

No Free Lunch Theorem

- The hypothesis class of all functions is not PAC Learnable

Theorem: Let A be any learning

algorithm (binary classification)

domain: X $Y \in \{0, 1\}$

of samples $\leq |X|/2$
Then there exists f (a function) and a distribution D on $X \times \{0, 1\}$ such that

- $L_D(f) = 0$ \rightarrow f is output by A on S
- $\mathbb{P}_{S \sim D^m} [L_D(A(S)) \geq 1/4] \geq 1/2$

Proof

Alg A sees m samples
of fun $X \rightarrow \{0, 1\} = 2^{2^m} = T$

f_1, f_2, \dots, f_T P_m
 D_1, D_2, \dots, D_T dist. $X \times \{0, 1\}$

$$D_i(x, y) = \begin{cases} 1/2^m & \text{if } f_i(x) = y \\ 0 & \text{otherwise} \end{cases}$$

Will prove:
 $\max_{f \in T} \mathbb{E} \sum_{i=1}^m L_{D_i}(A(S)) \geq 1/4$

Markov Inequality

Marginal of D_i on X is uniform

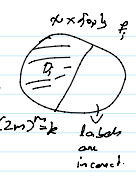
$$S = (x_1, x_2, \dots, x_m)$$

of possible S 's $(2^m)^m = k$ labels are incorrect

$$S_j = \{ (x_1, f_j(x_1)), \dots, (x_m, f_j(x_m)) \}$$

$$\mathbb{E}_{S \sim D^m} L_D(A(S)) = \frac{1}{k} \sum_{j=1}^k L_{D_i}(A(S_j))$$

$$\max_{S \sim D^m} \mathbb{E} L_D(A(S)) \geq \frac{1}{T} \sum_{i=1}^T$$



$$= \frac{1}{T} \sum_{i=1}^T \sum_{j=1}^k L_{D_i}(A(S_j))$$

$$\geq \min_{j \in 1..k} \frac{1}{T} \sum_{i=1}^T L_{D_i}(A(S_j))$$

$$\frac{1}{2^m} \sum_{x \in X} \mathbb{1}[A(S_j)(x) \neq f_i(x)]$$

Fix j , $S_j = (x_1, \dots, x_m)$

$X \setminus S_j = \{x_{p+1}, \dots, x_p\}$

$|S_j| \leq m \Rightarrow p \geq m$

$$\geq \frac{1}{2^m} \sum_{i=1}^p \mathbb{1}[A(S_j) \neq f_i(x_p)]$$

$$\geq \frac{1}{2^p} \sum_{i=1}^p \mathbb{1}[A(S_j) \neq f_i(x_p)]$$

$$\geq \min_j \frac{1}{2^p} \sum_{i=1}^p \frac{1}{T} \sum_{i=1}^T \mathbb{1}[A(S_j)(x_p) \neq f_i(x_p)]$$

$$\geq \min_j \frac{1}{2^p} \sum_{i=1}^p \frac{1}{T} \sum_{i=1}^T \mathbb{1}[A(S_j)(x_p) \neq f_i(x_p)]$$

$$\geq \min_j \frac{1}{2^p} \sum_{i=1}^p \frac{1}{T} (\tau_{i,2})$$

$$\geq \min_j \frac{1}{2^p} \sum_{i=1}^p \frac{1}{2} \geq 1/4$$