Bringing Innovative Load Balancing to NGINX

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ABSTRACT

Load balancing remains an important area of study in computer science largely due to the increasing demand on data centers and webservers. However, it is rare to see improvements in load balancing algorithms implemented outside of expensive specialized hardware. This research project is an attempt to bring these innovative techniques to NGINX, the industry leading open source load balancer and webserver.

In addition to implementing a new, native NGINX module, I have developed a simple workflow to benchmark and compare the performance of available load balancing algorithms in any given production environment. My benchmarks indicate that it is possible to take advantage of more sophisticated load distribution techniques without paying a significant performance cost in additional overhead.

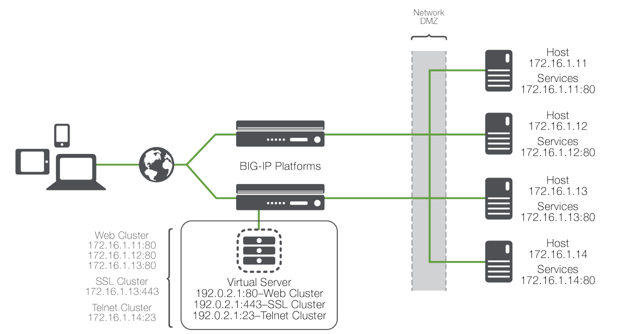


Figure 1: High performance load balancing architecture [8].

1 BACKGROUND

Ultimately, load balancing is a *balls into bins* problem: one must decide how best to distribute m balls into n bins such that each bin has roughly the same number of balls. Although this may sound simple, load balancing has remained a difficult problem in computer science. The major difficulties are due to the complexities of distributing tasks with two major unknowns: *load* and *time*. Load is a task's demand on the server, while *time* is related to both the duration of a task and its arrival. In short, load balancing is challenging because the arrival of a task, how long it will take to complete, and the computational resources it requires, are never predictable and always independent of each other.

These factors not only contribute to the complexities of designing load balancers, but they also make it difficult to model an environment for testing them. Furthermore, not all load balancers are the same. The *balls into bins* problem shows up in many areas of computing, everywhere from CPU task scheduling to telecommunication depends on a load balancer to get work done as efficiently as possible. Figure 1 shows the typical architecture for load balancing in high performance webserver environments.

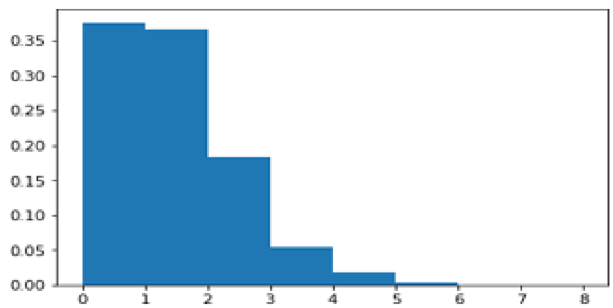
My research is motivated by improving the performance of load balancing on webservers because there has not been as much innovation compared to work done on the TCP/IP network stack or operating system schedulers. However, something all these areas have in common is the underlying statistical model of how tasks arrive that require distribution. This model is most commonly understood as a *Poisson distribution* [1], which is why I use them in my simulation environments to assign each request a unique weight representing their arrival time and load on the webservers. Figure 2 provides a visual representation what Poisson streams look like relative to the arrival times of requests at a given time interval.

Webserver load balancing strategies have hardly changed since their initial implementations. The two most popular algorithms are *random* and *round robin* (RR), the latter having a successful history in CPU scheduling, time-sharing systems, and DNS. These approaches work quite well under certain circumstances, but have significant drawbacks when considering how the internet is used today. For example, round robin works best only when distributing requests of a uniform duration. When RR is used as a CPU scheduler, discrete time quanta are guaranteed, but this is not the case for a webserver, where requests have an *unknown* duration and load. Largely, these disadvantages have been ignored because random and RR seem to do a "good enough" job and attention is primarily given to lower levels of networking and operating system design.

However, improving the ability to distribute load as uniformly as possible has several benefits that ought to be considered. For one thing, a web application spread across multiple servers using an inefficient load balancer will result in one or two machines handling the majority of the requests while others sit nearly idle. When this happens, it is common to add another server into the environment because it will make it less likely for a single machine to become overloaded. This is clearly not the best approach. By utilizing a better load balancing algorithm, a web application can get the most out of each available machine without risking a premature upgrade. But that's not all, reducing the total number of additional servers saves a lot of money, maintenance, and energy.

2 PROJECT DESCRIPTION

There are a number of load balancing algorithms that have been shown to increase the overall performance of webservers when used in place of random or RR, yet few are ever implemented in prevailing open source projects. The biggest advantage of using RR and random from a developers point of view is that they are intuitive algorithms that are easy to implement and maintain. While dedicated hardware load balancers continually take advantage of recent innovation [8], the open source community has been continually




```
import numpy.random as nr
import matplotlib.pyplot as plt

balls = 1000
bins = 8

s = nr.poisson(0.99, balls)
count, bins, ignored = plt.hist(s, bins, (0, bins))
plt.show()
```

Figure 2: What a Poisson distribution looks like

left behind. My research is an attempt to bring some of the most recent and successful load balancing techniques into NGINX, [1] the leading open source load balancer and webserver.

Of these innovations, the algorithm in particular that I want to focus on originally comes from Michael Mitzenmacher's 2001 paper, *The Power of Two Choices in Randomized Load Balancing* [6]. In this paper, Mitzenmacher outlines an algorithm called two-choices, which behaves exponentially superior to the traditional strategies like RR and random. Figure 3 illustrates the two-choices algorithm in what Mitzenmacher presents as the "supermarket model", where a customer wishes to enter the least busy checkout queue. The idea behind two-choices is that the efficient shopper only surveys two of the available queues and quickly enters the least crowded one. The less efficient shopper painstakingly compares every queue before making a decision. Mitzenmacher found that by selecting two random queues, it was possible to avoid the notorious "thundering herd" problem. If every customer was seeking the least crowded queue, then at any given time, everyone will be racing towards a single lane, largely ignoring everything else. Once that queue fills up, another one is chased down. With two-choices, multiple customers are not likely to be directed to the same queue, but they are very likely to avoid the most crowded one.

The aim of my research project is to study the behavior of these breakthrough load balancing techniques in a production environment. To accomplish this I have two goals: (1) Reproduce the work of Mitzenmacher and others relating to the efficiency of various load balancing strategies. (2) Implement two-choices as an NGINX module and test it against the other available load balancers.

3 EXPERIMENTAL SETUP

This project was initially inspired by a talk given by Tyler McMullen, titled *Load Balancing is Impossible* [5], where he outlines

[1]https://nginx.org

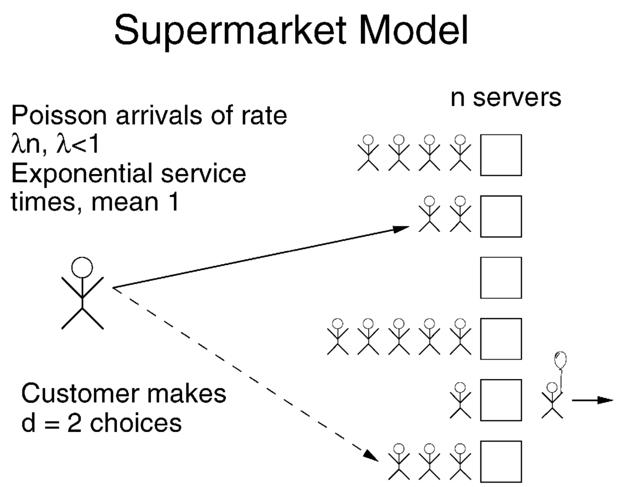


Figure 3: The two-choices load balancing algorithm as described in Mitzenmacher's paper.

the challenges load balancers face when dealing with the web as we know it today. I began my research by expanding the initial simulations given in his talk and soon I was able to construct an environment where I could reproduce the work presented in research papers regarding the two-choices algorithm.

I conducted my load balancing experimentation using an IPython notebook [7] running inside a python virtual environment because it enables portable and cross platform development. Using a Poisson stream with a mean of 0.99 as my request distribution model, I assigned a weight to each request to represent its arrival on the server. In the IPython notebook I model the load balancing in the following way: There is a list of length n representing the requests and a list of length m representing the available servers. The requests are passed to a load balancing algorithm which increments a counter belonging to a particular server by that request's weight. After all requests are distributed, the standard deviation of requests among each server is compared between algorithms. A perfect load distribution would therefore have a standard deviation of zero.

The algorithms I implemented were *random*, *round-robin*, and *two-choices*: Random chooses a server for each request independently and uniformly at random, RR distributes the request to each server one by one, and two-choices first selects two servers independently and uniformly at random and then chooses the server with the least load to process the request. Figure 5 provides minimal algorithm implementations used in my initial testing environment and gives a better sense of how my IPython simulation was organized.

The later stages of my research was done using special configuration files that allow my load balancing module to be dynamically linked to the system installation of NGINX. In addition, I utilized the Go programming language [2] to build a webserver which compiles into a native binary for execution on multiple machines and ports. All of the software components used in my research are provided within a single organized git repository. [3]

[2]https://golang.org/

[3]https://github.com/anschwa/capstone

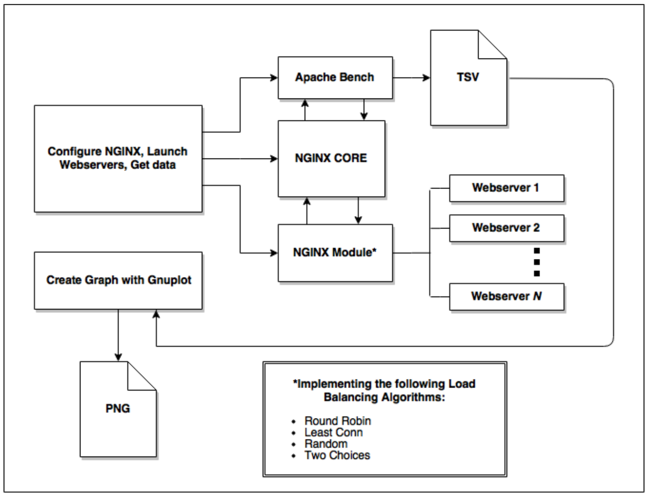


Figure 4: Software architecture for running simulations with NGINX.

3.1 NGINX Module Development

I developed two load balancing modules for NGINX: random and two-choices. The underlying load balancer for NGINX is RR, but it also provides a module called *least_conn*, which will distribute requests giving preference to the server with the least connections currently established. The two-choices module is implemented by incorporating the functionality provided by least_conn and my new random module. Both modules are compiled and dynamically linked into the system installation of NGINX because it makes development much easier. However, both modules can can be statically linked if desired. Although NGINX provides an API for writing modules in perl, I chose to implement them directly in C to eliminate any potential overhead that may skew the results. I also consider native NGINX module implementations more useful to the open source community.

In order to test the effectiveness of the load balancing algorithms, I created a simple webapp in Go that will simulate my production webserver environment. Go is an excellent language to use for this task because it has an extensive HTTP package in the standard library, compiles to native machine code, and does not need any additional dependencies to host a webserver.

The Go webapp generates a Poisson random number for each incoming request. This number is then used to determine how long the webapp will sleep for before sending back a response. I do this to simulate the unpredictability of request duration and load on the server. I chose to model my webserver environment with the Poisson process because it is well understood and commonly used to model the behavior of internet traffic. Naturally, this will not provide an accurate model for all production web applications, however, I have produced a workflow for benchmarking the performance of all NGINX load balancers, including two-choices, on any given system. This workflow will allow anyone to observe the performance of each algorithm in their own production environments. Figure 4 depicts the entire benchmarking workflow and the general software architecture of this project.

```
import numpy as np
import numpy.random as nr

rate = nr.poisson(0.99, requests)
DIST = [(w * 0.1) + 1 for w in rate]

def uniform_random(requests, servers):
   rand = nr.randint(low=0, high=servers, size=requests)
    load = [0] * servers
    for i in range(requests):
        weight = DIST[i]
        chosen_server = rand[i]
        load[chosen_server] += weight
    return np.std(load)

def round_robin(requests, servers):
    load = [0] * servers
    for i in range(requests):
        weight = DIST[i]
        chosen_server = i % servers
        load[chosen_server] += weight
    return np.std(load)

def two_choices(requests, servers):
    load = [0] * servers
    for i in range(requests):
        choice_one = nr.randint(0, servers)
        choice_two = nr.randint(0, servers)

        if load[choice_one] < load[choice_two]:
            best_choice = choice_one
        else:
            best_choice = choice_two

        weight = DIST[i]
        load[best_choice] += weight
    return np.std(load)
```

Figure 5: Simplified Python Implementations

3.2 Apache Bench Testing Strategy

The industry standard tool for benchmarking and measuring web server performance is a command line utility called Apache Bench, [4] or *ab*. The interface is quite simple, it allows you to specify how many total requests to send to a website and how many should be made concurrently. After sending the requests, ab will provide some useful information such as the total time to complete the requests, requests processed per second by the webserver, and the average time spent per request. I use these metrics to gauge the performance of the load balancers on NGINX in addition to graphing the latency of each request in the benchmark.

[4] https://httpd.apache.org/docs/2.4/programs/ab.html

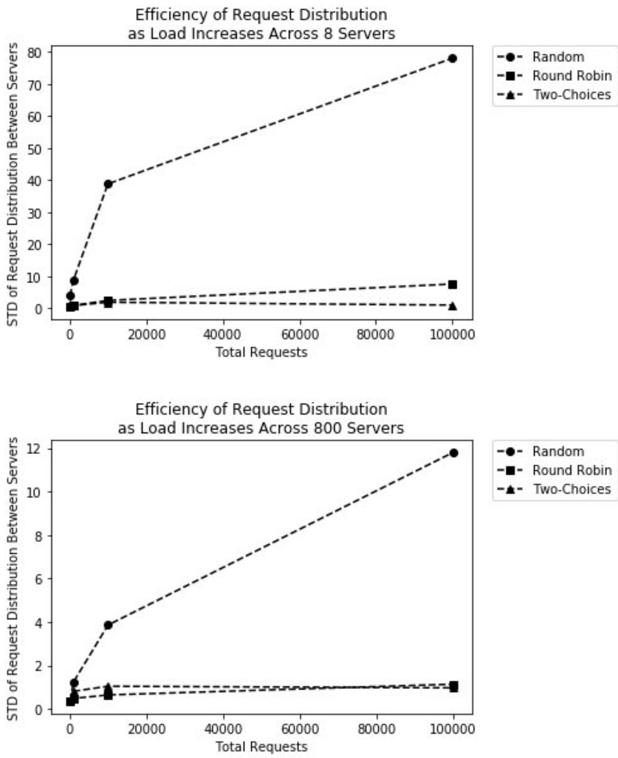


Figure 6: IPython notebook simulation results for random, round robin, and two-choices.

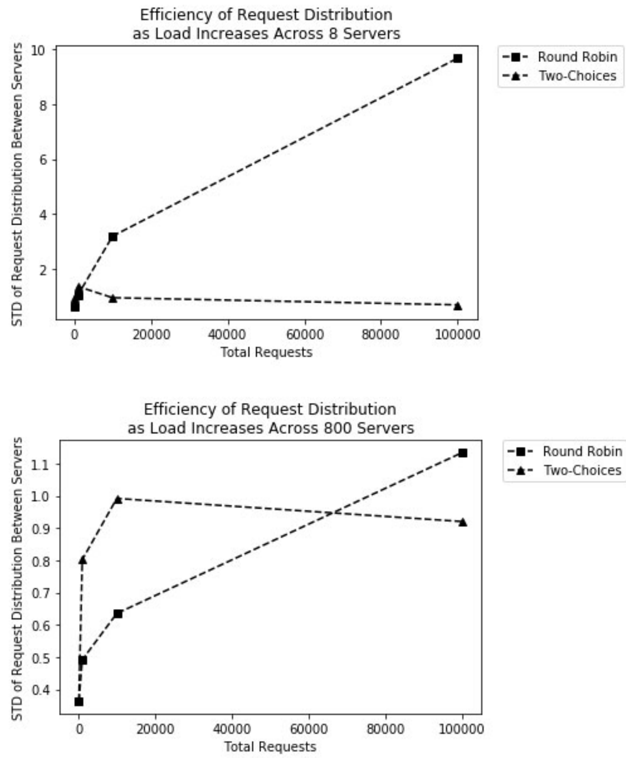


Figure 7: A closer look at the load distribution capabilities of round robin and two-choices.

4 RESULTS AND DISCUSSION

4.1 IPython Simulation Results

My initial simulations reaffirmed the results presented by Mitzenmacher. When requests are weighted, the standard deviation of two-choices approaches zero as the amount of requests being processed increases. As Figures 6 indicates, RR does much better than random, but has an increasing standard deviation as requests increase. Figure 8 highlights an important observation: RR always completes in the least amount of time, whereas two-choices takes more than twice as long to run. Also worth noting is that when the number of servers are increased, RR performs more similarly to two-choices, however, Figure 7 confirms that two-choices is clearly better at maintaining a uniform distribution of requests across all available servers. Although my experiments reaffirms that two-choices is the superior algorithm as far as load distribution, the results raise an important question: How will the overhead of two-choices affect the latency of a production webserver?

```
8 Servers:
  Random: 410 ms ± 79 ms per loop
  Round Robin: 371 ms ± 18.5 ms per loop
  Two Choices: 826 ms ± 171 ms per loop
800 Servers:
  Random: 414 ms ± 53.9 ms per loop
  Round Robin: 381 ms ± 24.5 ms per loop
  Two Choices: 784 ms ± 9.04 ms per loop
```

Figure 8: Latency of random, round robin, and two-choices in IPython simulation using the `timeit` module with format: (mean ± std. dev. of 7 runs, 1 loop each).

4.2 NGINX Simulation Results

My extensive benchmarking revealed no obvious distinction between load balancing algorithms running in NGINX. Regardless of the active module, performance remained about the same. However, there were some general trends regarding concurrent and total requests that were anticipated, namely, when you flood your webserver with requests, it takes longer to respond.

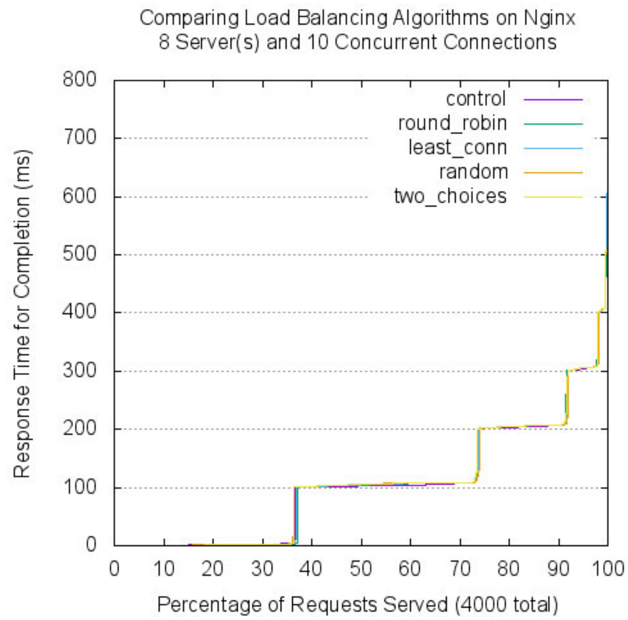
What these results do indicate, is that the overhead of a load balancer may become negligible when taking into account the total overhead associated with completing an HTTP request. In the earlier simulations with python, I was concerned that the increased latency of two-choices would make it an inconvenient load balancer in a production environment. However, my results show that we may be able to take advantage of two-choice's uniform load distribution abilities without paying much performance penalty.

Yet, the lack of a clear distinction in algorithms is a concern. It is a good indication that my experimental environment is not capable of simulating the conditions necessary to make high performance load balancing observable. I'm not completely dismayed because using `ab` to benchmark webserver performance is an industry standard. Although, employing a custom benchmarking technique for these experiments may have produced more obvious results. With that being said, I'm still confident in the viability of two-choices as a load balancer after running these experiments.

Additionally, the machine running all simulations can only launch up to 8 webservers, each processing up to 100 concurrent connections from `ab`. [5] While it is possible that the load balancing modules need to be tested with an NGINX configuration containing hundreds of servers, it may be an unrealistic expectation. When I initially contacted the NGINX mailing list about my research project, lead developer Maxim Dounin responded that algorithms like two-choices have never been considered for implementation because it was unlikely to effect performance unless one was using NGINX in a very large computing environment. [6]

Most of my findings are summarized by Figure 9. When the number of concurrent connections are kept relatively low, each load balancing module behaves nearly identical. However, as we increase the concurrent connections, we see that the vast majority of requests are completed under 500 ms, but approximately 5% of requests take thousands of milliseconds longer to complete. This behavior is a known issue with using Apache Bench, but it also addresses the problem load balancing attempts to solve. That is, once a webserver becomes overloaded, it is very hard for it to recover.

The stair-step pattern represented in these graphs unsurprisingly correspond directly with my Poisson distribution. Each incoming request will spend either 0, 100, 200, or 300 ms on the webserver before getting a response. The fact that we can visualize the Poisson stream almost exactly is another indication that the overhead of load balancing is negligible under these testing conditions and NGINX.



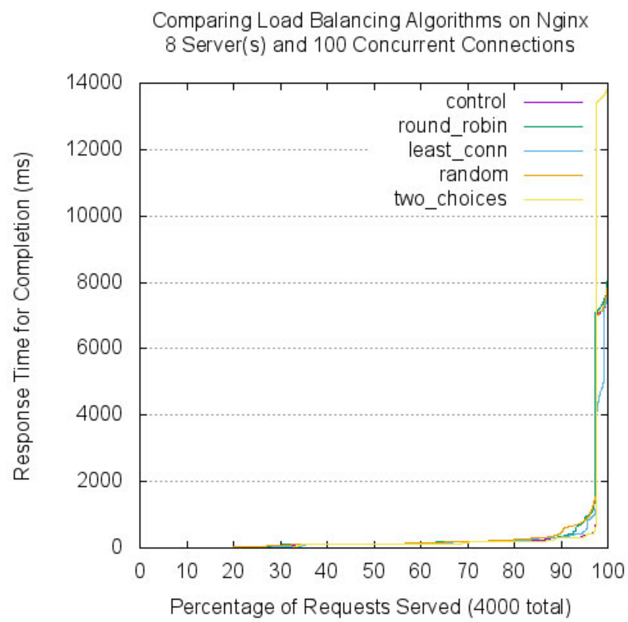


Figure 9: Each load balancing algorithm has near identical performance in NGINX according to the *ab* results.

In order to get a better sense of these seemingly homogeneous results, I constructed another visualization for examining the minimum, maximum, and average request latencies of each algorithm. It is possible to observe some additional trends using these new charts. Figure 10 reaffirms that under lower concurrency levels, performance is pretty uniform between algorithms. However, it remains unclear if any algorithm is superior under high levels of concurrency. While it appears two-choices may occasionally have

[5] Macbook Pro: Intel(R) Core(TM) i5-4288U CPU @ 2.60GHz, 16 GB 1600 MHz DDR3.
[6] "As far as I understand, *power of two choices* might be beneficial if you need to optimize time spent on comparing the load on different balanced servers, for example, when balancing very large number of servers. Or when trying to do distributed balancing with multiple load balancers, and query loads directly from balanced servers." (2017-09-27)

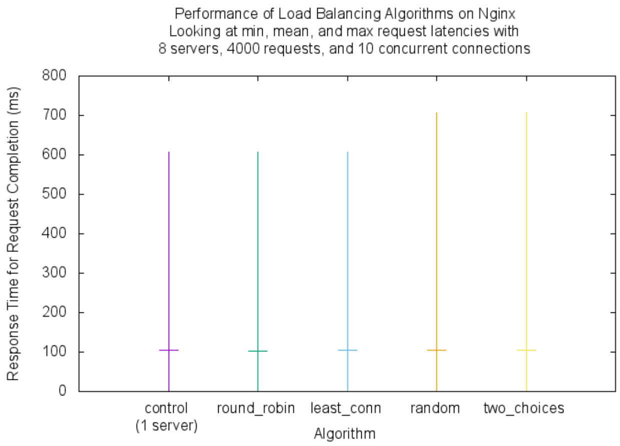


Figure 10: Under low levels of concurrency, there are less outliers so it's possible to see the slight variations in performance.

an advantage, Figure 11 serves as a reminder how a few latency outliers from Apache Bench can skew the graphs significantly.

Figure 12 gives a more complete overview of the ab benchmarking results from the simulations. While it is certainly true that higher concurrency levels increase the overall latency of the NGINX server, the median and mean latencies are not heavily effected.

5 RELATED AND FUTURE WORK

Overall, I'm excited by the outcomes of my capstone research project. If I continue running experiments on more sophisticated server environments I hope to get a more refined result set that will lead to a better understanding of NGINX load balancing performance. I plan to contribute my two-choices module upstream to the NGINX project as well as respond to any feedback I may get from the other open source developers. Additionally, it would be worthwhile to gather more data and research production web application server load more thoroughly. The Poisson distribution is a great statistical model for a proof-of-concept, but my research would definitely benefit from a richer statistical dataset. Load balancing for the most part is primarily a concern for large companies and data centers. For this reason, much of my background research involved learning how the big tech companies are approaching this problem. The prevailing strategies to the load balancing problem usually involves optimization deeper within the networking stack, where the problem can be more discretely defined and more generally applied.

5.1 Microsoft's JIQ

Join-Idle-Queue is the latest and greatest load balancing algorithm. It was developed by Microsoft and achieves greater performance than two-choices and another competing algorithm called join-shortest-queue. However, JIQ does not introduce communication overhead on the servers. This is achieved by only using local information about server load. The idea behind JIQ is to "decouple discovery of lightly loaded servers from job assignment" [3]. This

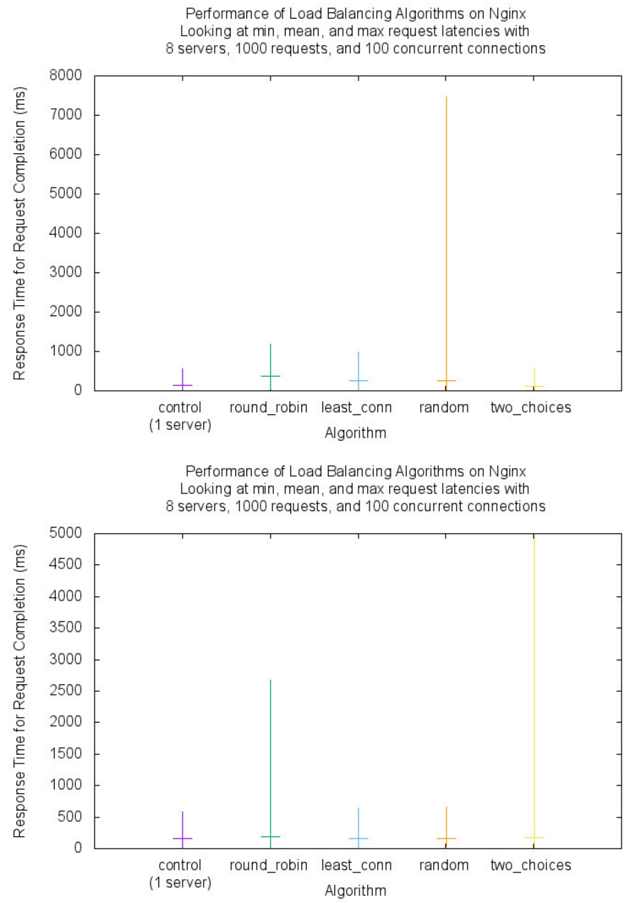


Figure 11: Although ab is a great benchmarking tool, results are often inconsistent due to a few outliers.

algorithm	concurrency	min	mean	[+/-sd]	median	max
control	10	1	107	123.6	103	1351
round_robin	10	1	106	102.5	105	607
least_conn	10	0	103	102.4	105	605
random	10	1	106	103.8	104	707
two_choices	10	0	101	100.6	104	603
control	50	1	108	103.0	103	613
round_robin	50	1	245	742.1	111	7187
least_conn	50	1	109	185.2	104	7100
random	50	1	187	321.4	118	3047
two_choices	50	1	146	257.6	106	4473
control	100	1	164	205.1	118	3186
round_robin	100	1	194	559.5	108	14004
least_conn	100	1	177	416.8	119	11747
random	100	1	212	559.0	132	13673
two_choices	100	1	187	334.4	115	3340

Figure 12: Raw ab statistics for 8 Servers and 4,000 total requests

is achieved through utilizing idle CPUs to make the load balancing decision. JIQ out-performs the competing advanced load balancing algorithms and much like my results, Microsoft notes that these load balancing strategies are most noticeable under extremely high server load.

5.2 Google's BBR

BBR stands for Bottleneck Bandwidth and Round-trip propagation time. It is a new congestion control algorithm developed and deployed by Google for increasing the throughput of TCP [2]. The purpose of the algorithm is to measure the current bottleneck of the network and only send enough data to "fill the pipe". The success of the algorithm comes from measuring network congestion in terms of its bottleneck instead of packet loss, which is how it is traditionally done. Additionally, it was found that maximum throughput is achieved when the loss rate was less than the inverse square of the bandwidth delay product (BDP). BBR is already implemented in the Linux kernel for TCP.

5.3 Facebook's Egress

Egress is a process for evaluating network latency and congestion through "performance aware routing" on Facebook's network [9]. The Egress paper explains some key elements of running a network on a massive scale that minimizes congestion. What Google did with TCP congestion, Facebook did with the border gateway protocol (BGP); they made it "capacity and performance aware". Essentially, Facebook had to optimize its point of presence (PoP) servers to have highly efficient routing algorithms by establishing shorter paths, to deliver content to its billions of users. This paper illustrates a common theme that traditional implementations of networking protocols are no longer sufficient.

5.4 Linux Socket Balancing: Epoll-and-Accept

An interesting problem about NGINX was discussed by Marek Majkowski of CloudFlare, where he examines how Linux schedules connections to sockets [4]. NGINX, like many applications may create multiple worker processes to increase performance at scale. On Linux, these processes communicate over sockets. On NGINX, a single socket "listens" for new connections and then distributes them to one of the available worker processes. This behavior is exactly like the load balancing discussed in this paper, except that instead of processing a request on another webserver, at this level, NGINX distributes new connections among OS processes. It is also possible to have a model where there are multiple listening sockets and multiple worker processors. Unfortunately for Linux, when distributing connections between sockets using `epoll()` to avoid blocking on the `accept()` system call, the scheduling behavior becomes Last-In-First-Out (LIFO). That is, the busiest process will be selected most often. Just like the thundering herd problem, this results in an unbalanced worker process load and a decrease in NGINX performance. However, by setting the `SO_REUSEPORT` socket option, each worker process will have a more uniform load at the cost of higher latency.

6 ACKNOWLEDGMENTS

I want to give a special thanks to David Barbella for being my Capstone Adviser and Charlie Peck for offering additional guidance during my project. I would also like to thank Maxim Dounin for answering my questions on the NGINX mailing list.

REFERENCES

[1] Micah Adler, Soumen Chakrabarti, Michael Mitzenmacher, and Lars Rasmussen. 1995. Parallel Randomized Load Balancing. In *In Symposium on Theory of Computing. ACM.* 119–130.

[2] Neal Cardwell, Yuchung Cheng, C Stephen Gunn, Soheil Hassas Yeganeh, and Van Jacobson. 2016. BBR: Congestion-based congestion control. *Queue* 14, 5 (2016), 50.

[3] Yi Lu, Qiaomin Xie, Gabriel Kliot, Alan Geller, James R Larus, and Albert Greenberg. 2011. Join-Idle-Queue: A novel load balancing algorithm for dynamically scalable web services. *Performance Evaluation* 68, 11 (2011), 1056–1071.

[4] Marek Majkowski. 2017. Why does one NGINX worker take all the load? *CloudFlare* (Oct. 2017). https://blog.cloudflare.com/the-sad-state-of-linux-socket-balancing/

[5] Tyler McMullen. 2016. Load Balancing is Impossible. (November 2016). https://www.youtube.com/watch?v=gas2v1emubU

[6] Michael Mitzenmacher. 2001. The Power of Two Choices in Randomized Load Balancing. *IEEE Transactions on Parallel and Distributed Systems* 12, 10 (2001), 1094–1104.

[7] Fernando Pérez and Brian E. Granger. 2007. IPython: a System for Interactive Scientific Computing. *Computing in Science and Engineering* 9, 3 (May 2007), 21–29. DOI:http://dx.doi.org/10.1109/MCSE.2007.53

[8] K Salchow. 2007. Load balancing 101: Nuts and bolts. *White Paper, F5 Networks, Inc* (2007).

[9] Brandon Schlinker, Hyojeong Kim, Timothy Cui, Ethan Katz-Bassett, Harsha V Madhyastha, Italo Cunha, James Quinn, Saif Hasan, Petr Lapukhov, and Hongyi Zeng. 2017. Engineering Egress with Edge Fabric. In *Proceedings of the ACM SIGCOMM 2017 Conference (SIGCOMM'17). ACM, New York, NY, USA.*