MapReduce TSQR

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TSQR

A = QR, $Q^TQ = I$, R upper triangular

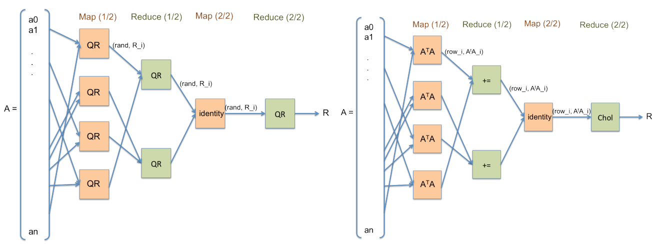
- Many more rows than columns → “tall and skinny” (TS)
- Lots of embarrassingly parallel work

Two methods for computing R

- “TSQR” algorithm by Demmel et. al [5] (slower, more stable)
- Cholesky decomposition on A^TA (faster, less stable)
- Both algorithms scale well

Make these algorithms run fast in the cloud [1], [4], [6]

- Implementations with Apache Hadoop MapReduce
- How does numerical stability factor in?



MapReduce schemes for TSQR (left) and Cholesky QR (right)

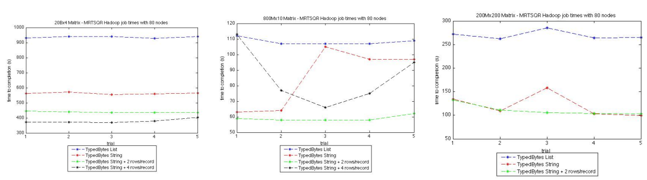
Data Serialization

TypedBytes storage [2], [3]

- Different data types in sequence file
- String format yields great improvement over list format

Packed rows

- Store 2 or 4 rows per record
- Performance can be significantly better, stay the same, or get worse



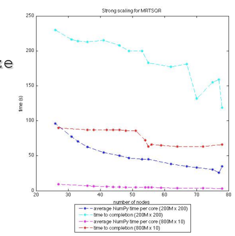
Strong Scaling

Difficult to control processor allocation

- In Hadoop, use `mapred.min.split.size` parameter
- Embarrassingly parallel work greedily consumes any extra resources

For TSQR, computation time small

- Hadoop overhead and disk reads dominate time



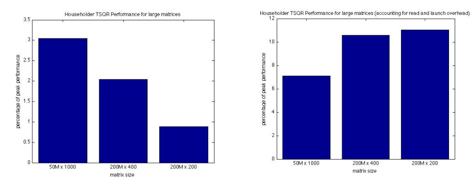
Peak Performance

How close to peak performance?

- 1-3% peak for large matrices
- For a MapReduce architecture, this is about what we except

Refining the model

- ~60 seconds for launch, cleanup overhead
- ~60 MB/s disk reads (1 TB SATA disks)
- → 7-11% peak



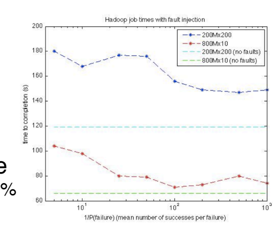
Fault Tolerance

Key advantage to Hadoop and other MapReduce architectures

- How does this affect performance?
- How does P(fault) affect performance?

Noticeable but manageable

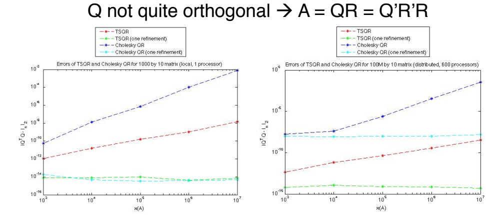
- Faults quickly introduce a 25% performance hit
- P(fault) ~= 1/5 → only 50% performance hit



Numerical Experiments

How stable are our algorithms?

- Compute R with TSQR and Cholesky
- $Q = AR^{-1}$, check $\|Q^TQ - I_n\|_2$
- Q not quite orthogonal → A = QR = Q’R’R



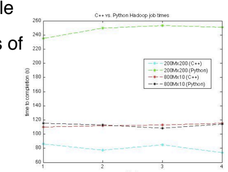
Streaming: C++ vs. Python

Use Hadoop streaming

- Python provides easy prototyping for testing algorithms at a large scale (both algorithms implemented in 100 lines of code)
- C++ can give us better performance

Number of columns matters

- 10 columns → about the same performance
- 200 columns → C++ takes 4x faster than Python



Future work

- Implement customized data storage
- Expand to other areas of linear algebra (e.g., LU) and tensor algebra
- Explicit formulation of Q
- Experiment with other MapReduce frameworks (e.g., Spark, Twister)

References

[1] Austin Benson. MapReduce TSQR code. https://github.com/arbenson/mrtsqr

[2] Klaas Bosteels. Dumbo. https://github.com/klbostee/dumbo

[3] Klaas Bosteels. TypedBytes. https://github.com/klbostee/typedbytes

[4] Paul G. Constantine and David F. Gleich. Tall and skinny QR factorizations in MapReduce architectures. In *Proceedings of the second international workshop on MapReduce and its applications,* MapReduce ’11, pages 43-50, New York, NY, USA, 2011. ACM.

[5] James Demmel, Laura Grigori, Mark F. Hoemmen, and Julien Langou. *Communication- optimal parallel and sequential QR and LU factorizations*. UCB/EECS-2008-89. August 2008.

[6] David Gleich. MapReduce TSQR code. https://github.com/dgleich/mrtsqr