Latency-Tolerant Software Distributed Shared Memory

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Abstract

We present Grappa, a modern take on software distributed shared memory (DSM) for in-memory data-intensive applications. Grappa enables users to program a cluster as if it were a single, large, non-uniform memory access (NUMA) machine. Performance scales up even for applications that have poor locality and input-dependent load distribution. Grappa addresses deficiencies of previous DSM systems by exploiting abundant application parallelism, often delaying individual tasks to improve overall throughput. For example, Grappa moves execution to the data for improved memory bandwidth; multiplexes thousands of tasks per core to tolerate long latency operations and overlap communication and computation; and aggregates small network messages into larger packets to better utilize network bandwidth.

We evaluate Grappa on (1) a simple in-memory map/reduce framework that is $10\times$ faster than Spark [67]; (2) a subset of the GraphLab API that is $1.33\times$ faster on average than native GraphLab [43]; and (3) an execution engine for the Raco relational query compiler that executes queries $13.5\times$ faster on average than Shark [28]. Implementing these frameworks on top of Grappa is easy, requiring only 60-690 lines of code. Even greater performance is possible by writing against the Grappa API directly: a native Grappa implementation of Breadth-First Search (BFS) is $1.8\times$ faster than the Grappa-GraphLab version. We conclude that Grappa provides a viable high-performance platform for in-memory data-intensive applications.

1 Introduction

Data-intensive applications (e.g., ad-placement, social network analysis, PageRank, etc.) make up an important class of large-scale computations. Typical computing infrastructures for these applications are a collection of multicore nodes connected via a high-bandwidth commodity network (a.k.a. a cluster). Scaling up performance requires careful partitioning of data and computation; i.e., programmers have to reason about data placement and parallelism explicitly, and for some applications, such as graph analytics, partitioning is difficult. This has led to a diverse ecosystem of frameworks — MapReduce [24], Dryad [38], and Spark [67] for data-parallel applications, GraphLab [43] for certain graph-based applications, Shark [28] for relational queries, etc. They ease development of analytics applications and provide performance by specializing to algorithmic structure and dynamic behavior. Importantly, their efficiency comes from trading off generality; applications that do not fit well into one particular model suffer in performance.

To support their high-level abstractions, the frameworks listed above employ optimizations at multiple levels. For example, at the system level, they batch requests and structure inter-node communication for more efficient use of commodity networks. At the application-specific level, they use data structures that judiciously exploit replication to avoid inter-node communication. Each of these infrastructures are built from scratch. Ideally, frameworks would share a single, carefully optimized runtime infrastructure that not only provides performance competitive with these custom infrastructures at the system level, but also simplifies the development of application-specific optimizations. Our goal is to present a general infrastructure, and show that a shared memory model can be made efficient at cluster-scale, providing a convenient abstraction for building both data-intensive applications and frameworks.

Software distributed shared memory (DSM) systems provide shared memory abstractions for clusters. Historically, these systems [14, 18, 40, 42] performed poorly, largely due to limited inter-node bandwidth, and the design decision of piggybacking on the virtual memory system. Applications were only suitable for a software DSM if they exhibited significant locality, limited sharing and coarse-grain synchronization – a poor fit for many modern data-analytics applications. Recently there has been a renewed interest in DSM research [25,46], sparked by the widespread availability of high-bandwidth low-latency networks with remote memory access (RDMA) capability. Exposing this communication ability to user-space also allows the compiler and/or runtime to provide the

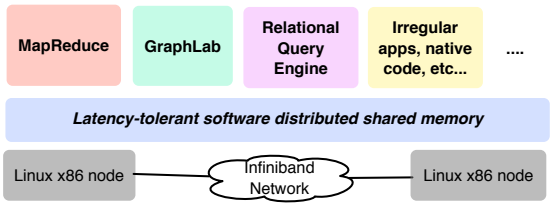


Figure 1: Overview of the Grappa system stack

global address space abstraction, gaining efficiencies by supporting sharing at a finer granularity than a page, avoiding the page-fault trap overhead, and enabling compiler optimizations on global memory accesses.

A general purpose DSM built for data-intensive applications must surmount several fundamental challenges, three of which we call out: (1) for complex analysis, inter-node communication is frequent due to poor locality; (2) inter-node communication often consists of small (32 byte or less) requests — even high-end RDMA-capable commodity networks become injection-rate limited at this packet size, and applications end up being constrained to only a tiny fraction of the bisection bandwidth of the cluster; and (3) some applications have highly input-dependent behavior and might require frequent, fine-grain synchronization. Fortunately, a DSM can overcome these challenges by exploiting two key characteristics of data-intensive applications: (a) they exhibit ample parallelism, and often parallelism that scales with the data-set; and (b) performance is not sensitive to the latency of execution of any individual unit of parallel work (task/thread), but rather to the throughput of execution of all of them — i.e., all that matters is when all work is done. That is the core observation that underpins our work.

In this paper we describe Grappa, a runtime DSM system for commodity clusters designed for data-intensive applications (Figure 1). To optimize for high throughput, Grappa focuses on execution throughput of all threads instead of latency of execution of any single one. To keep processing resources busy, it automatically switches among thousands of user-mode threads as they block on remote communication. In fact, Grappa further *increases* the latency of remote memory accesses: individual requests are queued at the sender until a sufficient number of them are available for the same destination. This increases packet size, maximizing the ability to exploit the available bisection bandwidth.

The runtime system is implemented in C++ for a cluster of x86 machines with an InfiniBand interconnect, and consists of three main components which will be covered in greater detail later: a global address space (§3.1), lightweight user-level tasking (§3.2), and an aggregating communication layer (§3.3). We demonstrate the generality and performance of Grappa as a common runtime by implementing three domain-specific platforms on top of it: a simple in-memory map/reduce framework; the GraphLab API; and a relational query processing engine. Comparing against GraphLab itself, we find that a simple graph representation in Grappa performs 2.5× better than GraphLab's random partitioning and 1.33× better than their best partitioning strategy, and scales comparably out to 128 cluster nodes. Grappa's query engine, on the other hand, performs 13.5× faster than Shark on a standard benchmark suite.

2 Frameworks for Data-Intensive Applications

In this section we argue that implementing analytics frameworks in a shared memory model is trivial but for these frameworks to run efficiently on *distributed* shared memory system, there are specific requirements that are non-trivial to provide. However, data-intensive applications have properties that can be exploited for efficient DSM implementations.

Shared-memory makes it *easy*. Below we briefly describe the three frameworks we focus on in this work and how they are implemented in a shared memory model using `forall` parallel loop constructs.

Map/Reduce Data parallel operations like map and reduce are simple to think of in terms of shared memory. Pseudocode for map and reduce are shown in Figure 2a. Map is simply a parallel loop over the input, which might be an array or other distributed data structure. It materializes intermediate results into a hash table. Reduce is a `forall` over each key in the the hash table.

GraphLab GraphLab is a platform for implementing machine-learning and graph-based applications [32, 43]. Many machine learning and graph analytics algorithms have been built using its high-level vertex-centric API. The latest version uses a 3-phase gather-apply-scatter (GAS) API for vertex programs to enable several optimizations pertinent to natural graphs. A simplified rendition of GraphLab's synchronous engine is shown in Figure 2b. In order to retrieve information for both vertices on each edge, *gather* and *scatter* phases must make fine-grained requests for one or the other vertex, or, if using GraphLab's split-vertex representation, the *apply* phase must do a gather and scatter on each vertex's replicas. Graph representations can be easily laid out in a shared address space, and the amount of communication between nodes depends on this layout. Also, since social network graphs have low diameter, algorithms that traverse them tend to have little locality. Note that a shared memory implementation of this vertex-centric API does not need to focus on careful scheduling of computation and data-movement.

Relational query execution Decision support, often in the form of relational queries, is an important domain of

```
void mapper(x) {
  k, v = compute(x)
  reducers[hash(k)].append(k,v)
}
void reducer(k, vals) {
  results.append(k,sum(vals))
}

forall (e : inputs)
  mapper(e)
forall ((k,vals) : reducers.groups)
  reducer(k, vals)
```

(a) Map/Reduce

```
while (graph.active_verts.size > 0) {
  // gather phase
  forall (Vertex v : graph.active_verts)
    forall (Edge e : v.in_edges)
      v.prog.gather(v, e);
  // apply phase
  forall (Vertex v : graph.active_verts)
    v.prog.apply(v);
  // scatter phase
  forall (Vertex v : graph.active_verts)
    forall (Edge e : v.out_edges)
      v.prog.scatter(v, e);
}
```

(b) GraphLab-like API

```
// FriendsOfFollowers(a,b,c) :-
//     FollowedBy(a,b),
//     Friends(b,c),
//     a > 10
forall(Tuple t : Friends)
  hash0.insert(t.get(0), t);

forall(Tuple t : FollowedBy) {
  if (t.get(0) > 10) {
    e = hash0.lookup(t.get(1))
    results.append(e)
  }
}
```

(c) Datalog query

Figure 2: Framework examples written for a shared memory system.

data-intensive workloads. Figure 2c shows how to perform a traditional hash join in a shared memory paradigm. All data is kept in hash tables stored in shared memory. Communication is a function of inserting into and looking up hash tables. One parallel loop builds a hash table, followed by a second parallel loop that filters and probes the hash table, materializing the results.

Distributed shared memory makes it *challenging*. The code in Figure 2 looks simple – and it is – but to execute it efficiently on a cluster is non-trivial. There are many challenges, but the key ones are:

Small messages Programs written to a shared memory model tend to access small pieces of data, which when executing on a DSM system lead to small inter-node messages. What were load or store operations become complex transactions involving small messages over the network. Conversely, programs written using a message passing library, such as MPI, expose this complexity to programmers, and hence encourage them to optimize it.

Poor locality As previously mentioned, data-insensitive applications often exhibit poor locality. For example, how much communication the $gather$ and $scatter$ operations in Figure 2b conduct is a function of the graph partition. Complex graphs frustrate even the most advanced partitioning schemes [32]. This leads to poor spatial locality. Moreover, vertices accessed vary wildly from iteration to iteration. This leads to poor temporal locality.

Need for fine-grain synchronization Typical data-parallel applications offer coarse-grained concurrency with infrequent synchronization — e.g., when done crunching all data in a partition. Conversely, graph-parallel applications exhibit fine-grain concurrency with frequent synchronization — e.g., when done processing work associated with a single vertex. Therefore, for a DSM solution to be general, it needs to support fine-grain synchronization.

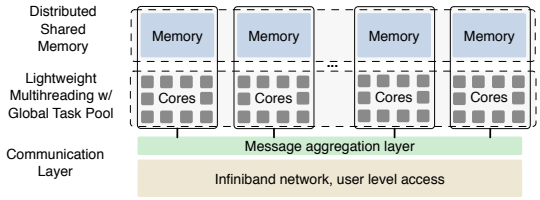


Figure 3: Grappa design overview

Fortunately, data-intensive applications have properties that can be exploited to make DSMs efficient:

Concurrency Data-intensive applications have abundant parallelism. In all three examples we see, at their heart, $forall$ loops which express parallelism.

Latency tolerance Performance isn't dependent on the latency of execution of any specific parallel task/thread, as it would be in for example a web server, but rather the aggregate execution of *all* tasks/threads.

These application properties can be tapped to implement an efficient DSM, which we explore in the next section by describing how Grappa's design addresses the challenges outlined earlier.

3 Grappa Design

Figure 3 shows an overview of Grappa's DSM system. Before describing the Grappa system in detail, we describe it's three main components:

Distributed shared memory The DSM system provides fine-grain access to data anywhere in the system. Every piece of global memory is owned by

a particular core in the system. Access to data on remote nodes is provided by *delegate* operations that run on the owning core. Delegate operations may include normal memory operations such as *read* and *write* as well as synchronizing operations such as *fetch-and-add* [33]. Due to delegation, the memory model offered is similar to what underpins C/C++ [16, 39], so it is familiar to programmers.

Tasking system The tasking system supports lightweight multithreading and global distributed work-stealing — tasks can be stolen from any node in the system, which provides automated load balancing. Concurrency is expressed through cooperatively-scheduled user-level threads. Threads that perform long-latency operations (i.e., remote memory access) automatically suspend while the operation is executing and wake up when the operation completes.

Communication layer The main goal of our communication layer is to aggregate small messages into large ones. This process is invisible to the application programmer. Its interface is based on active messages [63]. Since aggregation and deaggregation of messages needs to be very efficient, we perform the process in parallel and carefully use lock-free synchronization operations. For portability, we use MPI [45] as the underlying messaging library as well as for process setup and tear down.

3.1 Distributed Shared Memory

Below we describe how Grappa implements a shared global address space and the consistency model it offers.

3.1.1 Addressing Modes

Local memory addressing Applications written for Grappa may address memory in two ways: locally and globally. Local memory is local to a single core within a node in the system. Accesses occur through conventional pointers. Applications use local accesses for a number of things in Grappa: the stack associated with a task, accesses to global memory from the memory's home core, and accesses to debugging infrastructure local to each system node. Local pointers cannot access memory on other cores, and are valid only on their home core.

Global memory addressing Grappa allows any local data on a core's stacks or heap to be exported to the global address space to be made accessible to other cores across the system. This uses a traditional PGAS (partitioned global address space [27]) addressing model, where each address is a tuple of a rank in the job (or global process ID) and an address in that process.

Grappa also supports *symmetric* allocations, which allocates space for a copy (or proxy) of an object on every core in the system. The behavior is identical to performing a local allocation on all cores, but the local addresses of all the allocations are guaranteed to be identical. Symmetric objects are often treated as a *proxy* to a global object, holding local copies of constant data, or allowing operations to be transparently buffered. A separate publication [37] explored how this was used to implement Grappa's synchronized global data structures, including vector and hash map.

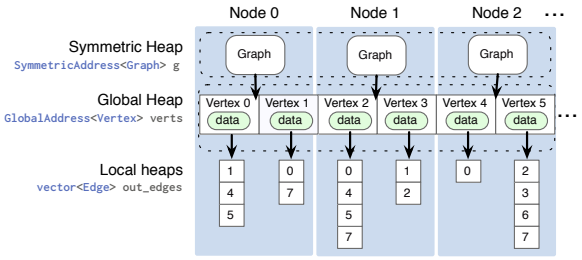


Figure 4: Using global addressing for graph layout.

Putting it all together Figure 4 shows an example of how global, local and symmetric heaps can all be used together for a simple graph data structure. In this example, vertices are allocated from the global heap, automatically distributing them across nodes. Symmetric pointers are used to access local objects which hold information about the graph, such as the base pointer to the vertices, from any core without communication. Finally, each vertex holds a vector of edges allocated from their core's local heap, which other cores can access by going through the vertex.

3.1.2 Delegate Operations

Access to Grappa's distributed shared memory is provided through *delegate* operations, which are short operations performed at the memory location's home node. When the data access pattern has low locality, it is more efficient to modify the data on its home core rather than bringing a copy to the requesting core and returning a modified version. Delegate operations [44, 48] provide this capability. While delegates can trivially implement *read*/*write* operations to global memory, they can also implement more complex *read-modify-write* and synchronization operations (e.g., *fetch-and-add*, mutex acquire, queue insert). Figure 5 shows an example.

A delegate operation can execute arbitrary code provided it does not lead to a context switch. This guarantees atomicity for all delegate operations. To avoid context switches, a delegate must only touch memory owned by a single core. A delegate is *always* executed at the home core of the data addresses it touches. We limit delegate operations to operate on objects stored on a single core

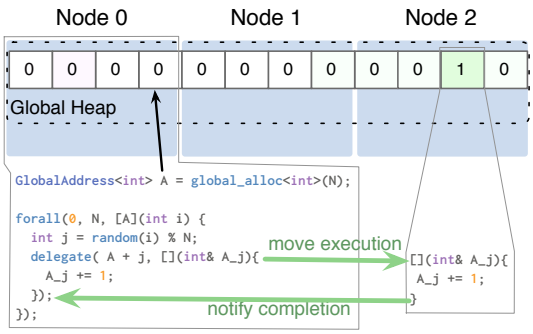


Figure 5: Grappa delegate example.

so they can be satisfied with a single network request. Given these restrictions, we can ensure that delegate operations for the same address from multiple requesters are always serialized through a single core in the system, providing atomicity with strong isolation. A side benefit is that atomic operations on data that are highly contended are faster. When programmers want to operate on data structures spread across multiple nodes, accesses must be expressed as multiple delegate operations along with appropriate synchronization operations.

3.1.3 Memory Consistency Model

Accessing global memory though delegate operations allows us to provide a familiar memory model. All synchronization is done via delegate operations. Since delegate operations execute on the home core of their operand in some serial order and only touch data owned by that single core, they are guaranteed to be globally linearizable [35], with their updates visible to all cores across the system in the same order. In addition, only one synchronous delegate will be in flight at a time from a particular task, i.e., synchronization operations from a particular task are not subject to reordering. Moreover, once one core is able to see an update from a synchronous delegate, all other cores are too. Consequently, all synchronization operations execute in program order and are made visible in the same order to all cores in the system. These properties are sufficient to guarantee a memory model that offers sequential consistency for data-race-free programs [4] (all accesses to shared data are separated by synchronization), which is what underpins C/C++ [16,39]. The synchronous property of delegates provides a clean model but is restrictive: we discuss asynchronous operations within the next section.

3.2 Tasking System

Each hardware core has a single operating system thread pinned to it; all Grappa code runs in these threads. The basic unit of execution in Grappa is a *task*. When a task ready to execute, it is mapped to a *worker* thread. Scheduling between tasks is carried out entirely in user-mode without operating system intervention.

Tasks Tasks are specified by a closure (or "function object" in C++ parlance) that holds both code to execute and initial state. The functor can be specified with a function pointer and explicit arguments, a C++ struct that overloads the parentheses operator, or a C++11 lambda construct. These objects, typically very small (on the order of 64 bytes), hold read-only values such as an iteration index and pointers to common data or synchronization objects. Task functors can be serialized and transported around the system, and are eventually executed by a worker thread.

Workers Workers execute application and system (e.g., communication) tasks. A worker is simply a collection of status bits and a stack, allocated at a particular core. When a task is ready to execute it is assigned to a worker, that executes the task functor on its own stack. Once a task is mapped to a worker it stays with that worker until it finishes.

Scheduling During execution, a worker yields control of its core whenever performing a long-latency operation, allowing the processor to remain busy while waiting for the operation to complete. In addition, a programmer can direct scheduling explicitly. To minimize context-switch overhead, the Grappa scheduler operates entirely in user-space and does little more than store state of one worker and load that of another. When a task encounters a long-latency operation, its worker is suspended and subsequently woken when the operation completes.

Each core in a Grappa system has its own independent scheduler. The scheduler has a collection of active workers ready to execute called the *ready worker queue*. Each scheduler also has three queues of tasks waiting to be assigned a worker. The first two run user tasks: a public queue of tasks that are not bound to a core yet, and a private queue of tasks already bound to the core where the data they touch is located. The third is a priority queue scheduled according to task-specific deadline constraints; this queue manages high priority system tasks, such as periodically servicing communication requests.

Whenever a task yields, the scheduler makes a decision about what to do next. First, any task in the system task queue whose deadline is imminent is chosen for execution. Second, the scheduler determines if any workers with running tasks are ready to execute; if so, one is scheduled. Finally, if no workers are ready to run, but tasks are waiting to be matched with workers, an idle worker is woken (or a new worker is spawned), matched with a task, and scheduled.

Context switching Grappa context switches between workers non-preemptively. As with other cooperative multithreading systems, we treat context switches as function calls, saving and restoring only the callee-saved state

as specified in the x86-64 ABI [10] rather than the full register set required for a preemptive context switch. This requires 62 bytes of storage.

Grappa's scheduler is designed to support a very large number of concurrently-active workers—so large, in fact, that their combined context data will not fit in cache. In order to minimize unnecessary cache misses on context data, the scheduler explicitly manages the movement of context data into the cache. To accomplish this, we establish a pipeline of ready thread references in the scheduler. This pipeline consists of *ready-unscheduled*, *ready-scheduled*, and *ready-resident* stages. When context prefetching is on, the scheduler is only ever allowed to run threads that are *ready-resident*; all other threads are assumed to be out-of-cache. The examined part of the ready queue itself must also be in cache. In a FIFO schedule, the head of the queue will always be in cache due to its spatial locality. Other schedules are possible as long as the amount of data they need to examine to make a decision is independent of the total number of threads.

When a thread is signaled, its reference is marked *ready-unscheduled*. Every time the scheduler runs, one of its responsibilities is to pick a *ready-unscheduled* thread to transition to *ready-scheduled*: it issues a software prefetch to start moving the task toward L1. A thread needs its metadata (one cache line) and its private working set. Determining the exact working set might be difficult, but we find that approximating the working set with the top 2-3 cache lines of the stack is the best naive heuristic. The thread data is *ready-resident* when it arrives in cache. Since the arrival of a prefetched cache line is generally not part of the architecture, we must determine the latency from profiling.

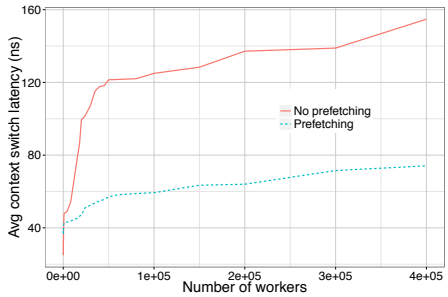


Figure 6: Average context switch time with and without prefetching.

Figure 6 shows the performance of this prefetching mechanism. At our standard operating point (≈1K workers), context switch time is on the order of 50ns. As we add workers, the time increases slowly, but levels off: we also ran with 500,000 workers (10 times what is shown in the figure) and found that context switch time was around 75ns. Without prefetching, context switching is limited by memory access latency. Conversely, with prefetching on, context switching rate is limited by memory bandwidth — we determine this by calculating total data movement based on switch rate and cache lines per switch in microbenchmark. As a reference point, for the same yield test using kernel-level Pthreads on a single core, the switch time is 450ns for a few threads and 800ns for 1000–32000 threads.

Work stealing When the scheduler finds no work to assign to its workers, it commences to steal tasks from public queues of other cores. It chooses a node at random until it finds one with a non-zero amount of work in its public task queue. The scheduler steals half of the tasks it finds at that node. Work stealing is particularly interesting in Grappa since performance depends on having many active worker threads on each core. Even if there are many active threads, if they are all suspended on long-latency operations, then the core is underutilized. The stealing policy must predict whether local tasks will likely generate enough new work soon; a similar problem is addressed in [61]. Because global memory accesses involve the core where the memory is physically located, in some cases it is a profitable programming decision to bind tasks to a particular core ahead of time. Such tasks are *not* stealable, however, potentially leading to load imbalance.

Expressing parallelism The Grappa API supports spawning individual threads, with optional data locality constraints. These threads may be full-fledged threads with a stack and the ability to block, or they may be *delegate threads*, which like delegate operations execute non-blocking regions of code atomically on a single core's memory. For better programmability, we support automatically generating tasks from parallel loop constructs, like the examples in Section 2. Grappa's parallel loops spawn tasks using a *recursive decomposition* of iterations, similar to Cilk's cilk_for construct [15], and TBB's `parallel_for` [54]. This generates a logarithmically-deep tree of tasks, stopping to execute the loop body when the number of iterations is below a user-definable threshold.

Grappa loops can iterate over an index space or over a region of shared memory. In the former case, tasks are spawned with no locality constraints, and may be stolen by any core in the system. In the latter case, tasks are bound to the home core of the piece of memory on which they are operating so that the loop body may optimize for this locality, if available. The local region of memory is still recursively decomposed so that if a particular loop iteration's task blocks, other iterations may run concurrently on the core.

3.3 Communication Support

Grappa's communication layer has two components: a user-level messaging interface based on active messages, and a network-level transport layer that supports request

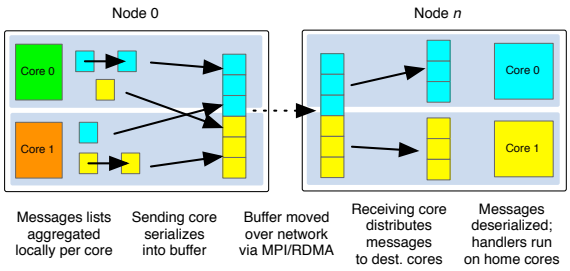


Figure 7: Message aggregation process.

aggregation for better communication bandwidth.

Active message interface At the upper (user-level) layer, Grappa implements asynchronous active messages [63]. Our active messages are simply a C++11 lambda or functor. We take advantage of the fact that our homogeneous cluster hardware runs the same binary in every process: each message consists of a template-generated deserializer pointer, a byte-for-byte copy of the functor, and an optional data payload.

Message aggregation Since communication is very frequent in Grappa, aggregating and sending messages efficiently is very important. To achieve that, Grappa makes careful use of caches, prefetching, and lock-free synchronization operations.

Figure 7 shows the aggregation process. Cores keep their own outgoing message lists, with as many entries as the number of system cores in a Grappa system. These lists are accessible to all cores in a Grappa node to allow cores to peek at each other's message lists. When a task sends a message, it allocates a buffer from a pool, determines the destination system node, writes the message contents into the buffer, and links the buffer into the corresponding outgoing list. These buffers are referenced only twice for each message sent: once when the message is created, and (much later) when the message is serialized for transmission. The pool allocator prefetches the buffers with the non-temporal flag to minimize cache pollution.

Each processing core in a given system node is responsible for aggregating and sending the resulting messages from all cores on that node to a set of destination nodes. Cores periodically execute a system task that examines the outgoing message lists for each destination node for which the core is responsible; if the list is long enough or a message has waited past a time-out period, all messages to a given destination system node from that source system node are sent by copying them to a buffer visible to the network card. Actual message transmission can be done purely in user-mode using MPI, which in turn uses RDMA.

The final message assembly process involves manipulating several shared data-structures (the message lists), so it uses CAS (compare-and-swap) operations to avoid high synchronization costs. This traversal requires careful prefetching because most of the outbound messages are *not* in the processor cache at this time (recall that a core can be aggregating messages originating from other cores in the same node). Note that we use a per-core array of message lists that is only periodically modified across processor cores, having experimentally determined that this approach is faster (sometimes significantly) than a global per-system node array of message lists.

Once the remote system node has received the message buffer, a management task is spawned to manage the unpacking process. The management task spawns a task on each core at the receiving system to simultaneously unpack messages destined for that core. Upon completion, these unpacking tasks synchronize with the management task. Once all cores have processed the message buffer, the management task sends a reply to the sending system node indicating the successful delivery of the messages.

3.3.1 Why not just use native RDMA support?

Given the increasing availability and decreasing cost of RDMA-enabled network hardware, it would seem logical to use this hardware to implement Grappa's DSM. Figure 8 shows the performance difference between native RDMA atomic increments and Grappa atomic increments using the GUPS cluster-wide random access benchmark using the cluster described in §4. The cluster has Mellanox ConnectX-2 40Gb InfiniBand cards connected through a QLogic switch with no oversubscription. The RDMA setting of the experiment used the network card's native atomic fetch-and-increment operation, and issued increments to the card in batches of 512. The Grappa setting issued delegate increments in a parallel for loop. Both settings perform increments to random locations in a 32 GB array of 64-bit integers distributed across the cluster. Figure 8(left) shows how aggregation allows Grappa to exceed the performance of the card by $25\times$ at 128 nodes. We measured the effective bisection bandwidth of the cluster as described in [36]: for GUPS, performance is limited by memory bandwidth during aggregation, and uses $\sim 40\%$ of available bisection bandwidth.

Figure 8(right) illustrates why using RDMA directly is not sufficient. The data also shows that MPI over InfiniBand has negligible overhead. Our cluster's cards are unable to push small messages at line rate into the network: we measured the peak RDMA performance of our cluster's cards to be 3.2 million 8-byte writes per second, when the wire-rate limit is over 76 million [11]. We believe this limitation is primarily due to the latency of the multiple PCI Express round trips necessary to issue one operation; a similar problem was studied in [31]. Furthermore, RDMA network cards have severely limited support for synchronization with the CPU [25, 46]. Finally, framing overheads can be large: InfiniBand 8-byte

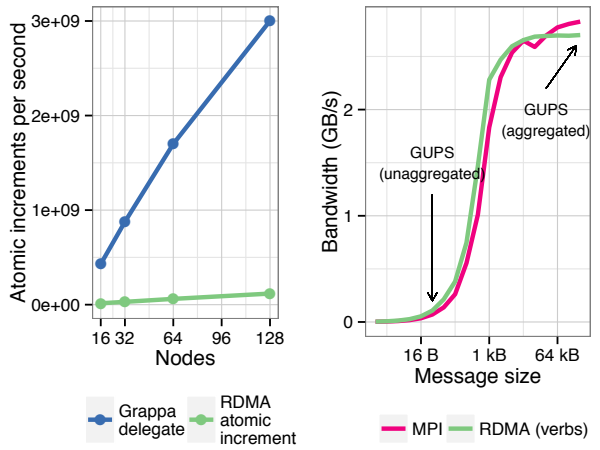


Figure 8: On the left, random updates to a billion-integer distributed array with the GUPS benchmark. On the right, ping-pong bandwidth measured between two nodes.

RDMA writes moves 50 bytes on the wire; Ethernet-based RDMA using RoCE moves 98 bytes. Work is ongoing to improve network card small message performance [1, 3, 26, 31, 50, 52, 55, 62]: even if native small message performance improves in future hardware, our aggregation support will still be useful to minimize cache line movement, PCI Express round trips, and other memory hierarchy limitations.

4 Evaluation

We implemented Grappa in C++ for the Linux operating system. The core runtime system system is 17K lines of code. We ran experiments on a cluster of AMD Interlagos processors with 128 nodes. Nodes have 32 cores operating at 2.1GHz, spread across two sockets, 64GB of memory, and 40Gb Mellanox ConnectX-2 InfiniBand network cards. Nodes are connected via a QLogic InfiniBand switch with no oversubscription. We used a stock OS kernel and device drivers. The experiments were run in a machine without administrator access or special privileges. GraphLab and Spark communicated using IP-over-InfiniBand in Connected mode.

4.1 GraphLab on Grappa

GraphLab is a platform for implementing graph-based applications easily and with high performance on clusters [32, 43]. GraphLab's clean "vertex program" abstraction exposes little about the underlying graph representation, making it very flexible in how it is implemented. We first choose a suitable graph representation, and then implement an engine to execute GAS vertex programs over that structure.

The graph data structure provided by the Grappa library, shown previously in Figure 4, is simple, doing random placement of vertices to cores and mapping each vertex's outgoing edges to the same core as the vertex. Parallel iterators are defined over the vertex array and over each vertex's outgoing edge list.

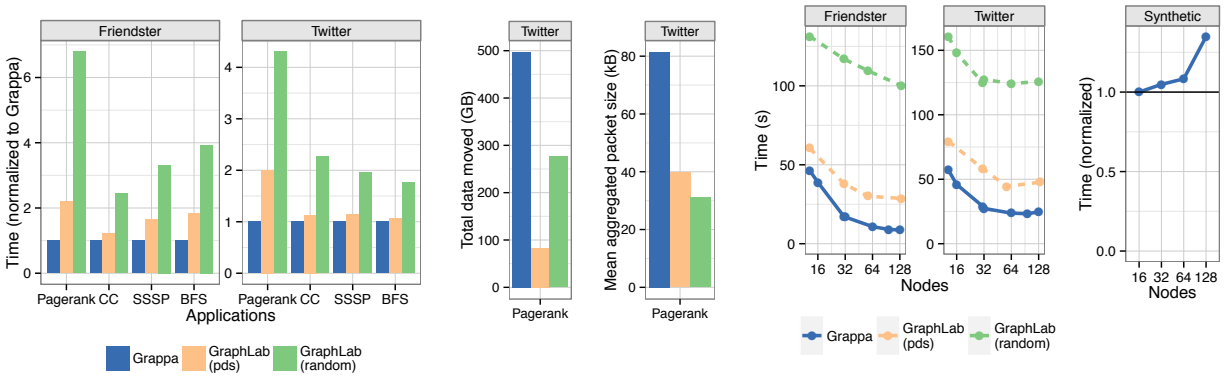
Using this graph representation, we implement a subset of GraphLab's synchronous engine, including the delta caching optimization, in ∼60 lines of Grappa code. Given our graph structure, we can efficiently support gather on incoming edges and scatter on outgoing edges; the other directions would require replicating edge or vertex data as GraphLab does. We specify the gather, apply, and scatter operations in a "vertex program" structure as in GraphLab's own API. Vertex program state is represented as additional data attached to each vertex. The synchronous engine looks much like Figure 2b, consisting of several parallel `forall` loops executing the gather, apply, and scatter phases within an outer "superstep" loop until all vertices are inactive.

Using this GraphLab API made it easy to implement 3 graph analytics applications using vertex program definitions equivalent to GraphLab's: PageRank, Single Source Shortest Path (SSSP), and Connected Components (CC). In addition, we implemented a simple Breadth-first search (BFS) application in the spirit of the Graph500 benchmark [34], which finds a "parent" for each vertex with a given source. The implementation in the GraphLab API is similar to the SSSP vertex program.

4.1.1 Performance

To evaluate Grappa's GraphLab API emulation, we ran each application on the Twitter follower graph [41] (41 M vertices, 1 B directed edges) and the Friendster social network [66] (65 M vertices, 1.8 B undirected edges). For each we run to convergence – for PageRank we use GraphLab's default threshold criteria – resulting in the same number of iterations for each. Additionally, for PageRank we ran with delta caching enabled, as it proved to perform better. For Grappa we use the no-replication graph structure; for GraphLab, we show results for random partitioning and the current best partitioning strategy: "PDS" which computes the "perfect difference set", but can only be run with $p^2 + p + 1$ (where p is prime) nodes. Most of the comparisons are done at 31 nodes for this reason.

Figure 9a depicts performance results at 31 nodes, normalized to Grappa's execution time. We can see that Grappa is faster than random partitioning on all of them (on average 2.57×), and 1.33× faster than the best partitioning, despite not replicating the graph at all. Both implementations of PageRank issue application-level requests on the order of 32 bytes (mostly communicating updated rank values). However, these would perform terribly on the network, so both systems perform their own aggregation. Figure 9b shows that though Grappa needs to move 2-4× more data due to its graph structure, it is



(a) Application performance (31 nodes)

(b) Communication metrics at 31 nodes on PageRank.

(c) Scaling PageRank: strong scaling on Twitter and Friendster, weak scaling on synthetic graphs.

Figure 9: *Performance characterization of Grappa's GraphLab API.* (a) shows time to converge (same number of iterations) normalized to Grappa, on the Twitter and Friendster datasets. (b) shows communication metrics for the PageRank data points. (c) shows scaling results for PageRank out to 128 nodes – Friendster and Twitter measure *strong* scaling, and *weak* scaling is measured on synthetic power-law graphs scaled proportionally with nodes.

able to aggregate larger packets. With this size of packet (30-80 kB) most of the network stack overhead (MPI or TCP) is amortized for both systems.

Figure 10 demonstrates the connection between concurrency and aggregation over time while executing PageRank. We can clearly see that each iteration, the number of concurrent tasks spikes as *scatter* delegates are performed on outgoing edges, which leads to a corresponding spike in bandwidth due to aggregating the many concurrent messages. At these points, Grappa achieves roughly 1.1 GB/s per node, which is 47% of peak bisection bandwidth for large packets discussed in §3.3.1, or 61% of the bandwidth for 80 kB messages, the average aggregated size. This discrepancy is due to not being able to aggregate packets as fast as the network can send them, but is still significantly better than unaggregated bandwidth.

Figure 9c(left) shows strong scaling results on both datasets. As we can see, scaling is poor beyond 32 nodes for both platforms, due to the relatively small size of the graphs – there is not enough parallelism for either system to scale on this hardware. To explore how Grappa fares on larger graphs, we show results of a weak scaling experiment in Figure 9c(right). This experiment runs PageRank on synthetic graphs generated using Graph500's Kronecker generator, scaling the graph size with the number of nodes, from 200M vertices, 4B edges, up to 2.1B vertices, 34B edges. Runtime is normalized to show distance from ideal scaling (horizontal line), showing that scaling deteriorates less than 30% at 128 nodes.

4.2 Relational queries on Grappa

We used Grappa to build a distributed backend to Raco, a relational algebra compiler and optimization framework

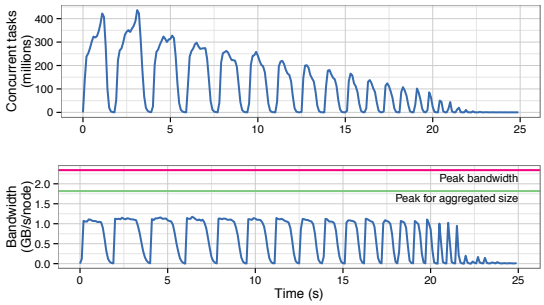


Figure 10: Grappa PageRank execution over time on 32 nodes. The top shows the total number of concurrent tasks (including delegate operations), over the 85 iterations, peaks decreasing as fewer vertices are being updated. The bottom shows message bandwidth per node, which correlates directly with the concurrency at each time step, compared against the peak bandwidth, and the bandwidth for the given message size.

[53]. Raco supports a variety of relational query language frontends, including SQL, Datalog, and an imperative language, MyriaL. It includes an extensible relational algebra optimizer and various intermediate query plan representations.

We compare performance of our system to that of Shark, a fast implementation of Hive (SQL-like), built upon Spark. We chose this comparison point because Shark is optimized for in-memory execution and performs competitively with parallel databases [65].

Our particular approach for the Grappa backend to Raco is source-to-source translation. We generate

`foralls` for each pipeline in the physical query plan (example shown in Figure 2c). We extend the code generation approach for *serial* code in [49] to generating parallel shared memory code. The generated code is sent through a normal C++11 compiler.

All data structures used in query execution (e.g. hash tables for joins) are globally distributed and shared. While in terms of programming model this a departure from the shared-nothing architecture of nearly all parallel databases, the locality-oriented execution model of Grappa makes the execution of the query virtually identical to that of these traditional designs. Grappa should excel at hash joins given that it achieves high throughput on random access.

Implementing the parallel Grappa code generation was a relatively simple extension of the generator for serial C++ code that we use for testing Raco. It required less than 90 lines of template C++/Grappa code and 600 lines of support and data structure C++/Grappa code to implement conjunctive queries, including two join implementations.

4.2.1 Performance

We focus on workloads that can be processed in memory, since storage is out of scope for this work. For Grappa, we scan all tables into distributed arrays of rows in memory, then time the query processing. To ensure all timed processing in Shark is done in memory, we use the methodology that Shark's developers use for benchmarking [2]. In particular, all input tables are cached in memory and the output is materialized to an in-memory table. The number of reducer tasks for shuffles was set to 3 per Spark worker, which balances overhead and load balance. Each worker JVM was assigned 52GB of memory. For all queries, we verified that the Spark workers were assigned tasks.

We ran conjunctive queries from SP^{2}Bench [56]. The queries in this benchmark involve many joins, which makes it interesting for evaluating parallel in-memory systems. We show results on 16 nodes in Figure 11a, grouped roughly by category: Q3b, Q3c, and Q1 have few join operations and small output, Q3a and Q9 have few join operations but larger output, Q5a, Q5b, and Q2 have many joins, and Q4 additionally has quadratic output size. Grappa has a geometric mean speedup of $13.5\times$ over Shark. A portion of the performance difference is from the efficiency of compiled C++ code vs. interpreted query in a JVM language. To understand how this influences the results we ran simpler queries, each isolating a single relational operator. For a select query of 1% selectivity, Grappa is $12.8\times$ faster (Figure 11b). Thus, for SP^{2}Bench queries with little use of join and small output (Q1, Q3b, and Q3c) we can attribute up to 1 order of magnitude of Grappa's speedup to difference in executable code. The remainder of the performance difference is attributable to Grappa's pipelined query plans vs. Shark's use of shuffle for joins [65]. Grappa's speedup on select with 99% selectivity falls to $4.23\times$, so Grappa's mechanism for materializing output (appending to a C++ STL vector) is slower. This accounts for the $2\times$ relative decrease in performance on Q3a and Q9. Although we see a single join on Shark comes much closer to the performance of Grappa, the large gap in the performance of Q4 suggests that Grappa benefits greatly from pipelining relative to the sequences of shuffle joins performed by Shark.

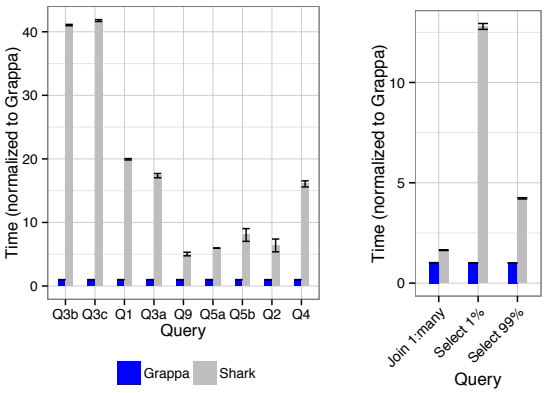


Figure 11: Relational query performance. (a) The SP^{2}Bench benchmark on 16 nodes. Query Q4 is a large workload so it was run with 64 nodes. (b) Single-operator microbenchmark queries

4.3 Iterative MapReduce on Grappa

We experiment with data parallel workloads by implementing an in-memory MapReduce API in 152 lines of Grappa code. The implementation involves a `forall` over inputs followed by a `forall` over key groups. In the all-to-all communication, mappers push to reducers. As with other MapReduce implementations, a combiner function can be specified to reduce communication. In this case, the mappers materialize results into a local hash table, using Grappa's partition-awareness. The global-view model of Grappa allows iterations to be implemented by the application programmer with a `while` loop.

4.3.1 Performance

We pick k-means clustering as a test workload; it exercises all-to-all communication and iteration. To provide a reference point, we compare the performance to the `SparkKMeans` implementation for Spark. Both versions use the same algorithm: map the points, reduce the cluster means, and broadcast local means. The Spark code caches the input points in memory and does not perist partitions. Currently, our implementation of MapReduce is not fault-tolerant. To ensure the comparison is fair, we

verified that no bytes were written to the filesystem by Spark. We run k-means on a dataset from Seaflow [59], where each instance is a flow cytometry sample of seawater containing characteristics of phytoplankton cells. The dataset is 8.9GB and contains 123M instances. The clustering task is to identify species of phytoplankton so the populations may be counted.

The results are shown in Figure 12a for $K = 10$ and $K = 10000$. We find Grappa-MapReduce to be nearly an order of magnitude faster than the comparable Spark implementation. Absolute runtime for Grappa-MapReduce is 0.13s per iteration for $K = 10$ and 17.3s per iteration for $K = 10000$; this compares to 1s and 170s respectively for Spark.

To understand this performance difference we profiled the Grappa-MapReduce version (Figure 12b). Except for small numbers of clusters, the problem is compute-bound as most execution time is spent in the map step. When we profile Spark at similarly large problem sizes we find that only 50% of the execution time is spent in the map step. This provides a good indicator of the raw execution time difference ($5\times$) between Spark and Grappa. This difference is likely due to a number of factors – data-structures, object serialization, JVM vs C++, garbage collection, etc. The remaining $2\times$ difference in performance is due to the $reduce$ step. Here we see, at large numbers of clusters, Grappa-MapReduce shuffle takes so little time as to be insignificant, while the Spark implementation spends much of its execution time in this step. We attribute this difference to the underlying Grappa runtime, which is designed to make small message traffic efficient. Figure 12c shows the rate of the 40-byte append delegates (32-byte vectors plus serializer overhead), which implement the all-to-all. We use K equal to number of cores to make sure all cores are reducers. We see that this workload utilizes an small fraction ($\approx 4\%$) of the small-message rate of Grappa (Figure 8).

4.4 Writing directly to Grappa

Not all problems fit perfectly into current restricted programming models – for many, a better solution can be found by breaking these restrictions. An advantage of building specialized systems on top of a flexible, high-performance platform is that it makes it easier to implement new optimizations into domain-specific models, or implement a new algorithm from scratch natively. For example, for BFS, Beamer's direction-optimizing algorithm has been shown to greatly improve performance on the Graph500 benchmark by traversing the graph "bottom-up" in order to visit a subset of the edges [12]. This breaks the GraphLab GAS abstraction. We implemented the new BFS algorithm directly on the existing graph data structure in 70 lines of code. Performance results in Figure 13 show that this algorithm's performance is nearly a factor of 2 better than the GraphLab abstraction can represent.

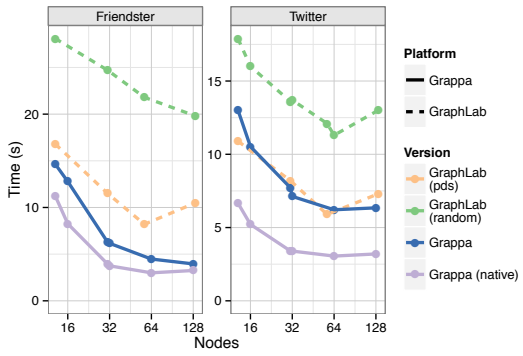
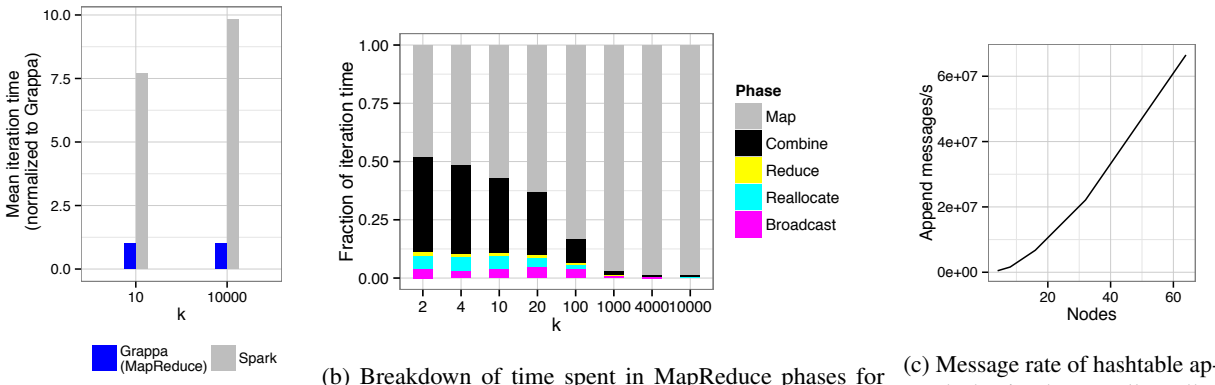


Figure 13: Scaling BFS out to 128 nodes. In addition to Grappa's GraphLab engine, we also show a custom algorithm for BFS implemented natively which employs Beamer's bottom-up optimization to achieve even better performance.

5 Related Work

Multithreading Hardware-based massive multithreading to tolerate latency include the Denelcor HEP [58], Tera MTA [9], Cray XMT [30], Simultaneous multithreading [60], MIT Alewife [5], Cyclops [8], and GPUs [29]. Hardware multithreading often pays with lower single-threaded performance that may limit appeal in the mainstream market. As a software implementation of multithreading for mainstream general-purpose processors, Grappa provides the benefits of latency tolerance only when warranted, leaving single-threaded performance intact.

Grappa's closest software-based multithreading ancestor is the Threaded Abstract Machine (TAM) [22]. TAM is a software runtime system designed for prototyping dataflow execution models on distributed memory supercomputers. Like Grappa, TAM supports inter-node communication, management of the memory hierarchy, and lightweight asynchronous scheduling of tasks to processors, all in support of computational throughput despite the high latency of communications. A notable conclusion [23] was that threading for latency tolerance was fundamentally limited because the latency of the top-level store (e.g. L1 cache) is in direct competition with the number of contexts that can fit in it. However, we find prefetching is effective at hiding DRAM latency in context switching. Indeed, a key difference between Grappa's support for lightweight threads and that of other user level threading packages, such as QThreads [64], TBB [54], Cilk [15] and Capriccio [13] is Grappa's context prefetching. Grappa's prefetching could likely improve from compiler analyses inspired by those of Capriccio for reducing memory usage.



(a) Performance for 64 nodes

(b) Breakdown of time spent in MapReduce phases for Grappa-MapReduce

(c) Message rate of hashtable appends that implement all-to-all

Figure 12: Data parallel experiments using k-means on a 8.9GB Seaflow dataset.

Software distributed shared memory Much of the innovation in DSM over the past 30 years has focused on reducing the synchronization costs of updates. The first DSM systems, including IVY [42], used frequent invalidations to provide sequential consistency, inducing high communication costs for write-heavy workloads. Later systems relaxed the consistency model to reduce communication demands. Release consistency, for example, allows updates to be buffered between synchronization events. Some systems further mitigated performance degradation due to false sharing by adopting multiple writer protocols that delay integration of concurrent writes made to the same page. The Munin [14, 18] and TreadMarks [40] systems exploited both of these ideas, but still incurred some coherence overhead. Paging strategies have presented an additional opportunity for innovation in reducing update cost: ownership and transmission of large pages make better use of processor page management mechanisms and network wire bandwidth when locality is abundant, but otherwise result in increased false sharing and wasted bandwidth moving large pages. Munin and Blizzard [57] allowed the tracking of ownership with variable granularity to address these problems. Grappa follows the lead of TreadMarks and provides DSM entirely at user-level through a library and runtime. FaRM [25] offers lower latency and higher throughput updates to DSM than TCP/IP via lock free and transactional access protocols exploiting RDMA, but remote access throughput is still limited to the RDMA operation rate which is typically an order of magnitude less than the per node network bandwidth.

Partitioned Global Address Space languages The high-performance computing community has largely discarded the coherent distributed shared memory approach in favor of the Partitioned Global Address Space (PGAS) model. Examples include Split-C [21], Chapel [19], X10 [20], Co-array Fortran [51] and UPC [27]. What is most different between general DSM systems and PGAS ones is that remote data accesses are explicit, thereby encouraging developers to use them judiciously. Grappa follows this approach, implementing a PGAS system at the language level, thereby facilitating compiler and programmer optimizations.

Distributed data-intensive processing frameworks There are many other data-parallel frameworks like Hadoop, Haloop [17], and Dryad [38]. These are designed to make parallel programming on distributed systems easier; they meet this goal by targeting data-parallel programs. There have also been recent efforts to build parameter servers for distributed machine learning algorithms using asynchronous communication and distributed key-value storage built from RPCs [6,7]. The incremental data-parallel system Naiad [47] achieves both high-throughput for batch workloads and low-latency for incremental updates. Most of these designs eschew DSM as an application programming model for performance reasons. However, a high-throughput DSM like Grappa is a useful building block on its own for applications or higher-level abstractions. Future work may expand Grappa to support low-latency networking for critical tasks similar to Naiad.

6 Conclusions & Future work

This work is based on the premise that writing data-intensive applications and frameworks in a shared memory environment is simpler than developing custom infrastructure from scratch. Based on this premise, we show that a DSM system can be efficient for this application space by judiciously exploiting the key application characteristics of concurrency and latency tolerance. Our data demonstrates that frameworks such as map/reduce, GraphLab, and query execution are both easy to build on this system and efficient. Our map/reduce and query execution implementations are an order of magnitude faster than the custom frameworks for each. Our vertex-centric

GraphLab-inspired API is $1.33\times$ faster than GraphLab, without the need for complex graph partitioning schemes.

While the core Grappa runtime is complete, there is a wealth of ongoing research and development. Presently there is no built-in fault-tolerance mechanism. The fundamental challenge with fault-tolerance with Grappa is the wealth of inter-node partial execution state. A straightforward solution is to rely on applications to checkpoint state at appropriate points. Research into generic mechanisms built into the runtime is ongoing. In addition work is ongoing on scaling Grappa up beyond 128 nodes. The challenge here is the network stack architecture. We are presently exploring a virtual overlay network built into the runtime to reduce buffer overhead and scale execution. Finally, while Grappa is designed to exploit pure commodity hardware, we continue to investigate semi-custom hardware, such as custom routers and programmable network interfaces to further improve performance.

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