Introduction to machine learning

1 Warm-up: Bayes classifier for scalar Gaussian mixtures

Let $(X_i, Y_i)_{1 \le i \le n}$ be independent variables in $\mathbb{R} \times \{0, 1\}$. Assume that $\mathbb{P}(Y_1 = 0) = 1/2$. Assume also that the distribution of X_1 given $\{Y_1 = 0\}$ (resp. $\{Y_1 = 1\}$) is Gaussian with mean μ_0 (resp. μ_1) and variance 1. The probability density function of X_1 is written g. Write

$$g_0: x \mapsto (2\pi)^{-1/2} \exp(-(x-\mu_0)^2/2)$$
 and $g_1: x \mapsto (2\pi)^{-1/2} \exp(-(x-\mu_1)^2/2)$.

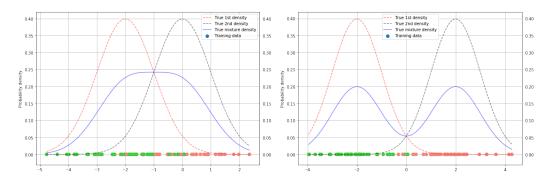


Figure 1: Samples and density when $\mu_0 = -2$ et $\mu_1 = 0$ (left) and $\mu_0 = -2$ and $\mu_1 = 2$ (right).

- 1. Provide an expression of a classifier h_* minimizing $h \mapsto \mathbb{P}(h(X) \neq Y)$.
- 2. Using Bayes rule, show that h_* depends only on g_1/g_0 .
- 3. Show that the Bayes classifier uses the mean between μ_0 and μ_1 to classify samples.

2 Bayes classifier

2.1 Uniform distributions

Assume that $(X,Y) \in \mathbb{R} \times \{0,1\}$ is defined on $(\Omega, \mathcal{F}, \mathbb{P})$ with $\mathbb{P}(Y=1) = \pi \in (0,1)$. Assume that conditionally on $\{Y=0\}$ (resp. $\{Y=1\}$) X has a uniform distribution on $[0,\theta]$ with $\theta \in (0,1)$ (resp. on [0,1]). Compute $\eta(X) = \mathbb{P}(Y=1|X)$.

2.2 Weighted risk

Assume that $(X,Y) \in \mathbb{R} \times \{0,1\}$ is defined on $(\Omega, \mathcal{F}, \mathbb{P})$. Using $\omega_0, \omega_1 > 0$, with $\omega_0 + \omega_1 = 1$, we consider the weighted risk:

$$\mathsf{R}(h) = \mathbb{E}[2\omega_Y \mathbb{1}_{Y \neq h(X)}].$$

Compute a classifier h_* minimizing $h \mapsto R(h)$ and $R(h_*)$.

3 Additional exercises

3.1 Bayes classifier: excess risk

Let $(X,Y) \in \mathbb{R}^d \times \{0,1\}$ be random variables defined on the same probability space $(\Omega, \mathcal{F}, \mathbb{P})$. For any classifier $h: \mathcal{X} \to \{0,1\}$, define its classification error by

$$R(h) = \mathbb{P}(Y \neq h(X))$$
.

The classifier h_* defined by:

$$h_*(x) = \operatorname{sign}(\eta(x) - 1/2),$$

where

$$\eta(X) = \mathbb{P}(Y = 1|X),$$

minimizes $h \mapsto \mathsf{R}(h)$.

1. Prove that

$$\mathsf{R}(h_*) = \mathbb{E}\left[\eta(X) \wedge (1 - \eta(X))\right] \leqslant \frac{1}{2}$$
.

2. Prove that for all classifiers h, the excess risk is given by

$$R(h) - R(h_*) = \mathbb{E}[|1 - 2\eta(X)| |h(X) - h_*(X)|].$$

3.2 Plug-in classifier

Let $(X,Y) \in \mathbb{R}^d \times \{-1,1\}$ be random variables defined on the same probability space $(\Omega, \mathcal{F}, \mathbb{P})$. For any classifier $h: \mathcal{X} \to \{-1,1\}$, define its classification error by

$$R(h) = \mathbb{P}(Y \neq h(X))$$
.

The classifier h_* defined by:

$$h_*(x) = \operatorname{sign}(\eta(x) - 1/2),$$

where

$$\eta(X) = \mathbb{P}(Y = 1|X)\,,$$

minimizes $h \mapsto \mathsf{R}(h)$. Given n independent couples $\{(X_i,Y_i)\}_{1\leqslant i\leqslant n}$ with the same distribution as (X,Y), an empirical surrogate for h_* is obtained from a possibly nonparametric estimator $\widehat{\eta}_n$ of η :

$$\widehat{h}_n: x \mapsto \operatorname{sign}(\widehat{\eta}_n(x) - 1/2).$$

1. Prove that for any classifier $h: \mathcal{X} \to \{-1, 1\}$,

$$\mathbb{P}(Y \neq h(X)|X) = (2\eta(X) - 1)\mathbb{1}_{h(X) = -1} + 1 - \eta(X)$$

and

$$\mathsf{R}(h) - \mathsf{R}(h_*) = 2\mathbb{E}\left[\left|\eta(X) - \frac{1}{2}\right| \, \mathbb{1}_{h(X) \neq h_*(X)}\right] \,.$$

2. Prove that

$$|\eta(x) - 1/2| \mathbb{1}_{\widehat{h}_n(x) \neq h_*(x)} \le |\eta(x) - \widehat{\eta}_n(x)| \mathbb{1}_{\widehat{h}_n(x) \neq h_*(x)},$$

where

$$\widehat{h}_n: x \mapsto \operatorname{sign}(\widehat{\eta}_n(x) - 1/2)$$
.

Deduce that

$$\mathsf{R}(\widehat{h}_n) - \mathsf{R}(h_*) \leqslant 2\mathbb{E}[|\eta(X) - \widehat{\eta}_n(X)|^2]^{1/2} \,.$$