

(a) (2)

فرقہ کی کثیم $C \subseteq X$ طورے $|C| = k+1$

$$\rightarrow \exists h \in H \text{ s.t. } \forall x \in C \quad h(x) = 1$$

فرقہ کی کثیم $C \subseteq X$ طورے $|C| = |X| - k + 1$

$$\rightarrow \exists h \in H \text{ s.t. } \forall x \in C \quad h(x) = 0$$

$$\forall C \quad \dim(H) \leq \min\{k, |X| - k\} \quad (I)$$

فرقہ کی کثیم $C \subseteq X$ طورے $|C| = m \leq \min\{k, |X| - k\}$

$$\delta_C = \sum y_i, \quad (y_1, \dots, y_m) \in \{0, 1\}^m$$

$$E \subseteq X \setminus C \quad \& \quad h \in H \quad h(x_i) = y_i$$

$$\forall x_i \in C \quad h(x_i) = 1 \quad \forall x \in X \setminus C$$

$\Rightarrow C$ is shattered by H

$$\Rightarrow \dim(H) \geq \min\{k, |X| - k\} \quad (II)$$

$$(I) \quad (II) \Rightarrow \dim(H) = \min\{k, |X| - k\}$$

(b2)

$$|C| = k+1$$

فرض می کنیم $C \subseteq k$ طوری که

$$\nexists h \in H \text{ s.t. } \forall x \in C \quad h(x) = 1$$

$$\Rightarrow \text{VC dim}(H) \leq k$$

$$|C| = m \leq k$$

فرض می کنیم $C = \{x_1, \dots, x_m\} \subseteq X$ طوری که

$$(y_1, \dots, y_m) \in \{0, 1\}^m \text{ و هیتطور}$$

$$\nexists h \in H \text{ s.t. } \forall x_i \in C \quad h(x_i) = y_i \text{ \& } h(x) = 0$$

$$(\forall x \in X \setminus C)$$

$$\Rightarrow \text{VC dim}(H) \geq k$$

$$\Rightarrow \text{VC dim}(H) = k$$

(4) فرض می کنیم $X = \mathbb{R}^d$

$$d \geq 2$$

هچنین

$$H = \{I_{\|x\|_2 \leq r} : r \geq 0\} \text{ \& }$$

if $x \neq (0, \dots, 0)$ then $\{x\}$ is shattered

if $\|x_1\|_2 \leq \|x_2\|_2 \Rightarrow y_1 = 0 \text{ \& } y_2 = 1$ is'nt obtained by any $h \in H$

$$H_A = \{(0,0), (1,1)\} \Leftarrow A = \{e_1, e_2\} \text{ قوت کی کیم}$$

$$\Rightarrow \{B \subseteq A : H \text{ shatteres } B\} = \{\emptyset, \{e_1\}, \{e_2\}\}$$

$$\Rightarrow \sum_{i=0}^d \binom{|A|}{i} = 3$$

Let H be the class of axis-aligned rectangles in \mathbb{R}^2 .

VC-dim $H = 4$ دائیم

Let $H \{x_1, x_2, x_3\}$ where $x_1 = (0,0)$, $x_2 = (1,0)$, $x_3 = (2,0)$

all the lablings except $(1,0,1)$ are obtained
thus $|H_A| = 7$, $|\{B \subseteq A : H \text{ shatteres } B\}| = 7$

$$\text{and } \leq \binom{|A|}{i} = 8$$

let $d \geq 3$ and consider class $H = \{\text{sign} \langle w, x \rangle : w \in \mathbb{R}^d\}$

of homogeneous half spaces we will prove a

theorem in CH9 that vcdim of this class is d .

$$\text{vcdim}(H) \geq 3$$

$\{e_1, e_2, e_3\}$ is shattered.

let $A = \{x_1, x_2, x_3\}$ where $x_1 = e_1$, $x_2 = e_2$ & $x_3 = \{1, 1, 1\}$
all the lablings except $(1, 1, -1)$ and $(1, -1, 1)$
are obtained. it follows that $|H_A| = 6$.

$|\{B \subseteq A : "H" \text{ shatteres } "B"\}| = 7$

and $\sum \binom{|A|}{i} = 8$

let $d=1$ and consider $H = \{I_{[x, t]} : t \in \mathbb{R}\}$
every singleton is shattered by H
and every set of size at least 2 isn't
shattered by H . choose any finite set $A \subseteq \mathbb{R}$
then each of the three terms in sauer's
inequality
equals $|A| + 1$.

(a) 6

$$\text{vcdim}(H_{\text{con}}^d) \leq \log |H_{\text{con}}^d| \leq 3 \log d \quad (b)$$

let $I \subseteq [d]$ be a subset of indices (c)
we will show that the labeling in which
exactly the elements $\{e_j\}_{j \in J}$ are
positive is obtained if $I = [d]$ picks
all positive hypothesis h_{empty}

if $J = \emptyset$, pick the all negative hypothesis

$x_1 \wedge \bar{x}_1$. Assume now that $\emptyset \subset J \subset [d]$

let h be hypothesis which corresponds

to the boolean conjunction $\bigwedge_{j \in J} x_j$. then $h(e_j) = 1$
if $j \in J$, and $h(e_j) = 0$ o.w.

So $C = \{e_j\}_{j=1}^d$ is shattered by H_{con}^d thus
 $H_{\text{con}}^d \gg d$.

(d) (6)

Assume by contradiction that there exists a set $C = \{c_1, \dots, c_{d+1}\}$ for which $|H_C| = 2^{d+1}$ define h_1, \dots, h_{d+1} and l_1, \dots, l_{d+1} as in the hint. by the pigeon hole principle, among h_1, \dots, h_{d+1} at least one variable occurs twice. Assume that h_1 and h_2 correspond to the same variable. Assume first that $h_1 = h_2$. then h_1 is true on c_1 since h_2 is true on c_1 . However this contradicts our assumptions. Assume now that $h_1 \neq h_2$ in this case $h_1(c_3)$ is negative, since h_2 is positive on c_3 . This again contradicts our assumptions.

First we observe that $|H'| = 2^d + 1$. thus (e)

$$\text{vc dim}(H') \leq \log |H| = d$$

Let $C = \{ (1, \dots, 1) - e_j \}_{j=1}^d = \{ (0, 1, \dots, 1) \}, \dots, (1, \dots, 1, 0) \}$

let $J \subseteq [d]$ be a subset of indices

we will show that the labeling in which exactly the elements $\{(1, \dots, 1) - e_j\}_{j \in J}$ are negative is obtained by the boolean conjunction $\bigwedge_{j \in J} x_j$. Finally if $J = \emptyset$, pick all positive hypothesis h_{\emptyset} . So C shattered.

let $C = \{1, 2, 3\}$

(9)

1	2	3	a	b	s
-	-	-	0,5	3,5	-1
-	-	+	2,5	3,5	1
-	+	-	1,5	2,5	1
-	+	+	1,5	3,5	1
+	-	-	0,5	1,5	1
+	-	+	1,5	2,5	-1
+	+	-	0,5	2,5	1
+	+	+	0,5	3,5	1

$\Rightarrow VC \dim(H) \geq 3$

let $C = [x_1, x_2, x_3, x_4]$ and assume that $x_1 < x_2 < x_3 < x_4$ then labeling $y_1 = y_3 = -1, y_2 = y_4 = 1$ is not obtained by any hypothesis in H .

Thus $\Rightarrow VC \dim(H) \leq 3 \Rightarrow VC \dim(H) = 3$

(a) (10)

assume that $m < d$, since otherwise the statement is meaningless. let c be a shattered set of size m . we assume that $X = C$ (since we can always choose distributions which are concentrated on C).

H contains all the functions from C to $\{0,1\}$. according to section 5, for every algorithm there exists a distribution D for which $\min_{h \in H} L_D(h) = 0$ but $E(L_D(A(\frac{1}{2}S))) \geq \frac{k-1}{2k} = \frac{d-m}{2d}$.

(b)

assume that $\text{vc dim}(H) = \infty$. let A be a learning algorithm. we show that A fails to PAC learn H . choose $\epsilon = \frac{1}{16}$, $\delta = \frac{1}{14}$. for any $m \in \mathbb{N}$, there exists a shattered set of size $d = 2$. Applying the above, we obtain that there exists a distribution D for which $\min_{h \in H} L_D(h) = 0$,

but $E(L_D(A(\delta))) \geq \frac{1}{4}$. Applying Lemma B1

that with probability at least $\frac{1}{8} > \delta$,

$$\underline{L_D(A(\delta)) - \min_{h \in H} L_D(h) = L_D(A(\delta)) \geq \frac{1}{8} > \epsilon.}$$

assume that $\forall i \in [r], \text{vc dim}(H_i) = d \geq 3$ (a) (11)

let $H = \bigcup_{i=1}^r H_i$. let $k \in [d]$, such that $T_H(k) = 2^k$

we will show that $k \leq 4d \log(2d) + 2 \log r$.

$$\Rightarrow T_H(k) \leq \sum T_{H_i}(k)$$

Since $d \geq 3$, by applying sauser's lemma on each of the terms T_{H_i} , we obtain $T_H(k) \leq r_m^d$

it follows that $k < d \log m + \log r$

$$\Rightarrow k < 4d \log(2d) + 2 \log r$$

a direct application of the result above (b)

yields a weaker bound. we need to employ

a more careful analysis.

As we ~~assumption~~ assume that $\text{vc dim}(H_1) = \text{vc dim}(H_2) = \dots = d$

let $H_1 \cup H_2$. let k be a positive integer such that $k \geq 2d+2$. we show that $\tau_H(k) < 2^k$. by

Sauer's lemma.

$$\begin{aligned}
 \tau_H(k) &\leq \tau_{H_1}(k) + \tau_{H_2}(k) \\
 &\leq \sum_{i=0}^d \binom{k}{i} + \sum_{i=0}^k \binom{k}{i} \\
 &= \sum_{i=0}^d \binom{k}{i} + \sum_{i=k-d}^k \binom{k}{i} \\
 &= \sum_{i=0}^d \binom{k}{i} + \sum_{i=0}^d \binom{k}{k-i} \\
 &\leq \sum_{i=0}^d \binom{k}{i} + \sum_{i=d+2}^k \binom{k}{i} \\
 &\leq \sum_{i=0}^d \binom{k}{i} + \sum_{i=d+1}^k \binom{k}{i} = \sum_{i=0}^k \binom{k}{i} = 2^k.
 \end{aligned}$$

chapter 9



Define a vector of auxiliary variables (1)

$\delta = (\delta_1, \dots, \delta_m)$ following the hint, minimizing the empirical risk is equivalent to minimizing the linear objective $\sum \delta_i$ under following constraints

$$\forall i \in [m] \quad w^T x_i - \delta_i \leq y_i, \quad -w^T x_i - \delta_i \leq -y_i.$$

it is left to translate the above into matrix form. let $A \in \mathbb{R}^{2m \times (m+d)}$ be the matrix

$$A = [X - I_m \quad -X - I_m], \text{ where } X_i = x_i \text{ for every } i \in [m]$$

let $v \in \mathbb{R}^{d+m}$ be the vector of variables $(w_1, \dots, w_d, \delta_1, \dots, \delta_m)$ define $b \in \mathbb{R}^{2m}$ to be

$$\text{the vector } b = (y_1, \dots, y_m, y_1, \dots, y_m)^T.$$

finally let $c \in \mathbb{R}^{d+m}$ be the vector $c = (0_d, 1_m)$

it follows that the optimization problem of minimizing the empirical risk can be expressed as the

following LP $\min c^T r$ s.t. $Ar \leq b$

~~following the hint~~

following the hint, let $d=m$, and for every (3)

$i \in [m]$, let $x_i = e_i$. let us agree that

$\text{sign}(0) = -1$, for $i=1, \dots, d$, let $y_i = 1$ be the

label of x_i . Denote by $w^{(t)}$ the weight vector which is maintained by the perceptron.

A simple inductive argument shows that for every

~~$i \in [d]$~~ , $i \in [d]$, $w_i = \sum_{j < i} e_j$.

it follows that for every $i \in [d]$, $\langle w^{(i)}, x_i \rangle = 0$

Hence all the ~~x_1, \dots, x_d~~ x_1, \dots, x_d are misclassified

then we obtain the vector $w = (1, \dots, 1)$ which is

consistent with (x_1, \dots, x_m) . we also

note that the vector $w^* = (1, \dots, 1)$ satisfies the requirements listed in the question.

consider all positive examples of the form $(\alpha, \beta, 1)$, where $\alpha^2 + \beta^2 + 1 \leq R^2$. (4)

observe that $w^* = (0, 0, 1)$ satisfies $y \langle w^*, x \rangle \geq 1$ for all such (α, β) , we show a sequence of \mathbb{R}^2 examples on which the perceptron makes R^2 mistakes. the idea of the construction is to start with the examples $(\alpha_1, 0, 1)$ where $\alpha_1 = \sqrt{R^2 - 1}$, on round t let the new example be such that the followings conditions hold (a) $\alpha^2 + \beta^2 + 1 = R^2$

$$(b) \langle w_t, (\alpha, \beta, 1) \rangle = 0$$

As long as we can satisfy both conditions, the perceptron will continue to err

observe that, by induction, $w^{(t-1)} = (a, b, t-1)$ for some scalars a, b . observe also that $\|w_{t-1}\|^2 = (t-1)R^2$.

that $a^2 + b^2 + (t-1)^2 = (t-1)R^2$

let us rotate $w^{(t-1)}$ the z axis so that it is of the form $(a, 0, t-1)$ and

we have $a = \sqrt{(t-1)R^2 - (t-1)^2}$ choose $\alpha = -\frac{t-1}{a}$

Then for every B : $\langle (a, 0, t-1), (\alpha, B, 1) \rangle = 0$

we need to verify that $\alpha^2 + 1 \leq R^2$,

because if it is ~~not~~ ~~True~~ True then we can

choose $B = \sqrt{R^2 - \alpha^2 - 1} \Rightarrow \alpha^2 + 1 = \frac{(t-1)^2}{\alpha^2} + 1$

$$= \frac{(t-1)^2}{(t-1)R^2 - (t-1)^2} + 1 = R^2 \frac{1}{R^2 - (t-1)} \leq R^2$$

where the last inequality assumes $R^2 > \underline{t}$.