6.842 Randomness and Computation April 18, 2022

Lectures on Learning Theory

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1 PAC Learning

The model of *learning from random, uniform examples* is as follows: Given the *example oracle* $\mathrm{Ex}(f)$ of a function f, pick m i.i.d. random variables $x_1, \dots, x_m$ uniformly (or from some distribution $\mathcal{D}$, which might not be known to the learner in general), and call $\mathrm{Ex}(f)$ to obtain m random labeled examples $(x_1, f(x_1)), \dots, (x_m, f(x_m))$; after seeing these examples, the learner outputs a hypothesis h of the function f.

Should we require $h = f$? This is probably too much to ask. However, we can at least require $\mathrm{dist}(h, f) := \mathbb{P}_{x \sim \mathcal{D}}(h(x) \neq f(x)) \leq \varepsilon$, where $\mathrm{dist}(h, f)$ is also called $\mathrm{error}_{\mathcal{D}}(h)$ with respect to f.

Definition 1. A *uniform distribution learning algorithm for a concept class* $\mathcal{C}$ is an algorithm $\mathcal{A}$ that, given $\varepsilon > 0$, $\delta > 0$ and access to $\mathrm{Ex}(f)$ for $f \in \mathcal{C}$, outputs a function h such that with probability at least $1 - \delta$, $\mathrm{error}(h)$ with respect to f is at most ε. This is called *probably approximately correct (PAC) learning.*

We are interested in the following parameters:

- m, the *sample complexity*;
- ε, the *accuracy* parameter;
- δ, the *confidence* parameter;
- the running time, which we hope to be $\mathrm{poly}(\log(\text{domain size}), 1/\varepsilon, 1/\delta)$;
- the *description* of h, which at least should be compact (i.e., $O(\log|\mathcal{C}|)$) and efficient to evaluate; it require $h \in \mathcal{C}$, then this is called *proper learning.*

Note that the uniform case is a special case of the PAC model. The more general PAC model is given $\mathrm{Ex}_{\mathcal{D}}(f)$ and bounds $\mathrm{error}_{\mathcal{D}}(h)$ with respect to f.

2 Learning Conjunctions

Let $\mathcal{C}$ be the class of conjunctions (i.e., 1-term DNF) over $\{0,1\}^n$. We cannot hope for 0-error from a sub-exponential number of random samples; to see this, note that it is hard to distinguish $f(x) = x_1 \cdots x_n$ and $f(x) = \mathsf{F}$. Algorithm 1 gives a polynomial time sampling algorithm for conjunction learning, where "**?**" indicates a parameter to be determined.

For x_i in the conjunction, it must be set in the same way in each positive example, so $i \in V$. For x_i not in the conjunction,

$$\mathbb{P}[i \in V] = \mathbb{P}\left[x_i \text{ is set is the same way in each of the } k \text{ positive examples}\right] = \frac{1}{2^{k-1}}.$$

By the union bound,

$$\mathbb{P}\left[\text{any } x_i \text{ not in the conjunction survives}\right] \leq \frac{n}{2^{k-1}} \leq \delta,$$

draw poly$(1/\varepsilon)$ samples
estimate $\mathbb{P}[f(x) = 1]$ to additive error at most $\pm\varepsilon/4$ and confidence at least $1 - \delta/2$
if *estimate is less than* $\varepsilon/2$ **then**
    return $h(x) = 0$
`(estimate is at least` $\varepsilon/2$`; see a new positive example every` $O(1/\varepsilon)$ `samples)`
collect **?** more positive examples
$V \leftarrow$ set of indices of variables that are set in the same way in each positive example
return $h(x) = \bigwedge_{i \in V} x_i^{b_i}$, *where each* b_i *indicates if* x_i *is complemented or not*

Algorithm 1: A polynomial time sampling algorithm for conjunction learning.

if we pick $k = \log(n/\delta)$. Therefore, if we need $\Omega(\log(n/\delta))$ positive examples, or $\Omega((1/\varepsilon)\log(n/\delta))$ total examples to rule out every x_i not in the conjunction.

3 Occam's Razor

In a high level, *Occam's Razor* claims the following:

- If we ignore the running time, then learning is easy (with a polynomial number of samples).
- The shortest explanation is the best.

To see the first claim, we consider the brute-force algorithm in Algorithm 2.

draw $M = (1/\varepsilon)(\ln|\mathcal{C}| + \ln|1/\delta|)$
search over all $h \in \mathcal{C}$ until find one consistent with the samples
return h

Algorithm 2: A brute-force learning algorithm that demonstrates Occam's Razor.

We say that a function h is *bad* if error(h) with respect to f is at least ε. For a bad function h,

$$\mathbb{P}[h \text{ is consistent with the samples}] \le (1-\varepsilon)^M.$$

By the union bound,

$$\mathbb{P}[\text{any bad function } h \text{ is consistent with the samples}] \le |\mathcal{C}|(1-\varepsilon)^M = |\mathcal{C}|(1-\varepsilon)^{\frac{1}{\varepsilon}\left(\ln|\mathcal{C}| + \ln\left|\frac{1}{\delta}\right|\right)} = \delta.$$

Hence, it is unlikely to output a bad hypothesis h. For example, for conjunction learning, this analysis requires $O((1/\varepsilon)(n + 1/\delta))$ samples, where Algorithm 1 has a better sample complexity. On the other hand, if we have a *good* hypothesis h,

(i) we can *predict* values of f on new random inputs according to distribution $\mathcal{D}$, since

$$\mathbb{P}_{x \sim \mathcal{D}}[f(x) = h(x)] \ge 1 - \delta;$$

(ii) we can *compress* the description of samples $(x_1, f(x_1)), (x_2, f(x_2)), \ldots, (x_m, f(x_m))$ from the naïve description which takes $m(\log|D| + \log|R|)$ bits, where D and R are the domain and the range of f, respectively, to the form "$x_1, \ldots, x_m$ plus the description of h" which requires $m \log|D| + \log|\mathcal{C}|$ bits only.

4 Learning via Fourier Representations

In this section, we study learning algorithms that are based on estimating the Fourier representation of a function f.

4.1 Approximating One Fourier Coefficient

Lemma 2. *For any $S \subset [n]$, one can approximate $\hat{f}(S)$ to within additive error γ (i.e., $|output - \hat{f}(S)| \leq \gamma$) with probability at least $1-\delta$ in $O(1/\gamma^2 \log 1/\delta)$ samples.*

Proof. Recall that $\hat{f}(S) = 2\,\mathbb{P}_{x\in\{0,1\}^n}[f(x) \neq \chi_S(x)] - 1$. Hence, we can approximate $\hat{f}(S)$ by estimating $\mathbb{P}_{x\in\{0,1\}^n}[f(x) \neq \chi_S(x)]$ and applying the Chernoff bound. □

4.2 Fourier Concentration and the Low Degree Algorithm

Definition 3. For all $\varepsilon \in (0,1)$ and $n \in \mathbb{N}$, we say that a function $f : \{\pm 1\}^n \to \mathbb{R}$ has $\alpha(\varepsilon, n)$-*Fourier concentration (f.c.)* if

$$\sum_{\substack{S\subset[n] \\ |S|>\alpha(\varepsilon,n)}} \hat{f}(S)^2 \leq \varepsilon.$$

For a Boolean function $f : \{\pm 1\}^n \to \{\pm 1\}$, Parseval's identity gives $\sum_{S\subset[n]} \hat{f}(S)^2 = 1$, so having $\alpha(\varepsilon, n)$-Fourier concentration implies that

$$\sum_{\substack{S\subset[n] \\ |S|\leq\alpha(\varepsilon,n)}} \geq 1 - \varepsilon.$$

The *low degree algorithm*, given in Algorithm 3, approximates a Boolean function with d-Fourier concentration, where $d = \alpha(\varepsilon, n)$.

take $m = O((n^d/\tau)\log(n^d/\delta))$ samples
foreach $S \subset [n]$ *such that* $|S| \leq d$ **do**
  $C_S \leftarrow$ estimate of $\hat{f}(S)$
let $h : \{\pm 1\}^n \to \mathbb{R}$ be defined by $h(x) = \sum_{S\subset[n]:|S|\leq d} C_S \chi_S(x)$
return sign $\circ h$ *as hypothesis*

Algorithm 3: The low degree algorithm given degree d, accuracy τ and confidence δ.

Proposition 4. *If f has d-Fourier concentration with $d = \alpha(\varepsilon, n)$, then $\mathbb{E}_{x\in\{0,1\}^n}[(f(x) - h(x))^2] \leq \varepsilon + \tau$ with probability at least $1-\delta$.*

Proof. First, we claim that each low degree Fourier Coefficient is well approximated, i.e., with probability at least $1-\delta$, we have $|C_S - \hat{f}(S)| \leq \gamma$ for all $S \subset [n]$ with $|S| \leq d$, where $\gamma = \sqrt{\tau/n^d}$. This can be proved using the Chernoff bound and the union bound.

Second, we show that if all low degree Fourier coefficients are well approximated, then h has a low ℓ_2-error. Suppose $|C_S - \hat{f}(S)| \leq \gamma$ for all $S \subset [n]$ such that $|S| \leq d$. Let $g : \{\pm 1\}^n \to \mathbb{R}$ be defined by

$$g(x) = f(x) - h(x).$$

By the linearity of the Fourier transform, for all $S \subset [n]$,

$$\hat{g}(S) = \hat{f}(S) - \hat{h}(S).$$

For all $S \subset [n]$ with $|S| > d$, we have $\hat{h}(S) = 0$, so $\hat{g}(S) = \hat{f}(S)$. For all $S \subset [n]$ with $|S| \leq d$, we have $|\hat{g}(S)| \leq \gamma$, so $\hat{g}(S)^2 \leq \gamma^2$. Therefore,

$$\begin{aligned}
\mathop{\mathbb{E}}_{x\in\{\pm1\}^n}\left[(f(x)-h(x))^2\right] &= \mathbb{E}\left[g(x)^2\right] = \sum_{S\subset[n]} \hat{g}(S)^2 && \text{(Parseval's identity)} \\
&= \sum_{\substack{S\subset[n] \\ |S|\leq d}} \hat{g}(S)^2 + \sum_{\substack{S\subset[n] \\ |S|>d}} \hat{g}(S)^2 \\
&\leq \sum_{\substack{S\subset[n] \\ |S|\leq d}} \gamma^2 + \sum_{\substack{S\subset[n] \\ |S|>d}} \hat{f}(S)^2 \\
&\leq \binom{n}{d} \cdot \gamma^2 + \varepsilon && \text{(by Fourier concentration)} \\
&\leq \tau + \varepsilon.
\end{aligned}$$

This completes the proof. $\square$

Proposition 5. *Let $f : \{\pm1\}^n \to \{\pm1\}$. Let $h : \{\pm1\}^n \to \mathbb{R}$. Then*

$$\mathop{\mathbb{P}}_{x\in\{\pm1\}^n}[f(x) \neq \operatorname{sign}(h(x))] \leq \mathop{\mathbb{E}}_{x\in\{\pm1\}^n}\left[(f(x)-h(x))^2\right]$$

Proof. Recall that

$$\mathop{\mathbb{E}}_{x\in\{\pm1\}^n}\left[(f(x)-h(x))^2\right] = \frac{1}{2^n} \sum_{x\in\{\pm1\}^n} (f(x)-h(x))^2, \tag{1}$$

$$\mathop{\mathbb{P}}_{x\in\{\pm1\}^n}[f(x) \neq \operatorname{sign}(h(x))] = \frac{1}{2^n} \sum_{x\in\{\pm1\}^n} \mathbb{1}_{f(x)\neq\operatorname{sign}(h(x))}. \tag{2}$$

We compare (1) and (2) term by term. Let $x \in \{\pm1\}^n$. If $f(x) = \operatorname{sign}(h(x))$, then $\mathbb{1}_{f(x)\neq\operatorname{sign}(h(x))} = 0 \leq (f(x)-h(x))^2$. If $f(x) \neq \operatorname{sign}(h(x))$, then $\mathbb{1}_{f(x)\neq\operatorname{sign}(h(x))} = 1 \leq (f(x)-h(x))^2$; see Figure 1 for an illustration.

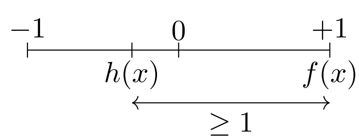

Figure 1: Illustrating the proof of Proposition 5.

$\square$

Theorem 6. *If a concept class $\mathcal{C}$ has Fourier concentration $d = \alpha(\varepsilon, n)$, then there exists a uniform distribution learning algorithm for $\mathcal{C}$ with $q = O((n^d/\varepsilon)\log(n^d/\delta))$ samples; i.e., this algorithm gets q samples and with probability at least $1-\delta$ outputs a hypothesis h' such that*

$$\mathop{\mathbb{P}}_{x\in\{\pm1\}^n}\left[f(x) \neq h'(x)\right] \leq 2\varepsilon.$$

Proof. Run the low degree algorithm with $\tau = \varepsilon$. By Proposition 4, we get a hypothesis h such that $\mathbb{E}_{x\in\{\pm1\}^n}[(f(x)-h(x))^2] \le \varepsilon + \varepsilon = 2\varepsilon$. Let $h' = \operatorname{sign} \circ h$. By Proposition 5, h' has error at most 2ε with respect to f. This completes the proof. $\square$

Following are examples of functions that have $\alpha(\varepsilon, n)$-Fourier concentration.

(i) Any function $f : \{\pm1\}^n \to \mathbb{R}$ that depends on at most k variables has

$$\sum_{\substack{S\subset[n]\\|S|>k}} \hat{f}(S)^2 = 0.$$

(ii) Let $T = \{i_1, \dots, i_k\} \subset [n]$ be such that $|T| = k$. Let $\mathsf{AND} : \{\pm1\}^n \to \{\pm1\}$ be defined by

$$\mathsf{AND}(x) = \begin{cases} -1, & \text{if } x_i = -1 \text{ for all } i \in T, \\ 1, & \text{otherwise.} \end{cases}$$

We claim that AND has $\log(4/\varepsilon)$-Fourier concentration. Note $\widehat{\mathsf{AND}}(S) = 0$ for all $S \subset [n]$ with $|S| > |T|$. If $|T| \le \log(4/\varepsilon)$, then we are done by definition. If $|T| > \log(4/\varepsilon)$, then

$$\widehat{\mathsf{AND}}(\emptyset)^2 = (1 - 2\,\mathbb{P}\,[f(x) \ne \chi_\emptyset(x)])^2 = \left(1 - 2 \cdot \frac{1}{2^{|T|}}\right)^2 > 1 - \varepsilon.$$

Therefore, AND has 0-Fourier concentration.

(iii) Let $T = \{i_1, \dots, i_k\} \subset [n]$ be such that $|T| = k$. Let $\overline{\mathsf{AND}} : \{\pm1\}^n \to \{\pm1\}$ be defined by

$$\overline{\mathsf{AND}}(x) = \begin{cases} 1, & \text{if } x_i = -1 \text{ for all } i \in T, \\ -1, & \text{otherwise.} \end{cases}$$

Let $f : \{\pm1\}^n \to \{0,1\}$ be defined by

$$\begin{aligned} f(x) &= \begin{cases} 1, & \text{if } x_i = -1 \text{ for all } i \in T, \\ 0, & \text{otherwise,} \end{cases} \\ &= \frac{1 - x_{i_1}}{2} \cdot \frac{1 - x_{i_2}}{2} \cdots \frac{1 - x_{i_k}}{2} \\ &= \frac{1}{2^k} \sum_{S\subset T} (-1)^{|S|} \chi_S(x). \end{aligned}$$

Note that all Fourier coefficients $\hat{f}(S)$ for $S \not\subset T$ are 0. Then

$$\overline{\mathsf{AND}}(x) = 2f(x) - 1 = -1 + \frac{2}{2^k} + \sum_{\substack{S\subset T\\S\ne\emptyset}} \frac{(-1)^{|S|}}{2^k} \chi_S(x).$$

(iv) ***Decision trees.*** Consider a decision tree T, e.g., Figure 2. For each leaf ℓ of T, let V_ℓ denote the set of indices of variables visited on the path from the root to leaf ℓ, and let $f_\ell : \{\pm1\}^n \to \{0,1\}$ be defined by

$$f_\ell(x) = \prod_{i\in V_\ell} \frac{1 \pm x_i}{2} \qquad \text{(“}\pm\text{” denotes a left turn or a right turn)}$$

$$= \frac{1}{2^{|V_\ell|}} \sum_{S \subset V_\ell} (-1)^{\#\text{ left turns taken in } S} \chi_S.$$

Let $f : \{\pm 1\}^n \to \{\pm 1\}$ be defined by

$$f(x) = \sum_{\ell\text{: leaf of } T} f_\ell(x)\,\mathrm{val}(\ell).$$

Note that for each $x \in \{\pm 1\}^n$, exactly one of the values $f_\ell(x)$ is 1 for leaves ℓ of T, and all others are 0. Moreover, for each leaf ℓ of T, the number of variables on which f_ℓ depends is at most the depth of ℓ. By the linearity of the Fourier transform,

$$\hat{f}(S) = \sum_{\ell\text{: leaf of } T} \widehat{f_\ell}(S)\,\mathrm{val}(\ell).$$

Therefore, $\hat{f}(S) = 0$ for all $S \subset [n]$ such that $|S|$ is greater than the depth of T.

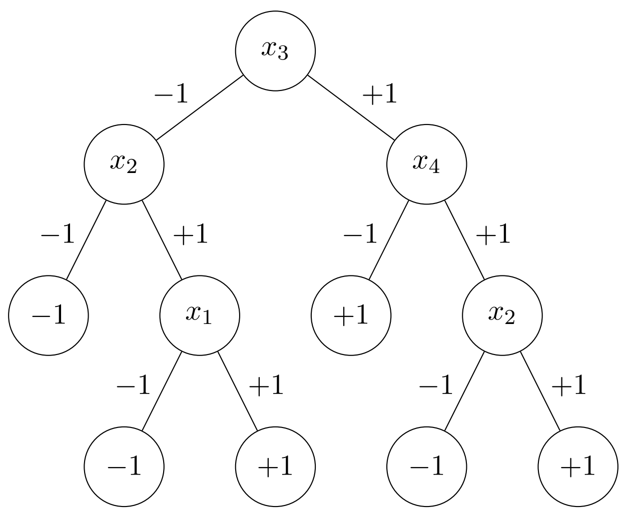

Figure 2: A decision tree.

(v) ***Constant depth circuits.*** Recall that a Boolean circuit is a DAG whose vertices are gates which represent operations (e.g., $\wedge, \vee, \neg$), constants $(1, 0)$ and variables $(x_1, \ldots, x_n)$. We allow each operation to have an unbounded number of inputs; the $\neg$ gate can have only one input. Can we compute the parity (XOR) of n bits in a constant depth with a polynomial-size input for each operation? The answe is "no," which follows from the switching lemma by Furst, Saxe and Sipser.

Theorem 7 (Hastad, Linial, Mansour and Nisan)**.** *For any function f computable via a size-s depth-d circuit,*

$$\sum_{\substack{S \subset [n] \\ |S| > t}} \hat{f}(S)^2 \le \alpha,$$

where $t = O(\log(s/\alpha))^{d-1}$.

Taking $s = \mathrm{poly}(n)$, $d = O(1)$ and $\alpha = O(\varepsilon)$ implies $t = O(\log^d(n/\varepsilon))$. Therefore, the low degree algorithm gives an $n^{O(\log^d(n/\varepsilon))}$ sample algorithm for learning.

(vi) ***Learning half-spaces.***

Definition 8. For $w \in \mathbb{R}^n$ and $\theta \in \mathbb{R}$, the function $h : \{\pm 1\}^n \to \{\pm 1\}$ defined by $h(x) = \text{sign}(w \cdot x - \theta)$ is called a *half-space function.*

Theorem 9. *A half-space function $h : \{\pm 1\}^n \to \{\pm 1\}$ has Fourier concentration $\alpha(\varepsilon) = c/\varepsilon^2$ for some constant c.*

Corollary 10. *The low degree algorithm learns half-spaces with $n^{O(1/\varepsilon^2)}$ samples.*

4.3 Noise Sensitivity

Definition 11. For $\varepsilon \in (0, 1/2)$, the *noise operator* $N_\varepsilon(x)$ randomly flips each bit of x with probability ε, given $x \in \{\pm 1\}^n$.

Definition 12. The *noise sensitivity* of a Boolean function $f : \{\pm 1\}^n \to \{\pm 1\}$ is defined to be

$$\text{NS}_\varepsilon(f) = \mathop{\mathbb{P}}_{\substack{x \in \{\pm 1\}^n \\ \text{noise}}} \left[f(x) \neq f\left(N_\varepsilon(x)\right) \right].$$

Following are examples of the noise sensitivity of a Boolean function.

(i) If $f(x) = x_1$, then $\text{NS}_\varepsilon(f) = \varepsilon$.

(ii) If $f(x) = x_1 \cdots x_k$, then

$$\begin{aligned} \text{NS}_\varepsilon(f) &= \mathbb{P}[f(x) = \mathsf{F}, f(N_\varepsilon(x) = \mathsf{T})] + \mathbb{P}[f(x) = \mathsf{T}, f(N_\varepsilon(x) = \mathsf{F})] \\ &= 2\,\mathbb{P}[f(x) = \mathsf{T}, f(N_\varepsilon(x) = \mathsf{F})] \\ &= 2 \cdot \frac{1}{2^k} \cdot (1 - (1-\varepsilon)^k). \end{aligned}$$

Therefore, if $\varepsilon \ll 1/k$, then $\text{NS}_\varepsilon(f) \approx \varepsilon k / 2^{k-1}$; if $\varepsilon \gg 1/k$, then $\text{NS}_\varepsilon(f) \approx (1 - e^{-\varepsilon k})/2^{k-1}$.

(iii) If $f(x) = \text{Maj}(x_1, \ldots, x_n)$, then $\text{NS}_\varepsilon(f) = O(\sqrt{\varepsilon})$.

To see this, note that $\text{Maj}(x)$ corresponds to a random walk on a line starting at 0, and that the location corresponds to the sum of the x_i's so far.

Fact 13. *If $X_1, \ldots, X_n \in \{\pm 1\}$ are i.i.d random variables, then $\mathbb{E}[|X_1 + \ldots + X_n|] = \sqrt{n}$, and (informally) $|X_1 + \ldots + X_n|$ is likely to be close to $\sqrt{n}$.*

Therefore, $N_\varepsilon(x)$ corresponds to a random walk on εn bits, where each flip displaces by ± 2. By Fact 13, the expected displacement is $2\sqrt{\varepsilon n}$.

Given $x \in \{\pm 1\}^n$, we consider the following process:

1. Talk a walk specified by x.
2. Continue the walk according to $2N_\varepsilon(x)$.

Pretend that the first walk leaves us at $\sqrt{n}$. By Markov's inequality,

$$\begin{aligned} \mathbb{P}[\text{the second walk takes us accross } 0] &= \frac{1}{2}\,\mathbb{P}[\text{the second displacement is greater than } \sqrt{n}] \\ &= \frac{1}{2} \cdot \frac{\mathbb{E}[\text{the second displacement}]}{\sqrt{n}} \\ &= \frac{1}{2} \cdot \frac{2\sqrt{\varepsilon n}}{\sqrt{n}} = \sqrt{\varepsilon}. \end{aligned}$$

(iv) ***Linear threshold functions (half-spaces).***

Theorem 14. *If f is a linear threshold function (i.e., a half-space), then* $\mathrm{NS}_\varepsilon(f) < 8.8\sqrt{\varepsilon}$.

(v) ***Parity functions.***

Proposition 15. *Let $S \subset [n]$ be such that $|S| = k$. Then*

$$\mathrm{NS}_\varepsilon\left(\chi_S\right) = \frac{1-(1-2\varepsilon)^k}{2}.$$

(vi) ***Any function.***

Theorem 16. *For any $f : \{\pm 1\}^n \to \{\pm 1\}$,*

$$\mathrm{NS}_\varepsilon(f) = \frac{1}{2} - \frac{1}{2}\sum_{S\subset[n]} (1-2\varepsilon)^{|S|}\hat{f}(S)^2.$$

The proof of Theorem 16 is in homework.

Next, we show the relation between noise sensitivity and Fourier concentration.

Theorem 17. *For any $f : \{\pm 1\}^n \to \{\pm 1\}$ and $\gamma \in (0, 1/2)$,*

$$\sum_{\substack{S\subset[n]\\ |S|\geq \frac{1}{\gamma}}} \hat{f}(S)^2 < 2.32\,\mathrm{NS}_\gamma(f).$$

Proof. We have

$$\begin{aligned}
2\,\mathrm{NS}_\gamma(f) &= 1 - \sum_{S\subset[n]} (1-2\gamma)^{|S|}\hat{f}(S)^2 && \text{(Theorem 16)}\\
&= \sum_{S\subset[n]} \left(\hat{f}(S)^2 - (1-2\gamma)^{|S|}\hat{f}(S)^2\right) && \text{(Boolean Parseval's identity)}\\
&= \sum_{S\subset[n]} \left(1-(1-2\gamma)^{|S|}\right)\hat{f}(S)^2\\
&\geq \sum_{\substack{S\subset[n]\\ |S|\geq \frac{1}{\gamma}}} \left(1-(1-2\gamma)^{\frac{1}{\gamma}}\right)\hat{f}(S)^2\\
&> \sum_{\substack{S\subset[n]\\ S|\geq \frac{1}{\gamma}}} \left(1-e^{-2}\right)\hat{f}(S)^2.
\end{aligned}$$

Therefore,

$$\sum_{\substack{S\subset[n]\\ |S|\geq \frac{1}{\gamma}}} \hat{f}(S)^2 \leq \mathrm{NS}_\gamma(f)\left(\frac{1}{1-e^{-2}}\right) < 2.32\,\mathrm{NS}_\gamma(f).$$

This completes the proof. $\square$

Corollary 18. *For any half-space $h : \{\pm 1\}^n \to \{\pm 1\}$,*

$$\sum_{\substack{S \subset [n] \\ |S| \geq O(1/\varepsilon^2)}} \hat{f}(S)^2 \leq \varepsilon.$$

Therefore, one can learn any half-space from $n^{O(1/\varepsilon^2)}$ random examples.

Corollary 19. *Any function of k half-spaces can be learned with $n^{O(k^2/\varepsilon^2)}$ samples.*

4.4 Learning Heavy Fourier Coefficients

Given $\theta > 0$ and black box access to $f : \{\pm 1\}^n \to \{\pm 1\}$, we want to

(i) output all coefficients $S \subset [n]$ such that $|\hat{f}(S)| \geq \theta$;

(ii) only output coefficients $S \subset [n]$ such that $|\hat{f}(S)| \geq \theta/2$.

The main idea is *exhaustive search with good pruning.* The search tree consists of n levels, each representing a variable x_i for $i \in [n]$. For each level $i \in [n]$, going left means $x_i \in S$, and going right means $x_i \notin S$. Informally, we only go down paths with lots of "weights," and we output leaves reached at the bottom level.

Fix $k \in \{0, \ldots, n\}$ representing the current level of search. Fix $S_1 \subset [k]$ representing the current node of search. Let $f_{k,S_1} : \{\pm 1\}^{n-k} \to \mathbb{R}$ be defined by

$$f_{k,S_1}(x) = \sum_{T \subset \{k+1,\ldots,n\}} \hat{f}\left(S_1 \cup T_2\right) \chi_{T_2}(x).$$

Note that we could replace χ_{T_2} with $\chi_{S_1 \cup T_2} = \chi_{S_1} \cdot \chi_{T_2}$, but χ_{S_1} remains the same. If $k = 0$, then

$$f_{0,\emptyset}(x) = \sum_{T_2 \subset [n]} \hat{f}\left(T_2\right) \chi_{T_2}(x) = f(x).$$

On the other hand, if $k = n$, then for any $S_1 \subset [n]$,

$$f(n, S_1)(x) = \sum_{T_2 \subset \emptyset} \hat{f}\left(S_1 \cup T_2\right) \chi_{T_2}(x) = \hat{f}\left(S_1\right).$$

The plan is to only go down paths with $\mathbb{E}[f_{k,S_1}(x)^2] \geq \theta^2$. There are several questions to answer:

(i) Can we compute it?

(ii) Does it bring us to right leaves? In other words, do we get to all heavy leaves, and do we get to junks (i.e., light leaves)?

(iii) How many paths do we take? In other words, are there a lot of dead ends, and is the running time good?

First, we show that there are not too many paths.

Lemma 20. *Let $f : \{\pm 1\}^n \to \{\pm 1\}$.*

(i) At most $1/\theta^2$ sets $S \subset [n]$ satisfy $|\hat{f}(S)| \geq \theta$.

(ii) For all $k \in \{0, \ldots, n\}$, at most $1/\theta^2$ functions f_{k,S_1} have $\mathbb{E}_{x \in \{\pm 1\}^{n-k}}[f_{k,S_1}(x)^2] \geq \theta^2$.

Lemma 20 implies that our algorithm explores at most $O(1/\theta^2)$ nodes of the search tree.

Proof. (i) By the Boolean Parseval's identity,

$$1 = \mathop{\mathbb{E}}_{x \in \{\pm 1\}^n} \left[f(x)^2 \right] = \sum_{S \subset [n]} \hat{f}(S)^2.$$

Therefore, if more than $1/\theta^2$ sets $S \subset [n]$ had $|\hat{f}(S)| \geq \theta$, then

$$\sum_{S \subset [n]} \hat{f}(S)^2 > \frac{1}{\theta} \cdot \theta^2 = 1,$$

a contradiction.

(ii) Let $k \in \{0, \ldots, n\}$. First, we claim that for all $S_1 \subset [k]$,

$$\mathop{\mathbb{E}}_{x \in \{\pm 1\}^{n-k}} \left[f_{k,S_1}(x)^2 \right] = \sum_{T_2 \subset \{k+1, \ldots, n\}} \hat{f}\left(S_1 \cup T_2\right)^2.$$

To se this, we have

$$\begin{aligned}
\mathop{\mathbb{E}}_{x \in \{\pm 1\}^{n-k}} \left[f_{k,S_1}(x)^2 \right] &= \mathop{\mathbb{E}}_{x \in \{\pm 1\}^{n-k}} \left[\left(\sum_{T_2 \subset \{k+1, \ldots, n\}} \hat{f}\left(S_1 \cup T_2\right) \chi_{T_2} \right)^2 \right] \\
&= \mathop{\mathbb{E}}_{x \in \{\pm 1\}^{n-k}} \left[\sum_{T_2, T_2' \subset \{k+1, \ldots, n\}} \hat{f}\left(S_1 \cup T_2\right) \hat{f}\left(S_1 \cup T_2'\right) \chi_{T_2}(x) \chi_{T_2'}(x) \right] \\
&= \sum_{T_2, T_2' \subset \{k+1, \ldots, n\}} \hat{f}\left(S_1 \cup T_2\right) \hat{f}\left(S_1 \cup T_2'\right) \mathop{\mathbb{E}}_{x \in \{\pm 1\}^{n-k}} \left[\chi_{T_2}(x) \chi_{T_2'}(x) \right].
\end{aligned}$$

Note that

$$\mathop{\mathbb{E}}_{x \in \{\pm 1\}^{n-k}} \left[\chi_{T_2}(x) \chi_{T_2'}(x) \right] = \begin{cases} 0, & \text{if } T_2 \neq T_2', \\ 1, & \text{if } T_2 = T_2'. \end{cases}$$

Therefore,

$$\mathop{\mathbb{E}}_{x \in \{\pm 1\}^{n-k}} \left[f_{k,S_1}(x)^2 \right] = \sum_{T_2 \subset \{k+1, \ldots, n\}} \hat{f}\left(S_1 \cup T_2\right)^2.$$

This proves the claim.

Therefore,

$$\begin{aligned}
1 &= \sum_{S \subset [n]} \hat{f}(S)^2 && \text{(Boolean Parseval's identity)} \\
&= \sum_{S_1 \subset [k]} \sum_{T_2 \subset \{k+1, \ldots, n\}} \hat{f}\left(S_1 \cup T_2\right)^2 \\
&= \sum_{S_1 \subset [k]} \mathop{\mathbb{E}}_{x \in \{\pm 1\}^{n-k}} \left[f_{k,S_1}(x)^2 \right] && \text{(above claim)}
\end{aligned}$$

Therefore, at most $1/\theta^2$ sets $S_1 \subset [k]$ have $\mathbb{E}_{x \pm \{\pm 1\}^{n-k}}[f_{k,S_1}(x)^2] \geq \theta^2$.

□