ECE 434: Problem Set 2

Due on October 26, 2023

Professor Chi Jin

Evan Dogariu Collaborators: Alex Zhang

Compute the exact VC dimension for the following boolean classes.

(a) Indicator functions on all half-spaces in \mathbb{R}^d :

$$\mathcal{F} := \left\{ f(x) = \mathbb{1}_{\left\{ w^T x < t \right\}} : w \in r^d, \ t \in \mathbb{R} \right\}$$

(b) Let \mathcal{F} be the collection of all polytopes in \mathbb{R}^2 , where we define a polytope in the plane as a convex hull of a collection of finitely many points.

Solution

Proof. (a) We first show that \mathcal{F} can shatter a collection of d+1 points. In particular, let $\{e_j\}_{j=1}^d$ denote the standard basis, and consider the collection $\{0, e_1, \ldots, e_d\}$ with 0 the origin. Let $(y_0, y_1, \ldots, y_d) \in \{0, 1\}^{d+1}$ be any arbitrary labeling of these points. We construct the vector w by saying that for $j = 1, \ldots, d$, let

$$w_j := \begin{cases} 1 & y_j = 1\\ -1 & y_j = 0 \end{cases}$$

Then, $w^T e_j = w_j$. Let $t := \begin{cases} 0 & y_0 = 1 \\ -0.1 & y_0 = 0 \end{cases}$. Then, we have $w^T e_j = w_j \le t \iff y_j = 1$ and also $w^T 0 = 0 \le t \iff y_0 = 1$, correctly classifying these points with these labels. Since this holds for all labelings, we have shattered these d + 1 points. So, the VC dimension is $\ge d + 1$.

Suppose now that we have an arbitrary collection of d+2 points, say $\{x_1, \ldots, x_{d+2}\}$. Note that we may lift to a higher dimension with homogenous coordinates, and so the function space

$$\tilde{\mathcal{F}} := \left\{ f(x) = \mathbb{1}_{\tilde{w}^T[x,1] \le 0} : \ \tilde{w} \in \mathbb{R}^{d+1} \right\}$$

is equal to \mathcal{F} (here, we use the notation [x, 1]) to describe concatenating 1 to the end of the vector x. $\tilde{\mathcal{F}} = \mathcal{F}$ since for any $\tilde{w} = [w, t] \in \mathbb{R}^{d+1}$ (here, $t \in \mathbb{R}$ and $w \in \mathbb{R}^d$) we know that $\tilde{w}^T[x, 1] \leq 0 \iff w^T x + t \leq 0 \iff w^T x \leq t$, and so for each function in one of the hypothesis classes we may find a corresponding function in the other. Define $\tilde{x}_j := [x_j, 1]$. Now, we know that since there are d + 2 points $\tilde{x}_j \in \mathbb{R}^{d+1}$, one of the points must be linearly dependent on the others. As such, there exist α_j 's in \mathbb{R} (at least one of which is nonzero) for which

$$\widetilde{x_k} = \sum_{j \neq k} \alpha_j \widetilde{x_j}$$

We will construct a labeling of the points that cannot be classified as follows: set

$$y_j = \begin{cases} 0 & j = k \text{ or } \alpha_j \le 0\\ 1 & j \ne k \text{ and } \alpha_j > 0 \end{cases}$$

Now, suppose by way of contradiction that some $\tilde{w} \in \mathbb{R}^{d+1}$ correctly classifies these points with this labeling. Therefore, for all $j \neq k$ we have that $\tilde{w}^T \tilde{x}_j \leq 0 \iff \alpha_j > 0$. So, looking at the k^{th} point,

$$\widetilde{w}^T \widetilde{x_k} = \widetilde{w}^T \left(\sum_{j \neq k} \alpha_j \widetilde{x_j} \right) = \sum_{j \neq k} \alpha_j \widetilde{w}^T \widetilde{x_j}$$

We know that each $\alpha_j \widetilde{w}^T \widetilde{x}_j \leq 0$ since they have opposite signs. Therefore, $\widetilde{w}^T \widetilde{x}_k \leq 0$ as well. However, we set $y_k = 0$, which would require that $\widetilde{w}^T \widetilde{x}_k > 0$ for correct classification. This is a contradiction, and so \widetilde{w}

cannot correctly classify these points with these labels. Since this holds for all labelings of all collections of d + 2 distinct points, the VC dimension is < d + 2.

(b) We claim that the VC dimension of \mathcal{F} is infinite. To see this, let $n \in \mathbb{N}$ be arbitrary; we will show we can shatter n points. Let $\{x_1, \ldots, x_n\} \subseteq \mathbb{R}^d$ be n distinct points distributed around the unit circle (say, the n^{th} roots of unity). Consider any arbitrary labeling $(y_1, \ldots, y_n) \in \{0, 1\}^n$ of these points (if less than 3 vertices are labeled 1 we can classify it trivially by infinitesimally encircling the line connecting the two 1-labeled points, infinitesimally encircling the only 1-labeled point, or drawing a far away polytope if $y_j = 0 \forall j$; so suppose WOLOG that at least 3 points have label 1). Define E to be the convex polygon formed by the convex hull of the points $\{x_j : y_j = 1\}$ (such that E contains its vertices). Then, $\mathbb{1}_E \in \mathcal{F}$ by definition. Also, since E contains its vertices, we know $y_j = 1 \implies x_j \in E$. Now, suppose that j is such that $y_j = 0$. Then, x_j cannot lie in E; to see this, consider the two points x_ℓ and x_r closest to x_j clockwise and counterclockwise for which $y_\ell = y_r = 1$. Then, the line connecting x_ℓ and x_r forms an edge of E by construction. However, the lines $x_j - x_\ell$ and $x_j - x_r$ are supporting hyperplanes of E, and so they are tangent to the boundary of E exactly at x_ℓ and x_r respectively, and otherwise lie entirely outside of E. Thus, $x_j \notin E$. So, we see that $x_j \in E \iff y_j = 1$, and so $\mathbb{1}_E$ correctly classifies this labeling. Since this holds for all labelings of the n points, the VC dimension is $\geq n$. Since this holds for all $n \in \mathbb{N}$, we are done.

Consider classification problem using indicator functions of all half spaces in \mathbb{R}^d (same as 1(a)):

$$\mathcal{F} := \{ f(x) = \mathbb{1}_{\{ w^\top x < t \}} : w \in \mathbb{R}^d, t \in \mathbb{R} \}.$$

Across this problem, we use 0-1 loss. Suppose that we indeed have the deterministic relation $Y = f^{\star}(X)$ holds under the true underlying data distribution D for certain $f^{\star} \in \mathcal{F}$. Prove that with probability at least $1 - \delta$, the population risk of ERM is $\leq C\sqrt{\frac{d \log(n/\delta)}{n}}$, where C is some absolute constant and $n \geq 2$ is the number of training samples.

Solution

Proof. Let $r(\cdot)$ denote the population risk and $\hat{r}(\cdot)$ denote the empirical risk. We have from Lecture 4 that with probability $\geq 1 - \delta$, the following bound holds:

excess risk
$$\equiv r(\hat{f}) - r(f^*) \le 4\mathcal{R}_n(\mathcal{F}) + 2B\sqrt{\frac{\log(1/\delta)}{2n}}$$

In the realizable setting, $r(f^*) = 0$, and so this is also a bound on the population risk of the ERM classifier \hat{f} . In the 0-1 classification setting, we know B = 1. Suppose first that n > d. Then, by Corollary 1 from Lecture 3, we may use our knowledge that the VC dimension of \mathcal{F} is d + 1 (see Problem 1(a)) to see

$$\mathcal{R}_n(\mathcal{F}) \le \sqrt{\frac{2\log(2) + 2(d+1)\log(en/(d+1))}{n}}$$

Since n > d, we know that $2 < e \le en/(d+1)$, and so $\log(2) \le \log(en/(d+1))$. Thus,

$$\mathcal{R}_n(\mathcal{F}) \le 2\sqrt{\frac{(d+1)\log(en/(d+1))}{n}}$$

We may certainly suppose that $\delta < \frac{d+1}{e}$, and so $\log(en/(d+1)) < \log(n/\delta)$. Since $d+1 \le 2d$, we get

$$\mathcal{R}_n(\mathcal{F}) \le 2\sqrt{2}\sqrt{\frac{d\log(n/\delta)}{n}}$$

So,

$$f(\hat{f}) \le 2\sqrt{2}\sqrt{\frac{d\log(n/\delta)}{n}} + \frac{2}{\sqrt{2}}\sqrt{\frac{\log(1/\delta)}{n}}$$

Since $n \ge 1 \implies \log(1/\delta) \le \log(n/\delta)$ and $d \ge 1$, we finally see

$$r(\hat{f}) \le 2\sqrt{2}\sqrt{\frac{d\log(n/\delta)}{n}} + \sqrt{2}\sqrt{\frac{d\log(n/\delta)}{n}} = 3\sqrt{2}\sqrt{\frac{d\log(n/\delta)}{n}}$$

as desired. Suppose now that $2 \le n \le d$. By boundedness of the functions in \mathcal{F} , we see that the Rademacher complexity $\mathcal{R}_n(\mathcal{F}) \le 1$ always (we have $\frac{1}{n} |\sum_i \epsilon_i f(x_i)| \le \frac{1}{n} \sum_i |\epsilon_i f(x_i)| \le \sup_x |f(x)| \le 1$ since $|\epsilon_i| = 1$). So,

$$r(\hat{f}) \le 4 + \sqrt{2}\sqrt{\frac{\log(1/\delta)}{n}} \le 4 + \sqrt{2}\sqrt{\frac{d\log(n/\delta)}{n}}$$

In this setting, $1 \leq \frac{d}{n}$. We may certainly take $\delta < \frac{n}{e} \implies e < \frac{n}{\delta} \implies 1 < \log(n/\delta)$. Together, we see that $1 \leq \sqrt{\frac{d \log(n/\delta)}{n}}$, from which we get that

$$r(\hat{f}) \le 4\sqrt{\frac{d\log(n/\delta)}{n}} + \sqrt{2}\sqrt{\frac{d\log(n/\delta)}{n}} = (4+\sqrt{2})\sqrt{\frac{d\log(n/\delta)}{n}}$$

Thus, if we take $C := \max\{4 + \sqrt{2}, 3\sqrt{2}\}$, the desired bound holds for all $n \ge 2$.

Consider ${\mathcal F}$ as the set of linear functions with bounded weights

$$\mathcal{F} = \{ f(x) = w^{\top} x : w \in \mathbb{R}^d, \, \|w\|_2 \le 1 \}$$

on domain $X = \{x \in \mathbb{R}^d, \|x\|_2 \le 1\}$. Prove that there exists an absolute constant c, C s.t. for any $\epsilon \in (0, 1)$:

$$\left(\frac{c}{\epsilon}\right)^d \le N(\epsilon, \mathcal{F}, \|\cdot\|_{\infty}) \le \left(\frac{C}{\epsilon}\right)^d$$

Solution

Proof. We note that for any $f, g \in \mathcal{F}$ given by $w_f, w_g \in \mathbb{R}^d$ respectively, we have that

$$|f - g||_{\infty} = \sup_{\|x\|_{2} \le 1} |w_{f}^{T}x - w_{g}^{T}x| = \sup_{\|x\|_{2} \le 1} |(w_{f} - w_{g})^{T}x|$$

This is maximized for $x^* = \frac{w_f - w_g}{\|w_f - w_g\|_2}$ obviously; in this case, we have $(w_f - w_g)^T x^* = \frac{\|w_f - w_g\|_2^2}{\|w_f - w_g\|_2}$, yielding $\|f - g\|_{\infty} = \|w_f - w_g\|_2$

So, let $B := \{w \in \mathbb{R}^d : \|w\|_2 \le 1\}$ denote the unit ball in \mathbb{R}^d . There is clearly a bijection between \mathcal{F} and B, and the above logic reveals that this maps the $\|\cdot\|_{\infty}$ norm on \mathcal{F} to the $\|\cdot\|_2$ norm on B. As such, $N(\epsilon, \mathcal{F}, \|\cdot\|_{\infty}) = N(\epsilon, B, \|\cdot\|_2)$.

We now seek to bound this covering number. Note that for any cover using *n* balls of radius ϵ , say with centers $\{x_1, \ldots, x_n\}$, we have $B \subseteq \bigcup_{j=1}^n B_{\epsilon}(x_j) \implies \operatorname{vol}(B) \leq \sum_{j=1}^n \operatorname{vol}(B_{\epsilon}(x_j)) = n\epsilon^d \operatorname{vol}(B)$, where we used that the volume of a union is upper bounded by the sum of the volumes (equality holds iff the union is almost disjoint). So, $n \geq \frac{1}{\epsilon^d}$ for all covers, and so this certainly holds for the minimal cover.

Now, we also know that the covering number is $\leq M(\epsilon, B, \|\cdot\|_2)$, the packing number, by Lemma 2 from Lecture 5. Consider any ϵ -packing of size n, which means we may fit n disjoint balls, say with centers $\{x_1, \ldots, x_n\} \subseteq B$, of radius $\frac{\epsilon}{2}$ inside B. Then, since these balls are disjoint and are contained in the closed ball of radius $1 + \frac{\epsilon}{2}$ about the origin (at worst case the center is on the boundary of B), we get

$$\bigsqcup_{j=1} B_{\epsilon/2}(x_j) \subseteq B_{1+\epsilon/2}(0) \implies \operatorname{vol}\left(\bigsqcup_{j=1} B_{\epsilon/2}(x_j)\right) = \sum_{j=1}^n \operatorname{vol}(B_{\epsilon/2}(x_j)) \le \operatorname{vol}(B_{1+\epsilon/2}(0))$$

So, since $\operatorname{vol}(B_r(x)) = r^d \operatorname{vol}(B)$, this becomes

$$n\left(\frac{\epsilon}{2}\right)^d \le \left(1 + \frac{\epsilon}{2}\right)^d \implies n \le \left(\frac{2 + \epsilon}{2} \cdot \frac{2}{\epsilon}\right)^d$$

For $\epsilon < 1$ we know $\frac{2+\epsilon}{2} \leq \frac{3}{2}$, and so

$$n \le \left(\frac{3}{2} \cdot \frac{2}{\epsilon}\right) = \left(\frac{3}{\epsilon}\right)^d$$

Since this holds for every packing of size n, it also holds for the maximal packing. So, $M(\epsilon, B, \|\cdot\|_2) \leq \left(\frac{3}{\epsilon}\right)^d$. Thus,

$$\left(\frac{1}{\epsilon}\right)^d \le N(\epsilon, B, \|\cdot\|_2) = N(\epsilon, \mathcal{F}, \|\cdot\|_\infty) \le \left(\frac{3}{\epsilon}\right)^d$$

and the result is proven. \blacksquare

Consider regression using function class \mathcal{F} , which is the set of all non-decreasing functions on domain \mathbb{R} with range Y = [-1, 1].

(a) Consider a fixed set of points $\{x_i\}_{i=1}^n$, and the corresponding distance:

$$\rho_n(f,g) = \sqrt{\frac{1}{n} \sum_{i=1}^n (f(x_i) - g(x_i))^2}$$

Prove that for any $\epsilon \in (0, 1)$, we have $N(\epsilon, \mathcal{F}, \rho_n) \leq (n+1)^{\left(\frac{1}{\epsilon}+1\right)}$.

(b) Use (a) to prove the following bound on Rademacher complexity:

$$\mathcal{R}_n(\mathcal{F}) \le c \cdot \sqrt{\frac{\log n}{n}}$$

for some absolute constant c.

(c) Use the above results to bound the excess risk of ERM with squared loss.

Solution

Proof. (a) Let $\epsilon \in (0, 1)$. We note that ρ_n measures the square root of average squared variation only on our test points. So, if we discretize the y-axis at scale $\frac{\epsilon}{2}$ (anything $< \epsilon$ suffices), functions taking the same discrete values at all of the x_j will have variation $< \epsilon$ at each x_j (less than $\frac{\epsilon}{2}$ in either direction), and so they will have ρ_n distance $< \epsilon$. Precisely, let $Y := \{-1, -1 + 2\epsilon, -1 + 4\epsilon, \ldots\} \subseteq [-1, 1]$; then, $|Y| = \lfloor \frac{2}{\epsilon} \rfloor$. We define a class of functions $\mathcal{G}_{n,\epsilon} \subseteq \mathcal{F}$ where for any set of n non-decreasing values (y_1, \ldots, y_n) from Y, there is a function in $\mathcal{G}_{n,\epsilon}$ that realizes those values precisely at $x_1, \ldots x_n$ in the non-decreasing order (i.e. $g(x_j) = y_j \forall j$). It is easy to see that for any $f \in \mathcal{F}$, there is some non-decreasing sequence $\{y_1, \ldots, y_n\} \subseteq Y$ such that $|f(x_j) - y_j| < \epsilon$ for all j by construction of Y. Since there is some $g \in \mathcal{G}_{n,\epsilon}$ realizing this sequence of y_j 's, we find that $|f(x_j) - g(x_j)| < \epsilon$ for all j, and so $\rho_n(f,g) < \epsilon$. Therefore, the set of ϵ -balls with centers in $\mathcal{G}_{n,\epsilon}$ covers \mathcal{F} . So, the minimal covering number must be less, yielding

$$N(\epsilon, \mathcal{F}, \rho_n) \le |\mathcal{G}_{n,\epsilon}|$$

We now must bound the cardinality of $\mathcal{G}_{n,\epsilon}$. This cardinality is precisely equal to the number of nondecreasing sequences of length n that can be taken from Y. By stars and bars, this equals

$$|\mathcal{G}_{n,\epsilon}| = \binom{|Y|+n}{n} = \frac{(\lfloor\frac{2}{\epsilon}\rfloor+n)!}{n!\lfloor\frac{2}{\epsilon}\rfloor!} \le \left(\frac{e(n+\lfloor\frac{2}{\epsilon}\rfloor)}{\lfloor\frac{2}{\epsilon}\rfloor}\right)^{\lfloor\frac{2}{\epsilon}\rfloor} \le \left(\frac{\epsilon en+2e}{2}\right)^{\lfloor\frac{2}{\epsilon}\rfloor} = \left(\frac{e}{2}\right)^{\lfloor\frac{2}{\epsilon}\rfloor} \cdot (\epsilon n+1)^{\lfloor\frac{2}{\epsilon}\rfloor}$$

I am unsure how to continue from here :)

(b) Consider a fixed set of points $\{x_i\}_{i=1}^n$. Using Theorem 2 from Lecture 5 and the bound from (a), we find

$$\mathcal{R}_n(\mathcal{F}(x_{1:n})) \le \inf_{\alpha > 0} \left\{ \alpha + \sqrt{\frac{2\log\left((n+1)^{(1+1/\alpha)}\right)}{n}} \right\} = \inf_{\alpha > 0} \left\{ \alpha + \sqrt{\frac{2(1+1/\alpha)\log\left(n+1\right)}{n}} \right\}$$

We know that $n + 1 \le n^2$ for all $n \in \mathbb{N}$, and so $\log(n + 1) \le 2\log(n)$. This gives

$$\mathcal{R}_n(\mathcal{F}(x_{1:n})) \le \inf_{\alpha>0} \left\{ \alpha + 2\sqrt{1 + \frac{1}{\alpha}} \sqrt{\frac{\log(n)}{n}} \right\}$$

Since $1 + \frac{1}{\alpha} \ge 1$, we know that $\sqrt{1 + \frac{1}{\alpha}} \le 1 + \frac{1}{\alpha} = \frac{\alpha + 1}{\alpha}$. Thus, letting $c_n := 2\sqrt{\frac{\log(n)}{n}}$,

$$\mathcal{R}_n(\mathcal{F}(x_{1:n})) \le \inf_{\alpha > 0} \left\{ \alpha + c_n \frac{\alpha + 1}{\alpha} \right\} = \inf_{\alpha > 0} \left\{ \frac{\alpha^2 + c_n \alpha + c_n}{\alpha} \right\}$$

The infimum is certainly less than or equal to the value at $\alpha = 1$. Plugging this in, we get

$$\mathcal{R}_n(\mathcal{F}(x_{1:n})) \le \frac{1 + c_n + c_n}{1} = 2c_n = 4\sqrt{\frac{\log(n)}{n}}$$

Since this holds for all fixed sets of points, we get the result that

$$\mathcal{R}_n(\mathcal{F}) \le 4\sqrt{\frac{\log(n)}{n}}$$

(c) Let $y, y', y^* \in Y$. Then, letting $\ell(\cdot, \cdot)$ be the squared loss,

$$|\ell(y,y^*) - \ell(y',y^*)| = |(y-y^*)^2 - (y'-y^*)^2| = |(y-y^*-y'+y^*)(y-y^*+y'-y^*)| = |y-y'| \cdot |y+y'-2y^*|,$$

where we used the difference of squares. Since $|y + y' - 2y^*| \le 4$ by boundedness of Y, we see that

$$|\ell(y,y^*)-\ell(y',y^*)|\leq 4|y-y'|$$

So, the square loss over this domain is 4-Lipschitz in the first slot. So, using Theorem 1 from Lecture 5, as well as part (b), we see that

$$\mathcal{R}_n(\ell \circ \mathcal{F}) \le 16\sqrt{\frac{\log(n)}{n}}$$

Therefore, we get the bound

excess risk
$$\leq 16\sqrt{\frac{\log(n)}{n}} + \text{small concentration terms}$$