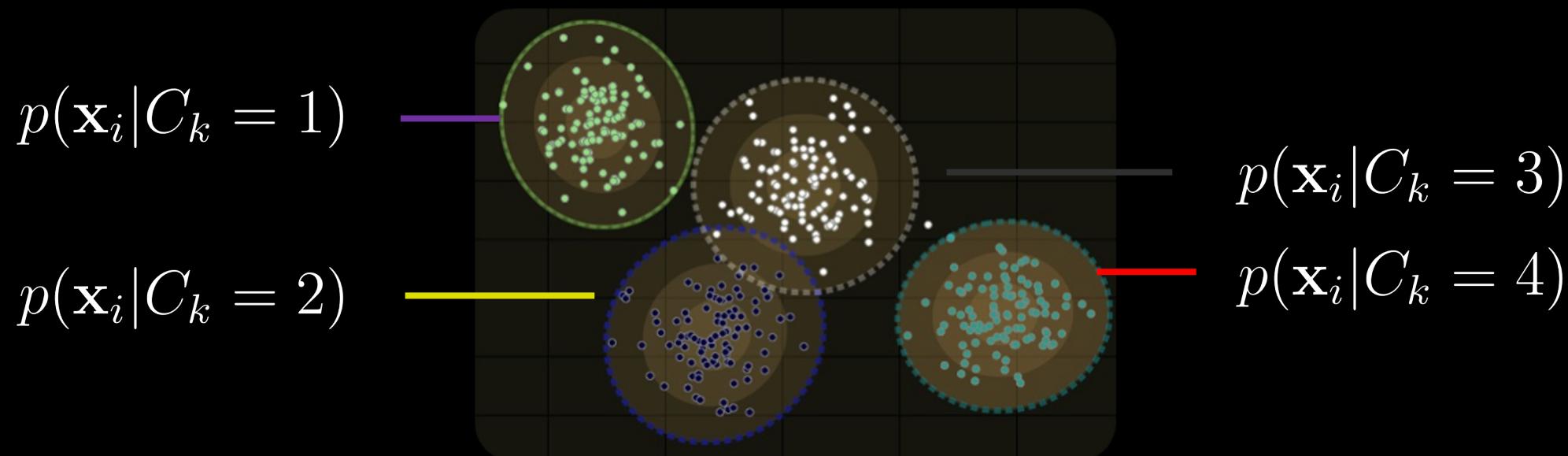
# Probabilistic interpretation of clustering

Performing optimization for the problem

We have the exact same issue as K-Means

If we knew the cluster parameters  $\theta_k = \{\mu_k, \Sigma_k\}$

- Then estimating  $p(\mathbf{x}_i|C_k)$  is easy
- And also consequently estimating  $p(C_k)$ 
  - **Maximum likelihood estimation**



# Probabilistic interpretation of clustering

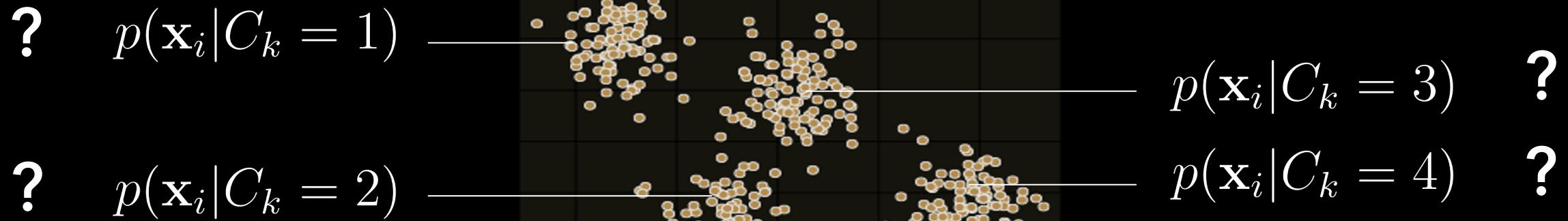
Performing optimization for the problem

- But in reality, we do not have access to  $\theta_k = \{\mu_k, \Sigma_k\}$

- Now estimating  $p(\mathbf{x}_i|C_k)$  and  $p(C_k)$  is hard
  - We need to address a much more complex problem

$$\max_{\theta_k} \sum_i \log \sum_k p(\mathbf{x}_i|C_k; \theta_k) p(C_k; \theta_k)$$

- Need a similar alternating approach



# Expectation-Maximization

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## Introducing Expectation-Maximization (EM)

All data (**X**) observable

- Use the *Maximum likelihood* estimator
- Optimize the analytic form of  $\mathcal{L}(\theta) = \log p(\mathbf{x}; \theta)$

Missing (**latent**) data

- The full data is **X** (observed) and **Z** (latent)
- The likelihood becomes

$$\mathcal{L}(\theta) = \log p(\mathbf{x}, \mathbf{z}; \theta)$$

Performing **optimization**

- As the likelihood is intractable in most cases
- We are going to approximate it

# Expectation-Maximization

EM iteratively maximizes likelihood

The complete likelihood is  $\mathcal{L}(\theta) = \log p(\mathbf{x}, \mathbf{z}; \theta)$

- Start from a random initial guess  $\theta^{(0)}$
- Then iteratively apply (until convergence)

Compute the expectation of the likelihood

*E-Step*

$$\mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\mathcal{L}(\theta)] = \sum_{\mathbf{z}} p(\mathbf{z}|\mathbf{x}; \theta^{(t)}) p(\mathbf{z}, \mathbf{x}; \theta^{(t)})$$

This function is called the Q-function  $Q(\theta; \theta^{(t)}) = \mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\mathcal{L}(\theta)]$

Compute parameters by maximizing the Q-function

*M-Step*

$$\theta^{(t+1)} = \operatorname{argmax}_{\theta} Q(\theta; \theta^{(t)})$$

# Expectation-Maximization

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Summarizing the algorithm in simple terms

- Start from a random initial guess
- Then iteratively apply (until convergence)

*E-Step*

1. Use current parameters (and observations) to reconstruct the hidden (latent) structure

*M-Step*

2. Use hidden structure (and observations) to re-estimate parameters

*Analysis*

- Very similar to simple K-means
- Consists of assignment and updates
- Can use *random initialization*
  - Problem of local minima

# Required tools for EM

---

Steps to **derive** the EM algorithm

1. Write the likelihood of the complete data (*decide distribution*)

$$\mathcal{L}(\theta) = \log p(\mathbf{x}, \mathbf{z}; \theta)$$

2. **E-step:** write the Q function (*expectation given the observed data*)

$$Q(\theta; \theta^{(t)}) = \mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\mathcal{L}(\theta)] = \sum_{\mathbf{z}} \underline{p(\mathbf{z}|\mathbf{x}; \theta^{(t)})p(\mathbf{z}, \mathbf{x}; \theta^{(t)})}$$

3. **M-step:** solve maximization (*deriving closed form solution if possible*)

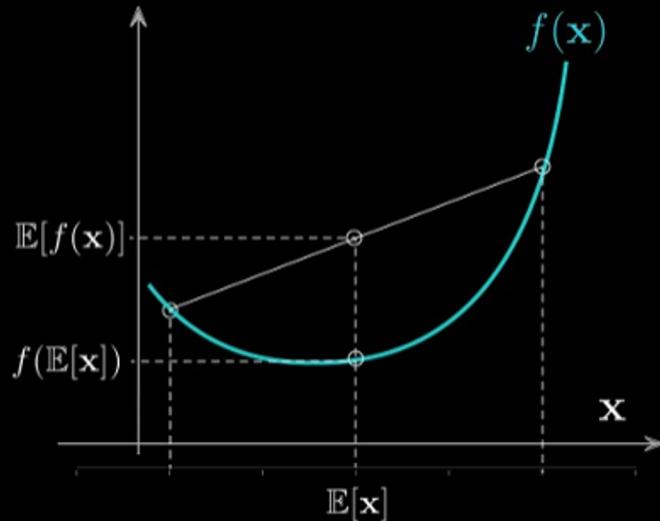
$$\theta^{(t+1)} = \operatorname{argmax}_{\theta} \underline{Q(\theta; \theta^{(t)})}$$

*Usually the Q-function is too complex to obtain directly*

Approximate it with **several tools**

- **Lower-bounding functions**
- **Kullback-Leibler divergence**
- **Jensen's inequality**

# Background knowledge

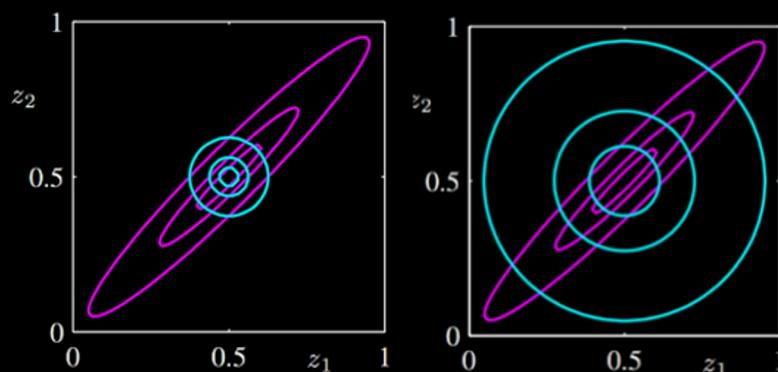


Jensen inequality  
If  $f : \mathbb{R} \rightarrow \mathbb{R}$  is a convex function  
 $\mathbb{E} [f(\mathbf{x})] \geq f (\mathbb{E} [\mathbf{x}])$

Kullback-Leibler divergence

Measure statistical difference between distributions

$$\mathcal{D}_{KL} [p(\mathbf{z}) \parallel q(\mathbf{z})] \neq \mathcal{D}_{KL} [q(\mathbf{z}) \parallel z(\mathbf{z})]$$



$$\mathcal{D}_{KL} [p(\mathbf{z}) \parallel q(\mathbf{z})] = \int p(\mathbf{z}) \log \frac{p(\mathbf{z})}{q(\mathbf{z})} d\mathbf{z}$$

- 
- $\mathcal{D}_{KL} [p(\mathbf{z}) \parallel q(\mathbf{z})] \geq 0. \quad \forall p, q$
  - $\mathcal{D}_{KL} [p(\mathbf{z}) \parallel q(\mathbf{z})] \neq \mathcal{D}_{KL} [q(\mathbf{z}) \parallel z(\mathbf{z})]$
  - $\mathcal{D}_{KL} [p(\mathbf{z}) \parallel q(\mathbf{z})] = 0$  only if  $p = q$

# Expectation Maximization

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Writing down the E(xpectation)-Step

We want to maximize the data likelihood

$$\mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\mathcal{L}(\theta)] = \sum_{\mathbf{z}} p(\mathbf{z}|\mathbf{x};\theta^{(t)}) p(\mathbf{z}, \mathbf{x}; \theta^{(t)})$$

However, distribution  $p(\mathbf{x}, \mathbf{z}; \theta)$  might be too complex

**Lower-bound idea**

Find a function that satisfies  $q_\theta(\mathbf{z}) \leq \mathcal{L}(\theta)$   
Then we know that  $\max_{\theta} q_\theta(\mathbf{z}) \rightarrow \max_{\theta} \mathcal{L}(\theta)$

**Problem:** Quality of lower-bound dictates quality of approximation

Instead of finding a fixed lower-bound  $q(\mathbf{z})$

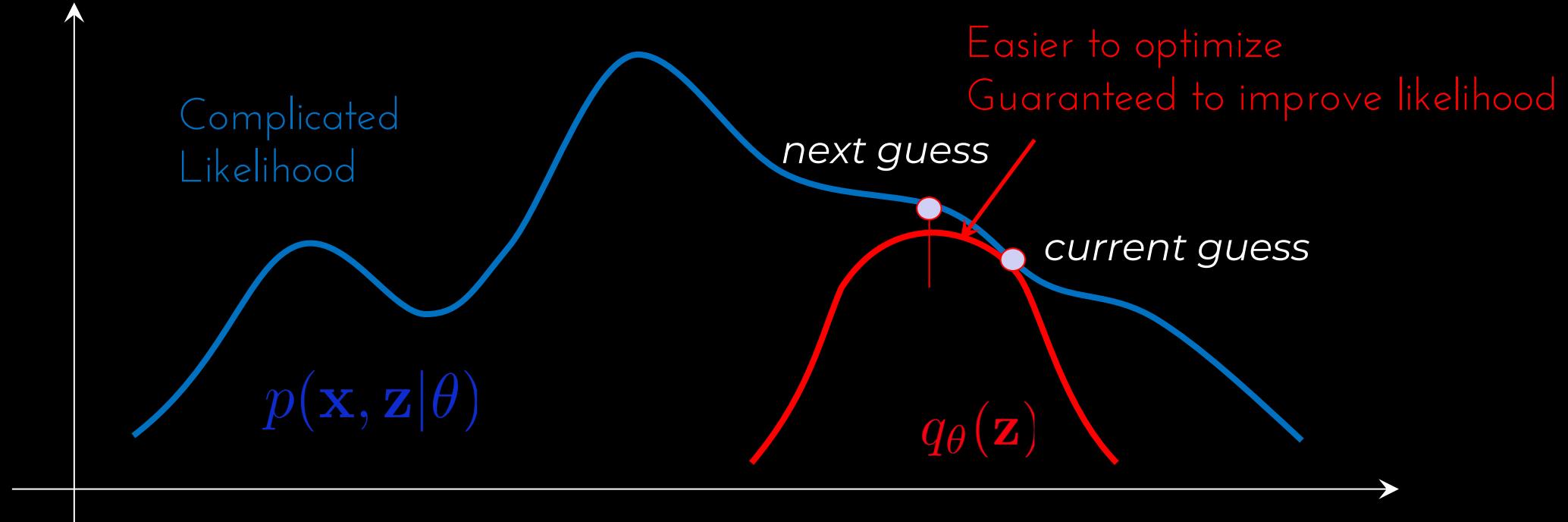
We aim to define a *parametric distribution*  $q_\theta(\mathbf{z})$

Then, we can minimize the difference to our function  $\mathcal{D} = \mathcal{L}(\theta) - q_\theta(\mathbf{z})$

# Intuitive understanding of *lower bounding*

Understanding the idea behind lower bounding

*How do we optimize the approximation*



E-step = computing the lower bound

M-step = maximizing the lower bound

# Expectation Maximization

How to maximize likelihood by pushing the lower bound ?

We can introduce directly the distribution

$$\mathcal{L}(\theta) = \log \sum p(\mathbf{x}, \mathbf{z}; \theta) = \log \sum \frac{q(\mathbf{z})p(\mathbf{x}, \mathbf{z}; \theta)}{q(\mathbf{z})}$$

Jensen's inequality

$$\begin{aligned} f(\mathbb{E}[\mathbf{x}]) &\geq \mathbb{E}[f(\mathbf{x})] \\ &\geq \sum_{\mathbf{z}} q(\mathbf{z}) \underbrace{\log p(\mathbf{x}, \mathbf{z}; \theta)}_{\text{Red arrow}} - \sum_{\mathbf{z}} q(\mathbf{z}) \log q(\mathbf{z}) \\ &= \sum_{\mathbf{z}} q(\mathbf{z}) \log [p(\mathbf{z}|\mathbf{x}; \theta)p(\mathbf{x}; \theta)] - \sum_{\mathbf{z}} q(\mathbf{z}) \log q(\mathbf{z}) \\ &= \sum_{\mathbf{z}} q(\mathbf{z}) \log \frac{p(\mathbf{z}|\mathbf{x}; \theta)}{q(\mathbf{z})} + \underbrace{\log p(\mathbf{x}; \theta)}_{\text{Constant with } q(\mathbf{z})} \\ &\quad \text{Red line} \\ &\quad \text{Red arrow} \\ &\text{Negative KL-divergence } \mathcal{D}_{KL}[q(\mathbf{z}) \parallel p(\mathbf{z}|\mathbf{x}; \theta)] \end{aligned}$$

Final expression

$$\mathcal{L}(\theta) \geq -\mathcal{D}_{KL}[q(\mathbf{z}) \parallel p(\mathbf{z}|\mathbf{x}; \theta)] + const$$

# Expectation-Maximization

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Optimizing the lower bound with respect to  $q(\mathbf{z})$

$$\mathcal{L}(\theta) \geq -\mathcal{D}_{KL} [q(\mathbf{z}) \parallel p(\mathbf{z}|\mathbf{x}; \theta)] + const$$

KL-divergence is non-negative, and equals to zero when

$$q(\mathbf{z}) = p(\mathbf{z}|\mathbf{x}; \theta)$$

Note: the calculation of  $q(\mathbf{z})$  is based on current  $\theta^{(t)}$

Therefore our optimal solution is simply

$$q(\mathbf{z}) = p(\mathbf{z}|\mathbf{x}; \theta^{(t)})$$

Next, we can optimize the parameters in the M-Step

$$\theta^{(t+1)} = \operatorname{argmax}_{\theta} \mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\log p(\mathbf{z}|\mathbf{x}; \theta)]$$

# Properties of EM

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## Issues with the EM algorithm

Note that the global optimal is not guaranteed

- Likelihood  $\mathcal{L}(\theta) = \log p(\mathbf{x}, \mathbf{z}; \theta)$  is usually non-convex
- EM is a greedy algorithm (alternative ascent)

Moving to a more general EM formulation

- We have explicitly assumed our density as Gaussian
- However, we noted that clustering is multi-modal
- This defines **Gaussian Mixture Models (GMM)**

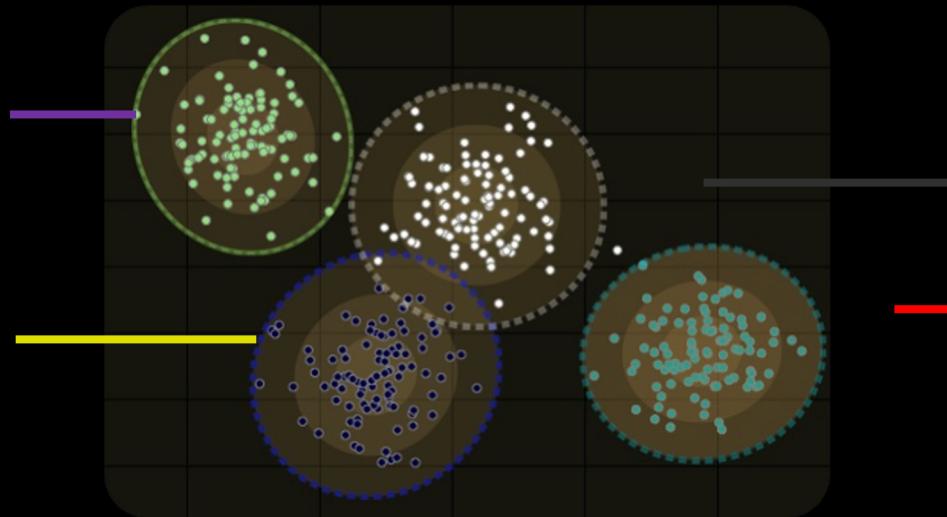
# Probabilistic interpretation of clustering

Formal definition of **probabilistic clustering**

We can *define one Gaussian distribution per cluster*

$$p(\mathbf{x}_i | C_k) = \mathcal{N}(\mu_k, \Sigma_k)$$

$$p(\mathbf{x}_i | C_k = 1)$$



$$p(\mathbf{x}_i | C_k = 2)$$

$$p(\mathbf{x}_i | C_k = 3)$$

$$p(\mathbf{x}_i | C_k = 4)$$

- However note that the full density is multi-modal
- Each mode represents a sub-population
  - Unimodal Gaussian for each group

**Mixing coefficients**

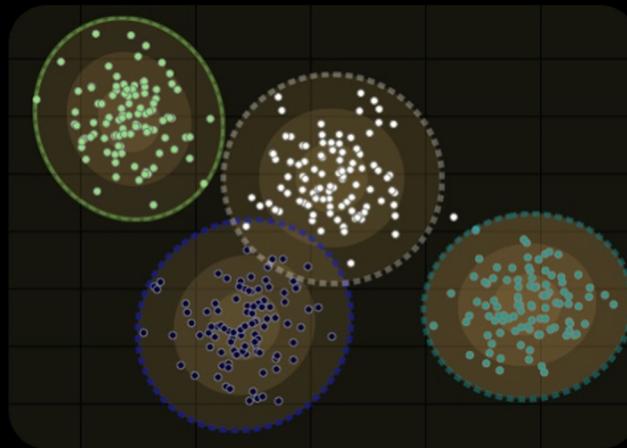
$$p(\mathbf{x}_i) = \sum_k p(\mathbf{x}_i | C_k) \underbrace{p(C_k)}_{\text{Unimodal}}$$

# Mixture models

We have seen with *Maximum Likelihood* how to deal with

$$p(\mathbf{x}|\theta) = \mathcal{N}(\mathbf{x}|\mu, \Sigma) \quad \theta = \{\mu, \Sigma\}$$

Now we have a more complicated **mixture** distribution



$$\begin{aligned} p(\mathbf{x}|\theta) &= \pi_1 \mathcal{N}(\mathbf{x}|\mu_1, \Sigma_1) \\ &+ \pi_2 \mathcal{N}(\mathbf{x}|\mu_2, \Sigma_2) \\ &+ \pi_3 \mathcal{N}(\mathbf{x}|\mu_3, \Sigma_3) \\ &+ \pi_4 \mathcal{N}(\mathbf{x}|\mu_4, \Sigma_4) \end{aligned}$$

Mixing coefficients

$$\theta = \{\pi_1, \pi_2, \pi_3, \pi_4, \mu_1, \mu_2, \mu_3, \mu_4, \Sigma_1, \Sigma_2, \Sigma_3, \Sigma_4\}$$

Mixture distribution

$$p(\mathbf{x}|\theta) = \sum_c \pi_c \mathcal{N}(\mathbf{x}|\mu_c, \Sigma_c)$$

# Gaussian Mixture Model (GMM)

The full distribution is a Gaussian Mixture Model (GMM)

$$p(\mathbf{x}|\theta) = \sum_c \pi_c \mathcal{N}(\mathbf{x}|\mu_c, \Sigma_c)$$

Generally speaking, *mixture models* are defined as sums of distributions

Components of a mixture model

Base distribution  
(here Gaussian) |  $p(\mathbf{x}|z=c, \theta) = \mathcal{N}(\mathbf{x}|\mu_c, \Sigma_c)$

Mixing probabilities  
(here memberships) |  $p(z=c|\theta) = \pi_c$

Note this implies constraints  $\pi_c \geq 0, \forall c$   $\sum_c \pi_c = 1$

Optimizing this model implies a complicated problem

$$\max_{\theta} p(\mathbf{x}|\theta) = \prod_{i=1}^N p(\mathbf{x}_i|\theta)$$

$$\max_{\theta} \prod_{i=1}^N \sum_c \pi_c \mathcal{N}(\mathbf{x}|\mu_c, \Sigma_c)$$

# Optimizing GMM

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As we have seen previously, we have a latent variable

$$p(z = c|\theta) = \pi_c$$

This defines *mixing probabilities*, with then

$$p(\mathbf{x}|z = c, \theta) = \mathcal{N}(\mathbf{x}|\mu_c, \Sigma_c)$$

Therefore, we can retrieve our model by marginalization

$$p(\mathbf{x}|\theta) = \sum_c p(\mathbf{x}|z = c, \theta)p(z = c|\theta)$$

If we knew the latent  $p(z = c|\theta)$  optimization is easy as

$$p(\mathbf{x}|z = c, \theta) = \mathcal{N}(\mathbf{x}|\mu_c, \Sigma_c) \quad \mu_c = \frac{\sum_i p(z = c|\mathbf{x}_i, \theta)\mathbf{x}_i}{\sum_i p(z = c|\mathbf{x}_i, \theta)}$$

However, we need to optimize both the means and the latent

Goal of the Expectation-Maximization algorithm

# Expectation-Maximization

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EM iteratively maximizes likelihood

The complete likelihood is  $\mathcal{L}(\theta) = \log p(\mathbf{x}, \mathbf{z}; \theta)$

- Start from a random initial guess  $\theta^{(0)}$
- Then iteratively apply (until convergence)

Compute the expectation of the likelihood

*E-Step*

$$\mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\mathcal{L}(\theta)] = \sum_{\mathbf{z}} p(\mathbf{z}|\mathbf{x}; \theta^{(t)}) p(\mathbf{z}, \mathbf{x}; \theta^{(t)})$$

This function is called the Q-function  $Q(\theta; \theta^{(t)}) = \mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\mathcal{L}(\theta)]$

Compute parameters by maximizing the Q-function

*M-Step*

$$\theta^{(t+1)} = \operatorname{argmax}_{\theta} Q(\theta; \theta^{(t)})$$

# Expectation-Maximization

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Optimizing the lower bound with respect to  $q(\mathbf{z})$

$$\mathcal{L}(\theta) \geq -\mathcal{D}_{KL} [q(\mathbf{z}) \parallel p(\mathbf{z}|\mathbf{x}; \theta)] + const$$

KL-divergence is non-negative, and equals to zero when

$$q(\mathbf{z}) = p(\mathbf{z}|\mathbf{x}; \theta)$$

Note: the calculation of  $q(\mathbf{z})$  is based on current  $\theta^{(t)}$

Therefore our optimal solution is simply

$$q(\mathbf{z}) = p(\mathbf{z}|\mathbf{x}; \theta^{(t)})$$

Next, we can optimize the parameters in the M-Step

$$\theta^{(t+1)} = \operatorname{argmax}_{\theta} \mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\log p(\mathbf{z}|\mathbf{x}; \theta)]$$

# E-Step for GMM

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We know the optimal approximation  $q(\mathbf{z}) = p(\mathbf{z}|\mathbf{x}; \theta^{(t)})$

So we simply need to compute the latent probabilities

$$\pi_{c,i} = p(z_i = c | \mathbf{x}, \theta)$$

Noting that we need to satisfy the constraint  $\sum_{c=1}^C \pi_{c,i} = 1$

Deriving the optimal solution

$$\begin{aligned} p(z = c | \mathbf{x}_i, \theta) &= \mathcal{N}(\mathbf{x}_i | \mu_c, \Sigma_c) \\ &= \frac{1}{\sqrt{(2\pi)^d \Sigma_c}} \exp \left[ -\frac{1}{2} (\mathbf{x}_i - \mu_c)^T \Sigma_c^{-1} (\mathbf{x}_i - \mu_c) \right] \end{aligned}$$

Then, we can simply normalize with  $\pi_{c,i} = \pi_{c,i} / \sum_{c=1}^C \pi_{c,i}$

# M-Step for GMM

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**M-step** seeks to optimize the parameters as

$$\theta^{(t+1)} = \operatorname{argmax}_{\theta} \mathbb{E}_{\mathbf{z}|\mathbf{x};\theta^{(t)}} [\log p(\mathbf{z}|\mathbf{x}; \theta)]$$

Writing out the full density

$$\begin{aligned}\mathbb{E}_{\mathbf{z}} [\log p(\mathbf{x}, \mathbf{z}|\theta)] &= \sum_i \sum_c q(z_i = c) \log \left( \frac{1}{Z} \exp \left[ -\frac{(x_i - \mu_c)^2}{2\sigma_c^2} \right] \pi_c \right) \\ &= \sum_i \sum_c q(z_i = c) \left( \log \frac{\pi_c}{Z} - \frac{(x_i - \mu_c)^2}{2\sigma_c^2} \right)\end{aligned}$$

Finding the maximum by deriving *one mean*

$$\frac{\partial}{\partial \mu_1} = \sum_i q(z_i = 1) \left( 0 - \frac{(x_i - \mu_1)(-1)}{2\sigma_1^2} \right) = \sum_i q(z_i = 1)x_i - \sum_i q(z_i = 1)\mu_1$$

Final solution

$$\mu_1 = \frac{\sum_i q(z_i = 1)x_i}{\sum_i q(z_i = 1)}$$

*Similar derivations for all parameters and multivariate case*

# Mixture density estimates

GMMs are useful for *density estimation*

- Consider the following distribution
- Example of *spectral harmonics*
- Clearly *not a single Gaussian*

*Mixture density estimates*

- Allows to directly target
- Provides a generative model on our data
- *Problem of number of components*

