

# Accurate Solutions of Totally Positive Linear Systems Application to Generalized Vandermonde Systems

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**Plamen Koev**

Department of Mathematics  
University of California - Berkeley

**Joint work with Prof. James Demmel**

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# DEFINITIONS AND GOALS

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- **Totally Positive (TP) Matrix** = All minors positive
- **Accurate** (Small relative error componentwise) and **Efficient** ( $O(n^3)$  or perhaps  $O(n^p)$ , independent of condition number)  
**Solution of  $Ax = b$**

– Small componentwise relative forward error:

$$|x_i - \hat{x}_i| \leq O(\epsilon)|x_i|$$

– Small componentwise relative backward error:

$$|A_{ij} - \hat{A}_{ij}| \leq O(\epsilon)|A_{ij}|$$

- In particular: **Totally Positive Generalized Vandermonde Matrices**

$$G_\lambda = \begin{bmatrix} x_1^{\lambda_n} & x_1^{1+\lambda_{n-1}} & \dots & x_1^{n-1+\lambda_1} \\ x_2^{\lambda_n} & x_2^{1+\lambda_{n-1}} & \dots & x_2^{n-1+\lambda_1} \\ & & \ddots & \\ x_n^{\lambda_n} & x_n^{1+\lambda_{n-1}} & \dots & x_n^{n-1+\lambda_1} \end{bmatrix},$$

$$0 < x_1 < x_2 < \dots < x_n,$$

$$0 \leq \lambda_n \leq \dots \leq \lambda_1 \text{ - integer; } |\lambda| = \lambda_1 + \dots + \lambda_n$$

– Tool to exploit structure: Schur functions

## New results

Type of Matrix		det(A)	$A^{-1}$	Any minor	GENP	GEPP	GECP	SVD	NENP	$Ax = b$ Frwrd*	$Ax = b$ Bckwrd*
Cauchy	Any	$n^2$	$n^2$	$n^2$	$n^3$	$n^3$	$n^3$	$n^3$	$n^2$	$n^2$	
	TP	$n^2$	$n^2$	$n^2$	$n^3$	$n^3$	$n^3$	$n^3$	$n^2$	$n^2$	$n^2$
Vandermonde	Any	$n^2$	No	No	No	No	$n^3$	$n^2$	No		
	TP	$n^2$	$n^3$	Exp	$n^2$	Exp	$n^3$	$n^2$	$n^2$	$n^2$	$n^2$
Polynomial Vandermonde Orthogonal Polynomials	Any	$n^2$	No	No	No	No	$n^3$		No		
	†	$n^2$	$n^3$				$n^3$		$n^3$		
Generalized Vandermonde	Any	No	No	No	No	No	No	No	No	No	No
	TP	$\Lambda n^2$	$\Lambda n^3$	Exp	$\Lambda n^2$	Exp	Exp	$\Lambda n^2$	$\Lambda n^2$	$\Lambda n^2$	$\Lambda n^2$

Big-O sense

\*Forward Bound:  $|x - \hat{x}| \leq O(\epsilon)|A^{-1}||b| \Rightarrow |x - \hat{x}| \leq O(\epsilon)|x|$  for  $A$ -TP and  $x$  checkerboard  
 Backward Bound:  $|A - \hat{A}| \leq O(\epsilon)|A|$ , where  $\hat{A}\hat{x} = b$ .

†  $0 < x_1 < \dots < x_n$  + Other conditions on the signs of the three-term recurrence

$\Lambda = (\lambda_1 + 1)(\lambda_2 + 1)^2 \dots (\lambda_p + 1)^2 p$ , where  $\lambda = (\lambda_1, \dots, \lambda_p)$ .

## Outline of this talk

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- Model of arithmetic
- Classical method for achieving the goals for simple examples –  
The Björck-Pereyra Method for Vandermonde Matrices
- How and why it works?
- Application to TP Generalized Vandermonde matrices

# How can we lose accuracy in computing in floating point?

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- $\text{fl}(a \otimes b) = (a \otimes b)(1 + \delta)$  model of arithmetic with no over/underflow
- OK to multiply, divide, add positive numbers  
Proof:  $1 + \delta$  factors can be factored out
- $x_i \pm x_j$ , where  $x_i$  and  $x_j$  are initial data (so exact)
- $(x_i + y_j)(x_i - y_{j-1})x_{i+1}/(x_{i-1} - y_j)$  - OK
- *Dangerous cancellation* when subtracting approximate results:

$$\begin{array}{r} .12345\mathbf{xxx} \\ - .12345\mathbf{yyy} \\ \hline .00000\mathbf{zzz} \end{array}$$

- We will compute everything using only allowable expressions
- Explains our interest in TP matrices, minors  $> 0$

# Classical Example: Vandermonde Linear Systems

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- The **Björck-Pereyra** methods solve  $Vy = b$ , where  $V$  is Vandermonde:

$$\begin{bmatrix} 1 & x_1 & \dots & x_1^{n-1} \\ 1 & x_2 & \dots & x_2^{n-1} \\ 1 & x_3 & \dots & x_3^{n-1} \\ & & \ddots & \\ 1 & x_n & \dots & x_n^{n-1} \end{bmatrix} \cdot \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} + \\ - \\ + \\ \vdots \\ - \end{bmatrix}$$

and  $0 < x_1 < \dots < x_n$ .

- In  $O(n^2)$  time
  - With small **forward** error:  $|y_i - \hat{y}_i| \leq O(\epsilon)|y_i|$
  - With small **backward** error: If  $\hat{V}\hat{y} = b$  then  $|V_{ij} - \hat{V}_{ij}| \leq O(\epsilon)|V_{ij}|$ .
- How does it work?
    - Newton interpolation

## The Björck-Pereyra Method (1970)

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- Polynomial interpolation:  $\frac{x}{f(x)} \left| \begin{array}{ccc} 1 & 2 & 3 \\ 2 & -1 & 14 \end{array} \right.$  by  $f(x) = a_1 + a_2x + a_3x^2$   
(alternating signs of  $f(x)$  for a purpose)

- E.g. solve:  $\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 2^2 \\ 1 & 3 & 3^2 \end{bmatrix} \cdot \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \\ 14 \end{bmatrix}.$

- GE:  $\begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 4 \\ 1 & 3 & 9 \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 3 \\ 0 & 2 & 8 \end{bmatrix} \Rightarrow \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 3 \\ 0 & 0 & 2 \end{bmatrix}$

- Instead: Newton Interpolation:

$x$	$f(x)$	$f[\cdot, \cdot]$	$f[\cdot, \cdot, \cdot]$
1	2	2	2
2	-1	$\frac{-1-2}{2-1} = -3$	-3
3	14	$\frac{14-(-1)}{3-2} = 15$	$\frac{15-(-3)}{3-1} = 9$

$$\begin{aligned}
 f(x) &= 2 - 3(x - 1) + 9(x - 1)(x - 2) \\
 &= 2 + 3 + 18 - (3 + 9 + 18)x + 9x^2 \\
 &= 23 - 30x + 9x^2
 \end{aligned}$$

- No dangerous cancellation

# Matrix Interpretation of the Björck-Pereyra Method

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- Matrix version of Newton interpolation

$$y = V^{-1}b = \begin{bmatrix} 1 & -1 & \\ & 1 & -1 \\ & & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & & \\ & 1 & -2 \\ & & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & & \\ & 1 & \\ & -\frac{1}{2} & \frac{1}{2} \end{bmatrix} \cdot \begin{bmatrix} 1 & & \\ -1 & 1 & \\ & -1 & 1 \end{bmatrix} \cdot \begin{bmatrix} 2 \\ -1 \\ 14 \end{bmatrix} = \begin{bmatrix} 23 \\ -30 \\ 9 \end{bmatrix}$$

- Notice:

- Bidiagonal Decomposition of  $V^{-1}$  (accurate)

- Checkerboard sign pattern

⇒ No dangerous cancellation ⇒ High relative accuracy

- Intrinsic property of all TP matrices

$$A^{-1} = \begin{bmatrix} 1 & - & \\ & 1 & - \\ & & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & & \\ & 1 & - \\ & & 1 \end{bmatrix} \cdot \begin{bmatrix} + & & \\ & + & \\ & & + \end{bmatrix} \cdot \begin{bmatrix} 1 & & \\ & 1 & \\ & - & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & & \\ - & 1 & \\ & - & 1 \end{bmatrix}$$

# Accuracy of the Björck-Pereyra Method for Vandermondes

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$$\begin{bmatrix} 1 & x_1 & x_1^2 & x_1^3 \\ 1 & x_2 & x_2^2 & x_2^3 \\ 1 & x_3 & x_3^2 & x_3^3 \\ 1 & x_4 & x_4^2 & x_4^3 \end{bmatrix}^{-1} = \begin{bmatrix} 1 & -x_1 & & \\ & 1 & -x_1 & \\ & & 1 & -x_1 \\ & & & 1 \end{bmatrix} \begin{bmatrix} 1 & & & \\ & 1 & -x_2 & \\ & & 1 & -x_2 \\ & & & 1 \end{bmatrix} \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & -x_3 \\ & & & 1 \end{bmatrix} \times \\
 \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & \frac{-1}{x_4-x_1} & \frac{1}{x_4-x_1} \end{bmatrix} \begin{bmatrix} 1 & & & \\ & 1 & & \\ & \frac{-1}{x_3-x_1} & \frac{1}{x_3-x_1} & \\ & \frac{-1}{x_4-x_2} & \frac{1}{x_4-x_2} & \frac{1}{x_4-x_2} \end{bmatrix} \begin{bmatrix} 1 & & & \\ \frac{-1}{x_2-x_1} & \frac{1}{x_2-x_1} & & \\ \frac{-1}{x_3-x_2} & \frac{1}{x_3-x_2} & \frac{1}{x_3-x_2} & \\ \frac{-1}{x_4-x_3} & \frac{1}{x_4-x_3} & \frac{1}{x_4-x_3} & \frac{1}{x_4-x_3} \end{bmatrix}$$

Accuracy ... OK

Other TP matrices? ... Yes. Cauchy

# The Björck-Pereyra Method for Cauchy Matrices

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- *Cauchy* matrices

$$C_{ij} = \frac{1}{x_i - y_j}$$

- TP, if  $x_1 > \dots > x_n > y_1 > \dots > y_n$

$$\begin{bmatrix} \frac{1}{x_1 - y_1} & \frac{1}{x_1 - y_2} & \frac{1}{x_1 - y_3} \\ \frac{1}{x_2 - y_1} & \frac{1}{x_2 - y_2} & \frac{1}{x_2 - y_3} \\ \frac{1}{x_3 - y_1} & \frac{1}{x_3 - y_2} & \frac{1}{x_3 - y_3} \end{bmatrix}^{-1} = \begin{bmatrix} 1 & \frac{-(x_1 - y_1)}{y_1 - y_2} & 0 \\ 0 & \frac{x_1 - y_2}{y_1 - y_2} & \frac{-(x_1 - y_2)}{y_2 - y_3} \\ 0 & 0 & \frac{x_1 - y_3}{y_2 - y_3} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & \frac{-(x_2 - y_1)}{y_1 - y_3} \\ 0 & 0 & \frac{x_2 - y_3}{y_1 - y_3} \end{bmatrix} \times$$

$$\begin{bmatrix} x_1 - y_1 & & \\ & x_2 - y_2 & \\ & & x_3 - y_3 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & \frac{-(x_1 - y_2)}{x_3 - x_1} & \frac{x_3 - y_2}{x_3 - x_1} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ \frac{-(x_1 - y_1)}{x_2 - x_1} & \frac{x_2 - y_1}{x_2 - x_1} & 0 \\ 0 & \frac{-(x_2 - y_1)}{x_3 - x_2} & \frac{x_3 - y_1}{x_3 - x_2} \end{bmatrix}$$

(Vadim Olshevsky, 1995)

- Unifying Characteristic?

# The Connection with Minors

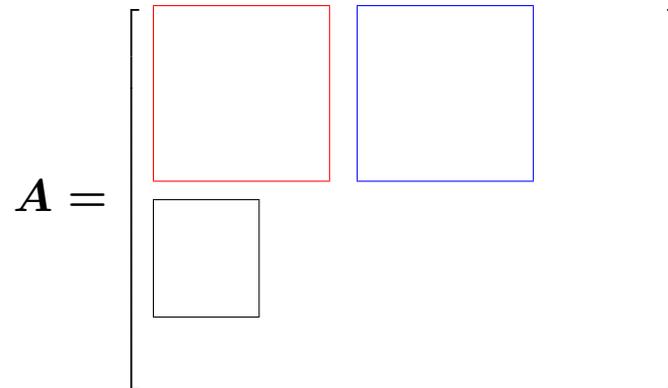
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- Which TP matrices permit *accurate* bidiagonal decomposition?
- Each entry is *product of quotients of initial minors*

$$L_{i+1,i}^{(k)} = -\frac{\det(A(i-k+2:i+1, 1:k))}{\det(A(i-k+2:i, 1:k-1))} \cdot \frac{\det(A(i-k+1:i-1, 1:k-1))}{\det(A(i-k+1:i, 1:k))}$$

## INITIAL MINORS

- Contiguous
- Include first row or column



## When can we solve TP linear system accurately

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- We can accurately solve TP linear systems iff we can compute accurate initial minors

- Initial minors of:

Cauchy  $\frac{\prod_{i < j} (x_j - x_i)(y_j - y_i)}{\prod_{i, j} (x_i + y_j)}$ ;

Vandermonde  $\prod_{i > j} (x_i - x_j)$

- Other classes?

## New results: TP Generalized Vandermonde Matrices

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- TP Matrices with initial minors that are easy to compute accurately  
Vandermonde and Generalized Vandermonde

$$V = \begin{bmatrix} 1 & x_1 & \dots & x_1^{n-1} \\ 1 & x_2 & \dots & x_2^{n-1} \\ & & \ddots & \\ 1 & x_n & \dots & x_n^{n-1} \end{bmatrix}, \quad G_\lambda = \begin{bmatrix} x_1^{\lambda_n} & x_1^{1+\lambda_{n-1}} & \dots & x_1^{n-1+\lambda_1} \\ x_2^{\lambda_n} & x_2^{1+\lambda_{n-1}} & \dots & x_2^{n-1+\lambda_1} \\ & & \ddots & \\ x_n^{\lambda_n} & x_n^{1+\lambda_{n-1}} & \dots & x_n^{n-1+\lambda_1} \end{bmatrix},$$

where  $0 < x_1 < x_2 < \dots < x_n$ ,  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n \geq 0$ ,  $|\lambda| = \lambda_1 + \dots + \lambda_n$

- Initial Minors for  $G_\lambda$ ?

$$\det(G_\lambda) = \det(V) \cdot s_\lambda(x_1, x_2, \dots, x_n)$$

- $s_\lambda$  - called **Schur function**
  - Polynomial with positive integer coefficients
  - Widely studied in combinatorics [Macdonald],  
group representation theory

- Example:

$$\det \begin{bmatrix} 1 & x_1^2 & x_1^4 \\ 1 & x_2^2 & x_2^4 \\ 1 & x_3^2 & x_3^4 \end{bmatrix} = \det \begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ 1 & x_3 & x_3^2 \end{bmatrix} \cdot (2x_1x_2x_3 + x_1^2x_2 + x_1x_2^2 + x_1^2x_3 + x_1x_3^2 + x_2^2x_3 + x_2x_3^2)$$

# Accuracy and Efficiency for TP Generalized Vandermonde Matrices

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- Example:

$$\det \begin{bmatrix} 1 & x_1^2 & x_1^4 \\ 1 & x_2^2 & x_2^4 \\ 1 & x_3^2 & x_3^4 \end{bmatrix} = \det \begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ 1 & x_3 & x_3^2 \end{bmatrix} \cdot (2x_1x_2x_3 + x_1^2x_2 + x_1x_2^2 + x_1^2x_3 + x_1x_3^2 + x_2^2x_3 + x_2x_3^2)$$

- Accuracy?

- $\det(V) = \prod_{i>j} (x_i - x_j)$  - YES.
- $s_\lambda$  - polynomial with nonnegative coefficients - YES.

- Efficiency?

- $\det(V) = \prod_{i>j} (x_i - x_j)$  - OK.
- $s_\lambda(x_1, x_2, \dots, x_n)$ ?
  - \* We are only interested in subtraction-free algorithms, thus:
 

$s_\lambda = f(\text{elementary symmetric polynomials})$	}	– useless
Jacobi – Trudi identity		
  - \* Have to evaluate as polynomial ...
  - \* ... which has exponentially many terms –  $n^{|\lambda|}$

# Computing the Schur Function

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- Def:  $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)$  is a **partition** of  $|\lambda| = \lambda_1 + \lambda_2 + \dots + \lambda_n$
- Schur functions are indexed by partitions  $s_\lambda(x_1, \dots, x_n)$
- Generalize the elementary symmetric functions

- Example:

$$\begin{aligned} s_{(2)}(x_1, \dots, x_n) &= \sum_{i \leq j} x_i x_j = \\ &= x_1 x_1 + (x_1 + x_2) x_2 + (x_1 + x_2 + x_3) x_3 + \dots + (x_1 + \dots + x_n) x_n \end{aligned}$$

- Cost:  $3n$ , although  $s_{(2)}$  has  $n^2$  terms.
- Same trick generalizes. Recursion + memoization. Macdonald:

$$s_\lambda(x, y) = \sum_{\mu < \lambda} s_\mu(x) s_{\lambda/\mu}(y),$$

$x, y$  - sets of indices

- Complexity reduces

from  $O(n^{|\lambda|})$  to  $\Lambda \cdot n$ ,

where

$$\Lambda = (\lambda_1 + 1)(\lambda_2 + 1)^2 \dots (\lambda_p + 1)^2$$

## New results

Type of Matrix		$\det(A)$	$A^{-1}$	Any minor	GENP GEPP	GECP	SVD	NENP	$Ax = b$ Frwrd*	$Ax = b$ Bckwrd*
Cauchy	Any	$n^2$	$n^2$	$n^2$	$n^3$	$n^3$	$n^3$	$n^2$	$n^2$	
	TP	$n^2$	$n^2$	$n^2$	$n^3$	$n^3$	$n^3$	$n^2$	$n^2$	$n^2$
Vandermonde	Any	$n^2$	No	No	No	No	$n^3$	$n^2$	No	
	TP	$n^2$	$n^3$	Exp	$n^2$	Exp	$n^3$	$n^2$	$n^2$	$n^2$
Polynomial Vandermonde Orthogonal Polynomials	Any	$n^2$	No	No	No	No	$n^3$		No	
	†	$n^2$	$n^3$				$n^3$		$n^3$	
Generalized Vandermonde	Any	No	No	No	No	No	No	No	No	No
	TP	$\Lambda n^2$	$\Lambda n^3$	Exp	$\Lambda n^2$	Exp	Exp	$\Lambda n^2$	$\Lambda n^2$	$\Lambda n^2$

Big-O sense

\*Forward Bound:  $|x - \hat{x}| \leq O(\epsilon)|A^{-1}||b| \Rightarrow |x - \hat{x}| \leq O(\epsilon)|x|$  for  $A$ -TP and  $x$  checkerboard

Backward Bound:  $|A - \hat{A}| \leq O(\epsilon)|A|$ , where  $\hat{A}\hat{x} = b$ .

†  $0 < x_1 < \dots < x_n$  + Other conditions on the signs of the three-term recurrence

$\Lambda = (\lambda_1 + 1)(\lambda_2 + 1)^2 \dots (\lambda_p + 1)^2 p$ , where  $\lambda = (\lambda_1, \dots, \lambda_p)$ .

## Conclusions

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- TP Structured linear systems can be solved very accurately, if initial minors factor
- Implies accurate  $A^{-1}$
- New application: Generalized Vandermonde Matrices
- New accurate algorithm for computing the Schur function
  - Extends to computing Jack polynomials
- Not in this talk: Accurate SVDs of
  - Some Polynomial Vandermonde Matrices
  - Weakly Diagonally Dominant M-matrices

## Open Problems

- Totally Positive Matrices in general appear impossible. Proof?
- Characterize which structured matrices permit accurate and efficient linear algebra

## Resources

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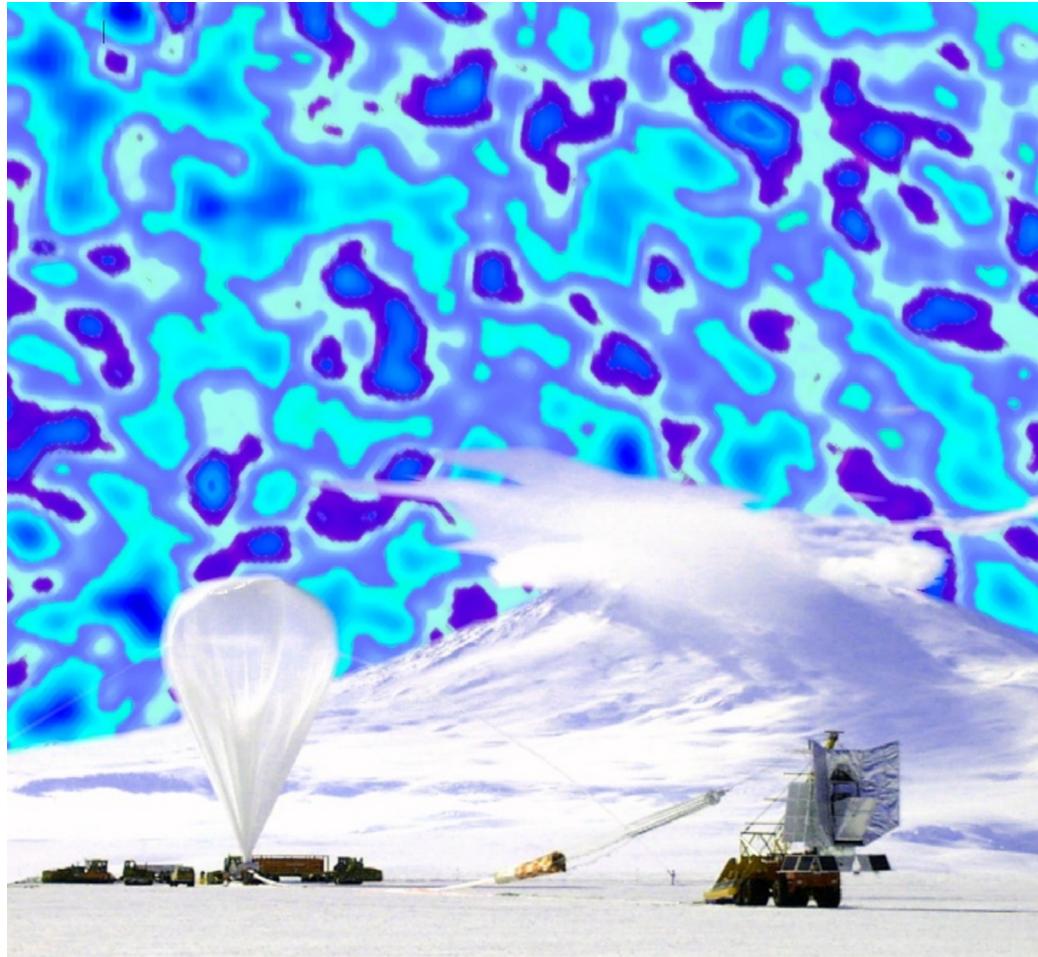
- These slides: [www.math.berkeley.edu/~plamen/hh02.pdf](http://www.math.berkeley.edu/~plamen/hh02.pdf)
- Reports:
  - Plamen Koev, *Accurate and Efficient Computations with Structured Matrices*, UC Berkeley Ph.D. thesis.
  - J. Demmel and P. Koev, Necessary and sufficient conditions for accurate and efficient rational function evaluation and factorizations of rational matrices. In *Structured matrices in mathematics, computer science, and engineering. II (Boulder, CO, 1999)*, pages 117–143. Amer. Math. Soc., Providence, RI, 2001.
  - J. Demmel and P. Koev, *Accurate and Efficient Matrix Computations with Totally Positive Generalized Vandermonde Matrices Using Schur Functions*, [www.math.berkeley.edu/~plamen/hagen.ps](http://www.math.berkeley.edu/~plamen/hagen.ps)
  - J. Demmel, M. Gu, S. Eisenstat, I. Slapničar, K. Veselić, and Z. Drmač. Computing the singular value decomposition with high relative accuracy. *Lin. Alg. Appl.*, 299(1–3):21–80, 1999.  
[www.cs.berkeley.edu/~demmel/DGESVD.ps](http://www.cs.berkeley.edu/~demmel/DGESVD.ps)
  - J. Demmel, *Accurate SVDs of structured matrices*. *SIAM J. Mat. Anal. Appl.*, 21(2):562–580, 1999.  
[www.netlib.org/lapack/lawns/lawn130.ps](http://www.netlib.org/lapack/lawns/lawn130.ps)

## Other Interests

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- Large scale parallel applications of structured matrices, e.g.

Computing the Power Spectrum of the Cosmic Microwave Background Radiation



- Lowered complexity from  $O(n^3)$  to  $O(n^{3/2})$

## Other Interests (2)

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- Computer Arithmetic

- Impact of model of arithmetic on algorithms

e.g.  $(1 + \delta)$  vs. IEEE

- Harry Diamond's Theorem and the Table Maker's Dilemma

$f$

$$g = f^{-1},$$

$$H = G \circ F,$$

$$H(H(H(x))) = H(H(x))$$

- Proved validity when  $f$  non strictly convex and IEEE arithmetic rounding to nearest even

- Computational noncommutative algebra

- Polynomial Identities in Matrix Algebras

- All identities of degree  $2k + 2$  in  $M_k(\mathbb{Z})$  follow from the *Standard Identity* of Amitsur-Levitzky of degree  $2k$ .