A Look at Communication-Intensive Performance in Julia

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Abstract—The Julia programming language continues to gain popularity both for its potential for programmer productivity and for its impressive performance on scientific code. It thus holds potential for large-scale HPC, but we have not yet seen this potential fully realized. While Julia certainly has the machinery to run at scale, and while others have done so for embarrassingly parallel workloads, we have yet to see an analysis of Julia’s performance on communication-intensive codes that are so common in the HPC domain. In this paper we investigate Julia’s performance in this light, first with a suite of microbenchmarks within and without the node, and then using the first Julia port of a standard, HPC benchmarking code, high-performance conjugate gradient (HPCG). We show that if programmers properly balance the computation to communication ratio, Julia can actually outperform C/MP in a cluster computing environment.

I. INTRODUCTION

The HPC community has been slow to adopt high-level, managed languages—increasingly popular in industry—due to their apparent performance overheads and due to the fact that rarely are these languages designed with the parallelism or behavior of large-scale scientific workloads in mind. However, such languages hold promise because they can relinquish the programmer from the burden of low-level details of the system like pointers, memory management, and type specification. This frees domain scientists from having to be systems programmers and allows them to instead focus on their application logic, thus reducing the “time to science.”

The de facto standard for programming large-scale machines involves some combination of MPI paired with C/C++/Fortran for inter-node parallelism, and runtime support such as OpenMP [1], pthreads [2], Cilk [3], or Qthreads [4] for handling intra-node parallelism. More recently, applications leverage heterogeneous hardware by using accelerator frameworks like OpenCL [5], OpenACC [6] or CUDA [7]. For domain experts, this makes the problem worse, since not only must they worry about the “how” of parallelism across nodes, they must also deal with accelerator offloading, synchronization, virtual memory, and other low-level details.

Ideally, the programmer would describe their problem in a high-level language and the underlying machinery of the language would take care of mapping the problem onto parallel and heterogeneous hardware. While we are not there yet, the community has made strides in language design, compiler technology, and parallel programming frameworks. Recent languages like Regent [8] and more established languages like Chapel [9], HPF [10], UPC [11], X10 [12], and Erlang [13] all have made significant contributions in bringing productive programming to the HPC world, yet they have not seen widespread adoption. For a language to flourish in the HPC community, it must be sophisticated (sporting a rich set of built-in functionality for scientific programming), intuitive, and mature. Most importantly, however, it must perform well for the increasingly broad set of large-scale applications that the scientific community employs.

The Julia language is an interesting point on this spectrum not only because it takes inspiration from other popular managed languages like Python and Ruby, but also because it was designed by domain experts with scientific and technical computing in mind. It thus has significant appeal for programmers brought up on Fortran and MATLAB. Unlike those languages however, Julia has targeted scalable parallelism from the start. Built atop the LLVM compiler framework, and sporting sophisticated features like dynamic dispatch, high-performance math libraries, and JIT compilation, Julia’s single-threaded performance for scientific problems approaches (or even surpasses) its low-level counterparts, C and Fortran. It also features intuitive parallel programming abstractions, and others have recently demonstrated its potential for petascale parallelism on a top supercomputer [14].

However, a large class of HPC applications involve significant inter-node communication to achieve parallelism. A classic example is stencil computations following the bulk-synchronous parallel (BSP) model, where in order to solve, e.g. a partial differential equation (PDE) describing some dynamical system, the domain is discretized and evolved in time using finite differences. While the programmer must carefully balance the communication/computation ratio with these methods, communication latencies due to language, library, system software, and network interfaces can make or break performance.

As far as we are aware, the Julia language has not yet been evaluated in this respect. Thus, in this paper, we seek to shed light on Julia’s performance for communication-intensive...
applications, both within and without the node. We investigate Julia using a range of single-node and multi-node microbenchmarks, as well as a port of a standard HPC benchmarking code encapsulating the above behavior, high-performance conjugate gradient (HPCG).

We make the following contributions:

- We provide a series of single-node and multi-node microbenchmarks for Julia.
- We evaluate the performance of Julia’s parallel programming abstractions, both on a single node and in a distributed environment.
- We present the first port of a standard, large-scale, communication-intensive code (HPCG) to Julia.
- We show through benchmarking that with a reasonable computation-to-communication ratio, Julia can actually outperform C in distributed message passing scenarios, demonstrating its potential for communication-intensive applications.

All code for our benchmarks and our experiments, as well as our experimental data will be made freely available upon acceptance. The remainder of this paper is organized as follows: Section II gives an overview of the Julia language and its focus on scientific computing and parallelism. Section III presents the evaluation of Julia for high-performance parallelism within the node. In Section IV we analyze Julia’s performance in a distributed environment. We discuss our results in Section V, outline related prior art in Section VI and conclude in Section VII.

II. BACKGROUND

In general, to be effective for efficient parallelism, a high-level language will have high-performance primitives or constructs which support:

- Mapping execution contexts to hardware precisely (e.g. NUMA and processor affinity)
- Hardware heterogeneity
- Low-latency communication between execution contexts (threads/tasks/processes)
- Low-latency creation and scheduling of tasks.
- Efficient exploitation of parallelism (e.g. parallel map()s or parallel loop constructs)

Much of the underlying machinery for the above will be hidden from the programmer.

Ideally the performance of the language will be close to the hardware’s capabilities, as is the case with lower-level languages. Some (including Julia’s designers) have made the argument that even if this is not true for the HLL, the benefit to programmer productivity and application development time should be considered as a counterbalance to the performance of the language, especially since development time can take several years for large HPC codes. This perspective may hold even more weight as new generations of domain experts and programmers are being taught with high-level languages. Unfortunately, this aspect of a language is more challenging to quantitatively measure in practice. If the HLL’s performance can match that of its lower-level counterpart, all the better, since we get the best of both worlds. We seek to find out if that is indeed the case for Julia.

Below we will outline the parallel programming primitives that Julia provides and discuss some salient choices by the language designers.

A. Overview of Julia

Julia [15] is a high-level programming language designed for numerical computing. Our main interest in Julia stems from its promising single-threaded performance (which the Julia developers have shown can approach that of C and Fortran), its native parallel constructs, its extensibility, and its rich set of user-developed packages. Particularly its performance relative to other high-level languages, which is in part due to its usage of LLVM’s JIT compilation framework, indicates that it might be a suitable candidate for communication-intensive HPC applications as well as for building parallel runtime systems which support even higher-level (possibly domain-specific) parallel languages. Some other noteworthy features of the Julia language include multiple dispatch, dynamic types, meta-programming features, light-weight user threads, easy support for native code invocation, and packages for distributed, parallel computing.

Julia is already being used to solve a wide array of problems in technical computing. For example, JuliaFEM [16] provides a concise programming framework for solving large-scale problems using finite element methods. Others have explored using high-level frameworks for GPU computing with Julia [17]. Chen et al. investigated using polymorphic code features in Julia applied to parallel and distributed computing [18]. It has also been shown to work well for classic scientific problems, such as convex optimization [19], PDE solving [20], and discrete event-driven simulation [21]. Data scientists and AI experts are increasingly employing Julia with success as well [22], [14].

B. Parallelism in Julia

Julia has an extensive array of features and packages that support parallel and distributed computing. Julia natively provides an abstraction for task parallelism called Tasks, which are essentially lightweight user threads. Once tasks are defined they are invoked using the @schedule macro.

Workers are an abstraction of processes and workers() is a function that returns an array of all workers deployed locally or remotely. Processes do not share memory by default but can communicate via Channels or by using SharedArrays, discussed later in this section. Multiple processes can be created locally and on other nodes by calling @addprocs.

Threads are Julia’s version of kernel threads. Others have evaluated the native threading support on multi-core machines [23]. With these threads, Julia allows the user to wrap a value in Threads.Atomic to avoid race conditions while accessing or modifying shared state. Similar to OpenMP, one can indicate that a code region is to be run on multiple threads using the @threads macro. A barrier is implicitly placed at the end of a @threads block and the code in
that block will run on the number of threads specified by the JULIA_NUM_THREADS environment variable, again similar to standard OpenMP programming practice. Additionally, Julia’s threading package includes a set of native atomic operations (usually provided by compiler built-ins in lower-level languages) via LLVM, in addition to higher-level synchronization primitives like locks, mutexes, and semaphores.

Communication between Julia processes is, by default, one-sided. It is accomplished using the `RemoteReference` and `RemoteCall` abstractions. A `RemoteReference` is made for exchanging information while `RemoteCall` is used to request the remote execution of a function. `RemoteCall` returns a `Future` object asynchronously—essentially a `RemoteReference`—and the result of the function can be obtained by calling `fetch` on the `Future` object. The `@spawn` and `@spawnat` macros are used to send work to an arbitrary and particular process, respectively. Julia also provides an `@everywhere` macro which specifies that its wrapped expression shall run on all available workers.

Fine-grained parallelism is provided by `@distributed` (for indicating that loop iterations run in parallel) and `pmap` (parallel mapping of a function over a collection). The Julia documentation points out that if the number of operations are large in number but not too complex (e.g., using synchronization), `@distributed` can be used to perform them. On the contrary, if the operations are complex and not numerous then use of `pmap` is recommended.

`@async` is a feature that can be used in scenarios where one wants to define work but is not ready to have them executed right away. `@async` will launch tasks locally and can be sent to other processes or workers using `remotecall_fetch()`. Julia has macros for specifying operations as `@sync` and `@async` as per need. `@sync` can be employed on an otherwise `@async` block and vice versa. This, however, does not mean that Julia will block a task that uses another `@async` task. `@async` can only block a synchronized function.

Channels and RemoteChannels allow the programmer to construct producer/consumer queues between local and remote processes, respectively. This is useful for transfer of primitive data across tasks. For more complex data sharing like an array, `SharedArray` and `DistributedArray` are used. A `SharedArray` can be accessed by all processes in parallel, with synchronization provided by the runtime. A `DistributedArray` is similar in concept but has the advantage of decomposing the array by distributing chunks across local and remote processes.

Julia supports this set of parallel and distributed operations and structures via the external packages `Distributed.jl` and `Threads.jl`. Importantly, Julia also sports a package to provide MPI bindings, which we will leverage in Section IV.

While other features of Julia are beyond the scope of this paper, we refer interested readers to other texts on the language [24], [25], [26], [27] and its design choices, as well as the official Julia documentation.[https://docs.julialang.org](https://docs.julialang.org)

III. PARALLELISM WITHIN THE NODE

In this section we present a series of experiments evaluating the performance of Julia’s runtime native parallelism primitives within a node compared to low-level implementations in C. Our goal is to get a sense of what kinds of barriers to parallel performance an HPC programmer might encounter on a compute node when using Julia.

A. Experimental Setup

All experiments were carried out on our in-house, 14-node cluster called mystic. Each node comprises a dual-socket (2 NUMA nodes), 16-core (2 hardware threads per physical core) Intel Xeon Silver SP 4108 (Skylake) CPU clocked at 1.80GHz and equipped with 64GB of 2.66 GHz DDR4 SDRAM. This machine runs Ubuntu 18.04 LTS with a stock Linux kernel version 4.15. We configured the BIOS to disable DVFS features.

For the Julia experiments, we use Julia version 1.3.1. All C/C++ benchmarks were compiled with the highest optimization level (O3) using the stock Ubuntu version of gcc (7.5). Unless otherwise noted, all experiments were conducted using 100 trials, with an additional 10 trials initially thrown out to mitigate cold start effects. Timing was conducted using Julia’s native `time_ns()` function and `clock_gettime()` in C using the `CLOCK_REALTIME` time source. The file system configuration has no influence on our experiments.

Many high-level languages support the notion of a task, a schedulable unit of work which may or may not have the ability to modify state. Tasks can essentially be thought of as glorified functions, but they can be moved around the system. Tasks may be mapped to threads or processes, but ultimately they should be very light-weight. The more overhead that the language introduces when creating and managing tasks, the coarser the units of work must be to amortize these costs, and the amount of parallelism available to the programmer is reduced. Julia has support for such tasks (with the `Task` abstraction), which they describe alternatively as light-weight coroutines or `green threads`. These are essentially user-level threads of which the underlying OS is unaware. Our first experiment measures the latency of creating these tasks. The baseline we compare against is the time taken to create a pthread (using `pthread_create()`). Since pthreads map directly to kernel threads (visible to the OS scheduler), we expect that the Julia tasks should be much cheaper to create. A comparison to an equivalent low-level user-threading package (e.g. Qthreads [4] or OpenMP tasks) would be ideal here, but we note that this is just to sanity check the task performance of Julia. We leave such a comparison for future work.

To make the comparison as fair as possible, in Julia we measure the time to create a task using the `Task()` function followed by a call to `schedule()` which places the created task on the task scheduler’s run queue (which is local to...
the current Julia process on a single core). Note that unlike most schedule() functions, this Julia version does not immediately yield to the scheduler.

Figure 1(a) shows the results (note the log-scale on the y axis). Creation of a pthread (kernel thread) costs roughly 20µs while Julia task creation and the subsequent schedule call costs only about 400ns. This is consistent with the creation throughput shown in the figure, and is in line with our expectations. However, tasks on a remote core must be scheduled on a remote worker process, which must be explicitly created with the addprocs() routine. While this routine takes roughly 400ms, one need only call it once, at runtime startup.

Often in HPC scenarios (i.e. many-task computing), there are many more tasks than there are hardware threads available in the system. This allows a high degree of concurrency when tasks perform blocking operations. It is important that tasks be light-weight to maximize this concurrency. Here we measure the context switching overhead of Julia tasks by creating two tasks in the same worker process, having them cooperatively yield() to each other a fixed number of times, and approximating the latency from the number of yields in the recorded time period. The same caveat as above applies to comparing kernel threads with user threads. For our baseline we use the same strategy with two pthreads pinned to the same core.

Figure 1(b) shows that Julia task context switching is roughly one order of magnitude faster than for pthreads. Again, this is to be expected since the kernel is not involved in a Julia context switch unless a task yields and there is nothing else to run.

For the next experiment, we attempt to get an estimate of the overheads of task operations between Julia workers. Julia’s native parallel processing features are based on one-sided task-launch operations (futures). When a future is created (using spawn()), its corresponding object is immediately returned to the caller, without blocking. The work associated with the future may complete immediately, or at some later point in time. The result is retrieved by an explicit call to (fetch()) the future. This call will block if the execution has yet to take place. Here we aim to investigate how the overheads of task creation relate to the amount of work performed for fine-grained tasks. For this experiment we created two benchmarks: a tunable benchmark which returns the first n Fibonacci numbers sequentially and a baseline benchmark which creates a null task that performs no actual work at all. The null task thus approximates the overheads of remote task creation.

Figure 2 depicts the results of spawning a remote task (on any available worker) for various task granularities (where again, the granularity is determined by the fib() argument). These are compared against the null task as we vary the number of Julia workers present in the system. We cap our experiment at 16 worker processes since the system has 16 physical cores. Note that here we are only spawning the task on a single remote worker, so the latency should remain the same, independent of the number of workers. However, looking at the figure this is not what we see. Instead, it seems that Julia’s
task scheduling across workers scales roughly linearly with the number of workers. While we make sure to create workers (@addprocs) before the experimental run, we suspected that Julia may be lazily creating workers on the spawn invocation. However, since we are throwing out the cold start trials, we believe this not to be the case. We found this effect surprising, and we have not yet determined its cause. These results were also confirmed by other comparisons [28] between inter-process runs and inter-node runs. Note that while the error bars (depicting one σ above and below the mean) are relatively small, we did see several significantly large outliers in this experiment in Julia’s case. The measurements shown here are after outlier removal using Tukey’s method with a constant of 1.5.

Often high-performance applications will need low-latency communication. This is needed to support explicit communication between tasks (e.g. using explicit messaging), implicit communication based on access to shared data, and event notification (e.g. in a parallel runtime system).

Event notification can signify conditions such as the creation of a task, the availability of data, an error condition, or the completion of a task. These notifications are particularly important for processes communicating via event channels. One of the most common software event notification mechanisms is a condition variable. A condition variable is essentially a queue protected by a mutex, and its interface comprises three functions: wait(), signal(), and broadcast(). A thread/task calls wait() to block execution until some condition becomes true (e.g., a unit of work is ready to execute, a message delivery has completed). The thread will then be descheduled and put on the condition variable’s queue until the condition becomes true, thus yielding the processor to another unit of execution. Some other thread will then call signal() to wake one waiting task and remove it from the queue, or call broadcast() to wake all waiting tasks. A common model in runtimes/HPC applications is to have worker threads/tasks spread across cores, where they wait on work to do with condition variables. Unfortunately, Julia’s Condition() construct only applies to Tasks on the same worker process, so there is no way to use them for cross-core notifications. To approximate this behavior, we used Julia’s RemoteChannel primitive, which is essentially a producer/consumer queue that can be referenced by Tasks running on different Julia worker processes. We create an unbuffered (0-element) RemoteChannel and issue a take() operation to simulate a condition variable wait(), and have a Task on a worker process running on a remote core issue a put() to simulate a condition variable signal(). We compare against a baseline implementation written in pthreads, which creates a remote thread whose job is to signal a condition that the local thread is waiting on (using pthread_cond_signal()). The remote thread takes a time stamp after signaling, and the local thread records a time stamp after waking up. We report the latency as the difference between these two timestamps. The violin plot in Figure 3 shows the results. We see a median latency of roughly 14µs for the Julia case, and a few microseconds for notification using the pthreads condition variable. The Julia version also shows a significantly higher variance in latency. While the performance gap is quite large, one should realize that the Julia notification is occurring across worker processes (OS processes) in separate address spaces, whereas in the pthreads, case this is happening between kernel threads sharing the same address space. While the notification latency for Julia is already fairly small, we expect it will shrink once proper threading support (with the attendant condition variable implementation) is mature.

In addition to simulating condition variables, channels can also be used to implement both one-sided and two-sided communication models. Julia exposes three operations on channels: put() to place an object on the queue, take() to remove an object from the queue, and fetch() to read the front of the queue (without removing the object). Ideally operations on channels will just be a read or write protected by a lock or an atomic operation. We compare Julia’s channel against a simple (unoptimized) producer/consumer queue written in C that is protected by a mutex from the pthreads library (pthread_mutex_t). Figure 4 shows the results. We see here that Julia’s channel operations are all very lightweight, each taking less than 100ns. The differences here with the C version are not significant, but the operations that Julia provides out of the box show promising performance.

An important requirement for any HPC-oriented high-level language is that it exploit parallelism well. To measure how well Julia maps computations automatically to execution contexts, we distributed the initialization of a 50MB array among worker contexts. We use Julia’s pmap() and @distributed features to achieve this, and compare against an OMP version using the parallel for looping construct and a custom pthreads implementation in C that performs

\[ x_{25\%} - 1.5IQR, x_{75\%} + 1.5IQR \]

These measurements not on the interval have been removed.
manual decomposition. Noting the log scale on the y-axis, we see in Figure 5 that the mean time to initialize the array using the parallel constructs in Julia is roughly five times smaller.

IV. DISTRIBUTED PARALLELISM

To get a realistic picture of how viable Julia is for communication-intensive HPC applications, we also measure its performance in a multi-node setting. An HPC application written in an HLL ideally will have performance close to that achieved by low-level languages, even when spread across nodes. To do this, we leverage the MPI.jl package, which provides bindings to the system-resident MPI library with a set of wrappers that allow overloading of the typical MPI functions. For all experiments, we use MPICH v3.3a2. The hardware configuration was previously described in Section III-A. Both Julia and C/C++ applications use the underlying system MPI library. The 14 nodes in our mystic cluster are connected in a star topology over 10Gb Ethernet (via Intel X550 NICs) configured with an MTU of 9000. Timings in the distributed environment are conducted by having rank 0 (the master node) record timestamps (we plan to incorporate measurements from all nodes).

In our first set of multi-node experiments, we approximate the typical bulk-synchronous parallel (BSP) code (e.g. a stencil computation) by creating a synthetic benchmark which consists of compute (memory reads/writes and floating point ops) and communication (message send/recv) steps. Each rank will perform a configurable amount of computation between communications, wherein computation consists of reads (a series of loads from an array), writes (a series of stores to an array), and flops (a series of floating point operations). As shown in the algorithm, in the communication step, ranks send data to their forward neighbor and then receive data from their backward neighbor. The ranks thus form a ring topology, as depicted in Figure 6. We compare the performance of two custom implementations of this BSP benchmark in both C and Julia. We varied the number of processes (MPI ranks) per node (1, 2, 4, and 8). The amount of work performed in each rank is kept constant, thus we are technically showing weak scaling with this experiment. We gather statistics over 100 iterations.

Figure 7 shows mean execution times (10 communications in Figure 7(a) and 100 in Figure 7(b)). Note that Julia’s MPI wrappers actually incur some overhead due to the polymorphism in the MPI.jl implementation. We suspected this might have a non-trivial overhead, so we also provided our own custom versions of the MPI wrappers with static type signatures (denoted with “opt” in the figures) and repeated experiments with those variants. This minor optimization essentially eliminates string comparisons and runtime type coercion. Communication in Julia seems to be more expensive than in its lower-level counterpart. Our optimization of bypassing dynamic dispatch by providing our own low-level wrappers appears to have no noticeable effect on performance. Perhaps more interestingly, we see that the performance difference scales with the number of MPI ranks. Since we are actually increasing the ranks per node rather than the absolute node count, the overheads in these experiments is likely coming from effects within the node. This would be consistent with what we saw in the spawn/fetch experiment.

To verify that communication is the issue, we took a more detailed look at the benchmark. Figure 8 shows the same experiment, but with the bars broken down per operation in the benchmark. In this figure the bars show what percentage of execution each operation comprised. In both cases, reads are relatively cheap. Interestingly, the C version writes (again, to an array) are more expensive relatively. Indeed, however, communications consume a more significant portion of the total execution time in the Julia version. However, as the number of communications increases, the difference between languages diminishes. Because both versions are ultimately using the same MPI implementation, we can rule out the communications themselves. While we are still investigating this effect, we suspect the culprit might be how Julia manages the underlying workers. Note that the figures here exaggerate the differences since the total execution time of this benchmark is in tens of milliseconds.

To further verify that the communications themselves were not the culprit, we conducted a ping-pong experiment with MPI for both languages, using both the normal Julia MPI wrappers and our custom implementation. The results are shown in Figure 9. We measure the ping-pong latency of a
round-trip send between two remote MPI ranks and report the mean latency (top) as we vary message size (up to 1MB). We also report the harmonic mean of message throughput (bottom). Outliers have been removed as in our spawn/fetch experiment. In this case, we see that Julia actually outperforms its lower-level counterpart, though we do see overlap in the error bars, and differences here will be in the µs range. Again, our minor optimization for Julia’s MPI wrappers appears to have no distinguishable effect. While the results are at odds with what we saw in our BSP experiment, we note that an obvious difference in these scenarios is that in this case, we only have two Julia worker processes, one per node. The improved communication performance in this scenario further supports our hypothesis above about quirks in worker management.

A. HPCG

The microbenchmarks give us a preliminary idea of how various native Julia constructs and operatives perform, and what kind of distributed performance we can expect to achieve. However, it is helpful to have a more realistic application to perform an evaluation with. Our goal here was to choose an application that is widely used and represents a broad range of HPC applications. To that end, we chose a standard, state-of-the-art benchmarking application that is used to evaluate top supercomputers today. We also wanted our effort to be useful for others to investigate Julia’s large-scale performance (perhaps on a much larger system).

The High-Performance Conjugate Gradients (HPCG) benchmark [29], [30] fits that bill. It is a tool for ranking computer systems based on a simple additive Schwarz, symmetric Gauss-Seidel preconditioned conjugate-gradient solver. It constructs a 3-dimensional, 27-point stencil matrix such that each
point, represented by coordinates $i$, $j$, and $k$ depends on the
value of the surrounding 26 points.

The generated matrix $(A)$ is sparse and has at least 27 non-zero
values for interior points [31]. The boundaries have 7 to 18 non-zero points depending on the boundary position. The Matrix $A$ is symmetric with positive eigenvalues (symmetric positive definite). It is stored in Compressed Sparse Row (CSR) format. The global domain of $M_x$, $M_y$, and $M_z$ in the $x$, $y$, and $z$ dimensions is distributed into a local domain of $N_x$, $N_y$, and $N_z$. Each local sub-grid is assigned
to a process (MPI rank). The total number of processes is
provided as an input parameter. These processes are distributed
into a 3D domain, where the total number of processes
$P = P_x \times P_y \times P_z$. The global domain $M_x$, $M_y$, $M_z$ can
be calculated as $(P_x \times N_x)(P_y \times N_y)(P_z \times N_z)$. A restriction
is also imposed on the domain for accuracy and efficiency
purposes. Minimum grid size in each dimension must be at
least 16 and the grid should be a multiple of 8.

We ported HPCG version 3.1 [4] to Julia and ran it varying
the local domain size ($N_x = N_y = N_z = 16, 32, 64$) and varying
the number of MPI ranks per node (from 1 to 16).

The results shown in Figure 10 are single iteration runs. Each
subfigure has a different local domain size, so each is showing
strong scaling for a particular parameter. We compare it to
the standard C++/MPI version of the benchmark (without
OpenMP support).

The results here are consistent with the results from our
BSP experiment. With a small local domain size (see Figure
10(a)), computation comprises a relatively small portion
of the execution time, as each processor will have little
work to do before having to communicate. In this setting we
will see the Julia overheads that we have seen in previous
experiments. The remarkable thing to note here is that as
the problem size per rank grows (see Figure 10(c)), thus
increasing the compute/communication ratio, Julia actually
starts to outperform the C++ version of the benchmark by
as much as 20%. Julia’s scaling also improves (as the C++
version worsens) as the number of ranks per node is increased
for the large local domain size.

Note that this benchmark communicates primarily with
point-to-point operations (MPI_Send and MPI_Recv in the
halo exchange). Though there are uses of collectives and bar-
riers scattered throughout the code (e.g. MPI_AllReduce),
they comprise very little of the total execution time.

The results from HPCG clearly suggest that Julia has
significant potential, even for HPC applications that heavily
employ synchronous communication. We note that our port
of HPCG is currently a prototype, and thus we expect its
performance relative to its low-level counterpart will improve
further as we adopt more idiomatic usage of the language and
as the language itself improves.

V. DISCUSSION

We now outline some of the issues we encountered with
porting a large benchmark from a low-level systems language
to a Julia, a high-level managed language. In order to have a
fair comparison between C++ and Julia’s version of HPCG
it was essential that we adopt it within the confines of
Julia’s abstractions. One major difference between C++ and
Julia is obviously the use of managed memory, which made
porting HPCG’s pointer-heavy manipulation of sparse matrices
a challenge.

Structures in HPCG like matrixValues, mtxIndG,
mtxIndL, which are pointer to pointer structures, are ported
to Julia using 2D arrays. matrixDiagonal is an array

of pointers that refer to the addresses of diagonal elements
in matrixValues. In Julia, this is replaced by an
array called curcols which stores the column indices of
matrixValues where the diagonal elements are stored.
Diagonal elements can be fetched for a given row index by
accessing curcols on the same index. Pointer arithmetic
is substituted by careful indexing as Julia is 1-indexed (´a la
Fortran) and C++ is 0-indexed.

In the function FillRandomVector(), the C++ version
uses rand() from the C standard library to fill a vector with
pseudo-random values. Because Julia uses a different PRNG
routine, and because we had to compare outputs between
versions for correctness, we modified this routine to fill vectors
with known, fixed values.

In the procedure ComputeOptimalShapeXYZ
in the C++ version, a complex for loop uses
MixedBaseCounter structures and its corresponding
functions to initialize, check bounds, and increment the
MixedBaseCounter structure. These are ported using
Julia’s looping constructs, which are slightly different. A
similar approach is used in GenerateProblem_ref.

Primitive data types in Julia passed as parameters to a
function and mutated in the function body will not retain
their altered values on return (as is standard in high-level
languages). However, HPCG uses a common C/C++ idiom of passing in pointers to primitive types to have the values mutated by the callee. The Julia versions of such functions must have slightly different structure to account for this. When possible, we followed Julia’s documented best practices for performance programming. This included making code type-stable, eliminating use of any global variables, eliding bounds checks for known-length arrays (@inbounds), and carefully tuning core HPCG math kernels for performance bottlenecks, e.g. by instrumenting the garbage collector and using Julia’s native profiler. We still, however, believe there is room to improve the performance.

While not reported in the figures, we did see a notable difference in the variance of Julia’s runs on the larger code. This is not entirely surprising, as jitter is a known pain point for applying managed languages in HPC settings (this is, of course, true for the underlying system as well [32], [33], [34]). In Julia’s case, two primary sources of non-determinism include the garbage collector and the JIT compiler. While others have looked at these effects for other languages [35], [36], we believe there is opportunity to optimize these features to avoid jitter for Julia (and other managed, technical computing languages). However, HPCG is not structured to be communication-intensive, unlike many HPC applications, so its success, while remarkable, does not yet demonstrate Julia’s broad applicability for large-scale, communication-intensive HPC applications.

Others have evaluated Julia in a multi-core setting [23], [41]. Hunold and Steiner study Julia’s MPI bindings [42], though in a more focused setting. Our results with the most substantial HPCG benchmark, however, do line up with their findings.

There also has been extensive work done in programming GPUs with Julia. In addition to the foundational GPUArrays package JuliaGPU [6] is a package in Julia which encompasses support for both NVIDIA and AMD GPUs. The NVIDIA CUDA boasts mature and full-featured packages for both low-level kernel programming as well as working with high-level operations on arrays. All versions of Julia are supported, and the functionality is actively used by a variety of applications and libraries.

VI. RELATED WORK

There has long been interest in bringing the convenience of high-level languages to bear for HPC. High-performance Fortran [10], Chapel [9], X10 [12], and Erlang [13], and Regent [8] are notable examples. While Python was not designed with HPC computing in mind, there are efforts in that community to adapt it for high-performance parallelism [37], [38], [39], [40].

Most recent work on Julia focuses on adapting it for practical problems in technical computing, several of which we described in Section II-A. From the HPC perspective, the most striking example is Celeste [14], the first large-scale HPC application written entirely in Julia. It was reported to achieve petascale performance on a NERSC supercomputer. However, Celeste is not structured to be communication-intensive, unlike many HPC applications, so its success, while remarkable, does not yet demonstrate Julia’s broad applicability for large-scale, communication-intensive HPC applications.

In this paper, we evaluated Julia using a range of microbenchmarks and macrobenchmarks both for shared-memory parallelism within the node and for distributed parallelism in a cluster computing setting. We showed that while Julia has slight overheads for communication between processes, these overheads are often outweighed by gains over its lower-level counterparts (C/C++). We demonstrated using a custom synthetic BSP benchmark and the first ever Julia port of a large-scale, HPC benchmark application (HPCG) that Julia can outperform C++/MPI even in a multi-node setting with synchronous communication. We believe these findings open up several lines of investigation into Julia as a first-class HPC language. First, we plan to extend our experiments to add comparisons to LLVM-compiled C/C++ code. We also plan to further investigate the source of communication anomalies between Julia’s worker processes. Finally, we hope to explore optimizations for sources of non-determinism in the Julia runtime and to scale our experiments to hundreds or even thousands of nodes.

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5 https://docs.julialang.org/en/v1/manual/performance-tips/index.html
6 Available at https://juliagpu.org/

Fig. 10. Strong scaling of the standard C++ implementation of HPCG compared to our Julia port.
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