Rank Revealing QR Methods for Sparse Block Low Rank Solvers

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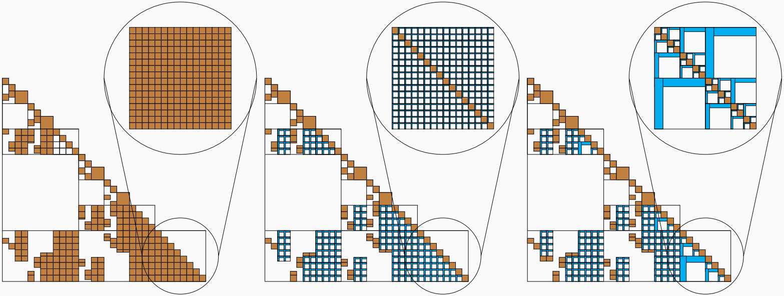
Background

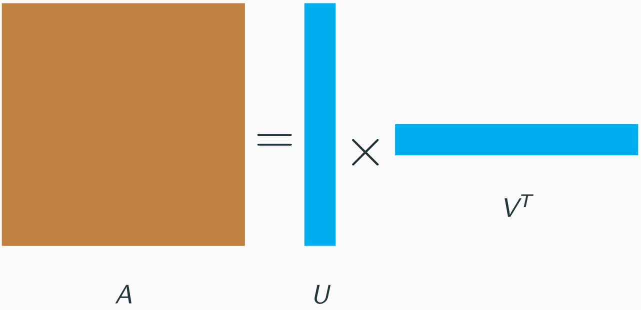
Background - ANR SaSHiMi Project

ANR SaSHiMi Project



- With: Mathieu Faverge, Pierre Ramet, Grégoire Pichon
- General Picture: Solve linear equations Ax=b for **large sparse systems**
- Full Rank Format: Too much memory usage
- Block Low Rank Format: Compression is possible, so less storage and faster
- Hierarchical Format: Even less computational complexity and memory consumption

Background - Block Low Rank Structure



$$A \in \mathbb{R}^{m \times n};\ U \in \mathbb{R}^{m \times r}; V \in \mathbb{R}^{n \times r}$$

- Compression reduces memory and cost of computations
- Fixed block size $\leq 300 \xrightarrow{\text{Future}}$ variable and larger
- All the compression algorithms were existent methods in this presentation
- In PaStiX, the rank is numerically decided to be the smallest rank at an user defined precision: $||A - UV^T||_F \leq \epsilon ||A||_F$

Background Information - Singular Value Decomposition(SVD)

Main Features

- SVD has the form: $A_{m\times n} = U_{m\times m}\Sigma_{m\times n}V_{n\times n}$
- Σ is a diagonal singular values matrix, U and V are the left and right singular vectors of A
- Two options for the threshold:
  - $\sigma_{k+1} \leq \epsilon$ ✗
  - $\sqrt{\sum_{i=k+1}^{n} \sigma_i^2} \leq \epsilon$ ✓ (to be consistent with QR methods)

Discussions

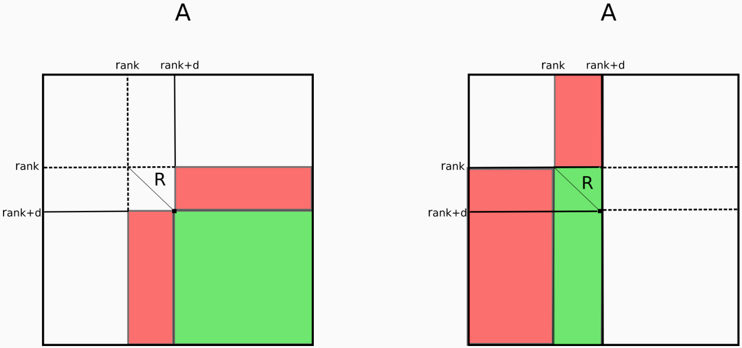
- ☺ Good accuracy
- ☹ Too costly

The aim of this study is to find closest ranks to SVD at the same precision with better performance

- Rank Revealing QR methods ($A = QR$)

Left Looking vs Right Looking Algorithms

Right Looking | Left Looking



- Red parts are read / Green parts are updated
- Right Looking: Unnecessary updates but more suitable for parallelism
- Left Looking: Eliminated unnecessary updates but more storage needed

Pivoting vs Rotating

- Rank revealing: gather important data and omit the remainings
- Two ways of data gathering methods:
    - Pivoting: $AP = Q_{AP}R_{AP}$
    - Rotation: $AQ_{Rot} = Q_{AQ}R_{AQ}$
- Pivoting: gather important data on the leftmost matrix
- Rotation: gather important data on the diagonal

Compression Methods

Rank Revealing QR Methods

- Partial QR with Column Pivoting (PQRCP)
    - LAPACK xGEQP3 modified by Buttari A.(MUMPS)
- Randomized QR with Column Pivoting (RQRCP)
    - Duersch J. A. and Gu M. (2017)
    - Martinsson P. G. (2015)
    - Xiao J., Gu M. and Langou J. (2017)
- Truncated Randomized QR with Column Pivoting (TRQRCP)
    - Duersch J. A., Gu M. (2017)
- Randomized QR with Rotation (RQRRT)
    - Martinsson P. G. (2015)

1) Partial QR with Column Pivoting (PQRCP)

Main Features

- Column pivoting: column with max 2-norm is the pivot
- $A = UV^T$ compression with column pivoting:
  - $AP = Q_{AP}R_{AP}$ is computed, where P is the permutation matrix
  - $U = Q_{AP}$ and $V^T = R_{AP}P^T$
- Right Looking

Discussions

- 😐 Need larger rank than SVD for the same accuracy
- ☹ Not fast enough
- To reduce the cost of pivot selection
  - Randomized method with pivoting

2) Randomized QR with Column Pivoting (RQRCP)

Main Features

- Create independent and identically distributed Gaussian matrix Ω of size $b \times m$, where $b \ll m$
- Compute the sample matrix $B = \Omega A$ of size $b \times n$
- Find pivots on B where the row dimension is much smaller than A
  - Less computations
  - Less communication
- Apply this pivoting to A like in PQRCP
- Right Looking
- Sample matrix updated

Discussions

- Similar accuracy to PQRCP
- Not fast enough
- To eliminate the cost of trailing matrix update:
  - Truncated randomized method with pivoting

3) Truncated Randomized QR with Column Pivoting (TRQRCP)

Main Features

- Left Looking
    - Trailing matrix is not needed
- Extra storage: Reflector accumulations
- More efficient on large matrices with small ranks

Discussions

- Fastest in sequential
- Similar accuracy to previous algorithms
- Can be improved to give closer ranks to SVD
- Instead of pivoting, apply a reasonable rotation to gather important information to the diagonal blocks
    - Randomized method with rotation

4) Randomized QR with Rotation (RQRRT)

Main Features

- Similar to RQRCP except:
  - Rotation applied to A
  - Resampling
- In Randomized QR with Column Pivoting (RQRCP):
  - $BP_B = Q_B R_B$
  - $AP_B = Q_{AP} R_{AP}$
  - $U = Q_{AP}$ and $V^T = R_{AP} P_B^T$
- In Randomized QR with Rotation (RQRRT):
  - $B^T = Q_B R_B$
  - $AQ_B = Q_{AQ} R_{AQ}$
  - $U = Q_{AQ}$ and $V^T = R_{AQ} Q_B^T$
- Right Looking

Discussions

- Ranks closest to SVD
- Slower and updates whole trailing matrix each iteration

Complexities

- Blue: No change, Green: Reduced cost, Red: More costly
- Matrix size n $\times$ n, block size b, rank k

Methods	Features
SVD: $\mathcal{O}(n^3)$	
PQRCP: $\mathcal{O}(n^2k)$	pivot finding $\mathcal{O}(n^2)$ trailing matrix update $\mathcal{O}(n^2k)$
PQRCP: $\mathcal{O}(n^2k) \xrightarrow{\text{Randomization}}$ RQRCP: $\mathcal{O}(n^2k)$	sample matrix generation (beginning) $\mathcal{O}(n^2b)$ pivot finding $\mathcal{O}(nb)$ update of sample matrix B $\mathcal{O}(nb^2)$ trailing matrix update $\mathcal{O}(n^2k)$
RQRCP: $\mathcal{O}(n^2k) \xrightarrow{\text{Truncation}}$ TRQRCP: $\mathcal{O}(nk^2)$	sample matrix generation (beginning) $\mathcal{O}(n^2b)$ pivot finding $\mathcal{O}(nb)$ update of current panel $\mathcal{O}(nk^2)$ update of sample matrix B $\mathcal{O}(nb^2)$
RQRCP: $\mathcal{O}(n^2k) \xrightarrow{\text{Rotation}}$ RQRRT: $\mathcal{O}(n^2k)$	resampling (each iteration) $\mathcal{O}(n^2b)$ rotation finding $\mathcal{O}(n^2k)$ rotation of A $\mathcal{O}(n^2k)$ trailing matrix update $\mathcal{O}(n^2k)$

- Flops cost ($<$ is less flops):
  TQRCP $<<$ PQRCP $<$ RQRCP $<$ RQRRT $<<$ SVD

Conclusion

- SVD: Smallest rank but too costly
- PQRCP: Right looking. Randomization is suggested for pivoting cost
- RQRCP: Unnecessary trailing matrix update. Truncation is introduced
- TRQRCP: Lowest cost, similar accuracy.
- RQRRT: Closest ranks to SVD. Most costly QR variant. Promising for parallelism
- In PaStiX, the smallest rank is decided numerically at an user defined precision

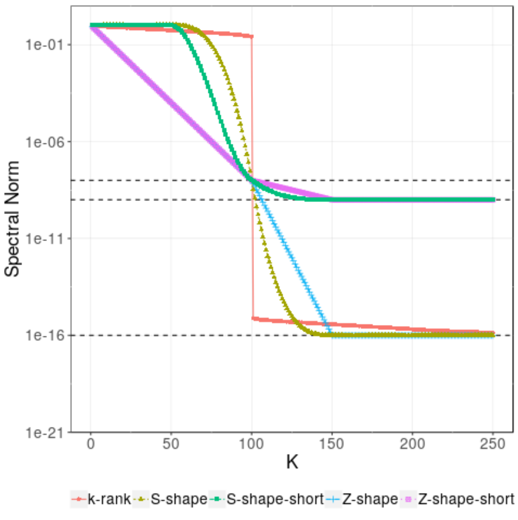
Numerical Results

Test Cases - Singular Values

For all Test Cases(Modes):

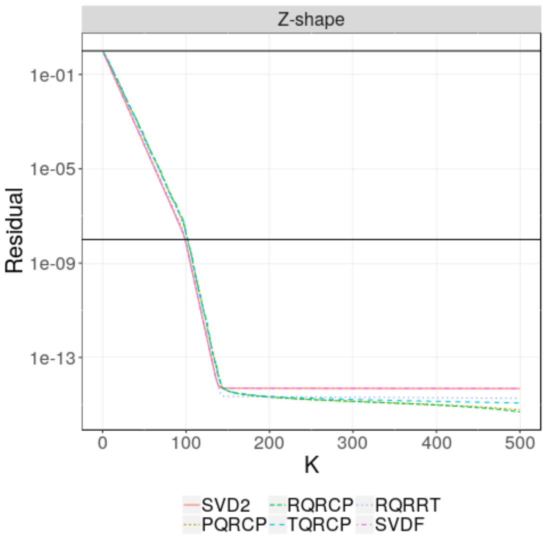
- Modes are different matrices
- Matrix Size 500
- Rank 100
- Generation Precision $\epsilon = 10^{-8}$
- $A = UDV^T$
  - D is a diagonal matrix with singular values
  - U and V are orthonormal random matrices

Spectral Norms



Stability - First Test Case Residual Norms

Index vs Error

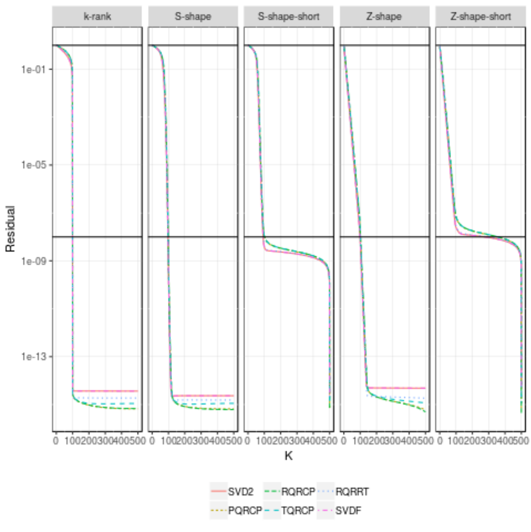


For all Methods:

- Mode 1
- Matrix is fully factorized without any stopping criterion
- Residual: $\frac{||A - U_K V_K^T||_F}{||A||_F}$
- K stands for index values of the matrix

Stability - All Test Cases Residual Norms

Index vs Error

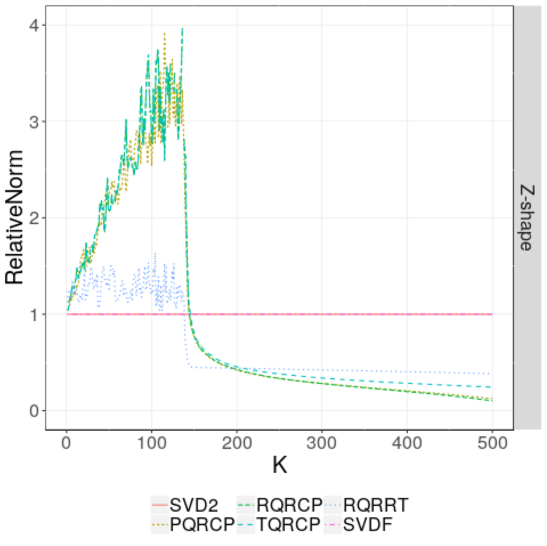


Stability - First Test Case Relative Residual Norms

Index vs Relative Error

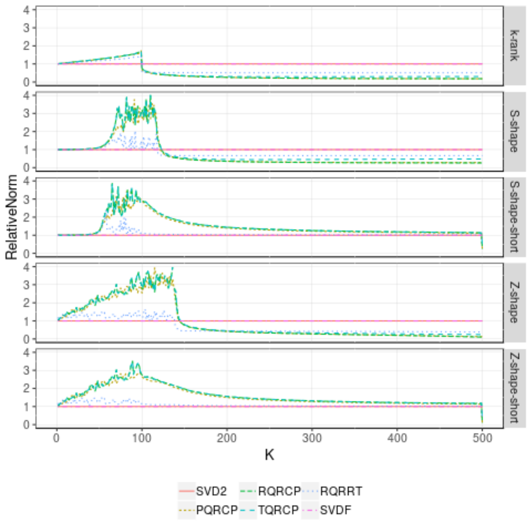
<u>For all Methods:</u>

- Matrix is fully factorized without any stopping criterion
- Relative Norm: $\frac{Residual}{Residual^{SVDF}}$
- K stands for index values of the matrix



Stability - All Test Cases Relative Residual Norms

Index vs Relative Error

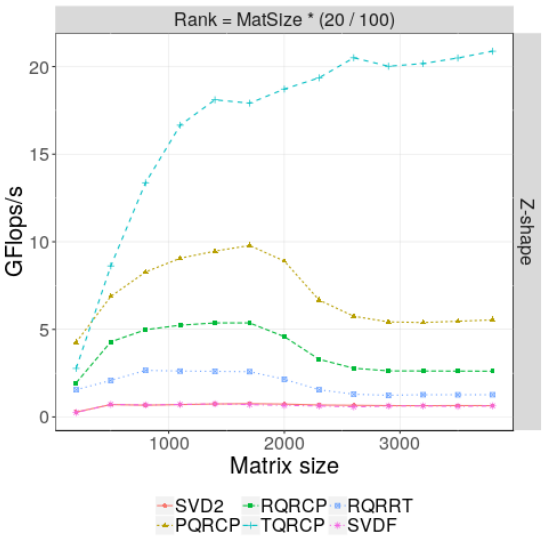


Performance - First Test Case Gflops

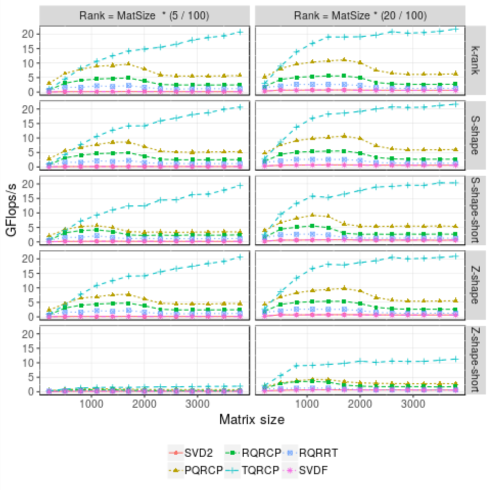
Matrix Size vs GFlops

For all Methods:

- Mode 1
- $Rank = Matrix\_size \times \frac{20}{100}$
- Different matrix sizes are checked
- Compression Precision $\epsilon = 10^{-8}$
- $GFlops = \frac{min(GFlops)}{t}$
- Threshold is applied



Matrix Size vs GFlops

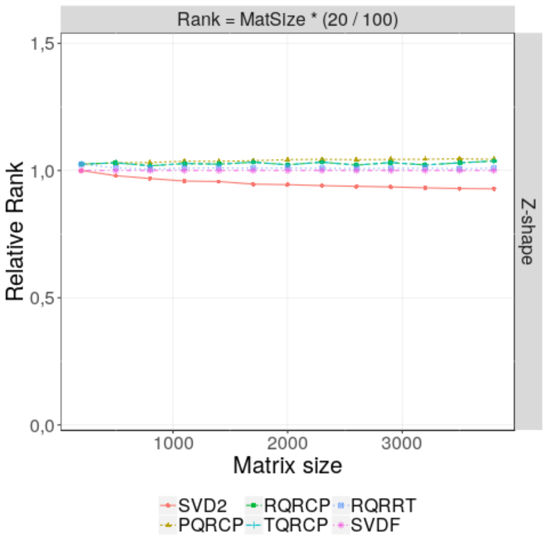


Compression Ranks - First Test Case Relative Rank

Matrix Size vs Relative Rank

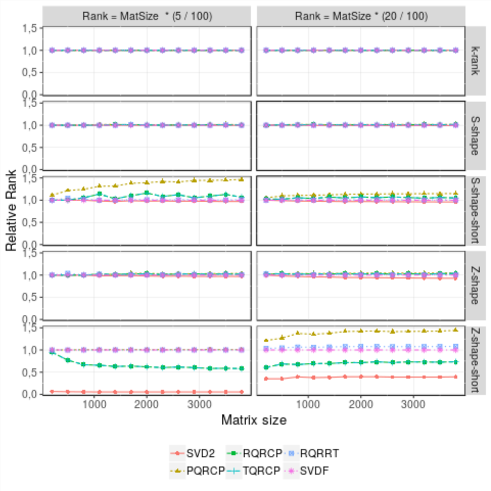
For all Methods:

- Mode 1
- $Rank = Matrix\_size \times \frac{20}{100}$
- Different matrix sizes are checked
- Compression Precision $\epsilon = 10^{-8}$
- $RelativeRank = \frac{comp\_rank}{comp\_rank^{SVDF}}$
- Threshold is applied



Compression Ranks - All Test Cases Relative Rank

Matrix Size vs Relative Rank



Perspective / Future Work

- Application in the parallel framework of PaStiX with real, larger and tricky matrices
    - Why PQRCP has more performance than RQRCP and TRQRCP?
    - RQRRT has the worst QR performance but is promising for parallel environment
    - Why RQRCP and TRQRCP finds smaller ranks than SVDF for the mode 3
    - Tuning the best method for the given parameters

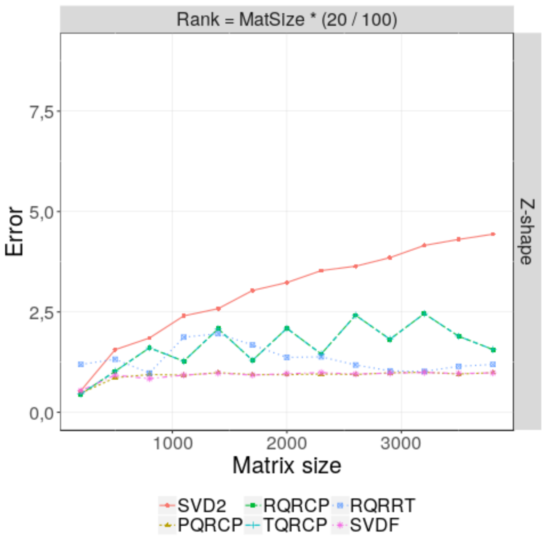
References

- Duersch, J. A.; Gu, M. (2017). "Randomized QR with Column Pivoting".
- Xiao, J.; Gu, M.; Langou, J. (2017). "Fast Parallel Randomized QR with Column Pivoting Algorithms for Reliable Low-rank Matrix Approximations".
- Martinsson, P. G. (2015). "Blocked Rank-revealing QR Factorizations: how randomized sampling can be used to avoid single-vector pivoting".

THANK YOU!

Accuracy - First Test Case

Matrix Size vs Relative Rank



For all Methods:

- Mode 1
- $Rank = Matrix\_size \times \frac{20}{100}$
- Different matrix sizes are checked
- Compression Precision $\epsilon = 10^{-8}$
- $Error = \frac{||A - U_k V_k^T||_F}{\epsilon ||A^{[0]}||_F}$
- Threshold is applied

Accuracy - All Test Cases

Matrix Size vs Relative Rank