

# Introduction to Machine Learning

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Homework 1  
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**Notice,** to get the full credits, please present your solutions step by step.

## Exercise 1: 2pts

Show that  $(1 - \epsilon)^m \leq e^{-m\epsilon}$ , where  $m \in \mathbb{N}$ .

**Solution:** There may be another condition lost, the  $\epsilon \in [-\infty, 1]$ , otherwise if  $\epsilon = 2$  and  $m = 2$ , the inequality is broken.

And with my condition, the question will be easy, we all know that

$$e^x \leq (1 - x), \forall x \in [-\infty, 1]$$

This is easy to prove. We can make the function

$$f(x) = e^{-x} - 1 + x$$

$f(x) = 0$  when  $x = 0$ , and  $f'(x) = 1 - e^{-x}$ , and we can know

$$f'(x) \begin{cases} \leq 0 & \text{if } x \leq 0 \\ > 0 & \text{if } x > 0 \end{cases} \quad (1)$$

So

$$0 \leq f(x)_{\min} \text{ when } x \in [-\infty, 1] \quad (1)$$

and for  $m = 0$ ,  $m = 1$ , the inequality is ok, and we can assume that the inequality is ok for all  $m \leq N$ , and for  $m = N + 1$ ,

$$(1 - \epsilon)^{N+1} = (1 - \epsilon)^N * (1 - \epsilon) \leq e^{-(N\epsilon)} * (1 - \epsilon)$$

then use (1) we have proved,

$$e^{-(N\epsilon)} * (1 - \epsilon) \leq e^{-(N\epsilon)} * e^{-\epsilon} = e^{-(N+1)\epsilon}$$

The inequality is ok for  $N+1$ , so we prove it!

■

## Exercise 2: Markov inequality 2pts

Let  $X$  be a nonnegative random variable on  $\mathbb{R}$ . Then, for all  $t > 0$ , show that

$$\mathbf{P}(X \geq t) \leq \frac{\mathbf{E}[X]}{t}.$$

**Solution:** For nonnegative random variable, we assume  $f(x)$  is the probability distribution function of the  $x$ ; for any  $t \geq 0$

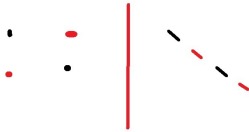
$$E(X) = \int_0^\infty xf(x)dx \geq \int_t^\infty xf(x)dx \geq t \int_t^\infty f(x)dx = tP(x \geq t)$$

This exactly the what we need. ■

### Exercise 3: VC-dimension 2pts

Assume that the instance space  $X = \mathbb{R}^2$  and the hypothesis space  $H$  be the set of all linear threshold functions defined on  $\mathbb{R}^2$ . Find  $VC(H)$  and prove it.

**Solution:**  $VC(H) = 3$ , and we know that three points can be shattered if points  $\in \mathbb{R}^2$  (there are all cases in the ppt), and we can construct samples that 4 points can't be shattered.



The red and black points represent two categories. ■

### Exercise 4: Learning intervals 4pts

Let the target concept class be  $C = \{[a, b] : a < b, a, b \in \mathbb{R}\}$  and the hypotheses class  $H = C$ , and the version space be  $VS_{H,D}$ . Each  $c \in C$  labels the points inside the interval positive and the others negative. A consistent learner will pick a consistent hypothesis—if any— $h \in H$  according to a set of i.i.d. samples  $\{(x_1, c(x_1)), (x_2, c(x_2)), \dots, (x_m, c(x_m))\}$  that obey an unknown distribution  $\mathcal{D}$ . Please find

$$\mathbf{P}[\exists h \in VS_{H,D} \text{ and } error_{\mathcal{D}}(h) > \epsilon],$$

and the corresponding sample complexity.

**Solution:** The learner can be sample, we make the the min negative points as the  $a'$  and the max positive point as  $b'$ .

We should find an upper bound of the probability because calculating it directly is very difficult and I don't know the bound I find is tight or not.

We use  $B$  to represent  $\exists h \in VS_{H,D}$  and  $error_{\mathcal{D}}(h) > \epsilon$ , and we should find an event  $E$  and  $P(E) \geq P(B)$ . and  $error_{\mathcal{D}}(D)$  can be defined as the integration of distribution functions between  $[a, a']$  and  $[b', b]$

How to define  $E$ ? This is very difficult to describe it clearly. If we limit the integration of distribution functions between  $[a, a']$  equal to  $\frac{\epsilon}{2}$  and  $[b', b]$  as same. we define  $E$  as none of train points hit the interval. So the  $P(B) \leq 2(1 - \frac{\epsilon}{2})^m \leq 2e^{-\frac{m\epsilon}{2}} \leq \delta$  (because it must be at least one interval is miss) So the complexity of sample  $m \geq 2\frac{\ln \frac{2}{\delta}}{\epsilon}$  ■