EECS 496-10 – Computational Learning Theory
Winter 2019
Problem Set 1

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Due: 2/12/19 by the beginning of class

Instructions: Atop your problem set, please write your name and list your collaborators. You may consult outside references, but cite all the resources used (e.g. which resources on the internet you consulted). You should not, however, search for answers to these questions. All problems in this assignment require proof.

Problems

1. What is the VC-dimension of axis-aligned rectangles? Use this VC analysis to straightforwardly conclude that axis-aligned are efficiently PAC learnable.

2. Recall that a Boolean literal is either a variable $x_i, i \in [1 \ldots n]$ or its negation $\bar{x}_i$. Give a membership and equivalence query algorithm for efficient exact learning of conjunctions of at most n Boolean literals. Are both equivalence and membership queries necessary for efficient exact learning? If not, do equivalence queries alone suffice? Do membership queries?

3. Consider the following variant of the PAC model. Given a target function $f : \mathcal{X} \to \{0, 1\}$, let $\mathcal{D}^+$ be the distribution over $\mathcal{X}^+ = \{x \in \mathcal{X} : f(x) = 1\}$ defined as $\mathcal{D}^+(a) = \mathcal{D}(a)/\mathcal{D}(\mathcal{X}^+)$ for $a \in \mathcal{X}^+$. And D^- is the distribution over $\mathcal{X}^-$ (defined analogously). In this model, the learner does not have access to D but is able to draw examples from both $\mathcal{D}^+$ and $\mathcal{D}^-$. A class is learnable in this model if a learner can produce a hypothesis h whose risk is $\leq \epsilon$ on both D^- and D^+ simultaneously. Show that if $\mathcal{H}$ is efficiently learnable in the standard PAC model then $\mathcal{H}$ is also efficiently learnable in this variant.

4. A k-fold union of hypotheses from a class $\mathcal{C}$ is a collection $c_1, \ldots, c_k \in \mathcal{C}$ that assigns the label $c_1(x) \vee \ldots \vee c_k(x)$ to example x. Give an explicit class $\mathcal{C}$ of (any) VC dimension d such that the class of k-fold unions of hypotheses from $\mathcal{C}$ has VC dimension greater than $(1+\epsilon)kd$ for sufficiently large values of k.[1]

5. Let $f : X \to \{+1, -1\}$ be a classifier, and let $C := \{-f, f\}$. Give as strong upper and lower bounds on $\mathfrak{R}_m(C)$ as you can. (For full credit, give bounds that are asymptotically tight in m for any D.)

6. Consider modifying the definition of PAC learning by getting rid of the δ parameter and letting ϵ serve as a bound on both the approximation error and the failure probability. In essence, the learner would be asked to produce a hypothesis h_S such that

$$\Pr_{S \sim D^m}[R(h_S) \leq \epsilon] \geq 1 - \epsilon$$

using a sample size polynomial in $1/\epsilon$, and the dependence on the other parameters would remain unchanged. Does this redefinition change which classes of functions are PAC learnable?

[1] An upper bound of $2kd \log_2(3k)$ is given in: Anselm Blumer, Andrzej Ehrenfeucht, David Haussler, and Manfred K. Warmuth. Learnability and the Vapnik- Xhervonenkis Dimension. J. ACM, 36(4): 929-965, 1989.