# The Numerical Analysis of Milvio Capovani 

Paolo Zellini

Dipartimento di Matematica, Università di Roma "Tor Vergata" zellini@mat.uniroma2.it

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## Scientific Computation vs. Computer Science

Smale, 1990: Schism or conflict between Scientific Computation and Computer Science.

|  | Scientific Computation | Computer Science |
| ---: | :--- | :---: |
| Mathematics | continuous | discrete |
| Problems | classical | newer |
| Goals | practical, immediate | long range |
| Foundations | none | developed |
| Complexity | undeveloped | developed |
| Machine, model | none | Turing |

Blum, Shub, Smale, 1989: Theory of computation and complexity over the real numbers, NP-completeness, Recursive Functions, Universal Machines.

Milvio Capovani: computational complexity, infomational content, models of computation (bilinear programs), algebraic theory of matrices

Analytical approach $\longrightarrow$ Combinatorial, algebraic approach
Arithmetizing analysis:

1. Foundations: all analysis could be based logically on a combination of ordinary arithmetic and passage to the limit (Weierstrass, Dedekind, Poincaré, Cantor)
2. Fredholm's theory of integral equations, whose kernels $K(x, y)$ can be treated as limits of matrices
3. Variational methods: Rayleigh, 1873; Ritz, 1906. Dirichlet problem: proof of a constructive existence theorem
4. Arithmetizing Analysis in principle $\longrightarrow$ Arithmetizing practically, effective procedures (complexity, error)

## Arithmetizing: Goldstine, von Neumann, Strang

H. Goldstine, J. von Neumann, 1946: "Our problems are usually given as continuous-variable analytical problems, frequently wholly or partly of an implicit character. For the purposes of digital computing they have to be replaced, or rather approximated, by purely arithmetical "finitistic" explicit (usually step-by-step or iterative) procedures." (Compare to Hilbert's foundational program)
G. Strang, 1994: "For engineers and social and physical scientists, linear algebra now fills a place that is often more important than calculus. My generation of students, and certainly my teachers, did not see this change coming. It is partly the move from analog to digital; functions are replaced by vectors. Linear algebra combines the insight of $n$-dimensional space with the applications of matrices"

Arithmetizing $\longrightarrow$ matrix computation

## Informational content

Numerical work is often concerned with operations on matrices belonging to special classes. Within a class the generic matrix is often specified by a number $k$ of parameters less than the numbers of elements. $\rightarrow$ Informational content of a matrix Measure of informational content: amount of memory required to store the matrix as compactly as possible in a computer (Forsythe, 1967)

1. Representation of a matrix in a computer (Forsythe)
2. Computational complexity (Capovani, Capriz, Bini, Bevilacqua, Zellini)
Compare to Chaitin, 1974: complexity of a string of bits as the minimum length of a program that generates the string
Capriz, Capovani, 1976: $\mathcal{C}_{n}^{k}=$ class of matrices $n \times n$ of informational content $k=$ manifold of dimension $k, k \leq n^{2}$, in the space of dimension $n^{2}$ of all real $n \times n$ matrices.

## Informational content and computational complexity

The case when $\mathcal{C}_{n}^{k}=$ is an algebra spanned by $k$ linearly independent matrices $J_{i}, i=1,2, \ldots, k$

Let $A=\sum_{i=1}^{k} a_{i} J_{i}, \quad B=\sum_{j=1}^{k} b_{j} J_{j}, \quad J_{i} J_{j}=\sum_{h=1}^{k} t_{h i j} J_{h}$ $t_{\text {hij }}=$ multiplication table

$$
A B=\sum_{i, j=1}^{k} a_{i} b_{j} J_{i} J_{j}=\sum_{h=1}^{k}\left[\sum_{i, j=1}^{k} t_{h i j} a_{i} b_{j}\right] J_{h}=\sum_{h=1}^{k} f_{h}(a, b) J_{h}
$$

where $f_{h}(a, b)=\sum_{i, j=1}^{k} t_{h i j} a_{i} b_{j}=$ bilinear form in the indeterminates $a, b$.
the last formula exhibits possible reductions in computational complexity

## tensor rank

$\operatorname{rk}\left(t_{h i j}\right)=$ rank of the tensor $t_{h i j}$ in a field $\mathcal{F}=$ minimum integer $q$ such that

$$
t_{h i j}=\sum_{r=1}^{q} u_{h r} v_{i r} w_{j r}
$$

for $3 q$ vectors $u_{h}, v_{h}, w_{h}, h=1,2, \ldots, q$ with elements in $\mathcal{F}$.
If the rank of $t_{h i j}$ is $q$, then the coefficients $c_{h}$ of $A B$ are

$$
c_{h}=\sum_{i, j=1}^{k} a_{i} b_{j} \sum_{r=1}^{q} u_{h r} v_{i r} w_{j r}=\sum_{r=1}^{q} u_{h r}\left(\sum_{i=1}^{k} a_{i} v_{i r}\right) \cdot\left(\sum_{j=1}^{k} b_{j} v_{j r}\right)
$$

i.e. $q$ non-scalar multiplications are sufficient (necessary when commutativity is not assumed) to compute $c_{h}$. Then the rank of the tensor $t_{h i j}$ of the multiplication table of $\mathcal{C}_{n}^{k}$ defines the multiplicative complexity of the product of two elements of $\mathcal{C}_{n}^{k}$.

## tensor rank and border rank, approximate algorithms

Let $\mathcal{F}$ be a field with infinite elements and $T=t_{h i j}$ a tensor on $\mathcal{F}$. $\operatorname{rkb}(T)=$ border rank of $T=$ minimum integer $t$ such that, for every $\varepsilon>0$ we have a tensor $E=e_{h i j}$, with $\left|e_{h i j}\right|<\varepsilon$, such that $\operatorname{rk}(T+E)=t$.
We have $\mathrm{rkb}(T) \leq \mathrm{rk}(T)$ and sometimes $\mathrm{rkb}(T)<\mathrm{rk}(T)$. For

$$
T=\left(\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right],\left[\begin{array}{ll}
0 & 1 \\
0 & 0
\end{array}\right]\right)
$$

we have $\operatorname{rkb}(T)=2$ and $\operatorname{rk}(T)=3$.
Bini, Capovani, Lotti, Romani, 1979-1980, 1981: Complexity of approximate algorithms, main applications to:

1. band Toeplitz matrices
2. matrix multiplication: algorithm of complexity
$O\left(n^{w}\right), w \leq 2.7798 \ldots$ for solving a system of $n$ linear equations, improving Strassen's limit $w \leq \log _{2} 7=2.807 \ldots$

## Algebra $\tau$

Bevilacqua, Capovani, 1972: algebra $\mathcal{C}_{n}^{k}=\tau$ of informational content $k=n$

$$
\tau_{5}=\left[\begin{array}{ccccc}
t_{1} & t_{2} & t_{3} & t_{4} & t_{5} \\
t_{2} & t_{1}+t_{3} & t_{2}+t_{4} & t_{3}+t_{5} & t_{4} \\
t_{3} & t_{2}+t_{4} & t_{1}+t_{3}+t_{5} & t_{2}+t_{4} & t_{3} \\
t_{4} & t_{3}+t_{5} & t_{2}+t_{4} & t_{1}+t_{3} & t_{2} \\
t_{5} & t_{4} & t_{3} & t_{2} & t_{1}
\end{array}\right]
$$

cross-sum condition: $t_{i-1, j}+t_{i+1, j}=t_{i, j-1}+t_{i, j+1}$
$\tau$ generated over $R$ by the matrix

$$
H=\left[\begin{array}{lllll}
0 & 1 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 1 \\
0 & 0 & 0 & 1 & 0
\end{array}\right]
$$

## structure and informational content 1

The class $\tau$ is now used (like the class of circulant matrices) in many problems in numerical linear algebra: matrix displacement decompositions, optimal preconditioning, complexity of Toeplitz matrices.
$\tau=$ example of class $\mathcal{C}_{n}^{k}$ with $k=n$ obtained by choosing an orthogonal matrix $Q$ of order $n$ and taking all matrices $G=Q D Q^{T}$ where $D=$ arbitrary real diagonal matrix. Compare to circulant matrices and to Hartley algebra (Bini, Favati, 1993).

Bini, Capovani, 1983: "We try to separate what is related to the structure of the class from what is related to the specific values (informational content) of the matrix"
$Q \rightarrow$ structure
$D \rightarrow$ informational content

$$
A=Q D_{A} Q^{T}, \quad A \text { generated by } H=Q D Q^{T}
$$

## structure and informational content 2

For all classes of matrices which are algebras generated by one matrix $H$ it is possible to accomplish completely such a separation between the structure and the informational content. In fact, if $H=Q D Q^{\top}$ and the class is generated by $H$, then all matrices $A$ of the class have the form $A=Q D_{A} Q^{T}$ (and commute with $H$ ).

Structure of $n$-dimensional commutative spaces $\sum_{k=1}^{n} a_{k} J_{k}$ of minimal informational content and minimal complexity, where $J_{k}$ are $(0,1)$ matrices with prescribed sum.
Zellini, 1979 and 1985; Grone, Hoffman, Wall, 1982; Bevilacqua, Zellini, 1989 and 1996, Bevilacqua, Di Fiore, Zellini, 1996;

This theoretical study has inspired numerical research: preconditioning tecniques, representations of a matrix $A$ as sums of products of matrices belonging to spaces $\sum_{k=1}^{n} a_{k} J_{k}$, using displacement rank.

## informational content and bordering 1

Representation of a band symmetric Toeplitz matrix (BST) $a_{i}-a_{j} \rightarrow i-j$
$B=\left[\begin{array}{ccccccc}1-3 & 2-4 & 3 & 4 & 0 & 0 & 0 \\ 2-4 & 1 & 2 & 3 & 4 & 0 & 0 \\ 3 & 2 & 1 & 2 & 3 & 4 & 0 \\ 4 & 3 & 2 & 1 & 2 & 3 & 4 \\ 0 & 4 & 3 & 2 & 1 & 2 & 3 \\ 0 & 0 & 4 & 3 & 2 & 1 & 2-4 \\ 0 & 0 & 0 & 4 & 3 & 2-4 & 1-3\end{array}\right] \in \tau_{n+2}, n=5$
$A=\left[\begin{array}{lllll}1 & 2 & 3 & 4 & 0 \\ 2 & 1 & 2 & 3 & 4 \\ 3 & 2 & 1 & 2 & 3 \\ 4 & 3 & 2 & 1 & 2 \\ 0 & 4 & 3 & 2 & 1\end{array}\right]=$ 7-diagonal BST matrix

## informational content and bordering 2

If $\mu_{i}$ are the eigenvalues of $B, \quad \mu_{1} \geq \mu_{2} \ldots \geq \mu_{n+2}$, then a representation of $B$ in the basis $I, H, \ldots, H^{n+1}$ gives the following representation of a $n \times n$ ( $n$ even) 7-diagonal BST Toeplitz matrix $A$, with elements $a_{1}, a_{2}, a_{3}, a_{4}$ :

$$
A=V P^{T}\left[\begin{array}{cc}
D_{1}+\mu_{1} v_{1} v_{1}^{T} & 0 \\
0 & D_{2}+\mu_{n+2} v_{2} v_{2}^{T}
\end{array}\right] P V
$$

where $D_{1}=\operatorname{diag}\left(\mu_{3}, \mu_{5}, \ldots, \mu_{n+1}\right), \quad D_{2}=\operatorname{diag}\left(\mu_{2}, \mu_{4}, \ldots, \mu_{n}\right)$, $P=$ permutation matrix, and $V, v_{i}, i=1,2$, do not depend on $a_{k}$.

Bini, Capovani, 1983: The eigenvalues $\lambda_{i}$ of $A$ satisfy $\mu_{i+2} \leq \lambda_{i} \leq \mu_{i}$
$V, v_{i} \rightarrow$ structure
$\mu_{i}=$ linear functions of $a_{1}, a_{2}, a_{3}, a_{4} \rightarrow$ informational content

## approximation, unconstrained minimization

Milvio Capovani, fundamental idea: the error in approximation is not always a cause of failure; by approximating a problem by a "better" one - where matrix algebras and fast transforms are involved - we can improve efficiency.
In quasi-Newton methods for unconstrained minimization in $R^{n}$ an analogous idea is used to reduce complexity. In fact, in the BFGS iterative step for $\min f(x), x \in R^{n}\left(B_{k}\right.$ positive definite)

$$
\begin{aligned}
& d_{k}=-B_{k}^{-1} \nabla f\left(x_{k}\right) \\
& x_{k+1}=x_{k}+\lambda_{k} d_{k} \\
& B_{k+1}=\Phi\left(B_{k}, s_{k}, y_{k}\right) \\
& s_{k}=x_{k+1}-x_{k} \text { and } y_{k}=\nabla f\left(x_{k+1}\right)-\nabla f\left(x_{k}\right)
\end{aligned}
$$

$B_{k}$ can be approximated, in Frobenius norm, by a matrix with strong structure ( $\tau$, circulant or others), reducing the informational content sufficient for convergence and leading to $O$ (nlogn) arithmetic operations per step, instead of $O\left(n^{2}\right)$ of BFGS (Di Fiore, Fanelli, Lepore, Zellini, 2003)

## Winograd-Parlett: FFT via circulants

Rader, 1968; McClellan, Rader, 1979: for $n$ prime, the nontrivial part of a Fourier transform $F_{n} x$ is the computation of $C y$, where $C$ is a special circulant of order $n-1$ and $y$ 's elements are a subset of $x$ 's elements.
Ciclic convolution on $n$ points as product of two polynomials mod $u^{n-1}-1$ (Winograd, 1978) $\rightarrow$ real spectral factorization of $C$
(Parlett, 1982)

$$
C=G D G^{T}
$$

$D$ is block diagonal with $2 \times 2$ and $1 \times 1$ blocks and G's elements are small integers, so $G$ and $G^{T}$ act via additions, and only the application of $D$ involves genuine multiplications. For $n=5$

$$
D=-\frac{1}{4} \oplus \frac{1}{2}\left(\cos \frac{1}{5} \pi+\cos \frac{2}{5} \pi\right) \oplus\left[\begin{array}{cc}
\sin \frac{2}{5} \pi & -\sin \frac{1}{5} \pi \\
\sin \frac{1}{5} \pi & \sin \frac{2}{5} \pi
\end{array}\right] i
$$

