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Exercise 10

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Problem 1. (*k*-means Clustering)

The set $\Phi = \{\mathbf{x}_i \mid i = 1, \dots, 6\}$ contains 2-dimensional data which belongs to 2 clusters $\mathcal{C} \in \{1, 2\}$, with

$$\mathbf{x}_1 = \begin{pmatrix} 7 \\ 0 \end{pmatrix}, \mathbf{x}_2 = \begin{pmatrix} 7 \\ 3 \end{pmatrix}, \mathbf{x}_3 = \begin{pmatrix} 9 \\ 1 \end{pmatrix}, \mathbf{x}_4 = \begin{pmatrix} 9 \\ 5 \end{pmatrix}, \mathbf{x}_5 = \begin{pmatrix} 3 \\ 7 \end{pmatrix}, \mathbf{x}_6 = \begin{pmatrix} 12 \\ 3 \end{pmatrix}.$$

The *k*-means clustering algorithm is used to cluster the samples for Φ .

- At a certain iteration, \mathbf{x}_1 and \mathbf{x}_3 are the center of cluster 1 and cluster 2, respectively. Assign each data sample in Φ to the appropriate cluster.
- Update the centers of the clusters according to the assignment in (a).
- Suppose that the Euclidian distance in the *k*-means clustering algorithm is replaced by the following distances

$$d_1(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|_1 = |x_1 - y_1| + |x_2 - y_2|,$$

$$d_\infty(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|_\infty = \max(|x_1 - y_1|, |x_2 - y_2|),$$

for any $\mathbf{x}, \mathbf{y} \in \Phi$, with $\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$ and $\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$.

Assign the data samples in Φ to the appropriate cluster, assuming \mathbf{x}_1 and \mathbf{x}_3 are the centers of cluster 1 and cluster 2, respectively.

Problem 2. (*Maximum Likelihood Clustering*) Suppose that $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n$ are n samples from g populations, each with Gaussian distribution $N_p(\boldsymbol{\mu}_k, \boldsymbol{\Sigma})$. The corresponding densities are:

$$f_k(\mathbf{u}) = \frac{1}{(2\pi)^{p/2} |\boldsymbol{\Sigma}|^{1/2}} \exp \left\{ -\frac{1}{2} (\mathbf{u} - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}^{-1} (\mathbf{u} - \boldsymbol{\mu}_k) \right\}, \mathbf{u} \in \mathbb{R}^p, k = 1, \dots, g.$$

- Define the cluster analysis problem as maximization of log-likelihood function and write down the respective optimization problem.
- Given clustering of samples S_1, \dots, S_g , find ML-estimation of $\boldsymbol{\Sigma}$.
- Show that if $\boldsymbol{\Sigma}$ is unknown, the ML-cluster analysis is equivalent to the following optimization problem:

$$\min_{S_1, \dots, S_g} \det(\mathbf{W})$$

where

$$\mathbf{W} = \sum_{k=1}^g \sum_{i \in S_k} (\mathbf{x}_i - \bar{\mathbf{x}}_k)(\mathbf{x}_i - \bar{\mathbf{x}}_k)^T.$$

- d) If Σ is known, show that ML-cluster analysis is equivalent to the following optimization problem:

$$\min_{S_1, \dots, S_g} \text{tr}(\mathbf{W}\Sigma^{-1}).$$

Problem 3. (*Discriminant Analysis*)

A training dataset consists of three-dimensional vectors belonging to two classes (also known as groups) denoted by the labels $y_i \in \{1, 2\}$. The dataset is given below.

Data	Label	Data	Label
$\mathbf{x}_1 = \begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix}$	$y_1 = 1$	$\mathbf{x}_4 = \begin{pmatrix} 1 \\ 1 \\ -1 \end{pmatrix}$	$y_4 = 2$
$\mathbf{x}_2 = \begin{pmatrix} 1 \\ -2 \\ 0 \end{pmatrix}$	$y_2 = 1$	$\mathbf{x}_5 = \begin{pmatrix} 0 \\ 2 \\ -1 \end{pmatrix}$	$y_5 = 2$
$\mathbf{x}_3 = \begin{pmatrix} 2 \\ 0 \\ -1 \end{pmatrix}$	$y_3 = 1$	$\mathbf{x}_6 = \begin{pmatrix} -1 \\ 1 \\ -1 \end{pmatrix}$	$y_6 = 2$

- Find the centering matrices, namely \mathbf{E}_1 and \mathbf{E}_2 .
- Find the average of the dataset, namely $\bar{\mathbf{x}}$.
- Find the averages over groups 1 and 2, namely $\bar{\mathbf{x}}_1$ and $\bar{\mathbf{x}}_2$.
- Find the matrix \mathbf{B} corresponding to the sum of squares between groups.

Now consider a different dataset where the inverse of the matrix \mathbf{W} corresponding to the sum of squares within groups, and the matrix \mathbf{B} corresponding to the sum of squares between groups, are given by

$$\mathbf{W}^{-1} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 3 & 2 \\ 2 & -2 \end{bmatrix}.$$

- In Fisher discriminant analysis the maximum value of $\frac{\mathbf{a}^T \mathbf{B} \mathbf{a}}{\mathbf{a}^T \mathbf{W} \mathbf{a}}$ over all $\mathbf{a} \in \mathbb{R}^2$ is needed. Calculate the value of

$$\max_{\mathbf{a} \in \mathbb{R}^2} \frac{\mathbf{a}^T \mathbf{B} \mathbf{a}}{\mathbf{a}^T \mathbf{W} \mathbf{a}}.$$

Hint: there is no need for calculating the vector \mathbf{a} that maximizes $\frac{\mathbf{a}^T \mathbf{B} \mathbf{a}}{\mathbf{a}^T \mathbf{W} \mathbf{a}}$.