MadLINQ: Large-Scale Distributed Matrix Computation for the Cloud

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Motivation

- MapReduce and DryadLINQ relational algebra operators not suitable for linear algebra computations
- Demand for efficient matrix computations;
  - Machine learning
  - Graph algorithms (graphs boil down to sparse matrices)
- Previous attempts failed to deliver;
  - ScaLAPACK [2] too low level (MPI Knowledge required)
  - HAMA built on top of MapReduce (still restrictive)

Key Components of MadLINQ

- Simple programming model for matrix computation
- New Fine Grained Pipelining (FGP) model
- Fault tolerance for FGP
- Integration with DryadLINQ [3]

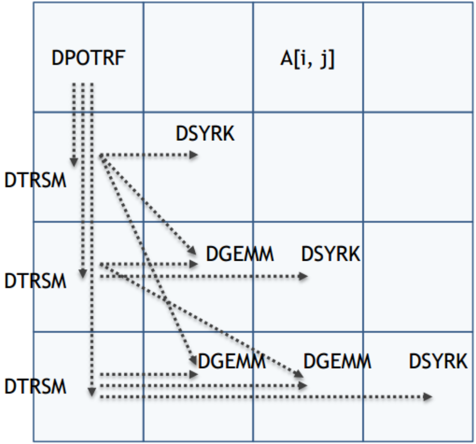
Tile Algorithms

- A tile is a sub-matrix.
- Entire matrix is partitioned into a grid of tiles.
- This idea is what gives rise to parallelism in matrix computation.
- Aim is to maximise cache localisation by exploiting the structured access of matrix algorithms.

Computation Example: Cholesky Decomposition

- Takes a symmetric positive-definite matrix
- Matrix is partitioned into tiles
- On the *k*-th iteration, tile operations employed to factorise;
  - diagonally (`DPOTRF`)
  - $n - k$ tiles below (`DTRSM`)
  - trailing tiles to the right (`DSYRK` and `DGEMM`)

Cholesky Decomposition Iteration



Programming Model

- C# constructs, allows DryadLINQ and MadLINQ integration.
- `Matrix` data abstraction in C# encapsulates tile representation.
- Programs expressed in a sequential fashion.
- Linear algebra library in C#

Example Application: Collaborative Filtering

- How to predict what other movies users will like given their rating of other movies.
- $R[i,j]$ is user j's rating of movie i.

CF Equation

$(R \cdot R^T) \cdot R$

becomes;

CF MadLINQ Code

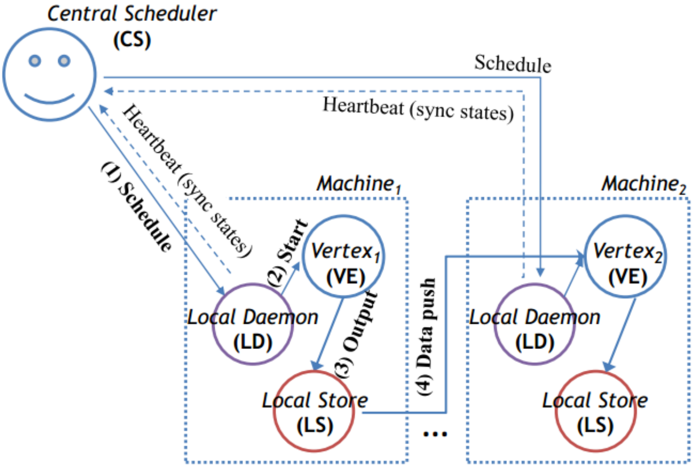
```
Matrix similarity = R.Multiply(R.Transpose());
Matrix scores = similarity.Multiply(R).Normalize();
```

* Matrix goes from sparse (users haven't seen most movies) to dense (every user has predicted score for every movie)

CF: Integration with DryadLINQ

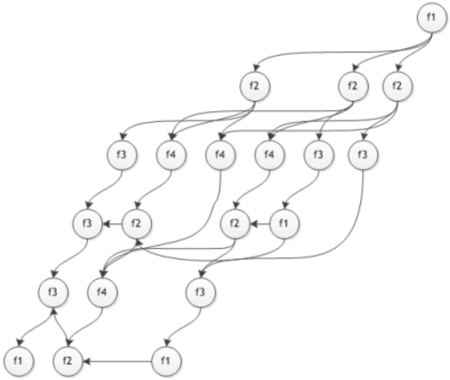
- DryadLINQ processes Netflix dataset
- This boils down to a MadLINQ `Matrix`
- MadLINQ does transposition, matrix multiplication and normalisation of R to get scores
- DryadLINQ generates top 5 list of movies for each user.

MadLINQ Architecture



Directed Acyclic Graph (DAG)

- DAG is dynamically expanded through symbolic execution to prevent explosion ($O(n^3)$ for Cholesky Decomposition)



- $f1$ through $f4$ are the tile operators discussed earlier (`DPOTRF`, `DTRSM`, `DSYRK` and `DGEMM` resp.)

FGP & Fault Tolerance

- Parallelism fluctuates with matrix computations
- Pipelining exploits vertex parallelism by increasing data granularity (recursively tiling matrices)

- Failure handling: Input blocks can be reconstructed from output blocks.
- Dependencies are calculated to reduce recovery cost.

Optimisations & Configuration

- From the authors experience, optimisations were made;
  - Prefetching of vertex data for a close to terminating node
  - Specifying order of matrix data (column or row first?)
  - Auto switching between sparse (compressed) and dense matrices.
- Configuration;
  - Smaller tiles $\implies$ higher parallelism
  - Granularity of computation is a block
  - Block size determined by number of non-zero elements

Observations & Applications

- Observations;
  - Pipelining performs better on larger problems
  - Pipeline approach on average 14.4% faster than ScaLAPACK
  - ScaLAPACK failed consistently using 32 cores (with no fault tolerance)
- Real world applications;
  - MadLINQ more efficient than MapReduce
  - For Collaborative Filtering (recall $(R \cdot R^T) \cdot R$) on 20k $\times$ 500k matrix (Netflix challenge). Mahout over Hadoop took over 800 minutes, as opposed to MadLINQ 16 (albeit Mahout produces results of higher accuracy)

Conclusion & Related Work

- DAGuE, a similar use of DAG for tiled algorithms but failed to provide fault tolerance and resource dynamics
- Future research ideas;
  - Auto-Tiling of matrices for matrix algorithms
  - Dynamic Re-Tiling (dynamic changing of tile sizes for graph algorithms)
  - Sparse matrices cause load imbalance. Methods required for handling these well.
- Concludes MadLINQ fills the void that is large scale distributed matrix and graph processing, using linear algebra.

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Questions