The VC dimension

\[ m \geq \log_2 \left( \frac{m + 1}{\epsilon} \right) \]

\[ \text{VC dimension} \]
The text contains mathematical expressions and definitions. The document appears to be discussing concepts related to VC dimension and hypothesis sets. The notation and equations suggest a focus on aspects of machine learning or theoretical computer science. However, the specific details are not entirely legible due to the handwriting style.
(c) Let $A$ be a non-empty set of feature vectors.

$C = \{03\}$

\[
\begin{array}{c|c|c|c}
& -1 & +1 & 0 \\
-1 & 1 & 0 & 1 \\
0 & 0 & 1 & 0 \\
\end{array}
\]

$$2^{103} = 2^{4} = 2$$

We can choose $\theta$.

And we have an example set.

\begin{itemize}
  \item $x_1, x_2$
  \item $(+,+,+)$, $(+,-,-)$, $(-,+,-)$, $(-,+,+)$, $(+,+,+)$
\end{itemize}

\[
\begin{array}{c|c|c|c}
& -1 & +1 & +1 \\
-1 & 1 & 0 & 1 \\
0 & 0 & 1 & 0 \\
\end{array}
\]

$$\text{VC dim}(H_t) = 1$$
\[ X = \mathbb{R}, \quad H = \{ \mathcal{h}_{a,b} \mid a < b \in \mathbb{R} \} \]

\[ \mathcal{h}_{a,b}(x) = 1 \quad \text{iff} \quad x \in [a,b] \]

Consider the interval \([0,1)\). Let \([a,b] \subseteq [0,1)\) and \(a < b \leq 1\).

**Proof:**

\[ \text{VCDim}(H) \geq 2 \]

For \( n \geq 2 \), let \( x_1, x_2, \ldots, x_n \in [0,1) \) be chosen uniformly at random and let \( a = \min x_i \) and \( b = \max x_i \). Then, \( [a,b] \subseteq [0,1) \)

\[ \text{VCDim}(H) = 2 \]
$X = \mathbb{R}^2$

$H = \{ h_{a_1, a_2, b_1, b_2} : a_1 < a_2 \text{ and } b_1 < b_2 \}$

$h_{a_1, a_2, b_1, b_2} (x_1, x_2) = 1$ if $x_1 \in [a_1, a_2]$ and $x_2 \in [b_1, b_2]$

$VC \text{ dim } (H) = 4$
$\text{VCdim}(H) = \log_2(H) \quad \text{for } \quad H \text{ non-empty class of sets}$

$|H_t| \geq 2^{|H_t|} = 2^{1c_1}$

$log |H_t| \geq 1c_1$

$log(|H_t| - 1) = log_2(H_t) - 1 \geq \log_2(H_t - 1)$

$log|H_t| = 1, \text{ VCdim} = 1$:

$\mathcal{H} \quad \text{halfspacess}$

$x = \mathbb{R}^d, H = \{ x \rightarrow \text{sign}(w \cdot x) : w \in \mathbb{R}^d \}$

$L_1, \ldots, L_d \in \mathbb{R}^d$

$w = (y_1, y_2, \ldots, y_d) \in \mathbb{R}^d$

$w \cdot x = \sum_{i=1}^{d} w_i x_i \Rightarrow w \cdot e_i = w_i = y_i$

$\text{sign}(w \cdot e_i) = \text{sign}(y_i) = y_i$

$\text{VCdim}(H) \geq d$
where $c_1, c_2$ are constants. Let $m_n^\varepsilon(\epsilon, \delta) = \min \{ \text{sample complexity} \}

\begin{align*}
    c_1 \frac{d + \log(1/\delta)}{\epsilon} &\leq m_n^\varepsilon(\epsilon, \delta) \\
    &\leq c_2 \frac{d \log(4/d) + \log(1/\delta)}{\epsilon}
\end{align*}

\text{VC dimension} \: \nu(H) \text{ is not \#d}

\text{ERM} \: m_{\nu}(\varepsilon, \delta) = \min \{ \text{other measures} \}

\text{as } \delta \to 0 \text{ and } \nu(H) \to \infty \text{, the VC dimension}

m \to \infty \text{ and } \nu \to \infty \text{, we have}\n
\nu > c \log \frac{m}{\delta}

\text{for some constant } c > 0.

Instead, we consider

\text{ERM} \: m_{\nu}(\varepsilon, \delta) \text{ as } \nu \to \infty \text{ and } \delta \to 0

\text{where } m_{\nu}(\varepsilon, \delta) \text{ is the \#sample required for ERM}

\text{with probability at least } 1 - \delta.

\text{The VC dimension} \: \nu(H) \text{ is not \#d}

\text{ERM} \: m_{\nu}(\varepsilon, \delta) = \min \{ \text{other measures} \}