

Advanced Data Analysis Homework 12

Information Science and Technology
Mathematical Informatics, M2
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Problem 1

We implement FDA. The source code is here¹.
The execution results are shown as follows:

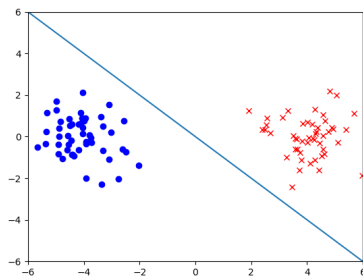


Figure 1: FDA with 2 classes, where there is no cluster structure within class.

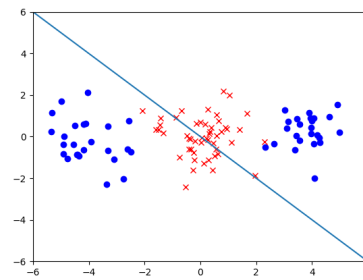


Figure 2: FDA with 2 class, where one of them consists of 2 separate sub clusters.

Both hyperplane can reduce dimensions of samples so that we can classify the data into correct classes.

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¹<https://github.com/Kota-Isayama/Advanced-Data-Analysis/blob/main/12/problem1.py>

Problem 2

We first derive the equation about $S^{(w)}$, then prove the one about $S^{(b)}$. We have

$$\begin{aligned}
S^{(w)} &= \sum_{y=1}^c \sum_{i:y_i=y} (\mathbf{x}_i - \boldsymbol{\mu}_y)(\mathbf{x}_i - \boldsymbol{\mu}_y)^T \\
&= \sum_{y=1}^c \sum_{i:y_i=y} (\mathbf{x}_i \mathbf{x}_i^T - \boldsymbol{\mu}_y \boldsymbol{\mu}_y^T) \\
&= \sum_{y=1}^c \sum_{i:y_i=y} \mathbf{x}_i \mathbf{x}_i^T - \sum_{y=1}^c n_y \boldsymbol{\mu}_y \boldsymbol{\mu}_y^T \\
&= \sum_{y=1}^c \sum_{i:y_i=y} \mathbf{x}_i \mathbf{x}_i^T - \sum_{y=1}^c \frac{1}{n_y} \left(\sum_{i:y_i=y} \mathbf{x}_i \right) \left(\sum_{i':y_{i'}=y} \mathbf{x}_{i'} \right)^T \\
&= \frac{1}{2} \sum_{y=1}^c \frac{1}{n_y} \left(\sum_{i:y_i=y} \sum_{i':y_{i'}=y} (\mathbf{x}_i \mathbf{x}_i^T + \mathbf{x}_{i'} \mathbf{x}_{i'}^T - 2\mathbf{x}_i \mathbf{x}_{i'}^T) \right) \\
&= \frac{1}{2} \sum_{y=1}^c \sum_{i:y_i=y} \sum_{i':y_{i'}=y} \frac{1}{n_y} (\mathbf{x}_i - \mathbf{x}_{i'})^2 \\
&= \frac{1}{2} \sum_{i,i'=1}^n Q_{i,i'}^{(w)} (\mathbf{x}_i - \mathbf{x}_{i'}) (\mathbf{x}_i - \mathbf{x}_{i'})^T,
\end{aligned}$$

where 4th equality is due to the definition of $\boldsymbol{\mu}_y$, 5th equality holds since $\sum_{i:y_i=y} \mathbf{x}_i \mathbf{x}_i^T = \frac{1}{n_y} \sum_{i:y_i=y} \sum_{i':y_{i'}=y} \mathbf{x}_i \mathbf{x}_i^T$ and $\sum_{i:y_i=y} \mathbf{x}_i \mathbf{x}_i^T = \frac{1}{2} \left(\sum_{i:y_i=y} \mathbf{x}_i \mathbf{x}_i^T + \sum_{i':y_{i'}=y} \mathbf{x}_{i'} \mathbf{x}_{i'}^T \right)$ and 7th equality is derived from the definition of $Q_{i,i'}^{(w)}$.

Then, we prove the equation about $S^{(b)}$. From $C = S^{(w)} + S^{(b)}$, where $C = \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T$, we have

$$\begin{aligned}
S^{(b)} &= C - S^{(w)} \\
&= \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T - \frac{1}{2} \sum_{i,i'=1}^n Q_{i,i'}^{(w)} (\mathbf{x}_i - \mathbf{x}_{i'}) (\mathbf{x}_i - \mathbf{x}_{i'})^T \\
&= \frac{1}{2} \sum_{i,i'=1}^n \frac{1}{n} (\mathbf{x}_i - \mathbf{x}_{i'}) (\mathbf{x}_i - \mathbf{x}_{i'})^T - \frac{1}{2} \sum_{i,i'=1}^n Q_{i,i'}^{(w)} (\mathbf{x}_i - \mathbf{x}_{i'}) (\mathbf{x}_i - \mathbf{x}_{i'})^T \\
&= \frac{1}{2} \sum_{i,i'=1}^n Q_{i,i'}^{(b)} (\mathbf{x}_i - \mathbf{x}_{i'}) (\mathbf{x}_i - \mathbf{x}_{i'})^T,
\end{aligned}$$

where third equation holds since

$$\begin{aligned}
\sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T &= \frac{1}{n} \sum_{i=1}^n \sum_{i'=1}^n \mathbf{x}_i \mathbf{x}_i^T \\
&= \frac{1}{2} \frac{1}{n} \sum_{i=1}^n \sum_{i'=1}^n (\mathbf{x}_i \mathbf{x}_i^T + \mathbf{x}_{i'} \mathbf{x}_{i'}^T) \\
&= \frac{1}{2} \frac{1}{n} \sum_{i=1}^n \sum_{i'=1}^n (\mathbf{x}_i - \mathbf{x}_{i'}) (\mathbf{x}_i - \mathbf{x}_{i'})^T \quad (\because \sum_{i=1}^n \mathbf{x}_i = \mathbf{0}).
\end{aligned}$$

Problem 3

We show $\text{rank}(S^{(b)}) \leq c - 1$, where c is the number of classes and $\sum_{i=1}^n \mathbf{x}_i = \mathbf{0}$. Since $\sum_{i=1}^n \mathbf{x}_i = \mathbf{0}$, we have

$$\begin{aligned}
\sum_{y=1}^c n_y \boldsymbol{\mu}_y &= \mathbf{0} \\
n_c \boldsymbol{\mu}_c &= - \sum_{y=1}^{c-1} n_y \boldsymbol{\mu}_y.
\end{aligned}$$

Then, from the definition of $S^{(b)}$,

$$\begin{aligned}
S^{(b)} &= \sum_{y=1}^c n_y \boldsymbol{\mu}_y \boldsymbol{\mu}_y^T \\
&= \sum_{y=1}^{c-1} n_y \boldsymbol{\mu}_y \boldsymbol{\mu}_y^T + n_c \boldsymbol{\mu}_c \boldsymbol{\mu}_c^T \\
&= \sum_{y=1}^{c-1} n_y \boldsymbol{\mu}_y \boldsymbol{\mu}_y^T - \frac{1}{n_c} \left(- \sum_{y=1}^{c-1} n_y \boldsymbol{\mu}_y \right) \left(- \sum_{y'=1}^{c-1} n_{y'} \boldsymbol{\mu}_{y'} \right)^T \\
&= \sum_{y=1}^{c-1} n_y \boldsymbol{\mu}_y \left(\boldsymbol{\mu}_y + \frac{1}{n_c} \sum_{y'=1}^{c-1} n_{y'} \boldsymbol{\mu}_{y'} \right)^T \\
&= \sum_{y=1}^{c-1} n_y \boldsymbol{\mu}_y \mathbf{z}_y^T,
\end{aligned}$$

where $\mathbf{z}_y = \boldsymbol{\mu}_y + \frac{1}{n_c} \sum_{y'=1}^{c-1} n_{y'} \boldsymbol{\mu}_{y'}$ is a vector. Generally, for any two vectors \mathbf{a}, \mathbf{b} of same dimension, $\text{rank}(\mathbf{a} \mathbf{b}^T) \leq 1$. This is because $\mathbf{a} \mathbf{b}^T$ can be represented as $(b_1 \mathbf{a}, b_2 \mathbf{a}, \dots, b_d \mathbf{a})$, where $\mathbf{b} = (b_1, b_2, \dots, b_d)^T$ and all $b_i \mathbf{a}$ have same direction. From the above, $\text{rank}(n_y \boldsymbol{\mu}_y \mathbf{z}_y^T) \leq$

1 for all y . Finally, we have

$$\begin{aligned}\text{rank}(S^{(b)}) &= \text{rank}\left(\sum_{y=1}^{c-1} n_y \mu_y \mathbf{z}_y^T\right) \\ &\leq \sum_{y=1}^{c-1} \text{rank}(n_y \mu_y \mathbf{z}_y^T) \\ &\leq c - 1,\end{aligned}$$

where first inequality holds due to the subadditivity of rank of matrices.

Problem 4

We implement least squares probabilistic classification based on a Gaussian kernel model:

$$q(y|\mathbf{x}; \boldsymbol{\theta}) = \sum_{i: y_i=y} \theta_i^{(y)} \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}_i\|}{2h^2}\right).$$

The source code is here².

In figure3, we show result when the number of classes is 3, the parameter $h = 2.0$ and the training sample size is 90.

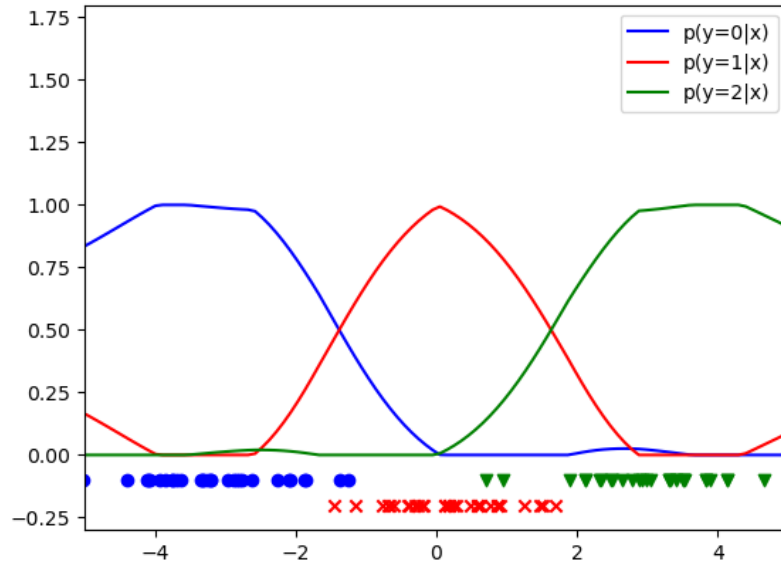


Figure 3: The least squares probabilistic classification based on a Gaussian kernel model, where $h = 2.0$.

²<https://github.com/Kota-Isayama/Advanced-Data-Analysis/blob/main/12/problem4.py>