

STA240 Final Project

Anthony Zhao, Abby Li, William Yan

Scenario 1

Customer Arrival

Poisson process (rate = λ)

- T_k : Arrival time of the k th customer
- W_k : Time between the $k - 1$ th arrival and the k th arrival

$$W_k = T_k - T_{k-1}.$$

$$W_k \sim \text{Pois}(\lambda)$$

where $\lambda = 5$ customers per hour

Service Time

$$S_k \sim \text{Exp}(\lambda)$$

where $\lambda = 6$ customers per hour, so the average customer needs to wait $1/6$ hours = 10 minutes.

Arrival Times

Open at 10am, close at 10pm, 5 customers arrive per hour on average

(Expressed in minutes after opening)

[1]	7.740219	9.999120	10.609184	18.872636	24.020133	28.291100
[7]	30.856584	43.897808	45.305376	49.139653	52.205852	52.291225
[13]	53.193630	59.614829	64.818087	69.834038	78.455901	80.939994
[19]	97.775911	99.660970	99.950087	101.768512	103.503894	103.962354
[25]	105.383493	123.241789	127.660131	130.540695	133.787696	146.175237
[31]	167.355173	175.789029	177.715756	189.252091	194.639219	197.065984
[37]	197.402851	211.522654	213.494293	221.653137	222.570392	231.387538
[43]	234.537606	235.205883	241.370710	252.514780	255.907988	274.251801
[49]	274.489324	274.836889	275.364864	282.989124	294.067864	294.579267
[55]	295.966617	299.893453	301.984833	315.940180	326.696706	326.780675
[61]	337.774267	339.941354	353.951355	357.645249	401.234376	408.369909
[67]	409.867689	425.006873	427.725484	437.115205	439.385691	440.060948
[73]	451.028466	459.809412	482.520053	485.808313	488.697602	490.941677
[79]	493.587513	496.969160	502.265192	506.555447	508.921832	516.911897
[85]	519.271801	522.395077	522.760927	527.613383	537.272545	540.065662
[91]	543.119006	547.080068	553.244399	563.228063	566.512064	575.943943
[97]	579.953130	580.925464	595.961832	598.243164	600.437756	618.836567
[103]	621.836564	622.590031	625.575909	626.773011	636.658736	637.725852
[109]	644.539666	647.120297	647.830928	658.401464	663.362935	667.576699
[115]	676.071382	690.265893	695.575545	704.400624	710.291872	710.471580

Arrival Times Analysis

In this simulation, the number of customers that will be arriving within the operating hours is 120, with the first customer arriving 7 minutes after opening and the last customer arriving 10 minutes before closing

Serving Times

The average customer takes $1/6$ hours, or 10 minutes to serve. So $\mu = 6$

(The number of minutes taken by each customer after sitting down in the restaurant)

[1] 6

Time of the day with arrival time

```
[1] "10:08" "10:10" "10:11" "10:19" "10:24" "10:28" "10:31" "10:44" "10:45"
[10] "10:49" "10:52" "10:52" "10:53" "11:00" "11:05" "11:10" "11:18" "11:21"
[19] "11:38" "11:40" "11:40" "11:42" "11:44" "11:44" "11:45" "12:03" "12:08"
[28] "12:11" "12:14" "12:26" "12:47" "12:56" "12:58" "13:09" "13:15" "13:17"
[37] "13:17" "13:32" "13:33" "13:42" "13:43" "13:51" "13:55" "13:55" "14:01"
[46] "14:13" "14:16" "14:34" "14:34" "14:35" "14:35" "14:43" "14:54" "14:55"
[55] "14:56" "15:00" "15:02" "15:16" "15:27" "15:27" "15:38" "15:40" "15:54"
[64] "15:58" "16:41" "16:48" "16:50" "17:05" "17:08" "17:17" "17:19" "17:20"
[73] "17:31" "17:40" "18:03" "18:06" "18:09" "18:11" "18:14" "18:17" "18:22"
[82] "18:27" "18:29" "18:37" "18:39" "18:42" "18:43" "18:48" "18:57" "19:00"
[91] "19:03" "19:07" "19:13" "19:23" "19:27" "19:36" "19:40" "19:41" "19:56"
[100] "19:58" "20:00" "20:19" "20:22" "20:23" "20:26" "20:27" "20:37" "20:38"
[109] "20:45" "20:47" "20:48" "20:58" "21:03" "21:08" "21:16" "21:30" "21:36"
[118] "21:44" "21:50" "21:50"
```

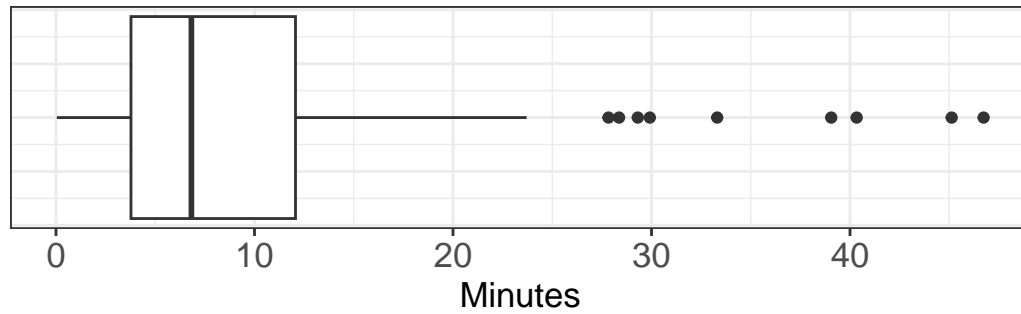
Waiting Times

	customer	arrival_time	service_length	service_start	service_end	waiting_time
1	1	7.740219	5.753559	7.740219	13.49378	0.000000
2	2	9.999120	16.216943	13.493779	29.71072	3.494659
3	3	10.609184	3.071809	29.710722	32.78253	19.101537
4	4	18.872636	1.719255	32.782531	34.50179	13.909895
5	5	24.020133	3.919356	34.501786	38.42114	10.481653

	time_of_day
1	10:08
2	10:10
3	10:11
4	10:19
5	10:24

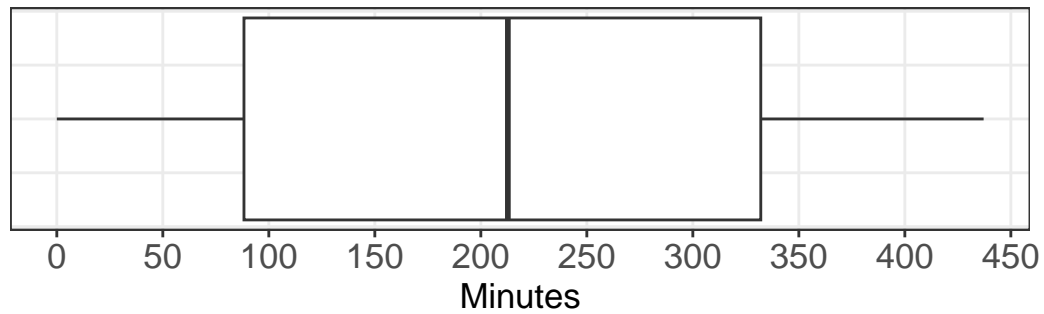
Serving and Waiting Times Analysis

Distribution of Service Times

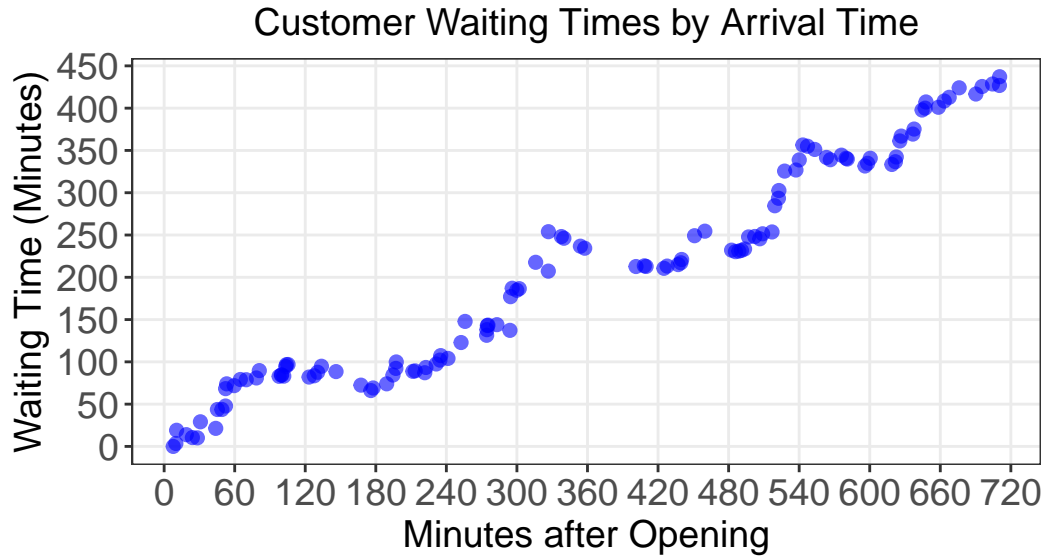


The average service time is 10 minutes, with the data skewed right, consistent with an exponential distribution. This indicates that service times tend to lower.

Waiting Times



Waiting times tends to be slightly right-skewed and on average, the waiting time is 203 minutes.



Scenario 2

Assumptions:

1. 5 dining tables and L chefs with operating hours 10am - 10pm. We choose here that $L = 2$
2. each table only seats one customer
3. service time modeled by an exponential distribution with rate $S = 3L$, so that the more chefs there are, the faster the service times become
4. 10 customers arrive every hour

Restaurant Profits

Assumptions:

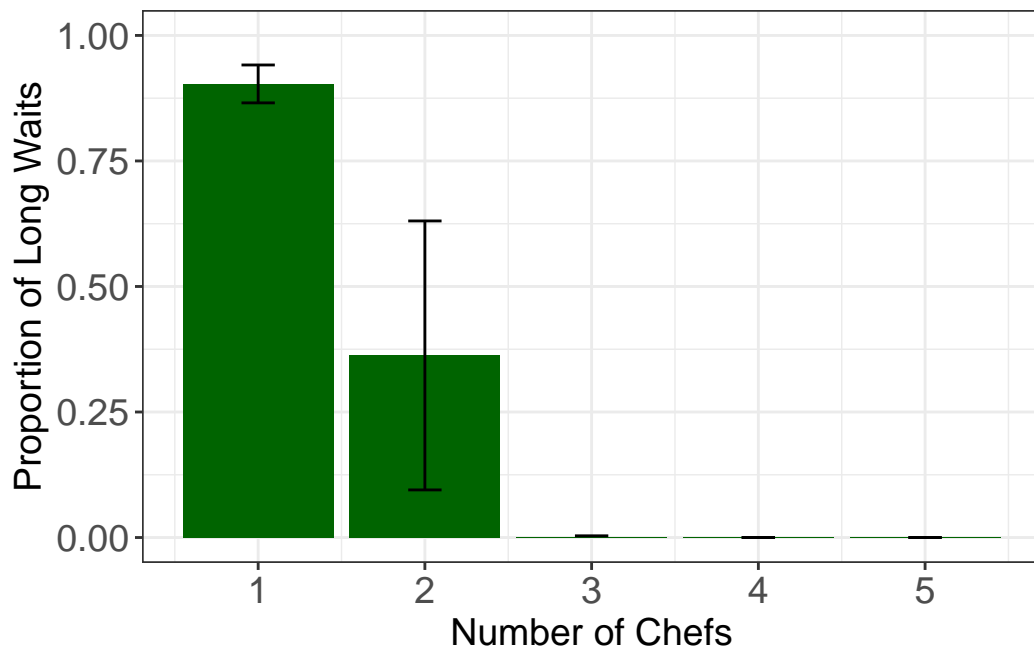
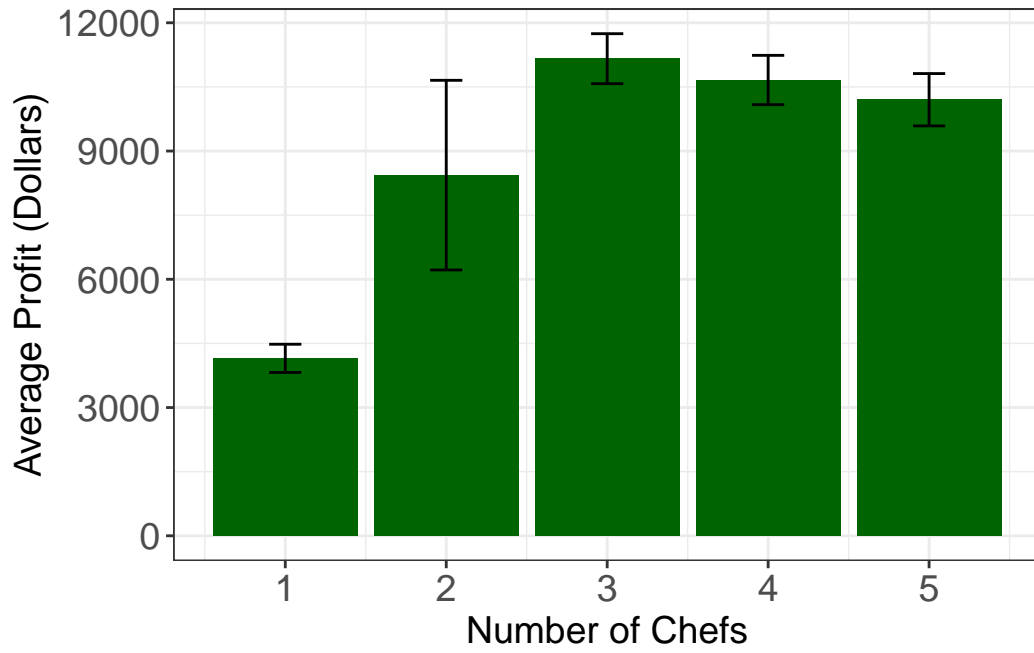
1. each customer spends \$50 per meal (customers who are still in the queue when the restaurant closes won't pay)
2. each chef earns a wage of \$40 per hour (paid for the entire duration of the restaurant's operating hours)
3. Each table cost \$80 per day (extra service cost, rent, etc.)

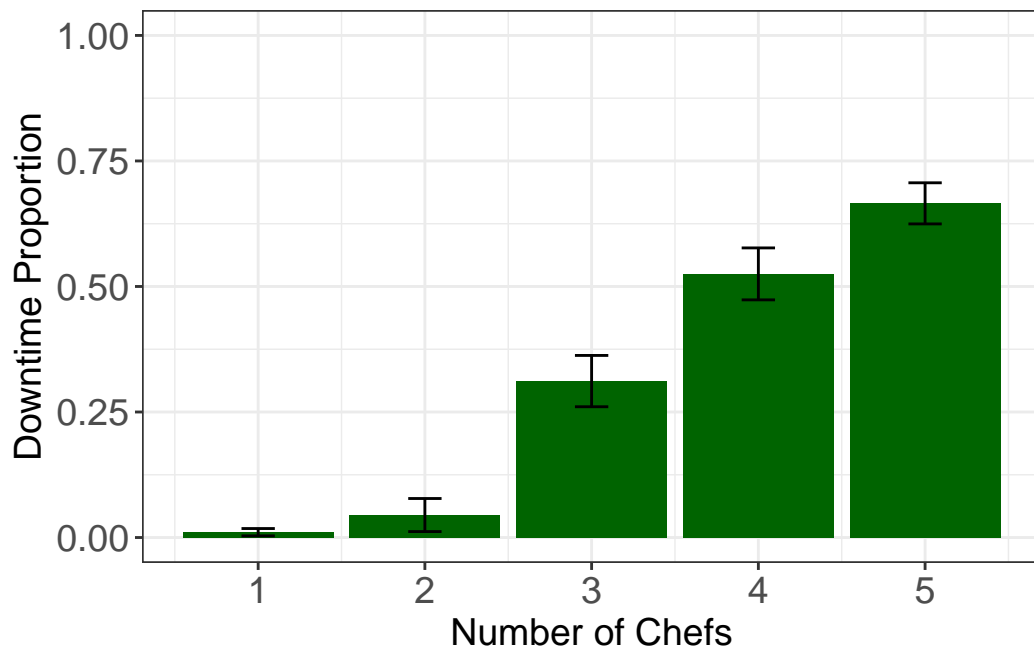
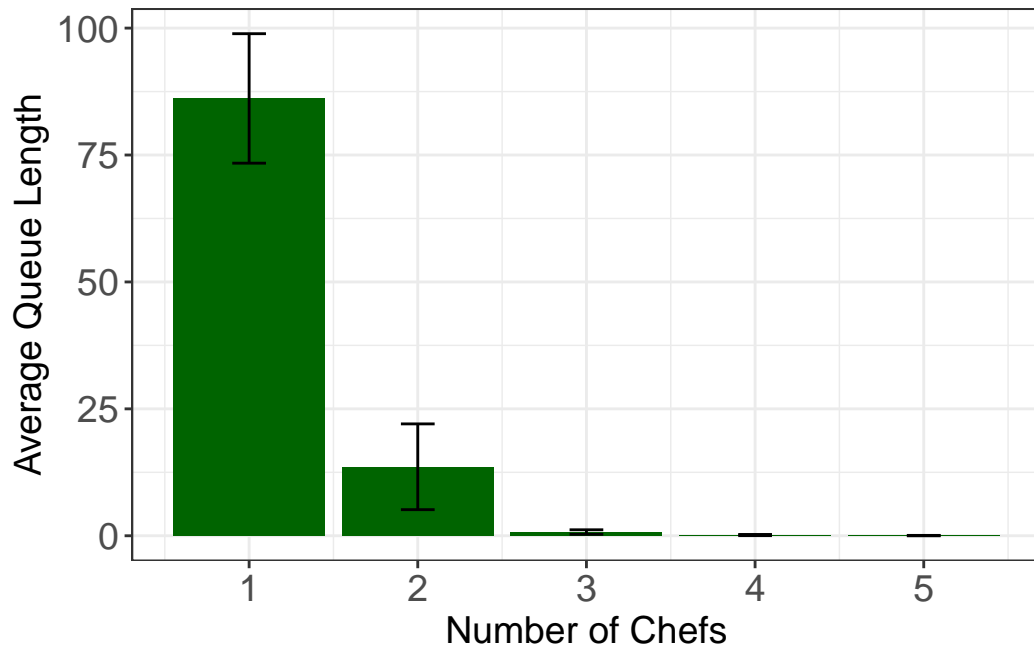
4. For customers who waited more than 30 minutes, they earn the restaurant half the amount of customers who didn't.

Maximizing Profits

With 5 tables, 24 customers arriving per hour, and these dollar amounts, how many chefs should we hire? We will run our simulation 100 times with 1 to 5 chefs on staff, to see which will maximize the expected profit.

	total_customers	profit	num_chefs	num_tables	avg_waiting_time	long_waits
1	354	5965	2	5	59.81920904	231
2	357	10930	4	5	0.18207283	0
3	352	11160	3	5	1.40340909	0
4	358	10500	5	5	0.05865922	0
5	341	9650	5	5	0.02932551	0
6	352	10200	5	5	0.01420455	0
7	360	4340	2	5	48.98888889	308
8	347	4145	1	5	158.05187320	309
	avg_queue_length	max_queue_length	avg_tables_occupied	downtime_proportion		
1	29.41111111	63	4.576389	0.04444444		
2	0.09027778	3	2.597222	0.50555556		
3	0.68611111	10	3.170833	0.34444444		
4	0.02916667	2	2.055556	0.67500000		
5	0.01388889	2	1.827778	0.71527778		
6	0.00694444	1	1.854167	0.71527778		
7	24.49444444	42	4.813889	0.00833333		
8	76.17222222	153	4.912500	0.00833333		



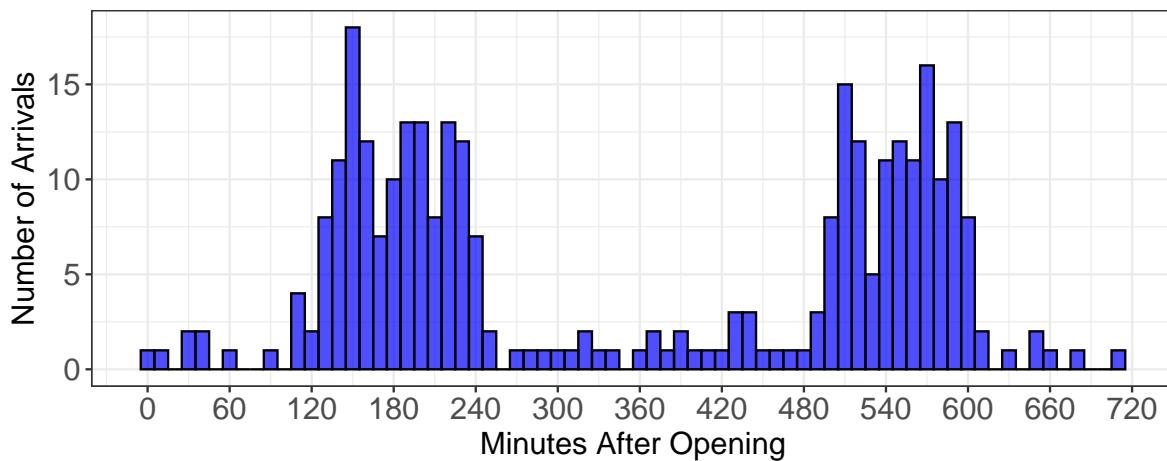


Scenario 3

To make the simulation more realistic, we have a third scenario.

Assumptions: 1. Open at 10am, close at 10pm 2. From 12pm to 2pm and 6pm to 8pm, 60 customers arrive every hour. Otherwise, 6 arrive every hour. 3. Instead of simulating service times with $\text{Exp}()$ where $\lambda = 3$ times the number of chefs, we do $\lambda = \ln(\text{chefs} + 1)$, so that additional chefs beyond 2 make more of an impact. 4. Each customer will sit for a minimum of 45 minutes. This flat value will be added to the simulated service time, and is unaffected by staffing. 5. In the profit calculation, there is a cost of adding additional tables (which are now variable), which is \$40 per table. 6. Chefs still cost \$40 per hour to hire, and each customer earns \$50.

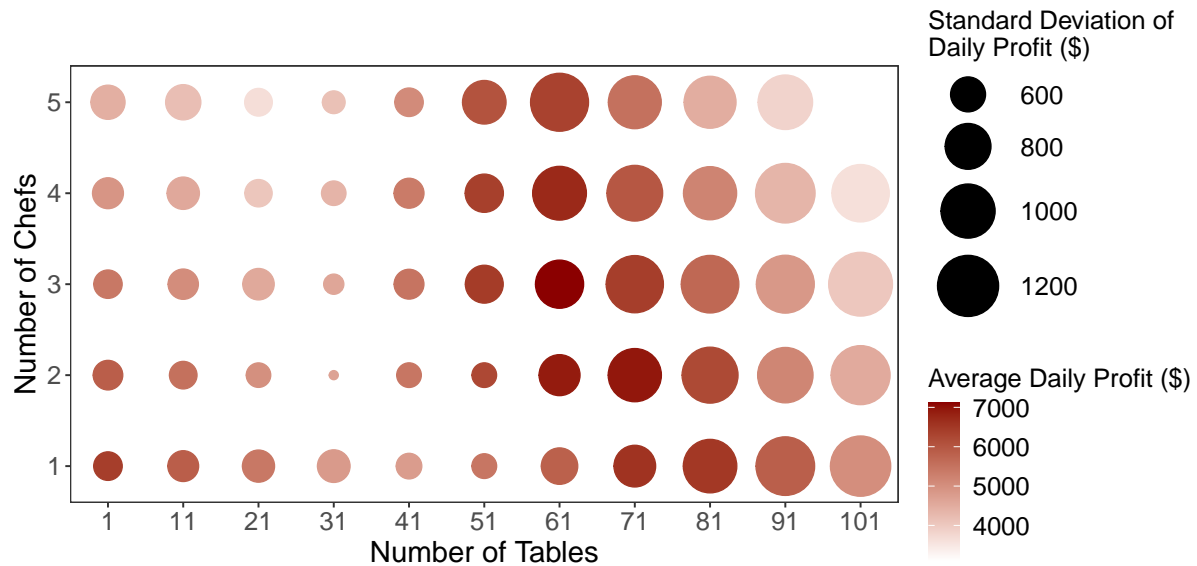
Arrival Times



Maximizing Profits

Under this scenario, how can we maximize profits?

``summarise()`` has grouped output by 'num_chefs'. You can override using the ``groups`` argument.



`summarise()` has grouped output by 'num_chefs'. You can override using the `groups` argument.

```
# A tibble: 5 x 19
  num_chefs num_tables mean_profit sd_profit mean_avg_waiting_time
    <dbl>      <dbl>      <dbl>    <dbl>          <dbl>
1         5        101        3106    1249.            0
2         4        101        3630    1091.            0
3         5         21        3660     504.           137.
4         5         91        3832    1011.            0
5         3        101        4044    1285.            0
# i 14 more variables: sd_avg_waiting_time <dbl>, mean_long_waits <dbl>,
# sd_long_waits <dbl>, mean_avg_queue_length <dbl>,
# sd_avg_queue_length <dbl>, mean_max_queue_length <dbl>,
# sd_max_queue_length <dbl>, mean_avg_tables_occupied <dbl>,
# sd_avg_tables_occupied <dbl>, mean_downtime_proportion <dbl>,
# sd_downtime_propotion <dbl>, mean_long_waits_proportion <dbl>,
# sd_long_waits_proportion <dbl>, description <chr>
```

