

Some implementation issues on the GKO algorithm

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Introduction

Our problem Solution of a matrix equation (NARE) with Cauchy-like matrices

(but I am **not** talking about this)

- Matrix iterations working on Cauchy-like matrices
- Led us to investigate on the existing algorithms – GKO
- Some (small) results that could be interesting also outside our problem

Cauchy-like matrices

Definition

C is **Cauchy-like** if there are $D_x = \text{diag}(x)$, $D(y) = \text{diag}(y)$ such that

$$D_x C - C D_y = G \cdot B = \square \cdot \square \quad (\text{rank } r \ll n)$$

If $x_i \neq y_j$, then C_{ij} can be recovered from the generators:

$$C_{ij} = \frac{G(i, :) \cdot B(:, j)}{x_i - y_j}$$

If this is not always possible, C is **partially reconstructible**

Notable example: ($r = 2$) from Toeplitz matrices, after a Fourier change of base

GKO: the idea

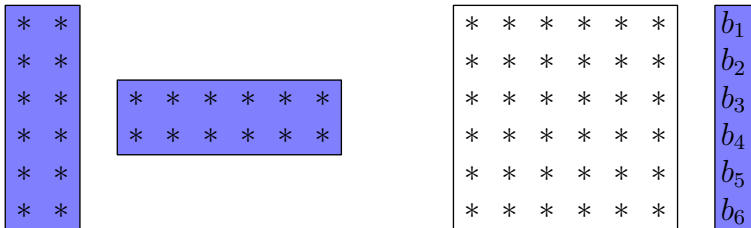
GKO algorithm [Gohberg–Kailath–Olshevsky, '95]

Theorem

The Schur complement of a Cauchy-like matrix is Cauchy-like. Its generators are a rank-1 update of $G(2:n, :)$ and $B(:, 2:n)$.

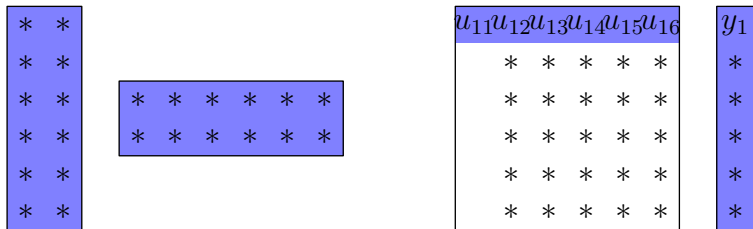
Gaussian elimination working on G and B only, reconstructing elements when needed

GKO step by step



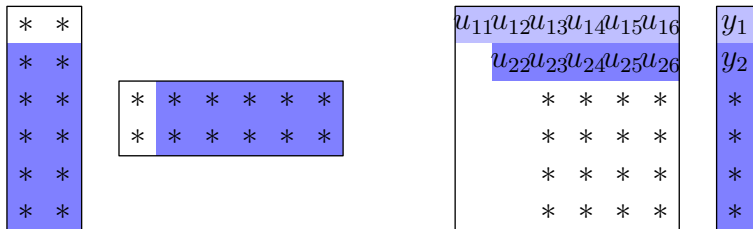
- reconstruct first column of L and use it to solve $Ly = b$ incrementally
- reconstruct first row of U and store it
- update the generators G and B

GKO step by step



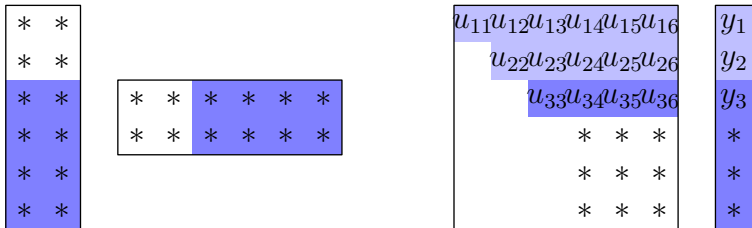
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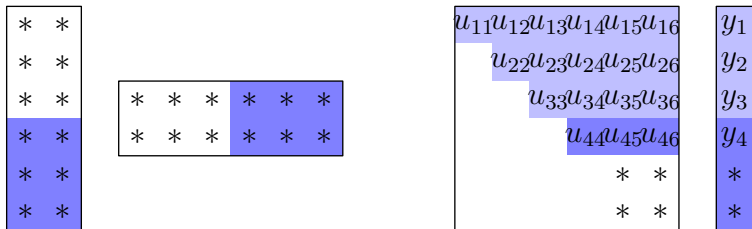
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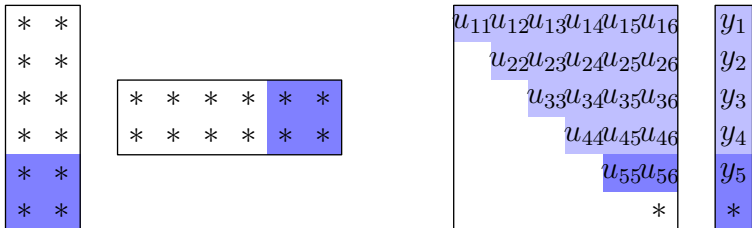
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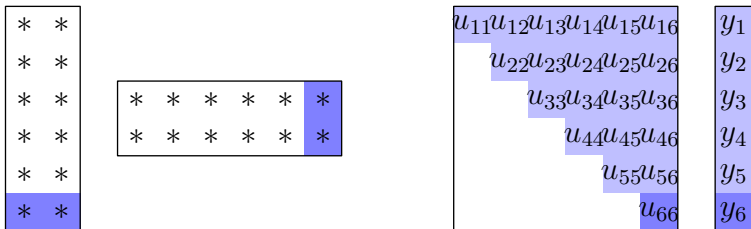
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GKO step by step



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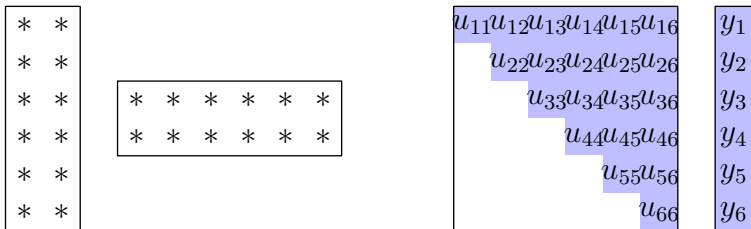
GKO step by step



- reconstruct first column of L and use it to solve $Ly = b$ incrementally
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and finally...

GKO step by step

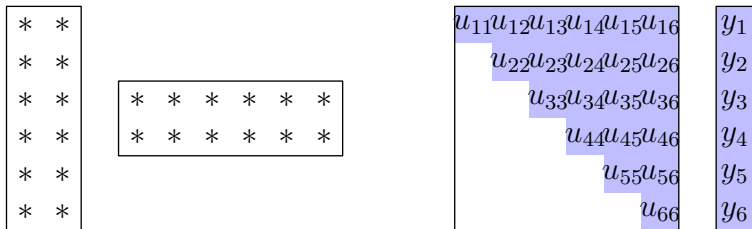


- reconstruct first column of L and use it to solve $Ly = b$ incrementally
- reconstruct first row of U and store it
- update the generators G and B

and finally...

- solve $Ux = y$ by back-substitution

GKO step by step



Problem We need to store U

- Why $O(n^2)$ temporaries for $O(n)$ input and output size?
- The maximum size that fits in memory is reduced
- Slower memory access (cache misses matter)

A solution: the extended matrix

Idea: first in [Kailath–Chun, '94], fully exploited by [Rodriguez, '06]
Matlab code [Aricò–Rodriguez]

$x = C^{-1}b$ is the Schur complement of the first block in

$$\begin{bmatrix} C & b \\ -I & 0 \end{bmatrix}$$

(b may be either $n \times 1$ or $n \times s$, multiple right-hand side)

- n steps of GKO on the extended matrix
- mixed Gaussian elimination: 1st column=GKO, 2nd column=traditional
- $-I$ is partially reconstructible Cauchy-like wrt $\text{diag}(y)$, $\text{diag}(y)$
- you need not store the matrix U

Extended matrix GKO step by step

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*	*	*	*	*	*	b_2
*	*	*	*	*	*	b_3
*	*	*	*	*	*	b_4
*	*	*	*	*	*	b_5
*	*	*	*	*	*	b_6
-1						
	-1					
		-1				
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				-1		
					-1	

Extended matrix GKO step by step

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*	*	*	*	*	*

*	*	*	*	*	*	y_1
	*	*	*	*	*	*
	*	*	*	*	*	*
	*	*	*	*	*	*
	*	*	*	*	*	*
	*	*	*	*	*	*
	*	*	*	*	*	*
	*	*	*	*	*	*
	-1					
		-1				
			-1			
				-1		
					-1	

Extended matrix GKO step by step

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*	*	*	*	*	*

*	*	*	*	*	*	y_1
	*	*	*	*	*	y_2
		*	*	*	*	y_3
			*	*	*	y_4
				*	*	*
				*	*	*
				*	*	*
				*	*	*
				*	*	*
					-1	
						-1

Extended matrix GKO step by step

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*	*	*	*	*	*	y_1
	*	*	*	*	*	y_2
		*	*	*	*	y_3
			*	*	*	y_4
				*	*	y_5
					*	y_6
						x_1
						x_2
						x_3
						x_4
						x_5
						x_6

Extended matrix GKO step by step

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*	*	*	*	*	*
*	*	*	*	*	*

*	*	*	*	*	*	y_1
	*	*	*	*	*	y_2
		*	*	*	*	y_3
			*	*	*	y_4
				*	*	y_5
					*	y_6
						x_1
						x_2
						x_3
						x_4
						x_5
						x_6

Extended matrix GKO

Notice:

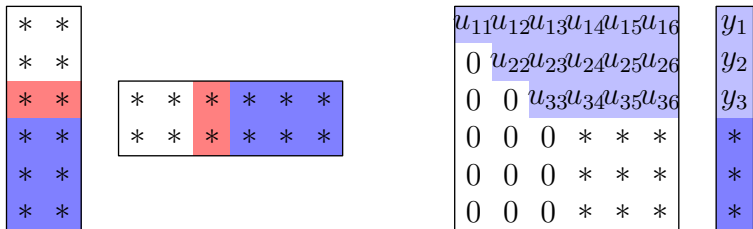
- In the $-I$ block, we divide by $y_i - y_j$ (with $j > i$):
 y must be injective (true in most applications)
- The $-I$ block diagonal is not reconstructible
Luckily whenever we need an element, it is -1

Cost: $6rn^2$ instead of $4rn^2$ flops of original GKO
($+2n^2s$ for back-substitutions with a $n \times s$ right-hand side)

but only $2n$ buffer space is needed

In practice, **faster** for large values of n

Another solution: the back-and-forth method

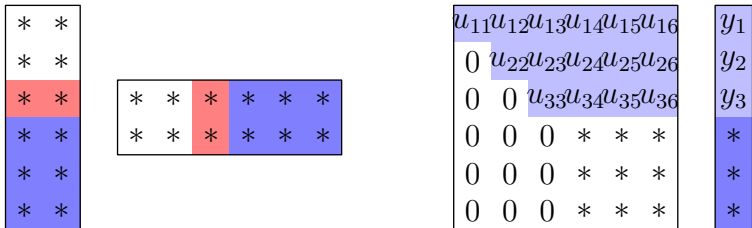


At each GKO step, we discard the top row of G and column of B :
 $G(k, :)$, $B(:, k)$

In practice, they stay in memory (no unnecessary allocations!)

Idea: can we use these to **undo** one GKO step?

Another solution: the back-and-forth method

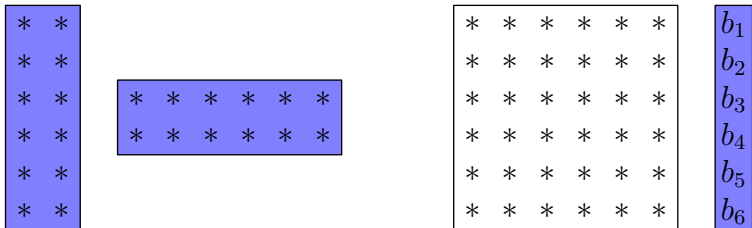


- u_{kk} (pivot) can be recovered: $u_{kk} = \frac{G(k,:)B(:,k)}{x_k - y_k}$
- So can the rest of the u -row, using the value of B after step k :

$$u_{k\ell} = \frac{G(k,:)B_{\text{before}}(:,\ell)}{x_k - y_\ell} = \frac{G(k,:)B_{\text{after}}(:,\ell)}{y_k - y_\ell}$$

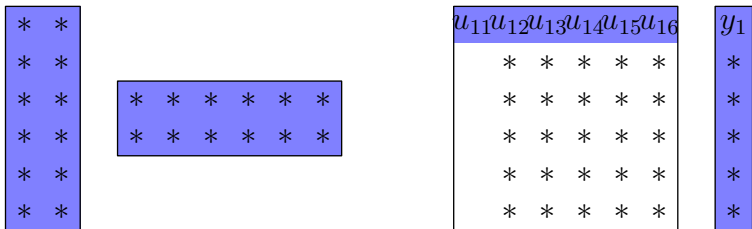
- Using u -row and B_{after} , we can undo the update to get B_{before}

Back-and-forth GKO step by step



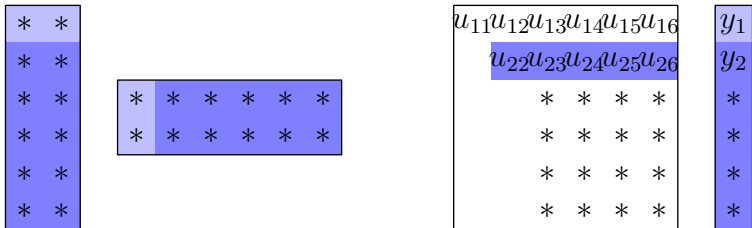
- GKO as usual
- Keep in memory the old parts of G and B
- Do not keep the old u_{ij} 's

Back-and-forth GKO step by step



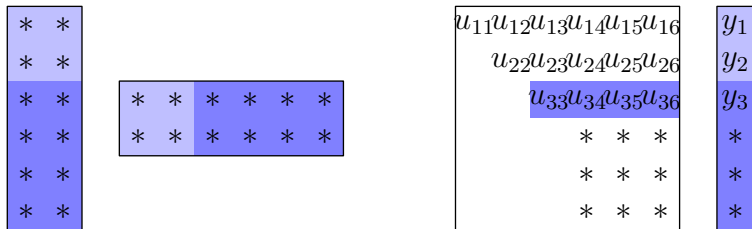
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Back-and-forth GKO step by step



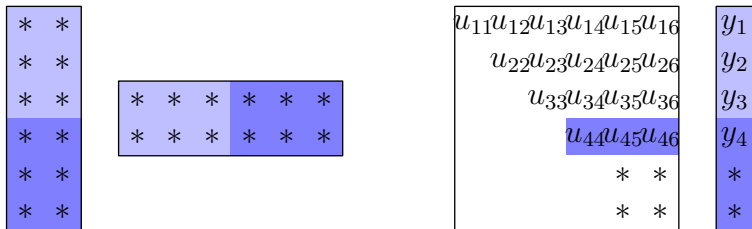
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Back-and-forth GKO step by step



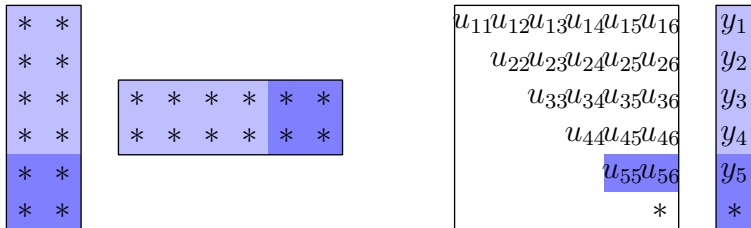
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Back-and-forth GKO step by step



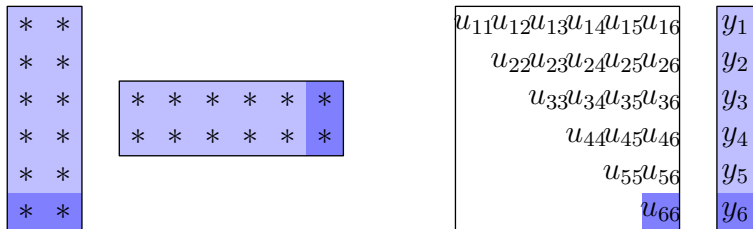
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Back-and-forth GKO step by step



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Back-and-forth GKO step by step



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Back-and-forth GKO step by step

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*	*	*	*	*	*

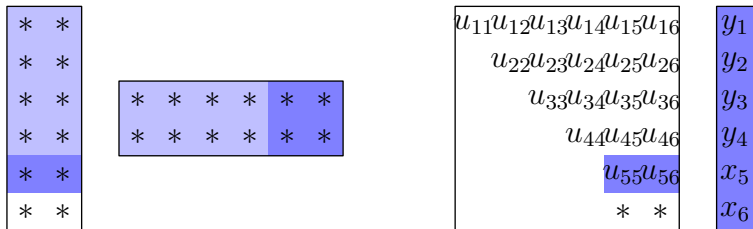
u_{11}	u_{12}	u_{13}	u_{14}	u_{15}	u_{16}
	u_{22}	u_{23}	u_{24}	u_{25}	u_{26}
		u_{33}	u_{34}	u_{35}	u_{36}
			u_{44}	u_{45}	u_{46}
				u_{55}	u_{56}
					u_{66}

y_1
y_2
y_3
y_4
y_5
x_6

For $k = n$ to 1:

- Reconstruct the k th row of u
- Use it to solve the k th equation of $Ux = y$ by back-substitution
- “downdate” B to its old value at step k of GKO

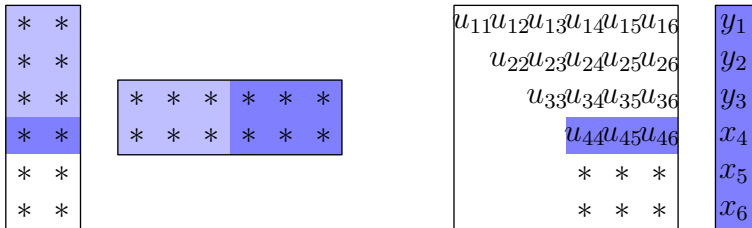
Back-and-forth GKO step by step



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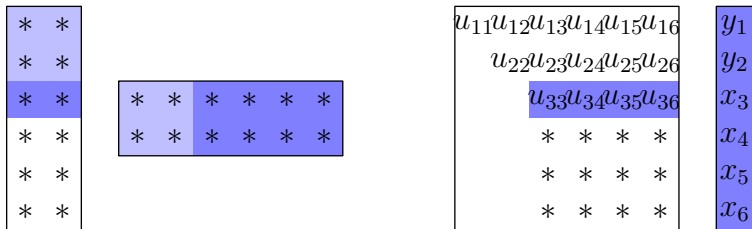
Back-and-forth GKO step by step



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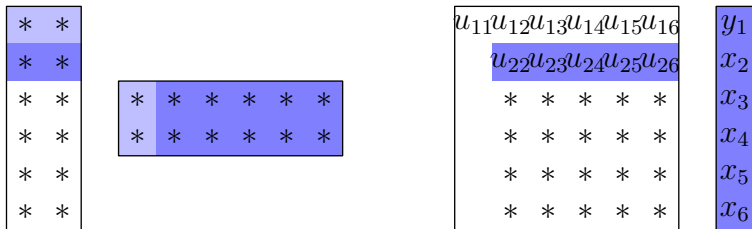
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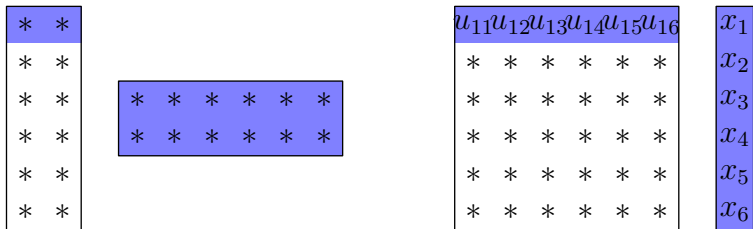
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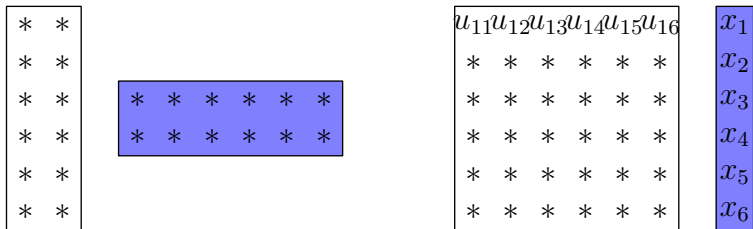
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Back-and-forth GKO step by step



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- “downdate” B to its old value at step k of GKO

Back-and-forth GKO: considerations

- “downdate” of G is not needed
- cost: $6rn^2$: same as Extended Matrix
- memory: input size + $2n$ temps: same as Extended Matrix
- both require $y_i \neq y_j$ for $i \neq j$
- similar numerical behaviour

Are they the same algorithm? **No**:

Key questions: where is L in Extended Matrix? Where is U ?

Extended Matrix – where are L and U ?

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*	*	*	*	*	*

*	*	*	*	*	*	y_1
	*	*	*	*	*	y_2
		*	*	*	*	y_3
			u_{44}	*	*	y_4
			*	*	*	*
			*	*	*	*
		v_{14}	*	*	*	*
		v_{24}	*	*	*	*
		v_{34}	*	*	*	*
		-1				
			-1			
				-1		

L : upper part as in GKO

$$U: (U^{-1})_{ij} = -\frac{v_{ij}}{u_{jj}}$$

EM vs. BF: numerical experiments

Forward errors

n	EM	BF
10	1.6E-12	1.6E-12
100	1.4E-05	1.4E-05
500	8.0E-01	8.0E-01

ill-conditioned Cauchy-like
nodes=1 + 0.3($i - j$)

n	EM	BF
10	7.9E-11	6.9E-11
100	2.0E-07	1.0E-07
500	1.3E-07	1.2E-07

Gaussian Toeplitz
 $a = 0.9$

Caveat: not to be taken too seriously:

- Implementation matters, small optimizations = huge differences
- Processor, cache size, cache efficiency issues

EM vs. BF: numerical experiments

n	CPU time		
	EM	BF	plain
100	1.3E-03	1.2E-03	8.5E-04
1000	1.1E-01	9.7E-02	8.6E-02
3000	1.03E+00	8.6E-01	1.7E+00
10000	1.3E+01	1.0E+01	3.5E+01

Caveat: not to be taken too seriously:

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EM vs. BF: other factors

- BF: *a posteriori error estimate*: did we reconstruct the original generators properly?
LU stability + generator growth
- BF: *preview* of the solution: after part 1, the entries of x arrive one at each step.
In Toeplitz computations, lower-sampled “preview”
- BF: the inner steps take less memory (vs. EM: every step takes $2nr$ memory)
Should fit better into cache

Trummer-like matrices: definitions

Definition

A **Trummer-like** matrix is a Cauchy-like matrix in which the non-reconstructible entries are the diagonal ones, i.e.

$$D_x T - T D_x = G \cdot B = \mathbf{1} \cdot \mathbf{1} \quad (\text{rank } r \ll n)$$

Appear in many contests:

- Trummer's problem [Gerasoulis et al., 88]
- Toeplitz computations, e.g. [Kailath–Olshevsky '97]
- Integral equations, e.g. the matrix equation we were solving

Displacement rank and algorithms

How to store them?

- Store generators G , B as every Cauchy-like matrix, **and**
- Store the diagonal separately

Structure is preserved

If $\text{TRk}(T) := \text{Rk}(D_x T - T D_x)$

- $\text{TRk}(T + S) = \text{TRk}(T) + \text{TRk}(S)$
- $\text{TRk}(TS) = \text{TRk}(T) + \text{TRk}(S)$
- $\text{TRk}(T^{-1}) = \text{TRk}(T)$

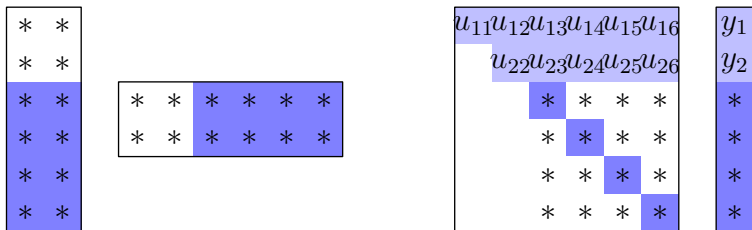
Our goal: space-efficient fast Trummer-like matrix computations:
 $T \cdot v$, $T \cdot S$, $T^{-1} \cdot v$, $T^{-1} \cdot S$

Matrix-vector operations

Matrix-vector product: easy! Recover T from its generators one row at a time, apply traditional M-v algorithm

Linear system solving $T^{-1}v$ idea in [Kailath-Olshevsky, '97]:

Traditional GKO + store and update diagonal elements separately



Matrix–matrix operations

Let $\nabla T := D_x T - T D_x$

Matrix–matrix product $T \cdot S$

- generators: $\nabla(TS) = T\nabla(S) + \nabla(T)S$
- diagonal: recover and multiply

Inverse T^{-1} (and product $T^{-1} \cdot S$)

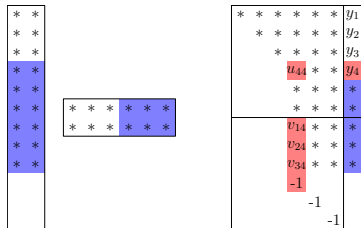
- generators: $\nabla(T^{-1}) = -T^{-1}\nabla(T)T^{-1}$
- diagonal: ??

No obvious algorithm to get $\text{diag}(T^{-1})$

How to get $\text{diag}(T^{-1})$?

Entries of U^{-1} : explicitly available with the Extended Matrix version of GKO

k th step: k th column of U^{-1}



Entries of L^{-1} : repeat on T^T : the LU factors of T^T are $U^T L^T$ (up to diagonal scaling with the pivots)

k th step: k th row of L^{-T}

We get the right entries at the right time to compute the diagonal:

$$U^{-1}L^{-1} = \begin{array}{|cccc|} \hline 1 & 2 & 3 & 4 \\ \hline & 2 & 3 & 4 \\ \hline & & 3 & 4 \\ \hline & & & 4 \\ \hline \end{array} \quad \begin{array}{|cccc|} \hline 1 & & & \\ \hline 2 & 2 & & \\ \hline 3 & 3 & 3 & \\ \hline 4 & 4 & 4 & 4 \\ \hline \end{array}$$

Implementing GKO+invdiag

Not exactly GKO twice: many computations are the same

$$\text{Schur_compl}(T^T) = [\text{Schur_compl}(T)]^T$$

- GKO is born symmetric: given generators of T , compute generators of $\text{Schur_compl}(T)$ — $4rn^2$ ops
- EM version: some extra work on G — $6rn^2$ ops
- Now we restore symmetry by doing the same on B — $8rn^2$ ops

In $(12r + 3)n^2$ ops we can build a full set of generators for T^{-1} :

- Solve $G' = T^{-1}G$
- Solve $B' = T^{-T}B$
- Compute $\text{diag}(T^{-1})$ with the above algorithm

Some numerical results

GKO+invdiag vs. a simpler strategy: choose v ,

$$T^{-1}v = \text{diag}(T^{-1})v + [T^{-1} - \text{diag}(T^{-1})]v$$

- $T^{-1}v$ computed with GKO
- $[T^{-1} - \text{diag}(T^{-1})]v$ computed easily from the generators
- solve for $\text{diag}(T^{-1})v$

This strategy loses accuracy because of cancellation errors:

n	GKO+invdiag	solve for $\text{diag}(T^{-1})v$
10	4.4E-16	5.8E-15
100	2.6E-14	1.4E-11
500	1.4E-12	3.9E-10
10	4.2E-15	1.2E-08
50	9.0E-08	1.6E-02

(random-generated Trummer-like M -matrices, diag+rank-1 matrices)

To sum up

- New $O(n)$ -storage GKO version (Back-and-forth)
Competitive with EM, some nice +'s
- GKO+invdiag to get $\text{diag}(T^{-1})$ for a Trummer-like T
Allows fast Trummer-like matrix computations
Also works when $\text{diag}(T)$ is reconstructible but ill-conditioned

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Thank you for your attention