

B.1: Intro to Sample Complexity

B.1.a

Let's exam the statement:

$$\begin{aligned}\mathbb{P}[\hat{R}_n(f) = 0] &= \mathbb{P}\left[\frac{1}{n} \sum_{i=1}^n \mathbf{1}\{f(x_i) \neq y_i\} = 0\right] \\ &= \prod_{i=1}^n 1 - \mathbb{P}[f(x_i) \neq y_i]\end{aligned}\tag{B.1.a}$$

Let's use the statement in the hypothesis. The statement was $R(f) > \epsilon$, which describes the event that $\mathbb{E}[\mathbf{1}\{f(x) \neq Y\}]$. so then $1 - R(f)$ describes expected value of the event that: $1 - \mathbb{P}(f(x_i) \neq y)$. And notice that $1 - R(f) < 1 - \epsilon < \exp(\epsilon)$, so then we can simplify the above expression into:

$$\begin{aligned}\prod_{i=1}^n 1 - \mathbb{P}[f(x_i) \neq y_i] &= (1 - R(f))^n \leq (\exp(\epsilon))^n = \exp(n\epsilon) \\ \implies \mathbb{P}[\hat{R}_n(f) = 0] &\leq \exp(n\epsilon)\end{aligned}\tag{B.1.a.1}$$

B.1.b

The results from the previous involves the hypothesis that $R(f) \geq \epsilon$, the theoretical risk of the model is larger than ϵ , therefore, under a larger scope the more appropriate inequality to make should be:

$$\mathbb{P}[\hat{R}_n(f) = 0 \wedge R(f) \geq \epsilon] \leq \exp(-n\epsilon)\tag{B.1.b.1}$$

For the proof, let's start with the following statement:

$$\begin{aligned}\mathbb{P}[f(f) > \epsilon \wedge \hat{R}_n(f) = 0] &= \mathbb{P}[\hat{R}_n(f) = 0 \mid R(f) > \epsilon] \mathbb{P}[R(f) > \epsilon] \\ \implies \mathbb{P}[f(f) > \epsilon \wedge \hat{R}_n(f) = 0] &\leq \mathbb{P}[\hat{R}_n(f) = 0 \mid R(f) > \epsilon] \leq \exp(-n\epsilon)\end{aligned}\tag{B.1.b.2}$$

Now, the statement $\exists f \in \mathcal{F} : R(f) > \epsilon \wedge \hat{R}_n(f) = 0$ implies that occurrence of at least one f that make the event true, hence, it's the union of the probability of each individual f in \mathcal{F} which can make it true.

$$\begin{aligned}\mathbb{P}[\exists f \in \mathcal{F} : R(f) > \epsilon \wedge \hat{R}_n(f) = 0] &= \mathbb{P}\left[\bigcup_{f \in \mathcal{F}} \{R(f) > \epsilon \wedge \hat{R}_n(f) = 0\}\right] \\ &\stackrel{\text{Union Bound}}{\leq} \sum_{f \in \mathcal{F}} \mathbb{P}[R(f) > \epsilon \wedge \hat{R}_n(f) = 0] \\ &\leq |\mathcal{F}| \exp(-n\epsilon)\end{aligned}\tag{B.1.b.3}$$

B.1.c

Let's assume that there exists instance where the bounds for what we derived on part (b) could be strict (I believe it should.), then we can re-arrange and get the expression that:

$$\begin{aligned}
 |\mathcal{F}| \exp(-\epsilon n) &\leq \delta & (\text{B.1.c.1}) \\
 \ln(|\mathcal{F}|) - \epsilon n &\leq \ln(\delta) \\
 -\epsilon n &\leq \ln(\delta) - \ln(|\mathcal{F}|) \\
 \epsilon &\leq \frac{\ln(\delta) - \ln(|\mathcal{F}|)}{-n} \\
 \epsilon &\leq \frac{\ln(\frac{|\mathcal{F}|}{\delta})}{n}
 \end{aligned}$$

Therefore, the largest ϵ is $\frac{1}{n} \ln(|\mathcal{F}|/\delta)$

B.1.d

We are proving the probability of the events $A \implies B$, where A, B are some kind of probabilistic events, Using some math we have: $\mathbb{P}(A \implies B) = 1 - \mathbb{P}(A \wedge \neg B)$, and in our case A is $\hat{R}_n(\hat{f}) = 0$ and B is $R(\hat{f}) - R(f^*) \leq \frac{\ln(|\mathcal{F}|/\delta)}{n}$.

Let's get into the math and I will label the steps and explain them.

$$\begin{aligned}
 \mathbb{P} \left[\hat{R}_n(\hat{f}) = 0 \implies R(\hat{f}) - R(f^*) \leq \frac{\ln(|\mathcal{F}|/\delta)}{n} \right] &\stackrel{(1)}{=} 1 - \mathbb{P} \left[\hat{R}_n(\hat{f}) = 0 \wedge R(\hat{f}) - R(f^*) \geq \frac{\ln(|\mathcal{F}|/\delta)}{n} \right] & (\text{B.1.d.1}) \\
 &\stackrel{(2)}{\geq} 1 - \mathbb{P} \left[\hat{R}_n(\hat{f}) = 0 \wedge R(\hat{f}) \geq \frac{\ln(|\mathcal{F}|/\delta)}{n} \right] \\
 &\stackrel{(3)}{\geq} 1 - \mathbb{P} \left[\hat{R}_n(\hat{f}) = 0 \wedge R(\hat{f}) \geq \epsilon \right] \\
 &\stackrel{(4)}{\geq} 1 - \mathbb{P} \left[\exists \hat{f} \in \mathcal{F} : \hat{R}_n(\hat{f}) = 0 \wedge R(\hat{f}) \geq \epsilon \right] \\
 &\stackrel{\text{B.1.b.3}}{\geq} 1 - |\mathcal{F}| \exp(-n\epsilon) \\
 &\geq 1 - \delta
 \end{aligned}$$

- (1) True because: $A \implies B = \neg(A \wedge \neg B)$.
- (2) True because $R(f^*) > 0$, meaning that $R(\hat{f}) - R(f^*) \leq \frac{1}{n} \ln(|\mathcal{F}|/\delta)$ implies that $R(\hat{f}) \geq \frac{1}{n} \ln(|\mathcal{F}|/\delta)$, which implies that the latter is a subset of the former, Therefore its probability is going to be higher. Justifying the inequality.
- (3) True because $\epsilon < \frac{1}{n} \ln(|\mathcal{F}|/\delta)$, and this is just what we proved in (c) of B.1. And because of this, whatever \hat{f} that makes $\hat{f} \geq \frac{1}{n} \ln(|\mathcal{F}|/\delta)$ will make $R(\hat{f}) \geq \epsilon$ as well, therefore the former is a subset of the latter, therefore the latter has a higher probability, justifying the inequality.
- (4) The probability of the existence of at least one is higher than the probability of the existence of any particular one, because the existence of any particular one has a prior that we chose that particular one to measure the imperical risk.

The last one just by the definition of δ .