
Mathematics of Machine Learning

Fall 2009

Assignment Sheet 3

Exercises marked with a \star can be handed in for bonus points. Due date is November 5.

Exercise 1 (\star)

Show that the VC dimension of the set system consisting of all n -dimensional axis aligned hyperrectangles is $2n$.

Exercise 2

Let \mathcal{C} be a concept class of boolean formulas (e.g. 3-CNF or 3-term DNF) and let \mathcal{C}^m be the restriction of \mathcal{C} to those boolean formulas which do not contain negative literals. Show that if \mathcal{C}^m is efficiently PAC learnable, then \mathcal{C} is efficiently PAC learnable.

Exercise 3

Let \mathcal{C}_n be the set of all algorithms c taking an n -bit string a as input and returning a single bit $c(a)$ in time $size(c)$. Show that if \mathcal{C} is efficiently PAC learnable, then *every* (polynomial time evaluatable) concept class is efficiently PAC learnable.

Exercise 4

A 1-*decision list* $L = \{(l_1, b_1), \dots, (l_k, b_k), b\}$ is defined by an ordered sequence of pairs (l_i, b_i) , where l_i is a literal over boolean variables x_1, \dots, x_n and b_i is a bit, and a default bit b . Given an n -bit string $a \in \{0, 1\}^n$, the value $L(a)$ is defined to be either b_j where j is the smallest index such that $l_j(a) = 1$, or b if no such j exists.

For example, for $L = \{(x_1, 1), (\neg x_4, 0), 1\}$, we have $L(0001) = 1$ (using the default bit), $L(0000) = 0$ (because $x_1 = 0$ and $\neg x_4 = 1$), and $L(1000) = 1$ (because $x_1 = 1$).

1. Design an efficient Occam algorithm for the concept class of 1-decision lists.
2. Conclude that 1-decision lists are efficiently PAC learnable. How many samples are required by the PAC learning algorithm?

Exercise 5 (\star)

Let \mathcal{C} be efficiently PAC learnable. Show that there is an efficient probabilistic Occam algorithm for \mathcal{C} . (It is enough to show that the *expected* running time of the Occam algorithm is polynomial.)