

# MLT Homework 5

Ana Borovac  
Jonas Haslbeck  
Bas Haver

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## Question 1

### Subquestion 1.1

Consider a hypothesis class  $\mathcal{H} = \cup_{n=1}^{\infty} \mathcal{H}_n$ , where for every  $n \in \mathbb{N}$ ,  $\mathcal{H}_n$  is finite. Find a weighting function  $w : \mathcal{H} \rightarrow [0, 1]$  such that  $\sum_{h \in \mathcal{H}} w(h) \leq 1$  and so that for all  $h \in \mathcal{H}$ ,  $w(h)$  is determined by  $|\mathcal{H}_{n(h)}|$ .

### Solution

Since we have a countably infinite union of finite sets, we know that the number of elements is countably infinite. Therefore, we can number them as:

$$h_1, h_2, \dots$$

If we pick weights as:

$$w(h_i) = \left( \frac{1}{2^{|\mathcal{H}_{n(h_i)}|}} \right)^i ; \quad i = 1, 2, \dots$$

the sum of the weights in the worst case would be, when  $|\mathcal{H}_{n(h_i)}| = 1$  ( $\forall i$ ) and we have infinity number of different hypothesis:

$$\sum_{i=1}^{\infty} w(h_i) = \sum_{i=1}^{\infty} \left( \frac{1}{2} \right)^i = 1$$

### Subquestion 1.2

Define such a function  $w$  when for all  $n$   $\mathcal{H}_n$  is countable (possibly infinite).

### Solution

Countably infinite union of countable sets is again a countable set, so we can choose the same weighted function as before.

## Question 2

*In this question we wish to show a No-Free-Lunch result for nonuniform learnability.*

### Subquestion 2.1

*Let  $A$  be a nonuniform learner for class  $\mathcal{H}$ . For each  $n \in \mathbb{N}$  define  $\mathcal{H}_n^A = \{h \in \mathcal{H} : m^{NUL}(0.1, 0.1, h) \leq n\}$ . Prove that each such class  $\mathcal{H}_n$  has a finite VC-dimension.*

### Solution

Because  $\mathcal{H}$  is nonuniform learnable, it is a union of agnostic PAC learnable hypothesis classes (Theorem 7.2). That is,  $\mathcal{H} = \bigcup_{n \in \mathbb{N}} \mathcal{H}_n^A$ , and  $\mathcal{H}_n^A$  is agnostic PAC learnable for all  $n \in \mathbb{N}$ . Because each  $\mathcal{H}_n^A$  is agnostic PAC learnable, it also has a finite VC-dimension, by the Fundamental Theorem of Statistical Learning (Theorem 6.7).

### Subquestion 2.2

*Prove that if class  $\mathcal{H}$  is nonuniformly learnable then there are classes  $\mathcal{H}_n$  so that  $\mathcal{H} = \bigcup_{n \in \mathbb{N}} \mathcal{H}_n$  and, for every  $n \in \mathbb{N}$ ,  $VCdim(\mathcal{H}_n)$  is finite.*

### Solution

This question was solved with the help of [1].

Let define:

$$\mathcal{H}_n = \{h \in \mathcal{H} : m^{NUL}(0.1, 0.1, h) \leq n\}$$

It is obvious that  $\mathcal{H} = \bigcup_{n \in \mathbb{N}} \mathcal{H}_n$ . From previous point we also know that  $VCdim(\mathcal{H}_n)$  is finite.

### Subquestion 2.3

*Let  $\mathcal{H}$  be a class that shatters some infinite set. Then for every sequence of classes  $(\mathcal{H}_n : n \in \mathbb{N})$  such that  $\mathcal{H} = \bigcup_{n \in \mathbb{N}} \mathcal{H}_n$ , there exists some  $n$  for which  $VCdim(\mathcal{H}_n) = \infty$ .*

### Solution

By assumption the hypothesis class  $\mathcal{H}$  shatters some infinite set  $K$ . Let  $(\mathcal{H}_n : n \in \mathbb{N})$  be a set of hypothesis classes, each having a finite VC-dimension. We define subsets  $K_n \subseteq K$  such that, for all  $n$ ,  $|K_n| > \text{VCdim}(\mathcal{H}_n)$ , and all subsets are nonoverlapping, so  $K_n \cap K_m = \emptyset$ .

Now, for each  $K_n$  we pick a function  $f_n : K_n \rightarrow \{0, 1\}$  so that no  $h \in \mathcal{H}_n$  agrees with  $f_n$  on the domain  $K_n$ . Such a function exists for all  $K_n$ , because  $\mathcal{H}_n$  does not shatter  $K_n$ , since  $|K_n| > \text{VCdim}(\mathcal{H}_n)$ .

Next, we define the function  $f : K \rightarrow \{0, 1\}$  by combining all  $f_n$ 's

$$f(k) = \begin{cases} f_1(k) & \text{if } k \in K_1 \\ \vdots \\ f_n(k) & \text{if } k \in K_n \end{cases}$$

where  $k \in K$  are singletons in  $K$ .

We define  $H_0 = \cup_{n \in \mathbb{N}} \mathcal{H}_n$ . By the construction of all  $f_n$ 's it follows that  $f$  is not contained in  $H_0$ . However,  $f \in \mathcal{H}$ , because  $\mathcal{H}$  shatters  $K$  by assumption. Put differently,  $f \in (\mathcal{H} \setminus H_0)$ .

This implies that  $(\mathcal{H} \setminus H_0) \neq \emptyset$ . And since we did not put any restrictions on  $\mathcal{H}_n$ 's except  $\text{VCdim}(\mathcal{H}_n) < \infty$ ,  $(\mathcal{H} \setminus H_0)$  must contain at least one hypothesis class that has infinite VC-dimension, which concludes the proof.

### Subquestion 2.4

Construct a class  $\mathcal{H}_1$  of functions from the unit interval  $[0, 1]$  to  $\{0, 1\}$  that is nonuniformly learnable but not PAC learnable.

### Solution

This question was solved with the help of [1].

Let denote:

$$\mathcal{H}_n = \{h_{a_1, \dots, a_n, b_1, \dots, b_n}; 0 \leq a_1 < b_1 \leq 1, \dots, 0 \leq a_n < b_n \leq 1\}$$

where:

$$h_{a_1, \dots, a_n, b_1, \dots, b_n}(x) = \begin{cases} 1; & a_1 \leq x \leq b_1 \text{ or } \dots \text{ or } a_n \leq x \leq b_n \\ 0; & \text{otherwise} \end{cases}$$

We claim that  $\text{VCdim}(\mathcal{H}_n) = 2n$ .

- $\text{VCdim}(\mathcal{H}_n) \geq 2n$ : We would like to show that  $\mathcal{H}_n$  shatters a set of  $2n$  points. Assume that  $0 \leq x_1 < \dots < x_{2n} \leq 1$ . Labeling for which we need the largest number of disjoint intervals is when  $x$ -es with even indexes are labeled 0 and others are labeled 1 (or vice versa). This is exactly  $n$  intervals that we need, so  $\mathcal{H}_n$  shatters  $\{x_1, \dots, x_{2n}\}$ .

- $\text{VCdim}(\mathcal{H}_n) \leq 2n$ : Now, we are going to take a set of  $2n + 1$  elements;  $0 \leq x_1 < \dots < x_{2n+1} \leq 1$ . If we want that  $\mathcal{H}_n$  shatters our set, there must exist a labeling function which can label the situation where  $x$ -es with odd indexes are labeled 1 and others are labeled 0. In order to do that we would need at least  $n + 1$  intervals, which we do not have. So,  $\mathcal{H}_n$  does not shatter a set of  $2n + 1$  elements.

Denote  $\mathcal{H} = \bigcup_{i=1}^{\infty} \mathcal{H}_n$ . From previous points we can conclude that  $\mathcal{H}$  is nonuniformly learnable. It is not PAC learnable due to  $\text{VCdim}(\mathcal{H}) = \infty$ .

### Subquestion 2.5

*Construct a class  $\mathcal{H}_2$  of functions from the unit interval  $[0, 1]$  to  $\{0, 1\}$  that is not nonuniformly learnable.*

#### Solution

This question was solved with the help of [1].

Define  $\mathcal{H}$  as a set of all intervals over  $[0, 1]$  (hypothesis labels an element with 1 if it is inside of at least one interval, otherwise it labels it with 0). It is obvious that  $\mathcal{H}$  shatters a set  $S = \{\frac{1}{n}; n \in \mathbb{N}\}$ . We also know that  $S$  is infinite. Therefore  $\mathcal{H}$  is not nonuniformly learnable (from previous points).

### Question 3

*Prove the Symmetrization Lemma (= double sample trick):*

*For any  $\epsilon > 0$  such that  $n\epsilon^2 \geq 2$ ,*

$$\sup_{f \in \mathcal{F}} P_n [(R(f) - R_n(f)) \geq \epsilon] \leq P_{2n} \left[ \sup_{f \in \mathcal{F}} (R'_n(f) - R_n(f)) \geq \frac{\epsilon}{2} \right]$$

*where  $R$  is the risk,  $R_n$  empirical risk for the sample  $Z_1, \dots, Z_n$  and  $R'_n$  empirical risk for ghost sample  $Z'_1, \dots, Z'_n$ .*

#### Solution

This question was solved with the help of [2].

Denote  $f^*$  a function that maximize  $(R(f) - R_n(f))$ . First, we would like to prove: If  $(R(f^*) - R_n(f^*) \geq \epsilon)$  and  $(R(f^*) - R'_n(f^*) \leq \frac{\epsilon}{2})$  then  $(R'_n(f^*) - R_n(f^*) \geq \frac{\epsilon}{2})$ .

$$\begin{aligned} \epsilon &< R(f^*) - R_n(f^*) \\ &= R(f^*) - R'_n(f^*) + R'_n(f^*) - R_n(f^*) \\ &\leq R'_n(f^*) - R_n(f^*) + \frac{\epsilon}{2} \end{aligned}$$

So,  $(R'_n(f^*) - R_n(f^*)) \geq \frac{\epsilon}{2}$ . If we write that with indicators:

$$I \left[ R(f^*) - R_n(f^*) > \epsilon, R(f^*) - R'_n(f^*) \leq \frac{\epsilon}{2} \right] \leq I \left[ R'_n(f^*) - R_n(f^*) \geq \frac{\epsilon}{2} \right]$$

Now, we are going to compute expected value over  $Z'_1, \dots, Z'_n$ :

$$I[R(f^*) - R_n(f^*) > \epsilon] P_n \left[ R(f^*) - R'_n(f^*) \leq \frac{\epsilon}{2} \right] \leq P_n \left[ R'_n(f^*) - R_n(f^*) \geq \frac{\epsilon}{2} \right]$$

With Chebishyev inequality we get and  $Var(f^*) \leq \frac{1}{4}$  (due to  $f^* \in [0, 1]$ ) :

$$P_n \left[ R(f^*) - R'_n(f^*) \leq \frac{\epsilon}{2} \right] \geq 1 - \frac{4Var(f^*)}{n\epsilon^2} \geq 1 - \frac{1}{n\epsilon^2} \geq \frac{1}{2}$$

Therefore:

$$\sup_{f \in \mathcal{F}} I[R(f) - R_n(f) \geq \epsilon] \leq 2P_n \left[ \sup_{f \in \mathcal{F}} (R'_n(f) - R_n(f)) \geq \frac{\epsilon}{2} \right]$$

Last, we again compute expectation but this time over  $Z_1, \dots, Z_n$ :

$$\sup_{f \in \mathcal{F}} P_n [R(f) - R_n(f) \geq \epsilon] \leq 2P_{2n} \left[ \sup_{f \in \mathcal{F}} (R'_n(f) - R_n(f)) \geq \frac{\epsilon}{2} \right]$$

## References

- [1] Gyora M. Benedek and Alon Itai. Nonuniform learnability. *J. Comput. Syst. Sci.*, 48(2):311–323, 1994.
- [2] Han Liu John Lafferty and Larry Wasserman. Concentration of measure. [www.stat.cmu.edu/~larry/=sml/Concentration.pdf](http://www.stat.cmu.edu/~larry/=sml/Concentration.pdf). Online; accessed 14 October 2018.