

Assignment 2 - AIT 512 Maths for ML

Due on **October 04, 2025**

September 27, 2025

The Iris Dataset (<https://archive.ics.uci.edu/dataset/53/iris>) is a well-known dataset used to test classifiers; it describes 4 attributes, per plant, of 3 different plants, namely **Iris-setosa**, **Iris-versicolor**, and **Iris-virginica**. It has 150 records with 50 records of each plant; compose the matrix of this dataset as $\mathbf{X} \in \mathbb{R}^{4 \times 150}$.

1. **Least-squares classifier:** Build a least-squares classifier to classify **Iris-setosa** from the other two plants; this is a binary classification problem. Present the confusion matrix (see the section on binary confusion matrix here: https://en.wikipedia.org/wiki/Confusion_matrix) for this classifier and comment on it. **Hints:**
 - Assign Label $y^i = +1$ to the data points corresponding to **Iris-setosa** and $y^i = -1$ for the rest.
 - Build a regression model $\vec{y} = \mathbf{X}^T \vec{\beta} + \nu \vec{1}$, where $\vec{y} \in \mathbb{R}^{150 \times 1}$ is the vector of labels and $\vec{\beta} \in \mathbb{R}^{4 \times 1}$, $\nu \in \mathbb{R}$ are the regression parameters. These can be found by *minimizing* $\|\vec{y} - \mathbf{X}^T \vec{\beta} - \nu \vec{1}\|^2$; in turn, this can be solved by minimizing a quadratic expression, say using <https://pypi.org/project/quadprog/>.
 - The least-squares classifier, which yields the predicted labels, \hat{y}_i , itself is given by $\hat{y}_i = \text{sign}(\vec{x}_i^T \vec{\beta} + \nu)$, where \vec{x}_i is the column describing the attributes for datapoint i from the matrix \mathbf{X} .
2. **Least-squares classifier for a reduced-dimension dataset:** Redesign the least-squares classifier, if possible, by reducing the dimension of the Iris dataset. Present the confusion matrix and compare performance with that obtained using the full-order dataset. Did reducing the dimensions change the performance drastically? If not, why?

Hints:

- Perform an SVD for the matrix $\mathbf{X} \in \mathbb{R}^{4 \times 150}$ and judiciously choose the largest singular values.
- Suppose the first 2 singular values are selected, so that $\hat{\mathbf{X}} = \sum_{i=1}^2 \sigma_i \vec{u}_i \vec{v}_i^T$ is the rank-2 approximation of this dataset; note that \vec{u}_i, \vec{v}_i are the corresponding singular vectors. Note that the dimension of $\hat{\mathbf{X}}$ is still 4×150 .
- A reduced dimension dataset (of dimension 2×150) can be determined from the product $\mathbf{U}^T \hat{\mathbf{X}}$, where \mathbf{U} is the matrix of singular vectors \vec{u}_i . (Observe the values of the elements of this product). The reduced dimension dataset should be similar to the plot shown in Fig. 1. Comment on why the operation $\mathbf{U}^T \hat{\mathbf{X}}$ reduces the dimension.

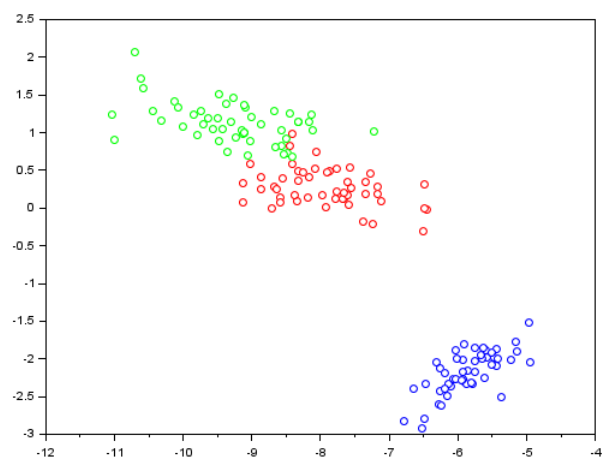


Figure 1: Iris Dataset with reduced dimensions