COS 511: Theoretical Machine Learning

Homework #2 — Due:
Sample size bounds, growth function, VC dimension — February 28, 2018

Problem 1

[10] As on Problem 1 on Homework #1, let $X = \mathbb{R}$, and let $\mathcal{C}_s$ be the class of concepts defined by unions of s intervals. Compute the VC-dimension of $\mathcal{C}_s$ exactly.

Problem 2

[15] For $i = 1, \ldots, n$, let $\mathcal{G}_i$ be a space of concepts ($\{0,1\}$-valued functions) defined on some domain X, and let $\mathcal{F}$ be a space of concepts defined on $\{0,1\}^n$. (That is, each $g_i \in \mathcal{G}_i$ maps X to $\{0,1\}$, and each $f \in \mathcal{F}$ maps $\{0,1\}^n$ to $\{0,1\}$.) Let $\mathcal{H}$ be the space of all concepts $h : X \to \{0,1\}$ of the form

$$h(x) = f(g_1(x), \ldots, g_n(x))$$

for some $f \in \mathcal{F}$, $g_1 \in \mathcal{G}_1, \ldots, g_n \in \mathcal{G}_n$.

Give a careful argument proving that

$$\Pi_{\mathcal{H}}(m) \leq \Pi_{\mathcal{F}}(m) \cdot \prod_{i=1}^{n} \Pi_{\mathcal{G}_i}(m).$$

[An **optional** continuation of this problem, applicable to feedforward networks, is given in Problem 5.]

Problem 3

[15] Show that Sauer's Lemma is tight. That is, for each $d = 0, 1, 2, \ldots$, give an example of a class $\mathcal{C}$ with VC-dimension equal to d such that for each m,

$$\Pi_{\mathcal{C}}(m) = \sum_{i=0}^{d} \binom{m}{i}.$$

Problem 4

This problem explores another general method for bounding the error when the hypothesis space is infinite.

Some algorithms output hypotheses that can be represented by a small number of examples from the training set. For instance, suppose the domain is $\mathbb{R}$ and we are learning a half-line of the form $x \geq a$ where a defines the half-line. A simple algorithm chooses the left most positive training example a and outputs the corresponding half-line, which is clearly consistent with the data. Thus, in this case, the hypothesis can be represented by a single training example.

More formally, let F be a function mapping labeled examples to concepts, and assume that algorithm A, when given training examples $(x_1, c(x_1)), \ldots, (x_m, c(x_m))$ labeled by some unknown $c \in \mathcal{C}$, chooses some $i_1, \ldots, i_k \in \{1, \ldots, m\}$ and outputs the consistent hypothesis $h = F((x_{i_1}, c(x_{i_1})), \ldots, (x_{i_k}, c(x_{i_k})))$. In a sense, the algorithm has "compressed" the sample down to a sequence of just k of the m training examples. (We assume throughout that $m > k$.)

a. [5] Give such an algorithm for axis-aligned hyper-rectangles in $\mathbb{R}^n$ with $k = O(n)$. (An axis-aligned hyper-rectangle is a set of the form $[a_1, b_1] \times \cdots \times [a_n, b_n]$, and the corresponding concept, as usual, is the binary function that is 1 for points inside the rectangle and 0 otherwise. For $n = 2$, this is the class of rectangles used repeatedly as an example in class.) Your algorithm should run in time polynomial in m and n.

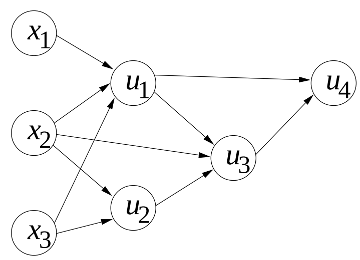
b. [15] Returning to the general case, assume as usual that the examples are chosen at random from some distribution D. Also assume that the size k is fixed. Argue carefully that the error of the output hypothesis h, with probability at least $1 - \delta$, satisfies the bound:

$$\mathrm{err}_D(h) \le O\left(\frac{\ln(1/\delta) + k \ln m}{m - k}\right).$$

[*Side note:* A difficult, long-standing open problem asks if it is always possible to find such a "compression scheme" whose size k is equal to (or proportional to) the VC-dimension d of the target class $\mathcal{C}$.]

Problem 5 – Optional (Extra Credit)

[15] This problem shows one way in which the methods we have been developing can be applied to *feedforward networks*, including (some) neural networks.



A feedforward network, as in the example above, is defined by a directed acyclic graph on a set of *input nodes* $x_1, \ldots, x_n$, and *computation nodes* $u_1, \ldots, u_N$. The input nodes have no incoming edges. One of the computation nodes is called the *output node*, and has no outgoing edges. Each computation node u_k is associated with a function $f_k : \mathbb{R}^{n_k} \to \{0, 1\}$, where n_k is u_k's indegree (number of ingoing edges). On input $\mathbf{x} \in \mathbb{R}^n$, the network computes its output $g(\mathbf{x})$ in a natural, feedforward fashion. For instance, given input $\mathbf{x} = \langle x_1, x_2, x_3 \rangle$, the network above computes $g(\mathbf{x})$ as follows:

$$\begin{aligned} u_1 &= f_1(x_1, x_2, x_3) \\ u_2 &= f_2(x_2, x_3) \\ u_3 &= f_3(u_1, x_2, u_2) \\ u_4 &= f_4(u_1, u_3) \\ g(\mathbf{x}) &= u_4. \end{aligned}$$

(Here, we slightly abuse notation, writing x_j and u_k both for nodes of the network, and for the input/computed values associated with these nodes.) The number of edges in the graph is denoted W.

In what follows, we regard the underlying graph as fixed, but allow the functions f_k to vary, or to be learned from data. In particular, let $\mathcal{F}_1, \ldots, \mathcal{F}_N$ be spaces of functions. As just explained, every choice of functions $f_1, \ldots, f_N$ induces an overall function $g : \mathbb{R}^n \to \{0, 1\}$ for the network. We let $\mathcal{G}$ denote the space of all such functions when f_k is chosen from $\mathcal{F}_k$ for $k = 1, \ldots, N$.

a. Prove that

$$\Pi_{\mathcal{G}}(m) \leq \prod_{k=1}^{N} \Pi_{\mathcal{F}_k}(m).$$

(Note that this is a generalization of Problem 2.)

b. Let d_k be the VC-dimension of $\mathcal{F}_k$, and let $d = \sum_{k=1}^{N} d_k$. Assume $m \geq d_k \geq 1$ for all k. Prove that

$$\Pi_{\mathcal{G}}(m) \leq \left(\frac{emN}{d}\right)^d.$$

c. Consider the typical case in which the functions f_k are linear threshold functions; as we know, this class of functions has VC-dimension $d_k = n_k + 1$. Give an exact expression for d in terms of N, n, and W. Conclude by deriving a "big-Oh" upper bound on the generalization error of any $g \in \mathcal{G}$ that is consistent with m random examples, assuming $m \geq d$. Your bound should hold with probability at least $1 - \delta$, and should be expressed in terms of N, n, W, m, and δ.