Performance modelling and simulation of skewed demand in complex systems

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Abstract. On-line Transaction Processing (OLTP) applications must frequently deal with the issue of skewed demand for some resources. This demand may overwhelm the whole system, affecting the owner's reputation and revenue. In this article we present a ticketing use case and argue that at each layer of the architecture, the distributed computing technologies of the Cloud may maintain throughput to the lower demand resources, maximising the available functionality of the system.

Keywords: Cloud, middleware, microservices, distributed databases, load-balancing, performance

1 Introduction

There are many high-profile examples of whole IT systems brought down by customer demand for part of their services. Customers were prevented from using any part of the London 2012 Olympic ticketing website on launch day to avoid demand overloading the system [18]. HBO Go was brought down by demand for the finale of "True Detective" [9]. Apple's iTunes Store suffered outage on the launch day of the iPhone 7 (new iPhone registration is carried out via an iTunes function) [23].

It is possible to design and build more resilient systems through effective use of Cloud technologies where higher than normal demand for one function or type of resource would not block access to the others. Skewed demand may be isolated so that it only affects parts of a system, or shared equally between different components. (The system may also adapt to demand by elastic scaling of resources, but this will not be considered as part of this paper).

We will briefly discuss Middleware, Microservices and Distributed Databases and show how they provide strategies for managing demand. In a complex system we need to examine the end to end impacts. Does removing a bottleneck at the Web or Worker Application layer shift the stress to the middleware, or the database? If we accept that some levels of demand cannot be met on a limited budget, and that some components will no longer meet the required throughput, how do we determine the impact on the remainder of the system? To examine these questions we will build models of an example system using different architectures; to test the models we will build out these systems and measure how demand impacts the throughput.

2 Background

We will consider an example system based on the Olympic ticketing use case above. Such a ticketing application may be generalised to any system for allocating and releasing other resources with variable demand.

Tickets will be for a multi-sport event, and each will consist of a ticket type (the sport), date, row, and seat number. The system will support three operations:

1. Search (for available tickets)
2. Book (allocate a ticket to a customer)
3. Return (customer releases a ticket allocation)

If it is not possible to search for or book tickets of one type because some component is overloaded due to demand, then the system should allow booking of other ticket types. It must also always be possible to return tickets of any type.

In this paper, we are considering the problem of high demand for types of ticket. This is not about the number of tickets available and we will not consider issues of fair allocation of scarce resources. The demand may be:

1. predictable - we know which functions or ticket types are going to have the highest demand; or
2. unknown - we discover the areas of highest demand once the application goes online.

3 Technologies

We consider current cloud technologies that may be useful in distributing throughput generated by high demand throughout the system, and in decoupling its components from each other.

3.1 Middleware

Good choice of middleware in our system will help ensure our components are connected, but loosely coupled. If, for example, a web server is blocked waiting for a response from a worker application carrying out a more expensive operation, then the throughput of the web server will be limited to that of the worker application. Also, failure of one of the processes in a distributed system may cause failure of the system as a whole.

Synchronous vs Asynchronous Middleware. With synchronous middleware such as Remote Procedure Call (RPC), the calling process is blocked until the called service completes and returns control to the caller. The system components are tightly coupled. This is undesirable for our ticketing application.

Distributed systems using some form of asynchronous middleware do not block when calling a remote service. Control is immediately passed back to the caller, and a response may be returned eventually, with the caller polling the remote service for the response, or the remote process calling a method in the caller to send the response.

The "return" operation use case does not require a direct response from the system. As long as the customer can rely on eventual guaranteed delivery of the return request, (and that the cost of their ticket will be refunded) then they do not need to wait for a direct response to their return.

Message-Oriented Middleware (MOM). MOM is a form of Asynchronous Middleware, commonly provided by Larger Cloud service providers such as Amazon Web Services and Microsoft Azure. These brokered message services provide an intermediate layer between senders and receivers, decoupling their communication. Message delivery may take minutes rather than milliseconds, but the service providers do provide configurable delivery guarantees [8].

There are two main messaging models, both of which are offered by Microsoft Azure Service Bus [16] for example.

Point-to-Point Queues. Azure Queues are a point-to-point service implementing First In, First Out (FIFO) message delivery. Many processes may send messages to a queue, and each message is received by one consumer - though it may be one of several consumers competing for messages from this queue. This competing consumer pattern offers a means of balancing load from our Web servers between our Worker Applications.

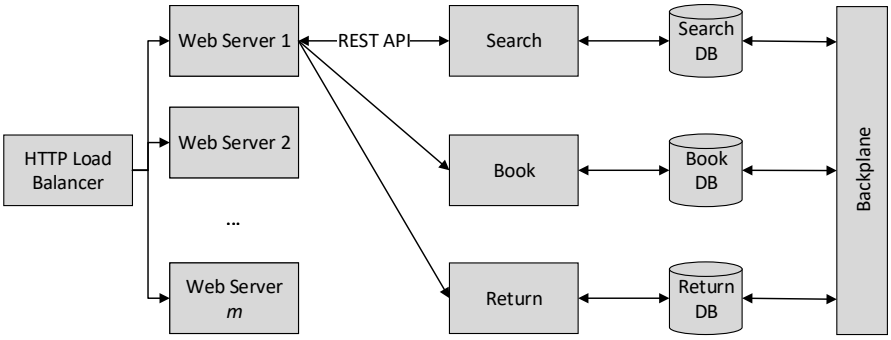
Publish/subscribe. Publish/subscribe (in Azure, topics and subscriptions) are a properly one-to-many or many-to-many communication mechanism. Any single producer may send one message to a topic, and then all consumers that subscribe to that topic receive a copy of the same message.

Evaluation. The MOM services from Microsoft and Amazon provide tools for monitoring the number of messages in a queue or topic, and middleware can be examined by measuring whether a queue size reaches a steady state, or grows faster than downstream services can consume the messages. However, this is affected more by the services using the middleware than the choice of middleware itself. This is likely to be best achieved by end to end measurement.

3.2 Microservices

Microservice architecture is an approach to structuring applications as suites of small services, defined by business capability verticals rather than technological layers [15] [20]. Each of our use case requirements - search for tickets, book tickets, return tickets - might be microservices with their own worker applications and data nodes. Ticket data would be denormalised across the data nodes and made eventually consistent via a backplane messaging service [21]. This would certainly isolate the demand for search, book and return from each other - returning tickets would not be blocked by a system where booking tickets was overloaded. We would need a lower level of granularity however to deal with skewed demand for a particular type of ticket, perhaps a separate microservice for booking each type.

Fig. 1. Microservices



Evaluation. As for middleware, evaluation of different microservices approaches depends on end to end measurement. However, one area of interest is the effi-

ciency of highly granular microservices. If the demand for the microservices is isolated then it is possible that some low demand services are underutilised.

3.3 Distributed databases

Modern databases both SQL and NoSQL are designed to scale both data and the load of operations accessing that data over many servers that do not share disk or RAM, so-called "shared nothing" architecture [6]. We may partition data *vertically*, dividing tables into groups of columns that may be placed on different data nodes; or *horizontally*, where the split is by row [1].

In our use case, the quantity of data does not approach the levels of "Big Data" applications. We are interested in partitioning as a means of scaling the demand for that data. Our ticketing system will not require a large number of columns and the three operations outlined do not have significantly different column requirements. Horizontal partitioning is most relevant. The partition key of a Ticket table may be the Ticket Type, the Date, or the seat Row. Demand for tickets is likely to vary by each of these attributes. An alternative partitioning strategy would be to on denormalised tables supporting the query, book and return operations. The load on each data node would follow the demand for the data types and operations placed there.

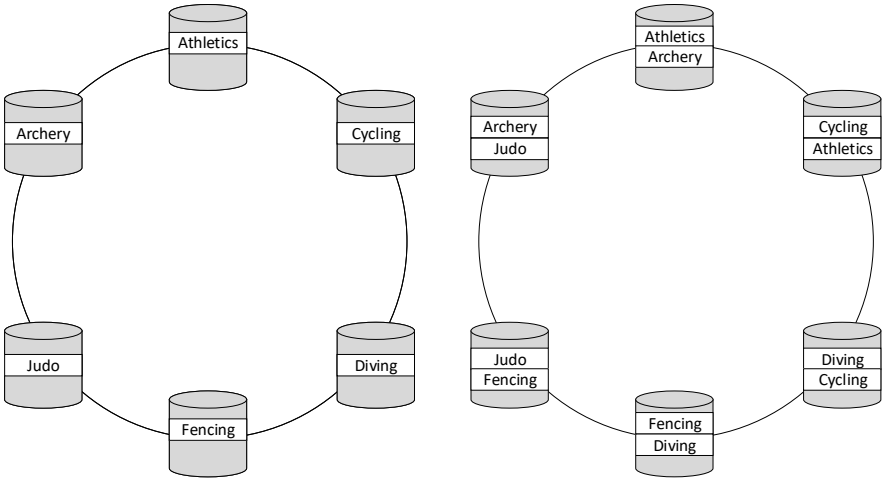
The scalability of distributed databases usually comes at the price of a relaxed consistency model - so-called BASE (Basically Available, Soft state, Eventually Consistent) rather than ACID (Atomic, Consistent, Isolated, Durable) transactions. In our ticketing system, eventual consistency is clearly sufficient for the return ticket scenario - returned tickets do not have to be made immediately available for booking. Individual ticket bookings must exist on only one partition to prevent the same ticket being booked more than once. Eventual consistency between search and book operations requires the customer to tolerate the concept of "reservation" of a ticket for a short period until a booking can be confirmed [21][6].

Another issue to be aware of is *replication*. Most distributed databases offer replication of data from one partition to another for availability. In our use case, if a data node is overloaded by demand, the system may failover to a copy of the data on another data node, but this will just transfer the demand elsewhere. If this is also the primary data node of an otherwise low demand data type, then it may be overwhelmed in turn.

Where the high demand is unknown in advance, we need an adaptive strategy. Workload-aware clustering algorithms do exist for the placement of new data, e.g. [13], but our use case has a fixed set of tickets. Re-placement of existing data onto different partitions would be likely to require many reads, writes and deletes.

Evaluation. A successful partitioning strategy will ensure that an individual operation only uses a single data node; that every data node is equally used when demand is evenly distributed; and that any impact from skewed demand is limited to the directly affected data node.

Fig. 2. Distributed database, without and with replication



4 System architectures

The proposed system will use distributed architectures. Users will access it from a web-based front end. Tickets will be stored in a database partitioned across several data nodes. In between the web servers and database will be a number of worker applications to service user requests, connected to the web servers by some middleware.

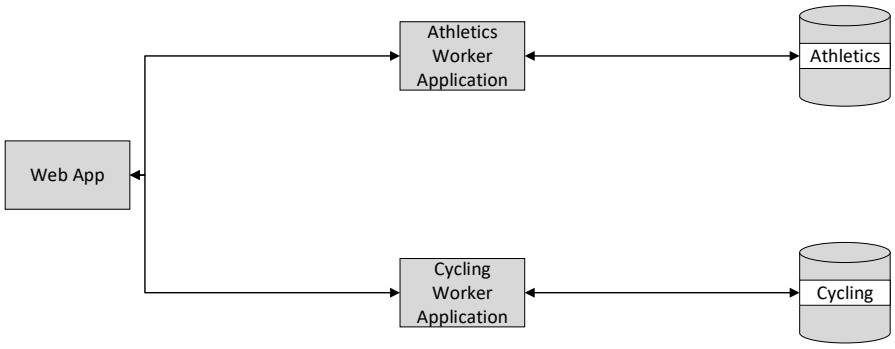
For each architecture it will be assumed that the web application will be designed to cope with the required demand, using a cluster of web servers where the throughput is managed using some HTTP Load Balancing algorithm [10], and potentially Elastic Scaling of servers e.g. using the autoscaling features of Amazon Web Services [2] or Microsoft Azure [17].

4.1 Simple microservices

There are two separate databases, one for Athletics tickets, one for Cycling. Athletics will have skewed demand.

It's expected that this architecture will lead to isolation of the skewed demand and that the results of testing the model will not be surprising, but that this will provide a useful control for other architectures.

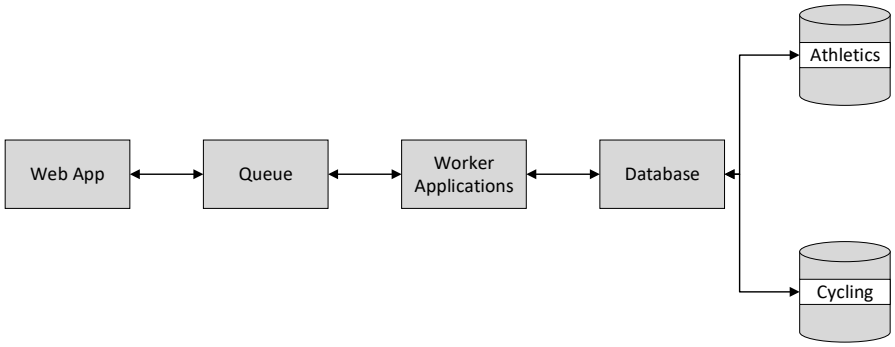
Fig. 3. Simple microservices architecture



4.2 Shared queue middleware

Requests via a shared queue to worker applications going to a distributed database with two nodes, Athletics and Cycling.

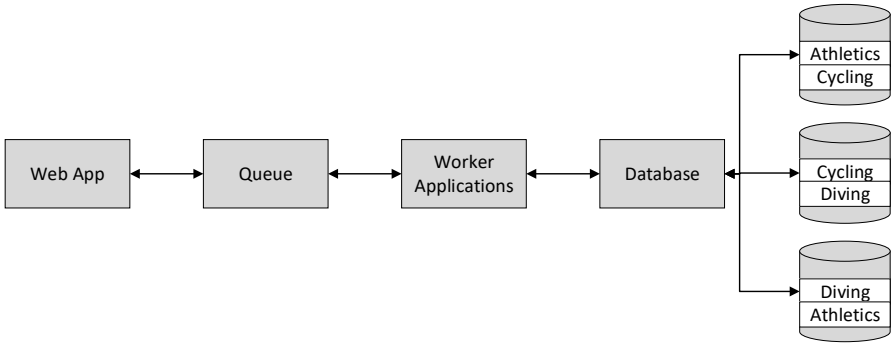
Fig. 4. Shared queue middleware architecture



4.3 Distributed database with replication

Requests via a shared queue to worker applications going to a distributed database with three nodes, Athletics, Cycling and Diving, where each partition is replicated on another node.

Fig. 5. Distributed database with replication architecture



5 Modelling

We can decouple worker applications from the front-end using asynchronous middleware. Shared middleware balances the load, microservice architecture isolates it. The system can adapt to current demand by using elastic scaling to create or destroy worker applications, and by using scaling groups we can ensure that the number of each application type is appropriate to the demand.

With care, we can use horizontal database partitioning to ensure that functions and/or data types are not shared between data nodes, isolating their demand from each other.

At the component level we can see whether an approach will balance or isolate load, or adapt to it, but at the system level we will need modelling techniques to predict the end to end throughput.

CloudSim. CloudSim [5] is a Java framework for developing cloud datacentre simulations. Much of it is concerned with modelling the efficient running of that infrastructure, for example the power usage, but it also includes utilisation models and may be useful for predicting the effect of elastic scaling.

CloudSim simulations require Java development for creation and modification, which is an overhead in building the models but offers more flexibility in applying them. Process Algebra has closed-form solutions, though there is a PEPA Workbench tool [11] that allows PEPA specifications to be parsed and run like programs, aiding experimentation on a range of action rates by automating repetitive calculations. Both currently have their place as they predict different quantities of interest.

Process Algebra. Process Algebras (such as PEPA or TIPP [12]) allow us to model throughput in interdependent processes, with a mixture of independent and shared actions operating at different rates. Each of our components can be described in this way, and queues have already been extensively modelled in PEPA [24]. The nature of process algebra as a mathematical language also means that it is possible to build a model of a whole system by composition of the component models.

Fig. 6. PEPA queue model

$$
\begin{aligned}
Website &\stackrel{def}{=} (request, r).Website \\
Worker &\stackrel{def}{=} (service, s).Worker \\
Queue_0 &\stackrel{def}{=} (request, r).Queue_1 \\
Queue_1 &\stackrel{def}{=} (service, s).Queue_0 \\
Website &\underset{request}{\bowtie} Queue_0[N] \underset{service}{\bowtie} Worker
\end{aligned}
$$

6 PEPA Component Models

6.1 Distributed database without replication

The PEPA model for a distributed database is shown in Figure 7.

Fig. 7. Distributed database PEPA model

$$
\begin{aligned}
a &= 1.0 - 10.0 \\
c &= 1.0 \\
db &= 5.0 \\
Website &\stackrel{def}{=} (book_a, a).Website + (book_c, c).Website \\
DB_1 &\stackrel{def}{=} (book_a, \top).DBsrv_1 \\
DBsrv_1 &\stackrel{def}{=} (dbsrv_1, \top).DB_1 \\
DB_2 &\stackrel{def}{=} (book_c, \top).DBsrv_2 \\
DBsrv_2 &\stackrel{def}{=} (dbsrv_2, \top).DB_2 \\
Service_1 &\stackrel{def}{=} (dbsrv_1, db).Service_1 \\
Service_2 &\stackrel{def}{=} (dbsrv_2, db).Service_2 \\
Website &\underset{book_a, book_c}{\bowtie} DB_1 \parallel DB_2 \underset{dbsrv_1, dbsrv_2}{\bowtie} Service_1 \parallel Service_2
\end{aligned}
$$

See the experimental results in Table 1.

Table 1. Distributed database experimental results

Rate	Throughput			
a	$book_a$	$book_c$	$dbsrv_1$	$dbsrv_2$
1	0.83	0.83	0.83	0.83
2	1.43	0.83	1.43	0.83
3	1.88	0.83	1.88	0.83
4	2.22	0.83	2.22	0.83
5	2.5	0.83	2.5	0.83
6	2.73	0.83	2.73	0.83
7	2.92	0.83	2.92	0.83
8	3.08	0.83	3.08	0.83
9	3.21	0.83	3.21	0.83
10	3.33	0.83	3.33	0.83

6.2 Distributed database with replication

See the experimental results in Table 2.

Fig. 8. Distributed database experimental results

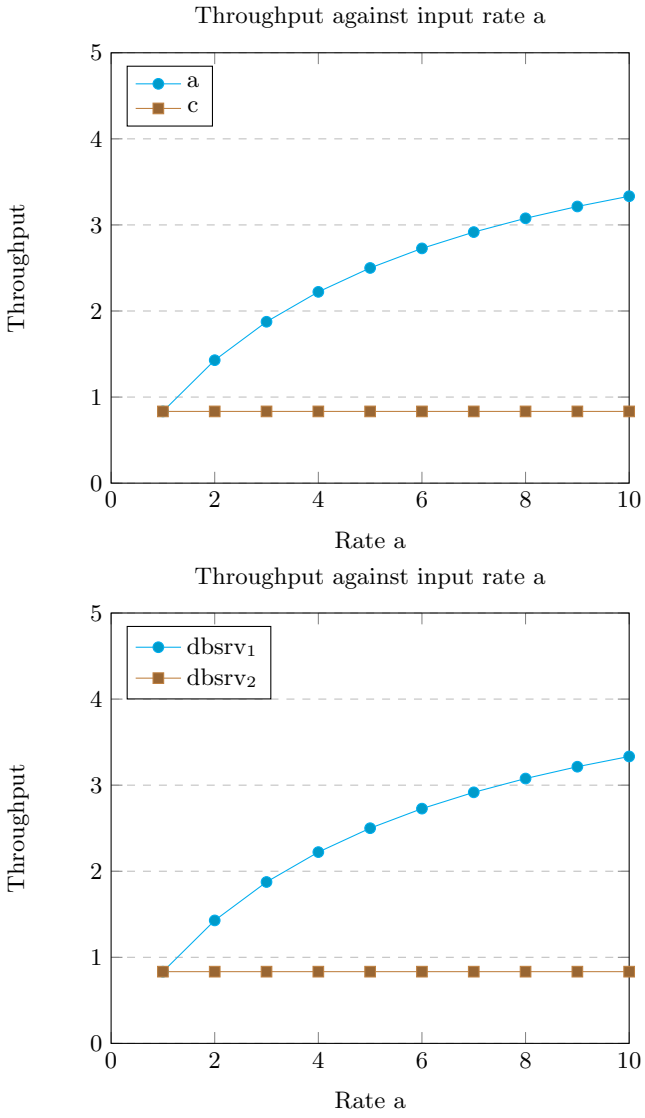


Fig. 9. Distributed database with replication PEPA model

$$
\begin{aligned}
a &= 1.0 - 10.0 \\
c &= 1.0 \\
d &= 1.0 \\
db &= 5.0 \\
Website &\stackrel{def}{=} (book_a, a).Website + (book_c, c).Website + (book_d, d).Website \\
DB_1 &\stackrel{def}{=} (book_a, \top).DBsrv_1 + (book_c, \top).DBsrv_1 \\
DBsrv_1 &\stackrel{def}{=} (dbsrv_1, \top).DB_1 \\
DB_2 &\stackrel{def}{=} (book_c, \top).DBsrv_2 + (book_d, \top).DBsrv_2 \\
DBsrv_2 &\stackrel{def}{=} (dbsrv_2, \top).DB_2 \\
DB_3 &\stackrel{def}{=} (book_d, \top).DBsrv_3 + (book_a, \top).DBsrv_3 \\
DBsrv_3 &\stackrel{def}{=} (dbsrv_3, \top).DB_3 \\
Service_1 &\stackrel{def}{=} (dbsrv_1, db).Service_1 \\
Service_2 &\stackrel{def}{=} (dbsrv_2, db).Service_2 \\
Service_3 &\stackrel{def}{=} (dbsrv_3, db).Service_3 \\
Website &\underset{book_a, book_c, book_d}{\bowtie} DB_1 \parallel DB_2 \parallel DB_3 \underset{dbsrv_1, dbsrv_2, dbsrv_3}{\bowtie} Service_1 \parallel Service_2 \parallel Service_3
\end{aligned}
$$

Table 2. Distributed database with replication experimental results

Rate	Throughput					
a	$book_a$	$book_c$	$book_d$	$dbsrv_1$	$dbsrv_2$	$dbsrv_3$
1	0.95	0.95	0.95	0.95	0.95	0.95
2	1.82	0.94	0.94	1.34	1	1.34
3	2.58	0.92	0.92	1.68	1.05	1.68
4	3.24	0.9	0.9	1.98	1.08	1.98
5	3.82	0.89	0.89	2.24	1.11	2.24
6	4.32	0.88	0.88	2.46	1.14	2.46
7	4.75	0.87	0.87	2.66	1.17	2.66
8	5.13	0.86	0.86	2.83	1.19	2.83
9	5.47	0.85	0.85	2.98	1.2	2.98
10	5.77	0.84	0.84	3.11	1.22	3.11

6.3 Shared middleware queue

Fig. 10. Distributed database with replication experimental results

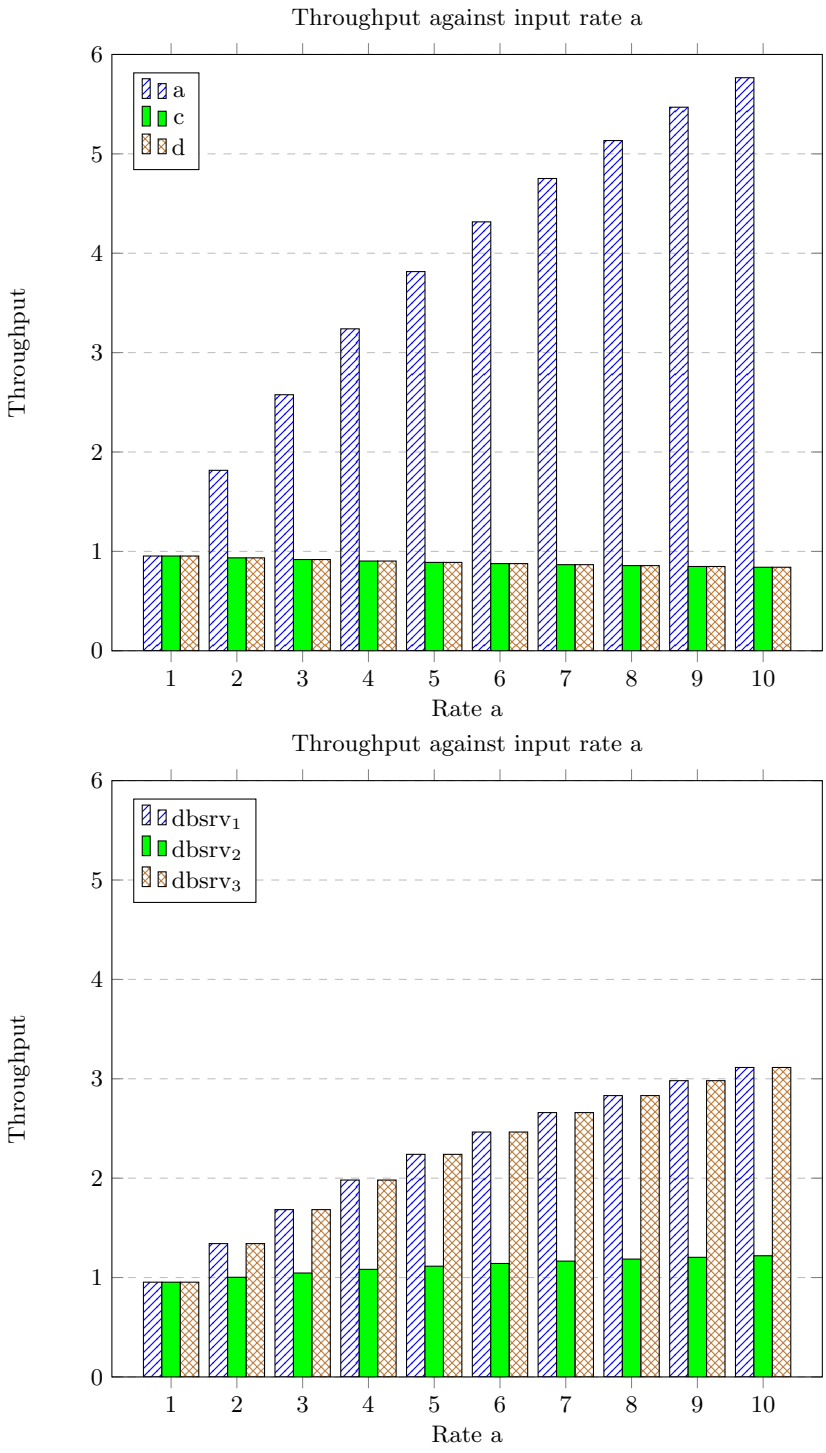
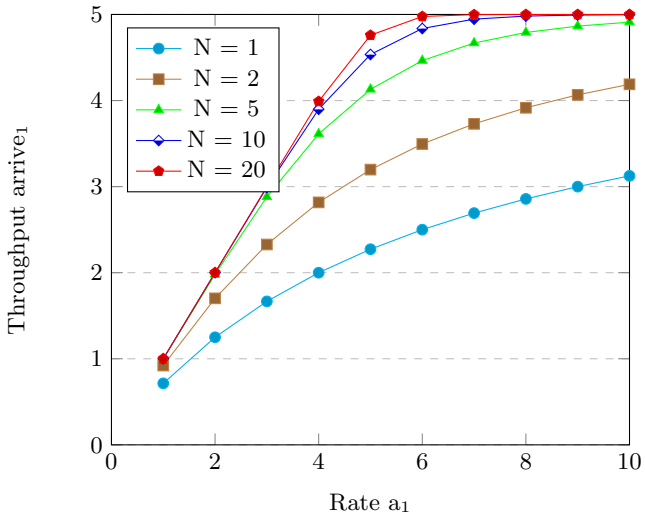


Fig. 11. Generic shared queue PEPA model

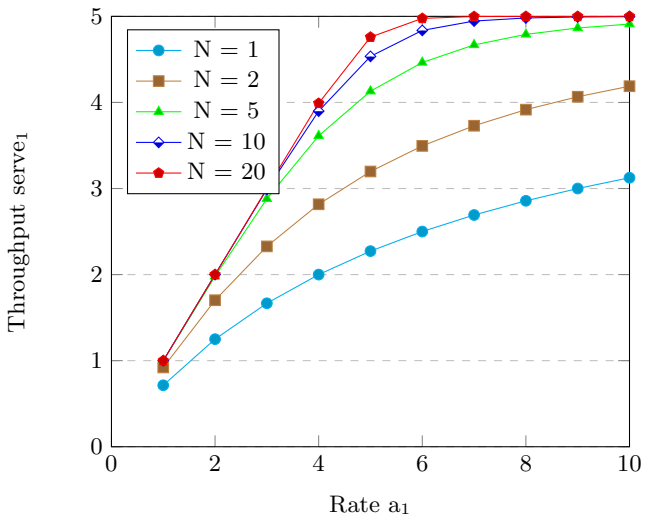
$$
\begin{aligned}
a_1 &= 1.0 - 10.0 \\
s_1 &= 5.0 \\
a_2 &= 1.0 \\
s_2 &= 5.0 \\
Arrival_1 &\stackrel{def}{=} (arrive_1, a_1).Arrival_1 \\
Service_1 &\stackrel{def}{=} (serve_1, s_1).Service_1 \\
Arrival_2 &\stackrel{def}{=} (arrive_2, a_2).Arrival_2 \\
Service_2 &\stackrel{def}{=} (serve_2, s_2).Service_2 \\
Q_0 &\stackrel{def}{=} (arrive_1, \top).Q_1 + (arrive_2, \top).Q_2 \\
Q_1 &\stackrel{def}{=} (serve_1, \top).Q_0 \\
Q_2 &\stackrel{def}{=} (serve_2, \top).Q_0 \\
Arrival_1 &\underset{arrive_1}{\bowtie} Q_0[N] \underset{serve_1}{\bowtie} Service_1 \underset{arrive_2}{\bowtie} Arrival_2 \underset{serve_2}{\bowtie} Service_2
\end{aligned}
$$

Fig. 12. Generic shared queue experimental results

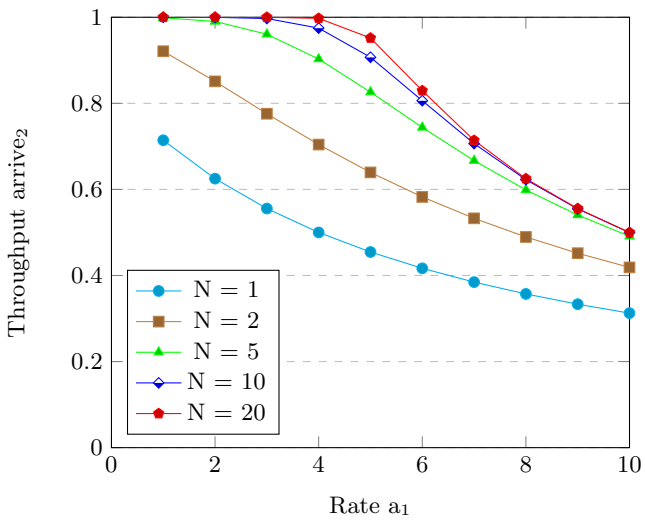
Throughput of arrive_1 against input rate a_1 for different queue lengths N



Throughput of serve_1 against input rate a_1 for different queue lengths N



Throughput of arrive_2 against input rate a_1 for different queue lengths N



7 PEPA System Models

7.1 Simple microservices

Fig. 13. Simple microservices PEPA model

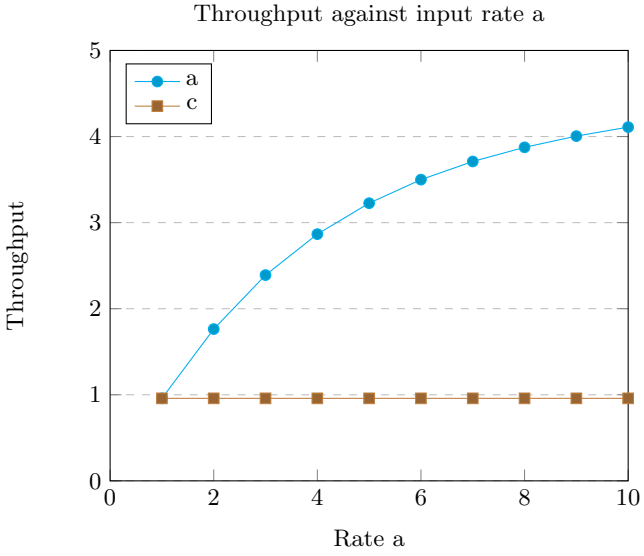
$$
\begin{aligned}
a &= 1.0 - 10.0 \\
c &= 1.0 \\
w &= 100.0 \\
db &= 5.0 \\
Website &\stackrel{def}{=} (book_a, a).Website + (book_c, c).Website \\
Worker_A &\stackrel{def}{=} (book_a, \top).WorkerSrv_A \\
WorkerSrv_A &\stackrel{def}{=} (worker_a, \top).Worker_A \\
Worker_C &\stackrel{def}{=} (book_c, \top).WorkerSrv_C \\
WorkerSrv_C &\stackrel{def}{=} (worker_c, \top).Worker_C \\
DB_1 &\stackrel{def}{=} (worker_a, w).DBsrv_1 \\
DBsrv_1 &\stackrel{def}{=} (dbsrv_1, db).DB_1 \\
DB_2 &\stackrel{def}{=} (worker_c, w).DBsrv_2 \\
DBsrv_2 &\stackrel{def}{=} (dbsrv_2, db).DB_2 \\
Service_1 &\stackrel{def}{=} (dbsrv_1, db).Service_1 \\
Service_2 &\stackrel{def}{=} (dbsrv_2, db).Service_2 \\
Service_1 &\underset{dbsrv_1}{\bowtie} DB_1 \underset{worker_a}{\bowtie} Worker_A \underset{book_a}{\bowtie} Website \underset{book_c}{\bowtie} Worker_C \underset{worker_c}{\bowtie} DB_2 \underset{dbsrv_2}{\bowtie} Service_2
\end{aligned}
$$

See the experimental results in Table 3.

Table 3. Simple microservices experimental results

Rate	Throughput					
a	$book_a$	$book_c$	$dbsrv_1$	$dbsrv_2$	$worker_a$	$worker_c$
1	0.96	0.96	0.96	0.96	0.96	0.96
2	1.76	0.96	1.76	0.96	1.76	0.96
3	2.39	0.96	2.39	0.96	2.39	0.96
4	2.87	0.96	2.87	0.96	2.87	0.96
5	3.23	0.96	3.23	0.96	3.23	0.96
6	3.5	0.96	3.5	0.96	3.5	0.96
7	3.71	0.96	3.71	0.96	3.71	0.96
8	3.87	0.96	3.87	0.96	3.87	0.96
9	4.01	0.96	4.01	0.96	4.01	0.96
10	4.11	0.96	4.11	0.96	4.11	0.96

Fig. 14. Simple microservices experimental results



7.2 Shared queue and distributed database

See the experimental results in Table 4.

Table 4. Shared queue and distributed database experimental results

Rate	Throughput					
a	$book_a$	$book_c$	$dbsrv_1$	$dbsrv_2$	$queue_a$	$queue_c$
1	1	1	1	1	1	1
2	2	1	2	1	2	1
3	2.99	1	2.99	1	2.99	1
4	3.9	0.97	3.9	0.97	3.9	0.97
5	4.47	0.89	4.47	0.89	4.47	0.89
6	4.69	0.78	4.69	0.78	4.69	0.78
7	4.74	0.68	4.74	0.68	4.74	0.68
8	4.76	0.59	4.76	0.59	4.76	0.59
9	4.76	0.53	4.76	0.53	4.76	0.53
10	4.76	0.48	4.76	0.48	4.76	0.48

7.3 Shared queue and distributed database with replication

See the experimental results in Table 5.

Fig. 15. Shared queue and distributed database

$$
\begin{aligned}
a &= 1.0 - 10.0 \\
c &= 1.0 \\
q &= 100.0 \\
db &= 5.0 \\
Website &\stackrel{def}{=} (book_a, a).Website + (book_c, c).Website \\
Q_0 &\stackrel{def}{=} (book_a, \top).Q_A + (book_c, \top).Q_C \\
Q_A &\stackrel{def}{=} (queue_a, \top).Q_0 \\
Q_C &\stackrel{def}{=} (queue_c, \top).Q_0 \\
DB_1 &\stackrel{def}{=} (queue_a, q).DBsrv_1 \\
DBsrv_1 &\stackrel{def}{=} (dbsrv_1, db).DB_1 \\
DB_2 &\stackrel{def}{=} (queue_c, q).DBsrv_2 \\
DBsrv_2 &\stackrel{def}{=} (dbsrv_2, db).DB_2 \\
Service_1 &\stackrel{def}{=} (dbsrv_1, db).Service_1 \\
Service_2 &\stackrel{def}{=} (dbsrv_2, db).Service_2 \\
Website &\underset{book_a, book_c}{\bowtie} Q_0[10.0] \underset{queue_a, queue_c}{\bowtie} DB_1 \parallel DB_2 \underset{dbsrv_1, dbsrv_2}{\bowtie} Service_1 \parallel Service_2
\end{aligned}
$$

Fig. 16. Shared queue and distributed database with replication

$$
\begin{aligned}
a &= 1.0 - 10.0 \\
c &= 1.0 \\
d &= 1.0 \\
q &= 100.0 \\
db &= 5.0 \\
Website &\stackrel{def}{=} (book_a, a).Website + (book_c, c).Website + (book_d, d).Website \\
Q_0 &\stackrel{def}{=} (book_a, \top).Q_A + (book_c, \top).Q_C + (book_d, \top).Q_D \\
Q_A &\stackrel{def}{=} (queue_a, \top).Q_0 \\
Q_C &\stackrel{def}{=} (queue_c, \top).Q_0 \\
Q_D &\stackrel{def}{=} (queue_d, \top).Q_0 \\
DB_1 &\stackrel{def}{=} (queue_a, q).DBsrv_1 + (queue_c, q).DBsrv_1 \\
DBsrv_1 &\stackrel{def}{=} (dbsrv_1, \top).DB_1 \\
DB_2 &\stackrel{def}{=} (queue_c, q).DBsrv_2 + (queue_d, q).DBsrv_2 \\
DBsrv_2 &\stackrel{def}{=} (dbsrv_2, \top).DB_2 \\
DB_3 &\stackrel{def}{=} (queue_d, q).DBsrv_3 + (queue_a, q).DBsrv_3 \\
DBsrv_3 &\stackrel{def}{=} (dbsrv_3, \top).DB_3 \\
Service_1 &\stackrel{def}{=} (dbsrv_1, db).Service_1 \\
Service_2 &\stackrel{def}{=} (dbsrv_2, db).Service_2 \\
Service_3 &\stackrel{def}{=} (dbsrv_3, db).Service_3 \\
Website &\underset{book_a, book_c, book_d}{\bowtie} Q_0[10.0] \underset{queue_a, queue_c, queue_d}{\bowtie} DB_1 \parallel DB_2 \parallel DB_3 \underset{dbsrv_1, dbsrv_2, dbsrv_3}{\bowtie} \\
&\quad Service_1 \parallel Service_2 \parallel Service_3
\end{aligned}
$$

Table 5. Shared queue and distributed database with replication experimental results

Rate	Throughput								
a	$book_a$	$book_c$	$book_d$	$dbsrv_1$	$dbsrv_2$	$dbsrv_3$	$queue_a$	$queue_c$	$queue_d$
1	1	1	1	1	1	1	1	1	1
2	2	1	1	1.46	1.08	1.46	2	1	1
3	3	1	1	1.92	1.16	1.92	3	1	1
4	4	1	1	2.38	1.24	2.38	4	1	1
5	5	1	1	2.84	1.32	2.84	5	1	1
6	5.98	1	1	3.29	1.4	3.29	5.98	1	1
7	6.93	0.99	0.99	3.72	1.47	3.72	6.93	0.99	0.99
8	7.76	0.97	0.97	4.09	1.51	4.09	7.76	0.97	0.97
9	8.4	0.93	0.93	4.38	1.51	4.38	8.4	0.93	0.93
10	8.83	0.88	0.88	4.56	1.47	4.56	8.83	0.88	0.88

7.4 Comparison

The system results are compared in Table 6.

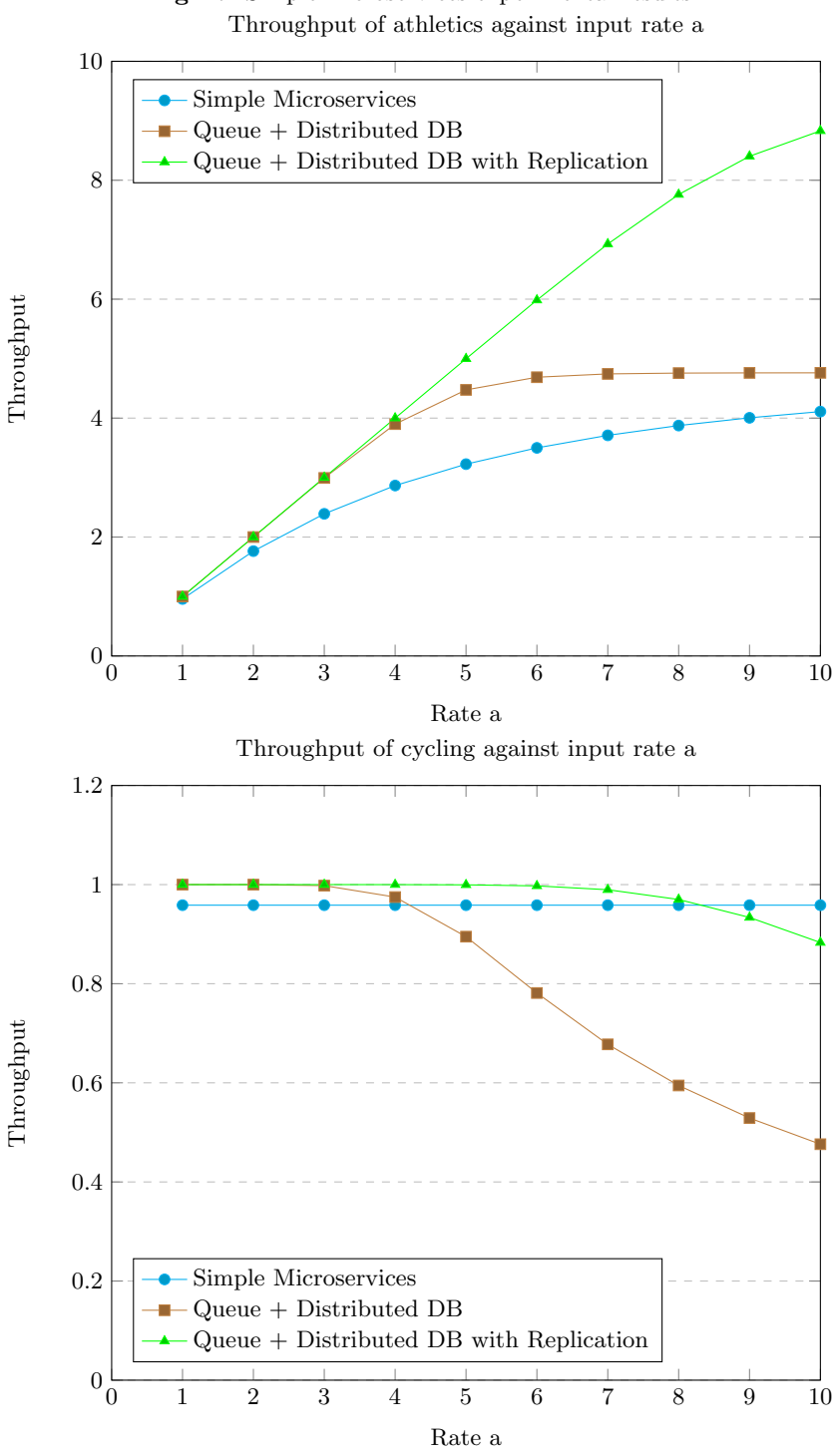
This shows that the simple microservices system does a good job of isolating the skewed demand from the rest of the system, but it is an inefficient use of the database resources. The actual throughput of the athletics demand is limited to its database's throughput, while the spare capacity of the cycling database goes unused. Using a distributed database with replication by contrast uses the capacity of two database nodes to serve the skewed demand, so that the actual throughput is much closer to the desired value.

(NOTE: the replication model uses 3 nodes, the others use 2 - need to compare like with like. Try all with 3 or replication with 2?)

Table 6. Comparison of system results

Rate	Microservices		Queue + Distributed DB		Queue + DB with Replication	
a	athletics	cycling	athletics	cycling	athletics	cycling
1	0.96	0.96	1	1	1	1
2	1.76	0.96	2	1	2	1
3	2.39	0.96	2.99	1	3	1
4	2.87	0.96	3.9	0.97	4	1
5	3.23	0.96	4.47	0.89	5	1
6	3.5	0.96	4.69	0.78	5.98	1
7	3.71	0.96	4.74	0.68	6.93	0.99
8	3.87	0.96	4.76	0.59	7.76	0.97
9	4.01	0.96	4.76	0.53	8.4	0.93
10	4.11	0.96	4.76	0.48	8.83	0.88

Fig. 17. Simple microservices experimental results



8 Built systems

Reference to github at [22]

General design decisions:

Cassandra [14][3] database. Create a Dbstress program and measured throughput of Cassandra node at 130 queries per second.

Measurement using Coda Hale Metrics [7].

Load testing using Apache JMeter [4].

8.1 Simple microservices

RESTful APIs using Java Spring [19].

Implemented a
control API which doesn't access the database.

Use JMeter with Poisson random timer (negative exponential distribution) with Cycling at a constant 10 threads/users and Athletics ramping up from 10-100 in steps of 10, so the desired demand is 20-200 requests per second.

Run the experiment 5 times and average the results (taking the maximum rolling 1 minute average for each number of users).

See the experimental results in Table 7.

Control shows that throughput approaches demand (difference likely to be due to random distribution, network latency, etc). However the Athletics demand is throttled by the database throughput. The Cycling throughput is unaffected by the Athletics demand.

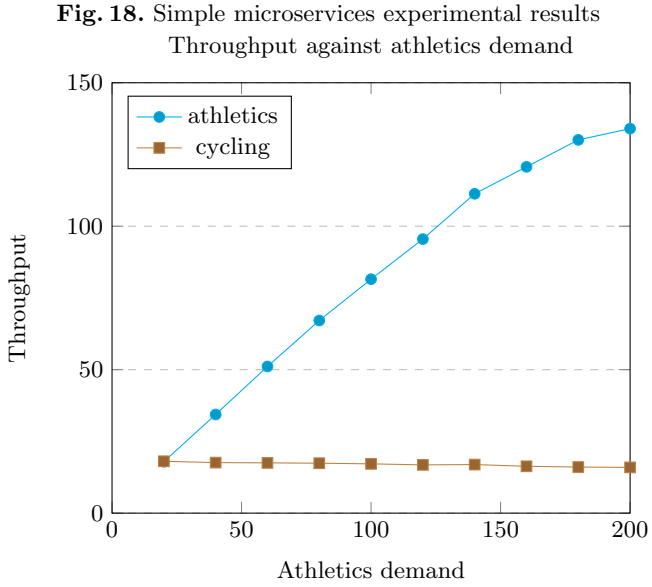
Table 7. Simple microservices experimental results

Athletics				Cycling			
users	rate	search	control	users	rate	search	control
10	20	17.92	19.286	10	20	18.076	19.252
20	40	34.386	37.672	10	20	17.614	18.992
30	60	51.114	56.442	10	20	17.522	18.962
40	80	67.132	74.61	10	20	17.402	18.754
50	100	81.54	92.586	10	20	17.176	18.732
60	120	95.518	111.598	10	20	16.824	18.7
70	140	111.298	131.43	10	20	16.928	18.83
80	160	120.698	150.494	10	20	16.326	18.852
90	180	130.088	168.29	10	20	16.062	18.826
100	200	134.01	185.846	10	20	15.936	18.718

8.2 Shared queue middleware

8.3 Distributed database with replication

Fig. 18. Simple microservices experimental results



9 Conclusion and Future Work

...

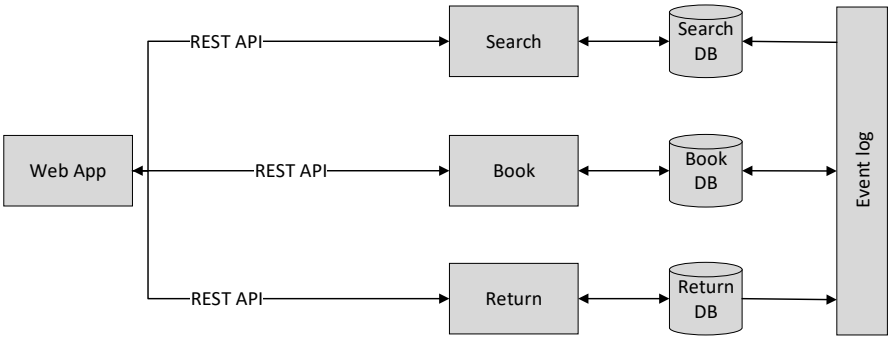
An interesting area of future work might be in using the modelling techniques in adaptive algorithms. A model might be used as a policy for elastic scaling, and compared with the performance of other right-sizing strategies; control theory, machine learning and other model based techniques including statistical.

9.1 Operational microservices

A more 'natural' microservices architecture partitions the system by operation (Book, Search, Return) with a separate database for each. The databases maintain eventual consistency via an event streaming application e.g. using Kafka.

1. Book is an event producer and consumer (produces when a ticket is booked, consumes returned tickets).
2. Search is an event consumer (consumes the state of tickets that are booked and returned).
3. Return is an event producer (produces returned tickets).

Fig. 19. Operational microservices architecture



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