

- Now we need to study the effect of a random partitioning on a t -product.

Lemma: Let $f(x)$ be n -variate & computable by a size- s multilinear depth- Δ formula.

If $X = Y \sqcup Z$, $|Y| = |Z| = n/2$, is random then with probability $1 - s \cdot \exp(-n^{\Omega(1/\Delta)})$:

the constants in Ω behave well

$$\Gamma_{Y,Z}^1(f) = s \cdot 2^{n/2} \cdot \exp(-n^{\Omega(1/\Delta)}).$$

Proof:

• By the previous lemma, write $f = g_0 + \sum_{i=1}^s g_i$ where $\deg g_0 \leq n/100$ & g_1, \dots, g_s are multilinear t -products.

• Note that g_0 's sparsity can be at most

$$\sum_{i \leq n/100} \binom{n}{i} = 2^{H_2(1/100) \cdot n - O(\log n)} < 2^{n/10}.$$

$\Rightarrow \Gamma_{Y,Z}^1(g_0) < 2^{n/10}$ (sub-additivity).

• All that remains is to bound $\Gamma_{Y,Z}^1(g_1)$ for a random partition $X = Y \sqcup Z$.

• Let $g = h_1 \cdots h_t$, $h_i \in \mathbb{F}[X_i]$, be a t -product for $X = \sqcup X_i$.

Let $Y_i := X_i \cap Y$ & $Z_i := X_i \cap Z$.

• Let $d_i := |\#Y_i - \#Z_i|/2$ be the imbalance between Y_i, Z_i in h_i .

X_i is called k -imbalanced if $d_i \geq k$.

Let $b_i := (\#Y_i + \#Z_i)/2 = \#X_i/2$.

• We have $\prod_{Y,Z}(g) = \prod_i \prod_{Y,Z}(h_i) \leq \prod_i 2^{\min(|Y_i|, |Z_i|)}$
 $= \prod_i 2^{b_i - d_i} = 2^{|X|/2} / \prod_i 2^{d_i}$.

\Rightarrow it suffices to show that one of the X_i 's is imbalanced (i.e. d_i is large).

• We need to estimate $|Y_i|$ on choosing a random $Y \in \binom{[n]}{n/2}$.

• The relevant probability is that of the hypergeometric distribution:

Claim: For a fixed set $A \in \binom{[n]}{a}$, $k \leq a \leq 2n/3$,
 $\Pr_{R \in \binom{[n]}{n/2}} [|R \cap A| = k] = O(1/\sqrt{a})$.

Proof: • $\Pr_R [|R \cap A| = k] = \binom{a}{k} \cdot \binom{n-a}{n/2-k} / \binom{n}{n/2}$
 • Call it $P(k)$.

• $P(k+1) > P(k)$ iff
 $(a-k) \binom{n/2-k}{k+1} > (k+1) \binom{n/2-a+k+1}{k}$ iff
 $\frac{an}{2} - k(a + \frac{n}{2}) > (k+1) \binom{n/2-a+k+1}{k}$

iff $k < \frac{a-1}{2}$.

• Thus, $P(k) \leq \binom{a}{\frac{a-1}{2}} \cdot \binom{n-a}{\frac{n}{2} - \frac{a-1}{2}} / \binom{n}{n/2}$
 $= O\left(\frac{\sqrt{n}}{\sqrt{a(n-a)}}\right) = O\left(\frac{1}{\sqrt{a}}\right)$. \square

(Stirling's approx.)

(k -balanced)

• Let Σ_i denote the event that $d_i < k$.
 • We have $\Pr \left[\bigwedge_{i=1}^t \Sigma_i \right]$ equal to
 $\Pr[\Sigma_1] \cdot \Pr[\Sigma_2 | \Sigma_1] \cdot \Pr[\Sigma_3 | \Sigma_1 \wedge \Sigma_2] \cdots$.

• $\Pr[\Sigma_1] = \Pr[N \cap X_1 \in [b_1 - k, b_1 + k]]$

which the above claim estimates as:

$$k \cdot O\left(\frac{1}{\sqrt{b_1}}\right) \quad (\text{assuming } k \leq b_1/2).$$

- Consider the event Σ_i given $\Sigma_1, \dots, \Sigma_{i-1}$.
Since X_1, \dots, X_{i-1} have been partitioned in a fairly balanced way ($\forall j \in [i-1], d_j < k$), we deduce that $|Y \cap (X_1 \cup \dots \cup X_{i-1})^c|$
$$= |Y \cap X| - |Y \cap (X_1 \cup \dots \cup X_{i-1})|$$
$$< n/2 - (b_1 - k + \dots + b_{i-1} - k)$$
$$= (n/2 - b_1 - \dots - b_{i-1}) + (i-1)k$$
$$\Rightarrow \text{The partition of } X' := (X_1 \cup \dots \cup X_{i-1})^c \text{ by } Y \cup Z \text{ is } (ik)\text{-balanced.}$$

- So, assuming $ik \ll n$, we can redo the calculation in the above claim & still get $\Pr[\Sigma_i | \Sigma_1 \wedge \dots \wedge \Sigma_{i-1}] = k \cdot O\left(\frac{1}{\sqrt{b_i}}\right)$.
$$\Rightarrow \Pr\left[\bigwedge_{i \in [t]} \Sigma_i\right] = O\left(\frac{k^t}{\sqrt{b_1 \dots b_t}}\right)$$

$$\Rightarrow \Pr_Y\left[T_{Y,Z}(g) > 2^{1X/2} \cdot 2^{-k}\right] = O\left(\frac{k^t}{\sqrt{b_1 \dots b_t}}\right)$$

• In particular, on fixing $k \leq t^{1/3}$, we get: $\Pr_Y [T_{Y,Z}(g) > 2^{n/2} \cdot 2^{-k}] = O\left(\prod_{i=1}^t t^{-1/6}\right)$
 $= O(t^{-t/6}) = \exp(-n^{\Omega(1/\Delta)})$.

$\Rightarrow \Pr_Y [T_{Y,Z}(f) > \delta \cdot 2^{n/2-k} =: \delta \cdot 2^{n/2} \cdot 2^{-t^\varepsilon}]$
 $= \delta \cdot \exp(-n^{\Omega(1/\Delta)})$.

Ω independent
of $\varepsilon \rightarrow$
if $\varepsilon \leq 1/3$

□

— Thus, there is an $\varepsilon \in (0, \frac{1}{3}]$ such that if $\delta \leq \exp(-t^\varepsilon)$ then $\Pr [T_{Y,Z}(f) = 2^{n/2}] < 1/10$.

$\Rightarrow f(x)$ could compute $\det(x)$ only if $\delta > 2^{t^\varepsilon} = \exp(n^{\Omega(1/\Delta)})$.

— This finishes (Raz, Yehudayoff '09) proof for \det_n or per_n against constant-depth multilinear model.

- We can also say something for multilinear formulas using the probability calculation seen above.

- The multilinear products of interest there are:

Defn: Multilinear $f = \prod_{i=1}^t g_i$, with partition $X = \bigsqcup_{i \in [t]} X_i$, is called a log-product if for all i , $|X|/3^i \leq |X_i| \leq 2 \cdot |X|/3^i$ and $|X_t| = 1$.

Lemma: Any size- s multilinear formula ϕ can be written as a sum of $(s+1)$ log-products.

Proof: • Let $|X| > 2$ & ϕ compute f .

• Let v be a node in ϕ that depends on variables X_v such that

assume fanin ≥ 2 in ϕ →

$$|X|/3 \leq |X_v| \leq 2 \cdot |X|/3$$

• By the formula properties, we have



$$f = \phi_v \cdot g + \phi_{v=0}$$

for some $g \in \mathbb{F}[X \setminus X_v]$.

- Note that $|X|/3 \leq |X \setminus X_v| \leq 2 \cdot |X|/3$.
- Moreover, since g has size $< s$, we can use induction & write it as a sum of $\leq \text{size}(g) + 1$ log-products.

Similarly, for $\phi_{v=0}$.

$\Rightarrow f$ is a sum of $(s+1)$ log-products. \square

- Now, we can estimate $\Gamma_{1/2}(h_1 \cdots h_t)$ for a log-product $h_1 \cdots h_t$, $t = O(\lg n)$.

Note that around $\frac{1}{2} \lg n$ many of these h_i 's do depend on at least \sqrt{n} many variables each.

\Rightarrow On doing the probability calculation we will get that $\Gamma_{1/2}(h_1 \cdots h_t)$ is high with prob. smaller than $n^{-\Omega(\lg n)}$.

(Raz '09) $\Rightarrow \det_n$ or per_n requires $n^{\Omega(\lg n)}$ size!