MadLINQ: Large-Scale Distributed Matrix Computation for the Cloud

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Motivation

Many existing methods for performing large-scale distributed matrix computations fall short.

MPI-based solutions:

- Requires understanding of low level MPI primitives.
- Entire problem must be maintained in memory for efficiency.

MapReduce-based solutions:

- Difficult to program.
- No reduce operation can proceed until all maps are finished.
The two goals of MadLINQ are:

- To provide a scalable, efficient, fault-tolerant, usable matrix computation engine.
- To integrate this engine into a general purpose parallel computing platform.
They introduce:

- A new programming model
- Fine-grained pipelining
- A new fault tolerance mechanism
- Optimizations (e.g. auto-switching of block representation)
The new programming model increases usability:

- Can handle dense and sparse matrices.
- Allows for easy representation of graph algorithms.
- Tile algorithms have an intuitive representation.
They provide a unified programming model of MadLINQ/DryadLINQ/C#.

Benefits of this include:

- MadLINQ functionality can be encapsulated in a large C# application.
- Can handle both linear algebra and relational algebra.
- Interoperability in a general purpose computing model.
Fine-grained pipelining intends to improve efficiency. It works as follows:

- Each vertex must produce data at a finer granularity (block).
- Tiling algorithm must work at the block level.
- Computation engine must be able to output partial results.

Fine-grained pipelining has a number of performance benefits.
Previous fault tolerance mechanisms do not work. MadLINQ uses lightweight dependency tracking as follows:

- Assumed that each set of output blocks can derive the set of input blocks needed to compute it.
- Query downstream vertices discovering the set of blocks it still requires.
- Process can be done recursively.
Extra features added were:

- Auto-switching of block representation – increases scalability.
- Pre-loading ready vertices onto occupied nodes which are about to finish.
- Adding order preference for requesting vertices.
Results – CPU Utilization

Figure: Source: Qian et al. (2012)
Results – Network Traffic

Figure: Source: Qian et al. (2012)
Results – Fault Tolerance

Figure: Source: Qian et al. (2012)
Results – Comparison of Performance

Figure: Source: Qian et al. (2012)
Three approaches have previously been used for large-scale matrix computation:

- HPC solutions
- MapReduce-based solutions
- Direct DAG execution
Examples of the three approaches are:

- **ScaLAPACK** is an example of an HPC solution. Compared to MadLINQ, it has weaker scaling and fault tolerance.

- **HAMA** performs matrix computations using MapReduce. Constrained by the semantics of MapReduce.

- **DAGuE** is an architecture for scheduling DAGs. It has no fault tolerance and its parallelism is bound by the tile level.
Ideas which could be investigated in the future are:

- Auto-tiling
- Dynamic re-tiling and re-blocking
- Better handling of sparse matrices
Criticism

- There is no mention of fault tolerance, backups or checkpointing for the centralized scheduler.

- The fault tolerance does not handle non-determinism (edges being randomly added to a graph).

- There is no evidence or explanation of how stragglers may be handled.
Criticism

- No insight is given into how one may choose parameters for execution.
- How costly is the action of switching between matrix representations in their auto-switching algorithm? Does the performance gain overcome the cost?
- More studies should be done into the real-world applicability of their pipelining and fault tolerance mechanisms.
To conclude:

- The authors have demonstrated a need for a new approach.
- They also achieve their original goals – producing a scalable, efficient, fault-tolerant, matrix computation engine which is integrated into a general purpose framework.
- There are smaller issues which need to be solved and more real-world tests need to be done.