

Multilinear models

- Multilinearity is a natural restriction on arithmetic circuits.

eg. det & per are multilinear polynomials. Can they be computed without computing monomials like x_i^j , $j > 1$?

Defn: A circuit C is multilinear if every gate computes a multilinear polynomial.

- We will first focus on multilinear depth-3 & prove exponential lower bounds.

- The measure, on polynomials, that will succeed is as follows.

Partition the variables X as $Y \cup Z$.

For a monomial m_y (resp. m_z) in the Y (resp. Z) variables, let $\text{coef}(m_y \cdot m_z)(f)$ denote the coefficient of $m_y m_z$ in $f(x)$.

Define matrix $M_{Y,Z}(f)$ as:

$$M_{Y,Z}(f) = \begin{pmatrix} \dots & \dots & \dots \\ \dots & \text{coef}(m_Y m_Z)(f) & \dots \\ \dots & \dots & \dots \end{pmatrix}$$

monomials in Z

monomials in Y

Defn: $\Gamma_{Y,Z}(f) := \text{rk } M_{Y,Z}(f)$.

For multilinear f , $\text{coef}(m_Y m_Z)(f) = (\partial_{m_Y m_Z} f)(\vec{0})$. So, $M_{Y,Z}(f)$ is also called the partial derivative matrix of f .

- It behaves well under ring operations:

Lemma (Sub-additivity): $\Gamma_{Y,Z}(f_1 + f_2) \leq \Gamma(f_1) + \Gamma(f_2)$.

Pf: Follows from the rank property of $A+B$ for matrices. \square

Lemma (Multiplicativity): For $f_1 \in \mathbb{F}[Y_1, Z_1]$, $f_2 \in \mathbb{F}[Y_2, Z_2]$ with $Y = Y_1 \cup Y_2$ & $Z = Z_1 \cup Z_2$,

we have $T_{Y,Z}(f_1 \cdot f_2) = T_{Y_1, Z_1}(f_1) \cdot T_{Y_2, Z_2}(f_2)$.

Proof:

• Note that $M_{Y,Z}(f_1 \cdot f_2)$ equals the tensor product $M_{Y_1, Z_1}(f_1) \otimes M_{Y_2, Z_2}(f_2)$.

• This follows from the disjointness of these subsets, which allows $\text{coef}(m_{Y_1} m_{Z_2})(f) = \text{coef}(m_{Y_1} m_{Z_1})(f) \cdot \text{coef}(m_{Y_2} m_{Z_2})(f)$.

• Rank property of a tensor product gives $T_{Y,Z}(f) = \prod_{i \in [2]} T_{Y_i, Z_i}(f_i)$. \square

Lemma (Mult. by Z -free): For any $g \in F[Y]^*$, $T_{Y,Z}(g \cdot f) = T_{Y,Z}(f)$.

Proof:

• If we consider the function field $F(Z)$, then g, f can be considered as polynomials in $F(Z)[Y]$.

• By "coefficient" extraction we can prove:

$$\overline{T}_{Y,Z}(gf) = \text{rk}_{\mathbb{F}} \{ (\partial_m(gf))|_{Z=0} \mid m \text{ is a monomial in } Z \}$$
↗ result in $\mathbb{F}[Y]$.

[Pf idea: column m_Z in $M_{Y,Z}(gf)$ exactly represents the polynomial in $\mathbb{F}[Y]$ which is the "coefficient" of m_Z in (gf) .

⇒ the rank of these Y -polynomials equals the column rank of $M_{Y,Z}(gf)$.]

• Now, using the Z -freeness of g , we get:

$$\overline{T}_{Y,Z}(gf) = \text{rk}_{\mathbb{F}} \{ g \cdot (\partial_m f)|_{Z=0} \mid m \text{ is a monomial in } Z \}$$

$$= \overline{T}_{Y,Z}(f).$$
□

Lemma: For any multilinear f , we have

$$\overline{T}_{Y,Z}(f) \leq 2^{\min(|Y|, |Z|)}.$$

Proof:

• Follows from the size of $M_{Y,Z}(f)$. □

- Eg. $f(Y, Z) = \prod_{i \in [n]} (y_i + z_i)$ proves the

optimality of the above upper bound as:

$$\Gamma_{Y, Z}^1(f) = \prod_{i \in [n]} \Gamma_{y_i, z_i}^1(y_i + z_i) = 2^n.$$

- The above example is merely depth-2!

Raz showed that the measure for $\Pi\Sigma$ can be significantly reduced if we consider a random partition of X .

Theorem (Upper bound) [Raz '09]: Let $f(x) = l_1 \dots l_d$ be an n -variate multilinear.

For a random partition $X = Y \cup Z$, $|Y| = |Z| = n/2$, we have whp:

$$\Gamma_{Y, Z}^1(f) \leq 2^{n/2 - n/32}.$$

Proof: • Wlog each l_i has support-size ≥ 2 , as univariate l_i 's do not change the

measure wrt any partition.

- Clearly, $\overline{T}_{Y,Z}(f) \leq 2^d$. Hence, we are done if $d < n/3$. (by multiplicativity)

Assume $d \geq n/3$.

- Since l_i 's are disjoint-support & many ($\geq n/3$) we get by an averaging argument that:

l_i 's with support-size 2 or 3 is $\geq d/4$.

[Otherwise, $> 3d/4$ l_i 's have support-size $\geq 4 \Rightarrow n > 3d$, a #.]

- We call these l_i 's small.
- Now for a small l_i , we have
$$\Pr_{Y,Z} [\text{support}(l_i) \subseteq Y \text{ or } Z] \geq 2 \cdot \frac{1}{2^3} = \frac{1}{4}.$$

$\Rightarrow \text{Exp}_{Y,Z} [\#i \mid \text{small } l_i \text{ is in } \mathbb{F}[Y], \mathbb{F}[Z]] \geq d/16.$

- These l_i 's stop contributing to $\overline{T}_{Y,Z}(f)$.

$$\Rightarrow \Gamma_{Y,Z}(f) \leq 2^{d-d/16} \leq 2^{n/2} \cdot 2^{-n/32}$$

(as $n/3 \leq d \leq n/2$) \square

Det_n & Per_n have high $\Gamma_{Y,Z}(\cdot)$

- Note that det_n has n^2 variables.

We will first reduce its variables to a random X , $|X| = 2m := 2 \cdot \frac{\sqrt{n}}{5}$, & then use a random partition $X = Y \cup Z$.

Theorem (Lower bound) [Raz'09]: With probability $\geq 1/2$, a random restriction σ of $\{x_{11}, \dots, x_{nn}\}$ to $X = Y \cup Z$, $|Y| = |Z| = m := \lfloor \sqrt{n}/5 \rfloor$, yields $\Gamma_{Y,Z}(\sigma \circ \text{det}_n) = 2^m$.

Proof:

- The map σ will fix $n^2 - 2m$ variables to \mathbb{F} values, in a certain way.
- The remaining $2m$ variables are X .
- Let us compute the probability that

• Clearly, $T_{y,z}(D_m) = 2^m$. (Multiplicativity)

$$\Rightarrow \Pr_{\sigma} [T_{y,z}(\sigma \circ \det_n) = 2^m] > 1 - \frac{4}{25} - \frac{1}{3} > 1/2. \quad \square$$

- Finally, we deduce an exponential lower bound against multilinear depth-3.

Corollary: \det_n or per_n require $2^{\Omega(\sqrt{n})}$ size multilinear depth-3 circuits.

Proof:

• Suppose $\det_n = C(\bar{x})$, for a multilinear $\Sigma^{\circ} \Pi \Sigma$ circuit C .

• We apply, as before, a random variable reduction σ both sides

$$\Rightarrow \sigma \circ \det_n = \sigma \circ C \quad (2m\text{-variate row}).$$

• The two theorems imply that

$$2^m \leq \delta \cdot 2^{2m/2 - 2m/32}$$

$$\Rightarrow D \geq 2^{m/16} = 2^{\sqrt{n}/80}.$$

□

- Note that this almost matches the best depth-3 complexity of \det_n .

Exercise: The same argument holds for per_n .

Generalizing to constant-depth multilinear

- (Raz, Yehudayoff '09) generalized the above ideas to get a result for multilinear depth- Δ circuits.

- Here, instead of a product of linear polynomials we work with the following:

Defn: A multilinear polynomial $f = g_1 \cdots g_t$ is called a t-product if:
each g_i depends on $\geq t$ variables.

Lemma: Let f be a multilinear n -variate d -degree polynomial that has a size- s multilinear (product)depth- Δ formula ϕ . Then, f can be written as a sum of: $\leq s$ multilinear t -products ($t = (n/100)^{1/2\Delta}$) & a multilinear polynomial of degree $\leq n/100$.

Proof:

- If $d \leq n/100$, then it is clear.
- Let $d > n/100$. Since ϕ is a formula of product-depth Δ , there is a product gate v of fanin $\geq (n/100)^{1/\Delta} =: t^2$.
- Let us expand the formula wrt this gate:

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

\uparrow output at v



- As ϕ_v is a product of t^2 polynomials we can group them to see that ϕ_v is multilinear t -product.
- As $\phi_{v=0}$ is of smaller size, we can recurse. □

- 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 \rightarrow

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

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

$$(a-k) \binom{n/2-k}{k} > (k+1) \binom{n/2-a+k+1}{k+1} \text{ iff}$$

$$\frac{an}{2} - k(a + \frac{n}{2}) > (\frac{n}{2} - a + 1) + k(\frac{n}{2} - a + 2)$$

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

• Thus, $P(k) \leq \binom{a}{\frac{a-1}{2}} \cdot \binom{n-a}{\frac{n}{2} - \frac{a-1}{2}} / \binom{n}{n/2}$

(Stirling's approx.)

$$= O\left(\frac{n}{\sqrt{a(n-a)}}\right) = O\left(\frac{1}{\sqrt{a}}\right). \quad \square$$

(k -balanced)

• Let Σ_i denote the event that $d_i < k$.

• We have $\Pr[\bigwedge_{i=1}^t \Sigma_i]$ equal to
 $\Pr[\Sigma_1] \cdot \Pr[\Sigma_2 | \Sigma_1] \cdot \Pr[\Sigma_3 | \Sigma_1 \wedge \Sigma_2] \dots$

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

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!