TTIC 31250: Introduction to

THEORY OF MACHINE LEARNING

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Homework 3

Solutions by

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Exercises

- 1. Think about what you would like to do for your project and propose it. Some ideas:
 - Read a paper from a recent COLT conference (say COLT 2013 through COLT 2017) and write a 4-5 page explanation of what it does. Papers can be found at: http://www.learningtheory.org/past-conferences-2/
 - Read a paper on learning theory from a recent related conference (ICML, NIPS) and write a 4-5 page explanation of what it does.
 - Think about a theoretical question, which could be modeling some machine learning setting, trying to give sufficient conditions for some approach to succeed, looking at a different model for how examples are selected or the kind of feedback the algorithm is given, etc. Write up your thoughts in 4-5 pages.
 - Conduct an experiment to compare different approaches to some problem. (Note: your approach doesnt have to turn out to be the best one!). Create a 4-5 page writeup explaining your experiment and findings.

For this homework I just want a brief description, such as "I plan to read and explain the paper X from conference Y" or "I would like to think about how to theoretically model Z".

I plan to read and explain the paper *Dynamic Local Regret for Non-Convex Online Forecasting* from conference NIPS 2019.

2. Consider the class \mathcal{C} of axis-parallel rectangles in \mathbb{R}^3 . Specifically, a legal target function is specified by three intervals $[x_1^{\min}, x_1^{\max}]$, $[x_2^{\min}, x_2^{\max}]$, and $[x_3^{\min}, x_3^{\max}]$, and classifies an example (x_1, x_2, x_3) as positive iff $x_1 \in [x_1^{\min}, x_1^{\max}]$, $x_2 \in [x_2^{\min}, x_2^{\max}]$, and $x_3 \in [x_3^{\min}, x_3^{\max}]$. Argue that $\mathcal{C}[m] = O(m^6)$.

Proof. Let

$$S = \{ (\boldsymbol{x}_1, y_1), \dots, (\boldsymbol{x}_m, y_m) : \boldsymbol{x}_i = (x_{i1}, x_{i2}, x_{i3})^\top \in \mathbb{R}^3, \ y_i \in \{0, 1\},$$

$$x_{i1} \neq x_{j1}, \ x_{i2} \neq x_{j2}, \ x_{i3} \neq x_{j3} \text{ for } i \neq j \}$$

with $|\mathcal{S}| = m$. For $(x_i, y_i) \in \mathcal{S}$, we can choose x_1^{\min} and x_1^{\max} in $\binom{m+1}{2} - 1 = \frac{m(m+1)}{2} - 1$ ways. To see this, we first arange x_{11}, \ldots, x_{m1} as $x_{(1),1} < \cdots < x_{(m),1}$. Then we divide \mathbb{R} into m+1 sets except m points,

$$(-\infty, x_{(1),1}), (x_{(1),1}, x_{(2),1}), \ldots, (x_{(m),1}, \infty).$$

So we can randomly throw x_1^{\min} and x_1^{\max} into these sets. There are $\binom{m+1}{2}-1$ ways, since $x_1^{\max}>x_{(n),1}$ and $x_1^{\min}< x_{(1),1}$ have the same effect. Also, note that the break points will not effect the labeling. Analogously, there are also $\frac{m(m+1)}{2}-1$ to choose x_2^{\min} and x_2^{\max} , as well as x_3^{\min} and x_3^{\max} . Combine the three dimensions, we can label $\mathcal S$ by at most totally

$$\left(\frac{m(m+1)}{2} - 1\right)^3 = O(m^6)$$

different ways, i.e., $C[m] = O(m^6)$.

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Problems

3. VC-dimension of Two-Layer Networks. Suppose that concept class \mathcal{H} has VC-dimension d. Now suppose we create a 2-layer network by choosing k functions h_1, h_2, \ldots, h_k from \mathcal{H} and then running their output through some other Boolean function f. That is, given an input x, the network outputs $f(h_1(x), \ldots, h_k(x))$. For a given f, call the class of all such functions TWO-LAYER $_{f,k}(\mathcal{H})$. Show that TWO-LAYER $_{f,k}(\mathcal{H})$ has VC-dimension $O(kd \log(kd))$. Note that we are only asking for an upper bound here, not a lower bound.

Hint: Suppose you have a set S of m data points. By Sauers lemma, we know there are at most $O(m^d)$ ways of labeling those points using functions in C. Use that to get an upper bound on the number of ways of labeling those points using functions in TWO-LAYER_{f,k}(C). Now select m so that this is less than 2^m which means the VC-dimension must be less than m.

Proof. Let $\mathcal{H}^k = \mathcal{H} \times \cdots \times \mathcal{H}$ be the cartesian product of k identical concept classes \mathcal{H} . For any sample \mathcal{S} with $|\mathcal{S}| = m$, the ways to label points in \mathcal{S} by \mathcal{H}^k , is exactly the product of the ways to label them by each \mathcal{H} . So

$$|\mathcal{H}^k[\mathcal{S}]| = |\mathcal{H}[\mathcal{S}]|^k \le \mathcal{H}[m]^k,$$

by the definition of $\mathcal{H}[m]$.

Let \mathcal{F} be the class of boolean function $f:\{0,1\}^k \mapsto \{0,1\}$, then for a given $f \in \mathcal{F}$, TWO-LAYER_{f,k}(\mathcal{H}) = $f \circ \mathcal{H}^k$. Since for any sample \mathcal{S} with $|\mathcal{S}| = m$,

TWO-LAYER_{f,k}(
$$\mathcal{H}$$
)[\mathcal{S}] = { $f(g(x)) : x \in \mathcal{S}, g \in \mathcal{H}^k$ }
= $\bigcup_{y \in \mathcal{H}^k} \{f(y)\},$

we have for a given $f \in \mathcal{F}$,

$$\begin{aligned} |\text{TWO-LAYER}_{f,k}(\mathcal{H})[\mathcal{S}]| &\leq \sum_{y \in \mathcal{H}^k} |\{f(y)\}| \\ &\leq 2|\mathcal{H}^k| \\ &\leq 2\mathcal{H}[m]^k. \end{aligned}$$

By Sauer's Lemma, $\mathcal{H}[m] \lesssim O(m^d)$. Thus,

TWO-LAYER_{f,k}(
$$\mathcal{H}$$
)[m] $\leq 2\mathcal{H}[m]^k \lesssim O(m^{kd})$.

Now, let S_0 be a set of size m that is shattered by TWO-LAYER_{f,k}(\mathcal{H}). Then

TWO-LAYER_{f,k}(
$$\mathcal{H}$$
)[\mathcal{S}_0] = $2^m \lesssim O(m^{kd})$,

i.e., $m \lesssim O(kd \log(m))$. Since $\log(m) \lesssim O(\log(kd \log(m))) \simeq O(\log(kd) + \log(\log(m)))$, i.e., $\log(m) \lesssim O(\log(kd))$, we have $m \lesssim O(kd \log(kd))$. As the VC-dimension of TWO-LAYER_{f,k}(\mathcal{H}) is the largest m such that there exists a sample \mathcal{S} with $|\mathcal{S}| = m$ that can be shattered by TWO-LAYER_{f,k}(\mathcal{H}), we conclude that TWO-LAYER_{f,k}(\mathcal{H}) has VC-dimension $\lesssim O(kd \log(kd))$.

In problems 4-6, you will prove that the VC-dimension of the class \mathcal{H}_n of halfspaces in n dimensions is n+1. (\mathcal{H}_n is the set of functions $a_1x_1 + \ldots + a_nx_n \geq a_0$, where a_0, \ldots, a_n are real-valued.) We will use the following definition: The convex hull of a set of points \mathcal{S} is the set of all convex combinations of points in \mathcal{S} ; this is the set of all points that can be written as $\sum_{x_i \in \mathcal{S}} \lambda_i x_i$, where each $\lambda_i \geq 0$, and $\sum_i \lambda_i = 1$. It is not hard to see that if a halfspace has all points from a set \mathcal{S} on one side, then it must have the entire convex hull of \mathcal{S} on that side as well.

4. Lower Bound Prove that VC-dim $(\mathcal{H}_n) \ge n+1$ by presenting a set of n+1 points in n-dimensional space such that one can partition that set with halfspaces in all possible ways. (And, show how one can partition the set in any desired way.)

Proof. Let $\mathbf{x}_0 = \mathbf{0} \in \mathbb{R}^n$ and $\mathbf{x}_i = \mathbf{e}_i \in \mathbb{R}^n$ for i = 1, ..., n, where \mathbf{e}_i is a unit vector with its *i*th entry being one. Let $\mathcal{X}_n = \{\mathbf{x}_i, i = 0, ..., n\}$.

If we want to label m different points $x_{i_1}, \ldots, x_{i_m} \in \mathcal{X}_n$ as 1,

- (a) If $x_{i_j} \neq 0$ for all j, then we can choose $f(x) = \sum_{j=1}^m x_j \geq \frac{1}{2}$.
- (b) If $x_{i_j} = 0$ for some j, then we can choose $f(x) = -\sum_{j \notin \{i_1, \dots, i_m\}} x_j \ge 0$.

Thus, \mathbf{x}_{i_j} will have label 1 and \mathbf{x}_k ($k \notin \{i_1, \ldots, i_m\}$) will have label 0. Also, this holds for $m = 1, \ldots, n$. For the case m = 0 or n + 1, we can choose $f(\mathbf{x}) \equiv 0 \geq 1$ and $f(\mathbf{x}) \equiv 0 \geq 0$, respectively.

Therefore, we can partition \mathcal{X}_n with halfspaces in all possible ways. So VC-dim $(\mathcal{H}_n) \geq n+1$.

5. Upper Bound Part 1 The following is "Radon's Theorem", from the 1920's.

Theorem. Let S be a set of n+2 points in n dimensions. Then S can be partitioned into two (disjoint) subsets S_1 and S_2 whose convex hulls intersect.

Show that Radon's Theorem implies that the VC-dimension of halfspaces is at most n + 1. Conclude that VC-dim $(\mathcal{H}_n) = n + 1$.

Proof. Let conv(S) denote the convex hull of S.

From Radon's Theorem, any sample S with n+2 points in n dimensions can be partitioned into two disjoint subsets S_1 and S_2 whose convex hulls intersect. If there is a halfspace can separate S_1 and S_2 , then it can also separate $\operatorname{conv}(S_1)$ and $\operatorname{conv}(S_2)$. To see this, without loss of generality, assume that points in S_1 and S_2 satisfy $\sum_{i=1}^n a_i x_i \geq a_0$ and $\sum_{i=1}^n a_i x_i < a_0$ respectively. Suppose that $S_1 = \{s_1, \ldots, s_m\}$, then for all $s \in \operatorname{conv}(S_1)$, we have $s = \sum_{j=1}^m \lambda_j s_j$ for $\lambda_j \geq 0$ and $\sum_{j=1}^m \lambda_j = 1$. As $\sum_{i=1}^n a_i s_j \geq a_0$, we have

$$\sum_{i=1}^{n} a_i s = \sum_{i=1}^{n} a_i \sum_{j=1}^{m} \lambda_j s_j = \sum_{i=1}^{m} \lambda_j \sum_{i=1}^{n} a_i s_j \ge a_0,$$

which means that s is on the same side with S_1 . So $\operatorname{conv}(S_1)$ is on the same side of the halfspace with S_1 . Analogously, $\operatorname{conv}(S_2)$ is on the same side of the halfspace with S_2 . So $\operatorname{conv}(S_1)$ and $\operatorname{conv}(S_2)$ are separated by the halfspace.

However, since $\operatorname{conv}(\mathcal{S}_1) \cap \operatorname{conv}(\mathcal{S}_2) \neq \emptyset$, there is no way to separate $\operatorname{conv}(\mathcal{S}_1)$ and $\operatorname{conv}(\mathcal{S}_2)$ by a halfspace. Contradiction. So \mathcal{S} with $|\mathcal{S}| = n + 2$ cannot be shattered by \mathcal{H}_n .

Therefore, VC-dim(\mathcal{H}_n) < n+2. From Problem 4, we have VC-dim(\mathcal{H}_n) = n+1.

6. **Upper Bound Part 2** Now we prove Radon's Theorem. We will need the following standard fact from linear algebra. If x_1, \ldots, x_{n+1} are n+1 points in n-dimensional space, then they are linearly dependent. That is, there exist real values $\lambda_1, \ldots, \lambda_{n+1}$ not all zero such that $\lambda_1 x_1 + \ldots + \lambda_{n+1} x_{n+1} = 0$.

You may now prove Radon's Theorem however you wish. However, as a suggested first step, prove the following. For any set of n+2 points x_1, \ldots, x_{n+2} in n-dimensional space, there exist $\lambda_1, \ldots, \lambda_{n+2}$ not all zero such that $\sum_i \lambda_i x_i = 0$ and $\sum_i \lambda_i = 0$. (This is called *affine dependence*.) Now, think about the lambdas...

Proof. For any set of n+2 points x_1, \ldots, x_{n+2} , let $y_i = x_i$ for $i = 1, \ldots, n$ and $y_{n+1} = x_{n+1} + x_{n+2}$. Then there exists $\omega_1, \ldots, \omega_{n+1}$ not all zero such that $\sum_{i=1}^{n+1} \omega_i y_i = \sum_{i=1}^{n+2} \omega_i x_i = 0$, where $\omega_{n+2} = \omega_{n+1}$. That is, there exists $\omega_1, \ldots, \omega_{n+2}$ not all zero such that $\sum_{i=1}^{n+2} \omega_i x_i = 0$.

Without loss of generality, assume that $\omega_{n+2} \neq 0$.

- (a) If $x_{n+2} = 0$, let $\omega_{n+2} = -\sum_{i=1}^{n+1} \omega_i$, then $\omega_1, \dots, \omega_{n+2}$ not all zero, $\sum_{i=1}^{n+2} \omega_i x_i = 0$ and $\sum_{i=1}^{n+2} \omega_i = 0$.
- (b) If $x_{n+2} \neq 0$, then

$$\sum_{i=1}^{n+1} \frac{\omega_i}{\omega_{n+2}} x_i + x_{n+2} = 0$$

and at least one of $\omega_1, \ldots, \omega_{n+1}$ is nonzero. Since there exists μ_1, \ldots, μ_{n+1} not all zero such that $\sum_{i=1}^{n+1} \mu_i x_i = 0$, let $\mu'_i = \frac{\mu_i}{\sum_{j=1}^{n+1} \mu_j} \left(-\frac{1}{\omega_{n+2}} \sum_{j=1}^{n+1} \omega_j - 1 \right)$, then $\sum_{i=1}^{n+1} \mu'_i = -\frac{1}{\omega_{n+2}} \sum_{j=1}^{n+1} \omega_j - 1$. Notice that $\sum_{i=1}^{n+1} \mu'_i x_i = 0$, we have

$$\sum_{i=1}^{n+1} \left(\frac{\omega_i}{\omega_{n+2}} + \mu_i' \right) x_i + x_{n+2} = 0$$

and

$$\sum_{i=1}^{n+1} \left(\frac{\omega_i}{\omega_{n+2}} + \mu_i' \right) + 1 = 1 + \sum_{i=1}^{n+1} \frac{\omega_i}{\omega_{n+2}} + \sum_{i=1}^{n+1} \mu_i' = 0.$$

Thus, we have proved the following lemma,

Lemma 1. For any set of n+2 points x_1, \ldots, x_{n+2} in n-dimensional space, there exist $\lambda_1, \ldots, \lambda_{n+2}$ not all zero such that $\sum_i \lambda_i x_i = 0$ and $\sum_i \lambda_i = 0$.

So, for any set of n+2 points in n-dimension space, there exists $\lambda_1, \ldots, \lambda_{n+2}$ not all zero such that $\sum_{i=1}^{n+2} \lambda_i x_i = \sum_{i=1}^{n+2} \lambda_i = 0$. Among the λ_i 's, there must be m>0 of them are positive. Without loss of generality, assume that $\lambda_1, \ldots, \lambda_m>0$ and $\lambda_{m+1}, \ldots, \lambda_{n+2}\leq 0$. Then

$$\sum_{i=1}^{m} \lambda_i x_i = \sum_{j=m+1}^{n+2} (-\lambda_j) x_j.$$

Since $\sum_{i=1}^{n+2} \lambda_i = \sum_{i=1}^m \lambda_i + \sum_{j=m+1}^{n+2} \lambda_j = 0$, we have $\sum_{i=1}^m \lambda_i = \sum_{j=m+1}^{n+2} (-\lambda_j)$. Let $p_i = \frac{|\lambda_i|}{\sum_{j=1}^m \lambda_j}$ for $i = 1, \dots, n+2$. Then

$$\sum_{i=1}^{m} p_i x_i = \sum_{j=m+1}^{n+2} p_j x_j,$$

 $p_i \geq 0$ and $\sum_{i=1}^m p_i = \sum_{j=m+1}^{n+2} = 1$. Let $\mathcal{S}_1 = \{x_1, \dots, x_m\}$ and $\mathcal{S}_2 = \{x_{m+1}, \dots, x_{n+2}\}$. Then $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$, $\mathcal{S}_1 \cap \mathcal{S}_2 = \emptyset$ and $\sum_{i=1}^m p_i x_i \in \operatorname{conv}(\mathcal{S}_1) \cap \operatorname{conv}(\mathcal{S}_2)$, which implies that $\operatorname{conv}(\mathcal{S}_1) \cap \operatorname{conv}(\mathcal{S}_2) \neq \emptyset$.