Dinghy: Horizontally Scaling Raft Clusters

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Abstract

With the introduction of Raft, distributed consensus has become more widely available in the use of cluster design. Different applications of distributed systems often require differing configurations, however, as these clusters begin to increase in the number of participating nodes, they become increasingly less efficient at coming to consensus. Current methods of scaling distributed systems generally implement some variation of data sharding, batch processing, or message coalescing. We investigate however, utilizing dynamically set timeouts and heartbeat intervals to increase network throughput, and propose methods to more effectively handle a growing number of nodes in a cluster, while analyzing their ability to increase the horizontal scalability of a Raft cluster.

1 Introduction

The Raft consensus algorithm originated to simplify the preexisting Paxos algorithm, while at the same time, solving the same core problem [17] with a similar efficiency. For years, Paxos had dominated distributed consensus. At its core it defined a way in which a system could come to agreement on a given state [13]. Though, Paxos can be incredibly hard to comprehend. Many papers have been published in an attempt to offer a clearer explanation as to how Paxos functions [14, 15], but it continues to be a difficult system to implement at a practical level.

Ultimately, these algorithms define a method for a system to agree on a state [9]. They work to build a fault tolerant approach to distributed systems, the *replicated state machine* [18]. In this context, a group of machines replicate a single state across themselves to create a fault tolerant system, that can handle the failure of $n/2 - 1$ nodes. The essential goal of consensus in terms of the *replicated state machine* is to reach a *univalent* state, from any *multivalent* state. Such algorithms specifically order state changes, to ensure that when applied, that all result in the same state [12, 17]. Raft also works to correct, and right, any nodes in a cluster in contradicting states. It does this via counting `election terms`, demonstrated as such:

We define two nodes in a cluster, with two corresponding state machines, M and N. We also define a function, $T(S)$, of some arbitrary state machine S, that is its current `term`, where T_c is the correct `term` in the cluster.

$$T_c = \begin{cases} M, & T(M) > T(N) \\ N, & T(M) < T(N) \\ \varnothing, & T(M) = T(N) \end{cases}$$

In order to keep some sense of order in the cluster, Raft keeps track of the number of leader elections that have occured with the `election term`. This is a system wide tally that is used to determine when a node may be behind or have conflicting information in its log. Many of these comparisons have to be made from node to node through heartbeat messages,

that also act to check for leader liveness [17]. But, as one might imagine, as you try to include more nodes in a cluster, the number of checks that have to be propogated to ensure an effective system drastically increases.

2 Scaling Distributed Systems

In practical applications, clusters of varying sizes are required. In some cases many nodes will be used, each replicating a small piece of data many times over. While in others, few nodes wil are used and larger chunks of data are replicated. Though in implementation, there are drawbacks to having a cluster with many nodes. As you continue to increase node number, various factors can lower a networks required time to reach consensus. Raft solves the consensus problem algorithmically, but let's, for example, take a look at a real world example where scaling comes into play.

We can imagine a large party of friends trying to decide where they want to go to eat for dinner. In this scenario in order to make an effective, and satisfying decision as to where the group should dine, each member of the group must be consulted. So the time in which it takes the entire group to come to an agreement increases as the size of the group increases.

In this large party, many more people will have to be consulted, and more options will have to be weighed before a choice is made. Though, compare this to just a few friends, who would be able to reach mutual agreement much faster, as they have less to consider, and fewer people that need to be taken into account before reaching a decision.

This principle is clearly demonstrated in distributed systems [16]. Adding more nodes to a cluster makes it more difficult for the network to handle faults and replicate its state. Demonstrated in Raft, the more *followers* in a system, the more heartbeats that have to be sent out to the *leader*, processed, responded to, and then confirmed [17].

Though we can also demonstrate the benefits of a larger cluster. A greater number of nodes in a cluster allows for greater fault tolerance. If we say there is a 25% chance that a node fails at some point, we can model the probability of a cluster reaching agreement as such:

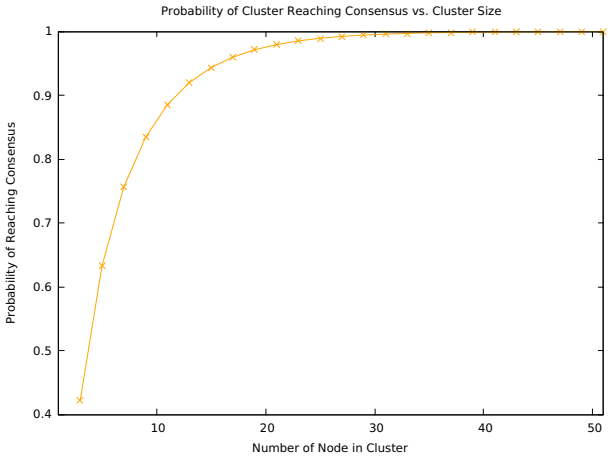
We define a function, $L(n)$, that is the probability a cluster of size n, can reach consensus given they have a 25% of failing. Essentially equivalent to the common *binomial cumulative density function.*

$$L(n) = 1 - \sum_{i=0}^{n/2-1} \binom{n}{i} (0.75)^i (0.25)^{n-i}$$

With this function, we model the probability given each cluster size:

$$\{(n, p) : n \in \{3, 5, 7, ..., 51\}, p = L(n)\}$$

Producing a distribution as such:



With this distribution we can see the theoretical benefits of a greater horizontal size. When increasing the number of servers, we initially see a great jump in the probability that the cluster reaches consensus. While this probability does increase, the servers quickly hit a point, in this instance at a size of about 30 servers, where the there are no observable benefits to fault tolerance.

Now we begin to look at some of the possible methods to scale distributed systems, each with varying degree of complexity and success.

2.1 Non-Voting Servers

One common way of increasing the capabilities of a large Raft cluster, is to change the voting status of additonal nodes. Usually when we discuss creating larger clusters, we mean creating a cluster of servers, each with full voting privileges. But every one of these members all having full voting power, requires extra considerations in the cluster. When you are a *full* node, you must participate in log replication, as well as be consulted when changes need to be made to the replicated log. So a common solution to this requirement for being a *full* voting server, is making some of the members *non-voting* servers. This allows for the node to participate in the cluster, gaining the benefits of the log replication, but not bogging down the cluster by increasing the quorum size [2]. Though it should be noted that this solution does not in any way solve the presented problem. Demoting nodes to a non-voting configuration, does not assist with the fault tolerance of the cluster. Supose you spin up a cluster with 5 full Raft servers, and 100 non-voting servers. If even just 3 of the full nodes fail, the system can no longer make progress, even though we have allocated resources for running a total of 105 servers because, the majority of the voting nodes have failed.

2.2 Sharding

There is also a way of scaling writes and reads. Some databases divide up the data their are trying to replicate using a process called *sharding*. A great example of this process can be found in Google's Spanner database [10]. *Sharding* works as a type of distributed load balances to balance the store of data across many consensus groups.

2.3 Batching

Other databases work to alter the process of sending or receiving inter-node messages. The Calvin database works to group messages, and specially schedule them in order to maintain consistency, and scalability [19].

3 Dinghy Algorithm

Like all other algorithms of its class, Raft has similar problems scaling. Though it has a distrinctly unique set of problems. It should be noted that we can consider Raft generally *synchronous*. That is, all nodes must reach a *univalent* state, before handling the replication of the next update to the log. Raft's use of a *leader*, requires all changes to the network state be processed through a single node, thereby essentially creating a synchronous cluster where in which *followers* have very little power to influence the cluster's state when there is a healthy *leader*. So when we discuss scaling in terms of a leader based methods we have to examine different properities of the algorithm.

Dinghy works as an embedded algorithm within Raft. It runs side by side the core Raft *follower* routines, in order to actively maintain historical statistics on a node. In its most base form Dinghy attempts to get a sense of the environment that a given server is running in and adjust some of its previously set, static parameters, and adjust them to a more appropriate level for the situation. The Lifeguard system works in a similar fashion, but with differing goals, and approaches, using a step function to help stop false positives, whereas Dinghy looks at historical averages [11].

In order to get an idea of message latency we average the elapsed time between the last P messages received, we call the *average message latency*, or t_{avg}. The selection of P in implementation is rather arbitrary, the larger, the more resistant the *average message latency* is to extreme latencies. So t_P is the Pth elapsed time behind, and t_c is the elapsed time between the two most recent messages.

$$t_{avg} = \frac{t_P + ... + t_c}{P}$$

Given that the *heartbeat interval* of a node is one tenth of the *heartbeat timeout*, we then, every few milliseconds, update the *heartbeat timeout* to $20 * t_{avg} + 10$ ms.

4 Testing Consensus

The big draw of Raft is its practicallity. It has allowed many the opportunity to implement distributed consensus, as it was designed to be understandable. So with this is mind, we maintain a similar dogma when it comes to testing the algorithms scalability. We wanted to design a test that would stress test the networks throughput given a certain size, given that Raft is overwhelmingly used in creating fault tolerant databases [1, 4, 5, 7].

With these considerations, we first decided the most common use case for this method of distributed consensus. The official Raft website contains a useful list of implementations [8]. Given its capabilities, Raft is overwhelmingly used for database replication , We elected to use a popular open source library written in Go, `hashicorp/raft` [6]. With this, we used an integer state in our cluster's state machine. We define the function $S(R)$, that is the current state of some arbitrary Raft node, R.

Our testing tracks the time it takes for a constant number of successive `Apply` operations to take place. The replicated state machine is being incremented every update, such that, after T_f, given a set of Raft nodes C,

$$\{r_1, r_2 \in C : S(r_1) = S(r_2)\}$$

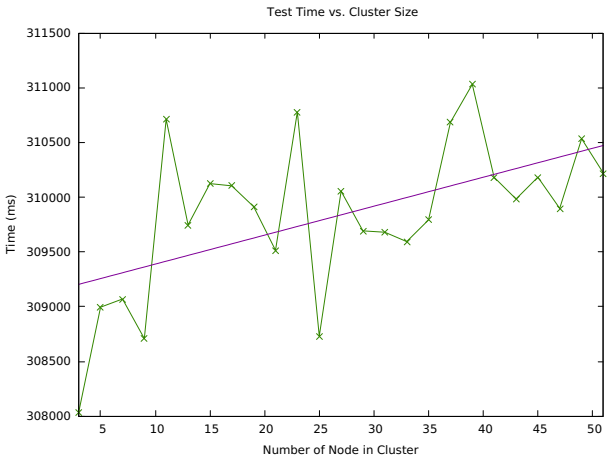
and the final number of applies, or commits for our test was the value of the final integer state of some arbitrary node in the cluster.

In our specific trials we timed how long it took the cluster to reach 1000 state changes [3]. We use this specific procedure in the testing of both our proposed algorithm, Dinghy, and the benchmarks of pure Raft.

5 Base Performance

Of course before we look into some potentially beneficial alterations we could make to Raft, we must examine the base algorithms ability to scale.

To demonstrate the increase in difficulty in reaching agreement when the number of nodes

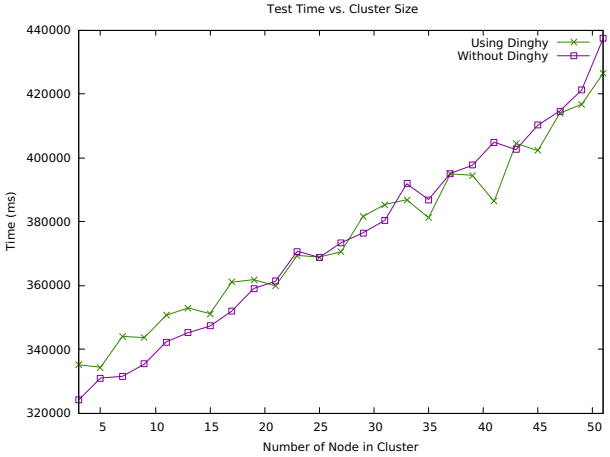


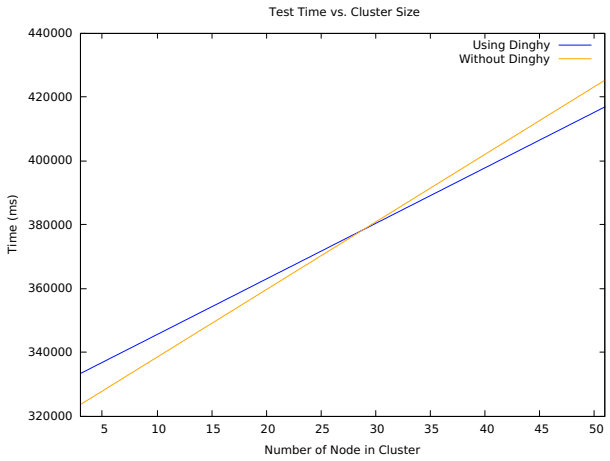
increase, we ran a test, as previously defined, where in which no nodes die. As we see in this test, as we increase the number of nodes in a cluster, even without any extra difficulties like delays or node failures, consensus becomes harder to achieve. After this observation we can start to investigate improving the rate at which the time it takes to reach distributed agreement.

6 Dinghy Performance

Testing the algorithm using the previously defined test.

With smaller clusters, Dinghy does not make any signficant changes toward the time it takes a cluster to run the test. Though as the number of servers participating in consensus increases, the time it takes for the cluster to run the test decreases.





7 Conclusion

It becomes more and more difficult for pure Raft to achieve distributed agreement with more participants in the process. More messages have to be exchanged in order to perform the same operation, while a leader can only process communication from so many nodes at a time. We presented an algorithm that can be used in order to optimize the *heartbeat timeout* and *interval* of a node in order to allow for greater message throughput, and a quicker detection of faulty *leaders*.

The Dinghy algorithm uses the average of the elapsed message times, in order to gain a better idea of network latency. Using this measure, timeouts can be recalculated to allow for a greater efficiency in handling a growing number of messages. So in use with a larger cluster, Dinghy can be utilized to provide better horizontal scaling.

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