Matrix Computations: In Seek of Frugality Matthieu Martel

matthieu.martel@univ-perp.fr

GreenDays 2024, Toulouse







Urgent Need of Green Computing!

More than **10%** of the world electric production is used by IT systems Distribution of power consumption of computer systems in the world:



Frugality mandatory to preserve the Planet:

- * For ecologic but also for economic reasons
- * Savings must address all aspects of IT: Storage, computing & networking

Scientific data:

- * Arrays of correlated numbers in IEEE754 floating-point formats
- * Rather smooth surfaces corresponding to the result of simulations or observations

Orders of magnitude¹:

- ✤ Panoramic Survey Telescope (Baltimore): > 1.6 petabytes
- * By around 2035, ITER will produce 2 petabytes of data on a daily basis
- * Climate data volumes and projections into 2030 for climate models (histogram)



¹wikipedia

Usual compression techniques not efficient for scientific data

- * zip (loseless) : compression rate pprox 2:1 for scientific data
- * Needs for lossy compression techniques to go beyong the 2:1 ratio
- Expected ratios: > 10:1

High precision not always needed (e.g. visualization)

Compressors are pipelines of transformations

Example: The JPEG Format²



²A. Hussain, A. Al-Fayadh, N. Radi, Image compression techniques: A survey in lossless and lossy algorithms, Computer Science Neurocomputing, 300:44–69 (2018)

Existing Tools for Lossy Scientific Data Compression

Two symetric approaches for floating-point number compression:

- * error = fct(compression rate) zfp
- compression rate = fct(error) sz

An example with zfp:3

- Interval volume renderings of compressed double-precision floating-point data on a 384 × 384 × 256 grid
- At 4 bits/double (16x compression) the image is visually indistinguishable from full 64-bit precision



³P. Lindstrom, Fixed-Rate Compressed Floating-Point Arrays, IEEE Trans. Vis. Comput. Graph. 20(12): 2674-2683 (2014)

Scientific data compression techniques such as zfp and sz:

Save storage Save networking Store computing

Principle: To compute directly with compressed matrices, without decompression Similar to **homomorphic encryption**⁴



Advantages:

- Avoids to compress/uncompress matrices before using them in computations
- Reduces elementary operations needed to perform the matrix operations
- ⁴J. Hee Cheon et al, Protecting Privacy through Homomorphic Encryption , Springer, 2021

The blaz Compressor⁵

- A matrix compressor: lossy, fixed rate (11.37:1), block based
- * Allows basic linear algebra among compressed matrices



blaz general workflow:



Currently supported operations:

- * Without uncompression: addition, subtraction, multiplication by constant
- With partial uncompression: dot product, multiplication

⁵M. Martel, Compressed Matrix Computations, IEEE/ACM Int. Conf. on Big Data Computing, Applications and Technologies, BDCAT, 2022.



Normalize:

- 1) Values replaced by differences between consecutive elements
- 2) Resulting values divided by mean slope between consecutive values



$$\Delta_{\mathbf{0},j+\mathbf{1}} = M_{\mathbf{0},j+\mathbf{1}} - M_{\mathbf{0},j}$$

$$\Delta_{i+1,0} = M_{i+1,0} - M_i, 0$$

$$\Delta_{i+1,j+1} = \frac{1}{2} \begin{pmatrix} (M_{i+1,j+1} - M_i, j+1) \\ + \\ (M_{i+1,j+1} - M_i + 1, j) \end{pmatrix}$$

$$0 < i, j < 7$$



Predict: Slope between consecutive values given by a ratio (8 bits signed integer)





Transform: 2D DCT stores highest coefficients into first lines & columns

$$D_{i,j} = \frac{1}{\sqrt{2N}} C_i C_j \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} M_{x,y} \cos\left[\frac{(2x+1)i\pi}{2N}\right] \cos\left[\frac{(2y+1)j\pi}{2N}\right]$$



$$C_u = \begin{cases} \frac{1}{\sqrt{2}} & \text{if } u = 0\\ 1 & \text{if } u > 0 \end{cases}$$



 8×8 block B of a compressed matrix encoded by:

- ★ f the value of B₀₀ (binary64)
- * s the mean slope s of B (binary64)
- * φ the scale factor to normalize the result of the DCT (8-bits integer)
- * C array of 28 8-bits values containing the coefficients quantized after the DCT

$$\mathsf{B} = \mathsf{B}_1 + \mathsf{B}_2$$

- ***** First elements: $f = f_1 + f_2$
- Mean slope: $s = s_1 + s_2$
- * Scale factor: We want $\varphi = \frac{127}{m}$ with $m = m_1 + m_2$ (m max slope). Then $\varphi = \frac{127}{m_1 + m_2} = \frac{127}{\frac{127}{\varphi_1} + \frac{127}{\varphi_2}} = \frac{1}{\frac{1}{\varphi_1} + \frac{1}{\varphi_2}} = \frac{\varphi_1 \varphi_2}{\varphi_1 + \varphi_2}$
- Discrete Cosine Transform, for two matrices M₁ and M₂:

$$DCT(M_1 + M_2) = DCT(M_1) + DCT(M_2)$$

The blaz Library: https://github.com/mmartel66/blaz 😱

typedef struct { int width, height; double *block_first_elts, *block_mean_slope; s 8 *compressed values; Blaz Compressed Matrix: Research Objects Reviewed Blaz Compressed Matrix *blaz compress(Blaz Matrix*); 28 Blaz Matrix* blaz uncompress(Blaz Compressed Matrix*); double blaz get matrix elt(Blaz Matrix*, int, int); void blaz set matrix elt(Blaz Matrix*, double, int, int); 36 double blaz get compressed matrix elt(Blaz Compressed Matrix*, int, int); void blaz set compressed matrix elt(Blaz Compressed Matrix*, double, int, int); 42 Blaz Matrix *blaz add(Blaz Matrix*, Blaz Matrix*); Blaz Compressed Matrix *blaz add compressed(Blaz Compressed Matrix*, Blaz Compressed Matrix*); 46 Blaz Matrix *blaz sub(Blaz Matrix*, Blaz Matrix*); Blaz Compressed Matrix *blaz sub compressed(Blaz Compressed Matrix*, Blaz Compressed Matrix*); Blaz Matrix *blaz mul cst(Blaz Matrix*, double); Blaz Compressed Matrix *blaz mul cst compressed(Blaz Compressed Matrix*, double); double blaz dot product(Blaz Matrix*, Blaz Matrix*, int, int); 58 double blaz dot product compressed(Blaz Compressed Matrix*, Blaz Compressed Matrix*, int, int);



- * Time measurement of operations in function of the size of the matrices
- * Time given in logarithmic scale
- * Left: Addition. Right: Multiplication by a constant

Accuracy Measurements: Test Functions







 $f_1(x,y) = x \times y$











 $f_4(x,y) = x^2 \times y^2$



Accuracy Measurements (mean relative errors)

	M_1	M_2	M_3	M_4	M_5	M ₆
Compression/Decompression						
blaz zfp	0.43% 0.0006%	0.39% 0.0009%	0.53% 0.02%	0.44% 0.002%	1.95% 0.13%	1.17% 0.15%
Additions (blaz & zfp)						
<i>M</i> ₁	_	0.98%	0.67%	0.91%	0.72%	0.78%
M_2	0.001%	_	0.62%	1.07%	1.76%	1.61%
M ₃	0.82%	0.12%	_	2.27%	0.71%	0.65%
M_4	0.03%	0.42%	0.27%	_	1.68%	1.70%
M_5	0.68%	1.62%	1.25%	0.89%	_	0.94%
M_6	0.31%	1.27%	0.25%	2.32%	0.16%	_

Case Study: Climate Simulation Data



- Scientific Data Reduction Benchmarks⁶
- SDRBench: https://sdrbench.github.io
- ✤ 3600 × 1800 matrices, (CESM-ATM dataset 1)



⁶K. Zhao, S. Di, X. Liang, S. Li, D. Tao, J. Bessac, Z. Chen, and F. Cappello, "SDRBench: Scientific Data Reduction Benchmark for Lossy Compressors", International Workshop on Big Data Reduction (IWBDR2020), in conjunction with IEEE Bigdata20.

Conclusion

- * It is possible to compute among compressed matrices
- * Related work: Precision tuning (programs: POP, neural networks)

Perspectives

- Extend blaz to more linear algebra operators (stencils, reductions, ...)
- Experiment on real-world applications
- Introduce various compression rates (add interpolation, change quantization)
- ★ Develop a parallel (MPI/GPU) version of blaz (block splitting ⇒ // scalability)





References

- M. Martel, Compressed Matrix Computations, IEEE/ACM International Conference on Big Data Computing, Applications and Technologies, BDCAT 2022
- T. Agarwal, H. Dam, P. Sadayappan, G. Gopalakrishnan, D. Ben Khalifa, M. Martel, What Operations can be Performed Directly on Compressed Arrays, and with What Error? 9th International Workshop on Data Analysis and Reduction for Big Scientific Data, ACM Press, 2023, (Best Paper Award)
- D. Ben Khalifa and M. Martel, Compile-Time Optimization of the Energy Consumption of Numerical Computations, Compiler Frontiers Workshop, ACM Press, 2024