# Example of Bayes predictor

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#### 1 BAYES ESTIMATOR AND BAYES RISK

Consider the following joint random variable (X, Y).

$$-- \mathfrak{X} = \{0, 1, 2\}$$

$$-- y = \{0, 1\}.$$

— X follows a uniform law on  $\mathfrak{X}$ .

$$Y = \left\{ \begin{array}{l} B(1/5) \text{ if } X = 0 \\ B(3/4) \text{ if } X = 1 \\ B(2/3) \text{ if } X = 2 \end{array} \right.$$

With B(p) a Bernoulli law with parameter p.

Compute the Bayes estimator and the bayes risk.

#### 1.1 Solution

#### 1.1.1 Bayes predictor, general case

We prove again the general result on the Bayes predictor in the case of binary classification. We have seen that the Bayes predictor is defined by

$$f^*(x) = \underset{z \in \mathcal{Y}}{\arg\min} \, \mathbb{E}\left[l(y, z) | X = x\right] \tag{1}$$

Hence

$$f^{*}(x) = \underset{z \in \mathcal{Y}}{\arg \min} E \left[ l(y, z) | X = x \right]$$

$$= \underset{z \in \mathcal{Y}}{\arg \min} P(Y \neq z | X = x)$$

$$= \underset{z \in \mathcal{Y}}{\arg \min} 1 - P(Y = z | X = x)$$

$$= \underset{z \in \mathcal{Y}}{\arg \max} P(Y = z | X = x)$$

$$= \underset{z \in \mathcal{Y}}{\arg \max} P(Y = z | X = x)$$
(2)

The optimal classifier selects the most probable output given X = x.

In this case:

$$- f^*(0) = 0$$

$$- f^*(1) = 1$$

$$- f^*(2) = 1$$

## 1.1.3 Bayes risk, general case

We have also seen that using the law of total expectation, with the "o-1" loss,

$$R^* = E[l(Y, f^*(X))]$$

$$= E_X[E_Y(l(Y \neq f^*(X)|X)]$$

$$= E_X[P(Y \neq f^*(X)|X)]$$
(3)

But we have

$$P(Y \neq f^*(X)|X = x) = P(Y \neq f^*(x))$$
(4)

We note  $\eta(x) = P(Y = 1|X = x)$ . Then,

— If 
$$\eta(x) > \frac{1}{2}$$
, then  $f^*(x) = 1$ , and  $P(Y \neq f^*(x)) = P(Y = 0) = 1 - \eta(x)$ 

— If 
$$\eta(x) < \frac{1}{2}$$
, then  $f^*(x) = 0$ , and  $P(Y \neq f^*(x)) = P(Y = 1) = \eta(x)$ 

In both cases,  $P(Y \neq f^*(x)) = \min(\eta(x), 1 - \eta(x))$ .

We conclude that

$$R^* = E_X \left[ \min(\eta(X), 1 - \eta(X)) \right]$$
 (5)

### 1.1.4 Application

In this setting:

$$R^* = \frac{1}{3} \frac{1}{5} + \frac{1}{3} \frac{1}{4} + \frac{1}{3} \frac{1}{3}$$

$$= \frac{1}{3} \left( \frac{1}{5} + \frac{1}{4} + \frac{1}{3} \right)$$

$$= \frac{1}{3} \left( \frac{12}{60} + \frac{15}{60} + \frac{20}{60} \right)$$

$$= \frac{1}{3} \left( \frac{47}{60} \right)$$

$$= \frac{47}{180}$$
(6)