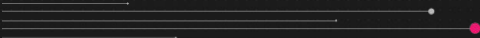


Performance Debugging: Finding Bottlenecks in Distributed Systems



Christian Grabowski - Backend Engineer
Github: [cpg1111](#) Twitter: [@christiang0817](#)

• About Me

- Backend Engineer @ NS1
- Total Linux Nerd
- <3 open source

• **About NS1**

- We run a global network of authoritative DNS servers
- This network is made up of many different services that each provide a unique function in order to deliver our product
- These services are distributed globally across 25 POPs
- We're always receiving traffic, and spikes in traffic will of course happen, so performance and reliability are important to us

• In a nutshell...

- Distributed systems are complicated, and as the system scales to handle the growth of a company, the complexity grows along with it.
- As a system scales, bottlenecks are bound to occur, but with this complexity, it becomes more and more difficult to identify these bottlenecks.
- This can be frustrating, because logically speaking, your system is working, but it's just not cutting it.

• In A Little More Detail

- Where do you start?
 - There are so many metrics to look at
 - There are so many tools out there for performance debugging
- How do I identify the bottleneck in a multiple services of a distributed system?
 - Is it my database? Is it my service? Is it how I use my database? Is it another service?
- How do I identify the bottleneck in a single process?
 - Is it my code? Is it a Library? Is it the OS?

There are many ways to approach the identification of said issues. Based on my experience, here are a couple cases that will aim to answer these questions.

Case 1: Metrics Aggregation Problems

- **Case 1**

Initial Issue

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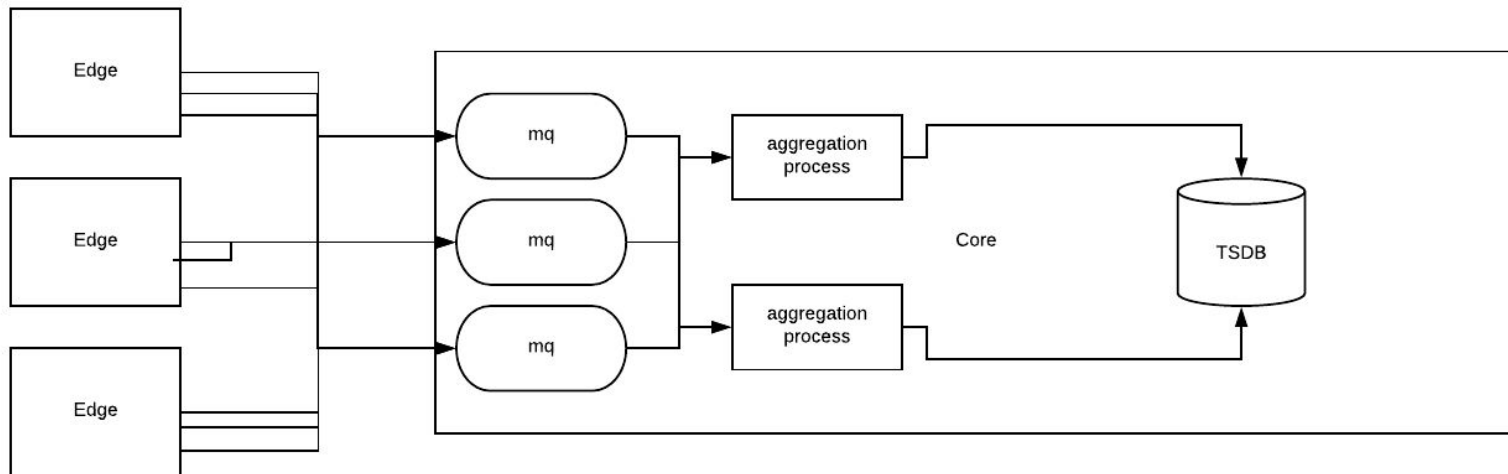
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- More timeseries, more problems

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 - Second approach was a sorted array of metrics sorted by last update that coincided with a map of metric name = aggregated value
- Sounds great right?

```

[4075623.871205] outboundd invoked oom-killer: gfp_mask=0x24000c0, order=0, oom_score_adj=0
[4075623.871210] outboundd cpuset=749b1d12085c451c0714abd85b6112795eafc8356d77083aaa0e578db8353143 mems_allowed=0-1
[4075623.871218] CPU: 3 PID: 104311 Comm: outboundd Not tainted 4.4.0-83-generic #106~14.04.1-Ubuntu
[4075623.871220] Hardware name: Dell Inc. PowerEdge C6320/082F9M, BIOS 2.4.2 01/09/2017
[4075623.871222] 0000000000000000 ffff883f95f87c80 ffffffff813ddefc ffff883f95f87d80
[4075623.871226] ffff8839e3664400 ffff883f95f87d10 ffffffff811fb976 0000000000000000
[4075623.871228] 0000000000000003 ffff883e85c5c1c0 ffff883fed469c60 ffff883ffde56e00
[4075623.871231] Call Trace:
[4075623.871240] [<ffffffff813ddefc>] dump_stack+0x63/0x87
[4075623.871246] [<ffffffff811fb976>] dump_header+0x5b/0x1d5
[4075623.871254] [<ffffffff81188b7b>] ? find_lock_task_mm+0x3b/0x80
[4075623.871257] [<ffffffff81189115>] oom_kill_process+0x205/0x3d0
[4075623.871260] [<ffffffff811f1abf>] mem_cgroup_out_of_memory+0x26f/0x2c0
[4075623.871263] [<ffffffff811f27dd>] mem_cgroup_oom_synchronize+0x30d/0x330
[4075623.871268] [<ffffffff811edb20>] ? mem_cgroup_events.constprop.50+0x30/0x30
[4075623.871271] [<ffffffff811897d5>] pagefault_out_of_memory+0x35/0x90
[4075623.871277] [<ffffffff8107ad1f>] mm_fault_error+0x67/0x140
[4075623.871282] [<ffffffff81068ef8>] __do_page_fault+0x3f8/0x430
[4075623.871284] [<ffffffff81068f52>] do_page_fault+0x22/0x30
[4075623.871290] [<ffffffff8180e9f8>] page_fault+0x28/0x30
[4075623.871292] Task in /docker/749b1d12085c451c0714abd85b6112795eafc8356d77083aaa0e578db8353143 killed as a result of limit of /docker/749b1d12085c451c0714abd85b6112795eafc83
56d77083aaa0e578db8353143
[4075623.871297] memory: usage 20971520kB, limit 20971520kB, failcnt 102
[4075623.871299] memory+swap: usage 0kB, limit 9007199254740988kB, failcnt 0
[4075623.871300] kmem: usage 0kB, limit 9007199254740988kB, failcnt 0
[4075623.871301] Memory cgroup stats for /docker/749b1d12085c451c0714abd85b6112795eafc8356d77083aaa0e578db8353143: cache:40KB rss:20971480KB rss_huge:804864KB mapped_file:0KB d
irty:0KB writeback:0KB inactive_anon:16KB active_anon:20970912KB inactive_file:0KB active_file:0KB unevictable:0KB
[4075623.871340] [ pid ] uid tgid total_vm rss nr_ptes nr_pmds swapents oom_score_adj name
[4075623.871496] [104302] 0 104302 5358032 5244843 10308 25 0 0 outboundd
[4075623.871506] Memory cgroup out of memory: Kill process 104302 (outboundd) score 1002 or sacrifice child
[4075623.882195] Killed process 104302 (outboundd) total-vm:21432128kB, anon-rss:20971236kB, file-rss:8136kB
[4075625.094650] init: outboundd_go main process ended, respawning ]

```

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- So what caused this?

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```
GET /metrics?snapshot=true
```

```
[  
  {  
    "name": "msgs.recv",  
    "time": 1257894000,  
    "stags": {"host": "a.host"},  
    "utags": ["bulk_size"],  
    "T": [20],  
    "V": 18500,  
    "N": 8  
  }, {  
    "name": "metrics.recv",  
    "time": 1257894000,  
    "stags": {"host": "a.host"},  
    "utags": ["type"],  
    "T": ["by_customer", "by_zone", "by_record"],  
    "V": 370000,  
    "N": 160  
  }  
]
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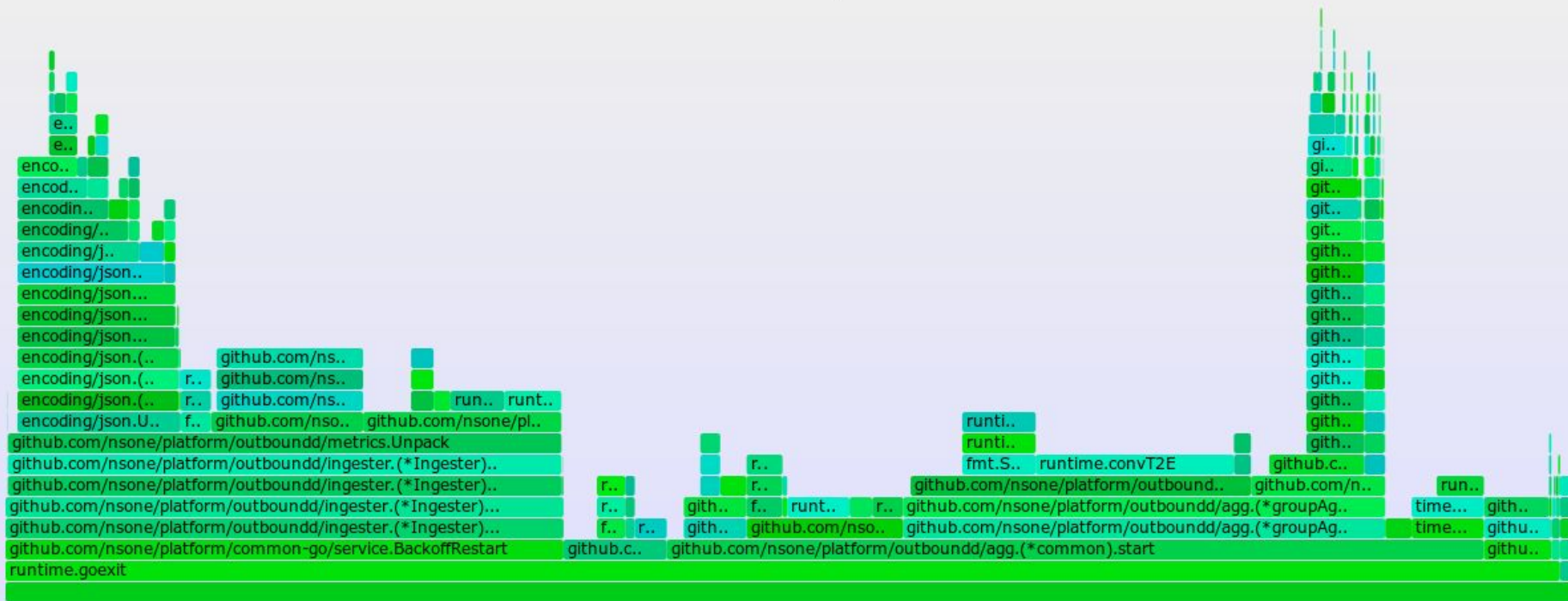
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4. Used Go's Benchmark testing to be able to compare changes

BenchmarkBTree_Insert1-8	2000000	753 ns/op
BenchmarkBTree_Insert10-8	300000	5460 ns/op
BenchmarkBTree_Insert100-8	20000	67481 ns/op
BenchmarkBTree_Insert1000-8	2000	831932 ns/op
BenchmarkBTree_Insert10000-8	200	9863054 ns/op
BenchmarkBTree_Insert100000-8	10	127574333 ns/op
BenchmarkBTree_Insert1000000-8	1	1899309427 ns/op
BenchmarkBTree_Remove1-8	300000000	5.65 ns/op
BenchmarkBTree_Remove10-8	30000000	53.9 ns/op
BenchmarkBTree_Remove100-8	3000000	543 ns/op
BenchmarkBTree_Remove1000-8	200000	5481 ns/op
BenchmarkBTree_Remove10000-8	30000	55950 ns/op
BenchmarkBTree_Remove100000-8	2000	691415 ns/op
BenchmarkBTree_Remove1000000-8	1	4412983369 ns/op
BenchmarkLLRB_Insert1-8	3000000	483 ns/op
BenchmarkLLRB_Insert10-8	300000	4486 ns/op
BenchmarkLLRB_Insert100-8	30000	52976 ns/op
BenchmarkLLRB_Insert1000-8	2000	672204 ns/op
BenchmarkLLRB_Insert10000-8	200	7843585 ns/op
BenchmarkLLRB_Insert100000-8	10	104467790 ns/op
BenchmarkLLRB_Insert1000000-8	1	1597383476 ns/op
BenchmarkLLRB_Remove1-8	300000000	5.39 ns/op
BenchmarkLLRB_Remove10-8	30000000	51.6 ns/op
BenchmarkLLRB_Remove100-8	3000000	519 ns/op
BenchmarkLLRB_Remove1000-8	300000	5163 ns/op
BenchmarkLLRB_Remove10000-8	30000	54560 ns/op
BenchmarkLLRB_Remove100000-8	2000	673192 ns/op
BenchmarkLLRB_Remove1000000-8	1	4016146227 ns/op

BenchmarkMapAggPut1-4	1000000	52489 ns/op	1656 B/op	29
allocs/op				
BenchmarkMapAggPut10-4	50000	101305 ns/op	8763 B/op	140
allocs/op				
BenchmarkMapAggPut100-4	10000	522084 ns/op	78651 B/op	1220
allocs/op				
BenchmarkMapAggPut1000-4	1000	1343539 ns/op	777050 B/op	12020
allocs/op				
BenchmarkMapAggPut10000-4	100	13487897 ns/op	7761038 B/op	120020
allocs/op				
BenchmarkMapAggPut100000-4	10	133272840 ns/op	77601172 B/op	1200021
allocs/op				
BenchmarkMapAggFlush1-4	500000	14246 ns/op	2272 B/op	37
allocs/op				
BenchmarkMapAggFlush10-4	20000	86255 ns/op	11789 B/op	175
allocs/op				
BenchmarkMapAggFlush100-4	10000	947855 ns/op	83198 B/op	1264
allocs/op				
BenchmarkMapAggFlush1000-4	1000	3805475 ns/op	788817 B/op	12063
allocs/op				
BenchmarkMapAggFlush10000-4	100	14738426 ns/op	7846638 B/op	120064
allocs/op				
BenchmarkMapAggFlush100000-4	10	133869511 ns/op	78407281 B/op	1200061
allocs/op				

- **Case 1**

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- Recreating production traffic

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 - Spray a bunch of messages at the message queue
 - Second approach → have our message queue copy production messages into the test environment
 - This required a lot of configuration
 - We were able to throttle the amount of traffic well

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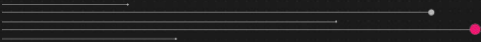
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What Did Not Work

- Being able to reproduce a production level load in a dev or testing environment
- Keeping a base comparison when making changes for the sake of performance
- Should've changed the initial service more iteratively, instead of a full rewrite immediately

Case 2: Public REST api slowing down



- **Case 2**

Initial Issue

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- Response times of our public api service are increasing and some were timing out

• Case 2

Initial Issue

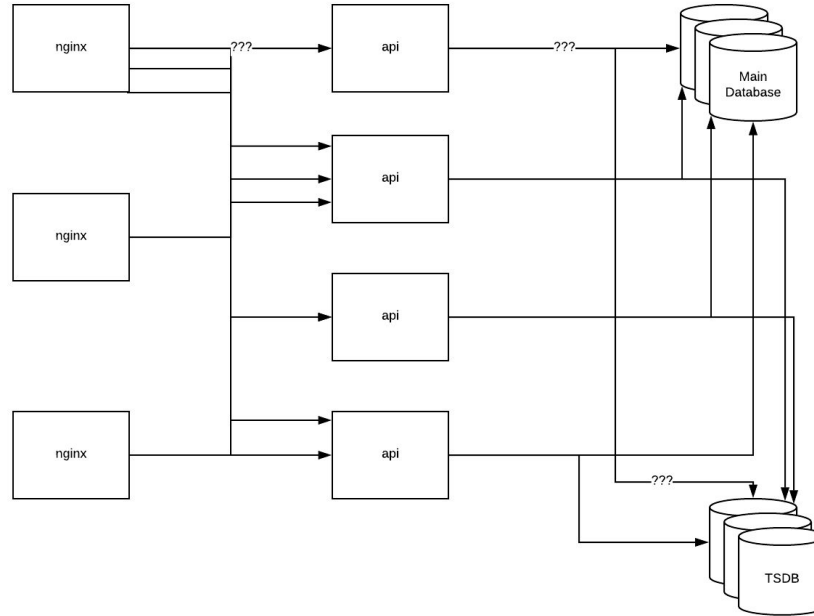
- Response times of our public api service are increasing and some were timing out
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• Case 2

Initial Issue

- Response times of our public api service are increasing and some were timing out
- A planned large influx of records to our database had put a much greater amount of load on our database
- Not all of our queries were optimized

• Case 2



- **Case 2**

Steps Taken

• Case 2

Steps Taken

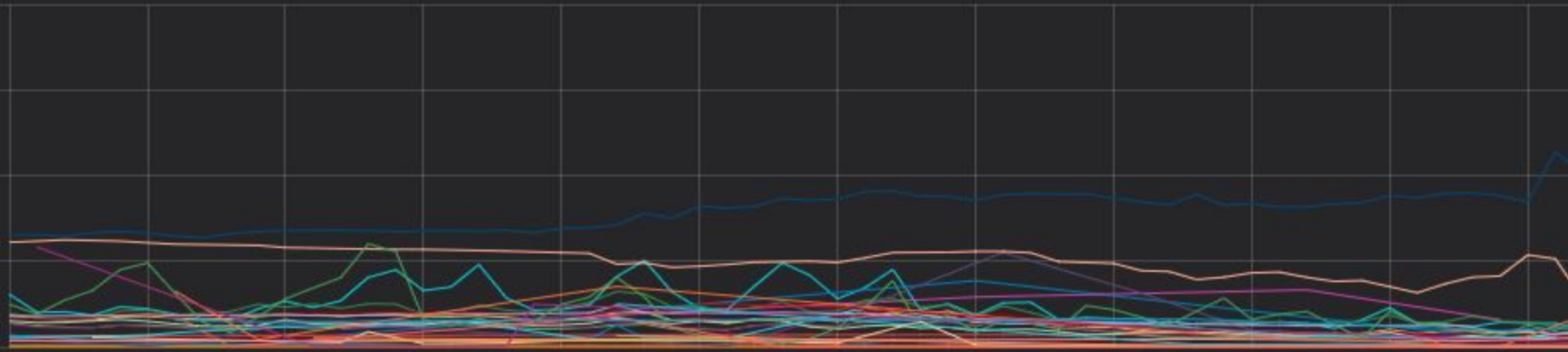
1. Instrument the IO of the api process

• Case 2

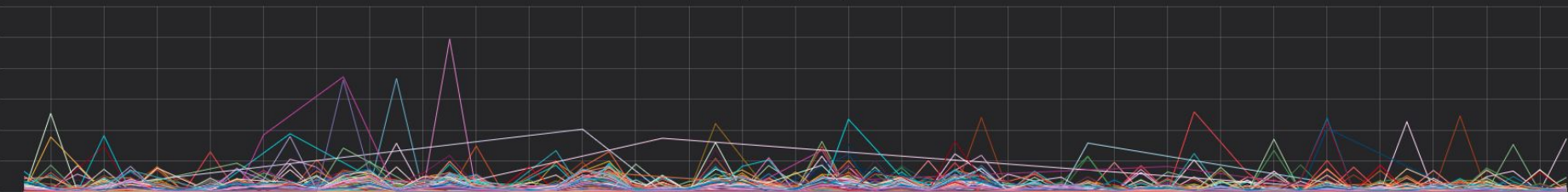
Steps Taken

1. Instrument the IO of the api process
 - Operational Metrics → How often is the api process querying the database? How often is a specific query being executed?

api response times (by resource)



MongoDB Query Latency



• Case 2

Steps Taken

1. Instrument the IO of the api process
 - Operational Metrics → How often is the api process querying the database? How often is a specific query being executed?
 - Distributed tracing → With small additions to our existing code, we could see how much time a block of code, or a round trip out to another service was taking

```
1 from nsone.util.tracing import ExportedTracingContext
2
3 TRACER = ExportedTracingContext(__name__)
4
5 def request(host, route, body):
6     with TRACER.trace("{}.{ {}".format(host, route)):
7         send(host, route, host)
8 _
```

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• Case 2

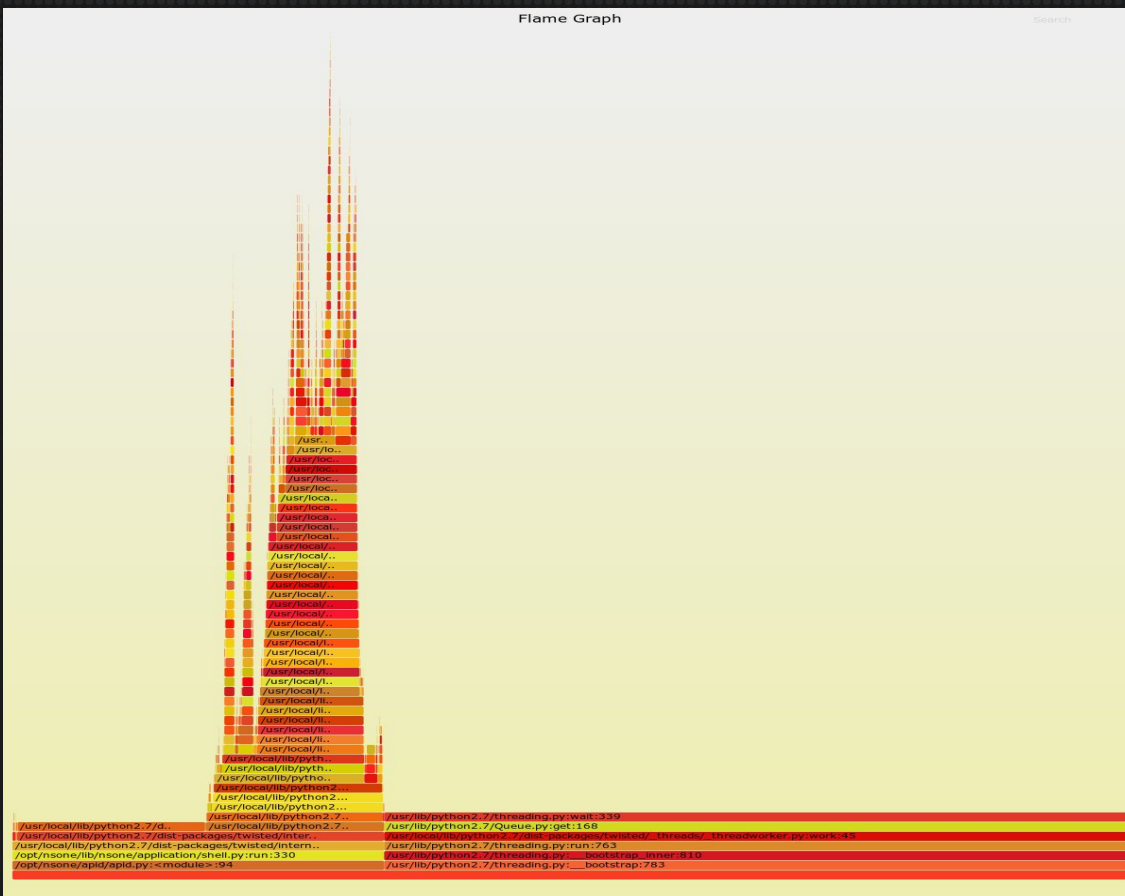
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 - Twisted uses async io

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2. Profile on-CPU for potential blocking code
 - Twisted uses async io
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• Case 2

Steps Taken

1. Instrument the IO of the api process
 - Operational Metrics → How often is the api process querying the database? How often is a specific query being executed?
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- › <TIMESTAMP> .025+0000 [conn109306794] command nsone.\$cmd command: count { count: "records", fields: null, query: { customer: zone: } } planSummary: COUNT { <INDEX> } ntoreturn:1 keyUpdates:0 numYields:73 locks(micros) r:4090477 reslen:48 2107ms
- › <TIMESTAMP> .573+0000 [conn109306647] command nsone.\$cmd command: count { count: "records", fields: null, query: { customer: zone: } } planSummary: COUNT { <INDEX> } ntoreturn:1 keyUpdates:0 numYields:104 locks(micros) r:4232800 reslen:48 2144ms
- › <TIMESTAMP> .214+0000 [conn109304828] command nsone.\$cmd command: count { count: "records", fields: null, query: { customer: } } planSummary: COUNT { <INDEX> } ntoreturn:1 keyUpdates:0 numYields:1560 locks(micros) r:4801824 reslen:48 2558ms
- › <TIMESTAMP> .296+0000 [conn109304828] command nsone.\$cmd command: count { count: "records", fields: null, query: { customer: } } planSummary: COUNT { <INDEX> } ntoreturn:1 keyUpdates:0 numYields:118 locks(micros) r:2828783 reslen:48 1482ms
- › <TIMESTAMP> .843+0000 [conn109306908] command nsone.\$cmd command: count { count: "records", fields: null, query: { customer: } } planSummary: COUNT { <INDEX> } ntoreturn:1 keyUpdates:0 numYields:150 locks(micros) r:2331646 reslen:48 1194ms
- › <TIMESTAMP> .738+0000 [conn109307005] command nsone.\$cmd command: count { count: "records", fields: null, query: { customer: zone: } } planSummary: COUNT { <INDEX> } ntoreturn:1 keyUpdates:0 numYields:116 locks(micros) r:4191979 reslen:48 2160ms
- › <TIMESTAMP> .475+0000 [conn109306647] command nsone.\$cmd command: count { count: "records", fields: null, query: { customer: , zone: } } planSummary: COUNT { <INDEX> } ntoreturn:1 keyUpdates:0 numYields:77 locks(micros) r:4167760 reslen:48 2127ms
- › <TIMESTAMP> .857+0000 [conn109304828] command nsone.\$cmd command: count { count: "records", fields: null, query: { customer: } } planSummary: COUNT { <INDEX> } ntoreturn:1 keyUpdates:0 numYields:257 locks(micros) r:4973431 reslen:48 2593ms

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3. Utilize instrumentation around our database queries
4. Based on the instrumentation, we identified the slow routes and queries

- **Case 2**

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- Through the use of the previously mentioned tools, we were able to identify specific routes, and queries that needed to be optimized
- Some of those queries we were able to remove all together
- We were able to observe these improvements the moment they went to production
- There were definitely some queries that given more time, would be ideal to move to a different, better suited database

Lessons Learned

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- Being able to keep your changes small and more iterative will yield you greater results in the long run.
- Having a baseline to compare changes for performance to is a must

Thank You

