## COMP760, SUMMARY OF LECTURE 11.

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- Dual characterization of approximate degree: Fix $\epsilon>0$, and let $f:\{0,1\}^{n} \rightarrow \mathbb{R}$ be given, $d=\operatorname{deg}_{\epsilon}(f) \geq 1$. Then there is a function $\Psi:\{0,1\}^{n} \rightarrow \mathbb{R}$ such that

$$
\begin{array}{ll}
\widehat{\psi}(S)=0 & (|S|<d) \\
\sum_{x \in\{0,1\}^{n}}|\psi(x)|=1 & \\
\sum_{x \in\{0,1\}^{n}} \psi(x) f(x)>\epsilon . &
\end{array}
$$

- Dual characterization of sign degree: Let $f:\{0,1\}^{n} \rightarrow \mathbb{R}$ be given. Then $\operatorname{deg}_{\epsilon}(f)>d$ if and only if there is a distribution $\mu$ over $\{0,1\}^{n}$ with

$$
\widehat{f \mu}(S)=\mathbb{E}_{\mu}\left[f(x) \chi_{S}(x)\right]=0 \quad(|S| \leq d)
$$

- Let $F$ be the ( $n, t, f$ )-pattern matrix. If we plug-in the $(n, t, \psi)$-pattern matrix $\Psi$, where $\psi$ is from the dual characterization of the approximate degree, in the lower-bound

$$
R_{\delta}(F) \geq \log \frac{\langle F, \Psi\rangle-2 \delta\|\Psi\|_{1}}{\|\Psi\| \sqrt{|X||Y|}}
$$

and use the bound from the previous lecture [She09, Theorem 4.3],

$$
\|\Psi\|=\max _{S: \widehat{\psi}(S) \neq 0} \sqrt{2^{n+t}\left(\frac{n}{t}\right)^{t-|S|}}|\widehat{\psi}(S)|
$$

together with the obvious bound

$$
|\widehat{\psi}(S)| \leq 2^{-t} \sum_{z}|\psi(z)|
$$

we obtain the following theorem:
Theorem 1 (She09, Theorem 4.8]). For the ( $n, t, f$ )-pattern matrix $F$, and $\epsilon>0$ and $\delta<\epsilon / 2$, we have

$$
R_{\delta}(F) \geq \frac{1}{2} \operatorname{deg}_{\epsilon}(f) \log (n / t)-\log \left(\frac{1}{\epsilon-2 \delta}\right) .
$$

- Let $F$ be the ( $n, t, f$ )-pattern matrix. Consider the $\left(n, t, 2^{-n}\left(\frac{n}{t}\right)^{-t} \mu f\right)$-pattern matrix $\Psi$, where $\mu$ is from the dual characterization of the approximate degree. Note that $\Psi(x, y)=$ $F(x, y) \nu(x, y)$ where $\nu$ is a probability measure on $X \times Y$, where $X$ and $Y$ respectively correspond to the rows and columns of $F$. Hence

$$
\operatorname{disc}_{\nu}(F)=\operatorname{disc}_{\text {uniform }}(\Psi) \leq\|\Psi\| \sqrt{|X||Y|}=\|\Psi\| \sqrt{2^{n}\left(\frac{n}{t}\right)^{t} 2^{t}} .
$$

Again using the bound from the previous lecture [She09, Theorem 4.3],

$$
\left.\|\Psi\|=\max \bigcup_{S: \widehat{\mu f}(S) \neq 0} \sqrt{2^{n+t}\left(\frac{n}{t}\right)^{t-|S|}} \widehat{\mu f}(S) \right\rvert\,
$$

together with

$$
|\widehat{\mu f}(S)| \leq 2^{-t} \sum_{z}|\mu(z)| \leq 2^{-t}
$$

we obtain the following theorem:
Theorem 2 ([She09, Theorem 4.13]). For the ( $n, t, f$ )-pattern matrix $F$,

$$
\operatorname{disc}(F) \leq\left(\frac{n}{t}\right)^{-\operatorname{deg}_{ \pm}(f) / 2}
$$

- It is well-known that he Minsky-Papert function

$$
\operatorname{MP}_{m}(x)=\wedge_{i=1}^{m} \vee_{j=1}^{4 m^{2}} x_{i j}
$$

satisfies $\operatorname{deg}_{ \pm}\left(\mathrm{MP}_{m}\right) \geq m$. Since the $\left(8 m^{3}, 4 m^{3}, \mathrm{MP}_{m}\right)$-pattern matrix is a submatrix of $[f(x, y)]_{x, y \in\{0,1\}^{4 m^{3}}}$ where $f(x, y):=\operatorname{MP}_{m}(x \wedge y)=\wedge_{i=1}^{m} \vee_{j=1}^{4 m^{2}}\left(x_{i j} \wedge y_{i j}\right)$, we conclude that

$$
\operatorname{disc}(f)=\operatorname{disc}(\neg f) \leq 2^{-\Omega(m)}
$$

which in particular shows that $f \notin \mathrm{PP}^{c c}$. Since $f \in P i_{2}^{c c}$ and $\neg f \in \Sigma_{2}^{c c}$ we conclude
Theorem 3. We have

$$
\Pi_{2}^{c c}, \Sigma_{2}^{c c} \nsubseteq \mathrm{PP}^{c c}
$$

Recall from the assignment 2 that

$$
\Pi_{1}^{c c}, \Sigma_{1}^{c c} \subseteq \mathrm{PP}^{c c}
$$

## References

[She09] Alexander A. Sherstov, Lower bounds in communication complexity and learning theory via analytic methods, Ph.D. thesis, The University of Texas at Austin, 82009.

