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Performance Modeling and Analysis of a Database Server with Write-Heavy Workload

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Abstract. Resource-optimization of the infrastructure for service oriented applications require accurate performance models. In this paper we investigate the performance dynamics of a MySQL/InnoDB database server with write-heavy workload. The main objective of our investigation was to understand the system dynamics due to the buffering of disk operations that occurs in database servers with write-heavy workload. In the paper, we characterize the traffic and its periodic anomalies caused by flushing of the buffer. Further, we present a performance model for the response time of the requests and show how this model can be configured to fit with actual database measurements.

Keywords: performance modeling, service-oriented analysis, database server, admission control.

1 Introduction

The processing and control of service-oriented applications, as web applications, mobile service management systems, media distribution applications, etc., are usually deployed on an infrastructure of server clusters. The rate at which the requests arrive can vary heavily both during a single day and during longer periods, due to user behavior patterns. Scaling for the worst traffic peaks can be expensive though and will result in most of the capacity being unused most of the time. Capacity planning and resource optimization is therefore needed, which require the design of accurate performance models that capture the system dynamics in high loads.

Previous work on control systems for service-oriented applications and systems has mainly focused on applications with CPU-intensive workload, for example web server systems and databases with read-only requests. For CPU-intensive workloads previous work has shown that the performance dynamics are accurately captured by a single server queue model, see for example, [1] and [4]. However, for applications including large databases (too large to store in main memory), hard drive dynamics will influence the performance dynamics

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in high loads. Typically the application will need to read data from disk on every database read. Write operations are however often buffered in the server to make them more efficient. For example, in [7] the authors examine different buffering/caching techniques for use with NFS (Network File System).

Writing to persistent media is often a slow process which should be avoided if possible. Further, writing performance is also affected by certain rules of locality. For example, writing sequential data to a hard drive can be many times faster than writing to random sectors. By buffering writes and completing them in sequential order, the writes are executed more efficiently. However, when the buffered writes are actually flushed to disk, the response times of the normal flow of traffic are heavily influenced. The server becomes occupied by work other than that of the normal flow of requests. Therefore, the system dynamics of server systems with write-heavy workload cannot be captured with the single server queueing models proposed for CPU-intensive workload.

In this paper we examine write-heavy workload on a MySQL database server using the engine InnoDB. The database is stored on a magnetic hard drive which results in the database server having to employ heavy buffering to speed up the writes. In the paper, the characteristics of write-heavy workload is examined. We develop a model and configure the model parameters using experiments in our testbed. We show in experiments that the model accurately captures the periodic anomalies that occur when the system needs to empty the buffer.

In Section 2 we present the lab environment used for the database measurements. In Section 3 we characterize the database traffic. In Section 4 we present the model developed for the traffic and discuss how to configure it. We also validate the model with lab measurements.

2 System Description

In this paper, we investigate the dynamics of database servers with write-heavy workload. The models and methods proposed in the paper are based on the results from experiments in our testbed. In this section, we first give an introduction to dirty page caching, which is used in many operative systems and database systems to improve the latencies when writing to disk. Further, we describe our testbed.

2.1 Page Cache

One common way to implement write-buffering is using a page cache. The storage is divided into fixed size pages. When data is written, the page being written to is first read from storage and then changed in memory and marked as dirty. Dirty pages are then kept in memory for some time before it is written back to disk and marked clean.

MySQL has several different storage engines, among them MyISAM and InnoDB. MyISAM has no built in cache for data. Instead it relies on the page caching features of the operating system. In this paper, we have used the storage engine InnoDB, which has its own system of pages which are buffered in the so called *buffer pool*. Pages are written to and read from disk directly using one of several methods for directly accessing the block storage device, bypassing the operating system page cache. The InnoDB engine tries to estimate the speed of the block device and the rate at which new pages are made dirty and from that it calculates how often and how many dirty pages need to be written to disk.

2.2 Testbed

We have used an experimental testbed. The testbed consists of one computer acting as traffic generator, and one database server. The computers were connected with a standard Ethernet switch.

The traffic generator was executed on an AMD Phenom II X6 1055T at 2.8 GHz with 4 GB main memory. The operating system was 64-bit Ubuntu 10.04.4 LTS. The traffic generator was implemented in Java, using the JDBC MySQL connector. The traffic generator used 200 working threads and generated MySQL queries according to a Poisson process with average rate λ queries per second. The behavior of the traffic generator was validated in order to guarantee that it was not a bottleneck in the experiments.

The database server had a 2.0 GHz Celeron processor and 256 MB main memory. The database files are on the system disk which is a standard 3.5" hard drive. It runs the 32-bit version of Ubuntu 10.04.4 LTS (Linux 2.6) and MySQL Server 5.1.41. The InnoDB engine was configured with 16 MB of buffer pool.

The structure of the relations in the database comes from the scalable Wisconsin Benchmark [6] and it has $n = 10^7$ tuples. The structure of the queries used all follow the following pattern:

```
UPDATE <relation> SET unique3=? WHERE unique1=?;
```

The question marks are replaced with uniformly distributed pseudo-random integers in the interval $[0, n[$. This query changes the value of one of the integer attributes of a random tuple.

3 Performance Characterization

In order to investigate the dynamics of a database server with write-heavy workload, we performed a series of experiments in our testbed presented in Section 2. In all the experiments, all requests included a MySQL UPDATE query, causing the system to write one database element to disk. Figure 1 illustrates the system behavior during an experiment where the average arrival rate, λ, was 25 requests per second. The figure shows that the system periodically have to pause the normal work and instead focus on the buffered dirty pages for some time. While the normal response times are below 0.2 seconds, response times of up to one second occur, because of these pauses. The number of requests that have these high response times are affected by the fact that requests are sent and queued up, even when the server is busy with the dirty pages.

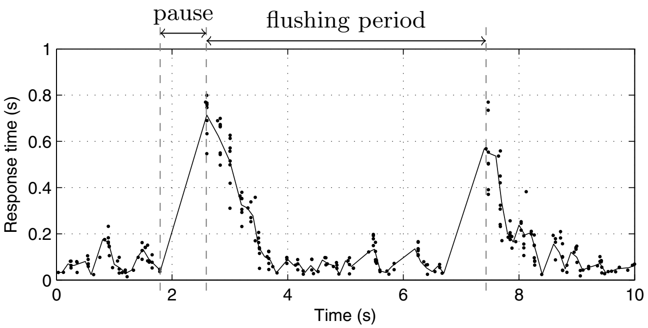

Fig. 1. Response time graph of the InnoDB system, UPDATEs only, with constant Poisson-traffic, $25/s$

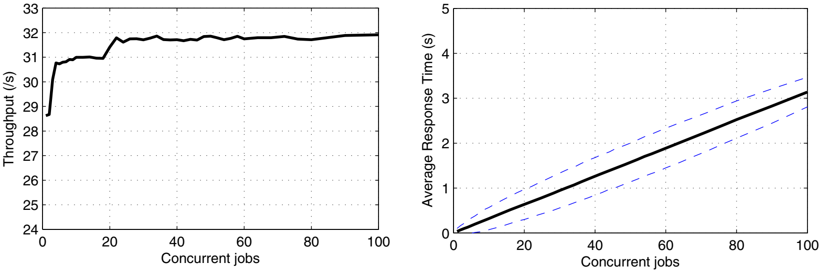

Fig. 2. N/P graph (left) and N/T graph (right) of the InnoDB system, UPDATEs only. Every point was run for 900 seconds.

The average response time as a function of the number of concurrent jobs is from now on referred to as the N/T graph. The throughput as a function of the number of concurrent jobs inside the server at all times is from now on referred to as the N/P graph. The N/T and N/P graphs for our system are shown in Figure 2.

It can be seen in the N/P graph that for a very small number of concurrent requests (up to 10), the throughput is much lower than for a higher number of concurrent requests. This is likely (to some extent, at least) because of network delays and buffering in lower protocol layers.

During high loads, the dirty page cache will be written to disk periodically. The period between two occurrences of disk writing, called the flushing period, depends on the arrival rate. As can be seen in Figure 1, an arrival rate of 25 requests per second results in a flushing period of approximately 5 seconds. Figure 3 shows the response times during an experiment with an average arrival rate of 12.5 requests per second, which results in a flushing period of approximately 10 seconds and an experiment with an average arrival rate of 18.75 requests per

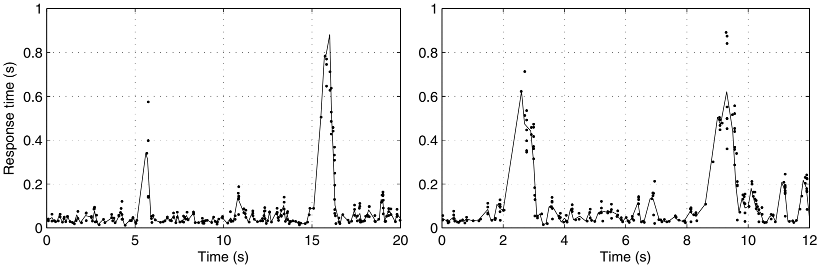

Fig. 3. Response time graph of the InnoDB system, UPDATEs only, with constant Poisson-traffic, 12.5/s (left), 18.75/s (right)

second, which results in a flushing period of approximately 7 seconds. These experiments show that the period between flushes of the buffer is inversely proportional to the arrival rate, since

$$25 \cdot 5 \approx 12.5 \cdot 10 \approx 18.75 \cdot 7 \tag{1}$$

4 Performance Model

In this section, we describe our proposed performance model, which captures the dynamics of our system.

4.1 Model Description

We propose a queuing network model shown in Figure 4. The model consists of three parts, a *Network delay (ND)*, a *Job queue (JQ)*, and a *Dirty page buffer (DPB)*. The ND is used to model the reduced throughput at very low numbers of concurrent requests. After passing the ND, requests enter the JQ. As requests are processed by the server, the user is acknowledged and one dirty page equivalent is placed in the DPB. The DPB has a fixed maximum size and when that is reached the server stops processing requests in the JQ and starts to process dirty pages from the DPB instead until the DPB is empty. When the DPB is empty, the server switches back and continues to work on the JQ.

As a request enters the server it is assigned a processing time. Our experiments have shown that the processing time for a request in the JQ and the processing

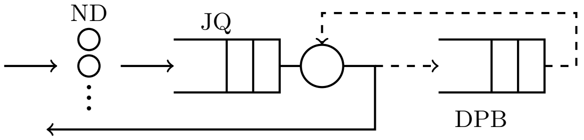

Fig. 4. The Model

time for one dirty page equivalent (T_{proc} and T_{dp}, respectively) can be modeled by an exponential distribution. Further, the time each request spends in the ND (T_{nd}) can be modeled as a sum of a constant and an exponentially distributed random number.

Further, the maximum size of the DPB is denoted DPB_{max} and it is a constant integer number. The maximum length of the DPB and one dirty page equivalent per request determine the inverse proportionality between flush period time and arrival rate shown in Equation (1).

4.2 Parameter Configuration

The model has the following parameters which must be configured:

$$T_{nd} \text{ distribution}, \mathrm{E}\left[T_{proc}\right], \mathrm{E}\left[T_{dp}\right], DPB_{max}$$

The maximum capacity of the DPB can be determined by measuring the period of flushes, p, for some high traffic with throughput P. Since p determines how often the DPB needs to be flushed and P determines how fast new dirty pages are put into the DPB, the max length of the DPB is $DPB_{max} = P \cdot p$.

By examining some experiment with high number of concurrent requests, a lower limit on the duration of the pause in processing ($\min(T_{pause})$) can be determined. By measuring the time between request departures and filtering out those that are $> \min(T_{pause})$, an average on the pause duration (T_{pause}) can be estimated. From these results, the mean of the dirty page processing time is given by $\mathrm{E}\left[T_{dp}\right] = T_{pause} \cdot {DPB_{max}}^{-1}$.

With the knowledge of T_{dp} and the throughput (P) when keeping high number of concurrent requests, the average processing time T_{proc} can be determined. By assuming that the server is always busy, the throughput can be assumed to be inversely proportional to the total processing time spent on every request. Since the server spends a total of $T_{proc} + T_{dp}$ time on every request, the average for the processing time is given by $\mathrm{E}\left[T_{proc}\right] = P^{-1} - \mathrm{E}\left[T_{dp}\right]$.

The distributions used for the network delay (T_{nd}) are determined by performing an experiment keeping one concurrent request in the system. The response times T are measured. Since the total response time of one single request is the sum of the network delay, the processing time plus that it has a probability of ${DPB_{max}}^{-1}$ to get $DPB_{max} \cdot T_{dp}$ added, the average network delay is given by $\mathrm{E}\left[T_{nd}\right] = \mathrm{E}\left[T\right] - \mathrm{E}\left[T_{proc}\right] - \mathrm{E}\left[T_{dp}\right]$.

4.3 Model Validation

In order to validate the proposed model, we developed a discrete-event simulation program, written in Java. By using the configuration method described in Section 4.2, we can conclude that the values in Table 1 make a good fit for our database server described in Section 2.

In Figure 5, the cumulative distribution function of the response times from an experiment with arrivals following the Poisson process with an average rate of

Table 1. Fitted model parameters

T_{proc}	Exp(0.0269)
T_{nd}	0.0025 + Exp(0.00049)
DPB_{max}	111
T_{dp}	Exp(0.00433)

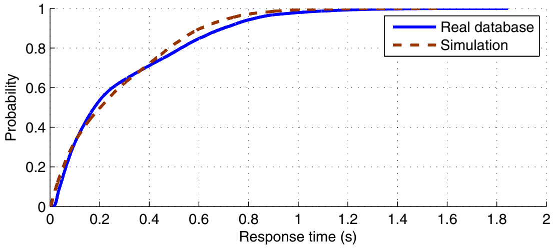

Fig. 5. Cumulative distribution function of response times from InnoDB database system, and the proposed model. Traffic is generated with a Poisson process with average 28 requests per second.

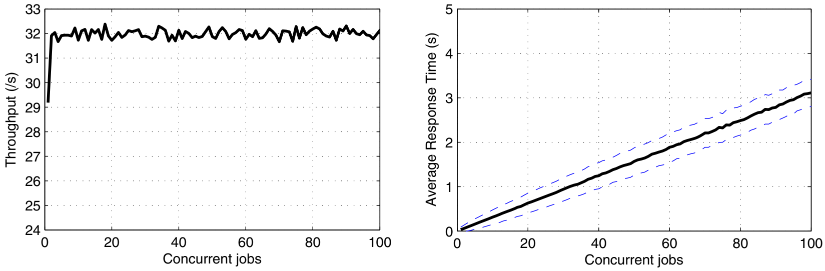

Fig. 6. N/T (top) and N/P (bottom) graph from the simulation of the model. Every number of parallel jobs was run for 900 seconds.

28 requests per second, are shown. One graph shows the results from a testbed experiment and one graph shows the results from the discrete-event simulation of the model. As can be seen in the graphs, the distribution of response times in the model fits accurately with the database experiment.

Further, the N/T and N/P graphs for the simulation is shown in Figure 6. These graphs can be compared with the graphs of the corresponding experiments, shown in Figure 2. The graphs show that the proposed model fits well with the real system.

5 Conclusions

Many service-oriented applications use database servers for storing data. When the applications have a workload that writes to a database stored on hard drives, disk writing optimizations introduce performance dynamics that may be difficult to monitor and control. Traditional queuing system models do not suffice when the response times show these periodic anomalies. In this paper, we have developed a performance model based on queueing systems for database servers with write-heavy workload. We validate our model using experiments in a testbed.

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