MadLINQ: Large-Scale Distributed Matrix Computation for the Cloud

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MadLINQ Project

● Goals
  ○ Scalable, efficient and fault-tolerant matrix computation system
  ○ Seamless integration of the system with a general purpose data-parallel computing system
Gap filled by MadLINQ

- Distributed execution engines (Hadoop, Dryad) and their “high-level language interfaces” (Hive, Pig, DryadLINQ) are subsets of relational algebra
- These systems are not native for solving problems involving linear algebra and matrix computation
Programming Model

- Matrix algorithms are expressed as sequential programs operating on **tiles**
- Expose to .NET developer via the **LINQ** technology
  - e.g. (Classes like Matrix, Tile)
// The input datasets
var ratings = PartitionedTable.Get(NetflixRating);

// Step 1: Process the Netflix dataset in DryadLINQ
Matrix R = ratings
    .Select(x => CreateEntry(x))
    .GroupBy(x => x.col)
    .SelectMany((g, i) => g.Select(x => new Entry(x.row, i, x.val)))
    .ToMadLINQ(MovieCnt, UserCnt, tileSize);

// Step 2: Compute the scores of movies for each user
Matrix similarity = R.Multiply(R.Transpose());
Matrix scores = similarity.Multiply(R).Normalize();

// Step 3: Create the result report
var result = scores
    .ToDryadLinq()
    .GroupBy(x => x.col)
    .Select(g => g.OrderBy()
        .Take(5));
System Architecture and Components

Figure 5. MadLINQ system architecture. The system consists of a Central Scheduler, and a Local Daemon, a Local Store and a Vertex Engine on each compute node.
DAG Generation

- List of running vertices and their children are kept in the memory of scheduler
- Frontier of the execution
- DAG is dynamically expanded through symbolic execution
  - Vertices are created based on operations/statements in the program and vertices are connected by data dependencies identified by tiles
  - Removes the need to keep a materialized DAG
Key Contributions

- Extra parallelism using fine-grained pipelining (FGP)
- Efficient on-demand failure recovery

Both enabled by the matrix abstraction
Fine-grained pipelining (FGP)
Fine-grained pipelining (FGP)

- In most DAG, the output of each vertex is “ready” at the same time, i.e. staged. If B depends on A, B waits for A to finish first.
- FGP: exchange data among computing nodes in a pipelined fashion (instead of staged) to aggressively overlap computation of depending vertices (i.e. connected with edges)
Fine-grained pipelining (FGP)

- Parallelism in matrix algorithm fluctuates in different phases/iterations
  - Reduce vertex-level parallelism
  - Cause bursty network utilization
- Introduce Inter-vertex pipelining
  - Vertices consume and produce data in blocks, which are essentially smaller tiles
  - Requirement: vertex computation must be expressed as a tile algorithm
Execution Mode

- **Staged**
  - A vertex is ready when its parents have produced all the data
  - Dryad or MapReduce

- **Pipelined**
  - A vertex is ready when each input channel has partial results
  - Default for MadLINQ
Fault-tolerant protocol

- Using lightweight dependency tracking, FGP allows for minimal recomputation upon failure.
- For any given set of output blocks $S$, we can automatically derive the set of input blocks that are needed to compute $S$ (backward slicing).
- Support arbitrary additions and/or removals of machines (dynamic capacity change).
Fault-tolerant protocol - Assumptions

1. Can infer the set of input blocks that a given output block depends on
   a. If not, the protocol falls back to staged model
2. Vertex computation is deterministic
Experiment Result (Cholesky Factorization)
Experiment Result (Cholesky Factorization)

![Graph showing network traffic over time for pipeline and staged methods.](image-url)
Experiment Result (Comparison to ScaLAPACK)

(a) Absolute running time

(b) Relative to ScaLAPACK
Optimization

- Pre-loading a ready vertex onto a computing node which will finish its current vertex soon
- Adding order-preference (e.g. row-major, column-major) when requesting input for a vertex
- Auto-switching of block representation depending on matrix sparsity
  - and invoke different math library
Configurable parameters

- **Tile size**
  - smaller tiles = more tile-level parallelism, but increases scheduling/memory overhead

- **Block size**
  - Underlying math libraries (e.g. Intel MKL) typically yield better performance for bigger blocks
  - But smaller block size => better pipelining
<table>
<thead>
<tr>
<th></th>
<th>Programmability</th>
<th>Execution model</th>
<th>Scalability</th>
<th>Failure-handling</th>
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</thead>
<tbody>
<tr>
<td>ScaLAPACK (HPC Solution)</td>
<td>Grid-based matrix partition; high expressiveness but difficult to program</td>
<td>Bulk Synchronous Parallel (BSP), one process per node, MPI-based communication</td>
<td>Problem size bounded by total memory size; performance bounded by synchronization overhead</td>
<td>Global checkpointing, superstep rollback and recovery, high performance impact</td>
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<tr>
<td>DAGuE (Tiles &amp; DAG)</td>
<td>Tile algorithm; high expressiveness; programmer must annotate data dependencies explicitly</td>
<td>One-level dataflow at tile level</td>
<td>Problem size bounded by total memory size; performance bound by parallelism at tile level</td>
<td>N/A</td>
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<td>HAMA (MapReduce)</td>
<td>Tile algorithm; expressiveness constrained by MapReduce abstraction</td>
<td>MapReduce; implicit BSP between map and reduce phases</td>
<td>No constraint on problem size; performance bounded by BSP model</td>
<td>Individual operator roll back at tile granularity</td>
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<tr>
<td>MadLINQ</td>
<td>Tile algorithm in modern language; high expressiveness for experimental algorithms</td>
<td>Dataflow at tile level, with block-level pipelining across tile execution</td>
<td>No constraint of problem size; performance bounded by tile-level parallelism, improved with block-level pipelining</td>
<td>Precise re-computation at block granularity</td>
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Table 1. Comparison with alternative approaches and systems.
What the paper didn’t explain much

- Where are the intermediate data stored?
- Does it assume full-use of the computing cluster (like Dryad)?
- CPU-bound v.s. IO-bound problems?
- How does it compare to DAGuE and HAMA?
Comments

- Seem to make use of property of matrix operation very well in DAG
- Doesn’t seem to bring new “system” invention
- Converting an algorithm into tile algorithm is the key to “gain” from this framework, but this is not easy and remains an active research area in HPC field