# Learning Theory - Homework 1

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# 1 Exercise 5.1

## 1.1 Statement

Prove that Equation (5.2) suffices for showing that  $P[L_D(A(S)) \ge 1/8] \ge 1/7$ .

#### 1.2 Solution

From equation 5.2 we have that  $\mathbb{E}[L_D(A'(S))] \geq 1/4$  for any algorithm A' and a well-chosen distribution D. We want to prove that  $P[L_D(A(S)) \geq 1/8] \geq 1/7$ . Note that we can write  $\theta = L_D(A(S))$  and then, using F as the cdf of D, we get:

$$p = P(\theta \ge 1/8) = \int_{1/8}^{1} F(\theta) d\theta \ge \int_{0}^{1} \theta F(\theta) d\theta - \int_{0}^{1/8} \theta F(\theta) d\theta \ge \mathbb{E}[\theta] - \frac{1}{8} \int_{0}^{1/8} F(\theta) d\theta \ge \frac{1}{4} - \frac{1}{8} (1 - p) = \frac{1}{8} + \frac{1}{8} p \quad (1)$$

From this we get that  $p \geq 1/7$ , which is exactly what we wanted to prove.

# 2 Exercise 6.2

#### 2.1 Statement

Given some finite domain set,  $\mathcal{X}$ , and a number  $k \leq |\mathcal{X}|$ , figure out the VC-dimension of each of the following classes (and prove your claims):

- 1.  $\mathcal{H}_{=k}^{\mathcal{X}} = \{h \in \{0,1\}^{\mathcal{X}} : |\{x : h(x) = 1\}| = k\}$ . That is, the set of all functions that assign the value 1 to exactly k elements of  $\mathcal{X}$ .
- 2.  $\mathcal{H}_{at-most-k} = \{h \in \{0,1\}^{\mathcal{X}} : |\{x : h(x) = 1\}| \le k \lor |\{x : h(x) = 0\}| \le k\}$

#### 2.2 Solution

In what follows, for each subproblem we use  $\mathcal{H}$  for the hypothesis classes for a shorter notation.

1. Given that any  $h \in \mathcal{H}$  assigns exactly k values of 1 for elements from  $\mathcal{X}$ , we can not have  $C \subseteq \mathcal{X}$  with |C| > k such that  $\mathcal{H}$  "shatters" C, as we could not do an all-one classification. Therefore,  $VCdim(\mathcal{H}) \leq k$ .

If  $|\mathcal{X}| \geq 2k$ , we can always find some  $h \in \mathcal{H}$  such that for a given  $C \subseteq \mathcal{X}$ , |C| = k, we obtain one of the  $2^k$  classifications of the elements of C. Therefore,  $VCdim(\mathcal{H}) = k$  for  $|\mathcal{X}| > 2k$ .

If  $|\mathcal{X}| < 2k$ , as we are restricted to have exactly k ones, we can have at most  $|\mathcal{X}| - k$  zeros, so  $VCdim(\mathcal{H}) \leq |\mathcal{X}| - k$ , but like in the previous case, we can achieve this upper bound.

In conclusion,  $VCdim(\mathcal{H}) = \min\{k, |\mathcal{X}| - k\}.$ 

2. If  $\mathcal{X} > 2k+1$ , for |C| = 2k+2, we can not have (k+1) elements classified as 1 and the other (k+1) classified as 0. However, for |C| = 2k+1, if we have more than k ones associated to C, we will implicitly have fewer than (k+1) zeros associated to C and vice versa. Therefore, we can find  $h \in \mathcal{H}$  to do any classification on C.

We are also restricted by the size of  $|\mathcal{X}|$  with respect to k, so  $VCdim(\mathcal{H}) = \min\{|\mathcal{X}|, 2k+1\}$ 

## 3 Exercise 6.5

#### 3.1 Statement

VC-dimension of axis aligned rectangles in  $\mathbb{R}^d$ : Let  $\mathcal{H}^d_{rec}$  be the class of axis aligned rectangles in  $\mathbb{R}^d$ . We have already seen that  $VCdim(\mathcal{H}^2_{rec})=4$ . Prove that in general,  $VCdim(\mathcal{H}^d_{rec})=2d$ .

#### 3.2 Solution

Suppose we have more than 2d points from  $\mathbb{R}^d$ . For each axis, we select the points with the minimum and the maximum coordinates. We therefore get a box defined by at most 2d points. The other points lie inside the box. Therefore, we can not classify the points defining the box with 1 and the inner points with 0 at the same time. This implies that  $VCdim(\mathcal{H}) \leq 2d$ . For 2d points, choosing them as  $(0,...,0,\pm 1,0,...,0)$  i.e. one-hot vectors, we see that for any subset of these points there is a box containing only them, so  $VCdim(\mathcal{H}) = 2d$ .

## 4 Exercise 6.8

#### 4.1 Statement

It is often the case that the VC-dimension of a hypothesis class equals (or can be bounded above by) the number of parameters one needs to set in order to define each hypothesis in the class. For instance, if H is the class of axis aligned rectangles in  $\mathbb{R}^d$ , then VCdim(H) = 2d, which is equal to the number of parameters used to define a rectangle in  $\mathbb{R}^d$ . Here is an example that shows that this is not always the case. We will see that a hypothesis class might be very complex and even not learnable, although it has a small number of parameters.

Consider the domain  $\mathcal{X} = \mathbb{R}$ , and the hypothesis class

$$\mathcal{H} = \{ x \mapsto \lceil \sin(\theta x) \rceil : \theta \in \mathbb{R} \} \tag{2}$$

(here we take [-1] = 0). Prove that  $VCdim(\mathcal{H}) = \infty$ .

#### 4.2 Solution

In order for  $VCdim(\mathcal{H}) = \infty$ , we have to show that  $\forall d \in \mathbb{N}, \exists C \subseteq \mathcal{X}, |C| = d$ , such that  $\mathcal{H}$  "shatters" C.

We fix  $d \in \mathbb{N}$  and build the set  $C = \{X_1, X_2, ..., X_d\}$  with binary representations  $X_j = 0.\underbrace{0...0}_{2^{d-j}}\underbrace{1...1}_{2^{d-j}}\underbrace{0...0}_{2^{d-j}}\underbrace{1...1}_{2^{d-j}}...$ , so that element  $X_j$  is composed from a

repetition of alternating 0/1 blocks of length  $2^{d-j}$ .

We use the fact that for a binary represented number  $x = 0.x_1x_2...$ , we get  $\lceil sin(2^m\pi x) \rceil = 1 - x_m$ . Considering now  $\theta = \{2^{2^d}\pi, 2^{2^{d-1}}\pi, ..., 2^0\pi\}$ , we obtain all the  $2^d$  possible classifications of C. To visualize it, we look at how C is mapped under the previous classification for d = 2:

d can be chosen arbitrarily, so we conclude that  $VCdim(\mathcal{H}) = \infty$ .

## 5 Exercise 6.9

#### 5.1 Statement

Let  $\mathcal{H}$  be the class of signed intervals, that is,  $\mathcal{H} = \{h_{a,b,s} : a \geq b, s \in \{-1,1\}\}$  where

$$h_{a,b,s}(x) = \begin{cases} s & \text{if } x \in [a,b] \\ -s & \text{if } x \notin [a,b] \end{cases}$$
 (3)

Calculate  $VCdim(\mathcal{H})$ .

#### 5.2 Solution

For the interval class, we had a VC-dimension of 2. Consider  $C \in \mathbb{R}$  with 3 points  $x_1 \leq x_2 \leq x_3$ . For the interval class, we could not do a classification (1,-1,1), but this is possible now with a classifier  $h_{a,b,-1}$  which has  $x_1 < a \leq x_2 \leq b < x_3$ .

However, for 4 points  $x_1 \leq x_2 \leq x_3 \leq x_4$ , we can not find a classifier in  $\mathcal{H}$  to give the classification (-1,1,-1,1), as this requires to have two disjoint intervals [a,b] and [c,d] either for s=-1 with  $a \leq x_1 \leq b < x_2 < c \leq x_3 \leq d < x_4$  or for s=1 with  $x_1 < a \leq x_2 \leq b < x_3 < c \leq x_4 \leq d$ .

In conclusion,  $VCdim(\mathcal{H}) = 3$ .

# 6 Exercise 7.3

#### 6.1 Statement

- Consider a hypothesis class  $\mathcal{H} = \bigcup_{n=1}^{\infty} \mathcal{H}_n$ , where for every  $n \in \mathbb{N}$ ,  $\mathcal{H}_n$  is finite. Find a weighting function  $w : \mathcal{H} \to [0,1]$  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  $n(h) = \min\{n : h \in \mathcal{H}_n\}$  and by  $|\mathcal{H}_{n(h)}|$ .
- (\*) Define such a function w when for all n,  $\mathcal{H}_n$  is countable (possibly infinite).

#### 6.2 Solution

• If we set  $w(h) = \frac{6}{(\pi n(h))^2} \frac{1}{|\mathcal{H}_{n(h)}|}$ , we get

$$\sum_{h \in \mathcal{H}} w(h) \le \sum_{n=1}^{\infty} \frac{6}{(\pi n)^2} \frac{1}{|\mathcal{H}_n|} |\mathcal{H}_n| = \frac{6}{\pi^2} \sum_{n=1}^{\infty} \frac{1}{n^2} = 1, \tag{4}$$

so we get a valid set of weights.

• Each set  $\mathcal{H}_n$  is countable, so within  $\mathcal{H}_n$ , there is a mapping from  $h \in \mathcal{H}_n$  to  $\mathbb{N}$ . Considering this, we associate an index i to each hypothesis  $h_i \in \mathcal{H}_n$ . Given  $h_i \in \mathcal{H}_{n(h)}$ , we compute  $w(h_i) = \left(\frac{6}{\pi^2}\right)^2 \frac{1}{n(h)^2} \frac{1}{i^2}$ . Therefore

$$\sum_{h \in \mathcal{H}} w(h) \le \sum_{n=1}^{\infty} \sum_{i=1}^{\infty} \left(\frac{6}{\pi^2}\right)^2 \frac{1}{n^2} \frac{1}{i^2} = \frac{6}{\pi^2} \sum_{n=1}^{\infty} \frac{1}{n^2} \frac{6}{\pi^2} \sum_{i=1}^{\infty} \frac{1}{i^2} = \frac{6}{\pi^2} \sum_{n=1}^{\infty} \frac{1}{n^2} = 1,$$
(5)

so we again get a valid set of weights.