Sparkle: Optimizing Spark for Large Memory Machines and Analytics

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Abstract

Spark is an in-memory analytics platform that targets commodity server environments today. It relies on the Hadoop Distributed File System (HDFS) to persist intermediate checkpoint states and final processing results. In Spark, immutable data are used for storing data updates in each iteration, making it inefficient for long running, iterative workloads. A non-deterministic garbage collector further worsens this problem. Sparkle is a library that optimizes memory usage in Spark. It exploits large shared memory to achieve better data shuffling and intermediate storage. Sparkle replaces the current TCP/IP-based shuffle with a shared memory approach and proposes an off-heap memory store for efficient updates. We performed a series of experiments on scale-out clusters and scale-up machines. The optimized shuffle engine leveraging shared memory provides 1.3x to 6x faster performance relative to Vanilla Spark. The off-heap memory store along with the shared-memory shuffle engine provides more than 20x performance increase on a probabilistic graph processing workload that uses a large-scale real-world hyperlink graph. While Sparkle benefits at most from running on large memory machines, it also achieves 1.6x to 5x performance improvements over scale out cluster with equivalent hardware setting.

1 Introduction

Apache Spark [24] is perhaps the most popular large scale data processing framework available today. Its popularity stems primarily from its capability for in-memory fault-tolerant computation on large-scale commodity clusters and support for a broad range of data processing and analytics applications, including SQL processing, machine learning, stream processing, and graph analytics. Spark, similar to other large-scale analytics frameworks [3, 15], is designed for a cluster of commodity low-end server machines following a scale-out architecture. Scale-out clusters are attractive as they enable such frameworks to crunch huge datasets in a cost-effective manner.

However, recently large memory servers equipped with 100s of GBs of DRAM and tens of cores, also known as scale-up systems, have become more available and affordable. For example, a 96 core, 1 TB machine is available for under $38K [6]. In fact, cloud service providers such as Amazon Web Services (AWS) now offer large memory instances with up to 1,952 GB of DRAM and 128 vCPUs [1]. Such scale-up systems are attractive since they can be provisioned and optimized for better performance compared to a cluster, especially when the workload is not embarrassingly parallel. As we show later in the evaluation (Section 4), for equivalent hardware configuration, a scale-up implementation provides at least 1.6x up to more than 5x speed-up over a scale-out system, with scale-up settings being especially beneficial to communication intensive workloads and large-scale iterative workloads in our experiments.

Given the growing availability of affordable scale-up servers, our goal is to bring the performance benefits of in-memory processing on scale-up servers to an increasingly common class of data analytics applications that process small to medium size datasets (up to a few 100GBs) that can easily fit in the memory of a typical scale-up server [11]. To achieve this, we choose to leverage Spark, an existing memory-centric data analytics framework with wide-spread adoption among data scientists. Bringing Spark's data analytic capabilities to a scale-up system requires rethinking the original design assumptions, which although effective for a scale-out system, are a poor match to a scale-up system resulting in unnecessary communication and memory inefficiencies.

Since Spark targets commodity scale-out clusters, it follows a shared-nothing architecture where data is partitioned across the nodes of a cluster. Spark hides partitioning and distribution through the concept of *resilient distributed datasets* (RDDs), an immutable collection of partitioned data created through deterministic transformations on data. Although most transformations on partitions can be performed independently by each node, several transformations such as joins and group-by require global communication to shuffle data between worker nodes, which Spark performs through the TCP/IP networking stack. While effective on scale-out systems interconnected with Ethernet, the networking stack introduces unnecessary copying and serialization/deserialization overheads in a scale-up system where communication can be performed through shared memory instead.

As Spark is implemented in Scala, a memory managed language based on the Java Virtual Machine (JVM), this leads to memory inefficiencies due to increased memory pressure put on the garbage collector (GC) by a large number of heap objects created when shuffling data, and immutable RDDs. Spark leverages immutability of RDDs to support fault tolerant computation by tracking how RDDs are constructed from other RDDs (lineage) and recomputing RDDs upon failure. This strategy, while generally effective, can hinder the scalability of Spark with memory intensive, iterative workloads, such as those common in large-scale machine learning applications (*e.g.*, gradient descent on a large data set) and large graphs analytics, which create and cache many RDD instances in managed memory, thus increasing memory consumption and putting pressure on the GC. To reduce pressure on the GC, Spark may evict cached RDDs. However, evicted RDD partitions have to be re-computed and re-cached when needed for the next iteration, which further evicts currently cached partitions. Eventually the re-computation can snowball, impeding any further progress on the current iteration.

To address the inefficiencies and scalability issues described above, we have designed and implemented *Sparkle*, an enhancement of Spark that leverages the large shared memory available in scale-up systems to optimize Spark's performance for communication and memory intensive iterative workloads. Further, we have open-sourced Sparkle [10].

Specifically, our work makes the following contributions in addressing the above challenges:

- A scalable shared-memory management scheme and allocator that allows worker processes to efficiently store data in native global shared memory without incurring the overhead of Java managed object representation.
- A shared-memory shuffle engine where shuffle map and reduce tasks communicate through references to global shared memory without incurring serialization/deserialization and copying overheads associated with communication through the networking stack.
- An off-heap memory store that allows data caching in global shared memory to reduce the pressure put on managed memory by the large number of RDDs typical in large-scale iterative workloads.
- A thorough evaluation that shows Sparkle's advantages compared against original Vanilla Spark on both scale-up and scale-out settings on a variety of workloads. Notably, Sparkle achieves 1.6x to 5x performance improvements over Spark running on scale out cluster with equivalent hardware setting.

2 Related Work

There has been a plethora of previous work that looked at optimizing the performance of Spark through various techniques. Below we review efforts that we find are most closely related.

Optimizing for scale-up machines. Appuswamy *et al.* explored the question of scale-up vs scale-out in the context of Hadoop [11]. They find that the scale-up approach can offer competitive and often better performance than scale-out for several workloads that can fit in the memory of a single server machine. To achieve this they propose several modifications to the Hadoop runtime that require no application changes. This includes optimizing the shuffle phase to transfer data by writing and reading to a local file system rather than copying data over the network. We initially considered this approach but quickly abandoned it in favor of our in-memory shuffle engine. The file system approach offered limited performance improvements due to contention inside the operating system kernel especially on large-scale machines such as Superdome X and also suffered from copying and serialization/deserialization overheads similar to the default networking approach.

Optimizing for HPC systems. Previous work has explored optimizing and tuning Spark for high-performance computing (HPC) systems. HPC systems pose several differences from systems found in data center environments, such as communicating through high-speed RDMA-enabled interconnects and storing all data to a global parallel file system like Lustre [7] due to lack of locally attached storage. Lu *et al.* accelerate the shuffle phase in Spark by leveraging RDMA to avoid the overhead of socket-based communication [21]. Chaimov *et al.* find that placing a large NVRAM buffer pool between compute nodes and the Lustre file system helps improve scalability of Spark running on a Cray XC machine [13]. Although these optimizations are less applicable to the data center today, they may become handy as the data center begins to adopt technologies like RDMA over Converged Ethernet (RoCE) [18].

Exploiting native memory. Project Tungsten from Databricks [9] aims to improve Spark's JVM memory management by pushing data structures into off-heap native memory via Java Unsafe APIs, thus reducing garbage collection overhead, as well as exploring code generation based on schema definitions. Most efforts to date have been devoted to improving Spark SQLs DataFrame based processing. FACADE provides a compiler pass that can transform existing data-centric applications, including Spark, to store objects in native off-heap memory with minimal application modifications required by the programmer [22]. Overall, our approach of completely rewriting the entire shuffle engine and introducing an off-heap store based on shared memory goes beyond laying out native in-memory data structures in individual JVM processes to more fully exploit the shared-memory pool.

Leveraging specialized data stores and formats. Key-value stores have been explored to scale machine learning algorithms such as gradient descent [20]. Most existing approaches rely on TCP/IP based methods for remote fetching of attributes. In our off-heap memory store, attributes (local or remote) are stored in native data structure layout and accessed directly via shared-memory, which shortens access latency and improves bandwidth utilization for bulk attribute access.

Spark DataFrame based processing has been extended to graph processing, called GraphFrames [14], with focus to support graph query processing. In DataFrames, the off-heap data structures are designed to represent to-be-queried data in a columnar format and to speed up local query processing. These data structures are local and private to individual Spark executors. In contrast, our off-heap memory store supports global direct memory access on the constructed data structures, which allows us to reduce shuffle stages for certain algorithm implementations. DataFrames inherits RDDs immutability and thus processing models represented in DataFrames is not updatable, whereas models stored in our attribute tables are updatable. It is also worth mentioning that since our globally visible data structures are constructed from shared-memory, these data structures survive even after all Spark executors are terminated when a Spark job is finished, and they can be accessed across different Spark jobs, or even for non-Spark applications when necessary.

In-memory storage systems support computing and transacting on large-scale data sets on in-memory platforms. Tachyon [19] provides a persistent store on off-heap memory. Apache Ignite [4] provides in-memory Shared RDDs for Spark jobs. Apache Arrow [2] is specialized in a columnar memory-layout for fast random access. Most systems still suffer from data movement issues such as serialization/deserialization while our off-heap memory store provides in-situ data structures that are globally sharable.

3 Sparkle Architecture

A key goal of Sparkle is to leverage the global shared memory architecture of scale-up machines so that worker processes can share data in a memory and communication efficient manner. We start by briefly reviewing how Sparkle's system architecture achieves this goal, and then dive into each Sparkle component.

3.1 System Overview

Figure 1 shows how Sparkle exploits global shared memory to transform Spark from a cluster-based scale-out architecture to a scale-up architecture. At the bottom, a retail memory broker (RMB) layer provides a native memory management scheme that allows higher layers allocate and free blocks of global shared memory in a scalable manner. Worker processes can use native shared memory to store data without incurring the memory overhead of Java managed object representation and communicate without suffering the overheads of copying and serializing/deserializing data through the networking stack.

For data shuffle, we have developed a shared-memory shuffle engine and integrated it into Spark under its pluggable shuffle interface. The shared-memory shuffle engine replaces the traditional TCP/IP-based shuffle with a shared memory approach to write to and retrieve shuffle data from the shared memory. Shuffle data is exchanged through shared-memory blocks managed by the retail memory broker rather than TCP/IP. Our solution is implemented in C++ for high performance, and it is integrated into Spark through JNI (Java Native Interface), which is a mechanism that enables native C/C++ code to be called from within JVM programs.

For data caching, we have developed an off-heap memory store that allows us to construct various large scale data structures in shared-memory regions managed by the RMB. The data structures developed include a sorted array and a hash table, to store intermediate data processing models, and to allow these models to be updated in place during iterations. Moreover, since these data structures are globally accessible by every Spark executor within the cluster, we can reduce the number of shuffle stages that are required to implement the iterative processing related algorithms. This is achieved by having the data written (or updated) in shared memory in the current processing

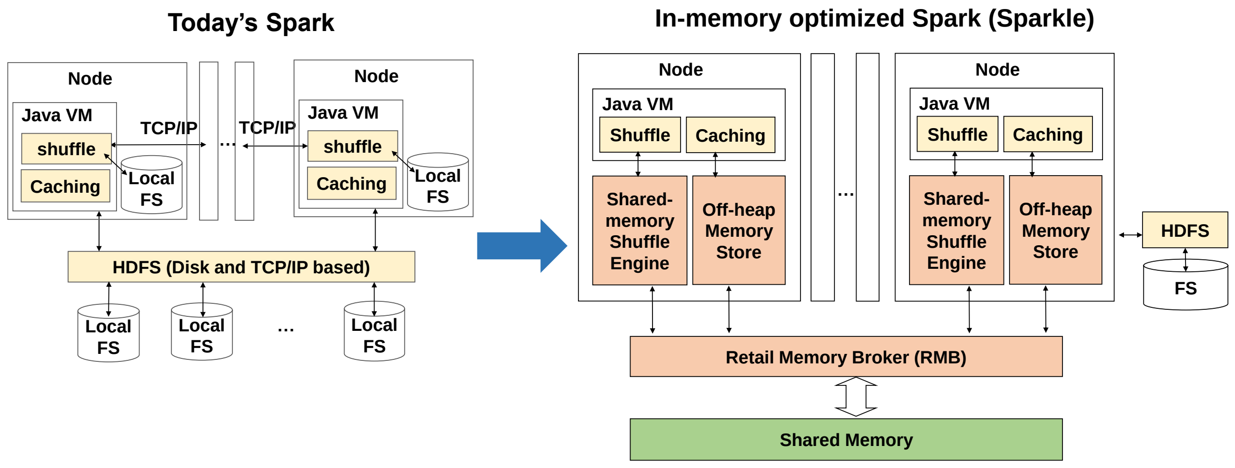


Figure 1: Sparkle using the global shared memory-based architecture to transform Spark from a cluster-based scale-out architecture to a scale-up architecture

stage by a single writer, to be read directly from shared memory by multiple readers in the next processing stage. As data stored in the off-heap memory store are mutable, RDD lineage cannot be used to reconstruct such data after a failure. To address this issue, the off-heap memory store provides fault tolerance through lightweight checkpoints that are taken at consistency points identified by the application developer.

The proposed off-heap memory store provides the following advantages: (1) mutable storage that can be used for iterative processing, thus resolving the problem of memory pressure from multiple immutable RDDs; (2) significantly reduced GC overhead; (3) more compact layout of attributes in memory store compared to Java objects; (4) globally shared data structures in off-heap memory store. These advantages allow processing of larger graph workloads with the same compute/memory resources.

3.2 Shared Memory Management

We provide a native memory management layer called the Retail Memory Broker (RMB) for use by higher-level system components, including the shuffle engine and the off-heap memory store. The broker exposes a shared heap abstraction to global memory, with users being able to dynamically create and destroy multiple shared heap instances over the global memory pool. Each heap instance is identified by a unique generation number.

A user can allocate and free variable-size chunks of memory from a heap instance through a malloc/free-like interface, and pass references to allocated memory to other processes for shared access. Although only a single owner process can allocate and free memory from a heap instance at a time, multiple processes can concurrently share and access memory associated with a heap. Under this model, a process that wishes to share data allocates a chunk of global memory, stores data in the memory chunk, and then passes a reference to the chunk to another process. The other process can use the reference to locate and access data directly from global memory, without having to first copy data into a local memory buffer. The malloc method also allows users to supply an optional location hint, which is the socket node to allocate memory from. This can be useful for processes that exhibit locality of reference such as shuffle map tasks that may wish to produce and store their output into physically close memory.

Destroying a heap instance frees up all memory chunks associated with that heap, which can be especially useful for collectively freeing up multiple objects that have a common lifetime. For example, intermediate objects created during the course of a shuffle stage all become dead and can be freed together when the stage completes. Supporting multiple heap instances gives us the benefit of efficiently managing memory objects with common lifetime similarly to region-based management [16, 23], while being able to manage memory of individual objects for better memory efficiency [12] as needed by the use case of the off-heap memory store.

The broker internally organizes the global memory pool into *zones* as shown in Figure 2. A zone is a fixed-size contiguous region of virtual memory backed by physical memory from a specific socket node, and each zone can be owned by at most one heap instance at a time. Zones enable: (1) locality-aware allocation in big-memory ma-

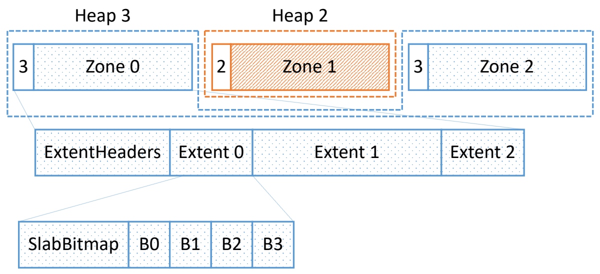


Figure 2: Multiple shared heap instances overlayed over a global memory pool, which is partitioned into fixed-size zones. Heap 2 comprises zone 1, and Heap 3 comprises zones 0 and 2.

chines with non-uniform access latency, (2) scalable concurrent allocation of shared memory by multiple processes sharing the global memory pool, and (3) efficient deallocation of multiple allocated memory blocks at once.

To allocate memory in a locality-aware manner, a heap finds a zone with enough space to satisfy the allocation request that is backed by memory from a socket node that matches the location hint. If the heap cannot find such a zone, the heap tries to acquire a new zone backed by memory that matches the location hint, otherwise it tries to acquire a zone from a node closest to the location hint. To acquire ownership, the allocator locks the zone by atomically writing the unique instance number associated with the heap.

To support variable-size memory allocation, the heap follows a hierarchical memory layout that splits zones into variable-size extents, and extents into same-size blocks. An extent is a contiguous subregion of zone space. Its length is a multiple of a configurable page size (default value set to 4KB) and can be as small as a page and nearly as large as a zone. A extent map at the beginning of the zone is used to track extents by recording the beginning and length of each extent. To speed up locating free extents, each process constructs a private extent-tree that tracks per-zone free extents by start address and length. When the size of the requested chunk is larger than the page size, the heap rounds up the allocation request to a page multiple and allocates an extent of that size. If the size of the requested chunk is smaller than the page size, then a single-page extent is allocated and formatted as a slab that splits the extent into smaller same-size blocks. The requested chunk is allocated into the smaller block that it can fit. A bitmap stored in the slab header is used to mark each allocated block in the slab using a bit per block.

The heap supports both freeing an individual memory block and collectively freeing all memory blocks allocated through a heap instance. To free a block, the heap locates the zone containing the block. If the zone is owned by the heap instance invoking the deallocation, then the heap can free the block. Otherwise, deallocation fails and it is the responsibility of the user to direct the free call to the heap and process owning the zone. To collectively free all memory allocated through a heap instance, the heap simply zeros all zone metadata of zones that match the given heap instance generation number.

The heap supports a limited form of fault tolerance: the heap guarantees the failure atomicity of individual allocation and free operations so that failures during such operations do not corrupt the global memory pool, but the heap requires the user to explicitly destroy a heap that is no longer needed after a failure so that heap memory can be reclaimed. Failure atomicity of individual operations is simplified by the simple hierarchical memory layout that allows incrementally turning a zone into an extent and an extent into a block using multiple failure-atomic steps. Each step is failure atomic as it updates a single memory word, such as setting a bit to mark a block as allocated.

We implement the global memory pool by memory mapping into each user process a common shared file that is backed by a memory-resident file system such as TMPFS. To support locality, zones within the file are preallocated to sockets in a round-robin fashion using libnuma. As each user process may map the shared file at a different location, processes cannot use absolute virtual addresses when passing references between each other. Instead, references use 64-bit offsets relative to the base of the memory-mapped file. Each process can then create the virtual address corresponding to the reference by adding the offset to its base virtual address. To hide this complexity from the programmer, we encapsulate the translation process into C++ smart pointers that transparently translate the relative offset into a virtual address and use the address to refer to the shared memory.

3.3 Shared-memory Shuffle Engine

Data processing in Spark is divided into stages that compute and communicate data. Data is "shuffled" when redistributing data from a source (Map) stage to a destination ($Reduce$) stage, to support the Spark operators dealing with processing of key/value pairs. Example operators include $GroupBy$ (to group together values sharing an identical key), $ReduceBy$ (to apply a reduce function on the grouped values sharing an identical key), $PartitionBy$ (to move keys into different partitions), and $SortBy$ (to sort keys with global ordering).

Figure 3 shows the architecture of the shared-memory shuffle engine and its integration with the RMB. The Map-side shuffle engine pushes key/value pairs received from the processing pipeline into the internal memory key/value buffer. The engine then sorts the stored keys

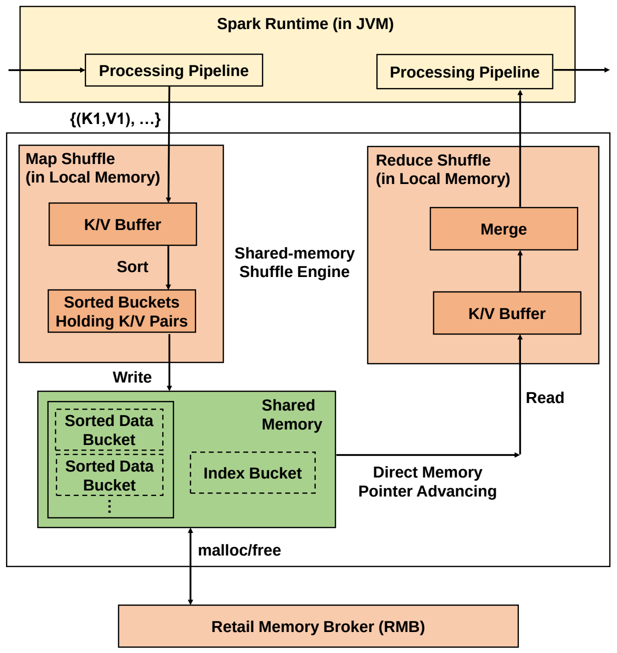


Figure 3: Shared-memory shuffle engine

and writes the key/value pairs to the shared memory, data bucket by data bucket. Each data bucket is allocated from the shared-memory region by the RMB.

The Map also writes index information about all of the data buckets into shared memory, as a special index bucket. A global pointer to the index bucket is sent to the Spark scheduler, which sends it to each destination $Reducer$. The $Reducer$ uses the global pointer to access the index bucket, from which data buckets can be retrieved by advancing the corresponding global data bucket pointer. The keys of the data buckets go through the merge engine (e.g., a priority queue), while the corresponding values are stored temporarily in the local memory buffers. The $Reduce$ processing pipeline stage pulls the keys (the merge engine output) and the merged values (in the local memory buffers) out of the shared-memory shuffle engine. To improve shuffle performance, we used several techniques. First, we optimized shuffle for key types compatible to C++ built-in types. Traditionally in shuffle, both keys and values are stored in the serialized $byte[]$ format, which gets copied and transferred blindly. Our approach directly writes keys with built-in C++ types (e.g., int, $long$, $float$, $double$, $string$ and $byte[]$) to the K/V buffers without serialization. Keys with arbitrary object types are serialized into $byte[]$. Second, since each Map or $Reduce$ process may have many concurrent Map or $Reduce$ tasks, we pool and re-use the key/value buffers after the completion of each task. This technique reduces the total amount of memory required for shuffle and speeds up shuffle dramatically. Third, we employ different shuffle schemes to separately handle operators that need ordering vs. non-ordered aggregation. In addition to the sort-based shuffle scheme shown in Figure 3, which is used for order-based operators such as $SortBy$, we have developed two additional schemes: hash-map merge and direct pass-through. The hash-map merge scheme, which performs key/value merging at the Reduce side using hash tables, is used by $GroupBy$ or $ReduceBy$ operators, which need key/value aggregation without ordering. The direct pass-through scheme, which allows the $Reducer$ to retrieve the Map buckets without ordering or aggregation, is used by $PartitionBy$.

3.4 Off-heap Memory Store

3.4.1 Overview

Figure 4 shows the overall architecture of the solution based on off-heap memory store that allows us to construct various large-scale data structures in shared-memory regions managed by RMB.

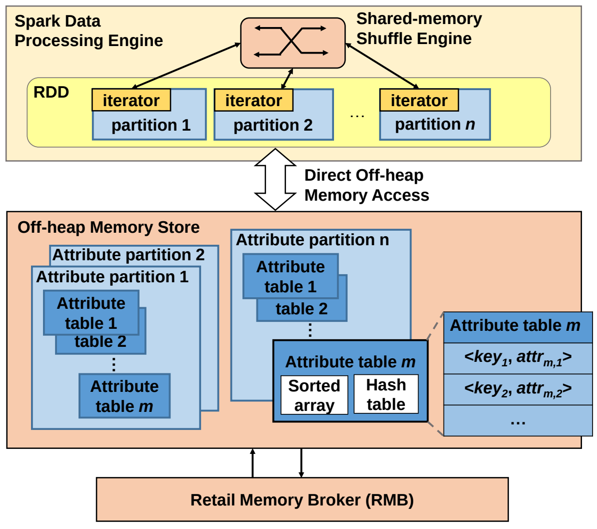


Figure 4: Off-heap memory store

Each RDD consists of partitions and each partition is represented as data structures including sorted array for linear scan and hash table for hash-based search, to store intermediate data processing models, and to allow these models to be updated in place during iteration.

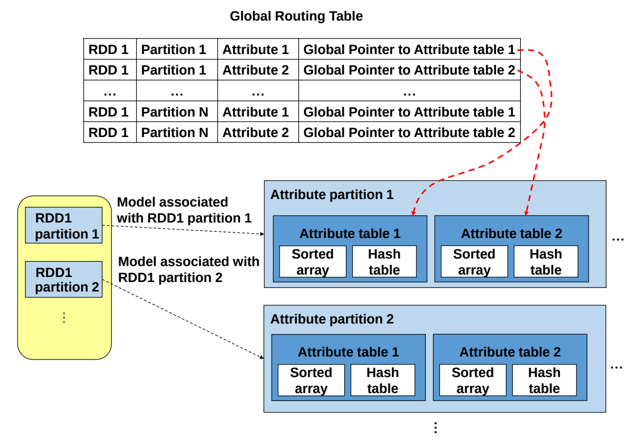
Each RDD is associated with at least one attribute $\{attr_1, attr_2, .., attr_k\}$. Each RDD partition corresponds to an attribute partition in off-heap memory store. In an attribute partition, each attribute $attr_j$ is allocated an attribute table, which stores as a sorted array and a hash table with pairs of $< key_i, attr_j, i >$. The off-heap memory store is inherently a distributed partitioned in-memory key/value store that can store and cache attributes for iterative processing.

An RDD partition, considered the owner of the corresponding attribute partition, creates and updates its attributes in each iteration. Other partitions are allowed read access to attribute partitions they do not own. In general, such read/write access requires synchronization. To speed up data processing, partitions often access (i.e., read or write) attributes in bulk. An RDD partition is constructed and cached at the job initialization phase. When the job finishes, the executor process terminates along with the cached RDD partition and the associated attribute partition. Thus, the off-heap memory store for attribute partition is inherently a caching store.

In the shared-memory based architecture supported by the shared memory machine, an RDD partition will have its own attribute partition created locally, i.e., co-located in the same shared-memory region. An attribute table is constructed via a sorted array data structure, which is laid out contiguously in the processs address space, in order to support fast bulk access. For a hash-based partition, direct memory access to a $< key, attr >$ pair is via a pointer to the corresponding shared-memory region. Subsequent pairs can be accessed by advancing the pointer.

3.4.2 Globally Accessible Data Structure

When each attribute partition associated with an RDD partition is created in the off-heap memory store, its global addresses are collected and stored as a global routing table (see Figure 5). This global routing table is then broadcast to each Spark executor so that the addresses become globally accessible.



Global Routing Table

RDD 1	Partition 1	Attribute 1	Global Pointer to Attribute table 1
RDD 1	Partition 1	Attribute 2	Global Pointer to Attribute table 2
...	...	...	...
RDD 1	Partition N	Attribute 1	Global Pointer to Attribute table 1
RDD 1	Partition N	Attribute 2	Global Pointer to Attribute table 2

Figure 5: Global routing table for globally accessible attribute partitions

Since these data structures are globally accessible by every Spark executor within the cluster, we can reduce the number of shuffle stages that are required during iterative processing algorithms. For example, for an edge partition, we create a global address table that contains offsets for the associated vertex attributes. This global address table is built when the input graph is loaded before the iterative processing. In each iteration, we retrieve the attribute values for the offsets in the global address table by global memory access as illustrated in Figure 6, instead of shipping the vertex attribute values through a shuffle step.

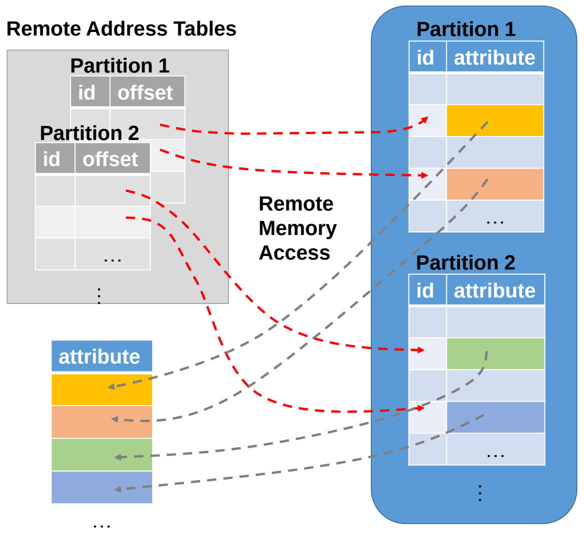


Figure 6: Global address table that contains associated attribute offsets for global memory access

This is achieved by having the data written (or updated) in shared memory in the current processing stage by a single writer which, in turn, is read directly from shared memory by multiple readers in the next processing stage. Note that because writing and reading are separated from different Spark stages due to Sparks bulk-synchronous processing paradigm, there exists no contention from simultaneous writing and reading.

3.4.3 Fault Tolerance

Big memory machines are made out of hundreds of independent compute units and other hardware components. Thus the overall system mean time between failure (MTBF) is low compared to standard MTBF (20 years) of individual components. Therefore applications running long periods of time (e.g. iterative ML workloads) on such big memory machines are vulnerable to hardware failures. In addition transient errors also contributes to system failures that requires node/ application restarts for recovery. Worker restarts/ system restarts during such application runs may result in loosing all the compute progress made till the failure and risks application starting the compute all the way from the beginning. Sparkle solves the problem by implementing an efficient checkpoint/ restart scheme for off-heap store to recover from possible hard/transient failures.

Sparkle provides a 'checkpoint_partitions()' library call to perform application level checkpoints. During the library call, each worker dumps the off-heap memory store RDD partition states associated with each worker process (partitions it owns) to the stable storage (SSDs) in parallel. Parallel applications that confirms to BSP processing model, often constitute of explicit synchronization points that requires all the worker participation (e.g. shuffle step, end of compute stage). Strategically checkpoint library calls ('checkpoint_partitions()') are placed before such synchronization points to create implicitly synchronized application checkpoints. That is during checkpoints each worker, snapshots the RDD partition state residing in the off-heap memory store along with a snapshot version number.

Sparkle implements asynchronous checkpoints. That is during a checkpoint library call, a worker first creates an in-memory copy of the RDD partitions that it manages with the steps, (1) allocating new memory buffers that is large enough to hold partition data (2) acquiring appropriate locks corresponding to the off-heap store partition (3) create a copy of the current partition state using 'memcpy()' call. After creating a copy of partition data (snapshot), the application is free to run ahead, and a background thread copies the created partition snapshot along with a version (we use a monotonically increasing counter per RDD partition) on to the stable storage (SSDs). By creating an in-memory copy of the partition data we move the slow block I/O time during partition snapshots out from the critical path of the application execution.

During an application restart, the library runtime first scans through partition snapshots stored in stable storage (SSDs) and choose the most recent common snapshot version across the all workers for each RDD. Note that the partition snapshots with same version number across partitions/ workers makes up a consistent state for the corresponding RDD and the all such checkpointed RDDs makes up the application consistent state for a application restart. After choosing the set of partitions that makes up the consistent restart state, it loads them to each of the workers address spaces and builds up the global routing table before starting the computation.

4 Experiments

We conducted a series of experiments to estimate the effectiveness of the shared-memory shuffle engine and off-heap memory store. Our baselines are Vanilla Spark on a scale-out cluster (Vanilla-Scaleout) and Vanilla Spark on a scale-up hardware (Vanilla-Scaleup).

Our experiments include micro-benchmarks ($GroupBy$, $Join$, $PartitionBy$, $ReduceBy$, and $SortBy$ Spark operators) and macro-benchmarks (TeraSort, PageRank and Belief Propagation (BP) applications). They represent typical Spark benchmarks and workloads.

In Section 4.1, we show that Sparkle's shared-memory shuffle engine enables micro-benchmark operations, PageRank, and TeraSort benchmark applications to run faster. We compare scale-up and scale-out experiment results for the above applications. Both sets of results show the benefits of running Sparkle on scale-up hardware.

In Section 4.2, we compare the performance of Sparkle vs. Vanilla Spark on a large memory machine, using larger data sets. We also show how the off-heap memory store decreases the memory footprint of the Belief Propagation algorithm on large graphs and enables faster execution.

4.1 Sparkle vs. Vanilla Spark on Scale-out and Scale-up

4.1.1 Experimental Parameters

We deploy Sparkle with 8 workers on an HPE Proliant DL580, a scale-up machine with 60 cores and 1.5TB DRAM across four NUMA nodes (sockets). Each worker is assigned 7 cores and 64 GB JVM memory. We used Spark 1.6.1 for the Vanilla Spark configurations in this section. For scale-up experiments, we deploy Vanilla Spark using the same configuration as Sparkle for comparison. For both Sparkle and Vanilla Spark on a scale-up machine, we bind each worker process to the CPU and memory of a NUMA node. Vanilla Spark uses TMPFS bound to a NUMA node to store the shuffle data and TCP/IP communication for shuffling, while Sparkle uses the shared-memory shuffle engine.

For the scale-out experiments, we use cluster configurations of 4, 8, 16 and 32 machines. For a fair comparison to scale-up, each Spark worker is set up using 7 cores (same CPU speed) and 64GB JVM memory to match the scale-up machine. In Section 4.1.2, we use a cluster of 4 machines with 56 cores and 512GB JVM memory so that the total resources (in terms of CPU cores and JVM memory size) for the scale-out and scale-up configurations is equivalent. In Section 4.1.3, we present experimental results running on cluster of 4, 8, 16, 32 machines with the same per-machine settings. We configure our scale-out cluster to use Infiniband [17] for network communication rather than Ethernet, as this hardware configuration gives us the best scale-out cluster configuration we can achieve in terms of network bandwidth and latency. In Section 4.1.4, we present experimental results running using the scale-up setting for Sparkle and Vanilla-Spark.

Our Spark operator micro-benchmarks processed 2 million key-value pairs for $GroupBy$, $Join$, $PartitionBy$ and 4 million key-value pairs for $ReduceBy$ and $SortBy$. For the PageRank experiments, we used two different ClueWeb graph data sets [5]: a 20 GB graph with around 100 million nodes and a 130 GB graph with around 600 million nodes. We refer to these data sets as $100M$ and $Full$, respectively. For the TeraSort experiments, we used a 256GB input data, with the same amount of intermediate data and sorted output data.

4.1.2 Comparing to Scale-out Solution

In this section, we compare Sparkle performance with Vanilla Spark deployed on scale-out clusters.

We ran the micro-benchmarks on Sparkle and Vanilla Spark on scale-out (Vanilla-Scaleout) with TCP/IP over Infiniband (IB). All scale-out experiments are performed using the same number of workers across configurations, where each worker uses the same number of CPU cores and size of JVM memory. The result is presented in Figure 7.

We observe that Sparkle outperforms the scale-out configuration in most cases due to the faster in-memory data access. We also observe slightly less improvement in Sparkle over the equivalent scale-out configuration for $Join$ and $PartitionBy$ operators (1.6x and 2.8x respectively). The computation time is more dominant than the shuffling time in the $Join$ operator and Sparkle mainly reduces network and serialization overhead in shuffle. $PartitionBy$ uses the direct pass-through shuffle scheme, which benefits less from the shared-memory shuffle engine than other schemes (see Section 3.3). For the rest of the micro-benchmark operators, we observed significant improvements from 3.6x to 5x over the equivalent scale-out setting.

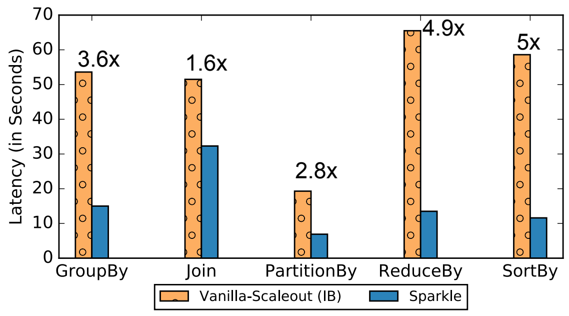


Figure 7: Micro-benchmark results with 2M and 4M key-value pairs on Sparkle vs. Vanilla-Scaleout

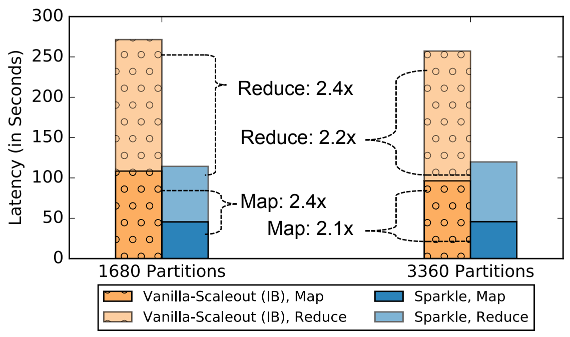


Figure 8: TeraSort application on Sparkle vs. Vanilla-Scaleout

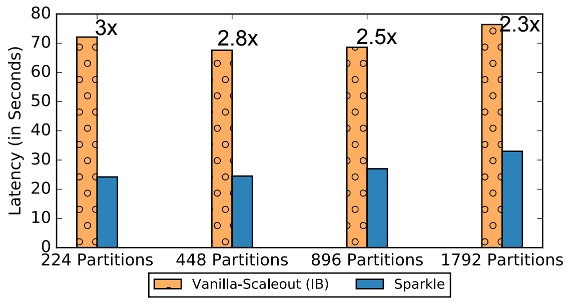


Figure 9: PageRank (100M) on Sparkle vs. Vanilla-Scaleout

In Figures 8, 9 and 10, we present our Sparkle performance in comparison with Vanilla-Scaleout for TeraSort and PageRank applications.

For TeraSort experiments, from Figure 8, we observe that Sparkle cuts the job completion time in half. The gain is slightly more in fewer partitions. Since TeraSort performs only one shuffle step using $PartitionBy$, less communication bound than computation, Sparkle benefits less from the shared-memory shuffle engine, while the scale-out cluster achieves slightly less overhead in reduce period with larger number of partitions (and hence higher data parallelism).

For PageRank experiments, we present both 100M and Full data set results. From Figures 9 and 10, we observe more than two times performance improvements from Sparkle to Vanilla-Scaleout. Unlike TeraSort results, we observe that the latency slightly increases with the number of partitions for both experiments due to the increasing size of data shuffling by larger number of partitions. This is because PageRank involves several shuffle steps with $ReduceBy$, which is more communication bound. Moreover $ReduceBy$ has more gain than $PartitionBy$ as shown in Figure 7, which makes PageRank using $ReduceBy$ has better gain for Sparkle than TeraSort using $PartitionBy$.

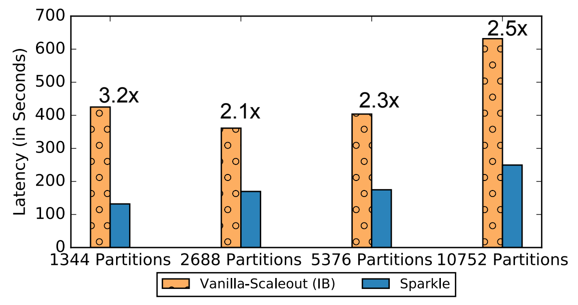


Figure 10: PageRank (Full) on Sparkle vs. Vanilla-Scaleout

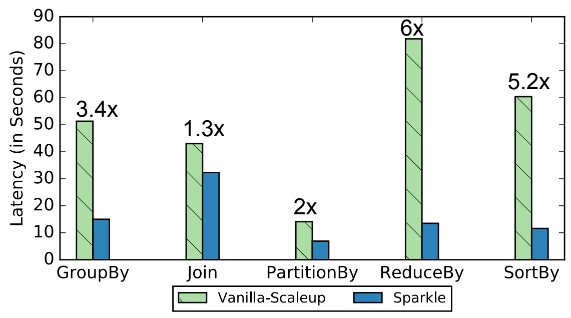


Figure 12: Micro-benchmark results with 2M and 4M key-value pairs on Sparkle vs. Vanilla-Scaleup

4.1.3 Resource Usage Comparison for Sparkle and Vanilla-Scaleout

We increase the size of cluster to match the Sparkle performance. We present the results of micro-benchmarks deployed on 4-, 8-, 16-, and 32-node clusters in Figure 11. Among these clusters the 4-node cluster has the same total hardware usage as Sparkle on a scale-up machine (as discussed in Section 4.1.1). In this figure, the dotted line denotes the job completion time achived by Sparkle and the bars denote the job completion times of Vanilla-Scaleout.

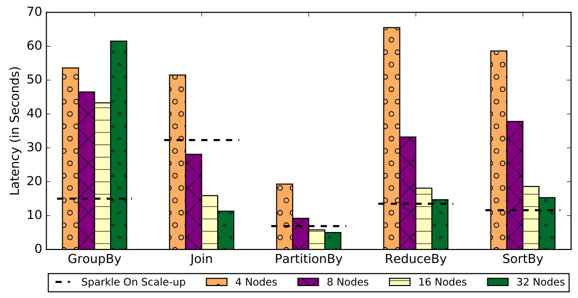


Figure 11: Resource usage comparison for micro-benchmarks

From Figure 11, we observe that starting from the equivalent hardware resource (4 nodes), scale-out cluster needs to increase its resource usage by 2 times ($Join$), 4 times ($PartitionBy$) and 8 times ($ReduceBy$) respectively, to achieve shorter job latencies than Sparkle on the scale-up. For $GroupBy$ and $SortBy$ experiments, Sparkle achieves a better job completion time than Vanilla-Scaleout on 32-node cluster (8 times resource usage comparing to Sparkle). Interestingly, we observe for $GroupBy$ operator, a larger cluster does not lead to a better performance. The 32-node cluster results in worse performance than the 4-node cluster. As discussed in Section 4.1.2 , the larger number of partitions introduces more shuffling data, especially for communication bound workloads, which starts becomes a major component in increasing the latency, and thus leads to a longer finishing time. Meanwhile Sparkle achieves a better performance by saving the network/serialization overhead without generating more partitions. This shows Sparkle's advantage towards operators with heavy partition overhead, which cannot be benefited by higher parallelism level.

4.1.4 Comparing to Scale-up Solution

For Sparkle vs. Vanilla-Scaleup, we observed overall the similar results of the scale-out experiments shown eariler. As presented in Figure 12, Sparkle achieves significantly higher improvement on Vanilla Spark for network-bound operators (e.g. $ReduceBy$ with 6 times improvement) while for compute-bound operators such as $Join$, Sparkle has less gain however it can still manage to achive 33% faster job running time than Vanilla Spark.

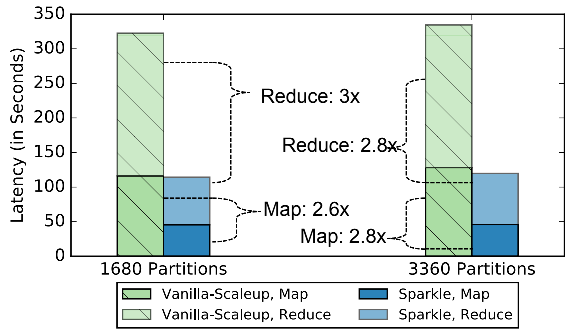


Figure 13: TeraSort on Sparkle vs. Vanilla-Scaleup

For TeraSort experiment in Figure 13, we observe Sparkle improves both map stage and reduce stage significantly, with 2.6x improvement for map and 2.8x improvement for reduce while using 1680 partitions, and 3x improvement for map and 2.8x improvement for reduce.

For PageRank experiment, as shown in Figures 14 and 15. Sparkle generally achieves 3x to 4.5x better performance than Vanilla-Scaleup. Similarly to the scale-out

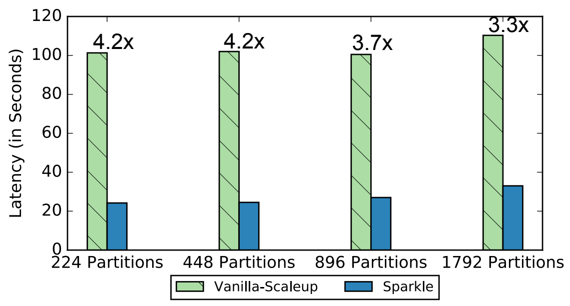


Figure 14: PageRank (100M) on Sparkle vs. Vanilla-Scaleup

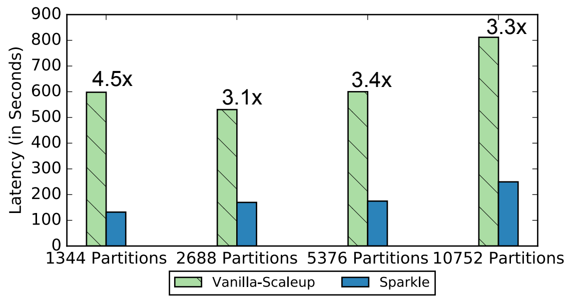


Figure 15: PageRank (Full) on Sparkle vs. Vanilla-Scaleup

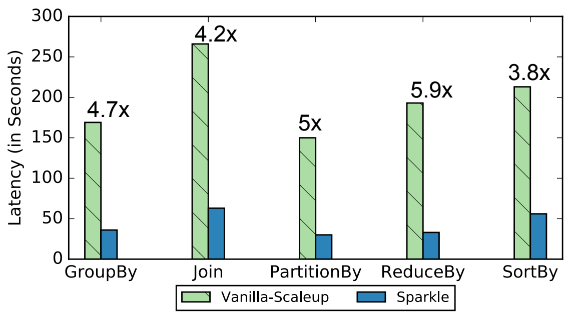


Figure 16: Micro-benchmark results with 5.4B key/value pairs on Superdome X

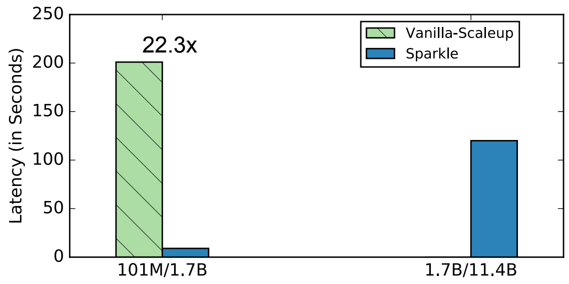


Figure 17: BP result on Sparkle vs. Vanilla Spark

results in Section 4.1.2, we found the latency for Vanilla-Scaleup increases with the number of partitions: The partition overhead starts to become significant when we use 10752 partitions.

4.2 Sparkle vs. Vanilla Spark on Large Memory Machine

We further performed our experiments with larger data sets to evaluate Sparkle vs. Vanilla Spark on a large memory machine. Our large memory platform is the Superdome X with 240 cores and 12 TB DRAM across 16 NUMA nodes (sockets). Each worker process is bound to the CPU and memory of a NUMA node. For Vanilla Spark, we used TMPFS bound to a NUMA node to store the shuffle data and TCP/IP communication for shuffling. Sparkle uses the shared-memory shuffle engine. We used Spark 1.2.0 with 45 executors each configured with 96 GB of JVM memory.

We tested micro-benchmarks processing 5.4B key/value pairs in both Sparkle and Vanilla Spark. Keys and values are C++ built-in data types.

Figure 16 shows the execution times of Sparkle and Vanilla Spark on 5.4B key/value pairs. The gains are from 3.8x to 5.9x, which are overall similar to those with smaller data sets shown in Section 4.1.

Finally we demonstrate graph processing for Sparkle with the off-heap memory store vs. Vanilla Spark. We used two large-scale graph workloads: 1) a web graph with 101 M nodes /1.7 B edges, and 2) a synthetic graph based on DNS data with 1.7 B nodes / 11.4 B edges. We can only run these workloads on Superdome X since these workloads consume lots of memory (see Table 1).

We chose belief propagation (BP) as a representative graph processing workload. BP is an iterative, message passing algorithm to perform inference on probabilistic graphical models. Each vertex is associated with a belief vector, and edges are associated with messages. In each iteration, a vertex aggregates all incoming messages, computes beliefs and computes new outgoing messages. New messages are computed using the current belief and the messages from the previous step. This increases the space complexity of the algorithm comparing with PageRank, which does not require storing messages. BP terminates when all messages have converged. We also implemented another BP algorithm leveraging Pregel API which supports basic graph processing (send, aggregate edge messages, and modify vertex attributes) in Spark GraphX. We used this Pregel-based BP as our baseline for Vanilla Spark.

In Sparkle BP, we store graph attributes in the off-heap memory store. During each iteration, attributes are retrieved from the store, computed and written back to the

Table 1: Memory used for BP

Graph size (nodes/edges)	Sparkle	Vanilla Spark
101M/1.7B	$\sim$144GB	>700GB
1.7B/11.4B	$\sim$1.1TB	Fails to run

store through direct off-heap memory access. The attributes are aggregated and the aggregated results are redistributed via the shared-memory shuffle engine. The data structures developed, including sorted array and hash table, store intermediate data processing models thus allowing for updates-in-place during iteration.

To further speed up graph processing in Sparkle BP, we developed a static graph partitioning mechanism to reduce vertex duplication across partitions, and offloaded the most computationally heavy routines (based on profiling) from Scala to C++.

As seen in Figure 17, for the first workload, Sparkle BP achieves >20x speed-up compared to BP with Vanilla Spark. The off-heap memory store contributes 4x, while the remaining speed-up mostly results from run-time support from the shared-memory shuffle engine and RMB. The average iteration time is about 13 sec., and it converges in about 10 iterations. The memory requirement is also reduced compared to the baseline: 144 GB off-heap without on-heap cache for Sparkle vs. more than 700 GB for Vanilla Spark (see Table 1).

We further optimized the Sparkle BP by taking advantage of the globally visible data structures in the off-heap memory store, by consolidating two shuffle stages (out of the total three stages in one iteration) into one single stage. These three shuffle stages are 1) the edge messages are aggregated, 2) the updated beliefs are reduced to find the maximum difference from the previous beliefs for convergence test, and 3) the updated beliefs are redistributed to the edge partitions. Here, the 3) shuffle stage is done through global memory access. Such optimization allows us to further reduce the per-iteration time of 13 sec. to 9 sec.

To further test scalability, we also ran the second workload (11.4 B edges), which is 2 min per iteration. The Vanilla Spark BP fails to run at this scale (see Figure 17).

We finally quantify the fault tolerance performance for the off-heap memory store by running checkpoint enabled version of the BP application on the first workload (101 M nodes /1.7 B edges). We aggressively insert checkpoint calls after each shuffle step of the BP application to simulate the worst case checkpoint overhead associated with the BP algorithm. Figure 18 shows that there is no significant difference between the checkpoint enabled BP for fault tolerance and the BP without fault tolerance in terms of the iteration time in both cases with and without shared-

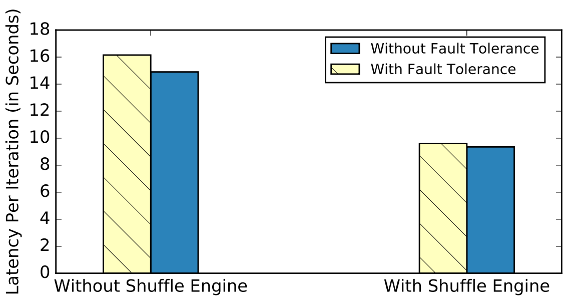


Figure 18: Fault tolerance comparison for BP

memory shuffle engine. When using the shared-memory shuffle engine, the gap gets even less. $\sim$8% execution time overhead compared its no checkpoint counterpart, in the worst case – thus confirming the efficiency of Sparkle fault tolerance implementation.

In this paper, our experiments have been done in Spark 1.6.1 and 1.2.0. We also experimented with a later Spark version (e.g., 2.0) for some of our workloads and obtained more or less similar gain for Sparkle. We expect that our Sparkle performance is not affected much for a different Spark version.

5 Conclusion

We have presented Sparkle, an enhancement of Spark that optimizes its performance on large memory machines for memory and communication intensive and iterative workloads. Comparisons to a scale-out cluster configuration show that a scale-up approach can achieve better performance for the same amount of memory and number of cores due to faster communication between compute nodes.

We have released Sparkle, our shuffle engine and off-heap memory store code to the public under Apache 2.0 License [10]. We have also released the generalized version of belief propagation algorithm [8].

Acknowledgments

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