

Simulation and Modelling

Serverless Cold Starts

Zack Reeves (CID: 01844549)

November 2022

Contents

1	Simulation	2
1.1	Cold Start Ratio and Loss Rate	2
1.2	Changing the Capacity of M	2
1.3	Modelling Request Generation and the Passage of Time	2
2	Analytical Modelling	3
2.1	Defining the State Space	3
2.2	CTMC Transition Diagram	3
2.3	Defining Measures	3
2.4	Solving the CTMC	3
A	Full Code	4
A.1	FaaS Simulation	4
A.2	Output Analysis	7
B	Results	9
B.1	Cold Start Ratio Data Varying M	9
B.2	Loss Rate Data Varying M	10

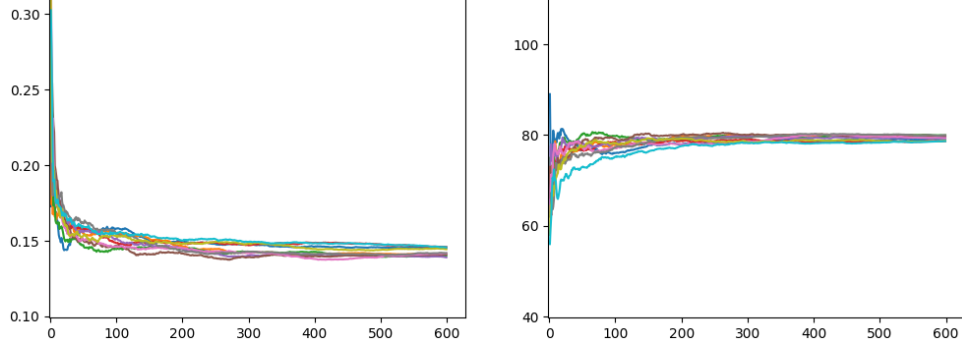
1 Simulation

1.1 Cold Start Ratio and Loss Rate

Python and a module, SimPy, were used to create a simulation of the FaaS system (see Appendix A for full code). The simulation was used to produce results for the following measures:

- C_{ratio} : No. cold starts/No. requests
- L_{rate} : No. lost requests/time

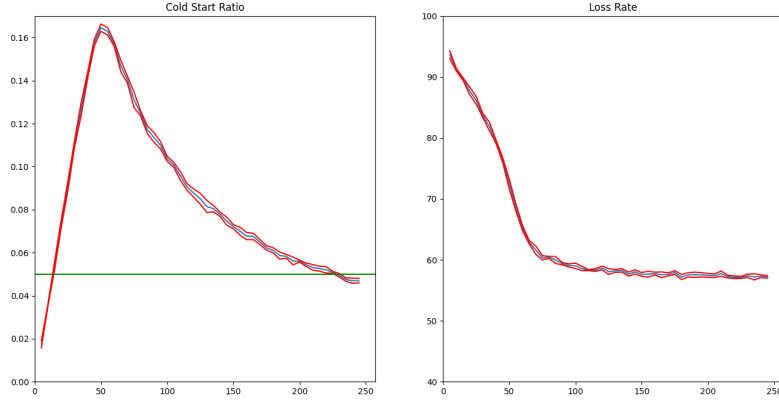
With capacity $M = 40$ and a simulation time of 10 minutes, the following data was produced



	Point Estimate	90% Confidence Intervals (10 individual replications)
Cold Start Ratio	0.1426	(0.1413, 0.1440)
Loss Rate	79.3631	(79.0700, 79.6562)

1.2 Changing the Capacity of M

The following data is produced by varying M from 5 to 245. It was produced using a simulation time of 5 minutes with 5 individual replications. Appendix B contains all the point estimates and confidence intervals.



At $M = 230$ the point estimate for the cold start ratio drops below 5% and at $M = 235$ the upper confidence interval drops below 5%.

1.3 Modelling Request Generation and the Passage of Time

As each function has an exponentially distributed inter-arrival time, the overall request generation can be managed by an aggregated Poisson process. When parsing the CSV trace, each function's invocations can be divided by 2592000 (conversion from 30 days to seconds). This gives the rate parameter for each function λ_f . Merging Poisson processes is done by summing the individual rate parameters.

$$\lambda = \sum_{f=1}^{10861} \lambda_f$$

Now the arrival processes have been merged, an exponential sample can be taken to determine the time until the next request. With a new request, a discrete distribution can be sampled to determine which function the request is for. The discrete distribution has buckets from 1 to 10861, one for each function, and the weights can be determined as

$$w_f = \frac{\lambda_f}{\sum_{f=1}^{10861} \lambda_f}$$

The output of this sample is the function that has made the request and the simulation can continue to determine whether the request is lost, incurs a cold start or starts being serviced. If a cold start is incurred an exponential sample is taken from the cold start distribution with $\lambda_{cold\ start} = 0.5$ to give the cold startup time before being serviced. Once the request is ready to be serviced, the function's service time is obtained by sampling an exponential distribution with

$$\lambda = \frac{1}{\text{Avg. service time (in seconds)}}$$

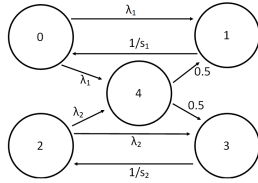
After this service time period, the request is complete. This is the process each request goes through from generation to loss/completion.

2 Analytical Modelling

2.1 Defining the State Space

- State 0: Function 1 is idle in memory
- State 1: Function 1 is executing in memory
- State 2: Function 2 is idle in memory
- State 3: Function 2 is executing in memory
- State 4: Either function is in cold start

2.2 CTMC Transition Diagram



λ_i = arrival rate of requests for function i
 s_i = avg. service time for function i
 0.5 is the cold startup rate

Infinitesimal Generator Matrix

$$Q = \begin{pmatrix} -(\lambda_1 + \lambda_2) & \lambda_1 & 0 & 0 & \lambda_2 \\ \frac{1}{s_1} & -(\frac{1}{s_1}) & 0 & 0 & 0 \\ 0 & 0 & -(\lambda_1 + \lambda_2) & \lambda_2 & \lambda_1 \\ 0 & 0 & \frac{1}{s_2} & -(\frac{1}{s_2}) & 0 \\ 0 & 0.5 & 0 & 0.5 & -1 \end{pmatrix}$$

2.3 Defining Measures

$$C_{ratio} = \frac{P_0 \cdot \lambda_2 + P_2 \cdot \lambda_1}{\lambda_1 + \lambda_2}$$

The rate of cold starts for function 2 plus the rate of cold starts for function 1 over the rate of requests

$$L_{rate} = (P_1 + P_3 + P_4) \cdot (\lambda_1 + \lambda_2)$$

The probability the server is already executing or in cold start times the rate of requests

2.4 Solving the CTMC

Solving the above CTMC yields the following probabilities:

Inputs	Probabilities	Measures
$\lambda_1 = 0.4133858025$ $\lambda_2 = 0.08635069444$ $s_1 = 0.0013$ $s_2 = 0.0001$	$P_0 = 0.7234592085512606$ $P_1 = 4.700006616908895E-4$ $P_2 = 0.1511208286707441$ $P_3 = 7.552059352854275E-6$ $P_4 = 0.12494241005695148$	$C_{ratio} = 0.25001658045186903$ $L_{rate} = 0.06267693284502052$

A Full Code

A.1 FaaS Simulation

Beneath is the full code used to simulate the FaaS system using python and SimPy.

```
1 import csv
2 import simpy
3 import numpy as np
4 import datetime
5 import matplotlib.pyplot as plt
6
7
8 def parse_csv(file):
9     # parses csv into to lists
10    # convert service times to seconds
11    # convert invocations into invocations/second
12
13    with open(file, mode='r') as csv_file:
14        csv_reader = csv.DictReader(csv_file)
15        lines = 0
16        lam = 0
17        sum_lam = 0
18        avg_service_times = []
19        avg_arrival_rates = []
20        weights = []
21        for row in csv_reader:
22            avg_service_times.append(int(row["AvgServiceTimeMillisec"])/1000)
23            lam = int(row["Invocations30Days"])/(30*24*60*60)
24            avg_arrival_rates.append(lam)
25            sum_lam += lam
26            lines += 1
27
28        # compiles a list of weights to be used in a discrete distribution sampler
29        for i in range(len(avg_service_times)):
30            weights.append(avg_arrival_rates[i]/sum_lam)
31
32
33    return avg_service_times, weights, sum_lam
34
35
36 class g:
37     no_runs = 1 # used to repeat with different M
38     no_trials = 5 # repeats each model this many times
39     sim_duration = 60*60*24 # runs sim for this many simulated seconds
40     f = 10861 # no. functions
41     cold_start = 0.5 #c old start rate
42     avg_service_times, weights, sum_lam = parse_csv('trace-final.csv')
43
44
45 class Request:
46     def __init__(self, f_id):
47         self.id = f_id
48
49
50 class Faas_Model:
51
52     def __init__(self, trial_no, m, file_name):
53         self.env = simpy.Environment()
54
55         self.trial_no = trial_no
56         self.m = m
57         self.results_file = file_name
58
59         # tracks status of each f 0: not in m, 1: idle, 2: executing
60         self.status = np.ones(self.m).tolist() + np.zeros(g.f-self.m).tolist()
61
62         # initializes memory with the first m functions all idle
63         self.idle_queue = np.arange(self.m).tolist()
64
65
66         # measures
67         self.request_counter = 0
68         self.cold_start_counter = 0
69         self.lost_request_counter = 0
70         self.memory_full_loss = 0
71         self.already_running_loss = 0
```

```

72     self.completions = 0
73
74     # lists for graphs
75     self.obs_time = []
76     self.obs_cold_ratio = []
77     self.obs_loss_rate = []
78
79     def generate_requests(self):
80         # generates requests using aggregate poisson process
81         # sample a discrete distribution to assign the request a function
82
83         while True:
84
85             yield self.env.timeout(generate_time_to_request())
86
87             self.request_counter += 1
88
89             r_id = int(np.random.choice(a=g.f, p=g.weights)) # split poisson to stream f
90             r = Request(r_id)
91
92             self.env.process(self.service_request(r))
93
94     def service_request(self, request):
95
96         # check if f is running and reject request
97         if self.status[request.id] == 2:
98             self.already_running_loss += 1
99             self.lost_request_counter += 1
100
101         # check if f is idle and start executing
102         elif self.status[request.id] == 1:
103
104             self.status[request.id] = 2
105             self.env.process(self.complete_request(request))
106
107         # if f is not in memory check if everything in memory is executing
108         else:
109             self.mem_in_use = self.status.count(2)
110
111             if self.mem_in_use >= self.m:
112                 # m is full reject request
113                 self.memory_full_loss += 1
114                 self.lost_request_counter += 1
115
116             else:
117                 # Check top of the idle queue for which function to remove
118                 evict = self.idle_queue[0]
119                 self.status[evict] = 0
120                 self.idle_queue = remove_values_from_list(self.idle_queue, evict)
121
122                 self.status[request.id] = 2
123
124                 self.cold_start_counter += 1
125
126                 # sample cold start time
127                 yield self.env.timeout(generate_time_to_start())
128
129                 self.env.process(self.complete_request(request))
130
131
132     def complete_request(self, request):
133         # remove f from idle queue
134         self.idle_queue = remove_values_from_list(self.idle_queue, request.id)
135
136         # sample service time
137         yield self.env.timeout(generate_time_to_service(request.id))
138
139         self.completions += 1
140
141         # return to idling, add f to the end of the idle queue
142         self.status[request.id] = 1
143         self.idle_queue.append(request.id)
144
145     def observe(self):
146         # records measure every second

```

```

148     while True:
149         try:
150
151             self.obs_cold_ratio.append(self.cold_start_counter/self.request_counter)
152             self.obs_time.append(self.env.now)
153             self.obs_loss_rate.append(self.lost_request_counter/self.obs_time[-1])
154         except:
155             pass
156         yield self.env.timeout(1)
157
158
159
160 def run(self):
161
162     # start sim
163     self.env.process(self.generate_requests())
164     self.env.process(self.observe())
165     self.env.run(until=g.sim_duration)
166
167     # Output to terminal
168     print(f'\nTrial {self.trial_no+1} of {g.no_trials}')
169     print(f'Simulated for {str(datetime.timedelta(seconds=g.sim_duration))}')
170     print(f'M Capacity: {self.m}')
171
172     print(f'\nRequests made: {self.request_counter}')
173     print(f'Requests lost: {self.lost_request_counter}')
174     print(f'Memory full lost: {self.memory_full_loss}')
175     print(f'Already Running lost: {self.already_running_loss}')
176     print(f'Completions: {self.completions}')
177     print(f'Cold starts: {self.cold_start_counter}')
178
179     print(f'\nCold start ratio = {self.obs_cold_ratio[-1]}')
180     print(f'Loss rate = {self.obs_loss_rate[-1]}\n')
181
182     # Output to graphs
183     ax.plot(model.obs_time, model.obs_cold_ratio, label=f'{self.m}')
184     ax2.plot(model.obs_time, model.obs_loss_rate, label=f'{self.m}')
185
186     # Output to csv
187     with open(self.results_file, "a") as f:
188         writer = csv.writer(f, delimiter=',')
189         results_to_write = [self.trial_no,
190                             self.obs_cold_ratio[-1],
191                             self.obs_loss_rate[-1]]
192         writer.writerow(results_to_write)
193
194
195 def generate_time_to_request():
196     # aggregated poisson
197     return np.random.exponential(scale=(1.0/g.sum_lam))
198
199 def generate_time_to_service(id):
200     # exponential service time sampler
201     return np.random.exponential(scale=(g.avg_service_times[id]))
202
203 def generate_time_to_start():
204     # exponential cold start time sampler
205     return np.random.exponential(scale=1.0/g.cold_start)
206
207 def remove_values_from_list(l, val):
208     # removes all values = val from list l
209     c = l.count(val)
210     for i in range(c):
211         l.remove(val)
212
213     return l
214
215
216 # initialize graphs
217 fig = plt.figure(figsize=(12, 6))
218
219 ax = fig.add_subplot(121)
220 ax2 = fig.add_subplot(122)
221
222 # each loop here modifies the size of m
223 for run in range(g.no_runs):

```

```

224     m = 40 + run * 5
225
226     #creates a cdv file for each size of m simulated and writes coloumn headers
227     file_name = f'sim_out/trial_results_{m}.csv'
228
229     with open(file_name, "w") as f:
230         writer = csv.writer(f, delimiter=',')
231         coloumn_headers = ["run", "cold_start_ratio", "loss_rate"]
232         writer.writerow(coloumn_headers)
233
234     #repeats this capacity
235     for trial in range(g.no_trials):
236         model = Faas_Model(trial, m, file_name)
237         model.run()
238
239 #finializes and shows graphs
240 ax.set_title('Cold Start Ratio')
241 ax2.set_title('Loss Rate')
242
243 ax.set_ylim([0, 0.3])
244 ax.set_xlim(left=0)
245
246 ax2.set_ylim([0, 100])
247 ax2.set_xlim(left=0)
248
249 plt.show()

```

A.2 Output Analysis

Below is the full code used to format the output of the simulation calculating key measures such as C_{ratio} and L_{rate}

```

1 import csv
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 def parse_csv(file):
6     # grabs data from sim output
7
8     with open(file, mode='r') as csv_file:
9         csv_reader = csv.DictReader(csv_file)
10
11         n = 0
12         csr = []
13         lr = []
14
15         for row in csv_reader:
16             csr.append(float(row["cold_start_ratio"]))
17             lr.append(float(row["loss_rate"]))
18             n += 1
19
20     return n, csr, lr
21
22 ms = []
23 csr_points = []
24 lr_points = []
25 csr_ci = []
26 lower_csr_ci = []
27 higher_csr_ci = []
28
29 lr_ci = []
30 lower_lr_ci = []
31 higher_lr_ci = []
32
33 #create CSVs for storing point estimtes and confidence intervals for each vlue of m
34
35 with open('data/cold_start_data.csv', "w", newline='') as f:
36     writer = csv.writer(f, delimiter=',')
37     coloumn_headers = ["M", "Point Estimate", "90% Confidence Interval"]
38     writer.writerow(coloumn_headers)
39
40 with open('data/loss_rate_data.csv', "w", newline='') as f:
41     writer = csv.writer(f, delimiter=',')
42     coloumn_headers = ["M", "Point Estimate", "90% Confidence Interval"]
43     writer.writerow(coloumn_headers)

```

```

44
45 #read each output
46 for i in range(49):
47     m = 40 + i*5
48     ms.append(m)
49
50     file_name = f'sim_out/trial_results_{m}.csv'
51
52     n, csr, lr = parse_csv(file_name)
53
54     csr_point_est = round(np.mean(csr), 4)
55     csr_points.append(csr_point_est)
56
57     lr_point_est = round(np.mean(lr), 4)
58     lr_points.append(lr_point_est)
59
60     #calculates point estimate and confidence interval for c_ratio
61     csr_confidence_interval = round((1.833*np.std(csr))/np.sqrt(n), 4)
62     csr_ci.append(csr_point_est)
63     lower_csr_ci.append(csr_point_est-csr_confidence_interval)
64     higher_csr_ci.append(csr_point_est+csr_confidence_interval)
65
66     #calculates point estimate and confidence interval for l_rate
67     lr_confidence_interval = round((1.833*np.std(lr))/np.sqrt(n), 4)
68     lr_ci.append(lr_point_est)
69     lower_lr_ci.append(lr_point_est-lr_confidence_interval)
70     higher_lr_ci.append(lr_point_est+lr_confidence_interval)
71
72     print(f'M Capacity: {m}')
73     print(f'Samples: {n}\n')
74
75     print(f'Cold Start Ratio:')
76     print(f'Point Estimate: {csr_point_est:.4f}')
77     ci = f'({csr_point_est-csr_confidence_interval:.4f}, {csr_point_est+csr_confidence_interval:.4f})'
78     print(f'Confidence Interval: {ci}\n')
79
80     with open('data/cold_start_data.csv', "a", newline='') as f:
81         writer = csv.writer(f, delimiter=',')
82         results_to_write = [m, f'{csr_point_est:.4f}', ci]
83         writer.writerow(results_to_write)
84
85     print(f'Loss Rate:')
86     print(f'Point Estimate: {lr_point_est:.4f}')
87     ci = f'({lr_point_est-lr_confidence_interval:.4f}, {lr_point_est+lr_confidence_interval:.4f})'
88     print(f'Confidence Interval: {(lr_point_est-lr_confidence_interval):.4f}, {(lr_point_est+lr_confidence_interval):.4f}\n')
89
90     with open('data/loss_rate_data.csv', "a", newline='') as f:
91         writer = csv.writer(f, delimiter=',')
92         results_to_write = [m, f'{lr_point_est:.4f}', ci]
93         writer.writerow(results_to_write)
94
95     fig = plt.figure(figsize=(16, 8))
96
97     ax = fig.add_subplot(121)
98     ax2 = fig.add_subplot(122)
99
100    ax.set_title('Cold Start Ratio')
101    ax2.set_title('Loss Rate')
102
103    ax.plot(ms, csr_points)
104    ax.plot(ms, lower_csr_ci, color='red')
105    ax.plot(ms, higher_csr_ci, color='red')
106    ax.axhline(y=0.05, color='green')
107
108    ax2.plot(ms, lr_points)
109    ax2.plot(ms, lower_lr_ci, color='red')
110    ax2.plot(ms, higher_lr_ci, color='red')
111
112    ax.set_ylim([0, 0.17])
113    ax.set_xlim(left=0)
114
115    ax2.set_ylim([40, 100])
116    ax2.set_xlim(left=0)

```



```
117
118 plt.show()
```

B Results

B.1 Cold Start Ratio Data Varying M

M	Point Estimate	90% Confidence Interval
5	0.0175	(0.0158, 0.0192)
10	0.0358	(0.0354, 0.0362)
15	0.0540	(0.0521, 0.0559)
20	0.0735	(0.0718, 0.0752)
25	0.0909	(0.0888, 0.0930)
30	0.1104	(0.1090, 0.1118)
35	0.1266	(0.1235, 0.1297)
40	0.1426	(0.1412, 0.1440)
45	0.1577	(0.1562, 0.1592)
50	0.1646	(0.1629, 0.1663)
55	0.1629	(0.1611, 0.1647)
60	0.1570	(0.1559, 0.1581)
65	0.1468	(0.1441, 0.1495)
70	0.1404	(0.1388, 0.1420)
75	0.1310	(0.1274, 0.1346)
80	0.1247	(0.1235, 0.1259)
85	0.1172	(0.1154, 0.1190)
90	0.1136	(0.1114, 0.1158)
95	0.1099	(0.1082, 0.1116)
100	0.1036	(0.1024, 0.1048)
105	0.1009	(0.0997, 0.1021)
110	0.0956	(0.0936, 0.0976)
115	0.0906	(0.0890, 0.0922)
120	0.0877	(0.0858, 0.0896)
125	0.0851	(0.0826, 0.0876)
130	0.0814	(0.0786, 0.0842)
135	0.0804	(0.0790, 0.0818)
140	0.0778	(0.0768, 0.0788)
145	0.0746	(0.0727, 0.0765)
150	0.0721	(0.0712, 0.0730)
155	0.0700	(0.0682, 0.0718)
160	0.0677	(0.0660, 0.0694)
165	0.0676	(0.0661, 0.0691)
170	0.0650	(0.0638, 0.0662)
175	0.0622	(0.0611, 0.0633)
180	0.0611	(0.0599, 0.0623)
185	0.0586	(0.0569, 0.0603)
190	0.0583	(0.0574, 0.0592)
195	0.0561	(0.0543, 0.0579)
200	0.0561	(0.0556, 0.0566)
205	0.0544	(0.0536, 0.0552)
210	0.0531	(0.0518, 0.0544)
215	0.0526	(0.0515, 0.0537)
220	0.0520	(0.0505, 0.0535)
225	0.0508	(0.0503, 0.0513)
230	0.0495	(0.0487, 0.0503)
235	0.0475	(0.0467, 0.0483)
240	0.0470	(0.0458, 0.0482)
245	0.0470	(0.0459, 0.0481)

B.2 Loss Rate Data Varying M

M	Point Estimate	90% Confidence Interval
5	93.6856	(93.0467, 94.3245)
10	91.1806	(90.9515, 91.4097)
15	89.6749	(89.4617, 89.8881)
20	87.7405	(87.1199, 88.3611)
25	86.1625	(85.5256, 86.7994)
30	83.6936	(83.3656, 84.0216)
35	81.8676	(81.1517, 82.5835)
40	79.3631	(79.0700, 79.6562)
45	76.3572	(75.9604, 76.7540)
50	72.4308	(71.5926, 73.2690)
55	68.5625	(67.9686, 69.1564)
60	65.2207	(64.7839, 65.6575)
65	62.8829	(62.6129, 63.1529)
70	61.5926	(60.9079, 62.2773)
75	60.3371	(59.9879, 60.6863)
80	60.3980	(60.2341, 60.5619)
85	59.9719	(59.4054, 60.5384)
90	59.3672	(59.1650, 59.5694)
95	59.0983	(58.8472, 59.3494)
100	59.0107	(58.5693, 59.4521)
105	58.5773	(58.2342, 58.9204)
110	58.3097	(58.2313, 58.3881)
115	58.3278	(58.0936, 58.5620)
120	58.6722	(58.3561, 58.9883)
125	58.0789	(57.6215, 58.5363)
130	58.1886	(57.9470, 58.4302)
135	58.2615	(57.9761, 58.5469)
140	57.6649	(57.3389, 57.9909)
145	58.0281	(57.6912, 58.3650)
150	57.5933	(57.2737, 57.9129)
155	57.6609	(57.1932, 58.1286)
160	57.7405	(57.5057, 57.9753)
165	57.5512	(57.0856, 58.0168)
170	57.6147	(57.3572, 57.8722)
175	57.9217	(57.6247, 58.2187)
180	57.1893	(56.7768, 57.6018)
185	57.5211	(57.1645, 57.8777)
190	57.5579	(57.1333, 57.9825)
195	57.5445	(57.1851, 57.9039)
200	57.4455	(57.1244, 57.7666)
205	57.3933	(57.0981, 57.6885)
210	57.7298	(57.2964, 58.1632)
215	57.2495	(57.0320, 57.4670)
220	57.1385	(56.9153, 57.3617)
225	57.1204	(56.9562, 57.2846)
230	57.3806	(57.1006, 57.6606)
235	57.1980	(56.6960, 57.7000)
240	57.3284	(57.0875, 57.5693)
245	57.1826	(56.9856, 57.3796)