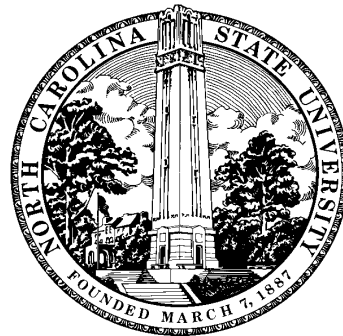


# On the complexity of the determinant

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## Matrix determinant definition

$$\det(Y) = \det\left(\begin{bmatrix} y_{1,1} & \cdots & y_{1,n} \\ y_{2,1} & \cdots & y_{2,n} \\ \vdots & & \vdots \\ y_{n,1} & \cdots & y_{n,n} \end{bmatrix}\right) = \sum_{\sigma \in S_n} \left( \text{sign}(\sigma) \prod_{i=1}^n y_{i,\sigma(i)} \right),$$

where  $y_{i,j}$  are from an *arbitrary commutative ring*,  
and  $S_n$  is the set of all permutations on  $\{1, 2, \dots, n\}$ .

Interesting rings:  $\mathbb{Z}$ ,  $\mathbb{K}[x_1, \dots, x_n]$ ,  $\mathbb{K}[x]/(x^n)$

## An important algebraic reduction

**Theorem** [Giesbrecht 1992] *Suppose you have a Monte Carlo randomized algorithm on a random access machine that can compute the determinant of an  $n \times n$  matrix in  $D(n)$  arithmetic operations.*

*Then you have a Monte Carlo randomized algorithm on a random access machine that can multiply two  $n \times n$  matrices in  $O(D(n))$  arithmetic operations.*

No proof is known for Las Vegas or deterministic algorithms.

(At the conference, Peter Bürgisser pointed out to me that  $D(n)^{1+o(1)}$  is achievable deterministically by designing a divide-and-conquer matrix multiplication algorithm from a sufficiently large fixed dimension.)

## Bit complexity of the determinant

With Chinese remaindering:  $(n \log \|A\|)^{1+o(1)}$  times matrix multiplication complexity.

Sign of the determinant [Clarkson 92]:  $n^{4+o(1)}$  if matrix is ill-conditioned.

Using denominators of linear system solutions [Pan 1989; Abbott, Bronstein, Mulders 1999]: fast when large first invariant factor.

Using fast Smith form method  $n^{3.5+o(1)} (\log \|A\|)^{2.5+o(1)}$  [Eberly, Giesbrecht, Villard 2000]

## Wiedemann's 1986 determinant algorithm

For  $u, v \in \mathbb{F}^n$  and  $A \in \mathbb{F}^{n \times n}$  and consider the sequence of field elements

$$a_0 = u^T v, a_1 = u^T A v, a_2 = u^T A^2 v, a_3 = u^T A^3 v, \dots$$

Let  $f^{(A)}(\lambda) = c_0 + c_1 \lambda + \dots + c_k \lambda^k \in \mathbb{F}[\lambda]$  with  $f^{(A)}(A) = 0$ .

Since  $u^T A^j f^{(A)}(A) v = 0$ , we have

$$\forall j \geq 0: c_0 a_{0+j} + c_1 a_{1+j} + \dots + c_k a_{k+j} = 0,$$

that is,  $\{a_i\}_{i=0,1,\dots}$  satisfies a linear recurrence.

By the Berlekamp/Massey (1969) we can compute in  $n^{1+o(1)}$  operations a minimal linear generator for  $\{a_i\}_{i=0,1,\dots}$

Wiedemann randomly perturbs  $A$  and chooses random  $u$  and  $v$ ; then  $\det(\lambda I - A)$  = the minimal recurrence polynomial of  $\{a_i\}_{i=0,1,\dots,2n-1}$ .

## Baby steps/giant steps algorithm [Kaltofen 1992/2000]

Detail of sequence  $a_i = u^T A^i v$  computation

Let  $r = \lceil \sqrt{2n} \rceil$  and  $s = \lceil 2n/r \rceil$ .

Substep 1. For  $j = 1, 2, \dots, r-1$  Do  $v^{[j]} \leftarrow A^j v$ ;

Substep 2.  $Z \leftarrow A^r$ ;

$[O(n^3)$  operations; integer length  $(\sqrt{n} \log \|A\|)^{1+o(1)}]$

Substep 3. For  $k = 1, 2, \dots, s$  Do  $u^{[k]T} \leftarrow u^T Z^k$ ;

$[O(n^{2.5})$  operations; integer length  $(n \log \|A\|)^{1+o(1)}]$

Substep 4. For  $j = 0, 1, \dots, r-1$  Do

For  $k = 0, 1, \dots, s$  Do  $a_{kr+j} \leftarrow \langle u^{[k]}, v^{[j]} \rangle$ .

Overall bit complexity  $(n^{3+1/2} \log \|A\|)^{1+o(1)}$ .

## Speed-up with fast matrix multiplication

Suppose  $k \times k$  matrices can be multiplied in  $O(k^{2.3755})$  ring operations.

Suppose  $k \times k^{0.29462}$  can be multiplied in  $k^{2+o(1)}$  ring operations.

Overall bit complexity reduces to  $n^{3.0281} (\log \|A\|)^{1+o(1)}$  bit operations.

## Coppersmith's 1992 blocking

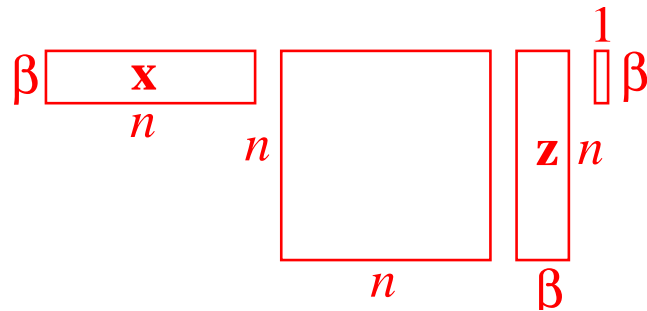
Use of the block vectors  $\mathbf{x} \in \mathbb{F}^{n \times \beta}$  in place of  $u$   
 $\mathbf{y} \in \mathbb{F}^{n \times \beta}$  in place of  $v$

$$\mathbf{a}_i = \mathbf{x}^T A^i \mathbf{y} \in \mathbb{F}^{\beta \times \beta}, \quad 0 \leq i < 2n/\beta + 2.$$

Find a minimal **matrix** polynomial generator

$$\mathbf{c}_0 \lambda^0 + \dots + \mathbf{c}_d \lambda^d \in \mathbb{F}^{\beta \times \beta}[\lambda], \quad d = \lceil n/\beta \rceil :$$

$$\forall j \geq 0: \sum_{i=0}^d \mathbf{a}_{j+i} \mathbf{c}_i = \sum_{i=0}^d \mathbf{x}^T A^{i+j} \mathbf{y} \mathbf{c}_i = \mathbf{0} \in \mathbb{F}^{\beta \times \beta}$$



Note:  $A$  must be in general position, otherwise  $d > \lceil n/\beta \rceil$  and more sequence elements are needed.



## Advantages of blocking

Sequence is shorter, therefore intermediate integers are shorter.

## Disadvantages of blocking

1. Block Berlekamp/Massey step more intricate and more expensive:  $\beta^{1.3755} n^{1+o(1)}$ .
2. Must compute  $\det(\mathbf{c}_0 + \cdots + \mathbf{c}_d \lambda^d)$ , which costs extra.  
After preconditioning  $A$ , with high probability

$$\det(I - \lambda A) = \det(\mathbf{c}_0 + \cdots + \mathbf{c}_d \lambda^d).$$

## Sketch of multivariable control theory

From  $(I - \lambda A)^{-1} = I + A\lambda + k^2\lambda^2 + \dots$

$$\mathbf{x}^T (I - \lambda A)^{-1} \mathbf{y} (\mathbf{c}_d + \dots + \mathbf{c}_0 \lambda^d) = R(\lambda) \in \mathbb{F}[\lambda]^{\beta \times \beta}$$

we obtain a matrix Padé approximation (“realization”)

$$\mathbf{x}^T (I - \lambda A)^{-1} \mathbf{y} = \sum_i \mathbf{a}_i \lambda^i = R(\lambda) (\mathbf{c}_d + \dots + \mathbf{c}_0 \lambda^d)^{-1}$$

Denominator on left side:  $\det(I - \lambda A)$ .

Denominator on right side:  $\det(\mathbf{c}_d + \dots + \mathbf{c}_0 \lambda^d)$ .

### ***Theorem 1***

*The determinant of an integer matrix can be computed in  $n^{2.6973} (\log \|A\|)^{1+o(1)}$  bit operations (at  $\beta = n^{0.507}$  and giant stepping  $s = n^{0.172}$ ).*

# Division-free determinant complexity

## Special sequence for Berlekamp/Massey

In[2] := S = {1,1,2,3,6,10,20,35,70,126,252,462,924,1716}

In[3] := BM[S, x]

Discrepancy for r = 1 is 1

L updated to 1, Lambda = 1

Discrepancy for r = 2 is 1

Lambda updated to  $1 - x$

Discrepancy for r = 3 is 1

L updated to 2, Lambda =  $1 - x - x^2$

Discrepancy for r = 4 is 0

Discrepancy for r = 5 is 1

L updated to 3, Lambda =  $1 - x - 2x^2 + x^3$

Discrepancy for r = 6 is 0

Discrepancy for r = 7 is 1

L updated to 4, Lambda =  $1 - x - 3x^2 + 2x^3 + x^4$

Discrepancy for r = 8 is 0

Discrepancy for r = 9 is 1

L updated to 5, Lambda =  $1 - x - 4x^2 + 3x^3 + 3x^4 - x^5$

Discrepancy for  $r = 10$  is 0

Discrepancy for  $r = 11$  is 1

$$L \text{ updated to } 6, \text{ Lambda} = 1 - x - 5x^2 + 4x^3 + 6x^4 - 3x^5$$

- x

Discrepancy for  $r = 12$  is 0

Discrepancy for  $r = 13$  is 1

$$L \text{ updated to } 7, \text{ Lambda} = 1 - x - 6x^2 + 5x^3 + 10x^4 - 6x^5$$

- 4x<sup>6</sup> + x<sup>7</sup>

Discrepancy for  $r = 14$  is 0

Special case for Wiedemann's determinant algorithm: for

$$C = \begin{bmatrix} 0 & 1 & & & \\ & 0 & 1 & & \\ & & \cdots & \cdots & \\ & & & 0 & 1 \\ c_0 & c_1 & \cdots & c_{n-2} & c_{n-1} \end{bmatrix} \quad c_i = (-1)^{\lfloor (n-i-1)/2 \rfloor} \binom{\lfloor (n+i)/2 \rfloor}{i}$$

and

$$a_i = \underbrace{[1 \ 0 \ 0 \ \dots \ 0]}_{u^T = e_1^T} \times C^i \times v, \quad v = \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_{n-1} \end{bmatrix}, \quad a_i = \binom{i}{\lfloor i/2 \rfloor}$$

the algorithm needs no divisions/decisions.

$$\text{Block algorithm: } \mathbf{x} = \begin{bmatrix} u & & \\ & \cdots & \\ & & u \end{bmatrix}, \quad \begin{bmatrix} C & & \\ & \cdots & \\ & & C \end{bmatrix} \quad \text{and} \quad \mathbf{y} = \begin{bmatrix} v & & \\ & \cdots & \\ & & v \end{bmatrix}.$$

Strassen's homotopy:

Compute  $\det(C + z(A - C))$  by truncated power series operations in  $\mathbb{Z}[z]/(z^{n+1})$ .

Polynomials in  $z$  are like integers: length  $\leftrightarrow$  degree.

### ***Theorem 2***

*The determinant and adjoint of a matrix over a commutative ring can be computed with  $O(n^{2.6973})$  ring additions, subtractions and multiplications. The characteristic polynomial with  $O(n^{2.8066})$  ring additions, subtractions and multiplications.*

## More recent results

Storjohann 2002, 2003: determinant of matrix with polynomials/integers in  $n^{2.3755} \times (\text{input degree/length})^{1+o(1)}$  field/bit operations.

Jeannerod and Villard 2003: inverse of matrix with polynomial entries in  $(n^3 \times (\text{input degree}))^{1+o(1)}$  straight-line steps.

Note: automatic differentiation does not preserve bit complexity:

$x^T y c$  where  $x, y$  are vectors with constant entries,  
 $c$  a large constant

takes  $O(n + \log |c|)$  bit operations,

$yc$  takes  $O(n \log |c|)$  bit operations [Villard 2003].