Advanced Systems Lab (Fall'16) – Third Milestone

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Grading

Section	**Points**
1	
2	
3	
4	
5	
Total	

Contents

1 System as One Unit

In this section I will build a very simple black-box model of the system.

1.1 Model

The system under test (SUT) in this section includes the middleware, memcached servers and the network between them. It does *not* include clients or the network between clients and middleware.

In this section I create an M/M/1 model of the SUT. This means the following definitions and assumptions:

- The queues have infinite buffer capacity.
- The population size is infinite.
- The service discipline is FCFS.
- Interarrival times and the service times are exponentially distributed.
- We treat the SUT as a single server and as a black box.

1.2 Problems of the model

The assumptions above obviously do not hold for our actual system. Especially strong is the assumption of a single server; since we actually have multiple servers, this model is likely to predict the behaviour of the system very poorly. A second problem arises from my very indirect method of estimating parameters for the model (and an arbitrary choice of time window) which introduces inaccuracies.

1.3 Data

The experimental data used in this section comes from the updated trace experiment, found in `results/trace_rep3` (short names `trace_ms*`, `trace_mw` and `trace_req` in Milestone 1). For details, see Milestone 2, Appendix A. As a reminder, that experiment had $S = 3$, $R = 3$, $W = 1\%$, $T = 5$ and $C = 192$.

The first 2 minutes and last 2 minutes were dropped as warm-up and cool-down time similarly to previous milestones.

1.4 Parameter estimation

Using the available experimental data, it is not possible to directly calculate the mean arrival rate λ and mean service rate μ so we need to estimate them somehow. I estimated both using throughput of the system: I take $\lambda = 10294 \frac{requests}{s}$ to be the *mean* throughput over 1-second windows, and $\mu = 12900 \frac{requests}{s}$ to be the the *maximum* throughput in any 1-second window, calculated from middleware logs. I chose a 1-second window because a too small window is highly susceptible to noise whereas a too large window size drowns out useful information.

1.5 Comparison of model and experiments

Table 1 shows a comparison of the predictions of the M/M/1 model with actual results from the trace experiment. The system is stable since $\rho < 1$.

It is clear that actual response time is much higher – about 40 times higher – than what the model predicts. This is because using M/M/1 for the SUT as a black box does not take into account internal parallelisation: we have $S \cdot T$ threads for `GET`s and S threads for `SET`s.

	metric	predicted	actual
1	response_time_mean	0.38	14.55
2	response_time_std	0.38	17.62
3	response_time_quantile50	0.27	12.00
4	response_time_quantile95	1.15	30.00
5	waiting_time_mean	0.31	13.22
6	waiting_time_std	0.38	17.06
7	utilisation	0.80	0.90
8	num_jobs_in_system_mean	3.95	149.79
9	num_jobs_in_system_std	4.42	
10	num_jobs_in_queue_mean	3.15	136.11
11	num_jobs_in_queue_std	4.26	
12	proportion_jobs_in_queue	0.80	0.91
13	num_jobs_served_in_busy_period_mean	4.95	
14	num_jobs_served_in_busy_period_std	13.19	
15	busy_period_duration_mean	0.38	
16	busy_period_duration_std	0.76	

Table 1: Comparison of experimental results ('actual') and predictions of the M/M/1 model ('predicted') for different metrics. Where the 'actual' column is empty, experimental data was not detailed enough to calculate the desired metric. All time units are milliseconds.

For a single thread to achieve the same throughput as K parallel threads, it needs to process each request K times faster. This doesn't explain the whole difference, though, given that in the trace experiment $K = 15$ (compared to the 40x difference in predicted and actual values we observe).

Another factor is queueing: since the M/M/1 model predicts a much lower response/service time, the queues in that model are also shorter. The number of jobs in each `GET` queue is $\frac{149.79}{S} = 30.0$ which is roughly 7 times more than what M/M/1 predicts. A longer queue means a longer waiting time.

The model does provide a reasonable estimate of the utilisation of the system and the proportion of jobs in queue (out of all jobs in the system). This is mostly because the inputs we gave to the model (arrival rate and service rate) were good estimates and not because the model itself is accurate.

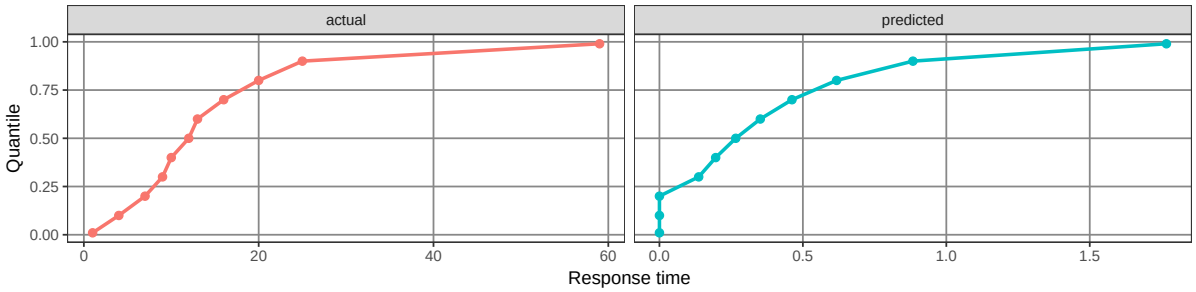


Figure 1: Quantiles of the response time distribution: experimental results and predictions of the M/M/1 model. Note the extreme difference in the response time scale.

The quantiles of the response time distribution are shown in Figure 1. M/M/1 appears to do a good job at predicting the shape of the distribution; however, the time scale is off by roughly 20x. As before, this is because M/M/1 does not account for parallelisation.

In summary, the model a) does not adequately take into account the internal structure of SUT, and b) does not predict empirical results with reasonable accuracy. For this reason, it is near worthless and we need to build more complex models in Sections 2 and 3.

2 Analysis of System Based on Scalability Data

In this section I will build a simple model of the system that assumes m parallel workers in the system, all dequeueing from a single queue.

2.1 Model

The system under test (SUT) in this section includes the middleware, memcached servers and the network between them. It does *not* include clients or the network between clients and middleware.

The assumptions and definitions of the M/M/m model are the same as for the M/M/1 model laid out in Section 1.1 with the following modifications:

- We treat the SUT as a collection of m servers.
- If any server is idle, an arriving job is serviced immediately.
- If all servers are busy, an arriving job is added to the queue.

The model built here does not account for the effect of replication. For this reason I will only use data from experiments for which $R = 1$.

2.2 Problems of the model

As in the previous section, the assumption of a single queue is inaccurate – we actually have S queues for `GET`s and S queues for `SET`s. Another inaccuracy is the M/M/m assumption that each server dequeues a request only once it has finished with the previous one: this is true if we consider each ReadWorker a separate server, but incorrect for WriteWorkers that are designed to be asynchronous (see Section 3.2 for a detailed discussion about this design).

2.3 Parameter estimation

We need to determine three parameters: the number of servers m, the arrival rate λ and the service rate of each server μ.

Let us first find m. SUT has S MiddlewareComponents, each of which has T read threads and 1 write thread, all of which ideally run in parallel (i.e. none are starved of resources). Thus I take $m := S \cdot (T + 1)$.

To estimate μ we can calculate the service time of each server (worker) as the time spent between dequeueing the request and sending it back to the client: $t_{service} := t_{returned} - t_{dequeued}$. From there we find $\mu := \frac{1}{t_{service}}$. Note that this calculation does not distinguish between `GET`s and `SET`s.

We can find λ as simply the mean throughput over 1-second windows, similarly to Section 1.1.

2.4 Data

The experimental data used in this section comes from Milestone 2 Section 2 and can be found in `results/replication`. For this section, only data from one repetition (rep. no. 5) and $R = 1$ were used (short names `replication-S*-R1-r5`), which gives a total of 3 distinct experiments. As a reminder, the experiments had $S \in \{3, 5, 7\}$, $W = 5\%$, $T = 32$ and $C = 180$.

The first 2 minutes and last 2 minutes were dropped as warm-up and cool-down time similarly to previous milestones.

	variable	predicted_3	actual_3	predicted_5	actual_5	predicted_7	actual_7
1	m	99.00	99.00	165.00	165.00	231.00	231.00
2	lambda	17242.28	17242.28	17676.91	17676.91	16885.81	16885.81
3	mu	346.12	346.12	327.62	327.62	305.28	305.28
4	response_time_mean	2.89	4.87	3.05	4.60	3.28	4.64
5	response_time_std	2.89	9.54	3.05	6.78	3.28	8.81
6	waiting_time_mean	0.00	1.98	0.00	1.54	0.00	1.36
7	waiting_time_std	0.00	5.80	0.00	4.51	0.00	4.55
8	num_jobs_in_system_mean	49.82	83.94	53.96	81.26	55.31	78.32
9	num_jobs_in_system_std	7.06		7.35		7.44	
10	num_jobs_in_queue_mean	0.00	34.12	0.00	27.31	0.00	23.01
11	num_jobs_in_queue_std	0.00		0.00		0.00	

Table 2: Comparison of experimental results and predictions of the M/M/m model, for $S \in \{3, 5, 7\}$. Where the 'actual' column is empty, experimental data was not detailed enough to calculate the desired metric. Variables 'm', 'lambda' and 'mu' were inputs to the model. All time units are milliseconds.

2.5 Comparison of model and experiments

Table 2 shows the results of modelling the system as M/M/m. Since $\rho < 1$, the model is stable for all cases. However, the table reveals an important shortcoming of the model: waiting times and the time spent in the queue are 0.

The reason becomes clear if we look at the formulas for calculating p_0 (the probability of 0 jobs in the system). As m goes to infinity, p_0 goes to zero (because the inverse of p_0 is a sum that goes to infinity). Even for finite values of $m \in [99, 231]$, p_0 is on the order of 10^{-32} to 10^{-77} (for rho=0.8). Since the probability of queueing ϱ also depends on p_0, this causes queueing to become nonexistent in the M/M/m model. Needless to say, this is a huge failure of the model.

There are some aspects in which the model performs well, though. Figure 2 shows that the model only slightly underestimates response time, although the variance estimate is too low. For the same reason the number of jobs in the system – which mostly depends on the ratio of the response time and network delay – is off by a relatively small factor.

2.5.1 Scalability

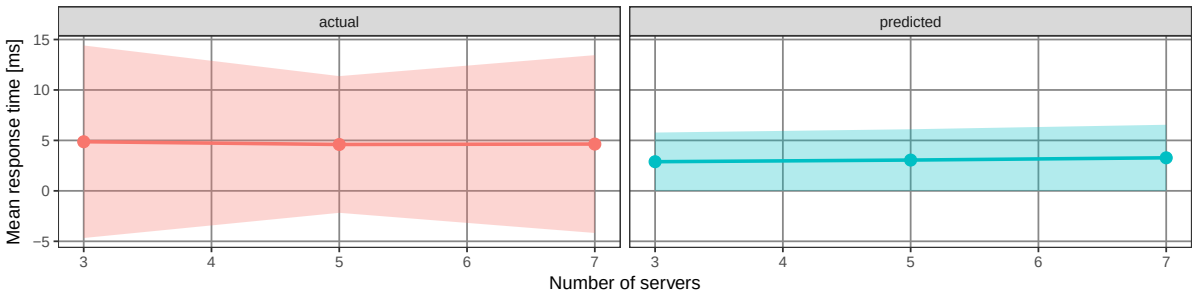


Figure 2: Predicted and actual mean response time of SUT (line with points) and standard deviation of the response time (semi-transparent ribbon).

Figure 2 shows the response time of SUT as a function of S and the M/M/m predictions of the same metric (exact numbers are shown in Table 2). The model is correctly able to capture the overall trend: there is almost no change in response time when S is changed. However, M/M/m underestimates the variance in response time; this is because of the nonexistent predicted queueing time discussed above. Furthermore, the model predicts a slight increase in response time as S increases (2.89 ms at $S = 3$ to 3.28 ms at $S = 7$), which we do not observe. The scalability of the system – especially with respect to `SETs` – is further discussed in

Section 3.2.

In summary, while M/M/m does a much better job than M/M/1 at capturing the behaviour of SUT, its main shortcoming – no queueing – renders the model useless for practical purposes (we want to build a queueing model!). This is the motivation for building a more complex model in Section 3.

3 System as Network of Queues

In this section, I will build a comprehensive network of queues model and identify bottlenecks in the system.

3.1 Model

The system under test (SUT) in this section includes the clients, middleware, memcached servers and the network between them.

Thus we can model SUT as a *closed* queueing network: the total number of jobs in the system is constant and equal to the concurrency parameter C we give to memaslap – each concurrent job in memaslap sends one request and waits for a response before sending the next one.

I will use the following definitions and assumptions:

- The queues have infinite buffer capacity.
- The population size is infinite.
- The service discipline is FCFS.
- Interarrival times and the service times are exponentially distributed.
- The clients have $Z = 0$ think time.

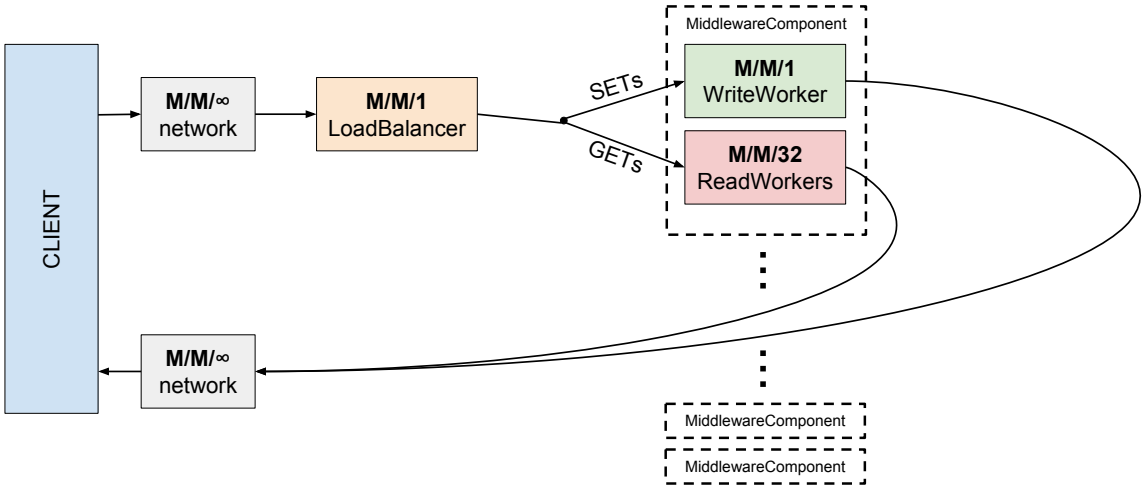


Figure 3: The queueing network model. Only one MiddlewareComponent out of S is shown. The network delay centers have identical service and are separated in the figure only for clarity.

Figure 3 shows the queueing network model used in this section. The client–middleware network time is modelled as a delay center. LoadBalancer – which consists of a single thread dequeueing from one queue – is modelled as an M/M/1 node.

There are two queues in each MiddlewareComponent and they are modelled as such: T ReadWorkers are dequeueing from a single queue of `GET`s and one WriteWorker is dequeueing from a queue of `SET`s. This gives rise to M/M/T and M/M/1 architectures, respectively.

There is no explicit modelling of memcached servers: instead, the network round-trip to memcached, the waiting time in memcached and the service time of memcached servers are all counted into the service time of Workers.

`GET`s and `SET`s are modelled separately, i.e. this is a *multiclass* queueing network.

To analyse the model, I will perform MVA using the Octave package queueing.

3.2 Problems of the model

One fundamental problem of the model is the simplification of not modelling memcached servers. This simplification makes sense for ReadWorkers because they block until a `GET` has been returned to the client, but since WriteWorkers are asynchronous, this is not an accurate model. A consequence of this is that replication has no effect on the predictions – if we want to find parameters from one configuration and use them to predict the performance for varying R, we will get exactly the same results.

However, after dequeueing a `SET` and sending it to memcached, a WriteWorker waits for 1 millisecond (using `Selector.select(long timeout)`) before proceeding to dequeueing the next element. As a consequence, if the response from memcached arrives within 1ms and no other responses are ready to be `select`ed, the behaviour is equivalent to blocking until a response is received. For a similar reason, if we increase S or R, WriteWorkers will get faster because there is less blocking on the `select()` method. (This also explains the behaviour seen in Milestone 2 Section 2).

For this reason, WriteWorkers exhibit a behaviour that is on average 'between' asynchronous and synchronous – and using a single M/M/1 model for the WriteWorker – memcached – WriteWorker part of SUT is a better approximation.

3.3 Parameter estimation

The inputs to the queueing network model are: S, T, C, W, and service times in each node of the network. The service times for each component are defined as follows (refer to Milestone 1 Figure 1 for timestamp definitions):

- $s_{network} = 0.5 \cdot (T_{ms} - T_{mw})$, where T_{ms} is the mean response time measured by memaslap, and $T_{mw} = mean(t_{returned} - t_{created})$ (mean response time measured by middleware)
- $s_{LoadBalancer} = mean(t_{enqueued} - t_{created})$
- $s_{WriteWorker} = mean(t_{returned} - t_{dequeued})$
- $s_{ReadWorker} = mean(t_{returned} - t_{dequeued})$

$s_{network}$ and $s_{LoadBalancer}$ are calculated separately for `GET`s and `SET`s (the names of Workers already imply that the service times are only calculated for one request type).

One issue with this definition is that $s_{network}$ includes the queueing time in LoadBalancer, but this is not an issue because the service time in that node is extremely low and thus, the queueing time is extremely low. Accordingly, our estimate for $s_{network}$ is not off by more than a few tenths of a percent.

3.4 Data

The experimental data used in this section comes from Milestone 2 Section 2 and can be found in `results/replication`. For this section, only data from one repetition (rep. no. 5) and one configuration ($S = 5$, $R = 1$) were used (short name `replication-S5-R1-r5`). As a reminder, that experiment had $W = 5\%$, $T = 32$ and $C = 180$.

3.5 Comparison of model and experiments

The predictions of the model match experimental results fairly well compared to the previous two Sections, as shown in Table 3. Total throughput is off by roughly 15% and the response time to `GET`s is off by 10% and so is the number of items in ReadWorkers. Response time to `SET`s is off by a factor of 2. This is explained when we consider the discussion in Section 3.2:

	variable	predicted	actual
1	throughput	20444.53	17668.03
2	mean_response_time_get	8.71	9.68
3	mean_response_time_set	11.20	21.21
4	mean_response_time	8.83	10.29
5	throughput_readworkers	19640.99	16784.63
6	throughput_writeworkers	803.54	883.40
7	mean_response_time_readworker	3.05	4.02
8	mean_response_time_writeworker	5.48	15.49
9	util_lb_get	0.08	0.06
10	util_lb_set	0.00	0.00
11	util_readworker	0.37	0.32
12	util_writeworker	0.50	0.55
13	items_network_get	111.04	94.89
14	items_network_set	4.59	5.05
15	items_readworkers	59.88	67.54
16	items_writeworkers	4.40	13.69

Table 3: Parameters of the system calculated using MVA. `lb` stands for LoadBalancer. The throughput and number of items in workers is given as the total over all threads. The response time of and number of items in LoadBalancer have been left out of the table because they were extremely low.

behaviour of WriteWorkers is much less predictable than that of ReadWorkers – but since there are many more `GET`s than `SET`s the throughput estimate is still reasonable.

In summary, the model is quite accurate for ReadWorkers but less accurate for the more unpredictable WriteWorkers.

3.5.1 Bottleneck analysis

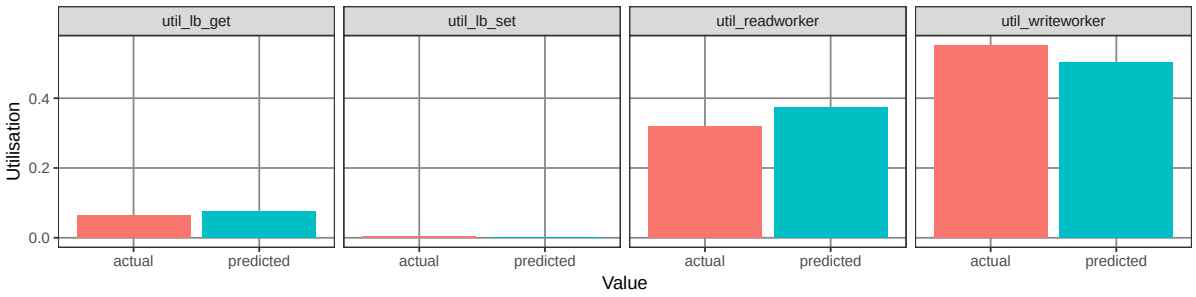


Figure 4: Predicted and actual utilisations of all queueing nodes that are not delay centers, for `GET`s and `SET`s. `lb` stands for LoadBalancer.

To find the bottleneck, we can compare utilisation of each node in the queueing network. Figure 4 shows that WriteWorkers are the bottleneck in the actual system as well as in the model. However, since only `SET`s pass through WriteWorkers, `GET`s have a different bottleneck – which is clearly ReadWorkers based on Figure 4.

We can estimate the upper bound on throughput by finding out what would happen if the bottlenecks had utilisation $U = 1$. For each WriteWorker, this is roughly 320 and for each ReadWorker roughly 10500 requests per second, and the total throughput of the system is bound above by roughly 49900 requests per second. The response time of a WriteWorkers is bound below by 3.1 ms and that of ReadWorker by 0.095 ms.

4 Factorial Experiment

In this section, I will use a $2^k r$ experiment to understand the system. Of special interest here is the proportion of `SET`s because the performance of `SET`s in SUT has an unusual dependence on parameters, as explained in Section 3.2.

4.1 Experimental question and experiment design

The goal of this section is to find out the factors that influence throughput of the system. In particular, I will investigate the effect of $k = 3$ factors – S (number of servers), R (replication level) and W (percentage of `SET`s in workload) – on total throughput of the system. Everything else will be kept fixed: the number of threads $T = 32$ and the number of clients $C = 180$.

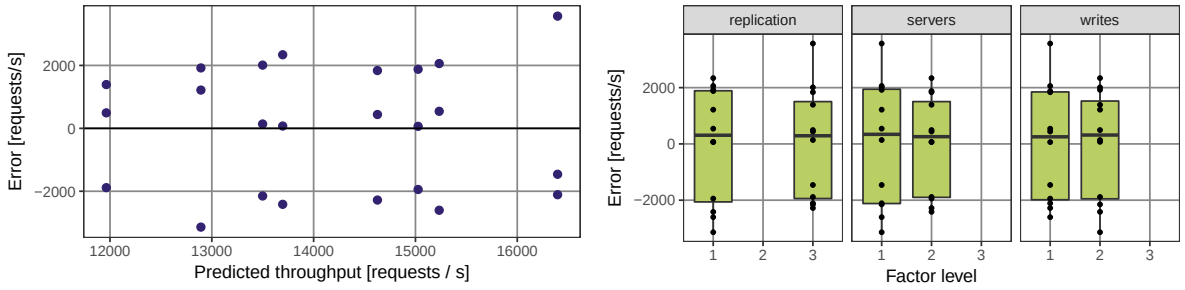
For each factor in $\{S, R, W\}$ we need to pick two levels. Since I expect throughput to monotonically increase with S, decrease with R, and decrease with W, we can use the minimum and maximum level for each factor in our $2^k r$ experiment: $S \in \{3, 7\}$, $R \in \{1, S\}$, and $W \in \{1, 10\}$.

4.2 Data

The experimental data used in this section comes from Milestone 2 Section 3 and can be found in `results/writes` (short name `writes-S*-R*-W*-r*` in Milestone 2). For each combination of S, R, and W we have $r = 3$ repetitions. This means data from $2^k \cdot r = 24$ distinct runs are used in this section.

The data table is available in Appendix A.

4.3 Results



(a) Error of the $2^k r$ model as a function of predicted throughput. Each point is one repetition of a configuration. Note the throughput axis does not include zero.

(b) Boxplot of the error distribution for all levels of all factors. The box shows the inter-quartile range (between 25th and 75th percentiles, IQR), with the median shown as a horizontal line. The top and bottom whisker show the highest and lowest value within $1.5IQR$ of the median. Experiment results are also plotted as single points. Note that each subplot contains all 24 data points.

Figure 5: Evaluation of the $2^k r$ model.

4.3.1 Checking assumptions

Before delving into the predictions of model we need to check whether assumptions we made in modelling actually hold.

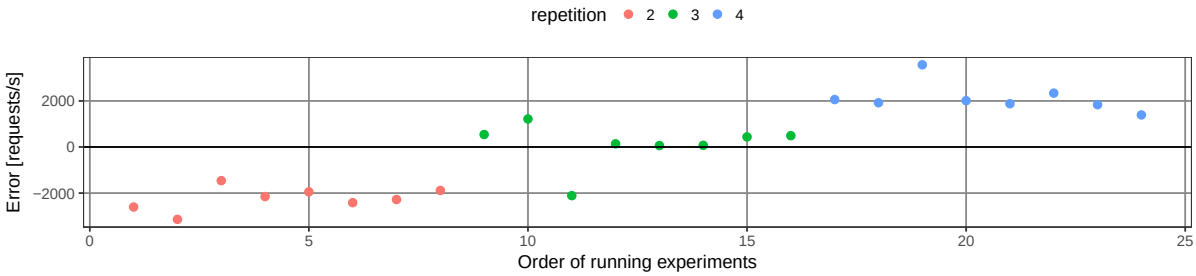


Figure 6: Error of the $2^k r$ model as a function of the order in which experiments were run. Color of the points shows the repetition number.

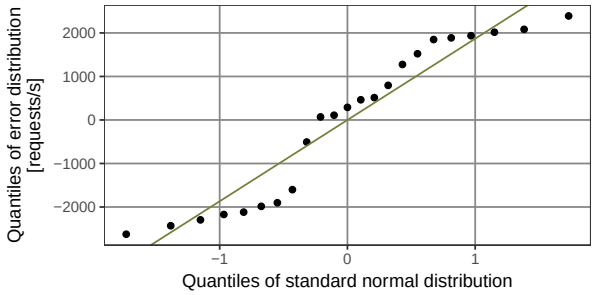


Figure 7: Quantiles of the residual distribution plotted against quantiles of the standard normal distribution. The straight line shows the best fit of a linear trendline through the points.

Independent errors The model assumes that errors are independently and identically distributed (IID). Figure 5a shows that error does not depend on the predicted throughput. Furthermore, errors do not depend on factor levels as shown in Figure 5b: the median and 25% and 75% percentiles of the error distribution are independent of the factor and the level.

Figure 6 shows that errors clearly depend on repetition. An obvious hypothesis here is that each successive repetition improved the throughput for some reason. However, repetition 2 was run on Nov 20, and both repetitions 3 and 4 were run on Nov 23 with a 6-hour difference; the resource group was hibernated and redeployed before each experiment. For this reason we can't accept the hypothesis that repetitions somehow affected each other.

Thus, the large variation in throughput between experiments can be explained in two ways: it could a) be caused by differing conditions in Azure between deployments, or b) be somehow inherent to the SUT. If b) were true, we would also see large variance *within* each deployment, which is not the case. This leaves us with option a): the conditions on Azure differed between employments – possibly due to different server or network allocation, or the total load in Azure, or some other factor.

Normally distributed errors The model assumes that errors are normally distributed. The quantile-quantile plot in Figure 7 shows that this is clearly not the case – the lowest quantiles are too low and medium-to-high quantiles too high for the distribution to be normal. This, however, is caused by the trimodality of the error distribution: the throughputs (and thus, errors) of each repetition individually are distributed much more closely to a normal distribution, but when we concatenate the repetitions, the result is trimodal.

Constant standard deviation As Figure 5b shows, the distribution looks similar at all factor levels, so the model assumption of a constant standard deviation holds.

4.3.2 Analysis of the model fit

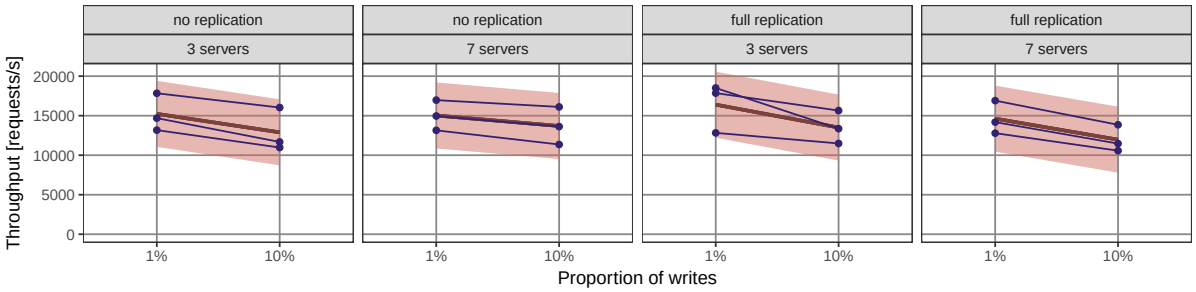


Figure 8: Throughput as a function of W. Each line with points shows the results of one repetition. The red line shows the throughput predicted by the $2^k r$ model; the light red ribbon shows the standard deviation that we would expect to see according to the model, if we were to run 3 repetitions.

Even though the deviation from the mean is high in our experiments, residuals are almost an order of magnitude smaller than throughput values, and there does not appear to be any definite trend in the mean or spread of the residuals, so the fit of the model is reasonable given the noisiness of the data. Given that the range of throughput values covered is small and the additive model is a reasonable fit, we don't need to use a multiplicative model.

Figure 8 shows the predictions of the model and actual results. The results of all repetitions have the same trend as the predicted mean, and stay within 1 standard deviation of the mean. This again confirms that the fit is decent.

4.3.3 Allocation of variation

	variable	coefficient_value	variation
1	x0_constant	14166.7	
2	xa_servers	-338.6	0.024
3	xb_replication	-45.4	0.000
4	xc_writes	-1153.8	0.276
5	x_ab	-487.6	0.049
6	x_bc	-236.3	0.012
7	x_ac	155.5	0.005
8	x_abc	-97.1	0.002
9	error		0.672

Table 4: Values of coefficients and allocation of variation for all variables in the 2^k model.

In Table 4 we find the coefficients for each variable in our model, together with the allocated variation. By far the most variation is explained by the error. This is caused by the large variation in throughput in different deployments, as discussed above.

Among other components, we find that the percentage of `SET`s (x_c) explains the most at 27.6%. Servers and replication together (x_{ab}) explains about 5%; all other variables explain less than 1/10th of the variation of x_c so can be considered insignificant.

These results can be directly mapped the system design. There are T times fewer WriteWorkers than ReadWorkers, so `SET`s to have a higher response time (see Milestone 2 for details); increasing the proportion of `SET`s therefore increases response time significantly.

The amount of servers S or replication R don't have a large effect individually; however, increasing both S and R from the minimum to the maximum increases the cost of `SET`s significantly ($S = 7, R = S$ means 7 writes are made to memcached servers for each `SET`, compared to 1 write if $S = 3, R = 1$), and thus has a strong effect on throughput (via increased response time).

5 Interactive Law Verification

In this section, I will check the validity of experiments from Section 2 of Milestone 2 using the Interactive Response Time Law (IRTL).

5.1 Model

We are assuming a closed system, i.e. clients wait for a response from the server before sending another request. Under this assumption, IRTL should hold:

$$R = \frac{N}{X} - Z$$

where R is mean response time, Z is waiting time in the client, N is the number of clients and X is throughput. In this section we test whether IRTL does in fact hold.

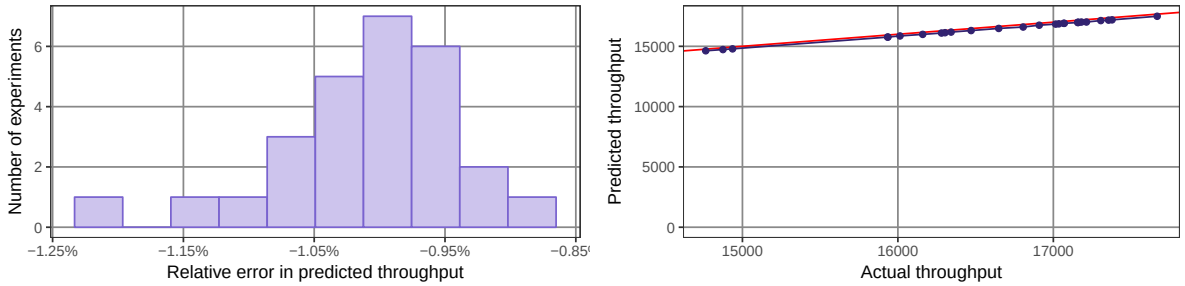
5.2 Data

The experimental data used in this section comes from Milestone 2, Section 2 (Effect of Replication) and can be found in `results/replication` (short name `replication-S*-R*-r*` in Milestone 2). This includes a total of 27 experiments in 9 different configurations.

The first 2 minutes and last 2 minutes were **not** dropped because IRTL should hold also in warm-up and cool-down periods. Repetitions at the same configuration were considered as separate experiments.

5.3 Results

Using IRTL, we can verify the validity of experiments by calculating the predicted throughput $X_{predicted}$ (given the number of clients C and mean response time R) and comparing it with actual throughput X_{actual}. This is precisely what I did for all experiments of Milestone 2, Section 2. $C = 180$ in all experiments, and both R and X_{actual} are aggregated results reported by the three memaslap instances generating load in that experiment.



(a) Histogram of the relative error of throughput predicted using IRTL, counting the number of experiments in a given error range. Note the horizontal scale does not include 0.

(b) Throughput predicted using IRTL (dark points), as a function of actual throughput calculated from experimental data. The red line shows hypothetical perfect predictions (the $x = y$ line). Note the horizontal scale does not include 0.

Figure 9: Evaluation of the validity of Milestone 2 Section 2 experiments

If we assume the wait time Z to be 0, we get a mean relative prediction error of -1.01%, defined as $\frac{X_{predicted} - X_{actual}}{X_{actual}}$. The distribution of these errors is shown in Figure 9a; the distribution looks reasonably symmetric. Figure 9b plots $X_{predicted}$ against X_{actual} and shows again that the predicted throughput is very close to actual throughput, but consistently smaller in all regions of the graph.

If we assume a nonzero Z and estimate it from the experiments, we get a mean estimated wait time of -0.111ms. Clearly this is impossible: wait time must be non-negative.

To explain these results, we need to answer the question: why is the actual throughput lower than the actual throughput? The most plausible hypothesis is that memaslap starts the clock for a new request before stopping the clock for the previous request – which would violate the closed system assumption. This could be caused by us using more virtual clients than CPU cores in each memaslap machine – a practice discouraged by the creators of memaslap.

Regardless of the exact reason of the deviation, the IRTL holds to a reasonably high accuracy. Perfect accuracy is impossible even without the middleware: in the baseline experiments (Milestone 1 Section 2), relative prediction error is 0.2%-0.5% in a selection of values of N that I checked.

Appendix A: Data for the factorial experiment

	servers	replication	writes	repetition_id	throughput
1	3	none	1	2	17836
2	3	none	1	3	14690
3	3	none	1	4	13173
4	3	none	10	2	16032
5	3	none	10	3	11676
6	3	none	10	4	10972
7	3	full	1	2	17855
8	3	full	1	3	18505
9	3	full	1	4	12828
10	3	full	10	2	15649
11	3	full	10	3	13360
12	3	full	10	4	11488
13	7	none	1	2	16969
14	7	none	1	3	14962
15	7	none	1	4	13147
16	7	none	10	2	16111
17	7	none	10	3	13622
18	7	none	10	4	11356
19	7	full	1	2	16905
20	7	full	1	3	14186
21	7	full	1	4	12789
22	7	full	10	2	13849
23	7	full	10	3	11471
24	7	full	10	4	10571

Table 5: Data used in building the 2^k model in Section 4.