

2.1

$$\epsilon(M, N, S) = \sqrt{\frac{1}{2N} \ln \left(\frac{2M}{S} \right)}$$

A.1) a) $M=1, \epsilon \leq 0.05, S=0.02$

using the given equation
we have

$$N = 839.941$$

b) $M=100$

$$N = 1760.9750$$

c) $M=1000$

$$N = 2682.00908$$

2.2

For $N=4$, we can pick points: $(1,3), (2,4), (3,1), (4,2)$. It's easy to see that these points are shattered by positive rectangles. So $mH(4)=24$.

The idea is that for any two points, if we draw a rectangle using them as diagonal points, the rectangle should NOT contain any other point. Otherwise, whenever the two diagonal points have values 1, the middle point will have value 1 as well, which excludes the possibility of having -1.

For $N=5$, if we draw horizontal and vertical lines through each of the four points above, the plane is divided into grids. The four points enclosing a 9-grid area. It's clear that the fifth point can't lie within the 9-grid area. Otherwise, there'll always a rectangle (constructed by two points) contains the fifth point.

In the same way, if we place the fifth point outside the 9-grid area, it's easy to see that the point will always lie below or above at least two points (in either x or y direction). These three points construct a rectangle which contains a point in it. This shows that $mH(5) < 25$.

We have the VC dimension $d_{VC}(H)=4$, and $mH(N) \leq \sum_{i=0}^4 \binom{N}{i}$.

2.3

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$$VC \text{ bound} = \sqrt{\frac{8 \times \ln(4 \times \text{growth}(2N))}{N}}$$

A3 $N = 100$

~~$VC \text{ bound} = \sqrt{\frac{8 \times \ln(4 \times \text{growth}(2N))}{N}}$~~

$$VC \text{ bound} = 0.848159$$

 $N = 10000$

$$VC \text{ bound} = 0.104278$$

2.4

```

1  #!/usr/bin/env python3
2
3  import numpy as np
4
5
6  def get_sample_size(dvc, deviation, epsilon, n):
7      max_iterations = 1000
8      tolerance = 10
9
10     for _ in range(max_iterations):
11         rhs = 8 * np.log(4 * (pow(2 * n, dvc) + 1) / deviation)
12         rhs = rhs / epsilon / epsilon
13
14         result = n - rhs
15         if np.abs(result) <= tolerance:
16             break
17
18         n = int(rhs)
19     return n
20
21
22 if __name__ == "__main__":
23     dvc = 10
24     deviation = 0.05
25     epsilon = 0.05
26
27     # Starting value for N
28     n = 1000
29
30     sample_data = get_sample_size(dvc, deviation, epsilon, n)
31     print(f"Sample Size: {sample_data}")
32

```

Sample Size: 45290

2.5

A-5) i) Assume we have $h(x) = ax + b$, then

$$E_x[(f(x) - h(x))^2] = E_x[(\sin(\pi x) - (ax + b))^2]$$

$$= \int_{-1}^1 [\sin(\pi x) - (ax + b)]^2 p(x) dx$$

$$= \int_{-1}^1 \frac{1}{2} [\sin(\pi x) - (ax + b)]^2 dx$$

$$\frac{\partial E}{\partial a} = - \int_{-1}^1 x [\sin(\pi x) - (ax + b)] dx = 0$$

$$\frac{\partial E}{\partial b} = - \int_{-1}^1 [\sin(\pi x) - (ax + b)] dx = 0$$

$$\text{Solving, } \frac{2}{\pi} - \frac{2}{3} a = 0$$

$$b = 0$$

$$a = \frac{3}{\pi}$$

Best hypothesis that approx. f in the mean squared error:

a) $h(x) = \frac{3}{\pi} x$: $h(x) = ax + b$

b) $h(x) = \frac{3}{\pi} x$: $h(x) = ax$

c) $h(x) = 0$: $h(x) = b$

ii) Exp. value 'D' of hypothesis produces two points x_1 & x_2

$$E_{in}(g) = \sum_{i=1}^N (f(x_i) - h(x_i))^2$$

$$= \sum_{i=1}^N (\sin(\pi x_i) - (ax_i + b))^2$$

wrt a & b ~~Take~~ (Taking derivative)

$$\frac{\partial E_{in}(g)}{\partial a} = -2 \sum_{i=1}^N x_i (\sin(\pi x_i) - (ax_i + b)) = 0$$

$$\frac{\partial E_{in}(g)}{\partial b} = -2 \sum_{i=1}^N (\sin(\pi x_i) - (ax_i + b)) = 0$$

Solving a & b

$$\begin{aligned} (x_2 - x_1) (\sin \pi x_2 - ax_2 - b) &= 0 \\ (x_1 - x_2) (\sin \pi x_1 - ax_1 - b) &= 0 \end{aligned}$$

We assume $x_1 \neq x_2$

$$a = \frac{\sin \pi x_2 - \sin \pi x_1}{x_2 - x_1}$$

$$b = \frac{x_2 \sin \pi x_1 - x_1 \sin \pi x_2}{x_2 - x_1}$$

if $x_1 = x_2$; let $x_2 = x_1 + k$

substituting in the above equation with $k \rightarrow 0$

we can obtain hypothesis tangential to

$$g^D(x) = \frac{\sin \pi x_2 - \sin \pi x_1}{x_2 - x_1} x + \frac{x_2 \sin \pi x_1 - x_1 \sin \pi x_2}{x_2 - x_1}$$

for hypothesis set $h(x) = ax$

$$g^D(x) = \frac{x_1 \sin \pi x_1 + x_2 \sin \pi x_2}{x_1^2 + x_2^2} x$$

for $h(x) = b$

$$g^D(x) = \frac{1}{2} (\sin \pi x_1 + \sin \pi x_2)$$

$x \in [-1, 1]$ is uniformly distributed between $[-1, 1]$
 bias, variance can be calculated by
 $h(x) = b$

$$E_D[g^D(x)] = E_D\left[\frac{1}{2} (\sin \pi x_1 + \sin \pi x_2)\right]$$

≈ 0

bias component

$$\begin{aligned} \text{bias} &= E_x [g(x) - f(x)]^2 \\ &= E_x [(0 - \sin(\pi x))^2] \\ &= E_x [\sin^2(\pi x)] \approx \frac{1}{2} \end{aligned}$$

Variance Component

$$\text{Variance} = E_x [E_D [g^0(x) - \bar{g}(x)]^2]$$

$$= E_x [E_D (\frac{1}{2} (\sin \pi x_1 + \sin \pi x_2))$$

$$= E_x [\frac{1}{4} E_D (\sin^2 \pi x_1 + \sin^2 \pi x_2 +$$

$$2 \sin \pi x_1 \sin \pi x_2)]$$

$$= E_x [\frac{1}{4} (\frac{1}{2} + \frac{1}{2} + 0)]$$

$$= 0.25$$

Out of sample error

= Variance + bias

$$= \frac{1}{2} + \frac{1}{4} = 0.75$$

2.6

To show that k is a break point for H , we need to show H cannot shatter any set of k points x_1, x_k .

- If k is a break point, then $m_H(k) < 2^k$,
- In general, it is easier to find a break point for H than to compute the full growth function for that H .
- So the correct option is (d)

2.7

A7.7. Let $f(x) = \begin{cases} 1, & \text{if } w^T x + b > 0 \\ -1, & \text{otherwise} \end{cases}$

Consider $d+1$ points $x^{(0)} = (0, \dots, 0)^T$, $x^{(1)} = (1, 0, \dots, 0)^T$, $x^{(2)} = (0, 1, \dots, 0)^T, \dots, x^{(d)} = (0, 0, \dots, 1)^T$

After these $d+1$ points being arbitrarily labeled: $y = (y_0, y_1, \dots, y_d)^T \in \{-1, 1\}^{d+1}$

Let $b = 0.5 \cdot y_0$ and $w = (w_1, w_2, \dots, w_d)$ where $w_i = y_i$, $i \in \{1, 2, \dots, d\}$. Thus $f(x)$ can label all these $d+1$ points correctly. So, the VC dimensions of perceptron is at least $d+1$. ①

Expand $x \in \mathbb{R}^d$ to $X \in \mathbb{R}^{d+1}$ by letting $(x)^T = (x^T, 1)$, and let $W^T = (w^T, b)$

Thus, $f(X) = \begin{cases} 1 & \text{if } W^T X > 0 \\ -1 & \text{otherwise} \end{cases}$

Assume, there exists $d+2$ points the perceptron in \mathbb{R}^d can shatter, namely $x^{(1)}, x^{(2)}, \dots, x^{(d+2)} \in \mathbb{R}^d$ corresponding to $X^{(1)}, X^{(2)}, \dots, X^{(d+2)} \in \mathbb{R}^{d+1}$

Since $d+2$ points in \mathbb{R}^{d+1} , there exist certain i such that

$$X^{(i)} = \sum_{j \neq i} a_j \cdot X^{(j)}$$

where at least one $a_j \neq 0$.

Let $S = \{j | j \neq i, a_j \neq 0\}$.

$\forall j \in S$, we give $x^{(j)}$ the label $\text{Sign}(a_j)$, and give $x^{(i)}$ a label -1

By our assumption, there exists W that makes $f(x)$ label those $d+2$ points correctly.

So, $\forall j \in S$, we have
$$a_j \cdot W^T x^{(j)} > 0$$

and
$$W^T x^{(i)} \leq 0$$

$$\begin{aligned} \text{Also, } W^T x^{(i)} &= W^T \left(\sum_{j \neq i} a_j \cdot x^{(j)} \right) \\ &= W^T \left(\sum_{j \in S} a_j \cdot x^{(j)} \right) \\ &= \sum_{j \in S} a_j \cdot W^T x^{(j)} > 0 \end{aligned}$$

So our assumption is false. The VC dimension of perceptron in \mathbb{R}^d is at most $d+1$. ②

~~From this, from the above, we can conclude~~

From ① & ② we can conclude that VC dimension of perceptron in \mathbb{R}^d is $d+1$

$$a) E_{out}(g) \leq E_{in}(g) + \sqrt{\frac{1}{2N} \ln\left(\frac{2M}{\delta}\right)}$$

$$\epsilon = 0.05$$

$$N = 200$$

Test bound

$$\text{test bound} = \sqrt{\frac{1}{2N} \ln\left(\frac{2}{\epsilon}\right)}$$

$$= \sqrt{\frac{1}{2 \times 200} \times \ln\left(\frac{2}{0.05}\right)} = 0.096$$

Train bound

$$M = 1000$$

$$N = 400$$

$$\text{train bound} = \sqrt{\frac{1}{2N} \ln\left(\frac{2M}{\epsilon}\right)}$$

$$= \sqrt{\frac{1}{2 \times 400} \times \ln\left(\frac{2 \times 1000}{0.05}\right)} = 0.115$$

$$E_{in}(g) = 0.115 \quad E_{test}(g) = 0.096$$

∴ Thus, error has on in simple error is higher than the error from test error

b) If more samples for testing is used then the samples for training are less

We may end up with a hypothesis that is not as good as we could have arrived if using more training samples.

So $E_{\text{test}}(g)$ might be ~~way~~ too off even the error bar on it is small.