

Parallel Tucker Decomposition with Numerically Accurate SVD

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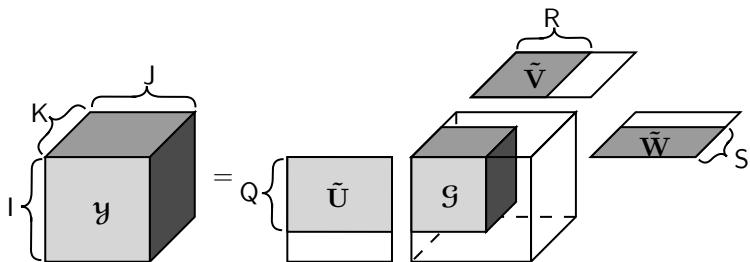
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Motivation and Introduction

- Tucker decomposition



Applications include

- Compression of multiway data (e.g. from physics simulations)
- Machine learning
- Signal processing

Sequentially Truncated Higher-Order SVD

```
function ST-HOSVD( $\mathcal{X}, t$ )  
   $\mathcal{Y} = \mathcal{X}$   
  for  $n = 0$  to  $N - 1$  do  
     $[\mathbf{U}, \mathbf{\Sigma}, \sim] = \text{SVD}(\mathbf{Y}_{(n)})$   
     $R_n = \min \left\{ R \mid \sum_{i=R+1}^{I_n} \sigma_i^2 \leq t^2 \|\mathcal{X}\|^2 / N \right\}$   
     $\mathbf{U}_n = \mathbf{U}(:, 1 : R_n)$   $\triangleright$   $n$ th factor matrix  
     $\mathcal{Y} = \mathcal{Y} \times_n \mathbf{U}_n^T$   $\triangleright$  TTM truncation  
  end for  
   $\mathcal{G} = \mathcal{Y}$   $\triangleright$  core tensor  
  return ( $\mathcal{G}, \mathbf{U}_0, \dots, \mathbf{U}_{N-1}$ )  
end function
```

Gram-SVD

```
function SVD( $\mathbf{Y}$ )  
   $\mathbf{G} = \mathbf{Y}\mathbf{Y}^T$   
   $[\mathbf{\Lambda}, \mathbf{U}] = \text{EIG}(\mathbf{G})$   
  return  $[\mathbf{U}, \mathbf{\Lambda}^{1/2}]$   
end function
```

QR-SVD

```
function SVD( $\mathbf{Y}$ )  
   $[\mathbf{Q}, \mathbf{R}] = \text{QR}(\mathbf{Y}^T)$   
   $[\mathbf{U}, \mathbf{\Sigma}, \sim] = \text{SVD}(\mathbf{R}^T)$   
  return  $[\mathbf{U}, \mathbf{\Sigma}]$   
end function
```

Numerical Accuracy Comparison

Theorem

Using a backward stable algorithm for SVD (such as the QR-SVD), the relative error of each computed singular value satisfies

$$\frac{|\tilde{\sigma}_i - \sigma_i|}{\sigma_i} = O\left(\varepsilon \frac{\|\mathbf{A}\|}{\sigma_i}\right). \quad (1)$$

Theorem

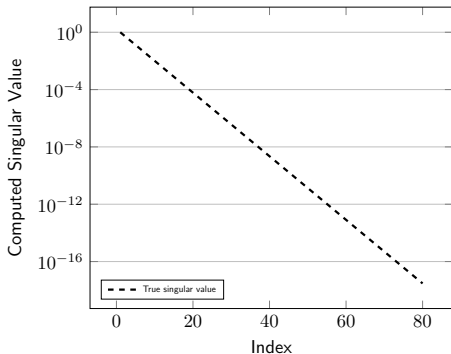
Using the Gram-SVD, the relative error of each computed singular value satisfies

$$\frac{|\tilde{\sigma}_i - \sigma_i|}{\sigma_i} = O\left(\varepsilon \left(\frac{\|\mathbf{A}\|}{\sigma_i}\right)^2\right) \quad (2)$$

- if there are small singular values, Gram SVD will have trouble determining the appropriate rank, R_n :

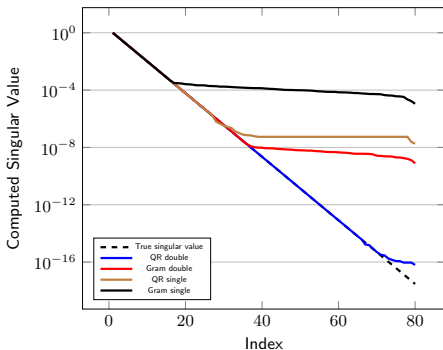
$$R_n = \min \left\{ R \mid \sum_{i=R+1}^{I_n} \sigma_i^2 \leq t^2 \|\mathbf{x}\|^2 / N \right\}$$

Numerical Experiment



- 80×512000 synthetic matrix with geometrically decreasing singular values from 1 to $1e-18$

Numerical Experiment



- 80×512000 synthetic matrix with geometrically decreasing singular values from 1 to $1e-18$
- Gram single < QR single < Gram double < QR double, in terms of accuracy.

Our Contributions

This project is built on top of TuckerMPI [BKK20], a parallel C++ library designed to compute Tucker decomposition efficiently.

Our goals:

- 1 Improve attainable accuracy for ST-HOSVD with reasonable increase in time
- 2 Achieve speedup over TuckerMPI while maintaining accuracy

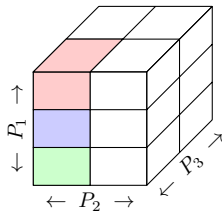
Our contributions:

- 1 We implemented our QR-SVD-based algorithm using TuckerMPI
- 2 We templated TuckerMPI to use single precision

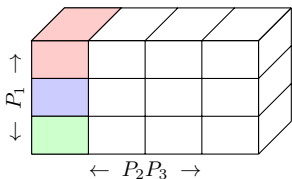
The following table shows the options that are available to the users

	Original TuckerMPI	Our implementation
Gram double	Yes	Yes
Gram single	-	Yes
QR double	-	Yes
QR single	-	Yes

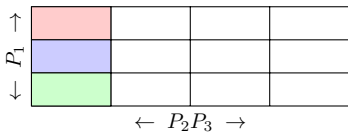
Data Distribution and Tensor Unfolding



Tensor distribution



Unfold processor grid

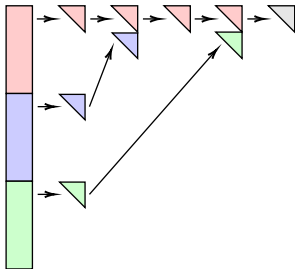


Unfold local tensor

Parallel Implementation



- QR is more expensive than Gram in terms of computation (almost 2x) and communication (increase by $O(\log P)$).

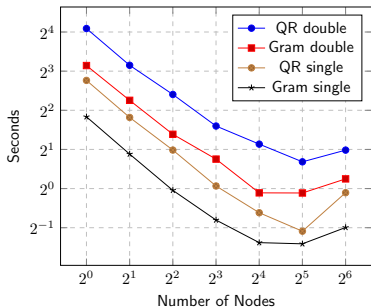


Tall Skinny QR (TSQR) [DGHL12]

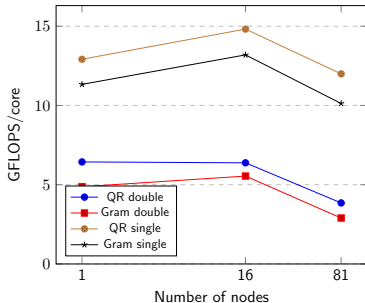
- Andes is a 704-node linux cluster at the Oak Ridge Leadership Computing Facility
- Each node has 2 16-core (AMD EPYC 7302 CPU) at 3 GHz

Scaling Performance on Synthetic Data

Strong Scaling



Weak Scaling



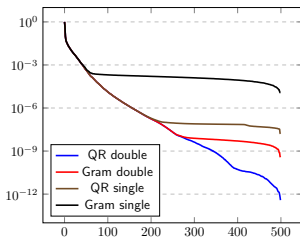
- Input: $256 \times 256 \times 256 \times 256$ tensor
- Output: $32 \times 32 \times 32 \times 32$ tensor

- Input: $250k \times 250k \times 250k \times 250k$ tensor where $k \in [1, 2, 3]$
- Output: $25k \times 25k \times 25k \times 25k$ tensor

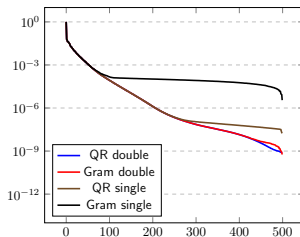
- 2x speed up from double to single precision
- QR single out-performs Gram double consistently
- Time increase from Gram double to QR double stays within 2x

Singular Values of Application Dataset

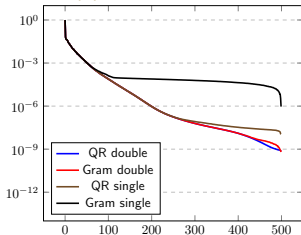
This $500 \times 500 \times 500 \times 11 \times 100$ 1.1TB dataset [KZCS16] is generated from a simulation of air-methanol combustion.



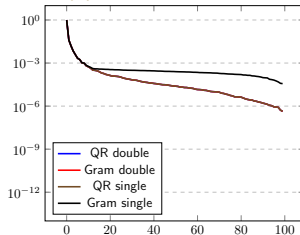
(a) Spatial Dim 1



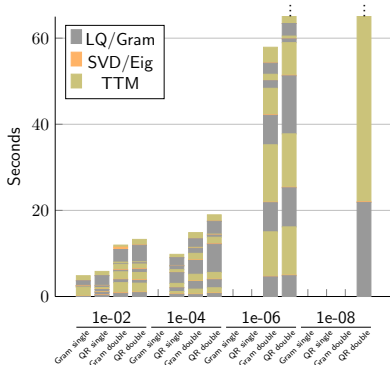
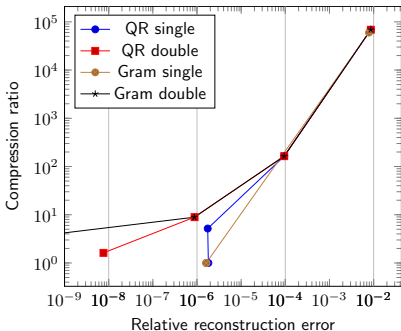
(b) Spatial Dim 2



(c) Spatial Dim 3



(d) Time Steps



Tolerance on relative error	Fastest method that satisfies the tolerance
$\text{tol} > 1e-2$	Gram Single
$1e-6 < \text{tol} < 1e-2$	QR Single
$1e-7 < \text{tol} < 1e-6$	Gram Double
$\text{tol} < 1e-7$	QR Double

- Implemented QR-SVD in parallel that improved the accuracy of the Tucker decomposition
- Using single precision resulted in 60% speed up for TuckerMPI library in real data
- The newly implemented algorithms should be used in most cases instead of Gram double

Feel free to email me at liz20@wfu.edu for comments and questions



G. Ballard, A. Klinvex, and T. G. Kolda.

TuckerMPI: A parallel C++/MPI software package for large-scale data compression via the tucker tensor decomposition.

ACM Transactions on Mathematical Software, 46(2), June 2020.



J. Demmel, L. Grigori, M. Hoemmen, and J. Langou.

Communication-optimal parallel and sequential QR and LU factorizations.

SIAM Journal on Scientific Computing, 34(1):A206–A239, 2012.



H. Kolla, X.-Y. Zhao, J. H. Chen, and N. Swaminathan.

Velocity and reactive scalar dissipation spectra in turbulent premixed flames.

Combustion Science and Technology, 188(9):1424–1439, 2016.