GCT Workshop - Online lecture series Lower bounds- Lecture 2

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Agenda: - Nisan's lower bound for non-commutative ABAs

- Kayal's measure of shifted partial derivatives
- Some lower bounds using shifted partials ad variants.
Recap: General lower bounds template:
$-\Gamma: \mathbb{F}[\bar{x}] \rightarrow \mathbb{R}$, as a proxy for size.
- For any $f \in e$, show $\Gamma(f)$ is "small"
- Heuristically verify that $T(R)$ is "large" for a random $R$
- Find hay in a haystack.

Some common measures:

$$
\begin{aligned}
& \triangleright \Gamma_{k}(f)=\operatorname{dim}\left(\partial^{=k}(f)\right) \\
& =\operatorname{dim}\left(\operatorname{sp}\left\{\frac{\partial^{k} f}{\partial m}: \quad m_{q \text { is a }} \quad \text { mon }{ }^{2}\right\}\right) \\
& \Gamma_{k}\left(x_{1} \ldots x_{n}\right)=\binom{n}{k} \\
& \Gamma_{k}\left(\operatorname{ESym}_{d}\right) \approx \min \left\{\binom{n}{k},\binom{n}{d-k}\right\} \\
& \Gamma_{k}(\operatorname{Det} n)=\binom{n}{k}^{2} \\
& \Gamma_{k}\left(l^{d}\right)=1 \\
& \Gamma_{k}\left(\nmid \ldots l_{d}\right) \leqslant\binom{ d}{k}
\end{aligned}
$$

Useful to prove $L B_{s}$ for $\Sigma N \Sigma$ and $\sum \pi^{[d]} \Sigma$.
$\Delta x=y \omega z$.

$$
\Gamma_{y \omega z}(f)=\operatorname{rakk}\left(M_{y \nu z}(f)\right)
$$

$$
\operatorname{coeff}_{f}\left(m_{1} m_{2}\right)
$$

$$
\begin{aligned}
& \Gamma_{y u z}\left(x_{1} \ldots x_{n}\right)=1 \\
& \Gamma_{y \cup z}(f(y) g(z))=1 \\
& \Gamma_{y U Z}\left(\operatorname{ESym}_{d}\right) \leqslant d
\end{aligned}
$$



$$
\operatorname{Row}(m)=\sigma_{y=0} \partial_{m}(f)
$$

very useful for multilinear \& non-commutative models.
$\triangle$ Other measures:
[Baur-strassen] $\Gamma_{\bar{a}}(f)=\#\{\bar{x}:(\nabla f)(\bar{x})=\bar{a}\}$.

$$
2^{s} \geqslant \Gamma \bar{a}\left(\sum x_{i}^{d}\right) \geqslant(d-1)^{n}
$$

[Mignon-Ressayre] $\Gamma_{x_{0}}(f)=\operatorname{rark}\left(\operatorname{Hess}\left(f_{0}\right)\left(x_{0}\right)\right)$ where $f\left(x_{0}\right)=0$.

$$
\begin{aligned}
& \Gamma_{x_{0}}(f) \leqslant 2 m \text { if } d c(f) \leqslant m . \\
& \Gamma_{x_{0}}\left(\text { Perm }_{n}\right)=n^{2}
\end{aligned}
$$

Other non-natural measures:
[kumar], [Chatterjee-Kumar-She-Volk], [Grigoriev-karpingki] etc.

Non-commutative models:
Alg. models where inputs may not commute (like say evaluated on matrices).

Stuff needs to be multiplied in the right order! ne Formulas $\subseteq$

$$
\subseteq \quad n c-A B P
$$


$\underset{\neq}{C}$


Them: [Nisan] exp. sep between ABPs \& circuits in the nc-world.

Rem: The usual depth rede. does not work.
[Nisan]: Given any hom-ne.poly $f$, we car exactly find the smallest home. $n c-A B P$ for $f$.


$$
\begin{aligned}
& f=\sum_{j=1}^{\omega_{i}} g_{j} \cdot h_{j} \\
& M^{(i)}(f)=
\end{aligned}
$$



In fact, we con build the smallest nom ABP for $f$.


$$
M^{(c)}(f)=\square
$$

Each colum is a poly
Inv: $g_{1}, ., g_{w}$ are columns in ${ }^{\text {deg }}$ the matrix $M_{i}$ that span all other columns.
What is column corr. to $m$ ? "Right derivative".
(Pick up all mons with " $m$ " at its and) $\Delta_{m}(f)=g$.
For any $m$ of $\operatorname{deg} d-i, \quad \Delta_{m}(f)=\sum \beta_{j} g_{j}$ Maintaining the invo
$M^{(i+1)}(f)$, and say $g_{1}^{\prime} \ldots g_{\gamma}^{\prime}$ is a basis $q$ columns.
$g_{a}^{\prime}=\Delta_{m^{\prime}}(f)$ where $m^{\prime}$ has deg $d-i-1$ $\begin{aligned} g_{a}^{\prime} H_{x_{1}} & =\sum_{k=1}^{n} \Delta_{x_{k} m^{\prime}}(f) \cdot x_{k} \\ & =\sum \beta_{j k} \cdot g_{j} \cdot x_{k} .\end{aligned}$


Partial derivatives and their friends.
Recall: $2^{\Omega(n)}$ lb for $\sum_{u \Sigma}$ celts computing $x_{1} \ldots x_{n}$ $\sum^{\prime \prime} l_{i}^{d}$
On: What if the model is sums of quadratics?

$$
\begin{aligned}
& \sum Q_{i}^{d / 2} ? \\
& \partial_{x}\left(Q^{d}\right)=Q^{d-1} \cdot \operatorname{lin} . \\
& \partial^{=k}\left(Q^{d}\right)=Q^{d-k} \cdot(\operatorname{deg} k)
\end{aligned}
$$

Obs: $\operatorname{dim}\left(\partial_{\prime \prime}^{\partial^{\prime k}}\left(Q^{d}\right)\right) \leqslant\binom{ n+k}{k}$

$$
\Gamma_{k}^{\prime \prime}\left(Q^{d}\right)
$$

$\Gamma_{k}(R) \stackrel{\text { hope }}{\sim} \min \left\{\frac{\binom{n+k}{n},\binom{n+d-k}{n}}{\text { useless. }}\right.$.
In fact, $\operatorname{dim} \partial^{a k}\left(\left(x_{1}^{2}+\ldots+x_{n}^{2}\right)^{d}\right) \approx\binom{n+k}{k}$
[kayal] What if we add shifts?

$$
x^{=l} \partial^{=k}\left(Q^{d}\right) \subseteq \operatorname{sp}\left\{Q^{d-k} \cdot(\operatorname{deg} k+l)\right\} .
$$

Obs: $\operatorname{dim}\left(x^{=l} \partial^{=k}\left(Q^{d}\right)\right) \leqslant\binom{ n+l+k}{n}$
$\Gamma_{k, l}(R) \quad \stackrel{\text { hope }}{\approx} \min \left\{\binom{n+k}{k}\binom{n+l}{n},\binom{n+l+d-k}{n}\right\}$.
does this work?

Finding the right parameter choices is tricky...
Strangely, the "right" $l \geqslant n$..

$$
\frac{\binom{n+k}{k}\binom{n+l}{n}}{\binom{n+k+l}{n}} \approx \frac{\left(\frac{n}{k}\right)^{k} \cdot\left(\frac{l}{n}\right)^{n}}{\left(\frac{l+k}{n}\right)^{n}}=\left(\frac{n}{k}\right)^{k} \cdot\left(\frac{l}{l+k}\right)^{n}
$$

Turns out, this does work! Can give an $n^{\Omega(k)} l b$.

Then [Kayal] $x_{1} \ldots x_{n}=\sum_{i=1}^{s} Q_{i}^{n / 2}$ and $\operatorname{aleg}\left(Q_{i}\right)=2$

$$
\Rightarrow \quad s=2^{\Omega(n)}
$$

More generally, $x_{1} \ldots x_{n}=\sum Q_{i}^{n / t} \Rightarrow s=2^{\Omega(n / t)}$.
Last time, we could go from $\Sigma \Lambda \Sigma$ to $\Sigma \prod^{[d]} \sum$ easily. Does the same work here?

$$
x^{=l} \partial^{-k}\left(Q_{1} \ldots Q_{d / 2}\right) \leq \operatorname{sp}\left\{\prod_{i \in S} Q_{i} \cdot\binom{\log _{k}}{k+l}:|s|=\frac{d}{2}-k\right\}
$$

Obs: $\operatorname{dim} x^{=l} \partial^{=k}\left(Q_{1} \ldots \theta_{d / 2}\right) \leqslant\binom{ d / 2}{k} \cdot\binom{n+l+k}{n}$.
We should $\quad \$ \quad \leq 2^{k / 2}=2^{-(k)}$
still get $a$ still get a $n^{\Omega(k)}$ lower bound.

Task: Find hay in the hay stack.
[Gupta-kamath-kayal-s] $2^{\Omega(\sqrt{n})}$ lb for $\sum \prod^{\sqrt{n}} \sum \frac{\sqrt{n}}{\pi}$ els computing Detn or Perm.
On: Why don't we just engineer a poly where this calculation is easy?
$\operatorname{dim} x^{=l} \partial^{=k}(f) \rightarrow$ always monomials

$$
\partial m(f)=m_{1}+m_{2}+
$$

Car we ensure that any two mons of $f$ have ged $<k$.
Build a poly from a code.

$$
C \subseteq \Sigma^{\alpha} \rightarrow f_{e} \in \mathbb{F}\left[x_{12}, x_{m}\right]^{=\alpha}
$$

Wart a code
with $m=|\Sigma| d$.


$$
\text { of distance }>d-k . \quad=\sum_{\left(\alpha_{1}, \alpha_{d}\right) \in C} x_{1, \alpha_{1}} \ldots x_{d, \alpha_{d}}
$$

Great! Now how large is $x^{=l} a^{=k}\left(f_{e}\right)$ ?


Fix one from each. $m, \ldots m_{R}$

$$
A_{i}=\left\{m_{i} \cdot m: \quad m \text { has deg } l\right\} .
$$

Wart to estimate $\left|\cup A_{i}\right| \geqslant \sum\left|A_{i}\right|-\sum_{i<j}\left|A_{i} \cap A_{j}\right|$
[Chillara-Mukhopalhyay). $\binom{n+l}{n}^{\downarrow}$ is small $\because$ dist.

A specific instantiation:

$$
\begin{aligned}
& N W_{n, d, a}\left(x_{1,1, \ldots} x_{1, d}\right)= \\
& \sum_{\substack{p \in \mathbb{F}_{n}[z] \\
\operatorname{deg} p<a}} x_{1, p(1)} \ldots x_{d, p(d)} \\
& \quad \in V N P
\end{aligned}
$$

- has $n^{a}$ monomials
- Any two monomials have ged-deg $<a$.

The: [kayal-Saha-S] An $\sum \prod_{\Omega(\sqrt{d})}^{\sqrt{d}} \sum \pi^{\sqrt{d}}$ ct computing $N W_{n, d, k}$ requires size $n^{\Omega(\sqrt{d})} \quad$ (for $k=\delta \cdot \sqrt{d}$ )

Them: [FLMS] Same bound for IMM.
The [kumar-Saraf] Same bound for $\sum \Pi^{\sqrt{d} / 10} \sum \pi^{10 \sqrt{\alpha}}$
Variants of concern:
$\triangle$ Adding in multilineor projections. $\square$ PPD: $\quad \pi_{m l} \cdot x^{=l} g^{=k}(f)$
Thu: [kayal-Limaye-Saha-Srinivasan] $n^{\Omega(\sqrt{d})}$ lb for how. depth 4 chis computing NW.
Thu: [kumar-Saraf] ... for IMM (also over all fields).
$\triangleright$ Adding in skew-ness: $\quad x=y \sqcup z$
but diff sizes.
Skew-Pastial Derivatives.: [kayal-Nair-Saha].

$$
|y| \gg|z| .
$$



LBs for multi-k-ic models.
$>$ Many other combinations of $\partial^{=k}, x^{=l}, \sigma_{y=0}, \pi_{m e l}$. [Chillara]: projected shifted skew partial derivatives. [Garg-Kayal-Saha]: Affine projections of partials.

