(Gaussian) Mixture Models and the Expectation Maximization Algorithm

Morteza Chehreghani
Chalmers University of Technology

May 15, 2018

Review of the Last Week

K-means objective corresponds to optimizing the following problem

$$\min_{\boldsymbol{\mu},\mathbf{Z}} R(\boldsymbol{\mu},\mathbf{Z};\mathbf{X}) \quad = \quad \min_{\boldsymbol{\mu},\mathbf{Z}} \sum_{n=1}^{N}\sum_{k=1}^{K} z_{nk}\|\mathbf{x}_n-\boldsymbol{\mu}_k\|_2^2.$$

$$\text{s.t.} \quad z_{nk}\in\{0,1\} \text{ and } \sum_{k=1}^{K} z_{nk}=1\ \forall n.$$

Where,
$\mathbf{X}=[\mathbf{x}_1;\ \cdots\ ;\mathbf{x}_N]\in\mathbb{R}^{N\times D}$,
$\boldsymbol{\mu}=[\boldsymbol{\mu}_1;\ \cdots\ ;\boldsymbol{\mu}_K]\in\mathbb{R}^{K\times D}$ and
$\mathbf{Z}\in\{0,1\}^{N\times K}$.

From Hard to Soft Clustering

- Relax the 'hard' constraint given by

$$z_{nk} \in \{0,1\}, \ \sum_{k=1}^{K} z_{nk} = 1 \ ,$$

- and replace it by a 'soft' constraint:

$$z_{nk} \in [0,1], \ \sum_{k=1}^{K} z_{nk} = 1 \ .$$

From Single to Mixture Models

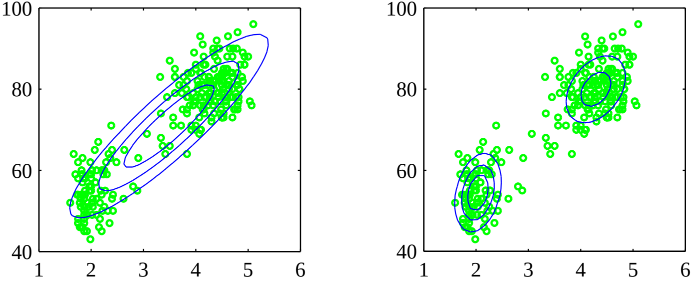
Old Faithful data set includes 272 measurements of eruptions of the Old Faithful geyser at Yellowstone National Park. Each measurement consists of

- the duration of the eruption in minutes;
- the time in minutes to the next eruption.

From Single to Mixture Models

Plots of the 'old faithful' data

- Horizontal axis: the duration of the eruption in minutes.
- Vertical axis: the time in minutes to the next eruption.



(a) Modeling data with a single Gaussian distribution fitted by maximum likelihood

(b) Modeling data by a linear combination of two Gaussians fitted by maximum likelihood

Gaussian Distrbution (1-D)

- Sample space $\mathcal{X} = \mathbb{R}$
- Definition:

$$p(x|\mu, \sigma) := \frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{(x-\mu)^2}{2\sigma^2})$$

- Statistics:

$$\mathrm{E}[X] := \mu, Var[X] := \sigma^2$$

Gaussian Distrbution (d-D)

- Sample space $\mathcal{X} = \mathbb{R}^n, \mathbf{x} = (x_1, .., x_d)^\top$
- Definition:
  $p(\mathbf{x}|\mu, \Sigma) := \frac{1}{(\sqrt{2\pi})^d |\Sigma|^{\frac{1}{2}}} \exp(-\frac{1}{2}(\mathbf{x} - \mu)^\top \Sigma^{-1} (\mathbf{x} - \mu))$

  where Σ is the covariance matrix and $|\Sigma|$ is its determinant

Generative Clustering

Generative approach

- Goal: explain the observed data $\{\mathbf{x}_n\}_{n=1}^{N}$ by a probabilistic model $p(\mathbf{x})$.
- We assume the parametric form of the model to be chosen apriori.
- The model has parameters that need to be learned in order to explain the observed data well.
- Today we will focus on Gaussian Mixture Model.

Clustering?

The model can be interpreted as assigning data points to different components/modes of a multimodal distribution.

Introduction to Mixture Models

- Mixture of K probability densities is defined as

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k p(\mathbf{x} \mid \boldsymbol{\theta}_k).$$

  Each probability distribution $p(\mathbf{x} \mid \boldsymbol{\theta}_k)$ is a component of the mixture and has its own parameters $\boldsymbol{\theta}_k$.

- Almost any continuous density can be approximated by using a sufficient number of component distributions.
- For a Gaussian component distribution the parameters $\boldsymbol{\theta}_k$ are given by the mean $\boldsymbol{\mu}_k$ and the covariance $\boldsymbol{\Sigma}_k$.

Elements of Mixture Models

Mixture models are constructed from:

- Component distributions of the form $p(\mathbf{x} \mid \boldsymbol{\theta}_k)$.
- Mixing coefficients π_k that give the probability of each component.

In order for $p(\mathbf{x})$ to be a proper distribution, we have to ensure that

$$\sum_{k=1}^{K} \pi_k = 1 \quad \text{and} \quad \pi_k \geq 0,\ 1 \leq k \leq K.$$

Therefore, the parameters $\pi_k, 1 \leq k \leq K$ define a categorical distribution representing the probability of each component.

Gaussian Mixture Model

The Gaussian Mixture Model (GMM) uses Gaussians as the component distributions.

The distribution (of a particular point $\mathbf{x}$) is witten as

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \, \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k).$$

- Given data points $\{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$, the goal is to learn (estimate) the unknown parameters $\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k$, and π_k such that we approximate the data as good as possible.
- This is equivalent to finding the parameters that maximize the likelihood of the given data.

GMM: Generative Viewpoint

We assume that the the model parameters $\boldsymbol{\Sigma}, \boldsymbol{\mu}, \boldsymbol{\pi}$ are given.

Then, given those parameters, we sample the data $\mathbf{x}_n$ as follows:

1. Sample a component (cluster) index k according to the probabilities π_k.
2. Sample a data point $\mathbf{x}_n$ from the distribution $p(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$.

Parameter estimation based on maximizing likelihood:
Revert this process: data is given, but the parameters are unknown and should be estimated.

Full Data Likelihood

We assume that the data points $\mathbf{x}_n$ are independent and identically distributed (i.i.d.). The probability or likelihood of the observed data $\mathbf{X}$, given the parameters is then otained by

$$p(\mathbf{X}|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \prod_{n=1}^{N} p(\mathbf{x}_n) = \prod_{n=1}^{N} \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k).$$

Maximum Log-Likelihood Formulation

Goal. find the parameters that maximize the likelihood of the data:

$$(\widehat{\boldsymbol{\pi}}, \widehat{\boldsymbol{\mu}}, \widehat{\boldsymbol{\Sigma}}) \in \underset{\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}}{\operatorname{argmax}}\, p(\mathbf{X} | \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}).$$

To simplify the calculation we take the logarithm, such that the product becomes a sum:

$$(\widehat{\boldsymbol{\pi}}, \widehat{\boldsymbol{\mu}}, \widehat{\boldsymbol{\Sigma}}) \in \underset{\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}}{\operatorname{argmax}} \sum_{n=1}^{N} \ln \left\{ \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \right\}.$$

Maximum Log-Likelihood Estimation

- Want to solve:

$$(\widehat{\boldsymbol{\pi}}, \widehat{\boldsymbol{\mu}}, \widehat{\boldsymbol{\Sigma}}) \in \underset{\boldsymbol{\pi},\boldsymbol{\mu},\boldsymbol{\Sigma}}{\operatorname{argmax}} \sum_{n=1}^{N} \ln \left\{ \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \right\}.$$

- Due to the presence of the summation over k inside the logarithm, the maximum likelihood solution for the parameters no longer has a closed-form analytic solution.

Maximum Log-Likelihood Estimation

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- We employ an elegant powerful algorithmic technique, called Expectation Maximization.

Maximum Log-Likelihood Estimation

- We want to solve:

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- Due to the presence of the summation over k inside the logarithm, the maximum likelihood solution for the parameters no longer has a closed-form analytic solution.
- We employ an elegant powerful algorithmic technique, called Expectation Maximization.
- Intuition: if we know to which clusters the data points are assigned, then computing the maximum likelihood estimate becomes straightforward.
- Hence: we introduce a latent (or hidden) variable for the assignment of data points to clusters.

Latent Variables

- Define K-dimensional binary random variable $\mathbf{z}$ with a 1-of-K representation.
- Only one element of $\mathbf{z}$ is equal to 1 and all other elements are 0, i.e.,

$$z_k \in \{0, 1\}, \quad \sum_k z_k = 1.$$

Latent Variables

- Define K-dimensional binary random variable $\mathbf{z}$ with a 1-of-K representation.
- Only one element of $\mathbf{z}$ is equal to 1 and all other elements are 0, i.e.,

$$z_k \in \{0, 1\}, \quad \sum_k z_k = 1.$$

- The marginal distribution over $\mathbf{z}$ is specified in terms of the mixing coefficients π_k, i.e.,

$$p(z_k = 1) = \pi_k.$$

Latent Variables and Data Likelihood

- $\mathbf{z}$ uses a 1-of-K representation. Thus, we write this distribution in the form of:

$$p(\mathbf{z}) = \prod_{k=1}^{K} \pi_k^{z_k}.$$

- Also, the conditional distribution of $\mathbf{x}$ given a particular instantiation (value) of $\mathbf{z}$ is a Gaussian distribution

$$p(\mathbf{x} \mid z_k = 1) = \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k).$$

- Therefore, we have:

$$p(\mathbf{x} \mid \mathbf{z}) = \prod_{k=1}^{K} \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)^{z_k}.$$

Marginal Distribution with Latent Variables

The marginal distribution of $\mathbf{x}$ can be obtained by summing the joint distribution over all possible states of $\mathbf{z}$ to yield:

$$p(\mathbf{x}) = \sum_{\mathbf{z}} p(\mathbf{z}) p(\mathbf{x} \mid \mathbf{z}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k).$$

For the full data log-likelihood we have:

$$\ln p(\mathbf{X} \mid \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \sum_{n=1}^{N} \ln \left\{ \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \right\}.$$

In the following, for the simplicity of prsentation, we assume that the covariances $\boldsymbol{\Sigma}$ are given (we do not need to estimate them).

Responsibilities

- $\gamma(z_k)$: probability of assigning a data point to a cluster

$$\gamma(z_k) := p(z_k = 1 \mid \mathbf{x})$$

- Remember the generative viewpoint!
- We shall view π_k as the prior probability of $z_k = 1$, and the quantity $\gamma(z_k)$ as the corresponding posterior probability once we have observed $\mathbf{x}$.

Overview of Expectation-Maximization

- We want to solve:

$$(\widehat{\boldsymbol{\pi}}, \widehat{\boldsymbol{\mu}}, \widehat{\boldsymbol{\Sigma}}) \in \underset{\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}}{\operatorname{argmax}} \sum_{n=1}^{N} \ln \left\{ \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \right\}.$$

- Due to the presence of the summation over k inside the logarithm, the maximum likelihood solution for the parameters no longer has a closed-form analytic solution.
- We employ an elegant powerful algorithmic technique, called Expectation Maximization.

Overview of Expectation-Maximization

- We employ an elegant powerful algorithmic technique, called Expectation Maximization.

- First, we select some initial values for the means and mixing coefficients. Then, we alternate between the following two updates called the E (expectation) step and the M (maximization) step:

  1. In the expectation step, the current values for the model parameters are used to compute the posterior probabilities (responsibilities) $\gamma(z_{nk})$.

  2. In the maximization step, the responsibilities are used to estimate the model parameters (e.g., means and mixing coefficients).

Expectation Step

- $\gamma(z_k)$: probability of assigning a particular data point to a cluster

$$\gamma(z_k) := p(z_k = 1 \mid \mathbf{x})$$

Bayes' rule

The conditional probability of A given B (posterior) can be obtained by:

$$p(A|B) = \frac{p(A)p(B|A)}{p(B)}.$$

We call $p(A)$ prior, $p(B|A)$ likelihood and $p(B)$ evidence.

Expectation Step

Bayes' rule

The conditional probability of A given B (posterior) can be obtained by:

$$p(A|B) = \frac{p(A)p(B|A)}{p(B)}.$$

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$\gamma(z_k) := p(z_k = 1 \mid \mathbf{x}) =?$

We use the Bayes' rule to get

$$\begin{aligned}\gamma(z_k) := p(z_k = 1 \mid \mathbf{x}) &= \frac{p(z_k = 1)p(\mathbf{x} \mid z_k = 1)}{\sum_{j=1}^{K} p(z_j = 1)p(\mathbf{x} \mid z_j = 1)} \\ &= \frac{\pi_k \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{j=1}^{K} \pi_j \mathcal{N}(\mathbf{x} \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}\end{aligned}$$

Estimating the Means

- We set the derivatives of $\ln p(\mathbf{X} \mid \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma})$ with respect to the means $\boldsymbol{\mu}_k$ to zero, and obtain:

$$0 = \sum_{n=1}^{N} \underbrace{\frac{\pi_k \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_j \pi_j \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}}_{\gamma(z_{nk})} \boldsymbol{\Sigma}_k^{-1}(\mathbf{x}_n - \boldsymbol{\mu}_k).$$

- Assume that $\boldsymbol{\Sigma}_k$ is not signular. Multiplying by $\boldsymbol{\Sigma}_k$ we obtain

$$\boldsymbol{\mu}_k = \tfrac{1}{N_k} \textstyle\sum_{n=1}^{N} \gamma(z_{nk}) \mathbf{x}_n, \quad N_k = \textstyle\sum_{n=1}^{N} \gamma(z_{nk})$$

- The mean $\boldsymbol{\mu}_k$ is obtained by taking a weighted mean of all the points in the data set.

Estimating the Variances

- If we set the derivative of $\ln p(\mathbf{X} \mid \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma})$ with respect to $\boldsymbol{\Sigma}_k$ to zero we obtain

$$\boldsymbol{\Sigma}_k = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk})(\mathbf{x}_n - \boldsymbol{\mu}_k)(\mathbf{x}_n - \boldsymbol{\mu}_k)^{\mathtt{T}}$$

Estimating the Coefficients

- Maximizing $\ln p(\mathbf{X} \mid \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma})$ with respect to the mixing coefficients π_k and taking account of the constraint which requires the mixing coefficients to sum to one, leads to the following Lagrangian

  $$\ln p(\mathbf{X} \mid \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) + \lambda(\sum_{k=1}^{K} \pi_k - 1)$$

  which gives

  $$0 = \sum_{n=1}^{N} \frac{\mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_j \pi_j \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)} + \lambda.$$

  $$\Rightarrow 0 = \sum_{n=1}^{N} \gamma(z_{nk}) + \pi_k \lambda = N_k + \pi_k \lambda.$$

  Then, $\sum_{k=1}^{K} \pi_k = 1$ leads to $\lambda = -N$. Thus,

  $$\pi_k = \frac{N_k}{N}.$$

Description of EM

Given a GMM, the goal is to maximize the likelihood function with respect to the parameters.

1. Initialize the means $\boldsymbol{\mu}_k$, and mixing coefficients π_k. Set the $\boldsymbol{\Sigma}_k$ to the given covariances.
2. **E-step.** Evaluate the responsibilities using the current parameter values

$$\gamma(z_{nk}) = \frac{\pi_k \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_j \pi_j \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}$$

3. **M-step.** Re-estimate the parameters using the current responsibilities

$$\begin{aligned} \boldsymbol{\mu}_k &= \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) \mathbf{x}_n \\ \pi_k &= \frac{N_k}{N} \qquad \texttt{where} \qquad N_k = \sum_{n=1}^{N} \gamma(z_{nk}) \end{aligned}$$

4. Compute the log-likelihood and check for the convergence of either the parameters or the log-likelihood.

Example of EM for Gaussian Mixture Models

Illustration of the EM algorithm using the Old Faithful data set.

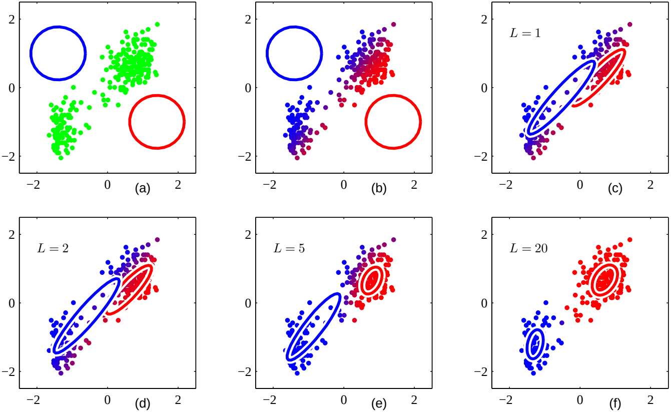


Figure: EM algorithm for mixture of two Gaussians. Note that here the covariance is also estimated (illustrated by the two ellipsoids).

EM and K-means Algorithm

- The K-means algorithm yileds a hard assignment of data points to clusters, but the EM algorithm performs a soft assignment based on the posterior probabilities.

- The K-means algorithm does not estimate the covariances of the clusters but only the cluster means.

EM and K-means Algorithm

- Consider a Gaussian Mixture Model in which the covariance matrices of the mixture components are given by $\epsilon \mathbf{I}$. Then, we have

$$p(\mathbf{x} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) = \frac{1}{(2\pi\epsilon)^{1/2}} \exp\left\{ -\frac{1}{2\epsilon} \|\mathbf{x} - \boldsymbol{\mu}_k\|_2^2 \right\}.$$

- Consider the EM algorithm in which ϵ is a fixed constant (i.e., we do not need to estimate the covariance matrix). Then

$$\gamma(z_{k,n}) = \frac{\pi_k \exp\{-\frac{1}{2\epsilon}\|\mathbf{x} - \boldsymbol{\mu}_k\|_2^2\}}{\sum_j \pi_j \exp\{-\frac{1}{2\epsilon}\|\mathbf{x} - \boldsymbol{\mu}_j\|_2^2\}}$$

EM and K-means Algorithm

- Consider the EM algorithm in which ϵ is a fixed constant, instead of a parameter to be re-estimated. Then

$$\gamma(z_{k,n}) = \frac{\pi_k \exp\{-\frac{1}{2\epsilon}\|\mathbf{x} - \boldsymbol{\mu}_k\|_2^2\}}{\sum_j \pi_j \exp\{-\frac{1}{2\epsilon}\|\mathbf{x} - \boldsymbol{\mu}_j\|_2^2\}}$$

- In the limit $\epsilon \to 0$, in the denominator the term for which $\|\mathbf{x}_n - \boldsymbol{\mu}_j\|^2$ is smallest, goes to zero most slowly, and hence the responsibilities $\gamma(z_{nk})$ for the data point $\mathbf{x}_n$ all go to zero except for term j, for which the responsibility $\gamma(z_{nj})$ will go to unity.

EM and K-means Algorithm

- In this limit, we obtain a hard assignment of data points to clusters, just as in the K-means, ie.e, each data point is assigned to the cluster having the closest mean.
- The EM re-estimation for the $\boldsymbol{\mu}_k$ then reduces to the K-means results.
- The re-estimation formula for the mixing coefficients simply re-sets the value of π_k to be equal to the fraction of data points assigned to cluster k, although these parameters no longer play an active role in the algorithm.

K-means vs EM

- The EM algorithm takes many more iterations to reach convergence compared with the K-means algorithm, and each cycle requires significantly more computation.
- The K-means algorithm can be used to find a suitable initialization for a Gaussian mixture model.
- The covariance matrices can be initialized to the sample covariances of the clusters found by the K-means algorithm.
- The mixing coefficients can be set to the fractions of data points assigned to the respective clusters.
- There will generally be multiple local maxima of the log likelihood function, and EM is not guaranteed to find the largest of these maxima.

Model Order Selection: General Principle

Trade-off between two conflicting goals:

Data fit:	We want to predict the data accurately, e.g., maximize the likelihood. The likelihood usually improves by increasing the number of clusters.
Complexity:	Choose a model that is not very complex which is often measured by the number of free parameters.

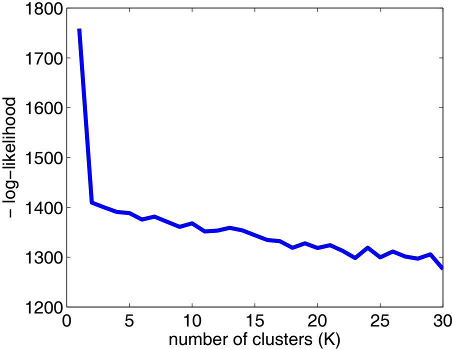
Find a trade-off between these two goals!

Decreasing the data fit costs when increasing K

Negative Log-Likelihood of data for K mixture Gaussians:

$$-\ln p(\mathbf{X} \mid \boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = -\sum_{n=1}^{N} \ln \left\{ \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_n \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \right\}.$$

The smaller the negative log-likelihood, the better the fit.



AIC and BIC

Trade-off

Achieve balance between data fit (measured by likelihood $p(\mathbf{X}|.)$) and model complexity. Complexity can be measured by the number of free parameters $c(\cdot)$.

Different principles to choose K

- *Akaike Information Criterion (**AIC**)*

$$AIC(\mathbf{U}, \mathbf{Z}|\mathbf{x}_1, \ldots, \mathbf{x}_N) = -\ln p(\mathbf{X}|.) + c(\mathbf{U}, \mathbf{Z})$$

AIC and BIC

Trade-off

Obtain a balance between data fit (measured by likelihood $p(\mathbf{X}|.)$) and model complexity. Complexity can be measured by the number of free parameters $c(\cdot)$.

Different principles to choose K

- *Akaike Information Criterion (**AIC**)*

$$AIC(\mathbf{U}, \mathbf{Z}|\mathbf{x}_1, \ldots, \mathbf{x}_N) = -\ln p(\mathbf{X}|.) + c(\mathbf{U}, \mathbf{Z})$$

- *Bayesian Information Criterion (**BIC**)*.

$$BIC(\mathbf{U}, \mathbf{Z}|\mathbf{x}_1, \ldots, \mathbf{x}_N) = -\ln p(\mathbf{X}|.) + \frac{1}{2} c(\mathbf{U}, \mathbf{Z}) \ln N$$

AIC and BIC

Which one is more strict on the model complexity?

AIC and BIC

Which one is more strict on the model complexity?

- Usually (on a large anough dataset), the BIC criterion penalizes complexity more than AIC.

AIC and BIC: Remarks and Example

Analysis

A single AIC (BIC) result is meaningless. One has to repeat the analysis for different Ks and compare the differences: the most suitable number of clusters corresponds to the smallest AIC (BIC) value.

Example (Mixture of Gaussians with fixed covariance)

Number of free parameters is (?)

AIC and BIC: Remarks and Example

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Example (Mixture of Gaussians with fixed covariance)

Number of free parameters is:

$$c(\mathbf{U}, \mathbf{Z}) = K \cdot D + (K - 1).$$

AIC and BIC example: 3 clusters

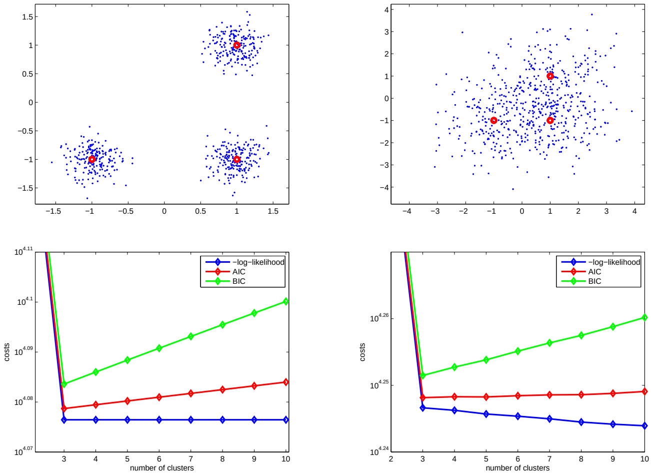

Figure: Model order selection on synthetic datasets with 3 clusters. Synthetic data has smaller variance on the left than on the right.

AIC and BIC example: 5 clusters

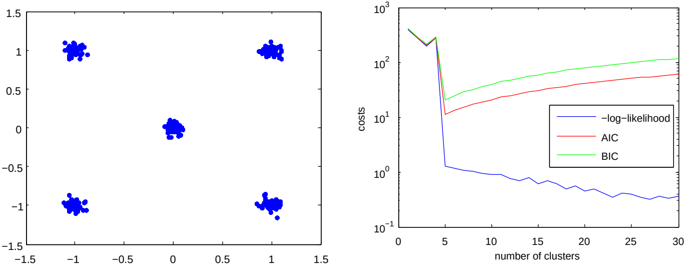

Figure: Model order selection on a synthetic dataset with 5 clusters.

Exercise 1

Can you write down the K-means cost function in the form of a matrix factorization problem?

$$\arg\min_{\boldsymbol{\mu},\mathbf{Z}} R(\boldsymbol{\mu},\mathbf{Z};\mathbf{X}) = \arg\min_{\boldsymbol{\mu},\mathbf{Z}} ||\mathbf{X}-\mathbf{Z}\boldsymbol{\mu}||_2^2$$

What about soft clustering?

Exercise 2

Consider a GMM with $\mathbf{\Sigma}_k = \sigma_k^2 \mathbf{I}$ and one of the component means equal to a data point: $\boldsymbol{\mu}_j = \mathbf{x}_n$.

1. Write down the log-likelihood for this data point (i.e. $\ln p(\mathbf{x}_n | \boldsymbol{\pi}, \boldsymbol{\mu}, \mathbf{\Sigma})$)
2. Calculate $p(\mathbf{x}_n | \boldsymbol{\mu}_j, \mathbf{\Sigma}_j)$, the probability of $\mathbf{x}_n$ given the j-th component.
3. In the limit $\sigma_k \to 0$, how does the probability in Question 3 change? Discuss the impact of this issue on the maximization of the likelihood function.
4. Can this situation occur in the case of a single Gaussian distribution (i.e., when $K = 1$)?
5. Propose a heuristic to avoid such a situation.

Information

Reference: Christopher M. Bishop, *Pattern Recognition and Machine Learning*, Chapter 9.

Questions? Send to Morteza Chehreghani, morteza.chehreghani@chalmers.se

Acknowledgement: Some of the slides are prepared based on past joint efforts with P. Pletscher.