CONSENSUS: BRIDGING THEORY AND PRACTICE

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I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality as a dissertation for the degree of Doctor of Philosophy.

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Abstract

Distributed consensus is fundamental to building fault-tolerant systems. It allows a collection of machines to work as a coherent group that can survive the failures of some of its members. Unfortunately, the most common consensus algorithm, Paxos, is widely regarded as difficult to understand and implement correctly.

This dissertation presents a new consensus algorithm called Raft, which was designed for understandability. Raft first elects a server as leader, then concentrates all decision-making onto the leader. These two basic steps are relatively independent and form a better structure than Paxos, whose components are hard to separate. Raft elects a leader using voting and randomized timeouts. The election guarantees that the leader already stores all the information it needs, so data only flows outwards from the leader to other servers. Compared to other leader-based algorithms, this reduces mechanism and simplifies the behavior. Once a leader is elected, it manages a replicated log. Raft leverages a simple invariant on how logs grow to reduce the algorithm's state space and accomplish this task with minimal mechanism.

Raft is also more suitable than previous algorithms for real-world implementations. It performs well enough for practical deployments, and it addresses all aspects of building a complete system, including how to manage client interactions, how to change the cluster membership, and how to compact the log when it grows too large. To change the cluster membership, Raft allows adding or removing one server at a time (complex changes can be composed from these basic steps), and the cluster continues servicing requests throughout the change.

We believe that Raft is superior to Paxos and other consensus algorithms, both for educational purposes and as a foundation for implementation. Results from a user study demonstrate that Raft is easier for students to learn than Paxos. The algorithm has been formally specified and proven, its leader election algorithm works well in a variety of environments, and its performance is equivalent to Multi-Paxos. Many implementations of Raft are now available, and several companies are deploying Raft.

Preface

This dissertation expands on a paper written by Diego Ongaro and John Ousterhout entitled *In Search of an Understandable Consensus Algorithm* [89]. Most of the paper's content is included in some form in this dissertation. It is reproduced in this dissertation and licensed under the Creative Commons Attribution license with permission from John Ousterhout.

Readers may want to refer to the Raft website [92] for videos about Raft and an interactive visualization of Raft.

Acknowledgments

Thanks to my family and friends for supporting me throughout the ups and downs of grad school. Mom, thanks for continuously pushing me to do well academically, even when I didn't see the point. I still don't know how you got me out of bed at 6 a.m. all those mornings. Dad, thanks for helping us earn these six (seven?) degrees, and I hope we've made you proud. Zeide, I wish I could give you a copy of this small book for your collection. Ernesto, thanks for sparking my interest in computers; I still think they're pretty cool. Laura, I'll let you know if and when I discover a RAMCloud. Thanks for listening to hours of my drama, even when you didn't understand the nouns. Jenny, thanks for helping me get through the drudgery of writing this dissertation and for making me smile the whole way through. You're crazy for having wanted to read this, and you're weird for having enjoyed it.

I learned a ton from my many labmates, both in RAMCloud and in SCS. Deian, I don't know why you always cared about my work; I never understood your passion for that IFC nonsense, but keep simplifying it until us mortals can use it. Ankita, you've single-handedly increased the lab's average self-esteem and optimism by at least 20%. I've watched you learn so much already; keep absorbing it all, and I hope you're able to see how far you've come. Good luck with your role as the new Senior Student. Thanks especially to Ryan and Steve, with whom I formed the first generation of RAMCloud students. Ryan, believe it or not, your optimism helped. You were always excited about wacky ideas, and I always looked forward to swapping CSBs ("cool story, bro") with you. You'll make a great advisor. Steve, I miss your intolerance for bullshit, and I strive to match your standards for your own engineering work. You continuously shocked the rest of us with those silent bursts of productivity, where you'd get quarter-long projects done over a single weekend. You guys also figured out all the program requirements before I did and told me all the tricks. I continue to follow your lead even after you've moved on. (Ryan, you incorrectly used the British spelling "acknowledgements" rather than the American "acknowledgments". Steve, you did too, but you're just Canadian, not wrong.)

Thanks to the many professors who have advised me along the way. John Ousterhout, my Ph.D.

advisor, should be a coauthor on this dissertation (but I don't think they would give me a degree that way). I have never learned as much professionally from any other person. John teaches by setting a great example of how to code, to evaluate, to design, to think, and to write *well*. I have never quite been on David Mazières's same wavelength; he's usually 10–30 minutes ahead in conversation. As soon as I could almost keep up with him regarding consensus, he moved on to harder Byzantine consensus problems. Nevertheless, David has looked out for me throughout my years in grad school, and I've picked up some of his passion for building useful systems and, more importantly, having fun doing so. Mendel Rosenblum carries intimate knowledge of low level details like x86 instruction set, yet also manages to keep track of the big picture. He's helped me with both over the years, surprising me with how quickly he can solve my technical problems and how clear my predicaments are when put into his own words. Thanks to Christos Kozyrakis and Stephen Weitzman for serving on my defense committee, and thanks to Alan Cox and Scott Rixner for introducing me to research during my undergraduate studies at Rice.

Many people contributed directly to this dissertation work. A special thanks goes to David Mazières and Ezra Hoch for each finding a bug in earlier versions of Raft. David emailed us one night at 2:45 a.m. as he was reading through the Raft lecture slides for the user study. He wrote that he found "one thing quite hard to follow in the slides," which turned out to be a major issue in Raft's safety. Ezra found a liveness bug in membership changes. He posted to the Raft mailing list, "What if the following happens?" [35], and described an unfortunate series of events that could leave a cluster unable to elect a leader. Thanks also to Hugues Evrard for finding a small omission in the formal specification.

The user study would not have been possible without the support of Ali Ghodsi, David Mazières, and the students of CS 294-91 at Berkeley and CS 240 at Stanford. Scott Klemmer helped us design the user study, and Nelson Ray advised us on statistical analysis. The Paxos slides for the user study borrowed heavily from a slide deck originally created by Lorenzo Alvisi.

Many people provided feedback on other content in this dissertation. In addition to my reading committee, Jennifer Wolochow provided helpful comments on the entire dissertation. Blake Mizerany, Xiang Li, and Yicheng Qin at CoreOS pushed me to simplify the membership change algorithm towards single-server changes. Anirban Rahut from Splunk pointed out that membership changes may be needlessly slow when a server joins with an empty log. Laura Ongaro offered helpful feedback on the user study chapter. Asaf Cidon helped direct me in finding the probability of split votes during elections. Eddie Kohler helped clarify the trade-offs in Raft's commitment rule, and Maciej Smoleński pointed out that because of it, if a leader were to restart an unbounded number of

times before it could mark entries committed, its log could grow without bound (see Chapter 11). Alexander Shraer helped clarify how membership changes work in Zab.

Many people provided helpful feedback on the Raft paper and user study materials, including Ed Bugnion, Michael Chan, Hugues Evrard, Daniel Giffin, Arjun Gopalan, Jon Howell, Vimalkumar Jeyakumar, Ankita Kejriwal, Aleksandar Kracun, Amit Levy, Joel Martin, Satoshi Matsushita, Oleg Pesok, David Ramos, Robbert van Renesse, Mendel Rosenblum, Nicolas Schiper, Deian Stefan, Andrew Stone, Ryan Stutsman, David Terei, Stephen Yang, Matei Zaharia, 24 anonymous conference reviewers (with duplicates), and especially Eddie Kohler for shepherding the Raft paper.

Werner Vogels tweeted a link to an early draft of the Raft paper, which gave Raft significant exposure. Ben Johnson and Patrick Van Stee both gave early talks on Raft at major industry conferences.

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Chapter 1

Introduction

Today's datacenter systems and applications run in highly dynamic environments. They scale out by leveraging the resources of additional servers, and they grow and shrink according to demand. Server and network failures are also commonplace: about 2–4% of disk drives fail each year [103], servers crash about as often [22], and tens of network links fail every day in modern datacenters [31].

As a result, systems must deal with servers coming and going during normal operations. They must react to changes and adapt automatically within seconds; outages that are noticeable to humans are typically not acceptable. This is a major challenge in today's systems; failure handling, coordination, service discovery, and configuration management are all difficult in such dynamic environments.

Fortunately, distributed consensus can help with these challenges. Consensus allows a collection of machines to work as a coherent group that can survive the failures of some of its members. Within a consensus group, failures are handled in a principled and proven way. Because consensus groups are highly available and reliable, other system components can use a consensus group as the foundation for their own fault tolerance. Thus, consensus plays a key role in building reliable large-scale software systems.

When we started this work, the need for consensus was becoming clear, but many systems still struggled with problems that consensus could solve. Some large-scale systems were still limited by a single coordination server as a single point of failure (e.g., HDFS [81, 2]). Many others included ad hoc replication algorithms that handled failures unsafely (e.g., MongoDB and Redis [44]). New systems had few options for readily available consensus implementations (ZooKeeper [38] was the most popular), forcing systems builders to conform to one or build their own.

Those choosing to implement consensus themselves usually turned to Paxos [48, 49]. Paxos had

dominated the discussion of consensus algorithms over the last two decades: most implementations of consensus were based on Paxos or influenced by it, and Paxos had become the primary vehicle used to teach students about consensus.

Unfortunately, Paxos is quite difficult to understand, in spite of numerous attempts to make it more approachable. Furthermore, its architecture requires complex changes to support practical systems, and building a complete system based on Paxos requires developing several extensions for which the details have not been published or agreed upon. As a result, both system builders and students struggle with Paxos.

The two other well-known consensus algorithms are Viewstamped Replication [83, 82, 66] and Zab [42], the algorithm used in ZooKeeper. Although we believe both of these algorithms are incidentally better in structure that Paxos for building systems, neither has explicitly made this argument; they were not designed with simplicity or understandability as a primary goal. The burden of understanding and implementing these algorithms is still too high.

Each of these consensus options was difficult to understand and difficult to implement. Unfortunately, when the cost of implementing consensus with proven algorithms was too high, systems builders were left with a tough decision. They could avoid consensus altogether, sacrificing the fault tolerance or consistency of their systems, or they could develop their own ad hoc algorithm, often leading to unsafe behavior. Moreover, when the cost of explaining and understanding consensus was too high, not all instructors attempted to teach it, and not all students succeeded in learning it. Consensus is as fundamental as two-phase commit; ideally, as many students should learn it (even though consensus is fundamentally more difficult).

After struggling with Paxos ourselves, we set out to find a new consensus algorithm that could provide a better foundation for system building and education. Our approach was unusual in that our primary goal was *understandability*: could we define a consensus algorithm for practical systems and describe it in a way that is significantly easier to learn than Paxos? Furthermore, we wanted the algorithm to facilitate the development of intuitions that are essential for system builders. It was important not just for the algorithm to work, but for it to be obvious why it works.

This algorithm also had to be complete enough to address all aspects of building a practical system, and it had to perform well enough for practical deployments. The core algorithm not only had to specify the effects of receiving a message but also describe what *should* happen and when; these are equally important for systems builders. Similarly, it had to guarantee consistency, and it also had to provide availability whenever possible. It also had to address the many aspects of a system that go beyond reaching consensus, such as changing the members of the consensus group.

These are necessary in practice, and leaving this burden to systems builders would risk ad hoc, suboptimal, or even incorrect solutions.

The result of this work is a consensus algorithm called Raft. In designing Raft we applied specific techniques to improve understandability, including decomposition (Raft separates leader election, log replication, and safety) and state space reduction (Raft reduces the degree of nondeterminism and the ways servers can be inconsistent with each other). We also addressed all of the issues needed to build a complete consensus-based system. We considered each design choice carefully, not just for the benefit of our own implementation but also for the many others we hope to enable.

We believe that Raft is superior to Paxos and other consensus algorithms, both for educational purposes and as a foundation for implementation. It is simpler and more understandable than other algorithms; it is described completely enough to meet the needs of a practical system; it has several open-source implementations and is used by several companies; its safety properties have been formally specified and proven; and its efficiency is comparable to other algorithms.

The primary contributions of this dissertation are as follows:

- The design, implementation, and evaluation of the Raft consensus algorithm. Raft is similar in many ways to existing consensus algorithms (most notably, Oki and Liskov's Viewstamped Replication [83, 66]), but it is designed for understandability. This led to several novel features. For example, Raft uses a stronger form of leadership than other consensus algorithms. This simplifies the management of the replicated log and makes Raft easier to understand.

- The evaluation of Raft's understandability. A user study with 43 students at two universities shows that Raft is significantly easier to understand than Paxos: after learning both algorithms, 33 of these students were able to answer questions about Raft better than questions about Paxos. We believe this is the first scientific study to evaluate consensus algorithms based on teaching and learning.

- The design, implementation, and evaluation of Raft's leader election mechanism. While many consensus algorithms do not prescribe a particular leader election algorithm, Raft includes a specific algorithm involving randomized timers. This adds only a small amount of mechanism to the heartbeats already required for any consensus algorithm, while resolving conflicts simply and rapidly. The evaluation of leader election investigates its behavior and performance, concluding that this simple approach is sufficient in a wide variety of practical environments. It typically elects a leader in under 20 times the cluster's one-way network latency.

- The design and implementation of Raft's cluster membership change mechanism. Raft allows adding or removing a single server at a time; these operations preserve safety simply, since at least one server overlaps any majority during the change. More complex changes in membership are implemented as a series of single-server changes. Raft allows the cluster to continue operating normally during changes, and membership changes can be implemented with only a few extensions to the basic consensus algorithm.

- A thorough discussion and implementation of the other components necessary for a complete consensus-based system, including client interaction and log compaction. Although we do not believe these aspects of Raft to be particularly novel, a complete description is important for understandability and to enable others to build real systems. We have implemented a complete consensus-based service to explore and address all of the design decisions involved.

- A proof of safety and formal specification for the Raft algorithm. The level of precision in the formal specification aids in reasoning carefully about the algorithm and clarifying details in the algorithm's informal description. The proof of safety helps build confidence in Raft's correctness. It also aids others who wish to extend Raft by clarifying the implications for safety of their extensions.

We have implemented many of the designs in this dissertation in an open-source implementation of Raft called LogCabin [86]. LogCabin served as our test platform for new ideas in Raft and as a way to verify that we understood the issues of building a complete and practical system. The implementation is described in more detail in Chapter 10.

The remainder of this dissertation introduces the replicated state machine problem and discusses the strengths and weaknesses of Paxos (Chapter 2); presents the Raft consensus algorithm, its extensions for cluster membership changes and log compaction, and how clients interact with Raft (Chapters 3–6); evaluates Raft for understandability, correctness, and leader election and log replication performance (Chapters 7–10); and discusses related work (Chapter 11).

Chapter 2

Motivation

Consensus is a fundamental problem in fault-tolerant systems: how can servers reach agreement on shared state, even in the face of failures? This problem arises in a wide variety of systems that need to provide high levels of availability and cannot compromise on consistency; thus, consensus is used in virtually all consistent large-scale storage systems. Section 2.1 describes how consensus is typically used to create replicated state machines, a general-purpose building block for fault-tolerant systems; Section 2.2 discusses various ways replicated state machines are used in larger systems; and Section 2.3 discusses the problems with the Paxos consensus protocol, which Raft aims to address.

2.1 Achieving fault tolerance with replicated state machines

Consensus algorithms typically arise in the context of *replicated state machines* [102]. In this approach, state machines on a collection of servers compute identical copies of the same state and can continue operating even if some of the servers are down. Replicated state machines are used to solve a variety of fault tolerance problems in distributed systems, as described in Section 2.2. Examples of replicated state machines include Chubby [11] and ZooKeeper [38], which both provide hierarchical key-value stores for small amounts of configuration data. In addition to basic operations such as *get* and *put*, they also provide synchronization primitives like *compare-and-swap*, enabling concurrent clients to coordinate safely.

Replicated state machines are typically implemented using a replicated log, as shown in Figure 2.1. Each server stores a log containing a series of commands, which its state machine executes in order. Each log contains the same commands in the same order, so each state machine processes

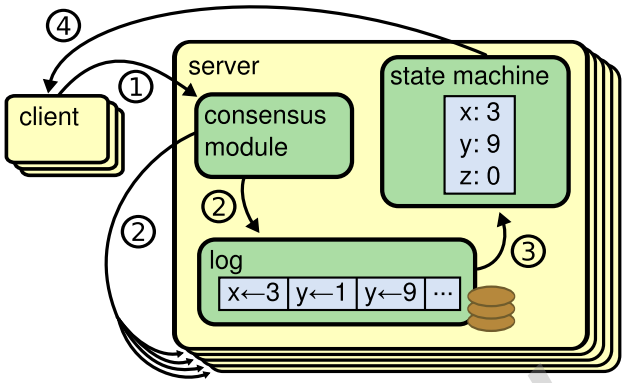


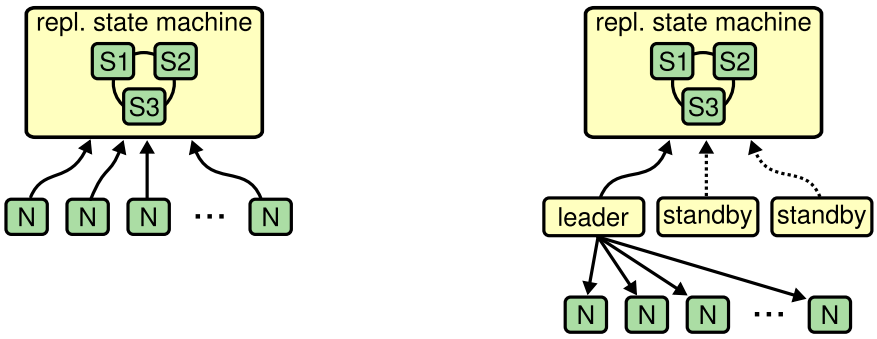
Figure 2.1: Replicated state machine architecture. The consensus algorithm manages a replicated log containing state machine commands from clients. The state machines process identical sequences of commands from the logs, so they produce the same outputs.

the same sequence of commands. Since the state machines are deterministic, each computes the same state and the same sequence of outputs.

Keeping the replicated log consistent is the job of the consensus algorithm. The consensus module on a server receives commands from clients and adds them to its log. It communicates with the consensus modules on other servers to ensure that every log eventually contains the same requests in the same order, even if some servers fail. Once commands are properly replicated, they are said to be *committed*. Each server's state machine processes committed commands in log order, and the outputs are returned to clients. As a result, the servers appear to form a single, highly reliable state machine.

Consensus algorithms for practical systems typically have the following properties:

- They ensure *safety* (never returning an incorrect result) under all non-Byzantine conditions, including network delays, partitions, and packet loss, duplication, and reordering.
- They are fully functional (*available*) as long as any majority of the servers are operational and can communicate with each other and with clients. Thus, a typical cluster of five servers can tolerate the failure of any two servers. Servers are assumed to fail by stopping; they may later recover from state on stable storage and rejoin the cluster.
- They do not depend on timing to ensure the consistency of the logs: faulty clocks and extreme message delays can, at worst, cause availability problems. That is, they maintain safety under an *asynchronous* model [71], in which messages and processors proceed at arbitrary speeds.



(a) The nodes in the cluster coordinate among themselves by reading from and writing to the replicated state machine.

(b) One leader actively manages the nodes in the cluster and records its state using the replicated state machine. Other standby servers are passive until the leader fails.

Figure 2.2: Common patterns for using a single replicated state machine.

- In the common case, a command can complete as soon as a majority of the cluster has responded to a single round of remote procedure calls; a minority of slow servers need not impact overall system performance.

2.2 Common use cases for replicated state machines

Replicated state machines are a general-purpose building block for making systems fault-tolerant. They can be used in a variety of ways, and this section discusses some typical usage patterns.

Most common deployments of consensus have just three or five servers forming one replicated state machine. Other servers can then use this state machine to coordinate their activities, as shown in Figure 2.2(a). These systems often use the replicated state machine to provide group membership, configuration management, or locks [38]. As a more specific example, the replicated state machine could provide a fault-tolerant work queue, and other servers could coordinate using the replicated state machine to assign work to themselves.

A common simplification to this usage is shown in Figure 2.2(b). In this pattern, one server acts as leader, managing the rest of the servers. The leader stores its critical data in the consensus system. In case it fails, other standby servers compete for the position of leader, and if they succeed, they use the data in the consensus system to continue operations. Many large-scale storage systems that have a single cluster leader, such as GFS [30], HDFS [105], and RAMCloud [90], use this approach.

Consensus is also sometimes used to replicate very large amounts of data, as shown in Figure 2.3. Large storage systems, such as Megastore [5], Spanner [20], and Scatter [32], store too