Machine Learning

1 Introduction

1.1 Binary Classification problem

Find a binary classifier : $h: \mathbb{R}^n \to \{-1, 1\}$ $x \mapsto h(x)$

So that $R_D(h) = \mathbb{P}_{(x,y)\sim D}[h(x) \neq y]$ is small. With :

- X : space of input data (image, text, sound, etc.)
- Y: space of label (e.g. $Y = \{-1, 1\}$)
- D: joint probability distribution of $(x, y) \in X \times Y$

 \rightarrow Objectif of ML : Risk Minimization for $h \in H$

Définition - Test error of h

Let $h \in H$, the test error of h is defined as:

$$R_D(h) = \mathbb{E}_{(x,y) \sim D}[\mathbb{1}_{h(x) \neq y}]$$
$$= \int_{X \times Y} \mathbb{1}_{h(x) \neq y} D(dx, y)$$

Remarque : Minimal $R_D(h)$: Bayes Classifier %D $h_{\text{Bayes}} = \operatorname*{argmax}_{y \in \{-1,1\}} \mathbb{P}_{(x,y) \sim D}[y|x]$

What is $P_{(x,y)\sim D}[y|x]$?

Example: Gaussians mixitures

Let
$$\mathbb{P}(y = -1) = \pi_0$$
, $\mathbb{P}(y = 1) = 1 - \pi_0$
 $\mathbb{P}(x|y = -1) = \mathcal{N}(\mu_1, \Sigma_1)$, $\mathbb{P}(x|y = 1) = \mathcal{N}(\mu_2, \Sigma_2)$

What are $\mathbb{P}(y = -1|x)$ and $\mathbb{P}(y = 1|x)$?

Using Bayes' theorem:

Texte manquant

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Théorème

Let H be all measurable functions from X to $\{-1, 1\}$. Then, $R_D(h) \ge R_D(h_{\text{Bayes}})$ for all $h \in H$.

Assume $D(dx, y) = \mathbb{P}(x|y)dx \cdot \mathbb{P}(y) = \mathbb{P}(y|x)\mathbb{P}(x)dx$

Then :
$$\begin{split} R_D(h) &= \mathbb{E}_{(x,y)\sim D}[\mathbbm{1}_{h(x)\neq y}] \\ &= \sum_{y\in\{-1,1\}} \int_X \mathbbm{1}_{h(x)\neq y} D(dx,y) \\ &= \sum_{y\in\{-1,1\}} \int_X \mathbbm{1}_{h(x)\neq y} \mathbb{P}(y|x) \mathbb{P}(x) dx \\ &= \int_X \mathbb{P}(y=1|x) \mathbbm{1}_{h(x)\neq 1} \mathbb{P}(x) dx + \int_X \mathbb{P}(y=-1|x) \mathbbm{1}_{h(x)\neq -1} \mathbb{P}(x) dx \end{split}$$

Why h_{Bayes} is optimal?

Texte manquant

1.2 Linear Classification problem

In general, D is unknown and $\mathbb{P}(x|y)$ is hard to model, $\mathbb{P}(y)$ prior to choose. Start from "simple" H: linear classifiers on $x \in \mathbb{R}^n$.

Définition - Linear classifier

A linear classifier is a function $h: \mathbb{R}^n \to \{-1,1\}$ of the form :

$$h(x) = \operatorname{sign}(\langle w, x \rangle + b)$$
$$= \operatorname{sign}(\sum_{i=1}^{n} w_i x_i + b)$$

with $w \in \mathbb{R}^n$ and $b \in \mathbb{R}$.

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