Exoshuffle: Large-Scale Shuffle at the Application Level

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Abstract

Shuffle is a key primitive in large-scale data processing applications that has inspired a myriad of implementations. While previous work has produced breakthroughs in shuffle performance, many applications do not benefit in practice because of the difficulty of evolving existing shuffle systems. Shuffle is often tightly integrated into a framework that offers a higher-level abstraction such as SQL. Integrating new shuffle designs into these frameworks requires significant development effort. Furthermore, distributed shuffle is used by many different end use cases, from high-throughput batch processing to low-latency online aggregation. These different use cases have driven the creation of new application frameworks, each of which must rebuild shuffle from scratch.

We enable shuffle flexibility by building distributed shuffle as a library. We use distributed futures as an intermediate layer for building distributed shuffle as a library and show how it enables the shuffle control plane to be decoupled from a common high-performance data plane based on Ray. We present Exoshuffle and show that we can: (1) rewrite previous shuffle optimizations as application-level libraries with an order of magnitude less code, (2) build a shuffle-agnostic data plane that provides performance and scalability competitive with specialized shuffle systems, and (3) enable latest applications such as ML training to easily leverage large-scale distributed shuffle.

1 Introduction

Shuffle is a key primitive in data processing. It is the foundation of the MapReduce model [11] and large-scale data processing applications such as distributed sort. Large-scale distributed shuffle is difficult to execute because it entails all-to-all communication to transfer data from the mappers to the reducers. This requires efficiently and reliably moving a large number of small intermediate blocks from each mapper to each reducer, across memory, disk, and network. For terabyte-scale data, this can result in millions of transfers. Furthermore, the system must be robust to potential node failures and data skew.

Applications of shuffle span a continually evolving range of execution models [11, 19, 49] and requirements, including scaling data size [38, 52] and adapting to new storage systems or hardware [4, 6]. Since the introduction of MapReduce, the industry and research community has repeatedly produced new shuffle implementations in response to these requirements. While this has collectively led to breakthroughs in shuffle performance and reliability, in practice many applications cannot benefit from such innovations because of the difficulty of evolving shuffle implementations.

Today’s shuffle implementations are tightly integrated into frameworks that hide the shuffle details under a higher-level abstraction such as SQL (Figure 1a). Thus, to reach end applications, shuffle builders have two options.

On one hand, they can integrate new shuffle designs into existing open-source frameworks such as Spark or Hadoop. Unfortunately, such integration rarely happens because it incurs a high development cost. Magnet, for example, uses push-based shuffle to achieve 30% end-to-end performance improvement [38]. However, Magnet took 19 months between publication and open-source release in the Spark project [13], with significant changes to system internals [37].

On the other hand, developers can rebuild the entire framework from the ground up. This is often necessary to interoperate with new application models. For example, online aggregation requires extensive modifications to the MapReduce system to stream results to the user [9]. Another example is data shuffling for ML pipelines. Distributed model training often requires repeatedly shuffling the training dataset between epochs to improve learning quality [21, 22], which requires fine-grained pipelining for efficiency. To support these applications, framework developers have turned to rebuilding shuffle from scratch, often with significant limitations to reduce the development cost.

In this paper, our goal is to design a common intermediate layer for distributed shuffle that would enable flexible, efficient, and portable implementations. Today, shuffle is built
in a monolithic manner, as an integral part of a higher-level framework or sometimes as a standalone service (Fig 1a). The key idea behind our solution is to expose distributed shuffle as a library (Fig 1b). By doing so, we can both: (1) allow shuffle builders to easily develop and integrate new shuffle designs, and (2) allow a broader set of applications to easily leverage existing shuffle optimizations.

The main challenge in providing shuffle-as-a-library is to design a suitable abstraction for building different shuffle implementations. Such a layer must be: (1) sufficiently high-level that it can abstract away common parts of different shuffle systems, such as block I/O and fault tolerance, (2) sufficiently low-level that arbitrary applications and frameworks can be built atop, and (3) high enough performance that shuffle libraries built atop can practically substitute for monolithic shuffle systems.

Monolithic shuffle systems generally build shuffle on top of messaging primitives like RPC and therefore tightly couple the shuffle control and data planes. RPC is used to implement both the control plane, which decides which blocks should be transferred to which nodes, and the data plane, which implements the physical block transfer between processes. Thus, although many optimizations such as push-based shuffle and fine-grained pipelining mainly involve control plane decisions, their implementations require rewriting much of the dataplane as well [9, 38].

We use distributed futures [26, 44, 45] as an abstraction to decouple the shuffle control plane from the shuffle data plane. Distributed futures are an extension of RPC that adds the ability to reference a globally shared and immutable object store. In contrast to RPC, for which all arguments must be copied from the caller to the executor, distributed futures allow the caller to pass arguments by pointer; the system then implements the physical data transfer to the executor through the shared object store. Distributed futures can also be passed before the data has been created, allowing the system to parallelize remote calls and pipeline data transfer with remote execution. For example, a mapper can be expressed as an RPC call, i.e. a task that returns a list of distributed futures, each representing one intermediate block. The caller can specify the shuffle by passing one distributed future to each reduce task.

While we are not the first to use distributed futures to execute shuffle [26, 34], our contribution is in showing how this abstraction can serve as a narrow waist for arbitrary shuffle algorithms. To do so, we study the design and implementation of a common data plane for shuffle libraries, i.e. the distributed futures backend. The data plane must deliver the same performance and reliability as a monolithic shuffle system. This is challenging because of the granularity of system operations: unlike a specialized shuffle system, which has a notion of a map and a reduce stage and can optimize transfer of intermediate blocks accordingly, a distributed futures system is not specific to shuffle and must treat each task and object as an independent unit. Indeed, while Dask offers a distributed futures-based shuffle, its developers actually recommend using a custom shuffle implementation that bypasses their distributed futures backend because of scheduler scalability limits [18].

Next, we identify the components of a distributed futures system that are necessary for performance and reliability of shuffle-as-a-library. First, to coordinate the shuffle between mappers and reducers, we use a shared-memory distributed object store that acts as an intermediary: map tasks store their outputs in the object store and reduce tasks retrieve their arguments from the object store. Second, for efficiency, the system transparently overlaps task execution with block I/O across the shared-memory object store, local disk, and network. Third, the system implements timely garbage collection to ensure memory availability and reduce write amplification. Finally, for fault tolerance, the system uses lineage reconstruction to ensure that each object required by the shuffle library is still reachable in the presence of failures.

Thus, we present Exoshuffle, a flexible shuffle system. We build Exoshuffle on Ray, a distributed futures system for Python [24, 45]. To meet the demands of large-scale shuffle, we extend Ray to support high-throughput spilling to disk and pipelining between block I/O and execution (§4). We show that the Exoshuffle implementations of previous shuffle strategies match the performance characteristics of their monolithic counterparts. We also run a 100 TB TeraSort benchmark on a cluster of 100 HDD nodes and find that Exoshuffle outperforms Spark by 1.8×. Finally, we show that Exoshuffle can easily integrate with applications such as distributed ML training, improving end-to-end training throughput by 2.4×. To summarize, our contributions are:

- Demonstrate how distributed futures can be used to rewrite a variety of monolithic shuffle optimizations as application-level libraries, with an order of magnitude less code.
- Design and implement a distributed futures backend that scales shuffle-as-a-library to 100 TB or more, matching or exceeding the performance of monolithic shuffle systems.
- Implement a broad set of applications on top of our backend to easily take advantage of previous shuffle work.
2 Motivation

Distributed shuffle dates back to MapReduce [11] and earlier. And yet, two decades later, we continue to produce new shuffle designs and implementations. This is because end applications using distributed shuffle have continually evolving requirements in environment, hardware, and performance. Here, we overview two lines of previous work in building shuffle systems to illustrate the challenges in simultaneously achieving flexibility and performance.

2.1 Large-Scale Distributed Sort

One of the earliest benchmarks for distributed shuffle was distributed sort [28], which measures throughput in records/s on dataset sizes of 1 TB or more. Many efforts have gone towards scaling throughput with the dataset size, for which the main difficulty is maintaining I/O efficiency and fault tolerance. In a MapReduce operation with \( M \) map tasks and \( R \) reduce tasks, shuffle creates \( M \times R \) intermediate blocks. For example, a 100 TB dataset with 2 GB partitions would result in 250 million blocks of 40 KB each. Each of these must be moved across memory, disk, and network at least once. This creates two challenges: (1) I/O efficiency as the number of mappers and reducers increases and the block size decreases, and (2) fault tolerance as the size of the cluster and therefore the chance of a node failure increases.

Previous I/O optimizations fall under two general categories: (1) reducing the number of small and random I/O accesses by merging intermediate blocks into larger ones at various stages [6, 38, 52] (Figures 2b and 2c), and (2) using pipelining to overlap I/O with execution [16, 38]. For example, push-based shuffle [15, 42] involves pushing intermediate outputs directly from the mappers to the reducers, allowing network and disk I/O to be overlapped with map execution, and optionally merging results on the reducer (Figure 2c) to improve disk write efficiency [6, 38].

While these solutions can improve throughput, they also come with high development cost. Each new operation, such as reduce-side merge, requires building additional protocols for coordinating block management and recovery. Other innovations are designed to leverage properties of the underlying storage system, such as virtually infinite scale in the case of disaggregated storage. However, although the ideas may be system-agnostic, the physical artifacts are often tightly integrated with proprietary storage systems, making them difficult to port to open-source frameworks. For example, Cosco [6] is designed specifically to leverage disaggregated storage but the system is proprietary; meanwhile, Magnet [38] is open-sourced as part of Spark but has yet to support disaggregated storage.

Furthermore, large-scale shuffle systems often come with more complicated deployment models. Depending on the application size, the system may need to deploy external shuffle services [3], in addition to the map and reduce task executors. Shuffle services decouple block lifetimes from map executors to minimize interruptions upon executor failures [48], which are more frequent in large clusters. Today, shuffle services are also used to coordinate more sophisticated shuffle protocols, such as push-based shuffle and reduce-side merge [38]. However, because these shuffle services are only necessary at very large scale (TBs or more), they are not included by default in systems like Spark and require a separate deployment process.

Thus, while there has been significant innovation in new shuffle designs, few of these are widely deployed [6, 39, 52]. Furthermore, it is nontrivial for an application to choose on the fly whether to use a particular shuffle algorithm; it requires both a priori knowledge of the application scenario and potentially an entirely different system deployment.

2.2 Random Shuffle in ML Training Pipelines

While much of the existing shuffle literature has focused on large-scale batch processing, there is also a need for performant shuffle in other application scenarios, such as online aggregation [9] and pipelining with downstream applications. An example of the latter is the random shuffle operation commonly used in deep learning training jobs.

To improve model convergence in deep learning, it is common practice to randomly shuffle the training dataset before feeding into GPU trainers to avoid bias on the order of the data [21, 22]. To minimize GPU pauses, the shuffle should be pipelined with the training execution (Figure 2d). Furthermore, it is desirable for end users to be able to trade off between performance and accuracy: shuffling across a
smaller window of the dataset can hurt end model accuracy but may be faster overall.

These differences make it difficult for ML pipelines to directly leverage existing monolithic shuffle systems. Systems like Hadoop and Spark are highly optimized for global shuffle operations, but are not designed to pipeline the shuffle with downstream executions: shuffle results cannot be read until the full shuffle is complete [9]. The results must be written out to an external store before they can be read by the training workers (Figure 2di). However, this leads to either high memory footprint, as it requires holding an additional copy of the dataset, or higher I/O overhead, if the shuffled data is written to disk before transfer to the GPU.

Fine-grained pipelining can improve efficiency. Figure 2dii shows an example in which the reduce tasks for a particular epoch are pipelined with the training computation. This allows results to be used as they become available while limiting memory footprint to a single partition. Alternatively, the application can also choose to shuffle the dataset in windows (Figure 2diii), improving pipelining at the cost of accuracy. Unfortunately, existing shuffle systems are not built for such fine-grained pipelining, and most big data systems that offer high-performance shuffle use a fundamentally different execution model from deep learning systems [10]. Thus, ML frameworks re-implement shuffle in data loaders designed specifically for ML training. However, this rebuilding means wisdom from "traditional" shuffle systems (e.g., MapReduce [11]) is often lost. For example, today’s popular data loaders run into solved problems: they are limited to out-of-core shuffle, run into OOM errors if users try to shuffle large windows ($\S$5.2.2).

3 Shuffle with Distributed Futures

For distributed futures to serve as an intermediate abstraction layer for shuffle, they should: (1) abstract out the common implementation details of different shuffle implementations, (2) be general enough to allow heterogeneous end applications to interface with the shuffle library, and (3) provide the same performance and reliability as monolithic shuffle systems. This narrow waist for distributed shuffle would enable both faster development for new shuffle implementations and portability to new application use cases.

Monolithic shuffle systems use messaging primitives, like RPC, as an intermediate abstraction layer. RPC is both general-purpose and high-performance, but it is too low-level to act as a useful intermediate layer for shuffle. Integrating push-based shuffle into Spark, for example, required 1k+ LoC for the RPC layer changes alone [37]. Much of this development effort lies in implementing new inter-task protocols for data transfer and integrating them alongside existing ones.

In contrast, distributed futures decouple the shuffle control plane from the data plane. This abstraction enables different shuffle libraries to share a common data plane. Optimizations like push-based shuffle can be implemented in an order of magnitude less code as a result.

In this section, we show how to express previous shuffle optimizations and application-specific shuffle variants as application-level programs with the distributed futures API. These simplified examples capture the logical execution DAG of the shuffle. Section 4 describes the physical execution of these programs and the details in achieving performance parity with monolithic shuffle systems.

3.1 Distributed Futures API

A distributed futures program invoke methods, known as tasks, that execute and return data on a remote node. When calling a remote function, the caller receives a distributed future that represents the eventual return value. The future is “distributed” because the return value may be stored anywhere in the cluster, e.g., at the node where the task executes. This avoids copying return values back to the caller, which can become a bottleneck for large data.

The caller can make use of a distributed future in two ways. First, the caller can create a DAG by passing a distributed future as an argument to another task. The system ensures that the dependent task does not run until all of its arguments are computed. Note that the caller can specify such dependencies before the value is computed and that the caller need not see the physical values. This gives the system control over parallelism and data movement, e.g., pipelining task execution with dependency fetching for other tasks, and allows the caller to manipulate data larger than local memory. Second, the caller can get the value of a distributed future using a get call, which fetches the value to the caller’s local memory. This is useful when consuming the output of a shuffle, as it allows the caller to pipeline its own execution with the shuffle. The caller can additionally use a wait call, which fetches values asynchronously, to pipeline data transfer to the local node.

Next, we demonstrate how these APIs can be used to implement various shuffle optimizations (Fig 2) as application-level programs. For illustration purposes, we use the distributed futures API adopted by Ray [24], a distributed futures system for Python. The `@ray.remote` annotation designates remote functions, and the `.remote()` operator invokes tasks.

3.1.1 Simple Shuffle

In Listing 1, `simple_shuffle` shows a straightforward implementation of the MapReduce paradigm illustrated in Figure 2a. The shuffle routine takes a `map` function that returns a list of map outputs, and a `reduce` function that takes a list of map outputs and returns a reduced value. $M$ and $R$ are the numbers of map and reduce tasks respectively. The two statements produce the task graph shown in Figure 2a. Note that the `.remote()` calls are non-blocking, so the entire task graph can be submitted to the system without waiting for any one task to complete.

This is effectively pull-based shuffle, in which shuffle blocks are pulled from the map workers as reduce tasks progress.
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\[
\text{def simple_shuffle}(M, R, \text{map}, \text{reduce}): \\
\text{map_out} = [\text{map}.\text{remote}(m) \text{ for } m \text{ in range}(M)] \\
\text{return ray.get([} \\
\text{\quad \text{reduce}.\text{remote}(\text{map_out}[:,r]) \text{ for } r \text{ in range}(R)]
\]

\[
\text{def shuffle_riffle}(M, R, F, \text{map}, \text{reduce}, \text{merge}): \\
\text{map_out} = [\text{map}.\text{remote}(m) \text{ for } m \text{ in range}(M)] \\
\text{merge_out} = [ \\
\text{\quad \text{merge}.\text{remote}(\text{map_out}[:,i:F:(i+1)*F,:])} \\
\text{\quad \text{for } i \text{ in range}(M/F)]} \\
\text{return ray.get([} \\
\text{\quad \text{reduce}.\text{remote}(\text{merge_out}[:,r]) \text{ for } r \text{ in range}(R)]
\]

\[
\text{def shuffle_magnet}(M, R, F, \text{map}, \text{reduce}, \text{merge}): \\
\text{map_out} = [\text{map}.\text{remote}(m) \text{ for } m \text{ in range}(M)] \\
\text{merge_out} = [ \\
\text{\quad \text{merge}.\text{remote}(\text{map_out}[:,i:F:(i+1)*F,:], m)} \\
\text{\quad \text{for } i \text{ in range}(M/F)]} \\
\text{return ray.get([} \\
\text{\quad \text{reduce}.\text{remote}(\text{merge_out}[:,r]) \text{ for } r \text{ in range}(R)]
\]

Listing 1. Shuffle algorithms as distributed futures programs.

Assuming a fixed partition size, the total number of shuffle blocks grows quadratically with the total data size. Section 5.1 shows empirical evidence of this problem: as the number of shuffle blocks increases, the performance of the naive shuffle implementation drops due to decreased I/O efficiency. Prior work [6, 38, 52] have proposed solutions to this problem, which we study and compare next.

3.1.1 Pre-Shuffle Merge Riffle [52] is a specialized shuffle system built for Spark. Its key optimization is merging small map output blocks into larger blocks, thereby converting small, random disk I/O into large, sequential I/O before shuffling over the network to the reducers. The merging factor $F$ is either pre-configured, or dynamically decided based on a block size threshold. As soon as $F$ map tasks finish on an executor node, their output blocks ($F \times R$) are merged into $R$ blocks, each consisting of $F$ blocks of data from the map tasks. This strategy, illustrated in Figure 2b, is implemented in Listing 1 (shuffle_riffle). The code additionally takes $F$ as the merging factor, and a merge function which combines multiple map outputs into one.

Riffle’s key design choice is to merge map blocks \textit{locally} before they are pulled by the reducers, as shown in the highlighted lines. For simplicity, the code assumes that the first $F$ map tasks are scheduled on the first worker, the next $F$ map tasks on the second worker, etc. In reality, the locality can be determined using scheduling placement hints and/or runtime introspection (§4.3). Section 5.1 shows that this implementation of Riffle-style shuffle improves the job completion time over simple shuffle.

3.1.3 Push-based Shuffle Push-based shuffle (Fig 2c) is an optimization that pushes shuffle blocks to reducer nodes as soon as they are computed, rather than pulling blocks to the reducer when they are required. Magnet [38] is a specialized shuffle service for Spark that performs this optimization by merging intermediate blocks on the reducer node before the final reduce stage. This improves I/O efficiency and locality for the final reduce tasks. shuffle_magnet in Listing 1 implements this design.

3.2 Applications

Because Exoshuffle implements shuffle at the application level, it can easily interoperate with other applications. Here, we demonstrate two example applications that use fine-grained pipelining with shuffle to improve end-to-end performance, evaluated in Section 5.2.

3.2.1 Online Aggregation with Streaming Shuffle Online aggregation [17] is an interactive query processing mode where partial results are returned to the user as soon as some data is processed, and are refined as progress continues. This is especially useful when the query takes a long time to complete. Online aggregation is difficult to implement in MapReduce systems because they require all outputs to be materialized before being consumed. Past work made in-depth modifications to Hadoop and Spark to support online aggregation [9, 51].

\[
\text{def streaming_shuffle}(\text{map}, \text{reduce}, \text{print_aggregate}): \\
\text{reduce_states} = [\text{None}] * R \\
\text{for } \text{r in range}(N): \\
\text{\quad map_results} = [\text{map}.\text{remote}(m*\text{r}+i) \text{ for } i \text{ in range}(M)] \\
\text{\quad ray.wait(\text{reduce_states})} \\
\text{\quad reduce_states} = [ \\
\text{\quad\quad \text{reduce}.\text{remote}(\text{reduce_state}, \text{\*map_results}[:,\text{r}])} \\
\text{\quad\quad \text{for } \text{r}, \text{\textit{reduce_state} in enumerate(\text{reduce_states})}] \\
\text{\quad \text{print_aggregate}.\text{remote}(\text{reduce_states})} \\
\text{return ray.get(\text{reduce_states})}
\]

Listing 2. Streaming shuffle and pipelined data loading for ML.

Online aggregation is straightforward to implement in Exoshuffle without the need to modify the underlying distributed futures system. Listing 2 shows the streaming_shuffle routine. It requires a modified reduce function that takes a reducer state and a list of map outputs and returns an updated state, and an aggregate function which combines the reducer states to produce aggregate statistics. Shuffle is executed in rounds. At the end of each round, the aggregation function is invoked with the reducer outputs, and will asynchronously print an aggregate statistic (e.g. sum) to the user. Note that the Exoshuffle user can simply swap between simple_shuffle and streaming_shuffle to get the semantics they desire.

3.2.2 Distributed ML Training with Pipelined Shuffle Exoshuffle also enables fine-grained pipelining for ML
training, as illustrated in Figure 2d. In Listing 2, model_training shows the code skeleton. On L13, the shuffle function (could be any in Listing 1) returns a set of distributed futures pointing to reducer outputs. They are passed immediately to the model trainer while shuffle executes asynchronously. As soon as a reducer block becomes available, the model trainer acquires it (line 17) and send it to the GPU for training. This achieves the fine-grained pipelining described in Figure 2d.

4 System Architecture

Section 3 describes the logical execution of shuffle DAGs. However, the logical DAG alone is not sufficient to achieve good performance. In this section, we describe the architecture of Exoshuffle via a realistic implementation of the push-based shuffle described in Section 3.1.3. We describe the transparent features provided by the underlying distributed futures implementation (§4.2) and the additional APIs that shuffle libraries use to achieve better performance (§4.3).

4.1 Example: Push-based Shuffle

```python
def push_based_shuffle(map, reduce):
    @ray.remote
def merge(*map_results):
        for results in zip(*map_results):
            yield reduce(results)

merge_results = numpy.empty((NUM_WORKERS, NUM_MERGE_ROUNDS, NUM_REDUCE_WORKERS_PER_WORKER))
num_tasks_per_round = NUM_WORKERS \* MAP_PARALLELISM

# Map and shuffle stage.
for rnd in range(NUM_ROUNDS):
    # Schedule a round of map tasks.
    for i in range(num_tasks_per_round):
        map_results = [
            map.options(num_returns=NUM_WORKERS).remote(
                parts[rnd*num_tasks_per_round+i])
            for i in range(num_tasks_per_round)
        ]
    # Wait for the previous round of merge tasks to finish.
    if rnd > 0:
        ray.wait(merge_results[:, rnd-1, :])
    # Schedule a round of merge tasks.
    for w in range(NUM_WORKERS):
        merge_results[w, rnd, :] = merge.options(
            node=w, num_returns=NUM_REDUCE_WORKERS_PER_WORKER)
            .remote(map_results[:, w])
    # Delete intermediate results from this round.
    del map_results

# Reduce stage.
return [[
    reduce.remote(*merge_results[w, :, rnd])
    for rnd in range(NUM_REDUCE_WORKERS_PER_WORKER)]
    for w in range(NUM_WORKERS)].flatten()
```

Listing 3. Implementation of two-stage shuffle.

Listing 3 shows a realistic implementation of push-based shuffle (§3.1.3) for a cluster of NUM_WORKERS nodes. The library takes a map and a reduce function as input. The remaining constants are chosen by the library according to the user-specified number of input and output partitions.

L11–29 comprise the map and merge stage, in which map results are shuffled, pushed to the reducer nodes, and merged. This stage pipelines between CPU (map and merge tasks), network (to move data between map and merge), and disk (to write out merge results). The map and merge tasks are scheduled in rounds for pipelining: L21–22 ensures that there is at most one round of merge tasks executing, and that they can overlap with the following round’s map tasks. Each round submits one merge task per worker node. Each merge task takes in one intermediate result from each map task from the same round and returns as many merged results as there are reduce partitions on that node.

Once all map and merge tasks are complete, we schedule all reduce tasks (L32–35) and return the distributed future results. Each reduce task performs a final reduce on all merge results for its given partition. To minimize unnecessary data transfer, the reduce tasks should be co-located with the merge tasks whose results they read.

4.2 Transparent System Facilities

Distributed futures are first-class references that allow the system to transparently manage data movement on behalf of the shuffle library. For example, L27 of Listing 3 specifies that one column of the distributed futures in map_results should be sent to each merge task. The remote call to merge on L25–27 prompts the execution system to transfer the corresponding physical data to the merge task’s location. Here, we discuss the transparent storage and I/O mechanisms provided by the distributed futures system to facilitate this data movement.

4.2.1 Shared-Memory Object Store

Previous monolithic shuffle systems implement distributed coordination via an external shuffle service (ESS), a specialized process deployed to each node that orchestrates block transfers (Fig 3a). This process is external to the executors, decoupling block transfers from map and reduce task execution. In Exoshuffle, we replace this service with a generic NodeManager that is responsible for both in-memory and spilled objects (Fig 3b).

We build on Ray’s shared-memory object store [24]. Objects in the store are immutable. Each per-node block manager (NodeManager, Fig 3b) hosts a shared-memory object store shared by all executors on that node. This decouples executors from blocks: once a task’s outputs are stored in its local object store, the NodeManager becomes responsible for the block. This keeps executors stateless and allows them to execute other tasks or exit safely while the NodeManager coordinates block movement. Shared memory enables zero-copy reads of object data on the same node, which avoids CPU and memory overhead. By making data immutable, we also avoid consistency concerns between object copies.

For simplicity and generality, objects must be fully allocated into shared memory before being read or spilled. It
is not possible to stream a single large object as the argument or return value of a task. However, executing on very large objects is also undesirable as it can lead to high memory pressure on the executors and reduces opportunity for pipelining. To achieve streaming semantics, the application must instead break up the large logical object into smaller objects that can be read one at a time. Thus, the main challenges in managing the shared-memory object store for shuffle are: (1) handling metadata for these fine-grained objects, and (2) pipelining shared memory usage across concurrent and remote tasks. The following extensions to the original Ray architecture [24] address these challenges and are necessary to supporting high-performance shuffle.

4.2.2 Block Management The NodeManager must ensure sufficient memory for both arguments and return values of locally executing tasks, while minimizing pauses from I/O operations such as spilling or network transfer.

Object Allocation and Pipelined Fetching. There are two categories of object memory allocations: new objects created for task returns (e.g., map task outputs), and copies of objects fetched remotely as task arguments (e.g., reduce task inputs). The memory subsystem queues and prioritizes object allocations to ensure forward progress while keeping memory usage bounded to a limit. This is critical for reducing thrashing within the object store, caused by requesting objects for too many concurrent requests, while leaving sufficient heap memory for task executors.

All memory allocations on a Ray worker node go into an allocation queue for fulfillment. If there is spare memory, the allocation is fulfilled immediately. Otherwise, requests are queued until the spilling process or garbage collection frees up enough memory. If memory is still insufficient, Ray falls back to allocating task output objects on the filesystem to ensure liveness. Spare memory besides the memory allocated to executing task arguments and returns is used to fetch the arguments of queued tasks. This enables pipelining between execution and I/O, i.e. restoring objects from disk or fetching objects over the network. For example, at L33 in Listing 3, all merge results are already spilled to disk and all reduce tasks are submitted at once. While earlier reduce tasks execute, the system uses any spare memory to restore merge results for the next round of reduce tasks from disk.

Object Spilling. Object spilling is transparent, so the application need not specify if or when it should occur. When the memory allocation subsystem has backlogged requests, Ray’s spilling subsystem migrates referenced objects to disk to free up memory. When a spilled object’s data is required locally for a task, e.g., because it is the argument of a queued task, the NodeManager copies it back to memory as described above. When requested by a remote node, the spilled object is streamed directly from disk across the network to the remote NodeManager. To improve I/O efficiency, Ray coalesces small objects into larger files before writing to the filesystem.

4.2.3 Fault Tolerance Exoshuffle relies on lineage reconstruction for distributed futures to recover objects lost to node failures [45], a similar mechanism to previous shuffle systems [11, 49]. In Ray, the application driver stores the object lineage and resubmits tasks as needed upon failure. This process is transparent to Exoshuffle, which runs at the application level. Still, Exoshuffle can use object references (§4.3.1) to specify reconstruction or eviction for specific objects.

Executor process failures are much more common than node failures. If reconstruction is required each time an executor fails, it can impede progress [38, 48]. Many previous shuffle systems use an external shuffle service to ensure map output availability in the case of executor failures or garbage collection pauses. Similarly, in Exoshuffle, executor process failures do not result in the loss of objects, because the object store is run inside the NodeManager as a separate process.

More sophisticated shuffle systems require additional protocols such as deduplication to ensure fault tolerance [6]. Distributed futures prevent such inconsistencies because they require objects to be immutable, task dependencies to be fixed, and tasks to be idempotent.

To reduce the chance of data loss, some shuffle system uses on-disk [38] or in-memory [6] replication of intermediate blocks to guard against single node failures. In Ray, objects are spilled to disk and transferred to remote nodes where
they are needed, which also results in multiple copies as long as the object is in scope. The application can also disable this optimization by deleting its references to the object (Listing 3, L29). In the future, we could allow the application to more finely tune the number of replicas kept, e.g., by passing this as a parameter during task invocation.

4.3 Application Control

For complex applications like distributed shuffle, it is difficult for a general-purpose system to make optimal decisions in every context. For example, optimally scheduling a computation DAG on a set of nodes is NP-hard [8]. While the system can make good use of heuristics, it is more robust to allow the application or library developer to apply domain-specific knowledge to achieve better performance. We describe additional APIs designed to give the shuffle library more control over the physical execution of the shuffle DAG.

4.3.1 First-Class Object References

While first-class references give the system control over data movement, achieving high performance requires the shuffle library to be aware of best practices to reduce unnecessary data transfers and copies. We describe some of the key primitives Exoshuffle uses.

**Multiple Returns.** This API enables passing only a portion of a task’s output to a subsequent task, analogous to a function returning multiple values. It concisely expresses the 1-to-n dependency between shuffle map and reduce tasks, ensuring that each task receives only the input data it needs, avoiding unnecessary data transfer and copy. For example, L16 of Listing 3 specifies that each map task should return NUM_WORKERS values, so that each merge task needs to read a fraction of the map task’s output.

**Pipelining with Generators.** Pipelining can help reduce peak memory usage and overlap disk I/O with task execution. We extend Ray with remote generators to facilitate pipelining, inspired by Python generators [35]. For example, in L4-5 of Listing 3, the merge task yields merged results one at a time, one for each reduce partition that will be scheduled on the same node. This reduces memory pressure on the merge executor, as it only needs to hold one merged result in memory at a time, and enables pipelining between task execution and background operations such as spilling.

**Write Amplification vs. Recovery Efficiency.** Distributed futures are reference-counted in Ray. While a distributed future is still in scope, Ray attempts to ensure at least one object copy in the cluster. By selecting which references to keep or drop, the shuffle library can make tradeoffs between reducing write amplification and improving data redundancy. For example, L29 of Listing 3 deletes the intermediate map results from the current round. This reduces write amplification, as the map results can be immediately dropped from memory without spilling to disk, but requires additional re-execution upon failure. Alternatively, the shuffle library can instead keep the intermediate references, resulting in additional disk writes but improved redundancy.

4.3.2 Task Scheduling

High throughput in shuffle requires a high level of task parallelism and good load balancing to reduce stragglers. By default, Ray provides a two-level distributed scheduler that tries to balance between bin-packing vs. load-balancing [24]. This is sufficient for map and reduce tasks in simple shuffle, as these can be executed anywhere in the cluster. However, some shuffle strategies (§§3.1.2 and 3.1.3) require more careful placement to improve performance.

**Data Locality.** Like many other data processing systems, Ray provides automatic data locality-based scheduling. This can be useful for cases like the reduce stage in push-based shuffle (Listing 3, L33), in which the tasks should be scheduled near the results of their upstream merge tasks.

However, because a reduce task reads results from multiple merge tasks, we must colocate a group of merge tasks with their downstream reduce task. This is particularly challenging for a distributed futures scheduler to automate because the merge tasks need to be co-located with future reduce tasks that are not yet scheduled. To handle this problem, we introduce node-affinity scheduling in Ray, which allows the application to pin tasks to a particular node. For example, Listing 3 uses this in L26 to colocate merge tasks for the same reducer. Node affinity is soft, meaning that Ray will choose another suitable node if the specified node fails.

**Pipelining.** The map and merge tasks in Listing 3 should be pipelined to allow map results to be shuffled concurrently with map execution. This task-level pipelining is challenging for a distributed futures system to determine automatically. Too many concurrent map tasks will reduce resources available to downstream merge tasks, and scheduling the wrong set of map and merge tasks concurrently prevents map outputs from being consumed directly by merge tasks, resulting in unnecessary disk writes. The shuffle library is better placed to determine that it should apply backpressure by limiting the number of concurrent map and merge tasks. The library can also determine that a round of merge tasks should be executed concurrently with the following round of map tasks. Exoshuffle implements this task-level pipelining with the wait API (Listing 3, L22), which blocks until a distributed future is computed but does not fetch it.

**Runtime Introspection.** Runtime introspection enables the application to dynamically inspect execution information about objects. For example, Exoshuffle can use this API to return the data location(s) of a reference to preserve data locality in the early-merge optimizations proposed by Ripple (Listing 1, L6–12), by getting the locations of map results and merging colocated results. Another example is straggler mitigation via the wait API, which returns a list of tasks that do not complete within a timeout. By exposing information about which objects are still pending computation, the
shuffle library can detect stragglers and submit speculative tasks.

5 Evaluation

We study the following questions in the evaluation:
- Can Exoshuffle libraries achieve performance and scalability competitive with monolithic shuffle systems? (§5.1)
- What benefits does Exoshuffle provide for end applications such as online aggregation and ML training? (§5.2)
- How does the distributed futures implementation contribute to Exoshuffle performance? (§5.3)

5.1 Shuffle Performance

5.1.1 Setup We create test environments on AWS EC2 using VMs targeted at data warehouse use cases. For the HDD cluster, we use d3.2xlarge: 8 cores, 64 GiB RAM, 6× HDD, 1100 MiB/s aggregate sequential throughput, 18K aggregate IOPS, 6 Gbps networking, burstable to 15 Gbps. For the SSD cluster, we use i3.2xlarge: 8 cores, 61 GiB RAM, NVMe SSD, 720 MB/s throughput, 180K write IOPS, 2.5 Gbps networking, burstable to 10 Gbps.

Workload. We run the Sort Benchmark (a.k.a. TeraSort or CloudSort [36]), as it is a common benchmark for testing raw shuffle system performance. This benchmark requires sorting a synthetic dataset of configurable size, consisting of 100-byte records with 10-byte keys.

Baselines. We compare to (1) Spark and (2) a theoretical job completion time based on disk I/O. We run Spark 3.2.0 on Hadoop 3.3.1 and use the built-in shuffle as a baseline. We disable compression of map output files according to the rules of TeraSort. This also allows for a fair comparison in terms of total bytes of disk I/O. For the theoretical baseline, we assume disk I/O is the bottleneck since empirically we find that disk I/O takes longer than network I/O and CPU processing in this benchmark. The baseline is calculated by \( T = \frac{4D}{B} \), where \( D \) is the total data size and \( B \) is the aggregate disk bandwidth of the cluster. \( D \) is multiplied by 4 because each datum needs to be read twice and written twice, a theoretical minimum for external sort [32].

Exoshuffle variants. We run Exoshuffle on Ray 1.11.0. We compare implementations of the following shuffle libraries:
- ES-simple, the simple shuffle variant (§3.1.1).
- ES-merge, pull-based shuffle with pre-shuffle merge, similar to that in Riffle (§3.1.2).
- ES-push, push-based shuffle similar to Magnet (§3.1.3).
- ES-push*, push-based shuffle further optimized to reduce write amplification (§4.1).

5.1.2 HDD Performance Figure 4a shows the job completion times of Exoshuffle variants running 1 TB sort on 10 HDD nodes. ES-simple matches the performance of Spark when the number of partitions is small, but becomes slower as the number of partitions increases. This is due to the system overhead for managing the intermediate shuffle blocks, which grow quadratically in scale. The push-based shuffle variants (ES-push*, -push*) achieve better performance regardless of the number of partitions, thanks to the merging of shuffle blocks to increase disk I/O efficiency and the pipelining of disk and network I/O. ES-merge runs slower than -simple because merging the map output blocks incurs additional disk writes, which outweighs the I/O efficiency savings when the number of partitions is small, and only shows benefits when the number of partitions increases. The Spark baseline shows comparable performance. In summary, Exoshuffle libraries demonstrate performance benefits that match the characteristics of their monolithic counterparts.

5.1.3 SSD Performance. Figure 4b shows the same benchmark and variants running on the SSD cluster. All variants of Exoshuffle outperform the Spark baseline, and display similar trends as on the HDD cluster. The run times of the optimized versions of Exoshuffle are also close to the theoretical baseline. Since the NVMe SSD supports much higher random IOPS, the I/O efficiency gains are less pronounced.

However, these shuffle optimizations do not always provide benefits. Figure 4c shows that when data fits in memory, ES-simple is 20–70% faster than -push* on 80 partitions. This is because disk I/O is not an issue, and merging blocks incurs more overhead. ES-push* becomes faster on 200 or more partitions, because as the number of tasks increases, push-based shuffle execution is better pipelined than pull-based shuffle. This shows that the most performant shuffle algorithm depends on the data size, layout and hardware environment, and Exoshuffle offers the flexibility to choose the most suitable algorithm at the application level, without having to deploy multiple systems.

5.1.4 100 TB Sort Performance To test performance at large scale, we run the Sort Benchmark at 100 TB scale with 2 GB input partitions (50,000 partitions) on a cluster of 100× d3.2xlarge VMs. For Exoshuffle, we run the ES-push* variant since it is the most optimized for scale. For Spark, we run both the native shuffle and the push-based shuffle service (denoted as Spark-push), which was introduced in Spark 3.2.0 to improve performance and scalability. We run Spark with compression on because Spark without compression becomes unstable at this scale.

Figure 4d shows the results. Exoshuffle outperforms both native Spark shuffle and the push-based shuffle service, despite Spark’s compression reducing total bytes spilled by 40%. The push-based shuffle in Spark improves shuffle performance by 1.6× because it reduces random disk I/O. Exoshuffle further improves performance over push-based Spark by 1.8×. This difference comes from reduced write amplification in ES-push*, which spills only the merged map outputs, while Spark-push also spills the un-merged map outputs. These
additional writes provide faster failure recovery through improved durability, albeit at the cost of performance. Exoshuffle allows the application to choose between these tradeoffs by using ES-push vs. -push*.

5.1.5 Fault Tolerance To test fault recovery, we fail and restart a random worker node 30 seconds after the start of the run. This results in both executor failure and data loss, as the worker’s local object store is also lost. In all cases, we rely on the distributed futures system to re-execute any lost tasks and to reconstitute any lost objects. Lineage reconstruction (§4.2.3) minimizes interruption time during worker failures. Figures 4a and 4b show run times with failures indicated with semi-shaded bars. For ES-push and -push*, recovering from a worker failure adds 20–50 seconds to the job completion time. The system uses this time to detect node failures and re-execute tasks to reconstruct lost objects. For ES-simple and -merge, a known bug in Ray currently prevents fault recovery from completing.

5.1.6 Implementation Complexity Crucially, Exoshuffle enables expression of different shuffle algorithms as application level code. Table 1 compares the lines of code of several monolithic shuffle systems with the lines of code needed to implement the corresponding shuffle algorithms in Exoshuffle. Exoshuffle libraries may not provide all the production features of monolithic counterparts, but many shuffle optimizations can be implemented in Exoshuffle with an order of magnitude less code, and keeping the same performance benefits (§5.1). By offering shuffle as a library, Exoshuffle also allows applications to choose the best shuffle implementation at run time without deploying multiple systems.

5.2 Shuffle Applications

The previous results show that Exoshuffle can feasibly substitute for monolithic shuffle systems in traditional sort-based benchmarks. Next, we show how Exoshuffle can also extend distributed shuffle support for a broader set of applications.

5.2.1 Online Aggregation with Streaming Shuffle We use a 1 TB dataset containing 6 months of hourly page view statistics on Wikipedia. We run an aggregation to get the ranking of the top pages by language on 10× r6i.2xlarge nodes with data loaded from S3. Figure 5 shows the difference between regular and streaming shuffle. The streaming shuffle takes 1.4× longer to run in total due to the extra computation needed to produce partial results. However, with streaming shuffle, the user can get partial aggregation results within 8% error4 of the final result in 18 seconds, 22× faster than regular shuffle. Exoshuffle makes it easy to switch between simple_shuffle and streaming_shuffle to choose between partial result latency and total query run time.

5.2.2 Distributed ML Training We demonstrate Exoshuffle’s ability to support fine-grained pipelining for ML training, by using the Ludwig framework [23] to train a deep classification model TabNet on the HIGGS dataset (7.5 GB). Training this model efficiently requires randomly shuffling the data per epoch before sending it into the GPU, while maintaining high throughput.

We first run the ML training on a single g4dn.4xlarge node. We compare two versions of Ludwig: Ludwig 0.4.0 uses Petastorm [14], which prefetches data in batches into a per-process memory buffer and performs random shuffle in the buffer. This is a design employed by many ML data loading frameworks such as tf.data [27] and PyTorch [40]. Its problem is that the shuffle window size is tied to the memory buffer size. Setting it too large results in OOM errors. In comparison, Ludwig 0.4.1 uses Ray Data [41] built upon the Exoshuffle design. Ray Data pipelines data loading and shuffling with GPU training (Fig 2d), and supports full shuffle across loading batches by storing data in the shared-memory object store. Figure 8 shows that model 4Error is computed using the KL-divergence $D_{KL} = \sum p \log(p/\tilde{p})$ where $p$ is the true statistic and $\tilde{p}$ is the sample statistic.

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| Shuffle Algorithm       | System LoC | Exoshuffle LoC |
|-------------------------|------------|---------------|
| Simple (§3.1.1)         | 2600 (Spark1) | 215           |
| Pre-shuffle merge (§3.1.2) | 4000 (Riffle2) | 265           |
| Push-based shuffle (§3.1.3) with pipelining (§4.1) | 6700 (Magnet3*) | 256           |
|                         | –          | 256           |

Table 1. Approximate lines of code for implementing shuffle algorithms in Exoshuffle versus in specialized shuffle systems.
The Exoshuffle architecture requires high-performance com-
multithreading, multiple Dask executor threads share data
choose between multiprocessing and multithreading. With
stores objects in executor memory and requires the user to
multiple executor processes on the same node (§4.2.1). Dask
of distributed futures systems, but they differ in architec-
ture. Ray uses a shared-memory object store that decouples objects from
both distributed futures systems, but they differ in architec-
ture. Ray fuses objects into at least 100 MB files
Ray fuses objects into at least 100 MB files
Fusing Writes. Ray fuses objects into at least 100 MB files
Prefetching Task Arguments. Ray prefetches task arguments in a pipelined fashion so that arguments are local to a
worker by the time the task is assigned. Figure 7 shows that
pipelined fetching of task arguments reduces the run time by 60–80% when compared with fetching objects once the task is assigned.

5.3 System Microbenchmarks
The Exoshuffle architecture requires high-performance com-
components from the underlying dataplane system to deliver
good performance. In this section, we study the the impact of these components on shuffle performance.

5.3.1 Shared-Memory Object Store We study the effect of a shared-memory object store that decouples objects from
executors by comparing Dask and Ray. Dask and Ray are both distributed futures systems, but they differ in architecture. Ray uses a shared-memory object store that is shared by multiple executor processes on the same node (§4.2.1). Dask stores objects in executor memory and requires the user to choose between multiprocessing and multithreading. With multithreading, multiple Dask executor threads share data
in a heap-memory object store, but the Python Global Interpreter Lock can severely limit parallelism. Dask in multiprocessing mode avoids this issue but uses one object store per worker process, so objects must be copied between workers on the same node. Thus, the lack of a shared-memory object store results in either reduced parallelism (multithreading) or high overhead for sharing objects (multiprocessing). It is also less robust as objects are vulnerable to executor failures.

We study these differences by running the same Dask task graph on Dask and Ray backends [43]. Figure 6 shows DataFrames sort performance on a single node (32 vCPUs, 244 GB RAM, 100 partitions). For Dask, we vary the number of executor processes and threads to show the tradeoff between memory usage and parallelism. Dask-on-Ray requires no configuration and uses 32 executor processes, 1 per vCPU.

On small data sizes, Dask with multiprocessing achieves about the same performance as Dask-on-Ray, but it is 3x slower with multithreading due to reduced parallelism. On larger data sizes, Dask with multiprocessing fails due to high memory pressure from extra object copies. Meanwhile, Ray’s shared-memory object store enables better stability and lower run time on all data sizes.

5.3.2 Small I/O Mitigations Ray implements two system-level optimizations for mitigating the small I/O problem: fusioning writes of spilled objects to avoid small disk I/O, and prefetching task arguments to hide network and disk latency (§4.2.2). To show the impact of these optimizations, we run a single-node microbenchmark that creates 16 GB total objects in a 1 GB object store, forces them to spill to disk, then re-
stores the objects from disk. We use object sizes ranging from
100 KB to 1 MB, as these are comparable to the shuffle block
sizes. We use a sc1 HDD disk since the disk I/O bottleneck is more pronounced on slower storage.

Fusing Writes. Ray fuses objects into at least 100 MB files then writes them to disk. Figure 7 shows the total run time stays constant across object sizes with default fusing. When fusing is off, the run time is 25% slower for 1 MB objects, and up to 12x slower when spilling 100 KB objects.

Prefetching Task Arguments. Ray prefetches task arguments in a pipelined fashion so that arguments are local to a worker by the time the task is assigned. Figure 7 shows that pipelined fetching of task arguments reduces the run time by 60–80% when compared with fetching objects once the task is assigned.
6 Related Work

Shuffle in Data Processing Systems. Many solutions to shuffle have been proposed [15, 20, 31–33, 46] since MapReduce [11] and Hadoop [2], with a focus on optimizing disk I/O and pipelining. Sailfish [31] is a notable example deployed at Yahoo which depends on a modified filesystem to batch disk I/O. Many recent shuffle systems have been built in industry for large-scale use cases [5, 6, 38, 52], but few have been open-sourced. Finally, today’s cloud providers often offer managed shuffle services [1, 4, 39]. However these are tightly integrated with proprietary cloud data services and are not accessible by other shuffle applications.

Hardware Environments. Hardware typically poses a range of constraints on shuffle design. For example, compute and memory may be either disaggregated [6, 30, 52] or co-located [38, 48]. Disk constraints also affect system design, e.g., SSDs provide better random IOPS than HDDs but wear out more quickly. Many existing shuffle systems have been motivated by such hardware differences. In Exoshuffle, because the distributed futures API abstracts block management, a shuffle developer can plug in different storage backends and optimize shuffle at the application level.

Other Shuffle Applications. Machine learning research [21, 22] shows that SGD-based model training benefits from random shuffling of the training dataset. Both TensorFlow [27] and PyTorch [40] have built specialized systems designed specifically to pipeline data loading with ML training. These data loaders, in addition to Petastorm [14], support distributed data loading and random shuffling but shuffling is limited to a local buffer capped by worker memory (§5.2.2).

DataFrames [29, 34, 47] are another class of applications in data science that depend on shuffle for operations such as groupby. While systems like Dask [34] and Spark [50] provide distributed DataFrames, developers continue to build new engines that optimize for specific application scenarios, such as multicore [12] or out-of-core performance [7]. Most of these engines are limited to single-node shuffle.

Intermediate Abstractions for Shuffle. Ciel [26] is the first to propose using distributed futures to express iterative distributed dataflow programs, including MapReduce. However, its implementation does not include features critical to large-scale shuffle performance, including intra-node parallelism, in-memory object storage, and automatic garbage collection [25]. Dask [34] is a distributed dataframe engine. However it cannot support large-scale shuffle using the distributed futures abstraction due to limitations in its scheduler and the lack of a shared-memory object store (§5.3.1). Finally, while we build on Ray’s design, such as a shared-memory object store [24] and lineage reconstruction [45], these previous versions are not sufficient to support large-scale shuffle as they do not include spilling to disk or pipelining between execution and I/O. Thus, while others have implemented shuffle on distributed futures before, ours is the first that we know of to reach the scale, performance, and reliability of monolithic shuffle systems.

Serverless functions, as used in Locus [30], are one alternative to distributed futures. However, serverless functions abstract only remote execution, while distributed futures also abstract the location of a function’s return value. While Locus leverages an existing serverless cache and persistent storage, it still must manage block movement manually. In addition, the disaggregation of CPU, memory and disk makes it impossible to implement locality-related optimizations. In contrast, distributed futures abstract block management in full and manage execution, memory, and disk collectively on each node.

7 Discussion

Distributed Futures. Distributed futures are rising in popularity due to their ease of use and flexibility [24, 26, 44]. In general however, the question of flexibility versus performance remains. Large-scale shuffle is one of the most challenging problems in big data processing, inspiring years of work. By showing that large-scale shuffle is possible on a generic and flexible distributed futures system, we hope to show that it is possible for other applications too.

Limitations. The ability to specify arbitrary tasks and objects with distributed futures is the key to its flexibility, but it is also the primary obstacle to performance. The system assumes that each task is independent for generality and stores metadata separately for each task and object. In contrast, monolithic shuffle systems have semantic information and can share metadata for tasks and objects in the same stage. Currently metadata overhead is the main limitation to executing Exoshuffle at larger scales. We plan to address this in the future by “collapsing” shared metadata, e.g., keeping one metadata entry for all \( N \) outputs of a task.

Architecturally, the primary limitation in Exoshuffle is the fact that an object must be loaded in its entirety into the local object store before it can be read (§4.2.1). Generators (§4.3.1) allow tasks to “stream” large outputs by breaking them into many smaller physical objects; future improvements include the described metadata optimizations and/or introducing APIs to stream objects larger than the object store, similar to Ciel [26]. Another limitation is in scheduling. Currently the distributed futures system may require hints from the shuffle library to determine which tasks should be executed concurrently and where to place tasks (§4.3.2). A more sophisticated scheduler may be able to determine these automatically.

Finally, we note that Exoshuffle does not yet address the problem of building a single shuffle implementation that can meet the requirements of all end applications. Here, we focused on the problem of shuffle system evolvability, a necessary but insufficient step towards the overarching goal. To truly build a universal shuffle implementation would require automatically picking the best shuffle library based on application, environment, and run-time information.
8 Conclusion

There is a longstanding tension between performance and flexibility in designing abstractions for distributed computing. Monolithic shuffle systems sacrifice flexibility in the name of performance; they must essentially rebuild shuffle from scratch to handle varying application scenarios. In this work, we show that this need not be the case. By building shuffle as a library on top of a common high-performance dataplane, Exoshuffle makes it possible to build efficient, flexible, and portable shuffle.

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