OpenMPIR

Implementing OpenMP tasks with Tapir

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ABSTRACT

Optimizing compilers for task-level parallelism are still in their infancy. This work implements a frontend which compiles a subset of OpenMP tasks to Tapir IR. This enables analyses and optimizations previously inaccessible to OpenMP codes. Initial performance results for the Barcelona OpenMP tasking suite and show performance improvements over existing OpenMP compiler implementations.

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1 INTRODUCTION

When writing task-parallel programs today, one has a large selection of programming models. Unfortunately, despite having significant overlap in semantics, parallel programming models like OpenMP, Cilk, Kokkos, HPX, Charm++, Qthreads, pthreads, MPI, Chapel, UPC, etc. have virtually no ability to interoperate, both at compile time and run time. In addition, many of these programming models are implemented as libraries, and therefore have no compiler support. There has been some recent work on specializing compilers to reason about libraries [?], but the fragmentation among the models that presents another challenge for compiler writers, which must choose a single model to analyze and optimize. An ideal solution would be some some form of common representation of parallelism that all IRs can share.

Internal representations (IRs) are the compiler objects on which almost all analyses and optimizations are performed. Historically, a major drawback for parallel codes is that IRs don't have the ability to represent, and therefore reason about, parallelism. This prevents the application of common optimizations to concurrent code. The recent work of Schardl et al. [?] has shown that standard compiler IRs can be extended to represent fork-join parallelism. In that work, by extending the LLVM instruction set with three instructions, they are able to capture all of the semantics to implement the semantics of Cilk, an extension to C. They suggested that a similar approach could be taken with OpenMP tasks.

In this work, we put that suggestion to the test, implementing OpenMP tasks by compiling them to Tapir instructions. This enables us to target non-openmp runtimes and compare performance to existing OpenMP implementations. Specifically, we run our prototype implementation on the Barcelona OpenMP task suite [?]. We discuss the kinds of optimizations this enables, and how the work could be extended to include other parallelism constructs and semantics in OpenMP. We also discuss the possibility of extending this work to other programming models, which would help to alleviate some of the fragmentation issues discussed above.

The contributions of this work include:

- A prototype frontend from OpenMP task constructs to Tapir IR
- Benchmarks of the implementation, showing performance improvements over existing OpenMP implementations
- An initial investigation into the reasons for the performance improvement

Our hope for this paper is that it moves the community towards a shared IR that can be used for many programming models. This work presented in this paper only represents a small step in that direction, and there is still a herculean amount of work required. We argue that the benefits vastly outweigh the costs, and hope to see more work follow suite.

1.1 Outline

The remainder of the paper is organized as follows: In Section **??** we give background and motivation for the paper. Following that, we describe OpenMP tasking in Section 4, and Tapir in Section 3. We then discuss the implementation, and how we compile OpenMP task constructs to Tapir IR in Section **??**. In Section **??** we describe the evaluation setup, including what implementations we compare to and how. We discuss the results of evaluation in Section 7, including possible explanations for discrepancies. Finally, we discuss how the many ways the work can be extended in Section 8.1, and conclude in Section 9.

2 BACKGROUND

Internal representations are a crucial part of modern compilers. By representing code in a generic, hardware-agnostic format, they allow both multiple frontends for different source

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languages, and multiple backends for different hardware, to all take advantage of a series of compiler optimizations and analyses.

LLVM is arguably the most successful IR to date [?]. By implementing a simple single static assignment (SSA) representation, it enables powerful optimizations that are effective for a wide range of programming languages and hardware [?].

Historically, LLVM has had a sequential semantics: there is no notion of concurrent or parallel processes. This resulted in existing compilers treating parallelism constructs as thin wrappers for calls into runtime systems. These calls are essentially impossible for the compiler to reason about, due to the complexity of runtimes being called.

This unfortunate situation was recently remedied by Schardl et al. [?]. By adding three instructions to LLVM, Tapir enables analyses and optimizations of parallel code. A full description

2.1 Fragmentation

In this section we discuss a significant challenge in HPC: fragmentation of parallel programming models. There are many, many, many ways to write parallel programs [?]. From libraries, to language extensions, to standalone languages, to combinations of the above, it can be hard to choose the right one. This means that when writing tooling, optimizations, or analyses, one has to choose which model to target. One common difficulty among all of these is that reasoning about parallel programs is hard [], and compilers can help []. Therefore any duplicated work is extremely costly. This is exactly analogous the problem LLVM helps to solve. Many optimizations and analyses can be applied across a wide range of programming languages and hardware, but until there was an effective IR, those were often duplicated, resulting in a lot of lost opportunity.

Addressing these concerns this is a major motivation for our turning to Tapir. By standardising a powerful but simple internal representation and building frontends and backends for it, one both make it easier to build optimizations and analyses for a given programming model, and avoid duplicating that work across different implementations. We'll return to this issue later in the paper when discussing potential limitations and challenges for Tapir for other hardware and

3 TAPIR

4 OPENMP TASKS

Initially, the cross-vendor OpenMP [?] shared memory programming model focused on the execution of data parallelism by a cooperating team of threads, e.g., dividing the iterations of a loop among the threads. Version 3.0 of the OpenMP API specification introduced support for lightweight asynchronous tasks, designated by the application developer and scheduled onto the team of threads by the OpenMP run time implementation. The `task` construct applied to a structured block of code creates an explicit task, and the `taskwait` construct waits for completion of all tasks generated by the current task.

Recursive task creations and synchronizations using the constructs result in an implicit directed acyclic graph (DAG) that allows both reasoning about and visualization of the program execution. Figure 1 shows some example code, a view of the task DAG, and a simplified execution schedule mapping the tasks to a team of two threads. In the example, the Nth Fibonacci number is calculated by recursively generating tasks to calculate the (N-1)th and (N-2)th Fibonacci numbers. The `taskwait` ensures that the child tasks have completed before their answers are combined to yield the final result.

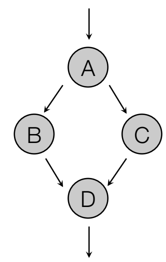
The initial design of the OpenMP task model [?] established a basic framework for asynchronous task parallel execution in OpenMP programs. Subsequent versions of the OpenMP specification up to the current version 4.5 have added additional new features to the tasking model. The `depend` clause codifies data dependences among tasks, indicating that a data location is an input or output of a task. The run time system ensures that a task is not scheduled until its input dependences are fulfilled. The `taskloop` construct combines groups of independent loop iterations into explicit tasks, enabling composition of concurrent loop execution and independent explicit tasks within the same OpenMP parallel region. The `taskgroup` construct waits on not only all child tasks, but all descendent tasks, providing a deep synchronization. The `taskwait` construct allows the application to indicate a point at which the implementation may suspend the current task to work on other tasks, as may be desired for long-running tasks that generate many others. The task concept was also leveraged to provide for asynchronous offload of data and computation to accelerators by applying the `nowait` clause to device constructs like the `target` construct to generate an asynchronous *target task*.

Several clauses for the `task` construct aim to optimize execution of tasks but can be safely ignored by an implementation that chooses to do so. The `mergeable` clause allows the implementation to omit creation of a new data environment for a descendent of a task marked with the `final` clause. The `priority` clause assigns an integer priority to the task and recommends the prioritization of tasks with higher priority values. The `untied` clause allows a task to be migrated between threads after suspension, which enables practical use of *work-first scheduling* (suspending the parent task in favor of executing each child task immediately on the thread where it is generated).

5 IMPLEMENTATION

Tapir is implemented as an extension to the LLVM instruction set. Clang is a C family compiler that has support for OpenMP extensions [?] and targets LLVM. The existing Clang OpenMP implementation mapps OpenMP constructs directly to OpenMP runtime library calls, by wrapping a C statement in a `CapturedStmt`. This replaces a C statement with a function call into the OpenMP runtime library. along

```
int fib(int n)
{                       // A
  if (n < 2)
    return n;
  else
  {
    int x, y;
    #pragma omp task
      x = fib(n-1);   // B
    #pragma omp task
      y = fib(n-2);   // C
    #pragma omp taskwait
    return (x+y);     // D
  }
}
```



Time	t_0	t_1	t_2
Thread 0	A	B	D
Thread 1		C	

Figure 1: Code, task graph, and schedule of a simple brute force recursive Fibonacci number calculation on two threads.

with a machine generated function who's body contains that statement.

For this work, we replaced a subset of the OpenMP implementation to generate Tapir IR instead of vanilla LLVM IR with OpenMP runtime calls. Specifically, we replace the two primary pragmas for task parallelism: `task_spawn` and `task_wait`. By re-using code from Schardl et al. for code generation of Cilk constructs, we were able to easily generate Tapir code for these OpenMP pragmas. The ease with which this was completed is a testament to the quality of the Tapir implementation.

While we did implement the codegen for the `task_spawn` and `task_wait` constructs, it's worth noting here that even for these pragmas, the implementation is incomplete. Currently, any clauses modifying the behaviour of the pragmas is ignored. Probably the most common semantics this will change of variable semantics, e.g. `shared` vs. `private`. Surprisingly, this had very effect on the correctness of the entire Barcelona OpenMP task suite. Indeed, it is likely that fixing this issue would increase the performance of this work marginally, due to reducing the number of memory copies for variables declared `private` in OpenMP code.

The surprising fact that program behaviour wasn't changed significantly is worth visiting here. We surmise that it is likely due to the variable semantics borrowed from the Cilk codegen and their relation to the OpenMP specification of semantics. In particular, *OpenMP doesn't specify any memory model for shared variables.* This results in the Cilk style of only writing to a shared variable at the end of a parallel section as a perfectly valid implementation of OpenMP's specification. In contrast, existing OpenMP implementations often write to shared variables on every write. This is a potential for performance discrepancy due to differing implementation-defined behaviour, and we will return to it when discussing performance on the Barcelona OpenMP task suite. There is of course the fact that technically, by copying the value of variables back to the surrounding context even for `private` variables, one isn't following the specification. We surmise that in practice this hasn't had an effect due to the fact that `private` variables are generally used for performance, rather than their semantic properties.

A very important property to discuss of the current implementation is the backend. This work has *only been on the frontend*, which means we use the only existing backend for Tapir. The existing backend is to generate calls into the Cilk runtime, `libcilkrts`. This obviously has many implications for adhering to the OpenMP specification. For example, environment variables such as `OMP_NUM_THREADS` are ignored, replaced by `CILK_NWORKERS`. We discuss some of these issues below, and return to address others in the future work section.

There are other issues that had to be overcome to run full OpenMP programs using Tapir as described above. Generally, a program has to contain other OpenMP pragmas in order to run parallel code. A standard pattern for building task-parallel OpenMP programs is to start a `parallel` pragma to spin up the necessary hardware threads, then have a `single` pragma to have only one thread continue on the specified statement. Then the other threads will get work from spawned tasks, instead of implicitly executing the same code in a data parallel style. For the purpose of this paper, we took the shortcut of replacing these pragmas with no-ops. This worked well for all examples except for one, in which after the `parallel` and `single` pragmas the top level task was called with an unnecessary `task` pragma. Because the wait was implicit and unhandled by our implementation, the simple fix was to remove the `task` pragma. This was the only change required to the source code. Our temporary no-op shortcut, of course, doesn't follow the OpenMP specification, and should be addressed by future work.

5.1 Example

To better understand how the OpenMP to Tapir compiler works, we turn to the `fib` example from Section 4. In Figure **??** we show how the code generated differs between the original

Clang implementation, which generates vanilla LLVM with calls into the OpenMP runtime, and.

6 EVALUATION

For evaluation we compared performance on the Barcelona OpenMP task suite to existing OpenMP implementations. The Barcelona OpenMP task suite is a set of tests intended to test performance of OpenMP implementations using both irregular and regular tasking. The benchmarks are described in Figure **??**.

- `Alignment`: aligns all protein sequences from an input file against every other sequence using the Myers and Miller [] algorithm. The alignments are scored and the best score for each pair is provided as a result. The scoring method is a full dynamic programming algorithm. It uses a weight matrix to score mismatches, and assigns penalties for opening and extending gaps. The output is the best score for each pair of them.
- `FFT`: computes the one-dimensional Fast Fourier Transform of a vector of n complex values using the Cooley-Tukey [**?**] algorithm. This is a divide and conquer algorithm that recursively breaks down a Discrete Fourier Transform (DFT) into many smaller DFT's. In each of the divisions multiple tasks are generated.
- `Fibonacci`: computes the n'th fibonacci number using a recursive paralellization. While not representative of an efficient fibonacci computation it is still useful because it is a simple test case of a deep tree composed of very fine grain tasks.
- `Floorplan`: kernel computes the optimal floorplan distribution of a number of cells. The algorithm gets an input file with cell's description and it returns the minimum area size which includes all cells. This minimum area is found through a recursive branch and bound search. We hierarchically generate tasks for each branch of the solution space. The state of the algorithm needs to be copied into each newly created task so they can proceed. This implies that additional synchronizations have been introduced in the code to maintain the parent state alive.
- `Health`: simulates de Columbian Health Care System [**?**]. It uses multilevel lists where each element in the structure represents a village with a list of potential patients and one hospital. The hospital has several double-linked lists representing the possible status of a patient inside it (waiting, in assessment, in treatment or waiting for reallocation). At each time step all patients are simulated according with several probabilities (of getting sick, needing a convalescence treatment, or being reallocated to an upper level hospital). A task is created for each village being simulated. Once the lower levels have been simulated synchronization occurs.
- `NQueens`: computes all solutions of the n-queens problem, whose objective is to find a placement for n queens on an $n \times n$ chessboard such that none of the queens attack any other. It uses a backtracking search algorithm with pruning. A task is created for each step of the solution.
- `Sort`: sorts a random permutation of n 32-bit numbers with a fast parallel sorting variation [**?**] of the ordinary mergesort. First, it divides an array of elements in two halves, sorting each half recursively, and then merging the sorted halves with a parallel divide-and-conquer method rather than the conventional serial merge. Tasks are used for each split and merge. When the array is too small, a serial quicksort is used so increase the task granularity. To avoid the overhead of quicksort, an insertion sort is used for very small arrays (below a threshold of 20 elements).
- `SparseLU`: computes an LU matrix factorization over sparse matrices. A first level matrix is composed by pointers to small submatrices that may not be allocated. Due to the sparseness of the matrix, a lot of imbalance exists. Matrix size and submatrix size can be set at execution time. While a dynamic schedule can reduce the imbalance, a solution with tasks parallelism seems to obtain better results []. In each of the sparseLU phases, a task is created for each block of the matrix that is not empty.
- `Strassen`: algorithm uses hierarchical decomposition of a matrix for multiplication of large dense matrices []. Decomposition is done by dividing each dimension of the matrix into two sections of equal size. For each decomposition a task is created.

In particular, we compare to GCC 7.1, Clang 4.0.1, and Intel 17.0.0. The machine used is a two socket Intel Xeon E5-2693 v3 machine with 132GB of memory, running Linux 4.11.4. It's worth noting that each of the other implementations comes with it's own runtime. In this sense, performance is a function of both the compiler and any optimizations it's able to perform, and the runtime. Understanding the interaction of these two parts is non-trivial, as we will see when discussing results.

As mentioned in the Section **??**, the gaps in the implementation changed program behaviour in a couple cases. In the case of `FFT`, we were forced to remove an unecessary `task` pragma, as the current implementation doesn't insert the implicit barrier at the end of a `parallel` region. This was a one line fix in the benchmark, and would be fixed properly by handling the `parallel` and `single` pragmas correctly in our implementation.

The second change in program behaviour due to our incomplete implementation was caused by the lack `critical` pragma and `atomic` pragmas. This issue showed up in the `Floorplan` benchmark. The `critical` pragma ensures that only one thread can executed the referred statement at a time. This should be fixable in the implementation by adding a simple code-localized synchronization generation in the IR. Similarly, the `atomic` pragma can be addressed by retaining a pointer to the shared stack variable, much like existing OpenMP implementations. It is worth noting that this behaviour was non-deterministic, and that roughly half of the time the Floorplan still returned correct results. As we will see, this makes for an interesting trade-off given the performance increase witnessed.

In our evaluation, we caught three kinds of errors:

- Non-determinism in result correctness
- Segmentation faults
- Timeouts (10 Minutes)

We set a timeout of 10 minutes, as at least one implementation was always finishing within 10 seconds, anything running more than 60 times slower becomes irrelevant. DUe to time constraints, correctness checks were not performed on every run, so it is possible some non-determinism was missed.

7 RESULTS

In this section we discuss the results of running our evaluation on our implementation, and how its performance compared to the existing implementations listed in Section **??**. See Figure **??** for a simple visualization of the performance. Each graph represents a single benchmark from the previously enumerated Barcelona benchmarks, and each bar represents one of the implementations.

The failure modes enumerated in Section **??** are denoted by asterisks in the implementation labels on the X axis. One asterisk refers to some incorrect answers. Two asterisks refers to time-out. Three asterisks refers to segmentation faults.

First, we can see that there is one failure for our implementation, on `Floorplan`. Note that the result is non-zero. In fact, while ICC and Clang finished in roughly 1-2 seconds, the our Tapir implementation was finishing in *0.02* seconds, and computing the correct result roughly half the time. This raises interesting questions on the cost/benefit relation of the OpenMP behaviour that our implementation is missing.

Other failures include ICC failing with segmentation faults on `FFT` and `Fibonacci`. While we haven't carefully diagnosed these failures, we suspect that the number of tasks spawned exceeded a limit in Intel's compiler. Note that the `FFT` failures were non-deterministic, occurring on roughly one in three runs. Clang failed with segmentation faults on every run of `SparseLU`. Again, we didn't have the time to investigate these failures, and are unsure what was causing them.

The final failures we saw were timeout failures. GCC was the only culprit for these failures. Recall that the timeout was set at 10 minutes, so any timeout means GCC was running at least approximately 60 times slower than the fastest implementation. For example, on the `FFT` benchmark, while our Tapir implementation was running in under 5 seconds, the GCC implementation was timing out at 600 seconds, so was at least 100 times slower.

7.1 Forensics

In this section we attempt to understand *why* the performance varies in the ways it does. While we can't hope to figure out every discrepancy in performance, we can hope to get some ideas for why the performance of our implementation is generally better, and where each of the implementations is spending its time.

Our primary tool for this task will be performance counters. It's worth noting that some information is difficult to infer from performance counters, such as sources of contention in runtimes, reasons for memory locality issues, etc. Still, it will give us some insight into performance bottlenecks in the program.

Before we begin understanding why, it's worth noting again that the scope of the work that this paper is responsible for is only the frontend. All performance gains due to the Cilk runtime we sadly cannot claim credit for.

Another import consideration is that we can break reasons for performance discrepencies into a few categories:

- Front-end code generation
- IR Optimizations
- Runtime efficiency

While we will try out best to distinguish between these in our forensics, it is difficult to do so with only performance counter information. A further investigation would require careful knowledge of each of the frontends and runtimes. One thing we can guess at is that despite the focus of the paper, *IR optimisations are unlikely to be the cause of performance improvements.* Our evidence for this comes from Shardl et al. []. While some IR optimisations have been implemented, they seem to have significantly more effect on parallel loop code , while the tasking code remains relatively unaffected by IR optimizations [].

8 DISCUSSION

8.1 Future Work

8.2 Related Work

9 CONCLUSION

We have shown that Tapir is an excellent IR target for OpenMP tasks. While not all of the semantics are covered, we have a path forward for many of them. We have shown that compiling to Tapir instructions allows for a straightforward compilation of OpenMP tasking programs to use the Cilk runtime system. We've also shown that this combination leads to better performance than existing OpenMP tasking implementations on the Barcelona OpenMP Tasking benchmark suite. Moving forward, we hope efforts like this one help to reduce the fragmentation of parallel runtimes, as well as make it easier to write optimization for parallel programs.

REFERENCES

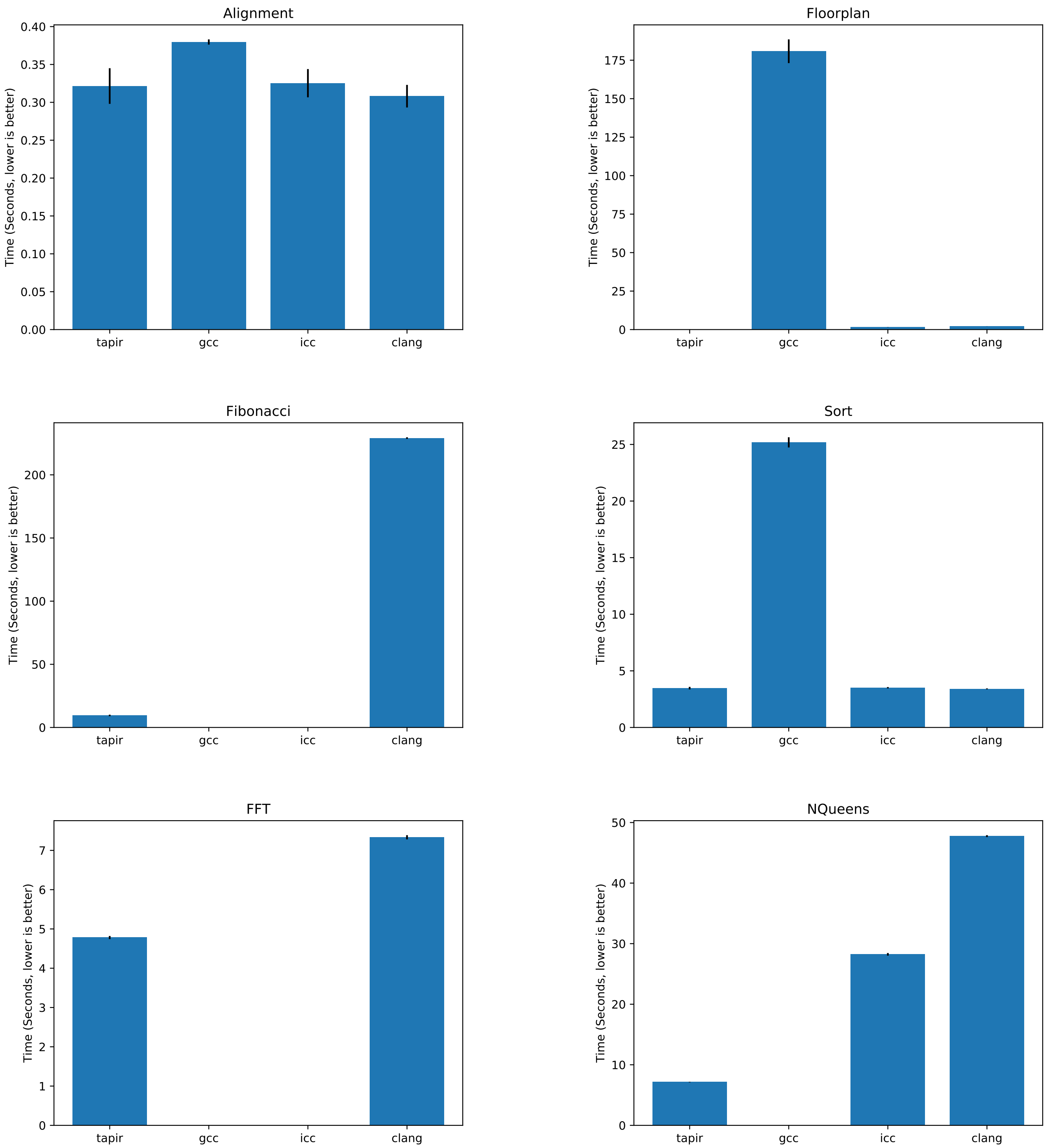
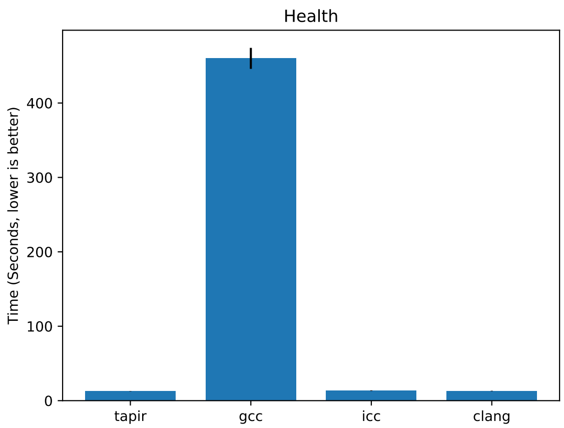
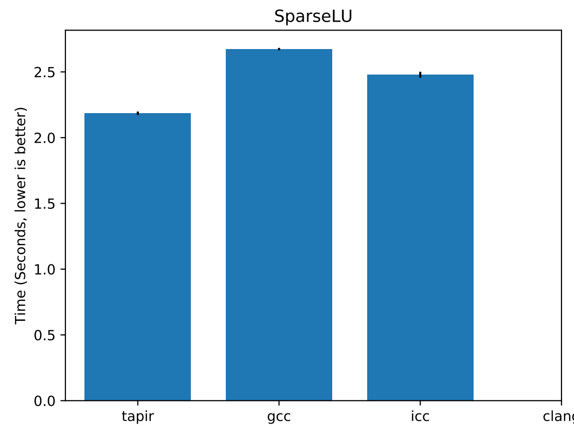


Figure 2: Barcelona OpenMP Task Suite Results





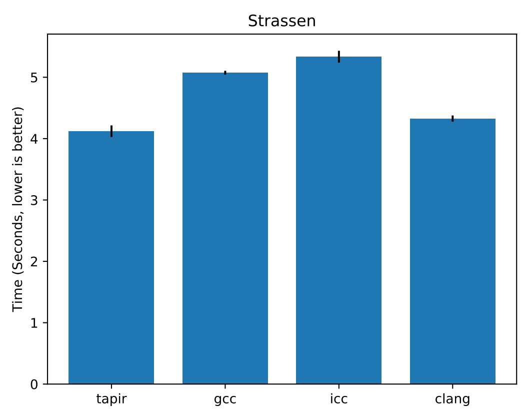


Figure 3: Barcelona OpenMP Task Suite Results (continued)