

HW 5 – Idan Michaeli 208429878, Itamar Yacoby 209794403

1. a. Let $x, y \in \mathbb{R}^n$, then

$$K(x, y) = 5K_1(x, y) + 4K_2(x, y) = 5\varphi_1(x)^T \varphi_1(y) + 4\varphi_2(x)^T \varphi_2(y)$$

We define $\varphi(x) = \begin{pmatrix} \sqrt{5}\varphi_1(x) \\ 2\varphi_2(x) \end{pmatrix}$ therefore we get that

$$5\varphi_1(x)^T \varphi_1(y) + 4\varphi_2(x)^T \varphi_2(y) = (\sqrt{5}\varphi_1(x)^T, 2\varphi_2(x)^T) \begin{pmatrix} \sqrt{5}\varphi_1(y) \\ 2\varphi_2(y) \end{pmatrix} = \varphi(x)^T \varphi(y)$$

Thus K is a kernel by definition and it's corresponding φ is defined as above.

b. Let K_1 be a kernel and let $\varphi_1(x): \mathbb{R}^n \rightarrow \mathbb{R}^m$ s.t. $n < m$ be its corresponding mapping and the data is linearly separable in the space \mathbb{R}^m . let $w = (w_1, \dots, w_m)$ be the weight vector of the linear classifier. denote $F(x) = w_0 + w_1\varphi_1^1 + \dots + w_m\varphi_m^1$ as the LC.

Consider $K = 5K_1 + 4K_2$ and $\varphi(x) = \begin{pmatrix} \sqrt{5}\varphi_1(x) \\ 2\varphi_2(x) \end{pmatrix}$ as found in last item, consider also

that $\varphi_2(x): \mathbb{R}^s \rightarrow \mathbb{R}^t$ where $s < t$.

let $w' = (w'_1, \dots, w'_m, \dots, w'_{m+t})$ be a weight vector. We will show that $G(x) = w' \varphi(x)$ is a linear classifier:

$$\begin{aligned} G(x) &= w'_0 + w'_1\varphi_1 + \dots + w'_{m+t}\varphi_{m+t} = \\ &= w'_0 + w'_1\sqrt{5}\varphi_1^1 + \dots + w'_m\sqrt{5}\varphi_m^1 + w'_{m+1}2\varphi_{m+1}^2 + \dots + w'_{m+t}2\varphi_{m+t}^2 \end{aligned}$$

We set $w' = \left(w_0, \frac{w_1}{\sqrt{5}}, \dots, \frac{w_m}{\sqrt{5}}, \underbrace{0, \dots, 0}_t \right)$, Therefore we get

$$\begin{aligned} G(x) &= w_0 + w_1\varphi_1^1 + \dots + w_m\varphi_m^1 + 0 \cdot \varphi_{m+1}^2 + \dots + 0 \cdot \varphi_{m+t}^2 = \\ &= \mathbf{w}_0 + \mathbf{w}_1\varphi_1^1 + \dots + \mathbf{w}_m\varphi_m^1 = \mathbf{F}(x) \text{ Which we know is a linear classifier.} \end{aligned}$$

Thus $w' = \left(w_0, \frac{w_1}{\sqrt{5}}, \dots, \frac{w_m}{\sqrt{5}}, \underbrace{0, \dots, 0}_t \right)$ is the requested weight vector.

c. We define the following mapping $\varphi: \mathbb{R} \rightarrow \mathbb{R}^N$ as follows:

$$\varphi(x) = \left(\underbrace{3, 3, \dots, 3}_x, \underbrace{0, 0, \dots, 0}_{N-x} \right)$$

$$\begin{aligned} \text{W.L.O.G, assume that } x \leq y, \text{ therefore we get } \varphi(x)^T \varphi(y) &= \begin{pmatrix} 3 \\ \vdots \\ 3 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \begin{pmatrix} \underbrace{3, 3, \dots, 3}_y & \underbrace{0, 0, \dots, 0}_{N-y} \end{pmatrix} = \\ &= \underbrace{3 \cdot 3 + \dots + 3 \cdot 3}_x + \underbrace{3 \cdot 0 + \dots + 3 \cdot 0}_{y-x} + \underbrace{0 \cdot 0 + \dots + 0 \cdot 0}_{N-y} = 9(1 + \dots + 1) = 9x = 9\min(x, y) \end{aligned}$$

2. Consider $R(h, s) = 200 \cdot h^{\frac{2}{3}} \cdot s^{\frac{1}{3}}$, Consider also $g(h, s) = 20h + 170s - 20,000$

$$L(h, s) = 200 \cdot h^{\frac{2}{3}} \cdot s^{\frac{1}{3}} + \lambda \cdot (20h + 170s - 20,000)$$

$$\frac{\partial}{\partial h} L(h, s) = \frac{400 \cdot s^{\frac{1}{3}}}{3 \cdot h^{\frac{1}{3}}} + 20\lambda = 0$$

$$\frac{\partial}{\partial s} L(h, s) = \frac{200 \cdot h^{\frac{2}{3}}}{3 \cdot s^{\frac{2}{3}}} + 170\lambda = 0$$

$$\frac{\partial}{\partial \lambda} L(h, s) = 20h + 170s - 20,000 = 0$$

$$\frac{\frac{400 \cdot s^{\frac{1}{3}}}{3 \cdot h^{\frac{1}{3}}}}{\frac{200 \cdot h^{\frac{2}{3}}}{3 \cdot s^{\frac{2}{3}}}} = \frac{-20\lambda}{-170\lambda} \rightarrow \frac{s}{h} = \frac{1}{17} \rightarrow h = 17 \cdot s$$

$$20 \cdot 17 \cdot s + 170s = 20,000$$

$$510 \cdot s = 20,000$$

$$s = \frac{20000}{510} = 39 \frac{11}{51}$$

$$h = 17 \cdot 39 \frac{11}{51} = 666 \frac{2}{3}$$

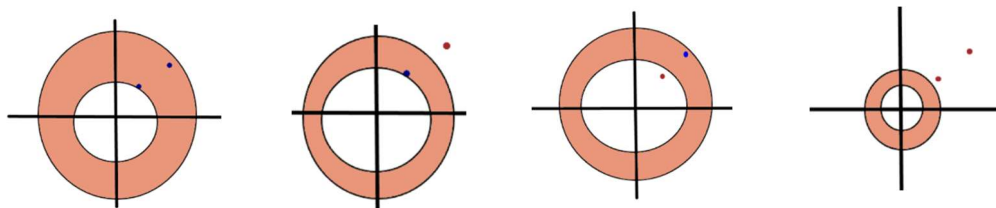
$$\lambda = \frac{200 \cdot \left(666 \frac{2}{3}\right)^{\frac{2}{3}}}{-170 \cdot 3 \cdot \left(39 \frac{11}{51}\right)^{\frac{2}{3}}} = -2.5927$$

Maximum Revenue:

$$200 \cdot \left(666 \frac{2}{3}\right)^{\frac{2}{3}} \cdot \left(39 \frac{11}{51}\right)^{\frac{1}{3}} = \mathbf{51,854.8158\$}$$

3. a.

$VC(H) \geq 2$, we show that there exists 2 points that we can shatter:



We prove now that $VC(H) < 3$:

Consider a set of 3 distinct points $\{v_1, v_2, v_3\}$.

Consider a ring that contains the 2 points with minimum and maximum euclidean distance.

There are at most 2 such points, denote that set of 2 points as S .

note that $S \subset \{v_1, v_2, v_3\}$.

Any ring that contains S , must also contain $\{v_1, v_2, v_3\}$, but there is at least one v_i that was not used in S , but still must be in the ring.

Therefore, the label assignment that labels all the points in S with $+$ and v_i with $-$ cannot be consistent with any ring.

$\Rightarrow VC(H) = 2$

b.

Let r_1^*, r_2^* s.t $r_1^* \leq r_2^*$ be the radiuses of the targeted ring.

Each instance viewed in the sample is drawn from an unknown distribution D and comprises of 2 features (position of the instance, (x_1, x_2)) and a target value, $+1$ if it's inside the ring and -1 otherwise.

The Algorithm:

We take the tightest ring so that all the positive points lie inside that ring.

(The maximum r_1 and minimum r_2 s.t every positive point (x_1, x_2) satisfies

$x_1^2 + x_2^2 \geq r_1$ and $x_1^2 + x_2^2 \leq r_2$).

The algorithm outputs r_1, r_2 s.t $r_1^* \leq r_1$ and $r_2 \leq r_2^*$

We define $r_\epsilon^1, r_\epsilon^2$ = the radiuses s.t the sum of the error of the annuluses

$A_{r_1} = h(r_1^*, r_1)$ and $A_{r_2} = h(r_2, r_2^*)$ is smaller than ϵ .

$r_\epsilon^1, r_\epsilon^2 = \operatorname{argmax}_{r_1} \operatorname{argmin}_{r_2} (P_{r_1}[(x, y) \in A_{r_1}] + P_{r_2}[(x, y) \in A_{r_2}] \leq \epsilon)$.

There are 2 cases:

case 1: $r_1 \leq r_\epsilon^1$ and $r_\epsilon^2 \leq r_2$ then the probability of both annuluses is smaller than ϵ .

case 2: $(r_1 < r_\epsilon^1 \text{ and } r_\epsilon^2 \leq r_2)$ or $(r_1 \leq r_\epsilon^1 \text{ and } r_\epsilon^2 > r_2)$ or $(r_1 > r_\epsilon^1 \text{ and } r_\epsilon^2 > r_2)$ then the probability of missing the annulus $h(r_1^*, r_\epsilon^1)$ or $h(r_\epsilon^2, r_2^*)$ or both respectively is:

$$p \leq 2 \cdot \left(1 - \frac{\epsilon}{2}\right)^m \leq 2 \cdot e^{-\frac{\epsilon m}{2}} \stackrel{m \geq \frac{2 \cdot \ln(\frac{2}{\delta})}{\epsilon}}{\leq} 2 \cdot e^{-\ln(\frac{2}{\delta})} = 2 \cdot e^{\ln(\frac{\delta}{2})} = \delta$$

Thus we receive that our concept is PAC – learnable

Sample and Time Complexity: $m(\epsilon, \delta) \in O\left(\frac{2}{\epsilon}, \ln\left(\frac{2}{\delta}\right)\right)$

c. $\epsilon = 0.05, \delta = 0.05$

$$1. m \geq \frac{1}{0.05} \left(4 \log \frac{2}{0.05} + 16 \log \frac{13}{0.05} \right) \approx 2993$$

$$2. m \geq \frac{2 \cdot \ln \left(\frac{2}{0.05} \right)}{0.05} \approx 147$$

We got a smaller m in the bound we found in item b, because in the direct approach we use the characteristic of the specific distribution rather than the VC bound which needs to apply to every distribution with the same VC dimension.

4.a. $VC(H_3) \geq 4$, this is the proof:

Consider any set of 4 distinct points $\{v_1, v_2, v_3, v_4\}$ s.t. $v_i \in \mathbb{R} \forall 1 \leq i \leq 4$

and $v_1 < v_2 < v_3 < v_4$.

given $m = 3$ we get a 7 node full binary tree with 4 leaves where each can classify as + or -.

Every non - leaf node represent a number in \mathbb{R} s.t a point v_i percolates down to the left child if v_i smaller than the node threshold, and percolates down to the right child if v_i greater or equal than the node threshold.

Every leaf represents an interval that is distinct from the other children (from the construction of the tree). Consequently, each leaf can represent a label for all the points in this interval.

Thus, any dichotomy of the points can be classified by these 4 leaves.

We prove now that $VC(H_3) < 5$:

Consider a set of 5 points $\{v_1, v_2, v_3, v_4, v_5\}$,

v_5 percolate down in the tree same as one of the $v_i (\forall 1 \leq i \leq 4)$

and therefore belong to the same interval as this v_i .

Suppose that v_i is classified as + and v_5 as -, therefore we get that the label assignment is not consistent (all the points in the interval represented by the leaf suppose to be classified the same).

This means that there is no set of size 5 that can be shattered by H , and therefore $VC(H) < 5$.

$\Rightarrow VC(H) = 4$.

b.

$VC(H) = 2^{m-1}$ which represents the number of leaves in a height m full binary tree.

Proof:

First we prove that $VC(H) \geq 2^{m-1}$:

Consider any set of 2^{m-1} distinct points $\{v_1, v_2, \dots, v_{2^{m-1}}\}$ s.t $v_i \in \mathbb{R} \forall 1 \leq i \leq 2^{m-1}$ and $v_1 < v_2 < \dots < v_{2^{m-1}}$.

given m we get a $2^m - 1$ node full binary tree with 2^{m-1} leaves.

Every non – leaf node represent a number in \mathbb{R} s.t a point v_i percolates down to the left child if v_i smaller than the node threshold, and percolates down to the right child if v_i greater or equal than the node threshold.

Every leaf represents an interval that is distinct from the other children (from the construction of the tree). Consequently, each leaf can represent a label for all the points in this interval.

Thus, any dichotomy of the points can classified by these 2^{m-1} leaves.

We prove now that $VC(H_3) < 2^{m-1} + 1$:

Suppose we add another point, v' .

v' percolate down in the tree same as one of the v_i ($\forall 1 \leq i \leq 2^{m-1}$).

Suppose that v_i is classified as + and v' as –, therefore we get that the label assignment is not consistent.

This means that there is no set of size $2^{m-1} + 1$ that can be shattered by H and therefore $VC(H) < 2^{m-1} + 1$.

$\Rightarrow VC(H) = 2^{m-1}$.