CSCI4230 Computational Learning Theory Lecturer: Siu On Chan Spring 2021 Based on Rocco Servedio's notes

Notes 10: Hypothesis testing

1. Chernoff bounds

Due to Herman Rubin X_1, \ldots, X_m independent $\{0, 1\}$ -valued random variables s.t. $\mathbb{P}[X_i = 1] = \mathbb{E}[X_i] = p$ for $1 \leq i \leq m$ $X \stackrel{\text{def}}{=} X_1 + \cdots + X_m$ ($\mathbb{E}[X] = mp$)

Theorem 1 (Multiplicative Chernoff). For all $0 \leq \gamma \leq 1$,



Also true for X_1, \ldots, X_m independent [0, 1]-valued (i.e. bounded) random variables Many proofs; see e.g. Mulzer "Five Proofs of Chernoff's Bound with Applications" if interested Exponential decay

2. Hypothesis testing

Fix $h \in \mathcal{H}$, how can we test whether h is bad? (i.e. $\operatorname{err}_{\mathcal{D}}(h, c) = \mathbb{P}_{x \in \mathcal{D}}[h(x) \neq c(x)] \geq \varepsilon$) Solution: Draw m independent labelled samples $(x^1, c(x^1)), \ldots, (x^m, c(x^m)),$

Compute (empirical error) $\widehat{\text{err}} \stackrel{\text{def}}{=} \frac{\#\text{samples } s.t. \ h(x^i) \neq c(x^i)}{m}$

By Chernoff bound, $\widehat{\operatorname{err}} \approx \operatorname{err}_{\mathcal{D}}(h, c)$

e.g. If h is bad, $p \stackrel{\text{def}}{=} \operatorname{err}_{\mathcal{D}}(h, c) \ge \varepsilon$,

$$\mathbb{P}\left[\widehat{\operatorname{err}} \leqslant \frac{\varepsilon}{2}\right] \leqslant e^{-\frac{1}{8}mp} \leqslant e^{-\frac{1}{8}\varepsilon m}$$

Further Improved Algorithm: Similar to Improved Algorithm

But only cover $1 - \varepsilon/2$ fraction of positive samples using S_{i_1}, \ldots, S_{i_k} Number of sets needed $k \leq \text{OPT} \cdot \ln(2/\varepsilon)$ (why?) Can show that $O\left(\frac{1}{\varepsilon}(\ln \frac{1}{\delta} + s \ln \frac{1}{\varepsilon} \ln n)\right)$ samples suffices (exercise)