

# Part II: Multi-class AdaBoost

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We want to address the  $K$ -class supervised classification problem. We observe  $n$  independent replicates  $(X^{(i)}, Y^{(i)})_{1 \leq i \leq n}$  of  $(X, Y)$ , where  $X \in \mathbb{R}^d$  and  $Y \in \mathcal{Y} = \{1, \dots, K\}$ . The goal is to construct a classifier  $g : \mathbb{R}^d \rightarrow \mathcal{Y}$  that predicts  $Y$  accurately via  $g(X)$ . In what follows,

$$\forall x \in \mathbb{R}^d, \forall k \in \mathcal{Y}, \pi_k(x) = \mathbb{P}(Y = k | X = x).$$

**Q1:** Derive the classifier  $g^*$  that minimizes  $R(g) = \mathbb{P}(g(X) \neq Y)$ .

The class  $Y$  can be encoded as a vector  $Z = (Z_1, \dots, Z_K)$  of  $\mathbb{R}^K$ :  $Y = k$  if and only if  $Z_k = 1$  and  $Z_j = \frac{-1}{K-1}$  for  $j \neq k$ . Let  $\mathcal{Z}$  denote the set of possible values of  $Z$ .

For any  $z \in \mathcal{Z}$  and  $f \in \mathbb{R}^K$ , consider the function

$$L(z, f) = \exp \left( -\frac{1}{K} \sum_{k=1}^K z_k f_k \right).$$

**Q2:** Let  $x \in \mathbb{R}^d$ . Show that the vector  $f^*(x) = (f_1^*(x), \dots, f_K^*(x))$  minimizing the function  $f \mapsto \mathbb{E}[L(Z, f) | X = x]$  under the constraint  $f_1 + \dots + f_K = 0$  is given by

$$\forall 1 \leq k \leq K, f_k^*(x) = (K-1) \left[ \ln \pi_k(x) - \frac{1}{K} \sum_{j=1}^K \ln \pi_j(x) \right].$$

**Q3:** Deduce that  $\pi_k(x) \propto \exp(f_k^*(x)/(K-1))$ , and express  $g^*$  in terms of the components of  $f^*$ .

From now on, let  $\mathcal{H}$  denote a finite set of functions from  $\mathbb{R}^d$  to  $\mathcal{Z}$ .

**Q4:** For any positive weights  $(\omega^{(i)})_{1 \leq i \leq n}$ , show that the pair  $(\beta^*, h^*)$  minimizing

$$(\beta, h) \mapsto \sum_{i=1}^n \omega^{(i)} L(Z^{(i)}, \beta h(X^{(i)}))$$

under the constraints  $\beta > 0$  and  $h \in \mathcal{H}$ , is given by

$$\begin{cases} h^* &= \arg \min_{h \in \mathcal{H}} \sum_{i=1}^n \omega^{(i)} \mathbb{I}_{\{h(X^{(i)}) \neq Z^{(i)}\}}, \\ \beta^* &= \frac{(K-1)^2}{K} \alpha^*, \end{cases}$$

with

$$\alpha^* = \ln \left( \frac{1 - \epsilon^*}{\epsilon^*} \right) + \ln(K-1) \quad \text{and} \quad \epsilon^* = \frac{\sum_{i=1}^n \omega^{(i)} \mathbb{I}_{\{h^*(X^{(i)}) \neq Z^{(i)}\}}}{\sum_{i=1}^n \omega^{(i)}}.$$

Our aim is to approximate  $f^*$  as a linear combination of functions in  $\mathcal{H}$ . Specifically, we consider

$$f_M = \sum_{m=1}^M \beta_m h_m,$$

where  $\beta_m > 0$  and  $h_m \in \mathcal{H}$  for all  $m$ .

**Q5:** Show that

$$\sum_{i=1}^n L(Z^{(i)}, f_M(X^{(i)})) = \sum_{i=1}^n \omega_M^{(i)} L(Z^{(i)}, \beta_M h_M(X^{(i)})),$$

where  $(\omega_m)_{1 \leq m \leq M}$  satisfies a recurrence relation to be determined.

**Q6:** Using the results of Q4 and Q5, propose an algorithm to estimate  $f^*$  (as defined in Q2).

**Q7:** Show that the classifier  $G : \mathbb{R}^d \rightarrow \mathcal{Y}$  derived from Q3 and Q6 is given by

$$G(x) = \arg \max_{k \in \mathcal{Y}} \sum_{m=1}^M \alpha_m \mathbb{I}_{\{g_m(x)=k\}},$$

where  $(\alpha_m)_{1 \leq m \leq M}$  and  $(g_m)_{1 \leq m \leq M}$  are to be specified.

**Q8:** Identify where the non-trivial generalization lies compared to AdaBoost.