Course: Machine learning By: Pavlo Mozharovskyi

Tutorial to Lecture 1: Brief introduction to machine learning

Task 1: Explore the Fisher's linear discriminant analysis (LDA).

- (a) Demonstrate on a short example that \hat{R}_1 (see Appendix) is a consistent estimator (for class "1") of the LDA error rate.
- (b) Obtain empirical distribution of the LDA error rate and of its estimator as \hat{R}_1 by calculating these over 2 000 random draws.
- (c) Compare these two distributions and verify their normality visually (use R-functions density and dnorm), with Shapiro-Wilk test (use R-function shapiro.test), and by the means of the QQ-plot (use R-function qqnorm).

Perform experiments in part (a) with training sample sizes 10 000 or (and) 100 000; in part (b) with training sample size 1000.

Perform (a), (b), and (c) for three cases of normal distribution, namely:

Model 1:
$$X|Y = 0 \sim N\left(\begin{pmatrix} 0\\0 \end{pmatrix}, \begin{pmatrix} 1&1\\1&4 \end{pmatrix}\right)$$
 and $X|Y = 1 \sim N\left(\begin{pmatrix} 1\\1 \end{pmatrix}, \begin{pmatrix} 1&1\\1&4 \end{pmatrix}\right)$;
Model 2: $X|Y = 0 \sim N\left(\begin{pmatrix} 0\\0 \end{pmatrix}, \begin{pmatrix} 1&1.1\\1.1&3 \end{pmatrix}\right)$ and $X|Y = 1 \sim N\left(\begin{pmatrix} 1.4\\2.1 \end{pmatrix}, \begin{pmatrix} 1&1.1\\1.1&3 \end{pmatrix}\right)$;
Model 3: $X|Y = 0 \sim N\left(\begin{pmatrix} 0\\0 \end{pmatrix}, \begin{pmatrix} 1&2.1\\2.1&9 \end{pmatrix}\right)$ and $X|Y = 1 \sim N\left(\begin{pmatrix} 3\\2.5 \end{pmatrix}, \begin{pmatrix} 1&2.1\\2.1&9 \end{pmatrix}\right)$.

Interpret the results.

Task 2: Find optimal k for the k-nearest neighbors classifier (kNN).

For models 1–3 from Task 1, study the behavior of the error rate of kNN dependent on k — the number of nearest neighbors. For this, plot error rate estimated by leave-one-out cross-validation (jackknife) against k. Increase sample size until having noticed a tendency, consider (odd) ks between 1 and half of the sample size. Use R-functions knn and knn.cv from R-package class.

Interpret the results.

Appendix

Error probability R_1 can be consistently estimated:

$$\hat{R}_1 = \Phi\left(\frac{\hat{u_0}}{\sqrt{\hat{v_0}}}\right),\,$$

where

$$\hat{u}_{0} = -\frac{\hat{\Delta}^{2}}{2(1-\frac{d}{n})},$$

$$\hat{v}_{0} = \frac{1}{(1-\frac{d}{n})^{3}} (\hat{\Delta}^{2} + \frac{d}{n\pi_{0}\pi_{1}}),$$

$$\hat{\Delta}^{2} = \frac{n-d-1}{n} (\bar{\boldsymbol{x}}_{1} - \bar{\boldsymbol{x}}_{0})^{T} \boldsymbol{S}^{-1} (\bar{\boldsymbol{x}}_{1} - \bar{\boldsymbol{x}}_{0}) - \frac{(n+2)d}{n_{0}n_{1}}.$$

with n being the length of the training sample, d — dimension, π_0 and π_1 — prior probabilities of the corresponding classes, n_0 and n_1 — their sample sizes, \bar{x}_0 , \bar{x}_1 , and S — consistent mean and covariance estimates.