Shuffling, Fast and Slow: Scalable Analytics on Serverless Infrastructure

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Abstract

Serverless computing is poised to fulfill the long-held promise of transparent elasticity and millisecond-level pricing. To achieve this goal, service providers impose a fine-grained computational model where every function has a maximum duration, a fixed amount of memory and no persistent local storage. We observe that the fine-grained elasticity of serverless is key to achieve high utilization for general computations such as analytics workloads, but that resource limits make it challenging to implement such applications as they need to move large amounts of data between functions that don't overlap in time. In this paper, we present Locus, a serverless analytics system that judiciously combines (1) cheap but slow storage with (2) fast but expensive storage, to achieve good performance while remaining cost-efficient. Locus applies a performance model to guide users in selecting the type and the amount of storage to achieve the desired cost-performance trade-off. We evaluate Locus on a number of analytics applications including TPC-DS, CloudSort, Big Data Benchmark and show that Locus can navigate the cost-performance trade-off, leading to 4×-500× performance improvements over slow storage-only baseline and reducing resource usage by up to 59% while achieving comparable performance with running Apache Spark on a cluster of virtual machines, and within 2× slower compared to Redshift.

1 Introduction

The past decade has seen the widespread adoption of cloud computing infrastructure where users launch virtual machines on demand to deploy services on a provisioned cluster. As cloud computing continues to evolve towards more elasticity, there is a shift to using *serverless* computing, where storage and compute is separated for both resource provisioning and billing. This trend was started by services like Google BigQuery [9], and AWS Glue [22] that provide cluster-free data warehouse analytics, followed by services like Amazon Athena[5] that allow users to perform interactive queries against a remote object storage without provisioning a compute cluster. While the aforementioned services mostly focus on providing SQL-like analytics, to meet the growing demand, all major cloud providers now offer "general" serverless computing platforms, such as AWS Lambda, Google Cloud Functions, Azure Functions and IBM OpenWhisk. In these platforms short-lived user-defined functions are scheduled and executed in the cloud. Compared to virtual machines, this model provides more fine-grained elasticity with sub-second start-up times, so that workload requirements can be dynamically matched with continuous scaling.

Fine-grained elasticity in serverless platforms is naturally useful for on-demand applications like creating image thumbnails [18] or processing streaming events [26]. However, we observe such elasticity also plays an important role for data analytics workloads. Consider for example an ad-hoc data analysis job exemplified by say TPC-DS query 95 [34] (See section 5 for more details). This query consists of eight stages and the amount of input data at each stage varies from 0.8MB to 66GB. With a cluster of virtual machines users would need to size the cluster to handle the largest stage leaving resources idle during other stages. Using a serverless platform can improve resource utilization as resources can be immediately released after use.

However, directly using a serverless platform for data analytics workloads could lead to extremely inefficient execution. For example we find that running the CloudSort benchmark [40] with 100TB of data on AWS Lambda, can be up to 500× slower (Section 2.3) when compared to running on a cluster of VMs. By breaking down the overheads we find that the main reason for the slowdown comes from slow data shuffle between asynchronous function invocations. As the ephemeral, stateless compute units lack any local storage, and as direct transfers between functions is not always feasible[1], intermediate data between stages needs to be persisted on shared storage systems like Amazon S3. The characteristics of the storage medium can have a significant impact on performance and cost. For example, a shuffle from 1000 map tasks to 1000 reduce tasks leads to 1M data blocks being created on the storage system. Therefore, throughput limits of object stores like Amazon S3 can lead to significant slow downs (Section 2.3).

Our key observation is that in addition to using elastic compute and object storage systems we can also provision *fast* memory-based resources in the cloud, such as in-memory Redis or Memcached clusters. While naively putting all data in fast storage is cost prohibitive, we can appropriately combine fast, but expensive storage with slower but cheaper storage, similar to the memory and disk hierarchy on a local machine, to achieve the best of both worlds: approach the performance of a pure in-memory execution at a significantly lower cost. However, achieving such a sweet spot is not trivial as it depends on a variety of configuration parameters, including storage type and size, degree of task parallelism, and the memory size of each serverless func-

[1] Cloud providers typically provide no guarantees on concurrent execution of workers.

tion. This is further exacerbated by the various performance limits imposed in a serverless environment (Section 2.4).

In this paper we propose Locus, a serverless analytics system that combines multiple storage types to achieve better performance and resource efficiency. In Locus, we build a performance model to aid users in selecting the appropriate storage mechanism, as well as the amount of fast storage and parallelism to use for map-reduce like jobs in serverless environments. Our model captures the performance and cost metrics of various cloud storage systems and we show how we can combine different storage systems to construct hybrid shuffle methods. Using simple micro-benchmarks, we model the performance variations of storage systems as other variables like serverless function memory and parallelism change.

We evaluate Locus on a number of analytics applications including TPC-DS, Daytona CloudSort and the Big Data Benchmark. We show that using fine-grained elasticity, Locus can reduce cluster time in terms of total core·seconds by up to 59% while being close to or beating Spark's query completion time by up to 2×. We also show that with a small amount of fast storage, for example, with fast storage just large enough to hold 5% of total shuffle data, Locus matches Apache Spark in running time on CloudSort benchmark and is within 13% of the cost of the winning entry in 2016. While we find Locus to be 2× slower when compared to Amazon Redshift, Locus is still a preferable choice to Redshift since it requires no provisioning time (vs. minutes to setup a Redshift cluster) or knowing an optimal cluster size beforehand. Finally, we also show that our model is able to accurately predict shuffle performance and cost with an average error of 15.9% and 14.8%, respectively, which allows Locus to choose the most appropriate shuffle implementation and other configuration variables.

In summary, the main contributions of this paper are:

- We study the problem of executing general purpose data analytics on serverless platforms to exploit fine-grained elasticity and identify the need for efficient shuffles.
- We show how using a small amount of memory-based fast storage can lead to significant benefits in performance while remaining cost effective.
- To aid users in selecting the appropriate storage mechanism, We propose Locus, a performance model that captures the performance and cost metrics of shuffle operations.
- Using extensive evaluation on TPC-DS, CloudSort and Big Data Benchmark we show that our performance model is accurate and can lead to 4×-500× performance improvements over baseline and up to 59% cost reduction compared to traditional VM deployments, and within 2× slower compared to Redshift.

2 Background

We first present a brief overview of serverless computing and compare it with the traditional VM-based instances. Next we discuss how analytics queries are implemented on serverless infrastructure and present some of the challenges in executing large scale shuffles.

2.1 Serverless Computing: What fits?

Recently, cloud providers and open source projects [25, 32] have proposed services that execute *functions* in the cloud or providing Functions-as-a-Service. As of now, these functions are subject to stringent resource limits. For example, AWS Lambda currently imposes a 5 minute limit on function duration and 3GB memory limit. Functions are also assumed to be *stateless* and are only allocated 512MB of ephemeral storage. Similar limits are applied by other providers such as Google Cloud Functions and Azure Functions. Regardless of such limitations, these offerings are popular among users for two main reasons: ease of deployment and flexible resource allocation. When deploying a cluster of virtual machines, users need to choose the instance type, number of instances, and make sure these instances are shutdown when the computation finishes. In contrast, serverless offerings have a much simpler deployment model where the functions are automatically triggered based on events, e.g., arrival of new data.

Furthermore, due to their lightweight nature, containers used for serverless deployment can often be launched within seconds and thus are easier to scale up or scale down when compared to VMs. The benefits of elasticity are especially pronounced for workloads where the number of cores required varies across time. While this naturally happens for event-driven workloads for example where say users upload a photo to a service that needs to be compressed and stored, we find that elasticity is also important for *data analytics* workloads. In particular, user-facing ad-hoc queries or exploratory analytics workloads are often unpredictable yet have more stringent responsiveness requirements, making it more difficult to provision a traditional cluster compared to recurring production workloads.

We present two common scenarios that highlight the importance of elasticitiy. First, consider a stage of tasks being run as a part of an analytics workload. As most frameworks use a BSP model [15, 44] the stage completes only when the last task completes. As the same VMs are used across stages, the cores where tasks have finished are idle while the slowest tasks or stragglers complete [3]. In comparison, with a serverless model, the cores are immediately relinquished when a task completes. This shows the importance of elasticity *within* a stage. Second, elasticity is also important *across* stages: if we consider say consider TPC-DS query 95 (details in 5), the query consists of 8 stages with input data per stage

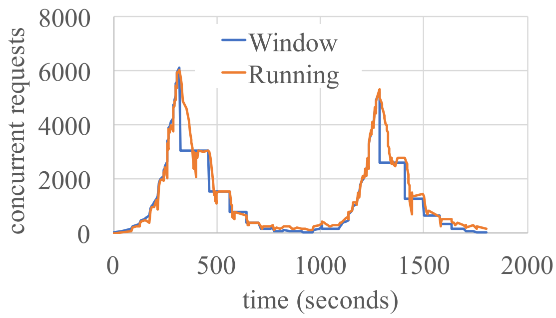


Figure 1: **S3 rate limiting in action. We use a TCP-like additive-increase/multiplicative-decrease (AIMD) algorithm to probe the number of concurrent requests S3 can support for reading 10KB objects. We see that S3 not only enforces a rate ceiling, but also continues to fail requests after the rate is reduced for a period of time. The specific rate ceiling can change over time due to S3's automatic data-partition scaling.**

varying from 0.8Mb to 66Gb. With such a large variance in data size, being able to adjust the number of cores used at every stage leads to better utilization compared to traditional VM model.

2.2 Analytics on serverless: Challenges

To execute analytics queries on a serverless infrastructure we assume the following system model. A driver process, running on user's machine, "compiles" the query into a multi-stage DAG, and then submits each task to the cloud service provider. A task is executed as one function invocation by the serverless infrastructure. Tasks in consecutive stages exchange data via a variety of communication primitives, such as shuffle and broadcast [11]. Each task typically consists of three phases: read, compute, and write [33]. We next discuss why the communication between stages i.e., the shuffle stage presents the biggest challenge.

Input, Output: Similar to existing frameworks, each task running as a function on a serverless infrastructure reads the input from a shared storage system, such as S3. However, unlike existing frameworks, functions are not co-located with the storage, hence there is no data *locality* in this model. Fortunately, as prior work has shown, the bandwidth available between functions and the shared storage system is comparable to the disk bandwidths [1], and thus we typically do not see any significant performance degradation in this step.

Compute: With serverless computing platforms, each function invocation is put on a new container with a virtualized compute core. Regardless of the hardware heterogeneity, recent works have shown that the almost linear scaling of serverless compute is ideal for supporting embarrassingly parallel workloads [16, 18].

Shuffle: The most commonly used communication pattern to transfer data across stages is the shuffle operation. The map stage partitions data according to the number of reducers and each reducer reads the corresponding data partitions from the all the mappers. Given M mappers and R reducers we will have $M * R$ intermediate data partitions. Unfortunately, the time and resource limitations imposed by the serverless infrastructures make the implementation of the shuffle operation highly challenging.

A direct approach to implementing shuffles would be to open connections between serverless workers [18] and transfer data directly between them. However, there are two limitations that prevent this approach. First cloud providers do not provide any guarantees on when functions are executed and hence the sender and receiver workers might not be executing at the same time. Second, even if the sender and receiver overlap, given the execution time limit, there might not be enough time to transfer all the necessary data.

A natural approach to transferring data between ephemeral workers is to store intermediate data in a persistent storage system. We illustrate challenges for this approach with a distributed sorting example.

2.3 Scaling Shuffle: CloudSort Example

The main challenge in executing shuffles in a serverless environment is handling the large number of intermediate files being generated. As discussed before, functions have stringent resource limitations and this effectively limits the amount of data a function can process in one task. For example to sort 100TB, we will need to create a large number of map partitions, as well as a large number of reduce partitions, such that the inputs to the tasks can be less than the memory footprint of a function. Assuming 1GB partitions, we have 10^5 partitions on both the map side and the reduce side. For implementing a hash-based shuffle one intermediate file is created for each (mapper, reducer) pair. In this case we will have a total of 10^{10}, or *10 billion* intermediate files! Even with traditional cluster-based deployment, shuffling 10 billion files is quite challenging, as it requires careful optimization to achieve high network utilization [31]. Unfortunately, none of the storage systems offered by existing cloud providers meets the performance requirements, while also being cost-effective. We next survey two widely available storage systems classes and discuss their characteristics.

2.4 Cloud Storage Systems Comparison

To support the diverse set of cloud applications, cloud providers offer a number of storage systems each with different characteristics in terms of latency, throughput, storage capacity and elasticity. Just as within a single machine, where we have a storage hierarchy of cache, memory and disk, each with different performance and cost points, we observe that a similar hierarchy can be applied to cloud storage systems. We next categorize two major storage system classes.

Slow Storage: All the popular cloud providers offer support for scalable and elastic blob storage. Examples of such systems include Amazon S3, Google Cloud Storage, Azure Blob Store. However, these storage systems are not designed to support high throughput on reading and writing small files. In fact, all major public cloud providers impose a global transaction limit on shared object stores [37, 7, 20]. This should come as no surprise, as starting with the Google File System [21], the majority of large scale storage systems have been optimized for reading and writing large chunks of data, rather than for high-throughput fine-grained operations.

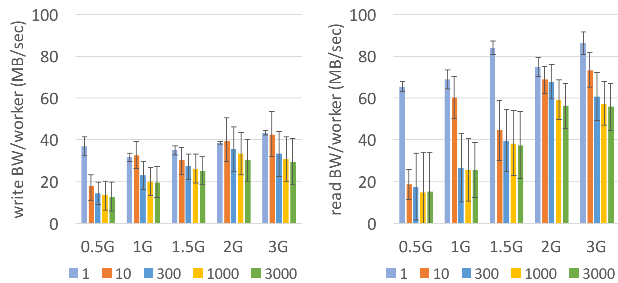
We investigated the maximum throughput that one can achieve on Amazon S3 and found that though the throughput can be improved as the number of buckets increases, the cloud provider throttles requests when the aggregate throughput reaches a few thousands of requests/sec (see Figure 1). Assuming a throughput of 10K operations per second, this means that reading and writing all the files generated by our CloudSort example could take around 2M seconds, or 500× slower than the current record [42]. Not only is the performance very low, but the cost is prohibitive as well. While the cost per write request is as low as \$0.005 per 1,000 requests for all three aforementioned cloud providers, shuffling 10^{10} files would cost \$5,000 alone for write requests. Thus, supporting large shuffles requires a more efficient and economic solution for storing intermediate data.

Fast Storage: One approach to overcome the performance limitations of the slow storage systems is to use much faster storage, if available. Examples of faster storage are in-memory storage systems backed by Memcached or Redis. Such storage systems support much higher request rates (more than 100,000 requests/sec per shard), and efficiently handle objects as small as a few tens of bytes. On the flip side, these systems are typically much more expensive than large-scale blob storage systems. For example to store 1GB of data for an hour, it costs 0.00319 cents in AWS S3 while it costs 2.344 cents if we use a managed Redis service such as AWS ElastiCache, which makes it 733× more expensive![2]

Given the cost-performance trade-off between slow (e.g., S3) and fast (e.g., ElastiCache) storage, in the following sections we show that by judiciously combining these two types of storage systems, we can achieve a cost-performance sweet spot in a serverless deployment that is comparable, and sometimes superior to cluster-based deployments.

3 Design

In this section we outline a performance model that can be used to guide the design of an efficient and cost-effective shuffle operations. We start with outlining our system model, and then discuss how different variables like worker memory size, degree of parallelism, and the type of storage system affect the performance characteristics of the shuffle operation.



(a) **write** (b) **read**

Figure 2: **S3 bandwidth per worker with varying concurrency (1 to 3000) and Lambda worker size (0.5G to 3G).**

Table 1: **Measured throughput (requests/sec) limit for a single S3 bucket and a single Redis shard.**

object size	10KB	100KB	1M	10M	100M
S3	5986	4400	3210	1729	1105
Redis	116181	11923	1201	120	12

3.1 System Model

We first develop a high level system model that can be used to compare different approaches to shuffle and abstract away details specific to cloud providers. We denote the function-as-a-service module as *compute cores* or *workers* for tasks. Each function invocation, or a worker, is denoted to run with a single core and w bytes of memory (or the worker memory size). The degree of the parallelism represents the number of function invocations or workers that execute in parallel, which we denote by p. The total amount of data being shuffled is S bytes. Thus, the number of workers required in the map and reduce phase is at least $\frac{S}{w}$ leading to a total of $(\frac{S}{w})^2$ requests for a full shuffle.

We next denote the bandwidth available to access a storage service by an individual worker as b bytes/sec. We assume that the bandwidth provided by the elastic storage services scale as we add more workers (we discuss how to handle cases where this is not true below). Finally, we assume each storage service limits the aggregate number of requests/sec: we denote by q_s and q_f for the slow and the fast storage systems, respectively.

To measure the cost of each approach we denote the cost of a worker function as c_l \$/sec/byte, the cost of fast storage as c_f \$/sec/byte. The cost of slow storage has two parts, one for storage as c_s \$/sec/byte, and one for access, denoted as c_a \$/op. We assume that both the inputs and the outputs of the shuffle are stored on the slow storage. In most cases in practice, c_s is negligible during execution of a job. We find the

[2]We note that ElastiCache is not "serverless", and there is no serverless cache service yet as of writing this paper and users need to provision cache instances. However, we envision that similar to existing storage and compute, fast storage as a resource (possibly backed by memory) will also become elastic in the future. There are already several proposals to provide disaggregated memory across datacenters [19] to support this.

Table 2: **Cloud storage cost from major providers (Feb 2019).**

	Service	\$/Mo/GB	\$/million writes
Slow	AWS S3	0.023	5
	GCS	0.026	5
	Azure Blob	0.023	6.25
Fast	ElastiCache	7.9	-
	Memorystore	16.5	-
	Azure Cache	11.6	-

above cost characteristics apply to all major cloud platforms (AWS, Google Cloud and Azure), as shown in Table 2.

Among the above, we assume the shuffle size (S) is given as an input to the model, while the worker memory size (w), the degree of parallelism (p), and the amount of fast storage (r) are the model knobs we vary. To determine the characteristics of the storage systems (e.g., b, q_s, q_f), we use offline benchmarking. We first discuss how these storage performance characteristics vary as a function of our variables.

3.2 Storage Characteristics

The main storage characteristics that affect performance are unsurprisingly the read and write **throughput** (in terms of requests/sec, or often referred as IOPS) and **bandwidth** (in terms of bytes/sec). However, we find that these values are not stable as we change the degree of parallelism and worker memory size. In Figure 2 we measure how a function's bandwidth (b) to a large-scale store (i.e., Amazon S3, the slow storage service in our case) varies as we change the degree of parallelism (p) and the worker memory size (w). From the figure we can see that as we increase the parallelism both read and write bandwidths could vary by 2-3×. Further we see that as we increase the worker memory size the bandwidth available increases but that the increase is sub-linear. For example with 60 workers each having 0.5G of memory, the write bandwidth is around 18 MB/s per worker or 1080 MB/s in aggregate. If we instead use 10 workers each having 3GB of memory, the write bandwidth is only around 40 MB/s per worker leading to 400 MB/s in aggregate.

Using a large number of small workers is not always ideal as it could lead to an increase in the number of small I/O requests. Table 1 shows the throughput we get as we vary the object size. As expected, we see that using smaller object sizes means that we get a lower aggregate bandwidth (multiplying object size by transaction throughput). Thus, jointly managing worker memory size and parallelism poses a challenging trade-off.

For fast storage systems we typically find that throughput is not a bottleneck for object sizes > 10 KB and that we saturate the storage bandwidth. Hence, as shown in Table 1 the operation throughput decreases linearly as the object size increases. While we can estimate the bandwidth available for fast storage systems using an approach similar to the one used for slow storage systems, the current deployment method where we are allocating servers for running Memcached / Redis allows us to ensure they are not a bottleneck.

Table 3: **Comparison of time taken by different shuffle methods. S refers to the shuffle data size, w to the worker memory size, p the number of workers, q_s the throughput to slow storage, q_f throughput to fast storage b network bandwidth from each worker.**

storage type	shuffle time
slow	$2 \times max(\frac{S^2}{w^2 \times q_s}, \frac{S}{b \times p})$
fast	$2 \times max(\frac{S^2}{w^2 \times q_f}, \frac{S}{b_{eff}})$, where $b_{eff} = min(b_f, b \times p)$
hybrid	$\frac{S}{r} T_{rnd} + T_{mrg}$, where $T_{rnd} = 2 \times max(T_{fb}, T_{sb}, T_{sq})$ $T_{mrg} = 2 \times max((\frac{Sw}{r})^2 T_{sq}, \frac{S}{r} T_{sb})$ $T_{fb} = \frac{r}{b_{eff}}$, $T_{sb} = \frac{r}{b \times p}$ $T_{sq} = \frac{r^2}{w^2 \times q_s}$

3.3 Shuffle Cost Models

We next outline performance models for three shuffle scenarios: using (1) slow storage only, (2) fast storage only, and (3) a combination of fast and slow storage.

Slow storage based shuffle. The first model we develop is using slow storage only to perform the shuffle operation. As we discussed in the previous section there are two limits that the slow storage systems impose: an operation throughput limit (q_s) and a bandwidth limit (b). Given that we need to perform $(\frac{S}{w})^2$ requests with an overall operation throughput of q_s, we can derive T_q, the time it takes to complete these requests is $T_q = \frac{S^2}{w^2 \times q_s}$, assuming q_s is the bottleneck. Similarly, given the per-worker bandwidth limit to storage, b, the time to complete all requests assuming b is bottleneck is $T_b = \frac{S}{b \times p}$. Considering both potential bottlenecks, the time it takes to write/read all the data to/from intermediate storage is thus $\max(T_q, T_b)$. Note that this time already includes reading data from input storage or writing data to output storage, since they can be pipelined with reading/writing to intermediate storage. Finally, the shuffle needs to first write data to storage and then read it back. Hence the total shuffle time is $T_{shuf} = 2 \times \max(T_q, T_b)$.

Table 4 shows our estimated running time and cost as we vary the worker memory and data size.

Fast storage based-shuffle. Here we develop a simple performance model for fast storage that incorporates the throughput and bandwidth limits. In practice we need to make one modification to factor in today's deployment model for fast storage systems. Since services like ElastiCache are deployed by choosing a fixed number of instances, each having some fixed amount of memory, the aggregate bandwidth of the fast storage system could be a significant bottleneck, if we are not careful. For example, if we had

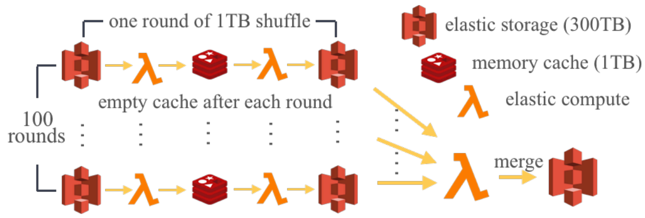


Figure 3: **Illustration for hybrid shuffle.**

Table 4: **Projected sort time and cost with varying worker memory size. Smaller worker memory results in higher parallelism, but also a larger numbers files to shuffle.**

worker mem(GB)	0.25	0.5	1	1.25	1.5
20GB time(s)	36	45	50	63	72
20GB cost($)	0.02	0.03	0.03	0.04	0.05
200GB time(s)	305	92	50	63	75
200GB cost($)	0.24	0.30	0.33	0.42	0.51
1TB time(s)	6368	1859	558	382	281
1TB cost($)	1.22	1.58	1.70	2.12	2.54

just one ElastiCache instance with 10Gbps NIC and 50G of memory, the aggregate bandwidth is trivially limited to 10Gbps. In order to model this aspect, we extend our formulation to include b_f, which is the server-side bandwidth limit for fast storage. We calculate the effective bandwidth as $b_{eff} = \min(b \times p, b_f)$.

Using the above effective bandwidth we can derive the time taken due to throughput and bandwidth limits as $T_q = \frac{S^2}{w^2 \times q_f}$ and $T_b = \frac{S}{b_{eff}}$, respectively. Similar to the previous scenario, the total shuffle time is then $T_{shuf} = 2 \times max(T_q, T_b)$.

One interesting scenario in this case is that as long as the fast storage bandwidth is a bottleneck (i.e. $b_f < b \times p$), using more fast memory improves not only the performance, but also reduces the cost! Assume the amount of fast storage is r. This translates to a cost of $p * c_l * T_{shuf} + r * c_f * T_{shuf}$, with slow storage request cost excluded. Now, assume we double the memory capacity to $2 \times r$, which will also result in doubling the bandwidth, i.e., $2 \times b_f$. Assuming that operation throughput is not the bottleneck, the shuffle operations takes now $\frac{S}{2b_f} = \frac{T_{shuf}}{2}$, while the cost becomes $p * c_l * \frac{T_{shuf}}{2} + 2 * r * c_f * \frac{T_{shuf}}{2}$. This does not include reduction in request cost for slow storage. Thus, while the cost for fast storage (second term) remains constant, the cost for compute cores drops by a factor of 2. In other words, the overall running time has improved by a factor of 2 while the cost has decreased.

However, as the amount of shuffle data grows, the cost of storing all the intermediate data in fast storage becomes prohibitive. We next look at the design of a hybrid shuffle method that can scale to much larger data sizes.

3.4 Hybrid Shuffle

We propose a hybrid shuffle method that combines the inexpensive slow storage with the high throughput of fast storage to reach a better cost-performance trade-off. We find that even with a small fast storage, e.g., less than $\frac{1}{20}$th of total shuffle data, our hybrid shuffle can outperform slow storage based shuffle by orders of magnitude.

To do that, we introduce a multi-round shuffle that uses fast storage for intermediate data within a round, and uses slow storage to merge intermediate data across rounds. In each round we range-partition the data into a number of buckets in fast storage and then combine the partitioned ranges using the slow storage. We reuse the same range partitioner across rounds. In this way, we can use a merge stage at the end to combine results across all rounds, as illustrated in Figure 3. For example, a 100 TB sort can be broken down to 100 rounds of 1TB sort, or 10 rounds of 10TB sort.

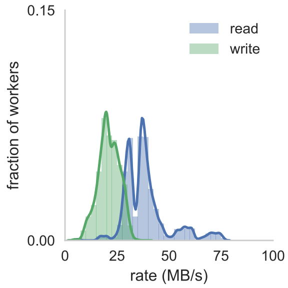
Correspondingly the cost model for the hybrid shuffle can be broken down into two parts: the cost per round and the cost for the merge. The size of each round is fixed at r, the amount of space available on fast storage. In each round we perform two stages of computation, partition and combine. In the partition stage, we read input data from the slow storage and write to the fast storage, while in the combine stage we read from the fast storage and write to the slow storage. The time taken by one stage is then the maximum between the corresponding durations of the stage when the bottleneck is driven either by (1) the fast storage bandwidth $T_{fb} = \frac{r}{b_{eff}}$, (2) the slow storage bandwidth $T_{sb} = r/(b * p)$, or (3) the slow storage operation throughput $T_{sq} = \frac{r^2}{w^2 \times q_s}$[3]. Thus, the time per-round is $T_{rnd} = 2 * max(T_{fb}, T_{sb}, T_{sq})$.

The overall shuffle consists of $\frac{S}{r}$ such rounds and a final merge phase where we read data from the slow storage, merge it, and write it back to the slow storage. The time of the merge phase can be similarly broken down into throughput limit $T_{mq} = (\frac{Sw}{r})^2 * T_{sq}$ and bandwidth limit $T_{mb} = \frac{S}{r} * T_{sb}$, where T_{sb} and T_{sq} follows from the definitions from previous paragraph. Thus, $T_{mrg} = 2 * max(T_{mq}, T_{mb})$, and the total shuffle time is $\frac{S}{r} * T_{rnd} + T_{mrg}$.

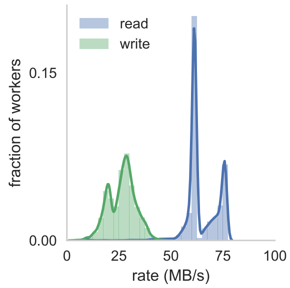
How to pick the right fast storage size? Selecting the appropriate fast storage/memory size is crucial to obtaining good performance with the hybrid shuffle. Our performance model aims to determine the optimal memory size by using two limits to guide the search. First, provisioning fast storage does not help when slow storage bandwidth becomes bottleneck, which provides an upper bound on fast storage size. Second, since the final stage needs to read outputs from all prior rounds to perform the merge, the operation throughput of the slow storage provides an upper bound on the number of rounds, thus a lower bound of the fast storage size.

Pipelining across stages An additional optimization we perform to speed up round execution and reduce cost is to pipeline across partition stage and combine stage. As shown in Figure 3, for each round, we launch partition tasks to read

[3] We ignore the fast storage throughput, as we rarely find it to be bottleneck. We could easily include it in our model, if needed.



(a) **500MB workers**



(b) **3GB workers**

Figure 4: **Lambda to S3 bandwidth distribution exhibits high variance. A major source of stragglers.**

input data, partition them and write out intermediate files to the fast storage. Next, we launch combine tasks that read files from the fast storage. After each round, the fast storage can be cleared to be used for next round.

With pipelining, we can have partition tasks and combine tasks running in parallel. While the partition tasks are writing to fast storage via `append()`, the merge tasks read out files periodically and perform atomic delete-after-read operations to free space. Most modern key-value stores, e.g., Redis, support operations such as append and atomic delete-after-read. Pipelining gives two benefits: (1) it overlaps the execution of the two phases thus speeding up the in-round sort, and (2) it allows a larger round size without needing to store the entire round in memory. Pipelining does have a drawback. Since we now remove synchronization boundary between rounds, and use `append()` instead of setting a new key for each intermediate data, we cannot apply speculative execution to mitigate stragglers, nor can we obtain task-level fault tolerance. Therefore, pipelining is more suitable for smaller shuffles.

3.5 Modeling Stragglers

The prior sections provided several basic models to estimate the time taken by a shuffle operation in a serverless environment. However, these basic models assume all tasks have uniform performance, thus failing to account for the presence of stragglers.

The main source of stragglers for the shuffle tasks we consider in this paper are network stragglers, that are caused by slow I/O to object store. Network stragglers are inherent given the aggressive storage sharing implied by the serverless architecture. While some containers (workers) might get better bandwidth than running reserved instances, some containers get between 4-8× lower bandwidth, as shown in Figure 4. To model the straggler mitigation scheme described above we initialize our model with the network bandwidth CDFs as shown in Figure 4. To determine running time of each stage we then use an execution simulator [33] and sample network bandwidths for each container from the CDFs.

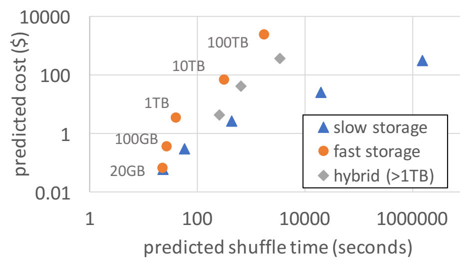


Figure 5: **Predicted time and cost for different sort implementations and sizes.**

Furthermore, our modeling is done for each worker memory size, since bandwidth CDFs vary across worker sizes.

There are many previous works on straggler mitigation [45, 4, 36, 2]. We use a simple online method where we always launch speculative copies after x% of tasks finish in the last wave. Having short-lived tasks in the serverless model is more advantageous here. The natural elasticity of serverless infrastructure makes it possible to be aggressive in launching speculative copies.

3.6 Performance Model Case Study

We next apply our performance model described above to the CloudSort benchmark and study the cost-performance tradeoff for the three approaches described above. Our predictions for data sizes ranging from 20GB to 100TB are shown in Figure 5 (we use experimental results of a real prototype to validate these predictions in Section 5). When the data shuffle size is small (e.g., 20GB or smaller), both the slow and fast storage only solutions take roughly the same time, with the slow storage being slightly cheaper. As the data size increases to around 100GB, using fast storage is around 2× faster for the same cost. This speed up from fast storage is more pronounced as data size grows. For very large shuffles ($\geq$ 10 TB), hybrid shuffle can provide significant cost savings. For example, at 100TB, the hybrid shuffle is around 6x cheaper than the fast storage only shuffle, but only 2x slower.

Note that since the hybrid shuffle performs a merge phase in addition to writing all the data to the fast storage, it is always slower than the fast storage only shuffle. In summary, this example shows how our performance model can be used to understand the cost-performance trade-off from using different shuffle implementations. We implement this performance modeling framework in Locus to perform automatic shuffle optimization. We next describe the implementation of Locus and discuss some extensions to our model.

4 Implementation

We implement Locus by extending PyWren [16], a Python-based data analytics engine developed for serverless environments. PyWren allows users to implement custom functions that perform data shuffles with other cloud services, but it lacks an actual shuffle operator. We augment PyWren with support for shuffle operations and implement the performance modeling framework described before to automatically configure the shuffle variables. For our implementation we use AWS Lambda as our compute engine and use S3 as the slow, elastic storage system. For fast storage we provision Redis nodes on Amazon ElastiCache.

To execute SQL queries on Locus, we devise physical query plan from Apache Spark and then use Pandas to implement structured data operations. One downside with Pandas is that we cannot do "fine-grained pipelining" between data operations inside a task. Whereas in Apache Spark or Redshift, a task can process records as they are read in or written out. Note this fine-grained pipelining is different from pipelining across stages, which we discuss in Section 3.4.

4.1 Model extensions

We next discuss a number of extensions to augment the performance model described in the previous section

Non-uniform data access: The shuffle scenario we considered in the previous section was the most general all-to-all shuffle scenario where every mapper contributes data to every reducer. However, a number of big data workloads have more skewed data access patterns. For example, machine learning workloads typically perform `AllReduce` or `broadcast` operations that are implemented using a tree-based communication topology. When a binary tree is used to do AllReduce, each mapper only produces data for one reducer and correspondingly each reducer only reads two partitions. Similarly while executing a broadcast join, the smaller table will be accessed by every reducer while the larger table is hash partitioned. Thus, in these scenarios storing the more frequently accessed partition on fast storage will improve performance. To handle these scenarios we introduce an access counter for each shuffle partition and correspondingly update the performance model. We only support this currently for cases like AllReduce and broadcast join where the access pattern is known beforehand.

Storage benchmark updates: Finally one of the key factors that make our performance models accurate is the storage benchmarks that measure throughput (operations per sec) and network bandwidth (bytes per second) of each storage system. We envision that we will execute these benchmarks the first time a user installs Locus and that the benchmark values are reused across a number of queries. However, since the benchmarks are capturing the behavior of cloud storage systems, the performance characteristics could change over time. Such limits change will require Locus to rerun the profiling. We plan to investigate techniques where we can profile query execution to infer whether our benchmarks are still accurate over extended periods of time.

5 Evaluation

We evaluate Locus with a number of analytics workloads, and compare Locus with Apache Spark running on a cluster of VMs and AWS Redshift/Redshift Spectrum[4]. Our evaluation shows that:

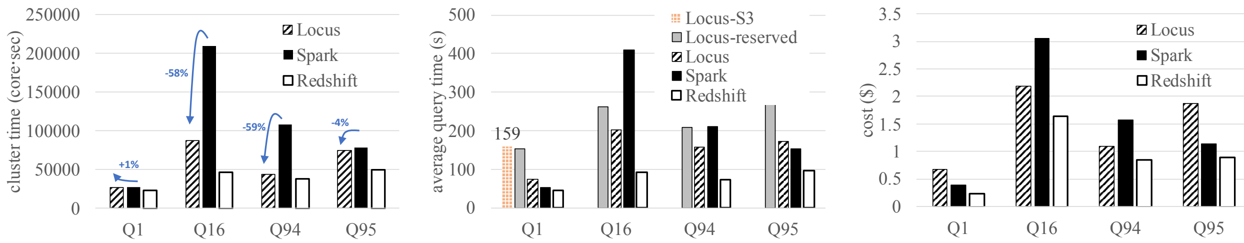
- Locus's serverless model can reduce cluster time by up to 59%, and at the same time being close to or beating Spark's query completion time by up to 2×. Even with a small amount of fast storage, Locus can greatly improve performance. For example, with just 5% memory, we match Spark in running time on CloudSort benchmark and are within 13% of the cost of the winning entry in 2016.
- When comparing with actual experiment results, our model in Section 3 is able to predict shuffle performance and cost accurately, with an average error of 15.9% for performance and 14.8% for cost. This allows Locus to choose the best cost-effective shuffle implementation and configuration.
- When running data intensive queries on the same number of cores, Locus is within 1.61 × slower compared to Spark, and within 2 × slower compared to Redshift, regardless of the baselines' more expensive unit-time pricing. Compared to shuffling only through slow storage, Locus can be up to 4×-500× faster.

The section is organized as follows, we first show utilization and end-to-end performance with Locus on TPC-DS [34] queries (5.1) and Daytona CloudSort benchmark (5.2). We then discuss how fast storage shifts resource balance to affect the cost-performance trade-off in Section 5.3. Using the sort benchmark, we also check whether our shuffle formulation in Section 3 can accurately predict cost and performance(5.4). Finally we evaluate Locus's performance on joins with Big Data Benchmark [8](5.5).

Setup: We run our experiments on AWS Lambda and use Amazon S3 for slow storage. For fast storage, we use a cluster of `r4.2xlarge` instances (61GB memory, up to 10Gbps network) and run Redis. For our comparisons against Spark, we use the latest version of Apache Spark (2.3.1). For comparison against Redshift, we use the latest version as of 2018 September and `ds2.8xlarge` instances. To calculate cost for VM-based experiments we pro-rate the hourly cost to a second granularity.[5] For Redshift, the cost is two parts using AWS pricing model, calculated by the uptime cost of cluster VMs, plus $5 per TB data scanned.

[4] When reading data of S3, AWS Redshift automatically uses a shared, serverless pool of resource called the Spectrum layer for S3 I/O, ETL and partial aggregation.

[5] This is presenting a lower cost than the minute-granularity used for billing by cloud providers like Amazon, Google.



(a) **Cluster time** (b) **Query latency** (c) **Cost**

Figure 6: **TPC-DS results for Locus, Apache Spark and Redshift under different configurations. Locus-S3 runs the benchmark with only S3 and doesn't complete for many queries; Locus-reserved runs Locus on a cluster of VMs.**

5.1 TPC-DS Queries

The TPC-DS benchmark has a set of standard decision support queries based on those used by retail product suppliers. The queries vary in terms of compute and network I/O loads. We evaluate Locus on TPC-DS with scale factor of 1000, which has a total input size of 1TB data for various tables. Among all queries, we pick four of them that represent different performance characteristics and have a varying input data size from 33GB to 312GB. Our baselines are Spark SQL deployed on a EC2 cluster with `c3.8xlarge` instances and Redshift with `ds2.8xlarge` instances, both with 512 cores. For Locus, we obtain workers dynamically across different stages of a query, but make sure that we never use more core·secs of Spark execution.

Figure 6(b) shows the query completion time for running TPC-DS queries on Apache Spark, Redshift and Locus under different configurations and Figure 6(a) shows the the total core·secs spent on running those queries. We see that Locus can save cluster time up to 59%, while being close to Spark's query completion time to also beating it by 2×. Locus loses to Spark on Q1 by 20s. As a result, even for now AWS Lambda's unit time cost per core is 1.92× more expensive than the EC2 `c3.8xlarge` instances, Locus enjoys a lower cost for Q1 and Q4 as we only allocate as many Lambdas as needed. Compared to Redshift, Locus is 1.56× to 1.99× slower. There are several causes that might contribute to the cost-performance gap: 1) Redshift has a more efficient execution workflow than that of Locus, which is implemented in Python and has no fine-grained pipelining; 2) `ds2.8xlarge` are special instances that have 25Gbps aggregate network bandwidths; 3) When processing S3 data, AWS Redshift pools extra resource, referred as the serverless Spectrum layer, to process S3 I/O, ETL and partial aggregation. To validate these hypotheses, we perform two what-if analyses. We first take Locus's TPC-DS execution trace and replay them to numerically simulate an pipelined execution by overlapping I/O and compute within a task. We find that with pipelining, query latencies can be reduced by 23% to 37%, being much closer to the Redshift numbers. Similarly, using our cost-performance model, we also find that if Locus's Redis nodes have 25Gbps links, the cost can be further reduced by 19%, due to a smaller number of nodes needed. Performance will not improve due to 25Gbps links, as network bottleneck on Lambda-side remains. Understanding remaining performance gap would require further breakdown, i.e., porting Locus to a lower-level programming language.

Even with the performance gap, an user may still prefer Locus over a data warehousing service like Redshift since the latter requires on-demand provisioning of a cluster. Currently with Amazon Redshift, provisioning a cluster takes minutes to finish, which is longer than these TPC-DS query latencies. Picking an optimal cluster size for a query is also difficult without knowledge of underlying data.

We also see in Figure 6(b) that Locus provides better performance than running on a cluster of 512-core VMs (Locus-reserved). This demonstrates the power of elasticity in executing analytics queries. Finally, using the fast storage based shuffle in Locus also results in successful execution of 3 queries that could not be executed with slow storage based shuffle, as the case for Locus-S3 or PyWren.

To understand where time is spent, we breakdown execution time into different stages and resources for Q94, as shown in Figure 7. We see that performing compute and network I/O takes up most of the query time. One way to improve overall performance given this breakdown is to do "fine-grained pipelining" of compute and network inside a task. Though nothing fundamental, it is unfortunately difficult to implement with the constraints of Pandas API at the time of writing. Compute time can also be improved if Locus is prototyped using a lower-level language such as C++.

Finally, for shuffle intensive stages such as stage 3 of Q94, we see that linearly scaling up fast storage does linearly improve shuffle performance (Figure 8).

5.2 CloudSort Benchmark

We run the Daytona CloudSort benchmark to compare Locus against both Spark and Redshift on reserved VMs.

The winner entry of CloudSort benchmark which ranks the cost for sorting 100TB data on public cloud is currently held by Apache Spark [42]. The record for sorting 100TB

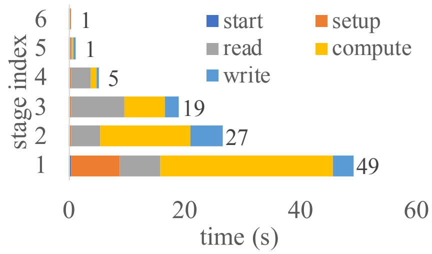


Figure 7: **Time breakdown for Q94. Each stage has a different profile and, compute and network time dominate.**

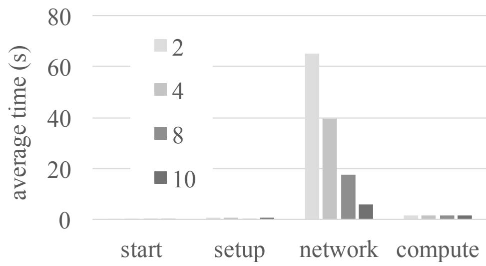


Figure 8: **Runtime for stage 3 of Q94 when varying the number of Redis nodes (2, 4, 8, 10).**

was achieved in 2983.33s using a cluster of 395 VMs, each with 4 vCPU cores and 8GB memory. The cost of running this was reported as $144.22. To obtain Spark numbers for 1TB and 10TB sort sizes, we varied the number of `i2.8xlarge` instances until the sort times matched those obtained by Locus. This allows a fair comparison on the cost. As discussed in Section 3, Locus automatically picks the best shuffle implementation for each input size.

Table 5 shows the result cost and performance comparing Locus against Spark. We see that regardless of the fact Locus's sort runs on memory-constrained compute infrastructure and communicates through remote storage, we are within 13% of the cost for 100TB record, and achieve the same performance. Locus is even cheaper for 10TB (by 15%) but is 73% more expensive for 1TB. This is due to using fast storage based-shuffle which yields a more costly trade-off point. We discuss more trade-offs in Section 5.3.

Table 6 shows the result of sorting 1TB of random string input. Since Redshift does not support querying against random binary data, we instead generate random string records as the sort input as an approximation to the Daytona CloudSort benchmark. For fair comparison, we also run other systems with the same string dataset. We see that Locus is an order of magnitude faster than Spark and Redshift and is comparable to Spark when input is stored on local disk.

We also run the same Locus code on EC2 VMs, in order to see the cost vs. performance difference of only changing hardware infrastructure while using the same programming language (Python in Locus). Figure 9 shows the results for running 100GB sort. We run Locus on AWS Lambda with various worker memory sizes. Similar to previous section, we then run Locus on a cluster and vary the number of `c1.xlarge` instances to match the performance and compare the cost. We see that both cost and performance improves for Locus-serverless when we pick a smaller memory size. The performance improvement is due to increase in parallelism that results in more aggregate network bandwidth. The cost reduction comes from both shorter run-time and lower cost for small memory sizes. For Locus-reserved, performance improves with more instances while the cost remains relatively constant, as the reduction in run-time compensates for the increased allocation.

We see that even though AWS Lambda is considered to be more expensive in terms of $ per CPU cycle, it can be cheaper in terms of $ per Gbps compared to reserved instances. Thus, serverless environments can reach a better

Table 5: **CloudSort results vs. Apache Spark**

Sort size	1TB	10TB	100TB
Spark nodes	21	60	395[31]
Spark time (s)	40	394	2983
Locus time (s)	39	379	2945
Spark cost ($)	1.5	34	144
Locus cost ($)	2.6	29	163

Table 6: **1TB string sort w/ various configurations**

	time	cost($)
Redshift-S3	6m8s	20.2
Spark RDD-S3	4m27s	15.7
Spark-HDFS ($)	35s	2.1
Locus ($)	39s	2.6

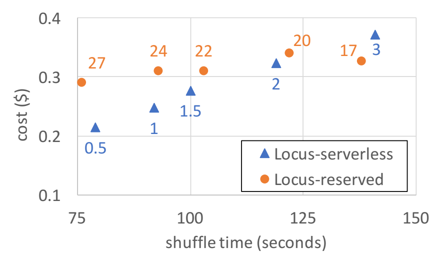


Figure 9: **Running 100GB sort with Locus on a serverless infrastructure vs. running the same code on reserved VMs. Labels for serverless series represents the configured memory size of each Lambda worker. Labels for reserved series represents the number of c1.xlarge instances deployed.**

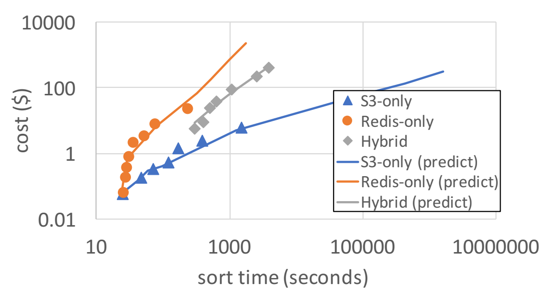


Figure 10: **Comparing the cost and performance predicted by Locus against actual measurements. The lines indicate predicted values and the dots indicate measurements.**

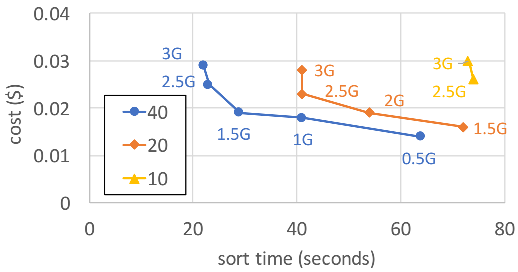


Figure 11: **10GB slow storage-only sort, with varying parallelism (lines) and worker memory size (dots).**

cost performance point for network-intensive workloads.

5.3 How much fast storage is needed?

One key insight in formulating the shuffle performance in Locus is that adding more resources does not necessarily increase total cost, e.g., increasing parallelism can result in a better configuration. Another key insight is that using fast storage or memory, sometimes even a small amount, can significantly shift resource balance and improve performance.

We highlight the first effect with an example of increasing parallelism and hence over allocating worker memory compared to the data size being processed. Consider the case where we do a slow storage-only sort for 10GB. Here, we can further increase parallelism by using smaller data partitions than the worker memory size. We find that by say using a parallelism of 40 with 2.5G worker memory size can result in 3.21× performance improvement and lower cost over using parallelism of 10 with 2.5G worker memory (Figure 11).

However, such performance increase does require that we add resources in a balanced manner as one could also end up incurring more cost while not improving performance. For example, with a 100GB sort (Figure 12), increasing parallelism from 200 to 400 with 2.5G worker memory size (Figure 12) makes performance 2.5× worse, as now the bottleneck shifts to object store throughput and each worker will run slower due to a even smaller share. Compared to the 10GB sort, this also shows that the same action that helps in one configuration can be harmful in another configuration.

Another way of balancing resources here is to increase parallelism while adding fast storage. We see this in Figure 12, where increasing parallelism to 400 becomes beneficial with fast storage as the storage system can now absorb the increased number of requests. These results provide an example of the kinds of decisions automated by the performance modeling framework in Locus.

The second insight is particularly highlighted for running 100TB hybrid sort. For 100TB sort, we vary the fast storage used from 2% to 5%, and choose parallelism for each setting based on the hybrid shuffle algorithm. As shown in Table 7, we see that even with 2% of memory, the 100TB sort becomes attainable in 2 hours. Increasing memory from 2% to 5%, there is an almost linear reduction in terms of end-to-end sort time when we use larger cache size.This matches the projection in our design discussion. Further broken down in Figure 13, we see that the increase of cost per time unit is compensated by reduction in end-to-end run time.

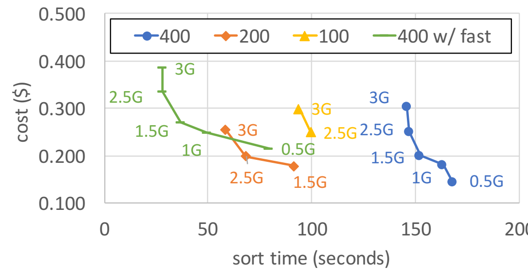


Figure 12: **100GB slow storage-only sort with varying parallelism (different lines) and worker memory size (dots on same line). We include one configuration with fast-storage sort.**

Table 7: **100TB Sort with different cache size.**

cache	5%	3.3%	2.5%	2%
time (s)	2945	4132	5684	6850
total cost ($)	163	171	186	179

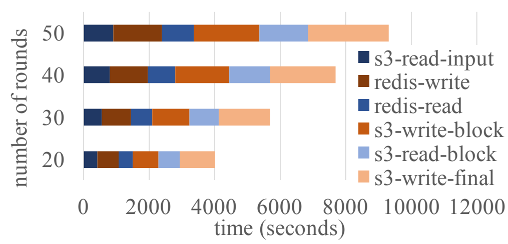


Figure 13: **Runtime breakdown for 100TB sort.**

5.4 Model Accuracy

To automatically choose a cost-effective shuffle implementation, Locus relies on a predictive performance model that can output accurate run-time and cost for any sort size and configuration. To validate our model, we ran an exhaustive experiment with varying sort sizes for all three shuffle implementations and compared the results with the predicted values as shown in Figure 10.

We find that Locus's model predicts performance and cost trends pretty well, with an average error of 16.9% for runtime and 14.8% for cost. Among different sort implementations, predicting Redis-only is most accurate with an accuracy of 9.6%, then Hybrid-sort of 18.2%, and S3-only sort of 21.5%. This might due to the relatively lesser variance we see in network bandwidth to our dedicated Redis cluster as opposed to S3 which is a globally shared resource. We also notice that our prediction on average under-estimates runtime by 11%. This can be attributed to the fact that we don't model a number of other overheads such as variance in CPU time, scheduling delay etc. Overall, similar to database query optimizers, we believe that this accuracy is good enough to make coarse grained decisions about shuffle methods to use.

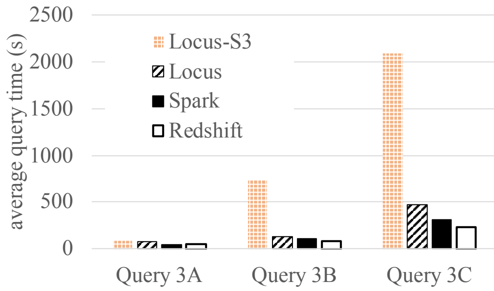


Figure 14: **Big Data Benchmark**

5.5 Big Data Benchmark

The Big Data Benchmark contains a query suite derived from production databases. We consider Query 3, which is a join query template that reads in 123GB of input and then performs joins of various sizes. We evaluate Locus to see how it performs as join size changes. We configure Locus to use 160 workers, Spark to use 5 `c3.xlarge`, and Redshift to use 5`ds2.8xlarge`, all totalling 160 cores. Figure 14 shows that even without the benefit of elasticity, Locus performance is within 1.75× to Apache Spark and 2.02× to Redshift across all join sizes. The gap is similar to what we observe in Section 5.1. We also see that using a default slow-storage only configuration can be up to 4× slower.

6 Related Work

Shuffle Optimizations: As a critical component in almost all data analytics system, shuffle has always been a venue for performance optimization. This is exemplified by Google providing a separate service just for shuffle [23]. While most of its technical details are unknown, the Google Cloud Shuffle service shares the same idea as Locus in that it uses elastic compute resources to perform shuffle externally. Modern analytics systems like Hadoop [39] or Spark [43] often provide multiple communication primitives and sort implementations. Unfortunately, they do not perform well in a serverless setting, as shown previously. There are many conventional wisdom on how to optimize cache performance [24], we explore a similar problem in the cloud context. Our hybrid sort extends on the classic idea of mergesort (see survey [17]) and cache-sensitive external sort [30, 38] to do joint optimization on the cache size and sort algorithm. There are also orthogonal works that focus on the network layer. For example, CoFlow [12] and Varys [13] proposed coordinated flow scheduling algorithms to achieve better last flow completion time. For join operations in databases, Locus relies on existing query compilers to generate shuffle plans. Compiling the optimal join algorithm for a query is an extensively studied area in databases [14], and we plan to integrate our shuffle characteristics with database optimizers in the future.

Serverless Frameworks: The accelerated shift to serverless has brought innovations to SQL processing [9, 5, 22, 35], general computing platforms (OpenLambda [25], AWS Lambda, Google Cloud Functions, Azure Functions, etc.), as well as emerging general computation frameworks [6, 18] in the last two years. These frameworks are architected in different ways: AWS-Lambda [6] provides a schema to compose MapReduce queries with existing AWS services; ExCamera [18] implemented a state machine in serverless tasks to achieve fine-grained control; Prior work [16] has also looked at exploiting the usability aspects to provide a seamless interface for scaling unmodified Python code.

Database Cost Modeling: There has been extensive study in the database literature on building cost-models for systems with multi-tier storage hierarchy [28, 27] and on targeting systems that are bottlenecked on memory access [10]. Our cost modeling shares a similar framework but examines costs in a cloud setting. The idea of dynamically allocating virtual storage resource, especially fast cache for performance improvement can also be found in database literature [41]. Finally, our work builds on existing techniques that estimate workload statistics such as partition size, cardinality, and data skew [29].

7 Conclusion

With the shift to serverless computing, there have been a number of proposals to develop general computing frameworks on serverless infrastructure. However, due to resource limits and performance variations that are inherent to the serverless model, it is challenging to efficiently execute complex workloads that involve communication across functions. In this paper, we show that using a mixture of slow but cheap storage with fast but expensive storage is necessary to achieve a good cost-performance trade-off. We presents Locus, an analytics system that uses performance modeling for shuffle operations executed on serverless architectures. Our evaluation shows that the model used in Locus is accurate and that it can achieve comparable performance to running Apache Spark on a provisioned cluster, and within 2 × slower compared to Redshift. We believe the performance gap can be improved in the future, and meanwhile Locus can be preferred as it requires no provisioning of clusters.

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