IMPROVED PARALLEL GAUSSIAN ELIMINATION FOR GRÖBNER BASIS COMPUTATIONS IN FINITE FIELDS

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- 2. Features of GBLA
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LINEAR ALGEBRA FOR GRÖBNER BASIS

COMPUTATIONS

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- Out of this data a matrix M is generated: Its rows correspond to polynomials, its columns represent all appearing monomials in the given order.
- Performing Gaussian Elimination on M corresponds to reducing the chosen subset of S-pairs at once.
- New data for the Gröbner basis can then be read off the reduced matrix: Restore corresponding rows as polynomials.

Specialize Linear Algebra for reduction steps in GB computations.

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```
1 3 0 0 7 1 0
1 0 4 1 0 0 5
0 1 6 0 8 0 1
0 1 0 0 0 7 0
0 0 0 0 1 3 1
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S-pair  \left\{ \begin{array}{c} 1 & 3 & 0 & 0 & 7 & 1 & 0 \\ 1 & 0 & 4 & 1 & 0 & 0 & 5 \end{array} \right. 
S-pair  \left\{ \begin{array}{c} 0 & 1 & 6 & 0 & 8 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 7 & 0 \end{array} \right. 
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Try to exploit underlying GB structure.

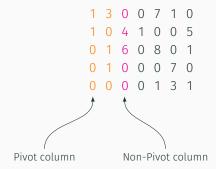
Main idea

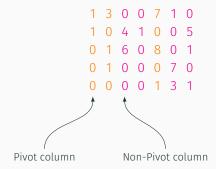
Do a static reordering before the Gaussian Elimination to achieve a better initial shape. Invert the reordering afterwards.

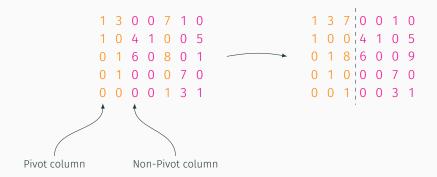
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1 3 0 0 7 1 0
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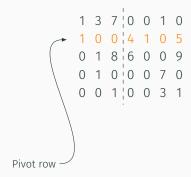
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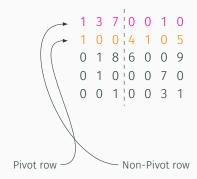


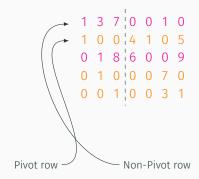


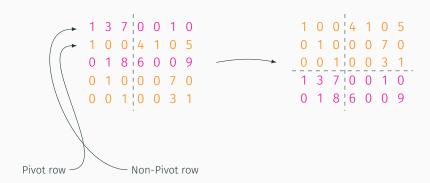


```
1 3 7 0 0 1 0
1 0 0 4 1 0 5
0 1 8 6 0 0 9
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3rd step: Reduce lower left part to zero

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4th step: Reduce lower right part

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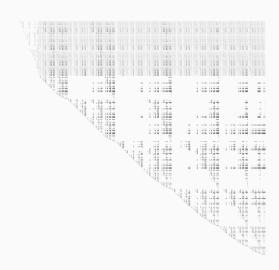
4th step: Reduce lower right part



5th step: Remap columns and get new polynomials for GB out of lower right part.

SO, WHAT DO "REAL WORLD" MATRICES FROM GB

COMPUTATIONS LOOK LIKE?



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full matrix: 21,182 × 22,207

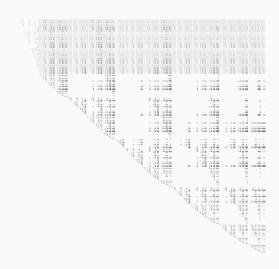
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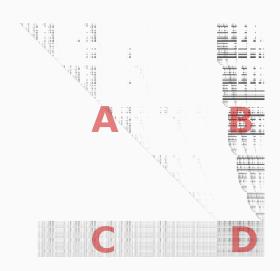
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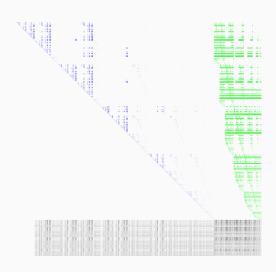
upper-left: 17,915 \times 17,915 known pivots
lower-left: 3,267 \times 17,915

upper-right: 17,915 \times 4,292
lower-right: 3,267 \times 4,292
new information
```

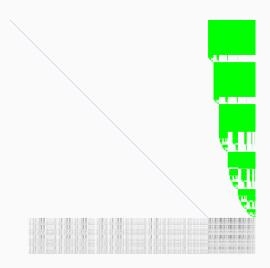




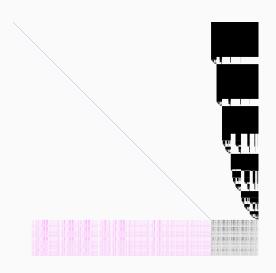
HYBRID MATRIX MULTIPLICATION A-1B



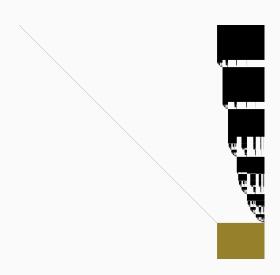
HYBRID MATRIX MULTIPLICATION A-1B



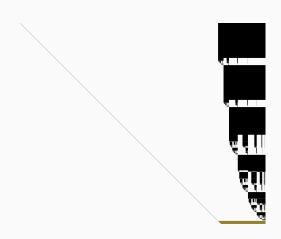
REDUCE C TO ZERO



GAUSSIAN ELIMINATION ON D



NEW INFORMATION



FEATURES OF GBLA

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http://hpac.imag.fr/gbla

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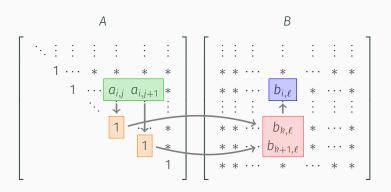
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- Can be used to optimize AXPY and TRSM operations in FL reduction.
- · Horizontal pattern taken care of canonically.
- · Need to take care of vertical pattern.

MULTILINE TRSM STEP



Exploiting horizontal and vertical patterns in the TRSM step.

Consider the following two rows:

$$r1 = [2 3 0 1 4 0 5],$$

 $r2 = [1 7 0 0 3 1 2].$

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Change order of operations.

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- 2. Carry out corresponding operations from B to D using updated C.
- 3. Reduce D.

GBLA MATRIX FORMATS

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Table 1: Old matrix format (legacy version)

Size	Length	Data	Description
uint32_t	1	b	version number
uint32_t	1	m	# rows
uint32_t	1	n	# columns
uint32_t	1	р	prime / field characteristic
uint64_t	1	nnz	# nonzero entries
uint16_t	nnz	data	# entries in matrix
uint32_t	nnz	cols	column index of entry
uint32_t	m	rows	length of rows

Table 2: New matrix format (compressing data and cols)

Size	Length	Data	Description
uint32_t	1	b	version number + information for data type of pdata
uint32_t	1	m	# rows
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uint32_t	1	р	prime / field characteristic
uint64_t	1	nnz	# nonzero entries
uint16_t	nnz	data	several rows are of type $x_i f_i$
uint32_t	nnz	cols	can be compressed for consecutive elements
uint32_t	m	rows	length of rows
uint32_t	m	pmap	maps rows to pdata
uint64_t	1	k	size of compressed colid
uint64_t	k	colid	compression of columns:
			Single column entry masked via (1 << 31);
			s consecutive entries starting at column c are stored as "c s"
uint32_t	1	pnb	# polynomials
uint64_t	1	pnnz	# nonzero coefficients in polynomials
uint32_t	pnb	prow	length of polynomial / row representation
_xinty_t	pnnz	pdata	coefficients of polynomials

Table 3: Storage and time efficiency of the new format

Matrix	Size old	Size new	gzipped old	gzipped new	Time old	Time new
F4-kat14-mat9		0.74GB	1.2GB	0.29GB	230s	66s
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New format vs. Old format

- · 1/3rd of memory usage.
- \cdot 1/4th of memory usage when compressed with gzip.
- Compression 4-5 times faster.



GBLA VS. FAUGÈRE-LACHARTRE

All timings in seconds.

Implementation	FL Imp	lement	GBLA v0.1			GBLA v0.2			
Matrix/Threads:	1	16	32	1	16	32	1	16	32
F5-kat13-mat5 F5-kat13-mat6	16.7 27.3	2.7 4.15	2.3 4.0	14.5 23.9		1.87 2.65	14.5 25.9	1.73 3.03	1.61 2.28
F5-kat14-mat7 F5-kat14-mat8	139 181	17.4 24.95	16.6 23.1	142 177		10.6 12.7	122 158	11.2 14.7	8.64 10.5
F5-kat15-mat7	629	61.8	55.6	633	55.1	38.2	553	46.3	30.7
F5-kat16-mat6	1,203	110	83.3	1,147	98.7	69.9	988	73.9	49.0
F5-mr-9-10-7-mat3	591	70.8	71.3	733	57.3	37.9	747	52.8	33.2
F5-cyclic-10-mat20 F5-cyclic-10-sym-mat17				2,589 2,463	274 465	209 405	2,074 2,391	171 275	152 245

GBLA VS. MAGMA V2.20-10

All timings in seconds.

Implementation	Magma	G	BLA v0.1	1	G	BLA v0.2	2
Matrix/Threads:	1	1	16	32	1	16	32
F4-kat12-mat9	11.2	11.4	1.46	1.60	11.3	1.40	1.40
F4-kat13-mat2 F4-kat13-mat3 F4-kat13-mat9	0.94 9.33 168	1.18 11.0 165	0.38 1.70 16.0	0.61 3.10 11.8	1.11 8.51 114	0.26 1.07 9.74	0.33 1.13 6.83
F4-kat14-mat8	2,747	2,545	207	165	1,338	104	65.8
F4-kat15-mat7 F4-kat15-mat8 F4-kat15-mat9	10,345 13,936 24,393	9,514 12,547 22,247	742 961 1,709	537 604 1,256	4,198 6,508 10,923	298 470 779	195 283 450
F4-rand16-d2-2-mat6 F4-rand16-d2-3-mat8 F4-rand16-d2-3-mat9 F4-rand16-d2-3-mat10 ¹		4,902 48,430	375 3,473 6,956 9,691	219 2,119 4,470 6,223	3,054 26,533	224 1,782 3,214 3,820	133 1,027 1,776 1,972

Note that Magma generates slightly bigger matrices for the given examples.

 $^{^{1}}$ Reconstruction fails due to memory consumption

OUTLOOK

• Optimizing GBLA for floating point and 32-bit unsigned int arithmetic.

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- · Deeper investigation on parallelization on networks.
- First steps exploiting **heterogeneous CPU/GPU platforms** for GBLA.

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