High-Performance Tensor Computations: Where Do We Stand?

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SIAM Conference on Computational Science and Engineering (via Zoom)







About me (and tensors)

	Taxonomy of contractions: Can you GEMM?	E. Di Napoli, D. Traver-Fabregat, P.B.
	"Towards an Efficient Use of the BLAS Library for Multilinear Tensor Contractions",	AMC 235, 2014
	Deufeure en ee andietiere	
	Performance prediction	E. Peise, P.B.
	"On the Performance Prediction of BLAS-based Tensor Contractions", PMBS, SC'14	
	Density Functional Theory: FLAPW methods	E. Di Napoli, E. Peise, P.B.
	"High-Performance Generation of the Hamiltonian and Overlap Matrices in FLAPW I	Methods", CPC 2017
	High-performance kernels	P. Springer, P.B.
	"TTC: A high-performance Compiler for Tensor Transpositions", ACM TOMS 44(2),	2017 + J. Hammond
"Design of a High-Performance GEMM-like Tensor-Tensor Multiplication", ACM TOMS 44(3), 2018		
	"Spin Summations: A High-Performance Perspective", ACM TOMS 45(1), 2019	+ D. Matthews
	High-intensity kernels	C. Psarras, L. Karsson, P.B.

"Concurrent Alternating Least Squares for multiple simultaneous Canonical Polyadic Decompositions", 2020

Matrices vs. Tensors

Historical overview

Linear Algebra Libraries: 1970s

"Basic Linear Algebra Subprograms for FORTRAN usage", ACM TOMS, 1979

BLAS-1

Linear Algebra Libraries: 1980s

BLAS-2: Mat-vec ops, ACM TOMS 1988. BLAS-3: mat-mat ops, ACM TOMS 1990

Linear Algebra Libraries: 1990s Solvers & eigensolvers, 1992

LAPACK

Linear Algebra Libraries: 1990s Distributed Memory, 1995, 1997

ScaLAPACK, PLAPACK, ...

LAPACK

Linear Algebra Libraries: 1990s Dense & Sparse, 1997

PETSc, ...

ScaLAPACK, PLAPACK, ...

LAPACK

Linear Algebra Libraries

and then more!

PETSc, Trilinos, ...

ScaLAPACK, PLAPACK, Elemental, ...

LAPACK, Plasma, SuperMatrix, Magma, ...

BLAS-1, BLAS-2, BLAS-3, ATLAS, BTO-BLAS, BLIS, ...

(Dense) Linear Algebra Libraries Salient features

- Community effort. Standardized interface
- ► Careful organization: support routines, linear-systems, eigen-decompositions
- Clear layering: functionality, parallelism

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But

- Rigid interface
- Black-box nature
- Often sub-optimal at small scale

$$x := A(B^{T}B + A^{T}R^{T}\Lambda RA)^{-1}B^{T}BA^{-1}y \qquad \dots \qquad E := Q^{-1}U(I + U^{T}Q^{-1}U)^{-1}U^{T}$$



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$$\begin{cases} C_{\dagger} := PCP^{T} + Q \\ K := C_{\dagger}H^{T}(HC_{\dagger}H^{T})^{-1} \end{cases} \qquad \Lambda := S(S^{T}AWAS)^{-1}S^{T}; \ \Theta := \Lambda AW; \ M_{k} := X_{k}A - I \\ X_{k+1} := X_{k} - M_{k}\Theta - (M_{k}\Theta)^{T} + \Theta^{T}(AX_{k}A - A)\Theta \end{cases}$$

$$K_{k} := P_{k}^{b} H^{T} (HP_{k}^{b} H^{T} + R)^{-1}; \quad x_{k}^{a} := x_{k}^{b} + K_{k} (z_{k} - Hx_{k}^{b}); \quad P_{k}^{a} := (I - K_{K} H) P_{k}^{b}$$

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$$y := \alpha x + y \qquad LU = A \qquad \cdots \qquad C := \alpha AB + \beta C$$

$$x := A^{-1}B \qquad C := AB^{T} + BA^{T} + C \qquad X := L^{-1}ML^{-T} \qquad QR = A$$

$$\cdots \qquad BLAS \qquad LAPACK \qquad \cdots$$

$$MUL \qquad ADD \qquad MOV$$

$$MOVAPD$$

$$VFMADDPD \qquad \cdots$$

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$$x := A(B^{T}B + A^{T}R^{T}\Lambda RI$$

$$\begin{array}{c} \text{LINEAR ALGEBRA \\ \text{MAPPING PROBLEM } \\ ("LAMP") \end{array} \qquad \overset{-1}{U}(I + U^{T}Q^{-1}U)^{-1}U^{T} \\ \hline X := A^{-1}B \end{array} \qquad \overbrace{C := AB^{T} + BA^{T} + C} \qquad X := L^{-1}ML^{-T} \qquad QR = A \\ \ldots \qquad & BLAS \qquad LAPACK \qquad \ldots \\ \hline MUL \quad ADD \quad MOV \\ \hline MOVAPD \\ \hline VFMADDPD \qquad \ldots \end{array}$$

.

C. Psarras, H. Barthels, "The Linear Algebra Mapping Problem. Current state of linear algebra languages and libraries". [arXiv:1911.09421]

H. Barthels, C. Psarras, "Linnea: Automatic Generation of Efficient Linear Algebra Programs", ACM TOMS, 2021. [arXiv:1912.12924]

Tensors





^{9 / 20}

► (At least) Two separate worlds

¹With notable differences.

- ► (At least) Two separate worlds
 - Computational physics / chemistry

 ${\sf Tensor} = {\sf Multi-linear} \ {\sf operator}$

 $Contractions = Generalization \ of \ matrix-matrix \ product$

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Data science

 $\mathsf{Tensor} = \mathsf{Collection} \text{ of data}$

 $Decompositions = Generalization of matrix factorizations^1$

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Data science

 $\mathsf{Tensor} = \mathsf{Collection} \text{ of data}$

Decompositions = Generalization of matrix factorizations¹

- > Terminology and notation vary (and conflict) even within one world
- Very few software efforts cut across the boundary

¹With notable differences.

MS14 (today) & MS79 (tomorrow)

(At least) Two separate worlds

Computational physics / chemistry

Quantum Chemistry: Ed Valeev, Devin Matthews, Edgar Solomonik Quantum Physics: Pan Zhang, Lei Wang, Miles Stoudenmire

Data science

Furong Huong, Hanie Sedghi, Vagelis Papalexakis

- Notation: Miles Stoudenmire
- Software: Edgar Solomonik

Tensors, presently

- ▶ No "Tensor BLAS" no collections of building blocks
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 Application-driven development: Publications scattered among diffents fields Re-invention of the wheel

Matlab and R packages with support for CP decomposition (subset)

- Tensor Toolbox by Bader, Kolda, & others https://www.tensortoolbox.org/
- Tensorlab by Vervliet, Debals, Sorber, Van Barel, & De Lathauwer https://www.tensorlab.net/index.html
- The N-way Toolbox by Bro & Andersson http://www.models.life.ku.dk/nwaytoolbox
- TensorBox by Phan, Tichavsky, & Cichocki https://github.com/phananhhuy/TensorBox
- Tensor Package by Comon & others http://www.gipsa-lab.fr/~pierre.comon/TensorPackage/tensorPackage.html

multiway by Helwig

https://cran.r-project.org/package=multiway

- ThreeWay by Giordani, Kiers, & Del Ferraro https://cran.r-project.org/package=ThreeWay
- rTensor by Li, Bien, & Wells https://cran.r-project.org/package=rTensor

C/C++ packages with support for CP decomposition (subset)

- Genten by SANDIA (Phipps) https://gitlab.com/tensors/genten
- SPLATT by Smith & Karypis https://github.com/ShadenSmith/splatt
- ParTI! by Li, Ma, & Vuduc https://github.com/hpcgarage/ParTI
- Cyclops by Solomonik & others https://github.com/cyclops-community

And then there's Python, Fortran, ...

Representative operations - building blocks candidates

Data layout operations

- Reshape
- Permute / transpose
- Sort (sparse)
- Convert data layout
- Partition

. . .

Distribute

Arithmetic operations

- Add, subtract, scale
- Inner product
- Norms
- Element-wise operations
- Tensor-times-vector (TTV)
- Tensor-times-matrix (TTM)
- MTTKRP

...

Contractions

Decompositions

- CP (CANDECOMP/PARAFAC)
- Tucker
- INDSCAL
- PARAFAC2
- CANDELINC
- DEDICOM

▶ ...

PARATUCK2

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PARATUCK2

In setting up a library, where to draw the boundaries?



Algorithms for CP (PARAFAC) decomposition

Hence all the different libraries

Algebraic algorithms

- Generalized Rank Annihilation Method
- Direct TriLinear Decomposition
- The "algebraic algorithm" by Domanov and De Lathauwer
- The "simpler algorithm" by Pimentel-Alarcón
- Alternating optimization algorithms
 - Alternating Least Squares
 - Fast ALS

▶ ...

. . .

- Hierarchical ALS
- Regularized ALS

All-at-once optimization algorithms

- Gradient descent
- (Damped) Gauss–Newton
- Nonlinear CG, GMRES
- Quasi-Netwon (e.g., L-BFGS)

Enhancements

...

- Line search
- Compression
- Randomization
- Transient constraints

Also . . .

Also ... one vs. many instances

Coupled-Cluster methods

 $\tau_{ii}^{ab} = t_{ii}^{ab} + \frac{1}{2} P_b^a P_i^i t_i^a t_i^b$ $\tilde{F}_e^m = f_e^m + \sum v_{ef}^{mn} t_n^f,$ $ilde{F}_e^a = (1-\delta_{ae})f_e^a - \sum ilde{F}_e^m t_m^a - rac{1}{2}\sum v_{ef}^{mn}t_{mn}^{af} + \sum v_{ef}^{an}t_n^{f},$ $\tilde{F}_i^m = (1 - \delta_{mi})f_i^m + \sum \tilde{F}_e^m t_i^e + \frac{1}{2}\sum_{e} v_{ef}^{mn} t_{in}^{ef} + \sum_{e} v_{if}^{mn} t_n^f,$ $\tilde{W}_{ei}^{mn} = v_{ei}^{mn} + \sum v_{ef}^{mn} t_i^f,$ $\tilde{W}_{ij}^{mn} = v_{ij}^{mn} + P_j^i \sum v_{ie}^{mn} t_j^e + \frac{1}{2} \sum v_{ef}^{mn} \tau_{ij}^{ef},$ $\tilde{W}_{ie}^{am} = v_{ie}^{am} - \sum \tilde{W}_{ei}^{mn} t_n^a + \sum_{e} v_{ef}^{ma} t_i^f + \frac{1}{2} \sum_{e} v_{ef}^{mn} t_i^{af},$ $ilde{W}^{am}_{ij} = v^{am}_{ij} + P^i_j \sum v^{am}_{ie} t^e_j + rac{1}{2} \sum v^{am}_{ef} au^{ef}_{ij},$ $z_i^a = f_i^a - \sum \tilde{F}_i^m t_m^a + \sum f_e^a t_i^e + \sum v_{ei}^m t_m^e + \sum v_{im}^{ae} \tilde{F}_e^m + \frac{1}{2} \sum$ $z_{ij}^{ab} = v_{ij}^{ab} + P_j^i \sum v_{ie}^{ab} t_j^e + P_b^a P_j^i \sum \tilde{W}_{ie}^{am} t_{mj}^{eb} - P_b^a \sum \tilde{W}_{ij}^{am} t_m^b + P_b^a P_j^a \sum v_{ij}^{am} t_m^b + P_b^a P_b^a \sum v_{ij}^{am} t_m^b P_b^a \sum v_{ij}^{am} t_m^b + P_b^a P_b^a \sum v_{ij}$

credits to D. Matthews, E. Solomonik, J. Stanton, and J. Gauss

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Coupled-Cluster methods

 $\tau_{ii}^{ab} = t_{ii}^{ab} + \frac{1}{2}P_b^a P_i^i t_i^a t_i^b,$ $\tilde{F}_e^m = f_e^m + \sum v_{ef}^{mn} t_n^f,$ $\tilde{F}_e^a = (1-\delta_{ae})f_e^a - \sum \tilde{F}_e^m t_m^a - \frac{1}{2}\sum_{vef} v_{ef}^m t_{mn}^a + \sum_{vef} v_{ef}^{an} t_n^f,$ $\tilde{F}_i^m = (1 - \delta_{mi})f_i^m + \sum_{e} \tilde{F}_e^m t_i^e + \frac{1}{2}\sum_{e} v_{ef}^{mn} t_{in}^{ef} + \sum_{e} v_{if}^{mn} t_n^f,$ $\tilde{W}_{ei}^{mn} = v_{ei}^{mn} + \sum_{f} v_{ef}^{mn} t_i^f,$ $\tilde{W}_{ij}^{mn} = v_{ij}^{mn} + P_j^i \sum v_{ie}^{mn} t_j^e + \frac{1}{2} \sum_{i} v_{ef}^{mn} \tau_{ij}^{ef},$ $\tilde{W}^{am}_{ie} = v^{am}_{ie} - \sum \tilde{W}^{mn}_{ei} t^a_n + \sum_{c} v^{ma}_{ef} t^f_i + \frac{1}{2} \sum_{c} v^{mn}_{ef} t^{af}_{in},$ $\tilde{W}^{am}_{ij} = v^{am}_{ij} + P^i_j \sum v^{am}_{ie} t^e_j + \frac{1}{2} \sum_i v^{am}_{ef} \tau^{ef}_{ij},$ $z_i^a = f_i^a - \sum_m \tilde{F}_i^m t_m^a + \sum_a f_e^a t_i^e + \sum_m v_{ei}^m t_m^a + \sum_m v_{im}^{ae} \tilde{F}_e^m + \frac{1}{2} \sum_n v_{i$ $z_{ij}^{ab} = v_{ij}^{ab} + P_j^i \sum v_{ie}^{ab} t_j^e + P_b^a P_j^i \sum \tilde{W}_{ie}^{am} t_{mj}^{eb} - P_b^a \sum \tilde{W}_{ij}^{am} t_m^b + P_b^a P_b^a \sum v_{ij}^{am} t_m^b + P_b^a \sum v_$ Finite Element 3D diffusion operator

```
TE.BeginMultiKernelLaunch();
TE("T2 e i1 i2 k3 = B k3 i3 X e i1 i2 i3", T2, B, X);
TE("T1 e i1 k2 k3 = B k2 i2 T2 e i1 i2 k3", T1, B, T2);
TE("U1_e_k1_k2_k3 = G_k1_i1 T1_e_i1_k2_k3", U1, G, T1);
TE("T1 e i1 k2 k3 = G k2 i2 T2 e i1 i2 k3", T1, G, T2);
TE("U2_e_k1_k2_k3 = B_k1_i1 T1_e_i1_k2_k3", U2, B, T1);
TE("T2 e i1 i2 k3 = G k3 i3 X e i1 i2 i3", T2, G, X);
TE("T1 e i1 k2 k3 = B k2 i2 T2 e i1 i2 k3", T1, B, T2);
TE("U3 e k1 k2 k3 = B k1 i1 T1 e i1 k2 k3", U3, B, T1);
TE("Z m e k1 k2 k3 = U_n e k1 k2 k3 D_e m_n k1 k2 k3", Z, U,
TE("T1 e i3 k1 k2 = B k3 i3 Z1 e k1 k2 k3", T1, B, Z1);
TE("T2 e i2 i3 k1 = B k2 i2 T1 e i3 k1 k2", T2, B, T1);
TE("Y_e_i1_i2_i3 = G_k1_i1 T2_e_i2_i3_k1", Y, G, T2);
TE("T1 e i3 k1 k2 = B k3 i3 Z2 e k1 k2 k3", T1, B, Z2);
TE("T2 e i2 i3 k1 = G k2 i2 T1 e i3 k1 k2", T2, G, T1);
TE("Y e i1 i2 i3 += B k1 i1 T2 e i2 i3 k1", Y, B, T2);
TE("T1 e i3 k1 k2 = G k3 i3 Z3 e k1 k2 k3", T1, G, Z3);
TE("T2 e i2 i3 k1 = B k2 i2 T1 e i3 k1 k2", T2, B, T1);
TE("Y e i1 i2 i3 += B k1 i1 T2 e i2 i3 k1", Y, B, T2);
TE.EndMultiKernelLaunch();
```

credits to A. Fisher - https://github.com/LLNL/acrotensor

credits to D. Matthews, E. Solomonik, J. Stanton, and J. Gauss

Same in data science: Gas Chromatography

Workflow

- 4. Fit model or rank $k \in [1, ..., 15]$, if needed, add non-negativity constraints Tensor decompositions: PARAFAC — PARAFAC2 — TUCKER
- 5. Determine whether or not one of the models is "right"
 - Determine which of the components represent chemical information

 - Start over; add/change constraints, change model

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Computation of each individual model: bandwidth bound!

Hence: "Concurrent Alternating Least Squares for multiple simultaneous Canonical Polyadic Decompositions", with C. Psarras, L. Larsson. (Submitted).

Summary

	Matrices	Tensors
Driver	performance, HW	applications
Community effort	BLAST/LAPACK/	group by group
Industry	wide support	not much
Standardization	interface,	"pointless"
Preferred outlet	ACM TOMS	—
Language support	plenty	language by language
Automation	plenty	TCE (2001), but then?

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Still a long way to maturity! — Thank you for the attention.