

# Homework #3B

Spring 2020, CSE 446/546: Machine Learning  
Prof. Kevin Jamieson and Prof. Jamie Morgenstern  
Due: 5/28/20 11:59 PM

B.1

a. Since  $R(f) > \epsilon$ :

$$\begin{aligned}\mathbb{P}(\hat{R}_n(f) = 0) &= \mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n (f(x_i) \neq y_i)\right) = \prod_{i=1}^n \mathbb{P}(f(x_i) \neq y_i) \\ &= (1 - \mathbb{P}(f(x_1) = y_1))^n = (1 - \mathbb{E}_{XY}[(f(X) = Y)])^n = (1 - R(f))^n \leq (1 - \epsilon)^n \leq e^{-n\epsilon}\end{aligned}$$

b. For every  $f \in \mathcal{F}$ , define  $A_f = \{R(f) > \epsilon \text{ and } \hat{R}_n(f) = 0\}$ . Note that  $\mathbb{P}(\{R(f) > \epsilon \text{ and } \hat{R}_n(f) = 0\}) = \mathbb{P}(\hat{R}_n(f) = 0 | R(f) > \epsilon) \mathbb{P}(R(f) > \epsilon) \leq \mathbb{P}(\hat{R}_n(f) = 0 | R(f) > \epsilon)$ . Then:

$$\mathbb{P}(\exists f \in \mathcal{F} : R(f) > \epsilon \text{ and } \hat{R}_n(f) = 0) \leq \mathbb{P}(\cup_{f \in \mathcal{F}} A_f) \leq \sum_{f \in \mathcal{F}} \mathbb{P}(A_f) \leq |\mathcal{F}| e^{-n\epsilon} \quad \square$$

c.  $|\mathcal{F}| e^{-n\epsilon} \leq \delta$  so  $\epsilon \geq \frac{1}{n} \log \frac{|\mathcal{F}|}{\delta}$   
so  $\epsilon^* = \frac{1}{n} \log \frac{|\mathcal{F}|}{\delta}$

d.  $1 - \mathbb{P}(\hat{R}_n(f) = 0 \text{ and } R(f) - R(f^*) > \epsilon^*)$   
 $\geq 1 - \mathbb{P}(\hat{R}_n(f) = 0 \text{ and } R(f) > \epsilon^*) \geq 1 - \mathbb{P}(\exists f \in \mathcal{F} : R(f) > \epsilon^* \text{ and } \hat{R}_n(f) = 0) \geq 1 - |\mathcal{F}| e^{-\epsilon^* n} \geq 1 - \delta$