DAGuE: A Generic Distributed DAG Engine for HPC

INNOVATIVE COMPUTING LABORATORY
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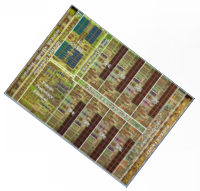
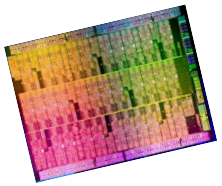
Hardware Complexity

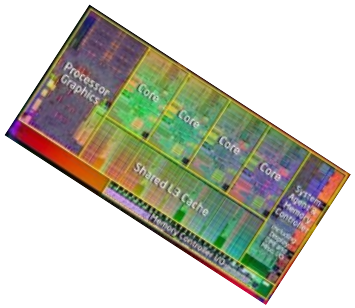
- Hierarchies of Multi-Cores
- Non Uniform Memory Access
- Accelerators
- Networks with deep hierarchies





Portability

- Programming Portability
- Performance Portability

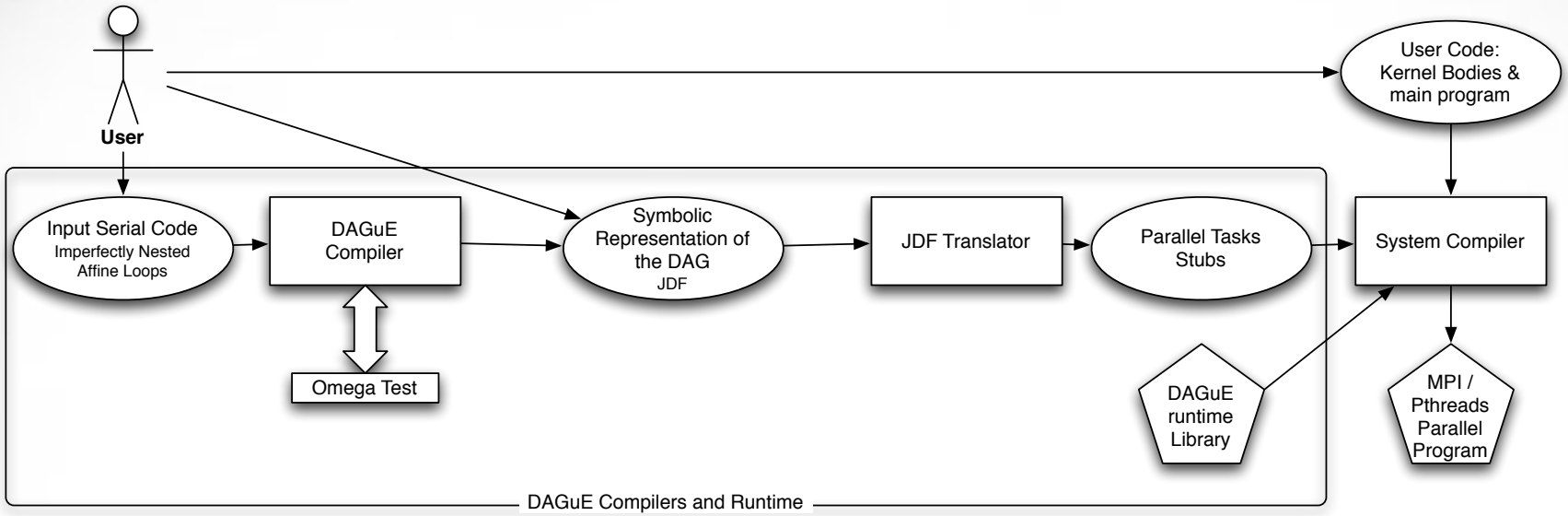


Calls for Dynamic / Asynchronous Programming Model

DAGuE Goals

- Keep the algorithm as simple as possible
  - Depict only the flow of data between tasks
  - *Distributed Dataflow Environment based on Dynamic Scheduling of (Micro) Tasks*
- Programmability: layered approach
  - Algorithm / Data Distribution
- Portability / Efficiency
  - Use all available hardware; overlap comm / comp
- Decouple “System issues” from Algorithm

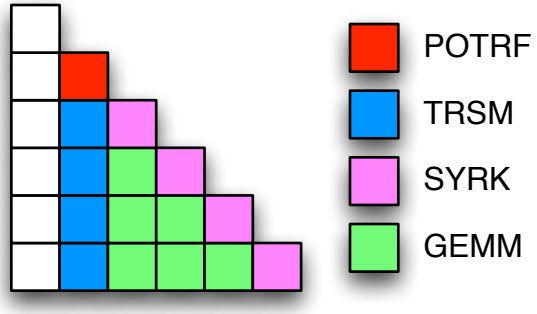
DAGuE toolchain



Example: Cholesky Factorization

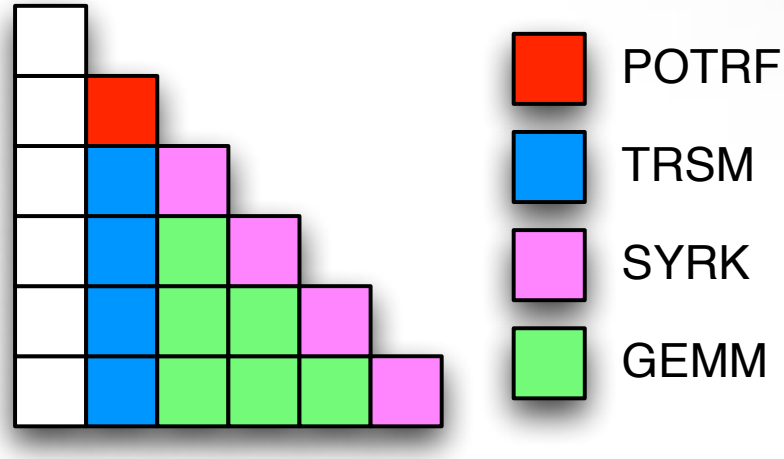
- Cholesky Decomposition
  - Let A be a real symmetric positive definite matrix
  - Find L such that $A = LL^T$

Tiled Algorithm in A. Buttari, J. Langou, J. Kurzak, and J. Dongarra, A class of parallel tiled linear algebra algorithms for multicore architectures, Parallel Computing, 2008



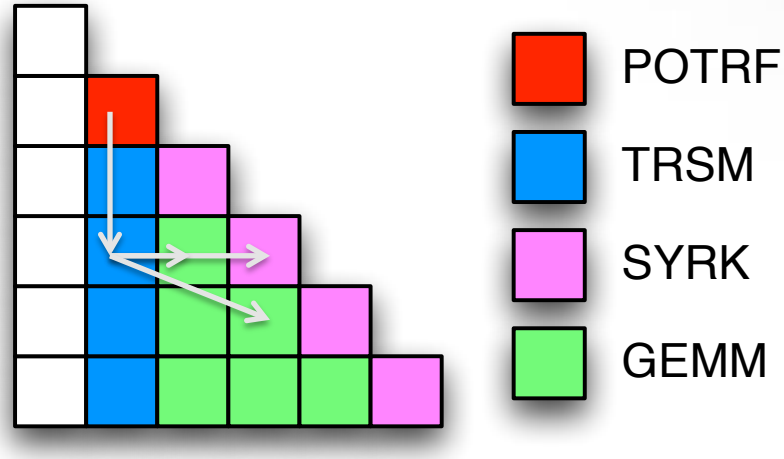
Input Format: SMPSS-Like

```
FOR k = 0..TILES-1
   A[k][k] ← DPOTRF(A[k][k])
   FOR m = k+1..TILES-1
      A[m][k] ← DTRSM(A[k][k], A[m][k])
   FOR n = k+1..TILES-1
      A[n][n] ← DSYRK(A[n][k], A[n][n])
      FOR m = n+1..TILES-1
         A[m][n] ← DGEMM(A[m][k], A[n][k], A[m][n])
```



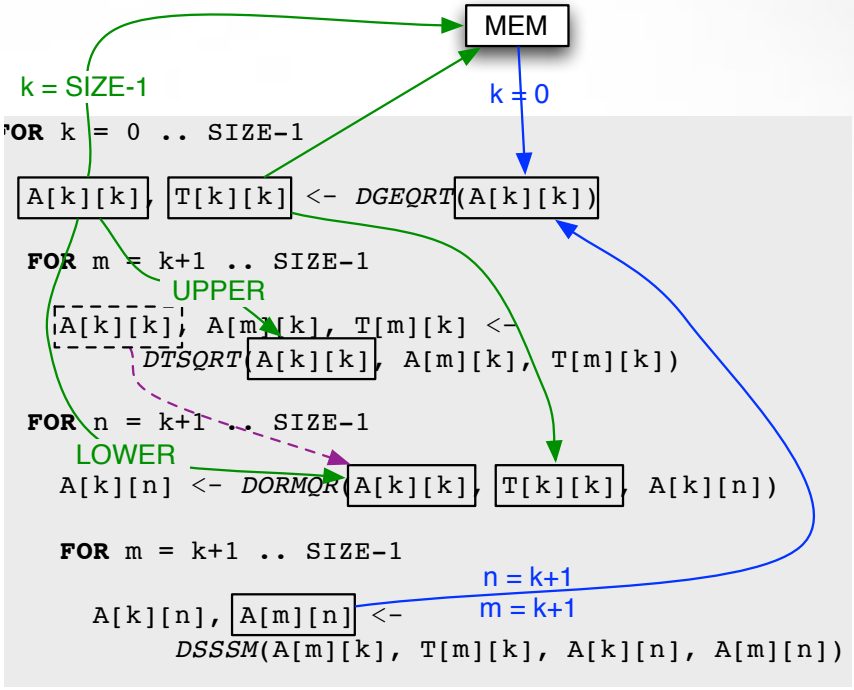
Input Format: Job Data Flow

```
TRSM(k, n)
// Execution space
k = 0..SIZE-1
n = k+1..SIZE-1
: A(n, k) // Parallel Partitionning
READ  T <- T POTRF(k)
RW    C <- (k == 0) ? A(n, k)
                    : C GEMM(k-1, n, k)
        -> A SYRK(k, n)
        -> A GEMM(k, n+1..SIZE-1, n)
        -> B GEMM(k, n, k+1..n-1)
        -> A(n, k)
```

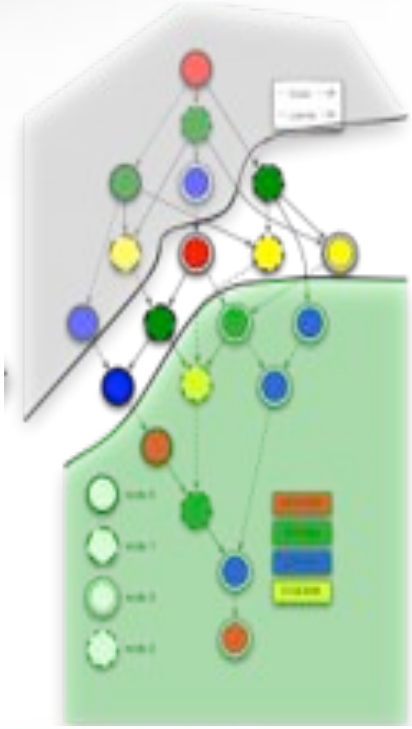


From Seq. to JDF

- DAGuE Compiler
  - Analysis the data flow using algebraic expressions
  - Omega Test used to compute algebraic relations between edges
    - Imperfectly nested affine loop tests
  - Anti-Dependencies may introduce additional control edges

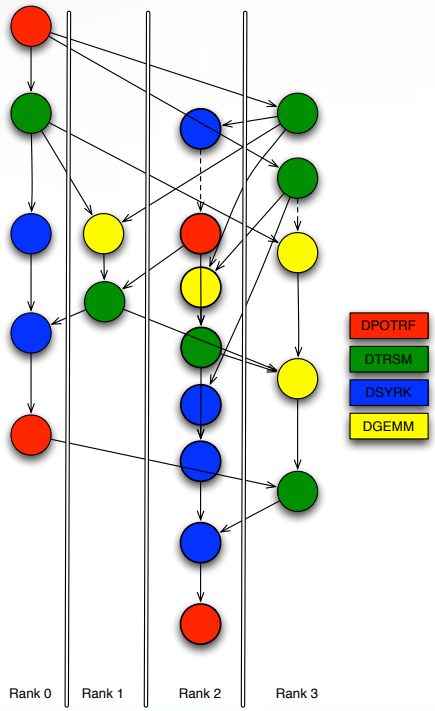


Runtime DAG Representation



- Every process has the algebraic DAG rep.
- Dist. Scheduling based on remote completion notifications
- NUMA / Cache aware Scheduling
- Work Stealing and sharing based on memory hierarchies

Runtime DAGuE Engine



- Data Distribution (and data/task affinity) imposes a task location
- On each node, the full DAG algebraic representation is available
- Each computing unit (core, GPU, etc.) runs its own instance of the DAGuE scheduler
- An additional communication thread sends completion notifications and data when necessary

Scheduling in DAGuE

- Based on Work Stealing
  - Shared data structures with atomic access operations
  - Uniform scheduler: all scheduler run with the global view of the DAG and the local view of progress (plus remote notifications)
  - Fully Distributed scheduler: all threads alternate between scheduling and work
- Main heuristic: data locality
  - DAGuE engine tracks data usage, and targets to improve data reuse
  - NUMA aware hierarchical bounded buffers to implement work stealing
- Users hints: tasks with “high priority”; Algebraic expressions for priorities
  - Insertion in waiting queue abides to priority, but work stealing can alter this ordering
- Communications heuristics
  - Communications inherits priority of destination task

Example: RTT

Sequential code:

```
B = ping(A[0]);
for(k = 1; k < NT-1; k++) {
      C = pong(B);
      B = ping(C);
}
A[0] = B;
```

- Read data into B using ping
- Call pong on B to make C
- Call ping on C to make B
- Iterate NT-1 times
- Save data

Example RTT: JDF

```
1   PING(k)
2   k = 0 .. NT          // Execution space
3   : A[0]               // Parallel partitioning
4    T <- (k == 0) ? A(0) : I PONG(k-1) [ATYPE]
5      -> (k == NT) ? A(0) : I PONG(k)  [ATYPE]
6
7   PONG(k)
8    k = 0 .. NT-1       // Execution space
9   : A[1]               // Parallel partitioning
10   I <- T PING(k)                     [ATYPE]
11     -> T PING(k+1)                   [ATYPE]
12
```

- The JDF Translator will create a stub (rtt.c / rtt.h) which includes two visible functions:
  - rtt_new(A, NT) creates a DAG generator for a specific data A
    - Data format includes accessors to discover the data distribution
  - rtt_destroy() frees the resources allocated by the new

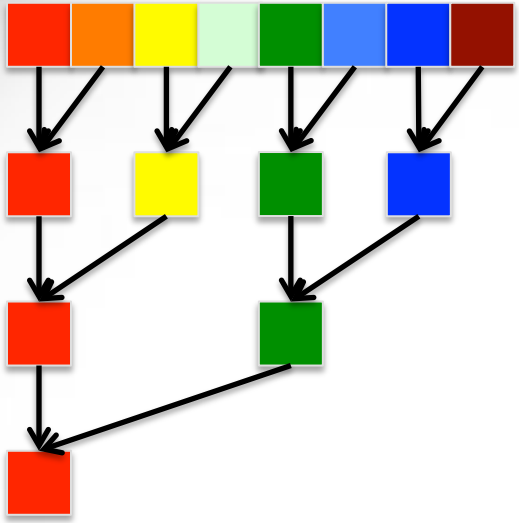
Example RTT: main program

```
#include "ping_pong.h"
int main( int argc, char** argv) {
  int size, rank; /* MPI_COMM_WORLD size and rank */
  dague_object_t* rtt;
  dague_matrix_t* A = dague_matrix( 1000, [ATYPE],
                                    "cyclic", 1, size );
  dague_t* mydag = dague_init("-c 1");
  rtt = rtt_new( A, rank, 1000);
  dague_enqueue( my_dag, rtt );
  dague_progress( my_dag );
  dague_fini( &my_dag );
}
```

Example: Reduction Operation

- Apply a user defined operator on each data and store the result in a single location.
- Suppose the operator is associative and commutative.

Example: Reduction Operation



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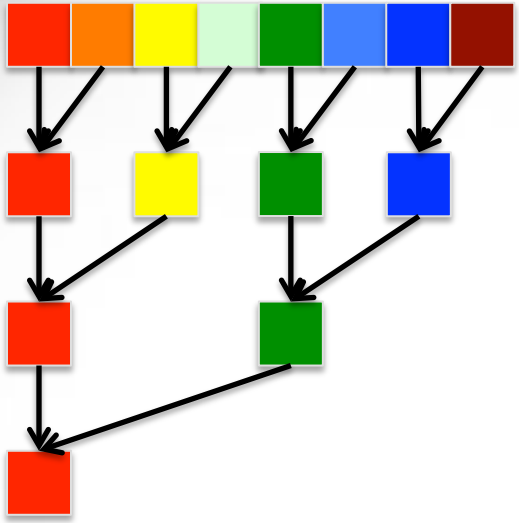
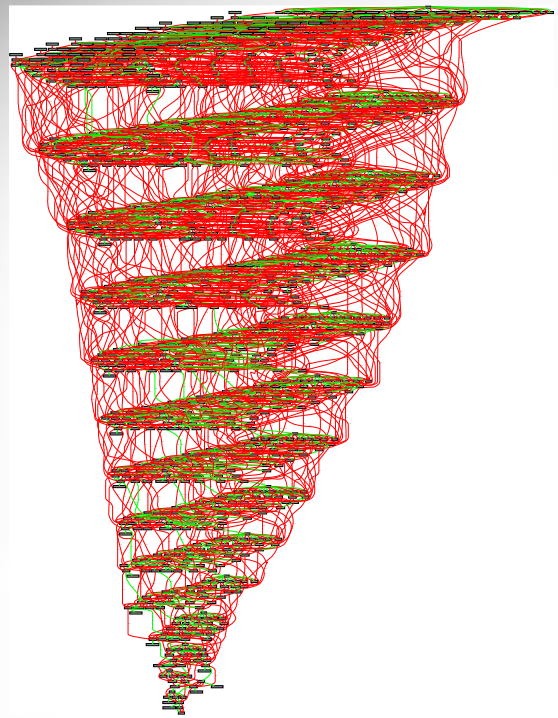
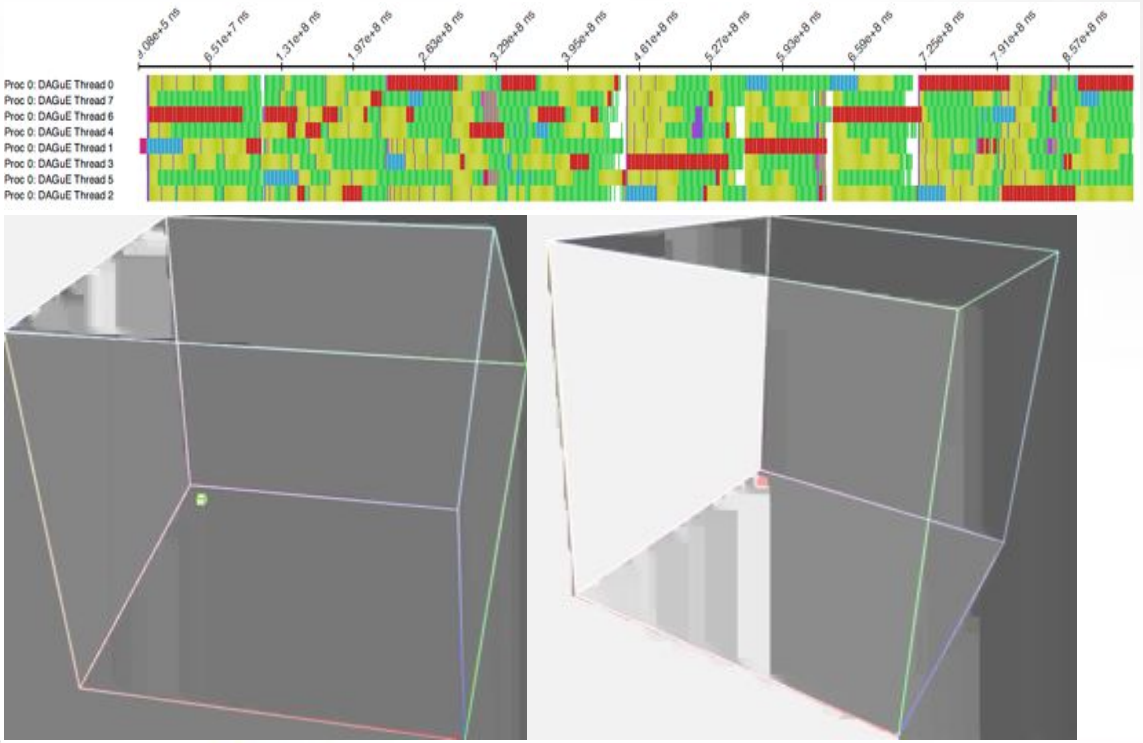
Example: Reduction Operation



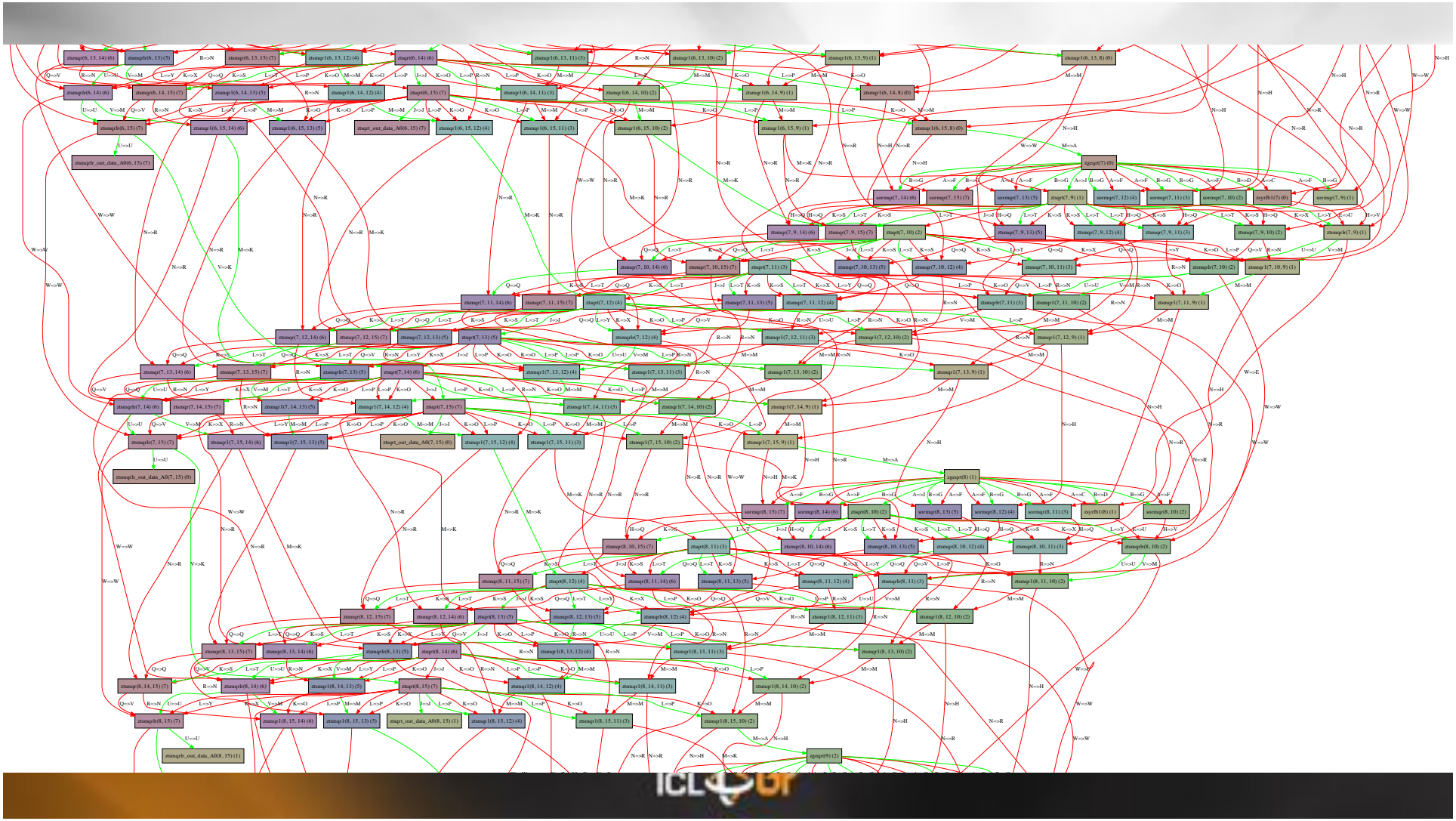
```
0  reduce(l, p)
     l = 1 .. depth+1
1    p = 0 .. (MT / (1<<l))
     : A( p )
     READ A <- (1 == l) ? A(2*p) : C reduce( l - 1, 2 * p )
2    READ B <- ((p * (1 << l) + (1 << (l-1))) >  MT)  ? A(0)
                <- (1 == l) ? A(2*p+1)
3               <- (1 != l)  ? C reduce(l - 1, p * 2 + 1)
     WRITE C -> ((depth+1) == l) ? R(p)
            -> (0 == (p%2)) ? A reduce(l+1, p/2)
                            :B reduce(l+1, p/2)
```

DAGuE: Analysis Tools





Hermitian Band Diagonal; 16x16 tiles



Experimental Platform

Dancer @ UTK

- 32 Cores (8 sockets)
- Intel Q9400 quad cores @ 2.5GHz
- 4GB RAM
- 2x 1GB/s ethernet
- 4 nodes with Fermi GPU
- 4 nodes with Tesla GPU

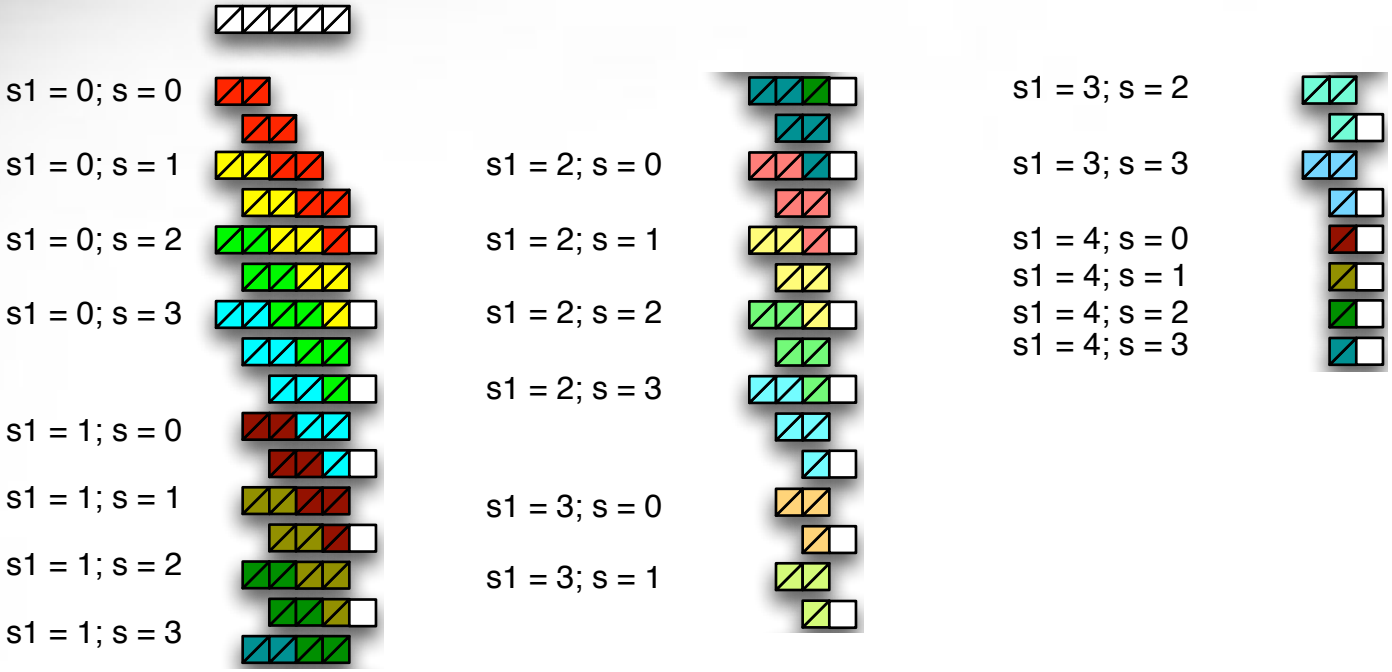
MKL-10.1.0.015 / gcc 4.4 / gfortran 4.4

Bulge Chasing in DAGuE

```
zhbrdt(s1,s,i)
  /* Execution space */
  s1 = 0..NT-2
  s = 0..NB-1
  i = s1..NT-2

  : A(0,i)

  /* A == data_A(0,i) */
  /* B == data_A(0,i+1) */

  RW    A <- (i==s1) & (0==s) & (0==i) ? A(0,i)
          <- (i==s1) & (0==s) & (i>=1) ? A zhbrdt(s1-1, NB-1, s1)
          <- (i==s1) & (s>=1)          ? A zhbrdt(s1, s-1, s1)
          <- (s1<i)                    ? B zhbrdt(s1, s, i-1)

          -> ((1+s)==NB) & (i==s1)     ? A(0,i)
          -> ((1+s)==NB) & ((1+s1)==i) ? A zhbrdt(s1+1, 0, s1+1)
          -> ((1+s)==NB) & ((1+s1)<i)  ? B zhbrdt(s1+1, 0, i-1)
          -> (i==s1) & ((1+s)<NB)      ? A zhbrdt(s1, s+1, i)
          -> (i>s1)                    ? B zhbrdt(s1, s+1, i-1)

  RW    B <- (0==s) & (0==s1)          ? A in_dat(i+1)
          <- (0==s) & ((NT-2)==i)      ? A zhbrdt_half(s1-1, NB-1)
          <- (0==s)                    ? A zhbrdt(s1-1, NB-1, i+1)
          <- ((NT-2)==i)               ? A zhbrdt_half(s1, s-1)
          <-                             A zhbrdt(s1, s-1, i+1)

          -> ((NT-2)==i)               ? A zhbrdt_half(s1, s)
          ->                             A zhbrdt(s1, s, i+1)
```

```
zhbrdt_half(s1,s)
  /* Execution space */
  s1 = 0..NT-1
  s = 0..NB-1

  : A(0,NT-1)

  /* A == data_A(0,i) */

  RW    A <- ((NT-1)!=s1)     ? B zhbrdt(s1, s, NT-2)
          <- (0==s)           ? A zhbrdt_half(s1-1, NB-1)
                              : A zhbrdt_half(s1, s-1)

          -> ((NT-1)==s1) & ((NB-1)==s) ? A(0,NT-1)
          -> ((NT-1)==s1)               ? A zhbrdt_half(s1, s+1)
          -> ((NT-2)==s1) & ((NB-1)==s) ? A zhbrdt_half(s1+1, 0)
          -> ((NB-1)==s)                ? B zhbrdt(s1+1, 0, NT-2)
                                        : B zhbrdt(s1, s+1, NT-2)
```

Bulge Chasing in DAGuE



Conclusion

- Hybrid programming (of dense LA) made easy(ier)
  - Portability: inherently take advantage of all hardware capabilities
  - Efficiency: deliver the best performance on tested algorithms
- Works well with Dense Linear Algebra with Direct Method
  - Sparse?
  - Branch and Bound?
  - Iterative Method?
- Let different people focus on different problems
  - Application developers on their algorithms
  - System developers on system issues

Related Works

- YML Like: read the DAG representation; unroll it (completely); schedule it (centrally)
- PLASMA / MAGMA / T-BLAS / STARPU like: seq. code -> new tasks + dep.; tasks window; sched. is dyn/stat
- PTG like: use a concise DAG representation to discover new tasks. Have a bounded ready list.

DAGuE uses a concise representation of the DAG, instantiates dynamically the tasks, scheduling is fully distributed and dynamic