

Lecture 10: Clustering Part II

Statistical Methods for Data Science

Yinan Yu

Department of Computer Science and Engineering

December 9, 2021

Today

- 1 Distribution clustering
 - Gaussian Mixture Models (GMM)
 - Parameter estimation: the EM algorithm
 - Hyperparameter K : AIC and BIC
- 2 Hierarchical clustering
- 3 Density clustering
- 4 Cluster validation
- 5 Summary

Learning outcome

- Be able to explain the difference between Gaussian naive Bayes classifier and GMM in terms of parameter estimation
- Be able to explain the objective function $Q(\theta)$ for GMM
- Understand what EM algorithm is used for and why we need it
- Be able to calculate AIC/BIC and use them to determine K for GMM
- Be able to explain the EM algorithm for one dimensional GMM
- Be able to explain the difference between K-means and the EM algorithm in terms of their assumptions and parameter estimation

Today

- 1 Distribution clustering
 - Gaussian Mixture Models (GMM)
 - Parameter estimation: the EM algorithm
 - Hyperparameter K : AIC and BIC
- 2 Hierarchical clustering
- 3 Density clustering
- 4 Cluster validation
- 5 Summary

Gaussian Mixture Models (GMM)

Four categories

Clustering models

- **Centroid clustering** (lecture 9)
- **Distribution clustering**
- Density clustering
- Hierarchical clustering

Gaussian Mixture Models (GMM) - overview

Distribution clustering:

- Each cluster is **modeled** using a probability distribution
- Each data point is **modeled** using a combination of all clusters

Gaussian Mixture Models (GMM) - overview

Distribution clustering:

- Each cluster is **modeled** using a probability distribution
- Each data point is **modeled** using a combination of all clusters

Gaussian Mixture Models:

- **Data \mathbf{x}** : a d dimensional feature vector $\mathbf{x} = [x_1, \dots, x_d]$

$$f(\mathbf{x}) = \sum_{k=1}^K \pi_k f(\mathbf{x} | k)$$

where

- $\pi_k = P(k) > 0$ and $\sum_{k=1}^K \pi_k = 1$;
- $f(\mathbf{x} | k)$ is a **d dimensional multivariate Gaussian PDF** describing cluster k .

Gaussian Mixture Models (GMM) - overview (cont.)

- Gaussian Mixture Model:

$$f(\mathbf{x}) = \sum_{k=1}^K \pi_k f(\mathbf{x} | k)$$

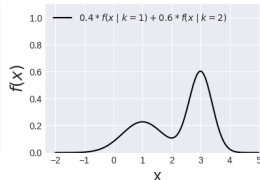
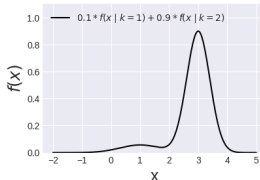
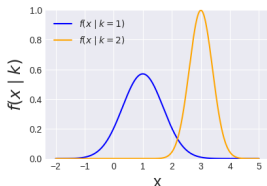
- Examples of the mixture distribution with $d = 1$

- Example 1: $\pi_1 = 0.1$, $\pi_2 = 0.9$

$$f(x) = 0.1 \times f(x | k = 1) + 0.9 \times f(x | k = 2) = 0.1 \times f(x | \mu_1, \sigma_1) + 0.9 \times f(x | \mu_2, \sigma_2)$$

- Example 2: $\pi_1 = 0.4$, $\pi_2 = 0.6$

$$f(x) = 0.4 \times f(x | k = 1) + 0.6 \times f(x | k = 2) = 0.4 \times f(x | \mu_1, \sigma_1) + 0.6 \times f(x | \mu_2, \sigma_2)$$

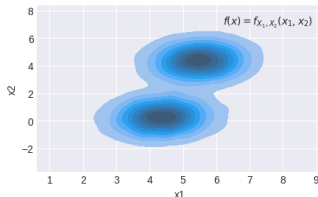


Gaussian Mixture Models (GMM) - overview (cont.)

- Examples of the mixture distribution with $d = 2$: $\pi_1 = 0.5$, $\pi_2 = 0.5$

$$f(\mathbf{x}) = 0.5 \times f(\mathbf{x} \mid k = 1) + 0.5 \times f(\mathbf{x} \mid k = 2) = 0.5 \times f(\mathbf{x} \mid \boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1) + 0.5 \times f(\mathbf{x} \mid \boldsymbol{\mu}_2, \boldsymbol{\Sigma}_2)$$

where $\boldsymbol{\mu}_k \in \mathbb{R}^2$ is the mean and $\boldsymbol{\Sigma}_k \in \mathbb{R}^{2 \times 2}$ is the covariance matrix



Gaussian Mixture Models (GMM) - overview (cont.)

Gaussian Mixture Models (GMM) - overview (cont.)

- **Data \mathbf{x}** : a d dimensional feature vector $\mathbf{x} = [x_1, \dots, x_d]$ with PDF $f(\mathbf{x}) = \sum_{k=1}^K \pi_k f(\mathbf{x} | k)$

Gaussian Mixture Models (GMM) - overview (cont.)

- **Data \mathbf{x}** : a d dimensional feature vector $\mathbf{x} = [x_1, \dots, x_d]$ with PDF $f(\mathbf{x}) = \sum_{k=1}^K \pi_k f(\mathbf{x} | k)$
- **Target y** : y is a set of K posterior probabilities; for $k = 1, \dots, K$

$$\underbrace{P(k | \mathbf{x})}_{\text{posterior}} = \frac{\underbrace{P(k)}_{\text{prior}} \underbrace{f(\mathbf{x} | k)}_{\text{likelihood of } k}}{\sum_{c=1}^K P(c) f(\mathbf{x} | c)}$$

Gaussian Mixture Models (GMM) - overview (cont.)

- **Data \mathbf{x}** : a d dimensional feature vector $\mathbf{x} = [x_1, \dots, x_d]$ with PDF $f(\mathbf{x}) = \sum_{k=1}^K \pi_k f(\mathbf{x} | k)$
- **Target y** : y is a set of K posterior probabilities; for $k = 1, \dots, K$

$$\overbrace{P(k | \mathbf{x})}^{\text{posterior}} = \frac{\overbrace{P(k)}^{\text{prior}} \overbrace{f(\mathbf{x} | k)}^{\text{likelihood of } k}}{\sum_{c=1}^K P(c) f(\mathbf{x} | c)}$$

It is **soft clustering** - \mathbf{x} is assigned to **all clusters** with a probability - the posterior $P(k | \mathbf{x})$.

Gaussian Mixture Models (GMM) - overview (cont.)

- **Data \mathbf{x}** : a d dimensional feature vector $\mathbf{x} = [x_1, \dots, x_d]$ with PDF $f(\mathbf{x}) = \sum_{k=1}^K \pi_k f(\mathbf{x} | k)$
- **Target y** : y is a set of K posterior probabilities; for $k = 1, \dots, K$

$$\underbrace{P(k | \mathbf{x})}_{\text{posterior}} = \frac{\underbrace{P(k)}_{\text{prior}} \underbrace{f(\mathbf{x} | k)}_{\text{likelihood of } k}}{\sum_{c=1}^K P(c) f(\mathbf{x} | c)}$$

It is **soft clustering** - \mathbf{x} is assigned to **all clusters** with a probability - the posterior $P(k | \mathbf{x})$.
Alternatively, y can be defined as the cluster index with the highest posterior probability, i.e.

$$y = \arg \max_{k \in \{1, \dots, K\}} P(k | \mathbf{x}) = \arg \max_{k \in \{1, \dots, K\}} P(k) f(\mathbf{x} | k)$$

Gaussian Mixture Models (GMM) - overview (cont.)

- **Data \mathbf{x}** : a d dimensional feature vector $\mathbf{x} = [x_1, \dots, x_d]$ with PDF $f(\mathbf{x}) = \sum_{k=1}^K \pi_k f(\mathbf{x} | k)$
- **Target y** : y is a set of K posterior probabilities; for $k = 1, \dots, K$

$$\overbrace{P(k | \mathbf{x})}^{\text{posterior}} = \frac{\overbrace{P(k)}^{\text{prior}} \overbrace{f(\mathbf{x} | k)}^{\text{likelihood of } k}}{\sum_{c=1}^K P(c) f(\mathbf{x} | c)}$$

It is **soft clustering** - \mathbf{x} is assigned to **all clusters** with a probability - the posterior $P(k | \mathbf{x})$.
Alternatively, y can be defined as the cluster index with the highest posterior probability, i.e.

$$y = \arg \max_{k \in \{1, \dots, K\}} P(k | \mathbf{x}) = \arg \max_{k \in \{1, \dots, K\}} P(k) f(\mathbf{x} | k)$$

- **Parameter**: the parameters of the mixture distribution $f(\mathbf{x})$
 - The parameters for each Gaussian likelihood $f(\mathbf{x} | k)$
 - The prior $P(k)$, typically denoted as π_k

Parameter estimation: the EM algorithm

Parameter estimation for GMM

- Parameter estimation

Parameter estimation for GMM

- **Parameter estimation**
 - What's special about this? We know how to do it! It's almost the same as the **Gaussian naive Bayes classifier**!

Parameter estimation for GMM

- **Parameter estimation**
 - What's special about this? We know how to do it! It's almost the same as the **Gaussian naive Bayes classifier**!
 - Let's discuss the key differences between these two algorithms

Parameter estimation for GMM

- **Parameter estimation**

- What's special about this? We know how to do it! It's almost the same as the **Gaussian naive Bayes classifier**!
- Let's discuss the key differences between these two algorithms
- **Set up**: given a data set $\mathcal{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$, we need to estimate the parameter of interest from \mathcal{X}

Parameter estimation for GMM

• Parameter estimation

- What's special about this? We know how to do it! It's almost the same as the **Gaussian naive Bayes classifier**!
- Let's discuss the key differences between these two algorithms
- **Set up**: given a data set $\mathcal{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$, we need to estimate the parameter of interest from \mathcal{X}

	Gaussian naive Bayes classifier	Gaussian Mixture Models
Parameter of interest	$P(k)$, Gaussian PDF $f(\mathbf{x} k)$, for $k = 1, \dots, K$	
Labels for data set \mathcal{X}	known	unknown
Interpretation	One label for each \mathbf{x}_i (hard assignment)	K probabilities for each \mathbf{x}_i (soft assignment)
Assumption	\mathbf{x}_i and \mathbf{x}_j independent for $i \neq j$	
	\mathbf{x}'_m and \mathbf{x}'_n independent for $m \neq n$ (NAIVE!)	\mathbf{x}'_m and \mathbf{x}'_n NOT necessarily independent for $m \neq n$

Parameter estimation for GMM (cont.)

In summary, we have the following additional challenges compared to the Gaussian naive Bayes classifier:

1. We **do not have the labels** - we cannot easily estimate $P(k)$ and $f(\mathbf{x} | k)$
2. The distribution $f(\mathbf{x} | k)$ is a **multivariate Gaussian PDF** and the features are **not necessarily independent** - now we need to explicitly work with **joint probability distributions** $f_{X_1, \dots, X_d}(x_1, \dots, x_d | k)$ and **covariance matrices**;

Parameter estimation for GMM (cont.)

In summary, we have the following additional challenges compared to the Gaussian naive Bayes classifier:

1. We **do not have the labels** - we cannot easily estimate $P(k)$ and $f(\mathbf{x} | k)$
2. The distribution $f(\mathbf{x} | k)$ is a **multivariate Gaussian PDF** and the features are **not necessarily independent** - now we need to explicitly work with **joint probability distributions** $f_{X_1, \dots, X_d}(x_1, \dots, x_d | k)$ and **covariance matrices**; the subscripts here are the indices for the dimensions of the feature space; they are not the indices for the data points - data points are still independent!

Parameter estimation for GMM (cont.)

In summary, we have the following additional challenges compared to the Gaussian naive Bayes classifier:

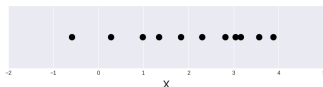
1. We **do not have the labels** - we cannot easily estimate $P(k)$ and $f(\mathbf{x} | k)$
2. The distribution $f(\mathbf{x} | k)$ is a **multivariate Gaussian PDF** and the features are **not necessarily independent** - now we need to explicitly work with **joint probability distributions** $f_{X_1, \dots, X_d}(x_1, \dots, x_d | k)$ and **covariance matrices**; the subscripts here are the indices for the dimensions of the feature space; they are not the indices for the data points - data points are still independent!

Let's focus on the first issue by working with **one dimensional** feature vectors so we don't get overwhelmed by dealing with all the problems at once

Note: in this lecture, we simply use θ to denote the estimate (instead of $\hat{\theta}$) in order to reduce clutter since the notations are already quite complex.

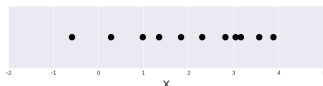
Parameter estimation for **one dimensional** GMM

- **Data:** x_1, \dots, x_N



Parameter estimation for **one dimensional** GMM

- **Data:** x_1, \dots, x_N



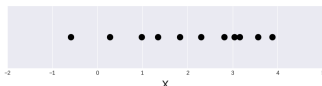
- **Random variable:** X_1, \dots, X_N i.i.d. with PDF

$$f(x) = \sum_{k=1}^K \pi_k f(x | k)$$

where $f(x | k)$ is a Gaussian PDF.

Parameter estimation for **one dimensional** GMM

- **Data:** x_1, \dots, x_N



- **Random variable:** X_1, \dots, X_N i.i.d. with PDF

$$f(x) = \sum_{k=1}^K \pi_k f(x | k)$$

where $f(x | k)$ is a Gaussian PDF.

The joint probability distribution of all data points is defined as

$$f_{X_1, \dots, X_N}(x_1, \dots, x_N) \stackrel{i.i.d.}{=} \prod_{i=1}^N f(x_i) = \prod_{i=1}^N \sum_{k=1}^K \pi_k f(x_i | k) \quad (1)$$

This is the **likelihood** of the **mixture distribution** given data x_1, \dots, x_N .

Parameter estimation for **one dimensional** GMM

- **Data:** x_1, \dots, x_N



- **Random variable:** X_1, \dots, X_N i.i.d. with PDF

$$f(x) = \sum_{k=1}^K \pi_k f(x | k)$$

where $f(x | k)$ is a Gaussian PDF.

The joint probability distribution of all data points is defined as

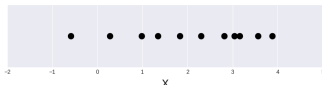
$$f_{X_1, \dots, X_N}(x_1, \dots, x_N) \stackrel{i.i.d.}{=} \prod_{i=1}^N f(x_i) = \prod_{i=1}^N \sum_{k=1}^K \pi_k f(x_i | k) \quad (1)$$

This is the **likelihood** of the **mixture distribution** given data x_1, \dots, x_N .

- **Parameter of interest:** π_k (prior), μ_k , σ_k , for all $k = 1, \dots, K$

Parameter estimation for **one dimensional** GMM

- **Data:** x_1, \dots, x_N



- **Random variable:** X_1, \dots, X_N i.i.d. with PDF

$$f(x) = \sum_{k=1}^K \pi_k f(x | k)$$

where $f(x | k)$ is a Gaussian PDF.

The joint probability distribution of all data points is defined as

$$f_{X_1, \dots, X_N}(x_1, \dots, x_N) \stackrel{i.i.d.}{=} \prod_{i=1}^N f(x_i) = \prod_{i=1}^N \sum_{k=1}^K \pi_k f(x_i | k) \quad (1)$$

This is the **likelihood** of the **mixture distribution** given data x_1, \dots, x_N .

- **Parameter of interest:** π_k (prior), μ_k , σ_k , for all $k = 1, \dots, K$
- **Parameter estimation method:** maximum likelihood estimation

Parameter estimation for one dimensional GMM (cont.)

- The **log likelihood** (cf. Eq. (1) on page 14) is defined as:

$$\begin{aligned} Q(\theta) &= \log L(\theta \mid x_1, \dots, x_N) = \log f_{X_1, \dots, X_N}(x_1, \dots, x_N) \\ &= \sum_{i=1}^N \log \left(\sum_{k=1}^K \pi_k f(x_i \mid k) \right) \end{aligned} \quad (2)$$

where $\theta = (\mu_1, \dots, \mu_K, \sigma_1, \dots, \sigma_K, \pi_1, \dots, \pi_K)$

Parameter estimation for one dimensional GMM (cont.)

- The **log likelihood** (cf. Eq. (1) on page 14) is defined as:

$$\begin{aligned} Q(\theta) &= \log L(\theta \mid x_1, \dots, x_N) = \log f_{X_1, \dots, X_N}(x_1, \dots, x_N) \\ &= \sum_{i=1}^N \log \left(\sum_{k=1}^K \pi_k f(x_i \mid k) \right) \end{aligned} \quad (2)$$

where $\theta = (\mu_1, \dots, \mu_K, \sigma_1, \dots, \sigma_K, \pi_1, \dots, \pi_K)$

- The parameters are estimated by **maximizing the log likelihood**

$$\hat{\theta} = \arg \max_{\theta} Q(\theta)$$

Parameter estimation for one dimensional GMM (cont.)

- The **log likelihood** (cf. Eq. (1) on page 14) is defined as:

$$\begin{aligned} Q(\theta) &= \log L(\theta \mid x_1, \dots, x_N) = \log f_{X_1, \dots, X_N}(x_1, \dots, x_N) \\ &= \sum_{i=1}^N \log \left(\sum_{k=1}^K \pi_k f(x_i \mid k) \right) \end{aligned} \quad (2)$$

where $\theta = (\mu_1, \dots, \mu_K, \sigma_1, \dots, \sigma_K, \pi_1, \dots, \pi_K)$

- The parameters are estimated by **maximizing the log likelihood**

$$\hat{\theta} = \arg \max_{\theta} Q(\theta)$$

- There is no closed-form solution due to the **summation** inside the log!

Parameter estimation for one dimensional GMM (cont.)

- The **log likelihood** (cf. Eq. (1) on page 14) is defined as:

$$\begin{aligned} Q(\theta) &= \log L(\theta \mid x_1, \dots, x_N) = \log f_{X_1, \dots, X_N}(x_1, \dots, x_N) \\ &= \sum_{i=1}^N \log \left(\sum_{k=1}^K \pi_k f(x_i \mid k) \right) \end{aligned} \quad (2)$$

where $\theta = (\mu_1, \dots, \mu_K, \sigma_1, \dots, \sigma_K, \pi_1, \dots, \pi_K)$

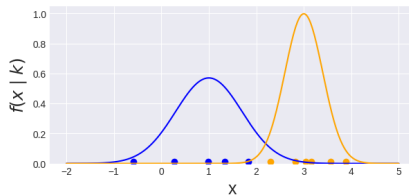
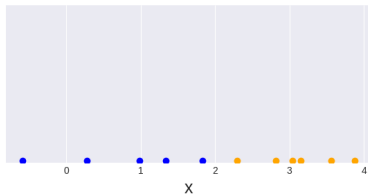
- The parameters are estimated by **maximizing the log likelihood**

$$\hat{\theta} = \arg \max_{\theta} Q(\theta)$$

- There is no closed-form solution due to the **summation** inside the log!
- We need to apply an iterative method to find the solution - the **EM algorithm**

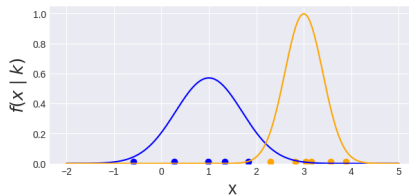
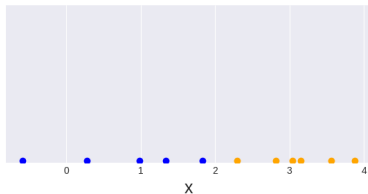
Intuition behind EM

Scenario 1: if we knew the label of each data point, the task would be to estimate the parameters (similar to Gaussian Naive Bayes)



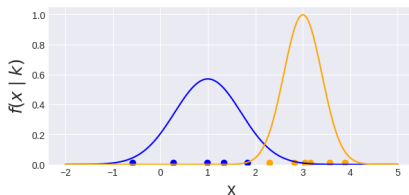
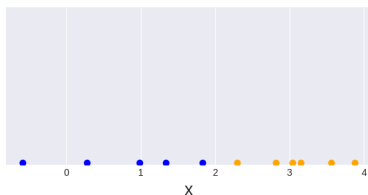
Intuition behind EM

Scenario 1: if we knew the label of each data point, the task would be to estimate the parameters (similar to Gaussian Naive Bayes)



Intuition behind EM

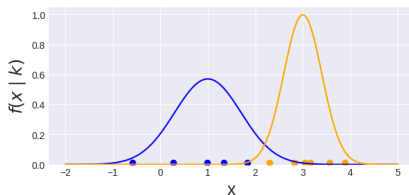
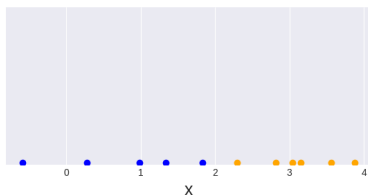
Scenario 1: if we knew the label of each data point, the task would be to estimate the parameters (similar to Gaussian Naive Bayes)



- $\pi_k = P(k) = \frac{N_k}{N}$, where N_k is the count of data points that belong to cluster k , i.e.
 $\pi_1 = P(\text{blue}) = \frac{5}{11}$ and $\pi_2 = P(\text{orange}) = \frac{6}{11}$

Intuition behind EM

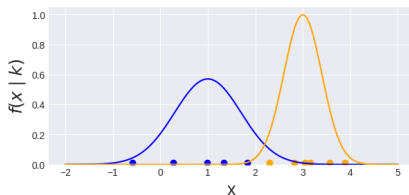
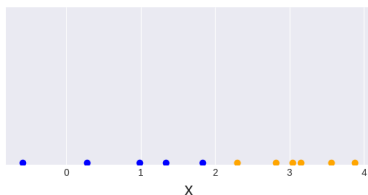
Scenario 1: if we knew the label of each data point, the task would be to estimate the parameters (similar to Gaussian Naive Bayes)



- $\pi_k = P(k) = \frac{N_k}{N}$, where N_k is the count of data points that belong to cluster k , i.e.
 $\pi_1 = P(\text{blue}) = \frac{5}{11}$ and $\pi_2 = P(\text{orange}) = \frac{6}{11}$
- $\mu_k = \frac{1}{N_k} \sum_{i=1}^{N_k} x_i$

Intuition behind EM

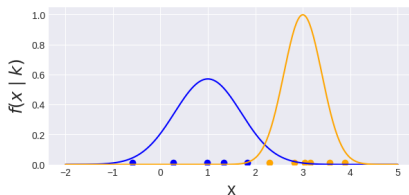
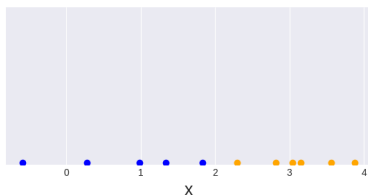
Scenario 1: if we knew the label of each data point, the task would be to estimate the parameters (similar to Gaussian Naive Bayes)



- $\pi_k = P(k) = \frac{N_k}{N}$, where N_k is the count of data points that belong to cluster k , i.e.
 $\pi_1 = P(\text{blue}) = \frac{5}{11}$ and $\pi_2 = P(\text{orange}) = \frac{6}{11}$
- $\mu_k = \frac{1}{N_k} \sum_{i=1}^{N_k} x_i$
- $\sigma_k^2 = \frac{1}{N_k} \sum_{i=1}^{N_k} (x_i - \mu_k)^2$

Intuition behind EM

Scenario 1: if we knew the label of each data point, the task would be to estimate the parameters (similar to Gaussian Naive Bayes)

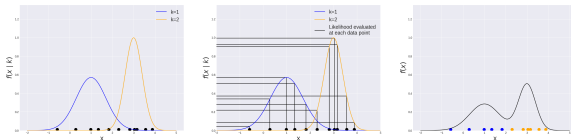


- $\pi_k = P(k) = \frac{N_k}{N}$, where N_k is the count of data points that belong to cluster k , i.e.
 $\pi_1 = P(\text{blue}) = \frac{5}{11}$ and $\pi_2 = P(\text{orange}) = \frac{6}{11}$
- $\mu_k = \frac{1}{N_k} \sum_{i=1}^{N_k} x_i$
- $\sigma_k^2 = \frac{1}{N_k} \sum_{i=1}^{N_k} (x_i - \mu_k)^2$

Scenario 1 \approx **maximization** step in the EM algorithm

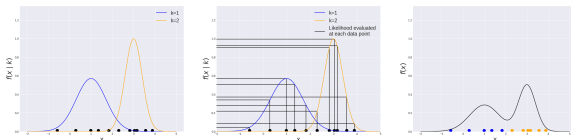
Intuition behind EM (cont.)

Scenario 2: if we knew the two priors $P(1)$, $P(2)$ and the two Gaussian distributions $f(x | 1)$, $f(x | 2)$, the task would be to compute the posterior probability $P(k | x)$ for $k \in \{\text{orange}, \text{blue}\}$; then we can assign each data point x to a cluster y by the maximum a posteriori estimation $y = \begin{cases} \text{blue}, & P(\text{orange} | x) < P(\text{blue} | x) \\ \text{orange}, & P(\text{orange} | x) \geq P(\text{blue} | x) \end{cases}$



Intuition behind EM (cont.)

Scenario 2: if we knew the two priors $P(1)$, $P(2)$ and the two Gaussian distributions $f(x | 1)$, $f(x | 2)$, the task would be to compute the posterior probability $P(k | x)$ for $k \in \{\text{orange}, \text{blue}\}$; then we can assign each data point x to a cluster y by the maximum a posteriori estimation $y = \begin{cases} \text{blue}, & P(\text{orange} | x) < P(\text{blue} | x) \\ \text{orange}, & P(\text{orange} | x) \geq P(\text{blue} | x) \end{cases}$



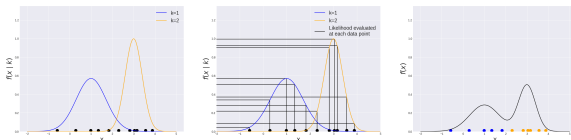
- **Prior:** $\pi_1 = P(z_1) = P(\text{blue})$, $\pi_2 = P(z_2) = P(\text{orange})$
- **Likelihood:** $f(x | \text{blue}) = \text{blue}$, $f(x | \text{orange}) = \text{orange}$
- **Posterior:**

$$P(\text{blue} | x) = \frac{P(\text{blue})f(x | \text{blue})}{P(\text{blue})f(x | \text{blue}) + P(\text{orange})f(x | \text{orange})}$$

$$P(\text{orange} | x) = \frac{P(\text{orange})f(x | \text{orange})}{P(\text{blue})f(x | \text{blue}) + P(\text{orange})f(x | \text{orange})}$$

Intuition behind EM (cont.)

Scenario 2: if we knew the two priors $P(1)$, $P(2)$ and the two Gaussian distributions $f(x | 1)$, $f(x | 2)$, the task would be to compute the posterior probability $P(k | x)$ for $k \in \{\text{orange}, \text{blue}\}$; then we can assign each data point x to a cluster y by the maximum a posteriori estimation $y = \begin{cases} \text{blue}, & P(\text{orange} | x) < P(\text{blue} | x) \\ \text{orange}, & P(\text{orange} | x) \geq P(\text{blue} | x) \end{cases}$



- **Prior:** $\pi_1 = P(z_1) = P(\text{blue})$, $\pi_2 = P(z_2) = P(\text{orange})$
- **Likelihood:** $f(x | \text{blue}) = \text{blue}$, $f(x | \text{orange}) = \text{orange}$
- **Posterior:**

$$P(\text{blue} | x) = \frac{P(\text{blue})f(x | \text{blue})}{P(\text{blue})f(x | \text{blue}) + P(\text{orange})f(x | \text{orange})}$$

$$P(\text{orange} | x) = \frac{P(\text{orange})f(x | \text{orange})}{P(\text{blue})f(x | \text{blue}) + P(\text{orange})f(x | \text{orange})}$$

Scenario 2 \approx **expectation** step in the EM algorithm

Intuition behind EM (cont.)

- In reality, we don't know any of these!

Intuition behind EM (cont.)

- In reality, we don't know any of these!
- The idea here is that we start with some initial guesses and alternate scenario 1 and 2 **iteratively** until convergence

Intuition behind EM (cont.)

- In reality, we don't know any of these!
- The idea here is that we start with some initial guesses and alternate scenario 1 and 2 **iteratively** until convergence
- This is essentially how the **Expectation-Maximization (EM) algorithm** works
 - **E-step (expectation)**: estimate the posterior for all data points given each cluster (scenario 2)
 - **M-step (maximization)**: estimate the parameters for each cluster (scenario 1)

Intuition behind EM (cont.)

- In reality, we don't know any of these!
- The idea here is that we start with some initial guesses and alternate scenario 1 and 2 **iteratively** until convergence
- This is essentially how the **Expectation-Maximization (EM) algorithm** works
 - **E-step (expectation)**: estimate the posterior for all data points given each cluster (scenario 2)
 - **M-step (maximization)**: estimate the parameters for each cluster (scenario 1)
- Disclaimer: the purpose of the scenario 1 and 2 is to build up some intuitions only; for details of the EM algorithm, please refer to the description in the next few slides

The EM algorithm: two main steps

Two main steps in the EM algorithm

- **E-step (expectation)**: compute the **posterior probability** of the cluster for each data point x_i

$$\gamma_{ik} = P(k | x_i) = \frac{\pi_k f(x_i | k)}{\sum_{c=1}^K \pi_c f(x_i | c)}, \quad \text{for all } k = 1, \dots, K$$

This posterior is also called the **responsibility**, denoted as γ_{ik}

- **M-step (maximization)**: estimate the parameters
 - $\pi_k = P(k) = \frac{N_k}{N}$, where $N_k = \sum_{i=1}^N \gamma_{ik}$ - **soft clustering**
 - $\mu_k = \frac{1}{N_k} \sum_{i=1}^N \gamma_{ik} x_i$
 - $\sigma_k^2 = \frac{1}{N_k} \sum_{i=1}^N \gamma_{ik} (x_i - \mu_k)^2$for each cluster $k = 1, \dots, K$

K-means as a special case of the EM algorithm

Expectation Step

- EM: **soft clustering** - posterior

$$\gamma_{ik} = P(k | x_i)$$

Why soft? - It is a probability, i.e. $\gamma_{ik} \in [0, 1]$

- K-means: **hard clustering** - equivalent to

$$\gamma_{ik} = \begin{cases} 1, & \text{if the centroid of cluster } k \text{ is the closest to } x_i \\ 0, & \text{otherwise} \end{cases}$$

Why hard? - It is a binary decision, i.e. $\gamma_{ik} \in \{0, 1\}$

Maximization Step

- EM: need to estimate μ_k, σ_k , where

$$\mu_k = \frac{1}{N_k} \sum_{i=1}^K \gamma_{ik} x_i, \quad \sigma_k^2 = \frac{1}{N_k} \sum_{i=1}^N \gamma_{ik} (x_i - \mu_k)^2, \quad N_k = \sum_{i=1}^N \gamma_{ik}, \quad \text{for } \gamma_{ik} \in [0, 1]$$

- K-means: only need to estimate μ_k , where

$$\mu_k = \frac{1}{N_k} \sum_{i=1}^N \gamma_{ik} x_i = \frac{1}{N_k} \sum_{x \in \text{cluster } k} x, \quad N_k = \sum_{i=1}^N \gamma_{ik}, \quad \text{for } \gamma_{ik} \in \{0, 1\}$$

The complete EM algorithm

- These two steps are the core of the EM algorithm

The complete EM algorithm

- These two steps are the core of the EM algorithm
- Besides that, there are some extra steps involved

The complete EM algorithm

- These two steps are the core of the EM algorithm
- Besides that, there are some extra steps involved
- The EM algorithm is an **iterative method**

The complete EM algorithm

- These two steps are the core of the EM algorithm
- Besides that, there are some extra steps involved
- The EM algorithm is an **iterative method**
- There are three important components in an iterative method:
 - 1) Initialization step
 - 2) Update the parameters in a while loop (the core, i.e. the maximization step and the expectation step)
 - 3) Stopping criteria

The complete EM algorithm (cont.)

- **1) Initialization step:** initialize π_k, μ_k, σ_k manually (randomly) or using, e.g. the K-means algorithm μ_k , for all $i = 1, \dots, N$, $k = 1, \dots, K$

The complete EM algorithm (cont.)

- **1) Initialization step:** initialize π_k, μ_k, σ_k manually (randomly) or using, e.g. the K-means algorithm μ_k , for all $i = 1, \dots, N$, $k = 1, \dots, K$
- **2) Update the parameters in a while loop:** repeat the expectation step and the maximization step until the stopping criteria are met; each repetition of this process is called **one iteration**

The complete EM algorithm (cont.)

- **1) Initialization step:** initialize π_k, μ_k, σ_k manually (randomly) or using, e.g. the K-means algorithm μ_k , for all $i = 1, \dots, N$, $k = 1, \dots, K$
- **2) Update the parameters in a while loop:** repeat the expectation step and the maximization step until the stopping criteria are met; each repetition of this process is called **one iteration**
- **3) Stopping criteria:** something you check (using e.g. a conditional statement) inside the while loop; if the stopping criteria are true, the loop shall be escaped - then you are done! There are two alternative stopping criteria for the EM algorithm:
 - Has the objective function, i.e. the log likelihood (cf. Eq. (2)), changed since the last iteration?
 - Have any of the parameters, i.e. π_k, μ_k, σ_k , changed since the last iteration?

Hyperparameter K : AIC and BIC

How to choose hyperparameter K

- For a given data set, we need to choose the number of clusters K

How to choose hyperparameter K

- For a given data set, we need to choose the number of clusters K
- Similar to K-means, we first estimate $\hat{\theta}$ and then we choose the K value that gives the best clustering quality

How to choose hyperparameter K

- For a given data set, we need to choose the number of clusters K
- Similar to K-means, we first estimate $\hat{\theta}$ and then we choose the K value that gives the best clustering quality
- Given an estimate $\hat{\theta}$ for a given number of clusters K , we introduce two **alternative** criteria for this task: **Akaike Information Criterion (AIC)** and **Bayesian Information Criterion (BIC)**

How to choose hyperparameter K (cont.)

How to choose hyperparameter K (cont.)

- Akaike Information Criterion (AIC)

$$\begin{aligned} AIC(K) &= \overbrace{-\log(\text{likelihood})}^{\text{How well the model explains data ("error")}} + \overbrace{c_K}^{\text{Complexity of the model}} \\ &= -Q(\hat{\theta}) + c_K \end{aligned}$$

How to choose hyperparameter K (cont.)

- Akaike Information Criterion (AIC)**

$$\begin{aligned}
 AIC(K) &= \underbrace{\text{How well the model explains data ("error")}}_{-\log(\text{likelihood})} + \underbrace{\text{Complexity of the model}}_{c_K} \\
 &= -Q(\hat{\theta}) + c_K
 \end{aligned}$$

- Bayesian Information Criterion (BIC)**

$$\begin{aligned}
 BIC(K) &= \underbrace{\text{How well the model explains data ("error")}}_{-\log(\text{likelihood})} + \underbrace{\text{Complexity of the model}}_{\frac{1}{2}c_K \log N} \\
 &= -Q(\hat{\theta}) + \frac{1}{2}c_K \log N
 \end{aligned}$$

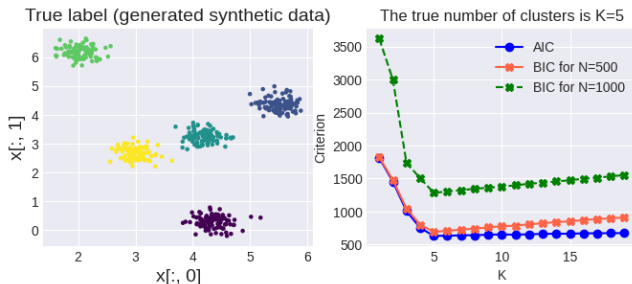
where c_K is the number of parameters to be estimated:

$$c_K = \underbrace{K \times d \times (d+1)/2}_{\text{covariance matrices}} + \underbrace{(K-1)}_{\text{priors}} + \underbrace{d \times K}_{\text{means}}$$

Note: an alternative definition is to multiply this definition of AIC and BIC by 2

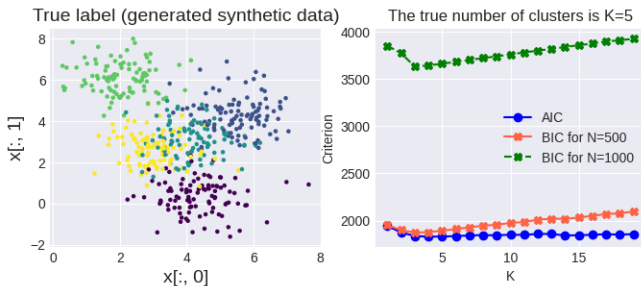
AIC vs BIC

- The idea is to find the best K that balances the “error” and the complexity of the model - **Occam's Razor** (cf. lecture 5) - if two models explain the data equally well, we choose the simpler one!
- BIC penalizes the complexity more than AIC - BIC increases more as K gets larger
- Example 1: well separated clusters



AIC vs BIC (cont.)

- Example 2: overlapping clusters



High dimensional GMM

- The second problem on page 13 is the high dimensional joint probability distribution of the correlated feature vectors
- In this course, we will not go into details of multivariate Gaussian distributions; nevertheless, the EM steps for $d > 1$ is presented as follows

Expectation Step

$$\gamma_{ik} = P(k | \mathbf{x}_i) = \frac{\pi_k f(\mathbf{x}_i | k)}{\sum_{c=1}^K \pi_c f(\mathbf{x}_i | c)}, \text{ for all } k = 1, \dots, K$$

Maximization Step

- $\pi_k = P(k) = \frac{N_k}{N}$, where $N_k = \sum_{i=1}^N \gamma_{ik}$
- $\boldsymbol{\mu}_k = \frac{1}{N_k} \sum_{i=1}^N \gamma_{ik} \mathbf{x}_i$
- $\boldsymbol{\Sigma}_k = \frac{1}{N_k} \sum_{i=1}^N \gamma_{ik} (\mathbf{x}_i - \boldsymbol{\mu}_k)(\mathbf{x}_i - \boldsymbol{\mu}_k)^T$ - note that \mathbf{x}_i is a column vector here

The covariance matrix $\boldsymbol{\Sigma}_k$ captures the dependence between features

Recap: GMM

- Gaussian Mixture Models (GMM) is a mixture distribution characterized by a mixture PDF

$$f(\mathbf{x}) = \sum_{k=1}^K \pi_k f(\mathbf{x} | k)$$

where each $f(\mathbf{x} | k)$ is a multivariate Gaussian PDF for each Gaussian component k **multivariate**
because $\mathbf{x} \in \mathbb{R}^d$ is a $d \geq 1$ dimensional feature vector

- $f(\mathbf{x})$ is the PDF of the mixture model with **parameters** $\theta = \{\mu_1, \dots, \mu_K, \Sigma_1, \dots, \Sigma_K\}$
- $f(\mathbf{x})$ is the **likelihood** of θ given data \mathbf{x}
- **Parameter estimation**: maximum **likelihood** estimation - given $\mathbf{x}_1, \dots, \mathbf{x}_N$

$$\hat{\theta} = \arg \max_{\theta} \sum_{i=1}^N \log(f(\mathbf{x}_i))$$

- No closed form solution - iterative algorithm for finding $\hat{\theta}$ - the EM algorithm
- Comparison to other techniques
 - Gaussian naive Bayes classifiers vs GMM
 - K-means vs the EM algorithm for parameter estimation

GMM: pros and cons

- Pros:
 - Relatively simple compared to other mixture models **we love Gaussians!**
 - Flexible due to the soft clustering criterion
- Cons:
 - Might get stuck on local optimum of the objective function
 - Convergence can be slow
 - Covariance matrix estimate might lead to divergence in case of small data set
 - Need to choose the hyperparameter K manually
 - Gaussian mixture assumption might not be true

Today

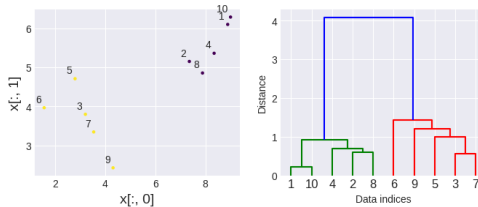
- 1 Distribution clustering
- 2 Hierarchical clustering**
- 3 Density clustering
- 4 Cluster validation
- 5 Summary

Agglomerative vs divisive

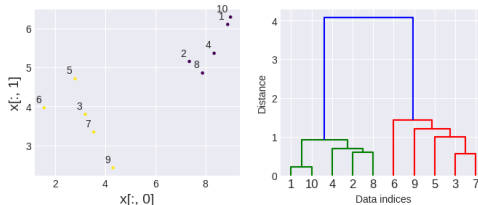
Two types of hierarchical clustering

- Agglomerative (bottom-up):
 - Start with each data point being its own cluster
 - Merge the closest clusters until there is only one cluster
- Divisive (top-down):
 - Start with one cluster
 - Split until each cluster contains only one data point

Agglomerative hierarchical clustering using a dendrogram

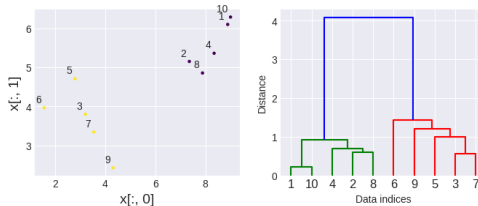


Agglomerative hierarchical clustering using a dendrogram



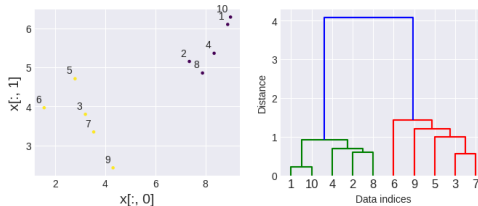
- Step 1: consider each data point as its own cluster; find the closest clusters - 1 and 10; group 1 and 10 into one cluster; the height of the dendrogram indicates the Euclidean distance

Agglomerative hierarchical clustering using a dendrogram



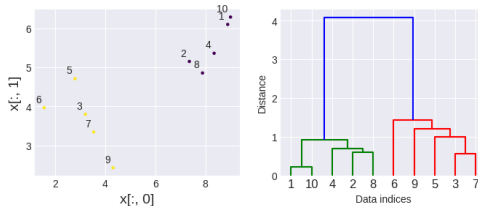
- Step 1: consider each data point as its own cluster; find the closest clusters - 1 and 10; group 1 and 10 into one cluster; the height of the dendrogram indicates the Euclidean distance - now we have 9 clusters in total

Agglomerative hierarchical clustering using a dendrogram



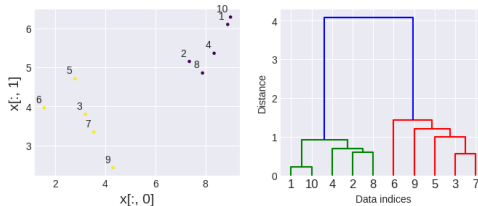
- Step 1: consider each data point as its own cluster; find the closest clusters - 1 and 10; group 1 and 10 into one cluster; the height of the dendrogram indicates the Euclidean distance - now we have 9 clusters in total
- Step 2: find the closest clusters - 3 and 7 - group 3 and 7 into one cluster

Agglomerative hierarchical clustering using a dendrogram



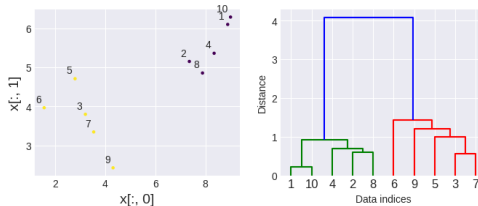
- Step 1: consider each data point as its own cluster; find the closest clusters - 1 and 10; group 1 and 10 into one cluster; the height of the dendrogram indicates the Euclidean distance - now we have 9 clusters in total
- Step 2: find the closest clusters - 3 and 7 - group 3 and 7 into one cluster
- Step 3: repeat until there is only one cluster left

Agglomerative hierarchical clustering using a dendrogram



- Step 1: consider each data point as its own cluster; find the closest clusters - 1 and 10; group 1 and 10 into one cluster; the height of the dendrogram indicates the Euclidean distance - now we have 9 clusters in total
- Step 2: find the closest clusters - 3 and 7 - group 3 and 7 into one cluster
- Step 3: repeat until there is only one cluster left
- Step 4: draw a horizontal line to split data into different clusters

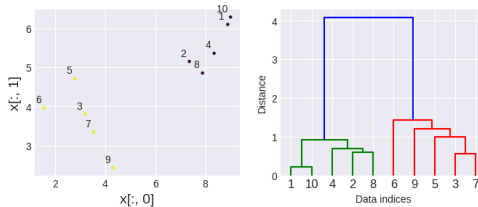
Agglomerative hierarchical clustering using a dendrogram



- Step 1: consider each data point as its own cluster; find the closest clusters - 1 and 10; group 1 and 10 into one cluster; the height of the dendrogram indicates the Euclidean distance - now we have 9 clusters in total
- Step 2: find the closest clusters - 3 and 7 - group 3 and 7 into one cluster
- Step 3: repeat until there is only one cluster left
- Step 4: draw a horizontal line to split data into different clusters

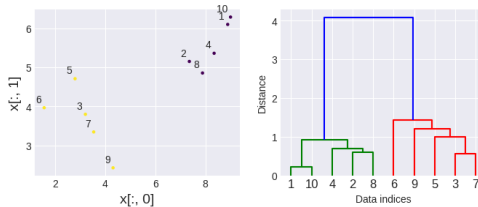
Divisive hierarchical clustering has a similar process (but top-down)

Distance between clusters - alternative linkages



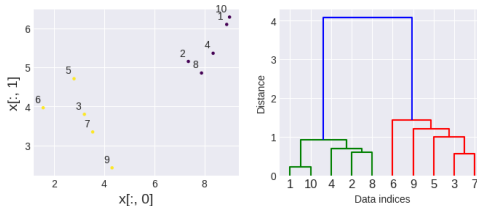
- The height of the dendrogram shows the distance between two clusters

Distance between clusters - alternative linkages



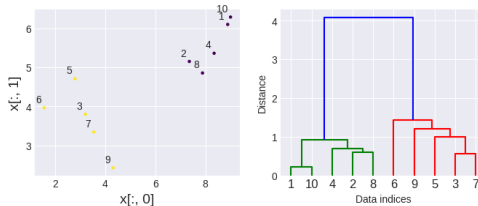
- The height of the dendrogram shows the distance between two clusters
- We need to choose how to compute the distance on the cluster level when there are more than one point in each cluster

Distance between clusters - alternative linkages



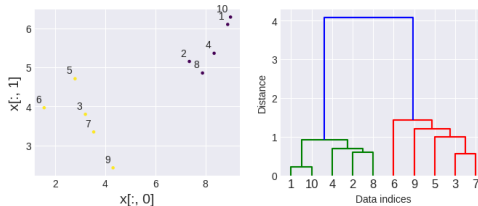
- The height of the dendrogram shows the distance between two clusters
- We need to choose how to compute the distance on the cluster level when there are more than one point in each cluster
- There are different alternatives to defined the distance between two clusters, e.g. the distance between cluster $\{1, 10\}$ and cluster $\{4, 2, 8\}$

Distance between clusters - alternative linkages



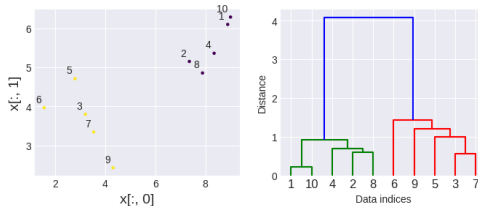
- The height of the dendrogram shows the distance between two clusters
- We need to choose how to compute the distance on the cluster level when there are more than one point in each cluster
- There are different alternatives to defined the distance between two clusters, e.g. the distance between cluster $\{1, 10\}$ and cluster $\{4, 2, 8\}$
 - **Single-linkage**: the distance between the closest pair, i.e. $dist(1, 4)$

Distance between clusters - alternative linkages



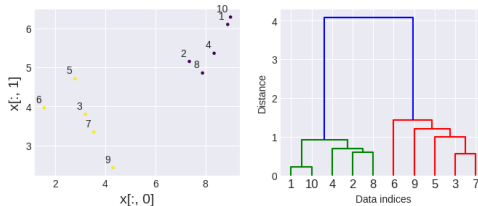
- The height of the dendrogram shows the distance between two clusters
- We need to choose how to compute the distance on the cluster level when there are more than one point in each cluster
- There are different alternatives to defined the distance between two clusters, e.g. the distance between cluster $\{1, 10\}$ and cluster $\{4, 2, 8\}$
 - **Single-linkage**: the distance between the closest pair, i.e. $dist(1, 4)$
 - **Complete-linkage**: the distance between the farthest pair, i.e. $dist(10, 8)$

Distance between clusters - alternative linkages



- The height of the dendrogram shows the distance between two clusters
- We need to choose how to compute the distance on the cluster level when there are more than one point in each cluster
- There are different alternatives to defined the distance between two clusters, e.g. the distance between cluster $\{1, 10\}$ and cluster $\{4, 2, 8\}$
 - **Single-linkage**: the distance between the closest pair, i.e. $dist(1, 4)$
 - **Complete-linkage**: the distance between the farthest pair, i.e $dist(10, 8)$
 - **Centroid**: the distance between two centroids, i.e.
 $dist(\text{centroid}(\{1, 10\}), \text{centroid}(\{4, 2, 8\}))$

Distance between clusters - alternative linkages



- The height of the dendrogram shows the distance between two clusters
- We need to choose how to compute the distance on the cluster level when there are more than one point in each cluster
- There are different alternatives to defined the distance between two clusters, e.g. the distance between cluster $\{1, 10\}$ and cluster $\{4, 2, 8\}$
 - **Single-linkage**: the distance between the closest pair, i.e. $dist(1, 4)$
 - **Complete-linkage**: the distance between the farthest pair, i.e $dist(10, 8)$
 - **Centroid**: the distance between two centroids, i.e.
 $dist(\text{centroid}(\{1, 10\}), \text{centroid}(\{4, 2, 8\}))$

In this example, $dist(\cdot, \cdot)$ is the Euclidean distance

Hierarchical clustering: pros and cons

- Pros:
 - No need to choose K
 - Easy to implement
 - Might give a meaningful taxonomy
- Cons:
 - Once two clusters are grouped, the action cannot be undone
 - Does not scale well with large data set
 - No well defined objective function

Today

- 1 Distribution clustering
- 2 Hierarchical clustering
- 3 Density clustering**
- 4 Cluster validation
- 5 Summary

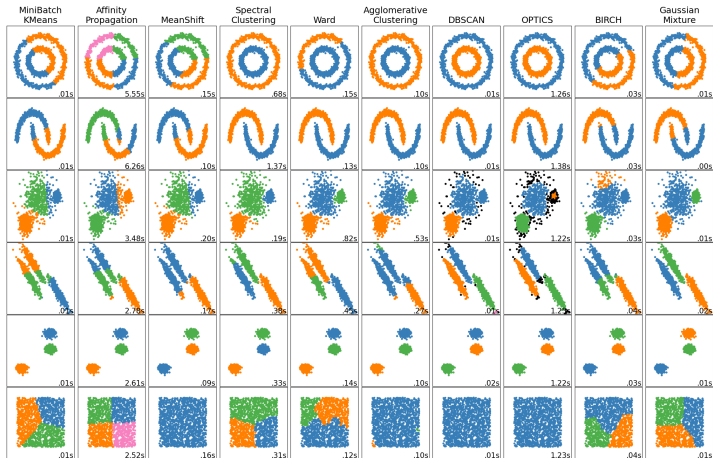
Introduction

- Idea: cluster data based on their closest points, i.e. the neighborhood
- Hyperparameter
 - Radius of the neighborhood ϵ
 - Minimum number of points n in its ϵ neighborhood

Density clustering: pros and cons

- Pros:
 - Handles clusters with arbitrary shapes
 - Handles noise explicitly
- Cons:
 - Sensitive to the sampling technique in the neighborhood
 - Need to choose the hyperparameters ϵ and n
 - Not optimal for clusters with varying density

Comparison (from Python scikit-learn)



Today

- 1 Distribution clustering
- 2 Hierarchical clustering
- 3 Density clustering
- 4 Cluster validation**
- 5 Summary

Validation criteria

Cluster validation is to evaluate the quality of clusters; there are two types of criteria: internal and external

Validation criteria

Cluster validation is to evaluate the quality of clusters; there are two types of criteria: internal and external

- Internal criteria: unsupervised; cluster labels are unknown
 - Algorithms that assume clusters with spherical shapes
 - Silhouette score
 - SSE
 - Many other indices, e.g. Davies–Bouldin index, Dunn index, etc
 - Algorithms that assume mixture distributions
 - AIC
 - BIC
 - Distance based criteria; more generic
 - Similarity matrix with data ordered by cluster indices

Validation criteria

Cluster validation is to evaluate the quality of clusters; there are two types of criteria: internal and external

- Internal criteria: unsupervised; cluster labels are unknown
 - Algorithms that assume clusters with spherical shapes
 - Silhouette score
 - SSE
 - Many other indices, e.g. Davies–Bouldin index, Dunn index, etc
 - Algorithms that assume mixture distributions
 - AIC
 - BIC
 - Distance based criteria; more generic
 - Similarity matrix with data ordered by cluster indices
- External criteria: supervised; ground truth labels are given
 - Purity
 - F1-score
 - Entropy and mutual information

Today

- 1 Distribution clustering
- 2 Hierarchical clustering
- 3 Density clustering
- 4 Cluster validation
- 5 Summary**

Summary

So far:

- Data types and data containers
- Descriptive data analysis: descriptive statistics, visualization
- Probability distributions, events, random variables, PMF, PDF, parameters
- CDF, Q-Q plot, how to compare two distributions (data vs theoretical, data vs data)
- Modeling
- Parameter estimation: maximum likelihood estimation (MLE) and maximum a posteriori estimation (MAP)
- Classification, multinomial naive Bayes classifier, Gaussian naive Bayes classifier
- Central limit theorem, interval estimation
- Hypothesis tests, comparison of two classifiers
- Clustering, cluster tendency
- Centroid clustering, k-means, parameter estimation, SSE, Silhouette score
- Gaussian Mixture Models, AIC/BIC
- EM algorithm in detail
- Hierarchical clustering, density clustering

Summary

So far:

- Data types and data containers
- Descriptive data analysis: descriptive statistics, visualization
- Probability distributions, events, random variables, PMF, PDF, parameters
- CDF, Q-Q plot, how to compare two distributions (data vs theoretical, data vs data)
- Modeling
- Parameter estimation: maximum likelihood estimation (MLE) and maximum a posteriori estimation (MAP)
- Classification, multinomial naive Bayes classifier, Gaussian naive Bayes classifier
- Central limit theorem, interval estimation
- Hypothesis tests, comparison of two classifiers
- Clustering, cluster tendency
- Centroid clustering, k-means, parameter estimation, SSE, Silhouette score
- Gaussian Mixture Models, AIC/BIC
- EM algorithm in detail
- Hierarchical clustering, density clustering

Next:

- Decision trees and random forest

