

Exercise Sheet 4

Exercise 1: Fisher Discriminant (10 + 10 + 10 P)

The objective function to find the Fisher Discriminant has the form

$$\max_{\mathbf{w}} \frac{\mathbf{w}^\top \mathbf{S}_B \mathbf{w}}{\mathbf{w}^\top \mathbf{S}_W \mathbf{w}}$$

where $\mathbf{S}_B = (\mathbf{m}_2 - \mathbf{m}_1)(\mathbf{m}_2 - \mathbf{m}_1)^\top$ is the between-class scatter matrix and \mathbf{S}_W is within-class scatter matrix, assumed to be positive definite. Because there are infinitely many solutions (multiplying \mathbf{w} by a scalar doesn't change the objective), we can extend the objective with a constraint, e.g. that enforces $\mathbf{w}^\top \mathbf{S}_W \mathbf{w} = 1$.

- (a) *Reformulate* the problem above as an optimization problem with a quadratic objective and a quadratic constraint.
- (b) *Show* using the method of Lagrange multipliers that the solution of the reformulated problem is also a solution of the generalized eigenvalue problem:

$$\mathbf{S}_B \mathbf{w} = \lambda \mathbf{S}_W \mathbf{w}$$

- (c) Show that the solution of this optimization problem is equivalent (up to a scaling factor) to

$$\mathbf{w}^* = \mathbf{S}_W^{-1}(\mathbf{m}_1 - \mathbf{m}_2)$$

Exercise 2: Bounding the Error (10 + 10 P)

The direction learned by the Fisher discriminant is equivalent to that of an optimal classifier when the class-conditioned data densities are Gaussian with same covariance. In this particular setting, we can derive a bound on the classification error which gives us insight into the effect of the mean and covariance parameters on the error.

Consider two data generating distributions $P(\mathbf{x}|\omega_1) = \mathcal{N}(\boldsymbol{\mu}, \Sigma)$ and $P(\mathbf{x}|\omega_2) = \mathcal{N}(-\boldsymbol{\mu}, \Sigma)$ with $\mathbf{x} \in \mathbb{R}^d$. Recall that the Bayes error rate is given by:

$$P(\text{error}) = \int_{\mathbf{x}} P(\text{error}|\mathbf{x}) p(\mathbf{x}) d\mathbf{x}$$

- (a) Show that conditional error can be upper-bounded as:

$$P(\text{error}|\mathbf{x}) \leq \sqrt{P(\omega_1|\mathbf{x})P(\omega_2|\mathbf{x})}$$

- (b) Show that the Bayes error rate can then be upper-bounded by:

$$P(\text{error}) \leq \sqrt{P(\omega_1)P(\omega_2)} \cdot \exp\left(-\frac{1}{2}\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu}\right)$$

Exercise 3: Fisher Discriminant (10 + 10 P)

Consider the case of two classes ω_1 and ω_2 with associated data generating probabilities

$$p(\mathbf{x}|\omega_1) = \mathcal{N}\left(\begin{pmatrix} -1 \\ -1 \end{pmatrix}, \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}\right) \quad \text{and} \quad p(\mathbf{x}|\omega_2) = \mathcal{N}\left(\begin{pmatrix} +1 \\ +1 \end{pmatrix}, \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}\right)$$

- (a) Find for this dataset the Fisher discriminant \mathbf{w} (i.e. the projection $y = \mathbf{w}^\top \mathbf{x}$ under which the ratio between inter-class and intra-class variability is maximized).
- (b) Find a projection for which the ratio is minimized.

Exercise 4: Programming (30 P)

Download the programming files on ISIS and follow the instructions.