

Homework 4

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1. *Collaborators and sources:* Guanghao Ye, Zixuan Xu.

Proof. Let L be a subset of the left vertices such that $|L| \leq n/2$. If $L = \emptyset$, then the result trivially holds. Hence, assume that $|L| \geq 1$. Let R_0 be the set of the right vertices. Then

$$\begin{aligned}
\mathbb{P}[|N(L)| < (1 + \varepsilon)|L|] &\leq \mathbb{P}[\exists R \subset R_0, |R| = \lfloor (1 + \varepsilon)|L| \rfloor, N(L) \subset R] \\
&\leq \sum_{\substack{R \subset R_0 \\ |R| = \lfloor (1 + \varepsilon)|L| \rfloor}} \mathbb{P}[N(L) \subset R] && \text{(union bound)} \\
&= \sum_{\substack{R \subset R_0 \\ |R| = \lfloor (1 + \varepsilon)|L| \rfloor}} \left(\frac{|R|}{n} \cdot \frac{|R| - 1}{n - 1} \cdots \frac{|R| - |L| + 1}{n - |L| + 1} \right)^3 \\
&\leq \binom{n}{\lfloor (1 + \varepsilon)|L| \rfloor} \left(\frac{\lfloor (1 + \varepsilon)|L| \rfloor}{n} \right)^{3|L|} && \text{(for } \varepsilon \leq 1) \\
&\leq \left(\frac{en}{\lfloor (1 + \varepsilon)|L| \rfloor} \right)^{\lfloor (1 + \varepsilon)|L| \rfloor} \left(\frac{\lfloor (1 + \varepsilon)|L| \rfloor}{n} \right)^{3|L|} && \text{(Stirling's approximation)} \\
&\leq \left(\frac{en}{\lfloor (1 + \varepsilon)|L| \rfloor} \right)^{(1 + \varepsilon)|L|} \left(\frac{\lfloor (1 + \varepsilon)|L| \rfloor}{n} \right)^{3|L|} && \text{(for } \varepsilon \leq 2e - 1) \\
&= \left(e^{1 + \varepsilon} \left(\frac{\lfloor (1 + \varepsilon)|L| \rfloor}{n} \right)^{2 - \varepsilon} \right)^{|L|} \\
&\leq \left(e^{1 + \varepsilon} \left(\frac{(1 + \varepsilon)|L|}{n} \right)^{2 - \varepsilon} \right)^{|L|} \\
&\leq \left(e^{1 + \varepsilon} \left(\frac{(1 + \varepsilon)}{2} \right)^{2 - \varepsilon} \right)^{|L|} && \text{(since } |L| \leq n/2)
\end{aligned}$$

Let $\varepsilon = 1/2$. Then $0 < e^{1 + \varepsilon}((1 + \varepsilon)/2)^{2 - \varepsilon} < 1/2$. Since $|L| \geq 1$, then

$$\begin{aligned}
\mathbb{P}[|N(L)| \geq (1 + \varepsilon)|L|] &\geq 1 - \mathbb{P}[|N(L)| < (1 + \varepsilon)|L|] \\
&\geq 1 - \left(e^{1 + \varepsilon} \left(\frac{(1 + \varepsilon)}{2} \right)^{2 - \varepsilon} \right)^{|L|} \\
&\geq 1 - e^{1 + \varepsilon} \left(\frac{(1 + \varepsilon)}{2} \right)^{2 - \varepsilon} \\
&> 1 - \frac{1}{2} = \frac{1}{2}.
\end{aligned}$$

This completes the proof. □

2. (a) *Collaborators and sources*: none.

Proof. Note that $\mathbb{1}_{\text{test accepts}} = (1 + f(x)f(y)f(z))/2$. By the Fourier transform of f and by linearity of expectation,

$$\begin{aligned}\mathbb{E}[f(x)f(y)f(z)] &= \mathbb{E} \left[\left(\sum_{S \subset [n]} \hat{f}(S) \chi_S(x) \right) \left(\sum_{T \subset [n]} \hat{f}(T) \chi_T(y) \right) \left(\sum_{U \subset [n]} \hat{f}(U) \chi_U(z) \right) \right] \\ &= \sum_{S, T, U \subset [n]} \hat{f}(S) \hat{f}(T) \hat{f}(U) \mathbb{E} [\chi_S(x) \chi_T(y) \chi_U(x \circ y \circ w)].\end{aligned}$$

Let $S, T, U \subset [n]$. For all $i \in [n]$, since $x_i, y_i \in \{\pm 1\}$, then $x_i^2 = y_i^2 = 1$. Hence,

$$\begin{aligned}\chi_S(x) \chi_T(y) \chi_U(x \circ y \circ w) &= \left(\prod_{i \in S} x_i \right) \left(\prod_{i \in T} y_i \right) \left(\prod_{i \in U} x_i y_i w_i \right) \\ &= \left(\prod_{i \in S \cap U} x_i^2 \right) \left(\prod_{i \in T \cap U} y_i^2 \right) \left(\prod_{i \in S \Delta U} x_i \right) \left(\prod_{i \in T \Delta U} y_i \right) \left(\prod_{i \in U} w_i \right) \\ &= \chi_{S \Delta U}(x) \chi_{T \Delta U}(y) \chi_U(w).\end{aligned}$$

If $S = T = U$, since w_1, \dots, w_n are all chosen independently and since $\mathbb{E}[w_i] = (-1) \cdot \delta + 1 \cdot (1 - \delta) = 1 - 2\delta$ for all $i \in [m]$, then

$$\mathbb{E} [\chi_{S \Delta U}(x) \chi_{T \Delta U}(y) \chi_U(w)] = \mathbb{E} \left[\prod_{i \in S} w_i \right] = \prod_{i \in S} \mathbb{E} [w_i] = (1 - 2\delta)^{|S|}.$$

Now, suppose that either $S \neq U$ or $T \neq U$. WLOG assume that $S \neq U$. Then $S \Delta U \neq \emptyset$. Let $j \in S \Delta U$. For $x \in \{\pm 1\}^n$, let $x^{\oplus j}$ be the vector obtained by flipping the j^{th} bit in x . Then we can partition $\{\pm 1\}^n$ into (unordered) pairs $(x, x^{\oplus j})$. Therefore,

$$\begin{aligned}\mathbb{E} [\chi_{S \Delta U}(x)] &= \frac{1}{2^n} \sum_{x \in \{\pm 1\}^n} \chi_{S \Delta U}(x) = \frac{1}{2^n} \sum_{\text{pairs } (x, x^{\oplus j})} (\chi_{S \Delta U}(x) + \chi_{S \Delta U}(x^{\oplus j})) \\ &= \frac{1}{2^n} \sum_{\text{pairs } (x, x^{\oplus j})} \left(x_j \prod_{i \in (S \Delta U) \setminus \{j\}} x_i + (-x_j) \prod_{i \in (S \Delta U) \setminus \{j\}} x_i \right) = 0.\end{aligned}$$

Since x, y and w are chosen independently, then for all $S, T, U \subset [n]$ such that either $S \neq U$ or $T \neq U$,

$$\mathbb{E} [\chi_{S \Delta U}(x) \chi_{T \Delta U}(y) \chi_U(w)] = \mathbb{E} [\chi_{S \Delta U}(x)] \mathbb{E} [\chi_{T \Delta U}(y)] \mathbb{E} [\chi_U(w)] = 0.$$

Therefore,

$$\begin{aligned}\mathbb{P}[\text{test accepts}] &= \mathbb{E} [\mathbb{1}_{\text{test accepts}}] = \mathbb{E} \left[\frac{1 + f(x)f(y)f(z)}{2} \right] = \frac{1}{2} + \frac{1}{2} \mathbb{E}[f(x)f(y)f(z)] \\ &= \frac{1}{2} + \frac{1}{2} \sum_{S, T, U \subset [n]} \hat{f}(S) \hat{f}(T) \hat{f}(U) \mathbb{E} [\chi_{S \Delta U}(x) \chi_{T \Delta U}(y) \chi_U(w)] \\ &= \frac{1}{2} + \frac{1}{2} \sum_{S \subset [n]} (1 - 2\delta)^{|S|} \hat{f}(S)^3.\end{aligned}$$

This completes the proof. \square

(b) *Collaborators and sources:* none.

Proof. Let $f : \{\pm 1\}^n \rightarrow \{\pm 1\}$ be a dictator function. Then $f = \chi_{\{j\}}$ for some $j \in [n]$. Therefore, $\hat{f}(\{j\}) = 1$ and $\hat{f}(S) = 0$ for all $S \subset [n]$ with $S \neq \{j\}$. By part (a),

$$\begin{aligned}
\mathbb{P}[\text{test accepts}] &= \frac{1}{2} + \frac{1}{2} \sum_{S \subset [n]} (1 - 2\delta)^{|S|} \hat{f}(S)^3 \\
&= \frac{1}{2} + \frac{1}{2} \left((1 - 2\delta)^{|\{j\}|} \hat{f}(\{j\})^3 + \sum_{\substack{S \subset [n] \\ S \neq \{j\}}} (1 - 2\delta)^{|S|} \hat{f}(S)^3 \right) \\
&= \frac{1}{2} + \frac{1}{2} \left((1 - 2\delta)^1 \cdot 1^3 + \sum_{\substack{S \subset [n] \\ S \neq \{j\}}} (1 - 2\delta)^{|S|} \cdot 0^3 \right) \\
&= \frac{1}{2} + \frac{1}{2}(1 - 2\delta) = 1 - \delta.
\end{aligned}$$

This completes the proof. □

(c) *Collaborators and sources:* none.

Proof. Let $f : \{\pm 1\}^n \rightarrow \{\pm 1\}$ be such that f passes with probability at least $1 - \varepsilon$ for some $\varepsilon \in (0, 1/2)$. By part (a),

$$1 - \varepsilon \leq \mathbb{P}[\text{test accepts}] = \frac{1}{2} + \frac{1}{2} \sum_{S \subset [n]} (1 - 2\delta)^{|S|} \hat{f}(S)^3.$$

Rearranging the above inequality and applying Parseval's identity yield

$$\begin{aligned} 1 - 2\varepsilon &\leq \sum_{S \subset [n]} (1 - 2\delta)^{|S|} \hat{f}(S)^3 \leq \left(\max_{S \subset [n]} (1 - 2\delta)^{|S|} \hat{f}(S) \right) \sum_{S \subset [n]} \hat{f}(S)^2 \\ &= \left(\max_{S \subset [n]} (1 - 2\delta)^{|S|} \hat{f}(S) \right) \cdot 1 = \max_{S \subset [n]} (1 - 2\delta)^{|S|} \hat{f}(S). \end{aligned}$$

Hence, there exists $S \subset [n]$ such that $(1 - 2\delta)^{|S|} \hat{f}(S) \geq 1 - 2\varepsilon$. Set $\delta = \varepsilon$ in the test. Then $(1 - 2\varepsilon)^{|S|} \hat{f}(S) \geq 1 - 2\varepsilon$. Since $\varepsilon \in (0, 1/2)$, then $1 - 2\varepsilon \in (0, 1)$, so $(1 - 2\varepsilon)^{|S|} \in (0, 1]$. Therefore,

$$\hat{f}(S) \geq \frac{1 - 2\varepsilon}{(1 - 2\varepsilon)^{|S|}} \geq \frac{1 - 2\varepsilon}{1} = 1 - 2\varepsilon.$$

This completes the proof. □

(d) *Collaborators and sources*: none.

By part (c), if f passes with probability at least $1 - \varepsilon$ for some $\varepsilon \in (0, 1/2)$, then there exists $S \subset [n]$ such that $(1 - 2\varepsilon)^{|S|} \hat{f}(S) \geq 1 - 2\varepsilon$ by setting $\delta = \varepsilon$ in the test. Since $\text{dist}(f, \chi_S) \in [0, 1]$, then $\hat{f}(S) = 1 - 2\text{dist}(f, \chi_S) \in [-1, 1]$. Since $\varepsilon \in (0, 1/2)$, then $1 - 2\varepsilon \in (0, 1)$. If $|S| \geq 2$, then $0 < (1 - 2\varepsilon)^{|S|} < 1 - 2\varepsilon$, so $(1 - 2\varepsilon)^{|S|} \hat{f}(S) < 1 - 2\varepsilon$, a contradiction. Therefore, one of the following two cases holds:

- (i) $|S| = 1$ and $\hat{f}(S) = 1$ (so $\text{dist}(f, \chi_S) = 0$, and $f = \chi_S$ is a dictator function);
- (ii) $|S| = 0$ and $\hat{f}(S) \geq 1 - 2\varepsilon$ (so $\text{dist}(f, \chi_\emptyset) \leq \varepsilon$).

Hence, if f is ε -close to $\chi_\emptyset \equiv 1$ (a non-dictator function), then f also passes with probability at least $1 - \varepsilon$.

Note that for any dictator function, say $\chi_{\{j\}}$ for some $j \in [n]$,

$$\mathbb{P}_{x \in \{\pm 1\}^n} [\chi_{\{j\}}(x) = 0] = \mathbb{P}_{x \in \{\pm 1\}^n} [x_j = 0] = \frac{|\{x \in \{\pm 1\}^n : x_j = 0\}|}{2^n} = \frac{2^{n-1}}{2^n} = \frac{1}{2}.$$

In other words, any dictator function equals 0 for half of the inputs, and 1 for the other half. We give a simple fix to the test by applying the following new test before the original test. For any sufficiently small $\eta > 0$, we independently and uniformly sample $\Theta(\log(1/\eta))$ random inputs from $\{\pm 1\}^n$, and reject if and only if more than $3/4$ of the values are 1. If f is ε -close to $\chi_\emptyset \equiv 1$ for some $\varepsilon \in (0, 1/8)$, then by the Chernoff bound,

$$\mathbb{P}[\text{new test rejects } f] = 1 - \mathbb{P}[\leq 3/4 \text{ of the values are 1}] \geq 1 - e^{-\Theta(\log(1/\eta))} = 1 - \Theta(\eta).$$

On the other hand, if f is a dictator function, then by the Chernoff bound,

$$\mathbb{P}[\text{new test accepts } f] = 1 - \mathbb{P}[\geq 3/4 \text{ of the values are 1}] \geq 1 - e^{-\Theta(\log(1/\eta))} = 1 - \Theta(\eta).$$

Hence, if f passes the combination of the new test and the original test with probability at least $1 - \varepsilon$ and with $\delta = \varepsilon$ in the original test for some sufficiently small $\varepsilon > 0$, then f is a dictator function with probability at least $1 - \Theta(\eta)$; on the other hand, if f is a dictator function, then the union bound implies that f passes the combined test with probability at least $1 - \Theta(\eta) - \delta$. This shows that the combined test is a dictator test.

3. Collaborators and sources: Guanghai Ye.

Proof. Let \mathcal{A} be a PAC learning algorithm for a class C that runs in $\text{poly}(\log n, 1/\varepsilon, 1/\delta)$ time. We denote by $\text{error}_{\mathcal{D}}(h) = \mathbb{P}_{x \sim \mathcal{D}}[h(x) \neq f(x)]$ the error of a hypothesis h with respect to f with inputs drawn from distribution \mathcal{D} . We denote by $\text{error}_S(h) = |\{x \in S : h(x) \neq f(x)\}|/|S|$ the error of h in the sample set S . We give a PAC learning algorithm in Algorithm 1 with running time $\text{poly}(\log n, 1/\varepsilon, \log(1/\delta))$. Let \mathcal{D} be the distribution of inputs.

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1  $\ell \leftarrow \lceil \log_2(3/\delta) \rceil$ 
2 foreach  $i \leftarrow 1, \dots, \ell$  do
3   run  $\mathcal{A}$  with accuracy  $\varepsilon/2$  and confidence  $1/2$ , obtaining a hypothesis  $h_i$ 
4    $m \leftarrow \lceil (12/\varepsilon^2) \log(6\ell/\delta) \rceil$ 
5   foreach  $j \leftarrow 1, \dots, m$  do
6     draw  $x_j \sim \mathcal{D}$ 
7    $S \leftarrow \{x_1, \dots, x_m\}$ 
8    $i^* \leftarrow \arg \min_{i \in [\ell]} (\text{error}_S(h_i))$ 
9 return  $h_{i^*}$ 

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Algorithm 1: A PAC learning algorithm with running time $\text{poly}(\log n, 1/\varepsilon, \log(1/\delta))$, given accuracy $\varepsilon > 0$ and confidence $\delta > 0$.

Since each call to \mathcal{A} runs in $\text{poly}(\log n, 1/\varepsilon)$ time, then the running time of Algorithm 1 is

$$O\left(\log \frac{1}{\delta}\right) \text{poly}\left(\log n, \frac{1}{\varepsilon}\right) + O\left(\frac{1}{\varepsilon^2} \log \frac{\log \frac{1}{\delta}}{\delta}\right) = \text{poly}\left(\log n, \frac{1}{\varepsilon}, \log \frac{1}{\delta}\right).$$

First, since $\mathbb{P}[\text{error}_{\mathcal{D}}(h_i) \leq \varepsilon/2] \geq 1 - 1/2 = 1/2$ for each $i \in [\ell]$, then

$$\mathbb{P}[\exists i \in [\ell], \text{error}_{\mathcal{D}}(h_i) \leq \varepsilon/2] \geq 1 - \left(1 - \frac{1}{2}\right)^\ell = 1 - \left(\frac{1}{2}\right)^{\lceil \log_2(\frac{3}{\delta}) \rceil} \geq 1 - \left(\frac{1}{2}\right)^{\log_2(\frac{3}{\delta})} = 1 - \frac{\delta}{3}.$$

Second,

$$\begin{aligned}
& \mathbb{P}\left[|\text{error}_{\mathcal{D}}(h_i) - \text{error}_S(h_i)| < \frac{\varepsilon}{4} \forall i \in [\ell]\right] \\
&= 1 - \mathbb{P}\left[\exists i \in [\ell], |\text{error}_{\mathcal{D}}(h_i) - \text{error}_S(h_i)| \geq \frac{\varepsilon}{4}\right] \\
&\geq 1 - \sum_{i=1}^{\ell} \mathbb{P}\left[|\text{error}_{\mathcal{D}}(h_i) - \text{error}_S(h_i)| \geq \frac{\varepsilon}{4}\right] \quad (\text{union bound}) \\
&= 1 - \sum_{i=1}^{\ell} \mathbb{P}\left[|\text{error}_{\mathcal{D}}(h_i) - \text{error}_S(h_i)| \geq \frac{\varepsilon}{4 \text{error}_{\mathcal{D}}(h_i)} \cdot \text{error}_{\mathcal{D}}(h_i)\right] \\
&\geq 1 - \sum_{i=1}^{\ell} 2 \exp\left(-\frac{1}{3} m \text{error}_{\mathcal{D}}(h_i) \cdot \left(\frac{\varepsilon}{4 \text{error}_{\mathcal{D}}(h_i)}\right)^2\right) \quad (\text{Chernoff bound}) \\
&= 1 - \sum_{i=1}^{\ell} 2 \exp\left(-\frac{m \varepsilon^2}{12 \text{error}_{\mathcal{D}}(h_i)}\right)
\end{aligned}$$

$$\begin{aligned}
&\geq 1 - \ell \cdot 2 \exp \left(- \frac{\lceil \frac{12}{\varepsilon^2} \log \frac{6\ell}{\delta} \rceil \cdot \varepsilon^2}{12 \cdot 1} \right) \\
&\geq 1 - 2\ell \exp \left(- \frac{\frac{12}{\varepsilon^2} \log \frac{6\ell}{\delta} \cdot \varepsilon^2}{12} \right) \\
&= 1 - 2\ell \exp \left(- \log \frac{6\ell}{\delta} \right) \\
&= 1 - 2\ell \cdot \frac{\delta}{6\ell} \\
&= 1 - \frac{\delta}{3}.
\end{aligned}$$

Since i^* minimizes $\text{error}_S(h_i)$ over $i \in [\ell]$, then by the union bound,

$$\begin{aligned}
\mathbb{P} \left[\text{error}_S(h_{i^*}) < \frac{3\varepsilon}{4} \right] &\geq \mathbb{P} \left[\exists i \in [\ell], \text{error}_S(h_i) < \frac{3\varepsilon}{4} \right] \\
&\geq \mathbb{P} \left[\left(|\text{error}_{\mathcal{D}}(h_i) - \text{error}_S(h_i)| < \frac{\varepsilon}{4} \forall i \in [\ell] \right) \wedge \left(\exists i \in [\ell], \text{error}_{\mathcal{D}}(h_i) \leq \frac{\varepsilon}{2} \right) \right] \\
&\geq 1 - \left(\frac{\delta}{3} + \frac{\delta}{3} \right) \\
&= 1 - \frac{2\delta}{3}.
\end{aligned}$$

By the union bound again,

$$\begin{aligned}
\mathbb{P} [\text{error}_{\mathcal{D}}(h_{i^*}) < \varepsilon] &\geq \mathbb{P} \left[\left(|\text{error}_{\mathcal{D}}(h_i) - \text{error}_S(h_i)| < \frac{\varepsilon}{4} \forall i \in [\ell] \right) \wedge \left(\text{error}_S(h_{i^*}) < \frac{3\varepsilon}{4} \right) \right] \\
&\geq 1 - \left(\frac{\delta}{3} + \frac{2\delta}{3} \right) \\
&= 1 - \delta.
\end{aligned}$$

This completes the proof. □