Assignment 3

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Question 1. We should show that if set

$$\{(x_i, y_i)\}_{i=1}^m \subseteq (\mathbb{R}^d, \{0, 1\})^m$$

as training set, and

$$h_s(x) = \begin{cases} 1 \text{ if } \exists i \in [m] \text{s.t } x_i = x \\ 0 \text{ o.w} \end{cases}$$

there exists a polynomial P_s such that:

$$h_s(x) = 1 \Leftrightarrow P_s(x) \ge 0$$

Proof. We can define P_s as:

$$P_s(x) = -\prod_{i=1}^{m} (||x - x_i||^2)$$

(Right to Left) if $\mathbf{h}_s(\mathbf{x}){=}1 \Rightarrow \exists \mathbf{i} \in [\mathbf{m}] \\ \mathbf{s}. \\ \mathbf{t} \\ \mathbf{x}_i = x \Rightarrow P_s(x) = 0$ so if $\mathbf{h}_s(\mathbf{x}){=}1 \Rightarrow P_s(x) = 0$ (Left to Right) if $\mathbf{h}_s(\mathbf{x}) \neq 1 \Rightarrow \forall \mathbf{i} \in [\mathbf{m}] \\ \mathbf{x}_i \neq x \Rightarrow P_s(x) < 0$ so if , $\mathbf{h}_s(\mathbf{x}) \neq 1 \Rightarrow P_s(x) < 0$

Question 2. We should proof that:

$$\mathop{E}_{S|x \sim D^m} \left[L_S(h) \right] = L_{(D,f)}(h)$$

Proof. by definition we konw:

$$L_S(h) = \frac{|i \in [m] : h(x_i) \neq f(x_i)|}{m}$$

we rewrite that as:

$$L_S(h) = \frac{\sum_{i \in [m]} 1_{\{h(x_i) \neq f(x_i)\}}}{m}$$

now we calculate expectection value:

$$\mathop{E}_{S|x \sim D^m} [L_S(h)] = \mathop{E}_{S|x \sim D^m} \left(\frac{\sum_{i \in [m]} 1_{\{h(x_i) \neq f(x_i)\}}}{m} \right)$$

Expectection is linear function so we have:

$$E_{S|x \sim D^m} \left(\frac{\sum_{i \in [m]} 1_{\{h(x_i) \neq f(x_i)\}}}{m} \right) = \sum_{i \in [m]} E_{S|x \sim D^m} \left(1_{\{h(x_i) \neq f(x_i)\}} \right)$$

We know expectection of indicator is probability function:

$$\sum_{i \in [m]} E_{S|x \sim D^m} \left(1_{\{h(x_i) \neq f(x_i)\}} \right) = \frac{1}{m} \sum_{i \in [m]} P_{S|x \sim D^m} \left(h(x_i) \neq f(x_i) \right) = \frac{1}{m} \times m \times \underbrace{P_{S|x \sim D^m} \left(h(x_i) \neq f(x_i) \right)}_{L_{(D,f)}(h)} = L_{(D,f)}(h)$$

Question 3.1. we want show that:

$$A \in \underset{h \in H_{rec}}{\operatorname{arg}} \min L_s(h)$$

Proof. It is clear that, A returns all the positive instances in the training set correctly. The tightest rectangle enclosing all positive examples beside realizability assumption guarantee all the negative instance labels correctly by A, so A is an ERM. \Box

Question 3.2. Show that if A receives a training set of size $\geq \frac{4 \log(4/\delta)}{\varepsilon}$ then, with probability of at least $1 - \delta$ it returns a hypothesis with error of at most ϵ

Proof. First we define R^* as in the hint. if R(S) be the rectangle returned by A, from definition of A it is clear that:

$$R(S) \subseteq R^*$$

If rec be the corresponding hypothesis with R(S), since errors occur outside of R(S) we have:

$$L_{(D,f)}(rec) = D(R^* \backslash R(S))$$

so

$$\{S: L_{(D,f)}(rec_s) > \varepsilon\} \subseteq \{S: S \cap (\bigcup_{i=1}^4 R_i) = \varnothing\}$$
$$D^m(\{S: L_{(D,f)}(rec_s) > \varepsilon\}) \le D^m(\{S: S \cap (\bigcup_{i=1}^4 R_i) = \varnothing\})$$

If we write right side as union of $\{S: S \cap R_i = \emptyset\}$:

$$D^{m}(\{S: L_{(D,f)}(rec_s) > \varepsilon\}) \le \sum_{i=1,2,3,4} D^{m}(\{S: S \cap R_i = \varnothing\})$$

and wen konw:

$$D^{m}(\{S: S \cap R_{i} = \varnothing\}) = \left(1 - \frac{\varepsilon}{4}\right)^{m}$$

so:

$$\sum_{i=1,2,3,4} D^m(\{S: S \cap R_i = \varnothing\}) \le 4 \times (1 - \frac{\varepsilon}{4})^m \le 4 \exp(\frac{-m\varepsilon}{4})$$

from assumption $m \ge \frac{4\log(4/\delta)}{\varepsilon}$ we conclude our proof.