Weighted Polynomial Approximations: Limits for Learning and Pseudorandomness

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Derandomizing Concentration Inequalities

• Chernoff-Hoeffding Bound: Let $v \in \mathbb{R}^n$ and $U_n \in \{-1, 1\}^n$ be uniform. Then

$$\Pr[|\langle U_n, v \rangle| \ge T ||v||_2] \le \exp(-\Omega(T^2)).$$

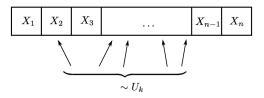
 Algorithmic applications, e.g. dimensionality reduction via Johnson-Lindenstrauss

$$\begin{bmatrix} -1 & 1 & 1 & \dots & -1 \\ 1 & -1 & 1 & \dots & 1 \end{bmatrix} \times \begin{bmatrix} -1 & 1 & \dots & -1 \\ 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Motivating question: What <u>pseudorandom</u> X suffice in place of U_n?

- Main result: Lower bound for derandomizing Chernoff via k-wise independence
- (Non-constructive) proof by way of polynomial approximations
- Similar ideas give lower bounds for agnostically learning halfpsaces

 $X \in \{-1,1\}^n$ is $\underline{k\text{-wise independent}}$ if every subset of k variables is uniform:



Simple and pervasive notion of pseudorandomness



Naturally gives rise to the Chernoff bound

Chernoff Bound from *k*-Wise Independence [Schmidt-Siegel-Srinivasan93]

Proof of Chernoff by moment bounds: Let $v \in \mathbb{R}^n$ be a unit vector

$$\begin{split} \Pr[|\langle U_n, v \rangle| \geq T] &= \Pr[(\langle U_n, v \rangle)^k \geq T^k] \\ &\leq \frac{E[\langle U_n, v \rangle^k]}{T^k} \qquad \text{(Markov's Inequality)} \\ &\leq \frac{k^{k/2}}{T^k} \qquad \text{(Khintchine-Kahane)} \end{split}$$

- For a tail bound of δ and $T=\sqrt{\log(1/\delta)},$ it suffices to take $k=O(\log(1/\delta))$
- Can replace U_n with any k-wise independent X, since $E[\langle X, v \rangle^k] = E[\langle U_n, \overline{v \rangle^k}]$

A k-wise independent X requires seed length $O(k \log n)$ [ABI86] \implies PRG with seed length $O(\log n \cdot \log(1/\delta)) = O(\log^2 n)$ Think of $\delta = 1/\operatorname{poly}(n)$

Question: Is the [SSS93] analysis optimal? (Or can k be reduced?)

Other PRGs for Chernoff:

Construction	Seed length
Probabilistic method	$O(\log n + \log(1/\delta)) = O(\log n)$
Small-bias spaces [NN90]	$O(\log n \cdot \log(1/\delta)) = O(\log^2 n)$
PRG for small space [Nis92,INW94]	$O(\log n \cdot \log(n/\delta)) = O(\log^2 n)$
PRG for Fourier shapes [GKM15]	$\tilde{O}(\log n + \log(1/\delta)) = \tilde{O}(\log n)$

Main Result

Theorem (Main)

Let $\delta \leq 1/\operatorname{poly}(n)$ and $T = \Theta(\sqrt{\log(1/\delta)})$. For $k = \Omega(\log(1/\delta))$, there exists a k-wise independent X for which

$$\Pr[|X_1 + \dots + X_n| \ge T\sqrt{n}] > \delta.$$

- Matches upper bound of [SSS93]
- Previous lower bound [SSS93] of

$$k \ge \Omega\left(\frac{\log(1/\delta)}{\log n}\right)$$

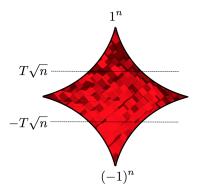
is constant for $\delta = 1/\operatorname{poly}(n)$

I Dual formulation of problem [Bazzi07, DGJSV09]: Chernoff bound via k-wise independence ⇔ Threshold function well-approximated by a degree-k polynomial

2 Lower bound k using real approximation theory

LP and dual formulations of derandomizing Chernoff by *k*-wise independence

"What is the worst tail bound given by a k-wise independent X?"



"What is the worst tail bound given by a k-wise independent X ?" Let $\psi(x)=\Pr[X=x]$

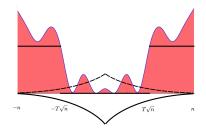
$$\begin{split} \max_{\psi} \sum_{x \in \{-1,1\}^n} \psi(x) \cdot \mathbb{1}(|x_1 + \dots + x_n| \ge T\sqrt{n}) \\ \text{s.t.} \sum_{x \in \{-1,1\}^n} \psi(x) \cdot \chi_S(x) &= 0 & \text{for all } |S| \le k \\ & \sum_{x \in \{-1,1\}^n} \psi(x) = 1 \\ & 0 \le \psi(x) \le 1 & \text{for all } x \in \{-1,1\}^n \end{split}$$

"What is the smallest L_1 -norm of any degree-k upper sandwiching polynomial?"

$$\begin{split} & \min_{p} \ 2^{-n} \sum_{x \in \{-1,1\}^n} p(x) \\ & \text{s.t. } \deg(p) \le k \\ & p(x) \ge \mathbb{1}(|x_1 + \dots + x_n| \ge T\sqrt{n}) \quad \text{for all } x \in \{-1,1\}^n \end{split}$$

Dual Formulation [Bazzi07]

"What is the smallest L_1 -norm of any degree-k upper sandwiching polynomial?"



Theorem: There exists a k-wise independent X with a tail bound worse than δ

\Leftrightarrow

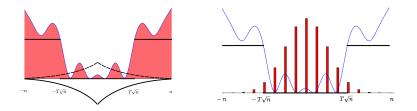
Every upper sandwich with $L_1\text{-norm}$ at most δ has degree greater than k

Goal: Lower bound the degree of any upper sandwich with low L_1 -norm

Simplifying the Problem

Symmetrization [MinskyPapert69]

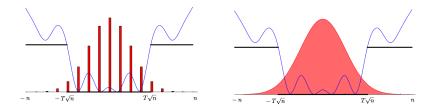
Any upper sandwich p can be turned into a univariate p^{sym} :



deg(p^{sym}) ≤ deg(p)
 p^{sym} is an upper sandwich for univariate threshold function
 L₁-norm of p = L₁-norm of p^{sym} under binomial distribution

Approximation by a Gaussian

 L_1 -norm of p^{sym} under binomial distribution \approx L_1 -norm of p^{sym} under Gaussian



Technical step: $p^{\rm sym}$ bounded at integers $\Rightarrow p^{\rm sym}$ bounded on reals [EhlichZeller64]

 $-T\sqrt{n}$

-n

Approximation by a Gaussian

$$\deg(p^{\mathsf{sym}}) = k \text{ and } L_1(p^{\mathsf{sym}}) \leq \delta \text{ (under binomial distribution)}$$

$$\implies p^{\mathsf{sym}}(t) \leq \delta n \text{ for all } t \in [-\sqrt{kn}, \sqrt{kn}]$$

Technical step: $p^{\rm sym}$ bounded at integers $\Rightarrow p^{\rm sym}$ bounded on reals [EhlichZeller64]

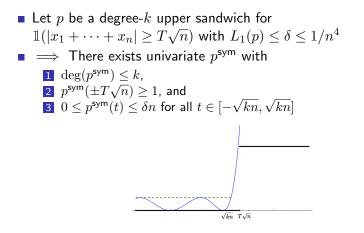
n

-n $-T\sqrt{n}$ $-\sqrt{kn}$ \sqrt{kn} $T\sqrt{n}$

n

 $T\sqrt{n}$

The Final Step



■ $p^{\text{sym}}(T\sqrt{n}) \le \delta n \cdot \text{Chebyshev}_k\left(\frac{T\sqrt{n}}{\sqrt{kn}}\right) \le \delta n \cdot \left(\frac{2T}{\sqrt{k}}\right)^k$ ■ Conclusion: $k \ge \Omega(\log(1/\delta))$

Recap

Theorem (Main)

Let $\delta \leq 1/\operatorname{poly}(n)$ and $T = \Theta(\sqrt{\log(1/\delta)})$. For $k = \Omega(\log(1/\delta))$, there exists a k-wise independent X for which

$$\Pr[|X_1 + \dots + X_n| \ge T\sqrt{n}] > \delta.$$

■ Dual formulation of problem [Bazzi07, DGJSV09]: Chernoff bound via k-wise independence ⇔ Threshold function well-approximated by a degree-k polynomial

2 By real approximation theory, $k \ge \log(1/\delta)$

Open Questions

- Explicit bad k-wise independent distribution? (cf. dual witnesses for approximate degree lower bounds [Špalek08, B.-Thaler13])
- Seed length needed for small-bias spaces? XORs of small-bias spaces?

Thank you!

Agnostically Learning Halfspaces

Learning with Noise: The Agnostic Model

"Techno Nightmares"







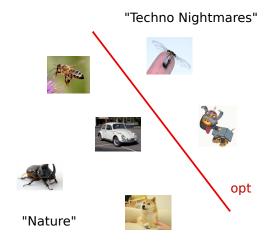




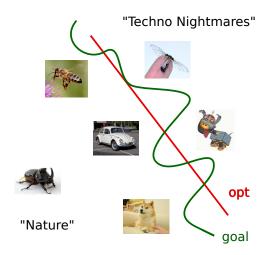
"Nature"



Learning with Noise: The Agnostic Model



Learning with Noise: The Agnostic Model



Agnostically Learning Halfspaces

- [KalaiKlivansMansourServedio05] gave an efficient algorithm under distributional assumptions
- E.g., if distribution on examples in \mathbb{R}^n is log-concave, then any halfspace \approx a low-degree polynomial
- Question: Can the log-concavity assumption be relaxed?
- This work: For mildly log-convex distributions, there exist halfspaces that cannot be approximated by polynomials of <u>any</u> <u>degree</u>
- Draws on *L*₁-approximation theory [NevaiTotik86,87]