

# CS 6350: Machine Learning Fall 2016

Gopal Menon

Homework 4

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## 1 PAC learning

1. [20 points total] A factory assembles a product that consist of different parts. Suppose a robot was invented to recognize whether a product contains all the right parts. The rules of making products are very simple: 1) you are free to combine any of the parts as they are 2) you may also cut any of the parts into two distinct pieces before using them. You wonder how much effort a robot would need to figure out the what parts are used in the product.

- (a) [5 points] Suppose that a naive robot has to recognize products made using only rule 1. Given  $N$  available parts and each product made out of these constitutes a distinct hypothesis. How large would the hypothesis space be? Brief explain your answer.

Since we have  $N$  available parts, the product can be made with any of the following number of parts, which would be the hypotheses space  $H$ .

$$H = \{1, 2, 3, \dots, N - 1, N\}$$

This means that the size of the hypotheses space  $H$  is

$$\begin{aligned} |H| &= 1 + 2 + 3 + \dots + N - 1 + N \\ &= \frac{N(N + 1)}{2} \end{aligned}$$

- (b) [5 points] Suppose that an experienced worker follows both rules when making a product. How large is the hypothesis space now? Explain.

Since each of the  $N$  parts can be used as is or broken into two, we have a total of  $3N$  possible parts. The reason is that we have  $N$  original parts and if each part is broken into two, we have  $2N$  broken parts. The total sum of the number of parts is  $N + 2N$  or  $3N$ . The product can be made out of unbroken parts or with broken parts or a combination of both. If broken parts are used, then both halves of the broken part are to be used. This means that the total number of parts from which the product can be made, is reduced to  $2N$ . Based on an argument

similar to the one given above for the previous answer, the size of the hypothesis space  $H$  will be

$$|H| = \frac{2N(2N+1)}{2}$$

- (c) [10 points] An experienced worker decides to train the naive robot to discern the makeup of a product by showing you the product samples he has assembled. There are 6 available parts. If the robot would like to learn any product at 0.01 error with probability 99%, how many examples would the robot have to see?

In order to learn a hypothesis with  $n$  dimensional features, with an error less than  $\epsilon$ , with a probability of  $1 - \delta$ , we would need  $m$  training samples, where  $m$  is given by

$$m > \frac{1}{\epsilon} \left( \log_e(|H|) + \log_e\left(\frac{1}{\delta}\right) \right)$$

In the case given above, since there are  $2N$  different parts that can be chosen to make up the product, the input space can be thought of as having  $2N$  dimensions since each dimension will be a binary variable which signifies whether a part has been used or not. So  $|H| = \frac{2N(2N+1)}{2} = \frac{2 \times 6(2 \times 6 + 1)}{2} = \frac{12 \times 13}{2} = 78$ ,  $\epsilon = 0.01$  and  $\delta = 1.00 - 0.99 = 0.01$ .

Substituting these values into the above in-equation, we get

$$\begin{aligned} m &> \frac{1}{0.01} \left( \log_e(78) + \log_e\left(\frac{1}{0.01}\right) \right) \\ &> 100 \times (\log_e(78) + \log_e(100)) \\ &> 100 \times (4.36 + 4.60) \\ &> 896.19 \end{aligned}$$

This means that the robot will need to look at at least 897 examples to learn a hypothesis.

2. [20 points, from Tom Mitchell's book] We have learned an expression for the number of training examples sufficient to ensure that every hypothesis will have true error no worse than  $\epsilon$  plus its observed training error  $error_S(h)$ . In particular, we used Hoeffding bounds to derive

$$m \geq \frac{1}{2\epsilon^2} (\ln(|H|) + \ln(1/\delta)).$$

Derive an alternative expression for the number of training examples sufficient to ensure that every hypothesis will have true error no worse than  $(1 + \epsilon)error_S(h)$ , where  $0 \leq \epsilon \leq 1$ . You can use general Chernoff bounds to derive such a result.

**Chernoff bounds:** Suppose  $X_1, \dots, X_m$  are the outcomes of  $m$  independent coin flips (Bernoulli trials), where the probability of heads on any single trial is  $Pr[X_i = 1] = p$  and the probability of tails is  $Pr[X_i = 0] = 1 - p$ . Define  $S = X_1 + X_2 + \dots + X_m$  to

be the sum of these  $m$  trials. The expected value of  $S/m$  is  $E[S/m] = p$ . The Chernoff bounds govern the probability that  $S/m$  will differ from  $p$  by some factor  $0 \leq \gamma \leq 1$ .

$$\begin{aligned} Pr[S/m > (1 + \gamma)p] &\leq e^{-mp\gamma^2/3} \\ Pr[S/m < (1 - \gamma)p] &\leq e^{-mp\gamma^2/2} \end{aligned} \tag{1}$$

## 2 VC Dimensions

- [10 points] Suppose you have a finite hypothesis space  $\mathcal{C}$ . Show that its VC dimension is at most  $\log_2 |\mathcal{C}|$  (Hint: You also prove this by contradiction.)
- [10 points] 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:

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

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

- [10 points] Suppose we have an instance space consisting of real numbers and a hypothesis space  $\mathcal{H}$  consisting of *two* disjoint intervals, defined by  $[a, b]$  and  $[c, d]$ . That is, a point  $x \in \mathbb{R}$  is labeled as positive if, and only if, either  $a \leq x \leq b$  or  $c \leq x \leq d$ . Determine the VC dimension of  $\mathcal{H}$ ?
- [15 points] We have a learning problem where each example is a point in  $\mathbb{R}^2$ . The concept class  $H$  is defined as follows: A function  $h \in H$  is specified by two parameters  $a$  and  $b$ . An example  $\mathbf{x} = \{x_1, x_2\}$  in  $\mathbb{R}^2$  is labeled as  $+$  if and only if  $x_1 + x_2 \geq a$  and  $x_1 - x_2 \leq b$  and is labeled  $-$  otherwise.

For example, if we set  $a = 0, b = 0$ , the grey region in figure ?? is the region of  $\mathbf{x} = \{x_1, x_2\}$  that has label  $+$ .

What is the VC dimension of this class?

- [**For 6350 Students**, 15 points] Let two hypothesis classes  $H_1$  and  $H_2$  satisfy  $H_1 \subseteq H_2$ . Prove:  $VC(H_1) \leq VC(H_2)$ .

## 3 AdaBoost

[15 points] You are given the following examples in the Table ??. You need to learn a model that minimize the error on this small dataset.

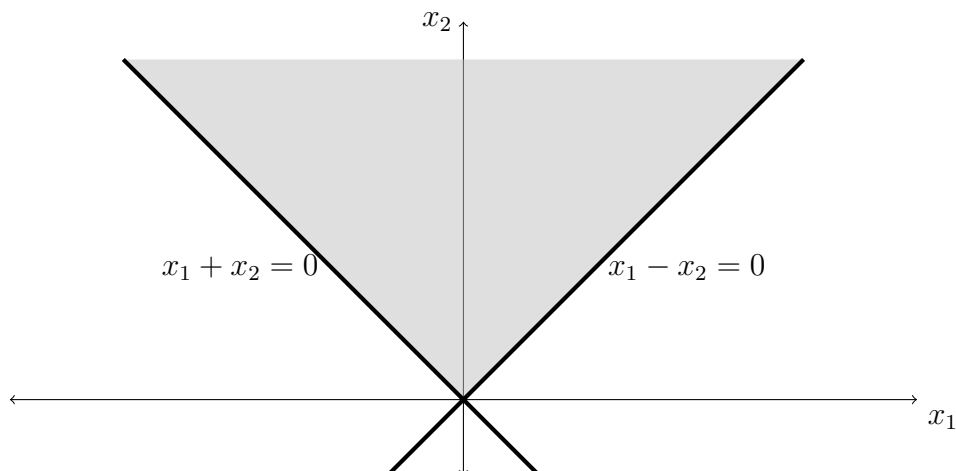


Figure 1: An example with  $a = 0, b = 0$ . All points in the gray region (extending infinitely) shows the region that will be labeled as positive.

Table 1: training set

$\mathbf{x} = [x_1, x_2]$	$y$
$[1, 1]$	-1
$[1, -1]$	+1
$[-1, -1]$	-1
$[-1, 1]$	-1

Assuming you are also given the following 4 weak hypothesis classifiers

$$\begin{aligned}
 h_a(\mathbf{x}) &= \text{sgn}(x_1) \\
 h_b(\mathbf{x}) &= \text{sgn}(x_1 - 2) \\
 h_c(\mathbf{x}) &= -\text{sgn}(x_1) \\
 h_d(\mathbf{x}) &= -\text{sgn}(x_2)
 \end{aligned}$$

Treat them as your weak classifiers( rule of thumb) for the following question.

Step through the full AdaBoost algorithm (Lecture Boosting slide P34) for 4 rounds by choosing  $h_t$  from the above 4 weak classifiers. Remember that you need to **choose a hypothesis** from  $h_a, h_b, h_c, h_d$  whose weighted classification error is **better than chance**. However, in this question, for easier grading, we have chosen  $h_a$  as the first hypothesis and show the values of  $\epsilon_1, \alpha_1, Z_1, D_1$  in Table ??.

For you answer, please follow the table template, report the hypothesis you choose and all the  $\epsilon_t, \alpha_t, Z_t, D_t$ , and the final hypothesis  $H_{final}(x)$  for *four subsequent rounds*.

Table 2: Choose  $h_a(\mathbf{x}) = \text{sgn}(x_1)$ ,  $\epsilon_1 = 1/4$ ,  $\alpha_1 = \frac{\ln 3}{2}$ ,  $Z_1 = \frac{\sqrt{2}}{3}$

$\mathbf{x} = [x_1, x_2]$	$y_i$	$D_1$	$D_1(i)y_i h_t(\mathbf{x}_i)$	$D_2$
[1,1]	-1	1/4	-1/4	
[1,-1]	+1	1/4	1/4	
[-1,-1]	-1	1/4	1/4	
[-1,1]	-1	1/4	1/4	