Foundations of Machine Learning
Courant Institute of Mathematical Sciences
Homework assignment 2 - Solution
February 21, 2006

## Problem 1: VC dimension [75 points]

(1) [25 points]
(a) [5 points] It suffices to show the existence of a set of $n+1$ points in $\mathbb{R}^{n}$ that can be shattered by halfspaces. Let $x_{0}$ be the origin and define $x_{i}$ as the point whose $i$ th coordinate is 1 and all others 0 . Let $y_{0}, y_{1}, \ldots, y_{n} \in\{-1,+1\}$ be an arbitrary set of labels for $x_{0}, \ldots, x_{n}$. Let $w$ be the vector whose $i$ th coordinate is $y_{i}$. Then, the classifier defined by the hyperplane of equation $w \cdot x+y_{0} / 2=0$ shatters $x_{0}, \ldots, x_{n}$ since:

$$
\begin{align*}
& \operatorname{sign}\left(w \cdot x_{0}+y_{0} / 2\right)=\operatorname{sign}\left(y_{0}+y_{0} / 2\right)=y_{0}, \text { and }  \tag{1}\\
& \forall i \geq 1, \operatorname{sign}\left(w \cdot x_{i}+y_{0} / 2\right)=\operatorname{sign}\left(y_{i}+y_{0} / 2\right)=y_{i}
\end{align*}
$$

(b) [10 points] It suffices to show that no set of $n+2$ points can be shattered by halfspaces. Let $X$ be a set of $n+2$ points. By Radon's theorem, it can be split into two sets $X_{1}$ and $X_{2}$ such that their convex hulls intersect.
Observe that when two sets of points $X_{1}$ and $X_{2}$ are separated by a hyperplane, their convex hulls are also separated by that hyperplane. Thus, $X_{1}$ and $X_{2}$ cannot be separated by a hyperplane and $X$ is not shattered.
(c) [10 points] Let $I_{1}=\left\{i \in[1, n+2]: x_{i} \in X_{1}\right\}$ and $I_{2}=\left\{i \in[1, n+2]: x_{i} \in X_{2}\right\}$. $x$ is in the convex hull of $X_{1}$ and $X_{2}$ iff there exist $\left(\alpha_{i}\right)_{i \in I_{1}}$ and $\left(\alpha_{i}\right)_{i \in I_{2}}$ such that

$$
\begin{align*}
x & =\sum_{i \in I_{1}} \alpha_{i} x_{i} \text { with } \sum_{i \in I_{1}} \alpha_{i}=1, \text { and }  \tag{2}\\
x & =\sum_{i \in I_{2}} \alpha_{i} x_{i} \text { with } \sum_{i \in I_{2}} \alpha_{i}=1
\end{align*}
$$

This leads to the following system of $n+1$ equations in $n+2$ unknown $\alpha_{i}$ :

$$
\left\{\begin{array}{l}
\sum_{i \in I_{1}} \alpha_{i} x_{i}-\sum_{i \in I_{2}} \alpha_{i} x_{i}=0  \tag{3}\\
\sum_{i \in I_{1}} \alpha_{i}-\sum_{i \in I_{2}} \alpha_{i}=0
\end{array}\right.
$$

which has a non-trivial solution. This proves Radon's theorem.
(2) [30 points] Let $m \geq 0$. Note the general fact that for any concept class $C=\left\{c_{1} \cap c_{2}: c_{1} \in C_{1}, c_{2} \in C_{2}\right\}$,

$$
\begin{equation*}
\Pi_{C}(m) \leq \Pi_{C_{1}}(m) \Pi_{C_{2}}(m) \tag{4}
\end{equation*}
$$

Indeed, fix a set $X$ of $m$ points. Let $Y_{1}, \ldots, Y_{k}$ be the traces of $C_{1}$ on $X$. By definition of $\Pi_{C_{1}}(X), k \leq \Pi_{C_{1}}(X) \leq \Pi_{C_{1}}(m)$. By definition of $\Pi_{C_{2}}\left(Y_{i}\right)$, The traces of $C_{2}$ on a subset $Y_{i}$ are at most $\Pi_{C_{2}}\left(Y_{i}\right) \leq$ $\Pi_{C_{2}}(m)$. Thus, the traces of $C$ on $X$ are at most

$$
\begin{equation*}
k \Pi_{C_{2}}\left(Y_{i}\right) \leq \Pi_{C_{1}}(m) \Pi_{C_{2}}(m) . \tag{5}
\end{equation*}
$$

For the particular case of $C_{k}$, using Sauer's lemma, this implies that

$$
\begin{equation*}
\Pi_{C_{k}}(m) \leq\left(\Pi_{C_{1}}(m)\right)^{k} \leq\left(\frac{e m}{n+1}\right)^{k(n+1)} \tag{6}
\end{equation*}
$$

If $(e m /(n+1))^{k(n+1)}<2^{m}$, then the VC dimension of $C_{k}$ is less than $m$. If the VC dimension of $C_{k}$ is $m$, then $\Pi_{C_{k}}(m)=2^{m} \leq$ $(e m /(n+1))^{k(n+1)}$. These inequalities give an upper bound and a lower bound on $\operatorname{VCdim}\left(C_{k}\right)$. As an example, using the identity: $\forall x \in$ $\mathbb{N}-\{3\}, \log _{2}(x) \leq x / 2$, one can verify that:

$$
\begin{equation*}
\operatorname{VCdim}\left(C_{k}\right) \leq 2(n+1) k \log (3 k) \tag{7}
\end{equation*}
$$

(3) [20 points]
(a) [5 points] When $C=A \cup B, \Pi_{C}(X) \leq \Pi_{A}(X)+\Pi_{B}(X)$ for any set $X$ since dichotomies in $\Pi_{C}(X)$ can be generated by $A$ or by $B$. Thus, for all $m, \Pi_{C}(m) \leq \Pi_{A}(m)+\Pi_{B}(m)$.
(b) [15 points] For $m \geq d_{A}+d_{B}+2$, by Sauer's lemma,

$$
\begin{align*}
\Pi_{C}(m) & \leq \sum_{i=0}^{d_{A}}\binom{m}{i}+\sum_{i=0}^{d_{B}}\binom{m}{i}=\sum_{i=0}^{d_{A}}\binom{m}{i}+\sum_{i=0}^{d_{B}}\binom{m-i}{i} \\
& =\sum_{i=0}^{d_{A}}\binom{m}{i}+\sum_{i=m-d_{B}}^{d_{B}}\binom{m}{i}  \tag{8}\\
& \leq \sum_{i=0}^{d_{A}}\binom{m}{i}+\sum_{i=d_{A}+2}^{d_{B}}\binom{m}{i}  \tag{9}\\
& <\sum_{i=0}^{m}\binom{m}{i}=2^{m} . \tag{10}
\end{align*}
$$

Thus, the VC dimension of $C$ is strictly less than $d_{A}+d_{B}+2$ :

$$
\begin{equation*}
\mathrm{VCdim}(C) \leq d_{A}+d_{B}+1 \tag{11}
\end{equation*}
$$

Is this bound tight (can you show that for any $d_{A}$ and $d_{B}$, there exist sets $A$ and $B$ such that equality holds)?

Problem 2: Sample complexity [25 points]
(a) [15 points] For $i=0, \ldots, n$, let $x_{i} \in\{0,1\}^{n}$ be defined by $x_{i}=$ $(\underbrace{1, \ldots, 1}_{i \text { 1's }}, 0, \ldots, 0)$. Then, $\left\{x_{0}, \ldots, x_{n}\right\}$ can be shattered by $C$. Indeed, let $y_{0}, \ldots, y_{n} \in 0,1$ be an arbitrary labeling of these points. Then, the function $h$ defined by:

$$
\begin{equation*}
h(x)=y_{i} \tag{12}
\end{equation*}
$$

for all $x$ with $i$ 's is symmetric and $h\left(x_{i}\right)=y_{i}$. Thus, $\operatorname{VCdim}(C) \geq$ $n+1$. Conversely, a set of $n+2$ points cannot be shattered by $C$ since at least two points would then have the same number of 1's and will not be distinguishable by $C$. Thus,

$$
\begin{equation*}
\operatorname{VCdim}(C)=n+1 \tag{13}
\end{equation*}
$$

(b) [5 points] Thus, in view of the theorems presented in class, a lower bound on the number of training examples needed to learn symmetric functions with accuracy $1-\epsilon$ and confidence $1-\delta$ is

$$
\begin{equation*}
\Omega\left(\frac{1}{\epsilon} \log \frac{1}{\delta}+\frac{n}{\epsilon}\right) \tag{14}
\end{equation*}
$$

and an upper bound is:

$$
\begin{equation*}
O\left(\frac{1}{\epsilon} \log \frac{1}{\delta}+\frac{n}{\epsilon} \log \frac{1}{\epsilon}\right) \tag{15}
\end{equation*}
$$

which is only within a factor $\frac{1}{\epsilon}$ of the lower bound.
(c) [5 points] This is trivial. For a training data $\left(z_{0}, t_{0}\right), \ldots,\left(z_{m}, t_{m}\right) \in$ $\{0,1\}^{n} \times\{0,1\}$ define $h$ as the symmetric function such that $h\left(z_{i}\right)=t_{i}$ for all $i=0, \ldots, m$.
Can you show that in view of the bounds given in (b), this algorithm is optimal?

