MPIgnite: An MPI-Like Language and Prototype Implementation for Apache Spark

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ABSTRACT
Scale-out parallel processing based on MPI is a 25-year-old standard with at least another decade of preceding history of enabling technologies in the High Performance Computing community. Newer frameworks such as MapReduce, Hadoop, and Spark represent industrial scalable computing solutions that have received broad adoption because of their comparative simplicity of use, applicability to relevant problems, and ability to harness scalable, distributed resources. While MPI provides performance and portability, it lacks in productivity and fault tolerance. Likewise, Spark is a specific example of a current-generation MapReduce and data-parallel computing infrastructure that addresses those goals but in turn lacks peer communication support to allow featherweight, highly scalable peer-to-peer data-parallel code sections.

The key contribution of this paper is to demonstrate how to introduce the collective and point-to-point peer communication concepts of MPI into a Spark environment. This is done in order to produce performance-portable, peer-oriented and group-oriented communication services while retaining the essential, desirable properties of Spark. Additional concepts of fault tolerance and productivity are considered. This approach is offered in contrast to adding MapReduce framework as upper-middleware based on a traditional MPI implementation as baseline infrastructure.

Keywords
MPI, Spark, data-parallel, task-parallel, Scala, peer-to-peer communication, parallel closures

1. INTRODUCTION
Since its introduction, MPI has served as a standardized means to communicate between processes peer- and group-wise in large-scale parallel applications. The arrival of Inter-net-scale data and the concomitant introduction of new computational problems requiring enormous processing capabilities have thrust the issues of High Performance Computing (HPC) into the spotlight and made them more relevant than ever. Interestingly, the usage and interest of MPI itself has not followed the “data deluge trend” [13]. Instead, a myriad of open, high-level frameworks have been created to address problems heretofore restricted to the domain of traditional HPC. However, they are targeted at developers without the domain expertise or access to expensive, specialized cluster or supercomputer infrastructure.

As large scale data analytics has become more mainstream, alternatives to traditional HPC have developed rapidly, with novel solutions to the particular challenges in the problem domains for which they were created. Many of the most popular of these frameworks, such as Hadoop [18] and the MapReduce [12] family of implementations, focus on exploiting the data parallelism that exists within the particular task (without intermediate communication between tasks as in MPI). These solutions are generally incongruous with MPI, where the lowest level of abstraction resides in a message moving between a pair of peer processes, or else a collective operation such as a numerical reduction (e.g., parallel sum) over a group of processes.

Inspired by the capabilities and appeal of these high-level analytics applications, we sought to introduce certain key concepts of traditional HPC, particularly the notion of peer message passing, into a commercially driven HPC-like framework. Both the traditional HPC and modern analytics communities would benefit greatly from such an amalgamation with symbiotic sharing of low-level performance concerns with high level application development. Additionally, the fault-tolerance advantages of the baseline framework could offer distinct advantages to the overall application; features not easy to achieve in current “pure MPI” middleware implementations and applications.

In this communication, we present a novel adaptation of the popular Apache Spark [22] data processing engine that has been augmented to incorporate a message passing Application Programmer Interface (API) for its parallel tasks. We show that this relatively minor modification to Spark gives rise to an original programming environment in which task parallelism and data parallelism can be used interchangeably. Furthermore, many of the recent advancements in cloud computing and modern object-oriented software de-
development can be leveraged freely, all the while maintaining the core computing patterns and concepts of the original MPI standard. In this effort, we have worked to retain these concepts and the semantics of the MPI operations but have not emphasized producing a literal language binding of the MPI standard or subset thereof.

While this work is still in its early stages, our design thus far, as described here, will lay the groundwork for a marriage of two thought-to-be mutually exclusive models of large scale distributed analytics and data processing. This combination will enable data scientists to utilize long-studied algorithms with message passing based task-parallel solutions easily; conversely, “traditional MPI developers” will be able to prototype or develop on a mature, modern, high-level platform with full access to state-of-the-art cluster data analysis.

The rest of the paper is organized as follows. We offer a brief background in Section 2 on several recent advancements in high level HPC, with a particular focus on the Apache Spark project, and recent work developing and integrating these models on existing HPC infrastructures. In section 3 we describe our approach for augmenting the Spark framework itself to support message passing. Section 4 describes certain examples “in action.” We discuss our results in Section 5 and propose certain avenues for future work as well while offering conclusions in Sections 6 and 7 respectively.

2. BACKGROUND

As essential background, we provide an overview of some high level computing frameworks developed in recent years. We then give an overview of the Apache Spark framework in particular, since it is the focus of our work. We conclude with certain related work of implementing Spark as middleware on HPC clusters.

2.1 High-level, large-scale computing

In this section, we consider “non-traditional” HPC environments and patterns of programming, originating from both industry and academia.

2.1.1 MapReduce

One of the most well-known and influential frameworks for large-scale, distributed analytics and data processing is MapReduce [12]. In MapReduce, data is distributed across a number of worker nodes by a master node, operations are performed to transform (i.e., map) the data to outputs, and results are reduced to a final output. The simplicity of the model, combined with its performance, led to its popularity and adoption by data-hungry organizations such as Google.

A greater portion of the appeal of MapReduce models apparently lies in their simplicity: many of the difficulties (whether actual or perceived) of programming distributed or cloud applications are abstracted away, freeing the developer to focus on the particulars of the application they are working on. In addition, the model is also general. It has since been shown that any computation can be described in terms of mapping and reducing data [21]. Fault tolerance in this system was integrated as an initial requirement, accomplished by utilizing recomputation to mitigate faults. Stragglers are handled in a similar fashion, automatically recomputing results on other nodes when results take longer than expected [12].

The most well known implementation of the MapReduce paradigm is the Apache Hadoop project [18], which also includes a distributed file system. Since its introduction, Hadoop has experienced widespread adoption by industry, government, and academia as an effective means of scaling large data processing tasks to commodity clusters and cloud instances.

2.1.2 TensorFlow

TensorFlow [1] was developed and open-sourced by Google. It was designed specifically to solve the complex task of training deep neural networks for machine learning. In TensorFlow, the basic level of abstraction for data is a tensor, an n-dimensional generalization of a matrix. These tensors pass through a dataflow execution graph, where the vertices are computational steps and the edges are outputs and inputs to or from these computations. This is similar to the parameter server architecture common before TensorFlow, but has the additional flexibility of mutable state and concurrent execution across execution sub-graphs [2]. A particular emphasis was placed on high level programming interface, allowing machine learning researchers to modify and test different program models quickly.

TensorFlow can operate in distributed and heterogeneous environments. Execution on GPUs and other specialized hardware is handled by unique kernel implementations of the high level operation used by the developer. When multiple nodes are being used, TensorFlow constructs the execution graph and algorithmically places operations on specific nodes. Once the graph is established, send and receive nodes are placed along vertices that cross machines, to limit memory and bandwidth when output from one vertex is transferred to two or more vertices on another machine. These communications are generally handled by either TCP/IP or Remote-Direct-Memory-Access (RDMA) transfers [1].

TensorFlow has grown to prominence since its original introduction, quickly becoming one of the de facto machine learning frameworks. Despite its relatively niche scope, we point it out as a successful intersection between high level programming and performance afforded by low level optimization.

2.1.3 Chapel

The Chapel programming language [4] was developed by Cray with an emphasis on productivity when developing parallel programs. Although its syntax is similar to that of C or FORTRAN, its unique abstractions and programming model provide a fresh take on parallel development. Chapel is a high level, global-view parallel language with a multithreaded execution model.

Chapel supports both data parallel and task parallel operations. For data parallelism, the basic unit of abstraction is a domain, or a named set of indices used to define collections for parallel execution [10]. Arrays of objects are instantiated by these domains, and Chapel supports a number of
common data parallel operations, such as forall loops (i.e., mappings), scans, and reductions. Users are also free to define their own operations, as well as fine tune the distribution of the work instead of defaulting to Chapel’s execution strategy.

Task parallelism is achieved through cogenin statements, which define the beginning of a block to be executed in parallel [10]. Coordination is achieved through synchronization variables and atomic sections, which serve as a higher level alternative to directly manipulating locks. As with data parallelism, the exact semantics of the synchronization variables can be customized by the developer, although this is not required.

Chapel provides many other features that are common in modern, mainstream programming languages. Useful features such as Object Oriented Programming and generic types come standard in Chapel, as well as some less often seen features like curried function calls [10]. Chapel’s integration of modern programming techniques with high level parallelism make it a great model of joining modern programming with classic HPC. Nonetheless, it is not in widespread use in classical HPC settings as of now.

2.2 Apache Spark

The Spark project [22] can reasonably be considered to be the successor to the Apache Hadoop project. Spark has been under active development in recent years, with a variety of application-specific libraries distributed along with the core data processing engine. These libraries include common routines for machine learning [17], data stream processing [21], structured data queries [4], and graph processing [20]. It has also seen widespread adoption in industry, and served as the basis for NADSort, a sorting system that recently won the 2016 CloudSort Benchmark as the fastest cloud data processing engine to sort 100TB of data [6].

Similarly to Hadoop, Spark utilizes a MapReduce paradigm, with several enhancements [21]. A notable improvement is that Spark will avoid writing intermediate results to disk whenever possible, leading to more efficient, in-memory execution. The fundamental layer of abstraction in Spark is the Resilient Distributed Dataset, or RDD [22]. RDDs are read-only collections of objects that can be divided into a number of partitions, each partition with the potential to reside on a different node in the cluster [22].

When an application is executed in Spark, the driver node will build an execution graph of the job [21]. There are two categories of operations that can be performed on an RDD: transformations and actions. Transformations are mappings of the data within an RDD, and their execution if deferred until an action is invoked. Actions are operations that require a usable result from an RDD, such as finding the maximum element or printing values to the console [22].

When an action is called on an RDD, the master node will create and potentially optimize a directed acyclic graph of the RDD’s execution [21]. It will then schedule a number of stages, where a stage boundary is determined by when data needs to be shuffled through the cluster. Each stage will have one or more tasks associated with it, where a task is the basic unit of execution. The stages and the RDD partitions are transmitted to the worker nodes, where the tasks are executed asynchronously in threads. Results are sent back to the master node, which schedules further stages or passes the final result back to the application.

The Spark framework is implemented in Scala [5], a derivative of Java that supports functional and object-oriented programming and that runs in the Java Virtual Machine (JVM). The framework also has APIs for both the Python and R programming languages [3]. The communication was originally handled by the Akka library, but since version 1.6, Spark relies on Netty to implement TCP communication across nodes in a cluster.

2.3 Spark on HPC Infrastructure

As work similar to ours, we present certain efforts to integrate Spark and its similar high level models directly into HPC architectures. Although Spark and its family of high level frameworks are generally designed for commodity hardware, we note that it is possible to adapt the framework for specialized clusters and gain performance from the unique attributes of the environment.

The Hadoop platform heavily leverages a custom distributed file system to store results of map and reduce tasks [18]. The MARIANE (MAPReduce Implementation Adapted for HPC Environments) [14] implementation of the MapReduce model seeks to abstract the storage component to the specific needs of the cluster. This includes NFS and GPFS file systems, and can be expanded to other file systems depending on the specific cluster architecture.

In Spark, RDD’s are immutable and can be recomputed from the execution graph if a partition should be lost because of failure [21]. Therefore, map tasks can be retained in memory when feasible for a performance boost, and not suffer from the same I/O bottleneck of writing to disk as MapReduce and Hadoop. However, Spark will experience a similar performance degradation when map results spill over to disk and shuffling partitions across the cluster. Chaimov et al. noted that repeated reads and writes to common files in Spark causes metadata operations that are significantly more pronounced on HPC distributed memory systems than commodity hardware with local storage [9]. They investigated techniques for removing this and similar bottlenecks when deploying Spark on the Lustre file system and observed effective scaling of up to $O(10^4)$ cores in an HPC installation.

Another consideration of running Spark on an HPC infrastructure is the scheduler and cluster manager. Spark can be deployed manually on a commodity cluster, or through a dedicated resource manager like Apache Mesos [15] or Apache YARN [19]. This can create a compatibility issue when attempting to run Spark as middleware on existing installations with their own schedulers and resource managers. Baer et al. successfully implemented an integration of Spark into the PBS batch scheduling environment [8]. This and the other integrations mentioned above demonstrate that
Spark, while designed for commodity hardware clusters, can and has been modified to operate on high performance infrastructure correctly.

3. APPROACH
Inspired by the history of MPI and the power and popularity of Apache Spark, we sought to implement an effective, peer-to-peer message passing scheme in Spark to demonstrate potential benefits. We note that, while similar in end goal, our approach integrates a core facet of HPC into the high level framework itself, rather than running Spark “as-is” or nearly so in an HPC environment, or attempting to expand MPI to emulate a MapReduce model.

3.1 Communication Implementation
The MPIIgnite framework introduced here serves as a prototype for integrating traditional HPC concepts in higher level environments, with the specific instance being message passing inside Apache Spark. For the purposes of this work, we sought to leverage existing communication infrastructure already in the Spark code, leading to a relatively simple modifications of the original project. This demonstrates the feasibility of combining the two paradigms in practice while also leaving room for specialized, optimized implementations when and where appropriate.

As with all distributed systems, communication between nodes in Spark is fundamental. The general architecture of Spark is a master-worker model. Even when Spark is executed locally on a single machine, tasks are transmitted to worker threads, and results and communicated back to the master. In the version of Spark we derived our work from (2.1), these communications are implemented as RPCs on top of asynchronous Scala futures in a local deployment and via TCP/IP connections in a cluster.

Since the groundwork for a message passing scheme was already built into Scala, we sought to repurpose it to suit our needs. Therefore, we introduced our own RPC methods specific to sending and receiving messages. We additionally created an API so that developers could access these communication methods in their driver programs with signatures similar to that of traditional MPI (discussed below). Since Scala natively supports futures and promises \(^3\), implementing non-blocking versions of both sending and receiving functions was straightforward.

Spark abstracts communication through RPC “endpoints” internally, which are interfaced through `RpcEndpointRef` reference objects. A single endpoint can have multiple references, and any reference can communicate through the endpoint. In both a local and clustered deployment, the workers have established endpoints to communicate with the driver. These communication channels are typically used to transmit status information, such as when a task completes or unexpectedly fails. For our purposes, we utilize these same endpoints to send and receive generic application messages.

For local deployments, the previous description is sufficient, since there is only one worker node. More care is needed for proper peer-to-peer message passing in a clustered deployment. In that case, scheduled tasks are distributed along with a mapping of the process rank to the unique worker identifier that is executing that process. When a message is being sent to another process, the worker will check the mapping to see if it has an RPC endpoint associated with that worker. If it does not, it requests the addressing information of that worker to establish an endpoint before transmitting the message. Workers maintain a collection of RPC endpoints for workers that gets augmented on an as-needed basis. This amortizes the cost of sending to new worker nodes as well as potentially reducing the number of networking connections for a given topology. Additionally, we buffer messages on the receiving worker, meaning that no network communication is necessary for receiving a previously sent message.

Implementing MPIIgnite’s communicators was facilitated by Scala’s object-oriented paradigm, since they can be naturally be utilized as objects with communication methods. In our framework, each communicator object maintains a mapping of the ranks going from the rank within the communicator to the rank in the default, or world, communicator. When a communicator is split to create a sub-communicator, every process participating in the split sends a message of its global rank, key and color to the lowest process rank participating in the split. That root process receives all the split information, groups it by color, and sorts it according to key. The sorted data is then configured to be a new rank mapping before broadcast back to the group.

To ensure that messages are not passed across subcommunicators, each communicator contains a context identifier field that is specific to the group that participated in the aforementioned split. Messages sent from that communicator are passed along with that identifier, and checked for equality at the receiving end to ensure can only occur within similar communicators. To facilitate splitting, the global communicator always has an identifier of 0, so internally messages can be sent and received directly.

In our initial implementation of MPIIgnite, all communications passed through the master node. Subsequent iterations advanced the model to allow for actual peer-to-peer communication by permitting messages to be sent directly between worker nodes. These two implementation iterations naturally gave rise to an interesting approach to the fault tolerance problem. Although not investigated in this work, we can potentially switch between peer-to-peer mode and master-worker mode internally when coping with faults. After recovery, peer-to-peer communication would resume.

3.2 Parallel Closures
The most important facet of our design is the API directly available to developers for programming their parallel code. We wanted an interface that would be both familiar to long-time MPI users as well as approachable to Spark uses who may have never written explicitly parallel code before. In addition, we wanted our environment to be flexible, allowing the user the freedom to use whichever style of programming best fit the domain of the application.

\(^3\)We recognize that this type of buffering is quite different from what typical MPI implementations choose to do. The first goal is functionality; we will work on enhanced scalability and performance in subsequent releases.
Our result from these goals is a system by which parallel sections of code are written as function closures. Since Scala is a functional language that supports functions as first-class objects, this was a logical solution that proved natural to implement. This is similar to Chapel’s method of defining parallel blocks with `cobegin` statements, except that our model uses full-fledged functions that can be referenced, imported, and passed as arguments. These functions can be defined anonymously at the location they are used, or defined elsewhere and be reused, leading to a more modular design than Chapel’s parallel blocks.

Once a parallel function has been defined (either anonymously or as a named value), the developer passes it to a `parallelizeFunc` method that MPIgnite provides to create an RDD (analogous to Spark’s `parallelize` function for creating an RDD from a dataset). From there, the user can call `execute` on the RDD to initiate the parallel execution. The number of threads of execution can be selected at runtime by a parameter passed to the `execute` function. The result of the execution will be an array of return values from each process, if any. This is nearly identical to the process of creating and transforming a typical RDD in standard Spark. Developers can select which portions of their applications should be executed in parallel by how they construct and utilize their parallel functions. Moreover, the process is interoperable with traditional data-parallel RDDs, enabling a single application to realize task (and/or data) parallel message passing without foregoing off-the-shelf Spark.

The closures can be as long or short as needed. Longer closures will prove more scalable, since the end of a closure forms an implicit synchronization barrier within the driver application. That is, once a closure is executed in the driver application, all instances of the parallel function must complete before the driver program can continue. Future work will explore potentially chaining these closures together asynchronously, affording large parallel sections composed of several smaller ones.

Parallel closures in our model do not currently support arguments other than the required `SparkComm` object (discussed below). We did not see the apparent need for this, since these closures have access to variables in their outer scope, demonstrated below in an example. Furthermore, parameters can be achieved by wrapping the closure in another function that does accept any needed parameters.

### 3.3 Similarities to MPI

Since one of our main goals was to develop an environment that would be familiar to long-time MPI developers, we made a number of design decisions to remain “in the spirit” of the standard. However, we specifically chose not to be backwards compatible or fully implement the function signatures of the standard for a number of reasons. Our main motivation for breaking from the standard was to bring a fresh perspective to an established programming model. Additionally, implementing all or even most of the standard would be technically substantial, particularly in the narrow scope of our prototype. Additionally, many language features leveraged freely in the C and FORTRAN implementations of MPI standard (such as out parameters) are not feasible within the Scala language.

Instead of attempting to reimplement MPI inside of Spark, we sought a blending (compromise of sorts) of the two models that would complement the features of both. As discussed in the previous section, parallel sections of an application are crafted inside of functions that are transformed into RDDs. Each function executed in parallel can be thought of a single instance of a true MPI program. Similarly, each instance of the parallel execution has a unique rank, and the total number of instances can be collected at runtime. These values are gathered from the `SparkComm` object, which is passed in to every instance of the function.

The `SparkComm` object in a parallel block is also used to send and receive messages, much like a communicator in MPI. Processes are denoted by their unique rank number and messages can be tagged for proper identification, as in MPI. Group communication is implemented from these primitives, though a possibly more efficient strategy is to utilize Spark’s built-in broadcasting [11] (to be considered as future work).

SparkComm objects can also be split into subcommunicators, in almost identical fashion to MPI. Our prototype also features the collective operations `broadcast` and `allReduce`. These are explained by example in the proceeding section. A notable enhancement of the `allReduce` function is that MPIgnite supports passing arbitrary reduction functions, fostered by the functional nature of the Scala language.

### 3.4 Communication Data Types

The general syntax of sending and receiving messages is similar to MPI, though with key differences. The `SparkComm` object defines `send` and `receive` methods for communication. However, instead of sending and receiving data buffers, true Scala objects make up the content of messages, provided those objects are serializable. This creates a simple, object oriented interface appropriate for Scala-style programming. In addition, calling `receive` evaluates to the object that is received in the blocking case, or a future of the object in the nonblocking case. The ability to send and receive first-class objects permits a higher level of abstraction when using our model. Data structures do not need to be derived or have message structures that are tightly coupled to their implementation.

### 4. EXAMPLES

The following examples provide a brief hands-on introduction to the usage of the MPIgnite framework. Emphasis has been placed on developing and executing the parallel blocks, and also the interprocess communication interfaces, all while keeping the samples small and easily digestible.[4]

The first listing below depicts a simple example of matrix-vector multiplication, and does not use any explicit interprocess communication. We start by defining the matrix and vector as two-dimensional and one-dimensional arrays, respectively (in Scala, arrays are created and indexed by parentheses). Next we define our parallel code block as both an anonymous function and an argument to the `par-
The `parallelizeFunc` method on the `SparkContext` object available to all Spark applications (denoted in the examples as the `sc` variable). The square brackets after the `parallelizeFunc` name indicate a type parameter of integer, since each parallel instance of our function will return a single integer of the row-vector multiplication. We then acquire the current process's rank through the `SparkComm` object to determine if this process is needed for any valuable work. Then we compute and return the result, the return value implicitly are the last expression of a function. Once the closure is parallelized, we execute it with eight concurrent instances and sum the partial results in the driver application.

### Listing 1: Matrix Multiplication with MPIgnite

```scala
val mat: Array[Array[Int]] = Array(  
  Array(1, 2, 3),  
  Array(4, 5, 6),  
  Array(7, 8, 9)  
)
val vec = Array(1, 2, 3)
val res = sc.parallelizeFunc[Int](
  (world: SparkComm) => {
    val rank = world.getRank
    if (rank < mat.length) {
      mat(rank).zip(vec)
        .map(a => a._1 * a._2).sum
    } else 0
  }).execute(8).sum
```

This example could have equivalently been written with traditional RDDs and a mapping function. However, being able to program in a task parallel setting is a good fit on to the problem domain, and does not sacrifice existing options. Additionally, since the scope of parallel sections is limited to function blocks, developers can incorporate both task parallel sections or traditional RDDs depending on their programming preferences and the application domain.

The next example depicts a simple ring application to show the message passing API of MPIgnite. In this instance, we define a function `ring` explicitly before parallelizing it. Similar to the previous example, the rank and size of the process is collected from the `SparkComm` object. Each process sends the token variable to the process after it, with the root process starting and receiving the token from the last process. Since `receive` in this example is blocking, no process other than the root will send until it has received the token.

The `send` function takes three arguments: the rank of the process to which data is being sent, the tag associated with the message, and the data object that is to be transmitted. The `receive` function has two arguments for the rank of the sending process and the message tag. Receiving also requires an additional type parameter (denoted by the square brackets) to indicate the type of data that is to be received. This is necessary to permit proper deserialization and casting.

### Listing 2: Message Passing in MPIgnite

```scala
def ring(world: SparkComm) = {  
  val token = 0  
  val rank = world.getRank  
  val size = world.getSize
  if (rank == 0) {  
    token = 42  
    world.send(rank + 1, 0, rank)  
    token = world.receive[Int](size - 1, 0)  
  } else {  
    token = world.receive[Int](rank - 1, 0)  
    world.send((rank+1) % size, 0, token)  
  }
}
val parallel = sc.parallelizeFunc(ring)  
parallel.execute(16)
```

To demonstrate nonblocking receive (recall that sending in MPIgnite is always nonblocking), our next example uses it exclusively. Making a nonblocking call to receive returns a future object, or a read-only placeholder for an asynchronous computation. Futures can be explicitly waited on or can have callbacks defined to execute on their success for failure.

### Listing 3: Nonblocking receive example

```scala
import scala.concurrent._
import ExecutionContext.Implicits.global

def evenOrOdd(sc: SparkContext) =  
  sc.parallelizeFunc((world: SparkComm)=>{  
    val (size, rank) = (world.getSize, world.getRank)
    if (rank < 5) {  
      world.send(rank + 5, 0, rank)
      val f = world.receiveAsync[Boolean](rank + 5, 0)
      println(s"Rank $rank: Waiting...")
      f.onSuccess {
        case b =>
          println(s"$rank is even: $b")
      }
    } else {  
      val r = world.receive[Int](rank - 5, 0)
      Thread.sleep(3000)
      world.send(rank - 5, 0, r % 2 == 0)
    }
  }).execute(10)
```

For the simplicity of the example, we initially import the `ExecutionContext.Implicits.global`. In Scala, futures are executed asynchronously through some `ExecutionContext` that can be explicitly created as a thread pool and passed to the `receiveAsync` function. In the above example, using the import allows the futures to implicitly utilize a global static thread pool. This is occasionally unadvisable, but convenient for our example.
Futures in the Scala language can be utilized by registering callback functions to execute with the result of the asynchronous computation upon completion, as done in the previous example. Alternatively, futures can be explicitly waited on by using the `Await.result(f)` function with the argument the future in question. This method of synchronization is analogous to the `MPI_Wait` function.

As a more complete example of the features of MPIIgnite, the next listing extends the previous matrix-vector multiplication to include a 2D decomposition.

**Listing 4: Matrix-vector multiplication with 2D data decomposition**

```scala
sc.parallelizeFunc((world: SparkComm) => {
    val worldRank = world.getRank
    val row = world.split(worldRank / 3, worldRank)
    val col = world.split(worldRank % 3, worldRank)
    val a = worldRank + 1
    val rowRank = row.getRank
    val colRank = col.getRank

    // Distribute the vector to the diagonal
    if (rowRank == row.getSize - 1)
        row.send(col.getRank, 0, 1+col.getRank)
    else None

    val multiplied = x_row match {
        case Some(x) =>
            col.broadcast[Int](colRank, x)
            a * x
        case None =>
            a * col.broadcast[Int](rowRank)
    }

    val result = row.allReduce[Int]({
        multiplied, (a: Int, b: Int) => a + b
    }).execute(9)
})
```

This example is specifically tailored to the 3x3 case presented earlier, but similar decompositions can be formed for non-square matrices of arbitrary size, since MPIIgnite has the basic communication functions. This example also employs several Scala language features like pattern matching and Options. We should note that recipients of a `broadcast` message only need to indicate the root rank of the broadcast.

For completeness, Figure 4 lists the MPIIgnite methods and the corresponding MPI functions. More methods will be augmented in future work.

5. DISCUSSION

Apache Spark has experienced broad success in recent years, both as an open source project and as an efficient data processing engine. Our work contributes to that success by incorporating a message passing scheme, substantially enhancing the programmability of the environment. This not only enables for established Spark developers to utilize task parallelism explicitly as they see fit, but also benefits authors of existing HPC concepts by giving them access to a high level framework without having to compromise their core MPI algorithms.

The closure syntax for developing parallel code sections was easily made possible by the high level nature of the Scala language. This pattern for developing parallel applications allows the parallel portions to be reasoned about and developed independently, permitting greater modularity and enhanced ease of maintenance. This in itself is not entirely new, since other languages like Chapel permit independent parallel blocks, but our framework does so through first-class functions. This means that they are be easily extended, wrapped, passed as arguments, and reused. Entire libraries can be written of common parallel functionality and serve as building blocks for complex parallel applications.

Furthermore, our work does not compromise the integrity of the Spark platform. A single application can support both parallelized functions unique to MPIIgnite as well as typical RDDs found in any Spark application. As such, the plethora of Spark libraries and resources remain pertinent to MPIIgnite developers via this backwards compatibility. This combination of specialized data parallelism with message passing task parallelism permits users of both camps to cross sides as they see fit. As parallel sections are independent and narrow instead of global as in MPI, they can harmoniously coexist when the problem domain requires a diverse strategy.

Despite the benefits previously described, MPIIgnite will obviously not be the best tool for every job. In spaces where latency is absolutely critical, a high level approach such as ours will likely be unsuitable without considerable optimization effort. However, we note that our platform can still benefit those use cases, albeit indirectly. Since Scala (and thus MPIIgnite) is so high level, it provides an environment that can be used for quick experimentation and rapid development. Therefore, MPIIgnite can serve as a prototyping tool for testing the feasibility of approaches and algorithms to problems before seeking a potentially costlier bare-metal solution.

6. FUTURE WORK

The MPIIgnite platform in its current form serves as a prototype to demonstrate the potential benefits of integrating HPC concepts into high level programming frameworks common in cloud computing. As such, there are many interesting avenues to extend this work in pursuit of its initial goals. The most obvious extension would be to create a more efficient implementation of the message passing scheme than presented here. Although a Scala-based JVM implementation will likely never reach the speed of a bare-metal C-based distribution of MPI, competitive performance would make the MPIIgnite model even more attractive in addition to the reasons already discussed.

In addition to efficiency, we hope to explore MPIIgnite’s potential for scalability. Since MPIIgnite was created with strategic additions to the core Spark framework, it stands to reason that MPIIgnite should scale as well as Spark does. Additionally, techniques for scaling like creating a hierarchy of master nodes to coordinate potentially thousands of
processes could be feasible with augmentations to Spark’s scheduling system.

Another area of future work that we are planning is a proper analysis of the closure model for parallel programming. Since Scala is very high level and natively supports these anonymous functions, they were a natural choice for our implementation of MPIgnite. This feature is not available in C or FORTRAN, so investigating this model and the potential to build reusable libraries of common and extensible parallel operations would be a worthwhile contribution to making the original MPI model more dynamic and extensible.

Also, providing sufficiently efficient adapters to incorporate 3rd-party MPI libraries (e.g., math libraries) is an important area of future work. Allowing these libraries to be instantiated with sufficient MPI support, or using a traditional MPI middleware underneath, yet enabling the present framework to function mostly unhampered, will require significant design work, experimentation, and engineering effort.

Finally, although briefly mentioned in this communication, this work can be extended with a thorough examination of integrating Spark’s fault tolerance with the message passing scheme. Fault tolerant MPI is an active area of research, and our model presented here provides a unique approach by building MPI into a framework that enables fault tolerance.

7. CONCLUSION

We chose the Apache Spark platform for our work in large part because of its popularity in the sphere of high level cloud computing. We sought to maximize impact by combining that general-purpose computing platform with the de facto standard of HPC, MPI, with one of the largest and most general-purpose high level computing platforms. The result is a framework that will “feel familiar” to long-time MPI developers, without compromising the power and generality of Spark itself. This opens the door for cloud computing developers to utilize the well studied algorithms and techniques of HPC in the comfort of their own framework. Similarly, traditional HPC developers can employ high level language concepts and sophisticated data parallelism for easier development and rapid prototyping.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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