Compiler optimization for massively parallel data flow

Tim Armstrong, Justin M. Wozniak, Michael Wilde, Ian T. Foster
TA, MW, IF: University of Chicago   JW, MW, IF: Argonne National Laboratory

Abstract

Distributed, dynamic data flow is an execution model well-suited for many large-scale parallel applications, particularly scientific simulations and analysis pipelines running on large, distributed-memory clusters. Swift is a high-level declarative language that allows flexible data flow composition of functions written in other programming languages such a C or Fortran.

Swift/T is a high performance, scalable re-implementation of Swift for massive distributed memory clusters.

This poster focuses on one aspect of the implementation: compiler optimization to improve execution efficiency and scalability. We show that compiler optimization can reduce communication overhead by 70-93% on distributed memory systems at scales up to thousands of cores. With compiler optimization, the high-level Swift language becomes competitive with hand-coded coordination logic for certain common styles of computationally intensive applications.

Swift/T Language & Execution Model

```
blob models[], res[][];
foreach m in [1:N_models] {
  models[m] = load(sprintf("model%i.data", m));
}

foreach i in [1:M] {
  foreach j in [1:N] {
    // initial quick evaluation of parameters
    p, m = evaluate(i, j);
    if (p > 0) {
      // run ensemble of simulations
      blob res2[];
      foreach k in [1:S] {
        res2[k] = simulate(models[m], i, j);
      }
      res[i][j] = summarize(res2);
    }
  }
}

// Summarize results to file
foreach i in [1:M] {
  file out<sprintf("output%i.txt", i)>;
  out = analyze(res[i]);
}
```

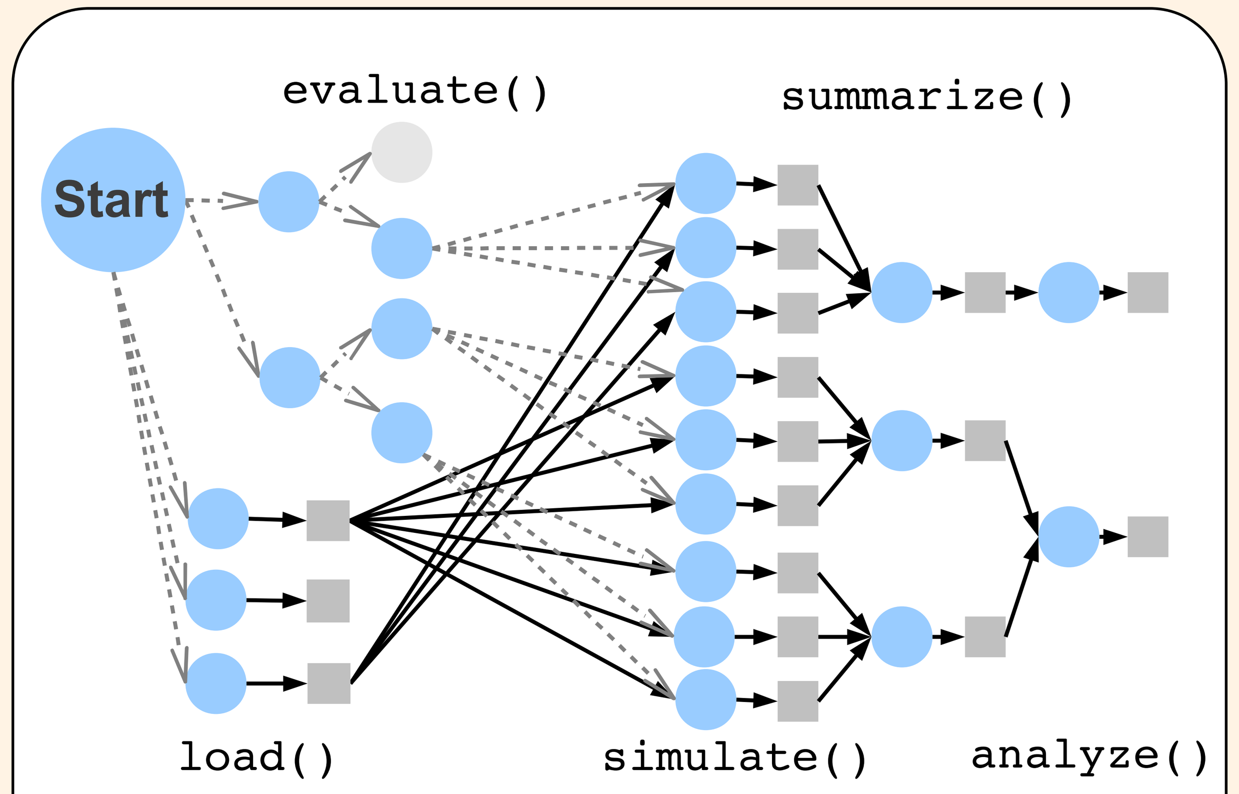


Figure 1: Visualization of parallel execution for M = 2, N = 2, S = 3, showing dynamic data dependencies. Blue circle: task, gray square: data, gray dashed line: task spawn, black line: data dependency

STC Optimizing Compiler

The STC compiler is an important part of the Swift/T toolchain. We depend on the compiler to translate high-level Swift/T scripts into efficient low-level code. This low-level code uses primitive operations for our distributed executor such as "get task", "put task", "fetch integer", "store integer", etc.

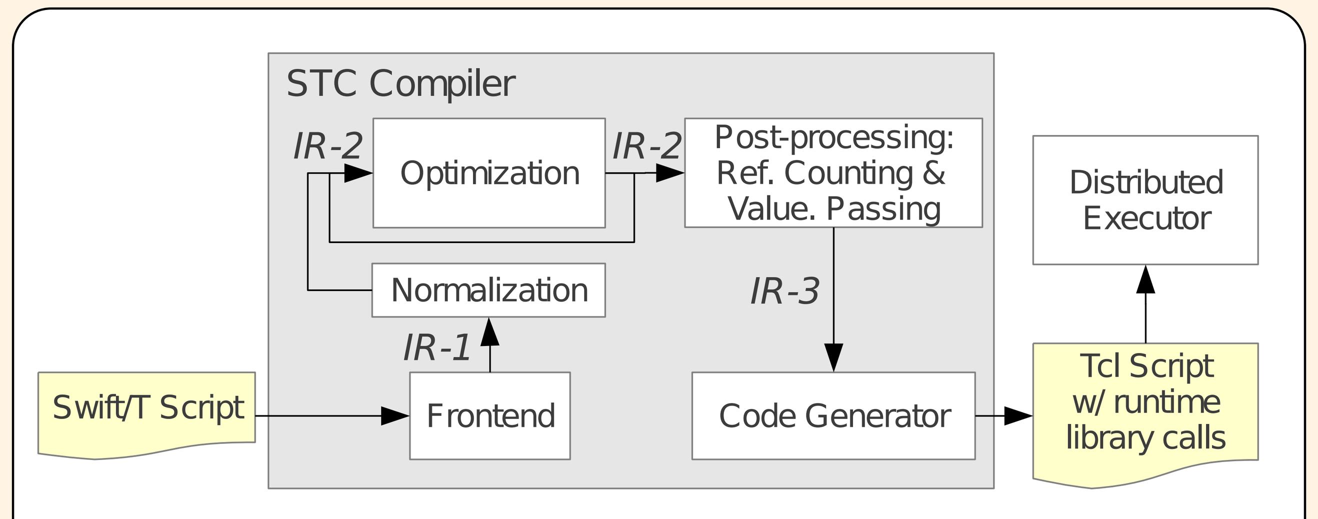
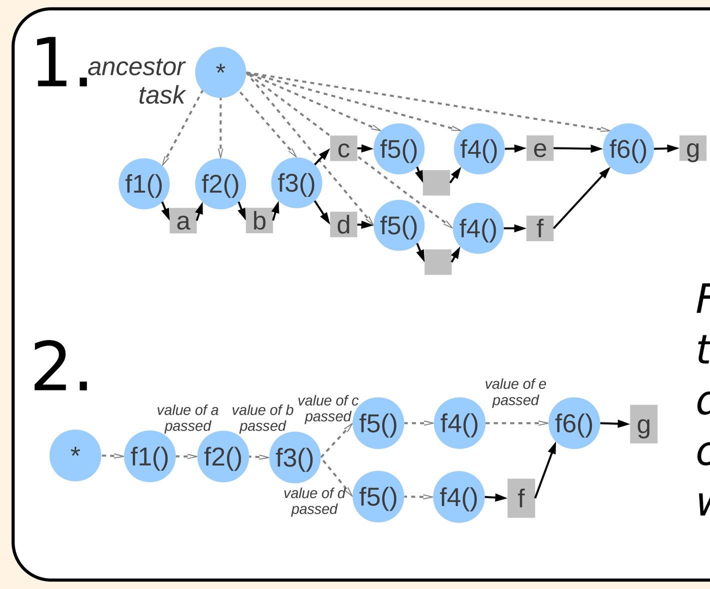


Figure 2: STC compiler architecture

Optimization Techniques

Standard compiler optimizations: constant folding, common subexpression elimination, dead code elimination, function inlining, loop invariant hoisting, etc.

Optimizations for asynchronous data flow: detection of finalized variables, task spawn deferral, task merging, etc.



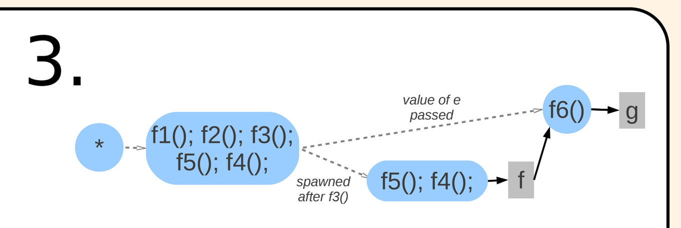


Figure 3: effect of compiler transformations. Runtime data dependencies and task spawn operations are eliminated without reduction in parallelism

Optimizations for reference counting: cancel and combine reference count operations; piggy-back reference counts on other messages; batch reference counts for loops. Reference counting is used for both memory management and for detecting when data structures are *finalized*. Optimization is critical to avoid high overhead.

Experimental Setup

Five benchmark applications were used:

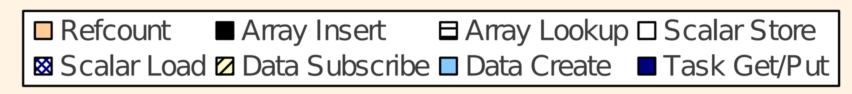
Sweep: a parameter sweep with two nested loops and completely independent tasks
Fibonacci: a synthetic divide-and-conquer application with the same dependency graph as a recursive Fibonacci calculation
Sudoku: a divide-and-conquer Sudoku solver that recursively prunes and divides the solution space, and terminates when solution found
Wavefront: 2D array with each cell a function of three neighbors
Simulated Annealing: an iterative optimization algorithm with a parallelized objective function.

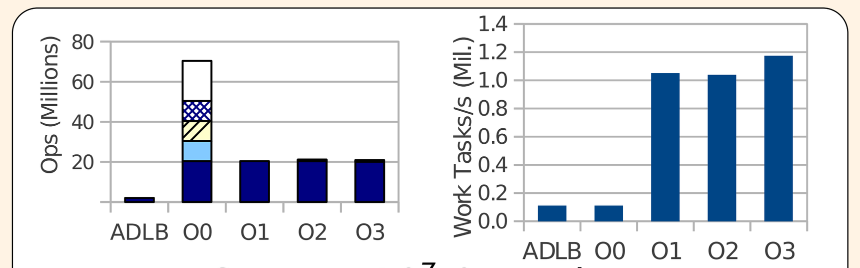
Four implementations were compared.
ADLB: hand-coded C using Swift's distributed runtime library directly
O0: Absolutely no optimizations: naïve compiled Swift/T
O1: Basic compiler optimizations: e.g. constant propagation
O2: More compiler optimizations: e.g loop invariant hoisting
O3: Aggressive optimization: e.g. function inlining, loop unrolling

We measure a) number of task and data operations (a good proxy for total communication) and b) application time-to-solution.

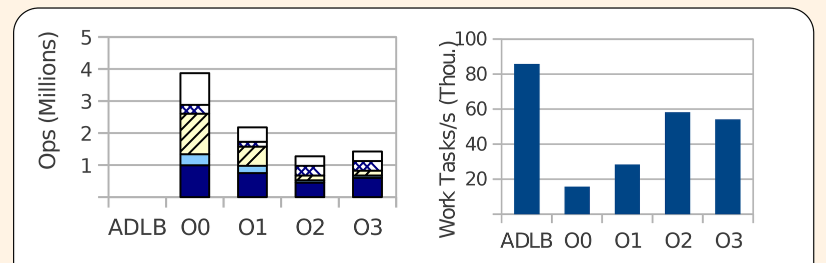
Benchmarks were run on the Beagle Cray XE6 supercomputer 2x12-core 2.1-GHz AMD Opteron 6100 per node. Ten nodes were used unless otherwise stated.

Results

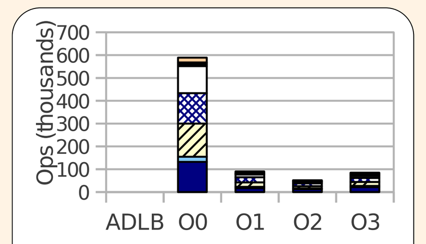




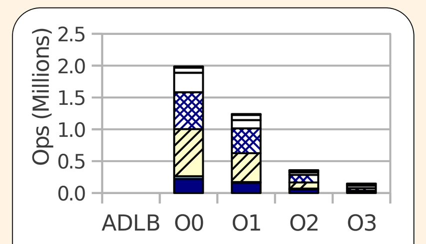
Sweep: 10^7 0s tasks



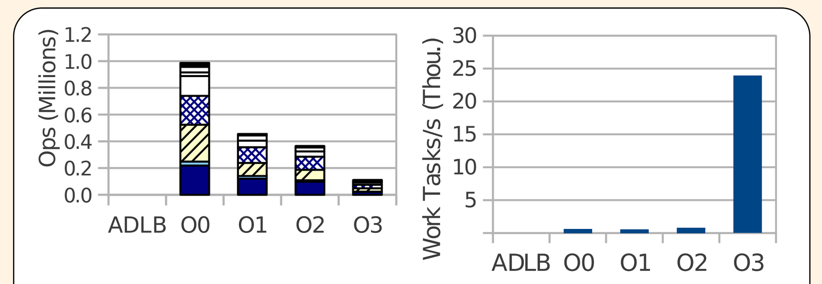
Fibonacci: n=24 0.2ms tasks



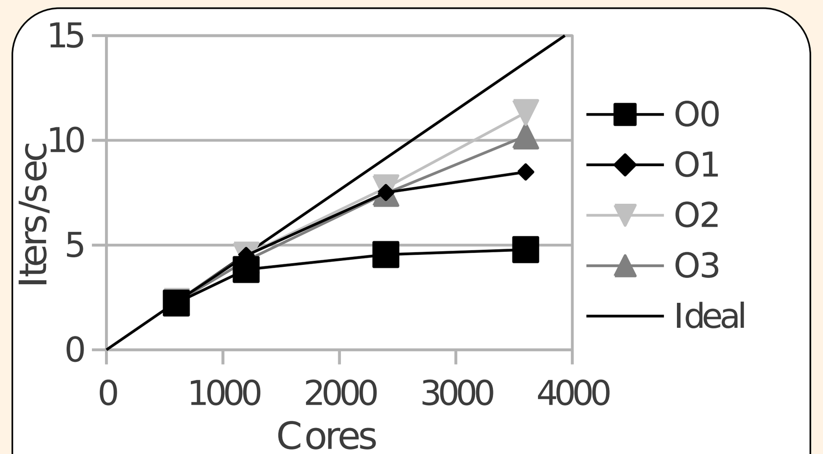
Sudoku: 100x100 board



Annealing: 125 iters, 100-way par.



Wavefront: 100x100, 0.2ms tasks



Annealing strong scaling: 5 params × 25 iters × 1000 ≈ 0.25s tasks

Compiler optimization reduces the number of runtime data and task operations and increases throughput. The benefit varies: basic optimizations always help, advanced optimizations help greatly with complex dataflow. Compiler optimization is essential for applications with short-running tasks and at large scale.

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Further reading

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[2] J. M. Wozniak, T. Peterka, T. Armstrong, J. Dinan, E. Lusk, M. Wilde, I. T. Foster, "Dataflow Coordination of Data-Parallel Tasks via MPI 3.0," in submission.
[3] J. M. Wozniak, T. Armstrong, M. Wilde, D. S. Katz, E. Lusk, I. T. Foster, "Swift/T Large-scale Application Composition via Distributed-memory Data Flow Processing," CCGrid'13
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[5] E. L. Lusk, S. C. Pieper, and R. M. Butler, "More scalability, less pain: A simple programming model and its implementation for extreme computing" SciDAC Rev. 2010