Advancing RPC for Data Services at Exascale

Jerome Soumagne[1], Philip Carns[2], and Robert B. Ross[2]
[1]The HDF Group
[2]Argonne National Laboratory

Abstract

Remote Procedure Call (RPC) has long been an inherent component of parallel file systems and I/O forwarding middleware in high-performance computing (HPC). RPCs are used in this environment to issue I/O operations and transfer data from compute nodes to gateway and server storage nodes. With HPC systems becoming more heterogeneous, data volumes reaching new thresholds, and I/O standing as the main bottleneck, there is a growing need in the HPC community to build distributed services and adopt new workflows that are, nonetheless, no longer dictated by monolithic parallel file systems. These include specialized storage, data analysis, and telemetry services that can be adapted to fit application needs. Parallel file system RPC facilities have never been exposed to service or middleware developers, however, leaving them with two choices: MPI or the low-level fabric network protocol. In this article, we show how an independent RPC framework can be used as a building block for developing user-level data services at exascale. We identify the design choices that must be considered in terms of both performance and resilience for HPC data services, and we discuss the directions taken to palliate current HPC system constraints.

1 Introduction

High-performance computing (HPC) facilities have traditionally been designed around *monolithic* file systems, which are tailored to scientific HPC workflows comprised of computation, storage, and data analysis. Scientific application users, whose needs depend on the application's domain, have been constrained to conform to system precepts and this standard workflow. While this has been a viable (but increasingly limiting) option for pre-exascale systems, increasing data volumes and increasing system complexity with emerging hardware are now forcing application users to adopt new *specialized* workflows. These specialized workflows not only achieve sustainable performance and perform data analysis in a timely manner at an increasing scale, but also better respond to application needs and provide data insights, for example through monitoring and telemetry service.

Creating specialized workflows requires the introduction of a collection of *data services* to the HPC ecosystem that must interact with both the system components (hardware and software) and the application. While some of those services may be provided by the system, the vast majority of data services are user-level services that are developed to augment the original HPC system software stack and better serve the application's performance or functionality needs. Data services (system-provided or user-provided) must respond, in most cases,

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to the same user prerequisites by ensuring performance, resilience, and ease of deployment. These prerequisites introduce engineering challenges that must be overcome when creating a new HPC data service—by no means an easy task. One such challenge is communication: data exchange between services is a critical aspect of specialized workflows that are composed of multiple services interacting with each other. Developing the messaging part of a data service component on an HPC machine can, for a new service developer, involve either using the low-level network fabric API, which requires a significant amount of work and expertise, or using the vendor installed MPI library [1] that takes advantage of the underlying network fabric. MPI itself, however, is not very suitable for developing such dynamical services that may come and go [2]. MPI implementations have consistently prioritized use by applications and not by service libraries.

Data services are already a well-established technology in the cloud, where remote procedure call (RPC) is the main technique used for sending messages to remote components. Google gRPC [3] or Facebook Thrift [4] are good examples of such frameworks. However, they are not well-suited to run on HPC systems because they (1) rely on the TCP/IP stack and do not take advantage of the low latency/high bandwidth HPC fabrics and (2) are not designed for exchanging very large amounts of data, a task that is left to the user. In contrast, RPC has been used as the communication pillar of distributed file systems (e.g., Lustre Networking (LNET) [5], Panasas [6]) and I/O forwarding layers (e.g., IOFSL [7]) that are specifically designed to send I/O requests on top of the underlying network fabric. The Network File System (NFS) [8] is also a good example of the use of RPC with large data transfers and therefore close to the use of RPC in an HPC system. The internal RPC facilities of these file systems (with the exception of NFS) have, nonetheless, never been directly exposed to users; instead, they have been deeply buried in the monolithic file system software stacks that often extend into kernel space. Other parallel file systems have implemented their own network abstraction layer to support multiple network fabrics and provide messaging capabilities that can support data services. However, they are not general-purpose RPC frameworks, and in most cases cannot be easily extracted from the file systems that they were designed for.

Based on both of those technologies and past experience with I/O forwarding, we introduced in [9] an RPC framework, called Mercury, that takes advantage of low-level HPC network fabrics and facilitates the development of user-level data services. Mercury is part of a more comprehensive suite of components named Mochi [10] that provides a collection of service components for the creation of specialized data services. We present in this paper how some of the design choices made for Mercury are essential for building an heterogeneous service workflow in an exascale HPC environment. In Section 2, we present some of the work that is similar to Mercury and approaches that we take to develop user-level data services. In Section 3, we give a brief overview of Mercury's architecture before focusing in Section 4 on the specific design points that make an RPC framework usable for HPC data services, supporting our claims by evaluation results. In Section 5, we present some of the data services that are successfully being deployed using Mochi and Mercury. In Section 6, we summarize our conclusions.

2 Related Work

A few other frameworks and suites of HPC data service components have been proposed using an approach similar to the one we used in Mercury. We present here three of the most notable frameworks.

DataSpaces [11] implements a scalable, semantically specialized shared-space abstraction that is dynamically accessible by all components and services in an application workflow, supporting both application/system-aware data placement and data movement. It relies on the *Decoupled and Asynchronous Remote Transfers* (DART) [12] layer, which is not defined as an explicit RPC framework, although it allows transfer of large amounts of data using a client/server model from applications running on the compute nodes of an HPC system to local storage or remote locations, in order to enable remote application monitoring, data analysis, code coupling, and data archiving. The key requirements that DART seeks to satisfy are minimizing data transfer overheads on the application; achieving high throughput, low latency data transfers; and preventing data losses.

To this end, DART is designed so that dedicated nodes (i.e., separate from the application compute nodes) asynchronously extract data from the memory of the compute nodes using remote direct memory access (RDMA).

The *Scalable Observation System* (SOSflow) [13] provides a broad set of online and in situ capabilities, including code steering via remote method invocation, data analysis, and visualization. SOSflow can couple together multiple sources of data, such as application components and operating environment measures, with multiple software libraries and performance tools. SOSflow's communication mechanism relies both on TCP sockets for on-node communication and on MPI for off-node communication. Its main communication pattern is a publish-and-subscribe mechanism and relies on a daemon that is launched as a background process in user space at the start of a job script, before the scientific workflow begins.

Faodel [14] provides a set of services for data management and exchange in HPC workflows. Three major components of Faodel are Kelpie, Opbox, and Lunasa. Kelpie provides a key-blob abstraction. OpBox is a library for implementing asynchronous communication between multiple entities in a distributed application, and provides the user with primitives for expressing a protocol as a state machine that the communication layer can process in an asynchronous manner. It also provides a naming service to locate components of an application. Lunasa provides user-level network memory management services and effectively acts as a memory registration cache for doing RDMA. Faodel relies on an evolution of the NNTI layer from the *NEtwork Scalable Service Interface* (Nessie) [15] RPC library. It provides an asynchronous RPC solution, designed to overlap computation and I/O. Nessie also provides a mechanism to handle bulk data transfers, which can use RDMA to transfer data efficiently from one memory to the other, and supports several network transports. Nessie uses the RPC interface to push control messages to the servers and exposes a separate one-sided API that is used to push or pull data between client and server.

3 Overview and Considerations

Mercury is designed around three key paradigms: provide reliable RPC functionality, support large data arguments, and take advantage of the HPC network fabrics. In terms of functionality, much more is needed when developing distributed HPC data services; but as opposed to RPC frameworks that are part of monolithic software stacks, Mercury remains as thin as possible in order to allow for reusability between various service components that must support different needs.

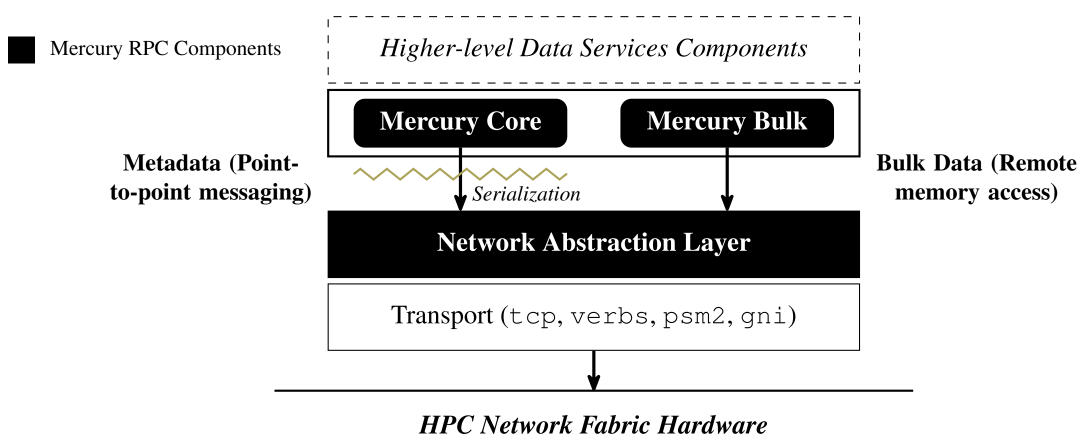


Figure 1: Overview of Mercury RPC components in the software stack.

As shown in Figure 1, Mercury is composed of two service-level components: a core RPC component, which is designed to serialize function arguments and send them to a remote target for execution using point-to-point messaging, and a bulk component, which is designed to handle large arguments (i.e., arguments that are generally larger than 4KB depending on the underlying protocol being used). This latter component enables the creation of memory descriptors that can be sent along with the other arguments to the RPC target to initiate raw memory transfers (without serialization) using remote memory access (RMA). In Section 4.1, we detail this scenario and its benefits. In order to support a large variety of HPC network fabrics, both of these components interface with a network abstraction layer that provides a minimum set of network primitives for both point-to-point messaging and one-sided RMA communication operations. Moreover, in order to reduce the burden of connection handshakes when the underlying network does not necessarily request it (also essential for scalability) and to support services that may come and go, remote peers are addressed through unconnected endpoints. Furthermore, in order to maximize throughput, all communication is made nonblocking through a callback-based approach that we detail in Section 4.5.

While these points describe the overall architecture of an RPC framework for HPC, additional key items can rapidly become prerequisites for creating an RPC framework that is designed to support data services. These include maximizing throughput, providing scaling, enabling flexibility, and ensuring resilience. In the following section we describe how one can enhance RPC to (1) leverage RDMA-capable networks; (2) support node-local service scaling and leverage multi-core processors; (3) enable flexible, node-local deployment scenarios and service composition; (4) bridge nodes between multiple HPC networks; (5) enable fault tolerance.

4 Enabling RPC for HPC Data Services

We do not compile an exhaustive list of features in this section. Instead, we focus on those features that are necessary to enable strong service scaling, performance, flexibility, and resilience for data services on emerging large-scale computing platforms.

4.1 HPC Network Support

As opposed to cloud-based RPC solutions that rely on TCP networking, HPC network fabrics provide dedicated solutions that offer both low latency and high bandwidth. To take advantage of these solutions, however, an RPC framework must leverage low-level vendor APIs such as InfiniBand™ Verbs, Intel® Performance Scaled Messaging 2 (PSM2), and Cray® Generic Network Interface (GNI). Rather than implementing Mercury's network abstraction layer directly on top of those APIs, we currently use OFI libfabric [16] as the intermediate layer that abstracts RDMA capabilities for RDMA-capable networks or emulated RMA (over point-to-point) for noncapable networks. Exposing native RDMA primitives is essential for taking full advantage of RDMA capable networks so that a data service can, for large data, leverage zero-copy transfers from the application's memory from/to the storage.

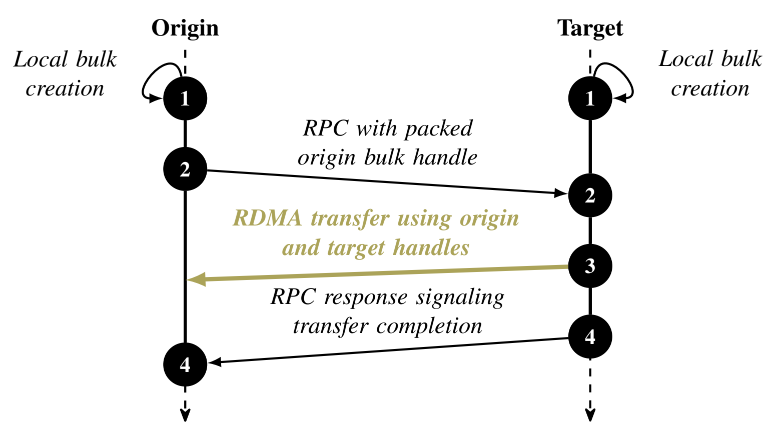
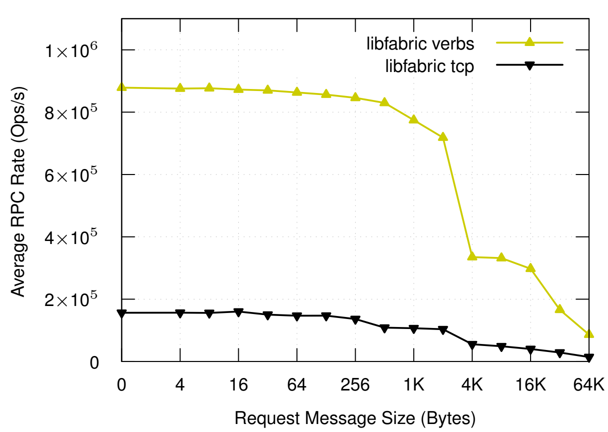


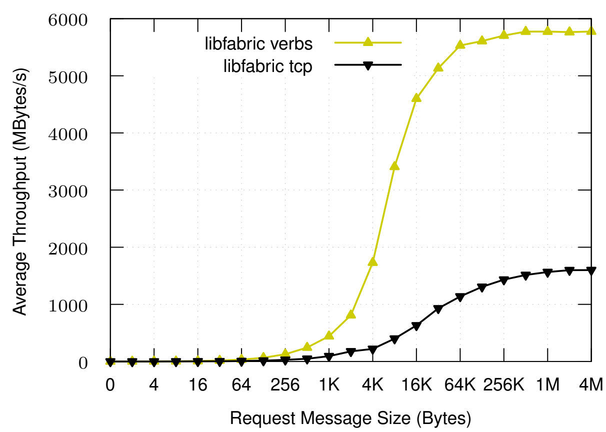
Figure 2: Four-step process of Mercury's bulk RDMA transfers.

Enabling RMA capabilities through Mercury's bulk component (see Figure 1) is a four-step process (see Figure 2). First, *bulk handles*, which are abstract memory descriptors, must be created on both origin and target processes. During handle creation, memory regions are registered (which in most cases corresponds to a physical hardware registration); this allows for the higher level data service to only expose memory pages that it wishes to access in either read-write or read-only mode. Second, an RPC is issued from the origin process to the target process with the serialized bulk handle of the origin process; this handshake allows the target process to gather virtual address information, registration keys, and so forth, which are necessary for the underlying protocol to post an RDMA operation. Third, the actual RDMA operation is posted using both the target's local bulk handle and the origin's handle that was transmitted through the RPC. Since bulk handles are abstract memory descriptors, more complex scenarios such as scatter/gather can be transparently implemented and even delegated to the hardware if the hardware provides this support, allowing for more efficient transfers. Finally, the RPC response is sent, effectively signaling the origin of the transfer completion. This server-driven four-step process is the most conventional model for data transfers in Mercury, but client-driven transfers are legal as well. The former is more commonly recommended for two reasons. First, it enables servers to throttle or re-order transfers according to load. Second, it makes the clients lighter weight and more scalable, since they do not have to track the state of server resources.

Evaluation. To show the importance of supporting this capability, we compare the RPC performance and "RPC with bulk" performance on an InfiniBand cluster (Cooley) that is equipped with 4X FDR Infiniband cards (56 Gb/s). Compared to TCP over the same network, our approach improves RPC throughput with close to 9×10^5 operations per second and close to 6,000 MB/s average throughput when performing RPC and bulk transfer through the native verbs interface. Note that the previous results do not use any multi-threading capabilities. We maintain a number of 32 RPCs in-flight to ensure sustained performance. Multi-threading support is discussed in the next section.



(a) RPC round-trip benchmark (32 RPCs in-flight).



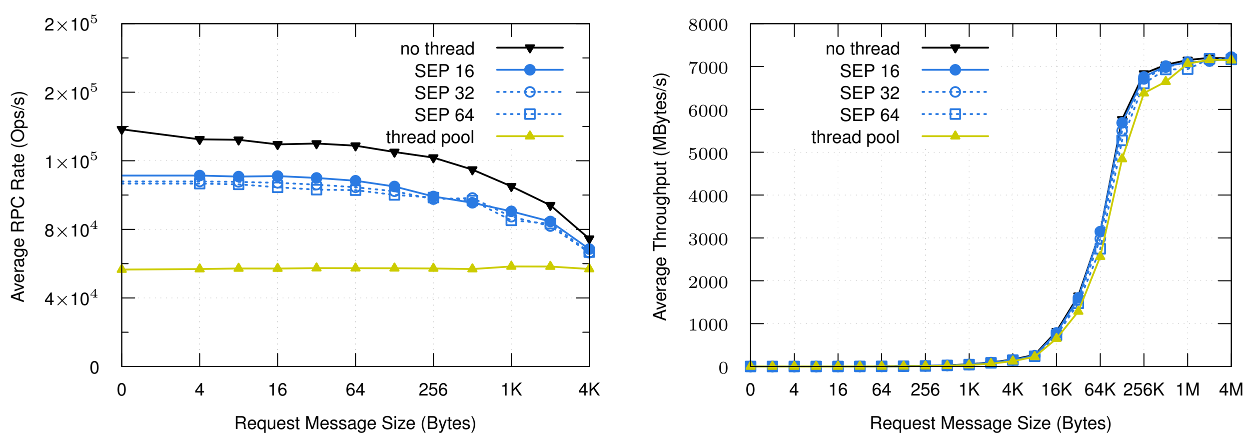
(b) Bulk transfer (server pull) benchmark (32 RPC in-flight).

Figure 3: Effect of leveraging RDMA network on InfiniBand cluster (FDR InfiniBand).

4.2 Multi-Core Architecture Support

With CPUs experiencing increasing core count and lower frequencies per core, data services are expected to take advantage of these architectures by either distributing the load of incoming RPCs across cores or by running multiple services co-located within the same node. Communication frameworks typically adopt one of two progress models: either *explicit* or *implicit*. *Explicit* progress implies that the user will regularly make progress calls to effectively check into network completion queues, poll file descriptors, etc. In contrast, an *implicit* progress model will make progress in background without any need for the user to be involved. However, this usually involves a background progress thread running to make progress while operations are being posted. While this may seem convenient, this “hidden” thread can become detrimental when running concurrently with other user’s threads, leading to unexpected scheduling issues. Therefore, to prevent this type of issues and give data services sufficient flexibility in how progress is ensured, we follow an explicit progress model. RPC is not only about messaging and communication, it is also about execution of user-defined function calls. When making progress, therefore, it is often desirable to decouple the RPC execution activities from the network progress activities, which leads us to actually adopt a *progress-and-trigger* model that gives services more control over the placement of the progress and execution threads. In this approach, implicit progress can be accomplished by the user by having a thread calling progress in background.

In a typical scenario, an RPC listener service will start posting RPC receive operations with memory bound to the thread posting the operations. Distributing the execution of these incoming RPCs across multiple threads (e.g., using a thread pool) can lead to several context switches at a significant performance penalty. To prevent this scenario, take advantage of multi-core architectures, and allow for node-local service scaling without costly creation of separate endpoints per thread, we make use of *scalable endpoints* (SEP) when available. Scalable endpoints are provided through libfabric [16] but can be extended through our network abstraction layer. Scalable endpoints allow for sharing a single endpoint resources between threads by assigning separate transmit and receive contexts (including completion queues) to each thread. When SEPs are used, context switches between threads no longer exist— a fundamental advantage for RPC multi-core architectures.



(a) RPC round-trip benchmark (32 RPCs in-flight).

(b) Bulk transfer benchmark (32 RPC in-flight).

Figure 4: Effect of using scalable endpoints on Cray XC40 (Aries interconnect).

Evaluation. To demonstrate the impact of context switches and emphasize the benefits of scalable endpoints, we run two benchmarks on the Theta supercomputer at the Argonne Leadership Computing Facility (ALCF). Theta is a Cray XC40 system with a second-generation Intel Xeon Phi processor and Cray Aries interconnect. Each compute node is a single Xeon Phi chip with 64 cores, 16 GB of Multi-Channel DRAM (MCDRAM), and 192 GB of DDR4 memory. Users typically take advantage of this architecture by either deploying multiple data services locally or by distributing incoming RPCs across cores. In order to do so using SEP, we assign each core to make progress and trigger calls on their own receive context. As shown in Figure 4, using SEP provides close match (in terms of operations per second) to the performance of workloads that do not use multi-threading. Distributing requests using a thread pool, in contrast, has a significant detrimental impact on RPC rate. Note that in all cases bulk transfers exhibit similar overall bandwidth, as context switches only represent a portion of the time spent when large data is transferred over the network.

4.3 Flexible Provisioning and Topology

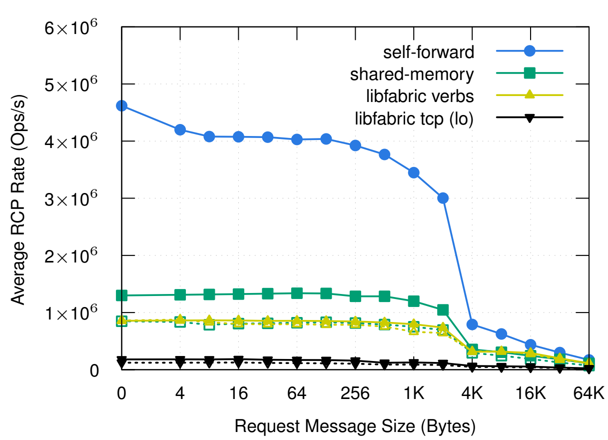
In the preceding section, we demonstrated node-level scaling when RPCs are made between separate nodes using the native interconnect. Additional optimization can be made, however, by being aware of node-local process placement, in order to ensure efficient composition of services.

4.3.1 Transparent Node-Local Deployment

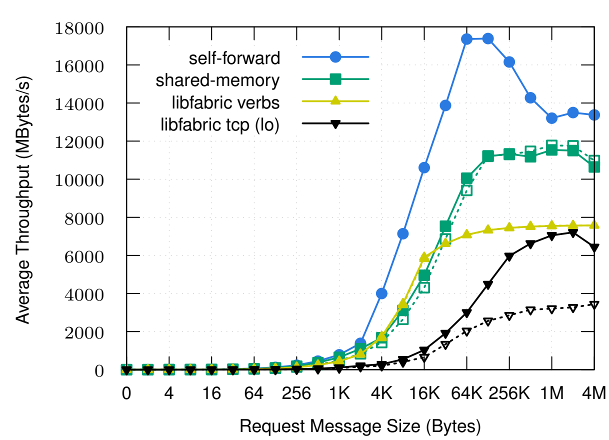
When deploying data services, it is common for some of these services to either issue RPCs to other local services (i.e., separate processes within the same node) or to send RPCs back to themselves (i.e., within the same process). The latter typically arises out of convenience, rather than creating a separate code path for that case. To achieve the former, Mercury can make use of shared-memory transparently by detecting that the target address is on the same node. Using lockless shared ring buffers and lockless queues, it is possible to achieve lockless transfers with very low latency. For bulk data transfers and to prevent any intermediate *memcpy*, zero-copy transfers (i.e, one single and direct copy from origin to target buffer) can be achieved using the Linux Cross-Memory Attach mechanism.

To achieve the latter, Mercury detects when the target address is the same as the origin address and sends RPCs using the same argument packing mechanism, by immediately queuing the RPC into a local completion queue, internally signaling completion to wake up any potential thread waiting in a progress call. Likewise, bulk data transfers are realized through a *memcpy* between source and destination buffers.

This combination of transparent shared-memory transfers between separate processes, loopback redirection within the same process, and over-the-wire transfers has shown substantial benefits when deploying data services in terms of performance and flexibility, since data services can treat all three scenarios identically.



(a) RPC round-trip benchmark (32 RPCs in-flight).



(b) Bulk transfer benchmark (32 RPC in-flight).

Figure 5: Comparison between node-local RPC mechanisms on InfiniBand cluster (FDR InfiniBand).

Evaluation. To illustrate this scenario on our InfiniBand cluster (Cooley), we compare in Figure 5 our two local RPC communication mechanisms to issuing RPCs either through the native interconnect (in this case InfiniBand Verbs) or through TCP and the loopback interface. The latter is one of the fallback mechanisms typically used when not using shared-memory. Cooley is equipped of dual-sockets nodes with Intel Xeon E5-2620 v3 CPUs. Consequently, performance varies depending on process placement and the NUMA nodes being used—performance when running on separate NUMA nodes is represented by a dotted line in Figure 5. In terms of both RPC operations per second and bulk throughput, these two mechanisms are very valuable, providing much better performance than both the native interconnect and TCP (1.3 MOps/s for shared-memory and more than 4 MOps/s for loopback execution). When running on separate NUMA nodes, shared-memory performance is naturally impacted, though RPCs with bulk transfer still perform at a much higher rate due to the use of Linux Cross-Memory Attach (CMA).

4.3.2 Service Composition

With node-level scaling and transparent node-local deployment in place, composing data services seems the next natural step. In order to provide flexible composition, the RPC API must not be specific to any implementation but rather rely only on *origin* and *target* concepts. The RPC mechanism then can be consistently employed to communicate between different service "servers" and "clients".

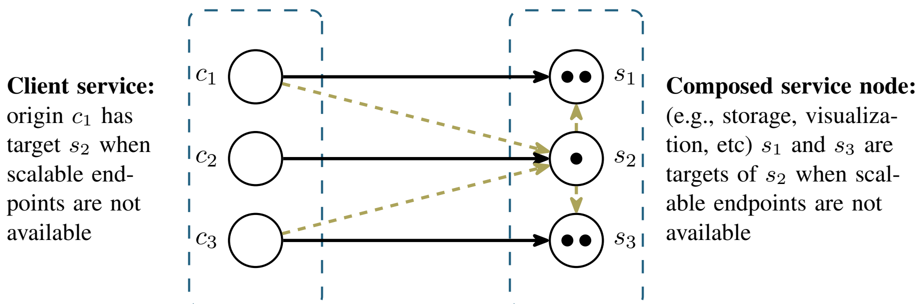


Figure 6: Composition of services with and without scalable endpoints.

When multiple services are colocated, there is also a need for addressing specific services and efficiently making progress. As shown in Figure 6, this can then be accomplished by using a "delegator" service, which can potentially become a bottleneck, or by using scalable endpoints addressing specific receive contexts directly through an ID that can be defined for each data service. When there is no hardware support for scalable endpoints, however, this functionality must be emulated by embedding a service ID into the RPC header and using that ID to distribute RPC requests to the corresponding service through that delegator. An alternative is to create multiple endpoints, one for each data service; but this is usually not recommended due to hardware resource limitations.

4.4 Multi-Network Support

As we bridge local and nonlocal communication mechanisms, supporting multiple fabrics follows a similar approach and relies on the same supporting components described in Sections 4.2 and 4.3. Mercury's architecture defines *classes* that physically correspond to one endpoint and *contexts* that correspond to completion queues and locally allocated resources. When using scalable endpoints as described in Section 4.2, we are in a scenario with one class (one endpoint) and multiple contexts (multiple completion queues) that share the same endpoint. When bridging multiple fabrics, we are in a scenario with multiple classes (multiple endpoints) and one or more contexts (completion queues) associated with each class.

The challenge is efficiently making progress over these separate classes and contexts. To facilitate this, Mercury provides two progress mechanisms, allowing for a service to either busy spin on each of these contexts to process requests as quickly as possible (at the cost of using more CPU resources), or to wait and sleep on this set of contexts until a new request arrives. In the latter case, we rely on Linux' file descriptor and *epoll* mechanism to wait. This allows for monitoring of both local event notifications and hardware queue notifications. This transparent notification mechanism allows a data service implementation to simply wait on a file descriptor rather than manually making progress on each of the interfaces/endpoints.

4.5 Resilience and Fault Tolerance

When supporting data services at scale, there are multiple approaches that one can take to define a resilient RPC mechanism (for instance, guaranteed delivery). One of the primary requirements for an RPC component is to allow services to recover after a fault has occurred (e.g., node failure, unresponsiveness of a service component) without compromising performance, by simply providing robust support for canceling operations that are pending. This implies reclaiming local resources that RPC operations have previously allocated and gracefully recovering from faults. It is important to note that we assume in that discussion the use of *reliable* unconnected endpoints in the transport layer, hence RPC requests do not get "lost". Ordering and tag matching are not critical for the transport to provide though (Mercury matches messages itself when needed). Mercury itself only provides *at-most* once semantics: nonblocking RPC requests are sent and a nonblocking response is sent back (unless it is explicitly stated not to do so). It is then up to services to make their own decision on how to react (e.g., retry, fail over, initiate a rebuild, etc). Both RPC and bulk data transfer operations may be interrupted if any of the peers involved no longer responds, in which case pending operations must be canceled. Canceling an operation that cannot complete, either because a fault has occurred or a timeout has been reached, is necessary in order to reach proper completion.

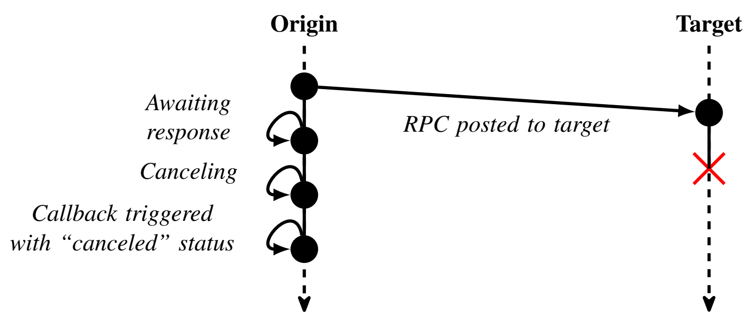


Figure 7: Cancelation of an RPC operation.

Cancelation of operations in Mercury is always an *asynchronous* and *local* operation. As shown in Figure 7, forwarding an RPC request is a nonblocking operation. Therefore, since Mercury follows a callback-based mechanism, completion of that operation is known from a user's perspective only when the callback that is associated to that operation is pushed to the local completion queue and later triggered after making both progress and trigger calls. When that callback is triggered, the state of the operation is reported to the user as *canceled*. Since operations are nonblocking, keeping cancelation an asynchronous operation instead of an operation that completes immediately is essential. This mechanism protects against races in the event that a peer response arrives after local cancelation has already succeeded. After the callback is triggered, it is then safe to re-use the existing RPC request handle to issue a retry for example.

Cancelation is the foundation for implementing timeout scenarios in data services in order to recover from a fault. When an internal fault occurs, however, cancelation of the operation is not always necessary if the RPC has not yet been posted, in which case that operation can simply be directly retried. This scenario is similar for all other nonblocking operations in Mercury, including bulk data transfers.

5 Applications and Use Cases

As mentioned in Section 1, Mercury is part of the Mochi suite of service of components. Mochi provides additional features on top of Mercury such as the notion of group membership, transparent user-level thread semantics, key/value stores, C++ and Python bindings. This work is further described in [10] along with additional use cases, including the following:

Intel's *Distributed Application Object Storage* (DAOS) [17] project provides a transactional and multidimensional object store for use in large-scale HPC environments with embedded storage directly attached to the compute fabric. DAOS is a vendor-backed push to provide an alternative to the traditional parallel file system and has the potential to extract higher performance out of emerging low latency storage technology by running in user space. DAOS is envisioned as a multiuser and persistent volume available to all applications. It therefore encompasses a variety of system management capabilities, including distributed authentication and device provisioning.

The *Unify* project, the successor to BurstFS [18], implements a temporary high-performance file system using local resources on nodes in the HPC system. In Unify, data is explicitly staged between the temporary Unify file system and the "permanent" parallel file system. The Unify team is exploring specialization in the form of multiple flavors of file systems, such as *UnifyCR* for checkpoint/restart workloads and a separate specialized version for machine learning workloads. This backend specialization allows Unify to optimize for different use cases without sacrificing the portability and common toolset advantages of a POSIX interface. UnifyCR, for example, uses user-space I/O interception, scalable metadata indexing, and colocated I/O delegation to optimize bursty checkpoint workloads while still presenting a traditional file system view of the data.

GekkoFS [19] implements a temporary and highly scalable file system providing relaxed POSIX semantics tailored to the majority of HPC applications. This type of specialization allows applications using the existing POSIX interface (under specific constraints) to see dramatic performance improvements as compared with file systems supporting the complete specification. The GekkoFS team has demonstrated millions of metadata operations per second, allowing it to serve applications with access patterns that were historically poor matches for file systems, and the team has shown rapid service instantiation times allowing new GekkoFS volumes to be started on a per-job basis.

Proactive Data Containers (PDC) [20] provides a data model in which a container holds a collection of objects that may reside at different levels of a potentially complex storage hierarchy and migrate between them. A PDC volume is instantiated for an application workflow and sized to meet workflow requirements for data storage and I/O. Objects can hold both streams of bytes and KV pairs, and additional metadata can be associated with objects as well. Unlike GekkoFS and UnifyCR, PDC does not present a conventional file system interface but instead provides a way of unifying application's memory and storage by providing object mapping semantics, which hide actual I/O transfers between storage hierarchies from the user.

6 Conclusion

To support data services at scale, a re-usable RPC component must be able to provide performance by enabling the use of all the underlying hardware and network fabrics, flexibility by facilitating service composition, and resilience by providing support for local cancelation. Mercury in that regard is already providing this functionality and is on the path of being used on production systems, to enable not only file system capabilities but to also provide specialized data service workflows as part of the Mochi suite of components.

We are also considering how to make use of collectives through Mercury and how to provide data services with optimized collective RPC operations (such as RPC broadcasts) that do not only rely on point-to-point messaging, which is a limitation when an RPC must be sent to a large number of targets. Furthermore, with accelerators (e.g., GPUs) that are now part of the HPC ecosystem, there is a growing interest in how to make efficient use of RDMA and address the accelerator's memory directly from a remote target. These are two future directions that we are considering to further evolve our RPC framework.

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References

[1] Argonne National Laboratory, "MPICH," 2013. [Online]. Available: http://www.mpich.org

[2] J. Zounmevo, D. Kimpe, R. Ross, and A. Afsahi, "On the Use of MPI in High-Performance Computing Services," in *Recent Advances in the Message Passing Interface*, 2013.

[3] Google Inc, "Protocol Buffers," 2012. [Online]. Available: https://developers.google.com/protocol-buffers

[4] M. Slee, A. Agarwal, and M. Kwiatkowski, "Thrift: Scalable Cross-Language Services Implementation," Facebook, 156 University Ave, Palo Alto, CA, Tech. Rep., 2007.

[5] F. Wang, S. Oral, G. Shipman, O. Drokin, T. Wang, and I. Huang, "Understanding Lustre Filesystem Internals," Oak Ridge National Lab., National Center for Computational Sciences, Tech. Rep., 2009, ORNL/TM-2009/117.

[6] B. Welch, M. Unangst, Z. Abbasi, G. Gibson, B. Mueller, J. Small, J. Zelenka, and B. Zhou, "Scalable Performance of the Panasas Parallel File System," in *Proceedings of the 6th USENIX Conference on File and Storage Technologies*, ser. FAST'08. USA: USENIX Association, 2008.

[7] N. Ali, P. Carns, K. Iskra, D. Kimpe, S. Lang, R. Latham, R. Ross, L. Ward, and P. Sadayappan, "Scalable I/O Forwarding Framework for High-Performance Computing Systems," in *IEEE International Conference on Cluster Computing and Workshops*, 2009, pp. 1–10.

[8] R. Sandberg, D. Golgberg, S. Kleiman, D. Walsh, and B. Lyon, *Design and Implementation of the Sun Network Filesystem*. USA: Artech House, Inc., 1988, pp. 379–390.

[9] J. Soumagne, D. Kimpe, J. Zounmevo, M. Chaarawi, Q. Koziol, A. Afsahi, and R. Ross, "Mercury: Enabling Remote Procedure Call for High-Performance Computing," in *2013 IEEE International Conference on Cluster Computing (CLUSTER)*, Sep. 2013, pp. 1–8.

[10] R. B. Ross, G. Amvrosiadis, P. Carns, C. D. Cranor, M. Dorier, K. Harms, G. Ganger, G. Gibson, S. K. Gutierrez, R. Latham, B. Robey, D. Robinson, B. Settlemyer, G. Shipman, S. Snyder, J. Soumagne, and Q. Zheng, "Mochi: Composing Data Services for High-Performance Computing Environments," *Journal of Computer Science and Technology*, vol. 35, no. 1, pp. 121–144, Jan 2020. [Online]. Available: https://doi.org/10.1007/s11390-020-9802-0

[11] C. Docan, M. Parashar, and S. Klasky, "DataSpaces: An Interaction and Coordination Framework for Coupled Simulation Workflows," *Cluster Computing*, vol. 15, no. 2, pp. 163–181, Jun. 2012. [Online]. Available: https://doi.org/10.1007/s10586-011-0162-y

[12] ——, “Enabling High-speed Asynchronous Data Extraction and Transfer Using DART,” *Concurr. Comput. : Pract. Exper.*, vol. 22, no. 9, pp. 1181–1204, 2010.

[13] C. Wood, S. Sane, D. Ellsworth, A. Gimenez, K. Huck, T. Gamblin, and A. Malony, “”a scalable observation system for introspection and in situ analytics”,” in *Proceedings of the 5th Workshop on Extreme-Scale Programming Tools*, ser. ESPT ’16. IEEE Press, 2016, pp. 42–49.

[14] C. Ulmer, S. Mukherjee, G. Templet, S. Levy, J. Lofstead, P. Widener, T. Kordenbrock, and M. Lawson, “”faodel: Data management for next-generation application workflows”,” in *Proceedings of the 9th Workshop on Scientific Cloud Computing*, ser. ScienceCloud’18. New York, NY, USA: Association for Computing Machinery, 2018. [Online]. Available: https://doi.org/10.1145/3217880.3217888

[15] J. Lofstead, R. Oldfield, T. Kordenbrock, and C. Reiss, “Extending Scalability of Collective IO through Nessie and Staging,” in *Proceedings of the Sixth Workshop on Parallel Data Storage*. New York, NY, USA: ACM, 2011, pp. 7–12.

[16] P. Grun, S. Hefty, S. Sur, D. Goodell, R. D. Russell, H. Pritchard, and J. M. Squyres, “A Brief Introduction to the OpenFabrics Interfaces - A New Network API for Maximizing High Performance Application Efficiency,” in *2015 IEEE 23rd Annual Symposium on High-Performance Interconnects*, Aug 2015, pp. 34–39.

[17] Intel Corporation, “DAOS: Revolutionizing High-Performance Storage with Intel Optane Technology,” https://www.intel.com/content/dam/www/public/us/en/documents/solution-briefs/high-performance-storage-brief.pdf, Jun. 2019.

[18] T. Wang, K. Mohror, A. Moody, K. Sato, and W. Yu, “An Ephemeral Burst-Buffer File System for Scientific Applications,” in *SC ’16: Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*, Nov 2016, pp. 807–818.

[19] M. Vef, N. Moti, T. Süß, T. Tocci, R. Nou, A. Miranda, T. Cortes, and A. Brinkmann, “GekkoFS—A Temporary Distributed File System for HPC Applications,” in *2018 IEEE International Conference on Cluster Computing (CLUSTER)*, Sep. 2018, pp. 319–324.

[20] J. Mu, J. Soumagne, H. Tang, S. Byna, Q. Koziol, and R. Warren, “A Transparent Server-Managed Object Storage System for HPC,” in *2018 IEEE International Conference on Cluster Computing (CLUSTER)*, Sep. 2018, pp. 477–481.