

Lecture 10 - 07-04-2020

1.1 TO BE DEFINE

1.2 MANCANO 20 MINUTI DI LEZIONE

$$\mathbb{E}[z] = \mathbb{E}[\mathbb{E}[z|x]] \quad \rightarrow \quad \mathbb{E}[Z|X=x]$$

$$\mathbb{E}[X] = \sum_{t=1}^m \mathbb{E}[x \cdot \Pi(A_t)] \quad A_1, \dots, A_m \text{ portion of sample law of total probability}$$

$$\begin{aligned} x \in \mathbb{R}^d \quad \mathbb{P}(Y_{\Pi(s,x)} = 1) &= \mathbb{E}[\Pi Y_{\Pi(s,x)} = 1] = \quad \text{Law of total probability} \\ &= \sum_{t=1}^m \mathbb{E}[\Pi\{Y_t = 1\} \cdot \Pi \cdot \{\Pi(s,x) = t\}] = \\ &= \sum_{t=1}^m \mathbb{E}[\mathbb{E}[\Pi\{Y_t = 1\} \cdot \Pi \cdot \{\Pi(s,x) = t\} | X_t]] = \end{aligned}$$

given the fact that $Y_t \sim \eta(X_t) \Rightarrow$ give me probability

$$\begin{aligned} Y_t = 1 \text{ and } \Pi(s,x) = t \text{ are independent given } X_Y \quad (e.g. \mathbb{E}[Z|X] = \mathbb{E}[x] \cdot \mathbb{E}[z]) \\ = \sum_{t=1}^m \mathbb{E}[\mathbb{E}[\Pi\{Y_t = 1\} | X_t] \cdot \mathbb{E}[\Pi(s,x) = t | X_t]] = \sum_{t=1}^m \mathbb{E}[\eta(X_t) \cdot \Pi \cdot \{\Pi(s,x) = t\}] = \\ = \mathbb{E}[\eta(X_{\Pi(s,x)})] \end{aligned}$$

$$\mathbb{P}(Y_{\Pi(s,x)} | X = x) = \mathbb{E}[\eta(X_{\Pi(s,x)})]$$

$$\begin{aligned} \mathbb{P}(Y_{\Pi(s,x)} = 1, y = -1) &= \mathbb{E}[\Pi\{Y_{\Pi(s,x)} = 1\} \cdot \Pi\{Y = -1|X\}] = \\ &= \mathbb{E}[\Pi\{Y_{\Pi(s,x)} = 1\} \cdot \Pi\{y = -1\}] = \mathbb{E}[\mathbb{E}[\Pi\{Y_{\Pi(s,x)} = 1\} \cdot \Pi\{y = -1|X\}]] = \end{aligned}$$

by independence i can split them

$$Y_{\Pi(s,x)} = 1 \quad y = -1 \quad \text{which is } 1 - \eta(x) \quad \text{when } X = x$$

$$= \mathbb{E} [\mathbb{E} [\Pi\{Y_{\Pi}(s, x)\} = 1 | X] \cdot \mathbb{E} [\Pi\{y = -1\} | X]] = \mathbb{E} [\eta_{\Pi(s, x)} \cdot (1 - \eta(x))] =$$

similarly:

$$\mathbb{P}(Y_{\Pi(s, x)} = -1, y = 1) = \mathbb{E} [(1 - \eta_{\Pi(s, x)}) \cdot \eta(x)]$$

$$\begin{aligned} \mathbb{E} [\ell_D(\hat{h}_s)] &= \mathbb{P}(Y_{\Pi(s, x)} \neq y) = \mathbb{P}(Y_{\Pi(s, x)} = 1, y = -1) + \mathbb{P}(Y_{\Pi(s, x)} = -1, y = 1) \\ &= \mathbb{E} [\eta_{\Pi(s, x)} \cdot (1 - \eta(x))] + \mathbb{E} [(1 - \eta_{\Pi(s, x)}) \cdot \eta(x)] \end{aligned}$$

Make assumptions on D_x and η :

1. $\forall X$ drawn from D_x $\max |X_t| \leq 1$
Feature values are bounded in $[-1, 1]$
all my points belong to this:

$$X = [-1, 1]^d$$

2. η is such that $\exists c < \infty$:

$$\eta(x) - \eta(x') \leq c \cdot \|X - x'\| \quad \forall x, x' \in X$$

It means that η is **Lipschitz** in X $c < \infty \Leftrightarrow \eta$ is continuous

using two facts:

$$\eta(x') \leq \eta(x) + c \|X - x'\| \quad \longrightarrow \quad \text{euclidean distance}$$

$$1 - \eta(x') \leq 1 - \eta(x) + c \|X - x'\|$$

$$X' = X_{\Pi(s, x)}$$

$$\begin{aligned} &\eta(X) \cdot (1 - \eta(x')) + (1 - \eta(x)) \cdot \eta(x') \leq \\ &\leq \eta(x) \cdot ((1 - \eta(x)) + \eta(x) \cdot c \|X - x'\|) + (1 - \eta(x)) \cdot c \|X - x'\| = \\ &= 2 \cdot \eta(x) \cdot (1 - \eta(x)) + c \|X - x'\| \end{aligned}$$

$$\mathbb{E} [\ell_d \cdot (\hat{h}_s)] \leq 2 \cdot \mathbb{E} [\eta(x) - (1 - \eta(x))] + c \cdot (E) [\|X - x_{\Pi(s, x)}\|]$$

where \leq mean at most

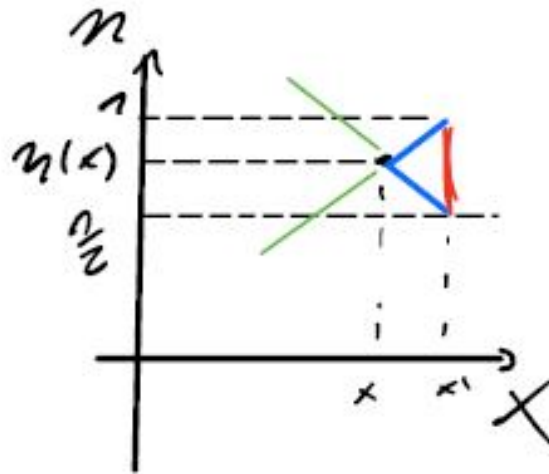


Figure 1.1: Point (2) - where $y = cx + q$ $y = -cx + q$

1.3 Compare risk for zero-one loss

$$\begin{aligned} \mathbb{E}[\min\{\eta(x), 1 - \eta(x)\}] &= \ell_D(f^*) \\ \eta(x) \cdot (1 - \eta(x)) &\leq \min\{\eta(x), 1 - \eta(x)\} \quad \forall x \\ \mathbb{E}[\eta(x) \cdot (1 - \eta(x))] &\leq \ell_D(f^*) \\ \mathbb{E}[\ell_d(\hat{l}_s)] &\leq 2 \cdot \ell_D(f^*) + c \cdot \mathbb{E}[\|X - X_{\Pi(s,x)}\|] \quad \eta(x) \in \{0, 1\} \end{aligned}$$

Depends on dimension: **curse of dimensionality**

$\ell_d(f^*) = 0 \iff \min\{\eta(x), 1 - \eta(x)\} = 0$ with probability = 1
to be true $\eta(x) \in \{0, 1\}$

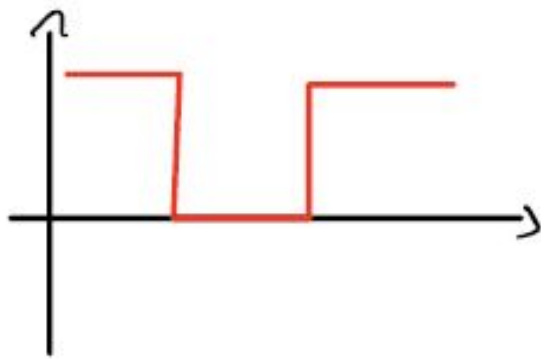


Figure 1.2: Point