Task Bench: A Parameterized Benchmark for Evaluating Parallel Runtime Performance

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Abstract

We present Task Bench, a parameterized benchmark designed to explore the performance of parallel and distributed programming systems under a variety of application scenarios. Task Bench lowers the barrier to benchmarking multiple programming systems by making the implementation for a given system orthogonal to the benchmarks themselves: every benchmark constructed with Task Bench runs on every Task Bench implementation. Furthermore, Task Bench’s parameterization enables a wide variety of benchmark scenarios that distill the key characteristics of larger applications.

We conduct a comprehensive study with implementations of Task Bench in 15 programming systems on up to 256 Haswell nodes of the Cori supercomputer. We introduce a novel metric, \textit{minimum effective task granularity} to study the baseline runtime overhead of each system. We show that when running at scale, 100 µs is the smallest granularity that even the most efficient systems can reliably support with current technologies. We also study each system’s scalability, ability to hide communication and mitigate load imbalance.

1 Introduction

The challenge of parallel and distributed computation has led to a wide variety of proposals for programming models, languages, and runtime systems. While these systems are well-represented in the literature, comprehensive and comparative performance evaluations remain difficult to find. Our goal in this paper is to develop a meaningful and useful framework for comparing the performance of parallel and distributed programming systems, to help users and developers evaluate the performance tradeoffs of these systems.

One approach to comparing the performance of different systems is through \textit{proxy-} or \textit{mini-apps}. Because they distill the key computational characteristics of a larger application, mini-apps can provide insight without the expense of developing a production code. However, despite the name, our experience is that mini-apps still require significant investment to develop to the level of quality needed for useful benchmarking. In many cases, the effort to tune for performance exceeds the effort to develop a correct implementation. As a result, implementations of mini-apps often do not reach the level of maturity required to compare systems. Few published studies compare more than a handful of systems [26].

We present Task Bench, a parameterized benchmark for exploring the performance of parallel and distributed programming systems under a variety of conditions. The key property of Task Bench is that it completely separates the system-specific implementation from the implementation of the benchmarks themselves. In all previous benchmarks we know of, the effort to implement \(m\) benchmarks on \(n\) systems is \(O(mn)\). Task Bench’s design reduces this work to \(O(m + n)\), enabling dramatically more systems and benchmarks to be explored for the same amount of programming effort. New benchmarks created with Task Bench immediately run on all systems, and new systems that implement the Task Bench interface immediately run all benchmarks.

Benchmarks in Task Bench are based on the observation that many applications can be modeled as a set of \textit{tasks}, or coarse-grain units of work, with dependencies between tasks representing the communication and synchronization required for distributed execution. A benchmark consists of a \textit{task graph} with tasks for each point in an \textit{iteration space}, and dependencies determined by a \textit{dependence relation}. This design permits a concise description of a wide variety of patterns relevant to scientific computing and large scale data analysis: trivial parallelism, halo exchanges (such as seen in structured and unstructured mesh codes), sweeps (such as used in the discrete ordinates method of radiation simulation), FFTs, trees (for divide and conquer algorithms), and so on. Tasks execute kernels with a variety of computational properties, including compute- and memory-bound operations of varying durations. Dependencies between tasks can be configured to carry communication payloads of varying size, permitting the design of communication-bound cases. Finally, multiple (potentially heterogeneous) task graphs can be executed concurrently to introduce task parallelism into the workload. Together, these design elements enable the exploration of a large space of application behaviors.

Adding a system to Task Bench involves implementing a set of standard services, such as executing a task or data transfer, simple enough to be implemented with reasonable effort.
to a level of quality sufficient for comparative studies. Task Bench provides a core library that encapsulates functionality shared among systems, which not only reduces implementation effort but also makes it much easier to achieve truly apples-to-apples comparisons between systems.

Using Task Bench we were able to quickly incorporate 15 very different parallel and distributed programming systems. By running all systems on common benchmarks we were able to quantify phenomena that have never before been measured. Most strikingly, the overheads of the systems we examine vary by more than five orders of magnitude, with popular, widely used systems at both ends of the spectrum! Clearly the slower systems have “good enough” performance for some class of applications, while presumably providing advantages in programmer productivity.

How does one predict whether the performance of a given system will be good enough for a particular application? Surprisingly, the most commonly reported performance metrics, weak and strong scaling, do not directly characterize the performance of the underlying programming system. Weak scaling can hide arbitrary amounts of runtime system overhead by using sufficiently large problem sizes, and strong scaling does not separate runtime system overhead from application costs (such as increased communication) that scale with the number of nodes when using progressively larger portions of a machine.

To characterize the contribution of runtime overheads to application performance, and as an example of the novel studies that can be done with Task Bench, we introduce a new metric called minimum effective task granularity (METG). Intuitively, for a given workload, METG(50%) is the smallest task granularity that maintains at least 50% efficiency, meaning that the application achieves at least 50% of the highest performance (in FLOP/s, B/s, or other application-specific measure) achieved on a given machine. The efficiency bound in METG is a key innovation over previous approaches, such as tasks per second (TPS), that fail to consider the amount of useful work performed (if tasks are non-empty [3, 6]) or to perform useful work at all (if tasks are empty [28]).

METG captures the essence of what is important in a weak or strong scaling study, the behavior at the limit of scalability. For weak scaling, METG(50%) corresponds to the smallest problem size that can be weak-scaled with 50% efficiency. For strong scaling, METG(50%) can be used to compute the scale at which performance can be expected to dip below 50% efficiency. We note that METG(50%) for a given runtime system will vary with the particular application and the underlying hardware—i.e., METG(50%) is not a constant for a given system, but we will see that individual systems have a characteristic range of METG(50%) values and that there is additional insight in the reasons that METG can vary.

A lower METG does not necessarily mean that performance for a particular workload is better. Two systems with METG(50%) of 100 µs and 1 ms, respectively, running an application with 10 ms average task granularity, are both likely to perform well. Only when task granularity approaches (or drops below) METG(50%) will they likely diverge. METG identifies the regime in which a given system can deliver good performance, and explains how different systems coexist with runtime overheads that vary by orders of magnitude.

We conduct a comprehensive comparative study of Task Bench implementations in 15 programming systems: Chapel [14], Charm++ [25], Dask [32], MPI [35], MPI+X (OpenMP, CUDA), OmpSs [17], OpenMP [1], PaRSEC [12], Realm [36], Regent [33], Spark [40], StarPU [7], Swift/T [39], Tensor-Flow [5], and X10 [15]. Using METG, we find that a number of factors—node count, accelerators, and complex dependencies, among others—individually or in combination contribute to an order of magnitude or greater increase in METG, even in the most efficient systems. While some systems can achieve sub-microsecond METG(50%) in best-case scenarios, we show that a more realistic bound for running nearly any application at scale is 100 µs with current technologies. Our study includes several asynchronous systems which are designed to provide benefits such as overlapped computation and communication. While small-scale benchmarks of these systems suffer from increased overhead, we find that the benefits of these systems become tangible at scale (provided the runtime overhead doesn’t increase beyond about 100 µs).

The paper is organized as follows: Section 2 describes the design of Task Bench. Section 3 discusses implementations in 15 programming systems. Section 4 defines the METG metric and its relationship to quantities of interest to application developers. Section 5 provides a comprehensive evaluation of Task Bench on up to 256 Haswell nodes of the Cori supercomputer [2] (GPU results are reported on Piz Daint [4]). Section 6 relates to previous efforts; Section 7 concludes.

2 Task Bench

To explore as broad a space of application scenarios as possible, Task Bench provides a large number of configuration parameters. The most important parameters are described in Table 1. These parameters control the size and structure of the task graph, the type and duration of the kernels associated with each task, and the amount of data associated with each dependence edge in the graph.

Task graphs are a combination of an iteration space (with a task for each point in the space) with a dependence relation. For simplicity, but without loss of generality, the iteration space in Task Bench is constrained to be 2-dimensional, with time along the vertical axis and parallel tasks along the horizontal. Tasks may depend only on tasks from the immediately preceding time step. Figure 1 shows a number of sample task graphs that can be implemented with Task Bench. Note that layout is significant—in particular, column i represents all tasks with index i in the iteration space over all the time.
The Task Bench core library is fully validating. Because the task graph configuration is explicitly represented (though unmaterialized) in Task Bench, this representation can be queried to determine exactly what dependencies a task should expect. The output of every task in Task Bench is unique, and all inputs are verified. An assertion is thrown if validation fails. These checks ensure that every execution of Task Bench, if it completes successfully, is correct. An evaluation of the performance impact of validation showed it to be less than 3% at the smallest task granularities in any Task Bench implementation, with a negligible effect on overall results.

Task Bench provides two main kernels that can be called from tasks: compute- and memory-bound. The compute-bound kernel executes a tight loop and is hand-written using AVX2 FMA intrinsics. The memory-bound kernel performs sequential reads and writes over an array, again with AVX2 intrinsics. The duration of both kernels can be configured by setting the number of iterations to execute; we use this ability to simulate the effects of varying application problem sizes. The memory-bound kernel is carefully written to keep the working set size constant as the number of iterations decreases, to avoid unwanted speedups due to cache effects.

### 3 Implementations

We have implemented Task Bench in the 15 parallel and distributed programming systems listed in Table 3. We describe the systems, and any salient details of their Task Bench implementations, below.

One challenge in targeting such a wide variety of systems is that the capabilities of the systems vary considerably.
For example, some systems are implicitly parallel, and provide some form of parallelism discovery from sequential programs, whereas others are explicitly parallel and require users to specify the parallelism in the program. For systems that provide both implicit and explicit parallelism, the form of parallelism used in Task Bench is emphasized in Table 3.

In all cases, members of the programming systems’ teams were consulted in the development and evaluation of the corresponding Task Bench implementations. Where assistance was provided, the insights helped ensure that we provide the highest quality implementations for each system.

### 3.1 Chapel

Chapel [14] is a parallel programming language with a multi-resolution approach, supporting parallelism at a variety of levels. Chapel’s core features are a partitioned global address space (PGAS), data distributions, tasks, synchronization primitives, and array promotion. For Task Bench, we target a low level of Chapel, using explicit task instantiation (via `coforall`), bulk access to distributed arrays for efficient data movement, and atomic integers for synchronization.

### 3.2 Charm++

Charm++ [25] is an explicitly parallel actor-based programming system. Actors, or chares, are objects in their own address space. Chares communicate data and synchronize via messages and can be moved to balance load. Our Task Bench implementation uses a chare array for the task graph, with one chare for each column. Messages implement dependencies; a task executes as soon as its dependencies are all available.

### 3.3 Dask

Dask [32] is an implicitly parallel task-based programming system for large scale data analytics with Python. Dask provides abstractions over distributed NumPy arrays and Pandas dataframes, and also a lower-level interface for launching tasks. We use the lower-level interface to implement Task Bench.

### 3.4 MPI

Our MPI [35] implementation of Task Bench represents the common case of point-to-point communication with distinct computation and communication phases. We experimented with a variety of implementation strategies and found the best performing to be using `MPI_Isend` and `MPI_Irecv` to implement the communication phase, posting receives before sends. Each task dependency maps to one send/receive pair in MPI. We also provide a bulk synchronous implementation which enforces the boundary between communication and computation with `MPI_Barrier`.

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1. Chapel uses GASNet to support non-Cray networks.
2. Charm++ provides additional backends for other networks.
3. Most MPI implementations provide additional backends for other networks.
4. Our evaluation only considers TensorFlow on a single node.
5. X10 also provides a PAMI backend on supported networks.
We provide two MPI+X implementations of Task Bench to evaluate the performance of hierarchical programming models. Our MPI+OpenMP implementation uses for-all-style parallel loops to execute tasks, interleaved with MPI point-to-point communication as above. Our MPI+CUDA implementation follows an offload model where data is copied to and from the GPU on every timestep.

3.6 OmpSs

OmpSs [17] is a programming model for loop- and task-based parallelism that is source-compatible with OpenMP. Our Task Bench implementation uses OpenMP 4.0-style task dependencies. Because OpenMP tasks have a fixed number of dependencies, we use a switch statement to implement the dynamic dependencies required for Task Bench. The implementation is otherwise straightforward.

3.7 OpenMP

OpenMP [1] is the industry standard API for loop-based parallelism on shared-memory systems, and supports task dependencies as of version 4.0. Our Task Bench implementation for OpenMP is similar to OmpSs and uses task dependencies. We tested with GNU GOMP and Intel KMP and found KMP to be better performing.

3.8 PaRSEC

PaRSEC is a task-based programming system supporting two distinct programming models: parameterized task graphs (PTG) [12] and dynamic task discovery (DTD) [23]. PTG is a dataflow model in which programmers write a concise, algebraic description of the tasks and dataflows in the program. This compressed representation is expanded into a full task graph by a source-to-source compiler.

In the DTD model, tasks are enumerated in program order (by executing the program), and dependencies between tasks are identified automatically based on the input and output data of tasks. A task depends on another task if it reads data written by the other task, and the data is copied automatically if the two tasks are executed on different nodes. To improve scalability, the program is executed in SPMD fashion on all nodes, and the user is responsible for eliding tasks that are not directly connected to those that are to be executed on the current node.

In our Task Bench implementation, we evaluate both PTG and DTD models, as well as a third option based on DTD that has additional manual optimizations applied to further reduce dynamic checks for what tasks should be executed on a node, which further improves scalability.

3.9 Realm

Realm [36] is an explicitly-parallel task-based programming model used internally by Legion [10] and Regent [33]. A Realm implementation of Task Bench is a limit study of what can be achieved with Legion or Regent.

Tasks in Realm are asynchronous, with dependencies defined by events passed from one task to another. Realm’s data model supports collections that live in a specific memory. Data must be explicitly copied, and the copies synchronized with tasks via events. Realm also supports a subgraph API that enables additional optimizations. We use subgraphs in the Task Bench implementation.

3.10 Regent

Regent [33] is an implicitly-parallel task-based language which implements the Legion programming model [10]. We use Regent rather than Legion directly because the Regent compiler provides a critical optimization that improves scalability [34].

3.11 Spark

Spark [40] is an implicitly-parallel programming model for large scale data analytics. The core abstractions in Spark are functional operators such as map, reduce, and join. Data in Spark are stored in resilient distributed datasets (RDDs): globally-visible, dynamically single-assignment data structures. Spark caches RDDs in memory to avoid unnecessary disk traffic.

Spark has tasks internally but they are not exposed to the user, so a Task Bench implementation must map the task graph to a set of operators that result in the desired execution. We use flatMap and groupByKey to generate task dependencies, and then mapPartitions to execute a series of tasks. An explicit hash partitioner ensures that Spark does not attempt to group multiple Task Bench tasks into a single Spark task, as tasks in Task Bench already represent coarse-grained units of work.

We performed extensive experiments to verify that no extraneous factors interfered with our Spark measurements. We disabled logging, ensured no RDDs are written to disk, confirmed there is no measurable overhead due to JNI calls from Java to C or due to the serialization of data structures, and cross-checked results with known cases that hit optimal task throughput in Spark.

3.12 StarPU

StarPU [7] is a task-based system that supports a sequential task flow (STF) programming model similar to PaRSEC’s DTD. Our Task Bench implementation in StarPU is very similar to PaRSEC.

3.13 Swift/T

Swift/T [39] is a parallel scripting language intended primarily for the composition of HPC workflows. Swift/T programs follow dataflow semantics, where every statement may potentially execute in parallel as soon as its dependencies are
satisfied; statements only execute sequentially when explicitly requested. The Swift/T compiler performs a number of optimizations to improve performance of highly parallel programs [6]. Our Task Bench in Swift/T is straightforward, using Swift/T’s dataflow semantics to capture dependencies on other tasks.

3.14 TensorFlow

TensorFlow [5] is a programming system designed for deep learning workloads. Although TensorFlow’s API exposes machine learning concepts, internally TensorFlow is a task graph execution engine, making it a good fit for Task Bench. TensorFlow programs operate via explicit graph construction. Task graphs are composed in Python and run by an execution engine written in C++. Our Task Bench implementation is straightforward.

3.15 X10

X10 [15] is an explicitly parallel programming language for place-based programming. The core features of X10 are places which represent distributed memories, a PGAS model where references to remote objects can be held (but can only be dereferenced on the local place), asynchronous tasks, and a place-changing construct to move the execution of a task to a remote place. X10 also supports a variety of synchronization primitives.

Our Task Bench implementation uses Rail.asyncCopy for efficient data movement between places, along with place-changing and atomic integers for synchronization. We use the native backend of X10, which compiles to C++.

4 METG

Given that Task Bench permits the rapid exploration of a large space of application scenarios, one question is how to characterize the overall performance of the programming systems under study. As noted earlier, the overheads of the systems we consider vary by more than five orders of magnitude. This makes it challenging to extract useful information from weak and strong scaling runs.

Existing studies of system efficiency typically report tasks per second (TPS). TPS results are difficult to interpret and apply, because efficiency (and thus the amount of useful work) is not constrained. With empty tasks [28], the resulting upper bound on task scheduling throughput fails to represent useful work within a realistic application. With non-empty tasks, since the efficiency of the overall application is typically not reported [3, 6], TPS is not a measurement of runtime-limited performance. Large tasks may be used to hide any amount of runtime overhead, while small tasks may result in a drop in total application throughput even as TPS increases.

We introduce minimum effective task granularity, or METG, an efficiency-constrained metric for runtime-limited performance. METG(50%) for an application $A$ is the smallest average task granularity (i.e., task duration) such that $A$ achieves overall efficiency of at least 50%. For example, in compute-bound applications efficiency can be measured as the percentage of the available FLOP/s achieved. On Cori with 1.26 TFLOP/s available per Haswell node, METG(50%) corresponds to the smallest task granularity achieved while maintaining at least 0.63 TFLOP/s per node. For applications not amenable to being characterized by raw FLOP/s or B/s,
an application-specific measure of performance can be used instead (e.g., mesh cells processed per second).

Figures 2 and 3 show how METG is calculated. The application, in this case an MPI implementation of the Task Bench stencil pattern in Figure 1b, is run on a single Haswell node of Cori with a problem size large enough that runtime is dominated by the application’s inner loops. This confirms that the application is properly configured and that the efficiency metric is achievable. The problem size is then repeatedly reduced while maintaining exactly the same hardware and software configuration (in particular, the same number of nodes and tasks). The expectation is that as problem size shrinks, performance will begin to drop and eventually approach zero, as shown in Figure 2. Systems with lower runtime overheads maintain higher performance at smaller problem sizes compared to systems with higher overheads.

To calculate METG, the data is replotted along axes of efficiency (i.e., as a percentage of the peak FLOP/s achieved) and task granularity (i.e., wall time x num. cores / num. tasks), as shown in Figure 3. Note that a task is defined broadly to be any continuously-executing unit of application code, and thus it makes sense to discuss tasks even in systems with no explicit notion of tasking, such as in MPI programs written in a bulk synchronous style. In this case, the tasks run a compute-bound kernel included in the Task Bench implementation, described in more detail in Section 2.

In Figure 3, efficiency starts at 100%. Initially task granularity shrinks with minimal change in efficiency. As tasks shrink further, efficiency drops more rapidly, leading to a vertical asymptote as overhead dominates useful work.

METG(50%) is the intersection of this curve with 50% efficiency, as shown by the red, dashed lines in Figures 2 and 3. At 50% efficiency, MPI achieves an average task granularity of 4.6 µs, thus the METG(50%) of MPI is 4.6 µs in this configuration. We use 50% because that is generally an acceptable level of efficiency in practice, and values above 90% can misrepresent the performance of some systems (see Section 5.1).

METG has a well-defined relationship with quantities of interest to application developers, namely weak and strong scaling. Figures 4 and 5 show the weak and strong scaling behavior of the MPI Task Bench running a stencil pattern at a variety of problem sizes. In these figures, the vertical axis is shown as wall time to emphasize the relationship to time-to-solution, but it could equivalently be shown as task granularity (as the number of tasks per execution is fixed). Intuitively, at larger problem sizes MPI is perfectly efficient. This can be seen at the top of each figure, with flat lines when weak scaling and ideally-sloped downward lines when strong scaling. Inefficiency begins to appear at smaller problem sizes, towards the bottom of the graph, where lines become more compressed. At the very bottom, the lines compress together as running time becomes dominated by overhead. Note that the shapes at the bottom of the strong and weak scaling curves are identical, and conform to the shape of the METG curve (marked by the red, dashed line).

METG therefore has a direct relationship with the smallest problem size that can be weak scaled to a given node count with a given level of efficiency. Using the formula for task granularity above, each run is 32 tasks wide and 1000 timesteps long, so task granularity is wall time divided by 1000 (since Cori has 32 cores per node). The 218 problem size in Figure 4 scales well initially because the task granularity of 20 µs is greater than the METG(50%) of MPI at small node counts (which is about 4.6-12 µs from 1-64 nodes) but not at higher node counts (which rises to 28 µs at 128 nodes and 61 µs at 256). Similarly, METG corresponds to the point at which strong scaling can be expected to stop. In Figure 5 the problem size 218 strong scales to 64 nodes, the point at which the scaling curve intersects METG(50%).

The METG metric has another useful property. Because METG is measured “in place” (i.e., without changing the number of nodes or cores available to the application), METG isolates effects due to shrinking problem size from effects due to increased communication and other resource issues as progressively larger portions of the machine are used.

### 5 Evaluation

We present a comprehensive evaluation of our Task Bench implementations on up to 256 Haswell nodes of the Cori supercomputer [2], a Cray XC40 machine. Cori Haswell nodes have 2 sockets with Intel Xeon E5-2698 v3 processors (a total of 32 physical cores per node), 128 GB RAM, and a Cray Aries interconnect. We use GCC 7.3.0 for all Task Bench implementations, and (where applicable) the system default MPI implementation, Cray MPICH 7.7.3. Versions and flags for the various systems are shown in Table 4.

For GPU experiments we use the Piz Daint supercomputer [4], a Cray XC50 with one Intel Xeon E5-2690 v3 (12 physical cores) and one NVIDIA Tesla P100 per node. We use GCC 6.2.0, Cray MPICH 7.7.2, and CUDA 9.1.85.

| System  | Version   | Notes          |
|---------|-----------|----------------|
| Chapel  | 1.18.0    | --fast         |
| Charm++ | 6.9.0     | --optimize     |
| Dask    | 1.1.5     |                |
| MPI(+X) | Cray MPICH 7.7.3 | -O3 |
| OmpSs   | 17.12.1   | -O3            |
| OpenMP  | Intel KMP 18.0.1.163 | -O3 |
| PaRSEC  | Git master branch | -O3 |
| Realm   | Git subgraph branch | -O3 |
| Regent  | Git subgraph branch | -fflow-spmd 1 |
| Spark   | 2.3.0     | Scala 2.11.8, Java 8 |
| StarPU  | 1.2.8     | -O3            |
| Swift/T | 1.4       | -O3            |
| TensorFlow | 1.12.0    |                |
| X10     | Git master branch | -O3 -NO_CHECKS |

Table 4. System version and configuration notes.
Figure 6. FLOPS vs problem size (stencil, 1 node). Higher is better.

Figure 7. Efficiency vs task granularity (stencil, 1 node). Higher is better.

5.1 Compute Kernel Performance

In theory, any system should achieve peak performance if the kernels are well-tuned and of sufficiently large granularity. In practice, many subtle pitfalls of implementation or configuration can easily lead to poor performance. Verifying that peak performance is achieved helps to ensure that evaluations of overhead and efficiency are well-grounded.

Figure 6 shows the FLOPS achieved with a compute-bound kernel with varying problem sizes (simulated by running the kernel for varying numbers of iterations). This is the full version of Figure 2. Each data point in the graph is the mean of 5 runs, with Task Bench configured to execute 1000 time steps of the stencil pattern. In the best case, we measure peak FLOPS of $1.26 \times 10^{12}$, which compares favorably with the officially reported number of $1.2 \times 10^{12}$ [2]. For the purposes of measuring efficiency, we use our empirically determined number as the baseline for 100% efficiency.

Most systems achieve or nearly achieve peak FLOPS. Some systems reserve a number of cores (usually 1 or 2) for internal runtime usage; these systems take a minor hit in peak FLOPS compared to systems which share all cores between the application and runtime. Some of the higher overhead systems struggle to achieve peak FLOPS, though in most cases the curves suggest that performance would continue to improve if we were to run larger problem sizes. Unfortunately, the excessive computational cost of running such tests makes this prohibitively expensive. For example, the Spark job in this case ran for over 6 hours.

Figure 7 plots efficiency (as a percentage of peak FLOP/s) against task granularity. As described in Section 4, this plot is used to calculate METG(50%). The red, dashed line shows the point where 50% efficiency is achieved. In most cases, task granularity asymptotes prior to the 50% efficiency point, though some systems continue to improve as efficiency drops further. Accounting for this effect is one of the main arguments in favor of METG with a reasonable efficiency threshold instead of measuring task scheduling throughput of empty tasks (effectively METG(0%)). Measuring performance using empty tasks can reward implementation strategies, such as devoting nearly 100% of system resources to the runtime system, that make no sense for real applications.

5.2 Memory Kernel Performance

Figure 8 shows performance with a memory-bound kernel. We measure a peak memory bandwidth of 79 GB/s, using a working set size of 0.5 GB. As discussed in Section 2, the kernels are designed to keep the working set constant as the number of iterations decrease to avoid noisy, superlinear effects in the results. For comparison, the OpenMP-enabled STREAM benchmarks [29] report up to 98 GB/s.

Not all cores are required to saturate memory bandwidth, reducing the impact of reserving cores for internal use. Most systems hit 100% of peak, unlike the compute-bound case.

The remaining experiments use compute-bound kernels.

5.3 Baseline Overhead

One question when considering different programming systems is: How much overhead does the system add? This question is tricky to answer directly because some systems introduce overhead inline (i.e., by running system internal processes on the same cores as application tasks), while other systems introduce overhead out-of-line (i.e., by dedicating one or more cores solely to runtime use). Some systems, like Charm++, Realm, and Regent, support both configurations.

To answer this question, we use the METG metric to determine the smallest task granularity that can be executed.
Figure 9. METG vs node count for different dependence patterns. Lower is better.

5.4 Scalability

METG is useful in part because it summarizes the overhead of each programming system in a single number. This makes it possible to evaluate METG at different node counts (shown in Figure 9) to see how it is impacted by changes in communication topology and latency. A key finding is that the gap between MPI and other systems shrinks as the complexity of the communication pattern grows, and even reverses as task parallelism is added in the form of multiple task graphs.

Spark, Swift/T and TensorFlow are omitted from comparisons with more complicated dependencies, as the overheads of these systems require excessive problem sizes (beyond what can be completed in 6 hours) to reach 50% efficiency.

The least complicated pattern (stencil) is most favorable to MPI, as it provides no opportunity for task parallelism. For the stencil pattern, the dominating factor is the basic overhead of executing a task, which is minimal for MPI as the Task Bench implementation simply executes tasks one after another in alternation with communication phases. In contrast, the asynchronous execution mechanisms of other systems are pure overhead in this scenario. The gap between MPI and other systems shrinks as the complexity of the communication pattern grows, and even reverses as task parallelism is added in the form of multiple task graphs.

We observe that the baseline overheads of different systems vary by over 5 orders of magnitude. It is worth remembering when considering this metric that this is a minimum effective task granularity. Therefore applications with an average task granularity of at least this value can usually be expected to execute efficiently. Typical task granularities will generally be determined by the application domain being considered. Most notably, for large-scale data analytics workloads, the higher METG values observed for Spark and TensorFlow are sufficient. In contrast, for high-performance scientific simulations, task granularities in the millisecond range are useful, as such applications communicate (e.g., for halo exchanges) much more frequently.
communication latencies require significantly larger tasks to achieve the same level of efficiency, so apparent differences in runtime overhead at small node counts can matter much less or not at all at larger node counts.

Most systems for HPC are highly scalable, but this is not true of all the systems included in this evaluation. Lower is better in Figure 9, and flat is ideal. Lines that rise with node count indicate less than ideal scaling. Most notably, Spark is primarily intended industrial data center applications with task granularities measured in tens of seconds. Spark uses a centralized controller, which limits throughput, and this is visible in the figure as the line for Spark immediately rises with node count. Keep in mind that Spark is being evaluated here with a non-trivial dependence pattern that is relatively unrepresentative of Spark's normal use cases. Spark is more efficient with trivial parallelism, as described in Section 5.5.

Implicitly parallel systems such as PaRSEC, StarPU and Regent that rely on runtime analysis to build the DAG can suffer from scalability bottlenecks if every node must consider the tasks executing on all other nodes. PaRSEC DTD and StarPU mitigate this partially by allowing the user to omit tasks not directly dependent on those executed by a given node. However, this DAG trimming approach requires dynamic checks that scale with the number of nodes and thus limit scalability [23]. Compile-time analysis can partially or fully mitigate this overhead. PaRSEC PTG improves over DTD by performing DAG expansion at compile time [23], but retains dynamic checks that limit scalability. PaRSEC shard includes additional manual optimizations over DTD, completely eliminating these dynamic checks. Regent uses a compile-time optimization to improve scalability [34]; the increase in METG beyond 16 nodes is due to a known bug in Realm barrier migration which the Realm Task Bench implementation is able to manually work around.

5.5 Number of Dependencies

The number of dependencies per task has a strong influence on overhead, as shown in Figure 10. This plot shows METG(50%) for the nearest dependence pattern, when varying the number of dependencies per task from 0 to 9.

The ratio in METG between 0 and 3 dependencies per task ranges from $1.01 \times 250 \times (\text{median} 2.9\times)$. The difference is most pronounced in systems that perform runtime work inline. For example, MPI achieves an METG of 390 ns with 0 dependencies, but this rises to 4.6 µs with 3 dependencies, a $12\times$ increase. This is unsurprising as in the case of 0 dependencies, no MPI_Isend calls are issued at all, so MPI has nothing to do aside from executing kernels as quickly as possible. Clearly, choosing a representative dependence pattern is important when estimating the performance of a workload or class of workloads.

5.6 Communication Hiding

Also of interest is the ability to hide communication latency in the presence of task parallelism. Figure 11 plots efficiency with varying amounts of communication, determined by the number of bytes produced by each task (and therefore communicated with each task dependency).

Asynchronous systems such as Charm++ demonstrate two benefits in these plots. First, by overlapping communication with computation, such systems execute smaller task granularities at higher levels of efficiency compared to the MPI implementations. Second, the asynchrony and scheduling flexibility from executing multiple graphs also makes the curves smoother, as spikes in latency due to interference from other jobs can be mitigated, leading to more predictable performance, especially at smaller message sizes.

5.7 Load Imbalance

One advantage of systems with asynchronous execution capabilities is the ability to mitigate load imbalance with little or no additional programmer effort, especially in the presence of task parallelism. To quantify this effect, Figure 12 plots task granularity vs efficiency curves under load imbalance where each task’s duration is multiplied by a uniform random variable between [0, 1]. The task durations are generated with a deterministic pseudo random number generator with a consistent seed to ensure identical task durations for all systems.

The MPI implementation of Task Bench, with its distinct computation and communication phases, suffers the most under load imbalance. The biggest difference is at large task granularities, where the imbalance effectively puts an upper bound on MPI efficiency. At smaller task granularities the effect shrinks and may even reverse as systems hit their fundamental limits due to overhead.

The remaining differences are due primarily to different scheduling behaviors. The execution of 4 simultaneous task graphs only partially mitigates the load imbalance between tasks. Systems that provide an additional on-node work stealing capability (such as Chapel with the distib scheduler) see additional gains in efficiency at large task granularities. However, the use of work-stealing queues can also impact throughput at small task granularities. For example,
Figure 11. Efficiency vs task granularity for varying communication (spread pattern, 5 dependencies per task, 4 task graphs, 64 nodes). Higher is better.

Figure 12. Efficiency vs task granularity under load imbalance (nearest pattern, 5 dependencies per task, 4 task graphs, 1 node). Higher is better.

Chapel’s default (non-work-stealing) scheduler outperforms Chapel distrib at very small task granularities. We do not consider Charm++ load balancers because the imbalance is non-persistent (i.e., timestep $t$ is uncorrelated with timestep $t+1$). We leave analysis of persistent load imbalance to future work.

5.8 Heterogeneous Processors
In order to determine the cost of scheduling tasks on the GPU, Figure 13 compares MPI and MPI+CUDA on the Piz Daint supercomputer. The CUDA compute kernel achieves a peak performance of $4.759 \times 10^{12}$ FLOP/s, which is very close to the officially reported number $4.761 \times 10^{12}$. The CPU achieves $5.726 \times 10^{11}$ FLOP/s. Note that the kernels perform different numbers of operations as the GPU requires more work to reach peak performance. The x-axis in Figure 13 is normalized to keep FLOPs constant for a given problem size.

Our MPI+CUDA implementation uses an offload model in which data is copied to and from the GPU on each step. We test two configurations: w1 uses 1 task per GPU, whereas w4 overdecomposes by 4×, using 4 MPI ranks per GPU to push work to the GPU in parallel. w4 achieves higher FLOP/s but drops more rapidly at smaller problem sizes, due to the overhead of scheduling 4× as many CUDA kernel launches.
In either case, the GPU requires more work to achieve high performance, and the overhead of copying data dominates at small task granularities, where the CPU achieves higher performance. While Figure 13 is not couched in terms of METG (as peak performance on CPU and GPU are very different), the conclusion here is similar to Section 5.4: The cost of sending data and tasks to the GPU imposes a higher task granularity to achieve the same efficiency than running on the CPU, reducing the advantage at small task granularities of very lightweight mechanisms such as those in MPI.

6 Related Work

Parallel and distributed programming systems are most commonly evaluated using proxy- or mini-apps, or microbenchmarks. Mini-apps are explicitly derived from larger applications and therefore have the advantage of bearing some relationship to the original. This advantage typically does not hold for microbenchmarks.

Though smaller than full applications, mini-apps can be challenging to implement to a level of quality sufficient for conducting comparative studies between programming systems. The largest study we know of, for the mini-app LULESH [26], compares 7 programming systems (Chapel, Charm++, CUDA, Lizzie, Locci, OpenMP, and MPI), each of which require a separate, tuned implementation (in contrast to Task Bench). Other studies usually lack a comprehensive evaluation, even if multiple implementations are available:

- The initial paper on PENNANT [18] includes an implementation that supports MPI/OpenMP/MPI+OpenMP; follow-up papers present an implementation in Regent [28, 33, 34].
- One follow-up paper for the mini-app CoMD describes a Chapel implementation [21] (comparison against reference only). Additional follow-up papers consider aspects of the reference implementation only [16, 31].
- A report on the Mantevo project [22] describes a number of mini-apps, but only includes self-comparisons based on reference implementations.
- A report on MiniAero [11] describes four implementations of the mini-app, but only includes performance results for three, and of those three only two can be compared in an apples-to-apples manner as the last implementation uses a structured rather than an unstructured mesh. Follow-up papers describe an additional implementation in Regent [28, 33, 34] (comparison against reference only).

Microbenchmarks can be easier to implement, but risk being unrepresentative of real applications. PRK Stencil [38] contains 2 kernels (which combined fit in under 50 lines of C++) and a halo exchange on a structured grid; an evaluation [37] compares MPI variants, SHMEM, UPC, Charm++, and Grappa. The NAS benchmark suite [8, 9] consist mostly of small kernels for dense array computations and has implementations in OpenMP [24], MPI and MPI+OpenMP [13], and Charm++ [27]. Neither PRK nor NAS achieve the breadth of coverage, flexibility, or ease of implementation of Task Bench. We believe the evidence for ease of implementation is clear; Task Bench is implemented for more systems than all previous mini-apps and microbenchmarks. Task Bench is also not a fixed set of benchmarks, and it is even easier to use Task Bench to generate new benchmarks.

System-specific benchmarks quantify specific aspects of system performance, such as MPI communication or collective latency [19, 20]. These measurements typically do not generalize beyond the immediate system they measure.

cOnCePTuAL [30] is a domain-specific language for writing network performance tests. cOnCePTuAL and Task Bench both enable the easy creation of new benchmarks, though cOnCePTuAL does so via scripting whereas Task Bench provides a set of configurable parameters. cOnCePTuAL also targets a lower level of abstraction, optimized more for testing messaging layers, whereas Task Bench is closer to application level and therefore enables comparisons of a broader set of parallel and distributed programming systems.

Limit studies of task scheduling throughput in various runtime systems often make additional assumptions. A popular assumption is the use of trivially parallel tasks [3, 6], which as shown in Section 5.5 underestimates (often substantially) the cost of scheduling a task and can also impact scalability.

7 Conclusion

Task Bench is a new approach for evaluating the performance of parallel and distributed programming systems. By separating the specification of a benchmark from implementations in various programming systems, it is possible to explore a broad space of application scenarios and to do so with a large number of programming systems. Our experiments have enabled the following insights:

- METG for current distributed programming systems varies by over 5 orders of magnitude. Clearly understanding the needed task granularity is an important consideration in choosing a programming system for a new application.
- While some systems support task granularities as small as 390 ns, this applies only to trivial dependencies and small CPU-based clusters. A number of factors (non-trivial dependencies, accelerators and cluster sizes in the hundreds of nodes) raise the METG that any system can reliably achieve by over an order of magnitude: 100 μs is a reasonable bound for most applications running at scale with current technologies.
- Systems that support asynchronous execution show benefits under balanced computation and communication, and load imbalance. However, these gains can be nullified by high baseline overheads.
• Systems for large scale data analysis require very large tasks (tens of seconds) to scale beyond small node counts, reflecting the very coarse tasks and lack of need for strong scaling performance in current workloads.

• Newer task-based systems have performance sufficient for weak scaling many HPC workloads, but more work is needed to strong scale the most demanding codes.

Not considered in our analysis is the impact of programming system features on programmer productivity and performance portability. Most applications do not operate at the absolute extreme of runtime-limited performance, and thus may choose to trade overhead for better usability. Our study helps to quantify the performance side of that tradeoff so that users can be better informed and developers can see the impact that features have on the performance of their programming systems.

Acknowledgment
This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of ASCR, under the contract number DE-AC02-76SF00515, by National Science Foundation under Grant No. ACI-1450300, and the Exascale Computing Project (17-SC-20-SC), a collaborative effort of the U.S. Department of Energy Office of Science and the National Nuclear Security Administration, under prime contract DE-AC05-00OR22725, and UT Battelle subawards 4000151974 and 89233218CNA000001. Experiments on the Cori supercomputer were supported by the National Energy Research Scientific Computing Center, a DOE Office of Science User Facility supported by the Office of Science of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231, and experiments on Piz Daint were supported by the Swiss National Supercomputing Centre (CSCS) under project ID d80.

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